Tangram: Bridging Immutable and Mutable Abstractions for Distributed Data Analytics

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Distributed Data Analytics Systems

Distributed data analytics systems in the last decade:

- From HPC (e.g., MPI), to general-purpose computing systems (e.g., MR, Spark), to specialized systems (e.g., Pregel, Parameter Server)

Distributed Data Analytics Systems

Classification according to data abstractions

Immutable	**Mutable**
TEZ	Parameter Server (PS)
hadoop MapReduce	PETUUM
Spark	Pregel Google
Microsoft DryadLINQ	TensorFlow
HIVE	GraphLab

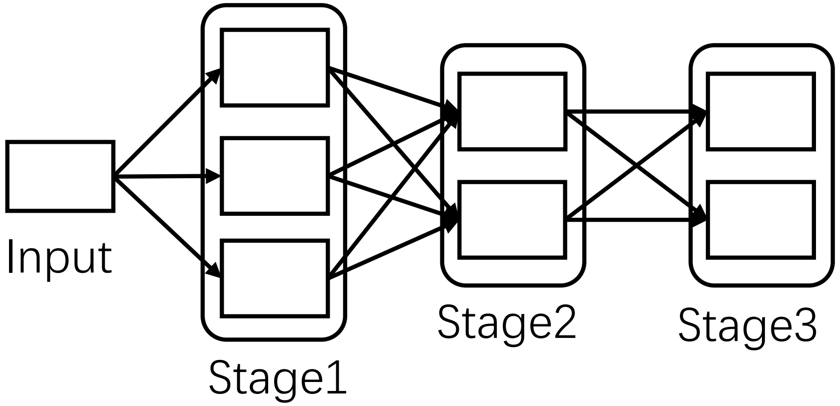
Immutable Abstraction

General purpose data analytics frameworks, e.g., MapReduce, DryadLINQ, Spark, etc.

- Functional programming models
- Use dataflow graphs to model the dependency among datasets

```
val textFile = sc.textFile("hdfs://…")
val counts = textFile.flatMap(line => line.split(" "))
                     .map(word => (word, 1))
                     .reduceByKey(_ + _)
```

Word Count in Spark



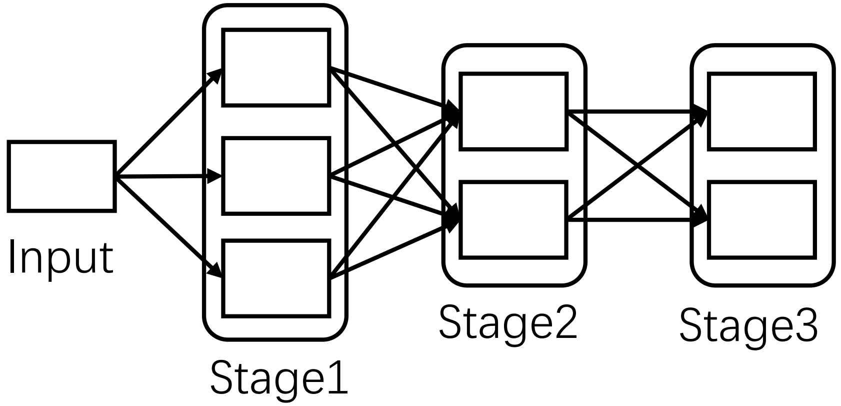
Immutable Abstraction

General purpose data analytics frameworks, e.g., MapReduce, DryadLINQ, Spark, etc.

+Efficient failure recovery (lineage-based recovery)

+Efficient load balancing (speculative execution)

- Inherently stateless
- Only support BSP (synchronous)

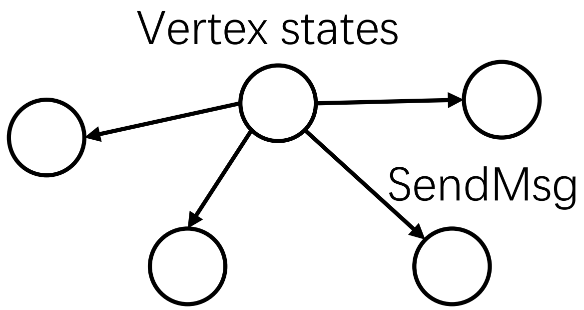


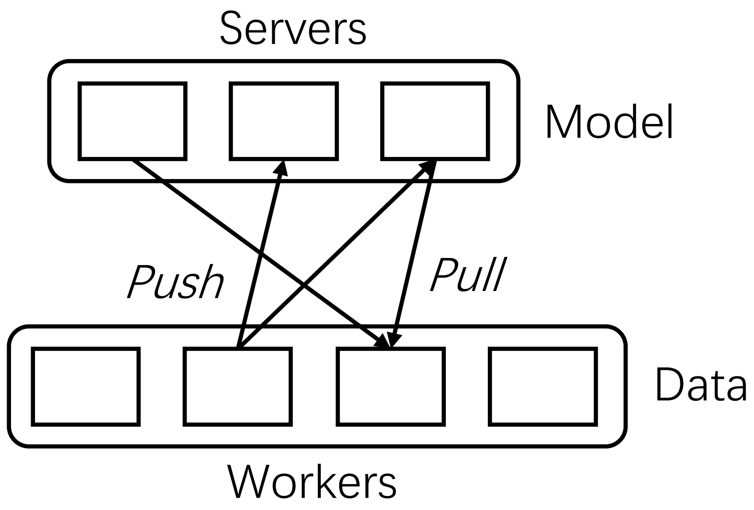
Mutable Abstraction

Specialized systems

- Vertex-centric graph analytics systems
  - E.g., Pregel, GraphLab, PowerGraph, etc
- Parameter-server-based machine learning systems
  - E.g., Parameter Server, Petuum, etc.

- Specialized programming models
- Stateful representation

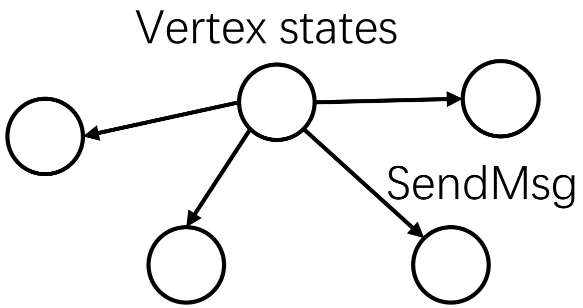


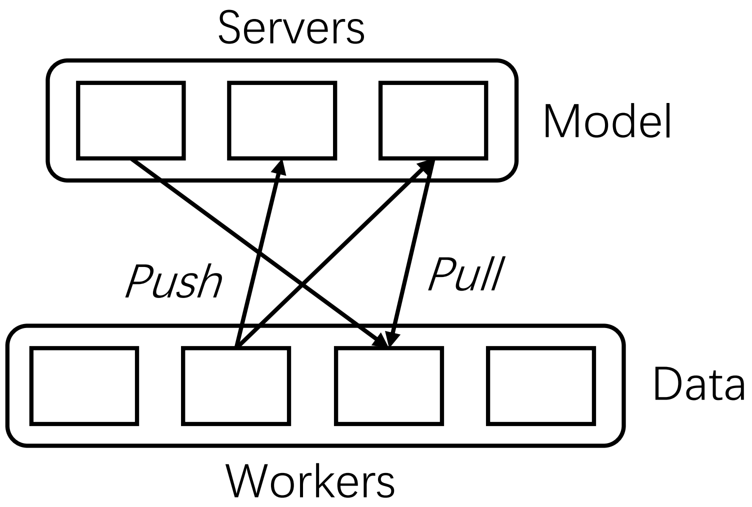


Mutable Abstraction

Specialized systems, e.g. Pregel, Parameter Server, etc.

+ Efficient for iterative workloads
+ May support asynchronous execution
- Require a full restart from the latest checkpoint (e.g., Pregel) or use expensive replication for fault tolerance (e.g., Parameter Server)
- Rely on the nature of the applications for load balancing





Immutable and Mutable Abstractions

Immutable	Mutable
+ Functional API + Fault tolerance + Load balancing	+ Stateful representation + Iterative and asynchronous execution
- Not natural for stateful representation - Only support BSP	- Fault tolerance - Load Balancing

Questions

- Can we **enjoy the benefits of both worlds**?
- Can the system **transparently determine the data mutability**?

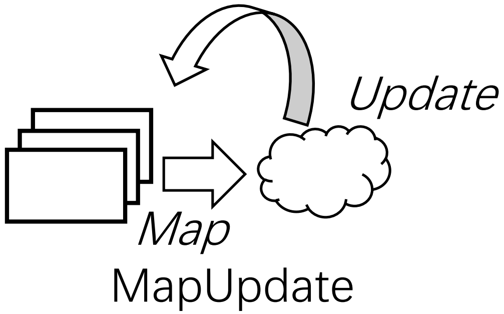
MapUpdate

MapReduce

- In the dataflow abstraction, we apply operations on collections (datasets) and generate new collections

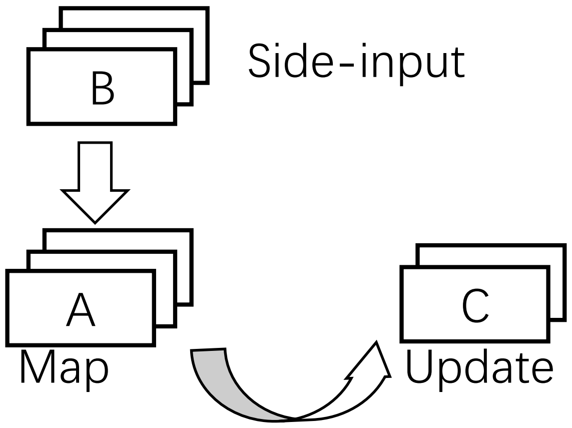
MapUpdate

- We make data collections mutable, and change the Reduce operation to a stateful Update operation



MapUpdate

A.**map**(B, map_func).**update**(C, update_func)



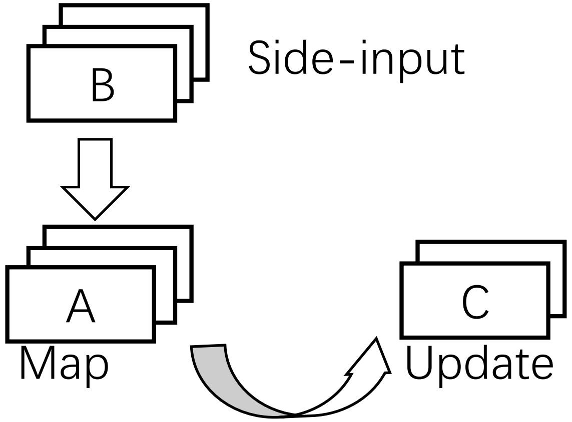
MapUpdate

A.**map**(B, map_func).**update**(C, update_func)

Map collection

Side-input collection

Update collection

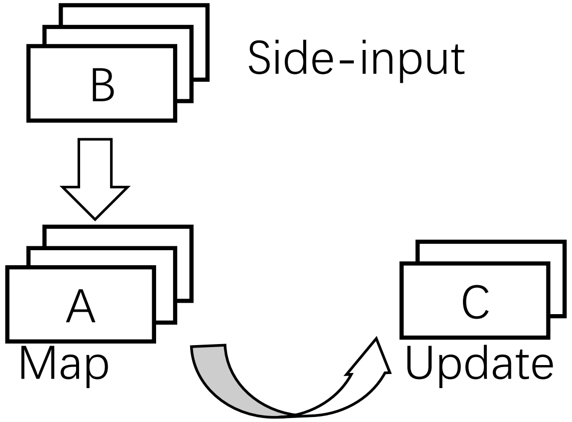


MapUpdate

A.**map**(B, map_func).**update**(C, update_func)

Map:
- functional and immutable

Update
- Stateful and in-place



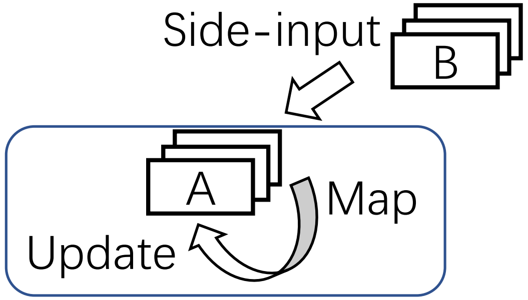
MapUpdate

Feature #1

Some or all of the map collection (A), side-input collection (B) and update collection (C) can be the same collection

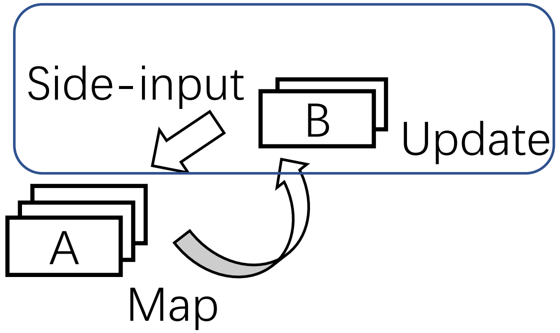
A.**map**(B, map_func).**update**(A, update_func)

- map = update



A.**map**(B, map_func).**update**(B, update_func)

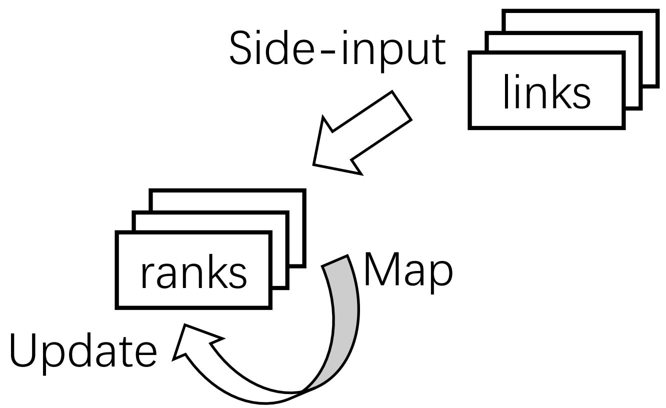
- side-input = update



MapUpdate: Example Application

A.**map**(B, map_func).**update**(A, update_func)

Vertex-centric Graph Analytics (PageRank)



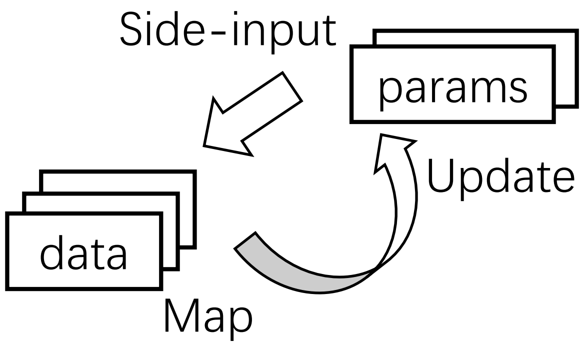

```
// Rank: (id, pr): (int, float)
// Link: (id, nb1, nb2...): (int, int, int...)
map_func(Rank r, Links links, Output o):
  for each neighbor nb in links[r.id]:
    o <- (nb.id, 0.85 * r.pr/len(links[r.id]))
update_func(Rank r, float contrib):
  r.pr += contrib

ranks.map(links, map_func)
     .update(ranks, update_func)
     .setIter(30)
```

map collection = update collection

MapUpdate: Example Application

A.map(B, map_func).update(B, update_func)

Iterative Machine Learning (Gradient Descent)



side-input collection = update collection

```
// Sample: (label,(k,v)..): (int, (int,float)..)
// Param: (k,v): (int, float)
// data: collection<Sample>
// params: collection<Param>
map_func(Sample sample, Params params, Output o):
  grad = CalcGrad(sample, params)
  o <- grad  // grad: ((k,v)...)

update_func(Param param, float update):
  param.val -= learning_rate * update

data.map(params, map_func)
    .update(params, update_func)
    .setIter(100).setStalenss(2)
```

MapUpdate

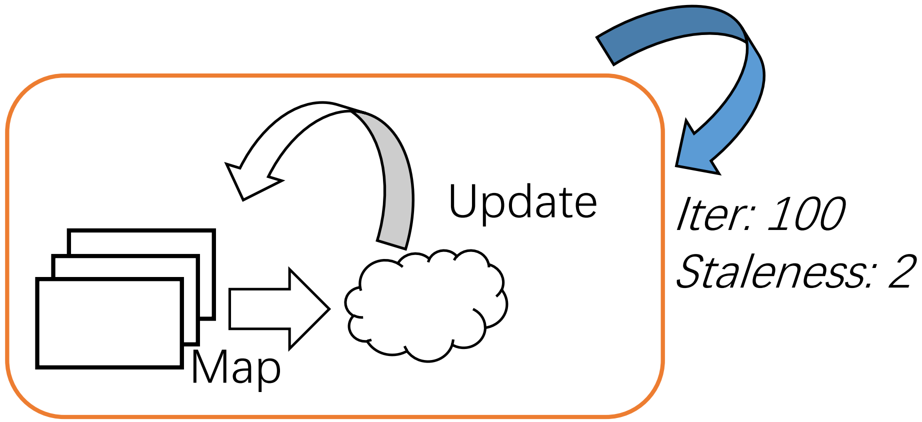
Feature #2

Supports iteration and asynchronous execution inherently

A.map(B, map_func).update(C, update_func)

.setIter(100)

.setStaleness(2)



MapUpdate

Feature #3

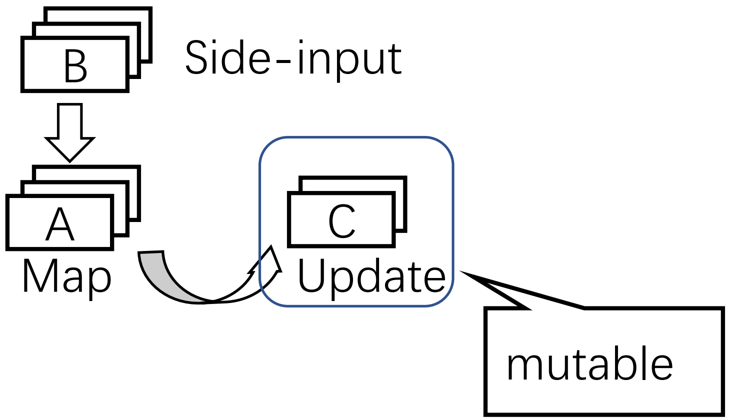
A simple mechanism to *determine whether a collection is mutable* in a MapUpdate plan:

- The update collection is mutable, and other collections, if different from the update collection, are considered immutable

A.**map**(B, map_func).**update**(C, update_func)

immutable

mutable



MapUpdate

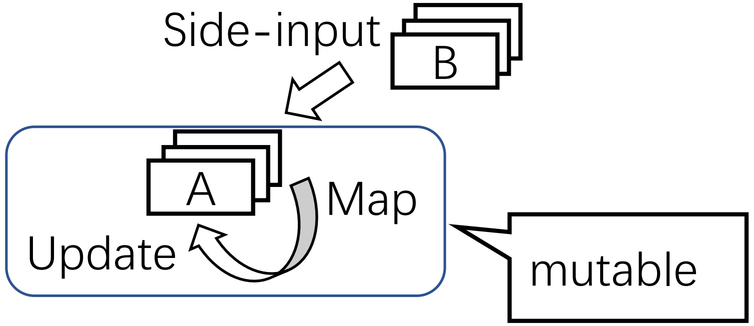
Feature #3

A simple mechanism to *determine whether a collection is mutable* in a MapUpdate plan

mutable

A.**map**(B, map_func).**update**(A, update_func)

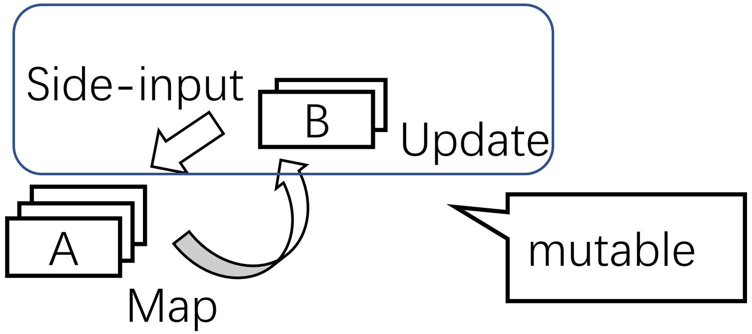
- map = update



mutable

A.**map**(B, map_func).**update**(B, update_func)

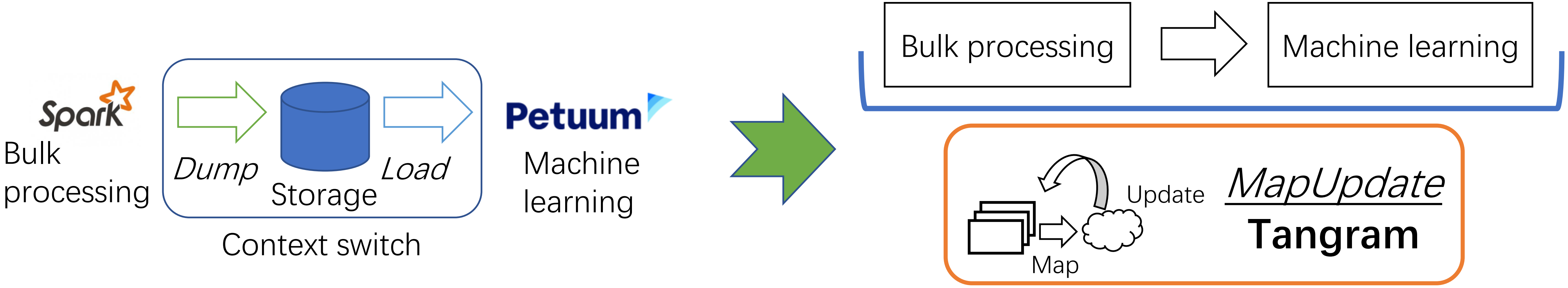
- side-input = update



MapUpdate: Example Application

Pipelined Workloads

- MapUpdate is especially useful for pipelined workloads
- Typical pipelines:
  - MapReduce-style data processing -> various data analytics -> testing
- Context switch overhead



Tangram

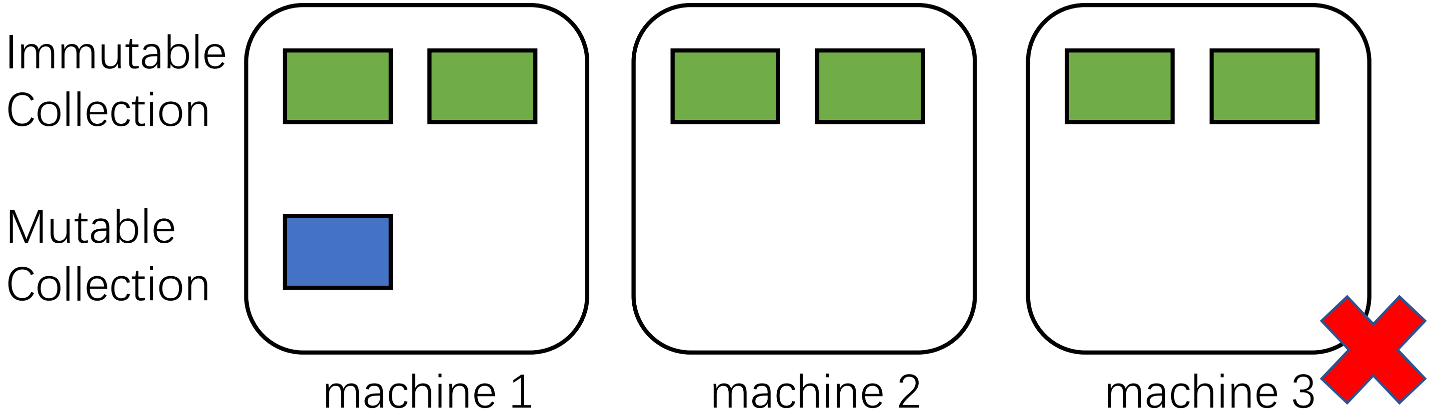
We implemented MapUpdate in Tangram

- Local Task Management
- Partition-based Progress Control
  - Support BSP, SSP and ASP execution models
  - Bitmap to record committed updates for each partition
- Context-Aware Failure Recovery

Context-Aware Failure Recovery

Tangram distinguishes two failure scenarios, i.e., local failure and global failure, and applies different failure recovery strategies

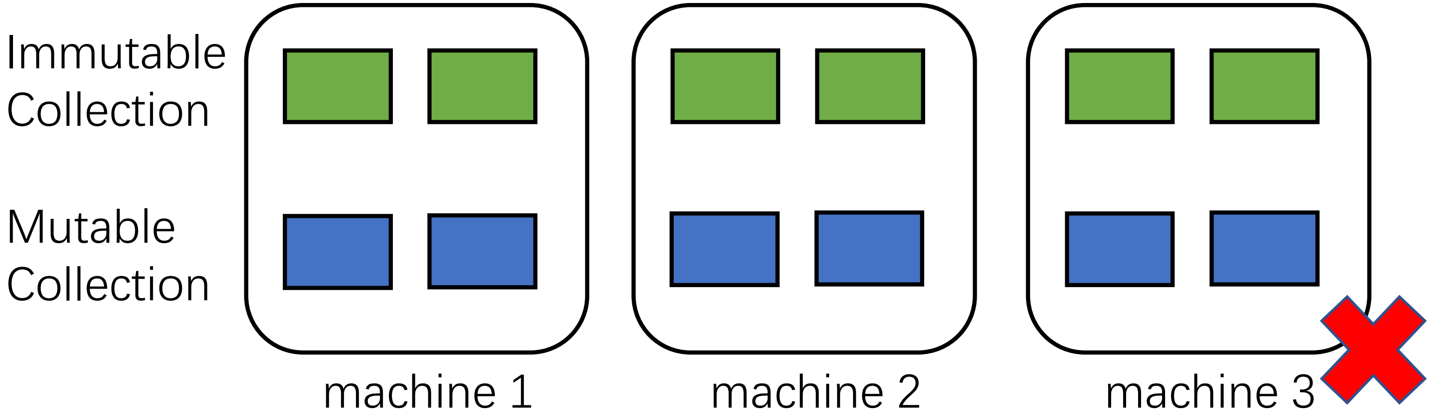
- Local failure: the failed machines do not hold update (mutable) partitions
  - Reloads the lost partitions (immutable) on the healthy machines in parallel and continues the execution



Context-Aware Failure Recovery

Tangram distinguishes two failure scenarios, i.e., local failure and global failure, and applies different failure recovery strategies.

- Global failure: the failed machines contain partitions of the update (mutable) collection
  - Rolls back to the latest checkpoint and reloads the mutable partitions
  - Reloads the lost immutable parts in parallel



Experiments

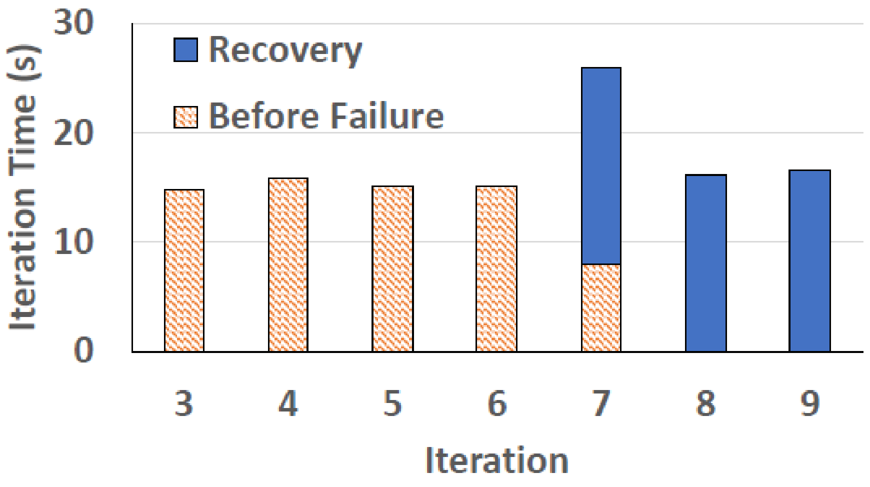
Settings:
- 20 machines, connected with 1Gbps Ethernet
- 20 machines, connected with 10Gbps Ethernet

Experiments
- Fault tolerance for local and global failures
- Expressiveness and performance on a wide range of workloads
- Efficiency in pipelined workloads

Experiments

Failure Recovery

- Local failure: K-means
  - No need to restart from the latest checkpoint
  - Tangram took 17.8 seconds to reload the lost training data (~6GB) and finish the 7th iteration (vs. 40 seconds in Spark)
  - Similar to Spark, while other mutable systems (e.g., Naiad, Petuum, PowerGraph) have to roll back to checkpoint

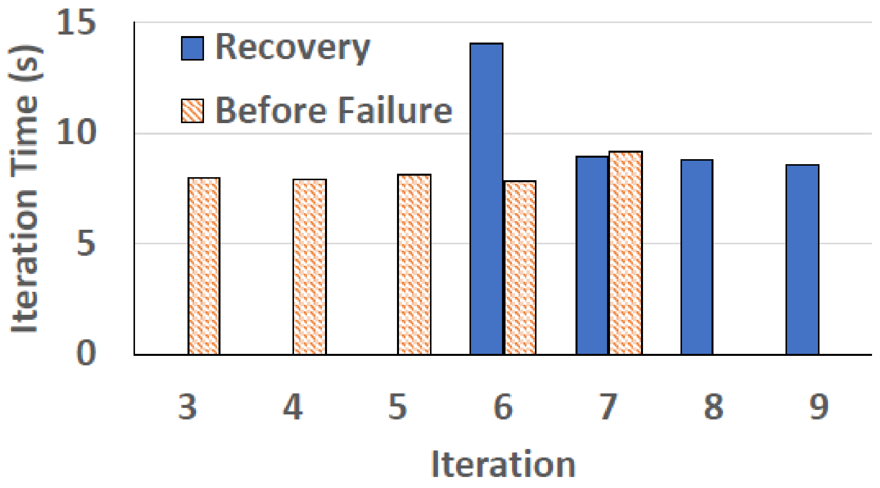


(a) Local Failure

Experiments

Failure Recovery

- Global failure: PageRank
  - Roll back to the latest checkpoint (iteration 5)
  - In total, Tangram took 29 seconds to recompute the 6th iteration and finish the 7th iteration (vs. 47 seconds in Spark)
  - Spark also requires a full recomputation from the latest checkpoint in this case (i.e., long lineage with wide dependency)



(b) Global Failure

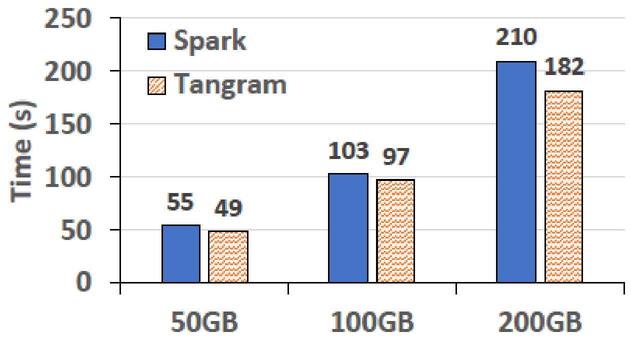
Experiments

Expressiveness and Efficiency

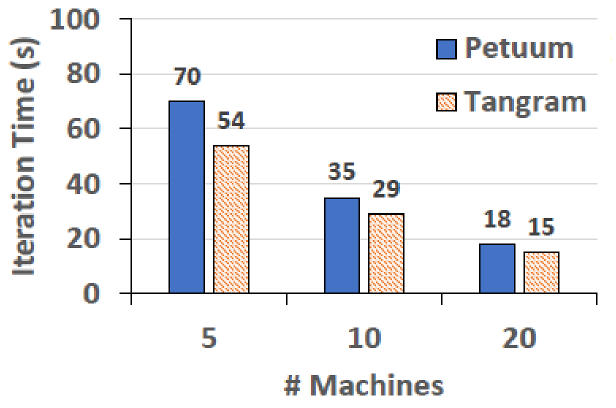
- Bulk Processing (vs. Spark)
- Iterative Machine Learning (vs. Petuum)
- Graph Analytics (vs. PowerGraph, etc)

Results

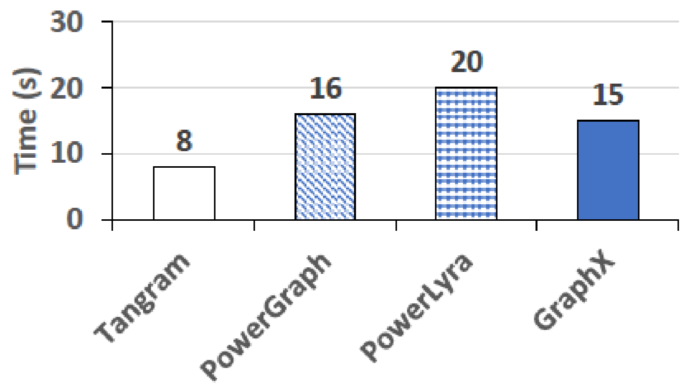
- Tangram can express a wide variety of workloads
- Tangram achieves comparable performance as specialized systems



Word Count



K-means

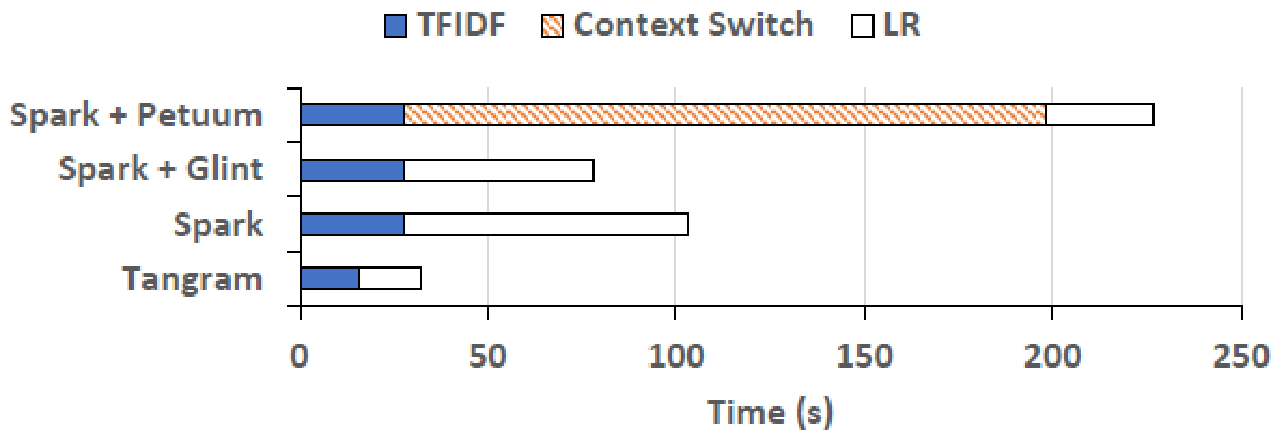


PageRank

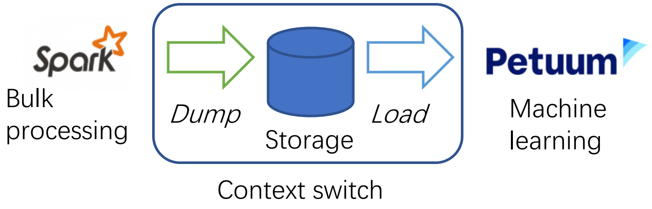
Experiments

Pipelined Workload: TF-IDF + LR

- Compared with Spark, Spark + Glint (a built-in PS), Spark + Petuum using a faster 10-Gbps network



- Spark + Petuum has high context-switch overhead
- Using Spark alone is not efficient
- Spark + Glint adds external dependencies and violates Spark's unified abstraction



Conclusions

- A novel programming model: MapUpdate
- Tangram: Enjoys the benefits of both worlds
  - Support asynchronous iterative workloads
  - Differentiated failure recovery and load balance