BDAPRO

APIs and Execution of Dataflow Programs

Chen Xu, Alireza RM, Quoc Cuong To

Slides prepared by Jonas Traub, Gábor Gévay, Alexander Alexandrov

Agenda

Theory

- Principles of parallelization frameworks (MapReduce)
- Principles and Execution Aspects of Dataflow Programs
- Comparison of runtime concepts

Practice

- Flink Batch Processing API
- Flink Stream Processing API

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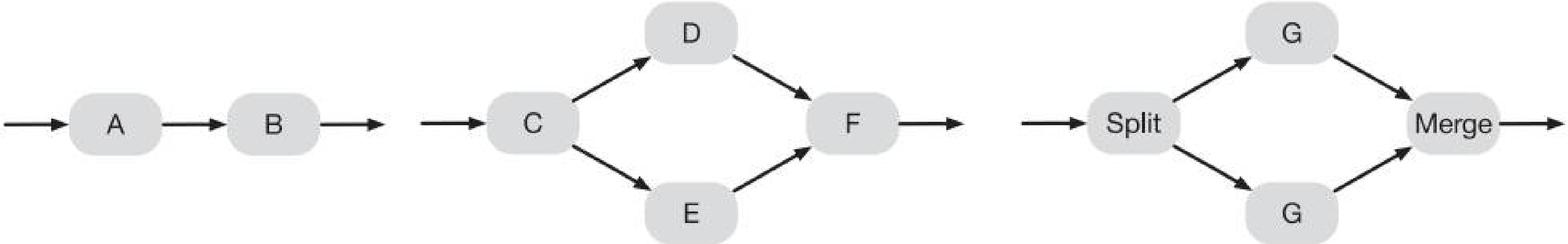
Principles of Parallelization Frameworks

Chen Xu

Slides prepared by Jonas Traub, Gábor Gévay, Alexander Alexandrov

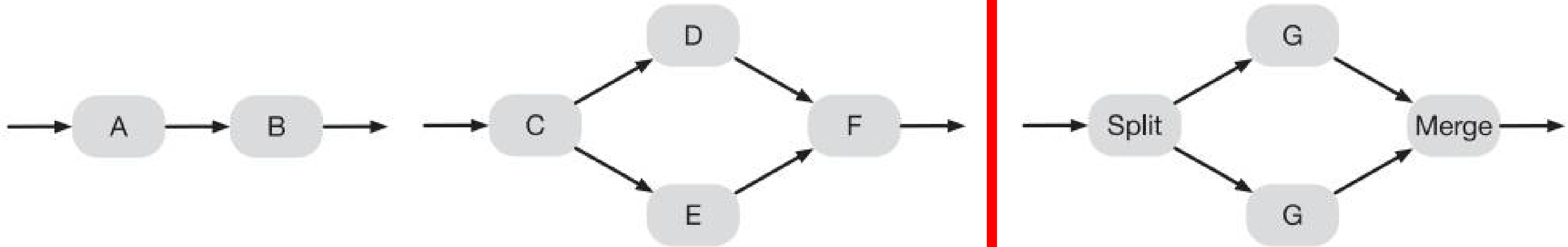
3 Types of Parallelization



(a) Pipeline-parallel A || B. (b) Task-parallel D || E. (c) Data-parallel G || G.

Source: Hirzel, M., Soulé, R., Schneider, S., Gedik, B., & Grimm, R. (2014). **A catalog of stream processing optimizations.** *ACM Computing Surveys (CSUR)*, *46*(4), 46.

3 Types of Parallelization



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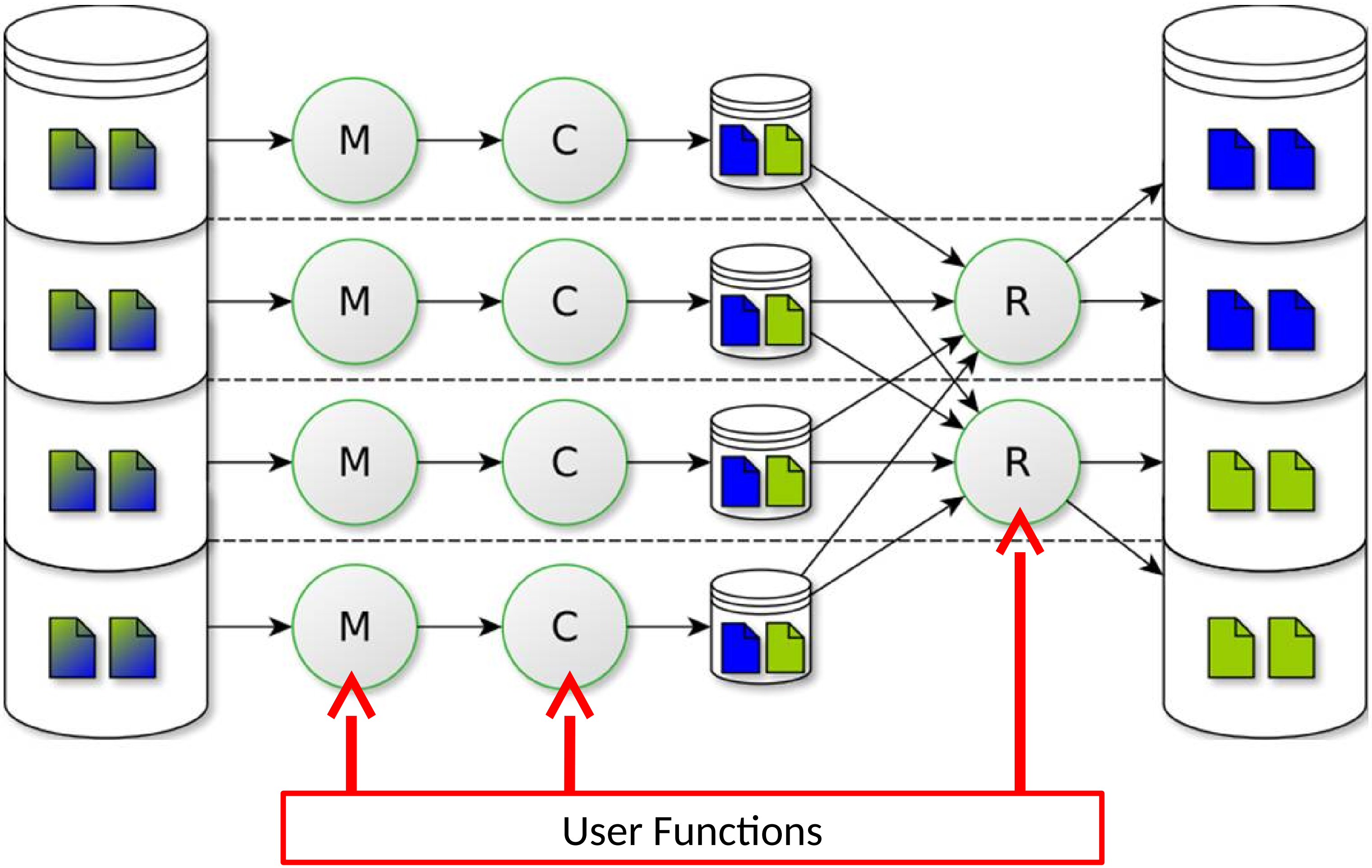
"Big Data" requires **data** parallelism!

Source: Hirzel, M., Soulé, R., Schneider, S., Gedik, B., & Grimm, R. (2014). **A catalog of stream processing optimizations.** *ACM Computing Surveys (CSUR)*, *46*(4), 46.

MapReduce



MapReduce Paper: Dean, Jeffrey, and Sanjay Ghemawat. "MapReduce: simplified data processing on large clusters." *Communications of the ACM* 51.1 (2008): 107-113.

MapReduce Example (Word Count)

```
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 result = 0;
  for each v in values:
    result += ParseInt(v);
  Emit(AsString(result));
```

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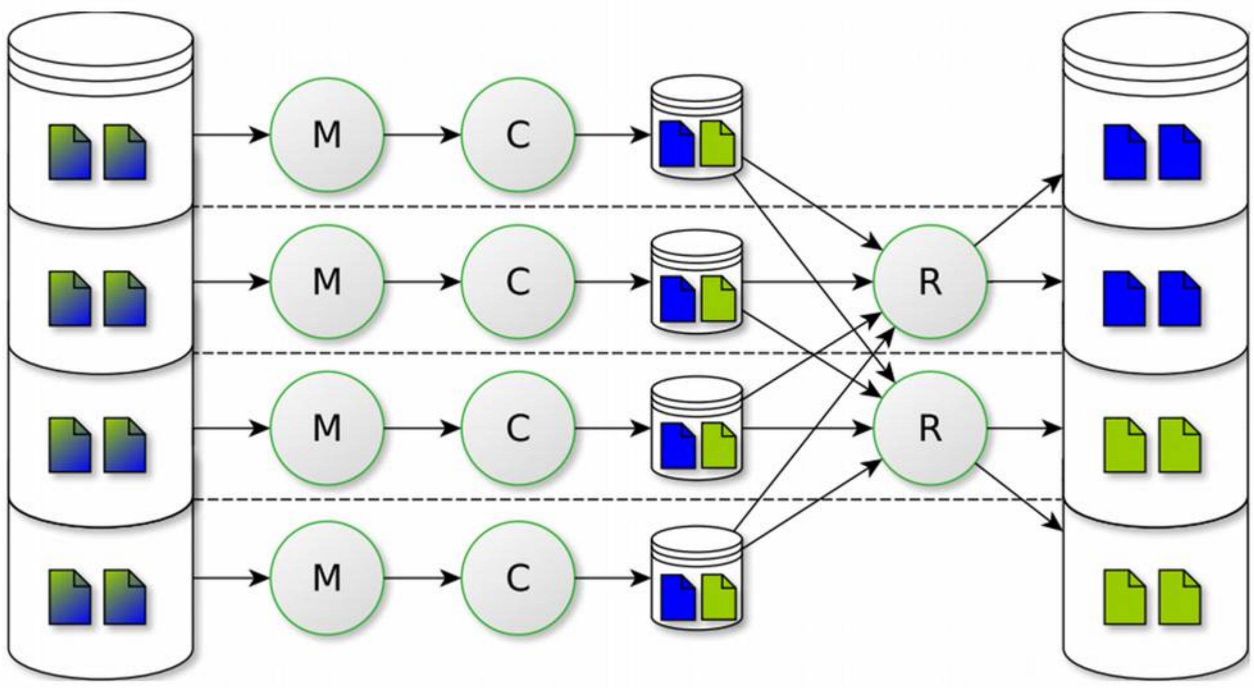
```

- Stateless functions!
- As many mapper instances as input (K,V) pairs.
- As many reducer instances as distinct keys in the output of the map phase
- Synchronization point and shuffling between Map and Reduce phase

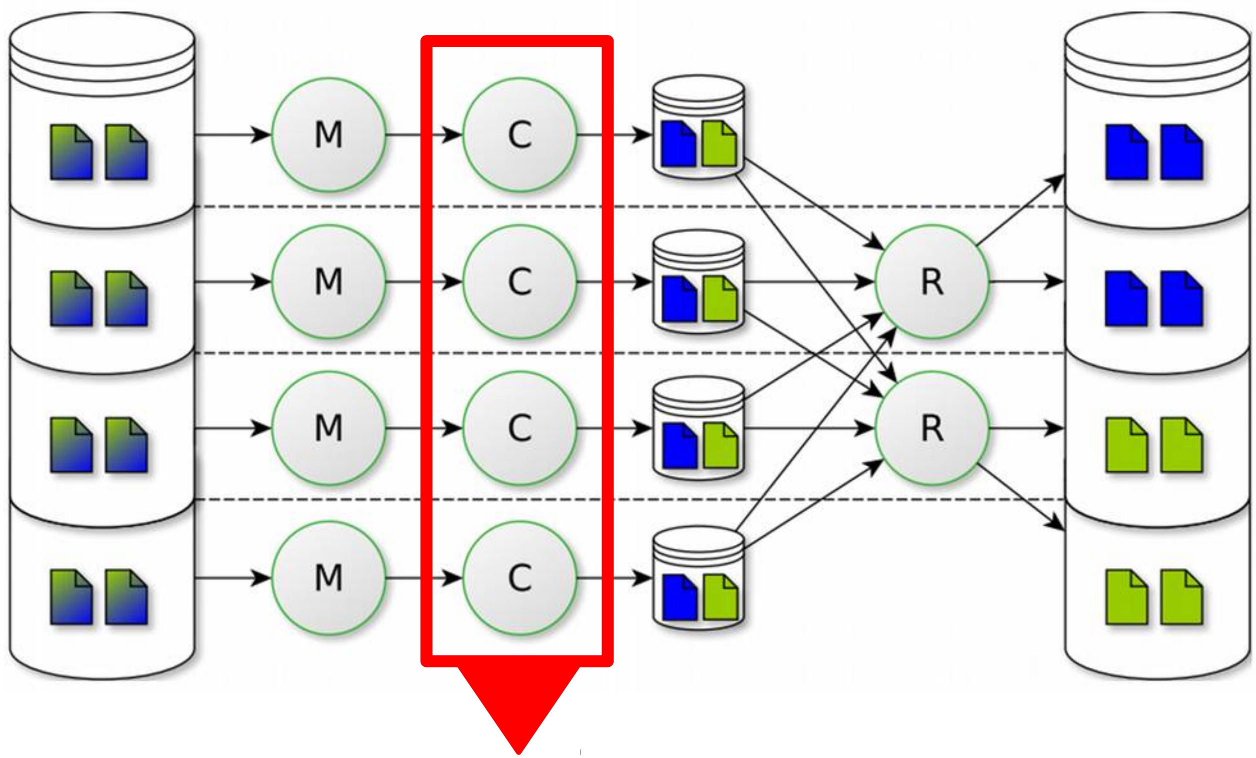
MapReduce Paper: Dean, Jeffrey, and Sanjay Ghemawat. "MapReduce: simplified data processing on large clusters." *Communications of the ACM* 51.1 (2008): 107-113.

MapReduce Example (Word Count)



	Input	Output
File Line 1:	Beer Beer Tea Coffee	
File Line 2:	Tea Tea Beer Tea	
Map 1:	(1, Beer Beer Tea Coffee)	[(Beer,1),(Beer,1),(Tea,1),(Coffee,1)]
Map 2:	(2, Tea Tea Beer Tea)	[(Tea,1),(Tea,1),(Beer,1),(Tea,1)]
Reduce 1	(Beer,[1,1,1])	(Beer,3)
Reduce 2	(Coffee,[1])	(Coffee,1)
Reduce 3	(Tea,[1,1,1,1])	(Tea,4)

MapReduce Example (Word Count)



The combine function:

- Extension to the plain MapReduce model
- Allows local pre-aggregation
  - Several combine instance may be present
    for each distinct key in the output of the map phase.
  - No synchronization point is required
    between Map and Combine.

BDAPRO
Flink API Presentations

Chen Xu, Alireza RM, Quoc Cuong To

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Flink Online Training by Data Artisans

Lectures, Hands-On Tasks, and Reference Solutions:

http://dataartisans.github.io/flink-training/index.html

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Principles and Execution Aspects of Dataflow Programs

Alireza RM

Slides prepared by Jonas Traub, Gábor Gévay, Alexander Alexandrov

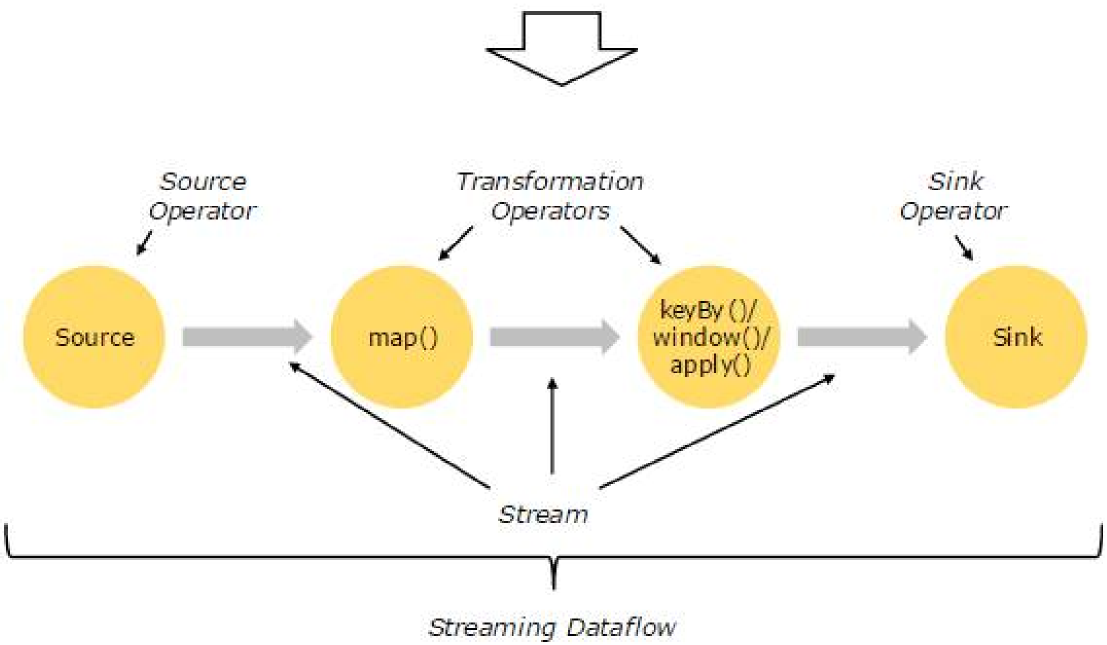
Programs and Dataflows

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

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

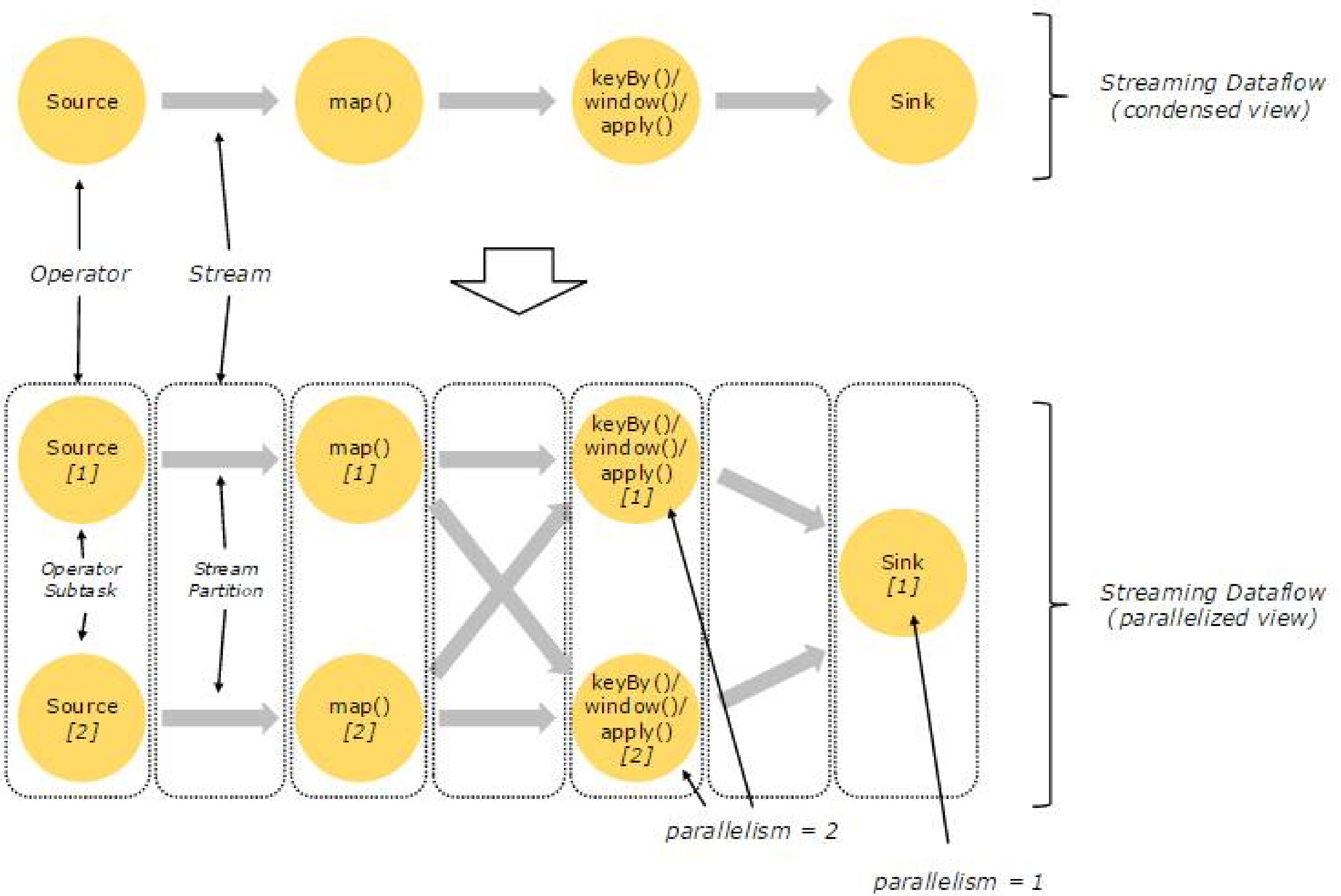
DataStream<Statistics> stats = events
        .keyBy("id")
        .timeWindow(Time.seconds(10))                                      Transformation
        .apply(new MyWindowAggregationFunction());

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



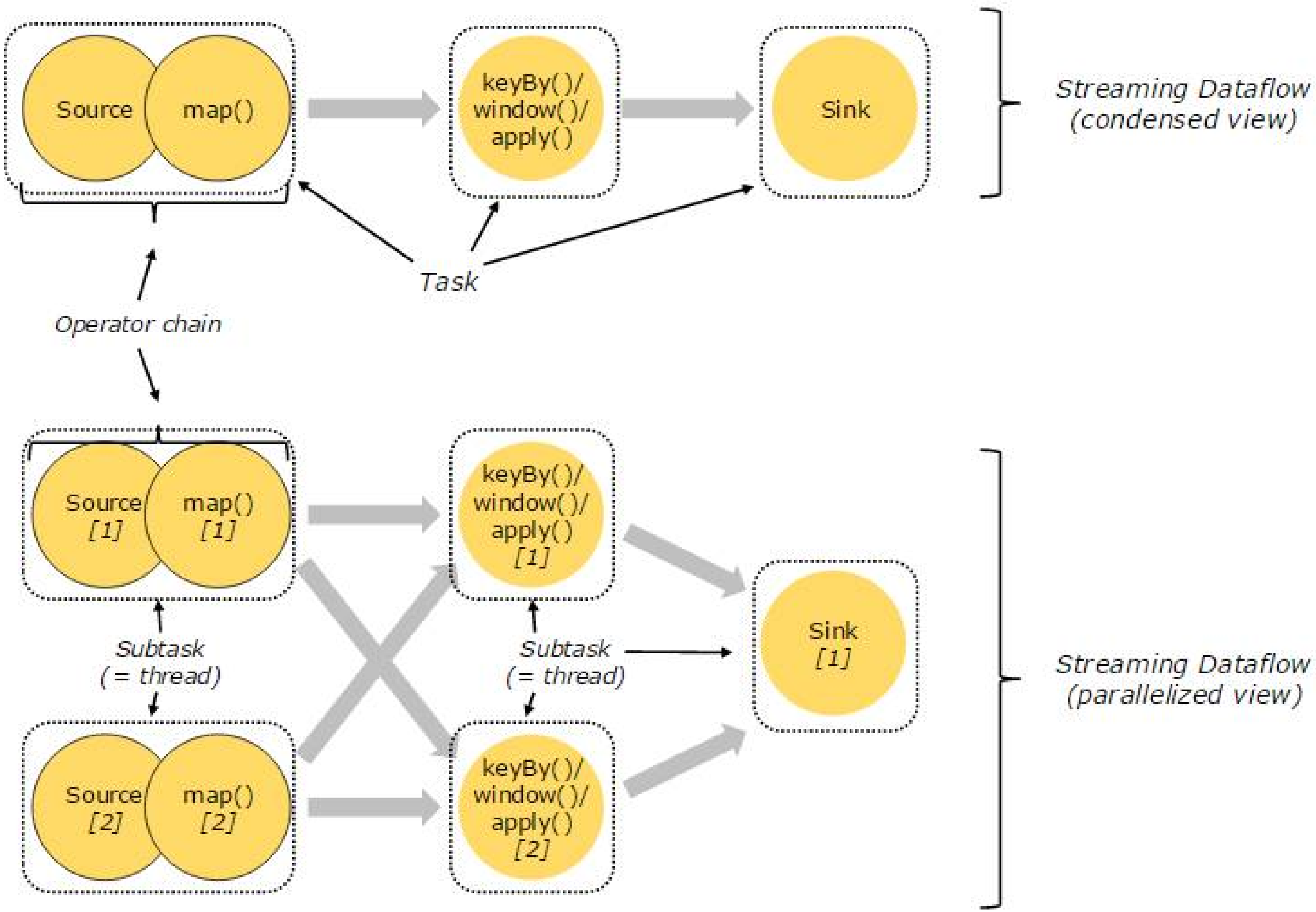
Source: https://ci.apache.org/projects/flink/flink-docs-master/concepts/concepts.html

Parallel Dataflows



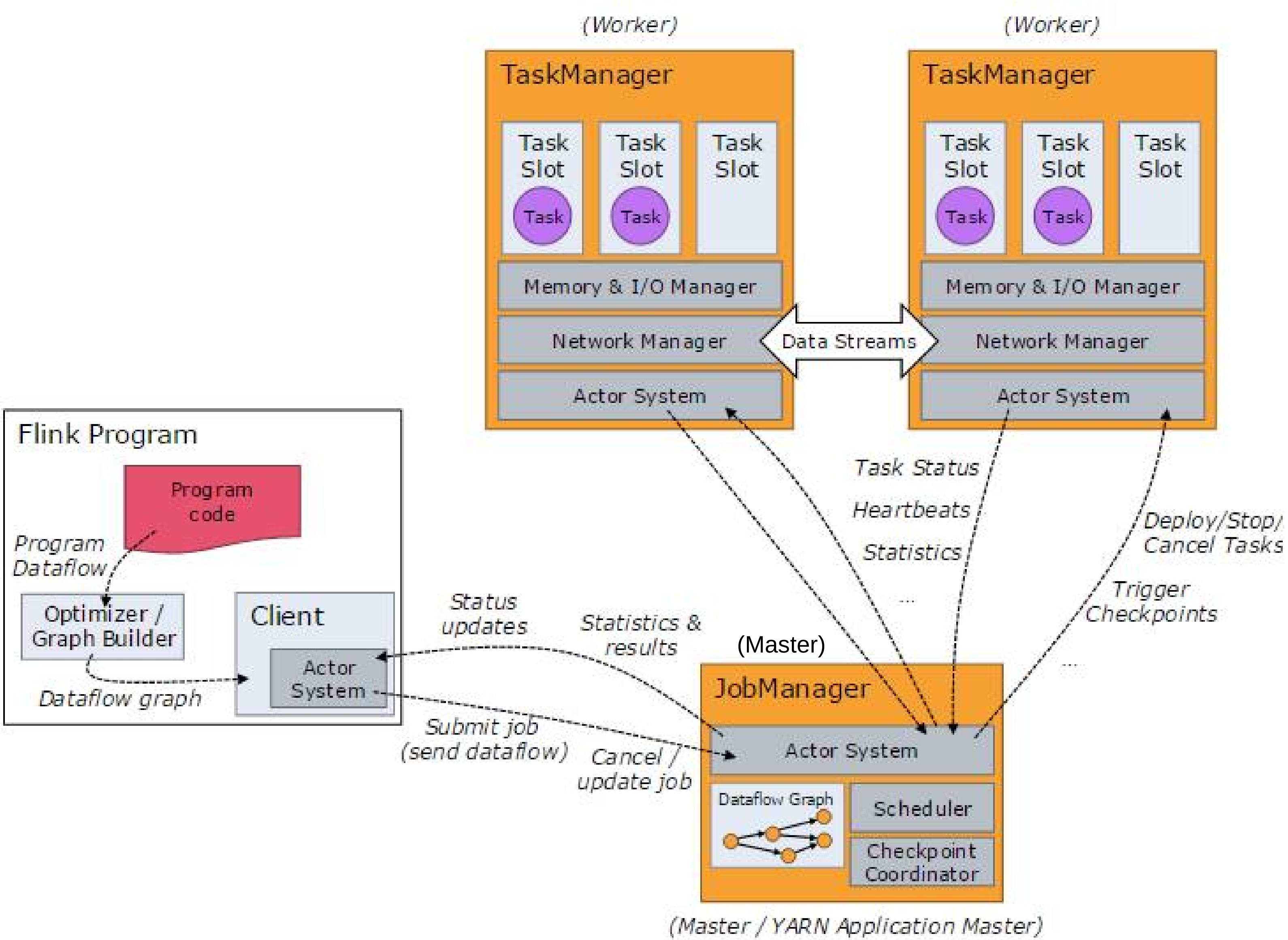
Source: https://ci.apache.org/projects/flink/flink-docs-master/concepts/concepts.html

Tasks & Operator Chains



Source: https://ci.apache.org/projects/flink/flink-docs-master/concepts/concepts.html

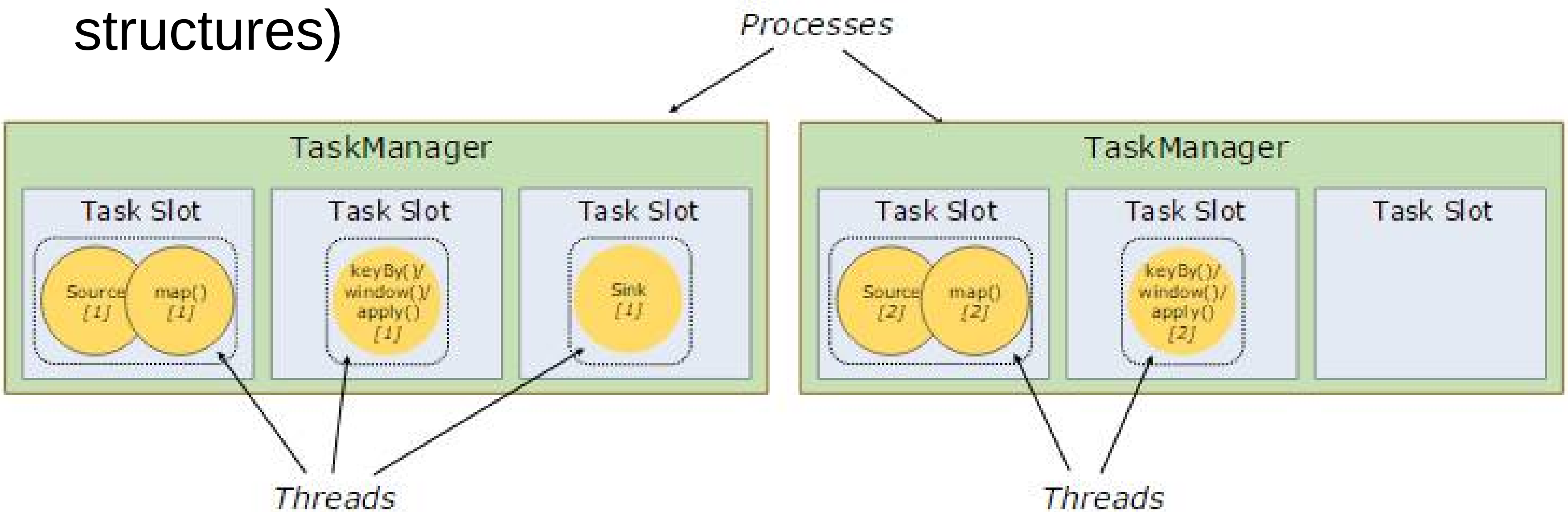
Distributed Execution (Flink Runtime)



Source: https://ci.apache.org/projects/flink/flink-docs-release-1.2/concepts/runtime.html

Workers, Slots, and Resources

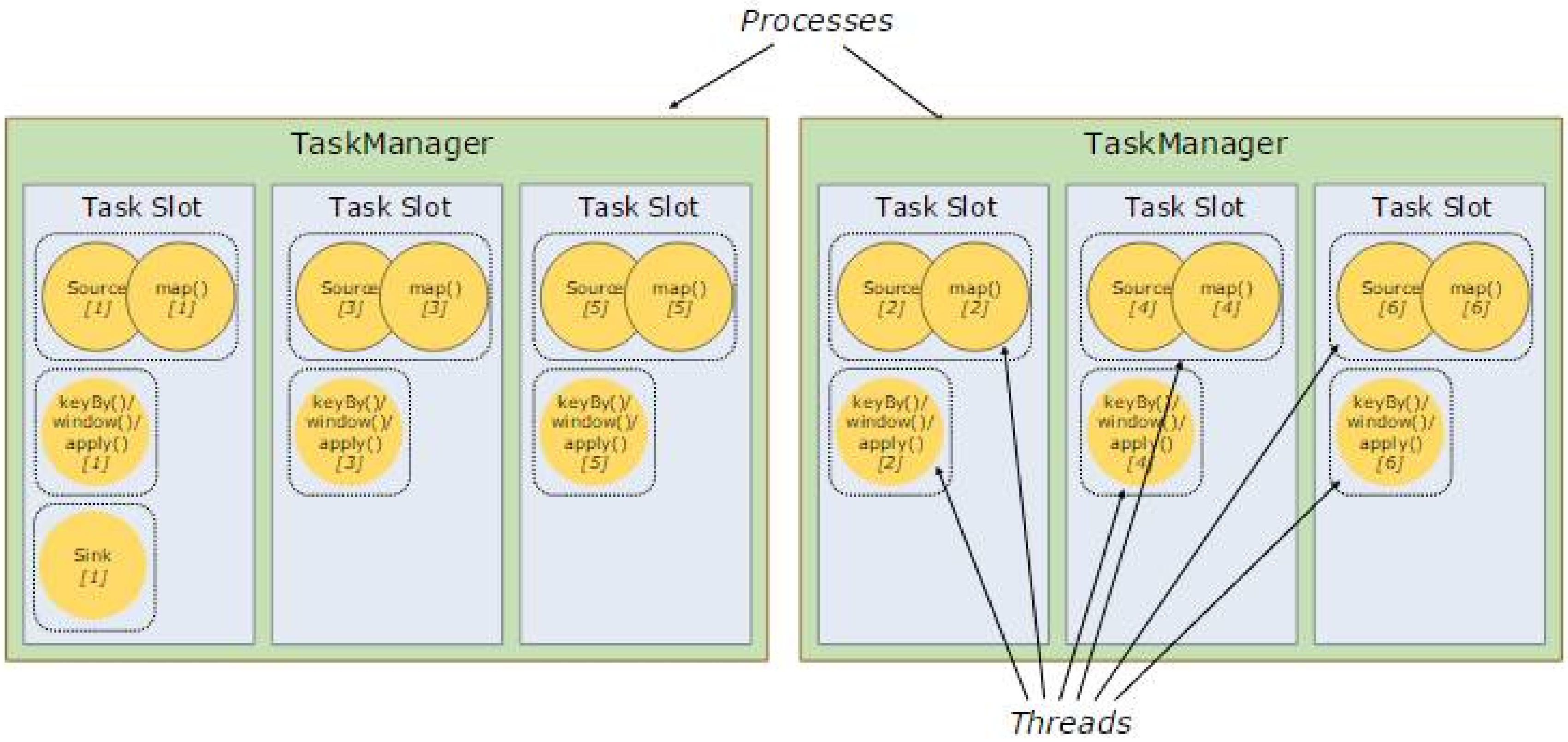
- Workers are JVM processes executing one or more tasks in separate threads
- Each worker has one or more task slots with fixed resources, e.g., memory
- One slot TaskManager runs in separate JVM otherwise subtasks share same JVM (share TCP, heartbeats, data structures)



Source: https://ci.apache.org/projects/flink/flink-docs-release-1.2/concepts/runtime.html

Workers, Slots, and Resources

- Subtasks of different tasks of same job can share slots
  - No need to calculate number of tasks of a program
  - Resource utilization by distributing heavy subtasks between TaskManagers



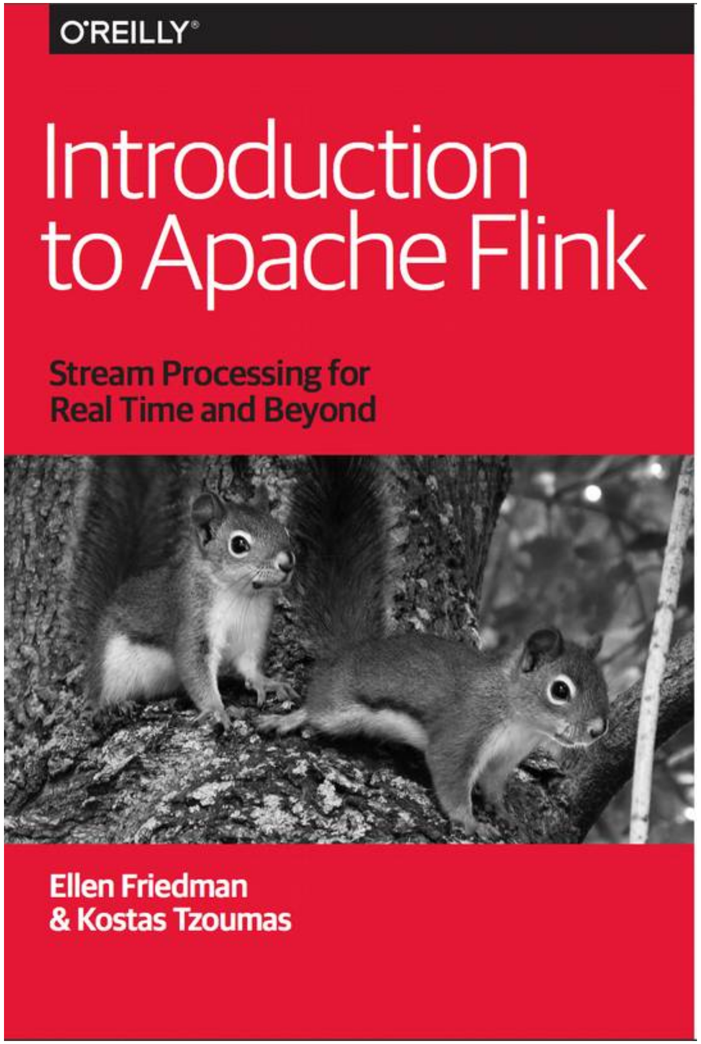
Source: https://ci.apache.org/projects/flink/flink-docs-release-1.2/concepts/runtime.html

Concepts of Dataflow Programs

Please find the full article in the Apache Flink Documentation:

https://ci.apache.org/projects/flink/flink-docs-master/concepts/concepts.html

Apache Flink: Recommended Reading



Introduction to Apache Flink

English; e-book; September 2016

Authors:
- Ellen Friedman
- Kostas Tzoumas

Available free
https://www.mapr.com/introduction-to-apache-flink

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Comparison of Runtime Concepts

Quoc Cuong To

Slides prepared by Jonas Traub, Gábor Gévay, Alexander Alexandrov

Pipelined vs. Batch Execution

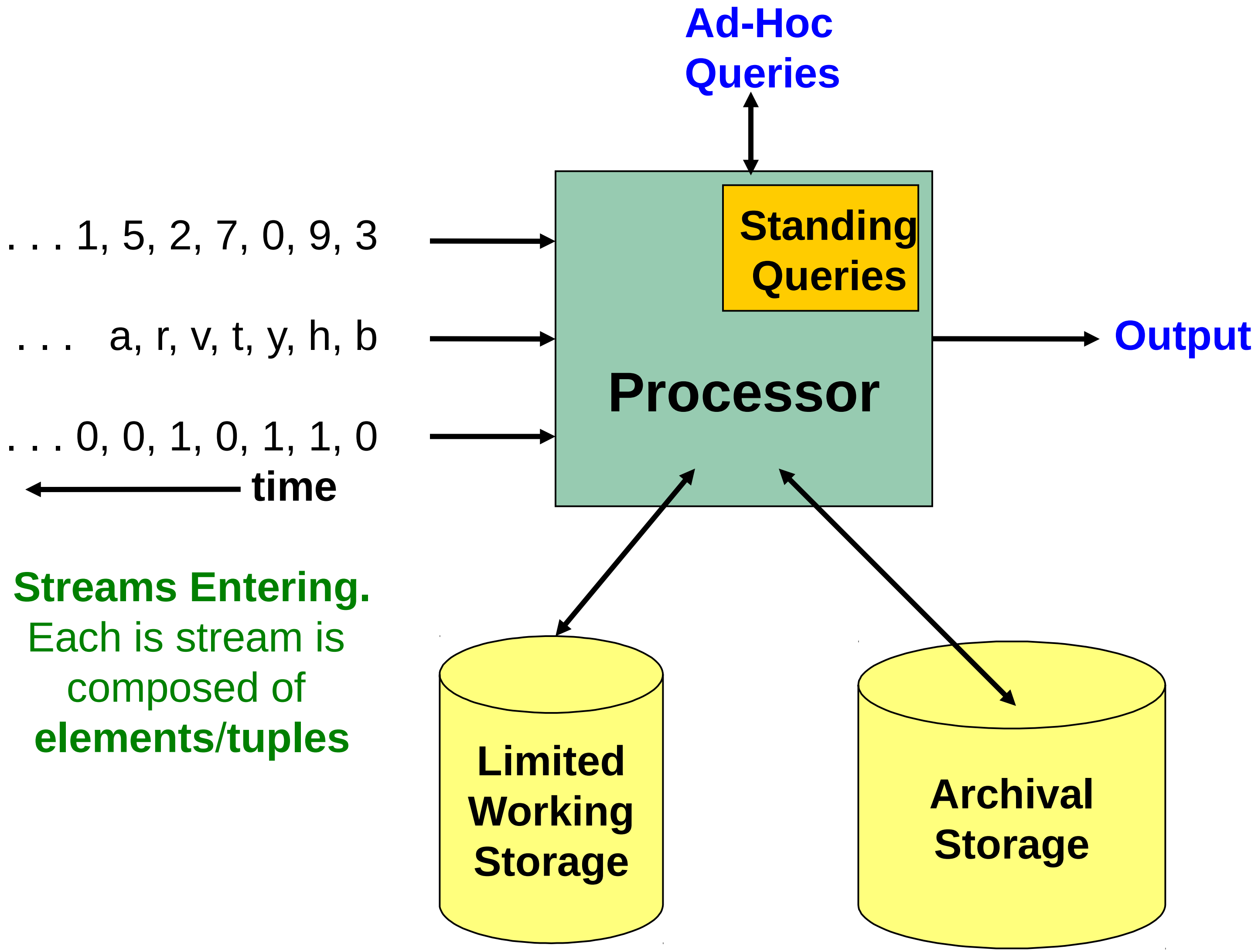
Batch Execution

- Finite data
- Allows synchronization points (w/o windowing)
- Stream processing in micro-batches

Pipelined Execution

- Conceptually infinite input data streams
- Enables low latency processing
- Native streaming support

The General Stream Processing Model



Streams Entering.
Each is stream is composed of **elements/tuples**

Souce: Rajaraman, A., & Ullman, J. D. (2012). Mining of massive datasets (Vol. 77). Cambridge: Cambridge University Press. Chapter 4 http://www.mmds.org/

Stream Processing vs. Batch Processing

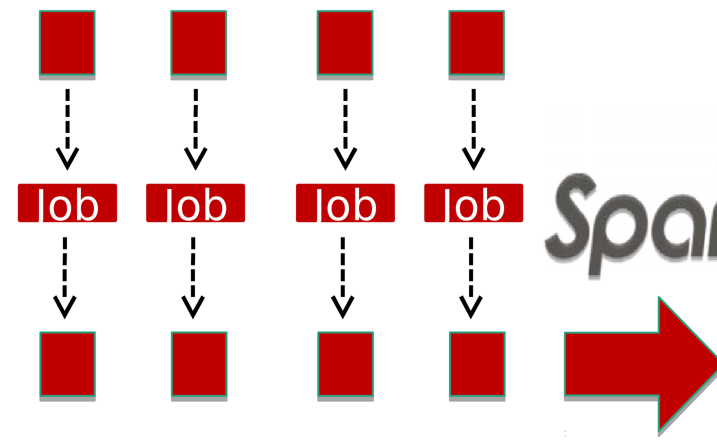
	Batch Processing	Stream Processing
INBOUND DATA	Data-items are pulled from storage as needed	Data-items are pushed to the system (externally controlled src.)
OPERATORS	Computation in stages; Operators run one after another Outputs are materialized in memory or on disk between stages	Full job graph is deployed; Long running operators Output data-items are directly sent to the next operator
QUERIES	Finite: Finished after the batch is processed	Long running: Continuously produce results for windows
RUNTIME	True streaming is not possible on a batch processing runtime	Batch processing can be done on a stream processing runtime

Native Streaming vs. D-Streams

Discretized Streams (D-Streams)

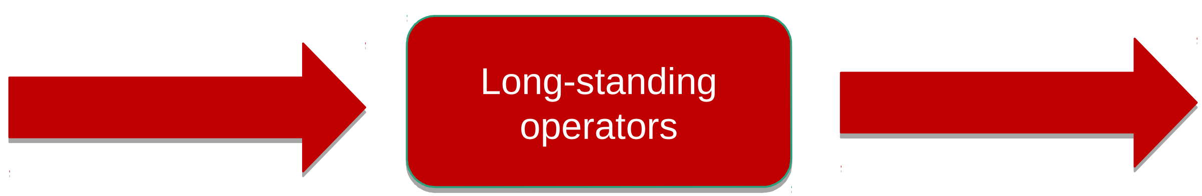
Paper by Zaharia, Matei, et al.:
"Discretized streams: an efficient and fault-tolerant model for stream processing on large clusters." 2012.

Stream discretizer




```
while (true) {
  // get next few records
  // issue batch computation
}
```

Native streaming




```
while (true) {
   // process next record
}
```

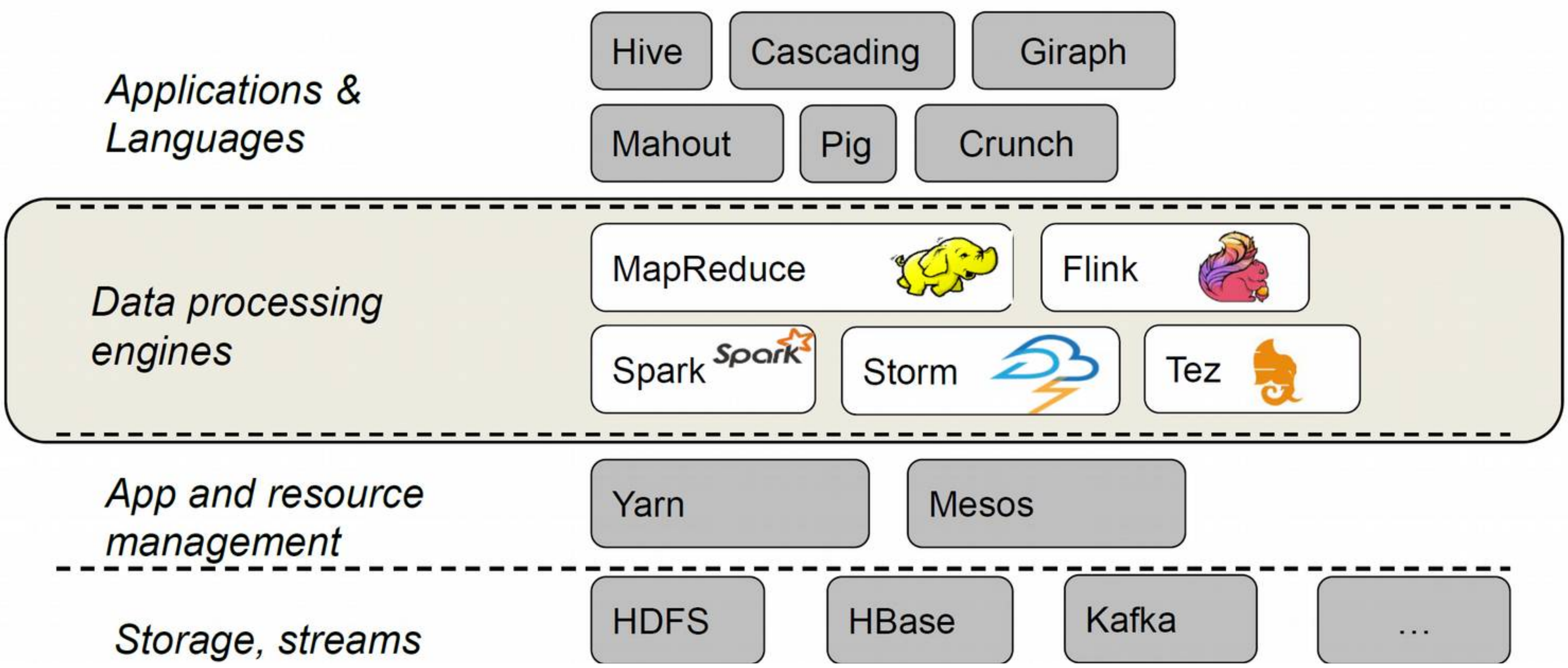
Slide by Gyula Fóra

Problems of Mini-Batch

- **Latency**: Each mini-batch schedules a new job, loads user libraries, establishes DB connections, etc
- **Programming model**: Does not separate business logic from recovery – changing the mini-batch size changes query results
- **Power**: Keeping and updating state across mini-batches only possible by immutable computations

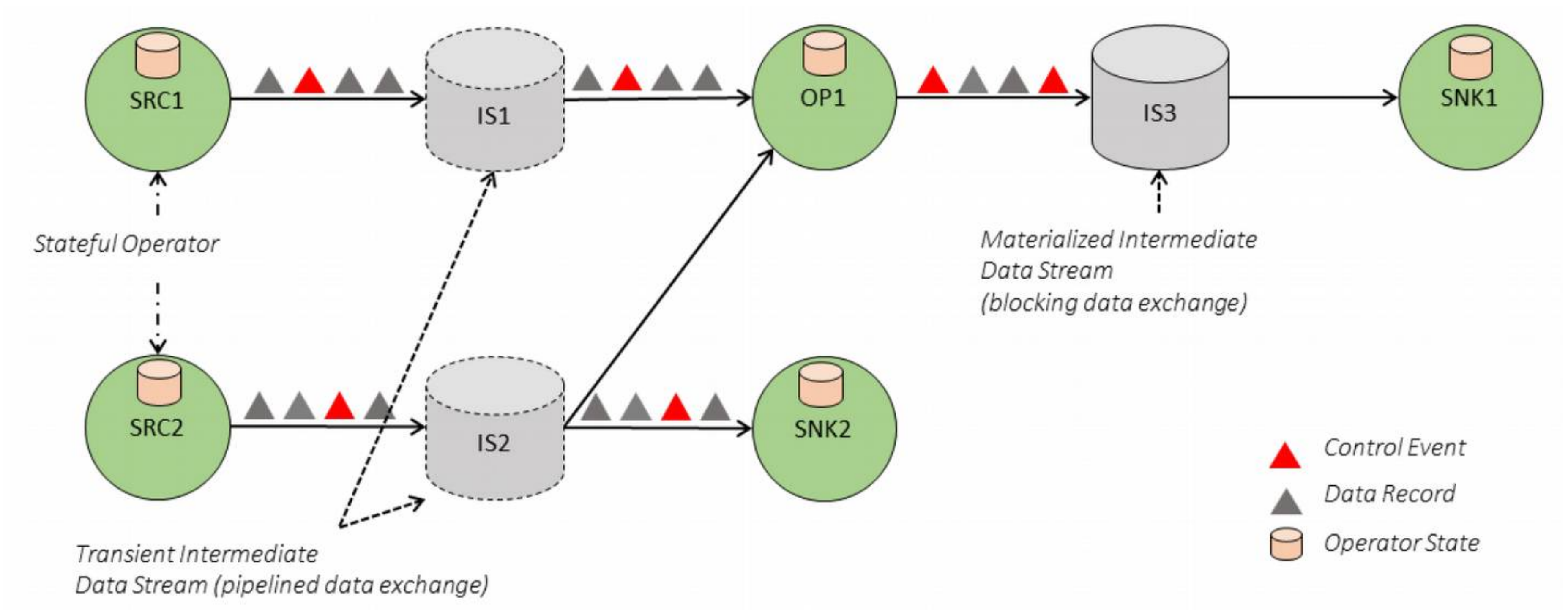
Slide by Tilmann Rabl

Flink in the Analytics Ecosystem



Flink Execution Model

- Flink program = DAG of operators and intermediate streams
- Operator = computation logic + state
- Intermediate streams = logical stream of records

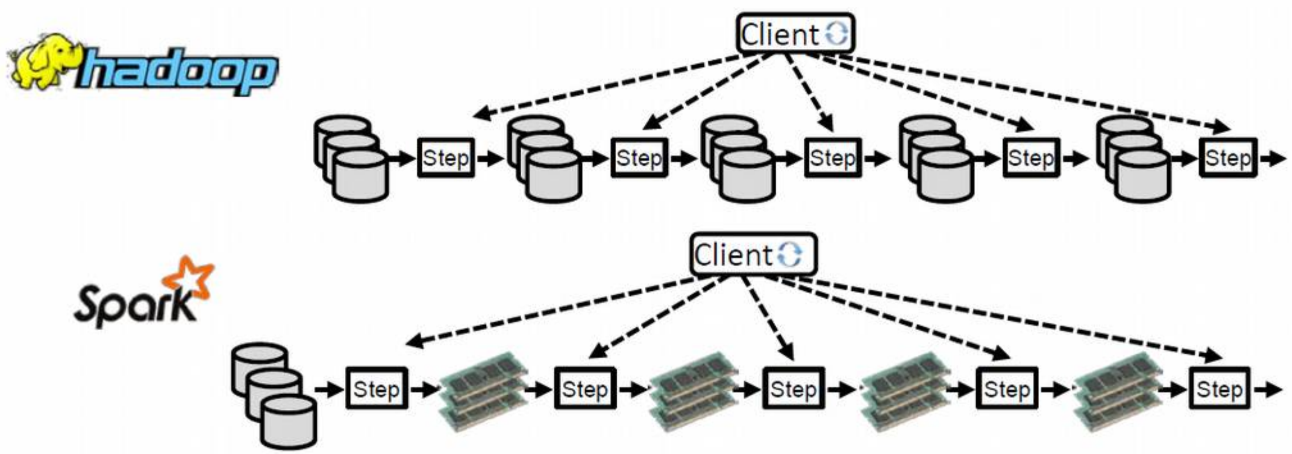


Built-in vs. driver-based looping

Driver-based looping

Loop outside the system, in driver program

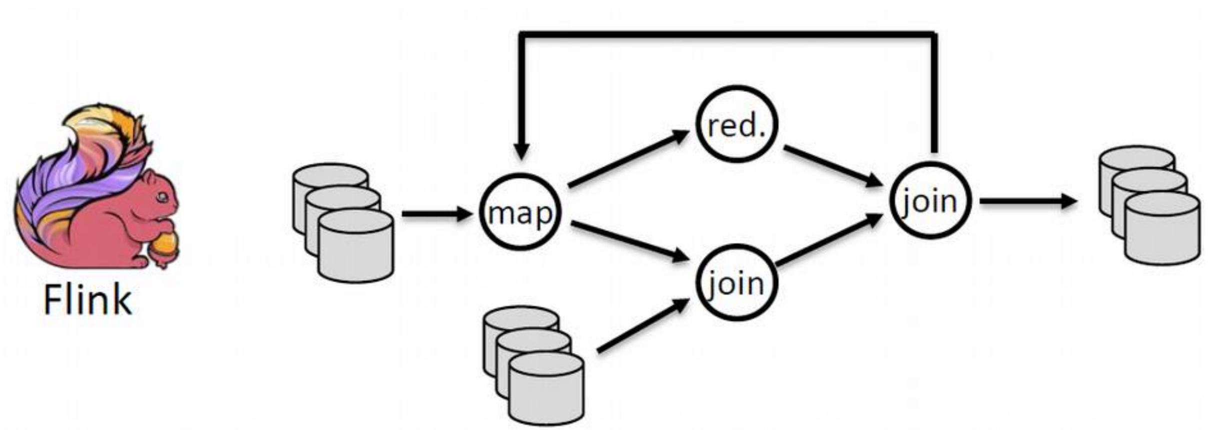
Iterative program looks like many independent jobs



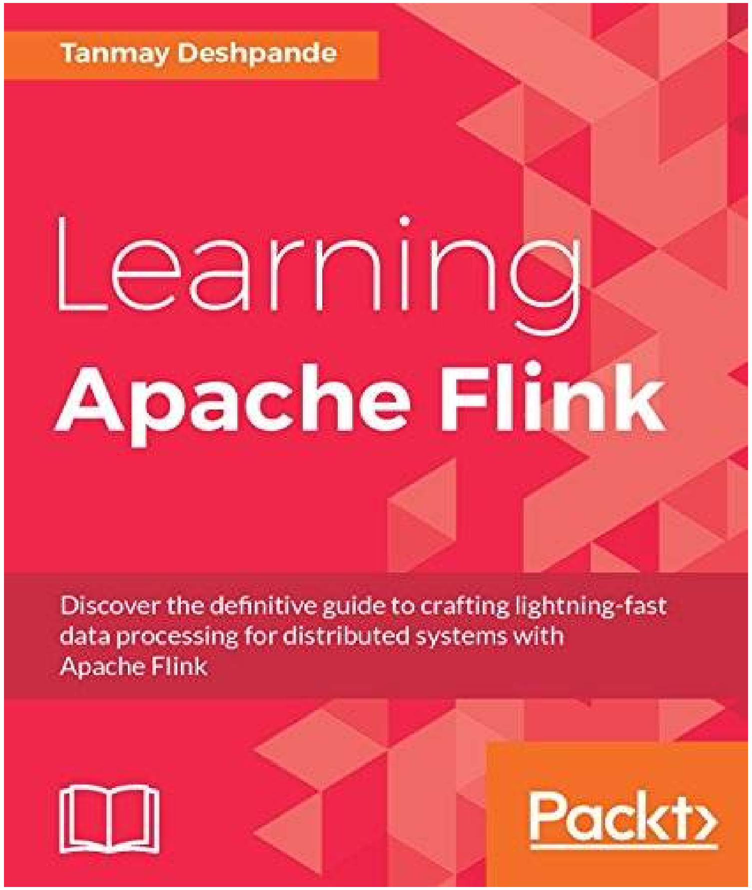
Native looping

Dataflows with feedback Edges

System is iteration-aware, can optimize the job



Apache Flink: Recommended Reading



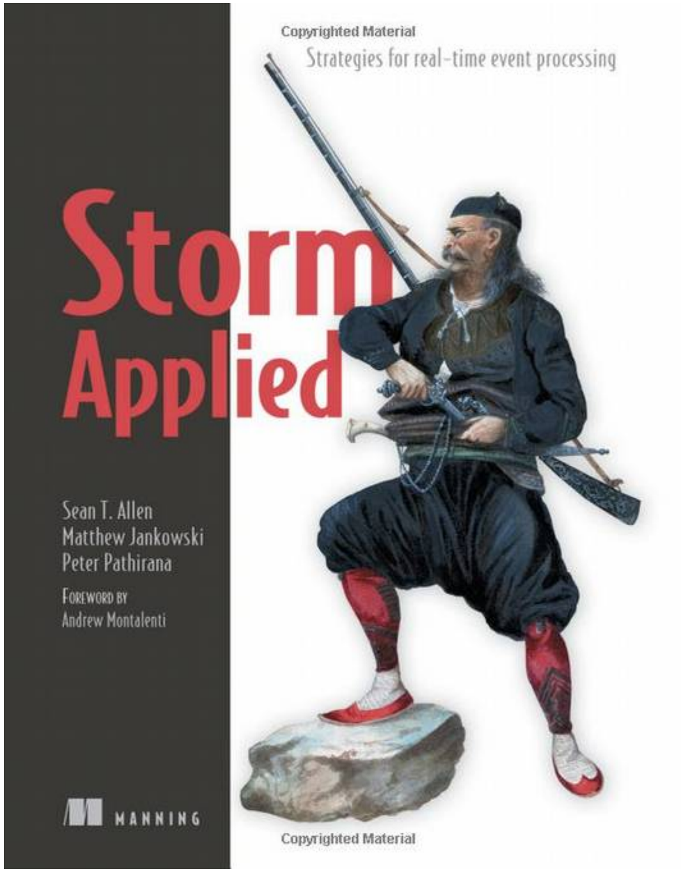
Learning Apache Flink

English; Paperback;

Authors:

Tanmay Deshpande

Apache Storm: Recommended Reading



Storm Applied: Strategies for Real-Time Event Processing

English; Paperback; April 2015

Authors:

- Sean T. Allen
- Peter Pathirana
- Matthew Jankowski

Available in TU-Berlin library

http://portal.ub.tu-berlin.de/TUB:TUB_LOCAL:tub_aleph002091017

BDAPRO Project Presentations

Chen Xu, Alireza RM, Quoc Cuong To