

To appear in: Richardson D, Castree N, Goodchild MF, Kobayashi AL, Liu W, Marston, eds, *The International Encyclopedia of Geography*, Wiley-Blackwell, Hoboken.

Neighborhood, conceptual

Christian Freksa and Arne Kreutzmann

University of Bremen

freksa@uni-bremen.de, kreutzma@informatik.uni-bremen.de

Abstract

In the abstract space of concepts, certain relations are semantically closer to one another than others. This is comparable to concrete geographic space, where certain locations are spatially closer to one another than others. The article presents the notion of *conceptual neighborhood*, a neighborhood structure defined over relations between concepts. Due to their relative semantic similarity, conceptually neighboring relations may be confused more easily than conceptually distant relations. Knowing about conceptual neighborhood of relations therefore is highly relevant for error detection and recovery as well as for robustness, as it drastically reduces the search for meaningful alternatives. It also supports correct interpretation of structured subjective concepts. Exploitation of conceptual neighborhood structures can reduce computation from non-tractable exponential to tractable polynomial complexity classes.

Main Text

The notion of conceptual neighborhood (CN) was introduced in the context of research in qualitative temporal and spatial reasoning to describe direct discrete transitions between temporal or spatial relations in dynamic worlds (Freksa 1991a, b). As a simple example, consider the relative position of two (time or space) points on a directed line. The points P and Q can be positioned in one of three relations: P *before* Q ($P < Q$), P *at* Q ($P = Q$), or P *after* Q ($P > Q$). Under continuous motion of the points direct transitions are possible from $P < Q$ to $P = Q$ and from $P = Q$ to $P > Q$; a direct transition from $P < Q$ to $P > Q$, however, is not possible; a transition will go through the intermediate relation =. The relation *before* ($<$) therefore is called a “conceptual neighbor” of the relation *at* ($=$) and the relation *at* ($=$) is called a conceptual neighbor of the relation *after* ($>$), whereas the relations *before* ($<$) and *after* ($>$) are not conceptual

neighbors, as no direct transition between them is possible (Fig. 1). Spatial or temporal entities connected through relations form spatial or temporal configurations.

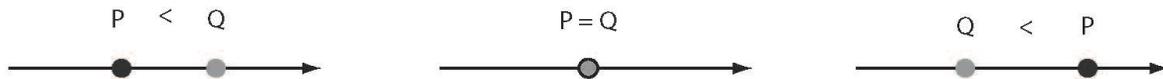


Fig. 1. Three qualitative temporal or spatial relations between two points P and Q: $P < Q$; $P = Q$; and $P > Q$ (shown as $Q < P$). Direct transitions are only possible between the conceptually neighboring relations $\{<, =\}$ resp. $\{=, >\}$.

The Role of Relations

Qualitative relations are abstract concepts that correspond to discrete classes of continuous-valued relations. If one variable is fixed, qualitative relations either correspond to a single, precise value (e.g. $P = Q$), or they subsume a whole range of values that are not further distinguished (e.g. $P < Q$).

Qualitative relations play an important role in conceptualizing spatial, temporal, and other configurations. They are robust with respect to small distortions that do not affect critical aspects of the configuration. Depending on the relations chosen to represent configurations, critical aspects may refer to topological properties (e.g., *disjoint*, *touching*, *overlapping*, *inside*), to orientation properties (e.g., *left*, *right*, *front*, *back*, *up*, *down*), to angles (*acute*, *right*, *obtuse*, *straight*), to distance (*near*, *far*), or others.

Informal Definition of Conceptual Neighborhood

The notion of conceptual neighborhood was first introduced for temporal relations (Freksa 1991a):

Two relations between pairs of events are (*conceptual*) *neighbors* if they can be directly transformed into one another by continuous deformation (i.e., shortening or lengthening) of the events.

This notion can be interpreted for spatial relations as follows:

Two relations between pairs of spatial entities are conceptual neighbors if they can be directly transformed into one another by continuous transformation.

This definition of conceptual neighbors addresses binary relations; it can be extended to ternary relations or to relations of higher arity in a straightforward manner.

The definition of conceptual neighborhood intentionally leaves room for interpretation. First, it does not specify exactly which continuous transformations are to be considered; second, it does not specify whether relations can be conceptual neighbors of themselves; and third, it does not

specify what is considered to be a continuous transformation. In his book *Qualitative Spatial Change* Galton (2000, Ch 7) examines the implications of different types of spatial change, given various notions of continuity; this results in different answers whether or not a two-dimensional region can be continuously transformed into a line segment.

In early days, the terms *closest-topological-relationship-graph* (Egenhofer and Al-Taha 1992) and *continuity network* (Cohn and Hazarika 2001) were used synonymously with conceptual neighborhood graph.

Formal Definition of Conceptual Neighborhood

In this section, the term *domain* refers to a mathematical structure. In Geographic Information Systems the typical domain used is the domain of 2d polygons extended to allow the inclusion of points and sometimes also of line segments. However, a circle or circle segment only can be approximated in such a domain..

Given a finite set of n-ary relations R over a domain D , then two distinct relations r_1 and r_2 are called conceptual neighbors if and only if there exists a continuous function $f \in C(D^n)$
 $f: R \rightarrow D^n$, such that
 $f(0) \in r_1$,
 $f(1) \in r_2$, and
 $f(t) \in r_1 \cup r_2$ for all $t \in [0, 1]$.

In the literature, concepts usually are not considered to be conceptual neighbors of themselves; therefore the above definition contains the requirement, that r_1 and r_2 are not identical. Further, conceptual neighborhood is often regarded as symmetric, which also directly follows from the above definition with $f^*(t) = f(1-t)$. However, applications usually only allow a subset of all possible continuous transformations due to the semantics in the domain, geometric or physical laws, dynamic properties, and so on.

Semantics

As CNs are derived from transitions in the represented domain, they depend on structural and dynamic properties of the domain and of the entities in the domain. To illustrate this, we will look at a slightly more complex example: rather than considering (zero-dimensional) points on (one-dimensional) lines we shall now look at extended one-dimensional spatial objects: line segments, which can move with respect to a directed line. Equivalently, we can think of time intervals (rather than 1-D spatial objects), which can be related to one another. We now can distinguish thirteen qualitative relations (Fig. 2):

Relation	Symbol	Pictorial Example
<i>before – after</i>	< >	
<i>equal</i>	=	
<i>meets – met by</i>	m mi	
<i>overlaps – overlapped by</i>	o oi	
<i>during – contains</i>	d di	
<i>starts – started by</i>	s si	
<i>finishes – finished by</i>	f fi	

Fig. 2 Thirteen qualitative relations between two linear extended objects on a directed line (or equivalently: two temporal intervals on the directed time line). Adapted from Freksa 1991a.

For each configuration of two intervals on the directed line, there is exactly one qualitative relation; i.e., the relations are jointly exhaustive and pairwise disjoint (the so-called “JEPD property”).

In the 1-dimensional world of linear extended objects / events we can conceive of different kinds of dynamics depending on physical properties of the entities involved and on the forces that act on these entities. For example, objects may be assumed to be fixed in location, or mobile, they may be rigid (i.e. non-deformable), elastic (deformable), divisible, or mergeable, and these operations may be symmetric or asymmetric; some of these properties may be combined in various ways. For example, (a) individual objects may expand or shrink at one end at a time; (b) objects may be rigid (fixed size), but able to move relative to one another; or (c) objects may be fixed in location but expand or shrink on both ends.

From a physical modeling, a cognitive, and a computational perspective it may be desirable to consider exclusively those relations that can be physically realized; however, obtaining conceptual neighborhood in a formal system in the case of restrictions on the domain poses a difficult challenge and generally results in more complex structures. This is due to the fact that abstract formal systems are not structurally constrained in the same ways as physical systems are. Therefore, formal approaches often use a more general notion of conceptual neighborhood for practical applications that does not take into account the restrictions of specific domains; these restrictions then are taken into account at a later stage of modeling.

It frequently happens in domains where different perspectives such as *empirical*, *theoretical*, or *practical* may become relevant, these perspectives impose different desiderata on the concepts employed, as each perspective may employ a different reference system. This is why some flexibility may be needed in order to relate these perspectives in a productive fashion. As

applications generally require more information than those encoded in typical conceptual neighborhoods, various extensions have been proposed.

Adding Further Transition Knowledge

Besides restricting the set of continuous transformations on the basis of structural properties of the domain, taking into account restrictions due to specific tasks or actions to be performed as well as implications from earlier processing can be of great value in applications. For example, in a control setting it is important to know which actions could result in a specific change on the qualitative level.

Action-Augmented Conceptual Neighborhoods

Conceptual neighborhood allows describing mandatory and possible changes but does not specify the cause or actions leading to such change. Assuming that all changes are caused by actions performed by the involved agents, the set of continuous functions can be divided into subsets such that each subset corresponds to a tuple describing the corresponding actions. For each tuple of actions the induced conceptual neighborhood can be determined. Dylla (2008) calls the resulting extension action-augmented conceptual neighborhood.

The asymmetrical nature of actions carries over to the action-augmented conceptual neighborhood. Further, due to abstractions actions might not result in a change on the conceptual level (see section “Perceptual uncertainty and coarse reasoning”) or could lead to different neighboring relations. Consequently, the resulting action-augmented conceptual neighborhood structure is complex and requires additional reasoning methods to be used for active agent control.

Dominance Spaces and Topological Mode Spaces

From a more theoretical point of view it is interesting to know what occurs at the transition from one relation to another and whether a relation can hold over an interval or only at single instant of time. An example is the motion of a pendulum that reaches its extreme deflection only at a single instant where its speed is zero. This kind of knowledge is not only important when estimating, what might be observable and what not, but also when conceptual neighborhoods from different relations will be employed simultaneously.

A relation u is said to dominate a relation v if the relation u has to hold at the transition point. Consequently, the relation describing a pendulum’s extreme deflection dominates the relation that describes a rising pendulum. A conceptual neighborhood structure extended by the notion of dominance is called *dominance space*. Topological mode spaces combine both dominance and possible temporal extend of relations. Galton proved a product theorem for topological mode spaces, which allows for directly computing the product of topological mode spaces. This is an important result for applications, as only basic topological mode spaces need to be determined, e.g. for single pairs of entities, to be able to calculate the topological mode space describing the simultaneous motions of arbitrarily large numbers of entities.

Conceptual Neighborhood Graphs

Depending on the ontology of the domain and the specific laws that rule the environment different conceptual neighborhood structures will be obtained. Nonetheless, all of these structures form a graph, either directed or undirected. As an example, imagine two people looking into an aquarium seeing and describing the changing relations of two of the fishes. Essentially they established a conceptual neighborhood structure, which is visualized as a graph in Figure 3. The observed relative size might change as the fish move in three dimensional space while the viewer only perceives a projection.

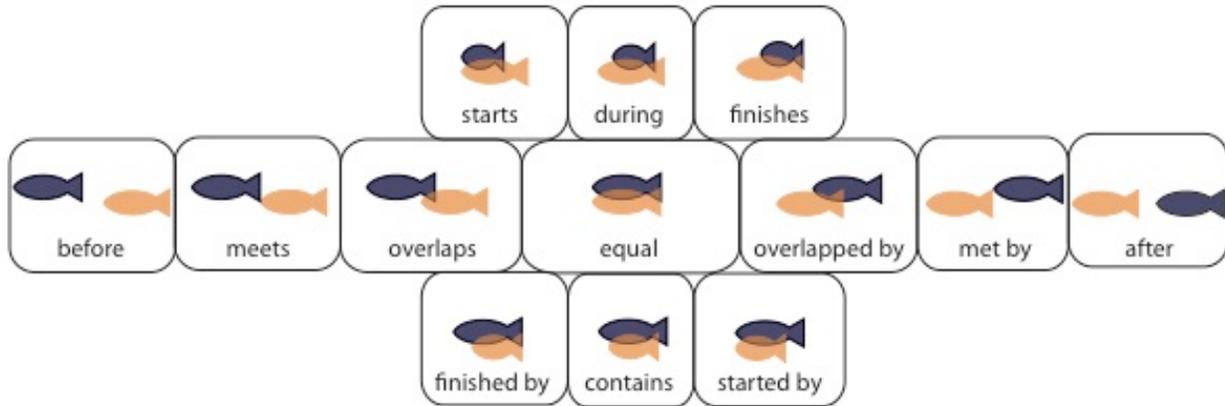


Fig. 3 The conceptual neighborhood graph for relations between intervals represented by two fishes. The relations are specifying the relative position of the light-ocher fish compared to the position of the dark-purple fish; see Fig. 2 for a clearer depiction of the 13 relations. Pictograms share a boarder if and only if they are conceptual neighbors.

Depending on the ontology of the domain, the specific laws that rule the environment, different CN-structures will be obtained. This is illustrated in Figure 4: the three CN-graphs each show nodes corresponding to thirteen qualitative relations (denoted by their symbols); the connections between the nodes illustrate the CN-transitions that may occur.

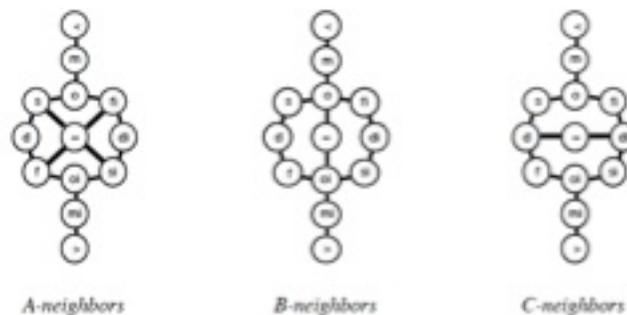


Fig. 4 Different dynamics in the domain induce different conceptual neighborhood structures: If only one of the four boundaries of two intervals (or linearly extended objects) can move at a time, the associated relation will create A-neighbors; if the durations of events (or the lengths of

objects), the associated relation will create B-neighbors; if the ‘temporal location’ of events (or the center of objects) is fixed but durations (or lengths) may vary, the associated relation will create C-neighbors (from Freksa 1992).

Relation Between Conceptual Neighborhood and Spatial Neighborhood

Tobler’s First Law of Geography states, *Everything is related to everything else, but near things are more related than distant things*. This insight suggests that near things may deserve a different treatment than distant things. Qualitatively, we may distinguish near things from distant things through the attributes “directly connected” vs. “not directly connected”. The special role of nearness and neighborhood is a particular property of space; it carries over to the domain of time to which space is closely connected through the laws of physics.

Similar insights exist in pattern recognition and scene analysis: As a rule of thumb, it is a good heuristic to assume that a pixel (say on a satellite image) maps the same land use category as the neighboring pixel; this rule is violated only at the (1-dimensional) boundaries of (2-dimensional) land use regions. Dealing with these – comparatively few – exceptions is considerably cheaper than treating each pixel without prejudice.

Accordingly for CNs: just as land use or other attributes are not randomly distributed over spatial regions, qualitative relations are not randomly distributed over conceptual spaces (Gärdenfors 2000). The rules for CNs are even stronger than for attributes of spatial neighborhood: while attributes of spatial neighbors are merely a heuristic rule of thumb, the rules for CNs correspond to intrinsic properties of spatial (or temporal) structures and processes. In these structures, there is no way that the neighborhood structure could be violated. This fact is exploited in CN-based reasoning.

Conceptual Neighborhood-Based Reasoning

Spatial reasoning in general can be reduced to the following inference pattern for three locations A, B, and C and two given relations r_1 and r_2 : If A is in relation r_1 to B and B is in relation r_2 to C then A is in relation R to location C (Freksa 1991b). In this way we can compose each element of a set of relations with itself and with each other element of the set to obtain a complete set of composition rules that govern the respective domain; this has been done, for example, by Allen (1983) in his famous paper on *Maintaining knowledge about temporal intervals*. By composing each of the 13 JEPD relations that may hold between two temporal intervals (Fig. 2) with each element of the same set of relations, we obtain $13 \times 13 = 169$ relations that describe the knowledge we can infer by applying two of these relations in sequence. For example, when an event A takes place *before* an event B and the event B takes place *before* an event C, we can infer that event A takes place *before* event C.

Not all of the 169 compositions are as straightforward as in this example: for certain compositions, the inferred relation differs from both constituent relations; for other compositions of constituent relations the inferred relation is ambiguous. For example, if event A *overlaps* event B and event B takes place *during* event C, then event A either *overlaps* or takes place *during* or *starts* event C; but other relations are not possible.

In the case of the 13 JEPD relations between temporal intervals, 72 compositions yield such ambiguous results. Three of these compositions do not permit any useful inference; for example, if event A takes place *before* event B and event B takes place *after* event C, any of the thirteen base relations between event A and event C may hold.

Allen observed that compositions that involve the *equal* relation yield trivial inferences that are identical to the second constituent relation involved; he therefore reduced the 13 x 13 composition table to a 12 x 12 matrix (which he called “transitivity table”).

But the structures of time and space exhibit much more regularity that can be exploited for reasoning. Specifically, if we arrange the composition table in such a way that neighboring entries correspond to conceptually neighboring constituent relations, we will observe that the inferences in the table behave in a rather regular and smooth way; this structure can be used to guide the inference. Most notably, we will observe that only a small fraction of theoretically conceivable combinations of JEPD relations will actually occur as inferences in spatial and temporal reasoning. Upon further analysis, we will observe that the inference sets of relations (i.e. the set of possible resulting JEPD relations that cannot be disambiguated through the inference) consists of conceptually neighboring relations, i.e. they correspond to situations that are obtained through continuous transformations in the domain.

This insight is not surprising if we analyze the reasons for the ambiguities in inferences: in qualitative temporal and spatial reasoning over temporal intervals or spatially extended objects the ambiguities in inferences are due to the fact that the premises yield coarse information wrt. the potential configurations of the entities as the boundaries of the objects are only partially fixed. As a consequence, only neighboring relations corresponding to the ambiguous sides of these boundaries are in question.

This consideration leads to a feature of qualitative spatial reasoning that is highly relevant for cognitive processing or more generally: for processing incomplete information in benign environments. By “benign environment” we mean environments, in which changes happen gradually rather than abruptly. In qualitative (categorical) views of the world, gradual changes correspond to smallest steps (= transitions between conceptual neighbors) whereas abrupt changes would correspond to jumps between non-neighboring relations.

Distances Between Relations

The distinction between conceptually neighboring and other relations induces the question whether further distinctions between relations may be useful. In particular, a neighbor of a neighbor may be considered closer than a non-neighbor. This becomes computationally relevant if we exploit conceptual neighborhood for reasoning. Thus, we can define a conceptual distance between relations. Based on the conceptual neighborhood graph a minimal distance between relations can be defined as the minimum number of neighborhood transitions between two relations (e.g. Goyal and Egenhofer 2001) for distances between cardinal direction relations).

Egenhofer and Al-Taha (1992) applied the notion of CN to reasoning about gradual changes of topological relationships. For example, rising water levels of a lake that will cause a lake that originally is *disjoint* from the house first to *meet* and then to *overlap* the region of the house. The

authors looked at conceptual neighborhoods within the framework of the 9-intersection model of topological relationships. The 9-intersection model describes topological relations between spatially extended objects in terms of the configurations of relations between their respective interiors, boundaries, and exteriors; this results in 9 sub-relations, each of which can take the value “empty” or “non-empty”. They observed that certain topological relations are distinguished by only a single sub-relation whereas others – including some conceptual neighbors – are distinguished by a larger number of sub-relations. Consequently, they defined distance between topological relations by the number of distinguished sub-relations in the 9-intersection model. Neighboring relations with the shortest distance were designated as the *closest topological relationship*.

Egenhofer and Mark (1995) used conceptual neighborhoods to describe topological relations between lines and regions; they confirmed that CNs correspond largely to the way humans conceptualize similarity of spatial relations. Egenhofer also analyzes spatial relations on spheres in terms of conceptual neighborhoods.

Coarse Relations

Conceptually neighboring relations, which are distinguished only through gradual transitions between semantically very close entities lead directly to the concept of a *coarse relation*. A coarse relation can be defined by a set of fine (base) relations, in which small distinctions (= transitions between neighboring relations) are ignored. The usefulness of coarse relations is two-fold: (1) coarse relations can be used to represent incomplete knowledge (here: knowledge in which distinctions between certain details are missing); (2) perceptual and conceptual knowledge frequently is structured in such a way that fine distinctions may be missing while the big picture is preserved. This seems to be particularly the case for knowledge relating to ‘benign’ domains such as time and space, which are conceptualized as continuous domains in which changes happen gradually, to a large extent. Such type of “incomplete” knowledge frequently can be represented through coarse qualitative relations on the basis of conceptual neighborhoods.

Reasoning Based on Coarse Relations

The next obvious step of what we can do with conceptual neighborhoods is to reason on the basis of coarse relations – particularly if they correspond in a natural way to the type of knowledge that is available through perception of space and time and through the conceptualizations we may have of them.

A classical approach of dealing with incomplete knowledge in artificial intelligence is by forming disjunctions of hypothetical completions of this knowledge, in other words: we would enumerate the potential alternatives that may hold under the incomplete specification. Reasoning over disjunctions is a computationally expensive process, as each disjunction may result in new sets of disjunctions; this leads to an exponential growth of complexity. Furthermore, replacing incomplete knowledge by disjunctions of complete knowledge is intuitively not very plausible, for the most part: it is a form of reasoning a detective may use to solve a puzzle with missing pieces; but for everyday tasks of dealing with coarse knowledge we are looking for

computationally cheap approaches that can deal with the coarse level of knowledge directly and yields results on a comparable level of precision (or resolution) as the premises.

This is an area of application for which coarse relations based on conceptual neighborhoods work very nicely: we can carry out reasoning directly on the basis of the coarse relations rather than on the more precisely specified JEPD base relations. In principle, it may be possible to maintain the JEPD property on a coarser level; in practice, this may be neither natural nor necessary; in fact, by choosing coarse relations in such a way that their applicability overlaps for certain temporal or spatial configurations, we may generate advantages that have similar benefits as coarse coding techniques in biological and technical systems: by forming conjunctions between overlapping coarse relations we actually can increase the precision / reduce the grain size of our inferences, provided that appropriate coarse knowledge is available. Freksa (1992) showed for the case of Allen's interval calculus that a suitable choice of coarse relations (semi-interval representation) based on conceptual neighborhoods allows for calculations on the same level of precision as the high-resolution interval approach used in the Allen calculus. The conceptual neighborhood-based composition tables are much more compact than composition tables using base relations as they exploit inherent structures of time and space to a much larger extent than the finer relations.

Conceptual neighborhood-based spatial problem solving preserves some of the special properties of time and space that make problem solving in space as efficient as it is; this efficiency disappears when we disintegrate spatial structures by describing them on the level of atomic relations, as we preferably do in formal reasoning.

Perceptual Uncertainty and Coarse Reasoning

The closer one looks at a real-world problem, the fuzzier becomes its solution (Zadeh's Principle of incompatibility)

The spatial resolution of visual perception in the eye or in a camera is limited by the granularity of the receptive fields in the eye or in the camera. As a consequence, certain conceptual distinctions between spatially similar situations may be difficult or impossible to perceive. For example, from some distance, we may not be able to visually distinguish whether two objects are almost touching one another but being spatially separated or whether they are actually touching, thus being spatially connected; similarly, we may not be able to distinguish perceptually whether two objects touch or barely overlap. All three conceptually distinct situations form a conceptual neighborhood of closely related spatial topological relations.

Interestingly, from a larger distance borders are perceived more clearly and more orderly than from close-by. For example, when we look down to earth from an airplane or when we view satellite images of the earth, certain spatial structures manifest themselves much more clearly even though the spatial resolution has been reduced. As transition zones between large regions become narrower they can be categorized more easily as lines at which the neighboring regions meet. This is a similar effect as we observe when looking at sketch maps or schematic maps that abstract from detail which is not informative for certain purposes.

Coarse spatial relations are more stable than fine spatial relations, as it typically requires many fine changes to change coarse spatial relations. When coarse spatial relations change, fine relations inevitably must have changed.

These observations are quite significant for information processing: anything we can validly infer on a coarse level of representation we should preferably infer on a coarse level, as (1) this requires less information; and (2) will be more stable.

Role of Conceptual Neighborhoods for Perception and Cognition

A crucial human ability to deal with perceptual and with conceptual information is to move between different object sizes (size constancy), different levels of granularity (resolution), and different levels of conceptualization of objects in a scene. For visual perception, this ability is facilitated through physical / geometrical properties of space, motion in space, and optical projection: when visually perceiving cognitive agents move towards a scene, objects are projected at a larger size, more details can be differentiated, and entities that were perceived as single objects from a distance will appear as aggregates of smaller constituent objects from nearby. In other words, in our everyday spatial experience, ‘vertical neighborhoods’ (Freksa and Barkowsky 1996) in a hierarchical or heterarchical representation that characterize relationships between visual objects and aggregates of objects that form new visual objects, are quite common and familiar to us from everyday experience.

The transitions between objects and aggregate objects have direct implications on spatial neighborhoods and on conceptual neighborhoods: obviously, only spatially neighboring objects will be optically separated / aggregated by moving towards / away from a scene; similarly, conceptually neighboring spatial relations between objects in a scene will be the first to be separated / aggregated as perception transforms between aggregates and their constituent objects. In other words: conceptual neighborhoods have a deep cognitive reality for our understanding of how parts and wholes relate to one another.

The relations between spatial entities and larger entities formed by them have significant implications on geography, map making, and map interpretation. An example is map generalization where individual houses are aggregated to make up residential areas, residential areas are aggregated to make up towns, etc. On the level of paths and roads, minor routes need to be eliminated at coarser resolutions without violating certain connectivity constraints. Maintaining correct topological relationships is an issue that can be dealt with by means of conceptual neighborhood.

Similarity: Conceptual Neighborhood vs. Fuzziness

Conceptual neighborhoods have a distinct relation to fuzzy sets: CNs can be considered discrete analogs to fuzzy sets. Whereas compatibilities of fuzzy relations typically change gradually as a relevant feature changes, the selection of a spatial or temporal relation changes in a transition to a conceptually neighboring relation in a discrete step. This corresponds to the way people typically talk about spatial and temporal relations: we select a label for a relation that appears to

be appropriate, being well aware, that a neighboring label also might fit. This awareness helps us to interpret semantically neighboring relation labels that may have been chosen by others due to subjective preference and/or due to not quite identical reference contexts.

Applications of Conceptual Neighborhood-Based Reasoning in Artificial Intelligence

There are a variety of applications of conceptual neighborhood; here we will present four rather distinct showcases.

Commonsense Reasoning

When describing events, such as a car overtaking another car, humans abstract to few key configurations assuming that it is clear how to fill the gaps. Commonsense reasoning focuses on methods to describe how “trivial” inferences can be achieved, instead of saving reproducible inferences explicitly. Addition and subtraction are examples for such kind of “inference”, as one could create a lookup table or describe the process of adding two numbers. Conceptual neighborhood based reasoning fills a similar role in event recognition and planning (see section “CN-based reasoning”), as often a key configuration cannot be observed directly but their occurrence can be inferred, e.g. that a pendulum had reached its highest position.

Learning Event Models

Learning of event models is used in the case of complex domains or where no previous knowledge about the domain is present. In such cases events and models are learned either unsupervised or semi-supervised, i.e. a teacher or ground truth is generally available. Often models can be simplified by exploiting the conceptual neighborhood. As discussed in the section “Perceptual uncertainty and coarse reasoning” some relations are hard to distinguish using sensors, e.g. if two objects are truly touching each other. Making the learning system aware of such uncertainty allows for more robust as well as more compact models.

Data Integration and Conflict Resolution

When integrating data from various sources, such as database or sensors, usually conflicting information exists. Further, the resulting data should not violate consistency constraints, for example, two lakes cannot overlap. Using conceptual neighborhood combined with a valid distance measure allows to first determine the required changes on the conceptual level, called relaxation, before calculating the changes on the lower level.

Finding Tractable Subsets of Calculi

Conceptual neighborhoods generally play an important role when determining tractable subsets of calculus. A generalized relation in a tractable subset only contains those relations that are pairwise conceptual neighbors. This has been shown by Nebel and Bürckert (1995) for the case of Allen's interval algebra. As a result, conceptual neighborhood can be exploited to reduce computation from non-tractable exponential to tractable polynomial complexity classes.

Concluding Remarks

Conceptual neighborhood is a fundamental notion in cognitive systems. It reflects how cognitive agents including humans, animals, and autonomous robots perceive, describe, and perform changes in spatio-temporal environments. The notion relates to psychology of perception, cognitive geography, artificial intelligence, as well as for cognitive modeling and process control. It has implications for visualization, autonomous robotics, and theoretical computer science. It is related to robustness, switching between coarse and fine representations, and to efficiency. Consideration of conceptual neighborhood may play an important role in the design of future reliable technology.

SEE ALSO: Tobler's First Law of Geography; Geographic Information Systems; spatial temporal reasoning; distance; topological relationships; Cognition and spatial behavior; Fuzzy classification and reasoning

References and Further Readings

References

- Allen J, 1983. Maintaining knowledge about temporal intervals. *CACM* 26, 11, 832-843.
- Cohn AG, Hazarika SM, 2001. Qualitative spatial representation and reasoning: An overview. *Fundamenta Informaticae* 46, 1-2, 1-29.
- Dylla F, 2008. An agent control perspective on qualitative spatial reasoning, *DISKI*, vol 320, IOS Press, Heidelberg.
- Egenhofer MJ, Al-Taha KK, 1992. Reasoning about gradual changes of topological relationships, Proc I Conf *GIS - From Space to Territory: Theories and Methods of Spatio-Temporal Reasoning on Theories and Methods of Spatio-Temporal Reasoning in Geographic Space*, 196-219, Springer-Verlag London. ISBN:3-540-55966-3
- Egenhofer MJ, Mark DM, 1995. Modeling conceptual neighborhoods of topological line-region relations, *I J Geographical Information Systems* 9, 5, 555-565.
- Freksa C, 1991a. Conceptual neighborhood and its role in temporal and spatial reasoning, in Singh M, Travé-Massuyès L, eds, *Decision Support Systems and Qualitative Reasoning*, 181-187, North-Holland, Amsterdam.

Freksa C, 1991b. Qualitative spatial reasoning, in Mark DM, Frank AU, eds, *Cognitive and linguistic aspects of geographic space*, 361-372, Kluwer, Dordrecht. doi: 10.1007/978-94-011-2606-9_20

Freksa C, 1992. Temporal reasoning based on semi-intervals, *Artificial Intelligence* 54 (1-2): 199-227. doi: 10.1016/0004-3702(92)90090-K. (Revised version of International Computer Science Institute Report TR-90-016, Berkeley, California 1990.)

Freksa C, Barkowsky T, 1996. On the relation between spatial concepts and geographic objects, in Burrough P, Frank A, eds, *Geographic objects with indeterminate boundaries*, 109-121, Taylor and Francis, London.

Gärdenfors P, 2000. *Conceptual Spaces*, Bradford Books, MIT Press, Cambridge, MA.

Galton AP, 2000. *Qualitative spatial change*. Oxford: Oxford University Press.

Goyal RK, Egenhofer MJ, 2001. Similarity of cardinal directions, in Jensen CS, Schneider M, Seeger B, Tsotras VJ, eds, *Advances in Spatial and Temporal Databases: Proc Seventh International Symposium, SSTD 2001, Redondo Beach, CA, LNCS 2121*, Springer.

Klippel A, 2012. Spatial information theory meets spatial thinking - Is topology the Rosetta Stone of spatio-temporal cognition? *Annals of the Association of American Geographers*, 102 (6), 1310-1328.

Further Readings

Ligozat G, Condotta J-F, 2005. On the relevance of conceptual spaces for spatial and temporal reasoning, *Spatial Cognition and Computation* 5(1), 1-27.

Cohn AG, Renz J, 2007. Qualitative spatial representation and reasoning, in Lifschitz V, van Harmelen F, Porter F, eds, *Handbook of knowledge representation*, Ch 13. Elsevier, München.

Chen J, Cohn AG, Liu D, Wang S, Ouyang J, Yu Q, 2015. A survey of qualitative spatial representations. *The Knowledge Engineering Review* 30, 1, 106-136.

Key Words: computational methods; representation; space and spatiality; space-time; spatial cognition