Beyond Shape

An exploration in alternative forms for data visualization

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Abstract

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This thesis explores the topic of alternative forms in data visualization and the ways visualization affects the communication of data it is based on, through the creation of a machine learning based data visualization system prototype.

It examines norms and ideals of data visualization as a set of systems aimed for simplification, situating visualization as a tool with the potential power to affect how we perceive the complexity of the world by either highlighting or obscuring information. It aims to critically highlight these norms by taking an exploratory aim to visualizing information by increasing potential interpretations of a particular set of data instead of reducing them.

Norms prevalent in the field of data visualization are explored, and through this, the concept of alternative is defined. Then the dataset to visualize is defined through an exploration of current discussions around issues of increasing amounts of data, the complexity of the systems producing that data and the interpretations they enforce through the data they produce. Through this, the concept of machine detected human emotions in a text is chosen as a particular example of computational reduction to be explored through the prototype.

In order to counteract this identified reduction in complexity, a system which produces a mapping between visual attributes and detected emotional attributes is proposed. The design of this system utilizes recognized critical design concepts by creating a type of post-optimal object: A visualization that causes more interpretations in its reader than reading the data itself. The process of visualization follows prevalent norms within the field but applies identified forms of alternativeness in order to create ambiguity in the visual artifacts created by the prototype. Machine learning methods are applied through a collaborative process in order to create an artificially intelligent system that automatically analyses the emotional values of a given text, and maps those to a particular set of figures.

Some of the visual artifacts are then tested on a set of users, in order to assess how the visualization might affect the communication of the data it is based on and how it succeeds in increasing interpretational complexity. While not aimed toward conclusive evidence, the result of the test seems to indicate success in increasing interpretational complexity, but a lack of success in communicating the numeric data the visualizations are based on – in this sense leading to the end-result no longer being a functional data visualization, but rather a form of data-driven illustration.

Keywords: Data visualization, machine learning, critical design, data art

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Denna avhandling behandlar alternativa former inom datavisualisering och sätten visualisering påverkar kommunicering av data. Genom att skapa en maskininlärningsbaserad datavisualiseringsprototyp undersöks de ideala normerna inom datavisualisering som en samling konventioner med förenkling som ändamål. Datavisualisering placeras som ett verktyg med förmågan att ändra hur vi uppfattar världens komplexitet genom att antingen framhäva eller undangömma information. Genom att ställa ett explorativt mål – att visualisera data genom att utvidga tolkningar istället för att reducera dem – är avsikten att kritiskt examinera de normer som förekommer i fältet.

Först undersöks fältet och genom detta definieras vad som kunde anses vara alternativ data-visualisering. Sedan identifieras ett komplext problem genom en utforskning av aktuella synpunkter runt den växande mängden data I världen omkring oss och komplexiteten av de system som producerar detta data. Genom detta väljs maskinbaserad detektion av människokänslor i text som ett problem där maskinbaserad reduktion av ett naturligt fenomen kan forskas genom visualisering.

För att motverka reduktionistisk behandling av komplicerade domän, föreslås ett system som producerar översättningar mellan emotionella egenskaper och visuella egenskaper. Konstruktionen av detta system använder sig av kritiska designmetoder genom att bygga ett postoptimalt objekt: En datavisualisering som inte försöker kommunicera data den består utav så klart som möjligt, utan istället försöker orsaka en ökande mängd tolkningar i sin läsare. Processen följer normer som är rådande I fältet, men med ändamålet att orsaka tvetydighet för läsaren. Ma-skininlärning används för att implementera en kollaborativt framställd översättningsmodell mellan de emotionella och de visuella egenskaperna.

Slutligen testas systemet genom en mätning av effekterna på läsare och på så sätt utvärderas visualiseringens förmåga att öka mängden tolkningar. Undersökningen har inte som mål att ge ett slutligt resultat för funktionaliteten av systemet, men skall fungera som guide för nästa iterationer. Undersökningen verkar visa att de producerade visualiseringarna lyckas i att öka mängden tolkningar för en bild till en nivå som påminner om tolkningarna för text, men lyckas inte att kommunicera känslorna från den lästa texten. Detta gör slutresultatet mer av en data-driven illustration, än en datavisualisering som termen konventionellt används.

Nyckelord: datavisualisering, maskininlärning, kritisk design, datakonst

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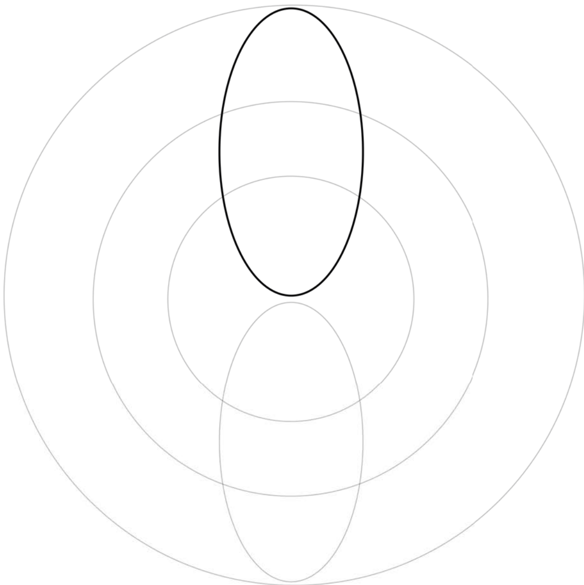
Content

Premise and process

The introduction. Contemplation on the reasoning of this thesis and the process applied throughout it. Introduction of the research question. A brief overview of the critical view proposed as a method, and an outline of the rest of the thesis.



Methodology & Research

About data visualization, honesty and new forms

A driving thought of this thesis is the exploration of the relationship between honesty of expression and effectiveness of expression in data visualization. As data visualization as a field of study and practice grows and matures, tools and practices are canonized, and the boundaries of what is considered "good visualization" are increasingly defined through the lens of a formalized view of data visualization practice. Current development within data visualization is strongly bound to the development of ever simpler and more powerful tools combined with a well-defined set of best practices and research-based reasoning behind them[1]. This provides easy access to what can be considered "good visualization" within this paradigm of development. Good templates and examples enable visualization to be used as a tool where it would have been cost prohibitive before, allowing non-expert users access to a mode of powerful expression, essentially democratizing the process of creating typical visualizations. This can be seen by the growth of the field and the increase in well-functioning visualizations of even complex data[2]. The potential downside to this is, that the standardization of output invites practitioners to use output forms without much critical thinking – relying on these standards where they

1 For instance, listen to the discussion about the future generation of visualization tools with Andy Kirk at datastori.es (Kirk, 2018)

2 As discussed in the yearly review of data visualization podcast datastori.es (Torban;Nussbaumer Knaflic;& Schwabish, 2018)

might not be applicable. Even quite eloquent and free-form tools are often technically confined to modes of well-determined output components or fragments: maps, bars, lines, donuts, arrows, circles and the like, all of which allow powerful expression of typical sets of data. The need to question these prevalent tools and modes comes into play when the data does not conform to the mode of expression available or the expression available becomes too convoluted for the audience. The complexity and sheer amount of information that surrounds us as users in a world of increasing quantification can be overwhelming, which in turn leads to new ways of reducing that information into easily digestible forms, lately often in the form of machine learning based systems. Here the proposal for a more critical design outlook onto visualization standards and practices arises, in order to look beyond the expected modes, not to overthrow any reigning ideology within the field, but to offer a look into other avenues to potentially explore. This thesis is based around building a case for such a critical mode of visualization for looking at a complex topic, through the exploratory research question:

How can we produce an experimental data visualization system that is able to undo oversimplification of data about complex subjects?

That is, how can approach a data visualization problem, where the origin of the data presented is too complex for the data itself to be presented by traditional modes of visualization in an honest manner? Through the application of critical or speculative design methods, is the resulting visualization able to provoke more thought about and around the subject matter, rather than simply accurately portraying the numeric data? And what are the technical solutions applicable to address this problem?

Research and design as a form of critical practice

This thesis follows roughly along lines of methods and tactics associated with critical and speculative design as presented by Matt Malpass[3], in order to approach the experimental attribute defined in the research question. Using design as a medium for inquiry, it aims for the end result to be affective over being explanatory. In this manner, the goal is to encourage the audience toward critical thought in the hope of unearthing new viewpoints on both the subject being visualized and visualization as a medium for communicating that subject. The aim is to diversify rather than simplify understanding of the problem posed, in terms of Mazé and Redström[4]. The intended end result of the practical part of the thesis is a form of a post-optimal object as imagined by Dunne, an object that moves beyond what is seen as an optimal user experience by existing norms, toward user-unfriendliness in order to provoke thoughts about itself in its users[5]. Focus is placed on the meaningful presence of the object created, aiming to shift thought from creating an optimized, rational experience toward the communication of meaning. Moving beyond the

3 In his Critical Design workbook *Critical Design in Context: History, Theory, and Practices* (Malpass, 2017)

4 "Perhaps a shared aim of critical design and design research is not simplification but diversification of the ways in which we might understand design problems, ideas, and boundaries." (Mazé & Redström, 2009, p. 35)

5 If user friendliness is the crux for optimal objects, user-unfriendliness defines an object as post-optimal. (Dunne, 2005, p. 35)

thoughts of the semantic turn within design – of optimizing an object through the human perception of its affordances[6] – toward an embrace of uncertainty, interpretation, and meaning in order to provide a view that is complementary to the lines of thinking that are most prevalent[7]. Utilizing emerging technologies as a base for the practical prototype, a speculative proposition is to be made about how these technologies are materialized in the world outside of their local contexts of specialized fields of science and engineering. The output of this proposed prototyped system uses strategies of what Malpass calls non-rational design[8]. By designing ambiguity into the relationship between the represented and its representation, the aim is to invite users both to make diverse interpretations and to react skeptically to the output and the system itself[9].

The thesis itself consists of four distinct parts. First, I explore the history and current state of the field through the viewpoint of a practitioner, building a context for this thesis within it. This assessment of the field will provide a basis for the viewpoint of the practical visualization project of the thesis – grounding it in the practice of data visualization and providing perspective for what could be called experimental within the prevalent norms of the field, providing a starting point for the speculative inquiry embodied in the practical work.

Second, I present a view of the world surrounding the field, positioning it in the larger context of society, exploring the ways the field of data visualization relates to and can affect society around it. This aims to unearth the need to question some of the dominant modes of information production,

6 Krippendorf uses James J. Gibsons term *affordance* (Gibson, 1966, p. 285) to describe the usability of objects – the sit-ability of a chair for instance. (Krippendorff, 2006, pp. 111–114)

7 Malpass, 2017, pp. 49–51

8 A term Malpass uses to describe methods presented by Gaver (Malpass, 2017, p. 64)

9 Ambiguity as a resource for design (Gaver, Beaver, & Benford, 2003, p. 240)

management, and presentation, building a case for how visualization can be utilized in this questioning. This contextual positioning describes the emergence of an actionable design brief for the practical visualization work of the thesis by identifying potential issues to approach by the means of visualization. It attempts to recognize artificial intelligence and machine learning concepts as emerging technology applicable in the creation of both the data and the visualization, in this way binding the process of visualization back to the idea of being a speculative vehicle for assessing that technology.

Third, I present the practical production part of the research, describing each part of the produced software machine and the reasoning behind them, binding back to the first and second parts where necessary, and assess the application of the produced prototype through a short user survey.

Fourth, I conclude by assessing the success of the prototype renders in relation to the posed research question, and present what was left unexplored and how the project might expand further.

While presented in this report in an ordered, chronological and separated manner, throughout the thesis process I employed a research through design inspired outlook, where the methods, practices, and processes of design practice employed inform the theoretical research throughout the process[10]. This is an iterative process – as pictured in Figure 1 – that can roughly be described as first hypothesizing a feature or a function based on existing knowledge, building that feature and then rationalizing its position within the system as a whole and reflecting on whether the whole still is coherent and the system more functional than before. If this is the case, then the built feature and the rationalizing theory is included and internalized in the system and informs the next iteration. If not, the feature and associated theory are not in-

10 Inspired by the Research Through Design process described in the paper *Research Through Design in HCI* (Zimmerman & Forlizzi, 2014, p. 168)

cluded as such, but this rejection certainly still informs the hypothesis of the next cycle.

Binding this formalization back to existing thoughts of design processes, it could be thought of as an application of the C-K-theory, where the design process is seen as the expansion of a Concept-space of new ideas and a Knowledge-space of validation[11]. Here the hypothesize phase exists within a Concept-space and the build, rationalize and reflect phases occupy a Knowledge-space to validate the hypothesized ideas.

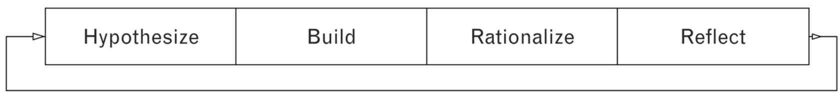
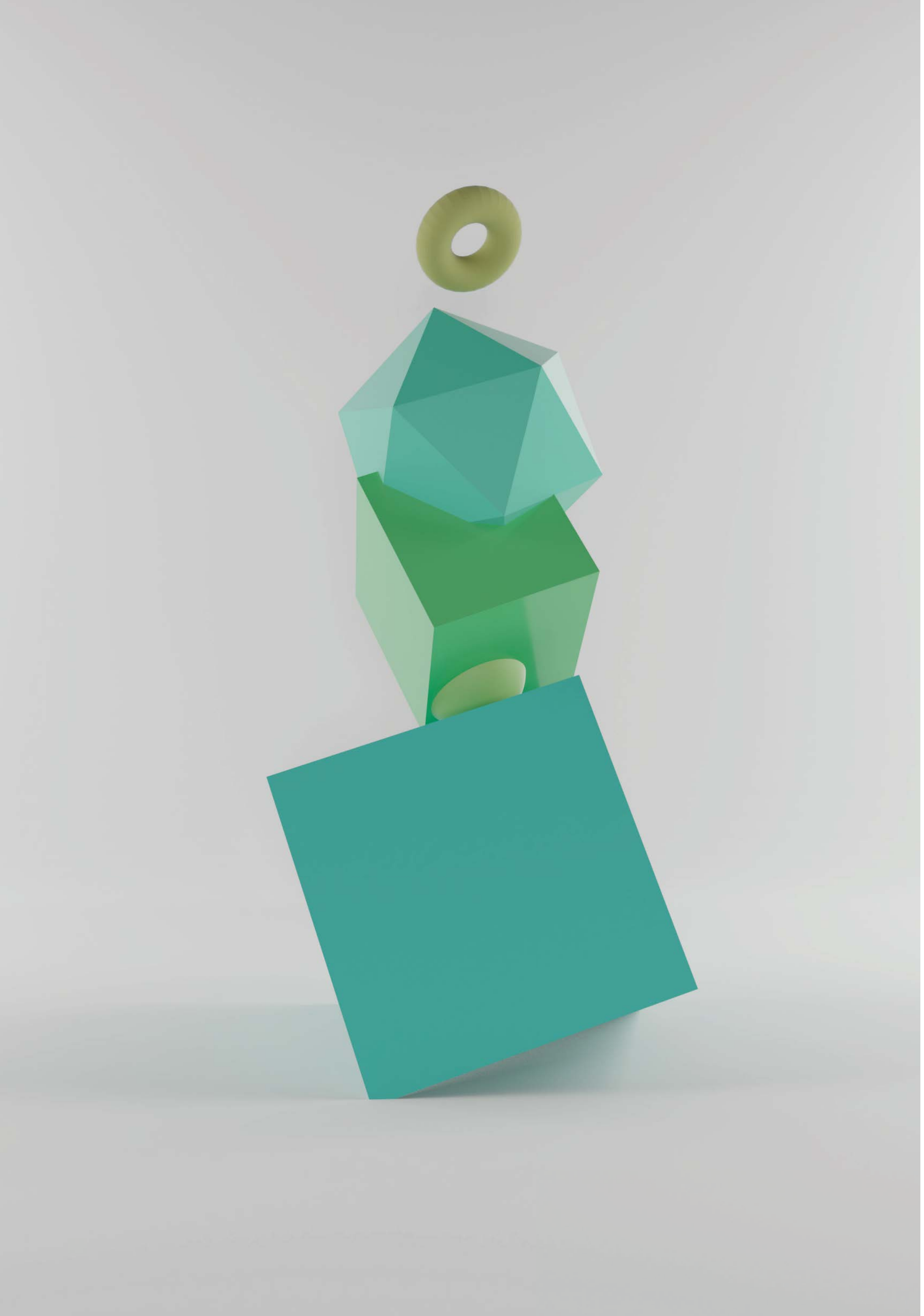


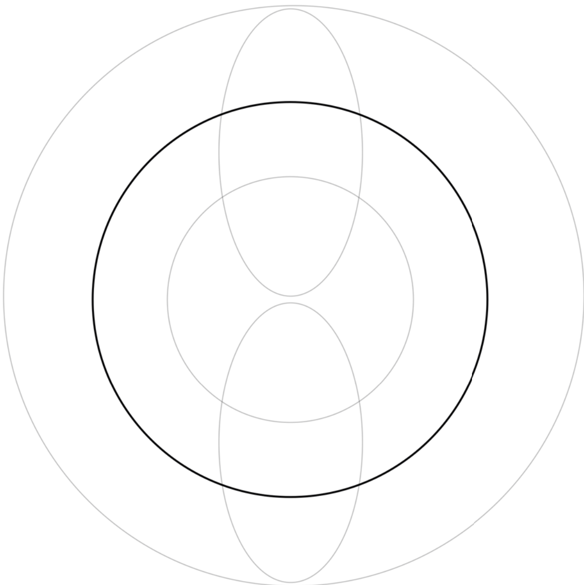
Figure 1: The design process applied

11 As expanded upon in *C-K design theory: an advanced formulation* (Hatchuel & Weil, 2009, pp. 9–11)



Context and position

Research into the context of the work created throughout the thesis process. Approaching the topic of what could be considered experimental within the field of data visualization through a simplified view of the history and development of the field and defining the subject of the visualization through an exploration of the world surrounding and related to the field.



Visualization

State of the practice

The current state of data visualization practice is that of systems and simplification. The simplification of graphics into sets of types, forms, and components, in order to build easily readable accurately communicating visual representations through easy, automated systems, enabling an increased proliferation of visualization in practical use.

Elijah Meeks eloquently reduces the current state of the practice to three "waves" of history, of which the third is currently building. The first wave is that of clarity: Borne out of statistics, this wave is exemplified by Edward Tufte's books championing simplicity of charts and purity of expression of numerical data[12]. The second wave is that of systemization, where the ideas presented in the first wave have been encoded into systems of visualization, that have then been programmed into computer applications that automate the creation of visualizations that follow said system. Meeks presents Leland Wilkinson's ideas of systematization of graphical forms – as presented in the book *Grammar of Graphics* – and their automation in software form as something defining of this wave of visualization.[13]

This limitation of history into waves seems useful to understand the state of practice today. The first wave can be seen as an initial regularization of data visualization practic-

12 Especially his first book on the subject, *The Quantitative Display of Information* is famous for coining terms such as *chartjunk*, *data-ink -ratio* and *data density* to describe a modernist approach to information design, where accuracy and effectiveness are key and ornament is crime (Tufte, 2001).

13 Meeks presented has presented these thoughts both in a keynote speech at Tapestry, a data storytelling conference (Meeks, Keynote at Tapestry 2018: Third Wave Data Visualization, 2018) as well as in writing for the Toward Data Science-platform (Meeks, 3rd Wave Data Visualization: Understanding the convergence of tools, audiences and modes, 2018).

es. There is a rich history of forms and ways of visualization that precede this, but Tufte and his peers could be seen as a starting point of the current practice and field of study, which highly values the clarity of expression of numerical data in graphical form and often appreciates visual minimalism: A statisticians view on data visualization. Other practitioners that could be placed in the wave of clarity and statistical accuracy could be such names as mathematician John Tukey with his use of computerized visualization in exploratory data analysis[14] and cartographer Jacques Bertin who pioneered a theory of meaning in graphical forms used for visualizing data in his work *Semiology of Graphics*[15]. The practitioners within this wave seem to strive for the ideal of a singular interpretation of a specific set of data, by eliminating what they consider errors and removing features that might be detrimental to communicating the pure numeric values of the data (see Figure 2).

The second wave could then be seen as the technological advancement of principles set by the first. Practitioners and scholars between the waves would progress the level of systematization of the practice toward what would become the systemic concept of a grammar for graphics presented by Leland Wilkinson. William S. Cleveland and Robert McGill undertook a scientific examination of graphical perception relying on principles presented by the first wave through the lens of psychophysics and elementary perceptual tasks[16]. Jock D. MacKinlay described the building of automation to build visualizations based on defined systems[17], and Robert L. Harris had by 1996 gathered a comprehensive reference list of visual tools and graph types[18]. Moving beyond the field of computer science, Colin Ware takes a positivist approach

14 As presented by Friedman and Stuetzle (Friedman & Stuetzle, 2002, pp. 1635–1636).
15 Esp. the chapter *General Theory* (Bertin, 1983, pp. 2–12)
16 Cleveland & McGill, 1984, pp. 532–535
17 MacKinlay, 1986
18 Harris, 1996

through the lens of perceptual psychology explains and justifies concepts of data visualization through a universal model of human perception[19], and presents a systemized model of the entire process of data visualization[20].

Wilkinson's *Grammar of Graphics* gathered aspects of these concepts into a comprehensive and thorough syntax of visual representation – the specification of an object-oriented graphics system as it is called in the book, the name a nod to its strong footing within computer science. Abstracting charts into a more general grammar, Wilkinson argues, gives more depth of expression by expanding the view of the practitioner from a single chart type to universal graphics components. Ggplot2, developed by Hadley Wickham, formalizes this grammar into an automated system in the statistical modeling language R. Wickham and ggplot2 expand upon Wilkinson's grammar – developing an "alternative parameterization" as Wickham calls it – but still relying on the same underlying visual principles[21]. Ggplot2 is by no means the only library inspired by the formalization of visualization elements presented in *Grammar of Graphics*. Meeks sees all current popular libraries of data visualization as to some extent inspired by the concept of grammar, building on top of the same principles, accustoming the field for the use of systems and optimizing these systems for use in the field[22]. The second wave allows the rapid creation and examination of data through multiple viewpoints through automated, systemized creation of graphics – communicating through a multitude of first wave viewpoints onto a set of data (see Figure 3).

19 Elaborated on especially in the chapter *Experimental Semiotics Based on Perception* and *A Model of Perceptual Processing* (Ware, 2004, pp. 5–22).
20 *Foundation for a Science of Data Visualization* (Ware, 2004, p. 4)
21 Wickham reconsiders Wilkinson's intertwined elements as separated layers, but the differences seem to be mainly mathematical (Wickham, 2010, pp. 3–4).
22 Meeks, 3rd Wave Data Visualization: Understanding the convergence of tools, audiences and modes, 2018

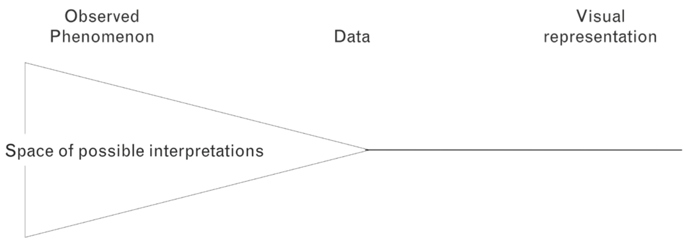


Figure 2: The communicational ideal of the First Wave

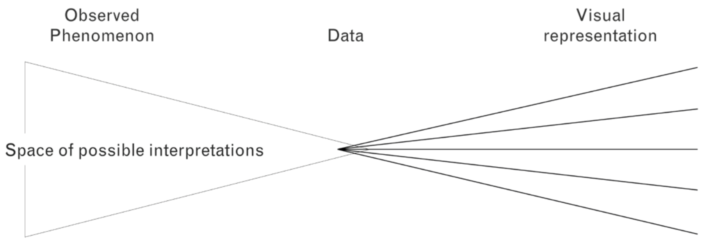


Figure 3: 2nd wave mode of communication

The Third Wave of data visualization

Moving back to Meeks' thoughts on the current state of visualization, he seems to argue that the forthcoming third wave of data visualization is about a shift in focus. Shifting toward design tendencies from a focus on technologies and human-centeredness as opposed to absolute clarity or legibility, through a convergence of tools for making, modes of making and audience expectations of visualization, into new forms of visuals and ways of evaluating visualizations[23]. The emergence of the field of user experience design since the second wave would support this kind of shift in thought toward optimizing the experience rather than the graph.

An example of change toward such thoughts of user-centricity can be seen for instance in Alberto Cairo's approach. He posits the field of data visualization as functional art – artistic expression constrained by functionality, objectivity, and precision[24]. He brings forward the dichotomy between emotion, aesthetics, and functionality, where the requirements of functionality are deeply set in the ideology of the second wave to which he argues emotion and aesthetics should be in submission. Moving away from systems as rigid truths, he champions a shift toward considering data visualization like the design of any usable object – through iteration, considering communicational goals and users[25].

Ben Shneiderman's approach to user interface design as a specific form of information visualization can also be seen as a part of this bridge between user experience and visual representation of data, mapping modes of user interaction to

23 Meeks, 3rd Wave Data Visualization: Understanding the convergence of tools, audiences and modes, 2018

24 Cairo, The Functional Art: An Introduction to Information Graphics and Visualization, 2013, p. 43

25 Cairo, The Truthful Art: Data, Charts, and Maps for Communication, 2016, pp. location 1973–2002

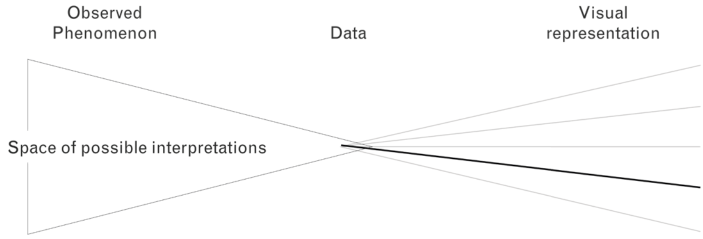


Figure 4: 3rd wave communication

types and forms of data – essentially providing a systemized mapping of data types to visual and interaction guidelines [26].

Meeks' argument seems to be about this kind of usefulness and usability – aspects that are common to other fields of software development and human-computer interaction – placing importance on the context of use as opposed to optimization of a single chart or even a single system. Applied to the field of data visualization this should lead to more holistic ways of thinking about visualization, not as optimizable presentations that are read by users but rather living data-representation structures that are interpreted by humans. Meeks posits his third wave as a question: What will be the determinant factors of the third wave as it breaks? The

26 And very successfully so, as his Visual Information Seeking Mantra of 'Overview first, zoom and filter, then details-on-demand' has become a ground truism for user interface design. (Shneidermann, 1996)

idea of user first design of visualization proposes a new ideal mode of communication, where interaction and narrative provide users singular interpretations that fit their needs while allowing the shifting of perspective should the designer allow, and the user choose, to follow an alternative path (see Figure 4).

I see this as a point where the existing structures, systems, and modes should be questioned, through the speculative use of visualization in order to explore this suggested new convergent modality and the notion of functionality within it. I claim that a too systems-optimized, performance oriented and reductionist view on visualizing data can be restricting on expressive power and honesty, ignoring underlying complexities in favor of perceived accuracy. Considering the definition of visualization – "the act or process of interpreting in visual terms or of putting into visible form"[27] – this a small subset of the entire scope but has gained great prominence within the industry of visualizing data. Robert Kosara presents visualization modes as a linear scale in his research on visualization criticism, as pictured in Figure 5, where pragmatic visualization is on one end and artistic visualization on the other[28].

The current state of the industry is firmly rooted within the pragmatic visualization end of this scale, optimizing for readability and recognizability. The entire spectrum is much wider though, progressing toward less and less readable and recognizable, on its way toward artistic visualization where these utilitarian requirements are no longer present. In this other end, data functions as raw material but the readability of information is not of as great concern as in the pragmatic paradigm of visualization prevalent in the industry.

Viégas and Wattenberg expand on the function of artistic visualization as purposefully breaking the set rules of the pragmatic visualization end of the spectrum – what they call committing sins – and through this maximizing instead

27 "Visualization" (Merriam-Webster, 2019)
28 Kosara, 2007, p. 3

of minimizing the point of view of the author.[29] Artistic visualization might not then be readable as such, but in eliminating readability it has an opportunity to place importance on conveying understanding rather than data itself. Through less readable and more sublime visualization – as Kosara calls it in the vein of Manovich[30] – it might then be possible to leave behind the idea of truth in data and focus more on truth in meaning to the extent it is necessary. What this means, is that it could give an opportunity to move away from a visual display of quantitative to one of more qualitative information. Through this, importance could then be placed on new aspects of the data presented, bringing forward new insights by forcing readers to think beyond the data presented. In their exploration of the convergence between critical and visualization theory, Dörk, Collins, Feng and Carpendale present similar thoughts through juxtaposing the pursuit of insight – the focus on understanding and conveying the data prevalent in visualization research – with the goal of making an impact on people's decisions and choices, highlighting the need to question how this impact is made[31].

These kinds of pursuits within the visualization community have been defined data or informative art, works of data visualization where data is processed and presented in a free form manner and a singular interpretation is not considered of importance[32]. In this sense, they are seen as something separate from mainstream data visualization. As something considered outside or beyond but containing the power to both express the data and covey a strong point of view, this end of the spectrum has the potential to be utilized to critically scrutinize the field, and in that way a natural angle of approach for the speculative approach of Beyond Shape.

29 Viégas & Wattenberg, 2007, pp. 9–10

30 Manovich describes data mapping as anti-sublime, as a primary concern of data visualization opposing it with Romantic art concerned with the sublime. (Manovich, Data Visualization as New Abstraction and Anti-Sublime, 2002, pp. 7-8)

31 Dörk, Collins, Feng, & Carpendale, 2013, p. 9

32 Koponen, Hildén, & Vapaasalo, 2016, p. 24

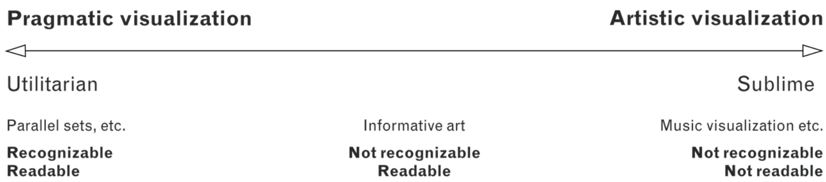
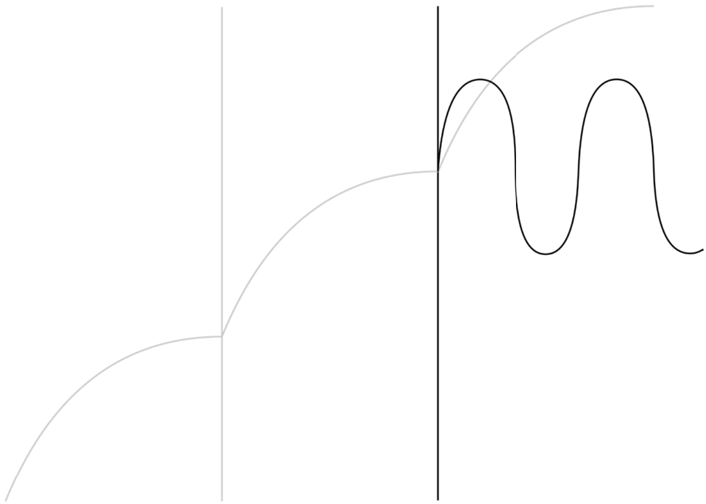


Figure 5: A scale of visualization



Alternatives

Alternative approaches and critique

The previously presented simplified narrative of the state of the practice today is of course by no means comprehensive. Several alternative outlooks and approaches have been taken to both complement, develop and criticize what I present as the mainstream of visualization. Exploration toward the more sublime can be seen within both visualization research and in more mainstream practice. Such a re-evaluation of the relationship between the data, its meaning, and its representation could be a step toward better ways of evaluating the validity and representational power of visualizations, and a place where I position Beyond Shape in the continuum of data visualization.

Lev Manovich has published extensively on the topic of artistic visualization and its relation to the history of contemporary visualization practice. In *What is Visualization?* he discusses the topic in depth, presenting the practice of information visualization as the reliance on principles of reduction and the use of spatial variables as a representational tool. Manovich criticizes the prevalent mode of visualization through presenting a model for non-reductive visualization he calls direct visualization, presenting tag clouds and book indices as examples of such formats. Direct visualization functions by not making reductions to the qualitative information communicated, although they might reduce dimensions of the quantitative information presented. As a "perfect example" of direct visualization principles applied to visualization work, he mentions *Listening Post* by Mark Hansen and Ben Rubin, an installation that presents unedited textual content scraped from internet discussion on a grid of screens as well as spoken out loud by a speech synthesizer[33]. In this

33 Video recording published by *MediaArtTube* is available on YouTube at https://youtu.be/dD36lajCz6A (Hansen & Rubin, 2001)

way, the work does not manipulate the data it presents, while also rejecting existing paradigms of form for visualizations, by taking the form of a custom-built installation.[34]

Giorgia Lupi speaks of the concept of data humanism as a potential new paradigm for looking at both data and its presentations. Data humanism is a pursuit for a more human approach toward the presentation of data, often shifting digital data to analog representation in its process. Lupi argues for a change from visualizing data itself – the medium of information exchange in our world – toward visualizing the meaning within or behind the data. A highlighted point is the human behind the data – the idea that data is ultimately formed by human activity, and thus it should be presented in a human way.[35]

In the *Dear Data* project, Lupi explores data humanism in practice together with Stefanie Posavec. In the project, the two designers visualized aspects of their everyday lives through hand-drawn postcards. They set a framework of what kinds of data to collect – pursuing types of data difficult to capture by computers – but leave the form of visual representation freeform. This way they communicate through card drawings throughout a year of data gathering and developing visual languages to fit the often very unique and personal datasets.[36]

In this work, the humanity behind the data is highlighted not only through the hand-drawn visualizations as well as the process to create them. The physical form of postcards record not only the data and its visual representation but also the journey of data transmission. Analog drawings in

34 Manovich, What is visualisation?, 2011, p. 16

35 Published both in Print Mag and Lupi's personal blog https://medium.com/@giorgialupi (Lupi, 2017)

36 As well as the documentation Posavec has published on her website (Posavec, Dear Data , 2019) and a talk at Creative Mornings (Posavec, Stephanie Posavec: Fragmented portraits in data & drawings , 2016) a book, *Dear Data*, has also been published on the subject, which was not acquired for reading to source this.

this respect record more of the visualization process than a digital representation would. In contrast to Manovich's idea of direct visualization, the presentation of data in Dear Data is far from raw or direct. The data is processed and reduced in manners effectively similar to those common in the mainstream practice of visualization, using spatial variables as a mode of representation. Regardless, the project succeeds in criticizing the prevalent forms of visualization through the ability to communicate qualitative information – the concept of humans behind both the data and its representation. The hand-drawn aesthetic mirrors effectively the hand procured nature of the data, communicating the fact that this data was handled and processed. By obscuring some of the accuracy of the numeric data by fuzziness in representation, the work honestly informs the reader of its fallible human origin.

Peter Hall approaches visualization through the lens of critical design. In his essay *Critical Visualization*, he presents the idea of the art of visualization as a critical practice. He uses the exploration into the agency of mapping by James Corner as a vehicle for thought, generalizing Corner's ideas from one form of visualization – maps – to encompass the general practice of visualization. Hall aligns the art of visualization with the arts of urban planning and architecture as being able to modify reality, not only concerned with the ultimate finished representation or product but also involved with the layers below: processing the data and setting the context from which the representation is formed. Quoting Corner discussing Minard's famous visualization of Napoleon's army in Russia[37]: "the map conditions how places on the land have come to exist in new relationships precisely through the vector of an event"[38]. That is, the visualization is

37 A classic in data visualization, an image by the Charles Joseph Minard that explores the diminishing of Napoleons troops through their Russian campaign. Published for instance on Wikipedia: https://en.wikipedia.org/wiki/File:Minard.png

38 Corner, 1999, p. 246

able to affect how the physical places it represents are considered through re-contextualizing them to a particular scenario. This gives visualization the ability to function as a critical practice, according to Hall.[39]

In the paper *Critical Visualization: a case for rethinking how we visualize risk and security* Hall, Heath and Coles-Kemp utilize the ideas of critical visualization as a method of research in the context of the TREsPASS project – a European Union funded project concerned with predictive risk estimation and assessment[40] – to assess the use of visualization within the cybersecurity field. By analyzing the cultural context of both this field and the position of visualization within it, they are able to highlight issues with the predominant mode of visualization within cybersecurity. They recognize a disconnection between the pursuit of usability and simplification within the predominant modes of data visualization and the ever more complex field of cybersecurity, where modes of implemented visualization perpetuate a dominant narrative of security as control. In order to overcome this predominant narrative, the researchers approach visualization interfaces through participatory research and physical modeling by visualizing the networks of stakeholders and actions in LEGO. The group conclude to a view, that by utilizing a participatory process, the level of a secure enough system can be determined. Data should be structured in a manner that a visual representation that is balanced between simplicity and complexity can be attained. Strategy for interface design should then be balanced between the representation of qualitative and quantitative information through reassessing the evaluation criteria for visualization based on this new balance, determined through the participatory research.[41]

The exploration by Hall et. al into visualization as a crit-

39 Hall, Critical Visualization, 2008, pp. 128–130
40 The TREsPASS Project, 2019
41 Especially the case studies and conclusions are of interest (Hall, Heath, & Coles-Kemp, Critical visualization: a case for rethinking how we visualize risk and security, 2015, pp. 101–107).

ical practice highlights the importance of understanding the context and effect of a visual representation. Through a situation-specific participatory approach to evaluation, the development of a visualization can be approached in a very flexible and user-oriented, manner. This seems to mirror arguments presented earlier for the third wave of visualization, where modes, forms, and user expectations ultimately would converge.

Kennedy et al. critically approach conventional modes of data visualization in their semiotic analysis of how mainstream visualizations communicate and how power is communicated through them. They argue that accepted conventions in data visualization provide visualizations with a feeling of potentially false objectivity and accuracy. The visual conventions they identify as the most persuasive rhetorical devices are two-dimensional viewpoints, simplistic and repetitive shapes, clean layouts and the inclusion of data sources. Two-dimensional shapes are able to create a feeling of objectivity through presenting a maximum amount of information at once, leading to a 'god-like' feeling of seeing everything without occlusion or perspective. The use of repetitive shapes taps into the human tendency to make order out of things, making what is presented feel in order as well. The abstraction into simple shapes lends to a feeling of a graphic being easier to read, while also potentially simplifying the data itself in the case of journeys on maps, for instance. Clean, clutter-free, modernist layouts contribute to a rhetoric of clarity, obscuring the complexity of the data presented. Included data sources meanwhile communicate transparency, whether or not the reader is expert enough to comprehend the data available, increasing the feeling of trustworthiness.[42]

These explorations of alternative modes and forms of visualization build a position for criticism through practice within the field through rejecting, questioning and scruti-

42 Kennedy, Hill, Aiello, & Allen, 2016, pp. 6–20

nizing the mainstream. Methods and tactics presented in the Approach and process -chapter can be seen reflected in these works, providing precedence for their use within the context data visualization. The ideas and projects Manovich presents can be seen as aiming toward the diversification of thought by rejecting simplification and meaningful presence through the focus on communicating qualitative information. Lupi and Posavec seem to similarly follow a philosophy of meaningful presence through humanization. The hand-drawn presentations apply methods of information ambiguity and form sorts of post-optimal objects by optimizing unique visual representations for each set of data, rejecting some of the prevalent visual conventions of maximizing clarity in order to communicate feelings over data. Hall et al. approach their subject by utilizing design as inquiry through a participatory process, while in his own work Hall produces a speculative proposition of how data visualization shapes the world. Kennedy et al. break down the rhetoric devices of a conventional visualization, mapping the current landscape so that methods that could go beyond those now prevalent can more easily be explored and speculated upon.

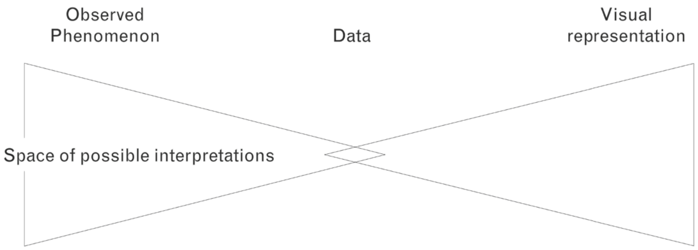
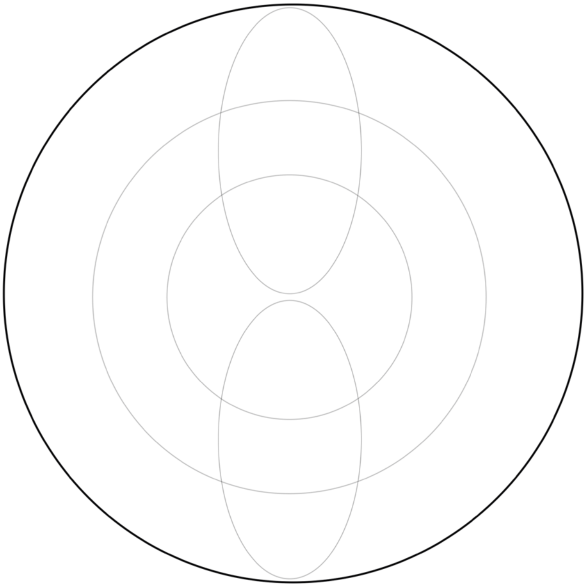


Figure 6: Ideal form of communication for Beyond Shape

Beyond Shape & the definition of experimental

The presented assessment of the field creates a distinction between normative and alternative ways of approaching and creating visualizations. This creates a basis for the definition of an experimental visualization for the context of this thesis: An experimental visualization attempts to approach visualization by means defined by the alternative approaches, in order to move beyond the boundaries of norms. Here the divide is then made between the first three waves and what I've called alternative forms, where the mainstream can be seen as roughly following along the ideals of pragmatic visualization, as presented on the scale in Figure 5, while the alternative forms moving further along the scale toward the sublime and artistic, in different ways and amounts.

Exploration of the alternative side then gives me a set of tools and practices which I can use to explore beyond the conventional means of data visualization: Rejection of simplification, communication of the qualitative over the quantitative, humanization through both a collaborative process and maintaining a level of ambiguity, and a set of visual guidelines to be wary and utilize in assessing the end result. Using the same visualization used to present the modes of communication within the three waves of mainstream visualization, the communicative ideal for Beyond Shape can be seen in Figure 6. The goal of the visualization is no longer to necessarily produce well-defined views out of the data, but instead attempt to accurately reflect the amount of interpretation put into producing the data in the amount of interpretation needed to read the image produced. The manner in which is to be done, is not by overwhelming the user with the amount of data or by possible perspectives and options as the issue would be approached through the ideals of the normative ways of visualization (see Figures 3 and 4), but by applying a layer of ambiguity in the representation – obscuring the numbers beneath to a suitable degree to bring fuzziness back into the interpretation.



The World

State of the surroundings

Benjamin Bratton presents the idea of the Stack as a structural model of contemporary society. The Stack describes the interconnected, convergent society of technologies minds and matter – of planetary scale computation – as a platform structured in layers, pictured in Figure 7. The Stack utilizes the software and hardware stack – the interdependent parts of technology required to produce software – as a metaphor for what Bratton calls an "accidental megastructure" that is our societal landscape.[43]

Bratton's work is related most to the societal level of the world, the political geographies defining states and communities and the sovereignty of those entities. But this computation-inspired arrangement Bratton describes is both reliant on and effects the systems and software within each stack layer, and as such, it seems a relevant option to consider as a starting point for societal context for the visualization work conducted within this thesis – as a piece of software situated in the world. And if the Stack is considered a relevant model of the world, the placement of a designed communication system within the Stack is relevant to explore.

Data visualization as a concept lies within the Interface layer of the Stack, the part of the Stack, where the user connects to the layers beneath. The ubiquitous interface of our age – the two-dimensional graphical user interface – is essentially a complex diagram, utilizing the same mechanisms of reduction and readability as visualizations of data through

43 Especially, the Introduction chapter, pp. 26–53 and the Platform and Stack, Model and Machine chapter, pp. 100–163 (Bratton, The Stack: On Software and Sovereignity, 2015).

diagrams[44]. As a user interacts with a graphical user interface, their actions are replicated throughout the Stack to perform the action afforded by the interface. This causes a ripple of effects within the Stack, as the CPU is activated, as physical servers are accessed, as a mechanic is called upon to fix the server infrastructure, as the factory produces an SSD drive, as silica dioxide is mined from the earth while states fight over borders that contain the mine. This ability to cause effects throughout the graphical user interface is the difference between the user interface and a classic diagram.

The layers of the Stack are adjacent but disconnected, which leads to the inevitability of mediated communication between layers. In this metaphor, the natural media for communication between layers is data. Each stack has inputs for data, processes it and outputs it somehow assessed or modified, and it is held together to the layer above and the layer below by data. Considering this gives data visualization as a practice an interesting position within the interface layer, of being able to give form to the connective tissue between the layers. Visualizing data gives us a view into how the stack functions, even the layers far underneath the user layer we are helplessly stuck on. While certainly not the only interface capable of communicating the data in the in-betweens, this does lead to a special kind of responsibility within the practice and study of data visualization. This responsibility I feel is much represented in the current pursuit of correctness and understandability within the field, its systems and the practices these systems are built on. The prevailing concept of accuracy in the presentation of the data visualized – optimizing graphs for data – seems like it is the embodiment of this responsibility. Practitioners in pursuit of correctness seem often to forget that each layer of the Stack manipulates the

44 Specifically, about the Interface layer of the Stack in Bratton's talk at the Institute for the Humanities, starting around the 45:45 mark. (Bratton, The Stack: Design and Geopolitics in the Age of Planetary-Scale computing, 2014)

data it outputs. The data as medium shifts, bends and warps as the layers shift, and data itself is always meta, about the layer but not the layer itself, and is then often an unreliable mediator. This leads to the contradiction of presenting unreliability or inaccuracy as accurately as possible, to optimize away the option of less accurate representation. The question arises: How to assess these inaccuracies and visually represent them honestly rather than accurately? This provides a conceptual base through which the practical visualization work in this thesis is approached.

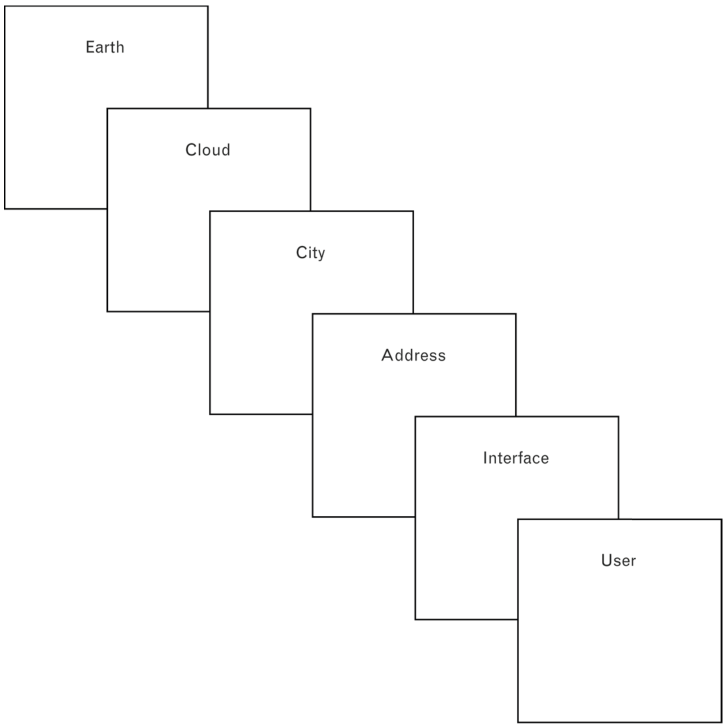


Figure 7: Bratton's Stack

User, Interface, Cloud, and Earth

Looking back at the progress within the field of visualization presented earlier, a lot of it seems to be dealing with the optimization of representation of the complexity of the real world. Much of the power of the tools and service we use, comes out of being effective at abstracting the layers beneath the immediate interface. Creating an opaque layer between users and understanding is then considered user-friendliness, usability or good design in our age of increasing access to flows of information. But regardless of making the complexity invisible is praised and prevalent, we are often overwhelmed.

James Bridle goes as far as calling the state of being a new dark age: "an age in which the value we have placed upon knowledge is destroyed by the abundance of that profitable commodity"[45]. While the situation might not be as dire as this, Bridle makes a statement of a worrisome future, one in which people know more their surroundings than ever but are able to affect it less than before. Bridle's argument is not based on a particular topic, but rather a broad look around the central question of how the world and emerging technology seems to currently function. He positions his thinking as an argument against computational thinking, which he describes as an extension to solutionism, a term recently popularized by Evgeny Morozov[46] as a pejorative for the belief in every problem being solvable, preferably by the application of technology[47]. Bridle poses computational thinking as internalized solutionism, a belief where it becomes impossible to be unable to represent the world computationally, that he argues is a dominant way of thinking about our existence[48]. As an example of its limita-

45 Bridle, New Dark Age: Technology and the End of the Future, 2018, p. 11
46 The chapter *Solutionism and Its Discontents* (Morozov, 2014)
47 Solutionism can be seen as a softer variation on the tune on a nomological account of technological determinism, where possible futures are limited by technology – where social change requires the application of specific technologies (Bimber, 1998, pp. 83–85).
48 Which in turn aligns computational thinking with normative forms of technological determinism – the adoption of reductionistic values of productivity and efficiency as norms to guide technological progress (Bimber, 1998, p. 82).

tions, he presents the work by Lewis Fry Richardson, where Richardson explored the lengths of borders in order to calculate the likelihood of conflict between countries. As Richardson would come to realize in his research, the measurement of the length of a border is completely dependent on the level of simplification of that border – this later bound into the canon of the study of fractals by Benoît Mandelbrot. That is, the level of simplification controls our perception of the world, acting as the opaque layer between us and understanding the world. What Bridle then argues for is literacy of systems and complexity. This literacy sets a requirement for new metaphors and language that are able to better describe the complexity of the systems on the layers below the representations.[49]

In his project *Autonomous Trap 001*, Bridle highlights his theory of systemic literacy in the context of contemporary systems of automation. While working on a self-driving car system – another project published as *Austeer* – the artist explored potential ways of interaction with a system of automation. He then found a symbol that both humans and the machine shared an understanding of: The parallel of a solid line and a dashed line, used to communicate the disallowing of crossing it from one direction. This symbol can then be used to communicate between humans and the car – in this project by encircling the car in a trap of virtual uncrossable barrier that for the system is very real.[50]

This type of communication between system and humans is a key component in helping people understand systems better and giving them a sense of agency over even very complicated systems like artificial intelligence driven automated entities. Development within the field of Human-Computer Interaction is starting to address this issue of control over seemingly black-box systems[51], but the languages and

49 Chapter *Chasm* (Bridle, New Dark Age: Technology and the End of the Future, 2018, pp. 1–16)

50 Bridle elaborates this project at the end of a talk at Eyebeam, from 1 hour 1 minute onward. (Bridle, Eyebeam: New Dark Age: Technology and the End of the Future, 2018)

51 Budiu, 2018

metaphors used to communicate the complexity of these systems to their users will certainly still develop. This requires critical input from the designers and developers of such systems not only on the representational layer but also in critical study and understanding of the processes that produce the data that is represented, a nascent field in itself[52].

Hito Steyerl writes about the deluge of data and its effects on our perception of the world in the book *Pattern Discrimination*. She argues that apophenia – the tendency to perceive meaningful connections of patterns between unrelated things[53] – is replacing concepts of postmodern paranoia expressed by Fredric Jameson. Where the paranoid imagination utilizes narrative plots and delusions to fill in what it cannot comprehend of the complexity of its surroundings, its apophenic counterpart stuffs these blanks by breaking down the paranoid narratives into causalities backed up by data. Steyerl questions computational methods of pattern recognition as potentially nothing more than modern apophenic devices, tools that divine meaning out of the "truckload of data" presented to them. She examines Google's experiments in inceptionism[54] – the reversal of pattern recognition neural networks to instead produce images of what they have been trained to recognize – as a way of seeing some of the underlying technological disposition: When random noise is forced through a system taught to learn a particular thing, it will see that particular thing within the noise – a computational take on Maslow's hammer[55]. This binds to her thoughts about the production of all this data – the fallibility of it, and the ways this fallibility is dealt with through exclusion. As the data is gathered of humans, about humans and processed by

52 Iliadis and Russo present Critical data studies as a field of research to systematically and critically study data (Iliadis & Russo, 2016, pp. 2–3)
53 *Apophenia* (Merriam-Webster, 2019)
54 Term coined in the Google AI blog https://ai.googleblog.com/2015/06/inceptionism-going-deeper-into-neural.html
55 "I suppose it is tempting, if the only tool you have is a hammer, to treat everything as if it were a nail.", Maslow's description of cognitive bias. (Maslow, 1966, p. 15)

humans, it is bound to be an error-filled mess. Highlighted by this is the difficulty of honesty in recognizing patterns within it without disinfecting the dirt first, and thus possibly wiping out some of the humanity of it. Steyerl has an ultimately optimistic call to action, opposing sifting and filtering: "One might as well have fun with it".[56]

Crawford and Joler approach one contemporary method of managing the ever-increasing complexity of the data about our surroundings through their dissection of an artificial intelligence system. They pick-apart the layers of technology behind the opaque interface that is the Amazon Echo -device. Designed to optimize away our daily contact with complexity, Crawford and Joler identify it doing so through a problematic, fractalesque network of supply-chains, physical infrastructure, and exploitation on the physical layers of the world. In the digital realm, the software requires quantification of nature and human behavior, fueling an aim of full quantification through data extraction. Everything that can be captured is logged and collected into datasets utilized for training and development of these systems in search of the boundaries of the field. Invisible human work for classifying, tagging and labeling through services like Amazon Mechanical Turk is employed to make mappings between captured data and human interpretation. In the push toward a potentially infinite horizon of technology, as Crawford and Joler put it, this process of quantification is applied to increasingly complex fields of human nature – emotions, attention, reputation – and the software might become simply an amplifier of the most popular interpretations of these fields.[57]

56 Steyerl, 2018, p. 20
57 Published as part of the Artificially Intelligent display at Victoria and Albert Museum and online at https://anatomyof.ai/ (Crawford & Joler, 2018)

Beyond Shape, the brief

In identifying a more specific topic to research through an exploratory visualization design, we must assess what the role and capabilities of visualization could be within the world surrounding it. If data visualization is a method for understanding our world – the earth layer and how it communicates with the other layers of the stack – as presented, and visualization has the power of affecting the state of that world as Hall argues[58], we could speculate upon how alternative different modes of visualization could change our perception of the world – the communication of information upward from the earth layer.

Then, we must approach a particular subject or issue that affects our perception, that fits the form of data visualization. Through the exploration of Steyerl and Bridle[59] into the state of the world, a concern about the sheer amount of information and how it relates to our actual understanding of it – "it" referring to both the world and the information – can be identified. Both seem to be against the thought of a reductionist approach toward processing information even when it is overwhelming – presented as the normative way of sense-making of data through pattern recognition and artificial intelligence systems – pointing to the question of alternative approaches of communication. I see this as directly related to the use of data visualization, as data visualization is by definition bound to the communication of data. The research question combined with the outlined speculative approach then becomes an inquiry into questioning existing modes of making sense of the world through the form of visualization. A data processing and visualization system managing and

58 As discussed in the previous section (Hall, Heath, & Coles-Kemp, Critical visualization: a case for rethinking how we visualize risk and security, 2015) (Hall, Critical Visualization, 2008)

59 See the previous section (Steyerl, 2018), (Bridle, New Dark Age: Technology and the End of the Future, 2018) and (Bridle, Eyebeam: New Dark Age: Technology and the End of the Future, 2018)

communicating vast amounts of data could then be used as a method of inquiry to both to reflect upon the field and the information presented as such. It should be able to diversify outlooks about modes of visualization and speculate about how those forms affect our perception of the data presented through the creation of something post-optimal, something that is no longer user-friendly. This should force users to think beyond the data presented into how it might have been produced and what it might represent prior to utilizing reductionist methods of managing the complexity of the source of the data.

Artificial intelligence systems as a particular subject for examination can then be approached through the writing of Crawford and Joler as presented earlier[60]. As the latest waves of AI and machine learning methods as a still-emerging technology are positioned as a solution to creating understanding out of vast amounts of information, they are both a potential tool for visualization creation and a point for critique, as powerful and effective reducers of complexities within the world into singular points of data. By using methods of teaching machines to interpret human behavior, a machine which reinterprets outputs of other machines back into something more human can be speculated on – a way of obscuring and creating ambiguity in the processing of data by applying a collaborative, additional layer in between the data to be visualized and the output visualization.

An example of a readily available and functional but clearly reductive way of utilizing a machine learning system can be identified in the task of assessing human emotions. It is an identified complex open topic spanning a wide range of fields of research, with varying views on

60 As discussed in the previous section (Crawford & Joler, 2018)

applicability[61] where – to me – a truly accurate machine-based assessment seems if not unlikely at least far more complex than numeric output can easily communicate – fulfilling the specification of complexity defined in the research question. The application of machine-assisted interpretations of emotions is an emerging topic within interface design[62], making it an interesting avenue of exploration from the point of view of the field of design as well.

Reflecting the research question of

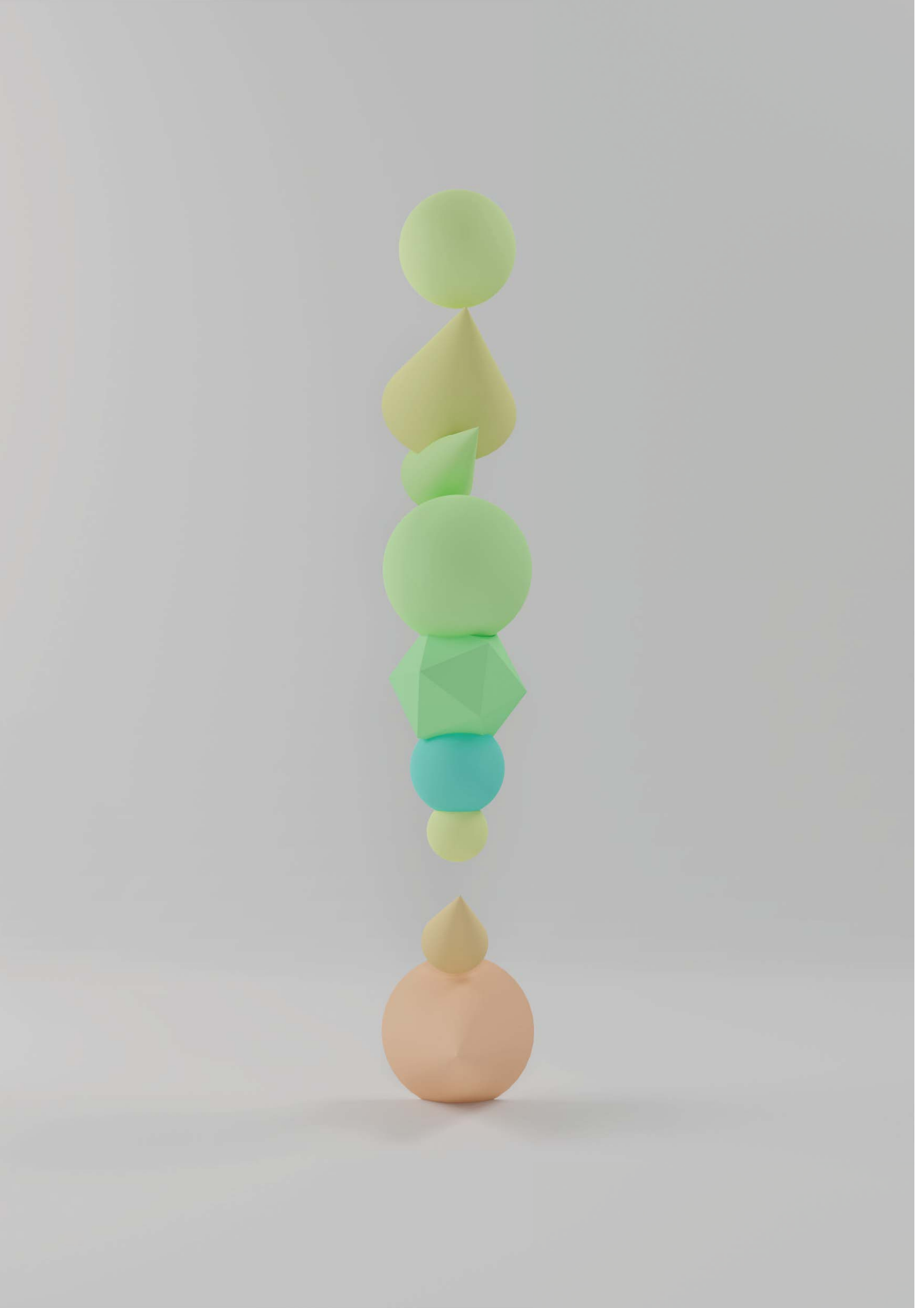
How can we produce an experimental data visualization system that is able to undo oversimplification of data about complex subjects?

with both the presented position within the field of visualization and the narrativized position of the world surrounding the field, an actionable design brief can be posed:

Design an experimental visualization system, that is able to expand the human interpretation of machine detected emotion data through the utilization of machine learning methods.

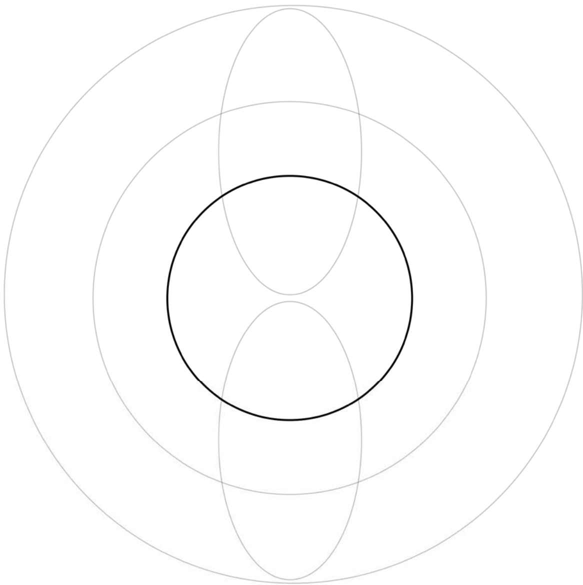
61 Recently for instance Celeghin et al. study the viability of the psychological concept neurobiological of basic emotions in their meta-analysis, cautiously confirming their biological existence (Celeghin;Diano;Bagnis;Viola;&Tamietto, 2017), while Thanapattheerakul et al. (Thanapattheerakul;Amoranto;Mao;& Chan, 2018) are inconclusive in their meta-analysis about the existence of coherent emotional expres-sion in current methods of emotion recognition. Simply as to say that the field is complex.

62 As purported by Pamela Pavliscak in her book, chapter The History and Future of Emotional Design (Pavliscak, Emotionally Intelligent Design, 2018, pp. 19–64) and a talk given at WebExpo (Pavliscak, The future of AI is emotionally intelligent, 2018).



Proposition and application

Proposal and prototype-level implementation
of an experimental visualization system.
An examination of the practical design work
of the thesis from concept to prototype.
A description of inputs and outputs. A presentation
of the structure of the application produced and the
documentation produced throughout the process.
The evaluation of the prototype its final
form in the scope of this thesis.



Beyond Shape

Beyond shape

Beyond shape is an experimental visualization system, designed to quantify, interpret and build visual representations of human emotions detected in text. It aims to do so in a manner that expands beyond the presented mainstream position of data visualization by not taking the accuracy of quantification as a given and admitting to possible shortcomings in the computer-assisted analysis that it utilizes by creating user-unfriendly, initially ambiguous output – a concept of which is imaged in Figure 8.

Through this, the goal is to communicate not only the result of the quantification process but also the interpretational uncertainty within, in this way hoping to build opportunities for new avenues of exploration within the field of data visualization. Realizing the subjectivity of interpretation of a complex subject like emotion, the system utilizes machine learning techniques in an attempt to undo, or at least question, the methods of reduction employed by artificial intelligence systems that interpret human actions. By creating a living, constantly rebuilding mapping of visual attributes to emotional attributes, it attempts to capture this interpretational subjectivity into a participatory quantification of its own, asking whether a reduction of a reduction can tell us something about the parts of its sum.

It is a machine that consists of modular serverless[63] parts – services that abstract away physical servers – and is built mainly onto the cloud platform Zeit[64]. The main machine consists of five main parts, as presented in Figure 9: A Consumer for the input of data, a Decoder for quantifying that data, an Interpreter for transcoding the data into other forms,

63 Serverless being a (rather oxymoronic) term that described ephemeral servers, spun up on request to serve a single function, coined by Ken Fromm (Fromm, 2012)

64 https://zeit.co/now

a Mapper that informs the Interpreter how to transcode and a Constructor that pieces together the data processed through the interpreter into visual representations. For this prototype phase of the application, a sixth, manual step of polishing the Constructor output is applied and referred to as the Renderer. These parts map to different conceptual stages in the visualization process, which can be roughly mapped to the four-stage process presented by Ware: Collection and storage of data (Consumer), processing and transformation of data (Decoder, Interpreter), graphics (Constructor, Renderer) and ultimately the perceiver[65]. What sets apart the Beyond Shape system from Wares model, is that through the Mapper an additional layer of human perception is added into the data processing part through a collaborative data mapping and machine learning functionality. Each part, its inputs, outputs, and functionality will be elaborated on in their own section.

65 Ware, 2004, p. 4

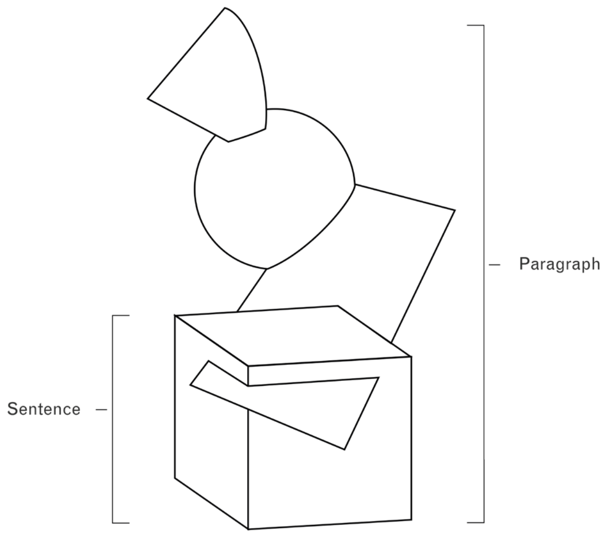


Figure 8: A concept image of the output of the Beyond shape -system

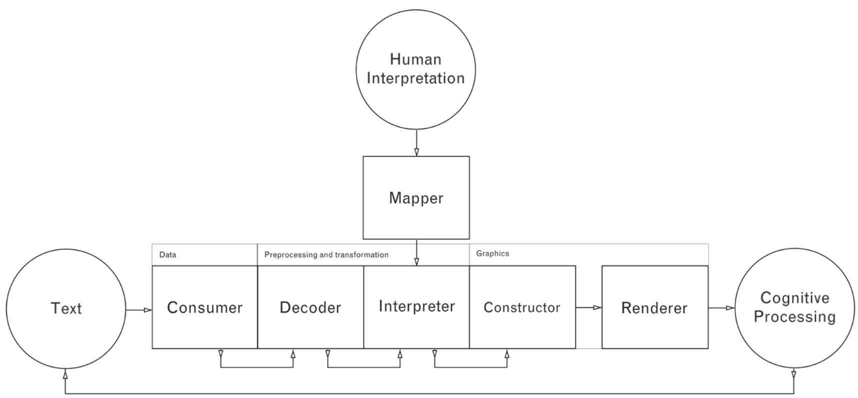


Figure 9: Machine architecture & process model

Consumer

The Consumer takes input media and parses it into data to be processed by other parts of the application. As such, it is not necessarily a separate piece of machinery, but a separate function which is required to get data into the machine. In practice, its visual representation is the user interface that enables data entry. For this prototype only a simple Consumer, suitable for testing purposes, was built as a separate application. Also, within the scope of this thesis, a selection was made to limit the format of input media to text, enabling its implementation through a simple HTML textarea-element pictured in Figure 10, not requiring a more complex interface. The functionalities of the Consumer were also integrated into the decoder and the constructor to enable rapid testing of the machine at different stages of the process (see Figure 11). Conceptually it is a separate functionality, and a part of future development could be to enable easier user participation in the process of creating visualizations by building a more robust separate application for users to input to be processed by the system, as well as enabling more types of media to be processed. The source code of the separate version of the decoder can be found in GitHub[66].

66 https://github.com/KODHAGe/shape-consumer

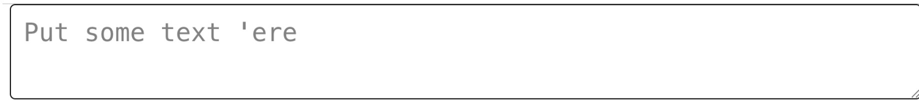


Figure 10: The visual manifestation of the Consumer within the Constructor: An HTML textarea.

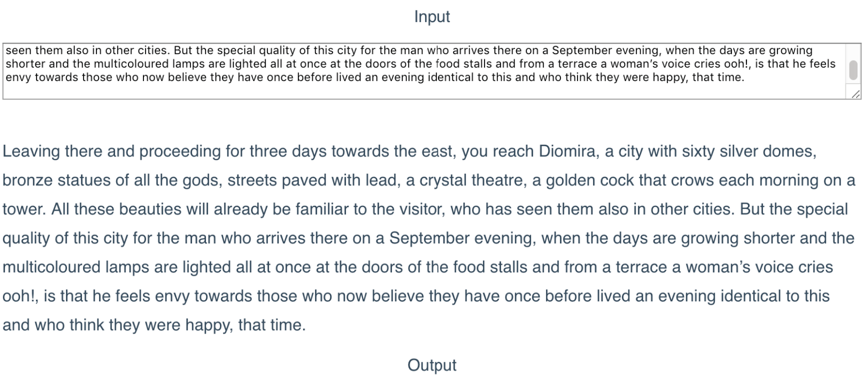


Figure 11: The separate Consumer used to test input and receive output about the Decoder functionality.

Decoder

The Decoder media parsed by the Consumer as input and outputs decoded numeric data about that input. Conceptually the input media could be of any digitally representable modality and technological capability exists to analyze at least video, images, sound, and text. But for the prototype produced within the scope of this thesis, input media is limited to text. This text is decoded into computational attributes and numeric data through integrated third-party software systems. The systems used are selected based on them being a part of analysis suites provided by large companies established within the technology industry – with the thought that as this software is provided by large companies it is more likely to have been implemented in production use by others than more obscure or smaller platforms. That is, these analysis platforms can be assumed to be common within their context, realistically being used for textual analysis within popular software.

The function of the Decoder is to provide analysis about the emotionality of the input. Thus, the second criterion for platform selection is that the software provides some output indicating emotionality within text input, that is either sentiment or emotion analysis. Ultimately three platforms, provided by Google, IBM and Microsoft were selected for the prototype.

Google's Cloud suite of tools provides a platform for natural language analysis, called Cloud Natural Language. The platform provides an analysis of grammar and entity detection within text. The emotional analysis component Cloud Natural Language provides is limited to detecting positive and negative sentiment, as well as sentiment per object detected.[67]

67 (Google, 2019)

The IBM Cloud platform provides access to several language analysis toolsets, the two of which identified as potentially interesting for the decoder being the Watson Tone Analyzer, and the Watson Personality Insights services. While Personality Insights provides an added range of emotional attributes as output, it is designed for a large corpus of text content, and as this project at this stage would function on the sentence to paragraph level, use was limited to the Tone Analyzer. The Tone Analyzer provides emotion detection of seven attributes, presented in the table below.[68]

The Microsoft Azure -platform provides a similar set of natural language analysis tools as the Google Cloud -platform, with entity, key phrase, and sentiment detection.[69]

It should be recognized that there are far more commercial platforms available for emotion analysis than those presented and implemented in this thesis, as well as open source projects and datasets that enable the running of a completely tailor-made solution, and those options should be explored further when adding capabilities to the platform. The selected systems all operate on a black box -basis, not informing the user of reasoning of coming to a particular conclusion and in this way not elaborating on how their functionality is produced – a developer needs to rely on that output given is reasonable. All services are part of their respective company's artificial intelligence selection of services, so the assumption can be made they utilize at least some machine learning principles instead of relying on completely dictionary-based models of emotion detection. As can be seen from Tables 1, 2 and 3, the full set of emotions for this prototype consists of 9 different variables: Anger, fear, joy, sadness, analytical, confident and tentative as assessed by the IBM Watson system, and positive and negative that are retrieved from both Google and Microsoft. The positive and

68 (IBM, Personality Insights Documentation, 2019) and (IBM, Tone Analyzer Documentation, 2019)
69 (Microsoft, 2019)

negative values received from these systems can then be cross-referenced and averaged to provide an insight into how this might affect the numbers provided – a cross-referencing of other emotion attributes could be added by other platforms if it seems useful, and the same attributes are available on other platforms. The source code for this part of the application, as well as cursory technical documentation is available on GitHub[70].

70 https://github.com/KODHAGe/shape-decoder

Table 1: Google's emotional attributes

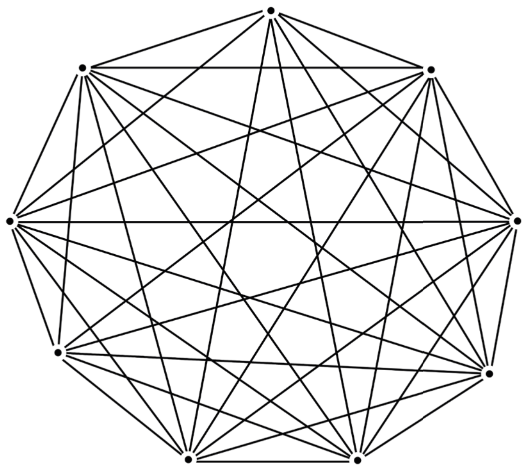
Google Natural Language	Attributes
	Positive sentiment
	Negative sentiment
	Sentiment per detected entity

Table 2: Watson emotional metrics

IBM Watson Tone Analyser	Attributes
	Anger
	Fear
	Joy
	Sadness
	Analytical
	Confident
	Tentative

Table 3: Azure emotional metrics

Azure	Metrics
	Positive sentiment
	Negative sentiment
	Sentiment per detected entity



Map the extremes

Interpolate the inbetweens

Figure 12: Conceptual model of the Mapper

Mapper

The Mapper includes the functionality of the software machinery which feeds an automated learning process with new data, enabling the Interpreter to learn about the correlations between emotional and visual attributes, the concept of which is modeled in Figure 12. The Mapper provides a crowd-sourced definition of the relation between emotional attributes and visual attributes in order to enable mapping these together algorithmically in a way that represents a potential common view of these combinations. Instead of relying on pairings provided by existing research, the Mapper provides a living, forever changing mapping by employing methods common to those used in machine learning. This mapping does not directly rely on imposed interpretations of the designer as such, but a view constructed out of the crowd. The imposing of a designed structure and limitations – and thus the agency of the designer – is of course not removed, but it is shifted toward the higher-level strategies utilized in the visualization and the specifics of implementation rather than the immediate interpretation of data to representation. The designer now shares some of their agency with the crowd by relinquishing part of control but remains in control of the visualization structure through the selection of attributes and control of the mapping process. Through this process, the limitations of data collection methods common to the production of datasets utilized in machine learning can be explored – effectively the Mapper creates a reduced model of a limited range of interpretations.

Defining visual variables

Before mapping can be enabled for the crowd, the mappable pairings need to be defined. The input variables – that is, the emotional variables provided by the Decoder – are mapped to visual representations. Here is where existing systems of visualization come to play. Users are likely to be familiar with common forms of visualizing data and to reduce friction of use within the application, familiarity should be seen as desirable. Different visualization systems were explored in order to collect a set of variables that can be seen as common to represent data, grounding Beyond Shape in the mainstream field of data visualization, in order to move beyond it.

In *Semiology of Graphics*, Bertin pioneers a set of visual variables he calls retinal variables that can be used to represent data in two-dimensional visualization.[71]

This influential first wave formalization of visual variables has since been assessed in the context of computerized data visualization by Sheelagh Carpendale with identified modifications or additions to consider regarding the specifics of digital displays and opportunities of 3D.[72]

In the portion about aesthetics in *Grammar of Graphics* Wilkinson also builds on the set established by Bertin, defining sub-attributes to greater specificity, and adding some attributes discussed by other academics, but generally follows along the same lines as originally presented by Bertin.[73]

Colin Ware, in his work *Information Visualization: Perception for Design* goes further in his search for a combination of vision science and visualization, tapping into research of preattentive processing for selection of visual attributes.[74] He uses a variation of these attributes as the basis for exploring the creation of glyph-based encoding of data, which is similar

71 Bertin, 1983, pp. 60–61
72 Carpendale, 2003, pp. 6–20
73 Wilkinson, 2005, pp. 274–292
74 Ware, 2004, pp. 151–152

to what the Beyond Shape system functionally does[75].

Cheryl Akner-Koler devotes a paper to three-dimensional visual analysis in sculpture. In this paper, she assesses and explains a multitude of attributes usable in visual analysis of three-dimensional objects from an aesthetics-oriented point of view, which is often not the main focus of the more computer science-oriented views presented. As Akner-Koler's listing of attributes and features is very thorough, I've omitted displaying some of the sub-attributes in the list below in order to focus on the top-level ones.[76]

Throughout the explored sets of visual variables, there are clear commonalities. Akner-Koler's definitions as listed here appear most thorough, but this might simply be due to the fact that she does not separate between features of objects and groups of objects – the other researchers presented seemed to assess groupings and systems of objects as separate subjects within their work, not directly relating to the object quality of symbols used. This makes Akner-Koler's approach interesting, as it is clearly distinct those of the other researcher's presented, while still retaining most of the top-level attributes of shape, orientation, dimensions, just going in much deeper in detail in the analysis of their contents. The object quality – or presence – of three-dimensional shapes, seems to be able to carry quite a bit more information than two-dimensional shapes based on the expression by Akner-Koler, compared to the analysis mainly focused on 2D shapes by the other researchers. While considered a perceptually difficult form to convey details about abstract numbers in traditional data visualization[77], a 3D shape might be able to communicate more information but less accurately, which would fit the goals of the system.

For mappable visual attributes, variables common to all research were first selected: Shape, orientation and size,

75 Ware, 2004, p. 183
76 Akner-Koler, 2007
77 Koponen, Hildén, & Vapaasalo, 2016, pp. 99–100

providing materiality to the shape. Akner-Koler does not explore material as part of her visual analysis framework as it is concerned with shape, but the other researchers include some form of color and texture, which were also included. Finally, all researchers who have considered the variables on digital displays have included transparency and motion as variables, which were also chosen for consideration.

I then considered these visual variables through the technical restrictions imposed on the output. A couple of graphics programming frameworks were selected based on familiarity with said frameworks: three.js, p5js, Processing, and OpenFrameworks[78]. All frameworks support these common visual features pretty much out-of-the-box, so no selected attribute needs to be discarded due to technical impossibility. One rejection is still made through this technical analysis: Motion as an attribute not as clearly defined as the others, and animation requiring more programming work on the inspected frameworks than the other attributes, is discarded for this initial prototype phase. Ultimately, the selection is then: Shape, orientation, size, color, texture, and transparency.

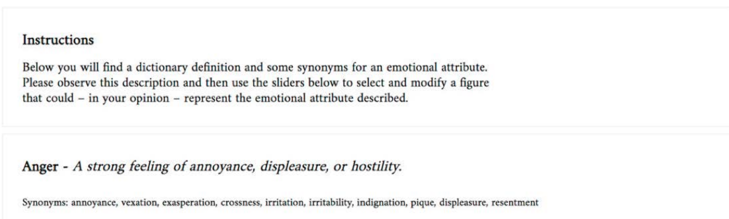


Figure 13: Instructions and emotional attribute as presented in the Mapper.

78 https://threejs.org/, https://p5js.org/, https://processing.org/ and https://openframeworks.cc/ respectively.

Table 4: Bertin's visual variables

Bertin	Attributes
	Shape
	Orientation
	Color (hue)
	Texture
	Value (brightness)
	Size

Table 5: Carpendales amendments to Bertins variables

Carpendale	Attributes
	Shape
	Perspective
	Hue
	Saturation
	Value
	Texture
	Value
	Size in three dimensions
	Depth
	Occlusion
	Transparency
	Motion

Table 6: Leland Wilkinson's visual attributes

Wilkinson	**Attributes**
	Position
	Size
	Shape
	Rotation
	Resolution
	Color (Brightness, Hue, Saturation)
	Texture (Granularity, Pattern, Orientation)
	Blur
	Transparency
	Motion
	Sound
	Text

Table 7: Colin Ware's visual attributes

Ware	Attributes
	Form (line orientation, line length line width, line collinearity, size, curvature, spatial grouping, blur, added marks, numerosity)
	Color (hue, intensity)
	Motion (flicker, direction of motion)
	Spatial Position (2d position, stereoscopic depth, convex/concave shape from shading)

Table 8: Akner-Koler's visual attributes

Akner-Koler	Attributes
	Four basic visual elements of form and space (volume, plane, line point)
	Dimensions of elements (height, width, point)
	Proportions
	3-D primary geometric forms (curved, straight)
	Axis
	Curves
	Order (dominant, subdominant, subordinate)
	Axial relationships
	Comparative relationships
	Joined forms (intersectional forms)
	Transitional forms (divide, adapt, merge, distort)
	Forces in relationships
	Evolution of form
	3-D spacial matrix
	Organizational framework
	Symmetry and asymmetry
	Balance
	Orientation (direction, position, tip)

Participatory mapping process

I then built a graphical user interface to enable participants to map an emotional attribute to the presented set of visual attributes, by presenting them an emotional attribute and having them manipulate a shape to their subjective interpretation of that emotional attribute. The emotional attribute is presented together with a short instruction of how to operate the Mapper and a dictionary definition and a list of synonyms of the attribute as visible in Figure 13 and in the Mapper application online[79].

First, the user selects the main shape. For this prototype, users are not enabled to fully manipulate the forms, but a range of shapes are provided for the user to choose from. The provided shapes are common 3D primitives – cone, cylinder, plane, toroid, and spheroid – and platonic solids – tetrahedron, cuboid, octahedron, dodecahedron, and icosahedron (see Figure 14)

Once a shape has been selected, the participant can modify the visual variables available to that shape with sliders for each. The variables are deconstructed out of the general set presented in the previous chapter to attributes that work for the particular shape: Position is broken down to rotation on the x-, y-, and z-axes, size becomes width, height, and length or a combination of those with radius or scale where applicable. Color is broken down into hue and lightness, with value kept static to keep color somewhat harmonious. Texture becomes gloss, as this was a simple attribute to implement technically to give a sense of control of the roughness or "grain" of the object as Bertin originally called it. Finally, transparency is controlled by an opacity attribute. Once the participant has completed the set of mappings, the result will be stored with appropriate user metadata, in order to allow further classification of the data. Partially filled sets are

79 https://shape-mapper.now.sh/

continuously saved in order to minimize data loss, but these are separable from those filled to completion for the dataset provided to the Interpreter. The output is a dataset of emotional variables mapped to a set of visual variables.

As the aim is to explore the methods utilized in machine learning, the method of participation is similar to one that could be imagined to be used in any machine learning dataset gathering process, as described for instance in Callison-Burchs' and Dredze's process for creating speech and language datasets[80]: Utilizing the micro-work platform provided by Amazon, Mechanical Turk. Mechanical Turk – and other similar crowdsourcing platforms such as Crowdflower – have quickly become an essential part of not only machine learning processes, but the processes of quantification in science. Their popularity in the research community has risen to the extent that it has been called a "Golden age for survey research" in the JSTOR blog[81]. While mired by ethical and social concerns about the low-pay and exploitational dynamic between workers and employers in the service, there is an undoubted rise of utilizing Mechanical Turk as an underlying platform which provides us the human understanding that is relied upon in research. For instance, tracked the utilization of Mechanical Turk as a research method in psychological research. By observing empirical papers published in *Journal of Personality and Social Psychology and Personality*, *Social Psychology Bulletin* and *Psychological Science* they saw a rise from under 10% in all journals to near 45%, over 40% and almost 20% respectively of papers published mentioning the platform as a resource between 2012 and 2015.[82]

For Mechanical Turk the Mapper needs to be broken down into what is called Human Intelligence Tasks, or HITs on the platform. A HIT is any task you want a worker to perform and is the completion of a HIT is the basis of payment for the

80 Callison-Burch & Dredze, 2010, pp. 1–5
81 Samuel, 2018
82 Zhou & Fisbach, 2016, p. 2

worker, paid when the employer – or requester in Mechanical Turk language – accepts the result of the HIT. The simplest way to break down the Mapper into HITs, is to present each emotional variable as a single task. A single variable Mapper HIT is thus created for each emotional variable through the Mechanical Turk interface, which allows an external interface to be embedded for use within the Mechanical Turk system, as pictured in *Figure 15*.

After first running a test of the survey outside the Mechanical Turk -platform, it was then embedded as an outside source within the platform interface. As the survey was embedded, a dual confirmation system was employed, where the worker would first indicate they finished the task by confirming their answer, before clicking the Submit-button provided by the platform which marks the task done (see Figure 16). In this way, some of the surveys that were likely not filled completely can be discriminated when processing the data.

The Turk workers were also provided a feedback field, to leave their comments about the HIT. Perhaps surprisingly, quite a few of the workers left feedback, although the field was optional. Some explained their reasoning for their selection, some just commenting that they felt the survey was either good or weird or offering constructive criticism and some reporting bugs they experienced with the survey. A selection of unedited feedback from the Turk workers is presented in Figure 17.

An initial test run of 10 HITs per emotion was run to test both the Mapper and the Mechanical Turk platform for running it. As this testing round provided no feedback about breaking bugs, the HITs were increased to 100 per emotional attribute and ran again, resulting in a total of 990 initial answers sourced from Mechanical Turk, out of which 850 were marked completed. While relatively small, this dataset functions as ground truth data for training a prediction model for shape attributes but is expanded upon whenever anyone fills the mapper survey, which is also available publicly outside the Mechanical Turk -platform for anyone with the link[83]. All the source code for the application is also publicly available in its own repository on GitHub[84].

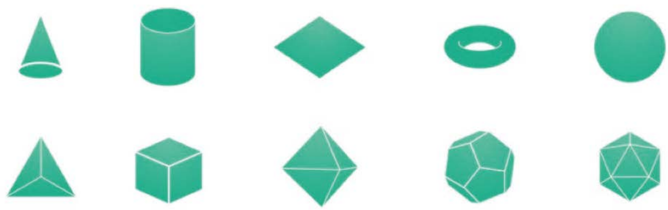


Figure 14: Shapes available for user selection in the Mapper

83 https://shape-mapper.now.sh/
84 https://github.com/KODHAGe/shape-mapper

Figure 15: A single attribute HIT embedded in the Mechanical Turk platform

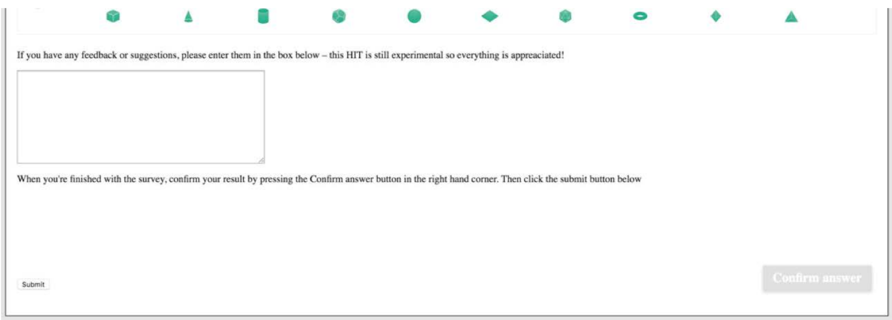


Figure 16: The double-confirmation system

Very strange survey

To me selecting a shape and maybe color to the emotion makes complete sense, but building the shape height, x and y rotation, etc makes no sense at all.

DIFFERENT - STRANGE....IN A GOOD WAY! :)

You can ask for other feelings!

good

COMPLICATED

good

GOOD

GOOD

GOOD

GOOD

it could be good if the different faces of the polihedron could have different colors

This shape has an "empty" middle which could indicate sadness.

THESE EXPERIMENTS ARE FUN!

You can list all the emotional attributes in only one HIT.

Not sure the shape matches the one described on slider. Would prefer a shape with a hexagonal frontal aspect.

Fun! Would love to do more of these.

The Borg!

NOTHING

EXCELLENT

Figure 17: Feedback received through the Mechanical Turk -platform

Interpreter

The Interpreter is the part of the application within which the decoded input from the Decoder is used to determine a set of encoded outputs by utilizing data from the Mapper. It utilizes the dataset from the Mapper directly and is able to constantly rebuild when as the dataset changes, always redefining the deterministic model of interpretation it produces.

Pre-processing

Pre-processing is the retrieving, filtering and sorting of a dataset to provide a so-called clean version for that fits into whatever system used for further processing. Cleaning data in this context means removing partially filled data and handling cases of outliers. The Mapper provides a field which notes whether or not the user clicked the confirm-button, which is used as the first step of processing to eliminate those rows not deemed complete by their creator. This enables for instance easy elimination of test data that might have been accumulated in the dataset from previewing and moving around sliders within the Mapper, as well as the elimination of data by Mechanical Turk users who might not have read the instructions clearly or simply clicked the submit-button to claim the payment of the task. The second step is to handle outliers. As this is a very small dataset on a very subjective topic, this is very much massaging the dataset into a better fit, which should be addressed by gathering a larger dataset for any true production version. As the end result is a reduction of opinions presented in the dataset, this is a way of strengthening the view of the majority of answers and artificially creating stronger correlations – which can help mask the quality of the dataset itself. Medians are calculated for each visual attribute per each emotional at-

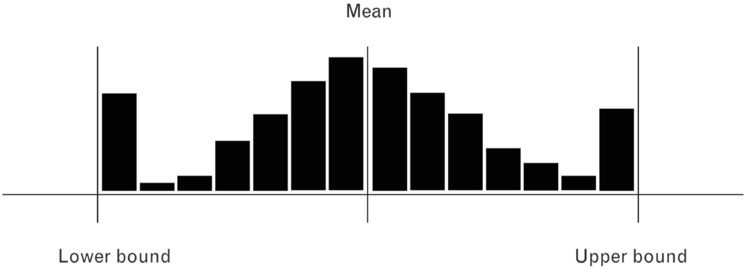


Figure 18: The dataset after clamping

tribute, and then a standard deviation calculation is used to determine how much of the data will be seen as outliers. The rows with outliers could then be entirely removed, but as the dataset provided by the Mapper is so small, and each row has other data within it, the selection is made to instead clamp the outliers into a maximum and minimum range of values determined by a bound multiplier to the standard deviation calculation in the pre-processing stage. This means a standard deviation multiplied with the bound multiplier will be used to determine a maximum and minimum value for every value in the dataset per emotional attribute. Any values lower or higher than the bound will then be considered as equal to the maximum or minimum value, essentially clamping the dataset (see Figure 18). This reduces variance in the resulting dataset and highlights differences between emotional attributes if there are any.

Modeling

As a part of the concept of the Machine as a black box, a neural network type model is selected for building the statistical model that provides interpretations. In a neural net algorithm, layers of computational neurons are fired off on a base set of data, inspired by the function of neurons in a brain. Multiple layers of these neurons are interconnected sequentially, with each connection being assigned a weight. These weights determine the relationship between the output and the input of a net, and modeling such a network is essentially manipulating the weights based on input data until a suitable output is found (see Figure 19)[85].

The model is effectively trying to automatically form a function between inputs x and outputs y, f(x) = y where f() is a complex function produced by the neural network. Through this function, the system is able to map selected arbitrary inputs to selected arbitrary outputs, with the performance determined by whether the relationship between the two was viable to represent through a function in the first place. Understanding of the input and output data helps and the importance of is something that is highlighted as a necessity for creating a successful model by professionals in the field[86]. But such understanding is not at all necessary for building a functional model.

A multi-layer perceptron -type neural net is built in tensorflow.js by following a tutorial for tensorflow.js[87], a version of the Google built, Python based Tensorflow machine learning framework built for JavaScript. As its inputs, the network takes emotion-answers from the mapper, where each emotion is dummy variable encoded – the emotion selected for that particular answer is encoded as true and all other emo-

85 Nielsen, 2015
86 For instance, see Peter Wardens blog (Warden, 2018).
87 Originally a model for predicting baseball pitches (Kreeger, 2019).

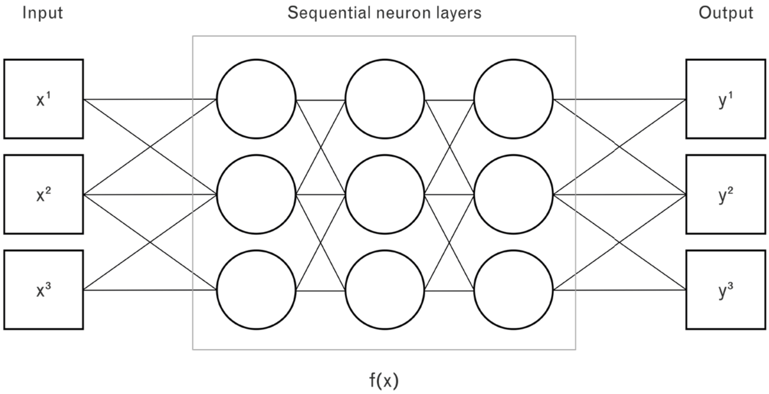


Figure 19: Conceptual model of a neural network.

tions as false. Outputs are mapped to the visual attributes of the mapper. As optimization of the network model, settings and data pre-processing is an iterative process of running the network to analyze output, a simple output visualizer is built to iteratively explore what the output of the network looks like in different stages of the process. Initial tests were run with a single shape, a cuboid, and a single emotional attribute, Anger, with varying amounts of training iterations (see Figure 20).

When a satisfactorily visually specific form of Anger was formed, and the network seems to start converging to a visually similar form of anger even if training iterations are increased, Sadness and the combination of Anger and Sadness were added to the visualized output. Soon after that also the calculation of shape was implemented in the model. Looking at the results, as presented in Figure 21, shape selection seems to be quite volatile for specific emotions even on a high level of iterations, but usually sticks to shifting between a few shapes. As the shapes function as categories with no visual interpolation available between them, this is an understandable result. When color, orientation and size seem to stabilize in the visual representations it can be determined that the learning process has concluded for that particular version of the Interpreter. The tensorflow.js -platform is very flexible and has many so-called hyperparameter[88] optimizations that can be applied. Testing version 30 of the model was split into a release version 1 and published on GitHub[89], where all hyperparameters, preprocessing settings and other configuration is available for viewing.

88 A parameter that is set before the learning process begins https://towardsdatascience.com/what-are-hyperparameters-and-how-to-tune-the-hyperparameters-in-a-deep-neural-network-d0604917584a.

89 https://github.com/KODHAGe/shape-interpreter.

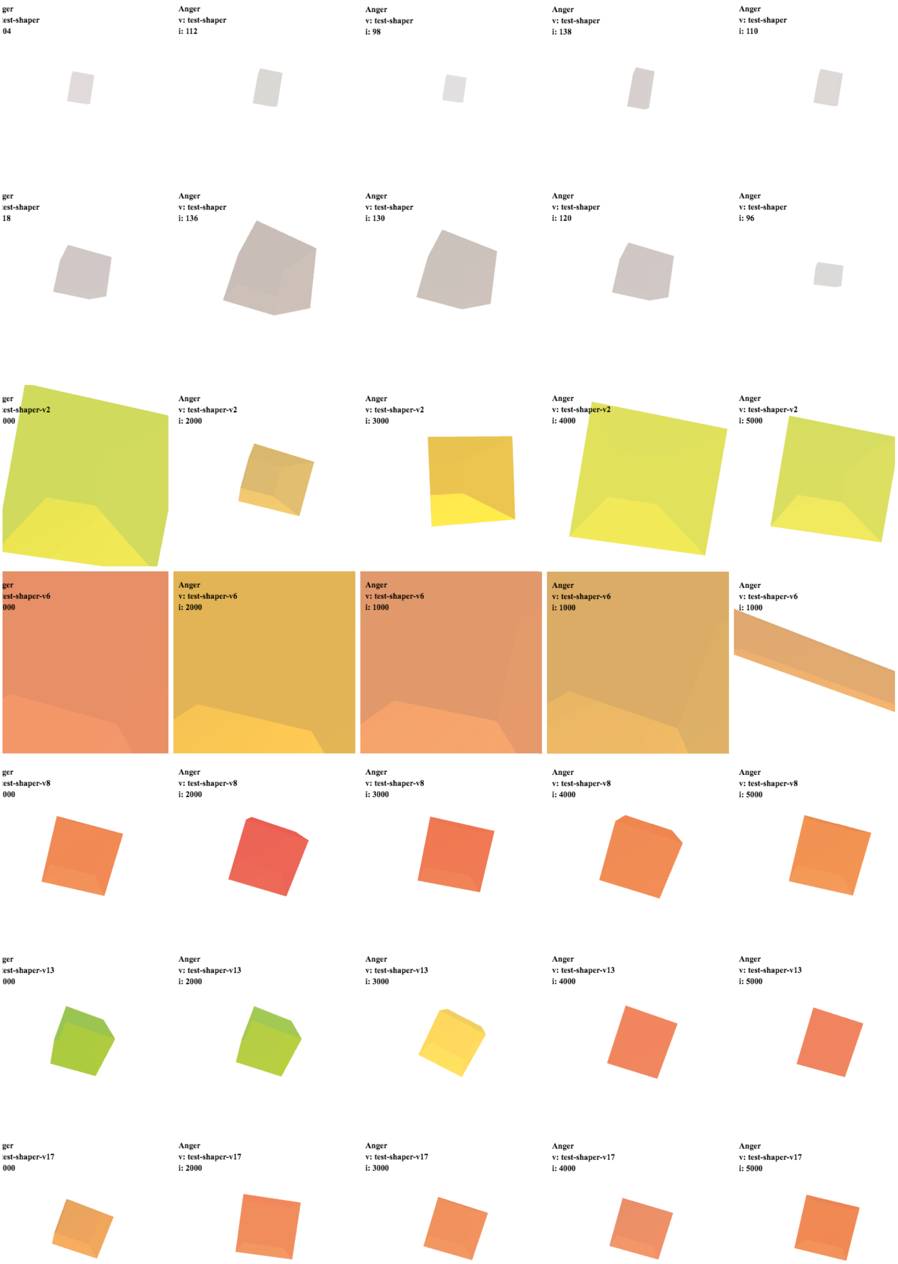


Figure 20: Variations of initial output of the Interpreter

Figure 21: Sadness, Anger and Sad & Angry in Interpreter iteration 30

Constructor

The Constructor builds visual representations of the determined by the parameters of the Interpreter. It produces three-dimensional shapes viewable in a web browser, based on text input which in this prototype version is entered into a Consumer component within the constructor, that then sets in motion the Decode, Interpret, Construct -process, that provides the final image.

Visual exploration

The visual component of the Constructor is the first part of the application that was developed as a concept, while not yet sure what its end goal or aim would be, as the illustration of a poem on the back page of a notebook (see Figure 22). Ultimately it evolved through the process of research and development to become something completely different than what originally suspected, but still providing a core of inspiration for the thesis topic and visual concept. The original sketch is that of a jagged sculpturesque uncut gemstone, with each facet thought to present some aspect of the data that would provide its structure when turned into a digital form. Here the three-dimensional gemstone form would provide ambiguity in the information presented, in this way challenging its reader to interpret more into and out of the image, the concept being this would become a slightly user-unfriendly but still to some extent legible representation of data. The embodiment of the data into a form that reminds of the physical could give the data a different presence than a traditional visualization, numbers giving way for meaning, but with the shapes still being learnable and discernable from each other providing some readability, binding the visual concept strongly to the critical design approach proposed.

This approach was then pursued by some research into

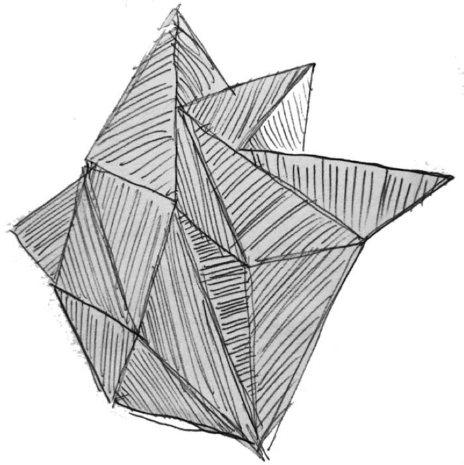


Figure 22: First drawn image of what would become the Constructor

crystalline forms both as visual inspiration and to determine whether such forms would be technically feasible to produce for the prototype version of the visualization. Pentti Eskola elaborates on the formation and structure of crystals in his popular science book from the 1940's, Atomit ja Kiteet. He describes how crystalline structures are formed through combinations of smaller particles that are aligned into regular forms, and those regular forms growing into and out of other such regular forms. He describes the processes and structures through simple illustrations of different crystal forms and structures, that form a starting point for visual exploration of structures formed out of more simple geometric shapes (Figure 23, 24 and 25).[90]

An approach of exploring how crystalline structures function mathematically is considered but ultimately discarded due to the complexity of producing a visualization that would accurately follow the formation of crystalline struc-

90 One of the more precious thrift-store finds throughout the process of this thesis (Eskola, 1948).

tures. But further exploration of crystalline structure formation for a more elaborate placement functionality in the Constructor could prove useful for future development.

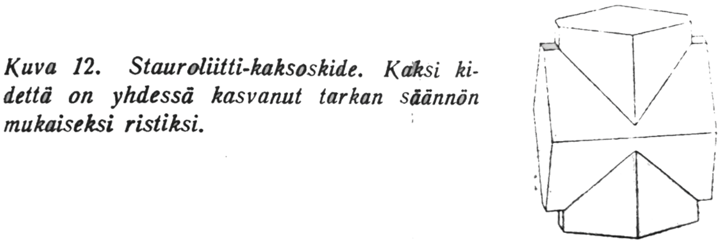


Figure 23: Picture of a staurolite crystal[91]

Figure 24: Image of a group of baryte crystals[92]

91 Eskola, 1948, p. 19
92 Eskola, 1948, p. 27

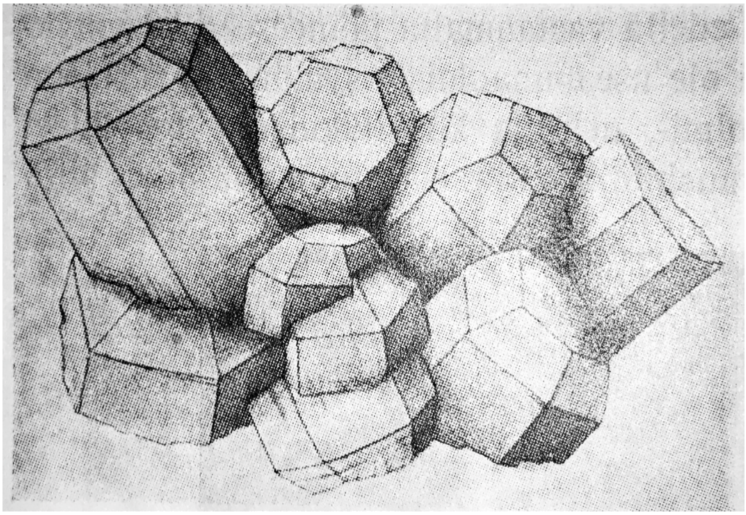


Figure 25: A group of apatite crystals[93]

Markus Rissanen examines the forms, their incidence and representational attributes in visual culture, binding them to the concept of basic forms: The square, circle, and triangle. Rissanen divides forms into two modes, perceptual and conceptual. The perceptual forms are those attempting and succeeding to mimic patterns that occur in nature – how nature looks to the eye – while conceptual forms are human interpreted abstractions of such forms – how nature works under the hood. He explores how the basic forms, while conceptual as such, can be used to form complex structures and patterns that present imagined perceptual forms, sometimes even inspiring new scientific findings of such forms, such as Penrose tiling preceding the finding of quasicrystals in nature.[94]

Rissanen's research inspires to take things back a from modeling crystalline structures as such, but to rather consider what they are – collections of three-dimensional basic

93 Eskola, 1948, p. 30
94 Especially chapters 5 and 6 (Rissanen, 2017, pp. 105–149).

shapes that collectively form structures which appear as crystalline, as visible also from the images in Eskola's work. A separation into modeling separate shapes, not an entire structure simplifies the technical aspect of data mapping – instead of mapping data into a complex mesh, each piece of data can be mapped into a separate shape, while the entirety will still hold all complexity by combining these shapes into a whole, a concept of which can be seen in Figure 26.

Figure 26: A sketchbook drawing of potential Constructor output

Prototype

The prototype was built using Aframe[95], a virtual reality ready 3D-framework for web browsers. The selection was made in part due to existing capabilities cutting down development time, as well as an interest to try out augmented reality features to give the visualized shapes a further embodied feeling. Ultimately the AR-features of Aframe, while available through experimental WebXR[96] features or an external library, are currently in a very raw state as the focus has been on VR-features. But as the WebXR standard matures, and support moves to that standard, AR-features will hopefully improve.

The functionality of the Constructor-prototype is rather simple compared to the Decoder and Interpreter: It is a presentation layer for Interpreter output data. The visual encoding comes out of the Interpreter and can be used pretty much as is to create a shape that corresponds to that encoding. These shapes are then placed in the scene in a chronological order, where the emotional closeness of adjacent shapes is taken into account by placing emotionally similar objects closer or even overlapping each other (see Figure 27). A user can input media through the consumer-component, which will automatically trigger the entire machine cycle, presenting the user with a constructed object of the media they input.
The source code for the Constructor is available in its own repository on GitHub[97] and the prototype application is accessible online[98].

95 https://aframe.io/
96 A W3 standard to replace WebVR that provides better support for all immersive realities.
97 https://github.com/KODHAGe/shape-constructor
98 https://shape-constructor.now.sh

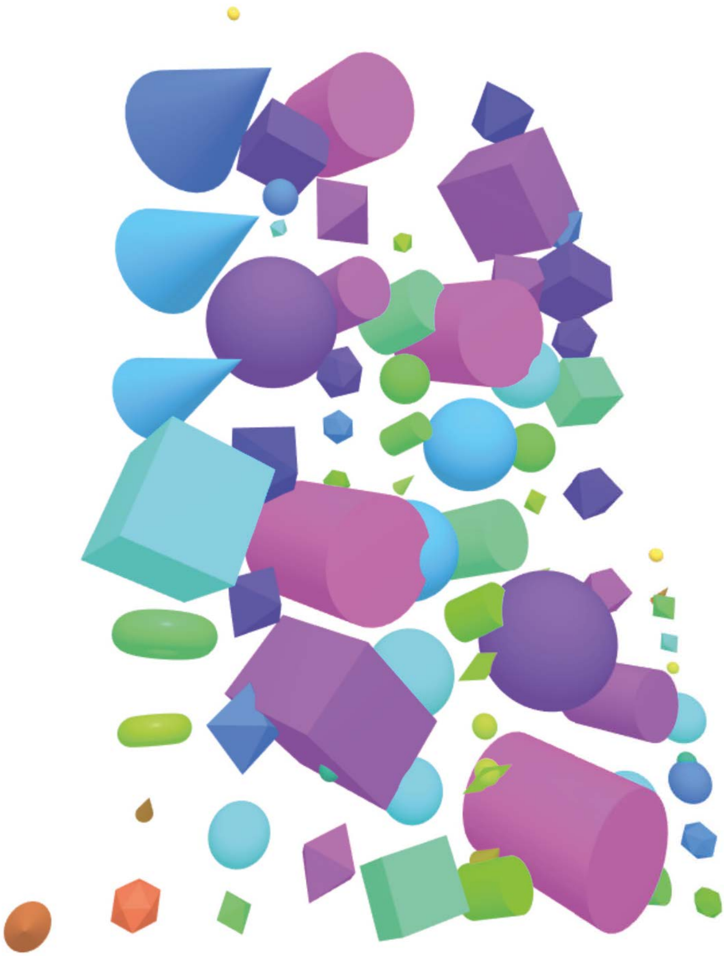


Figure 27: A matrix of emotion attributes and interpolations between them directly from the Constructor.

Renderer

The Renderer concludes the visualization process through a finishing step producing visual representations through simulation of physical materials and light. This is included as a part of the prototype while not an integral part of the machine, as it is a manual step to polish visualizations produced by the Constructor for viewing. The renders are produced out of GLTF[99] exports from the Constructor imported into Blender (see Figure 28 and 29)[100]. The Blender imported figure retains the visual attributes of the Constructor model but allows for more complex illumination and perspective control, through which better images of the scenes can be constructed, improving the material quality of the visualizations. The blender scenes and rendered images are available for viewing and download via GitHub[101].

Figure 28: First rendered test shape-structure

99 GL Transmission Format
100 3D-graphics software, https://en.blender.org/
101 https://github.com/KODHAGe/shape-renders

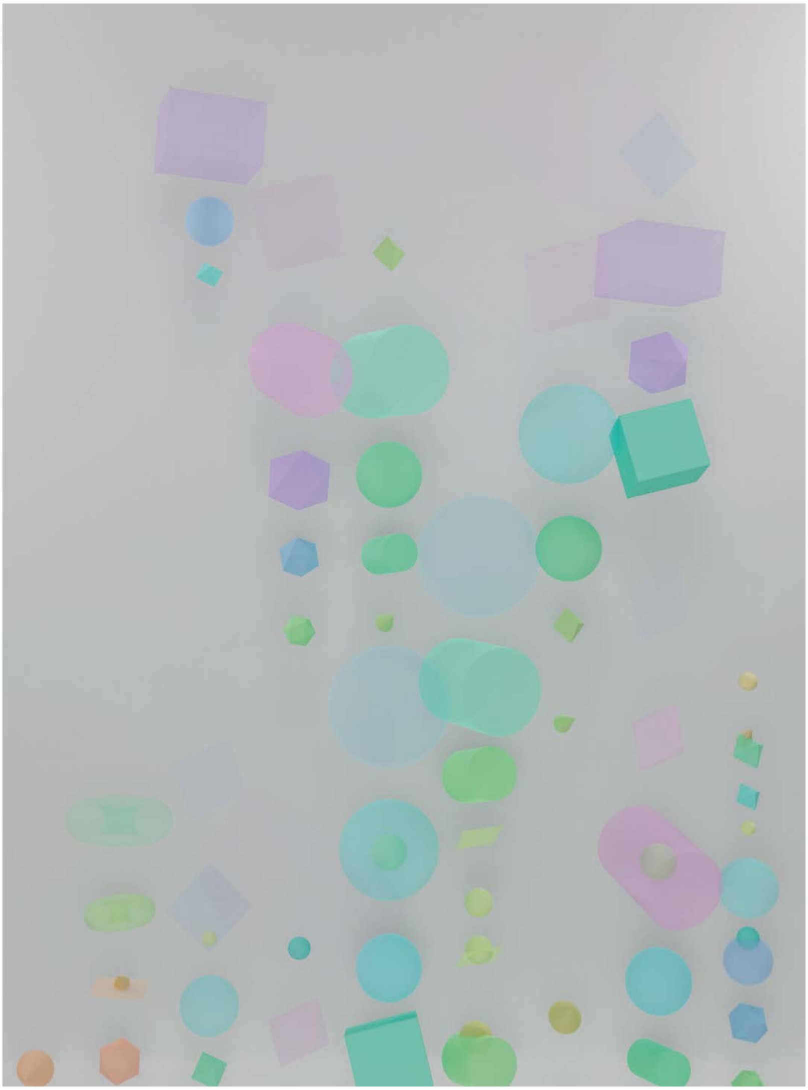


Figure 29: A rendered image of a matrix of all feelings and combinations.

Evaluation

A human assessment of the produced renders was organized to help evaluate the end-result. While the system itself ending at the Constructor is dynamic and not dependent on the input, the ultimate renders are based on a set of pre-determined content processed through the Renderer (see Figures 30, 31 and 32) The input content for the user validation was a selection of seven short pieces of text selected a from larger set of sources that have been interesting to me throughout my studies at the Media Lab, to bind this thesis back to its roots in a sense. The sources were picked to represent multiple textual types: fiction, non-fiction,n

and poetry, with an expectation that these texts would exceed in expressive complexity most common use cases for machine-based language assessment, like social media crawling. The selected texts were not used to test the system during development, to avoid over-optimization for specific texts and to give a view of how the system functions for arbitrary content.

Implementation

A subset of three visualizations and texts was selected from all the rendered sets[102]. Initial tests were held as in-person interviews. Participants were given a form[103] to assess the three visualizations (Figures 30, 31 and 32) grading them on a scale of 0–10 for each of the emotional attributes used in the prototype, with a separate certainty value for each. This

102 In the very first test seven images and texts were used instead of three, but the total amount of selected images and texts was determined to be too heavy to complete in a single interview session. The number of images and texts were then cut down to a selection of three for the next tests, based on which text-image-pairs were considered most ‘interesting’ and gathered most feedback in the open-ended question in the initial interview.

103 Appendix 1, includes all original seven images rendered

is complemented by an open-ended question that allows testers to elaborate on how they read a particular visualization. After assessing the visualizations, each participant makes a similar assessment of the three source texts[104].

Beyond the initial interviews, the selected three images and texts were then assessed further with the same method, combining in-person and online interviews with unsupervised surveys on Google Forms, to gather a total of almost 40 responses from 12-13 people per image/text pair, participants chosen through a convenience sampling method. This produced a limited dataset with three interpretations on the same subject: The emotional attributes that the Decoder detects in the text, a human interpretation of the text and a human interpretation of the visualization. These were then compared to provide insight into how the interpretations change from phase to phase.

104 See Appendix 2 which includes all original seven texts, or the texts accompanying Figures 30, 31 and 32 for the selected three.

Figure 30: Render for Invisible Cities

"Travellers return from the city of Zirma with distinct memories: a blind black man shouting in the crowd, a lunatic teetering on a skyscraper's cornice, a girl walking with a puma on a leash. Actually many of the blind men who tap their canes on Zirma's cobblestones are black; in every skyscraper there is someone going mad; all lunatics spend hours on cornices; there is no puma that some girl does not raise, as a whim. The city is redundant: it repeats itself so that something will stick in the mind. I too am returning from Zirma: my memory includes dirigibles flying in all directions, at window level; streets of shops where tattoos are drawn on sailors' skin; underground trains crammed with obese women suffering from the humidity. My travelling companions, on the other hand, swear they saw only one dirigible hovering among the city's spires, only one tattoo artist arranging needles and inks and pierced patterns on his bench, only one fat woman fanning herself on a train's platform. Memory is redundant: it repeats signs so that the city can begin to exist." [105]

105 Cities & Signs 2 (Calvino, 1974, p. 19)

"I really have discovered something at last.

Through watching so much at night, when it changes so, I have finally found out.

The front pattern does move—and no wonder! The woman behind shakes it!

Sometimes I think there are a great many women behind, and sometimes only one, and she crawls around fast, and her crawling shakes it all over.

Then in the very bright spots she keeps still, and in the very shady spots she just takes hold of the bars and shakes them hard.

And she is all the time trying to climb through. But nobody could climb through that pattern—it strangles so; I think that is why it has so many heads.

They get through, and then the pattern strangles them off and turns them upside-down, and makes their eyes white!

If those heads were covered or taken off it would not be half so bad." [106]

106 Passage on page 33 of the Project Gutenberg edition without images (Perkins Gillman, 2008).

Figure 31: Render for The Yellow Wallpaper

“Humans like jewels.
Each facet an outward
facing fragment of a
haphazardly constructed
whole.

You are a sum of
parts, but also each
part. And no one
will ever know
your shape.

Feel it for
a second maybe,
know some particular
nook or peak
like their own
back pocket, sure.

But only you have
a chance of ever
realizing where your
lowest valleys and highest tops
lie.

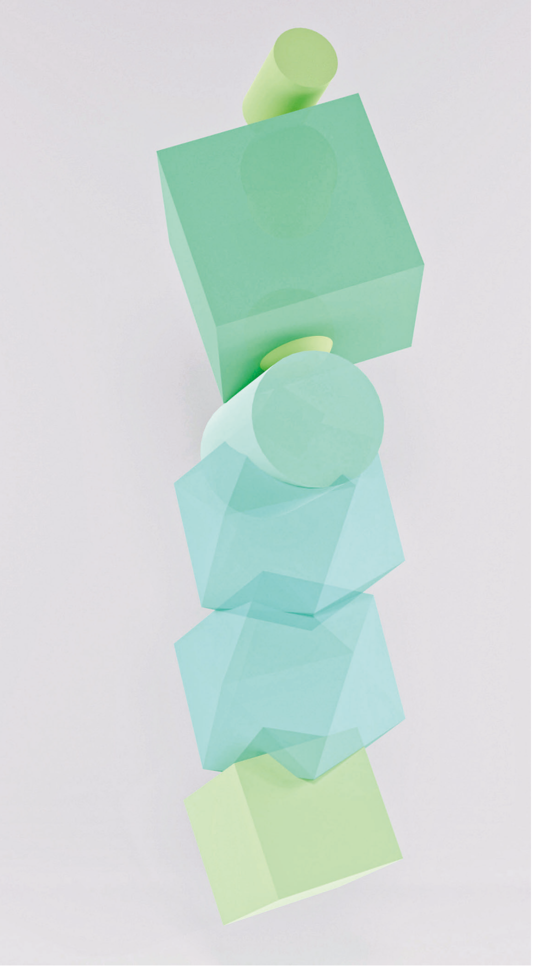


Figure 32: Render for Shard

You split and you splinter, creating new facets, splitting old ones.
Your shape is constantly changing, evolving, devolving.
Bring detail into things by breaking them apart.
Become more. Deep, interesting, wise, experienced. Most of us don't have big clean surfaces.”[107]

107 Original content for this thesis project

Results

As the dataset gathered is very limited and the interviewees were gathered on a convenience basis, no conclusive validation is attempted to be made through this survey, but it should be seen as a pilot test through which the next iteration of development for both system and test could be developed, should development continue. This is a quick overview of the results; the full set of data is available at the time of publication of this thesis in a publicly viewable Google Sheet[108].

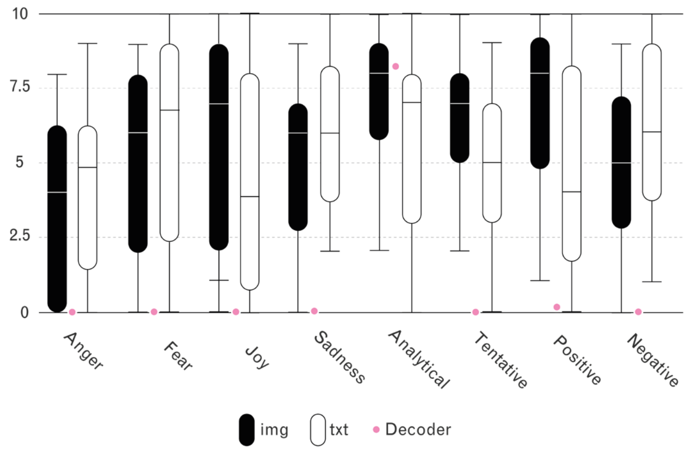


Figure 33: Box plots of the Invisible Cities -passage, n=13

108 The dataset is split into separate tabs for general overview and correlation calculation, survey answers per text/image pair and both form-collected and transcribed (but not translated) open answer comments at https://docs.google.com/spreadsheets/d/1UlU8FusRi5bfE7SJdtP1ioahJX4xitJI6oLtumbFVQw/edit?usp=sharing

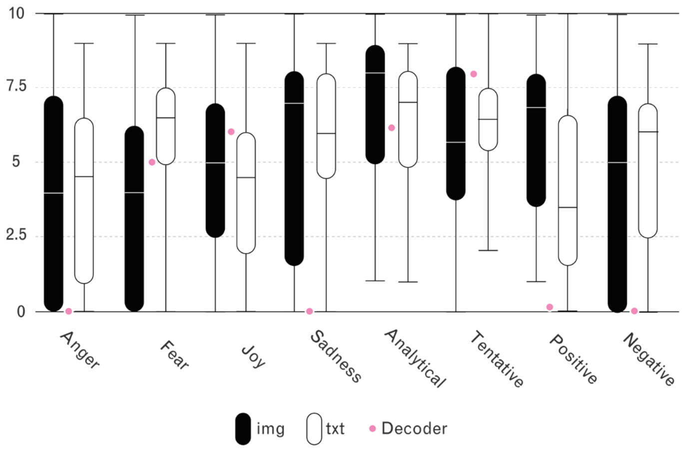


Figure 34: Box plots of The Yellow Wallpaper, n=12

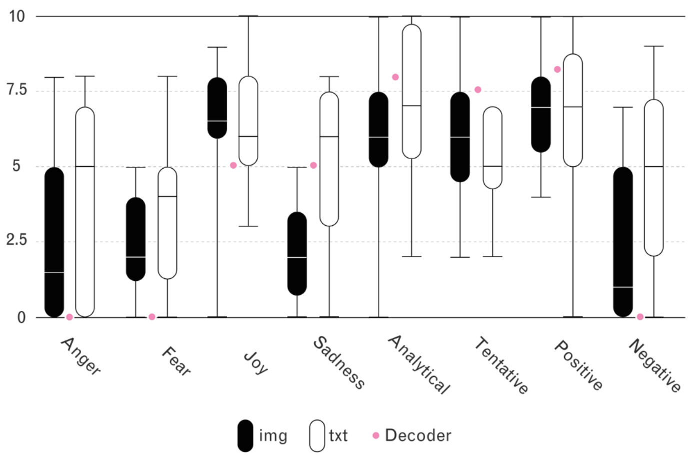


Figure 35: Box plots of Shard, n=13

Through the data gathered from the user tests, I pose three questions to provide views on what kind of effect the *Beyond Shape* visualization might have:

Is there a difference between how humans interpreted the text compared to the interpretation of the Decoder? How valid are the machine interpretations of the text*?*

Juxtaposing the human interpretations of both text to that of the Decoder, there are differences as expected. Human interpretation is wider and fuzzier than that returned by the Decoder, with more variance in answers. The Decoder much more readily returns zeros in different categories, while humans are more cautious in their assessment overall. The most extreme case can be seen in the case of *Invisible Cities* (IC, Figure 33), where the Decoder picked a single attribute over all others, reducing the entire passage to a value of Analytical, while human interpretation is much more varied. In *The Yellow Wallpaper* (YP, Figure 34) and *Shard* (SH, Figure 35) the Decoder output seems much more similar to that of the human assessment, with especially in the case of SH correlating strongly with the participants' assessments of the text.

Is there a difference between how humans interpreted the text and how they interpreted the visualization? Did the visualization succeed in conveying the information in the text while increasing the uncertainty of interpretations?

In the cases of YW and IC the interpretation of the text and the image do not seem to correlate. So, looking at it this way, the emotions present in the text do not seem to translate into the reading of the image. Uncertainty is certainly present, with average values for the certainty of assessment for images hovering around 5-6 out of 10 (YW 6.3, IC 5.9 and SH 5.2). These are quite close to the average uncertainty of text interpretation (YW 5.875, IC 4.55 and SH 5.23). Comparing this with a hypothetical traditional visualization of the Decoder output, where certainty in numbers would likely close in on the ceiling of 10 if visualized according to prevalent norms, the images Beyond Shape generates manage to keep an uncertainty – a requirement for interpretation – in the visualization that traditional modes might not. In the open answers similar results can be seen, where the interpretation of SH exhibits some similarity, while the others seem to not communicate. But the open answers do highlight the requirement for interpretation of the image as well. The following is a selection of quotes, some translated from Finnish and some grammatically corrected:

Shard, text:
"Optimism mixed with a very slight tinge of melancholy."
"This was very inspiring and joyful"
"Plenty of joy, tells about opportunities and malleability"
"The overwhelming emotions I feel from this come from a place of wonder and humbleness. There's a tinge of wistfulness but it's more appreciative than anything and there is little anger or fear"

Shard, image:
"the colors and shapes indicate happiness, precision, joy, and reasonableness"
"This image brings up positive feelings for me, rather than negative ones. I think it is definitely analytical due to the way the shapes fit together, and the colors are what makes it more positive. The shapes also fit together despite this not exactly being logical, which also seems positive."
"Not very happy"
"Extremely analytical"

The Yellow Wallpaper, text:
"Exhilaration mixed with fear and paranoia."

"cloud"
"The text describes more of an observation than any other emotion."
"Quite analytical"
"Temporary joy, the ability to escape only through death"

The Yellow Wallpaper, image:
"Energetic shape(s) with lots of action. Maybe a bit malicious."
"The pastel, light color palette made this image less associated with significant negative emotions however its apparent toppling over and instability added to some apprehension and concern."
"I had an overall positive feeling from this photo"
"Being geometric is being analytical"

Invisible Cities, text:
"The writer is a passive perceiver, who attempts to keep their feelings at bay. The text transmits a restrained melancholy"
"Everything about this text was off-putting and made me very fearful"
"I think based on the paragraph that it is more on the negative side and it doesn't have a lot of sense in the way that it is presented. This is a non-fiction story that isn't really cohesive, so I rated it accordingly."
"A sad rat race, that runs in its own depressing way"

Invisible Cities, image:
"A neutral, slightly alert and defensive shape."
"This figure shows me no emotion that is of anger or negativity when I see it I feel pleasant and safe."
"This was a rather benign image that was soothing rather than causing consternation."
"This looks like a tree or flower and makes me happy"
"Telekinetic donut"

Is there a difference between how humans interpreted the visualization and how the Decoder interpreted the text?

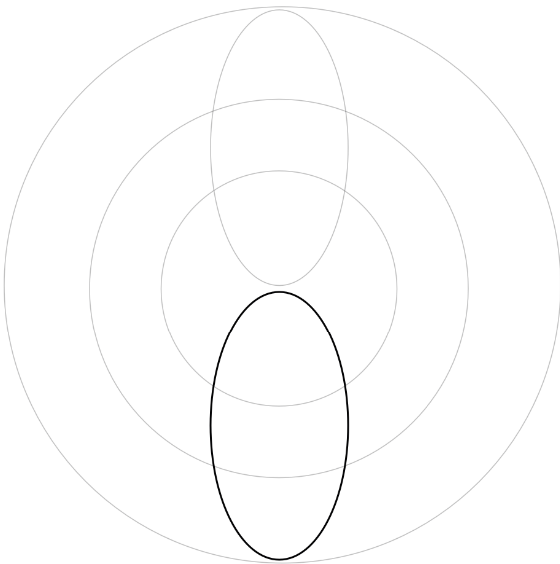
Did the visualizations add uncertainty and variance to the human interpretation, compared to simply reading the direct quantification, while still being valid visualizations of that data?

As discussed in the previous answer, the addition of uncertainty and variance in interpretation compared to directly viewing Decoder output definitely seems successful. Whether the images are capable of transmitting any data seems less likely – that is, they seem to not be able to function as pragmatic visualizations. The SH interpretations of the text, the image and by the Decoder seemed to correlate at a high rate, but as neither of the other two pairs does, it seems likely to be a coincidence rather than a particular feature of the text/image pair.

Overall, the results of the survey seem to point to that the visualizations do not communicate the numeric data particularly well – the interpretation of the images does not correspond with the interpretation of the Decoder. The interpretation of the images also does not particularly follow the interpretation of the texts, so it is not able to create connections between the text and the image – the generated image being reliant on the output of the Decoder, which does not particularly correspond with the interpretation of the text. The interesting outlier is SH, where all three interpretations – Decoder of the text, humans of the text and humans of the image – seem to correlate (Figure 35). To determine whether this is just a coincidence would require further testing and testing on different texts.

Conclusions

The end and a loop back to the beginning.
Assessment of success and effect,
with identified avenues for further research.



Conclusion

I assess the end result of the visualization process by reflecting it against the research question:

How can we design and produce an experimental data visualization that is able to undo oversimplification of data about complex subjects?

I approached the research question through concepts of a critical design model, in an attempt to apply these to explorative visualization design. By exploring the current state of the field, the concept of what could be considered as experimental within data visualization was mapped, determining it for the scope of this thesis. Experimental or alternative forms can through this be defined as visualizations that pursue a more sublime take on visual representation, with a reduced emphasis on clarity of communication compared to the forms prevalent in the field. By then exploring the world surrounding the field, I identified a topic to research through exploratory visualization – the issue of an ever-increasing amount of information about the world that we need to process. I examine artificial intelligence and machine learning methods as a proposed emerging solution to this problem, where the amount of reduction applied to data and the complexity of the process is problematic. As a specific example of a problematic case, I applied this exploratory visualization to the field of machine interpretation of human emotions in text, as this is a specific case with clear issues that at the very least corresponds to the concept of a 'complex subject' as presented in the research question.

I then applied this research into forming a more actionable variation of the research question:

Design a visualization system, that is able to expand the human interpretation of machine detected emotion data through the utilization of machine learning methods.

I approached this brief by iteratively designing and programming the Beyond Shape -system prototype. Beyond Shape takes text input and parses it into emotion attributes by means of popular machine intelligence services, but instead of attempting to directly visualize the data as is, it applies a set of tactics informed by both the critical design approach defined in the Premise and Process -chapter, as well as the definition of exploratory as it is approached in the Context and Position -chapter. The system uses a participatory process for transcoding the extracted emotional attributes from a text into visual attributes identified through researched conventions presented in the Mapper -section. This participatory process informs a machine learning system that builds a mapping between emotion attributes and what is essentially arbitrary shapes. This application of an additional, autonomous interpretational layer to traditional visualization process-models makes Beyond Shape exploratory in its process, although similar mappings of data to seemingly arbitrary shapes exist in mainstream data visualization109. As this process adds layers of interpretation between the data and its visualization, it also fulfills the ideals of what is defined as alternative visualizations in *Alternative approaches and Critique toward the waves* -section as well as some of the proposed critical design methods applied by working against the reductionist ideal present in mainstream visualization, to create less user-friendly and more ambiguous artefacts through the obfuscation of data. Visually I aimed to then produce something not easily readable – as would be the ideal in usual data visualization practice – that would force the reader to interpret the data which would expand the breadth of possible interpretations.

In order to assess the success of these ideas, and to form a base for further development, a small sample user

109 See for instance Ware's explorations on glyphs (Ware, 2004, pp. 176–186), Chernoff's faces (Chernoff, 1973), Fuchs et al. on Leaf glyphs (Fuchs;Jäckle;Weiler;& Schreck, 2015) and others.

test was arranged. This user test provided me with some insight into how readers perceive and interpreted the end-results of the Beyond Shape prototype and the input texts. By comparing the interpretations of the texts and the visuals, I could then determine a certain uncertainty about the communicativeness of the produced work – while essentially successful in what the research question aims to explore: The visualizations are able to generate a breadth of interpretations far wider than simply reading the data might, undoing oversimplification. But in doing so, the data itself becomes illegible and from a traditional data visualization perspective, it becomes more of a data-driven illustration than what would usually be called a data visualization. This illustration is in my view a data visualization in every technical sense, just an extremely ineffective one, communicating mainly the difficulty of interpreting emotions rather than the emotions themselves, and highlights some of the limitedness of the mainstream position and ideals of data visualization.

In this way this thesis contributes to the body of exploring possibilities in data visualization: It explores the boundaries of the norms within current practice and attempts to unearth something that might lie beyond by applying an uncommon approach – both conceptually and technologically – to the creation of data visualization.

Further research & Avenues untaken

In order for the visualization to better correspond to human interpretations of the numeric output of the Decoder, a much larger body of Mapper-pairings should be gathered. The dataset used is very limited for the purposes of machine learning and in this way very unlikely to provide satisfactory results in creating a mapping between emotional and visual attributes.

The machine learning practices applied in Beyond Shape should also be explored further, there is a large body of research into generative artificial intelligence that has not been explored at all widely enough to draw conclusions about the functionality of the concept – empirically it seems to technically work, but as the results of the limited survey show, the communicative aspect is quite poor as it currently stands.

User testing should also be done with a larger amount of different works, different types of works and longer documents. Emphasis should be placed on interviewing users over a survey questionnaire, as the interview answers seemed to provide much more interesting insight compared to the independently filled online survey. The case of SH should be tested further, to see whether the correlation between interpretations is down to chance.

Beyond conclusions and direct steps, there is a body of research that has been considered or has even inspired some of the end-result in a non-trivial way but has been excluded from this thesis due to time, narrative or relevance reasons. I have collected here a list of some of these topics, people and avenues of exploration that I wish to acknowledge as important to the subject, but that I've had to knowingly omit:

Academic research into uncertainty visualization, *Critical Fabulations* by Daniela Rosner [110], generative art and its relation to data visualization or data art, the emerging field of artificial intelligence art and artists like Gene Kogan[111] or AICAN[112], Jentery Sayers' list of things to consider *Before You Make a Thing*[113], and the entire course materials of *Prototyping Pasts + Futures*[114], the book and concept of *Datafied Society*[115], Xenographics[116] as a form of artistic visualization, the SciArt-community[117] and that brand of looking at the combination of science and art, data sculptures as an art form[118], the latest developments in combining machine learning and data visualization published by Benoît Frénay[119], *Critical Theory and Interaction Design* by Bardzell, Bardzell and Blythe[120], *Visual Complexity: Mapping Patterns of Information* by Manuel Lima[121].

110 https://mitpress.mit.edu/books/critical-fabulations
111 http://genekogan.com/
112 https://www.aican.io/
113 https://jentery.github.io/ts200v2/notes.html
114 https://jentery.github.io/ts200v2/
115 http://www.oapen.org/search?identifier=624771
116 https://xeno.graphics/
117 https://www.sciartmagazine.com/
118 http://dataphys.org/list/tag/data-sculpture/
119 https://bfrenay.wordpress.com/visualisation-and-interpretation-in-ml/
120 https://mitpress.mit.edu/books/critical-theory-and-interaction-design
121 http://www.visualcomplexity.com/vc/book/

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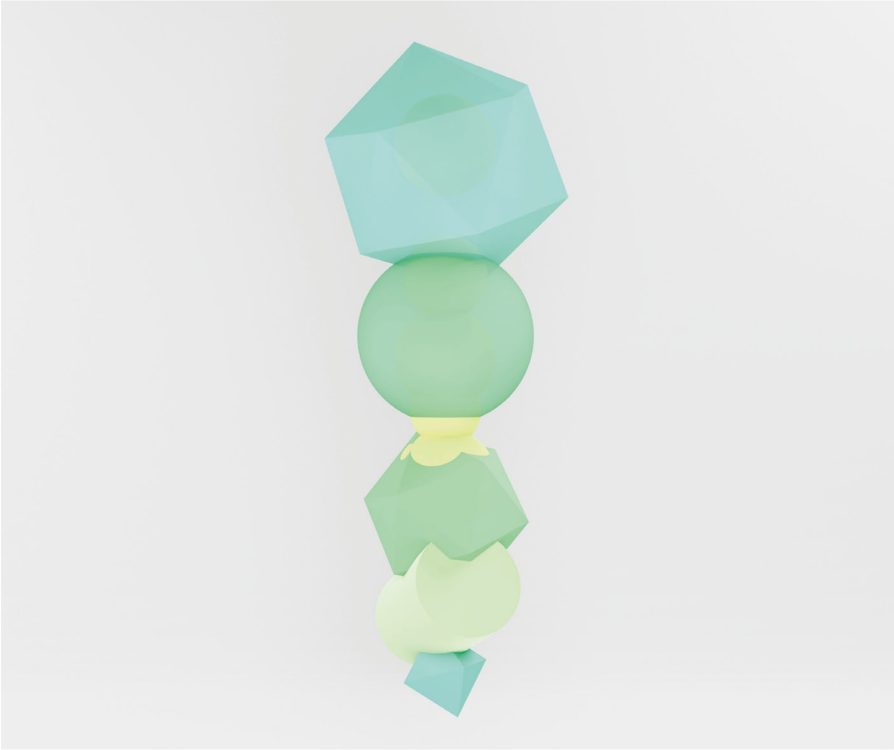
Appendix 1

Please rate presence of the following list of emotions in visualization you see,, and your certainty of that interpretation – how precise do you feel this assessment to be – on a scale of 0-10 in the table below.

Emotion	**Amount**	**Certainty**
Anger		
Fear		
Joy		
Sadness		
(being) Analytical		
Tentativeness		
Positivity		
Negativity		

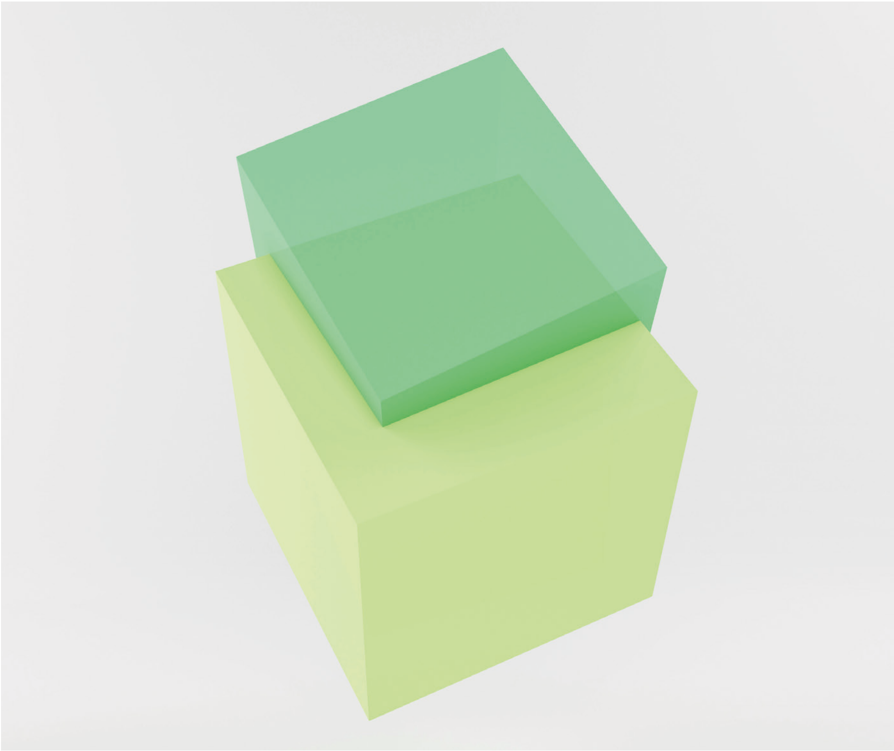
Please describe your interpretation freely; Why did you come to this assessment?



Please rate presence of the following list of emotions in visualization you see,, and your certainty of that interpretation – how precise do you feel this assessment to be – on a scale of 0-10 in the table below.

Emotion	**Amount**	**Certainty**
Anger		
Fear		
Joy		
Sadness		
(being) Analytical		
Tentativeness		
Positivity		
Negativity		

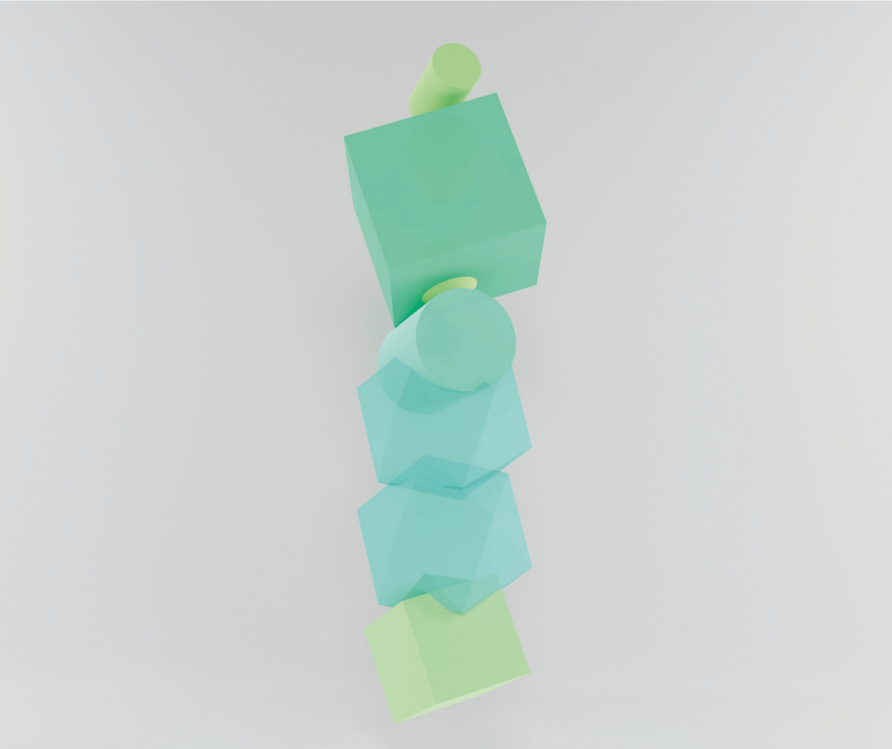
Please describe your interpretation freely; Why did you come to this assessment?



Please rate presence of the following list of emotions in visualization you see,, and your certainty of that interpretation – how precise do you feel this assessment to be – on a scale of 0-10 in the table below.

Emotion	Amount	Certainty
Anger		
Fear		
Joy		
Sadness		
(being) Analytical		
Tentativeness		
Positivity		
Negativity		

Please describe your interpretation freely; Why did you come to this assessment?



Please rate presence of the following list of emotions in visualization you see,, and your certainty of that interpretation – how precise do you feel this assessment to be – on a scale of 0-10 in the table below.

Emotion	Amount	Certainty
Anger		
Fear		
Joy		
Sadness		
(being) Analytical		
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Anger		
Fear		
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Anger		
Fear		
Joy		
Sadness		
(being) Analytical		
Tentativeness		
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Emotion	**Amount**	**Certainty**
Anger		
Fear		
Joy		
Sadness		
(being) Analytical		
Tentativeness		
Positivity		
Negativity		

Please describe your interpretation freely; Why did you come to this assessment?

Appendix 2

Travellers return from the city of Zirma with distinct memories: a blind black man shouting in the crowd, a lunatic teetering on a skyscraper's cornice, a girl walking with a puma on a leash. Actually many of the blind men who tap their canes on Zirma's cobblestones are black; in every skyscraper there is someone going mad; all lunatics spend hours on cornices; there is no puma that some girl does not raise, as a whim. The city is redundant: it repeats itself so that something will stick in the mind. I too am returning from Zirma: my memory includes dirigibles flying in all directions, at window level; streets of shops where tattoos are drawn on sailors' skin; underground trains crammed with obese women suffering from the humidity. My travelling companions, on the other hand, swear they saw only one dirigible hovering among the city's spires, only one tattoo artist arranging needles and inks and pierced patterns on his bench, only one fat woman fanning herself on a train's platform. Memory is redundant: it repeats signs so that the city can begin to exist.
(Calvino, 1974, p. 19)

Please rate presence of the following list of emotions in visualization you see,, and your certainty of that interpretation – how precise do you feel this assessment to be – on a scale of 0-10 in the table below.

Emotion	**Amount**	**Certainty**
Anger		
Fear		
Joy		
Sadness		
(being) Analytical		
Tentativeness		
Positivity		
Negativity		

Please describe your interpretation freely; Why did you come to this assessment?

A home transformed by the lightning
the balanced alcoves smother
this insatiable earth of a planet, Earth.
They attacked it with mechanical horns
because they love you, love, in fire and wind.
You say, what is the time waiting for in its spring?
I tell you it is waiting for your branch that flows,
because you are a sweet-smelling diamond architecture
that does not know why it grows.
(Scholl, 2017)

Please rate presence of the following list of emotions in visualization you see,, and your certainty of that interpretation – how precise do you feel this assessment to be – on a scale of 0-10 in the table below.

Emotion	Amount	Certainty
Anger		
Fear		
Joy		
Sadness		
(being) Analytical		
Tentativeness		
Positivity		
Negativity		

Please describe your interpretation freely; Why did you come to this assessment?

Still, it gets confusing.
Even for people who like a variety of salad dressings.
Bodies becoming as rearrangeable as they are.
People and their bodies being inseparable as they are.
That is, the message is the material.
People and their stories being inseparable as they are.
Material also being the message, logically.
Cultures and their stories being inseparable as they are.
Their medium also being the message, as we all know.
Bodies and their cultures being as inseparable as they are.
(Tomasula, 2004)

Please rate presence of the following list of emotions in visualization you see,, and your certainty of that interpretation – how precise do you feel this assessment to be – on a scale of 0-10 in the table below.

Emotion	**Amount**	**Certainty**
Anger		
Fear		
Joy		
Sadness		
(being) Analytical		
Tentativeness		
Positivity		
Negativity		

Please describe your interpretation freely; Why did you come to this assessment?

Humans like jewels.
Each facet an outward
facing fragment of a
haphazardly constructed
whole.

You are a sum of
parts, but also each
part. And no one
will ever know
your shape.

Feel it for
a second maybe,
know some particular
nook or peak
like their own
back pocket, sure.

But only you have
a chance of ever
realizing where your
lowest valleys and highest tops
lie.

You split and you splinter, creating new facets, splitting old ones.
Your shape is constantly changing, evolving, devolving.
Bring detail into things by breaking them apart.
Become more. Deep, interesting, wise, experienced. Most of us don't
have big clean surfaces.

Please rate presence of the following list of emotions in visualization you see,, and your certainty of that interpretation – how precise do you feel this assessment to be – on a scale of 0-10 in the table below.

Emotion	Amount	Certainty
Anger		
Fear		
Joy		
Sadness		
(being) Analytical		
Tentativeness		
Positivity		
Negativity		

Please describe your interpretation freely; Why did you come to this assessment?

I really have discovered something at last.

Through watching so much at night, when it changes so, I have finally found out.

The front pattern does move—and no wonder! The woman behind shakes it!

Sometimes I think there are a great many women behind, and sometimes only one, and she crawls around fast, and her crawling shakes it all over.

Then in the very bright spots she keeps still, and in the very shady spots she just takes hold of the bars and shakes them hard.

And she is all the time trying to climb through. But nobody could climb through that pattern—it strangles so; I think that is why it has so many heads.

They get through, and then the pattern strangles them off and turns them upside-down, and makes their eyes white!

If those heads were covered or taken off it would not be half so bad.

(Perkins Gillman, 2008)

Please rate presence of the following list of emotions in visualization you see,, and your certainty of that interpretation – how precise do you feel this assessment to be – on a scale of 0-10 in the table below.

Emotion	Amount	Certainty
Anger		
Fear		
Joy		
Sadness		
(being) Analytical		
Tentativeness		
Positivity		
Negativity		

Please describe your interpretation freely; Why did you come to this assessment?

Now I put these paradoxes and contradictions before you at the beginning, dismaying though they may be, because I believe that the relations between art and technics give us a significant clue to every other type of activity, and may even provide an understanding of the way to integration. The great problem of our time is to restore modern man's balance and wholeness: to give him the capacity to command the machines he has created instead of becoming their helpless accomplice and passive victim; to bring back, into the very heart of our culture, that respect for the essential attributes of personality, which Western man lost at the moment he displaced his own life in order to concentrate on the improvement of the machine. In short, the problem of our time is how to prevent ourselves from committing suicide, precisely at the height and climax of our one-sided mechanical triumphs. (Mumford, 1952, p. 11)

Please rate presence of the following list of emotions in visualization you see,, and your certainty of that interpretation – how precise do you feel this assessment to be – on a scale of 0-10 in the table below.

Emotion	Amount	Certainty
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Negativity		

Please describe your interpretation freely; Why did you come to this assessment?

Stylistic moods permeate whole periods and cultures, and they indirectly determine the kinds of creations – artistic, scientific, technological – that people in them come up with. They exert gentle but definite "downward" pressures. As a consequence, not only are the alphabets of a given period and area distinctive, but one can even recognize "the same spirit" in such things as teapots, coffee cups, furniture, automobiles, architecture, and so on, as Donald Bush clearly demonstrates in his book The Streamlined Decade. One can be inspired by a given typeface to carry its ephemeral spirit over into another alphabet, such as Greek, Hebrew, Cyrillic, or Japanese. In fact, this has been done in many instances (see Figure 13-10). The problem I am most concerned with in my research is whether (or rather, how) susceptibility to such a "spirit" can be implanted in a computer program. (Hofstadter, 1985, p. 285)

Please rate presence of the following list of emotions in visualization you see,, and your certainty of that interpretation – how precise do you feel this assessment to be – on a scale of 0-10 in the table below.

Emotion	Amount	Certainty
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Joy		
Sadness		
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Please describe your interpretation freely; Why did you come to this assessment?

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