

Ontology-based Access to Temporal Data

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Challenges in the Big Data era

40 ZETTABYTES

[43 TRILLION GIGABYTES]
of data will be created by 2020, an increase of 300 times from 2005

6 BILLION PEOPLE
have cell phones



Volume SCALE OF DATA

It's estimated that
2.5 QUINTILLION BYTES

[2.3 TRILLION GIGABYTES]
of data are created each day

Most companies in the U.S. have at least
100 TERABYTES
[100,000 GIGABYTES]
of data stored

The New York Stock Exchange captures

1 TB OF TRADE INFORMATION
during each trading session



By 2016, it is projected there will be

18.9 BILLION NETWORK CONNECTIONS

— almost 2.5 connections per person on earth



Velocity ANALYSIS OF STREAMING DATA

Modern cars have close to
100 SENSORS
that monitor items such as fuel level and tire pressure



The FOUR V's of Big Data

From traffic patterns and music downloads to web history and medical records, data is recorded, stored, and analyzed to enable the technology and services that the world relies on every day. But what exactly is big data, and how can these massive amounts of data be used?

As a leader in the sector, IBM data scientists break big data into four dimensions: **Volume, Velocity, Variety and Veracity**

Depending on the industry and organization, big data encompasses information from multiple internal and external sources such as transactions, social media, enterprise content, sensors and mobile devices. Companies can leverage data to adapt their products and services to better meet customer needs, optimize operations and infrastructure, and find new sources of revenue.

By 2015
4.4 MILLION IT JOBS
will be created globally to support big data, with 1.9 million in the United States



As of 2011, the global size of data in healthcare was estimated to be

150 EXABYTES
[161 BILLION GIGABYTES]



30 BILLION PIECES OF CONTENT
are shared on Facebook every month



Variety DIFFERENT FORMS OF DATA

By 2014, it's anticipated there will be

420 MILLION WEARABLE, WIRELESS HEALTH MONITORS

4 BILLION+ HOURS OF VIDEO
are watched on YouTube each month



400 MILLION TWEETS
are sent per day by about 200 million monthly active users



1 IN 3 BUSINESS LEADERS

don't trust the information they use to make decisions



in one survey were unsure of how much of their data was inaccurate

Veracity UNCERTAINTY OF DATA

Poor data quality costs the US economy around

\$3.1 TRILLION A YEAR

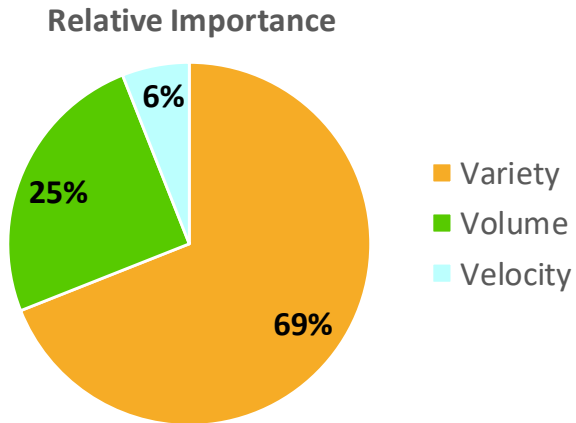


unibz

IBM

Variety, not volume, is driving Big Data initiatives

MIT Sloan Management Review (28 March 2016)



<http://sloanreview.mit.edu/article/variety-not-volume-is-driving-big-data-initiatives/>

How much time is spent searching for the right data?



Important problem: searching for data and establishing its quality

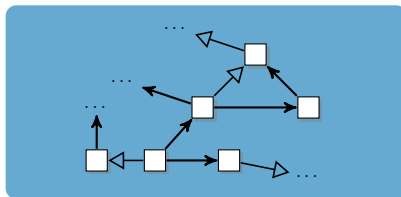
Example: in oil&gas, engineers spend 30–70% of their time on this
(Crompton, 2008)

Solution: Ontology-based data access (OBDA)



Data Sources \mathcal{S}
*autonomous and
heterogeneous*

Solution: Ontology-based data access (OBDA)



Ontology \mathcal{O}

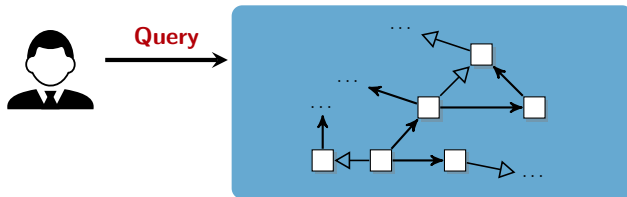
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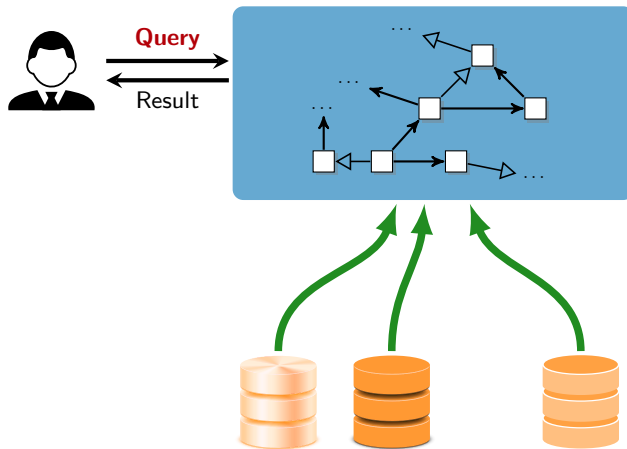


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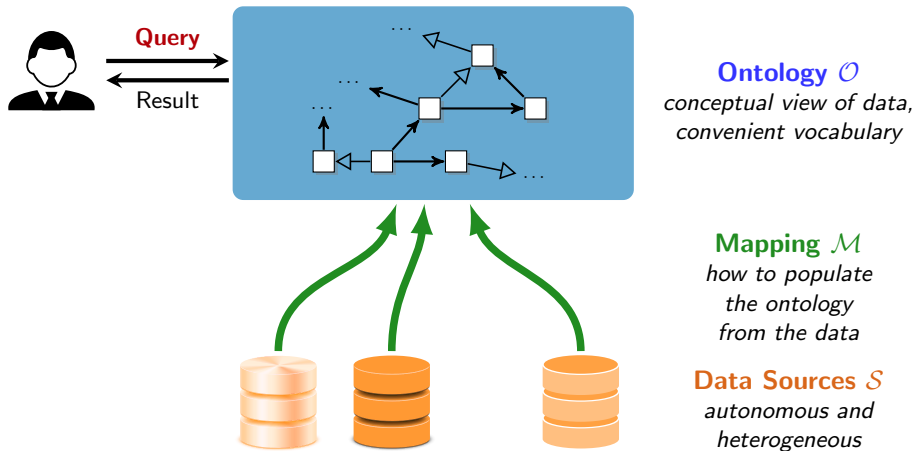


Ontology \mathcal{O}
*conceptual view of data,
convenient vocabulary*

Mapping \mathcal{M}
*how to populate
the ontology
from the data*

Data Sources \mathcal{S}
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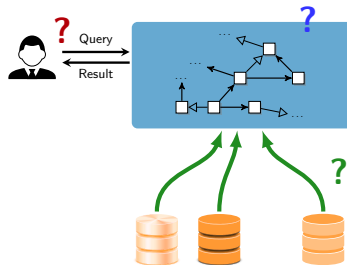


Reduces the time for translating information needs into queries from days to minutes.

OBDA framework – Which languages to use?

The choice of the right languages needs to take into account the tradeoff between expressive power and efficiency of query answering.

Note: We are in a setting where data plays a prominent role, so **efficiency with respect to the data** is the key factor.



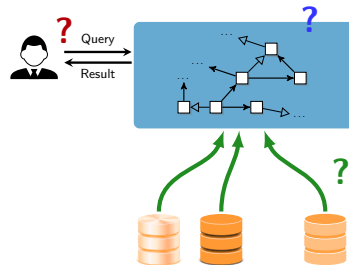
The W3C has standardized languages that are suitable for OBDA:

- ① **Ontology \mathcal{O}** : expressed in **OWL 2 QL** [W3C Rec. 2012]
- ② **Query**: expressed in **SPARQL** [W3C Rec. 2013] (v1.1)
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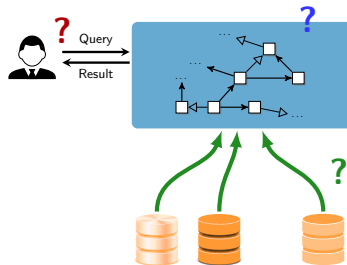
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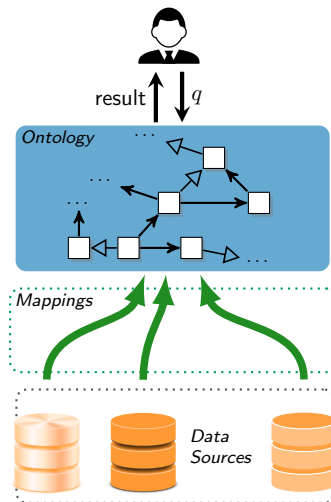
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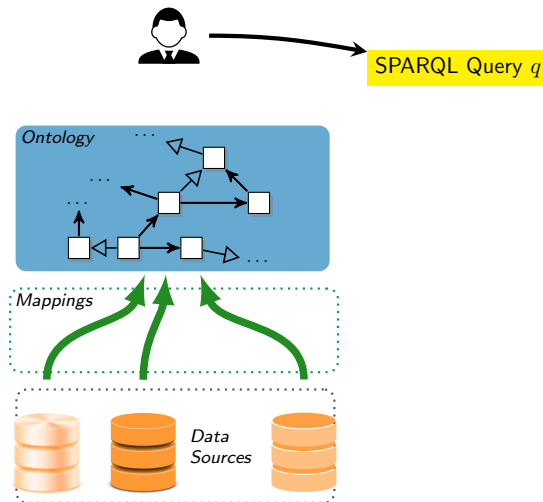
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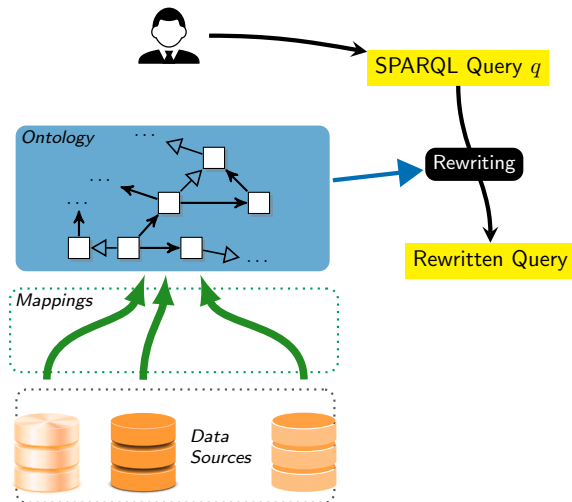
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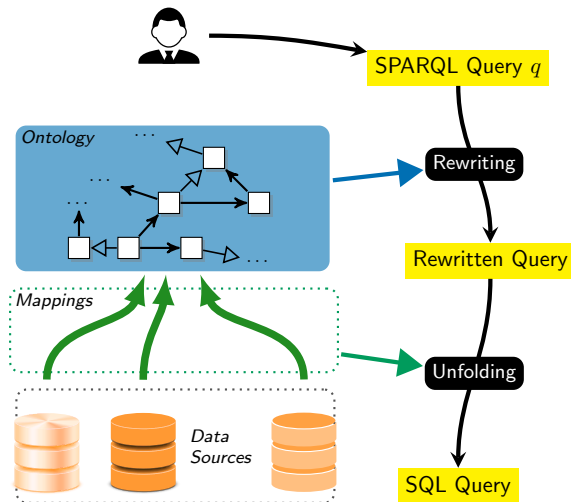
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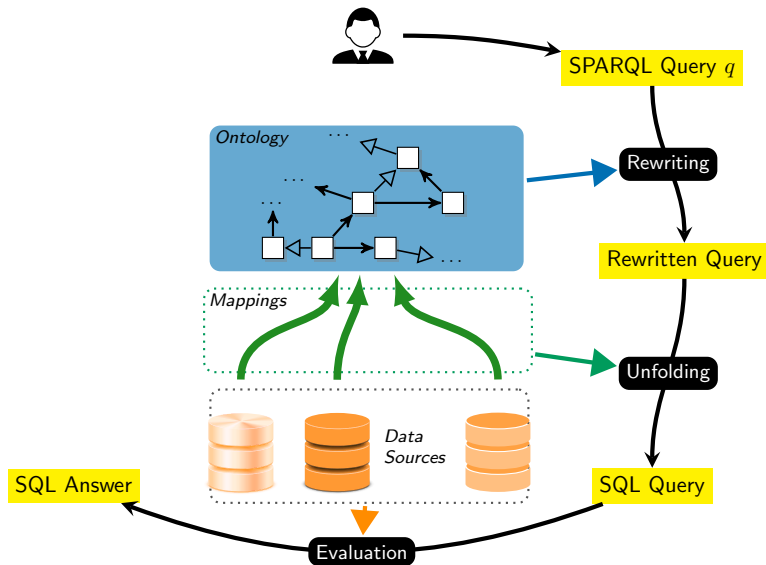
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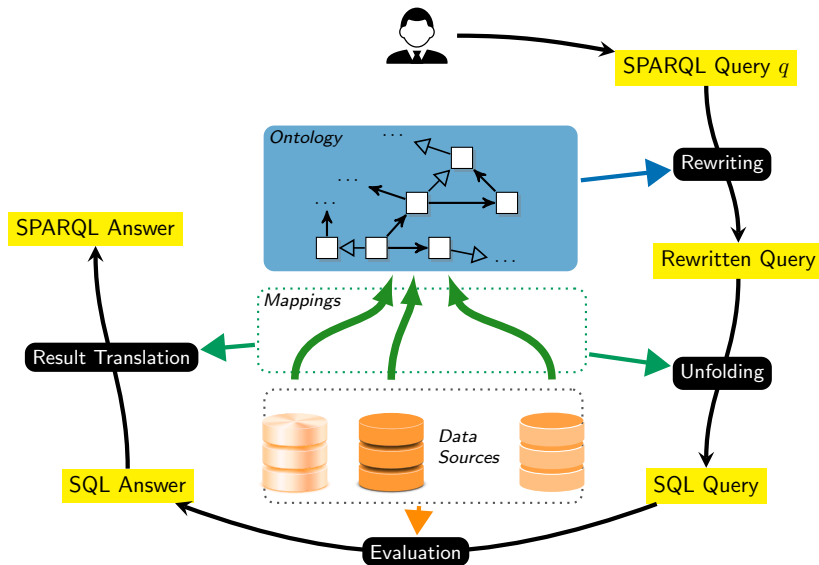
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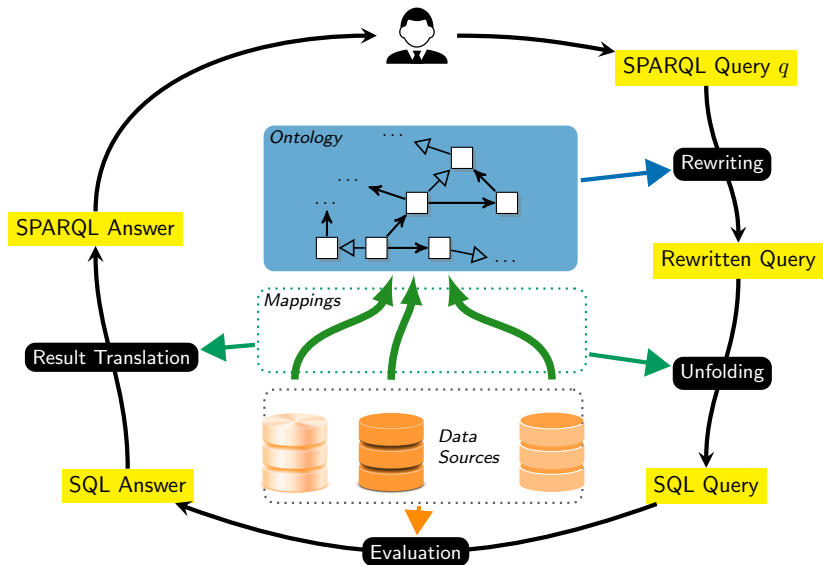
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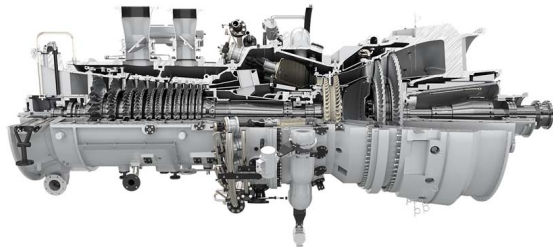


Outline

- 1 Motivation
- 2 Temporal OBDA Framework
- 3 Ontology Layer
- 4 Mapping Layer
- 5 Query Answering for Temporal OBDA
- 6 Summary and Future Work

Siemens Energy Services

- **Monitor** gas and steam turbines.
- **Collect data** from 50 remote diagnostic centers around the world.
- Centers linked to a **common central DB**.
- Turbines are highly complex, with 5 000–50 000 sensors each.
- Engineers compute KPIs, and extract data from maintenance reports using ETL tools.



Objective: retrospective diagnostics

i.e., detect **abnormal** or **potentially dangerous** events.

Example request

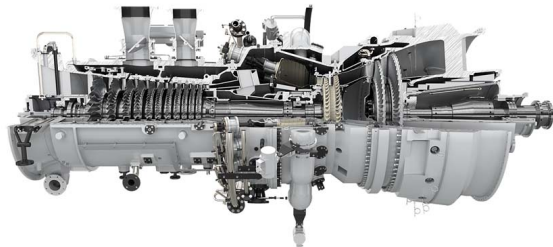
Find the gas turbines deployed in the train with ID T001, and the time periods of their accomplished purgings.

Events

- Involve a number of sensor measurements.
- Have a certain **temporal duration**.
- Occur in a certain **temporal sequence**.

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To capture such a complex scenario . . .

. . . we need to **enrich OBDA with temporal features**.

Approaches proposed in the literature:

1. Use standard ontologies and extend queries with temporal operators

[Gutiérrez-Basulto and Klarman 2012; Baader, Borgwardt, and Lippmann 2013; Klarman and Meyer 2014; Özçep and Möller 2014; Kharlamov et al. 2016]

However:

- Query language gets significantly more complicated.
- Effort is shifted from design time to query time.

2. Extend both query and ontology with linear temporal logic (LTL) operators

[Artale, Kontchakov, Wolter, et al. 2013; Artale, Kontchakov, Kovtunova, et al. 2015]

However:

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We propose a different approach to temporal OBDA

- At the ontology level, we have both **static** and **temporal predicates**:
 - Static predicates to represent ordinary facts.
E.g., `Burner(b01)`, `isMonitoredBy(b01,mf01)`
 - Temporal predicates to represent **temporal facts** with a **validity interval**
E.g., `HighRotorSpeed(rs01)@[2017-06-06 12:22:50, 2017-06-06 12:23:40)`
We consider both open and closed intervals:
 $A(d)@(t_1, t_2)$, $A(d)@[t_1, t_2)$, $A(d)@(t_1, t_2]$, $A(d)@[t_1, t_2]$
- The ontology is expressed in OWL 2 QL \leadsto First-order rewritability.
- We enrich it with static and **temporal rules**.
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Formal framework for temporal OBDA

A **traditional OBDA specification** is a triple $\mathcal{P} = \langle \mathcal{O}, \mathcal{M}, \mathcal{S} \rangle$

- \mathcal{O} is an **ontology**.
- \mathcal{M} is a set of **mapping assertions** between ontology and data sources.
- \mathcal{S} is a **database schema**.

Temporal OBDA builds on traditional OBDA.

A **temporal OBDA specification** is a tuple $\mathcal{P}_t = \langle \Sigma_s, \Sigma_t, \mathcal{O}, \mathcal{R}_s, \mathcal{R}_t, \mathcal{M}_s, \mathcal{M}_t, \mathcal{S} \rangle$

- Σ_s is a static vocabulary.
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- \mathcal{O} is an ontology.
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Static ontology – Example

We use an **ontology** to model the **static knowledge** about

- machines and their deployment profiles
- component hierarchies
- sensor configurations
- functional profiles

We still use **OWL 2 QL** as the static ontology language.

Devices consist of parts, and these are monitored by many different kinds of sensors (temperature, pressure, vibration etc.).

GasTurbine \sqsubseteq Turbine	$\exists \text{isDeployedIn} \sqsubseteq$ Turbine
SteamTurbine \sqsubseteq Turbine	$\exists \text{isDeployedIn}^- \sqsubseteq$ Train
PowerTurbine \sqsubseteq TurbinePart	$\exists \text{isPartOf} \equiv$ TurbinePart
Burner \sqsubseteq TurbinePart	$\exists \text{isPartOf}^- \sqsubseteq$ Turbine
RotationSpeedSensor \sqsubseteq Sensor	$\exists \text{isMonitoredBy} \sqsubseteq$ TurbinePart
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Static rules

However, OWL 2 QL is not able to capture all the static knowledge required, e.g., in the [Siemens](#) use case.

We complement this ontology with **nonrecursive Datalog static rules**.

Example: turbine parts monitored by different co-located sensors (e.g., temperature, rotation speed)

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ColocSensors(tb, ts, rs)  $\leftarrow$  Turbine(tb), isPartOf(pt, tb),  
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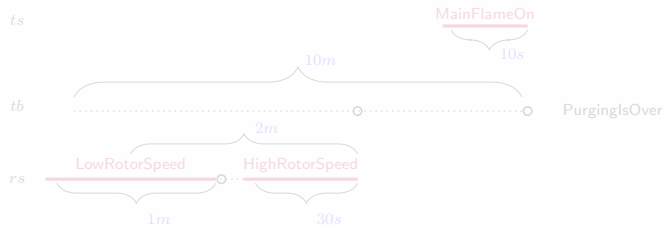
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Temporal rules

Siemens is interested in detecting **abnormal situations**, and monitoring **running tasks**.

“Purging is Over” is a complex event of a turbine



We model this situation with **metric temporal rules**:

$$\begin{aligned} \text{PurgingIsOver}(tb) \leftarrow & \exists_{[0s, 10s]} \text{MainFlameOn}(ts) \wedge \\ & \diamond_{(0, 10m)} (\exists_{(0, 30s)} \text{HighRotorSpeed}(rs) \wedge \\ & \quad \diamond_{(0, 2m)} \exists_{(0, 1m)} \text{LowRotorSpeed}(rs)) \wedge \\ & \text{ColocTempRotSensors}(tb, ts, rs). \end{aligned}$$

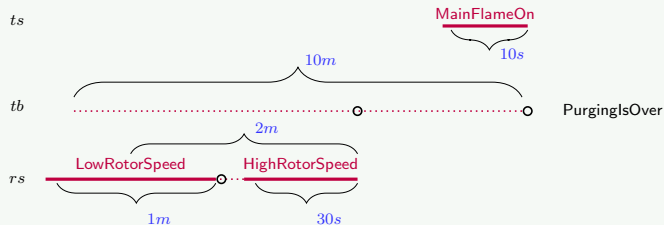
$$\text{HighRotorSpeed}(tb) \leftarrow \text{rotorSpeed}(tb, v) \wedge v > 1260.$$

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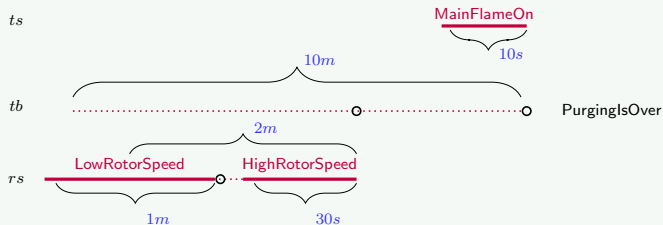
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We use *DatalogMTL*

DatalogMTL is a Horn fragment of **Metric Temporal Logic (MTL)**.

A *DatalogMTL* program is a finite set of rules of the form

$$A^+ \leftarrow A_1 \wedge \dots \wedge A_k \quad \text{or} \quad \perp \leftarrow A_1 \wedge \dots \wedge A_k,$$

where

- each A_i is either $\tau \neq \tau'$, or defined by the grammar

$$A ::= P(\tau_1, \dots, \tau_m) \mid \boxplus_{\varrho} A \mid \boxminus_{\varrho} A \mid \lozenge_{\varrho} A \mid \Diamond_{\varrho} A$$

where ϱ denotes a (left/right open or closed) interval with non-negative endpoints,

- A^+ does not contain \lozenge_{ϱ} or \Diamond_{ϱ} (since this would lead to undecidability).

Query evaluation in *DatalogMTL*

[Brandt, Kalayci, et al. 2017; Brandt, Güzel Kalayci, et al. 2018]

Theorem

Answering *DatalogMTL* queries is EXPSpace-complete in combined complexity.

We consider the **nonrecursive fragment** *Datalog_{nr}MTL* of *DatalogMTL*:

- sufficient expressive power for many real-world situations
- computationally well-behaved

Answering *Datalog_{nr}MTL* queries:

- Is PSPACE-complete in combined complexity.
- Is in AC^0 in data complexity.
- Can be **reduced to SQL query evaluation**.

Hence, *Datalog_{nr}MTL* is well suited as a temporal rule language for OBDA.

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Data sources: schema and data

Data sources often contain **temporal information** in the form of **time-stamps**.

Example data schema \mathcal{S} for the Siemens data

It includes time-stamped sensor measurements and deployment details:

```
tb_measurement(timestamp, sensor_id, value),  
tb_sensors(sensor_id, sensor_type, mnted_part, mnted_tb),  
tb_components(turbine_id, component_id, component_type).
```

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A corresponding data instance \mathcal{D}_0 :

tb_measurement		
<i>timestamp</i>	<i>sensor_id</i>	<i>value</i>
2017-06-06 12:20:00	rs01	570
2017-06-06 12:22:50	rs01	1278
2017-06-06 12:23:40	rs01	1310
...
2017-06-06 12:32:30	mf01	2.3
2017-06-06 12:32:50	mf01	1.8
2017-06-06 12:33:40	mf01	0.9
...

tb_sensors			
<i>sensor_id</i>	<i>sensor_type</i>	<i>mnted_part</i>	<i>mnted_tb</i>
rs01	0	pt01	tb01
mf01	1	b01	tb01
...

tb_components		
<i>turbine_id</i>	<i>component_id</i>	<i>component_type</i>
tb01	pt01	0
tb01	b01	1
...

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- 2 Temporal OBDA Framework
- 3 Ontology Layer
- 4 Mapping Layer**
- 5 Query Answering for Temporal OBDA
- 6 Summary and Future Work

Static mapping assertions in \mathcal{M}_s

Static mapping assertions: $\Phi(\vec{x}) \rightsquigarrow \Psi(\vec{x})$

- $\Phi(\vec{x})$ is a **query** over the **source schema** \mathcal{S}
- $\Psi(\vec{x})$ is an **atom** with predicate in Σ_s

Example

```
SELECT sensor_id AS X FROM tb_sensors  
WHERE sensor_type = 1  $\rightsquigarrow$  TemperatureSensor(X)  
  
SELECT component_id AS X FROM tb_components  
WHERE component_type = 1  $\rightsquigarrow$  Burner(X)  
  
SELECT mnted_part AS X, sensor_id AS Y FROM tb_sensors  $\rightsquigarrow$  isMonitoredBy(X,Y)
```

These mappings retrieve from the database ordinary facts.

```
Burner(b01), TemperatureSensor(mf01),  
isMonitoredBy(pt01,rs01), isMonitoredBy(b01,mf01).
```

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SELECT sensor_id AS X FROM tb_sensors
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- **begin** and **end** are variables returning a date/time.
- '**<**' is either '(' or '[', and similarly for '**>**'.
- $\Psi(\vec{x})$ is an **atom** with predicate in Σ_t .
- t_{begin} is either **begin** or a date-time constant, and similarly for t_{end} .

Example

```
SELECT * FROM (
  SELECT sensor_id, value, timestamp AS begin,
         LEAD(timestamp,1) OVER W AS end
  FROM tb_measurement, tb_sensors
  WINDOW W AS (PARTITION BY sensor_id ORDER BY timestamp)
  WHERE tb_measurement.sensor_id = tb_sensors.sensor_id AND sensor_type = 0
) SUBQ WHERE value > 1260                                 $\rightsquigarrow$  HighRotorSpeed(sensor_id)@[begin,end]
```

These mappings retrieve from the database **temporal facts**.

HighRotorSpeed(rs01)@[2017-06-06 12:22:50, 2017-06-06 12:23:40)

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Concrete syntax for temporal OBDA specifications

Temporal OBDA specification $\mathcal{P}_t = \langle \Sigma_s, \Sigma_t, \mathcal{O}, \mathcal{R}_s, \mathcal{R}_t, \mathcal{M}_s, \mathcal{M}_t, \mathcal{S} \rangle$

- Σ_s is a static vocabulary,
- \mathcal{O} is an ontology,
- \mathcal{R}_s is a set of static rules,
- \mathcal{M}_s is a set of static mapping assertions,
- \mathcal{S} is a database schema.
- Σ_t is a temporal vocabulary,
- \mathcal{R}_t is a set of temporal rules,
- \mathcal{M}_t is a set of temporal mapping assertions,

Component	defines predicates in	in terms of predicates in	Adopted language
\mathcal{O}	Σ_s	Σ_s	OWL 2 QL
\mathcal{R}_s	Σ_s	Σ_s	non-recursive Datalog
\mathcal{R}_t	Σ_t	$\Sigma_s \cup \Sigma_t$	<i>Datalog_{nr}</i> MTL
\mathcal{M}_s	Σ_s	\mathcal{S}	R2RML / Ontop
\mathcal{M}_t	Σ_t	\mathcal{S}	R2RML / Ontop

Ontop mapping syntax

[PrefixDeclaration]

```
st:      http://siemens.com/temporal/ns#
xsd:     http://www.w3.org/2001/XMLSchema#
obda:    https://w3id.org/obda/vocabulary#
```

[MappingDeclaration] @collection [[

```
mappingId mappingRSA1260
target      st:HighRotorSpeed/{sensor_id} obda:hasStatus
            st:HighRotorSpeed.
interval    [ {begin}^^xsd:dateTimeStamp, {end}^^xsd:dateTimeStamp )
source
    SELECT sensor_id, begin, end FROM (
        SELECT sensor_id, value, timestamp AS begin,
            LEAD(timestamp, 1) OVER W AS end
        FROM MEASUREMENT
        WINDOW W AS (PARTITION BY sensor_id ORDER BY timestamp)) SUBQ
    WHERE value > 1260
]]
```

Temporal OBDA instance

A **temporal OBDA instance** is a pair $\mathcal{J} = \langle \mathcal{P}_t, \mathcal{D} \rangle$

- \mathcal{P}_t is a temporal OBDA specification,
- \mathcal{D} is a database instance compliant with the database schema \mathcal{S} in \mathcal{P}_t .

To represent the facts generated by \mathcal{J} , we use **RDF Datasets**.

(We follow the model proposed by the W3C RSP Community Group.)

The **temporal fact** `HighRotorSpeed(rs01)@[2017-06-06 12:22:50, 2017-06-06 12:23:40]`

is modeled as the **named graph** `GRAPH g_0 {(rs01, a, HighRotorSpeed)}`

and a set of triples in the **default graph**, to model the **time interval**:

```
( $g_0$ , a, time:Interval),  
( $g_0$ , time:isBeginningInclusive, true), ( $g_0$ , time:isEndInclusive, false),  
( $g_0$ , time:hasBeginning,  $b_0$ ), ( $g_0$ , time:hasEnd,  $e_0$ ),  
( $b_0$ , time:inXSDDateTimeStamp, '2017-06-06 12:22:50'),  
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Query answering

Example query

*“Find the gas turbines deployed in the train with the ID T001 and the **time periods** of their accomplished purgings”.*

This corresponds to the query: $Q(tb)@u$, where $Q(tb)$ is defined as

$$Q(tb) \leftarrow \text{Train}(T001), \text{GasTurbine}(tb), \\ \text{isDeployedIn}(tb, T001), \text{PurgingsIsOver}(tb).$$

In “temporal” SPARQL syntax:

```
PREFIX ss: <http://siemens.com/ns#>
PREFIX st: <http://siemens.com/temporal/ns#>

SELECT ?tb ?left_edge ?begin ?end ?right_edge
WHERE {
  ?tb a ss:GasTurbine ;
      ss:isDeployedIn ss:train_T001 .
  {?tb a st:PurgingsIsOver}@<?left_edge,?begin,?end,?right_edge>
}
```

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```

```
SELECT ?tb ?left_edge ?begin ?end ?right_edge
```

```
WHERE {
```

```
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```

```
      ss:isDeployedIn ss:train_T001 .
```

```
  {?tb a st:PurgingsIsOver}@<?left_edge,?begin,?end,?right_edge>
```

```
}
```

Equivalent standard SPARQL query

```

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}

```

... is translated into the following standard SPARQL query:

```

PREFIX time: <http://www.w3.org/2006/time#>
...
SELECT ?tb ?left_edge ?begin ?end ?right_edge
WHERE {
    ?tb a ss:GasTurbine ;    ss:isDeployedIn ss:train_T001 .
    GRAPH ?g { ?tb a st:PurgingIsOver . }
    ?g a time:Interval ;
        time:isBeginningInclusive ?left_edge ;
        time:hasBeginning [ time:inXSDDateTimeStamp ?begin ] ;
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```

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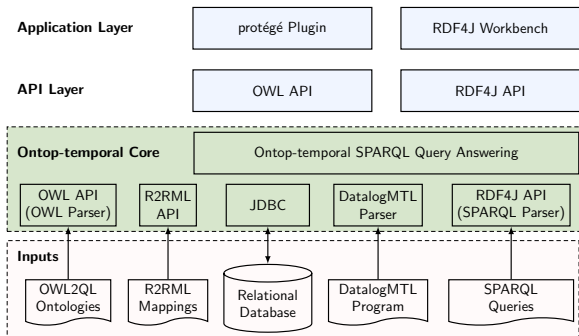
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The Ontop-temporal system

We have implemented the temporal OBDA framework in the **Ontop-temporal** system [Güzel Kalayci et al. 2018], as an extension of *Ontop*.

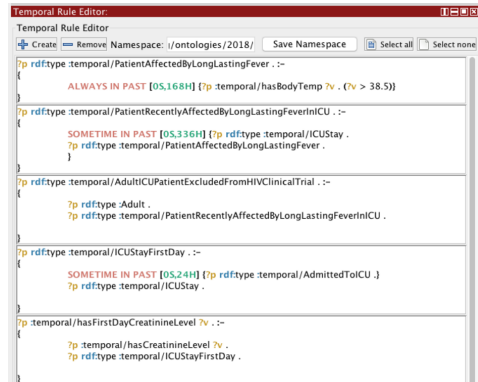
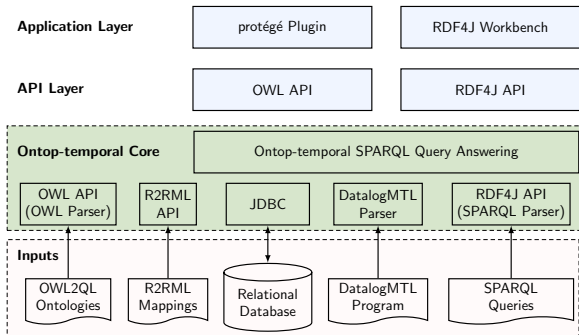
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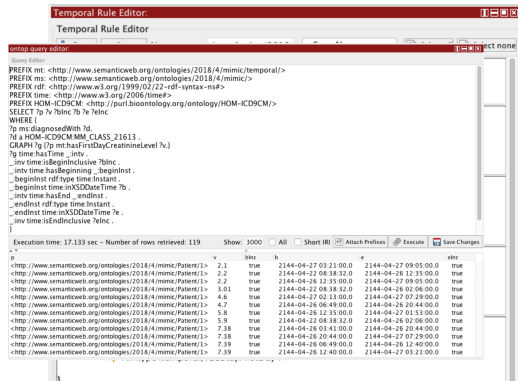
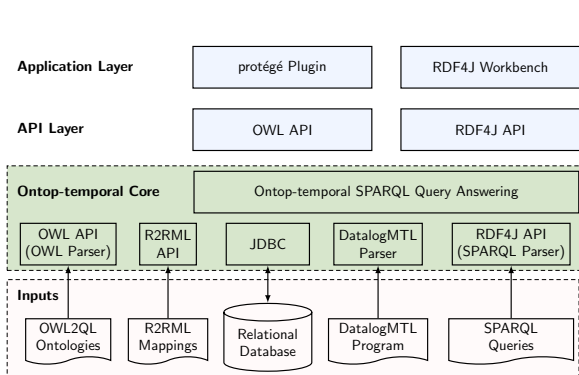
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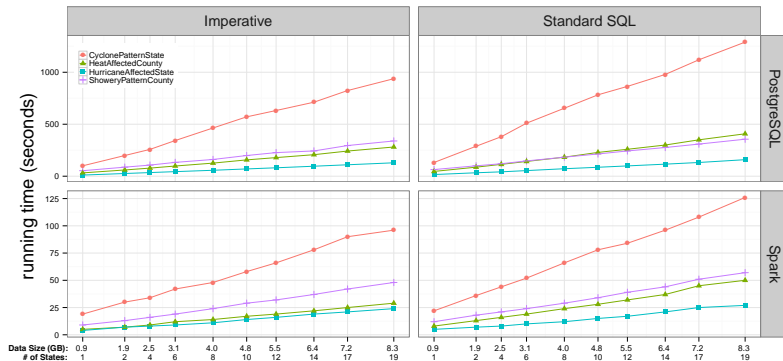


Evaluation [Brandt, Güzel Kalayci, et al. 2018; Güzel Kalayci et al. 2018]

Done on three **real-world** use cases from **different domains**: MesoWest, MIMIC-III, and Siemens.

Evaluation with respect to two aspects:

- **utility evaluation** over MIMIC-III, MesoWest, and Siemens use-cases
- **scalability evaluation** over MesoWest and Siemens use-cases



Outline

- 1 Motivation
- 2 Temporal OBDA Framework
- 3 Ontology Layer
- 4 Mapping Layer
- 5 Query Answering for Temporal OBDA
- 6 Summary and Future Work**

Summary and future work

Contributions

- A novel **temporal OBDA framework**.
- A **temporal rule language** for modeling complex temporal events.
- Implementation of the framework in the **Ontop-temporal** system.
- Extensive **evaluation** of the system over real-world data from different domains.

Future work

- Extension of temporal OBDA with **temporal aggregates**.
- Support for **streaming data**.
- **Optimization** and support for **parallel processing**

Thanks

Thank you for your attention!

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- Elem Güzel Kalayci (unibz)
- Roman Kontchakov (Birkbeck)
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- Guohui Xiao (unibz)
- Michael Zakharyashev (Birkbeck)

OBDA framework developed in Bolzano

The logo for the ontop framework, featuring the word "ontop" in a stylized orange font with a horizontal line through the middle of the letters.

ontop.inf.unibz.it/

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