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Parallel and Continuous Join Processing for Data Streams

Thèse pour l'obtention du grade de docteur

Table of Contents

Introduction

- Google: 24 PB / day
- Facebook: 10 million photos + 3 billion “likes” / day
- Youtube: 800 million visitors / month

Issues

- The size of Data.
- The flip side of size is speed.
- Transfer cost.
- Dynamic data — Data Stream

Dynamic Data Stream

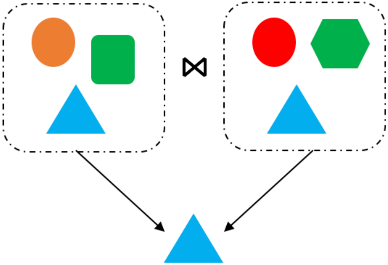
- Persistent **Static** Relations: **Batch-oriented** data processing
- Transient **Dynamic** Data Streams: Real-time **stream** processing

- **Architecture Level:** add or remove computational nodes based on the current load
- **Application Level:** withdraw old results and take new data into account

Objective: parallel and continuous processing for Join operation

Join:

- Find the common elements of several data sets under a specified condition.
- Popular and often used operation in the big data area.



Type:

- Data Driven Join : kNN (Data Parallelism)
- Query Driven Join : Semantic Join on RDF data (Task Parallelism)

Part I: Data Driven Stream Join (kNN)

- Introduction
- Survey about Parallel Solutions on MapReduce
    - Parallel Workflow
    - Theoretical Analysis
    - Experiment Result
- Continuous kNN
- Conclusion

Outline

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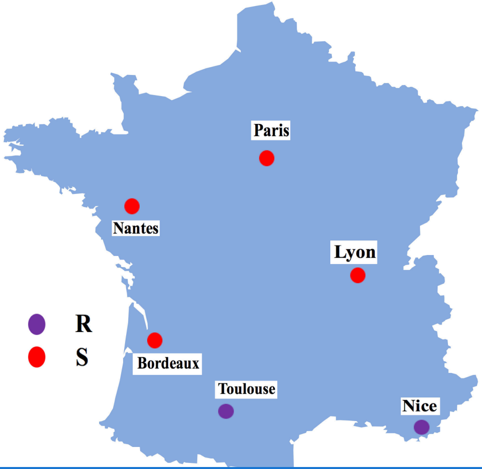
Introduction

Definition: kNN

Given a set of query points R and a set of reference points S, a k **nearest neighbor join** is an operation which, for each point in R, discovers the k nearest neighbors in S.

An Example of kNN Join

For each city in R, find the nearest city in S. (1-NN)



- **R:** Query Set
- **S:** Reference Set

- Query never changes
- Data format changes: GPS (2 Dimensions), Twitter (77 Dimensions), Images (128 Dimensions) etc.

Introduction: Basic Idea

- Nested Loop – Calculate the Distances

```
for(int r : R){
    for(int s : S){
        Distance(r, s);
    }
}
```

- Sort – Find the top k smallest distance for each element

Problem: Data Intensive and Computation Intensive

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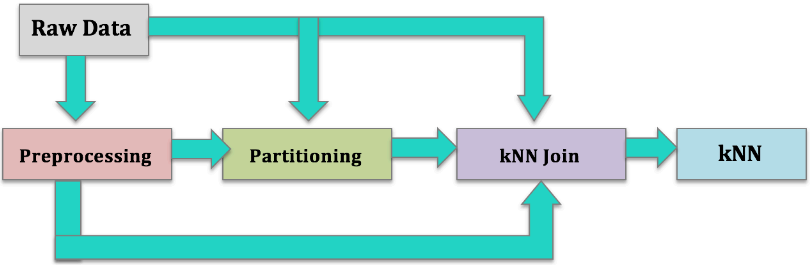
First Result: Parallel Workflow



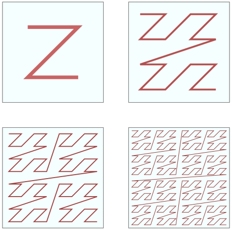
Data Preprocessing : Reduce the dimension of data

The curse of dimensionality: Too difficult to calculate in high dimension space.

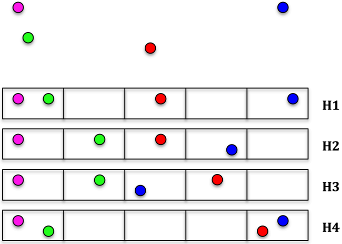
Solution: Project data from high dimension space to a low dimension one while preserving the locality information

Data Preprocessing – Reducing the dimension of data

Space Filling Curve (Z-Value)



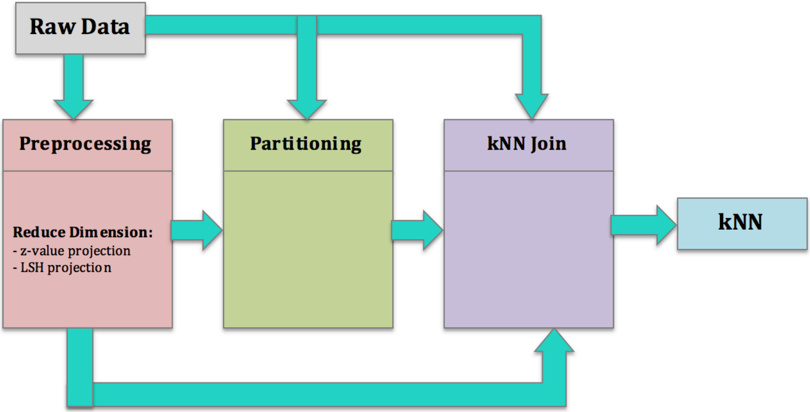
LSH: Locality Sensitive Hashing



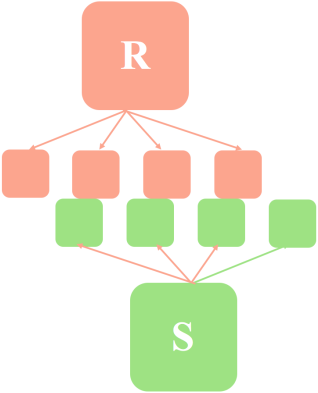
[z-value]: Efficient parallel kNN joins for large data in MapReduce, EDBT 2012, Chi Zhang et. al.

[LSH]: RankReduce - processing K-Nearest Neighbor queries on top of MapReduce, LSDS-IR 2010, Aleksandar Stupar et. al.

Parallel Workflow

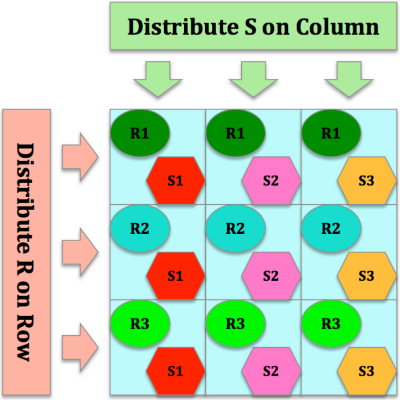


Data Partitioning



Purpose: Cut big data sets into smaller ones

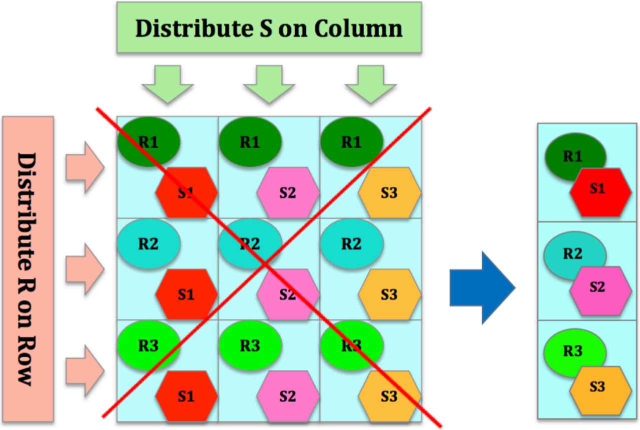
Data Partitioning – Basic Idea (Block Nested Loop)



Problem: n^2 tasks for calculating pairwise distances; wastes a lot of hardware resources, and ultimately leads to low efficiency.

Data Partitioning – Motivation

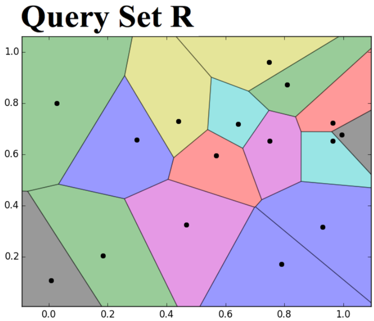
Purpose: Reduce the task number from n^2 to n



Data Partitioning – Distance Based Partitioning Strategy – Voronoi Diagrams

This strategy wants to have the most relevant points in each partition.

1. Partition Query Set R
2. Use same diagrams to partition S



Take neighbor cells

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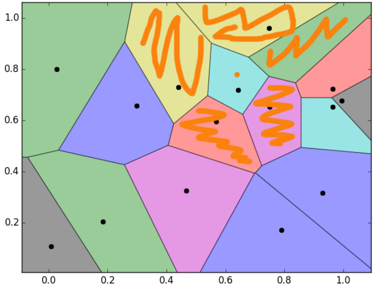
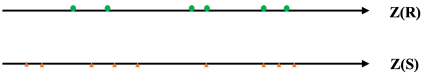


Take neighbor cells

Data Partitioning – Size Based Partitioning Strategy – Z-Value (or LSH)

This strategy wants to make each partition have equal size in order to achieve a good load balance.

1. A Sample of R
2. Partition the sample into equal sized partitions
3. Find corresponding partition in S for each R



Take 3 partitions

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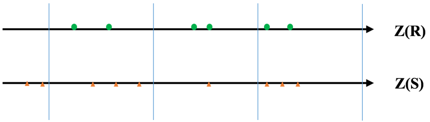

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Data Partitioning – Size Based Partitioning Strategy – Z-Value (or LSH)

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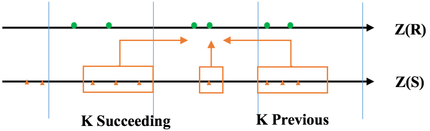
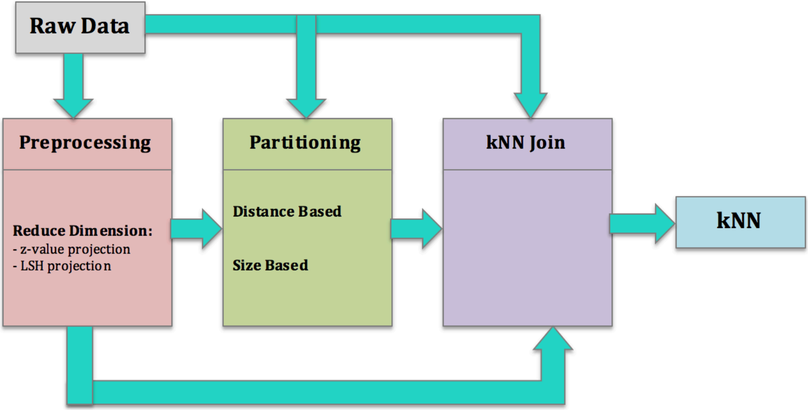


Take 3 partitions

Parallel Workflow



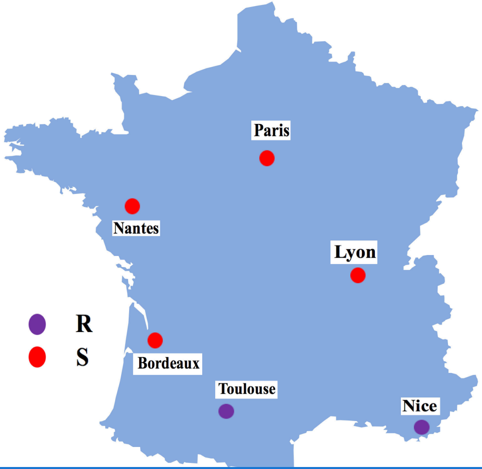
Computation

- One job — Directly give the global results
- Two consecutive jobs — First give the local results, then merge the local results into the global results

Purpose: reduce the number of elements to be sorted.

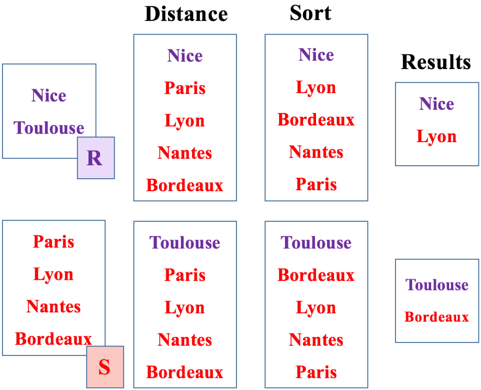
Computation – Example

For each city in $\mathcal{R}$, find the nearest city in $\mathcal{S}$. (1-NN)



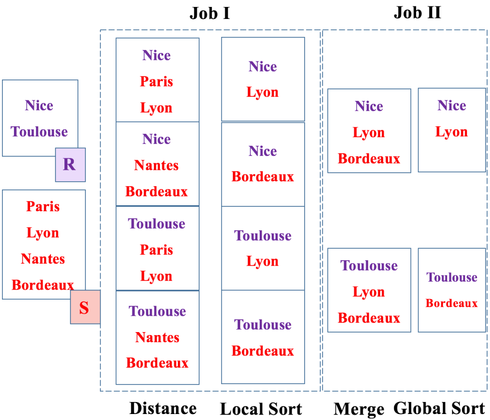
Computation – Example

One Job:

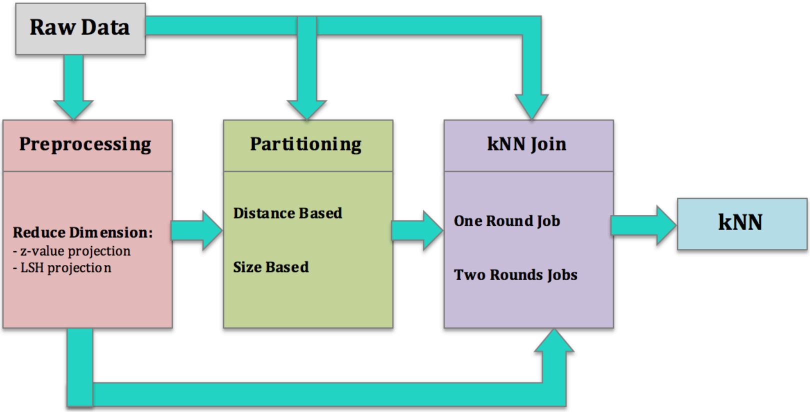


Computation – Example

Two Jobs:



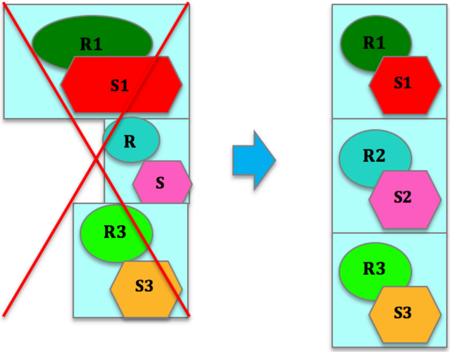
Parallel Workflow



Result 2: Theoretical Analysis

- Load Balance
- Accuracy
- Complexity

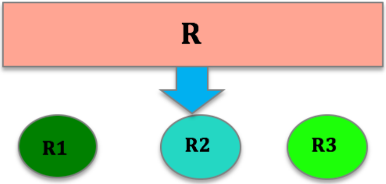
Load Balance



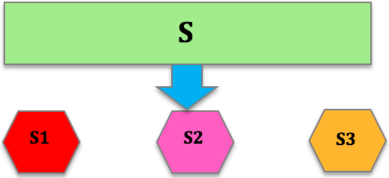
Sub-Optimal Load Balance

Partition one, deduce the other:

(1) Partition R into equal-sized



(2) Partition S into equal-sized



(1) is better in the worst case.

Accuracy

Accuracy: Number of correct results obtained

- **Z-Value**
  - Depends on k
  - Shift of data — move data in the direction of a random vector
  - Increase number of shifts of data to decrease error rate
- **LSH**
  - Depends on parameter tuning
  - Increase the number of hash functions to decrease error rate

Complexity

- **Number of MapReduce jobs:** starting a job requires some initial steps.
- **Number of Map tasks and Reduce tasks used to calculate kNN$(R_i \ltimes S)$:** the larger this number, the more network communication
- **Number of final candidates for each object r_i:** Finding the top k results is very time consuming.

Result 3: Experimental Analysis

Cluster Setting

- Two clusters of Grid'5000 with Hadoop 1.3 (3 replications, 1 slot per node)

Datasets

- **OpenStreetMap** Geo dataset contains geographic XML data in two dimensions — Low Dimension
- **Caltech 101** It is a public set of images, which contains 101 categories of pictures of different objects. (Speeded Up Robust Features — 128 dimensions) — High Dimension

Methods Evaluated

- **H-BkNNJ** Naive Method – Without preprocessing and partitioning – One Job
- **H-BNLJ** Block Nested Loop – Without preprocessing and partitioning – Two Jobs
- **PGBJ** Based on Voronoi – Preprocessing: Select Pivots – Distance Based Partitioning – One Job
- **H-zkNNJ** Based on Z-Value – Preprocessing: z-value – Size Based Partitioning – Two Jobs
- **RankReduce** Based on LSH – Preprocessing: LSH – Size Based Partitioning – Two Jobs

Evaluation Result – Verify the theoretical Analysis

Execution Time for Geo dataset (2 dimensions):

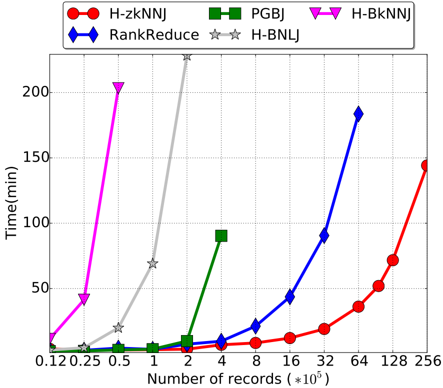
H-BkNNJ: Naïve

H-BNLJ: Block Nested Loop

PGBJ: Voronoi

H-zkNNJ: z-value

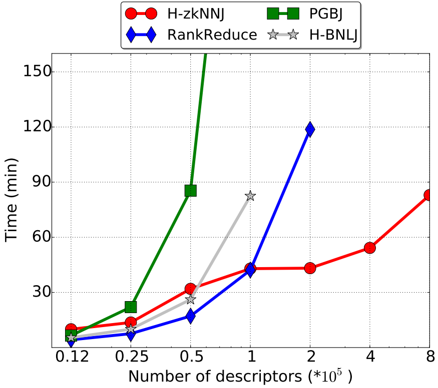
RankReduce: LSH



Evaluation Result – Surprise

Execution Time for Image dataset (128 dimensions):

H-BkNNJ: Naïve
H-BNLJ: Block Nested Loop
PGBJ: Voronoi
H-zkNNJ: z-value
RankReduce: LSH



Conclusions of the survey

- Clear and detailed view of the current algorithms for processing kNN on MapReduce
- Fine grained analysis both theoretical and experimental for each algorithm to obtain the best performance.
- Match algorithm with typical use case

Limitation of the existing algorithms

- Non of them can process data streams

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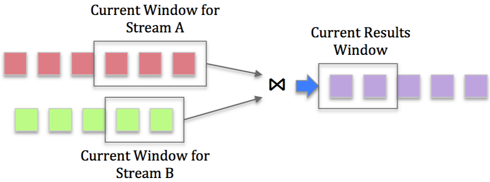
Sliding Window Model – Motivation

- Unbounded sequence of elements which can not be wholly stored in bounded memory
- New items in a stream are more relevant than older ones.

Sliding Window Model

Maintaining a moving window of the most recent elements in the stream



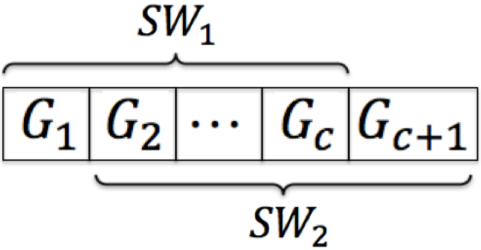
Sliding Window — Two Strategies

- **Re-Execution Strategy**
  - **Eager Re-execution Strategies** — Generating new results right after each new data arrives
  - **Lazy Re-execution Strategies** — Re-Executing the query periodically
- **Data Invalidation Strategy**
  - **Eager Invalidation Strategies** — Scanning and moving forward the sliding window upon arrival of new data
  - **Lazy Re-execution Strategies** — Removing old data periodically and require more memory to store data waiting for expiration

Sliding Window – Two Strategies

- **Re-Execution Strategy**
  - Eager Re-execution Strategies
  - Lazy Re-execution Strategies
- **Data Invalidation Strategy**
  - Eager Expiration Strategies
  - Lazy Invalidation Strategies

Re-Execution and Expiration Period – Generation



Different types of dynamic kNN joins

- Static R and Dynamic S (SRDS)
  - Exists rarely in real applications.
  - Reuse the parallel methods
- Dynamic R and Static S (DRSS)
  - Most used scenario in real applications
  - Example: find restaurant for moving users
  - Reuse Random Partition method
- Dynamic R and Dynamic S (DRDS)
  - General situation
  - Example: find Pokémon for moving players
  - Basic Method + Advanced Method

Dynamic R and Dynamic S – Basic Method (Sliding Block Nested Loop)

n^2 tasks for each generation

		S in i^{th} Generation			
		S_1	S_2	...	S_n
R in i^{th} Generation	R_1	$G_i(R_1, S_1)$	$G_i(R_1, S_2)$	...	$G_i(R_1, S_n)$
	R_2	$G_i(R_2, S_1)$	$G_i(R_2, S_2)$	...	$G_i(R_2, S_n)$
	...	...	...	...	...
	R_n	$G_i(R_n, S_1)$	$G_i(R_n, S_2)$	...	$G_i(R_n, S_n)$

Dynamic R and Dynamic S – Advanced Method (Naive Bayes Partitioning)

Purpose: n tasks for each generation:

- Partition new data items
- No time to repartition old ones

Solution: Classification for new data items based on Naive Bayes Theory

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Conclusion

- A detail survey for parallel kNN join on MapReduce
- Continuous kNN Join for Data Streams
- Theoretical and Experimental Analysis

Part II: Query Driven Stream Join (RDF)

- Introduction
- Query Decomposition and Data Partition
- Parallel and Distributed Query Plan
- Continuous Join
- Implementation
- Experiment Result
- Conclusion

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Introduction – RDF Data Model

- **R**esource **D**escription **F**ramework
- Describe semantic relations among data.
- Triples in form of *<subject, predicate, object>* (e.g. *<Sophie, hasSister, Ray>*)

Introduction – SPARQL Query Language

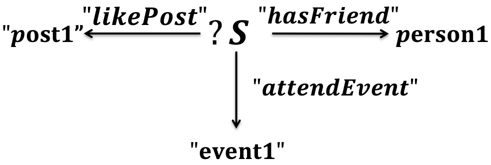
- SPARQL is a W3C recommendation query language for querying RDF data.
- The basic component of a SPARQL query is the triple patterns.
- A triple pattern is a special kind of triple where S, P and O can be either a literal or a variable.

An Example (Triple Pattern Representation):

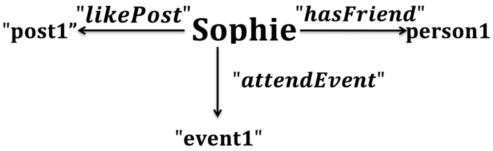
```
SELECT ?S
WHERE{
   Q1     ?S "hasFriend" person1 .
   Q2     ?S "likePost" "post1" .
   Q3     ?S "attendEvent" "event1"
}
```

Introduction – SPARQL Query Example

Graph Representation for SPARQL Query:

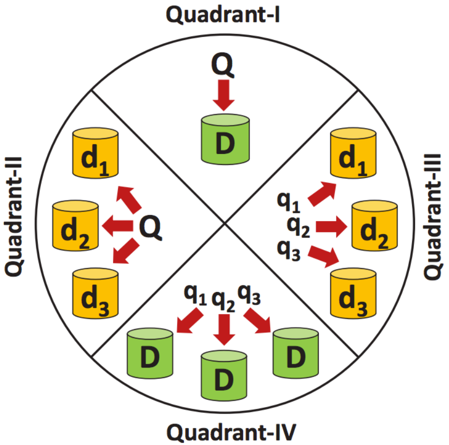


Graph Representation for RDF Data:



Related Works – 4 Types of Processing

- QI: Centralize
- Q2 and Q4: Distribute either data or query
- Q3: Distribute both data and query (We use this manner)



DREAM: distributed RDF engine with adaptive query planner and minimal communication, PVLDB 2015, Mohammad Hammoud et. al.

Related Work – Partitioning Strategies for RDF graphs

- Vertex Partitioning methods for graphs.
  - High overhead of loading big RDF graphs into the existing graph partitioner.
  - Requires the entire graph information in order to make decisions
  - Replication of the boundary of each partition in order to reduce the transmission of data
- Hash Partitioning based on indexes
  - Too many indexes (up to 15)

General Distributed Processing Steps

- Partition the RDF streams, and distribute these sub-streams to different nodes
- Decompose the queries into sub-queries and assign these sub-queries to the appropriate nodes
- Reply rapidly to the changes of data (the expiration of old data, and the update of new data), and return the results in real-time

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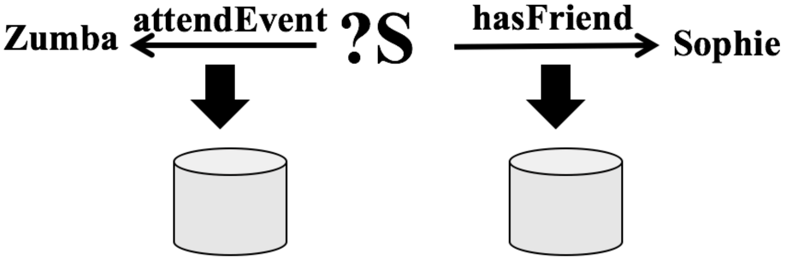
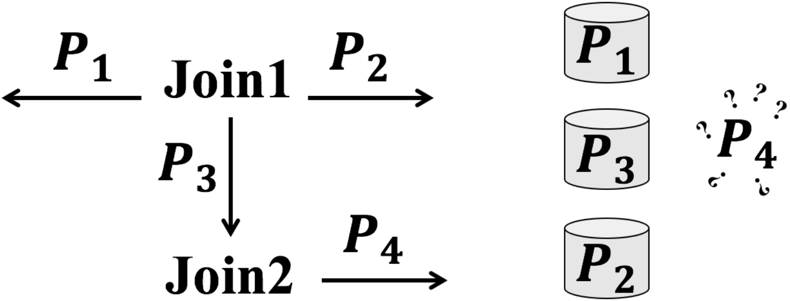
Query Decomposition

Decomposition Strategy: Divide the queries into triple patterns, send each triple pattern to different machines.

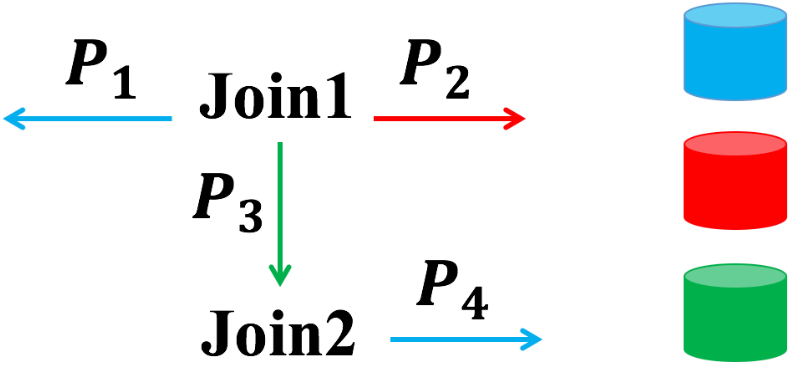


Sub-Query Scheduling



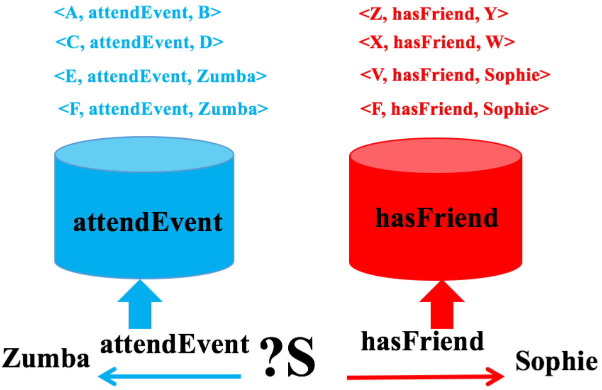
Sub-Query Scheduling

Edge Coloring Method: Maximize Parallelism



Data Partitioning

Partitioning Strategy: The triples will be assigned to the nodes that hold the triple pattern with the same predicate.



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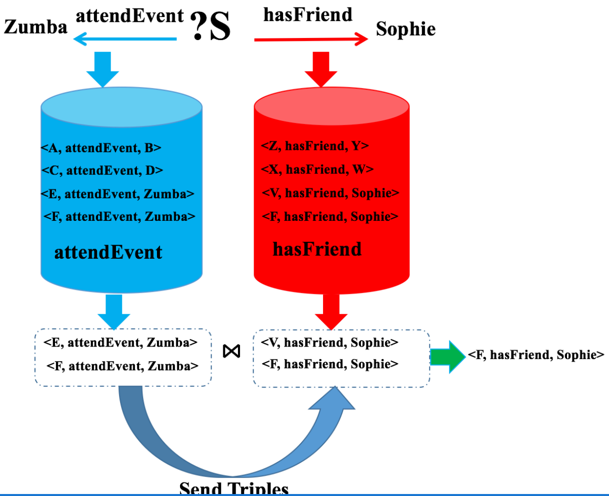
Challenges

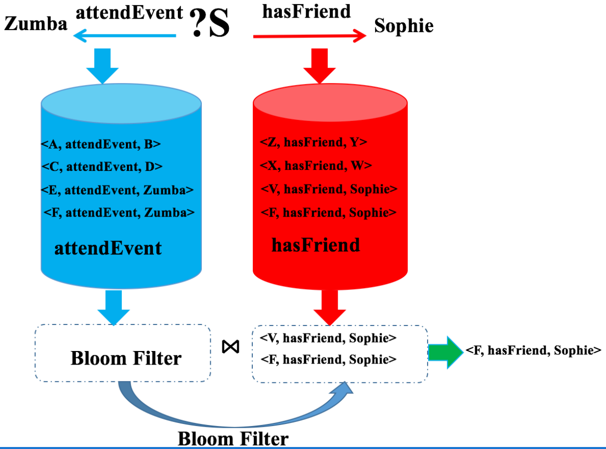
- Communication among nodes
- Join of the intermediate results produced by each triple pattern
- Order of sending and receiving information

Communication



Communication

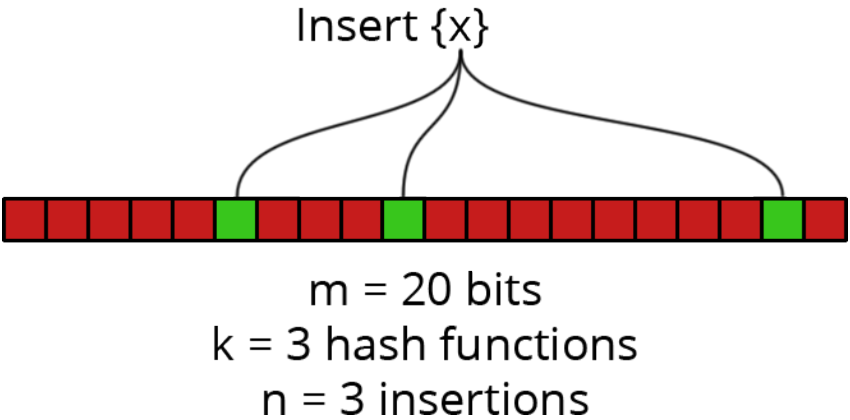
Do not send triples, send a function saying that we already met these triples



Communication among nodes – Bloom Filter

m = 20 bits
k = 3 hash functions
n = 3 insertions

Communication among nodes – Bloom Filter



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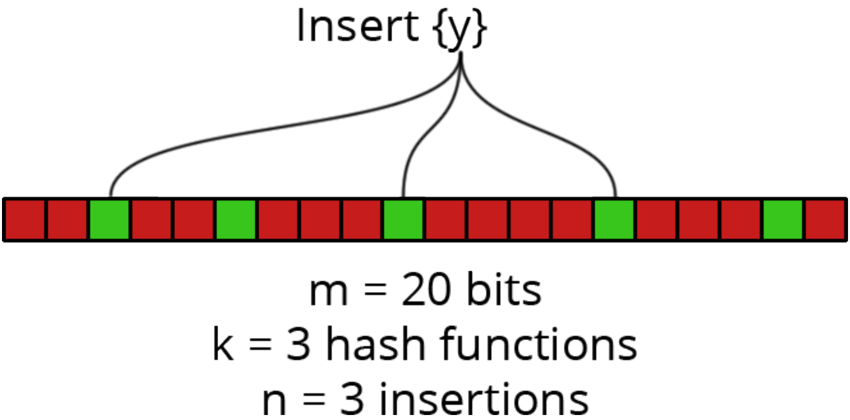

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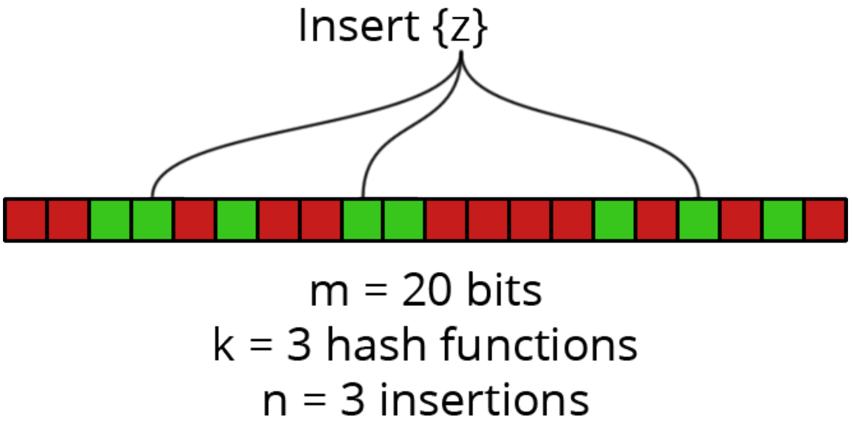

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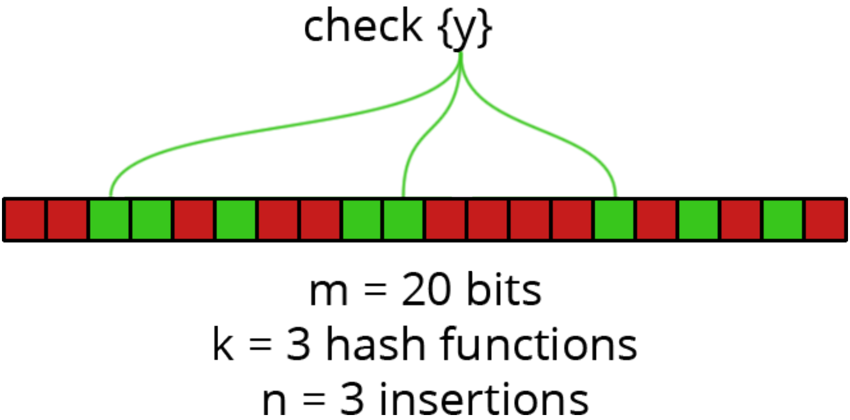

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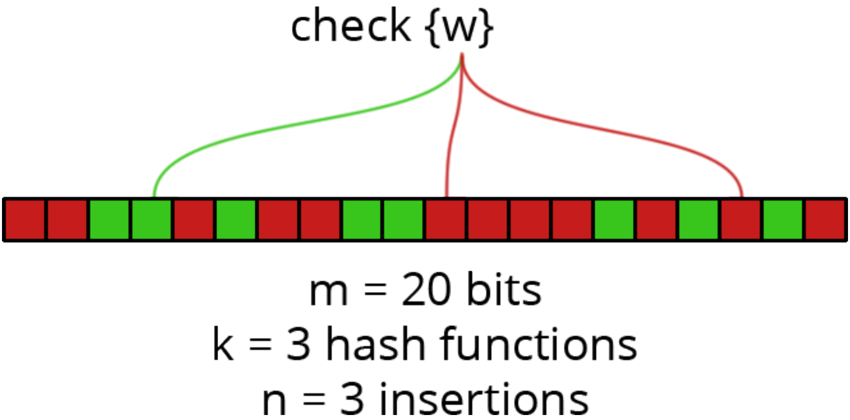

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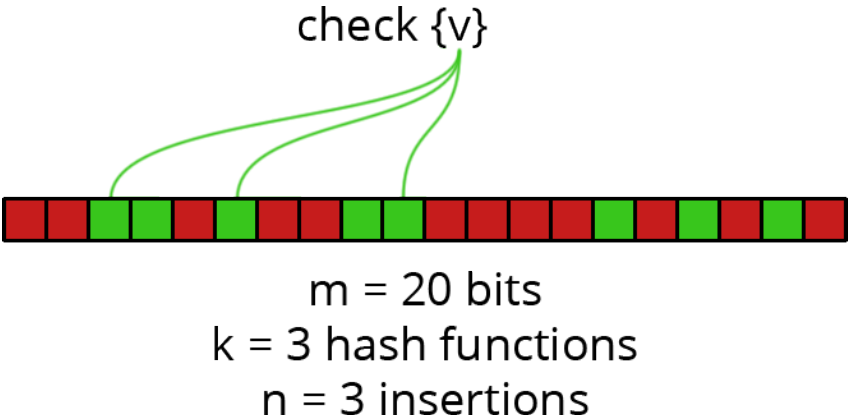


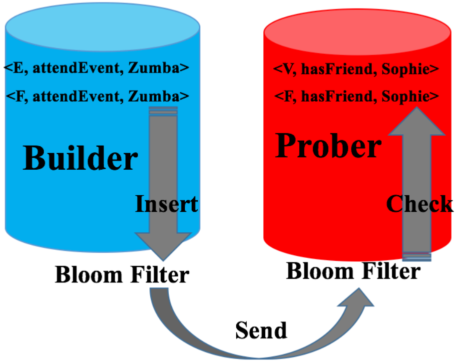
Communication among nodes – Bloom Filter

False Positive Rate

$$p = \left(1 - e^{-\frac{nk}{m}}\right)^k$$

Bloom Filter – Build and Probe

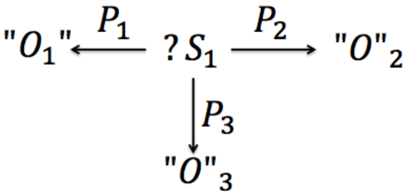
- **Builder:** create bloom filters.
- **Prober:** use bloom filters

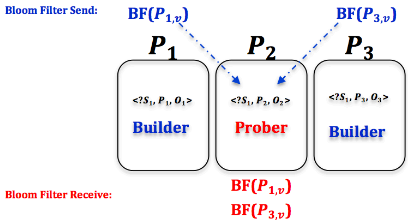


Question: Which triple patterns should be **Builders**, and which ones should be **Probers**?

The join of the intermediate results – Structure Based Rules

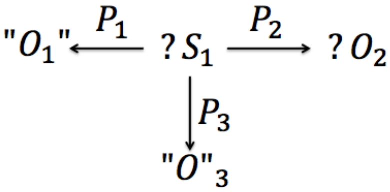
Rule 1: 1-Variable Join

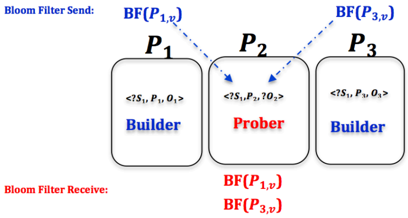




The join of the intermediate results – Structure Based Rules

Rule 2: 2-Variable Join

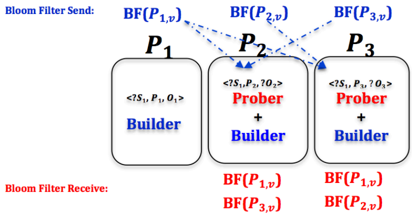




The join of the intermediate results – Structure Based Rules

Rule 3: Multiple-Variable Join

$$\begin{tikzcd} \text{"}O_3\text{"} & ?S_1 \arrow[l, "P_3"'] \arrow[r, "P_1"] \arrow[d, "P_2"] & ?O_1 \\ & ?O_2 & \end{tikzcd}$$



Question: what is the sending and receiving order?

Sending and Receiving orders

Rule 4: Query Topological Sort

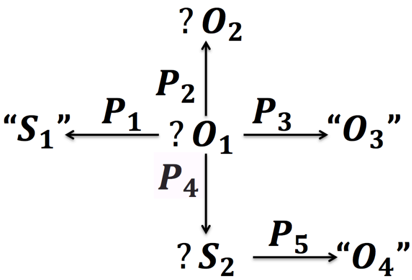
Purpose: Find the dependencies for each variable

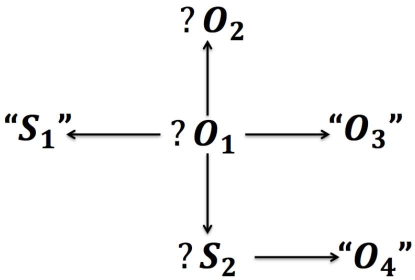
Query Topological Sort

Query Topological Sort is a topological sort for the query graphs, where the constant nodes on the graph have higher priority than the variable nodes at the same level.

The order of sending and receiving information

Rule 4: Query Topological Sort





Results: $\{\text{“}O_4\text{"}, ?S_2, \text{“}S_1\text{"}, \text{“}O_3\text{"}, ?O_2, ?O_1\}$

Outline

- Introduction
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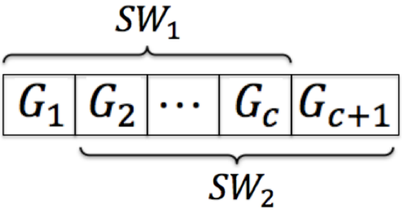
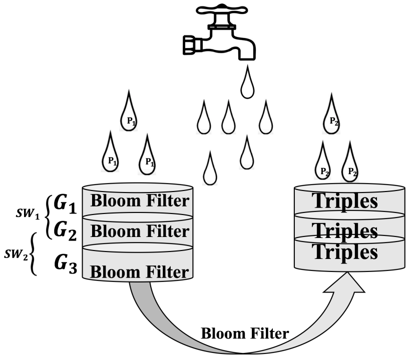
- Parallel and Distributed Query Planner
- Continuous Join
- Implementation
- Experiment Result
- Conclusion

Continuous Join: Sliding Window + Sliding Bloom Filter





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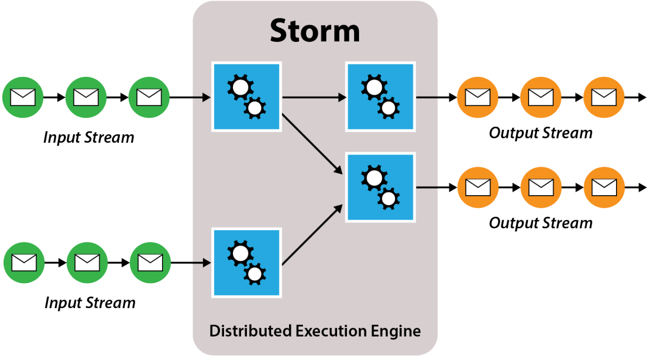
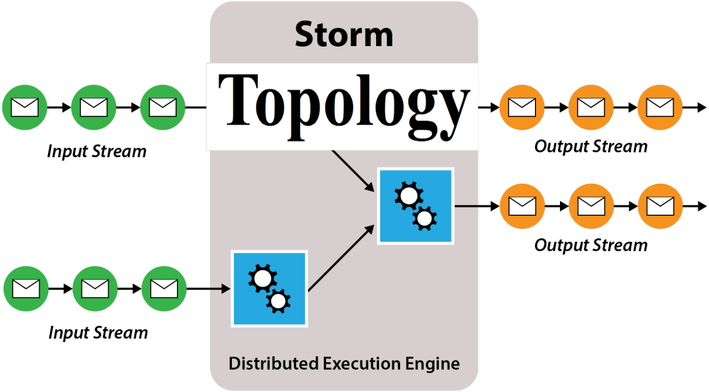
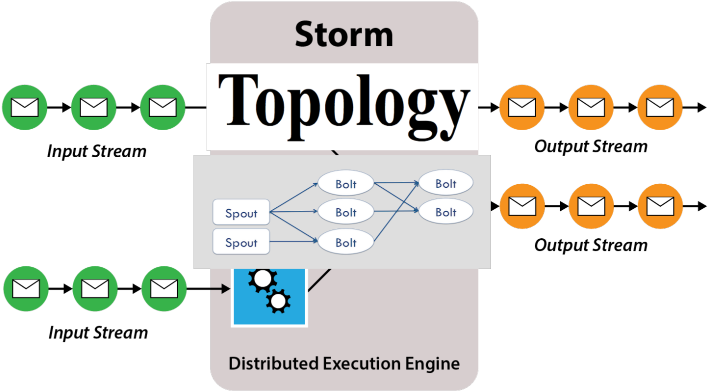
Apache Storm



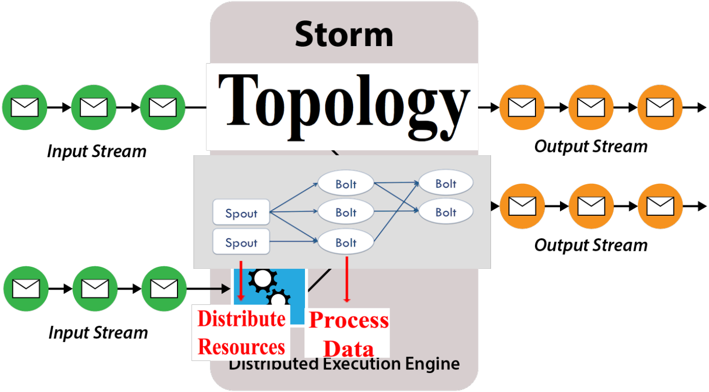
Apache Storm



Apache Storm

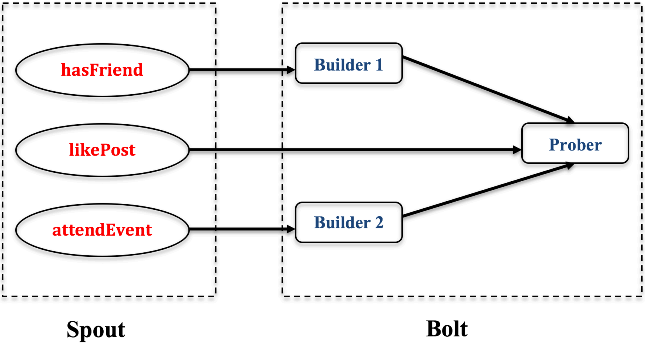


Apache Storm



Implementation

```
SELECT ?S
WHERE{
  Q1    ?S "hasFriend" person1 .
  Q2    ?S "likePost" "post1" .
  Q3    ?S "attendEvent" "event1"
}
```



Implementation

```
SELECT ?S
WHERE{
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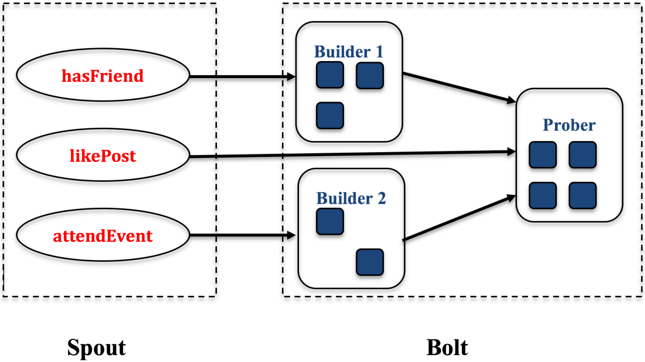

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Experiment Setting

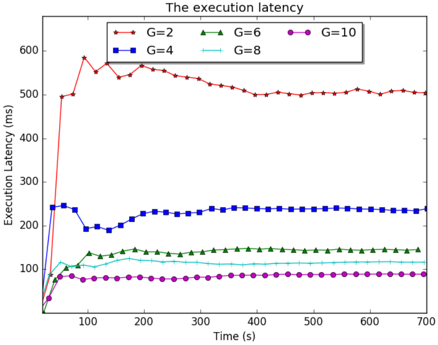
- We evaluate the system on Grid 5000, with 11 nodes. 1 Master (Nimbus), 10 Slaves (Supervisor).
- The Storm version is 1.0, and we only use one slot on each machine.
- Apache Jena API is used for reading triples.

- Synthetic data
  - The RDF triples generated in Spouts are distributed to the nodes according to their predicate.

Execution Lateny

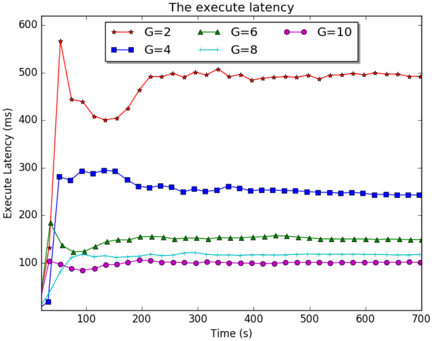
Sliding Window Size = 800 (1-Variable Join)

More Generations $\Rightarrow$ More frequent updates $\Rightarrow$ Faster

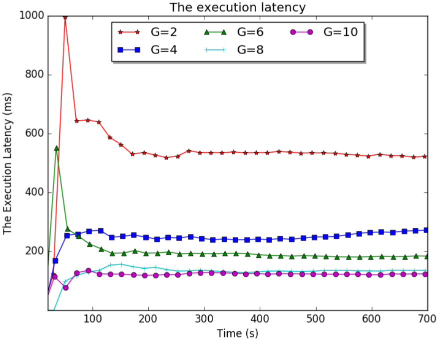


Execution Latency

2-Variable Join

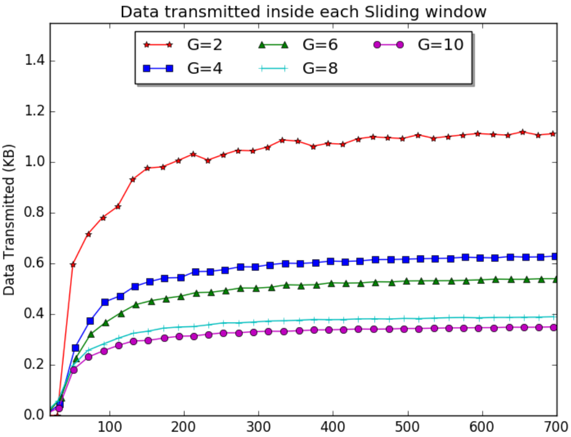


Multiple-Variable Join



Data Transmitted – Sliding Window Size = 800

Multiple-Variable Join



Accuracy

We got 100% correct results — Surprise!

Large Bloom Filters but very few matching elements.

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Conclusion

- Parallel and distributed join processing on RDF streams
- Distribute both data and queries
- Efficient
  - Time
    - Execution Latency less than 600 ms
  - Space — 400 times more efficient than without using Bloom FIlters

Conclusion and Future Work

Conclusion

- Data Driven Join
  - Data Preprocessing
  - Data Partitioning
  - Data Computation
- Query Driven Join
  - Query Decomposition
  - Communication among Sub-Queries
  - Combine results of Sub-Queries

Future Work

- Enrich the Naive Bayes re-partitioning strategy for kNN stream join (theoretical and experimental analysis and proof — Accuracy, Load Balance)
- Enrich the SPARQL query engine by providing operations such as FILTER, OPTIONAL, etc.

Future Applications

- Real Time Recommendation System Based on kNN
- Real Time Natural Language Processing System Based on RDF

Publications:

- **K Nearest Neighbour Joins for Big Data on MapReduce: a Theoretical and Experimental Analysis — TKDE 2016 — Ge Song**, J. Rochas, L. Beze, F. Huet, F. Magoulès
- **Solutions for Processing K Nearest Neighbor Joins for Massive Data on MapReduce — PDP 2015 — Ge Song**, J. Rochas, F. Huet, F. Magoulès
- **A Hadoop MapReduce Performance Prediction Method — HPCC 2013 — Ge Song**, Z. Meng, F. Huet, F. Magoulès, L. Yu, X. Lin
- **A Game Theory Based MapReduce Scheduling Algorithm —** Springer New York — **Ge Song**, L. Yu, Z. Meng, X. Lin
- **Detecting topics and overlapping communities in question and answer sites — SNAM 2014 —** Z. Meng, F. Gandon, C.Zucker, **Ge Song**
- **Empirical study on overlapping community detection in question and answer sites — ASONAM 2014 —** Z. Meng, F. Gandon, C. Zucker, **Ge Song**

Thank You!