

A Scale-Out RDF Molecule Store for Distributed Processing of Biomedical Data

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Overview

- Motivation.
- Scale-Out Architecture.
- RDF Molecules and Extensions.
- Ontology Development, Integration and Model.
- Results.

Motivation

- Many projects (size, scope, scale).
- Many different sizes of data (MB, GB, TB, PB).
- Large total amount of data.
- Many databases (~230 PPI databases).
- Many names (LSID, URLs, local ids).
- Many different semantics (text, vocabulary, data models, ontologies).
- Variety of quality (missing data, incorrect, manually/automatically created).
- Varying provenance (sometimes none at all).
- Changing or incomplete domain knowledge.

Motivation (continued)

- Why does Scale Matter?
	- – $-$ Improved coverage as there is not much overlap between data sets.
	- –– Greater confidence by verifying the data and our model.
	- and the state of the state $-$ Feedback to improve data quality.
	- – $-$ Leads to better queries:
		- Find all mammalian protein-protein interactions.
		- Find all interactions between 2 pathways.

Scale-Out Architecture

- Add nodes to increase reliability, storage and processing without scaling out maintenance.
- Google
	- 10,000 Distinct MapReduce Programs.
	- 100,000 Jobs Executed/Day.
	- 20 Petabytes of Data Processed/Day.
- Nutch Search Engine, IBM, Moreira and Michael et al
	- Newton's Law beats Moore's.
	- Linear Scaling from 10 ~2,000 nodes.
	- Same price, scale out performs 4 times better.
- "Scientific Data Management in the Coming Decade", Jim Grey et al
	- $-$ Bandwidth ≥ Latency².
	- Better Metadata better selectivity of data processing.
	- Semantic Web should be used for common terminologies.
	- MapReduce bring computation to data.

Technologies

- Hadoop
	- MapReduce.
	- –— HDFS (Hadoop Distributed File System).
- HBase
	- – $-$ A column database built on HDFS.
- ZooKeeper
	- $-$ Distributed service co-ordination and configuration.
- Hosting
	- – Local Cluster, Amazon EC2, Google (one day App Engine?).

What is an RDF Molecule?

- A way to decompose an RDF Graph, containing blank nodes, into subgraphs.
- Creates context for a blank node so they are globally addressable just like URIs and Literals.

Diagram from: Ding, L., et al., "Tracking RDF Graph Provenance using RDF Molecules."

An RDF Graph Across Computing Nodes

Our Extensions

- Hierarchical Structure
	- –Molecules within molecules.
	- –— Linking Triples (_1 context1 _2, _2 context2 _3).
	- Reflects certain domain models (PPI).
- Ordering
	- –By Most Grounded (head triple) to Least Grounded.
	- –— By String Value.
- Algorithms
	- $-$ Decomposition.
	- –— Merging.

Relational View of Integrated Data

Graph View of Integrated Data

Advantages of RDF Molecules

- Lightweight context, without names.
- Distributed Processing
	- **Links of the Company** $-$ Enough context without requiring the entire graph.
	- – $-$ Allows answers to be combined from many nodes.
- Conceptual Integration
	- and the state of the Many names, many databases reference the same thing.
	- – $-$ Find inconsistencies and remove or resolve them.
- Structural Integration
	- and the state of the $-$ Lean Graph, merging removes redundant triples.
- Represents foreign key/multiple relations.

Disadvantages of RDF Molecules

- Existing RDF graphs ("local graphs") need to be converted to molecule based graphs ("global graphs").
- Costs
	- –— Extra Join.
	- Redundancy Removal.
- General Problems
	- –Agree on structure and rewrite existing code.
	- –- Lack of Blank Node Round Tripping in SPARQL requires subqueries or API usage.

The Ontology

BioMANTA Extensions

- \bullet Instances of classes e.g. Experimental Methods fromBioPAX ontology.
- • DisjointClasses(Experimental Observation, Unspecified Observation, Predicted Observation, Inferred Observation)
	- Allows n-ary, multiple observations of the same interaction.
	- Context:
		- sourceOfData identity of 3rd party resource.
		- observedCellType the cell type in which the experimental observation occurred.
		- method type the type of evidence for a particular observation type (e.g. experimentalMethod, inferenceMethod, etc).
		- subCellularLocalisation a BioPAX entity, with a range from Gene Ontology's cellular component hierarchy.
	- $-$ Inferred Observations from ontological (OWL) classification.
	- $-$ Predicted Observations from data analysis or data mining.

Integration Process

- PSI-MI to RDF
	- – $-$ XML to RDF
- Add UniProt to Local Protein IDs
	- – $-$ Local ID \rightarrow UniProtID
- Add Sequence to Local Protein IDs
	- $-$ Local ID \rightarrow Sequence
- Protein Merging
	- Create Molecules.
	- –Merge based on UniProt ID and Sequence.
	- Those with the same UniProt IDs but different Sequences are "warnings" and are to be removed.

Integrated PPI Data Sourcess

Protein Merge Performance

Interesting Dataset Characteristics

- One DIP File: 12 450 proteins, 60 duplicate pairs of proteins (~0.5%).
- IntAct and DIP have multiple IDs per UniProt ID.
- DIP, IntAct, MINT: 13 430 proteins, 290 Merged (~2%), 10 differed (MINT).
- Two IntAct Yeast Files:

Conclusions

- Scale-out architecture provides improved performance and reliability but demands restricted programming interfaces and data structures.
- RDF Molecules provide a way to do distributed processing over RDF sub-graphs.
- Our model utilizes RDF Molecules to integrate disparate datasets and produce a large amount of easily extensible provenance data.

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Links

Web Site

• http://biomanta.org/

Results

• http://biomanta.org/downloads/

JRDF

• http://jrdf.sf.net/