Introduction to Apache Spark

This Lecture

Course Objectives and Prerequisites

What is Apache Spark?

Where Big Data Comes From?

The Structure Spectrum

Apache Spark and DataFrames

Transformations and Actions

Course Objectives

Experiment with use cases for Apache Spark

» Extract-Transform-Load operations, data analytics and visualization

Understand Apache Spark's history and development

Understand the conceptual model: DataFrames & SparkSQL

Know Apache Spark essentials

» Transformations, actions, pySpark, SparkSQL

» Basic debugging of Apache Spark programs

» Where to find answers to Spark questions

Course Prerequisites

Basic programming skills and experience

Some experience with Python 2.7

» Take this Python mini-course to learn Python quickly

Google Chrome web browser

» *Internet Explorer, Edge, Safari are not supported*

What is Apache Spark?

Scalable, *efficient analysis* of *Big Data*

What is Apache Spark?

Scalable, efficient *<u>analysis</u>* of *<u>Big Data</u>*

This lecture

What is Apache Spark?

Scalable, *efficient analysis* of *Big Data*

Next lecture

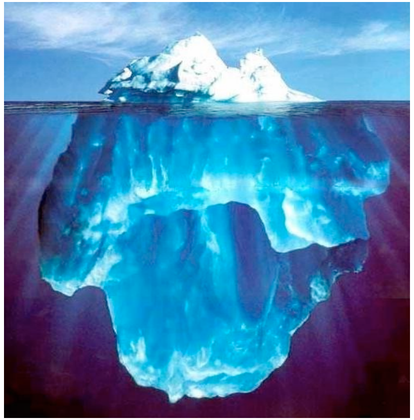
What is Apache Spark?

Scalable, *efficient analysis* of *<u>Big Data</u>*

Where Does Big Data Come From?

It's all happening online – could record every:

- » Click
- » Ad impression
- » Billing event
- » Fast Forward, pause,…
- » Server request
- » Transaction
- » Network message
- » Fault
- » …



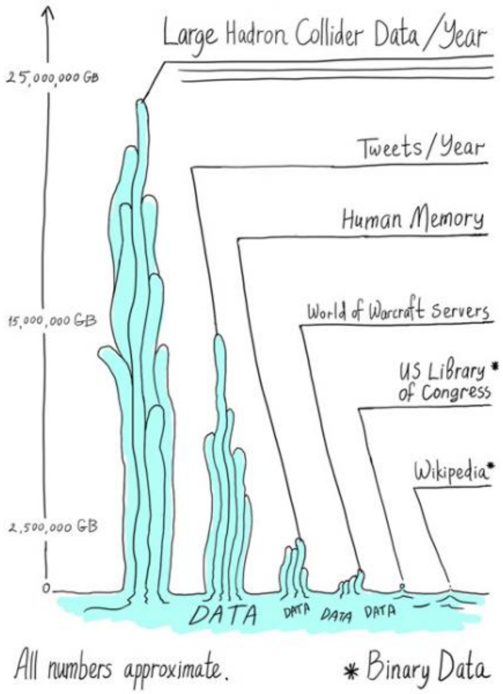
Where Does Big Data Come From?

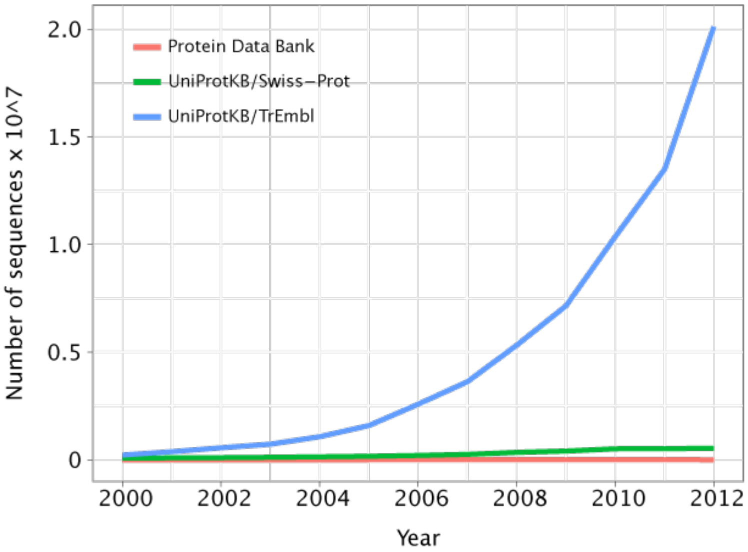
User Generated Content (Web & Mobile)

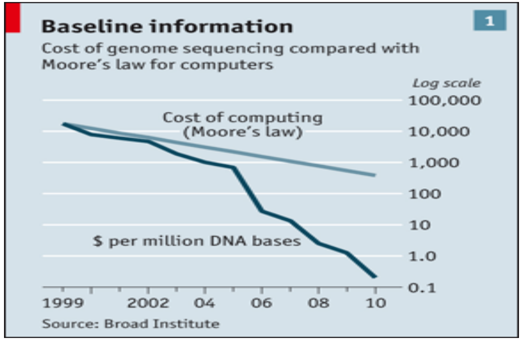
- » Facebook
- » Instagram
- » Yelp
- » TripAdvisor
- » Twitter
- » YouTube
- » …

Where Does Big Data Come From?

Health and Scientific Computing

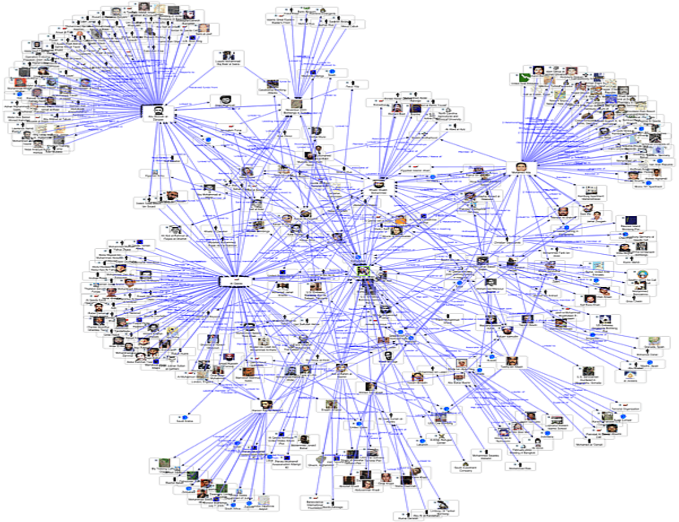






Images: http://www.economist.com/node/16349358
http://gorbi.irb.hr/en/method/growth-of-sequence-databases/
http://www.symmetrymagazine.org/article/august-2012/particle-physics-tames-big-data

Graph Data



Lots of interesting data has a graph structure:

- Social networks
- Telecommunication Networks
- Computer Networks
- Road networks
- Collaborations/Relationships
- …

Some of these graphs can get quite large
(e.g., Facebook user graph)

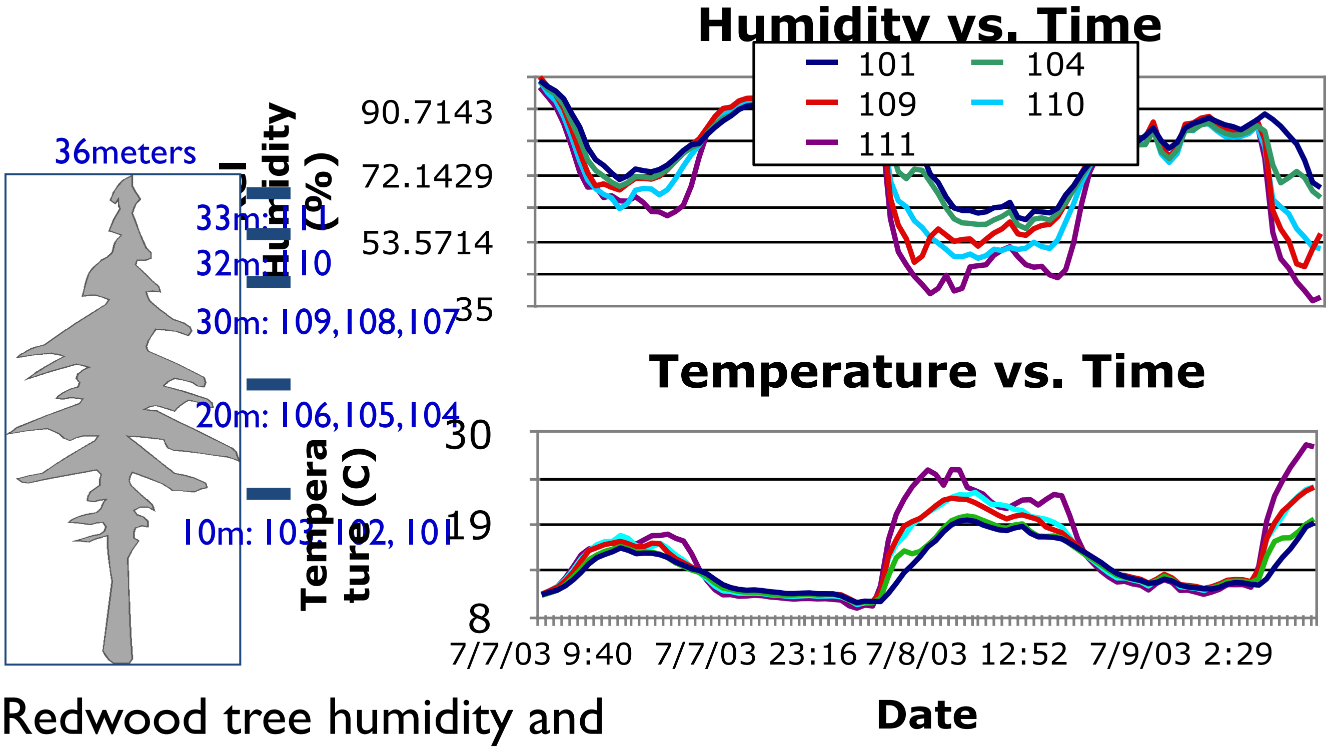
Log Files – Apache Web Server Log

```
uplherc.upl.com - - [01/Aug/1995:00:00:07 -0400] "GET / HTTP/1.0" 304 0
uplherc.upl.com - - [01/Aug/1995:00:00:08 -0400] "GET /images/ksclogo-medium.gif HTTP/
1.0" 304 0
uplherc.upl.com - - [01/Aug/1995:00:00:08 -0400] "GET /images/MOSAIC-logosmall.gif
HTTP/1.0" 304 0
uplherc.upl.com - - [01/Aug/1995:00:00:08 -0400] "GET /images/USA-logosmall.gif HTTP/
1.0" 304 0
ix-esc-ca2-07.ix.netcom.com - - [01/Aug/1995:00:00:09 -0400] "GET /images/launch-
logo.gif HTTP/1.0" 200 1713
uplherc.upl.com - - [01/Aug/1995:00:00:10 -0400] "GET /images/WORLD-logosmall.gif HTTP/
1.0" 304 0
slppp6.intermind.net - - [01/Aug/1995:00:00:10 -0400] "GET /history/skylab/skylab.htm[redacted]
HTTP/1.0" 200 1687
piweba4y.prodigy.com - - [01/Aug/1995:00:00:10 -0400] "GET /images/launchmedium.gif
HTTP/1.0" 200 11853
tampico.usc.edu - - [14/Aug/1995:22:57:13 -0400] "GET /welcome.html HTTP/1.0" 200 79[redacted]
```

Machine Syslog File

```
dhcp-47-129:CS100_1> syslog -w 10
Feb  3 15:18:11 dhcp-47-129 Evernote[1140] <Warning>: -[EDAMAccounting read:]: unexpected field ID 23 with type 8.  Skipping.
Feb  3 15:18:11 dhcp-47-129 Evernote[1140] <Warning>: -[EDAMUser read:]: unexpected field ID 17 with type 12.  Skipping.
Feb  3 15:18:11 dhcp-47-129 Evernote[1140] <Warning>: -[EDAMAuthenticationResult read:]: unexpected field ID 6 with type 11.  Skipping.
Feb  3 15:18:11 dhcp-47-129 Evernote[1140] <Warning>: -[EDAMAuthenticationResult read:]: unexpected field ID 7 with type 11.  Skipping.
Feb  3 15:18:11 dhcp-47-129 Evernote[1140] <Warning>: -[EDAMAccounting read:]: unexpected field ID 19 with type 8.  Skipping.
Feb  3 15:18:11 dhcp-47-129 Evernote[1140] <Warning>: -[EDAMAccounting read:]: unexpected field ID 23 with type 8.  Skipping.
Feb  3 15:18:11 dhcp-47-129 Evernote[1140] <Warning>: -[EDAMUser read:]: unexpected field ID 17 with type 12.  Skipping.
Feb  3 15:18:11 dhcp-47-129 Evernote[1140] <Warning>: -[EDAMSyncState read:]: unexpected field ID 5 with type 10.  Skipping.
Feb  3 15:18:49 dhcp-47-129 com.apple.mtmd[47] <Notice>: low priority thinning needed for volume Macintosh HD (/) with 18.9 <= 20.0 pct free space
```

Internet of Things:



Redwood tree humidity and temperature at various heights

Internet of Things: RFID tags

California FasTrak Electronic Toll Collection transponder

Used to pay tolls

Collected data also used for traffic reporting

- » http://www.511.org/

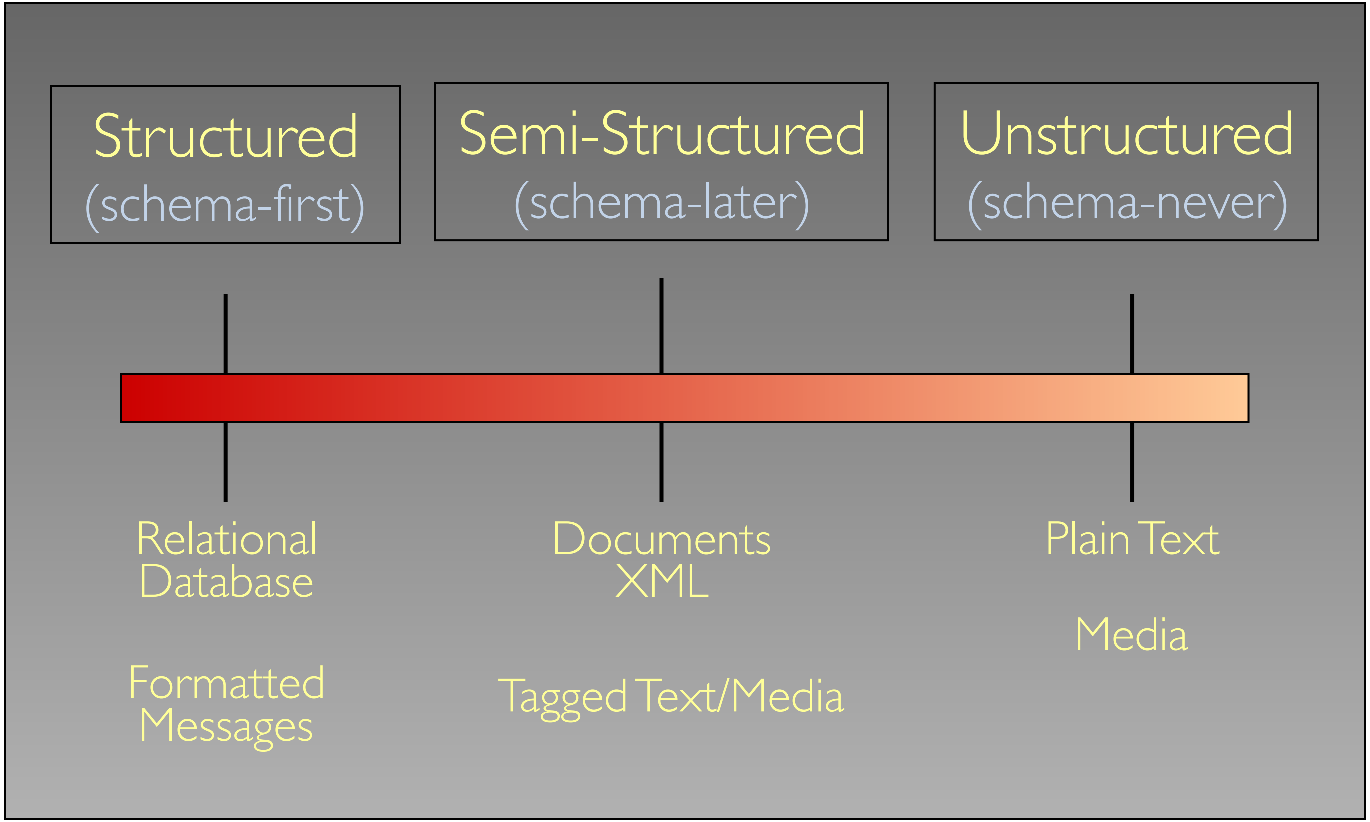
http://en.wikipedia.org/wiki/FasTrak

Key Data Management Concepts

A ***data model*** is a collection of concepts for describing data

A ***schema*** is a description of a particular collection of data, using a given data model

The Structure Spectrum



Semi-Structured Tabular Data

One of the most common data formats

A ***table*** is a collection of ***rows*** and ***columns***

Each column has a ***name***

Each cell may or may not have a ***value***

Semi-Structured Data

Each column has a ***type*** (string, integer, …)

» Together, the column types are the ***schema*** for the data

Two choices for how the ***schema*** is determined:

» Spark dynamically infers the ***schema*** while reading each row

» Programmer statically specifies the ***schema***

Tabular Data Example

Fortune 500 companies

» Top 500 US closely held and public corporations by gross revenue

	A	B	C	D	E	F	G	H	I
1	rank	company	cik	ticker	sic	state_location	state_of_incorporation	revenues	profits
2	1	Wal-Mart Stores	104169	WMT	5331	AR	DE	421849	16389
3	2	Exxon Mobil	34088	XOM	2911	TX	NJ	354674	30460
4	3	Chevron	93410	CVX	2911	CA	DE	196337	19024
5	4	ConocoPhillips	1163165	COP	2911	TX	DE	184966	11358
6	5	Fannie Mae	310522	FNM	6111	DC	DC	153825	-14014
7	6	General Electric	40545	GE	3600	CT	NY	151628	11644
8	7	Berkshire Hathaway	1067983	BRKA	6331	NE	DE	136185	12967
9	8	General Motors	1467858	GM	3711	MI	MI	135592	6172
10	9	Bank of America Corp.	70858	BAC	6021	NC	DE	134194	-2238
11	10	Ford Motor	37996	F	3711	MI	DE	128954	6561
12	11	Hewlett-Packard	47217	HPQ	3570	CA	DE	126033	8761
13	12	AT&T	732717	T	4813	TX	DE	124629	19864
14	13	J.P. Morgan Chase & Co.	19617	JPM	6021	NY	DE	115475	17370
15	14	Citigroup	831001	C	6021	NY	DE	111055	10602
16	15	McKesson	927653	MCK	5122	CA	DE	108702	1263
17	16	Verizon Communications	732712	VZ	4813	NY	DE	106565	2549
18	17	American International Group	5272	AIG	6331	NY	DE	104417	7786
19	18	International Business Machines	51143	IBM	3570	NY	NY	99870	14833
20	19	Cardinal Health	721371	CAH	5122	OH	OH	98601.9	642.2
21	20	Freddie Mac	37785	FMC	2800	PA	DE	98368	-14025

http://fortune.com/fortune500/

Protein Data Bank

```
HEADER    APOPTOSIS                               23-DEC-12   3J2T
TITLE     AN IMPROVED MODEL OF THE HUMAN APOPTOSOME
COMPND    MOL_ID: 1;
COMPND   2 MOLECULE: APOPTOTIC PROTEASE-ACTIVATING FACTOR 1;
COMPND   3 CHAIN: A, B, C, D, E, F, G;
COMPND   4 SYNONYM: APAF-1;
COMPND   5 ENGINEERED: YES;
COMPND   6 MOL_ID: 2;
COMPND   7 MOLECULE: CYTOCHROME C;
COMPND   8 CHAIN: H, I, J, K, L, M, N
SOURCE    MOL_ID: 1;
SOURCE   2 ORGANISM_SCIENTIFIC: HOMO SAPIENS;
SOURCE   3 ORGANISM_COMMON: HUMAN;
SOURCE   4 ORGANISM_TAXID: 9606;
SOURCE   5 GENE: APAF-1, APAF1, KIAA0413;
SOURCE   6 EXPRESSION_SYSTEM: SPODOPTERA FRUGIPERDA;
SOURCE   7 EXPRESSION_SYSTEM_COMMON: FALL ARMYWORM;
KEYWDS    APOPTOSIS PROTEASE ACTIVATING FACTOR-1, APAF-1, CYTOCHROME C,
KEYWDS   2 APOPTOSIS
EXPDTA    ELECTRON MICROSCOPY
AUTHOR    S.YUAN,M.TOPF,C.W.AKEY
REVDAT   2   17-APR-13 3J2T    1       JRNL
REVDAT   1   10-APR-13 3J2T    0
```

PDB Format:
Field #, Values
Field #, Values
Field #, Values
...

http://www.rcsb.org/pdb/files/3J2T.pdb

Structured Data

A **relational data model** is the most used data model

» **Relation**, a table with rows and columns

Every relation has a **schema** defining each columns' ***type***

The programmer must statically specify the ***schema***

[redacted]

Example: Instance of Students Relation

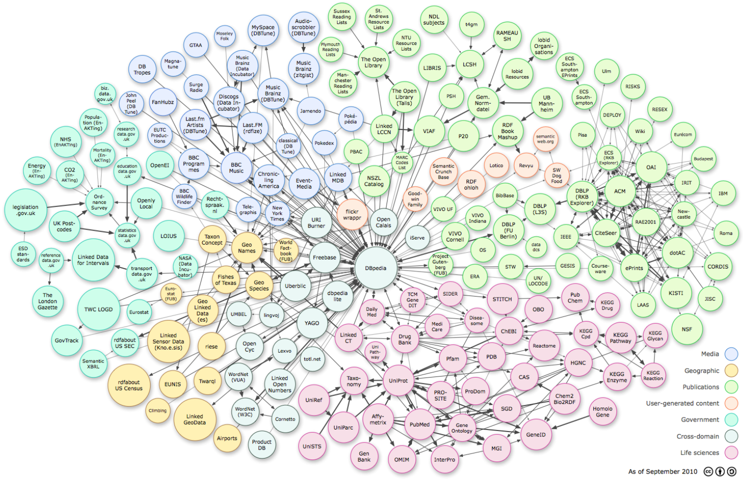
`Students(`*`sid`*`:string, `*`name`*`:string, `*`login`*`:string, `*`age`*`:integer, `*`gpa`*`:real)`

sid	name	login	age	gpa
53666	Jones	jones@eecs	18	3.4
53688	Smith	smith@statistics	18	3.2
53650	Smith	smith@math	19	3.8

Whither Structured Data?

Conventional Wisdom:

» Only 20% of data is structured



Decreasing due to:

» Consumer applications

» Enterprise search

» Media applications

http://upload.wikimedia.org/wikipedia/commons/2/23/Lod-datasets_2010-09-22_colored.png

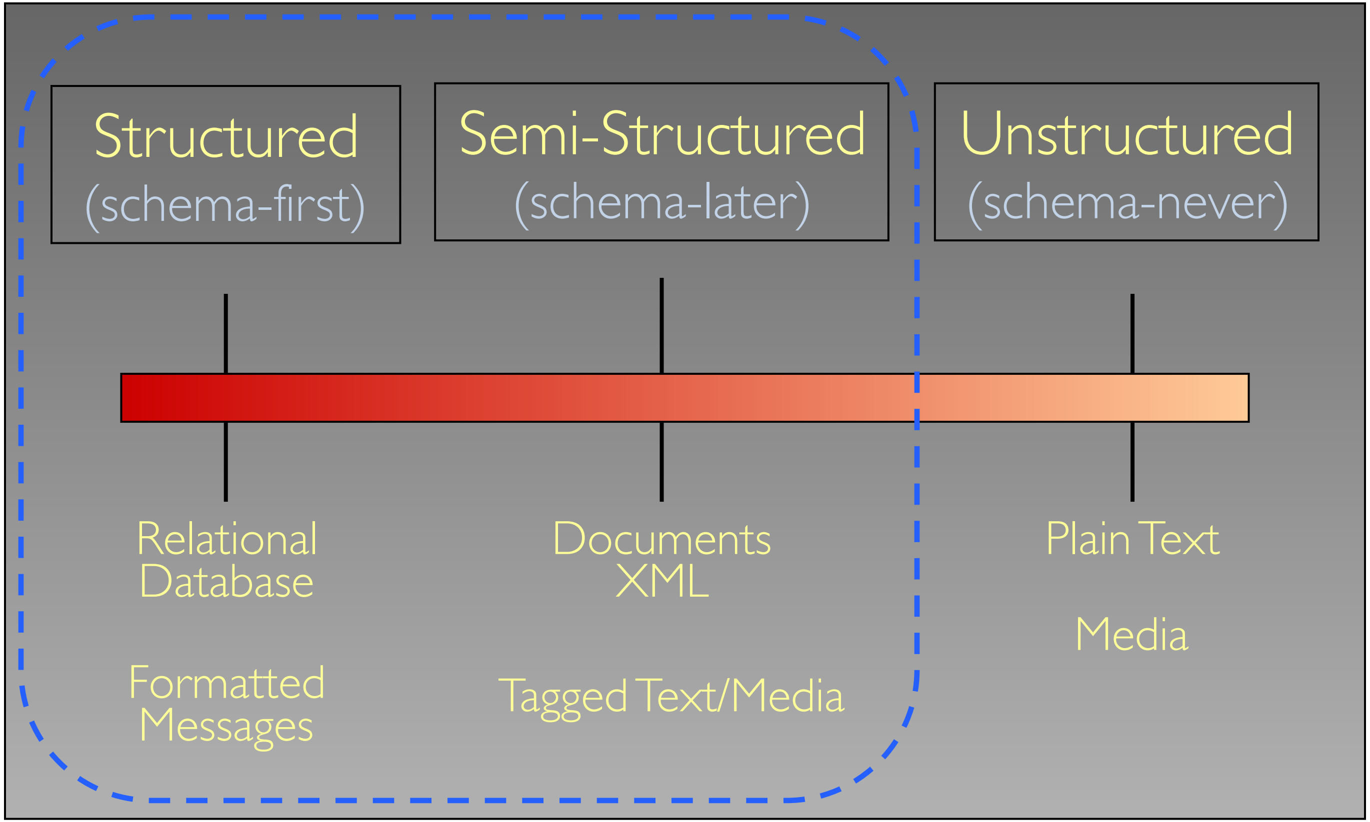
Unstructured Data

Only one column with string or binary type

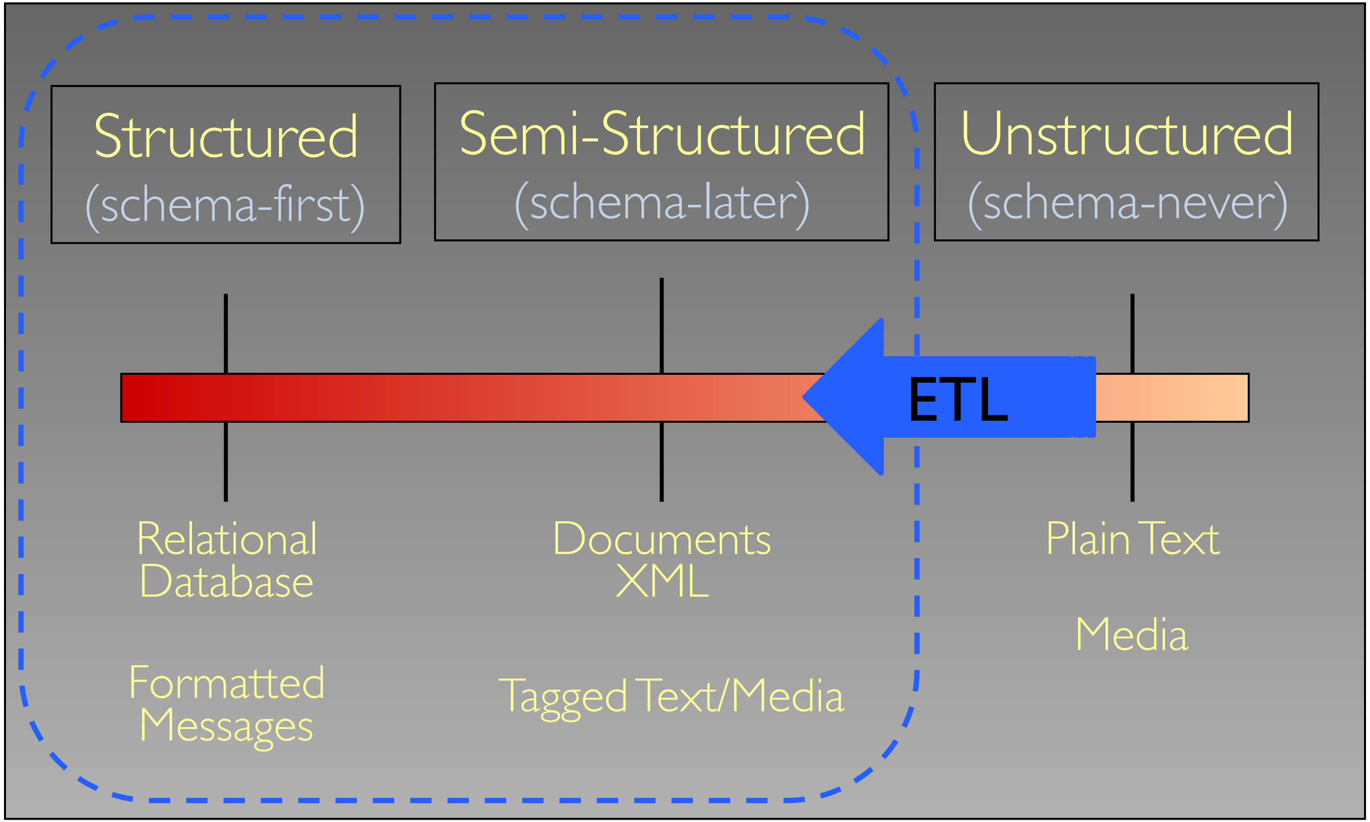
Examples:

- » Facebook post
- » Instagram image
- » Vine video
- » Blog post
- » News article
- » User Generated Content
- » …

The Structure Spectrum



The Structure Spectrum



Extract-Transform-Load

- Impose structure on unstructured data

What is Apache Spark?

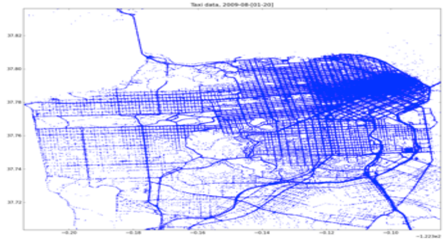
Scalable, *efficient* *<u>analysis</u>* of *Big Data*

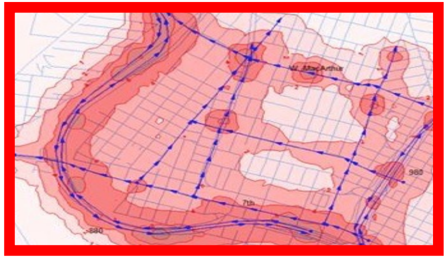
Some Traditional Analysis Tools

Unix shell commands (grep, awk, sed), pandas, R

All run on a single machine!

What Can You do with Big Data?





Crowdsourcing + Physical modeling + Sensing + Data Assimilation

=

http://traffic.berkeley.edu

Real World Spark Analysis Use Cases

Big Data Genomics using ADAM

Conviva optimizing Internet video stream delivery

Data processing for wearables and Internet of Things

Personalized Yahoo! news pages

Analytics for Yahoo! advertising

Capital One product recommendations

The Big Data Problem

Data growing faster than computation speeds

Growing data sources

» Web, mobile, scientific, …

Storage getting cheaper

» Size doubling every 18 months

But, stalling CPU speeds and storage bottlenecks

Big Data Examples

Facebook's daily logs: **60 TB**

1,000 genomes project: **200 TB**

Google web index: **10+ PB**

Cost of 1 TB of disk: **~$35**

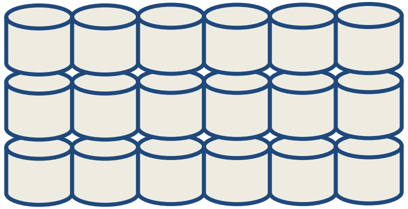
Time to read 1 TB from disk: **3 hours**
(100 MB/s)

[redacted]

The Big Data Problem

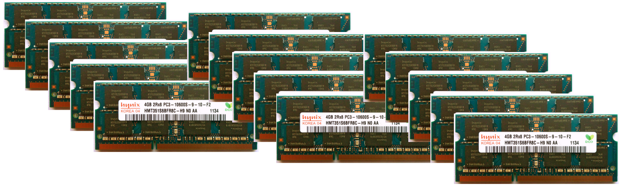
One machine can not process or even store all the data!

Solution is to **distribute** data over cluster of machines



Lots of hard drives

… and CPUs



… and memory!

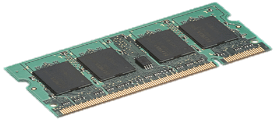
Distributed Memory

Big Data

Word	Index	Count
I	0	1
am	2	1
Sam	5	1
I	9	1
am	11	1
Sam	14	1

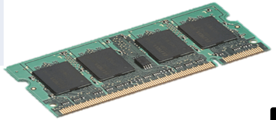
I	0	1
am	2	1

Partition 1



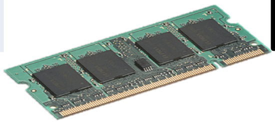
Sam	5	1
I	9	1

Partition 2



am	11	1
Sam	14	1

Partition 3



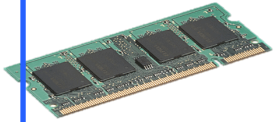
Spark DataFrames

Big Data

Word	Index	Count
I	0	1
am	2	1
Sam	5	1
I	9	1
am	11	1
Sam	14	1

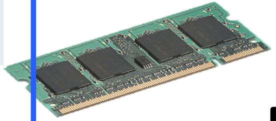
I	0	1
am	2	1

Partition 1



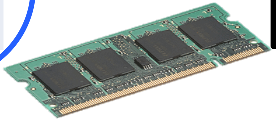
Sam	5	1
I	9	1

Partition 2



am	11	1
Sam	14	1

Partition 3



DataFrame

The Spark Computing Framework

Provides programming abstraction and parallel runtime to hide complexities of fault-tolerance and slow machines

"Here's an operation, run it on all of the data"

- » I don't care where it runs (you schedule that)
- » In fact, feel free to run it twice on different nodes

Apache Spark Components

Spark SQL

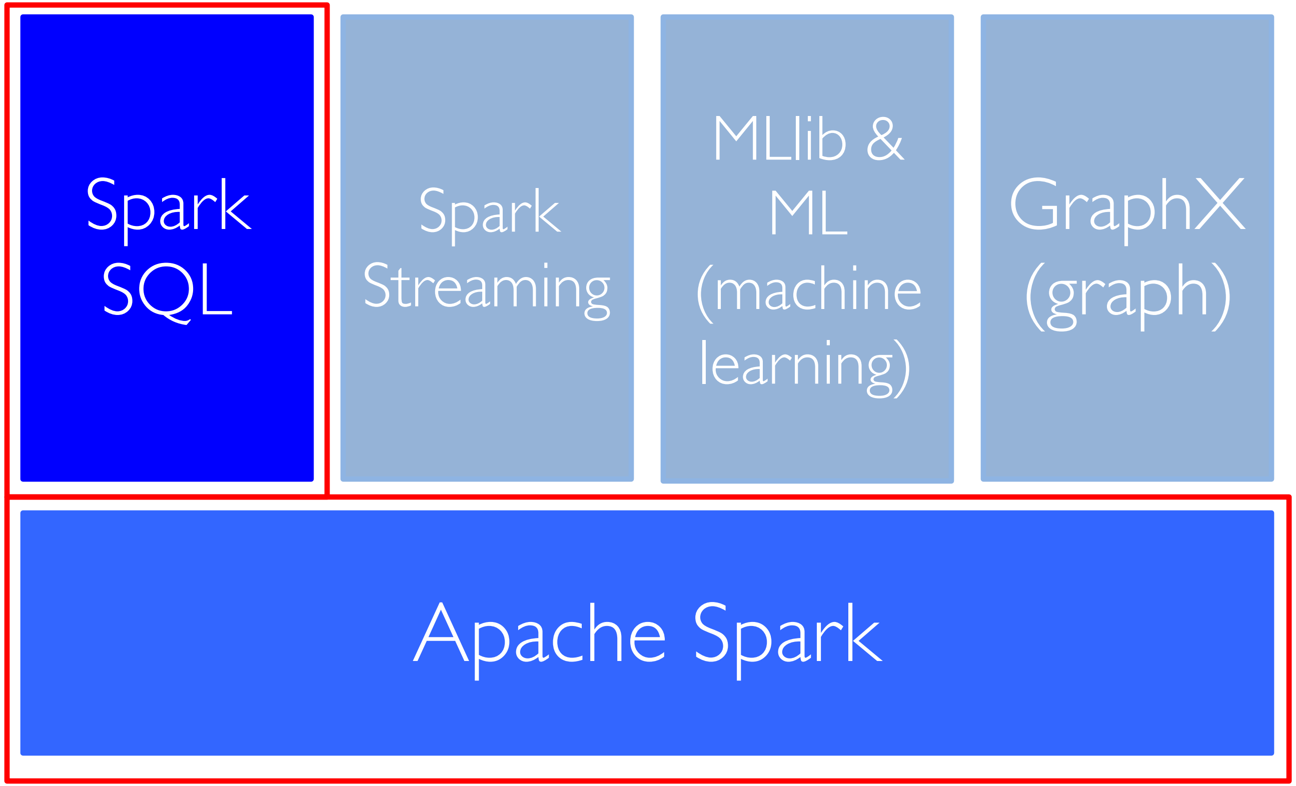
Spark Streaming

MLlib & ML (machine learning)

GraphX (graph)

Apache Spark

Apache Spark Components



Apache Spark References

http://spark.apache.org/docs/latest/programming-guide.html

http://spark.apache.org/docs/latest/api/python/index.html

http://spark.apache.org/docs/latest/api/python/pyspark.sql.html

Python Spark (pySpark)

We are using the Python programming interface to Spark (pySpark)

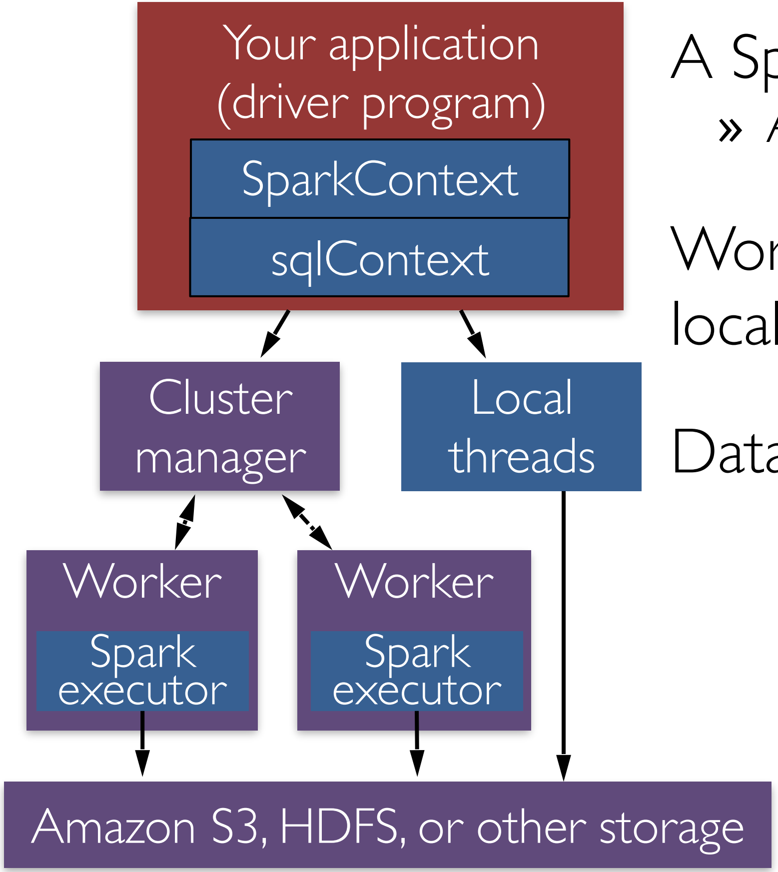
pySpark provides an easy-to-use programming abstraction and parallel runtime:

- » "Here's an operation, run it on all of the data"

DataFrames are the key concept

[redacted]

Spark Driver and Workers



A Spark program is two programs:

» A **driver program** and a **workers program**

Worker programs run on cluster nodes or in local threads

DataFrames are distributed across workers

Spark and SQL Contexts

A Spark program first creates a **`SparkContext`** object

- » **`SparkContext`** tells Spark how and where to access a cluster
- » pySpark shell, Databricks CE automatically create **`SparkContext`**
- » iPython and programs must create a new **`SparkContext`**

The program next creates a **`sqlContext`** object

Use **`sqlContext`** to create DataFrames

In the labs, we create the SparkContext and sqlContext for you

Spark Essentials: Master

The **`master`** parameter for a **`SparkContext`** determines which type and size of cluster to use

Master Parameter	Description
`local`	run Spark locally with one worker thread (no parallelism)
`local[K]`	run Spark locally with K worker threads (ideally set to number of cores)
`spark://HOST:PORT`	connect to a Spark standalone cluster; PORT depends on config (7077 by default)
`mesos://HOST:PORT`	connect to a Mesos cluster; PORT depends on config (5050 by default)

In the labs, we set the master parameter for you

DataFrames

The primary abstraction in Spark

- **Immutable once constructed**
- Track lineage information to efficiently recompute lost data
- Enable operations on collection of elements in parallel

You construct DataFrames

- by *parallelizing* existing Python collections (lists)
- by *transforming* an existing Spark or pandas DFs
- from *files* in HDFS or any other storage system

DataFrames

Each row of a DataFrame is a [Row](Row) object

The fields in a Row can be accessed like attributes

```
>>> row = Row(name="Alice", age=11)
>>> row
Row(age=11, name='Alice')
>>> row['name'], row['age']
('Alice', 11)
>>> row.name, row.age
('Alice', 11)
```

DataFrames

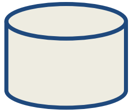
Two types of operations: *transformations* and *actions*

Transformations are lazy (*not computed immediately*)

Transformed DF is executed when action runs on it

Persist (cache) DFs in memory or disk

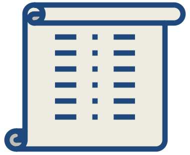
Working with DataFrames

Create a DataFrame from a data source:  <list>

Apply *transformations* to a DataFrame: select filter

Apply *actions* to a DataFrame: show count

`show` action causes **`createDataFrame`**, **`filter`**, and **`select`** transforms to be executed



Creating DataFrames

Create DataFrames from Python collections (lists)

```
>>> data = [('Alice', 1), ('Bob', 2)]
>>> data
[('Alice', 1), ('Bob', 2)]
>>> df = sqlContext.createDataFrame(data)
[Row(_1=u'Alice', _2=1), Row(_1=u'Bob', _2=2)]
>>> sqlContext.createDataFrame(data, ['name', 'age'])
[Row(name=u'Alice', age=1), Row(name=u'Bob', age=2)]
```

No computation occurs with **`sqlContext.createDataFrame()`**

- Spark only records how to create the DataFrame

pandas: Python Data Analysis Library

Open source data analysis and modeling library

- » An alternative to using R

pandas DataFrame: a table with named columns

- » The most commonly used pandas object
- » Represented as a Python Dict (column_name → Series)
- » Each pandas Series object represents a column
    - • 1-D labeled array capable of holding any data type
- » R has a similar data frame type

Creating DataFrames

Easy to create pySpark DataFrames from pandas (and R) DataFrames

```
# Create a Spark DataFrame from Pandas
>>> spark_df = sqlContext.createDataFrame(pandas_df)
```

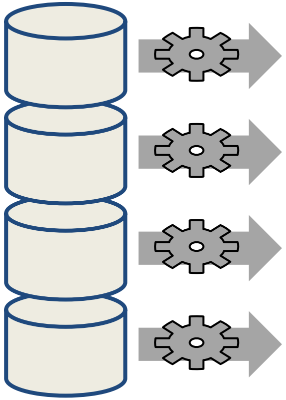
Creating DataFrames

From HDFS, text files, JSON files, Apache Parquet, Hypertable, Amazon S3, Apache Hbase, SequenceFiles, any other Hadoop `InputFormat`, and directory or glob wildcard: `/data/201404*`

```
>>> df = sqlContext.read.text("README.txt")
>>> df.collect()
[Row(value=u'hello'), Row(value=u'this')]
```

Creating a DataFrame from a File

```
distFile = sqlContext.read.text ("...")
```



Loads text file and returns a DataFrame with a single string column named "value"

Each line in text file is a row

Lazy evaluation means no execution happens now

Spark Transformations

Create new **`DataFrame`** from an existing one

Use ***lazy evaluation***: results not computed right away – Spark remembers set of transformations applied to base **`DataFrame`**

- » Spark uses *Catalyst* to optimize the required calculations
- » Spark recovers from failures and slow workers

Think of this as a recipe for creating result

Column Transformations

The apply method creates a **`DataFrame`** from one column:

```
>>> ageCol = people.age
```

Column Transformations

The apply method creates a **`DataFrame`** from one column:

```
>>> ageCol = people.age
```

You can select one or more columns from a **`DataFrame`**:

```
>>> df.select('*')
```

* selects all the columns

[redacted]

Column Transformations

The apply method creates a **`DataFrame`** from one column:

```
>>> ageCol = people.age
```

You can select one or more columns from a **`DataFrame`**:

```
>>> df.select('*')
```

* selects all the columns

```
>>> df.select('name', 'age')
```

* selects the **name** and **age** columns

Column Transformations

The apply method creates a **`DataFrame`** from one column:

```
>>> ageCol = people.age
```

You can select one or more columns from a **`DataFrame`**:

```
>>> df.select('*')
```

* selects all the columns

```
>>> df.select('name', 'age')
```

* selects the **name** and **age** columns

```
>>> df.select(df.name,
              (df.age + 10).alias('age'))
```

* selects the **name** and **age** columns,
increments the values in the **age** column by 10,
and renames (alias) the **age +10** column as **age**

More Column Transformations

The drop method returns a new **`DataFrame`** that drops the specified column:

```
>>> df.drop(df.age)
[Row(name=u'Alice'), Row(name=u'Bob')]
```

Review: Python `lambda` Functions

Small anonymous functions (not bound to a name)

```
lambda a, b: a + b
```

» returns the sum of its two arguments

Can use lambda functions wherever function objects are required

Restricted to a single expression

[redacted]

User Defined Function Transformations

Transform a **`DataFrame`** using a User Defined Function

```
>>> from pyspark.sql.types import IntegerType
>>> slen = udf(lambda s: len(s), IntegerType())
>>> df.select(slen(df.name).alias('slen'))
```

* Creates a `DataFrame` of [`Row`(slen=5), `Row`(slen=3)]

[UDF](UDF) takes named or lambda function and the return type of the function

Other Useful Transformations

Transformation	Description
`filter(func)`	returns a new `DataFrame` formed by selecting those rows of the source on which *func* returns true
`where(func)`	`where` is an alias for `filter`
`distinct()`	return a new `DataFrame` that contains the distinct rows of the source `DataFrame`
`orderBy(*cols, **kw)`	returns a new `DataFrame` sorted by the specified *column(s)* and in the sort order specified by *kw*
`sort(*cols, **kw)`	Like `orderBy`, `sort` returns a new `DataFrame` sorted by the specified *column(s)* and in the sort order specified by *kw*
`explode(col)`	returns a new row for each element in the given array or map

`func` is a Python named function or `lambda` function

Using Transformations (I)

```
>>> df = sqlContext.createDataFrame(data, ['name', 'age'])
[Row(name=u'Alice', age=1), Row(name=u'Bob', age=2)]
```

Using Transformations (I)

```
>>> df = sqlContext.createDataFrame(data, ['name', 'age'])
[Row(name=u'Alice', age=1), Row(name=u'Bob', age=2)]

>>> from pyspark.sql.types import IntegerType
>>> doubled = udf(lambda s: s * 2, IntegerType())
>>> df2 = df.select(df.name, doubled(df.age).alias('age'))
[Row(name=u'Alice', age=2), Row(name=u'Bob', age=4)]
```

* selects the **name** and **age** columns, applies the UDF to **age** column and aliases resulting column to **age**

Using Transformations (I)

```
>>> df = sqlContext.createDataFrame(data, ['name', 'age'])
[Row(name=u'Alice', age=1), Row(name=u'Bob', age=2)]

>>> from pyspark.sql.types import IntegerType
>>> doubled = udf(lambda s: s *2, IntegerType())
>>> df2 = df.select(df.name, doubled(df.age).alias('age'))
[Row(name=u'Alice', age=2), Row(name=u'Bob', age=4)]
```

* selects the **name** and **age** columns, applies the UDF to **age** column and aliases resulting column to **age**

```
>>> df3 = df2.filter(df2.age > 3)
[Row(name=u'Bob', age=4)]
```

* only keeps rows with **age** column greater than 3

Using Transformations (II)

```
>>> data2 = [('Alice', 1), ('Bob', 2), ('Bob', 2)]
>>> df = sqlContext.createDataFrame(data2, ['name', 'age'])
[Row(name=u'Alice', age=1), Row(name=u'Bob', age=2),
   Row(name=u'Bob', age=2)]
>>> df2 = df.distinct()
[Row(name=u'Alice', age=1), Row(name=u'Bob', age=2)]
```

* only keeps rows that are distinct

Using Transformations (II)

```
>>> data2 = [('Alice', 1), ('Bob', 2), ('Bob', 2)]
>>> df = sqlContext.createDataFrame(data2, ['name', 'age'])
[Row(name=u'Alice', age=1), Row(name=u'Bob', age=2),
   Row(name=u'Bob', age=2)]
>>> df2 = df.distinct()
[Row(name=u'Alice', age=1), Row(name=u'Bob', age=2)]
```

* only keeps rows that are distinct

```
>>> df3 = df2.sort("age", ascending=False)
[Row(name=u'Bob', age=2),
   Row(name=u'Alice', age=1)]
```

* sort ascending on the **age** column

Using Transformations (III)

```
>>> data3 = [Row(a=1, intlist=[1,2,3])]
>>> df4 = sqlContext.createDataFrame(data3)
[Row(a=1, intlist=[1,2,3])]
>>> df4.select(explode(df4.intlist).alias("anInt"))
[Row(anInt=1), Row(anInt=2), Row(anInt=3)]
```

- turn each element of the `intlist` column into a `Row`, alias the resulting column to `anInt`, and select only that column

GroupedData Transformations

groupBy(*cols) groups the **DataFrame** using the specified columns, so we can run aggregation on them

GroupedData Function	Description
`agg(*exprs)`	Compute aggregates (avg, max, min, sum, or count) and returns the result as a `DataFrame`
`count()`	counts the number of records for each group
`avg(*args)`	computes average values for numeric columns for each group

Using GroupedData (I)

```
>>> data = [('Alice',1,6), ('Bob',2,8), ('Alice',3,9), ('Bob',4,7)]
>>> df = sqlContext.createDataFrame(data, ['name', 'age', 'grade'])
>>> df1 = df.groupBy(df.name)
>>> df1.agg({"*": "count"}).collect()
[Row(name=u'Alice', count(1)=2), Row(name=u'Bob', count(1)=2)]
```

Using GroupedData (I)

```
>>> data = [('Alice',1,6), ('Bob',2,8), ('Alice',3,9), ('Bob',4,7)]
>>> df = sqlContext.createDataFrame(data, ['name', 'age', 'grade'])
>>> df1 = df.groupBy(df.name)
>>> df1.agg({"*": "count"}).collect()
[Row(name=u'Alice', count(1)=2), Row(name=u'Bob', count(1)=2)]

>>> df.groupBy(df.name).count()
[Row(name=u'Alice', count=2), Row(name=u'Bob', count=2)]
```

Using GroupedData (II)

```
>>> data = [('Alice',1,6), ('Bob',2,8), ('Alice',3,9), ('Bob',4,7)]
>>> df = sqlContext.createDataFrame(data, ['name', 'age', 'grade'])
>>> df.groupBy().avg().collect()
[Row(avg(age)=2.5, avg(grade)=7.5)]
```

Using GroupedData (II)

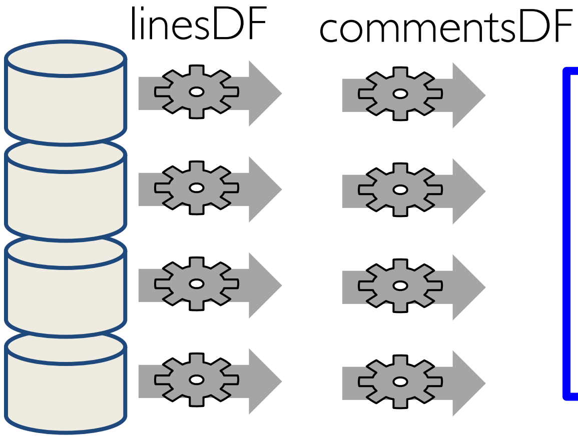
```
>>> data = [('Alice',1,6), ('Bob',2,8), ('Alice',3,9), ('Bob',4,7)]
>>> df = sqlContext.createDataFrame(data, ['name', 'age', 'grade'])
>>> df.groupBy().avg().collect()
[Row(avg(age)=2.5, avg(grade)=7.5)]

>>> df.groupBy('name').avg('age', 'grade').collect()
[Row(name=u'Alice', avg(age)=2.0, avg(grade)=7.5),
    Row(name=u'Bob', avg(age)=3.0, avg(grade)=7.5)]
```

Transforming a DataFrame

```
linesDF = sqlContext.read.text('...')

commentsDF = linesDF.filter(isComment)
```



Lazy evaluation means nothing executes – Spark saves recipe for transforming source

[redacted]

Spark Actions

Cause Spark to execute recipe to transform source

Mechanism for getting results out of Spark

Some Useful Actions

Action	Description
`show(n, truncate)`	prints the first *n* rows of the **`DataFrame`**
`take(n)`	returns the first *n* rows as a list of **`Row`**
`collect()`	return all the records as a list of **`Row`** WARNING: make sure will fit in driver program
`count()`+	returns the number of rows in this **`DataFrame`**
`describe(*cols)`	Exploratory Data Analysis function that computes statistics (count, mean, stddev, min, max) for numeric columns – if no columns are given, this function computes statistics for all numerical columns

+**`count`** for **`DataFrames`** is an action, while for **`GroupedData`** it is a transformation

Getting Data Out of DataFrames (I)

```
>>> df = sqlContext.createDataFrame(data, ['name', 'age'])
>>> df.collect()
[Row(name=u'Alice', age=1), Row(name=u'Bob', age=2)]
```

Getting Data Out of DataFrames (I)

```
>>> df = sqlContext.createDataFrame(data, ['name', 'age'])
>>> df.collect()
[Row(name=u'Alice', age=1), Row(name=u'Bob', age=2)]

>>> df.show()
+-----+---+
| name|age|
+-----+---+
|Alice|  1|
|  Bob|  2|
+-----+---+
```

Getting Data Out of DataFrames (I)

```
>>> df = sqlContext.createDataFrame(data, ['name', 'age'])
>>> df.collect()
[Row(name=u'Alice', age=1), Row(name=u'Bob', age=2)]

>>> df.show()
+-----+---+
| name|age|
+-----+---+
|Alice|  1|
|  Bob|  2|
+-----+---+

>>> df.count()
2
```

[redacted]

Getting Data Out of DataFrames (II)

```
>>> df = sqlContext.createDataFrame(data, ['name', 'age'])
>>> df.take(1)
[Row(name=u'Alice', age=1)]
```

Getting Data Out of DataFrames (II)

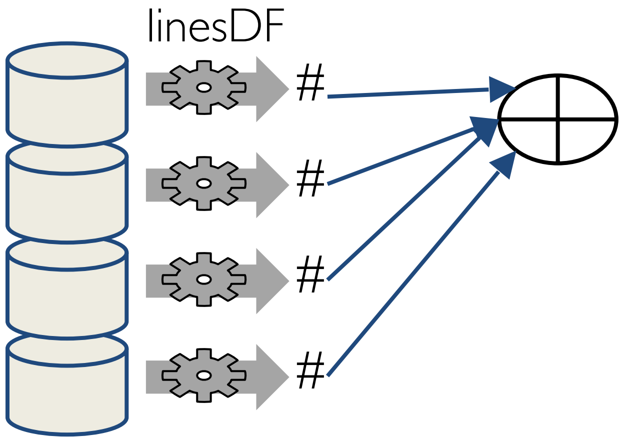
```
>>> df = sqlContext.createDataFrame(data, ['name', 'age'])
>>> df.take(1)
[Row(name=u'Alice', age=1)]

>>> df.describe()
+-------+------------------+
|summary|               age|
+-------+------------------+
|  count|                 2|
|   mean|               1.5|
| stddev|0.7071067811865476|
|    min|                 1|
|    max|                 2|
+-------+------------------+
```

Spark Programming Model

```
linesDF = sqlContext.read.text('...')

print linesDF.count()
```

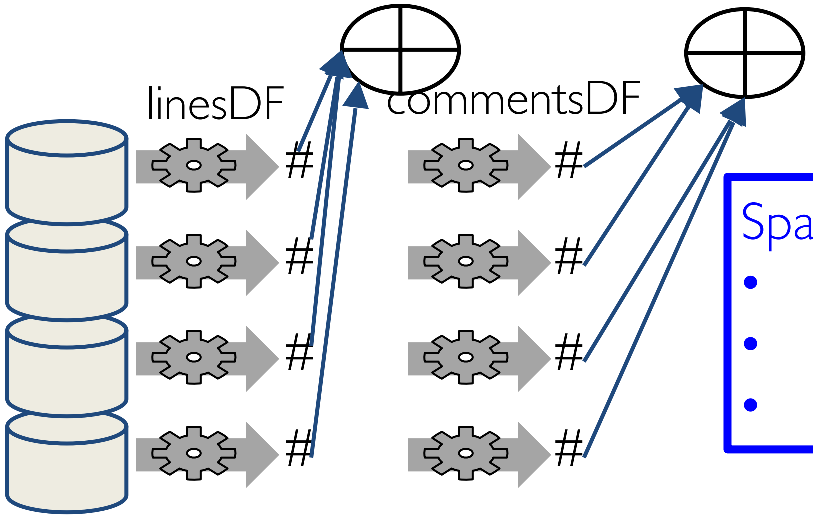


`count()` causes Spark to:

- read data
- sum within partitions
- combine sums in driver

Spark Programming Model

```
linesDF = sqlContext.read.text('...')
commentsDF = linesDF.filter(isComment)
print linesDF.count(), commentsDF.count()
```

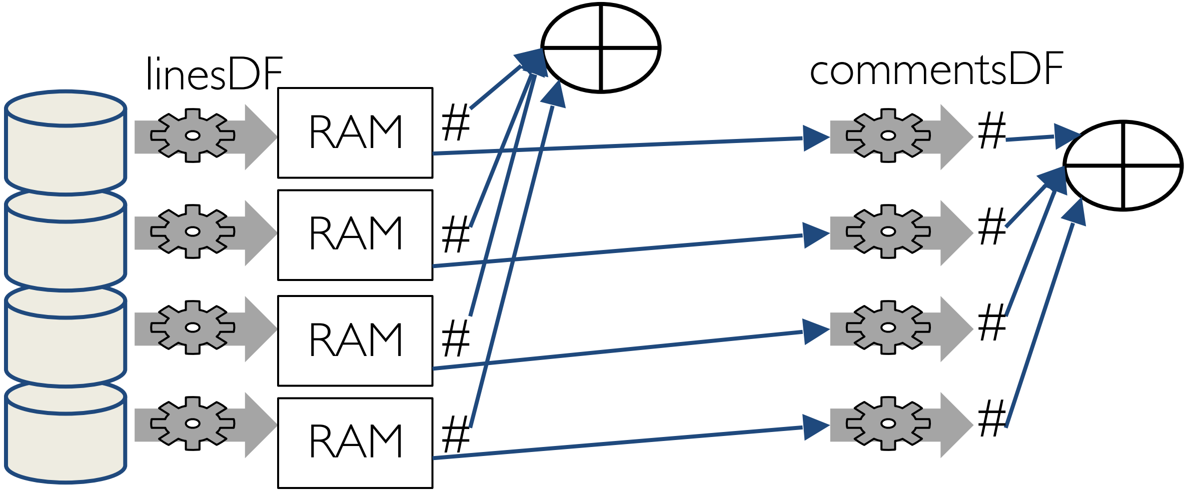


Spark recomputes linesDF:
- read data (again)
- sum within partitions
- combine sums in driver

[redacted]

Caching DataFrames

```
linesDF = sqlContext.read.text('...')
linesDF.cache() # save, don't recompute!
commentsDF = linesDF.filter(isComment)
print linesDF.count(),commentsDF.count()
```



Spark Program Lifecycle

1. Create DataFrames from external data or createDataFrame from a collection in driver program

2. Lazily transform them into new DataFrames

3. **`cache()`** some DataFrames for reuse

4. Perform actions to execute parallel computation and produce results

Local or Distributed?

Where does code run?

» Locally, in the driver

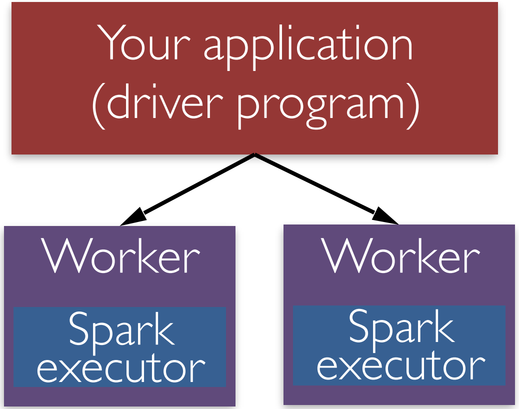
» Distributed at the executors

» Both at the driver and the executors

Very important question:

» Executors run in parallel

» Executors have much more memory



[redacted]

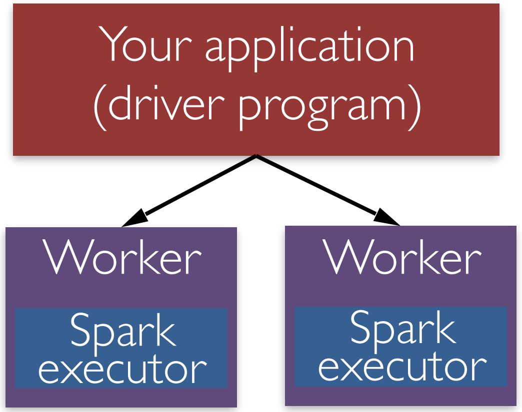
Where Code Runs

Most Python code runs in driver

» Except for code passed to transformations

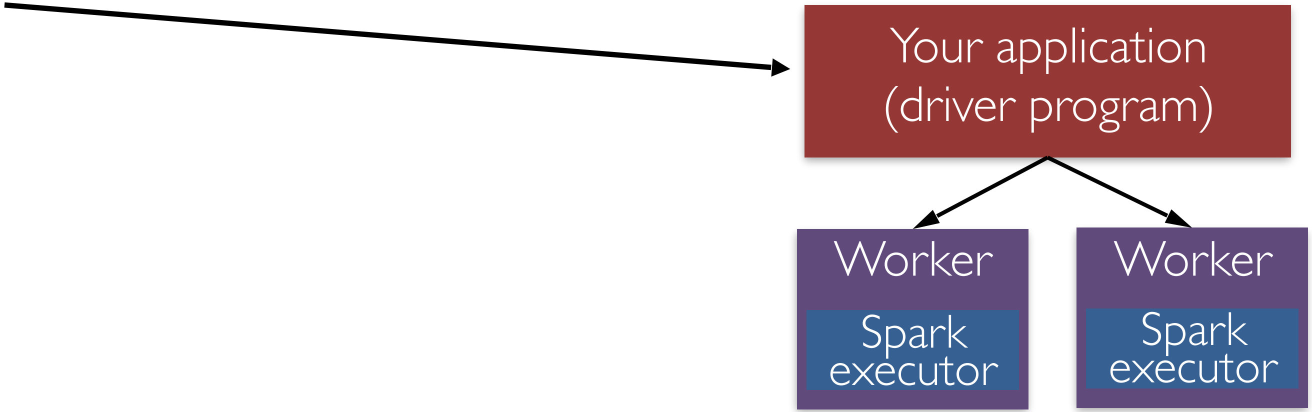
Transformations run at executors

Actions run at executors and driver



Examples

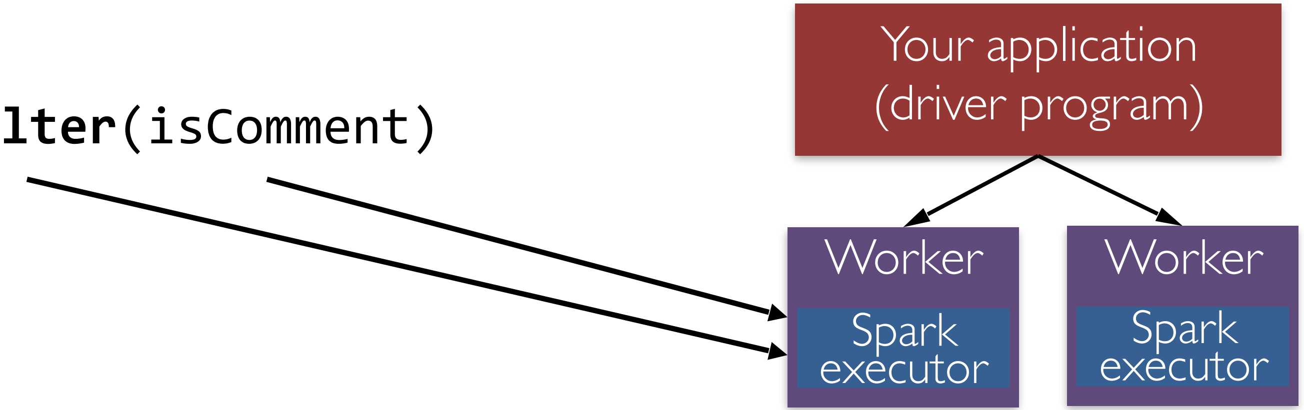
```
>>> a = a + 1
```



Examples

```
>>> a = a + 1

>>> linesDF.filter(isComment)
```

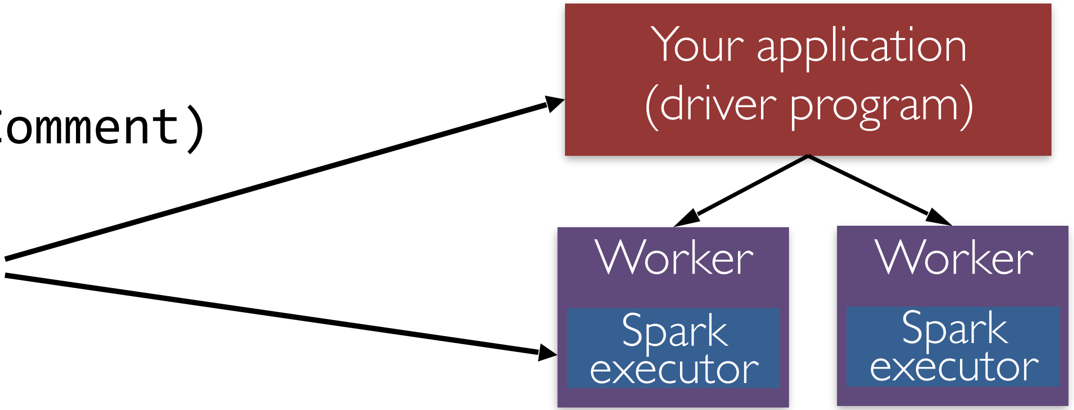


Examples

```
>>> a = a + 1

>>> linesDF.filter(isComment)

>>> commentsDF.count()
```



How Not to Write Code

Let's say you want to combine two DataFrames: **`aDF`**, **`bDF`**

You remember that **`df.collect()`** returns a list of **`Row`**, and in Python you can combine two lists with **`+`**

A naïve implementation would be:

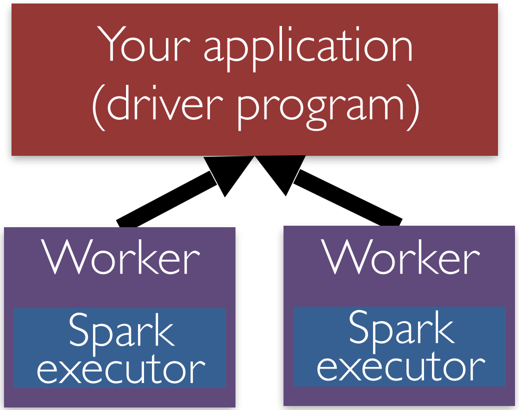
```
>>> a = aDF.collect()
>>> b = bDF.collect()
>>> cDF = sqlContext.createDataFrame(a + b)
```

Where does this code run?

`a + b`

```
>>> a = aDF.collect()
>>> b = bDF.collect()
```

* <u>all</u> distributed data for **a** and **b** is sent to driver



What if **a** and/or **b** is very large?

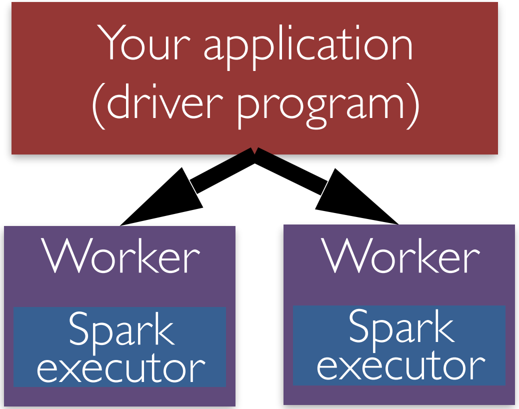
» Driver could run out of memory: Out Of Memory error (OOM)

» Also, takes a long time to send the data to the driver

`a + b`

```
>>> cDF = sqlContext.createDataFrame(a + b)
```

* all data for **`cDF`** is sent to the executors



What if the list **`a + b`** is very large?

» Driver could run out of memory: Out Of Memory error (OOM)

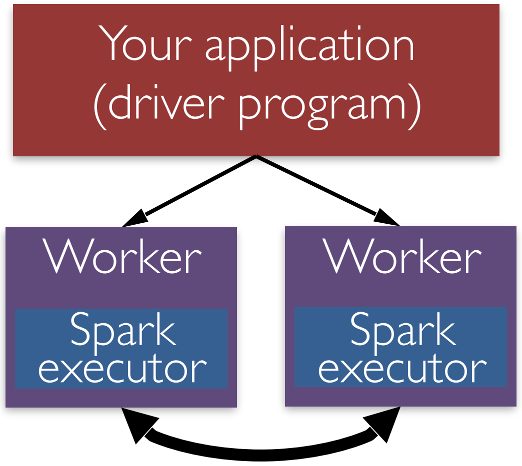
» Also, takes a long time to send the data to executors

The Best Implementation

```
>>> cDF = aDF.unionAll(bDF)
```

Use the `DataFrame` reference API!

- » `unionAll()`: "Return a new `DataFrame` containing union of rows in this frame and another frame"
- » Runs <u>completely</u> at executors:
  - Very scalable and efficient



Some Programming Best Practices

Use Spark Transformations and Actions wherever possible

- » Search **`DataFrame`** reference API

Never use **`collect()`** in production, instead use **`take(`*`n`*`)`**

`cache()` **`DataFrames`** that you reuse a lot