

Towards Efficient Semantically Enriched Complex Event Processing and Pattern Matching

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OVERVIEW

Introduction

Traditional Vs Real-Time Data Processing

Event Processing Vs Time Axis

Complex Event Processing

SEMANTIC COMPLEX EVENT PROCESSING

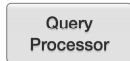
PROPOSED APPROACH

CONCLUSION

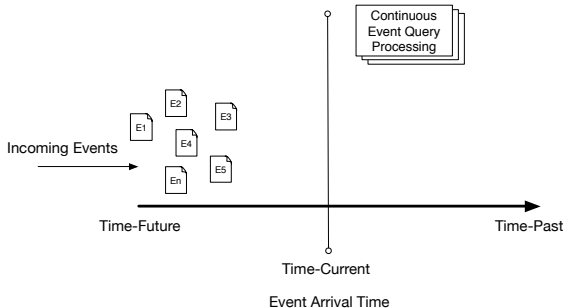
TRADITIONAL VS REAL-TIME DATA PROCESSING

Traditional Data Processing

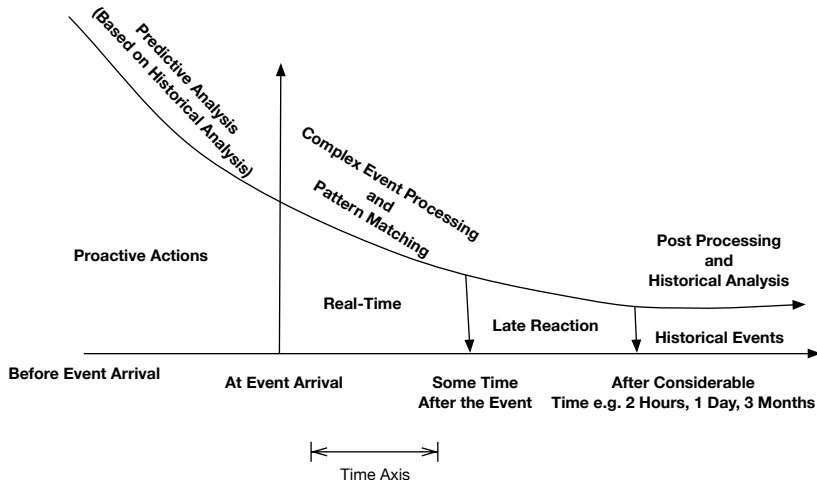
One Shot Database Queries



Real-Time Data Processing

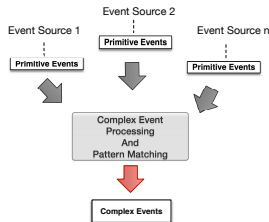


EVENT PROCESSING VS TIME AXIS



COMPLEX EVENT PROCESSING

- ▶ Aggregation, derivation of Primitive Events
- ▶ Occurrence and non-occurrence of certain events
- ▶ Imposing Temporal Constraints (application of certain rules)
- ▶ For Instance
 - ▶ Detection of state changes based on observations (If total consumed electricity > 10MWatt)
 - ▶ Matching sequence of events that describes a scenario (If $A < 10$ AND $B > 40$ OR $B < 80$ AND $C > 90$)



OVERVIEW

Introduction

SEMANTIC COMPLEX EVENT PROCESSING

SCEP

State-of-the-art SCEP

Foundational Challenges for SCEP

PROPOSED APPROACH

CONCLUSION

SCEP

- ▶ Complex Event Processing + Stream Reasoning + Semantic Technologies (rules & ontologies) + Heterogeneous Data Handling?
- ▶ Incoming Stream Reasoning + Background Knowledge
- ▶ Distributed into TWO flavours
 - ▶ Stream Reasoning (Real Time + Background Information + Aggregation through Windows) (C-SPARQL, CQELS....)
 - ▶ Pattern Matching (Sequence, Optional, Negation) (EP-SPARQL)

STATE-OF-THE-ART SCEP

	Continuous Query	Background Knowledge	Data Model	Event Processing (Per Query)	Historical Data (No Dedicated Management)	Underlying Engine	Parallel and Distributed Multi-Query Processing	Temporal Operators (Pattern Matching)
C-SPARQL	✓	✓	Triple Based	Centralised	✗	ESPER	✓	✗
CQLES	✓	✓	Triple Based	Centralised	✗	ESPER	✓	✗
EP-SPARQL	✓	✓	Triple Based	Centralised	✓	ETAILS	✗	✓
Streaming SPARQL	✓	✓	Triple Based	Centralised	✗	DYNAQUEST	✗	✗
TA-SPARQL	✗	✓	Triple Based	Centralised	✓	TUPELO	✗	✗

*Streaming the Web: Reasoning over Dynamic Data: *Alessandro Margara, Jacopo Urbani, Frank van Harmelen, Henri Bal*

STATE-OF-THE-ART SCEP

- ▶ Complex Pattern Matching (Approaches)
 - ▶ Relational Community
 - ▶ NFA, EDG, RETE algorithm, Rule based system
 - ▶ Semantic Web Community
 - ▶ RETE algorithm, Logical Rule based system
 - ▶ How about NFA and EDG in SCEP context?
 - ▶ NFA and EDG are proven to be the most efficient for Pattern Matching in relational community

*Non-Deterministic Finite Automata

*Event Detection Graphs

FOUNDATIONAL CHALLENGES FOR SCEP

- ▶ *Distributed Event Processing (per Query)*: Moving from centralised push based event processing
- ▶ *Distributed Temporal Pattern Matching*: Dedicated language for Pattern Matching (Implementation of Kleene Closure, Negation in distributed manner)
- ▶ *Historical Management of Events*: Storing and Partitioning of events
- ▶ *Defining Event Boundaries*: Triple based to Graph based streaming, preserving graph model to implement Event boundaries
- ▶ *Predictive Event Processing*: A new paradigm for SCEP
- ▶ *Stream Reasoning + CEP*: Combing two different worlds

OVERVIEW

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SEMANTIC COMPLEX EVENT PROCESSING

PROPOSED APPROACH

Event and Stream Data Model

Query Model and Language Specification

CONCLUSION

EVENT AND STREAM DATA MODEL

- ▶ Considering RDF as first class citizen (even for temporal reasoning, instead relying on external engines)
- ▶ Temporally Annotated RDF Named Graph
($\langle NG, [ts, te] \rangle$)

```
<http://www.streaminginfo.com/ElecGen> [st1,et1]
  :gen1 :hasName 'PowGen-Sect1'.
  :gen1 :hasLocation 'St-Etienne'.
  :gen1 :hasCurrentPower '60'.
```

PROPOSED DATA MODEL

- ▶ Data Partitioning ==> Optimises query time
- ▶ Summarisation ==> Merging of similar NG
- ▶ Event Boundaries ==> With NG
- ▶ Access Control ==> With NG
- ▶ Provenance Tracking ==> With NG
- ▶ Fact Assignment ==> With Time Interval

QUERY MODEL AND LANGUAGE SPECIFICATION

- ▶ Former Query Models
 - ▶ Reliance on Triple-Based Data Model
 - ▶ Uses black-box approach (delegation to external Engines)
 - ▶ Overhead in query and data translation
 - ▶ Query Semantics not suitable for distributed processing per query (SPARQL Extensions...)

PROPOSED QUERY MODEL

```

1 PREFIX sm: <http://example.com/sm>
2 PREFIX lv: <http://example.com/lv>
3 Select *
4 Within 12 hours
5 From Stream S1 <http://example.org/streams/
6 powersource> Window From Now 10 mins
7 From Stream S2 <http://example.org/streams/
8 weathersource> Window From Now 10 mins
9 From Stream S3 <http://example.org/streams/
10 elecappliance> Window From Now 10 mins
11 Where {
12 SEQ ( EVENTPATT A, (EVENTPATT B)+, (EVENTPATT C AND
13 EVENTPATT B))
14 DEFINE EVENTPATT A ON S1 { ?event rdfs:subclassof owl:
15 thing; sm:events[ sm:eventType sm:powersource,
16 id ?id; sm:power ?genpow]. GRAPH <http://example.
17 org/streams/sourcelocation> {?id lv:name ?locName}
18 FILTER( ?id = 'gen1', ?pow = '60') }
19
20 DEFINE EVENTPATT B ON S2 { ?event rdfs:subclassof owl:
21 thing; sm:events[ sm:eventType sm:weathersorce; sm
22 :id ?id; sm:temp ?temp; sm:pressure ?pres]. FILTER(
23 ?id = 'Wsource1', ?temp = '20', ?pres='10') }
24
25 DEFINE EVENTPATT C ON S3 { ?event rdfs:subclassof owl:
26 thing; sm:events[ sm:eventType sm:electricappliance
27 ; sm:name ?name; sm:usagepower ?pow; sm:loadclass ?
28 load]. FILTER( ?id = 'heater', ?pow <?genpow ?load=
29 '10-100Watt') }
30 }

```

Annotations:

- Stream Source Selection, Temporal Operators (points to line 5)
- Pattern Duration (points to line 4)
- Temporal Pattern Description (points to line 12)
- KB Integration (points to line 14)

(a)

Sub-Query 1 (Event Pattern A)

```

1 Select *
2 From Stream S1 <http://example.org/streams/powersource>
3 Window From Now 10 mins
4 Where {
5 (?event rdfs:subclassof owl:thing;
6 sm:events[ sm:eventType sm:powersource;
7 sm:id ?id;
8 sm:power ?pow]. )
9 FILTER( ?id = 'gen1', ?pow = '60')
10 }

```

Sub-Query 2 (Event Pattern B)

```

1 Select *
2 From Stream S2 <http://example.org/streams/
3 weathersource> Window From Now 10 mins
4 Where {
5 (?event rdfs:subclassof owl:thing;
6 sm:events[ sm:eventType sm:weathersorce;
7 sm:id ?id;
8 sm:temp ?temp;
9 sm:pressure ?pres].)
10 FILTER( ?id = 'Wsource1', ?temp = '20', ?pres='10')
11 }

```

Sub-Query 3 (Event Pattern C)

```

1 Select *
2 From Stream S3 <http://example.org/streams/
3 elecappliance> Window From Now 10 mins
4 Where {
5 (?event rdfs:subclassof owl:thing; sm:events[ sm:
6 eventType sm:electricappliance; sm:name ?name; sm:
7 usagepower ?pow; sm:loadclass ?load]. )
8 FILTER( ?id = 'heater', ?pow <?genpow ?load=
9 '10-100Watt')
10 }

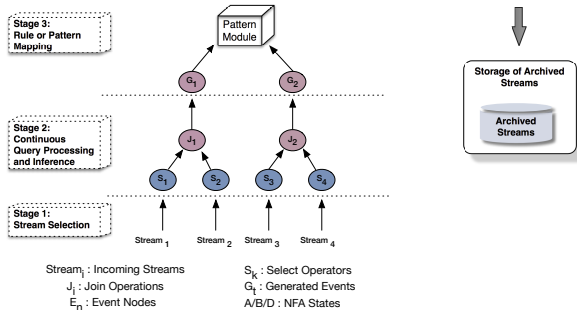
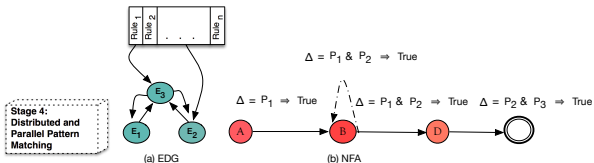
```

Annotations:

- Rewritten Subqueries (Stream Processing) (points to the top of the sub-queries)

(b)

SYSTEM OVERVIEW



PROPOSED MODEL

- ▶ Supports Triple based and NG based data model
- ▶ Offers event source based Filtering
- ▶ Historical management of events through summarisation (Facts Assignments)
- ▶ Provide dedicated design for SCEP (No Data or Query Translation unlike EP-SPARQL and other systems)
- ▶ Distributed and parallel sub-query processing with query rewriting

PROPOSED MODEL

- ▶ Integrating stream processing and CEP
- ▶ Offers various new operators including, Sequencing, Kleene Closure and Negation for RDF Graph patterns
- ▶ Allows NFA and EDG to be used in the context of SCEP through query rewriting (from Rule based to State based system)

OVERVIEW

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PROPOSED APPROACH

CONCLUSION

CONCLUSION

- ▶ Annotated RDF NG enables temporal reasoning at RDF level
- ▶ Our data/query model and query rewriting allows
 - ▶ Annotated NG based event data model
 - ▶ Historical management of stream data
 - ▶ Integration of various new operators for RDF Graphs (Kleene Closure, Negation)
 - ▶ Integration of NFA and EDG in the context of SCEP
 - ▶ Parallel and distributed event processing (per query)

Questions?



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