Spatiotemporal-Thematic Data processing in Semantic Web

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Abstract. *This chapter presents practical approaches to data processing in space, time and theme dimensions using current Semantic Web technologies. It describes how we obtain geographic and event data from Internet sources and also how we integrate them into an RDF store. We briefly introduce a set of functionalities in space, time and semantics. These functionalities are implemented based on our existing technology for main-memory based RDF data processing developed at the LSDIS Lab. A number of these functionalities are exposed as REST Web services. We present two sample client side applications that are developed using a combination of our services with Google maps service.*

1 Introduction

Web search is one of the most successful applications in the Internet as exemplified by widely used search engines. Semantic Web is aimed to improve the capability of such a system beyond a simple keyword search. In the spatiotemporal context, the integration of time and space for searching data sources has been addressing retrieval of the position of entities. With popularity of spatial data on the Web and increasing adoption of Semantic Web technologies, the idea of Geospatial Semantic Web is introduced (Egenhofer 2002). Adding temporal dimension alongside spatial and semantic dimensions (Mennis et al. 2000; Perry et al. 2006) increases our analytical capabilities and requires addressing new data integration challenges. This chapter describes our approach to integrating spatial information with event data (i.e., temporal and thematic data) and performing semantic, spatial and temporal analysis on the results. Using spatial and temporal data where available can increase accuracy and efficiency of processes such as disambiguation (as we show in section 2.3).

The technical contributions of this chapter are in three areas:

- We represent spatial data using Semantic Web technology (RDF) and enhance this information with spatial relations. We experimented with a geographic dataset of the state of Georgia for which we generated RDF metadata representing major geographic features and their topological relations.
- We enrich event data by relating them to associated spatial data. Specifically, we add geographic positions to event descriptions (by geo-coding the address of the venues). We also relate address information (street, zip code, state) to the spatial data described above.
- We introduce a set of processes on spatial, temporal and semantic dimension of events and show applications built using these processes. Using a set of semantic analytic and event query processing tools, we show how the generated data can be used to build applications.

This chapter is organized as follows. Section 2 gives an overview of our data acquisition and preparation including integration issues and disambiguation. In Section 3, we present a set of operations for querying space, time and semantics. Section 4 presents our experimental systems using the data and operations introduced previously. We discuss the related work in Section 5, and Section 6 provides conclusions.

2 Data Preparation

We discuss preparation of two types of data in this section: first, geographic data from Census Bureau (http://tiger.census.gov/) and second, entertainment events from several sources on the Web. The resulting datasets are publicly available on LSDIS Web site (http://lsdis.cs.uga.edu/projects/semdis/spatiotemporal/).

2.1 Geographic Data

We prepared RDF metadata from four different datasets of counties, urban areas, roads and water bodies. The source of the datasets is publicly available geographic information provided by the U.S. Census Bureau for the states of

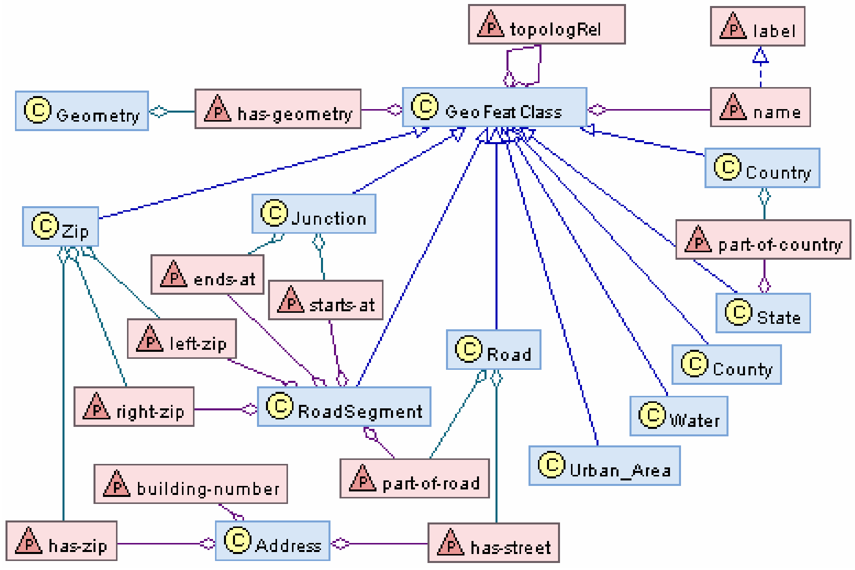


Figure 1. The RDF schema for geographic features. C and P denote RDF classes and properties, respectively

Georgia and Florida. We enhanced the RDF dataset by adding the topological relations between entities. Figure 1 illustrates the model in which the data is represented –illustration of RDF schemas in figures one, two and three are generated by RDF-Gravity (http://semweb.salzburgresearch.at/apps/rdf-gravity/). The main components of this model are as follows:

- Geographic Feature Class is the super-class of the main geographic entity classes. These entities are transformed to RDF with their corresponding attributes.
- Geometry class is foreseen in the model to keep position and shape of geographic features and complies with the OGC Simple Feature Specification (Open GIS Consortium, 1999) (Figure 2). However, we did not populate our RDF datasets by the geometry of these objects. In fact, one of our objectives in this work has been that of performing semantic analysis on the spatial objects while relying on existing spatial processing engines (as presented in section 4.1).
- Topological Relations are added values obtained using the Oracle Spatial engine (Oracle 2005, Section 1.8) —e.g., relations between zip and state, county and state, road and county, venues and towns. We use these relations for associating events without keeping the geometries in our RDF data store. As a result during the process of finding associations we only perform retrieval operations on the topological relations stored in the RDF store.
- Address is a placeholder that can be used in any other data set to relate other objects (e.g., venue in Figure 3) to spatial entities, such as zip, road and state.

2.2 Event Data

The event data discussed here are extracted from three different Web sites: eventful.com, atlanta.creativeloafing.com and ticketmaster.com (see Table 1). For scraping we used NekoHtml Java library (http://java-source.net/open-source/html-parsers/nekohtml). Different programs crawl and extract events from these Web sites. Data items obtained and modeled for every event include (Figure 3):

- Event title: It is a phrase containing a few words briefly describing an event.

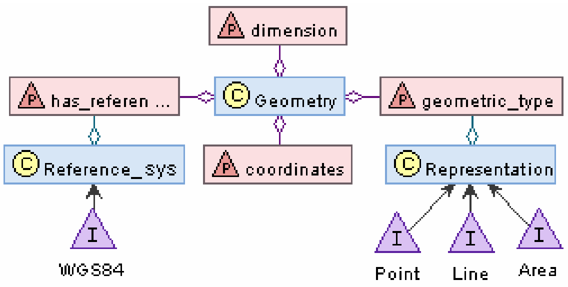


Figure 2. OGC Geometry model on RDF

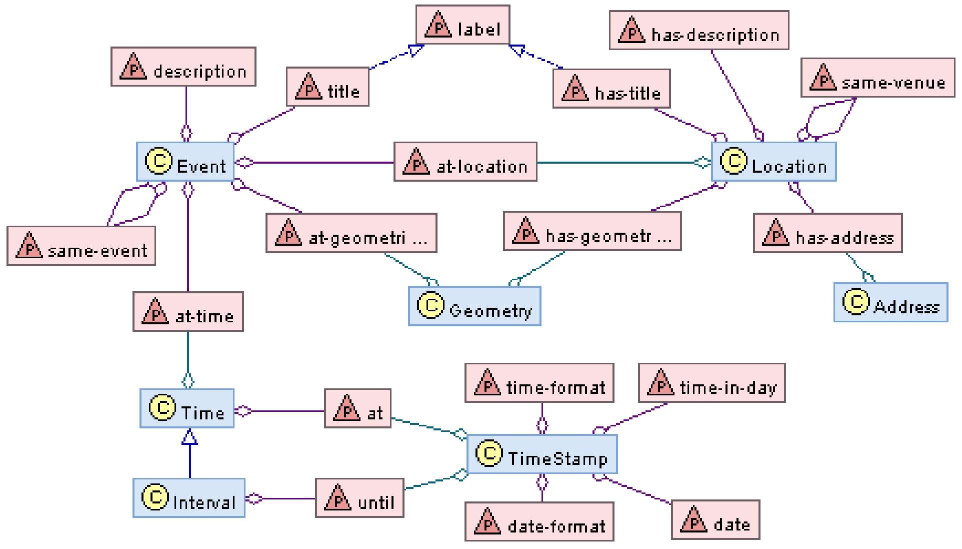


Figure 3. RDF schema for events and their time and venue.

- Event time: It could be a time point or a time interval. In most of the cases we have only the starting-time because most of the events in our event data sources consistently provide it.
- Event location: It is the venue where the event takes place. The above sites provide users with the information about the venue of every event. The data we extracted related to the venues are as follows:
  - Title: It presents the name of the venue.
  - Address: This class relates venues to the spatial data (see event model in Figure 1). This class is generated according to the extracted data.
  - Geometry: Keeps the geographic position and the shape of the venue or the event (Figure 2). The geometry information is obtained from the Yahoo geo-coding service (http://developer.yahoo.com/maps). Events are also related to geometry class for special cases where an event occurs in a position without a venue, such as an accident.

2.3 Data Integration and Disambiguation

Schematic and semantic integration of the data sets obtained from several sources is the next step (Sheth, 1999). The schematic integration has not been a major challenge considering flexibilities provided by RDF. Semantic integration however presented significant challenges. Due to the use of several data sources for events and venues, obtaining different event (or venue) resources referencing the same real world entity is inevitable. This problem is known as the reference reconciliation or entity disambiguation problem (Dong et al. 2005; Tejada et al. 2001). Furthermore, various forms of objects may be incompatibilities or conflicts (Kashyap and Sheth, 1996). Such ambiguities are resolved during our integration process.

Exiting disambiguation approaches typically rely on either text matching such as (Li et al. 2005) or object attribute matching (Dong et al. 2005; Tejada et al. 2001). Our approach extends traditional methods by incorporating spatial and temporal attributes. We used a combination of two stages of position matching and then title matching for resolving ambiguity of the identity of venues. For events, the disambiguation process is performed in three steps: Time Matching, Venue Matching and finally Title Matching. Figure 4 illustrates an example disambiguation process for event E1 by matching it against other events. Table 1 shows the number of events and venues extracted from different sources (in June 2006). The numbers in parentheses show how many venue addresses failed during the geo-coding

Table 1. Number of extracted events and venues

	Events	Venues
creativeloafing.com	10739	807(-18)
eventful.com	1419	717(-284)
ticketmaster.com	311	34(0)
Total	12469	1558(-302)
Total after disambiguation	12156	1267(-302)

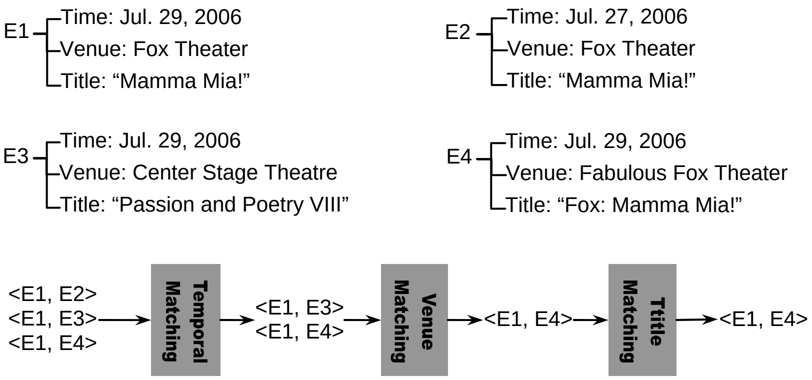


Figure 4. Illustration of an example for event disambiguation.

process. The higher number of incomplete or false addresses for eventful.com was expected as the information on this site is entered by internet users. The last row of Table 1 shows the number of unique events and venues after the disambiguation process.

During the extraction process, we obtained events that we were not immediately able to classify due to lack of information. However, we are able to improve the event classification by the knowledge acquired from their venues. First, our system assigns usage tags to venues specifying the type of events taking place in a venue. Second, for every unclassified event, the system classifies the event based on the usage tags assigned to its venue. Finally, we created required relations between the address of venues and the geographic features such as roads and zip codes in our geographic dataset.

As part of the integration process, we relate the event data to our spatial data through addresses. A complete address allows us to disambiguate a street name and resolve it to URI’s in our geographic data where possible. In other words, road or street names are not kept as literals but rather by a property from an address to a road instance. The service for resolving a street name of an address to a street URI in our spatial data set is publicly available (http://lsdis.cs.uga.edu:8080/SemDisServices).An advantage of this process is that it allows us to relate a venue to roads or streets. This facilitates responding to queries such as finding all venues (or events) at a specific street.

3 Spatial Temporal and Semantics Analysis

In this section we introduce a set of spatial, temporal and thematic (or semantic) operations we provide on our event dataset. These operations are used in our STT (spatial, temporal and thematic) disambiguation process, also used by the sample application described in Section 4.2. The main focus of these operations is finding STT proximity in these three dimensions.

We measure proximity in space based on a distance function. Finding nearest neighbor for a position is a known operator in the spatial domain. We define this functionality by the following operation:

(1) *nearestEvent (type, pos, n)*

where type is the type of event of interest, pos defines the position for the neighborhood function, and n defines the number of events in the result list. The result list is sorted by the distance from pos. An example of such proximity query is “finding the closest musical play near my office”:

nearestEvent(<musical_play>, <33.946, -83.374>, 1)

We extend the above proximity operation in time as measured through the following two functions:

(2) *nearestEventBefore(type, t, n)*
nearestEventAfter(type, t, n)

where type is the event type of interest, t specifies the time for the neighborhood measure, and n defines number of events in the sorted result list. The result of nearestEventBefore is in descending order and that of nearestEventAfter is in ascending order. An example of such a query is a request to “find 10 speeches right after the working hour on July 22”:

nearestEventAfter(<class>, <July 22, 2006, 17:30>, 10)

We use the association ranking developed at LSDIS and introduced in (Aleman-Meza et al. 2005) as a measure for semantic proximity:

(3) *associatedEvent(type, resource, n)*

where type is again the event type of interest and resource determines an instance in the RDF graph. This function finds an event that is associated to the resource through a path in the RDF graph and returns the ones ranked highest. An example of such request is a query to find a performance involving a particular favorite artist or an event organized by a specific charity organization:

associatedEvent(<comedy_play>, <Reed Martin>, 1)

The proximity operators shown above operate on each of the dimensions. However, one may look for a nearest musical show in both temporal and spatial dimension. In such cases the nearest neighbor in temporal and spatial dimensions often are not necessarily the same events. For example, an event e1 is the nearest event in temporal vicinity (one hour) of our requested time and spatial vicinity of 20 miles while event e2 is the nearest event in spatial vicinity of our requested location (3 miles) but takes place four hours after our preferred time.

There is a need for a compromise or prioritization to identify a more suitable events in such cases. Using cost coefficient we define a spatiotemporal nearest neighborhood position as follows:

(4) *nearestEventBefore(type, t, pos, tCost, dCost)*
nearestEventAfter(type, t, pos, tCost, dCost)

where type is the event type of interest, t and pos declare the point of interest in time and space dimensions, *tCost* is the cost of time difference per hour, and *dCost* is the cost of the distance per mile. The above function returns those events that minimize the following cost function:

(5) *cost(e) = (tCost*timeDiff(time(e), t)) + (dCost*dist(position(e), pos))*

and returns a list of events sorted by the cost function. Finally, adding a parameter to the query in (6) for finding an event associated to an entity can satisfy major proximity queries:

(6) *nearestEvent(type, t, pos, res, tCost, dCost, rank)*

An example of such a query is “find a theater play starring a particular actor and taking place close to my office after working hour on 22nd July.” However, if the venue is close to the office, one may be willing to wait a day or two, rather than traveling a long way to the neighboring town and join the event right away:

nearestEvent(<theater_play>,<July 22, 2006, 17:30>, <33.946, -83.374>,
<Reed Martin>, 6, 1, 0.2)

By setting *tCost* = 6 and *dCost* = 1, we express the fact that for the cost of traveling 1km we would wait 6 hours. Finally, by setting rank to 0.2, in fact, we accept most of events that have any association with ‘Read Martin.’ Alternatively, an application may wish to bias this cost function to favor time (e.g., it may be preferable to drive 20 miles than to go to an event that impinges on the dinner time so far as the event is on the preferred day).

4 Sample Applications

This section introduces two applications that work with our datasets. The first application is intended to show how spatial information can contribute to semantic analytic operations. This application is based on a generic semantic analytic tool that finds and ranks semantic associations in an RDF graph. With the addition of spatial knowledge to our dataset, this tool can associate events in the spatial dimension. The second application is intended to demonstrate how this integrated dataset allows retrieval of event data. This application uses the proximity functions introduced in the previous section to find suitable entertainment events. We enable users to search the event data using the integration of proximity constraints in space, time and semantics. In fact, the new semantic proximity dimension is introduced to the known spatial and temporal proximity dimensions.

4.1 Adding Spatial Information to Semantic Analysis

First, we show how spatial relations can enrich semantic associations. In short, a semantic association is a sequence of resources and properties in an RDF graph in a way that from each resource there is one property to the succeeding resource (Anyanwu and Sheth, 2003). There can be a very large number of semantic associations between two re-

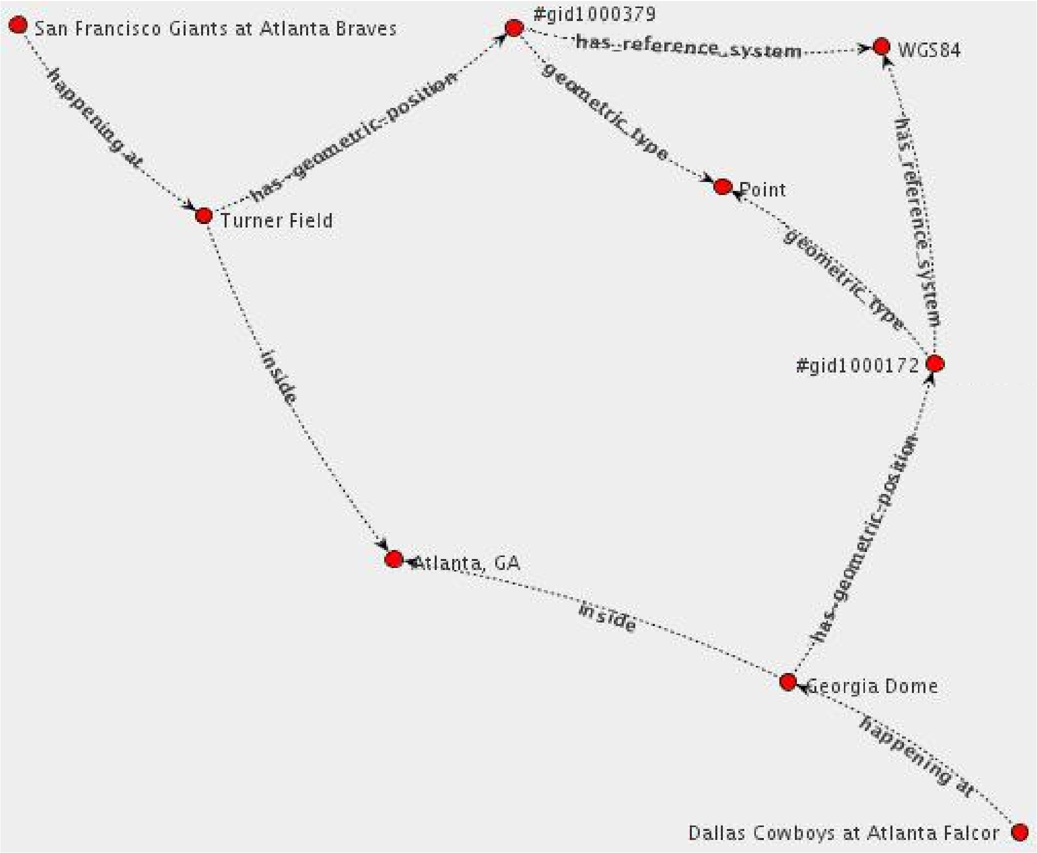
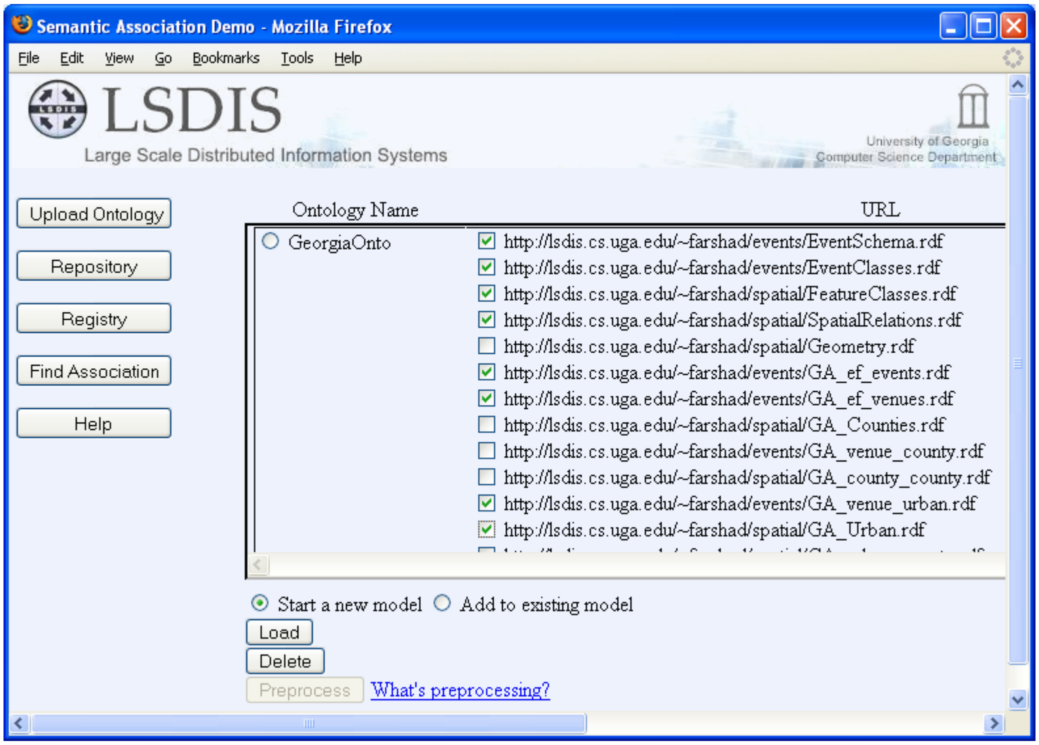


Figure 5. Several paths associating two events.

sources – often much larger than the number of documents that a search engine can find in response to keywords. A simple example showing three different paths associating two events are illustrated in Figure 5 (Graph illustration is done using JUNG programming library ─http://jung.sourceforge.net). Each of the paths conveys a different semantics based on the semantics of the intermediate edges on the path. One shows that both events are taking place in Atlanta, the other shows that both have geometries according to WGS84. While the former may be an interesting fact, the later is an assumption we took for granted while processing the geometric data. Depending on our requirements we may have different priorities in finding such associations. This makes the issue of ranking semantic associations very important as well as challenging. Several approaches for finding and ranking these associations are discussed in (Aleman-Meza et al. 2005). By means of adding spatial information to entities in the RDF ontologies, spatial objects and their topological relations take part in identifying and ranking the semantic associations.

Figure 6 shows how different RDF ontologies can be selected and loaded into the system for finding semantic associations. The ontologies are organized in modules to avoid unnecessary loading of data into memory. For example, if urban areas are of our interest we do not load the spatial information about counties.

In the next step, we run one of our semantic association ranking algorithms and also add an ability to visualize these associations. A query to find associations between “Dallas Cowboys” and “Chicago Cubs” results in a number of associations. An association that contains spatial relations is illustrated in Figure 7 (left). The association shows that both teams have matches scheduled at venues in Atlanta. As two of the resources in the association are venues and related to geographic positions, we are able to illustrate them on a map. The visualization of the venues in our example path (Georgia Dome and Turner Field), using Google map API is shown in Figure 7 (right). The above system is publicly available at LSDIS Web site (http://lsdis.cs.uga.edu:8080/SemanticAssociationDemo/).


Semantic Association Demo - Mozilla Firefox
File Edit View Go Bookmarks Tools Help
LSDIS
Large Scale Distributed Information Systems
University of Georgia
Computer Science Department
Upload Ontology
Repository
Registry
Find Association
Help
Load
Delete
Preprocess
What's preprocessing?

Ontology Name	URL
○ GeorgiaOnto	☑ http://lsdis.cs.uga.edu/~farshad/events/EventSchema.rdf
	☑ http://lsdis.cs.uga.edu/~farshad/events/EventClasses.rdf
	☑ http://lsdis.cs.uga.edu/~farshad/spatial/FeatureClasses.rdf
	☑ http://lsdis.cs.uga.edu/~farshad/spatial/SpatialRelations.rdf
	☐ http://lsdis.cs.uga.edu/~farshad/spatial/Geometry.rdf
	☑ http://lsdis.cs.uga.edu/~farshad/events/GA_ef_events.rdf
	☑ http://lsdis.cs.uga.edu/~farshad/events/GA_ef_venues.rdf
	☐ http://lsdis.cs.uga.edu/~farshad/spatial/GA_Counties.rdf
	☐ http://lsdis.cs.uga.edu/~farshad/events/GA_venue_county.rdf
	☐ http://lsdis.cs.uga.edu/~farshad/spatial/GA_county_county.rdf
	☑ http://lsdis.cs.uga.edu/~farshad/events/GA_venue_urban.rdf
	☑ http://lsdis.cs.uga.edu/~farshad/spatial/GA_Urban.rdf

● Start a new model ○ Add to existing model

Figure 6. Loading RDF metadata sets to find semantic associations.

4.2 Semantics as a Dimension alongside Space and Time

In this section, we show how an application using the functionalities introduced in Section 3 is able to find suitable events. As the first step, a set of REST Web services based on the functionalities in section 3 are exposed to the

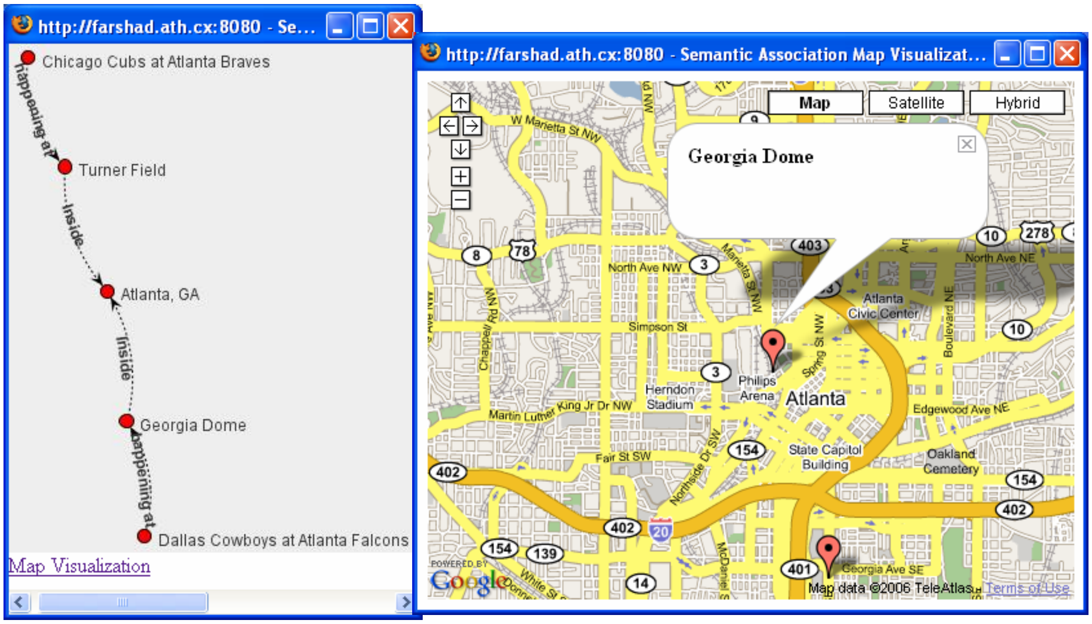
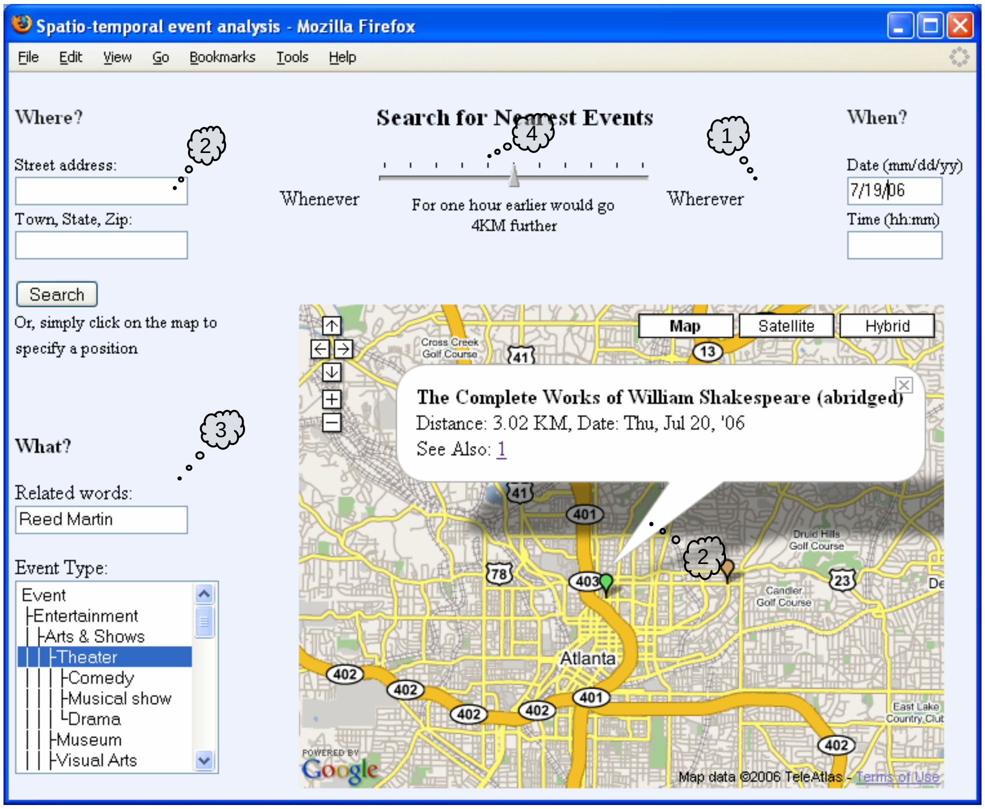


Figure 7. A semantic association involving spatial relations on the left. Geographic entities in the association are illustrated on the right.



Spatio-temporal event analysis - Mozilla Firefox

Search for Nearest Events

Where?

Street address:

Town, State, Zip:

Or, simply click on the map to specify a position

What?

Related words: Reed Martin

Event Type: Theater

When?

Date (mm/dd/yy): 7/19/06

Time (hh:mm):

For one hour earlier would go 4KM further

The Complete Works of William Shakespeare (abridged)

Distance: 3.02 KM, Date: Thu, Jul 20, '06

See Also: 1

Figure 8. A sample application based on our proximity functionality.

Web. The spatial processing of the operators is implemented using the Oracle Spatial Module (Oracle 2005). We mainly relied on Oracle for its spatial indexing capabilities. For RDF processing we used SemDis API (http://lsdis.cs.uga.edu/projects/semdis/api/). It is an API for accessing RDF data store with several different implementations for different purposes. We used the Java implementation for this application. The implemented services are publicly available at LSDIS Web site (http://lsdis.cs.uga.edu:8080/SemDisServices). We provide a client-side application that allows a user to specify a set of request parameters. These parameters are used to invoke our REST services as follows:

1. Time: date and time of day (default: current browser time)
2. Space: location by specifying an address or by clicking on the map. In the case of entering an address, the client geo-codes the address using Google geo-coding service on the client-side (unlike the integration process where we used Yahoo geo-coding process) and then sends the position.
3. Semantics: semantics of events can be constrained in two ways. First, by specifying an event type, the user can narrow down the type of events. Second, by providing keywords that we relate to the resources in our RDF graph and then associate with the events in our dataset.
4. Costs: cost ratio of time and space. The application provides a slider that helps the user to specify the importance of the temporal constraint as related to the spatial constraint. The cost ratio is translated to a verbal sentence describing the preference expressed by the ratio. For example, how much one would be willing to travel to join an event that takes place an hour earlier; or, how long one would wait to travel one kilometer less.

Finally, the result of the service invocation is displayed on the map. A snapshot of the client side user interface is presented in Figure 8. The example illustrates a query where a user looks for a theater show nearest to a point she specified on the map and around 19th July, 2006. She also indicates an interest in events related to Reed Martin. The system found a show on 20th July, 3km from the indicated point. Furthermore, Reed Martin is both a writer and a player in “The Complete Works of William Shakespeare.”

5 Related Work

Our work is related to previous work in different domains, namely, data acquisition, spatial data modeling in RDF, disambiguation, and finally event modeling and processing. We used tailored Java code (using NekoHtml library) for web scraping, because of the flexibility in generating output RDF datasets and in scheduling of extractors. However, as Semantic Web technologies are gaining popularity, more extraction tools (Hammond et al. 2002) and specifications (Hazaël-Massieux and Connolly, 2006) are becoming available with enhanced capabilities. We believe that in mid-term future, there will be more RDF metadata available as well as better alternative tools for data extraction.

On modeling of spatial information, activities of the RDF community are limited to modeling latitude and longitude of points (http://www.w3.org/2003/01/geo/). We used a more expressive model by adopting Open GIS Consortium specification in (Open GIS Consortium, 1999). Another alternative in this area would be adopting GML (Open GIS Consortium, 2005). GML is a more complex specification, and we believe such level of complexity is not necessary for lightweight spatial processing such as the type of semantic applications discussed here. However, enterprise-centric and scientific semantic applications may benefit from more complex specifications.

Work on disambiguation can be divided into two categories: disambiguation of objects in text as in (Li et al. 2005) and disambiguation of objects from different datasets as in (Dong et al. 2005) and (Tejada et al. 2001). Our work is similar to (Dong et al. 2005) and (Tejada et al. 2001) in the sense that they are also concerned with object disambiguation based on object attributes. However, we take advantage of temporal and spatial attributes of venues and events.

Part of this work is about event modeling and processing. There is a good body of work on spatiotemporal data processing; however, this chapter is aiming at modeling and processing in semantics, space and time. A similar work in this domain that pays reasonable attention to the STT dimensions is presented in (Westermann and Jain, 2006). It presents an event-based system for a different domain of application, multimedia information management, and a vision of emerging event-based applications.

6 Conclusion

The focus of this chapter is presenting our practical approaches for integrating semantics, space and time. Considering that the amount of information related to events is increasing, we explored the integration of spatial, temporal and thematic information from different sources on the Web. We show how information related to the space time and theme of events can be integrated. The chapter also presents query operators that allow integrating constraints on proximity in these dimensions.

We present a description of steps for data preparation and integration. We introduce a subset of proximity operators developed at LSDIS for querying event data. Finally, we discuss two systems implemented using the Web and the Semantic Web infrastructure working with spatial, temporal and thematic data.

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