Towards Platial Joins and Buffers in Place-Based GIS

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ABSTRACT

Place-based GIS are still a novel research topic and break with some traditions of established systems. The typical spatial perspective is based on geometric reference systems that include coordinates, distances, topology, and directions; while the alternative *platial* perspective is usually characterized by place names and descriptions as well as semantic relationships between places. In past decades, space-based geographic information systems have made significant progress in terms of theories, models, functionalities, and applications. In contrast, place-based GIS are not yet well developed, although there is an increasing interest in platial and especially relational approaches. In this paper we take an example-driven, first step towards introducing place-based versions of the well known spatial join and buffer operations, and apply them to deal with place-based semantic compression and expansion in DBpedia.

Categories and Subject Descriptors

D.3.1 [**Formal Definitions and Theory**]: [Semantics]; F.3.2 [**Semantics of Programming Languages**]: [Operational semantics]

General Terms

Theory, Experimentation

Keywords

Place, platial operations, platial join, platial buffer

1. INTRODUCTION

Space and *place* are two fundamental concepts in geography, and more broadly in social sciences, humanities, and information science [44, 46, 22, 20, 26, 3]. Space is more abstract and generic while the notion of place is more tangible to humans. Our understanding of space is related to the sense of place we inhabit and experience. Place names are pervasive in human discourse, documents, and social media while location needs to be specified. In geographic information systems and science the spatial perspective is studied based on geographic reference systems that include coordinates, distances, topology, and directions; while the alternative "platial" perspective is based on (explicitly stated) relations between places, place names, and descriptions of places. Consequently, additional semantic reference systems are required for the interpretation of platial data and queries.

Goodchild (2011) discussed the idea of formalizing *place* in the digital world and addressed the relationship between the informal world of human discourse and the formal world of digitally represented geography [18]. He argued that a new interdisciplinary field may emerge involving GIS techniques, social science, and digital data. In this field, the concept of *place* might occupy a central position. Moreover, advanced platial studies are required to engage citizens in knowledge production and place sharing. Additionally, theories, techniques, and applications of place-based GIS (PBGIS) could stimulate research interests in academic fields related to semantics and computational models of place.

In the past five decades of development, space-based GIS have made important progress in terms of theories, models, functionalities, and applications [37]. However, the PBGIS is still in its infancy even while gazetteers provide some of the functions one would expect from such a system [19]. In order to locate place names on a map with precise coordinates to support geographic information retrieval (GIR), way-finding, and spatio-temporal knowledge organization, efforts have been taken to convert platial identifiers to their spatial footprints [14, 34]. One major mechanism is the use of gazetteers, which conventionally contain three core elements of geographic features: place names, feature types, and spatial footprints [24, 25]. Digital gazetteers play an important role in digital library services for geographically linking digital resources to locations, including collections of georeferenced photographs, reports relating to specific areas, news and stories about places, remote sensing images, and even music [17]. Such geospatial enabled libraries are known as *geolibaries* and are supported by gazetteers, e.g., the Alexandria digital library (ADL) gazetteer at the University of California Santa Barbara (UCSB) [23] and the Getty Thesaurus of Geographical Names (TGN)[1]. Unfortunately, most of the place-based reference systems lack semantically enabled reasoning capabilities and analysis func-

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[1] http://www.getty.edu/research/tools/vocabularies/tgn

tions, though some efforts have been made through implementing ontologies of place in semantic modeling systems [30].

To bridge this gap, we outline the design of place-based GIS operations using semantics, namely *platial join* and *platial buffer*, and apply them to infer place-based statistics. Additionally, these methods are employed to deal with place-based semantic compression and expansion in the context of DBpedia[2]. The underlying idea and promise of platial operations in general is that they give access to a more cognitive and linguistic view of location and the process of locating (entities or events).

The paper is structured as follows. In Section 2, we compare space and place from a GIS perspective and discuss how each guides us in the design of novel PBGIS. We then proceed to illustrate the *platial join* and *platial buffer* operations in Section 3. These platial operations are used to derive the place-based statistics and semantic inferences in experiments based on DBpedia in Section 4. We conclude and discuss future work in Section 5.

2. SPACE VERSUS PLACE

In this section we review a few core notions of GIS with respect to the distinction of space vs place.

2.1 Accuracy, Precision vs. Ambiguity, Vagueness

In space-based GIS, position (e.g., longitude and latitude), map projection, direction (angle), and distance are well formalized. Accuracy is used to measure the degree of correctness to which a measured value of spatial information is in line with respect to some higher-level observation or convention. In addition, precision us employed as a statistical measure of repeatability or level of exactness and is important for accurate geospatial feature representation, analysis, and mapping. In spatial databases, precision is usually expressed as the number of significant digits. Wieczorek et al. (2004) discussed estimates of uncertainty for georeferencing locality descriptions based on coordinate-precision measures [47]. In short, the quality and the reliability of spatial data depend on the accuracy and precision of the coordinate systems.

Place, in contrast, implies ambiguity and vagueness [5, 48]. A place name is usually taken to differentiate one place from another or as a mental handle for communication. These names, however, are not unique identifiers and there is also ambiguity to what region of space they exactly refer to. For example, *New York* can refer to different places, such as *New York State*, *New York City*, or a small inhabited place *New York* in Santa Rosa, Florida. In addition, a place often has multiple toponyms, including historic names and vernacular names, and names in different languages which local communities would prefer to use. *New York City*, may also be referred to as *New Orange* or *New Amsterdam* according to the Getty TGN. Researchers have developed various techniques to disambiguate place names in GIR, such as the co-occurrence models [41] and the conceptual density-based approach [8].

The representative coordinates of places in gazetteers or in encyclopedic knowledge systems can be different, e.g., the geo-referenced point representation of the inhabited place of *New York City* is located at (40° 42' 00", -74° 00' 00") in the Getty TGN, at (40° 42' 51", -74° 0' 21") by geonames.org, and at (40° 48' 31", -74° 1' 13.39") according to Wikipedia. In addition, some terms and expressions of places themselves are vague. A classic example is *downtown*; Montello et al. (2003) asked participants to draw the spatial footprints of *downtown Santa Barbara* and proposed various ways of addressing the resulting individual differences of preferences to places [40]. Fuzzy-set-based methods have been widely used to extract the intermediate boundaries of vague places in GIS and in spatial cognition [7, 45, 40]. Kernel-density surfaces and Voronoi diagram-based methods are also used to generate the approximate regional extents of the associated place names [4, 31, 33].

The linguistic expressions of place referring to locations can be ambiguous as well. One reason is the intrinsic uncertainty of locality phrases themselves, e.g., "nearby cities of Santa Barbara" and "staying far away from downtown". The spatial distances being referred to by *near* or *far* depend on the geographic context and current situation, e.g., the mode of transportation. Other aspects include the uncertain distribution range of target objects, the imprecision and the vagueness of spatial relationships (such as the internal cardinal direction relations), the imperfection of reference objects, and the uncertainty of assertions [21, 35]. Liu et al. (2009) proposed to use the concept of uncertainty fields to handle these problems associated with topological, directional, and metric spatial assertions [35].

Considering the intrinsic ambiguity and vagueness of place, there is a need to formalize the semantic relationships of places before defining platial GIS operations. Bernad et al. (2013) propose the use of description logic (DL) in formalizing the notion of semantic location relationships [6].

2.2 Heterogeneity vs. Homogeneity

One of the general properties of geographic information is heterogeneity [16]. Geo-data is essentially heterogeneous and full of variations such that it is impossible to generalize certain attributes from one location to the whole space, though spatial dependence does exist. In contrast to space, a place normally has a boundary defined by either a geopolitical or social entity, i.e., by convention, or the individuals' perception and cognition. Inside the boundary of a place, the distinguished characteristics of landscape or culture are homogeneous[3] and different from other places. For example, a particular region within Santa Barbara County is known for its wines and vineyards and this region is not homogeneous in terms of other attributes since it can be distinguished from other parts of Santa Barbara county by the production of wines and the characteristics of the landscape.

The term *sense of place* has been defined and used in many disciplines [9], such as geography, anthropology, psychology, and economics. The term describes the combination of characteristics that humans perceive or relate to a certain portion of space making it distinguishable from other places. In previous work, it was demonstrated that thematic topics extracted from Web documents including Wikipedia and travel blogs can be used to estimate geographic regions even without direct place references such as place names or coordinates [1]. With the increasing availability of data from social media and relation-centric paradigms such as

[2]http://dbpedia.org

[3]or the place can be divided into smaller subdivisions.

Linked Data, platial information will play an important role in retrieving information, answering queries and discovering knowledge.

2.3 Proximity vs. Similarity

Individuals are used to measuring distances in space as part of their everyday experience, and navigation systems are just one example. When talking about the relatedness of place, does physical proximity matter? Adams and McKenzie (2013) applied topic modeling on a set of travel blogs to infer thematic place patterns and similarities between places from natural language descriptions [2]. The results reflect Tobler's first law of Geography that near places are more similar than distant places by using relative entropy measures. In another research, Liu et al. (2013) proposed a method for capturing the relatedness between geographical entities based on the co-occurrences of their place names on Web pages [36]. They found that two neighboring provinces generally have similar co-occurrence patterns and the frequency of co-occurrences exhibits a distance-decay effect.

However, in discussing specific attributes of place, such as population, similar places are not necessarily near to each other. In fact, for a number of reason, they may be dispersed in space and the hierarchical configuration of places may even support these effects, e.g., in case of state capitols. This indicates that proximity is one dimension of a (semantic) similarity measure but not the only one. Built on existing work on semantic similarity, place similarities and analogies will undoubtably be a fruitful research area in the future.

Analogous to Tobler's first law of Geography, one could argue that *"Every place is related to other places, but more similar places are more interlinked"*. With Linked Data, such assumptions are testable in principle but will require a robust metric for place similarity first.

2.4 Absoluteness vs. Relatedness

The *where* question can be answered in space via spatial footprints, e.g., UCSB can be geo-located by a point feature at (34° 24' 47.56", -119° 50' 42.64") or a polygon of the campus. However, from a place-based perspective, UCSB would be rather characterized based on descriptions and relations, e.g., via Isla Vista's student community, the role UCSB plays as part of the University of California network, or classes and majors offered due to the proximity to the ocean. Thus, to some extent, a place can be anchored by referring to other places without the need to locate it in space [28]. Recently, Winter and Freksa [48] apply the notion of contrasts in places for answering *where* questions and demonstrate how locations can be identified by place names and the level of granularity when it is necessary to be addressed.

2.5 Multi-Dimension vs. Order, Hierarchy

Space has been represented and analyzed as points (zero-dimension), polylines (one-dimension), polygons (two-dimension) and three-dimensional space (e.g., spheroids) as well as spatio-temporal space in GIS [32, 39, 49]. As argued by Golledge (1995), order and sequence in one dimension are comprehensible and can be easily understood, but two or more dimensional spaces are cognitively difficult and can cause confusion. In Figure 1, for example, people usually take the reference object RA as a closer place to the target P rather than the actual nearest place RB in another street segment.

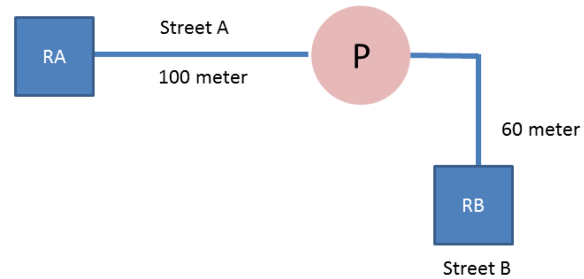

Figure 1: The absolute and cognitive closeness in referencing place. (Adapted from Golledge [15])

Hierarchical structure is common to both physical systems and to human cognition [15], e.g., river networks, administrative divisions. The hierarchy allows us to build relationships between places such as part-whole relationship and also support human cognition of places. The example of neighboring cities introduced in Section 3.2 illustrates that the linguistic expression of *"neighboring cities"* is rather platial in nature (as opposed to spatial) as it relies on place hierarchies and not necessary to spatial proximity.

3. TOWARDS PLACE-BASED GIS OPERATIONS

In this section we outline how platial joins and buffers could be defined and how they differ from their spatial counterparts.

3.1 Platial Join

Before diving into PBGIS operations, it may be valuable to review the parallel spatial operations. The major difference between spatial and platial perspectives is the involvement of coordinates. Let us look at the *spatial join* function, which is used to combine two or more datasets based on the spatial relationships. In Esri's ArcGIS software[4], the *spatial join* analysis is specifically defined to merge attributes from one geometric feature (joined feature) to another (target feature) based on the spatial relationship between them, including match operators such as *intersect, contain, within, cross, touch, or closest*. A case study on *spatial joins* that inspired us to think about *platial joins* is the aggregation of object attributes near boundaries between place entities. For example, Figure 2 shows the spatial distribution of tornado touchdowns (points) in the States of Texas, Oklahoma, Arkansas, and Louisiana from the year 1950 to 2011. Notice that a tornado (ID: 13562) occurred on the boundary between *Irion County* and *Tom Green County* in Texas. When processing the historical analysis of this tornado disaster, it is difficult to determine which counties should form the spatial joined based on number of injured people. It may be arbitrarily joined to either county based on the spatial join operation. In the textual report, however, the country from which these injured people came, is more clearly recorded. Thus, one can do a platial join of tornado points to county

[4] http://resources.arcgis.com/en/help/main/10.1/index.html#//00080000000q000000

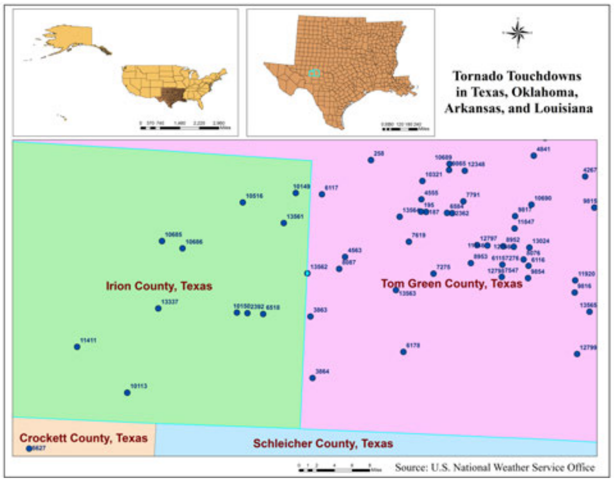

Figure 2: An example of spatially joined tornadoes to counties.

Figure 3: The spatial distribution of neighboring cities (towns) of Santa Barbara within the 65-miles-spatial-buffer zone.

polygons based on a semantic predicate such as *"locatedAt"*. Furthermore, the operation can automatically infer the aggregation results for higher hierarchical place entities (i.e., the involved US states in this example) based on the relation that a *County* is *"partOf"* a *State*.

Analogous to *spatial join*, the purpose of the *platial join* is to attach the properties or characteristics from the join entities to the target place using semantics. In other words, the *Platial Join* operation involves the aggregation of properties (attributes) $\{A_i | i = 1, 2, 3 \cdots\}$ from one or multiple place entities S to the target place entity T based on merge rules (such as *sum, average, first, last*) and their topological predicates P, including the *part-whole* relation, the *"locatedAt"* relation, and other spatial relationships [11], e.g., *touch, overlap, equals, contains, inside, and intersects*. A merge *rule* is applied when more than one entity are matched to a target place (when Join_Count > 1).

Most of these relations have been implemented on the Semantic Web to support the query of Linked Spatiotemporal Data using the SPARQL[5] and GeoSPARQL[6] query languages. Thus, we can processed both quantitative and qualitative semantic reasoning and derive knowledge about places based on the platial operations. One issue that needs attention is the variable type in platial join: *extensive or intensive* [37]. Spatially extensive variables (such as population) are true only for the whole area of a place and could be joined directly, while spatially intensive variables (such as densities, rates, or proportions) are potentially true for every part of a place, if the area is homogeneous; but we cannot simply join such intensive variables. For example, the percentage of males in place A is 40% with a total population of 100,000 and that in place B is 50% with a total population of 200,000. Obviously, we should not get a value of 45% using the join operation, and instead we need to use weighted average to derive the correct value.

3.2 Platial Buffer

In space-based GIS, the *buffer* operation involves the creation of new polygons from points, polylines, and polygons according to a specified distance to identify nearby features [10]. In GIR, it is used to find objects or places of interests (POIs) within the buffer zone of a location, e.g., restaurants within 2 miles of UCSB. In PBGIS, can we still derive similar location information or knowledge based purely on semantic reasoning (without coordinates)?

The results of a spatial buffer can be different from the platial version. For example, which cities or towns neighbor Santa Barbara? According to a local website[7], neighbors includes Isla Vista, Goleta, Ballard, Buellton, Carpinteria, Guadalupe, Los Olivos, Montecito, Orcutt, Santa Ynez, Solvang, and Summerland. A brief analysis reveals that the maximum distance between these neighboring cities and Santa Barbara is approximately 65 miles. This implies that we could find all neighboring cities by applying the *spatial buffer* function to Santa Barbara with a 65 miles radius (Figure 3). However, this would also result in Ventura, Oxnard, Thousand Oaks, and other nearby cities being included. Most likely these cities were not listed on the Web page because they belong to the neighboring county of Ventura and thus jointly form another platial subdivision. Other effects also play a role here. For instance, one would probably name San Diego as a nearby city to Los Angeles just because of its size and importance in Southern California. This indicates that the nearness of a place is context dependent and does not simply rely on a fixed distance. Instead, the hierarchical structure and the connectivity of places should be considered.

Currently, there are two understandings of *platial buffers*. One method applies the Euclidean-distance buffer on place, which much consider cognitive context due to the uncertainty of qualitative spatial reasoning about distances and directions referring to places [12, 38]. For instance, Iarri et al. discussed three types of *inside* constraints based on the metric buffer of a place; it can refer to an area either within a buffer of a given place, within a boundary from a given point inside the place, or a certain distance away from the place boundary [27]. An alternative way to process the *platial buffer*, which we propose in this paper, is based on the topological distance (connectivity or hierarchy) and seman-

[5]http://www.w3.org/TR/rdf-sparql-query
[6]http://www.w3.org/2011/02/GeoSPARQL

[7]http://www.santabarbaraca.com

tic relations between places. Rada et al. (1989) introduced a conceptual distance between two entities by counting the number of links in the shortest path on the semantic net [43]. Given such a distance, if someone is interested in information related to second-level neighboring cities (neighbors of the first-neighbors) of a city, which is often necessary during travels, we can infer this from the relationship *"neighbor of"* between cities on the Linked Data Web even without considering the coordinates and physical distances.

The *platial buffer* operation involves identifying neighboring places (first-degree buffer) or other n-degree connected places for a target based on the semantic relations. The n-degree represents the number of semantic links that connect the places under consideration.

Given the spatial-join example of cities neighboring Santa Barbara above, a 1st-degree platial buffer operation based on the semantic relationship *"neighbor of"* to can be employed from a platial-join perspective in order to ascertain the neighbors of the neighboring cities of the target place. This is done through the application of 2nd-degree platial buffers from Linked Data.

4. APPLICATION

In the following section we use examples from DBpedia to illustrate the use of platial operations. The DBpedia dataset is interlinked based on the Resource Description Framework (RDF) data model in the form of *subject-predicate-object* triple expressions.

4.1 Example of Platial Join

The first experiment demonstrates the use of the SPARQL query language to implement the platial join operation on cities/towns which are located in Santa Barbara County. The purpose of the query is to return its total population (in Figure 4). To start, we need to find all cities/towns which have the predicates *"partOf"* Santa Barbara County, and then sum their *"populationTotal"* based on the aggregate algebra rules[8]. The join result is: 388,411. This number is less than the population of the county 423,895 for the year 2010. This reveals the fact that some people live in unincorporated areas outside of the city boundaries. Figure 5 shows a region (highlighted in blue) between the city of Goleta and the city of Santa Barbara, which explains some of the missing population. If all existing *"countyOf"* relations were available on the Linked Data Web, we could perform platial join operations on counties in the state of California[9]. The resulting population from the 58 counties matches the total population of California 37,253,956 in the same year because no individuals reside outside the county boundaries. The result can also be derived from the operation on all regions with FIPS codes in California without coordinate information. Another example of platial join is to get the average number of rainy days for each month in a higher hierarchical region based on the predicate *"dbpprop:monthRainDays"* in all sub-regions, e.g., from the weather statistics at the level of cities/towns to infer county level information[10]. Thus, such place-based operations have the potential to support data compression and expansion as it is not necessary to

[8] http://www.w3.org/TR/sparql11-query/#defn_aggSum

[9] http://dbpedia.org/page/List_of_counties_in_California

[10] http://dbpedia.org/page/Santa_Barbara,_California

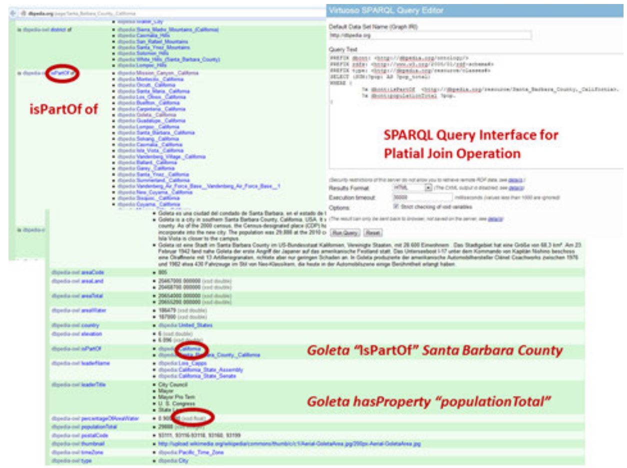

Figure 4: A platial join example to get the total population of all cities/towns inside Santa Barbara County.

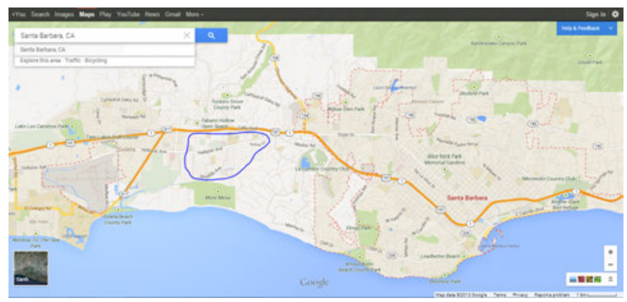

Figure 5: An example of the household area (blue color highlighted) between the city boundary of Goleta and the city boundary of Santa Barbara (red dotted line).

store all materialized data.

4.2 Example of Platial Buffer

As discussed in Section 3.2, the *platial buffer* can help to identify the n-degree connected places for a target place based on its semantic relations. We can process this operation to get the 1st-degree nearby cities of a place based on the predicate *"dbpedia-owl:nearestCity"* or 2nd or 3rd-degree nearby cities.

Another example of a *platial buffer* is the ability to infer the connection graphs of subway systems. Figure 6 shows the Beijing Subway System and its serving lines labeled via the *"isPartOf of"* predicate. Two lines have a first-degree connection if they share at least one common station supporting the public transit. For example, the DongDan Station serves both subway Line 1 and Line 5 in Beijing and is labeled as *"dbpedia-owl:servingRailwayLine"* for *"dbpedia:Line_1,_Beijing_Subway"* and *"dbpedia:Line_5,_Beijing_Subway"*. Similarly, the Lines 2, 4, 9, 10 can be connected to Line 1 after processing of the 1st-degree platial buffer. Furthermore, Lines 6, 8, 13, 15 can be connected to Line 1 with a 2nd-degree platial buffer operation. The platial configuration (schematic diagram) of the Beijing Subway System (see Figure 7) can

Figure 6: Beijing Subway System DBpeia page and Dongdan Station page.

Figure 7: Beijing Subway Map.

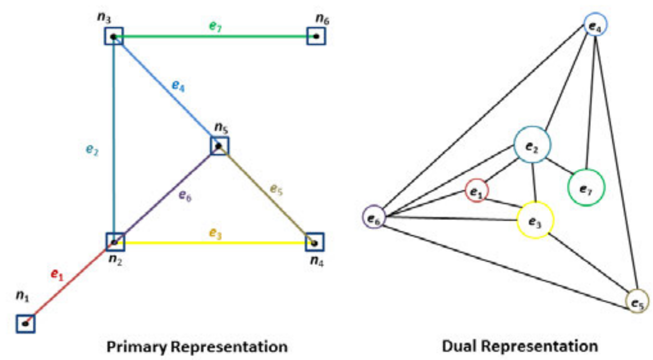

Figure 8: Two representations of the connectivity graph of a street network.

be automatically built if we add the ordering information of stops for each line on DBpedia.

The *platial buffer* can also be applied to urban planning and complex networks. There is already some research on the dual representation of physical street networks where streets are transformed into nodes and intersections are transformed into edges, in contrast to the primary geometric representation [42]. Several studies have applied such a structure to predict urban traffic flow and network centrality comparison [13, 29]. In a dual graph system such as an urban street networks, we can easily derive the n-degree connected streets to a target street by processing the n-degree *platial buffer* operation based on the topology. In Figure 8, it is clear that the street segment e_1 is connect to all other line segments by applying a 2nd-degree buffer operation in the dual graph.

5. CONCLUSIONS AND FUTURE WORK

Place descriptions are pervasive in documents and human discourse when locations need to be specified. As discussed in previous sections, the nature of place is cognitively defined, hierarchically organized and semantically interlinked. In this work, we highlight issues related to the representation and the analysis of place, analogous to coordinate-based functionality. The fundamental principles of platial operations rely on relations between places and multi-medial descriptions instead of distance, direction, and so forth as commonly seen in classical GIS. Note that topology is important in both spatial and platial worlds. We propose two place-based GIS operations, e.g., platial join and platial buffer, and apply them to various examples. We argue that the *platial join* operation might be more effective than *spatial join* to merge the attributes of entities to target places near boundaries. The challenge of platial joins lies in explicitly dealing with complex spatial relationship descriptions like *"partially overlap"* rather than only the simple predicts *"part of"* or *"inside"*. Specific aggregation rules need to be considered. In addition, *platial buffer* is useful to infer the hierarchical and other linked relations (e.g., the n-degree neighboring cities, the n-degree connectivity in bus/subway transit networks and in dual-graph street networks). Given the limitations of platial data, some results based on automatic semantic inference may be uncertain or incomplete.

Our work offers novel insights on the platial operations using semantics, and makes contributions to the next frontier of GIScience research on place. Undoubtedly, the platial operations rely on semantic representations of places, and will benefit from increasing availability of Linked Data and the enrichment of semantic links. This paper just provides a starting point.

In future work, we plan to test the listed operations on more diverse applications and identify application areas that may benefit most from place-based operations. Furthermore, other platial functions analogous to spatial versions need to be discussed. What is platial association? Can we develop techniques for detecting patterns in place-based GIS? What is platial density? How does one define platial uncertainty? What other platial theories, models and techniques are emerging to constitute research on platial information systems and platial information science?

6. ACKNOWLEDGMENTS

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