Intuitive Direction Concepts

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Abstract

Experiments in this article test the hypothesis that formal direction models used in artificial intelligence correspond to intuitive direction concepts of humans. Cognitively adequate formal models of spatial relations are important for information retrieval tasks, cognitive robotics, and multiple spatial reasoning applications. We detail two experiments using two objects (airplanes) systematically located in relation to each other. Participants performed a grouping task to make their intuitive direction concepts explicit. The results reveal an important, so far insufficiently discussed aspect of cognitive direction concepts: Intuitive (natural) direction concepts do not follow a one-size-fits-all strategy. The behavioral data only forms a clear picture after participants' competing strategies are identified and separated into categories (groups) themselves. The results are important for researchers and designers of spatial formalisms as they demonstrate that modeling cognitive direction concepts formally requires a flexible approach to capture group differences.

1 Introduction

Direction relations between locations or objects in space are considered fundamental to human spatial cognition (e.g., [65]). It is not surprising that the community of spatial researchers has responded with numerous studies, both formal and behavioral, to understand cognitive direction concepts and has provided models that capture the nature of how humans make sense of direction information (e.g., [12]). While precise information in the form of coordinates and derived angles may be available to specify the relation between objects in space, it has been established that humans naturally do not use this level of precision [43]. To enable a seamless integration of cognitive and artificial systems, for example in geospatial information retrieval tasks, qualitative strategies employed by humans need to be captured formally in such a way that computational systems are able to communicate with natural cognitive systems. However, despite enormous research efforts there are still unanswered questions regarding what intuitive direction concepts are and which levels of granularity humans use to understand direction information; which factors change concepts and intuitive levels of granularity; how formal models can be designed such that they capture intuitive direction concepts adequately; and, how linguistic expressions map onto concepts.

In this article, we focus on symbolic (qualitative) approaches as they have the potential to be a bridge between the spatial information considered essential for natural and for artificial cognitive agents [23]. Symbolic approaches are onmipresent in spatial applications such as query and retrieval scenarios [1, 3, 6, 9], tasks involving the formalization of (geo)spatial concepts, change, and processes [10, 36, 32, 18], and in spatial database applications to specify spatial knowledge and integrity constraints [50, 33, 55, 52]. Acquiring a better understanding of human conceptualization and usage of direction relations and evaluating the suitability of different formalisms to capture humans' intuitive understanding of direction are crucial to improve the performance of symbolic approaches in the application areas mentioned above. To this end, we conducted two experiments to test the hypothesis that proposed direction calculi (see Section 2) correspond to the intuitive direction concepts of humans. The results allow for a deeper understanding of how humans make sense of direction information revealing that competing strategies are an essential cognitive reality that should be reflected in formal characterizations too. In other words, just like other areas of spatial cognition, such as wayfinding, are acknowledging that humans differ with respect to strategies they use to understand space [60], it is important to extend this line of thought to spatial (direction) concepts.

The remainder of the article is structured as follows: First, we briefly review literature on direction concepts in Section 2. Section 3 details two behavioral experiments we conducted to shed light on cognitive direction concepts in two different yet related scenarios (airplanes from a bird's eye and side view perspective). We discuss visualizations we developed to reveal participants' competing strategies and show that only acknowledging different strategies provides a sound (analytical) explanation of human behavior. We discuss the results in the light of existing literature and formal models in Section 4 and provide a general reflection and future avenues of research in the conclusions.

2 Background

One of the first things we can observe about cognitive direction concepts is that humans do not conceptualize (i.e., use individual concepts) for every potential direction that can possibly be perceived. That is, humans do not demonstrate natural and intuitive capacity dealing with infinitely precise directional information. For most situations, qualitative information about directions—in the sense of a fairly small number of equivalence classes—seems to be sufficient for natural cognitive agents. The way these equivalence classes capture continuous information about directions in a qualitative way has been referred to as *qualitative metrics* [21, 44]. Various studies show that even though humans may perceive angular information more precisely, humans conceptualize and remember it with limited precision (e.g., [7, 22, 42, 58, 63]).

Inspired by the idea of qualitative metrics, spatial information science has developed numerous approaches to formalizing direction concepts. We cannot review all of them here but will summarize the main contributions (see also Figure 1 and [40]). Qualitative direction calculi either deal with absolute or relative directions. Absolute direction calculi are typically developed as binary calculi specifying the relation between two objects, referred to as the *reference object* (RO) and the *located object* (LO), with respect to an absolute reference direction. The main examples of this class are cardinal direction calculi in which the direction of the located objects is determined in relation to, for example, the straight north direction. An important distinction for cardinal direction calculi has been proposed by Frank [19]: projection-based (Fig. 1(a)) versus cone-shaped (Fig. 1(b)). In projection-based calculi, the main directions N, W, S, E form the linear axes, while NW, SW, SE, NE are planar sectors. In cone-based approaches, the sector boundaries of the main directions are shifted by 45 degree such that N, W, S, E become planar sectors. An example of the projection-based approach is the well-studied point-based cardinal direction calculus by [39] (Fig. 1(a)). It uses nine basic relations to locate RO and LO. The cardinal direction calculus by Goyal and Egenhofer [29, 28] (Fig. 1(c)) deals with extended objects by using the minimum bounding rectangle around the reference object to form the frame of reference for determining the direction of the located object. Since the calculus deals with extended objects, the located object can overlap several direction sectors such that relations need to be represented as binary matrices. Renz and Mitra [54] describe an absolute direction calculus, the Star calculus, in which the sector boundaries can be adapted allowing for the representation of direction information at different levels of granularity.

Relative direction calculi do not require a reference direction. They either are ternary calculi dealing with three objects (*origin*, *referent*, and *located* object) as in Ligozat's FlipFlop calculus [38] and Freksa's Doublecross calculus [24] (Fig. 1(d)); or, binary calculi that involve basic entities with an intrinsic direction. Examples for the latter are the dipole and OPRA calculus families: Calculi from the dipole family [47] (Fig. 1(e)) define relations for the relative orientation of two line segments. In the OPRA calculus [45] (Fig. 1(f)), directed points are used and each point is relatively located to the other point based on a locally instantiated reference system (within each point). The level of granularity can be adapted using a special parameter.

The psychological and linguistic literature offers a substantial amount of insights into the conceptualization of directions and the relation between cognitive representations of directions and their linguistic descriptions. There are a number of excellent overview publications [37, 65, 17, 61]. Due to space limitations, it is not possible to provide a comprehensive review. More importantly, most of the existing research focuses on evaluating and specifying the semantics of

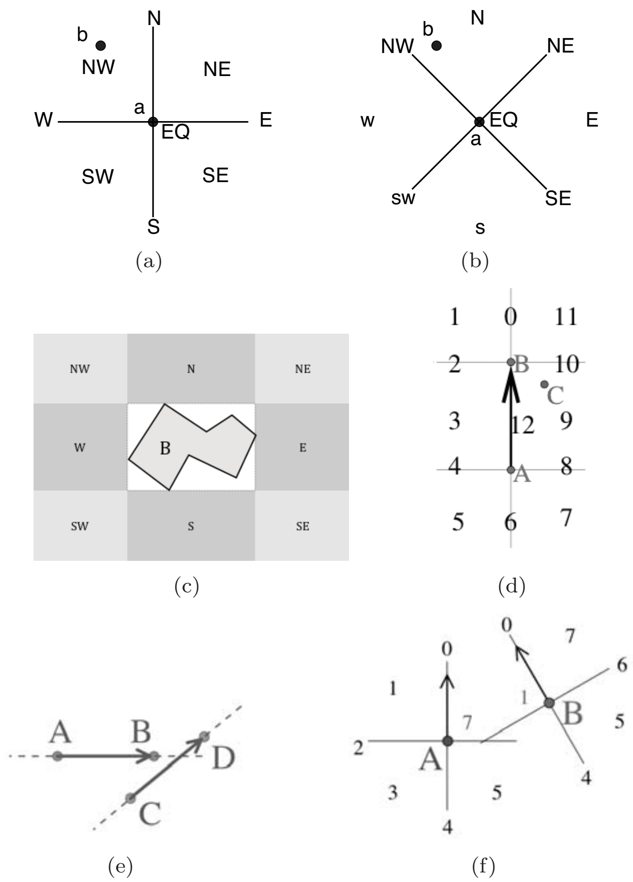

Figure 1: Overview of direction calculi. (a) projection-based cardinal direction calculus; (b) cone-shaped cardinal direction calculus; (c) cardinal direction for extended objects; (d) doublecross calculus; (e) dipole calculus; (f) OPRA calculus.

particular spatial prepositions, that is, research is targeting the question: what are possible interpretation of prepositions such as *on, under,* or *above* [16]. Our research approach is different: it addresses whether any of the proposed direction formalisms discussed above reflects intuitive (human) direction concepts. We will make connections to existing behavioral research results in Section 4.

3 Experimental evaluation of direction concepts

To be able to efficiently analyze humans' intuitive concepts of space, time, and space-time, and to test the hypothesis that a proposed formal model is cognitively adequate, we have developed a framework that combines experiment design, data collection, and data analysis [35, 34]. The central component is CatScan, a software we designed to administer free-classification (also referred to as category construction or grouping) experiments. The software is designed to be compatible with the Amazon Mechanical Turk's (AMT)[1] crowdsourcing environment. By employing AMT, the challenge of recruiting an adequate participant pool is reduced significantly. AMT has gained widespread recognition in the scientific community with its demonstrated reliability, efficiency, and validity. For instance, it has been shown that results obtained from AMT are largely comparable with lab experiments [49, 8]. Additionally, research on the demographics of Turkers (i.e., participants recruited to perform the Human Intelligence Tasks on AMT) has shown that general population characteristics are better reflected compared to classic on-campus lab experiments [56]. In the following, we describe two experiments we performed with CatScan via AMT in order to investigate human conceptualizations of direction relations with respect to both direction concepts and their linguistic descriptions. We will demonstrate that investigating group strategies of participants is essential for fundamental spatial concepts such as directions, not just for more complex cognitive processes such as wayfinding.

3.1 Experiment 1 - Bird's Eye View

We selected a two-airplane scenario to elicit intuitive direction. A similar scenario has recently been employed by Holmes and Wolff [31] to evaluate the relation between linguistic expressions and concepts. All formal approaches for absolute direction information discussed in Section 2 are potentially suitable for modeling cognitive direction concepts in these scenarios. Our experiment tests the hypothesis that at least one of the formal models proposed captures the intuitive direction concepts of humans. Our results will thereby provide guidance on selecting an appropriate formalism. Lack of such guidance has been identified as one major drawback in promoting qualiative formalisms [59].

Material

We created a set of 72 icons for this experiment showing two airplanes from a bird's eye perspective (see Figure 2). The icons were generated as follows: Two

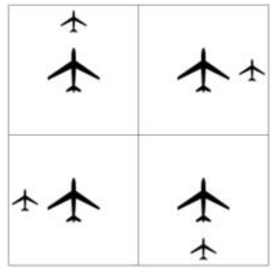

Figure 2: Four examples of icons that were created showing two airplanes. Angles between the big plane (RO) and the small plane (LO) in counterclockwise order are: 0, 90, 180, and 270 degree.

differently scaled versions of the same airplane image from a bird's eye perspective were combined to form individual icons. The smaller plane was placed along a circle around the larger plane located in the center of the icon. Placement was based on the center points of the minimum bounding boxes around each plane. The placement started with an angle of 0 degrees corresponding to the straight up position and was then increased in 5 degree steps counterclockwise. This resulted in $360/5 = 72$ icons for this experiment. Figure 2 shows four examples at 0, 90, 180, and 270 degrees.

Participants

Through AMT, we recruited 37 participants for this experiment. We excluded seven based on obvious and repeated errors they made in creating direction categories. We considered directions as outliers if they were 15 or more degrees apart from the main group. Participants' had to have at least two such outliers to be excluded. Most participants who were excluded made several obvious mistakes. 13 of the remaining 30 participants were female and the average age of all 30 participants was 30.53 (max: 64, min: 19).

Procedure

Individual experiments were posted to AMT's website as HITs (Human Intelligence Tasks). Once a HIT was accepted by a worker, s/he was instructed to download the stand-alone Java version of CatScan and work on the experiment with a unique participant number assigned to her/him. At the beginning of the experiment, participants were required to enter their demographic information such as age, gender, native language, and educational background. After that, participants were asked to read the experiment instructions which introduced the basics of the experiment. Participants were only allowed to proceed after a certain time and had to enter text into a box to ensure that they read and understood the instructions. A warm-up task was set up to acquaint participants with the interface and the idea of category construction by sorting animals into groups. In the main experiment, all 72 icons were initially displayed on the left panel of the screen. Participants were asked to sort icons into categories they had to create on the right panel of the screen (see Figure 3 for a mock-up experiment). They were given the following instructions: *In the following experiment we will show you icons depicting two airplanes. Your task is to sort the icons that we will present you with on the left side of the screen into groups on the right. Please sort them based on how similar the icons are. [] You decide which icons belong together. There is no right or wrong group for the icons. You can create as many groups as you think are appropriate but do not simply put all icons into a single group.* Once all icons were sorted into the categories created by the participants, they were able to proceed to the second part of the experiment. Here they were presented with the groups they created, one group at a time, and asked to provide a short label (no more than five words) and a detailed description to articulate the rationale(s) of their category construction behavior. Upon the completion of the second part, CatScan generated a zip file that participants then had to upload to AMT. The zip file contains log files, grouping behavior, as well as the linguistic descriptions.

Results

During the experiment, the number of groups created by each participant and the time (in seconds) each participant spent on the grouping task were automatically recorded by CatScan. Participants created 4.80 groups on average with a standard deviation of 1.76, and they spent 515.18 seconds on the grouping task on average with a standard deviation of 319.61 seconds. In the following, we describe the most important results of our analysis of the collected data.

Cluster analyses The category construction behavior of each participant was recorded by CatScan in individual similarity matrices (ISMs). An ISM is a 72×72 binary matrix that encodes the similarity rating between all pairs of icons (72 is the total number of icons used in the experiment). For each pair of icons in the experiment, the corresponding similarity rating is 1 if they are placed into the same group by that participant, and 0 if not. By summing up all 30 ISMs in the experiment, an overall similarity matrix (OSM) is obtained. In the OSM, the similarity rating for a pair of icons ranges from 0 (lowest similarity possible) to 30 (highest similarity possible).

To reveal the category construction behavior of all participants, we performed cluster analyses based on the OSM. Following a suggestion from Clatworthy and colleagues [11], we used three different clustering methods (average linkage, complete linkage, and Ward's method) and compared the clustering structure to validate the results. Regardless of the cluster level we chose, that is, the number of clusters we assumed as a result, the composition of clusters (icons belonging to 'the same' cluster) was never consistent. In other words, in strong contrast to essentially all previous experiments on topological concepts [35] and recommendations in the literature on number of participants needed for cluster analysis [62], the cluster validation method failed to reveal the dom-

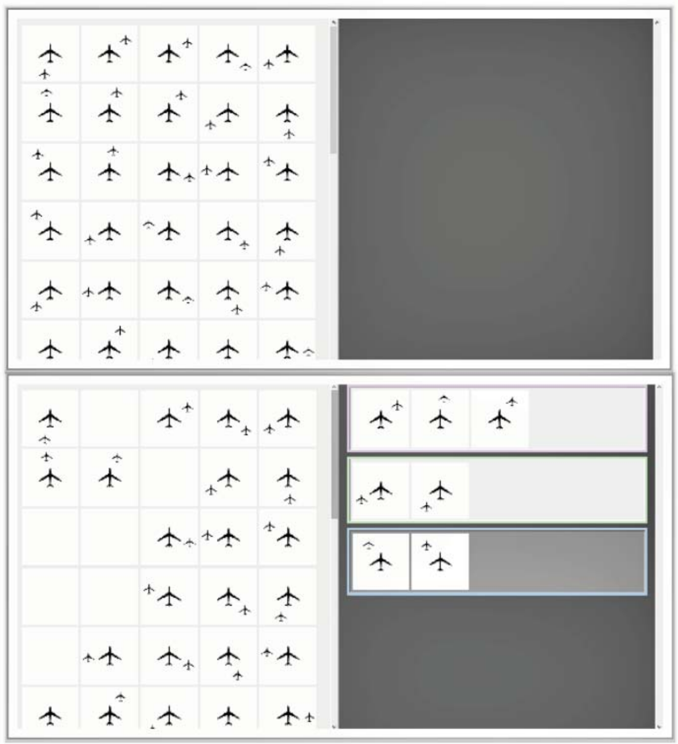

Figure 3: Top: Screenshot of the CatScan interface at the beginning of the main experiment. Bottom: Screenshot of the interface of an ongoing mock-up experiment.

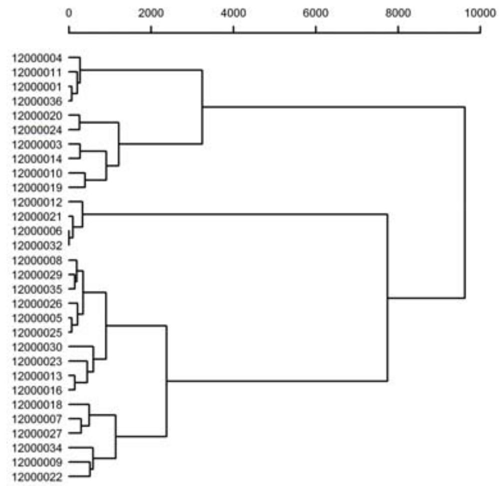

Figure 4: Participant similarity analysis.

inant clustering structure; individual/group direction concepts seem to be so diverse that no uniquely agreed upon conceptualization of direction concepts is emerging.

Participant similarity analysis Intrigued by the fact that the cluster validation method failed, that is, that it did not produce consistent results at any clustering level, we focused on analyzing strategies and similarities between participants. Participant similarity analysis measures the similarity between participants based on individual similarity matrices (ISMs). To this end, a 30-by-30 between-participant similarity matrix (BSM) was constructed to encode the similarity of category construction behavior for each pair of participants. In the BSM, the similarity between a pair of participants is determined by computing the Hamming distance between the ISMs of two participants. The Hamming distance is calculated by counting the total number of cells that differ between two ISMs. Since ISMs are binary-coded matrices (i.e., only contain values 0 and 1), the larger the Hamming distance is, the less similar two participants are in terms of their overall category construction behavior. Cluster analysis using Ward's method performed on the BSM (see Figure 4 for the resulting dendrogram) allowed us to identify participants who employed similar category construction strategies.

To better understand individual differences as well as group-strategies, we visualized individual participant data using star plots (Figure 5). Each star plot visualizes the category construction behavior of one participant. In each star plot, every icon (from the original stimulus) in the experiment is symbolized as a single line (ray) that corresponds to the direction/angle from the larger airplane to the smaller airplane. The color of each line in each individual star plot is

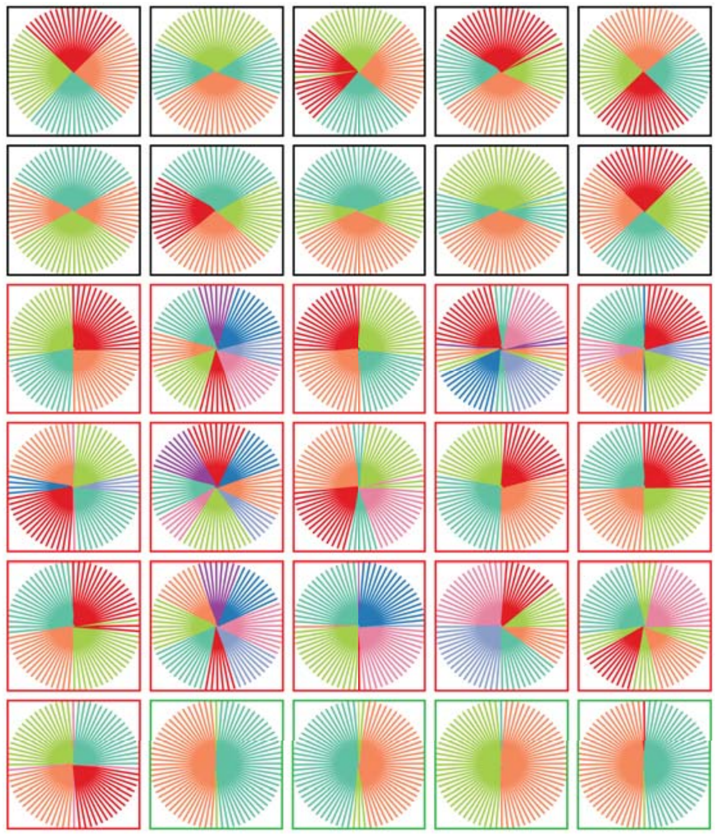

Figure 5: This visualization shows individual star plots for all 30 participants. The star plots are ordered by results from the participant similarity analysis using Hamming distance. Clusters of similar participants are indicated by different colors of the bounding box. The visual inspection of this visualization corroborates the identification of three distinct category construction strategies.

assigned based on category membership assigned by the participant. Hence, lines with the same color indicate that the icons represented by these lines were placed into the same category in the experiment.

From the star plot figure it is possible to infer which icons were placed into the same category and observe the size (total number of icons) of each category as well as the overall number of categories by inspecting the lines. In addition, we also added the results from the participant similarity analysis (see above) to the star plot figure. The star plots are ordered and marked with bounding boxes in distinct colors based on one of the three clusters that participants fall into based on participant similarity analysis (Figure 4).

Figure 5 shows that the four participants in the green category (participants whose star plots are surrounded by green bounding boxes) employed a half-plane categorization approach. All participants within this category distinguished between west and east (left and right, respectively; to avoid terminological confusion we will use cardinal directions to refer to participants direction concepts) spanning almost entire half-planes. Additionally, participants singled out direction concepts along the north-south axis. They differ, however, with respect to their conceptualization of this important axis: some focus on alignment and do not distinguish between north and south, others make this distinction explicitly.

The ten participants in the black category either used a four or three category cone-shape approach. The defining characteristic of this group is that all participants used cone-shaped direction concepts spanning 35 degrees to 130 degrees; no axes are singled out. Participants who created four groups used north, east, south, and west directions. Participants who created three groups distinguished between the north and south directions, keeping the east and west directions categorized together (airplanes were next to each other with no distinction on which side the smaller airplane was).

The sixteen participants in the red category (as identified through the participant similarity analysis) are more varied than the other two categories and exhibit a wider range of strategies. These strategies include quadrants, which create distinguishable borders along the north-south and east-west axis; quadrants plus explicit axes; finer cone-shaped categories with eight categories, some of which may be axes; and a combination of quadrants and cones.

We ran our cluster validation approach (comparing three different clustering methods) on the sub-groups. Green and black both yielded high agreements. The green three cluster solution was a perfect match, while the four cluster solution singled out the straight back/south icons. The four cluster solution for the black group had four icons that were assigned to different clusters. These were icons at the border of the cone-shaped direction categories. The red group showed the most disagreements, as expected giving their diverse nature. The most agreement yielded a four cluster solution with five icons (direction) being "misclassified". All five icons are at the boundary of the four main quadrants.

3.2 Experiment 2 - Side View

The important finding of experiment 1 was that after taking into account group differences, the analysis is making more sense. To corroborate this finding, we conducted a second experiment. To introduce a different scenario that nonetheless could be modeled in a similar way to experiment 1, we used again two airplanes but this time presented them from the side. We will refer to this experiment as the side-view experiment.

Participants

We recruited 45 new participants. Of these 45 participants 15 were excluded based on the same criteria we applied to exclude participants from the bird's eye experiment. Of the remaining 30 participants 12 were female and the average age was 32.38 (max: 19, min: 58).

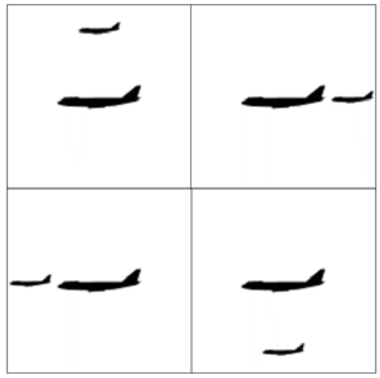

Figure 6: Stimuli from the side-view experiment. Shown are four angles between two airplanes: 0, 90, 180, and 270 degree (ordered counterclockwise in the image).

Materials

72 icons were created in the same way as in experiment 1. The difference was that the two airplanes were shown from a side-view. Figure 6 shows four examples.

Procedure

The procedure was the same as in experiment 1.

3.2.1 Results

Participants created 4.73 groups on average with a standard deviation of 2.28, and they spent 521.16 seconds on the grouping task on average with a standard deviation of 478.84 seconds. We performed two two-tailed t-tests to compare the bird's eye experiment with the side-view experiment. The results show that there is no significant difference comparing the number of groups created ($t(58) = -0.12$, $p = 0.91$) or the amount of time spent on grouping task ($t(58) = 0.05$, $p = 0.96$).

Cluster analyses Slightly more consistent compared to results from experiment 1, the different cluster analyses (average linkage, complete linkage, and Ward's method) agreed on a three cluster solution with the exception of five icons (directions). The three clusters are above, below, and in-line (not axes but narrow sectors). The five inconsistently classified directions were at category boundaries.

Participant similarity analysis We followed the strategy we developed to analyze the experiment 1 data and performed a participant similarity analysis using Hamming distance and visualized the category construction behavior of each participant in the form of star plots.

Category construction strategies Figure 7 shows the star plots visualizing the ISMs of the individual participants. The five participants in the green group sorted directions into three or four cone-shaped categories only with slightly varying cone sizes. Participants who created three groups distinguished between in-front-of and behind, with above and below being in the same category. Participants who created four groups distinguished four cone-shaped direction categories.

The thirteen participants in the black group created cone-shaped direction concepts but with smaller categories for airplanes being in-line. They predominantly distinguished three categories (above, below, and in-front-of and behind together) or four (separating in-front-of and behind).

The twelve participants in the red group (similar to the bird's eye experiment) are more diverse than the other two groups, that is, they employed a wider range of category construction strategies. Category construction strategies varied between finer cone-shaped categories and quadrants. Two participants in the red group created 'only' four groups and both generally employed quadrants. Two participants created five groups: One used a cone-shape categorization method but added two distinctions of "in-front-of and below" and "in-front-of and above" while the other three categories distinguished between "above", "below", and "behind". The second participant with five groups was slightly less consistent in his/her categorization behavior. The rest of the group created six or more categories; a majority created fine-grained cone-shaped groups.

Performing cluster validation on the identified sub-groups led to better validated clustering structures: three inconsistent icons in a four cluster solution in the green group; the black group also had three inconsistent icons but for the three cluster solution (above, below, and in-line); the red group also has three inconsistent direction icons assuming an eight cluster solution.

Linguistic analysis The main focus of this article has been on the analysis of direction concepts. However, we are collecting linguistic descriptions at the end of each category construction task by asking participants to provide a short label and a longer description. With this combination we are in the position of adding to central questions in the cognitive and spatial sciences, that is, what is the relation between spatial concepts, their linguistic descriptions, their formal representation, and the stimulus (as a representation of real world scenarios). While we do not claim to provide a conclusive answer, we can add valuable insights into the many-to-many [65] relationship between linguistic expressions and cognitive concepts.

Figures 8 and 9 show a visualization we developed and that we applied to the subsets of participants identified in both experiments discussed above. The figures show the grouping behavior of all participants in each of the subgroups (green, black, and red for both birds-eye and side-view). Each ray corresponds

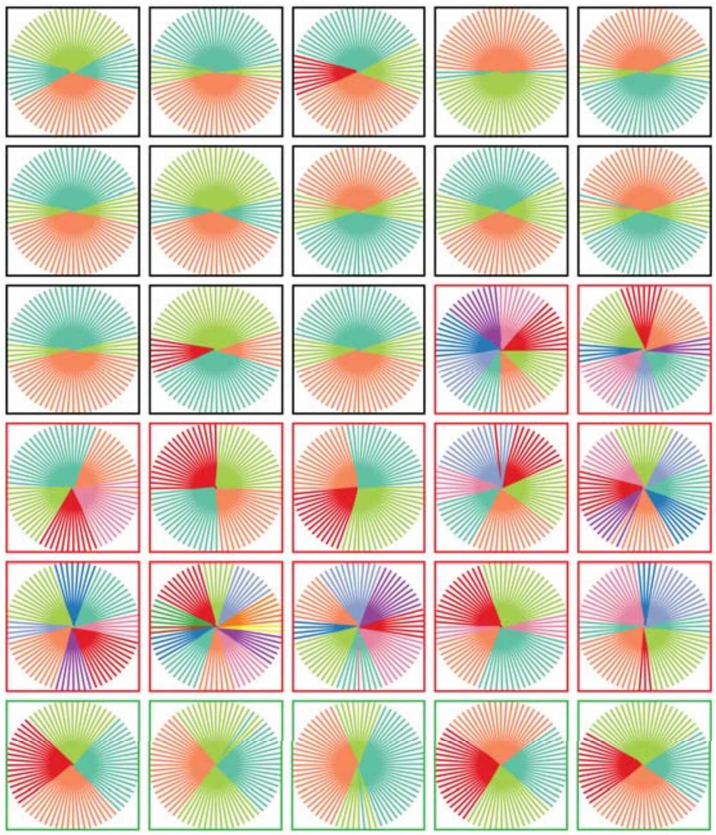

Figure 7: This visualization shows individual star plots of all 30 participants in the side-view experiment. The star plots are ordered by results from the participant similarity analysis using Hamming distance. Clusters of similar participants are indicated by different colors of the bounding boxes. The visual inspection of this visualization corroborates the distinction of three distinct category construction strategies.

to one direction category a participant created; its angle is the bisecting line of the angle interval covered by the icons from that category. The length of a ray is indicative of the size (in degrees) of a direction category: the longer the ray the larger the direction category. Hence, half-planes are represented by long rays, axes by short ones. At the end of each ray, loosely associated with its end point, we placed the short linguistic descriptions participants provided (reduced to the linguistic expression of the direction relation). This combination allows for associating direction concepts with their corresponding linguistic descriptions. To avoid confusion, we excluded from this visualization cases where participants joined opposite directions into the same category (e.g., side-by-side, in-line). Additionally, we scaled linguistic expressions according to their frequency (higher frequency = larger font size) which allowed us to summarize descriptions in case participants provided the same term.

Some observations regarding the linguistic expressions are: Corresponding to the conceptual diversity found in the red groups of both experiments, the linguistic expressions are also more diverse in these groups. A finer level of granularity (as found in the red groups) leads to a more varied linguistic repertoire. Linguistic description are more diverse at secondary (diagonal) compared to primary (horizontal and vertical) axes. Absolute and relative reference frames as well as alternative reference frames (e.g. clock, numbering quadrants) are used. Certain linguistic expressions (e.g., *East, West*) seem to have a more narrow interpretation than others (e.g., *left, right*). While almost all participants used the larger airplane as the reference object, in the sideview experiment some participants reversed the airplanes' roles (or even mixed them) resulting in linguistic labels such as *below* in the same quadrant as *above*.

4 Discussion

The results reveal several important aspects of cognitive direction concepts. To structure the discussion, we will first look into the role invariants play in spatial concepts that are considered to be fundamental. For the purpose of this discussion we distinguish three different types of spatial concepts that differ with respect to how salient transitions are between individual relations/concepts, that is, information considered as being invariant. Example, if topology is a type of a spatial concepts, *disconnected* and *externally connected* would be individual relations. Galton [26] pointed out that qualitative spatial and temporal formalisms gain their power by identifying salient discontinuities between otherwise invariant equivalence classes and that these discontinuities have a cognitive reality, too (potentially). This case can be made for temporal calculi such as Allen's interval algebra [2] as well as prominent topological formalisms [14]. However, while the salience of individual relations in these calculi is often intimately linked to perceptual salience, not all transitions between individual relations within these calculi have to be salient to the same degree. For example, while *distance* is often considered a fundamental concept of spatial information [27, 48], individual cognitive distance concepts such as *near* or *far* are not asso-

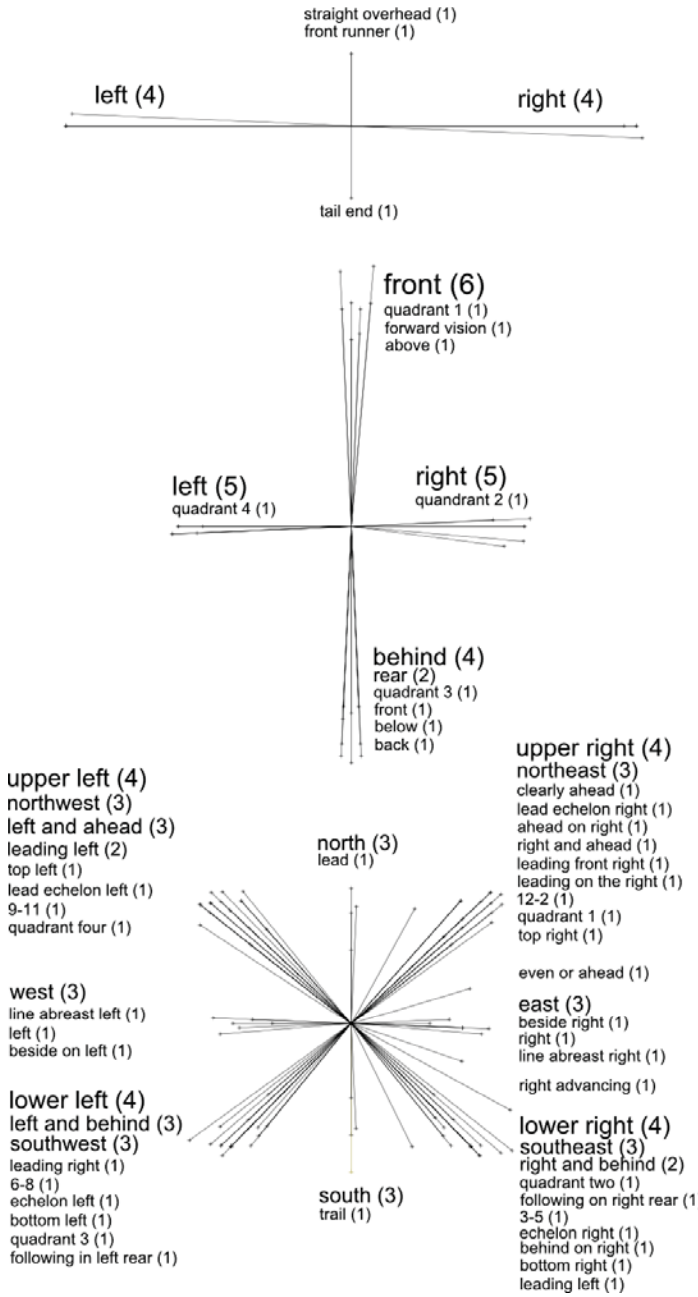

Figure 8: Birdseye direction concepts separated by group (green, black, red, see Figure 5). Rays are summaries of a direction concept; numbers and font size correspond to term frequencies.

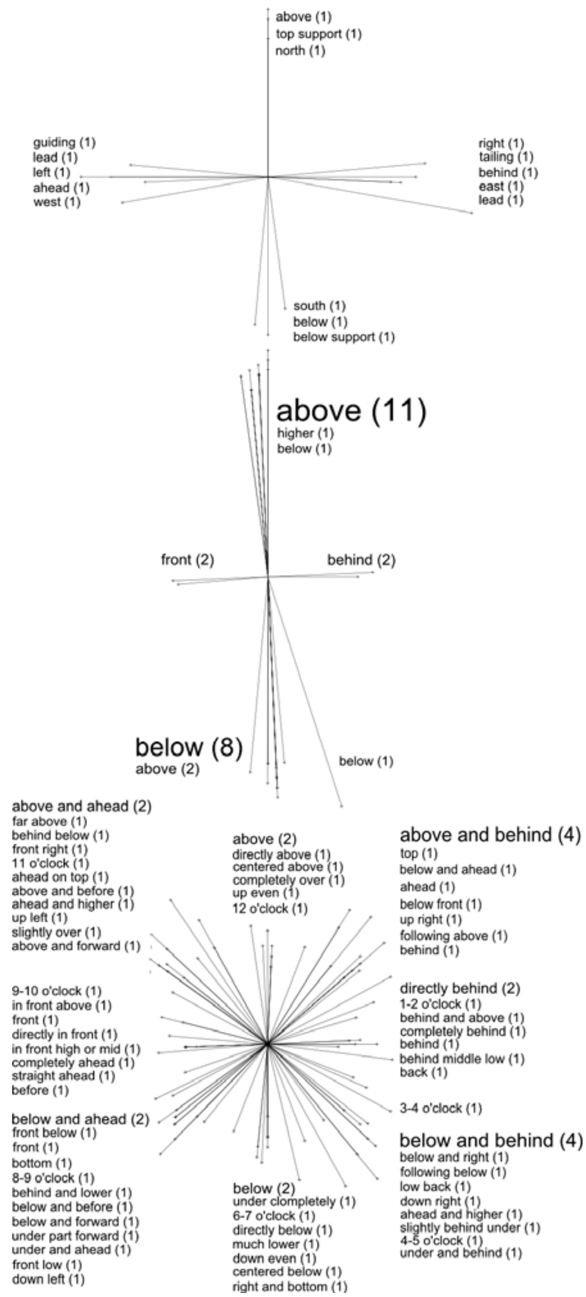

Figure 9: Sideview direction concepts separated by group (green, black, red, see Figure 7). Rays are summaries of a direction concept; numbers and font size correspond to term frequencies.

ciated with salient discontinuities in the world that can be perceived directly and unambiguously (maybe with the exception of comparing two directly perceivable distances) (e.g., [25]). If we allow *topology* (transitions between relations are perceptually salient and defined) and *distance* as being two ends of a spectrum of how well transitions between individual relations can be perceived, we can place the *direction* concepts we addressed here somewhere in-between. The reason why we consider directions as being in-between is that characteristics of objects and corresponding reference frames are often salient perceptually, although they might not be as prominent as, for example, topological transitions. Following Bryant [5], up-and-down distinctions are strongest, followed by front-and-back, with left-and-right being the least prominent. Intrinsic properties such as the distinguishable front side of an object or the direction of movement allow for establishing direction concepts such as front-and-back as well as left-and-right (to a lesser extend) and are tied to perceivable object/environmental characteristics [64]. It is important to note, though, that in case of directions prototypical relations (e.g., of in-front-of) are potentially very salient, but that boundaries of concepts, especially at finer levels of granularity, are often vague [66].

A topic less prominently featured in recent research on directions is the existence of competing individual or group strategies. In our experiments, a more consistent pattern only emerged after participants' strategies were taken into account by performing similarity analyses on the participants (see Figure 4). Participant similarity analysis was taken as a basis for splitting participants into distinct subgroups. After the subgroups were identified, cluster validation techniques indicated a more stable conceptual structure within subgroups. The category construction behaviors observed in the subgroups correspond to formal qualitative calculi. The behavioral results reflect the broad distinctions that are made by [20] into cone-shaped direction concepts and those based on half-planes (here referred to as quadrants), as well as the acknowledgment of different levels of granularity [30]. Given that these strategies are largely mutually exclusive, only a parameterized calculus such as the Star calculus [54] would be able to handle these differences.

Our results also add to recent discussions in the cognitive sciences on the relation between direction concepts, linguistic descriptions, the perception of categories, intuitive concepts, and how to formalize cognitive processes. For example, [31] proposed the so called *semantic clusters hypothesis.* It addresses the challenge many researchers feel with respect to characterizing the relation of individual words (e.g., prepositions) and cognitive concepts. This hypothesis asserts that "Language may be a better reflection of the conceptual system at the level of clusters of words than at the level of individual words. According to the semantic clusters hypothesis, clusters of words capture salient conceptual distinctions." [31]. Our linguistic analysis supports the semantic cluster hypothesis but also adds to it: For individual direction concepts we can indeed find that participants referred to them in the same way and that different terms are used for almost identical concepts. Interestingly, the diversity of linguistic expressions is different for primary and secondary axes and dependent on the reference inducing qualities of the reference object (comparing birdseye against sideview with the latter being more diverse).

Additionally, the intuitiveness of concepts has been recently discussed [51]. The question of how may concepts people use intuitively, how they are communicated through language, or how they can be formally modeled are core questions in the cognitive sciences (both natural and artificial). Many unsupervised learning approaches take inspiration from human conceptualization processes. Medin and collaborators [41] make the point that humans normally use and create only a tiny subset of the many ways that information could be partitioned, and that a central question in the cognitive sciences is to reveal principles that underlie category construction behavior. Pothos and collaborators [51] point out that the purpose of many models which are built around unsupervised learning is to provide hypotheses about the computational principles associated with category construction. Our research results clearly demonstrate that there is not a one-size-fits-all approach to determine intuitive direction concepts. Participants used different strategies to construct direction categories as revealed through the participant similarity analysis. This has important consequences for modeling approaches as it will be important to take alternative views explicitly into account for designing efficient interfaces at the human-machine-interface [46, 13] or to develop and assess unsupervised learning approaches.

5 Conclusions and outlook

In addition to many research efforts on the relation between direction concepts, their linguistic representation, and formal specifications of direction categories our research shows the importance of acknowledging group differences in the way that direction categories are intuitively constructed. As briefly discussed, this has far-reaching consequences for suggesting appropriate formal calculi, an issue that has been identified as being critical for increasing their applicability [59]. Individual strategies have gained widespread attention in several areas of spatial cognition (e.g., wayfinding) but are less prominently discussed when it comes to spatial knowledge considered to be fundamental. Our results clearly show that there is no one-size-fits-all approach to modeling direction concepts and that in addition to external contextual factors, group and individual strategies require more attention.

There are several avenues for future research: First, symbolic representations of spatio-temporal information are omnipresent in the spatial sciences and related fields. These approaches are often built around a relatively small number of relations; an implicit or explicit assumptions is frequently made that these relations correspond to human spatial information processing. It is therefore self-evident that these *proposals* should be evaluated. The framework we have developed is ideally suited for this task and can be applied to essentially all approaches built on calculi using JEPD (jointly exhaustive and pairwise disjoint) relations. Examples are Renolen's basic types of change [53], approaches to defining perceptual topology (e.g., perceived connectedness such as a settlement, see [15]), or Brunet's chorematic modeling [4]. This would allow for responding to the call by Schultz and collegues [59] to provide guidance on when to use a certain calculus (and when not to). Second, while category construction tasks are acknowledged in many research areas within and outside the cognitive sciences, they are certainly not mainstream [57, 34]. We have shown that by combining category construction tasks with cluster validation and visual analytics approaches they are a valuable tool for gaining critical insights into cognitive conceptualization processes. Besides developing specific visualization approaches for specific experiments (e.g., the star visualizations for directions) we are also working on including recent approaches to sequence analysis and especially to the analysis of the linguistic descriptions as well as cluster validation. Last but not least, it would be intriguing to scale up the data collection and repeat the experiments with larger numbers of participants in order to further substantiate our findings on individual and group strategies.

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Notes

[1] `https://www.mturk.com/mturk/`