EE 542

Lecture 13: Hadoop and Spark in the Cloud

Internet and Cloud Computing

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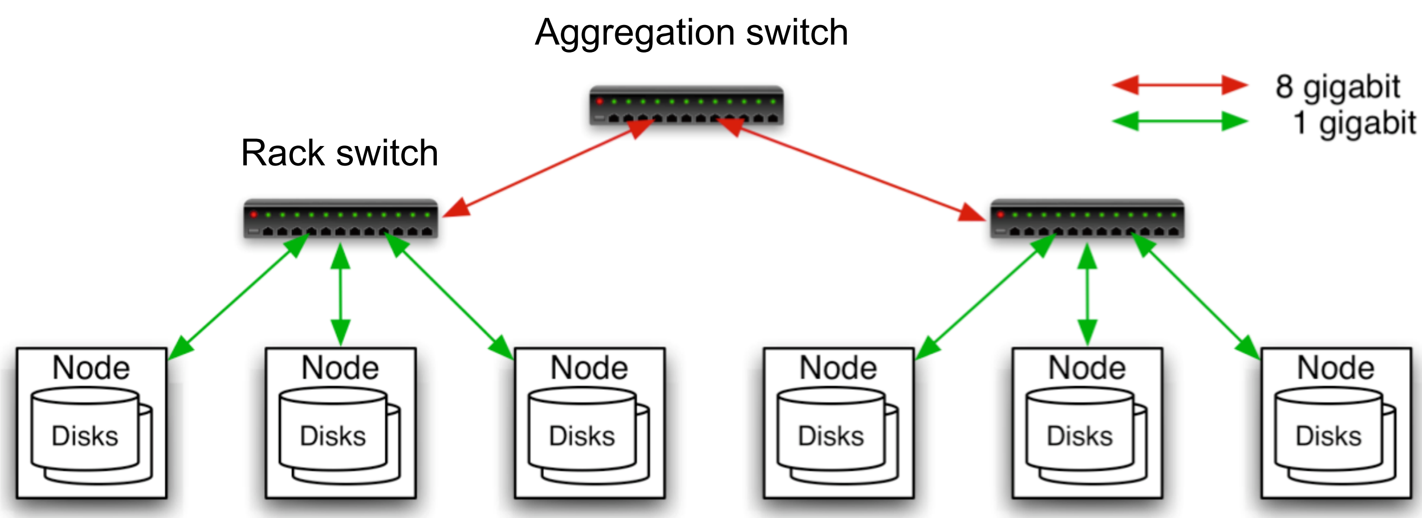
Some of the Slides borrowed from UC Berkeley AMP Lab

MapReduce

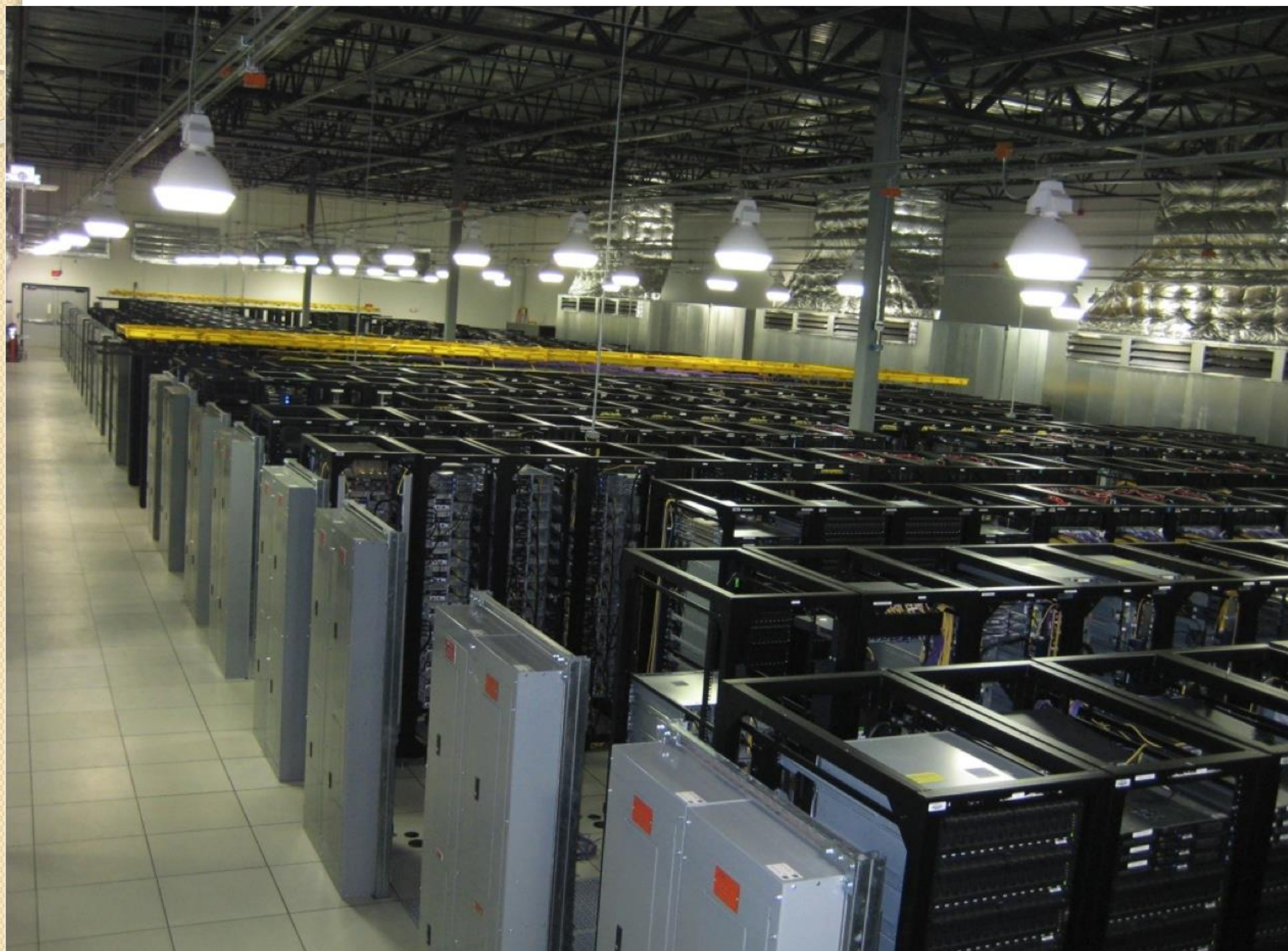
- Programming model for data-intensive computing on commodity clusters
- Pioneered by Google
  - Processes 20 PB of data per day
- Popularized by Apache Hadoop project
  - Used by Yahoo!, Facebook, Amazon, …

Hadoop Cluster



- 40 nodes/rack, 1000-4000 nodes in cluster
- 1 Gbps bandwidth in rack, 8 Gbps out of rack
- Node specs (Facebook):
  8-16 cores, 32 GB RAM, 8 × 1.5 TB disks, no RAID

Hadoop Cluster



Challenges of Cloud Environment

- Cheap nodes fail, especially when you have many
  - Mean time between failures for 1 node = 3 years
  - MTBF for 1000 nodes = 1 day
  - **Solution:** Build fault tolerance into system

- Commodity network = low bandwidth
  - **Solution:** Push computation to the data

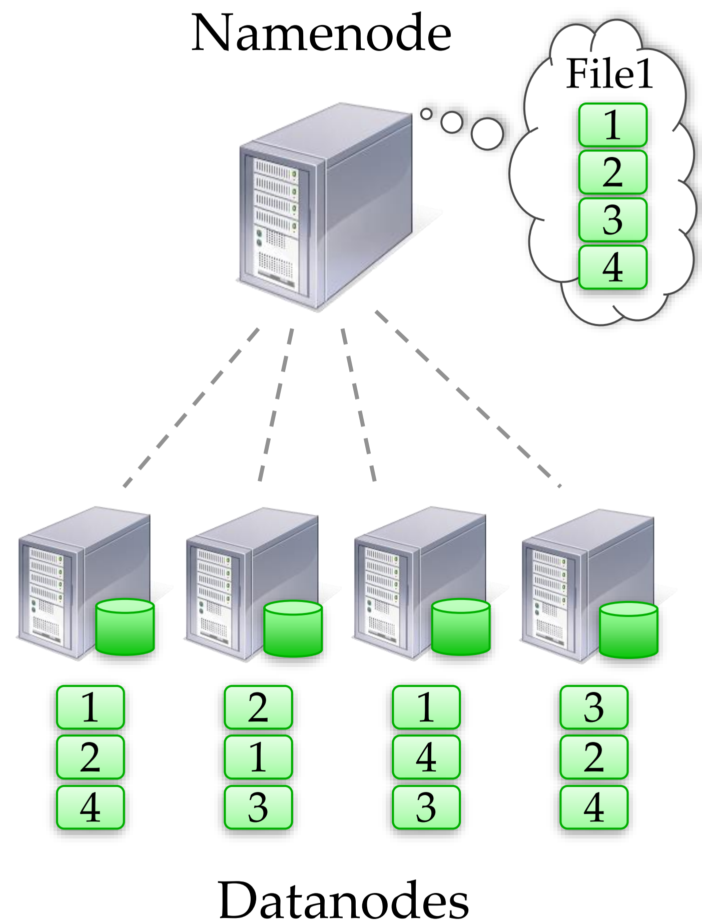
- Programming distributed systems is hard
  - **Solution:** Restricted programming model: users write data-parallel "map" and "reduce" functions, system handles work distribution and failures

Hadoop Components

- Distributed file system (HDFS)
  - Single namespace for entire cluster
  - Replicates data 3x for fault-tolerance
- MapReduce framework
  - Runs jobs submitted by users
  - Manages work distribution & fault-tolerance
  - Colocated with file system

Hadoop Distributed File System

- Files split into 128MB blocks
- Blocks replicated across several datanodes (often 3)
- Namenode stores metadata (file names, locations, etc)
- Optimized for large files, sequential reads
- Files are append-only



MapReduce Execution Details

- Mappers preferentially scheduled on same node or same rack as their input block
  - Minimize network use to improve performance
- Mappers save outputs to local disk before serving to reducers
  - Allows recovery if a reducer crashes
  - Allows running more reducers than # of nodes

Fault Tolerance in MapReduce

1. If a task crashes:
   - Retry on another node
     - OK for a map because it had no dependencies
     - OK for reduce because map outputs are on disk
   - If the same task repeatedly fails, fail the job or ignore that input block

➢ Note: For the fault tolerance to work, *user tasks must be deterministic and side-effect-free*

Fault Tolerance in MapReduce

2. If a node crashes:
   - Relaunch its current tasks on other nodes
   - Relaunch any maps the node previously ran
     - Necessary because their output files were lost along with the crashed node

Fault Tolerance in MapReduce

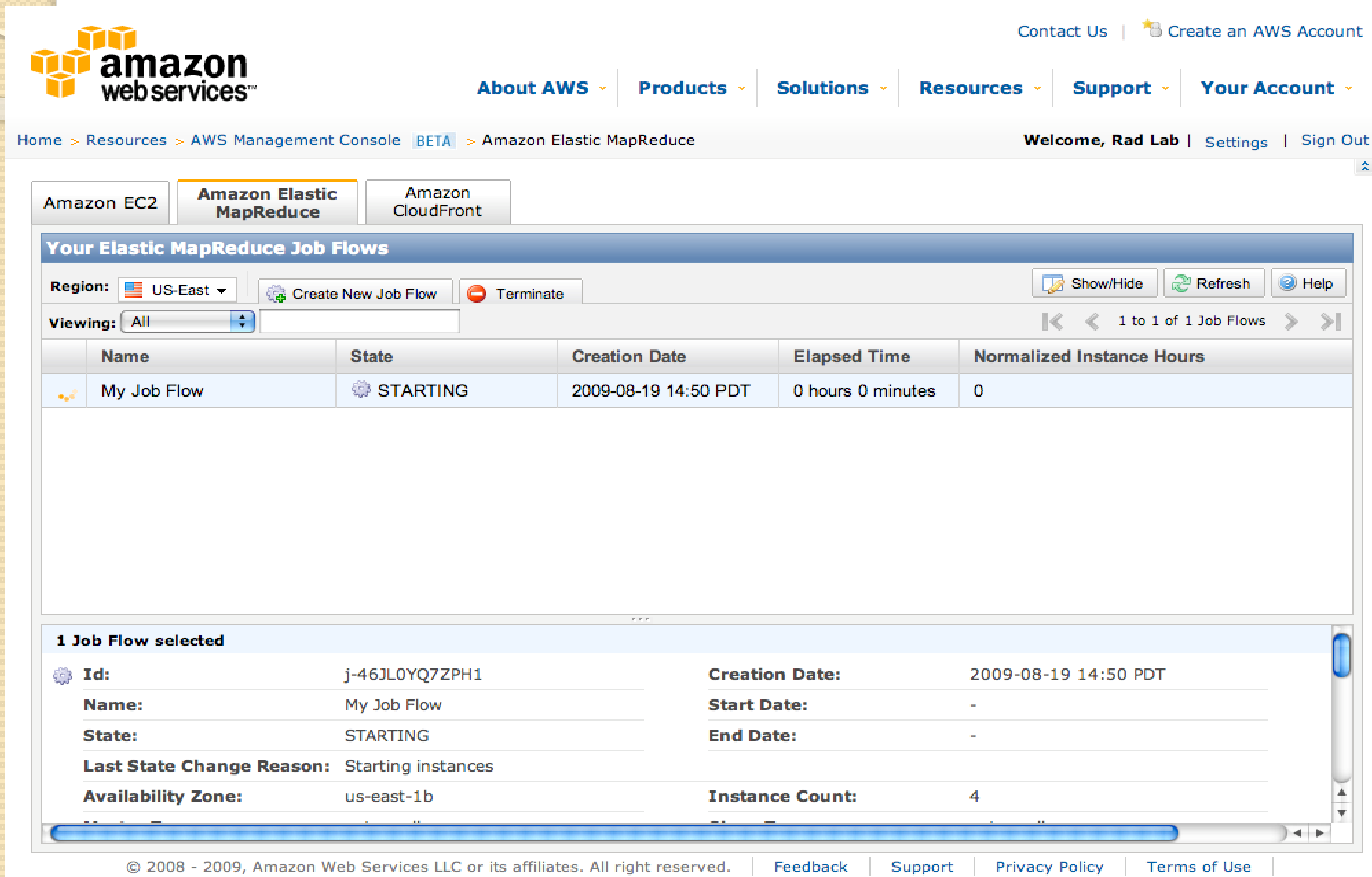
3. If a task is going slowly (straggler):
   - Launch second copy of task on another node
   - Take the output of whichever copy finishes first, and kill the other one

- Critical for performance in large clusters (many possible causes of stragglers)

Amazon Elastic MapReduce

- Web interface and command-line tools for running Hadoop jobs on EC2
- Data stored in Amazon S3
- Monitors job and shuts machines after use

Elastic MapReduce UI



MapReduce

- Programming model for data-intensive computing on commodity clusters
- Pioneered by Google
  - Processes 20 PB of data per day
- Popularized by Apache Hadoop project
  - Used by Yahoo!, Facebook, Amazon, …
- Industry Trending Toward Spark
  - Quickly Being Adopted by Big Data Industry

Limitations of MapReduce

- MapReduce is great at one-pass computation, but inefficient for *multi-pass* algorithms
- No efficient primitives for data sharing
- State between steps goes to distributed file system
- Slow due to replication & disk storage
- No control of data partitioning across steps

Spark Programming Model

- Extends MapReduce with primitives for efficient data sharing
  - "Resilient distributed datasets"
- Open source in Apache Incubator
  - Growing community with 100+ contributors
- APIs in Java, Scala & Python

Resilient Distributed Datasets (RDDs)

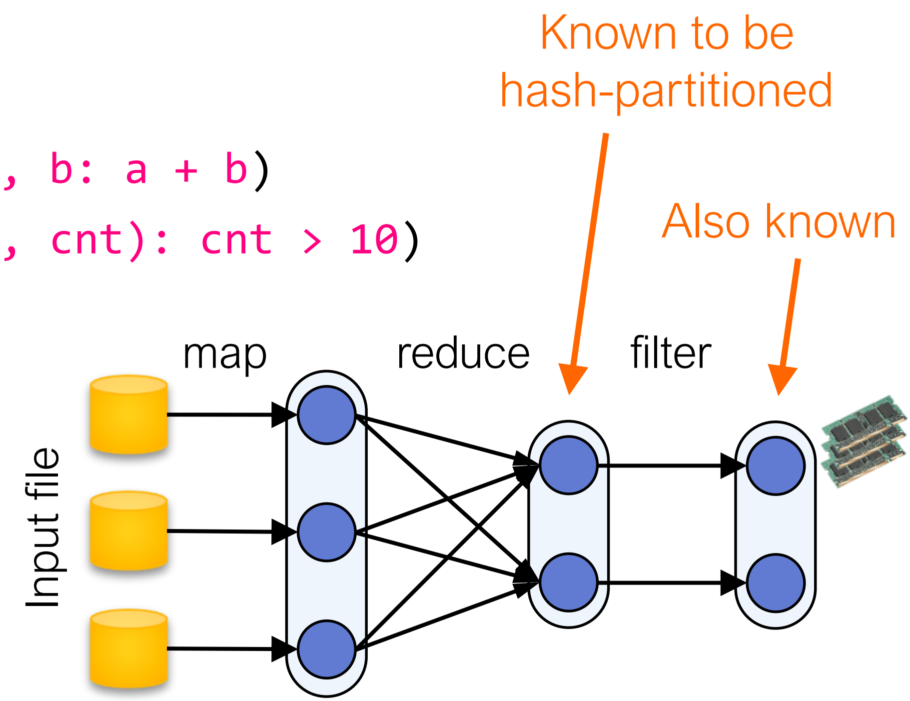
- Collections of objects stored across a cluster
- User-controlled partitioning & storage (RAM, disk, …)
- Automatically rebuilt on failure

```
urls = spark.textFile("hdfs://...")
records = urls.map(lambda s: (s, 1))
counts = records.reduceByKey(lambda a, b: a + b)
bigCounts = counts.filter(lambda (url, cnt): cnt > 10)
```

```
bigCounts.cache()

bigCounts.filter(
  lambda (k,v): "news" in k).count()

bigCounts.join(otherPartitionedRDD)
```



Spark

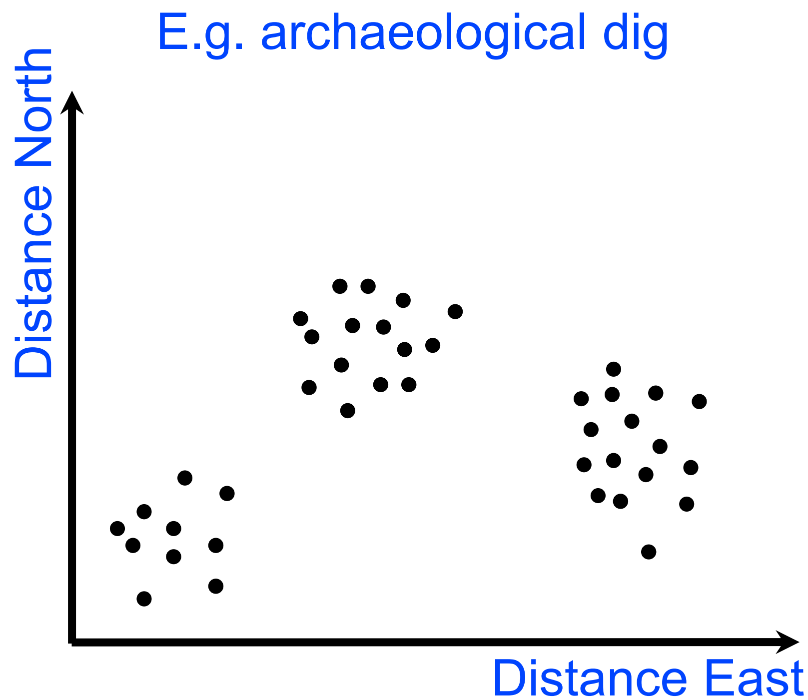
- In-Memory Computation
  - For 64-bit computers TB of data in RAM
  - Designed to transform data in-mem and not in disk
  - Supports parallel distributed processing of data
  - 100x in memory and 10x on disk then Hadoop
- General programming model
  - Use normal sequential programming
  - No need for maps and reduce operations

Spark: Key Advantages

- Ability for On-disk Data Sorting
  - Tuned for large scale of data sorting on disk
  - The world record of on-disk large scale data sorting
- Efficient Use of Cache
  - Mesos which is a distributed system kernel for caching the intermediate dataset
  - Multiple iterations on the cached dataset
- In-memory Tuned Library
  - MLlib library for in-memory tuned operations
- Faster Launch with Virtual Machine

Clustering

Grouping data according to similarity



Clustering

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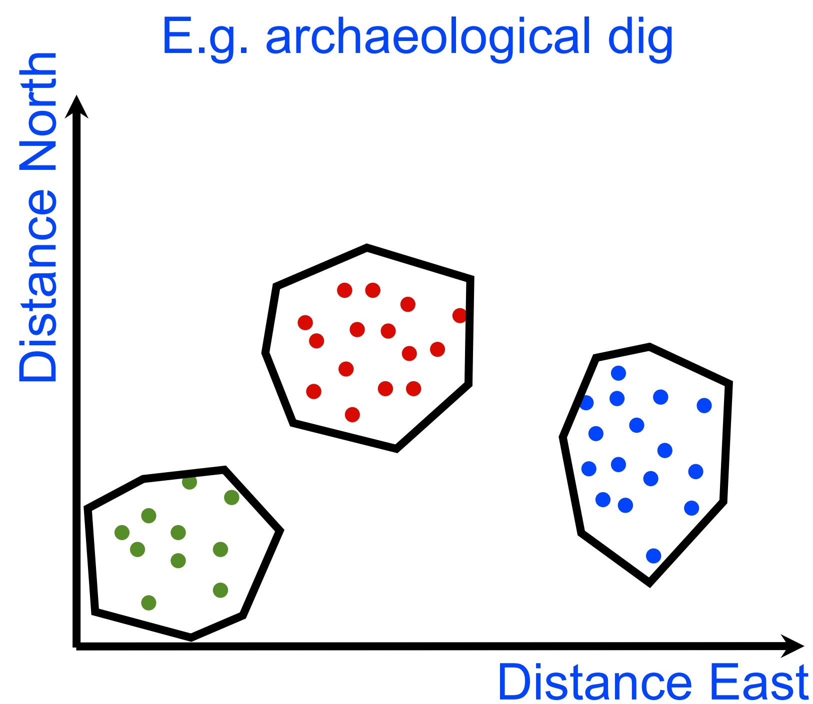
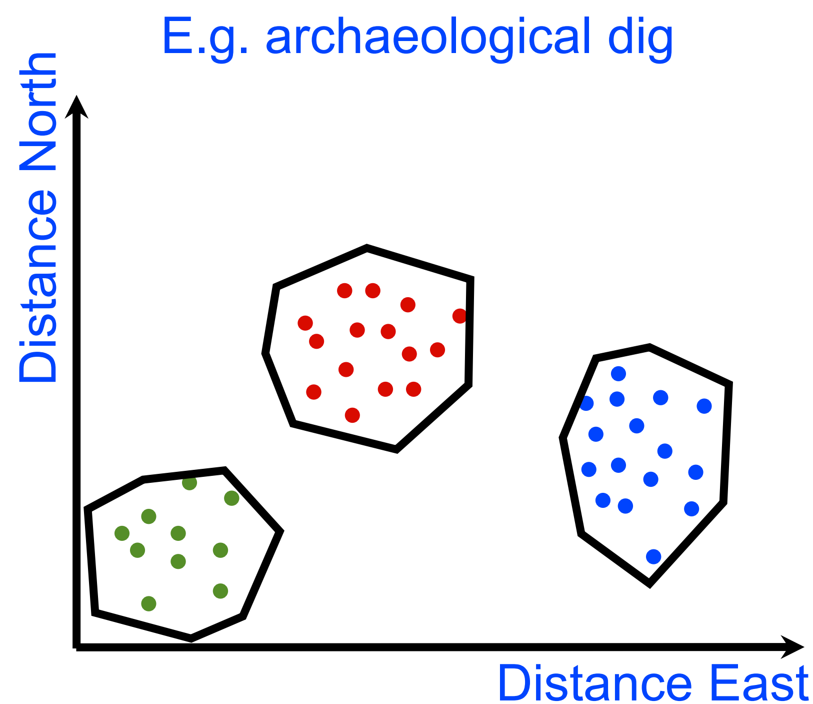


Clustering with Spark

K-Means: preliminaries

Benefits

- Popular
- Fast
- Conceptually straightforward

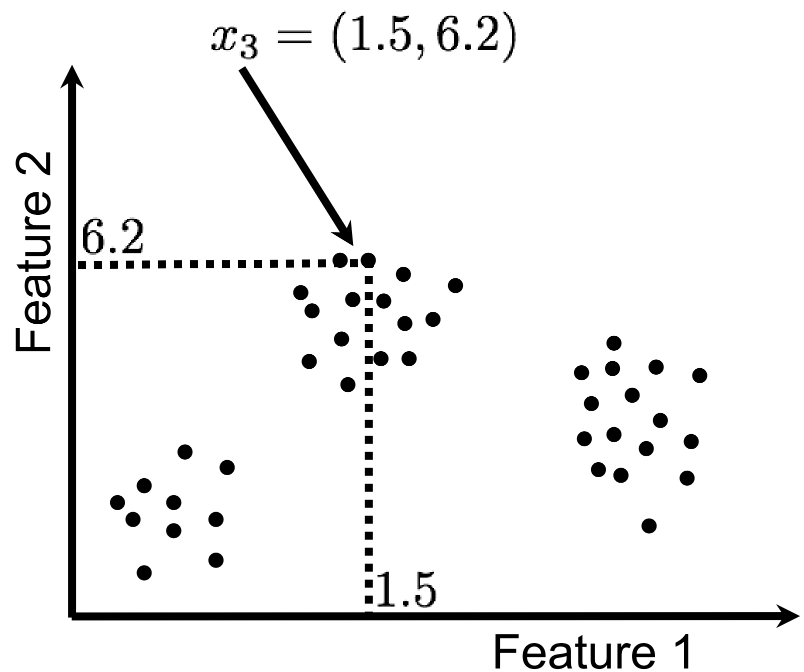


Clustering with Spark

K-Means: preliminaries

Data: Collection of values

```
data = lines.map(line=>
    parseVector(line))
```

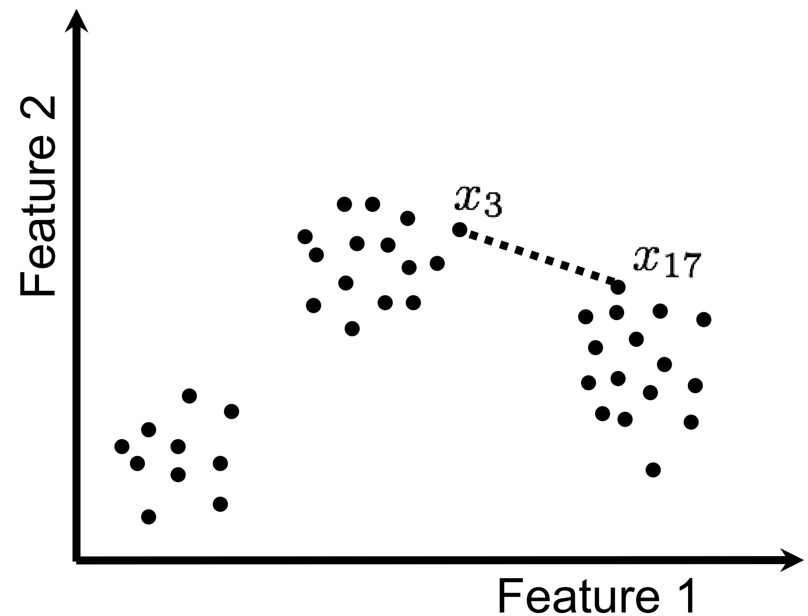


Clustering with Spark

K-Means: preliminaries

Dissimilarity:
Squared Euclidean distance

```
dist = p.squaredDist(q)
```



Clustering with Spark

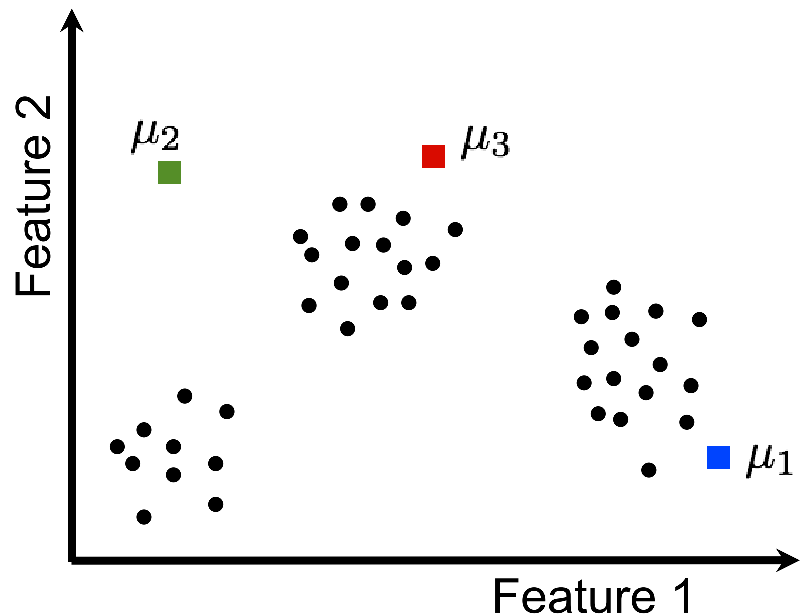
K-Means: preliminaries

K = Number of clusters

$\mu_1, \mu_2, \ldots, \mu_K$

Data assignments to clusters

$S_1, S_2, \ldots, S_K$



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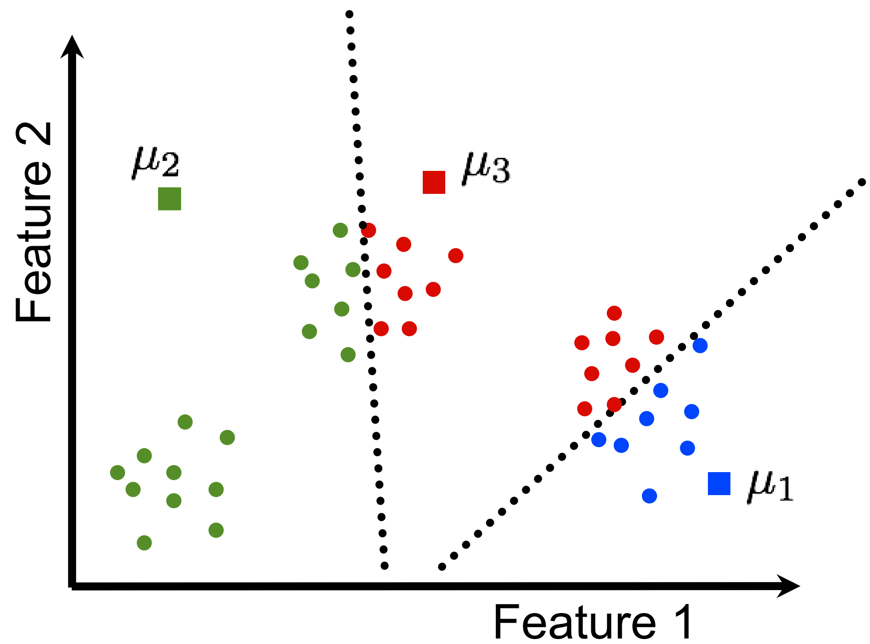
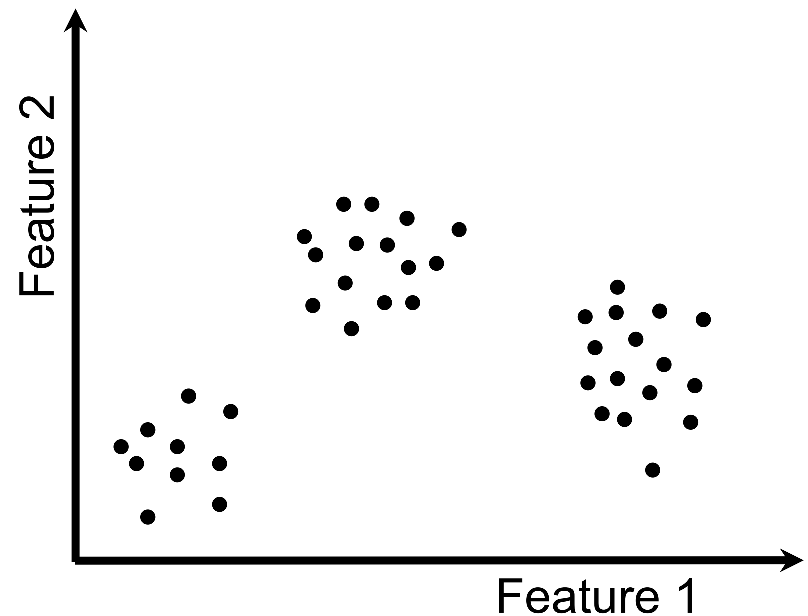


Clustering with Spark

K-Means Algorithm

- Initialize K cluster centers
- Repeat until convergence:
    Assign each data point to the cluster with the closest center.
    Assign each cluster center to be the mean of its cluster's data points.



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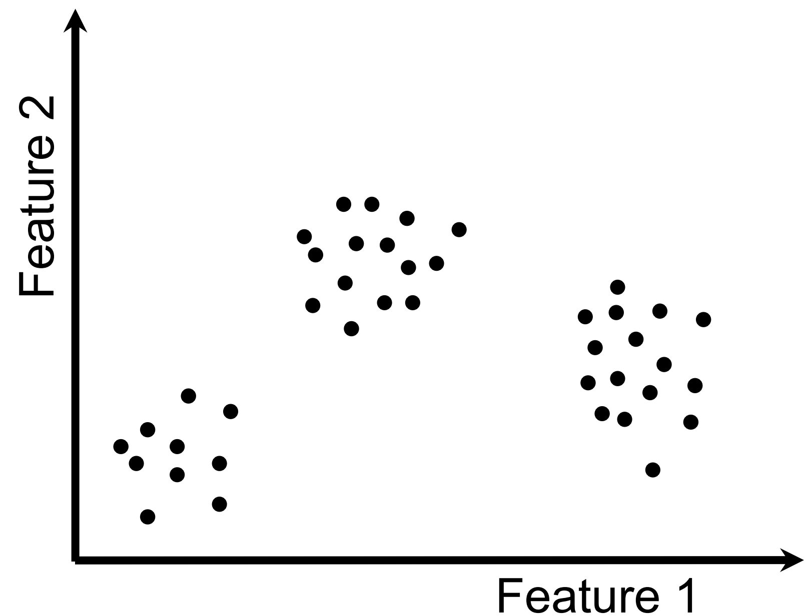

Clustering with Spark

K-Means Algorithm

- Initialize K cluster centers

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centers = data.takeSample(
    false, K, seed)
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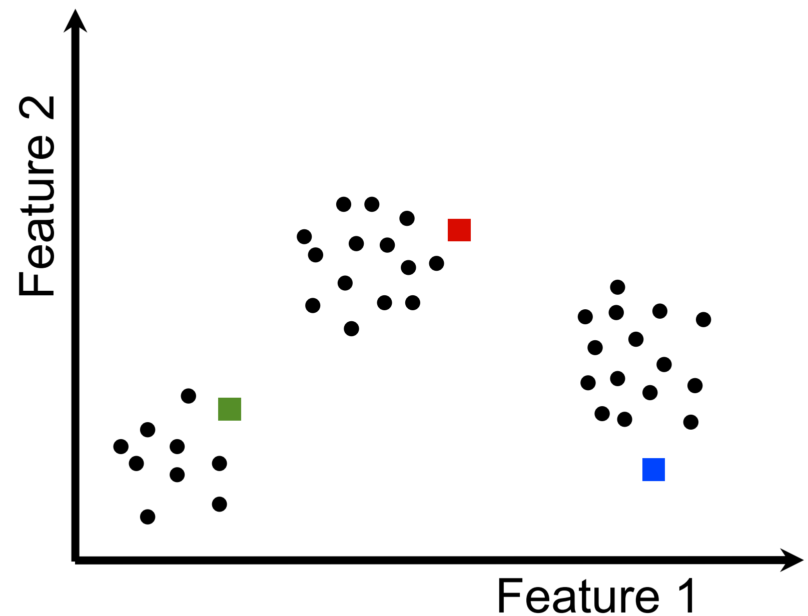

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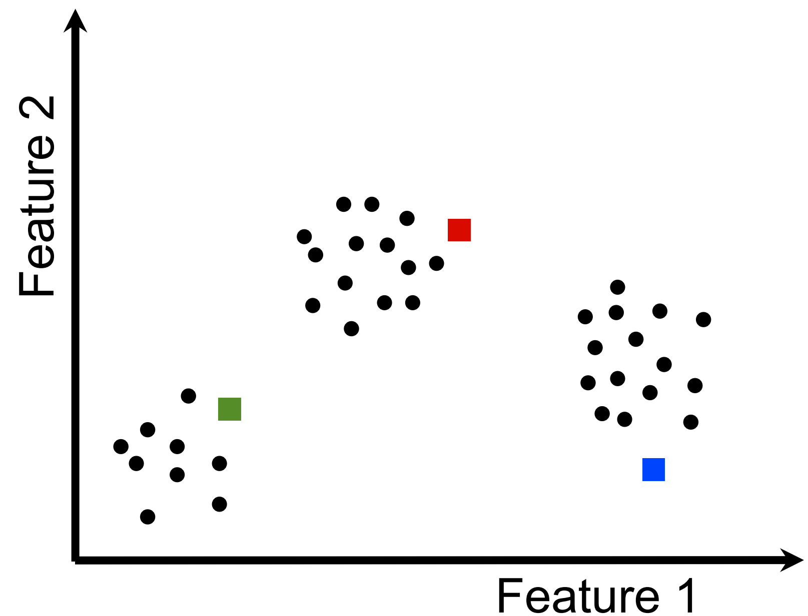

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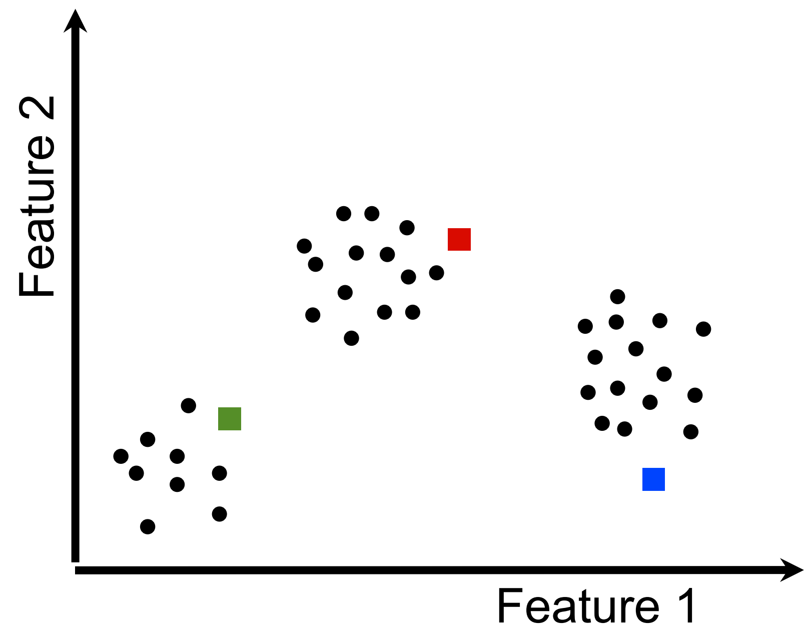

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closest = data.map(p =>

(closestPoint(p,centers),p))
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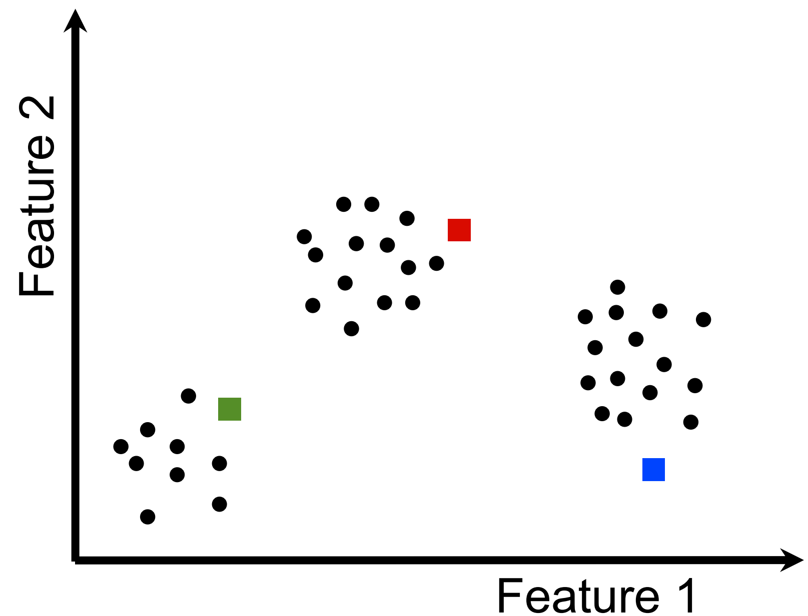
Assign each cluster center to be the mean of its cluster's data points.



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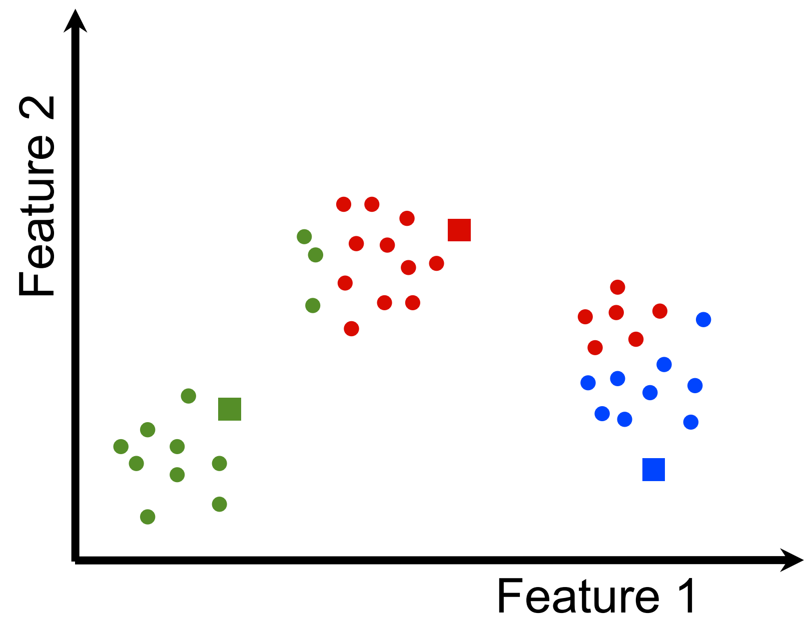

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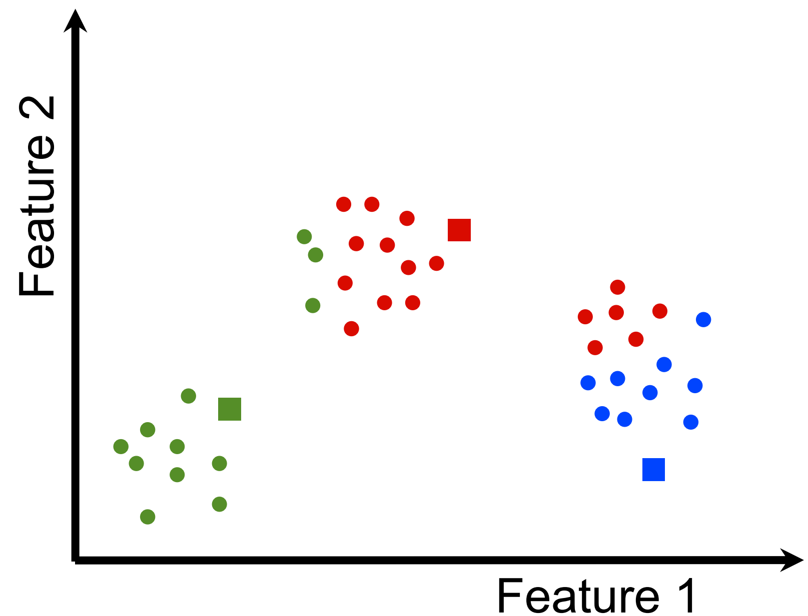

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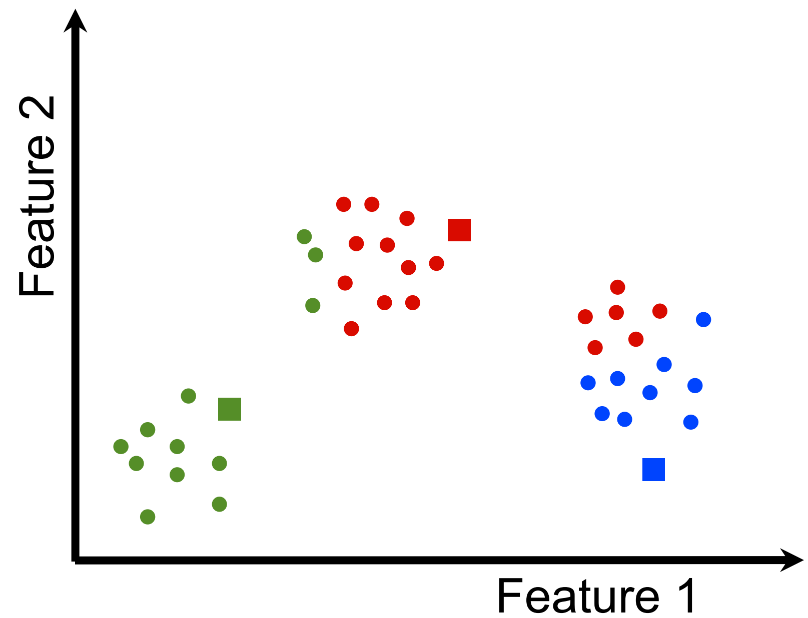

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```
closest = data.map(p =>

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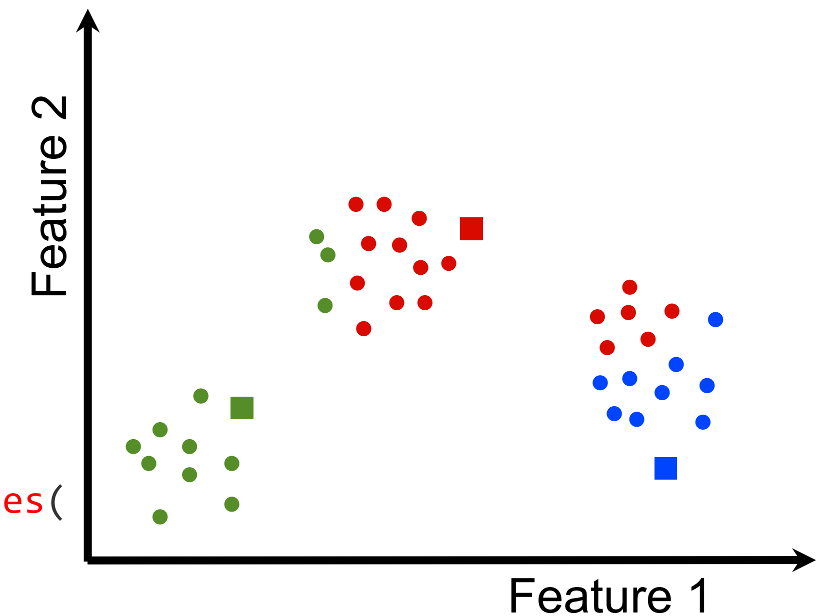
pointsGroup =
    closest.groupByKey()

newCenters = pointsGroup.mapValues(
    ps => average(ps))
```



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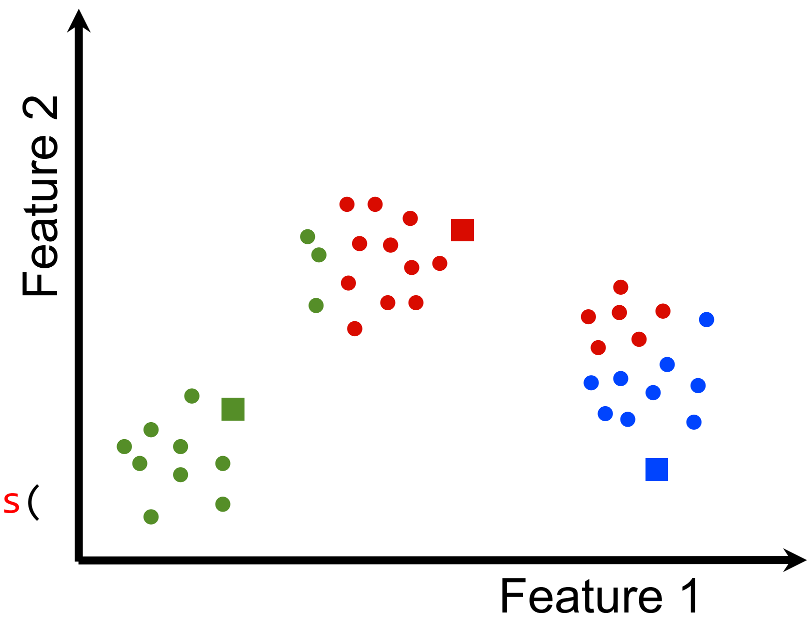

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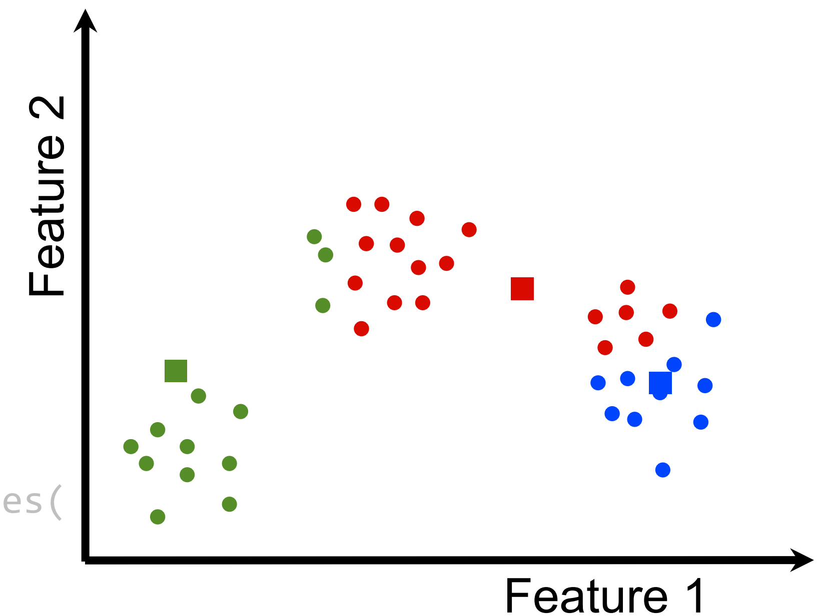

Clustering with Spark

K-Means Algorithm

- Initialize K cluster centers

```
centers = data.takeSample(
    false, K, seed)
```

- Repeat until convergence:

```
while (dist(centers,
             newCenters) > ε)
closest = data.map(p =>
   (closestPoint(p,centers),p))
pointsGroup =
    closest.groupByKey()
newCenters =pointsGroup.mapValues(
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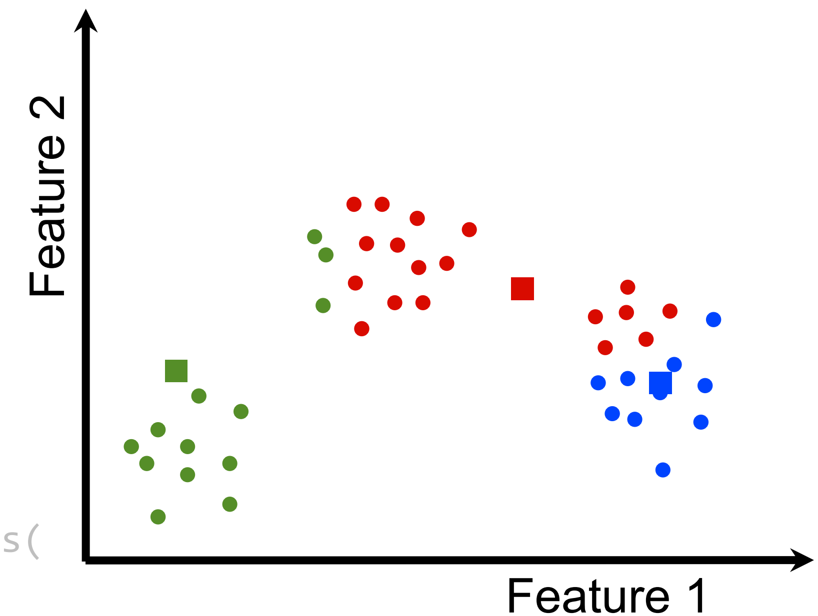

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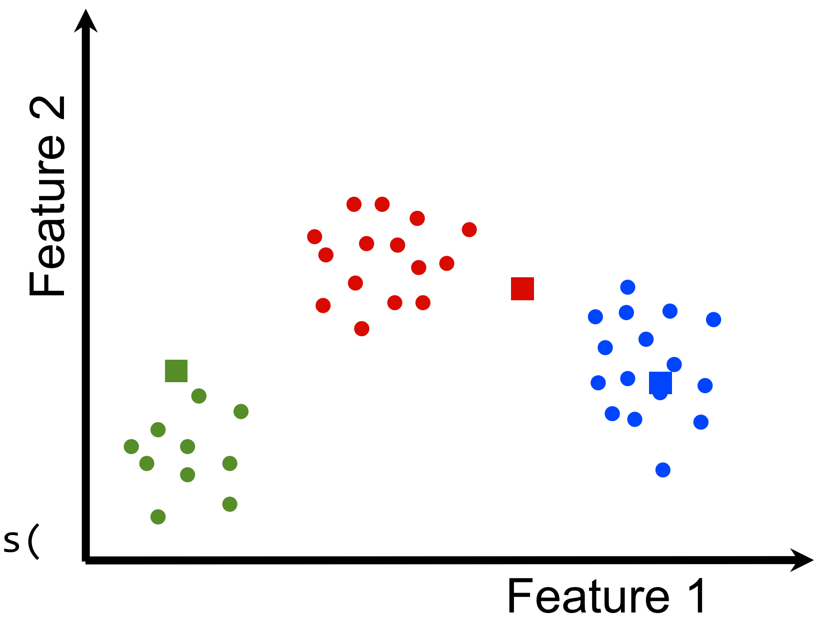
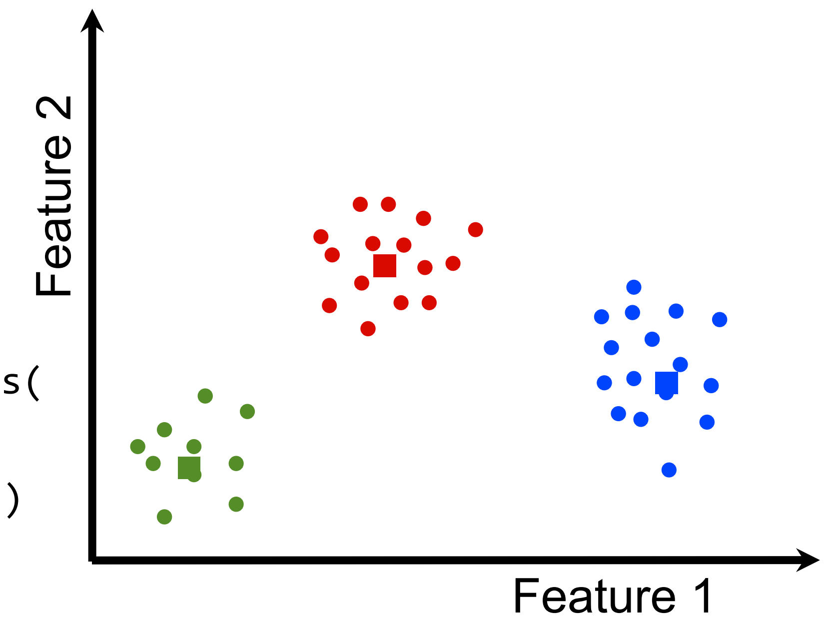


Clustering with Spark

K-Means Source

```
centers = data.takeSample(
    false, K, seed)
while (d > ε)
{
  closest = data.map(p =>
     (closestPoint(p,centers),p))
  pointsGroup =
      closest.groupByKey()
  newCenters =pointsGroup.mapValues(
      ps => average(ps))
  d = distance(centers, newCenters)
  centers = newCenters.map(_)
}
```

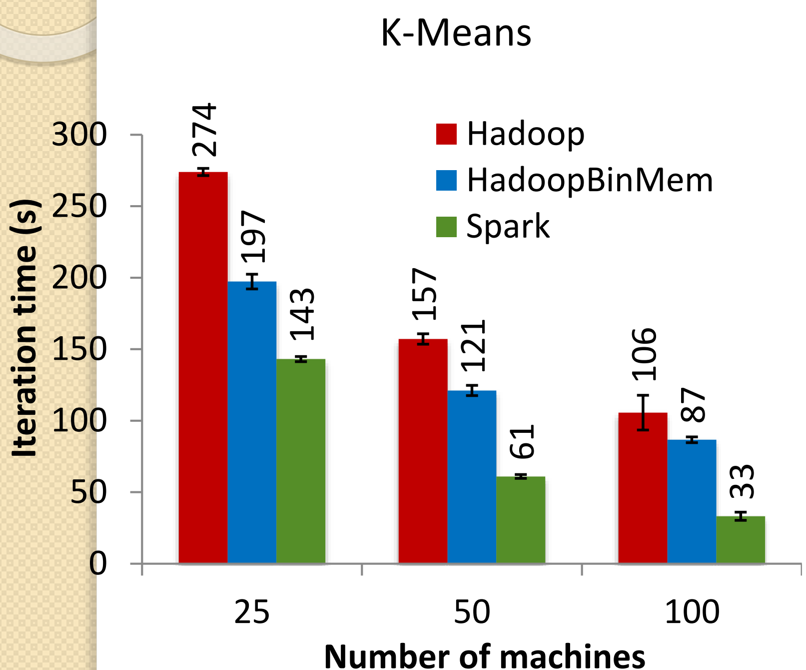


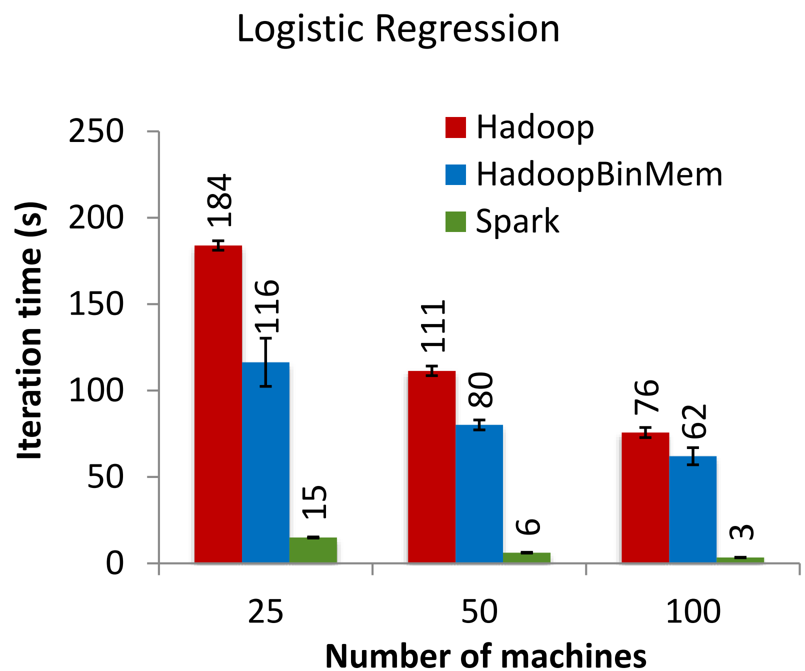
Clustering with Spark

Ease of use

- Interactive shell:
  - Useful for featurization, pre-processing data
- Lines of code for K-Means
  - Spark ~ 90 lines
  - Hadoop/Mahout ~ 4 files, > 300 lines

Performance





[Zaharia et. al, NSDI'12]

K-Means in MLlib

- http://spark.apache.org/docs/latest/mllib-clustering.html#k-means
- Available for Multiple Languages
  - Scala
  - Java
  - Python