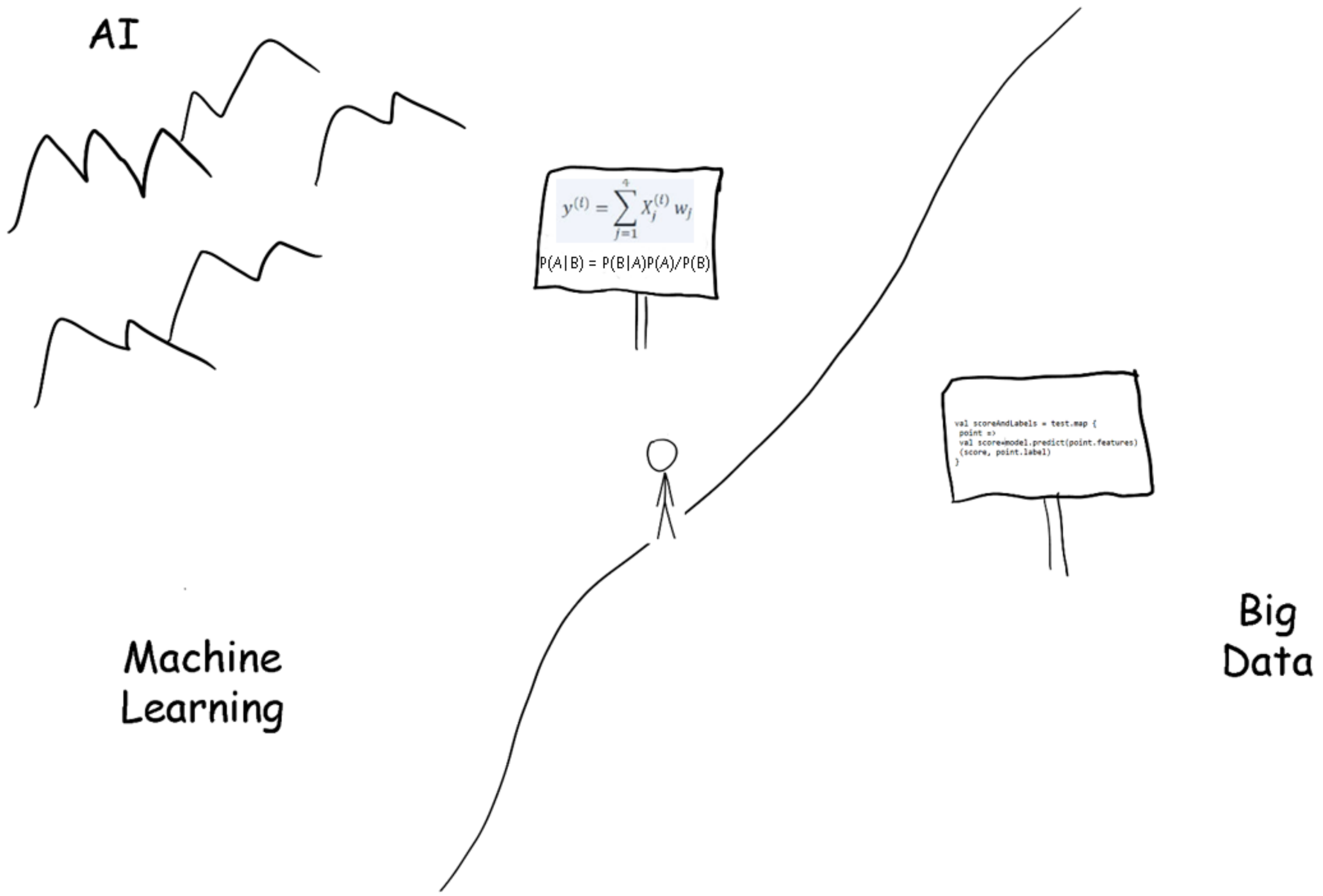
Big Data Science

Bryon Gill
Pittsburgh Supercomputing Center

The Journey Ahead



$$y^{(t)} = \sum_{j=1}^{4} X_j^{(t)} w_j$$

P(A|B) = P(B|A)P(A)/P(B)

```
val scoreAndLabels = test.map {
 point =>
 val score=model.predict(point.features)
 (score, point.label)
}
```

As the Data Scientist wanders across the ill-defined boundary between Data Science and Machine Learning, in search of the fabled land of Artificial Intelligence, they find that the language changes from programming to a creole of linear algebra and probablity and statistics.

Big data is a broad term for data sets so large or complex that traditional data processing applications are inadequate.

—*Wikipedia*

You're gonna need a bigger boat.

—*Chief Brody*

Once there was only small data...

A classic amount of “small” data

Find a tasty appetizer – Easy!

Find something to use up these cherries – grumble...

What if....

Less sophisticated is sometimes better…

“Chronologically” or “geologically” organized.
Familiar to some of you at tax time.

Get all articles from 2007.

Get all papers on “fault tolerance”
– grumble and cough

Indexing will determine your individual performance.
Teamwork can scale that up.

The culmination of centuries…

Find books on Modern Physics (DD# 539)

Find books by Wheeler

where he isn't the first author – grumble…

Your only hope…

Then data started to grow.

1956 IBM Model 350

5 MB of data!

But still pricey. $

Better think about what you want to save.

And finally got **BIG**.

8TB for $130

Whys:

Storage got cheap

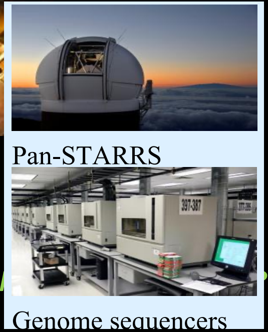
So why not keep it all?

Today data is a hot commodity $

And we got better at generating it

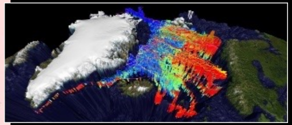
= Facebook
Deep Learning
IoT
Science...

10 TB *


Pan-STARRS
Genome sequencers
(Wikipedia Commons)

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

Wikipedia Commons


http://www.arctic.noaa.gov/report11/biodiv_whales_walrus.html

**Actually, a silly estimate. The original referen[illegible]ntions a more accurate 208TB, and in 2013 the digital collection alone was 3PB.*

A better sense of biggish

Size

- 1000 Genomes Project
  - AWS hosted
  - 260TB
- Common Crawl
  - 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) (also soon to be hosted on Bridges)
  - Only about 2.5TB per year, but...
  - 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."*

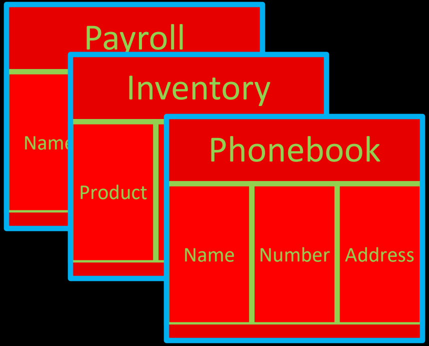
3 V's of Big Data

- Volume
- Velocity
- Variety

Good Ol' SQL couldn't keep up.

MySQL PostgreSQL Oracle SQLite

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



Why it *wasn't* fashionable:

- Schemas set in stone:
  - Need to define before we can add data
  - Not a fit for *agile development*

    "What do you mean we didn't plan to keep logs of everyone's heartbeat?"

- 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.

So we gave up: Key-Value

Redis, Memcached, Amazon DynamoDB, Riak, Ehcache

```
GET 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
```

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

How does a pile of unorganized data solve our problems?

Sure, giving up ACID buys us a lot performance, but doesn't our crude organization cost us something? Yes, but remember these guys?

This is what they look like today.

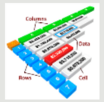
Document

```
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

Cassandra Google BigTable APACHE HBASE

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

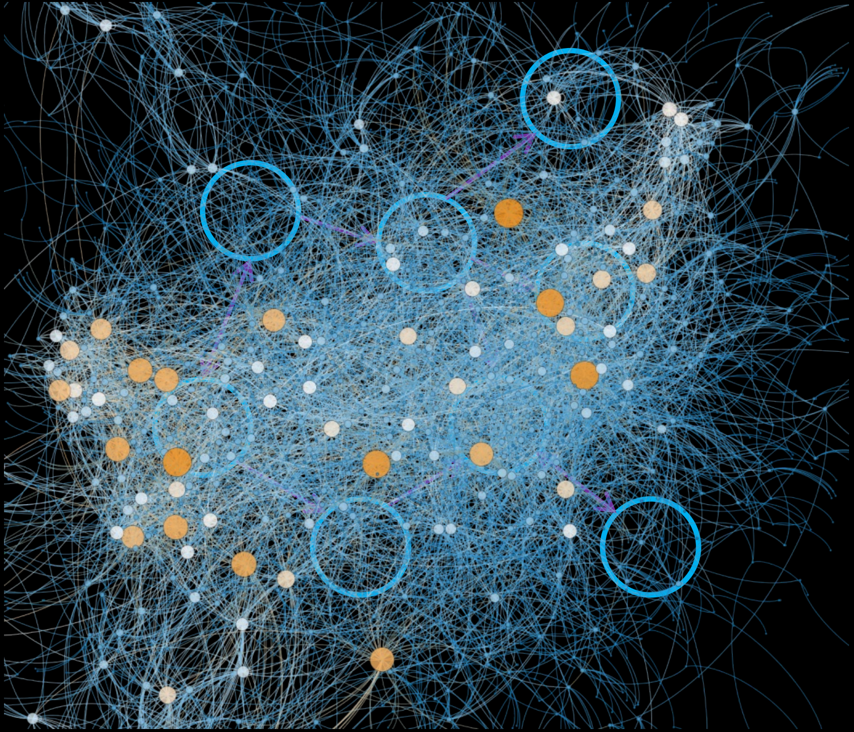
- No predefined schema
- Can think of this as a 2-D key-value store: the value may be a key-value store itself
- Different databases aggregate data differently on disk with different optimizations

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

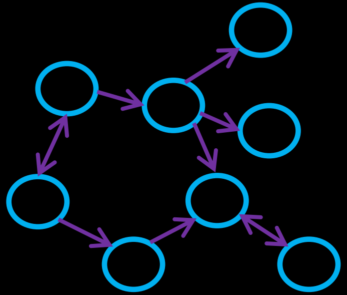
- Great for semantic web
- Great for graphs 😉
- Can be hard to visualize
- Serialization can be difficult
- Queries more complicated



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 or *ontology* (RDFS) to define rules
    - "The object of ‘homepage’ must be a Document.“
    - "Link from an actor to a movie must connect an object of type Person to an object of type Movie."

```
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
```

Graph Databases

- These are not curiosities, but are behind some of the most high-profile pieces of Web infrastructure.

- They are definitely *big* data.

Microsoft Bing Knowledge Graph	Search and conversations.	~2 billion primary entries ~55 billion facts
Facebook		~50 million primary entries ~500 million assertions
Google Knowledge Graph	Search and conversations.	~1 billion entries ~55 billion facts
LinkedIn graph		590 million members 30 million companies

Hadoop & Spark

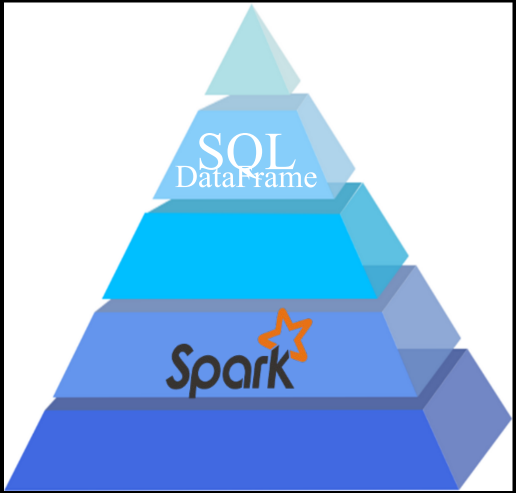
~~What kind of databases are they?~~

Frameworks for Data

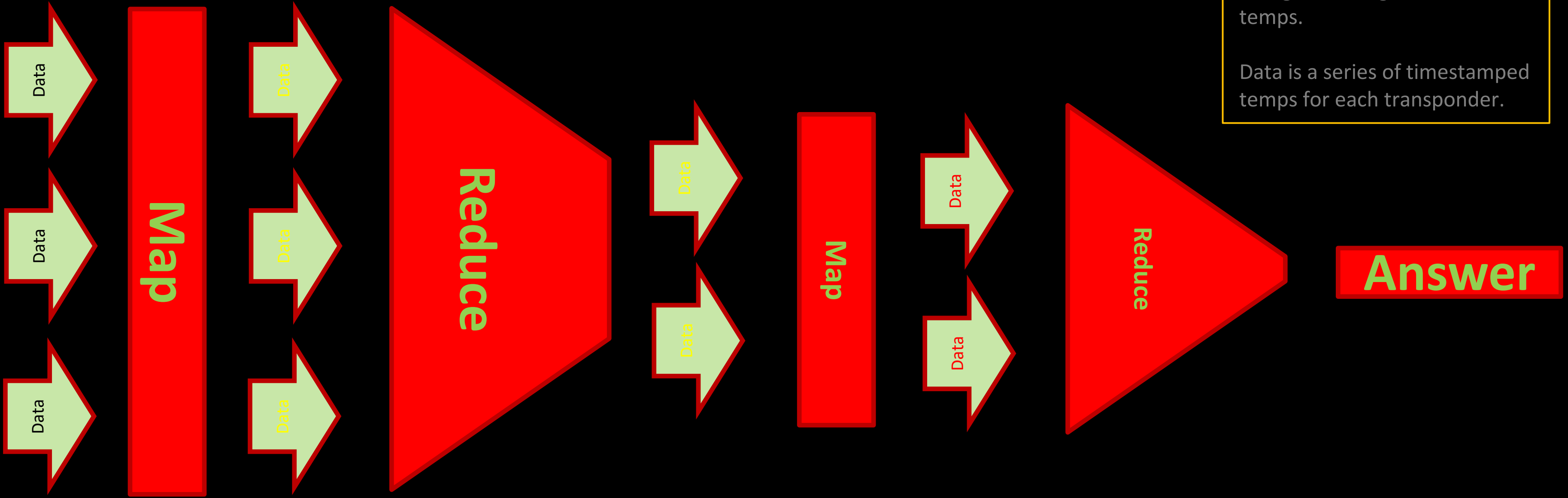
These are both frameworks for distributing and retrieving data. Hadoop is focused on disk based data and a basic map-reduce scheme, and Spark evolves that in several directions that we will get in to. Both can accommodate multiple types of databases and *achieve their performance gains by using parallel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

The mother of Hadoop was necessity. It is trendy to ridicule its primitive design, but it was the first step.

We have repurposed many of these blocks to build a better framework.



Programming = MapReduce



Ex: Need to find any recent big swings in Bering Sea surface temps.

Data is a series of timestamped temps for each transponder.

Transponder ID -> Geo Coordinates
00154301 -> 59.33, 177.60
04435354 -> 56.71, 171.73
04539340 -> 25.18, -118.89

Only keep data for Bering Sea
00154301 -> 59.33, 177.60
04435354 -> 56.71, 171.73

Find biggest change at each transponder in last 24h

00154301 -> 30
04435354 -> 5

Keep any over 20 degrees

00154301 -> 30

Hadoop Ecosystem Lives On

hadoop

HDFS

Apache Ambari

And lots more...

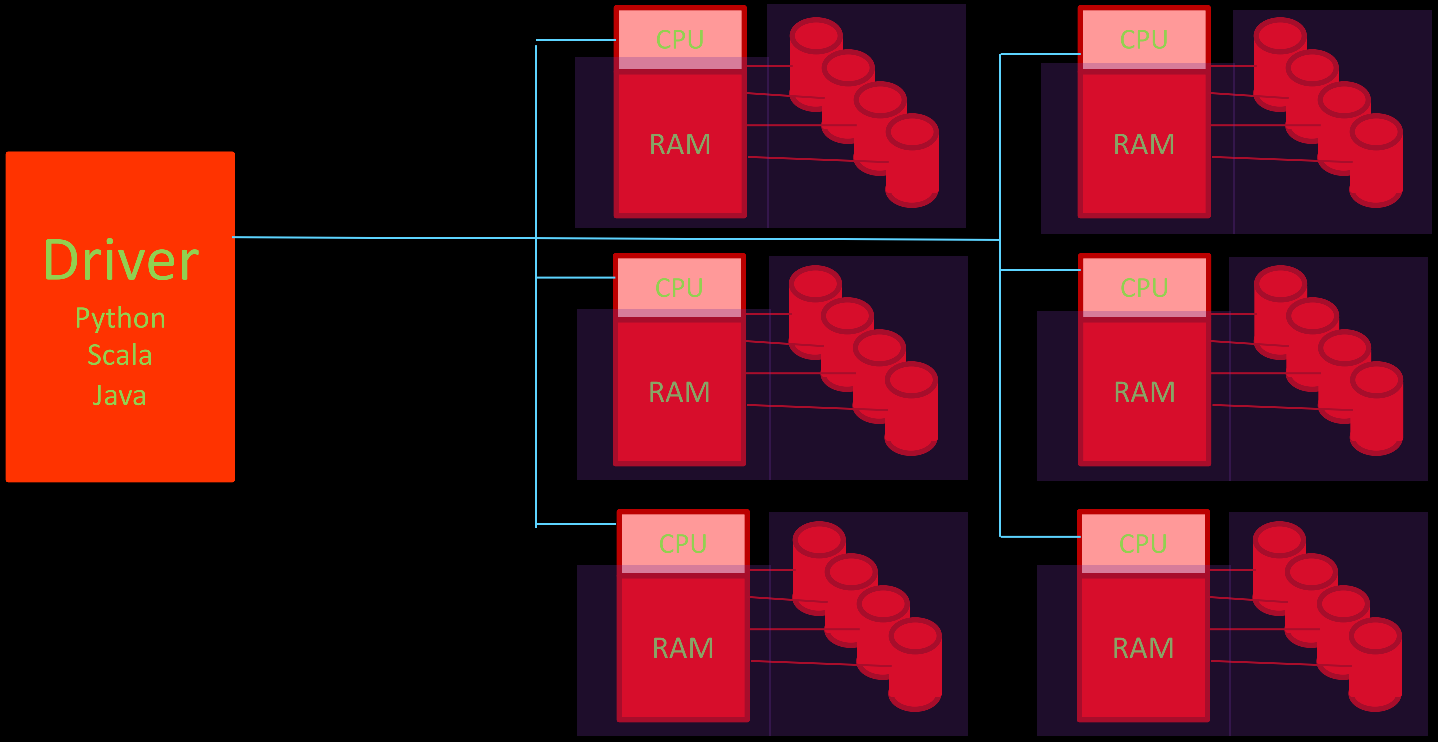
Spark Capabilities

(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.

Same Idea (improved)



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_rdd = sc.textFile("nasa_serverlog_20190404.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 filesystem, to start. Your standalone programs will have to specify one:

```
from pyspark import SparkConf, SparkContext
conf = SparkConf().setMaster("local").setAppName("Test_App")
sc = SparkContext(conf = conf)
```

You would typically run these scripts like so:

```
spark-submit Test_App.py
```

Simple Example

```
>>> lines_rdd = sc.textFile("nasa_serverlog_20190404.tsv")

>>> HubbleLines_rdd = lines_rdd.filter(lambda line: "Hubble" in line)

>>> HubbleLines_rdd.count()
47

>>> HubbleLines_rdd.first()
'www.nasa.gov\shuttle/missions/61-c/Hubble.gif‘
```

Read into RDD

Transform

Actions

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*.	Same Size
filter(func)	Return a new RDD by selecting the elements for which *func* returns true.	Fewer Elements
flatMap(func)	*func* can return multiple items, and generate a sequence, allowing us to “flatten” nested entries (JSON) into a list.	More Elements
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/reference/api/pyspark.RDD.html#pyspark.RDD

Common Actions

Action	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/reference/api/pyspark.RDD.html#pyspark.RDD

Transformations vs. Actions

Transformations go from one RDD to another[1].

Actions bring some data back from the RDD.

Transformations are where the Spark machinery can do its magic with lazy evaluation and clever algorithms to minimize communication and parallelize the processing. You want to keep your data in the RDDs as much as possible.

Actions are mostly used either at the end of the analysis when the data has been distilled down (*collect*), or along the way to "peek" at the process (*count*, *take*).

[1] Yes, some of them also create an RDD (parallelize), but you get the idea.

Pair RDDs

- Key/Value organization is a simple, but often very efficient schema, as we mentioned in our NoSQL discussion, but how do we regain some of the functionality that RDBMS systems offered us?

- Spark provides special operations on RDDs that contain key/value pairs. They are similar to the general ones that we have seen.

- RDDs are Tuples. If you have an RDD *all* of whose elements happen to be tuples of two items, it is a Pair RDD and you can use the key/value operations that follow.

Pair RDD Operations

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.

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.

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

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.

Joins Are Quite Useful

Any database designer can tell you how common joins are. Let's look at a simple example. We have (here we create it) an RD

And an RDD with all of our customers' addr

To create a mailing list of special coupons fo join on the two datasets.

If you are coming from a Pandas DataFrame background, *joins* are congruent with the *Merge* functions. If you've used them, you may have noticed that they can take some time with even small datasets. They do not scale well.

```
>>> best_customers_rdd = sc.parallelize([("Joe", "$103"), ("Alice", "$2000"), ("Bob", "$1200")])

>>> customer_addresses_rdd = sc.parallelize([("Joe", "23 State St."), ("Frank", "555 Timer Lane"), ("Sally", "44
Forest Rd."), ("Alice", "3 Elm Road"), ("Bob", "88 West Oak")])

>>> promotion_mail_rdd = best_customers_rdd.join(customer_addresses_rdd)

>>> promotion_mail_rdd.collect()
[('Bob', ('$1200', '88 West Oak')), ('Joe', ('$103', '23 State St.')), ('Alice', ('$2000', '3 Elm Road'))]
```

Spark Anti-Patterns

Here are a couple code clues that you are not working with Spark, but probably against it.

```
for loops, collect in middle of analysis, large data structures
```

```
...

intermediate_results = data_rdd.collect()

python_data = []

for datapoint in intermediate_results:
    python_data.append(modify_datapoint(datapoint))

next_rdd = sc.parallelize(python_data)

...
```

Ask yourself, "would this work with billions of elements?". And likely anything you are doing with a for is something that Spark will gladly parallelize for you, if you let it.

Who needs this Spark stuff?

As we do our first Spark exercises, you might think of several ways to accomplish these tasks that you already know. For example, Python *Pandas* is a fine way to do our following problem, and it will probably work on your laptop reasonably well. But they do not scale well*.

However we are learning how to leverage scalable techniques that work on very big data. Shortly, we will encounter problems that are considerable in size, and you will leave this workshop knowing how to harness very large resources.

Searching the *Complete Works of William Shakespeare* for patterns is a lot different from searching the entire Web (perhaps as the 800TB *Common Crawl* dataset).

So everywhere you see an RDD, realize that it is a actually a parallel databank that could scale to PBs.

* See Panda's creator Wes McKinney's "10 Things I Hate About Pandas" at https://wesmckinney.com/blog/apache-arrow-pandas-internals/

Optimizations

We said one of the advantages of Spark is that we can control things for better performance. There are a multitude of optimization, performance, tuning and programmatic features to enable better control. We quickly look at a few of the most important.

- Persistence
- Partitioning
- Parallel Programming Capabilities
- Performance and Debugging Tools

Performance & Debugging

We will give unfortunately short shrift to performance and debugging, which are both important. Mostly, this is because they are very configuration and application dependent.

Here are a few things to at least be aware of:

- SparkConf() class. A lot of options can be tweaked here.
- Spark Web UI. A very friendly way to explore all of these issues.

IO Formats

Spark has an impressive, and growing, list of input/output formats it supports. Some important ones:

- Text
- CSV
- SQL type Query/Load
  - JSON (can infer schema)
  - Parquet
  - Hive
  - XML
  - Sequence (Hadoopy key/value)
  - Databases: JDBC, Cassandra, HBase, MongoDB, etc.
- Compression (gzip…)

And it can interface directly with a variety of filesystems: local, HDFS, Lustre, Amazon S3,...

Spark Streaming

Spark addresses the need for streaming processing of data with a API that divides the data into batches, which are then processed as RDDs.

There are features to enable:

- Fast recovery from f
- Load balancing
- Integration with sta
- Integration with oth

15% of the "global datasphere" (quantification of the amount of data created, captured, and replicated across the world) is currently real-time. That number is growing quickly both in absolute terms and as a percentage.

A Few Words About DataFrames

As mentioned earlier, an appreciation for having some defined structure to your data has come back into vogue. For one, because it simply makes sense and naturally emerges in many applications. Often even more importantly, it can greatly aid optimization, especially with the Java VM that Spark uses.

For both of these reasons, you will see that the newest set of APIs to Spark are DataFrame based. This is simply SQL type columns. Very similar to Python pandas DataFrames (but based on RDDs, so not exactly).

We haven't prioritized them here because they aren't necessary, and require a little more code to line up the types properly. But some of the latest features use them.

And while they would just complicate our basic examples, they are often simpler for real research problems. So don't shy away from using them.

Creating DataFrames

It is very pretty intuitive to utilize DataFrames. Your elements just have labeled columns.

A *row RDD* is the basic way to go from RDD to DataFrame, and back, if necessary. A "row" is just a tuple.

```
>>> row_rdd = sc.parallelize([ ("Joe","Pine St.","PA",12543), ("Sally","Fir Dr.","WA",78456),
                              ("Jose","Elm Pl.","ND",45698) ])
>>>
>>> aDataFrameFromRDD = spark.createDataFrame( row_rdd, ["name", "street", "state", "zip"] )
>>> aDataFrameFromRDD.show()
+-----+--------+-----+-----+
| name|  street|state|  zip|
+-----+--------+-----+-----+
|  Joe|Pine St.|   PA|12543|
|Sally| Fir Dr.|   WA|78456|
| Jose| Elm Pl.|   ND|45698|
+-----+--------+-----+-----+
```

Just Spark DataFrames making life easier…

Data from *https://github.com/spark-examples/pyspark-examples/raw/master/resources/zipcodes.json*

```
{"RecordNumber":1,"Zipcode":704,"ZipCodeType":"STANDARD","City":"PARC PARQUE","State":"PR","LocationType":"NOT ACCEPTABLE","Lat":17.96,"Long":-66.22,"Xaxis":0.38,"Yaxis":-0.87,"Zaxis":0.3,"WorldRegion":
{"RecordNumber":2,"Zipcode":704,"ZipCodeType":"STANDARD","City":"PASEO COSTA DEL SUR","State":"PR","LocationType":"NOT ACCEPTABLE","Lat":17.96,"Long":-66.22,"Xaxis":0.38,"Yaxis":-0.87,"Zaxis":0.3,"World
{"RecordNumber":10,"Zipcode":709,"ZipCodeType":"STANDARD","City":"BDA SAN LUIS","State":"PR","LocationType":"NOT ACCEPTABLE","Lat":18.14,"Long":-66.26,"Xaxis":0.38,"Yaxis":-0.86,"Zaxis":0.31,"WorldRegion
```

```
>>> df = spark.read.json("zipcodes.json")
>>> df.printSchema()
root
 |-- City: string (nullable = true)
 |-- Country: string (nullable = true)
 |-- Decommisioned: boolean (nullable = true)
 |-- EstimatedPopulation: long (nullable = true)
 |-- Lat: double (nullable = true)
 |-- Location: string (nullable = true)
 |-- LocationText: string (nullable = true)
 |-- LocationType: string (nullable = true)
 |-- Long: double (nullable = true)
 |-- Notes: string (nullable = true)
 |-- RecordNumber: long (nullable = true)
 |-- State: string (nullable = true)
 |-- TaxReturnsFiled: long (nullable = true)
 |-- TotalWages: long (nullable = true)
 |-- WorldRegion: string (nullable = true)
 |-- Xaxis: double (nullable = true)
 |-- Yaxis: double (nullable = true)
 |-- Zaxis: double (nullable = true)
 |-- ZipCodeType: string (nullable = true)
 |-- Zipcode: long (nullable = true)
```

```
>>> df.show()
+-------------------+-------+-------------+-------------------+-----+--------------------
|               City|Country|Decommisioned|EstimatedPopulation|  Lat|            Location
+-------------------+-------+-------------+-------------------+-----+--------------------
|        PARC PARQUE|     US|        false|               null|17.96|NA-US-PR-PARC PARQUE
|PASEO COSTA DEL SUR|     US|        false|               null|17.96|NA-US-PR-PASEO CO...
|       BDA SAN LUIS|     US|        false|               null|18.14|NA-US-PR-BDA SAN ...
|  CINGULAR WIRELESS|     US|        false|               null|32.72|NA-US-TX-CINGULAR...
|         FORT WORTH|     US|        false|               4053|32.75| NA-US-TX-FORT WORTH
|           FT WORTH|     US|        false|               4053|32.75|   NA-US-TX-FT WORTH
|    URB EUGENE RICE|     US|        false|               null|17.96|NA-US-PR-URB EUGE...
|               MESA|     US|        false|              26883|33.37|       NA-US-AZ-MESA
|               MESA|     US|        false|              25446|33.38|       NA-US-AZ-MESA
|           HILLIARD|     US|        false|               7443|30.69|   NA-US-FL-HILLIARD
|             HOLDER|     US|        false|               null|28.96|     NA-US-FL-HOLDER
|               HOLT|     US|        false|               2190|30.72|       NA-US-FL-HOLT
|          HOMOSASSA|     US|        false|               null|28.78|  NA-US-FL-HOMOSASSA
|       BDA SAN LUIS|     US|        false|               null|18.14|NA-US-PR-BDA SAN ...
|      SECT LANAUSSE|     US|        false|               null|17.96|NA-US-PR-SECT LAN...
|      SPRING GARDEN|     US|        false|               null|33.97|NA-US-AL-SPRING G...
|        SPRINGVILLE|     US|        false|               7845|33.77|NA-US-AL-SPRINGVILLE
|        SPRUCE PINE|     US|        false|               1209|34.37|NA-US-AL-SPRUCE PINE
|           ASH HILL|     US|        false|               1666| 36.4|   NA-US-NC-ASH HILL
|           ASHEBORO|     US|        false|              15228|35.71|   NA-US-NC-ASHEBORO
+-------------------+-------+-------------+-------------------+-----+--------------------
```

And Sometime DataFrames Are Limiting

DataFrames are not as flexible as plain RDDs, and it isn't uncommon to find yourself fighting to do something that would be simple with a map, for example. In that case, don't hesitate to flip back into a plain RDD.

```
>>> row_rdd = sc.parallelize([ ("Joe","Pine St.","PA",12543), ("Sally","Fir Dr.","WA",78456),
                                ("Jose","Elm Pl.","ND",45698) ])

>>> aDataFrameFromRDD = spark.createDataFrame( row_rdd, ["name", "street", "state", "zip"] )

>>> another_row_rdd = aDataFrameFromRDD.rdd
```

Notice that this is not even a method, it is just a property. This is a clue that behind the scenes we are always working with RDDs.

A minor technicality here is that the returned object is actually a "Row" type. You may not care. If you want it be the original tuple type then

```
>>> tuple_rdd = aDataFrameFromRDD.rdd.map(tuple)
```

Note that when our map function is a function that already exists, there is no need for a lambda.

Speaking of pandas, or SciPy, or...

Some of you may have experience with the many Python libraries that accomplish some of these tasks. Immediately relevant to today, *pandas* allows us to sort and query data, and *SciPy* provides some nice clustering algorithms. So why not just use them?

The answer is that Spark does these things in the context of having potentially huge, parallel resources at hand. We don't notice it as Spark is also convenient, but behind every Spark call:

- every RDD could be many TB in size
- every transform could use many thousands of cores and TB of memory
- every algorithm could also use those thousands of cores

So don't think of Spark as just a data analytics library because our exercises are modest. You are learning how to cope with Big Data.

Other Scalable Alternatives: Dask

Of the many alternatives to play with data on your laptop, there are only a few that aspire to scale up to big data. The only one, besides Spark, that seems to have any traction is Dask.

It attempts to retain more of the "laptop feel" of your toy codes, making for an easier port. The tradeoff is that the scalability is a lot more mysterious. If it doesn't work - or someone hasn't scaled the piece you need - your options are limited.

At this time, I'd say it is riskier, but academic projects can often entertain more risk than industry.

Numpy like operations

```
import dask.array as da
a = da.random.random(size=(10000, 10000),
                     chunks=(1000, 1000))
a + a.T - a.mean(axis=0)
```

Dataframes implement Pandas

```
import dask.dataframe as dd
df = dd.read_csv('/.../2020-*-*.csv')
df.groupby(df.account_id).balance.sum()
```

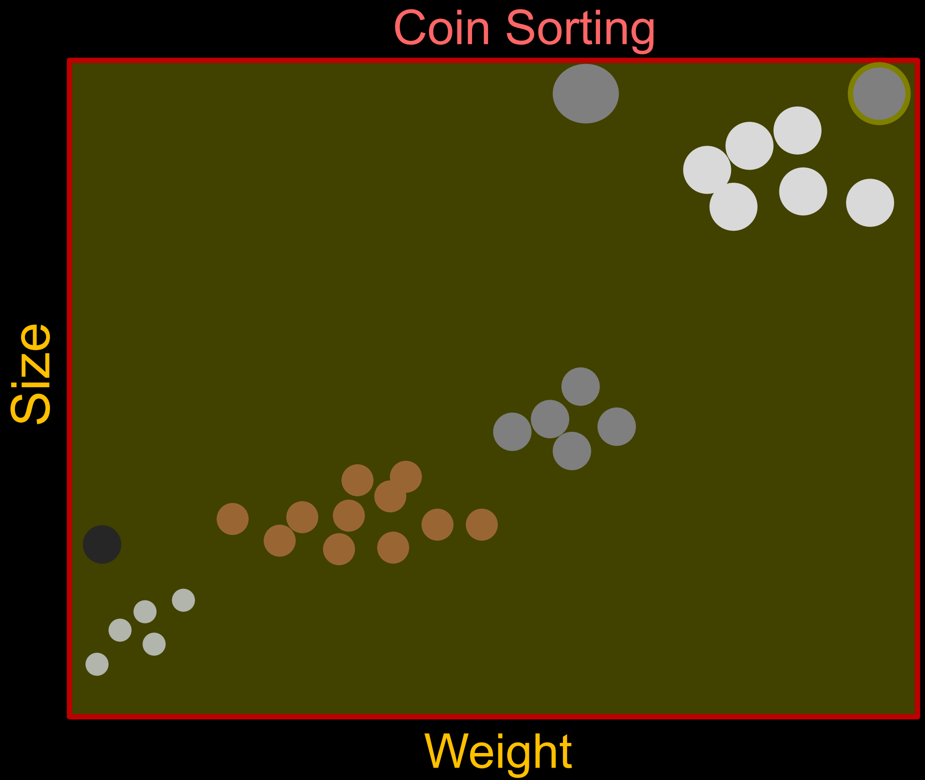
Pieces of Scikit-Learn

```
from dask_ml.linear_model import \
LogisticRegression
lr = LogisticRegression()
lr.fit(train, test)
```

Drill Down?

Clustering

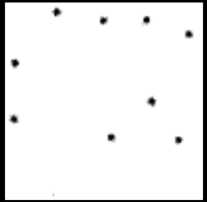
Clustering is a very common operation for finding grouping in data and has countless applications. This is a very simple example, but you will find yourself reaching for a clustering algorithm frequently in pursuing many diverse machine learning objectives, sometimes as one part of a pipeline.



Clustering

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

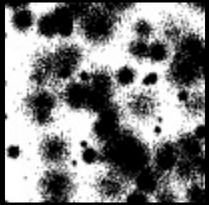
You might thi ensional spaces.



But it can get

From 1900 until 1956 humans were considered to have 48 chromosomes, instead of 46, based upon the interpretation of this camera lucida image.

Sometimes y tart with. Often you don't.
How hard can ere?



We're going to briefly look at an example with 5000 2D points. We want to figure out how many clusters there are, and their centers. Let's look at how we might approach this problem with pyspark.

Finding Our Way

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

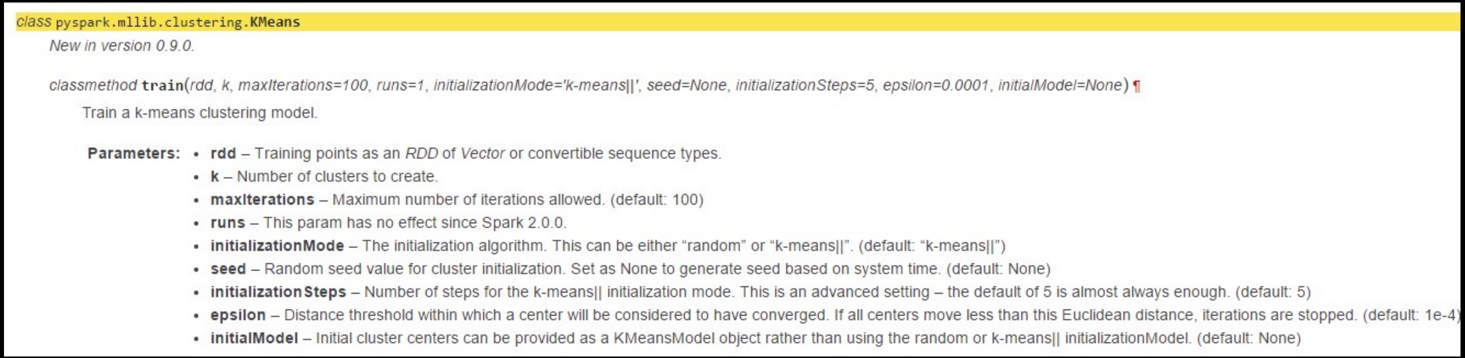
Finding Clusters

```
      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /__ / .__/\_,_/_/ /_/\_\   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])])
>>>
>>>
>>> from pyspark.mllib.clustering import KMeans
```

Read into RDD

Transform

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

```
      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /__ / .__/\_,_/_/ /_/\_\   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])])
>>>
>>> from pyspark.mllib.clustering import KMeans
>>>
>>> for clusters in range(1,30):
...     model = KMeans.train(rdd3, clusters)
...     print (clusters, model.computeCost(rdd3))
...
```

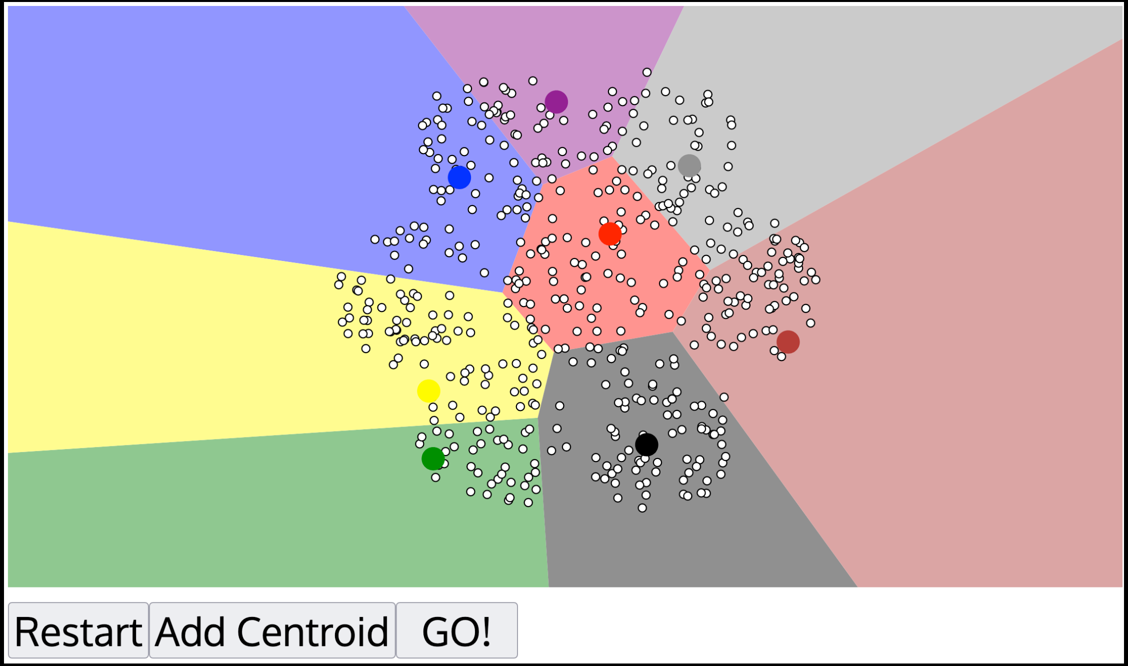
Let's see results for 1-30 cluster tries

```
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
```

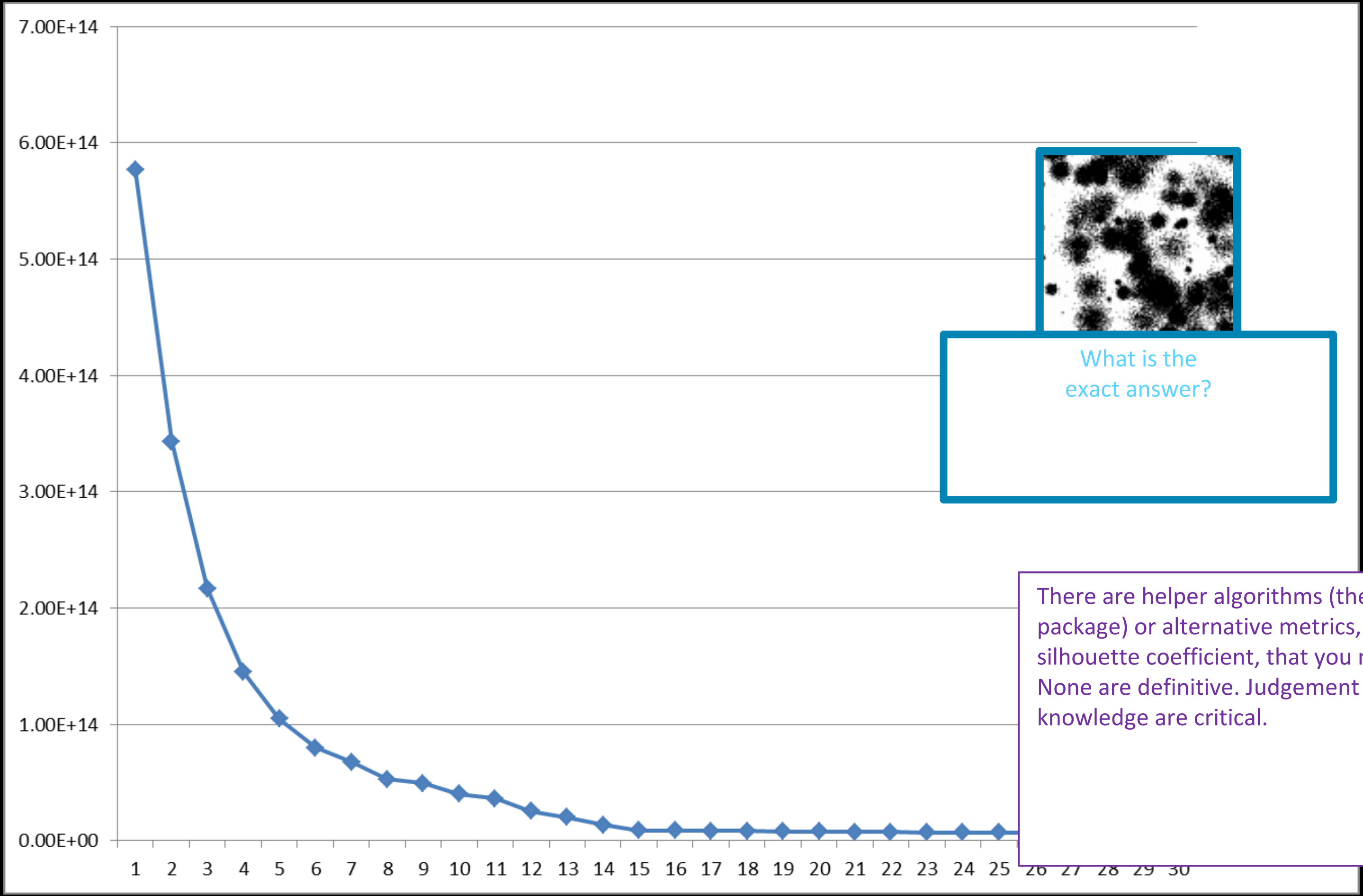
Clustering

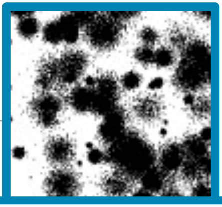
A beautiful visualization of the K-means algorithm :

https://www.naftaliharris.com/blog/visualizing-k-means-clustering/



Finding Clusters





What is the exact answer?

There are helper algorithms (the python kneed package) or alternative metrics, such as the silhouette coefficient, that you might consider. None are definitive. Judgement and domain knowledge are critical.

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
```

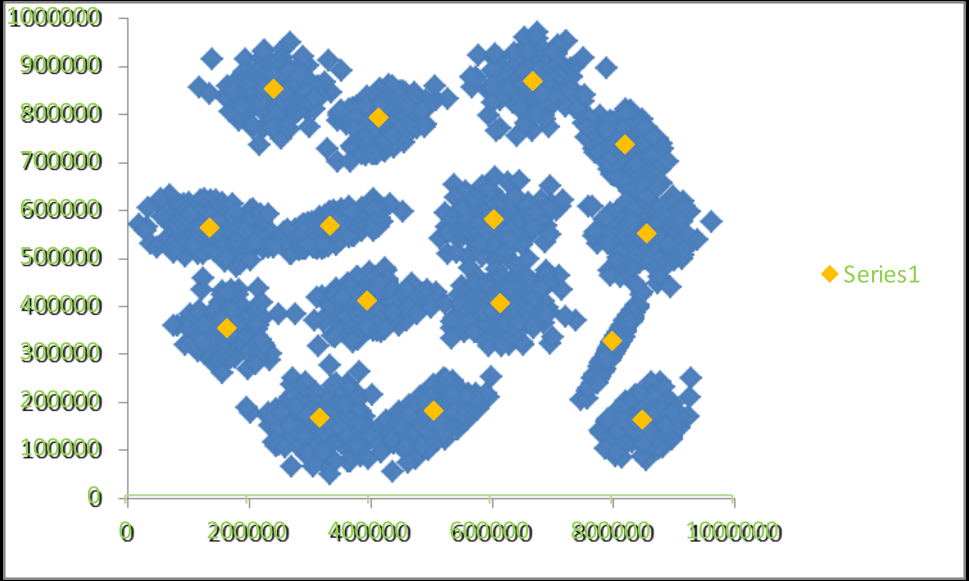
```
12 2.31466520037e+13
13 1.91856542103e+13
14 1.4933202312e+13
15 1.3506302755e+13
16 8.7757678836e+12
17 1.60075548613e+13

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

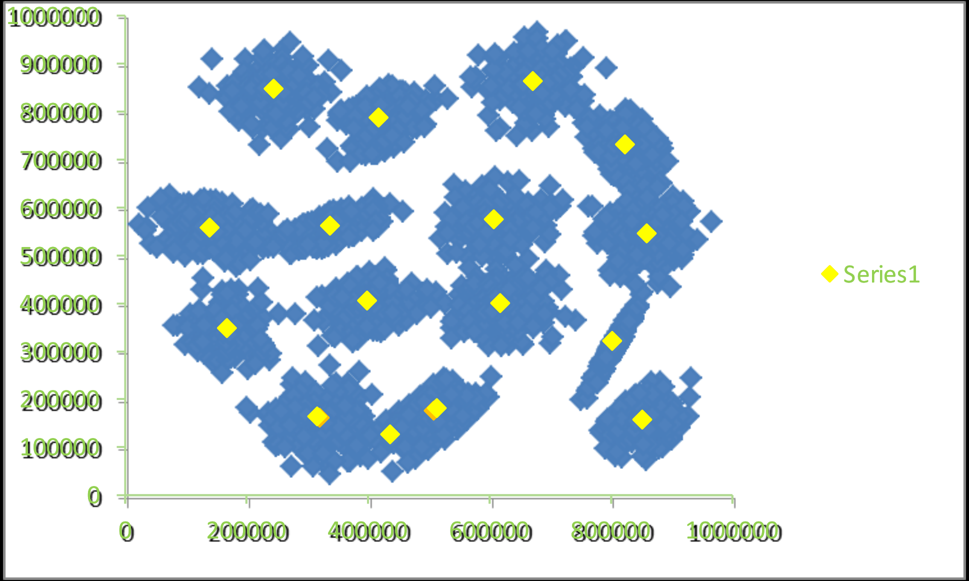
```
>>> for trials in range(10):                         #Try ten times to find best result
...    for clusters in range(12, 16):                #Only look in interesting range
...        model = KMeans.train(rdd3, clusters)
...        cost = model.computeCost(rdd3)
...        centers = model.clusterCenters            #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?

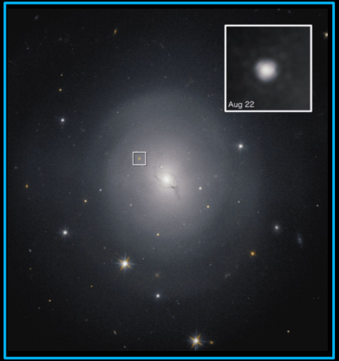

1000000
900000
800000
700000
600000
500000
400000
300000
200000
100000
0
0
200000
400000
600000
800000
1000000
◆ Series1

16 Clusters


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

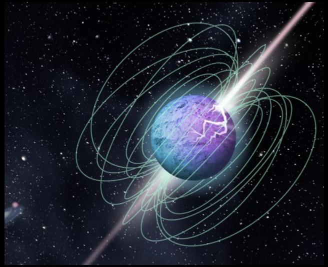
We are closer to leading edge science than you might think.

The LIGO gravitational wave detector was able to confirm the collision of two neutron stars with both a gamma ray satellite and optical and other electromagnetic spectrum telescopes. For these transient events, it requires rapid real-time signal analysis to steer other instruments to the proper celestial coordinates. The 2 second gamma-ray burst was detected 1.7 seconds after the GW merger signal. 70 observatories were able to mine signatures in the following days. Even so, the refined location alert took a long time, and much improvement lies ahead.



This rapid processing requirement will only become more extreme as the Square Kilometer Array comes fully on-line. It will generate over an Exabyte of data a day. It will require extreme real-time processing to classify and compress this data down to an archivable size.

In April 2020, astronomers picked up some bursts of activity, in the X-ray band of the spectrum, a "run-of-the-mill" magnetar. But the team found that, shortly after the magnetar burst in the X-ray band, CHIME picked up two sharp staccato peaks in the radio band, within several milliseconds of each other, signaling a fast radio burst. The researchers were able to track the radio bursts to a point in the sky that was within a fraction of a degree of SGR 1935+2154 — the same magnetar that was blasting out X-rays around the same time. The team used calibration data from other astrophysical sources to estimate the magnetar's brightness. They calculated that the magnetar, in the fraction of a second that the FRB flashed, was 3,000 times brighter than any other magnetar radio signal that has yet been observed. Happening in our own galaxy, thousands of times brighter than any other pulse we've ever seen.



Strange, repeating radio signal near the center of the Milky Way has scientists stumped

This article (www.livescience.com/strange-radio-source-milky-way-center) is the summary of the paper (arxiv.org/pdf/2109.00652.pdf) that looks an awful lot like what we are doing.

Dimensionality Reduction

We are going to find a recurring theme throughout machine learning:

- Our data naturally resides in higher dimensions
- Reducing the dimensionality makes the problem more tractable
- And simultaneously provides us with insight

This last two bullets highlight the principle that "learning" is often finding an effective compressed representation.

As we return to this theme, we will highlight these slides with our Dimensionality Reduction badge so that you can follow this thread and appreciate how fundamental it is.