Categorical Influences on Spatial Bias

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Chapter to appear in T. L. Hubbard (Ed.), *Spatial Biases in Perception and Cognition*,

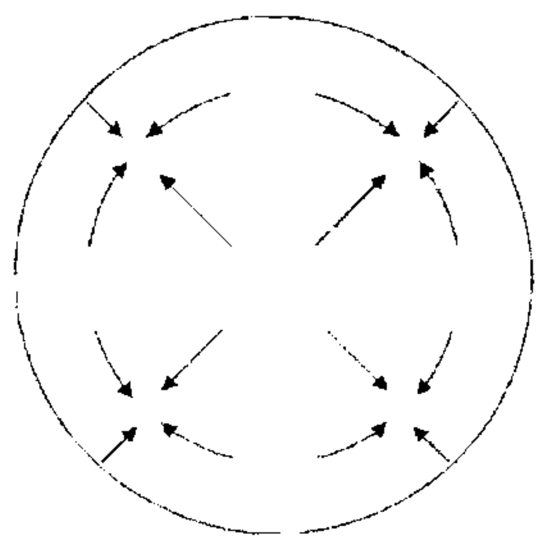
Cambridge University Press.

Navigation is an essential part of adaptation for any mobile species, humans included. We need to search for food and water, return to shelter for sleep, and avoid dangers that include both stationary and moving threats. Because these functions are vital for survival and reproduction, it would be natural to expect that we would have a cognitive and neural system that can accurately encode the spatial environment and that might even operate automatically. Instead, human spatial judgments show odd biases, and even outright incoherencies. Such phenomena are surprising. But we need to face facts: there is now a large literature documenting spatial biases and oddities, usefully gathered together in this volume.

Note, however, that not all of these biases are necessarily the target of evolutionary pressure, and some do not constitute likely threats to survival. Simplifying heuristics for spatial relations at geographic scale (e.g. lining up geographic areas along north-south or east-west axes, Tversky, 1981; judging the relative locations of cities in terms of the relative locations of their states, Stevens & Coupe, 1978) may reflect how we deal with knowledge derived from maps rather than actual travel, a task probably not subject to evolutionary pressure. Errors in judgments of local environments seem a bit more serious, as when Stanford undergraduates draw El Camino Real running north to south rather than from northwest to southeast (Tversky, 1981), when students at the University of Michigan or Northwestern represent their campus as locations clustered into regions with inter-region distances exaggerated with respect to intra-region ones (Hirtle & Jonides, 1985; Uttal, Friedman, Hand & Warren, 2010) or when people prefer to start journeys by going as directly as possible towards their goal, leading to differences between return journeys and initial routes, and longer routes than necessary (Bailenson, Shum & Uttal, 2000). But these errors may reflect rational reductions in cognitive load, given their relatively low cost, probably at worst, arriving at a goal a few minutes later than necessary (Bailenson et al., 2000).

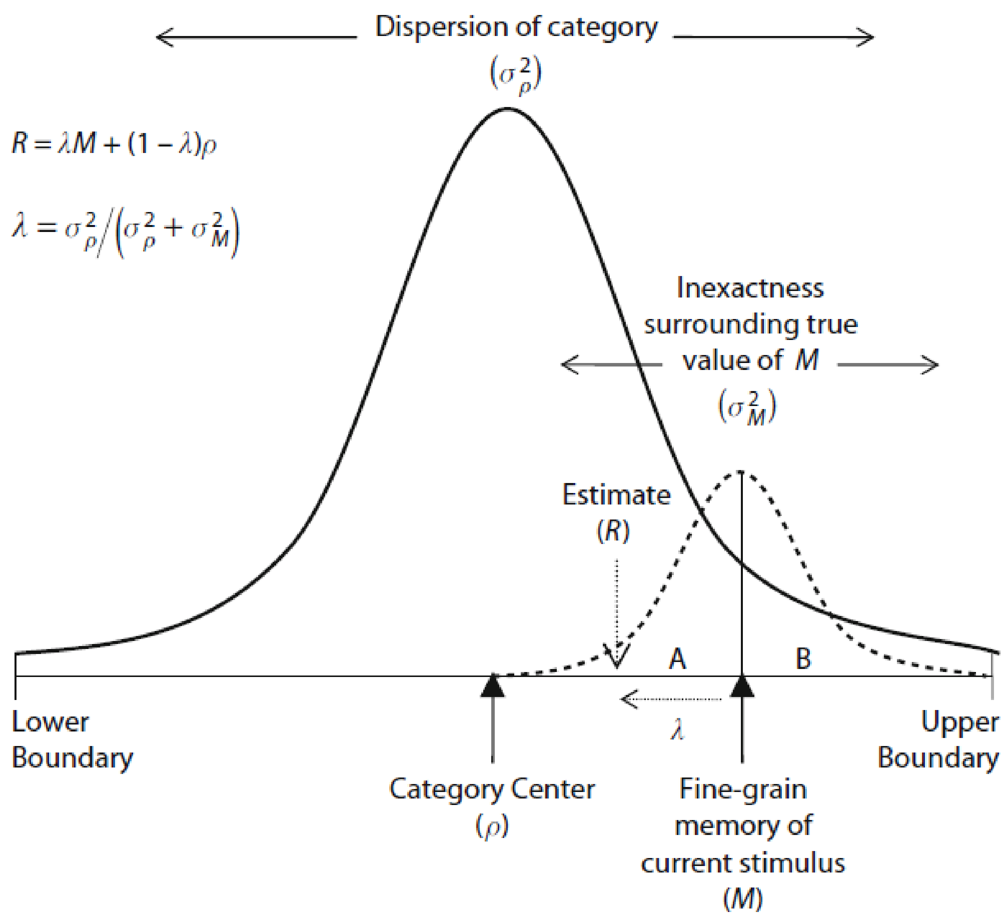
Spatial judgments that seem downright illogical pose a more troubling challenge to the idea that evolution should have ensured adequate spatial functioning. One well-studied phenomenon of this kind is asymmetries, i.e., when people judge a distance from point A to point B as different from the distance from point B to point A (Baird, Wagner & Noma, 1982; Holyoak & Mah, 1982; McNamara & Diwadkar, 1997; Sadalla, Burroughs & Staplin, 1981). Another example occurs when participants in virtual reality experiments do not realize that they are in impossible environments (Kluss, Marsh, Zetzsche & Schill, 2015; Warren, Rothman, Schnapp & Ericson, under review; Zetzsche, Wolter, Galbraith & Schill, 2009). Impressed by these incoherencies, but also arguing from the overall literature on spatial bias, some investigators have suggested that our spatial representations are non-metric or even associative (Foo, Warren, Duchon, & Tarr, 2005; McNamara, 1991; Tversky, 1981). As Tversky (1981, p. 432) put it: *Cognitive maps may be impossible figures*.

So, how has our species survived? One answer might be that associative spatial representations are "good enough" to get around the environment. However, there is an alternative. Huttenlocher, Hedges and Duncan (1991) proposed 25 years ago that spatial representations are fundamentally accurate and coherent, even while exhibiting oddities and biases. In their Category Adjustment Model (CAM), fine-grained representations of location are nested within categories. When the fine-grained information is relatively uncertain, categorical information is more heavily weighted, and the result is bias towards the location of the category prototype. The distinction between categorical and fine-grained information maps well onto analogous distinctions between categorical and coordinate information (Kosslyn, 1987) and between qualitative and quantitative information (Forbus, 2011; Klippel, 2012). CAM adds the idea of an adaptive combinatorial process.



This combinatorial process has been mathematically modeled in Huttenlocher et al. (1991) and in subsequent papers. It can be intuitively understood using the diagram in Figure 1. The arrows show the idealized results of multiple experiments in which participants saw dots located in circles, and then located those dots after brief delays. Point estimates move towards the centroid of the four quarters of the circle, as divided by horizontal and vertical lines. Points move farther when they are farther from the centroid, resulting in increased bias for those points. Boundaries also exert effects, by truncating the distributions of locational uncertainty. For example, a point towards the circumference of the circle cannot move outward without crossing the boundary of the circle, an unlikely violation (Huttenlocher, Hedges, Lourenco, Crawford & Corrigan, 2007). Overall, the effect of combining fine-grained and category information is to increase accuracy by constraining location given uncertainty, even at the price of introducing bias.

A somewhat more formal explanation of CAM can be derived from Figure 2, taken from Duffy, Huttenlocher, Hedges and Crawford (2010). The larger normal distribution shows the likelihood of any particular point's location, given that we know only that it is within the category, centered at the category prototype and truncated at the boundaries. The smaller normal distribution shows the likelihood of a point's location as determined by fine-grained memory. This distribution is much more constrained, but also has inexactness. It could be centered at any point within the overall category distribution.



CAM applies to various kinds of judgments, not just spatial ones. In fact, the earliest publications concerning the model involved time estimation (Huttenlocher, Hedges & Prohaska, 1988, 1992; Huttenlocher, Hedges & Bradburn, 1990). Subsequent applications of the model concentrated on category judgments (Huttenlocher, Hedges & Vevea, 2000), and much subsequent work on the model has focused on forming categories for stimuli such as fat and thin fish or long and short lines.

CAM is a Bayesian model in that it weights categorical information more heavily as the variability and hence uncertainty of fine-grained information increases. In this sense, it is quite similar to Bayesian models of sensory combination and its development (e.g., Ernst & Banks, 2002; Nardini, Begus & Mareschal, 2013) and also quite similar to Bayesian models of combination of spatial information from path integration and from landmarks and its development (e.g., Nardini, Jones, Bedford & Braddick, 2008; Zhao & Warren, 2015a, 2015b). An overview of CAM and its relation to other Bayesian approaches to spatial behavior explains this family of approaches in more detail (Cheng, Shettleworth, Huttenlocher & Rieser, 2007). CAM is similar, but less similar, to Bayesian models of reasoning and its development, which utilize probabilities of one event given another, with the probabilities based on priors either gathered by prior experience or built in or both, e.g., Oaksford & Chater, 2001; Perfors, Tenenbaum, Griffiths & Xu, 2011).

Crucially, CAM can explain asymmetries in spatial judgment. Newcombe, Huttenlocher, Sandberg, Lie and Johnson (1999) demonstrated this aspect of the model. Experiment 1 again used the paradigm of estimating the location of dots in circles. People saw two dots sequentially. One of them was closer to the category prototype (i.e., the centroid of one of the quadrants of the circle shown in Figure 1) and the other point was farther away. They were then shown the location of one of the dots (either the first- or the second-presented one), and asked to locate the other dot. When the to-be-estimated dot was between the fixed dot and the centroid, over-estimation of the distance was predicted, and found. When the centroid is between the to-be-estimated dot and the fixed dot, under-estimation was predicted, and found. An additional prediction was also confirmed, namely that this pattern would be stronger when the to-be-estimated dot had been presented first, because fine-grained information about its location would have decayed and hence the category information would be more heavily weighted. The bottom line is that asymmetries of various kinds and magnitudes are expected, and their nature and size can be predicted, from a model in which people generate spatial estimates from underlying information without bias,

Two subsequent experiments used a different paradigm, examining asymmetries more directly. Participants were asked to learn a simple map showing locations such as a church and son in a hypothetical town. They learned the map either as a whole (in Experiment 2), or one quadrant at a time (in Experiment 3). In both cases, locations were grouped into quadrants by clustering around a centrally-located spatial prototype, such as the HOSPITAL in the upper left, further highlighted by an asterisk rather than a point, designated with a star and labeled in capital letters. After reaching a learning criterion, participants' spatial memory was tested in a series of pair-wise reproduction tests. One building (e.g., hospital) was shown and a second point (e.g., church) had to be placed relative to it. CAM accurately predicted when asymmetries would and would not be found.

We see then, overall, that the delineation of CAM and the fact that it explains asymmetries offer some hope of reconciling reflections on the evolutionary value of accurate spatial representations with the facts of spatial bias. In the context of this promise, the main purpose of this chapter is to review the various directions work on CAM has taken since its initial formulation, covering six topics: (1) creating and testing a process model of CAM, (2) examining how CAM might be used in the real world, (3) addressing the basis of natural spatial categories, (4) evaluating whether the categories used in spatial estimation align with linguistically-marked spatial categories, (5) exploring development and individual differences, (6) criticisms of CAM.

Testing CAM through Formulating a Process Model

Although CAM has much in common with research on a Bayesian approach to sensory combination, there is a crucial difference, namely the difficulty of separately measuring the reliability of categorical and fine-grained information, and then determining if the combination process uses that information to increase reliability. Separate measurement is challenging, given that one kind of information is hierarchically nested within the other. Huttenlocher, Hedges and their collaborators have instead relied on mathematical models showing that the use of categorical models improves the reliability of fine-grained information considered alone and is hence a Bayesian process (e.g., Huttenlocher et al., 2007).

Empirical research to deal with the issue of separate measurement of component processes and combined judgments is also potentially possible. One promising approach was charted by Friedman, Ludvig, Legge and Vuong (2013) who presented a model of combining two dimensions. They worked with x and y coordinates given their use of geographic stimuli. Using spatial judgment data gathered either in a perceptual or in a semantic context, they performed analyses separately for each single dimension (i.e., x-axis or y-axis), and then evaluated the two-dimensional (or combined) situation. More work of this kind is needed.

Another route forward is to test an implementation or process model of how CAM operates, rather than staying at the computational or algorithmic levels (Marr, 1982), and hence to test whether CAM makes predictions that are empirically confirmed. Work using this strategy began with examining the effect of delay, which should increase category bias by decreasing the accuracy of fine-grained information. Along similar lines, increased cognitive load might be expected to increase bias by making fine-grained information harder to encode and maintain. A second process question is whether category adjustment in fact occurs during retrieval, reflecting weighting of two underlying sources of information, neither of which contains bias but which vary in certainty. A contrasting possibility is that the two kinds of information blend with each other as an ongoing process during retention (e.g., Spencer & Hund, 2002).

Does Decreasing Reliability of Fine-Grained Information Increase Bias?

The passage of time, and the addition of interference, should degrade the accuracy and reliability of fine-grained information quite quickly in short-term dot-location experiments, hence increasing the weighting of category information and leading to increases in bias. One set of findings has already been discussed; Newcombe et al. (1999) found the over- and under-estimations that would lead to asymmetries only with first-presented dots, which had been subject to longer delays than second-presented dots. The effects of delay have also been confirmed in other studies, including in natural environments (Holden, Newcombe & Shipley, 2013), with children (Hund & Plumert, 2002, 2005) and in angle estimation (Crawford, Huttenlocher & Engebretson, 2000), although there were no effects of a 15-second delay in another study (Haun, Allen & Wedell, 2005).

Cognitive load might also sap the ability to encode and/or maintain fine-grained estimations, and increased cognitive load has recently been found to increase categorical bias in the estimation of line lengths (Allred, Crawford, Duffy & Smith, 2016). However, the number of locations to be remembered and the presence or absence of a concurrent task did not increase categorical bias in the same spatial estimation study that failed to find an effect of delay (Haun et al., 2005). One explanation for these null effects may be that participants in Haun et al. (2005) showed categorical effects that were very pronounced even though they only had to encode one location and had no concurrent interference task. This pattern suggests poor fine-grained coding even in the baseline condition, making it difficult to observe any increases in the effects of categories.

Fine-grained information does not always decay over time. It is acquired and retained in natural environments that are repeatedly experienced, as when university students get to know their campus (Uttal, Friedman, Hand & Warren, 2010). In fact, we would hope that such information would be robustly encoded, because without it, the kind of adaptive navigation that we imagine evolution should ensure would be challenging. However, there is evidence that cognitive load may be a factor in acquiring fine-grained information for natural spaces; working memory is significantly correlated with more accurate spatial estimates in learning a virtual environment (Weisberg & Newcombe, 2016).

Does Combination Occur at Retrieval?

Using the dots-in-a-circle task, Sampaio and Wang (2009) found that people prefer the correct location when it is pitted against their own (biased) estimate in a recognition task, suggesting maintenance of unbiased information and supporting a combination-at-retrieval model. Using natural scenes, Holden, Newcombe and Shipley (2015) replicated this key result, and also performed a further manipulation, in which participants were allowed to skip trials if unsure. However, in 25% of the cases, people were not allowed to skip the trial, and instead compelled to respond. Recognition trials could thus be sorted into the cases where people were sure enough about location to want to respond versus trials on which they had considerable uncertainty. The key prediction was that categorical information would be most heavily weighted when participants were unsure and were forced to respond anyway. Indeed, such a pattern was observed to a truly striking extent. When people were relatively sure, they preferred the correct location in a recognition test, as shown in the panel at the top right. When they were unsure, they preferred the category prototype, even in recognition, as shown in the panel at the lower right.

Categories and Combination in the Real World

Remembering the locations of dots in circles for very brief periods of time is clearly not the same kind of task as navigating in an environment. Learning the highly schematic maps used by Newcombe et al. (1999) doesn't take us much closer to spatial reality. Thus, a crucial challenge for CAM is whether it applies to the real world. Posing this question also involves us in asking another vital question, namely what determines spatial categories in the real world. To move towards real-world contexts and to begin to explore the nature of natural spatial categories, Holden, Curby, Newcombe and Shipley (2010) studied memory for dot locations on photographs of natural scenes, such as sand dunes, mountain scenes or lakes. To define the categories in order to investigate the predictions of CAM, there were both conceptual and perceptual categories to be considered. For example, people have a concept of "lake", but they also see the shadows and reflections on the lake's surface as different in color and other visual characteristics from the clear blue color of the lake elsewhere. To evaluate CAM, we began by defining categories in the scenes in two ways: using a perceptual clustering machine algorithm and also by obtaining judgments by human observers. Interestingly, these two methods converged quite well. This agreement may suggest that people use perceptual variations to sub-categorize concepts such as lake, or may suggest that people also have concepts such as "shadow" and "reflection". In any case, bias was found towards the center of scene categories, just as bias is exhibited towards the prototype of a quadrant of a circle. Holden et al. (2010) collected further data using inverted versions of the photos, which we thought would primarily weaken access to the conceptual content, and color-negative versions of the photos, which might interfere more with perceptual than with conceptual processing. People showed categorical bias effects in both cases, although the categories were somewhat different, both from each other and from the natural scenes.

Natural scenes move us toward the real world, but not all the way into it. If we would like to use CAM in thinking about spatial navigation in the actual three-dimensional world, we need to conduct experiments in that world. There have started to be efforts to do so. Holden, Newcombe and Shipley (2013) asked participants to remember the location of dots flashed with a laser pointer on the three-dimensional world, e.g., a bench. We again found bias towards the center of spatial regions. Pyoun, Sargent, Dopkins and Philbeck (2013) also found category effects, in an analogue of the work on the circle in which participants were placed in a real circular arena. People seemed to divide a surrounding circle into halves not quarters, considering there to be a front half (ahead of them) and a rear half (behind them). Furthermore, the category prototypes were not at the center of those two halves, but rather "pulled forward" so that they were within the field of vision, on the left and right sides of the front half. Even after people rotated, they preserved this organization when offered cues as to where the front and rear had been (either doors or objects such as a lamp).

Spatial Categories in the Real World

In the asymmetry experiments involving maps conducted by Newcombe et al. (1999), the quadrant organization was suggested by the stimuli (clustering locations and adding stars and capitalized labels). In the circle experiments, the gravitational vertical and the corresponding vertical are very powerful categorization cues, which can also organize other geometric shapes (Wedell, Fitting & Allen, 2007). But the natural environment is rarely structured completely by convenient external organization or by a gravitation-imposed axis structure. Further, the power of the gravitation-defined axes for the circle actually poses a challenge to the Bayesianism of CAM. People are resistant to organizing their spatial memory in other ways even when evidence accumulates that the frequencies of dot locations are not uniform (Huttenlocher, Hedges, Corrigan & Crawford, 2004). They can be pushed into using stable external cues when the circle rotates (Fitting, Wedell & Allen, 2007), as they should when horizontal and vertical bisection become unreliable categorical cues. But the resistance to using frequency data remains troubling. From a Bayesian point of view, it is important to be flexible in using categories and to rely on categories that are stable, e.g., shadowed areas are poor categories for anything but short-term spatial tasks because shadows shift with time of the day, and whether the sun is shining. Interestingly, after repeated trials, people utilize information about the density of locational distributions even in the circle (Lipinski, Simmering, Johnson & Spencer, 2010), acting in a Bayesian way by taking into account the probability that a point falls into a particular local area.

Most of the research on the formation of category prototypes in CAM has focused on attributes of objects, i.e., fatness of fish, length of lines. In such cases, prototypes might be running averages, but they might also weight recent examples more heavily or early examples more heavily. Sailor and Antoine (2005) found evidence for greater influence from recent examples, but Duffy, Huttenlocher, Hedges and Crawford (2010) found instead that people use running averages as their central tendencies or categories. Prototypic line lengths increased if stimuli were getting progressively larger, and decreased if they were getting progressively smaller. There was no greater influence from recent items. Duffy et al. (2010) did not evaluate possible primacy effects, but Duffy and Crawford (2008) had done so, and found them. Is this adaptive? Duffy and Crawford argue that it may be, because forming a category prototype quickly provides support for subsequent memory, and the likelihood that it is erroneous may not usually be high.

There has been less attention to how spatial prototypes are formed, for various reasons. However, Crawford and Duffy (2010) report a primacy effect: participants form a category prototype that is too far to the left when they have seen a sequence of dots in a rectangle presented from left to right, and too far to the right when they have seen a dot sequence progressing from right to left. Similarly, for children as old as 9 and 11 years, though not for adults, category effects are seen only when locations are learned in a temporally grouped way and/or placed in an order that emphasizes the categorical grouping (Hund, Plumert & Benney, 2002). People group categorically by the identities of the objects in experiments using objects with varying identities instead of plain dots (Crawford & Jones, 2011; Hund & Plumert, 2003; Sampaio & Wang, 2010), possibly forming categories of the "fruit section" and so forth.

From a Bayesian point of view, it is important to use the smallest available categories, because location is then more effectively constrained. Holden, Newcombe, Resnick and Shipley (2015) were able to evaluate the interacting use of perceptual and conceptual information and the ideas of flexibility and constraint by contrasting categorical bias in experts and novices. Expert geologists and participants with little geological knowledge viewed pictures in which categories were available to the experts that novices would be likely to miss. In some cases, the expert categories were smaller than the perceptual categories which were the only spatial categories available to novices. In other cases the expert categories were larger. We found that novices showed categorical bias towards the perceptual categories. The expert geologists also showed such bias when the perceptual category was smaller and hence constrained location more than their expert category would have done. They used their expert categories when they offered further constraint. These data strikingly confirm that spatial categories have both perceptual and conceptual bases, that they are flexible, and that they are adaptive in that they utilize the smallest available category to provide more accurate spatial estimation.

Becoming a geologist is a lengthy process, so it may be that the formation of conceptual spatial categories takes some time. Indeed, the Uttal et al. (2010) study of Northwestern undergraduates' knowledge of their campus did not find categorical clustering of campus locations in first-year students, but such grouping was present in the sophomores, juniors and seniors. Furthermore, Newcombe and Chiang (2007) did not find that participants easily formed strong categories of countries on hypothetical maps, even though a series of studies by Friedman and colleagues have found pronounced categorical effects for geographic knowledge in the real world (Friedman, 2009; Friedman & Brown, 2000a, b; Friedman, Brown & McGaffey, 2002; Friedman, Kerkman, Brown, Stea & Cappello, 2005;

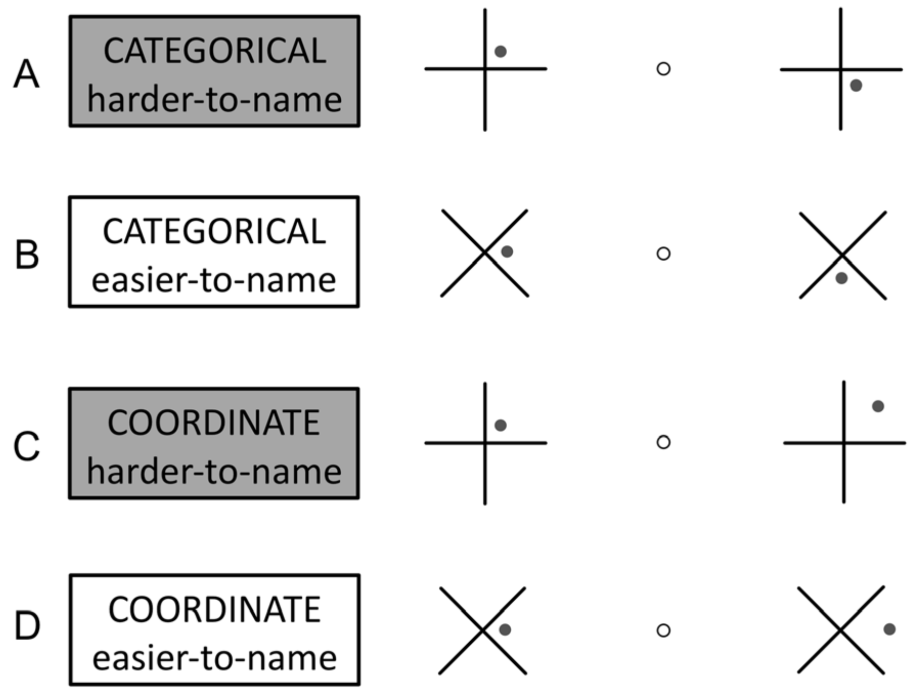
Friedman & Montello, 2006). Such categorical effects begin to appear between 9 and 11 years of age, perhaps reflecting the growth of awareness of countries and their distinctive characteristics (Kerkman, Friedman, Brown, Stea & Carmichael, 2003).

Spatial Categories and Linguistic Categories

Contrasting views concerning the relations between language and thought are one of the longest-running controversies in cognitive science. Recently, in the spatial domain, a great deal of attention has been focused on relative and absolute frames of reference. Languages vary in which they prefer, and strong positions have been taken on whether such variation transforms spatial thought (Gleitman & Papafragou, 2012; Levinson, 2003). A second language-thought issue in the spatial domain, however, has been whether the categories that language encodes with single words correspond to the nonlinguistic categories used in thought. Research on this topic has typically involved small closed sets of spatial terms such as front/back/left/right or above/below/left/right. Hayward and Tarr (1995) claimed to find close correspondence between linguistic terms and non-linguistic thought for the latter foursome, with categories centered on the vertical and horizontal dimensions. This finding is surprising in the light of the dot-in-circle experiments, in which the category prototypes were in the top right, bottom left and so forth, with the horizontal and vertical axes constituting the quadrant boundaries. Using a common paradigm to examine the contrasting findings, Crawford, Regier and Huttenlocher (2000) showed that there was indeed a contrast between non-linguistic category prototypes and spatial language, and suggested that language refers to the boundaries of non-linguistic categories rather than to the prototypes used in estimating spatial location. Thus, they suggest that there is a mismatch, albeit an understandable and functional one, between linguistic spatial categories and nonlinguistic spatial categories.

Kranjec, Lupyan and Chatterjee (2014) worked with categorical and coordinate (i.e., fine-grained) tasks. Dots were located within quadrants defined either by horizontal and vertical axes, or by diagonal axes, as shown in Figure 3. They label the former as "harder-to-name" because the quadrants in this case require two words not one, e.g., *top right* not simply *top*. However, this case could also be called "easier-to-encode" in the sense that these axes provide the quadrants typically used for improving retrieval of coordinate information using categorical adjustment. Kranjec et al. found that the accuracy of coordinate information was higher in the "easier-to-encode" case. This pattern again suggests a contrast between linguistic and non-linguistic categories.

The categorical and coordinate terminology used by Kranjec et al. was taken from Kosslyn (1987). As we have mentioned, Kosslyn's approach did not tackle the problem of how these two kinds of information may be combined and used together. But it did tackle a different problem that Huttenlocher and her collaborators never addressed, namely the neural substrates of the two kinds of information. Kosslyn proposed that encoding and maintaining coordinate information was a right-hemisphere function and encoding and maintaining categorical information was a left-hemisphere function, convenient enough if language picks out categories. Further research has provided considerable support for this hypothesis (e.g., Amorapanth, Widick & Chatterjee, 2009; Kosslyn, Koenig, Barrett, Cave, Tang & Gabrieli, 1989).



Thinking about these neural facts suggests an approach to the problem of the relation between spatial language and spatial thought. In the domain of color, Gilbert, Regier, Kay and Ivry (2006) found that perception is congruent with linguistic terms in the left hemisphere (as suggested by experiments lateralizing input to the right visual field) but not congruent in the right hemisphere. Similar patterns were found for categorization of profiles of cats and dogs (Gilbert, Regier, Kay & Ivry, 2006, 2008) and for novel figures that participants learned to categorize (Holmes & Wolff, 2012). As Regier and Kay (2009) put it, "Whorf was half right". Perhaps this approach can be extended to spatial categories. The right hemisphere, which is primarily concerned with coordinate or fine-grained information, might use the kind of categories that best address unreliability in that kind of information, in a combinatorial process. By contrast, without a strong concern with the reliability of fine-grained information, the left hemisphere might aim to maximize accuracy and precision of the usage of linguistic terms by centering categories on the easily-encoded axes. Evaluation of this hypothesis is needed; one method might be to use Kranjec et al.'s paradigm in a design that would allow for evaluation of hemispheric differences.

In pursuing the question of spatial categories and linguistic encoding, we also need to move beyond the small, closed fields of spatial terminology, such as above/below, because the spatial categories used in natural scenes, natural environments, and geological categories involve irregular shapes, many of which have names, although not all do. The names, however, suggest shapes (e.g., *crater* suggests a concave depression) but the particular shape is not strongly constrained. It is this kind of spatial meaning that Landau and Jackendoff (1993) had in mind when they discussed nouns as encoding spatial information. Whether or not names for these categories matter for their use in a combinatorial process has not been investigated. But if the names matter, they can't matter too much. For instance, consider that the geologists in Holden et al. (2015) did not use the expert categories for which they surely have names if a smaller novice category more narrowly constrained a location.

Development, Aging, and Individual Differences

Considerable research has been done on children's ability to estimate spatial location, converging on the view that there is evidence of early competence in both fine-grained and categorical estimation, as well as evidence of combinatorial processes (see review by Holden & Newcombe, 2013). At the same time, we also see developmental change, of a variety of kinds and with a variety of probable causes. First, the exactness of fine-grained estimation increases; increases in spatial precision have been used to model development in many tasks (Simmering, Schutte & Spencer, 2008). Second, categories may change, becoming richer as well as finer with development as more categories are acquired, especially in the natural environment, where categories have semantic content. Third, increases in working memory capacity may allow for combinatorial processes of wider scope (Sandberg, Huttenlocher & Newcombe, 1996). Fourth, feedback from the success of way finding and searches for lost objects may lead to progressive refinement in Bayesian combination. Such change has yet to be evaluated for CAM in the natural environment, but has been found for sensory combination (Nardini et al., 2013) and for combination of path integration and landmark use (Nardini et al., 2008).

There is not yet much research on individual differences in spatial location memory, other than age differences. A few papers have started to appear, however. Holden, Duff-Canning and Hampson (2015) found that women emphasize categorical information more than men in encoding both dots-in-a-circle and natural scenes, with this emphasis likely occurring during encoding, perhaps due to differential attention (see also Holden & Hampson, 2014, on sex differences in angle estimation). Crawford, Landy and Salthouse (2016) reanalyzed data from a large study of cognitive aging. They found that spatial working memory capacity was related to spatial bias for a task involving memory for the location of a dot on a computer screen. Lower-capacity individuals showed higher bias, as predicted from data already reviewed suggesting that working memory is relevant to the acquisition of fine-grained information. If such information is less reliable, we expect greater bias. In addition, in an important methodological development, Crawford et al. fitted separate models to individual data sets, which has never been done previously. They found that only some people showed patterns that were consistent with CAM. A good proportion of participants showed different patterns, which will need further exploration.

Criticisms of CAM

Over the years, CAM has been the target of a variety of criticisms. Some of them are a matter of theoretical taste. For example, Barth, Lesser, Taggart and Slusser (2015) argued that a Bayesian approach is not needed for spatial estimation tasks, because a simpler psychophysical model is sufficient to explain the data. While that is probably true, Bayesianism may be considered the more attractive interpretive framework because it explains a wider variety of phenomena, generates more predictions about behavior in other situations, and provides a psychological model of what is occurring when. Indeed, much of this chapter has reviewed tests of this model and overviewed its scope.

Other investigators have focused on the issue possibly implicit in the Barth et al. criticism, namely whether perceptual factors are sufficient to account for some of the phenomena discussed in this chapter, without invoking cognitive and conceptual issues. An early exchange involved research on the perceived and remembered tilt of lines in right-angled frames. Tversky and Schiano (1989) had explored the tilt of lines in L-shaped frames in the context of research on people's use of graphs. Responses varied depending on whether people thought they were looking at graphs or not, and Tversky and Schiano argued that there is a perceptual bias even when there isn't a conceptual one. Engebretson and Huttenlocher (1996) used L-shaped and also V-shaped frames without interpretive contexts, and found varying bias patterns that depended on the certainty with which vertical and horizontal lines can be remembered, which fit the CAM framework. This exchange did not develop into controversy, however, as Tversky and Schiano (1997) simply agreed that the phenomena were interesting, although seeing them as not inconsistent with their interpretation or with prior research on such displays.

The issue of the relevance of perceptual and conceptual phenomena to bias effects has continued to generate varying views. In a series of articles, Spencer and his colleagues (e.g., Simmering et al., 2008) have argued for the adequacy of a fundamentally perceptual account in their Dynamic Field Theory (DFT) approach. Furthermore, Friedman, Montello, and Burte (2012) found that category effects in experiments on placements of geographic locations were similar even when participants saw polygons shaped like Alberta or California and had to remember the location of dots, suggesting that perception alone could account for the phenomena. However, these criticisms do not explain the importance of the expert categories used in location estimations by geology experts (Holden et al., 2015).

Furthermore, Crawford, Huttenlocher and Engebretson (2000) showed that line estimation in the context of the Muller-Lyer illusion has both perceptual and conceptual components.

Conclusion

We have reviewed a variety of evidence concerning the success of CAM in explaining why and when people show biases in spatial memory. This debate is part of a more general debate about the existence of cognitive maps. After all, if spatial location judgments are subject to biases and (worse) illogical judgment patterns, it's hard to see how they could be map-like. Recent models of cognitive maps are, however, starting to suggest rapprochements. There may be locally metric representations with broad directional relations among them (Chrastil & Warren, 2013, 2014; Jacobs & Schenk, 2003; Kuipers & Byun, 1991), along with individual differences in the ability for formation of both the component representations and the directional relations (Schinazi, Nardi, Newcombe, Shipley & Epstein, 2013; Weisberg & Newcombe, 2016; Weisberg, Schinazi, Newcombe, Shipley, & Epstein, 2014).

This view, derived from cognitive, behavioral and modeling approaches, is beginning to converge with data at the neural level. The discovery of grid cells (Hafting, Fyhn, Molden, Moser & Moser, 2005), and their gradation from finer to broader tunings at various levels (Giocomo, Zilli, Fransén & Hasselmo, 2007) has combined with decades of work on place cells and head direction cells to begin to create a sophisticated model of way-finding and spatial representation. Interestingly, grid cells and place cells seem to encode spatial relations in particular enclosed spaces, raising the question of how the spaces are identified (e.g., Julian, Keinath, Muzzio & Epstein, 2015) and inter-related (Grieves, Jenkins, Harland, Wood & Dudchenko, 2016).

In turn, debates about both biases in spatial representation and cognitive maps are part of a wider effort to determine the nature and limits of human rationality, to understand the role of evolution in shaping "good enough" rationality to ensure adaptation, survival and reproduction, and to trace the origins and development of this "good enough" rationality while avoiding the extremes of nativism and empiricism

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