A Computational Model for Context and Spatial Concepts

Juergen Hahn, Paolo Fogliaroni, Andrew U. Frank and Gerhard Navratil

Abstract A natural language interface can improve human-computer interaction with Geographic Information Systems (GIS). A prerequisite for this is the mapping of natural language expressions onto spatial queries. Previous mapping approaches, using, for example, fuzzy sets, failed because of the flexible and context-dependent use of spatial terms. Context changes the interpretation drastically. For example, the spatial relation "near" can be mapped onto distances ranging anywhere from kilometers to centimeters. We present a context-enriched semiotic triangle that allows us to distinguish between multiple interpretations. As formalization we introduce the notation of contextualized concepts that is tied to one context. One concept inherits multiple contextualized concepts such that multiple interpretations can be distinguished. The interpretation for one contextualized concept corresponds to the intention of the spatial term, and is used as input for a spatial query. To demonstrate our computational model, a next generation GIS is envisioned that maps the spatial relation "near" to spatial queries differently according to the influencing context.

Keywords Computational model for context · Context · Spatial concepts · Contextualized concept · Near

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1   Introduction

A fundamental question in the field of Geographic Information Science concerns the development of a natural language interface for GIS (Montello and Freundschuh 2005). In order to establish a natural language interface for GIS, spatial terms (i.e. spatial relations and spatial regions (Montello et al. 2003) have to be mapped onto spatial queries. In this paper we address the mapping of spatial relations. Previous approaches to model spatial terms concluded that their interpretation is mostly context–dependent (Wang 1994; Raubal and Winter 2002; Yao and Thill 2006). For example, the spatial relation "near" can be mapped onto distances ranging from thousands of kilometers (e.g. "the moon is near the Earth") to a few centimeters (e.g. "the cup is near the milk bottle").

A central question is always: what is context? In the scope of this work we consider context to be any piece of ancillary or surrounding information that influences the interpretation of a concept of interest. The semiotic triangle (Ogden and Richards 1946) (reviewed in Sect. 2) explains the process of interpretation in a triadic mode, including an object in reality, a concept formed by a cognitive agent, and a term. We introduce an enriched version of the triangle that also includes context, and show how such a modification allows for disambiguating the interpretation of spatial concepts.

A cognitive agent refers to objects in reality by externalizing a context-influenced concept. A concept is, by its very nature, an abstract entity that only exists in the human mind. It therefore cannot be measured in terms of, or categorized by, physical properties. Concepts have been proven (Rosch and Mervis 1975) to be fuzzy, and to include prototypes. This also holds true for spatial concepts, e.g. **downtown**[1] (Montello et al. 2003), **north south** (Montello et al. 2014), **near** (Fisher and Orf 1991; Wang 1994). Prototypes change with the influence of context (Osherson 1999; Aerts and Gabora 2005). For example, a prototypical example for the concept **tree** is different in Sweden and in Greece. We argue that the interpretation of a spatial term relates to the prototype of a concept. To account for the possibility that a concept can inherit multiple prototypes we introduce the notion of *contextualized concepts*. One concept is represented by many contextualized concepts, where each contextualized concept has one prototype and is linked to one context. A contextualized concept is built from grounded observations of reality (Kuhn 2009) observed in a particular context.

Many possible interpretations are narrowed down to a single one by making context explicit for concepts and observations. This resulting interpretation is used as mapping from a spatial term onto a spatial query.

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[1]Throughout the paper we will use special formatting to indicate when a term is used to denote a **concept**.

In summary the contributions of this paper are:

- enrichment of the semiotic triangle with context
- derivation of an abstract model
- formalization of the abstract model as a computational model

This paper is structured as follows: First, the semiotic triangle is reviewed to show how representations (terms) are connected with concepts that refer to observations in reality in Sect. 2. Next the properties for concepts are pointed out, and we emphasize the influence context has on concepts. Second, the idea and a formalization of it are presented in Sect. 3. Third, this formalization is translated into a computational model in Sect. 4. Fourth, the model is initialized with data, and the usage of the algorithms is demonstrated in mapping the spatial relation "near" according to contexts: walking, driving, and going uphil are mappedl into different spatial queries in Sect. 5.

2 State of the Art

To achieve mapping from spatial relations or general spatial terms to spatial queries, it is necessary to understand how spatial terms represent reality. Spatial relations are symbols that refer to spatial configurations, such as near or above. The semiotic triangle by Ogden and Richards (1946) is a conceptual model that links symbols (e.g. a word, a drawing, a map, or a gesture), reality, and concepts (see Fig. 1). Each edge of this triangle represents one of the three main phases of representation: abstraction, externalization, and interpretation. On the right corner of the triangle lies physical reality. Physical reality is experienced in the form of exemplars, and abstracted to form a concept in our mind (represented by the top corner of the triangle). When we want to externalize a concept, for example during a communication process, we use a symbol. Symbols are located on the left corner of the triangle, and are successfully interpreted (as are the corresponding concepts) if they are *grounded* (Kuhn 2009) to the subsets of physical reality (the exemplars) that we intended to refer to (indicated by the dotted line).

Possible misunderstandings or misinterpretations arise if the same symbol does not evoke the same typical exemplar in different subjects. One reason is the many-to-many connection between a symbol and the exemplars that it refers to Chandler (2007). For example, in mathematics there is the concept of **neutral element** for a

Fig. 1 Semiotic triangle from Ogden and Richards (1946)
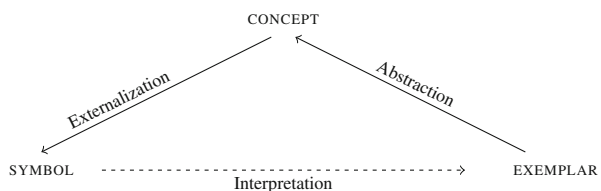
binary operation. Without specifying the operation (e.g. addition, multiplication) it is not clear which exemplar it refers to (e.g. 0, 1). Another reason is that concepts are formed and adjusted over time from repeated observations of reality (Von Glasersfeld 1995). Since no two persons have identical experiences, the "same" concept can never be completely aligned in two person's minds.

It was already suggested in the past (Von Glasersfeld 1995; Fisher 2000; Worboys 2003) that context plays a role in aligning concepts. Fisher (2000) studied the case of directional concepts and suggested that one way to avoid (or reduce) misinterpretations is to make explicit the frame of reference (context) that the given directional concepts are embedded in. More generally, Von Glasersfeld (1995) states that successful interpretation is only possible if the context of the speaker and that of the listener are compatible; which means that the speaker and the listener must have experienced exemplars of a concept in "similar" contexts (cf. Weiser and Frank 2013).

2.1   (Spatial) Concepts

A concept is an abstract entity that only exists in the human mind; according to Seiler (2001), it is "*primarily a cognitive structure*" that helps us to make sense of the world. The entities from which a concept is derived are called, throughout this work, *instances* or *exemplars*.

According to Freksa and Barkowsky (1996), spatial concepts are all those "*notions that describe spatial aspects of a subset of the world*". Examples of spatial concepts are **near**, **downtown**, and **lake**. Spatial concepts are central to human cognition (Mark et al. 1999) as they help us to distinguish, categorize, and thus make sense of the physical stimuli we perceive through our senses.

Psychological experiments showed that concepts include prototypes. By using a category–membership verification technique, cognitive psychologist Rosch (1973, 1999) showed that concepts posses a graded structure. Within this structure, a prototype is abstracted from the experienced exemplars (Rosch and Mervis 1975) based on a typicality judgment function. Another modeling approach represents a concept as multiple experienced exemplars (Nosofsky 2011). Both theories share that the membership of an exemplar to a concept is judged within their typicality to the existing concept.

In the field of geographic information science, several studies have previously aimed at characterizing (geo)spatial concepts. Mark et al. (1999) empirically demonstrated that people judge mountains, lakes, and oceans as typical exemplars of the generic concept **geographical feature**. Further studies (Mark et al. 1999) revealed that spatial concepts are typically organized according to a hierarchical structure, and have vague boundaries. For example, it was shown by Smith and Mark (1998) that geographical factors like size or scale induce conceptual hierarchies—as in the case of bodies of water: pond, lake, sea, ocean. Also, it has been shown (Mark and Turk 2003; Mark 1993) that linguistic, cultural, and individual variability influences the

creation and the structuring of spatial concepts. Montello et al. (2014, 2003) investigated the fuzziness of the extension of spatial concepts. They showed that the spatial concept **downtown** Santa Barbara is conceived differently by different subjects.

In the field of geoinformation, multiple approaches have been used to model spatial concepts, such as, for example: qualitative spatial reasoning (Frank 1992), fuzzy sets (Wang 1994; Robinson 2000), multi-valued logic (Fisher 2000; Duckham and Worboys 2001; Worboys 2001), formal concept analysis (Frank 2006), and more. All these formalizations do not account for context explicitly, and scientists concluded that context has a major impact. In contrast, we use context as the base formal drive to determine the interpretation.

2.2 Context and Its Influence on Concepts

According to Kuhn (2005), "*context is an overloaded term and has many aspects. Some of them are relatively easy to handle through domain separation […]. Others are much harder to deal with […]*". Bazire and Brézillon (2005) analyzed 150 different definitions of context collected on the Web. They find that, although different, they all share some common structure, and conclude that the definition of context is highly domain–dependent. This is also true for the spatial domain (Huang et al. 2014).

According to Freksa and Barkowsky (1996), there are three main types of relations that determine the meaning of a concept: (i) relations between a concept and its exemplars, (ii) relations between concept and context, and (iii) relations between concept exemplars and context.

Like any other type of concept, spatial concepts are influenced by context. Several studies have been carried out to study the context–concept influence. Burgio et al. (2010) and Tversky (2003) investigated the influence of context on spatial terminology. Both studies show that context influences spatial descriptions at the level of scale and granularity. Egenhofer and Mark (1995) investigated how different contexts influence the concept **geographic space**. They found, for example, that in a "city" context the interpretation evokes typical exemplars such as streets, buildings, and parks, while in a "country" context these become mountains, lakes, and rivers. Talmy (2003, p.231) argued that the spatial relations "on" and "in" are used for vehicles differently, depending on the existence of a walkway in the vehicle—e.g. on a bus versus in a car. Smith and Mark (1998) showed that the relation "in" in the context "the island is in the lake" means *the island protrudes from the surface of the lake* while in the context "the submarine is in the lake" the interpretation is *the submarine is completely submerged within the corresponding three-dimensional volume*.

Aerts and Gabora (2005) presented a quantum-mechanical model for concepts and influencing contexts. Their model showed that context is also the driving factor in modeling concept combination.
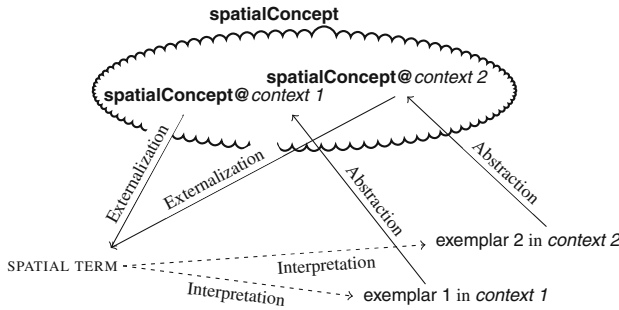
Fig. 2 Semiotic triangle from Ogden and Richards (1946) used for geographic information science by Kuhn (2005), enriched with context. The exemplars of the same concept, observed in different contexts. If the context is not explicitly reported with symbolic externalization, the symbol can be misinterpreted (many-to-many relation). Misinterpretations vanish if the context is specified, because a one-to-one connection between an exemplar and the symbol is created

3 An Abstract Model for Context–Dependent Concepts

In the scope of this work we consider context to be any piece of ancillary or surrounding information that influences the interpretation of a concept of interest. This means that the same concept is possibly associated to different typical exemplars in different contexts.

The core idea is to establish a one-to-one connection between a symbol (with ambiguous semantics) and an observed exemplar based on the context. Context selects from the many interpretations of the symbol a single applicable one—i.e. it reduces a many-to-many relation to a simple one-to-one. This idea is schematized in Fig. 2, which describes the process of abstracting one **spatialConcept**[2] from two experiences (exemplars) observed in two different contexts: *context 1* and *context 2*. Exemplar 1 is experienced in *context 1*, while exemplar 2 is experienced in *context 2*. This generates for the given concept what we call *contextualized concepts*, denoted by **spatialConcept@***context 1* and **spatialConcept@***context 2*, respectively. Externalizing **spatialConcept** without also giving context does not allow for a definitive interpretation, as the symbol used can refer to many of the exemplars we have experienced. If, conversely, we clearly state that the spatial term is in a particular context, the ambiguity vanishes, and it becomes clear that we intend either exemplar 1 or exemplar 2.

Through the use of contextualized concepts, context structures observed exemplars. The use of contextualized concepts falls into the class of *"compose-and-conquer"* of context uses (Bouquet et al. 2003). This compose-and-conquer approach "takes a context to be a theory of the world that encodes an agent's perspective of it and that is used during a given reasoning process" (Akman and Surav 1996). Every

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[2]In order to remove ambiguity we use special formatting to indicate a *context*, an exemplar of a concept, or a concept in a specific context (denoted **concept@***context*).

context partitions the mental contents, which is similar to Fauconnier's idea of mental spaces (Fauconnier 1994).

In order to formalize the idea sketched in Fig. 2 we model context with a lattice structure. In general, a lattice is a partially ordered set under a partial order relation with two binary functions: $\wedge$ called *meet* and $\vee$ called *join* (Gratzer 2009). Given two elements a and b of the lattice, the function meet creates an *infimum* such that $a \wedge b = inf\{a, b\}$ meaning that there exists a greatest element that is lower or equal to a and b. The function join creates a *supremum* of two elements: $a \vee b = sup\{a, b\}$ meaning that there exists a least element that is bigger or equal to both elements. A bounded lattice is a lattice with an upper bound element (i.e. $\top$) and a lower bound (i.e. $\bot$) element.

The partial order relation "*is stronger than or equal to*", denoted $\leq$, applies for context. An example for a context lattice is shown in Fig. 3. The $\top$ element is called *universal context*, meaning the absence of context. The contexts "stronger" than the $\top$ element are called *basic contexts* (e.g. *ctx 1*, *ctx 2*, and *ctx 3* in Fig. 3) and these are used to derive through the meet operation any other context combination (e.g. *ctx 1 ∧ 2*). The last element ("strongest" context) of the lattice is the $\bot$ element which is called *empty context* and indicates nonsense—i.e. meaningless context.

Note that not all the infima in the lattice of contexts correspond to contexts that make sense, or that are realizable. In Fig. 3, these contexts are represented in grey. One is *ctx 1 ∧ 3*, and, consequently, every infimum of this context does not make sense. In Fig. 3 there is only one such infimum: *ctx 1 ∧ 2 ∧ 3*. An example for two contexts that do not make sense is included in the example presented in Sect. 5.

The number of contexts (including top and bottom elements) in the lattice obeys the rule $2^n + 1$, where n is the number of basic contexts. Let us look at the lattice as consisting of $n + 2$ levels: level 0 corresponds to the top element and level $n + 1$ corresponds to the bottom element. Level l comprises the lattice elements
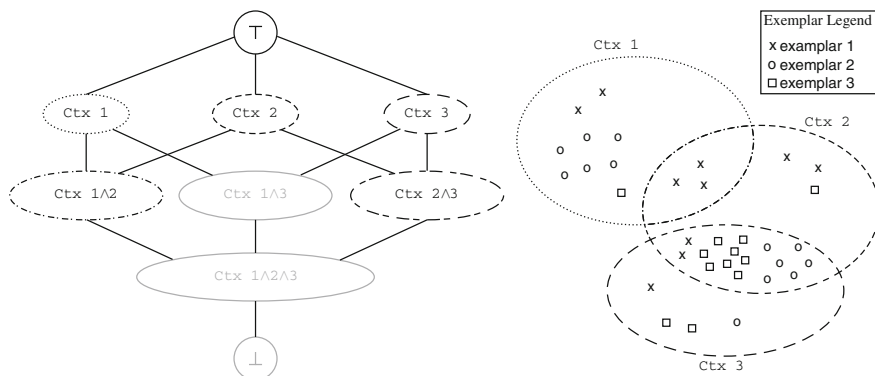
Fig. 3 Relation between observations of exemplars in reality (on the *right*) and contexts (on the *left*) for one concept. Contexts are organized in a lattice where infimum contexts corresponds to intersections of the former contexts. Some infima can be impossible in reality, which results in an empty mapping λ. Impossible contexts (*ctx 1 ∧ 3* and *ctx 1 ∧ 2 ∧ 3*) are reported in *gray*

corresponding to l-combinations of the base contexts. Then, the number of elements at level l is equal to $\binom{n}{l}$ and the total number of elements is $\sum_{l=1}^{n} \binom{n}{l} = 2^n - 1$. This is the number of all possible combinations except the void ones. Counting top and bottom elements as well, we obtain the formula: $2^n + 1$, which is in the order of $O(2^n)$.

Contexts are linked to concepts via contextualized concepts. One context links to one contextualized concept, which is composed of a set of exemplars. The selection of the exact subset of exemplars is achieved by the mapping λ (Aerts and Gabora 2005). In Fig. 3 the mapping λ is represented by styling the borders of contexts in the lattice and subsets of exemplars for one concept in the same way. The mapping λ can be used to represent a concept in a tabular form. We call this table *observation table* because the exemplars are observed in reality. The connection to reality guarantees that other agents can make the same observations grounded in reality (Kuhn 2009). The columns of this table denote contextualized concepts, the rows denote exemplars. The entries indicate how many times a given exemplar has been observed in a given context. For example, Table 1 represents an observation table for the **spatialConcept** abstracted from observations shown in Fig. 3.

Frequency values for each exemplar in the contexts *ctx 1* ∧ *ctx 3* and *ctx 1* ∧ *ctx 2* ∧ *ctx 3* are zero. A zero frequency value reflects that no exemplar was observed. This can occur either in the case of a meaningless context, or if there has been no observation yet. The model does not distinguish between meaningless contexts and not-yet-experienced contexts. It resembles what can also be found in child learning processes (Twaroch and Frank 2005).

The observation frequencies from the observation table are used to calculate the prototypical exemplar for a contextualized concept. As a typicality measure for exemplars, the amount of observations per exemplar is used. The exemplar with the most observations is considered the prototypical exemplar for the contextualized concept. Depending on the context, different typical exemplars can be calculated. For example, consider the data from Table 1, the typical exemplar for the contextualized concept **spatialConcept@**⊤ is exemplar 2, and for the **spatialConcept@***context 3* it is exemplar 3.

The prototypical exemplar of a contextualized concept is used as a mapping from a spatial term onto a spatial query. By making the context explicit, a one-to-one

Table 1 Observation table for a **spatialConcept** for different contexts according to the example depicted in Fig. 3

Spatial concept	@⊤	@ ctx 1	@ ctx 2	@ ctx 3	@ ctx 1 ∧ ctx 2	@ ctx 2 ∧ ctx 3	@ ctx 1 ∧ ctx 3	@ ctx 1 ∧ ctx 2 ∧ ctx 3
Exemplar 1	10	5	7	3	3	2	0	0
Exemplar 2	13	6	6	7	0	6	0	0
Exemplar 3	12	1	9	10	0	8	0	0

Values indicate how many times an exemplar of a **spatialConcept** (in the rows) has been observed in different contexts (in the columns)

relation between grounded observations and the spatial term is achieved. Having a one-to-one relation, the observations experienced in the same context are selected and used to calculate the prototypical exemplar. The prototypical exemplar is then used as input for a spatial query.

4 A Computational Model for Context-Dependent Concepts

The formalization of the previous approach results in a computational model. The implementation includes three parts: the context lattice, the mapping (λ) from contexts to observations, and the calculation of the prototypical exemplar. The necessary operations and data structures are described with pseudocode and can be implemented in a variety of programming paradigms (e.g. object-oriented, relational algebras, functional). Our implementation using a functional paradigm can be downloaded here: https://hackage.haskell.org/package/ContextAlgebra.

Context is implemented as a list of elements:

$$\textbf{\textit{context}} : [contextName_1, contextName_2, \dots, contextName_n]$$

An element is an arbitrary data type that supports equality comparison, for simplicity assume that these are names (e.g. character or string). **Basic contexts** include one entry in the list (e.g. [**context 1**]), while infima contexts include multiple entries (e.g. [**context 1**, **context 2**]). The context lattice is implemented as a container for all contexts as well as the empty and universal contexts. The lattice operations MEET[3] and JOIN are implemented as an intersection and union of lists.

A contextualized concept is implemented as a multiset[4] of observations that map to a context in the context lattice. The *observation* data type is realized as a pair consisting of the observed exemplar and a context:

$$\text{exemplar} : exemplarName$$
$$observation : (\text{exemplar}, \textbf{\textit{context}})$$

The context is built with the same structure and types as the contexts included in the context lattice which provides the mapping λ. A particular contextualized concept of interest is the **spatialConcept@**$\top$ which includes all observations for all contexts. All other contextualized concepts refer to a subset of observations.

The calculation of the prototypical exemplar for a contextualized concept is achieved by the functions: FILTER and COMPUTETYPICALITY.

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[3]Algorithms are indicated with a small caps typeface.

[4]The multiset is capable of holding the same entry multiple times, in contrast to a set.

The function FILTER takes a context (*ctx*) as input parameter and returns a contextualized concept (**spatialConcept@***ctx*). All the observations listed in the **spatialConcept@**⊤ are checked, and if one is found whose context coincides with the filter context it is added to **spatialConcept@***ctx*. This function relies on the equality operator and on a function CONTEXT that returns the context of an observation given in input. All contextualized concepts can possibly be stored for ease of accessibility.

Algorithm 1 Given an exemplar and a contextualized concept, the function COMPUTETYPICALITY computes the typicality of the exemplar in the context associated to the contextualized concept.

1: **function** COMPUTETYPICALITY(exemplar, **spatialConcept@***context*)
2:     obsForExemplar ← ∅
3:     **for** ∀ observation ∈ **spatialConcept@***context* **do**
4:         **if** exemplar == EXEMPLAR(observation) **then**
5:             obsForExemplar ← obsForExemplar ∪ observation
6:     **return** AMOUNT(obsForExemplar) / AMOUNT(**spatialConcept@***context*)

The function COMPUTETYPICALITY takes an exemplar and a contextualized concept as input parameters, and returns the typicality of the given exemplar for the context corresponding to the contextualized concept in input. This is called *contextual typicality* and takes values in the range [0, 1]. It is computed by counting the number of exemplars equal to the one given, and by dividing this number by the number of elements in the contextualized concept. This function relies on the equality operator for exemplars (denoted ==), the AMOUNT( ) function to enumerate exemplars, and on the function EXEMPLAR( ) returning the exemplar of an observation given in input. COMPUTETYPICALITY is further used to calculate the prototypical exemplar of a contextualized concept.

5   Case Study: Mapping the Spatial Relation "near" onto Spatial Queries

There exist many scenarios where context plays an important role, and to which the presented model could therefore be applied. Some of these include:

- Detection of landmarks has to be context-aware because landmarks depend on context (e.g. night or day (Winter et al. 2005)).
- Different map layers can be displayed depending on context, e.g. the request "I need a map to find the pub" intends a city street map, in contrast to the request "I need a map for hiking" where hiking paths should be included.
- Interpreting spatial relations has to make use of context for mapping to a metric distance.

In the following section we apply the model as a case study of the spatial relation "near", and show how such a concept can be encoded in spatial queries according to context. The aim is to show how "near" is mapped onto different metric distances according to the influencing context.

5.1 The Case Study of "near"

In general, spatial terms are influenced by many contexts, e.g. weather, mobility, time of the day, neighborhood, transportation mode, terrain. In this case study the reasonable set of exemplary basic contexts are the following: *walking*, *driving*, and *uphill*. These contexts can be derived by information obtained from sensors commonly available in modern smartphones. For example, the difference between *walking* and *driving* can be derived from speed data computable either from GNSS or accelerometers, while the *uphill* context can be derived by matching position and elevation information. The whole lattice of contexts that can possibly influence the interpretation of **near** is generated by recursively executing the function MEET on the available contexts—shown in Fig. 4. Note that the context *walking* ∧ *driving* obtained by combining the basic contexts *walking* and *driving* is not realizable, as one cannot drive and walk at the same time. This is indicated by the grey border. Accordingly, any infima deriving from this context (in this example *walking* ∧ *driving* ∧ *uphill* and ⊥) are also not realizable.

The corresponding observation table is given in Table 2. The reported observations are an educated guess driven by common sense and by the results presented by Wallgrün et al (2014), who evaluated the interpretation of **near** in a corpus of web documents. How observations can be reliably collected is not the focus of this work, however in Sect. 6 we outline some possibilities that could lead to future work.

Fig. 4 Bounded context lattice for the case study of "near". *Grey* boundaries indicate impossible contexts
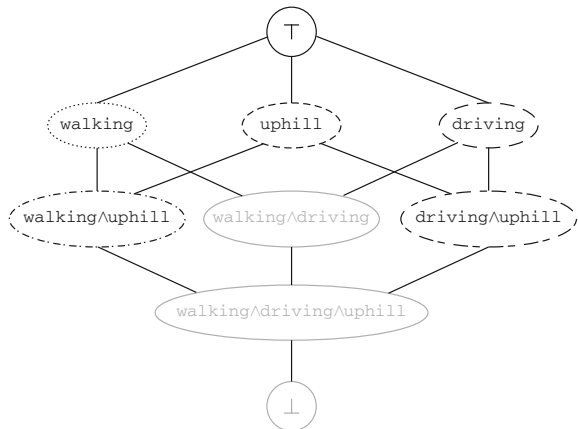
Table 2 Observation table for the concept **near** for different contexts

near (m)	@⊤	@ *walking*	@ *uphill*	@ *driving*	@ *walking* ∧ *uphill*	@ *driving* ∧ *uphill*	@ *walking* ∧ *driving*	@ *walking* ∧ *driving* ∧ *uphill*
50	4	4	4	0	4	0	0	0
100	10	5	7	3	3	2	0	0
150	10	6	3	4	2	1	0	0
300	13	7	6	6	1	5	0	0
450	13	6	6	7	0	6	0	0
1000	14	4	8	9	0	7	0	0
5000	12	1	9	10	0	8	0	0
10000	7	0	5	7	0	5	0	0
Sum	83	33	48	46	10	34	0	0

The last row shows the sums of observations in different contexts, and is provided to compute exemplar typicality

Given the context lattice and the observation table, typicality values and prototypical exemplars for the contextualized concepts are generated through the functions FILTER and COMPUTETYPICALITY (introduced in Sect. 4) as follows. The observation sets for each contextualized concept (**near**@*ctx*) are obtained by executing the function FILTER(*ctx*) for each context *ctx* in the lattice. The contextual typicality values are then computed by executing the function COMPUTETYPICALITY(e, **near**@*ctx*) for each *ctx* in the lattice and each observed exemplar e in **near**@⊤. The exemplar with the highest contextual typicality is selected as the prototypical exemplar. Typicality values for the contextualized concepts we will be using in our example are plotted in Fig. 5, where the prototypical exemplars are colored in black.
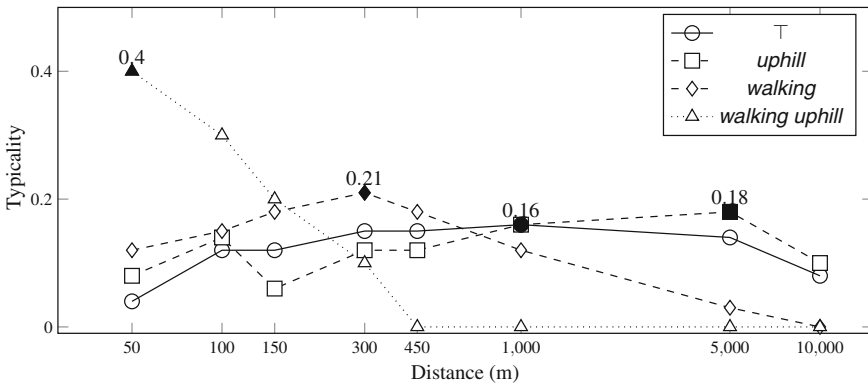
Fig. 5 Contextual typicalities for the concept **near** in different contexts; different *line* styles denote different context as reported in the legend. Points with filled markers indicate prototypical exemplars, and thus the interpretation for the concept in a given context

5.2 Examples for the Mapping of "near" onto Spatial Queries

Imagine a next–generation personalized geographic information system (PersonalizedGIS (Abdalla et al. 2013)) installed on a user's smartphone. The GIS part has access to classical geographic information (particularly, points of interest and elevation data). The personalized part is an implementation of the computational model presented in Sect. 4. Also, imagine that the system has seen the same situations as its user, in the sense that the observations given in Table 2 match with a high level of precision the concept **near** in the user's mind.

The user attends a conference in Lisbon (Portugal) and needs to find a restaurant near his or her current position. The user asks the PersonalizedGIS: *"Please show all the restaurants near me"*. Imagine a natural language processing algorithm that extracts the spatial relation "near" as well as the influencing contexts for such inputs. The result for this input is "near" and no influencing context. The absence of context indicates that every observation from the observation table (Table 2) has to be considered, which is represented by the contextualized concept **near@**⊤. The prototypical exemplar for **near@**⊤ is 1000 m (conduct Fig. 5) which is included as a metric value in the following (pseudo SQL) spatial query by the PersonalizedGIS:

```
SELECT coords FROM restaurants
WHERE distance(actual_coords, coords) <= 1000 m;
```

Assume further that the smartphone with the PersonalizedGIS is equipped with an accelerometer that detects the mode of transportation. Now the user asks the above query while moving with the smartphone. The acceleromters detects the motion "walking", which prompts the PersonalizedGIS to influence **near** by *walking*. So, rather than retrieving the prototypical exemplar for **near@**⊤, it retrieves the prototypical exemplar for **near@***walking*. The prototypical exemplar is 300 m which can be used in the spatial query shown above by the PersonalizedGIS.

The PersonalizedGIS can narrow down the interpretation even further by traversing the context lattice automatically. Assume the function GETSTRONGERCONTEXTS for the context lattice outputs all infima for a given context. For this example the function is executed with GETSTRONGERCONTEXTS(*walking*) which outputs the infima: *walking* ∧ *uphill* and *walking* ∧ *driving*. The *walking* ∧ *driving* context is nonsense and is not taken into further account. The *walking* ∧ *uphill* context is used to narrow down the interpretation of the spatial term. For both contexts (**near@***walking* ∧ *uphill* and **near@***walking*) prototypical exemplars are 50 m and 300 m. These metric values are used as input to a refined spatial query. The refined query the PersonalizedGIS then executes, retrieving all those restaurants that are closer than 300 m, but excluding those that are uphill in respect to the current location (`actual_elevation <= rest.elevation`), unless they are closer than 50 m:

```
SELECT rest.* FROM (
    SELECT coords, elevation FROM restaurants
    WHERE distance(actual_coords, coords) <= 300 m
) AS rest WHERE
actual_elevation <= rest.elevation
AND distance(actual_coords, rest.coords) <= 50 m
```

6 Conclusions and Outlook

In this paper a computational model to map spatial terms onto spatial queries is introduced. In the review of the semiotic triangle, the problem of the many-to-many relation of symbols to objects in reality is identified as a main problem for computational models. We argue that context establishes a one-to-one connection between symbols and objects in reality. Our formalization is inspired by a quantum-mechanical approach presented by Aerts and Gabora (2005). The computational model integrates context and connects it to a concept underlying the externalized spatial term. In an envisioned next-generation GIS, the computational model is used to map the spatial term "near" onto different spatial queries dependent on context.

The envisioned GIS for the spatial relation "near" draws upon a set of observations that were assumed to be given. This is an important aspect that must be addressed in future work. In a realistic scenario the contexts can be derived from smartphone sensors. For example, the contexts: walking, driving, biking, etc. can be detected through accelerometer data or a mix of sensors, provided that ranges for the sensor values are detected that correspond to different contexts. Another mechanism that remains to be solved is aligning the observation base with the observations in the mind of a user. Feedback from the user can be used to gradually align the observations with the concepts in a user's mind, as for example: "Was this distance near for you?". It remains an open question how to get a user properly involved in such a mechanism. Perhaps via some sort of gamification process?

A more theoretical direction for future work concerns the investigation of the relations between the model presented in this paper—especially the distributions that exemplars take in a given context—and fuzzy membership functions (Zadeh 1965). Can the model be reinterpreted with classical fuzzy set theory? Would this add some benefits to operations and inferences that can be made when considering several contexts? Some previous work that addressed the problem of modeling concepts like **near** and **far** with fuzzy membership functions is presented by Wang (1994). Wang finds that **near** cannot be opportunely represented with a unique membership function. Rather, he suggests that more functions must be conceived as context information changes.

The mutual influence of several (contextualized) concepts warrants further investigation. Some previous work about concept combination for GIS is presented, for

example, by Hahn and Frank (2014) where thematic maps are selected on the basis of context.

Finally, for real usage of the model in applications it would be necessary to determine which contexts must be considered that can effectively influence a spatial concept.

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