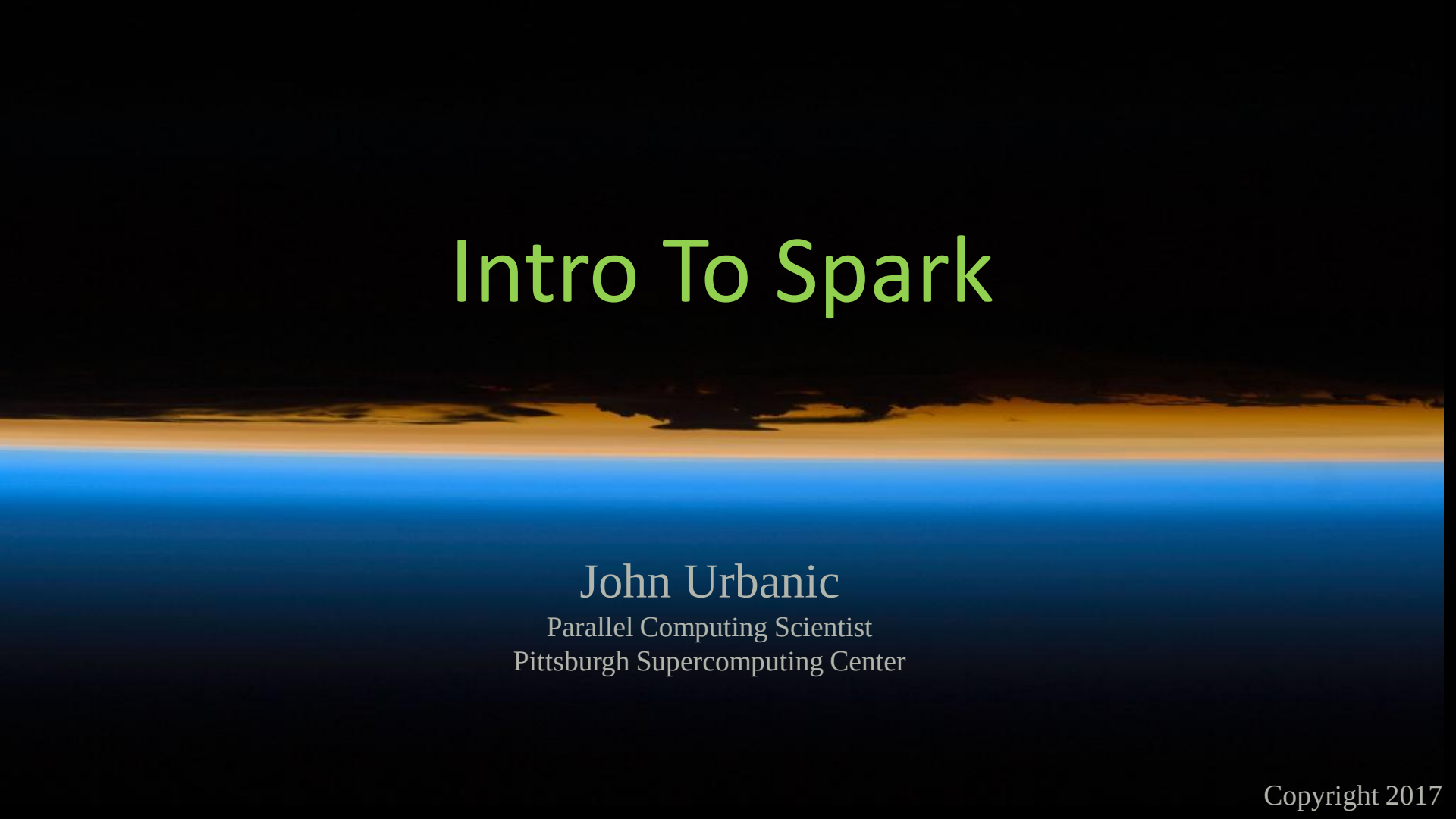

Intro To Spark
John Urbanic
Parallel Computing Scientist
Pittsburgh Supercomputing Center
Copyright 2017

Firing Up The Hands-On

Let's make sure all is well with our hands-on environment first.

Grab a node

```
interact
```

We have hundreds of packages on Bridges. They each have many paths and variables that need to be set for their own proper environment, and they are often conflicting. We shield you from this with the wonderful modules command. You can load the two packages we will be using as

Spark

```
module load spark
```

Tensorflow (Not now! But later)

```
module load tensorflow/1.1.0
source $TENSORFLOW_ENV/bin/activate
```

Copy over our exercise data, and move into an interesting starting point

```
cp –r ~training/BigData .
cd BigData/Shakespear
```

Start up Spark

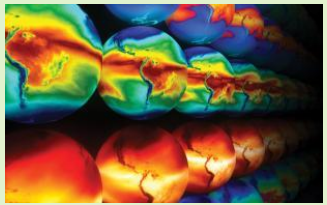
```
pyspark
```

You may see a lot of noise (warning! Warning!) which you should ignore as long as you get a nice "Wecome to Spark" message at the end.

The Shift to Big Data

Pan-STARRS telescope
http://pan-starrs.ifa.hawaii.edu/public/

Genome sequencers
(Wikipedia Commons)



NOAA climate modeling
http://www.ornl.gov/info/ornlreview/v42_3_09/article02.shtml

New Emphases

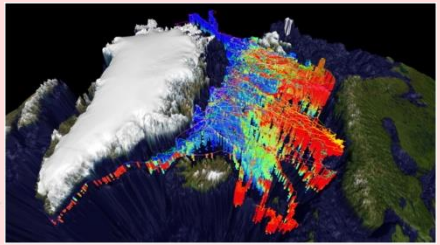
Social networks and the Internet

Video
Wikipedia Commons

Library of Congress stacks
https://www.flickr.com/photos/danlem2001/6922113091/

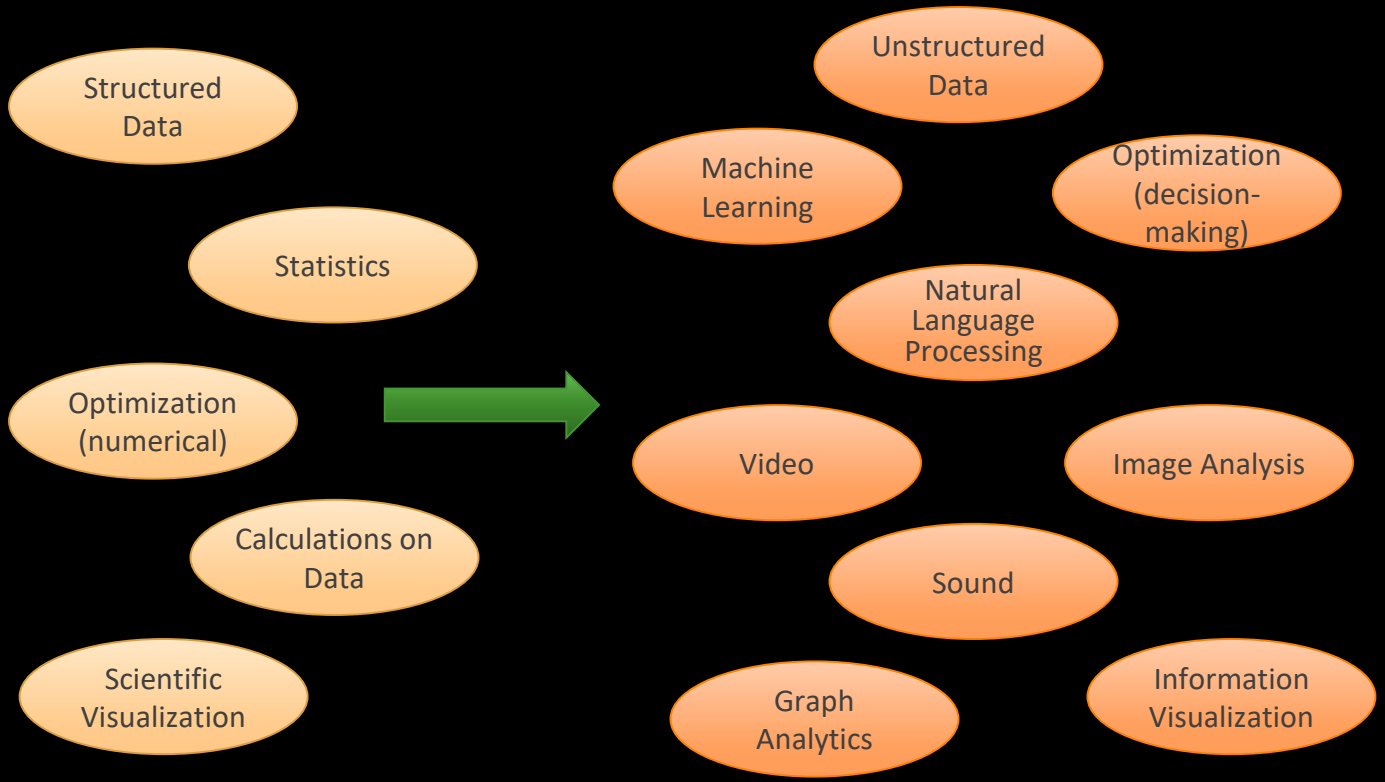
Collections
Horniman museum: http://www.horniman.ac.uk/get_involved/blog/bioblitz-insects-reviewed

Legacy documents
Wikipedia Commons



Environmental sensors: Water temperature profiles from tagged hooded seals
http://www.arctic.noaa.gov/report11/biodiv_whales_walrus.html

Challenges and Software are Co-Evolving



Programming Language

- We have to pick something
- Pick best domain language
- Python
- But not “Pythonic”
- I try to write generic pseudo-code
    - If you know Java or C, etc. you should be fine.

Warning! Warning!

Several of the packages we are using are very prone to throw warnings about the JVM or some python dependency.

We’ve stamped most of them out, but don’t panic if a warning pops up here or there.

In our other workshops we would not tolerate so much as a compiler warning, but this is the nature of these software stacks, so consider it good experience.

Our Setup For This Workshop

After you copy the files from the training directory, you will have:

```
/BigData
        /Clustering
        /MNIST
        /Recommender
        /Shakespeare
```

Datasets, and also cut and paste code samples are in here.

Implications of “Big”

A classic amount of “small” data

Find a tasty appetizer – Easy!

Find something to use up these oranges – grumble…

What if….

Even sophistication has its limits.

Find books on Modern Physics (DD# 539)

Find books by Wheeler

where he isn't the first author – grumble…

Your only hope…

A better sense of biggish

Size

- 1000 Genomes Project
  - AWS hosted
  - 260TB
- Common Crawl
  - Soon to be hosted on Bridges
  - 300-800TB+

Throughput

- Square Kilometer Array
  - Building now
  - Exabyte of raw data/day – compressed to 10PB
- Internet of Things (IoT) / motes
  - Endless streaming

Records

- GDELT (Global Database of Events, Language, and Tone)
  - 250M rows and 59 fields (BigTable)
  - *"during periods with relatively little content, maximal translation accuracy can be achieved, with accuracy linearly degraded as needed to cope with increases in volume in order to ensure that translation always finishes within the 15 minute window…. and prioritizes the highest quality material, accepting that lower-quality material may have a lower-quality translation to stay within the available time window."*

If it is all about the queries vs. the data, what options do we have?

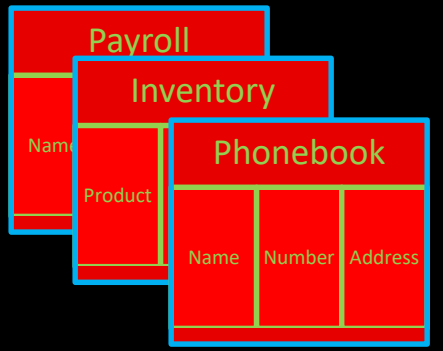
Let’s map out a few provinces:

- SQL
- No SQL
  - Key/Value
  - Document
  - Column
  - Graph
- Analysis / Machine Learning

Good Ol' SQL

MySQL, Postgres, Oracle, etc.

```
SELECT  NAME, NUMBER, FROM PHONEBOOK
```



Why it isn't fashionable:

- Schemas set in stone:
  - Need to define before we can add data
  - Not a fit for "agile development"
- Queries often require accessing multiple indexes and joining and sorting multiple tables
- Sharding isn't trivial
- Caching is tough
  - ACID (Atomicity,Consistency,Isolation,Durability) in a *Transaction* is costly.

NoSQL

- Everything Else?
- Not only SQL
- Was effectively *NoACID*
- Now maybe *NoRelational*

Key-Value

Redis, Memcached, Amazon DynamoDB, Riak, Ehcache

```
GET foo
```

foo	bar
2	fast
6	0
9	0
0	9
text	pic
1055	stuff
bar	foo

- Certainly agile (no schema)
- Certainly scalable (linear in most ways: hardware, storage, cost)
- Good hash might deliver fast lookup
- Sharding, backup, etc. could be simple
- Often used for “session” information: online games, shopping carts

```
GET cart:joe:15~4~7~0723
```

Document

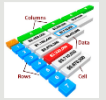
Cassandra, CouchDB, MongoDB

```
GET foo
```

- Value must be an object the DB can understand
- Common are: XML, JSON, Binary JSON and nested thereof
- This allows server side operations on the data

```
GET plant=daisy
```

- Can be quite complex: Linq query, JavaScript function
- Different DB's have different update/staleness paradigms

foo	
2	<CATALOG> <PLANT> <COMMON>Bloodroot</COMMON> <BOTANICAL>Sanguinaria canadensis</BOTANICAL> <ZONE>4</ZONE> <LIGHT>Mostly Shady</LIGHT> <PRICE>$2.44</PRICE> <AVAILABILITY>031599</AVAILABILITY> </PLANT> <PLANT> <COMMON>Columbine</COMMON> <BOTANICAL>Aquilegia canadensis</BOTANICAL> <ZONE>3</ZONE> <LIGHT>Mostly Shady</LIGHT> <PRICE>$9.37</PRICE> <AVAILABILITY>030699</AVAILABILITY> </PLANT> .
6	JSON
9	XML
0	Binary JSON
bar	JSON XML
12	XML XML

Wide Column Stores

Google BigTable, Cassandra, HBase

```
SELECT Name, Occupation FROM People WHERE key IN (199, 200, 207);
```

- No predefined schema
- Can think of this as a 2-D key-value store: the value may be a key-value store itself
- Different databases aggregate data differently on disk with different optimizations

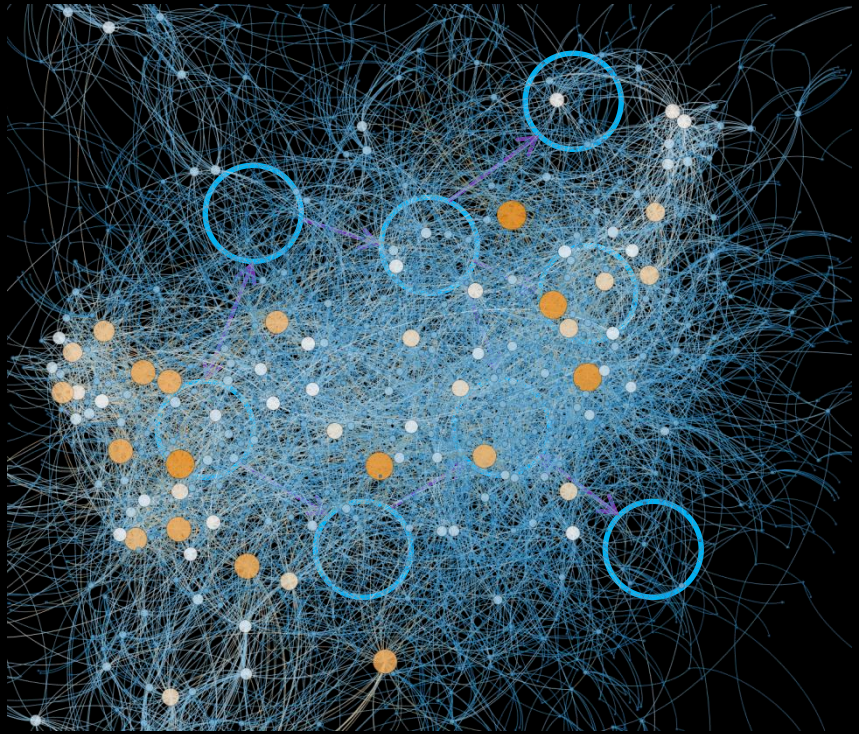
Key			
Joe	**Email:** joe@gmail	**Web:** www.joe.com	
Fred	**Phone:** 412-555-3412	**Email:** fred@yahoo.com	**Address:** 200 S. Main Street
Julia	**Email:** julia@apple.com		
Mac	**Phone:** 214-555-5847		

Graph

Neo4J, Titan, GEMS

- Great for semantic web
- Great for graphs 

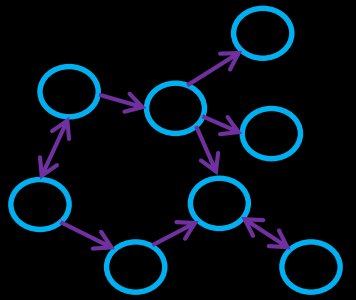
- Can be hard to visualize
- Serialization can be difficult
- Queries more complicated



From *PDX Graph Meetup*

Queries

SPARQL, Cypher



SPARQL (W3C Standard)

- Uses Resource Description Framework format (triple store)
- RDF Limitations
  - No named graphs
  - No quantifiers or general statements
    - “Every page was created by some author”
    - “Cats meow”
- Requires a schema (RDFS) to define rules
    - "The object of ‘homepage’ must be a Document.“

```
SELECT ?name ?email
WHERE {
          ?person a foaf:Person.
          ?person foaf:name ?name.
          ?person foaf:mbox ?email.
}
```

Cypher (Neo4J only)

- No longer proprietary
- Stores whole graph, not just triples
- Allows for named graphs
- …and general Property Graphs (edges and nodes may have values)

```
SMATCH (Jack:Person
  { name:‘Jack Nicolson’})-[:ACTED_IN]-(movie:Movie)
RETURN movie
```

Hadoop & Spark

Frameworks for data

These are both frameworks for distributing and retrieving data. Hadoop is focused on disk based data and a basic map-reduce scheme, and Spark attempts evolves that in several directions that we will get in to. Both can accommodate multiple types of databases and *achieve their performance gains by using parallel workers*. You are about to learn a lot more, but here are a few concrete examples:

Hadoop

- HBASE: modeled after BigTable and a natural fit
- HIVE: SQL-like HiveQL converts to the underlying map/reduce (often much slower)

Spark

- Spark SQL
- GraphX
- MLlib: stats, clustering, optimization, regression, etc.

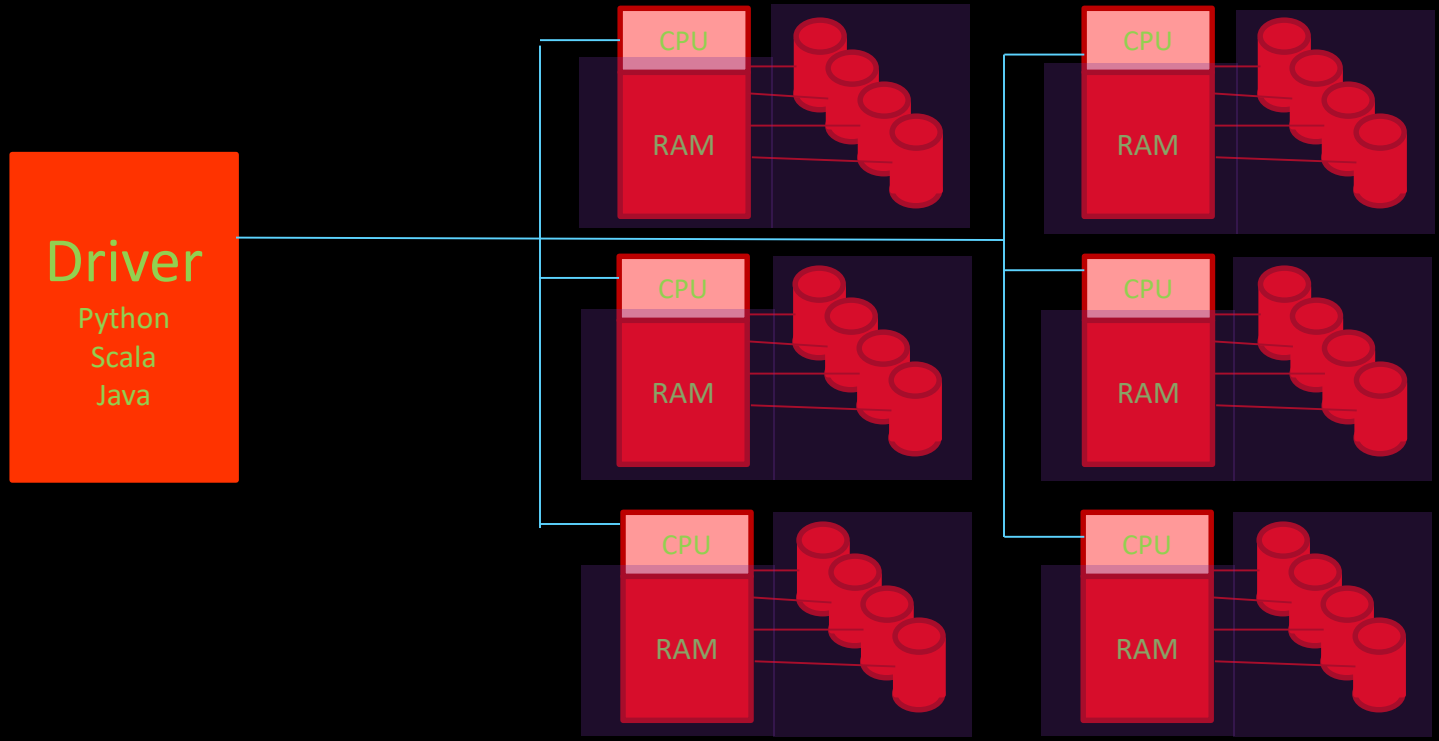
Spark Capabilities

(i.e. Hadoop shortcomings)

- Performance
  - First, use RAM
  - Also, be smarter
- Ease of Use
  - Python, Scala, Java first class citizens
- New Paradigms
  - SparkSQL
  - Streaming
  - MLib
  - GraphX
  - …more

But using Hadoop as the backing store is a common and sensible option.

Parallel Idea



RDD

Resilient Distributed Dataset

Spark Formula

1. Create/Load RDD
   Webpage visitor IP address log
2. *Transform* RDD
   ”Filter out all non-U.S. IPs”
3. But don’t do anything yet!
   Wait until data is actually needed
   Maybe apply more transforms (“distinct IPs)
4. Perform *Actions* that return data
   Count “How many unique U.S. visitors?”

Simple Example

```
>>> lines = sc.textFile("nasa_19950801.tsv")
```

Read into RDD

Spark Context

The first thing a Spark program requires is a context, which interfaces with some kind of cluster to use. Our pyspark shell provides us with a convenient *sc*, using the local filesytem, to start. Your standalone programs will have to specify one:

```
conf = SparkConf().setMaster("local").setAppName("Test App")
sc = SparkContext(conf = conf)
```

Simple Example

```
>>> lines = sc.textFile("nasa_19950801.tsv")

>>> stanfordLines = lines.filter(lambda line: "stanford" in line)

>>> stanfordLines.count()
47

>>> stanfordLines.first()
u'glim.stanford.edu\t-\t807258357\tGET\t/shuttle/missions/61-c/61-c-patch-small.gif\t‘
```

Lambdas

We'll see a lot of these. A lambda is simply a function that is too simple to deserve its own subroutine. Anywhere we have a lambda we could also just name a real subroutine that could go off and do anything.

When all you want to do is see if "*given an input variable line, is "stanford" in there?*", it isn't worth the digression.

Most modern languages have adopted this nicety.

Common Transformations

Transformation	Result
map(func)	Return a new RDD by passing each element through *func*.
filter(func)	Return a new RDD by selecting the elements for which *func* returns true.
flatMap(func)	*func* can return multiple items, and generate a sequence, allowing us to "flatten" nested entries (JSON) into a list.
distinct()	Return an RDD with only distinct entries.
sample(…)	Various options to create a subset of the RDD.
union(RDD)	Return a union of the RDDs.
intersection(RDD)	Return an intersection of the RDDs.
subtract(RDD)	Remove argument RDD from other.
cartesian(RDD)	Cartesian product of the RDDs.
parallelize(list)	Create an RDD from this (Python) list (using a spark context).

Full list at http://spark.apache.org/docs/latest/api/python/pyspark.html#pyspark.RDD

Common Actions

Transformation	Result
collect()	Return all the elements from the RDD.
count()	Number of elements in RDD.
countByValue()	List of times each value occurs in the RDD.
reduce(func)	Aggregate the elements of the RDD by providing a function which combines any two into one (sum, min, max, …).
first(), take(n)	Return the first, or first n elements.
top(n)	Return the n highest valued elements of the RDDs.
takeSample(…)	Various options to return a subset of the RDD..
saveAsTextFile(path)	Write the elements as a text file.
foreach(func)	Run the *func* on each element. Used for side-effects (updating accumulator variables) or interacting with external systems.

Full list at http://spark.apache.org/docs/latest/api/python/pyspark.html#pyspark.RDD

Optimizations

We said one of the advantages of Spark is that we can control things for better performance. Some of the most effective ways of doing that are:

- Persistence
- Partitioning

We won’t have time to get into these today, but be aware that this kind of control is available.

Pair RDDs

- Key/Value organization is a simple, but often very efficient schema, as we mentioned in our NoSQL discussion.
- Spark provides special operations on RDDs that contain key/value pairs. They are similar to the general ones that we have seen.
- On the language (Python, Scala, Java) side key/values are simply tuples.

Pair RDD Transformations

Transformation	Result
reduceByKey(func)	Reduce values using *func*, but on a key by key basis. That is, combine values with the same key.
groupByKey()	Combine values with same key. Each key ends up with a list.
sortByKey()	Return an RDD sorted by key.
mapValues(func)	Use *func* to change values, but not key.
keys()	Return an RDD of only keys.
values()	Return an RDD of only values.

Note that all of the regular transformations are available as well.

Two Pair RDD Transformations

Transformation	Result
subtractByKey(otherRDD)	Remove elements with a key present in other RDD.
join(otherRDD)	Inner join: Return an RDD containing all pairs of elements with matching keys in self and other. Each pair of elements will be returned as a (k, (v1, v2)) tuple, where (k, v1) is in self and (k, v2) is in other.
leftOuterJoin(otherRDD)	For each element (k, v) in self, the resulting RDD will either contain all pairs (k, (v, w)) for w in other, or the pair (k, (v, None)) if no elements in other have key k.
rightOuterJoin(otherRDD)	For each element (k, w) in other, the resulting RDD will either contain all pairs (k, (v, w)) for v in this, or the pair (k, (None, w)) if no elements in self have key k.
cogroup(otherRDD)	Group data from both RDDs by key.

Full list at http://spark.apache.org/docs/latest/api/python/pyspark.html#pyspark.RDD

Simple Example

```
>>> x = sc.parallelize([("a", 1), ("b", 4)])

>>> y = sc.parallelize([("a", 2), ("a", 3)])

>>> z = x.join(y)

>>> z.collect()
[('a', (1, 2)), ('a', (1, 3))]
```

Pair RDD Actions

As with transformations, all of the regular actions are available to Pair RDDs, and there are some additional ones that can take advantage of key/value structure.

Transformation	Result
countByKey()	Count the number of elements for each key.
lookup(key)	Return all the values for this key.

Full list at http://spark.apache.org/docs/latest/api/python/pyspark.html#pyspark.RDD

SparkSQL and DataFrames

SparkSQL is a Spark componant that enables SQL (or similar Hive Query Language) queries. It uses *DataFrames*, which is a *Dataset* that has been organized into named columns. It can allow for some very convenient manipulation:

```
# spark is an existing SparkSession, which precedes all this usage
df = spark.sql("SELECT * FROM table")

# Create a DataFrame from the content of a JSON file
df = spark.read.json(“phonebook.json")

# Print the schema in a tree format
df.printSchema()
```

DataFrames is a new Spark API that allows for some serious optimization due to knowledge about the data structure. We won’t exploit that today, but it is significant and a logical extension of the things we will do.

MLlib

MLib rolls in a lot of classic machine learning algorithms. We barely have time to touch upon this interesting topic today, but they include:

- Useful data types
- Basic Statistics
- Classification (including SVMs, Random Forests)
- Regression
- Dimensionality Reduction (Princ. Comp. Anal., Sing. Val. Decomp.)
- Algorithms (SGD,…)
- Clustering…

Using MLlib

One of the reasons we use spark is for easy access to powerful data analysis tools. The MLlib library gives us a machine learning library that is easy to use and utilizes the scalability of the Spark system.

It has supported APIs for Python (with NumPy), R, Java and Scala.

We will use the Python version in a generic manner that looks very similar to any of the above implementations.

There are good example documents for the clustering routine we are using here:

http://spark.apache.org/docs/latest/mllib-clustering.html

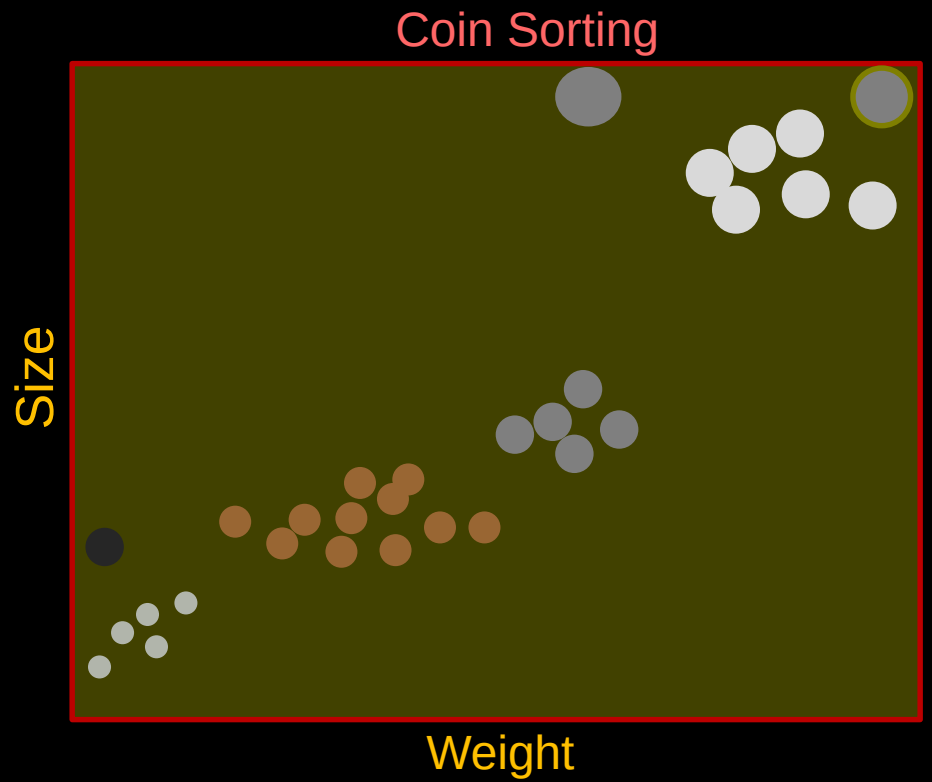
And an excellent API reference document here:

http://spark.apache.org/docs/latest/api/python/pyspark.mllib.html#pyspark.mllib.clustering.KMeans

I suggest you use these pages for all your Spark work.

Clustering

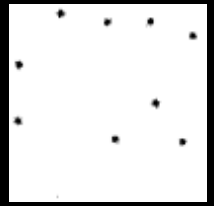
Clustering is a very common operation for finding grouping in data and has countless applications. This is a very simple example, but you will find yourself reaching for a clustering algorithm frequently in pursuing many diverse machine learning objectives, sometimes as one part of a pipeline.



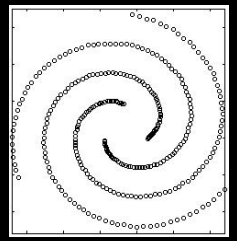
Clustering

As intuitive as clustering is, it presents challenges to implement in an efficient and robust manner.

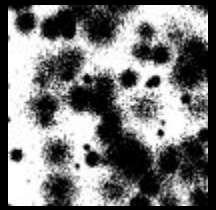
You might think this is trivial to implement in lower dimensional spaces.



But it can get tricky even there.



Sometimes you know how many clusters you have to start with. Often you don't.
How hard can it be to count clusters? How many are here?



We will start with 5000 2D points. We want to figure out how many clusters there are, and their centers. Let's fire up pyspark and get to it…

Finding Clusters

```
br06% interact
...
r288%
r288% module load spark
r288% pyspark
```

```
      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /__ / .__/\_,_/_/ /_/\_\
      /_/

Using Python version 2.7.5
SparkContext available as
>>>
>>> rdd1 = sc.textFile("50
>>>
>>> rdd2 = rdd1.map(lambda
>>> rdd3 = rdd2.map(lambda
>>>
>>> rdd3.persist(StorageLe
>>>
```

DD

words and integers

is around

*RDD map() takes a function to apply to the elements. We can certainly create our own separate function, but lambdas are a way many languages allow us to define trivial functions “in place”.

Finding Our Way

```
>>> rdd1 = sc.textFile("5000_points.txt")
>>> rdd1.count()
5000
>>> rdd1.take(4)
[u'    664159    550946', u'    665845    557965', u'    597173    575538', u'    618600    551446']
>>> rdd2 = rdd1.map(lambda x:x.split())
>>> rdd2.take(4)
[[u'664159', u'550946'], [u'665845', u'557965'], [u'597173', u'575538'], [u'618600', u'551446']]
>>> rdd3 = rdd2.map(lambda x: [int(x[0]),int(x[1])])
>>> rdd3.take(4)
[[664159, 550946], [665845, 557965], [597173, 575538], [618600, 551446]]
>>>
```

Finding Clusters

```
____              __
   / __/__  ___ _____/ /__
  _\ \/ _ \/ _ `/ __/  '_/
 /__ / .__/\_,_/_/ /_/\_\   version 1.6.0
    /_/

Using Python version 2.7.5 (default, Nov 20 2015 02:00:19)
SparkContext available as sc, HiveContext available as sqlContext.
>>>
>>> rdd1 = sc.textFile("5000_points.txt")
>>>
>>> rdd2 = rdd1.map(lambda x:x.split())
>>> rdd3 = rdd2.map(lambda x: [int(x[0]),int(x[1])])
>>>
>>> rdd3.persist(StorageLevel.MEMORY_ONLY)
>>>
>>> from pyspark.mllib.clustering import KMeans
```

Read into RDD

Transform

Let's keep this around

Import Kmeans

class pyspark.mllib.clustering.**KMeans**

New in version 0.9.0.

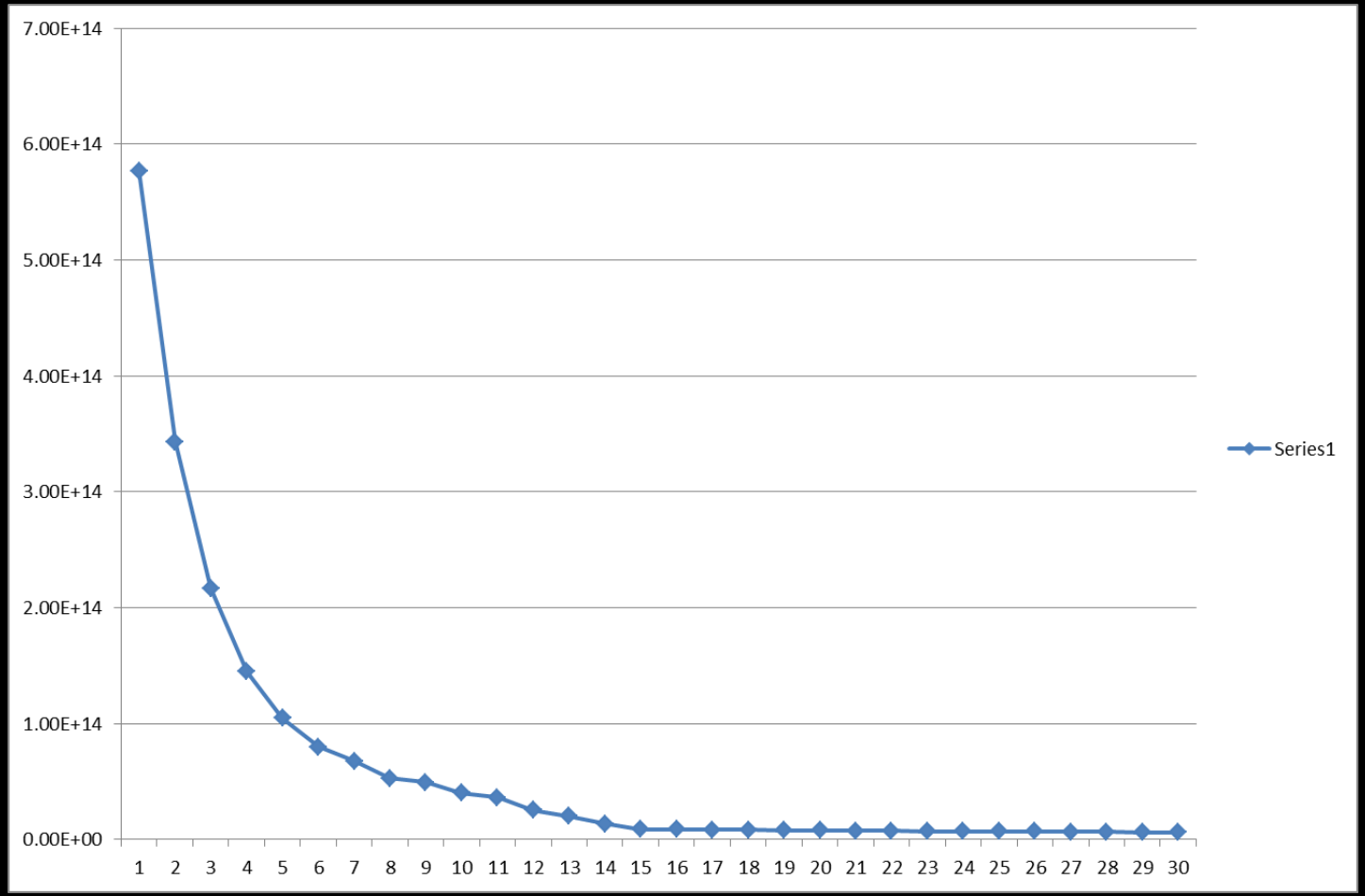
classmethod **train**(*rdd, k, maxIterations=100, runs=1, initializationMode='k-means||', seed=None, initializationSteps=5, epsilon=0.0001, initialModel=None*) ¶

Train a k-means clustering model.

Parameters:

- **rdd** – Training points as an *RDD* of *Vector* or convertible sequence types.
- **k** – Number of clusters to create.
- **maxIterations** – Maximum number of iterations allowed. (default: 100)
- **runs** – This param has no effect since Spark 2.0.0.
- **initializationMode** – The initialization algorithm. This can be either "random" or "k-means||". (default: "k-means||")
- **seed** – Random seed value for cluster initialization. Set as None to generate seed based on system time. (default: None)
- **initializationSteps** – Number of steps for the k-means|| initialization mode. This is an advanced setting – the default of 5 is almost always enough. (default: 5)
- **epsilon** – Distance threshold within which a center will be considered to have converged. If all centers move less than this Euclidean distance, iterations are stopped. (default: 1e-4)
- **initialModel** – Initial cluster centers can be provided as a KMeansModel object rather than using the random or k-means|| initializationModel. (default: None)

Finding Clusters



Finding Clusters

```
 ____              __
/ __/__  ___ _____/ /__
_\ \/ _ \/ _ `/ __/  '_/
/__ / .__/\_,_/_/ /_/\_\   version 1.6.0
   /_/

Using Python version 2.7.5 (default, Nov 20 2015 02:00:19)
SparkContext available as sc, HiveContext available as sqlContext.
>>>
>>> rdd1 = sc.textFile("5000_points.txt")
>>>
>>> rdd2 = rdd1.map(lambda x:x.split())
>>> rdd3 = rdd2.map(lambda x: [int(x[0]),int(x[1])])
>>>
>>> rdd3.persist(StorageLevel.MEMORY_ONLY)
>>>
>>> from pyspark.mllib.clustering import KMeans
>>>
>>> for clusters in range(1,30):
...     model = KMeans.train(rdd3, clusters)
...     print clusters, model.computeCost(rdd3)
...
```

Let's see results for 1-30 cluster tries

```
1 5.76807041184e+14
2 3.43183673951e+14
3 2.23097486536e+14
4 1.64792608443e+14
5 1.19410028576e+14
6 7.97690150116e+13
7 7.16451594344e+13
8 4.81469246295e+13
9 4.23762700793e+13
10 3.65230706654e+13
11 3.16991867996e+13
12 2.94369408304e+13
13 2.04031903147e+13
14 1.37018893034e+13
15 8.91761561687e+12
16 1.31833652006e+13
17 1.39010717893e+13
18 8.22806178508e+12
19 8.22513516563e+12
20 7.79359299283e+12
21 7.79615059172e+12
22 7.70001662709e+12
23 7.24231610447e+12
24 7.21990743993e+12
25 7.09395133944e+12
26 6.92577789424e+12
27 6.53939015776e+12
28 6.57782690833e+12
29 6.37192522244e+12
```

Right Answer?

```
>>> for trials in range(10):
...     print
...     for clusters in range(12,18):
...         model = KMeans.train(rdd3,clusters)
...         print clusters, model.computeCost(rdd3)
```

```
12 2.45472346524e+13
13 2.00175423869e+13
14 1.90313863726e+13
15 1.52746006962e+13
16 8.67526114029e+12
17 8.49571894386e+12

12 2.62619056924e+13
13 2.90031673822e+13
14 1.52308079405e+13
15 8.91765957989e+12
16 8.70736515113e+12
17 8.49616440477e+12

12 2.5524719797e+13
13 2.14332949698e+13
14 2.11070395905e+13
15 1.47792736325e+13
16 1.85736955725e+13
17 8.42795740134e+12

12 2.31466242693e+13
13 2.10129797745e+13
14 1.45400177021e+13
15 1.52115329071e+13
16 1.41347332901e+13
17 1.31314086577e+13

12 2.47927778784e+13
13 2.43404436887e+13
14 2.1522702068e+13
15 8.91765000665e+12
16 1.4580927737e+13
17 8.57823507015e+12
```

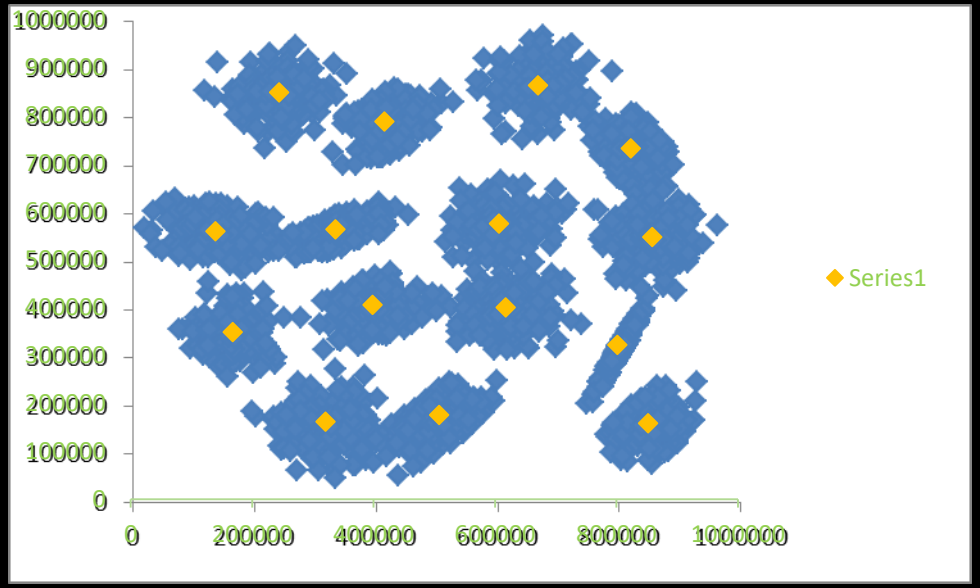
```
12 2.31466520037e+13
13 1.91856542103e+13
14 1.49332023312e+13
15 1.3506302755e+13
16 8.7757678836e+12
17 1.60075548613e+13

12 2.5187054064e+13
13 1.83498739266e+13
14 1.96076943156e+13
15 1.41725666214e+13
16 1.41986217172e+13
17 8.46755159547e+12

12 2.38234539188e+13
13 1.85101922046e+13
14 1.91732620477e+13
15 8.91769396968e+12
16 8.64876051004e+12
17 8.54677681587e+12

12 2.5187054064e+13
13 2.04031903147e+13
14 1.95213876047e+13
15 1.93000628589e+13
16 2.07670831868e+13
17 8.47797102908e+12

12 2.39830397362e+13
13 2.00248378195e+13
14 1.34867337672e+13
15 2.09299321238e+13
16 1.32266735736e+13
17 8.50857884943e+12
```

Find the Centers

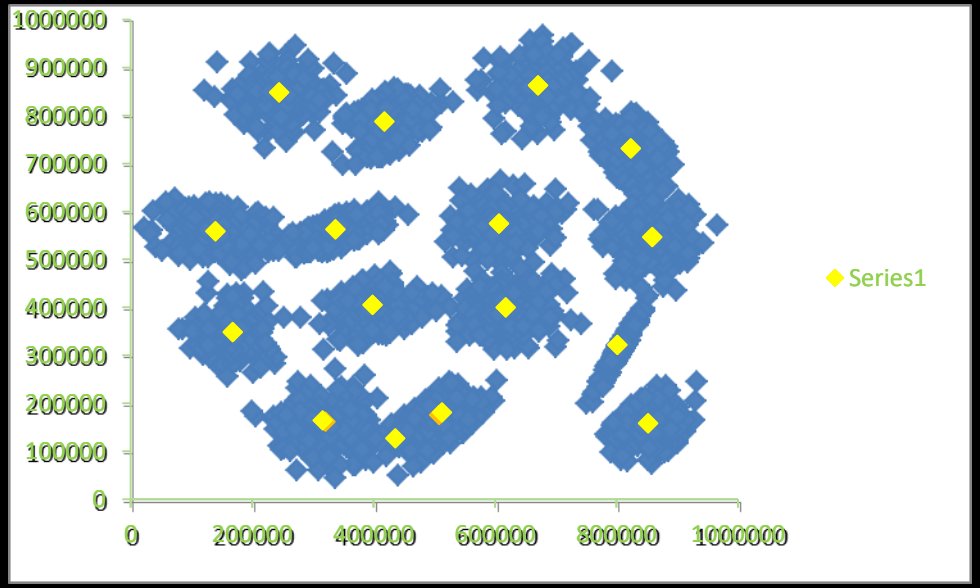
```
>>> for trials in range(10):                    #Try ten times to find best result
...     for clusters in range(12, 16):          #Only look in interesting range
...         model = KMeans.train(rdd3, clusters)
...         cost = model.computeCost(rdd3)
...         centers = model.clusterCenters      #Let's grab cluster centers
...         if cost<1e+13:                      #If result is good, print it out
...            print clusters, cost
...            for coords in centers:
...              print int(coords[0]), int(coords[1])
...            break
...
```

```
15 8.91761561687e+12
852058 157685
606574 574455
320602 161521
139395 558143
858947 546259
337264 562123
244654 847642
398870 404924
670929 862765
823421 731145
507818 175610
801616 321123
617926 399415
417799 787001
167856 347812
15 8.91765957989e+12
670929 862765
139395 558143
244654 847642
852058 157685
617601 399504
801616 321123
507818 175610
337264 562123
858947 546259
823421 731145
606574 574455
167856 347812
398555 404855
417799 787001
320602 161521
```

Fit?


1000000
900000
800000
700000
600000
500000
400000
300000
200000
100000
0
0
200000
400000
600000
800000
1000000
Series1

16 Clusters


1000000
900000
800000
700000
600000
500000
400000
300000
200000
100000
0
0
200000
400000
600000
800000
1000000
Series1

Run My Programs Or Yours

execfile()

```
[urbanic@r005 Clustering]$ pyspark
Python 2.7.11 (default, Feb 23 2016, 17:47:07)
[GCC 4.8.5 20150623 (Red Hat 4.8.5-4)] on linux2
Type "help", "copyright", "credits" or "license" for more information.Welcome to
      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /__ / .__/\_,_/_/ /_/\_\   version 2.1.0
      /_/

Using Python version 2.7.11 (default, Feb 23 2016 17:47:07)
SparkSession available as 'spark'.
>>>
>>>
>>> execfile("clustering.py")
1 5.76807041184e+14
2 3.73234816206e+14
3 2.13508993715e+14
4 1.38250712993e+14
5 1.2632806251e+14
6 7.97690150116e+13
7 7.14156965883e+13
8 5.7815194802e+13
...
...
...
```

If you have another session window open on bridge's login node, you can edit this file, save it while you remain in the editor, and then run it again in the python shell window with execfile().

You do *not* need this second session to be on a compute node. Do not start another interactive session.

Shakespeare, a Data Analytics Favorite

Applying data analytics to the works of Shakespeare has become all the rage. Whether determining the legitimacy of his authorship (it wasn't Marlowe) or if Othello is actually a comedy (perhaps), it is amazing how much research has sprung from the recent analysis of 400 year old text.

We're going to do some exercises here using a text file containing all of his works.

Some Simple Problems

We have an input file, Complete _Shakespeare.txt, that you can also find at http://www.gutenberg.org/ebooks/100.

Make sure it is in your current directory. Start “pyspark” and load the data in the usual manner:

```
>>> rdd = sc.textFile("Complete_Shakespeare.txt")
```

Let’s try a few simple exercises.

1) Count the number of lines

2) Count the number of words

3) Count unique words

4) Count the occurrence of each word

5) Show the top 5 most frequent words

These last two are a bit more challenging. One approach is to think “key/value”. If you go that way, think about which data should be the key and don’t be afraid to swap it about. ‘Nuff said.

Some Simple Answers

```
>>> rdd = sc.textFile("Complete_Shakespeare.txt")
>>>
>>> rdd.count()
124787
>>>
>>> rdd.flatMap(lambda x: x.split()).count()
904061
>>>
>>> rdd.flatMap(lambda x: x.split()).distinct().count()
67779
>>>
words = rdd.flatMap(lambda x: x.split())
key_value = words.map(lambda x: (x,1))
>>>
>>> key_value.take(5)
[(u'The', 1), (u'Project', 1), (u'Gutenberg', 1), (u'EBook', 1), (u'of', 1)]
>>>
>>> word_counts = key_value.reduceByKey(lambda x,y: x+y)
>>> word_counts.take(5)
[(u'fawn', 11), (u'considered-', 1), (u'Fame,', 3), (u'mustachio', 1), (u'protested,', 1)]
>>>
flipped = word_counts.map(lambda x: (x[1],x[0]))
>>> flipped.take(5)
[(11, u'fawn'), (1, u'considered-'), (3, u'Fame,'), (1, u'mustachio'), (1, u'protested,')]
>>>
>>> results = flipped.sortByKey(False)
>>> results.take(5)
[(23407, u'the'), (19540, u'I'), (18358, u'and'), (15682, u'to'), (15649, u'of')]
>>>
>>>
results = rdd.flatMap(lambda x: x.split()).map(lambda x: (x,1)).reduceByKey(lambda x,y: x+y).map(lambda x: (x[1],x[0])).sortByKey(False)
```

Turn these into k/v pairs

Reduce words

Flip keys and values so we can sort on wordcount instead of words.