Apache Flink- A System for Batch and Realtime Stream Processing

Lecture Notes

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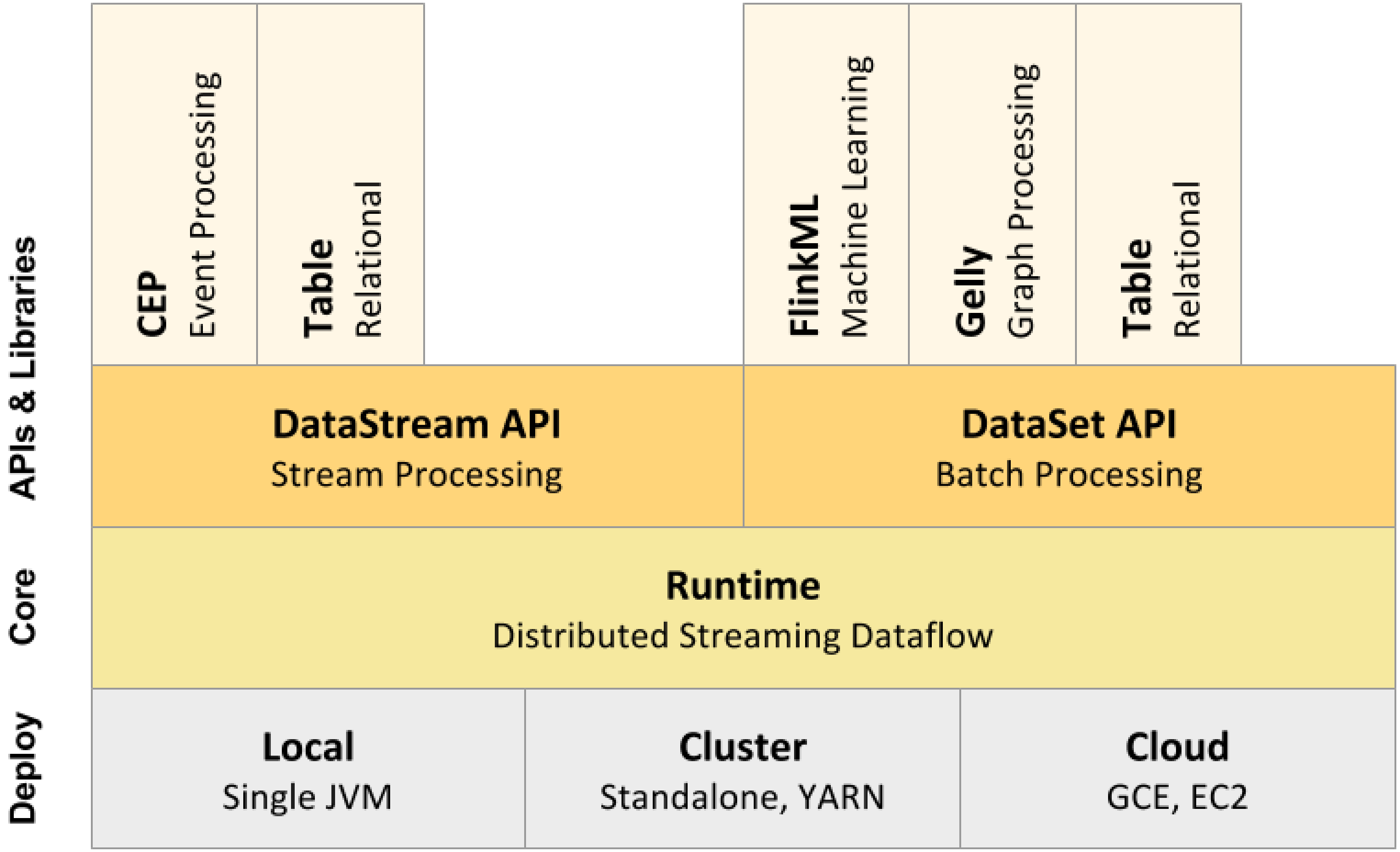
Introduction to Apache Flink

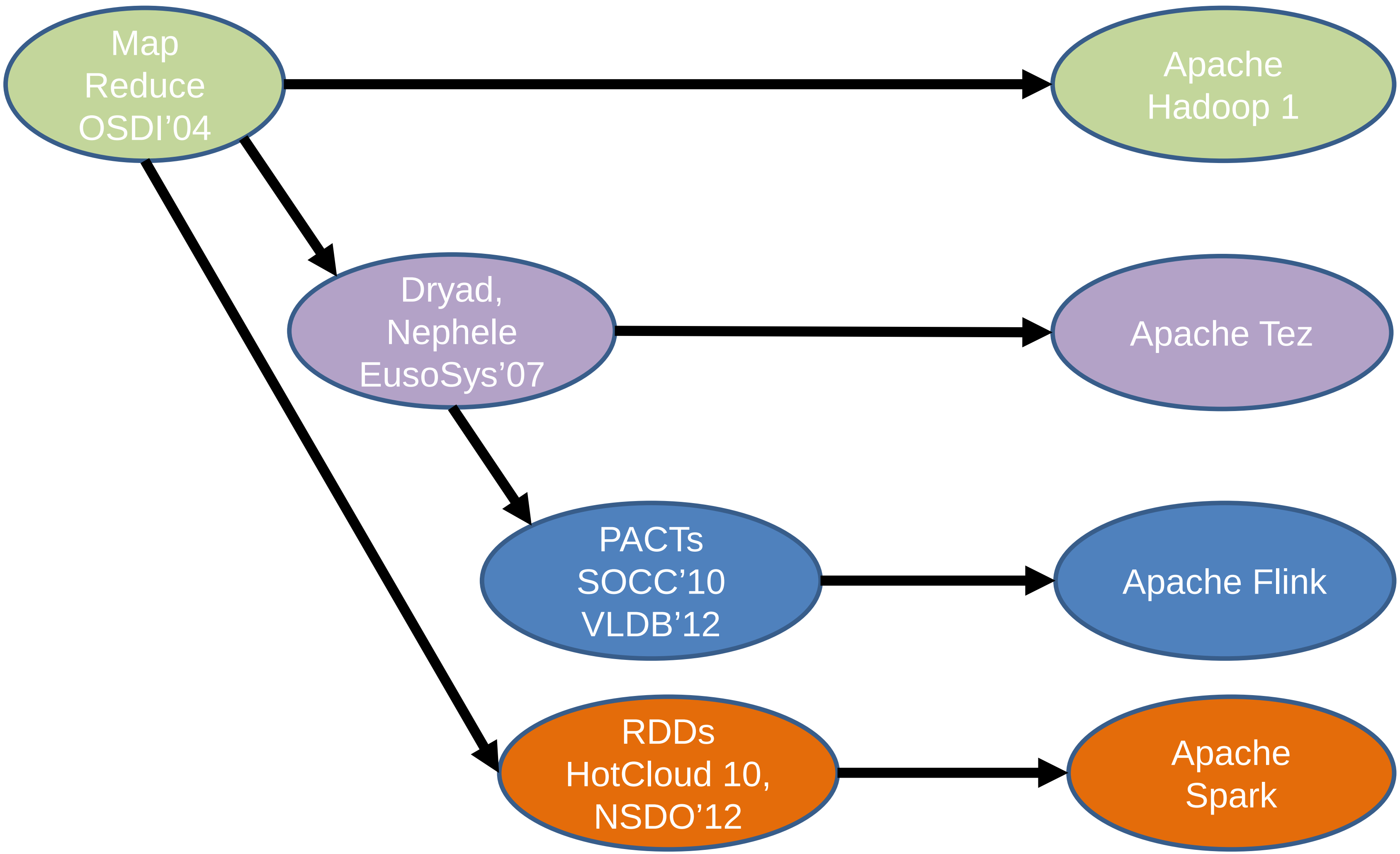
- Apache Flink is an open source

  Stream Processing Framework
- Low latency
- High throughput
- Stateful Operators
- Distributed Execution
- Developed at the Apache Software Foundation
- 1.0.0 released in March 2016, used in production

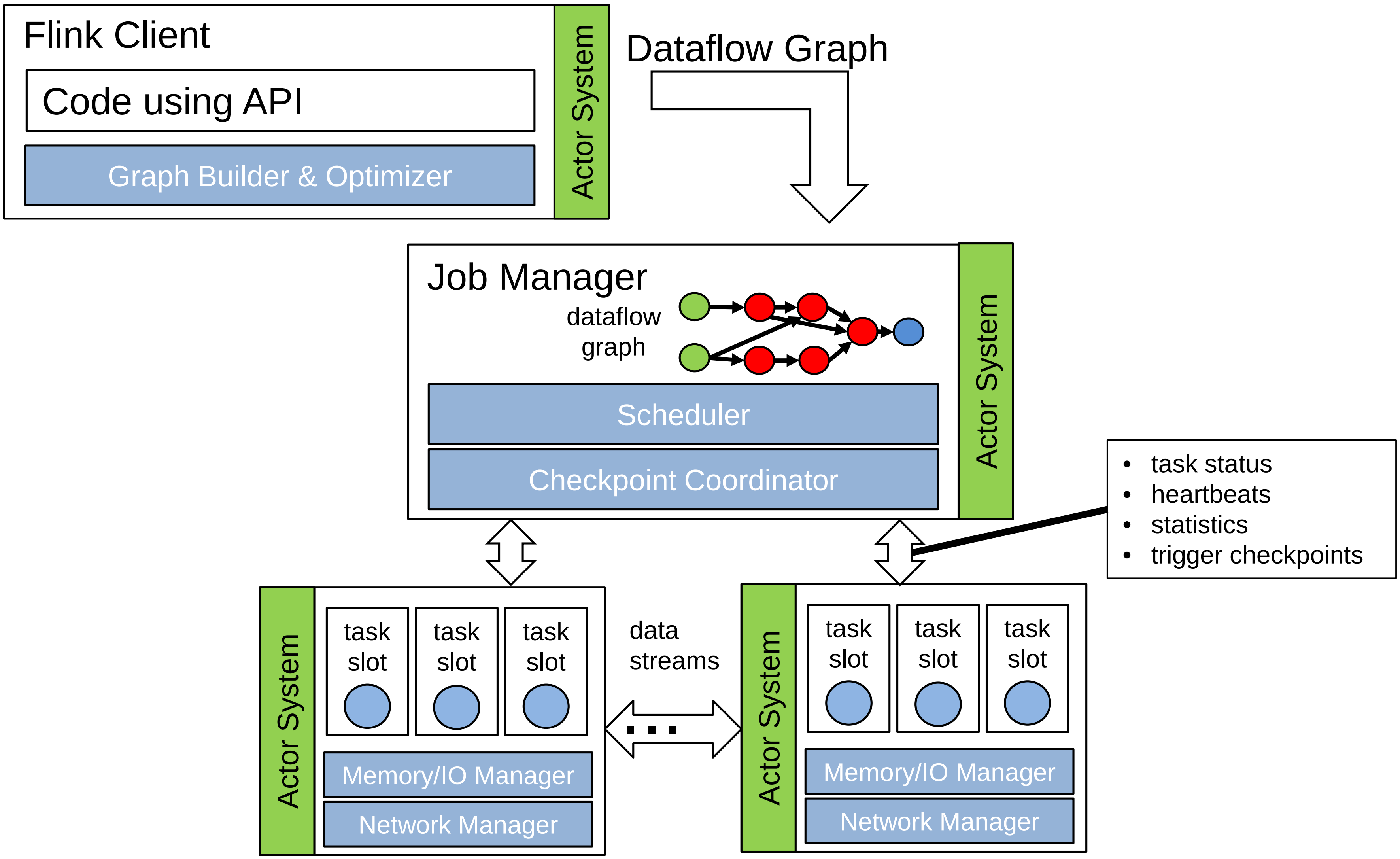
Flink Software Stack



System Legacy

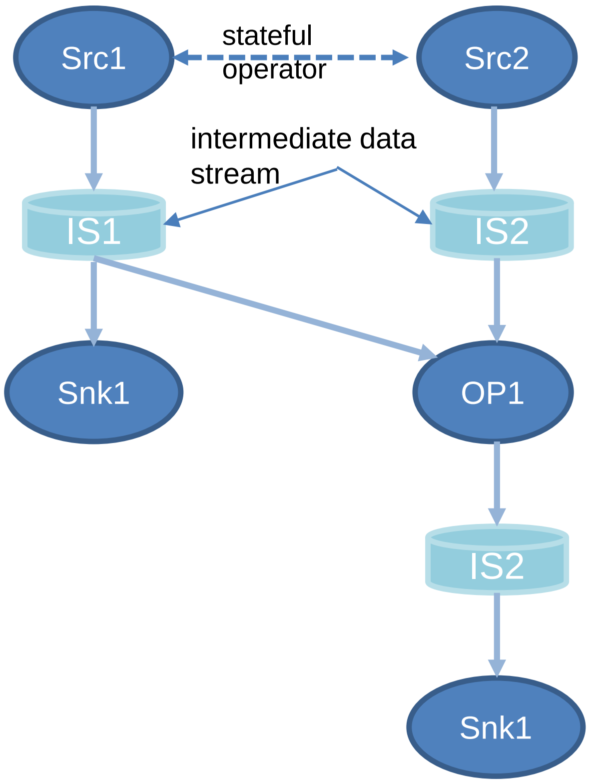


Architecture



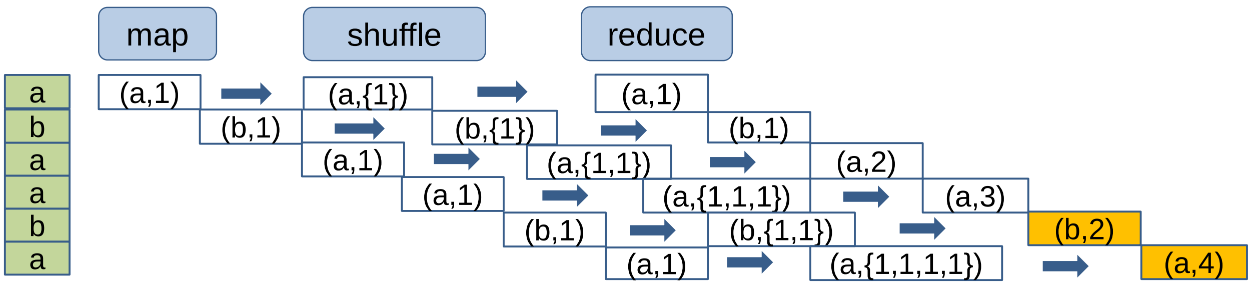
Dataflow Graphs

- all APIs (e.g. DataSet, DataStream,) compile to Dataflow Graphs
- (stateful) operators (filter, joins,..) = nodes
- data streams = links
- in parallel processing split into:
  - operators are executed in subtasks
  - stream partitions
- streams may p2p, broadcast, merge, fan-out, repartitions

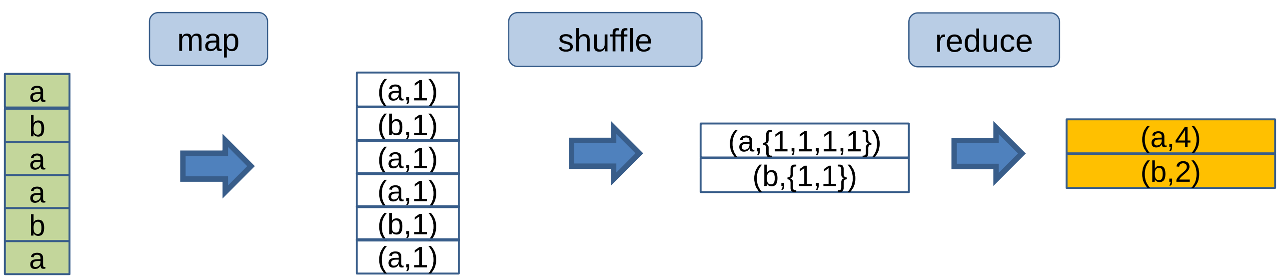


Intermediate Data Streams

- core abstraction for data exchange
- may or may not be materialized on disk
- **pipelined execution**: data is continuously produced, buffered and consumed



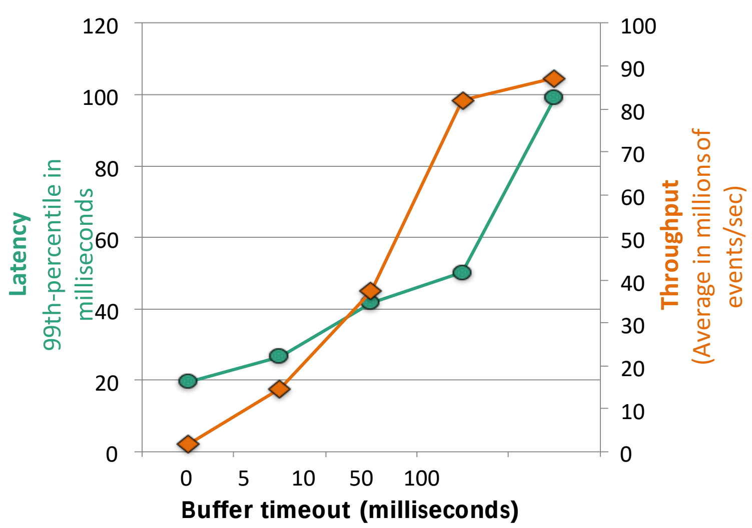
- **blocking data exchange**: output is generated, stored and then exchanged with the consumer. (->complete intermediate results of a stream must be stored)



Latency and Throughput

Data exchange based on buffers:
- data record ready => one/many buffers
- buffer is sent to consumer when it is full / time out

$\Rightarrow$ the large buffers increase throughput (less overhead)
$\Rightarrow$ low time out enable low latencies
(real time processing = data is processed within a guaranteed time limit)

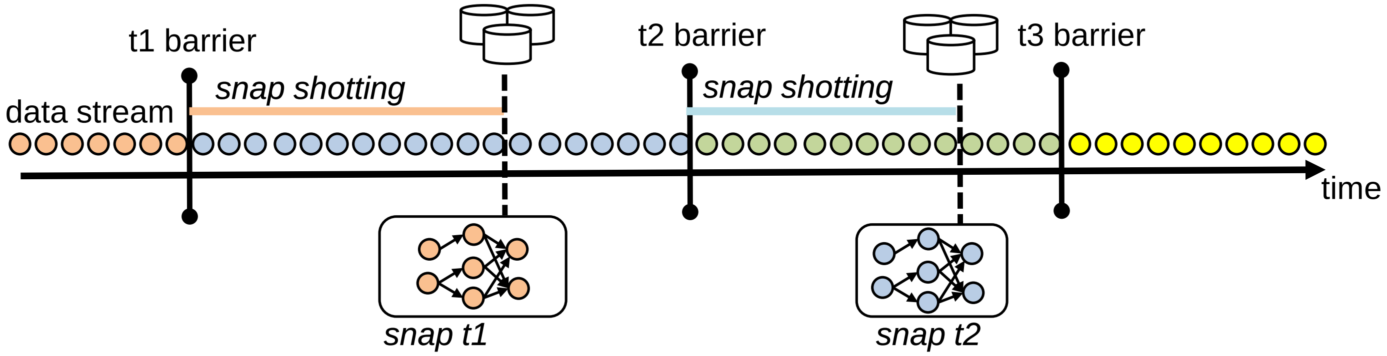


Control Events and Fault Tolerance

- Examplary types of **control events**:
  - **check point barrier**: coordinate checkpoints by dividing stream into pre-checkpoint and post-checkpoint
  - **watermarks**: signaling the progress of event-time within the stream partition
  - **iteration barriers**: signals end of a superstep for iterative processing
- Control events are **injected into the stream** and provide operator nodes the position in the data set.
- reliable execution with **exactly once**
- **consistency is guaranteed** (no availability on all nodes)
- check-pointing and partial re-execution
- based on the assumption that data source is **persistent and replayable** (e.g. files, Apache Kafka)
- regular snapshots to **prevent unbounded recomputation**

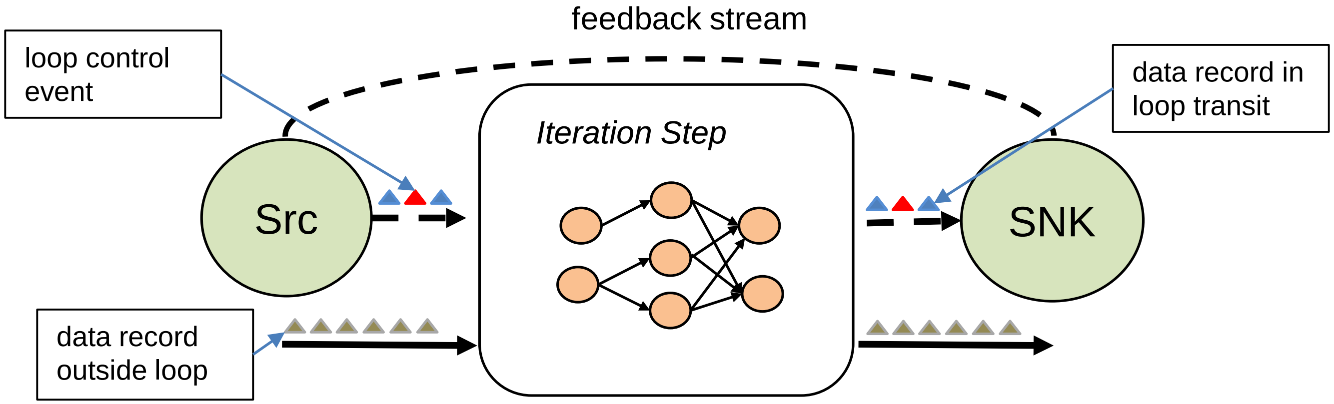
Asynchronous Barrier Snapshotting

- barrier corresponds to a logical time => separate the stream to mark the snapshotted part
- barriers are injected into the stream
- wait until all barriers from input are received
- write out state to durable storage (=disk)
- checkpoint barriers are sent from upstream to downstream after checkpoint
- recovery: restart computation from the last successful snapshot



Iterative Data Flows

- Iterative algorithms are often employed for Data Mining, Machine Learning or Graph processing
- in other cloud-based computation frameworks (e.g. Hadoop, Spark):
  - run a loop in the client program
  - in each iteration a parallel execution is started (compare to k-Means on Hadoop)
- Flink provides an integrated iteration processing
- iteration step = special operators contain execution graphs
- iteration head and iteration tail are connected via feedback stream (handles what to keep between iterations)



Stream Processing with Dataflows

- **Flink manages time**: out-of-order events, windows, user-defined states
- **two notions of time**:
  - event time: time when the event is originated (e.g. timestamp)
  - processing time: wall-clock time of processing the event at worker X
- **Skew between both is possible** in distributed environments: *objects may arrive out of order with respect to event time*
- **low watermarks**: mark global progress measure (e.g. all events lower than timestamp t have entered an operator)
- Watermarks **originate at the sources of the graph**
- **operators decide** how to react
- operators with multiple inputs forward **minimal watermarks**

Stateful Streams Processing

- stateless operators: operator works independent for all inputs
  - for example simple map function in word count : `lambda x: (x,1)`
  - no memory, not depending on the input order
- stateful operators: operator has an internal state
  - for example: regression function: $a \cdot x+t$.
    (a and t are trained over the stream of input data)
  - the state stores models parameters
- states are incorporated into the API by :
  - operator interfaces registering local variables
  - operator-state abstractions for declaring portioned key-value states as there associated operations
- states can be checkpointed

Stream Windows

- Stateful operator configured via:
  - **assigner**: assigns each record to one/many logical windows
  - **trigger(optional)**: states the time an operation on the windows is performed
  - **evictor(optional)**: defines which records to retain in each window
- Predefined operator available e.g. sliding time window
- user-defined functions allow flexible customizing

Examples:

```
stream
.window(SlidingTimeWindows.of(Time.of(6, SECONDS), Time.of(2, SECONDS))
.trigger(EventTimeTrigger.create())
```

```
stream
.window(GlobalWindow.create())
.trigger(Count.of(1000))
.evict(Count.of(100))
```

Batch Processing

- batch processing can be considered as special case of streams (bounded streams)
- Syntax for batch processing can be defined in a simpler way
- additional options for optimizing the processing might be possible

⇒ Flink offers additional functionality for batch processing

⇒ Blocked execution: break up large computations to isolated stages

⇒ No periodic snapshotting when overhead is large
instead use last materialized intermediate stream

⇒ blocking is implemented as an operator explicitly waiting until the complete input is consumed => runtime environment does not distinguish

⇒ disk spill-off might become necessary

⇒ Flink provides a dedicated DataSet API with familiar functions e.g. map

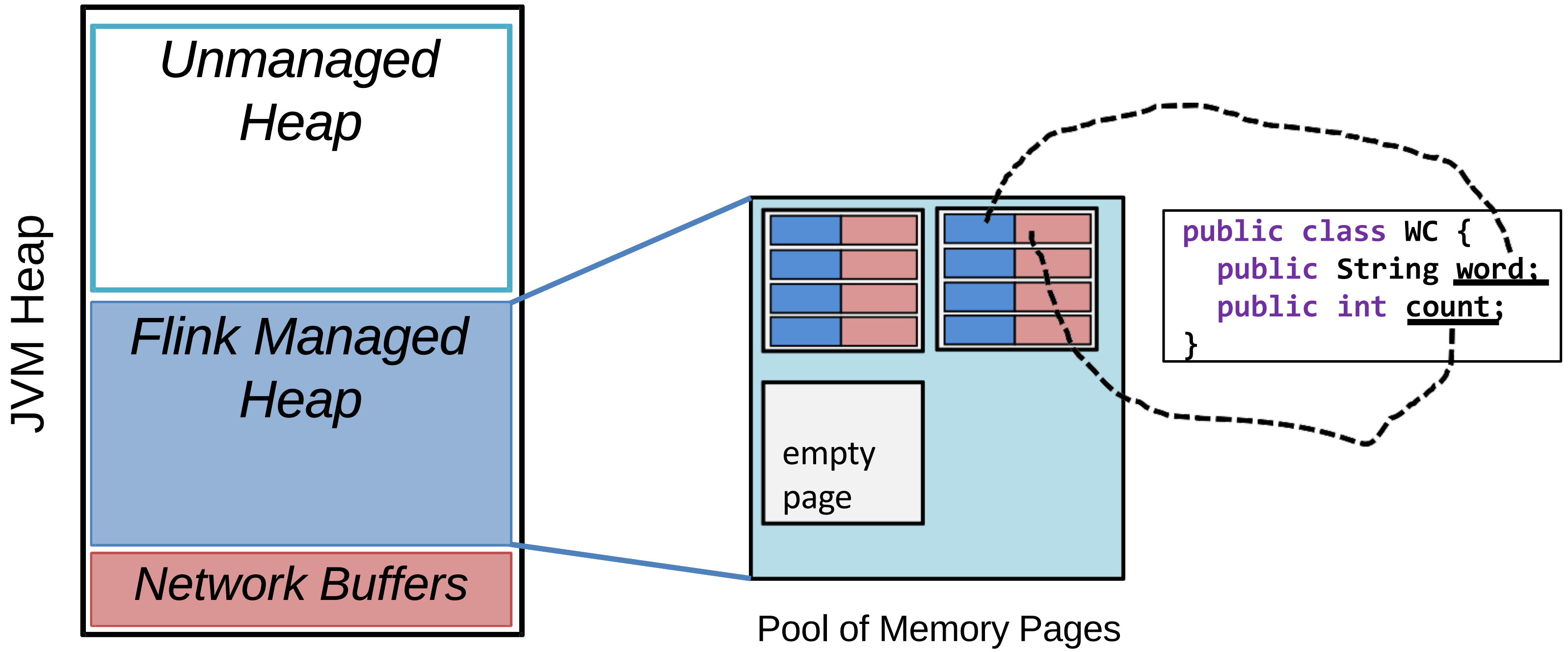
⇒ Query optimization is used to transform API programs into efficient graphs

Query Optimization

- query optimizer is built on techniques from parallel databases:
  - plan equivalence
  - cost modeling
  - interesting-property propagation
- problem the operators have no predefined semantics (user defined functions!)
- cardinality and cost-estimation are hard to perform for the same reasons
- support execution strategies such as:
  - repartition and broadcast
  - sort-based grouping
  - sort- and hash-based joins
- Optimizer evaluated physical plans by interesting property propagation
- costs include disk I/O and CPU cost
- to handle user defined functions, hints are allowed

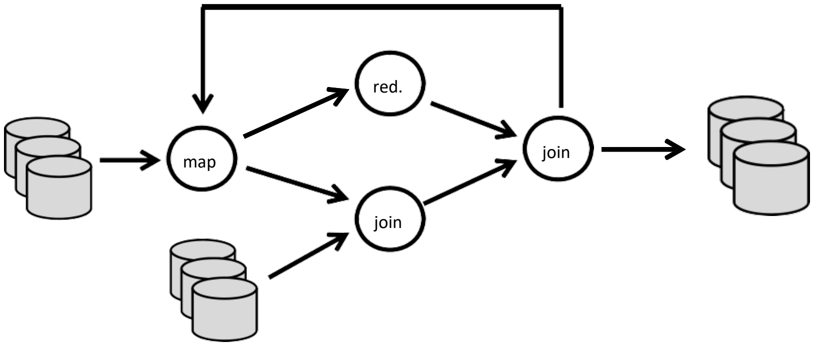
Memory Management

- Flink serializes data into memory segments instead of using the JVM heap
- operations work as much as possible on the binary data
  => reduces the overhead for serialization /deserialization
- for arbitrary objects, Flink uses type inference and custom serialization
- Binary representation and storing data off-heap reduces garbage collection overhead
- spilling data to disk is still fallback in case



Batch Iterations

- iterative methods are common in data analytics:
  - parallel gradient descent
  - expectation maximization
- Parallelization methods for iterative methods
  - Bulk Synchronous Parallel (BSP)
  - Stale Synchronous Parallel (SSP)
- Flink allows various iteration methods by providing iteration control events
- For example: in BSP mark begin and end of supersteps
- includes novel optimization concepts:
  - delta iterations: exploit sparse computational dependencies



Word Count in Java

```
ExecutionEnvironment env = ExecutionEnvironment.getExecutionEnvironment();
DataSet<String> text = readTextFile (input);
DataSet<Tuple2<String, Integer>> counts= text
.map (l -> l.split("\\W+"))
.flatMap ((String[] tokens,
Collector<Tuple2<String, Integer>> out) -> { Arrays.stream(tokens)
.filter(t -> t.length() > 0)
.forEach(t -> out.collect(new Tuple2<>(t, 1)));
    })
.groupBy(0)
.sum(1);
env.execute("Word Count Example");
```

API Examples

k-Means in Java

```
ExecutionEnvironment env = ExecutionEnvironment.getExecutionEnvironment();

DataSet<Point> points = getPointDataSet(params, env);
DataSet<Centroid> centroids = getCentroidDataSet(params, env);

IterativeDataSet<Centroid> loop = centroids.iterate(params.getInt("iterations",
10));

DataSet<Centroid> newCentroids = points.map(new
SelectNearestCenter()).withBroadcastSet(loop, "centroids").map(new CountAppender())
.groupBy(0).reduce(new CentroidAccumulator())
.map(new CentroidAverager());

DataSet<Centroid> finalCentroids = loop.closeWith(newCentroids);

DataSet<Tuple2<Integer, Point>> clusteredPoints = points
.map(new SelectNearestCenter()).withBroadcastSet(finalCentroids, "centroids");
```

References

- https://flink.apache.org/
- Carbone et. Al: Apache Flink: Stream and Batch Processing in a Sinlge Engine, IEEE Bulletin of the Technical Committee on Data Engineering, 2015
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