

IoT-Intelligence and Web Stream Reasoning

*Towards Complex Reasoning over Big Data Streams with
Answer Set Programming*

Alessandra Mileo

Senior Research Fellow

Insight Centre for Data Analytics, NUIG

alessandra.mileo@insight-centre-org

Ali Intizar

Research Fellow

Insight Centre for Data Analytics, NUIG

ali.intizar@insight-centre-org

IoT- Intelligence at *Unit for Reasoning & Querying (URQ)*

1. Representation and linking
2. Finding what we need
3. Dynamic Problem Solving
(Stream Reasoning)



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Smart Cities

Enterprise
Communication



**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

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Semantic
Web

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Semantic
Web

Service Oriented
Architectures

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Continuous
constraint
checking

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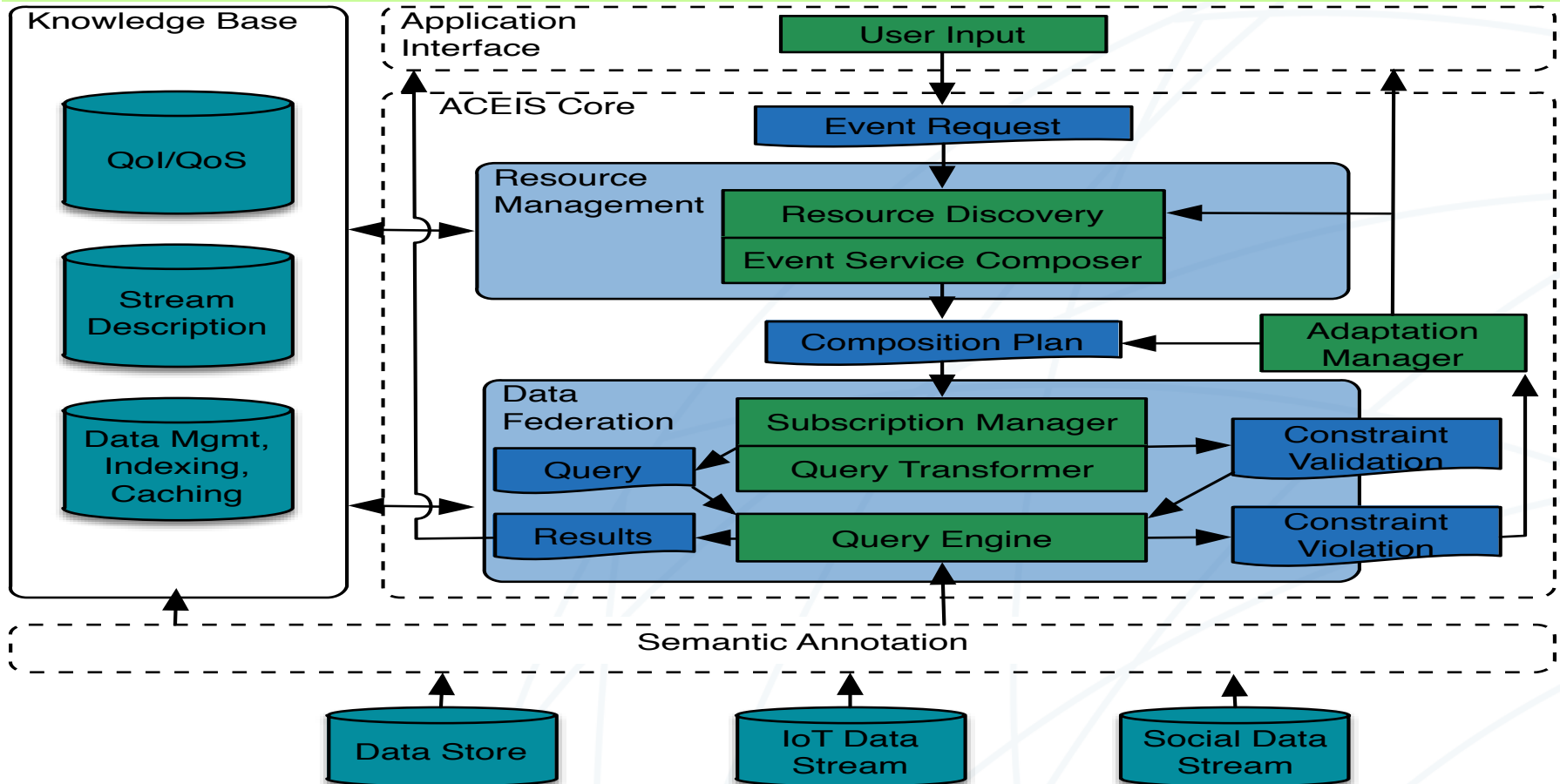
DSMS and
CEP

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.
- How to derive event service compositions efficiently?
 - Construct and utilize an Event Reusability Hierarchy for event service composition.

Gao, F., Ali, M.I., Curry, E., Mileo, A.: *On Discovery and Integration of Urban Data Streams for Realtime Smart City Applications*. J. Data Semantics (2015) to appear

Automated Complex Event Implementation System



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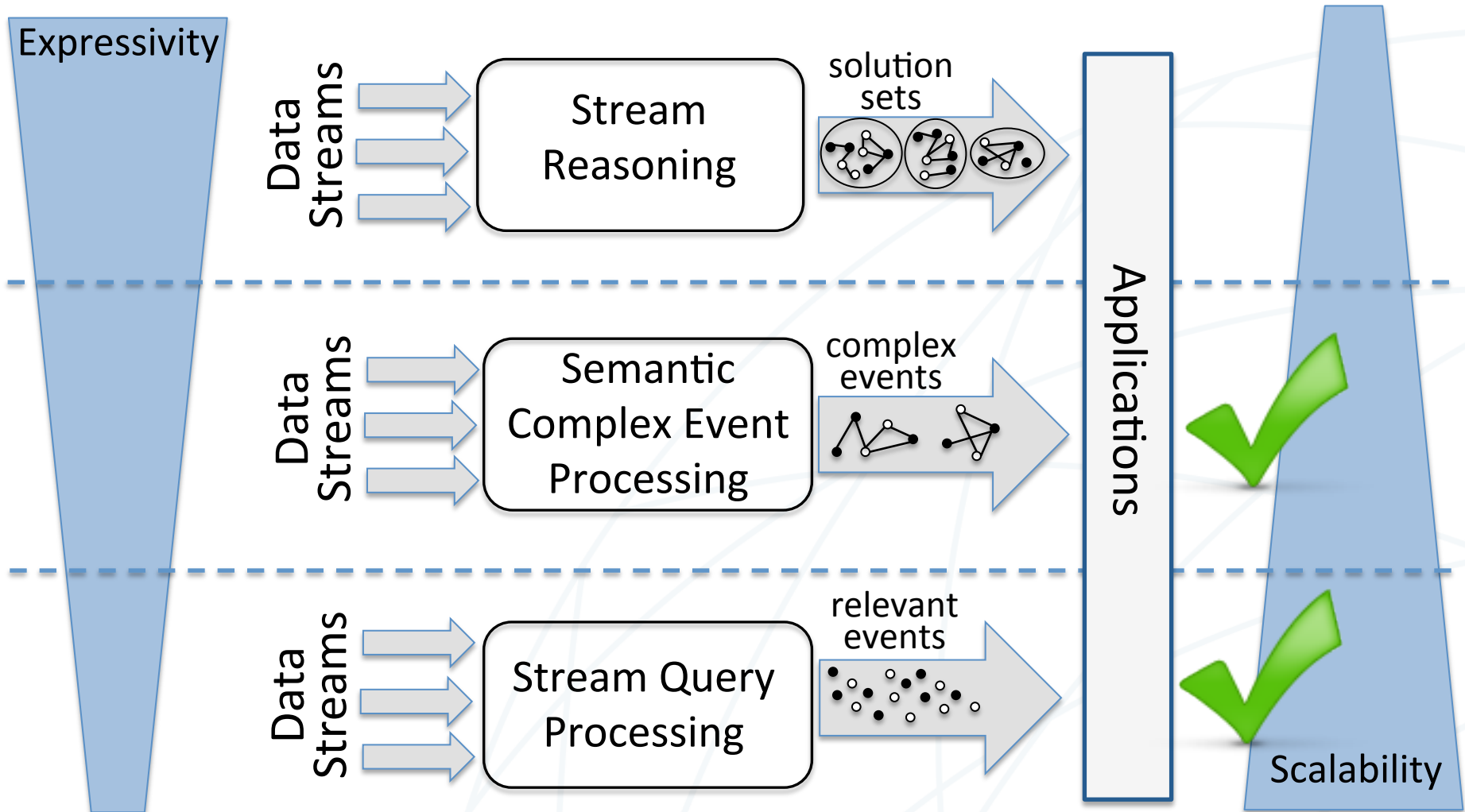


Smart Cities

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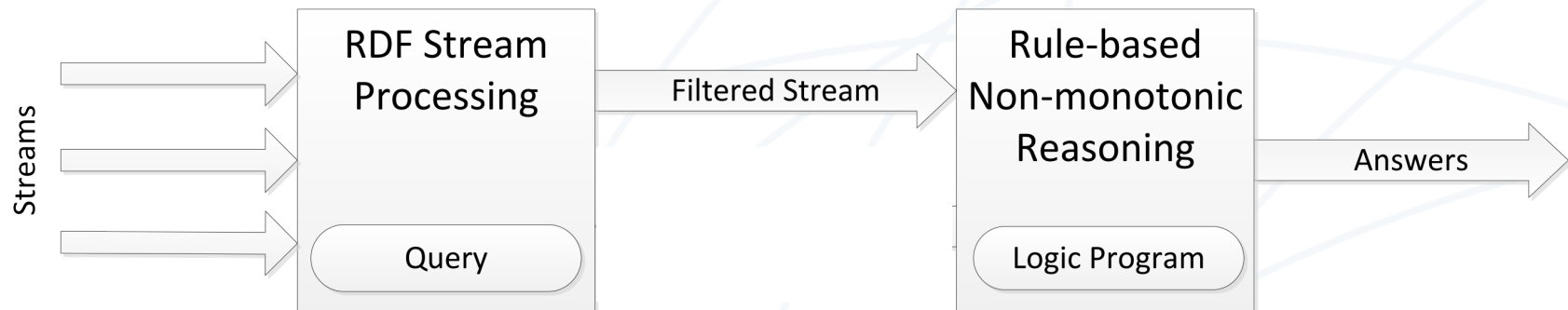


How to leverage the IoT and Semantic Web infrastructure for (efficient) Web Stream Reasoning?



The StreamRule idea

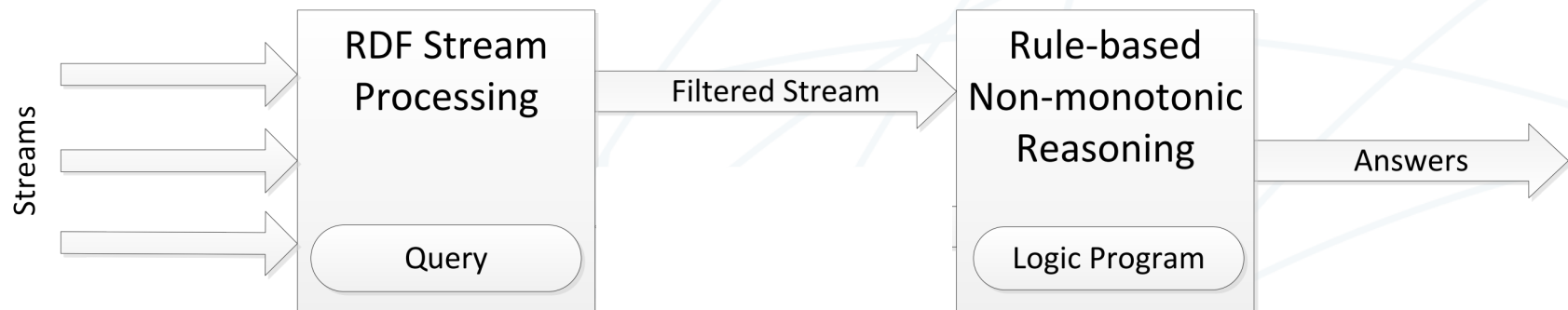
- 2-tier approach: not all data streams are relevant for complex reasoning
- Enrich the ability of complex reasoning over data streams
- Keep the solution scalable
- Leverage existing engines from both stream processing and non-monotonic reasoning research areas



Mileo, A., Abdelrahman, A., Polcarpio, S., Hauswirth, M.: Streamrule: A *nonmonotonic stream reasoning system for the Semantic Web*. In: RR 2013, 247–252

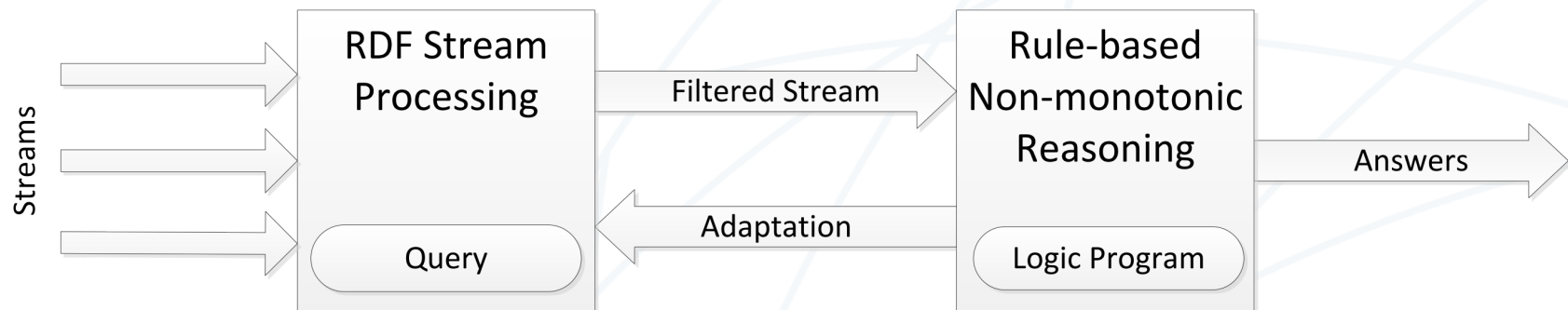
Limitations

- The more expressive the inference task, the longer it takes to perform reasoning
- Bottleneck when results are returned not as fast as the next input arrives



Limitations

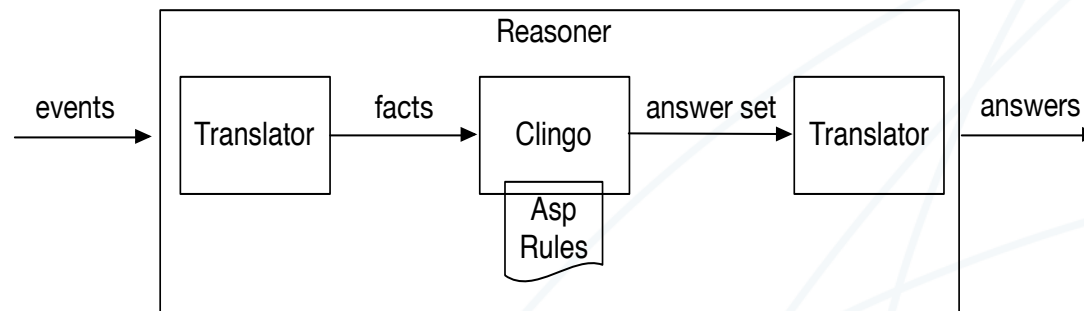
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Adaptation Heuristics: ongoing work

- More than an engineering problem
 - How to model interactions between RSP and ASP components, including different semantics, input split, window-size tuning,...
- Design and runtime features
 - E.g. operational semantics (design) and throughput (runtime)
- Streaming rate and window size: where's the tradeoff?
- Reasoning Complexity: how far can we go? How can we parametrise the complexity to estimate the execution time

Goal



Given a fixed streaming size S with fixed complexity C and unit of time U , find a window size W such that the time required to process S events using windows of size W is less than or equal to one unit of time

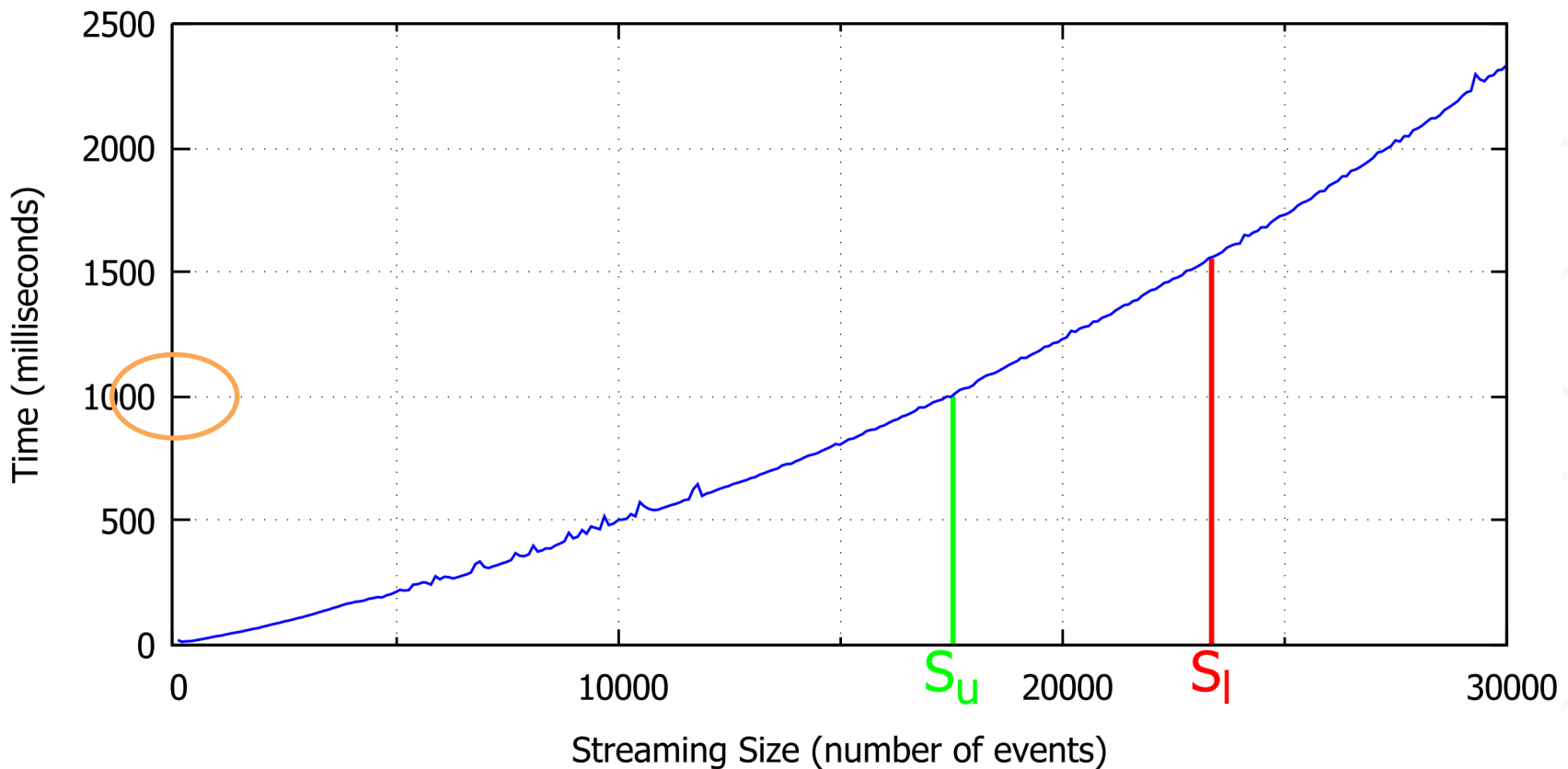
$$T_{\omega}(S, W) \leq U$$

Germano, S., Pham, T.L., Mileo, A.: *Web stream reasoning in practice: on the expressivity vs. scalability tradeoff*. In: Web Reasoning and Rule Systems - 9th International Conference, RR 2015, Berlin, Germany, August 4-5, 2015, Proceedings. (2015) 105–112

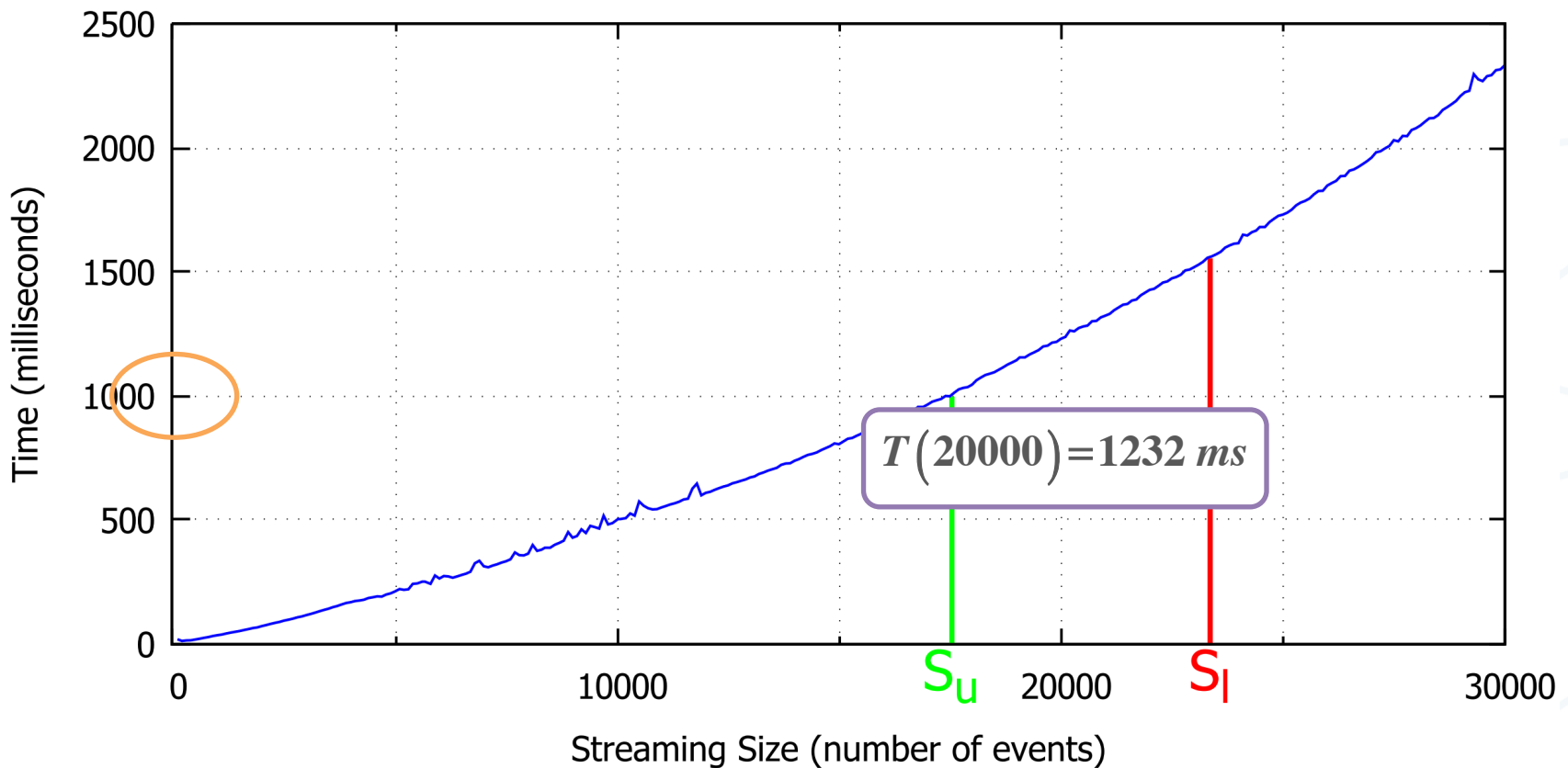
Experimental setup

- Dataset
 - Simulated randomly generated events of the type
event(type, name, value, latitude, longitude)
E.g. event(weather, strong-wind, 2014-11-26T13:00:00, 38.011736, 12.186724)
- Reasoning tasks
 - Ranking event criticality
 - Contextualizing events based on user status
 - Default rule to detect changes in event criticality
- Run
 - Streaming size up to 30000
 - Reasoner triggered 20 times for each S

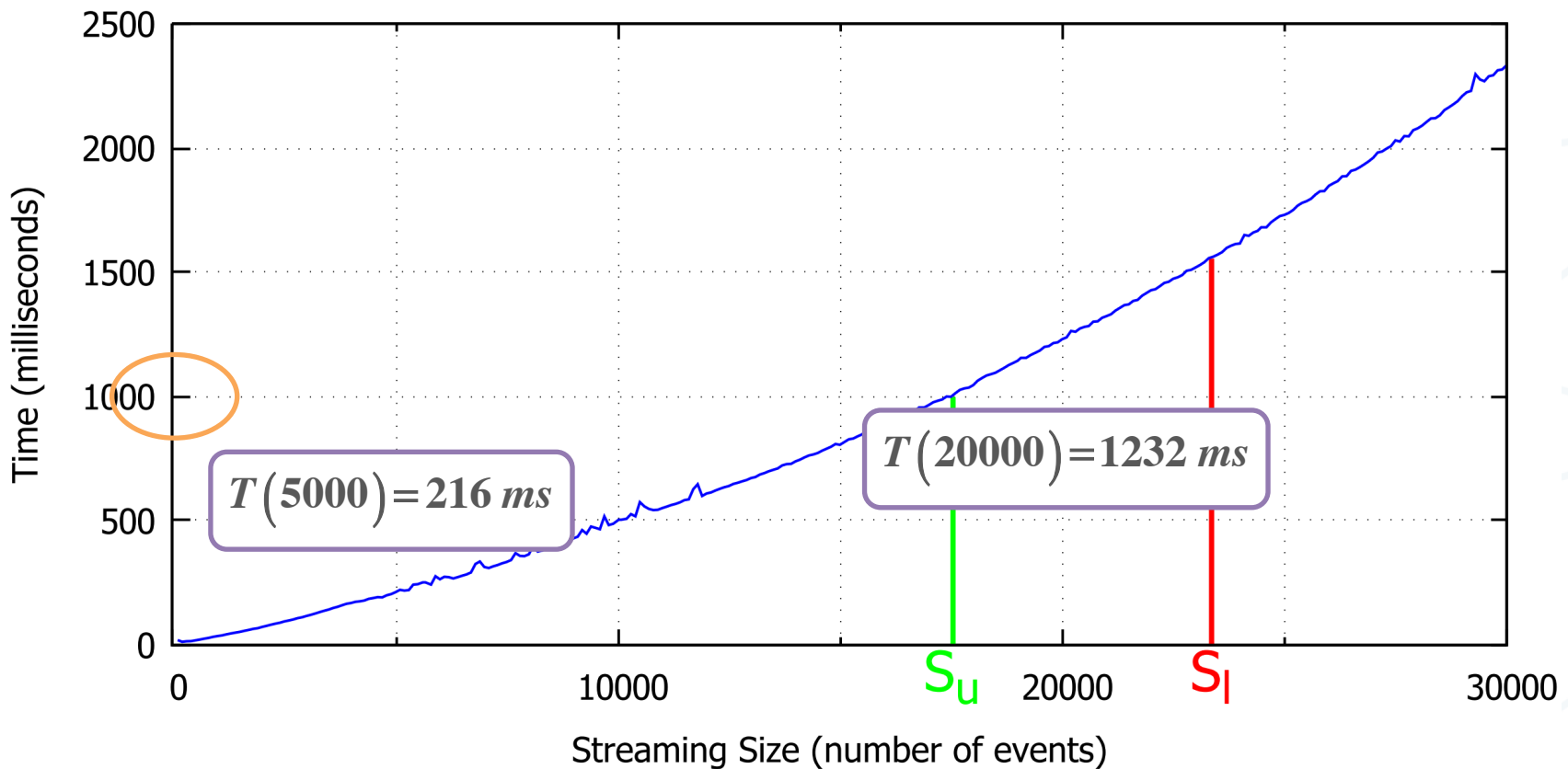
Empirical Results



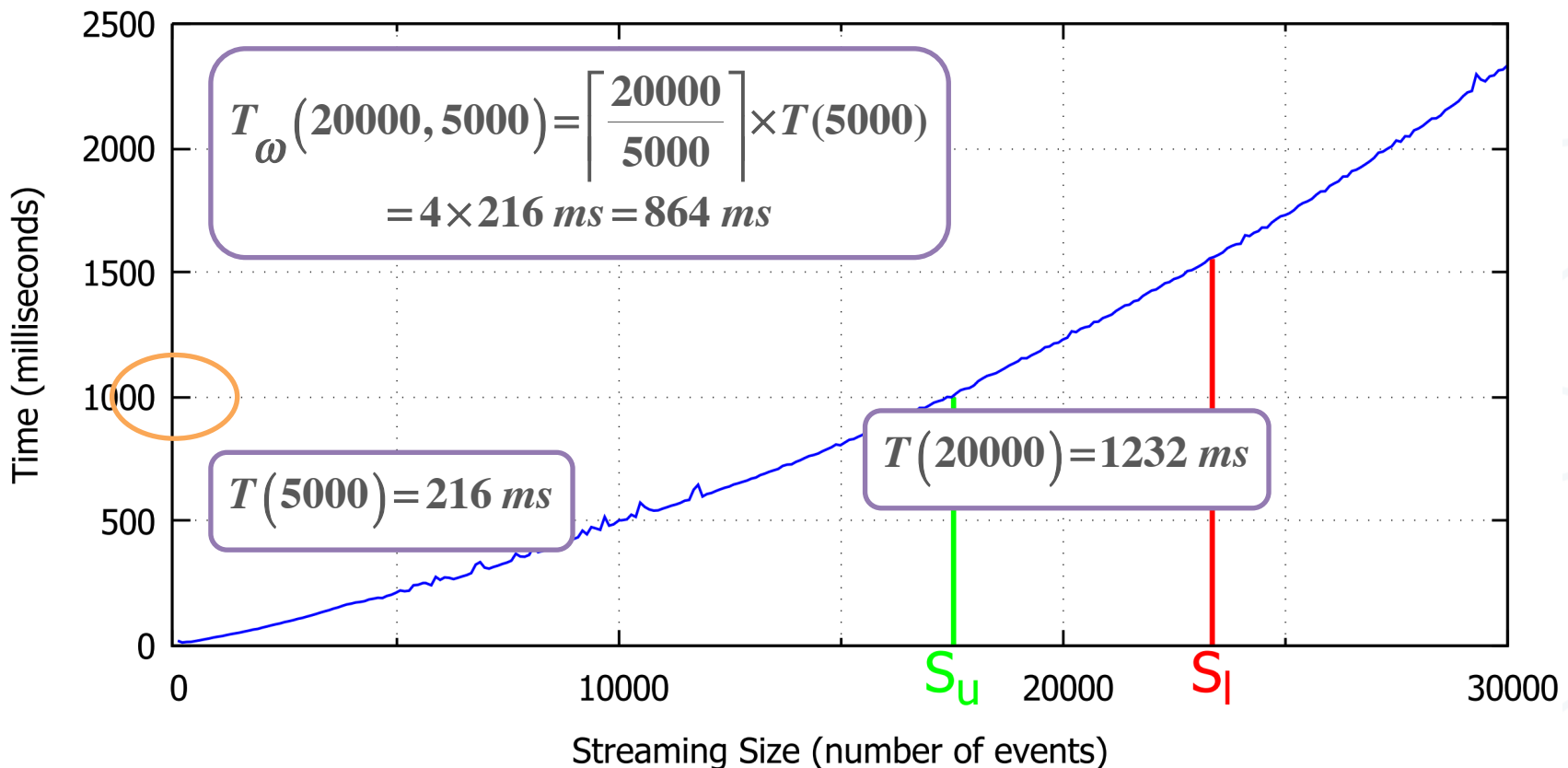
Empirical Results



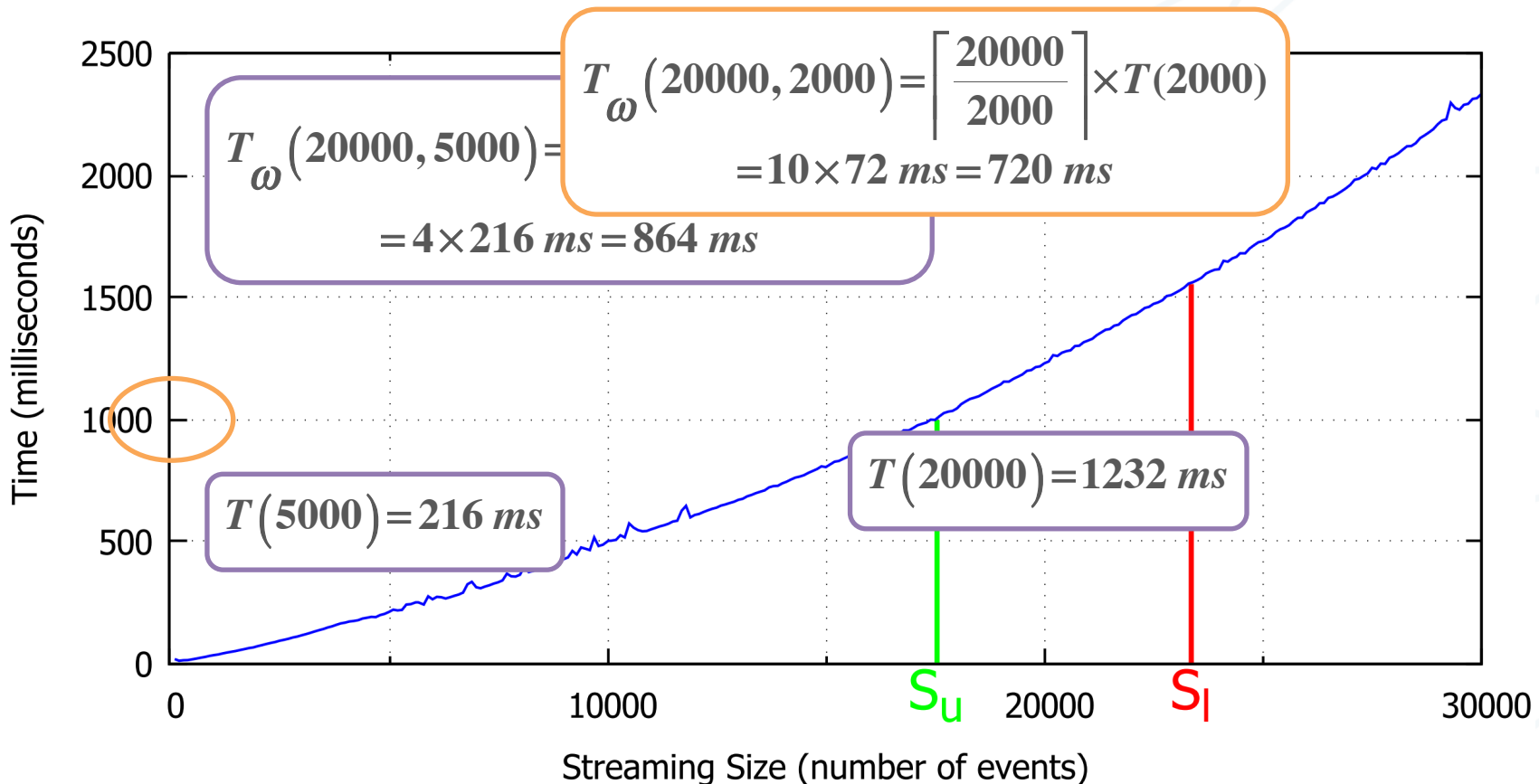
Empirical Results



Empirical Results



Empirical Results



Ongoing work

- Relaxing the independence assumption
 - Extended notion of dependency graph
 - Possibly use duplication
 - Smaller input sets given to the same ASP program
 - Demonstrate correctness of results
- Going parallel
 - Explore parallelism of SPARK for higher scalability
 - Requires to map an ASP program to SPARK jobs
- Correlation between reasoning complexity and execution time



Dealing with Uncertainty and learning relational structures

IoT data are messy: deal with uncertainty

- Expressive inference
 - non-monotonicity, noisy, partial and inconsistent data
- “ease of” declarative logic-based reasoning to model a problem/ domain. Still we need to manage uncertainty and non-monotonicity
- 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

Nickles, M., Mileo, A.: *Web stream reasoning using probabilistic answer set programming*. In: Web Reasoning and Rule Systems (RR) 2014. (2014) 197–205

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What is PrASP then?

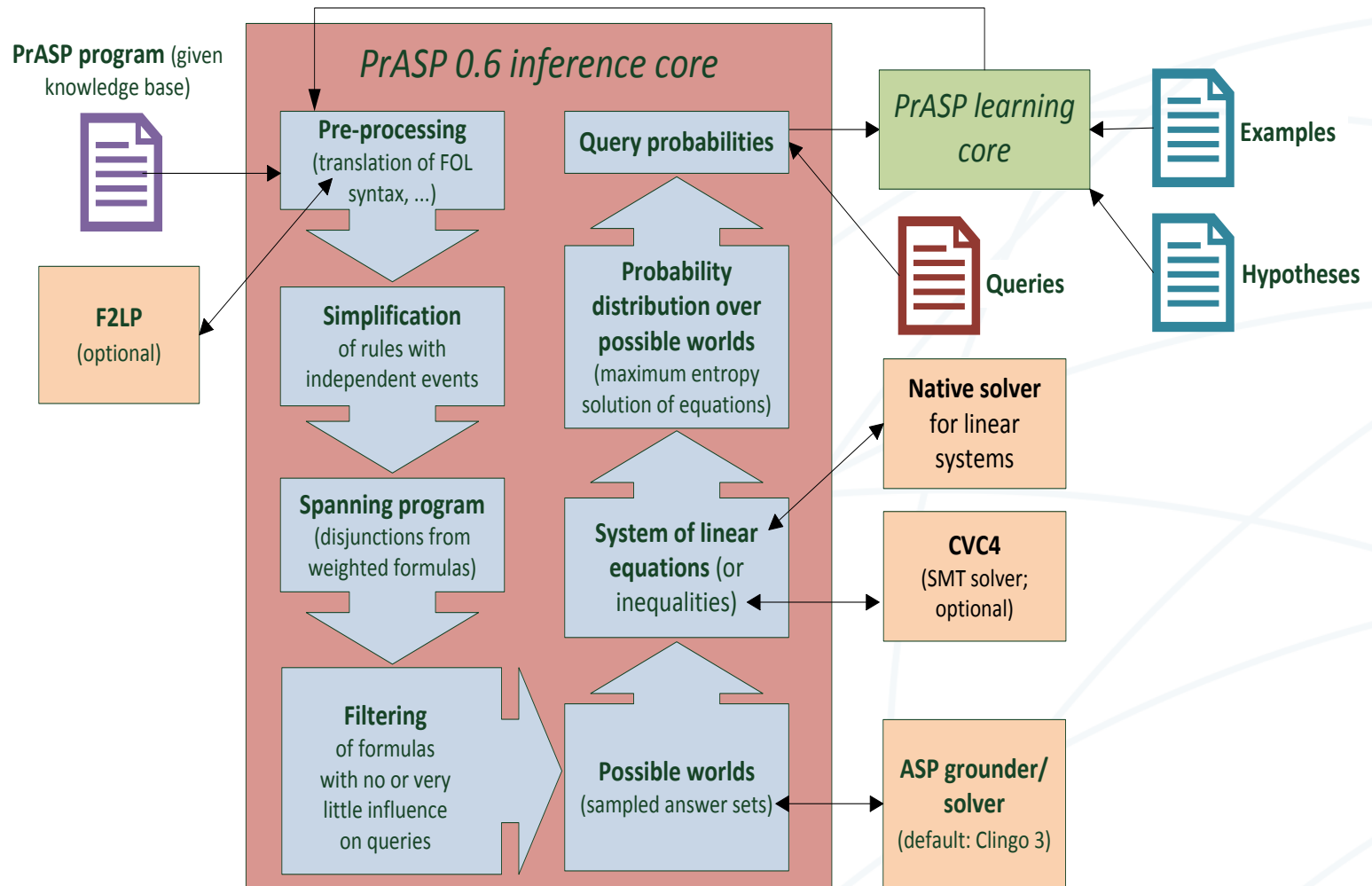
PrASP is...

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

PrASP can...

... represent, use infer and learn probabilistic knowledge

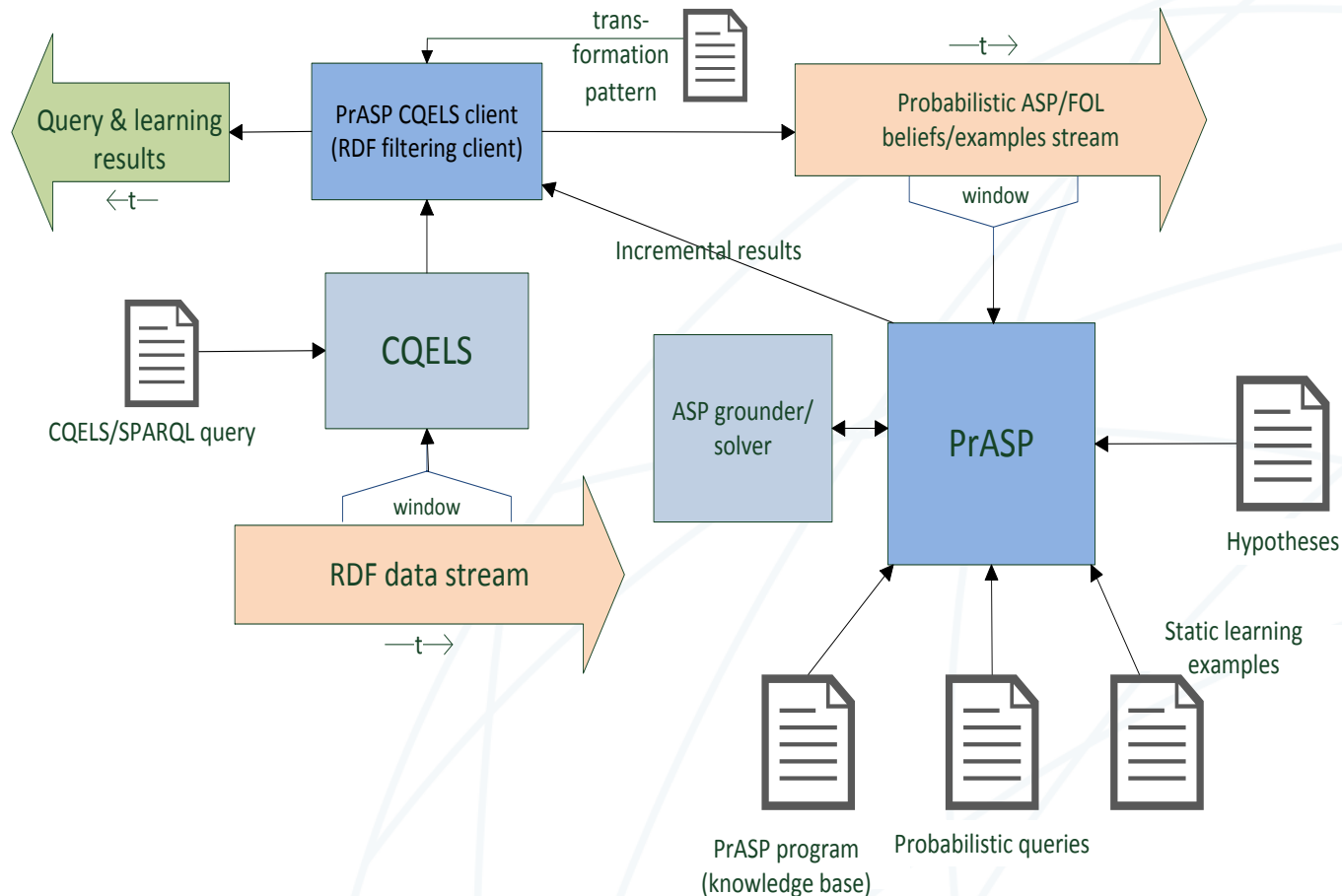
Matthias Nickles, Alessandra Mileo: *A System for Probabilistic Inductive Answer Set Programming*. SUM 2015: 99-105



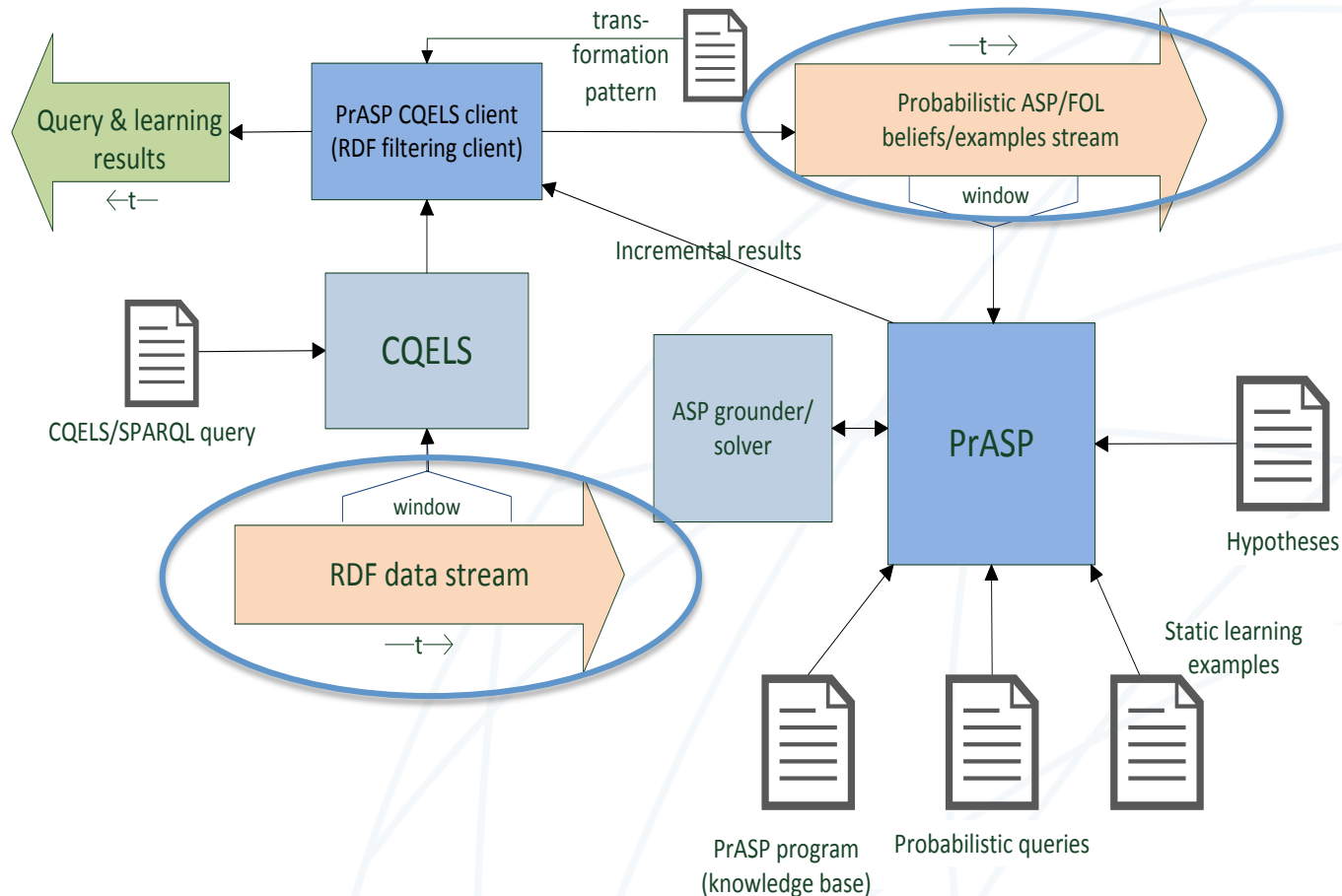
Streaming PrASP

- Streaming **new beliefs** are added incrementally to a loaded PrASP program
- Streaming **new learning examples** are added to the set of learning examples **E**
- Assert/Retract, time decay and sliding windows supported
- Windows prefixes realized by a caching mechanism (no reactive ASP used) for faster processing
- Preprocessing based on RDF query processing over streams (SPARQL 1.1 + streaming operators)

Streaming PrASP framework

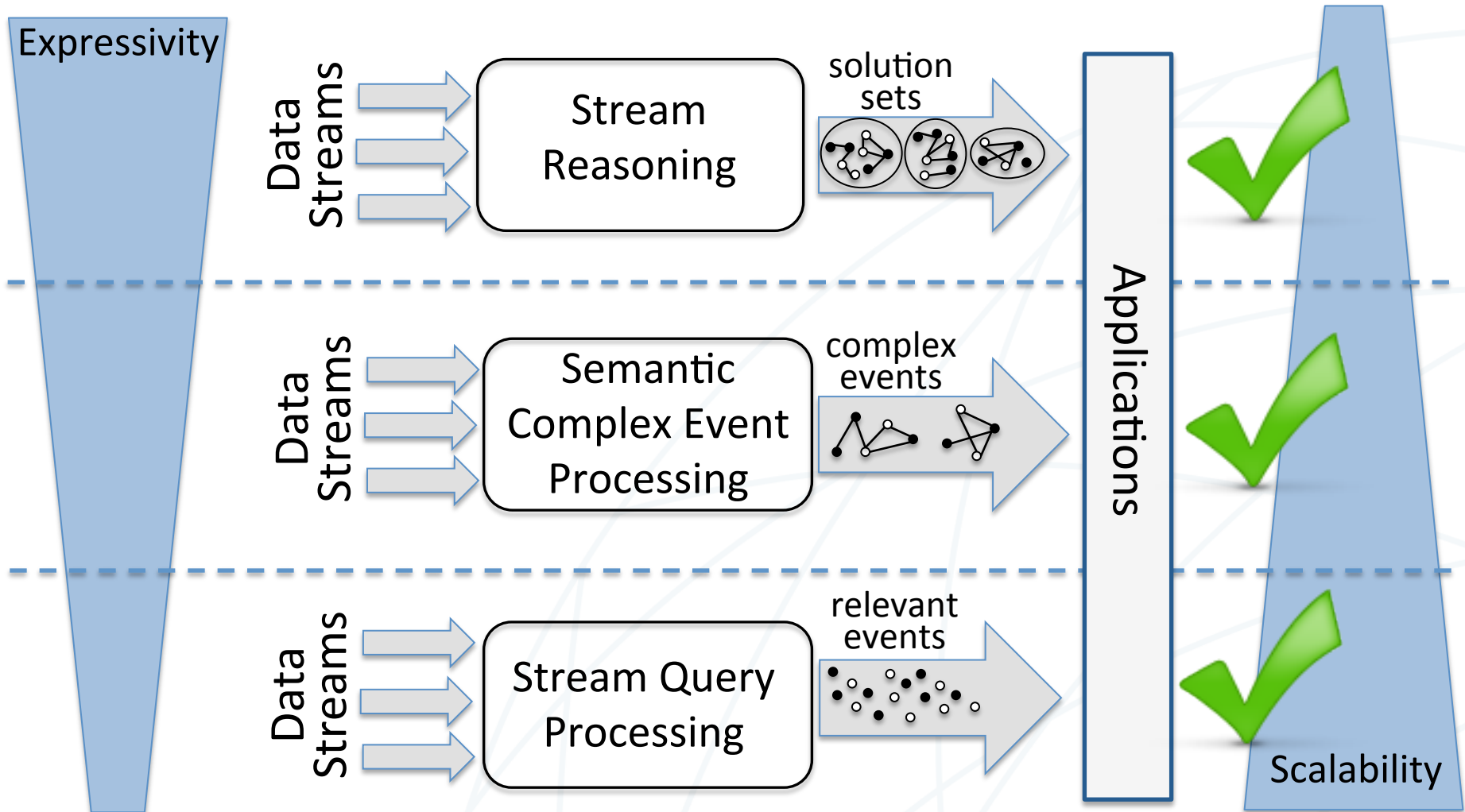


Streaming PrASP framework



Ongoing work

- More experiments on Web Stream Reasoning with PrASP
 - Looking for Usecase Scenarios and DATA to test PrASP
 - Building a set of modules that can be downloaded and used for feedback
- Continuously exploring options for optimization, especially in the learning task
- More ambitious goals
 - Structure Learning
 - Relation between Streaming ASP and PrASP (currently not using Streaming ASP)



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