An Introduction to Graph Analytics Platforms

(Very Short Version)

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University of Waterloo
David R. Cheriton School of Computer Science

Outline

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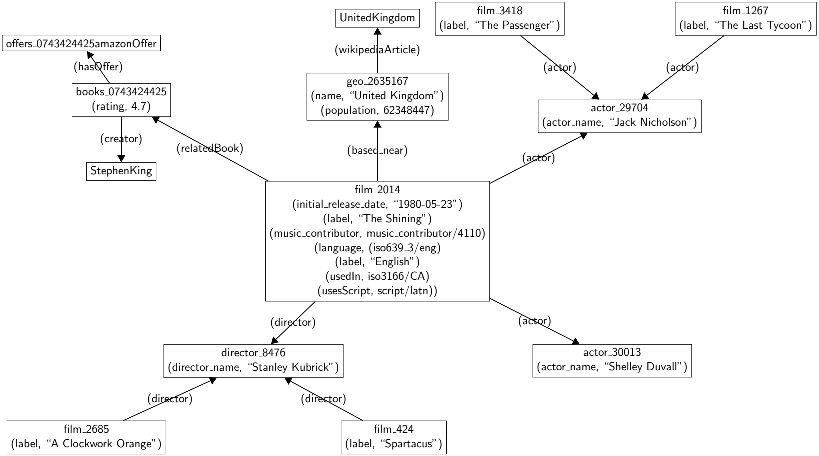
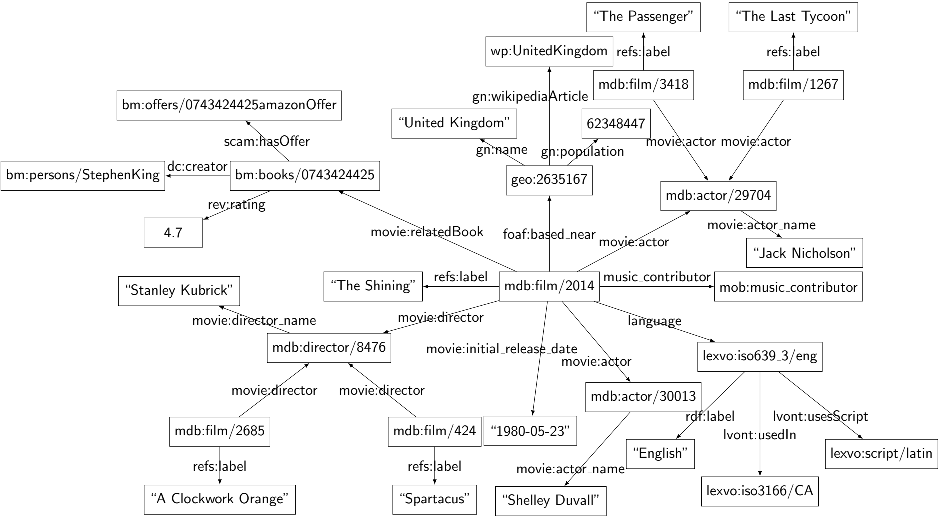
Graph Types

Property graph



Graph Types

RDF graph



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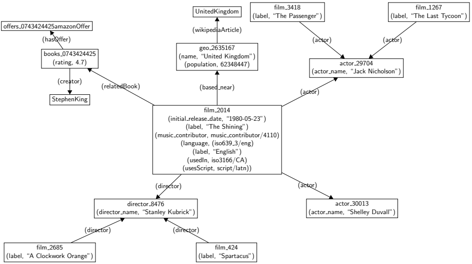

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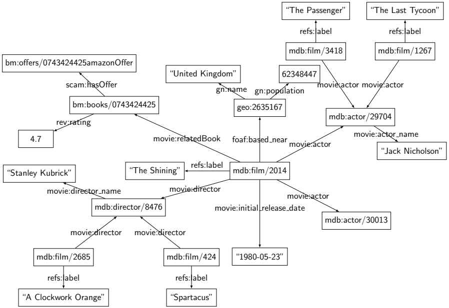

- Workload: Online queries and analytic workloads
- Query execution: Varies

- Workload: SPARQL queries
- Query execution: subgraph matching by homomorphism

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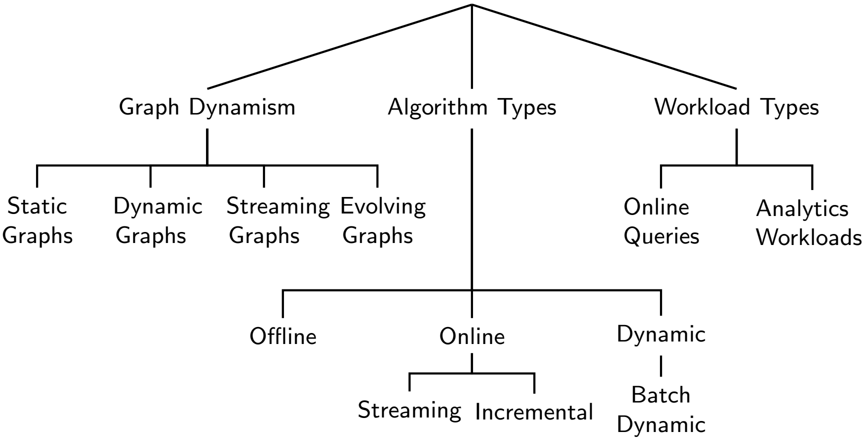
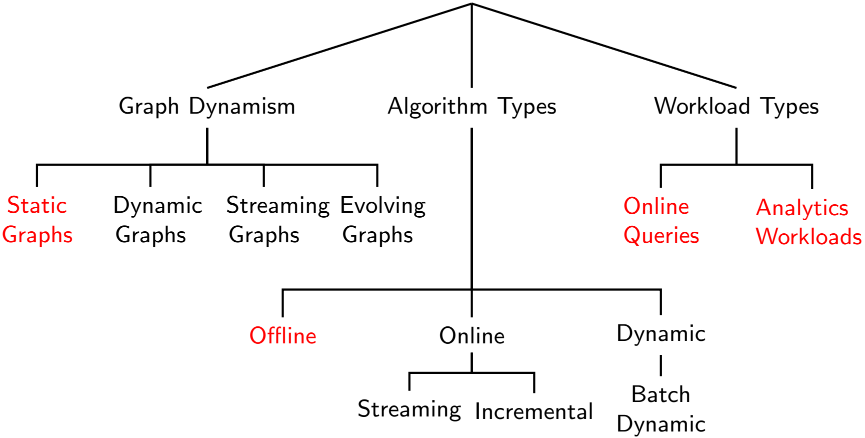
Classification Summary



Example Design Points



Compute the query result/perform analytic computation over the graph as it exists.

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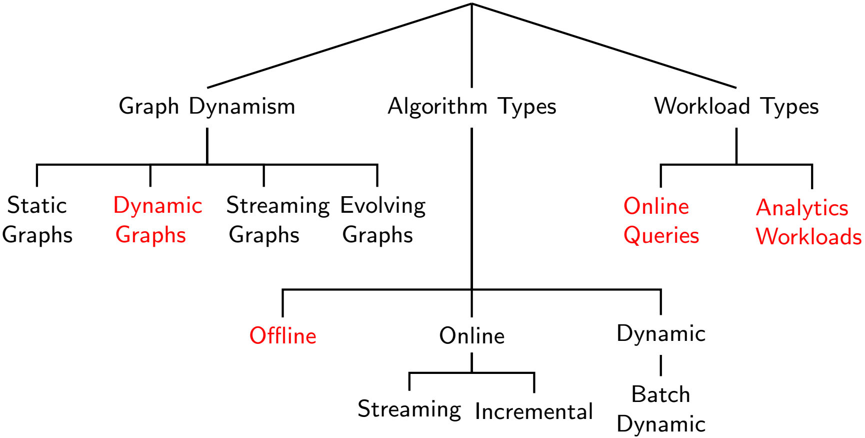

Compute the query result/perform analytic computation on each snapshot from scratch.

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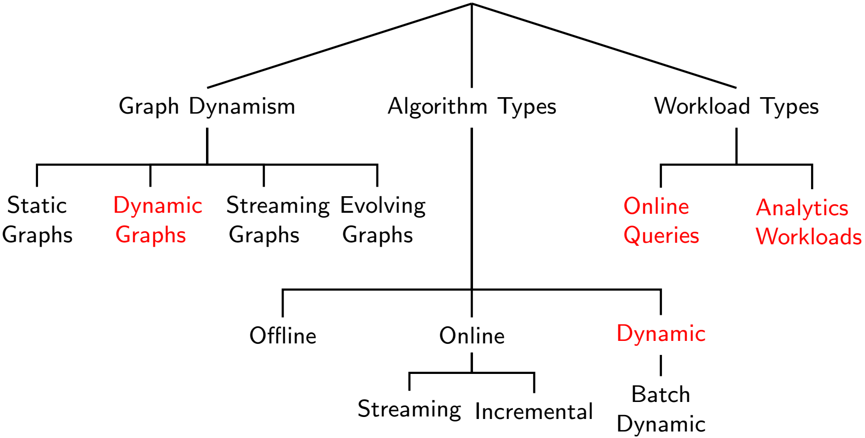
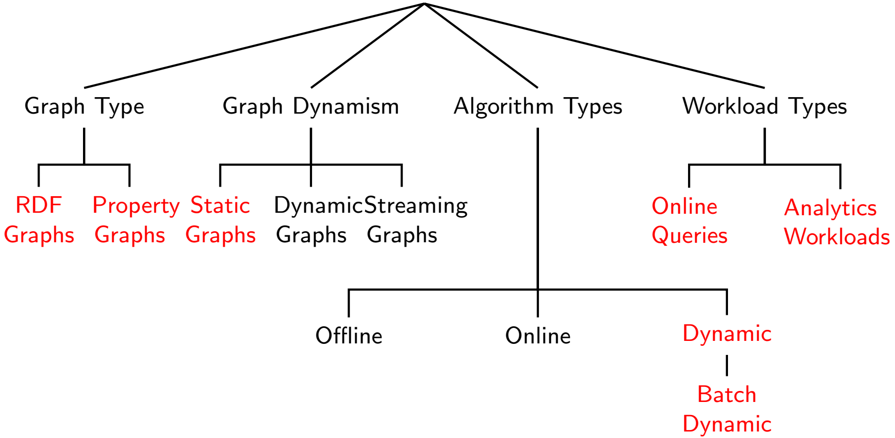


Continuously compute the query result/perform analytic computation as the input changes.

Example Design Points – Not all alternatives make sense



Dynamic (or batch-dynamic) algorithms do not make sense for static graphs.

Scale-up or Scale-out? [Lin, 2018]

- Scale-up: Single machine execution
  - Graph datasets are small and can fit in a single machine – even in main memory
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- Scale-out: Parallel execution
  - Graph data sets grow when they are expanded to their storage formats

Dataset	$\|V\|$	$\|E\|$	Regular size	Single Machine*
Live Journal	4,847,571	68,993,773	1.08GB	6.3GB
USA Road	23,947,347	58,333,344	951MB	9.09GB
Twitter	41,652,230	1,468,365,182	26GB	128 GB
UK0705	82,240,700	2,829,101,180	48GB	247GB
World Road	682,496,072	717,016,716	15GB	194GB
CommonCrawl2014	1,727,000,000	64,422,000,000	1.3TB	Out of memory

* Using (PowerLyra)

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  - Some graphs are very large: Alibaba: several billion vertices, >100 million edges
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We focus on parallel graph analytics systems

Graph Partitioning

- Edge-cut (vertex-disjoint)
  - Achieve disjoint partitions by allocating each vertex to a partition
  - Objective 1: Partitions should be balanced
  - Objective 2: Minimize edge-cuts (to reduce communication)
  - Good for graphs with low-degree vertices, not for power-law graphs
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- Hybrid
  - Edge-cut for low-degree vertices/vertex-cut for high-degree ones
  - PowerLyra [Chen et al., 2015]

Graph Workloads

Online graph querying

- Reachability
- Single source shortest-path
- Subgraph matching
- SPARQL queries

Offline graph analytics

- PageRank
- Clustering
- Connected components
- Diameter finding
- Graph colouring
- All pairs shortest path
- Graph pattern mining
- Machine learning algorithms (Belief propagation, Gaussian non-negative matrix factorization)

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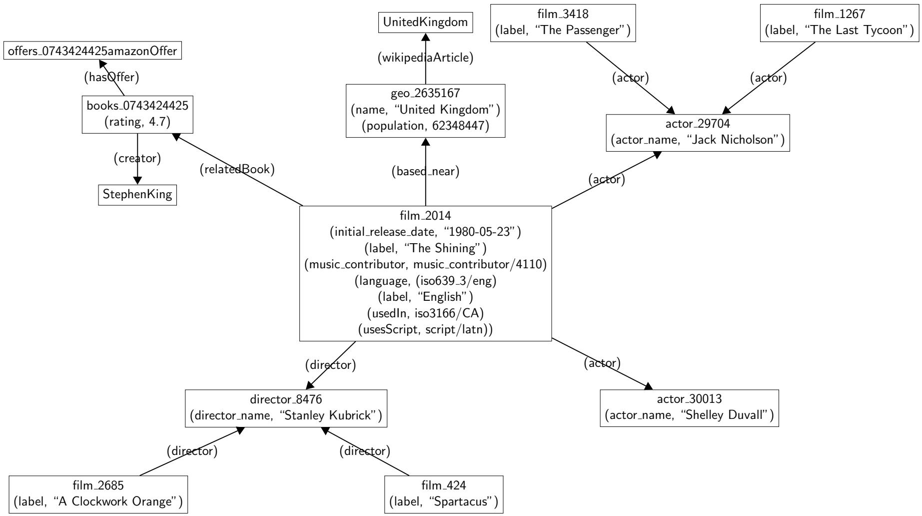
Reachability Queries



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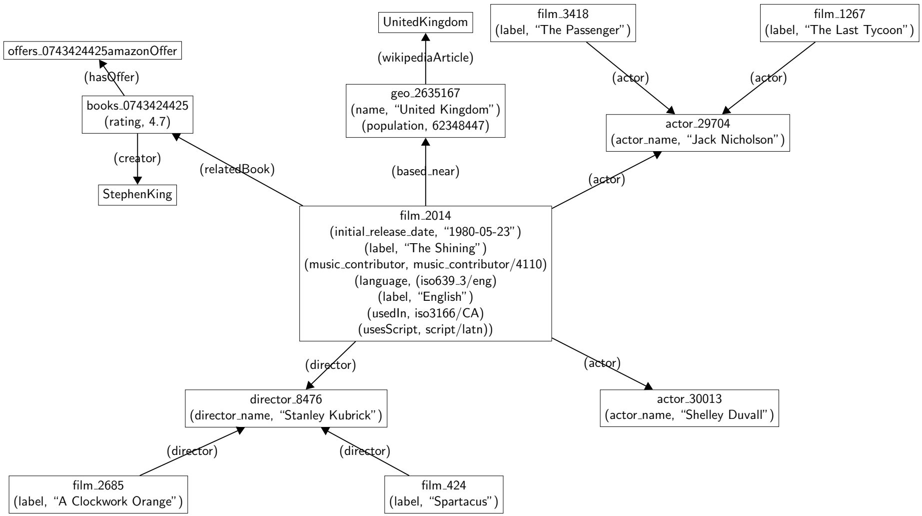
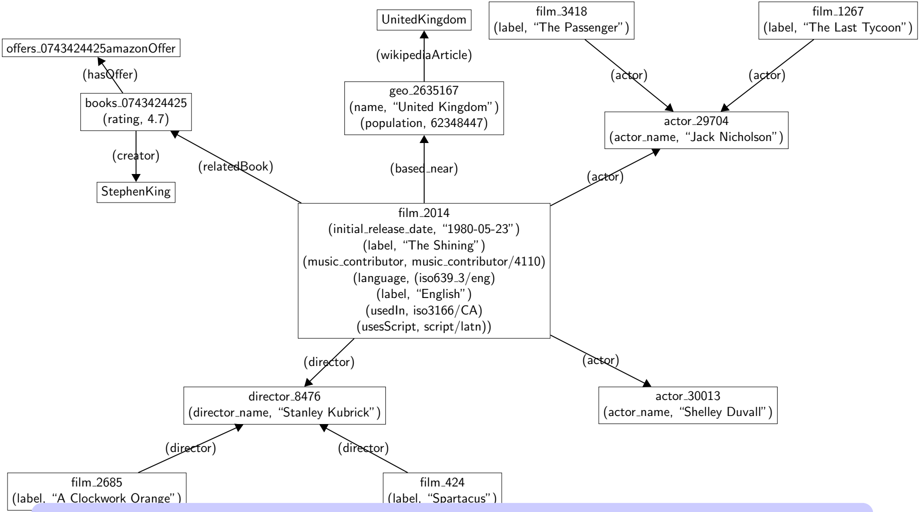


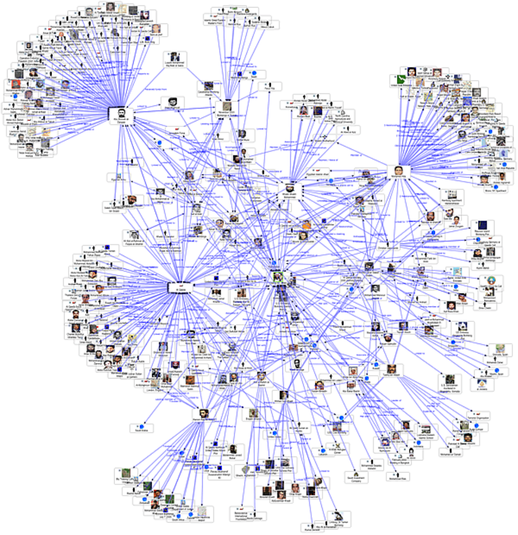
Can you reach film_1267 from film_2014?

Reachability Queries



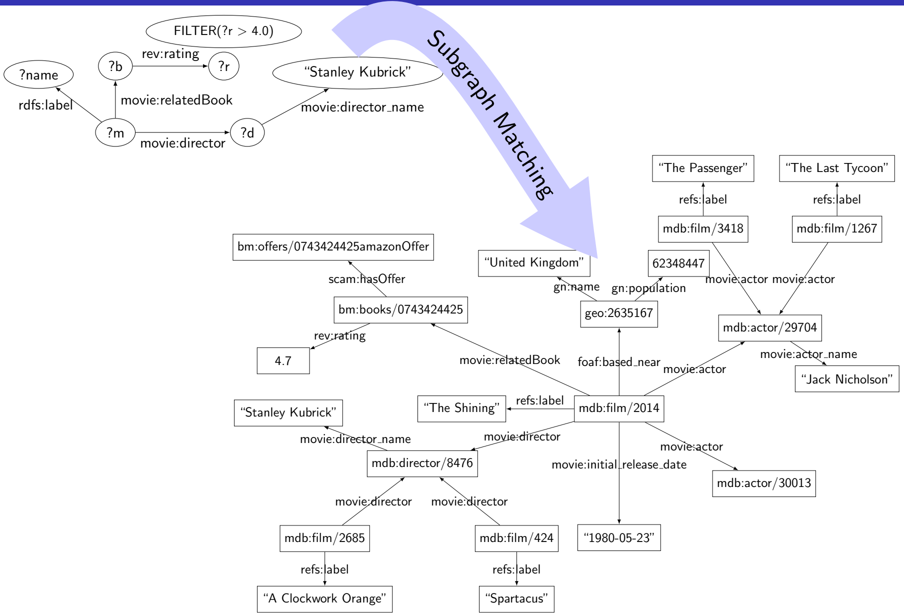
Is there a book whose rating is > 4.0 associated with a film that was directed by Stanley Kubrick?

Reachability Queries



Think of Facebook graph and finding friends of friends.

Subgraph Matching



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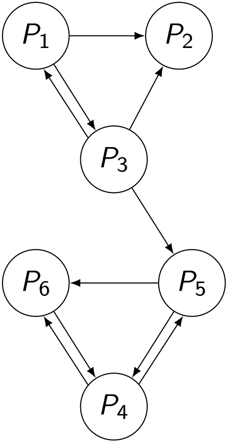
PageRank Computation

A web page is important if it is pointed to by other important pages.



$$r(P_i) = (1-d) + d \sum_{P_j \in B_{P_i}} \frac{r(P_j)}{|F_{P_j}|}$$

(let $d = 1$)

$$r(P_2) = \frac{r(P_1)}{2} + \frac{r(P_3)}{3}$$

$$r_{k+1}(P_i) = \sum_{P_j \in B_{P_i}} \frac{r_k(P_j)}{|F_{P_j}|}$$

B_{P_i}: in-neighbours of P_i

F_{P_i}: out-neighbours of P_i

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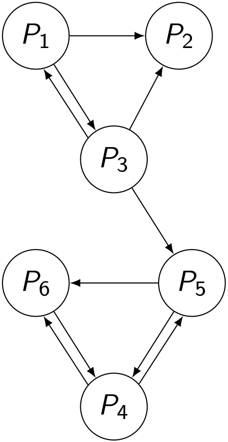

$$r_{k+1}(P_i) = \sum_{P_j \in B_{P_i}} \frac{r_k(P_j)}{|F_{P_j}|}$$

Iteration 0	Iteration 1	Iteration 2	Rank at Iter. 2
$r_0(P_1) = 1/6$	$r_1(P_1) = 1/18$	$r_2(P_1) = 1/36$	5
$r_0(P_2) = 1/6$	$r_1(P_2) = 5/36$	$r_2(P_2) = 1/18$	4
$r_0(P_3) = 1/6$	$r_1(P_3) = 1/12$	$r_2(P_3) = 1/36$	5
$r_0(P_4) = 1/6$	$r_1(P_4) = 1/4$	$r_2(P_4) = 17/72$	1
$r_0(P_5) = 1/6$	$r_1(P_5) = 5/36$	$r_2(P_5) = 11/72$	3
$r_0(P_6) = 1/6$	$r_1(P_6) = 1/6$	$r_2(P_6) = 14/72$	2

Iterative processing
Touch each vertex

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Can MapReduce be Used for Graph Analytics?

- Yes; `map` and `reduce` functions can be written for graph analytics workloads
  - Scalable Graph processing Class $\mathcal{SGC}$ [Qin et al., 2014]
  - Connected component computation [Kiveris et al., 2014; Rastogi et al., 2013]
- Not suitable for iterative processing due to data movement at each stage
  - No guarantee that computation will be assigned to the same worker nodes in the next round
- High I/O cost
  - Need to save in storage system (HDFS) intermediate results of each iteration

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- There are systems that address these concerns
  - HaLoop [Bu et al., 2010, 2012]
  - GraphX over Spark [Gonzalez et al., 2014]

Spark System

- Spark objectives
  - Better support for iterative programs
  - Provide a complete ecosystem
  - Similar abstraction (to MapReduce) for programming
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  - Better support for iterative programs
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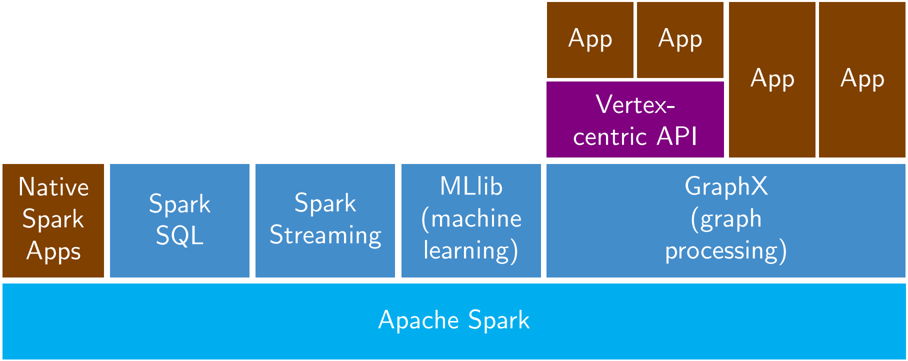
  - Maintain MapReduce fault-tolerance and scalability
- Fundamental concepts
  - RDD: Reliable Distributed Datasets
  - Caching of working set
  - Maintaining lineage for fault-tolerance

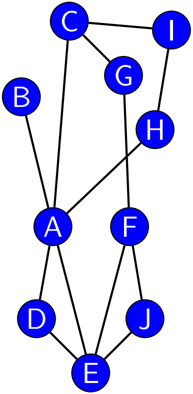
GraphX

[Gonzalez et al., 2014]

- Built on top of Spark
- Objective is to combine data analytics with graph processing
  - Unify computation on tables and graphs
- Carefully convert graph to tabular representation
- Native GraphX API or can accommodate vertex-centric computation



GraphX: Representation of Graphs as Tables



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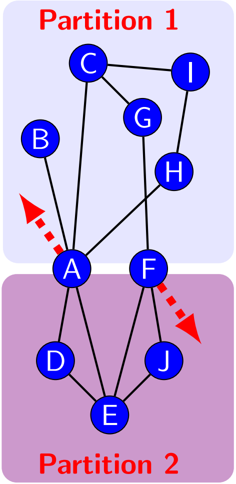

Edge-disjoint partitioning

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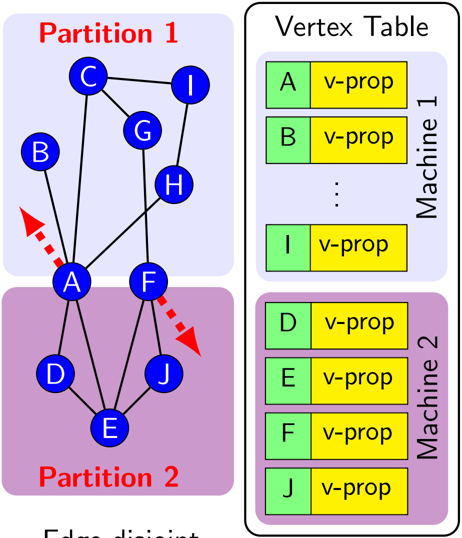

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(RDD)
v-prop:vertex prop.

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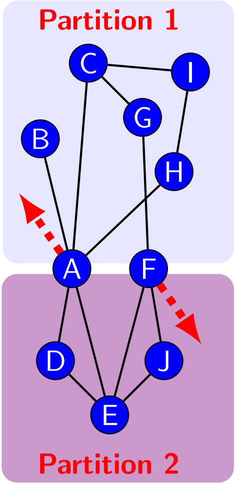

Edge-disjoint partitioning

Vertex Table

A	v-prop	Machine 1
B	v-prop	
⋮		
I	v-prop	
D	v-prop	Machine 2
E	v-prop	
F	v-prop	
J	v-prop	

(RDD)
v-prop:vertex prop.

Edge Table

A	e-prop	B
A	e-prop	C
⋮		
F	e-prop	G
A	e-prop	D
A	e-prop	E
⋮		
E	e-prop	F

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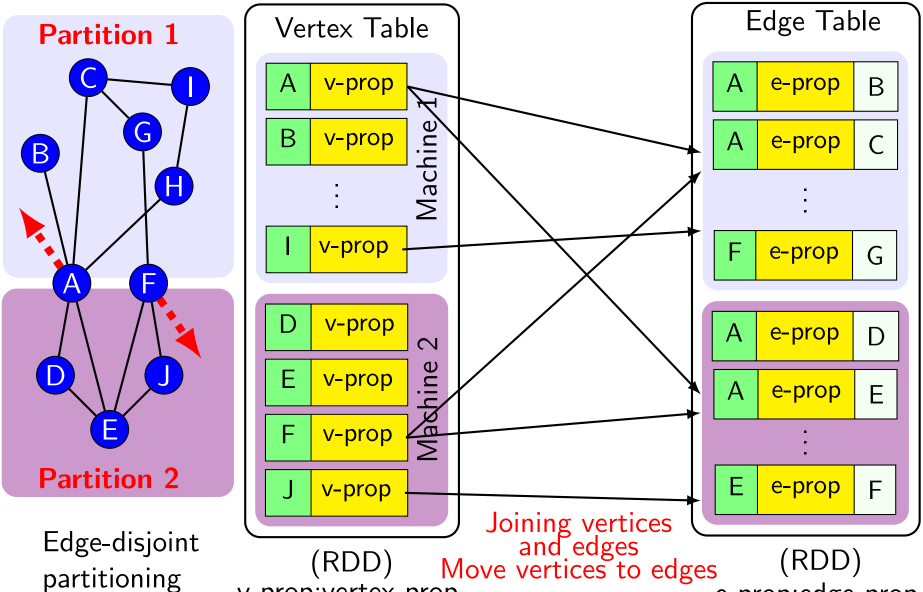

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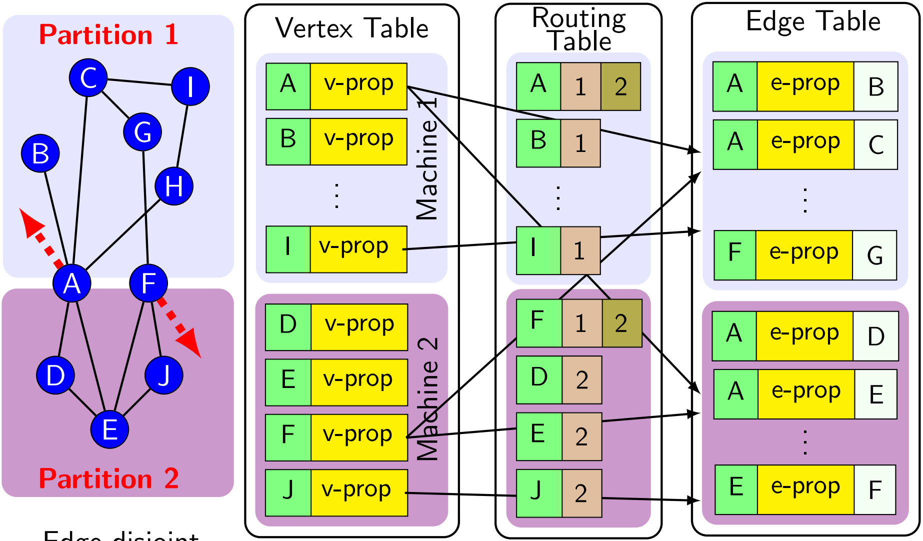

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Classification of Graph Processing Systems [Han, 2015]

- Programming model
- Computation model

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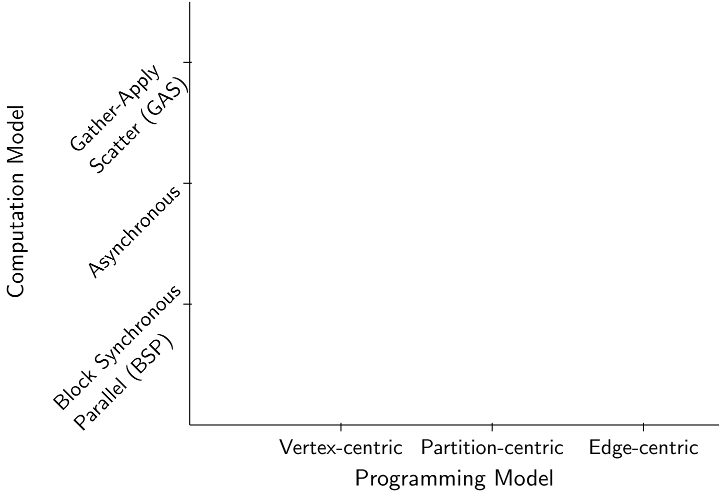

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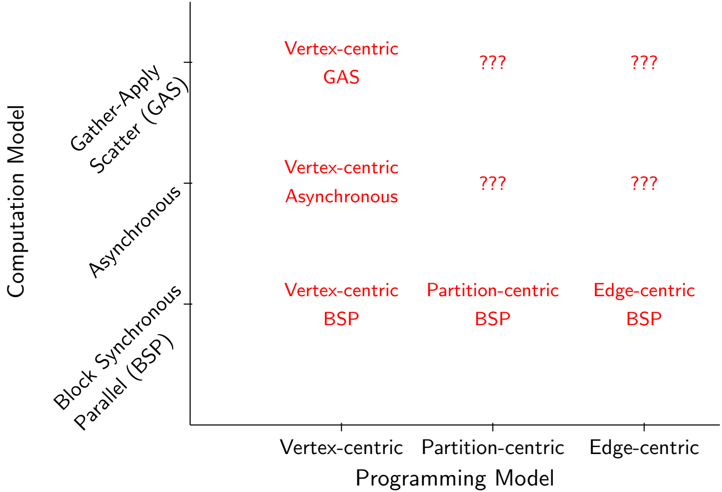
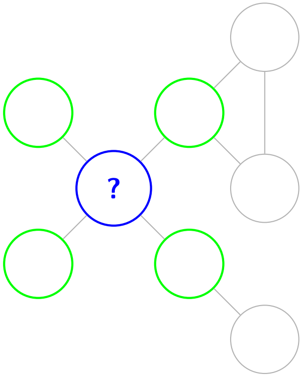


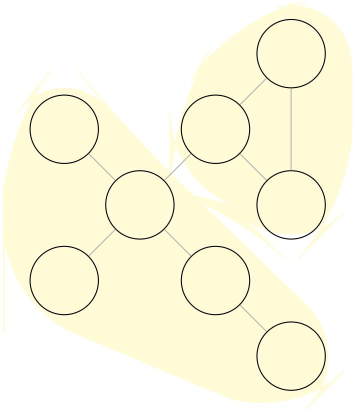
Programming Models

- Vertex-centric
  - Computation on a vertex is the focus
  - "Think like a vertex"
  - Vertex computation depends on its own state + states of its neighbors
  - `Compute(vertex v)`
  - `GetValue()`, `WriteValue()`



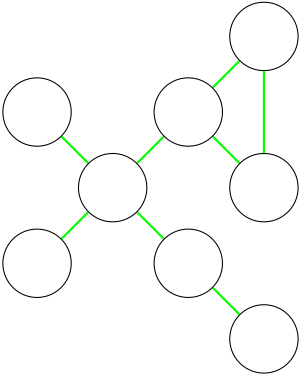
Programming Models

- Vertex-centric
- Partition-centric (Block-centric)
  - Computation on an entire partition is specified
  - "Think like a block" or "Think like a graph"
  - Aim is to reduce the communication cost among vertices



Programming Models

- Vertex-centric
- Partition-centric (Block-centric)
- Edge-centric
  - Computation is specified on each edge rather than on each vertex or block
  - `Compute(edge e)`



Computational Models

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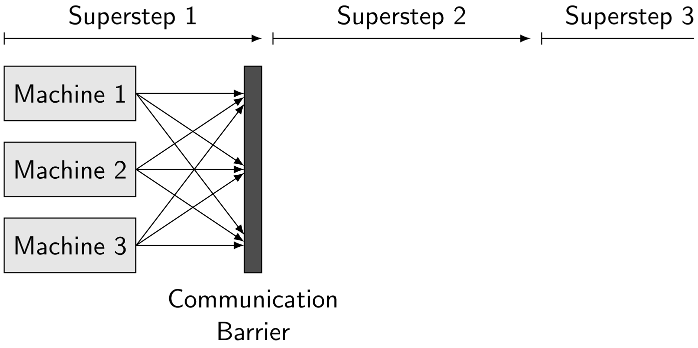

Each machine performs computation on its graph partition

At the end of each superstep results are pushed to other workers

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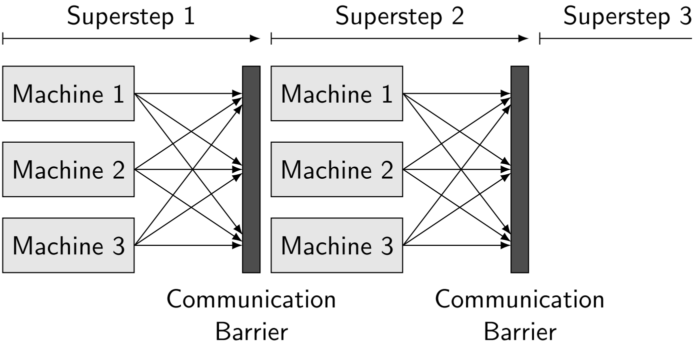

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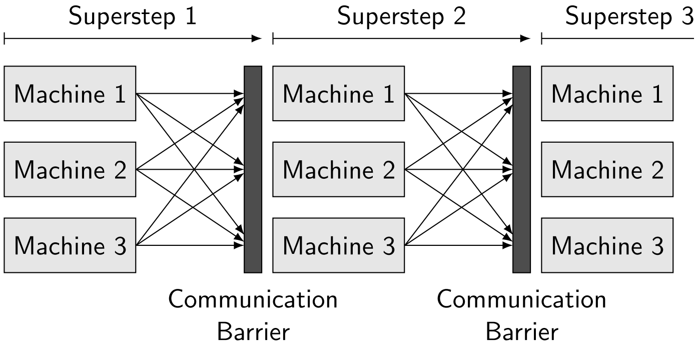

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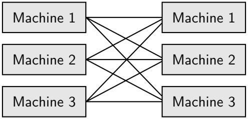

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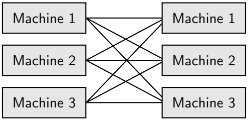

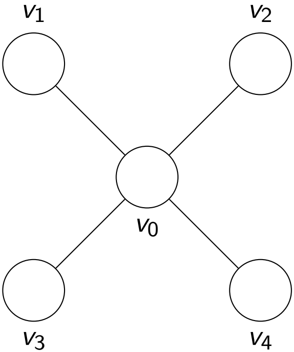

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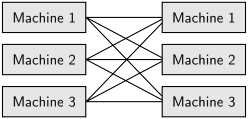

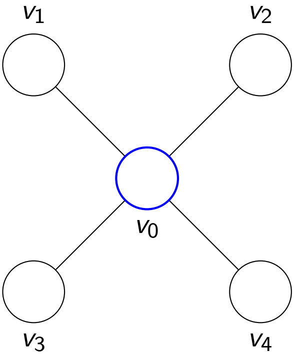

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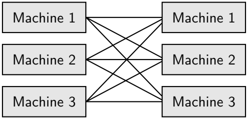

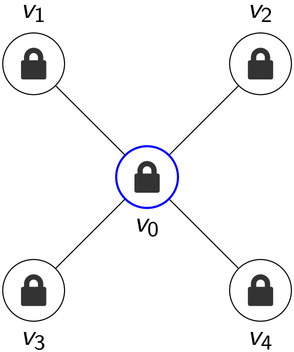

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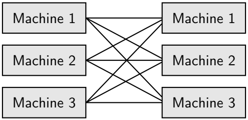

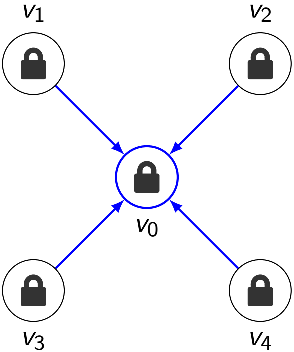

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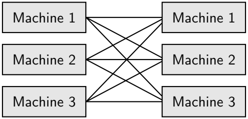
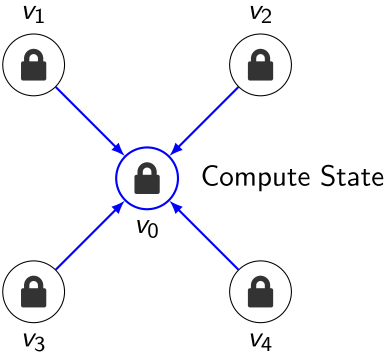
  - Implemented via distributed locking
  - Consider vertex-centric program





Computational Models

- Block Synchronous Parallel (BSP) [Valiant, 1990]
- Asynchronous Parallel
    - No communication barriers. ✓
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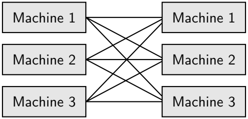

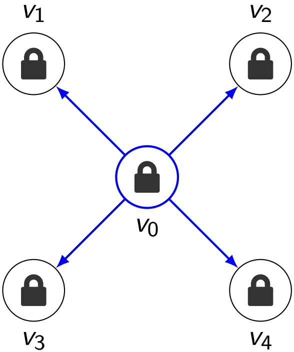

Computational Models

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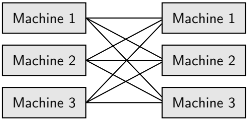
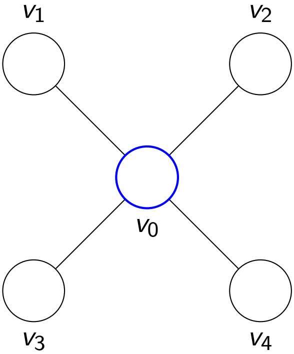




Computational Models

- Block Synchronous Parallel (BSP) [Valiant, 1990]
- Asynchronous Parallel
- Gather-Apply-Scatter (GAS)
  - Similar to BSP, but pull-based
  - Gather: pull state
  - Apply: `Compute` function
  - Scatter: Update state
  - Updates of states separated from scheduling

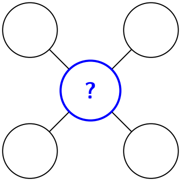
Real-World Graph Characteristics

- Read-world graphs have skewed vertex degree distribution
  - Common in power-law graphs
  - Problem: imbalanced communication workloads
- Real-world graphs have large diameters
  - Common in road networks, web graphs, terrain meshes
  - Problem: one superstep per hop $\Rightarrow$ too many supersteps
- Real-world graphs have high average vertex degree
  - Common in social networks, mobile communication networks
  - Problem: heavy average communication workloads

Outline

Vertex-Centric BSP Systems

- "Think like a vertex"
- `Compute(vertex v)`



Vertex-Centric BSP Systems

- "Think like a vertex"
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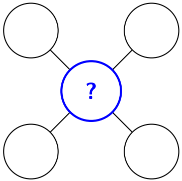
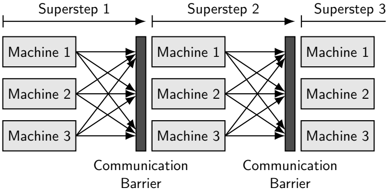
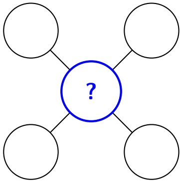
- BSP Computation – push state to neighbor vertices at the end of each superstep

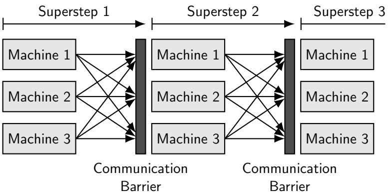


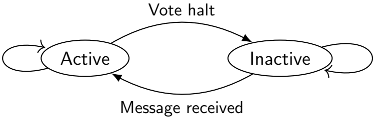


Vertex-Centric BSP Systems

- "Think like a vertex"
- `Compute(vertex v)`
- BSP Computation – push state to neighbor vertices at the end of each superstep
- Continue until all vertices are inactive
- Vertex state machine







- "Think like a vertex"
- `Compute(vertex v)`
- BSP Computation – push state to neighbor vertices at the end of each superstep
- Continue until all vertices are inactive
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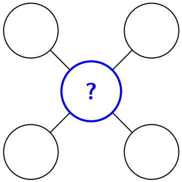
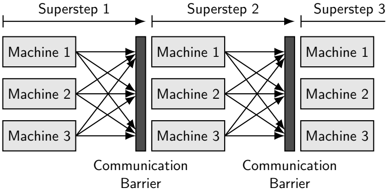
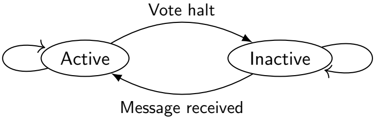
- Example systems: Pregel [Malewicz et al., 2010], Apache Giraph, GPS [Salihoglu and Widom, 2013], Mizan [Khayyat et al., 2013], Trinity [?]







Vertex-Centric Asynchronous Systems

- "Think like a vertex"
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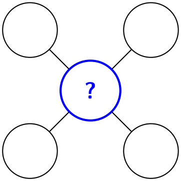
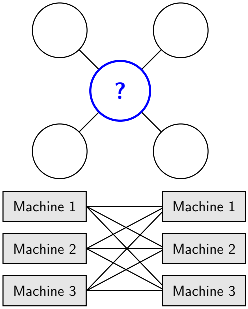


Vertex-Centric Asynchronous Systems

- “Think like a vertex”
- `Compute(vertex v)`
- Supersteps exist along with synchronization barriers, but ...
- `Compute(vertex v)` function can see messages it was sent in the same superstep as well as those that come at the end of the previous superstep



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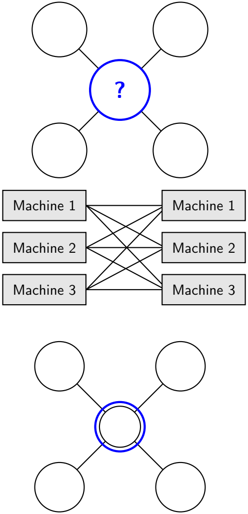

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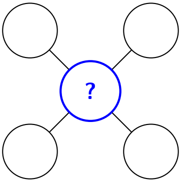

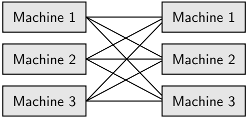

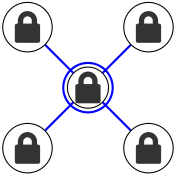

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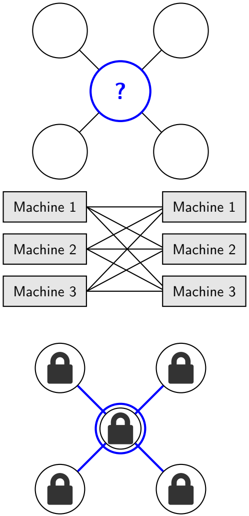

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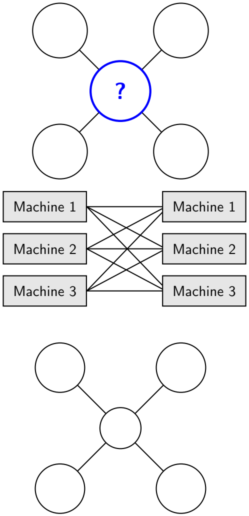

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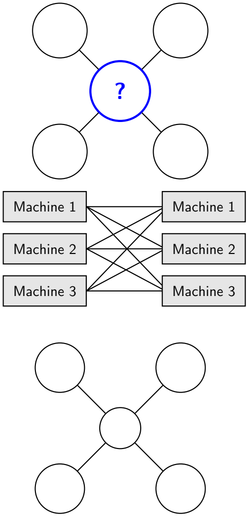
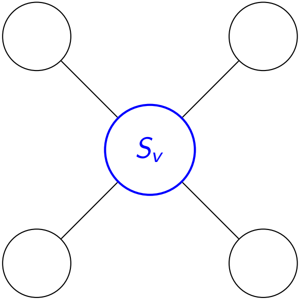
- Supersteps exist along with synchronization barriers, but ...
- `Compute(vertex v)` function can see messages it was sent in the same superstep as well as those that come at the end of the previous superstep
- Consistency of vertex states: distributed locking
- Consistency issues: no guarantee about input to `Compute()`
- Example systems: GRACE [Wang et al., 2013], GiraphCU [Han and Daudjee, 2015]



Vertex-Centric GAS Systems

- "Think like a vertex"
- Gather phase
  - Gather local computation from neighbours if vertex v: called *scope* S_v
- Apply phase
  - `Compute(v, Sv)`
- Scatter phase
  - `Compute(v, Sv)` produces $S_v^{'}$ (scattering state)
- Example: GraphLab [Low et al., 2012]
- Synchronous version
  - Similar to vertex-centric BSP, except pulling S_v rather than pushing
- Asynchronous version different

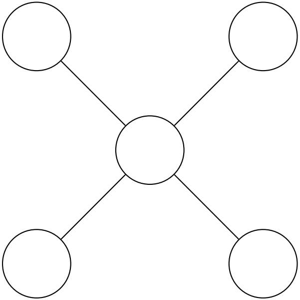


Vertex-Centric GAS Systems – Asynchronous

procedure $\textsc{GraphLab\_Async}(G = (V, E, D), \mathcal{T})$

return Modified $G = (V, E, D')$
end procedure

- Graph mutation restricted to vertex states

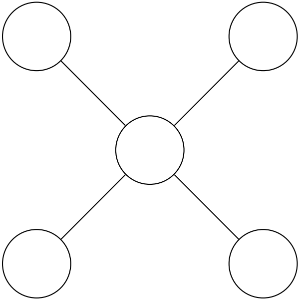


Vertex-Centric GAS Systems – Asynchronous

procedure $\textsc{GraphLab\_Async}(G = (V, E, D), \mathcal{T})$
while $\mathcal{T}$ is not empty **do**

end while
return Modified $G = (V, E, D')$
end procedure

- Graph mutation restricted to vertex states

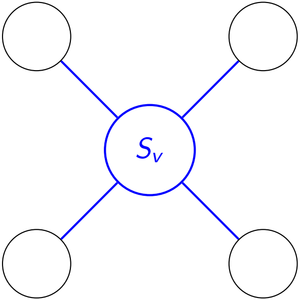


Vertex-Centric GAS Systems – Asynchronous

procedure $\textsc{GraphLab\_Async}(G = (V, E, D), \mathcal{T})$
while $\mathcal{T}$ is not empty **do**
    $v \leftarrow \texttt{RemoveNext}(\mathcal{T})$

end while
return Modified $G = (V, E, D^{'})$
end procedure

- Graph mutation restricted to vertex states

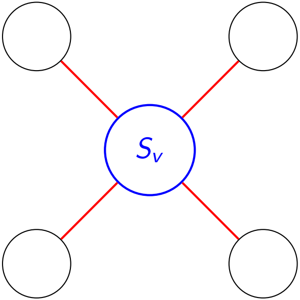


Vertex-Centric GAS Systems – Asynchronous

procedure $\textsc{GraphLab\_Async}(G = (V, E, D), \mathcal{T})$
while $\mathcal{T}$ is not empty **do**
  $v \leftarrow \texttt{RemoveNext}(\mathcal{T})$
  $\texttt{Compute}(v, S_v) \rightarrow (\mathcal{T}', S_v')$

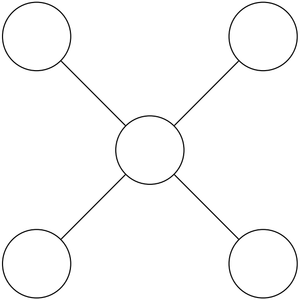
end while
return Modified $G = (V, E, D')$
end procedure

- Graph mutation restricted to vertex states
- Computing S_v' updates (scatters) states of the vertices in scope



Vertex-Centric GAS Systems – Asynchronous

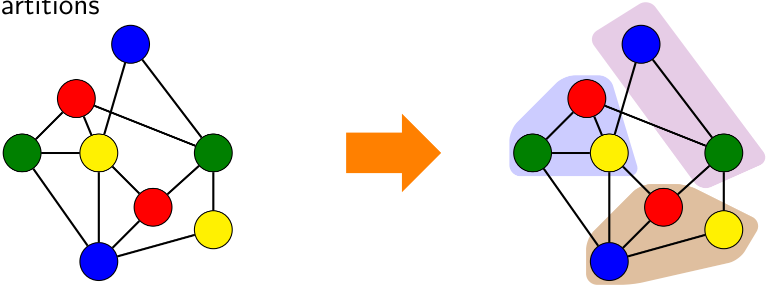
procedure GraphLab_Async($G = (V, E, D), \mathcal{T}$)
while $\mathcal{T}$ is not empty **do**
    $v \leftarrow$ `RemoveNext`$(\mathcal{T})$
    `Compute`$(v, S_v) \rightarrow (\mathcal{T}', S'_v)$
    $\mathcal{T} \leftarrow \mathcal{T} \cup \mathcal{T}'$
end while
return Modified $G = (V, E, D')$
end procedure



- Graph mutation restricted to vertex states
- Computing S'_v updates (scatters) states of the vertices in scope
- Computation of new states S'_v separated from computation of new $\mathcal{T}'$
    - `RemoveNext()` can remove any vertex $\rightarrow$ scheduling separated from state scatter

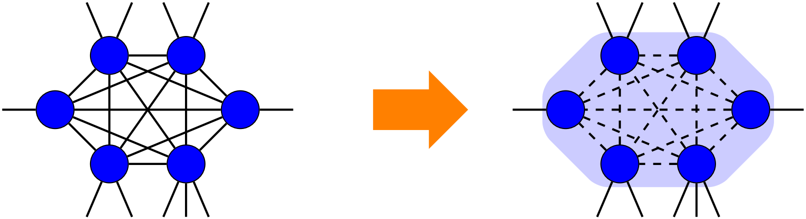
Partition- (Block-)Centric BSP Systems

- Blogel [Yan et al., 2014]: "Think like a block"; also "think like a graph" [Tian et al., 2013]
- Better handles the characteristics of real-world graphs by reducing communication
- Exploit the partitioning of the graph
- Message exchanges only among blocks
- Within a block, run a serial in-memory algorithm; BSP between partitions



Benefits of Partition- (Block-)Centric BSP

- High-degree vertices inside a block send no messages
- Fewer number of supersteps
- Fewer number of blocks than vertices



Edge-Centric BSP Systems

- "Think like an edge"
- `Compute(edge e)`
- Number of edges $\gg$ number of vertices
  - More computation but perhaps fewer messages
  - Operate on unsorted sequence of edges $\Rightarrow$ no random access
- X-Stream [Roy et al., 2013]

Outline

1. Introduction – Graph Types
2. Property Graph Processing
   - Classification
   - Online querying
   - Offline analytics
3. Graph Analytics Approaches
   - MapReduce & Variants
   - Classification of Native Approaches
4. Graph Analytics Systems
5. OLAP-Style Analytics
   - Graph Summarization
   - Snapshot-based Aggregation
   - Graph Cube
   - Pagrol
   - Gagg Model

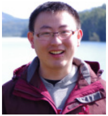
OLAP Over Graphs

- OLAP in RDBMS
  - Usage: Data Warehousing + Business Intelligence
  - Model: Multidimensional cube
  - Operations: Roll-up, drill-down, and slice and dice
- Analytics that we discussed over graphs is much different
- Can we do OLAP-style analytics over graphs?
  - There is some work
    - Graph summarization [Tian et al., 2008]
    - Snapshot-based Aggregation [Chen et al., 2008]
    - Graph Cube [Zhao et al., 2011]
    - Pagrol [?]
    - Gagg Model [Maali et al., 2015]

Acknowledgements

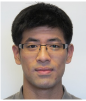
This presentation draws upon collaborative research and discussions with the following colleagues

Khaled Ammar, U. Waterloo



Xiaofei Zhang, U. Waterloo (U. Memphis)

Khuzaima Daudjee,U. Waterloo



Young Han, U. Waterloo (Google)

Thank you!

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