Databricks

Building and Operating a Big Data Service Based on Apache Spark

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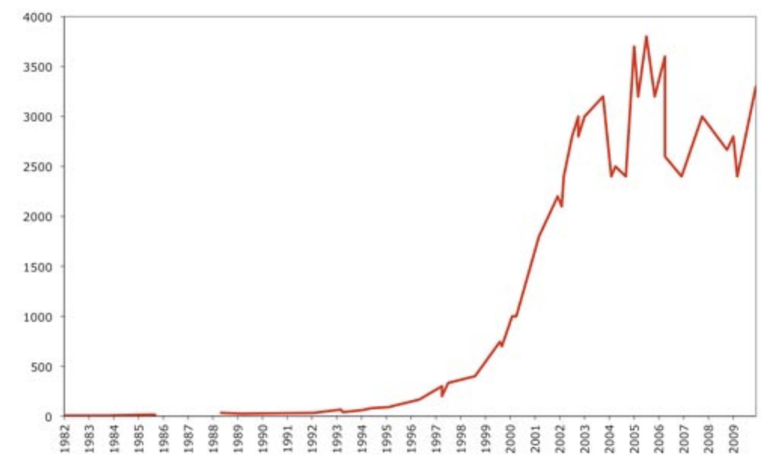
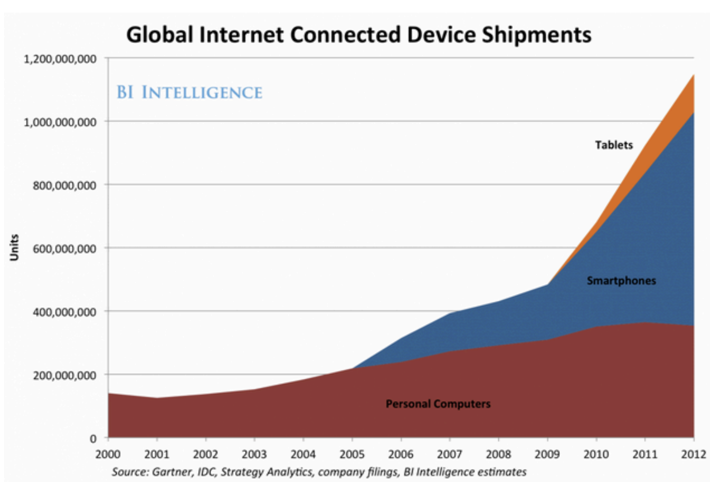
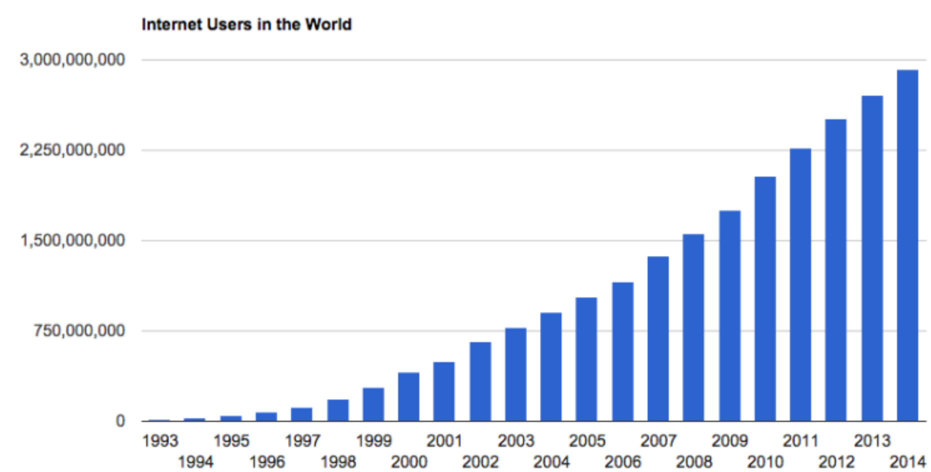
Cloud Computing and Big Data

- Three major trends
  - Computers not getting any faster
  - More people connected to the Internet
  - More devices collecting data
- Computation moving to the cloud







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The Dawn of Big Data

- Most companies collect lots of data
  - Cheap storage (hardware, software)
- Everyone is hoping to extract *insights*
  - Great examples (Netflix, Uber, Ebay)
- Big Data is Hard!

WORKING WITH BIG DATA IS HARD

"Through 2017, 60% of big-data projects will fail to go beyond piloting and experimentation and will be abandoned."

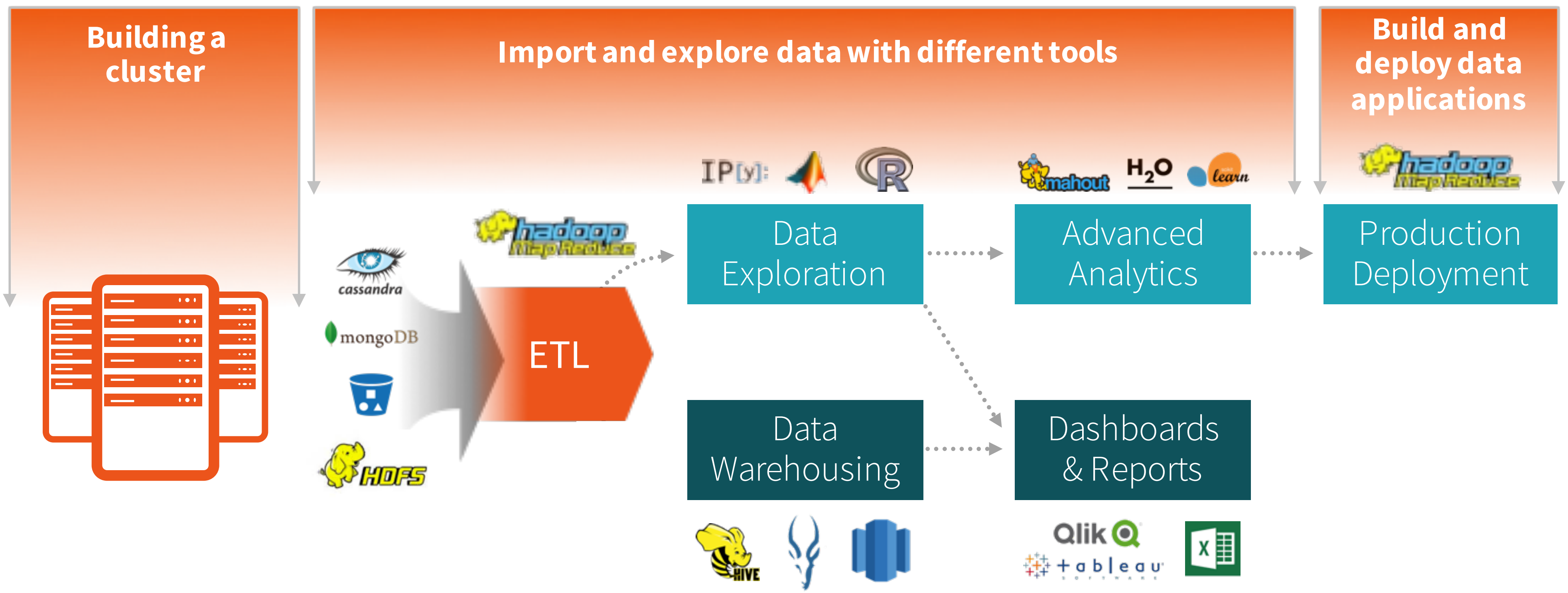
GARTNER

Big Data is Hard

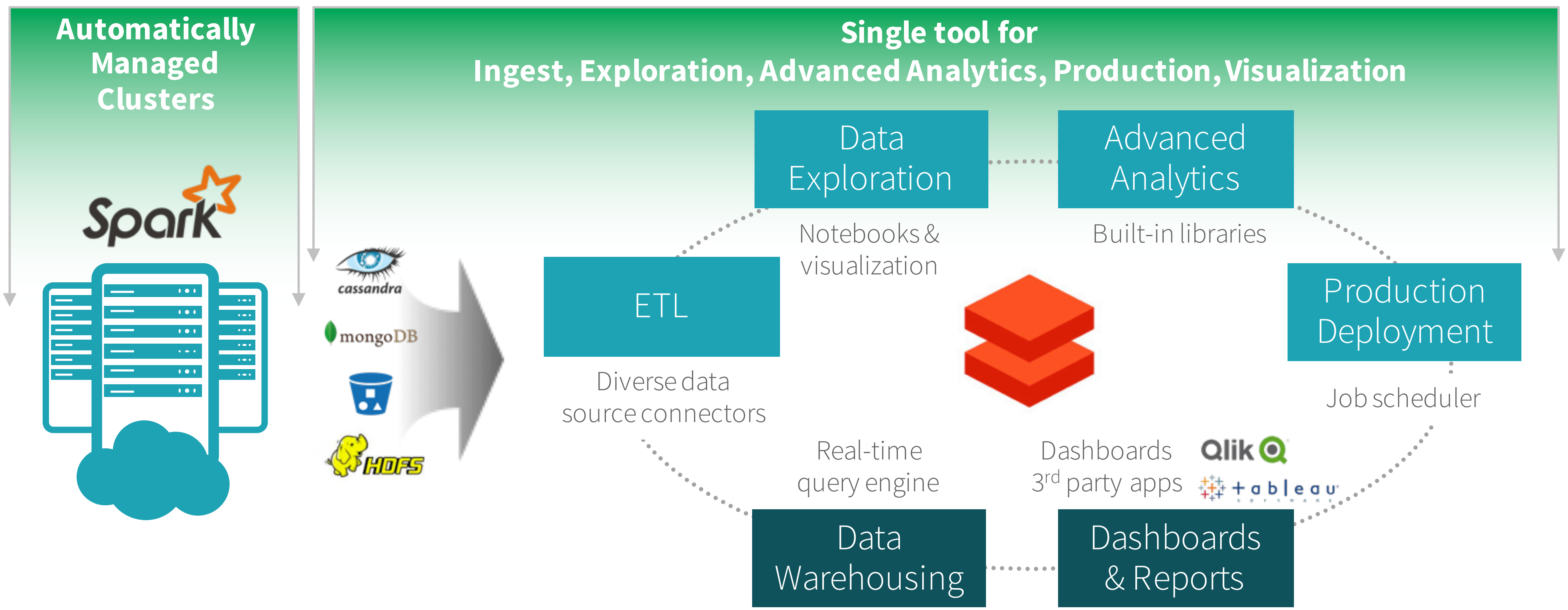
- Compute the average of 1,000 integers
- Compute the average of 10 terabyte of integers

Goal: Make Big Data Simple

The Challenges of Data Science



Databricks is an End-to-End Solution



Databricks in a nutshell

Talk outline

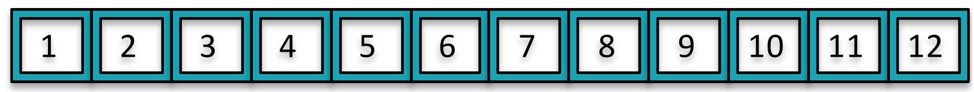
- Apache Spark
  - ETL, interactive queries, streaming, machine learning
- Cluster and Cloud Management
  - Operating thousands of machines in the cloud
- Interactive Workspace
  - Notebook environment, Collaboration, Visualization, Versioning, ACLs
- Lessons
  - Lessons in building a large scale distributed system in the cloud

PART I:
Apache Spark

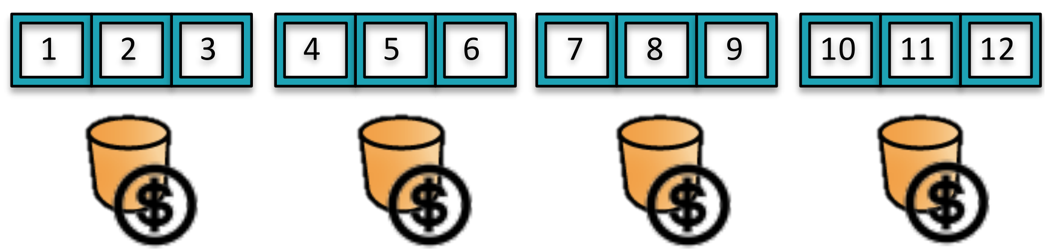
What we added to to Spark

Apache Spark

- Resilient Distributed Datasets (RDDs) as core abstraction
  - Collection of objects
  - Like a `LinkedList <MyObjects>`

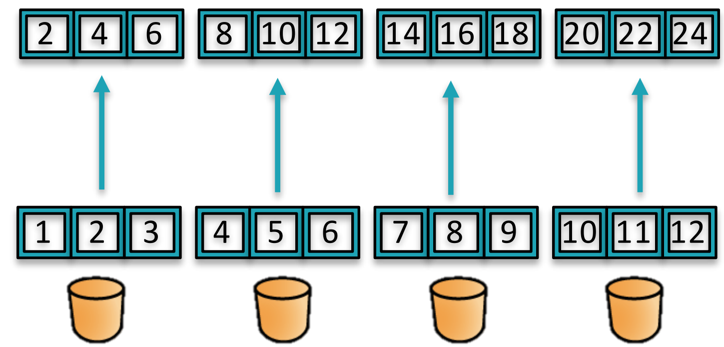


- Spark RDDs are **distributed**
  - RDD collections are partitioned
  - RDD partitions can be cached
  - RDD partitions can be recomputed



RDDs continued

- RDDs can be composed
  - All RDDs initially derived from data source
  - RDDs can be created from other RDDs
  - Two basic operations: `map` & `reduce`
  - Many other operators: `join`, `filter`, `union` etc

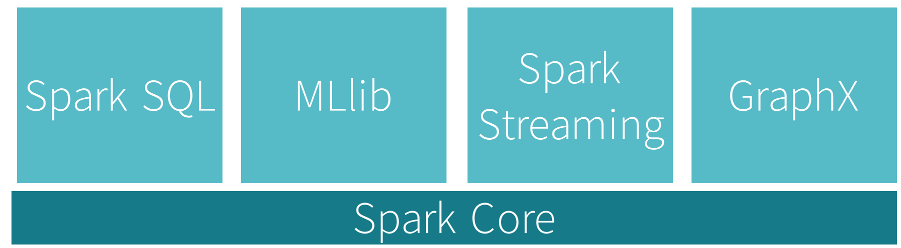



```
val text = sc.textFile("s3://my-bucket/wikipedia")
val words = text.flatMap(line => line.split(" "))
val pairs = words.map(word => (word, 1))
val result = pairs.reduceByKey((a, b) => a + b)
```

Spark Libraries on top of RDDs

- SQL (Spark SQL)
  - Full Hive SQL support with UDF, UDAFs, etc
  - how: Internally keep RDDs of row objects (or RDD of column segments)

- Machine Learning (MLlib)
  - Library of machine learning algorithms
  - how: Cache an RDD, repeatedly iterate it



- Streaming (Spark Streaming)
  - Streaming of real-time data
  - how: Series of RDDs, each containing seconds of real-time data

- Graph Processing (GraphX)
  - Iterative computation on graphs (e.g. social network)
  - how: RDD of Tuple<Vertex, Edge, Vertex> and perform self joins

Unifying Libraries

- Early user feedback
  - Different use cases for R, Python, Scala, Java, SQL
  - How to intermix and go across these?

- Explosion of R Data Frames and Python Pandas
  - DataFrame is a table
  - Many procedural operations
  - Ideal for dealing with semi-structured data

- Problem
  - Not declarative, hard to optimize
  - Eagerly executes command by command
  - Language specific (R dataframes, Pandas)

Unifying Libraries

- Early user feedback
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Common performance problem in Spark

```
val pairs = words.map(word => (word, 1))
val grouped = pairs.groupByKey()
val counts = grouped.map((key, values) => (key, values.sum))
```

- Problem
  - Not declarative, hard to optimize
  - Eagerly executes command by command
  - Language specific (R dataframes, Pandas)

Spark Data Frames

- Procedural DataFrames vs declarative SQL
  - Two different approaches
- Developed DataFrames for Spark
  - DataFrames situated above the SQL optimizer
  - DataFrame operations available in R, Python, Scala, Java
  - SQL operations return DataFrames

```
users = context.sql("select * from users") # SQL
young = users.filter(users.age < 21) # Python
young.groupBy("gender").count()

tokenizer = Tokenizer(inputCol="name", outputCol="words") # ML
hashingTF = HashingTF(inputCol="words", outputCol="features")
lr = LogisticRegression(maxIter=10, regParam=0.01)
pipeline = Pipeline(stages=[tokenizer, hashingTF, lr])
model = pipeline.fit(young) # model
```

Proliferation of Data Solutions

- Customers already run a slew of data management systems
  - MySQL category, Cassandra category, S3 category, HDFS category
  - ETL all data over to Databricks?
- We added Spark Data Source API
  - Open APIs for implementing your own data source
  - Examples: *CSV, JDBC, Parquet/Avro, ElasticSearch, RedShift, Cassandra*
- Features
  - Pushdown of predicates, aggregations, column pruning
  - Locality information
  - User Defined Types (UDTs), e.g. vectors

Proliferation of Data Solutions

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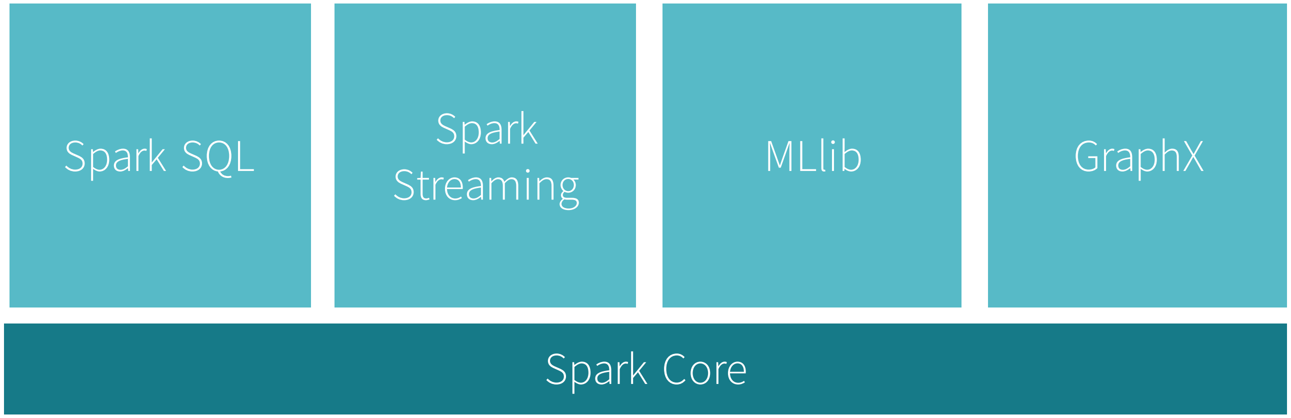
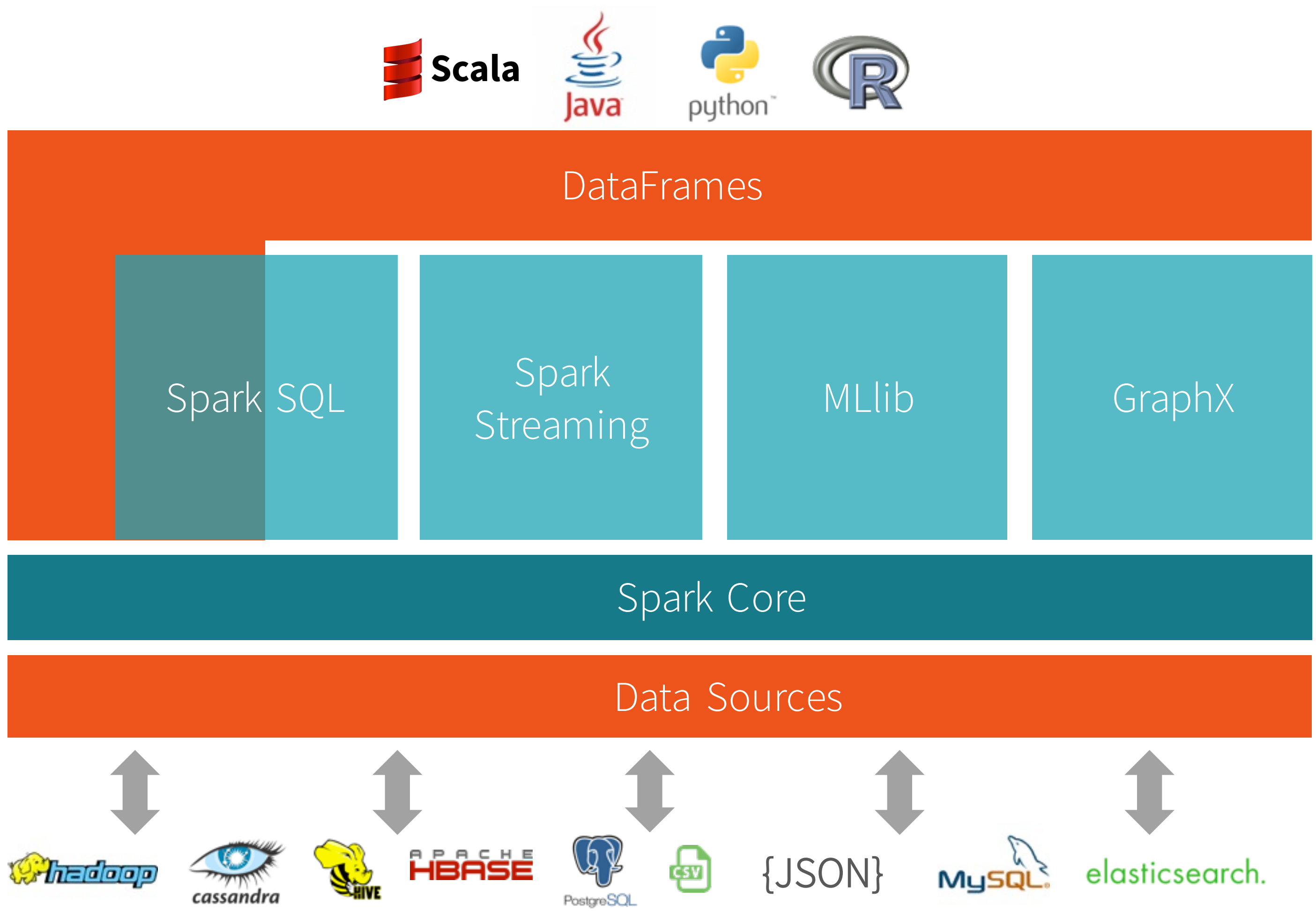
```
class PointUDT extends UserDefinedType[Point]
{
  def dataType = StructType(Seq(
    StructField ("x", DoubleType),
    StructField ("y", DoubleType) ))

  def serialize(p: Point) = Row(p.x, p.y)

  def deserialize(r: Row) =
    Point(r. getDouble (0), r. getDouble (1))
}
```

Modern Spark Architecture

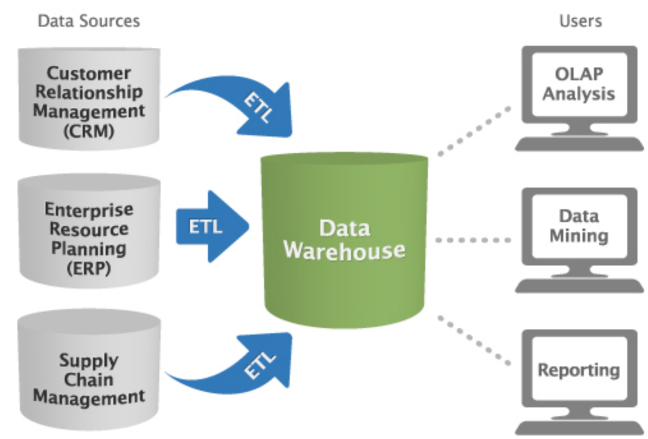


Modern Spark Architecture

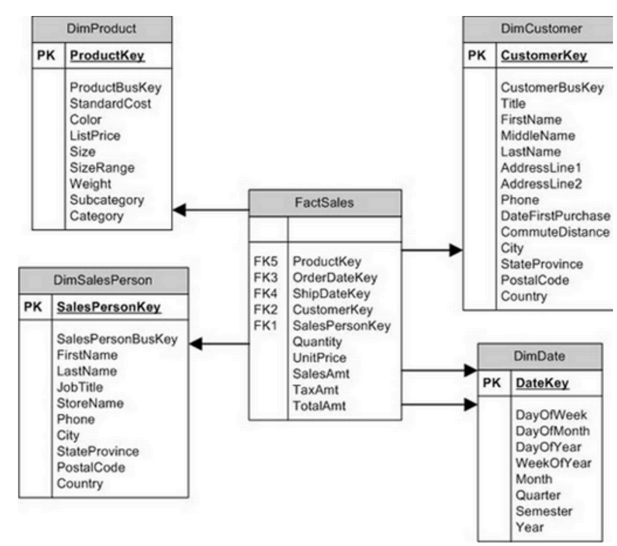


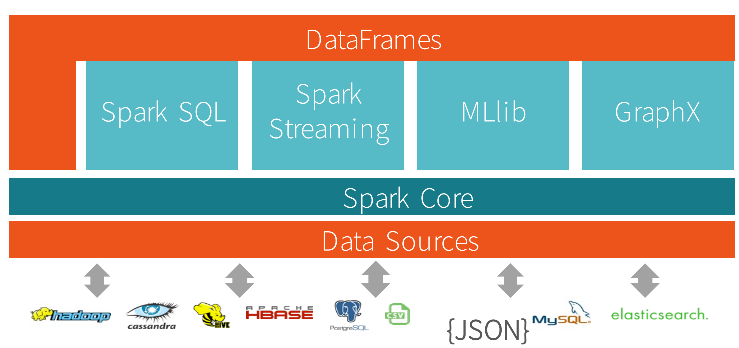
Databricks as just-in-time Datawarehouse

- Traditional datawarehouse
  - Every night ETL all relevant data to a warehouse
  - Precompute cubes of fact tables
  - Slow, costly, poor recency



- Spark JIT datawarehouse
  - Switzerland of storage: NoSQL, SQL, cloud, …
  - Storage remains at source of truth
  - Spark used to directly read and cache date





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PART II:
Cluster Management

Spark as a Service in the Cloud

- Experience with Mesos, YARN, …
  - Use off-the-shelf cluster manager?

- Problems
  - Existing cluster managers were not cloud-aware

Cloud-Aware Cluster Management

- Instance manager
  - Responsible for acquiring machines from cloud provider

- Resource manager
  - Schedule and configure isolated containers on machine instances

- Spark cluster manager
  - Monitor and setup Spark clusters

Databricks Instance Manager

Instance manager's job is to manage machine instances

- Pluggable cloud providers
  - General interface that can be plugged in with AWS, …
  - Availability management (AZ, 1h), configuration management (VPCs)
- Fault-handling
  - Terminated or slow instances, spot price hikes
  - Seamlessly replace machines
- Payment management
  - Bid for spot instances, monitor their price
  - Recording cluster usage for payment system

Databricks Resource Manager

Resource manager's job is to multiplex tenants on instances

- Isolates tenants using container technology
  - Manages multiple versions of Spark
  - Configures firewall rules, filters traffic
- Provides fast SSD/in-memory caching across containers
  - ramdisk for a fast in-memory cache, `mmap` to access from Spark JVM
  - Bind-mount into containers for shared in-memory cache

Databricks Spark Cluster Manager

Spark CM's job is to setup Spark clusters and multiplex REPLs

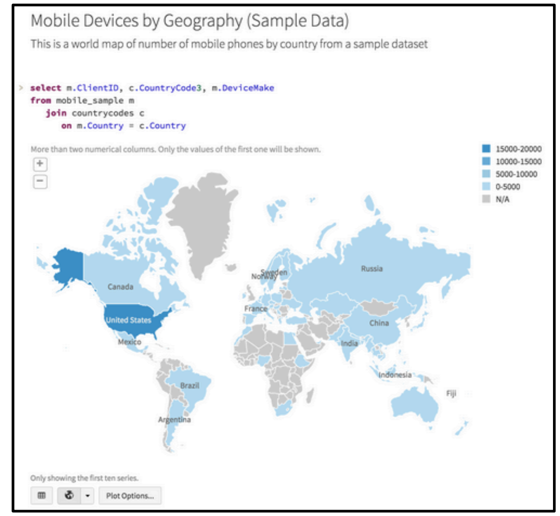
- Setting up Spark clusters
  - Currently using Standalone mode Spark
  - Dynamic resizing of clusters based on load (wip)

- Multiplexing of multiple REPLs
  - Many interactive REPLs/notebooks on the same Spark cluster
  - `ClassLoader` isolation and library management

PART III:
Interactive Workspace

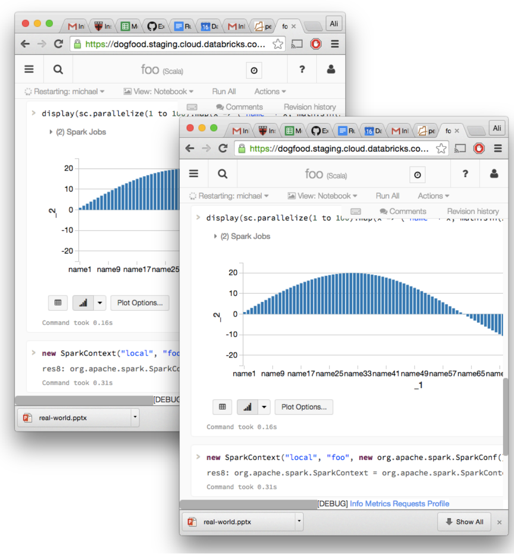
Collaborative Workspace

- Problem
  - Real time collaboration on notebooks
  - Version control of notebooks
  - Access control on notebooks



Pub/sub-based TreeStore

- Web application server
  - Stores an in-memory representation of Databricks workspace
- TreeStore is a directory service + a pub-sub service
  - In-memory tree structure representing:
    directories, notebooks, commands, results
  - Browsers subscribe to subtrees and get notifications on updates
  - Special handler sends delta-updates over web sockets
- Usage
  - Subscribe to a notebook, see live edits of notebook
  - Used to create a collaborative environment



PART IV:
Lessons

Lessons

- Loose coupling necessary but hard
  - Narrow well-defined APIs, backwards compatibility, upgrades
- State management very hard at scale
  - Legacy state: databases, configurations, machines, data formats…
- Cloud software development is superior
  - Two week sprints, two week releases, SCRUM …
- Testing is key for evolution and scale
  - Step-wise refinement for extension, testing pyramid 70/20/10
- Combine bottom-up with top-down approach
  - Top-down for quick results, bottom-up for modularity/reuse

Thank you & Questions

Databricks is hiring, taking interns, . . .

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