Adaptive IoT Intelligence for Smart City Applications

From Data Streams to Actionable Knowledge

Alessandra Mileo
Senior Research Fellow
Insight Centre for Data Analytics, NUI Galway
alessandra.mileo@insight-centre.org

Ali Intizar
Postdoctoral Researcher
Insight Centre for Data Analytics, NUI Galway
ali.intizar@insight-centre.org
Future: INTERNET of EVERYTHING
Smart City Applications: Challenges

- Interoperability of Data and Processes
- Optimal Data Source Discovery & On-demand Federation:
  - Optimal data source selection while taking application constraints and user preferences into account
  - Automated composition of primitive data services/streams into complex events
- Real-time Detection of City events
- Adaptive Urban Reasoning:
  - Ensure that the “best” remains “best”
  - Filter the detected events based on user’s context
- User Centric Decision Support
Smart City Applications: Challenges

- Interoperability of Data and Processes
- Optimal Data Source Discovery & On-demand Federation:
  - Optimal data source selection while taking application constraints and user preferences into account
  - Automated composition of primitive data services/streams into complex events
- Real-time Detection of City events
- Adaptive Urban Reasoning:
  - Ensure that the “best” remains “best”
  - Filter the detected events based on user’s context
- User Centric Decision Support
Smart City Applications: Challenges

• Interoperability of Data and Processes
• Optimal Data Source Discovery & On-demand Federation:
  • Optimal data source selection while taking application constraints and user preferences into account
  • Automated composition of primitive data services/streams into complex events
• Real-time Detection of City events
• Adaptive Urban Reasoning:
  • Ensure that the “best” remains “best”
  • Filter the detected events based on user’s context
• User Centric Decision Support
Data Interoperability

IoT-intelligence abstracts from silos moving towards a connected digital layer.
Not just dealing with large Volumes...

... but also Data Dynamicity:

Fasten Seat Belts!
The Problem
The Goal
Keep it Simple
Continuous Query Evaluation over Linked Streams (CQELS)
Scalable processing model for unified Linked Stream Data and LOD

Combines data pre-processing and an adaptive cost-based query optimization algorithm

Experimental evaluation shows great performance (response time and scalability)
Linked Stream Middleware (LSM)
Keep it Simple
Linked Stream Middleware

Diagram showing the components and processes involved in linked stream middleware, including data acquisition, linked data, data access, and application layers. The diagram highlights the integration of various components such as SPARQL Endpoint, Mashup Composer, Linked Sensor Explorer, Streaming channels, LD Query Processor, CQELS engine, Web server, Virtuoso, and CQELS (Stream Proc.). The data bus connects to stream sources and is equipped with 115000 sensors.
LSM: Live Flight Info

### LSM: Live Flight Info

<table>
<thead>
<tr>
<th>Flight</th>
<th>Destination</th>
<th>Location</th>
<th>Speed</th>
<th>Departure</th>
<th>Transit</th>
<th>Arrival</th>
</tr>
</thead>
<tbody>
<tr>
<td>EY4W</td>
<td>LON</td>
<td>EY4W</td>
<td>17426.0 feet</td>
<td>unknown</td>
<td>unknown</td>
<td>unknown</td>
</tr>
<tr>
<td>RY24LJ</td>
<td>AMS</td>
<td>RY24LJ</td>
<td>316.0 kts</td>
<td>unknown</td>
<td>unknown</td>
<td>unknown</td>
</tr>
<tr>
<td>SDWZ</td>
<td>LON</td>
<td>SDWZ</td>
<td>19220.0 feet</td>
<td>unknown</td>
<td>unknown</td>
<td>unknown</td>
</tr>
<tr>
<td>BA7191</td>
<td>LHR</td>
<td>BA7191</td>
<td>340.0 kts</td>
<td>unknown</td>
<td>unknown</td>
<td>unknown</td>
</tr>
<tr>
<td>BA162</td>
<td>LHR</td>
<td>BA162</td>
<td>26100.0 feet</td>
<td>unknown</td>
<td>unknown</td>
<td>unknown</td>
</tr>
<tr>
<td>EZY340</td>
<td>LHR</td>
<td>EZY340</td>
<td>351.0 kts</td>
<td>unknown</td>
<td>unknown</td>
<td>unknown</td>
</tr>
<tr>
<td>NAOS1F</td>
<td>LHR</td>
<td>NAOS1F</td>
<td>337.0 kts</td>
<td>unknown</td>
<td>unknown</td>
<td>unknown</td>
</tr>
<tr>
<td>RY82PB</td>
<td>LHR</td>
<td>RY82PB</td>
<td>33775.0 feet</td>
<td>unknown</td>
<td>unknown</td>
<td>unknown</td>
</tr>
<tr>
<td>BRU51</td>
<td>LHR</td>
<td>BRU51</td>
<td>33350.0 feet</td>
<td>unknown</td>
<td>unknown</td>
<td>unknown</td>
</tr>
</tbody>
</table>

**Search:**
- **Location:**
  - Latitude: 51.500325
  - Longitude: -0.127144

**Sensors:**
- WebCam
- Satellite
- Snowfall
- Flood
- Radar
- Road Activity
- Traffic
- Station
- Bus Stop
- Train
- Airport
- Bus
- Flight

**Map and Tools:**
- Login/Register
LSM: Live Trains Info

Alessandra Mileo - Insight Centre for Data Analytics
LSM: Live Traffic Info
LSM Demo
Smart City Applications: Challenges

- Interoperability of Data and Processes
- Optimal Data Source Discovery & On-demand Federation:
  - Optimal data source selection while taking application constraints and user preferences into account
  - Automated composition of primitive data services/streams into complex events
- Real-time Detection of City events
- Adaptive Urban Reasoning:
  - Ensure that the “best” remains “best”
  - Filter the detected events based on user’s context
- User Centric Decision Support
What streams do I need and how “good” are they? (Stream Discovery and Federation)
Quality and context-aware stream discovery

• What information do I need?
  – Data interoperability: Semantic descriptions
  – Interface interoperability: streams as event services
• How good is it?
  – ADAPT to quality requirements and preferences for data source selection
  – Efficient processing of event logic
Summary of the Approach

• How to describe complex event services?
  – Create an Event Service Ontology with Event Patterns.
• How to determine if two event patterns are functionally equivalent?
  – Create and compare canonical event patterns to find substitutes.
• How to create event compositions and choose the optimal?
  – Top-down traverse to find functionally-equivalent canonical patterns.
  – Estimation of the traffic demand.
• How to derive event service compositions efficiently?
  – Construct and utilize an Event Reusability Hierarachy for event service composition.
Automated Complex Event Implementation System
ACEIS data model: OWL-S and SSN

Namespaces:
- default: <http://www.insight-centre.org/ces#>
- rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
- owls: <http://www.daml.org/services/owl-s/1.2/Service.owl#>
- owls-sp: <http://www.daml.org/services/owl-s/1.2/ServiceParameter.owl#>

Legend:
- Class
- Object property
- subClassOf
- Data property
Annotation of sensor streams

• A sensor service description is annotated as:

\[ \text{sdesc} = (\text{td}, \text{g}, \text{qd}, \text{Pd}, \text{Fold}, \text{fd}) \]

• Similarly, a sensor service request is annotated:

\[ \text{sr} = (\text{tr}, \text{Pr}, \text{Folr}, \text{fr}, \text{pref}, \text{C}) \]
On-Demand Stream Federation

- **Event Request:**
  - User/Application defines an event request using CES Ontology

- **Procedure:**
  - Derive canonical forms of event patterns of CESs.
  - Apply tree isomorphism algorithms over the canonical event patterns and the event request to identify reusable or equivalent event patterns.
  - Generate all possible composition plans.
  - Aggregate NFPs and compare aggregated NFP values against constraints on event request to filter out unsatisfied composition plans.
  - Optimization using Genetic Algorithm (GA)
  - Rank the remaining composition plans based on preferences (soft constraints).
Running example

Query

OR

SEQ

e1

e3

Event Service 1

type= e1
loc=loc1

e1

Event Service 2

type= e2
loc=loc2

e2

Event Service 3

type= e3
loc=loc3

e3

Event Service 4

type= e4
loc=loc4

Composition Plan

OR

SEQ

e4

e3

loc=loc4
loc=loc3
Smart City Applications: Challenges

- Interoperability of Data and Processes
- Optimal Data Source Discovery & On-demand Federation:
  - Optimal data source selection while taking application constraints and user preferences into account
  - Automated composition of primitive data servicesstreams into complex events
- Real-time Detection of City events
- Adaptive Urban Reasoning:
  - Ensure that the “best” remains “best”
  - Filter the detected events based on user’s context
- User Centric Decision Support
Adaptive Urban Reasoning

- Continuous detection of changes that can affect decision making:
  - When do I need a new solution/answer?
  - Tradeoff between accuracy and required user-feedback
  - Need to consider user experience

- The importance of Adaptivity:
  - Improve robustness (the best answer at any time)
  - Improve scalability of Decision Support (relevant/critical events are filtered to be used in decision making)
Adaptive Urban Reasoning

... in stream federation (Technical Adaptation)

- Monitoring quality updates of streaming sources
- Evaluate criticality of the update (based on query-related constraints and requirements)
- React to this change (discover new streaming sources)

... in Decision Support (Contextual Filtering)

- Filtering events related to a user activity/decision task
- Evaluating criticality of related events
- React to this change (find better answers)
Technical Adaptation

Constraint Validation

- Degradation in stream quality is considered as constraints violation
- Better performance but can lead to the possibility of having better quality streams not considered

Adaptation Manager deals with constraint violations:

- Switching to alternative streams: only candidate streams selected by composition plan are considered as substitute for stream switching
- Re-generation of the composition plan and consideration of all the available (registered) stream.
Contextual filtering

Input

• List of detected events
• Contextual information (user status, feedback, query/response, profiles)
• Partial correlations between user status and events

Output

• Ranking of relevant and critical events (based on user context), which can trigger re-computation of inference results
Demo and Examples

Non-Functional Preferences

Rate

Specify interval

Start Date: [blank]  Stop Date: [blank]

Please specify non-functional properties and constraints

- Latency < [blank] Value ms 1.0
- Price < [blank] Value euro 1.0
- Security < [blank] Value level 1.0
- Accuracy < [blank] Value % 1.0
- Completeness < [blank] Value % 1.0
- Bandwidth
Demo and Examples

Please choose from the below datasets (at least 1)

- Traffic
  - Avg. Speed
  - Vehicle Count
  - Estimated Time

- Air pollution

- Weather
  - Humidity
  - Temperature
  - Wind Speed
Demo and Examples

[Map showing Aarhus city with起点和终点标记]

Start point:
Christiansbjerg, Aarhus, Denmark

Finish point:
Viby, Denmark

pick on map
Smart City Applications: Challenges

- Interoperability of Data and Processes
- Optimal Data Source Discovery & On-demand Federation:
  - Optimal data source selection while taking application constraints and user preferences into account
  - Automated composition of primitive data services/streams into complex events
- Real-time Detection of City events
- Adaptive Urban Reasoning:
  - Ensure that the “best” remains “best”
  - Filter the detected events based on user’s context
- User Centric Decision Support
IoT-Intelligence

“People want answers, not numbers”
(Steven Glaser, UC Berkley)

Going from Data to Answers is the “smart” bit
How to leverage the IoT infrastructure for (efficient) stream reasoning?
Perceptions and Intelligence

Actionable intelligence

Abstraction and perceptions

Structured data (with semantics)

Raw sensory data

Data

Information

Knowledge

Wisdom

IoT-Intelligence
Perceptions and Intelligence

- **Raw sensory data**
- **Structured data (with semantics)**
- **Abstraction and perceptions**
- **Actionable intelligence**

- **Data**
- **Information**
- **Knowledge**
- **Wisdom**

IoT-Intelligence
The StreamRule idea

- Fully-fledged system
  - from data streams to complex problem solving
- CQELS as pre-processor
  - to select, filter, aggregate, integrate streaming data
- Streaming Answer Set Programming as stream reasoning layer for complex problem solving
  - recursion, defaults, constraint checking, solution enumerations, abduction, planning, etc.

in other words...
StreamRule is coupling:

- the linked data stream query processing power of **CQELS**
- the expressivity and reasoning capabilities of Answer Set Programming with the CLINGO4 stream reasoning solver
- … in a 2-tier approach so that the size of the input is reduced as the reasoning task becomes more computationally intensive.
Stream Reasoning with ASP: What’s new?

- Normal Answer Set Programs are written to work with static knowledge and rules.
- **Streaming ASP** allows to externally input data into logic programs and reason upon them to produce dynamic solutions (answer sets) to dynamic problems.
- Implements time-decaying, incremental, logic inference.
StreamRule

RDF Files (e.g. maps)

Web of Data

LSM Wrappers

Query Processing

CQELS & ACEIS processor

Filtered Stream

Clingo/DLV

Rule-based Expressive Reasoning

Application

Sensor Streams

Query

Logic Program

Scalability requires adaptation!

Alessandra Mileo - Insight Centre for Data Analytics
Adaptation Heuristics: ongoing work

- More than an engineering problem
  Multi-Context Systems to model interactions between “contexts”

- Design and runtime features

- Streaming rate and window size (initial evaluation)

- Complexity of the reasoning (future work)
StreamRule Running Examples
Dealing with Uncertainty and learning relational structures
IoT data are messy: deal with uncertainty

- Expressive inference
  - non-monotonicity, noisy, partial and inconsistent data
- Probabilistic rules for uncertain knowledge and learning by example
  - represent, use, infer and learn probabilistic knowledge (PrASP)

Can we (learn the) answer to questions about uncertain knowledge using qualitative (declarative) inference in dynamic environments?
What is Streaming PrASP

A framework that uses:

1. PrASP as an uncertainty reasoning server to reason over Streaming Web Data
2. Continuous Query Processing over Linked Data Streams for data filtering

What is PrASP then?
PrASP is...

... an experimental Statistical Relational Learning (SRL) reasoner based on Answer Set Programming (ASP)

PrASP can...

... represent, use infer and learn probabilistic knowledge
PrASP Example

- Position estimation for a moving target
- Streaming Input:
  - Uncertain positions (from sensor data)
  - Sensed variation of speed w.r.t. a default speed
- PrASP program:
  - ASP encoding of the localization problem (generate & test)
  - Constraints on invalid locations and speed coherence
  - Uncertain background knowledge
- PrASP output:
  - Updated probabilities of hypothesis expressed as formulas
Streaming PrASP framework

- Query & learning results
- PrASP CQELS client (RDF filtering client)
- CQELS
- RDF data stream
- ASP grounder/solver
- PrASP
  - Probabilistic ASP/FOL beliefs/examples stream
  - PrASP program (knowledge base)
  - Probabilistic queries
  - Static learning examples
  - Hypotheses

- Transformation pattern
- Incremental results
PrASP 0.6 inference core

Pre-processing
(translation of FOL syntax, ...)

Query probabilities

Probability distribution over possible worlds
(maximum entropy solution of equations)

System of linear equations (or inequalities)

Possible worlds
(sampled answer sets)

Simplification of rules with independent events

Spanning program
(disjunctions from weighted formulas)

Filtering of formulas with no or very little influence on queries

PrASP program (given knowledge base)

F2LP (optional)

PrASP learning core

Native solver for linear systems

CVC4
(SMT solver; optional)

ASP grounder/solver
(default: Clingo 3)

Examples

Queries

Hypotheses
PrASP Running Examples
Expressivity Vs. Scalability Tradeoff

1. Raw sensory data
2. Structured data (with semantics)
3. Abstraction and perceptions
4. Actionable intelligence

- Data
- Information
- Knowledge
- Wisdom
Expressivity Vs. Scalability Tradeoff

- Actionable intelligence
- Abstraction and perceptions
- Structured data (with semantics)
- Raw sensory data
Adaptive IoT Intelligence for Smart City Applications

*From Data Streams to Actionable Knowledge*

Alessandra Mileo
Senior Research Fellow
Insight Centre for Data Analytics, NUI Galway
alessandra.mileo@insight-centre.org

Ali Intizar
Postdoctoral Researcher
Insight Centre for Data Analytics, NUI Galway
ali.intizar@insight-centre.org