DataStream API

Windows & Time



Apache Flink® Training



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Windows and Aggregates

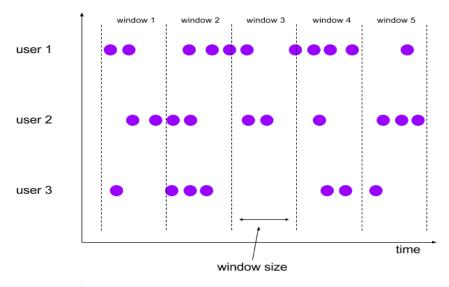
Windows



- Aggregations on DataStreams are different from aggregations on DataSets
 - You cannot count all records of an unbounded stream
- Aggregations make sense on windowed streams
 - A window is a finite subset of stream elements

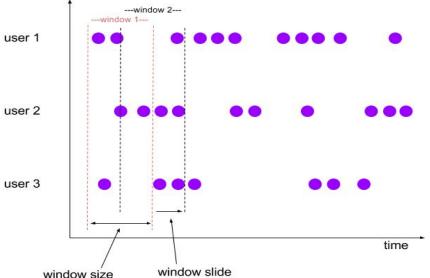
Tumbling and Sliding Windows





Tumbling:

aligned, fixed length, non-overlapping windows



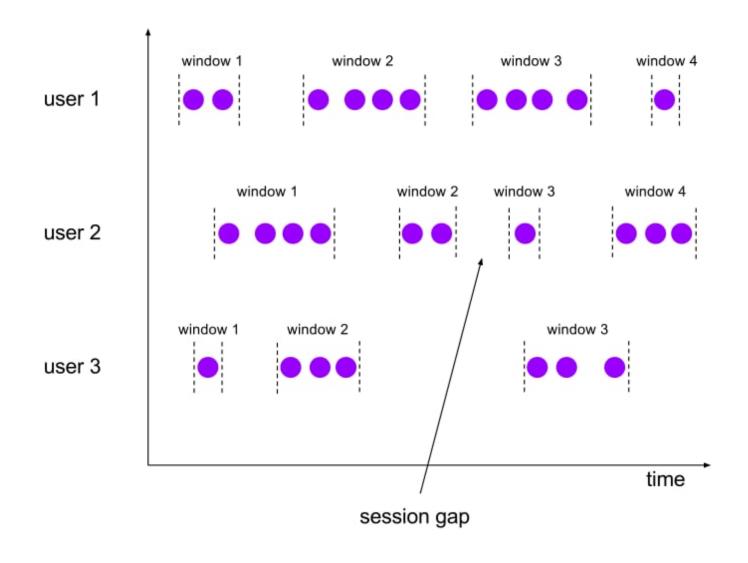
Sliding:

aligned, fixed length, overlapping windows

Session Windows



Non-aligned, variable length windows.



Specifying Windowing



Predefined Keyed Windows



- Tumbling time window .timeWindow(Time.minutes(1))
- Sliding time window

 timeWindow(Time.minutes(1), Time.seconds(10))
- Tumbling count window .countWindow(100)
- Sliding count window
 .countWindow(100, 10)
- Session window.window(SessionWindows.withGap(Time.minutes(30)))

Non-keyed Windows



Windows on non-keyed streams are not processed in parallel!

```
stream.windowAll(...)...
```

- stream.timeWindowAll(Time.seconds(10))...
- stream.countWindowAll(20, 10)...

Aggregations on Windowed Streams



```
DataStream<SensorReading> input = ...
input
  .keyBy("key")
  .timeWindow(Time.minutes(1))
  .apply(new MyWastefulMax());
public static class MyWastefulMax implements WindowFunction
    SensorReading,
                                    // input type
   Tuple3<String, Long, Integer>, // output type
   Tuple,
                                    // key type
    TimeWindow> {
                                    // window type
   @Override
    public void apply(
        Tuple key,
        TimeWindow window,
        Iterable<SensorReading> events,
        Collector<Tuple3<String, Long, Integer>> out) {
        int max = 0;
        for (SensorReading e : events) {
            if (e.f1 > max) max = e.f1;
        out.collect(new Tuple3<>(Tuple1<String>key).f0, window.getEnd(), max));
```



state





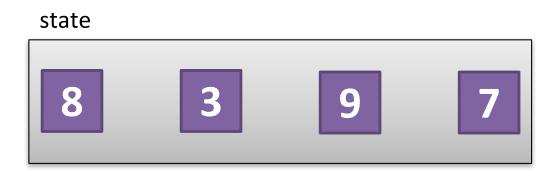
state















Incremental Window Aggregation



```
DataStream<SensorReading> input = ...
input
  .keyBy("key")
  .timeWindow(Time.minutes(1))
  .reduce(new MyReducingMax(), new MyWindowFunction());
private static class MyReducingMax implements ReduceFunction<SensorReading> {
 public SensorReading reduce(SensorReading r1, SensorReading r2) {
      return r1.value() > r2.value() ? r1 : r2;
private static class MyWindowFunction implements WindowFunction
  SensorReading, Tuple2<Long, SensorReading>, String, TimeWindow> {
      public void apply(String key,
                    TimeWindow window,
                    Iterable<SensorReading> maxReadings,
                    Collector<Tuple2<Long, SensorReading>> out) {
          SensorReading max= maxReadings.iterator().next();
          out.collect(new Tuple2<Long, SensorReading>(window.getStart(), max));
```







8, 3, 9 7 9



8, 3 9 <u>\$\sigma\\$\ 9</u>



8 9 = 9





window trigger

Operations on Windowed Streams



- reduce(reduceFunction)
 - Apply a functional reduce function to the window
- fold(initialVal, foldFunction)
 - Apply a functional fold function with a specified initial value to the window
- Aggregation functions
 - sum(), min(), max(), and others

Custom window logic



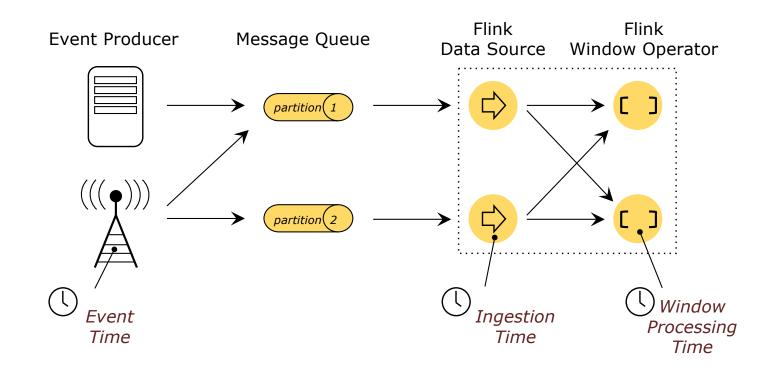
- The DataStream API allows you to define very custom window logic
- GlobalWindows
 - a flexible, low-level window assignment scheme that can be used to implement custom windowing behaviors
 - only useful if you explicitly specify triggering, otherwise nothing will happen
- Trigger
 - defines when to evaluate a window
 - whether to purge the window or not
- Careful! This part of the API requires a good understanding of the windowing mechanism!

Handling Time Explicitly

The biggest change in moving from batch to streaming is handling time explicitly

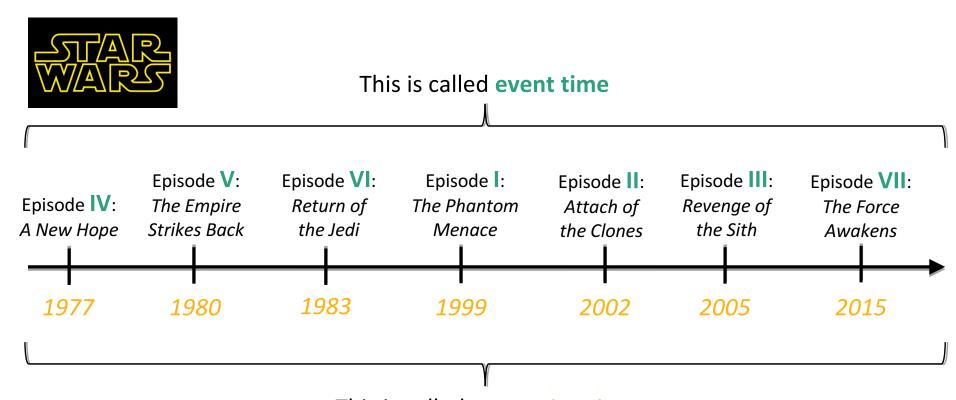
Different Notions of Time





Event Time vs Processing Time





This is called *processing time*

Setting the StreamTimeCharacteristic



```
final StreamExecutionEnvironment env =
   StreamExecutionEnvironment.getExecutionEnvironment();
env.setStreamTimeCharacteristic(TimeCharacteristic.EventTime);

// alternatively:
// env.setStreamTimeCharacteristic(TimeCharacteristic.IngestionTime);
// env.setStreamTimeCharacteristic(TimeCharacteristic.ProcessingTime);
```

Choosing Event Time has Consequences

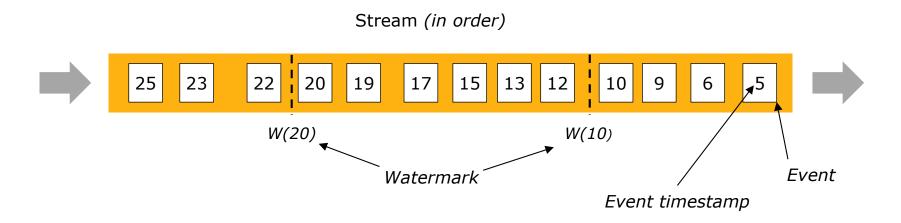


- With event time, Flink needs to know
 - how to extract timestamps from stream elements
 - when enough event time has elapsed that a time window should be triggered

Watermarks



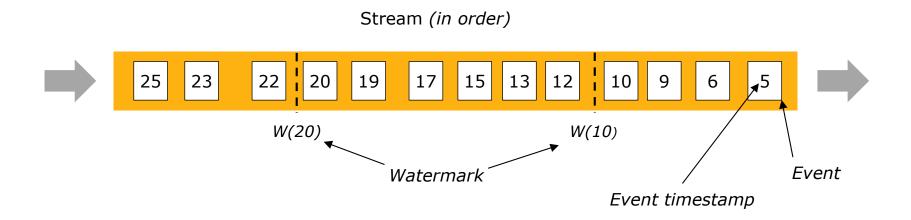
- Watermarks mark the progress of event time
- They flow with the data stream and carry a timestamp
- Watermarks assert that all earlier events have (probably) arrived



Perfect Watermarks



 When stream elements are in order (or in order by key), we can achieve perfect watermarking





 When events are out-of-order, we often assume there is some bound to how out-of-order they can be

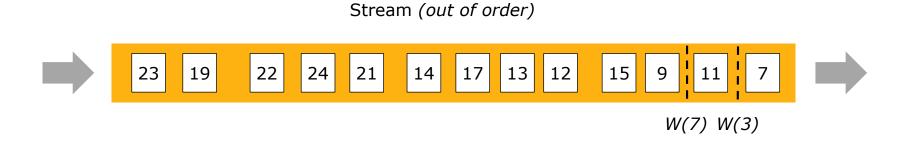
23 19 22 24 21 14 17 13 12 15 9 11 7 W(3)

Stream (out of order)

maxOutOfOrderness = 4



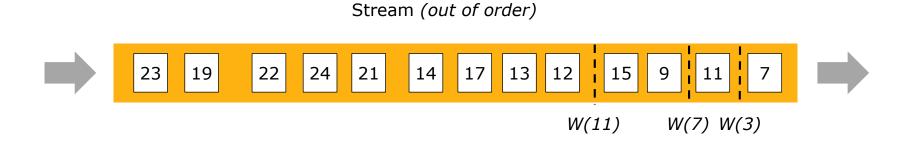
 Each time a new maximum timestamp arrives, we have enough info to emit a new Watermark



maxOutOfOrderness = 4



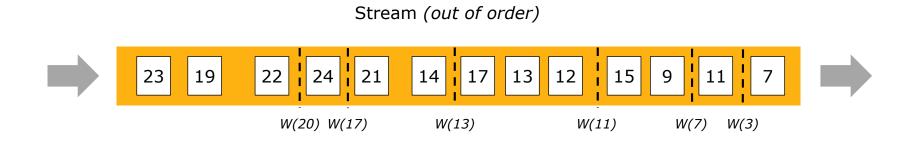
 Each time a new maximum timestamp arrives, we have enough info to emit a new Watermark



maxOutOfOrderness = 4



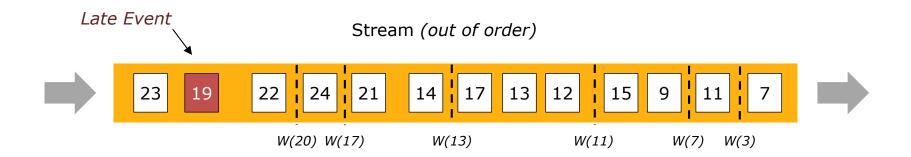
 Each time a new maximum timestamp arrives, we have enough info to emit a new Watermark



Watermarks define Lateness

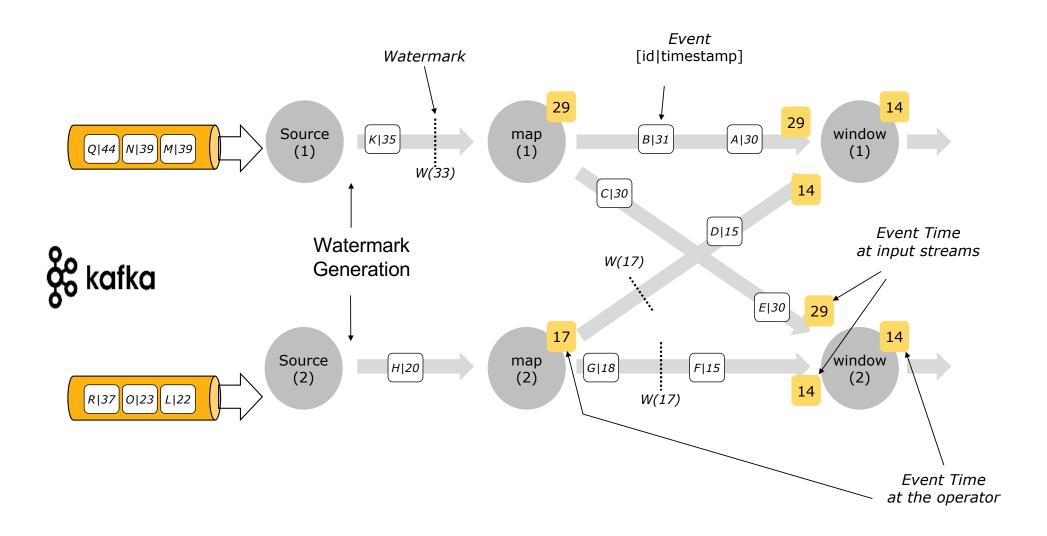


• Elements where timestamp < currentWatermark are late



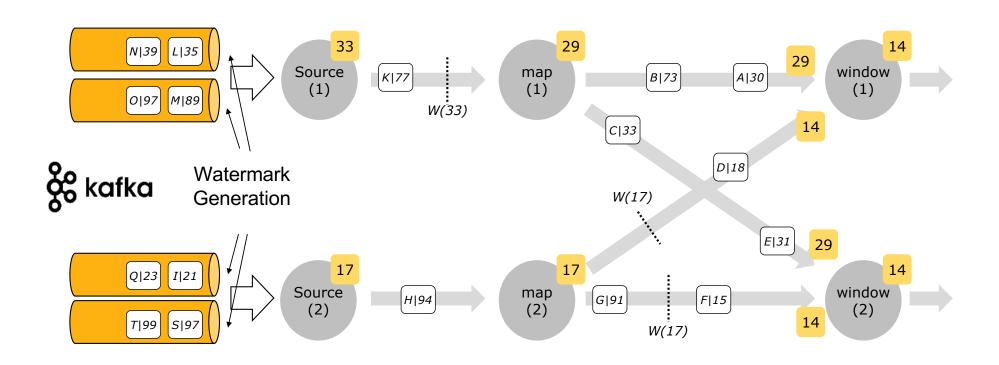
Watermarks in Parallel





Per-Kafka-Partition Watermarks





Watermarking



- Perfect
- (Un)comfortably bounded by fixed delay
 - too slow: results are delayed
 - too fast: some data is late
- Heuristic
 - allow windows to produce results as soon as meaningfully possible, and then continue with updates during the allowed lateness interval

Pre-defined timestamp extractors / watermark emitters



- AscendingTimestampExtractor
 - For special case when timestamps are in ascending order
- BoundedOutOfOrdernessTimestampExtractor
 - Periodically emits watermarks that lag a fixed amount of time behind the max timestamp seen so far

Example



```
stream
    .assignTimestampsAndWatermarks(new MyTSExtractor())
    .keyBy(...)
    .timeWindow(...)
    .addSink(...);
public static class MyTSExtractor extends
  BoundedOutOfOrdernessTimestampExtractor<TaxiRide> {
    public TaxiRideTSExtractor() {
        super(Time.seconds(MAX EVENT DELAY));
   @Override
    public long extractTimestamp(TaxiRide ride) {
        return ride.startTime.getMillis();
```

References



 The Dataflow Model: A Practical Approach to Balancing Correctness, Latency, and Cost in Massive-Scale, Unbounded, Out-of-Order Data Processing

https://research.google.com/pubs/pub43864.html

Documentation

- https://ci.apache.org/projects/flink/flink-docs-release-1.2/dev/event_time.html
- https://ci.apache.org/projects/flink/flink-docs-release-1.2/dev/event_timestamps_watermarks.html
- https://ci.apache.org/projects/flink/flink-docs-release-1.2/dev/windows.html

Blog posts

- http://flink.apache.org/news/2015/12/04/Introducing-windows.html
- http://data-artisans.com/how-apache-flink-enables-new-streamingapplications-part-1/
- https://www.mapr.com/blog/essential-guide-streaming-first-processingapache-flink
- http://data-artisans.com/session-windowing-in-flink/