Pivotal Visualization

Pivotal Visualization: A Design Method to Enrich Visual Exploration

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THESIS

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Wei Li

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voorzitter	prof.dr. L. Chen
1e promotor	dr. M. Funk.
	prof.dr.ir. A.C. Brombacher.
Promotiecommissieleden	dr. M. Funk
	prof.dr.ir. A.C. Brombacher
	prof.dr.ir. J.J. van Wijk
	prof.dr. K.-.L. Ma (UC Davis, Computer Science)
	prof.dr.ir. F. van Langevelde (Wageningen University, Environmental Sciences)
	prof.dr. R. Bernhaupt

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Pivotal Visualization

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Preface

2015 was an important year in my life because that is the year when I have decided to go for PhD research and luckily took the opportunity at the department of Industrial Design of TU/e. Researching into an academic topic is challenging as producing scientific content is very much different than proposing a design solution. This means, in addition to acquiring new skills, a mindset shift is also necessary. At the very beginning, I was not very sure about how this extensive hard work will lead into. But I was quite sure this would be a totally different and challenging experience. Looking back from today, I'm thankful for this invaluable knowledge gained from a half year exchange program in TU/e prior to my PhD.

I was told that a PhD life is like a lone walk into the endless darkness. Unfortunately, that is true. I came to realize that the only way to generate useful knowledge is to dive into the vast unknowns and restlessly search for an insight. It was not easy. However, it helps to grow as a researcher. And the persistence slowly pays off.

Living in a different culture always gives me exceptional inspirations. But sometimes it also makes even the most trivial things hard. I was lucky because I was surrounded by the most supportive and most intelligent group of people I met in the Netherlands. First, I owe Mathias Funk, my first promoter, a great debt of thanks for his support and encouragement during my PhD. Mathias' knowledge and creativity seems to be boundless. From him, I learned to not only tackle difficult scientific problems, but also take charge and act proactively to cope with unexpected situations. Working with him is one of the most rewarding experiences in my PhD. Second, I must thank Aarnout C. Brombacher, my second promoter, without whom my research would be totally different. Aarnout is simply unbeatable, both intellectually and physically. His wisdom and kindness are my best source of inspiration. Apart from academic duties of my research projects, Aarnout set a role model for being a scholar as well as a leader at the same time. The opportunity to work with him is invaluable for any young researcher who wants to grow fast.

This final spot is reserved for my dearest parents in China. Their support is

long-lasting and spiritual. The encouragement from them overseas means a lot over my PhD years. My gratitude to them is beyond words.

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Introduction 1

Overview: *This chapter orients the reader to the topic of data visualization with historical examples. It enumerates the new features of visualizations under modern technological landscape to set the discussion context under which visualizations' role as augmenting human capacities is explained. The research questions of this thesis are put forward in the last section.*

1.1 Why Visualization?

Complexity poses challenges to understanding. It either slows down our sense-making or renders the task simply impossible. Visualization is a method to facilitate cognitive processes through visual deliberations. When confronting the complexity induced by a large amount of information, a pictorial representation usually helps to unfold the invisible associations and underlying patterns from scattered information. Data visualization in particular is the art of transforming such complexity into intuitive visual formats. Thanks to this, our essential abilities for data-related tasks such as comparisons [1], associations, or predictions, are empowered.

[1]: Grammel et al. (2010), "How Information Visualization Novices Construct Visualizations"

A common misconception about visualizations is they are constructed through computers or other digital facilities. However, the dependence on digital media is helpful but not integral. Technological advancements have changed both the design in terms of the final product as well as the development in terms of the authoring tool chain. Despite such a significant impact, the core function of data visualization remains constant — to let the meaning behind data surface. This is justified by the resemblance of working mechanisms in historical examples before the existence of digital technologies.

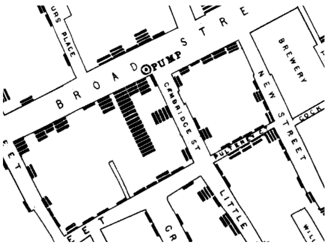


Figure 1.1: Snow's London cholera map: cholera cases counts in the neighborhood shown as bar stacks perpendicular to the streets.

Snow's cholera map shown in Figure 1.1 is one of the classics of its time. The visualization is designed to analyze the spread of epidemic during 1854 cholera outbreak in London. In the work he presented to the London Epidemiological Society, John Snow mapped the number of death cases as stacked bars perpendicular to the streets of affected households. The map exhibits the concentration effect of death cases in a spatial context, which leads to the suspicion around a pump at Broad Street. The hypothesis regarding the pump being the source of disease is later confirmed by the cessation of the epidemic after shutting it down. Without being a cartographer, Snow's visualization demonstrates the power of visual depiction which has revealed critical insights for decision-making.

Effective views of data not only aids the resolution of the problem but also brings us a different, likely a more pleasant, way of knowing. The more intuitive view of data paves the way for acquiring new knowledge to extend our conceptualization of the matter. But in the meanwhile, it can also give us the ability to avoid misconceptions or over-estimations accompanied by the caveat of over-simplification.

Table 1.1: Anscombe's quartet: four data sets

I		**II**		**III**		**IV**	
x	*y*	*x*	*y*	*x*	*y*	*x*	*y*
10	8.04	10	9.14	10	7.46	8	6.58
8	6.95	8	8.14	8	6.77	8	5.76
13	7.58	13	8.74	13	12.74	8	7.71
9	8.81	9	8.77	9	7.11	8	8.84
11	8.33	11	9.26	11	7.81	8	8.47
14	9.96	14	8.1	14	8.84	8	7.04
6	7.24	6	6.13	6	6.08	8	5.25
4	4.26	4	3.1	4	5.39	19	12.5
12	10.84	12	9.13	12	8.15	8	5.56
7	4.82	7	7.26	7	6.42	8	7.91
5	5.68	5	4.74	5	5.73	8	6.89

For example, descriptive statistics can provide quantitative summaries of data. But the application without sufficient discretion may lead to a distorted view of them. To demonstrate the possible misleading statistical descriptions, statistician Francis Anscombe [2] nominated four data sets (Table 1.1) which display distinctive distribution characteristics (Figure 1.2) yet show no difference in statistical features (Table 1.2). The comparison between the visualization and statistical profile makes

Table 1.2: Anscombe's quartet: statistical features

Property	Value	Accuracy
Mean of $\boldsymbol{x}$	9	exact
Sample variance of $\boldsymbol{x}$	11	exact
Mean of $\boldsymbol{y}$	7.5	0.01
Sample variance of $\boldsymbol{y}$	4.125	$\pm$ 0.003
Correlation	0.816	to 3 decimal places
Regression line	$\boldsymbol{y} = 3.00 + 0.500\boldsymbol{x}$	0.01 and 0.001 respectively
Coefficient	0.67	to 2 decimal places

it self-evident that the unique character of data can be easily overlooked without visual plots of data. The visualization of data in this case functions as an utility to re-examine the statistical outcomes with visual perceptions, which reveals the hidden disagreement between statistical description and nuanced visual patterns. The nominated data set is later remembered as Anscombe's Quartet, which reminds us the importance of visual awareness in data analyses to avoid careless interpretations. As visualizations provide an interface to our inherent visual pattern recognition ability, it makes leveraging this ability to apply discretion and restore a more accurate view of data more convenient.

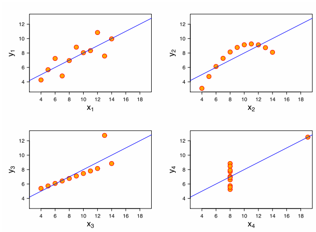


Figure 1.2: Anscombe's quartet: distinctive distribution of same statistic features.

[2]: Anscombe (1973), "Graphs in Statistical Analysis"

Comparing the two cases above, we can see that visualizations both improve the quantity of knowing, i.e. uncovering unknown connections, and quality of knowing, i.e. avoiding oversimplifications. These advantages are not limited in the few presented cases or domains. The wide applicable value can be further justified by examples such as Ibry's Visual Train Schedule [3] or Minard's visual history of Napoleon's Russian Campaign [4], ranging from commute planning to strategic rationales such as warfare investigation. Because of the wide applicability, we are intrigued to outline the underlying reasons

[3]: Marey (1885), *La méthode graphique dans les sciences expérimentales et principalement en physiologie et en médecine*

[4]: Tufte (1986), *The Visual Display of Quantitative Information*

explaining the core effectiveness of visualizations abstracted from aforementioned domains. To answer this question, it is helpful to look deep into how visualizations essentially work. Here we would like to unfold our brief elaboration on this issue, which will be expanded by the arguments afterwards.

Human beings are like other creatures. We are equipped with primitive senses and instincts to capture the things around us as we use physical abilities to navigate and cast our influence based on assumptions of the situation [5]. Thus, the connections with the world we make are results of the interplay of two processes — the perception and our influence upon the world, i.e. the process of making sense of the world and making changes to it accordingly. The visual system is a Darwinian gift for the first process. It efficiently describes a large array of objects around us and elevates them into patterns, based on which we form quick judgments and make informed actions.

[5]: Boyd et al. (2018), *A Discourse on Winning and Losing*

However, to make connections between two entities, there are boundaries and distances to overcome. If we use *distance* to symbolize the extent of involved challenges in perception and influence, the size of this *distance* depends on the very subject matter to perceive (or influence) and its compatibility with our innate abilities. For instance, infrared is useful to track heat sources, but such radiations are imperceptible to human eyes. Therefore, extra *distance* such as the utilization of specialized equipment needs to be considered. Like infrared to the human visual system, complex, chaotic, and abstract subjects are also difficult to comprehend with our innate abilities. This is when tool making becomes necessary to push our natural limits in making sense and casting influence over these matters. Visualization design is an essential step to aid the first process of sense-making.

To document a faithful description of a complex matter, data follow a human-defined schema to repetitively capture certain features of the subject. The provenance of data abstraction gives order and discreteness to the observed matter, providing the basic materials to shape our understanding of the subject. But the crystallization and accumulation of data also introduces an additional layer of overhead between our direct perception and the subject matter, increasing the *distance* between the two.

What makes data visualizations powerful is they enhance the perception from two ends — our primitive senses and the utility ease of data abstraction — to build a common ground between people and the data. On one hand, it connects closely with the data abstraction, modifying its format and changing the transformation parameters whenever necessary. On one hand, it employs the most intuitive communication means of visuals to bring complexities closer to our innate processing capacities, make reasoning with abstract information a more analogue process. Despite the extra engineering effort, visualizations actually narrows down the *distance* between complexity and perception from the human-centered perspective. So the view of complex matters is augmented to a faster and more insightful level.

1.2 Designing Computerized Visualization

Information technologies are casting a universal impact upon many facets in modern society, giving rise to a surge of data-enabled applications. The examples like these can be found in domains such as finance [6] or healthcare [7]. Technological advancements have not only eliminated the laborious manual efforts in recording, labeling, and organizing information, but also brought systemic disruptions throughout data collection, transmission, storage, retrieval, and visualization pipeline. The

[6]: Flood et al. (2016), "The Application of Visual Analytics to Financial Stability Monitoring"

[7]: Li et al. (2016), "MetricScalpel: Analyzing Diagnostic Outcomes with Exploratory Data Visualization"

new paradigm has contributed a significant abundance of data [8], of which the complexity is reflected by both the structure of data [9] and the size of data [10]. In addition to improved efficiency regarding collecting, processing, or distributing data, new technologies also give birth to apparatuses that expanded the landscape of data collection, unveiling unimagined research subjects such as atmospheric analysis [11], satellite tracking [12, 13], or oceanographic study [14, 15].

[8]: Kelling et al. (2009), "Data-Intensive Science"
[9]: Mutton et al. (2003), "Visualization of Semantic Metadata and Ontologies"
[10]: Althoff et al. (2017), "Large-Scale Physical Activity Data Reveal Worldwide Activity Inequality"
[11]: Kennedy et al. (2008), "Quantifying Uncertainty in the Biospheric Carbon Flux for England and Wales"
[12]: Benke et al. (2015), "Application of Geovisual Analytics to Modelling the Movements of Ruminants in the Rural Landscape Using Satellite Tracking Data"
[13]: McKenzie et al. (2016), "Assessing the Effectiveness of Different Visualizations for Judgments of Positional Uncertainty"
[14]: Arsenault et al. (2004), "A System for Visualizing Time Varying Oceanographic 3D Data"
[15]: Lewis et al. (2008), "Mapping Uncharted Waters"

Digitized information and data are essential to the modernization of communications. Either for scientific research or daily life, data have become a proxy for our perception and influence on the world. In most cases, the influence part is usually the ultimate goal to apply practical changes. But it only comes after sufficient knowledge is gained. Thus, the ability to "see" clearly urges us to divert more attention toward the sense-making of data. This means revamping the visualizations to suffice the demanding intensity of modern analyses is becoming more relevant as data collection technologies continue to evolve.

To build matching sense-making capacities, a few technological innovations are in sight. First, the cheap supply of (mobile) graphic processing power and display media promise the possibilities to fit visualization applications into any flexible format. It can easily be installed into office walls, street corners, or simply carried in the pockets. Second, digitized platforms permit dynamic updates on the graphic content based on the supplied data, meaning the appearances of visualization works are no longer fixed and static. Visualization designers create software to enable reusable charts and graphs that can be economically reproduced to accommodate different purposes and diverse user inputs [16, 17]. Seasoned drawing skills like cartographers are no longer mandatory. Instead, visualization design shift their attention toward identifying a category of tasks or services of an unvarying problem theme associated with the data type. This transformation creates a layer of flexibility

[16]: Sicat et al. (2019), "DXR"
[17]: Murphy (2013), "Data Visualization and Rapid Analytics"

between the data and the design. Visualizations are expected to accommodate and adapt to changing questions and fulfill compound missions in the new technological landscape.

1.3 Traits of Modern Visualization

Academic explorations and industrial iterations in the past decades have led to a few emerging traits in modern visualization design, providing guiding scaffolds to new studies in the field. These traits are prevalent in the design and implementation of recent visualization studies. Here we summarize the significant ones from the perspective of this thesis.

1) Modern visualizations leverage interactivity to exhibit the most relevant part of information. It is increasingly common that visualizing the entire data set is either unhelpful to viewers' sense-making or simply technically impossible due to the sheer size of data. For these cases, simplification methods are necessary. Implementing mechanisms into the visualization pipeline for a reduced data set can produce cleaner results based on it. After visual spaces are economically allocated to emphasize on the unique features data, it is necessary to support users' decision upon which patterns are more prominent in the final presentation. Therefore, visualizations need to follow a two-step combination of operations: performing transitions to expose details-on-demand [18] and use interactions to support the decision on which part to expose. Modern visualizations allow users to navigate, manipulate, aggregate, and assimilate data, and build up preliminary knowledge to guide follow-up explorations.

[18]: Shneiderman (1986), *Designing the User Interface*

2) The placement and role of machine automation is attracting (academic) interests in recent visualization design. State-of-the-art machine learning (ML) and artificial intelligence (AI) have enabled some autonomous high-level, pseudo-human pattern recognition abilities [19] from large data sets with minimum-to-no need for data reduction. The systems are designed to autonomously tune the models to improve their judgments [20], making them less dependent on human interventions. But the integration of ML and AI functionalities introduces caveats such as trust and transparency issues or the under-supply of steerability. Therefore, pure black-box systems are replaced with ones featuring visualization interfaces to moderate these caveats. The design of these visualization interfaces involves reimagining the relationships between data, human, and machine [21–23]. And a key role of visualizations in this endeavor is to give machine not only the abilities to extract machine-readable patterns from data and gradually convert them into categories and definitions [24], but also to translate the internal patterns into human-readable formats to avoid the caveats. Visualization design pertaining to this issue involves investigating the contextualized reasons why the system should not be fully automated and where to install the necessary visual, interactive steps so that judgments from human pattern recognition are respected.

[19]: Fan et al. (2016), "Approaching Human Level Facial Landmark Localization by Deep Learning"

[20]: Tian et al. (2019), *ELF OpenGo*

[21]: Wang et al. (2019), "Designing Theory-Driven User-Centric Explainable AI"

[22]: Peck et al. (2019), "Data Is Personal"

[23]: Amershi et al. (2019), "Guidelines for Human-AI Interaction"

[24]: Wright et al. (2010), "Sparse Representation for Computer Vision and Pattern Recognition"

3) Data are analyzed in a specific domain, where the corresponding visualization should be contextualized with the help of domain knowledge. Data are abstract representations of a domain-specific problem. Designing visualization for the data is not only about arranging a truthful representation of it, but also decoding abstract values to tangible ideas with meaningful references to the context. Even for general-purpose idioms like bar charts and box plots, customization to adapt the design to problem characteristics are necessary for successful interpretation [25]. The foundation of these efforts is the study of domain requirements and the consultancy from domain experts. The more complex the tasks are, the more extensiveness of investigation into the domain context is required. The domain knowledge

[25]: Streit et al. (2014), "Bar Charts and Box Plots"

is usually acquired along with the extensive domain studies consisting of a series of discussions to lay down verifiable pain-points in the current state and analytical gaps, which are to be addressed in the subsequent evaluation-iteration loops.

1.4 Visualization to Augment Human Capacity

Since the three aforementioned considerations in visualization design share the common dependence on man-machine relationships, the study of human factors is thus indispensable. But a general insight into this issue requires us to look beyond certain characters of a niche user group and their influence to the system. We need to focus on the fundamental meaning of visualizing data (either with the help of computers or not) and its impacts on man-machine relationships in a broader sense. An inspiration to this question can be found in an early ambition pioneered by Douglas Engelbart in 1962 [26, 27]. In the age when human-machine interaction is still in its infancy, Engelbart's vision indicates that systems can leverage externalized symbols and concepts to orchestrate sophisticated hierarchical structures by which human intellectual effectiveness is improved. In short, the design and development of modern digital tools serves a simple and explicit purpose — to augment human intellect.

[26]: Carter et al. (2017), "Using Artificial Intelligence to Augment Human Intelligence"
[27]: Engelbart (2001), "Augmenting Human Intellect: A Conceptual Framework (1962)"

Moreover, Engelbart has explicitly mentioned generating understanding through visual communication, balancing machine efficiency and human capability, and developing comprehension with methods such as hypothesis testing with human computer interaction [27], which significantly overlap with major themes in modern visualization design.

[27]: Engelbart (2001), "Augmenting Human Intellect: A Conceptual Framework (1962)"

Engelbart's legacy is continuously revisited [28, 29] after the

[28]: Digest (2016), *Elephant Footprint*
[29]: Bardini (2000), *Bootstrapping*

very proposal nearly half a century ago. We can see that the principle of augmenting human intelligence is still valuable and inspiring. However, due to the reasons stated above (§ · 1.2), the challenge in designing visuals and interactions to amplify human intellect with data is not disappearing but proliferating. Therefore, it is reasonable to link the role of visualization design to this vision and question how assisting human's information consumption and thinking capacity facing the new technological landscape is achieved with visualization design. Following this effort, this thesis reports on a series of experiments for the discovery of a design methodology to augment human intelligence in the face of data complexity. More specifically, we explore along the theme of how to *visually amplify human abilities in finding useful knowledge from complex data*, which is essentially a way of *augmenting human intellect* from the data visualization's point of view. Based on this motivation, we initiate the research project by laying down the following research questions:

- How to effectively characterize the design context to facilitate explorations in problem-driven visualization research?
- Which cognitive process in scientific reasoning is constructive to conceptualize novel exploration facilitation methods?
- How can the findings from our studies be theoretically generalized as a replicable method to scaffold future design?

To answer these three questions, we will start by investigating recent literature that shares the same interest in promoting human understanding and knowledge discovery (chapter 2). Following the literature, we approach research questions by employing a theoretical framework to address the discovered opportunities, the result of which builds the theoretical foundation for the pivotal visualization method (chapter 3). The proposed method is experimented in two studies with explicit references to case details in the gaming context (chapter 4) and spatial-temporal movement context (chapter 5). Then, we connect the theoretical components in chapter 3 to the vivid examples to demonstrate applicability of our method and systemically refine the according lessons to provide guidance for future needs (chapter 6). We conclude our research in chapter 7 which marks the end of this thesis.

Visualization and Human Augmentation 2

Overview: *This chapter is a literature study that collects and analyzes existing approaches that intersect with the principle of augmenting human intelligence from the visualization perspective. The study specifies three non-trivial desiderata in modern visualization design, based on which it identifies opportunities concerning domain knowledge embodiment and hypothesis generation. The study sets the motivation background of the proposition of the pivotal visualization design method.*

2.1 Desiderata

From its original context, we can see that the principle of augmenting human intellect has the explicit implication of exploiting modern digital infrastructure and utilities to improve human capacities. From a visualization design perspective, systems are qualified by their advantages in visually assisting human capacities in making sense of data [30]. Thanks to the interactive visual environment provided by the system, the dominating human capacities in unveiling questions and patterns facing data complexity is amplified. However, this advantage is non-trivial to keep up with the latest advancement of information systems [31, 32]. The involved desiderata are threefold:

[30]: Tory et al. (2004), "Human Factors in Visualization Research"

[31]: Behrisch et al. (2019), "Commercial Visual Analytics Systems–Advances in the Big Data Analytics Field"
[32]: Muller et al. (2019), "How Data Science Workers Work with Data"

Human Factors Compliance

For most branches of design disciplines, the design solution is specified in a limited design space where compliance with the boundary conditions is a must. Visualization design also needs to consider a few inherent limitations. One of the most significant limitations relates to the human-factors [30], or more specifically the natural limits in human perceptions. Besides the human-factor studies on the context specific level [33–35] where case and task dependent behavioral clues with specific application implications are discussed in respective domain contexts, these fundamental limitations are case-independent patterns based on discoveries from cognitive science. These insights reveal insurmountable bottlenecks regardless of the data, problem, or visualization method.

[33]: Wallner et al. (2019), "Aggregated Visualization of Playtesting Data"
[34]: Simon et al. (2019), "Finding Information on Non-Rectangular Interfaces"
[35]: Mylavarapu et al. (2019), "Ranked-List Visualization"

The first bottleneck is the upper limit of visual information transference. According to cognitive scientists, the information bandwidth of the human visual system caps at around 10 Mbps [36, 37], indicating a hard ceiling for visualization design to cope with. However, the real allowed information flow can be significantly reduced as we do not expect the user's perception to work at peak performance at all time. The deficit in information readability and intuitiveness can exhaust visual perception by a large margin if not treated properly. There are also explorations into increasing the transfer rate by integrating other channels/modalities such as auditory, tactile senses [38, 39]. The results from these explorations are not promising as the amount of added flow is trivial compared to the dominating visual channel [40, 41].

[36]: Snyder et al. (1977), "Information Capacity of Eyes"
[37]: Koch et al. (2006), "How Much the Eye Tells the Brain"
[38]: Yeo et al. (2004), "SonART: A Framework for Data Sonification, Visualization and Networked Multimedia Applications"
[39]: Madhyastha et al. (1995), "Data Sonification"
[40]: Hermann et al. (1999), "Listen to Your Data: Model-Based Sonification for Data Analysis"
[41]: Hermann (2002), "Sonification for Exploratory Data Analysis"

Our short-term memory is also not perfect at dealing with data complexity. Study shows that human knowledge acquisition does not follow a continuous model [42]. Instead, our minds group mental elements into discrete "chunks" in the memory,

[42]: Ware (2012), *Information Visualization*

updating their priority and organization in response to emerging tasks in the real-time [42]. These chunks have relatively fixed numbers and sizes with possible improvements from training [43]. But the improvements are not to keep up with the ever-growing information overload in modern data analyses. Visualization design is an effort to cope with these limits instead of imagining how to defeat them. Interaction techniques such as focus-and-context, or zoom-and-detail [44, 45] are are invented to filter out irrelevant parts and highlight the most interesting subsets to streamline the visualized complexity. More approaches in visual analytics [46] aim at the similar goal of reducing information representation with parameterized model aggregation.

[43]: Kliegl et al. (1987), "Mnemonic Training for the Acquisition of Skilled Digit Memory"

[44]: Cockburn et al. (2008), "A Review of Overview+detail, Zooming, and Focus+context Interfaces"

[45]: Amraii et al. (2014), "Explorable Visual Analytics Knowledge Discovery in Large and High – Dimensional Data"

[46]: Keim et al. (2008), "Visual Analytics"

On top of the fundamental limits, contextualized human factors are also important. For instance, suitable screen brightness for the working environment [42] or sufficient refresh rate to capture the change frequency [47]) provide actionable knowledge to draft the design basis [30, 48]. Clarifying these factors asks for inputs from the context-based studies, which are not suitable for general discussion here. We will pay attention to these issues in detailed cases in chapter 4 and chapter 5.

[47]: Moritz et al. (2019), "Falcon"

[30]: Tory et al. (2004), "Human Factors in Visualization Research"

[48]: Dasgupta et al. (2018), "Human Factors in Streaming Data Analysis"

Transparency

As we mentioned in the previous section, interaction techniques to enable filtering and subsetting can help reduce the amount of information presentation. One key advantage of these techniques is they simulate the natural physical movements (e.g. focus-and-context, or zoom-and-detail) to convey the underlying computational processes, making them familiar and intuitive to human conception. But the same advantage is not achievable with all the techniques to cover every case. For instance, the sheer number of relations or dimensions in the data may be too expensive to produce a visual summary

[49]: Stolper et al. (2014), "Progressive Visual Analytics"
[50]: Fekete et al. (2002), "Interactive Information Visualization of a Million Items"
[51]: Silver et al. (2016), "Mastering the Game of Go with Deep Neural Networks and Tree Search"
[52]: Cios et al. (2013), *Data Mining Methods for Knowledge Discovery.*
[53]: Grzymala-Busse et al. (2000), "Data Mining and Rough Set Theory"
[45]: Amraii et al. (2014), "Explorable Visual Analytics Knowledge Discovery in Large and High – Dimensional Data"
[54]: Alon et al. (2003), "Discovering Clusters in Motion Time-Series Data"
[55]: Elzen et al. (2011), "Baobab-View"
[56]: Krause et al. (2016), "Interacting with Predictions"
[57]: Endert et al. (2017), "The State of the Art in Integrating Machine Learning into Visual Analytics"
[58]: Goh et al. (2012), "Online Map-Matching Based on Hidden Markov Model for Real-Time Traffic Sensing Applications"
[23]: Amershi et al. (2019), "Guidelines for Human-AI Interaction"
[59]: Chen (2018), *The Value of Interaction in Data Intelligence*
[60]: Zhang et al. (2019), "Automatic Feature Engineering by Deep Reinforcement Learning"
[61]: Miller (2017), *Explanation in Artificial Intelligence*
[21]: Wang et al. (2019), "Designing Theory-Driven User-Centric Explainable AI"

of [49, 50], or the abstract nature of the problem (the reasoning of an AI-based go player for example) is tricky to be explored in a visual space [51]. For these circumstances, model-based summary may be applied as a pre-stage component to aggregate the information into presentable sizes [45, 52, 53]. In fact, model-based simplifications are getting momentum in latest visualization research [54–57]. However, the sophistication of integrated models [23, 58–60] for simplified representations produces opaque data pipelines, which gives rise to the transparency issues of information systems [21, 61].

The concept of transparency and the accompanying symptoms are multifaceted: Samek, Wiegand, and Müller [62] refer to non-transparent as "not clear what information in the input data makes them actually arrive at their decisions." Springer and Whittaker [63] note that being non-transparent is the inability to give "an explanation of why a model made a given prediction". According to Angelini et al. [64], a system is non-transparent if it behaves as "an algorithmic black box without any means to observe, interject, and reconfigure it on the fly". The proliferated discussions around transparency (cf. ACM Conference on Fairness, Accountability, and Transparency: https://facctconference.org) indicates that it is not a trivial problem. One of the reasons is poor transparency raises the threshold and potentially hurts the usability of a system. From a user's perspective, transparency issues eliminate the information parts that are consequential to the ease of reasoning and follow-up decision-making, causing unnecessary speculative guesses while increasing the learning burden. These drawbacks prohibit the analysts, who usually hold little knowledge of the underlying automation mechanism, from smooth adoption of the system or even using it at all [65, 66].

In addition to usability concerns, poor transparency also prohibits the development of a proper trust relationship between the user and the system [67–69]. Imagine a route planning app prompts the driver to alternate the path toward his workplace due to construction roadblocks without revealing the reason information. The driver may reject the recommendation as a system error and instead rely on his knowledge. This exemplifies that under-trust in the system lowers the usage of well-functioning automation systems, which is economically unsound [70]. If the user gives full trust to a system without precaution, the unnoticed error may snowball until it leads to fatal losses [71]. The malfunctions of Boeing 737-Max jetliners are examples of giving too much execution authority to the error prevention system which were originally designed to automatically adjust human errors [72]. Human pilots were simply not given sufficient situation awareness and control over automation to avoid the crash. Transparency issues are also important in similar action-critical scenarios such as fire emergencies [73], medical diagnosis [74], or air traffic controls [75].

The provision of transparency is based on the exposure of internal processes that produce the simple outcomes. When the final outcome is ready, it is possible to compare them against one's judgments and experiences to make adjustments in the next operation, which potentially mitigates the drawbacks of transparency issues. However, these self-adjustments are crude workarounds which still affect the users' confidence in decision-making [76, 77]. In the meanwhile, data analyses need to be vigilant in unconventional patterns. As an opaque system may only produce final results in the end of the pipeline, contradictory patterns and trends in the middle, which may contain valuable information, are eliminated. The analyst may falsely assume his/her earlier assumption is perfectly reflected by the data as no contradicting evidence shows otherwise. The existence of such a possibility can be justified by the oversimplification error demonstrated by the Anscombe's Quartet in § · 1.1 Why Visualization?. Treatment to this caveat is more essential if the analyst's goal is to explore for knowledge instead

[62]: Samek et al. (2017), *Explainable Artificial Intelligence*

[63]: Springer et al. (2019), "Progressive Disclosure"

[64]: Angelini et al. (2018), "A Review and Characterization of Progressive Visual Analytics"

[65]: Westin et al. (2016), "Automation Transparency and Personalized Decision Support"

[66]: Yang et al. (2017), "Evaluating Effects of User Experience and System Transparency on Trust in Automation"

[67]: Holzinger et al. (2017), *What Do We Need to Build Explainable AI Systems for the Medical Domain?*

[68]: Hagras (2018), "Toward Human-Understandable, Explainable AI"

[69]: Adadi et al. (2018), "Peeking Inside the Black-Box"

[70]: Zuboff (1988), "Dilemmas of Transformation in the Age of the Smart Machine"

[71]: Parasuraman et al. (1997), "Humans and Automation"

[72]: Wendel (2019), "Technological Solutions to Human Error and How They Can Kill You"

[73]: Lee et al. (2004), "Trust in Automation: Designing for Appropriate Reliance"

[74]: Xie et al. (2019), "Outlining the Design Space of Explainable Intelligent Systems for Medical Diagnosis"

[75]: Riveiro et al. (2014), "Effects of Visualizing Uncertainty on Decision-Making in a Target Identification Scenario"

[76]: Wright et al. (2019), "Agent Transparency and Reliability in Human–Robot Interaction"
[77]: Sinha et al. (2002), "The Role of Transparency in Recommender Systems"

of seeking a confirmatory result from an existing question.

Explorability

Transparency makes internal processes of a system inspectable to human eyes. However, explorability, namely the quality of being explorable, requires the system to continuously update the information disclosure in response to stacking inquiries produced by user actions. Instead of clearly presenting the inner process of how a system reaches to a conclusion (i.e. transparency), explorability demands a new layer of flexibility on top of existing interactivity which is already widely implemented in recent visualization works.

Data explorations resemble the process of navigating a maze of many sub-routes. Wrangling the features in different regions of data is like testing or trying different sub-routes for a pathway out. Rejecting a few hypotheses (as dead ends) is necessary to narrow down the search space for suitable model parameters. The iterative process of hypothesizing and experimenting would eventually lead to the solution of the maze with the analysts' persistence. It is important to note that a discovery of a dead end in the maze does not reject all the accumulated knowledge as one can start over from a previous crossroad with different directions but not the very beginning. In data exploration, previous knowledge also plays a role in the continuation of analysis. The difference is going back to the previous crossroad requiring dedicated support for flexible navigation, which pertains to the ability of answering user's questions through improving approximations. For this case, an approximation improving its accuracy is like a path growing its length to approach the real exit in a maze. This flexibility in contriving improved versions of approximations is indispensable to data exploration [74]. The very paradigm following this routine of

[74]: Xie et al. (2019), "Outlining the Design Space of Explainable Intelligent Systems for Medical Diagnosis"

assimilating new knowledge by active trials of approximations is known as the *exploratory data analyses* (EDA) [78].

[78]: Tukey (1977), "Exploratory Data Analysis"

To perform the trials and identify valuable approximations, explorable systems need to give the user more control to search operations for extra diversity of the asked questions. This is especially true when a user needs to build familiarity with data by initial experimentation. Contrasting to traditional analysis where systems work straight to the final result initiated by a single input, explorable systems carry out the analyses by answering the gradual inputs from users, i.e. users' on-going actions are useful resources to adjust the system and therefore respected by design [59]. This type of flexibility eliminates the headache of pinpointing the inputs before familiarity of data, achieving the diversity of questions by paying hospitality to user's curiosity, interest, and intent, which are essential elements in learning about data. Because the explorable systems enable such a dynamic and user-driven approach as opposed to a static and processing-driven one, it can exploit a greater potential of the systems' analytic power.

[59]: Chen (2018), *The Value of Interaction in Data Intelligence*

Explorable systems depend on several key elements to take effect: Firstly, the system needs to be receptive to users' (subjective) inputs and respond to them timely to realize an interactive knowledge discovery process [79]. Secondly, the system should feature plausible user interface design so that users can intuitively carry out their tasks by smooth explorations, not being bothered by the unnecessary obscurity by amateur interface design [80]. Thirdly, the system should allow for decoupling the entire analytical chain into incremental steps so that small discoveries by trials and errors can build up as the exploration continues. Comprehensive understanding of the objective problem is usually a result of gradual approximations [81]. And finally, a considerable size of the exploration space should be supported [82, 83], allowing the user to freely construct hypotheses by manipulating multiple result-sensitive dimen-

[79]: Frawley et al. (1992), "Knowledge Discovery in Databases"

[80]: Quinn (1992), "Explorability"

[81]: Lakkaraju et al. (2017), *Interpretable & Explorable Approximations of Black Box Models*

[82]: Klahr et al. (1988), "Dual Space Search during Scientific Reasoning"

[83]: VAN Joolingen et al. (1997), "An Extended Dual Search Space Model of Scientific Discovery Learning"

[45]: Amraii et al. (2014), "Explorable Visual Analytics Knowledge Discovery in Large and High – Dimensional Data"

[84]: Jeong et al. (2009), "iPCA"
[56]: Krause et al. (2016), "Interacting with Predictions"
[71]: Parasuraman et al. (1997), "Humans and Automation"

sions instead of manually browsing over plain data points [45]. Achieving explorability as a systemic effect is a non-trivial task as the implementation difficulty to cover all these components tends to scale with analytic complexity in information systems [56, 71, 84].

In sum, the inherent human factor limits (such as limits in visual perception) motivates the application of complexity reduction methods, among which models without easily understood natural metaphors challenges human observation of the underlying behaviors of the system. Accommodating domain knowledge in visualization systems can facilitate the interpretation of the visual outcomes. But there are several gaps to be filled. For instance, exposing flexible controls to support knowledge generation tasks requires the systemic support for explorability (of data or model behavior), which is practically non-trivial for its multifaceted requirements. Thus, the aforementioned desiderata are closely intertwined with each other. A closer look at the interactions between the desiderata shows that the contribution in one may force a chain effect globally (Figure 2.1), which suggests design improvements to any are affected by systematic considerations. This systematic consideration is closely examined from different angles in latest works, which we put forward three main categories to discuss.

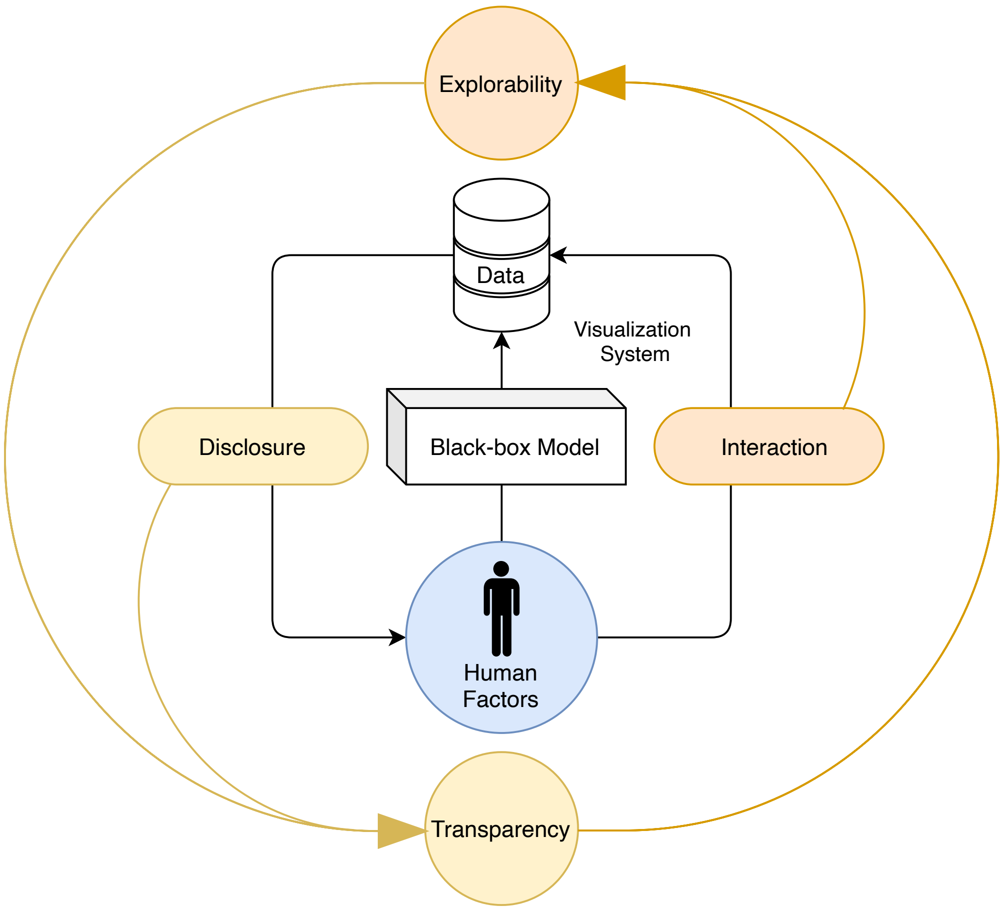


Figure 2.1: The Relationships of Desiderata: human factors (blue circle around human) are a primitive concern that leads to the application of machine models for simpler visual representation because human factors such as cognitive bottlenecks are impossible to bypass when involving human interference. The sophistication of machine models makes their internal structures increasingly imperceptible, causing black-box issues in the visualization system. Thanks to the support for interaction in visualization systems, explorations with data can lead to disclosure of its internal processes. As a consequence, the additional knowledge of the internal processes leads to improved transparency, which in turn gives rise to the explorability of the system. Designers need to systematically address the concerns in each step to augment human-led explorations.

2.2 Efforts

Related works from different research themes inspire new visualization design methods. With regards to the aforementioned categorization by the three desiderata, we summarize these themes of related works as known efforts to approach the desiderata with respective perspectives and interests.

Human-Centered Design

Visualizations are not only information interfaces. They are also interaction interfaces just like the other human-computer interfaces which communicate human intentions and present machine feedback. The theme of human-centered design (HCD) models the behaviors, routines, expectations of specific human groups as a basis to inform the design of human-machine interface [85, 86]. This endeavor is essentially learning the human user and designing systems accordingly so that the outcome would be well-compatible with real usage scenarios with least effort from the human users. The interface design in visualization systems often require similar interaction design objectives, where exclusive user studies are carried out before and after the system implementation to guide the design and verify its effectiveness. The wide inclusion of user evaluations in application-based visualization research are direct exemplifications for this.

[85]: Jokela et al. (2003), "The Standard of User-Centered Design and the Standard Definition of Usability"
[86]: Oviatt (2006), "Human-Centered Design Meets Cognitive Load Theory"

In the previous stage, visualization designers conduct extensive user study to clarify and gain insights regarding the users' tasks and analysis routines. In addition to finding the cognitive and ergonomic bottlenecks (based on lower level principles (§ · 2.1 Human Factors Compliance)), designers also need to characterize the application context of visualization techniques. This can not be achieved without assimilating new knowledge specific to the domain. This effort is not auxiliary preparation but a rather essential pillar of the entire project, which sometimes can exceed the workload of exact implementation in terms of the proportional time and effort (an 8 months long investigation [87] for instance).

[87]: Wu et al. (2018), "iTTVis"

The collected data from the pre-design stage are distilled into key user requirement points, which are used. Analyzing the requirements also contributes to the identification of crucial tasks, which are chains of discrete actions motivated by the explicit domain questions to inform the later design conceptualization. Reflective design choices are made to streamline the analysis process relating to the tasks. The elaborate command of the visual presentation should serve the identified tasks with extra considerations into the concerns such as transparency, performance, robustness, accuracy, or reliability. HCD in this regard involves leveraging innate human perception rules such as the attention-effective placement of visual elements [34], moderating reading error-rates [35], or color choices [88, 89] as well as extensive considerations for the specific context. In real practices, the process of designing with human-orientation can also be carried out iteratively following the loop as shown in Figure 2.2.

[34]: Simon et al. (2019), "Finding Information on Non-Rectangular Interfaces"

[35]: Mylavarapu et al. (2019), "Ranked-List Visualization"

[88]: Lin et al. (2013), "Selecting Semantically-Resonant Colors for Data Visualization"

[89]: Harrower et al. (2003), "ColorBrewer.Org"

The post-design stage proceeds with a ready prototype to test. This stage assumes that the implemented system follows the requirements and tasks specified in the before stage. In addition to finding explicit evidence to justify the design's effectiveness, verifying the design in a real usage scenario helps to uncover overlooked insights about the real user behaviors using the system. This part of the user study consolidates our knowledge about human users in terms of reception of the system as well as limits and caveats to avoid in the given design context.

In sum, the essential goal of the HCD effort is to ensure the shaping of the final design aligns not only with basic human

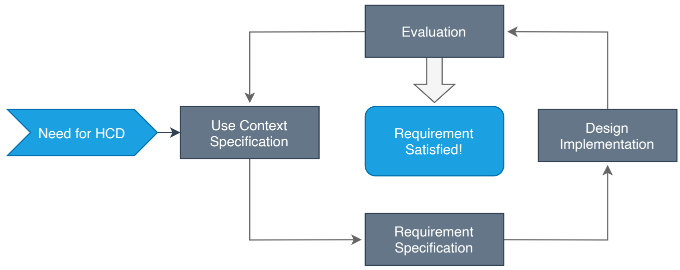


Figure 2.2: The loop of activities in Human-Centered Design according to Jokela et al.

factors but also the explicit needs for task requirements. It is an intention to tweak the design with respect to human limits or needs instead of the other way around.

Explainable Artificial Intelligence

Modern algorithmic models allow us to offload part of the data analysis work to the machine to uncover data patterns for us. However, with increased complexity, the integrated model raises the threshold to interpret the systems' behaviors [26], leading to black-box systems which pose challenges to the systems' adoptions.

[26]: Carter et al. (2017), "Using Artificial Intelligence to Augment Human Intelligence"

For the most widely applied models in data analysis, deep artificial neural networks (DNNs) are among the most sophisticated ones. Each derivation, such as convolutional neural networks (CNNs), generative adversarial networks (GANs), recurrent neural networks (RNNs), equips machines with higher level pattern recognition capabilities by modifying or adding another building block to the network structure. These models turn raw data into machine-friendly layers of abstractions, processing them by algorithmic operations with little human interventions. Because of the unprecedented application potentials of many sectors [90–92], these technologies can turn nearly any data-related problems into algorithmic processes

[90]: Chui et al. (2018), "Notes from the AI Frontier: Insights from Hundreds of Use Cases"
[91]: Savadjiev et al. (2019), "Demystification of AI-Driven Medical Image Interpretation"
[92]: Bex et al. (2017), "Introduction to the Special Issue on Artificial Intelligence for Justice (AI4J)"

Table 2.1: A non-exhaustive list of visualization tools for common (deep) artificial neural networks

Tool	Model Type	Author	Year
CNNVis [95]	CNN	Liu et al.	2017
ReVACNN [96]	CNN	Chung et al.	2016
RNNVis [97]	RNN	Ming et al.	2017
LSTMVis [98]	RNN (i.a. LSTM)	Strobelt et al.	2018
DeepEyes [99]	Generic	Pezzotti et al.	2018
ActiVis [100]	Generic	Kahng et al.	2018
DGMTracker [101]	GAN, VAE	Liu et al.	2018

of identifying, predicting, or categorizing as long as the data can suffice. But the wide applicability is achieved through abstraction, which basically removes the original semantics data and only focuses on the informational variations. Such transformations mimic part of human intellectual activities but do not reproduce human's sensitivity to the problem context. As a consequence, the advantage of abstracting higher-level patterns with models makes the machine processes further distant from human reasoning as it departs from the explicit contexts where meanings originate from [93, 94]. The explainable artificial intelligence (XAI) is an endeavor to particularly tackle this issue.

XAI is a manifold concept that is still working toward a unifying definition [69, 102, 103]. Guidotti et al. [102] regard the provision of "an 'interface' between humans and a decision maker that is at the same time both an accurate proxy of the decision maker and comprehensible to humans" to be the defining feature of XAI. Barredo Arrieta et al. [103] advocate to include the audience as a key component to assess explainability, taking into account the goals and cognitive skills of a user group. In addition to understandability and trust-worthiness, Gunning [104] also related XAI closely to machine learning techniques that makes AI manageable to human operators.

[93]: Rysiew (2021), "Epistemic Contextualism"
[94]: McKenna (2015), "Contextualism in Epistemology"

[69]: Adadi et al. (2018), "Peeking Inside the Black-Box"
[102]: Guidotti et al. (2018), "A Survey of Methods for Explaining Black Box Models"
[103]: Barredo Arrieta et al. (2020), "Explainable Artificial Intelligence (XAI)"

[102]: Guidotti et al. (2018), "A Survey of Methods for Explaining Black Box Models"

[103]: Barredo Arrieta et al. (2020), "Explainable Artificial Intelligence (XAI)"

[104]: Gunning (2017), *Explainable Artificial Intelligence (XAI)*

More domain dependent elaborations can be found in ongoing references [105–107].

[105]: Tjoa et al. (2019), *A Survey on Explainable Artificial Intelligence (XAI)*
[106]: West (2018), *The Future of Work: Robots, AI, and Automation*
[107]: Zhu et al. (2018), "Explainable AI for Designers"

Visualization-related accounts of XAI and its relevant facilitation are mostly one or a mixture of three major branches. The first one is to provide a global, explicit representation of the entirety of the underlying model. This way, the engineering work such as tweaking and debugging are supported with ground reference to the exact running logic [108]. Improvements like optimization and customization are, therefore,easier to make. Explainability in this way is more frequently seen in models like decision trees and rule-based expert systems [109], of which models themselves can be described with memorable structures.

[108]: Miller (2019), ""But Why?"

[109]: Hind (2019), "Explaining Explainable AI"

Another branch is to locate the salient internal representation (i.e. direct or indirect abstraction from raw data in the middle layer) and find its causality or mutual influence to the external representation [110–112]. By semantically visualizing internal representations [113, 114] and clarifying the connections between interacting parts [95], how machines reach certain decisions are delineated to human perceptions and rationals.

[110]: Chen et al. (2016), "InfoGAN"
[111]: Bau et al. (2018), *GAN Dissection*
[112]: Horel et al. (2019), *Towards Explainable AI*

[113]: Olah et al. (2017), "Feature Visualization"
[114]: Rauber et al. (2017), "Visualizing the Hidden Activity of Artificial Neural Networks"
[95]: Liu et al. (2017), "Towards Better Analysis of Deep Convolutional Neural Networks"

The last branch of XAI is represented by Guidotti et al.'s notion of "proxy", where explainability is realized by visualizing a reduced entity derived from the less intuitive decision-making model. The explanation is thus acquired by studying the behavior of the proxy instead of the ground details (e.g. enormous layers of neurons in deep learning). Liu et al. [101] visualizes large-scale time series data recorded from the training process of generative models to virtually reproduce its training process, the resolution of which is sufficient to preserve the outliers yet without the annoyance of visual clutters. Xu et al. [115] utilize the combination of model compression and dimension reduction techniques to project deep classifiers into simpler forms, producing a visualization (i.e. Darksight [115]) that is more

[101]: Liu et al. (2018), "Analyzing the Training Processes of Deep Generative Models"

[115]: Xu et al. (2018), *Interpreting Deep Classifier by Visual Distillation of Dark Knowledge*

informative than standard methods. Instead of confronting the model's complexity directly, the Interpretable Mimic Learning (IML) proposed by Chen et al. [110] learns from the deep learning models and presents human interpretable features with little or no performance compromise.

[110]: Chen et al. (2016), "InfoGAN"

As mentioned before, complex models like (deep) ANN effectively reduce the manual labor in pattern recognition with data but are harder to interpret. Visualizations in this regard tame not only the traditional data complexity but also the unprecedented model complexity as well. Utilizing visualization techniques to mitigate undesirable side-effects caused by higher degree of abstractions is gaining momentum in the cross-section between the ML/AI community and the visualization community in recent years. This seems to indicate the complexity of either data or the added artificial facilities in the visualization pipeline poses equal challenges to sense-making. Visualization design should strive for removing the barriers in both aspects to promote transparency and explorability.

Progressive Visual Analytics

Knowledge discovery processes can also be supported progressively [116, 117] with visualization techniques [64, 118, 119]. By providing extra controllability over the middle steps in data analysis, the analytic process can maximize the value in each outcome to develop new rationales one following another. Visual analytics (visualization with data mining/analytic capabilities [120]) supporting this progressive approach is referred to as progressive visual analytics (PVA). In one way, PVAs dissect monolithic algorithmic pipelines into controllable subparts, exposing controllable parameters to steer the algorithmic process. In another way, the entirety of the data set is reduced to a smaller size, allowing it to be consumed by chunk sizes that are possible for quick computation and early feedback [64,

[116]: Schulz et al. (2016), "An Enhanced Visualization Process Model for Incremental Visualization"

[117]: Pezzotti et al. (2017), "Approximated and User Steerable tSNE for Progressive Visual Analytics"

[64]: Angelini et al. (2018), "A Review and Characterization of Progressive Visual Analytics"

[118]: Fekete et al. (2019), "Progressive Data Analysis and Visualization (Dagstuhl Seminar 18411)"

[119]: Turkay et al. (2018), *Progressive Data Science*

[120]: Keim et al. (2008), "Visual Analytics"

121]. For instance, Jo, Seo, and Fekete [122, 123] keep an updating cache of newly indexed data in k-Nearest Neighbor (kNN) algorithms to enable approximate queries following most recent user interactions. Pezzotti et al. [117] trade partial accuracy of the t-distributed Stochastic Neighbor Embedding (t-SNE) algorithm for lower latency to provide steeribility for in-progress intervention. HARVEST [124] pays special attention to the integration of available and recent knowledge in the progression of knowledge discovery. InsightsFeed [125] exemplified a set of interface design guidelines featuring explicit support for feedback and control.

[64]: Angelini et al. (2018), "A Review and Characterization of Progressive Visual Analytics"
[121]: Mühlbacher et al. (2014), "Opening the Black Box"
[122]: Jo et al. (2017), "A Progressive K-d Tree for Approximate k-Nearest Neighbors"
[123]: Jo et al. (2020), "PANENE"
[117]: Pezzotti et al. (2017), "Approximated and User Steerable tSNE for Progressive Visual Analytics"
[124]: Gotz et al. (2006), "Interactive Visual Synthesis of Analytic Knowledge"
[125]: Badam et al. (2017), "Steering the Craft"
[119]: Turkay et al. (2018), *Progressive Data Science*

A key advantage of the progressive manner is to make intermediate results accessible. The results are useful because they provide valuable information which is consequential to the follow-up phases [119]. If XAIs are regarded as upgrading the models to reveal the semantics of inner representation or monitor the classification process, PVA approaches are less aggressive in adding new building blocks on top of the ML models. They are rather about applying structural changes [118] of the entire analytic system to accompany the model with more granular interactivity for easy interventions. The interfaces supporting the interactivity expose the parameters to the human controls, which, as noticed by Badam, Elmqvist, and Fekete [125], opens up user interface design questions concerning how visualizations can be adapted to support PVAs.

[118]: Fekete et al. (2019), "Progressive Data Analysis and Visualization (Dagstuhl Seminar 18411)"

[125]: Badam et al. (2017), "Steering the Craft"

The responsiveness of an intelligent system is a salient factor to influence both user experience and task performance but hard to guarantee when the analytic involves heavy computation and large scale data. According to human factor experiments [126], visual responses that take longer than 500ms can significantly restrain a system's maneuverability. Considering explorability is realized by frequent and flexible visual navigation, longer responses can certainly undermine the explorability of a system. Since the delay of response is often associated with the amount

[126]: Liu et al. (2014), "The Effects of Interactive Latency on Exploratory Visual Analysis"

of computation required by data size to process, chunking the data into smaller batches can moderate the waiting time. Even doing so may add up the total time for computation, users can have higher qualitative satisfaction without sacrificing significant performance loss compared to the instantaneous display of outcomes in terms of insight discovering rate [127]. This can be even further improved by combining layered visual design with multi-thread processing [128], which better ensures front-end representations stay in sync with underlying computation.

[127]: Zgraggen et al. (2017), "How Progressive Visualizations Affect Exploratory Analysis"

[128]: Piringer et al. (2009), "A Multi-Threading Architecture to Support Interactive Visual Exploration"

The exchange for speed and flexibility with data chunking may also yield less accurate outcomes as results are inferred from a fraction instead of the entirety of data. This drawback makes managing the increased data uncertainty relevant. ProReveal [129] uses programmed safeguards to manage this effect by preventing biased or incorrect hypotheses in the early stage to overly consume computation time and avoid false positive discoveries. QUDE [130] controls the error rate caused by overloaded simultaneous hypotheses (i.e. multiple hypotheses testing error) by implementing dedicated sample testes. Angelini, May, and Santucci [131] highlight the need to include subjective measures such as expressiveness and reliability in quality assessments of an analytic system to cover more inclusive factors on the global scale. For the same concerns, Stolper, Perer, and Gotz [49] advocate the user-centeredness of PVAs, arguing "a visualization should provide the analyst with apparent affordances for adjusting and directing the analytic, in addition to effectively communicating the results of the analysis to the analyst."

[129]: Jo et al. (2019), "ProReveal"

[130]: Zhao et al. (2017), "Controlling False Discoveries during Interactive Data Exploration"

[131]: Angelini et al. (2019), "On Quality Indicators for Progressive Visual Analytics"

[49]: Stolper et al. (2014), "Progressive Visual Analytics"

As a visualization approach, PVAs balance the progression of computer and human actions in terms of time resources and cognitive workload, making each step perceptible and maneuverable to smoothly collaborate with human thinking. It practically organizes the power of computation and the importance of early user reports together to mitigate the drawbacks of either side. The PVA approach can be especially seen as an effort to systematically place explorability in many possible slots of a system to transform it into a more open and assistive facility.

2.3 Opportunities

The above approaches contribute to the aforementioned desiderata from respective angles. These emerging efforts help us to conceptualize a few potentially overlooked objectives under the goal of improving human capacity in knowledge discovery.

Augmented Hypothesis Generation

The desideratum of explorabiliy (§ · 2.1 Explorability) is associated with superior efficiency in generating hypotheses. In visualization design, superior explorability means more flexibility to support agile approximations to the answers as opposed to one-shot queries (or tests) to validate a fixed hypothesis. The seemingly less efficient approximations open up the chance of interbreeding of thoughts and experiments, with each step contributing more nuanced and inspiring hypotheses.

[132]: Moritz et al. (2017), "Trust, but Verify"

Regarding the goal of improving hypothesis generation, Moritz et al. [132] proposed the concept of *optimistic visualization* where workload in verification is condensed to make room for maximizing the early approximations. The method advocates sacrificing hypotheses quality in exchange for quickly generations of hypothesis batches in the initial exploration stage. Optimistic visualization's emphasis on number advantage in hypotheses (or visual exploration in general) should be practiced with caution because of the risk of false claims. As noted by a caveat in statistics (cf. multiple hypotheses testing error), eliciting too many hypotheses loosely at once may lead to erroneous results. This produced error can be potentially regulated by statistical methods such as the Bonferroni Correction [133] and Benjamini-Hochberg Correction [134]. But adapting these methods to support explorations is not trivial [130]. **Therefore, we change our focus from the number of hypothesis generation toward the ease of locating the right questions, which can be a daunting task when the analyst experiences significant uncertainty of the problem itself** (§ · 3.1 Problem Uncertainty).

[133]: Armstrong (2014), "When to Use the Bonferroni Correction"

[134]: Noble (2009), "How Does Multiple Testing Correction Work?"

[130]: Zhao et al. (2017), "Controlling False Discoveries during Interactive Data Exploration"

Visual Embodiment of Domain Knowledge

The idea of explanation is crucial to the general knowledge finding. However, to the best of our knowledge, the literature around XAI has not clarified the link between the criteria of a sound explanation and the explanations currently feasible. The XAIs exhibit the potential to convert machine friendly processes and information to semantic symbols and analogue images, significantly eliminating the threshold of algorithmic and mathematical reasoning into computational processes. But in a social context an explanation is typically given from and to a human. The current treatments usually ignore such social properties of an explanation in a context-sensitive context, where explanations differ by the explainee or situation [108]. Current AI-infused systems only provide that context-awareness with naive approaches such as predefining usage scenarios [135], mining salient vectors [136], or state identifications [137], assuming that the context can be sufficiently captured through the parameters. We argue that context-awareness in this regard is more of the adaptations of AIs instead of explanations of the subject matter.

[108]: Miller (2019), ""But Why?"

[135]: Nascimento et al. (2018), "A Context-Aware Machine Learning-Based Approach"

[136]: Zeng (2019), "Context Aware Machine Learning"

[137]: Krause et al. (2006), "Context-Aware Mobile Computing"

When it comes to context-sensitivity, humans, or more specifically domain experts, are the most reliable providers of such a resource for their rich knowledge into the data collection settings and the research background. Incorporating domain knowledge is a norm in visualization tool-making for a steady long period of time. The knowledge is often exploited to pinpoint the requirements which shape the later design planning, answering questions such as what plotting technique to use or how the interactivity should be implemented to carry the tasks. However, the valuable assets are used to merely reinforce the interpretation of generated graphs after the data analysis takes place with a ready system. During the analysis, the role of domain knowledge in the essential visual expression and content is somehow weak or even missing compared to procedures in the early stages (data cleaning or pre-processing [138]). Therefore, we argue that the inability to cast the influence of domain knowledge to the content level is an under-exploitation, with which little assistance is leveraged to unpack the fundamental problem from the knowledge assistance perspective, cf. § · 3.2 Guidance from Knowledge Assistance.

[138]: Alonso et al. (2002), "Combining Expert Knowledge and Data Mining in a Medical Diagnosis Domain"

Realizing that domain-originated knowledge (whether explicit or not) holds the potential of informing critical clues to the analyses, embedding the knowledge into the visual analytical environment presumably actualizes the merit of integrating domain knowledge into different stages of data analysis [139]. This motivates us to search for potential design methods that use domain knowledge not only to inform the visualization interface design but also to be integrated into the visualized information essence.

[139]: Kopanas et al. (2002), "The Role of Domain Knowledge in a Large Scale Data Mining Project"

As noted by Choo and Liu [140], injecting human knowledge in complex systems (such as ones incorporating the deep learning models) is challenging. The extent of this challenge seems to correlate with the complexity of the model. Current work [129] only provides definitions of rules and filters as a way to include

[140]: Choo et al. (2018), *Visual Analytics for Explainable Deep Learning*

[129]: Jo et al. (2019), "ProReveal"

domain knowledge into the visualization pipeline which is only enough to address the regulation of machine executions. Although this can be improved, the accurate representation of injected knowledge as well as the intermediate results (from either small batches of data or a sub-module of algorithm), which determines the reliability of intelligent systems [140], is less mentioned by the latest work. **Thus, a focus on the representation of embodied domain knowledge should be included in the future discussion.**

We can imagine that the future implementations with joint benefits of transparency (potentially provided by XAIs) and explorability (potentially provided by PVAs) allow us to partially inject human knowledge into the model by interactions. However, this thesis primarily focuses on the discovered opportunities above, which are main themes that motivate the pivotal visualization method.

Pivotal Visualization 3

__Overview:__ This chapter elaborates on the theoretical model of pivotal visualization. It unfolds the core idea of the proposed design method following the structural order of problem scope, theorem, method, and effect. It briefly discusses the application context of pivotal visualization to set the stage for the studies in the next chapters.

3.1 Problem Uncertainty*

The emphasis on problem orientation is a signature character of the design discipline [141, 142]. Designers perceive, interpret, structure and solve design problems to develop a proper solution [142, 143]. Similarly, the problem-driven research in visualization [144] focuses more on design method, rationale, evaluation, and reflection than its technique-driven counterpart. In this regard, visualization design is the integration of the two as it is about applying the same problem-solving mentality to facilitate human understanding of data. As data are used to represent certain features of a problem, the very effort of visualization design can be translated as "create new structures and relationships in a user's understanding of the problem" [145] instead of acquisitions of isolated facts.

[141]: Smith et al. (1993), "Conceptual Foundations of Design Problem Solving"
[142]: Dorst (2004), "On the Problem of Design Problems - Problem Solving and Design Expertise"
[143]: Huppatz (2015), "Revisiting Herbert Simon's "Science of Design""
[142]: Dorst (2004), "On the Problem of Design Problems - Problem Solving and Design Expertise"
[144]: Sedlmair et al. (2012), "Design Study Methodology"
[145]: Chang et al. (2009), "Defining Insight for Visual Analytics"

Part of this section is based on the published work W. Li, *M. Funk, and A. C. Brombacher, Toward Visualizing Subjective Uncertainty: A Conceptual Framework Addressing Perceived Uncertainty through Action Redundancy, in EuroVis Workshop on Reproducibility, Verification, and Validation in Visualization (EuroRV3), 2018.*

Regarding the structures and relationships to understand a problem, the self-evident numeric relationships (such as colinearity of numbers, hierarchical structures of graph nodes, or spatial approximations between vector clusters) and the implicit, non-evident ones only are obviously different. The first type of relationships are discrete and easily inferrable by rigorous programs such as search algorithms or statistical model. The second type are acquired with the help from the awareness of problem context, which usually involves tacit knowledge or intuition.

This dichotomy is best illustrated by the types of questions asked during the data analysis: Questions concerning self-evident relations are verifiable with crisp processes (usually in the form of a statistical model or a routine algorithm). As long as the raw data suffices certain quality standard, the presented relationships can be accepted as credible answers to the hypothesis. Examples of this type questions can be "what is the most significant producer of carbon emission in North America?" or "how does the oil price correlate with the global food price in the past decade?" However, data analyses often need to deal with the other type of questions. These questions are not easily answerable with the same methods as they involve implicit, undocumented clues which are beyond what raw data can provide. Examples of these can be "how to determine the satisfactory level of groups of amusement park visitors?" or "what could happen to the wildlife in the nearby natural reserve if we establish a manufacturing facility in the area?"

As an increase in data quality only contributes to soundness and credibility of data but does not expose additional structures of the problem, improvement in data quality contributes differently to these two types of questions. Usually, reducing data quality imperfections such as loss of accuracy, precision, or a missed value point in a data file directly impact the quality of answers to the former type as unreliable information can lead to inaccurate or false discoveries. Although the later type of questions receives the same benefit, additional research is still needed to produce plausible answers.

Therefore, the structures and relationships based on which we build our understanding of the problem are more complicated than how it first appears. Some of the relationships are inherent in data. With technical facilities, we can mitigate some data imperfections to facilitate the location of such relationships. But some of the other ones are implicit, which require human efforts to collect deeply embedded knowledge incrementally. With the accumulation of insights, the structure of the problem is thus perceivable thereafter by stitching together the pieces of relationships. Making sense of data requires paying attention to both the self-evident relationships and structures as well as the implicit ones. When either issue is insufficiently treated, uncertainty escalates to plague the understanding. Based on a broader sense of uncertainty [146], we define ones caused by insufficient familiarity with the implicit relationships and structures that characterize the uniqueness of the problems as *problem uncertainty* whereas ones caused by loss-of-detail in information provision as *data uncertainty*. In data analyses, both types of uncertainty undermine analysts' confidence and obscures structural knowledge generation, hindering the understanding of research problems, and consequently, the ultimate accomplishments of research objectives [147, 148].

[146]: Li et al. (2018), "Toward Visualizing Subjective Uncertainty: A Conceptual Framework Addressing Perceived Uncertainty through Action Redundancy"

[147]: Cooke (1991), *Experts in Uncertainty: Opinion and Subjective Probability in Science*

[148]: Helton (1997), "Uncertainty and Sensitivity Analysis in the Presence of Stochastic and Subjective Uncertainty"

Characterizing problems is indispensable in the early stage of design practice. Doing so in a visualization design context requires the designer to unpack the problem into different levels of abstractions [149]. For instance, a generic partition algorithm can deal with problems across domains, while empirical knowledge about the recurring skews in the data sampling apparatus is critical but only applicable to the current analysis. In addition to the nested model by Munzner [149], which sorts

[149]: Munzner (2009), "A Nested Model for Visualization Design and Validation"

different layers by their granularity of task clarification, we propose a leveled model of specificity which focuses on the width of application coverage regarding a question, i.e. how much the question is deeply embedded to this specific problem (Figure 3.1). We argue that even for low-level algorithmic decisions, problem uncertainty still arises as long as the answers of these questions cannot be found in the data alone and nuanced understanding of the problem is lacking to form hypotheses. Thus, problem uncertainty can exist on any level of this specific model.

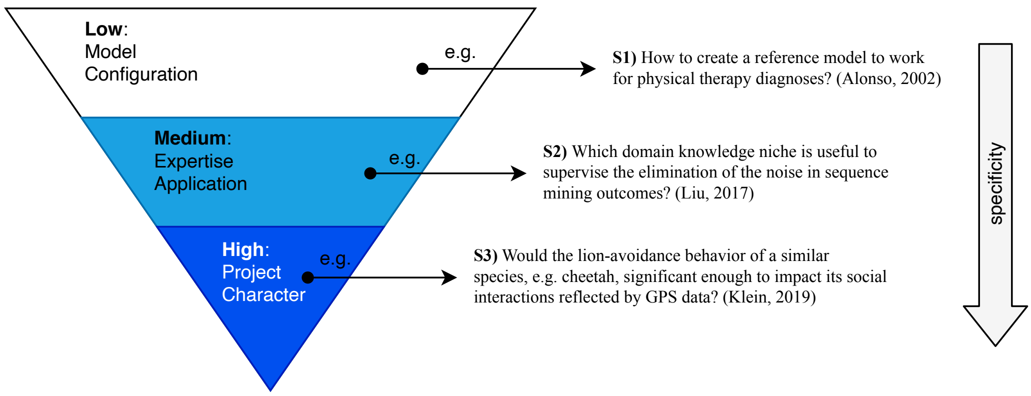


Figure 3.1: Specificity Levels of Problem Uncertainty: questions with a higher problem specificity are closer linked to the exclusive character of the underlying problem whereas ones of lower specificity consider shared traits of the problem from an abstraction form.

Reducing problem uncertainty on these levels paves the way for data exploration and consequent hypothesis generation. However, hypothesis generation is not and should not be about aimless random guesses as there are too many potentially irrelevant question niches to distract the research. Without an objective to guide the procedure, time wasted on laborious work is likely. The procedural nature of exploratory knowledge finding – analysts start with an estimation or interest and gradually adjust the question for deeper insights – requires inspirational starting points. Therefore, it is important to address this issue early in real practice. Analysts need an utility of guidance to exploit limited knowledge of problem to foster a starting point to being the exploration.

Characterization of the problem is the essential goal of reducing problem uncertainty. To support the guidance of exploration, it is advantageous to 1) integrate existing knowledge of problem and 2) transform such knowledge into another type which contribute to the awareness of potential structures and relationships of the problem beyond the information provided by data. The utility of guidance should support gradual relevance of certain facets of the problem character based on which a more comprehensive picture is retrieved through consecutive explorations.

3.2 Addressing Problem Uncertainty

Guidance from Knowledge Assistance

Facilitating explorations through the guidance of knowledge assistance in the visual analytics context is coined as Knowledge-Assisted Visual Analytics (KAVA for short). In KAVA, knowledge assistance can usually be exploited as systematic, explicit knowledge (such as the Industry Foundation Classes schema in infrastructure management [150] or the diagnostic rules in rehabilitation [151]) to serve as standards reference for professional judgment. The explicit knowledge (usually objectively defined in the domain field) can be formally or semi-formally defined as explicit knowledge store (also, EKS). KAVA systems can leverage these (formalized) explicit knowledge as canonical reference for classification or validation jobs. The knowledge assistance in this form is primarily static feature sets which often referred as rules. We see wide adoptions of these in

[150]: Motamedi et al. (2014), "Knowledge-Assisted BIM-Based Visual Analytics for Failure Root Cause Detection in Facilities Management"

[151]: Wagner et al. (2019), "KAVA-Gait"

rule-based expert systems, which defines the first generation of AI [152]. Because the rules are pre-defined and static, a user can only influence the system's operations by the placement of these rules with little influence over their internal structures.

[152]: Russell et al. (1995), *Artificial Intelligence*

However, if the explicit domain knowledge is not readily formalized or sufficiently applicable to reduce problem uncertainty, a process of knowledge externalization is required to convert implicit/tacit knowledge to external representations [153]. For instance, the tacit knowledge of effective data views can be externalized by collecting subjective rating on the quality of system-generated views [154]. As one of the four knowledge transfer processes (i.e. internalization, externalization, collaboration, and combination), Wang et al. [155] recommended storing user-generated knowledge during the analytical process into a knowledge database to improve follow-up research. The benefit of this approach has been realized in cases such as filtering or color-encoding call sequences in malware analysis [156], or guiding the mesh simplification algorithm for urban textures [157], which alleviates one or more of the typical problem uncertainty as in Figure 3.1.

[153]: Federico et al. (2017), "The Role of Explicit Knowledge"

[154]: Boukhelifa et al. (2013), "Evolutionary Visual Exploration"

[155]: Wang et al. (2009), "Defining and Applying Knowledge Conversion Processes to a Visual Analytics System"

[156]: Aigner et al. (2018), "KAVA-Time: Knowledge-Assisted Visual Analytics Methods for Time-Oriented Data"

[157]: Chang et al. (2008), "Legible Simplification of Textured Urban Models"

The openness toward individual's partial, tacit knowledge is gaining interest [158] partially because the context-dependent mental constructs from individuals may have substantial benefits [53]. For instance, the *knowledge discovery in databases* (KDD) paradigm values subjectivity as a rather important role in securing new knowledge from data regardless of whether it takes the form of a user input of the subjective interestingness [79] or an individual's serendipity and intuition [159]. Both the belief function in Dempster-Shafer theory and the choice of k in k-means clustering depend on subjective decisions of inputs instead of objective computation results. In these cases, the reliance on subjectivity is unavoidable. In fact, many data related tasks in modern data analyses such as data cleaning, data mining, and machine learning, to some extent, all collaborate

[158]: Chung et al. (2016), "Knowledge-Assisted Ranking"

[53]: Grzymala-Busse et al. (2000), "Data Mining and Rough Set Theory"

[79]: Frawley et al. (1992), "Knowledge Discovery in Databases"

[159]: Di Blas et al. (2017), "Exploratory Computing"

with people's subjectivity despite avoiding subjectivity has been a long-standing concern in scientific research.

Criticisms against subjectivity claim that analyst's subjectivity can be narrowed by and biased toward the analyst's own experience [160, 161]. For instance, the inertia of accustomed workflows may prevent the adaptation of corrected ones [160], or the coincidental existence of an inferior one may render the evaluation of the current candidate more appealing than it really is (cf. attraction effect [162]). As these caveats are hard to eliminate [163], safety measurements are necessary to manage the potential caveats when exploiting the value of user-generated knowledge [164, 165].

[160]: Dimara et al. (2020), "A Task-Based Taxonomy of Cognitive Biases for Information Visualization"
[161]: Choi et al. (2019), "Concept-Driven Visual Analytics"
[162]: Dimara et al. (2017), "The Attraction Effect in Information Visualization"
[163]: Pannucci et al. (2010), "Identifying and Avoiding Bias in Research"
[164]: Tukey (1962), "The Future of Data Analysis"
[165]: De Bie (2010), *Maximum Entropy Models and Subjective Interestingness*

Procedural Knowledge with Semantic Interaction

Knowledge assistance can be formulated at the pre-design stage of an analytic tool. This type of assistance are feasible before the actual data exploration because they are based on either objective and unvarying explicit knowledge or criteria and rules that are easily externalized as formal descriptions by domain experts. For instance, the Business Process Model and Notation (BPMN) method can rigorously define a business model following the operations determined by the organization objectives (Figure 3.2). The system then executes the program describing the business model to get outcomes of task specifications with little or no support for interactions [166]. As a comparison, user-generated, context-dependent knowledge can be accumulated during the interaction stage. If applied wisely, the latter type of knowledge can be leveraged to guide the next loop of discover, save, and reuse iteratively [167], yielding waves of new knowledge chunks to better reveal the structures and relationships of the research problem, which gradually decreases the problem uncertainty. For instance,

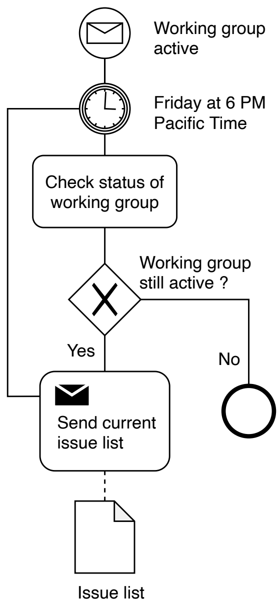


Figure 3.2: An example of Business Process Model and Notation depiction

[166]: Kluza et al. (2019), "Formal Model of Business Processes Integrated with Business Rules"

[167]: Xiao et al. (2006), "Enhancing Visual Analysis of Network Traffic Using a Knowledge Representation"

[153]: Federico et al. (2017), "The Role of Explicit Knowledge"

[168]: Green et al. (2010), "ALIDA"

[156]: Aigner et al. (2018), "KAVA-Time: Knowledge-Assisted Visual Analytics Methods for Time-Oriented Data"

the visually identified patterns in network traffic can be interactively represented to the system which makes it ready for reuse in future classifications [167]. Here, we characterize the former type of knowledge assistance as *declarative* as it contains explicit definitions and unambiguous descriptions, while the latter being *procedural* since the rules are refined by human-in-the-loop approaches.

Declarative knowledge, as an important part of the domain knowledge pool, can be formalized easily and be fed into machines. Procedural knowledge which usually lacks a formal standard which is often hard to describe with discrete languages, need to be exploited through the indirect approach. According to Federico et al. [153], procedural knowledge can be captured by accumulating the implication of tacit knowledge inferred from semantic interactions [168], i.e. user interaction supported with a vocabulary of domain-related actions/concepts. By operating visual interfaces, procedural knowledge can also be parameterized [156] and represented in machine friendly formats [167]. This process can be realized by system passively capturing the procedural knowledge while user is performing the exploration. For instance, as a user is sorting sport action events to prioritize on the most significant events during the game, the system can derive sorting functions from the user inputs and depict the used parameters to allow interactive refinements of the model [158]. Using this knowledge as input to recursively generate new ones is known as intelligent data analysis [169]. A visualization design concept specialized at the retrieval of user inputs is the *semantic interaction*.

To disambiguate semantic interaction in visualization design from semantic visualization [9, 170, 171], which extracts semantic elements (concepts, individuals, relations) by mining ontology structures from a knowledge database (of similar usage with EKS as described in § · 3.2 Guidance from Knowledge Assistance), the notion of semantic interaction in visualization design focuses on creating a semantic abstraction so that knowledge about the working details of the algorithms is not necessary — semantic interaction systems will be responsible for capturing the user's intention and translate them from mental artifacts to algorithmic adjustments [172]. The user's intention can be modeled based on record of interactions over time so that model adaptations can happen to generate approximations to the interesting features [173]. For instance, the underlying model of a visual analytic system can adjust its spatial layout of textual documents by monitoring user interactions [174], which can improve the quality of identification of interesting text. In this case, the first adjustment may not produce the optimal layout but a useful approximation for the follow-up iterations.

Semantic interaction embraces visual metaphors to communicate hypotheses [173], through which the user can passively read the symbolic representations of the model (e.g. boxes as grouped text documents) or actively configure the visual space to externalize their assertions (e.g. labeling, annotating, filtering, or organizing the document or document group). The graphical means provides an intuitive channel of intelligence interchange which allows for quick sense-making as well as iteration of hypotheses. This is important because creating a flexible environment for procedural assimilation of knowledge [145] synchronizes well with the psychological nature of human knowledge building, which immediate declarative answers are usually not instantly available [175].

[167]: Xiao et al. (2006), "Enhancing Visual Analysis of Network Traffic Using a Knowledge Representation"

[158]: Chung et al. (2016), "Knowledge-Assisted Ranking"

[169]: Hand (1998), "Intelligent Data Analysis"

[170]: Nazemi et al. (2010), "Semantic Visualization Cockpit: Adaptable Composition of Semantics-Visualization Techniques for Knowledge-Exploration"

[171]: Sheth et al. (2004), "Semantic Visualization: Interfaces for Exploring and Exploiting Ontology, Knowledgebase, Heterogeneous Content and Complex Relationships"

[9]: Mutton et al. (2003), "Visualization of Semantic Metadata and Ontologies"

[172]: Endert et al. (2015), "Semantic Interaction"

[174]: Endert et al. (2011), "Unifying the Sensemaking Loop with Semantic Interaction"

[173]: Endert (2014), "Semantic Interaction for Visual Analytics"

[145]: Chang et al. (2009), "Defining Insight for Visual Analytics"

[175]: Park et al. (2018), "ConceptVector"

3.3 Knowledge Building as Dual Space Search

Existing visualization designs are already capable of leveraging exploited (declarative) knowledge to either contribute new (declarative) knowledge (as in intelligent data analysis) or guide user specifications (i.e. the interactivity taken to explore a subset) (§ · 3.2 Addressing Problem Uncertainty). While performing analyses following such a pattern, people tend to make discoveries following a strategy of consistently comparing the gathered data to their expectations, based on which new goals are set to explain possible discrepancies [176]. Klein et al. describe the combination of "goals, expertise, and stance" with data as *data-frames*, which play a central role in sense making by guiding the next steps in choosing, interpreting, and incorporating new data [177]. For instance, what strategy do the intelligence professionals follow may substantially steer the interpretation of available intelligence to assess the likelihood of a nuclear threat during the 1962 Cuban Missile Crisis [178]. The devised tactic may determine the discovery of new data, which may leads to conformity or conflict of current "frames" (of human) by either contrast or synthesis of evidences (of data). Under these conditions, the distinction and interplay between human and data, conceptual and factual is quite visible.

[176]: Dunbar (1993), "Concept Discovery in a Scientific Domain"

[177]: Klein et al. (2007), "A Data-Frame Theory of Sensemaking"

[178]: Moore et al. (2011), "Data-Frame Theory of Sensemaking as a Best Model for Intelligence"

In fact, the complementary duality of human vs. data, conceptual vs. factual is prevalent in many discovery processes, pointing to a fundamental feature in knowledge building in general. According to Klahr and Dunbar [82], scientific reasoning consists search processes in two problem spaces: the hypothesis space, containing each generated hypothesis during the discovery process, and the experiment space, containing possible experiments to validate certain hypotheses. In these spaces, the hypotheses are human conceptions and the ex-

[82]: Klahr et al. (1988), "Dual Space Search during Scientific Reasoning"

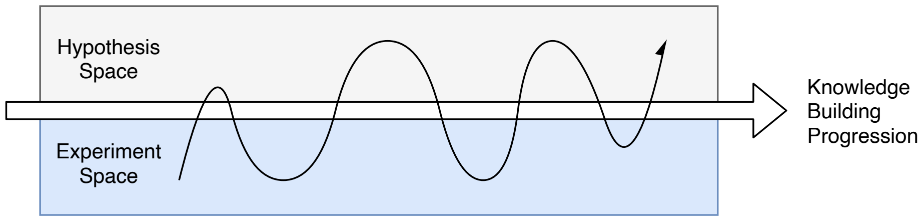


Figure 3.3: The Dual Space Search Model: Scientific reasoning with data progresses as a continuous search process in two complimentary spaces. The hypothesis contributes to the experiment and the experiment triggers new hypotheses. A researcher fluently switches between the two spaces to explore novel knowledge.

periments are factual validations. Search in the hypothesis space is guided both by prior knowledge (long-term memory) and experimental results, which takes place in the experiment space. In turn, the current hypothesis invokes a search in the experiment space to generate information to formulate new hypotheses. In this loop, knowledge is built through a continuous search activity switching between two complimentary spaces (Figure 3.3).

Data analysis which may not rigorously replicate the scientific reasoning process is also a version of dual space search process. Take Snow's cholera map (Figure 1.1 in chapter 1) for example, the discovery of denser death cases near a pump as a factual evidence triggers the hypothesis of the potential correlation between infection rate and proximity to the pump's location. Verifying this hypothesis by counting the death numbers near all the other pumps can work as experiments for quick mental validation✍. Klahr and Dunbar's dual space model was introduced decades ago before the arrival of Internet and big data. Today, the unaddressed complexity of data can easily disrupt the workload distribution between the two spaces. For instance, as comprehensive knowledge of raw data become less affordable, hypothesis generation would not easily assume timely sense-making of all available data, whereas the time cost

✍: Historical facts indicate the presented map is primarily used as a communication tool to convince local authorities.

of experiments, if well defined, can be effectively moderated by improved computing capacity. As such a tendency is becoming more salient, the smoothness of traveling between the two spaces drops exponentially. This gap can be justified by adding data representation to extend the original model in a later revisited version of the paper [179].

[179]: Schunn et al. (1995), "A 4-Space Model of Scientific Discovery"

In the same way of how semantic interaction promotes procedural knowledge finding, the progression of hypothesis-experiment loop can also benefit from the visual abstraction to lower the mental workload. Metaphoric representations of factual data in the search spaces is plausible because it repeats the design philosophy of utilizing visual abstraction in semantic interaction — replacing the need for detailed knowledge to reduce learning overhead (§ · 3.2 Procedural Knowledge with Semantic Interaction).

Exploiting a visual and semantically sensible representation of data is a way to augment dual space search. In the experiment space, new evidences from last loop, which can be poorly formatted, need an intuitive representation to stay consistent with the user's prior tacit knowledge to facilitate new hypotheses, i.e. being able to trigger immediate judgments or inspirations according to prior experience. This is important because the tacit knowledge, as a valuable asset to derive new knowledge [169], is often not readily externalized or even hardly externalizable since it mostly resides in human mental models [153]. Instead, the analyst may use ambiguous descriptions or heuristics to rationalize new findings as moving along the dual spaces. For instance, a diagnosis expert may assume an irregularity in patient visits in recent days but unable to find a crisp definition of the irregularity pattern or "feeling". The variation of color or distribution shape of visitors by weekdays may provide a subtle replacement of the intuitive judgment. If the visualization system is capable of capturing the semantics of irregularities in a more coherent manner, it will play smoothly with existing

[169]: Hand (1998), "Intelligent Data Analysis"

[153]: Federico et al. (2017), "The Role of Explicit Knowledge"

mental model of the expert's reasoning which leads to easier formation of the next hypothesis. As we are working toward a comprehensive understanding of the data problem (§ · 3.1) through procedural steps [177], the semantic visual abstraction of evidences (from the experiment space) is useful as it enables faster paces in searching for new hypotheses by removing interpretation barriers and making shortcuts to expert users' tacit knowledge for smoother reasoning process [180].

[177]: Klein et al. (2007), "A Data-Frame Theory of Sensemaking"

[180]: Shipman et al. (1999), "Formality Considered Harmful"

The hypothesis space may also benefit from semantic abstractions as new hypotheses can be built on top of the concepts represented by the semantics. For instance, the analyst can ask questions like "is the effect of *irregularity* growing?" or "is there any historical record of such an *irregularity*?". As experiments leveraging machine capacity are easier with unambiguous definitions (e.g. event frequencies, conditional rules), the necessity of turning a hypothesis into a visual format remains an open question. However, visualized hypotheses have resulted plausible effects in terms of usability and user experience gains [181] and model manipulation effectiveness [182].

[181]: Zgraggen et al. (2015), "(S, Qu)Eries"

[182]: Bardohl et al. (2004), "Integrating Meta-Modelling Aspects with Graph Transformation for Efficient Visual Language Definition and Model Manipulation"

Data inspire hypotheses. Hypotheses lead to new evidence. We see the cumulative nature of knowledge generation a core feature of the dual space search model. This, however, is poorly reflected by existing knowledge assistance implementations. On the experiment side, once new data are presented, the knowledge assistance provided by the system merely facilitate professional judgment with readily externalized, explicit knowledge [150, 151]. On the hypothesis side, supporting methods are provisions of casual expectations by textual inputs [161] or numeric predictions with primitive visual depictions [183]. How the latest experiment result and a novel hypothesis are linked to reinforce each other is unclear.

[161]: Choi et al. (2019), "Concept-Driven Visual Analytics"

[183]: Heyer et al. (2020), "Pushing the (Visual) Narrative"

Visualizations in general value insights as a key indicator of effective knowledge generation. According to North [184]'s

[184]: North (2006), "Toward Measuring Visualization Insight"

account of insight, there are five criteria to meet, namely "complex, deep, qualitative, unexpected, and relevant". North's proposition amplifies the need for visualizations to touch a deeper, comprehensive, qualitative layer of the data problem, at which the aforementioned methods may fall short. Thus, supporting the dual space search for knowledge generation beyond primitive quantitative inferences becomes relevant. In addition to that, we would argue for a design method that also pays close attention to the explicit support of cumulative hypothesis generation and experimentation in accordance with the dual space search process.

3.4 Semantic Attribute

Hypothesis Search

Framing hypotheses requires both searching for interesting patterns and devising structured statements. There are distinctive processes governed by different principles.

On the searching part, hypotheses are usually triggered by local patterns which are expected to be experimented and generalized to solidify as useful knowledge [179]. Therefore, the assumption in an established hypothesis is inherently linked to a subset of features of interest. However, the location and identification of the sub-features are not always clear. This is where eliciting initial concepts and introducing semantics becomes helpful. With simple keywords, a concept can initialize a coherent interest which creates a focused search space. The step is mostly user-driven. For example, the user can specify a subspace of interest leveraging domain specific prior knowledge, generic prior knowledge, internal and external goals, or personal attributes [83]. In this way, the concept functions

[179]: Schunn et al. (1995), "A 4-Space Model of Scientific Discovery"

[83]: VAN Joolingen et al. (1997), "An Extended Dual Search Space Model of Scientific Discovery Learning"

as a helpful constraint to ensure concentrated search in the hypothesis space [176].

[176]: Dunbar (1993), "Concept Discovery in a Scientific Domain"

The semantics derived from the concepts also set the "seeds" for semantically similar cases to converge and snowball in the experiment space. For instance, a document analysis system can leverage a keyword input as a seed to retrieve relevant terms by semantic similarity, from which the user can further refine its lexical associations with the rest of the corpora data by interactive experiments such as linking with semantic groups or filtering our irrelevant concepts [175]. By continuing searching and refining, deeper and more nuanced hypotheses are possible thanks to the cumulative knowledge by the convergence and snowballing of relevant information pieces. However, the semantic representation of such a concept, whether as a constrain or "seed", is scarcely a design objective. We argue that a semantically sensible visualization of the concept can make a novel type of knowledge assistance by itself [153].

[175]: Park et al. (2018), "ConceptVector"

[153]: Federico et al. (2017), "The Role of Explicit Knowledge"

On the statement part, organizing mental artifacts into structures is essential. The Human Cognition Model (HCM) suggested by Green, Ribarsky, and Fisher [185] places emphasis on the batch hypotheses generation of human capacities (also seen in *optimistic visualization* [132]) matched by the machine capacities to validate the hypothesis with a "matrix"of prove or disprove. One of the advantages of this approach is that it maximizes the concurrency of living hypothesis-experiment threads which reduces the time cost. However, each experiment result has no influence over the other hypotheses. Thus, this compartmentalized structure of mental artifacts (i.e. each hypothesis search and validation work in its own separated space) hinders the depth of exploration. To support the depth of the hypothesis search space (i.e. the vertical height of the hypothesis space in the dual space search model, cf. Figure 3.3), we need to ensure previous discoveries (e.g. earlier notes of small experiment results) can contributes to the latest exploration

[185]: Green et al. (2008), "Visual Analytics for Complex Concepts Using a Human Cognition Model"

[132]: Moritz et al. (2017), "Trust, but Verify"

[186]: Shrinivasan et al. (2009), "Connecting the Dots in Visual Analysis"

context [186]. The relationships between these hypotheses can thus provide hierarchical structure of the piecemeal knowledge, one inspiring another, creating hypothesis statements with improving detail and quality.

[161]: Choi et al. (2019), "Concept-Driven Visual Analytics"

[187]: Bollen (2012), "Instrumental Variables in Sociology and the Social Sciences"

[188]: Didelez et al. (2010), "Assumptions of IV Methods for Observational Epidemiology"

[189]: Faucett et al. (2002), "Survival Analysis Using Auxiliary Variables Via Multiple Imputation, with Application to AIDS Clinical Trial Data"

In the face of problem uncertainty, the hypothesis search is a progressive effort. As one tends to search in narrow spaces where hypotheses and experiments are framed and tested provisionally [161], we suggest that enhancements to hypothesis search should leverage semantic integration of concept as well as continued exploit of existing hypotheses to make more "complex, deep, qualitative, unexpected, and relevant" insights accessible.

Reinforcing with a Novel Attribute

When analyzing a phenomenon, it is useful to introduce a non-existing variable as an instrument to bridge a gap in the reasoning. In observational epidemiology [187] and social studies [188], the introduced variable is called instrumental variable (IV), which is used to regulate the disturbance upon known variables (observable variables) or verify endogenous covariations. For instance, analyzing the effect of a respondent's education on the prestige of first occupation might use his/her father's education as a IV for respondent's education. Survival analysis in clinical trials [189] can include an auxiliary variable to restore missing information (e.g. event time) and improve estimation efficiency with fewer errors.

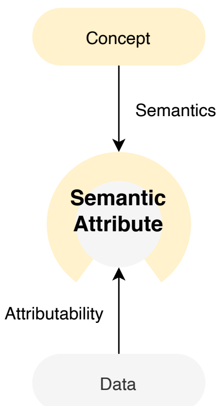


Figure 3.4: Semantic Attribute: the auxiliary attribute that combines domain concept and raw data for deeper hypothesis search.

Under the goal of enhancing hypothesis search with a concept, we introduce a new variable that combines the semantics (derived from the concept) and the attributability of data variable (Figure 3.4). It interfaces with an preliminary semantic to project a meaning or concept into the analysis context featuring calculations based on factual data. It is designed to address problem uncertainty by leveraging human ability in conceptualization such as common sense, creativity, or domain expertise and machine ability in verification and data aggregation through computation. The composition of a semantic attribute has an expert-driven ideation and a domain-dependent formal definition. Such an arrangement is to mitigate undesirable side effects of subjective conceptualization explained in § · 3.2 Guidance from Knowledge Assistance (the former) by ensuring its compliance with ground data features via a rigorous formula (the latter). The expectation is to expose the implicit, under-explored facet which is only accessible in the deeper area of search space (§ · 3.3 Knowledge Building as Dual Space Search).

The introduced semantic attribute thus functions as a pivot, which is a critical point that passes inaccessible knowledge to a reachable range. The visualization approach featuring the semantic attribute for the same effect is identified as "pivotal effect", which we will give more detailed definition and elaboration in § · 3.5 The Pivotal Effect.

3.5 The Pivotal Effect

The pivotal effect, which is achieved by introducing a semantic attribute and implanting it into the visualization pipeline, is the defining character of pivotal visualization. We clarify the concept and application method of pivotal effect in this section.

Concept

The first appearance of *pivoting* as a hypothesis supporting feature can be found in the anchor recommendation functionality

[190]: Lin et al. (2020), "Dziban: Balancing Agency & Automation in Visualization Design via Anchored Recommendations"

in Dziban [190], where an auxiliary view of unexplored information is presented to adjust the user's hypothesis for better questions. The auxiliary view here works as a stepping-stone toward deeper, more informed hypotheses instead of the usual ultimate answer, which contributed a plausible boost to the research. An apparent intersection between the pivoting view and pivotal visualization is the shared principle of leveraging an indirect view to improve the visual analyses — pivotal visualization constructs novel representation using derived semantic attributes instead of experimental hypotheses. However, the pivotal visualization aims to strike a systemic effect in the dual space search model comparing to Dziban's one-shot support for modified hypotheses:

Firstly, the pivotal effect is realized by a dynamic variable that encompasses a range of questions instead of one. For instance, the auxiliary view in Dziban's case is a static outcome of a query result from a given question. The view updates as the static parameter set is replaced by another question. The possible derivations from the original hypotheses are unaddressed. As a comparison, leveraging a semantic attribute instead of a new view allows for decomposing the initial hypothesis to one or more key concepts. This polymorphic nature of semantic attributes support not only a simple value but a multivariate context. Thus, the identification and formulation of semantic attributes scaffolds a novel search space instead of an onetime representation of a static pattern as what Dziban provides. The pivotal effect is not a hypothesis adjustment facility but augmentation to support the multifacetedness of the hypotheses.

Secondly, the pivotal effect extends the reachability of domain knowledge. Domain knowledge usually helps the analyst to relate the hypothesis to the necessary sub-group or sub-feature of data, by which a hypothesis is formed. The formed hypothesis leverages a data view to continue a follow-up experiment. However, this convention only uses domain knowledge to modify the data view instead of internalizing the knowledge as part of the substantial materials to assist hypothesis conceptualization with the visualization system. The pivotal effect closes this gap by the visual embodiment of domain knowledge, casting influence throughout the visualization pipeline from drafting initial concepts to the ultimate experiments for conclusive knowledge.

These two points distinguish pivotal visualization as a design method with more profound impacts to the explorations. To back up this concept of pivotal effect, we add theoretical anatomy consisting of clearly defined rationales and implementation scaffolds, with which the non-trivial effort in realizing the pivotal effect can benefit from. We continue the extensive elaborations by illustrative figures and formal definitions in the next section.

Formalism

An Asymmetric Model of the Dual Space Search

The dual space search model [82] illustrates the underlying pattern of knowledge discovery. It underlines the duality and gradual, cumulative nature of knowledge discovery. Through constructing hypotheses and conducting experiments, the consistency of new knowledge can be verified with known information. However, the model presents two problem spaces as symmetrical blocks, which may contradict reality in some cases. For instance, the very effort of experimentation requires data to support as ground facts. Ideally, every new hypothesis in the hypothesis space is justifiable (or falsifiable) by experimenting with the corresponding data. However, in reality, the provision of data is not inexhaustible — insufficient information can suspended the experiments in the middle ground of neither

[82]: Klahr et al. (1988), "Dual Space Search during Scientific Reasoning"

yes nor no. Then, the hypothesis in this situation is invalid as it contributes no extra knowledge. Therefore, the exploration space of all valid hypotheses (determined by the variety and depth of hypotheses) needs to satisfy the verifiability (or experimentability) of hypotheses assuming that the domain expertise and the prior knowledge remains constant without altering the analyst. Since experiments of hypotheses need to be supported by data, a shortage of data availability threatens the how much of the hypotheses can be experimented. However, this detrimental effect only goes in one direction from experiment space to hypothesis space — reducing the number of hypotheses have no substantial influence on the provision of data and the associated experimentability. We found that such a unidirectional dependency, where the hypothesis space is constructed on top of (and therefore limited by) the experiment space and the experiment space is largely determined by data availability under the hood, is overlooked by the symmetric notation of dual space as in Figure 3.3. This inconvenience motivates us to devise a modified version of the dual space model to accommodate the asymmetric relationship between the two search spaces. As a result, we have conceptualized a model featuring an asymmetric adaption from the original dual space structure as in Figure 3.5.

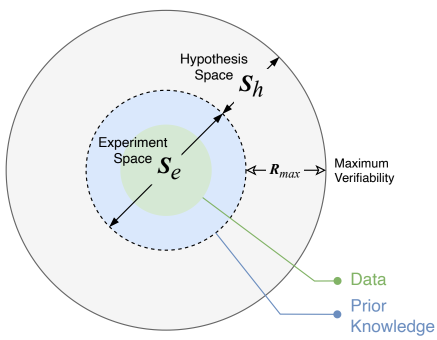


Figure 3.5: An asymmetrical depiction of two problem spaces: the area of experiment space depends on the availability of data (green region). The hypothesis space is extended from the experiment space (blue area), the thickness of which relies on the maximum distance of verifiability of experiments (R_{max}). A dashed line between hypothesis space and experiment space indicates the dual space search can travel between as in the symmetrical model.

The new asymmetrical model utilizes concentric circles to represent exploration spaces where areas of the inner circles (i.e. data, experiment space) support the areas of the hypothesis space. In this model, the experiment space is determined by the ground data and related inferences based on previously externalized declarative knowledge (§ · 3.2 Procedural Knowledge with Semantic Interaction). Here, we use *prior knowledge* to represent all sorts pre-existing knowledge regardless if it is externalized with the aforementioned process or not for simplicity. Similar to the original model, the experiment space and the surrounding hypothesis space share a common border (dashed line in Figure 3.5 Asymmetrical Problem Spaces), indicating both spaces are traversable for hypothesis/experiment searching. The new model includes data availability as an integral factor, which facilitates the explanation of the advantages of pivotal effect.

While making explorations in the two spaces, the areas may increase, updating the proportions of each in the total area for knowledge exploration. For instance, an upsurge of infection number in certain demographic niche provides important fresh ground knowledge to possibly explain the epidemiological cause of the disease. The new data from the diagnosis report can be used to test the hypothesis that medical experts hold, giving them stronger validation support to solidify their knowledge of the disease. The expert may rethink their hypothesis if the previous one is wrong, or continue to form new ones based on that for more detailed understanding. This process invokes the expansion of the experiment space as latest discovery brings more evidence to validate the hypothesis or inspire more hypothesis which was not accessible before the new data is available. Similarly, improved prior knowledge can also affect hypothesis space, making deeper or more efficient (i.e. more likely to be proved as true) hypothesis possible. Given that the contribution of new data or improved prior knowledge to each dependent region is unknown, we only use the figure to mark the structure of the model instead of the exact areas of each, which may vary to the specific situation.

The hypothesis space is unique because it has an open border outside, indicating it is less confined and flexible for extension since the hypotheses themselves are not inherently required to be true and one can freely have a growing number of hypotheses as long as they are relevant to the research. The outside border we used is only to indicate the limit number of *valid* hypotheses, i.e. the hypotheses verifiable in current setup. The closer a hypothesis is located to the outer border, the less verifiable it is. Here, we denote the verifiability (or experimentable) of a hypothesis by $\boldsymbol{h}$. $\boldsymbol{h}$ decreases as its distance to ground knowledge $\boldsymbol{d}$ increases. Assuming no additional data or more capable analyst can be leveraged, a hypothesis it is not verifiable if it is located beyond the maximum limit of verifiability $\boldsymbol{R_{max}}$ (i.e. $\boldsymbol{h} > \boldsymbol{R_{max}}$). Thus, we can conclude that the hypothesis is inconsequential and out of scope (Figure 3.6). We use sentences like "the raised question cannot be answered by experimenting with available data alone" or simply "this collected data is irrelevant to this issue" to describe situations like this.

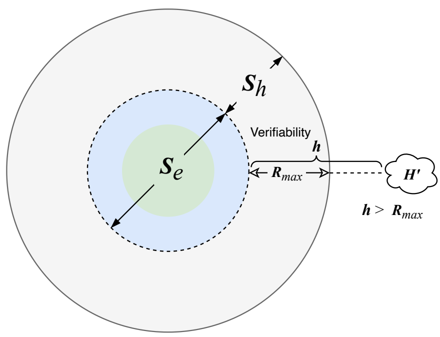


Figure 3.6: An Unverifiable Hypothesis: Bigger distance from experiment space $\boldsymbol{h}$ indicates the hypothesis is less easier to experiment and verify. If the verifiability $\boldsymbol{h}$ goes beyond the boundary of what current experiment space can support (i.e. $\boldsymbol{h} > \boldsymbol{R_{max}}$), the hypothesis is our of scope and inconsequential to deriving meaningful knowledge.

Since exploration involve search in both of the spaces, we define the exploration space $\boldsymbol{E}$ as the union of hypothesis space $\boldsymbol{S_h}$ and experiment space $\boldsymbol{S_e}$, i.e. $\boldsymbol{E} = \boldsymbol{S_h} \cup \boldsymbol{S_e}$.

Therefore, this asymmetrical model raises two important facts: 1) the unidirectional dependency toward ground knowledge, and 2) the bounded verifiability of hypotheses.

The Pivotal Effect with a Semantic Attribute

A reference to this asymmetric model makes it easier to illustrate the realization of pivotal effect through the introduction of a semantic attribute.

Firstly, it aligns well with our common sense as a broader diversity in the hypothesis generation is helpful to capture novel ideas. However, overloading the analysis with random, scattered hypotheses can lead to distractions, which undermines the likelihood of deeper discoveries on a focused theme. It will be more productive and revealing if the piecemeal findings can assist each other under a common problem realm. For instance, in soccer game analyses, the pressure on the ball shares similar patterns as the same on players [191]. The analyses of one contributes to another as both involve understanding the dynamic of the common theme of pressure. From a design perspective, a connection that apparently wraps these two problems together will help to address this issue of random and scattered hypotheses without a focus. If we can converge the hypotheses forming to concentrate on a coherent theme, the hypotheses can thus inform another, leading to a structured understanding of the problem (as explained in § · 3.4 Hypothesis Search). In this example, the concept of pressure can perform the function of a semantic attribute that converges threads of inquiries to create enough focus for the non-salient knowledge (e.g. the interaction between ball pressure and movements of

[191]: Andrienko et al. (2017), "Visual Analysis of Pressure in Football"

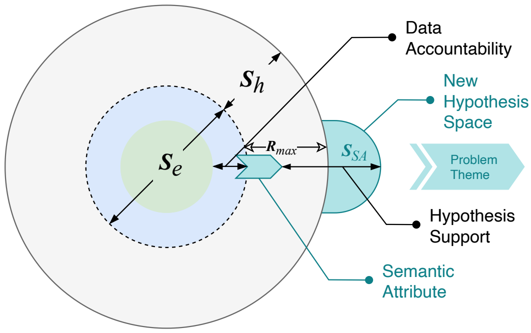


Figure 3.7: Implanting semantic attribute in the asymmetric model creates a pivotal effect which enables 1) coherent explorations toward a problem theme and 2) ground knowledge extension permitting inward attributability of hypotheses and enabling outward novel hypothesis space.

players), which is harder to access if hypotheses are scattered in pieces.

Secondly, as the concept in a semantic attribute incorporates tacit domain knowledge and inferences from data, it enriches the ground knowledge in the experiment space (the union of green and the blue area) while keeping the verifiability intact. The embodiment of a concept allows the analyses to perform with hypotheses on the level of concepts (instead of feature parameters). The rigorous match to the source data (determined by its composition, cf. Figure 3.4) allows an interface to be established for bidirectional reasoning — accessing existing knowledge and data in the experiment space from hypotheses (inward) and catalyze new experiment outcomes to inspire new hypotheses (outward). Therefore, the explorations in the dual space search based on the semantic attribute ensures the hypothesis-experiment cycle is lifted to the domain conceptualization level but not easily derailed by loose definitions of concepts.

The aforementioned advantages are explained by Figure 3.7, where the mechanism and composition of the pivotal effect are illustrated. Here we depict the semantic attribute as an extruded knob instead of a full circle to represent the problems adhering to the concept, i.e. topics of a common theme surrounding that semantics. This depiction tells that 1) the semantic attribute intersects with prior knowledge in the sense that they both leverage the domain knowledge while semantic attributes do not require a rigorously externalized format of the knowledge, 2) a semantic attribute implies a specified direction of search driven by the concept of relevant domain knowledge. Thus, the semantic attribute guides the experiment space toward a designated theme and extends the original hypothesis space $S'_h = S_h \cup S_{SA}$. New questions leveraging the concept in semantic attribute can therefore happen in the new realm. Thus, the total exploration space is expanded as

$$E' = S'_h \cup S_e = (S_h \cup S_{SA}) \cup S_e$$

, thus

$$E' > E$$

given the unmodified maximum verification distance R_{max}.

This expansion of exploration space has a systemic effect on knowledge discovery. We employ a model to summarize the pivotal effect on this process. Assume no new data are collected, the constant amount of raw data is denoted by d and the prior knowledge (externalized declarative domain knowledge) based on that is denoted by I_d. Then, the available ground knowledge for experimentation is the sum of the two, i.e. $K_0(d) = d + I_d$. Since knowledge discovery is a cumulative search process, the size of discovered knowledge grows in time. We distinguish the time spent in hypothesizing as t_h and the time spent in experimenting as t_e. Thus, a complete hypothesis-experiment cycle takes the time of l, i.e.

$$l = t_h + t_e \tag{3.1}$$

If we use $\boldsymbol{l_i}$ to denote the time spent for the *i*-th loop of hypothesis-experiment cycle, $\boldsymbol{n}$ is number of loops given the exploration time $\boldsymbol{t}$, then $\boldsymbol{n, t}$ suffices $\sum_{i=0}^{n} l_i \leqslant t < \sum_{i=0}^{n+1} l_i$. Therefore, the time and data dependent model of discovered knowledge is defined as:

$$\boldsymbol{K(t, d) = d + I_d + \sum_{i=0}^{N(t)} Q_i(E)} \tag{3.2}$$

where $\boldsymbol{Q_i(E)}$ is the knowledge chunk discovered in the *i*-th hypothesis-experiment loop based on exploration space $\boldsymbol{E}$, and $\boldsymbol{N(t)}$ is the function to find number of loops $\boldsymbol{n}$ given the time $\boldsymbol{t}$. Since improving exploration space augments knowledge discoveries, $\boldsymbol{Q}$ is positively correlated to $\boldsymbol{E}$, i.e. $\rho_{Q,E} \geqslant \mathbf{0}$. Thus, an exploration space boost from $\boldsymbol{E}$ to $\boldsymbol{E'}$ improves knowledge discovery from $\boldsymbol{Q_i(E)}$ to $\boldsymbol{Q_i(E')}$ in each loop, contributing to the search productivity and the quality of new discoveries.

The side-effect of increasing the exploration space is the extra time budget in forming hypothesizing ($\boldsymbol{t_h}$) and experimenting ($\boldsymbol{t_e}$), which sum up to a longer loop time $\boldsymbol{l}$ (Equation 3.1). We suppose the experiment time to take up a larger proportion of the total loop time after an exploration space improvement. This is a result of respective effects on the two spaces:

On the experiment space side, a semantic attribute adds new information on top to the experiment space, which contributes to a larger scope of information. It takes a longer time to search in a larger experiment space. Thus the time $\boldsymbol{t_e}$ is expected increase. Also, verification with concepts in the semantic attributes requires the knowledge exchange with the related domain knowledge, which only resides in human minds and is not easily accelerated by computation. The domain knowledge in this case acts as a gatekeeper to improve the quality of generated knowledge, at the cost of time efficiency.

Conversely, the time cost for hypothesis search t_h is likely to decrease because semantic representation eases the conceptualization by eliminating the mental workload of understanding the underlying data complexity (§ · 3.2 Procedural Knowledge with Semantic Interaction). In a hypothesis search, validating a hypothesis (checking) often costs much less resource than forming one (searching). This aligns with our daily experience. For instance, when performing the data analyst to study the carbon emission in different states in US, the assumptions of whether population contributes more significantly to the emission than industrialization is an outcome of thoughtful reasoning, which usually takes a period contemplation longer than fact-checking with software tooling.

As we try to combine the two opposing effects on the efficiencies of exploring the two spaces, the added time cost from additional experiment space is apparently overshadowed by the boost in hypothesizing efficiency. This is because the boost in human productivity in searching hypotheses contributes a larger time difference comparing to the negligible additional time cost to cover a larger experiment space with software facilitation. Therefore, in a fixed total time t of hypothesis-experimentation, the average time cost of each loop after the space expansion $\bar{l}'$ is expected to be lower, i.e. $\bar{l}' \leqslant \bar{l}$, resulting in more loops of search, i.e. $n' \geqslant n$, which leads to an amplification to the total amount of discovered knowledge $K(t, d)$ as in Equation 3.2.

In sum, the pivotal effect produced by implanting a semantic attribute to the asymmetric search model can achieve improved knowledge discovery. It enables faster search of deeper, more focused hypotheses even when the research objective is complicated with problem uncertainty.

Visual Depiction

The manipulation of visual artifacts enables a dialogue between human and machine [192, 193]. Likewise, to make the pivotal effect tangible to the user, visual depiction is essential. Visual encoding in visualization design is the process that transforms raw data into visual mappings such as colors [89], shapes [55, 194], or spatial locations [195]. In this process, the visual variables need to consider the intrinsic matching of data variables. For instance, the hue differences of colors can be leveraged to distinguish categorical data, while shape dimensions like height (or size) are suitable for numeric data. We also prefer to use screen locations to present the inherent spatial relations in GPS coordinates. However, semantic attribute is easily mapped like the variables in the raw data because of its incorporation with the semantics of concept. Visual design for the concept needs to be both context-sensitive (e.g. the intensity gauge of network traffic flows) to be seamless with the original variables and feature-rich (e.g. flexible layout reconfiguration) [196] to accommodate various angles to explore problems associated with the concept.

[192]: Liu et al. (2010), "Mental Models, Visual Reasoning and Interaction in Information Visualization"
[193]: Cai et al. (2019), "Human-Centered Tools for Coping with Imperfect Algorithms During Medical Decision-Making"

[89]: Harrower et al. (2003), "ColorBrewer.Org"

[194]: Javed et al. (2012), "Exploring the Design Space of Composite Visualization"
[55]: Elzen et al. (2011), "BaobabView"

[195]: Slack et al. (1992), "Encoding Information through Spatial Relations."

[196]: Shneiderman et al. (2006), "Network Visualization by Semantic Substrates"

Accurate and quick interpretation of conveyed semantics depends on its close alignment with the visual encoding [88]. Some conventions in cartography such as blue for water and green for forests are good examples following this rule. Theoretically, the Form-Semantics-Function model [197] treats semantics as a function in the domain vocabulary to create resemblance between the visual metaphor (i.e. the analogy to a domain feature by the design of a single visual variable or the organization of visual variables) and the domain function. Simoff [197] divides the transfer of semantics into *common semantics* (i.e. semantics sharing similar notions in both source domain and target domain, e.g. symmetry and balance) in generic space versus *new semantics* (i.e. semantics revealing

[88]: Lin et al. (2013), "Selecting Semantically-Resonant Colors for Data Visualization"

[197]: Simoff (2008), "Form-Semantics-Function – A Framework for Designing Visual Data Representations for Visual Data Mining"

unique characters between form metaphors and functions, e.g. thickness of a border stroke and the priority of that task) in the blend space✍. Simoff [197] argues that the design of visualized semantics should focus on revealing the unique characteristics of certain domain functions with new semantics in the blend space, which motivates the design effort to emphasize more on the novel unknown aspects beyond the existing domain concepts. Thus, the visual design of a semantic attribute should not only explain just the semantics but also invoke new relationships, formal manifests, and visual expressions of new semantics in the visualization system [198].

✍: The type of semantics is the defining feature of the two spaces. There are 4 spaces in total including source space of form and target space of function.

[198]: Rind et al. (2019), "Towards a Structural Framework for Explicit Domain Knowledge in Visual Analytics"

Focusing on the creative function of inspiring new thoughts, the semantic attribute may further extend the concept into deviated sub-concepts to assist various analytic scenarios, resulting versions of visual forms supported by respective data translations. For instance, a quantitative measurement of a pair can be translated into graphical relationship of a group, or scalar values could be translated to temporal paths. Such deviations project the semantic attributes non-intrusively into the analytical environment, facilitating quick interpretations and knowledge generations leveraging the parent concept [161].

[161]: Choi et al. (2019), "Concept-Driven Visual Analytics"

The visual design for a semantic attribute depends on a set of unique features in the data, the problem context, and the domain interest. Therefore, one fixed formula to encompass every little design consideration is practically impossible. So we apply a brief abstraction to the visual design method. Built on top of that, chapter 4 and chapter 5 will elaborate the complete implementation details to substantiate the benefits of pivotal visualization in explicit cases.

3.6 Study Context: Investigating Implicit Behaviors

As the development of digitization of everyday things goes on, complex problems are increasingly possible to be represented by data, which opens up the possibility of data-driven and data-reliant studies of behaviors. Such a trend is already taking place in the behavior studies of animals [199, 200] as well as humans [201–203]. As the scope of and depth of the study expand, applications of data analysis techniques based on modern apparatus becomes prevalent.

[199]: Ware et al. (2006), "Visualizing the Underwater Behavior of Humpback Whales"
[200]: Cakmak et al. (2020), "MotionGlyphs: Visual Abstraction of Spatio-Temporal Networks in Collective Animal Behavior"
[201]: Zeng et al. (2020), "EmoCo"
[202]: Meire et al. (2016), "The Added Value of Auxiliary Data in Sentiment Analysis of Facebook Posts"
[203]: Wu et al. (2019), "ForVizor"

The data-empowered behavior analysis requires treatments to the quality and availability of data, which is determined by the data provenance stage. There are two major data provenance approaches to collect behavior data (as opposed to the classic manual input or labeling in the historical cases (§ · 1.1 Why Visualization?)): 1) using digital sensory to capture a selected feature set from the physical world and storing them in a (semi-)defined schema, or 2) accumulating system logs from open-ended virtual environments where people can participate via an agent living in a platform (e.g. video games and social network services). This difference in the origination of data can be divided by the notions of *sensory data* versus *log data*.

The sensory data and log data in our studies have three differences: **1) they are used to describe behaviors in different time-spaces**. Sensory data is observed in real world bounded by universal natural physical laws, while log data only follows the system-defined behavioral rules which may not be consistent depending on the system. **2) They are prone to different vulnerabilities.** sensory data need to consider potential fidelity loss as limited by the sensing capacity or physical situation. This issue does not exist in log data. The transmission, storage, and computation errors can negatively affect the data quality of both. **3) The reproducibility of ground truth are different.** If log data only stores every state change during the process, a deterministic system can basically reproduce the entirety of the process without loss of fidelity. This does not hold true for sensory data as only the selected features in the interested phenomena, events, or processes are logged for analysis. The analysis therefore only covers certain aspect of the behavior as long as it provides sufficient evidence for the argument.

Awareness of this distinction and the possible consequent advantages or disadvantages are constructive to the hypothesis generation and interpretation of experiment results. For example, since GPS data are sensory, the location specified by the coordinates might be incorrect under certain weather conditions or geographic occlusions (e.g. atmospheric effects, sky blockage [204]). Considering this, frequent sudden turbulence of movement trajectory in certain areas might be recognized as a place of poor signal instead of real intensive movements. Also, because different virtual environments support different types of behaviors, the analysis method for certain behavior need to be adjusted or even redesigned for similar insights. For instance, the play duration of an attempt can reflect opposite player competitiveness in puzzle-based games and survival challenge games.

[204]: Husnjak et al. (2015), "Telematics System in Usage Based Motor Insurance"

In the upcoming chapters, each of the two studies use one of the aforementioned data types respectively. One is based on sensory data from wild animals in the open space while the other is the log data from video game replays. In both studies, we have turned our focus on the behavior patterns of living entities because behavior problems contain non-exhaustible influencing factors (e.g. heterogeneous internal states and external conditions) [205–208]. Therefore, the research problems concerning behaviors can be near-infinite as they are hardly determined by the limited data only, which makes them suitable candidates for analyzing data facing high problem

[205]: Einhorn et al. (1981), "Behavioral Decision Theory"
[206]: Hastie (2001), "Problems for Judgment and Decision Making"
[207]: Nathan (2008), "An Emerging Movement Ecology Paradigm"
[208]: Wilson et al. (2014), "Wild State Secrets"

uncertainty. Facing this, we develop the pivotal visualization design method, whose components and effects are illustrated by the asymmetric dual space search model. The theoretical model of pivotal visualization explained in this section presents an approach to augment knowledge discovery under problem uncertainties. We unfold the application details of the pivotal visualization method with complete studies starting from the next chapter.

Study A: Visualizing Players' Strategy Choice and Action Complexity in Video Games

4

Overview: *Behaviors in game plays can be analyzed through saved replay data. This chapter* presents a previously published study that demonstrates how pivotal visualization can establish a novel perspective into the actions, timings, strategies in game plays for learning experts. The explored implementation tracks the dynamics between* behavior complexity *and performance change as players improve.* Strategy patterns *are depicted through a customized glyph system (i.e. Strategy Signature) to visualize structural differences in strategy. We allow easy access of contextual information to verify discovered insights against raw attributes. Evaluation with expert users shows that the system effectively reduced their time and effort in finding interesting sub-groups and gave them unexplored angles of behavior complexity to contemplate player's skill growth.*

4.1 Introduction

In addition to providing entertaining challenges, a video game also makes an open platform to collect diverse user interactions. The inputs during a game play are gestalt results of perception, conceptualization, problem framing, and iterative learning. Thus, the play data derived from game logs are valuable assets to study players' individual preferences as well as learning

* This chapter is based on the published work W. Li, *M. Funk, Q. Li, and A. Brombacher, Visualizing Event Sequence Game Data to Understand Player's Skill Growth through Behavior Complexity, Journal of Visualization, May 2019.*

patterns. The visualizations facilitating this task are being developed to enable fast and flexible exploration into players' behavior patterns [209], lowering the barrier of data analysis with domain knowledge informed judgment [210].

[209]: Wallner et al. (2013), "Visualization-Based Analysis of Gameplay Data – A Review of Literature"

[210]: Chen et al. (2009), "Data, Information, and Knowledge in Visualization"

For either self-improvement [211, 212] or game design [213], player performance is a common concern in the field of game analytics. Visualizations can effectively reduce the effort to rate the game plays or players by visual comparison. However, finding the performance differences and investigating the cause of them are different because different levels of understanding are involved — the chronicle perspective of how players learn and improve over time can exhibit valuable details to extract a more structured view of how players play a game. This involves insights into the implicit strategy choices, execution-and-refinement loops, or the individual learning styles which are not easy to measure and therefore statistically analyzed. Therefore, it is necessary to design visualizations specifically to study the performances and learning processes by scrutinizing the variations of strategies over time from multiple perspectives.

[211]: Yohannis et al. (2015), "Visualization of User-Learning Game Interaction Unveiling Learner's Learning Patterns"

[212]: Ikeda et al. (2013), "Visual-Motor Sequence Learning by Competitive Fighting Game Experts"

[213]: Bowman et al. (2012), "Toward Visualization for Games"

To understand the strategy variations, we employ *action complexity* and *strategy patterns* as the semantic attributes. The former is observed by the heterogeneity of players inputs, to facilitate the insights into the learning patterns in video games whereas the latter is glyph system encoding strategy characteristics to delineate the intensity of in situ strategy shift (i.e. the tendency toward incremental improvements of consecutive strategies v.s. abrupt reconceptualization of new strategies). The result is a web-based interactive visualization tool that allows learning experts to reason with a wider range of hypotheses regarding how players improve their games through repetitive trials. Evaluations with the learning experts show that the pivotal effect supported by the two semantic attribute can effectively boost research productivity with which several unseen patterns are successfully discovered.

To the best of our knowledge, our visual analysis approach is novel in the game domain in terms of the integration of behavior complexity and the support of insight into repeated learning processes. This study illustrates how pivotal visualization can be implemented to exemplify its effectiveness in the game analytics domain. We argue that the explorations into the behavior complexity and its relation to discrete action data, performance outcomes, and most importantly strategy abstractions in this study elicits reusable knowledge for research of similar interests. We mention a few highlights in this study: 1) We exemplified an integrated visualization following the pivotal visualization approach which enables a view of implicit action complexity for learning behavior study. 2) We invented a novel glyph system for medium length event sequence to extract players' strategy characteristics for self-comparisons of consecutive attempts as well as between-player preferences differences.

4.2 Literature Related to This Study

Related works to this study are three-fold. This first focuses on recent works applying visualization techniques to analyze game data. The second discusses how complexity can be derived using entropy-based models. The last covers techniques that summarize event sequences beyond video game related fields.

Visual Analysis For Games

Visualization of game data can be differentiated by design purposes influenced mostly by the targeted users, based on which the design rationales can vary significantly [209, 214]. Following such a distinction, the two most recognizable types of visualizations are the entertainment oriented-visualization and the developer-oriented visualization. The entertainment-oriented visualizations are also noted as "playful visualization" [214, 215] because visualizations under this umbrella is mostly driven by the need to extend the enjoyment of the game itself. Entertainment features such as on-line community [216] or achievement system [217] are integrated to motivate participation and player engagement. In contrast, the developer-oriented approach cares less about how much extra appeal the visualization be added to the game by itself. Their primary focus is to use the game log data to reproduce the gaming process for postmortem analyses based on which playing experience can be understood to iterate the game design [218–220]. For instance, game designers can use the derived insights from visualizations to deliberately tweak and adjust the game design at specific stage/phase to streamline the experience journey of the game.

[209]: Wallner et al. (2013), "Visualization-Based Analysis of Gameplay Data – A Review of Literature"
[214]: Medler et al. (2011), "Analytics of Play"
[215]: Caillois et al. (2001), *Man, Play, and Games*
[214]: Medler et al. (2011), "Analytics of Play"
[216]: Medler (2011), "Player Dossiers"
[217]: Medler et al. (2011), "Data Cracker"

[218]: Farooq et al. (2015), "Interpreting Behaviors of Mobile Game Players from In-Game Data and Context Logs"
[219]: Ribeiro et al. (2017), "Visualizing Log-File Data from a Game Using Timed Word Trees"
[220]: Li et al. (2017), "A Visual Analytics Approach for Understanding Reasons behind Snowballing and Comeback in MOBA Games"

Comparing to these two categories, our study has a significant distinction as the design requirement is centered upon the learning behaviors instead of gaming or game development, which may require specific considerations that are not fully covered by the aforementioned works. Prior works in this regard are few but interesting. Farooq, Baek, and Kim [218] extracts player behavior model in a routine manner, but the dynamic difference between time and individual is less observed. Hernández, Duarte, and Dodero [221] utilize Process Mining to build behavior models in serious games (video game with educational purposes), but lacks advanced visualization and interactions. Wallner [222] used a transition-focused approach to seek evidence on progressive changes of behavior patterns — specifically with event sequence data. However, the study primarily emphasize on technical implementation instead of visual design.

[218]: Farooq et al. (2015), "Interpreting Behaviors of Mobile Game Players from In-Game Data and Context Logs"
[221]: Hernández et al. (2017), "An Architecture for Skill Assessment in Serious Games Based on Event Sequence Analysis"
[222]: Wallner (2015), "Sequential Analysis of Player Behavior"

The player behaviors are often inferred from primitive measurements such resources, items, or movement locations. Therefore, it is often required to synthesize abstract metrics beyond these primitive factors to describe higher level behavior patterns. Moura, el-Nasr, and Shaw [223] summarized time-dependent actions of the selected session into a static diagram to display behavior patterns in an action role-playing game (A-RPG) game. Similarly, Li et al. [220] uses derived metrics to reveal the mechanism behind snowballing effect (one side of rival teams accumulates advantages unvaryingly) in multiplayer online battle arena (MOBA games). However, the used abstraction methods are mostly designed for numeric attributes, which are incompatible with categorical events.

[223]: Moura et al. (2011), "Visualizing and Understanding Players' Behavior in Video Games"

[220]: Li et al. (2017), "A Visual Analytics Approach for Understanding Reasons behind Snowballing and Comeback in MOBA Games"

These previous work either displays insufficient treatment to our case or noticeable-to-major incompatibilities with the objective of our study. Therefore, an unexplored approach to speculate the learning patterns and the related behaviors is motivated.

Informational Complexity with Entropy

In information theory, entropy is a measurement of the heterogeneity of possible states in a system. Similar entropy-based principles can also achieve plausible results in measuring the complexity of human behaviors [224, 225].

[224]: Fussell (2005), "Measuring the Early Adult Life Course in Mexico"
[225]: Chu et al. (2014), "Visualizing Hidden Themes of Taxi Movement with Semantic Transformation"

For action events in a video game, measuring the complexity of gaming actions is essentially measuring the randomness or the lack of order in a given set of categorical data. To achieve this, there are several applicable methods. They are Complexity Index [226], the Turbulence [227] and Longitudinal Entropy [226]. However, the first two methods are sensitive on the sequence length, which are prone to duplicate noise of repetitive user inputs despite the same underlying intention. Considering this,

[226]: Gabadinho et al. (2011), "Analyzing and Visualizing State Sequences in R with TraMineR"

[227]: Elzinga et al. (2007), "De-Standardization of Family-Life Trajectories of Young Adults"

[226]: Gabadinho et al. (2011), "Analyzing and Visualizing State Sequences in R with TraMineR"

the Longitudinal Entropy which streamlines the essential information quantity, suits the best for its consistent performance in both verbose and short sequence.

Given the $\boldsymbol{p_i}$ is the proportion of positions of the same action $\boldsymbol{i}$ and $\boldsymbol{A}$ is the alphabet size of all the possible actions. The formula of complexity can be defined as:

$$\boldsymbol{H(p_A) = -\sum_{i=1}^{a} p_i log(p_i)}$$

Provided the complexity can be quantified as scalar values, visualization of behavior complexity can be made possible. But how the behavior complexity varies especially in the context of repetitive gaming process is not touched by existing visualization work.

Techniques in Summarizing Event Sequences

Making sense of massive event sequence is hard. Some authors use mining algorithms to find a simplified subset of events as a representative of similar ones. Their techniques usually vary in the sensitivity on different attributes to categorize sequences based on particular domain requirements. For example, Chen, Xu, and Ren [228] designed a "soft pattern matching" mechanism to summarize multiple event sequences that tolerates minor inconsistencies of events for less cluttered results. Unger et al. [229] use both semantic similarity and temporal similarity to form meaningful clusters. Apart from automated pattern extraction, user defined matching rules before visual inspection or statistical analysis are also possible. Works like Cappers and Wijk [230] and Zgraggen et al. [181] adapted query languages and regular expressions to remove noise data and unrelated sequences with graphical user interfaces. Thus, categories

[228]: Chen et al. (2018), “Sequence Synopsis”

[229]: Unger et al. (2018), “Understanding a Sequence of Sequences”

[230]: Cappers et al. (2018), “Exploring Multivariate Event Sequences Using Rules, Aggregations, and Selections”

[181]: Zgraggen et al. (2015), “(S, Qu)Eries”

sorted by different rules form accordingly with cleaner visual result. However, this approach is more useful to find the most representative (i.e. most common or frequent) patterns. The techniques for scenarios when identifying frequent sequences is less important are insufficiently explored

There are also ways to improve the sense making in event sequences with primarily visual design. For example, *LifeFlow* [231] and *CoCo* [232] summarizes low cardinality patient journey events with a tree structured view. *MatrixWave* [233] achieved the summarization by mostly layout design, which is appealing because direct visual representation without the loss of information is proven to be highly effective. However, scalability issues may arise when information density increases and visual clutter is unlikely to be avoided easily.

[231]: Wongsuphasawat et al. (2011), "LifeFlow"

[232]: Malik et al. (2015), "Cohort Comparison of Event Sequences with Balanced Integration of Visual Analytics and Statistics"

[233]: Zhao et al. (2015), "MatrixWave"

4.3 Project Background

Lix: Game as a Data Platform

Puzzle games are a genre that has a low-entrance barrier for most novice players. Unlike intensive action or shooter games, puzzle games are less demanding on fast reflexes and prior experience, making them more inclusive toward wider demographic groups including both male and female, senior and junior participants [234]. This advantage ensures the analysis of learning is not biased toward a particular niche and the insights are more representative of learning behavior patterns in the general population. As learning are progressive processes, the study of learning behavior requires multiple batches of game logs containing consecutive attempts to reconstruct the timeline of progressive adjustments. The game choice needs to consider the time cost to quickly generate game log batches produced by discrete retrials. Furthermore, to eliminate the influence of

[234]: Brown (2017), *Who Plays Video Games?*

non-player factors, we prefer deterministic games (i.e. same input will always produce a fixed result regardless of the player and the time of attempts) as oppose to non-deterministic ones (i.e. the game progresses as a join product of player control and non-controllable variables such as behaviors of other players or random environmental influences) to ensure players' performance variations are faithful reflections of individual learning. Considering these criteria, the game Lix suits the study context well as it suffices easy player onboarding, quick and steady data production, and deterministic gaming mechanism.

Figure 4.1: Lix Game: little bots (lixes) are spawned automatically from the black square hole in the middle left. The control bar at the bottom indicates jumper is currently selected and ready to be triggered on one of the lixes. The middle right part of the picture shows a deep tunnel into the ground made by miner s. Yellow bars at the tunnel's entrance are built by platformer s, which can support upcoming lixes walking on them. The destination is out of current screen frame to the right, which can be found by mouse hovering on the right boarder of the screen to scroll over.

✍: http://www.lixgame.com

Lix is an open-source variation of Lemmings, which was originally developed in 1991 by DMA Design✍. The game consists of puzzle-like challenges, where a new "lix (the autonomous walking bots)" is spawned into a two-dimensional virtual world every a few seconds until a top number of 20 (Figure 4.1). Lixes walks restlessly by default which may potentially be killed by encountering hazards such as falling into water. Each lix turns back if hits an impassable obstacle such as a wall or a hill. Actions (such as jumper) can be triggered with a lix, practicing the ability to interact or change the corresponding landscape, which may help the other lixes to pass over or take a safer path otherwise. For example, a player can trigger a miner to dig a tunnel into a hill or trigger a platformer which modifies the pathway to make it less steep to pass safely. A list of available actions are platformer jumper climber floater batter blocker nuke exploder and miner. During the play, players arrange good timing and actions to help the lixes arrive at the destination with the least loss-of-unit. A top score of 20 is possible if all of the lixe members safely arrived at the destination.

Expert Background

Five domain experts (E1 E5) are involved in the project: E1 is a researcher with 4 years of research experience in studying human learning in game scenarios, who is also the maker of the data collection program to extract data from native replay files. E2 is a game researcher with a strong background in game visualization as well as data mining. E3 is a researcher with industry experience of video games and is familiar with modern game development processes. He has contributed widely applied user research methods in the game environment. The rest two (E4 and E5) are junior research assistants specialized at data analytics and informatics. E4 and E5 are responsible for purposing possible new analytic methods to meet certain requirements. Only E1 is a proficient player among all the experts.

The research is exploratory in the sense that all the experts do not have crisp questions for the data collection. The objective is to find as many as possible new ways to develop a proper description of learning behaviors by exploiting the data. From their awareness of the game domain, it is acknowledged that learning pattern is deeply tangled with the in-game decision-makings as players progress. The experts are interested in exploring novel angles in understanding the actions especially by ways beyond known statistic models.

Data Description

The raw data consist of numerous actions from 15 players with 271 sessions in total (a new session ends when an attempt or trial to win is over). An action is recorded every time a player triggers an ability with a lix (possibly one of the actions shown in the control bar in Figure 4.1). Each action is described by eight attributes, including the *Player* as the player's identifier, the $\boldsymbol{n}$-th *Attempt* of this player, the *Action* type (like jumper), the number of elapsed frames updated (*Update*) when action is triggered upon the $\boldsymbol{m}$-th *Lix* by spawning order. The game uses result to mark the end of an attempt. The number of *Saved*

Table 4.1: An Example of Raw Data Scheme: beginning data points of the first attempt by Player 1

Player	Attempt	Action	Update	Lix	Saved	Ability	Second
1	1	JUMPER	76	0			
1	1	PLATFORMER	158	2			
1	1	PLATFORMER	174	3			
...	...	...	...	...	...	...	...
1	1	RESULT	9205	NA	0	4	614

lix will be counted as the final score when result is triggered. The data also summarize used unique actions (*Ability*) and the attempt's used time (*Second*).

Players are recruited from college students with not prior experience with the game. Lix has many built-in stages (i.e. virtual worlds of challenges) to choose from. We selected a novice level (easiest of all four levels) to moderate the challenge in case the learning is crippled for being overly difficult to some players. We encourage the player to freely learn and test their solutions as much as possible.

4.4 User Study

We conduct user studies in three phases to uncover the domain requirements as preparations to design the visualization. The first phase is to obtain a general sense of the current workflow to find possible pain points. The second phase iterates versions of design mock-ups to test out the most suitable design pattern. The last phase concludes the design requirements for the final implementation.

Phase I: Domain Investigation

Process

In this phase, we conduct semi-structured interviews with the domain experts during which their current working routine and existing discoveries are shared. We ask questions regarding how insights were generated by current methods (e.g. E4 and E5) shared their findings from explorations with R packages), during which experts are free to suggest new functionalities with specifications of their explicit needs. Their sharing also clarifies the used apparatus for extracting raw data from the game's native replay files. Each player plays a single session at a time with a free choice on how many attempts are good enough to represent their skills. Players play in isolation one after another without any awareness or influence of others' game play. This ensures later players cannot learn from earlier ones even tried the same challenge.

Pain Points

A few pain points in their current workflow are identified with the process above. For instance, we found the analysis operations are cumbersome as it requires laborious reconfiguration by editing the source code to experiment different hypotheses. Also, their sequence mining algorithm can produce some simple results but the experts seem to struggle with interpreting the results and relating them to certain behavior insights. This potentially indicates that the experts lack a direct access to the game context from which they can reason with the awareness of related factors to the mining results. It is also reported that visualizations by the generic plotting methods in R packages, which they use frequently, is too primitive and lacking levels of detail on demand. They wish to immediately test newly formulated inquiries on the fly which is unfortunately not well-supported by the current workflow.

Phase II: Iterating Alternatives

We use visual mock-up (as an effective method to communicate design ideas [235]) is to quickly flesh out the design concepts to search solutions that possibly fill the gaps in current workflows. As most domain experts (except E2) are not knowledgeable about visualization designs, we employed co-design sessions to elaborate on details and go through an iterative process to solidify the final plan for the design of functions and layouts (Figure 4.2).

[235]: Ferreira et al. (2007), "Agile Development Iterations and UI Design"

As discussions continue, the design details are enriched by iterative versions of visual design with adjustments confirmed by the designer and the expert users. This process also helps us obtained a crisper sense of how the visualization is likely to be used in clinical settings which are unlikely to be possible without such an effort. For instance, the experts may occasionally look into the time intervals between actions to understand the solution based on which they can generalize some patterns of strategies. Also, as learning behavior study, one may want to know whether the player is decisive or hesitative. A reference to the time differences maybe necessary for this case.

Phase III: Summarizing Requirements

Works in the previous phases help us enlist a few critical tasks to be supported in the final design. To ensure the implementation aligns with the facilitation of these tasks, we explain the most significant requirements to consider both in the explicit design and afterward implementation.

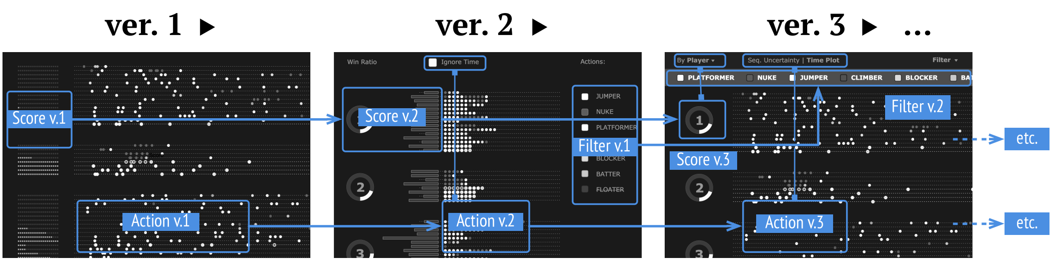


Figure 4.2: Alternative designs and rationale history (color bleached for presentation): *Ver.1* differentiates action types with color. Actions of a single attempt are represented by a horizontally line with the distance determined by the time elapsed in between. Scores are numerically displayed on the left. *Ver.2* Added a) aggregated player performance, b) a filter to show/hide certain action to focus on an action subset, c) the "ignore time" checkbox to discard time intervals for simple sequences. *Ver.3* joins the sequence action view and timed action view through a switch to accommodate different tasks.

***R1**: information display design should feature player orientation.* Since learning behaviors are highly related to player characteristics, the insights into how individual difference or group similarity based on people are essential to the research. Visual design of the interfaces should provide clear affordance for such player-orientation. Therefore, the visual elements corresponding to each data attribute should prioritize the prominence of player distinctions. Comparisons between players, which emphasize on the subtle individual differences in behavior patterns, are highly valued by the experts.

***R2**: the support for exploring the relevance between anomalies and raw attributes.* When raw data are summarized, the reduced view of data often hides the potential risk of overlooking important information. This means a quick peek into the information context of an anomaly is useful to locate deeper causes of a phenomenon or connections of a pattern. Also, a lot of efforts are wasted because the analysts lack efficient ways to revise certain episodes in a game play. Considering the data size is not too significant, exposing rich details of high granularity of behavior traces is possible and constructive, which also eliminates a substantial amount of effort of reviewing game plays.

R3*: improvement cycles by attempts should be supported to exhibit the chronicle strategy evolvement based on previous attempts.* Beyond performance as a result, the experts also care about the patterns of incremental changes that preceded before a strategy improvement or a success. As learning is a primary focus of our study, the details in the process of performance improvements are particularly valuable in the study of learning behavior patterns. Designing a view to allow easy comparison of consecutive attempts is needed for the analyses.

R4*: an efficient way to describe the qualitative differences between playing styles.* Based on experience gained from the prior attempts, each player could contribute novel successful plays through different techniques or procedures. The differences in strategies are qualitative and lack of an intuitive differentiation method. A visual means to catalyze the discovery of similarity between attempts and players is as useful as exhibiting the differences between the involving attempts of the same player. Visually identities of qualitative traits in strategies, which are faster to compare than statistical categorizations, are believed to be effective in this regard.

R5*: the delineation of complexity in player strategies compositions.* Experts frequently use "complexity" when describing player action combinations. However, such complexity is loosely-defined, usually perceived by the naive visual impression of the heterogeneity or density of actions in a sequence. This shallow interpretation is insufficient for comparison when sequences are complex or the qualitative differences are too insignificant to be directly observable. Also, the higher level trends of complexity turbulence are hard to conceive when actions are merely discretely positioned. The graphical account of the complexity variations should be implemented to support the complexity view of the action data.

4.5 Method

We employed a few novel methods to satisfy the requirements defined above, which serves as essential pillars in the design of visualization.

Behavior Complexity as a Semantic Attribute

To support the analysis of actions in a variety of angles, we introduce the semantic attribute of behavior complexity to this study. Here, the behavior complexity is defined as the measured heterogeneity of action data driven by the individual behaviors throughout the process of certain event, which is, in this case, playing a video game. When the observed actor uses more diverse type of actions, his/her next move becomes less predicable as the predictions need to choose from many pre-existing options. For instance, if a player retrospectively uses many miner s with very occasional jumper s during an attempt, his/her next move is significantly likely to be another miner . But if a player is just getting started and he/she wants to randomly test out the many functions of different moves without a concrete plan (which appears to be supported by some data series), the next move is nearly impossible to predict accurately because the actions seem to follow no rules and the resulted data look like noises comparing to ones of a well-defined configuration of a strategy. Behavior complexity in this regard is the attribute that put the subtle differences between these two types of behavior patterns into perspective. The higher the behavior complexity, the more diverse actions an actor could perform, which consequently makes him/her less predictable.

Hereby, assuming behavior complexities are influenced by a lot of invisible internal drivers of the actor (e.g. how much patience a game player has for the particular challenge, how anxious a player is during the play) as well as the external challenge (e.g. the game stage). Due to individual differences, the emitted behavior complexities can range from totally loss of order (high complexity) to steady repentance of uniform actions (low complexity). Following the gaining of experience, the complexity of actions (by attempts) will regress to one or a few centroids as solutions to a specific objective usually confines to a limited finite number. Thus, by examining the behavior complexity in different periods or scenarios, undiscovered patterns of learning behaviors can be observed despite we have no direct access to the internal drivers of the actor. In this way, the behavior complexity plays the role of a semantic attribute as it pivots the most obscure part of learning behavior (i.e. the internal processes) to external variations (i.e. action data), which can be visualized to interface with human pattern recognition abilities for knowledge finding. Visualizations based on this construct thus exemplifies the pivotal effect of behavior complexity (as the semantic attribute) in the context of puzzle games.

Quantification of Behavior Complexity

The strategy for this type of puzzle based game is defined by a set of action combinations, which outcomes are series of event sequences. A quantification result of the sequences should be designed to capture the heterogeneity of actions of varying length to represent the behavior complexity. Therefore, we employ longitudinal entropy which calculate the information quantity produced by the action sequences. This method is only sensitive to the order and state distribution of actions (usually a subset of the available actions). Since the complexity of actions may be an indicator of undetermined thinking facing a challenge [146], an increase of the information entropy of action combinations can supposedly be induced by cognitive stress. Because of the relationship, we implement the data processing flow to make the link between the action heterogeneity and behavior complexity apparent to reflect deeper insights in the learning behaviors, cf. Figure 4.3:

[146]: Li et al. (2018), "Toward Visualizing Subjective Uncertainty: A Conceptual Framework Addressing Perceived Uncertainty through Action Redundancy"

- ▶ Data points as discrete actions are aggregated into event sequences by every player attempt. The original temporal order of each action is preserved but the time stamps are discarded.
- ▶ Quantify the longitudinal entropy [226] of each action sequence.
- ▶ Store the quantification result as behavior complexity in a new column.

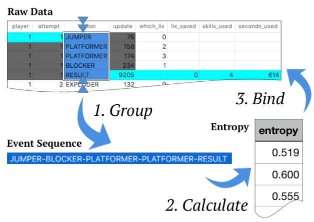


Figure 4.3: We nest (or group) individual actions and store them as action sequences (in string format) by per player per attempt and calculate longitudinal entropy of each as behavior complexity.

[226]: Gabadinho et al. (2011), "Analyzing and Visualizing State Sequences in R with TraMineR"

Required Complexity or Redundant Complexity

The measurement of behavior complexity opens up a new angle into the study of learning based on simple categorical sequences. The complexity can increase as a result of knowledge accumulation to devise new, advanced solutions. But it could also relate to necessary complications by imposing redundant, inconsequential actions. Likewise, simple actions of less behavior complexity may not be premature termination of the game or a sign of unskillfulness because of poor knowledge of many other actions. It could also be interpreted as refined strategy executed by finer, more accurate motor skills by the player as long as the full scores are never compromised by less complex action combinations. So there should not be a simple, one-way explanation to the measurement arguing that the increase or decrease of behavior complexity is always an advantage or disadvantage.

For an easier discussion, we define the complexity that can be reduced without damaging the final score as *redundant complexity*, while the minimum complexity of actions required to pass the stage as *required complexity*. The definition of the two concepts provides two functions. First, it raises the awareness of undesired over-complication, which may not be a reflection of meaningful growth but immaturity of a solution instead. Second, the ratio of redundant complexity and required complexity may be an indicator of stage difficulty on the basis of players may find some stages difficult to reduce the redundant complexity, suggesting the stage to be a difficult one.

As the astute readers may have noticed, the judgment of behavior complexity is rather difficult and more essential to the study than the quantification of it. To ensure the fidelity of insights, behavior complexities should always be contextually interpreted to understand the deeper cause of such a variation and challenged by domain expertise. This consideration provides strong reasons to understand the semantic attribute of behavior complexity by visualizing the multivariate context of gaming.

Strategy Pattern as a Semantic Attribute

Despite that some strategies are close in the complexity level, the exact solution may contain fundamentally different patterns which are not captured by numeric complexity alone. This means complexity per se is good at telling the subtleties in strategy composition. To summarize the qualitative difference in strategy and playing style, we need a firm grasp on how strategies differ from or resemble with each other. To this end, behavior complexity may not be ideal to suffice this goal. To address this problem, we employed a glyph system (i.e. Strategy Signature) to make qualitative features of strategies more distinguishable. As a key attribute to understand the behaviors, the qualitative strategy patterns are semantically represented by visual graphs, which makes the subtle differences in the diversity of playing styles more apparent to the human perception.

On the implementation level, Strategy Signature (SS) is glyph based model which renders a (long) action sequence into a compact circular polyline glyph (Figure 4.4). The shape of each SS is determined by the action type and order of appearance of each action in an attempt. The position of each action in a sequence $\boldsymbol{A}$ is determined through a polar coordinate system, which can be mathematically defined as the following:

$$\boldsymbol{A = (r_t \cdot \sin\theta_c,\ r_t \cdot \cos\theta_c)}$$

where

$$\boldsymbol{r_t = \frac{t}{N} \cdot R \quad and \quad \theta_c = \frac{c}{N} \cdot 2\pi}$$

Here, each position takes a radial angle $\boldsymbol{\theta}$ (determined by its order number $\boldsymbol{c-th}$ in a rule-of-thumb ordered list of actions) and the distance to the center $\boldsymbol{r}$ (determined by the time order $\boldsymbol{t}$). $\boldsymbol{N}$ ($\boldsymbol{N = 9}$ in Figure 4.4) is the length of action sequence. $\boldsymbol{R}$ is the maximum radius of the outer line.

This model ensures that same actions will always be aligned to the same radial direction, which is useful to tell the usage and frequency of certain actions. Like shown in Figure 4.4, the produced shape is sensitive to the time order of actions, which facilitates the distinction between sequences of similar action statistics but different time order.

With the new glyph system, we can easily judge the diversity of strategies such as sorting the strategies into a few typical categories. While preserving the subtle differences between similar ones, incremental changes and variation in strategy in consecutive attempts are still observable. Visualization based

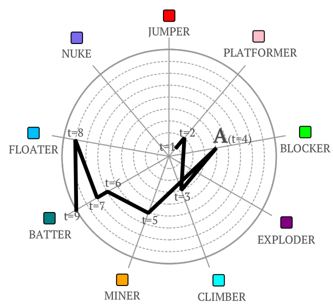


Figure 4.4: Example: Strategy Signature of event sequence platformer - platformer - climber - blocker - miner - batter - batter - floater - batter

on SS makes both commonality and distinction of strategy patterns recognizable with a glimpse. The pivotal effect based on this semantic attribute levitates the strategy patterns as a result of diversity of playing styles from the details of discrete action sequences, which facilitates the hypothesis forming with a higher level of concept (i.e. strategy pattern) without the need to read the discrete actions.

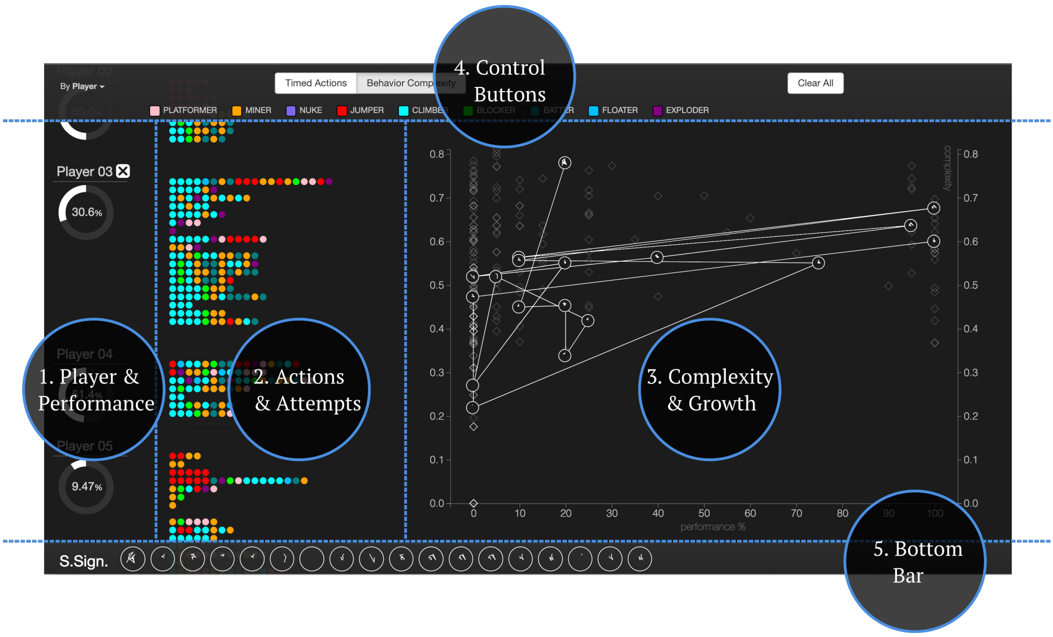


Figure 4.5: The default view layout has 3 views and 2 panels: 1) Player & Perfomance shows percentage of acquired scores by the player; 2) Actions & Attempts places actions horizontally following lines of consecutive attempts; 3) Complexity & Growth delineates complexity against performances in numeric scores; 4) Control Buttons are used to either indicate or change current view mode or and apply filter to certain action combinations; 5) Bottom Bar is dedicated to display Strategy Signatures.

4.6 Design

Layout

The overall design of the visualization can be found in Figure 4.5, where the interface is composed of a few cohesive views (section 1 3) divided by natural spaces instead of linear dividers for visual clearance. The layout begins with the control bottoms on the top to globally manipulate the display of data (more details in § · 4.6 Interactivity). In the main body area, columns from left to right are focusing on *1. player & performance*, *2. actions & attempts*, and *3. complexity & growth*. SSes are horizontally aligned at the bottom of the screen for easy comparison.

The first two columns depict all actions in the order of attempts and players. User can use mouse scrolling to browse the entire data set vertically to have a overview of all the actions in data. While triggering the scrolling interaction, the first two colomns, i.e. *player & performance* and *actions & attempts*, stays in sync with each other such as the location change in *actions & attempts* will drag *player* together to ensure actions and attempts are always adjacently displayed with the corresponding player(**R1**). The third column of *complexity & growth* is a summary of all and therefore stays afloat to vertical scrolling.

Visual Encoding

Analysts' inquiries demand a variety of information formats and scopes. For instance, the distinction between individual actions and the complexity of all the actions in an attempt may require different views to find an answer with. Following this, we highlight a few important key points to be supported by dedicated design treatments through visual encoding in this section.

Action

The most primitive attributes in the data are the distinctive types of actions by the players. With the voluminous number of actions, the workload of read action sequence as well as any tasks related to such effort is significant correlated to the ease of differentiating the action types. Considering this, we employ the pre-attentive channel of color for this task [236]. As suggested by cognitive science, the choice of nine vibrant colors can make the dots different action instantly distinguishable on a dark background, cf. left of Figure 4.7. The distribution of actions is easily skimmable with the visual patterns of colors that are fast to read and effortlessly processed by the subconscious mind. Skimming through the action dots gives the user a direct grasp on the details of discrete events (**R2**).

[236]: Healey et al. (1996), "High-Speed Visual Estimation Using Preattentive Processing"

To make the hierarchical order of actions, attempts, and players visually apparent, actions of a single attempt are depicted as round circles, organized in horizontal lines, and placed in juxtaposition to the players. In this way, the varying numbers of attempts by a player as numbers of actions in each attempt are intuitively organized together to make levels of details apparent to the viewer.

Complexity & Performance Growth

Behavior complexities and player scores are displayed in the same view next to the actions on the right, cf. Figure 4.6. This view is used to study the interaction between behavior complexity and the outcome performance, through with checking of covariance of achieved score and complexity value is allowed.

On the technical level, this view suppresses the discrete actions and depicts an individual attempt as a single point, in which attempts of higher scores are placed closer to the right and more complex ones are placed to the right. Note that the performances (x-axis) are displayed in percentage and behavior complexities (y-axis) are normalized to $[0, 1]$. The point takes the shape of a diamond to make positions more comparable with four sharp corners white border to bring up the contrast against the dark background.

As basic scatterplots do not communicate grouping and temporal orders that we need, the lines joining the points by attempts and players are plotted to describe the gradual steps of consecutive attempts. The explicit order of the-one-before, previous, current, next and the-one-after (Figure 4.6) is highlighted in colors of blue or red, of which the blue ones are before the current selection and the red ones are beyond. Ones near the "current" selection are filled with the corresponding color and one-step-further ones are simply outlined instead. This design enhances basic scatterplot with the extra ability to delineate the relationship of temporal order in a sub-group.

Strategy

Users can quickly skim through the colors of the dots to obtain a general view of used actions in the attempts. However, the similarity and difference in strategies take a considerable amount of visual memory [237] to make comparisons. This is even more challenging if the attempts are distantly presented (cf. Fitts' Law [238]) or repeated comparison between more attempts are required. Therefore, a space-saving, memorable representation is needed. This motivates the technique of SS (as introduced in § · 4.5 Strategy Pattern as a Semantic Attribute), with which we can encode the sequences into glyphs that have significant less visual information to read as well as to display.

[237]: Luck et al. (2013), "Visual Working Memory Capacity"

[238]: Fitts (1954), "The Information Capacity of the Human Motor System in Controlling the Amplitude of Movement."

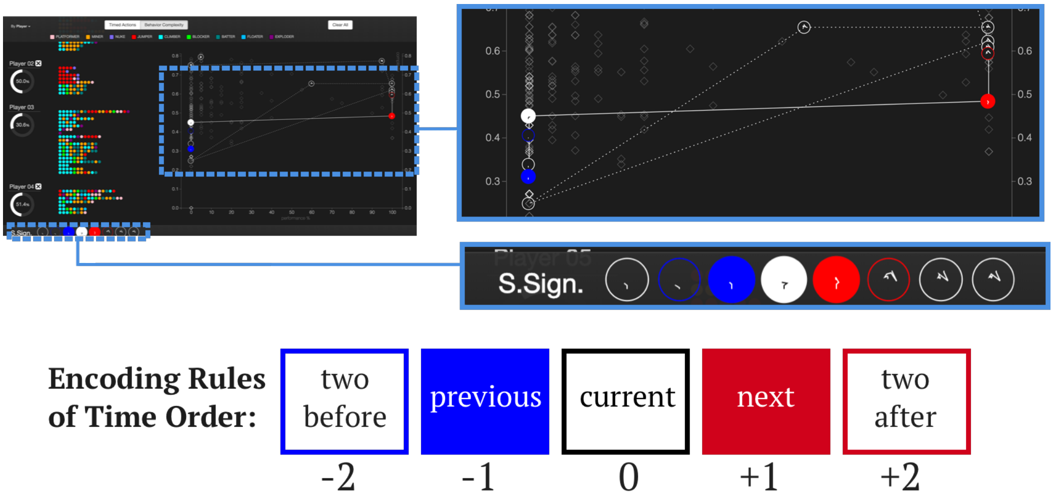


Figure 4.6: Visual encoding of time order in growth journey in terms of learning. Big circles in contrast with diamond shape highlight the player selection. Among the circles (attempts) of current selection, the order of attempts are distinguished by visual appearances. We use blue, white, and red to indicate past, current selection, and future respectively. Strategy Signatures are collectively displayed at the Bottom Bar to discern how strategies evolve by iterations. In this case, Player 2 experiences a dramatic strategy shift after the 5th attempt and scores impressively after the 4th attempt.

Figure 4.7 is an example of how two distinctive strategies by Player 2 are illustrated. As the two shown strategies are very different in term of action choices, SS produces highly distinctive shapes to reflect the difference. The design of SS is also capable of showing differences in time order even the action choices are the same. A subtle adjustment of strategy is detectable but categorizable to strategy pattern. For instance, *strategy1* frequently uses jumper as a starter action, the similarity of the attempts is visually perceivable through its SS output. It is also discernible that the player modifies some of the ending actions by mixing more miners in the last a few attempts. We can tell the difference as the last signature takes more triangular shape than the preceding ones (**R3**).

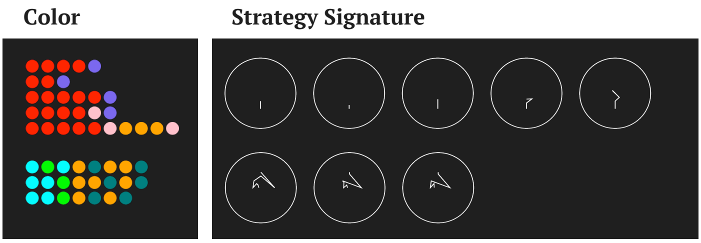


Figure 4.7: Two distinctive strategies reflected by color (left) and SS (right)

Interactivity

In this section, we describe how relevant information is visualized as a result of the interactions such as selection, hovering or inspections and how they are closely designed to answer user questions.

Action Filter

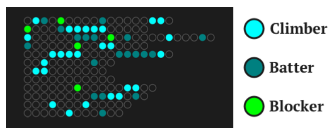


Figure 4.8: Filtered view to only show climber , blocker and batter actions of attempts by Player 7 for better focus.

Action filter can create a focused view on an interested subset of actions. This can be useful to study the exact influence of chosen actions by their distribution among attempts and players. For instance, the user may want to study how certain action(s) would determine the win or loss of an attempt (**R2**). To do this, the user can click on the unwanted actions on the Action Filter to gray out the irrelevant action types for a cleaner result (Figure 4.8). This also facilitates comparisons of action distributions across different attempts and players. For example, Figure 4.8 shows that Player 7 uses much less climber s in his/her latter attempts comparing to beginning ones. This may signify very clear behavior pattern that the player may learn to use fewer, more refined actions as he/she learns. Such a functionality enables us to see the actions' frequency distribution within or between players, based on which we can infer the performance improvements or progression patterns in time (**R1, R3**).

Switching View Modes

We implemented two view modes for different analysis scenarios. The behavior complexity view shown in Figure 4.5 features a more condensed display of information of player's overall performance (shown in percentage under the player label), action sequences, strategy character adjacently to assist the analysis with behavior complexity. To make room for this advance configuration of information display, this design uses a more aggregated view as events are depicted with summarized SSes and complexities while the detailed temporal information of raw data is sacrificed. Thus, the attribute of interval time between actions is not visible to the user in this mode.

To provide a higher fidelity of the player's play progress with sufficient contextual information (**R2**), a user can leverage the switcher to restore the time intervals between actions by clicking on the *Timed Actions* button at the top of the screen (Figure 4.9). In this mode, event actions take full screen width to place back the actions on horizontal time axes. The scale of time axes is universally shared, meaning all attempts of all players can be vertically compared by its distance to the left origin. A user can inspect the exact timestamp of an action by hovering on the actions (depicted as colored dots), cf. Figure 4.9.

If the user selected a player in the timed action mode, the selection will be preserved after switching back to the behavior complexity mode (§ · 4.6 Player & Action Selection). This allows the user to dive right into the details of a specific play process in detail without repeating the selection. The knowledge of detailed action intervals gives the user a view of not only the action compositions but also the pace of the gaming. For instance, the player can play at a faster pace at the beginning of an attempt while gradually slows down as he/she realizes he/she is about to lose the game. Also, some player may exhibit

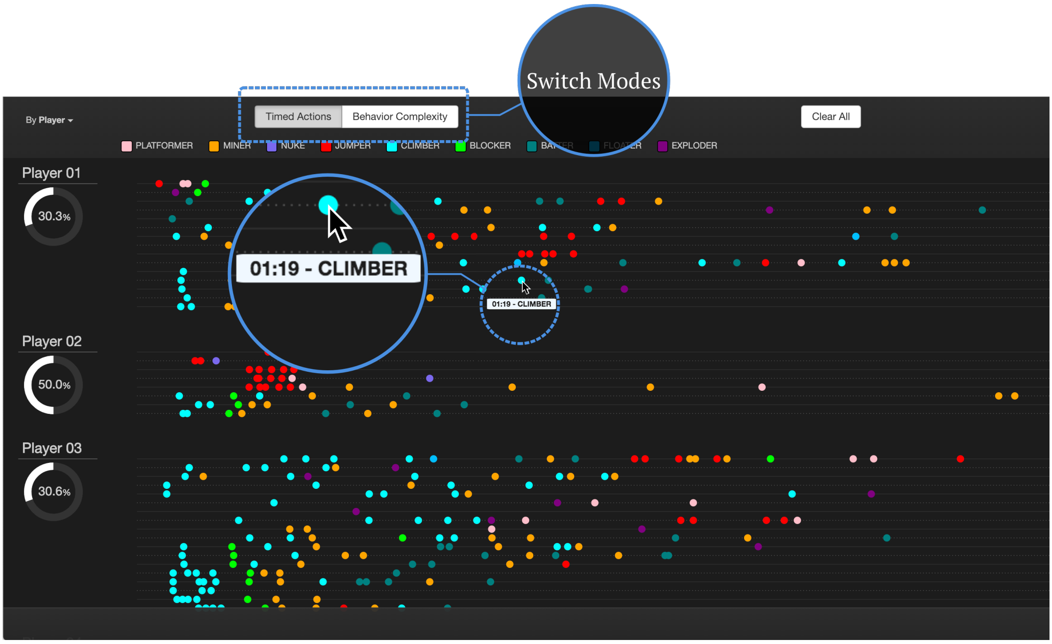


Figure 4.9: Switched to Timed Actions mode: actions are positioned left-to-right following the time order. Mouse hovering interaction will trigger the time stamp label of selected action.

a similar pattern but based on very opposite sentiments during playing. This kind of granular understanding of the potential experience of the game, such as haste or hesitation, is useful to understand player performances and learning behaviors.

Player & Action Selection

According to **R1**, the interaction design should support player-orientation in the display of information. The previous sections have elaborated on how such a principle is applied to the display of actions, attempts, and strategies. When it comes to communicating complexity or performance, we also implemented the selection functionality to support keeping a track of the foremost actions. The selection of actions, like selected players when switching view modes, are preserved in both modes until intentionally cleared. After some actions are selected, significant visual clutters by irrelevant actions are faded to support comparisons across screens by vertical scrolling.

To trigger the selection of a player, the user can click the player's label on the rightmost column (i.e. *1. player & performance* in Figure 4.5). A player selection event will draw the growth journey of the corresponding player on the rightmost column (i.e. *3. complexity & growth* in Figure 4.5). The diamond points in the presented scatterplot renders all the attempts of the selected player(s). Diamond points are linked together with different line appearances – dashed lines for previously selected player while solid line for the most recent selection. This allows selection of one or more players to compare their lines are growth journeys. The SS glyphs of the last selection (a player instead of a single attempt) will be drawn to the bottom bar (i.e. *5. bottom bar* in Figure 4.5). The user can hover on any of the SSes to quickly find the temporally neighboring attempts, which appearances are mutated according to the rule in § · 4.6.

This design allows the three aspects of the player learning - the complexity change, the performance change (with player growth line) (**R5**) and the strategy modification (the bottom bar) (**R4**) to be studied with an holistic interactive view, giving answers to a variety of questions relating to these attributes.

4.7 Evaluation

To validate the effectiveness of this system, we conducted separated semi-structured evaluations with the aforementioned domain experts. The evaluation process is divided into two sessions, the orientation session and self-guided session. The goal of the evaluations is to help us verify 1) how much the design is effective to meet the identified requirements in § · 4.4, and 2) to which extent the visualization can facilitate knowledge generation of unknown aspects (i.e. supporting novel exploration spaces in pivotal visualization).

In the orientation session, an introduction is given to each of the experts to explain the key functionality of the visualization. The view and control are demonstrated interactively with the real prototype. Experts were asked to repeat the demonstrated task again to ensure their sufficient familiarity of the design. Lastly, a short period is left to the expert to experience the prototype freely. Any discovered questions about the visualization during the period will be answered immediately. The self-guided session is an expert-driven session, in which the experts were given full access to the system and follow their own research interest or curiosity to analyze the game log data by themselves. We ask the experts to speak out loud and record their feedback with the computer's microphone. We also kept a video recording of all the second sessions.

An immediate discovery is that the visualization indeed help them discover insights faster than earlier workflows. As some early confirmatory analysis based on their prior knowledge suggests, the learning ability of Player 2 is remarkable as browsing with visualization can quickly locate a sharp performance increase in the player performance history. Also, the popularity of miner among all players is intuitively conveyed rather than statistically measured. Beyond the confirmation of discoveries that were already possible in previous workflows, we elaborate on how the visualization design helps the experts in identifying previously inaccessible novel patterns. These discoveries are usually associated with the implicit concept of strategies and complexities, which are exclusively supported by pivotal

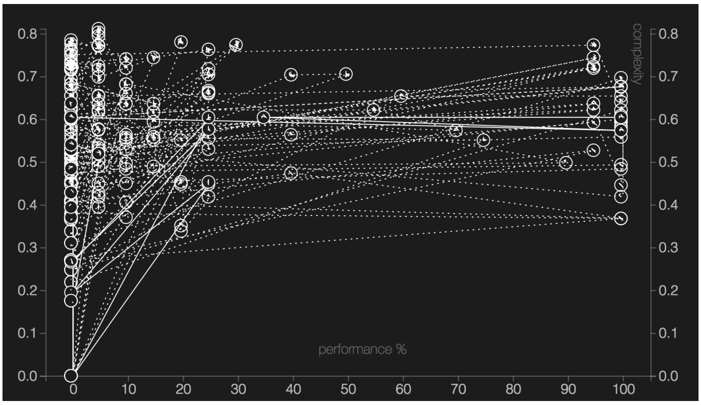


Figure 4.10: Behavior Complexity Growth: The lines tends to link the bottom left corner to the upper right, suggesting experience gain co-existed with complexity increase on the global level.

visualization design.

Novel Discoveries

D1 - Complexity Increase

Intrigued by the idea of quantifying behavior complexity, expert clicked to turn on all the player's label to display the general trend of all the behavior complexities of all attempts of all players. The hypothesis is there is a general correlation between performances and behavior complexities, thus peak performances ought be polarized toward the lower or higher bound of behavior complexities. By doing so, the global pattern of complexity distribution with performance is shown (Figure 4.10).

From this depiction, we can see that growth lines are heavily intertwined, indicating that the interaction between performances and complexities is not straightforward, i.e. there are regional cases where the complexity increase has neutral or opposite effect on performance than normal. This confirms the prior assumption of high heterogeneity in growth patterns vis-à-vis behavior complexities. Having said that, the rough pattern of players starting from less complex attempts and gradually reaching higher scores with more complex moves seems to be visible. This pattern of low score with low complexity to high score with high complexity is well represented by the growth line of Player 2 in Figure 4.6. To verify the pattern with more contextual information, the expert refers to the SSes and exact actions on the left to see how Player 2 progresses in the game. The expert then discovered a three-stage pattern in the player's behavior: *1)* Player 2 began by experimenting with several jumpers and nukes, *2)* Player 2 included some extra miners and found a working solution, *3)* Player 2 continued to refine the solution by removing the unnecessary jumpers followed by a few solutions with more diverse actions of increased behavior complexity.

This discovery by the expert confirms that visualization of behavior complexities organized by player attempts is useful to assist the novel finding of complexity increase in players' learning progressions. Despite the initial hypothesis of simple correlation between complexity and performance is not supported by the visualization results on the global level. The continued exploration into details makes the expert aware of the subtle improvement of iterative attempts, which helps to explain the potential motivation behind certain learning patterns with the insight into behavior complexities variations (**R1, R5**).

D2 - "Tail Optimization" Behavior

To locate the best performers of the game, the expert glimpses through the attempts of highest score percentage (left-most area in the scatterplot of *3. complexity & growth* in Figure 4.5). The growth lines indicate that a plenty of players continues to play with some degree of modification of earlier attempts.

This can be seen as a sign of polishing existing solutions or exploring new solution once they figured out how to pass the stage. As this part of the behavior tends to happen in the later stage of the learning progress (growth line), we use "tail optimization" to represent continued adjustments after at least one successful attempt like these.

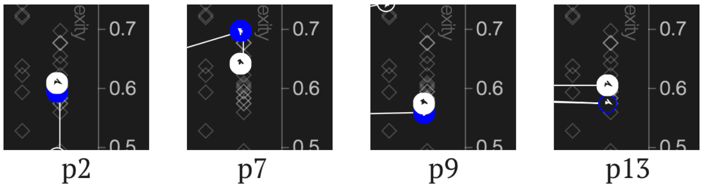


Figure 4.11: Tail Optimization: Final adjustments to improve previous success.

To study the "tail optimization" behavior, the expert selects Player 2, 7, 9 and 13 for their steady high performance in the last a few attempts. By comparing the growth lines of these players, the expert finds that, among attempts with highest scores in the latter stage, ones with the complexity over 0.63 or below 0.58 will eventually converge toward 0.6, which is also where most successful attempts resides (Figure 4.11). This seems to justify our earlier assumption that the solution to a specific level requires a fixed amount of complexity (cf. the required complexity in § · 4.5) to win. Despite the players are not aware of the concept of redundant complexity in § · 4.5, their optimization efforts for simpler actions can be explained as an intention to remove previously unnecessary moves for more efficient solutions. However, the hypothesis assuming "tail optimization" behaviors lead to better solutions are unfortunately challenged by the follow-up experimentation — evidences from the visualization suggests that, comparing to more efficient solutions, players more often add more behavior complexities to their solution to surprisingly "over-complicate" their solutions after they win, which contradicts with the goal of optimization.

To better understand the context of this behavior, the expert switches the view mode to *timed actions* to see how the behavior is reflected by previously suppressed time interval information. This attempt is fruitful. The expert soon discovers that player's latter successful attempts nearly always take less time to finish. This suggests that player prefers to trade for shorter time consumption at the cost of extra behavior complexity. In other words, faster is more important to leaner actions for most players.

This discovery demonstrates how the semantic attribute of behavior complexity is experimented with additional evidence to validate the hypothesis, which in this case is the players "tail optimizations"(**R1**). It also justifies the need and benefit of retrieving additional contextual information on demand, which in this case is the time consumption of each attempts(**R2**).

D3 - Strategy Categories

An advantageous quality of this game is its possibility of multiple solutions. This means the same stage can simultaneously have more than one way to pass. Given the minor difference in exact execution, the expert finds that similarities among attempts of same strategies can be visually identified with SS. And there are few clusters each of which represents an approach to win by itself.

As SS converts the action sequences into legible shapes, attempts of players are presented in a reduced visual format with which the similarities between solutions are observable. For instance, the best attempts by Player2, 3, 4, 6, 13 share very similar shape in their SSes, cf. *i* in Figure 4.12. The expert also identifies a slightly deviated solution from this cluster in the SS shapes of Player 9 and Player 7's solutions. As a contrast, the solutions of Player 14, 14, 5 are significantly different as one

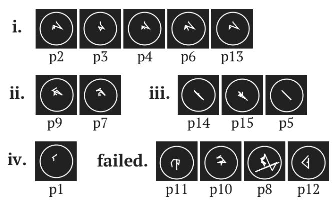


Figure 4.12: Successful solution templates (i. iv) v.s. failed best attempts (failed): Strategy Signature facilitates the visual categorization of solutions.

can easily see by the shape of SSes (Figure 4.12). This validates that SSes can produce highly discernible contrast in shapes' appearances.

Once the successful patterns of attempts are visually known to the expert, SSes can work as a utility to help the expert predict the success rate of an attempt by comparing the SS shape of an input attempt with successful templates of known working solutions. The *failed* cluster in Figure 4.12 are ones picked as the attempts of highest scores from players who never made it. From the SS shapes we can see that these attempts failed to align with any of the successful templates, which may help to explain why these players never managed to get a full score till the end of learning.

The discovery of categorization power of SS (as similar successful solutions can be clustered into templates) is a surprise to us as well as the experts. We use SS to unveil an undiscovered pattern among solutions, from which new explorations such as finding more templates or comparing these templates are possible. With SS, the semantics of strategy patterns are visually presented to allow experts to investigate the versatile ways of playing by different players (**R4**), which presumably lead to new hypotheses based on the knowledge of such versatility and the convergence toward established solution templates.

Expert Feedback

In addition to discoveries presented by enlisted cases above, we conducted dedicated interviews with the experts to collect their feedback on the overall design of the visualization. We specifically prompted the experts by revising the initial requirements in § · 4.4. We use the data from these interviews to benchmark the effectiveness of our design against the previously proposed requirements.

Generally, the experts approve that our design is useful to their analysis task particularly in identifying interesting patterns on the players or attempts level while preserving the subtle differences in ground data level. This flexibility helps the expert to leverage their domain knowledge easily. For instance, their domain knowledge in learning behavior suggests that players exhibiting higher persistence in learning can be labeled as long-term performers, meaning their performance snowballs remarkably with long-term accumulation of experience. In this regard, this visualization system gives them explicit hints to verify such knowledge. When E3 finds the gradual strategy improvements by Player 5, he confirms such a principle with "...specially that you can see that they approached simpler and simpler solutions using climber and miner." The exhibited persistence is a valuable positive trait in learning, according to E1. E1, E2, E3, and E4 report that design also substantially facilitates the understanding of player growths in terms of learning progression. The visual approach helps them to see clearly how the strategy transformation and refinement would influence the score (as the sole performance indicator) in each consecutive attempts (**R3**).

The growth lines (*3. complexity & growth* in Figure 4.5) and action dots (*2. actions & attempts* in Figure 4.5) produce clear depictions of inherent multivariate attributes as well as derived semantic attribute of behavior complexity of the selected player. Supported by the interactions (§ · 4.6), the experts can fluently zoom into interested aspects of attributes (**R1, R2**). "I like that fact that you can quickly gain an overview about which are the most dominant ability used by players, (such as) P2 focus on jumpers, and across all players you find a lot of red, pink, light, blue, and orange, indicating that platformer, miner, climber, and jumper are abilities that players gravitate towards.", said by E3. The interactivity also enables the analysts to scrutinize the efforts of repeated attempts and how the player learns from them (**R3**).

"The global view of complexity trend is very inspiring (**R5**)", stated E5. Although the quantity of collected data points are limited to validate if the correlations related to behavior complexities. E5 believes this inspires new research questions to unlock new knowledge about learning behaviors and more discussions in this regard should be continued.

The use of SS is novel according to all the experts. Before experimenting with the visualization, E5 believes that the best solution is a modest deviation from the solution based on the successful attempts of Player 2, cf. *i* in Figure 4.12. And the solution by Player 5 is a very risky and less recommended approach. Thanks to the SS, E1 rediscovers an important successful solution represented by Player 14 and 15. This leads to a radical change on the view of diversity of solutions (**R4**). "Yes, maybe the other (strategy *iii* in Figure 4.12) is a viable solution.", said E1.

In general, experts believe the visualization design can facilitate generating new knowledge from the game log data and boosting their research productivity. They are especially convinced by the advantages of the visual approach of identifying behavioral patterns. E2 makes positive remarks on the interface design, saying that the interfaces are well-organized and polished and the interactions and transitions are coherent and intuitive to understand. The aesthetic appeal of the design is a bonus to its analytical capability.

The experts are also asked to share their opinions on possible insufficiency of the design. The outcomes are mainly two-fold: 1) The Timed Action view is a bit difficult to find (by E3). A user may only navigate in the default view mode, assuming that temporal information is simply discarded for ease of visualization (by E4). 2) E1 and E4 also suggest a possibility to view a chosen set of action sequences of the dots and squeeze them into a condensed view to eliminate vertical scrolling.

4.8 Discussion

Applicability & Limitation

We employed two novel methods in to support the pivotal design method — the entropy-based approach to quantify behavior complexity in game learning and the glyph based visual technique to extract characteristics of a categorical sequence. While it is safe to assume that the visualization system can achieve comparable effectiveness with data from similar puzzle-based games, we focus our discussion of the applicability and limitations by looking into the technical potentials of the two methods.

The behavior complexity enables an objective perspective of the quantity of heterogeneity in an event sequence. We employed a entropy-based method to strictly measure how complex an attempt is, which was previously implicit and unobservable. As the challenge in analyzing game log data can grow with advanced mechanisms in modern video games, techniques to make the complexity of behaviors explicit and observable are going to be more and more valuable to the behavior studies for game designers as well as professional trainers. Regarding this, we consult game experts to discuss the generalizability of this approach in latest popular games. The following genres and examples are identified as a result:

- Tower defense games like Plants vs. Zombies [239], where choices of plant defenders are encoded as events and key to the play. In these games, the construction of defenders is likely to cost a certain amount of resources,

[239]: Electronic-Arts (2016), *Plants vs Zombies Video Games - PopCap Studios - Official EA Site*

which makes streamlining the token use (like action use in lix) equally relevant toward skillful game play. Likewise, the complexity of construction and building choices still remains an indicator of skillfulness as lower resource consumption means more late game elasticity and snowballing potential. Considering the huge genre [240], applicable games can be many.

[240]: (2019), *Tower Defense*

- We also find our approach applicable to fighting games like Street Fighters [241], in which players can repeatedly perform combos (a series of controlled attacks all at once) and combat routines can be analyzed. In this genre, the damage dealt can be regarded as the score achieved. Players with better attack accuracy are likely to produce more damage impact within a smaller set of moves (e.g. heavy punch, jump backward). Substantial adjustments to current design are needed to accommodate other factors such as the character choice and time consumption for fair assessments.

[241]: Capcom (2018), *Street Fighter V | Rise Up!*

The application potentials outside of game analytics are also worth-considering, as the method essentially converts behavior complexity from event sequences. In scenarios of where the analysis of people's behavior is non-trivial, investigating the complexity of behavior can also help to the analysis. For instance, awareness of the complexity of hospital operations in the IT system [242] may contribute critical insights into the streamlining of the care-giving process, while increasing the behavior complexity of the visitors in an amusement park [243] may be beneficial enrich the entertainment experience.

[242]: Spaulding et al. (2013), "Event Sequence Modeling of IT Adoption in Healthcare"

[243]: Liu et al. (2017), "Patterns and Sequences"

There are also limitations to consider while applying the used methods. For instance, future application of the behavior complexity should be mindful that the entropy based method is a very aggressive simplification as it can suppress critical important information such as the interval time between actions, which can be equally informative to describes the complexity of behaviors. Moreover, the SS displays categorical events with a pre-determined alphabet of actions, the order which follows a rule-of-thumb instead of a logical order, which could be prone to unknown biases. The SS method is also sensitive to the cardinality of sequences, i.e. the produced visual result may become illegible as the number of event types surpasses a threshold. Our limited test suggests that the number of action types should be no more than 12 to guarantee an optimum result.

Summary

The study targets at the analysis of behaviors in video game learning, where analyses need to derive deeper behavior level concepts based on basic action records. Following the pivotal visualization design method as the scaffold, we employ novel methods to establish semantic attributes to facilitate this goal. The semantic attributes extend the exploration space with the concept of behavior complexity and strategy pattern (depicted via SSes), enabling domain experts to sketch unprecedented hypotheses (§ · 4.7 Novel Discoveries) while keeping the newly derived concepts attributable with data. Despite some of the early hypotheses are not supported by the experiments with semantic attributes, analyses enhanced by the provision of behavior complexity and strategy patterns contribute critical insights that substantially steered the follow-up research questions, leading to new realms of knowledge which are impossible without the pivotal effect. The exclusive benefits are three-fold as the visualization enables the experts to: 1) join behavior complexity and performance in the context of qualitative strategy differences, 2) explore how players' solutions evolves with attempts iterations, and 3) categorize a template of successful solutions.

The above benefits supported by domain experts' use cases indicate that our substantiation of pivotal visualization approach in the study context of learning behavior achieves expected soundness, which is also supported by the final evaluation. Therefore we conclude that the pivotal visualization approach is effective in enhancing experts' knowledge discovery abilities in the exploration of uncertain learning behavior patterns during video game play.

Study B: Visualizing Movement Relatedness among Free-roaming Animals | 5

Overview: *Movement ecology is a maturing field that derives ecological insights from animals' movements. For all the available technologies, GPS tracking has the biggest potential to examine movement patterns at a larger scope, capturing a number of entities spanning across an ecological-meaningful area and time frame. Focusing on lower level interactions of movements, this study is based on a published work that investigates the tricky interactions between animals. In this study*, the proximity-based, time-dependent semantic attribute of* movement relatedness *is put forward and supported by the visual presentation of the spatial-temporal contexts, social surroundings, and underlying data uncertainties in a multi-species setting. The attribute of* movement relatedness *is extended into the pairwise (PW) or individual-to-group (i-G) modes for respective analysis scenarios. The visualization implementation concerning these two modes exposes the non-salient influence potentials between moving entities, such as one to another individual or one to another group of animals. According to expert evaluation, the system design contributes valuable clues in analyzing multi-species movements patterns and characterizing signs of potential interactions, generating critical insight to educate late stage mathematical modeling for batch processing.*

* The study in this chapter is based on the published work W. Li, *M. Funk, J. Eikelboom, and A. Brombacher, Visual Exploration of Movement Relatedness for Multi-species Ecology Analysis, arXiv:2001.11163 [cs], Jan. 2020.* and the submitted work W. Li, *M. Funk, J. Eikelboom, and A. Brombacher, Mov'inFinder:*

5.1 Introduction

Animal movement has been one of the most intriguing subjects since ancient times. The earliest exploration by Aristotle (384 - 322 BC) dates back to the 4th century BC [244]. Thanks to modern technologies, our scientific discovery methods are no longer bounded to direct measurements and human senses. Technical means as proxies to monitor animal movements have evolved with recent developments in sensory technology, telecommunication [245–248], geographic information system (GIS) [249–251], and data mining [252, 253]. These multi-disciplinary efforts maximize the potential of data-driven approaches to address complex behavior patterns such as community dynamics [254], or responses to land-use change [255]. However, the conceptualization of these patterns demands next level analytical capabilities to accommodate unprecedented research challenges such as exploring "how and why animals interact with conspecifics, and how and why they compete and reproduce." [256]. Movement ecologists are requiring dedicated sense-making technology to unlock the full wealth of ecological data at scale [257].

Animal movement can be captured in many ways [208, 247, 248] depending on the research problem. Spatial movement plays a central role in many ecological researches [207, 244, 258]. In addition to the benefit of summarizing movement patterns over larger areas, recent trends in movement ecology begin to focus on movements of smaller regions to scrutinize behaviors at a local level [259], particularly how discrete entities' movements are influenced [260–263]. In this view, cross-species interactions such as host – parasite, predator – prey, or plant – herbivore [264, 265] (known as *antagonistic interactions* among

Visual Investigation for Movement Influences between Multi-species Animals in Ecology Analysis, TVCG, April 2021.

[244]: Holden (2006), "Inching Toward Movement Ecology"

[245]: Cagnacci et al. (2008), "Managing Wildlife"

[246]: Gor et al. (2017), "GATA"

[247]: Hoflinger et al. (2015), "Motion Capture Sensor to Monitor Movement Patterns in Animal Models of Disease"

[248]: Qin Jiang et al. (2004), "Recognition of Human and Animal Movement Using Infrared Video Streams"

[249]: Teimouri et al. (2018), "Deriving Animal Movement Behaviors Using Movement Parameters Extracted from Location Data"

[250]: Sarkar et al. (2015), "Analyzing Animal Movement Characteristics From Location Data"

[251]: Wang et al. (2016), "A New Method for Discovering Behavior Patterns among Animal Movements"

[254]: Nathan et al. (2008), "A Movement Ecology Paradigm for Unifying Organismal Movement Research"

[255]: Kranstauber et al. (2011), "The Movebank Data Model for Animal Tracking"

[257]: Spretke et al. (2011), "Exploration Through Enrichment"

[247]: Hoflinger et al. (2015), "Motion Capture Sensor to Monitor Movement Patterns in Animal Models of Disease"

[248]: Qin Jiang et al. (2004), "Recognition of Human and Animal Movement Using Infrared Video Streams"

[208]: Wilson et al. (2014), "Wild State Secrets"

ecologists) are more discernible because individual behaviors and discrete actions are typically investigated at a finer scale.

However, the discrete movements in local scales may not be sufficiently explained by isolated movement trajectories. To understand the meaning or motivation behind certain behaviors on a higher level, aggregated, long term rules need to be derived from basic movements based on the social, territorial contexts [258, 266]. This is exemplified by a recent study in human behavior [267] uncovering that the spatial approximations can be effective predictors of human social ties. Regarding this, it is reasonable to assume that meaningful insights regarding the relationship between animal individuals can also be studied through their spatial relations. Designing visualization support for this mission is non-trivial as it can contribute visual and intuitive results to complement existing quantification methods in the search for clues of the less approachable motivations and meanings (or internal states in ecological sense) behind the apparent movements. Our study is therefore motivated by the a need to facilitate the ecological research in this problem niche.

Methodologically, we employ visual techniques to exhibit the ecological evidences concerning relational behaviors with spatial movement data. This is only possible by visualizing movements details not only as individuals trajectories but also the potential influence between them. Therefore, we enable the movement analyses by introducing the semantic attribute of *movement relatedness*, which is an indicator of social intimacy or potential predatory threats in wild environments. The system interprets animal relations in two modes — *pairwise* (PW) and *individual-to-group* (i-G). The former considers only the one-plus-another mutual relations between two entities. The latter analyzes one entity by comparing its relationship to all the others on the global level. The system extensively covers animations to convey the movement vividly. Controlled by a

[244]: Holden (2006), "Inching Toward Movement Ecology"
[207]: Nathan (2008), "An Emerging Movement Ecology Paradigm"
[258]: Westley Peter A. H. et al. (2018), "Collective Movement in Ecology"
[259]: Holyoak et al. (2008), "Trends and Missing Parts in the Study of Movement Ecology"
[260]: Giuggioli et al. (2013), "Stigmergy, Collective Actions, and Animal Social Spacing"
[261]: Polansky et al. (2011), "A Framework for Understanding the Architecture of Collective Movements Using Pairwise Analyses of Animal Movement Data"
[262]: Strandburg-Peshkin et al. (2018), "Inferring Influence and Leadership in Moving Animal Groups"
[263]: Torney et al. (2018), "Inferring the Rules of Social Interaction in Migrating Caribou"
[264]: Pires et al. (2012), "Interaction Intimacy Organizes Networks of Antagonistic Interactions in Different Ways"
[265]: Hagen et al. (2012), "Biodiversity, Species Interactions and Ecological Networks in a Fragmented World"
[266]: Slingsby et al. (2016), "Exploratory Visual Analysis for Animal Movement Ecology"
[258]: Westley Peter A. H. et al. (2018), "Collective Movement in Ecology"
[267]: Eagle et al. (2009), "Inferring Friendship Network Structure by Using Mobile Phone Data"

"playback" control system, movement transitions of scattered data points is depicted with a transitional trace line, which can be temporally adjusted and algorithmically smoothed. Taking the appearance of a reduced visual language, the system is tested to be effective in maximizing domain experts' ability in finding potential alignment and pairing of cross-species movements via aggregated view of long-term relation and movement relatedness by group. The pivotal visualization instantiated in the study results the following contributions:

- a trace-animation-based visual communication of movements and time varying movement relatedness, and
- the support of novel exploration space based on pairwise and individual-to-group comparison of animal's spatial situations.

5.2 Literature Related to This Study

Visualization in Movement Ecology

Movements are usually referred as locomotive movements in the field of movement ecology. Location changes are useful clues to reveal ecological patterns in problems such as resource use [268], population dynamics [256], and climate influence [269] between individuals, groups, or species. Many ecologists have prior experiences of using visualizations in their research. Generic visualization tools (e.g. Movebank [255], AMV [270], Env-DATA [271]) are employed to support common tasks like trajectory plotting and multivariate filtering. As they are compatible with a wide range of species and data types to accommodate many research projects, the generic functionalities are sufficient candidates for basic movement analyses.

[268]: Roshier et al. (2008), "Animal Movement in Dynamic Landscapes"

[256]: Cagnacci et al. (2010), "Animal Ecology Meets GPS-Based Radiotelemetry"

[269]: Ferreira et al. (2011), "BirdVis"

[255]: Kranstauber et al. (2011), "The Movebank Data Model for Animal Tracking"

[270]: Kavathekar et al. (2013), "Introducing AMV (Animal Movement Visualizer), a Visualization Tool for Animal Movement Data from Satellite Collars and Radiotelemetry"

However, some research tasks require analytic aggregation capabilities. Drosophigator [272] uses statistics from heterogeneous data sources to generate visualized predictions of the spread of invasive species. Xavier and Dodge [273] integrates environment data to study the connectivity (a technical term in ecology indicating the degree of environmental variables affecting its inhabitants in an area [274–276]) of landscape characteristics and animal behaviors. Konzack et al. [277] analyze the migratory trajectories to recognize the stopovers among gulls' movements.

[272]: Seebacher et al. (2018), "Visual Analysis of Spatio-Temporal Event Predictions"

[273]: Xavier et al. (2014), "An Exploratory Visualization Tool for Mapping the Relationships Between Animal Movement and the Environment"

[274]: Taylor et al. (1993), "Connectivity Is a Vital Element of Landscape Structure"

[275]: Baguette et al. (2007), "Landscape Connectivity and Animal Behavior"

[276]: Lima et al. (1996), "Towards a Behavioral Ecology of Ecological Landscapes"

[277]: Konzack et al. (2018), "Visual Exploration of Migration Patterns in Gull Data"

The visual design is also important to communicate the aggregated results in relation to the problem domain. Slingsby and van Loon [266] discuss the design choices of visual encoding in ecology visualization, suggesting that the use of visual language needs to convey "ecological meanings" to support contextualized reasoning. Spretke et al. [257] put forward the "enrichment" method to enhance analytical reasoning with visual representation of attributes like speed, distance, duration in the geographical context, allowing quick hypothesis iterations on local subsets.

[266]: Slingsby et al. (2016), "Exploratory Visual Analysis for Animal Movement Ecology"

[257]: Spretke et al. (2011), "Exploration Through Enrichment"

Aggregation of attributes might be useful to understand a movement behavior, but behaviors are better explained in a context where influence of peers and surroundings are considered [254]. Since the interest in entity level behaviors is rising [259], the mutual influence between multiple entities can be a worthy starting point for upcoming visualization research.

[254]: Nathan et al. (2008), "A Movement Ecology Paradigm for Unifying Organismal Movement Research"

[259]: Holyoak et al. (2008), "Trends and Missing Parts in the Study of Movement Ecology"

Trajectory Analysis

Manually searching for patterns in the long, twisted, and sometimes cluttered movement trajectories can be daunting. This makes event detection algorithms necessary as they alleviate the cognitive load for experts. The execution of automatic event detection usually requires defining a set of parameters, such as time window, speed, heading, and mutual distance, to narrow down the search space to a subset of trajectory fragments [278–281]. The detection outcomes are usually visualized on top of the movement trajectories with reference to the original geographic context. As the detection processes are sensitive to the subject animal and landscape context [280], we need flexible visualization controls to cope with the distinct characteristics of movements for consistent results [278]. For example, Andrienko et al. [281] suggested a bottom-up approach where the detected elementary interactions (a concept derived from Bertin's elementary level of analysis [282], meaning "particular instances of interaction between individual objects") are used as key clues to understand group level patterns. Bak et al. [278] propose a method to boost the performance in event detection at larger scale. The extra performance gain can thus be allocated to support interactive parameter input, through which the visual feedback of outcomes makes an essential part of the interactive loop to guide the next iteration. Bak et al. [278] also mentions the classification of four types of higher level encounter patterns, which seems to be a continuation from Andrienko et al. [281]'s advocacy of characterizing elementary patterns.

[278]: Bak et al. (2012), "Scalable Detection of Spatiotemporal Encounters in Historical Movement Data"
[279]: Andrienko et al. (2011), "An Event-Based Conceptual Model for Context-Aware Movement Analysis"
[280]: Siqueira et al. (2011), "Discovering Chasing Behavior in Moving Object Trajectories"
[281]: Andrienko et al. (2008), "Uncovering Interactions between Moving Objects"
[282]: Bertin (2010), *Semiology of Graphics*

Movement interactions are multifaceted. A visual feedback loop for adaption and fine-tuning of the analytic system is indispensable to detect potential interactions. Also, automatic techniques mostly solve lower level tasks such as matching route similarity or spatial-temporal closeness between trajectories. Recognizing general patterns and questioning with alternative assumptions are still a job of human expertise. Thus, we need to keep a open mind to the machine results but, at the same time, expose visual details for domain judgment.

Visualization of Spatial Temporal Movements

As a convention, most movement data are plotted by either discrete coordinate points [266] or linked trajectories [277, 283] on a 2-dimensional map. However, simultaneous considerations into both spatial and temporal variations are necessary to avoid false identification of collocations (i.e. mistakenly regarding position overlaps at different time period as real meetings). There are several approaches sufficing this criterion.

A common treatment here is the Space Time Cube (STC) [284–286], which projects the temporal dimension in the z-axis of a 3D view. In STC, real collocation of two entities are depicted as the neighboring points in a 3D space. But it makes visualization work prone to problems like loss of perspective and obfuscation [287, 288]. Since the third dimension is devoted for the time differences, subjects that travel in the third dimension [289] may cause compatibility issues. AMV [270] includes a workaround that does not use a 3D space. It do so by confining trajectories to the local duration and presents relative movements only by removing the distraction of temporally distant trajectory parts. But the fine details of proximity variations in a selected duration is not supported. Alternatively, abstracting movements from their geospatial context, as explored by Crnovrsanin et al. [290], is also a possible way to clarify the subjects' spatial temporal relations.

In sum, facilitating the analyses of wildlife behaviors via visualizations is a non-trivial problem. Many open gaps to support in the study of space-time relatedness with visualizations remains unaddressed. The flexible interactions of quick selection, navigation, and visual adjustments [291] for movement data analyses provided by visualizations would be both challenging and beneficial to the field of movement ecology research.

[266]: Slingsby et al. (2016), "Exploratory Visual Analysis for Animal Movement Ecology"

[277]: Konzack et al. (2018), "Visual Exploration of Migration Patterns in Gull Data"

[283]: Shamoun-Baranes et al. (2012), "Analysis and Visualization of Animal Movement"

[284]: Hedley et al. (1999), "Hagerstrand Revisited: Interactive Space-Time Visualizations of Complex Spatial Data"

[285]: Gatalsky et al. (2004), "Interactive Analysis of Event Data Using Space-Time Cube"

[286]: Kraak (2003), "The Space - Time Cube Revisited from a Geovisualization Perspective"

[287]: Walsh et al. (2016), "Temporal-Geospatial Cooperative Visual Analysis"

[288]: Amini et al. (2015), "The Impact of Interactivity on Comprehending 2D and 3D Visualizations of Movement Data"

[289]: Andrienko et al. (2018), "Clustering Trajectories by Relevant Parts for Air Traffic Analysis"

[270]: Kavathekar et al. (2013), "Introducing AMV (Animal Movement Visualizer), a Visualization Tool for Animal Movement Data from Satellite Collars and Radiotelemetry"

[290]: Crnovrsanin et al. (2009), "Proximity-Based Visualization of Movement Trace Data"

[291]: Andrienko et al. (2013), *Visual Analytics of Movement*

5.3 Context and Requirements

In this section, we describe the basic setup of the domain research including the expert collaborators, metadata, apparatus (for data collection), and domain requirements.

Project Background

The domain problem targets at multi-species, free-roaming animals in a South African nature reserve. The researchers' primary interest lies in the behavior along space-time variations. Instead of analyzing relationships with natural landscapes, the experts need visual insights into behaviors of individual animals and how they would influence each other, which is also a valuable compensation to their current tool sets. Individual interactions are also potential to later applications such as to analyze other species, or even human social interactions.

Two ecologists are invited as domain experts (E1 and E2). Both of the them have extensive research experience with animal movements studies. E1 has a background in movement ecology, spatial analysis. E2 also works in quantitative ecology and environmental sciences. They both conduct quantitative data analysis with R✍ and use field-specific packages to plot the movements either by spatial attributes (map) or numeric attributes (bar chart or line chart). However, they both find their current tools limiting. For example, they both have complains about the lack of support in converting the multidimensionality of movement trajectories into easily consumable information. E2 also emphasized on the analysis challenge when dealing with multi-entity temporal-spatial variations.

✍: R is a free software environment for statistical computing and graphics. More details at *https://www.r-project.org*

Data Description

For data collection, ecologists attach GPS collars [292] to each of the 25 tracked animals (Figure 5.1). The subjects consist of 5 lions, 10 wildebeests and 10 zebras. The entire data collection lasted for roughly 30 months, which captures periodic changes of climate though different seasons. To ensure sufficient battery life, collar tag sensors were programmed to obtain and store GPS coordinates by every two hours. Therefore, the movement data is composed of fairly sparse timed geolocation points, which itself imposes challenges such as locational uncertainties between two neighboring data points.

[292]: Handcock et al. (2009), "Monitoring Animal Behaviour and Environmental Interactions Using Wireless Sensor Networks, GPS Collars and Satellite Remote Sensing"

Figure 5.1: GPS Collar: The device steadily stores the GPS coordinates following a synchronized time interval.

Beyond the limits of device capacities, unpredictable weather conditions and landforms also induces loss-of-fidelity issues in the tracking data [293]. The cause of such a data quality compromise can be any incidents of physical impact, wet situations by rainy days or water areas, or signal blockages by geographic occlusions. As a result, the collected data are likely contain one or both of the following errors: **a**) unrealistic values, i.e. two subsequent data points have impossibly large position difference in between which is evidently an error, and **b**) missing points, i.e. failure to record a data point at the programmed time.

[293]: Hurford (2009), "GPS Measurement Error Gives Rise to Spurious 180° Turning Angles and Strong Directional Biases in Animal Movement Data"

Due to aforementioned the caveats, pre-processing the data is needed for smooth analyses later [294]. The domain experts proceeded with the removal operations to deal with the first type of error (error **a**), resulting in unstable trajectories with irregular gaps of varying length on it. They also trimmed off the unusable parts at the beginning or ending of every animal tracking (an extreme case of error **b**), resulting in temporally uneven starting and endings points in the trajectories. This process lefts two problems. First, the locations of missing points need to be inferred from previous or later (realistic) data points. Second, the visualization needs to accommodate

[294]: Bjørneraas et al. (2010), "Screening Global Positioning System Location Data for Errors Using Animal Movement Characteristics"

varying number of “on-stage” animals as some may appear or disappear later than the others.

Requirements

Integrating a visual approach into existing analytic workflow requires shared understanding from both ecology and visual analysis. The requirement study with the domain experts continues for six months, after which we devise five design requirements as guidelines to add new capabilities to the research workflow. We begin with draft design proposals in the form of low-fi visual sketches, which inspire nuanced discussions to pin-point their most prominent concerns that are difficult to be explained by words. Draft animations are employed to communicate complex interactive effects. Versions of animations to portray the movement dynamics are iterated via Processing [295] sketches, in which the communication effectiveness is evaluated respectively. Some useful insight about requirement niches are discovered through also co-design sessions with the experts. The sessions are supported by diagrams and paper sketches where experts take a more active role to freely propose ideas though accustomed media formats to explain the intended functionalities. To pilot for likely insights and also unexpected misinterpretations, qualitative surveys were also conducted in an expanded user group (7 people) of both experts and non-experts. We used structured questionnaires to prioritize the requirements and balance conflicting directions. With constant refinements, we conclude that the visualization design should facilitate movement ecology research by addressing the design requirements in the following aspects:

R1 - Allowing the complexity of spatial temporal movements to be easily interpreted through a simple and constraint visual language.

The experts understand the challenges of multidimensionalilty in the collected data. But their experience with interactive visualizations does not go beyond relatively simple ones such as density plots or static trajectory drawings. Developing advanced functionalities may help but the accompanied steep learning curves can raise some other concerns that undermines the adaptability due to the existence of accustomed operation processes and mental models. So the analytical flexibility come with visual exploration is preferably supported by simple and intuitive visual expressions, based on which implicit movement patterns are easier to recognize. Being powerful though, the implemented visualization system should demand minimal extra explanations which can break the flow of data analysis work. The experts expect it to support the experimentation of most recent hypothesis based on newly discovered knowledge, the verification of which may facilitate the model building with the assistance of existing analytical pipelines.

R2 - Supporting interactive navigation into any subset or sub-region of the spatial-temporal space.

Considering a 2.5-years-long time frame of the project, browsing the global timeline means navigating through roughly 4000 data points for every 2 weeks of tracking time. Additionally, the patterns can exist in any level of time scopes, e.g. movement difference in days and nights, weeks and even seasons. Granular time windows should be implemented as movement patterns are sensitive to the observation time frame. Picking a time point or selecting a temporal duration of a customizable length allows for the autonomy to iterate over multiple time lengths for the particular research task.

R3 - Treatments to the identified imperfections in collected data.

Being aware of the existing data quality issues, it is relevant to have built-it mechanisms to reproduce smooth, consistent visual results while not hidden the underlying imperfections.

Instead of ignoring unreliable data points, visually communicating the uncertainties is advantageous for making sound judgments. Therefore, the visualization should not only tolerate the unsteady internal data streams during the interaction process, but also facilitate distinguishing the visual results of questionable data points from the solid, trustworthy ones.

R4 - Supporting comparisons between movements of different species.

Animals of the same species share behavioral similarities. And the opposite can be true for ones different species. But the extent of difference varies between comparisons. For instance, we would expect more behavioral commonalities between the wildebeests and zebras as both species are herbivores, while many commonalities may not persist between species of potential predatory threats such as wildebeests and a lions, as one being herbivores and the other being predators. This contrast of behavioral tendency is presumed by common sense but not rigorously studied by visualized data. To explore species-sensitive aspects of movement behaviors, the awareness of species differences is needed. The visualization system should allow them to visually disintegrate the behavior differences as influenced by the species composition.

R5 - Exhibiting the clues to investigate relationships between animals.

Movement behavior is a complex problem which can be influenced by many environmental factors. It is also not surprising that animals would influence each other's movements in more or less subtle ways from slight movement deviations to social interactions. Understanding how animals would influence or interact with each other by their movements in either intra-species or inter-species settings can contribute to valuable ecological insights. In our case, studying the dynamics of how animals are closely bounded to each other and verifying the persistency of such a bounding play a fundamental role in the analyses regarding animal's mutual influences and interactions.

The above requirement list from R1 to R5 is sorted by a loosely connected dependency order where satisfying the latter, higher level ones may require the support from the former, basic ones.

5.4 Design Rationale

In search for proper methods and to convert the requirements to executable guidelines, we present a few conceptual elaborations as cornerstones to scaffold pivotal visualization design in this study.

Parametric Trace Animation

As aforementioned, context adaptability is important in movement analysis. For addressing contextualized research problems characterized by local variables such species, speed, or group size, parameterizing the visualization to adapt the visual results extends the adaptability and, therefore, suffices a reasonable choice. In our case, larger time interval size is used to record movement locations. Straight lines connecting location points would appear cluttered with angular shapes and present few clues to anticipate the movements between locations. Regarding this issue, trajectory smoothing [296] can be helpful as the visualized path can help to build visual heuristics to makes potential behavior patterns easier to uncover and trajectories of different individual more visually distinguishable. The smoothing also produces other effects that will benefit the analysis. For example, the smoothing will make sharper turns with slower animals (ones with shorter distance between

[296]: Sacha et al. (2017), "Dynamic Visual Abstraction of Soccer Movement"

with consecutive points), while the opposite applies to faster moving animals (Figure 5.2). Domain experts can also use a middle point in the curve to adjust their estimations of the heading if necessary.

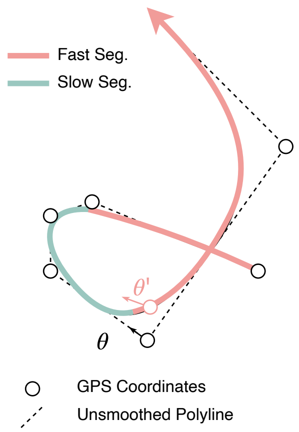


Figure 5.2: Differences by applying line smoothing: 1) Slower movements tend to produce more complex, sharper turns and while the opposite is true for faster movements. 2) Smoother trajectory shape also adjusts the assumption of heading directions, e.g. $\theta \neq \theta'$.

A decision upon the right amount of smoothness and trajectory shape requires careful deliberation and calibration. To facilitate iterative reconfiguration, instant visual feedback of parameter adjustments can make such a process more productive. This helps domain experts to understand the effect of each parameter to facilitate easier interpretation of trajectory lines regarding **R1** and creates adaptability for different analytic scenarios. We understand that the domain experts may occasionally wish to fact-check the raw data points. Therefore, smoothing should be implemented as optional so that reverting to the primitive angular traces of discrete locations points is still possible.

Movement Relatedness as the Semantic Attribute

The inherent entanglement of space and time (defined as *spatio-temporal dependency* in GIS) is a key challenge in movement analysis [297]. Observations in the spatial domain without the consideration of temporal stability may result in unreliable or even false positive discoveries [291]. As the time variance is traditionally less focused, assisting domain experts to think temporally is essential [298].

[297]: Demšar et al. (2015), "Analysis and Visualisation of Movement"

[291]: Andrienko et al. (2013), *Visual Analytics of Movement*

[298]: Andrienko et al. (2010), "Space, Time and Visual Analytics"

To find potential interactions between animals, spatial proximity should be discussed in a local time context. Following on this principle, we propose movement relatedness (MR) as a concept that describes the relationships with spatial-temporal references. In this study, the MR works as a semantic attribute to support the pivotal effect of outlining the potential influences or interactions between moving animals. Before move on to the definition and sub-forms of MR, we distinguish movement relatedness from proximity because MR concerns the distance variations in a medium-to-long time range to indicate the likelihood of potential influences or interactions, whereas proximity is only a measurement of distance in between points in a fixed time point. Therefore, the MR is partially informed by proximity as it can be derived from the trends of physical proximity in time.

We employ two basic modes for inspecting how related animals are bonded to each other by their movements – the *pairwise* (**PW**) MR and the *individual-to-group* (**i-G**) MR. The pairwise approach takes two entities as input and displays their dynamic relation variations. The i-G approach takes a focal entity and displays how closely it is connected to the rest of the animal group over time. These two modes are extended form the very idea of MR, which compliment each other for different tasks. For example, the **PW** mode can be used to verify the extent and strength of relation in a suspicious pair, while finding potential interaction candidates can only be supported by **i-G** mode (**R5**). The visual presentation of the two is based on different type of information qualitatively or quantitatively. We give each a detailed definition as follows:

Pairwise MR ($\boldsymbol{P_{ij}(t),\ t \in T,\ i,j \in A}$) is a time dependent scalar value describes physical proximity ($\boldsymbol{d_{ij}}$) comparing to the maximum distance ($\boldsymbol{M}$) bounded in the captured area, i.e. $\boldsymbol{P_{ij} = M - d_{ij}}$. Here, $\boldsymbol{T}$ represents all the possible states in the global timeline, while $\boldsymbol{i}$ and $\boldsymbol{j}$ are two elements from all the animals ($\boldsymbol{A}$). MR of one versus multiple targets enables comparison between more candidates and is more complex than the pairwise counterpart. Because the collective i-G MR pattern $\boldsymbol{G_x(t)}$ is rather a structural, multivariate representation that is contextually understood by considering explicit movement trajectory, relative proximity, and heading directions which involves constant changing features among multiple targets, it deserves a different notion to represent. Suppose $\boldsymbol{x}$ is the focal animal (the one to be compared with the rest of the group) and a time range from $\boldsymbol{t_1}$ to $\boldsymbol{t_R}$ is considered, the i-G MR is formulated as $\boldsymbol{G_x(t) = \{P_{xa}(t) \mid a, x \in A \ and \ x \neq a, \ t = \{t_1, t_2, ..., t_R\}\}}$. Here, we deal with the intricacies that are difficult to be summarized as a quantitative measurement (e.g. the complex relationships between $\boldsymbol{x}$ and multiple moving entities), we implemented a combination of visual components to delineate the implicit patterns and variations.

Uncertainty Awareness

The uncertainty awareness is believed to be useful in improving decision-making [75, 299]. Communicating uncertainty is important in our case because it can false signal the absence of one entity in a mutual relationship, which could mislead the experts' judgment and indicate a termination of related session. To avoid this, we take a series of measures: Firstly, we perform linear interpolation to fill the missing gaps to ensures steady data flow for the well-functioning of relation derivation model. Secondly, we treat the interpolated data points differently by labeling and measuring their reliability. This is realized by assigning a special Boolean label, i.e. interpolated or null, and a measurement of uncertainty extent. The measurement is computed as follows: given the current index $\boldsymbol{i}$ and index range of consecutive missing data points $\boldsymbol{[c, c']}$ ($\boldsymbol{i \in [c, c], \ \ i, c, c' \in N}$), the degree of uncertainty $\boldsymbol{U}$ can be formulated as: $\boldsymbol{U = min(|i-c|, |i-c'|)}$, i.e. the uncertainty in current data point $\boldsymbol{i}$ will be determined by the index distance to the nearest (temporally) reliable data point (Figure 5.3).

Thus, the uncertainty information prepared to be visualized with different levels of awareness (**R3**). The experts can make judgment on the credibility and integrity of a pattern by also referencing the visualized uncertainty [300].

[300]: Sacha et al. (2016), "The Role of Uncertainty, Awareness, and Trust in Visual Analytics"

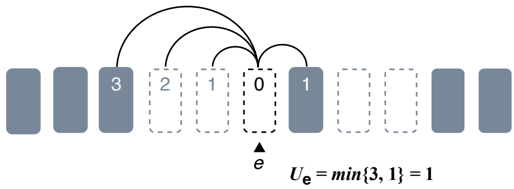


Figure 5.3: Degree of Uncertainty: a value U is calculated from its distance to the nearest reliable data point. The interpolated data points (i.e. $U > 0$) are explicitly labeled as so.

5.5 System Description

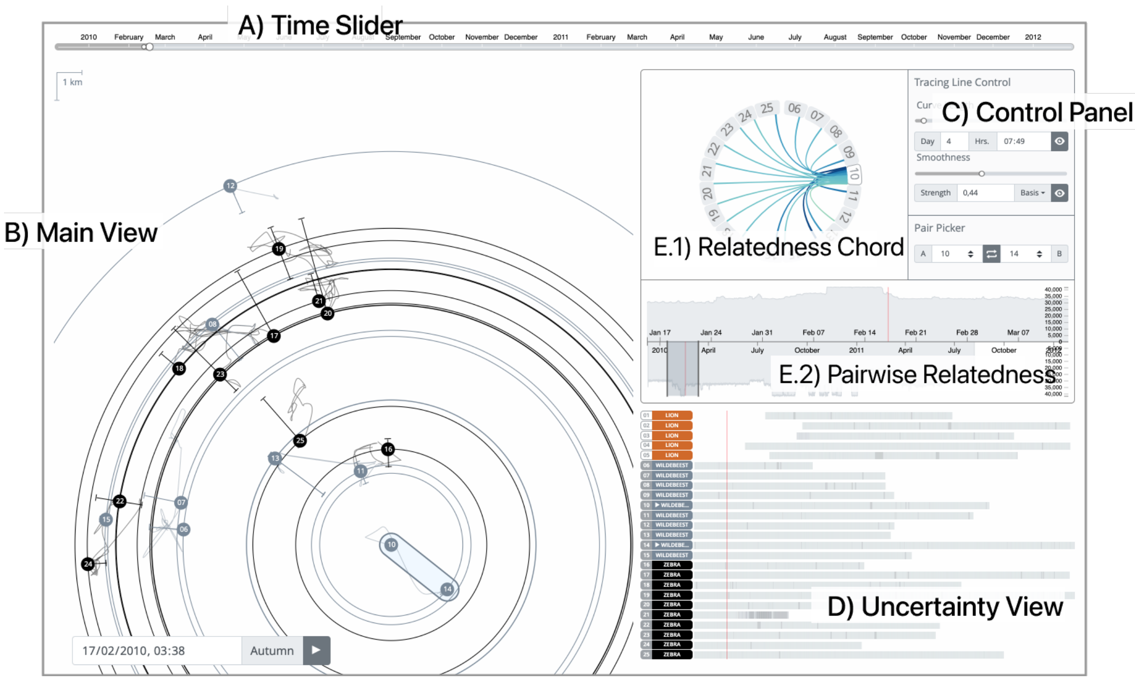


Figure 5.4: Interface Overview: A) Time Slider: a slider to indicate and cast change to the current position in the global timeline. B) Main View: a 2D space to display geo-spatial MR. C) Control Panel: control widgets to fine tune parameters for animation or pick animal pairs. D) Uncertainty View: an overview of collective data stability and availability. E.1) MR : A chord diagram to display MR between multiple entities. E.2) Pairwise MR: Interactive line chart for long term pairwise MR display.

We implemented our visualization system in an interactive, web-based application with D3.js. It consists of a main view, peripheral views, and control areas, see Figure 5.4. The functionalities are results from § · 5.3 Requirements and § · 5.4 Design Rationale. **Main area** (Figure 5.4 B) displays movements and trace lines in relation to their original geographical patterns. **Time Slider** (Figure 5.4 A) is a time reader and controller to set the global "current" time and indicate the length of covered duration, which is shown as the red line along the center (Figure 5.4 C). Trace line adjustments and animal pair selector is placed in the control panel. Uncertainty in the data are indicated separately by each animal along the time progression (Figure 5.4 D). MR measurements can be found in Figure 5.4 E1, E2. We expand with more details in the rest of this section.

Movement Encoding

Moving animals are represented as animating locations, each with an ID and a species color. Species are colored to resemble the animal's natural appearance: orange for lion, cool gray for wildebeest, and black for zebra.

Each animal entity draws a trace line with the same color of itself, the length of which corresponds to the global duration. As time coverage is the same for every trace line, drastic movements (bigger distance between steps) will appear longer than sedentary animals, creating a contrast that enables comparison between animal individuals by its movements intensity. Thus, outlier movements can stand out more clearly.

To improve the readability of movement trajectories (as explained in § · 5.4 Parametric Trace Animation), we applied parametric smoothing to the trace lines. The technique is partially inspired by Sacha et al. [296]'s trajectory simplification, we integrated commonly used methods like cubic basis spline,

[296]: Sacha et al. (2017), "Dynamic Visual Abstraction of Soccer Movement"

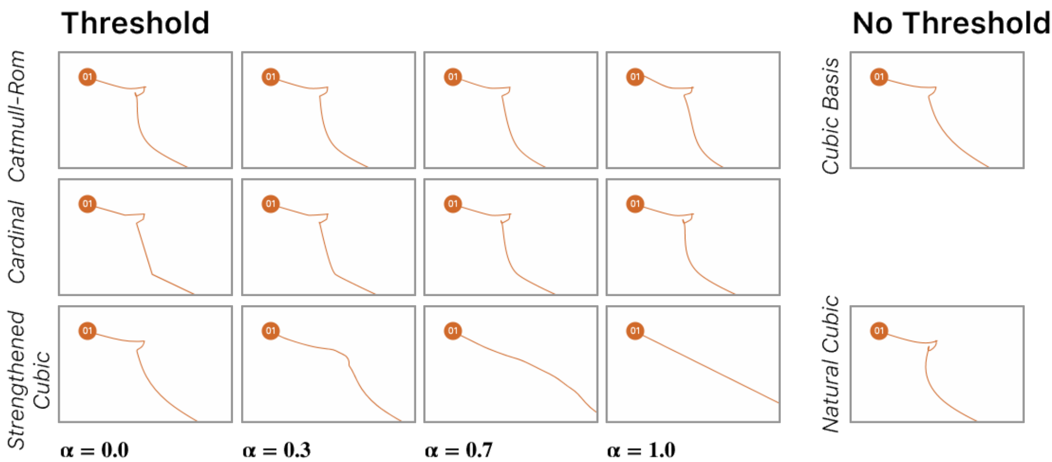


Figure 5.5: Curve Adjustments & Settings: Experts can leverage their domain knowledge to tweak smoothing functions and smoothness threshold for the desired result.

natural cubic spline, straightened cubic basis spline based on Holten [301]'s edge bundles (originally developed for bundling hierarchical edges), Cardinal spline, Catmull-Rom spline with D3.js' curve interpolation functions. This flexibility in configuration (Figure 5.5) can be fine-tuned by mode or intensity. Here, the mode determines the type of underpinning smoothing function and the intensity, specified by a linear α value between 0 and 1, offers the option to adjust the amount of smoothness: $\alpha = 0$ means no smoothing at all and $\alpha = 1$ means smoothest. The goal is to give domain experts extensive free options to pinpoint the right parameter to draw trajectories that caters to their analysis scenarios.

[301]: Holten (2006), "Hierarchical Edge Bundles"

Uncertainty Encoding

Uncertainties can be visualized following the temporal axis in (Figure 5.6). The thin horizontal heatmaps in this view

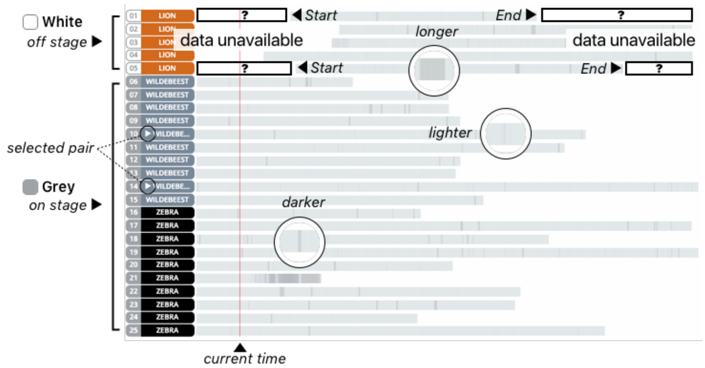


Figure 5.6: Uncertainty View: displaying data quality issues with temporal context. The view provides a sense of whether the data quality can be trusted around current point in time. Labels on the right show whether the animal's data is currently available to be displayed on main view to the left. The white "⊳" signs inside animal labels indicate the selected state of an animal pair for pairwise MR analysis. Visual clutter can be mitigated by clicking on the label to hide certain animal subsets.

depicts the data issues in three aspects: 1) the start and end time of available data, 2) the general distribution, and 3) the degree of uncertainty (by depth of color), cf. § · 5.4 Uncertainty Awareness. The time context is useful to guide expert to skip certain segments by informing where to expect reliable data.

In the spatial domain, moving entities will change both appearance and size once uncertainty happened in the data (Figure 5.7). Filled circles change to dashed outlines, expanding their sizes to indicate a dilution of positional accuracy. Its opacity also decreases along with the size increase, telling the viewer that the system is unsure about exact location of current animal.

Expert can leverage both display methods to avoid risky interpretations and apply self-discretions with their domain knowledge.

Movement Relationship Encoding

The MR can be understood through different setups. We describe two modes to treat them respectively: the MR between

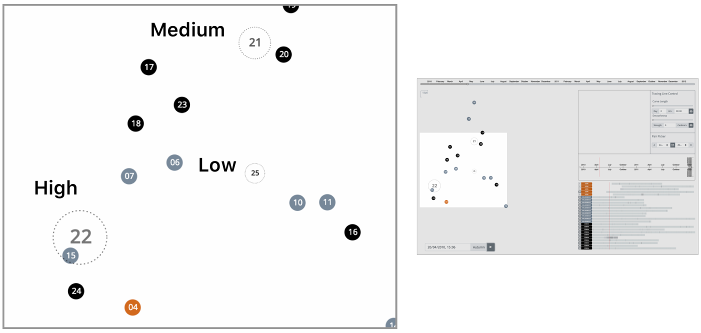


Figure 5.7: Uncertainty in Spatial Movements: Empty circles are shown to tell the end of available data. A circle with expanding area indicates movements are visualized with diminishing accuracy.

two individuals (pairwise) and one individual comparing to a group of the rest (i-G).

Granular variation of $\boldsymbol{P_{ij}(t)}$ is plotted with a line chart. Overview-and-zoom functionality [44] is needed here considering the amount of details in 2.5 years of data points. So we implemented a vertically mirrored line chart below it with different purposes for each half – the bottom one can be brushed to select the time range and the top side displays zoomed details of the brushed area., cf. B) in Figure 5.8.

[44]: Cockburn et al. (2008), "A Review of Overview+detail, Zooming, and Focus+context Interfaces"

The chord diagram can provide an overview of MR of all possible pairs being presented in the main view. Ones with higher MRs are drawn in bolder and more saturated ribbons while lighter appearance applied for the lower MR, cf. A) in Figure 5.8. The delineation reacts differently to a duration and fixed time point. If a duration is selected, the system calculates averaged proximities of all intervals in the range to determine the ribbons' appearance: $\boldsymbol{\overline{P}_{ij} = \frac{1}{R} \cdot \sum_{s=1}^{R} P_{ij}(t_s)}$. This approach is very similar to the pairwise mode but more aggregated. Experts can brush and drag to tweak the duration length. Such operations are useful to answer questions like "Were the animals' movements more clustered (related) during the past eight hours? Were they the same for last two days?". It is a

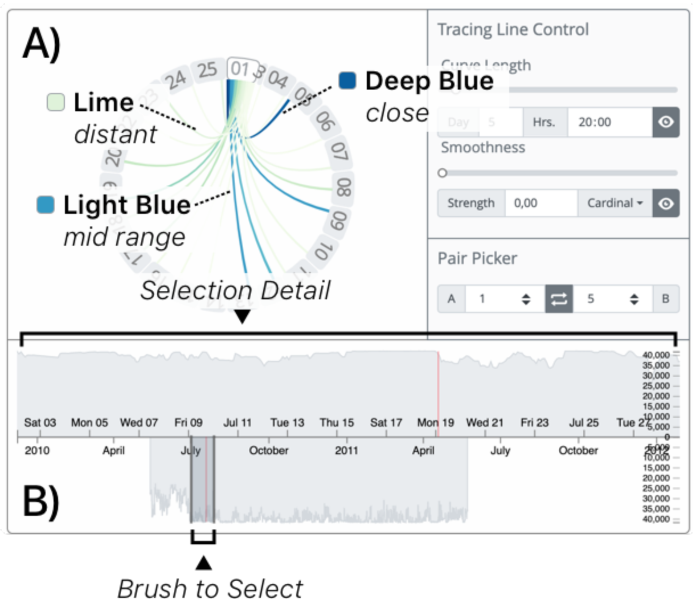


Figure 5.8: Pairwise MR in two views: A) Chord diagram with each ribbon for any possible pair in the given time range; B) Interactive line chart with separated brush-to-zoom functionality.

simpler and more straightforward way to search for patterns without looking at the spatial changes in the main view.

Geographical pattern of the i-G MR ($G_x(t)$) is displayed in the main view where spatial distribution and social context are sensitive aspects. The individuals can be focused by clicking on its circle in the main view. The interaction halts any ongoing animations and creates an array of concentric circles. MRs of animals concerning the focal animal can be visually examined (Figure 5.9). Radii of the circles indicate the spatial proximity to the animal: $r = P_{xa}$. The circles sort proximity of animals with scattered distances and moving trends (came closer or went further) into an egocentric diagram where unidirectional comparison of proximity is possible. Based on this, proximities of current time is easy to tell by circle sizes. The less explicit moving trends, however, are illustrated by the

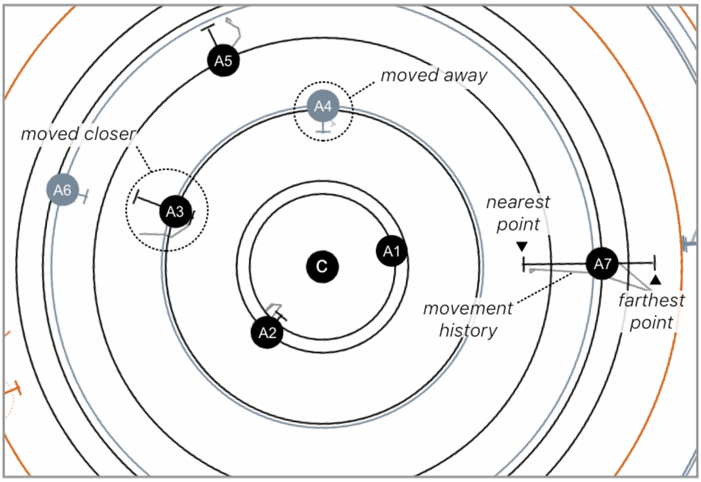


Figure 5.9: i-G MR in Main View: Animal movements are displayed in relation to the focal animal C. Their MR in the duration is aggregated and represented by capped lines which ends are used to indicate the nearest and farthest distance to the focal animal. Here we can see that A3 has moved closer to C and A4 has become more distant judging by the overall trend. Despite located at different directions to C, the distance comparison between A4 and A3 is still intuitive and apparent.

trace lines and MR error bars. Here, the former corresponds to the movement trajectory of the duration and the latter is a depiction to analyze the trend of MR: line caps on both ends of the error bars are determined by the maximum and minimum values of relative proximity in the duration. Thus, whether an entity is drawing closer or moving farther can be read from the negative/positive sum of relatedness, which is derived by comparing length of error bars from the inside (positive relatedness) and outside (negative relatedness) of the proximity circle. For instance, ones with much larger outer length suggests the underlying animal spend most of the recent time in places more distant to the focal animal than its current location, which means it tends to move farther considering the past period. The trace line here is to verify the judgment on the trend of MR change with exact movement details.

5.6 Use Case

We tested the visualization system with domain experts to validate its usefulness in practical environments. Specifically, the system is hosted online as a web application, and we recorded two sessions of screen interactions and verbal communications remotely via Skype. No specific tasks were given during the experiment. Experts are encouraged to explain their reasoning following the think-aloud protocol [302], and support the explanation with domain knowledge if necessary. Two sessions with total length of 105 minutes are video recorded for the post-hoc analysis. We keep notes of the highlights with reference to their time slider position, flow of interaction, experts' interpretation, filter settings, as well as the video time. We report on our observation of cases in the rest of this section.

[302]: Boren et al. (2000), "Thinking Aloud"

Checking Seasonal Distribution Change

Background: Seasonal climate change impacts many aspects in an ecosystem. Ecologists need to understand how this is reflected in animal movements. Fortunately, the raw data covers sufficient season cycles in a multi-annual time frame. Thus, seasonal differences in movement distributions can be visually compared.

Method: By either picking a specific position on the global time slider with mouse or manual input of time digits (**R2**), experts can quickly preview the general distribution of animal locations. Either way, the season (resp. to the Southern Hemisphere) display on the time ticker will change to the specified time. The experts also turn on the trace line to portray areas of denser movements by following two steps (**R1**): 1) they extend the trace line duration length to 90 days (meaning location history of roughly three months) and 2) they move the "current" time to

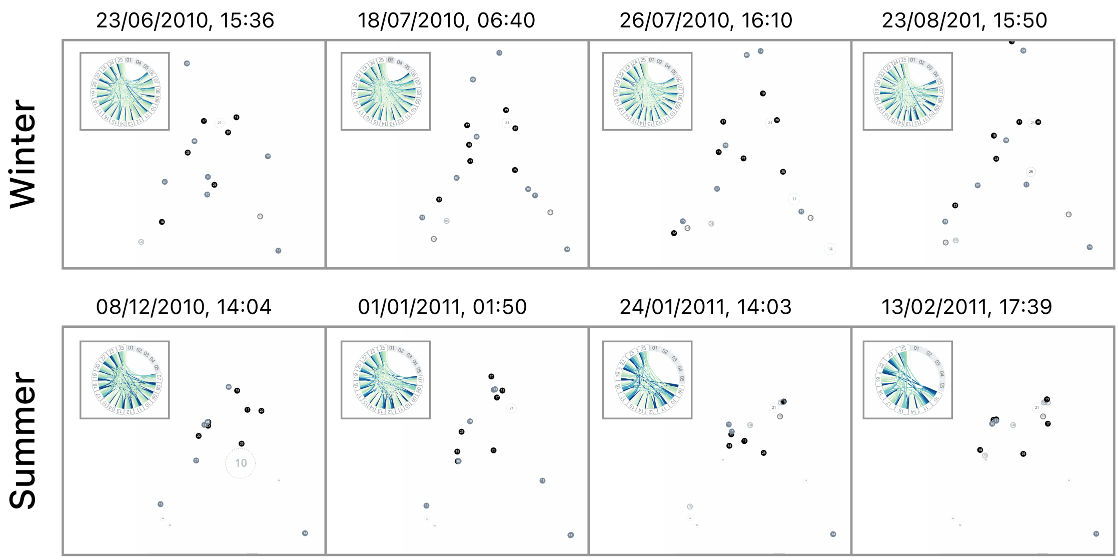


Figure 5.10: Herbivore spatial distribution and general MR level between summer and winter time. Chord diagram with more saturated ribbons indicates more related spatial distribution of entities.

the end of the season precisely by digits, e.g. "**28/02/2011 00 : 00**". Thus, a long trajectory would take on a nested shape within which condensed areas indicate frequent visits in particular regions. They can also filter out herbivores or predators to make clean comparisons between species across different time of the year (**R4**). Experts use the overall color tone of the ribbons in the chord diagram altogether to tell how close animals are forming (local) groups.

Insight: Figure 5.10 are snapshots of animal distributions in winter vs. summer. It is observable that the herbivores tend to spread loosely in winter and gather closer during summer. Such a pattern tends to gravitate toward a few specific regions as it can be shown in the long term season trajectory (Figure 5.11). The experts believe that this could be caused by the periodic

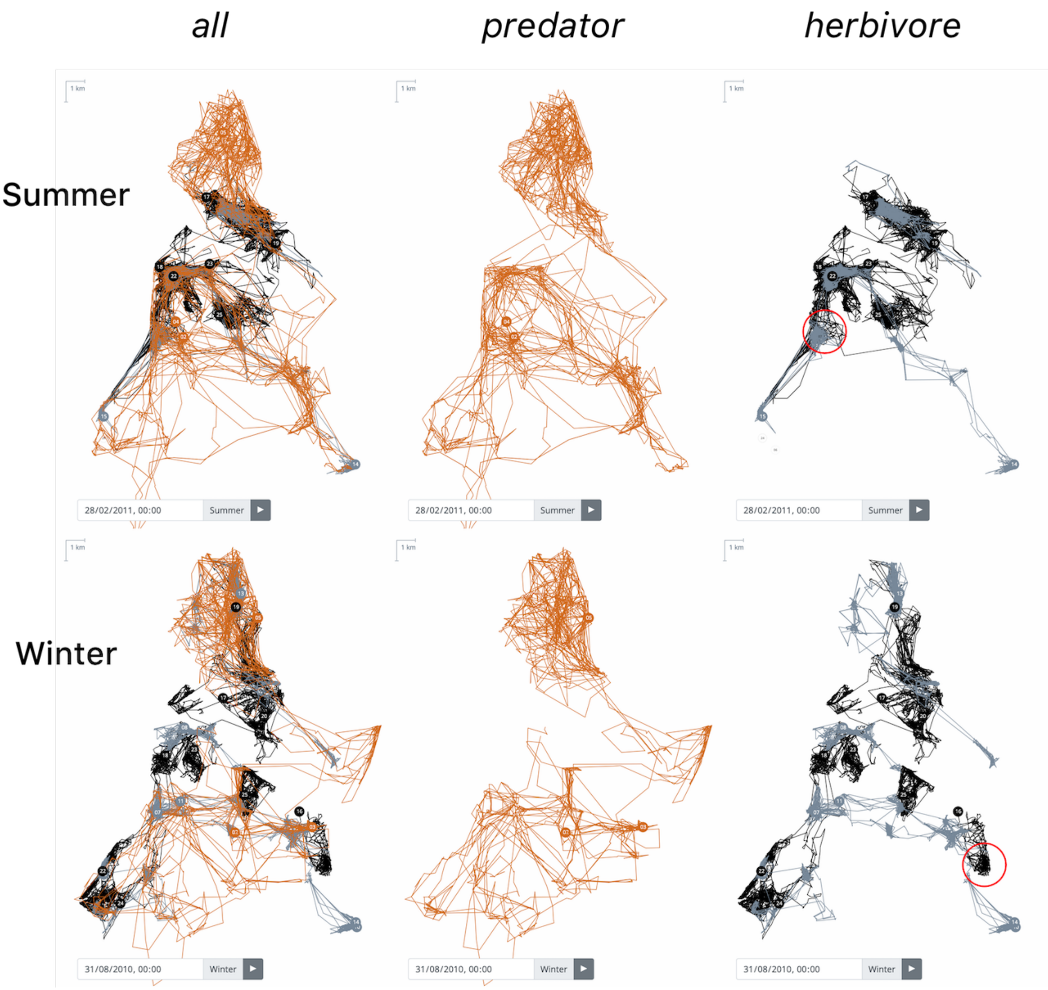


Figure 5.11: Long trajectory covering the movement paths of the entire season. Such configuration is useful to detect popular regions in a specific time of the year. Herbivores tend to concentrate in small patches in the center of the map during summer.

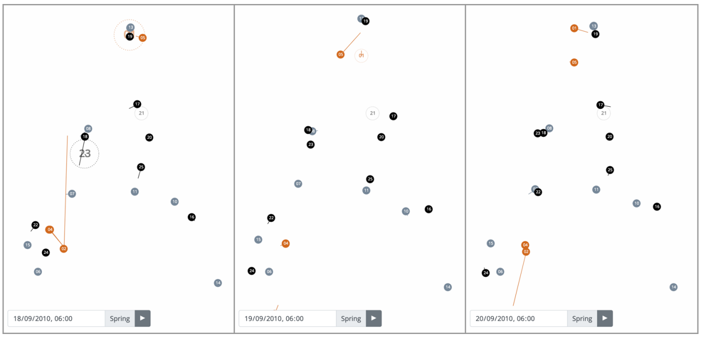


Figure 5.12: Absolute Travel Distance with Bundle Curve ($\alpha = 0$) : Predators travels much more during night hours.

rainfall change in a year which leads to denser natural resource such as vegetation and water accumulations in some regions. The outcome shows that the concentration of natural resources attracts herbivores while such a trend is less obvious among the predators. Also, the shape and size (without smoothing) of trace lines can provide useful clues regarding the relative sedentary v.s. active state of an animal: longer, more dispersed lines indicate more active behaviors in the area, while the more condensed, wiggling lines suggests more sedentary ones. From the comparisons between summer months and winter months, experts has experimented some immediate hypotheses that correlate to seasonal changes — 1) season does have effect on the concentration tendencies of animals, 2) such tendency is more significant among herbivores than predators and 3) relative sedentary states are most observed among herbivores during the winter.

Species Difference in Night Travel Distance

Background: Another potential influence on animal behavior is day-night transition. Unlike most birds who tend to rest during most of the night hours, some mammals may react to day-night alternation differently in order to ensure their survival. The changes in temperature, visibility, as well as the effect of chronobiology could have heterogeneous effects on the movements of species. How the behavior difference could be visually reflected by geographical patterns is intriguing.

Method: The expert starts with setting the current time to 06:00 am on a random day and changes the trace line curve length to 9 hours. The main view displays movements trajectories of the last 9 hours — from 09:00 pm the day before to 06:00 am current time. They can use arrow keys to jump to consecutive days without changing the time of day and trace line length. As a result, the common pattern in night movements are more directly exposed to the viewer (Figure 5.12) (**R2**). As the shape of trace lines can be morphed with type and smoothness, the experts select "bundle" for curved type and slide the $\boldsymbol{\alpha}$ value to maximum smoothing ($\boldsymbol{\alpha = 1}$), which produces straight lines that connect only the origin and destination of the entire movement, cf. Figure 5.5. This aggressive smoothing technique allows the experts to make sense of the absolute travel distance during the night hours (**R1**).

Insight: Like the example in Figure 5.12, experts found little correlation between the night activities and geographical distributions. However, the night travel distances of predators (lions) are distinctively longer than ones from herbivores. This indicates that lions are more active during the nights while wildebeests and zebras tend to stay and rest as much as possible in the nights.

Examining Grouping/Pairing Behavior

Background: Nuanced understanding of animal social interactions with an awareness of species traits plays a key role in the study of animal behaviors. As mentioned before, the grouping and pairing are difficult to detect with the visualization of mere locations due to spatial-temporal dependency. Instead, visualizing the dynamic MR can support the ecologists to investigate the strength of social bounding in pairs.

Method: When experts find that two animals of the same species are potentially forming a pair as they stay together drawing close, comparable traces, the experts select the corresponding animal pair in the dropdown menu from the control panel (Figure 5.4 C). The global pairwise MR is then plotted to delineate the intimacy between the two animals. Ups and downs that vary from month to month or season to season can be observed (Figure 5.13). As the expert brushes on the lower half of the chart around the current time, indicated by a vertical red line, fine variation of MR in the brushed zone are magnified to a daily or hourly level of detail for examination (**R5**). By checking the line shape of MR on both macro and micro level, experts can make more reflective judgments on the grouping or pairing behavior.

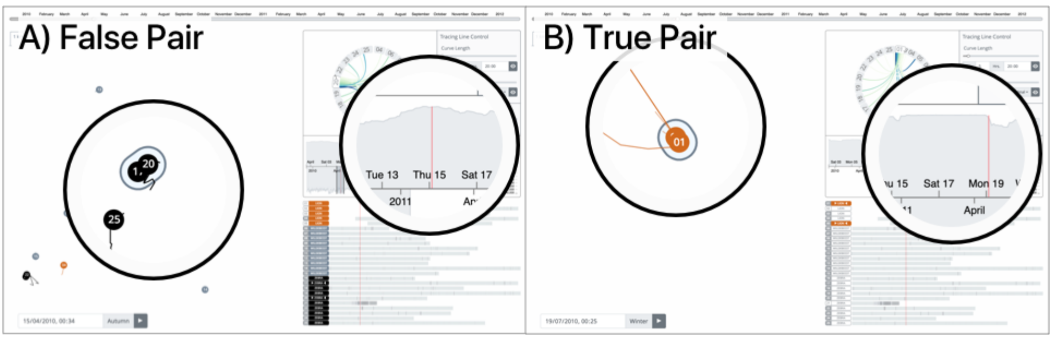
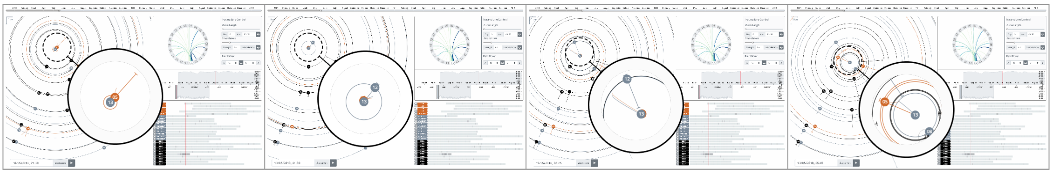


Figure 5.13: Pairing Examples: A) Zebras 20 and 17 seem to be socially close but their MR does not hold strong for long enough. B) Distance between lions 1 and 5 have diminished for roughly 2.5 km in the last 5 days 20 hours (filtered). Stable high pairwise MR is found repeatedly between the two lions.

Insight: The situation in Figure 5.13 A) can be easily identified as pairing or grouping behavior if only looked at their temporary collocation from their trace line. The blue ribbon in the chord diagram that connects animal 17 and 20 seems to confirm that for the past 20 hours, the two are staying rather close together. But the pairwise MR view suggests that such relation is constantly changing and unstable. Thus, attributing grouping or pairing behavior in this case is deemed questionable by the experts, yielding further investigations. Another example in Figure 5.13 B) tells a very different story of stable pairing — lions 1 and 5 have approached each other and maintained near maximum MR for a rather extended time. Since the phenomenon has repeated several times, experts believe the pattern is a more reliable indicator of a strong social pairing. Reusing the same technique, experts have also discovered similar patterns between lions 2 and 4, wildebeests 12 and 13. A stable one-month long pairing is also found between wildebeests 10 and 14. But the time window for this is too small comparing to the other groups and no further rejoining is found. More in-depth investigation is therefore needed to determine the pairing is strong. The visualization support of MR confirms that a safer identification of intimate pairs requires evidence of close movements for longer period. Members of strong social pairings are likely to rejoin each other soon after separation.

Analyzing Multi-Species relation

Background: Unlike the MR within the same species, the inter-species MR may indicate threat instead of cooperation particularly between predators and herbivores. According to E1, a real predation process usually takes place within 3-5 minutes, which is beyond the frequency resolution of the employed GPS devices. However, unexplored behavioral patterns and multi-species interactions can still take place over the span of hours, according to E1. The experts would like to use inter-species MR to investigate possible instances of such behaviors.



1.a) Approaching | 1.b) Diverted | 2) Stalking | 3) Separating

Figure 5.14: Three Stages of a Potential Encounter: 1.a) Increased the MR between lion 5 and group of wildebeest 9, 12, 13 suggests the movement pattern of one approaching a group of animals. 1.b) Wildebeest 12 has diverted from the group. 2) Stabled MR (diminishing capped line length for MR variance) shows the two species kept close distance during the most of preceding 4 hours. 3) Lion 5 moved away accompanied by MR decrease. Both wildebeest 9 and 13 were found active after potential encounter.

Method: Animals of more than one species can be seen as a potential stalking if one movement trace follows another continuously. The smoothed trace line with duration length set to several hours can be used to validate if the exact travel path fits well (**R1**). The expert uses the numerical input to fine-tune the trace line length to estimate the exact stalking time window. Clicking on one of the animals in the main view will trigger the i-G MR of between the selected animal and the distant one(s) of a different species B. This lets the experts knows the distance other animal(s) have covered to approach the selected one. In this case, the start and end of such episodes can be inferred with the help of pairwise relation.(**R5**).

Insight: The example in Figure 5.14 illustrates how inter-species interactions can be studied through their spatial-temporal relatedness. The involved animals are lion 5 and wildebeests 9, 12, 13. Through each stage, the MR would show an increase-stable-decrease process in the inter-species MR episode. The development of such a pattern can be interpreted as a hypothetical threat between predators and herbivores by the experts. Without concrete ground truth like onsite direct observations, we can only assert the likelihood.

5.7 Evaluation

We invited the experts (§ · 5.3 Project Background) to give conclusive remarks on the design. The evaluation starts with an open questions-and-answers session of 20 minutes each, during which we first clear up confusions on both sides, e.g. assumptions of animal behavior, or misinterpretation of visual variables. After that, each expert summarizes a final evaluation in written form. The result was collected by delivering questionnaires containing questions in three implicit themes to validate the design's usefulness – the enabling, the facilitating, and the applicability. *Enabling* emphasizes the aspects that provide novel analytical capabilities to find undiscovered insights whereas *facilitating* consists of cases where the system solves their existing problems with a significant productivity boost. *Applicability* addresses the conditions and contexts under which the system would achieve its maximum value. The experts were required to return the questionnaires within 24 hours. We unfold the findings followed by our discussions following the three-themes structure based on the questionnaires data.

Enabling

According to E1, an animal can be influenced not only by variation in environmental conditions but also by the behavior and location of another individual or group of animals. Because of displacements in space and time, such relationships are difficult to explore visually. The visualization system allows the experts to analyze movement through space-time variations (**R1**) of individual animals as well as the relationships between them (**R5**). E1 asserts that exploration into inter-individual interactions is enabled by the chord diagram with color-coded MR.

Regarding the pairwise relationships, the ability to zoom into specific time periods (in pairwise MR) is very convenient and easy to use. E2 believes the visualization system highlighted an important capability which is visualizing data along temporal dimension, particularly how MR changes over time (**R2**).

Both of the experts report that the i-G MR enables a visual understanding of the relatedness with actual distance between individuals in smaller time frames. The variation range of MR raises the awareness of the time dependency in shorter movement trends. Unexpected patterns would emerge after testing and exploring with varying time scales (**R2**). E2 believes that the view mode is not only useful for generating ecological insights or hypotheses, but also creates more contextual awareness for the analysis.

Facilitating

Before using the system, plotting static figures is their primary way of visual analysis for movements. According to their comments, the visualization creates depictions beyond static figures, without which the dynamics in movements are otherwise hard to interpret. "(Such functionality) is very needed in data exploration", states E1 (**R1**).

As they are fully aware of the difficulties introduced by inconsistent data, the new visual approach to check data availability/uncertainty is well-appreciated. "To me, this is a very useful tool for exploration of movement data, allowing to focus on different potential problems, such as sociality between individuals, movements relative to predators, home ranging, etc." says E1. The expert also confirms that the awareness of uncertainty is reinforced by trace lines and smoothing parameters which can be used to smooth out uncertain measurements (**R3**). E2 appreciates the quick configuration changes on the fly.

He says, "It makes comparisons between configurations very convenient." (**R1**).

Applicability

Movement ecology research often requires calculating implicit features from the data such as road impact [303] or stigmergy [260]. When the optimal features to describe animal behaviors are still unclear and yet to be confirmed, the research becomes challenging. Based on their experience, the experts believe that the system can play a key role in their exploratory stage of analysis, where setting different parameters and scoping down to subsets of data need to be frequently adjusted. Under such circumstances, a comprehensive integration of capabilities that can produce easy to interpret visual insights with quick and convenient configuration changes is essential. According to E2, visualizing certain variables in a spatial-temporal way has changed their way of computing variables, doing analysis, and develop new hypotheses or insights.

[303]: Klar et al. (2009), "Effects and Mitigation of Road Impacts on Individual Movement Behavior of Wildcats"

[260]: Giuggioli et al. (2013), "Stigmergy, Collective Actions, and Animal Social Spacing"

5.8 Next Iteration

Newly Discovered Gaps

Although the current system design suffices previously defined design requirements (§ · 5.3 Context and Requirements), we plan to move on with an upgraded system. The planning of the upgrade is based on insights gained in the previous design process and the newly discovered gaps. To investigate explicitly what new functionalities the next iteration should enable or optimize, we invited two visualization experts (V1 and V2) to the evaluation group in addition to the aforementioned domain experts (E1 and E2). They altogether share useful feedback and suggestions which lead to the general direction of integrating more advanced tasks and usability improvements. A more detailed analysis of these inputs are the following:

G1) the clarity and added value of the chord diagram need improvement. In the previous domain evaluation, the usage of chord diagram is repetitively explained due to an experts' reoccurring confusion. This may indicate that the visual encoding is not sufficiently intuitive for the successful adoption. From the visualization experts side, V2 also expresses similar doubt about the design choice of chord diagram — its analytical benefit is not comparable to its visual weight in the user interface. Although the color differences in the chord diagram create strong contrast to accelerate the reading of potential related movements, no additional insights can be derived as skimming through the main view can achieve similar results. Therefore, we conclude that the chord diagram has usability and functionality flaws to reconsider in the next iteration.

G2) a global level view to provide hints for exploration is unprovided. We observe that domain experts' initial interactions with the system are mostly blind and random. They tend to begin by randomly picking several time points from the global timeline to get quick snap shots of location distributions, the inference from which helps them build initial understanding and locate interesting time periods. As the familiarity with the system increases, specifying a time window to include trace lines is discovered to ease this task. We argue that there can be a more efficient way if 1) global information over the temporal axis can be provided to prompt the explorations along the temporal dimension, or b) view of the previous time pick would provide useful information for the next time choice. This concern is raised by V1 and verifiable with the documented Skype video sessions. Regarding this, we think higher level exploration guidance on the temporal dimension is necessary.

In addition to identified gaps above, we are encouraged to bring more analytical capabilities to provide richer information of movements. For instance, the current group selection only allows for selection of pairs. The dynamics of MRs of animal groups of three or more entities can be more nuanced and complex. Informing the clues in this regard can be helpful to support more hypotheses. Following this thread, V2 also suggests that we could derive an aggregated layer of movement patterns to delineate more information on top of existing trajectory depictions.

These inputs help us to scaffold the next design iteration, the detail of which is explained in the following section.

Design Improvements

A Basic Landscape Context

The landscape characteristics are ignored in the last version. This is because the project focuses on movement relations and the landscape context is sacrificed because of its secondary importance. However, our experiments show that the landscape context is revealing in many aspects. As we implemented a background with the data source from the online map service platform Mapbox ✍ and reverted the y-axis to match the true north of landscape. The outcome (Figure 5.15) exhibits some important lessons.

✍: https://www.mapbox.com

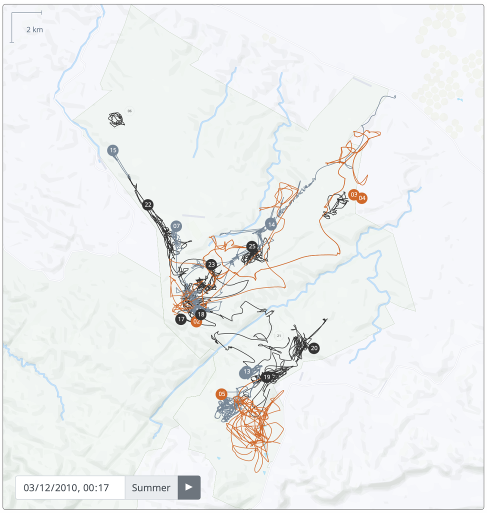


Figure 5.15: Landscape Map: A low-resolution map to show the major landscape characters such as water areas, grasslands, and reserve borders.

For example, the added landscape context helps to explain the segmentation of two significant crowds of animals during summer seasons (animals tend to cluster into certain areas as explained by Figure 5.11) – a separation by the river cutting from the Southwest to the Northeast corner in the natural reserve (Figure 5.15). The trajectories rarely cross the river. This indicates rivers can impact the frequency of traveling in some directions. Also, we see part of the movement paths are heavily influenced by the shape of the border (left side of Figure 5.15). This indicates the chance of a group of animals walking along the border. If so, the placement of a hard barrier can play a significant role on the formation of moving groups as freer movement patterns are coerced to the shape of the border. The later case tells us that the traveling path of animals may still be affected by barriers such as resource distribution or the reserve's border shape.

With the examples above, the importance of landscape context is apparently under-estimated in the previous design as the

MRs of even small scale groups (pairwise relations), which is the focus of our analytical interest, can be largely affected by certain physical hindrances in the landscapes. The provision of landscape information can avoid false interpretations where, for instance, the distribution of water, herbs, fences are the main cause of traveling path instead of social dynamics between animals. Consideration into this issue leads us to prioritize the landscape as an essential part of our system redesign.

Global View of MR

The analyses of MR need to consider movements in the temporal space and the spatial space simultaneously, which are tricky on a single two-dimensional plane. The previous design to analyze pairwise MR is mostly designed to solve this issue. It enables a novel view with which false pairing can be easily detected. The design objective to enhance this core functionality in the next iteration is to accommodate more advanced hypotheses, which can be divided into three parts:

1) flexible group selection: MRs of animal pairs can be analyzed in pairs. However, group members of more than two entities are possible and equally interesting to the analyses. To this end, we remove the two drop-down menus for the pair selection and replace that with free-form lasso selection (pointer drawing circles to enclose desired group members) in the main view. The back-end analytical model is redesigned to calculate a density index as the new the relatedness value to accommodate group members of more than two ($\boldsymbol{n} \geqslant \mathbf{2}$). Theoretically, the new design allows a group size up to all the displayed animals available.

Figure 5.16: Grouping Candidates: The system can automatically generate multiple assumptions of potential groups similar to the current selection (brighter polygon with animal 06, 08, 23) with the derived parameter ε.

2) generated grouping hypotheses: When applying a lasso selection, the system performs a Kruskal's Euclidean Minimum Spanning Tree (EMST) process [304] to derive a distance-based grouping tolerance ε. Under the hood, the algorithms takes the longest edge in the generated tree, which guarantees all the members specified by the lasso are reachable, formally:

[304]: Kruskal (1956), "On the Shortest Spanning Subtree of a Graph and the Traveling Salesman Problem"

$$\varepsilon = Max\{\ mst(lassoSelectionCoordinates)\ \}$$

where $n \geqslant 2$. The system then takes the distance parameter ε to search for other potential groups which are reachable within the distance threshold of ε Figure 5.16. The search task is achieved by applying the density-based clustering algorithm of DBSCAN [305] upon all the shown animals (excluding manually excluded ones by clicking on the labels in the uncertainty view Figure 5.4 D)) to automatically generate similar grouping candidates to prompt the next action.

[305]: Ester et al. (1996), "A Density-Based Algorithm for Discovering Clusters in Large Spatial Databases with Noise"

3) searching similar cases in all time points: The automatic generation of group candidates on the map takes one input and scales the hypothesis to the global level in the spatial dimensions. We apply the same idea to the temporal dimension to capture grouping status along the global timeline of each animal. More specifically, after clustering with $\boldsymbol{\varepsilon}$ on currently displayed locations is finished, the same parameter is exploited as a global threshold to determine if the given animal $\boldsymbol{a}$ is contained by a group over all time points. The result of animal's grouping status history (GSH), i.e. $\boldsymbol{GSH_a}$, is thus composed as:

$$\boldsymbol{GSH_a = [sa_{t_0}, sa_{t_1}, sa_{t_2}, \ldots, sa_{T_a}]}$$

where $\boldsymbol{sa_{t'}}$ is a Boolean value which indicates the grouping status of animal $\boldsymbol{a}$ at time point $\boldsymbol{t'}$, $\boldsymbol{t_0} \leqslant \boldsymbol{t'} \leqslant \boldsymbol{T_a}$, and $\boldsymbol{T_a}$ is the time point of the final appearance of the animal $\boldsymbol{a}$. Since the GSH is dependent on the specific animal $\boldsymbol{a}$, we add a layer of detail to reuse the 25 bars in the uncertainty view (Figure 5.4 D)) to display each GSH. The visual comparison of the GSH helps to examine the stability of groupings (the size of which can be more than two members) as exploration candidates. The expert can quickly click on positions of any bars in the uncertainty view to jump into interesting episodes such as the initial forming of a group or the time point where new member(s) may join the group. This view also includes all the members of all the time into a holistic view, based on which the user can decide which group's subtle variations of the MR strength (i.e. the location density of the group) to examine in the MR view, which is only slightly adapted from the pairwise MR view in the last version (E.2 of Figure 5.4).

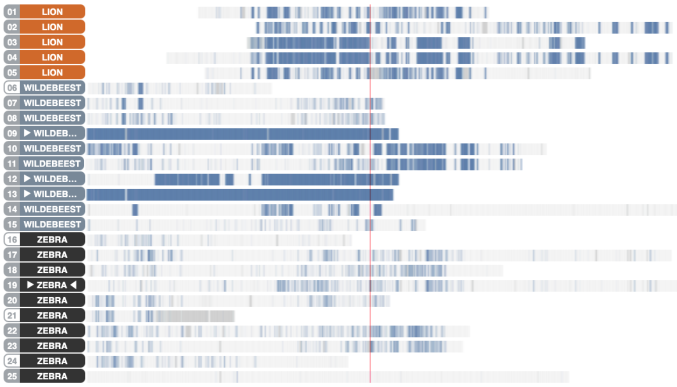


Figure 5.17: Grouping Status History: a global view to see if the animal is in a group (blue) or not (gray) according to current ε.

To sum, these improvements provide two novel views of the global MRs. The first improvement paves the way to more advanced analyses of multiple members with easier and more flexible selections. The latter two improvements either provide the global view of spatial relations or a global view of temporal relations — two essential pillars to support the next level MR analyses. These improvements collectively enable overviews of information on the larger context, potentially guiding the user's attention to the next relevant interest region. The new design in this regard is likely to meet the gap of **G2**.

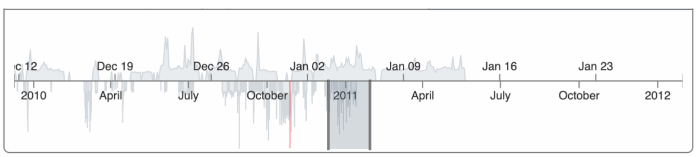


Figure 5.18: Movement Relatedness View: the new design supports the same interactivities of dragging and brush-to-zoom, whereas the y-axis can represent the strength of relatedness of group size of more than two entities.

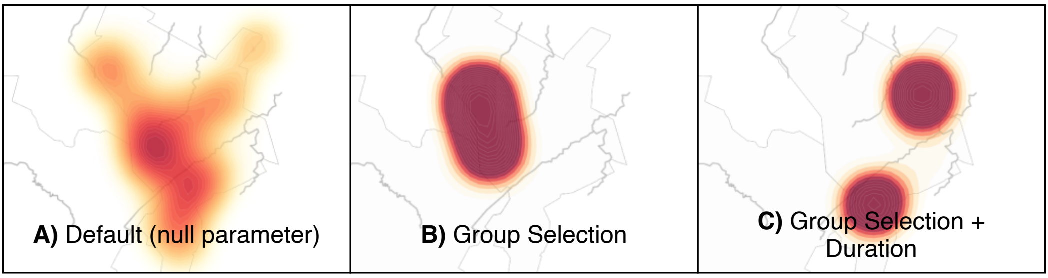


Figure 5.19: Heatmap Examples: A) The default state: showing locations of all animals of all time in a heatmap if not parameter is specified. B) Group selection: showing location densities where selected animals are close enough to be grouped by ε. C) Group selection within a time duration: showing location densities of selected groups existing within the specified time window.

Substituting the Chord Diagram with a Contour Heatmap

As mentioned in § · 5.8 Newly Discovered Gaps, the employment of the chord diagram has raised interpretability and usefulness concerns. We decide to switch for a different view where the spatial distribution is the primary focus. The motivation behind such a change are twofold: 1) We have redesigned new features that are helpful to serve the same purpose of original design. More specifically, automatic grouping generation and GSH in the uncertainty view already aids in the finding of potential members to include or exclude into or from a group. This makes the original design less irreplaceable. 2) The added landscape map background makes the main view more visually loaded, especially the trace lines and the concentric plots are shown on top. This leaves little room for more aggregated visual artifacts on top of the main view if more information is being used to aid the analysis. Our solution to this problem is to employ a down-scaled map to display generalized spatial information for the tasks where detailed landscape character information is not critical. Thus, the new map is responsible for patterns of large regional distributions, whereas insights concerning small distance steps or detailed land characters remain in the main view.

As the analyses of MRs can happen at any level of individual, group, or all members concerning varying time windows, the information aggregation can take data inputs of large and small Figure 5.19. Therefore, we employed a normalized density-estimation method to accommodate varying input lengths while keeping visual consistency and interpretability intact. The visualization result is a contour heatmap implemented through d3.js' built-in API. In the new design, the information input is determined by the parameter of group size $\boldsymbol{n}$ (up to 25, can be an individual when $\boldsymbol{n} = \mathbf{1}$) and time selection $\boldsymbol{r}$ (can be specified as a point or a duration, $\boldsymbol{r} = \boldsymbol{null}$ means all time points are selected). Since a normalization is applied, the depicted color only indicates the effect of concentration instead of the exact number of points. This also avoids extreme visual results of indistinguishable heavy or light colors.

The new design is significantly more readable and understandable according to a preliminary user study with E1 and E2 (**G1**). The expert user can select individuals to identify the potential home range of the animal. Applying a time selection on top of that can generate visual patches to study potential migrations from region A to region B (**C** in Figure 5.19). Selection of groups also helps to tell if the company between selected members is relatively sedentary or dynamic by the spread of the spatial distribution. The heatmap automatically responds to parameter adjustments in the main view, time selection in the timeline, or other parameters in the control panel Figure 5.4. No additional configuration is required to provide the assistive view to track aggregated higher level patterns from the side. The new design should add richer and more nuanced information to help the MR research.

5.9 Discussion

Comparing to most of other visualization works in supporting ecological research [199, 269, 270, 306, 307], this study emphasizes more on individual level inquiries, particularly potential interactions or threats. The study into these issues initially came as a wicked problem that lacks a proper structure. For example, the experts are not supported with sufficient clues to conceptualize deep analyses such as what to look into when scrutinizing a potential encounter, or how animal pairs form and lively endure. This is a typical situation when the research questions contains a high level of problem uncertainty (§ · 3.1 Problem Uncertainty). This hindrance makes pivotal visualization a worthy option to support the research from a knowledge finding perspective.

[269]: Ferreira et al. (2011), "BirdVis"
[306]: Grundy et al. (2009), "Visualisation of Sensor Data from Animal Movement"
[270]: Kavathekar et al. (2013), "Introducing AMV (Animal Movement Visualizer), a Visualization Tool for Animal Movement Data from Satellite Collars and Radiotelemetry"
[199]: Ware et al. (2006), "Visualizing the Underwater Behavior of Humpback Whales"
[307]: Klein et al. (2019), "Visual Analytics for Cheetah Behaviour Analysis"

In this study of wildlife animal movements, the perspective of MR puts the related information into clarified vision of movements in a relational context. This new semantic attribute is not only a metric to aggregate proximity in time but also a variation pattern with a domain-friendly interpretation. Although the explicit emergence of patterns are difficult to summarize with simple words. The semantics in MR, either driven by numeric variations or depicted though graphic representations, expose intuitive patterns that helps the expert to understand unobserved facets of the complex movements by animals of different species in diverse time frames. The pivotal effect provided by the semantic attribute of MR makes easy access to the unstable nature of animal pairings (Figure 5.13) as well as other subtleties such as the likely length of social bonding, presumable pre-stages before a stalking behavior. By the cases in § · 5.6 Analyzing Multi-Species relation and § · 5.6 Examining Grouping/Pairing Behavior, we can see that the application of pivotal visualization in this study not only contributes novel clusters of hypotheses, but also supports rigorous experimentation of these hypotheses with factual data (§ · 5.4 Movement Relatedness as the Semantic Attribute). This dual space support (hypothesis space and experiment space, cf. § · 3.3 Knowledge Building as Dual Space Search) together extends the total exploration space (§ · 3.5 Effect of a Semantic Attribute) to reach deeper, more sophisticated understanding of behaviors instead of just movements.

We acknowledge that distribution and behavior patterns in relation to local resource change and land feature are as interesting to many ecologists, for example, the influence of seasonal change and its consequences to water access as in § · 5.6 Checking Seasonal Distribution Change. However, reasoning with more comprehensive environmental factors requires detailed, up-to-date GIS data to describe as how temperature and rainfall changes are explicitly reflected in the local landform, which is unfortunately unfeasible at the time of this study. More fundamentally, the validation of visual interpretations such as predatory threat (§ · 5.6 Analyzing Multi-Species relation) relies on obtaining ground truth data, for instance, onsite automatic video recordings of lion kills or discovered cadavers near the reported locations. Like before, the evidence is even more expensive to get as someone would need to travel and look to verify. In this regard, the visualization is helpful as it guides us toward how future research could be improved by obtaining additional knowledge and data.

5.10 Summary

This chapter introduces a visual exploration system for movement ecologists to discover individual level insights in animal movements. It exemplifies how the pivotal visualization design method facilitates a field research project which, like many of its kind, are complicated by insufficiencies in measurement capacities. Therefore, following the study in chapter 4, it deals with extra uncertainties caused by data imperfections in addition to the problem uncertainties. From an empiricism perspective, the treatment of data uncertainty is more consequential to the experimentation support than the hypothesis-forming support counterpart in a dual space search process (§ · 3.3 Knowledge Building as Dual Space Search). Its influence to the pivotal effect is detrimental but limited — problem uncertainty remains existential to the application of the pivotal visualization approach.

Although analyzing individual level interactions has been touched by previous works [291, 297], a visualization tool that analyze small scale animal interactivity through the lens of MR is novel. Experts confirm the design is useful in identifying of general movement patterns as well as locating possible pairing and matching in different time frames. The practicality of MR approach is supported by real cases and novel insights. As a visualization effort targeting the emerging field of movement ecology [207, 244], we see the study in this chapter as a useful contribution to support nuanced insights in fine-grained relationships of multi-species animals.

[297]: Demšar et al. (2015), "Analysis and Visualisation of Movement"
[291]: Andrienko et al. (2013), *Visual Analytics of Movement*

[207]: Nathan (2008), "An Emerging Movement Ecology Paradigm"
[244]: Holden (2006), "Inching Toward Movement Ecology"

Reflections and Discussions 6

Overview: *This chapter summarizes reflections from the applications of pivotal visualization in the two study contexts. We discuss general takeaways as well as particular findings following the theoretical narrative structure of pivotal visualization as in chapter 3. By drawing connections from the theoretical model to practical details, this chapter discusses the applicability of pivotal visualization regarding the theoretical components of problem uncertainty, semantic attribute, and the pivotal effect.*

6.1 Overview

Key Results

This chapter aims to generalize how pivotal visualization is applied in the study A and study B. By referring to the explicit examples in the studies, we outline the commonalities vs. differences of how pivotal visualization as a design method augments explorations leveraging the semantic attributes in each context. The outcome is presented in Table 6.1.

The leftmost column of Table 6.1 provides an overview of key components in the theoretical model of pivotal visualization (chapter 3), following which we fill the key results by their commonalities and differences. The commonalities provide tested guidelines to assist the deployment of pivotal visualization in other scenarios. The differences highlight the parts where adaptations to include context-dependent factors are necessary. By looking through the table, we summarize that the commonalities play a more prominent role than the differences. This indicates that the theoretical model succeeded in capturing the most fundamental aspects of designing via the pivotal visualization approach in practice.

Continued development by adding results from more studies following this schema should contribute more executable hints for the early conception of design plans in future cases.

Method and Objective

Revisiting the studies from a retrospective allows us to derive finer descriptions of pivotal visualization. As explained in chapter 3, the implementation of pivotal visualization is multifaceted and structured following the several stages in the analysis pipeline. A project following the pivotal visualization approach begins with the identification of problem uncertainty, which determines the knowledge assistance and the definition of semantic attributes. Then, the pivotal effect realized through visual expressions of semantic attribute(s) extends the exploration space to create unprecedented possibilities for new domain relevant hypotheses and experiments.

Table 6.1: Key Components in Pivotal Visualization reflected in the Studies

Component	**Commonality**	**Difference**	
		Study A	Study B
Problem Uncertainty	the disconnection between research objectives and data	the required concept that are unobservable	the required concept is influenced by both observable and unobserved features
Semantic Attribute	supporting knowledge assistance according to the question sub-modules	two parallel forms: *action complexity* and *strategy signature*	one parent form with plural variants: *pairwise* and *i-G*
Exploration Space	to uncover findings beyond immediate visualization with data	exploration space regarding the actions complexity and qualitative strategy differences of attempts	exploration space regarding movement relatedness in two modes
Focus & Continuity	ensures findings are relevant, consistent, and interlinked	**by rejection**: complexity increase with score ▷ "tail optimization" anomaly	**by generalization**: social tie resilience of wildebeests ▷ predatory threat from lion

Following the theoretical breakdown in chapter 3, we extract study-dependent reflections as well as study-independent insights with explicit references to problem uncertainty, knowledge assistance, pivotal effect, conceptualization of semantic attribute, and effect on exploration space and processes under the umbrella of pivotal visualization. By the comparisons of commonalities and contrasts in each separated context, the instantiations of pivotal visualization design allows the earlier rationales to be confronted with the actualized effects, from which we distill the design experiences and lessons to consolidate the theoretical framework. This effort would contribute useful inspirations to find links between the theoretical framework and detail design planning in varying contexts.

6.2 Unpacking Problem Uncertainty

The knowledge discovery in both studies is inhibited by a variety of problem uncertainties. Instead of focusing on the apparent differences in application domains, we can also study the problem uncertainties from their roots, i.e. a more general perspective about the deeper cause concerning the birth and shaping of the problem uncertainties. Here, we discuss two perspective of their origins — the data collection policy versus the angle of interests (taken by explicit research objectives).

The Data Collection Side

Despite the problem uncertainties are largely unaffected by data quality issues (§ · 3.1 Problem Uncertainty), they can still be affected by the policy (instead of the means) of data collection. For gaming analyses, the lack of measurement of the internal states behind player behaviors are intrinsic and not improvable with increased apparatus capacity. This same is true for animals' social behaviors — we can only give hypothetical explanations to the intention of certain movements, but we certainly do not have the access to an animal's instincts and motivations in the movement regardless of the tracking duration and frequency. However, some uncertainties are results of practical trade-offs instead of fundamental inaccessibility. For instance, trade-offs between battery life, portability, and trajectory resolution are often necessary to balance the conflicting concerns under practical limitations. As a result, the technically optimal measurements can be practically infeasible, which produces compromised data resolutions. Since movements are the sole material for investigating animal group behaviors in study B, assumptions of the underlying logic of a behavior heavily rely on accurate interpretations of movement traces. Thus, visual results based on compromised data quality can cause increased problem uncertainty.

In this regard, the seemingly identical problem uncertainty (both as insufficiency in knowledge support) could have very different root causes — one is because the kind of knowledge is inherently inaccessible from the data perspective while the other is because the optimal data quality is sacrificed due to technological or economic reasons. The former is challenging and can only be gradually mitigated by improved (visual) exploration methods, while the solution to the latter is more straightforward as the uncertainty can be effectively reduced with better supplement of budgets, time, or device capacities. Pinpointing the cause of problem uncertainty is useful to devise the reduction method accordingly. Fortunately, this can be done by recognizing the supporting data types, i.e. sensory data versus log data as explained in § · 3.6 Study Context. For instance, if the project data contain sensory attributes, the expenditures in device, people, and time should be sufficiently allocated to keep problem uncertainty of the second cause under a manageable threshold. Otherwise, the expert may be busy dealing with the noise or distortion of data and distracted by false depictions.

The Research Objective Side

What plays a more significant role in the problem uncertainty is the knowledge we intend to generate from analyzing the data collected in a project. In both studies, it is evident that the exact problem uncertainties are driven by the research objectives of the project. But the research objective in the two studies influences the problem uncertainty implicitly. Take study A (chapter 4) for an example, learning experts aim to understand players' learning which may lead to optimal training routines. But the observations of learning patterns are inaccessible at the very beginning. Therefore, the analysis approaching this research objective needs auxiliary support from smaller actionable questions on the bottom level. In other words, the researchers need to dissect the monolithic research objective into sub-modules like: 1) How to summarize and compare learning attempts of categorical labels instead of scalar values when arithmetic relations of attempts and players are not given by data? 2) How to reflect the non-linearity in the progression of players' skill improvements (i.e. anomalies contrasting steady score increase with more attempts)? 3) As play styles and strategies are qualitatively diverse, how to efficiently describe them to collectively consider this qualitative difference in the comprehensive analyses? (Table 6.1) Concrete answers to these questions are hard to achieve as the questions themselves are roughly defined and only semi-formulated, leaving the researchers to deal with the ambiguities that come before the ability to definite crisp hypothesis.

Similarly, study B (chapter 5) concentrates on how animals' movement behaviors influence each other. This research objective is complicated by several question sub-modules. These include: 1) How to treat the signal losses (occasional missing points as well as continuous poor signal over a duration) to avoid misconceptions of group movements? 2) How to limit visual clutter produced by spatial-temporal multi-dimensionality, presumably by filtering out irrelevant segments in years-long trajectories? 3) How to exploit the temporal context to verify potential interaction scenes with species-specific considerations? 4) How to facilitate the search for potential candidates of future interactions concerning one animal? (Table 6.1)

When the link between possible pathways of hypotheses and experiments with data and the research objective is unclear, the problem uncertainty arises. The above questions are examples of more specific sub-modules where researchers need additional know-hows to mediate the raw data to support the exploration toward the research objective. Because a resolution of the research objective begin to emerge as knowledge pieces start snowballing, the sufficient exploration means, which gradually fills the gaps between data and question sub-modules, are essential to complete the whole loop of raw data, question sub-modules, and the research objective, paving the way to progressively reduce the problem uncertainty in general.

As aforementioned (§ · 3.2 Guidance from Knowledge Assistance), knowledge assistance, which is known to support the procedural explorations, is applicable to reduce problem uncertainty in this regard. And one critical resource to build that knowledge assistance is the experts' partial, tacit knowledge (§ · 3.2 Addressing Problem Uncertainty). However, because the tacit knowledge is, by definition [308], not easily documented, locating the most relevant tacit knowledge to pinpoint a suitable knowledge assistance for visual analysis is hard. One way to narrow down the search scope is to begin with the subtle connections between the question sub-modules and the missing knowledge assistance. When the definition of knowledge assistance follows the interests of questions sub-modules, problem

[308]: Foos et al. (2006), "Tacit Knowledge Transfer and the Knowledge Disconnect"

uncertainty can be reduced by exploring with the assistance of relevant tacit knowledge. This benefit can be explained with explicit examples.

Table 6.2: Specificity Levels of Questions Sub-modules: question sub-modules by their relative abstract-specific levels to the explicit problem contexts (cf. Figure 3.1) (S1 = Model Configuration, S2 = Expertise Application, S3 = Project Character)

		Question sub-modules	**S1**	**S2**	**S3**
Study A	A-1)	How to summarize and compare learning attempts of categorical labels instead of scalar values when arithmetic relations of attempts and players are not given by data?	✓	✓	✓
	A-2)	How to reflect the non-linearity in the progression of players' skill improvements (i.e. anomalies contrasting steady score increase with more attempts)?	✓	✓	
	A-3)	As play styles and strategies are qualitatively diverse, how to efficiently describe them to collectively consider this qualitative difference in the comprehensive analyses?	✓	✓	✓
Study B	B-1)	How to treat the signal losses (occasional missing points as well as continuous poor signal over a duration) to avoid misconceptions of group movements?	✓		
	B-2)	How to limit visual clutter produced by spatial-temporal multi-dimensionality, presumably by filtering out irrelevant segments in years-long trajectories?	✓	✓	
	B-3)	How to exploit the temporal context to verify potential interaction scenes with species-specific considerations?		✓	✓
	B-4)	How to facilitate the search for potential candidates of future interactions concerning one animal?	✓		✓

Take study A, for example, a reduced visual language to capture strategy modifications along consecutive attempts facilitates comparisons and grouping of strategies, which helps to the analyses of learning progression (relating to question sub-module A-2 in Table 6.2). Building knowledge assistance in this regard supports the analyses of varying strategies. As a comparison, tacit knowledge of the Lix's game mechanism (i.e. how the discrete actions supports a pathway toward the lixes' destination) is useful when explaining the cause of certain actions, but knowledge assistance focusing on this task contributes little regarding the question sub-modules in Table 6.2. Additionally, it is very likely that the application of this part of knowledge is automatic and visualization support for knowledge assistance as such may not be necessary. For example, an expert can provide ad-hoc explanations as he/she contemplates on fine-level details of the action data as long as he/she knows one solution to this puzzle is to dig a tunnel with either miner or nuke. For this case, knowledge assistance may be better allocated for other gaps in the project to mitigate the problem uncertainty.

To further identify the most effective knowledge assistance within the question sub-modules (i.e. considering multiple choices of knowledge assistance which all relates to a question sub-module), this effort can be further enhanced by characterizing the knowledge assistance with relevance to the specificity levels of problem uncertainty in § · 3.1 Problem Uncertainty.

Take study B, for example, question sub-module B-1) requires the expert to devise a data pre-processing model to substitute missing or wrong data with interpolations. The expert's tacit knowledge for this case can help rule out unrealistic values (e.g. large steps beyond possible movement speed, too long sedentary period to maintain survival). But this effort has only small dependence on the knowledge of specific problem context (S1) — adapting the generic linear interpolation for spatial-temporal data by considering the aforementioned unrealistic patterns can mostly suffice. As providing higher fidelity for movement data contributes limited additional knowledge to support novel explorations, supporting knowledge assistance in this regard holds lower potential to further reduce the problem uncertainty. To this end, question sub-module B-3) in Table 6.2 makes a good comparison against B-1). In B-3), time is a dimensionless primitive attribute that requires no additional abstraction or transformation. The challenge of issues related to B-3) is incorporating the temporal thinking into the analyses. Eliciting tacit knowledge associated with the temporal dimension is challenging as we intuitively relate movement interactions to spatial contexts instead of temporal contexts. This contradicts with B-1) as the temporal thinking in animal movements is complicated by the diversity of species. The mental model supporting his temporal thinking is constantly updated with latest knowledge assistance. Because the model to interpret the temporal-related behaviors is constantly changing, it is difficult to predict its evolvement and reconfigure the model by a programmed process. Therefore, knowledge assistance to incorporate the temporal context yields more benefit to the snowballing of the knowledge, which ultimately enables explorations to reduce problem uncertainties more effectively. The above example explains how it is usually more productive to focus the knowledge assistance on questions of higher specificity levels (Figure 3.1).

As we can see, the distinction of problem uncertainties can be driven by two forces of data collection policy and research objectives. We discuss the above insights to facilitate the understanding of uncertainties, and more importantly, to facilitate the development of uncertainty reduction methods. Based on our rationales of knowledge assistance choices, we use the empirical lessons from the studies to illustrate a rigorous process to locate and refine the knowledge assistance, which is informative to the definition of semantic attributes.

6.3 Forming Semantic Attribute

After the suitable knowledge assistance is defined with the above process, using a key concept (e.g. *relatedness* between animals or *complexity* of behaviors) to assemble pieces of tacit knowledge is necessary to create that knowledge assistance. This is because visual patterns generated based on a concept are closer related to the semantics in the explicit problem, making the intuitive explanations of them more accessible. As project characters are most specific to the explicit problem, interpretations such as "a steady relatedness" or "a group of complex attempts by Player X" are illustrated by the visual patterns. Following this way, embedding the concept into the visual context ensures the seamless integration of knowledge assistance in a visual analysis environment, unveiling new hypothesis space for more investigations around that concept.

However, a concept alone is not enough to realize the function of a semantic attribute. To make the concept also compatible with other attributes in the visualization system, it needs a rigorous format. This format includes a formal description supported by the data or their transformation models. Such a description provides the analytical function of the semantic attribute so that the hypotheses based on the visual semantics are able to be experimented with other attributes in the context. The analytical function of a semantic attribute can indicate nuanced variations and provide attributability of the hypotheses on top of the semantics. For instance, study A leverages semantic attributes to investigate players' experience in each stage through the varying complexities in visual depictions (cf. Figure 4.6). Study B leverages semantic attributes to search for segments of potential encounters by visually tracing the trends in movement relatedness (cf. Figure 5.13 and Figure 5.14). Visual anomalies in the above cases may trigger new hypotheses relating to the concept in the semantic attributes. Further experiments may be conducted with visual explorations or quantified outputs. Experts may want to adjust the hypothesis or simply reject it if there is a disagreement with the visualized semantics or simply raw data. This verifying ability provided by the rigorous format of concepts in the semantic attributes adds an experiment space extension to follow-up the hypothesis space extension by the concept in the semantic attributes.

Forming the semantic attribute can be versatile in considering specific analytical requirements. In some cases, the attribute is a cohesive and integral one — they illustrate an unvarying concept to provide additional explanation or analytical power. However, semantic attributes can also adapt to different forms according to specific analytical purposes. In some other cases, the semantic attribute may have multiple subtypes. These instances inherit similar core concepts from one parent concept but with varying forms. The semantic attribute in study A better reflects the former case. There, the attribute of *action complexity* satisfies a monolithic definition of a concept without any sub-types, while the *strategy signature* serves a whole different purpose (§ · 4.6 Strategy). As a comparison, the attribute of *movement relatedness* in study B has two co-existing sub-types: one is a single-variable index visualized along the temporal axis. The other is a compound, multi-variable attribute with only graphical representation (Figure 5.9). From practical experience in the studies, we realized that forming the semantic attribute for the research objective is not like pairing the key for the lock. Flexible conceptualization with parallel attributes or attribute sub-types are not only possible but also important for the analysis. However, the number of semantic attributes and its sub-types should be restrained to avoid extra overhead in both computation and interpretation. Too many concepts to process all at once potentially undermines the usability or performance of the outcome view.

6.4 Pivotal Effect by Visual Exploration

The systematic benefit of the pivotal visualization approach is referred to as the pivotal effect, which is realized through the visualization of semantic attributes. This effect benefits knowledge discovery in two ways: 1) extending exploration space to provide extra accessibility of hidden insights, and 2) ensuring the focus and continuity of explorations to promote consistency in a procedural process (§ · 3.5 Concept). We further explain these effects in the study contexts.

Extending the Exploration Space

The exploration space is a finite region and naturally confined by the technical feasibility, information availability, personnel limitations. To extend the exploration space means to add novel, non-overlapping area(s) to the existing space (Figure 3.7). This is an iterative effort. The realized size of extended exploration space determines the effectiveness of a pivotal effect. In the initial stage of study A, identifying key actions or action combinations (some referred as "motifs" [309]) that secures winning attempts is drawing a lot of effort as being a common practice in event sequence analyses [221, 309–311]. As the experts dig deeper, the associations between action combinations and other attributes such as performance scores, spent time seems to be equally interesting. For instance, experts try to verify if longer and more laborious attempts (containing many used

[309]: Maguire et al. (2013), "Visual Compression of Workflow Visualizations with Automated Detection of Macro Motifs"

[310]: Guo et al. (2019), "Visual Progression Analysis of Event Sequence Data"

[309]: Maguire et al. (2013), "Visual Compression of Workflow Visualizations with Automated Detection of Macro Motifs"

[221]: Hernández et al. (2017), "An Architecture for Skill Assessment in Serious Games Based on Event Sequence Analysis"

[311]: Li et al. (2020), "SSRDVis"

actions) contributes to higher scores. But the follow-up procedures can hardly go beyond correlation finding between the primal measurements. These efforts fail to present game play as a learning progress during which a player can experience different episodes of trial and error. As justified by the evaluation, the semantic attribute of *action complexity* (§ · 4.5 Behavior Complexity as a Semantic Attribute) exposes novel sectors of knowledge regarding the learning to the experts. The new exploration space featuring complexities in the attempts makes the overall increase of action complexity toward higher scores and "tail optimizations" (§ · 4.7 Novel Discoveries) visually distinguishable. A number of new hypotheses and experiments regarding the concept of action complexity like these are revealed by the pivotal effect. Likewise, the semantic attribute of *movement relatedness* (§ · 5.4 Movement Relatedness as the Semantic Attribute) makes the relationship between moving entities easy to reason with. The novel experiment space of local spatial-temporal context can help to reject false pairings and verifying possible predatory threats.

Searching in the newly extended exploration space is supported by interactive visualizations interfaces. The visual design of these interfaces makes the exploration spaces "tangible" and closer to analysts' control, which promises swift transitions between the hypothesis building and experimentation for deeper insights.

Coherent Explorations

Increased exploration space allows for more knowledge finding possibilities. But the extension of exploration space by semantic attributes has another benefit that stabilizes the exploration trajectory from drifting away from the overarching research objective. As we know, traditional EDA tends to leverage scattered strands of explorations to find valuable insights. Many of the fruitful outcomes are gathered solely by serendipity. This approach can be rather ineffective if the research objective is deep and complex, requiring repeated inquiries focusing on the multiple aspects of the same issue. When the communication between the explorations into similar issues is supported by a common ground of the explicit concept (§ · 3.5 Effect of a Semantic Attribute), explorations can become more effective. This gives reasons to the earlier effort in identifying a focus before supporting the knowledge assistance (§ · 6.2 The Research Objective Side). Evaluation outcomes in the studies affirm that narrowing down the coverage of knowledge assistance to closely match the research objective safeguards the coherence of explorations. For instance, the discovery of "tail optimization (acute complexity turbulence after full score)" behavior in study A is evoked by a contradiction against the previous assumption of "higher complexities coexists with higher scores" — visual results in the sub-group of later successful attempts proves the assumption is not valid in the ending phase of skilled players. The counter-intuitiveness experienced by the experts motivates the verification of this hidden behavior pattern. In this case, the coherence of explorations ensures the attention paid to previous exploration leads to more nuanced explanations of the later, unexplored questions.

The sequential pattern of explorations one following another is believed to be more effective explorations without a coherent structure. This is also true in study B. The pairwise relatedness informs critical evidence suggesting animals' social ties are resilient — they tend to restore to previous intimate state after short separations of two entities. But reapplying this knowledge to cross-species interactions may produce inconsistency because of probable predation threads between the species. Reusing the same logic to test for differences between species with potential predatory relationships uncovers the unusual behavior pattern between two wildebeests and a lion (cf. § ·

5.6 Analyzing Multi-Species relation). This may potentially represent typical stalking behaviors between a predator and two potential prey. This follow-up test elicits more complicated and nuanced findings compared to previous insights or salient pairings between animals. This again demonstrates the value of coherence in the explorations for deep and nuanced knowledge.

6.5 Limitations

From the examples in chapter, we can see that pivotal visualization is a design method that exploits the value of semantic attributes to make fundamental improvements to the exploration spaces. The interactive, visual interfaces pursue the research objective by continuously refining findings and questions to achieve the pivotal effect to facilitate the experts' tasks. The effectiveness of this design method is justified by the expert evaluations. However, we need to acknowledge two limitations in the method. The first is the expertise threshold in identifying the knowledge assistance in the early stage while the second is lack of support for redefining the semantic attribute during the analysis.

Since the support of knowledge assistance is oriented toward the research objective, providing the knowledge assistance to sufficiently support the research objective inevitably adds the threshold of expertise relating to the domain. Therefore, the risk that the domain experts fail to suffice a certain knowledgeable degree is not negligible. The studies covered in this thesis have resulted in insightful discoveries considering the experts we collaborated with. But the chance that the same effectiveness is not repeated across different experts' levels needs to be future verified. Therefore, performance instabilities among a wider group of experts should be warned.

Moreover, the dependency of expert knowledge also prolongs the user study time budget. Our experience shows that the pivotal visualization method takes another layer of complexity of pinpointing the domain concept (in the semantic attribute) on top of existing requirement clarifications. The time spent on each study varies significantly ranging from 2.5 months to 6 months. We have not measured the time precisely for iterating the domain concept. But the rough estimation is about 25% to 35% of total time.

Our current account of pivotal visualization is implemented based on one or a set of pre-defined semantic attribute(s), i.e. once the semantic attribute is built into the system, there is little support to adjust the semantic attributes to new contexts afterwards. Although the requirement for semantic attribute adjustments is not evident in our studies, it may be critical for certain other use cases, especially when the defined semantic attribute fails to follow the new discoveries in the analysis. For this case, we partially attribute this inconvenience to the aforementioned cost issue of semantic attributes — developing support to adjust the semantic attribute within the visualization system is even more considerable than defining semantic attributes per se.

Conclusions 7

Overview: *This chapter summarizes the work presented in previous chapters. We give conclusive remarks to the outcomes and contributions of pivotal visualization as a design method. Lastly, we outline future directions to continue our research.*

7.1 Outcomes

Data visualization is to facilitate human understanding of complex data. In new technological landscape, we reemphasize on the importance of augmenting human sense-making beside the increasing analytical capacity of machines. In the light of such a goal, pivotal visualization is proposed as a design method to use visualizations as an interface to the obscured knowledge in a problem domain instead of the data used to describe the problem. This method augments human abilities in conceptualizing novel hypotheses based on semantics of domain-informed concepts. These hypotheses followed by the consequent experiments enable novel explorations, revealing under-explored insights and inspiring new research questions. The interactive visualizations based on this method allow these new insights and questions to cohesively contribute to each other along the concept in the semantic attribute so that new knowledge pieces accumulate the reinforce each other. Evaluation outcomes suggest that this proposition have received expected soundness in both studies as the experts have successfully discovered novel insights which are catalyzed by the respective pivotal effect in each context.

In the beginning of this thesis (§ · 1.4 Visualization to Augment Human Capacity), we have outlined research questions to search and crystallize critical factors that could improve visualization design for knowledge discovery.

Regarding the first question of

- ▶ How to effectively characterize the design context to facilitate explorations in problem-driven visualization research?

experiments from the studies show that the problem uncertainty is closely related to the asked questions driven by the research objectives. In a problem-driven research context, the design of visualization interfaces is sparsely informed by the research objective per se but rather the consequent question sub-modules as representations of the problem uncertainties in the specific context (§ · 6.2 The Research Objective Side). In this way, characterizing the design problem to facilitate the research objective is mainly pinpointing most relevant problem uncertainties in that context. The outcome of an accurate problem characterization then provides guidance to the identification of knowledge assistance, which provides exploration facilitation to mitigate the problem uncertainty and clarify the underlying problem at research.

We also raise the question of

- ▶ Which cognitive process in scientific reasoning is constructive to conceptualize novel exploration facilitation methods?

Our investigation into this question leads to the conceptualization of the asymmetric model of dual space search (§ · 3.5 An Asymmetric Model) based on VAN Joolingen and De Jong [83]'s dual space search model✍ in scientific reasoning (§ · 3.3 Knowledge Building as Dual Space Search). On one hand,

[83]: VAN Joolingen et al. (1997), "An Extended Dual Search Space Model of Scientific Discovery Learning"

✍: The model is an extension from the original dual space search model proposed by Klahr and Dunbar [82].

we identify the alignment between the hypothesis-experiment loop in scientific reasoning and the data explorations with data visualizations. On the other hand, we proposed a necessary adaptation of this model to consider that an exploration space is finite and restricted by the inference power of ground data and existing domain knowledge. As discovering knowledge is the product of explorations, the inability to enhance knowledge discovery can also be explained by the inability to effectively extend the exploration space. This discovery draws our attention to the question of how to improve knowledge discovery by indirectly modifying the exploration space.

By asking

- ▶ How can the findings from our studies be theoretically generalized as a replicable method to scaffold future design?

we frame our theory with a rigorously defined model (as elaborated in § · 3.5 Formalism). In this model, we have included the influence of data, semantic attribute, exploration space, and time upon the discovered knowledge as an outcome. This notation clarifies the relations between each factor in the general process of data exploration. The clarification helps us describe the mechanism of the pivotal effect and illustrate how it contributes to both the quality and productivity of knowledge discovery.

Pivotal visualization in a nutshell is a design method enabling the pivotal effect which assists knowledge discovery by and from novel exploration spaces. The application of this method should be aware of the induced problem uncertainties determined by the research objective and identify relevant knowledge assistance support accordingly. The visualization of semantic attributes embodying that knowledge assistance then creates a visual, interactive environment that provide treatments to the problem uncertainties, making novel explorations possible.

7.2 Contributions

A Macro-level Design Method in Visualization

Pivotal visualization is proposed as a design *method* than a design *technique*, which is a thorough plan to provide cohesive rationales scaffolding each procedure in a visualization design project on the macro-level. We consider this macro-level contribution as a design effort following Simon [312]'s account of design, which features a managerial role of design leading to a "preferred state". Instead of *techniques* to improve the visual artifacts and interactivity of visualizations, the design *method* of pivotal visualization here plays a meta-level role that assist the designer in navigating through the visualization creation process for improved design outcomes.

[312]: Simon (1978), *The Sciences of the Artificial*

As Moere and Purchase [313], van Wijk [314], and Judelman [315] have stated, design is an integral part of visualization. By elaborating on the design method of pivotal visualization, this thesis presents a viable interpretation of this idea, with which we wish to inspires more discussions in the intersection between scientific and designerly accounts of visualization creation.

[313]: Moere et al. (2011), "On the Role of Design in Information Visualization"
[314]: van Wijk (2013), *VIS 2013 Capstone*
[315]: Judelman (2004), "Aesthetics and Inspiration for Visualization Design"

A Theoretic Model to Augment Exploration

The conceptualization of pivotal visualization is not possible without introducing the mental constructs such as exploration space and semantic attributes. Explorations in data analyses are commonly practiced but loosely described without further details regarding its explicit function. The construct of exploration space from scientific reasoning provides an intuitive analogy to the progression of iterative data exploration. Being probably the most significant reason for analyzing data with interactive visualizations, how explorations progress in the dual space of hypotheses and experiments is thus made evident. This account of explorations lays a conceptual cornerstone of the thesis.

First, it motivates the provision of semantic attribute, which essentially embeds human knowledge to the exploration process for both hypothesis and experiment improvements. Second, it elicits a unique perspective of augmenting exploration: instead of providing higher degrees of freedom with more nuanced interactivities to visualization interfaces, we demonstrate a systemic way to augment exploration by making improvements to the essential exploration space to the advantage of knowledge accumulation. This follow-up visual design enables the substantiation of semantic attribute and actualization of exploration space improvements.

A HITL Approach to Data Analyses

Human-in-the-loop (HITL) is a widely-respected criterion in modern data analyses [316–318]. While the general public are awed by the surprising power of machine learning [20], continued applications of machine automation give rise to the increasing concerns of transparency issues (§ · 2.1 Transparency). From a knowledge discovery perspective, black-box systems tend to generate outcomes without revealing a convincing thinking process. Even if the outcomes can reach a satisfactory level of consistency and reliability, human are unable to learn from the systems' reasoning and replicate such a knowledge for their independent judgments. As seeking for useful knowledge is an inherent human desire, we argue that a substantial amount

[316]: Endsley et al. (1995), "The Out-of-the-Loop Performance Problem and Level of Control in Automation"
[317]: Shahriari et al. (2016), "Taking the Human Out of the Loop"
[318]: Kambhampati (2019), "Synthesizing Explainable Behavior for Human-AI Collaboration"
[20]: Tian et al. (2019), *ELF OpenGo*

of criticism against non-transparent machine learning models can be moderated if we can gain general knowledge from processes instead of only the outcomes. The experimental practice of training professional Go players with AI [319–321] is one the pioneering effort in this regard. However, the knowledge transfer is still rudimentary, which requires attentive manual interpretations of AI actions by highly skilled players.

[319]: Frank (2017), *AlphaGo Teach Coaches People to Play Go like Google DeepMind's AI*
[320]: Hanqi (2020), "Ke Jie: I'm Envious of People Who Can Learn Go with AI Now. They Can Avoid a Lot of Wasted Time That I Did."
[321]: Missingham (2017), *Give up the things I know and start over by learning from Master AlphaGo*

Aligning the pivotal visualization to this endeavor, the advantage of leverage human knowledge to improve visual explorations for more insights is apparent. Pivotal visualization places human intelligence as the driving force behind every step of it. The identification of knowledge assistance allows the human expert to formulate research questions more closely to the research objective. The conceptualization of semantic attributes incorporates human intelligible semantics into the visual exploration. Improved exploration spaces then support hypothesis generation, which is originally a human mental process. Thus, no information is obscured from human rationalization end-to-end in the entire pipeline. Therefore, the analyses are carried out through visual dialogues, where all the beginning, process, and outcomes of a analysis can be directly interpreted by the human expert.

In a more general sense, the pivotal visualization method considers visualizations as knowledge discovery apparatus. The human-in-the-loop principle puts strong emphasis on the human involvement in the process of machine inferences. Our method confirms such a principle as human awareness and interventions are supported throughout the pivotal effect. Moreover, pivotal visualization is a viable human-in-the-loop approach as it gives a higher priority to the design improvements to facilitate human-exclusive capacities (such as curiosity and hypothesizing) than just analytical utility.

7.3 Future Work

Applying pivotal visualization to different study contexts is a non-trivial job. The lessons we have learned from the two studies identify context-sensitive factors (e.g. different composition of uncertainty, cf. § · 6.2 Unpacking Problem Uncertainty) as well as context-independent advantages (e.g. facilitating behavior studies, cf. § · 3.6 Study Context). Beside the known contradictions and commonalities (§ · 6.1 Overview), we plan to continue applying the theoretical model (chapter 3 Pivotal Visualization) in more realms such as urban transportation, mobility patterns under emergency, or virtual social behaviors online. The underlying theme is that behaviors of individuals take place in a larger context but not verbally communicated.

We will also investigate the possibility of integrating stochastic models into the definition of semantic attributes. Candidates are, but not limited to, Hidden Markov Models, Brownian Motion, Lévy Walks. What these models have in common is that they present vivid analogies to natural behaviors. The visualizations featuring these models can help to reveal abstract patterns of behaviors together with the graphical representations. Valuable insights may be derived from the overlays between the analogue and abstract depictions of behaviors. The conflicts and inconsistencies between model outputs and the visualized real behaviors are critical materials to inspire new discoveries. By leveraging pivotal visualization, we can augment human experts' ability in understanding the nuance beyond reduced descriptions from models and conceiving out-of-box narratives to the complexities in behaviors.

Moreover, the definition of a semantic attribute takes both a domain concept and a rigorous formula to provide attributability with raw data (Figure 3.4). Developing that concept is mostly a result of human effort due to the necessary manual effort in identifying knowledge assistance. The formula for data attributability, however, can be otherwise. This may indicate an opportunity to match the human proposed concept with a automatically generated formula on-the-fly if the advancement of semantic pattern matching in natural language processing suffices [322]. Such a possibility need to be verified with cross-disciplinary collaborations to further test, plan, and iterate. The potential success in this regard should be able to tackle the challenges of expertise threshold in the identification of knowledge assistance and lack of support for semantic attribute redefinition as mentioned in § · 6.5 Limitations.

[322]: Cambria et al. (2014), "Jumping NLP Curves"

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