

Big Data Pipelines with Scala

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github.com/kanterov/ lambdaconf-2017-bigdata

Who am 1?

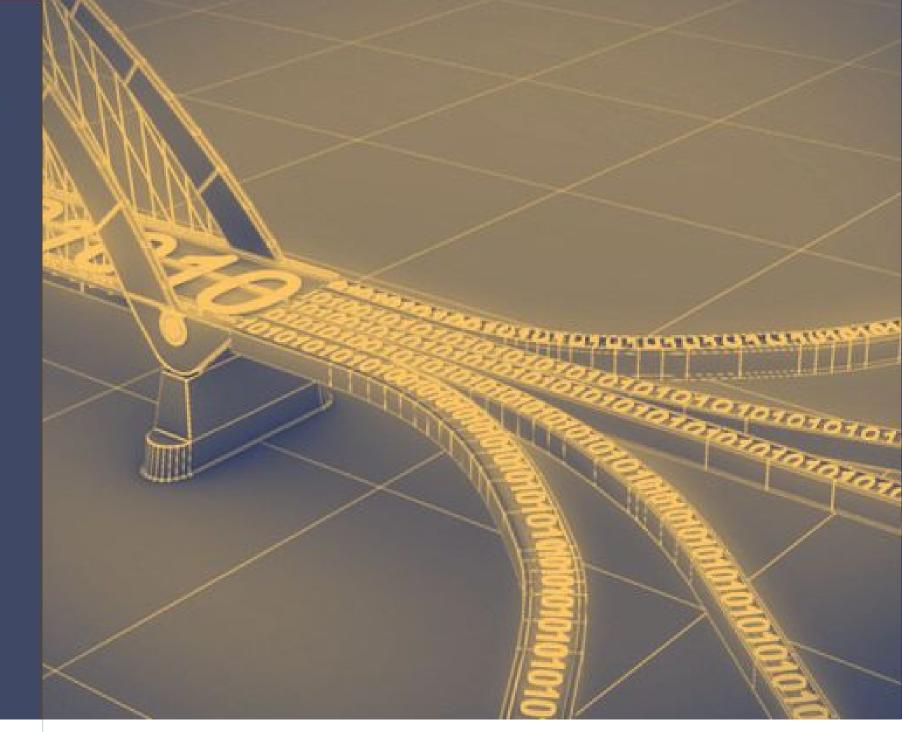
- DATA @ Spotify
- Functional
 Programming and
 Cofree Coffee
- In Scala since 2012



We are hiring!



```
9 function addNumbers(a, b) {
                                           returns the total. Demonstrates simple
13 // Takes the
14 // recursion.
15 function totalForArray(a)
                                            ptal) {
      currentTotal addNumber
                                            tal arr.shift());
      (arr.length 0) {
       totalForArray(currentTotal arr);
          currentTotal;
    // Or you could just us
function totalForArray
           arr.reduce(ad
32 function average(
              count /
   function ave
                              igth, totalForArray(arr));
                        cociated with the property of an tion method like map, hence the ropertyName) {
                       (item) {
                      [propertyName];
```



Batch Pipelines and Big Data

Functional Programming and Big Data

From Batch to Streaming



Fast Facts

- 100M+ Active Users
- 50M+ Subscribers
- 30M+ Songs
- 2B+ Playlists

Hadoop@Spotify



Hadoop@Spotify

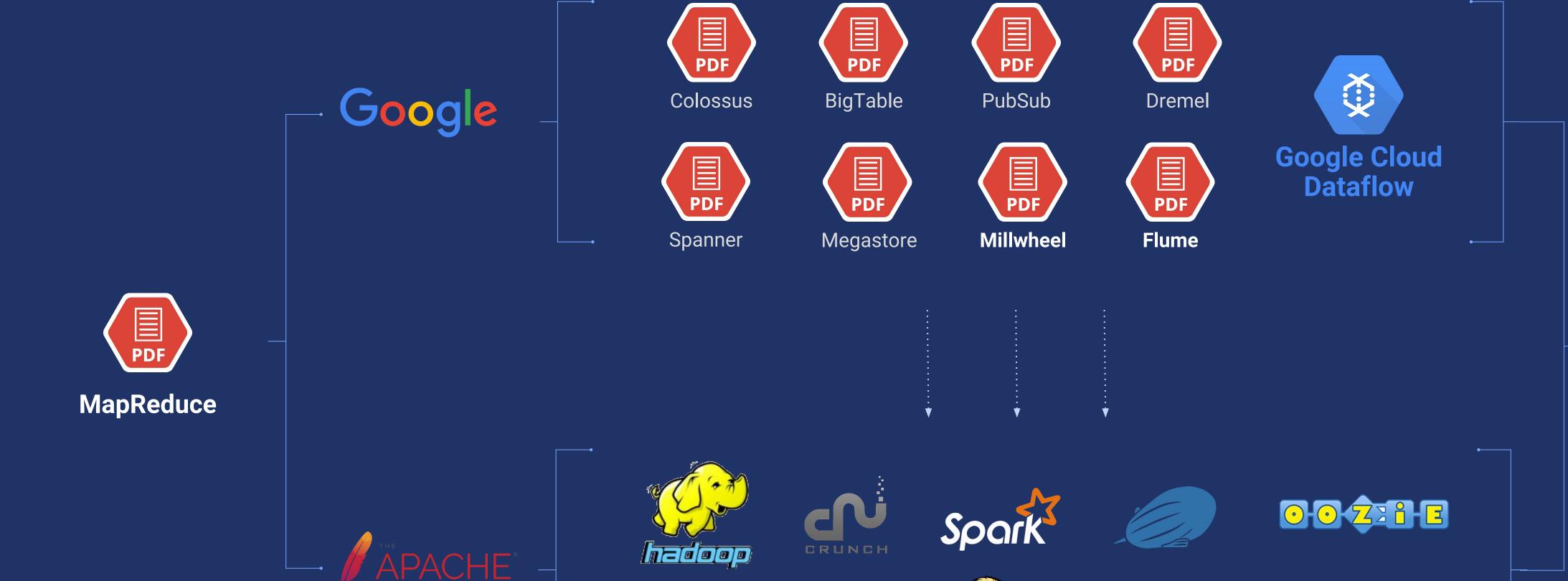
- On-Premise
- 2,500 nodes
- 100 PB Disk
- 100 TB RAM
- 100B+ events per day
- 20K+ jobs per day





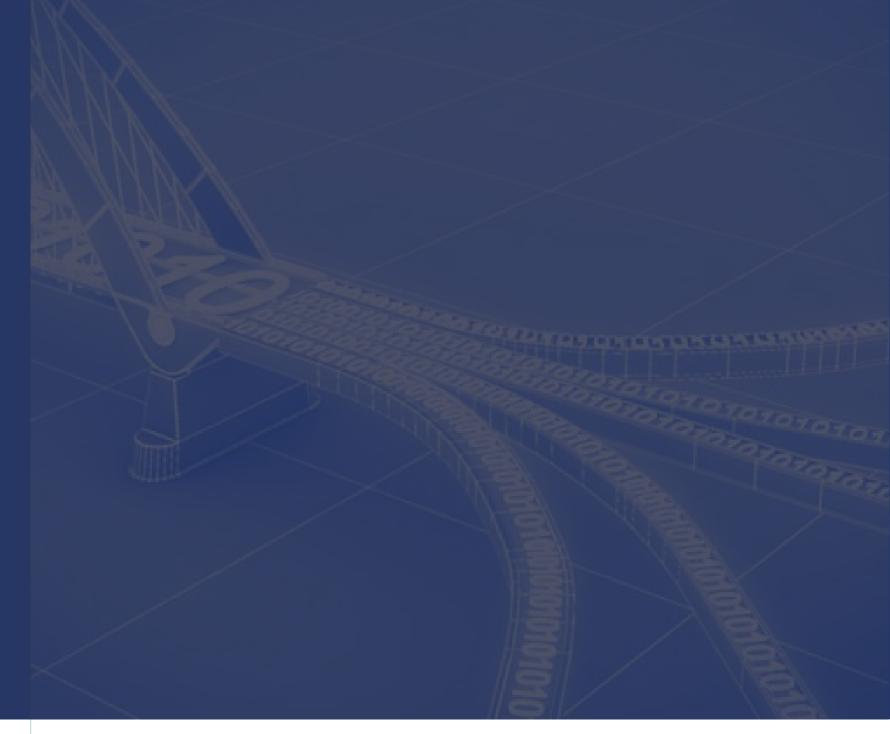
Moving to Google Cloud

The Evolution of Big Data Ecosystem



APACHE DRILL





Unit

Batch Pipelines and Big Data

Functional Programming and Big Data

From Batch to Streaming

MapReduce: Batch Processing

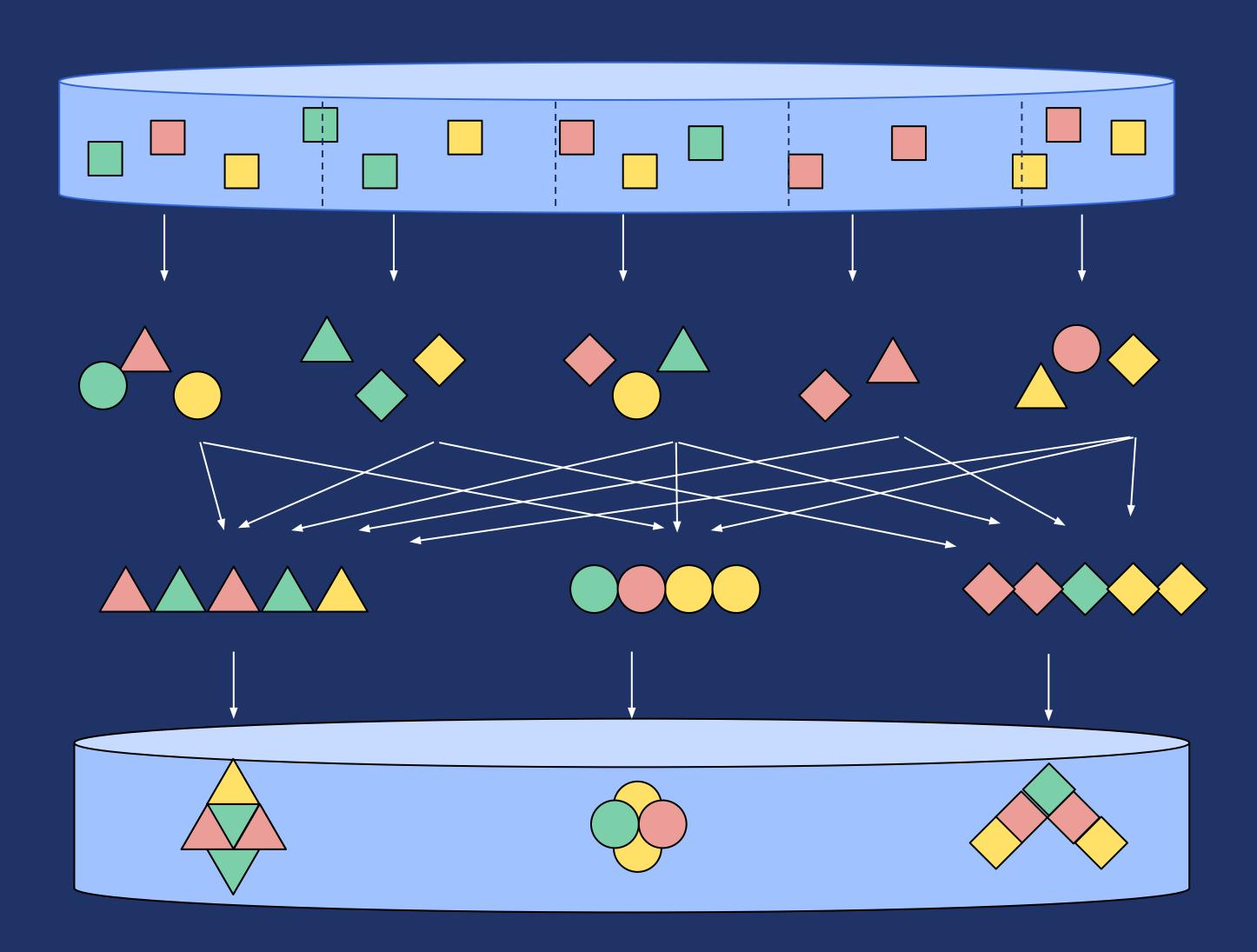
(Prepare)

Map

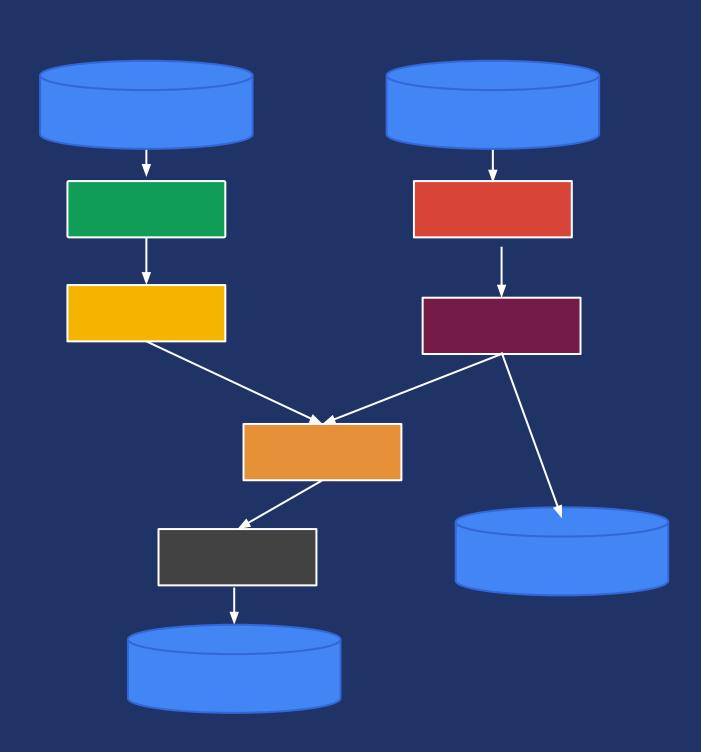
(Shuffle)

Reduce

(Produce)



Apache Beam



- High Level API
- User provides DAG of computations to be performed
- SDK available for Java and Python
- Runs on
 - Google Dataflow
 - Apache Spark
 - Apache Apex
 - Apache Flink

Scio

Latin /'ʃi.o/, ['ʃiː.o] Verb: I can, know, understand, have knowledge.

```
case class TrackCount(trackId: TrackId, plays: Long)

case class PlayTrack(userId: UserId, trackId: TrackId)

playTracks
   .map(track => (track.trackId, 1L))
   .reduceByKey(_ + _)
   .map { case (trackId, plays) => TrackCount(trackId, plays) }
```

```
trait SCollection[A] {
 def map[B](f: A => B): SCollection[B]
 def flatMap[B](f: A => Iterable[B]): SCollection[B]
 def filter(f: A => Boolean): SCollection[A]
implicit class PairSCollectionOps[K, V](
  self: SCollection[(K, V)]) {
 def reduceByKey(f: (V, V) => V): SCollection[(K, V)]
 def sum(implicit V: Semigroup[V]): SCollection[(K, V)]
```

Proprietary & Confidential Project Title 00.00.2015

Unit 01.

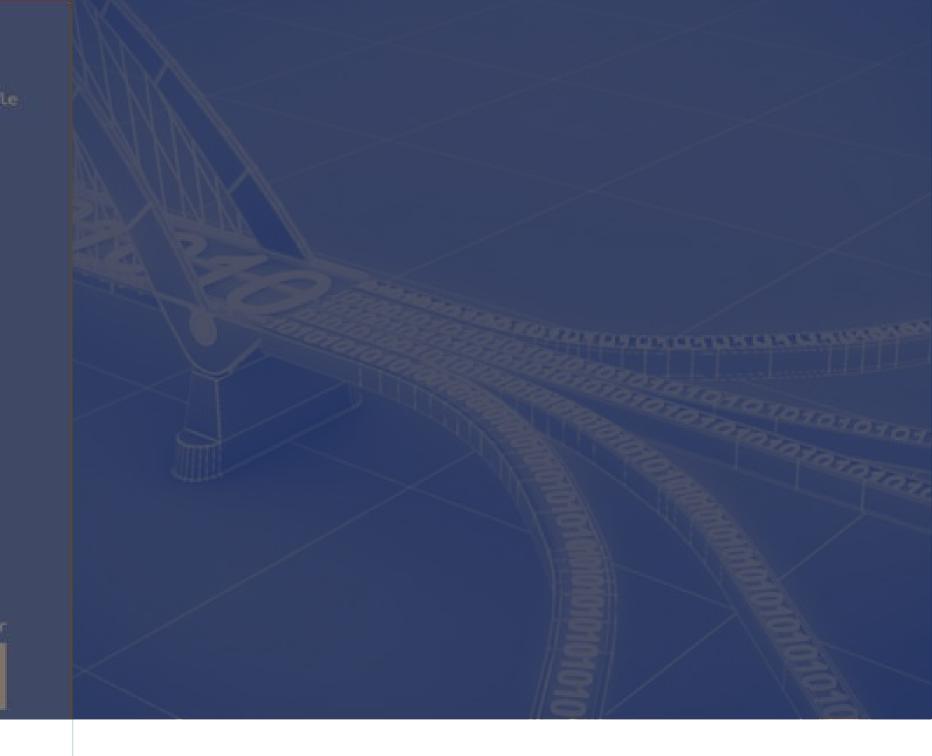
1. open sbt and run pipeline

- \$./sbt shell
- > unit-1
- > test-unit-1
- > avro-read in/play_track/
- > avro-read out/play_count/

2. output total content hours per user

3. output top n users by content hours

```
9 function addNumbers(a, b) {
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                                   returns the total. Demonstrates simple
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                                    prat) {
                                    tal arr.shift());
    currentTotal addNumber
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22 currentTotal;
27 function totalForArray
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                   (item) {
                  [propertyName];
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Immutable Data

```
case class TrackCount(trackId: TrackId, plays: Long)

case class PlayTrack(userId: UserId, trackId: TrackId)

playTracks
   .map(track => (track.trackId, 1L))
   .reduceByKey(_ + _)
   .map { case (trackId, plays) => TrackCount(trackId, plays) }
```

Second-Order Functions

```
case class TrackCount(trackId: TrackId, plays: Long)

case class PlayTrack(userId: UserId, trackId: TrackId)

playTracks
   .map(track => (track.trackId, 1L))
   .reduceByKey(_ + _)
   .map { case (trackId, plays) => TrackCount(trackId, plays) }
```

First-Class Functions and Lambdas

```
case class TrackCount(trackId: TrackId, plays: Long)

case class PlayTrack(userId: UserId, trackId: TrackId)

playTracks
   .map(track => (track.trackId, 1L))
   .reduceByKey(_ + _)
   .map { case (trackId, plays) => TrackCount(trackId, plays) }
```

Pattern-Matching

```
case class TrackCount(trackId: TrackId, plays: Long)

case class PlayTrack(userId: UserId, trackId: TrackId)

playTracks
   .map(track => (track.trackId, 1L))
   .reduceByKey(_ + _)
   .map { case (trackId, plays) => TrackCount(trackId, plays) }
```

Composition

```
def contentHours(playTracks: SCollection[PlayTrack]):
  SCollection[ContentHours] = ...
def topUsers(n: Int, playTracks: SCollection[PlayTrack]):
  SCollection[ContentHours] = {
  contentHours(playTracks)
    .top(n)(Ordering.by( .msPlayedSum))
    .flatMap(x => x)
```

ootify

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What Can Go Wrong

Problem: Skewed Data

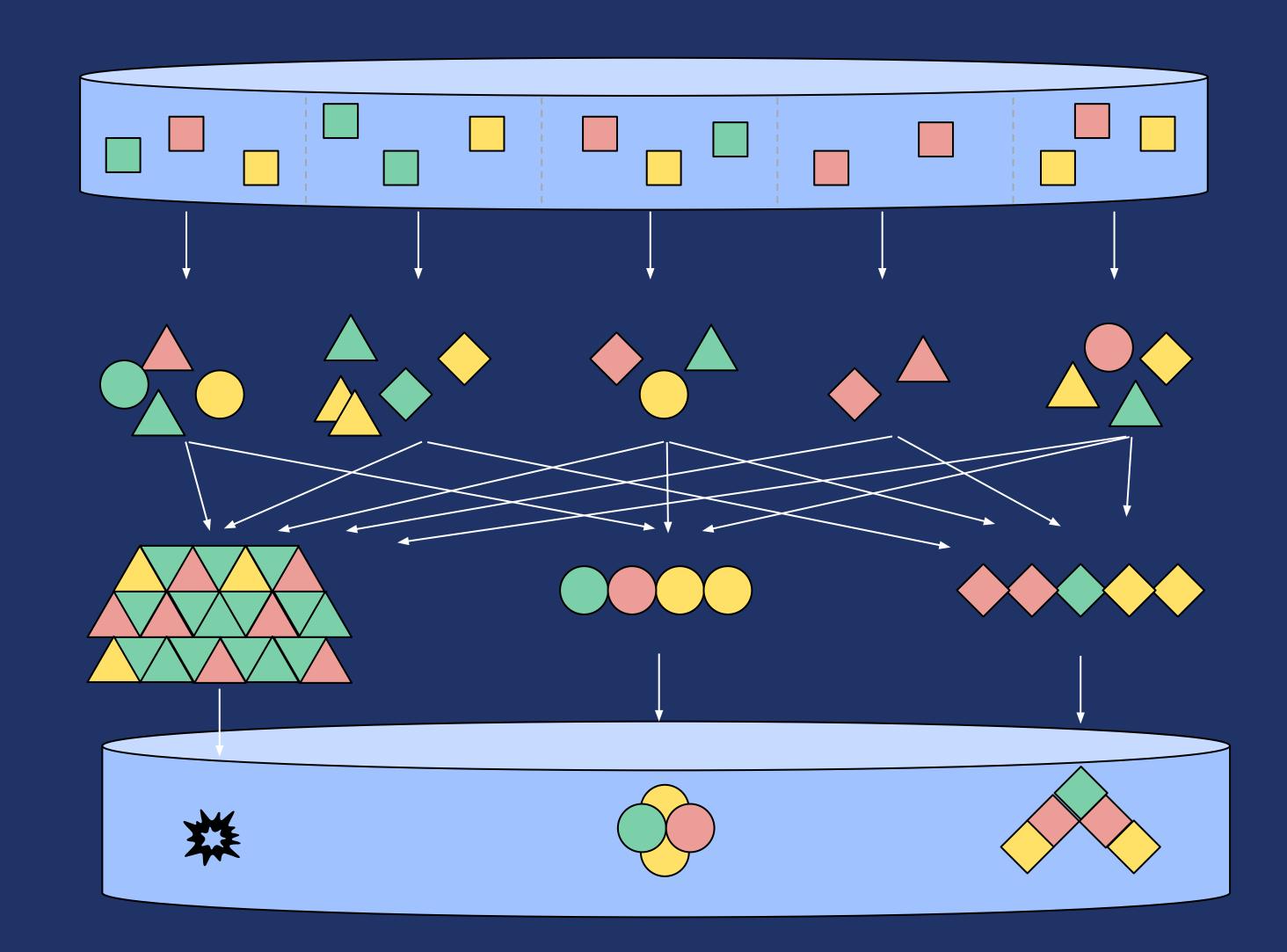
(Prepare)

Map

(Shuffle)

Reduce

(Produce)



Hot Key Fanout

```
def withHotKeyFanout(hotKeyFanout: K => Int):
    SCollectionWithHotKeyFanout[K, V]
```

- adds intermediate step to reduce skewed keys
- hotKeyFanout determines number of nodes

Hash Join

```
def hashJoin[W](that: SCollection[(K, W)]):
    SCollection[(K, (V, W))]
```

- replicates that to all workers
- right side should be tiny and fit into memory

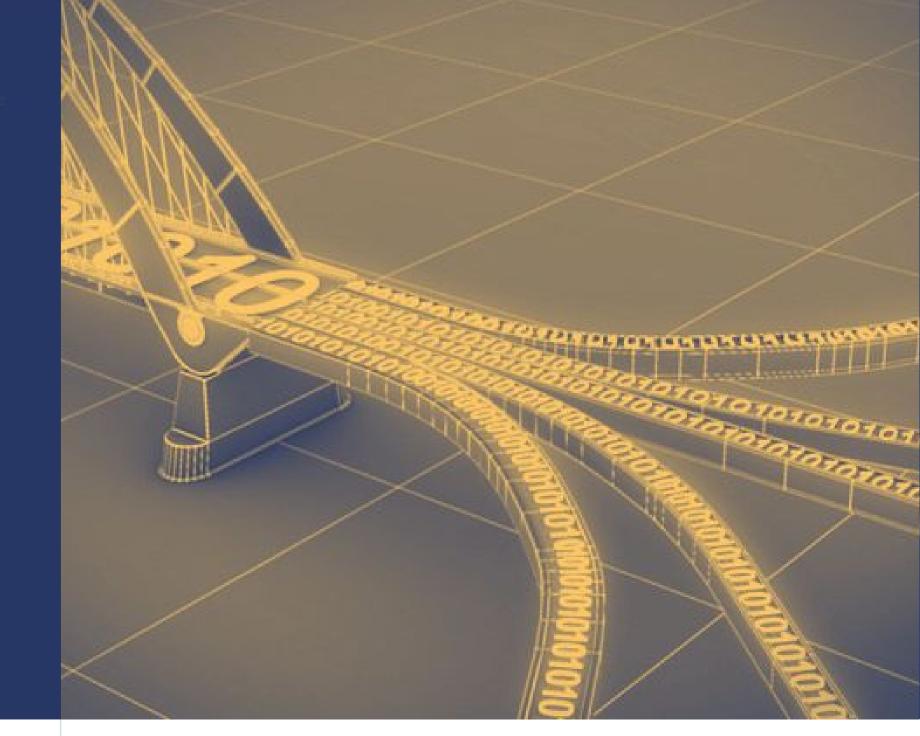
Skewed Join

```
def skewedJoin[W](that: SCollection[(K, W)]):
    SCollection[(K, (V, W))]
```

- adds intermediate step with hashJoin of hot keys
- uses Count-Min-Sketch to find hot keys

Testing your Code

```
See ./src/test/scala/us.lambdaconf/
4_tests.scala
```

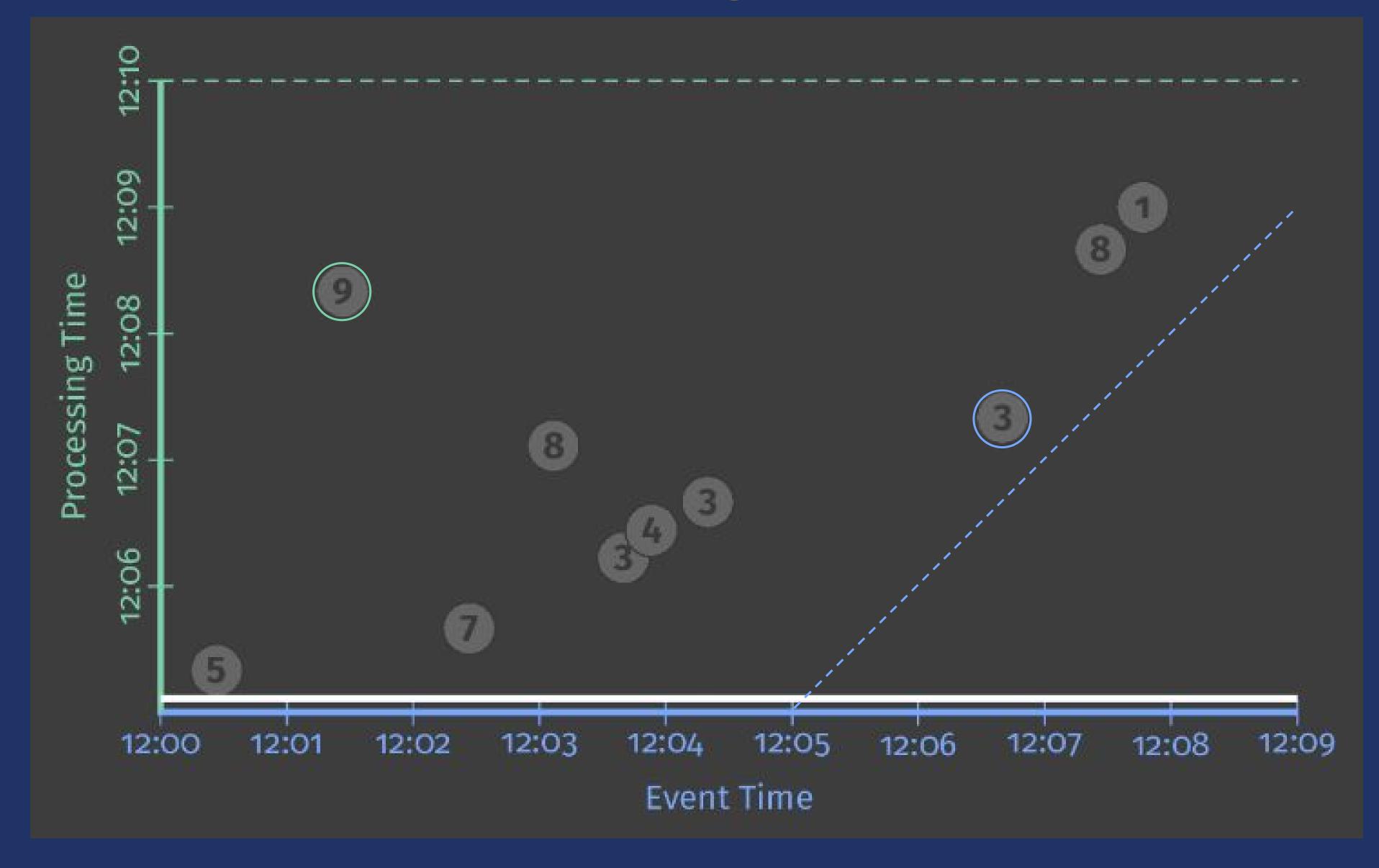


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Event Time vs. Processing Time



What are you computing?

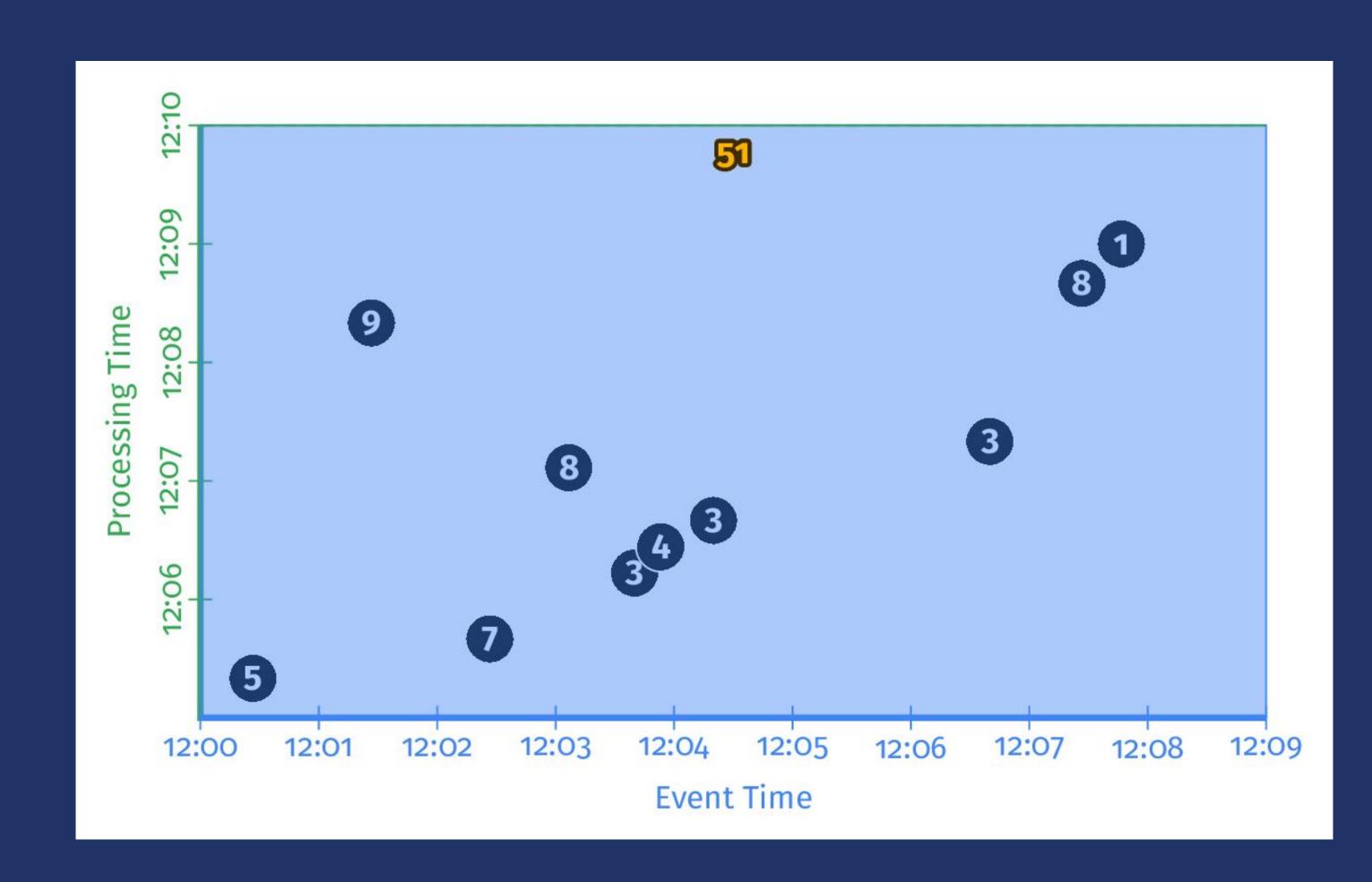
Where in event time?

When in processing time?

How do refinements relate?

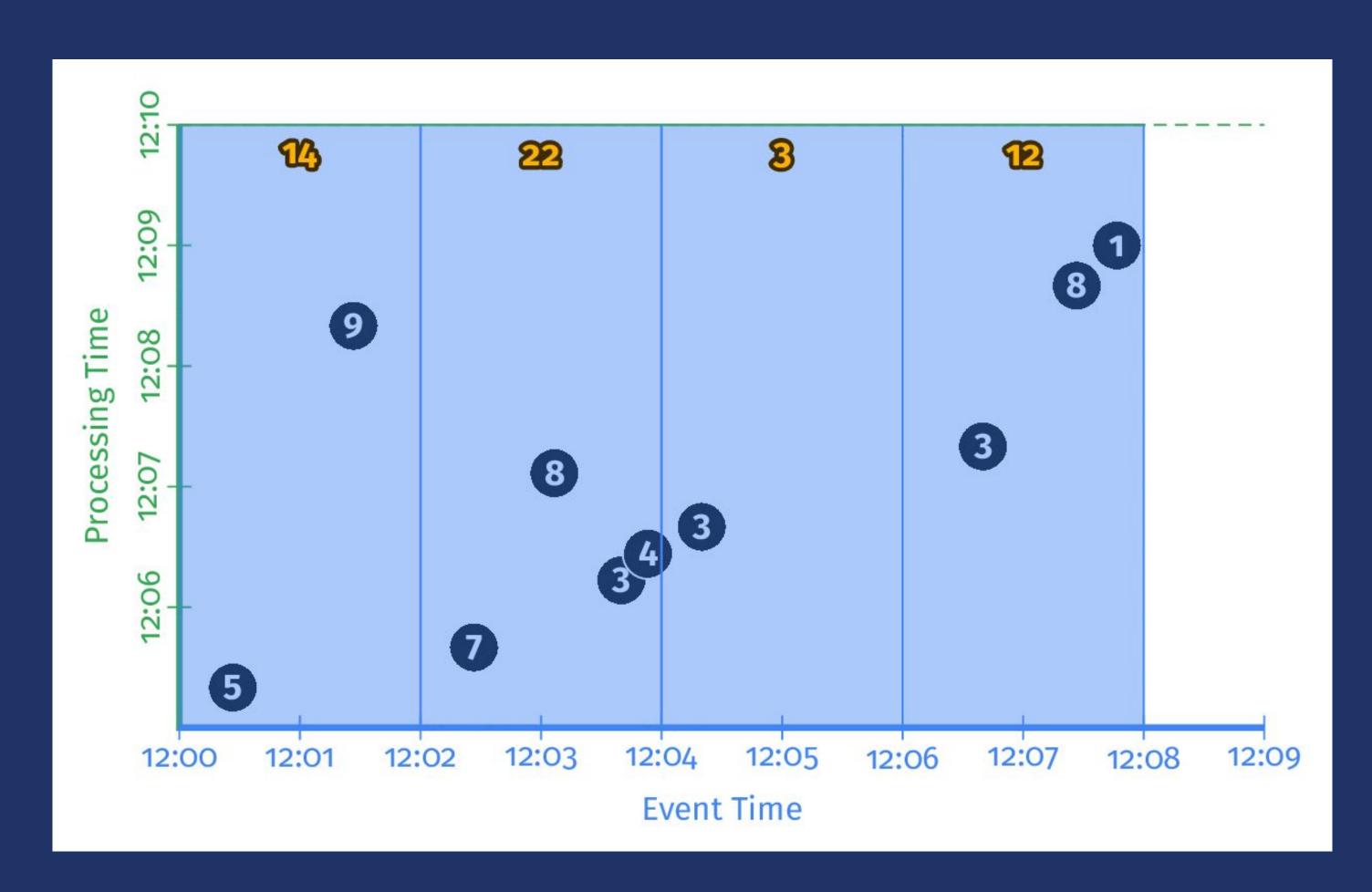
The Beam Model: What is Being Computed?

```
playTracks
.map(_.msPlayed)
.sum
```



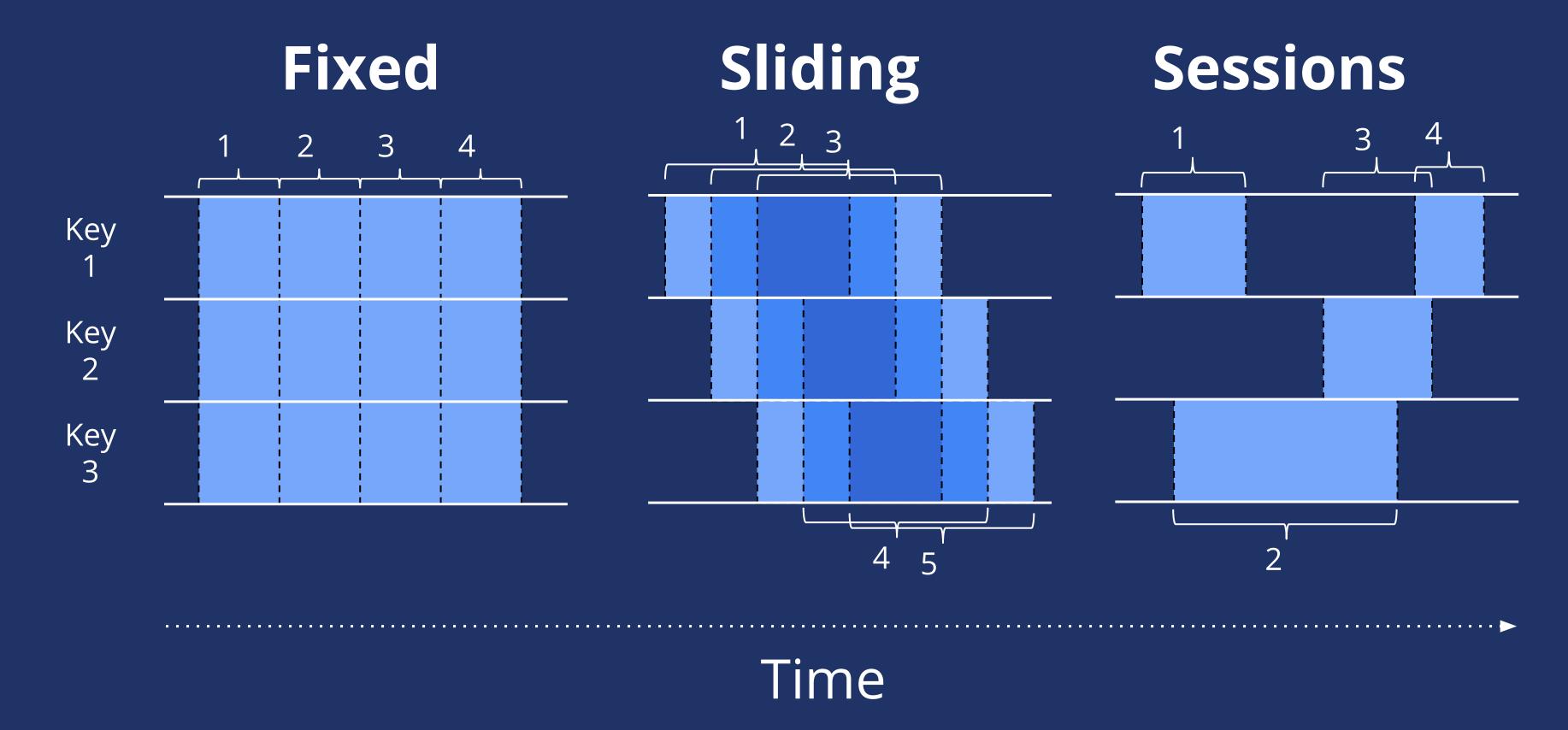
The Beam Model: Where in Event Time?

```
playTracks
  .map(_.msPlayed)
  .withFixedWindows(minutes(2))
  .sum
```



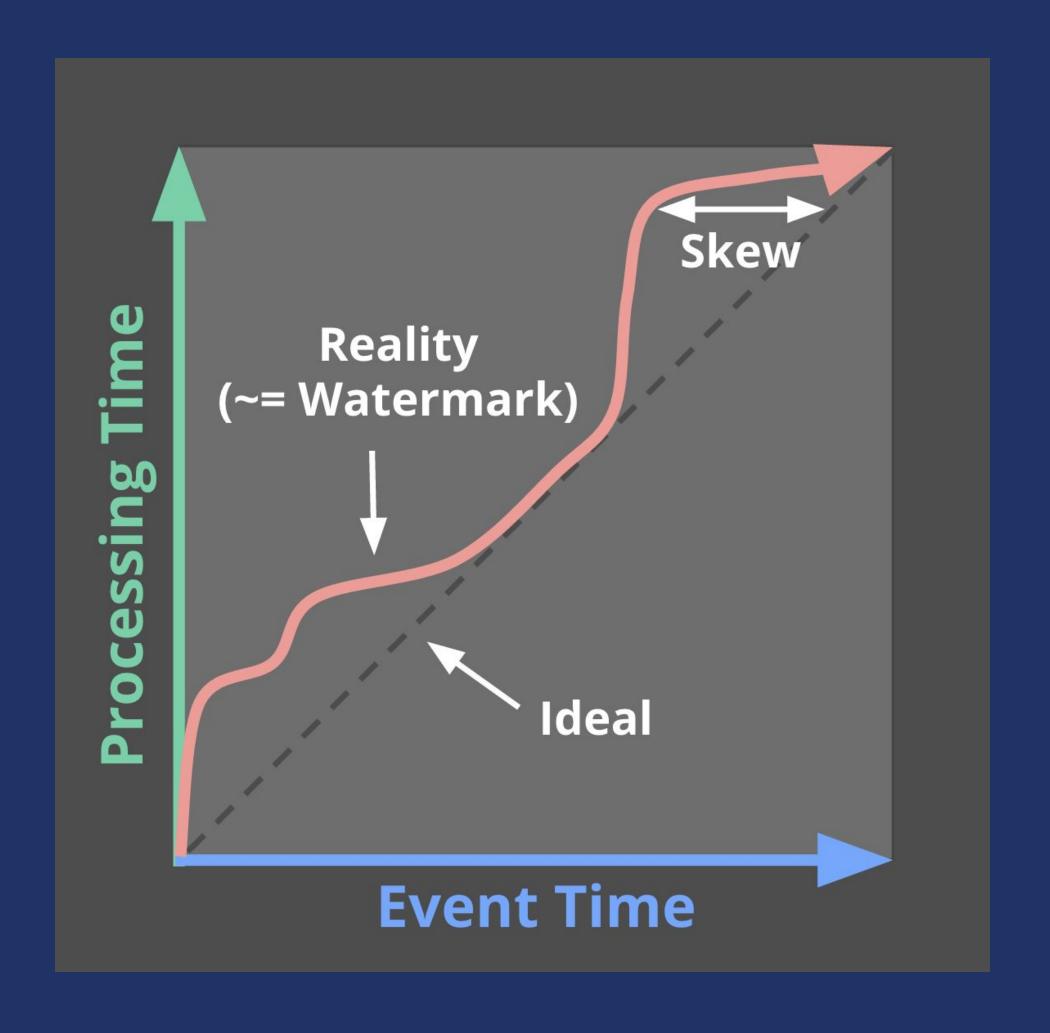
Where in event time?

Windowing divides data into event-time-based finite chunks.



Often required when doing aggregations over unbounded data.

When in processing time?



Triggers control when results are emitted.

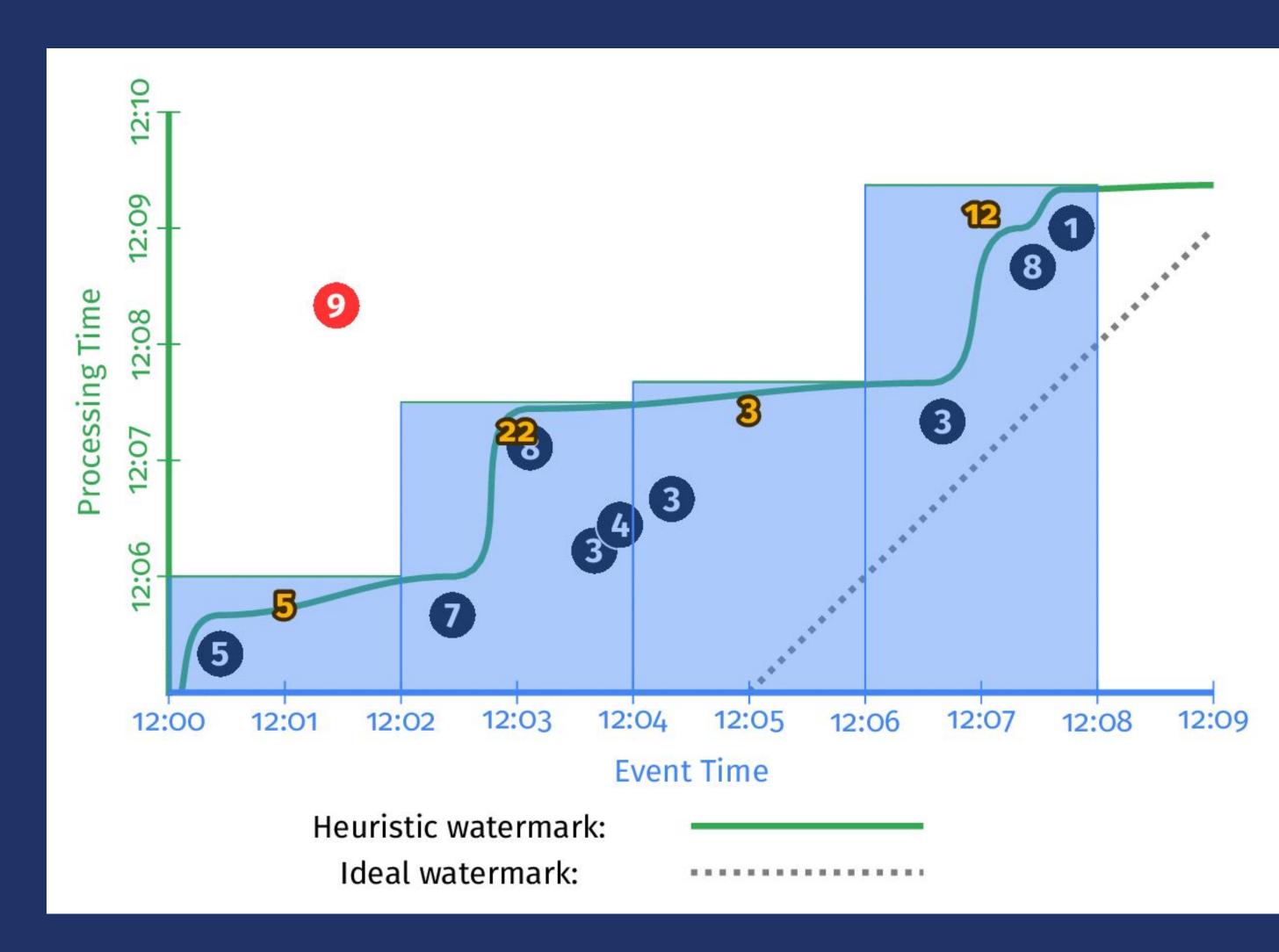
Triggers are often relative to the watermark.

The Beam Model: When in Processing Time?

```
val trigger =
  AfterWatermark.pastEndOfWindow()

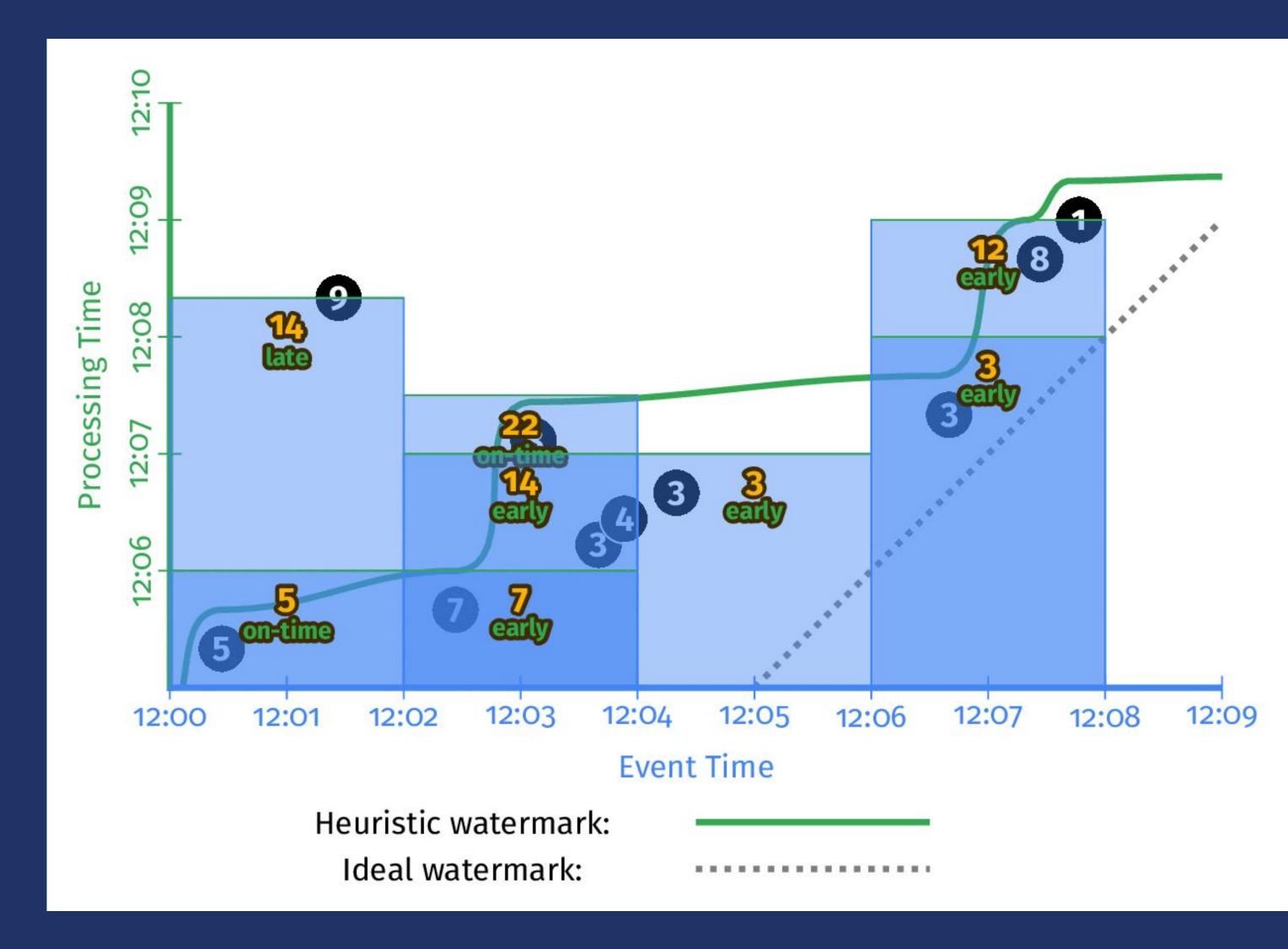
val options = WindowOptions(trigger)

playTracks
  .map(_.msPlayed)
  .withFixedWindows(
    duration = minutes(2),
    options = options)
  .sum
```

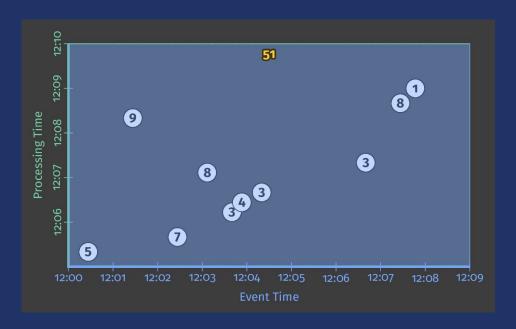


The Beam Model: How do Refinements Relate?

```
val trigger = AfterEach.inOrder(
 Repeatedly. forever(
   AfterProcessingTime
     .pastFirstElementInPane()
     .plusDelayOf(minutes(1))
 ).orFinally(
   AfterWatermark.pastEndOfWindow()),
 Repeatedly. forever(
   AfterPane
     .elementCountAtLeast(1)))
val options = WindowOptions()
trigger = trigger,
 allowedLateness = days(1),
 accumulationMode =
  ACCUMULATING_FIRED_PANES)
```



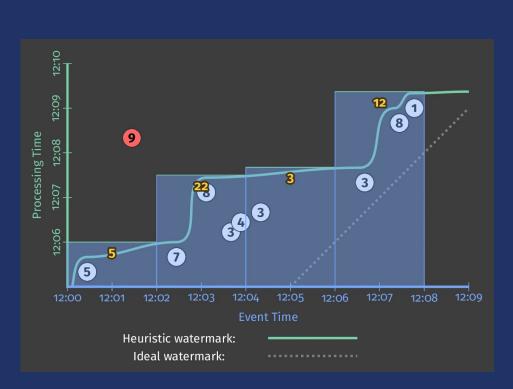
Customizing What When Where How



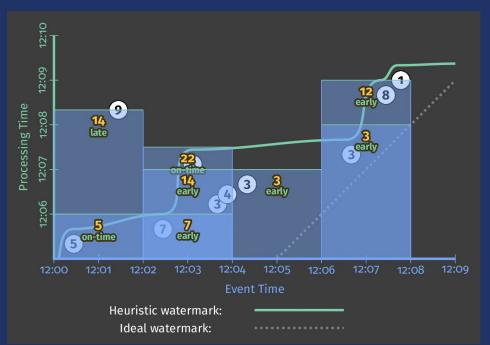
1.Classic Batch



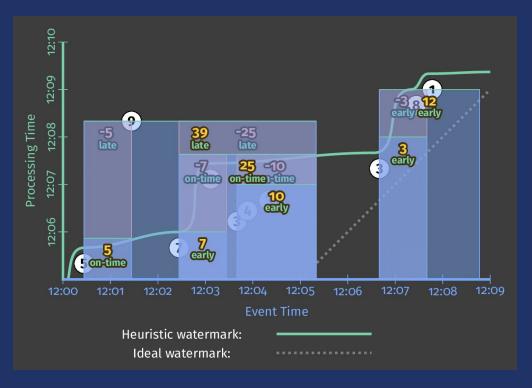
2. Batch with Fixed Windows



3. Streaming



4. Streaming with Speculative + Late Data



5. Streaming With Retractions

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Unit 03.

- 1. override windowing options, set accumulation strategy for late events
- 2. drop events late more than 1 day
- 3. accumulate late events iff batch has more than 3 elements

4. wait for one hour for last event before closing the window

Learn More!

- github.com/spotify/scio
- beam.apache.org

