



Apache Spark as a Platform for Powerful Custom Analytics Data Pipeline

Misha Chernetsov, Grammarly
Apache Spark Meetup, SF
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About Me: Misha Chernetsov

Data Team Lead @ Grammarly

Kindle @ Amazon

Building Analytics Pipelines (5 years)

Coding on JVM (12 years), Scala + Spark (3 years)

@chernetsov



Analytics @ Consumer Product Company

Tool that helps us better understand:

- Who are our users?
- How do they interact with the product?
- How do they get in, engage, pay, and how long do they stay?



Analytics @ Consumer Product Company

We want our decisions to be

data-driven

Everyone: product managers, marketing, engineers, support...



Analytics @ Consumer Product Company



Example Report 1 – Daily Active Users

Number of
unique active
users by day



dummy data!

Calendar Day



Example Report 2 – Comparison of Cohort Retention Over Time

Cohort	week 1	week 2	week 3	week 4	week 5
<all>	3.07%	9.49%	6.43%	3.90%	1.93%
Mon Mar 13 - Mon Mar 20	6.82%	3.05%	9.60%	6.95%	1.38%
Mon Mar 20 - Mon Mar 27	6.69%	1.71%	8.35%	2.39%	.213%
Mon Mar 27 - Mon Apr 03	6.52%	1.52%	5.02%	5.561%	
Mon Apr 03 - Mon Apr 10	5.25%	7.75%	.325%		
Mon Apr 10 - Mon Apr 17	1.67%	.506%			
Mon Apr 17 - Mon Apr 24	.962%				
Mon Apr 24 - Mon May 01					

dummy data!



Example Report 3 – Funnel Analysis

Step 1. Users who visited a certain landing page



Step 2. Users who installed a product after Step 1.



dummy data!

Step 3. Users who created an account after Step 2 and Step 1.



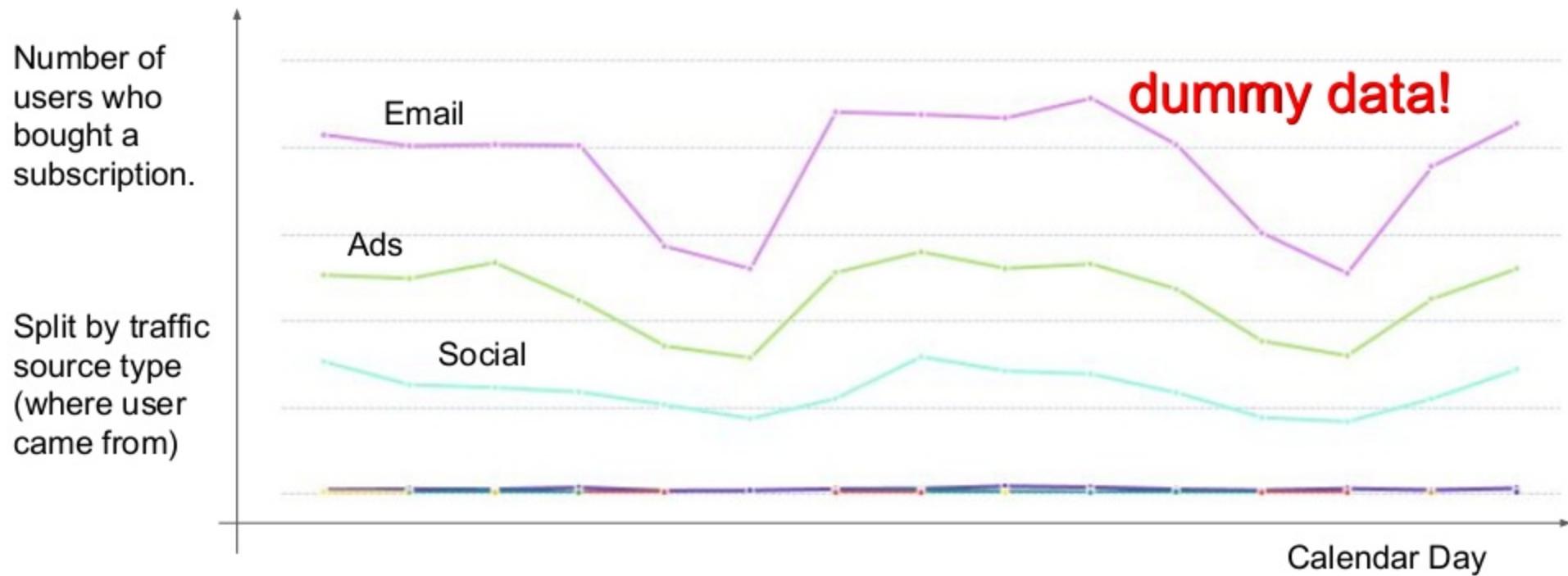
Step 1

Step 2

Step 3



Example Report 4 – Payer Conversions By Traffic Source



Example: Data

- Landing page visit
 - URL with UTM tags
 - Referrer



- Subscription purchased
 - Is first in subscription



Example: Data

```
{  
  "eventName": "page-visit",  
  "url": "...?utm_medium=ad",  
  ...  
}
```



```
{  
  "eventName": "subscribe",  
  "period": "12 months",  
  ...  
}
```



Everything is an Event



Example: Data

```
{  
  "eventName": "page-visit",  
  "url": "...?utm_medium=ad",  
  ...  
}
```



Slice by

```
{  
  "eventName": "subscribe",  
  "period": "12 months",  
  ...  
}
```

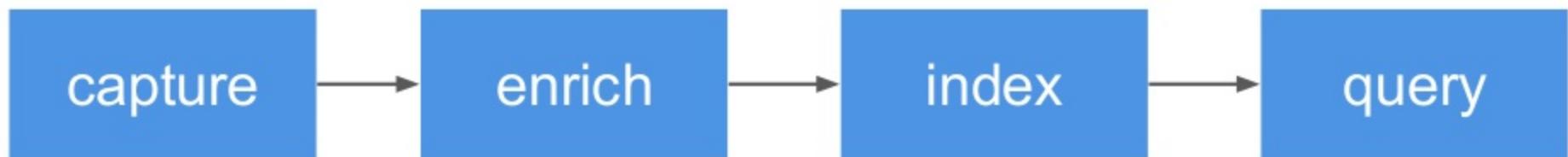


Plot

Enrich and/or Join

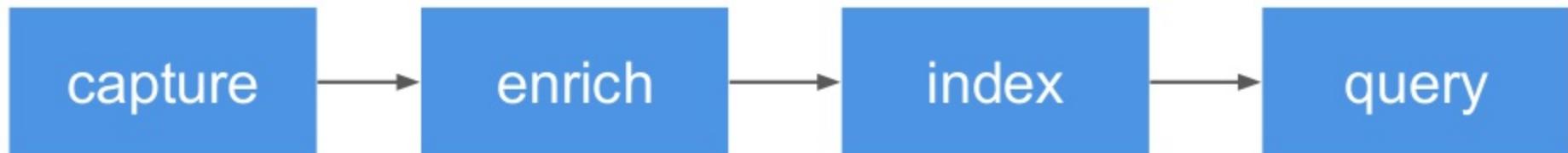


Analytics @ Consumer Product Company



Use 3rd Party?

1. Integrated Event Analytics
2. UI over your DB



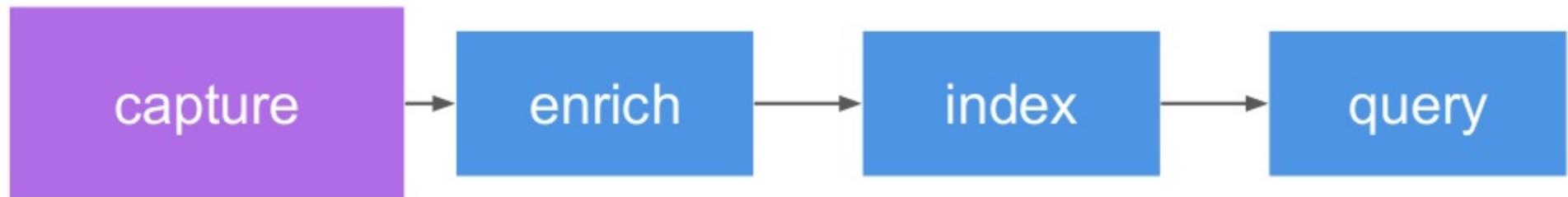
Pre-aggregation / enriching
is still on you.

Reports are not tailored for your
needs, limited capability.

Hard to achieve accuracy and trust.



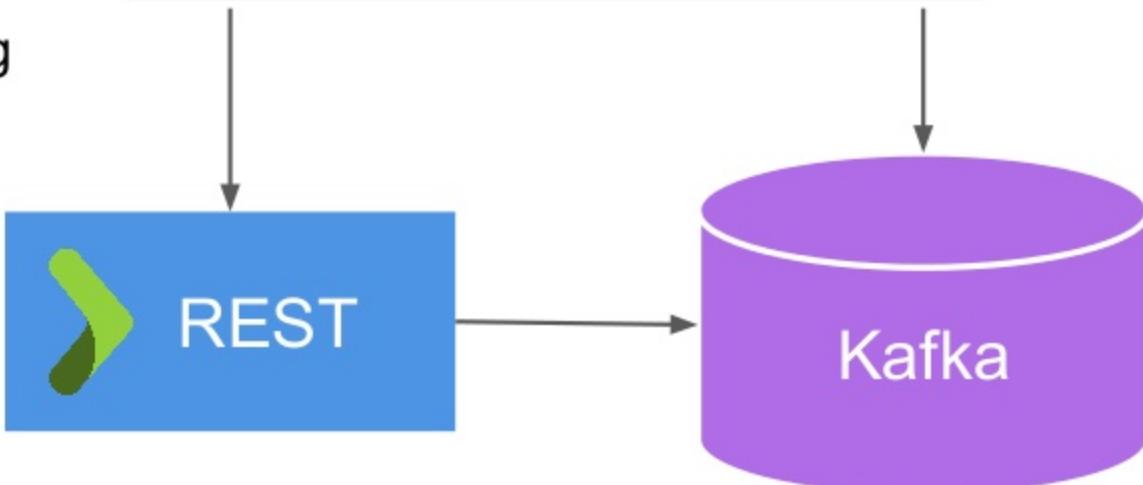
Build Step 1: Capture



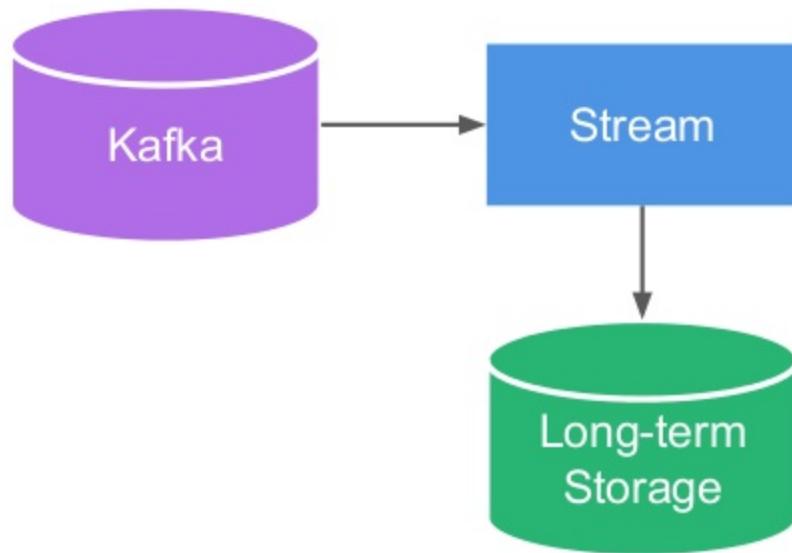
Capture

- Always up, resilient
- Spikes / back pressure
- Buffer for delayed processing

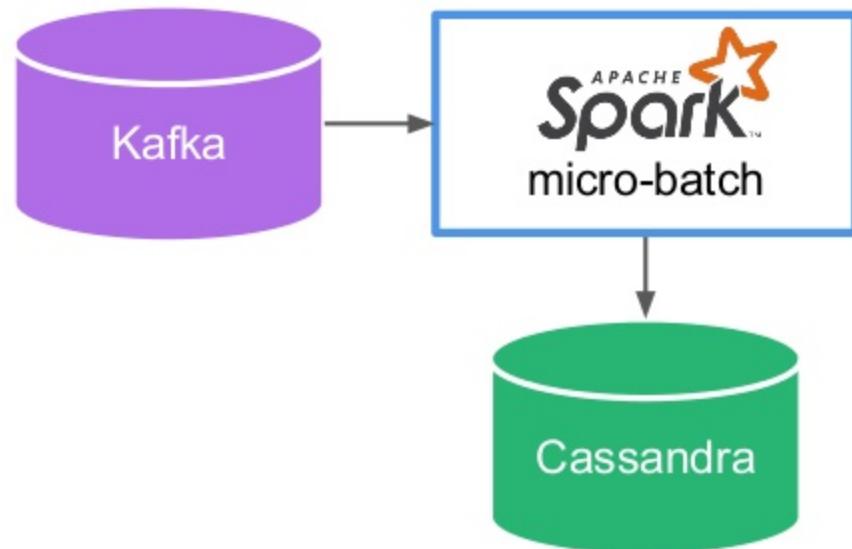
```
{  
  "eventName": "page-visit",  
  "url": "...?utm_medium=paid",  
  ...  
}
```



Save To Long-Term Storage



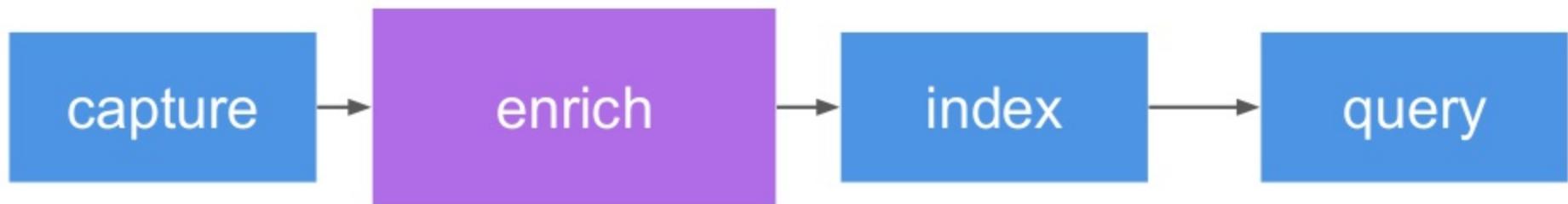
Save To Long-Term Storage



```
val rdd = KafkaUtils.createRDD[K, V](...)  
rdd.saveToCassandra("raw")
```



Build Step 2: Enrich



Enrichment Phase 1: User Attribution



Enrichment Phase 1: User Attribution

```
{  
  "eventName": "page-visit",  
  "url": "...?utm_medium=ad",  
  "fingerprint": "abc",  
  ...  
}
```



```
{  
  "eventName": "subscribe",  
  "userId": 123,  
  "fingerprint": "abc",  
  ...  
}
```



Enrichment Phase 1: User Attribution

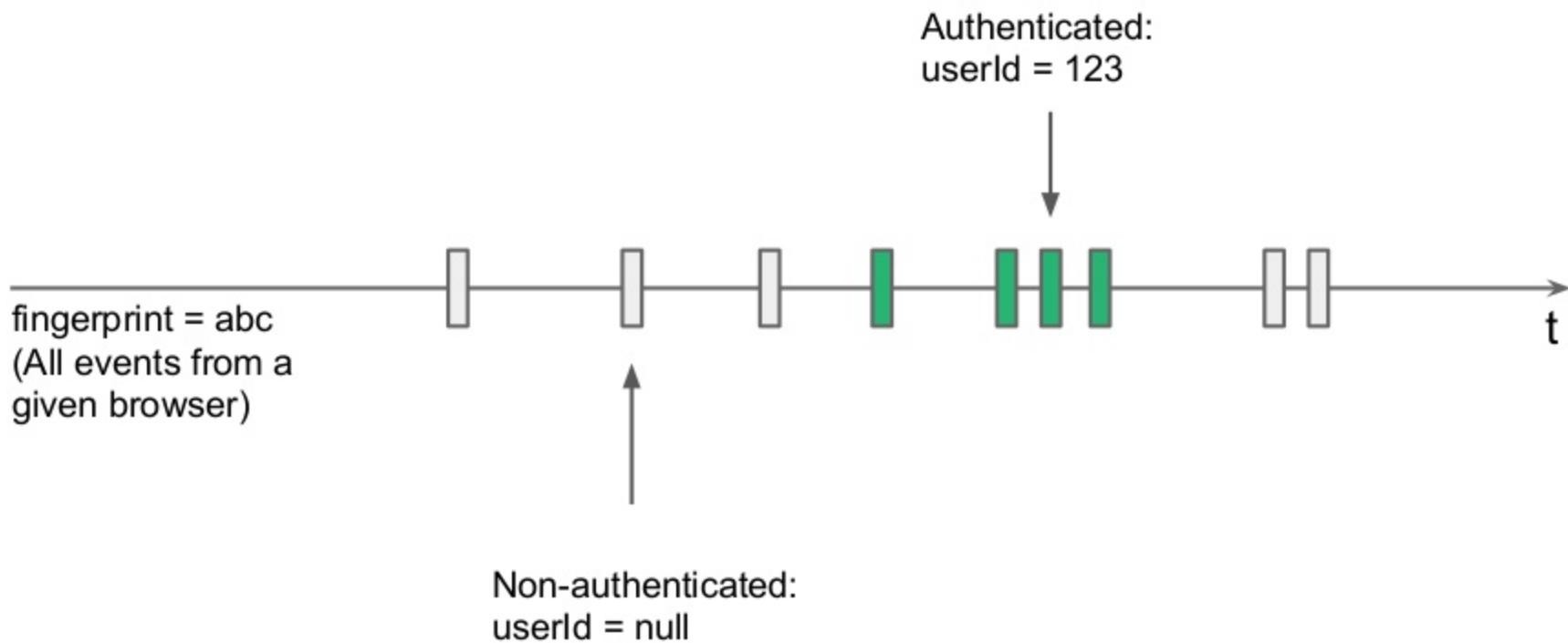
```
{  
  "eventName": "page-visit",  
  "url": "...?utm_medium=ad",  
  "fingerprint": "abc",  
  "attributedUserId": 123,  
  ...  
}
```



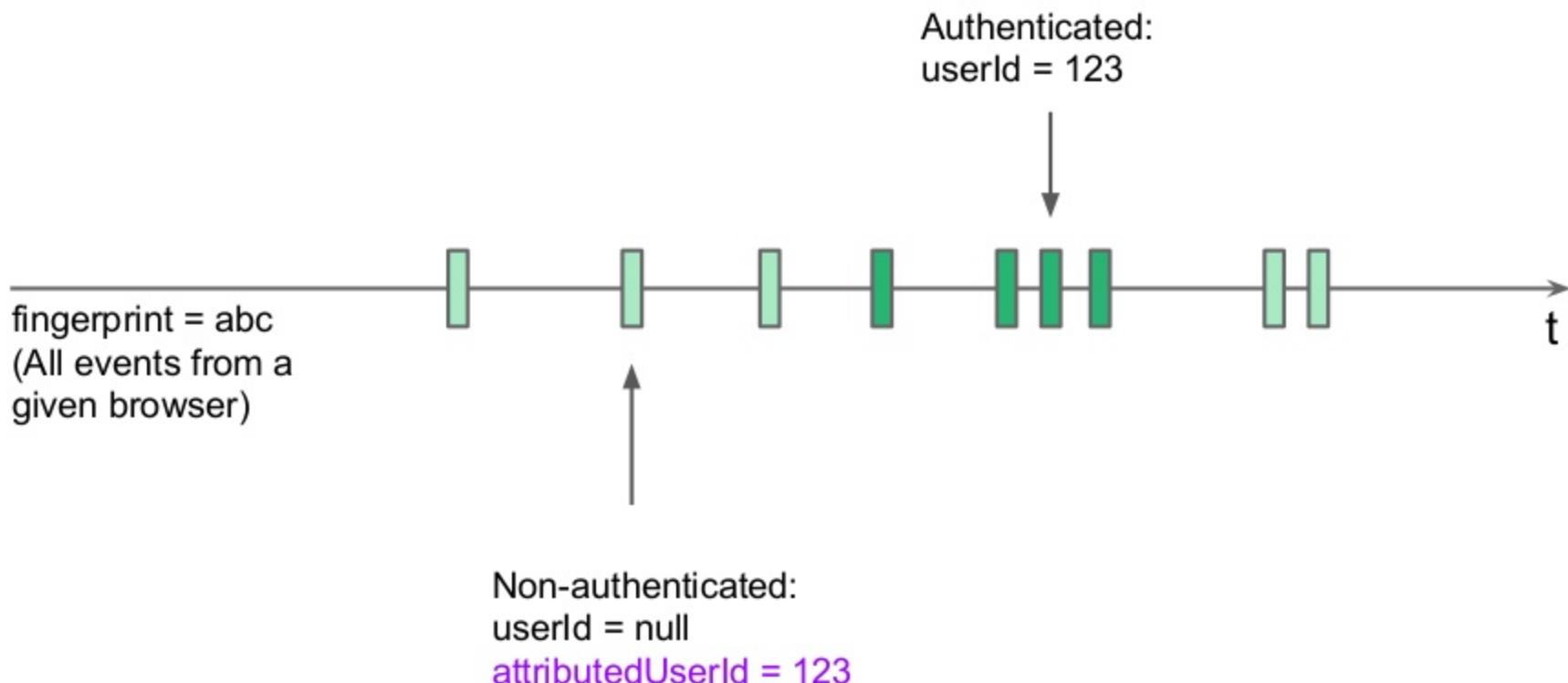
```
{  
  "eventName": "subscribe",  
  "userId": 123,  
  "fingerprint": "abc",  
  ...  
}
```



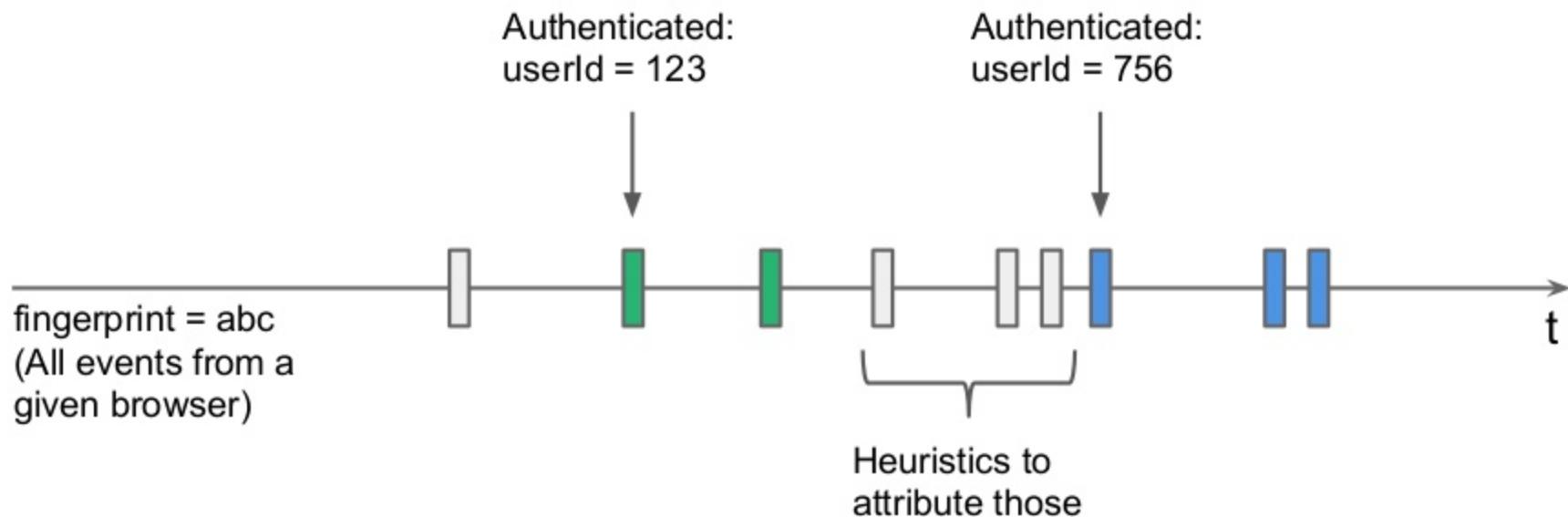
Enrichment Phase 1: User Attribution



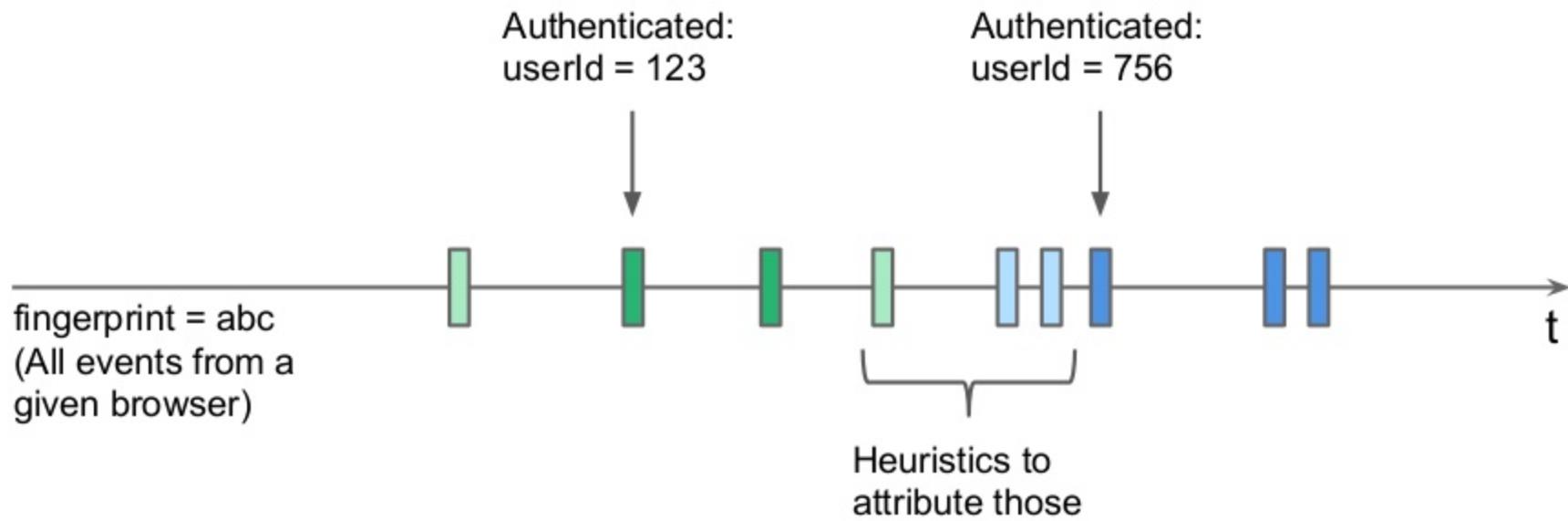
Enrichment Phase 1: User Attribution



Enrichment Phase 1: User Attribution



Enrichment Phase 1: User Attribution



Enrichment Phase 1: User Attribution

```
rdd.mapPartitions { iterator =>
```

```
}
```



Enrichment Phase 1: User Attribution

```
rdd.mapPartitions { iterator =>  
    val buffer = new ArrayBuffer()  
  
    }  
}
```



Enrichment Phase 1: User Attribution

```
rdd.mapPartitions { iterator =>  
  
    val buffer = new ArrayBuffer()  
  
    iterator  
        .takeWhile(_.userId.isEmpty)  
        .foreach(buffer.append)  
    val userId = iterator.head.userId  
  
}
```



Enrichment 1: User Attribution

```
rdd.mapPartitions { iterator =>  
  
    val buffer = new ArrayBuffer()  
  
    iterator  
        .takeWhile(_.userId.isEmpty)  
        .foreach(buffer.append)  
    val userId = iterator.head.userId  
  
    buffer.map(_.setAttributedUserId(userId)) ++ iterator  
}
```



Enrichment 1: User Attribution

```
rdd.mapPartitions { iterator =>  
    val buffer = new ArrayBuffer() ← Can grow big and  
    iterator                                          OOM your worker for  
        .takeWhile(_.userId.isEmpty)                    outliers who use  
        .foreach(buffer.append)                         Grammarly without  
    val userId = iterator.head.userId                  ever registering  
                                                }  
    buffer.map(_.setAttributedUserId(userId)) ++ iterator
```



Spark & Memory

By default we should operate in User Memory (small fraction).

Spark Memory

`spark.memory.fraction = 75%`

User Memory

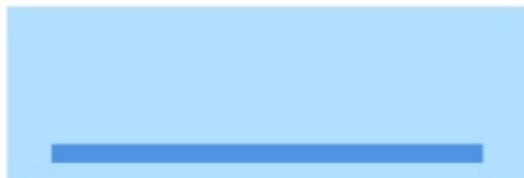
$100\% - \text{spark.memory.fraction} = 25\%$

Let's get into Spark Memory and use its safety features.



Spark Memory Manager & Spillable Collection

Memory



Disk



Spark Memory Manager & Spillable Collection

Memory

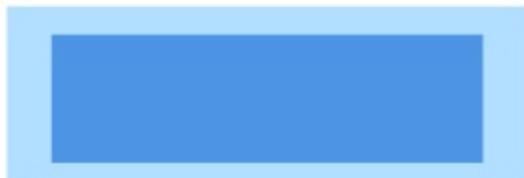


Disk



Spark Memory Manager & Spillable Collection

Memory

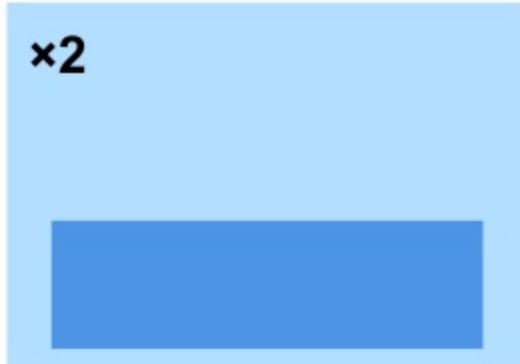


Disk



Spark Memory Manager & Spillable Collection

Memory



Disk



Spark Memory Manager & Spillable Collection

Memory



Disk



Spark Memory Manager & Spillable Collection

Memory

Disk



Spark Memory Manager & Spillable Collection

Memory

Disk



Spill to Disk



Spark Memory Manager & Spillable Collection

Memory

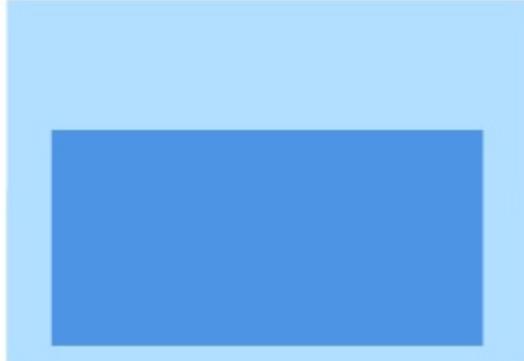
Disk

Spill to Disk



Spark Memory Manager & Spillable Collection

Memory



Disk



TaskMemoryManager

```
public long acquireExecutionMemory(long required, ...)
```

```
public void releaseExecutionMemory(long size, ...)
```



Spillable

```
trait Spillable {  
  
    abstract def spill(inMemCollection: C): Unit  
  
    def maybeSpill(currentMemory: Long, inMemCollection: C) {  
        try x2 if needed  
    }  
}
```

call on every append to collection



SizeTracker

```
trait SizeTracker {
```

```
    def afterUpdate(): Unit = { ... }
```

Call on every append.
Periodically estimates size
and saves samples.

```
    def estimateSize(): Long = { ... }
```

Extrapolates

```
}
```



Custom Spillable Collection

- Get outside User Memory (25%), use Spark Memory (75%)
- Be safe with outliers
- Spark APIs: Could be a bit friendlier and high level



Enrichment Phase 1: User Attribution

```
rdd.mapPartitions { iterator =>  
  
    val buffer = new SpillableBuffer() ← Can safely grow in  
    iterator mem while enough  
    .takeWhile(_.userId.isEmpty) free Spark Mem. Spills  
    .foreach(buffer.append) to disk otherwise.  
    val userId = iterator.head.userId  
  
    buffer.map(_.setAttributedUserId(userId)) ++ iterator  
}
```



Enrichment Phase 2: Calculable Props



Enrichment Phase 2: Calculable Props

```
{  
  "eventName": "page-visit",  
  "url": "...?utm_medium=ad",  
  "fingerprint": "abc",  
  "attributedUserId": 123,  
  ...  
}
```



```
{  
  "eventName": "subscribe",  
  "userId": 123,  
  "fingerprint": "abc",  
  ...  
}
```



Enrichment Phase 2: Calculable Props

```
{  
  "eventName": "page-visit",  
  "url": "...?utm_medium=ad",  
  "fingerprint": "abc",  
  "attributedUserId": 123,  
  ...  
}
```



```
{  
  "eventName": "subscribe",  
  "userId": 123,  
  "fingerprint": "abc",  
  "firstUtmMedium": "ad",  
  ...  
}
```



Enrichment Phase 2: Calculable Props Engine & DSL

```
val firstUtmMedium: CalcProp[String] =  
  (E \ "url").as[Url]  
    .map(_.param("utm_source"))  
    .forEvent("page-visit")  
    .last
```



Enrichment Phase 2: Calculable Props Engine & DSL

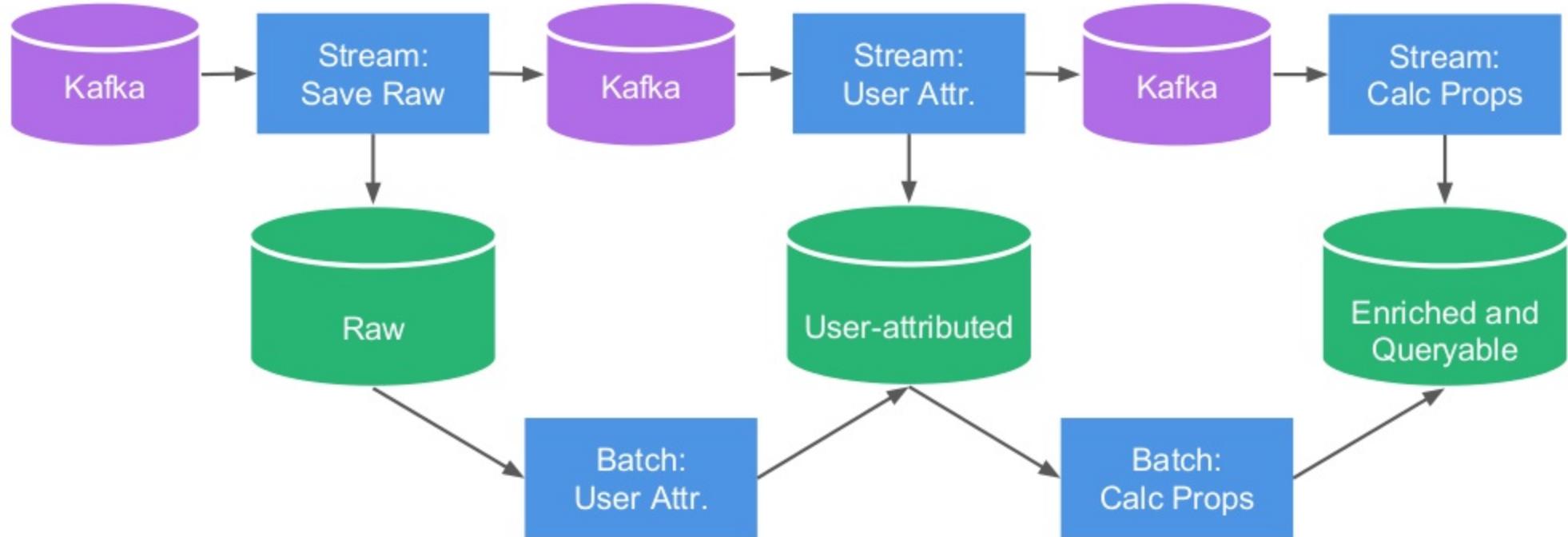
- Type-safe, functional
- Composable
- Similar to Scala collections API
- Batch & Stream (incremental)



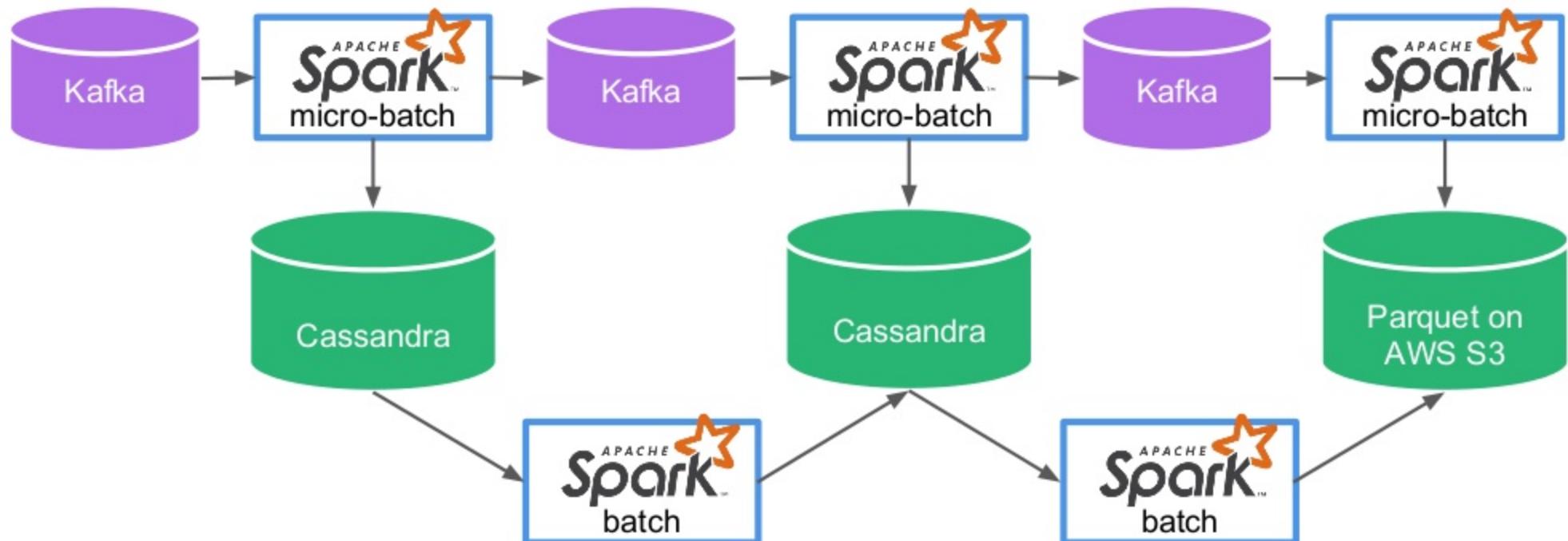
Enrichment Phase 3: Spark Pipeline



Spark Pipeline



Spark Pipeline

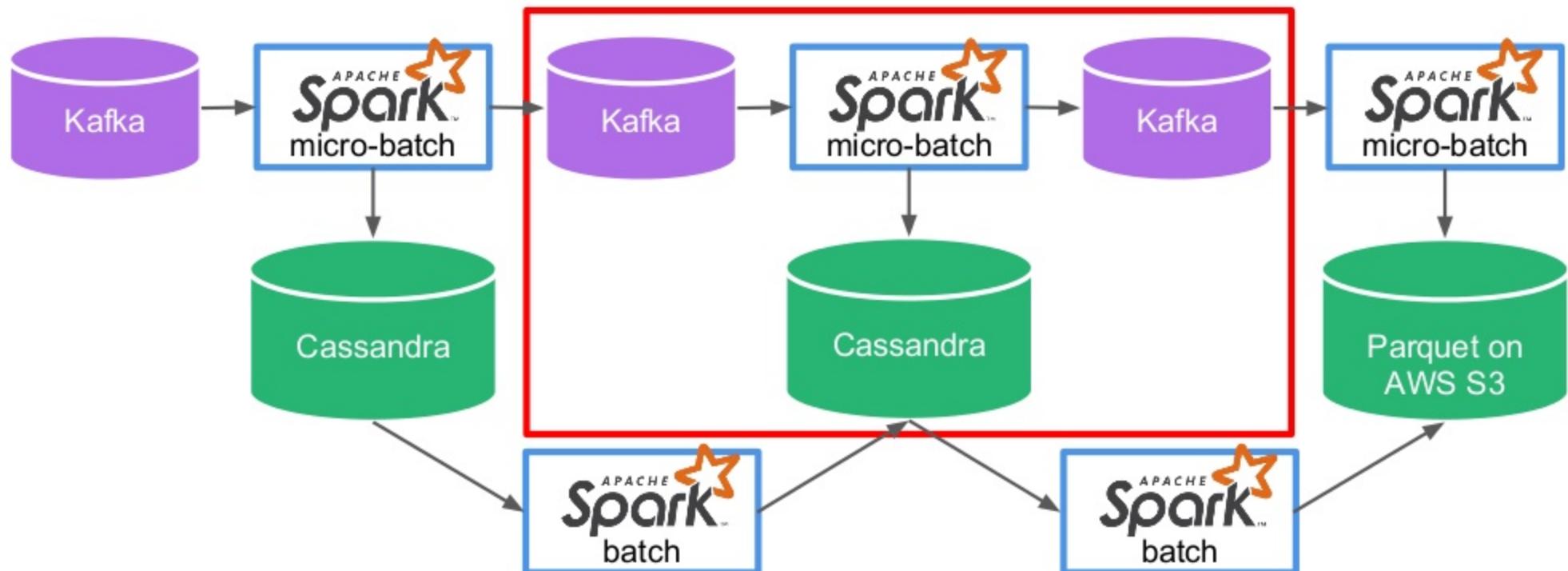


Enrichment Phase 3: Spark

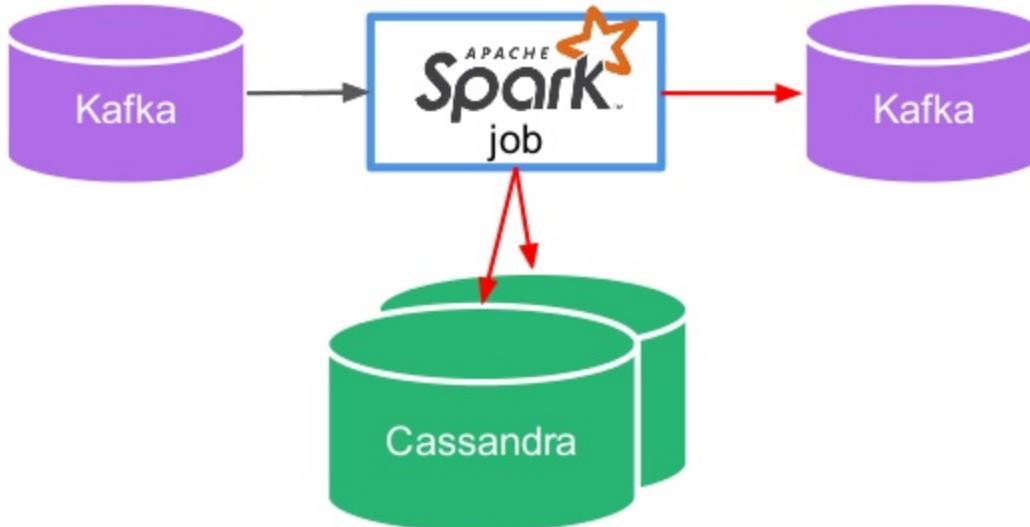
- Connectors for everything
- Great for batch
 - Shuffle with spilling
 - Failure recovery
- Great for streaming
 - Fast
 - Low overhead



Save to Long-term Storage



Multiple Output Destinations



Multiple Output Destinations: Try 1

```
val rdd: RDD[T]  
  
rdd.sendToKafka("topic_x")  
  
rdd.saveToCassandra("table_foo")  
  
rdd.saveToCassandra("table_bar")
```



Multiple Output Destinations: Try 1

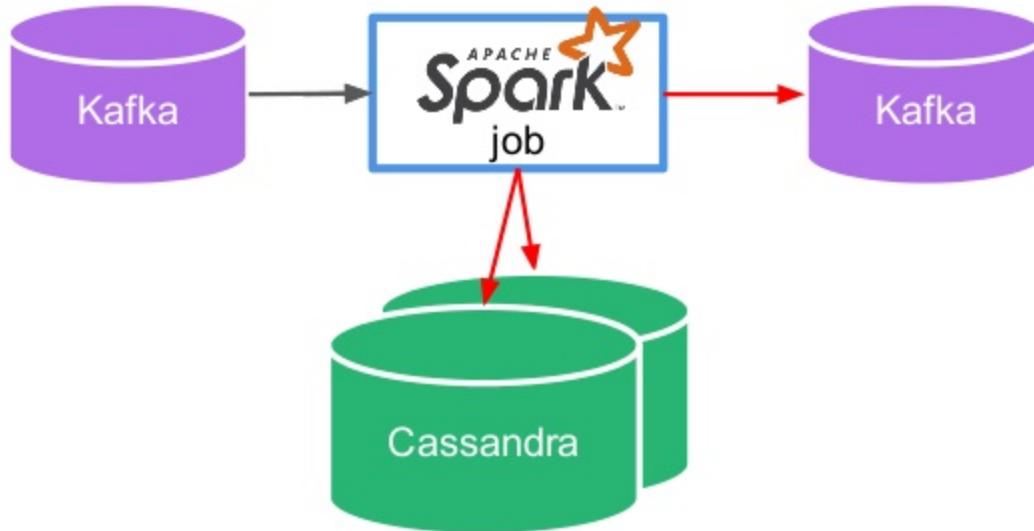
```
rdd.saveToCassandra(...)
```

```
rdd.foreachPartition(...)
```

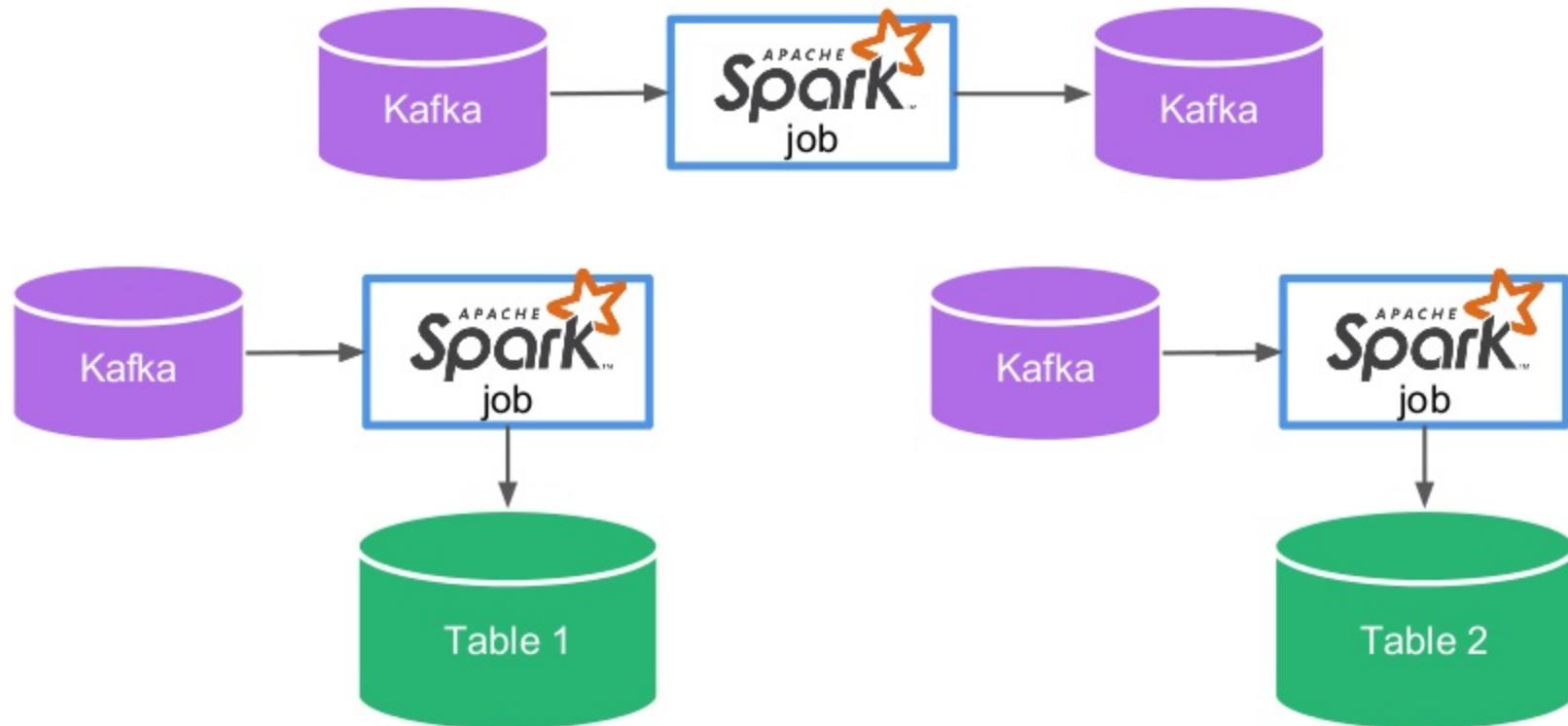
```
sc.runJob(...)
```



Multiple Output Destinations: Try 1



Multiple Output Destinations: Try 1 = 3 Jobs

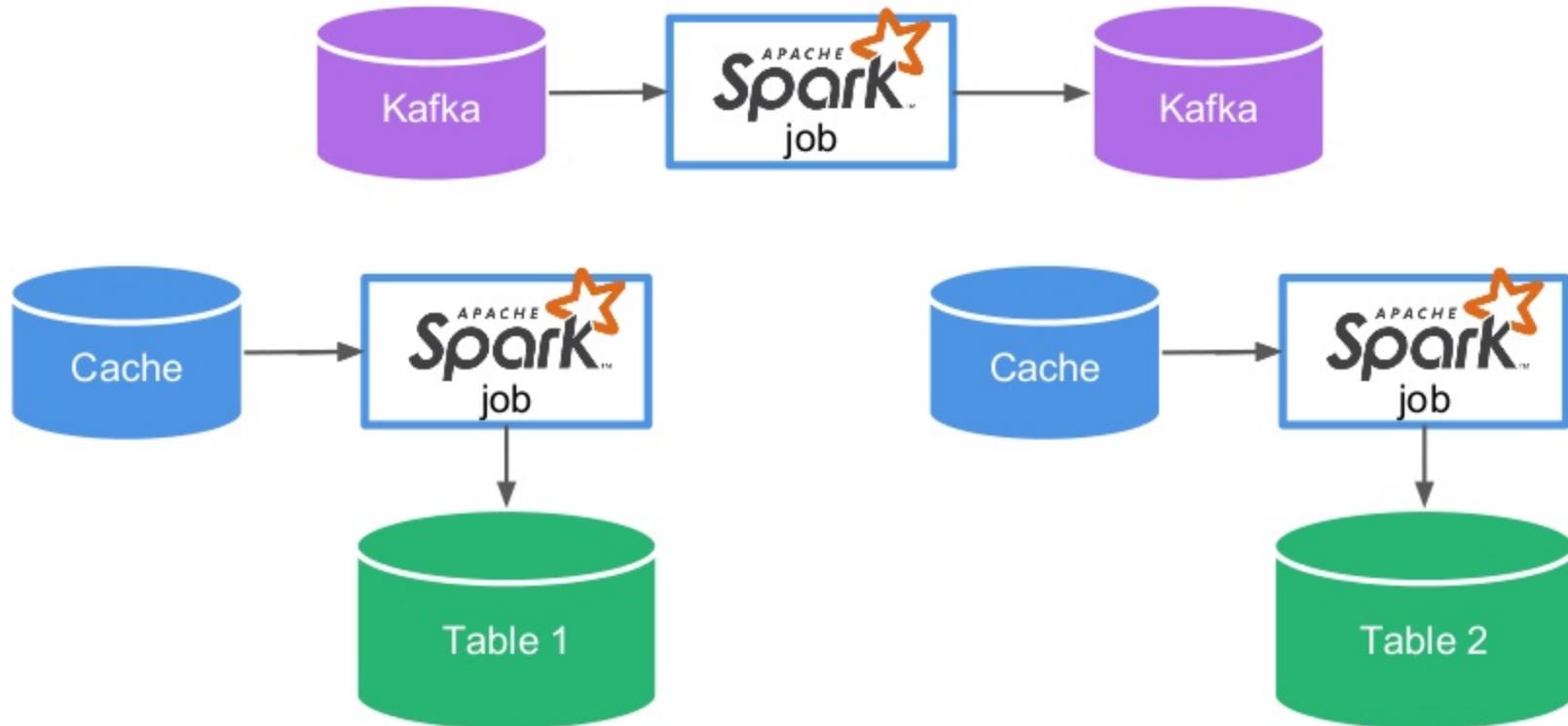


Multiple Output Destinations: Try 2

```
val rdd: RDD[T]  
  
rdd.cache()  
  
rdd.sendToKafka("topic_x")  
  
rdd.saveToCassandra("table_foo")  
  
rdd.saveToCassandra("table_bar")
```



Multiple Output Destinations: Try 2 = Read Once, 3 Jobs



Writer

```
rdd.foreachPartition { iterator =>
```

```
}
```



Writer

```
rdd.foreachPartition { iterator =>  
  
    val writer = new BufferedWriter(  
        new OutputStreamWriter(new FileOutputStream()))  
    )  
  
}
```



Writer

```
rdd.foreachPartition { iterator =>  
  
    val writer = new BufferedWriter(  
        new OutputStreamWriter(new FileOutputStream()))  
    )  
  
    iterator.foreach { el =>  
        writer.writeln(el)  
    }  
}
```



Writer

```
rdd.foreachPartition { iterator =>  
  
    val writer = new BufferedWriter(  
        new OutputStreamWriter(new FileOutputStream(...)))  
    )  
  
    iterator.foreach { el =>  
        writer.writeln(el)  
    }  
  
    writer.close() // makes sure this writes  
}
```

- Buffer
- Non-blocking
- Idempotent / Dedupe



AndWriter

```
andWriteToX = rdd.mapPartitions { iterator =>  
}  
}
```



AndWriter

```
andWriteToX = rdd.mapPartitions { iterator =>  
    val writer = new XWriter()  
  
    val writingIterator = iterator.map { el =>  
        writer.write(el)  
    }  
}
```



AndWriter

```
andWriteToX = rdd.mapPartitions { iterator =>  
    val writer = new XWriter()  
  
    val writingIterator = iterator.map { el =>  
        writer.write(el)  
    }.closing(() => writer.close)  
}
```

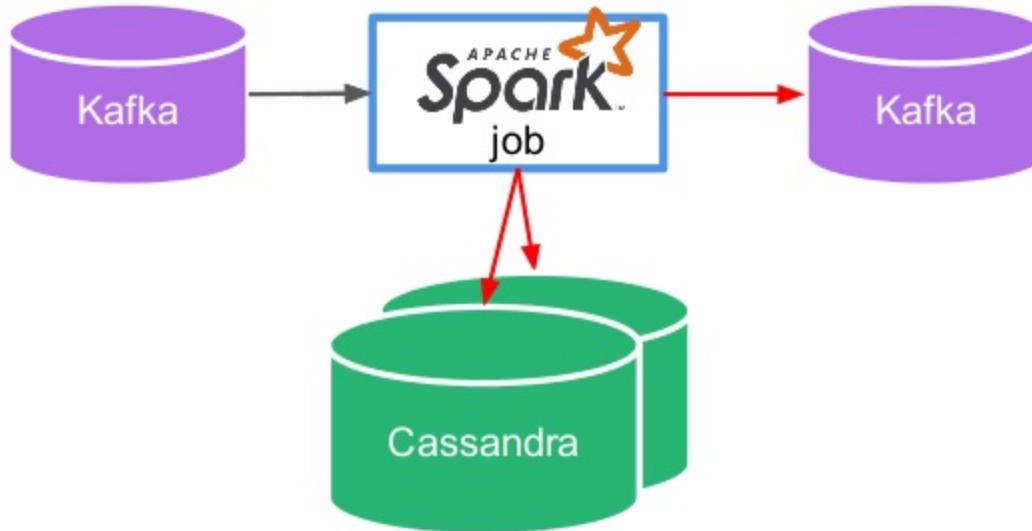


Multiple Output Destinations: Try 3

```
val rdd: RDD[T]  
  
rdd.andSaveToCassandra("table_foo")  
    .andSaveToCassandra("table_bar")  
    .sendToKafka("topic_x")
```



Multiple Output Destinations: Try 3



And Writer

- Kafka
- Cassandra
- HDFS

Important! Each andWriter will consume resources

- Memory (buffers)
- IO



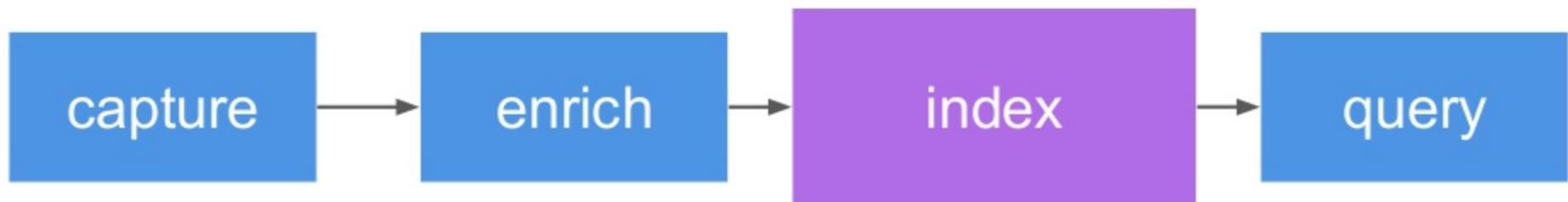
Some Stats



- Thousands of events per second
- Terabytes of compressed data



Build Step 3: Index

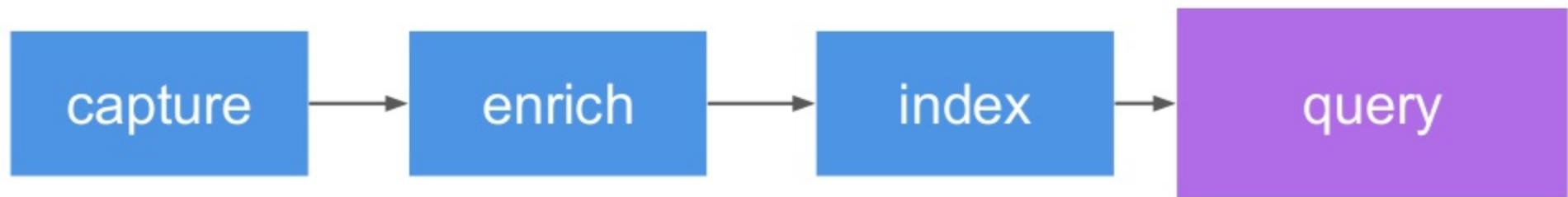


Index

- Parquet on AWS S3
- Custom partitioning: By eventName and time interval
- Append changes, compact + merge on the fly when querying
- Randomized names to maximize S3 parallelism
- Use and tweak s3a for max performance and read after write S3 consistency
- Support flexible schema, even with conflicts!



Build Step 4: Query



Hardcore Query

- DataFrames
- Spark SQL Scala dsl / Pure SQL
- Zeppelin



Casual Query

- Plot by day
- Unique visitors
- Filter by country
- Split by traffic source (top 20)
- Time from 2 weeks ago to today



Option 1: SQL

```
// 1) materialize query details

val aggValue: AggValue = segmentQuery.aggValue.getOrElse(AggValue(CountFun, Literal(1L, LongType)))

var byLimit: Int = segmentQuery.by.flatMap(_.limit).getOrElse(50)
byLimit = math.min(200, math.max(0, byLimit))

val now: Long = Platform.currentTimeMillis
val segmentTime: SegmentTime = SegmentTime.build(segmentQuery, now)

// 2) then the event names needed for the query

val eventNameFilter = EventNameFilter(segmentQuery.event)
val eventNames = sqlConnector.withConnection(implicit connection => IndexCellsDAO.listAllEventNames.filter(
    eventNameFilter).toSeq)

// 3) prepare predicate

val predicate = And(
    segmentQuery.filter.map(_.cast(BooleanType)).getOrElse(
        if (aggValue.aggFunction == CountFun) IsNotNull(aggValue)
    )
)

// 4) prepare projections

var projections: Seq[NamedExpression] = Seq()

// slot
projections ::= (if (segmentTime.isExplosive) {
    DaySlotExplosionExpression
} else if (segmentTime.isSubDay) {
    SubDaySlotExpression($"xts")
} else {
    DaySlotExpression
}).as("slot")

// value
if (aggValue.aggFunction.valueNeeded) {
    projections ::= aggValue.valueExpression.cast(DoubleType).as("value")
}
```

Quickly gets complex

```
// by
if (segmentQuery.by.nonEmpty) {
    projections ::= segmentQuery.by.map(_.byExpression).get.cast(StringType).as("by")
}

// pidHash
if (segmentQuery.isUnique) {
    projections ::= $"pidHash"
}

// ts
if (segmentQuery.isUnique && (aggValue.aggFunction.valueNeeded || segmentQuery.by.nonEmpty && segmentQuery
    projections ::= (if (segmentTime.isMultiDay) StsExpression($"xts") else $"xts").as("ts")
}

and df

r.withConnection { implicit connection =>
    (eventNames, segmentTime.days)
}

// taking only the first layer for now
if (cells.isEmpty) return Future.successful(SegmentQueryResult.empty(now))

val traversal: Traversal = Traversal.build(cells, predicate, projections, ordered = false)
if (traversal.isEmpty) return Future.successful(SegmentQueryResult.empty(now))

val traversalPlan: TraversalPlan = traversalPlanBuilder.build(traversal)
if (traversalPlan.isEmpty) return Future.successful(SegmentQueryResult.empty(now))

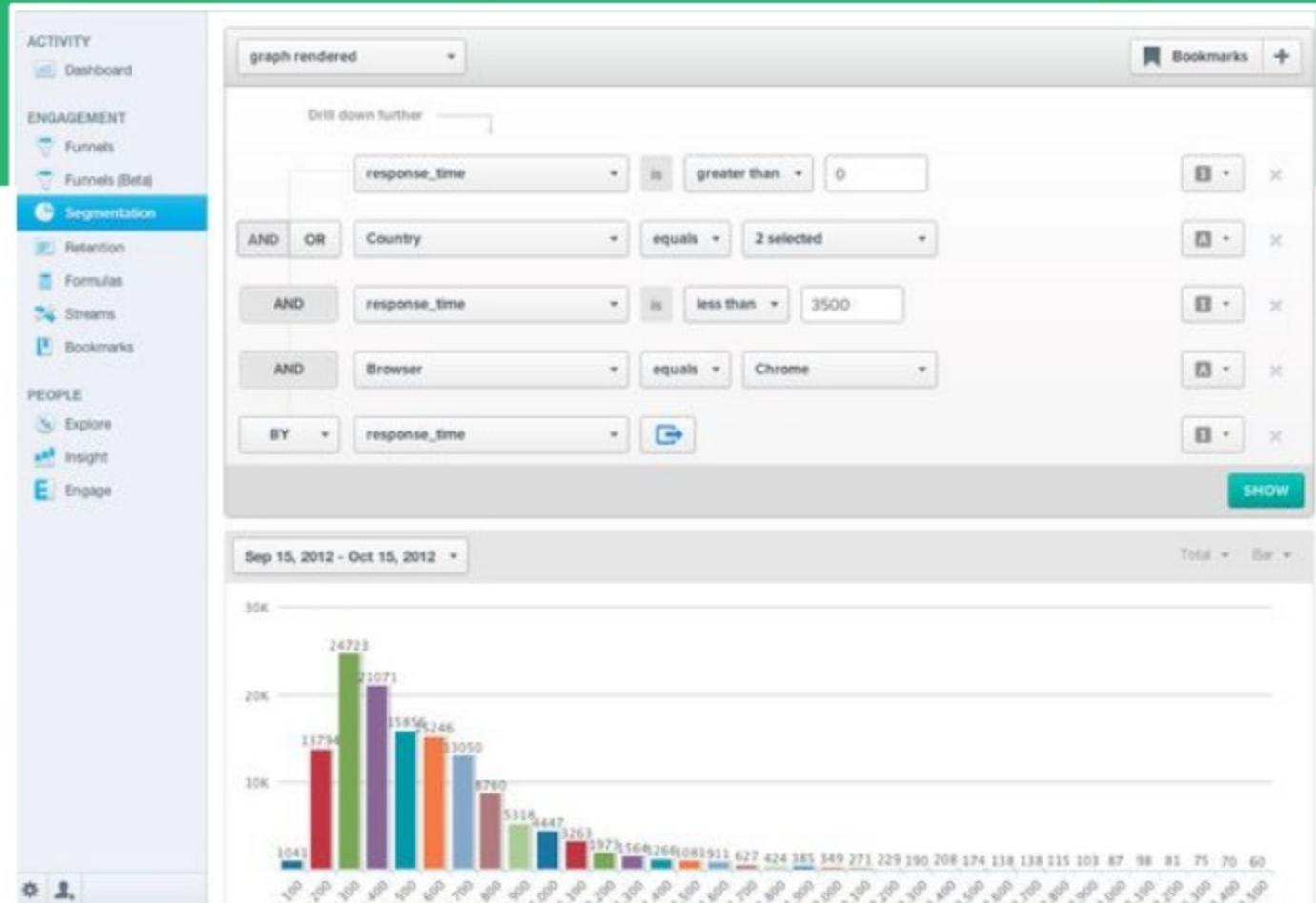
val init = () => {
    SegmentTime.setCtx(segmentTime)
}

var df: DataFrame = indexTraverser.traverseDF(traversalPlan, init, sparkContext, sqlContext)

// 6) explode explosion into slot if needed
```

Option 2: UI

Too expensive
to build, extend
and support



Option 3: Custom Query Language

```
SEGMENT "eventName"  
WHERE foo = "bar" AND x.y IN ("a", "b", "c")  
UNIQUE  
BY m IS NOT NULL  
TIME from 2 months ago to today  
STEP 1 month SPAN 1 week
```



Option 3: Custom Query Language

SEGMENT "eventName"

WHERE foo = "bar" AND x.y IN ("a", "b", "c")

UNIQUE

BY m IS NOT NULL

TIME from 2 months ago to today

STEP 1 month SPAN 1 week

Expressions



Spark Expressions

```
class Expression {  
    def eval(input: InternalRow = null): Any  
}
```



Spark Expressions

```
class Expression {  
    def eval(input: InternalRow = null): Any  
}  
  
case class Add(left: Expression, right: Expression)  
    extends Expression {  
  
    override def eval(input: InternalRow = null): Any {  
        left.eval(input).asInstanceOf[Int]  
        + right.eval(input).asInstanceOf[Int]  
    }  
}
```



Scala Parser Combinators

```
val termExpression: Parser[Expression] = ???
```

```
val addParser = termExpression ~  
  ("+" ~> termExpression) ^^ {  
    case e1 ~ e2 => Add(e1, e2)  
 }
```



SEGMENT

```
lazy val eventParser: Parser[Seq[String]] =  
  ((EVENT | FROM) .? ~> rep1sep(strLit, ", ")).map(_.flatten)
```

```
lazy val filterParser: Parser[Option[Expression]] =  
  ((FILTER | WHERE) ~> expression) .?
```



Take expression parser
from Spark SQL Parser

```
lazy val timeParser: Parser[SegmentTime] = ...
```



SEGMENT

```
lazy val segmentQueryParser: Parser[SegmentQuery] = {  
    SEGMENT ~> eventParser ~ filterParser ~  
    byParser ~ timeParser ^^ {  
        case event ~ filter ~ by ~ time =>  
            SegmentQuery(event ~ filter ~ by ~ time)  
    }  
}
```



Option 3: Custom Query Language

- Segment, Funnel, Retention
- UI & as DataFrame in Zeppelin
- Spark <= 1.6 – Scala Parser Combinators
- Reuse most complex part of expression parser
- Relatively extensible



Quick Demo!



Conclusion

- Custom versatile analytics is doable and enjoyable
- Spark is a great platform to build analytics on top of
 - Enrichment Pipeline: Batch / Streaming, Query
- Would be cool to see even deep internals slightly more extensible

We are hiring!



olivia@grammarly.com

<https://www.grammarly.com/jobs>

Questions?

