An Ontological Analysis of Observation Collections

Editor(s): Name Surname, University, Country
Solicited review(s): Name Surname, University, Country
Open review(s): Name Surname, University, Country

Auriol Degbelo
Institute for Geoinformatics - University of Muenster, Heisenbergstrasse 2, 48149 Muenster, Germany
E-mail: degbelo@uni-muenster.de

Abstract. The Semantic Sensor Web community has extensively discussed the concept of 'observation', providing ontologies for it. 'Observation collection', however, have been comparatively less examined. Monitoring spatial and temporal variations of phenomena is a task which requires observation collections (not just single observations) for their completion. This paper presents an ontological analysis of observation collections. The analysis helps to identify five essential parameters for the characterization of observation collections in the Sensor Web, namely: collector, observable, members, spatial ordering, and temporal ordering. Changes in one of these parameters lead necessarily to a new observation collection. The article presents also an Ontology Design Pattern for observation collections which implements some of the ideas introduced in the analysis. The design pattern distinguishes three main types of observation collections: time series, trajectories, and coverage.

Keywords: observation collection, ontology design pattern, time series, coverage, trajectory

1. Introduction

Observations are central to empirical science, and the Sensor Web community has provided detailed discussions of the concept (see for instance [14,15]). These discussions relate observations to other elements involved in their generation such as the sensor, the feature of interest (and its particular property observed), the sampling feature and the stimulus. Despite a great amount of work discussing observation in the context of the Sensor Web, there are still few discussions specifically focusing on observation collections[1]. It is true, observation collections can be aggregated to produce a single observation, but this paper argues that observation collections are sufficiently distinct from single observations to deserve their own treatment in observation ontologies. At least three reasons suggest this:

- Monitoring requires at least two observations: for instance, many applications of sensor networks in smart cities listed in [31] (e.g., monitoring of energy distribution infrastructures, pipeline monitoring, water level monitoring, air quality monitoring, health monitoring, room occupancy monitoring) rely on collections of observations, not single observations;
- Spacing, spatial extent, sampling intensity - terms commonly used in scientific discourse (e.g., [20, 18]) - can only be understood when talking about collections of observations, not single observations;
- Ferreira et al. [22] suggested three basic data types (i.e., time series, trajectory, and coverage) from which one can derive more complex data types such as objects and events. All these three

[1] The detailed discussion of time series observation in [32] is one exception.

types refer to collections of observations, not single observations.

Though the concept of observation collection is relevant to many application scenarios in the Sensor Web, it seems to have been ignored within the field. It is occasionally mentioned (e.g., as 'observation offering' in [11] or as 'time series observations' in [32]), but the field still needs a better understanding of the concept itself on the one hand, and its relationship to the cognate concept of single observation on the other hand.

This article provides an ontological analysis of observation collections. An ontological analysis is defined in this context after Guarino as "the process of eliciting and discovering relevant distinctions and relationships bound to the very nature of the entities involved in a certain domain, for the practical purpose of disambiguating terms having different interpretations in different contexts" [27]. Wood and Galton's classification criteria for collectives [52] is used to perform the analysis in Section 2. A taxonomy of observation collections is introduced in Section 3. Section 4 presents an ontology design pattern for observation collections as well as illustrative examples of its use. Section 5 presents related work and Section 6 concludes the paper.

2. An analysis of observation collections

An observation collection is a collection of single observations (or 'observations' for short). Observation collections and observations are social objects in the sense of the DOLCE Ultra Light (DUL) upper ontology[2]. There is however one important difference between the two which relates to their process of generation: an observation is generated by observing the physical reality[3]; an observation collection is produced by gathering other social objects (i.e., observations). In terms of DUL, an observation collection can be viewed as a DUL:Configuration ('A collection whose members are organized according to a certain schema that can be represented by a Description') while an observation may be regarded as a DUL:Situation ('A relational context created by an observer on the basis of a Description').

Wood and Galton [52] presented a review of existing ontologies (including DOLCE and the Basic Formal Ontology) for the representation of collectives[4], and proposed a taxonomy allowing the classification of around 1800 distinct types of collectives. Adapting their reflections to the specific case of collections of observations leads to the following statements:

- An observation collection is a *concrete particular*, not a type, nor an abstract entity;
- An observation collection is a *continuant*, that is, it is to be thought of as enduring over a period of time, existing as a whole at each moment during that period, and possibly undergoing various types of change over that period;
- An observation collection has multiple observations (and only observations) as *members*. In line with [51], the *member-collection* relationship is a more specific kind of *part-of* relation. Winston et al. [51] also point out that membership in a collection is determined based on one of two factors: spatial proximity or social connection. As regards observation collections, membership in an observation collection is determined based on *social connection* (not spatial proximity). Social connection, called 'coherence' by Wood and Galton [52] is discussed below.

The next subsections provide a more detailed analysis of observation collections using the five distinguishing features for collectives proposed in [52]: membership, coherence, spatial location, roles, and depth. The terminology used for the analysis is consistent with the SSN ontology [14]. The analysis draws on ideas from [17].

2.1. Membership

According to [52], collectives can have a constant membership (i.e., same members throughout their lifetime) or a variable membership (i.e., different members at different times), constant or variable cardinality, and a cardinality which may be reduced to one, or not.

As regards membership, this work holds the view that observation collections have a constant membership, that is, they *cannot* contain different observations at different times. The following example from [17] presents the reason for this choice. Figure 1a depicts

[2] `http://www.ontologydesignpatterns.org/ont/dul/DUL.owl` (last accessed: March 22, 2016). A DUL:SocialObject is an object that is created in the process of social communication.

[3] This idea can be found in [14,36,35,38,47].

[4] 'Collective' from [52] is equivalent to 'collection' in this article.

the evolution of the temperature in a city during the past three days, and suggests that 'the temperature in the city has been increasing over the last three days'. In Figure 1b, a new observation (made say this morning) has become available, and is added to the previous three observations in the collection from Figure 1a. Figure 1b suggests a new trend for the temperature, namely that 'the temperature in the city has been increasing over the past three days, but slightly decreasing since this morning'.

The point of the example is that the addition of a single observation to an observation collection potentially leads to different assessments of a situation. A logical consequence from this is that subtraction of a single observation from an observation collection leads potentially to different assessments of a situation. That is, different observation collections are associated with potentially different information contents. For that reason, it is suggested that observation collections have exactly the same members at any time. Addition of an observation to (or subtraction of an observation from) an existing observation collection produces *new* and *distinct* observation collections.

Constant membership connotes *constant cardinality*, i.e., an observation collection has n members, where n is a natural number. n must be greater than one. An observation collection with only one observation is viewed in the current work as *a single observation*.

The standpoint on membership adopted here implies that an entity is *either* a single observation *or* an observation collection. It cannot be both. In addition, the previous paragraphs suggest that observation collections are *like* mathematical sets because they are identified through their members. However, and in line with previous work (e.g., [5,10,28,52]), observation collections are *not* seen as sets. The main difference between the two lies in the fact that sets are *abstract* entities, whereas collections are *concrete* entities. The implications of this subsection for the Semantic Sensor Web are as follows:

- I1: Two observation collections are identical if and only if they have the same members;
- I1*: Two observation collections with different size are not identical (I1* is a corollary of I1).

2.2. Coherence

According to [52], coherence refers to that in virtue of which many observations taken together form an observation collection. Coherence is the reason why one can regard an assemblage of observations as an observation collection. The coherence of an observation collection lies in the fact that all observations belonging to the collection are generated by observing the *same observed property*. An observation collection is an *externally caused collection* because it results from the action of a *collector* (i.e., someone who decides to group different observations and form a whole out of them). This implications of this subsection for knowledge representation in the Semantic Sensor Web are twofold:

- I2: An observation collection in which (at least) two observations are found to relate to different observed properties is incoherent;
- I3: Since the collector is the one who decides to group observations and generate a collection based on them, there are multiple, and all equally valid ways of generating observation collections from a given set of observations $\{O_1, O_2, ..., O_n\}$. In fact, k = $2^n - n - 1$[5] distinct observation collections can be produced based on a given set of n observations $\{O_1, O_2, ..., O_n\}$. [Do we then represent that original set?]

2.3. Spatial location

As [52] indicates, there are various possibilities regarding the characterization of the spatial location of a collection. For example, the collection might be assigned a location (or not) and this location might be fixed or variable. It is worth mentioning three points regarding observations collections:

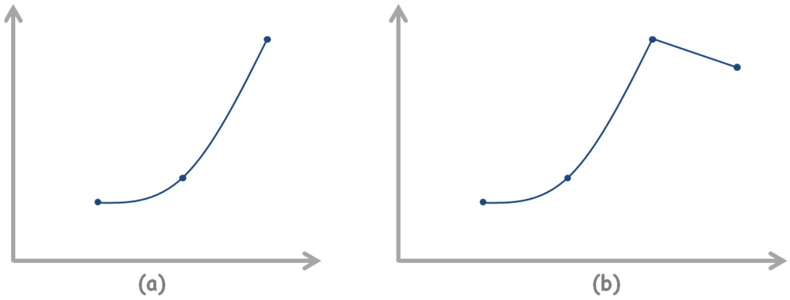
- *an observation can have a spatial location, and this location is fixed*: the location of the observation is the location of the sensor[6] which has produced that observation. A sensor cannot be at two locations at the same time, therefore an observation always has a fixed (or unique) location. In line with [4,6,7,13,25,26], spatial location is seen as a *relation* between an entity (i.e., the observation) and a spatial region[7].

[5]The number of all subsets of $\{O_1, O_2, ..., O_n\}$ is 2^n, from which one needs to subtract the empty set (i.e., one element), and $\binom{n}{1}$=n subsets of size 1.

[6]This location might be georeferenced or not. Stasch et al. [47] use the ability to produce an observation with georeferenced location as a distinguishing criterion between sensors and geosensors. The reason for modelling the location of an observation as the location of the sensor was presented in [17].

[7]A 'spatial region' in this article is an identifiable portion of space, and a 'temporal region' is an identifiable portion of time.

Fig. 1. Temperature in a city - two examples of observation collections (from [17])



– *an observation collection can be ascribed a spatial location*: this location is the spatial region occupied by the locations of each observation. This spatial region is called 'footprint' (in line with [23]), and methods for generating footprints for sets of points were discussed in [23][8].
– *an observation collection cannot move (i.e., change its spatial location)*: this follows from the fact that (i) observation collections always have the same members, (ii) the location of these members is fixed, and (iii) the location of the observation collection is derived from the location of its members.

There is one consequence of these features for knowledge representation in the Semantic Sensor Web, namely that:

– I4: Two distinct observation collections can have the same location, but observation collections with different locations are necessarily distinct.

2.4. *Ordering and differentiation of roles*

Ordering is important for observation collections because different orderings of the same observations lead potentially to different information contents for the observation collection. Ordering is important for all three types of observation collection. Consider for example the observation collection mentioned in [22], and obtained by gathering air pollution values produced by cars equipped with GPS devices and air pollution sensors in a city. Different sequencings of air pollution values entail different trends for air pollution variation over time (*time series*); different sequencings of car locations suggest different trends for car location variation over time (*trajectory*); and different spatial orderings (i.e., the associated locations to air pollution values) imply different trends for air pollution variation within the city limits.

The fact that spatial and temporal orderings matter to observation collections entails that all members of an observation collection *do not play the same role*. In particular, there is always an observation that plays the role of *first*, and an observation that plays the role of *next*[9]. The choice of the *first* observation and the *next* of another one might be straightforward or involve some arbitrariness, depending on whether time or space is used as ordering scheme. Using time as ordering scheme for a time-series, the *first* observation is the one that was produced first, and the *next* observation is the subsequent one. Conversely, while computing the total spacing of a coverage data type (a task that necessitates spatial ordering), one can take any location (of the irregularly spaced set of locations) as the *first*, and the *next* location as the closest one in terms of distance[10].

With reference to [52], an observation collection is a *partitioned collection*, because (i) the *first* observation plays the role of 'leader', and (ii) there is a further differentiation of roles within the rest of the collection. Consider for example an observation collection $\{O_1, O_2, ..., O_n\}$ where n is a natural number greater than 2. Adding an explicit ordering means that O_1 is the 'leader' of $\{O_2, ..., O_n\}$, O_2 is the leader of $\{O_3,..., O_n\}$, and so on[11].

[8][23] discussed also 'extended footprints', i.e., the case where one would also like to represent the spatial region occupied by the points themselves.

[9]There is no need to explicitly define the last observation of a collection: the last observation is the one that has no next.

[10]While looking for the closest location in terms of distance, further arbitrariness creeps into when more than one location can play the role of 'next'.

[11][17] suggested to view observation collections as a hierarchically differentiated collection. However, doing so will only allow an

In summary, ordering (spatial or temporal) should *always* be made explicit while representing observation collections in the Semantic Sensor Web. That is,

- I5: *List* is the suitable abstract data type for the specification of observation collections.

2.5. Depth

The depth of a collection refers to the fact that members of a collection can themselves be collections or not. Since most entities can be viewed as collectives at some level of granularity, [52] suggested to define base-level entities (i.e., entities which are not themselves considered as collectives in a certain context) in order to avoid an infinite regress. The viewpoint adopted here is that observations are the base-level entities of an observation collection. An observation *cannot* have other entities as *members*. This standpoint is consistent with the point of view presented in Section 2.1, namely that an entity is *either* an observation *or* an observation collection. The depth of an observation collection is therefore 1. Consequently,

- I6: It is not a good modelling practice to have an observation modelled as having other observations as members (e.g., an observation as a subclass of DUL:Configuration).

2.6. Summary of this analysis

This section has offered an analysis of modelling choices regarding observation collections. It complements previous treatments of observation ontologies in the literature which dealt only with single observations. The main points presented are:

- observation collections are concrete particulars, not types, nor abstract entities;
- the coherence of observation collections lies in the fact that they are gatherings of observations of the same observed property;
- observation collections should be modelled as having constant membership to reflect the fact that the addition (or subtraction) of one observation to an existing observation collection may significantly affect the information content of the existing observation collection;
- observations are the base-level entities of observation collections and observation collections have a fixed spatial location;
- spatial and temporal orderings matter to observation collections, and should therefore be documented explicitly.

The analysis has extracted five essential parameters for the characterization of observation collections in the Semantic Sensor Web, namely: *collector*, *observed property*, *members*, *spatial ordering*, and *temporal ordering*. Changes in one of these parameters lead necessarily to a *new* observation collection.

3. A taxonomy of observation collections

As mentioned in Section 1, Ferreira et al. [22] suggested three basic data types from which one can derive more complex data types: time series, trajectory, and coverage. Following [22], a *time series* represents the variation of a property over time at a fixed location; a *trajectory* represents how locations or boundaries of an object evolve over time; and a *coverage* represents the variation of a property within a spatial extent at a time[12]. These data types are three different types of observation collections.

3.1. Different types of time series

Henson et al. [32] suggest four distinct types of time series: interval-based non-cumulative, interval-based cumulative, event-based non-cumulative and event-based cumulative. *Interval-based non-cumulative time series* are a collection of interval-based non-cumulative observations, i.e., independent observations of the measured property which were generated at regular time intervals. *Interval-based cumulative time series* are a collection of interval-based cumulative observations, i.e., observations produced at regular time intervals and which represent cumulative values of the measured property. *Event-based non-cumulative time se-*

ordering between the first observation (i.e., O_1), and the rest of the collection (i.e., $\{O_2, ..., O_n\}$), missing the fact that there is also a need for an explicit ordering of the elements within $\{O_2, ..., O_n\}$.

[12] 'Coverage' in [22] has a different connotation than 'coverage' in vocabularies such as Dublin Core (`http://dublincore.org/documents/dces/`) or DCAT (`https://www.w3.org/TR/2014/REC-vocab-dcat-20140116/`). Coverage in [22] is consistent with the use of coverage by the Open Geospatial Consortium (OGC) to refer to the *variation of a property over an area at a specific time*. It refers neither to the spatial or temporal topic of a resource, nor to its spatial applicability, nor to the jurisdiction under which a resource is relevant.

ries are a collection of event-based non-cumulative observations, i.e., independent observations of the measured property which were generated as a result of a predefined event[13]. *Event-based cumulative time series* are a collection of event-based cumulative observations, i.e., observations which represent the cumulative value of the measured property and were produced as a result of a predefined event. The four types of time series are depicted on Figure 2.

3.2. *Different types of trajectories*

Following [2], trajectories may be divided into raw trajectories (a.k.a. sample trajectories) and semantic trajectories. The latter is derived from the former through a processing step where geographic information which characterizes important geographic places of a trajectory is added. Simply said, a *raw trajectory* is a set of temporally-indexed positions (a.k.a. "fixes") whereas a *semantic trajectory* aggregates the geographic information that is necessary for the analysis of the trajectory (see [9]). An ontology design pattern for semantic trajectories was proposed in [34]. A third type of trajectory is what Wang et al. [50] have termed augmented trajectories ([48] calls them marked trajectories). An *augmented trajectory* includes additional thematic information about the object. Examples of thematic information include the velocity (of a car), the tiredness (of pedestrians), and the body temperature (of tracked animals). It is worth mentioning that the three subclasses of trajectories introduced in this paragraph are *not disjoint* (e.g., a trajectory may be both augmented and semantic). Figure 3 shows the three types of trajectories[14].

4. Illustrative examples

Figure 4 shows the taxonomy of observation collections introduced in the previous section. This taxonomy has been implemented as a content ontology design pattern [24] (ODP) for observation collections in the Web Ontology Language [16,49] (OWL). Two additional classes (not shown on Figure 4) are part of the ODP: observation (which are components of observation collections), and the collector (individual or institution which has grouped observations to form an observation collection). The ODP is available for download at `https://goo.gl/Rm6cfY`. Though some challenges need to be overcome to facilitate the adoption of ODPs (for a recent summary, see [8]), ODPs present some advantages such as increased reuse and increased interoperability. Recent examples of ODPs include the ODP for representing digital video resources [40], the ODP for data integration in the library domain [41], a pattern for capturing the intents underlying designs [46], and the ODP for life cycle assessment data [37]. The competency questions of the ODP for observation collection presented in this work are:

- what are observations belonging to an observation collection?
- what are available time series about a certain phenomenon (e.g., GDP or temperature)? what are available cumulative/non-cumulative time series about a certain phenomenon? what are available interval-based/event-based time series about a certain phenomenon?
- what are available coverage datasets about a certain phenomenon (e.g., rainfall, unemployment)?
- what are available raw trajectories of an object? what are available semantic trajectories of an object? what are available augmented trajectories of an object?
- what is the collector of an observation collection (this question refers to the publisher or author of an observation collection, and can be answered using existing vocabularies such as Dublin Core[15])?

4.1. *Time series*

An example of time series data is the evolution of the gross domestic product per capita of a country (e.g., Germany) over years. More specifically, the evolution of the gross domestic product per capita of a country years is an interval-based, non-cumulative

[13] An event is defined here after [39] as "anything that happens or is observed as happening at an instant - or over an interval - of time, and which is relevant for the observer". Examples of events include 'high water level' events or 'flooding threshold exceeded' events (see [39]), and bucket tip events (see [32]).

[14] There are alternative ways of classifying trajectories which would be relevant for the Semantic Sensor Web. For instance trajectories could be classified according to whether they represent continuous or discontinuous paths (see [19]), or according to transportation modes (e.g., bike, car, tram, bus, see [3]). This work has adopted the trichotomy of raw, semantic, and augmented trajectory because the concepts of raw and semantic trajectory are already well-known to the Semantic Sensor Web community.

[15] `http://dublincore.org/documents/dcmi-terms/`

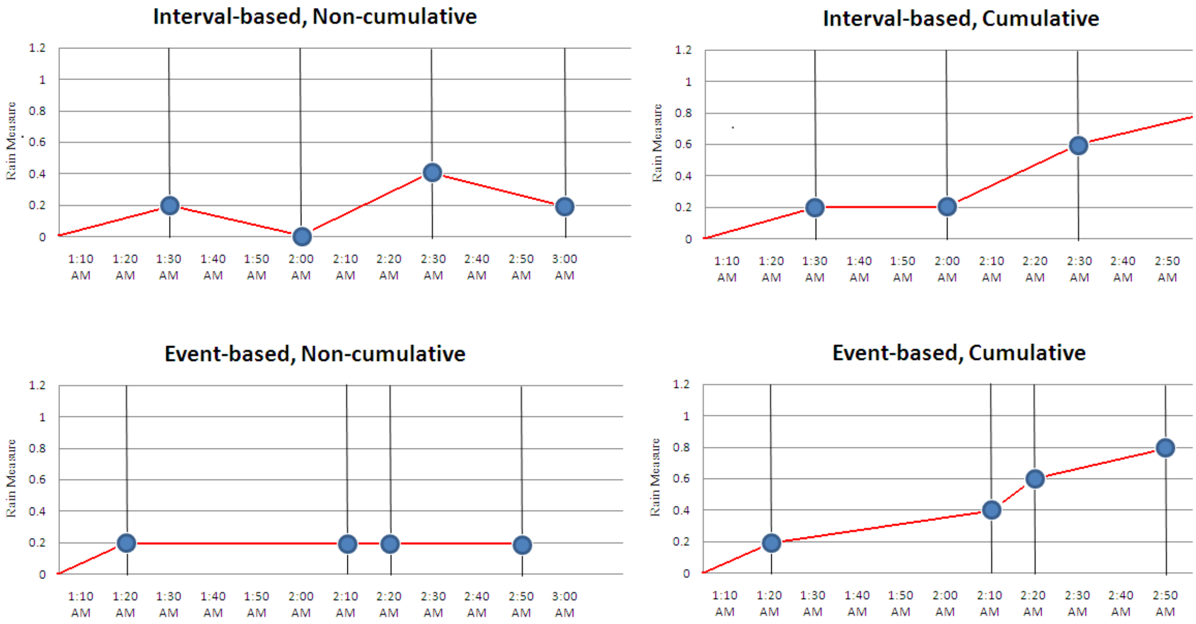


Fig. 2. Four types of time series (figures taken from [32]). The Y axes [not labeled on this figure] refer to measures of the amount of rainfall in millimeters.

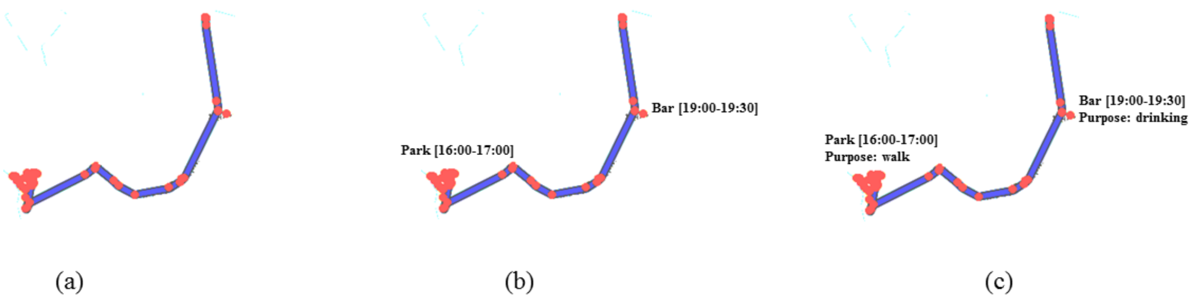


Fig. 3. Raw, semantic and augmented trajectories. (a) is a set of GPS tracks exported from Google Maps and anonymized; (b) aggregates some of the GPS tracks spatially and provides information about places visited; (c) provides some more information about the purpose of the visits.

time series: interval-based because recorded at regular interval (in this case a year), and non-cumulative because GDP values are estimated every year (independently of previous years' values). A concrete example is the evolution of Germany's GDP over the past years (2010-2014)[16]. Listing 1 presents a possible annotation of this dataset using the ODP previously introduced.

[16]The data about Germany's GDP has been retrieved from `http://www.tradingeconomics.com/germany/gdp-per-capita` (last accessed: June 07, 2016).

4.2. Trajectories

The GeoLife dataset [53] is a dataset from Microsoft Research Asia, generated by 182 users and spanning over five years (April 2007 - August 2012). According to its publisher, a GPS trajectory of this dataset is represented by a sequence of time-stamped points, each of which contains the information of latitude, longitude and altitude. The GeoLife dataset is therefore a raw trajectory dataset. Listing 2 presents a possible annota-

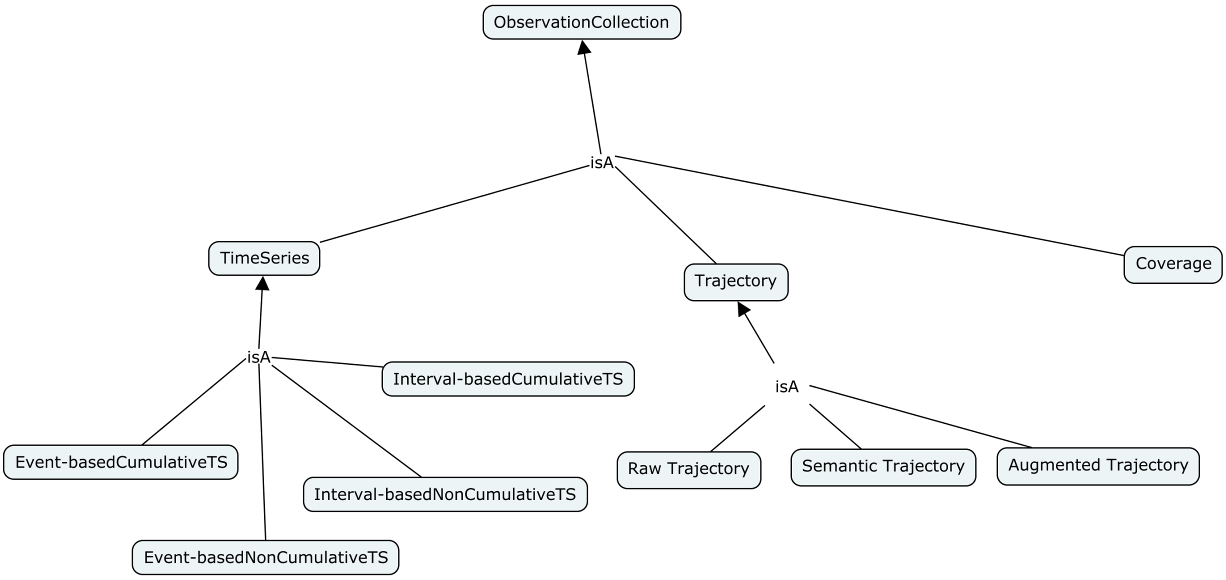


Fig. 4. A taxonomy of observation collections.

tion of the first five entries of the "Data 000" (a portion of this dataset) using the ODP.

4.3. *Coverage*

The unemployment dataset from Muenster in 2015 published recently by the Muenster City Council is an example of coverage dataset: it represents the variation of a property (i.e., unemployment) over a certain region (i.e., Muenster) at a certain time (i.e., 2015). The dataset is available for download at `http://goo.gl/reBQA4` (last accessed: June 21, 2016). The dataset shows that the city of Muenster (North-Rhine-Westphalia, Germany) has six boroughs named 'Mitte', 'West', 'Nord', 'Ost', 'Südost', and 'Hiltrup' respectively. Listing 3 presents an example annotation of this dataset using the ODP previously introduced. The complete Well-Known-Text (WKT) geometries of these six boroughs are available at `https://git.io/vo7Xd`.

5. Related work

As mentioned at the outset of this article, focused discussions of observation collections have not abounded in the Semantic Sensor Web community. The community has, by and large, discussed single observations. A relevant work worth mentioning at this point is [21]. Ferreira et al. [21] proposed to access spatiotemporal observations from different kinds of data sources using RDF framework and SPARQL language. Their approach, which is at the moment a work in progress, intends to rely on 'observation' from the OGC Observation and Measurements specification, the OGC GeoSPARQL schema, as well as the three abstractions of time series, trajectories, and coverage. However they seem (as is often the case) to conflate single observations and observation collections under the generic term of 'observation'.

Ontological analyses relevant to the Semantic Sensor Web have covered concepts as diverse as software engineering metamodels [45], observations and measurements [42,43], power types [29], community [1], relationship [30], terrain data [44], collectives [10,28], but not specifically addressed observation collections. Likewise, the GeovoCamp [33] has produced a number of useful ontology design patterns (e.g., [12,34,37]), but not yet provided a simple ODP for observation collections. The current work has proposed one generic pattern for observation collections which can, as Section 4 showed, be extended to fit more specific domains (e.g., economics, demographics). One drawback of the pattern proposed is that it is not community-driven (patterns built by communities of scholars and practitioners have greater chances for adoption), yet an achievement of the work lies in the provision of some greater conceptual clarity which can inform the design of subsequent observation collections ontologies/taxonomies/vocabularies.

Listing 1: Example annotation of Germany's GDP dataset using the ODP for observation collections

```
@prefix dcterms: <http://purl.org/dc/terms/>.
@prefix dbpedia: <http://dbpedia.org/ontology/> .
@prefix ex:      <http://example.org/>. # exemplary name space
@prefix dcat:    <http://www.w3.org/ns/dcat#> .
@prefix foaf:    <http://xmlns.com/foaf/0.1/> .
@prefix geo:     <https://www.w3.org/2003/01/geo/wgs84_pos> .
@prefix geof:    <http://www.opengis.net/ont/geosparql#> .
@prefix org:     <http://www.w3.org/ns/org#> .
@prefix qb:      <http://purl.org/linked-data/cube#> .
@prefix obs:     <https://github.com/aurioldegbelo/observationcollections>. # namespace for the ODP of observation collections
@prefix owl:     <http://www.w3.org/2002/07/owl#> .
@prefix pav:     <http://purl.org/pav>  .
@prefix rdf:     <http://www.w3.org/1999/02/22-rdf-syntax-ns#> .
@prefix rdfs:    <http://www.w3.org/2000/01/rdf-schema#> .
@prefix sdmx-attribute:  <http://purl.org/linked-data/sdmx/2009/attribute#> .
@prefix sdmx-dimension:  <http://purl.org/linked-data/sdmx/2009/dimension#> .
@prefix sf:      <http://www.opengis.net/ont/sf#> .

# -- general information about the gdp dataset (the gdp dataset is a interval-based non cumulative time series) -- #
ex:dataset1 a qb:ObservationGroup, dcat:Dataset, obs:ObservationCollection, obs:TimeSeries, obs:IntervalBasedNonCumulativeTS;
        rdfs:label       "Germany GDP"@en;
        dcterms:title    "Germany GDP"@en;
        rdfs:comment     "Per capita annual GDP for Germany between 2010 and 2014 "@en;
        dcterms:description "Per capita annual GDP for Germany between 2010 and 2014 "@en;
        # List as appropriate type to represent time series
        obs:hasMember  (ex:obs1,  ex:obs2, ex:obs3, ex:obs4, ex:obs5); # Note that there is, at the moment of this writing,
        # no predicate linking an observation collection to a list of component observations in the rdf data cube vocabulary)
        dcterms:publisher   ex:orga1;
        rdfs:seeAlso     "http://www.tradingeconomics.com/germany/gdp-per-capita".

ex:obs1 a qb:Observation, obs:Observation;
        ex:hasGDPvalue 37147.02;
        sdmx-dimension:refArea "Germany";
        sdmx-dimension:refPeriod "2010"^^xsd:gYear;
        sdmx-attribute:unitMeasure "USD".

ex:obs2 a qb:Observation, obs:Observation;
        ex:hasGDPvalue 38470.84;
        sdmx-dimension:refArea "Germany";
        sdmx-dimension:refPeriod "2011"^^xsd:gYear;
        sdmx-attribute:unitMeasure "USD".

ex:obs3 a qb:Observation, obs:Observation;
        ex:hasGDPvalue 39274.36;
        sdmx-dimension:refArea "Germany";
        sdmx-dimension:refPeriod "2012"^^xsd:gYear;
        sdmx-attribute:unitMeasure "USD".

ex:obs4 a qb:Observation, obs:Observation;
        ex:hasGDPvalue 39208.76;
        sdmx-dimension:refArea "Germany";
        sdmx-dimension:refPeriod "2013"^^xsd:gYear;
        sdmx-attribute:unitMeasure "USD".

ex:obs5 a qb:Observation, obs:Observation;
        ex:hasGDPvalue 39717.7;
        sdmx-dimension:refArea "Germany";
        sdmx-dimension:refPeriod "2014"^^xsd:gYear;
        sdmx-attribute:unitMeasure "USD".

# publisher of the gdp dataset (the publisher is the collector)
ex:orga1 a obs:Collector, org:Organization, foaf:Agent, dcterms:Agent;
        rdfs:label "Trading Economics"@en .
```

6. Conclusion

Observations and observation collections are central to the Semantic Sensor Web. Though the concept of observation has benefited from extensive discussions, observation collections seem to have been largely ignored in the field. In fact, observation collections are in many cases assimilated to single observations, and referred to as 'observation'. This article has brought forward the argument that an observation collection and a single observation are sufficiently distinct to deserve separate treatments in observation ontologies. In addition, the article offered an ontological analysis of observation collections, and a documentation of the practical implications of the analysis for the Semantic Sensor Web. Finally the work presented an ontology design pattern for observation collections encoded in OWL as well as examples of its use. It is the author's

Listing 2: Example annotation of the Geolife dataset using the ODP for observation collections

```
# -- general information about the Geolife dataset (the GeoLife dataset is a raw trajectory) -- #
ex:dataset2 a qb:ObservationGroup, dcat:Dataset, obs:ObservationCollection, obs:Trajectory, obs:RawTrajectory;
        rdfs:label       "GeoLife GPS trajectories"@en;
        dcterms:title    "GeoLife GPS trajectories"@en;
        rdfs:comment     "GeoLife GPS trajectories, first five entries of the dataset number '000' "@en;
        dcterms:description "GeoLife GPS trajectories, first five entries of the dataset number '000' "@en;
        # List as appropriate type to represent trajectories
        obs:hasMember (ex:obs6, ex:obs7, ex:obs8, ex:obs9, ex:obs10); # There is, at the moment of this writing,
        # no predicate linking an observation collection to a list of component observations in the rdf data cube vocabulary)
        dcterms:publisher  ex:orga2 ;
        dcterms:issued  "2012-08-09"^^xsd:date;
        pav:version "1.2.2";
        rdfs:seeAlso    "http://research.microsoft.com/en-us/downloads/b16d359d-d164-469e-9fd4-daa38f2b2e13/".

ex:obs6 a qb:Observation, obs:Observation;
        geo:lat 39.984702;
        geo:long 116.318417;
        geo:alt 149,9616; # the original value (492 feet) has been converted to meters (factor: 0.3048)
        # to be consistent with the geo vocabulary
        sdmx-dimension:refPeriod "2008-10-23T02:53:04"^^xsd:datetime .

ex:obs7 a qb:Observation, obs:Observation;
        geo:lat 39.984683;
        geo:long 116.31845;
        geo:alt 149,9616; # the original value (492 feet) has been converted to meters (factor: 0.3048)
        # to be consistent with the geo vocabulary
        sdmx-dimension:refPeriod "2008-10-23T02:53:10"^^xsd:datetime .

ex:obs8 a qb:Observation, obs:Observation;
        geo:lat 39.984686;
        geo:long 116.318417;
        geo:alt 149,9616; # the original value (492 feet) has been converted to meters (factor: 0.3048)
        # to be consistent with the geo vocabulary
        sdmx-dimension:refPeriod "2008-10-23T02:53:15"^^xsd:datetime .

ex:obs9 a qb:Observation, obs:Observation;
        geo:lat 39.984688;
        geo:long 116.318385;
        geo:alt 149,9616; # the original value (492 feet) has been converted to meters (factor: 0.3048)
        # to be consistent with the geo vocabulary
        sdmx-dimension:refPeriod "2008-10-23T02:53:20"^^xsd:datetime .

ex:obs10 a qb:Observation, obs:Observation;
        geo:lat 39.984655;
        geo:long 116.318263;
        geo:alt 149,9616; # the original value (492 feet) has been converted to meters (factor: 0.3048)
        # to be consistent with the geo vocabulary
        sdmx-dimension:refPeriod "2008-10-23T02:53:25"^^xsd:datetime .

# publisher of the GeoLife dataset (the publisher is the collector)
ex:orga2 a obs:Collector, org:Organization, foaf:Agent, dcterms:Agent;
        rdfs:label "Microsoft Research Asia"@en .
```

hope that the discussion provided will serve as a basis for the design of ontology design patterns for the numerous scenarios in the Semantic Sensor Web where more than single observations are required.

References

[1] J. P. A. Almeida and G. Guizzardi. An ontological analysis of the notion of community in the RM-ODP enterprise language. *Computer Standards and Interfaces*, 35(3):257–268, 2013. doi:10.1016/j.csi.2012.01.007.

[2] L. O. Alvares, V. Bogorny, B. Kuijpers, J. A. F. de Macedo, B. Moelans, and A. Vaisman. A model for enriching trajectories with semantic geographical information. In H. Samet, C. Shahabi, and M. Schneider, editors, *Proceedings of the 15th Annual ACM International Symposium on Advances in Geographic Information Systems (GIS '07)*, pages 22:1–22:8, Seattle, Washington, USA, 2007. ACM. doi:10.1145/1341012.1341041.

[3] F. Biljecki, H. Ledoux, and P. van Oosterom. Transportation mode-based segmentation and classification of movement trajectories. *International Journal of Geographical Information Science*, 27(2):385–407, 2013. doi:10.1080/13658816.2012.692791.

[4] T. Bittner. On ontology and epistemology of rough location. In C. Freksa and D. M. Mark, editors, *Spatial Information Theory - Cognitive and Computational Foundations of Geographic Information Science (COSIT'99)*, pages 433–448, Stade, Germany, 1999. Springer-Verlag Berlin Heidelberg. doi:10.1007/3-540-48384-5_28.

[5] T. Bittner, M. Donnelly, and B. Smith. A spatio-temporal ontology for geographic information integration. *International Journal of Geographical Information Science*, 23(6):765–798, 2009. doi:10.1080/13658810701776767.

Listing 3: Example annotation of the Muenster Unemployment dataset using the ODP for observation collections

```
# -- general information about a coverage dataset: the Muenster Unemployment dataset -- #
ex:dataset3 a qb:ObservationGroup, dcat:Dataset, obs:ObservationCollection, obs:Coverage;
        dcterms:title   "Arbeitslose in Muenster und den Stadtbezirken"@de
        rdfs:label      "Unemployed in Muenster and Boroughs"@en;
        dcterms:title   "Unemployed in Muenster and Boroughs"@en;
        rdfs:comment    "Statistics about unemployment in the city of Muenster and its boroughs in 2015"@en;
        dcterms:description "Statistics about unemployment in the city of Muenster and its boroughs in 2015"@en;
        # List as appropriate type to represent coverage
        obs:hasMember   (ex:obs11, ex:obs12, ex:obs13, ex:obs14, ex:obs15, ex:obs16);
        dcterms:publisher   ex:orga3 ;
        dcterms:issued  "2016-05"^^xsd:gYearMonth;
        rdfs:seeAlso    "http://goo.gl/reBQA4".

ex:obs11 a qb:Observation, obs:Observation;
        ex:hasUnemploymentValue 3259;
        sdmx-dimension:refArea _:MuensterMitte;
        sdmx-dimension:refPeriod "2015-12-15"^^xsd:date .

_:MuensterMitte a dbpedia:Borough;
        rdfs:label       "Mitte"@en , "Mitte"@de ;
        geof:hasGeometry  [ a    sf:MultiPolygon ;
        geof:asWKT  "MULTIPOLYGON (((7.6018098 51.9652058, ..., 7.6018098 51.9652058)))"^^geof:wktLiteral
                          ] .

ex:obs12 a qb:Observation, obs:Observation;
        ex:hasUnemploymentValue 1442;
        sdmx-dimension:refArea _:MuensterWest;
        sdmx-dimension:refPeriod "2015-12-15"^^xsd:date .

 _:MuensterWest a dbpedia:Borough;
    rdfs:label  "West"@en , "West"@de ;
    geof:hasGeometry   [ a  sf:MultiPolygon ;
                            geof:asWKT  "MULTIPOLYGON (((7.5603785 51.9154652, ..., 7.5603785 51.9154652)))"^^geof:wktLiteral
                          ] .

ex:obs13 a qb:Observation, obs:Observation;
        ex:hasUnemploymentValue 1591;
        sdmx-dimension:refArea _:MuensterNord;
        sdmx-dimension:refPeriod "2015-12-15"^^xsd:date .

_:MuensterNord a dbpedia:Borough;
    rdfs:label  "Nord"@en , "Nord"@de ;
    geof:hasGeometry   [ a  sf:MultiPolygon ;
                            geof:asWKT  "MULTIPOLYGON (((7.6604258 51.9867668, ..., 7.6604258 51.9867668)))"^^geof:wktLiteral
                          ] .

ex:obs14 a qb:Observation, obs:Observation;
        ex:hasUnemploymentValue 528;
        sdmx-dimension:refArea _:MuensterOst;
        sdmx-dimension:refPeriod "2015-12-15"^^xsd:date .


_:MuensterOst a dbpedia:Borough;
         rdfs:label "Ost"@en , "Ost"@de ;
     geof:hasGeometry   [ a  sf:MultiPolygon ;
                            geof:asWKT  "MULTIPOLYGON (((7.6617392 51.9801364, ..., 7.6617392 51.9801364)))"^^geof:wktLiteral
                          ] .

ex:obs15 a qb:Observation, obs:Observation;
        ex:hasUnemploymentValue 934;
        sdmx-dimension:refArea _:MuensterSuedost;
        sdmx-dimension:refPeriod "2015-12-15"^^xsd:date .


_:MuensterSuedost a dbpedia:Borough;
        rdfs:label  "Suedost"@en , "Suedost"@de ;
    geof:hasGeometry   [ a  sf:MultiPolygon ;
                            geof:asWKT  "MULTIPOLYGON (((7.688071 51.9460114, ..., 7.688071 51.9460114)))"^^geof:wktLiteral
                          ] .

ex:obs16 a qb:Observation, obs:Observation;
        ex:hasUnemploymentValue 1219;
        sdmx-dimension:refArea _:MuensterHiltrup;
        sdmx-dimension:refPeriod "2015-12-15"^^xsd:date .

_:MuensterHiltrup a dbpedia:Borough;
        rdfs:label  "Hiltrup"@en , "Hiltrup"@de ;
    geof:hasGeometry   [ a  sf:MultiPolygon ;
                            geof:asWKT  "MULTIPOLYGON (((7.6508926 51.8784304, ..., 7.6508926 51.8784304)))"^^geof:wktLiteral
                          ] .

# publisher of the Unemployment dataset of Muenster    (the publisher is the collector)
ex:orga3 a obs:Collector, org:Organization, foaf:Agent, dcterms:Agent;
        rdfs:label "Stadt Muenster - Amt fuer Stadtentwicklung, Stadtplanung und Verkehrsplanung"@de ;
        rdfs:label "Muenster City Council - Office for city development, city planning and transportation planning"@en.
```

[6] T. Bittner and B. Smith. Formal ontologies for space and time. Technical report, 2003.

[7] T. Bittner and S. Winter. On ontology in image analysis. In P. Agouris and A. Stefanidis, editors, *Integrated Spatial Databases: Digital Images and GIS: International Workshop (ISD'99)*, pages 168–191, Portland, Maine, USA, 1999. Springer-Verlag Berlin Heidelberg. doi:10.1007/3-540-46621-5_11.

[8] E. Blomqvist, P. Hitzler, K. Janowicz, A. Krisnadhi, T. Narock, and M. Solanki. Considerations regarding Ontology Design Patterns. *Semantic Web*, 7(1):1–7, 2016. doi:10.3233/SW-150202.

[9] V. Bogorny, B. Kuijpers, and L. O. Alvares. ST-DMQL: a semantic trajectory data mining query language. *International Journal of Geographical Information Science*, 23(10):1245–1276, 2009. doi:10.1080/13658810802231449.

[10] E. Bottazzi, C. Catenacci, A. Gangemi, and J. Lehmann. From collective intentionality to intentional collectives: an ontological perspective. *Cognitive Systems Research*, 7(2):192–208, 2006. doi:10.1016/j.cogsys.2005.11.009.

[11] A. Bröring, J. Echterhoff, S. Jirka, I. Simonis, T. Everding, C. Stasch, S. Liang, and R. Lemmens. New generation sensor web enablement. *Sensors*, 11(3):2652–2699, 2011. doi:10.3390/s110302652.

[12] D. Carral, S. Scheider, K. Janowicz, C. Vardeman, A. Krisnadhi, and P. Hitzler. An ontology design pattern for cartographic map scaling. In P. Cimiano, O. Corcho, V. Presutti, L. Hollink, and S. Rudolph, editors, *The Semantic Web: Semantics and Big Data, 10th International Conference (ESWC 2013)*, pages 76–93, Montpellier, France, 2013. Springer Berlin Heidelberg. doi:10.1007/978-3-642-38288-8_6.

[13] R. Casati and A. C. Varzi. The structure of spatial localization. *Philosophical Studies*, 82(2):205–239, 1996. doi:10.1007/BF00364776.

[14] M. Compton, P. Barnaghi, L. Bermudez, R. García-Castro, O. Corcho, S. Cox, J. Graybeal, M. Hauswirth, C. Henson, A. Herzog, V. Huang, K. Janowicz, W. D. Kelsey, D. Le Phuoc, L. Lefort, M. Leggieri, H. Neuhaus, A. Nikolov, K. Page, A. Passant, A. Sheth, and K. Taylor. The SSN ontology of the W3C semantic sensor network incubator group. *Web Semantics: Science, Services and Agents on the World Wide Web*, 2012. doi:10.1016/j.websem.2012.05.003.

[15] S. J. D. Cox. Ontology for observations and sampling features, with alignments to existing models. *Semantic Web Journal*, 2016. doi:10.3233/SW-160214 (in press).

[16] B. Cuenca Grau, I. Horrocks, B. Motik, B. Parsia, P. Patel-Schneider, and U. Sattler. OWL 2: the next step for OWL. *Web Semantics: Science, Services and Agents on the World Wide Web*, 6(4):309–322, 2008. doi:10.1016/j.websem.2008.05.001.

[17] A. Degbelo. *Spatial and temporal resolution of sensor observations*. IOS Press, 2015.

[18] A. Degbelo and W. Kuhn. A conceptual analysis of resolution. In V. Bogorny and L. Namikawa, editors, *XIII Brazilian Symposium on Geoinformatics*, pages 11–22, Campos do Jordão, Brazil, 2012.

[19] S. Dodge, R. Weibel, and A.-K. Lautenschütz. Towards a taxonomy of movement patterns. *Information Visualization*, 7(3):240–252, 2008. doi:10.1057/palgrave.ivs.9500182.

[20] J. L. Dungan, J. N. Perry, M. R. T. Dale, P. Legendre, S. Citron-Pousty, M. J. Fortin, A. Jakomulska, M. Miriti, and M. S. Rosenberg. A balanced view of scale in spatial statistical analysis. *Ecography*, pages 626–640, 2002. doi:10.1034/j.1600-0587.2002.250510.x.

[21] K. R. Ferreira, D. B. F. C. Almeida, and A. M. V. Monteiro. A RDF vocabulary for spatiotemporal observation data sources. In C. Davis Jr. and K. R. Ferreira, editors, *GeoInfo*, pages 156–161, Campos do Jordão, Brazil, 2014.

[22] K. R. Ferreira, G. Câmara, and A. M. V. Monteiro. An algebra for spatiotemporal data: from observations to events. *Transactions in GIS*, 2013. doi:10.1111/tgis.12030.

[23] A. Galton and M. Duckham. What is the region occupied by a set of points? In M. Raubal, H. Miller, A. Frank, and M. Goodchild, editors, *Geographic Information Science: Fourth International Conference*, pages 81–98, Münster, Germany, 2006. Springer Berlin Heidelberg. doi:10.1007/11863939_6.

[24] A. Gangemi and V. Presutti. Ontology design patterns. In S. Staab and R. Studer, editors, *Handbook on ontologies*, pages 221–243. Springer Berlin Heidelberg, 2nd edition, 2009. doi:10.1007/978-3-540-92673-3_10.

[25] P. Grenon. BFO in a Nutshell: A bi-categorial axiomatization of BFO and comparison with DOLCE (IFOMIS Report 06/2003). Technical report, Institute for Formal Ontology and Medical Information Science (IFOMIS), 2003.

[26] P. Grenon and B. Smith. SNAP and SPAN: towards dynamic spatial ontology. *Spatial Cognition and Computation*, 4(1):69–104, 2004. doi:10.1207/s15427633scc0401_5.

[27] N. Guarino. Ontologies and ontological analysis: an introduction, 2008. tutorial at FOIS 2008.

[28] G. Guizzardi. Representing collectives and their members in UML conceptual models: an ontological analysis. In J. Trujillo, G. Dobbie, H. Kangassalo, S. Hartmann, M. Kirchberg, M. Rossi, I. Reinhartz-Berger, E. Zimányi, and F. Frasincar, editors, *Advances in Conceptual Modeling - Applications and Challenges*, pages 265–274, Vancouver, British Columbia, Canada, 2010. Springer Berlin Heidelberg. doi:10.1007/978-3-642-16385-2_33.

[29] G. Guizzardi, J. P. A. Almeida, N. Guarino, and V. A. de Carvalho. Towards an ontological analysis of powertypes. In O. Papini, S. Benferhat, L. Garcia, M.-L. Mugnier, E. L. Fermé, T. Meyer, R. Wassermann, T. Hahmann, K. Baclawski, A. Krisnadhi, P. Klinov, S. Borgo, O. Kutz, and D. Porello, editors, *Proceedings of the Joint Ontology Workshops 2015 Episode 1: The Argentine Winter of Ontology co-located with the 24th International Joint Conference on Artificial Intelligence (IJCAI 2015)*, Buenos Aires, Argentina, 2015. CEUR-WS.org.

[30] G. Guizzardi and G. Wagner. What's in a relationship: An ontological analysis. In Q. Li, S. Spaccapietra, E. Yu, and A. Olivé, editors, *27th International Conference on Conceptual Modeling (ER 2008)*, pages 83–97, Barcelona, Spain, 2008. Springer. doi:10.1007/978-3-540-87877-3-8.

[31] G. P. Hancke, B. d. C. e. Silva, and G. P. Hancke Jr. The role of advanced sensing in smart cities. *Sensors*, 13(1):393, 2013. doi:10.3390/s130100393.

[32] C. A. Henson, H. Neuhaus, A. P. Sheth, K. Thirunarayan, and R. Buyya. An ontological representation of time series observations on the semantic sensor web. In O. Corcho, M. Hauswirth, and M. Koubarakis, editors, *Proceedings of the 1st SemSensWeb2009 Workshop on the Semantic Sensor Web (Collocated with ESWC 2009)*, Heraklion, Greece, 2009. CEUR-WS.org.

[33] P. Hitzler, K. Janowicz, and A. A. Krisnadhi. Ontology

modeling with domain experts: the GeoVocamp experience. In C. D'Amato, F. Lécué, R. Mutharaju, T. Narock, and F. Wirth, editors, *Proceedings of the 1st International Diversity++ Workshop co-located with the 14th International Semantic Web Conference (ISWC 2015)*, pages 31–36, Bethlehem, Pensylvania, USA, 2015. CEUR-WS.org.

[34] Y. Hu, K. Janowicz, D. Carral, S. Scheider, W. Kuhn, G. Berg-Cross, P. Hitzler, M. Dean, and D. Kolas. A geo-ontology design pattern for semantic trajectories. In T. Tenbrink, J. Stell, A. Galton, and Z. Wood, editors, *Spatial Information Theory - 11th International Conference (COSIT 2013)*, pages 438–456, Scarborough, UK, 2013. Springer International Publishing. doi:10.1007/978-3-319-01790-7_24.

[35] K. Janowicz. Observation-driven geo-ontology engineering. *Transactions in GIS*, 16(3):351–374, 2012. doi:10.1111/j.1467-9671.2012.01342.x.

[36] K. Janowicz and M. Compton. The Stimulus-Sensor-Observation ontology design pattern and its integration into the semantic sensor network ontology. In K. Taylor, A. Ayyagari, and D. De Roure, editors, *The 3rd International workshop on Semantic Sensor Networks*, Shanghai, China, 2010. CEUR-WS.org.

[37] K. Janowicz, A. Krisnadhi, Y. Hu, S. Suh, P. Weidema, B. Rivela, J. Tivander, D. E. Meyer, G. Berg-Cross, P. Hitzler, W. Ingwersen, B. Kuczenski, C. Vardeman, Y. Ju, and M. Cheatham. A minimal ontology pattern for life cycle assessment data. In E. Blomqvist, P. Hitzler, A. Krisnadhi, T. Narock, and M. Solanki, editors, *Proceedings of the 6th Workshop on Ontology and Semantic Web Patterns (WOP 2015)*, Bethlehem, Pensylvania, USA, 2015. CEUR-WS.org.

[38] W. Kuhn. A functional ontology of observation and measurement. In K. Janowicz, M. Raubal, and S. Levashkin, editors, *GeoSpatial Semantics: Third International Conference*, pages 26–43, Mexico City, Mexico, 2009. Springer Berlin Heidelberg. doi:10.1007/978-3-642-10436-7_3.

[39] A. Llaves and W. Kuhn. An event abstraction layer for the integration of geosensor data. *International Journal of Geographical Information Science*, 28(5):1085–1106, 2014. doi:10.1080/13658816.2014.882513.

[40] P. Mitzias, M. Riga, S. Waddington, E. Kontopoulos, G. Meditskos, P. Laurenson, and I. Kompatsiaris. An ontology design pattern for digital video. In E. Blomqvist, P. Hitzler, A. Krisnadhi, T. Narock, and M. Solanki, editors, *Proceedings of the 6th Workshop on Ontology and Semantic Web Patterns (WOP 2015)*, Bethlehem, Pensylvania, USA, 2015. CEUR-WS.org.

[41] P. OBrien, D. Carral, J. Mixter, and P. Hitzler. An ontology design pattern for data integration in the library domain. In E. Blomqvist, P. Hitzler, A. Krisnadhi, T. Narock, and M. Solanki, editors, *Proceedings of the 6th Workshop on Ontology and Semantic Web Patterns (WOP 2015)*, Bethlehem, Pensylvania, USA, 2015. CEUR-WS.org.

[42] F. Probst. Ontological analysis of observations and measurements. In M. Raubal, H. Miller, A. Frank, and M. Goodchild, editors, *Geographic Information Science: Fourth International Conference*, pages 304–320, Münster, Germany, 2006. Springer Berlin Heidelberg. doi:10.1007/11863939_20.

[43] F. Probst. Observations, measurements and semantic reference spaces. *Applied Ontology*, 3(1):63–89, 2008. doi:10.3233/AO-2008-0046.

[44] S. Riehemann and D. Elenius. Ontological analysis of terrain data. In L. Liao, editor, *Proceedings of the 2nd International Conference on Computing for Geospatial Research & Applications*, pages 10:1–10:8, Washington, DC, USA, 2011. ACM. doi:10.1145/1999320.1999330.

[45] F. B. Ruy, R. A. Falbo, M. P. Barcellos, and G. Guizzardi. An ontological analysis of the ISO/IEC 24744 metamodel. In P. Garbacz and O. Kutz, editors, *Formal Ontology in Information Systems - Proceedings of the Eighth International Conference (FOIS 2014)*, pages 330–343, Rio de Janeiro, Brazil, 2014. IOS Press. doi:10.3233/978-1-61499-438-1-330.

[46] M. Solanki. DIO: A pattern for capturing the intents underlying designs. In E. Blomqvist, P. Hitzler, A. Krisnadhi, T. Narock, and M. Solanki, editors, *Proceedings of the 6th Workshop on Ontology and Semantic Web Patterns (WOP 2015)*, Bethlehem, Pensylvania, USA, 2015. CEUR-WS.org.

[47] C. Stasch, K. Janowicz, A. Bröring, I. Reis, and W. Kuhn. A stimulus-centric algebraic approach to sensors and observations. In N. Trigoni, A. Markham, and S. Nawaz, editors, *GeoSensor Networks: Third International Conference*, pages 169–179, Oxford, United Kingdom, 2009. Springer Berlin Heidelberg. doi:10.1007/978-3-642-02903-5_17.

[48] C. Stasch, S. Scheider, E. Pebesma, and W. Kuhn. Meaningful spatial prediction and aggregation. *Environmental Modelling & Software*, 51:149–165, 2014. doi:10.1016/j.envsoft.2013.09.006.

[49] W3C OWL Working Group. OWL 2 Web Ontology Language Document Overview (Second Edition) - W3C Recommendation 11 December 2012 (http://www.w3.org/TR/2012/REC-owl2-overview-20121211/; last accessed: May 31, 2016), 2012.

[50] J. Wang, M. Duckham, and M. Worboys. A framework for models of movement in geographic space. *International Journal of Geographical Information Science*, pages 1–23, 2015. doi:10.1080/13658816.2015.1078466.

[51] M. E. Winston, R. Chaffin, and D. Herrmann. A taxonomy of part-whole relations. *Cognitive science*, 11(4):417–444, 1987. 10.1207/s15516709cog1104_2.

[52] Z. Wood and A. Galton. A taxonomy of collective phenomena. *Applied Ontology*, 4(3):267–292, 2009. doi:10.3233/AO-2009-0071.

[53] Y. Zheng, X. Xie, and W. Ma. GeoLife: A collaborative social networking service among user, location and trajectory. *IEEE Data Engineering Bulletin*, 33(2):32–40, 2010. doi:10.1.1.165.4216.