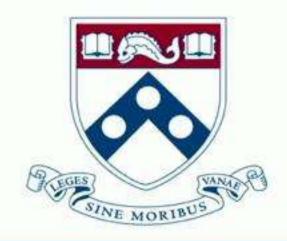
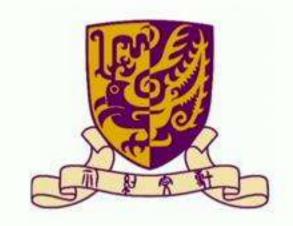
Optimizing Declarative Graph Queries at Large Scale

Qizhen Zhang, Akash Acharya, Hongzhi Chen⁺, Simran Arora, Ang Chen^{*}, Vincent Liu, Boon Thau Loo University of Pennsylvania, ⁺The Chinese University of Hong Kong, ^{*}Rice University



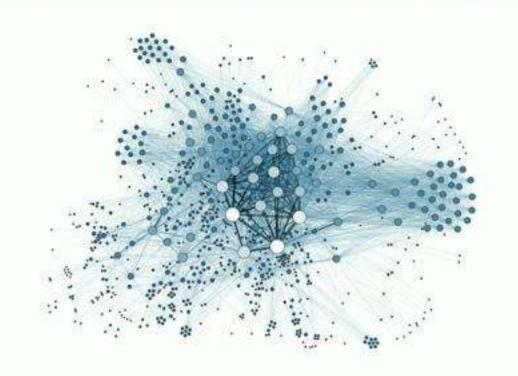




Graphs Are Important

Graph processing is everywhere

· Web graph, social networks, road networks...



Graphs Are Important & Large

Graph processing is everywhere

- Web graph, social networks, road networks...
- They are increasingly large (scaling from billions to trillions).

The largest workloads are deployed at massive scales

- Clouds
- Data centers

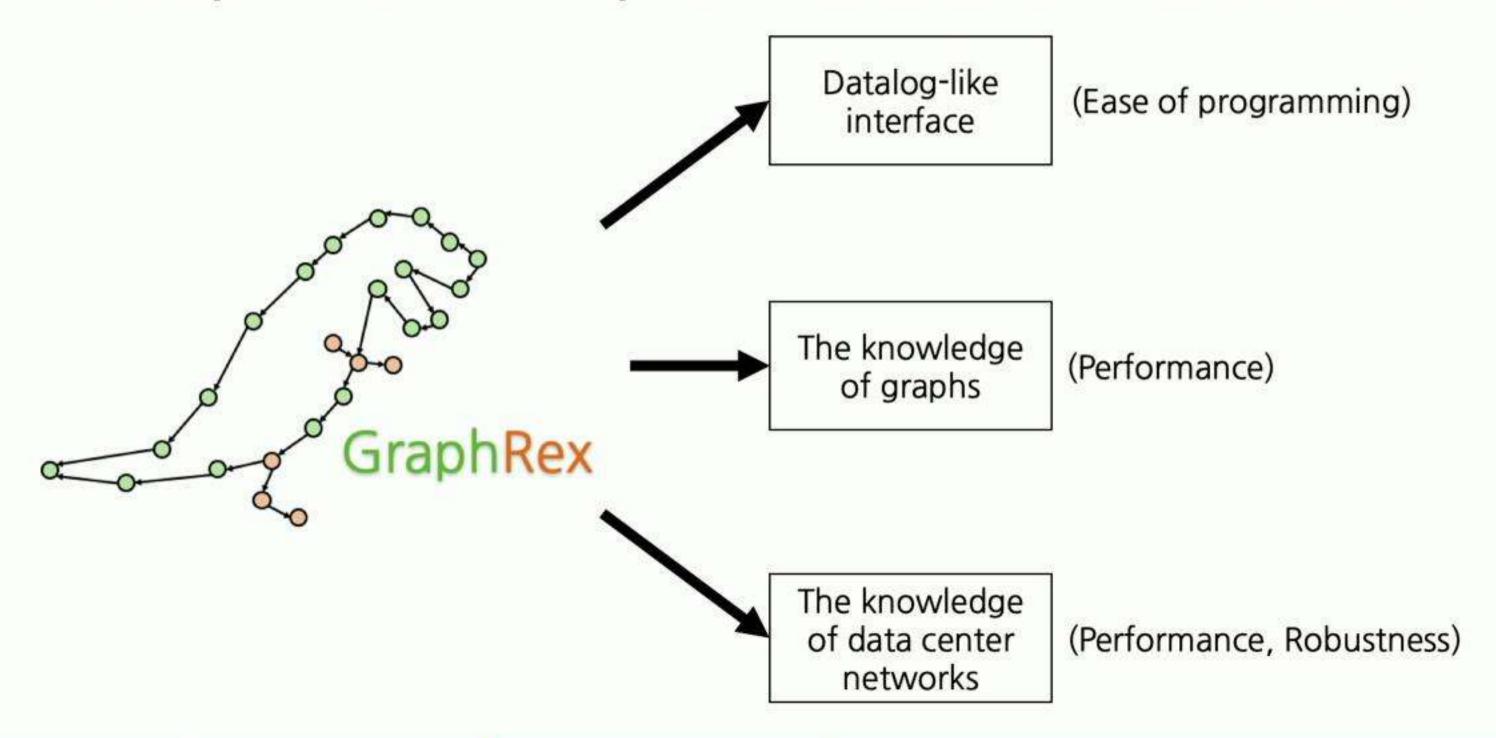
Large deployments require:

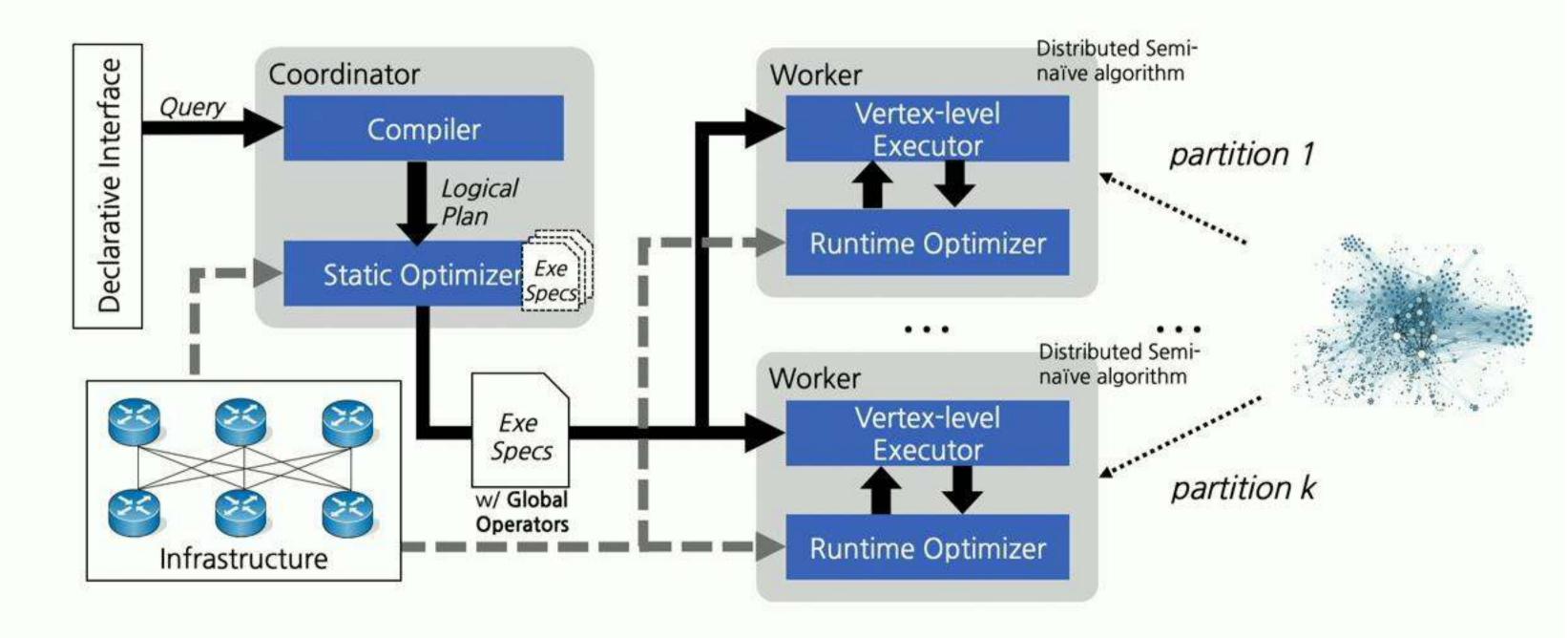
- Robustness
- Ease of programming
- Performance
- Achieving three is difficult

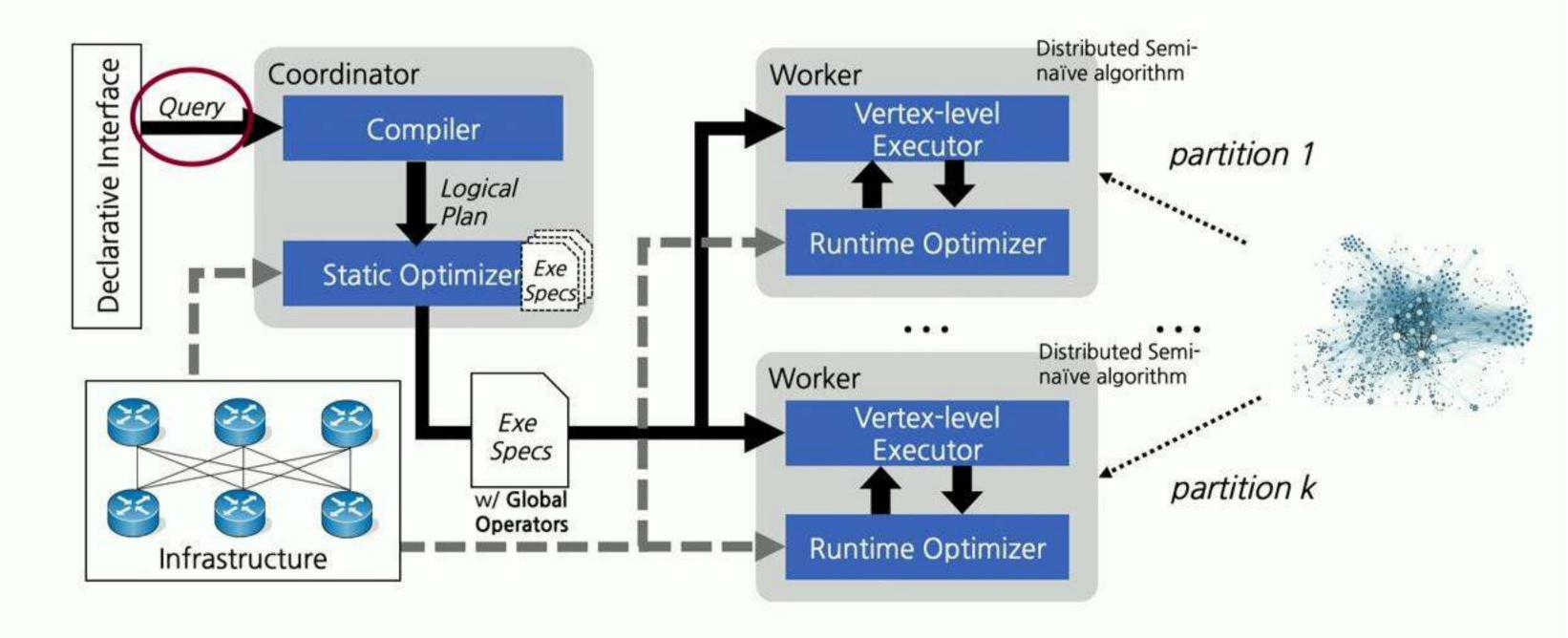
Challenges at Large Scales

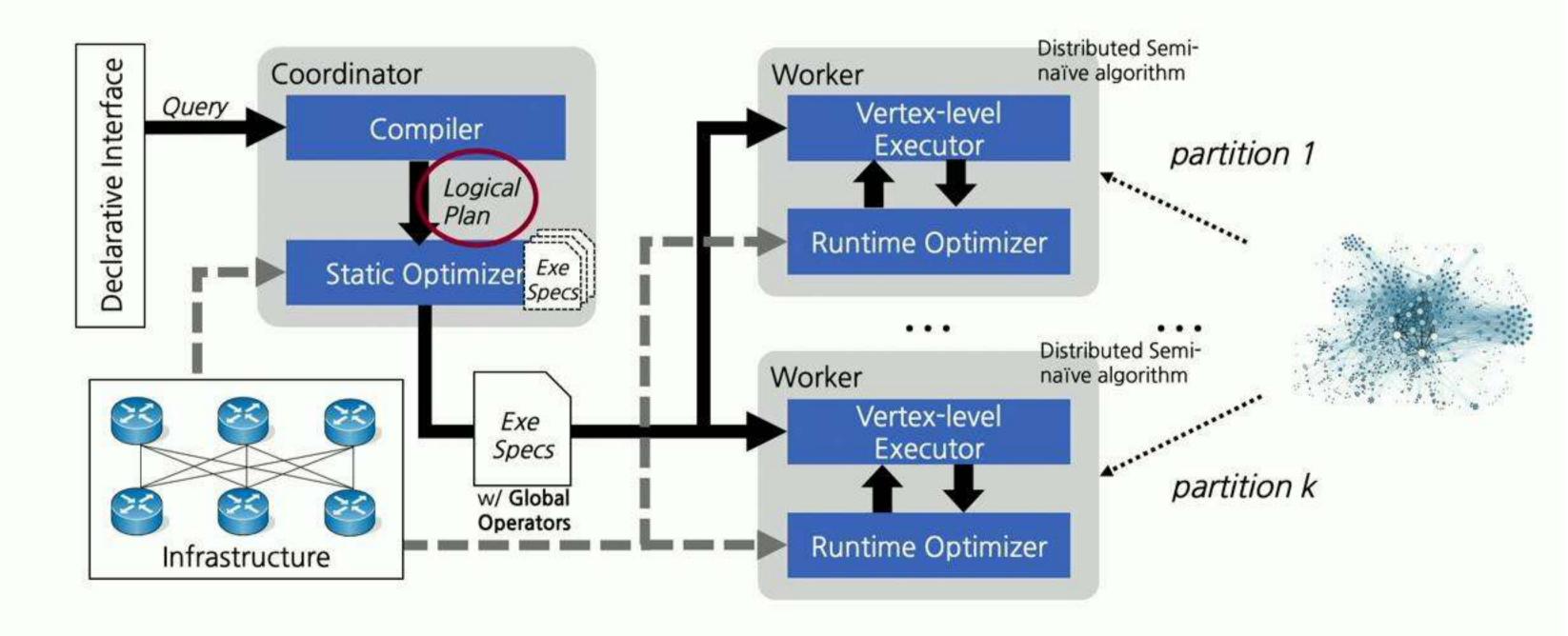
- The impact of real-world graph characteristics
 - Power-law distribution: the optimal query execution may differ based on which part of the graph is being processed.
 - Dense connectivity: significant duplication.
- The impact of data center characteristics
 - Oversubscription
 - Link failures
 - Background traffic, etc.

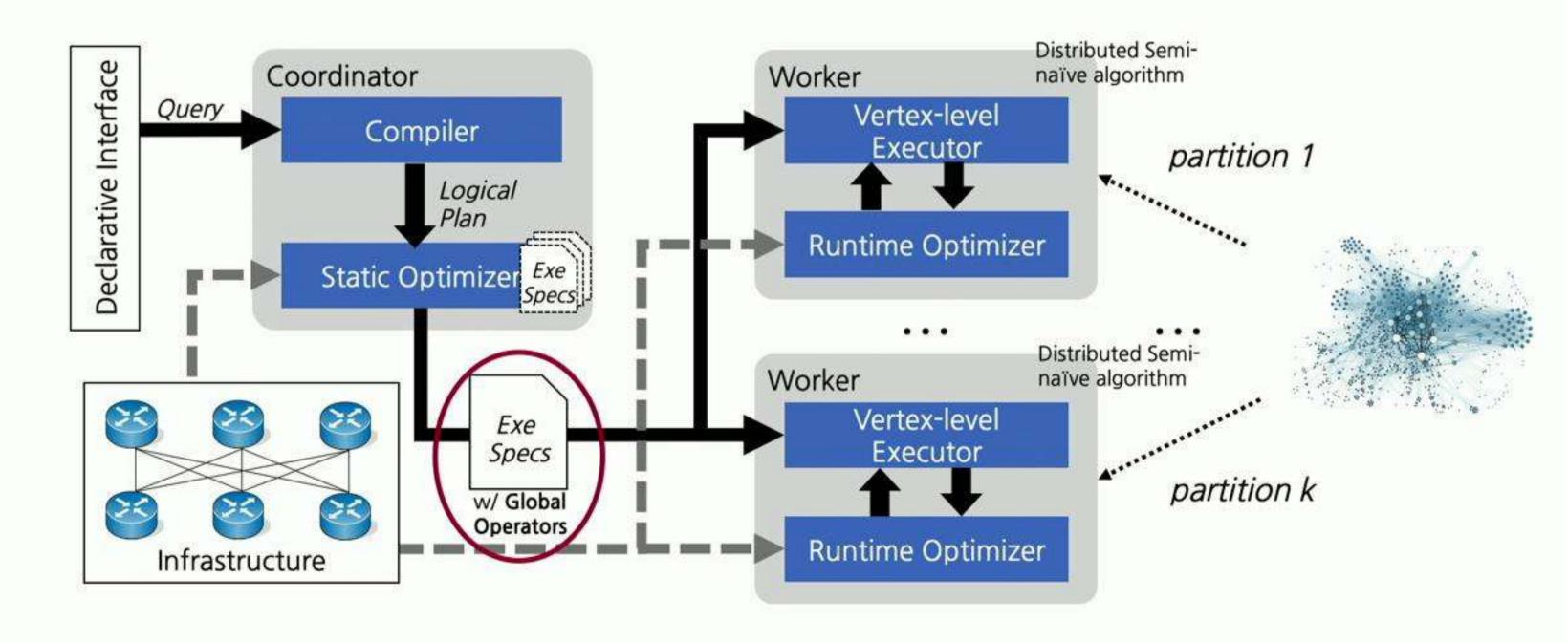
GraphRex: Graph Recursive Execution

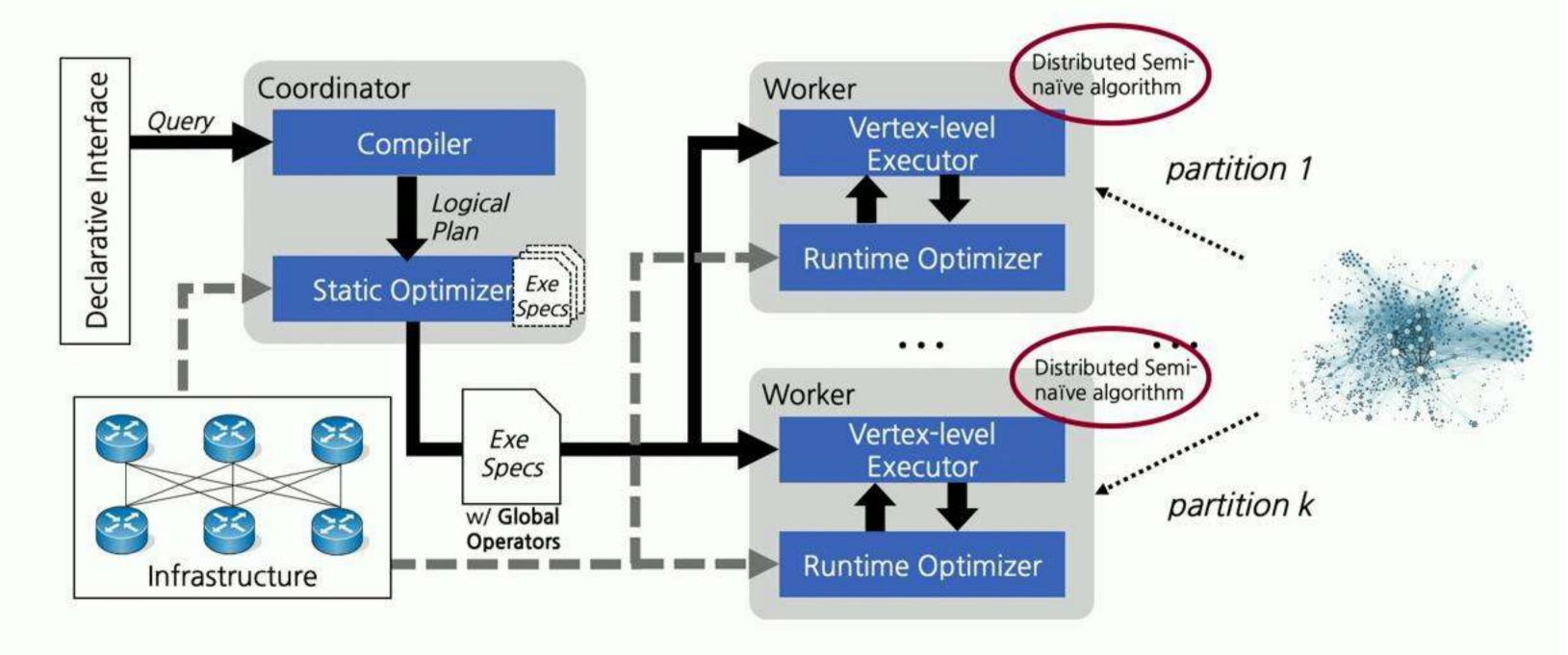












Outline

Motivation & Proposal

Data Center Background

Data Center-Centric Optimization

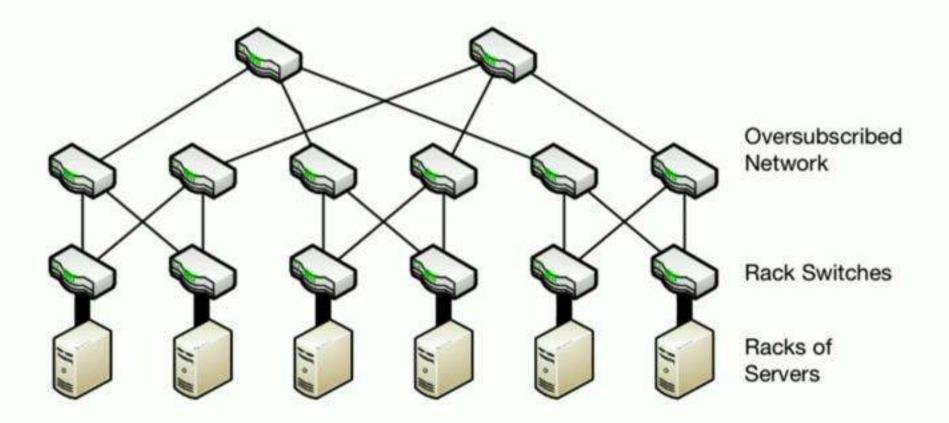
Graph-Centric Optimization

Evaluation

Conclusion

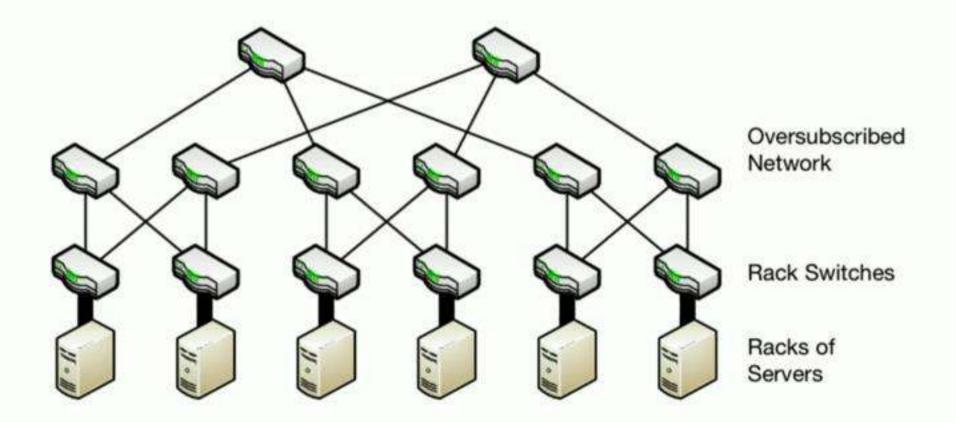
Data Center Background

Design principles are consistent for most cloud data centers.



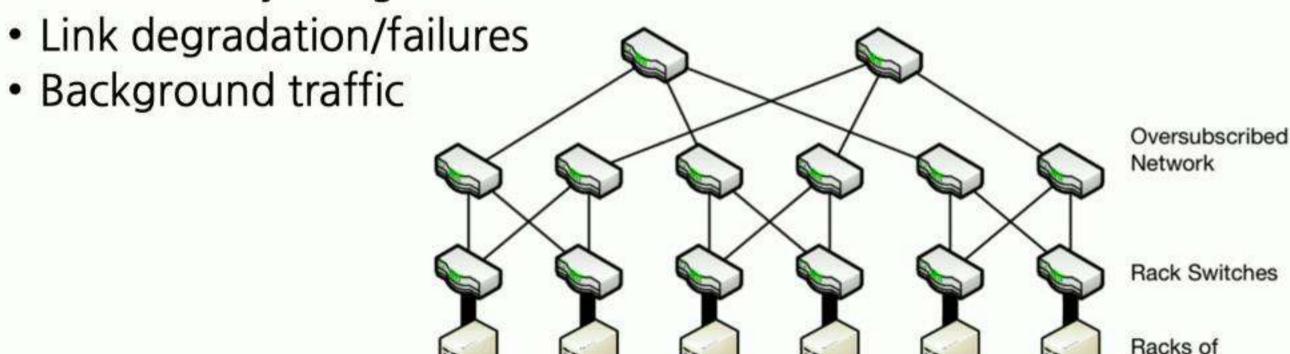
Data Center Background

- Design principles are consistent for most cloud data centers.
- The network is oversubscribed.



Data Center Background

- Design principles are consistent for most cloud data centers.
- The network is oversubscribed.
 - Intentionally designed



Servers

Outline

Motivation & Proposal

Data Center Background

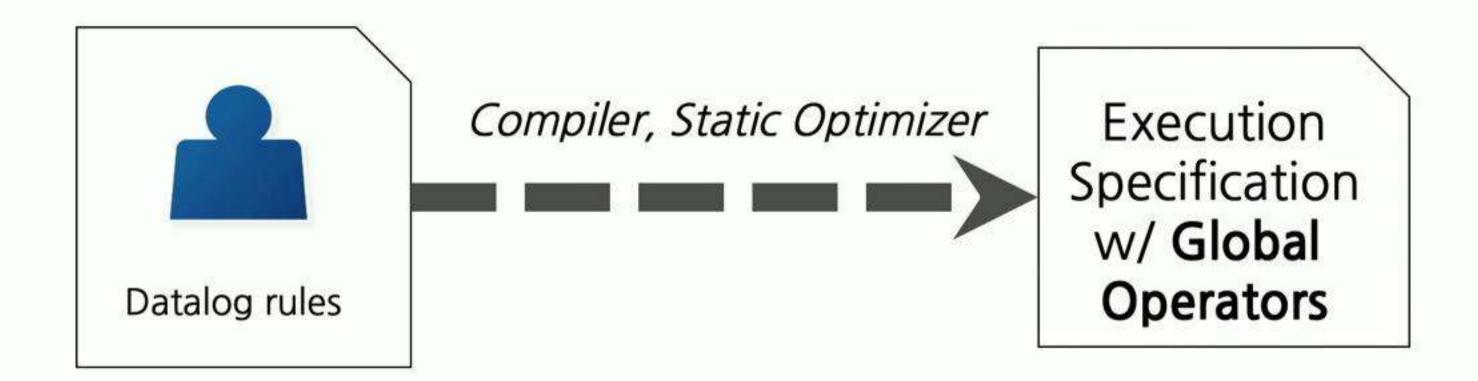
Data Center-Centric Optimization

Graph-Centric Optimization

Evaluation

Conclusion

Query Processing



Global Operators

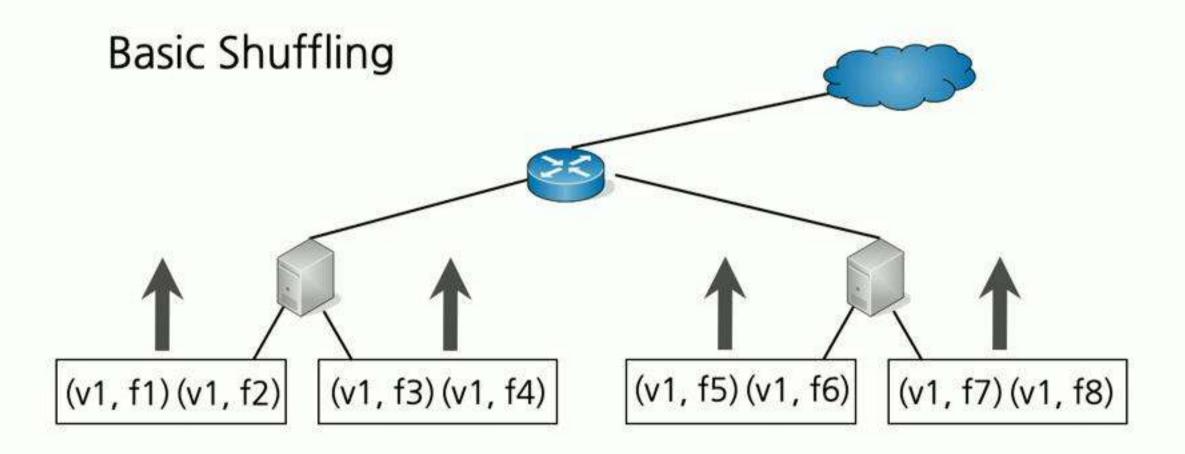
Operators that are optimized at runtime to minimize communications.

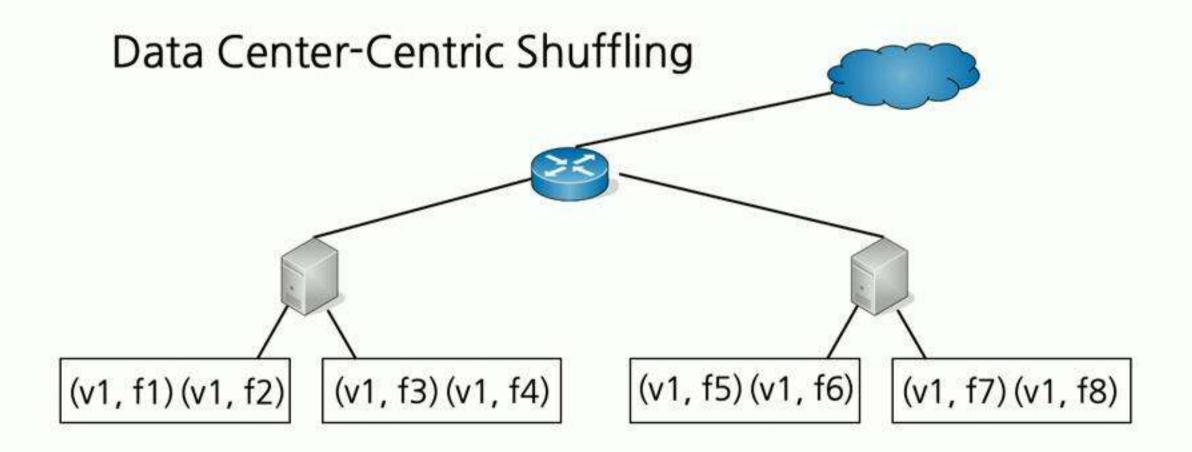
- graph characteristics
- infrastructure characteristics

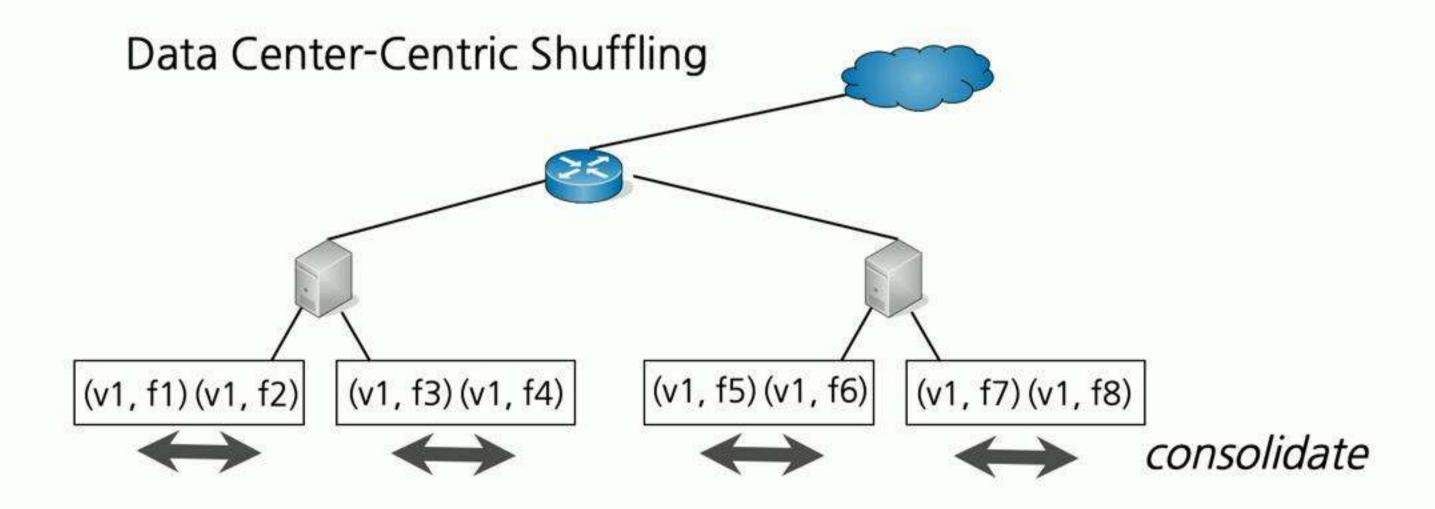
Global Operators

Operators that are optimized at runtime to minimize communications.

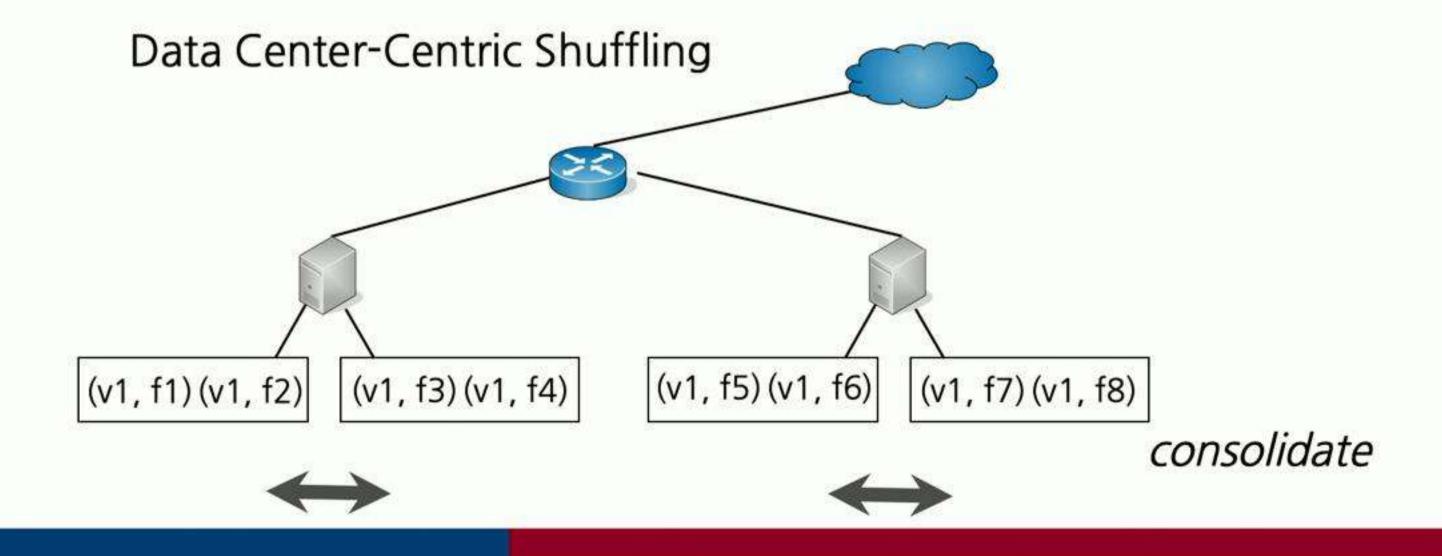
- graph characteristics
- infrastructure characteristics
- SHUFF: efficient shuffle operations
- JOIN: deduplication for binary joins
- ROUT: fine-grained join ordering for multi-way joins
- AGG: efficient aggregation evaluation



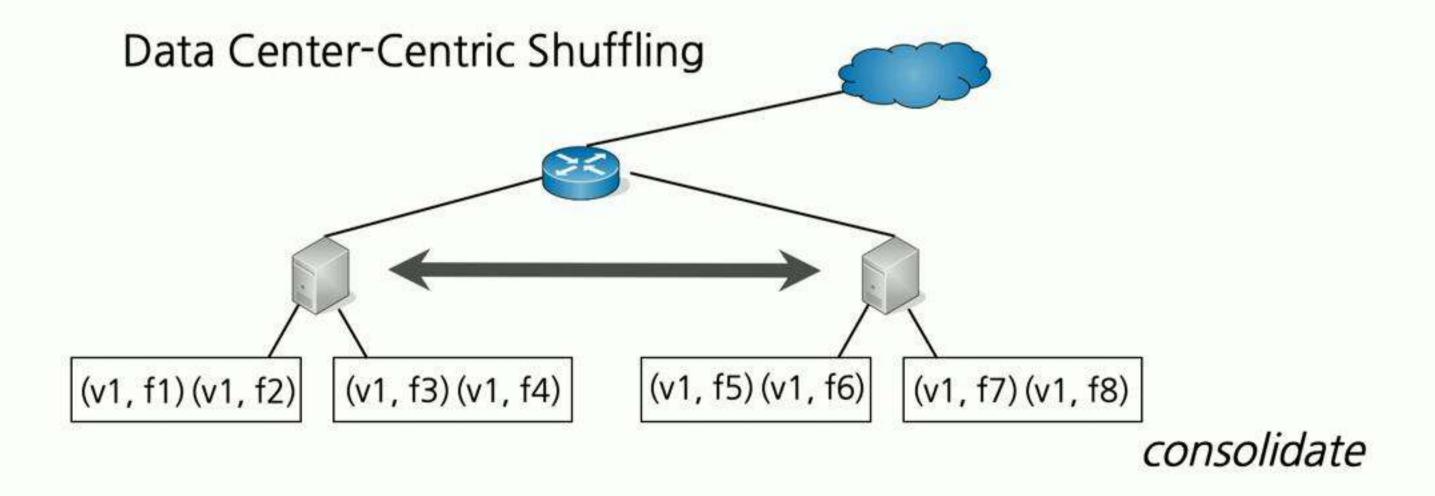


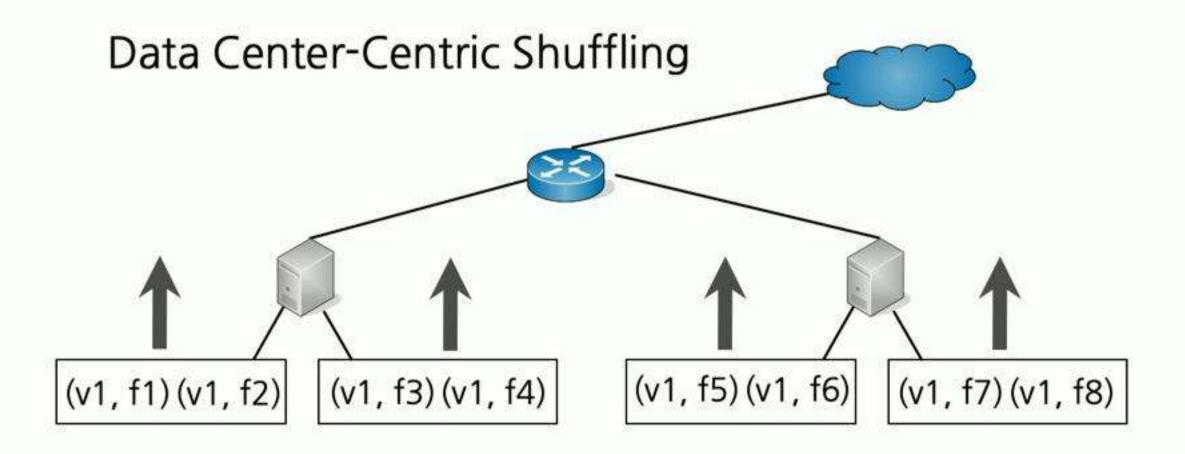


SHUFF encompasses most network communication in GraphRex



12





SHUFF encompasses most network communication in GraphRex

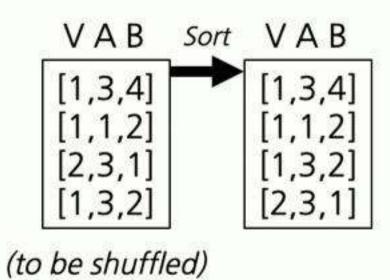
Optimization: Columnization & Compression

V A B
[1,3,4]
[1,1,2]
[2,3,1]
[1,3,2]

(to be shuffled)

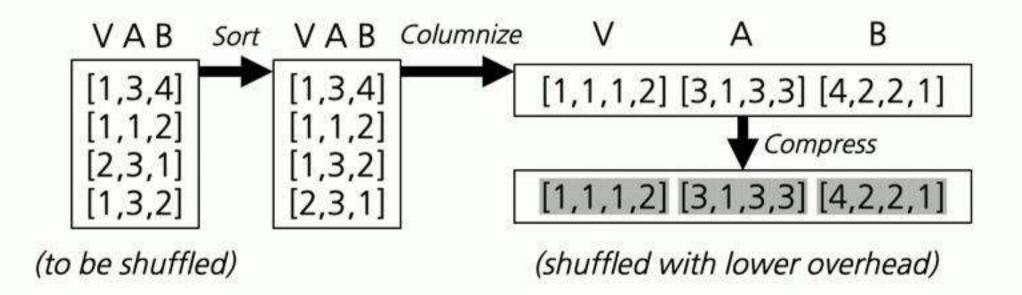
SHUFF encompasses most network communication in GraphRex

Optimization: Columnization & Compression



SHUFF encompasses most network communication in GraphRex

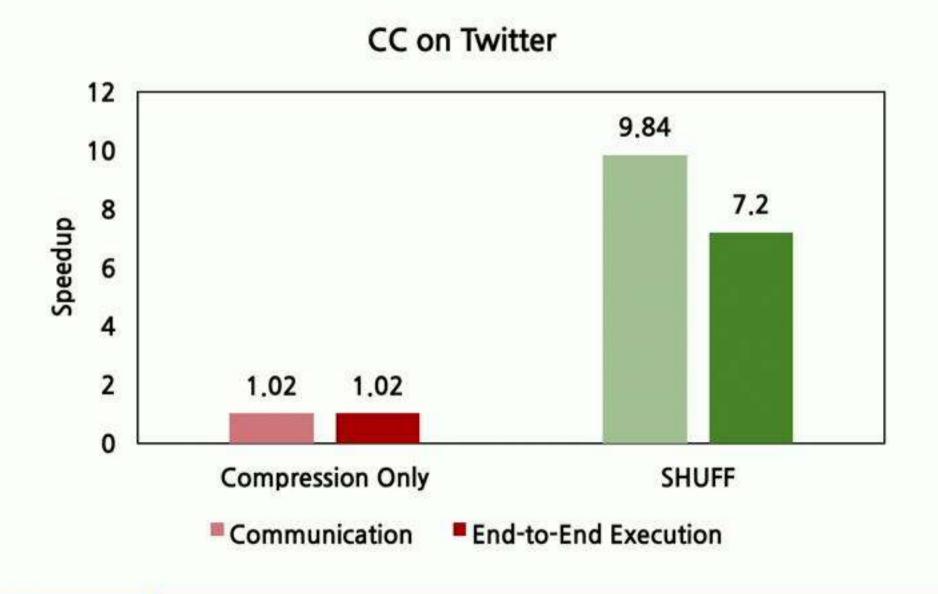
Optimization: Columnization & Compression



SHUFF encompasses most network communication in GraphRex

Optimization: Hierarchical Network Transfer

```
Three-Level Hierarchical Network Transfer
for each server S:
   workers_in_a_server = getWorkers(S)
   LocalShuffle(workers_in_a_server)
   consolidate messages
for each rack R:
   workers_in_a_rack = getWorkers(R)
   LocalShuffle(workers_in_a_rack)
   consolidate messages
globalShuffle(all_workers)
```



ROUT finds the optimal join order at tuple level for multi-way joins

Multi-Way Join

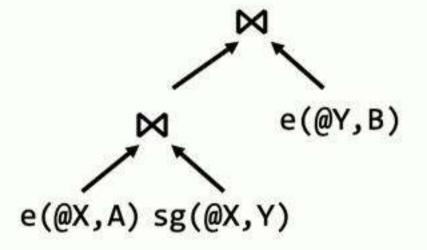
```
sg(A,B) := e(X,A), sg(X,Y), e(Y,B)
```

ROUT finds the optimal join order at tuple level for multi-way joins

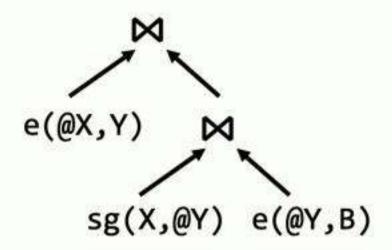
Multi-Way Join

$$sg(A,B) := e(X,A), sg(X,Y), e(Y,B)$$

Order 1: from left to right



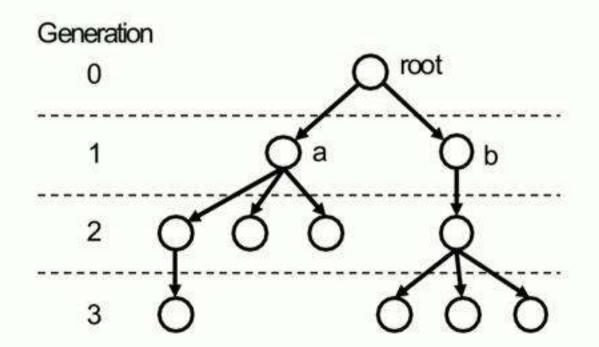
Order 2: from right to left



ROUT finds the optimal join order at tuple level for multi-way joins

Multi-Way Join

$$sg(A,B) :- e(X,A), sg(X,Y), e(Y,B)$$



sg(a, b)

Order 1 [[e ⋈ sg] ⋈ e] Order 2 [e ⋈ [sg ⋈ e]]

ROUT finds the optimal join order at tuple level for multi-way joins

Multi-Way Join

sg(A,B) := e(X,A), sg(X,Y), e(Y,B)

sg(a, b)



ROUT finds the optimal join order at tuple level for multi-way joins

Multi-Way Join

$$sg(A,B) := e(X,A), sg(X,Y), e(Y,B)$$

 Generation
 Order 1
 Order 2

 0
 [[e ⋈ sg] ⋈ e]
 [e ⋈ [sg ⋈ e]]

 1
 2
 G2 Cost:
 3
 1

 3
 G3 Cost:
 1
 3

sg(a, b)

ROUT finds the optimal join order at tuple level for multi-way joins

Multi-Way Join

$$sg(A,B) := e(X,A), sg(X,Y), e(Y,B)$$

 Generation
 Order 1
 Order 2

 0
 [[e ⋈ sg] ⋈ e]
 [e ⋈ [sg ⋈ e]]

 1
 a
 b
 G2 Cost:
 3
 1

 2
 G3 Cost:
 1
 3

 3
 Total Cost:
 4
 4

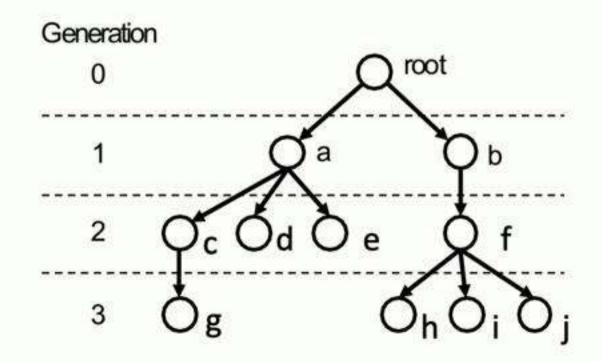
Order 1 and Order 2 are equally bad. Power-law degree distribution makes them worse.

sg(a, b)

ROUT finds the optimal join order at tuple level for multi-way joins

Optimization: Adaptive Join Ordering

Enumerate all possible join orders for each newly generated tuple, and select the minimum-cost order.

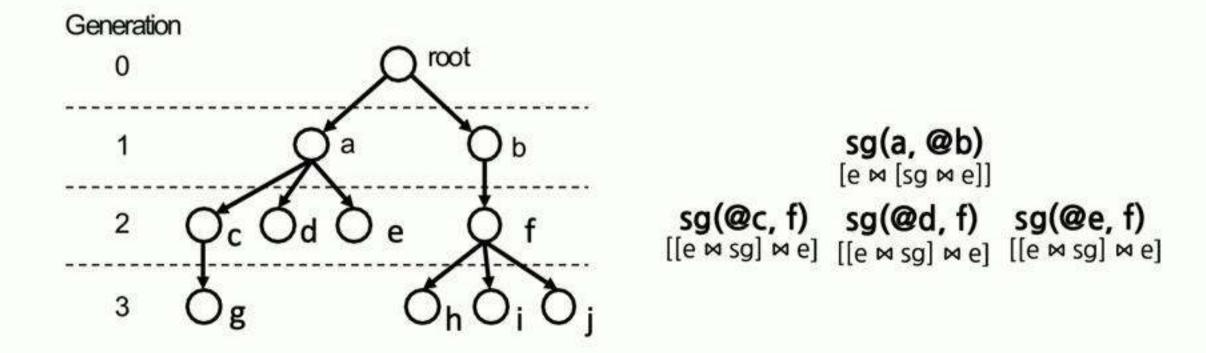


sg(a, @b) [e ⋈ [sg ⋈ e]]

ROUT finds the optimal join order at tuple level for multi-way joins

Optimization: Adaptive Join Ordering

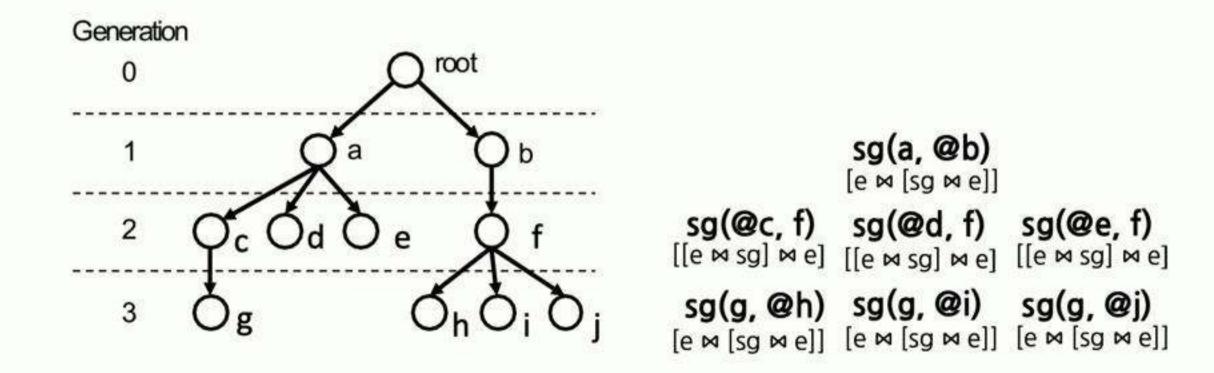
Enumerate all possible join orders for each newly generated tuple, and select the minimum-cost order.



ROUT finds the optimal join order at tuple level for multi-way joins

Optimization: Adaptive Join Ordering

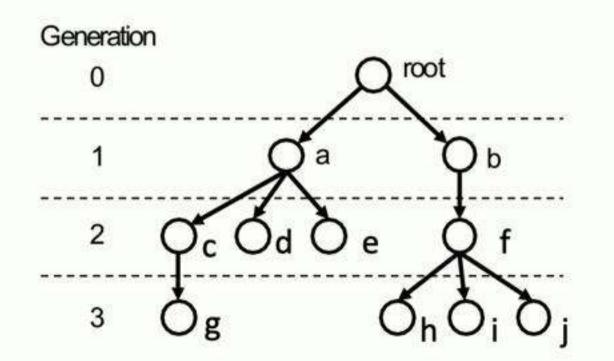
Enumerate all possible join orders for each newly generated tuple, and select the minimum-cost order.



ROUT finds the optimal join order at tuple level for multi-way joins

Optimization: Adaptive Join Ordering

Enumerate all possible join orders for each newly generated tuple, and select the minimum-cost order.



sg(a, b)

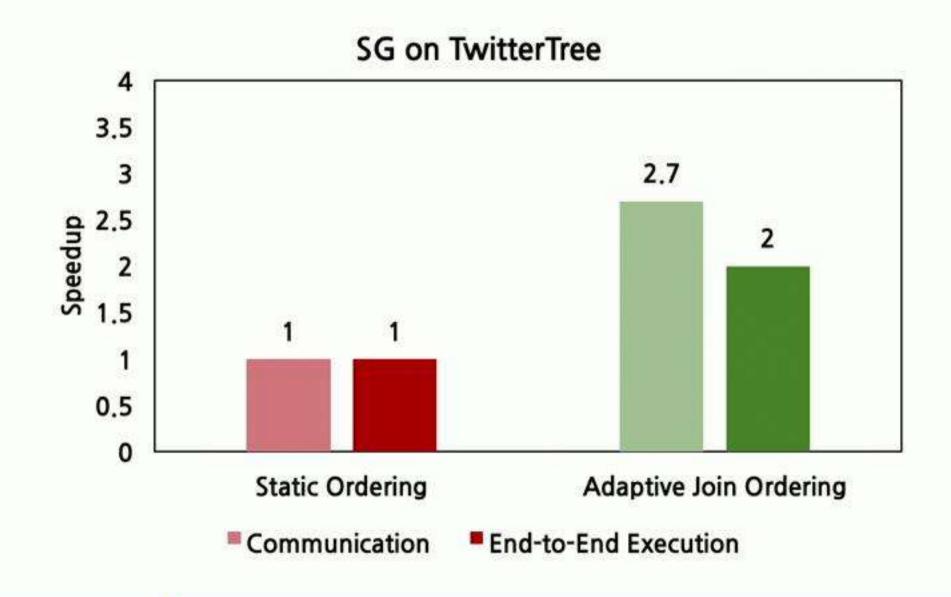
Adaptive Join Ordering

G2: '

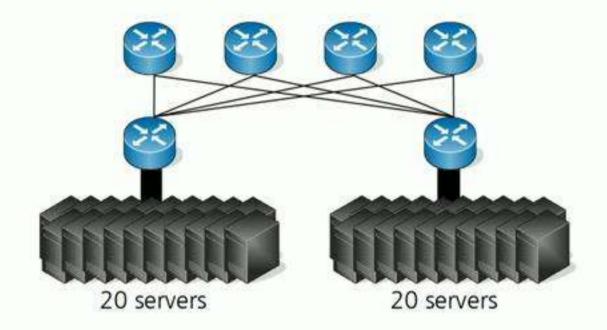
G3: 1

Total: 2

ROUT finds the optimal join order at tuple level for multi-way joins



Setup

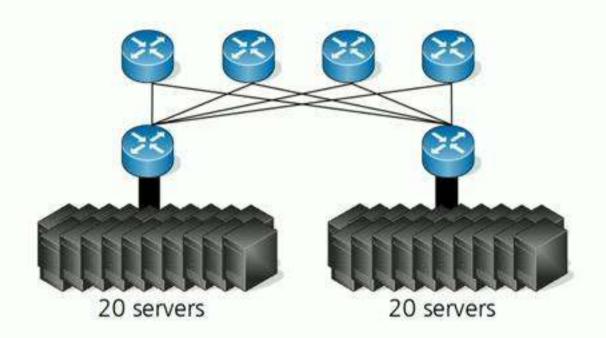


CPU: 1600 threads

Memory: 6.4 Terabytes

Network: 10 Gb/s links (5:1 oversubscription ratio)

Setup



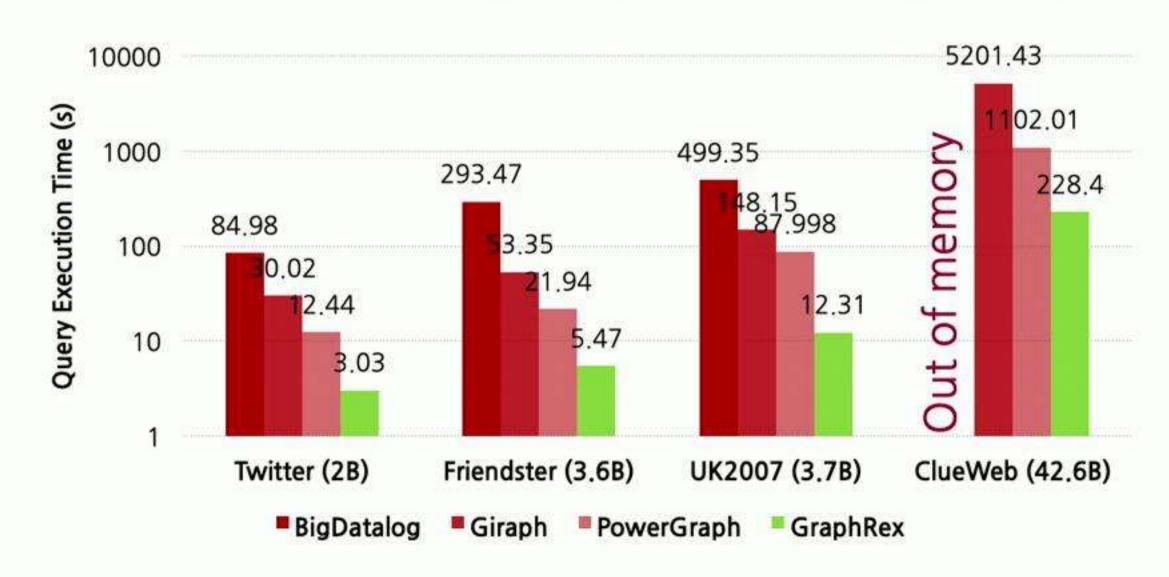
| Graph | #Vertices | #Edges | Raw Size |
|------------|----------------|---------------|----------|
| Twitter | 52.6 millions | 2 billions | 12 GB |
| Friendster | 65.6 millions | 3.6 billions | 31 GB |
| UK2007 | 105.9 millions | 3.7 billions | 33 GB |
| ClueWeb | 978.4 millions | 42.6 billions | 406 GB |

CPU: 1600 threads

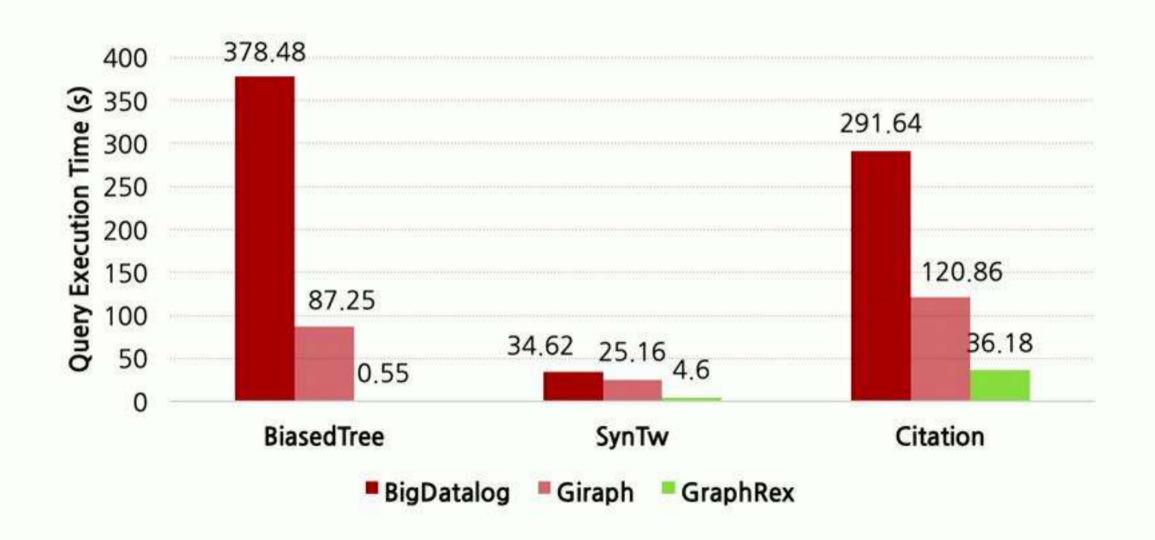
Memory: 6.4 Terabytes

Network: 10 Gb/s links (5:1 oversubscription ratio)

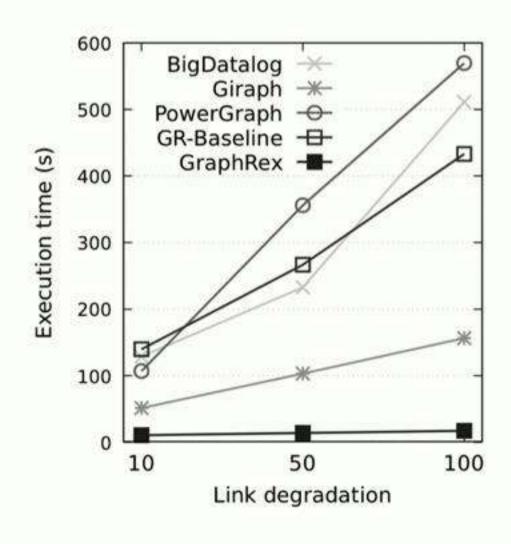
Overall Performance (SSSP): 4X - 54X Speedup

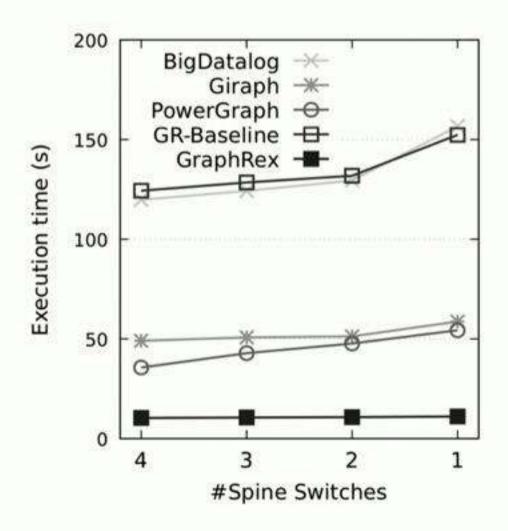


Multi-Way Join Performance: 3.3X - 688X Speedup



Robustness (Link Failures & Oversubscription)





Conclusion

- Communication bottlenecks the performance of large-scale graph processing.
- Achieving (1) ease of programming, (2) performance and (3) robustness needs the codesign between interface and optimizations.
- Efficient large-scale graph query processing requires the framework to be aware of data center infrastructure and graph data characteristics.

Future Work

- Query graph streams.
- Resource changes are normal and significant, especially prominent in streaming processing (long running).
- Failures can happen during query execution.
- No fixed (early-binding) plan is optimal.
- Optimizations have to consider multiple dimensions.
 - Workloads
 - Infrastructure
 - Random changes: both workloads and infrastructure

Thank you!

Questions?

Future Work

- Query graph streams.
- Resource changes are normal and significant, especially prominent in streaming processing (long running).
- Failures can happen during query execution.
- No fixed (early-binding) plan is optimal.
- Optimizations have to consider multiple dimensions.
 - Workloads
 - Infrastructure
 - Random changes: both workloads and infrastructure