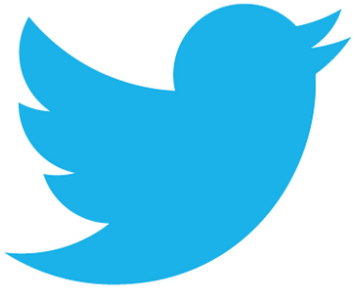
# Parallel Programming Principle and Practice

## Lecture 9 — Programming for Big Data Processing

# What is big data?

**A massive volume of both structured and unstructured data that is too large to process with traditional database and software techniques.**

- 34K likes every minute
- It deals with 3-4 PB data every day
- 1 billion active user



- It generates 12TB data daily
- 200 million users generate 230 million tweets daily


- 2 million search every minute
- It deals with 20 PB data every day

# Application of big data analytics

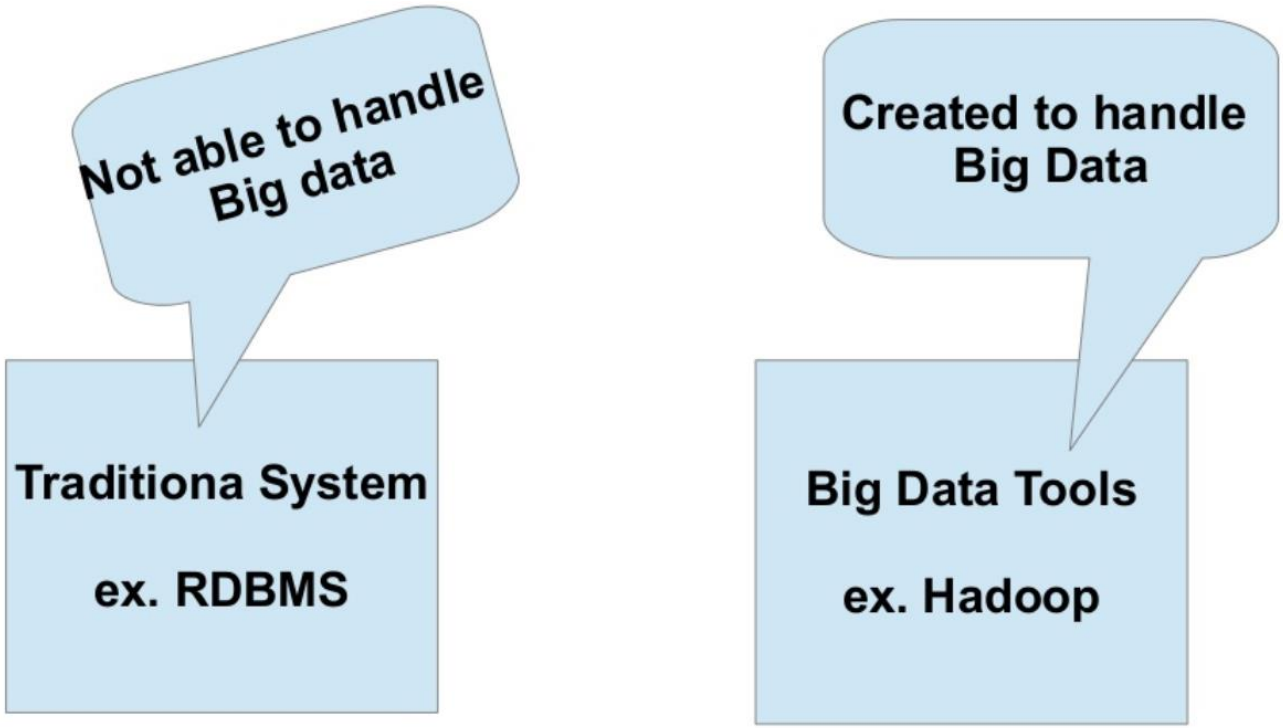
Smart healthcare

Manufacturing

Traffic control

Trading analytics

# Tools for handling big data analytics



# Outline

- Programming for batch data processing
- Programming for graph processing
- Programming for stream processing

# PROGRAMMING FOR BATCH DATA PROCESSING

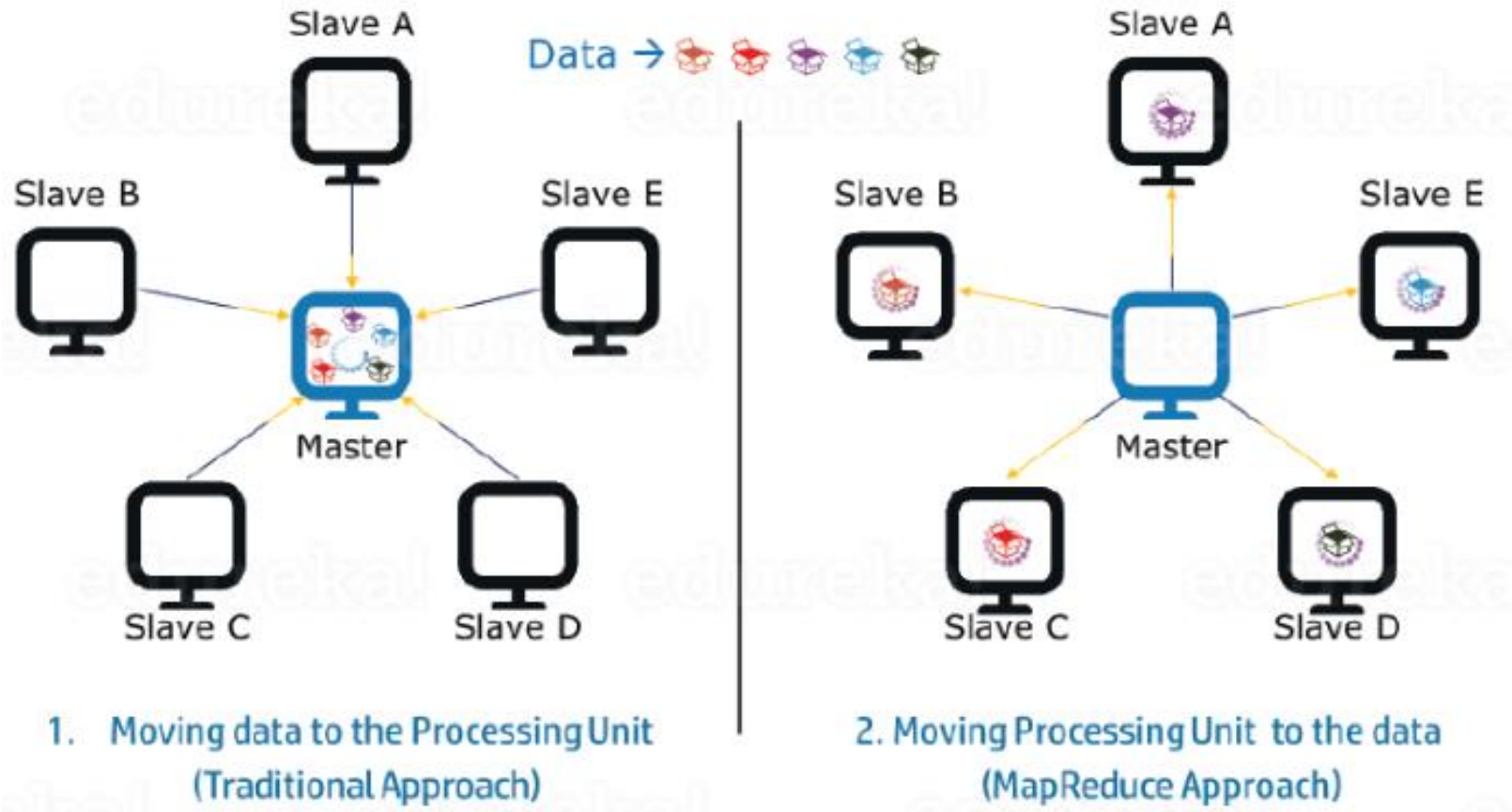
# Outline

- Background of batch data processing
- Programming model for batch data processing
- MapReduce framework

# Batch data processing

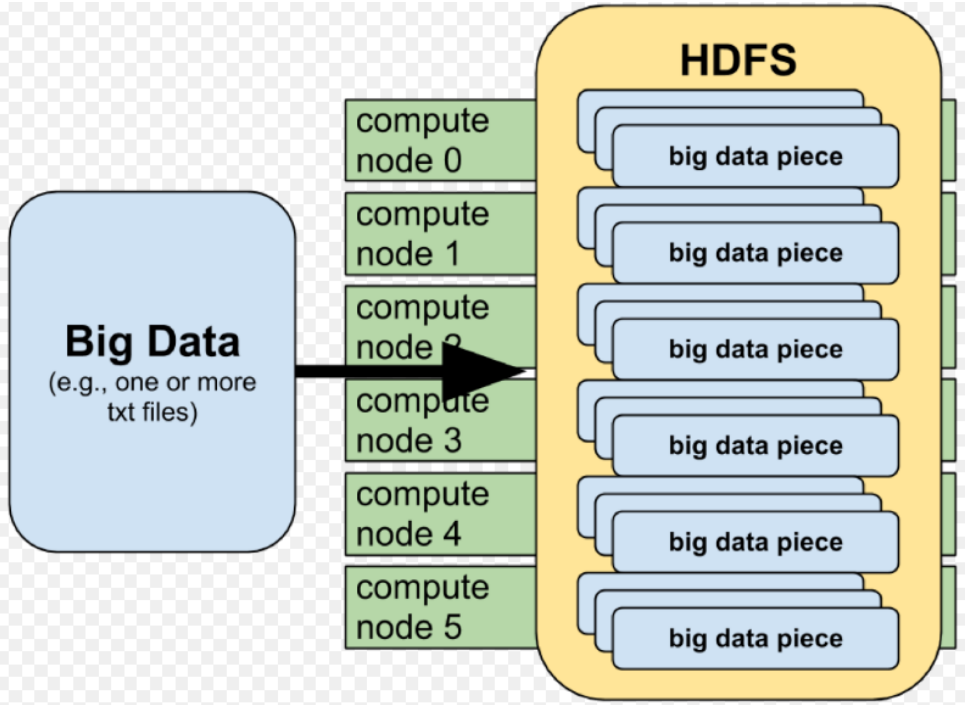
- Big data analytics usually contain tasks that perform batch data processing
  - Tasks that can be executed offline without user interaction
  - It process all data records in batch
  - Tools for batch processing of big data
- Challenge
  - Data placement, computation overhead
- Solution
  - Parallel execution on clusters with thousands of machines
  - Moving processing unit to the data

# Big data placement



# Parallel batch data processing

- Divide the input data into pieces
- Distribute the pieces on nodes and manage the data with distributed file system
- Parallel process of data piece on each node
- Aggregate the results



# Challenges for programmers

- Data placement
  - Data division, redundancy
- Computing parallelization
  - Synchronization between processes, consistency
- Communication
- Fault tolerant
- Load balancing

# Solution

- A general abstraction for special-purpose applications
  - Express the various simple computation
  - Hide the details of parallelization, such as fault-tolerance, data distribution, and load balancing
  - Provide powerful interfaces to users
  - Programmers can implement the application code without considering the messy parallelization details
  - Automatic parallelization and distribution of large-scale computation

**A general programming interface for various special-purpose applications is required!**

# Outline

- Background of batch data processing
- Programming model for batch data processing
- MapReduce framework

# Programming model for batch data processing

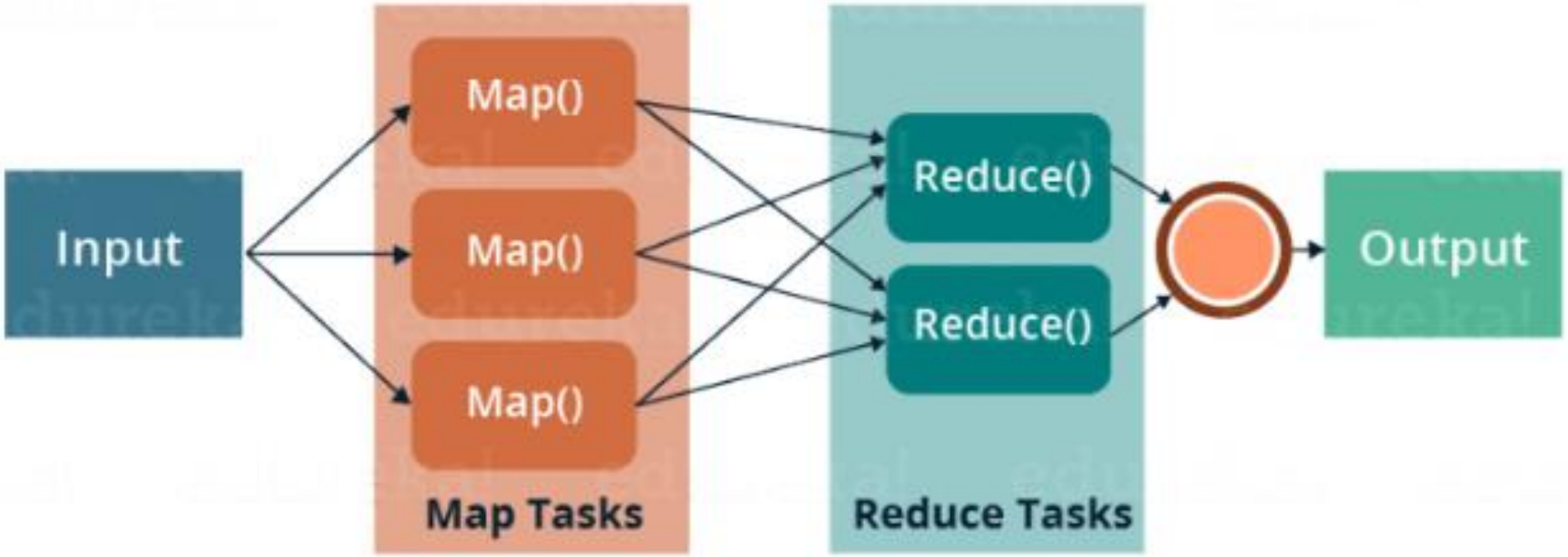
- Inspired by primitives of Lisp and other functional languages
- Most of our computations can be represented by a map and reduce operator to each logical record in the input dataset
  - The map and reduce operator are interfaces for programmers
- We can develop a general framework **MapReduce** for batch data processing
  - Provide the powerful map/reduce interface for programmers
  - Deal with parallelization details transparently and automatically

# Program model

- Read a lot of data
- **Map**: extract something you care about from each data record
- Shuffle and sort the data
- **Reduce**: aggregate, summarize, filter, or transform the intermediate data
- Write the final results

**Users can change the definition of map and reduce to fit different problems**

# Program model



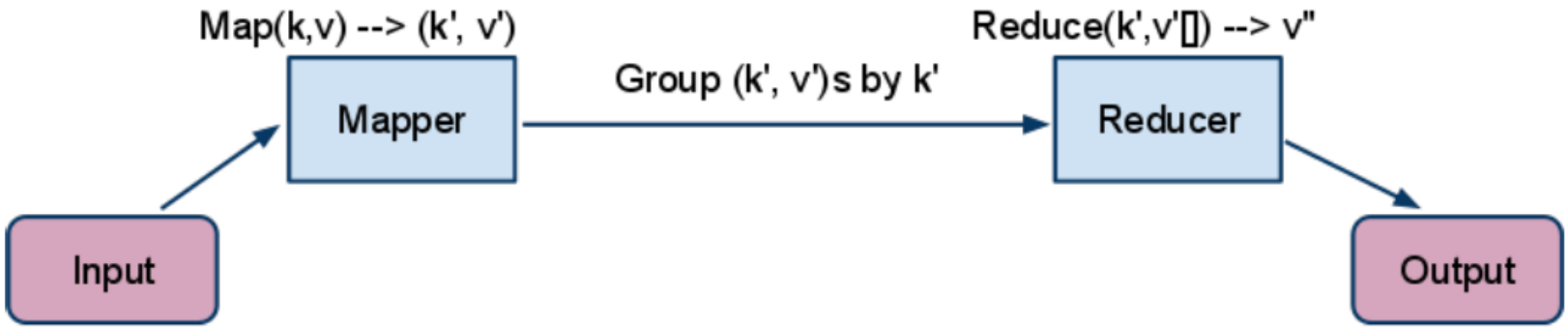
# Map/reduce abstraction for large-scale data

- Divide the large-scale input dataset into splits
- Distribute all splits on machines
- Perform map operator on each split
- Shuffle and sort intermediate results
- Perform reduce operator on each sorted results
  - Aggregate the intermediate results
- Generate final output

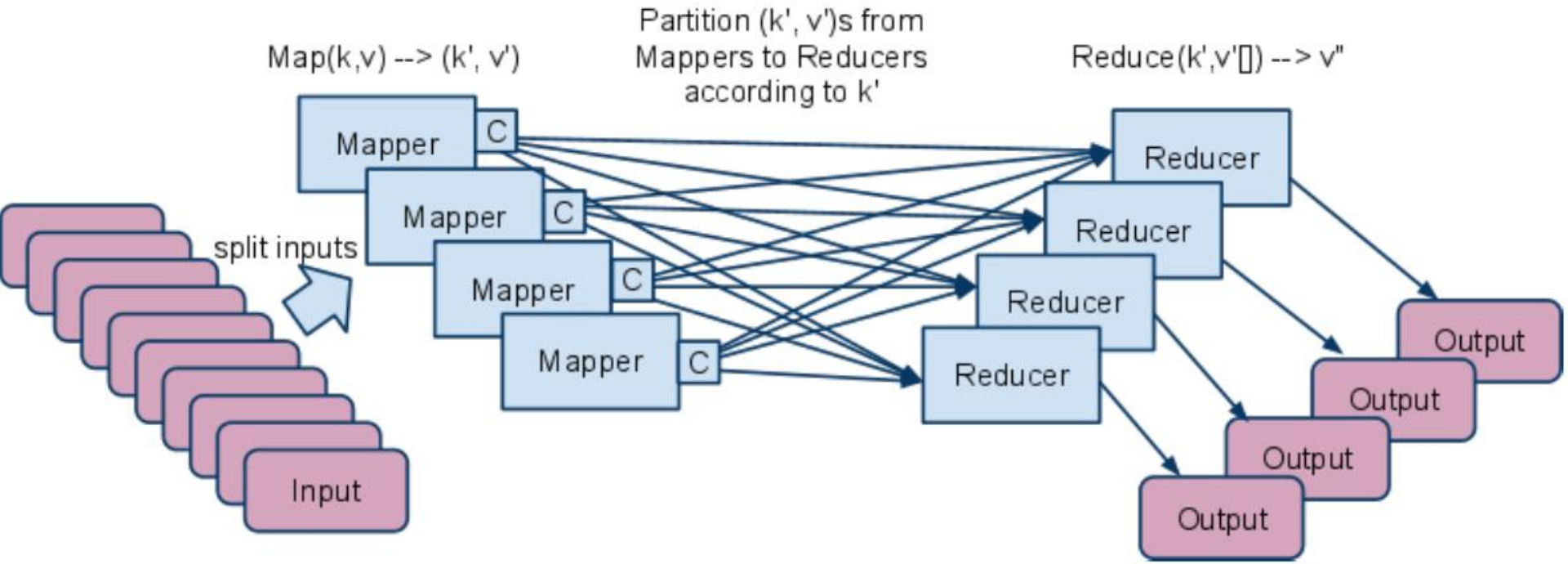
**Programmers only need to specify the map and reduce operator without considering other details.**

# Map/reduce operators

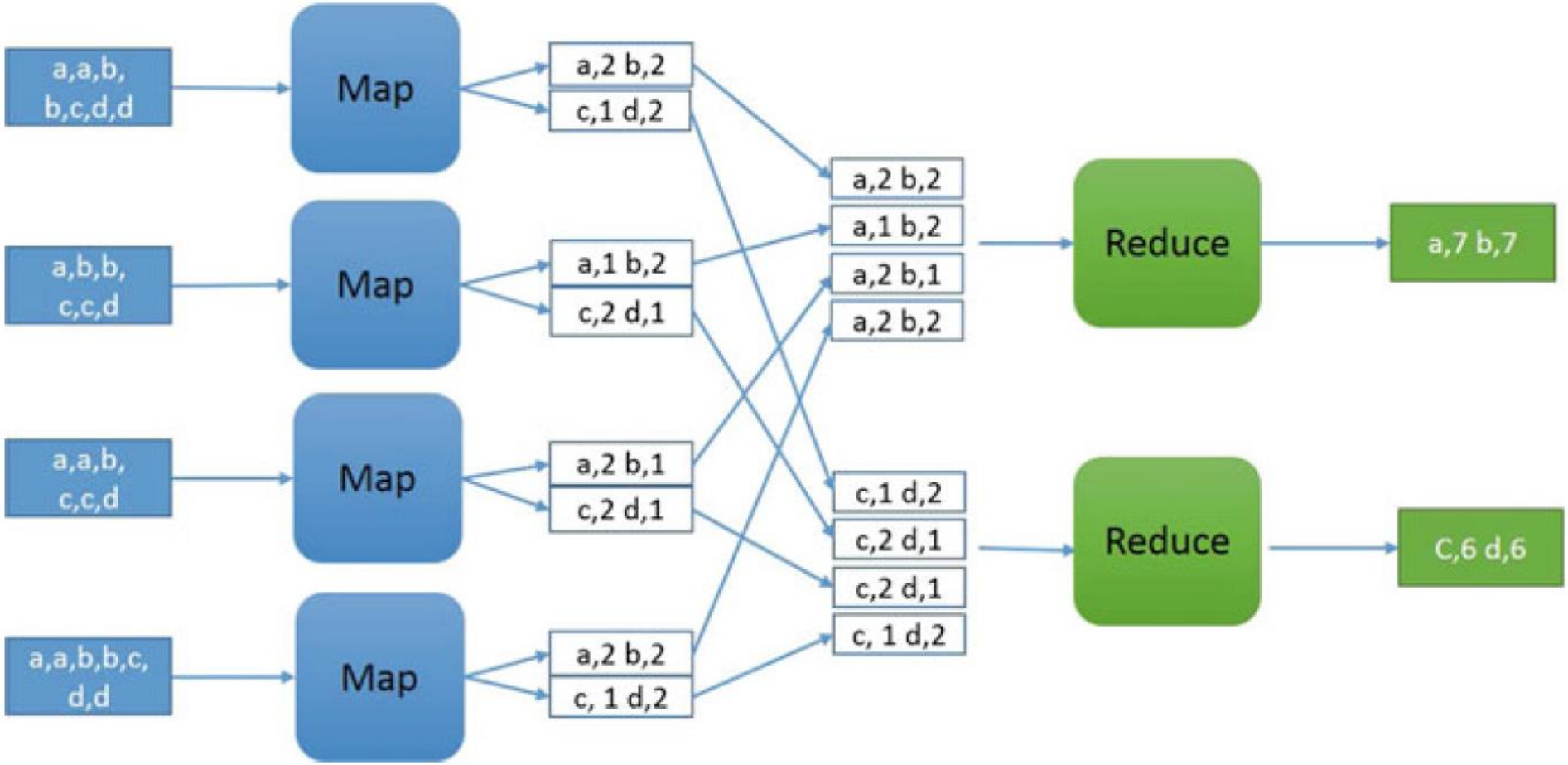
- Programmers specify two primary functions
  - map (k, v) → <k', v'>
  - reduce (k', [v']) → <k'', v''>
  - All v' with the same k' are sent to the same reducer (shuffle)



# Map/reduce abstraction for large-scale data



# Word count solution



# Word count solution

```
//Pseudo-code for "word counting"
map(String key, String value):
  // key: document name,
  // value: document contents
    for each word w in value:
      EmitIntermediate(w, "1");

reduce(String key, Iterator values):
  // key: a word
  // values: a list of counts
    int word_count = 0;
    for each v in values:
      word_count += ParseInt(v);
    Emit(key, AsString(word_count));
```

# Outline

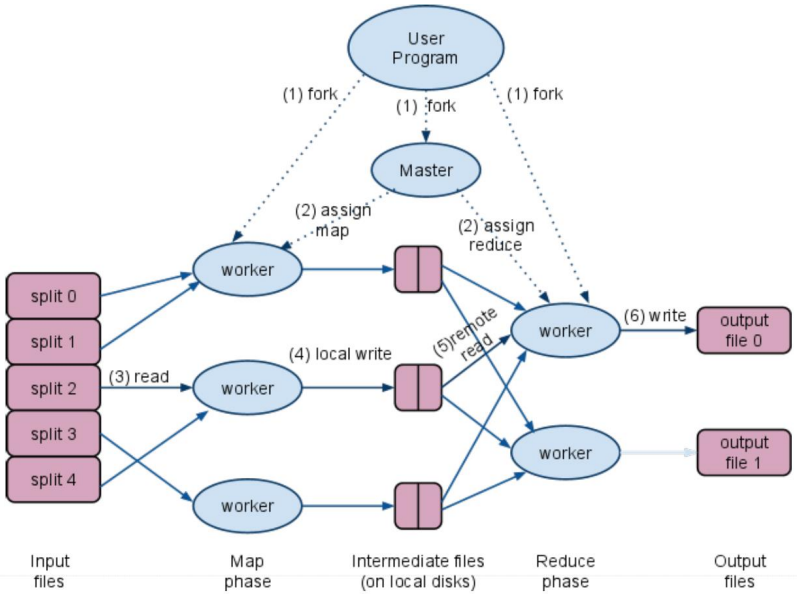
- Batch data processing
- Programming model for batch data processing
- MapReduce framework

# Functions of MapReduce framework

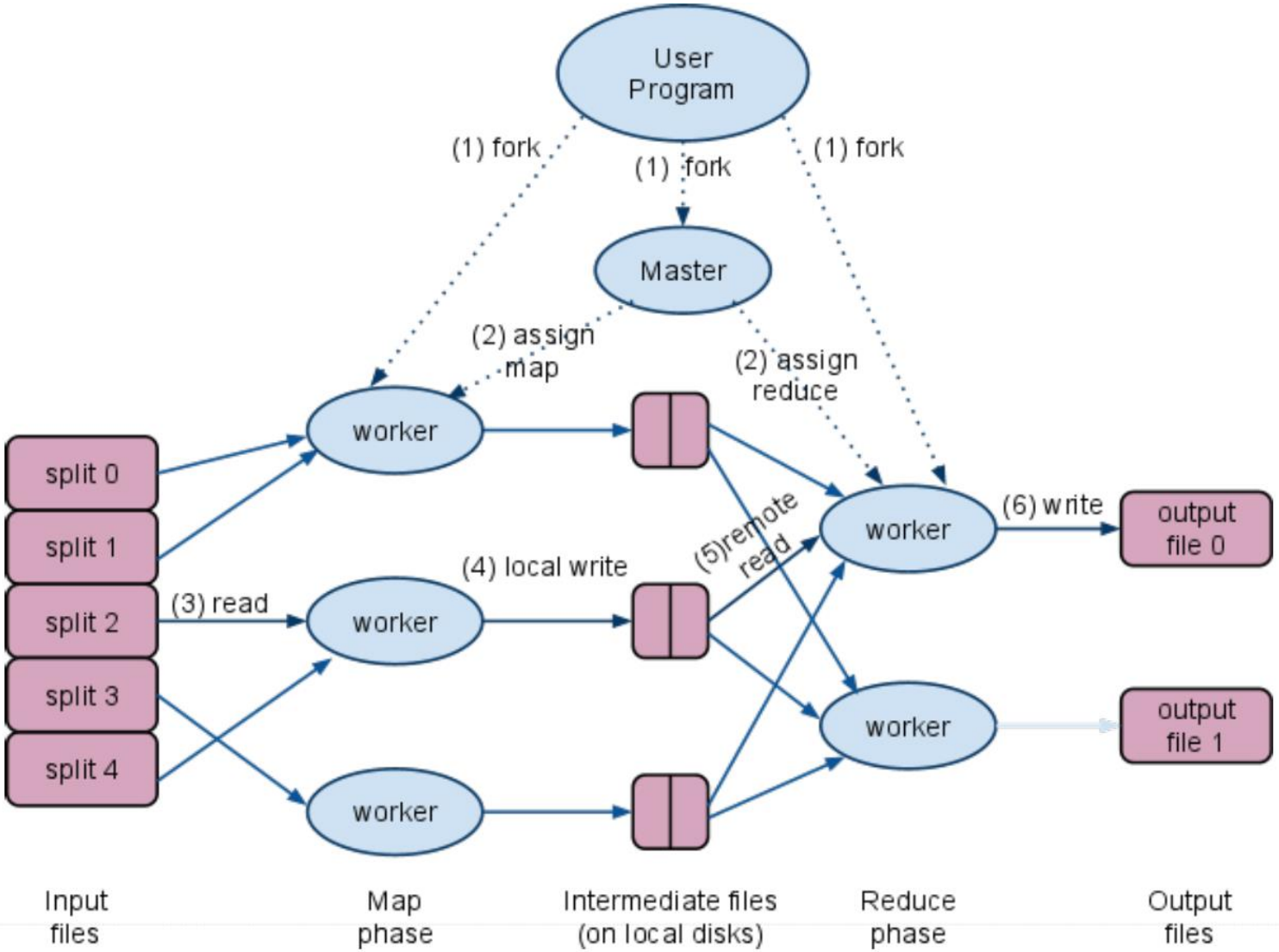
- Programmers specify the map/reduce operators, MapReduce framework should handle
  - Data distribution
    - Split data for multiple workers, move processes to data
  - Synchronization
    - Shuffle intermediate data
  - Fault tolerance
    - Detect failed machines and automatically restart, recover the failed tasks
  - Scheduling
    - Load balancing, detect stragglers
  - Scalability
    - Fast growing dataset, extension of machines

# Architecture of MapReduce framework

- One master, many workers
- Master assigns map/reduce task to a free worker
- Workers perform the assigned tasks with corresponding input data
- Master schedules the tasks, handles the failed workers

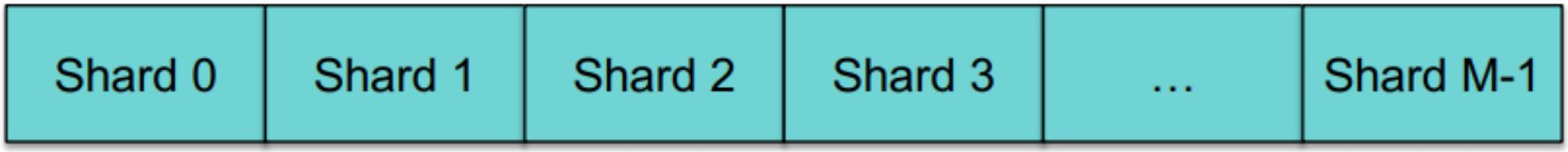


# Execution overview of MapReduce framework



# Step 1: split input files into shards

- Break up the input data into M pieces (typically 64MB)

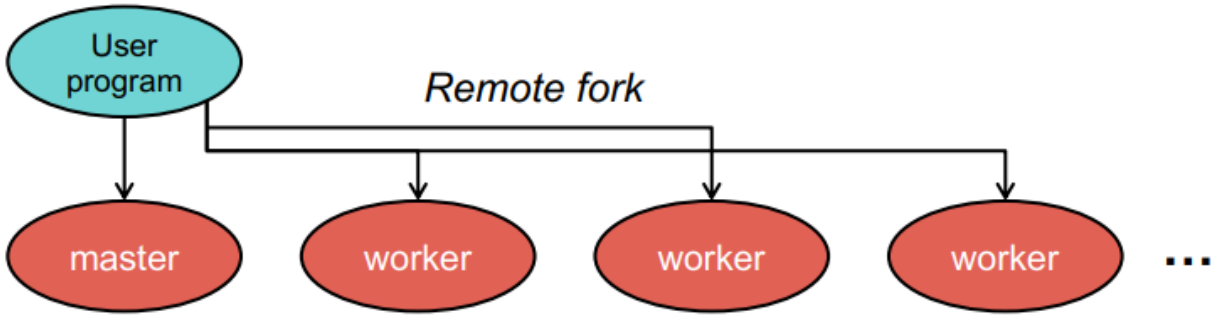



Input files

Divided into *M* shards

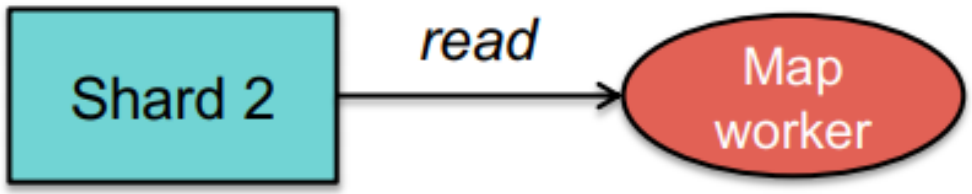
# Step 2: fork processes

- Start up many copies of the program on a cluster of machines
  - One master: scheduler and coordinator
  - Lots of workers
- Idle workers are assigned
  - Map tasks (each works on a shard) – there are M map tasks
  - Reduce tasks (each works on intermediate pairs) – there are R reduce tasks
    - R is defined by the user



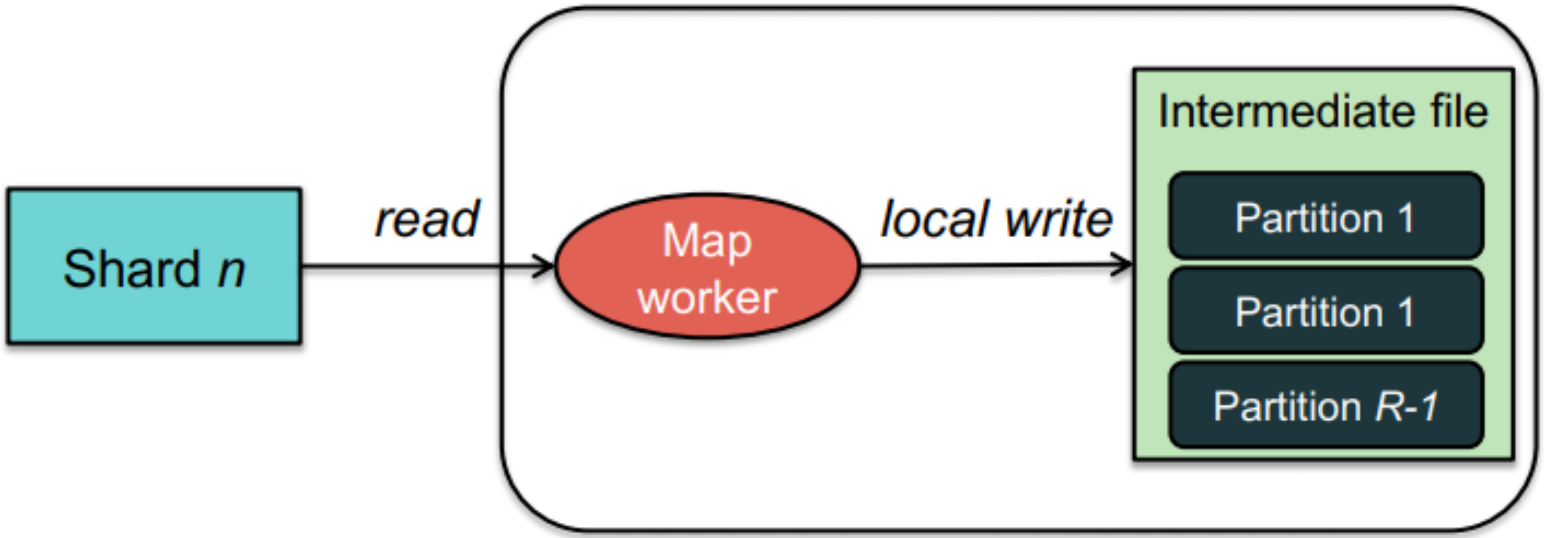
# Step 3: run map tasks

- Map worker reads the input shard assigned to it
- Parse key/value pairs out of the input shard
- Pass each pair to the user-specified map function
  - Produce intermediate key/value pairs
  - Intermediate pairs are buffered in memory



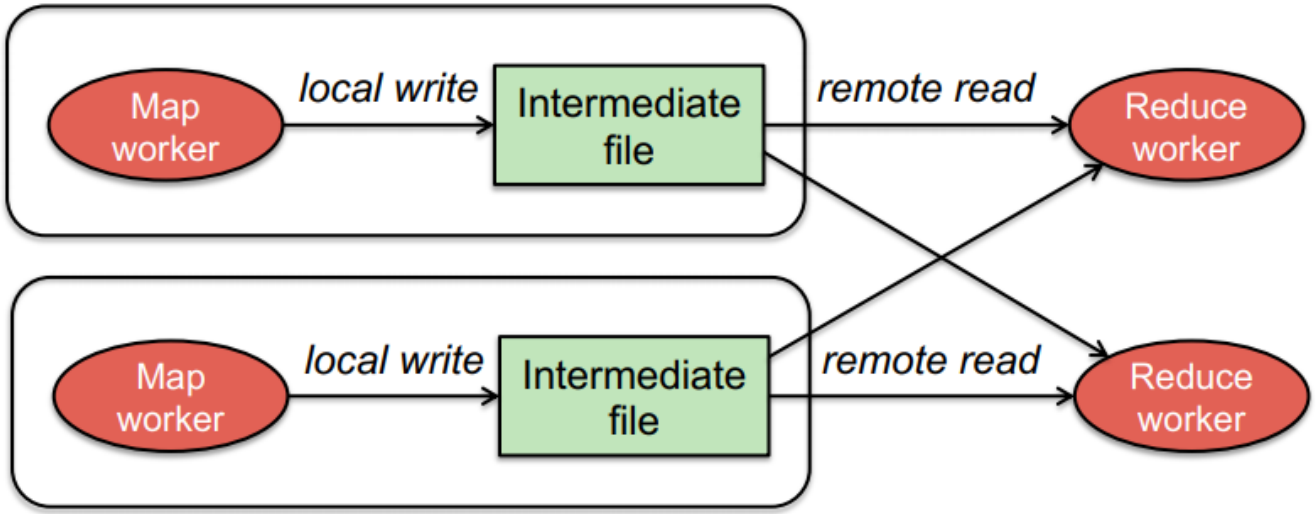
# Step 4: create intermediate files

- Intermediate pairs produced by map worker are periodically written to the local disk
  - Partitioned into R regions by a partitioning function
  - Sort all intermediate pairs by keys



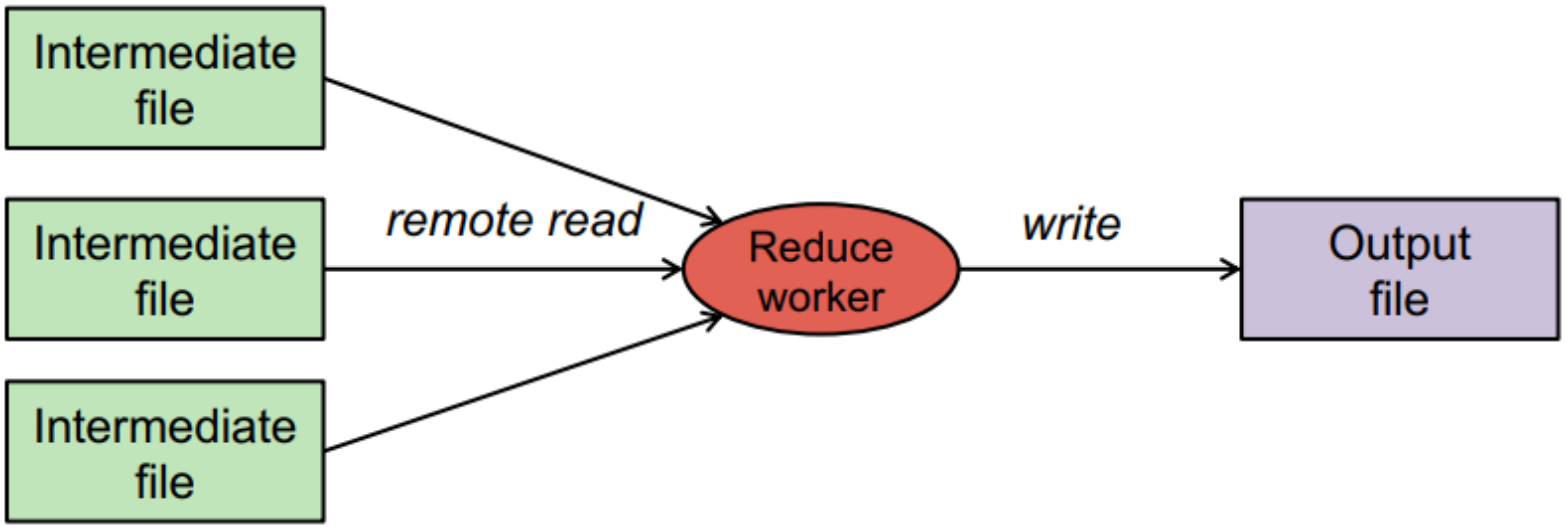
# Step 5: sorting

- Reduce worker gets notified by the master about the location of intermediate files for its partition
- Read the data from the local disk of the map workers
- Sorts the data by the intermediate keys
- All pairs with the same key are grouped together



# Step 6: run reduce tasks

- Pass the sorted and grouped pairs to the user-specified reduce function
- The output of reduce function is appended to an output file

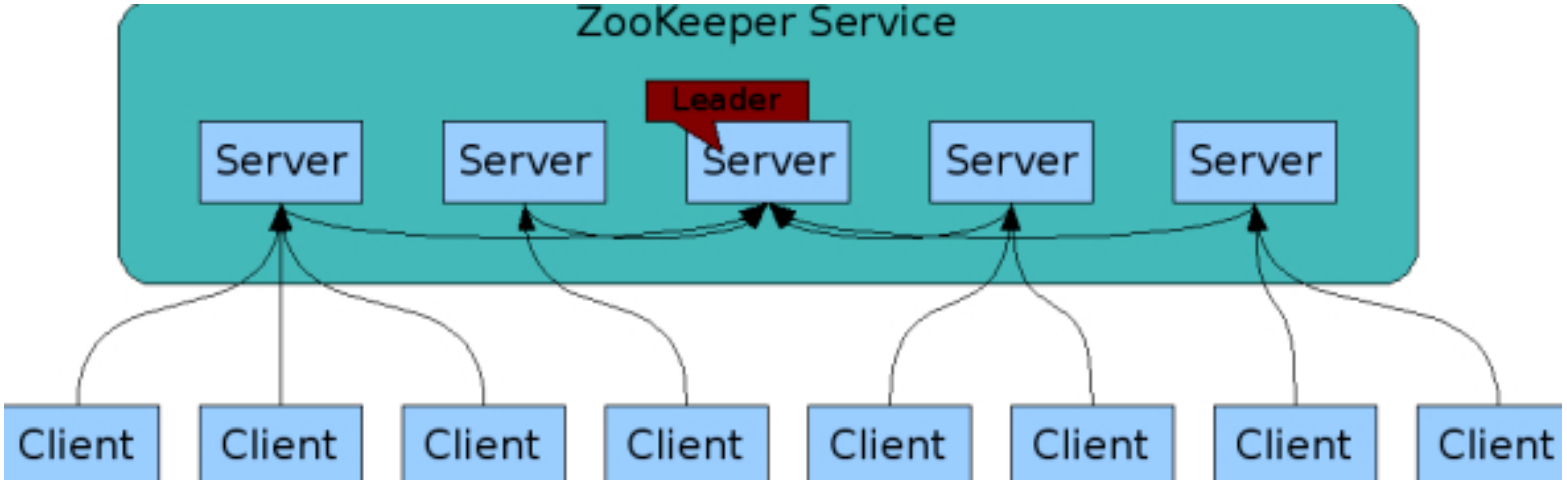


# Step 7: return to user

- When all map and reduce tasks have completed, the master wakes up the user program
  - The output of MapReduce is saved in R files
- The MapReduce call in the user program returns

# Coordinate

- A centralized service for MapReduce framework
  - Maintain configuration information of the framework
  - Provide distributed synchronization between processes
  - Guarantee the consistency of the framework
  - Apache Zookeeper, Google Chubby, etc.

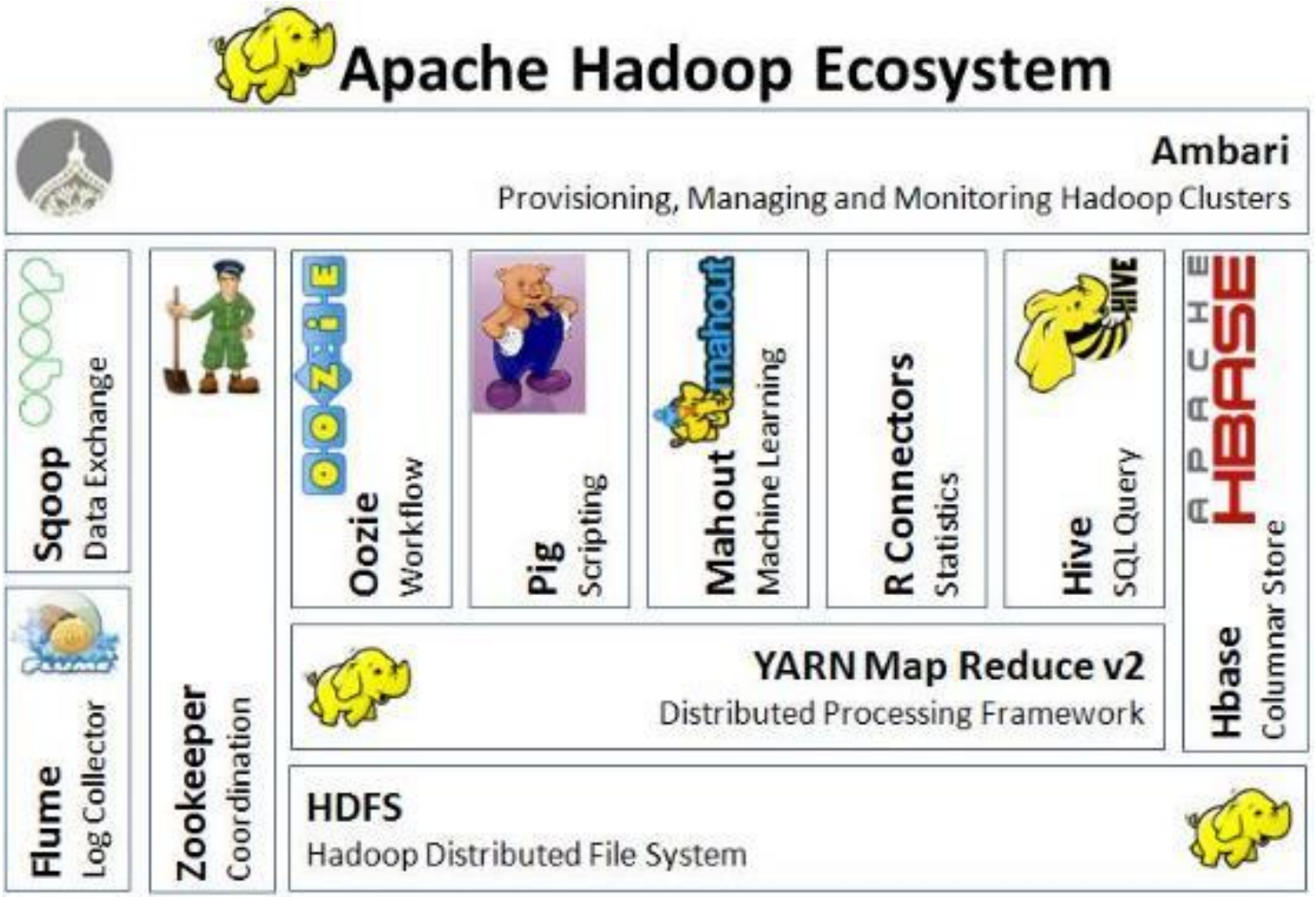
# Fault tolerance

- Worker failure
  - Detect failure via periodic heartbeats
  - Master reschedules the tasks to other workers
  - Re-execute completed and in-progress map tasks
  - Re-execute in-progress reduce tasks
  - Task completion committed through master
- Master failure
  - Select a new master
  - Recover the master according to the checkpoint on distribute filesystem

# MapReduce implementations

- Google has a proprietary implementation in C++
- Hadoop is an open-source implementation in Java
  - Developed by Yahoo, used in production
  - An Apache project
  - Rapidly expanding software ecosystem
- Lots of custom research implementations
  - For GPUs, FPGAs, etc.

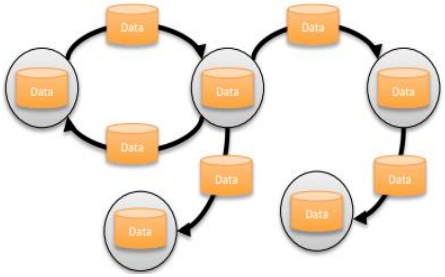
# Ecosystem of Hadoop



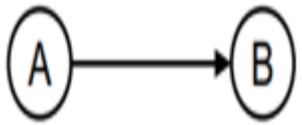
# PROGRAMMING FOR GRAPH PROCESSING

# What is graph?

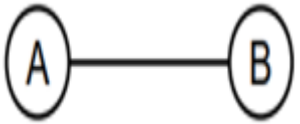
- A graph is a collection of vertices connected by edges (G = (V, E) )



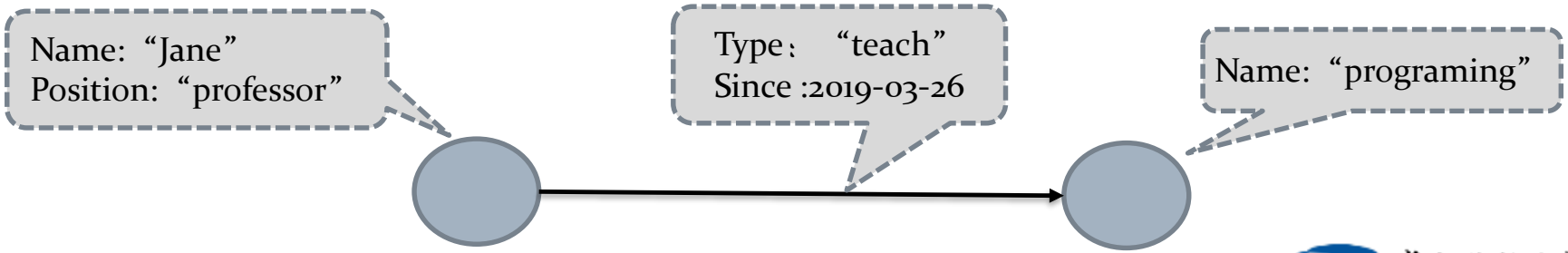

- Edge may be directed (from A to B)



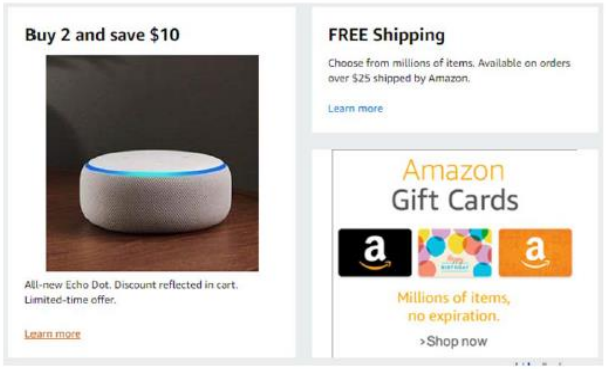

or undirected (between A and B)




- Vertices and edges may have properties



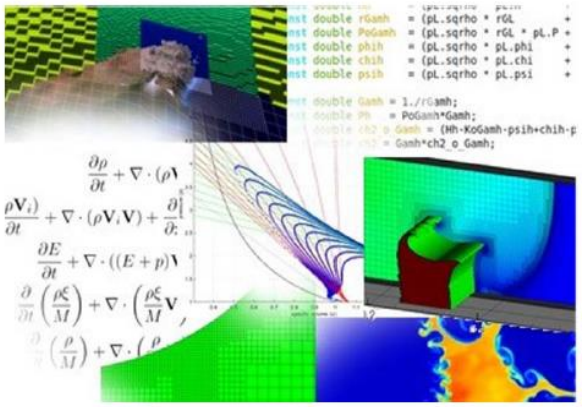
# Graph processing is universal




advertising recommendation


social network analysis


network ranking



scientific calculation

# Graph size is increasing


> 1 M vertices
> 100 M edges
*Distributed graphLab-2012

advertising network

> 1 B vertices
> 1 T edges
*Facebook Engineering Blog

social media

> 50 B vertices
> 1 T edges
*NSA Big Graph Experiment - 2013

internet

> 100 B vertices
> 100 T edges
*NSA Big graph Experiment - 2013

scientific calculation

# Challenges of graph processing

## Data-driven computation

- Computation for graph task is closely related to vertex and edge
- Computation structure is hard to predict before running, hard to parallel

## Irregular structure

- Hard to divide the irregular structure of graph with good quality

## Poor access locality

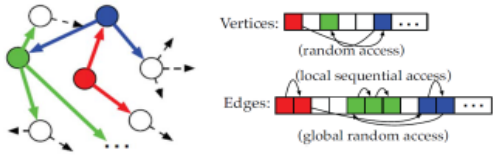
- Non-contiguous access for vertex/edge
- Existing caching mechanisms can only accelerate access with good locality

## Access/computation ratio is high

- Large number of access lead to CPU waiting

# Graph processing vs traditional processing

- **Compute intensive**
  Computation complexity is high, easy to cover memory latency
- **Sequential memory access**
  Date is stored in memory sequentially
- **High data parallelism**
  No complex dependency between different data, convenient for parallel processing
- **Good locality**
  With good spatial and time locality

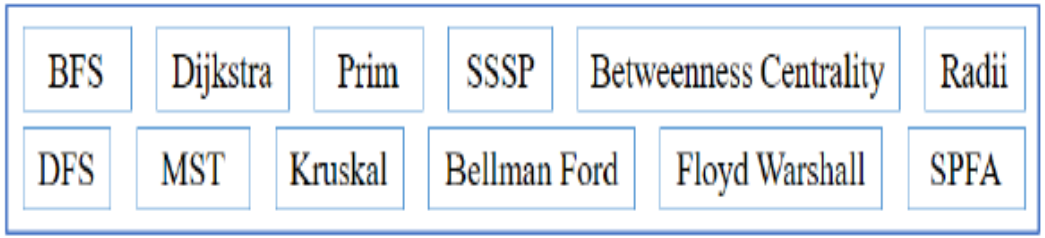



- **Low computation/access ratio**
  Little computation in each node, hard to cover latency
- **Large random access**
  There is a large number of random access requests across the region
- **Complex data dependency**
  Difficult to explore parallelism, a lot of data conflicts
- **Unstructured distribution**
  Uneven distribution of vertex degree, serious load balancing problems and communication overhead

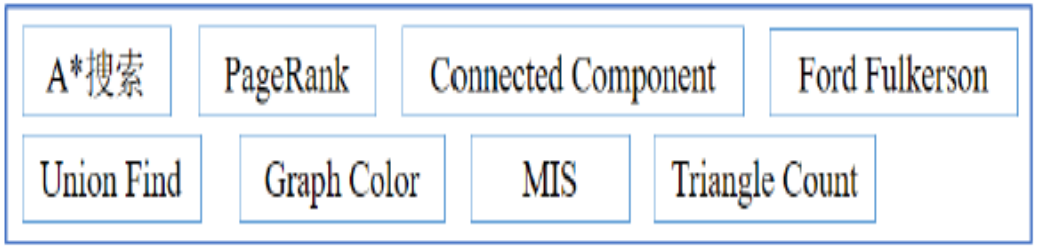
# Graph algorithm

- **Traversal-centric algorithms**
  - Require a specific way to traverse the graph from a particular vertex
  - Have a large number of random access
- **Computation-centric algorithms**
  - A large number of operations in each iteration
  - All nodes participate in each iteration

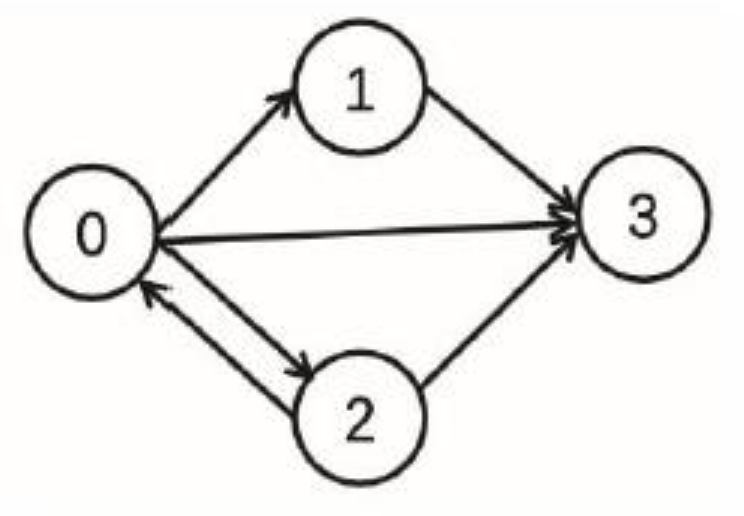
Traversal-centric algorithms



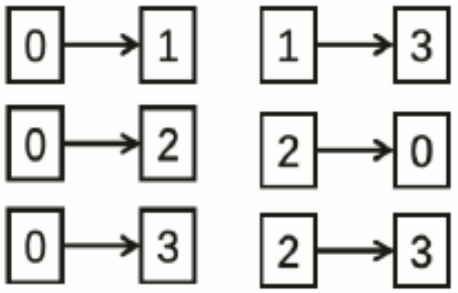

Computation-centric algorithms



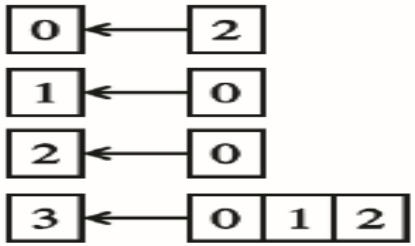
# Graph storage




Graph Topology

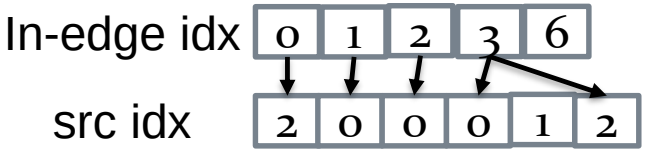



Edge list




Adjacent list

Access efficiency vs Compact ratio




CSR (Compressed Sparse Row)

# Graph processing frameworks

## Programming Model

**Vertex Centric:** Pregel[SIGMOD'10]
**Edge Centric:** X-Stream[SOSP'13]
**Path Centric:** PathGraph[SC'14]
**Subgraph centric:** Blogel[VLDB'14]

## Graph Partition Strategy

**Vertex Cut:** Pregel[SIGMOD '10]
**Edge cut:** PowerGraph[OSDI'12]
**Hybrid Cut:** PowerLyra[EuroSys '15]

## Computation Strategy

**Pull vs push**

**Synchronous vs Asynchronous**

## Typical System

**Pregel :** SIGMOD 2010
**PowerGraph:** OSDI 2012
**GraphChi:** OSDI 2012

# Graph programming model

## Programming model

- Easy and concise to use
- Flexible to express different graph tasks
- Efficient to fit in computation architecture

## Exiting programming model

- Vertex-centric
- Edge-centric
- Path-centric
- Subgraph-centric

# Programming model: vertex-centric

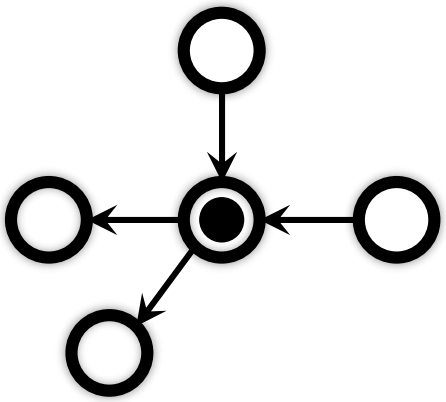
**Coding graph algorithms as vertex-centric programs to process vertices in parallel and communicate along edges**

-- "*Think as a Vertex*" philosophy

Example: *PageRank*

A centrality analysis algorithm to iteratively rank each vertex as a weighted sum of neighbors' ranks

$$R_i = 0.15 + 0.85 \sum_{(j,i) \in E} \omega_{ij} R_j$$



```
COMPUTE(v)
  foreach n in v.in_nbrs
    sum += n.rank / n.nedges
  v.rank = 0.15 + 0.85 * sum
  if !converged(v)
    foreach n in v.out_nbrs
      activate(n)
```

# Programming model: vertex-centric

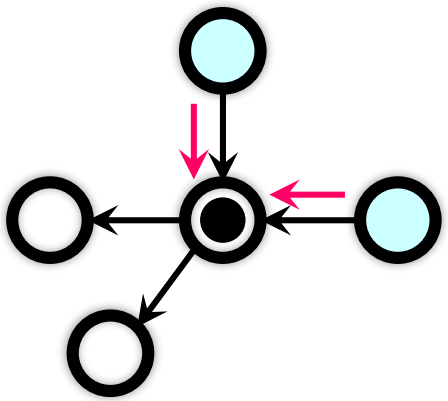
**Coding graph algorithms as vertex-centric programs to process vertices in parallel and communicate along edges**

-- "*Think as a Vertex*" philosophy

Example: *PageRank*

A centrality analysis algorithm to iteratively rank each vertex as a weighted sum of neighbors' ranks

$$R_i = 0.15 + 0.85 \sum_{(j,i) \in E} \omega_{ij} R_j$$



Gather data from neighbors via in-edges

```
COMPUTE(v)
  foreach n in v.in_nbrs
    sum += n.rank / n.nedges
  v.rank = 0.15 + 0.85 * sum
  if !converged(v)
    foreach n in v.out_nbrs
      activate(n)
```

# Programming model: vertex-centric

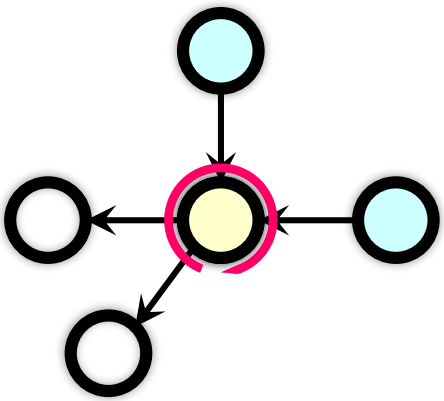
**Coding graph algorithms as vertex-centric programs to process vertices in parallel and communicate along edges**

-- "*Think as a Vertex*" philosophy

Example: *PageRank*

A centrality analysis algorithm to iteratively rank each vertex as a weighted sum of neighbors' ranks

$$R_i = 0.15 + 0.85 \sum_{(j,i) \in E} \omega_{ij} R_j$$



Update vertex with new data

```
COMPUTE(v)
  foreach n in v.in_nbrs
    sum += n.rank / n.nedges
  v.rank = 0.15 + 0.85 * sum
  if !converged(v)
    foreach n in v.out_nbrs
      activate(n)
```

# Programming model: vertex-centric

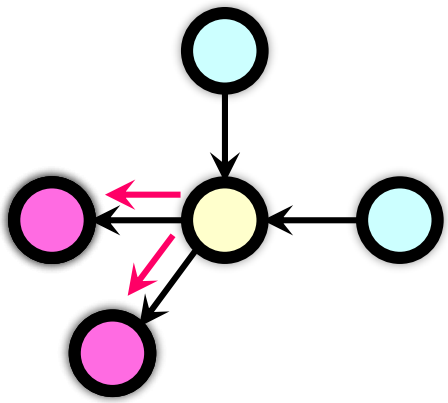
**Coding graph algorithms as vertex-centric programs to process vertices in parallel and communicate along edges**

-- "*Think as a Vertex*" philosophy

Example: *PageRank*

A centrality analysis algorithm to iteratively rank each vertex as a weighted sum of neighbors' ranks

$$R_i = 0.15 + 0.85 \sum_{(j,i) \in E} \omega_{ij} R_j$$



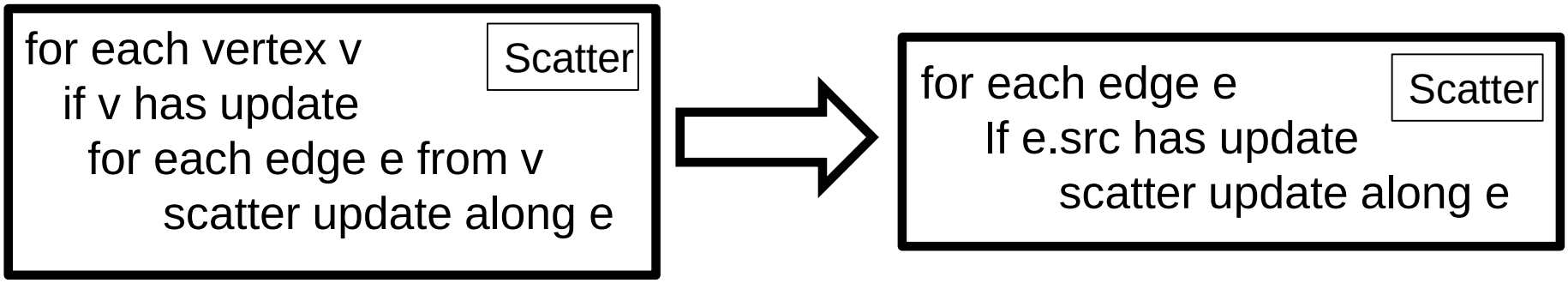
Scatter data to neighbors via out-edges

```
COMPUTE(v)
  foreach n in v.in_nbrs
    sum += n.rank / n.nedges
  v.rank = 0.15 + 0.85 * sum
  if !converged(v)
    foreach n in v.out_nbrs
      activate(n)
```

# Programming model: edge-centric

**Coding graph algorithms as edge-centric programs to process edges in parallel, where edge is the minimum parallel processing unit.**

-- "*Think as an Edge*" philosophy




**Vertex-Centric** **Transformation** **Edge-Centric**

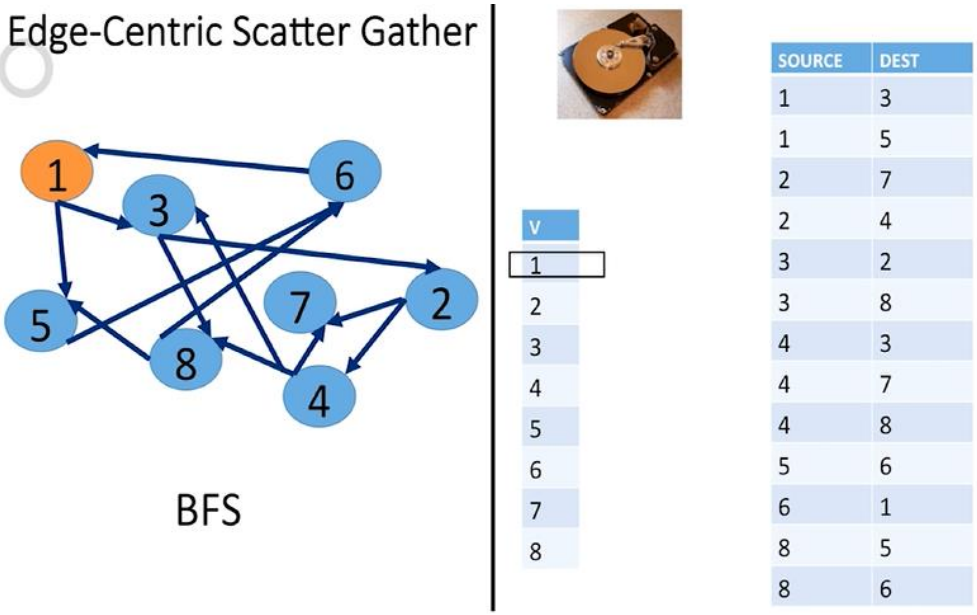
--Balanced load for fine-grained parallel processing unit
--Better locality for sequential access of the edges

# Programming model: edge-centric

**Coding graph algorithms as edge-centric programs to process edges in parallel, where edge is the minimum parallel processing unit.**

-- "*Think as an Edge*" philosophy

*Example: BFS*




**Edge-Centric Scatter Gather for BFS**

Edge-centric Scatter-Gather

```
edge_scatter(edge e)
 send update over e
```

```
update_gather(update u)
 apply update u to u.destination
```

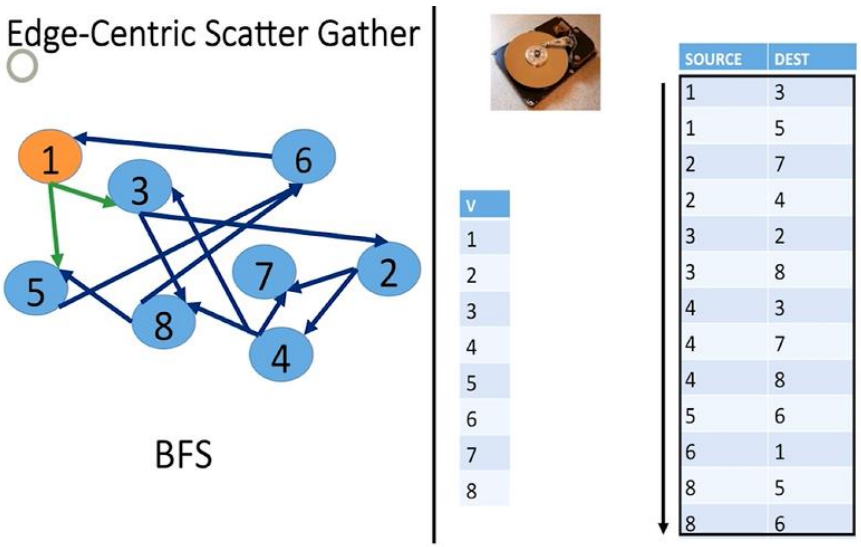
```
while not done
  for all edges e
    edge_scatter(e)
  for all updates u
    update_gather(u)
```

# Programming model: edge-centric

**Coding graph algorithms as edge-centric programs to process edges in parallel, where edge is the minimum parallel processing unit.**

-- "*Think as an Edge*" philosophy

*Example: BFS*




**Edge-Centric Scatter Gather for BFS**

Edge-centric Scatter-Gather

```
edge_scatter(edge e)
 send update over e
```

```
update_gather(update u)
 apply update u to u.destination
```

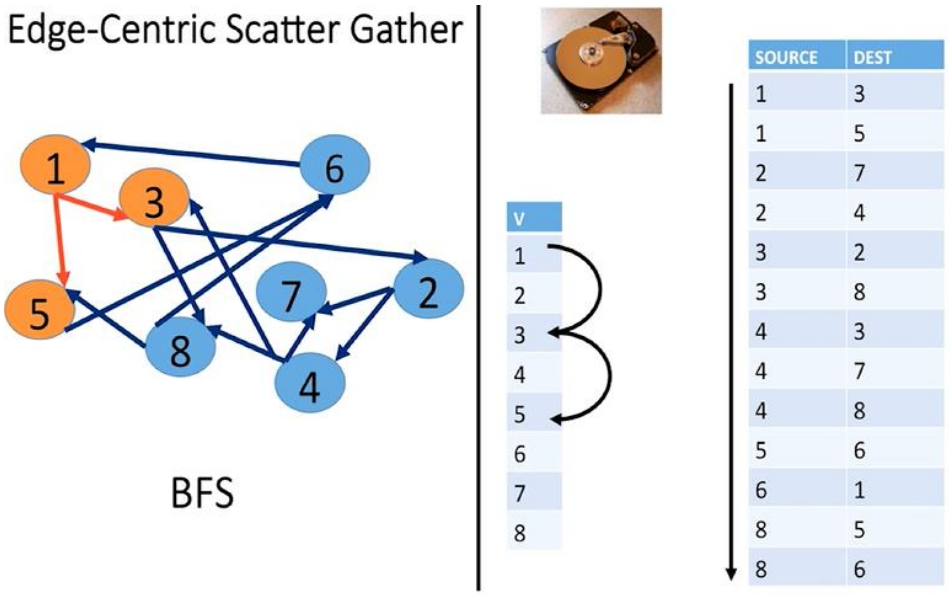
```
while not done
  for all edges e
    edge_scatter(e)
  for all updates u
    update_gather(u)
```

# Programming model: edge-centric

**Coding graph algorithms as edge-centric programs to process edges in parallel, where edge is the minimum parallel processing unit.**

-- "*Think as an Edge*" philosophy

*Example: BFS*




**Edge-Centric Scatter Gather for BFS**

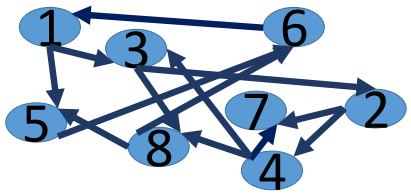
Edge-centric Scatter-Gather

```
edge_scatter(edge e)
 send update over e

update_gather(update u)
 apply update u to u.destination

while not done
  for all edges e
    edge_scatter(e)
  for all updates u
    update_gather(u)
```

# Programming model: edge-centric

**Coding graph algorithms as edge-centric programs to process edges in parallel, where edge is the minimum parallel processing unit.**

-- "*Think as an Edge*" philosophy




| V |
|---|
| 1 |
| 2 |
| 3 |
| 4 |
| 5 |
| 6 |
| 7 |
| 8 |

| SOURCE | DEST |
|---|---|
| 1 | 3 |
| 1 | 5 |
| 2 | 7 |
| 2 | 4 |
| 3 | 2 |
| 3 | 8 |
| 4 | 3 |
| 4 | 7 |
| 4 | 8 |
| 5 | 6 |
| 6 | 1 |
| 8 | 5 |
| 8 | 6 |

Transformation

| V |
|---|
| 1 |
| 2 |
| 3 |
| 4 |
| 5 |
| 6 |
| 7 |
| 8 |

| SOURCE | DEST |
|---|---|
| 1 | 3 |
| 1 | 5 |
| 2 | 7 |
| 2 | 4 |
| 3 | 2 |
| 3 | 8 |
| 4 | 3 |
| 4 | 7 |
| 4 | 8 |
| 5 | 6 |
| 6 | 1 |
| 8 | 5 |
| 8 | 6 |

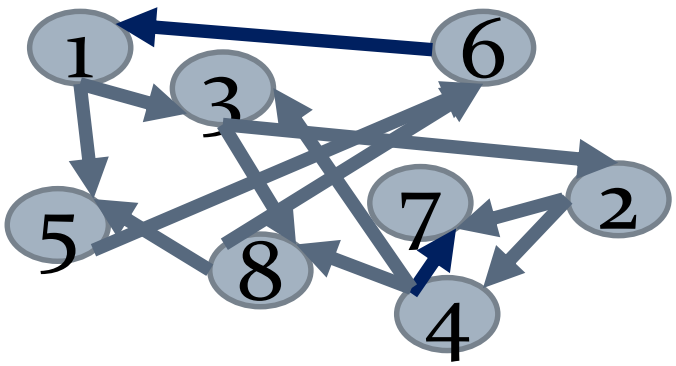
Random accesses over edges

**Vertex-Centric Scatter Gather for BFS**

Sequential accesses over edges

**Edge-Centric Scatter Gather for BFS**

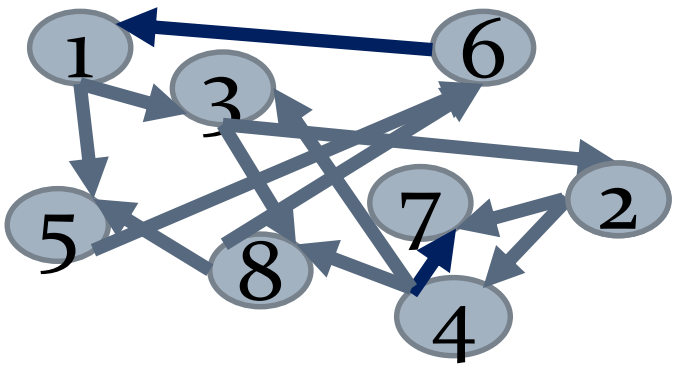
# Illustration of vertex-centric BFS




| V |
|---|
| 1 |
| 2 |
| 3 |
| 4 |
| 5 |
| 6 |
| 7 |
| 8 |

| SOURCE | DEST |
|---|---|
| 1 | 3 |
| 1 | 5 |
| 2 | 7 |
| 2 | 4 |
| 3 | 2 |
| 3 | 8 |
| 4 | 3 |
| 4 | 7 |
| 4 | 8 |
| 5 | 6 |
| 6 | 1 |
| 8 | 5 |
| 8 | 6 |

# Illustration of edge-centric BFS



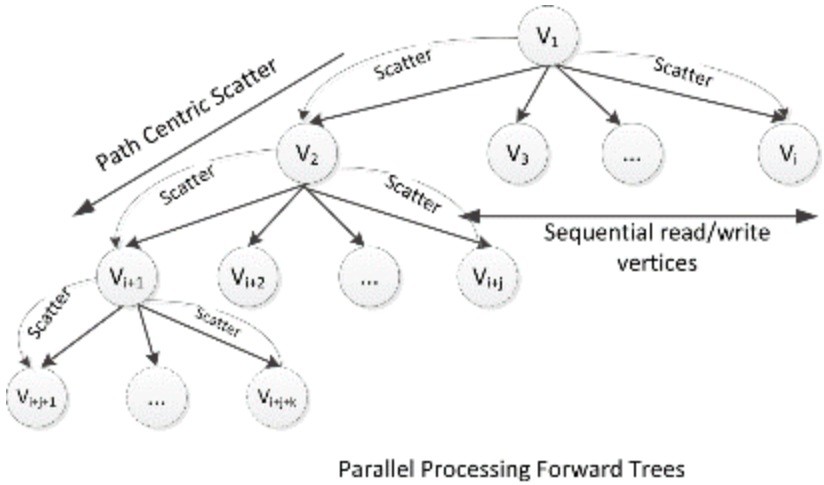

| V |
|---|
| 1 |
| 2 |
| 3 |
| 4 |
| 5 |
| 6 |
| 7 |
| 8 |

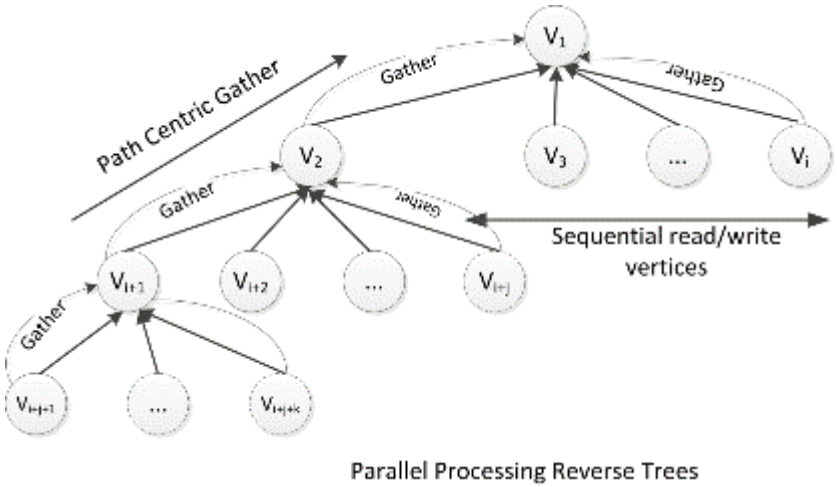
| SOURCE | DEST |
|---|---|
| 1 | 3 |
| 1 | 5 |
| 2 | 7 |
| 2 | 4 |
| 3 | 2 |
| 3 | 8 |
| 4 | 3 |
| 4 | 7 |
| 4 | 8 |
| 5 | 6 |
| 6 | 1 |
| 8 | 5 |
| 8 | 6 |

# Programming model: path-centric

Computation model

- Scatter or gather: faster method
- Process graph following paths: improve locality



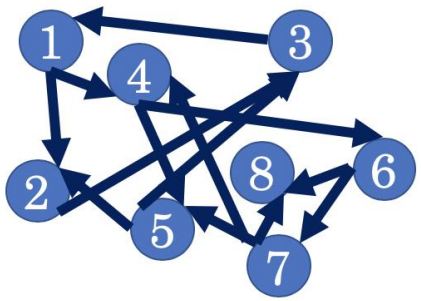



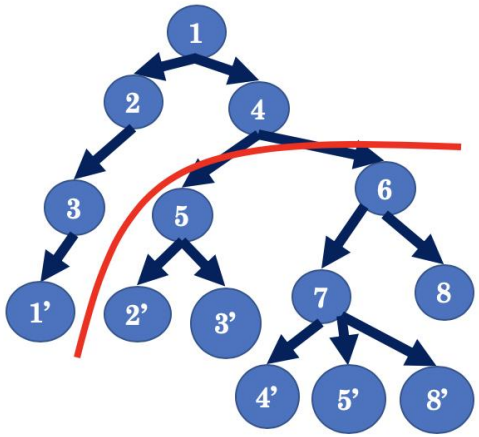

Path Centric Scatter

Path Centric Gather

# Programming model: path-centric

- In order to achieve it, generate edge travel tree for each graph, then partition tree into multiple parts
  - edge travel tree: each edge is visited once. So, each branch of the tree is a path. The right graph is an edge traversal tree of the left graph.
- Each partition with forward-visited tree and backward-tree
- Each partition can parallelly executed



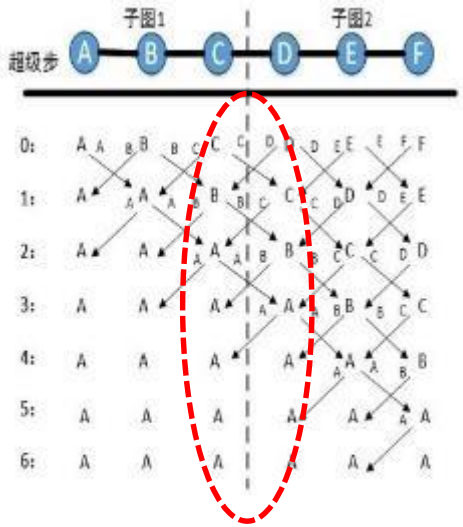

```
1: for each iteration do
        2: parfor each p of Partitions
        do
        3:      Gather(p);
        4: end parfor
        5: sync;
6: end for
```

# Programming model: subgraph-centric

**Coding graph algorithms as subgraph-centric programs to process vertices/edges via taking subgraph as the minimum parallel processing unit.**

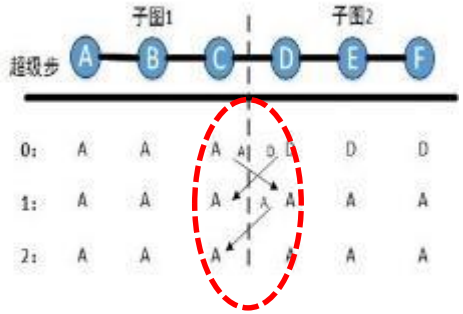
-- "*Think as a Subgraph*" philosophy

- First, it divides the graph data into different subgraphs
- Then, it updates all vertices of each subgraph until the subgraph converges
- Finally, it transmits the updated state information of the subgraph to other subgraphs




Many high cost global synchronization operations

Vertex-Centric Scatter Gather for CC




Less global synchronization operations

Subgraph-centric Scatter Gather for CC

--It not only ensures better data locality, but also can transform many high cost global synchronization operations to low overhead local ones.

- The status information can only be propagated one-hop in each super-step for vertex/edge centric
- 7 super-step to converge for vertex/edge-centric
- 3 super-step to converge for subgraph-centric

# Programming model: subgraph-centric

**Coding graph algorithms as subgraph-centric programs to process vertices/edges via taking subgraph as the minimum parallel processing unit.**

-- "*Think as a Subgraph*" philosophy

- First, it divides the graph data into different subgraphs

**examples of subgraphs**

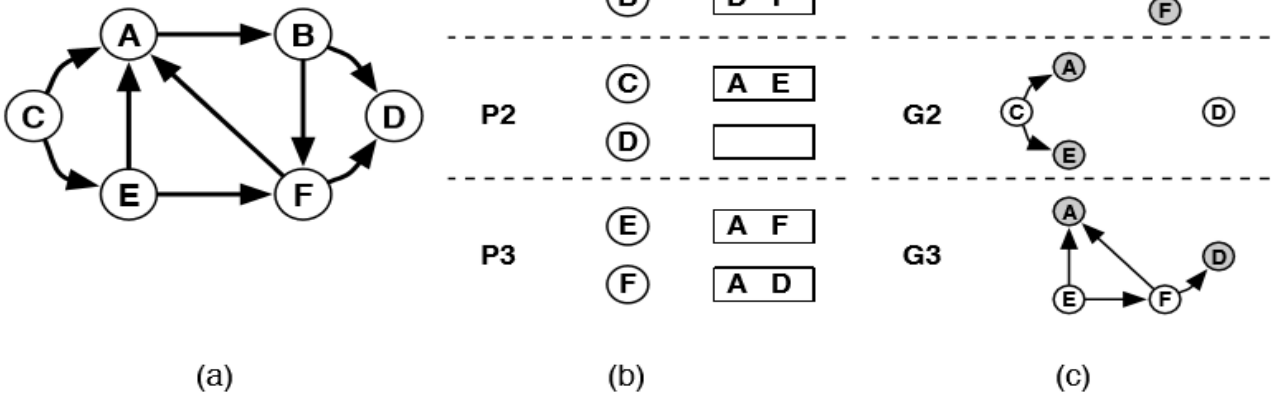



Figure (a) shows the original graph.

Figure (b) divides the set of vertices in the original graph into partitions.

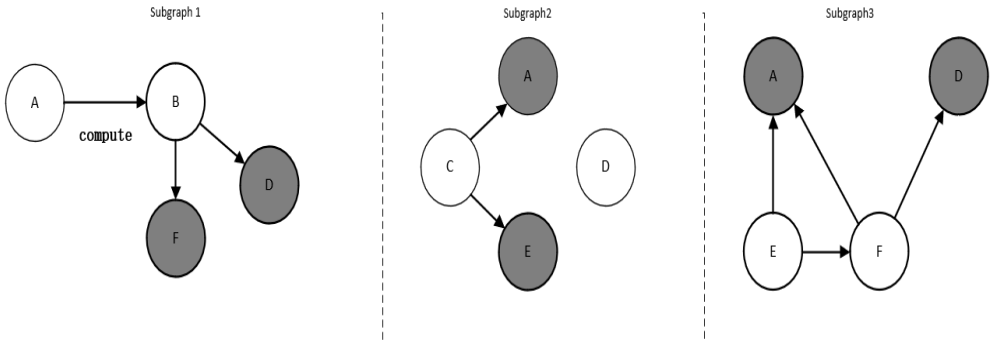
Figure (c) shows examples of subgraphs.

# Programming model: subgraph-centric

**Coding graph algorithms as subgraph-centric programs to process vertices/edges via taking subgraph as the minimum parallel processing unit.**

-- "*Think as a Subgraph*" philosophy

- Then, it updates all vertices of each subgraph until the subgraph converges.




**TLASG model**

## TLASG model

Compute(vertex v)
update all vertices of subgraph

```
block_update(subgraph subg)
  while not done
    for all vertices v that have   updates
      compute(vertex v)
  apply updates from inbound edges of subgraph
```

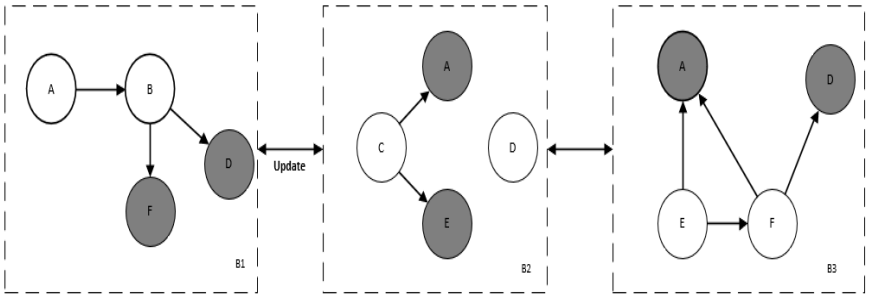
```
while not done
  for all subg that have updates
    block_upddate(subg)
```

# Programming model: subgraph-centric

**Coding graph algorithms as subgraph-centric programs to process vertices/edges via taking subgraph as the minimum parallel processing unit.**

-- "*Think as a Subgraph*" philosophy

- Finally, it transmits the updated state information of the subgraph to other subgraphs.




## TLASG model

```
Compute(vertex v)
 update all vertices of subgraph

block_update(subgraph subg)
  while not done
    for all vertices v that have   updates
      compute(vertex v)
  apply updates from inbound edges of subgraph

while not done
  for all subg that have updates
    block_upddate(subg)
```

# Graph processing frameworks

## Programming Model

**Vertex Centric:** Pregel[SIGMOD'10]
**Edge Centric:** X-Stream[SOSP'13]
**Path Centric:** PathGraph[SC'14]
**Subgraph centric:** Blogel[VLDB'14]

## Graph Partition Strategy

**Vertex Cut:** Pregel[SIGMOD '10]
**Edge cut:** PowerGraph[OSDI'12]
**Hybrid Cut:** PowerLyra[EuroSys '15]

## Computation Strategy

**Pull vs push**

**Synchronous vs Asynchronous**

## Typical System

**Pregel :** SIGMOD 2010
**PowerGraph:** OSDI 2012
**GraphChi:** OSDI 2012

# Graph partition

**Graph is too large to hold in single node memory.**

**Goal of graph partition**

- Balance workload between machines
- Minimize communication
- Maximize the computation efficiency within each machine

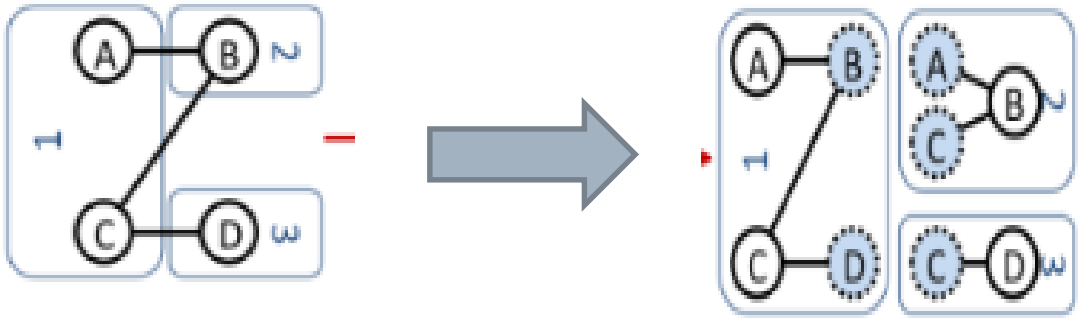
**Graph partition method**

- Edge-cut
- Vertex-cut
- Hybrid-cut

# Graph partition: edge-cut

**Pregel**[SIGMOD'08] and **GraphLab**[VLDB'12]

- Focus on exploiting locality
- Partitioning: use edge-cut to evenly assign vertices along with all edges
- Computation: aggregate all resources (i.e., messages or replicas) of a vertex on local machine



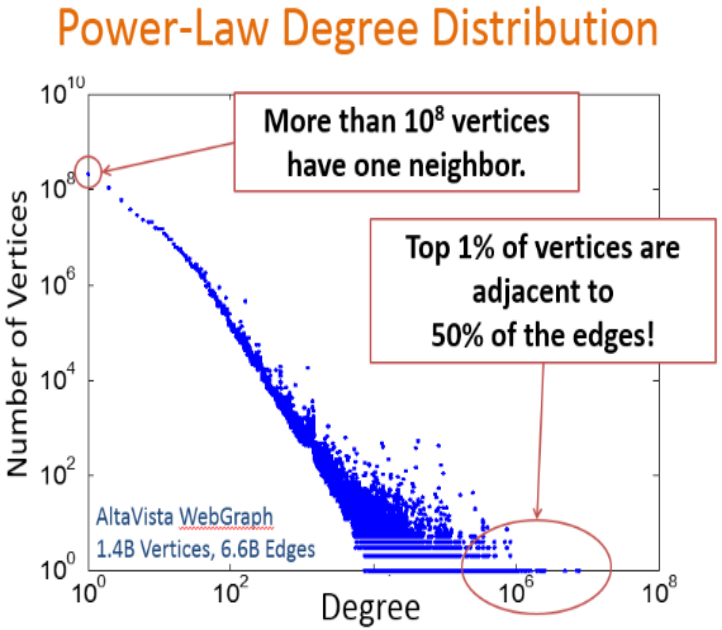
# Graph partition: edge-cut

## Natural Graphs are Skewed

Graphs in real-world

- *Power-law* degree distribution (aka Zipf's law or Pareto)

"most vertices have relatively few neighbors while a few have many neighbors" -- *PowerGraph*[OSDI'12]




Case: SINA *Weibo*

- 167 million active users

#1 

#2 

#100 

#Follower : 77,971,093 76,946,782 ··· 14,723,818 ····· 397 ····· 69 ·····

# Disadvantages of edge-cut

## Load balance

- Work imbalance for high degree vertices, as computation, storage, and communication are linear with the degree of vertices

## Difficult to partition

- Natural graphs are difficult to partition to minimize the communication, and maximize work balance

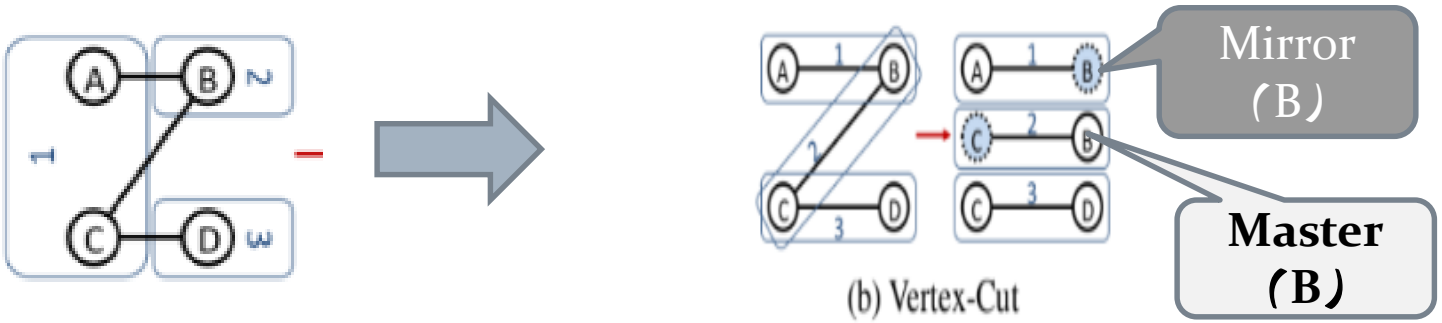
## Limited parallelism

- No parallelism possible within individual vertices

# Graph partition: vertex-cut

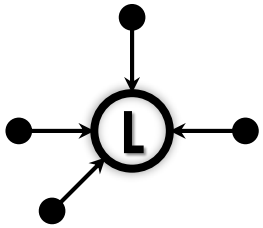
**PowerGraph** [OSDI'12] and **GraphX**[OSDI'14]

- Focus on exploiting parallelism
- Partitioning: use vertex-cut to evenly assign edges with replicated vertices
- Computation: decompose the workload of a vertex into multiple machines



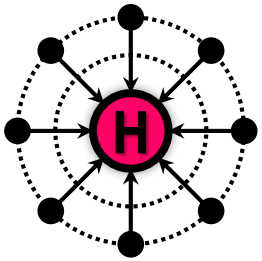
# Is vertex–cut perfect for power-law graph?

**Low**-degree vertex




397

**High**-degree vertex




77,971,093

## Locality

make resource locally accessible to hidden network latency

⇐ Conflict ⇒


## Parallelism

evenly parallelize the workloads to avoid load imbalance

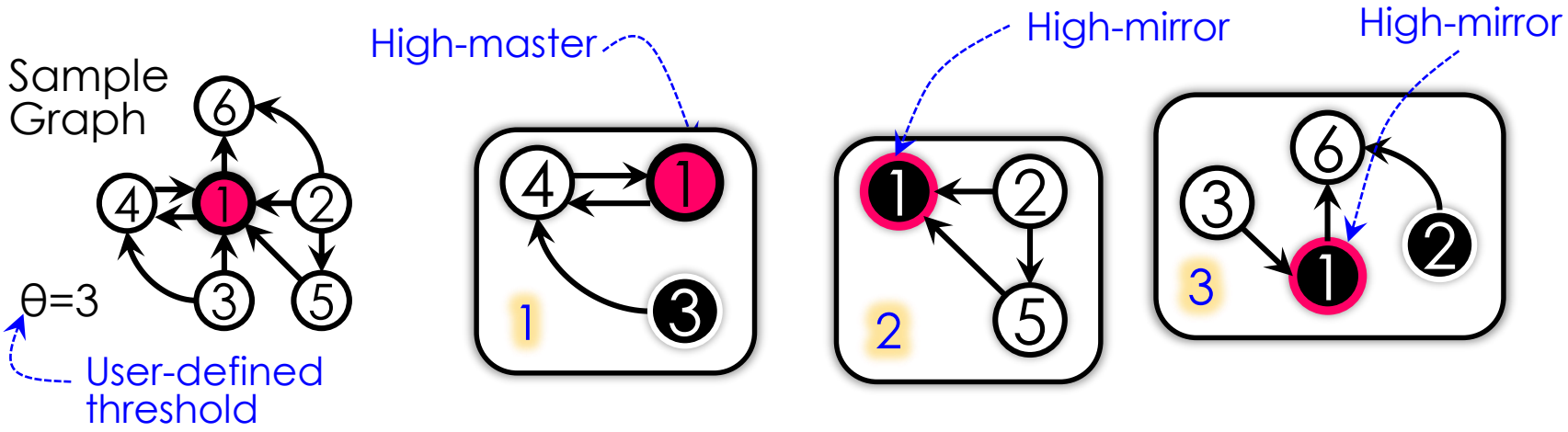
100-million users each with 100 followers

100 users each with 100-million followers

# Graph partition: hybrid-cut

Hybrid-cut: differentiate the graph partitioning for low-degree and high-degree vertices

- Low-cut (inspired by *edge-cut*): reduce mirrors and exploit locality for low-degree vertices
- High-cut (inspired by *vertex-cut*): provide balance and restrict the impact of high-degree vertices
- Efficiently combine low-cut and high-cut



# Graph processing frameworks

## Programming Model

**Vertex Centric:** Pregel[SIGMOD'10]
**Edge Centric:** X-Stream[SOSP'13]
**Path Centric:** PathGraph[SC'14]
**Subgraph centric:** Blogel[VLDB'14]

## Graph Partition Strategy

**Vertex Cut:** Pregel[SIGMOD '10]
**Edge cut:** PowerGraph[OSDI'12]
**Hybrid Cut:** PowerLyra[EuroSys '15]

## Computation Strategy

**Pull vs push**

**Synchronous vs Asynchronous**

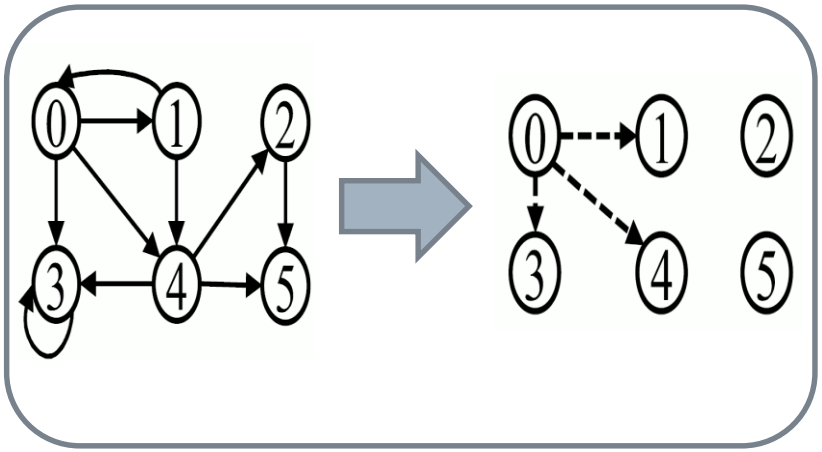
## Typical System

**Pregel :** SIGMOD 2010
**PowerGraph:** OSDI 2012
**GraphChi:** OSDI 2012

# Message passing: push model

Push updates to the neighbors

- Selectively schedule to reduce computation
- Lead to the write-write conflict on a destination vertex from multiple sources




```
parallel_for (int vSrc = 0; vSrc < numVertices; ++vSrc) {
    if (!frontier.contains(vSrc)) continue;
    for (int d = 0; d < vertex[vSrc].outdegree; ++d) {
        const int vDst = vertex[vSrc].outneighbor[d];
        if (converged.contains(vDst)) continue;
        atomicCAS(vertex[vDst].value,
            compute(vertex[vSrc].value, vertex[vDst].value)); } }
```

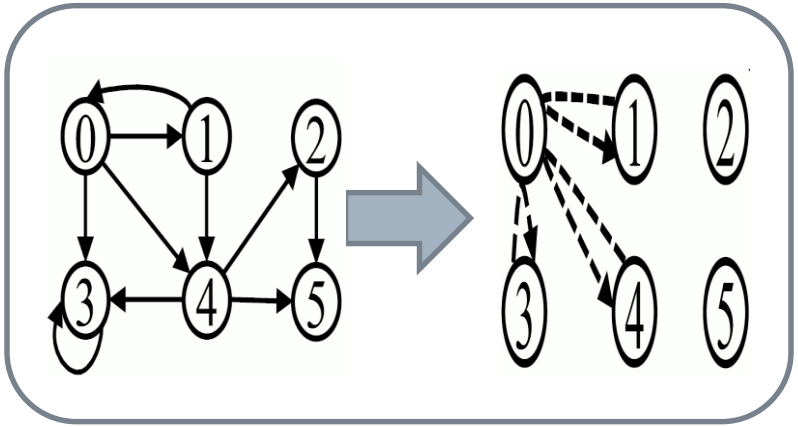
Push-based message implementation

Ref. Genimi (OSDI 2016) , Grazella (PPoPP 2018)

# Message passing: pull model

Get update from incoming neighbors

- Do not have the write-write conflict
- Scan all incoming neighbors can incur redundant computation since some nodes may not active



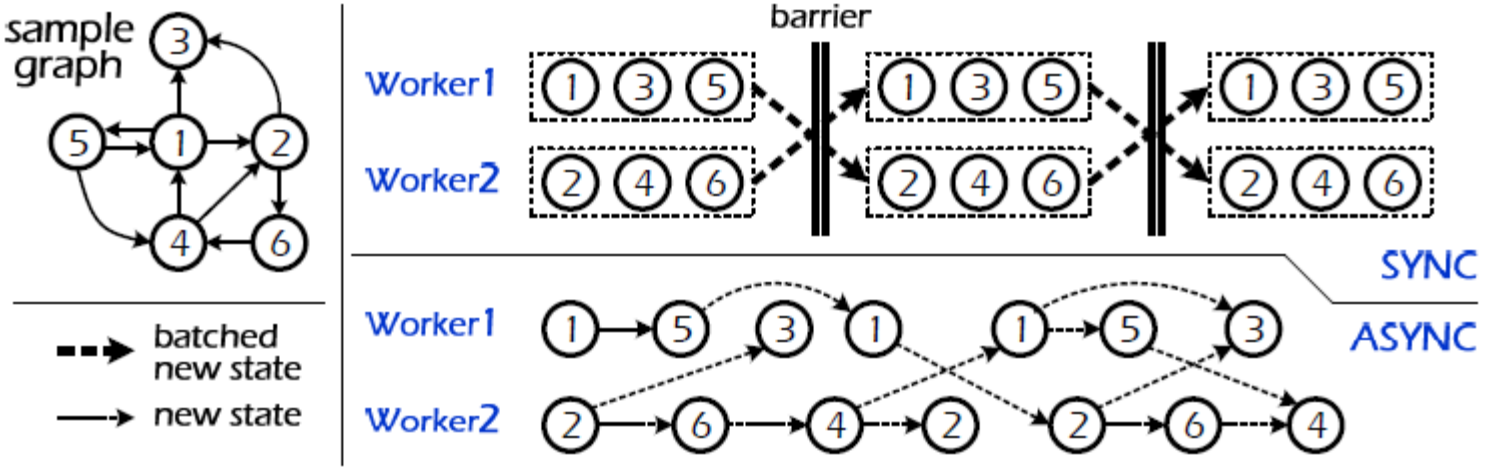

```
parallel_for (int vDst = 0; vDst < numVertices; ++vDst) {
    if (converged.contains(vDst)) continue;
    for (int s = 0; s < vertex[vDst].indegree; ++s) {
        const int vSrc = vertex[vDst].inneighbor[s];
        if (!frontier.contains(vSrc)) continue;
        vertex[vDst].value =
            compute(vertex[vSrc].value, vertex[vDst].value); } }
```

Pull-based message implementation

Ref. Genimi (OSDI 2016), Grazella (PPoPP 2018)

# Schedule model

## Synchronous vs Asynchronous

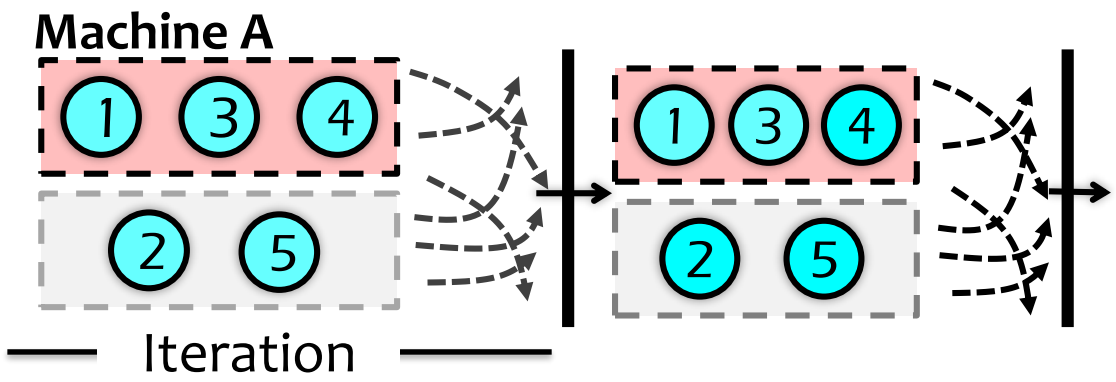



| | *Sync* | *Async* |
|---|---|---|
| Properties | | |
| Communication | Regular | Irregular |
| Convergence | Slow | Fast |
| Favorites | | |
| Algorithm | I/O-intensive | CPU-intensive |
| Execution Stage | High Workload | Low Workload |
| Scalability | Graph Size | Cluster Size |

Ref. **PoweSwitch PPoPP 2015**

# Schedule model: sync model

Scheduling:




Current iteration active vertex

next iteration active vertex

Pseudocode

**while** (*iteration* ≤ *max*) *do*

if $V_a$== ∅ then break

$V'_a \leftarrow \emptyset$

**foreach** v ∈ $V_a$ do

A ← **compute**(v)

$V'_a \leftarrow V'_a \cup A$

**barrier to update**

$V_a \leftarrow V'_a$

iteration ++

Ref. **PoweSwitch PPoPP 2015**

# Schedule model: sync model

## Advantages of synchronous model

1. Batching massages which improves of network utilization
2. Better for algorithm with much communication needed
3. With light computation for each node

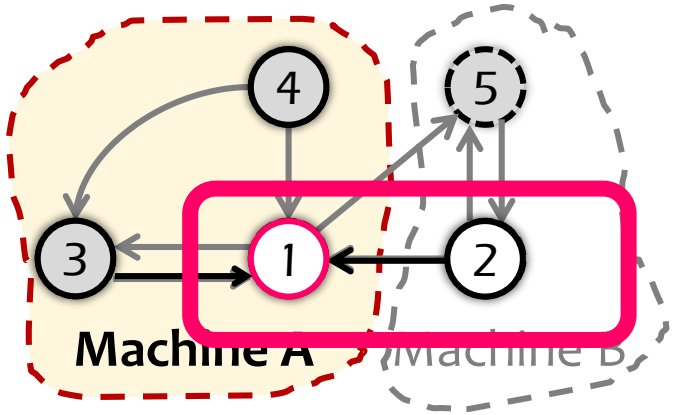
## Disadvantages of synchronous model

1. Uneven convergence problem
2. Straggler problem
3. Not suitable for some algorithms, eg. Graph Coloring and Clustering based on Gibbs Sampling

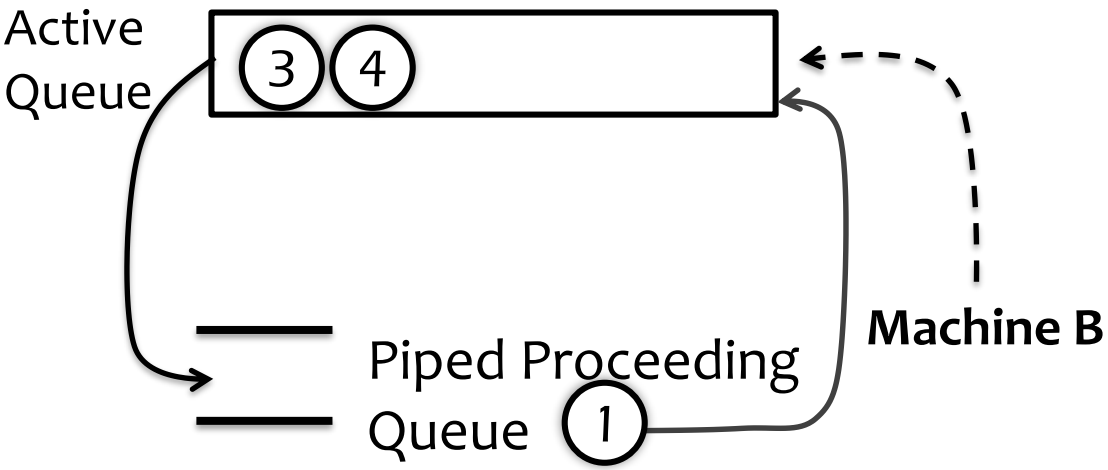
Ref. **PoweSwitch PPoPP 2015**

# Schedule model: async model

Scheduling:




Internal State (e.g. Machine A):




Pseudocode

**while** ($V_a$ != ∅) *do*

- v = **dequeue**( $V_a$ )
- A ← **compute**(v)
- $V'_a$ ← $V'_a$ ∪ A
- **signal across machines**

Ref. **PoweSwitch: PPOPP 2015**

# Schedule model: async model

**Advantages of asynchronous**

1. Speedup convergence
2. Better for CPU-bound algorithm

**Disadvantages of asynchronous**

1. Lock cost caused by vertex contention
2. Asynchronous model sends messages frequently, and CPU frequently encapsulates TCP/IP packets, which wastes the utilization of CPU

Ref. **PoweSwitch PPoPP 2015**

# Graph processing frameworks

## Programming Model

**Vertex Centric:** Pregel[SIGMOD'10]
**Edge Centric:** X-Stream[SOSP'13]
**Path Centric:** PathGraph[SC'14]
**Subgraph centric:** Blogel[VLDB'14]

## Graph Partition Strategy

**Vertex Cut:** Pregel[SIGMOD '10]
**Edge cut:** PowerGraph[OSDI'12]
**Hybrid Cut:** PowerLyra[EuroSys '15]

## Computation Strategy

**Pull vs push**

**Synchronous vs Asynchronous**

## Typical System

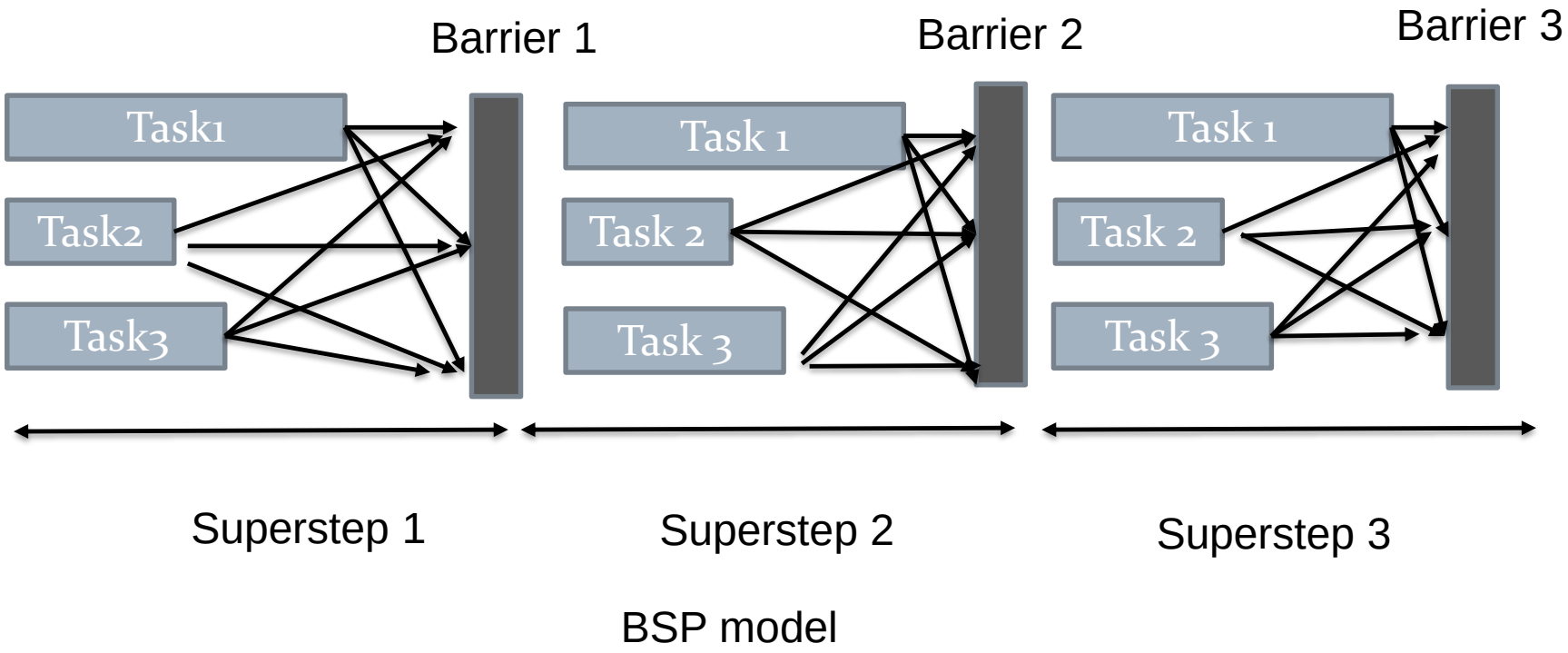
**Pregel :** SIGMOD 2010
**PowerGraph:** OSDI 2012
**GraphChi:** OSDI 2012

# Graph processing system

- **In-memory single-node graph system**
  - Ligra, GraphMat, Polymer
- **Out-of core single-node graph system**
  - GraphChi, TurboGraph, X-Stream, PathGraph, GridGraph, FlashGraph
- **Distributed graph system**
  - Pregel, PowerGraph, GraphLab, GraphX, PowerSwitch, PowerLyra, Gemini
- **Graph system on accelerator**
  - GPU based, e.g. CuSha, WS, Gunrock, IrGL, Groute
  - FPGA based
  - ASIC based
  - NVM based

# Pregel

- Large scale graph-parallel processing platform developed by Google
- Utilize BSP (bulk synchronous parallel) model

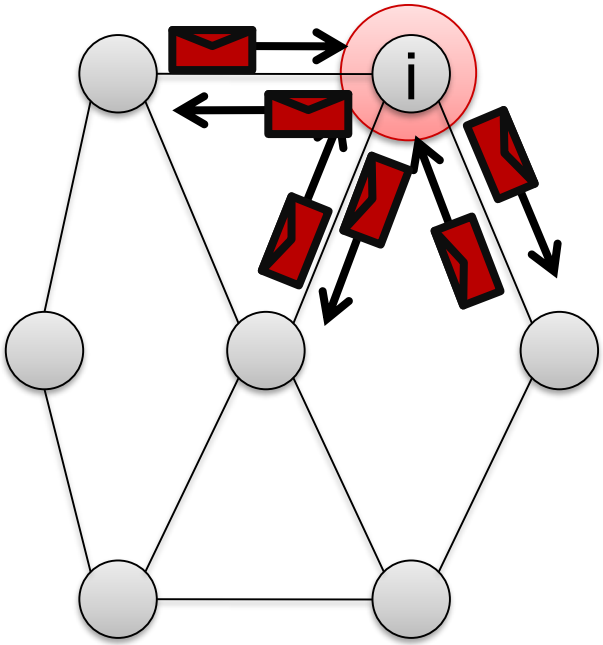



BSP model

# Pregel

- Large scale graph-parallel processing platform developed by Google
- Utilize BSP (bulk synchronous parallel ) model
- Vertex-Programs interact by sending messages

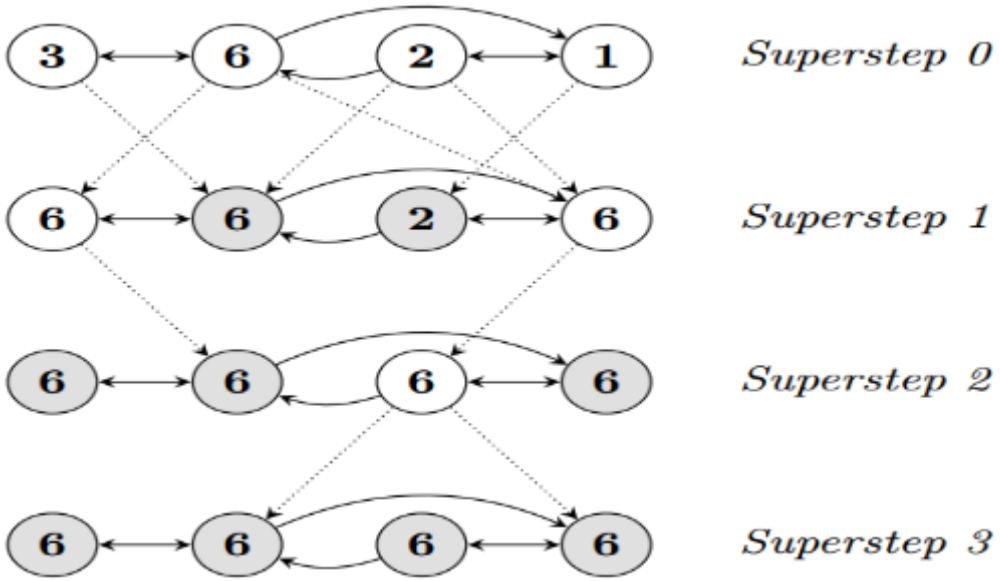
```
Pregel_PageRank(i, messages) :
  // Receive all the messages
  total = 0
  foreach( msg in messages) :
    total = total + msg

  // Update the rank of this vertex
  R[i] = 0.15 + total

  // Send new messages to neighbors
  foreach(j in out_neighbors[i]) :
    Send  msg(R[i] * w_ij) to vertex j
```




Ref : Malewicz et al. [PODC'09, SIGMOD'10]

# Pregel

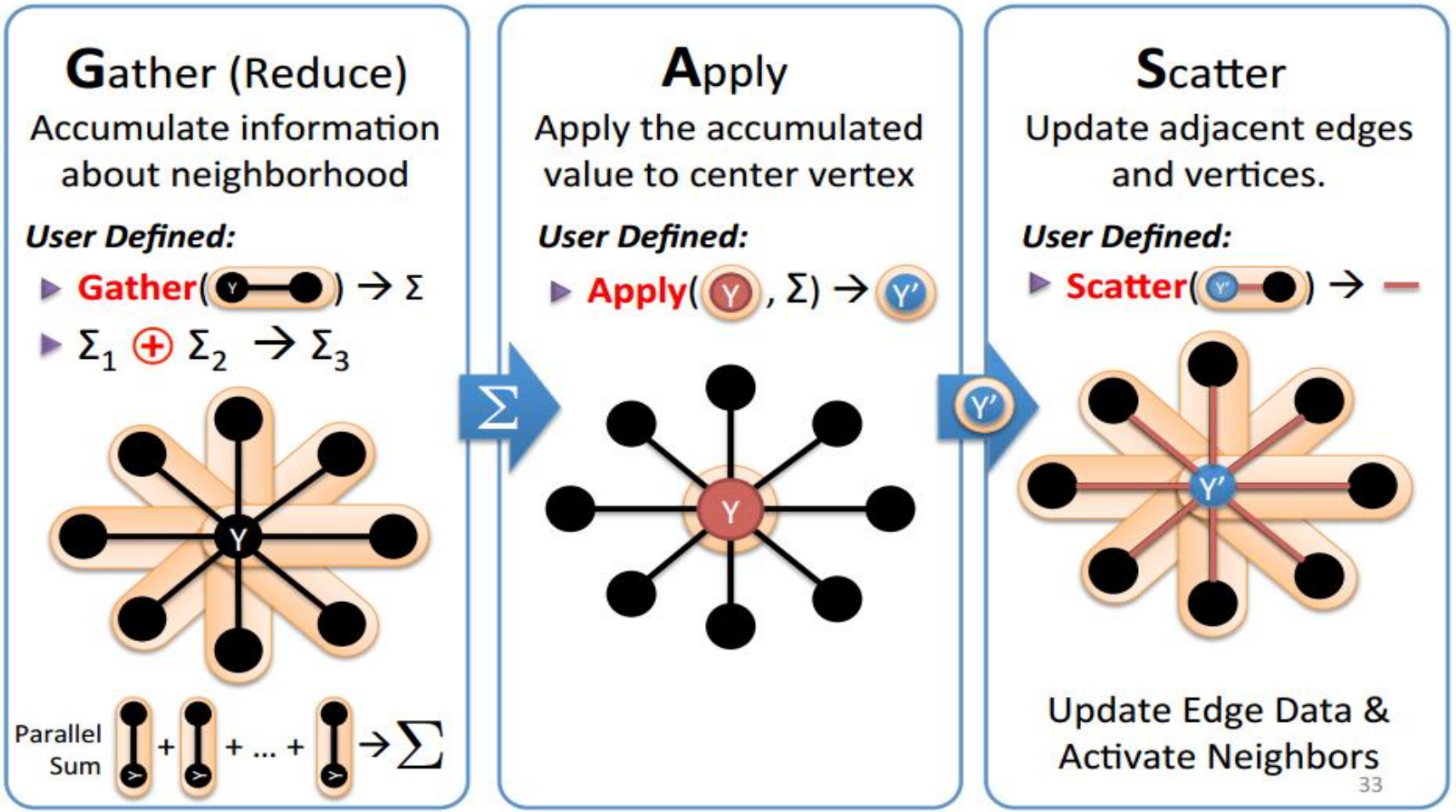
- Large scale graph-parallel processing platform developed by Google
- Utilize BSP (bulk synchronous parallel ) model
- Vertex-Programs interact by sending messages.
- Iteration until convergence




Maximum value example for Pregel

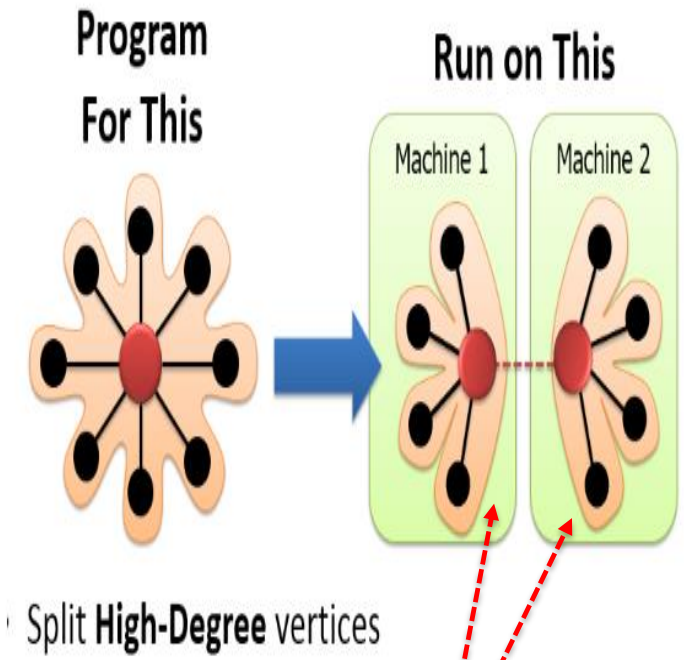
# PowerGraph

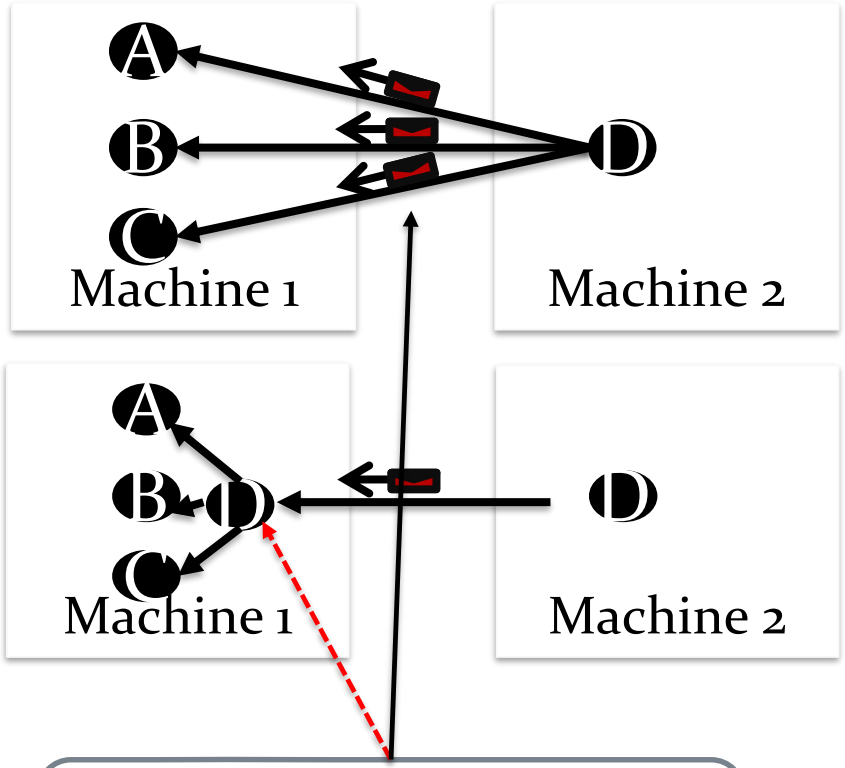
Introduce GAS programming model



# PowerGraph

Edge-cut for power-law graph




Cut high-degree vertex can balance workload

Image node can reduce communication between node

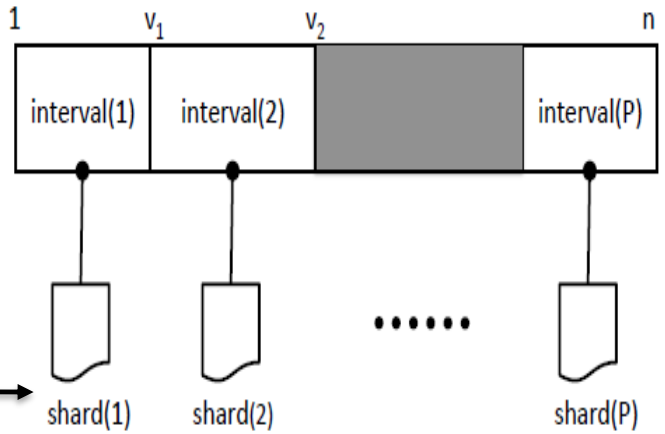
# GraphChi

- Challenges for distributed graph computation
  - Partitioning a graph is difficult (especially for power law graphs)
  - Distributed graph processing incurs too much communication cost
- Could we compute big graphs on a single machine?
- **GraphChi :** Single-node out-of-core graph processing system
  - Goal: maximize sequential disk access while loading graph into memory (500x speedup for disk sequential vs random)
  - Method: Execute on individual subgraphs once a time with parallel sliding window (PSW) , load subgraphs efficiently from disk

# GraphChi

**PSW:** parallel sliding window

- Vertices are partitioned into interval, each corresponds to a shard on disk
- **A shard on disk** include all in-edges for all vertices in corresponding interval




- Edges in a shard are sorted by source vertices
- Bring benefit for date access from disk
- Incur much preprocessing cost

Shard 1

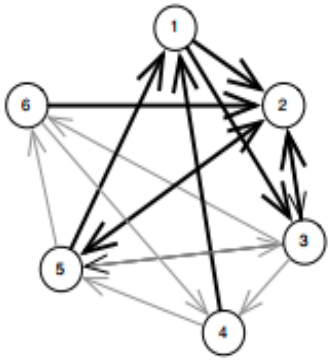
| src | dst | value |
|---|---|---|
| 1 | 2 | 0.3 |
| 3 | 2 | 0.2 |
| 4 | 1 | 1.4 |
| 5 | 1 | 0.5 |
| | 2 | 0.6 |
| 6 | 2 | 0.8 |

Shard 2

| src | dst | value |
|---|---|---|
| 1 | 3 | 0.4 |
| 2 | 3 | 0.3 |
| 3 | 4 | 0.8 |
| 5 | 3 | 0.2 |
| 6 | 4 | 1.9 |

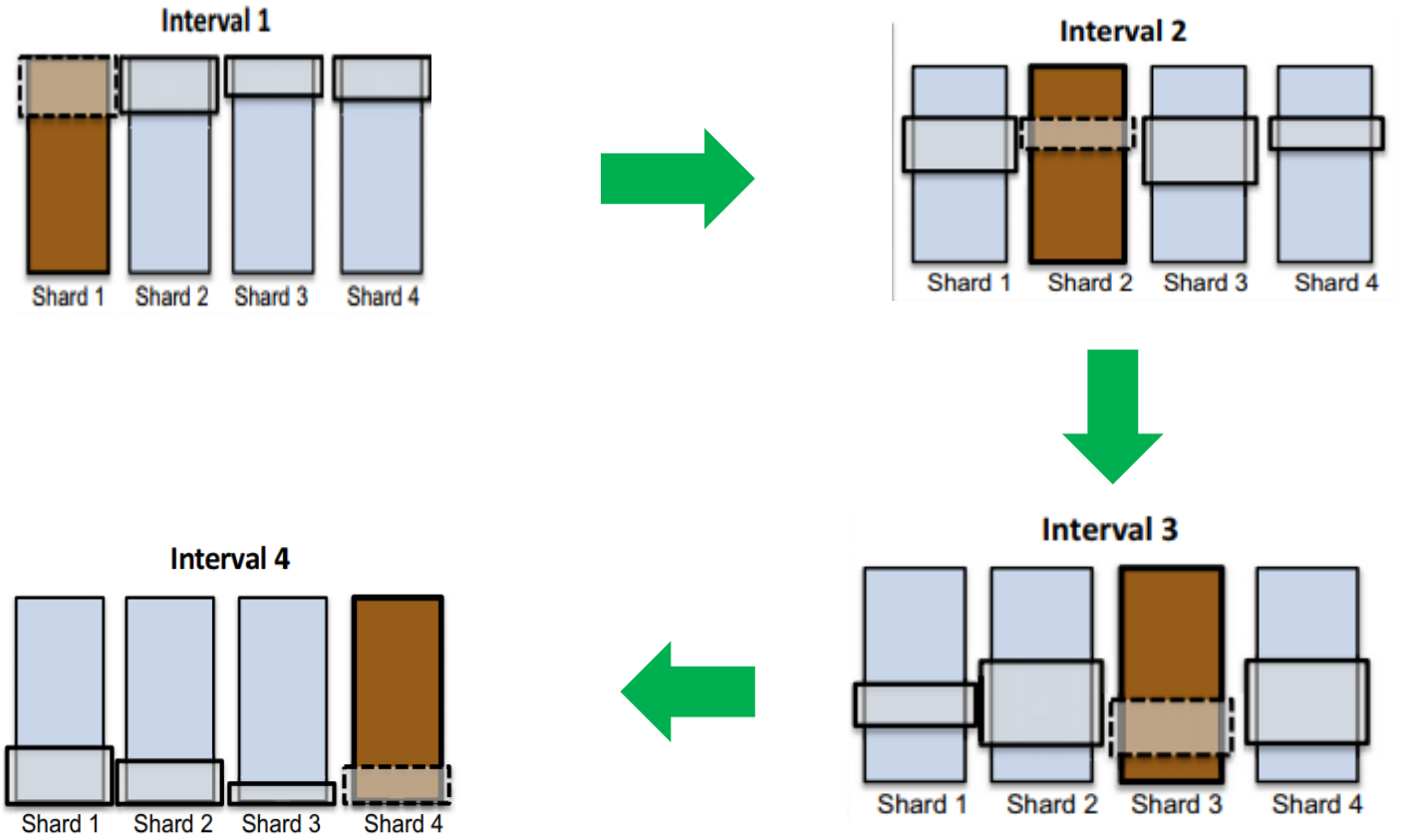
Shard 3

| src | dst | value |
|---|---|---|
| 2 | 5 | 0.6 |
| 3 | 5 | 0.9 |
| | 6 | 1.2 |
| 4 | 5 | 0.3 |
| 5 | 6 | 1.1 |



# GraphChi

- Slide window to process one intervals with shard one by one



# GraphChi

- Processing workflow for one interval
  (eg. Processing Interval 1)

**Step 1: Load all in-edges from shard 1 into memory for vertices of interval 1**

**(1 sequential disk read)**

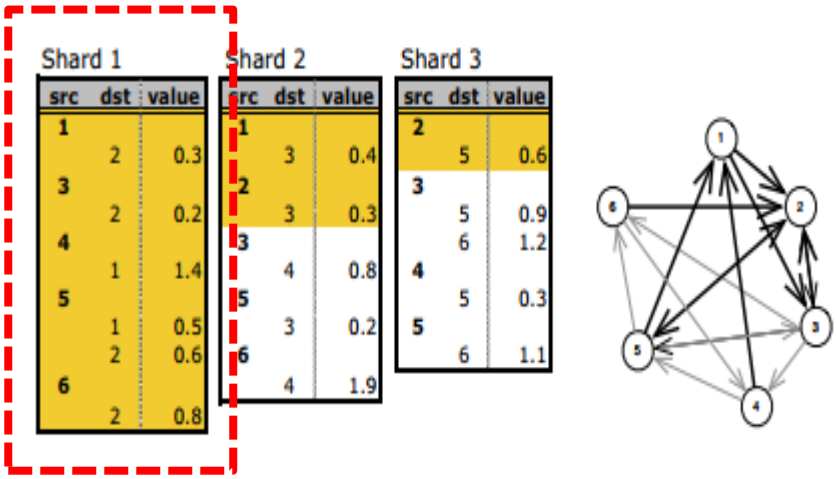



Fig. Execution interval 1 (with vertices 1, 2)

# GraphChi

- Processing workflow for one interval (eg. Processing Interval 1)

Step 1: Load all in-edges from shard 1 into memory for vertices of interval 1

**Step 2: Load all out-edges in memory form other shards for vertices of interval 1**

**( P-1 sequential reads)**

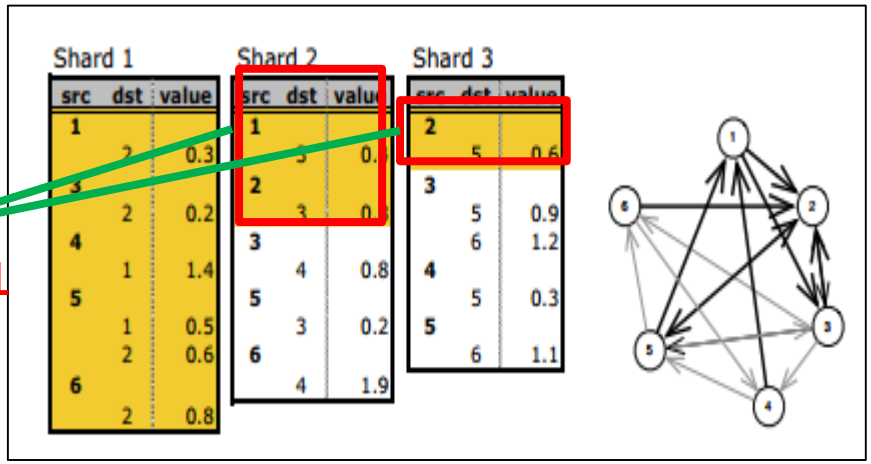



Fig. Execution interval (vertices 1, 2)

# GraphChi

- Processing workflow for one interval (eg. Processing Interval 1)

Step 1: Load all in-edges from shard 1 into memory for vertices of interval 1

Step 2: Load all out-edges in memory form other shard for vertices of interval 1

**Step 3: Update-function is executed on interval's vertices (vertex 1, 2 ).**

**(vertices-centric processing)**

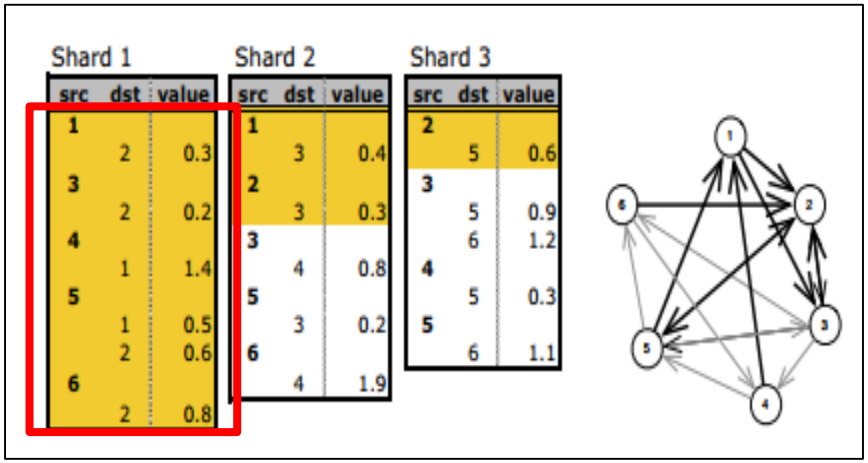



Fig. Execution interval 1 (with vertices 1, 2)

# GraphChi

- Processing workflow for one interval (eg. Processing Interval 1)

Step 1: Load all in-edges from shard 1 into memory for vertices of interval 1

Step 2: Load all out-edges in memory form other shard for vertices of interval 1

Step 3: Update-function is executed on interval's vertices (vertex 1, 2 )

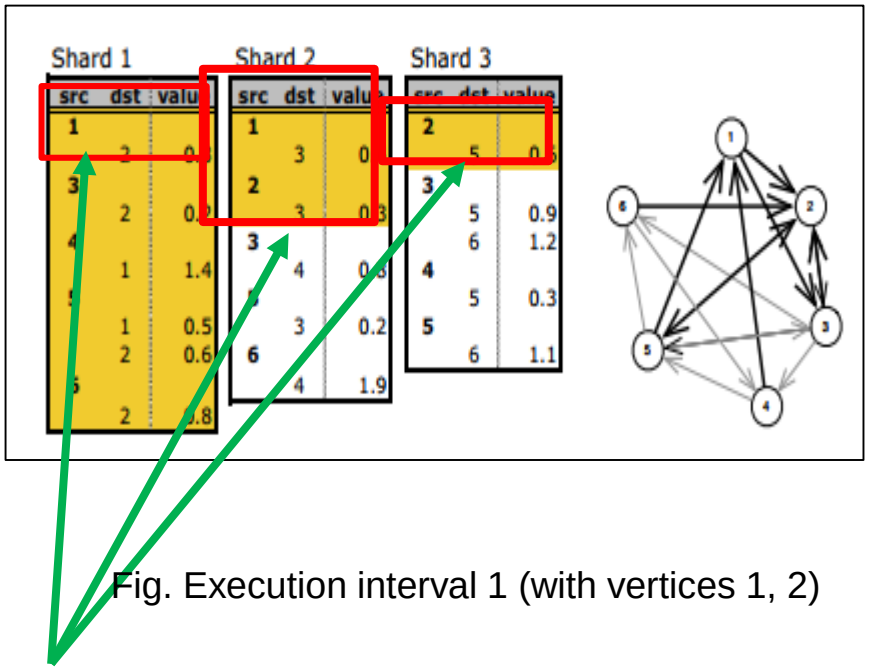



Fig. Execution interval 1 (with vertices 1, 2)

Step 4: **Commit to disk, updates are written back to disk (p sequential disk write)**

# GraphChi

- Processing workflow for one interval (eg. Processing Interval 2)

Step 1: Load all in-edges from shard 2 into memory for vertices of interval 2

Step 2: Load all out-edges in memory form other shard for vertices of interval 2

Step 3: Update-function is executed on interval's vertices (vertex 3, 4 )

Step 4: Commit to disk, update are written back to disk
(p sequential disk write)

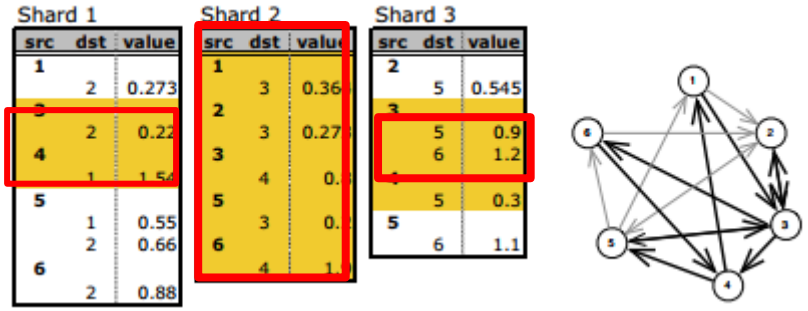



Fig. Execution interval 2 (vertices 3, 4)

# PROGRAMMING FOR STREAM PROCESSING

# Outline

- Stream data and stream applications
- Real-time stream processing
- Ecosystems and programming models

# What is stream?

# What is stream?

- A stream is a continuous and unbounded sequence of data elements made available over time

- Stream data in big data era
  - Volume, continuous and unbounded
  - Variety, changes quickly
  - Velocity, high speed incoming
  - Value, needs to be processed in near real-rime




# Stream applications


“ 11 - 11 ”


(Didi) Real-time Traffic Monitoring


Hot Search Topics Ranking

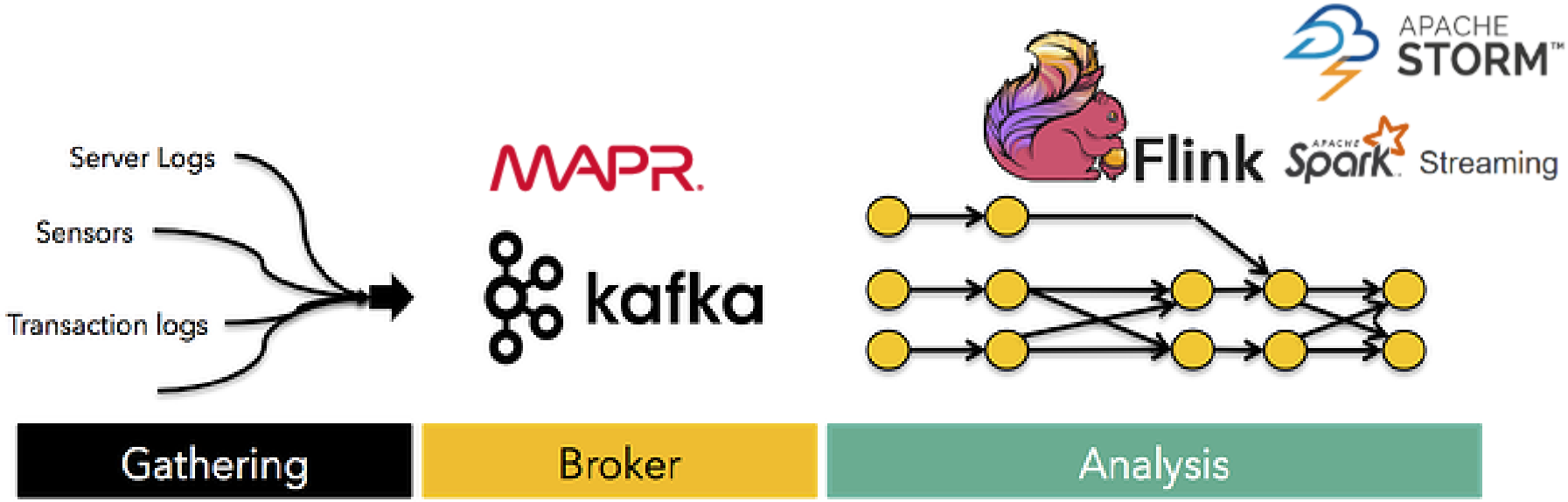
Market Transaction

# Outline

- Stream data and stream applications
- Real-time stream processing
- Ecosystems and programming models

# Common stream architecture

- Collect data from a variety of data sources
- Make data streams available for consumption
- Real-time stream processing



# Data model - Tuples

- A tuple is the basic data element that can be processed independently

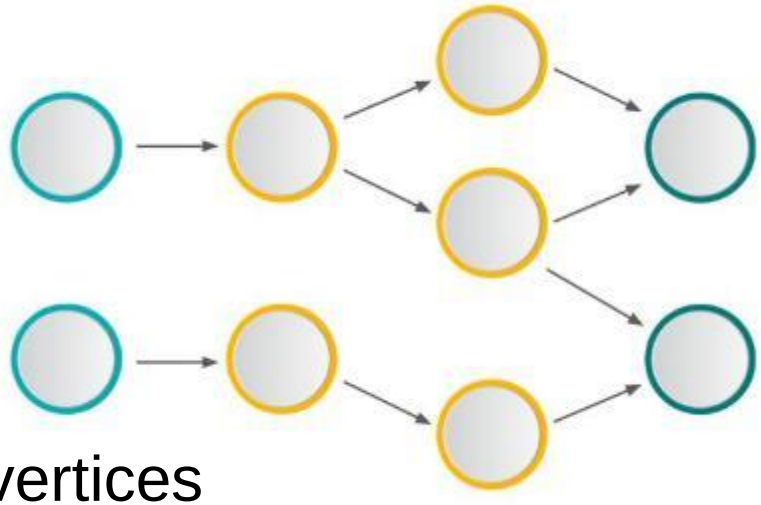
- Each tuple can be represented as a list of values. ( $t$ = < $value_1$, $value_2$, $value_3$,...> )


```
{
   "user_id": 17055506,
   "timestamp": 1421777578,
   "status":"Hello world!"
}
```

# Application model - DAG

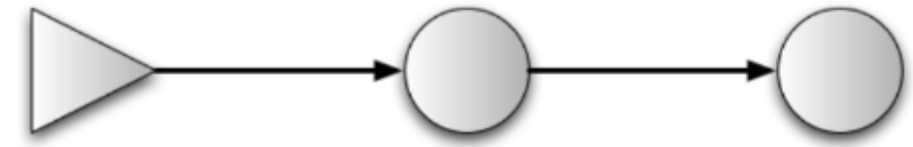
- Stream application can be modeled as a Directed Acyclic Graph (DAG)
  - Vertex: a simple operator

    executes common user defined function, e.g., map, filter, reduce, join,…



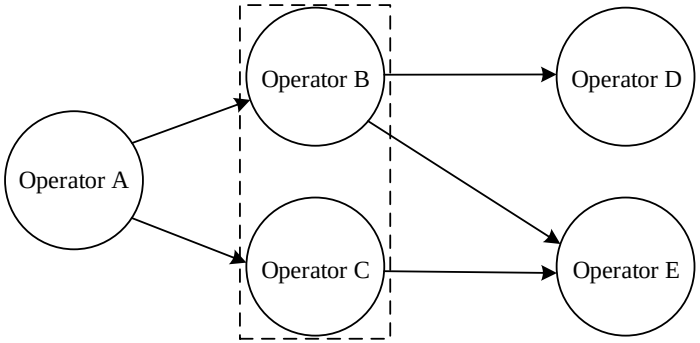
  - Edge: routing tuples between vertices

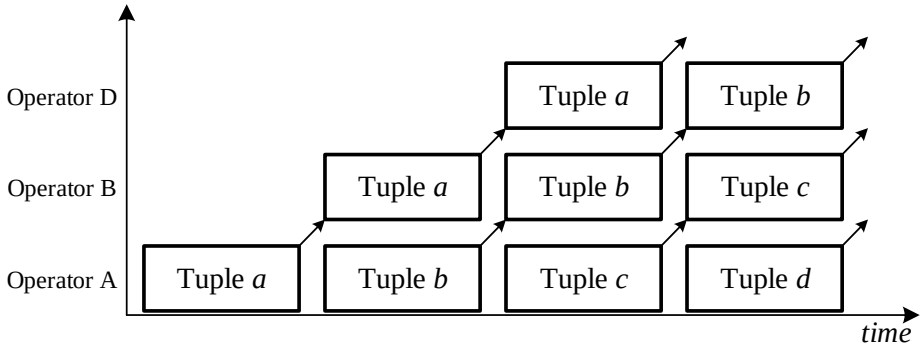
- A simple example: Twitter Word Count



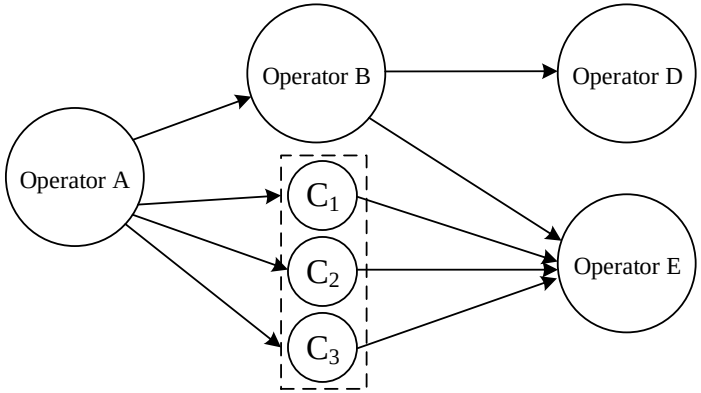
# Parallisms in stream processing

- Stream processing exploits pipeline parallism and task parallism by using DAG model



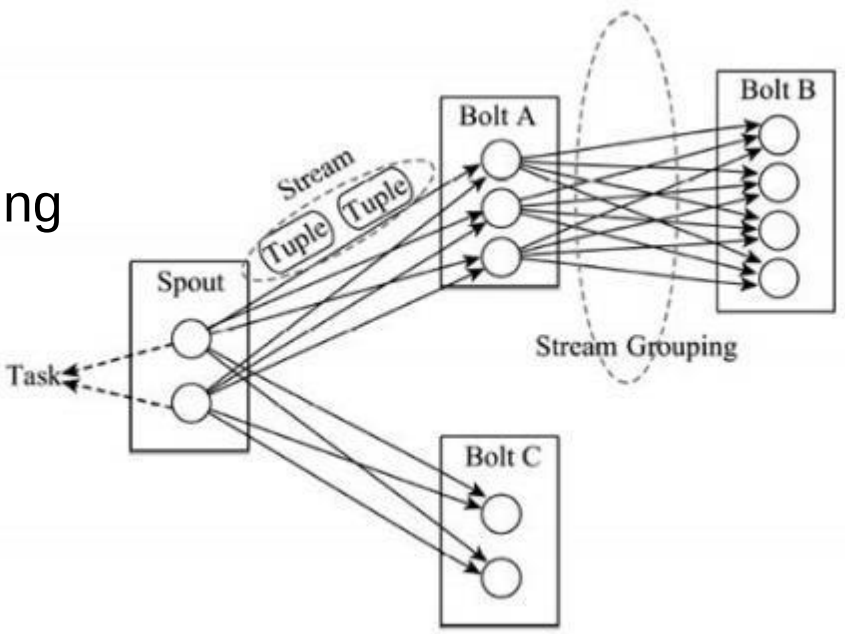

- Stream processing system can generate multiple instances for each operator to achieve high data parallism



# Tuples grouping and dispatching

- Tuples are partitioned into different groups and dispatched to different instances of operators

- Grouping strategies
  - Key Grouping: hash based partitioning
  - Shuffle Grouping: round-robin
  - All Grouping: broadcast
  - Global Grouping: all to one
  - Others



# Programming: step by step

1. Read input streams from data sources and generate a sequence of tuples
   - Kafka, HDFS, Flume, …
2. Build the DAG for a stream application
3. Specify the degree of parallisms for each operator and the data grouping strategies
   - Depending on different platform APIs

**Development part for programmers**

4. Submit the program to the cluster
   - Deployment
   - Fault Tolerant
   - Dashboard
   - …

**Managed by platforms**

**Transparent to programmers**

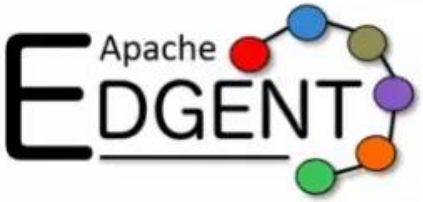
# Outline

- Stream data and stream applications
- Real-time stream processing
- Ecosystems and programming models

# Ecosystems

**Open Source Stream Processing Frameworks**













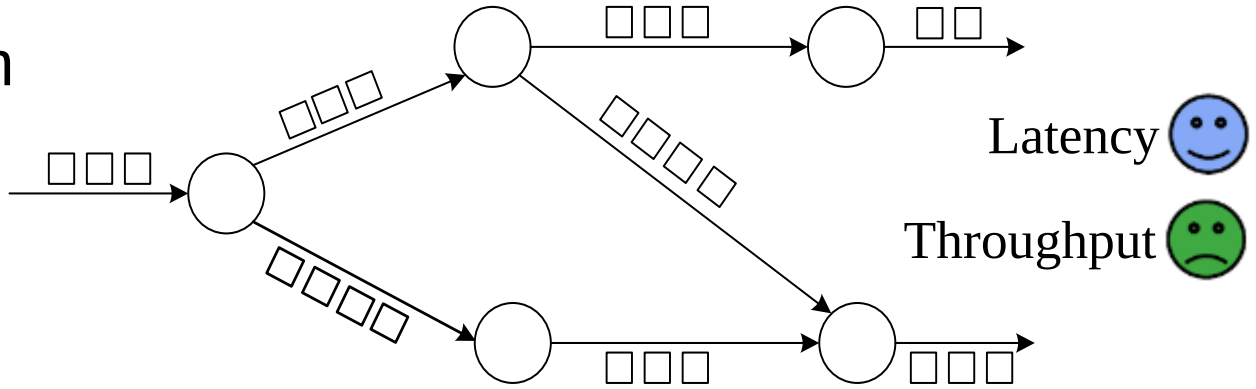




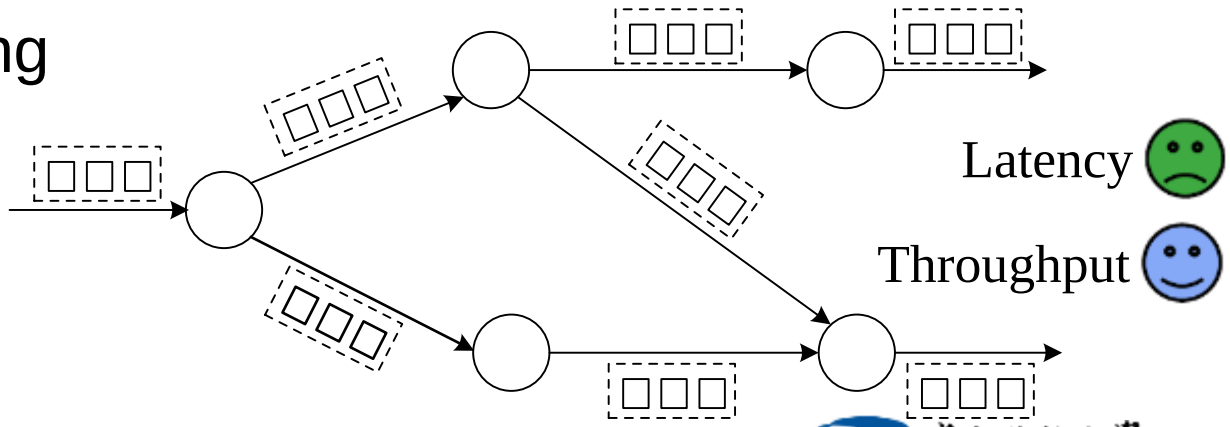

Apache Gearpump

# Two different programming models

- Continuous dataflow: process tuples one by one
  - Apache Storm
  - Apache Flink

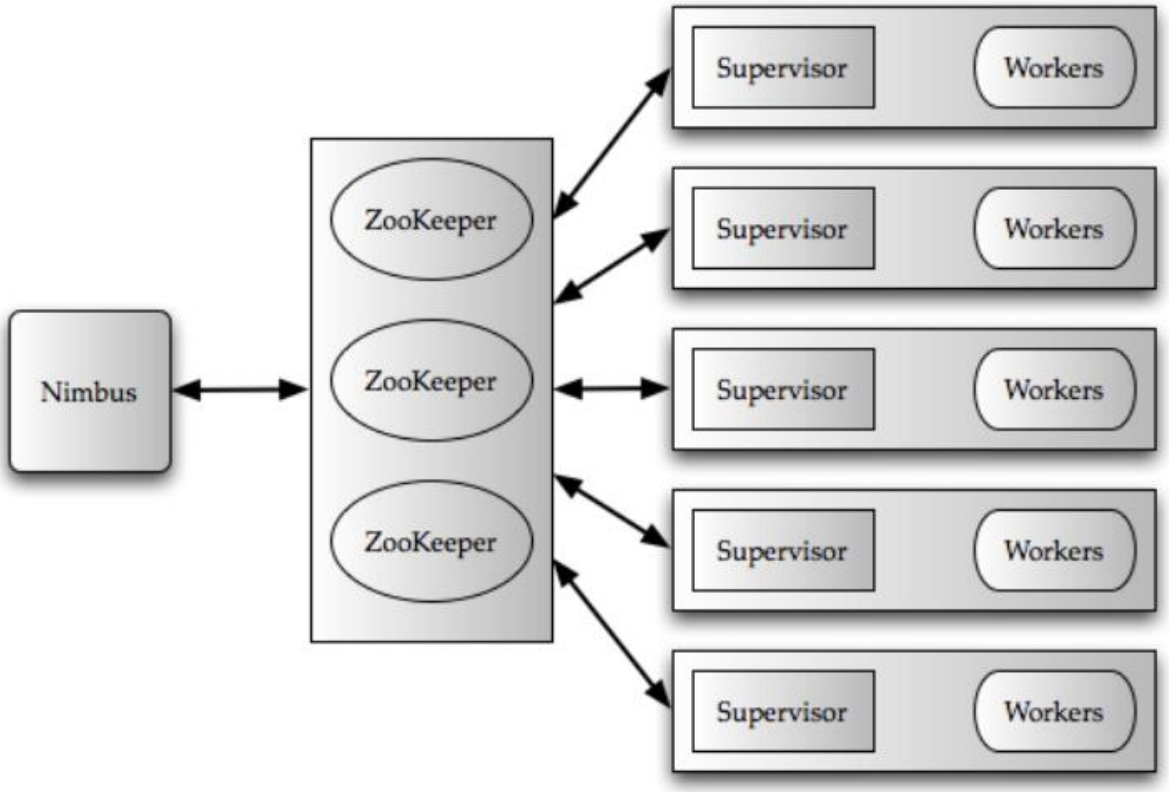



- Micro-batch: process tuples in small batches
  - Spark Streaming



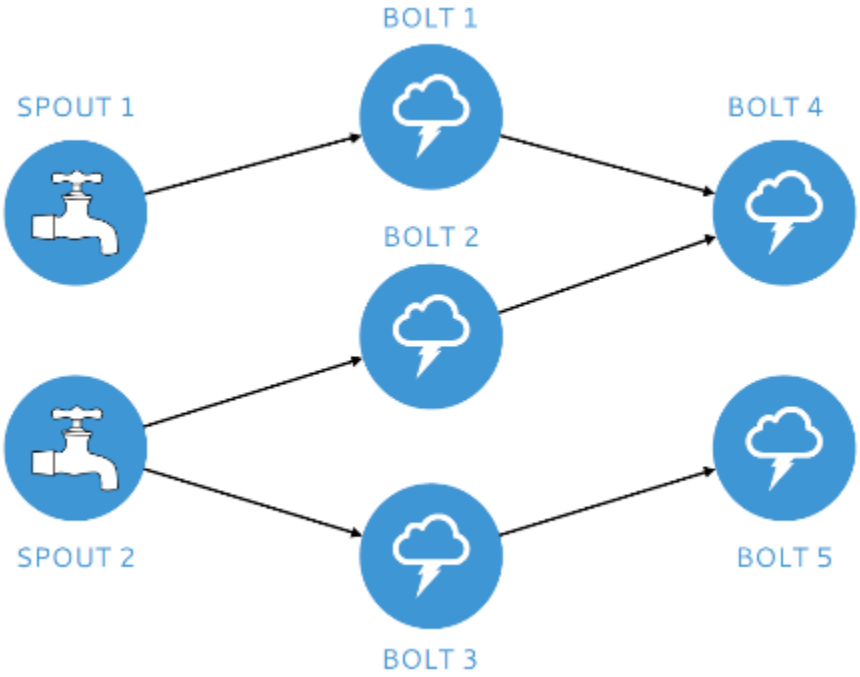
# Apache Storm

- Storm is a classic continuous dataflow based distributed stream processing system developed by Twitter. It has many variations such as JStorm in Alibaba.



# DAG model: topology

- Two kinds of components
  - Spout: read streams from sources and generates tuples
  - Bolt: execute a simple user defined function for tuples
- Each spout and bolt can generate multiple instances as multiple tasks and partition them in different nodes



# Use case: word count on Storm

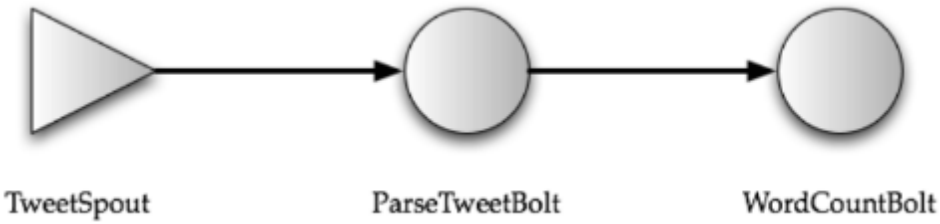
- Topology Building

```
TopologyBuilder tb = new TopologyBuilder();

tb.setSpout("TweetSpout", kafkaSpout(), 4);

tb.setBolt("ParseTweetBolt", new ParseBolt(), 4).setNumTasks(8).shuffleGrouping("TweetSpout");

tb.setBolt("WordCountBolt", new CountBolt(), 4).fieldsGrouping("Split", new Fields("ParseTweetBolt"));
```

*Specify the degree of parallism*

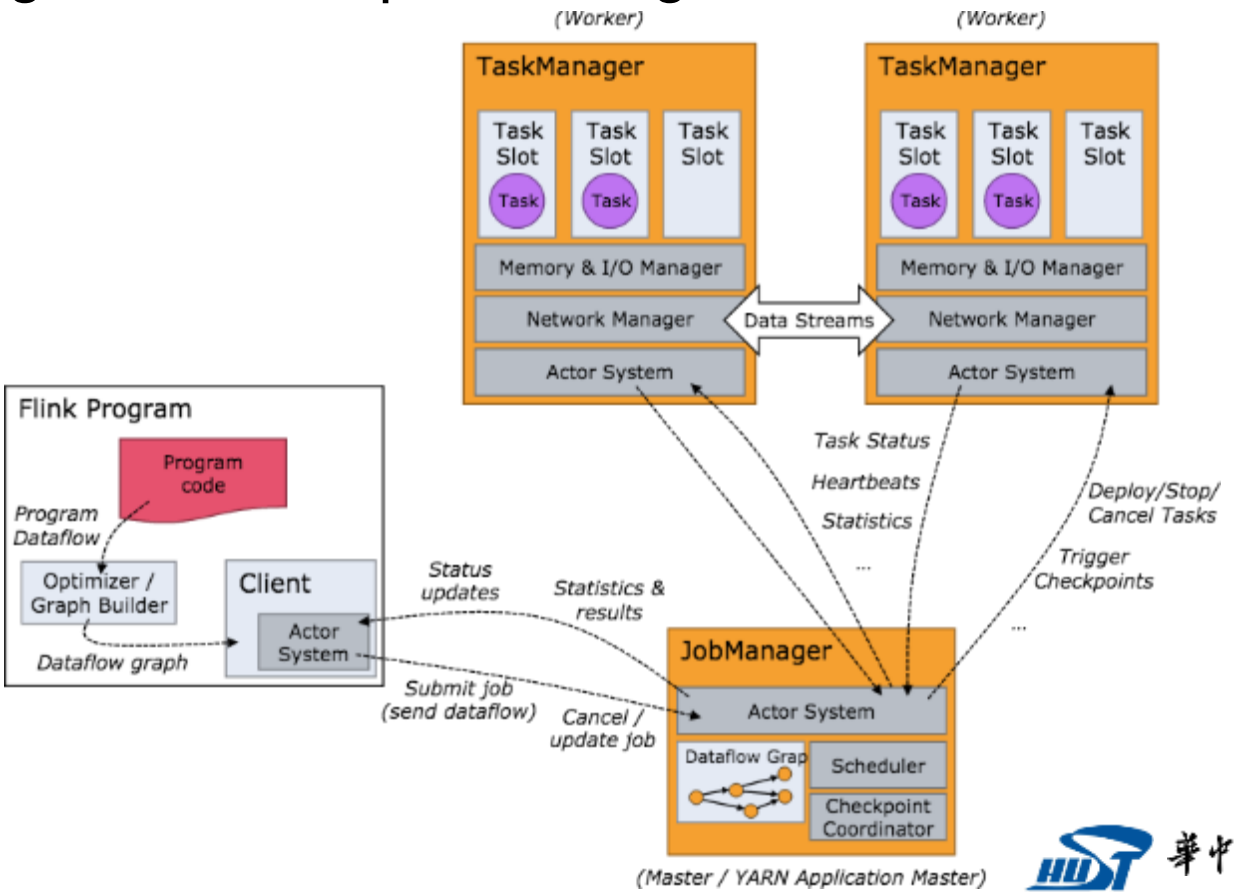
*User defined functions*

*Specify the grouping strategies*



# Apache Flink

- Flink is one of the most popular continuous dataflow based distributed stream processing system, which can also support big data batch processing



# DAG model: stream & transformation

- Flink's DAG model is almost like that in Storm, which contains one source operator, one sink operator and mulitple transformation operators
  - Transformation can be user defined functions or many pre-defined operations provied by Flink API, e.g., flatmap, map, reduce, windows, ...

# Use case: word count on Flink

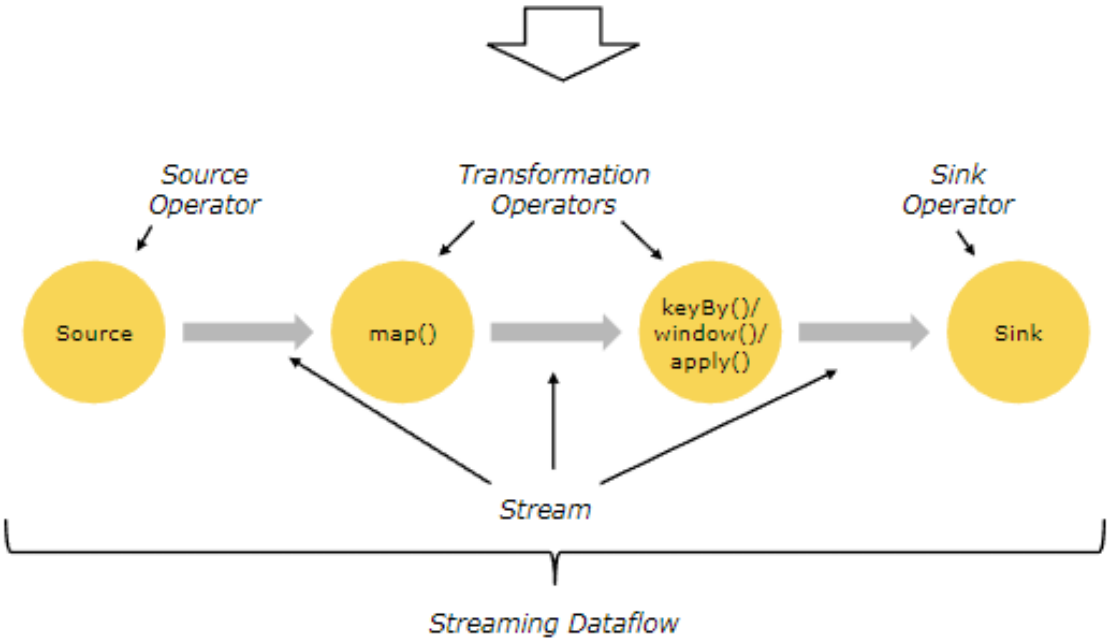
```
DataStream<String> lines = env.addSource(
                                new FlinkKafkaConsumer<>(…));

DataStream<Event> events = lines.map((line) -> parse(line));

DataStream<Statistics> stats = events
        .keyBy("id")
        .timeWindow(Time.seconds(10))
        .apply(new MyWindowAggregationFunction());

stats.addSink(new RollingSink(path));
```

*Source*

*Transformation*

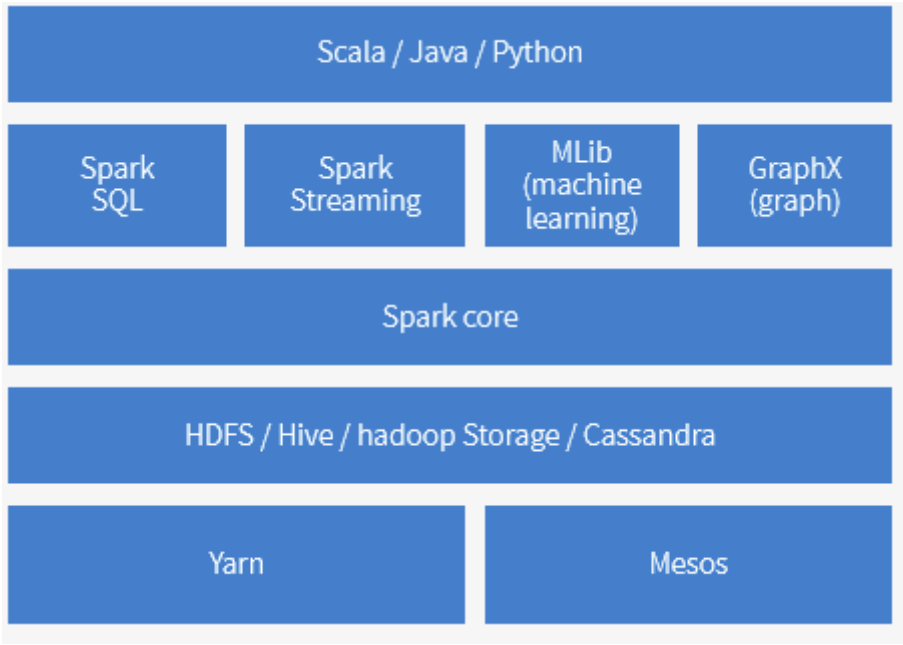
*Transformation*

*Sink*



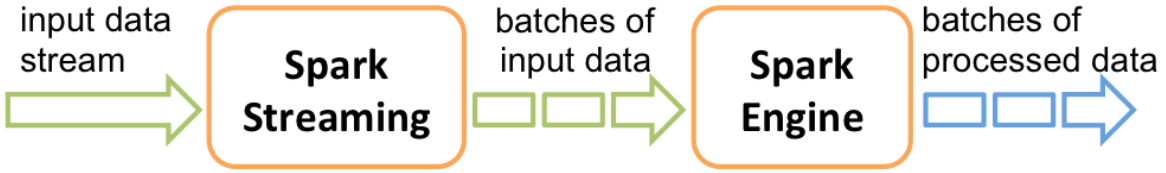
# Spark Streaming

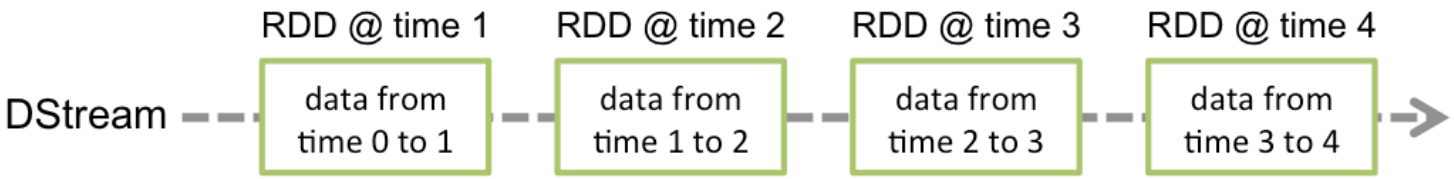
- Spark Streaming is an extension of the core Spark API, it is a classical micro-batch based distributed stream processing system

# Discretized streams and RDDs

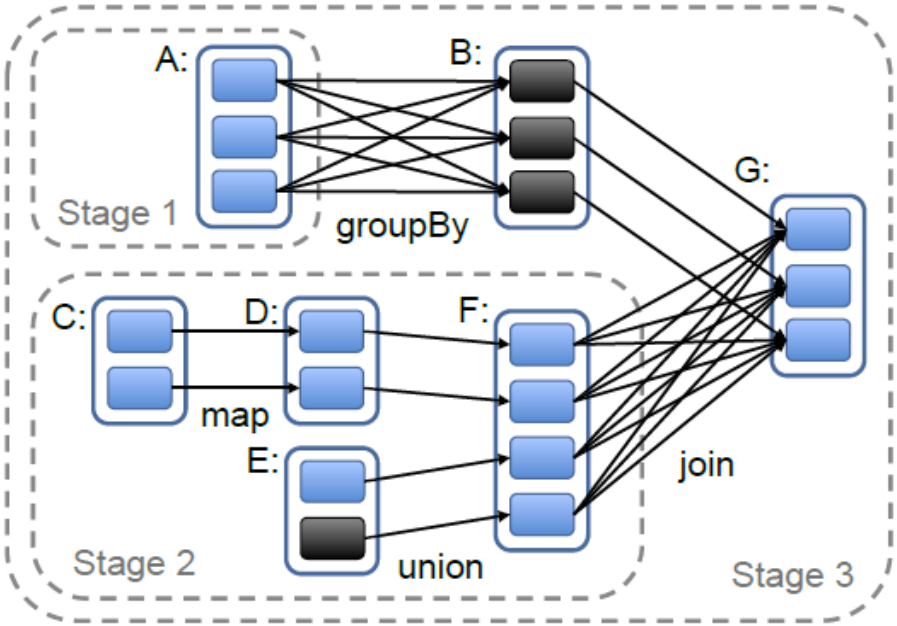
- The basic data abstraction of Spark Streaming is discretized streams
  - Tuples in a fixed interval (e.g., 1s) are partitioned into a small batch, and transformed to RDD by using Spark engine

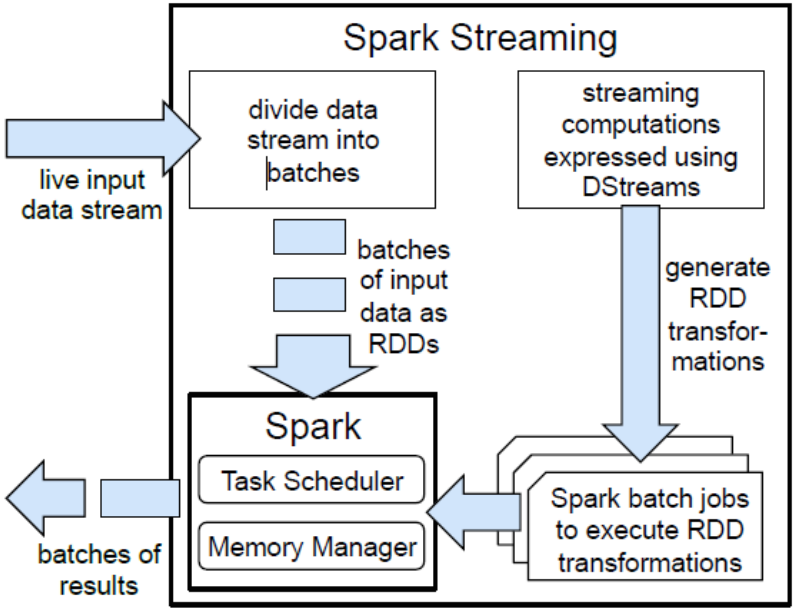


# DAG model: RDD transformations

- Spark Streaming executes RDD transformations for each small batch of tuples and generates batches of results



# Word count on Spark Streaming

- Essentially the same as batch processing

```
JavaRDD<String> textFile = sc.textFile("hdfs://...");
JavaPairRDD<String, Integer> counts = textFile
    .flatMap(s -> Arrays.asList(s.split(" ")).iterator())
    .mapToPair(word -> new Tuple2<>(word, 1))
    .reduceByKey((a, b) -> a + b);
counts.saveAsTextFile("hdfs://...");
```