

SPARK AT OOYALA

EVAN CHAN
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Who is this guy?

- Staff Engineer, Compute and Data Services, Ooyala
- Building multiple web-scale real-time systems on top of C*, Kafka, Storm, etc.
- Scala/Akka guy
- Very excited by open source, big data projects
- @evanfchan



Agenda

- Ooyala and Big Data
- What problem are we trying to solve?
- Spark and Shark
- Our Spark/Cassandra Architecture
- Spark Job Server



OOYALA AND BIG DATA



OOYALA

Powering **personalized** video
experiences across all
screens.



COMPANY OVERVIEW

Founded in 2007

Commercially launch in 2009

230+ employees in Silicon Valley, LA, NYC,
London, Paris, Tokyo, Sydney & Guadalajara

Global footprint, 200M unique users,
110+ countries, and more than 6,000 websites

Over 1 billion videos played per month
and 2 billion analytic events per day

25% of U.S. online viewers watch video
powered by Ooyala



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TRUSTED VIDEO PARTNER

CUSTOMERS



Bloomberg

ESPN



MIRAMAX

Geeknet 

VICTORIA'S
SECRET

DELL

THE
NORTH
FACE



WHOLE
FOODS
MARKET

Telegraph

The
Washington
Post



STRATEGIC PARTNERS

Panasonic

ERICSSON 



YAHOO!
JAPAN

Telefonica



Microsoft



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We have a large Big Data stack

- > 250GB of fresh logs every day
- Total of 28TB of data managed over ~200 Cassandra nodes
- Traditional stack: Hadoop, Ruby, Cassandra, Ruby...
- Real-time stack: Kafka, Storm, Scala, Cassandra
- New stack: Kafka, Akka, Cassandra, Spark, Scala/Go



Becoming a big Spark user...

- Started investing in Spark beginning of 2013
- 2 teams of developers doing stuff with Spark
- Actively contributing to Spark developer community
- Deploying Spark to a large (>100 node) production cluster
- Spark community very active, huge amount of interest



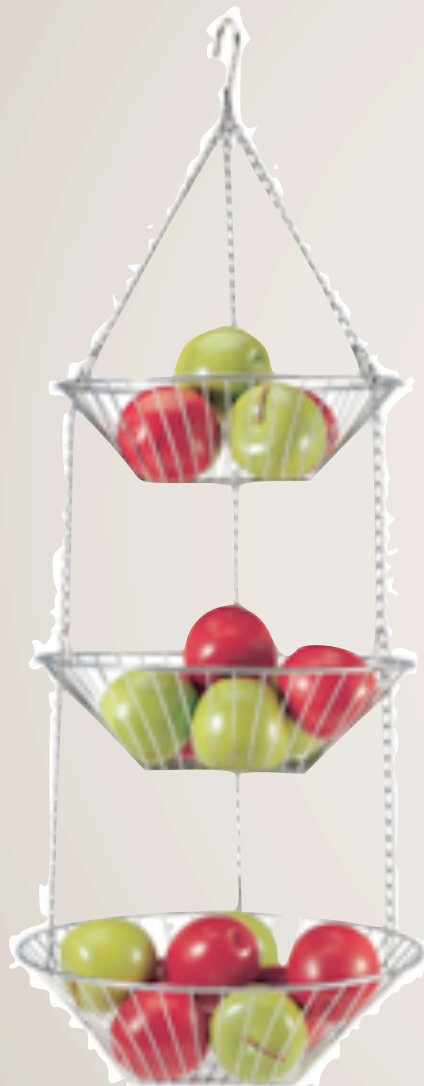
WHAT PROBLEM ARE WE TRYING TO SOLVE?



From mountains of raw data...



To nuggets of truth...



- **Quickly**
- **Painlessly**
- **At scale?**



TODAY: PRECOMPUTED AGGREGATES

- Video metrics computed along several high cardinality dimensions
- Very fast lookups, but inflexible, and hard to change
- Most computed aggregates are never read
- What if we need more dynamic queries?
 - Top content for mobile users in France
 - Engagement curves for users who watched recommendations
 - Data mining, trends, machine learning



THE STATIC - DYNAMIC CONTINUUM



100% Precomputation

- Super fast lookups
- Inflexible, wasteful
- Best for 80% most common queries

100% **Dynamic**

- Always compute results from raw data
- Flexible but slow



WHERE WE WANT TO BE



Partly **dynamic**

- Pre-aggregate most common queries
- Flexible, fast dynamic queries
- Easily generate many materialized views



INDUSTRY TRENDS

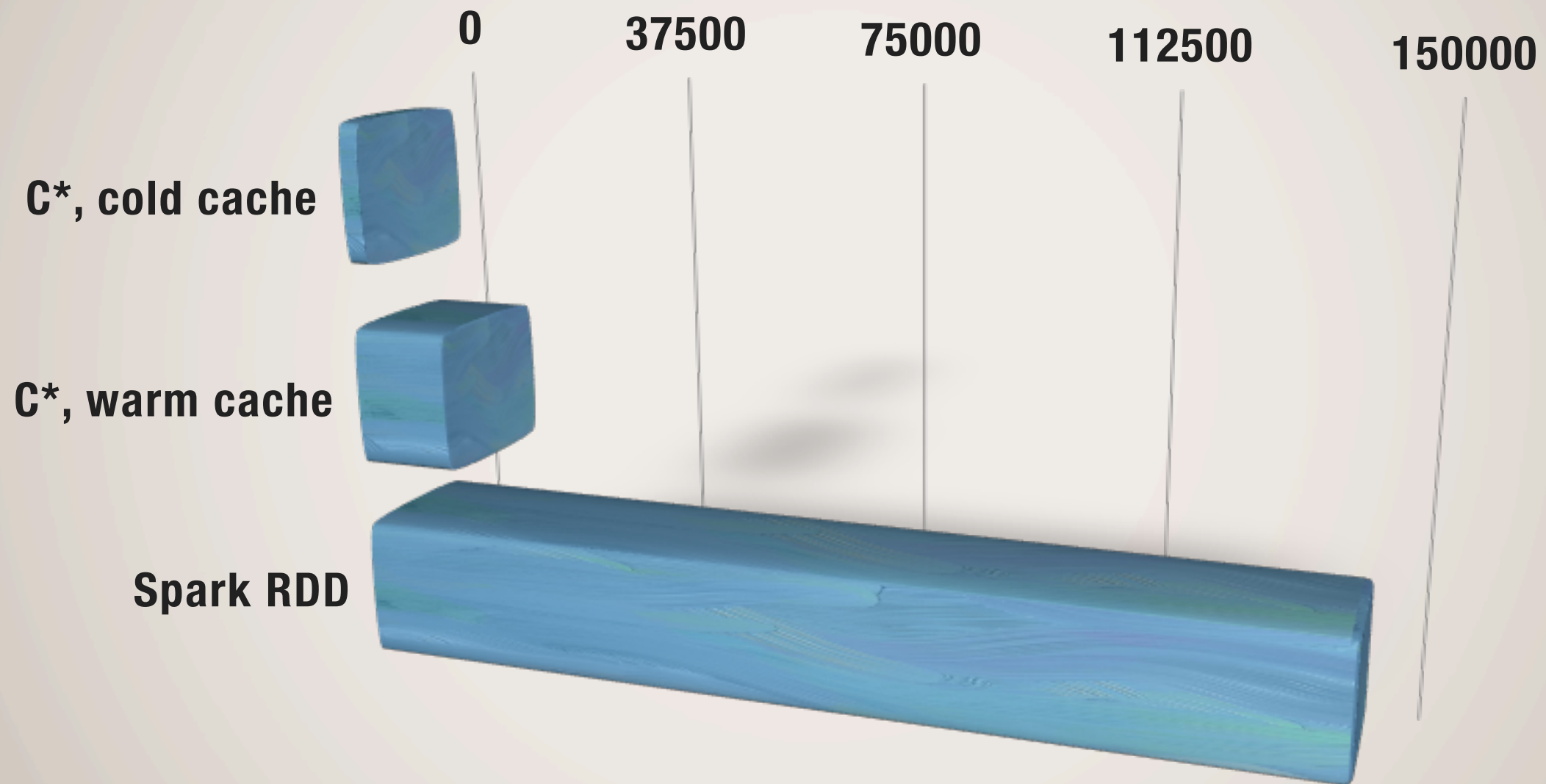
- Fast execution frameworks
 - Impala
- In-memory databases
 - VoltDB, Druid
- Streaming and real-time
- Higher-level, productive data frameworks



WHY SPARK?



THROUGHPUT: MEMORY IS KING



6-node C*/DSE 1.1.9 cluster,
Spark 0.7.0

Spark cached RDD 10-50x faster than raw Cassandra



DEVELOPERS LOVE IT

- “I wrote my first aggregation job in 30 minutes”
- High level “distributed collections” API
- No Hadoop cruft
- Full power of Scala, Java, Python
- Interactive REPL shell



SPARK VS HADOOP WORD COUNT

```
file = spark.textFile("hdfs://...")
```

```
file.flatMap(line => line.split(" "))  
  .map(word => (word, 1))  
  .reduceByKey(_ + _)
```

```
1 package org.myorg;  
2  
3 import java.io.IOException;  
4 import java.util.*;  
5  
6 import org.apache.hadoop.fs.Path;  
7 import org.apache.hadoop.conf.*;  
8 import org.apache.hadoop.io.*;  
9 import org.apache.hadoop.mapreduce.*;  
10 import org.apache.hadoop.mapreduce.lib.input.FileInputFormat;  
11 import org.apache.hadoop.mapreduce.lib.input.TextInputFormat;  
12 import org.apache.hadoop.mapreduce.lib.output.FileOutputFormat;  
13 import org.apache.hadoop.mapreduce.lib.output.TextOutputFormat;  
14  
15 public class WordCount {  
16  
17     public static class Map extends Mapper<LongWritable, Text, Text, IntWritable>  
18     {  
19         private final static IntWritable one = new IntWritable(1);  
20         private Text word = new Text();  
21  
22         public void map(LongWritable key, Text value, Context context) throws  
23         IOException, InterruptedException {  
24             String line = value.toString();  
25             StringTokenizer tokenizer = new StringTokenizer(line);  
26             while (tokenizer.hasMoreTokens()) {  
27                 word.set(tokenizer.nextToken());  
28                 context.write(word, one);  
29             }  
30         }  
31  
32         public static class Reduce extends Reducer<Text, IntWritable, Text,  
33         IntWritable> {  
34             public void reduce(Text key, Iterable<IntWritable> values, Context context)  
35             throws IOException, InterruptedException {  
36                 int sum = 0;  
37                 for (IntWritable val : values) {  
38                     sum += val.get();  
39                 }  
40                 context.write(key, new IntWritable(sum));  
41             }  
42         }  
43  
44         public static void main(String[] args) throws Exception {  
45             Configuration conf = new Configuration();  
46  
47             Job job = new Job(conf, "wordcount");  
48  
49             job.setOutputKeyClass(Text.class);  
50             job.setOutputValueClass(IntWritable.class);  
51  
52             job.setMapperClass(Map.class);  
53             job.setReducerClass(Reduce.class);  
54  
55             job.setInputFormatClass(TextInputFormat.class);  
56             job.setOutputFormatClass(TextOutputFormat.class);  
57  
58             FileInputFormat.addInputPath(job, new Path(args[0]));  
59             FileOutputFormat.setOutputPath(job, new Path(args[1]));  
60  
61             job.waitForCompletion(true);  
62         }  
63     }  
64 }
```



ONE PLATFORM TO RULE THEM ALL



Bagel -
Pregel on
Spark

SHARK
HIVE on Spark

Spark Streaming -
discretized stream
processing

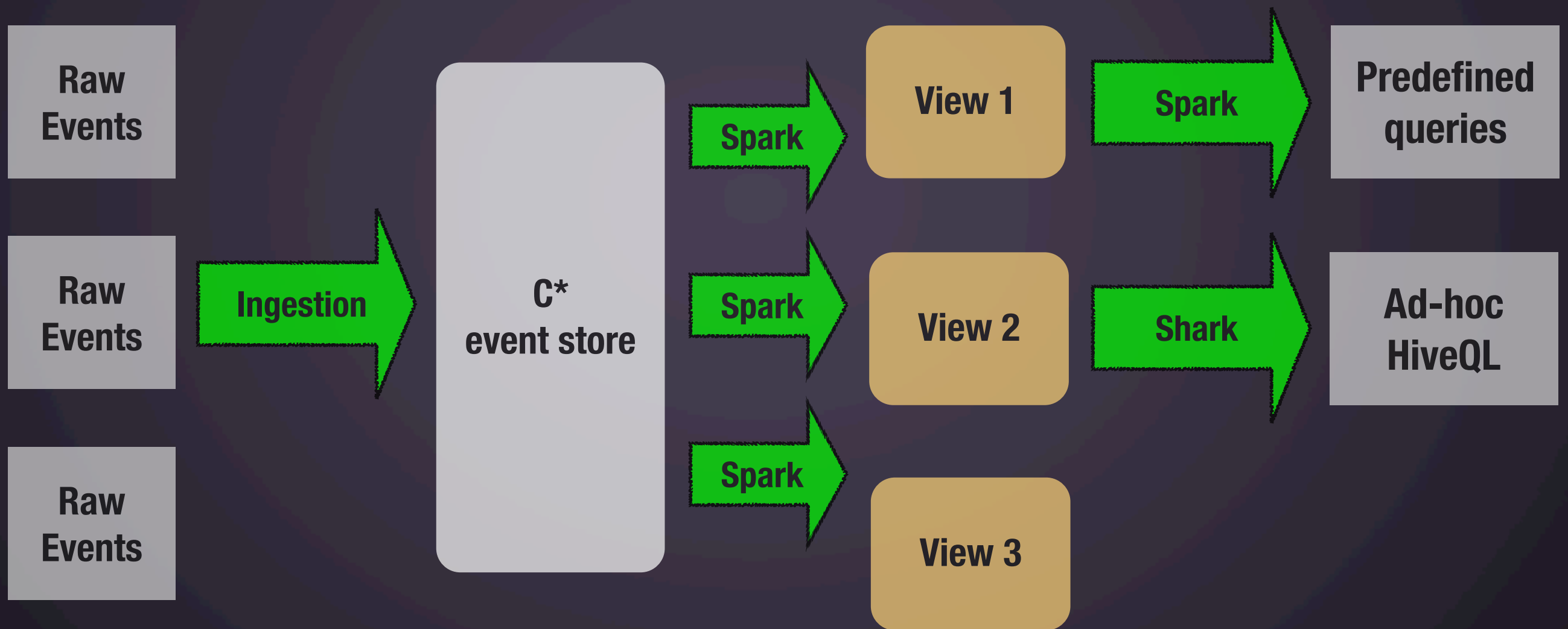
- Fewer platforms == lower TCO
- Much higher code sharing/reuse
- Spark/Shark/Streaming can replace Hadoop, Storm, and Impala
- Integration with Mesos, YARN helps



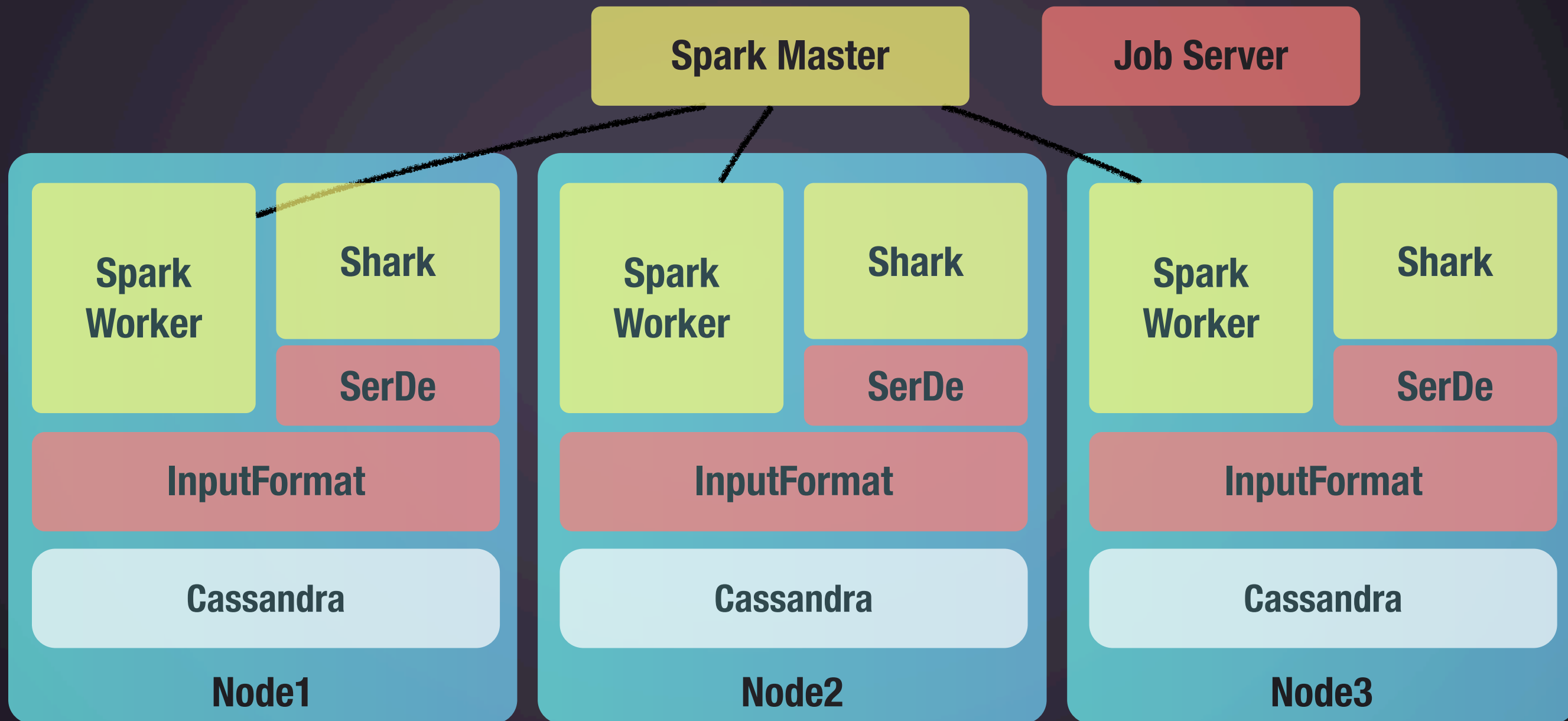
OUR SPARK ARCHITECTURE



From raw events to fast queries



Our Spark/Shark/Cassandra Stack



CASSANDRA SCHEMA

Event CF

	t0	t1	t2	t3	t4
2013-04-05 T00:00Z#id1	{event0 : a0}	{event1: a1}	{event2: a2}	{event3: a3}	{event4: a4}

EventAttr CF

	ipaddr: 10.20.30.40:t1	videoid:45678:t1	providerId:500:t0
2013-04-05 T00:00Z#id1			



INPUTFORMAT VS RDD

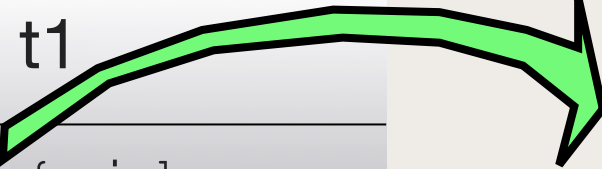
- You can easily use InputFormats in Spark using `newAPIHadoopRDD()`.
- Writing a custom RDD could have saved us **lots** of time.

InputFormat	RDD
Supports Hadoop, HIVE, Spark, Shark	Spark / Shark only
Have to implement multiple classes - InputFormat, RecordReader, Writeable, etc. Clunky API.	One class - simple API.
Two APIs, and often need to implement both (HIVE needs older...)	Just one API.



UNPACKING RAW EVENTS

	t0	t1	UserID	Video	Type
2013-04-05T00:00Z#i	{video: 10, type: 5}	{video: 11, type: 1}	id1	10	5
2013-04-05T00:00Z#id	{video: 20, type: 5}	{video: 25, type: 9}			



UNPACKING RAW EVENTS

	t0	t1
2013-04-05 T00:00Z#id	{video: 10, type:5}	{video: 11, type:1}
2013-04-05 T00:00Z#id	{video: 20, type:5}	{video: 25, type: 9}



UserID	Video	Type
id1	10	5
id1	11	1



UNPACKING RAW EVENTS

	t0	t1
2013-04-05T00:00Z#id	{video: 10, type: 5}	{video: 11, type: 1}
2013-04-05T00:00Z#i	{video: 20, type: 5}	{video: 25, type: 9}

UserID	Video	Type
id1	10	5

id1	11	1
-----	----	---

id2	20	5
-----	----	---



UNPACKING RAW EVENTS

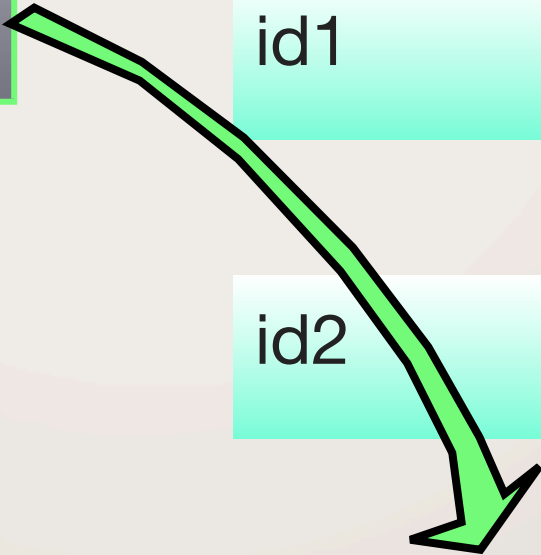
	t0	t1
2013-04-05 T00:00Z#id	{video: 10, type:5}	{video: 11, type: 1}
2013-04-05 T00:00Z#id	{video: 20, type:5}	{video: 25, type:9}

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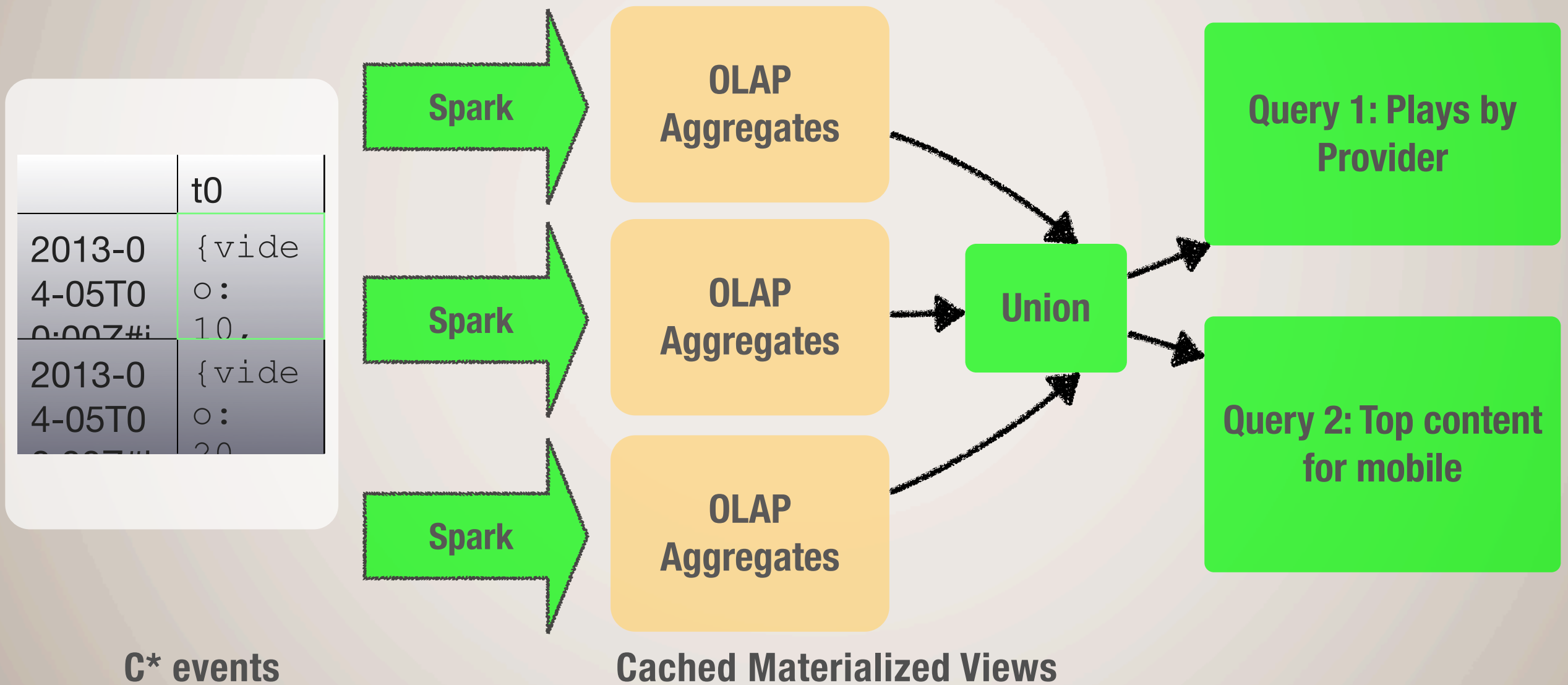
id1	11	1
-----	----	---

id2	20	5
-----	----	---

id2	25	9
-----	----	---



EXAMPLE: OLAP PROCESSING



PERFORMANCE #'S

Spark: C* -> OLAP aggregates
cold cache, 1.4 million events

130 seconds

C* -> OLAP aggregates
warmed cache

20-30 seconds

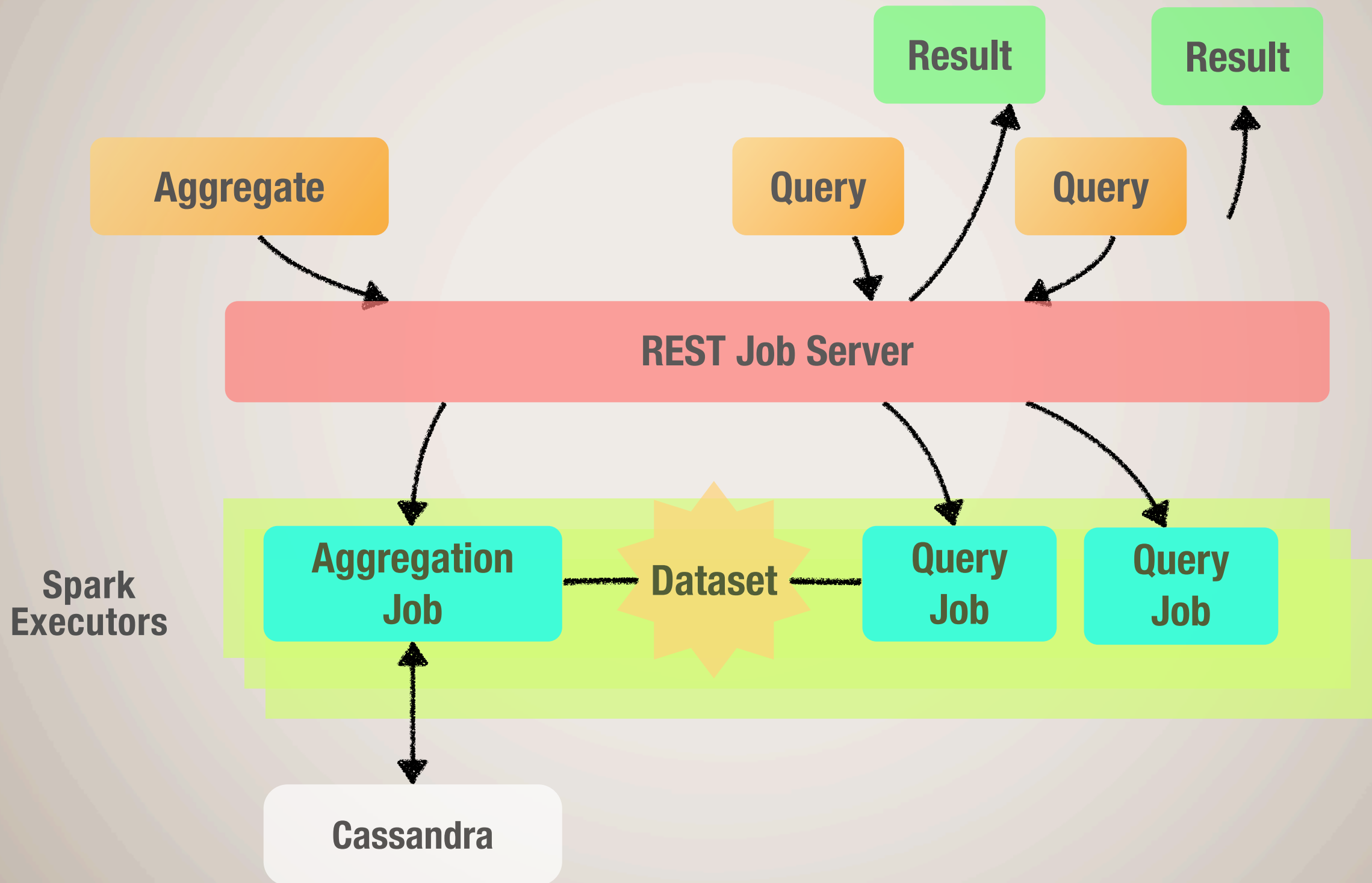
OLAP aggregate query via
Spark
(56k records)

60 ms

6-node C*/DSE 1.1.9 cluster,
Spark 0.7.0



OLAP WORKFLOW



FAULT TOLERANCE

- Cached dataset lives in Java Heap only – what if process dies?
- Spark lineage – automatic recomputation from source, but this is expensive!
 - Can also replicate cached dataset to survive single node failures
- Persist materialized views back to C*, then load into cache -- now recovery path is much faster



SPARK JOB SERVER



JOB SERVER OVERVIEW

- Spark as a Service – Job, Jar, and Context management
- Run ad-hoc Spark jobs
- Great support for sharing cached RDDs across jobs and low-latency jobs
- Works with Standalone Spark as well as Mesos
- Jars and job history is persisted via pluggable API
- Async and sync API, JSON job results
- Contributing back to Spark community in the near future



EXAMPLE JOB SERVER JOB

```
/**
 * A super-simple Spark job example that implements the SparkJob trait and
 * can be submitted to the job server.
 */
object WordCountExample extends SparkJob {
  override def validate(sc: SparkContext, config: Config): SparkJobValidation = {
    Try(config.getString("input.string"))
      .map(x => SparkJobValid)
      .getOrElse(SparkJobInvalid("No input.string"))
  }

  override def runJob(sc: SparkContext, config: Config): Any = {
    val dd = sc.parallelize(config.getString("input.string").split(" ").toSeq)
    dd.map((_, 1)).reduceByKey(_ + _).collect().toMap
  }
}
```



SUBMITTING AND RUNNING A JOB

◆ `curl --data-binary @../target/mydemo.jar localhost:8090/jars/demo`

OK[11:32 PM] ~

◆ `curl -d "input.string = A lazy dog jumped mean dog" 'localhost:8090/jobs?appName=demo&classPath=WordCountExample&sync=true'`

```
{
  "status": "OK",
  "RESULT": {
    "lazy": 1,
    "jumped": 1,
    "A": 1,
    "mean": 1,
    "dog": 2
  }
}
```



THANK YOU

And YES, We're HIRING!!

ooyala.com/careers