TuX^2: Distributed Graph Computation for Machine Learning

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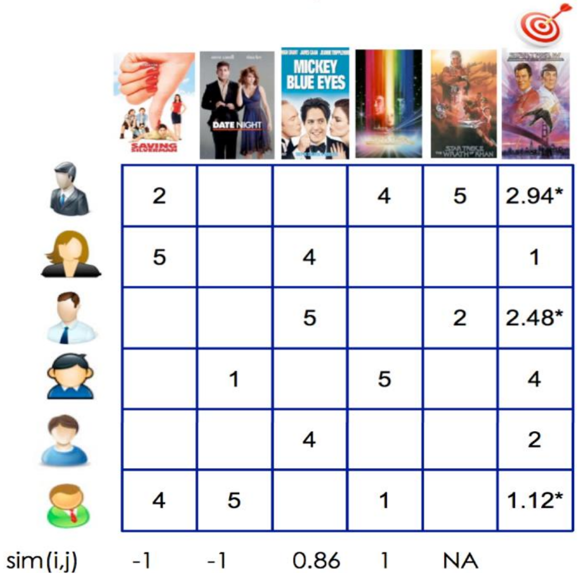
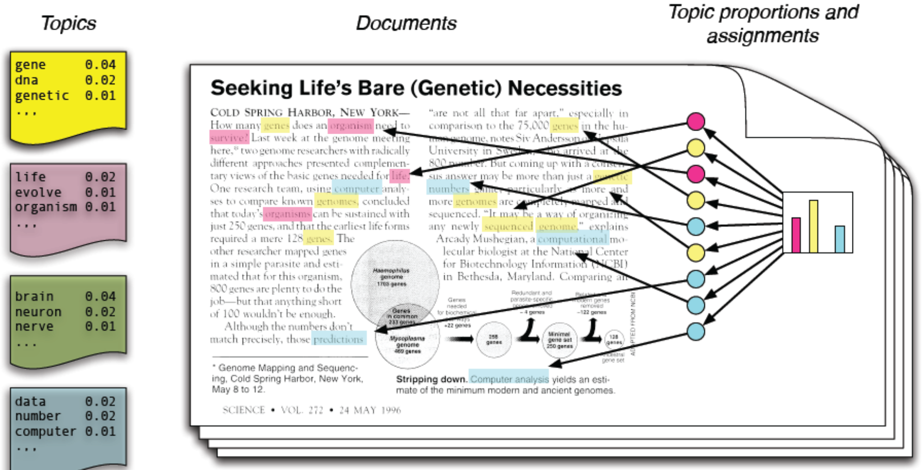
NSDI'17, Boston, MA

Machine Learning(ML) in real world

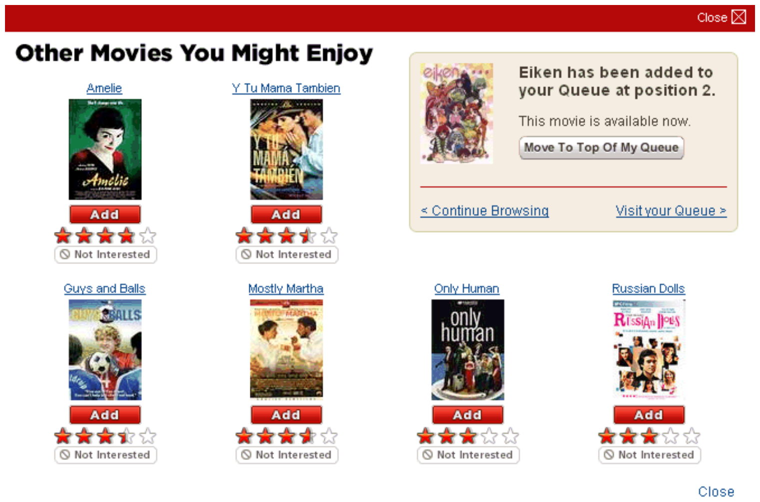


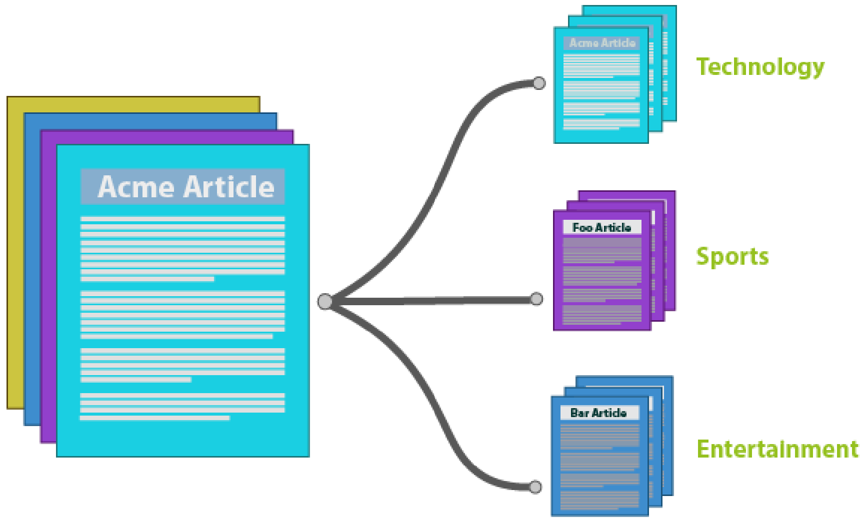
Recommendation

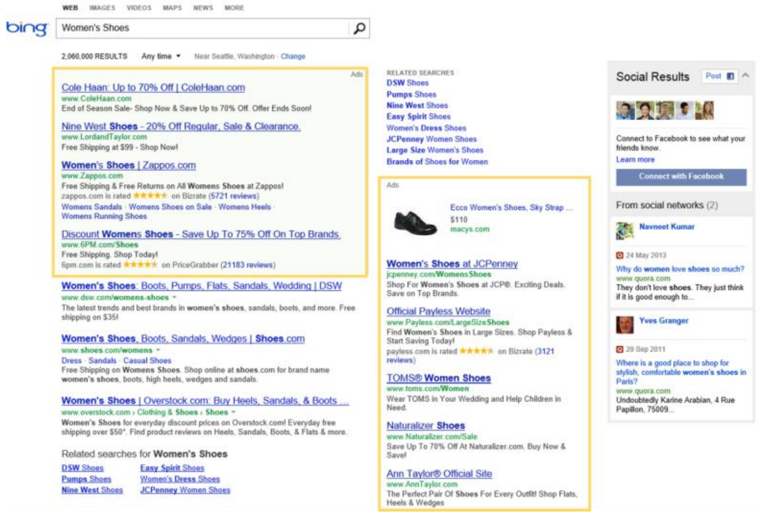


Topic Model

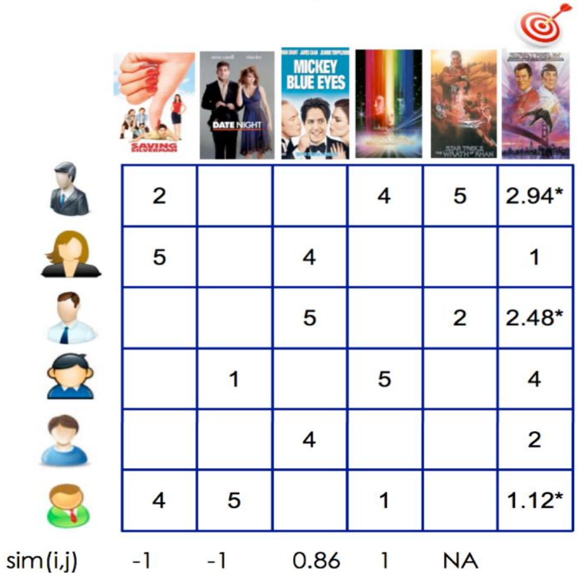
Click Prediction





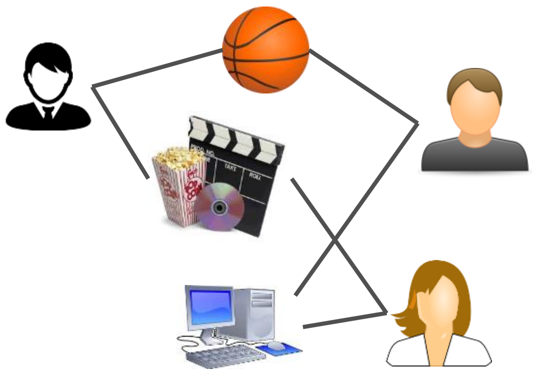


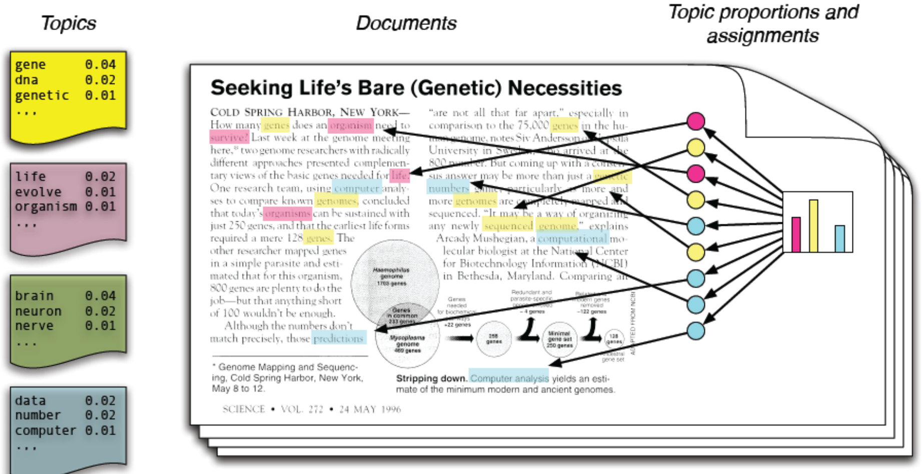
Graph Structures in Machine Learning



	2			4	5	2.94*
	5		4			1
			5		2	2.48*
		1		5		4
			4			2
	4	5		1		1.12*
sim(i,j)	-1	-1	0.86	1	NA	

Recommendation





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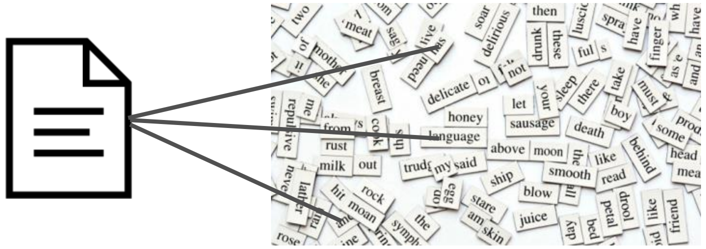
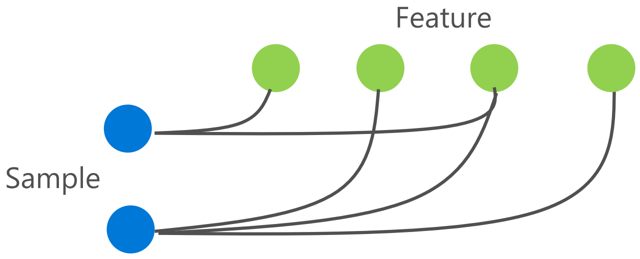


Click Prediction



Advantages of Graph Engine

Simple programming model (e.g. GAS)

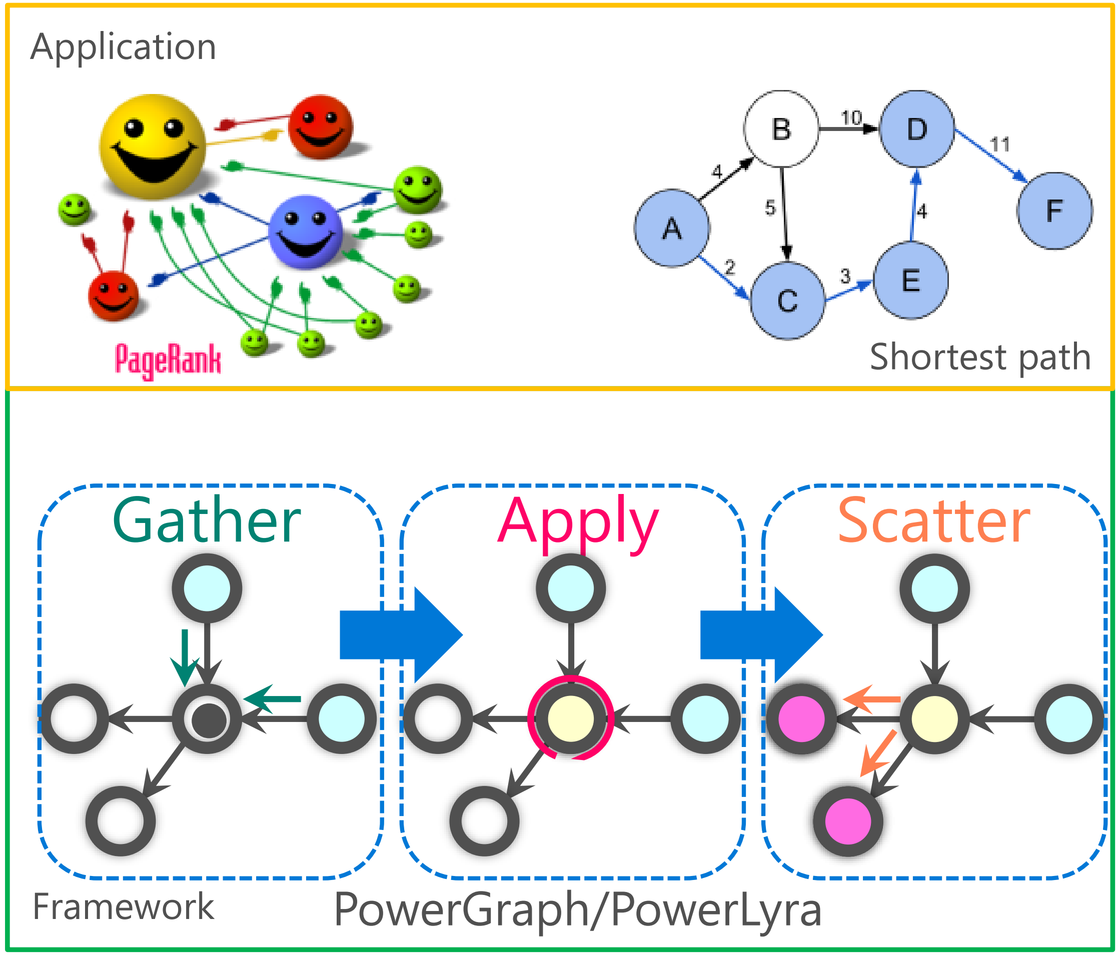
- PageRank, Shortest path, etc.

Graph-aware optimization

- Data layout [Grace(ATC'12), Naiad(SOSP'13)]
- Partitioning [PowerLyra(EuroSys'15)]

Scalability to trillion-edge

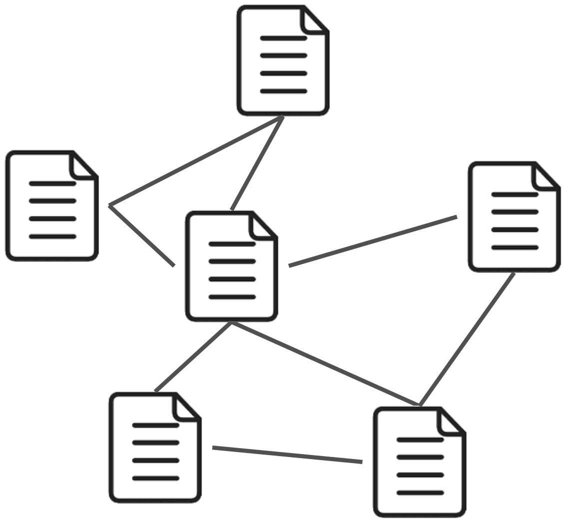
- GraM (SoCC'15)
- Chaos (SOSP'15)
- One Trillion Edges (VLDB'15)



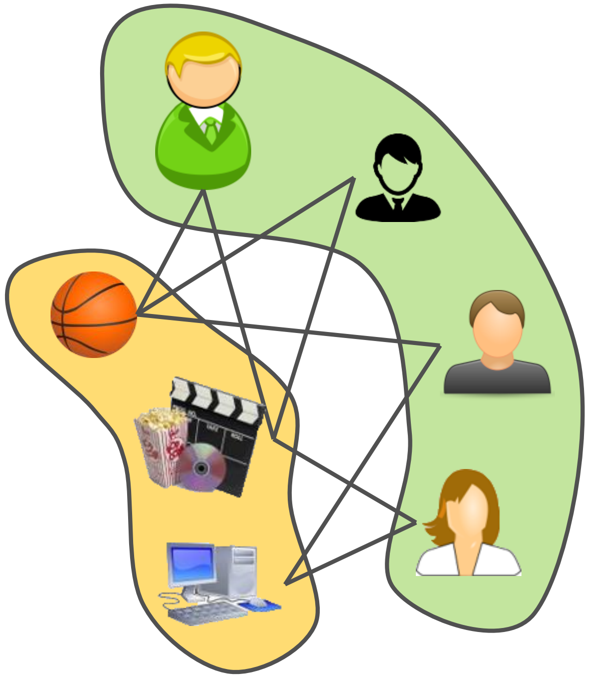
*GAS figure from PowerLyra slides

Gaps for ML on Graph Engine

1. Heterogeneous vertices



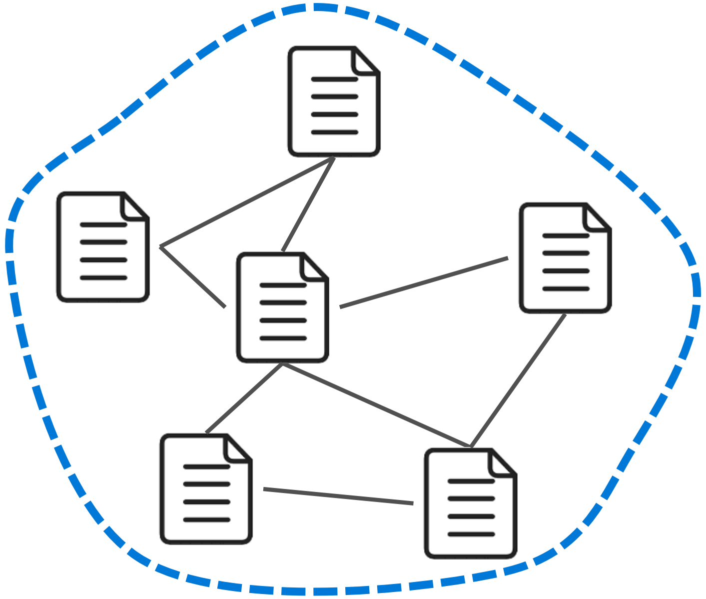
PageRank
for WebPage Ranking



Matrix Factorization(MF)
for Recommendation

Gaps for ML on Graph Engine

2. Mini-Batch

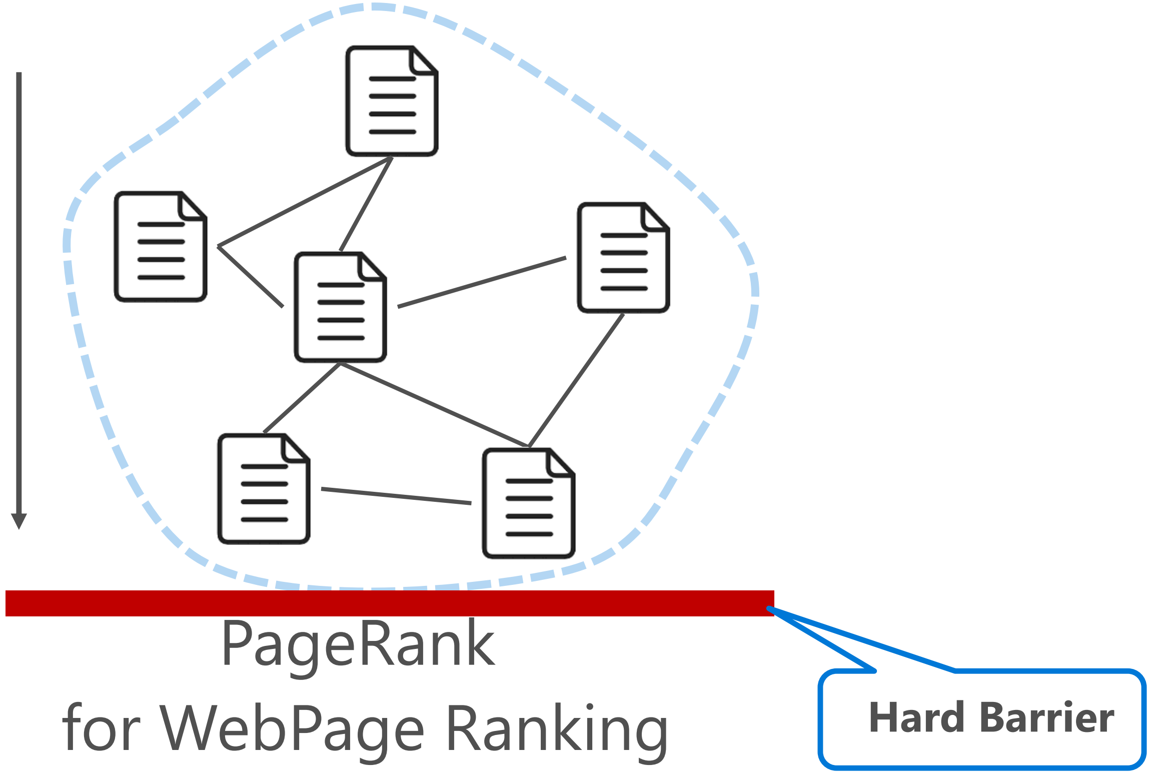


PageRank
for WebPage Ranking

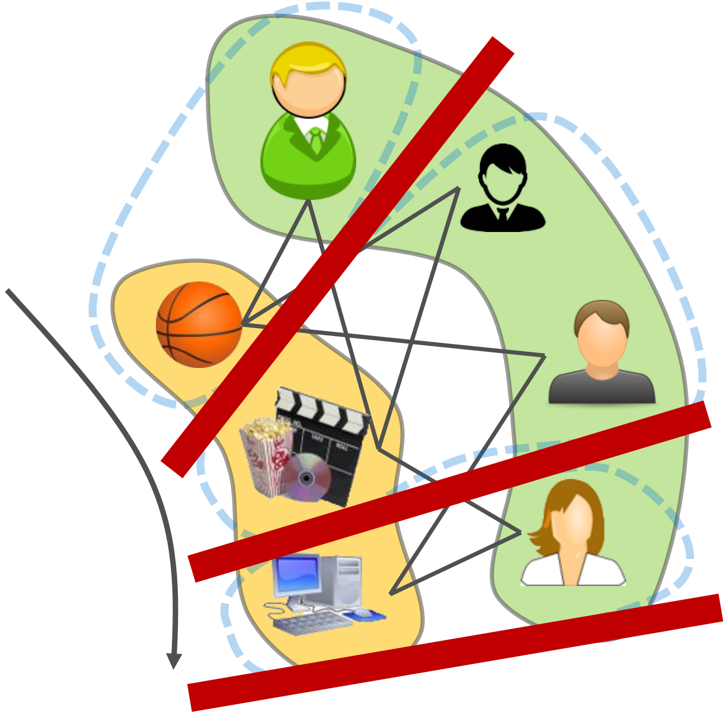
Matrix Factorization(MF)
for Recommendation

Gaps for ML on Graph Engine

3. Flexible consistency



PageRank
for WebPage Ranking



Matrix Factorization(MF)
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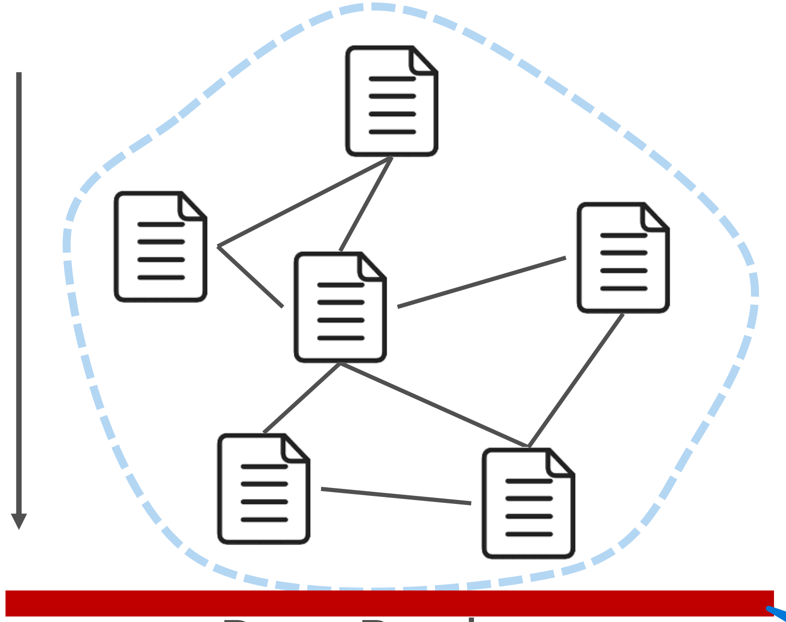
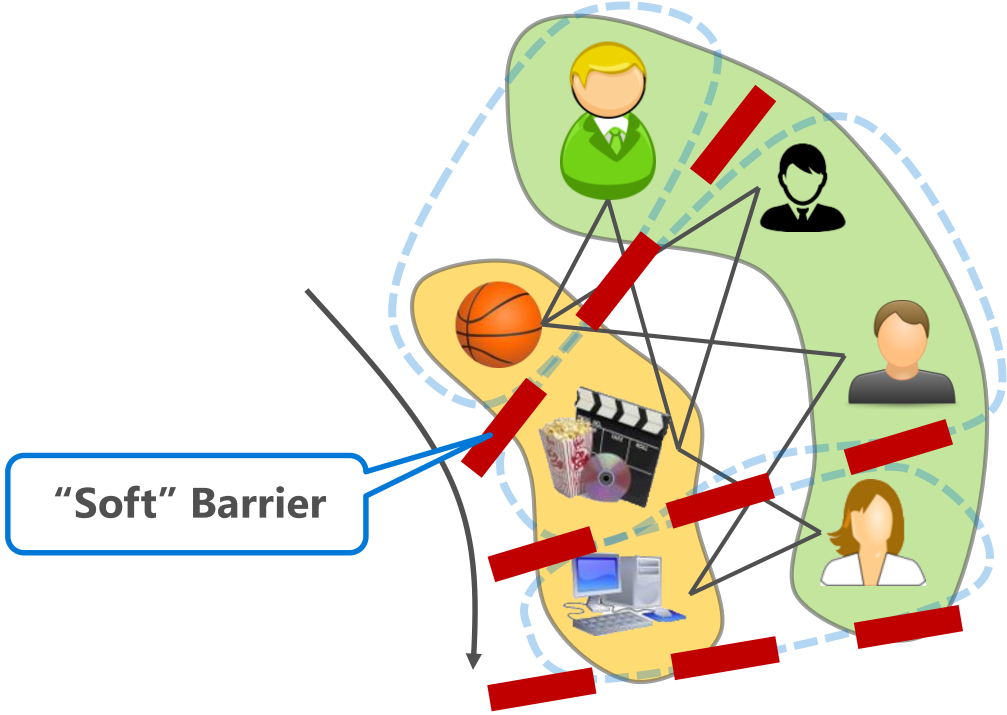
Gaps for ML on Graph Engine

3. Flexible consistency



PageRank
for WebPage Ranking



Matrix Factorization(MF)
for Recommendation

We propose: TuX^2

Bridge Graph and ML research in one system

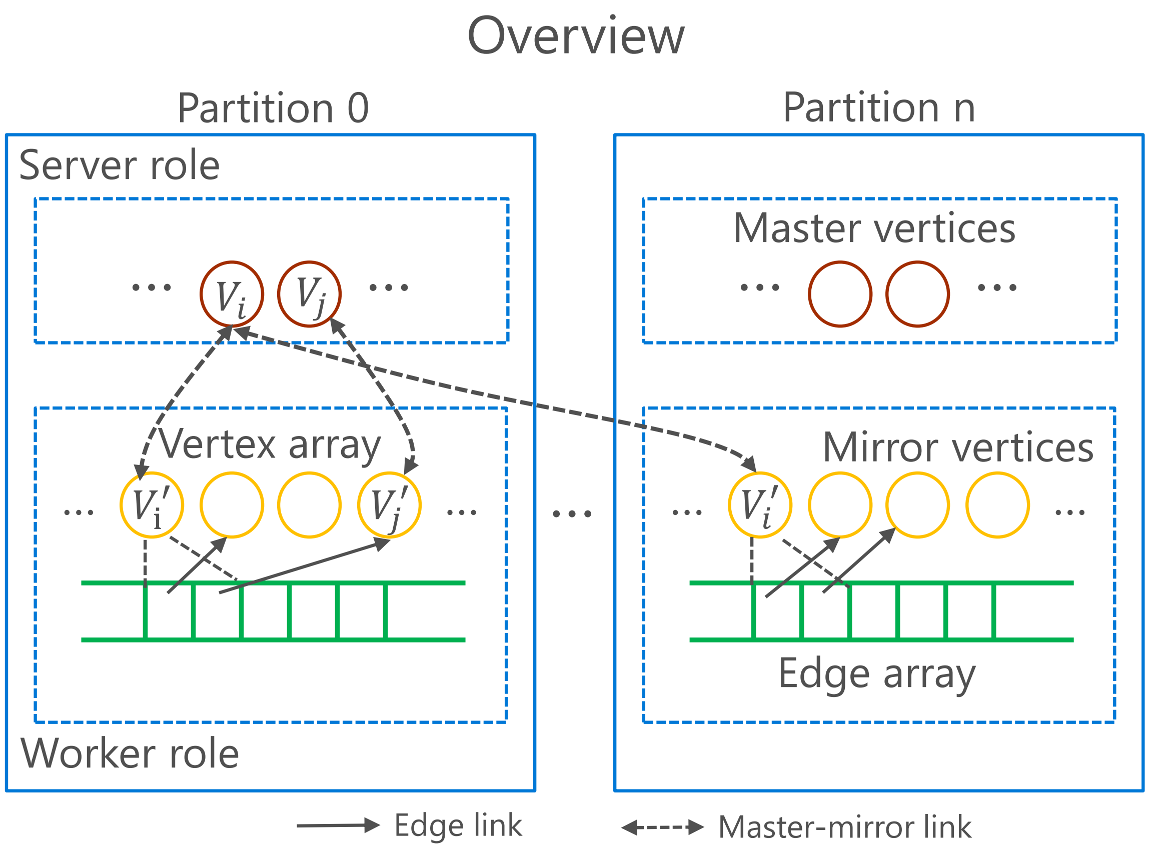
Extend for distributed machine learning

- Scheduling: Stale Synchronous Parallel (SSP) based scheduling
- DataModel: Heterogeneous data model
- Programming: MEGA (Mini-batch, Exchange, GlobalSync, and Apply) graph model

Outperform both Graph and ML systems on ML algorithms

- **10x** vs. PowerGraph/PowerLyra
  - Mainly due to MEGA model and heterogeneity optimization
- **48%** vs. Petuum/Parameter-Server(P-S)
  - Mainly due to graph-based optimization

System Architecture



Vertex-cut approach

- Effective for power-law graph
- Naturally fits P-S model
  - Master vertices as the global state
  - Mirror vertices as the local cache

Key designs

Scheduling: Stale Synchronous Parallel (SSP) based scheduling

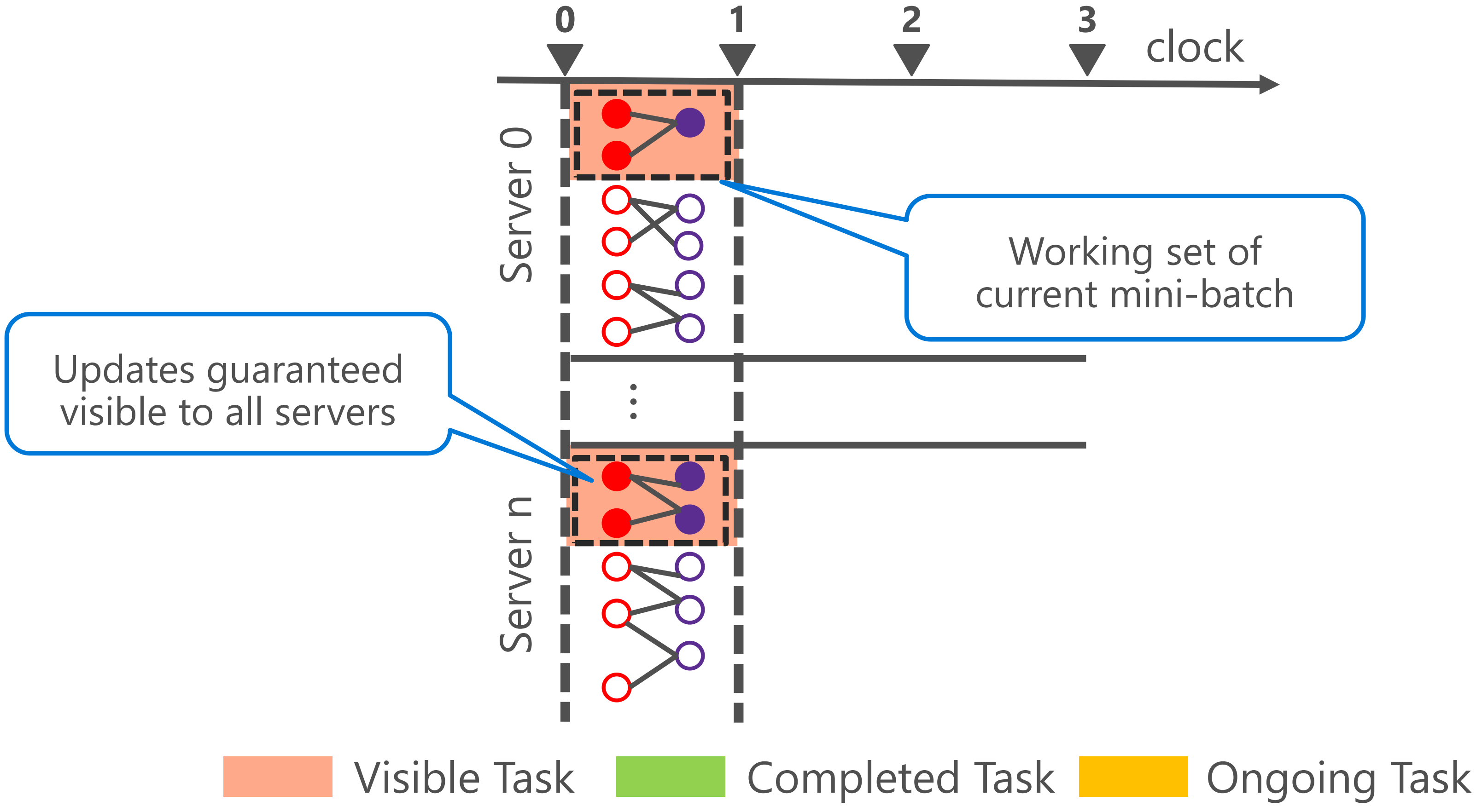
DataModel: Heterogeneous data model

Programming: MEGA graph model

Stale Synchronous Parallel in TuX^2

Slack of 1 clock as an example

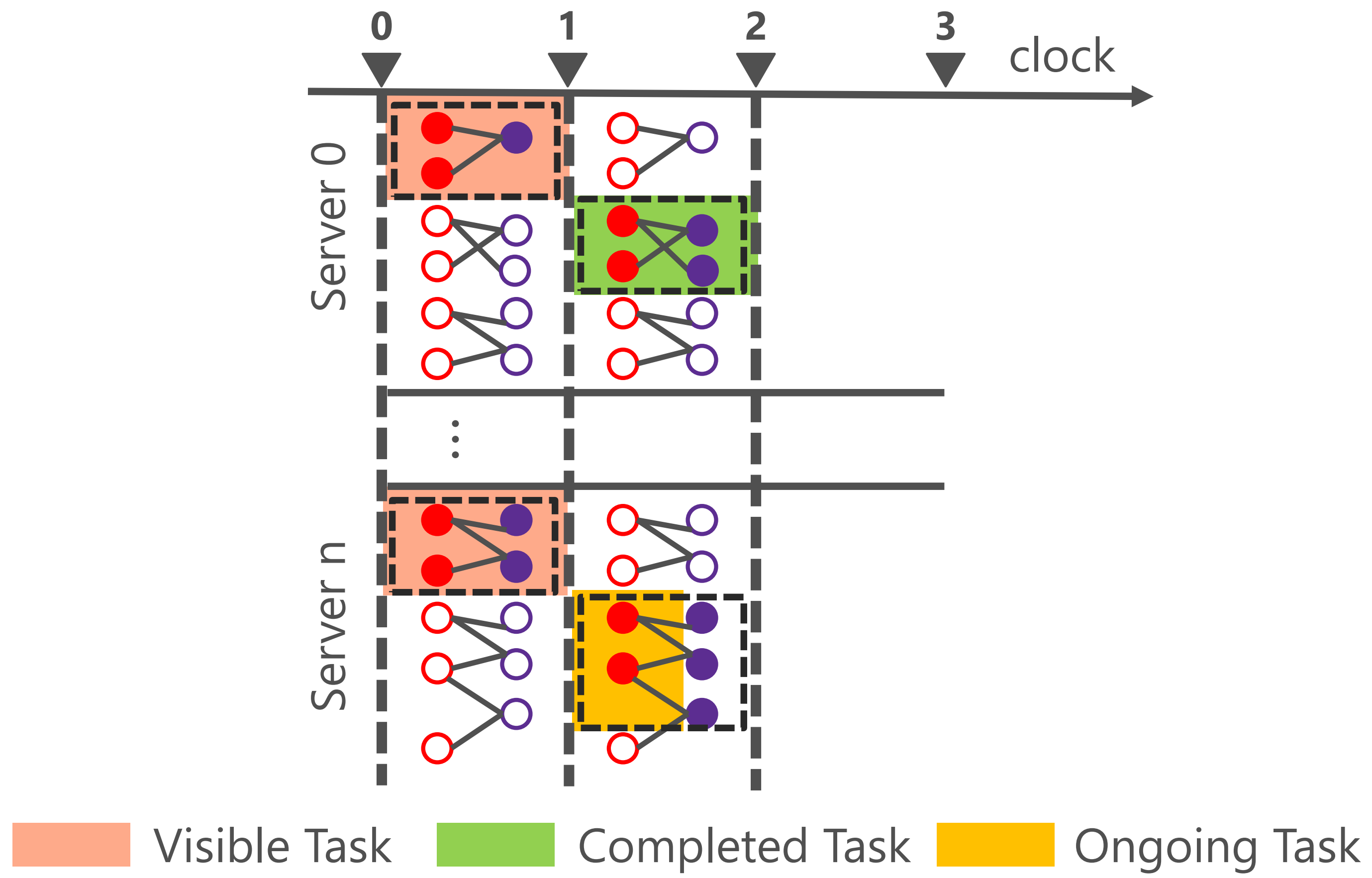
- All servers finish clock1



Stale Synchronous Parallel in TuX^2

Slack of 1 clock as an example

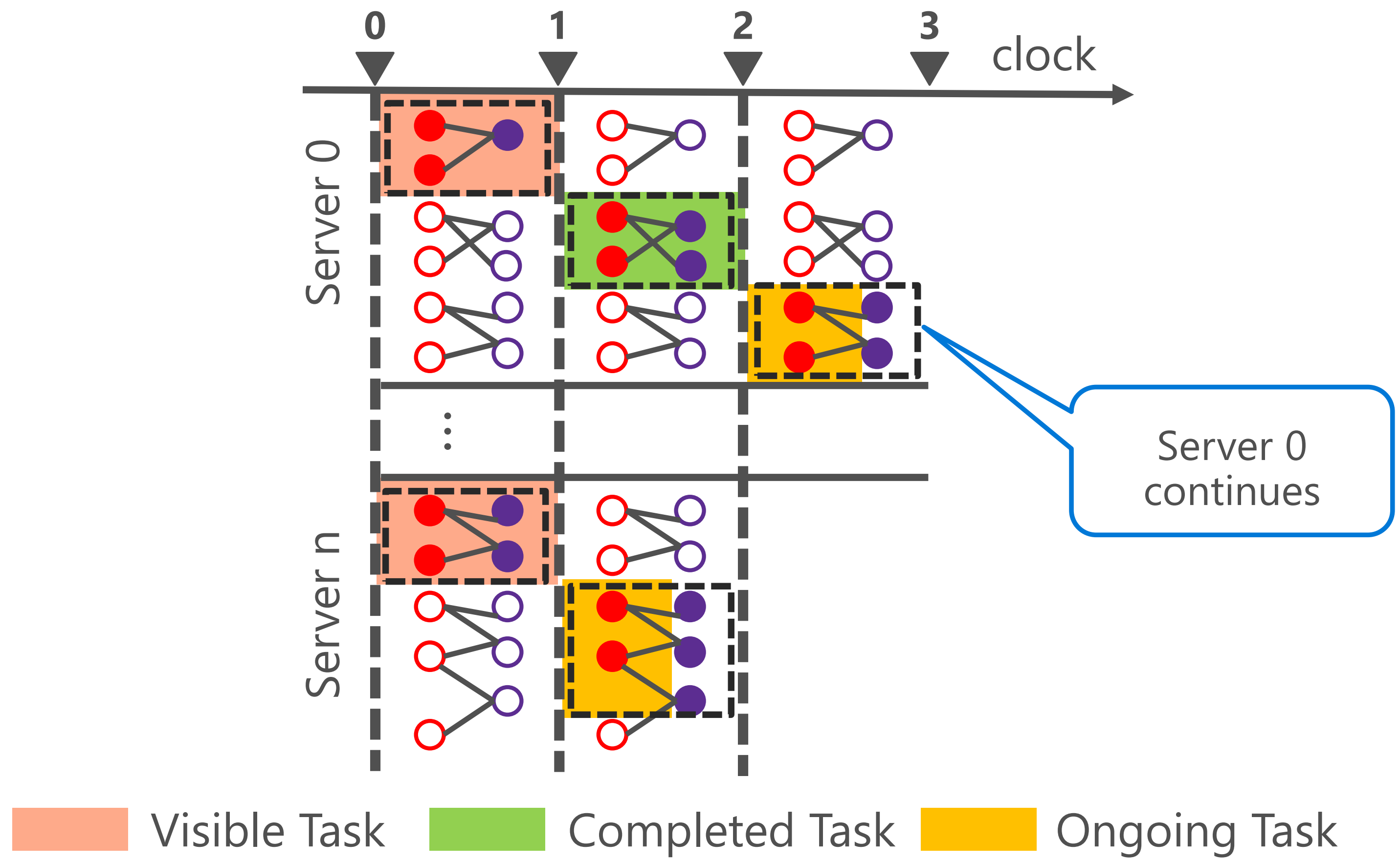
- Slowest server (n) is in clock2
- Fastest server (0) finishes clock2



Stale Synchronous Parallel in TuX^2

Slack of 1 clock as an example

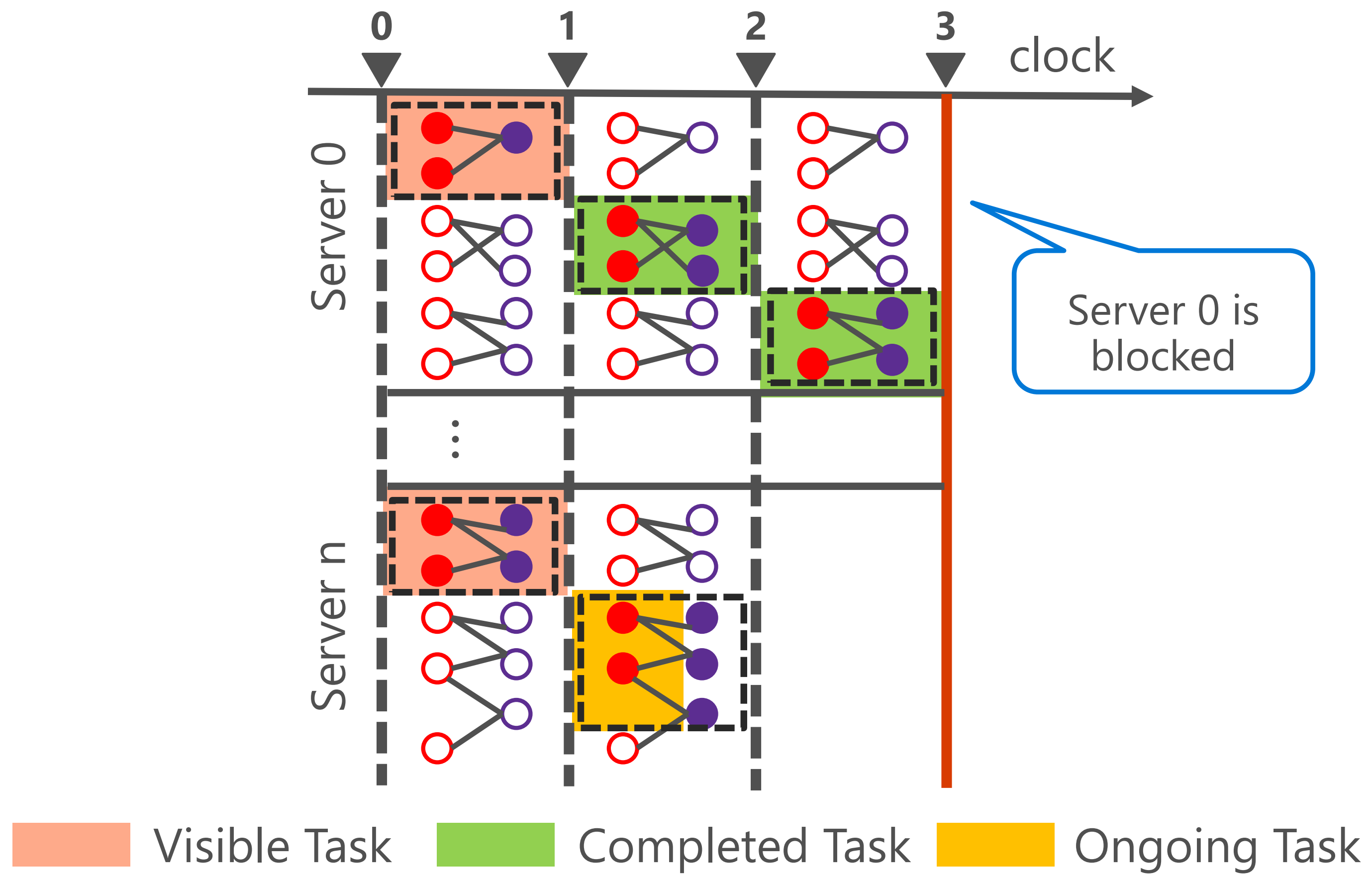
- Slowest server (n) is in clock2
- Fastest server (0) finishes clock2
  - within the staleness bound
  - continue



Stale Synchronous Parallel in TuX^2

Slack of 1 clock as an example

- Slowest server (n) is in clock2
- Fastest server (0) finishes clock3
  - reaching the max slack bound
  - blocked



Key designs

Scheduling: Stale Synchronous Parallel (SSP) based scheduling

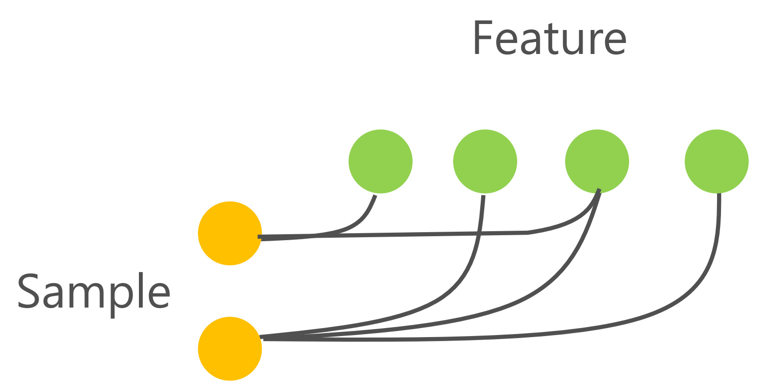
DataModel: Heterogeneous data model

Programming: MEGA graph model

Heterogeneity in ML

Heterogeneous Vertices

- Different properties
  - E.g. Logistic Regression
    - Sample: Label; Feature: Weight, Gradient



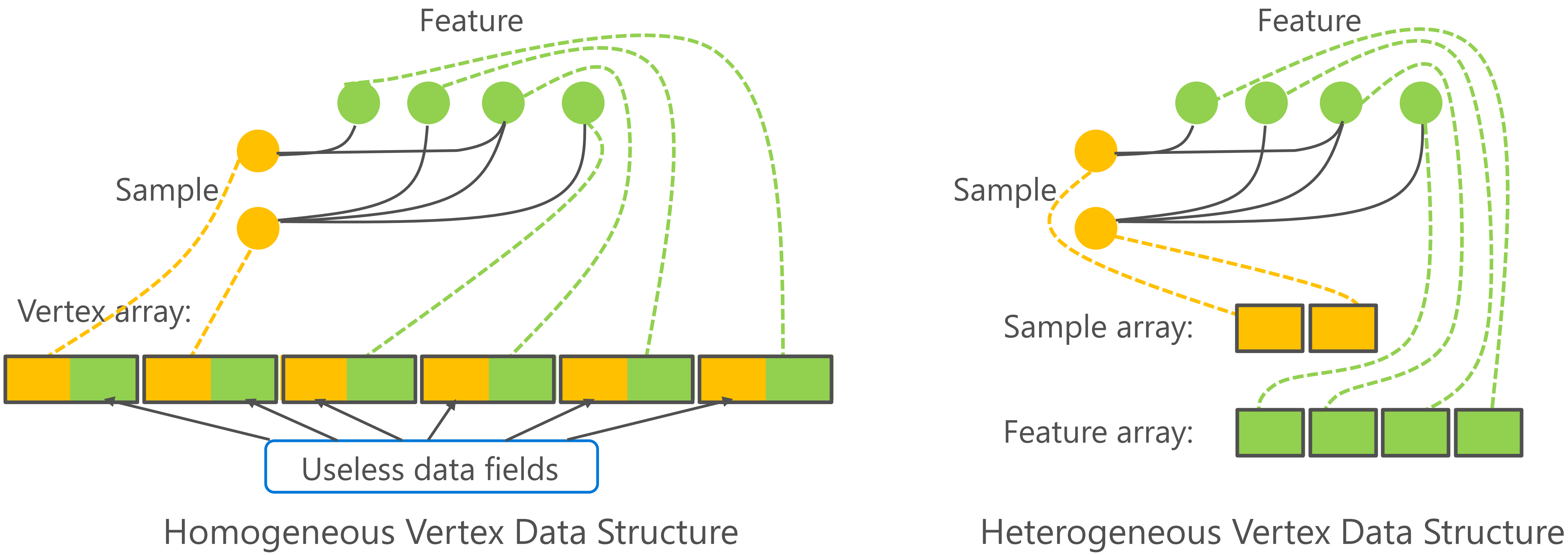
Benefit

- Heterogeneity for compact data structure
- Heterogeneity for efficient execution
- Heterogeneity for less network traffic

Heterogeneity for compact data structure

E.g. Logistic Regression

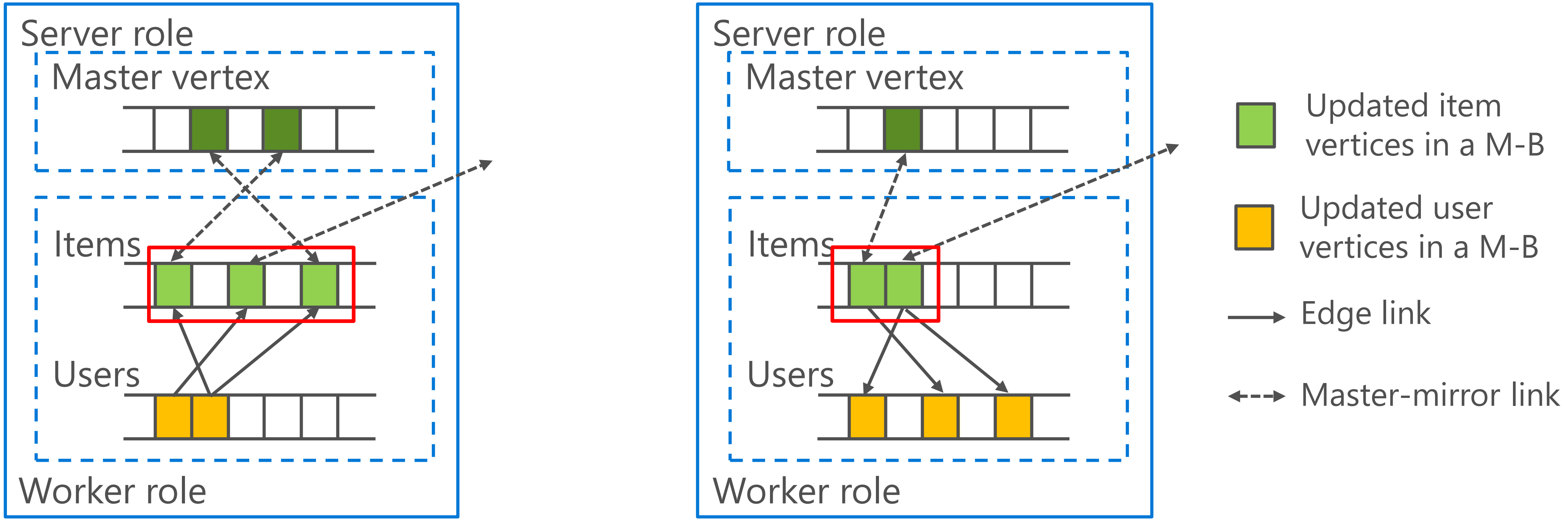
- Sample: Label; Feature: Weight, Gradient



Heterogeneity for efficient execution

E.g. Mini-Batch MF for recommendation

- Benefits of scanning items
  - Sequential access for locality when syncing
  - Less overhead tracing the updated vertices



Scan user vertices

Scan item vertices

Key designs

Scheduling: Stale Synchronous Parallel (SSP) based scheduling

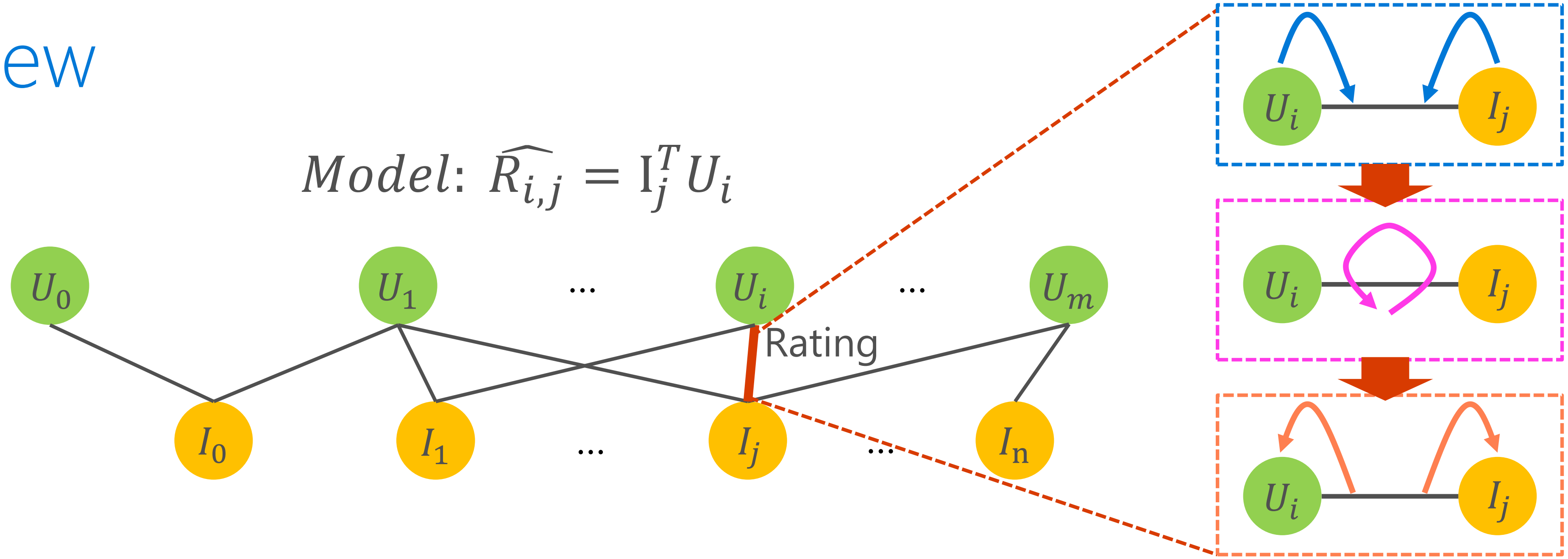
DataModel: Heterogeneous data model

Programming: MEGA graph model

MEGA: e.g. Mini-batch MF for recommendation

Graph View

$$Model: \widehat{R_{i,j}} = \mathrm{I}_j^T U_i$$



Exchange(v_user, v_item, edge, a_user, a_item, context)

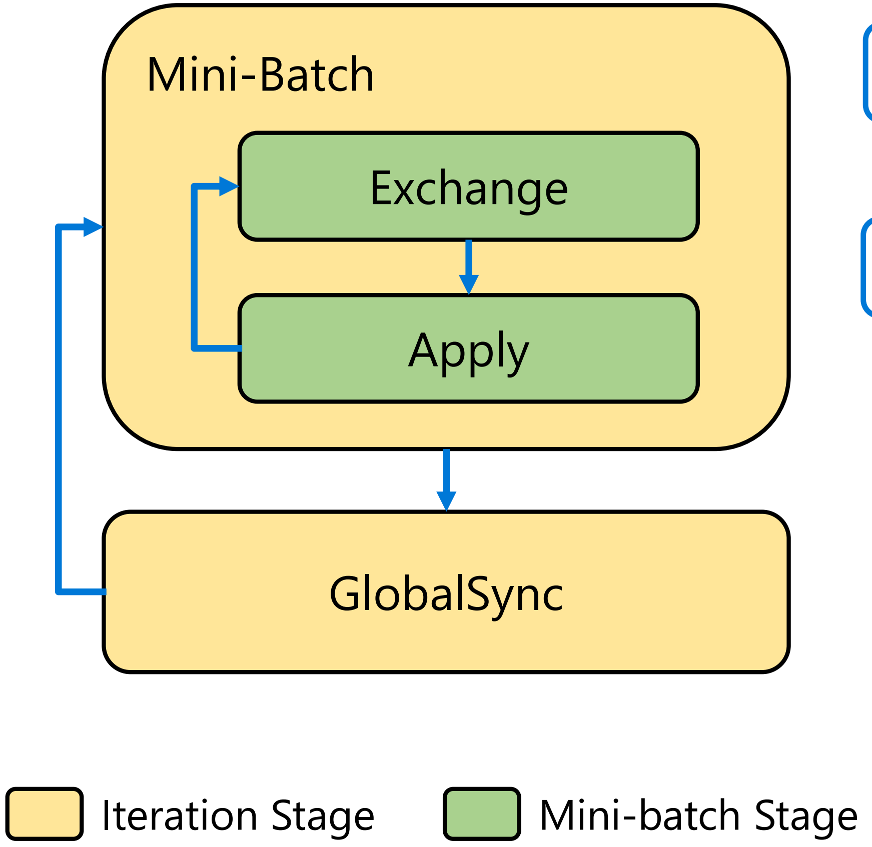
```
pred=PredictRating(v_user, v_item);
loss=edge.rating–pred;
context.loss+=loss^2;
(a_user, a_item)+=Gradient(loss, v_user, v_item);
```

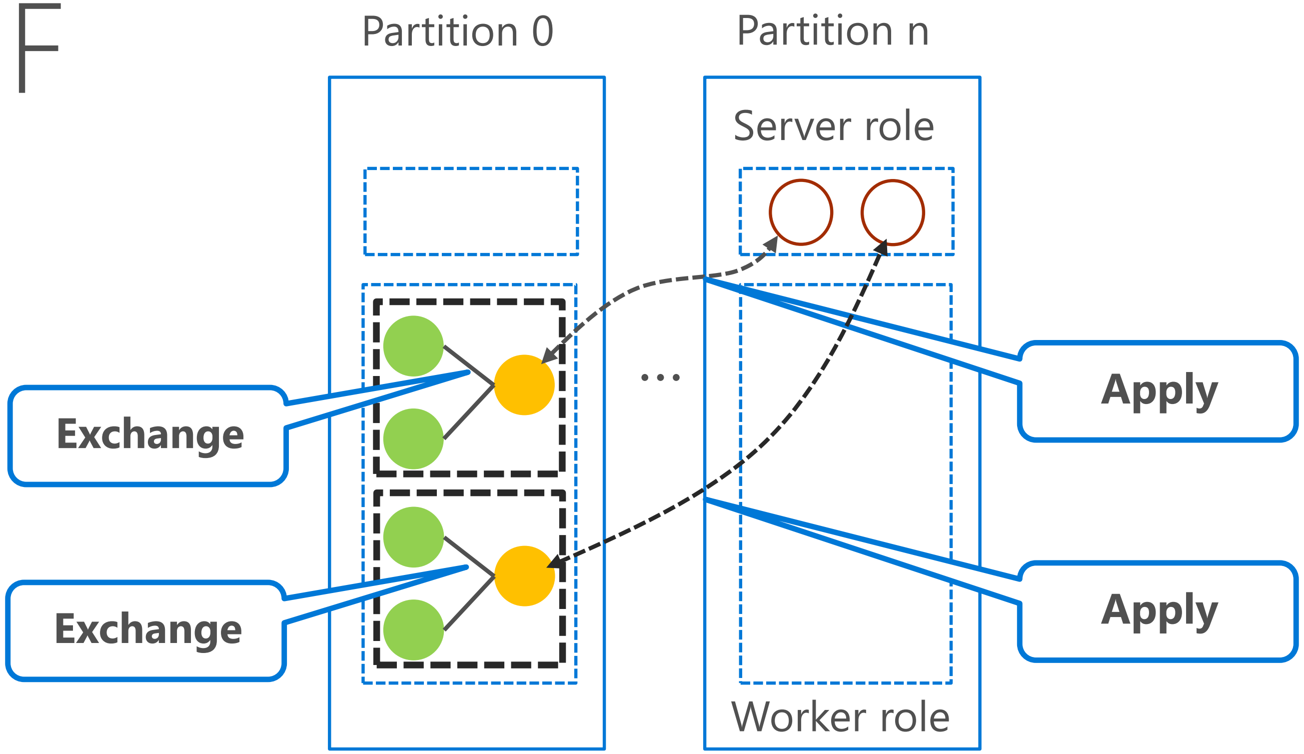
Apply(ver, accum, context)

```
ver.data +=accum;
```

Example: Mini-batch MF

Compose stage






```
StageSequenceBuilder(ExecStages)
 mbStage = new MiniBatchStage();
 mbStage.SetBatchSize(100, asEdge);
 mbStage.Add(ExchangeStage);
 mbStage.Add(ApplyStage);
 ExecStages.Add(mbStage);
 ExecStages.Add(GlobalSyncStage);
```

Experiment setup

Machine information

- 16 CPU cores, 256GB memory, 54Gbps InfiniBand NIC

Typical ML algorithms

- MF, LDA, BlockPG

Large-scale dataset

- Up to 64 billion edges graph

Dataset name	# of users/ docs/samples	# of items/ words/features	# of edges
NewsData(LDA)	7.3M	418.4K	1.4B
AdsData(BlockPG)	924.8M	209.3M	64.9B
Netflix(MF)	480.2K	17.8K	100.5M
Synthesized(MF)	30M	1M	6.3M

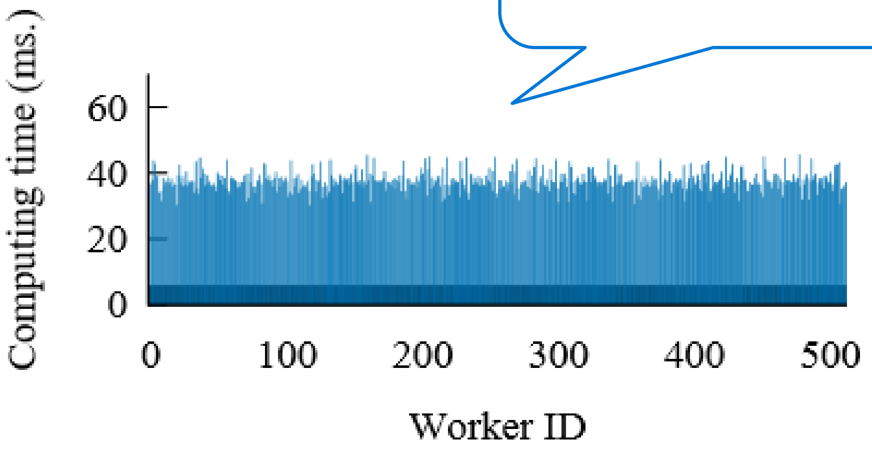
Evaluation

Compare to Parameter Server

- **48%** improvement on 32 servers!
- Algorithm: BlockPG
- Dataset: Microsoft private AdsData (64B edges)

Balance workload with vertex-cut!

Imbalance in Parameter Server

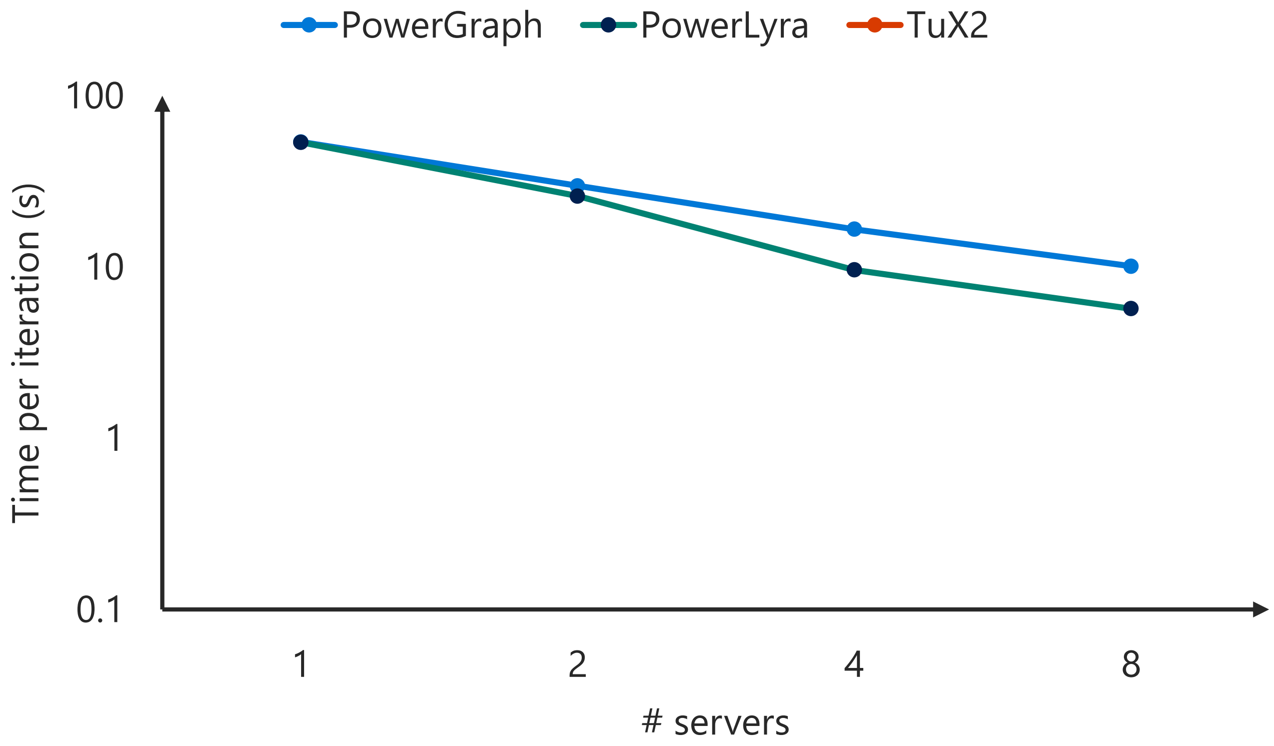


Balance in TuX2

Evaluation

Compare to PowerGraph, PowerLyra

- Algorithm: Matrix Factorization
- Dataset: Netflix



Evaluation

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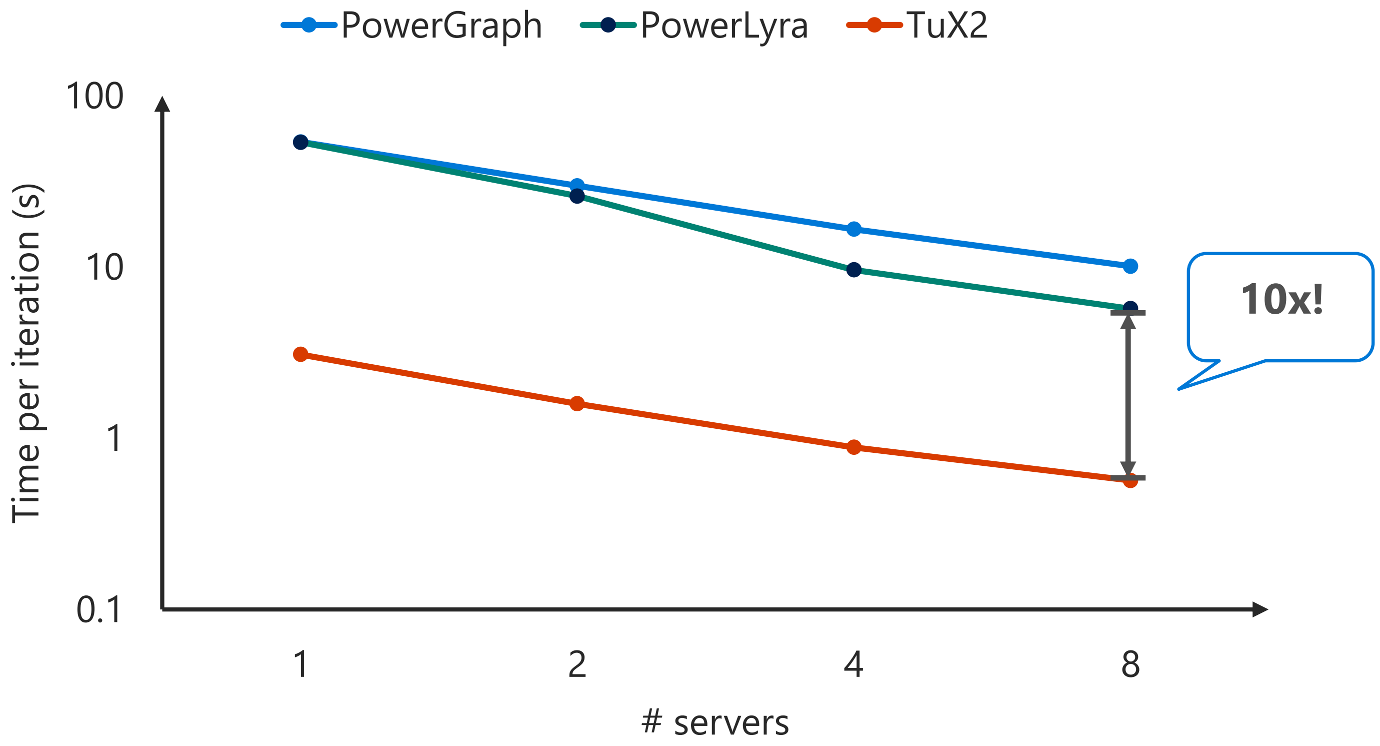

Conclusion

TuX^2: advocates the convergence of graph computation and distributed machine learning

- Introduce important machine learning concepts to graph computation
- Define a new, flexible graph model to express ML algorithms efficiently
- Demonstrate TuX^2 outperform existing Graph and ML systems in representative ML algorithms respectively

Thanks!
Q&A