Specification of Semantic Trajectories Supporting Data Transformations for Analytics: The datAcron Ontology

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Abstract
Motivated by real-life emerging needs in critical domains, this paper proposes a coherent and generic ontology for the representation of semantic trajectories, in association to related events and contextual information, to support analytics. The main contribution of the proposed ontology is twofold: (a) The representation of semantic trajectories at varying, interlinked levels of spatio-temporal analysis, (b) enabling data transformations that can support analytics tasks. The paper presents the ontology in detail, in connection to other well-known ontologies, and demonstrates how data are represented at varying levels of analysis, enabling the required data transformations. The benefits of the representation are shown in the context of supporting visual analytics tasks in the air-traffic management domain.

1 Introduction
Many critical domains w.r.t. economy and safety, such as the Maritime and the Aviation domains, where Maritime Situation Awareness (MSA) and Air Traffic Management (ATM), respectively, impose emergent and challenging problems, require analysis of moving objects’ behaviour over time: Challenges concern effective detection and forecasting of moving entities’ trajectories, as well as recognition and prediction of important events by exploiting information about objects’ behaviour and contextual data. Due to these needs, semantic trajectories are turned into ‘first-class citizens’, forming a paradigm shift towards operations that are built and revolve around the notion of trajectory.

Motivated by these needs, our work focuses on trajectories and aims to build solutions towards managing data that are connected via, and contribute to enriched views of trajectories: Doing so, we revisit the notion of semantic trajectory and build on it. Specifically, it is expected that we will be able to represent, store and manipulate the wealth of information available in disparate and heterogeneous data sources, integrated in a representation where trajectories are the main entities, towards computing meaningful moving patterns so as to recognize and predict the behaviour and states of moving objects. Therefore, motivated by real-life emerging needs in MSA and ATM domains, this paper proposes a coherent and generic ontology for the representation of semantic trajectories, in association with related events and contextual information.

Specific contributions that this work makes are as follows: (a) The main contribution of the proposed ontology is the representation of semantic trajectories at varying levels of spatio-temporal analysis: Trajectories can be seen as temporal sequences of moving objects’ positions derived from raw data, of raw data aggregations signifying meaningful events (generalizing on the stops and moves model [12]), providing a synoptic view of raw trajectories [9], as temporal sequences of meaningful trajectories segments (each revealing specific behaviour, event, goal, activity etc), or as mere geometries. Representations at any such level of analysis are linked to each other, as well as to contextual information and co-occurring events.

(b) It shows how data transformations are supported via enhanced SPARQL queries to support analytics tasks. Such transformations can adapt available data to the analysis goals or to specific requirements of the methods that the analyst wants to apply. Although transformations considered are generic, these are exemplified in the ATM domain via concrete examples to effectively support visual analytics in important real-world cases.

The paper is organised as follows: Section 2 motivates the need of an ontology that supports the representation of semantic trajectories at varying levels of detail and outlines the data transformations requirements for supporting analytics tasks. Section 3 presents the main contribution, which is the datAcron ontology for semantic trajectories. Section 4 presents how data transformations are enabled via the specification of enhanced SPARQL queries in specific cases from the ATM domain, supporting visual analytics tasks. The paper concludes with related works in section 5 and concludes with remarks in section 6.

2 Motivation, Terminology, Objectives and Scope
The proposed ontology is a generic conceptual framework for the representation of semantic information relevant to the
movement of objects, revolving around the notion of trajectory. To make the objectives of this ontology clear and provide concrete examples for its use, we elaborate in a scenario from the air traffic management (ATM) domain, concerning flow management (FM). Before that, we explain the basic notions of trajectory, event and contextual information.

2.1 Trajectories, events and contextual information

Starting from the definitions of raw, structured and semantic trajectories provided in [9], a raw trajectory is a temporal sequence of raw data specifying the moving object’s spatio-temporal positions. Raw data can be aggregated, analyzed and semantically annotated, providing multiple abstractions of a trajectory. A maximal sequence of raw data that comply with a given pattern defines an episode [9]. In this work we focus on events as a generalisation of episodes, taking also into consideration -in conjunction to movement data- contextual information (i.e. any information -mostly about the environment of an object- that affects its movement, including other trajectories). Events represent specific, aggregated or abstract happenings instantiating an event pattern (whose description is not part of the ontology). While events may concern anything that happens in the environment of a moving object, we focus on those events that are related to the trajectory of a moving object.

A structured trajectory (simply, trajectory) consists of a sequence of trajectory parts that can be either raw positions reported from sensing devises, aggregations of raw positions referred as semantic nodes or simply nodes, or trajectory segments.

A semantic node provides a meaningful abstraction or aggregation of raw positions. For example, a set of raw positions may signify a “turn” event: This set can be represented as a single semantic node, associated to a low-level event of type “turn”. A trajectory segment is a trajectory itself, part of a whole trajectory. Segmentation of trajectories can be done with different objectives depending on the application and target analysis. Any trajectory part may be associated with an event that co-occurs with it spatially and/or temporally: E.g. A bad weather region may co-occur with a trajectory crossing-it (thus, related spatially) during a time period (related temporally).

A semantic trajectory is a meaningful sequence of trajectory parts, signifying events, activities, goals, etc. of moving entities.

2.2 The flow management domain

Mobility analysis tasks require a wealth of information from disparate and heterogeneous sources. As a running example for the types of entities that can be represented, their interlinking with moving objects’ trajectories specified at varying levels of analysis, and of data transformations to spatial and time series of events, we elaborate in scenarios from the air traffic management (ATM) domain, concerning flow management (FM). FM is an extremely important service for airlines to operate in a safe and efficient way, complementary to Air Traffic Control (ATC). The objective of FM is to ensure an optimum flow of air traffic to or through areas within which traffic demand at times exceeds the available capacity of the ATC system.

The entities of particular interest for the FM domain are:

- **Air blocks**, specified by geometries, which are static spatial 2D projections of airspace volumes.
- **Sectors**, which are static spatial 3D objects comprising airspace volumes that are defined by air blocks, with lower and upper flight levels.
- **Flight information regions** (FIR) that are static spatial 3D objects. Each of them is the responsibility of a certain control unit. For Europe, there are usually 2 divisions for the lower and upper air spaces. FIRs are quite large: some FIRs cover entire counties (Belgium and Luxembourg are joined in one FIR), and some countries are divided into two or more FIRs. Spain, for instance, has the same 3 FIRs regardless upper or lower air space.
- **Sector configurations** are alternative divisions of airspace into sectors. These constitute the minimum unit that an Air Traffic Controller operates. The number of sectors dividing the FIR space may vary, hence allowing to operate the FIR with the appropriate number of controllers according to demand conditions, ensuring safety of operations.
- **Opening schemes or active configurations** are the sector configurations actually deployed in a given airspace with time intervals of their validity.
- **Capacities** are referring to sectors (a.k.a. traffic volumes): for each sector and time unit, the capacity value of that sector may be either undefined (if the sector is not active at that time) or specify the upper limit of the number of flights in any time period with pre-specified duration (typically one hour). The capacities consider controllers workload, and are fixed values for the same sectors every time they are active.
- **Flight plans** are specifications of trajectories consisting of spatial events of flights crossing air blocks and sectors, and flying over specific waypoints (fixed co-ordinates among which airways are set). Each event specifies the entry (resp. exit) coordinates, flight level and time to (resp. from) a sector, or the time that the flight will fly over a waypoint. Flight plans specify other information such as estimated take-off time, and, in case of delay caused by a regulation, the calculated take-off time of the flight.
- **Predicted weather** is a spatial time series of multiple weather attributes referring to 3D locations (longitude, latitude, altitude).
On each operation day, the flow management monitoring process analyses periodically (typically every 20 minutes) the demand for each sector, by counting the expected number of flights in the sector during the next period (typically one hour, to match the definition of capacity). If a potential demand versus capacity imbalance is detected (a hotspot) a regulation may be applied to adjust the demand values to the available capacity.

Although the reason to apply a regulation may vary to bad weather conditions, strikes, etc., for the purposes of this article we focus on regulations applied due to hotspots. Therefore, a regulation is a special type of event that occurs as a measure that a flow manager takes to solve an excess of demand. The attributes of any regulation include the location (sector), start and end times, and reason codes (e.g. "C" for delays).

Regulations usually result in delays in the departure time of flights crossing that area, which introduces yet another factor of unpredictability to airlines’ operations. Therefore, airlines need to predict the occurrence of regulations well in advance, so as to reduce unpredictability. Identifying patterns of regulations is important towards this goal.

To make the objectives of the proposed ontology clear we show how data for the above entities in the FM domain can be provided to support identifying regulations’ patterns, interdependencies between affected flights and areas, and supporting the choice of sector configurations based on expected demands. These cases are explained in detail in section 4.

2.3 Objectives

We aim to provide a coherent and generic ontology for integrating all data from disparate sources, representing fully-fledged semantic trajectories at varying levels of spatio-temporal analysis.

By means of this ontology we aim at supporting (a) services for answering spatio-temporal queries concerning vessels’ trajectories along with aspects that affect and are affected by the mobility of moving objects, thus providing all the necessary information that analytics tasks require, (b) transformations between different representations of data required for analytics tasks.

As already mentioned, transformations can adapt available data to the analysis goals or to specific requirements of the methods that the analyst wants to apply. Transformations aim to extract relevant parts of the data or reduce irrelevant details, converting movement data from one form to another, to support different task foci: movers, spatial, events, space, and time. The role of data transformation is to prepare data for analysis, that is, to convert data to a form fitting a task or required by an analytical tool, maybe changing the structure of the data [2].

Following the approach of [10], the queries that this ontology must satisfy in the first place can be seen as combinations of three basic components: (a) space (where), (b) time (when), (c) object (what). These components can be used in three basic types of queries:

- Retrieve the objects (e.g. flights) in a region (e.g. a sector) for a time period (when&where → what).
- Retrieve the location (or geometry) occupied (resp. covered) by an object (e.g. a flight plan) or set of objects (e.g. flights), at a given time instant or period (when&what → where).
- Retrieve the time periods that a non-empty set of objects (e.g. a set of flights) appears in a specific location or area (e.g. cross a specific sector or FIR) (i.e. where&what → when).

![Figure 1. Conversions between different representations](http://ai-group.ds.unipi.gr/datacron_ontology/)

Exploiting these fundamental types of queries, and to a greater extent than other representations of trajectories, we aim to show how the proposed ontology supports transformations between different representations of data, for the benefit of analysis tasks’ effectiveness. Such generic transformations are depicted in Figure 1 [3] and will be demonstrated using data from the above-mentioned FM entities. Briefly, as Figure 1 shows, trajectories integrate spatial events (e.g. entering or exiting a sector) (transformation I), while these events, similarly to trajectories, may be aggregated to spatial time series: Place-based, such as hotspots detected in sectors (transformation III), or link-based, such as flows of flights between pairs of sectors (transformation II). Projections of these time series may result to spatially-referenced time series or to spatial situations (transformations VI). These transformations impose specific requirements to answering queries, regarding aggregations, extraction of events and projections of data, demonstrated in subsequent sections of this article.

3 The datAcron Ontology

The datAcron ontology (http://ai-group.ds.unipi.gr/datacron_ontology/) was developed by group consensus over a period of 12 months following a data-driven approach according to the HCOME methodology [7]. It has been designed to be used as a core ontology for the MSA and ATM domains, towards supporting analysis tasks. Its development has been driven by ontologies related to our objectives (e.g. DUL, SimpleFeature, NASA Sweet and SSN) as well as schemas and specifications regarding data sources from the different domains.
3.1 Core vocabulary and overall structure

According to the above specifications, and illustrated in Figure 2, a trajectory (Trajectory) can be segmented to trajectory parts (TrajectoryParts), each including other segments and/or more semantic nodes. Each semantic node may be associated with a specific raw position or a temporally ordered sequence of raw positions of a moving object.

The generic pattern of specifying structured trajectories is presented in section 3.2.

Figure 2. The main concepts and relations of the proposed ontology.

Trajectories and trajectory parts can be associated with contextual information, as well as with events (dul:Event). Although events may happen independently from the trajectory but co-occur with the trajectory, we focus on happenings on the trajectory itself (e.g. a “turn” or a “gap of communication”) and to moving object’s information (e.g. vessel in a protected or in a bad-weather area). Patterns for the specification of events and their associations to trajectory parts are presented in section 3.2, together with types of contextual information represented and respective associations to trajectories.

3.2 Patterns of semantic trajectories

As already said, the proposed ontology enables the specification of trajectories at various level of abstraction. Figure 3 illustrates the generic pattern of raw and structured trajectories.

The main concept in this pattern is the Trajectory, which is a subclass of Spatio-Temporal Structured Entity (ST_StructuredEntity). This, being a subclass of dul:Region represents a region in a dimensional space and time, used as a value for a quality of an Entity, while it also represents (structured) trajectories and their parts. A structured trajectory, as well as any of its parts, can be a temporal sequence of TrajectoryPart entities.

Direct subclasses of Trajectory are the
- IntendedTrajectory: planned trajectories build by an dul:InformationEntity such as a FlightPlan,
- ActualTrajectory: trajectories constructed from actual positioning data, after some processing of the raw positional data,
- RegulatedTrajectory: intended trajectories that have been modified by an operational event such as a regulation,
- SyntheticTrajectory: trajectories constructed by a simulation process, and
- RawTrajectory: trajectories constructed by the raw (unprocessed) sequence of positions of the moving object.

An ActualTrajectory can be further distinguished to a ClosedTrajectory (i.e. a trajectory that has reached its destination) and to an OpenTrajectory (i.e. a trajectory in progress).

Figure 3. The pattern of structured trajectories. Domain specific concepts in gray

The TrajectoryPart can be further distinguished to one of the following subclasses:
- Segment: associated to a spatial region and a time proper interval.
- Node: associated to a point in space and a time instant or time period. The latter holds in case the node aggregates several raw positions. A Node can be the result of a data processing component computing compressions or aggregations of the raw positioning data.
- RawPosition: represents the raw (unprocessed) positioning data. Each raw position instance is associated to a point in space and a time instant.

A specific trajectory, as well as any of its trajectory parts, being instances of dul:Region can be associated to their parts via the dul:hasPart property or via the subproperties hasInitial, hasLast which indicate the first and last part of the ST_StructuredEntity, respectively. For instance, a trajectory may comprise a sequence of trajectory segments, who on their own turn comprise other segments, nodes, or raw positions, and so on. The temporal sequence of structured entities is specified by means of the property dul:precedes. Trajectories related via the property dul:precedes represent subsequent trajectories of a specific object, and thus keep a long history of its movement. It must be noticed that this combination of properties allow to sharing trajectory parts between trajectories with no ambiguity: For instance, a trajectory node can be shared between the actual and the intended trajectory of an aircraft.

Each structured entity (i.e. trajectory or trajectory part) can be associated to a specific geometry (sf:Geometry), representing a point or region of occurrence, and a temporal entity (dul:TimeInterval) specifying a time interval of occurrence. The Geometries of structured entities can be serialized into Well-Known-Text (WKT) and asserted
as values to the property hasWKT, which is sub-property of geosparql:hasSerialization.

Finally, trajectories can be members of TrajectoryCluster entities, via the dul:hasMember property.

Figure 4. The pattern of trajectories linked with events. Domain specific concepts in gray

Towards the specification of semantic trajectories, trajectories are associated with events and contextual information. Specifically, each trajectory and trajectory part, being instances of ST_StructuredEntity, can be associated via the property occurs with events, as illustrated in Figure 4. An event can be associated with other events via the properties dul:hasConstituent or dul:hasPart: This is the case for high-level events associated with other high-level or low-level events. An event involves at least one participant (associated via the property dul:hasParticipant) and it holds for a specific TimeInterval specified by the property dul:hasTimeInterval. An event can be:
- LowLevel, in case its detection requires data from a single trajectory,
- HighLevel, in case its detection requires contextual data and maybe, data from multiple trajectories. For example, events of type EnterSector involve information about active sectors along with trajectories. As another example, hotspots require data about active sectors and multiple trajectories.
- Operational, if they are issued by domain specific operators, affecting regions or groups of entities for a specific time interval. For example, a regulation (Regulation) is applied on a sector and remains active for a time interval, and indirectly affects all the intended trajectories crossing the sector. A trajectory is linked through the property affectedBy, with corresponding regulation.
- Environmental, if they are due to the environment of moving objects. Extreme weather condition are such events.

It must be noticed that associating events to trajectory parts satisfies the requirement to associate multiple events to varying levels of trajectory analysis, according to the information used for the detection of each event: For instance, a low-level “turn” event may co-occur with a low-level “descend” event and thus, both events may be associated to the same semantic node. In addition to that, this semantic node may be associated to a trajectory segment which in its own turn is associated with events of type “DescendingPhase” and “CrossingSector”.

Figure 5. The pattern of trajectories linked with contextual information. Domain specific concepts in gray

In addition to events, trajectory parts of semantic trajectories can be linked to contextual information. As already mentioned above, contextual information is any information -mostly about entities in the environment of a moving object, including other trajectories- that affect by its movement. Such information may be archival information concerning static aspects of the environment (e.g. airports, airspaces, etc), dynamic (e.g. changing sector configurations), or streaming (e.g. forecasted weather conditions). The pattern for linking trajectory parts with contextual information is illustrated in Figure 5. Without loss of generality, subsequent paragraphs and Figure 5 show associations to contextual entities related to FM scenarios, although other cases may be also specified.

Weather conditions are very important to trajectories in the MSA and ATM domains: Each TrajectoryPart can be associated with entities of type WeatherCondition, which is defined as a subclass of ssn:FeatureOfInterest, (i.e. the entity whose properties are being estimated or calculated in the course of an observation).

Of particular interest to the FM and MSA domains are airspace regions. Structured entities can be linked to spatial regions (instances of dul:Region) of particular interest through the properties within and dul:nearTo.

Also, the departure and destination of a trajectory can be considered as contextual information, linked via the properties hasDeparture and hasDestination, respectively. The properties range to the class dul:PhysicalPlace, which can be further refined to domain specific classes such as Airport, Heliport, or Port.

A FlightPlan is also a domain specific entity dul:InformationEntity which is associated to an IntendedTrajectory or a RegulatedTrajectory, via the property reportsTrajectory.

4 Data Transformations for Analytics

In this section, we show how data transformations are supported that are necessary for more advanced analysis tasks, such as discovery of patterns of regulations (denoted FM01), and prediction of sector configurations (denoted FM02).

4.1 Flow management use-cases

Following the analytics requirements in FM, we describe two use-cases that require advanced data transformations.
FM01. Towards discovering patterns of regulations, we need to (a) discover regular temporal patterns of regulations applied to sectors, and (b) discover interdependencies between sectors based on regulations.

For FM01(a) we generate time series of counts of regulations per area of interest (e.g. sectors or FIR) by time periods of a chosen length (e.g., 1 hour). Among these time series, we aim to find time series with high periodicity (daily and weekly time cycles). For FM01(b), we need to find “patterns between sectors”, where regulations in some sectors or groups of sectors often lead to regulations in other sectors. These regulations can be found as follows: Regulations in sectors $S_1$ and $S_2$ may be related if the regulation applied in $S_1$ affects the times where flights enter $S_2$ resulting to a new hotspot. This task can be further supported by discovering re-occurring links between sectors. Two sectors are linked via a “link event” if regulated flights cross both sectors during a particular time interval. This can be achieved by computing time series of link existence: for each pair of sectors ($S_1, S_2$) for which link events exist, we need to compute time series with values 1 for the time intervals when links between $S_1$ and $S_2$ existed and 0 for the remaining time intervals. Time series with multiple peaks would signify interrelationships between sectors, possibly caused by the airspace design (density of airways connecting waypoints in certain sectors) or by the density of traffic flows between certain points in space in specific periods (e.g. holidays).

FM02. In this case the aim is to predict the choice of sector configurations based on expected demands. To this end, we compute the expected demands by aggregating the flight plans into spatial time series by suitable sectors and time intervals. Two time-dependent attributes may be computed for any sector $S$: entry hourly count (how many flights enter $S$ during each time interval) or occupancy count (how many flights are present in $S$ during each occupancy period). Occupancy count, used in this paper, concerns overlapping occupancy periods of predefined duration. We may view the occupancy period as a sliding time window, shifted by a number of time units specified by the “time step”. That is, two parameters of temporal aggregation are used: occupancy period duration (e.g., 1 hour) and time step, which is smaller than the occupancy period duration (e.g., 15 minutes).

Overview. FM01(a) requires a spatial events to spatial time series (place-based) transformation (Figure 1), FM01(b) requires a transformation from trajectories to spatial time series (link-based), and FM02 a transformation from trajectories to spatial time series (place-based).

4.2 Evaluation of data transformations

We have setup a Jena triple store which holds the datasets involved for the FM scenarios and activated a SPARQL 1.1 endpoint. Our datasets (regulations, flight plans, etc.) are real data from April 2016. All data transformations presented in this section have been implemented on top of SPARQL queries to the endpoint, which produce data for visual analysis tasks, in particular for pattern detection and analysis. All illustrations have been produced by the V-Analytics tool [2].

Although some of the aggregate computations can be enabled by the COUNT function of SPARQL, the time series computation requires iterative SPARQL queries. For this reason, we use an iterative procedure that poses an enhanced, parametrized SPARQL query, whose parameters are updated in each iteration. The iterative process results to a sequence of queries for subsequent time periods. Specifically, given a duration $\Delta t \neq 0$ and a period $[\text{TimeStart}, \text{TimeEnd}]$, the $i$-th query of $n$ iterations, concerns the time period $[\text{TimeStart} + i \cdot \Delta t, \text{TimeStart} + (i + 1) \cdot \Delta t]$. The SPARQL queries are also enhanced by a suite of spatial (based on the Region Connection Calculus) and temporal (based on Allen’s interval algebra) functions, implemented in the <http://java.datAcron.unipi.gr.sparql_functions> namespace to verify spatiotemporal relations.

Figure 6. Regulations by FIR

FM01(a). The case FM01(a) requires a spatial events to spatial time series aggregate data transformation (Figure 1, (III)). In particular, it requires the computation of time series of counts of regulations with a particular reason code, in time intervals of a chosen length. The parametrised query for a given airspace, (e.g. $\text{airspace} = \text{Airspace_LBTA_411}$), is as follows:

```
PREFIX : <http://www.datacron-project.eu/datAcron#>
PREFIX dul: <http://www.ontologydesignpatterns.org/DUL.owl#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
PREFIX myfn: <java:datAcron.unipi.gr.sparql_functions:>
SELECT (COUNT(DISTINCT ?regulation) AS ?count) WHERE {
  ?regulation a ?regulation; dul:hasRegion $airspace$; dul:hasTimeInterval ?t1; ?t2; TimeStart ?t1; TimeEnd ?t2.
  FILTER(myfn:overlaps(?t1, ?t2, $airspace$); ?t1^^xsd:DateTime, ?t2^^xsd:DateTime))
}
```

Figure 7. Trajectories associated to regulations
A procedure iterates and poses a query for each regulation type and each subsequent occupancy period in the overall period (e.g. [2016 – 04 – 01, 2016 – 04 – 30]). The variables assigned at each iteration are as follows: $\text{Regulation}$ (regulation type), $\text{Start}$ (time window start), $\text{End}$ (time window end). The function $\text{myfn:overlaps}/4$ realises the temporal overlap relation in Allen’s interval algebra.

Results from these queries can be aggregated at varying levels of airspace partitioning granularity. While aggregations at the level of FIRs provide some useful patterns, as depicted in Figure 6, patterns at lower levels of spatial granularity (e.g. at the level of airlocks - not depicted here) are difficult to be detected. In particular, at FIR level, we clearly observe large numbers of regulations in 209LE (central part of Spain) on Fridays daytime (6:00 - 18:00), Saturdays (6:00-24:00) and, in some weeks, on Sundays. In 079LE (East) we see frequent regulations on Fridays and, in some weeks, on Saturdays. There are only a few regulations in 208LE (West).

The query will assert triples relating sectors affected from temporally overlapping regulations. Therefore, the time series of trajectories crossing sectors affected by temporally overlapping regulations can be retrieved by the query:

```
PREFIX : <http://www.datacron-project.eu/dataCron#>
PREFIX rdf: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX myfn: <java:datAcron.unipi.gr.sparql_functions.>

SELECT (COUNT(DISTINCT ?s) AS ?count) WHERE {
  ?s :associatedByOverlappingRegulationWith [] .
  ?t :intendedToCross ?s .
  $t0$ dul:hasRegion ?s ; dul:hasTimeInterval /:TimeStart $t0$ ;
  $t0$ :hasTimeInterval /:TimeEnd $t1$. 
  FILTER(myfn:overlaps(?t0, ?t1, $t_start$, $t_end$))
}
```

where $\text{start}$ and $\text{end}$ are the start time and end time of the occupancy time period window that slides across the time line. Two of the trajectories crossing sectors affected by regulations are depicted in Figure 7, where the location of regulations is depicted by the (red) dots.

Finally, exploiting the generated links for sectors ($S_x, S_y$) affected by temporally overlapping regulations $R_1, R_2$, we can count the links for a given time interval and a given period. Thus, the time series can be constructed by a sequence of parametrized queries of the form:

```
PREFIX : <http://www.datacron-project.eu/dataCron#>
PREFIX rdf: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX myfn: <java:datAcron.unipi.gr.sparql_functions.>

SELECT DISTINCT ?s WHERE {
  ?s :associatedByOverlappingRegulationWith [] .
  ?r dul:hasRegion ?s ; dul:hasTimeInterval ?t .
  FILTER(myfn:during_sf(?ts, ?te, $t_start$, $t_end$))
}
```

where $\text{start}$ and $\text{end}$ are the start and end times respectively of the sliding time window of the parametrized query.

As depicted in Figure 8, we got (a) total counts of regulated flights between each pair of locations of regulations and (b) their daily time series. Line thickness corresponds to the total counts of regulated flights. Lines have larger curvatures at their ends. Time graphs show the time series for links between pairs of regulation locations. We have observed several peak values in the time series. Six links have peaks on April 28. These links are highlighted on the map.

**FM02.** To support the FM02 case we need to compute expected demands by counting the number of flight plans in each sector for any occupancy period of a specific duration.

Considered that each flight plan is an intended trajectory, the basic query is to retrieve the series of sectors (in this case, both active and inactive) crossed by the intended trajectory, and the entry/exit times for each sector. For example, the following query returns the sectors crossed by the trajectory of a given flight plan, e.g. $\text{flight_plan_AA51147955}$:
importing information of the appropriate form at various levels of analysis. We have demonstrated data transformation and visual analytics in Flow Management scenarios of ATM using the proposed ontology. We overcame the limitations of SPARQL 1.1 w.r.t. data transformation requirements, by implementing a suite of functions for verifying spatio-temporal relations and parametrized SPARQL queries that can be iteratively processed on our customized datAcron endpoint.

As a future work, we plan to also demonstrate data transformations for maritime scenarios and extend the implemented suite of functions for our customized SPARQL endpoint.

6 Concluding remarks
This work presents the core specifications and usage in data transformation of the datAcron ontology. This ontology describes trajectories of moving objects at various levels of analysis, towards decision support making and event recognition. We have demonstrated data transformation and visual analytics in Flow Management scenarios of ATM using the proposed ontology.