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Spatial Semantics for Better Interoperability and Analysis: Challenges and Experiences in Building Semantically Rich Applications in Web 3.0

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Spatial Semantics for Better Interoperability and Analysis:
Challenges And Experiences In Building Semantically Rich Applications In Web 3.0
(Keynote at the 3rd Annual Spatial Ontology Community of Practice Workshop (SOCoP), USGS Reston, VA, December 03, 2010)

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Thanks: Cory Henson, Prateek Jain & Kno.e.sis Team. Ack: NSF and other Funding sources.
Semantics as core enabler, enhancer @ Kno.e.sis

15 faculty
45+ PhD students & post-docs
Excellent Industry collaborations (MSFT, GOOG, IBM, Yahoo!, HP)
Well funded
Multidisciplinary
Exceptional Graduates
Web (and associated computing) evolving

Enhanced Experience, Tech assimilated in life

Situations, Events

Objects

Patterns

Keywords

Web as an oracle / assistant / partner
- “ask the Web”: using semantics to leverage text + data + services

Web of people, Sensor Web
- social networks, user-created casual content
- 40 billion sensors

Web of resources
- data, service, data, mashups
- 4 billion mobile computing

Web of databases
- dynamically generated pages
- web query interfaces

Web of pages
- text, manually created links
- extensive navigation

Computing for Human Experience
Variety & Growth of Data

• Variety/Heterogeneity

Many intelligent applications that involve fusion and integrated analysis of wide variety of data
Web pages/documents, databases, Sensor Data, Social/Community/Collective Data (Wikipedia), Real-time/Mobile/device/IoT data, Spatial Information, Background Knowledge (incl. Web of Data/Linked Open Data), Models/Ontologies...

• Exponential growth for each data: e.g. Mobile Data

2009: 1 Exabyte (EB)
2010 US alone: 40+ EB.
Estimate of 2016-17 (Worldwide): 1 Zettabyte (ZB) or 1000 Exabytes.
A large class of Web 3.0 applications...

- utilize larger amount of historical and recent/real-time data of various types from multiple sources (lot of data has spatial property)
- not only search, but analysis of or insight from data – that is applications are more “intelligent”
- This calls for semantics: spatial, temporal, thematic components; background knowledge
- This talk: spatial semantics as a key component in building many Web 3.0 applications
A Challenging Example Query

What schools in Ohio should now be closed due to inclement weather?

Need domain ontologies and rules to describe type of inclement weather and severity.

Integration of technologies needed to answer query

1. Spatial Aggregation
2. Semantic Sensor Web
3. Machine Perception
4. Linked Sensor Data
5. Analysis of Streaming Real-Time Data
Technology 1
Spatial Aggregation

- What schools are in Ohio?
- What weather sensors are near each of the school?
Spatial Aggregation

• Utilizes partonomy in order to aggregate spatial regions
• To query over spatial regions at different levels of granularity
  • Data represents “low-level” districts (school in district)
  • Query represents “high-level” state (school in state)
Increased Availability of Spatial Info

Schools in Ohio

Google Maps

Search for schools in Ohio.

Schools near Ohio

- Westerville City Schools: Main Office
  - More info
  - 950 County Line Rd, Westerville, OH - (614) 797-5200
  - 1 review
  - “and I have found Westerville north offers something for everyone academically…”

- Olentangy Liberty High School
  - More info
  - 3584 Home Rd, Powell, OH - (740) 657-4200
  - 2 reviews
  - “program and plenty of extra curriculars. … The school also has more…”

- Westerville City Schools: Main Office
  - More info
  - 303 S Otterbein Ave, Westerville, OH - (614) 797-6000
  - 1 review
  - “an excellent school… at Westerville South High School. They…”
Accessing Can Be Difficult

Google Maps

Search Google Maps for "Schools in Greene County" and access the map for E. Green St, Scottville, Mason, MI 49454.
Must Ask for Information the “Right” Way

Google Maps
Schools in Greene County, Ohio

Xenia High School - more info
503 Kinsey Rd, Xenia, OH - (937) 372-6083
2 reviews - Write a review
"Xenia High seems like the typical high school. The staff seem to be average and ..."

Xenia Community Schools - more info
578 E Market St, Xenia, OH - (937) 376-2961
Write a review

Spring Hill Elementary School - more info
560 Ormaby Dr, Xenia, OH - (937) 372-6461
Write a review
Why is This Issue Relevant?

• Spatial data becoming more significant day by day.

• Crucial for multitude of applications:
  – Social Networks like Twitter, Facebook ...
  – GPS
  – Military
  – Location Aware Services: Four Square Check-In
  – weather data

• Spatial Data availability on Web continuously increasing.

Naïve users contribute and correct spatial data too which can lead to discrepancies in data representation.

E.g. Geonames, Open Street Maps
What We Want

Automatically align conceptual mismatches

User’s Query

Semantic Operators

Spatial Information of Interest
What is the Problem?

- Existing approaches only analyze spatial information and queries at the lexical and syntactic level.

- Mismatches are common between how a query is expressed and how information of interest is represented.
  - Question: “Find schools in NJ”
  - Answer: Sorry, no answers found!
  - Reason: Only counties are in states.

- Natural language introduces much ambiguity for semantic relationships between entities in a query.
  - Find Schools in Greene County.
What Needs to be Done?

• **Reduce users’ burden** of having to know how information of interest is represented and structured to enable access by broad population.

• **Resolve mismatches** between a query and information of interest due to differences in granularity to improve recall of relevant information.

• **Resolve ambiguous relationships** between entities based on natural language to reduce the amount of wrong information retrieved.
Existing Mechanism for Querying RDF

- SPARQL
- Regular Expression Based Querying Approaches
“Find Schools Located in the State of Ohio”
In a Perfect Scenario

School  Ohio

parent feature
In a Not so Perfect Scenario

- School
- County
- Ohio

parent feature
Proposed Approach

- Define operators to ease writing of expressive queries by implicit usage of semantic relations between query terms and hence remove the burden of expressing named relations in a query.
- Define transformation rules for operators based on work by Winston’s taxonomy of part-whole relations.
- Rule based approach allows applicability in different domains with appropriate modifications.
- Partonomical Relationship Based Query Rewriting System (PARQ) implements this approach.
Meta Rules for Winston’s Categories

Transitivity
(a φ-part of b) (b φ-part of c) (a φ-part of c)
Dayton place-part of Ohio Ohio place-part of US Dayton place-part of US

Overlap
(a place-part of b) (a place-part of b) (b overlaps c)
Sri Lank place-part of Indian Ocean Sri Lank place-part of Bay of Bengal Indian Ocean overlaps with Bay of Bengal

Spatial Inclusion
(a place-part of b) (a place-part of b) (b overlaps c)
White House instance of Building Barack is in the White House Barack is in the building
Slight and Severe Mismatch

SELECT ?school
WHERE {
  ?state geo:featureClass geo:A
  ?schools geo:featureClass geo:S
  ?state geo:name "Ohio"
  ?schools geo:parentFeature ?state
}

Query Re-Writer

SELECT ?school
WHERE {
  ?state geo:featureClass geo:A
  ?schools geo:featureClass geo:S
  ?state geo:name "Ohio"
  ?school geo:parentFeature ?county
  ?county geo:parentFeature ?state
}
<table>
<thead>
<tr>
<th></th>
<th>Ease of Writing</th>
<th>Expressivity</th>
<th>Works in all scenarios</th>
<th>Schema agnostic</th>
</tr>
</thead>
<tbody>
<tr>
<td>SPARQL</td>
<td>X</td>
<td>√</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>PSPARQL</td>
<td>√</td>
<td>√</td>
<td>X</td>
<td>√</td>
</tr>
<tr>
<td>Our Approach (PARQ)</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
</tbody>
</table>
Evaluation

• Performed on publicly available datasets (Geonames and British Ordnance Survey Ontology)

• Utilized 120 questions from National Geographic Bee and 46 questions from trivia related to British Administrative Geography

• Questions serialized into SPARQL Queries by 4 human respondents unfamiliar with ontology

• Performance of PARQ compared with PSPARQL and SPARQL
Sample Queries

• “In which English county, also known as "The Jurassic Coast" because of the many fossils to be found there, will you find the village of Beer Hackett?”

• “The Gobi Desert is the main physical feature in the southern half of a country also known as the homeland of Genghis Khan. Name this country.”
<table>
<thead>
<tr>
<th>Respondent</th>
<th>System</th>
<th># of Queries Answered</th>
<th>Precision</th>
<th>Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Respondent1</td>
<td>PARQ</td>
<td>82</td>
<td>100%</td>
<td>68.3%</td>
</tr>
<tr>
<td></td>
<td>SPARQL</td>
<td>25</td>
<td>100%</td>
<td>20.83%</td>
</tr>
<tr>
<td>Respondent2</td>
<td>PARQ</td>
<td>93</td>
<td>100%</td>
<td>77.5%</td>
</tr>
<tr>
<td></td>
<td>SPARQL</td>
<td>26</td>
<td>100%</td>
<td>21.6%</td>
</tr>
<tr>
<td>Respondent3</td>
<td>PARQ</td>
<td>61</td>
<td>100%</td>
<td>50.83%</td>
</tr>
<tr>
<td></td>
<td>SPARQL</td>
<td>19</td>
<td>100%</td>
<td>15.83%</td>
</tr>
<tr>
<td>Respondent4</td>
<td>PARQ</td>
<td>103</td>
<td>100%</td>
<td>85.83%</td>
</tr>
<tr>
<td></td>
<td>SPARQL</td>
<td>33</td>
<td>100%</td>
<td>27.5%</td>
</tr>
</tbody>
</table>
## PARQ - vs - PSPARQL

<table>
<thead>
<tr>
<th>System</th>
<th>Precision</th>
<th>Recall</th>
<th>Execution time/query in seconds</th>
</tr>
</thead>
<tbody>
<tr>
<td>PARQ</td>
<td>100%</td>
<td>86.7%</td>
<td>0.3976</td>
</tr>
<tr>
<td>PSPARQL</td>
<td>6.414%</td>
<td>86.7%</td>
<td>37.59</td>
</tr>
</tbody>
</table>

Comparison for National Geographic Bee over Geonames

<table>
<thead>
<tr>
<th>System</th>
<th>Precision</th>
<th>Recall</th>
<th>Execution time/query in seconds</th>
</tr>
</thead>
<tbody>
<tr>
<td>PARQ</td>
<td>100%</td>
<td>89.13%</td>
<td>0.099</td>
</tr>
<tr>
<td>PSPARQL</td>
<td>65.079%</td>
<td>89.13%</td>
<td>2.79</td>
</tr>
</tbody>
</table>

Comparison for British Admin. Trivia over Ordnance Survey Dataset
Spatial Aggregation Conclusion

• Query engines expect users to know the dataset structure and pose well formed queries
• Query engines ignore semantic relations between query terms
• Need to exploit semantic relations between concepts for processing queries
• Need to provide systems with behind the scenes rewrite of queries to remove burden of knowing structure of data
Technology 2

Semantic Sensor Web (SSW)

• What is inclement weather?
• What sensors in Ohio are capable of detecting inclement weather?
• What sensors are near schools in Ohio?
• What observations are these sensors generating NOW?
• Are these observations providing evidence for inclement weather?
Semantic Sensor Web

Utilizes ontologies to represent and analyze heterogeneous sensor data

- Sensor-observation ontology
- Spatial ontology
- Temporal ontology
- Domain ontologies (i.e., weather ontology)

Generates abstractions (that matter to human decision making) over sensor data

- Analysis of data to detect and represent interesting features (i.e., objects, events, situations)
Semantic Sensor Web

Utilizes semantic technologies to bridge the divide between the “real-world” and the Web (critical to Cyber-Physical systems)

Physical Space (“real-world”)  Information Space (Web)

Environment  Observation  Sensor

Event ID/Understanding,  Situation Awareness

Sensor Data

Semantic Sensor Web
Sensors are now ubiquitous, and constantly generating observations about our world.
However, these systems are often stovepiped,
with strong tie between sensor network and application
We want to set this data free
With freedom comes new responsibilities ....

- All sensors reporting position
- All connected to the Web
- All with metadata registered

- All readable remotely
- Some controllable remotely
1) How to discover, access and search the data?

Web Services

- OGC Sensor Web Enablement (SWE)
2) How to integrate this data together when it comes from many different sources?

Shared knowledge models, or Ontologies

- syntactic models – XML (SWE)
- semantic models – OWL/RDF (W3C SSN-XG)
The SSN-XG Deliverables

- Ontology for semantically describing sensors
- Illustrate the relationship to OGC Sensor Web Enablement standards
- Semantic annotation of OGC Sensor Web Enablement standards
3) Make streaming numerical sensor data meaningful to web applications and naïve users?

Symbols more meaningful than numbers
- analysis and reasoning (understanding through perception)
SSW demo with Mesowest data

http://knoesis.org/projects/sensorweb/demos/semsos_mesowest/ssos_demo.htm
Technology 3

Active Machine Perception

• Are these observations providing evidence for inclement weather?
Machine Perception

- Task of extracting meaning from sensor data
- Perception is the act of choosing from alternative explanations for a set of observations (Intellego Perception)
- Perception is a active, cyclical process of explaining observations by actively seeking – or focusing on – additional information (Active Perception)
- Active Perception cycle is driven by prior knowledge
Goal to Obtain

Awareness of the Situation

observe → perceive → “Real-World”

Web
Formal Theory of Machine Perception

- Specification
- Implementation
- Evaluation

Enable Situation Awareness on Web

Must utilize *abstractions* capable of representing observations and perceptions generated by either people or machines.

![Diagram showing the process of observing, perceiving, and relating to the "Real-World" through abstractions.](image-url)
Observation of Qualities

Both people and machines are capable of observing qualities, such as redness.

Formally described in a sensor/observation ontology.
Both people and machines are also capable of perceiving entities, such as apples.

* Formally described in a perception ontology
Ability to perceive is afforded through the use of background knowledge. For example, knowledge that apples are red helps to infer an apple from an observed quality of redness.

Formally described in a domain ontology.
The ability to perceive *efficiently* is afforded through the *cyclical exchange* of information between observers and perceivers.

Traditionally called the Perception Cycle (or Active Perception)
Integrated Perception Cycle

Integrated together, we have an abstract model – capable of situation awareness – relating observers, perceivers, and background knowledge.

Observer observes Quality

Perceiver perceives Entity

sends percept

sends focus

inheres in
Specification of Perception Cycle (in set theory)

<table>
<thead>
<tr>
<th>Term</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$G = (C, P, E, Q, PQ)$</td>
<td>Typed bipartite graph</td>
</tr>
<tr>
<td>$C$</td>
<td>Set of all concepts</td>
</tr>
<tr>
<td>$P$</td>
<td>Set of all possible percepts</td>
</tr>
<tr>
<td>$E \subseteq (C \times P)$</td>
<td>Set of all edges linking concepts to percepts (concept explains percept)</td>
</tr>
<tr>
<td>$Q$</td>
<td>Set of all quality types</td>
</tr>
<tr>
<td>$PQ: P \to Q$</td>
<td>One-to-one function from percept to associated quality type</td>
</tr>
</tbody>
</table>

**Valid (Valid Set of Percepts):** $P \to \text{Boolean}$

$$\text{valid(ps)} \Rightarrow (ps \subseteq P) \land (\forall p_1, p_2 \in ps \mid (p_1 \neq p_2) \Rightarrow (PQ(p_1) \neq PQ(p_2)))$$

**Extraneous:** $P \times \text{Powerset}(C) \to \text{Boolean}$

$$\text{extraneous}(p, cs) \Leftrightarrow (p \in P) \land (cs \subseteq C) \land (\neg \text{discriminating}(p, cs))$$

**Discriminating:** $P \times \text{Powerset}(C) \to \text{Boolean}$

$$\text{discriminating}(p, cs) \Leftrightarrow (p \in P) \land (cs \subseteq C) \land (c \in C) \land 
(((cs = \{c\}) \land (\{c, p\} \in E)) \lor (\exists c_1, c_2 \in cs : ((c_1, p) \in E) \land ((c_2, p) \in E)))$$

**Expected:** $P \times \text{Powerset}(C) \to \text{Boolean}$

$$\text{expected}(p, cs) \Leftrightarrow (p \in P) \land (cs \subseteq C) \land (\neg \text{empty}(cs)) \land (\forall c \in cs : (c, p) \in E)$$

**Explains:** $C \times \text{Powerset}(P) \to \text{Boolean}$

$$\text{explains}(c, ps) \Leftrightarrow (c \in C) \land (ps \subseteq P) \land \text{valid(ps)} \land (\forall p \in ps : (c, p) \in E)$$

**Perception Process:** $\text{Powerset}(P) \to \text{Powerset}(C)$

$$\text{perception-process}(ps) = \{ c \in C \mid (ps \subseteq P) \land \text{explains}(c, ps) \}$$

**Focus Candidates:** $\text{Powerset}(C) \to \text{Powerset}(Q)$

$$\text{focus-candidates}(cs) = \{ q \in Q \mid (cs \subseteq C) \land (p \in P) \land \text{discriminate}(p, cs) \land (q = PQ(p)) \}$$

**Observation Process:** $Q \to P$

$$\text{observation-process}(q) = \{ p \in P \mid ** \text{observe the real-world quality with type } q \in Q \text{ and generate } p **\}$$

**Choose:** $\text{Powerset}(Q) \to Q$

$$\text{choose}(qs) = \{ q \in Q \mid (qs \subseteq Q) ** \text{choose some } q \text{ from the set } qs **\}$$

**Perception Cycle:** $\text{Powerset}(C) \times \text{Powerset}(P) \to \text{Powerset}(C)$

**Definition:** (perception-cycle(cs $\subseteq C$, ps $\subseteq P$))

$$\text{perception-cycle}(cs, ps) = $$

IF empty(focus-candidates(cs)) THEN cs
ELSE LET aux $=$ ps U \{ observation-process(choose(focus-candidates(cs))) \}
IN perception-cycle(perception-process(aux), aux)

**Call:** (perception-cycle($C$ = set of all concepts, () = empty set of percepts))

$$\text{perception-cycle}(C()) = ?$$
Implementation of Perception Cycle
We demonstrated **50% savings in resource requirements** by utilizing background knowledge within the Perception Cycle.
Trusted Perception Cycle Demo

http://www.youtube.com/watch?v=lTxzghCjGgU
http://knoesis.org/projects/sensorweb/demos/trusted_perception_cycle/
Technology 4

Linked Sensor Data

• What schools are in Ohio?
• What inclement weather necessitates school closings?
• What sensors in Ohio are capable of detecting inclement weather?
• What sensors are near schools in Ohio?
• What observations are these sensors generating NOW?
Linked Sensor Data

- Knowledge/representations from SSW are accessible on LOD

- LinkedSensorData
  - Descriptions of ~20,000 weather stations
  - Weather stations linked to featured defined in Geonames.org

- LinkedObservationData
  - Description of storm related observations
  - ~1.7 billion triples, ~170 million weather observations
  - Updated in real-time with current observations and abstractions
Linked Open Data

Community-led effort to create openly accessible, and interlinked, semantic (RDF) data on the Web
What is Linked Sensor Data

Weather Sensors

Sensor Dataset

GPS Sensors

Satellite Sensors

Camera Sensors
Sensors Dataset (LinkedSensorData)*

- RDF descriptions of ~20,000 weather stations in the United States.
- Observation dataset linked to sensors descriptions.
- Sensors link to locations in Geonames (in LOD) that are nearby.

*First Initiative for exposing Sensor Data on LOD
What is Linked Sensor Data

Recommended best practice for exposing, sharing, and connecting pieces of data, information, and knowledge on the Web using URIs and RDF

RDF – language for representing data on the Web

GeoNames Dataset

Sensor Dataset

Publicly Accessible
RDF descriptions of hurricane and blizzard observations in the United States.

The data originated at MesoWest (University of Utah)

Observation types: temperature, visibility, precipitation, pressure, wind speed, humidity, etc.

<table>
<thead>
<tr>
<th>Name</th>
<th>Storm Type</th>
<th>Date</th>
<th>#Triples</th>
<th>#Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALL</td>
<td></td>
<td></td>
<td>1,730,284,735</td>
<td>159,460,500</td>
</tr>
<tr>
<td>Bill</td>
<td>Hurricane</td>
<td>August 17 - August 22, 2009</td>
<td>231,021,108</td>
<td>21,272,790</td>
</tr>
<tr>
<td>Ike</td>
<td>Hurricane</td>
<td>September 1 - September 13, 2008</td>
<td>374,094,660</td>
<td>34,430,964</td>
</tr>
<tr>
<td>Gustav</td>
<td>Hurricane</td>
<td>August 25 - August 31, 2008</td>
<td>258,378,511</td>
<td>23,792,818</td>
</tr>
<tr>
<td>Bertha</td>
<td>Hurricane</td>
<td>July 6 - July 17, 2008</td>
<td>278,235,734</td>
<td>25,762,568</td>
</tr>
<tr>
<td>Wilma</td>
<td>Hurricane</td>
<td>October 17 - October 23, 2005</td>
<td>171,854,686</td>
<td>15,797,652</td>
</tr>
<tr>
<td>Katrina</td>
<td>Hurricane</td>
<td>August 23 - August 30, 2005</td>
<td>203,386,049</td>
<td>18,832,041</td>
</tr>
<tr>
<td>Charley</td>
<td>Hurricane</td>
<td>August 9 - August 15, 2004</td>
<td>101,956,760</td>
<td>9,333,676</td>
</tr>
<tr>
<td></td>
<td>Blizzard</td>
<td>April 1 - April 6, 2003</td>
<td>111,357,227</td>
<td>10,237,791</td>
</tr>
</tbody>
</table>
Linked Datasets

- Observation KB
  - ~2 billion triples
  - MesoWest
  - Dynamic + Archive

- Sensor KB
  - 20,000+ systems
  - MesoWest
  - ~Static

- Location KB (Geonames)
  - 230,000+ locations
  - Geonames
  - ~Static

Example:
- 72°F
  - 1 procedure
  - Thermometer
  - Location: Dayton Airport
Sensor Discovery Application

Current Observations from MesoWest

Weather Station ID

Weather Station Coordinates

Phenomena

GeoNames – Geographic dataset
Sensor Discovery on Linked Data Demo

http://knoesis.org/projects/sensorweb/demos/sensor_discovery_on_lod/sample.htm
Technology 5

Analysis of Streaming Real-Time Data

• What observations are these sensors generating NOW?
Analysis of Streaming Real-Time Data

• Conversion from raw data to semantically annotated data in real-time
• Analysis of data to generate abstractions in real-time
Real Time Streaming Sensor Data

Storing Abstractions (Events) obtained after reasoning on the LOD

Semantic Analysis using Ontology for Event Detection
Linked Open Data

Mostly

STATIC

As of March 2009
Huge Volumes!!
Too Much Data

(Data grows faster than storage!!)
Huge amounts of Sensor Data!!

Abstractions over data (Events)
Observations relevant to events
Workflow Architecture for Managing Streaming Sensor Data
Answering the Challenge Query
The Query

What schools in Ohio should now be closed due to inclement weather?

—needs to be divided into sub-queries that can be answered using technologies previously described
What Schools Are in Ohio?

- Need partonomical spatial relations
  - What counties are contained in Ohio?
  - What districts are contained in a county?
  - What schools are contained in a district?

- Geonames.org contains these partonomical spatial relations

- Spatial aggregation executes the partonomical inference to convert the general query into sub-queries that can be answered

Uses: spatial aggregation and LOD
What is Inclement Weather?

• Need domain ontology that describes characteristics of inclemental weather
• Example
  Icy Roads => freezing temperature & precipitation (rain or snow)
• Uses: SSW
What Inclement Weather Necessitates School Closings?

• Need school policy information on rules for closing (e.g., for icy road conditions)
• Data.gov on LOD contains large amount of such policy information

• Uses: LOD
What Sensors in Ohio Are Capable of Detecting Inclement Weather?

• Need ontological descriptions of sensors and weather in order to match sensor capabilities to weather characteristics
  • Temperature sensor → freezing temperature
  • Rain gauge sensor → precipitation
• LinkedSensorData has descriptions of ~20,000 weather stations on LOD
• Uses: SSW and LOD
Sensors Near Schools in Ohio?

- Spatial analysis: match school locations (in Ohio) to sensor locations that are nearby
- Sensor descriptions in LinkedSensorData contain links to nearby features (such as schools)

- Uses: SSW and LOD
What Observations are These Sensors Generating NOW?

- Need to semantically annotate raw streaming observations in real-time
- Need to make these current/real-time annotations accessible by placing them on LOD (i.e., LinkedObservationData)

- Uses: SSW, LOD, Streaming Data
Are These Observations Providing Evidence for Inclement Weather?

- Analysis of observation data using background knowledge
- Generation of abstractions that are easier to understand

- Uses: SSW, Perception
**Spatial Aggregation References** ([http://knoesis.org/research/semweb/projects/stt/](http://knoesis.org/research/semweb/projects/stt/))


**Machine Active Perception References**


**Linked Sensor Data References** ([http://wiki.knoesis.org/index.php/LinkedSensorData](http://wiki.knoesis.org/index.php/LinkedSensorData))

- Harshal Patni, Satya S. Sahoo, Cory Henson and Amit Sheth, **Provenance Aware Linked Sensor Data**, 2nd Workshop on Trust and Privacy on the Social and Semantic Web, Co-located with ESWC, Heraklion Greece, 30th May - 03 June 2010.
http://knoesis.org