Apache Flink Streaming

DATA-DRIVEN DISTRIBUTED DATA STREAM PROCESSING

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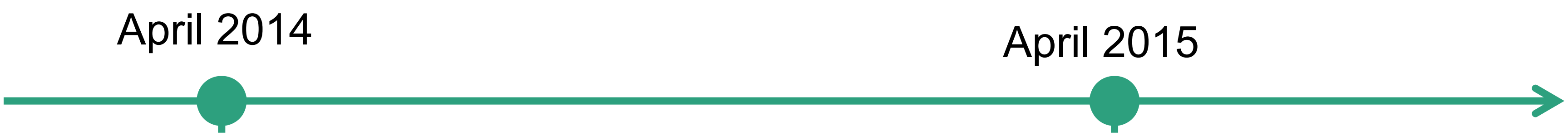
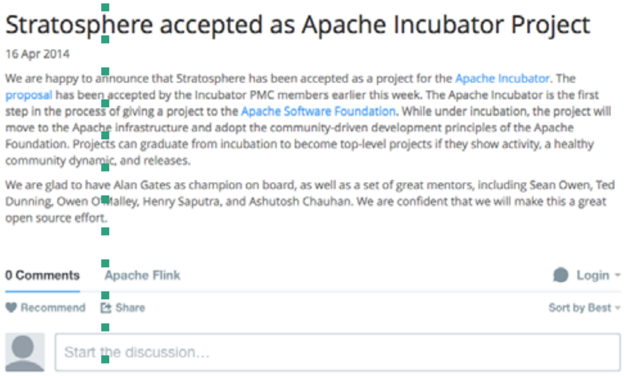
1 year of Flink - code



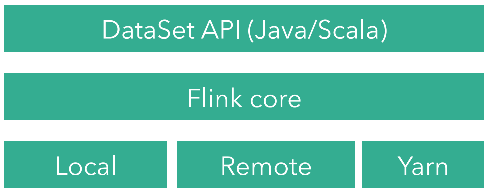


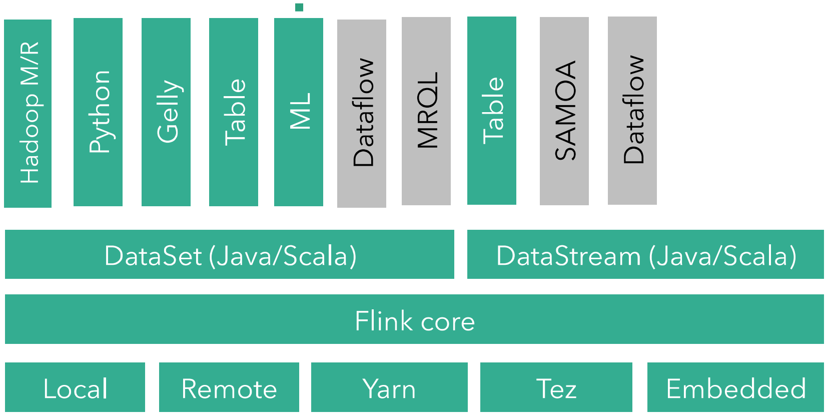
Stratosphere accepted as Apache Incubator Project

16 Apr 2014

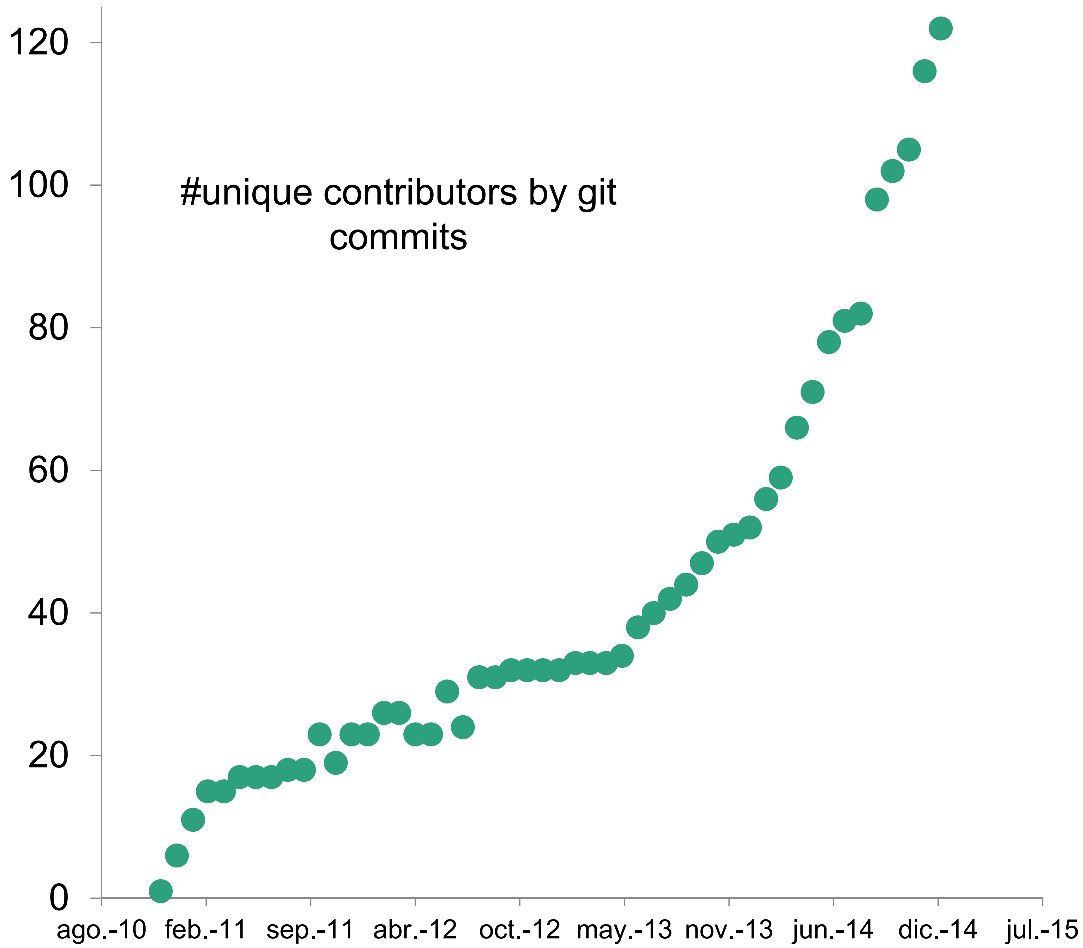
We are happy to announce that Stratosphere has been accepted as a project for the Apache Incubator. The proposal has been accepted by the Incubator PMC members earlier this week. The Apache Incubator is the first step in the process of giving a project to the Apache Software Foundation. While under incubation, the project will move to the Apache infrastructure and adopt the community-driven development principles of the Apache Foundation. Projects can graduate from incubation to become top-level projects if they show activity, a healthy community dynamic, and releases.

We are glad to have Alan Gates as champion on board, as well as a set of great mentors, including Sean Owen, Ted Dunning, Owen O'Malley, Henry Saputra, and Ashutosh Chauhan. We are confident that we will make this a great open source effort.





Community growth



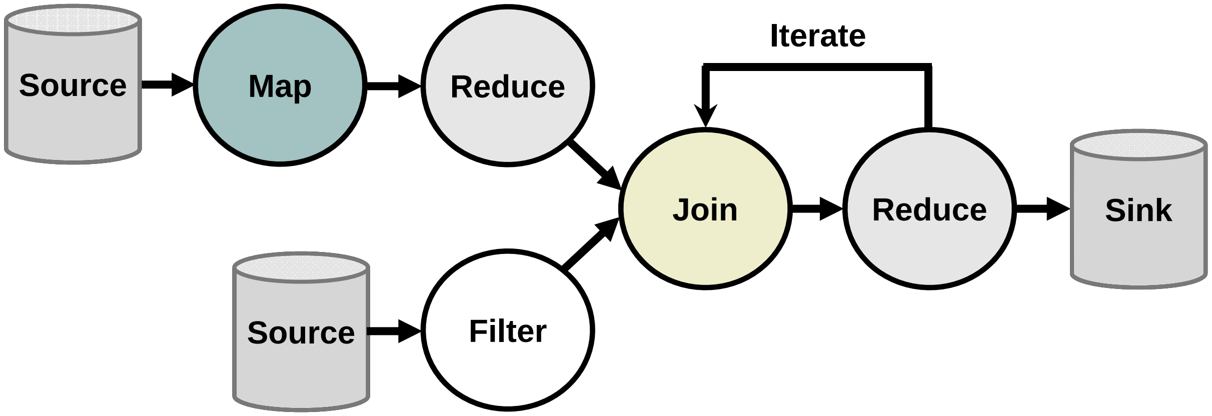
Introduction

- The Flink Vision
- Flink Stack Overview
- Programming Model
- Execution Model

What is Apache Flink

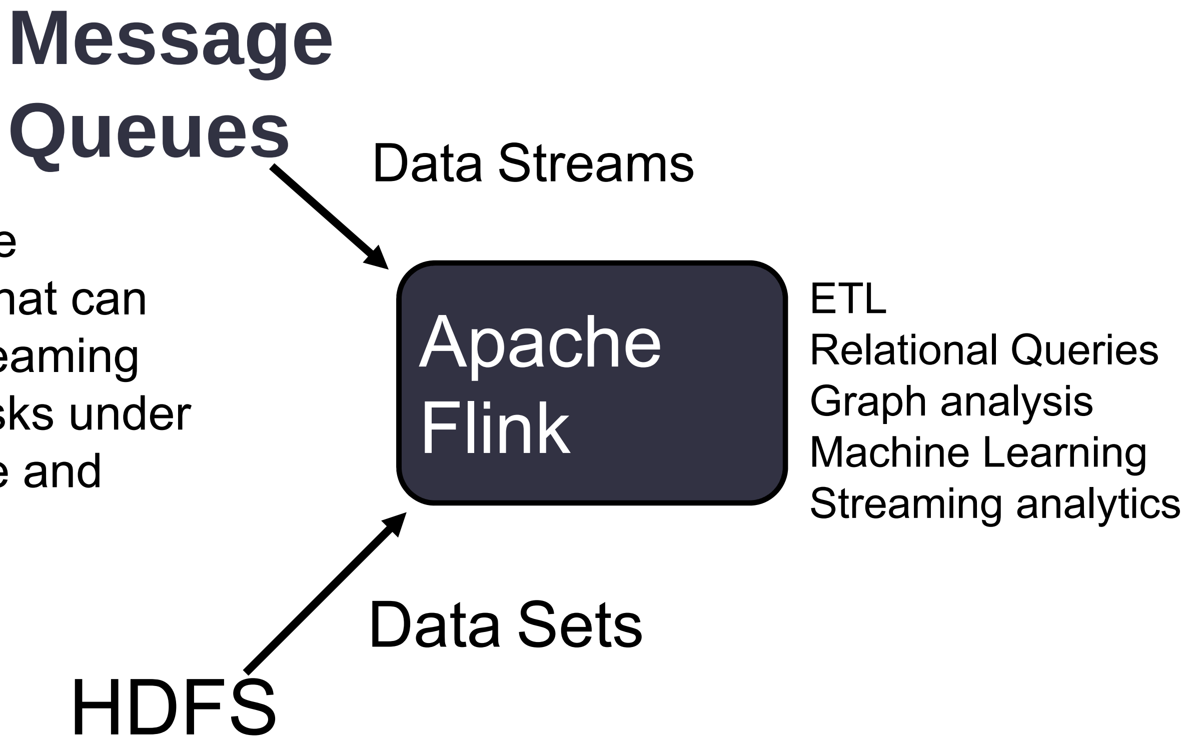
Distributed Data Flow Processing System

- Focused on large-scale data analytics
- Unified real-time stream and batch processing
- Easy and powerful APIs in Java / Scala (+ Python)
- Robust and fast execution backend



THE FLINK VISION

“Provide a use-case complete solution that can unify batch and streaming data processing tasks under the same codebase and execution runtime”



Message Queues

Data Streams

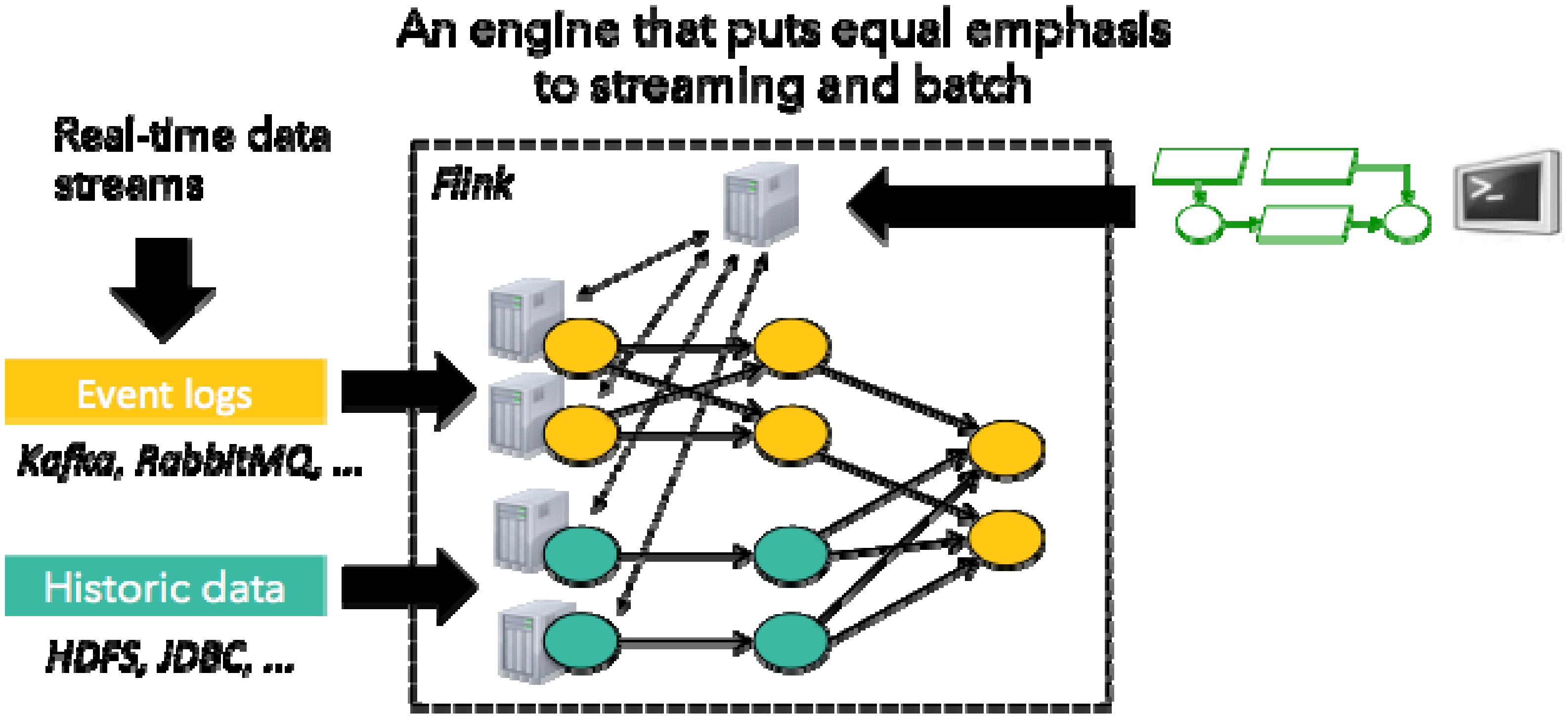
Apache Flink

ETL
Relational Queries
Graph analysis
Machine Learning
Streaming analytics

Data Sets

HDFS

WHAT ARE WE BUILDING



An engine that puts equal emphasis to streaming and batch

Real-time data streams

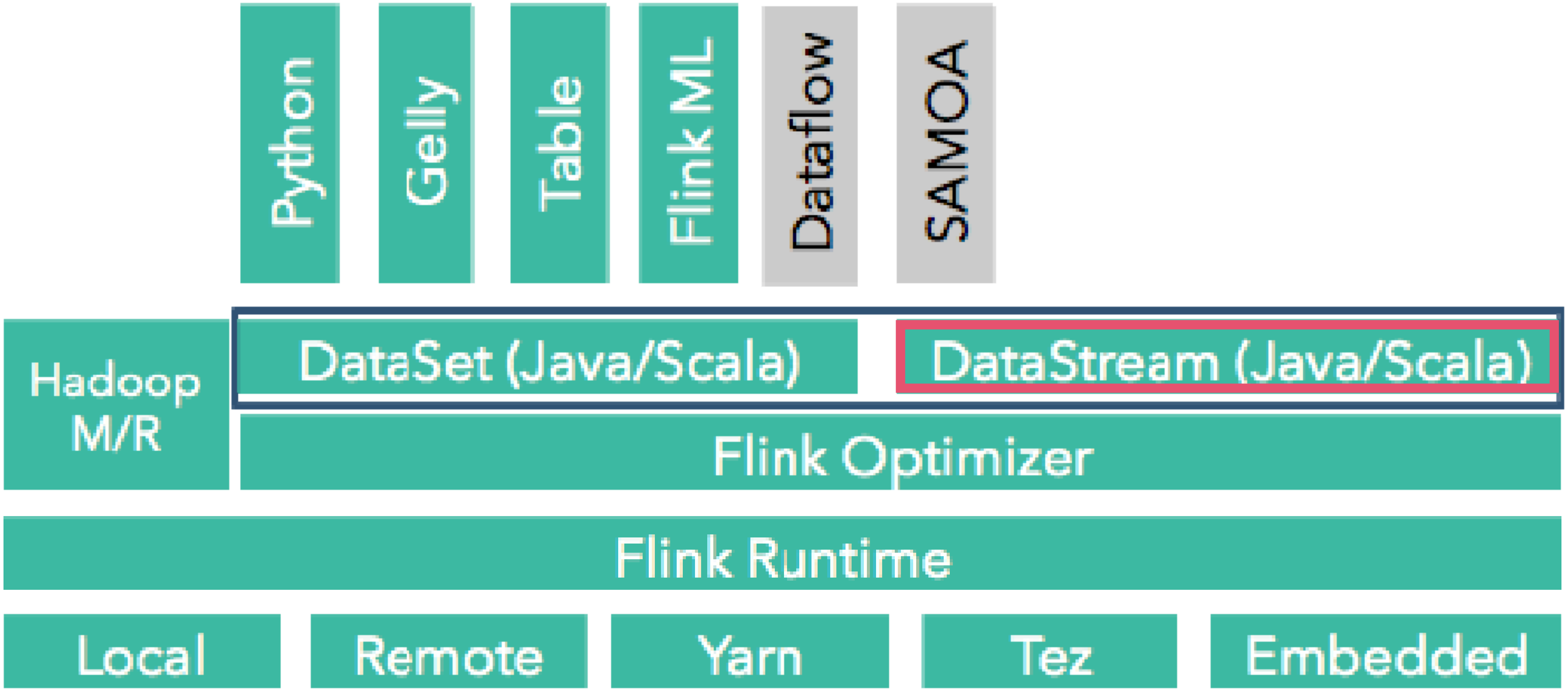
Event logs

Kafka, RabbitMQ, ...

Historic data

HDFS, JDBC, ...

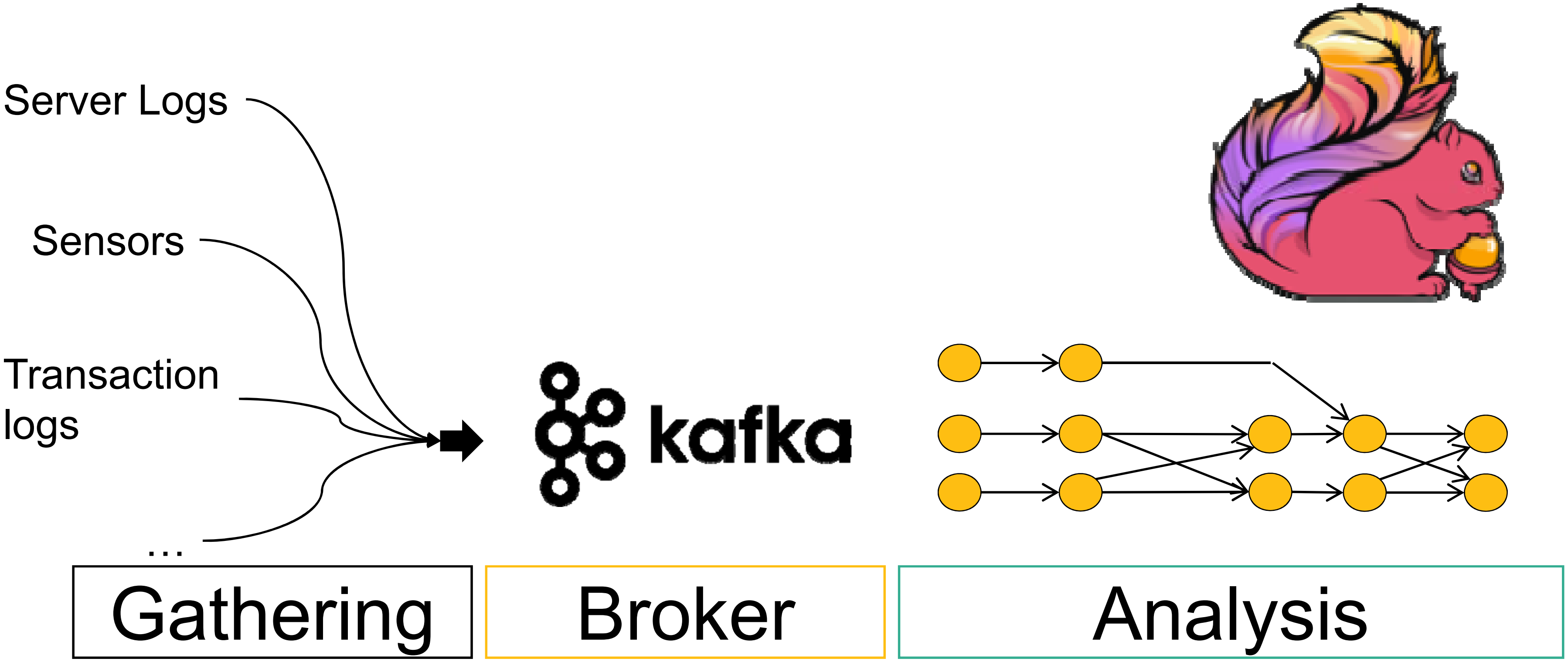
THE FLINK STACK



Stream processing

- ***Data stream***: Infinite sequence of data arriving in a continuous fashion.
- ***Stream processing***: Analyzing and acting on real-time streaming data, using continuous queries

3 Parts of a Streaming Infrastructure



Server Logs

Sensors

Transaction logs

…

Gathering

Broker

Analysis

Streaming landscape

Apache Storm

- True streaming over distributed dataflow
- Low level API (Bolts, Spouts) + Trident

Spark Streaming

- Stream processing emulated on top of batch system (non-native)
- Functional API (DStreams), restricted by batch runtime

Apache Samza

- True streaming built on top of Apache Kafka, state is first class citizen
- Slightly different stream notion, low level API

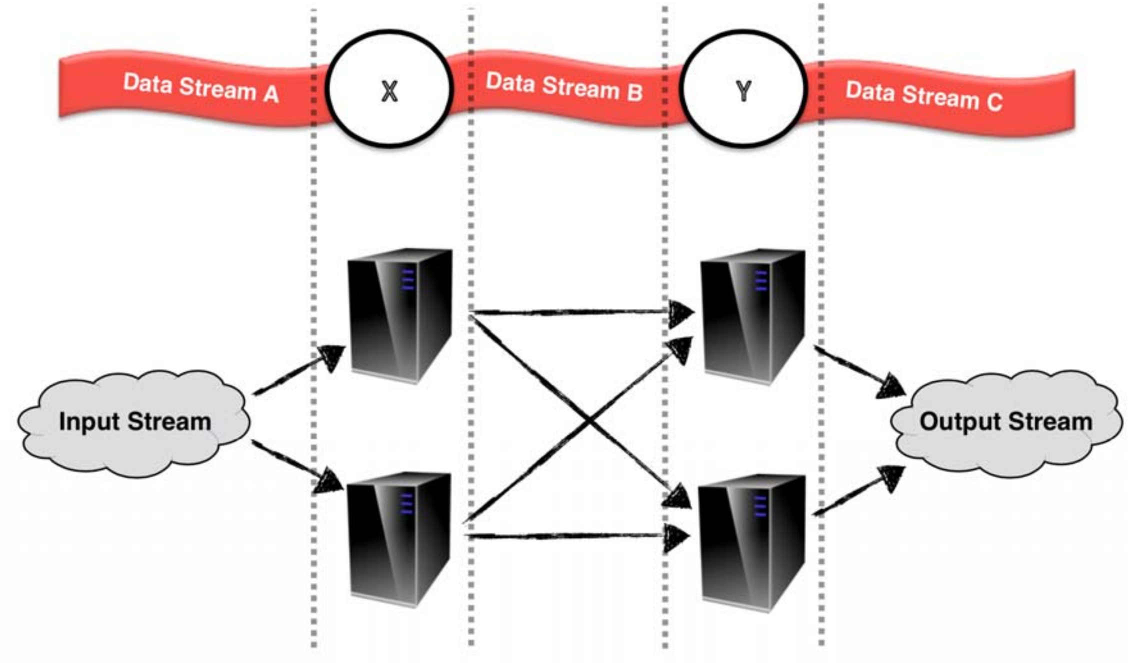
Apache Flink

- True streaming over stateful distributed dataflow
- Rich functional API exploiting streaming runtime; e.g. rich windowing semantics

Flink Streaming

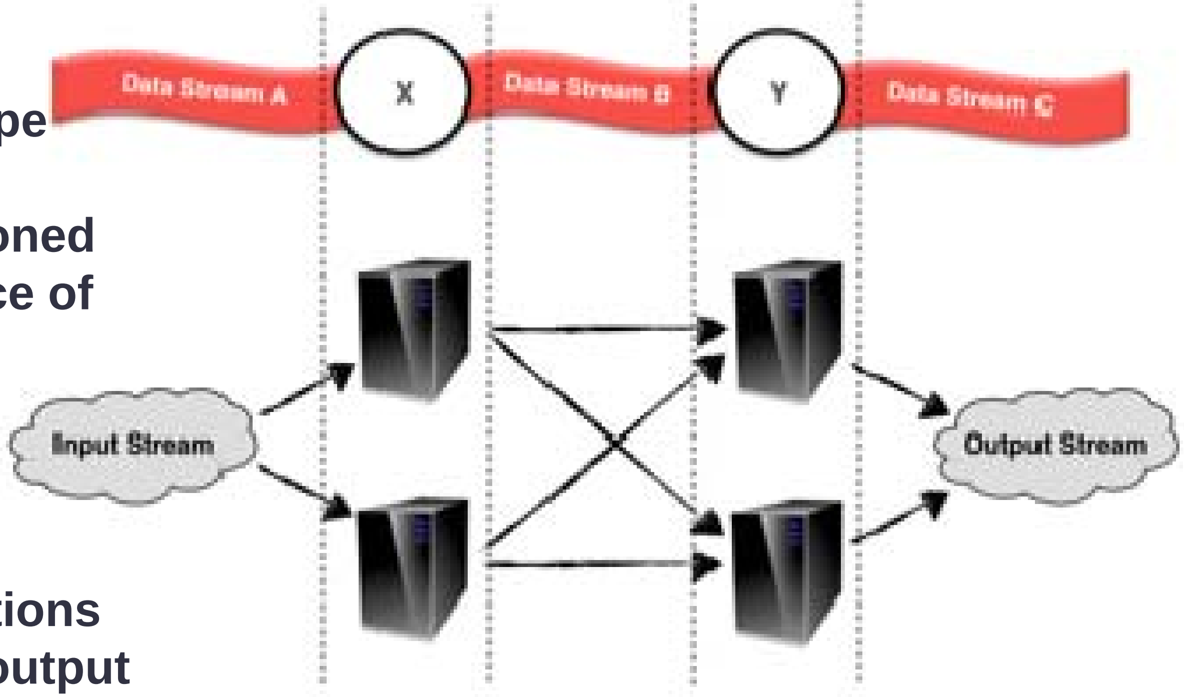
What is Flink Streaming

- Native, low-latency stream processor
- Expressive functional API
- Flexible operator state, stream windows
- Exactly-once processing semantics



PROGRAMMING MODEL

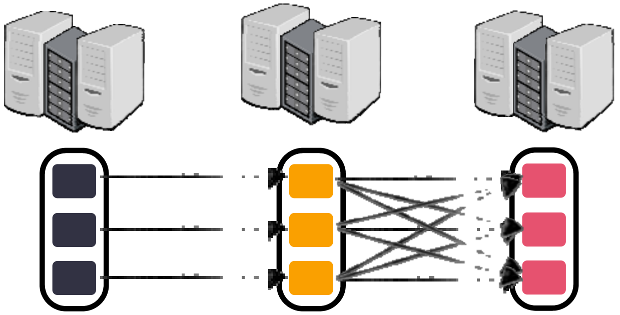
- Data Stream
  - An abstract data type representing an unbounded, partitioned immutable sequence of events
- Stream Operators
  - Stream transformations that generate new output Data Streams from input ones



EXECUTION MODELS

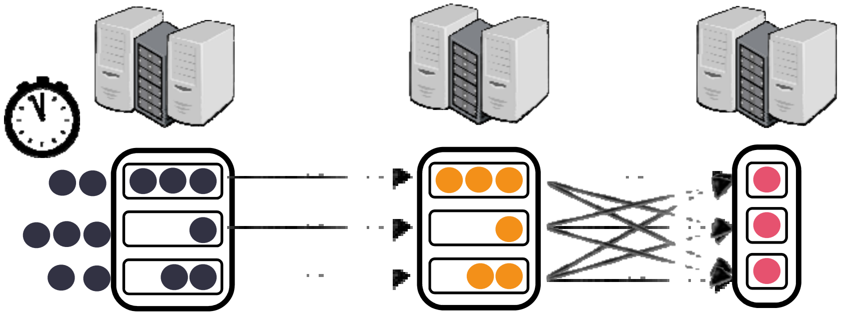
1) BAtched/Stateless (scheduled in Batches)

STATELESS SHORT-LIVED TASKS



(Hadoop, Spark)

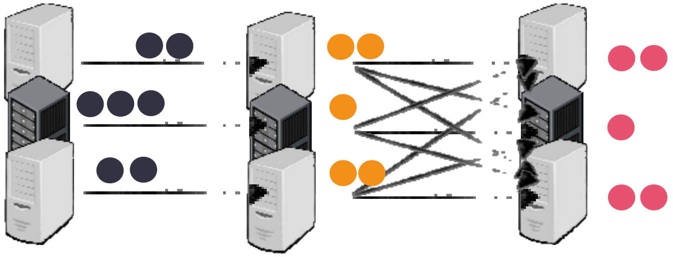
DISTRIBUTED STREAMING OVER BATCHES



(Spark Streaming)

2) DataFlow/STATEFUL (continuous/scheduled once)

long-lived task execution

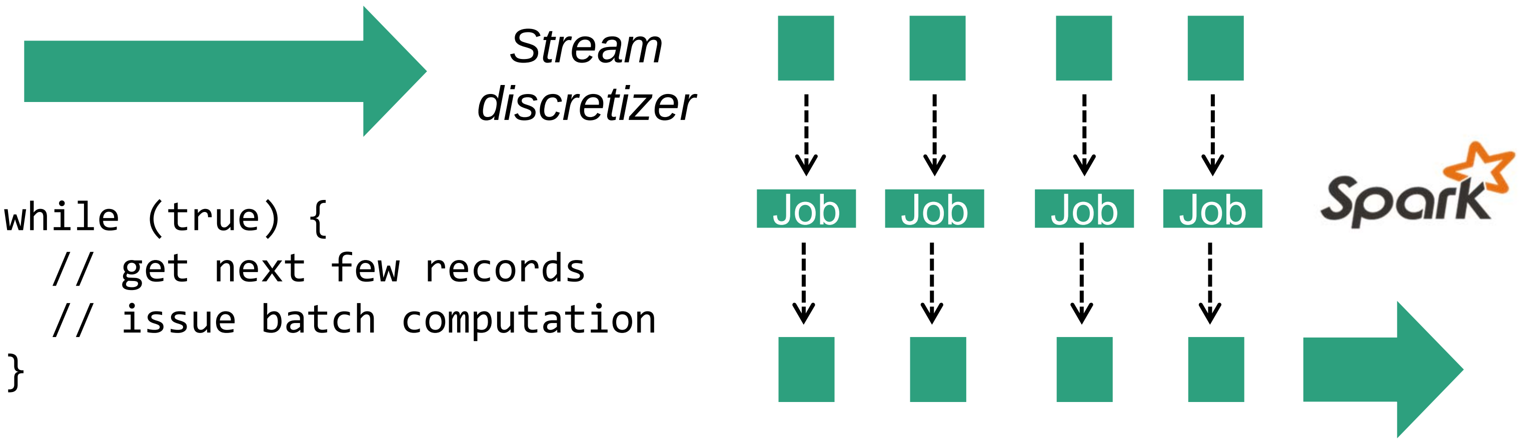


state is kept inside tasks

(Storm, Samza, Naiad, Flink)

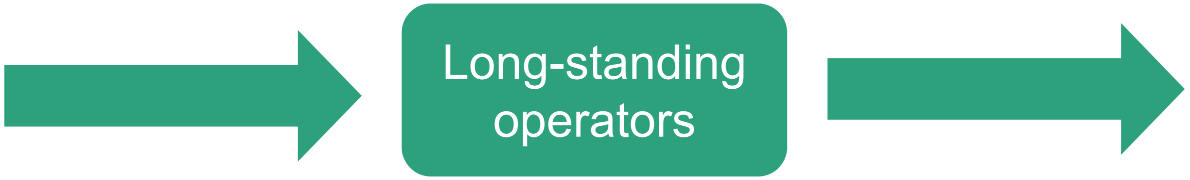
Native vs non-native streaming

Non-native streaming



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

Native streaming



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

WHY DATAFLOW

1) BATCHED/STATELESS (SCHEDULED IN BATCHES)

- Trivial Fault Tolerance (lost batches can be recomputed)
- High Throughput
- High Latency (batching latency)
- Limited Expressivity (stateless nature of tasks)

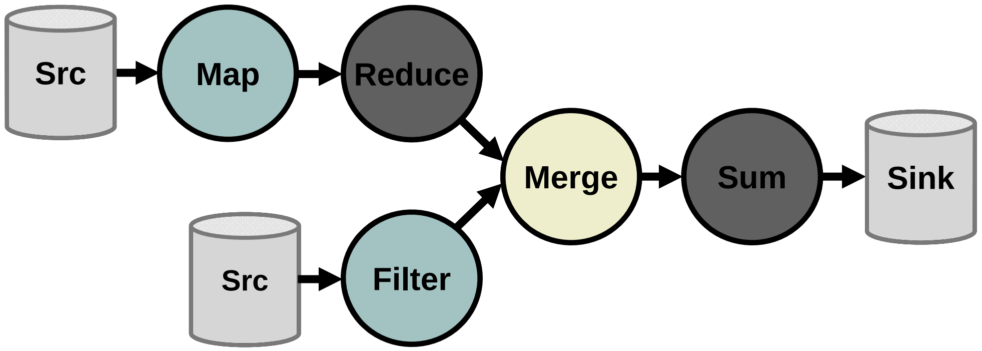
2) DATAFLOW/STATEFUL (CONTINUOUS/SCHEDULED ONCE)

- Low Latency
- True Streaming
- Non trivial Fault Tolerance
  - (tasks should recover from consistent state)

API OVERVIEW

- Stream Sources, Sinks
- Transformations
- Windowing Semantics

Overview of the API



- Data stream sources
  - File system
  - Message queue connectors
  - Arbitrary source functionality
- Stream transformations
  - Basic transformations: *Map, Reduce, Filter, Aggregations*…
  - Binary stream transformations: *CoMap, CoReduce*…
  - Windowing semantics: *Policy based flexible windowing (Time, Count, Delta…)*
  - Temporal binary stream operators: *Joins, Crosses*…
  - Native support for iterations
- Data stream outputs
- For the details please refer to the programming guide:
  - http://flink.apache.org/docs/latest/streaming_guide.html

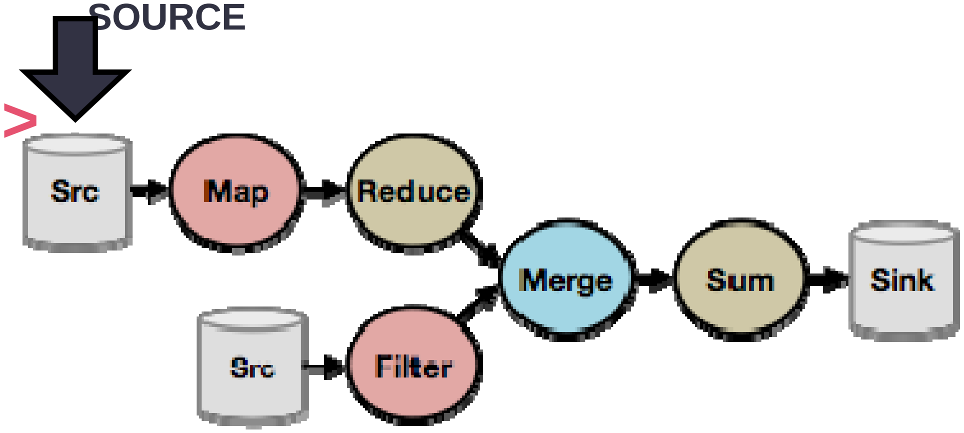
TRANSFORMATIONS

Basic Transformations

- map, filter, reduce, aggregations (eg. max, sum)
- reduce is incremental Stream(1, 2, 3, 4, …).sum => Stream(1, 3, 6, 10,…)

- DataStream Sources

MESSAGE QUEUE
FILE SYSTEM
TCP SOCKET
CUSTOM SOURCE



Binary Transformations

- merge (union) , coMap, coReduce (two streams)
- join, cross (defined per window)

Binary stream transformations

- Apply shared transformations on streams of different types.
- Shared state between transformations
- *CoMap, CoFlatMap, CoReduce…*

```
public interface CoMapFunction<IN1, IN2, OUT> {

      public OUT map1(IN1 value);
      public OUT map2(IN2 value);

}
```

STREAM WORD COUNT

```
case class Word(word: String, count: Long)

val input = env.socketTextStream(host, port);
val words = input.flatMap {ln => ln.split("\\W+")}
                 .map(w => Word(w,1))
val counts = words.groupBy("word").sum("count")
                  .print()
```

- **In grouped streams, for each incoming tuple the selected field is transformed to the aggregated value**

WINDOWING SEMANTICS

- Trigger and Eviction policies
  - window(<eviction>, <trigger>)
  - window(<eviction>).every(<trigger>)

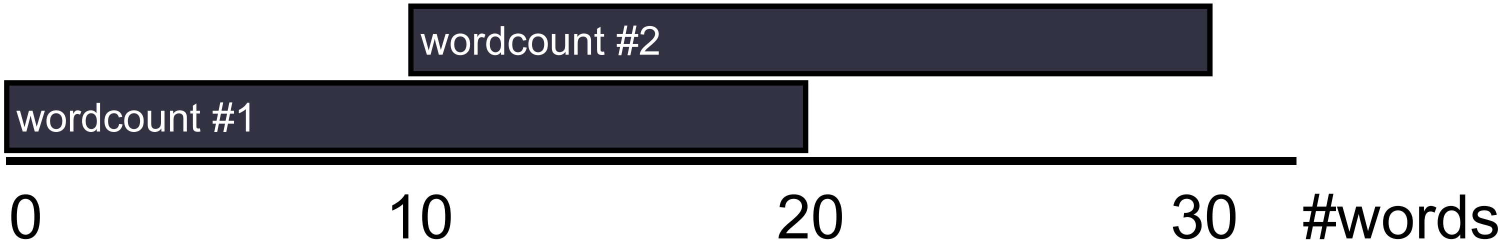
- Built-in policies:
  - Time: Time.of**(length, TimeUnit/Custom timestamp)**
  - Count: Count**.**of**(windowSize)**
  - Delta: Delta**.**of**(treshold, Distance function, Start value)**

- Window transformations:
  - Reduce
  - mapWindow

- Custom trigger and eviction policies can also be trivially implemented

WINDOWED WORDCOUNT

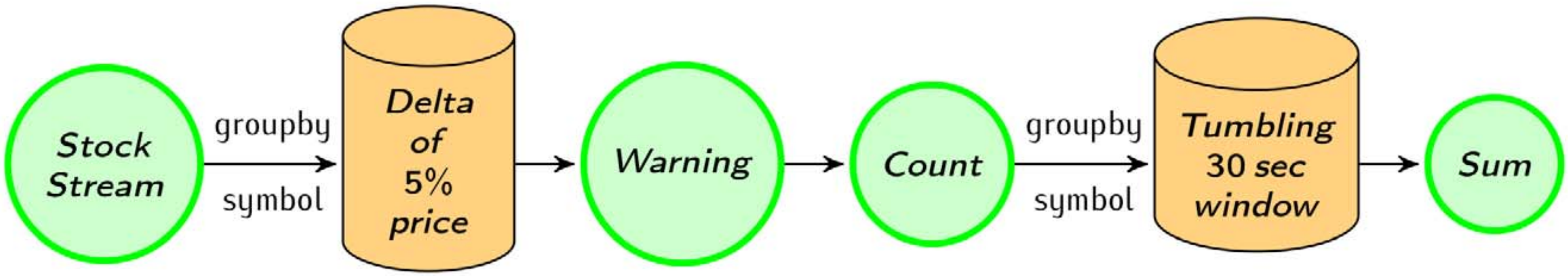
```
case class Word(word: String, count: Long)

val input = env.socketTextStream(host, port);
val words = input flatMap {
            line => line.split("\\W+").map(Word(_,1)) }
                    .window(Count.of(20)).every(Count.of(10))
val counts = words.groupBy("word").sum("count")
```

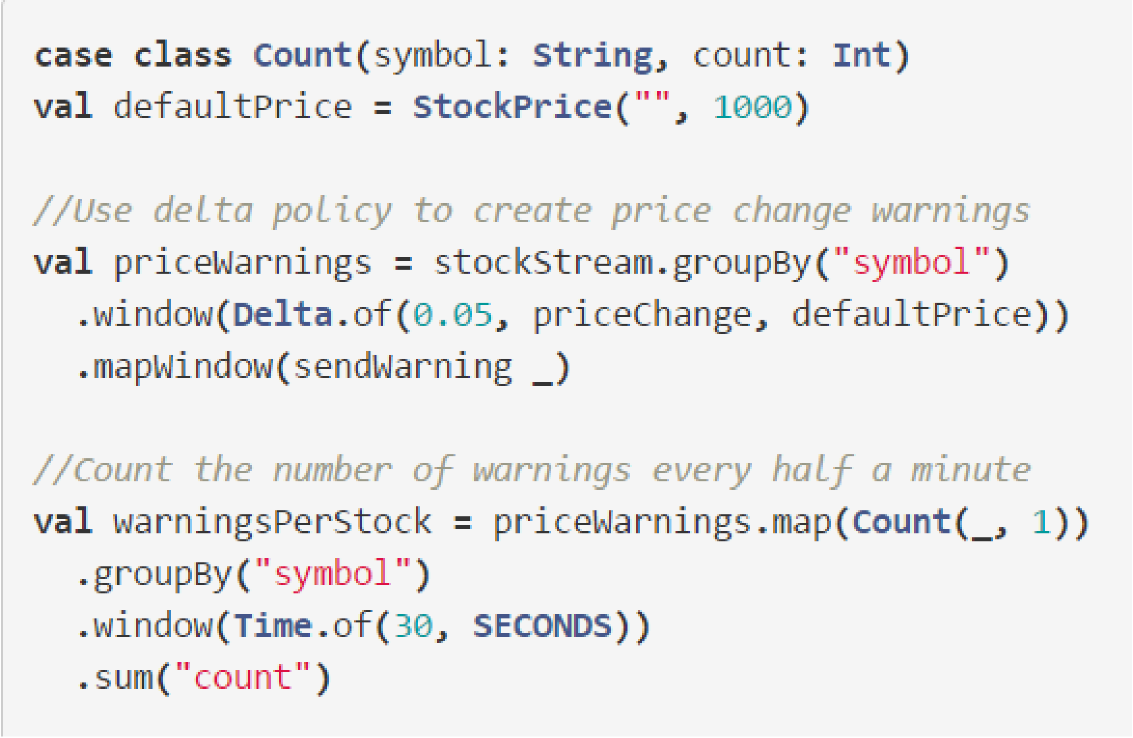


wordcount #2

wordcount #1

Flexible windows





```
case class Count(symbol: String, count: Int)
val defaultPrice = StockPrice("", 1000)

//Use delta policy to create price change warnings
val priceWarnings = stockStream.groupBy("symbol")
  .window(Delta.of(0.05, priceChange, defaultPrice))
  .mapWindow(sendWarning _)

//Count the number of warnings every half a minute
val warningsPerStock = priceWarnings.map(Count(_, 1))
  .groupBy("symbol")
  .window(Time.of(30, SECONDS))
  .sum("count")
```

More at: http://flink.apache.org/news/2015/02/09/streaming-example.html

Performance

- Performance optimizations
  - Effective serialization due to strongly typed topologies
  - Operator chaining (thread sharing/no serialization)
  - Different automatic query optimizations

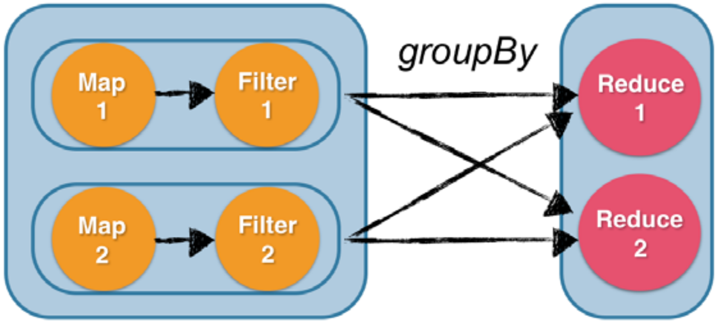
- Competitive performance
  - ~ 1.5m events / sec / core
  - As a comparison Storm promises ~ 1m tuples / sec / node

OPTIMISATIONS

- **Window Pre-aggregates**
  - Implemented: sliding (panes), tumbling/jumping window pre-aggregates
  - Pending: Operator Sharing, Optimistic pre-aggregations

- **Operator Chaining**
  - Collapsing multiple operators into a single execution thread

- **Operator Reordering**



Fault Tolerance

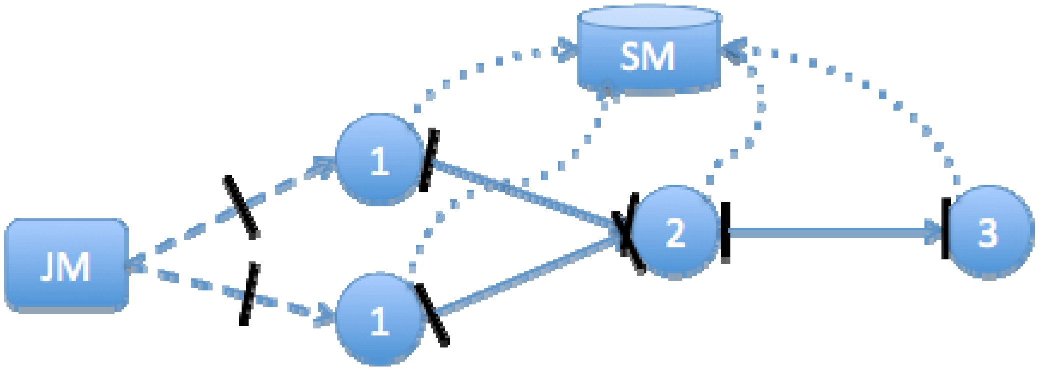
Overview

- Fault tolerance in other systems
  - Message tracking/acks (Storm)
  - RDD re-computation (Spark)

- Fault tolerance in Apache Flink
  - Based on consistent global snapshots
  - Algorithm inspired by Chandy-Lamport
  - Low runtime overhead, stateful exactly-once semantics

PROCESSING GUARANTEES

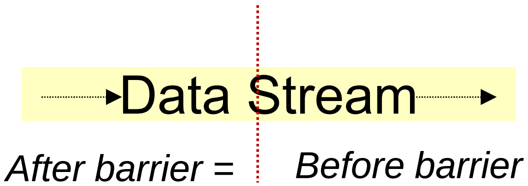
- ★ **Explicit state representation**
- ★ **Periodic minimal state snapshotting**
- ★ **Partial execution graph recovery**
- ★ **Towards exactly-once processing semantics**



Checkpointing / Recovery

Pushes checkpoint barriers through the data flow

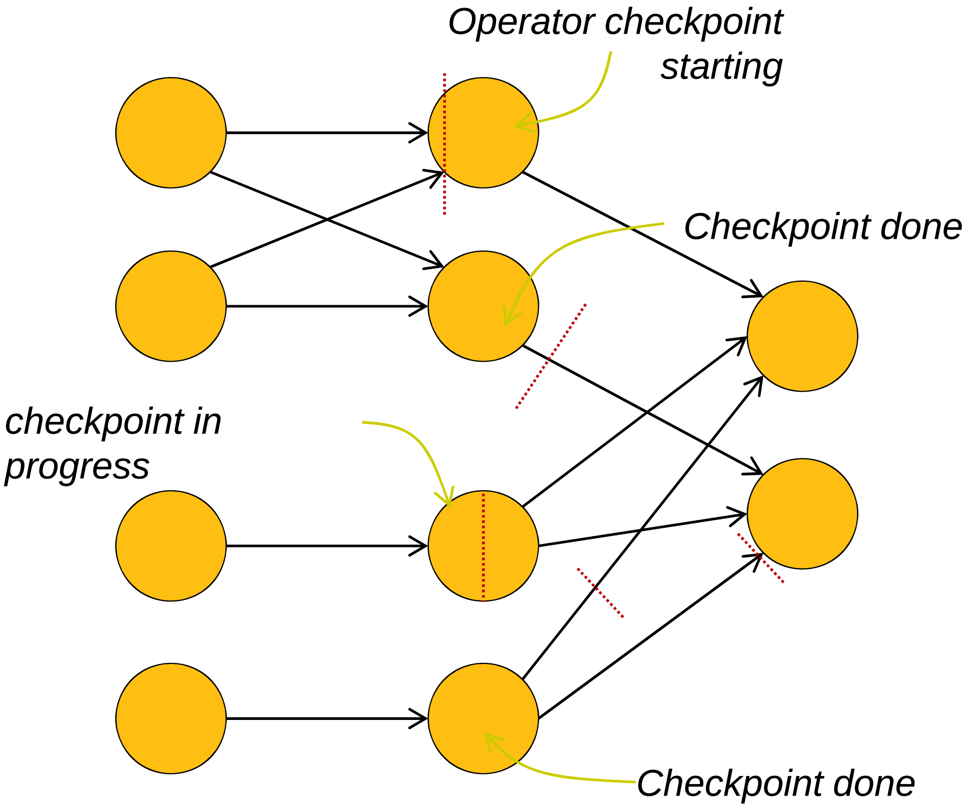
barrier



Data Stream

After barrier =
Not in snapshot
(backup till next snapshot)

Before barrier =
part of the snapshot



Operator checkpoint starting

Checkpoint done

checkpoint in progress

Checkpoint done

Asynchronous Barrier Snapshotting for globally consistent checkpoints

State management

- State declared in the operators is managed and checkpointed by Flink
- Pluggable backends for storing persistent snapshots
  - Currently: JobManager, FileSystem (HDFS, Tachyon)
- State partitioning and flexible scaling in the future

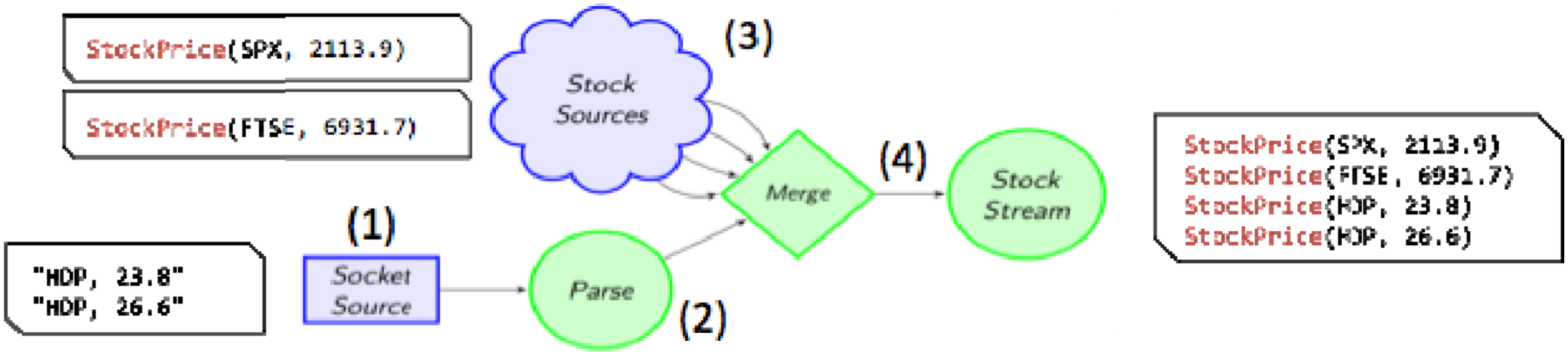
A USE CASE

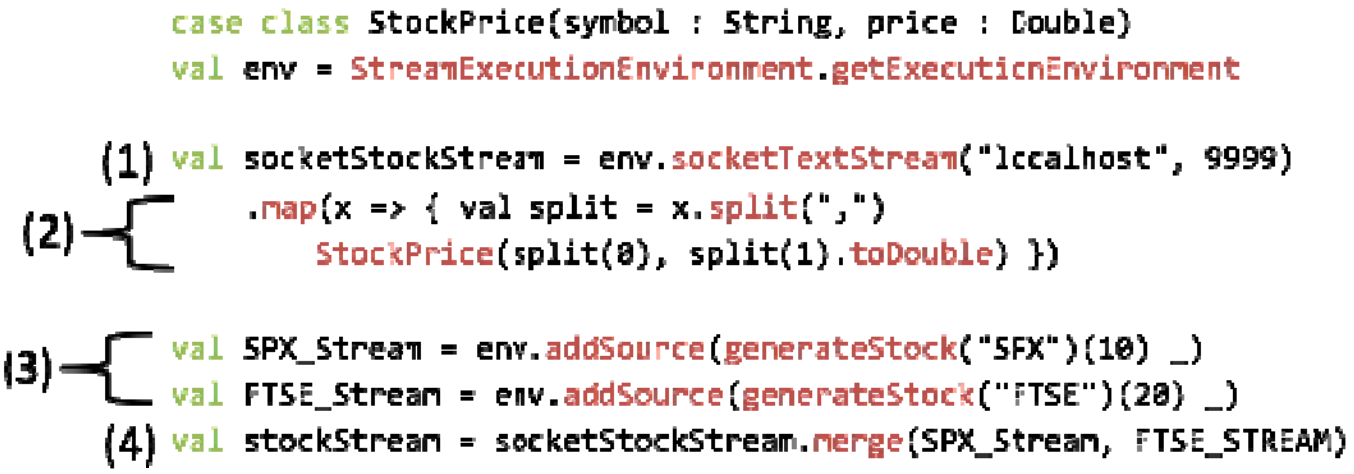
- Get stock price updates from multiple sources
- Generate online statistics on the stock data
- Detect stock price fluctuations
- Detect twitter trends on stock mentions
- Correlate trends and fluctuations

USE CASE STEPS

- Stock DataStream creation
- Rolling window analytics
- Detecting stock price fluctuations
- Detecting trends from twitter streams
- Correlating stock fluctuations with trends
- Detailed explanation and source code on our blog
  - http://flink.apache.org/news/2015/02/09/streaming-example.html

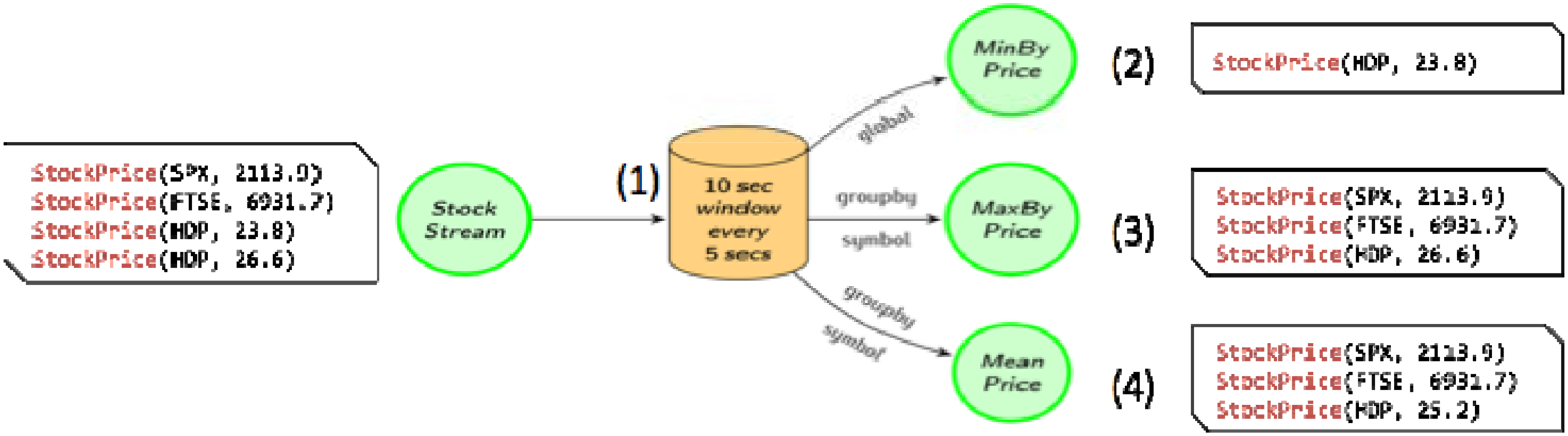
CREATING STOCK STREAMS





```
        case class StockPrice(symbol : String, price : Double)
        val env = StreamExecutionEnvironment.getExecutionEnvironment

(1)     val socketStockStream = env.socketTextStream("localhost", 9999)
(2) ─┬        .map(x => { val split = x.split(",")
     └            StockPrice(split(0), split(1).toDouble) })

(3) ─┬  val SPX_Stream = env.addSource(generateStock("SPX")(10) _)
     └  val FTSE_Stream = env.addSource(generateStock("FTSE")(20) _)
(4)     val stockStream = socketStockStream.merge(SPX_Stream, FTSE_STREAM)
```

ROLLING ANALYTICS



```
StockPrice(SPX, 2113.9)
StockPrice(FTSE, 6931.7)
StockPrice(HDP, 23.8)
StockPrice(HDP, 26.6)
```

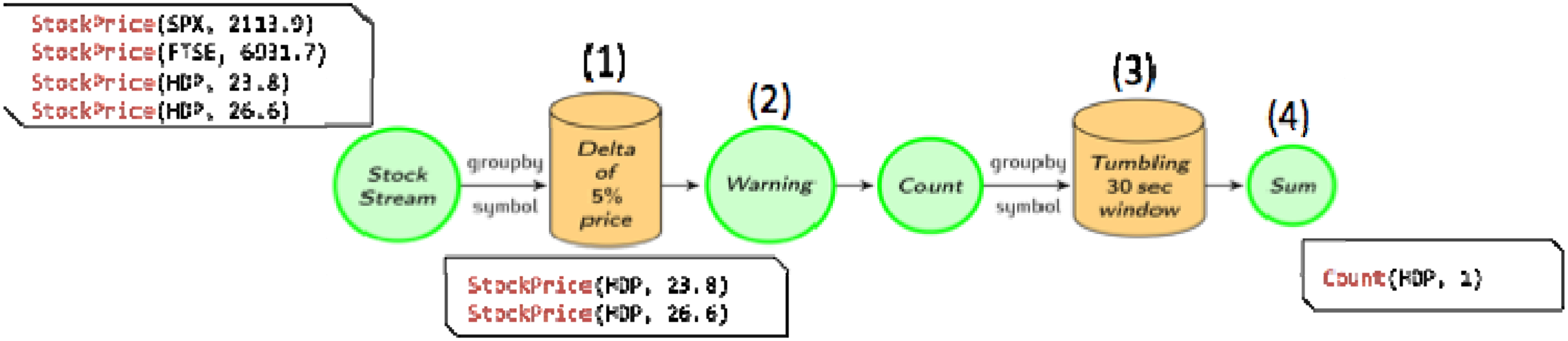
(2)
```
StockPrice(HDP, 23.8)
```

(3)
```
StockPrice(SPX, 2113.9)
StockPrice(FTSE, 6931.7)
StockPrice(HDP, 26.6)
```

(4)
```
StockPrice(SPX, 2113.9)
StockPrice(FTSE, 6931.7)
StockPrice(HDP, 25.2)
```

```
    val windowedStream = stockStream
(1)   .window(Time.of(10, SECONDS)).every(Time.of(5, SECONDS))

(2) val lowest = windowedStream.minBy("price")
(3) val maxByStock = windowedStream.groupBy("symbol").maxBy("price")
(4) val rollingMean = windowedStream.groupBy("symbol").mapWindow(mean _)
```

STOCK PRICE FLUCTUATIONS



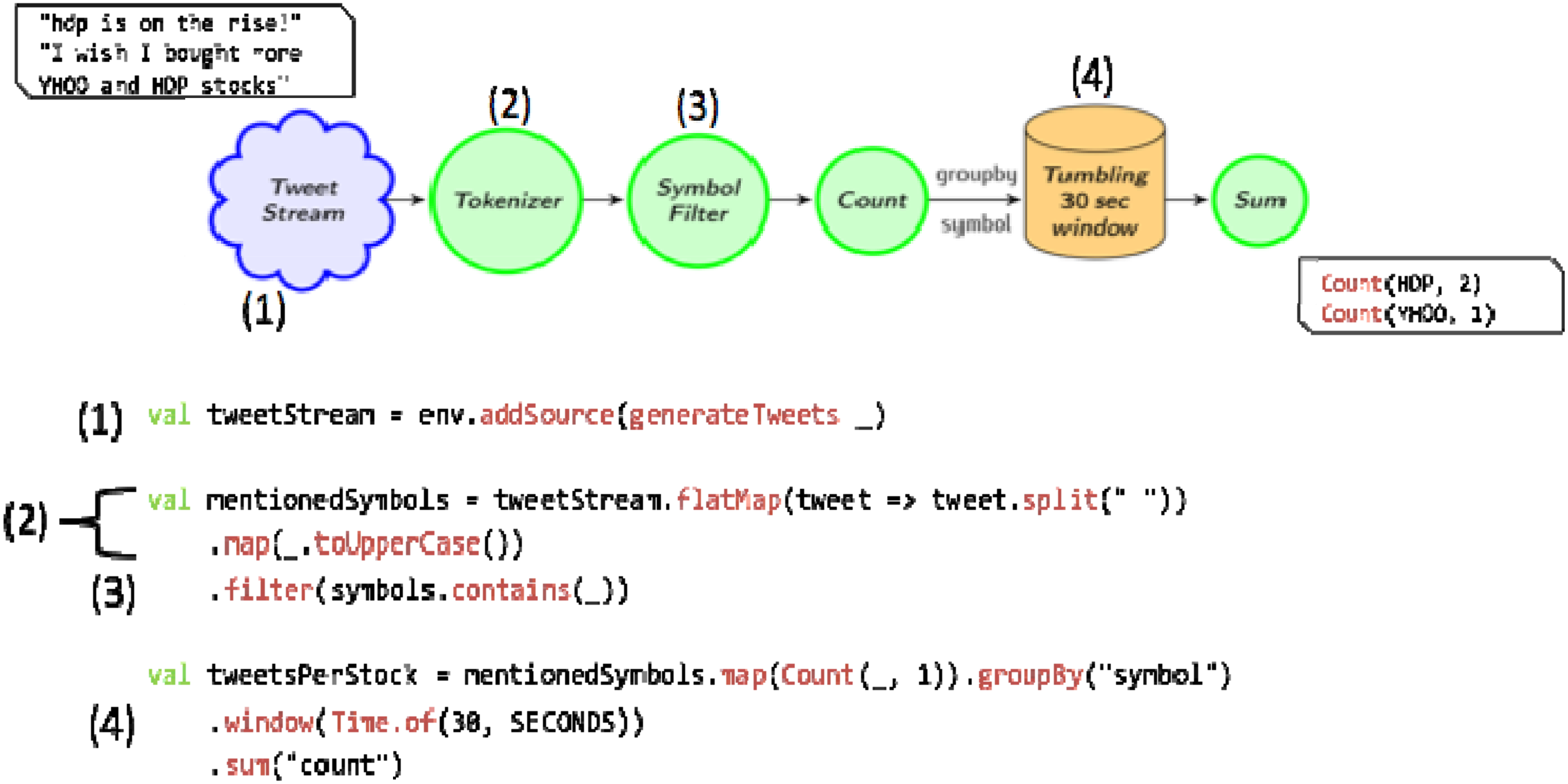
```
StockPrice(SPX, 2113.9)
StockPrice(FTSE, 6931.7)
StockPrice(HDP, 23.8)
StockPrice(HDP, 26.6)
```

```
StockPrice(HDP, 23.8)
StockPrice(HDP, 26.6)
```

```
Count(HDP, 1)
```

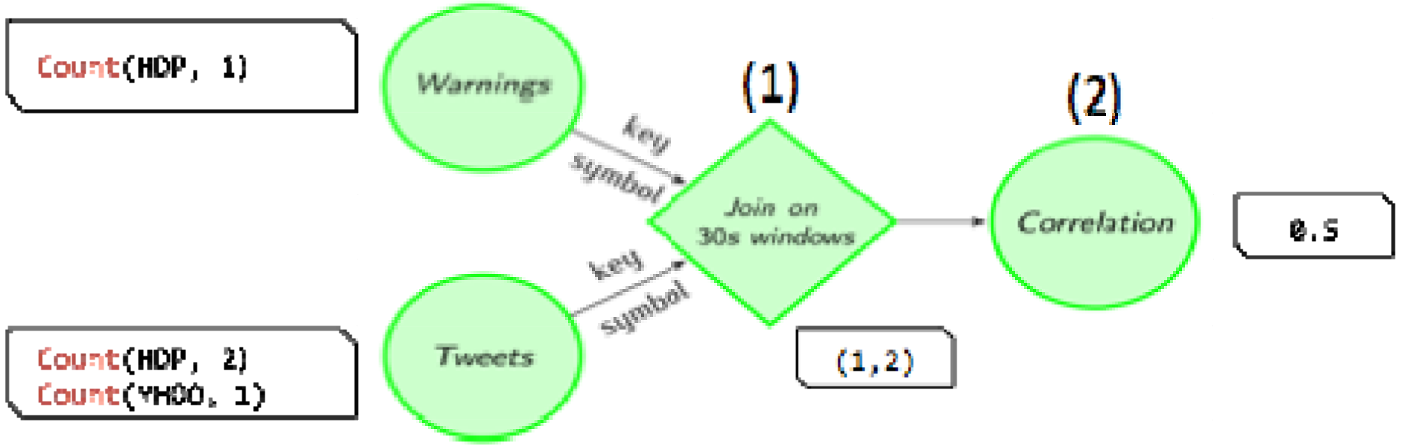
```
    case class Count(symbol : String, count : Int)

    val priceWarnings = stockStream.groupBy("symbol")
(1)     .window(Delta.of(0.05, priceChange, defaultPrice))
(2)     .mapWindow(sendWarning _)

    val warningsPerStock = priceWarnings.map(Count(_, 1)) .groupBy("symbol")
(3)     .window(Time.of(30, SECONDS))
(4)     .sum("count")
```

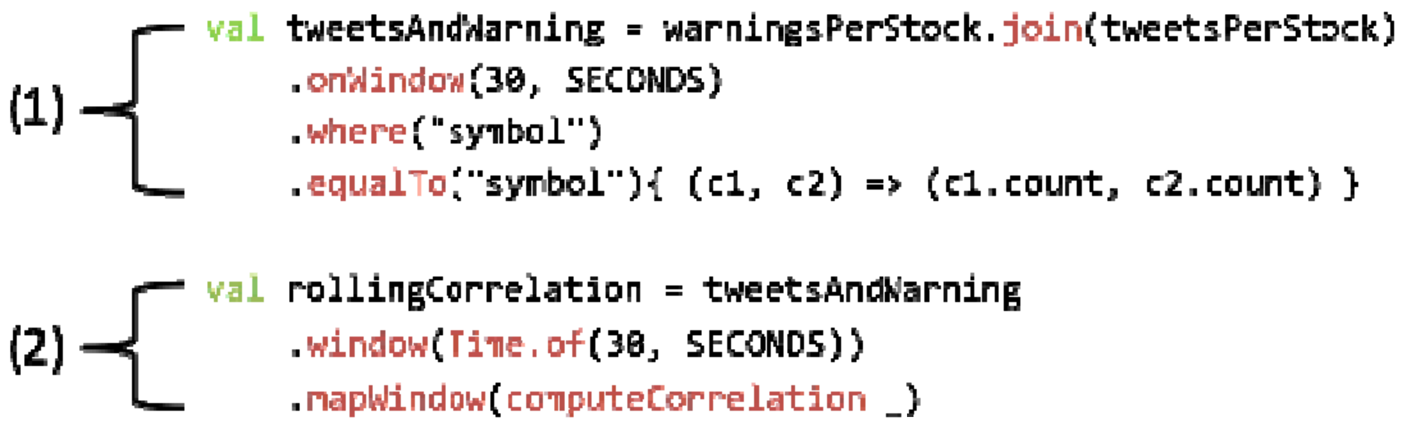
CREATING TREND STREAMS



```
(1)    val tweetStream = env.addSource(generateTweets _)

(2) ─{ val mentionedSymbols = tweetStream.flatMap(tweet => tweet.split(" "))
           .map(_.toUpperCase())
(3)        .filter(symbols.contains(_))

       val tweetsPerStock = mentionedSymbols.map(Count(_, 1)).groupBy("symbol")
(4)        .window(Time.of(30, SECONDS))
           .sum("count")
```

JOINING STREAMS





```
      val tweetsAndWarning = warningsPerStock.join(tweetsPerStock)
(1)       .onWindow(30, SECONDS)
          .where("symbol")
          .equalTo("symbol"){ (c1, c2) => (c1.count, c2.count) }

      val rollingCorrelation = tweetsAndWarning
(2)       .window(Time.of(30, SECONDS))
          .mapWindow(computeCorrelation _)
```

Background slides

ONGOING WORK

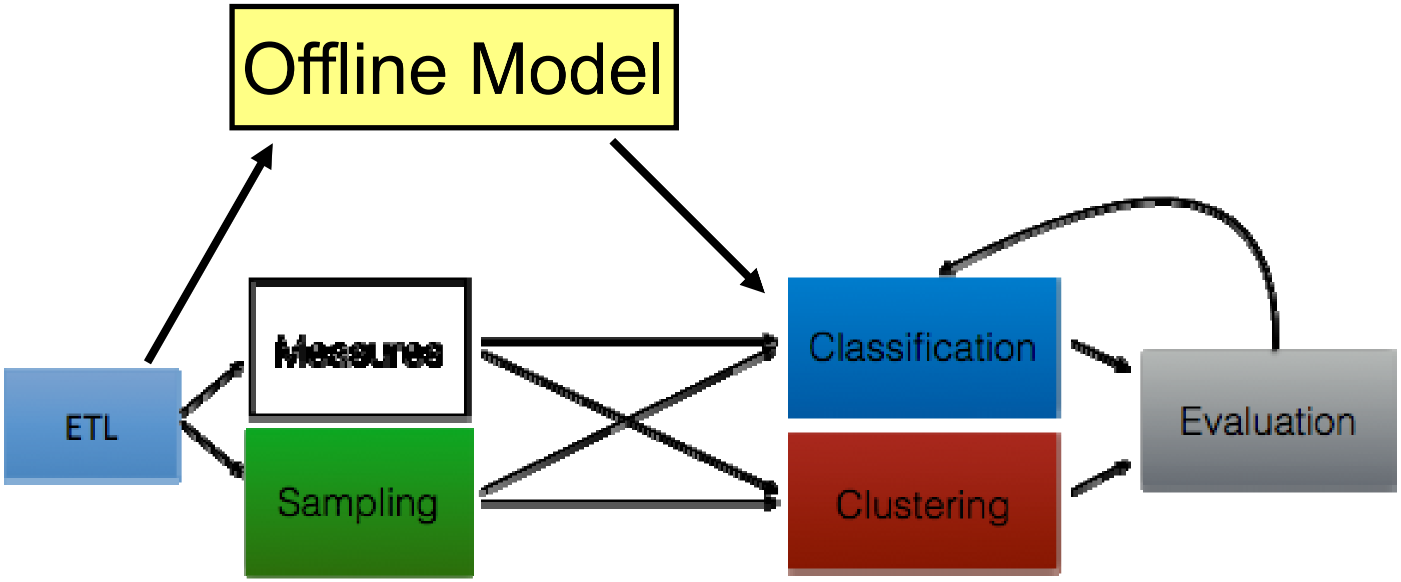
- Machine Learning Pipelines
- Streaming Graphs

Streaming roadmap for 2015

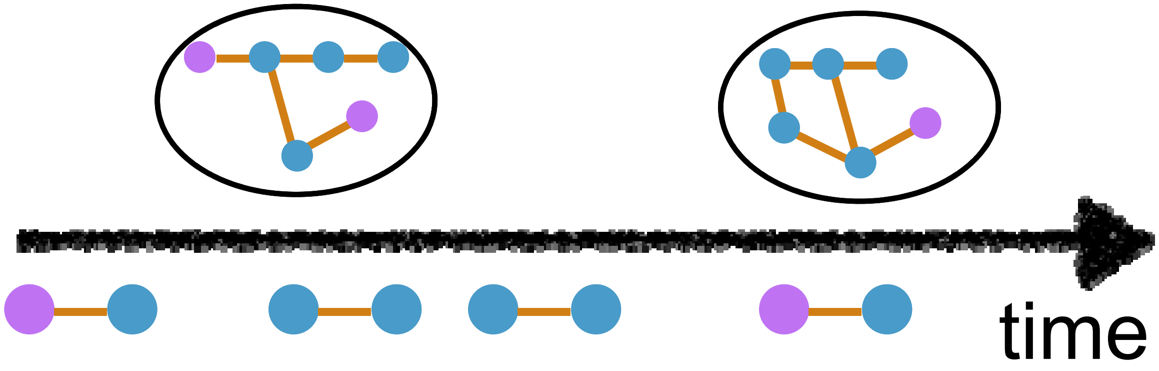
- Improved state management
  - New backends for state snapshotting
  - Support for state partitioning and incremental snapshots
  - Master Failover
- Improved job monitoring
- Integration with other Apache projects
  - SAMOA (PR ready), Zeppelin (PR ready), Ignite
- Streaming machine learning and other new libraries

ML PIPELINES

Combining **scikit-learn** and **MOA** for a first-ever distributed, **multi-paradigm** ML pipelines library



STREAMING GRAPHS



- Streaming newly generated graph data
- Keeping only the **fresh** state in memory
- Continuously computing graph approximations

INTEGRATIONS

- Apache Samoa (incubating)
- Flink Deployments with Karamel
- Table API
- Google DataFlow API (done)
- Apache Storm Compatibility Layer

LINKS

Project Website: https://flink.apache.org/

Project Repo: https://github.com/apache/flink

Streaming Guide: http://ci.apache.org/projects/flink/flink-docs-master/streaming_guide.html

User Mailist: user@flink.apache.org