Towards Comparing RDF Stream Processing Semantics

Minh Dao-Tran Harald Beck Thomas Eiter

1st Workshop on High-Level Declarative Stream Processing

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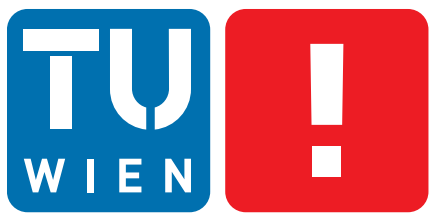

FAKULTÄT
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Faculty of Informatics

COMMUNITY & BUSINESS GROUPS

RDF STREAM PROCESSING COMMUNITY GROUP

The mission of the RDF Stream Processing Community Group (RSP) is to define a common model for producing, transmitting and continuously querying RDF Streams. This includes extensions to both RDF and SPARQL for representing streaming data, as well as their semantics. Moreover this work envisions an ecosystem of streaming and static RDF data sources whose data can be combined through standard models, languages and protocols. Complementary to related work in the area of databases, this Community Group looks at the dynamic properties of graph-based data, i.e., graphs that are produced over time and which may change their shape and data over time.

Recent Developments in RSP

RSP Query Engines:

- C-SPARQL [Barbieri *et al.*, 2010]
- CQELS [Phuoc *et al.*, 2011]
- SPARQL_{Stream} [Calbimonte *et al.*, 2010]
- ...

Benchmarking systems:

- LSBench [Phuoc *et al.*, 2012]
- SRBench [Zhang *et al.*, 2012]
- CSRBench [Dell'Aglio *et al.*, 2013]
- YABench [Kolchin and Wetz, 2015]

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All comparison at the operational level!

Comparison at the Semantics Level?

Outline

Running scenario

RDF & RDF Stream Processing (RSP)

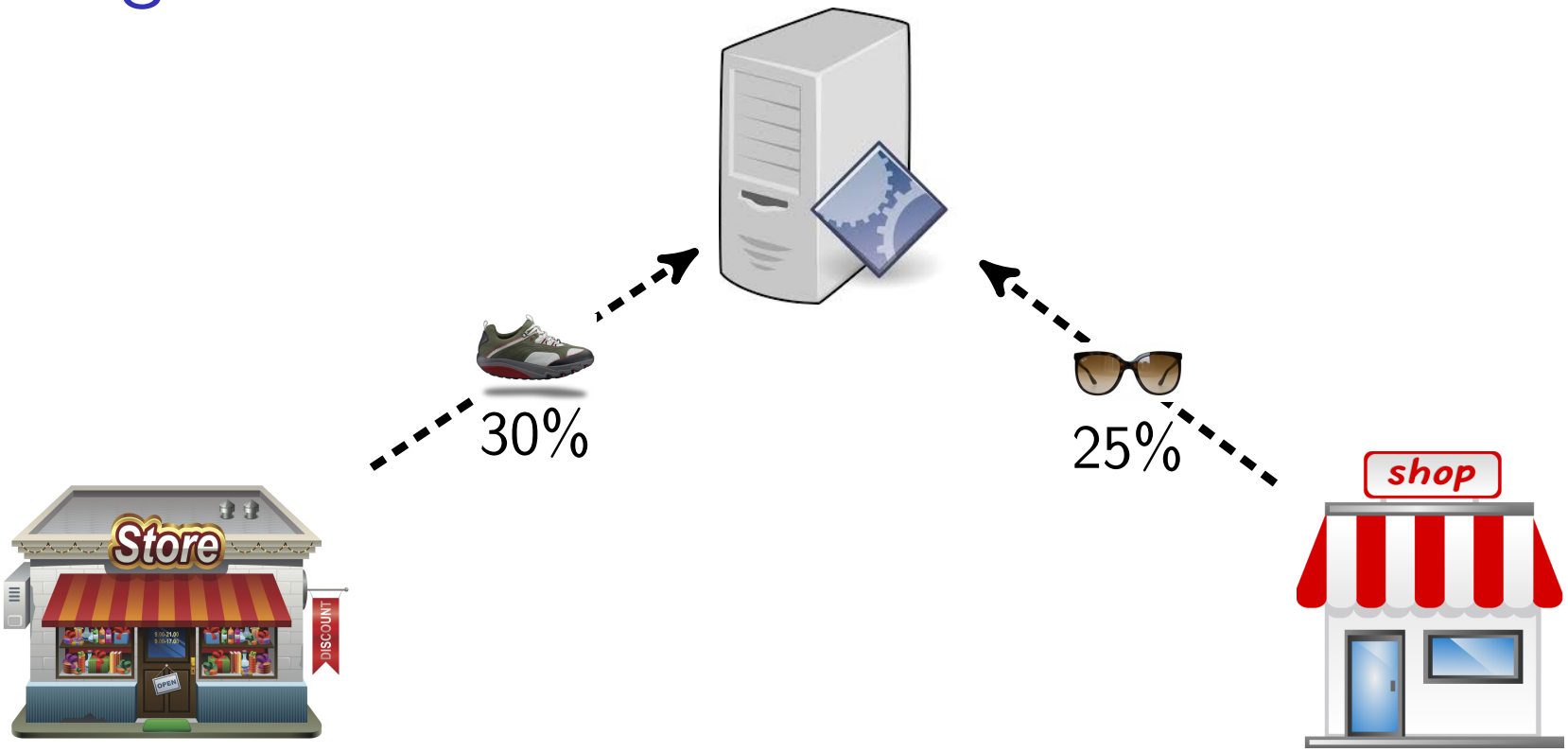
A **L**ogic for **A**nalyzing **R**easoning over **S**treams (LARS [Beck *et al.*, 2015])

Capturing RSP with LARS

Running Scenario

Running Scenario

Running Scenario



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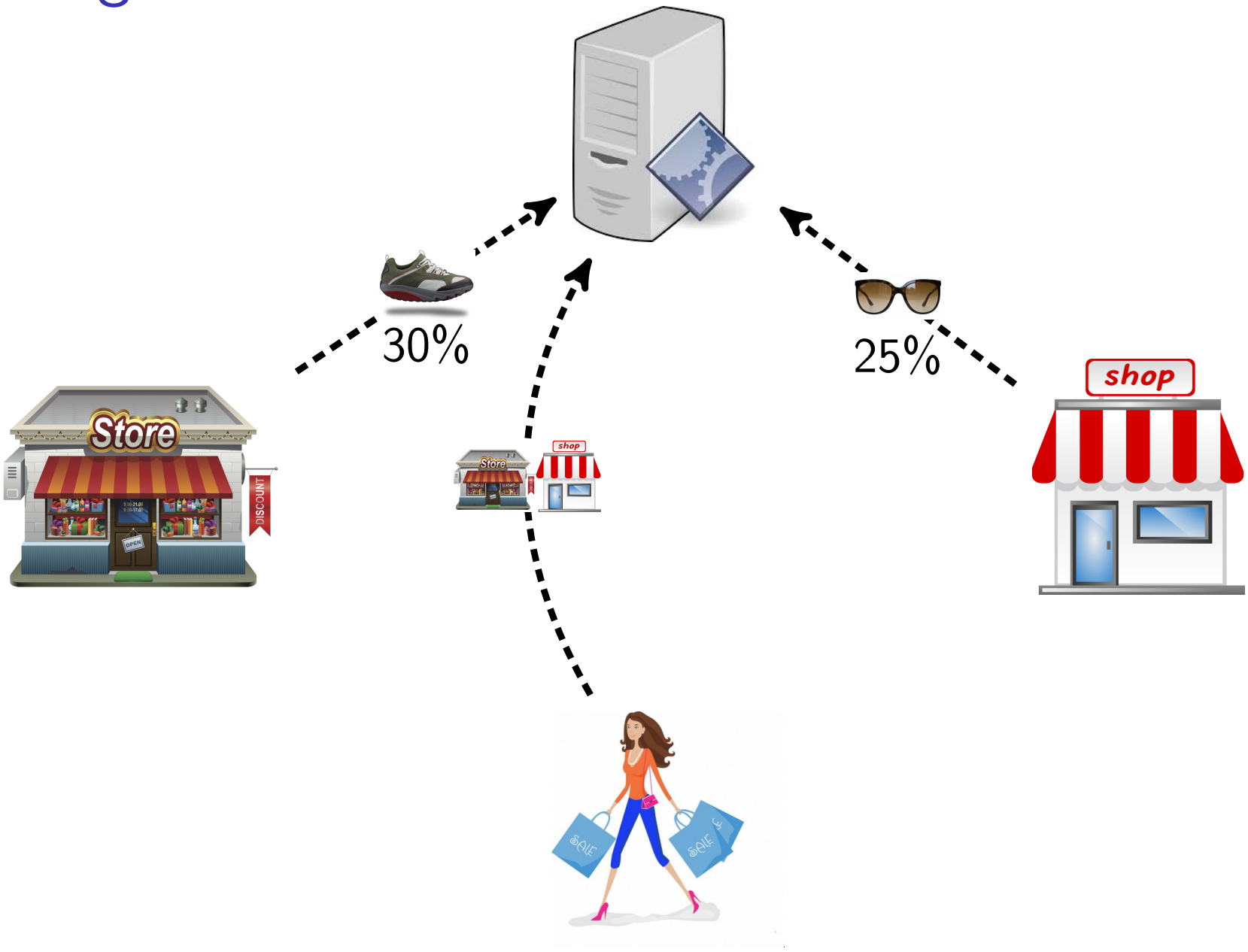

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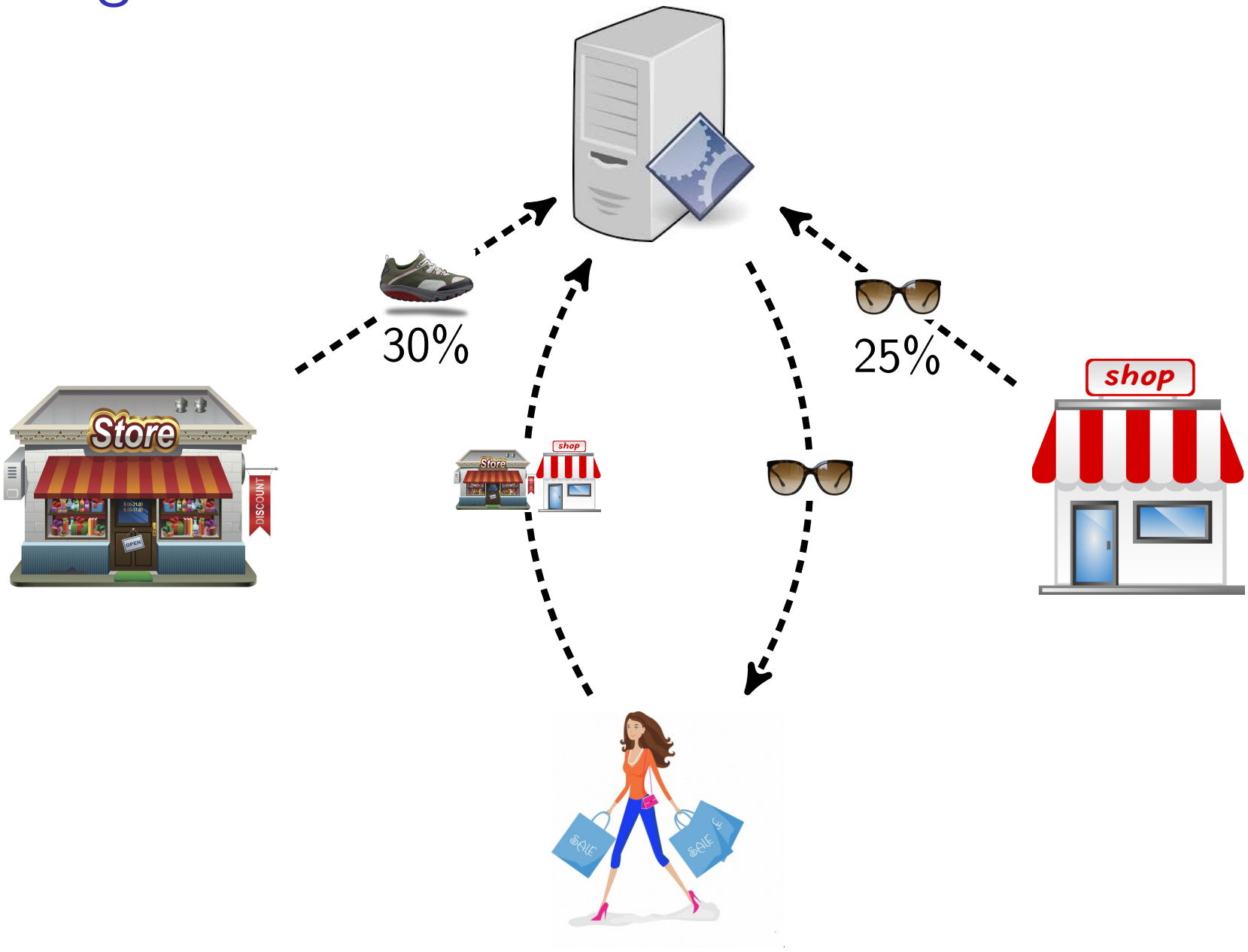
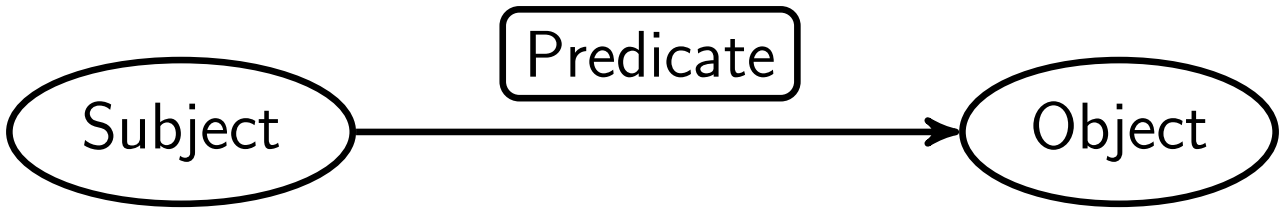


RDF

RDF



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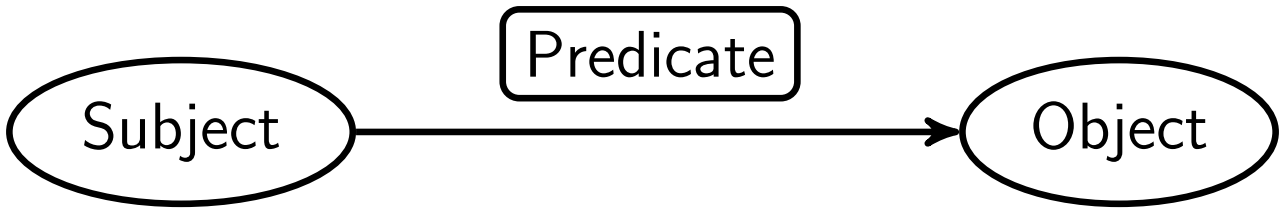

$$G = \{ :\text{“mbt”} \ :\texttt{g\_classify} \ :1. \quad :\text{“rayban”} \ :\texttt{g\_classify} \ :0. \ \ldots \}$$

$$g_1 = \{:\texttt{a} \ :\texttt{offers} \ :\texttt{c}_1. \quad :\texttt{c}_1 \ :\texttt{on} \ :\text{“mbt”}. \quad :\texttt{c}_1 \ :\texttt{reduce} \ :30.\}$$

$$g_2 = \{:\texttt{b} \ :\texttt{offers} \ :\texttt{c}_2. \quad :\texttt{c}_2 \ :\texttt{on} \ :\text{“rayban”}. \quad :\texttt{c}_2 \ :\texttt{reduce} \ :25.\}$$

$$g_3 = \{:\text{“claire”} \ :\texttt{isNear} \ :\texttt{a}. \quad :\text{“claire”} \ :\texttt{isNear} \ :\texttt{b}.\}$$

SPARQL

```
SELECT

FROM



WHERE
```

SPARQL

```
SELECT ?shop ?product ?percent
FROM



WHERE
```

SPARQL

```
SELECT ?shop ?product ?percent
FROM   <http://products>
       <http://coupons_snapshot>
       <http://locations_snapshot>
WHERE
```

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SELECT ?shop ?product ?percent
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```

$\mu = \{?\text{shop} \mapsto \text{a}, ?\text{product} \mapsto \text{“rayban”}, ?\text{percent} \mapsto 25\}$

RDF Stream Processing Queries in C-SPARQL

```
SELECT ?shop ?product ?percent
FROM   <http://products>
       <http://coupons_stream>   [RANGE 30m]
       <http://locations_stream> [RANGE 5m]
WHERE  {?shop    :offers     ?coupon.
        ?coupon  :reduce     ?percent.
        ?coupon  :on         ?product.
        ?user    :isNear      ?shop.
        ?product :g_classify ?gender.
FILTER (?percent >= 20 && ?gender != 1)}
```

RDF Stream Processing Queries in CQELS

```
SELECT ?shop ?product ?percent
FROM   <http://products>
WHERE {
    <http://coupons_stream> [RANGE 30m] {
        ?shop    :offers     ?coupon.
        ?coupon  :reduce     ?percent.
        ?coupon  :on         ?product.}
    <http://locations_stream> [RANGE 5m] {
        ?user    :isNear      ?shop.}
        ?product :g_classify ?gender.
FILTER (?percent >= 20 && ?gender != 1)}
```

Key Differences between C-SPARQL and CQELS

	C-SPARQL	CQELS
create snapshot	merge patterns on input streams into the default graph	apply patterns on input streams
execution mode	pull-based	push-based

Modeling RSP Queries $Q = (V, P, \mathcal{D}, \mathcal{S})$

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$$
\begin{aligned}
V &= \{\texttt{?shop}, \texttt{?pname}, \texttt{?percent}\} \\
P &= (P_1 \cup P_2 \cup P_3) \text{ FILTER } R \\
P_1 &= \left\{ \begin{array}{lll} \texttt{?shop} & \texttt{:offers} & \texttt{?coupon.} \\ \texttt{?coupon} & \texttt{:on} & \texttt{?product.} \\ \texttt{?coupon} & \texttt{:reduce} & \texttt{?percent.} \end{array} \right\} \\
P_2 &= \{\ \texttt{?user} \quad \texttt{:isNear} \quad \texttt{?shop.}\ \} \\
P_3 &= \{\ \texttt{?product} \quad \texttt{:g\_classify} \quad \texttt{?gender.}\ \}
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R &= (\texttt{?percent} \geq 20 \;\&\&\; \texttt{?gender} \neq 1)
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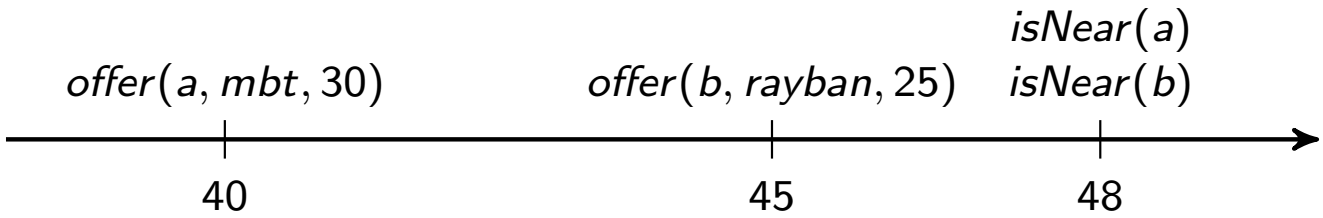
R &= (\texttt{?percent} \geq 20\ \texttt{\&\&}\ \texttt{?gender} \neq 1) \\
\mathcal{D} &= \{\texttt{<products>}\} \\
\mathcal{S} &= \left\{ \begin{array}{l} (\texttt{<http://coupons>}, \texttt{[RANGE 30m]}, P_1), \\ (\texttt{<http://locations>}, \texttt{[RANGE 5m]}, P_2) \end{array} \right\}.
\end{aligned}
$$

LARS in a Nutshell: Stream Representation

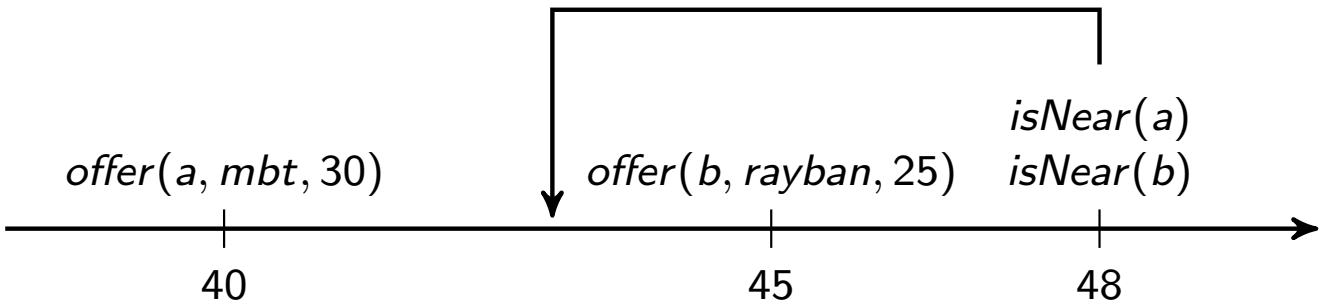
$S = (T, \upsilon)$



$T = [0, 50]$

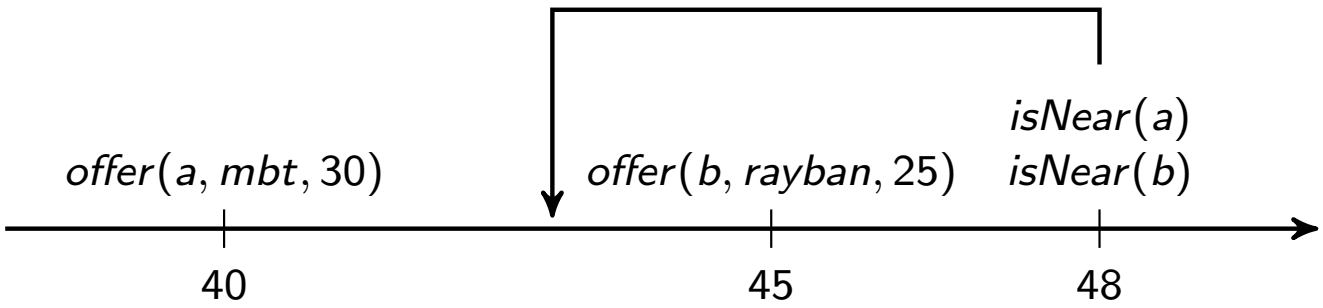
$$\upsilon = \left\{ \begin{array}{l} 40 \mapsto \{offer(a, mbt, 30)\}, 45 \mapsto \{offer(b, rayban, 25)\} \\ 48 \mapsto \{isNear(a), isNear(b)\} \end{array} \right\}$$

LARS in a Nutshell: Window functions



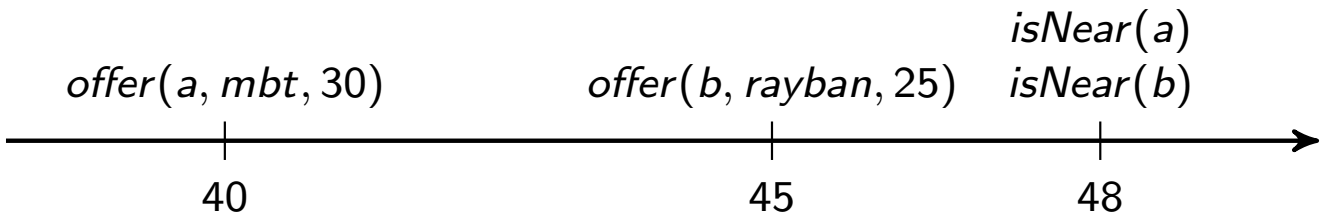
$$S' = w_\iota(S, t, \vec{x})$$

LARS in a Nutshell: Window functions



$$S' = w(S, 48, (5, 0, 1)) = ([43, 48], \left\{ \begin{array}{l} 45 \mapsto \{offer(b, rayban, 25)\} \\ 48 \mapsto \{isNear(a), isNear(b)\} \end{array} \right\})$$

LARS in a Nutshell: LARS formulas



$\alpha ::=$

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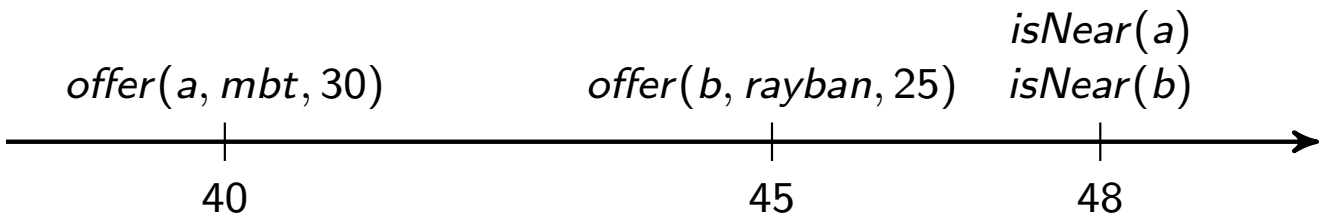

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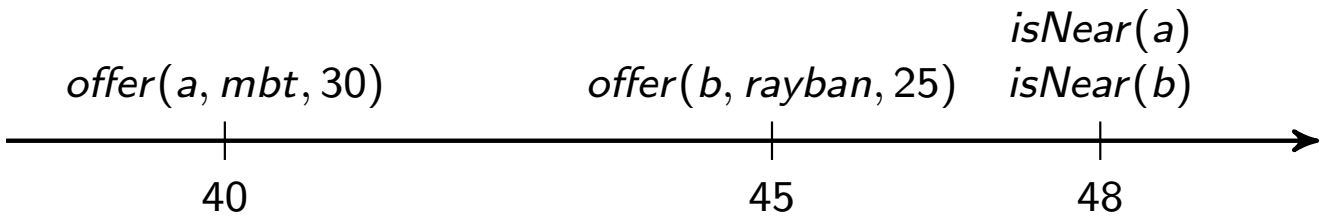

$$\alpha ::= a \mid \neg\alpha \mid \alpha \wedge \alpha \mid \alpha \vee \alpha \mid \alpha \rightarrow \alpha \mid \Diamond\alpha \mid \Box\alpha \mid @_t\alpha$$

- various ways for time references

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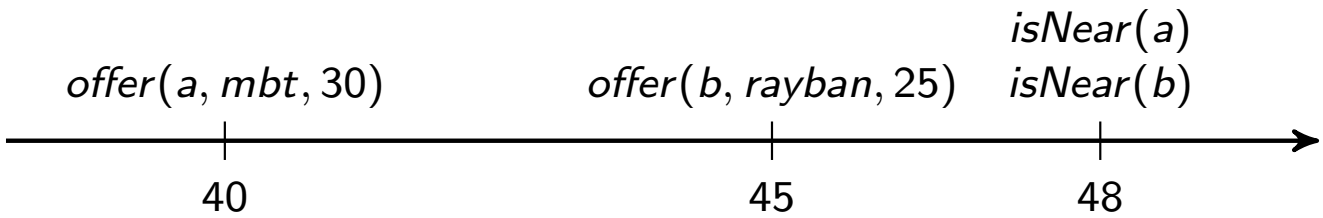

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- various ways for time references
- window operators with possibility to nest

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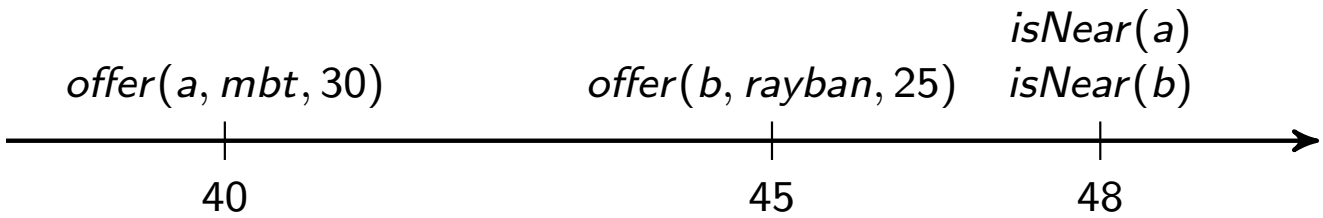

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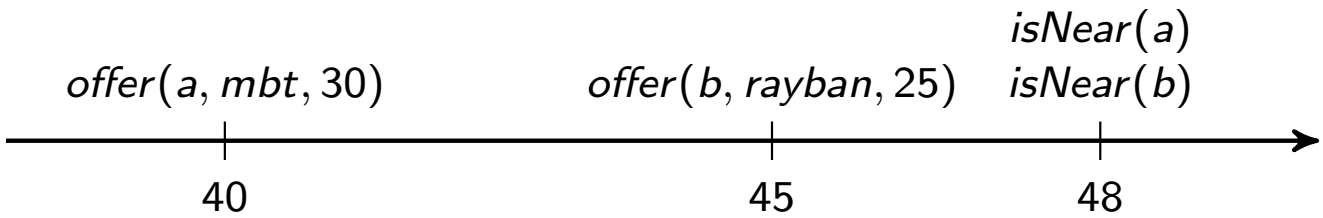

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- various ways for time references
- window operators with possibility to nest
- $\boxplus^{10}\Diamond offer(Sh, Pr, Pe)$
- $\boxplus^{5}\Box isNear(a)$

LARS in a Nutshell: LARS rules/programs

$$\alpha \leftarrow \beta_1, \ldots, \beta_j, \text{not } \beta_{j+1}, \ldots, \text{not } \beta_n.$$

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LARS in a Nutshell: Semantics

- extend Answer Set Programming semantics
- answer streams: input stream + intentional facts + satisfaction + minimality

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$I = ([0, 50], \upsilon_I)$ where

$$\upsilon_I = \left\{ \begin{array}{l} 40 \mapsto \{\mathit{offer}(a, \mathit{rayban}, 30)\} \\ 45 \mapsto \{\mathit{offer}(b, \mathit{rayban}, 25)\} \\ 48 \mapsto \{\mathit{isNear}(a), \mathit{isNear}(b), \mathit{ans}(b, \mathit{rayban}, 25)\} \end{array} \right\}$$

LARS to Analyze RSP Queries

Translations from RSP queries to LARS programs:

- offer the correspondence between query answers and answer streams
- capture differences in RSP queries:
  - execution modes
  - creating snapshots

Translations at a Glance

Capture push-, pull-based execution modes:

$$
\begin{aligned}
\mathit{trigger}(r) &= H(r) \leftarrow B(r), \texttt{trig}. \\
\mathit{trigger}(P) &= \{\mathit{trigger}(r) \mid r \in P \wedge B(r) \neq \emptyset\} \\
\rhd(P) &= \mathit{trigger}(P) \cup \{\texttt{trig} \leftarrow \boxplus_{\mathit{NOW}}\, p(\vec{X}). \mid p \in \mathcal{A}^{\mathcal{I}}\} \\
\lhd(P, U) &= \mathit{trigger}(P) \cup \{\texttt{trig} \leftarrow \boxplus_{\mathit{NOW}} @_T \mathit{true}, T \,\%\, U = 0.\}
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Capture SPARQL operators: extend a translation from SPARQL to Datalog [Polleres, 2007]

Conclusions and Future Work

- A unified query model for RSP
- Translations from RSP queries to LARS programs
- Next:
  - Comparing RSP semantics by comparing translated LARS programs
  - Equivalance of LARS programs

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