Semantic Representation and Scale-up of Integrated Air Traffic Management Data

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NASA Ames Research Center

International Workshop on Semantic Big Data, San Francisco, USA, July 1, 2016

Work funded by NASA's Aeronautics Research Mission Directorate

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Aviation Data is Big Data

- **Volume**: 30M+ flights yearly
  3.6B passengers forecast for 2016
- **Variety**: flight tracks, weather maps, aircraft maintenance records, flight charts, baggage routing data, passenger itineraries
- **Velocity**: high frequency data from aircraft surveillance systems and on-board health & safety systems 24x7

New Project

Build a **large queryable semantic repository** of air traffic management **(ATM)** data using semantic integration techniques

? The **Big** Question ?

Can semantic representations scale up to accomplish practical tasks using Big Data?

→ Conduct a scale-up experiment to answer the question

Outline

- Aviation Data Integration Problem
- Semantic Integration Approach
- Design of our Scale-up Experiment
- Results
- Approaches to Improving Scale-up Performance
- Conclusions

Background: Aviation Data Integration Problem

- NASA researchers require historical ATM data for future airspace concept development & validation
- NASA Ames' **ATM Data Warehouse** archives data collected from FAA, NASA, NOAA, DOT, industry
  - Warehouse captures 13 sources of aviation data:
    - flight tracks, advisories, weather data, delay stats
    - some from live feeds and some from periodic updates
  - Data holdings available back to 2009
  - 30TB of data; some in a database; most in flat files

Problem: Non-integrated Data

- ATM Warehouse data is replicated & archived in its original format
- Data sets lack standardization
  - data formats
  - nomenclature
  - conceptual structure

- **Possible cross-dataset mismatches:**
  - terminology
  - scientific units
  - temporal/spatial alignment
  - conceptualization organization

- To analyze and mine data, researchers must download data and write special-purpose integration code for each new task

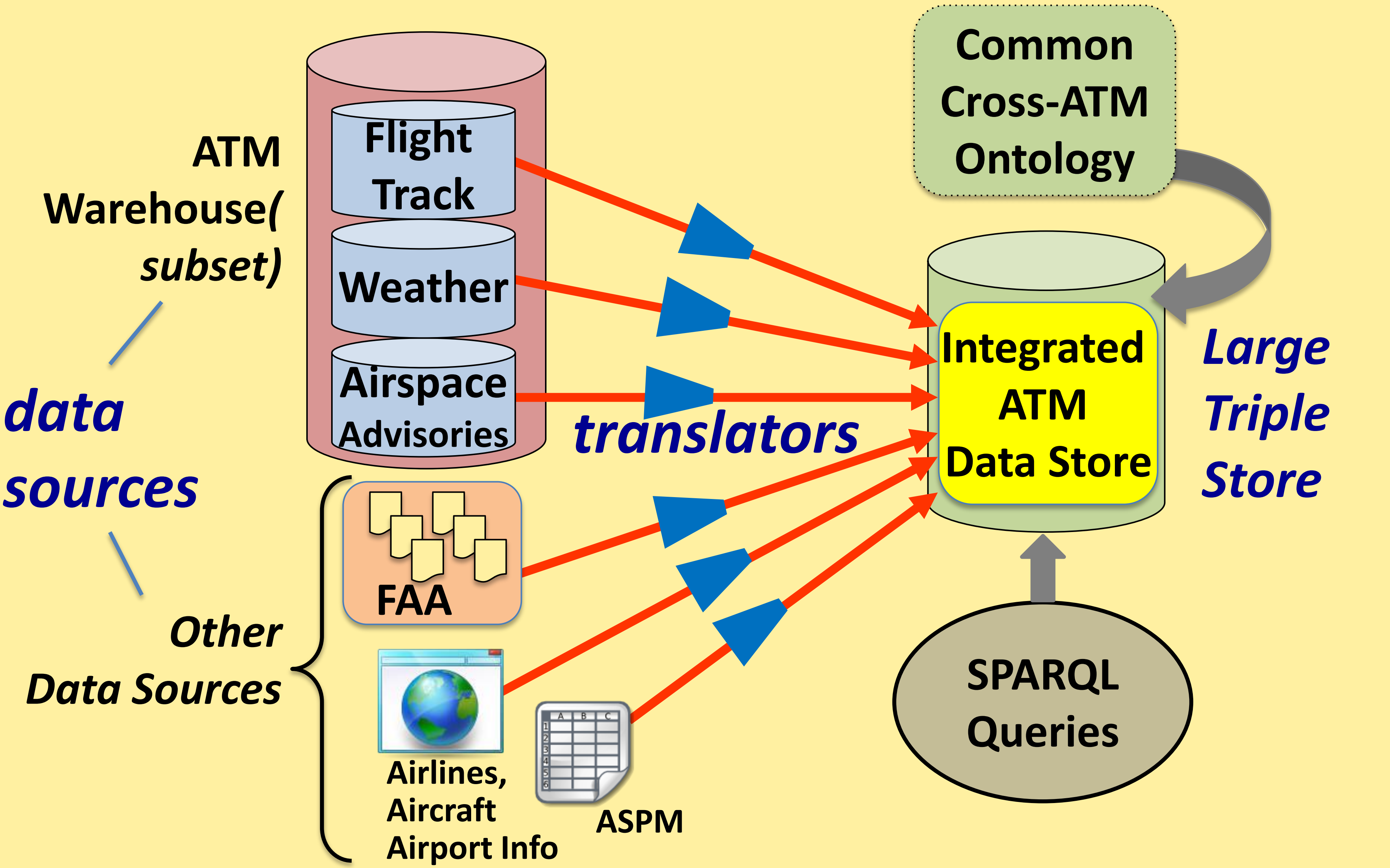
  ➔ <u>Huge time sink</u>!

Proposed Solution

Relieve users of responsibility for integration

Integrate Warehouse data sources
on the server side
using **Semantic Integration**

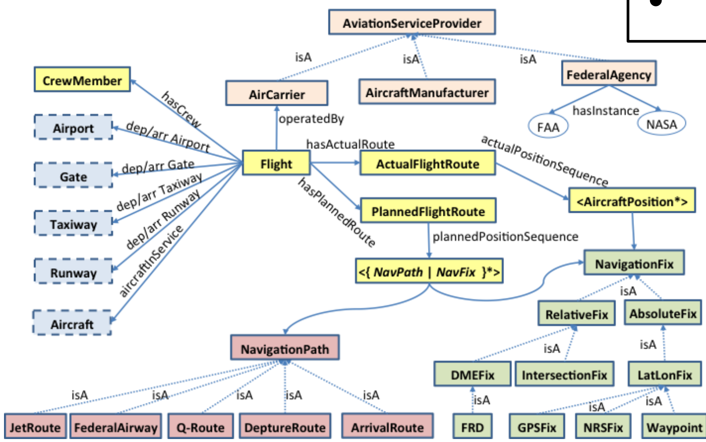
Semantic Integration Approach:
Prototype System Diagram



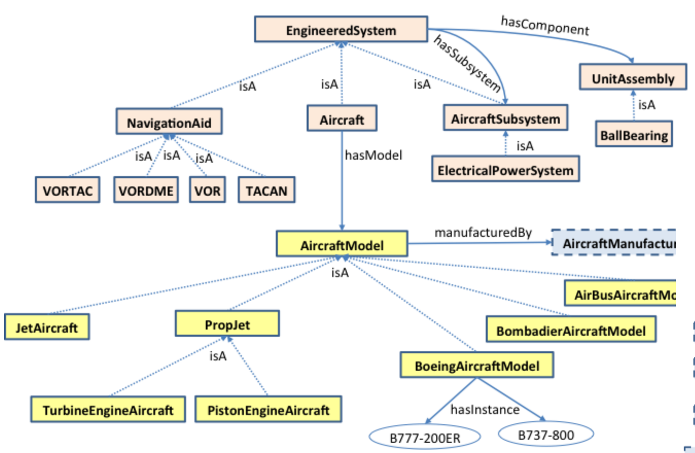
ATM Ontology

- 150+ classes
- 150+ datatype properties
- 100+ object properties

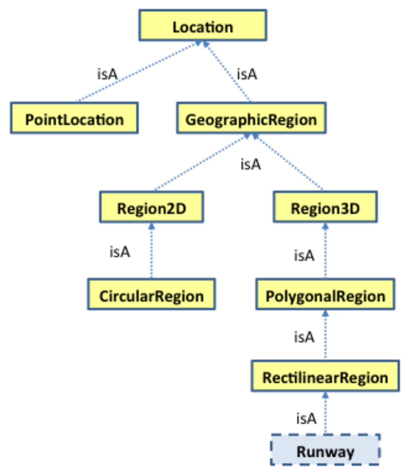
Flight & Navigation



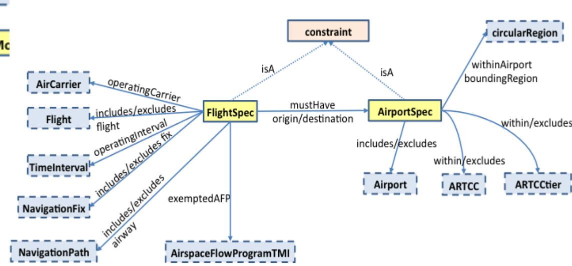
Aviation Equipment



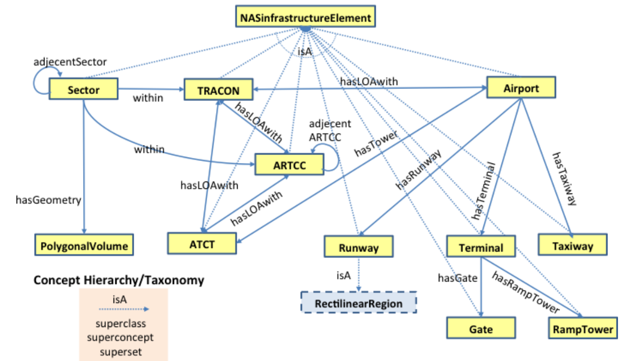
Spatial Representation



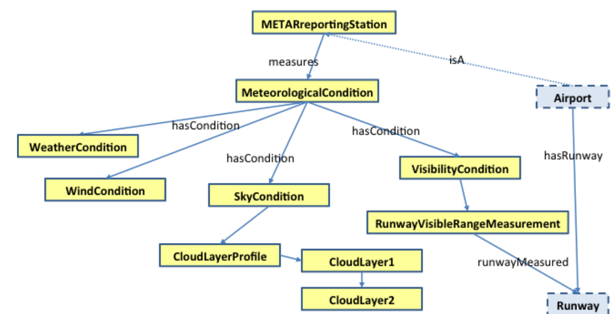
Flight/Airport Constraints



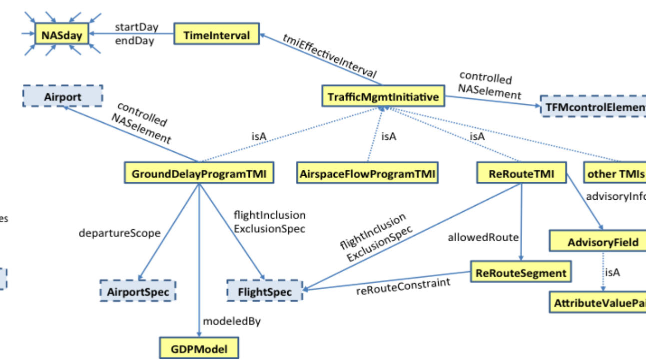
Airspace Infrastructure



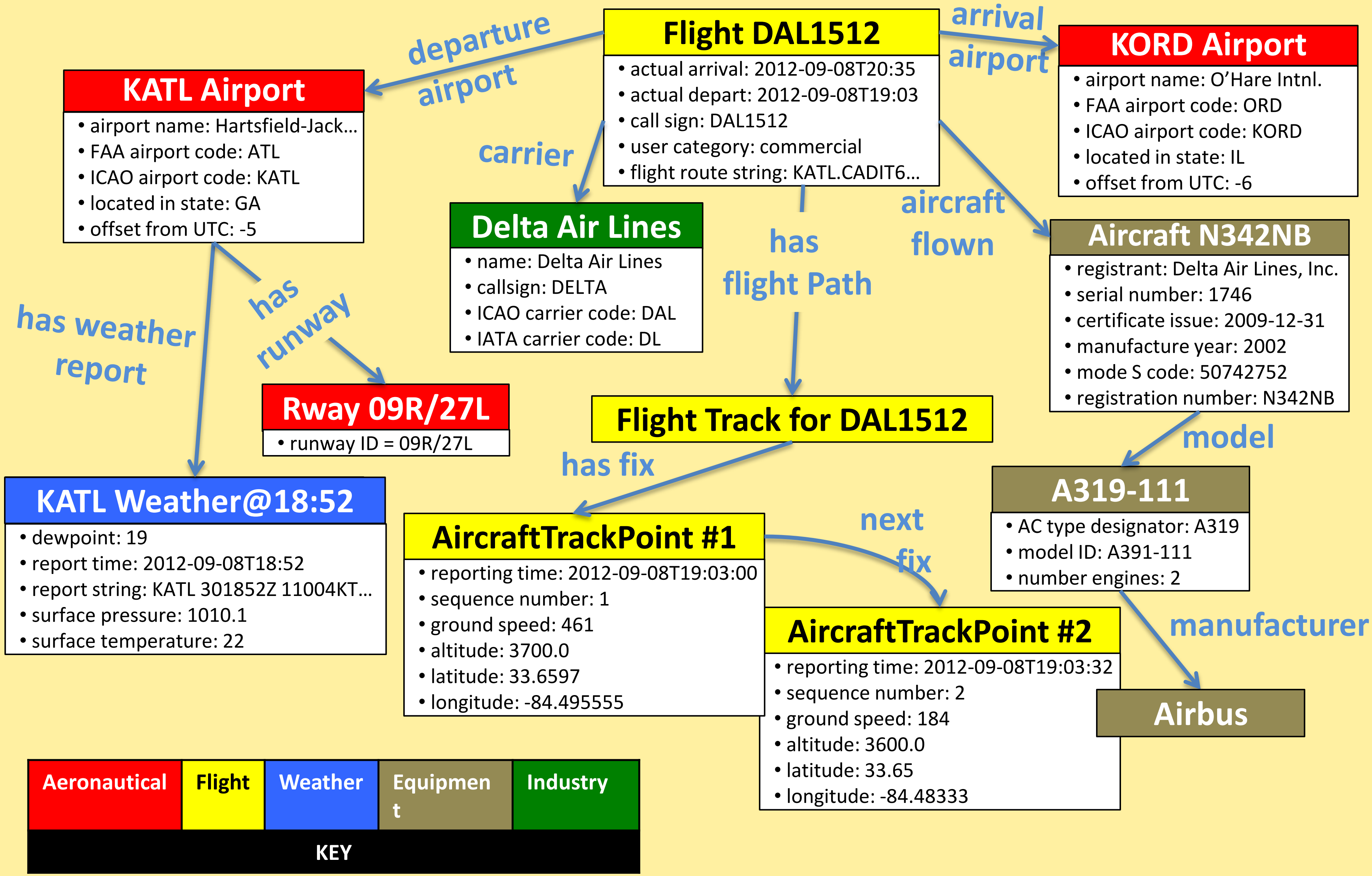
Meteorology



Traffic Management Initiatives (TMIs)



Ontology Representation of a Flight



Experimental Methodology

1. Develop ontology
2. Write data source translators
3. Run translators to generate data for a period covering one day of air traffic to/from a major airport (Atlanta): 1342 flights; ~2.4M triples
4. Load data into two commercial triple stores (AllegroGraph/Franz and GraphDB/Ontotext)
5. Develop a set of SPARQL performance benchmark queries and run on both triple stores
6. Replicate one day's worth of data x 31 to approximate one month of air traffic: ~40+K flights; ~36M triples*
7. Run queries again to compare results

*Estimate: 10B triples/yr. for US domestic flights

Sample Benchmark SPARQL Queries

- from a set of 17 queries for evaluating performance on scale-up -

- Flight Demographics:
  - F1: Find Delta flights using A319s departing Atlanta-area airports
  - F3: Find flights with rainy departures from Atlanta airport
- Airspace Sector Capacity:
  - S6: Find the busiest US airspace sectors for each hour in the day
- Traffic Management Statistics:
  - T1: Find flights that were subject to ground delays
- Weather-Impacted Traffic:
  - W1: Calculate hourly impact of weather on flight delays
- Flight Delay Data:
  - A3: Compare hourly airport arrival capacity with demand

Results for 17 benchmark queries

Flight Period	Execution Time		
	Min	Max	Avg
1 Day	11 ms	9.6 sec	1.19 sec
1 Month	8 ms	1651.2 sec *(170x increase)*	96.65 sec *(80x increase)*

Observations:

- ~30% of queries experienced no increase in execution time
- ~60% of queries scaled in proportion to increase in triples
- 1 query experienced exponential increase (350x – 700x, depending on triple store)

<u>Conclusion</u>: Scaling to multi-year flight periods does not appear feasible *unless* multi-hour or multi-day response times are acceptable

Query #	Execution Time in Milliseconds				Scale Factor	
	2.4M triples		36M triples		36M/2.4M ratio	
	Store #1	Store #2	Store #1	Store #2	Store #1	Store #2
A1	49	197	53	210	1.08	1.07
A2	36	176	37	147	1.03	0.84
A3	12	37	8	31	0.67	0.84
F1	98	64	2584	324	26.37	5.06
F2	36	28	298	96	8.28	3.43
F3S	466	482	12462	5070	26.74	10.52
S1S	1033	4749	726565	1651215	703.35	347.70
S2	11	858	59	19363	5.36	22.57
S3	1844	6060	35500	115389	19.25	19.04
S4	1786	4991	34985	108882	19.59	21.82
S5	1096	1412	11170	31199	10.19	22.10
S6	4825	9640	96846	163205	20.07	16.93
T1	32	43	269	171	8.41	3.98
T2	11	28	8	42	0.73	1.50
T3	193	68	268898	259	1393.25	3.81
W1	11	33	426	130	38.73	3.94
W2	11	37	11	39	1.00	1.05

5 Potential Scale-Up Approaches

1. **Hardware**: triple ‘appliances’ for faster storage, retreival & processing
2. **Algorithm**: better graph matching algorithms
3. **Software**: better query planners; new indexing approaches

↑ Hardware designers, researchers, triple store architects (1,2,3)
↓ Application developers, triple store users (4,5)

4. **Query reformulation**: rewrite queries
5. **Triple reduction**: reduce graph search space

4. Query Reformulation

- SPARQL queries can (in theory) be rewritten to improve efficiency
- Lack of transparency regarding how SPARQL queries are translated into code and executed makes rewriting difficult
- Tools to assist with optimization are missing or poorly documented
- <u>Wanted</u>!: ■performance monitoring tools ■query plan inspector ■index formulation tools
- SQL performance analysis tools are mature; SPARQL tools are primitive (in our experience)

Current Status Update

- Have scaled up to 1 month of actual flight data from the three NY Metropolitan airports:
  ~257M triples
  → considerably more than the 36M/month reported for Atlanta airport in the paper

- Will be re-testing benchmark queries against this data, but not easily comparable to existing data due to changed geographic region

Summary

- Described a real-world practical application for big semantic data: integrating *heterogeneous ATM data*
- Reviewed experiments performed to scale-up data and measure impact on query performance
- Discussed approaches to improving performance

Conclusion: Adequate tools not yet available to support real-world performance tuning for SPARQL queries in commercial triple stores

Caveat: Experience limited to only 2 triple stores!

In the end

Q: Can semantic representations scale to accomplish practical tasks using Big Data?

A: Well, I'm *still* not sure!

(…to be continued)

Triple Reduction

- Reduce the underlying search space by modifying the representation
- Undesirable trade-off possible:
  → trade representational fidelity for efficiency

Example: *representation of Aircraft Track Points*

TrackPoint Representation Tradeoff

Representation #1 vs. Representation #2

(2 inst. per minute: ~70% of all instances) (1 inst. per minute: ~54% of all instances)

Representation #1

AircraftTrackPoint

- reporting time: 2012-09-08T19:03:00
- sequence number: 31
- ground speed: 461

hasFix

GeographicFix

- altitude: 3700.0
- latitude: 33.6597
- longitude: -84.495555

Representation #2

AircraftTrackPoint

- reporting time: 2012-09-08T19:03:00
- sequence number: 31
- ground speed: 461
- altitude: 3700.0
- latitude: 33.6597
- longitude: -84.495555