

# Lambda Architecture with Spark Streaming, Kafka, Cassandra, Akka, Scala

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# Who Is This Person?

- Spark Cassandra Connector committer
- Akka contributor - 2 new features in Akka Cluster
- Big Data & Scala conference speaker
- Currently Sr Software Engineer, Analytics @ DataStax
- Sr Cloud Engineer, VMware,CrowdStrike,SpringSource...
- Prev Spring committer - Spring AMQP, Spring Integration

# Talk Roadmap

**What** Lambda Architecture & Delivering Meaning

**Why** Spark, Kafka, Cassandra & Akka integration

**How** Composable Pipelines - Code

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I need fast access  
to historical data  
on the fly for  
predictive modeling  
with real time data  
from the stream



# Lambda Architecture

A **data**-processing architecture designed to handle *massive quantities* of data by taking advantage of both **batch and stream processing** methods.

- Spark is one of the few data processing frameworks that allows you to seamlessly integrate batch and stream processing
  - Of petabytes of data
  - **In the same application**

# Your Code

Spark  
Streaming  
real-time

Spark  
Streaming  
Kafka

Spark  
Cassandra  
Connector

MLlib  
machine learning



Spark Core



Akka Cluster



Apache Kafka Cluster

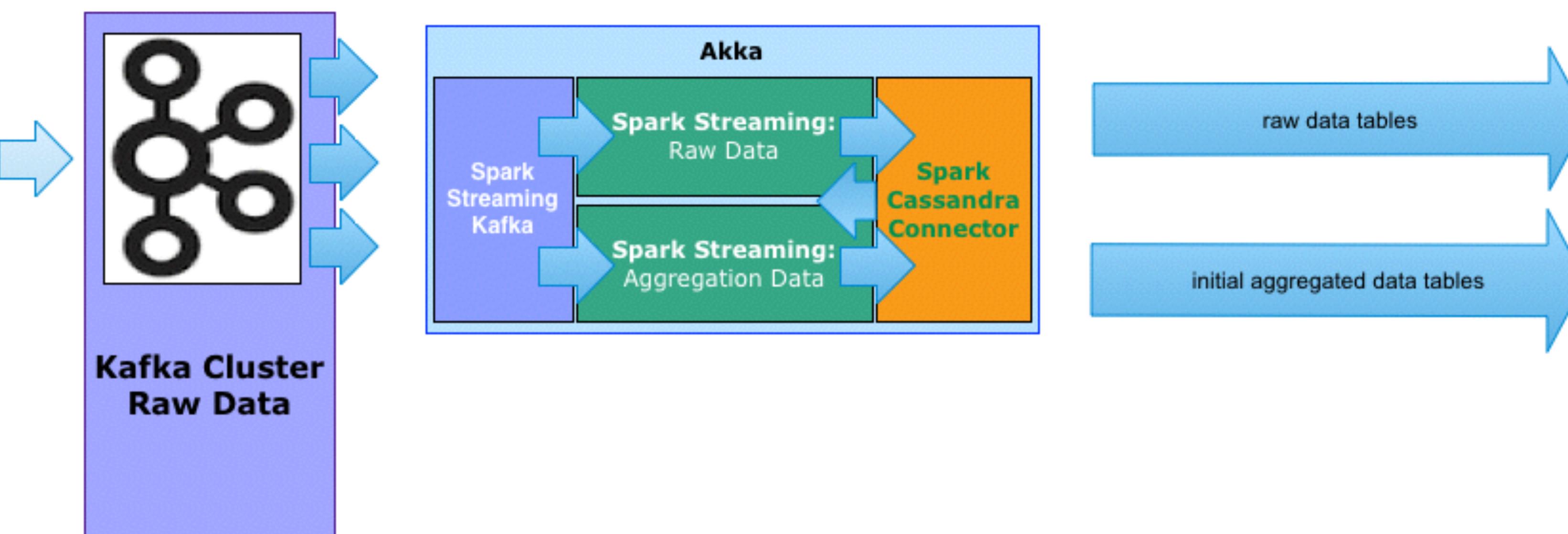


Apache Cassandra Cluster

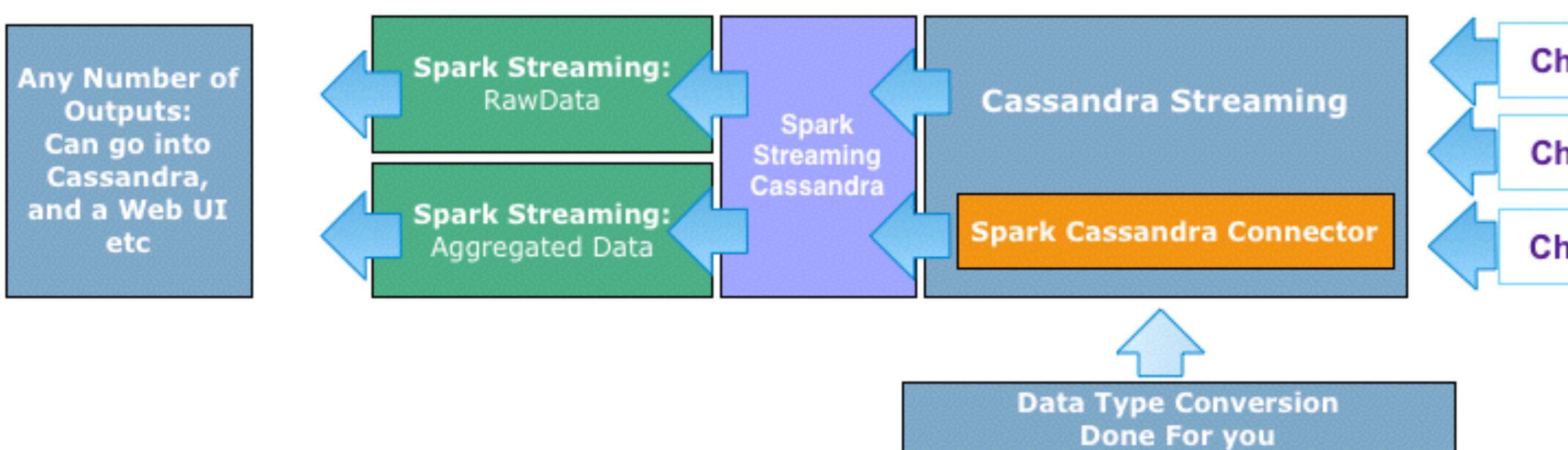
## Data Producers



## Ingestion, Aggregation & Analysis Data Flow: Receives Data On Capture



## Consumers: Decoupled From Ingestion Data Flow: Receives Data Once Safely Stored



**Cassandra Cluster**



KillrWeather is a reference application (work in progress) showing how to easily achieve Lambda Architecture with Apache Spark Streaming, Apache Cassandra, Apache Kafka and Akka for fast, streaming computations on time series data in asynchronous event-driven environments. — [Edit](#)

167 commits

3 branches

0 releases

4 contributors



branch: master +

killrweather / +

Code

Issues 6

Pull requests 3

Wiki

Pulse

Graphs

Settings

SSH clone URL

git@github.com:killrweath

Minor use case addition.



helena authored 19 seconds ago

latest commit 1f1988cf68



data

Adding much bigger data file

7 months ago



diagrams

Version upgrades.

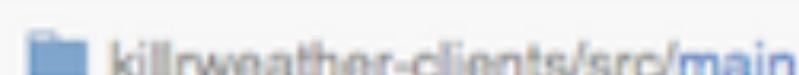
7 days ago



killrweather-app/src

Version upgrades for: Spark, Connector, Akka, Akka Streams and Scala ...

14 hours ago



killrweather-clients/src/main

Version upgrades for: Spark, Connector, Akka, Akka Streams and Scala ...

14 hours ago



killrweather-core/src/main

Version upgrades for: Spark, Connector, Akka, Akka Streams and Scala ...

14 hours ago



killrweather-examples/src/main

Added new logback configs and finalized log levels.

3 months ago



project

Version upgrades for: Spark, Connector, Akka, Akka Streams and Scala ...

14 hours ago



sigar

Added Sigar for test metrics collection via Akka Cluster, handled IT ...

8 months ago



.gitignore

Adding first diagram.

7 months ago



Moving Data Between Systems Is  
*~~Difficult~~ Risky and Expensive*



# How Do We Approach This?



# Strategies

- Scalable Infrastructure
- Partition For Scale
- Replicate For Resiliency
- Share Nothing
- Asynchronous Message Passing
- Parallelism
- Isolation
- Data Locality
- Location Transparency

# My Nerdy Chart

Strategy	Technologies
Scalable Infrastructure / Elastic	Spark, Cassandra, Kafka
Partition For Scale, Network Topology Aware	Cassandra, Spark, Kafka, Akka Cluster
Replicate For Resiliency	Spark, Cassandra, Akka Cluster all hash the node ring
Share Nothing, Masterless	Cassandra, Akka Cluster both Dynamo style
Fault Tolerance / No Single Point of Failure	Spark, Cassandra, Kafka
Replay From Any Point Of Failure	Spark, Cassandra, Kafka, Akka + Akka Persistence
Failure Detection	Cassandra, Spark, Akka, Kafka
Consensus & Gossip	Cassandra & Akka Cluster
Parallelism	Spark, Cassandra, Kafka, Akka
Asynchronous Data Passing	Kafka, Akka, Spark
Fast, Low Latency, Data Locality	Cassandra, Spark, Kafka
Location Transparency	Akka, Spark, Cassandra, Kafka



Lightning-fast cluster computing

Download   Libraries   Documentation   Examples   Community   FAQ

Apache Spark™ is a fast and general engine for large-scale data processing.

## Speed

Run programs up to 100x faster than Hadoop MapReduce in memory, or 10x faster on disk.

Spark has an advanced DAG execution engine that supports cyclic data flow and in-memory computing.



### Latest News

One month to Spark Summit 2015 in San Francisco (May 15, 2015)

Announcing Spark Summit Europe (May 15, 2015)

Spark Summit East 2015 Videos Posted (Apr 20, 2015)

Spark 1.2.2 and 1.3.1 released (Apr 17, 2015)

Archive

[Download Spark](#)

## Ease of Use

Write applications quickly in Java, Scala or Python.

Spark offers over 80 high-level operators that make it easy to build parallel apps. And you can use it interactively from the Scala and Python shells.

```
text_file = spark.textFile("hdfs://...")  
text_file.flatMap(lambda line: line.split())  
    .map(lambda word: (word, 1))  
    .reduceByKey(lambda a, b: a+b)
```

Word count in Spark's Python API

### Built-in Libraries:

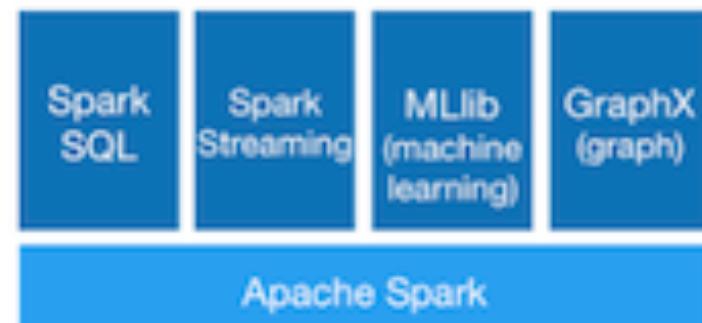
Spark SQL  
Spark Streaming  
MLlib (machine learning)  
GraphX (graph)

[Third-Party Packages](#)

## Generality

Combine SQL, streaming, and complex analytics.

Spark powers a stack of high-level tools including [Spark SQL](#), [MLlib](#) for machine learning, [GraphX](#), and [Spark Streaming](#). You can combine these libraries seamlessly in the same application.



## Runs Everywhere

Spark runs on Hadoop, Mesos, standalone, or in the cloud. It can access diverse data sources including HDFS, Cassandra, HBase, and S3.

You can run Spark using its [standalone cluster mode](#), on [EC2](#), on Hadoop YARN, or on [Apache Mesos](#). Access data in [HDFS](#), [Cassandra](#), [HBase](#), [Hive](#), [Tachyon](#), and any Hadoop data source.



- Fast, distributed, scalable and fault tolerant cluster compute system
- Enables Low-latency with complex analytics
- Developed in 2009 at UC Berkeley AMPLab, open sourced in 2010
- Became an Apache project in February, 2014



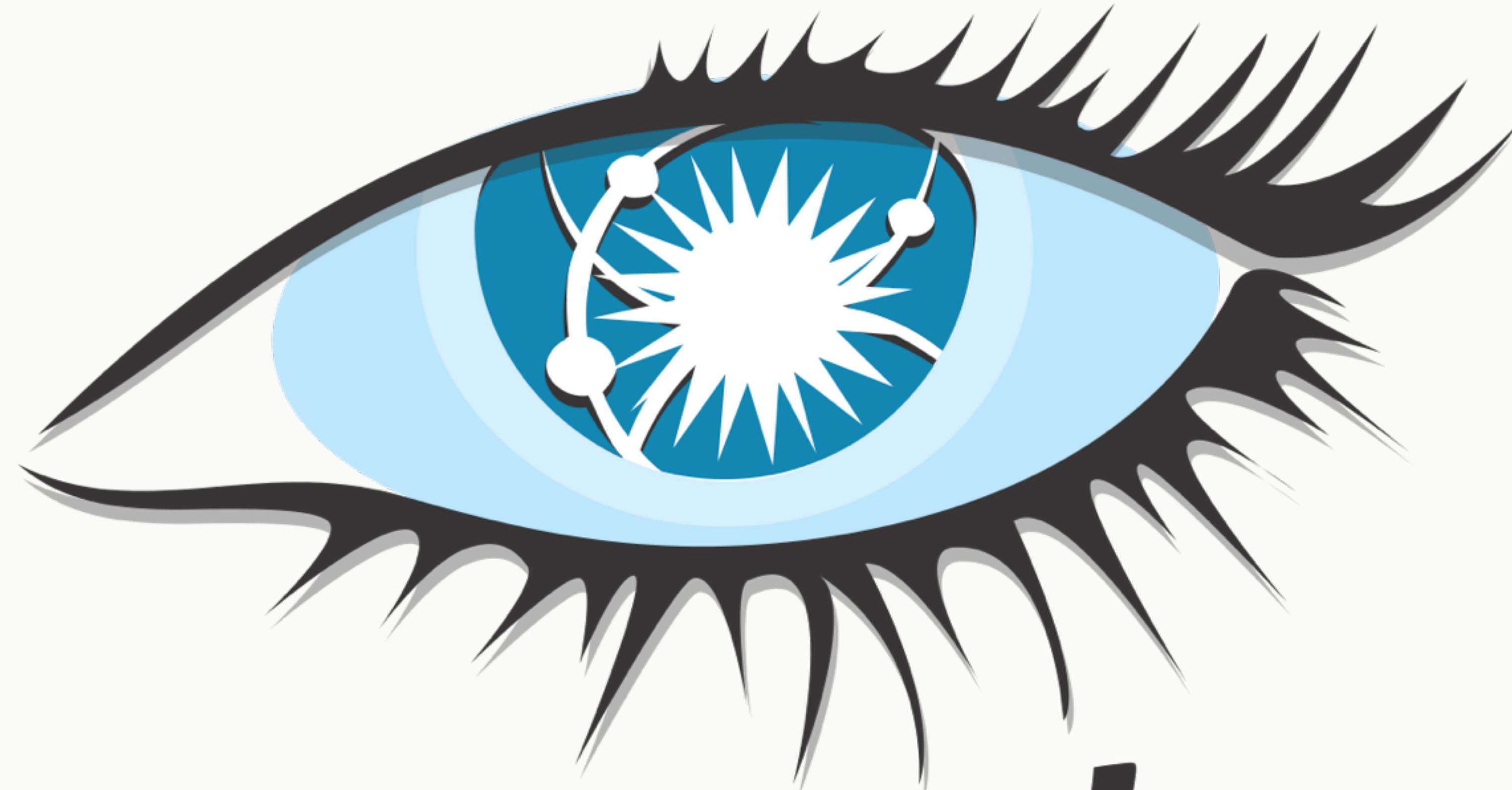
# kafka

- High Throughput Distributed Messaging
- Decouples Data Pipelines
- Handles Massive Data Load
- Support Massive Number of Consumers
- Distribution & partitioning across cluster nodes
- Automatic recovery from broker failures

# Speaking Of Fault Tolerance...



The one thing in your infrastructure  
you can *always* rely on.

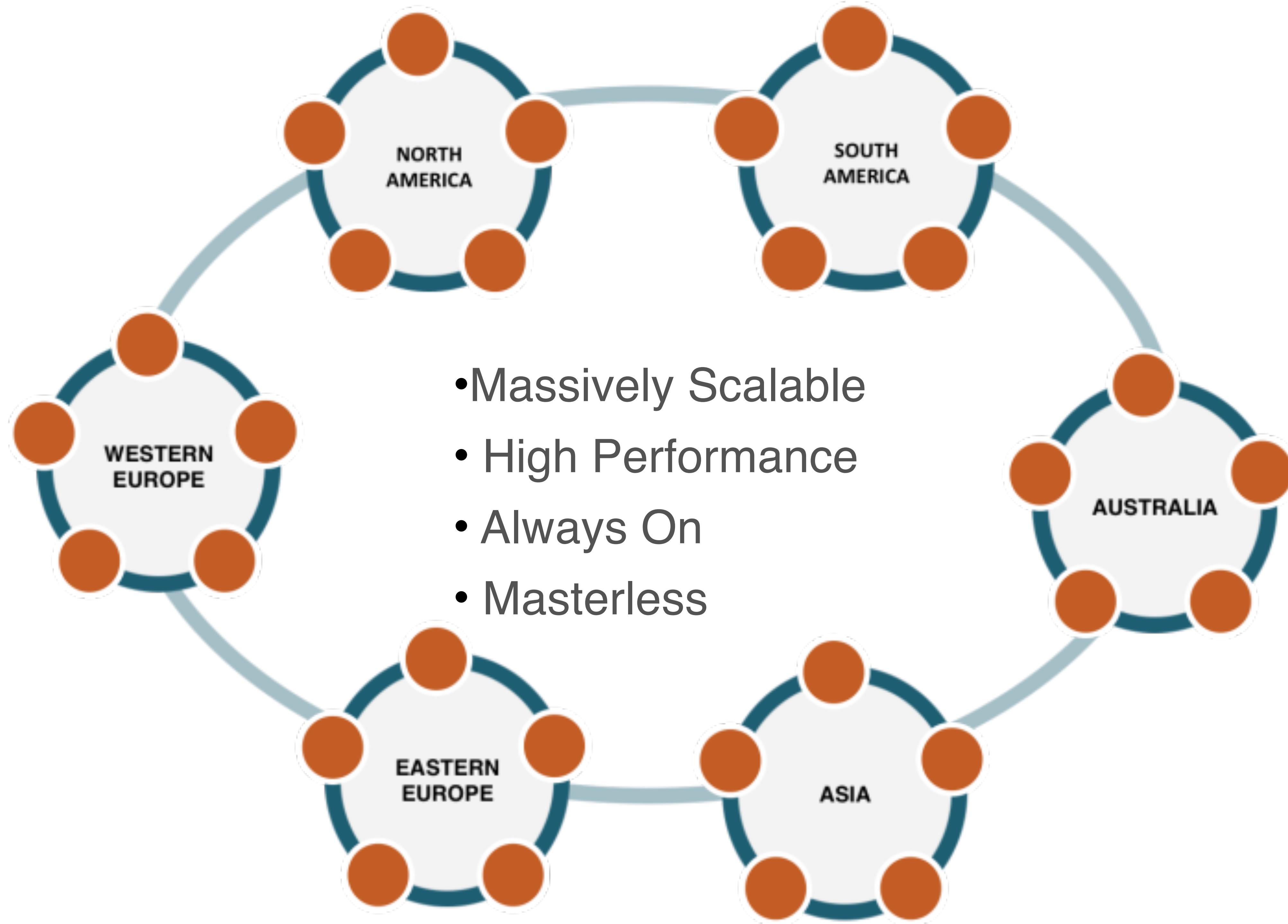


cassandra



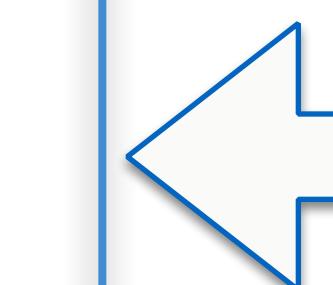
"During Hurricane Sandy, we lost an entire data center. *Completely. Lost. It.*  
Our data in Cassandra never went offline."







- Fault tolerant
  - Hierarchical Supervision
  - Customizable Failure Strategies & Detection
- Asynchronous Data Passing
- Parallelization - Balancing Pool Routers
- Akka Cluster
  - Adaptive / Predictive
  - Load-Balanced Across Cluster Nodes



I've used Scala  
with these  
every single time.



- Stream data from Kafka to Cassandra
- Stream data from Kafka to Spark and write to Cassandra
- *Stream from Cassandra to Spark - coming soon!*
- Read data from Spark/Spark Streaming Source and write to C\*
- Read data from Cassandra to Spark



- Distributed Analytics Platform
- Easy Abstraction for Datasets
- Support in several languages
- Streaming
- Machine Learning
- Graph
- Integrated SQL Queries
- Has Generalized DAG execution

All in one package

And it uses Akka

# Most Active OSS In Big Data



apache / spark  
mirrored from <git://git.apache.org/spark.git>

Watch ▾ 427   Star 2,285   Fork 2,044

November 11, 2014 – December 11, 2014   Period: 1 month ▾

Overview	
	154 Active Pull Requests
	10 Merged Pull Requests
	154 Proposed Pull Requests
	0 Active Issues
	0 Closed Issues
	0 New Issues

Excluding merges, **317 authors** have pushed **297 commits** to master and **3,546 commits** to all branches. On master, **702 files** have changed and there have been **38,458 additions** and **18,021 deletions**.

A bar chart showing the number of pull requests proposed by 154 different people. The x-axis lists 154 individuals, each with a small profile picture. The y-axis represents the count of pull requests, ranging from 0 to over 150. The bars are orange.

154 Pull requests proposed by 82 people



Alpha / Pre-alpha

Spark SQL  
*SQL*

Spark  
Streaming  
*Streaming*

MLLib  
*Machine  
Learning*

GraphX  
*Graph  
Computation*

Spark R  
*R on Spark*

Spark Core Engine

# Apache Spark - Easy to Use API

Returns the top (k) highest temps for any location in the year

```
def topK(aggregate: Seq[Double]): Seq[Double] =  
  sc.parallelize(aggregate).top(k).collect
```

Returns the top (k) highest temps ... in a Future

```
def topK(aggregate: Seq[Double]): Future[Seq[Double]] =  
  sc.parallelize(aggregate).top(k).collectAsync
```

# Use the Spark Shell to quickly try out code samples

Available in  Scala

## Spark Shell

```
scala> val rdd3 = rdd2.filter(_ > 5)
rdd3: org.apache.spark.rdd.RDD[Int] = FilteredRDD[5] at filter at <console>:63

scala> rdd3.collect
res6: Array[Int] = Array(6, 8, 10, 12)
```

and  python

## Pyspark

```
>>> x.collect()
[Row(ckey1=u'Seven', data1=u'Seven', pkey=u'Seven'), Row(ckey1=u'Four', data1=u'Four', pkey=u'Four'), Row(ckey1=u'Three', data1=u'Three', pkey=u'Three'), Row(ckey1=u'Six', data1=u'Six', pkey=u'Six'), Row(ckey1=u'Eight', data1=u'Eight', pkey=u'Eight'), Row(ckey1=u'Five', data1=u'Five', pkey=u'Five'), Row(ckey1=u'New Value', data1=u'Newer Value', pkey=u'One'), Row(ckey1=u'Two', data1=u'Two', pkey=u'Two')]
```

# Collection To RDD

```
scala> val data = Array(1, 2, 3, 4, 5)
data: Array[Int] = Array(1, 2, 3, 4, 5)
```

```
scala> val distributedData = sc.parallelize(data)
distributedData: spark.RDD[Int] =
spark.ParallelCollection@10d13e3e
```

# Not Just MapReduce



```
def aggregate[U](zeroValue: U)(seqOp: (U, T) → U, combOp: (U, U) → U): U
    Aggregate the elements of each partition, and then the results for all the partitions.

def cache(): RDD.this.type
    Persist this RDD with the default storage level (MEMORY_ONLY).

def cartesian[U](other: RDD[U])(implicit arg0: ClassTag[U]): RDD[(U, U)]
    Return the Cartesian product of this RDD and another one, that is, the product of every element in this RDD with every element in other.

def checkpoint(): Unit
    Mark this RDD for checkpointing.

def coalesce(numPartitions: Int, shuffle: Boolean = false): RDD[T]
    Return a new RDD that is reduced into numPartitions partitions.

def collect[U](f: PartialFunction[T, U])(implicit arg0: Ordering[T]): Seq[U]
    Return an RDD that contains all matching values by applying f.

def collect(): Array[T]
    Return an array that contains all of the elements in this RDD.

def context: SparkContext
    The org.apache.spark.SparkContext that this RDD was created on.

def count(): Long
    Return the number of elements in the RDD.

def countApprox(timeout: Long, confidence: Double = 0.95): Double
    Approximate version of count() that returns a potentially incomplete result.

def countApproxDistinct(relativeSD: Double = 0.05): Long
    Return approximate number of distinct elements in the RDD.

def countApproxDistinct(p: Int, sp: Int): Long
    Return approximate number of distinct elements in the RDD.

def countByValue()(implicit ord: Ordering[T] = null): Map[T, Long]
    Return the count of each unique value in this RDD as a map of (value, count).

def countByValueApprox(timeout: Long, confidence: Double): Double
    Approximate version of countByValue().

def dependencies: Seq[Dependency[_]]
    Get the list of dependencies of this RDD, taking into account whether it depends on external data or not.

def distinct(): RDD[T]
    Return a new RDD containing the distinct elements in this RDD.
```

```
def glom(): RDD[Array[T]]
    Return an RDD created by coalescing all elements within each partition into arrays.

def groupBy[K](f: (T) → K, p: Partitioner)(implicit kt: KeyType[K]): RDD[(K, Iterator[T])]
    Return an RDD of grouped items.

def groupBy[K](f: (T) → K, numPartitions: Int)(implicit kt: KeyType[K]): RDD[(K, Iterator[T])]
    Return an RDD of grouped elements.

def groupBy[K](f: (T) → K)(implicit kt: ClassTag[K]): RDD[(K, Iterator[T])]
    Return an RDD of grouped items.

val id: Int
    A unique ID for this RDD (within its SparkContext).

def intersection(other: RDD[T], numPartitions: Int): RDD[T]
    Return the intersection of this RDD and another one.

def intersection(other: RDD[T], partitioner: Partitioner): RDD[T]
    Return the intersection of this RDD and another one.

def intersection(other: RDD[T]): RDD[T]
    Return the intersection of this RDD and another one.

def isCheckpointed: Boolean
    Return whether this RDD has been checkpointed or not.

def iterator(split: Partition, context: TaskContext): Iterator[T]
    Internal method to this RDD; will read from cache if applicable, or otherwise read from disk.

def keyBy[K](f: (T) → K): RDD[(K, T)]
    Creates tuples of the elements in this RDD by applying f.

def map[U](f: (T) → U)(implicit arg0: ClassTag[U]): RDD[U]
    Return a new RDD by applying a function to all elements of this RDD.

def mapPartitions[U](f: (Iterator[T]) → Iterator[U], p: Partitioner): RDD[U]
    Return a new RDD by applying a function to each partition of this RDD.

def mapPartitionsWithContext[U](f: (TaskContext, Iterator[T]) → Iterator[U]): RDD[U]
    Return a new RDD by applying a function to each partition of this RDD.

def mapPartitionsWithIndex[U](f: (Int, Iterator[T]) → Iterator[U]): RDD[U]
    Return a new RDD by applying a function to each partition of this RDD.

def max()(implicit ord: Ordering[T]): T
    Returns the max of this RDD as defined by the implicit Ordering[T].
```

```
def min()(implicit ord: Ordering[T]): T
    Returns the min of this RDD as defined by the implicit Ordering[T].

var name: String
    A friendly name for this RDD.

val partitioner: Option[Partitioner]
    Optionally overridden by subclasses to specify how they are partitioned.

def partitions: Array[Partition]
    Get the array of partitions of this RDD, taking into account whether the RDD is checkpointed or not.

def persist(): RDD.this.type
    Persist this RDD with the default storage level (MEMORY_ONLY).

def persist(newLevel: StorageLevel): RDD.this.type
    Set this RDD's storage level to persist its values across operations after the first time it is computed.

def pipe(command: Seq[String], env: Map[String, String] = Map()): RDD[String]
    Return an RDD created by piping elements to a forked external process.

def pipe(command: String, env: Map[String, String]): RDD[String]
    Return an RDD created by piping elements to a forked external process.

def pipe(command: String): RDD[String]
    Return an RDD created by piping elements to a forked external process.

def preferredLocations(split: Partition): Seq[String]
    Get the preferred locations of a partition (as hostnames), taking into account whether the partitioner is specified or not.

def randomSplit(weights: Array[Double], seed: Long = Utils.random.nextInt()): Seq[RDD[T]]
    Randomly splits this RDD with the provided weights.

def reduce(f: (T, T) → T): T
    Reduces the elements of this RDD using the specified commutative and associative reduce function.

def repartition(numPartitions: Int)(implicit ord: Ordering[T] = null): RDD[T]
    Return a new RDD that has exactly numPartitions partitions.

def sample(withReplacement: Boolean, fraction: Double, seed: Long): RDD[T]
    Return a sampled subset of this RDD.

def saveAsObjectFile(path: String): Unit
    Save this RDD as a SequenceFile of serialized objects.

def saveAsTextFile(path: String, codec: Class[_ <: CompressionCodec]): Unit
    Save this RDD as a compressed text file, using string representations of elements.
```

# Spark Basic Word Count

```
val conf = new SparkConf()  
    .setMaster(host).setAppName(app)
```

```
val sc = new SparkContext(conf)
```

```
sc.textFile(words)  
    .flatMap(_.split("\\s+"))  
    .map(word => (word.toLowerCase, 1))  
    .reduceByKey(_ + _)  
    .collect
```

# RDDs Can be Generated from a Variety of Sources



Scala Collections



Textfiles



# RDD Operations

```
16 object SparkWordCount extends WordCountBlueprint {  
17  
18     sc.textFile("./src/main/resources/data/words")  
19         .flatMap(_.split("\\s+"))  
20         .map(word => (clean(word), 1))  
21         .reduceByKey(_ + _)  
22         .collect foreach println |  
23 }
```

Transformation

Action

# Setting up C\* and Spark



DSE > 4.5.0

Just start your nodes with  
`dse cassandra -k`

## Apache Cassandra

Follow the excellent guide by Al Tobey

<http://tobert.github.io/post/2014-07-15-installing-cassandra-spark-stack.html>



# When Batch Is Not Enough

# Your Data Is Like Candy

**Delicious: you want it now**

# Your Data Is Like Candy

**Delicious: you want it now**

## **Batch Analytics**

Analysis after data has accumulated

Decreases the weight of the data by the time it is processed



**Both in same app = Lambda**

## **Streaming Analytics**

Analytics as data arrives.

The data won't be stale and neither will our analytics



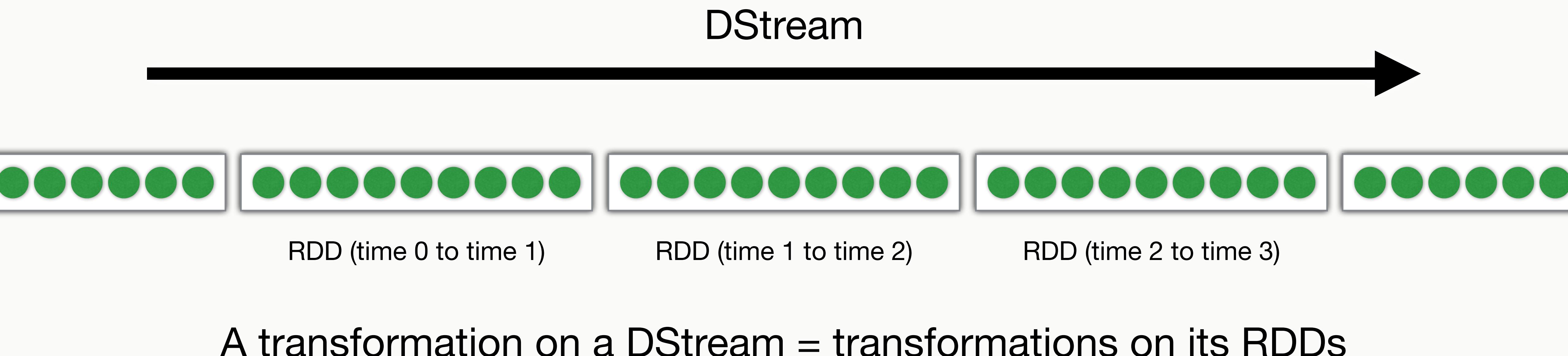
# Spark Streaming

- I want results continuously in the event stream
- I want to run computations in my even-driven async apps
- Exactly once message guarantees

# DStream (Discretized Stream)

Continuous stream of micro batches

- Complex processing models with minimal effort
- Streaming computations on small time intervals



# Basic Streaming: FileInputStream

```
val conf = new SparkConf().setMaster(SparkMaster).setAppName(AppName)  
val ssc = new StreamingContext(conf, Milliseconds(500))
```

```
ssc.textFileStream("s3n://raw_data_bucket/")  
  .flatMap(_.split("\\s+"))  
  .map(_.toLowerCase, 1))  
  .countByValue()  
  .saveToCassandra(keyspace, table)
```

```
ssc.checkpoint(checkpointDir)  
ssc.start()  
ssc.awaitTermination
```

The batch streaming interval

Starts the streaming application piping  
raw incoming data to a Sink

# ReceiverInputDStreams

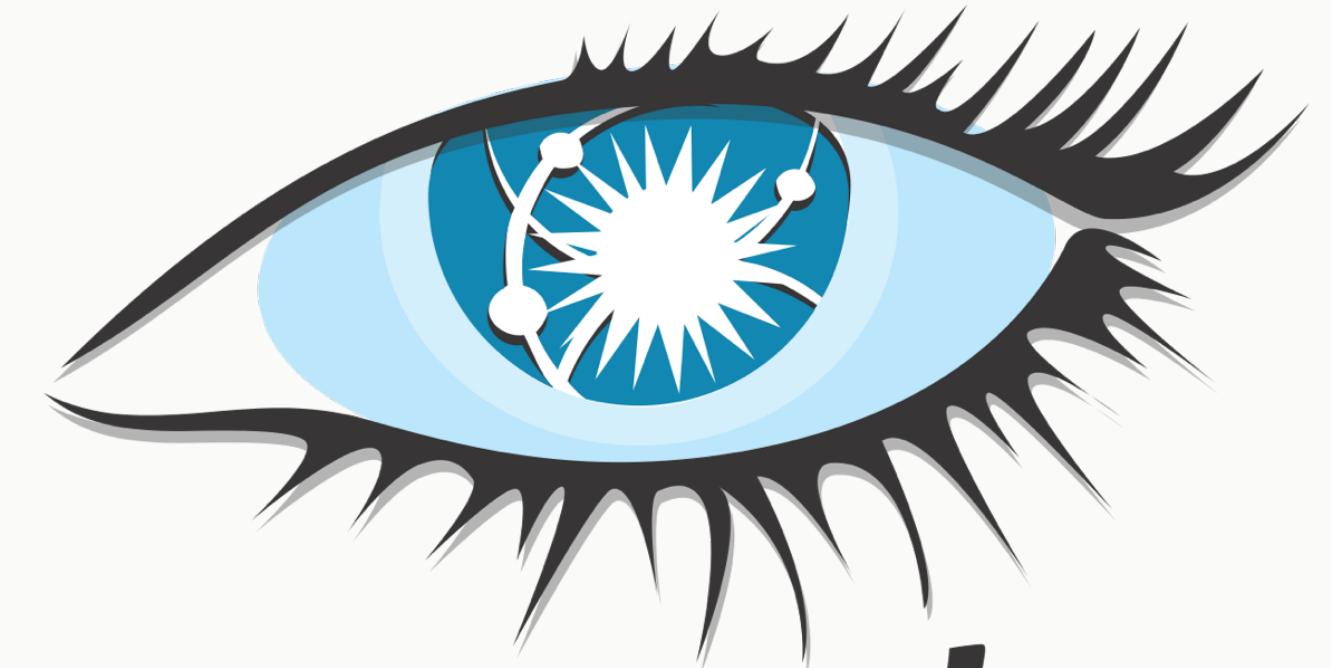
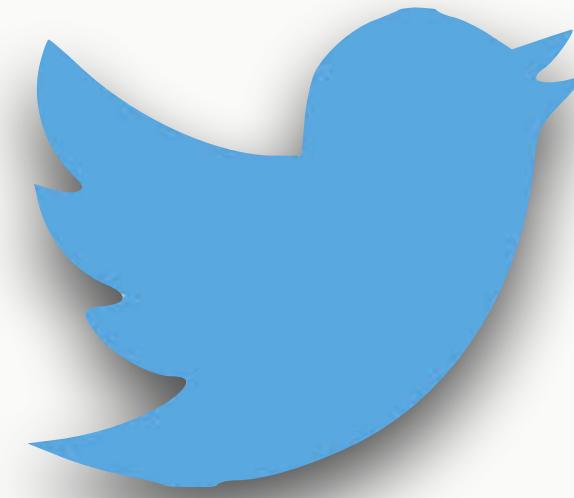
DStreams - the stream of raw data received from streaming sources:

- Basic Source - in the StreamingContext API
- Advanced Source - in external modules and separate Spark artifacts

## Receivers

- Reliable Receivers - for data sources supporting acks (like Kafka)
- Unreliable Receivers - for data sources not supporting acks

# Spark Streaming External Source/Sink



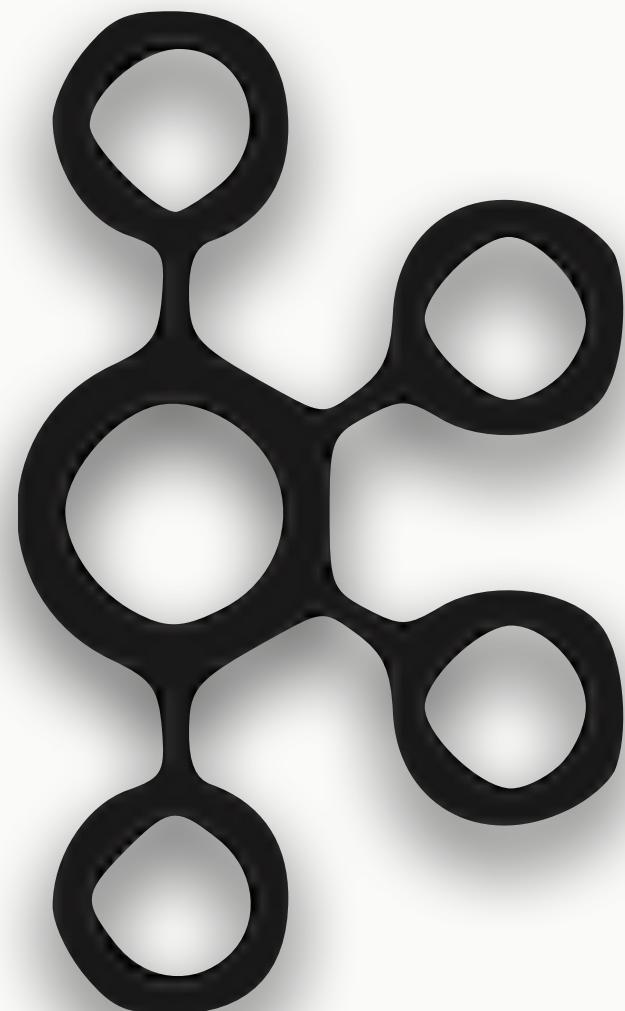
*cassandra*



TCP/IP



akka



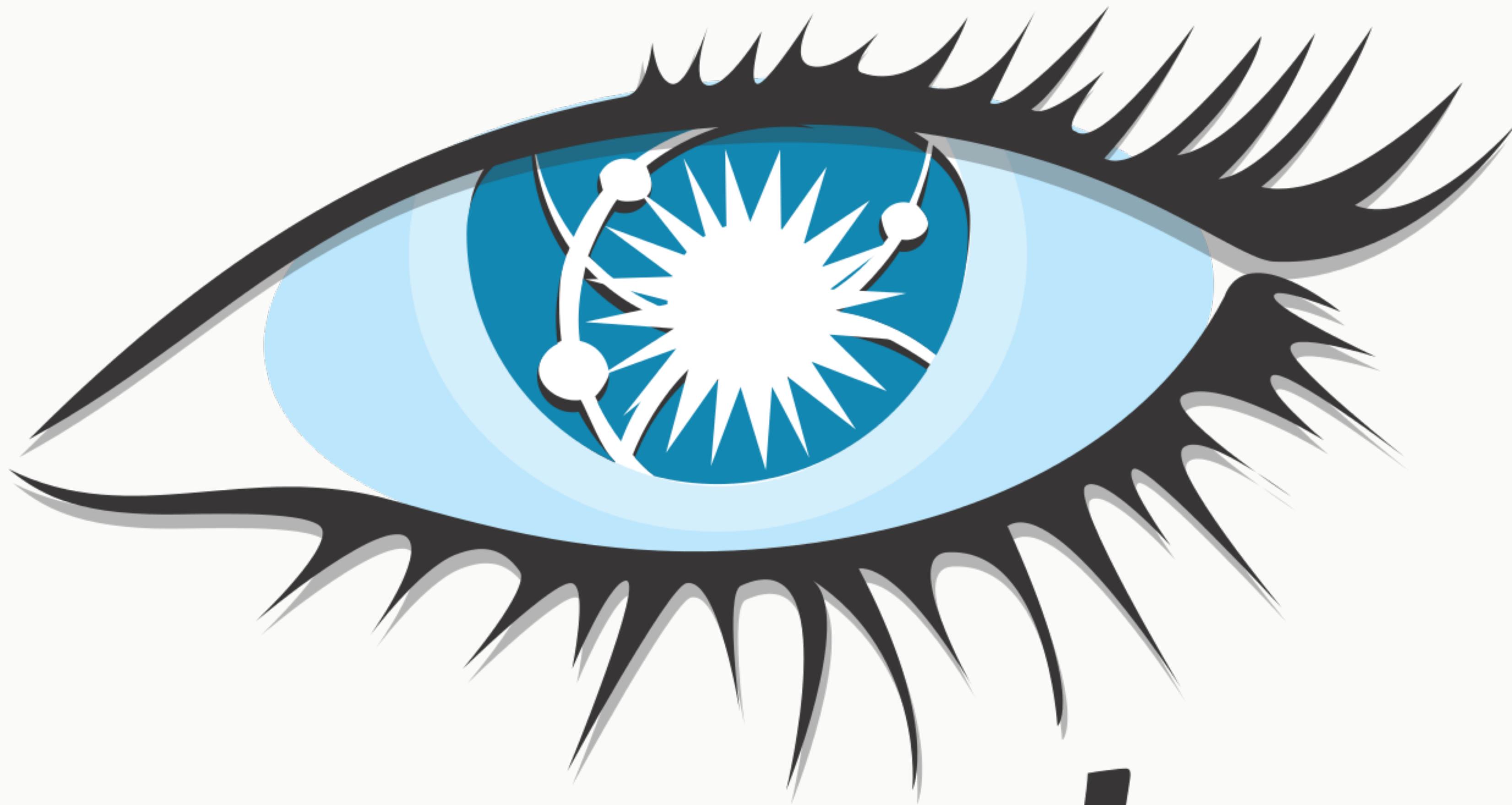
# Streaming Window Operations

kvStream

```
.flatMap { case (k,v) => (k,v.value) }  
.reduceByKeyAndWindow((a:Int,b:Int) =>  
  (a + b), Seconds(30), Seconds(10))  
.saveToCassandra(keyspace,table)
```

Window Length:  
Duration = every 10s

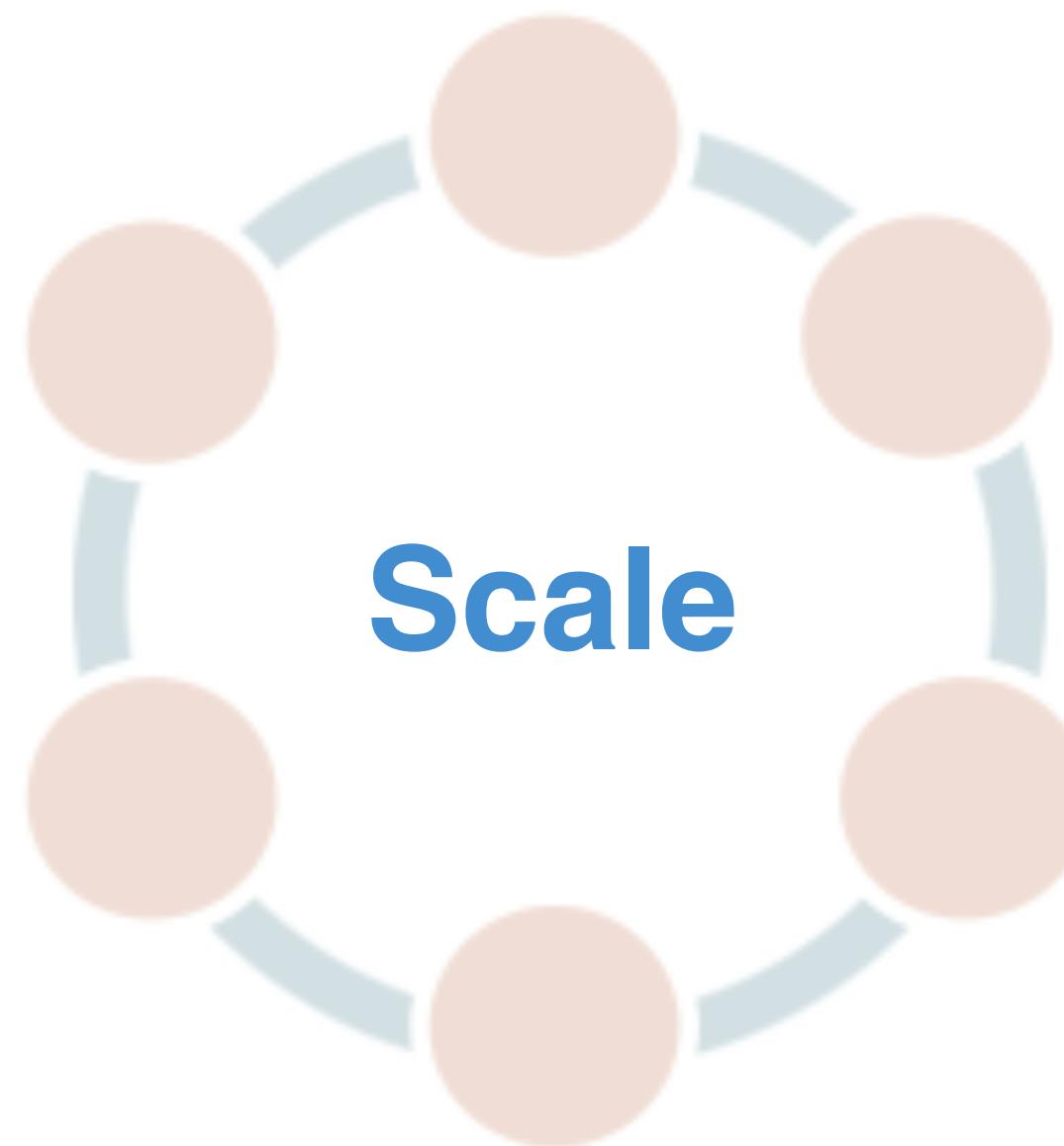
Sliding Interval:  
Interval at which the window operation  
is performed = every 10 s



cassandra



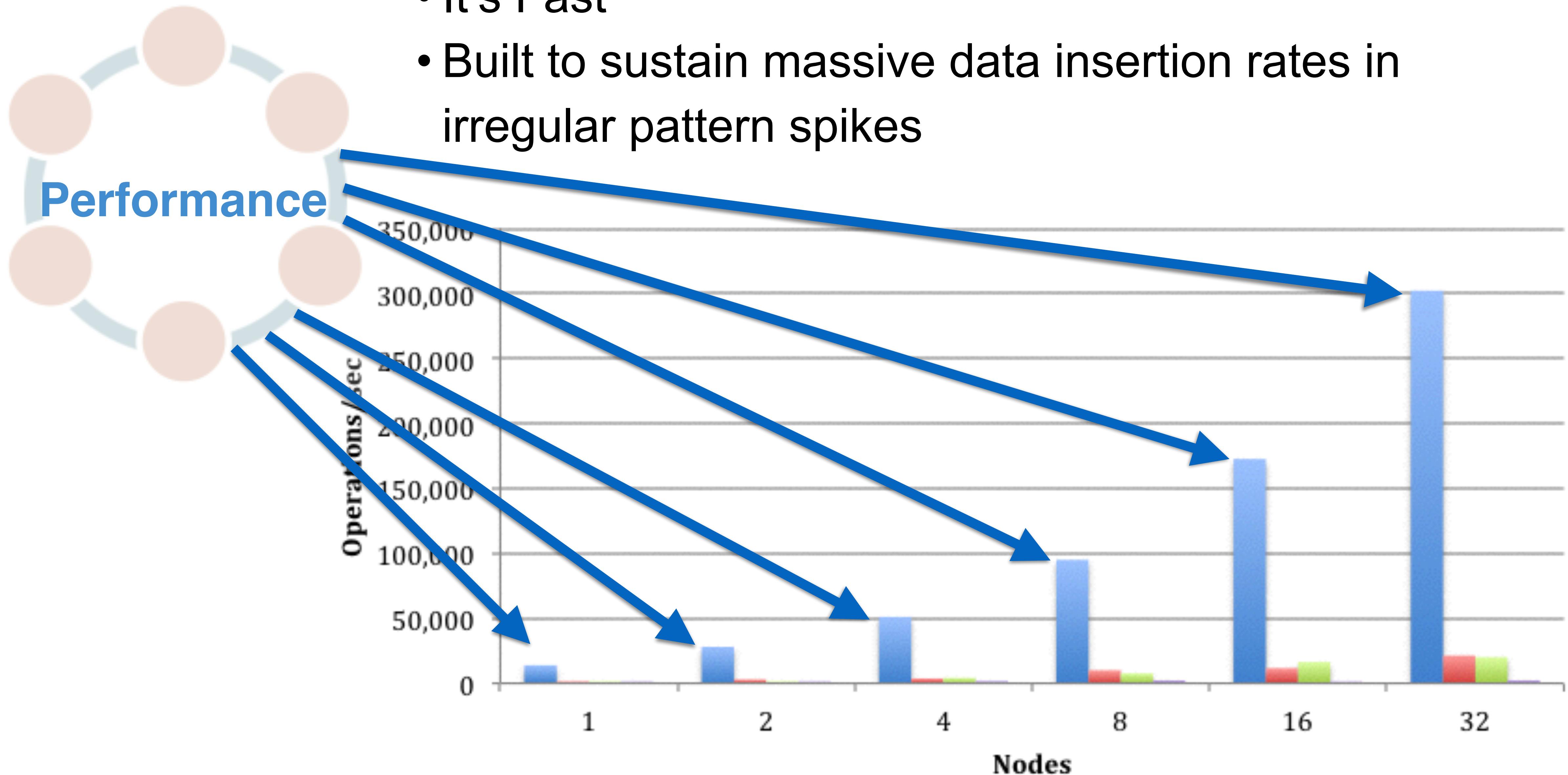
# Apache Cassandra



- Scales Linearly to as many nodes as you need
- Scales whenever you need

# Apache Cassandra

- It's Fast
- Built to sustain massive data insertion rates in irregular pattern spikes



# Apache Cassandra

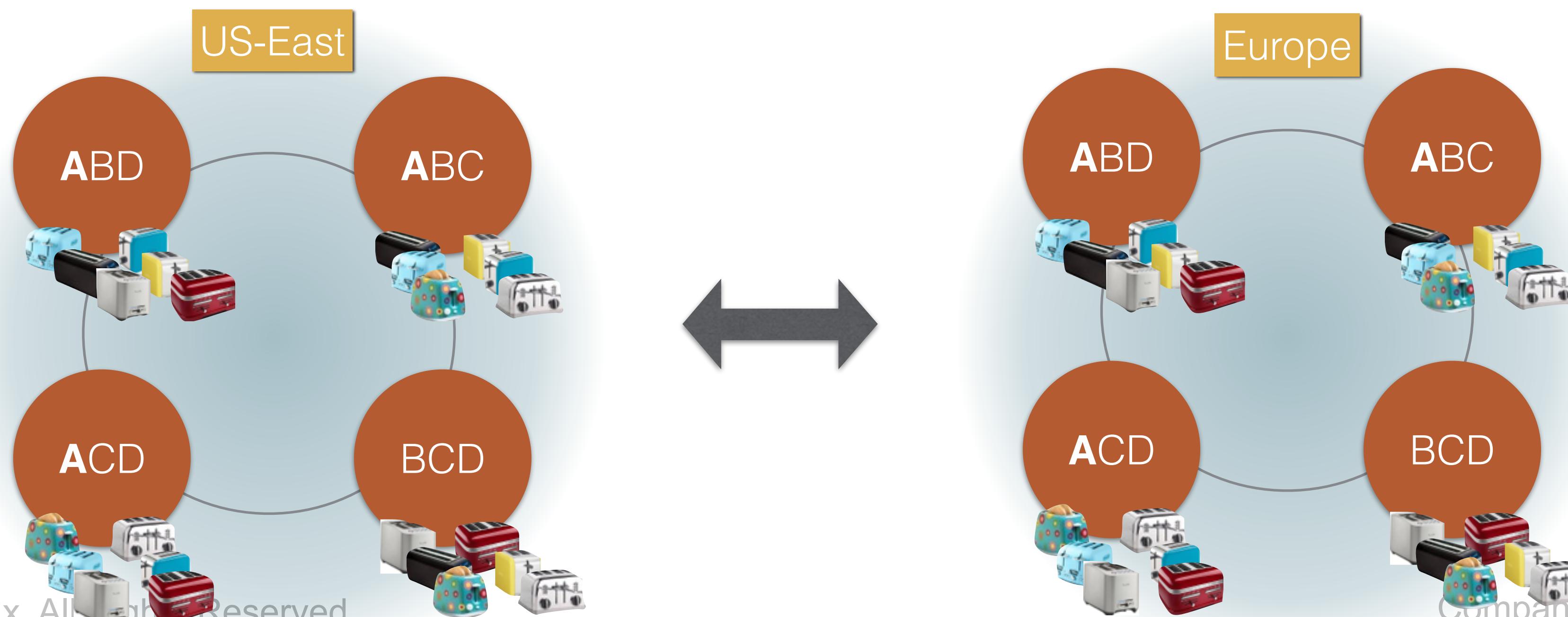


- Automatic Replication
- Multi Datacenter
- Decentralized - no single point of failure
- Survive regional outages
- New nodes automatically add themselves to the cluster
- DataStax drivers automatically discover new nodes

# Fault Tolerance & Replication

**How many copies of a data should exist in the cluster?**

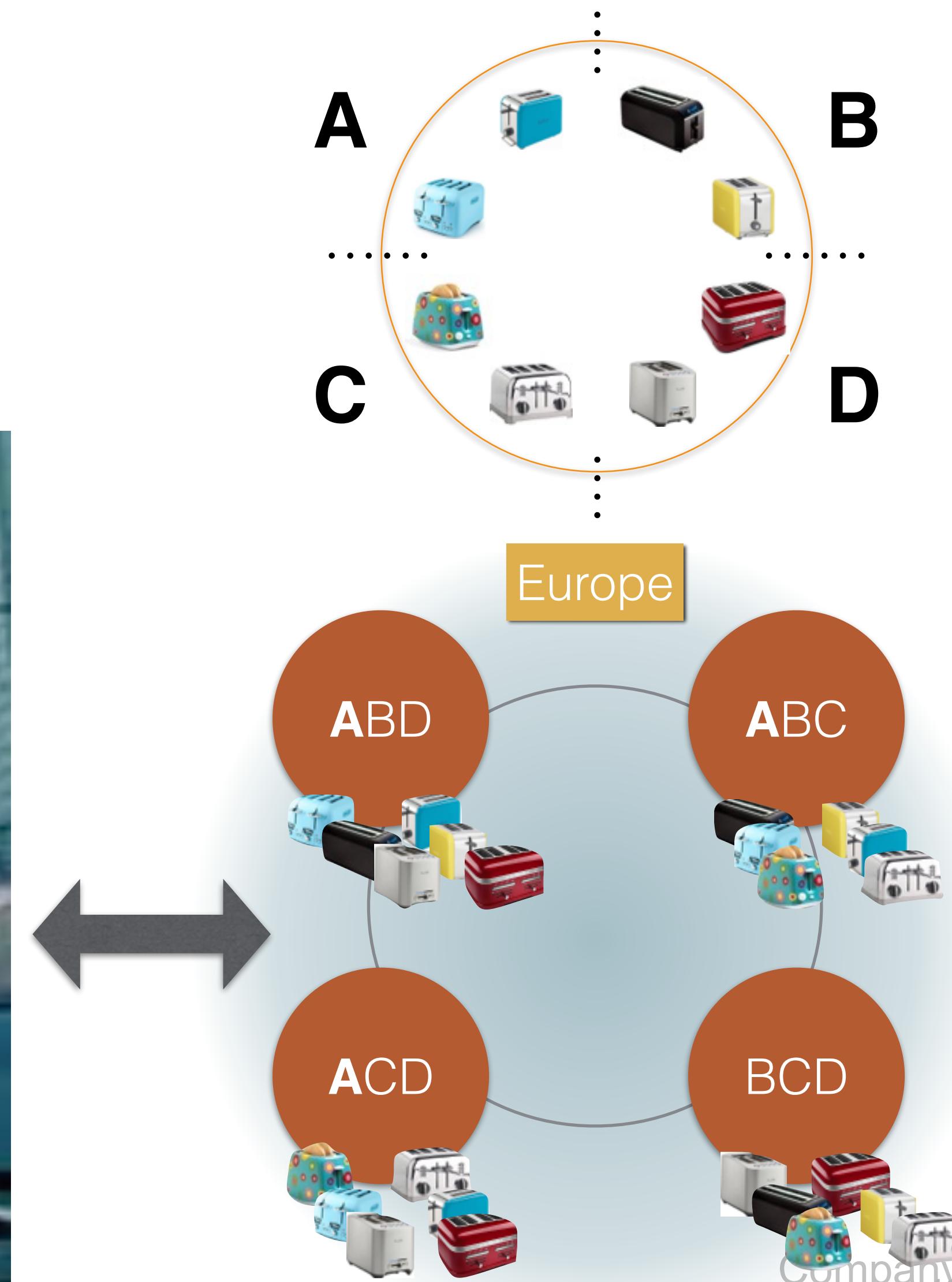
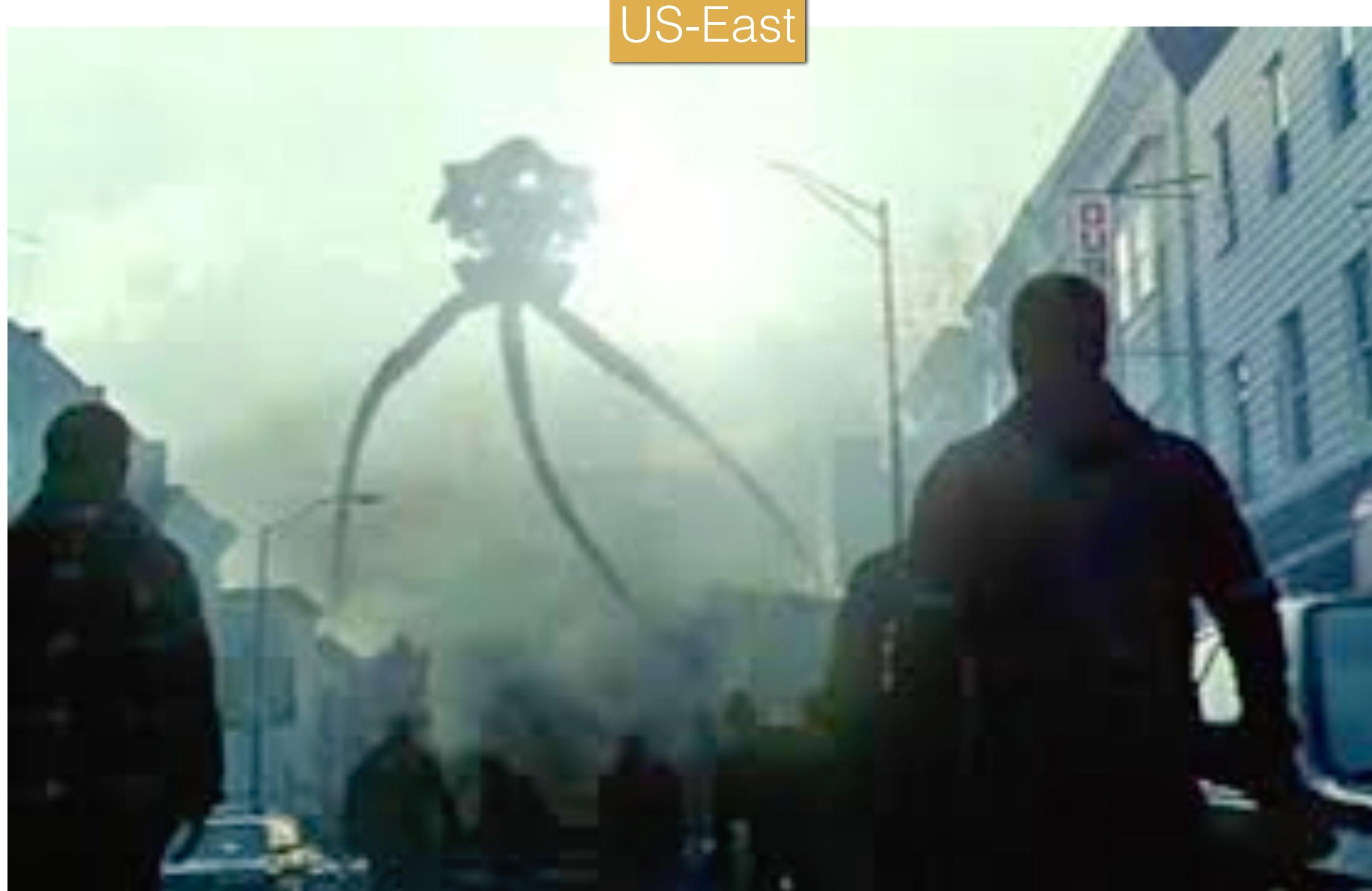
ReplicationFactor=3



# Fault Tolerance & Replication

**How many copies of a data should exist in the cluster?**

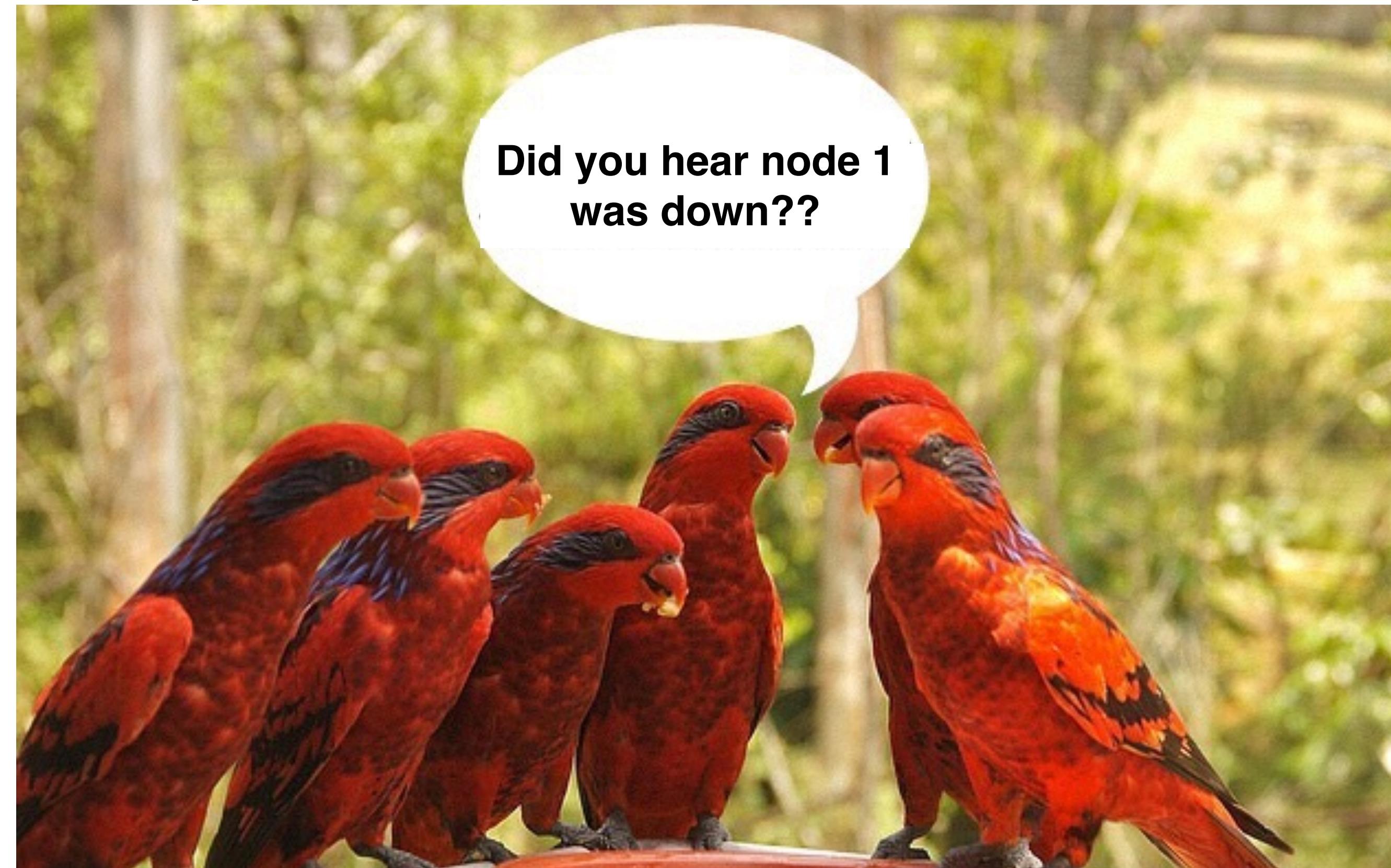
ReplicationFactor=3



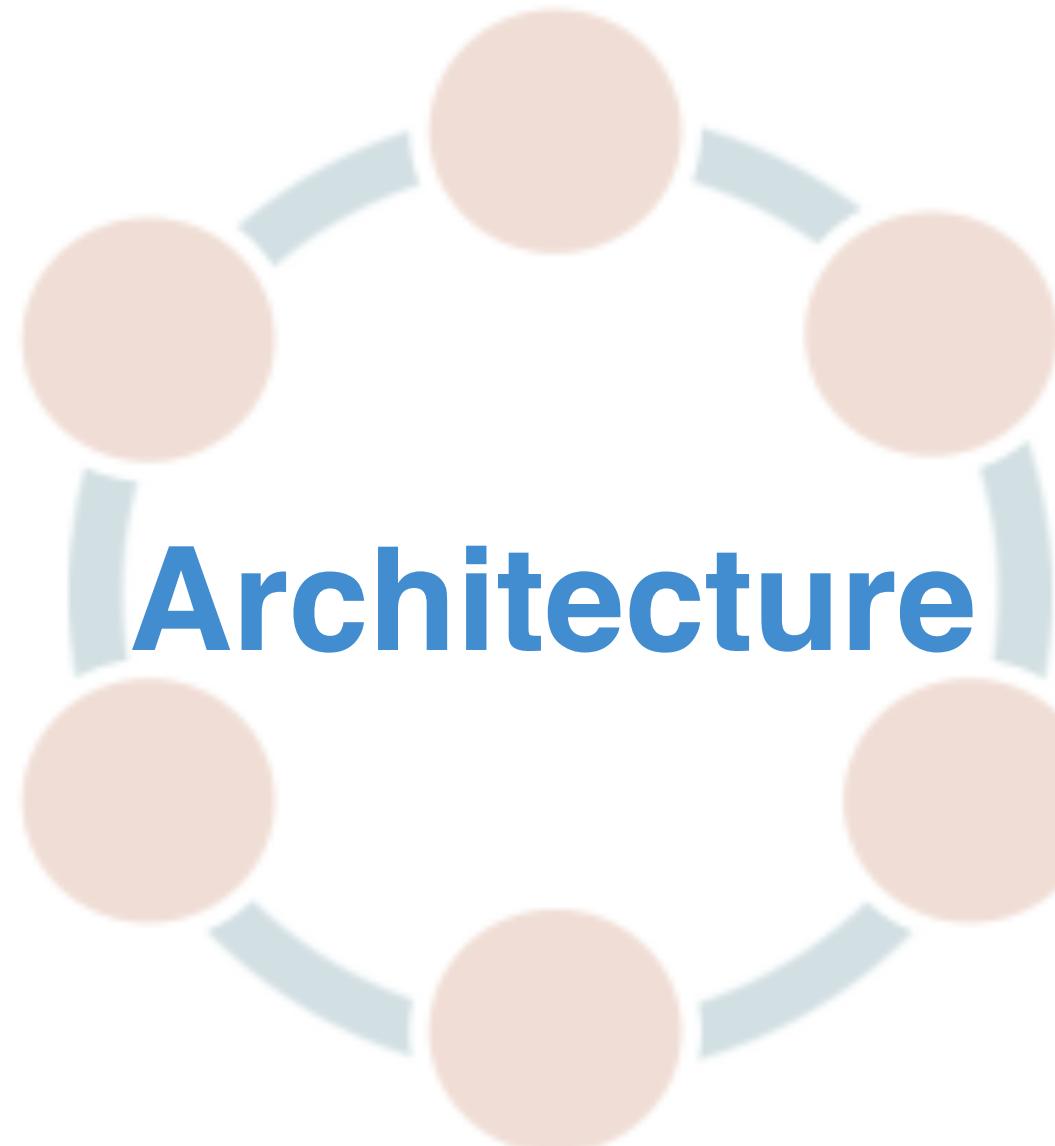
# Apache Cassandra



- Consensus - Paxos Protocol
- Sequential Read / Write - Timeseries
- Tunable Consistency
- Gossip:



# Apache Cassandra



- Distributed, Masterless Ring Architecture
- Network Topology Aware
- Flexible, Schemaless - your data structure can evolve  
seamlessly over time

# Cassandra @ Netflix

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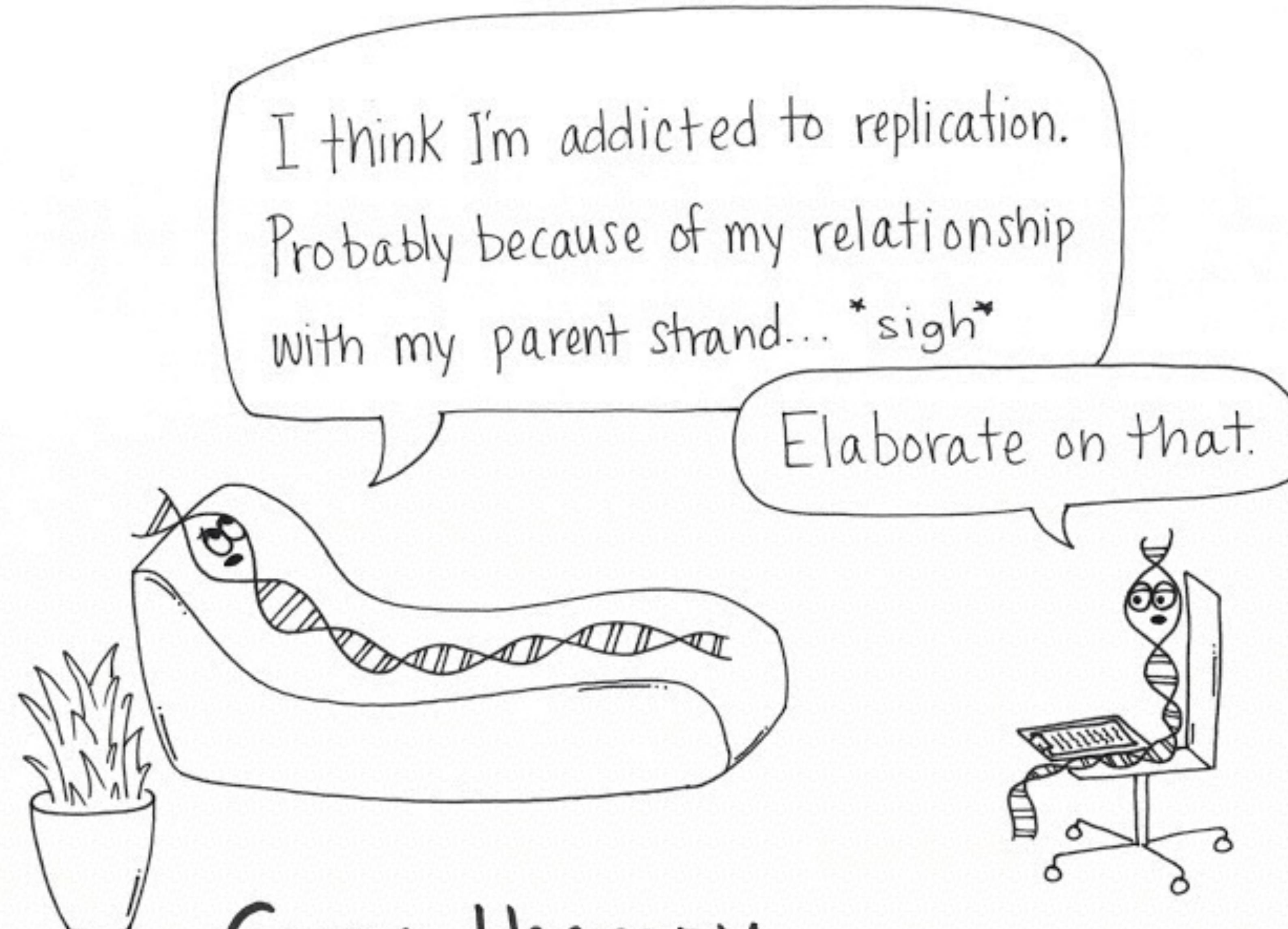
- 90% of streaming data is stored in Cassandra
- Data ranges from customer details to Viewing history to streaming bookmarks
- High availability, Multi-region resiliency and Active-Active



# C\* At CERN: Large Hadron Collider

- ATLAS - Largest of several detectors along the Large Hadron Collider
- Measures particle production when protons collide at a very high center of mass energy
- - Bursty traffic
- - Volume of data from sensors requires
  - - Very large trigger and data acquisition system
  - - 30,000 applications on 2,000 nodes

# Genetics / Biological Computations



Gene therapy.

Beatrice the Biologist



CARTOONSTOCK  
.com

Search ID: Jcep1193

# IoT

I THINK MY NEST SMOKE  
ALARM IS GOING OFF.  
GOOGLE ADWORDS JUST  
PITCHED ME A FIRE  
EXTINGUISHER AND AN OFFER  
FOR TEMPORARY HOUSING.



# CQL - Easy



```
CREATE TABLE users (
    username varchar,
    firstname varchar,
    lastname varchar,
    email list<varchar>,
    password varchar,
    created_date timestamp,
    PRIMARY KEY (username)
);
```

```
INSERT INTO users (username, firstname, lastname,
    email, password, created_date)
VALUES ('hedelson','Helena','Edelson',
['helena.edelson@datastax.com'],'ba27e03fd95e507daf2937c937d499ab','2014-11-15 13:50:00')
IF NOT EXISTS;
```

- Familiar syntax
- Many Tools & Drivers
- Many Languages
- Friendly to programmers
- Paxos for locking

# Timeseries Data

```
CREATE TABLE weather.raw_data (
    wsid text, year int, month int, day int, hour int,
    temperature double, dewpoint double, pressure double,
    wind_direction int, wind_speed double, one_hour_precip
    PRIMARY KEY ((wsid), year, month, day, hour)
) WITH CLUSTERING ORDER BY (year DESC, month DESC, day DESC, hour DESC);
```



C\* Clustering Columns



Writes by most recent  
Reads return most recent first



**Cassandra will automatically sort by most recent for both write and read**

A record of every event, in order in which it happened, per URL:

```
CREATE TABLE IF NOT EXISTS requests_ks.timeline (
    timesegment bigint, url text, t_uuid timeuuid, method text, headers map <text, text>, body text,
    PRIMARY KEY ((url, timesegment), t_uuid)
);
```

**timeuuid** protects from simultaneous events over-writing one another.

**timesegment** protects from writing unbounded partitions.

```
val multipleStreams = (1 to numDstreams).map { i =>
    streamingContext.receiverStream[HttpRequest](new HttpReceiver(port))
}

streamingContext.union(multipleStreams)
    .map { httpRequest => TimelineRequestEvent(httpRequest) }
    .saveToCassandra("requests_ks", "timeline")
```

# Spark Cassandra Connector



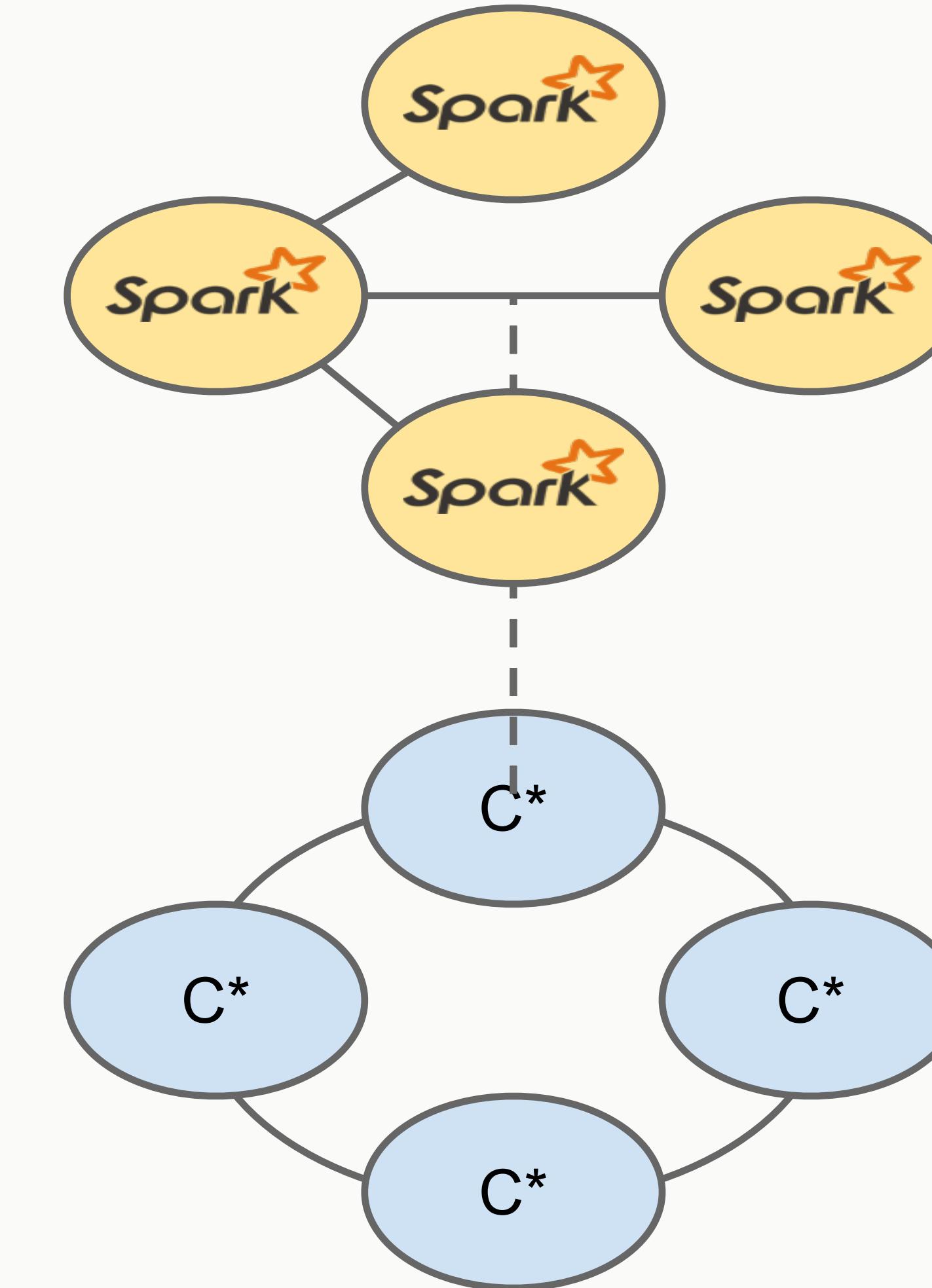
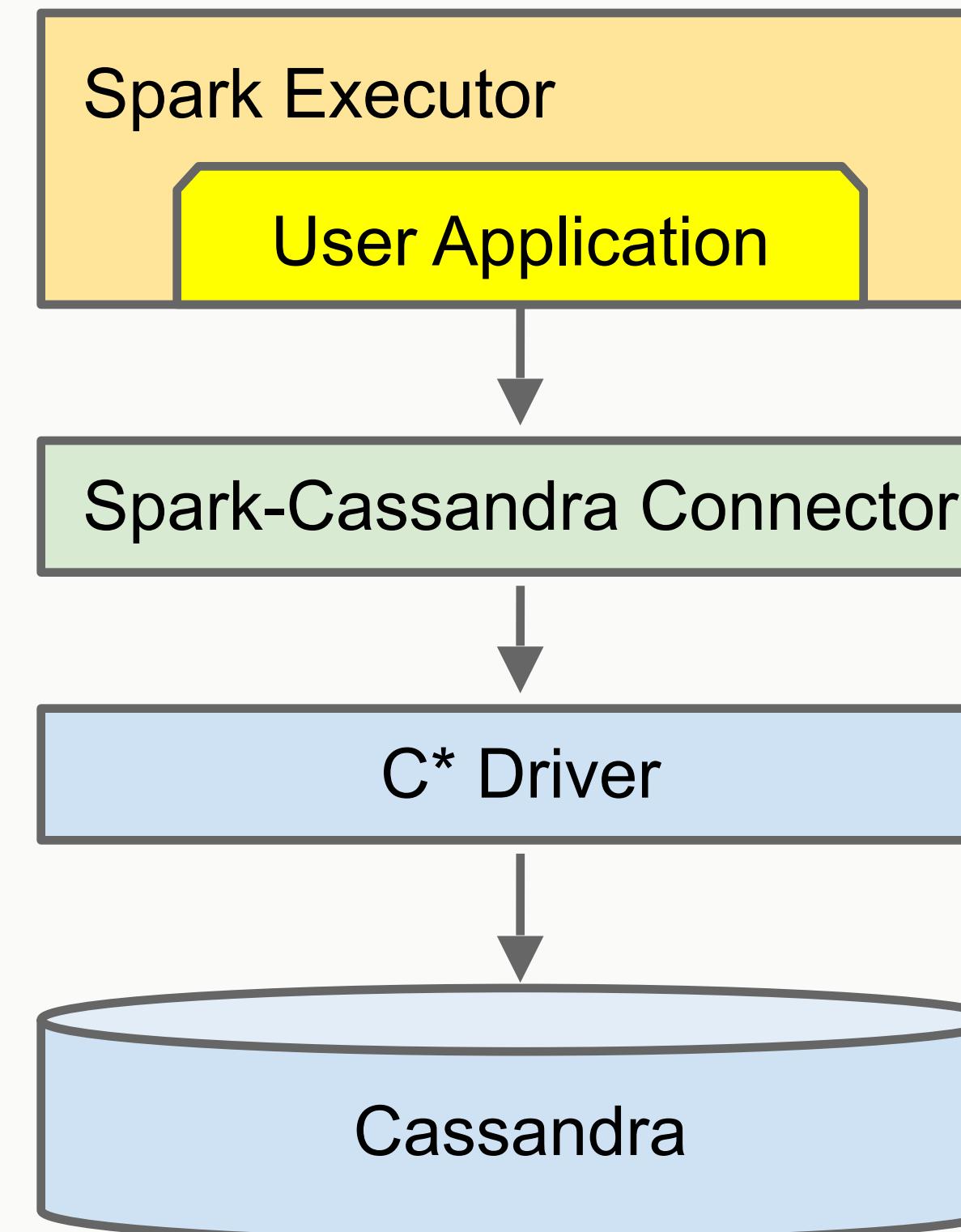
# Spark Cassandra Connector

<https://github.com/datastax/spark-cassandra-connector>

- NOSQL JOINS!
- Write & Read data between Spark and Cassandra
- Compatible with Spark 1.3
- Handles Data Locality for Speed
- Implicit type conversions
- Server-Side Filtering - SELECT, WHERE, etc.
- Natural Timeseries Integration



# Spark Cassandra Connector



# Writing and Reading

**SparkContext**

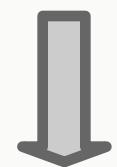
```
import com.datastax.spark.connector._
```

**StreamingContext**

```
import com.datastax.spark.connector.streaming._
```

# Write from Spark to Cassandra

SparkContext



```
sc.parallelize(Seq(0,1,2)).saveToCassandra("keyspace", "raw_data")
```

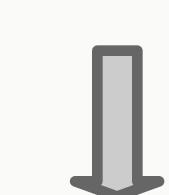
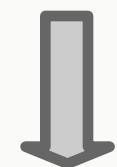
Keyspace



Table

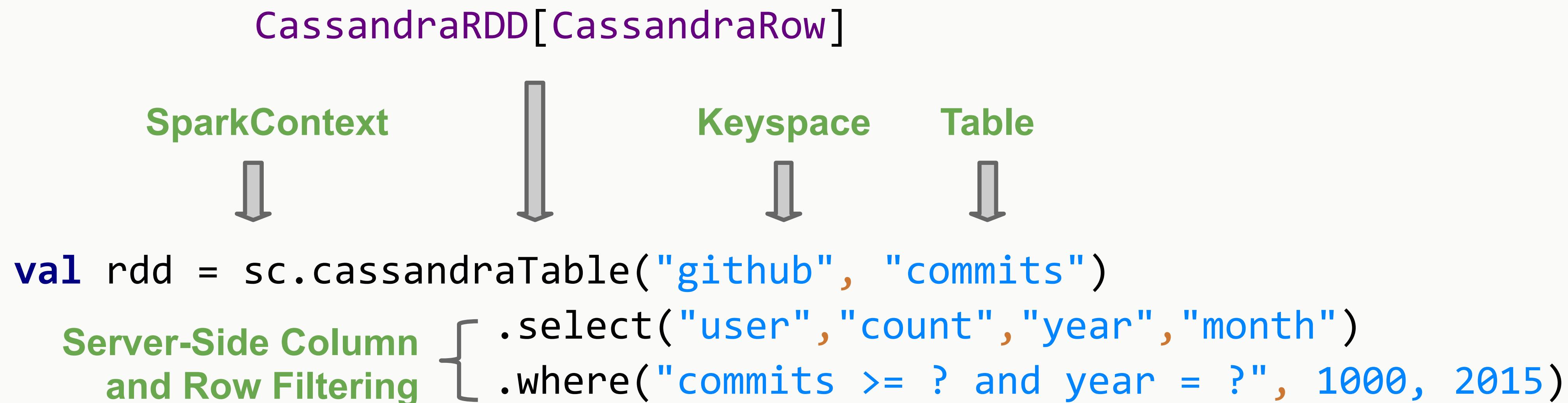


Spark RDD    JOIN with NOSQL!

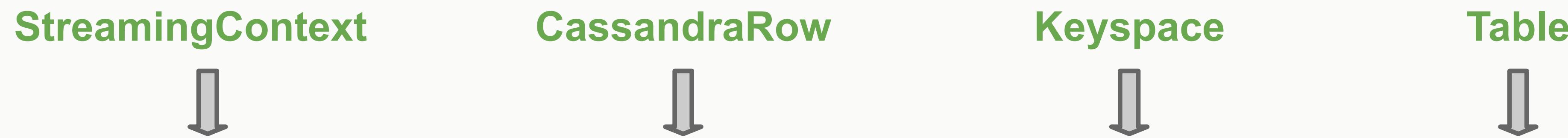


```
predictionsRdd.join(music).saveToCassandra("music", "predictions")
```

# Read From C\* to Spark



# Rows: Custom Objects



```
val rdd = ssc.cassandraTable[MonthlyCommits]("github", "commits_aggregate")
    .where("user = ? and project_name = ? and year = ?",
          "helena", "spark-cassandra-connector", 2015)
```

# Rows

```
val tuplesRdd = sc.cassandraTable[(Int,Date,String)](db, tweetsTable)
  .select("cluster_id", "time", "cluster_name")
  .where("time > ? and time < ?",
    "2014-07-12 20:00:01", "2014-07-12 20:00:03")
```

```
val rdd = ssc.cassandraTable[MyDataType]("stats", "clustering_time")
  .where("key = 1").limit(10).collect
```

```
val rdd = ssc.cassandraTable[(Int,DateTime,String)]("stats", "clustering_time")
  .where("key = 1").withDescOrder.collect
```

# Cassandra User Defined Types

```
CREATE TYPE address (      ←  
    street text,  
    city text,  
    zip_code int,  
    country text,  
    cross_streets set<text>  
);
```

*UDT = Your Custom Field Type In Cassandra*

# Cassandra UDT's With JSON



```
{  
  "productId": 2,  
  "name": "Kitchen Table",  
  "price": 249.99,  
  "description" : "Rectangular table with oak finish",  
  "dimensions": {  
    "units": "inches",  
    "length": 50.0,  
    "width": 66.0,  
    "height": 32  
  },  
  "categories": {  
    {  
      "category" : "Home Furnishings" {  
        "catalogPage": 45,  
        "url": "/home/furnishings"  
      },  
      {  
        "category" : "Kitchen Furnishings" {  
          "catalogPage": 108,  
          "url": "/kitchen/furnishings"  
        }  
    }  
  }  
}
```

```
CREATE TYPE dimensions (  
  units text,  
  length float,  
  width float,  
  height float  
)
```

```
CREATE TYPE category (  
  catalogPage int,  
  url text  
)
```

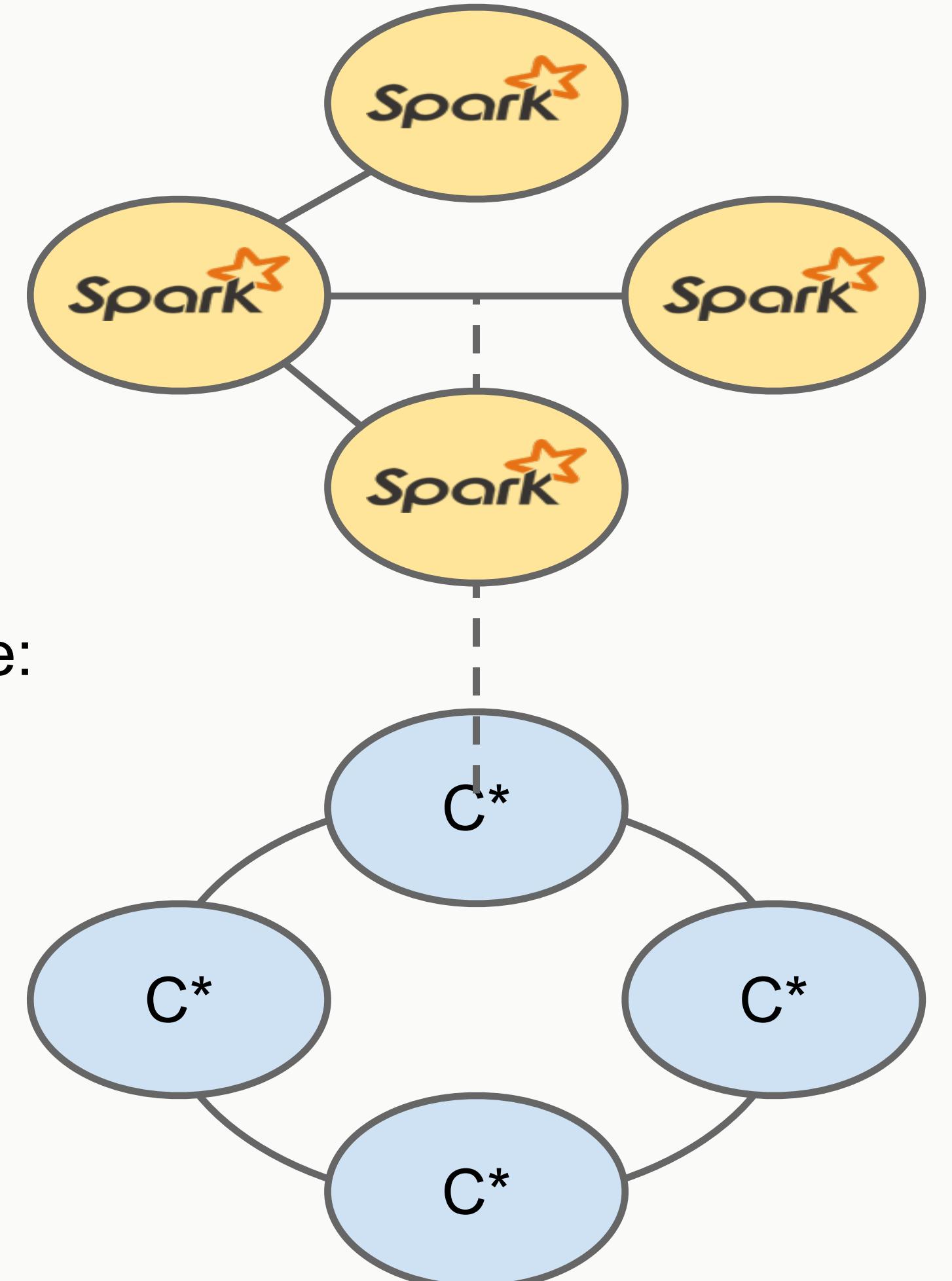
```
CREATE TABLE product (  
  productId int,  
  name text,  
  price float,  
  description text,  
  dimensions frozen <dimensions>,  
  categories map <text, frozen <category>>,  
  PRIMARY KEY (productId)  
)
```

# Data Locality

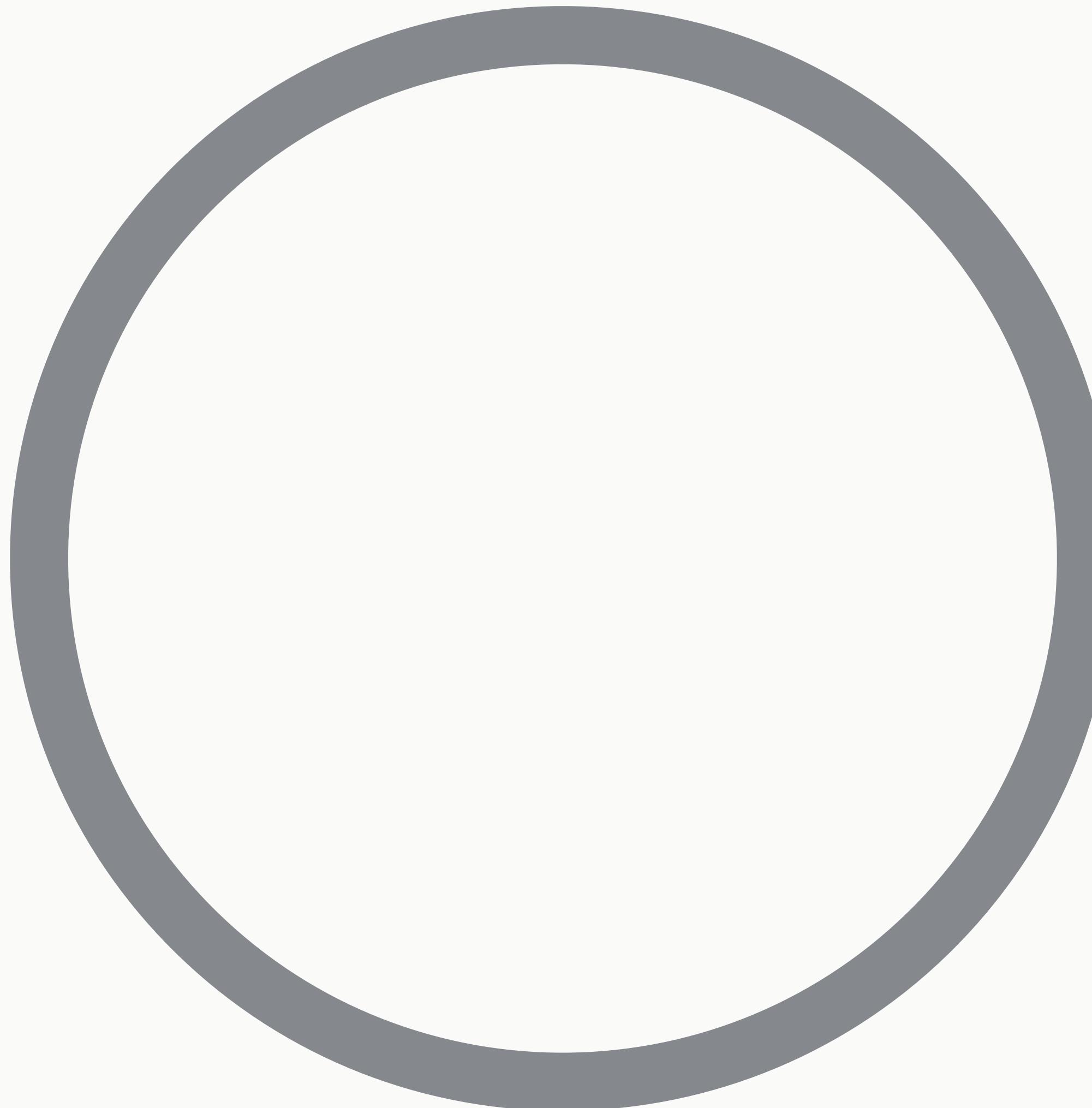
- Spark asks an RDD for a list of its partitions (splits)
- Each split consists of one or more token-ranges
- For every partition
  - Spark asks RDD for a list of preferred nodes to process on
  - Spark creates a task and sends it to one of the nodes for execution

Every Spark task uses a CQL-like query to fetch data for the given token range:

```
SELECT "key", "value"  
FROM "test"."kv"  
WHERE  
    token("key") > 595597420921139321 AND  
    token("key") <= 595597431194200132  
ALLOW FILTERING
```

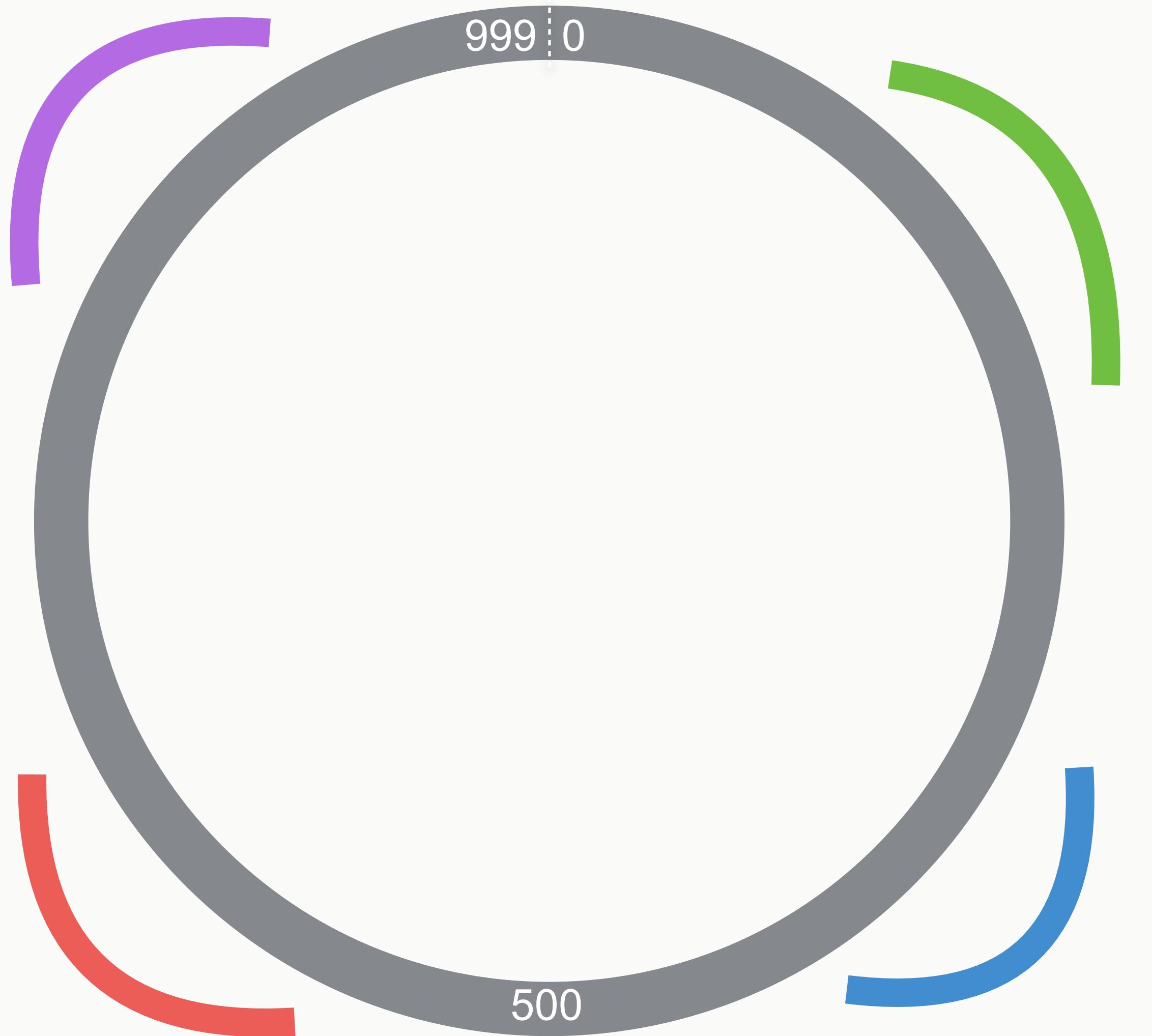


# Cassandra Locates a Row Based on Partition Key and Token Range



All of the rows in a Cassandra Cluster are stored based on their location in the *Token Range*.

# Cassandra Locates a Row Based on Partition Key and Token Range



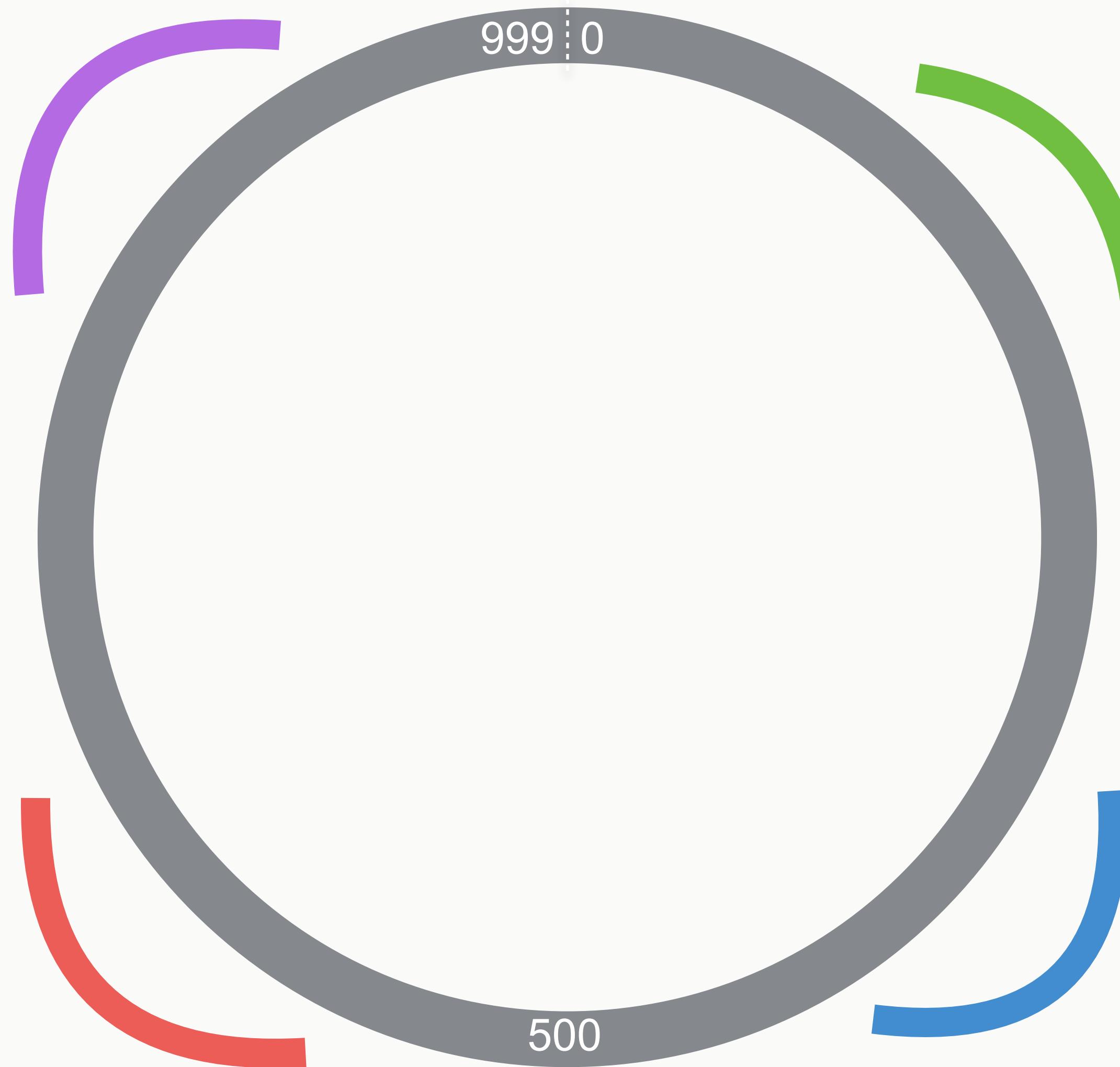
New York City/  
Manhattan:  
Helena

Warsaw:  
Piotr & Jacek

San Francisco:  
Brian, Russell &  
Alex

Each of the *Nodes* in a Cassandra Cluster is primarily responsible for one set of *Tokens*.

# Cassandra Locates a Row Based on Partition Key and Token Range



New York City  
750 - 99

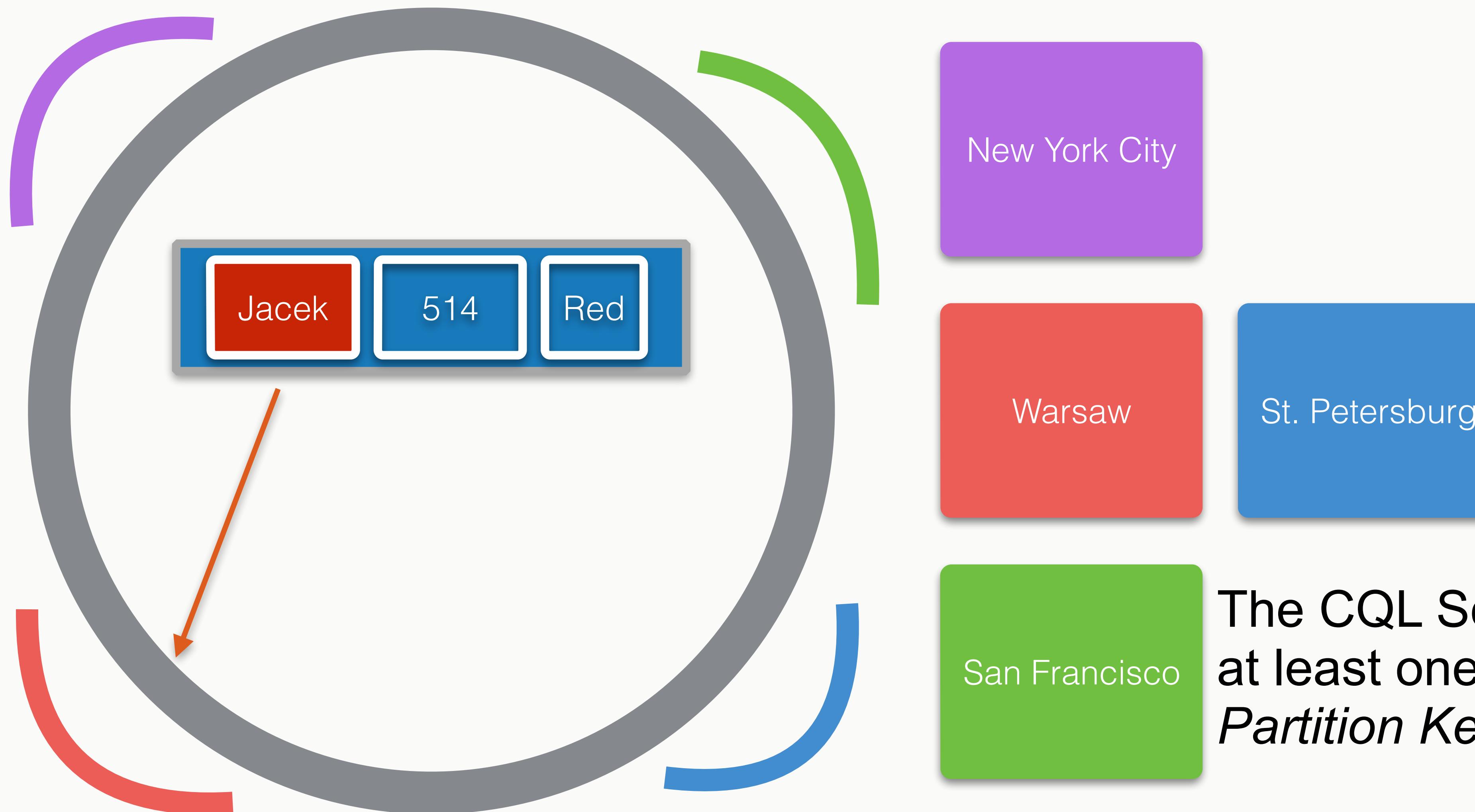
Warsaw  
350 - 749

San Francisco  
100 - 349

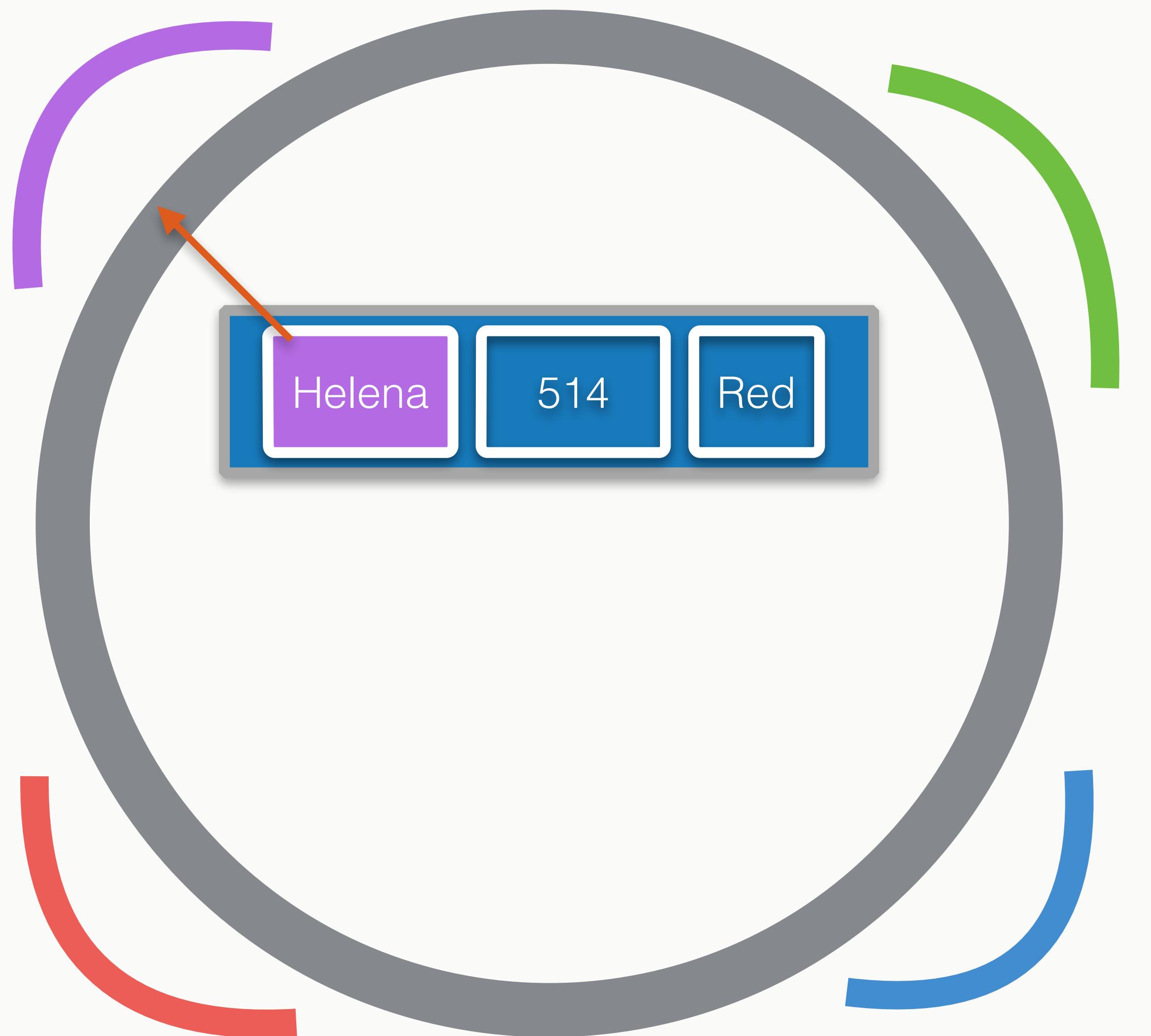
St. Petersburg

Each of the *Nodes* in a Cassandra Cluster is primarily responsible for one set of *Tokens*.

# Cassandra Locates a Row Based on Partition Key and Token Range



# Cassandra Locates a Row Based on Partition Key and Token Range



New York City

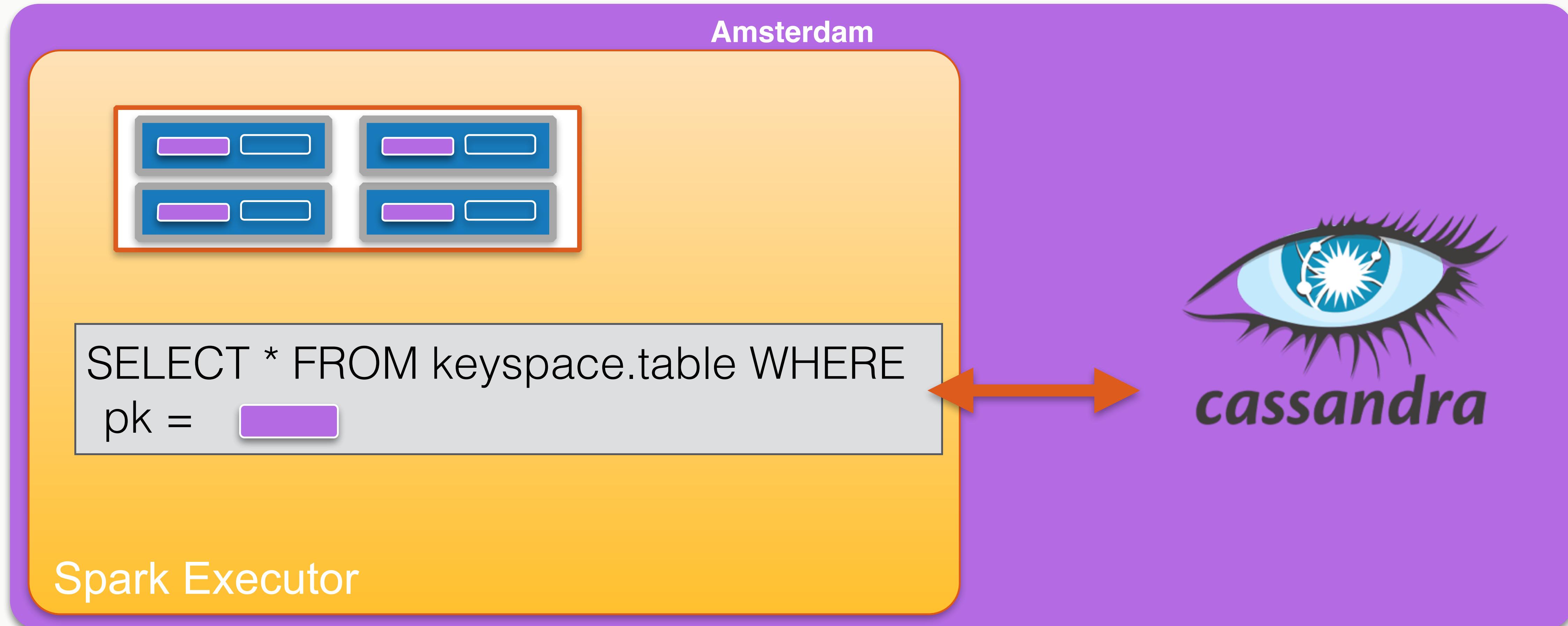
Warsaw

San Francisco

The hash of the *Partition Key* tells us where a row should be stored.

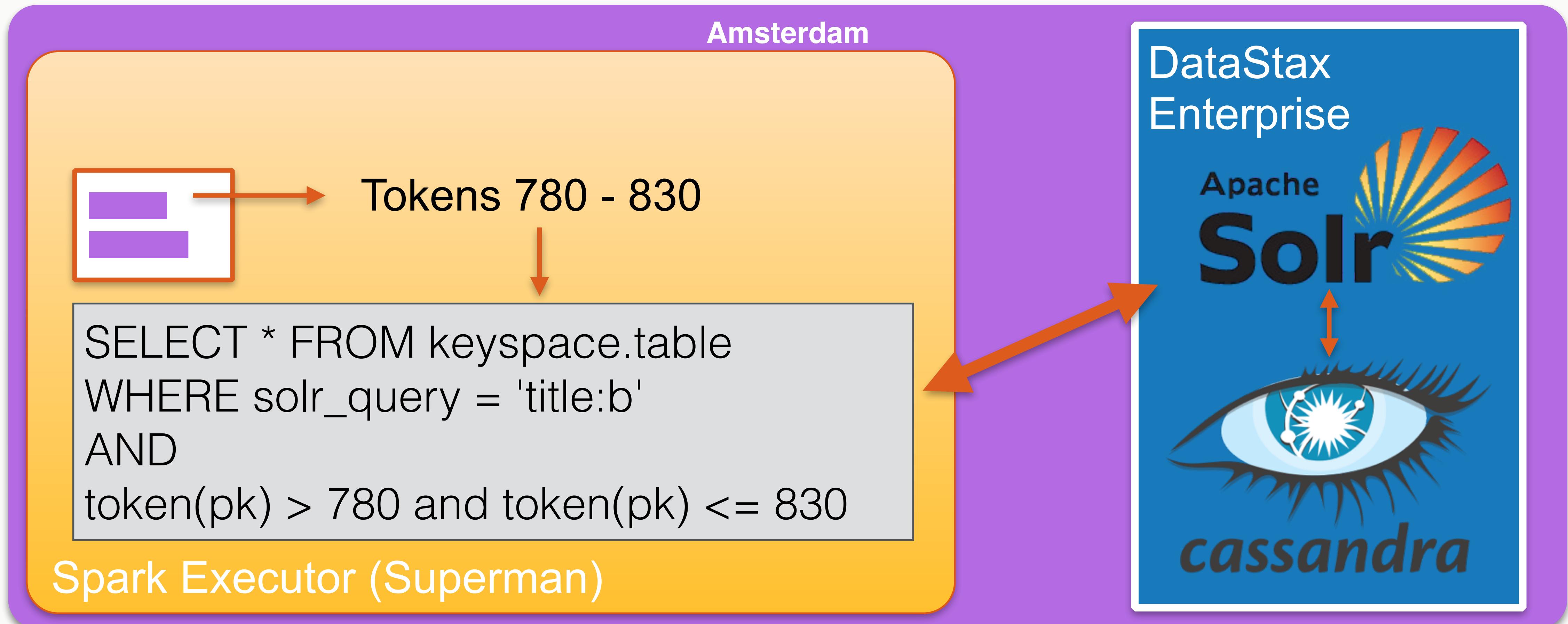
St. Petersburg

# The Spark Executor uses the Connector to Pull Rows from the Local Cassandra Instance



The C\* Driver pages spark.cassandra.input.page.row.size CQL rows at a time

# DataStax Enterprise Enables This Same Machinery with Solr Pushdown



# Composable Pipelines With Spark, Kafka & Cassandra

DATASTAX

The DataStax logo consists of the word "DATASTAX" in a bold, black, sans-serif font. To the right of the "X" character, there are five teal-colored dots arranged in a staggered pattern: one dot above and to the left of the "X", two dots above and to the right, one dot below and to the left, and one dot below and to the right.

# Spark SQL with Cassandra

```
import org.apache.spark.sql.cassandra.CassandraSQLContext

val cc = new CassandraSQLContext(sparkContext)
cc.setKeyspace(keyspaceName)
cc.sql("""
    SELECT table1.a, table1.b, table.c, table2.a
    FROM table1 AS table1
    JOIN table2 AS table2 ON table1.a = table2.a
    AND table1.b = table2.b
    AND table1.c = table2.c
    """)
.map(Data(_))
.saveToCassandra(keyspace1, table3)
```

# Spark SQL with Cassandra & JSON



```
cqlsh> CREATE TABLE github_stats.commits_aggr(user VARCHAR PRIMARY KEY, commits INT...);
```

```
val sql = new SQLContext(sparkContext)

val json = Seq(
    """{"user":"helena","commits":98, "month":3, "year":2015}""",
    """{"user":"jacek-lewandowski", "commits":72, "month":3, "year":2015}""",
    """{"user":"pkolaczk", "commits":42, "month":3, "year":2015}""")

// write
sql.jsonRDD(json)
  .map(CommitStats(_))
  .flatMap(compute)
  .saveToCassandra("stats", "monthly_commits")

// read
val rdd = sc.cassandraTable[MonthlyCommits]("stats", "monthly_commits")
```

# Spark Streaming, Kafka, C\* and JSON

```
KafkaUtils.createStream[String, String, StringDecoder, StringDecoder](  
  ssc, kafkaParams, topicMap, StorageLevel.MEMORY_ONLY)  
  .map { case (_, json) => JsonParser.parse(json).extract[MonthlyCommits]}  
  .saveToCassandra("github_stats", "commits_aggr")
```

```
cqlsh> select * from github_stats.commits_aggr;
```

user	commits	month	year
pkolaczk	42	3	2015
jacek-lewandowski	43	3	2015
helena	98	3	2015

(3 rows)

# Kafka Streaming Word Count

```
sparkConf.set("spark.cassandra.connection.host", "10.20.3.45")
val streamingContext = new StreamingContext(conf, Seconds(30))
```

```
KafkaUtils.createStream[String, String, StringDecoder, StringDecoder] (
  streamingContext, kafkaParams, topicMap, StorageLevel.MEMORY_ONLY)
  .map(_._2)
  .countByValue()
  .saveToCassandra("my_keyspace", "wordcount")
```

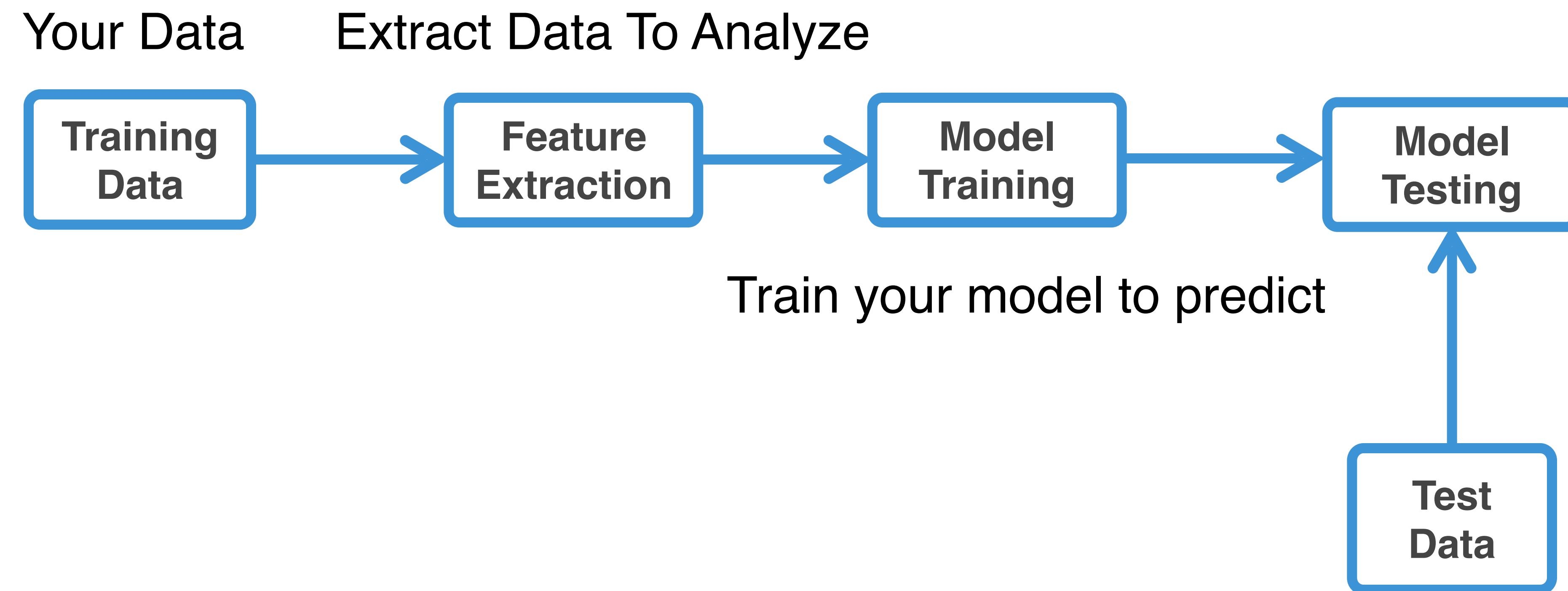
# Spark Streaming, Twitter & Cassandra



```
CREATE TABLE IF NOT EXISTS keyspace.table (
    topic text, interval text, mentions counter,
    PRIMARY KEY(topic, interval)
) WITH CLUSTERING ORDER BY (interval DESC)
```

```
/** Cassandra is doing the sorting for you here. */
TwitterUtils.createStream(
    ssc, auth, tags, StorageLevel.MEMORY_ONLY_SER_2)
    .flatMap(_.getText.toLowerCase.split(""\s+"))
    .filter(tags.contains(_))
    .countByValueAndWindow(Seconds(5), Seconds(5))
    .transform((rdd, time) =>
        rdd.map { case (term, count) => (term, count, now(time)) })
    .saveToCassandra(keyspace, table)
```

# Spark MLLib



# Spark Streaming ML, Kafka & C\*

```
val ssc = new StreamingContext(new SparkConf()..., Seconds(5))

val testData = ssc.cassandraTable[String](keyspace, table).map(LabeledPoint.parse)

val trainingStream = KafkaUtils.createStream[K, V, KDecoder, VDecoder](
    ssc, kafkaParams, topicMap, StorageLevel.MEMORY_ONLY)
    .map(_.value).map(LabeledPoint.parse)

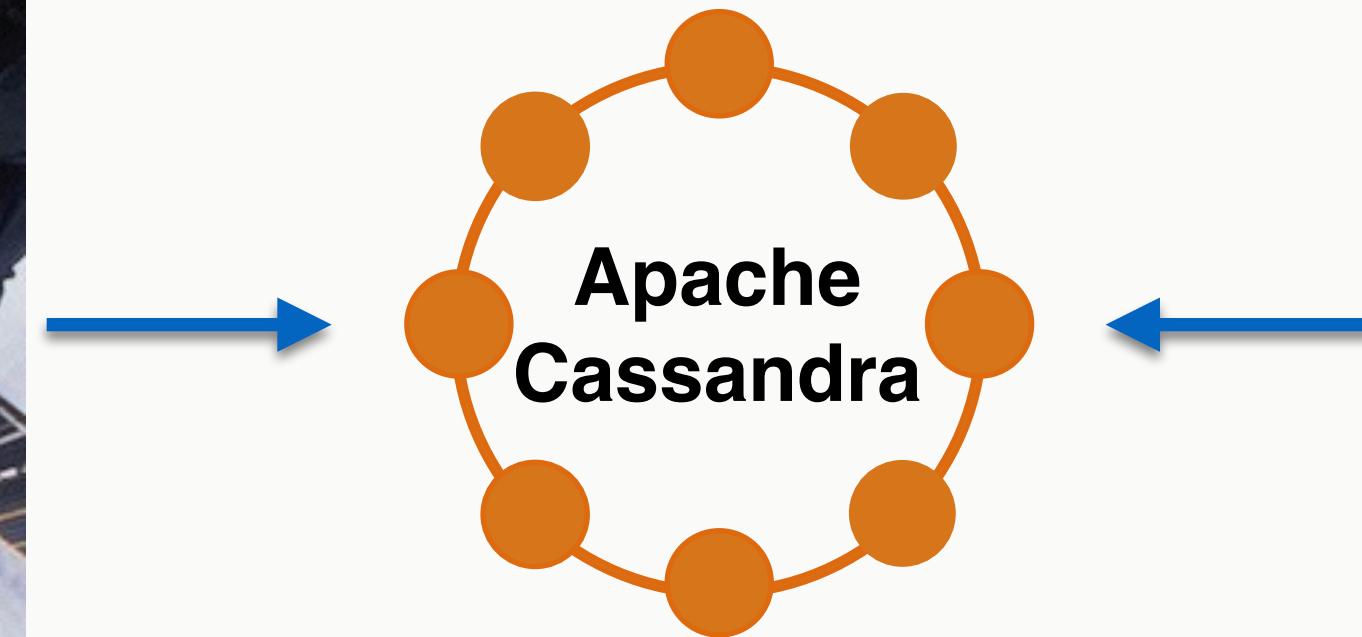
trainingStream.saveToCassandra("ml_keyspace", "raw_training_data")

val model = new StreamingLinearRegressionWithSGD()
    .setInitialWeights(Vectors.dense(weights))
    .trainOn(trainingStream)

//Making predictions on testData
model
    .predictOnValues(testData.map(lp => (lp.label, lp.features)))
    .saveToCassandra("ml_keyspace", "predictions")
```

# KillrWeather

- Global sensors & satellites collect data
- Cassandra stores in sequence
- Application reads in sequence



# Data model should look like your queries



## Queries I Need

- Get data by ID
- Get data for a single date and time
- Get data for a window of time
- Compute, store and retrieve daily, monthly, annual aggregations

## Design Data Model to support queries

- Store raw data per ID
- Store time series data in order: most recent to oldest
- Compute and store aggregate data in the stream
- Set TTLs on historic data

# Data Model

```
CREATE TABLE daily_temperature (
    weather_station text,
    year int,
    month int,
    day int,
    hour int,
    temperature double,
    PRIMARY KEY (weather_station,year,month,day,hour)
);
```

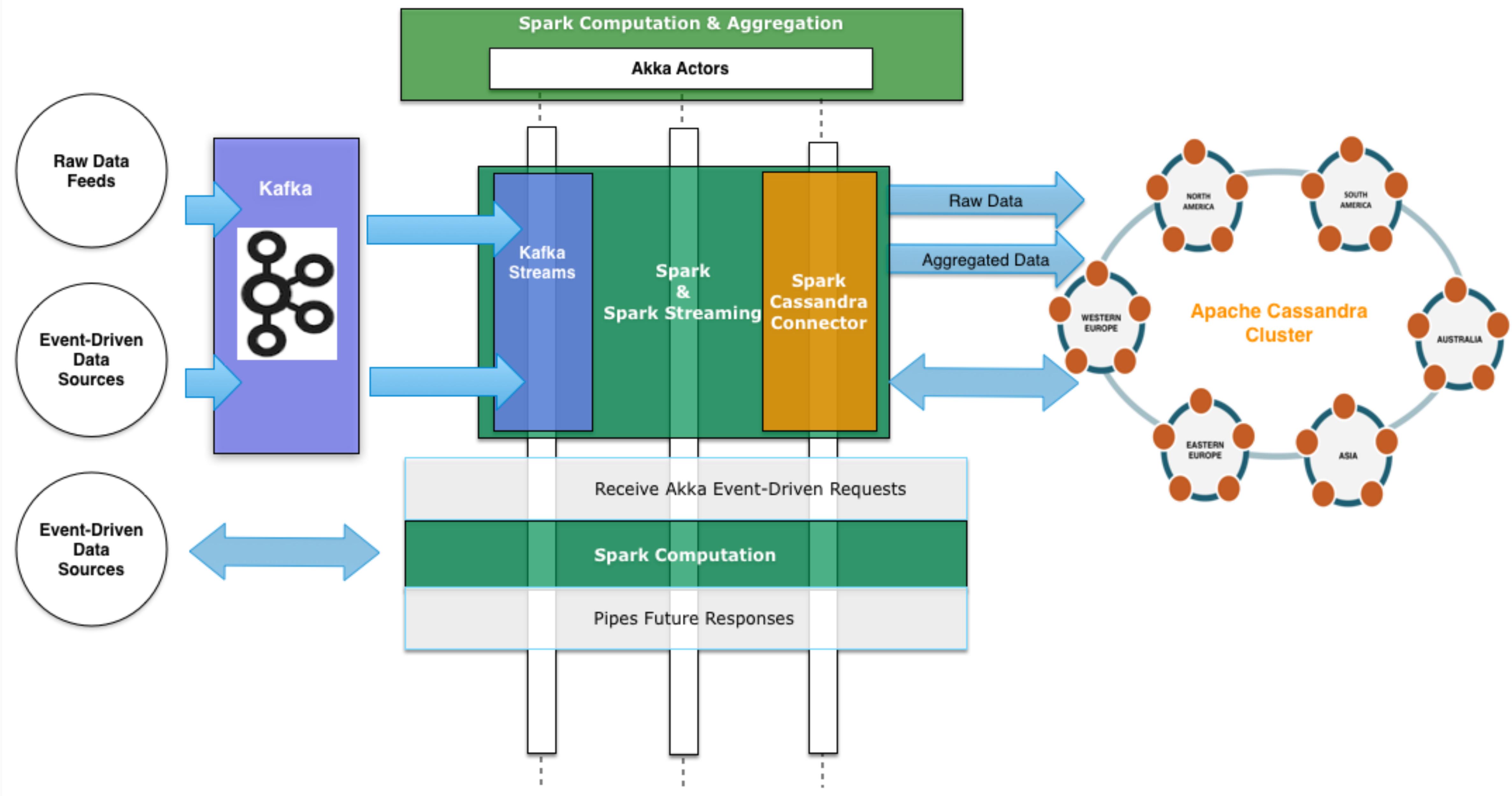
- Weather Station Id and Time are unique
- Store as many as needed

```
INSERT INTO temperature(weather_station,year,month,day,hour,temperature)
VALUES ('10010:99999',2005,12,1,7,-5.6);
```

```
INSERT INTO temperature(weather_station,year,month,day,hour,temperature)
VALUES ('10010:99999',2005,12,1,8,-5.1);
```

```
INSERT INTO temperature(weather_station,year,month,day,hour,temperature)
VALUES ('10010:99999',2005,12,1,9,-4.9);
```

```
INSERT INTO temperature(weather_station,year,month,day,hour,temperature)
VALUES ('10010:99999',2005,12,1,10,-5.3);
```



# Load-Balanced Data Ingestion

```
class HttpNodeGuardian extends ClusterAwareNodeGuardianActor {  
  
    cluster.joinSeedNodes(Vector(...))  
  
    context.actorOf(BalancingPool(PoolSize).props(Props(  
        new KafkaPublisherActor(KafkaHosts, KafkaBatchSendSize))))  
  
    Cluster(context.system) registerOnMemberUp {  
        context.actorOf(BalancingPool(PoolSize).props(Props(  
            new HttpReceiverActor(KafkaHosts, KafkaBatchSendSize))))  
    }  
  
    def initialized: Actor.Receive = { ... }  
  
}
```

# Client: HTTP Receiver Akka Actor

```
class HttpDataIngestActor(kafka: ActorRef) extends Actor with ActorLogging {
    implicit val system = context.system
    implicit val askTimeout: Timeout = settings.timeout
    implicit val materializer = ActorFlowMaterializer(
        ActorFlowMaterializerSettings(system))

    val requestHandler: HttpRequest => HttpResponse = {
        case HttpRequest(HttpMethods.POST, Uri.Path("/weather/data"), headers, entity, _) =>
            headers.toSource collect { case s: Source =>
                kafka ! KafkaMessageEnvelope[String, String](topic, group, s.data:_*)
            }
            HttpResponse(200, entity = HttpEntity(MediaTypes.`text/html`))
        .getOrElse(HttpResponse(404, entity = "Unsupported request"))
        case _: HttpRequest =>
            HttpResponse(400, entity = "Unsupported request")
    }

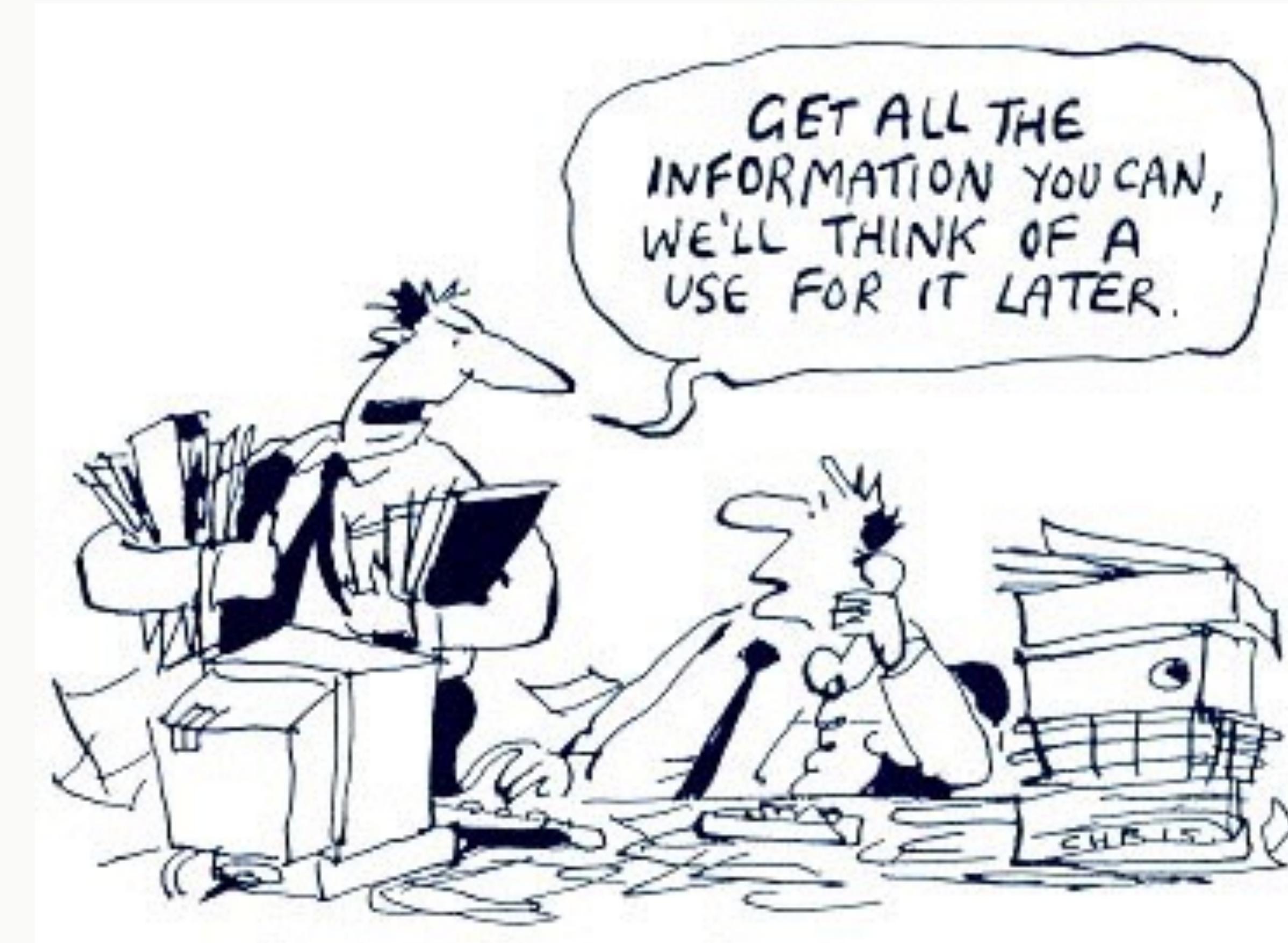
    Http(system).bind(HttpHost, HttpPort).map { case connection =>
        log.info("Accepted new connection from " + connection.remoteAddress)
        connection.handleWithSyncHandler(requestHandler) }
}

def receive : Actor.Receive = {
    case e =>
}
```

# Client: Kafka Producer Akka Actor

```
class KafkaProducerActor[K, V](config: ProducerConfig) extends Actor {  
  
    override val supervisorStrategy =  
        OneForOneStrategy(maxNrOfRetries = 10, withinTimeRange = 1.minute) {  
            case _: ActorInitializationException => Stop  
            case _: FailedToSendMessageException => Restart  
            case _: ProducerClosedException => Restart  
            case _: NoBrokersForPartitionException => Escalate  
            case _: KafkaException => Escalate  
            case _: Exception => Escalate  
        }  
  
    private val producer = new KafkaProducer[K, V](producerConfig)  
  
    override def postStop(): Unit = producer.close()  
  
    def receive = {  
        case e: KafkaMessageEnvelope[K,V] => producer.send(e)  
    }  
}
```

# Store raw data on ingestion



# Store Raw Data From Kafka Stream To C\*

```
val kafkaStream = KafkaUtils.createStream[K, V, KDecoder, VDecoder]  
  (ssc, kafkaParams, topicMap, StorageLevel.DISK_ONLY_2)  
  .map(transform)  
  .map(RawWeatherData(_))
```

```
/** Saves the raw data to Cassandra. */  
kafkaStream.saveToCassandra(keyspace, raw_ws_data)
```

**Now we can replay on failure  
for later computation, etc**

```
/** Now proceed with computations from the same stream.. */  
kafkaStream...
```

# Let's See Our Data Model Again

```
CREATE TABLE weather.raw_data (
    wsid text, year int, month int, day int, hour int,
    temperature double, dewpoint double, pressure double,
    wind_direction int, wind_speed double, one_hour_precip
    PRIMARY KEY ((wsid), year, month, day, hour)
) WITH CLUSTERING ORDER BY (year DESC, month DESC, day DESC);
```

```
CREATE TABLE daily_aggregate_precip (
    wsid text,
    year int,
    month int,
    day int,
    precipitation counter,
    PRIMARY KEY ((wsid), year, month, day)
) WITH CLUSTERING ORDER BY (year DESC, month DESC, day DESC);
```

# Efficient Stream Computation

```
class KafkaStreamingActor(kafkaPm: Map[String, String], ssc: StreamingContext, ws: WeatherSettings)
  extends AggregationActor {
  import settings._

  val kafkaStream = KafkaUtils.createStream[String, String, StringDecoder, StringDecoder](
    ssc, kafkaParams, Map(KafkaTopicRaw -> 1), StorageLevel.DISK_ONLY_2)
    .map(_.value.split(","))
    .map(RawWeatherData(_))

  kafkaStream.saveToCassandra(CassandraKeyspace, CassandraTableRaw)

  /** RawWeatherData: wsid, year, month, day, oneHourPrecip */
  kafkaStream.map(hour => (hour.wsid, hour.year, hour.month, hour.day, hour.oneHourPrecip))
    .saveToCassandra(CassandraKeyspace, CassandraTableDailyPrecip)

  /* Now the [[StreamingContext]] can be started. */
  context.parent ! OutputStreamInitialized

  def receive : Actor.Receive = {...}
}
```

Gets the partition key: Data Locality  
Spark C\* Connector feeds this to Spark

Cassandra Counter column in our schema,  
no expensive `reduceByKey` needed. Simply  
let C\* do it: not expensive and fast.

```
/** For a given weather station, calculates annual cumulative precip - or year to date. */
class PrecipitationActor(ssc: StreamingContext, settings: WeatherSettings) extends AggregationActor {

  def receive : Actor.Receive = {
    case GetPrecipitation(wsid, year)      => cumulative(wsid, year, sender)
    case GetTopKPrecipitation(wsid, year, k) => topK(wsid, year, k, sender)
  }

  /** Computes annual aggregation. Precipitation values are 1 hour deltas from the previous. */
  def cumulative(wsid: String, year: Int, requester: ActorRef): Unit =
    ssc.cassandraTable[Double](keyspace, dailytable)
      .select("precipitation")
      .where("wsid = ? AND year = ?", wsid, year)
      .collectAsync()
      .map(AnnualPrecipitation(_, wsid, year)) pipeTo requester

  /** Returns the 10 highest temps for any station in the `year`. */
  def topK(wsid: String, year: Int, k: Int, requester: ActorRef): Unit = {
    val toTopK = (aggregate: Seq[Double]) => TopKPrecipitation(wsid, year,
      ssc.sparkContext.parallelize(aggregate).top(k).toSeq)

    ssc.cassandraTable[Double](keyspace, dailytable)
      .select("precipitation")
      .where("wsid = ? AND year = ?", wsid, year)
      .collectAsync().map(toTopK) pipeTo requester
  }
}
```

# Efficient Batch Analytics

```
class TemperatureActor(sc: SparkContext, settings: WeatherSettings)
  extends AggregationActor {
  import akka.pattern.pipe

  def receive: Actor.Receive = {
    case e: GetMonthlyHiLowTemperature => highLow(e, sender)
  }

  def highLow(e: GetMonthlyHiLowTemperature, requester: ActorRef): Unit =
    sc.cassandraTable[DailyTemperature](keyspace, daily_temperature_aggr)
      .where("wsid = ? AND year = ? AND month = ?", e.wsid, e.year, e.month)
      .collectAsync()
      .map(MonthlyTemperature(_, e.wsid, e.year, e.month)) pipeTo requester
}
```

**C\* data is automatically sorted by most recent - due to our data model.**

**Additional Spark or collection sort not needed.**



**@helenaedelson**  
**github.com/helena**  
**slideshare.net/helenaedelson**



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