#### Optimizing Data Placement for Distributed Computation

#### WATERLOO

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#### **Based on**

- Lukasz Golab, Marios Hadjieleftheriou (AT&T), Howard Karloff (Yahoo), Barna Saha (AT&T), Distributed data placement to minimize communication costs via graph partitioning, SSDBM 2014
- Available at www.engineering.uwaterloo.ca/~lgolab



# Background

- Popular big data trend
  - Shared-nothing clusters of servers
  - Distributed storage and processing
  - Great for jobs that parallelize easily
    - E.g., count the number of documents containing some string
  - But data-intensive jobs require data migration



# Background

- CoHadoop [VLDB 2011, EI-Tabakh et. al.]
   User can give file co-location hints
- Our Goal
  - Given the query workload, can we automatically place the data on a computing cluster to minimize data transfer cost?



- m queries, Q\_1 through Q\_m
- n tables, T\_1 through T\_n,
   then ith table having size w\_i
- A query requires one or more tables
- For each Q\_i and T\_j required by Q\_i, a data transfer volume C\_ij



- In general,
  - Table = data item, file, table partition, etc.
  - Query = anything that processes data, etc.



- k servers, S\_1 through S\_k,
  - the jth server having storage capacity s\_j and processing capacity p\_j
- Every query runs on a server
  - copies the data it needs to its server
  - does some processing
- Every table is stored on a server
  - we'll get to replication later



- Assign each query and table to a server in a way that
  - minimizes the the total data transfer cost during query execution
  - and does not violate the server storage and processing capacities



### Assumptions

- Storage capacity of any one server < sum(w\_i), the total size of the tables</li>
- Processing capacity of any one server < m (the number of queries)
- Otherwise, just use one server, and data transfer cost = 0
- Queries are data-intensive



## Solution #1

- Formulate an optimization problem and solve it using CPLEX
  - Extremely slow due to complexity of the problem (NP-hard, as we prove in the paper)

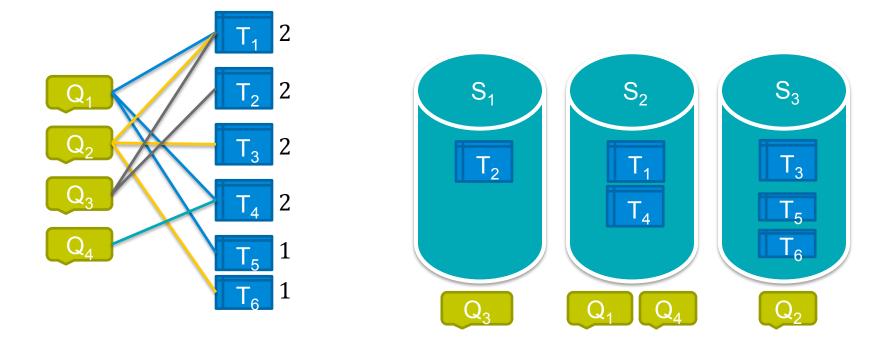


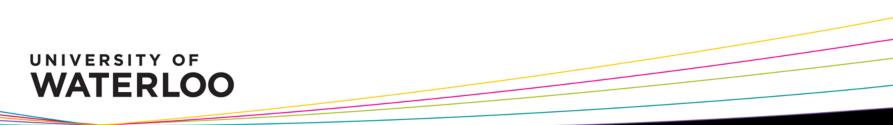
## Solution #2

- Compute an approximate solution
- Reduce our problem to graph partitioning
  - Still NP-hard but efficient approximation algorithms exist
  - E.g., METIS

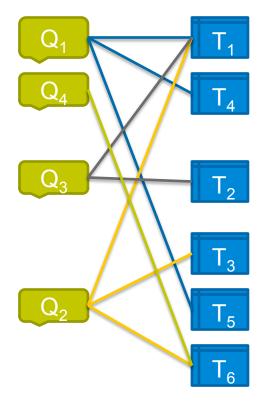


#### Example





# **Bipartite Graph Partitioning**



- Queries on the left
- Tables on the right
- Each query node has processing weight 1
- Each table node has storage weight w\_i
- Each edge from Q\_i to T\_j has weight C\_ij

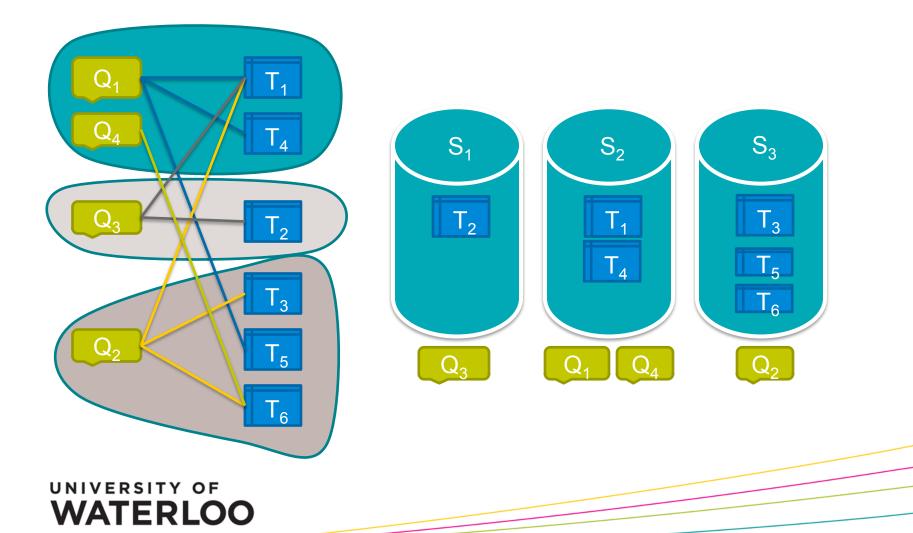
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## Reduction to Graph Partitioning

- Partition the query graph:
  - Into k parts
  - Each with sum(w\_i) <= server storage capacity and num. queries <= server processing capacity
  - To minimize the weight of the cut edges
- Claim: this reduction solves our problem



#### Example



## **Previous Work**

- OLTP setting: minimize the number of distributed transactions [VLDB 2010, Curino et. al.]
- Modeled as hypergraph partitioning

   More general than graph partitioning → worse performance



# **Hypergraph Partitioning**

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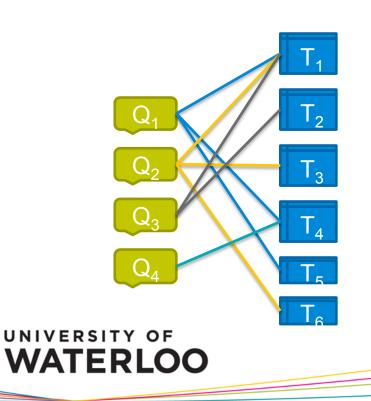
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- Tables are nodes
- Queries are hyperedges
- Cost of cutting a hyperedge = 1



## Replication

- What if we store up to or exactly r copies of each table?
- Optimization program gets even more complex and slow
- We propose 2 algorithms using graph partitioning as a subroutine



# Algorithm #1

- Pretend the server capacities are s\_i/r and p\_i/r
- Run graph partitioning once
   Place one copy of each table

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- Randomly permute the servers
  - Place second copy of each table

# **Problem with Algorithm #1**

- Some tables may end up with < r copies</li>
- E.g.,
  - **1**-2-3-4-5-6-7-8
  - **1**-7-5-6-2-8-**4**-3
  - 5-3-1-8-6-7-4-2



# Algorithm #2

- Partition servers into r groups
- Run graph partitioning using the first group of k/r servers
- Remove the m/r cheapest queries
- Run graph partitioning using the second group of k/r servers
  - Repeat with ALL tables but only the remaining queries
- Remove the m/r cheapest queries

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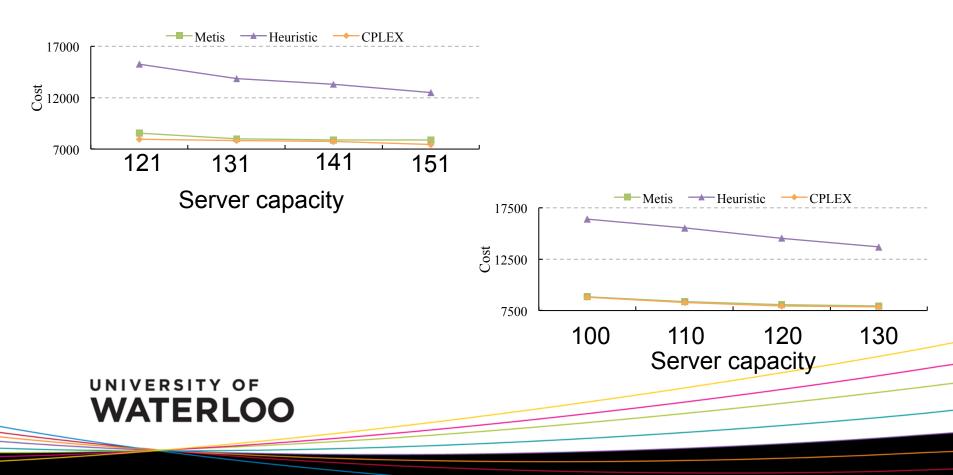
## **Experimental Results**

- Optimization program solved by CPLEX vs. graph partitioning solved by METIS vs. simple heuristic
  - Using a workload similar to TPC-DS (24 tables, 99 queries)
- Scalability experiments using very large random query graphs



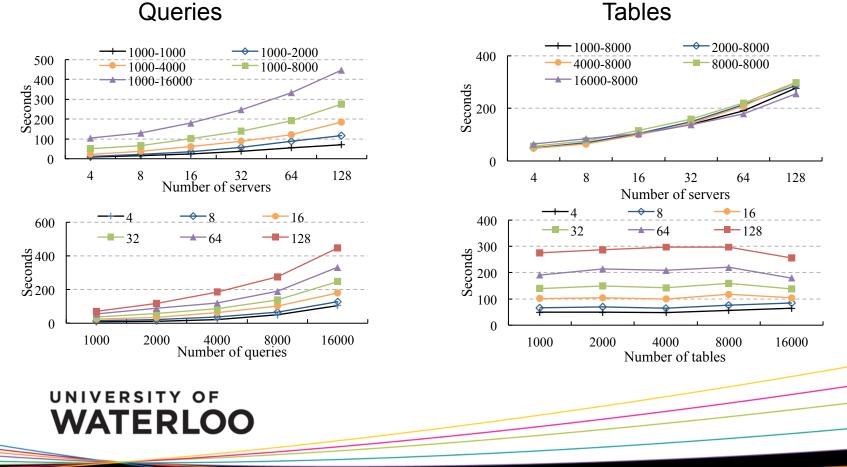
#### **Sample Results**





### Scalability

- number of queries: 1000-16000
- number of tables: 1000-16000
   Queries



## See Paper For

- Replication algorithm #2 is better
- Extension to complex workflows
  - Intermediate results



# Summary

- Careful data placement is necessary when running data-intensive queries on a cluster
- Provided data placement algorithms via graph partitioning
- Future work: combine table/query partitioning with data placement

