EXPLORING THE ANCHOR-POINT HYPOTHESIS OF SPATIAL COGNITION*

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Abstract

The anchor-point hypothesis of spatial cognition, according to which primary nodes or reference points anchor distinct regions in cognitive space, brings together certain frequently reported apparent properties of mental maps: the regionalization and hierarchical organization of cognitive space, and the active role of salient cues in structuring spatial cognition. After a brief overview of the state of the art in cognitive mapping research, the anchor-point hypothesis is first explored conceptually, and then one particular version of it, the 'tectonic plates' hypothesis, is made operational. For that second part of the study, cognitive configurations derived from five subjects selected from a larger sample taken in Goleta, California are analyzed using three different methods, and features transcending any method-specific biases are identified. Although not entirely unambiguous, these first results seem encouraging and warrant further research in this direction.

Introduction

To the extent that they exist at all, cognitive maps appear to have certain properties that already are relatively well established. For example, as will be discussed in the following, there is ample evidence in the literature for *regionalization* and route segmentation (one-dimensional regionalization) in such maps, for the important *role of salient spatial elements* (cues) of different sorts in orientation, in recall, and in the recognition of other cues, and for the presence of *hierarchical organization* in both regional structure and in systems of cues in cognitive representations.

Despite the strength of this accumulating evidence, there have been very few attempts to integrate all three of the above aspects of cognitive maps into one coherent theoretical scheme. The anchor-point hypothesis presented in this paper attempts to achieve just such a synthesis, whereby regionalization (that is, the breakdown of space into discrete regions), salient cue function, and hierarchical structure are brought together in the context of a tentative theory of the cognitive organization of space. According to this hypothesis, primary nodes or reference points anchor distinct regions in cognitive maps in any given environment. These anchors and the linkages between them provide a skeletal hierarchical structure for representing and organizing cognitive information about space (Golledge, 1978, 1984).

The paper consists of two main parts. The first part explores the conceptual underpinnings of the anchor-point hypothesis, such as the nature of anchor-points as potential elements of spatial knowledge representation, and the different forms in which they may be expected to manifest themselves in the course of empirical research. The second major part describes an empirical study designed to make operational one relatively simple version of the anchor-point hypothesis, and discusses its

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results. In order to place this study in the proper perspective relative to other recent work in spatial cognition, we begin with a brief overview of the state of the art in cognitive mapping research.

1. State of the Art in Cognitive Mapping Research

Much of the recent work in spatial cognition has stressed the fundamental non-homogeneity of cognitive spatial representations. In particular, results from many different experimental studies seem to point to the conclusion that spatial knowledge is represented hierarchically, that it is structured in discrete spatial units, and that salient cues play a key role in its organization and retrieval.

Thus, in an often quoted paper, Stephens and Coup (1978) discussed experiments in which they identified systematic errors occurring when subjects made large-scale directional judgments (for example, is Reno, Nevada east or west of San Diego, California?). They suggested that some decisions appear to be made with respect to a superordinate/subordinate locational system and that errors may be due in part to basing such judgment tasks on a hierarchical knowledge framework. The critical idea expressed in the Stephens and Coup experiments is an important one: it appears highly likely that a close cognitive association exists between elements such as landmarks and the area in which those landmarks are located, and that such elements may take on some of the general informational characteristics (correct or incorrect) of the area in which they are located. Thus, it would make sense to argue that since the state of California is commonly recognized as being further west than the state of Nevada, individual places in the state of Nevada.

This type of finding has considerable implications for our understanding of spatial knowledge organization as being hierarchical and regionalized. As another example, Wilton (1979) indicates that the response times involved in making distance judgments are slower across clusters than within clusters of features such as landmarks thought to belong together in some way. Similar findings are reported by Maki (1981). In a recent study, Hirtle and Jonides (1985) extend these results about response times to the actual ordinal values of comparative distance estimates within versus across clusters of landmarks at the city level. They find that distances that are roughly equal on the Euclidean map are consistently judged to be shorter if they lie within regions defined by clusters of landmarks than if they lie across such regions. These results confirm the findings of Allen (1981) who studied the one-dimensional case of route (rather than area) knowledge organization. Allen found evidence of segmentation in his subjects' knowledge of routes and also that across-segment distances were consistently judged to be longer than identical within-segment distances. All this supports the contention that some type of cognitive regionalization of space underlies spatial judgments, even those referring only to pairs of points.

As far as the function of salient cues is concerned, Stephens (1976) finds that priming occurs for cities within the same state, but not in neighboring states. ('Priming' refers to the experimental effect whereby the presentation of selected cues in some sequence affects the probability of recognition of a target cue presented subsequently.) Shute (1984) shows that priming also occurs at the neighborhood or microspace level, but it does not work uniformly in both directions within a hierarchy of cue salience. She indicated, for example, that presentation of a lower-level cue in

a sequence based on increasing spatial proximity to some higher-order cue will increase the likelihood of recognizing that cue, but that the reverse (higher-order cues helping recognize a proximal lower-order cue) is not true. This result is very interesting as it may help explain the findings by Lee (1970), Sadalla and Staplin (1980) and other researchers (Cadwallader, 1979) regarding the asymmetric nature of many interpoint distance judgments. Indeed, in a space where some types of relations between points are not symmetric, it is to be expected that violations of metric symmetry may also occur.

Much of the research mentioned so far supports the relevance of the conceptual scheme first proposed by Lynch (1960). In discussing the cognitive images of cities, Lynch suggested that the urban environment (and probably any environment) is known as a structure of landmarks, nodes, paths, edges and districts. The critical importance of landmarks has been widely accepted and provides a rationale for the vast number of subsequent studies using spatial cues in various spatial judgment tasks. The segmentation or regionalization of space by boundaries and the ready identification of districts, whether delimited by concrete boundaries or not, is shown by the studies mentioned above to have considerable relevance for spatial judgments, whether of the point-to-point or the area-to-area kind. There is a direct parallel between this organizational model for spatial information and a large volume of work in psychophysics and cognitive science stressing the significance of general concept location within clusters of concepts, and the effects of barriers or boundaries between or surrounding such clusters (see, for instance, Kosslyn et al., 1974). In a spatial context these results have been further examined and extended by Cohen et al. (1978) and Newcombe and Liben (1982).

The essence of much of the above work is that some type of conceptual clustering seems to take place, whether of spatial or non-spatial information, and that this seems to have an effect on judgments depending on whether the elements involved in these judgments lie within the same or different clusters. Further, the notion of hierarchically organized information is compatible with this scheme, in the sense that both the features within the clusters and the clusters themselves may well be of different degrees of importance or salience. Building on that idea, Golledge (1978) and Spector (1978) suggested a hierarchically structured and regionalized scheme for cognitive spatial organization. That scheme, which we propose to further develop in this paper, was named the 'anchor-point theory'. The theory (rather, hypothesis) argued that key landmarks, nodes and areas individually and jointly 'anchor' subregions of space and link together hierarchically the items of information acquired about that space. A cognitive map therefore would be, as Downs and Stea (1973) had already suggested, an incomplete, segmented, metrically distorted representation, with the accuracy of relational information (spatial and non-spatial) varying considerably within regions and across regions. Further work by Golledge and Rushton (1972), Golledge and Zannaras (1973), Tobler (1976), Golledge (1978), Spector (1978), Golledge and Spector (1978), Richardson (1979, 1982) and Golledge, et al. (1982) has shown that it is possible to represent an important part of such a cognitive map, and in particular, the latent spatial structure of judged proximity relations between pairs of well-known places, on the Euclidean two-dimensional surface. Such a representation has been called a cognitive configuration (Golledge et al., 1969; Golledge, 1974, 1985). However, there is evidence that as one attempts to recover relative distance information about places at lower hierarchical levels of salience, the

simple Euclidean relations may no longer hold even approximately, and indeed, as Baird et al. (1982) and Golledge and Hubert (1982) suggest, the resulting information may be impossible to represent in any two-dimensional Minkowskian space and may even prove difficult to represent in more complex hyperbolic or elliptical spaces. It thus seems that no single one of the simpler existing uniform geometries is capable of capturing the complete structure of the spatial relationships existing in an individual's cognitive configuration. It is with this basic methodological limitation in mind, that we attempt the further development and operationalization of the anchor-point hypothesis.

2. Defining the Notion of 'Anchor-Point'

Although intuitively the basic idea of anchor-points is straightforward, the notion proves difficult to define in practice. Part of the difficulty lies in the fact that several other concepts in geography and cognitive science are somehow related to the notion of anchor-points, and yet the similarities are often more confusing than helpful. Other definitional questions relate to the types of knowledge relevant to the anchor-point hypothesis, the problems of representing anchor-points operationally, the problems of identifying the anchor-points in individual cognitive representations, and so on. In the following discussion an attempt is made to clarify some of the main conceptual issues involved.

2.1 Anchor-points and related notions

The very statement of the anchor-point hypothesis, as given above, suggests a number of familiar concepts from geography, psychology and cognitive science. Among these are the notions of landmarks, spatial hierarchies, and nodes in semantic nets.

Landmarks. Much of the work in spatial cognition has focused on the concept of imageability. In brief, this assumes that there will be elements in any given environment (natural or built) which by virtue of their distinctive features (for example, form, color, size, visual uniqueness), or by virtue of some symbolic meaning attached to them (places of historic importance, of religious or socio-cultural significance, etc.), stand out from among the other things in the environment. Because such elements are outstanding, literally, they are likely to be perceived, remembered, and used as reference points by a large number of people in that environment. This is the notion of 'landmark' as popularized by Lynch's seminal work on the 'Image of the City'. Anchor-points (anchors for short) are closely related to landmarks, both concepts being defined as cognitively salient cues in the environment. However, as represented in the literature, landmarks tend to be collectively as well as individually experienced as such, whereas anchors refer to individual cognitive maps. Although one would expect to find several local landmarks among the anchors in a person's cognitive map, many anchors (such as the location of home and work) would be too personal to have any significance for other, unrelated individuals. Further, landmarks are primarily treated as part of a person's factual knowledge of space, whereas anchor-points are supposed to perform in addition active cognitive functions, such as helping organize spatial knowledge, facilitating navigational tasks, helping estimate distances and directions, etc. Finally, landmarks are concrete, visual cues, whereas anchor-points may be more abstract elements that need not even be point-like (e.g., a river or a whole city in a cognitive map at the regional level). In brief, we may think of anchor points as personalized, process-oriented, occasionally abstracted features that may or may not coincide with the collectively experienced landmarks defining the public 'image of the city'.

Spatial hierarchies. For any given cognitive environment, and any given individual, a hierarchy of anchor points is postulated. However, this is a hierarchy of cognitive salience rather than spatial scale: that is, the personally most important features on a subject's cognitive map are expected to 'anchor' the secondary features, which in turn serve as anchors for features of lower significance, and so on. Still, there is a spatial scale dimension to the anchor-point idea, since, for the same individual, one may define anchor-point hierarchies at the international, national, regional, urban, neighborhood, or even single route level. It follows that the spatial features serving as anchors for a given person are likely to be very different in nature depending on the spatial scale involved in the cognitive representation. For example, at the most highly disaggregated level, an individual's cognitive map would be dominated by neighborhood or community elements, which in turn could be tied to higher-order elements, such as commonly recognized landmarks at the city level. It is also to be expected that as one moves in scale beyond the local activity space, the idosyncratic component would play a decreasingly important role in anchor-point selection. An individual's cognitive map of the United States, for example, would be anchored by the locations of important cities such as New York, Chicago, San Francisco, Denver or Los Angeles, by linear elements such as the Mississippi River or the Rockies, and by areal elements such as the Great Lakes or the South. Although here again we would expect places that have been of some importance in the person's life to figure as anchor-points on his or her map of the nation, it is highly unlikely that home, work and habitual grocery shopping locations will play any role.

Irrespective of spatial scale, however, the notions of multiple anchoring elements, hierarchical structure, and localized dominant-subordinate relationships on that structure are key parts of the anchor point hypothesis.

Nodes in semantic nets. There are some close (and not accidental) analogies between anchor-points and primary nodes in semantic nets, as expounded in the work of Quillian et al. (1968). Both the anchor-point hypothesis and semantic net theory postulate a hierarchical network of nodes (representing places or concepts, respectively), connected by links, representing relations, spatial or conceptual, respectively. In both hypotheses the primary nodes at each hierarchical level are the major organizational elements of the representation; in both cases associations may be made between different node complexes through a process of 'spreading activation'. However, the differences between these two types of concepts are no less substantial. First, an anchor-point network is assumed to be some transform of a configuration of points and lines in actual Euclidean space: a semantic net, by contrast, represents a conceptual structure with no direct analog in the observable world. Anchor points in cognitive maps may therefore have direct empirical referents (places), whereas nodes in semantic nets may have none (as when they represent abstract concepts). As a further consequence, cognitive maps may have metric properties whereas semantic nets can only have topological ones. Another difference is that semantic nets allow for considerable heterogeneity in the type of concepts represented (nouns representing concrete things, abstract concepts, verbs, adjectives, linguistic constructs such as 'is-a', etc.), whereas anchor-point hierarchies only consist of places, and links between these places (the latter may correspond to real routes between places or may be more

abstract, relational links). Finally, semantic nets are meant to be representations of declarative knowledge only: in the case of anchor-point configurations, it is very difficult to disassociate the declarative from the procedural or functional and also the relational aspect of spatial knowledge. These differences drastically limit the usefulness of the analogy between semantic nets and anchor-point hierarchies. Obviously, however, confirmation of the existence of a hierarchical network of anchor points in cognitive maps would immediately raise questions about the connective structure of such networks, and the types of information that may flow over them, very similar to those discussed in the context of semantic net theories.

2.2 Types of knowledge implicit in the anchor-point idea

Any valid representation of a cognitive map must be compatible with at least the following four commonsense aspects of spatial knowledge:

- a. *knowing-what*, or the capacity for recognition, recall and description of spatial elements;
- b. *knowing-how*, or the knowledge necessary to accomplish actual or mental navigational tasks either along single routes or over an area;
- c. knowing-where (absolute), and possibly also 'knowing-when', for non-permanent elements of the environment, or the associational knowledge needed to identify cognized elements of the environment with their localized referents in actual space (and time), and configurations of such elements with corresponding real-world Euclidean configurations;
- d. knowing-where (relational), or the knowledge of the relations of relative distance and direction, contiguity, serial order, etc. Thus, relational knowledge is valid within a given space (in this case, either objective or subjective), whereas 'associational' knowledge maps two different spaces onto each other, by establishing associations between specific points in one space and specific points in the other.

The categories of 'knowing-what' and 'knowing-how' correspond fairly closely to the declarative-procedural knowledge distinction of cognitive science (Anderson, 1982). 'Knowing-where' in its relational form must underlie any kind of network knowledge such as that implicit in the semantic-nets hypothesis. *Associational* knowing-where, however, seems to be a category peculiar to spatial knowledge, that can be related to a characteristic of cognitive maps briefly discussed earlier: namely, the fact that, unlike semantic nets, cognitive configurations (a) may have metric as well as topological properties, and (b) must correspond to actual configurations in geographic space.

This suggests that representing anchor-points operationally may not be a task exactly analogous to representing nodes in semantic nets. In addition to the intrinsic (absolute) and relational properties of anchor points (e.g. 'big expensive grocery store, next to children's school'), we need to specify their associational properties as well, e.g., 'about ten minutes' drive from here', where 'here' no longer is a free-floating concept such as 'big' or 'school' or even 'next to', but a brute empirical spatial reality. Specifying coordinates for the main anchor-points ('fixing' them) because their locations are presumed to be very well known would associate them correctly with objective space on paper, but the question arises as to whether this would correspond to anything psychologically meaningful in the context of a theory of spatial knowledge organization. That we have missed out the associational

dimension of spatial knowledge in our study is evident from the fact that on many of the individual cognitive configurations obtained, the home and work cues are considerably displaced relative to their actual location on the map, although these are presumably the best-known places for each person. Indeed, the cognitive map described and analyzed in the second part of this paper can only capture relational and, to some extent, declarative spatial knowledge.

2.3 Identifying anchor-points in individual representations

Almost by definition, anchor-points are the most important elements in a person's cognitive map. But 'importance' may be understood in many ways. Thus, any of the following properties may make a feature of the environment an anchor point:

- a. Properties intrinsic to the object, such as perceptual or symbolic salience;
- b. Relational-spatial properties, such as location within daily activity space, frequency of interaction, location near key decision points, etc.
- c. Relational non-spatial properties, such as actual or potential significance in a person's life.

We have attempted to capture these aspects of anchor points through a multidimensional measure of 'familiarity', which includes: recognizing the sight or name of a spatial cue, knowing where it is, and interacting frequently with it (Table 1). Two features of the environment that may fairly safely be assumed to correspond to anchor-points in every person's mental map, because of their particularly salient properties, are one's home and place of work: we have included these at the outset among each of our subject's anchor-points. In general however, there appears to be no obvious method for identifying individual anchor-points, even after the familiarity scores have been obtained for each subject for a standard set of cues. This is because of the difficulty of combining unambiguously the familiarity measures obtained along the several dimensions considered, and because of individual differences in discrimination when rating the cues. The issue is discussed in more detail in Gale and Halperin (1985). Hoping to resolve that problem in a subsequent study, we decided to concentrate for the present on home and work as the primary anchors, and only use the familiarity scores obtained for the remaining cues as guides in the evaluation of our findings.

3. Possible Forms of the Anchor-point Hypothesis with respect to the Structure of Mental Maps

Anchor-points are supposed to help organize spatial cognitive information and structure mental maps. This assumption is compatible with any of the following hypotheses (and possibly several more), which can be tested experimentally on the cognitive-map configurations obtained for each subject in our study. All three of these hypotheses concern static configurations, since our cross-sectional data did not allow us to examine evolving structures. The dynamic properties of cognitive configurations obtained from subjects learning a new environment were explored in Golledge (1974). Ongoing work along similar lines seeks to combine the geometric approach taken in that and the present research with the 'computational' approach to spatial learning developed in Golledge *et al.* (1985).

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TABLE 1
Familiarity ratings

	Subject A126											
Cue	1	2	3	4	5	6	7	8	9	10	11	12
Spatial	9	9	9	6	9	2	8	1	7	6	7	7
Visual	8	8	8	8	8	1	8	1	8	8	8	6
Name	9	9	9	9	9	2	9	2	9	9	9	9
Interact	7	8	8	2	8	1	5	1	5	3	7	7
						Subj	ect D0	98				
Cue	1	2	3	4	5	6	7	8	9	10	11	12
Spatial	6	9	9	1	9	9	9	1	9	9	9	9
Visual	5	ģ	8	1	6	ģ	7	î	9	9	9	9
Name	6	ģ	9	î	7	ģ	ģ	1	9	ý	9	ģ
Interact	2	ģ	ý	ì	6	ģ	7	i	ģ	ģ	ģ	ģ
						Subj	ect El	02				
Cue	1	2	3	4	5	6	7	8	9	10	11	12
Spatial	9	9	9	8	9	9	9	6	0	9	9	9
Spanai Visual	4	8	8	9	9	3	8	2	8 8	9	7	3
Visuai Name	7	9	9	9	9	6	9	6	9	9	9	7
Interact	4	7	5	3	9	1	9	2	7	9	9	2
						Subj	ect J16	69				
Cue	1	2	3	4	5	6	7	8	9	10	11	12
Spatial	9	7	9	7	9	3	9	1	9	9	9	9
Visual	ģ	4	9	ģ	ģ	2	7	i	8	8	8	8
Name	ģ	9	9	ý	ģ	7	ģ	2	8	7	8	8
Interact	9	3	9	4	ģ	í	9	1	6	6	9	5
						Subj	ect K2	03				
Cue	1	2	3	4	5	6	7	8	9	10	11	12
C 4: - 1	0	7	0	9	9	3	9	2	0	9	9	8
Spatial	9	7 8	9 9	9	9	2	9	3	9 9	9	8	7
Visual	9	8 9	9	9	9	7	9	8	9	9	9	9
Name	9 7	3	5	4	8	1	8	1	4	8	9	2
Interact	,	3	J	4	o	1	o	1	4	O	7	2

3.1 The 'tectonic plates' hypothesis

Major anchor-points define associated *regions* on the mental map. There is a high level of coordination within these regions but only topological information about between-region relations (Siegel and White, 1975; Golledge, 1984). According to this

hypothesis, cues associated with a particular anchor-point will be displaced (distorted) in the same direction as the anchor point itself, so that the whole corresponding region will 'move' in one piece, relative to the regions defined by other anchor points. Three alternative procedures for identifying that effect are described and applied in section 5 below. The information available for these tests is limited in our study to the outputs of the TRILAT program (see following section), and specifically to the displacement vectors or 'distortions' obtained by comparing the cognized with the actual location of each cue on a cognitive configuration.

3.2 The 'magnifying glass' hypothesis

The assumption here is that areas around major anchor-points tend to be well known. Because a person's mental map will need to accommodate more detail for these areas, the corresponding regions will be 'stretched out', so that cues within these regions will tend to be displaced outwards with respect to the corresponding anchor-point. This hypothesis is also in agreement with the so-called 'power law' in distance judgments described by several researchers (Golledge *et al.*, 1969; Briggs, 1973, 1976; Lowrey, 1973; Burroughs and Sadalla, 1979; Cadwallader, 1979; Sadalla and Staplin, 1980), stating that a power function best describes the relationship between objective and subjective distance because short distances tend to be overestimated relative to longer distances. To test this hypothesis, one would need first to normalize the distortions of the other cues relative to the distortion vector of the corresponding anchor point.

3.3 The 'magnet' hypothesis

Alternatively, a major anchor point may function as a magnet, drawing towards it the other points in the corresponding region. This effect may be directional (evidenced in the normalized distortions of these points), metrical (resulting in a foreshortening of cognized distances towards the anchor-point), or both. There is an implication here that distances from/to an anchor-point tend to be underestimated, which may or may not be empirically viable, especially since it seems to contradict the 'power law' mentioned above.

It may be noted that the first hypothesis is compatible with either of the other two, so that combined effects may exist.

4. The Experiment and the Data

The setting for this study was defined by the boundaries of 12 contiguous census tracts in Goleta, California (Figure 1). Bounded on the north by the Santa Ynez mountains and on the south by the Pacific Ocean, the area is a coastal lowland strip approximately three to four times longer in the east—west direction than it is wide. Using census tract population data, a probability-proportional-to-size strategy, and a telephone company address directory, a sample of 57 subjects who both lived and worked in the area was obtained.

Preliminary questionnaires administered throughout the study area in conjunction with a parallel consumer behaviour survey (Golledge and Wrigley, 1985) were used to establish a set of 12 prominent locational cues. These cues were the locations most frequently cited by residents asked to list the ten best-known places in the study area. Having defined this set of commonly known places, subjects in the present

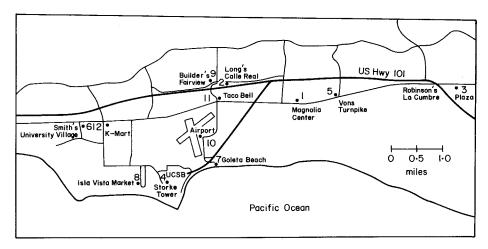


FIGURE 1. Study area and location of cues.

study were first asked to rate their familiarity with each of the 12 cues (on a nine-point linear scale) based upon four criteria: (a) spatial—Do you know where it is? (b) visual—How easily could you recognize a picture of it? (c) name—How familiar is the name of that place? (d) interaction—How often do you see or visit this place? (see Gale and Halperin, 1985 for details).

Next, the subjects were given a pairwise proximity judgment task involving their own home and work locations in addition to the set of 12 common cues. The cues were presented in pairs. The instructions given to each subject were to begin by assigning a score of 9 to the pair or pairs of cues thought to be the furthest apart, and a score of 1 to the pair or pairs thought to be the closest together. The remaining pairs of cues were then to be scaled accordingly between 9 and 1. In all, each subject made a total of 91 pairwise estimates, yielding (under the assumption of symmetry) a complete 14×14 matrix of proximities. Tobler's trilateration procedure TRILAT (see Golledge and Rushton, 1972; Gale and Costanzo, 1982) was chosen to derive map configurations from these subjective ordinal judgments. In its present automated form the trilateration procedure is a two-dimensional metric algorithm. Beginning with an $n \times n$ matrix, \mathbf{D} , of proximities, d_{ij} , and a starting configuration of n points, the procedure iterates to find a new configuration such that $(d_{ij} - d^*_{ij})^2$ is minimized, where the d^*_{ij} represent distances calculated between the solution coordinates.

In the present case, the initial configuration used was that given by the actual locations of the 12 common cues, plus each individual's home and work locations. Thus, a vector drawn from the original (objective) location of each cue to its new (cognized) location in the solution configuration represents a measure of displacement of that cue relative to objective space in the corresponding subject's cognitive representation of the area. Taken together, the set of vectors represents a transformation from objective to subjective space portrayed graphically in two-dimensional Euclidean terms. The TRILAT procedure also yields an error ellipse, a measure of the variability or 'fuzziness' in the estimates for each point.

5. Testing the 'Plate Tectonics' Hypothesis

Of the three possible forms of the anchor-point hypothesis outlined earlier, 'plate tectonics' seemed the most promising candidate for testing with the available data. Indeed, any likely 'magnifying glass' effect could be very hard to distinguish from that of the so-called 'power law', a phenomenon that is well established empirically quite independently of any notion of anchor point. On the other hand, the 'magnet' hypothesis seemed *a priori* less plausible precisely because it runs counter to the power law.

The plate tectonics hypothesis, which became the focus of our preliminary tests, posits the existence in mental maps of coherent spatial regions structured around selected highly familiar cues (the anchors) and displaced in the same general direction as the corresponding anchors. In our study, the data available for testing for that effect were the distortion vectors for the set of 14 cues on each map, the location of at least two cues per map that had to be anchors by any reasonable definition (home and work), and the individual familiarity scores for the 12 common cues, useful for assessing the chances of some of these other cues being anchors for any given subject. The fuzziness data were not used in these preliminary tests, although an earlier study by Gale (1982) had found a statistically significant negative correlation between amount of fuzziness and degree of familiarity. Assuming that a cluster of contiguous points defines a region, evidence of directional correlation between the distortion vector of each presumed anchor and those of the cues in its vicinity would provide support for the hypothesis. Conversely, many possible other findings would not be compatible with it, at least in its basic form; for instance, strongly overlapping regions (indicating a large proportion of cues assigned to more than one anchor); a high proportion of cues not seeming to belong to any anchored region; a high incidence of regions containing 'holes', i.e. cues in the interior of anchored regions but not belonging to them on the basis of the directional criterion; regions that seem to be anchored around cues of low familiarity, that ought not to be anchors by definition; and so on. Thus, in principle, the hypothesis is testable with the available data.

Any early attempt to detect structure within invisible and intangible spaces is likely to encounter some delicate conceptual and methodological problems. Our investigation of the geometrical and topological structure of cognitive space is no exception to this. Because several subtle questions regarding measurements in cognitive space could not be settled *a priori*, we opted for a methodological exploration of our data, rather than conventional statistical testing based on some pre-selected technique. Thus, we approached the data with three different methods (two exploratory, one confirmatory), the assumption being that the more robust aspects of any anchor-point structures, if at all present, ought to be detectable over and above any method-specific effects. These methods: Galois lattice analysis, relative-proximity analysis, and single-link cluster analysis, are presented below, together with a discussion of their relative performance on a set of five cognitive configurations, each one drawn from a different census tract, but otherwise randomly selected.

5.1 The Galois lattice approach

Our first route to operationalizing the plate tectonics hypothesis, based on the Galois lattice methodology (Macgill, 1985), is exploratory. The idea here is to approach the data without any preconceived notions about which of the 14 cues on a map may be

anchors, or about whether there are any such special points at all, and then to look for evidence of highly familiar cues dominating distinct regions.

The Galois lattice method (which is similar to Q-analysis in many important respects: see Gould, 1980) appears well suited for that task. Its purpose is to bring out the similarities among a set of objects (X, Y, Z, \ldots) on the basis of shared characteristics (a, b, c, \ldots) . The output of a Galois lattice analysis is a hierarchical ordering of single objects, pairs of objects, triples, quadruples, ..., sharing subsets of characteristics, each object cluster occupying a node on a lattice together with a listing of the characteristics that define that particular cluster. The structure of the lattice, with its graphic depiction of the set-theoretic operations of meet and join, gives a visually highly readable representation of the relations of overlap, containment, partial containment, dominance etc. holding between the different subgroups of objects in the data set. Most importantly for our purposes, the method also helps identify any individual elements that may bind together the objects in a group: in our case, these focal elements would be no other than the anchor points, binding together the secondary cues on the different plates.

In this application, the set of objects and the set of characteristics were the same (the cues). The general relation 'object X has characteristic Y' represented in the binary matrix underlying the lattice is here re-interpreted as 'cue X is proximal to cue Y', whereby the following definition of proximity is used: two cues are proximal on a given cognitive map if they are closer together than the mean distance between all pairs of cues on that map and if the directional association of their distortion vectors is greater than the mean directional association between all pairs on that map. Because the whole notion of anchor points and associated tectonic plates only makes sense in cognitive space, not in objective space, distances between cues are measured on the cognitive rather than the actual map, i.e. between the tips rather than the bases of the distortion vectors. This choice however is not entirely without problems, as will be discussed below.

The Galois lattice for subject A126 is shown in Figure 2. It is an 8-level hierarchy containing 19 nodes. A typical node of the form (acdeg, cdf) may be read as follows: 'cues a,c,d,e and g are all proximal to c,d and f', suggesting that the latter subset of cues bind the former together on the basis of the criteria of nearness and directional association used in this analysis. A tentative interpretation of such a statement could be that cues c,d and f serve as anchors for the others in the cluster at the given hierarchical level.

This particular lattice shows two distinct branches suggesting two distinct regions, of which incidentally one contains the home (13) and the other the work (14) location. One cue, number 8, dropped out of the analysis as unrelated to all else, and indeed that cue was rated very low on the familiarity scale by the subject. At the top of the left branch appear two 7-dimensional clusters, one linked together by cues 1 and 13 and the other by cue 11. Cue 13 is the subject's home location and in terms of the proximity criteria used it is indeed indistinguishable from cue 1, which too happens to be highly familiar (Table 1). Cue 11 is a cue of high, but not the highest, familiarity. On the other branch cue 14, the subject's workplace, does not appear as a 'binding' cue until 3 levels down from the top of the hierarchy. Cue 12, which tops that branch, happens to have a moderate familiarity rating for that subject; however, the locations of cues 12 and 14 are so close on the objective map that it may not be possible for the crude methodology used to differentiate between them effectively.

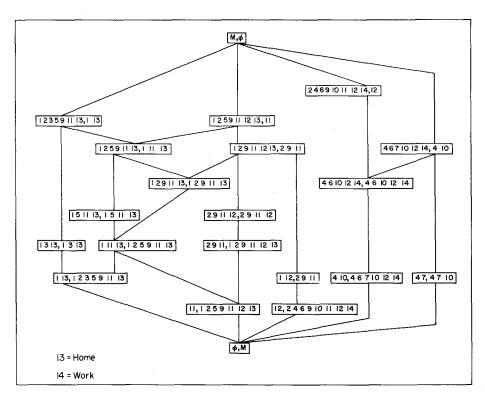


FIGURE 2. Galois lattice for subject A126.

Certain other features of the lattice seem less positive or easily interpretable. For instance, the different groups and subgroups identified show a fair amount of overlap (shared subsets of cues) both horizontally and across the levels of the hierarchy, especially on the left-hand branch. Intuitively, one would expect on the basis of the tectonic-plates hypothesis a fairly clear partitioning of cues into distinct plates at the different horizontal levels, and fairly strong nesting of sub-plates vertically. However, further reflection shows that it is not possible to interpret the hierarchical structure of the lattice literally as an anchor-point hierarchy, as a large part of the former is bound to be an artifact of the methodology. As an example, the number of levels on the lattice is largely determined by nothing more substantial than the dimensionality (number of defining elements) of the highest-ranking point(s). In any case, our set of 14 cues is clearly too small to allow for more than one basic level of anchors and plates to be distinguished. Because of this limitation, we have not been able in this study to explore an important tenet of the anchor point hypothesis, the multi-level hierarchical structuring of cognitive space.

Four further sample configurations were examined using the Galois lattice approach, and all five were also subjected to relative-proximity analysis and cluster analysis. The results are compared and discussed below, following a brief presentation of the two other methods used.

5.2 The relative proximity approach

The second approach used is confirmatory. Now we assume at the outset that certain cues (specifically: home and work) are anchors, and we look for evidence of coherent regions associated with them. The methodology in this case is fairly straightforward: a cue is associated with one of the two presumed anchors if it is both nearer and more closely associated with it directionally than with the other. Again, distance measurements are taken in cognitive space (between the displaced positions of the cues), since it is where the cues are thought to be with respect to the anchor-points, not where they actually are, that is significant for the purposes of this analysis.

This simple-minded methodology has one definite advantage over the Galois lattice approach in that it uses genuinely binary criteria to help set up the incidence matrix (e.g., 'cue X is closer to anchor A than to anchor B') and does not involve the conversion of continuous distance and angle variables into binary ones through the use of arbitrary cut-off values (here, mean distance and mean directional association). On the other hand, it clearly is not neutral with respect to the expected outcomes: overlapping regions (an important kind of negative evidence for the hypothesis) cannot arise with this method. Also, we have estimated that some 50% of all remaining cues (6 in this case) would be assigned to any two selected cues by chance alone. The maps we have analyzed using this method (Figure 3) seem to show a better-than-chance allocation of cues to the home and work anchors, but any pronouncements as to the significance of these findings must await proper statistical tests.

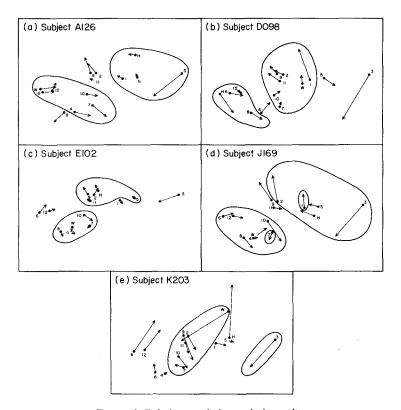


FIGURE 3. Relative-proximity analysis results.

5.3 Single-link cluster analysis

Finally, the five sample configurations were also explored using a conventional clustering method, single-link cluster analysis. Single-link was chosen over other common clustering algorithms because we wished to exploit the 'chaining' property of that method, compatible with the idea of cognitive association implicit in the anchor-point hypothesis. In some ways, single-link cluster analysis is similar to Galois lattice analysis. Both methods are exploratory rather than confirmatory; also, both are hierarchical, although in neither case is it possible to give a literal interpretation to the resulting hierarchies in the context of the anchor-point framework. There are also some important differences. First, the single-link method is not confined to binary data, and indeed here we used real values for the distances and angles between the cues. The Galois lattice algorithm, on the other hand, is more datafriendly: it clusters the data without first working on, or transforming them in any way (see Macgill, 1984). A further difference is that single-link cluster analysis, like our relative-proximity approach, imposes partitions on the set of cues, whereas the Galois lattice method allows for overlapping subsets. This makes for 'cleaner' clusters, and thus better-looking outcomes in the single-link case, although one might argue that the unforced though less clear-cut groupings of the Galois method are truer to the actual structure of the data (Gould, 1981). Finally, the Galois lattice analysis has the great advantage of highlighting the pivotal points in each cluster, which, as mentioned earlier, is a very useful feature in the present context where the search is not only for regional clusters, but also for the corresponding anchoring cues. The output of the single-link cluster analysis can of course also be represented graphically, either as a dendrogram or as contour lines on the two-dimensional point configuration (Figure 4).

Whatever the comparative merits and drawbacks of each of these methods might be, the purpose here was not to compare their performance: rather, the search was for underlying patterns sufficiently robust to persist through different methodological reformulations. Whether such patterns were actually detected will be the topic of the following section.

5.4 Some preliminary results

A table comparing the output of the analysis of the five configurations using all three methods is reproduced in the Appendix. The results of the relative-proximity analysis are also illustrated in Figure 3. Here we discuss each of the test subjects' configurations separately.

Configuration A126. The most notable outcome of the Galois lattice analysis of this configuration, (Figure 2), which was the division of the cognitive space into two main regions, one of them containing the home and the other the work location, is largely supported by the two other methods. Relative-proximity analysis also yields two plates, of which one is identical to a level-6 grouping on the Galois lattice, containing work, whereas the other is part of the dominant level-8 grouping on the other side of the lattice, containing home (Figure 3(a)). Only three cues are not assigned to either plate by the method, and may be interpreted as forming an autonomous small region on the subject's cognitive map. Finally, single-link cluster analysis identifies two regions at level 10, one containing home and the other work, and these are identical to two of three level-6 plates of the Galois lattice.

Configuration D098. The Galois analysis of configuration D098 reveals a loosely

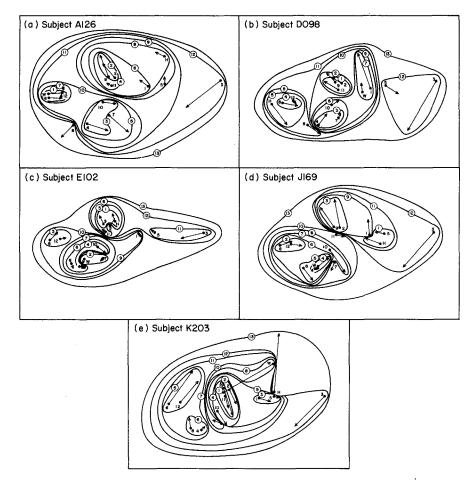


FIGURE 4. Single-link cluster analysis results.

interconnected, highly fragmented lattice containing 67 elements (as opposed to only 19 in the case of A126). This indicates a large number of high-dimensional cues competing for dominance. 'Work' appears as the single most important cue at level 6, fairly high up, but the group of cues it dominates is only one out of five at that level. 'Home' does not appear as a binding cue until level 4, and then again it is only one out of a group of four cues binding together a relatively small (4-dimensional) plate. In general, 'home' and 'work' appear at very different regions of the lattice, but this is mainly due to their considerable physical separation on the objective map. Unlike the previous case, the Galois lattice analysis of configuration D098 does not seem to support the hypothesis. The other two methods, by contrast, produce results that appear as good as those for configuration A126, and indeed, both identify practically the same two plates (cluster analysis at level 10). The fact that both these methods *force* contiguous partitions on the set of cues should be kept in mind, however, in the face of the less encouraging results of the Galois analysis.

Configuration E102. This yields another highly fragmented Galois lattice (51 elements) that is very disconnected, at the higher levels in particular. 'Work' and

'home' appear as binding cues at levels 5 and 4, respectively, but the sub-regions formed by them overlap and compete with 8 and 10 others at these levels. Relative-proximity analysis identifies two plates for 'home' and 'work' that are fairly similar to those centered around these same cues on the Galois lattice, but leaves four cues unassigned. The cluster analysis identifies almost identical plates relatively early on (at level 8), but the graphical representation of the clusters (Figure 4) shows a number of contorted shapes that also suggest less-than-optimal regionalization.

Configuration J169. The Galois analysis of configuration J169 shows an 8-dimensional region dominated by the work location, and a second, 6-dimensional one dominated by home. Both these regions (with some minor variations) are found again at the lower levels of the cluster analysis. The relative-proximity analysis of this configuration exhibits an unusual feature in that inside each of the regions associated with home and work there is one vector that does not seem to 'belong' (Figure 3(d)). The resulting 'hole' could be interpreted as counter-evidence for the hypothesis or as evidence for the existence of local subplates inside the major regions, presumably at a lower hierarchical level. However, the two other methods do not support this finding (both show at least one of the two problem cues as being well integrated), and it is likely that the apparent anomaly is no more than an artifact of the relative-proximity method.

Configuration K203. The Galois lattice of configuration K203 presents two clearly distinct regions, one 7-dimensional plate containing work (though not dominated by it), and a second one, containing all the remaining cues except for home and cue number 3. The home cue indeed plays no role in the analysis, and is connected to no other points. The cluster analysis closely agrees with this result. Also, the relative-proximity analysis identifies a plate that roughly corresponds to the one containing work in the two other cases. This configuration is noteworthy for the very large distortions of both the home and work locations (the two cues that ought to be best known to the subject), suggesting possibly unreliable data. The very convoluted shapes of the cluster analysis results (Figure 4(e)) reinforce this impression.

Beyond such possibly pathological cases, there are other types of cognitive configurations that seem to cause problems for the general methodology used or for the plate tectonics hypothesis itself. For example, if the home and work locations are very close together (thus perhaps defining a region in common), all three analytic methods described in this section break down. Similarly, if the distortions for home and work are very small, not only are these methods virtually inapplicable in practice, but the tectonic plates hypothesis itself becomes somewhat questionable. Indeed, beyond the considerable measurement error inherent in very small displacement vectors, there would be in this case no leading plate displacement direction to speak of. If such small distortions for home and work turn out to be a common occurrence, one might wish to examine either of the two other forms of the anchorpoint hypothesis. However, as things stand, there is enough positive evidence for the tectonic plates hypothesis to encourage further exploration.

6. Discussion

Although these few results seem encouraging, an analysis of the full sample is required before we may venture any plausible generalizations. Even then, the limit-

ations of our data and methods impose some definite constraints on the quality and variety of the results we may hope to get out of this particular study.

6.1 Limitations of the experiments and the data

Several limitations of the available data should be mentioned at this point. First, the small set of cues precludes any more extensive testing for multi-level hierarchies of anchor points and associated regions. Also, the twelve cues chosen, while being the most familiar ones among all the local landmarks for our sample as a whole, are not necessarily all well known to each individual subject. This may have occasioned a number of wild guesses, rather than estimates, in the pairwise distance estimation experiment. Lacking any measure of response confidence, we have no way of knowing how many of the cue displacements recorded on our maps may be the result of highly unreliable input. Along similar lines, we have not tested for robustness in the responses by repeating the experiment with the same subjects a second time. Further, we have not tested for symmetry in the distance estimates, although many studies have shown the existence of directional bias in estimates towards vs away from the center of the study area (Lee, 1970; Golledge et al., 1969; Briggs, 1972). All this amounts to an unknown degree of uncertainty regarding the reliability of our set of cognitive maps, quite apart from any methodological questions stemming from our use and interpretation of the underlying TRILAT algorithm. That uncertainty is particularly disturbing as all three methods used to test the plate tectonics hypothesis, and the second one in particular, are sensitive to small differences in cue displacement and direction of distortion. More thorough experiments in a future study should remove a large part of these doubts.

6.2 Conceptual difficulties

Other difficulties are more conceptual than methodological or technical. We have already mentioned the problem of a possible asymmetry in the distance estimates according to whether they are made towards, or away from, the center of the study area, which could affect the location of the displaced cues on the maps and thus the 'cognitive distances' measured between these. Similarly, we have already pointed out how the likely effect of a 'power law' (overestimation of short distances) inside highly familiar areas could confound a possible 'magnet' effect of anchor-points, and make the 'magnifying glass' hypothesis very difficult to test. More subtly, the power law could also confound the tectonic plates version, by moving cues on the cognitive map away from the anchor to which they would normally belong, and thus perhaps closer to a competing anchor. This is actually not the only conceptual problem with the tectonic plates hypothesis as formulated here. The stipulation that the distortion of subordinate cues on any given plate be in the same general direction as that of its anchor precludes cues that are thought to be much closer to some anchor than they really are, but lie on the 'wrong' side of it as far as distortion is concerned, from being assigned to that anchor (see, for example, cue no. 11 on Figure 3(d)). This is the kind of occurrence that the 'magnet' hypothesis would have picked up, but not any of the other two alternatives.

7. Conclusion

Despite all the difficulties, this first exploration has succeeded in providing some

tangible, positive indications in support of a very abstract hypothesis regarding spatial cognition. Even more importantly perhaps, we have shown that such a hypothesis is in principle testable using easily obtainable data and current analytic procedures. Many of the problems we have identified could be resolved with a larger sample of subjects and cues, more systematic experiments, more thorough and extensive analyses, and some additional explorations, such as the search for a time transform underlying the cognitive maps. Even under the best circumstances, however, there are limits to what a general geometric approach such as the one taken here might be expected to achieve when it comes to the study of intangibles such as human cognition. For one, the cognitive maps produced in this way can only reflect relational (and to some unknown degree, declarative) knowledge, whereas the anchor point notion, as discussed earlier, also involves procedural and associational knowledge at the very least.

But although we may not expect to elucidate spatial cognition completely with the existing geographic tools, we would like to think that the preliminary encouraging evidence in favor of the tectonic plates hypothesis produced in this research, and in the more detailed studies we hope will follow, will eventually incite more geographers psychologists, cognitive scientists, mathematicians, and others to join us in this quest. If this is indeed the case, we may look forward to the day when the present heavy quotes around the words 'cognitive map' will no longer be needed.

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Appendix
Comparative Results of the Three Methods of Analysis

Single-Link Cluster	L1 (6 W) L2 (6 W) 2 9) L3 (6 W) (2 9) (4 10) L4 (6 W) (2 9 11) (4 10) L5 (6 W) (2 9 11) (4 10) L6 (6 W) (1 2 9 11) (4 7 10) L7 (6 12 W) (1 2 9 11) (4 7 10) L8 (6 12 W) (1 2 9 11 H) (4 7 10) L9 (6 12 W) (1 2 9 11 H) (4 7 10) L10 (4 6 7 10 12 W) (1 2 5 9 11 H) L11 (1 2 4 5 6 7 9 10 11 12 H W) L12 (1 2 3 4 5 6 7 8 9 10 11 12 H W) L14 (all)	L1 (2 11) L2 (2 9 11) L3 (2 9 11) (4 7) L4 (2 9 11) (4 7) (6 12) L5 (2 9 11) (4 7) (6 12) L6 (2 9 11) (4 7 10) (6 12 H) L7 (2 9 11) (4 7 10) (6 12 H) L9 (2 9 11) (4 7 10) (6 8 12 H) L9 (2 9 11) (14 7 10) (6 8 12 H) L10 (1 2 4 7 9 10 11 W) (6 8 12 H) L11 (1 2 4 7 8 9 10 11 W) (6 8 12 H) L12 (1 2 4 7 8 9 10 11 W) (6 8 12 H) L13 (41) L14 (41)
Relative-Proximity	(1 3 5 H) (4 6 7 10 12 W) <2 9 11, 8>*	(1 2 7 9 10 11 W) (6 8 12 H) (3, 4, 5) 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
Galois-Lattice	A126 L8 (2469101112 W, 12) L7 (1235911 H, 1 H) (12591112 H, 11) L6 (125911 H, 1 11 H) (1291112 H, 2911) (4671012 W, 410) L5 (12911 H, 12911 H) (461012 W, 461012 W) L4 (1511 H, 1511 H) (29112, 29112) L3 (13 H, 13 H) (1 11 H, 125911 H) (2911, 1291112 H) L2 (1 H, 1235911 H) (112, 2911) (47, 4710) (410, 4671012 W) L1 (11, 125911 12 H) (12, 2461011 12 W)	D098 L8 (1467812 W, 10) L7 (4678910 W, 4) (467810 12 H, 6) L7 (467910 H, 7) (12479 H W, 9) L6 (24910 H, W, W) (1279 H W, 29 H) L6 (24910 H, W, W) (1279 H W, 29 H) L6 (12910 H, W, 47 W) L5 (12910 H, H) (2479 H, 79) L5 (12911 H, 9W) (279 H W, 9 H) (467810 L, 610) (4679 H, 7) (46810 L, 6810 H, 6812 H, 6812) L4 (129 H, 129 H) (147 W, 9 H) (24910, 710) (249 H, 79 W) (279 H, 279 H) (2910 H, 17W) (2911 W, 2911 W) (46710, 46810) (46711, 71) (46810, 46810) (46810 H, 79 W) (6810, 46810, 46810) (46811, 74) (6810, 46810) (46810, 710) (6810, 6810 H, 78)

(continues)

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L11 (2 9 11 H) (1 4 6 7 8 10 12 W) (3 5)
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                 L12 (2 3 5 9 11 H) (1 4 6 7 8 10 12 W)
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                           L3 (9 H) (7 W) (6 L2)

L4 (9 H) (7 W) (6 L2) (4 10)

L5 (9 11 H) (7 W) (6 12) (4 10)

L6 (9 11 H) (7 W) (6 12 (4 8 10)

L7 (9 11 H) (7 W) (6 12 (4 8 10)

L7 (9 11 H) (4 7 8 10 W)

L8 (2 9 11 H) (4 7 8 10 W)

L9 (2 9 11 H) (1 4 7 8 10 W)

L10 (2 9 11 H) (1 4 6 7 8 10 12 W)
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                  (M L) (H 6)
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                    L13 (all)
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                       222432786
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                       (2 5 9 11 H) (4 7 8 10 W) (1, 3, 6, 12)
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                       E102 L7 (1 2 7 8 10 12 W, 10)

L6 (4 7 8 10 12 W, 8)

L5 (2 5 9 10 H, 2) (4 6 8 12 W, 4) (1 7 8 10 11, 7)

(2 6 9 11 13, 9) (7 9 11 H W, 11) (4 6 8 10 12, 12)

(4 8 10 11 W, W) (7 8 10 12 W, 8 10)
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                 L2 (3 5, 3 5) (4 12, 4 6 8 12) (6 9, 6 9)
(7 10, 1 7 8 10) (7 W, 8 10 11) (8 10, 7 8 10 12 W)
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                    (4 8 10 12, 8 12) (4 8 12 W, 4 8) (4 8 10 W, 8 W) (8 10 12 W, 8 10 W)
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                            (4 8 10, 8 12 W) (4 8 12, 4 8 12) (4 8 W, 4 8 W) (7 8 10, 7 8 10) (8 10 11, 7 W) (8 10 12, 8 10 12) (8 12 W, 4 8 10) (9 11 H, 9 11 H)
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                (11, 7 9 11 H W) (12, 4 6 8 10 12) (H, 2 9 11 H)
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                       L4 (46912, 6) (2911 H, H) (12710, 110)
(17810, 710) (2911 H, 9 H) (46812, 412)
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                      (6, 46912) (7, 1781011) (8, 4781012 W)
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                (8 12, 4 8 10 12) (8 W, 4 8 10 W) (7 11, 7 11)
                                                                                                                                                                                                                                                                                                                                                                                                                      (9, 1 2 4 7 9 11 W) (10, 1 4 6 7 8 10 12 W)
                                                                                                                                                                                                                                                                                                                                                         (1, 1 2 9 10 11) (3, 3 5) (4, 4 6 7 8 9 10 W)
                          (29 11, 12 7 9 11 W) (46 10, 46 78 10) (47 9, 47 9) (47 10, 46 7 10) (48 9, 47 9 W) (4 10 W, 4 10 W)
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                            (2 3 5, 5) (1 7 10, 1 7 10) (4 6 12, 4 6 12)
                                                                                                                                                                                                                                       (6 8, 4 6 8 10 12 H) (6 10, 4 6 7 8 10 12)
(6 11, 7) (6 H, 6 8 12 H)(7 9, 2 4 7 9 11)
(7 W, 2 4 9 10 11) (8, 12, 6 8 10 12 H)
(9 10, 1 4 7 W) (9 W, 2 4 9 11 W)
                                                                                                                                                                                                                                                                                                                                                                                         (6, 46781012H) (7, 246791011)
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                           LI (2, 2 5 9 10 H) (4, 4 6 9 12) (5, 2 3 5)
                                                                                                                                                                            L2 (1 10, 1 10) (3 5, 3 5) (4 7, 4 6 7 9 10) (4 10, 4 6 7 8 10 W) (4 W, 4 9 10 W)
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                     (9, 2 6 9 11 13) (10, 1 2 7 8 10 12 W)
                                                                                                                                                    (6 8 12, 6 8 12 H) (7 9 14, 2 4 9 11)
                                                                                                                    (4 12 H, 6 8) (6 8 10, 4 6 10 12)
L3 (2 4 10, 7 W) (2 4 11, 7 9 W)
                                                                                                                                                                                                                                                                                                                                                                                                                                                      (14, 249 10 11 W)
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                 _
[3
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(continued)

L1 (5 H) L2 (5 H) (6 12) L3 (5 H) (6 12) L4 (5 H) (6 12) (2 9) L4 (5 H) (6 12) (2 9) (4 W) L5 (5 H) (6 12) (2 9) (4 W) L6 (5 H) (4 6 8 12 W) (2 9) L7 (5 H) (4 6 8 10 12 W) (2 9) L8 (5 H) (4 6 7 8 10 12 W) (2 9) L9 (5 H) (4 6 7 8 10 12 W) (2 9) L10 (5 H) (4 6 7 8 10 11 12 W) L12 (1 2 5 9 H) (4 6 7 8 10 11 12 W) L13 (11 2 5 9 H) (4 6 7 8 10 11 12 W) L14 (all)	L1 (9 11) L2 (2 9 11) L3 (2 9 11) L4 (2 9 11) (1 5) L4 (2 9 10 11) (1 5) L5 (2 9 10 11) (6 12) L6 (2 9 10 11) (6 12) L6 (2 9 10 11) (4 6 8 12) L8 (2 9 10 11) (4 6 8 12) L8 (2 9 10 11) (4 6 8 12) L9 (1 2 5 9 10 11) (4 6 8 12) L10 (1 2 5 7 9 10 11 W) (4 6 8 12) L11 (1 2 4 5 6 7 8 9 10 11 12 W) L13 (11 (1 2 4 5 6 7 8 9 10 11 12 W) L14 (all)
(2 3 5 H) (4 7 8 10 W) (3, 4, 5)	(2 7 9 10 11 W) (1 5, 4 8, 6 12, 3, H)
J169 L8 (46 8 9 10 11 12 W, W) L7 (46 7 8 10 12 W, 8) (46 8 10 11 12 W, 4 12 W) (4 7 8 10 11 12 W, 10) L6 (12 3 5 7 H, H) (4 7 8 10 12 W, 8 10) (4 8 10 11 12 W, 4 10 12 W) (4 6 8 10 12 W, 4 8 12 W) (4 8 10 11 12 W, 4 10 12 W) (4 6 8 10 12 W, 4 8 12 W) (4 8 10 12 W, 4 8 10 12 W) (4 10 11 12 W, 4 10 11 12 W) (4 12 9 H, 1 2) (7 8 10 H, 7) (1 2 9 W, 9) (12 5 H, 1 H) (1 3 5 H, 5 H) (4 8 12 W, 4 6 8 10 12 W) (4 10 12 W, 4 8 10 11 12 W) (4 8 12 W, 4 6 8 10 12 W) (4 10 12 W, 4 8 10 11 12 W) (5 5 H, 1 H) (3 5 H, 3 5 H) (7 8 10, 7 8 10) (4 12 W, 4 6 8 10 11 12 W) (5 H, 1 2 5 H) (10 H, 7) (1 H, 12 5 H) (6 H, 1 2 5 9 H) (10, 4 7 8 10 11 12 W) (7 12 9 W) (10, 4 7 8 10 11 12 W) (9, 1 2 9 W) (10, 4 7 8 10 11 12 W)	K203 L7 (1 2 5 9 10 11 W, 2 9 11) L6 (1 2 5 9 10 11, 1 2 9 11) L5 (1 2 5 9 10, 11, 1 2 5 9 11) (1 2 9 10 11, 1 2 9 10 11) (2 7 9 11 W, W) L4 (1 2 9 11, 1 2 5 9 10 11) (2 9 11 W, 2 9 11 W) (4 6 8 12, 12) (4 7 8 12, 8) L3 (2 9 11, 1 2 5 9 10 11 W) (4 8 12, 4 8 12) (7 8 W, 7) L2 (6 12, 6 12) (7 8, 7 8) (7 W, 7 W) (8 12, 4 8 12) (9 11, 1 2 5 9 10 11 W) L1 (3, 3) (7, 7 8 W) (8, 4 7 8 12) (12, 4 6 8 12) (H, H)

* Cues in angular brackets are not assigned.