Towards Analytics Aware Ontology Based Access (OBDA) to Static and Streaming Data

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Ontology Based Data Access

Main Idea

- an approach to Data integration
- ontology
  - provides a common schema over several DBs
  - mediates data and data consumers
- mappings
  - “connect” ontology and DBs
- virtual data integration approach
  - data stays where it was
  - data transferred to consumers on demand
  - automatic query processing: semantic queries → data queries
Success Stories

OBDA systems

- Include: D2RQ, Mastro, morph-RDB, Ontop, OntoQF, Ultrawrap, Virtuoso, Optique
- Implement from some to all OBDA features

OBDA has been applied

- cultural heritage
- governmental organizations
- Industry
  - Statoil
  - Siemens
  - E-commerce

Where are the OBDA limits?
Hard case for OBDA

Siemens turbine monitoring example:

- Detect alerting temperature behavior
- Can be done by queries that ask for
  - reliable sensors reporting alerting temp. (patterns)

Terminology

- Reliable: good avg. score (>=90%) of validation tests
- Alerting: similar to what we saw last year when there was an alerting situation
- Similar: Pearson correlated by at least 0.75

In a given turbine report all temperature sensors that are reliable, i.e., with the average score of validation tests at least 90%, and whose measurements within the last 10 min were similar, i.e., Pearson correlated by at least 0.75, to measurements reported last year by a reference sensor that had been functioning in a critical mode.

Q: return reliable sensors reporting alerting temp.
Hard case for OBDA

Important components of the query

- access to both static and streaming data
  - Streaming: data currently produced by sensors
  - Static: historic from last year; turbine structural data
- analytics
  - Average score
    - aggregate function
  - At least 90%
    - Value comparison
  - Pearson correlation

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Existing OBDA

Support

- static relational data/queries
- streaming data/queries
- but not both

Are good for conjunctive queries but not for

- analytics
  - epistemic semantic: analytics over “semantic” answers
  - encoding in mappings

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Inefficient
- Requires large data transfer
- Ignore source capabilities

brittle and inflexible
- Requires encoding of specific values in mappings
- query dependent

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OBDA 2.0: for a Big company

Big company

- data processing is analytics oriented
- has DBs of various kinds

Should become: Analytics Aware

- by supporting declarative representations of basic analytics operations

Requires:

- analytics aware
  - ontologies, mappings, query languages capable of capturing analytical operators
- new Q. processing techniques to cope with them
  - rewriting, unfolding
OBDA 2.0: for a Big company

Should become: **Source and Cost Aware**

- by supporting data sources of various types
  - live and archived streams
  - relational DBs
  - other DBs
- by offering a robust
  - query planning
  - query optimization

for estimating the cost of different plans, and use such estimates to produce low-cost plans
Outline: Overview of Our OBDA 2.0

Analytics Aware
- Ontologies
- Queries
- Mappings
- Query transformation
  - Ontology → Data queries

Analytics, Source, and Cost Aware
- Query planning and optimisations
- Experiments
Analytics Aware Ontology: DL-Lite\textsuperscript{agg}

Main Ideas
- Why DL-Lite: classical DL-Lite is designed for OBDA
- Extensions
  - Concepts that are based on aggregation of Att values
    \[
    \geq 0.9 \ (\min test\text{Score}) \sqsubseteq \text{Reliable}.
    \]
- Semantics
  - Closed-world semantics for new (aggregate) concepts
  - Open-world semantics is meaningless
- Conjunctive query answering
  - Tractable when aggregate function computation is tractable
  - Thanks to closed-world interpretation of predicates involved in aggregation [1]

\[
B \rightarrow A \mid \exists R, \quad C \rightarrow B \mid \exists F, \quad E \rightarrow \circ_r(\text{agg } F), \quad R \rightarrow P \mid P^-.\]

Analytics and Source Aware QL: STARQL

Input
- Static analytics aware ontology and data set
- Collection of streams: life and archived

Output
- Stream of data sets

Conjunctive queries
- Standard agg: count, avg

Diagnostic queries
- Advanced agg: Pearson correlation
Query Transformation

Process Overview:

\[ Q_{\text{starql}} \approx Q_{\text{StatCQ}} \land Q_{\text{Stream}} \xrightarrow{\text{rewrite}} Q'_{\text{StatUCQ}} \land Q'_{\text{Stream}} \xrightarrow{\text{unfold}} Q''_{\text{AggSQL}} \land Q''_{\text{Stream}} \approx Q_{\text{sql}} \]

- Rewriting
  - Essentially: standard perfect reformulation algorithm for DL-Lite
- Unfolding
  - Relies on mappings of 2 kinds
    - Standard concepts
    - Aggregate concepts

Mapping for aggregate concepts:

\[ \left( \geq 0.9 \ (\min \ textscore) \right)(x) \leftarrow \text{SELECT } x \text{ FROM } \text{unfold}(\text{rewrite}(\text{testscore}(x, y))) \text{ GROUPBY } x \text{ HAVING } \min(y) \geq 0.9 \]
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Optimization of Data Queries: ExaStream

Exastream: Data-Stream Management System

- our streaming extension of SQLite DB engine
- SQL\(\oplus\) queries
  - SQL enhanced with
    - User Def. Func. (for analytics)
- smart query planner based on
  - query
  - available stream/static DBs
  - execution environment
- parallelism and distribution on a cloud
  - to accelerate analytics
  - distribution of queries & data to multiple worker nodes

Query execution cycle
- Q registers at Gateway Server \(\rightarrow\) parsed and fed to the Scheduler
- Scheduler places Qs on available Workers and optimizes their execution
Our Query Optimisations

Analytical operations of 3 types
- live-stream operations
  - analytical tasks on live streams
- static-data operations
  - analytical tasks on static information
- hybrid operations
  - analytical tasks on live-streams & static data

Basic Optimizations & strategies
- data views
  - compute static analytical tasks ahead of live-stream operations
- adaptive indexing
  - adaptively building main-memory indexes on batches of cached stream tuples
View Based Optimisations

Ex: pre-computation of AVG for streaming analytics

- **Measurements**
  - raw data
  - archived part of a data stream
  - has time & actual measurements

- **Windows**
  - pre-computed data
  - stores the windowing mechanism
  - has window-id, starting, and ending point
  - has frequently asked aggregates, e.g., AVG

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Evaluation

View Based Optimization (1 node)

- measured
  - time to process a live-stream
  - against 100,000 archived ones
  - time is divided
    - to join-time & aggregate time

- Outcome
  - for Pearson correlation
    - time gain: 8.18%
  - for AVG and MIN
    - optimizer prunes many unnec. joins

Intra-query Parallelism (1-16 nodes)

- distribution of pre-computed views among nodes
- significant time decrease
Summary

Discussed
- hard cases for OBDA
  “Siemens real-time turbine diagnostics”
- for them we need OBDA 2.0
  - analytics awareness
  - source and cost awareness

Introduced
- Example OBDA 2.0
- Experiments