



Performance, Parallelism, and Distributed Data Analytics with Spark

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CS8 – Computational Structures in Data Science

<http://inst.eecs.berkeley.edu/~cs88>

Lecture 13

April 25, 2016



Computational Concepts Toolbox

- Data type: values, literals, operations,
- Expressions, Call expression
- Variables
- Assignment Statement
- Sequences: tuple, list
- Dictionaries
- Data structures
- Tuple assignment
- Function Definition Statement
- Conditional Statement
- Iteration: list comp, for, while
- Lambda function expr.
- Higher Order Functions
 - as Values, Args, Results
- Higher order function patterns
 - Map, Filter, Reduce
 - Function factories
- Recursion
 - Linear, Tail, Tree
- Abstract Data Types
- Mutation
- Object Oriented Programming
- Classes
- Iterators and Generators
- **Exceptions**
 - assert, try, except, raise





Today: Performance and Parallelism

- **Understanding ways of looking at performance**
 - Complexity – asymptotic scaling
 - Amdahl's Law – impact of enhancements (including parallelism)
- **Data analytics in the cloud – SPARK**
 - Map / reduce paradigm
 - RDDs
 - Arrays, Key-Value, Data frames / Tables
- **HKN survey before lab**
- **Lab – Hands on with Databricks / SPARK**
- **Administrative**
 - Next week review, No new homework
 - Final: FRIDAY, MAY 13, 2016 8-11A, Location: 306 SODA
 - Review session to be scheduled



Complexity – asymptotic analysis

- **Example: Matrix Multiply**
 - How many Multiplies? Adds? Ops? How much time ?
 - As a function of n ?

```
for i in 0 to n-1:
  for j in 0 to n-1:
    C[i][j] = 0
    for k in 0 to n-1:
      C[i][j] = C[i][j] + A[i][k]*B[k][j]
```

We say it is $O(n^3)$ “big-O of n^3 ” as an *asymptotic upper bound*

$\text{time}(n) < c \cdot n^3$, for some suitably large constant c for any instance of the inputs of size n .



A subtle example

- What is the “complexity” of finding the average number of factors of numbers up to n ?

```
def factors(n):  
    return [x for x in range(2, max(n, ceil(sqrt(n))))  
            if n % x == 0]  
  
def ave_factor(n):  
    all_factors = map(factors, range(n))  
    all_lens = map(len, all_factors)  
    return sum(all_lens)/n
```

$n^{1/2}$ points to `ceil(sqrt(n))`
 n points to `range(n)`

```
from timeit import default_timer as timer  
  
def timeit(fun):  
    """ Rtn timer for fun(i) in secs. """  
    def timer_fun(i):  
        start = timer()  
        fun(i)  
        end = timer()  
        return (end-start)  
    return timer_fun
```



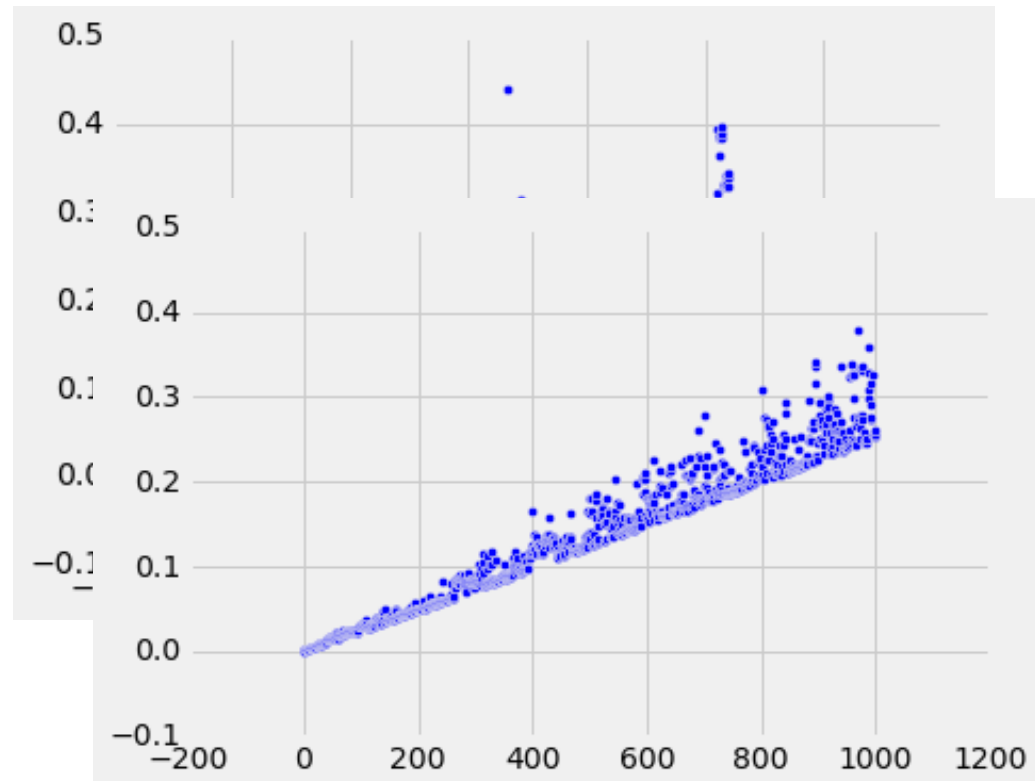
How long does factors take?

```
In [9]: tbl = Table().with_column('n', np.arange(0,1000, 1))
tbl['factors'] = tbl.apply(factors, 'n')
tbl['n_factors'] = tbl.apply(len, 'factors')
tbl['secs'] = tbl.apply(timeit(factors), 'n')
tbl
```

Out[9]:

n	factors	n_factors	secs
0	[]	0	9.76503e-06
1	[]	0	2.40898e-06
2	[]	0	1.34797e-06
3	[]	0	3.49898e-06
4	[2]	1	2.74903e-06
5	[]	0	2.43704e-06
6	[2, 3]	2	3.019e-06
7	[]	0	2.78e-06
8	[2, 4]	2	3.28396e-06
9	[3]	1	3.74601e-06

... (990 rows omitted)



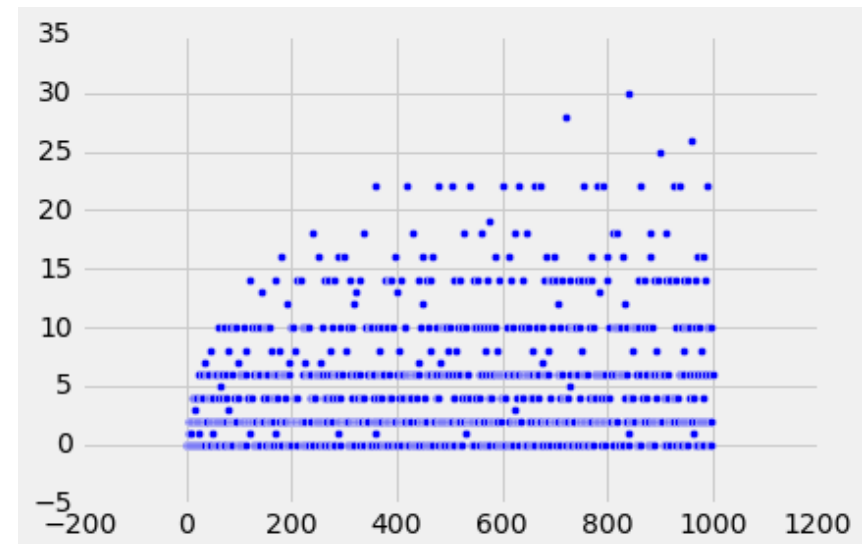
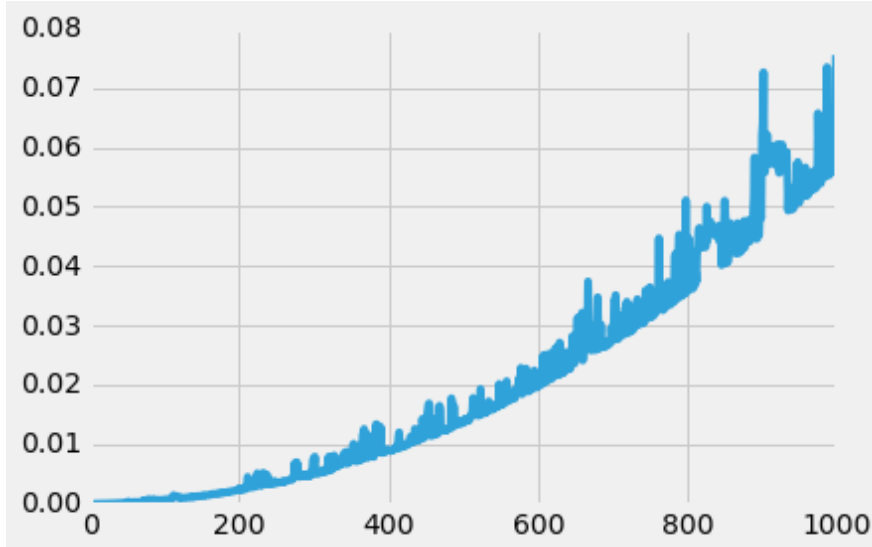


A subtle example

- What is the complexity of finding the average number of factors of numbers up to n ?

```
def factors(n):  
    return [x for x in range(2, max(n, ceil(sqrt(n))))  
            if n % x == 0]  
  
def ave_factor(n):  
    all_factors = map(factors, range(n))  
    all_lens = map(len, all_factors)  
    return sum(all_lens)/n
```

$n^{1/2}$ points to the range argument in factors(n)
 n points to the range argument in map(factors, range(n))



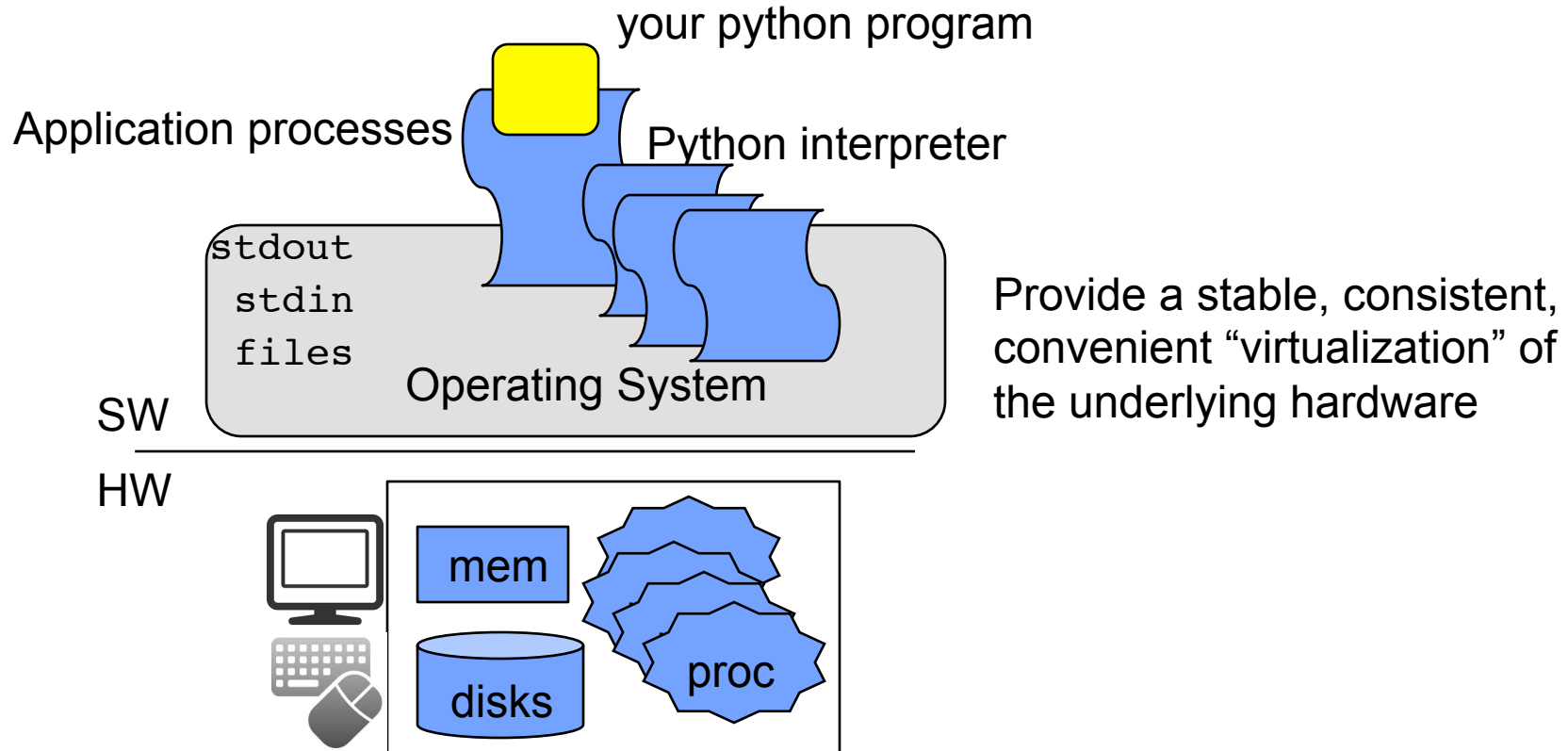


Amdahl's Law

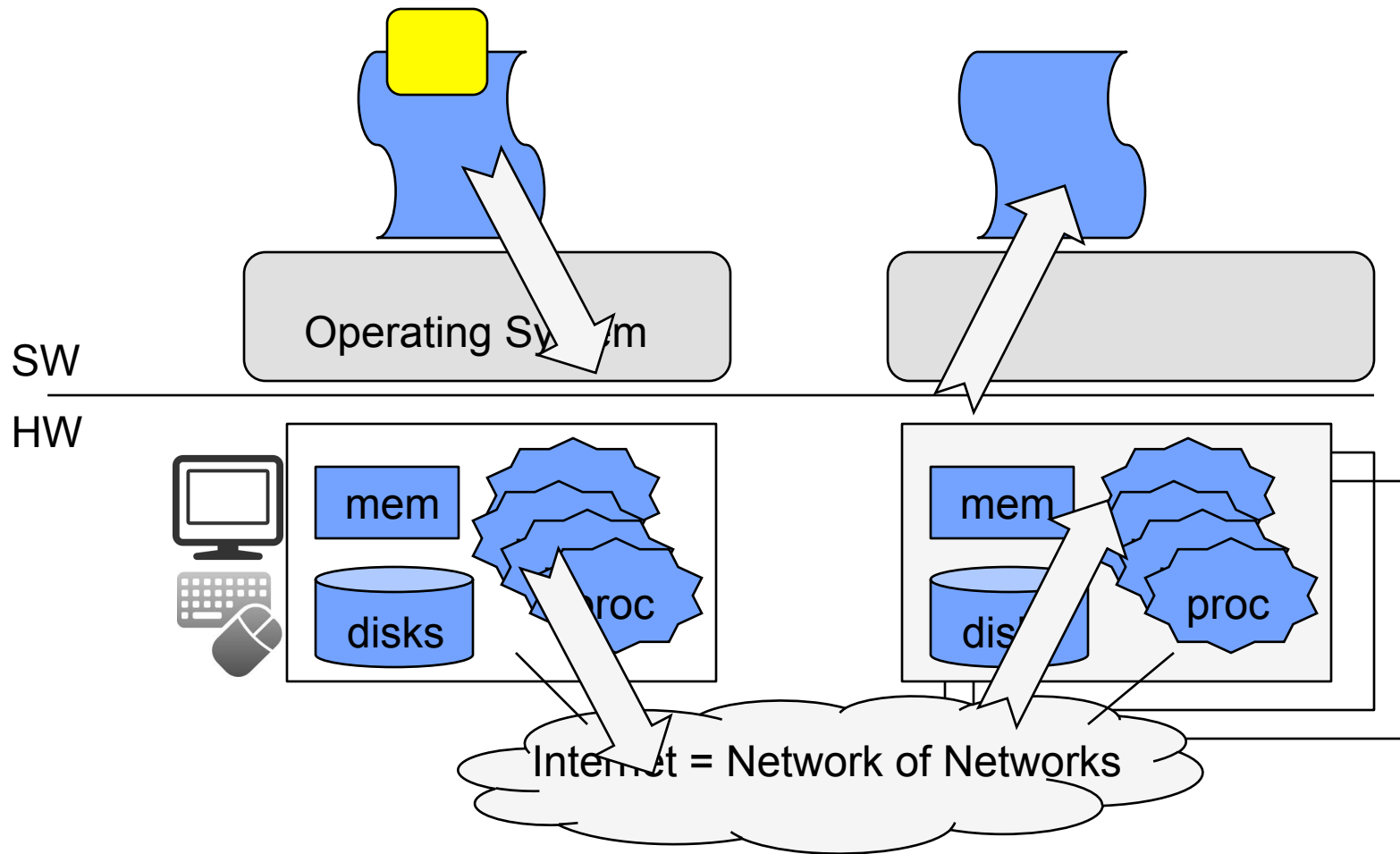
- Let $T_1(n)$ be the time to execute the program serially, and
- $T_p(n)$ be the time with parallelism p , and
- s_n be the fraction of the program that remains serial when parallelized
- $\text{SpeedUp}(n) = T_1(n) / T_p(n)$
$$\leq \frac{T_1(n)}{s_n T_1(n) + (1-s_n) T_1(n)/p} < 1/s_n$$
- Often, as the data gets large, the work that can be parallelized grows faster than the size of the data



Layers of Computer Systems

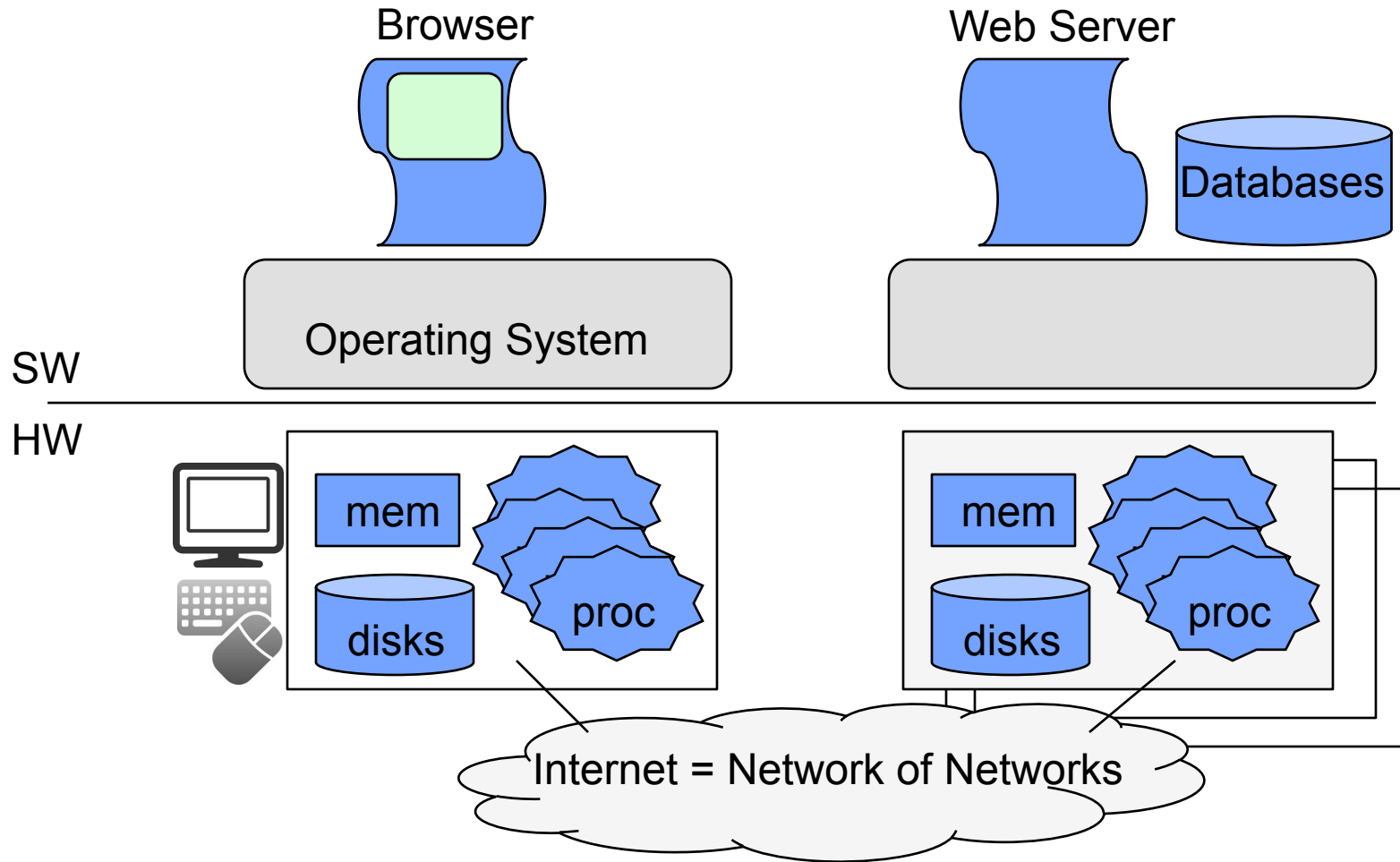


Distributed Computer Systems



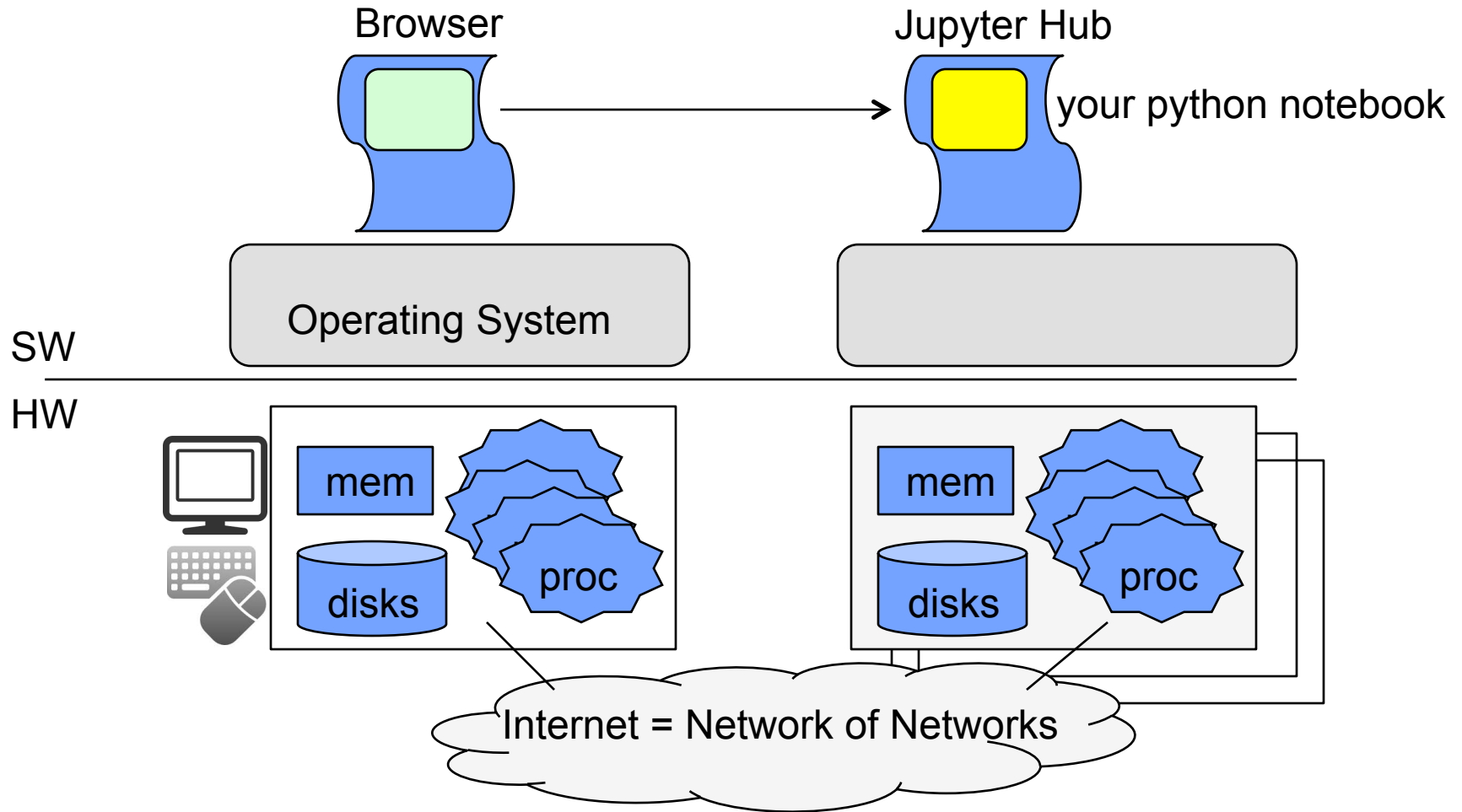


Distributed Computer Systems



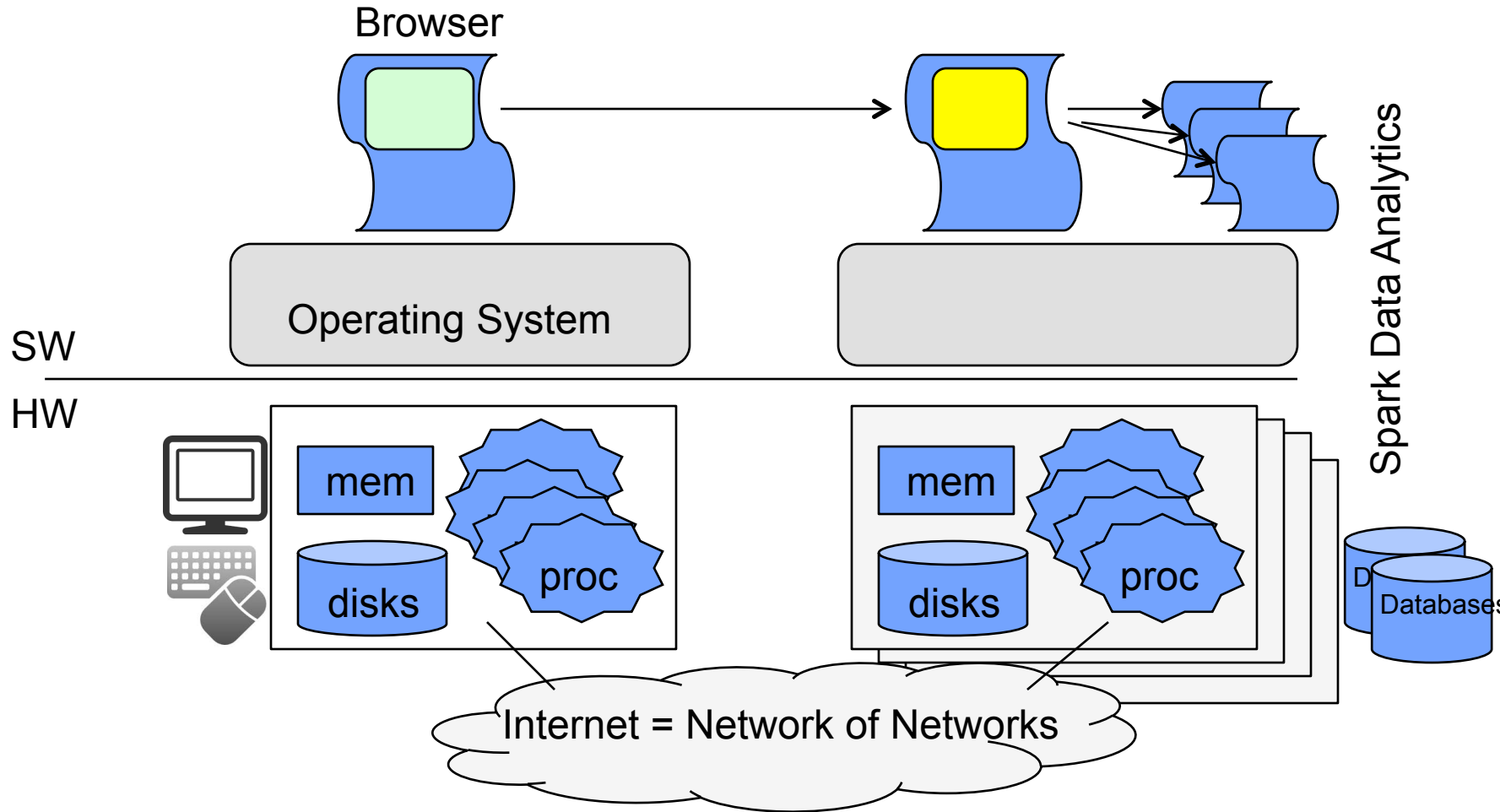


In Data8





... on BIG DATA



Big Data Examples

- Facebook daily logs: 60 Terabytes (60,000 GB)
- 1,000 Genomes: 200 TB
- Google web index: 10+ Petabytes (10,000 TB)
- Time to read 1 TB @ 100 MB/s ? – 3 hours
- Clusters – thousands of complete computer systems, networked closely
 - (mostly) independent failures
 - Engineered at massive scale





Apache Spark (from Berkeley)

- Data processing system that provides a simple interface to analytics on large data
- A Resilient Distributed Dataset (RDD) is a collection of values or key-value pairs
- Support the operations you are familiar with
 - Data-Parallel: map, filter, reduce
 - Database: join, union, intersect
 - OS: sort, distinct, count
- All of can be performed on RDDs that are partitioned across machines

King Lear

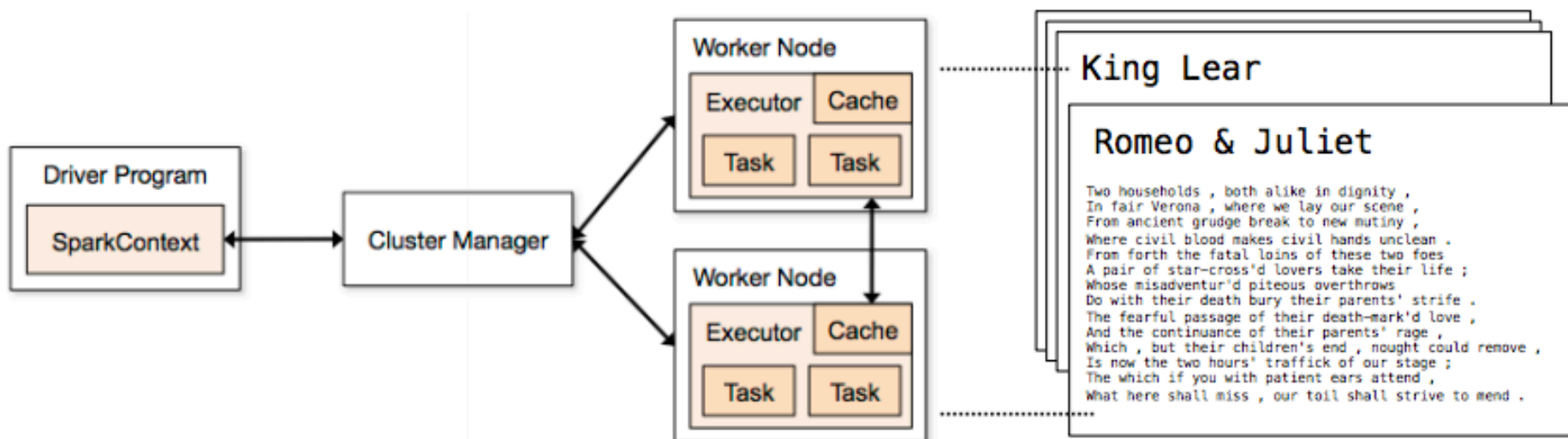
Romeo & Juliet

Two households , both alike in dignity ,
In fair Verona , where we lay our scene ,
From ancient grudge break to new mutiny ,
Where civil blood makes civil hands unclean .
From forth the fatal loins of these two foes
A pair of star-cross'd lovers take their life ;
Whose misadventur'd piteous overthrows
Do with their death bury their parents' strife .
The fearful passage of their death-mark'd love ,
And the continuance of their parents' rage ,
Which , but their children's end , nought could remove ,
Is now the two hours' traffick of our stage ;
The which if you with patient ears attend ,
What here shall miss , our toil shall strive to mend .

Spark Execution Model


Processing is defined centrally and executed remotely


- A RDD is distributed over workers
- A driver program defines transformations and actions on RDDs
- A cluster manager assigns task to workers
- Workers perform computation, store data, & communicate with each other
- Final results communicate back to driver








Spark Context



databricks


Home


Workspace


Recent


Tables



L12 (Python)

Attached: My Cluster ▾ View: Code ▾ File ▾ Run All

```
> # Default Spark Context  
sc
```

Out[2]: <__main__.RemoteContext at 0x7f5d8a5e5410>
Command took 0.03s

```
> sc.defaultParallelism
```

Out[3]: 3
Command took 0.04s



RDD of values

```
> n = 1000  
data = range(n)  
rdd_data = sc.parallelize(data)  
rdd_data
```

Out[5]: ParallelCollectionRDD[31] at parallelize at PythonRDD.scala:423

Command took 0.07s



Looking at results

```
> n = 1000
data = range(n)
rdd_data = sc.parallelize(data)
rdd_data
```

Out[5]: ParallelCollectionRDD[31] at parallelize at
Command took 0.07s

```
> rdd_data.take(10)
```

▼ (1) Spark Jobs

► Job 0 [View](#) (Stages: 1/1)

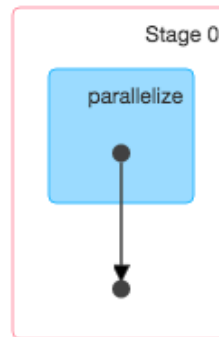
Out[6]: [0, 1, 2, 3, 4, 5, 6, 7, 8, 9]

Command took 1.72s

>

Sun 24 April

▼ DAG Visualization



Completed Stages (1)

Stage Id	Pool Name	Description	Submitted	Duration	Tasks: Succeeded/Total	Input
0	2873135457951023881	rdd_data.take(10) runJob at PythonRDD.scala:393 +details	2016/04/24 23:26:17	0.6 s	1/1	



Map / Collect

```
> n = 12  
data = xrange(2,n+2)  
rdd_data = sc.parallelize(data)  
rdd_data.map(factors).collect()
```

▼ (1) Spark Jobs

▶ Job 4 [View](#) (Stages: 1/1)

Out[12]: [[], [], [2], [], [2, 3], [], [2, 4], [3], [2, 5], [], [2, 3, 4, 6], []]

Command took 0.12s



Data Distribution

```
> # Let's see how the data is distributed - glom  
rdd_data.glom().collect()
```

► (1) Spark Jobs

```
Out[14]: [[2, 3, 4, 5], [6, 7, 8, 9], [10, 11, 12, 13]]
```

Command took 0.07s

```
> sc.parallelize(range(100), 10).glom().collect()
```

► (1) Spark Jobs

```
Out[15]:
```

```
[[0, 1, 2, 3, 4, 5, 6, 7, 8, 9],  
 [10, 11, 12, 13, 14, 15, 16, 17, 18, 19],  
 [20, 21, 22, 23, 24, 25, 26, 27, 28, 29],  
 [30, 31, 32, 33, 34, 35, 36, 37, 38, 39],  
 [40, 41, 42, 43, 44, 45, 46, 47, 48, 49],  
 [50, 51, 52, 53, 54, 55, 56, 57, 58, 59],  
 [60, 61, 62, 63, 64, 65, 66, 67, 68, 69],  
 [70, 71, 72, 73, 74, 75, 76, 77, 78, 79],  
 [80, 81, 82, 83, 84, 85, 86, 87, 88, 89],  
 [90, 91, 92, 93, 94, 95, 96, 97, 98, 99]]
```

Command took 0.27s



Distribute/Map/Reduce

Attached: My Cluster View: Code File Run All

Publish Comments Revision history

```
> sc.parallelize(range(100), 10).glom().collect()
```

▸ (1) Spark Jobs

Out[15]:

```
[[0, 1, 2, 3, 4, 5, 6, 7, 8, 9],  
 [10, 11, 12, 13, 14, 15, 16, 17, 18, 19],  
 [20, 21, 22, 23, 24, 25, 26, 27, 28, 29],  
 [30, 31, 32, 33, 34, 35, 36, 37, 38, 39],  
 [40, 41, 42, 43, 44, 45, 46, 47, 48, 49],  
 [50, 51, 52, 53, 54, 55, 56, 57, 58, 59],  
 [60, 61, 62, 63, 64, 65, 66, 67, 68, 69],  
 [70, 71, 72, 73, 74, 75, 76, 77, 78, 79],  
 [80, 81, 82, 83, 84, 85, 86, 87, 88, 89],  
 [90, 91, 92, 93, 94, 95, 96, 97, 98, 99]]
```

Command took 0.27s

```
> # Spread, transform, reduce on a lot more data  
from operator import add  
n = 10000  
data = range(n)  
rdd_data = sc.parallelize(data, 9)  
rdd_factors = rdd_data.map(factors)  
rdd_lens = rdd_factors.map(len)  
rdd_lens.reduce(add)/float(n) # python 2 be careful
```

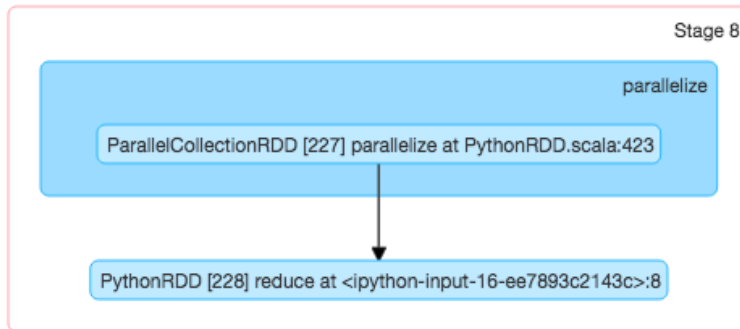
▾ (1) Spark Jobs

▸ Job 8 View (Stages: 1/1)

Out[16]: 7.3646

Command took 1.71s

Jobs Stages Storage Environment Executors SQL JDBC/ODBC Server



▸ Show Additional Metrics

▾ Event Timeline

☐ Enable zooming

■ Scheduler Delay
■ Task Deserialization Time
■ Shuffle Read Time
■ Executor Computing Time
■ Shuffle Write Time
■ Result Serialization Time



Summary Metrics for 9 Completed Tasks



Encapsulating the Parallelism

```
> def p_ave_factors(n):  
    data = range(n)  
    rdd_data = sc.parallelize(data, sc.defaultParallelism*3)  
    rdd_factors = rdd_data.map(factors)  
    rdd_lens = rdd_factors.map(len)  
    return rdd_lens.reduce(add)/float(n)
```

Command took 0.08s

```
> p_ave_factors(10000)|
```

► (1) Spark Jobs

Out[20]: 7.3646

Command took 1.71s



Summary: RDD operations (so far)

- **Transformation**

<https://spark.apache.org/docs/latest/programming-guide.html#transformations>

- map(fun), filter(fun)
- flatMap(fun) – each item may be mapped to zero or more outputs
- sample, union, intersection, distinct
- join

- **Action**

- reduce(fun), collect(), count(), first(), take(n)



Key-value RDDs

```
> # Key value stores, start as list of tuples, not dictionary
  from operator import add
  d = [('one', 1), ('two', 2), ('one', 3), ('free', 5), ('free', 42)]
  d_rdd = sc.parallelize(d)
  d_rdd.groupByKey().collect()
```

► (1) Spark Jobs

Out[1]:

```
[('one', <pyspark.resultiterable.ResultIterable at 0x7f7e0e424c50>),
 ('free', <pyspark.resultiterable.ResultIterable at 0x7f7e0cb30450>),
 ('two', <pyspark.resultiterable.ResultIterable at 0x7f7e0cb30150>)]
```

Command took 1.34s

Map the values in a group
- not add

```
> d_rdd.groupByKey().mapValues(sum).collect()
```

► (1) Spark Jobs

Out[6]: [('one', 4), ('free', 47), ('two', 2)]

Command took 0.38s



Key-Value RDD operations

```
> d_rdd.reduceByKey(add).collect()
```

▸ (1) Spark Jobs

```
Out[7]: [('one', 4), ('free', 47), ('two', 2)]
```

Command took 0.28s

```
> d_rdd.countByKey()
```

▸ (1) Spark Jobs

```
Out[8]: defaultdict(<type 'int'>, {'two': 1, 'free': 2, 'one': 2})
```

Command took 0.17s

```
> d_rdd.reduceByKeyLocally(add)
```

▸ (1) Spark Jobs

```
Out[10]: {'free': 47, 'one': 4, 'two': 2}
```

Command took 0.12s



Summary: RDD operations (cont)

- **Transformation**

<https://spark.apache.org/docs/latest/programming-guide.html#transformations>

- map(fun), filter(fun)
- flatMap(fun) – each item may be mapped to zero or more outputs
- sample, union, intersection, distinct, join
- groupByKey(), reduceByKey(fun), aggregateByKey, sortByKey

- **Action**

- reduce(fun), collect(), count(), first(), take(n)
- takeSample
- countByKey



Building an RDD from a text file

```
> import os.path
baseDir = os.path.join('databricks-datasets')
inputPath = os.path.join('cs100', 'lab1', 'data-001', 'shakespeare.txt')
fileName = os.path.join(baseDir, inputPath)

shakespeareRDD = sc.textFile(fileName)
shakespeareRDD.take(14)
```

► (1) Spark Jobs

Out[12]:

```
[u'1609',
 u'',
 u'THE SONNETS',
 u'',
 u'by William Shakespeare',
 u'',
 u'',
 u'',
 u'
          1',
 u' From fairest creatures we desire increase,',
 u" That thereby beauty's rose might never die,",
 u' But as the ripper should by time decease,',
 u' His tender heir might bear his memory:',
 u' But thou contracted to thine own bright eyes,']
```

Command took 0.28s



Count, Filter and stats

```
> shakespeareRDD.count()
```

▸ (1) Spark Jobs

Out[13]: 122395

Command took 0.63s

```
> import string
string.split
sp_words = shakespeareRDD.map(string.split).filter(lambda x: len(x) > 0)
sp_words.map(len).stats()
```

▸ (1) Spark Jobs

Out[14]: (count: 112902, mean: 7.82377637243, stdev: 2.70356395722, max: 21.0, min: 1.0)

Command took 1.31s



flatMap

```
> def clean_word(s):  
    res = ""  
    for c in s:  
        if c in string.ascii_letters:  
            res += c  
    return res
```

Command took 0.07s

```
> sp_flat = sp_words.flatMap(lambda x:x).map(string.lower).map(clean_word).filter(lambda x: len(x)>0)  
sp_flat.take(10)
```

► (1) Spark Jobs

Out[16]:

```
[u'the',  
 u'sonnets',  
 u'by',  
 u'william',  
 u'shakespeare',  
 u'from',  
 u'fairest',  
 u'creatures',  
 u'we',  
 u'desire']
```

Command took 0.22s



Values => Key-Value

```
> from operator import add
sp_kv = sp_flat.map(lambda x: (x,1)).reduceByKey(add).sortBy(lambda x: x[1], ascending=False)
sp_kv.take(20)
```

▼ (3) Spark Jobs

- ▶ Job 13 [View](#) (Stages: 2/2)
- ▶ Job 14 [View](#) (Stages: 1/1, 1 skipped)
- ▶ Job 15 [View](#) (Stages: 2/2, 1 skipped)

Out[17]:

```
[(u'the', 27361),
 (u'and', 26028),
 (u'i', 20681),
 (u'to', 19150),
 (u'of', 17463),
 (u'a', 14593),
 (u'you', 13615),
 (u'my', 12481),
 (u'in', 10956),
 (u'that', 10890),
 (u'is', 9134),
 (u'not', 8497),
 (u'with', 7771),
 (u'me', 7769),
 (u'it', 7678),
 (u'for', 7558),
 (u'be', 6857),
 (u'his', 6857),
 (u'your', 6655),
 (u'this', 6602)]
```

Details for Job 15

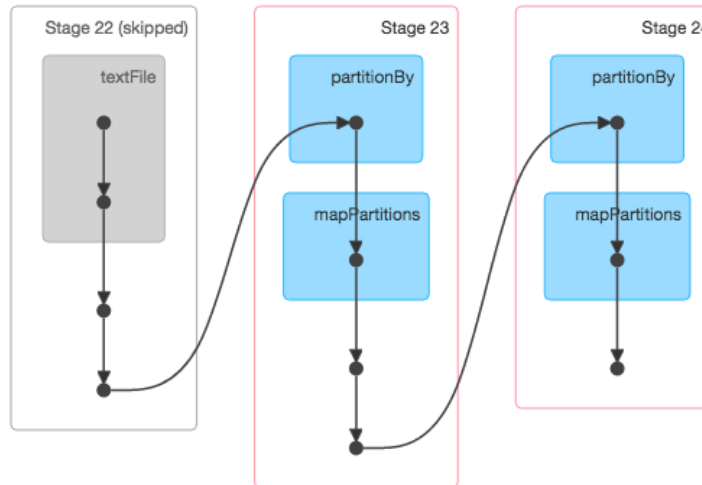
Status: SUCCEEDED

Job Group: 628891043112620844_9007556272146961988_0dc5beb06c1d44c3904f04d795e41b21

Completed Stages: 2

Skipped Stages: 1

- ▶ [Event Timeline](#)
- ▼ [DAG Visualization](#)



Completed Stages (2)

Stage Id	Pool Name	Description	Submitted	Duration	Tasks: Succeeded/Total	Input
24	628891043112620844	from operator import add sp_kv = sp_flat.map(la... runJob at PythonRDD.scala:393 +details	2016/04/25 05:07:19	21 ms	1/1	
23	628891043112620844	from operator import add sp_kv = sp_flat.map(la... sortBy at <ipython-input-17-a79f625fad0b>:2 +details	2016/04/25 05:07:19	0.1 s	2/2	



Data Frames / SQL

```
> if "mnt/" not in [x.name for x in dbutils.fs.ls("/")] or 'cs61a/' not in [x.name for x in dbutils.fs.ls("/mnt")]:
    dbutils.fs.mount('s3n://AKIAJUIYIB0AUUTJ3G5A:SU%2FsifB7wuzeWexDJCMTBVxG7MLIbZkk4ZcB+qzd@berkeley-cs61a','/mnt/cs61a/')
reviews_dataset = '/mnt/cs61a/yelp_reviews_dataset_small.json'
reviews = sqlContext.read.json(path=reviews_dataset)
reviews.show()
```

► (2) Spark Jobs

business_id	date	review_id	stars	text	type	user_id	votes
vcNAWiLM4dR7D2nww...	2007-05-17	15SdjuK7DmYqUAj6r...	5	dr. goldberg offe...	review	Xqd0DzHaiyRqVH3WR...	[1,0,2]
vcNAWiLM4dR7D2nww...	2014-01-02	kMu0knsSUFW2DZXqK...	5	Top notch doctor ...	review	jE5xVugujSaskAoh2...	[0,0,0]
vcNAWiLM4dR7D2nww...	2014-01-08	onDPFgNZpMk-bT1zl...	5	Dr. Eric Goldberg...	review	QnhQ8G51XbUpVEyWY...	[0,0,0]
vcNAWiLM4dR7D2nww...	2014-08-01	bOJD0Kc3wGioat3oS...	1	I'm writing this ...	review	tAB7GJpUuaKF4W-3P...	[0,0,1]
vcNAWiLM4dR7D2nww...	2014-12-12	QzjRXUNSGk3PySEcg...	5	I love Dr. Goldbe...	review	GP-h9colXgkT79BW7...	[0,0,0]
UsFtqoBl7naz8AVUB...	2014-10-29	7N9j5YbBHBW6qguE5...	2	Wing sauce is lik...	review	PP_xoMSYlGr2pb67B...	[0,0,0]
cE27W9VPgO88Qxe4o...	2014-07-11	S-G0D8Cy7PnqShoBZ...	4	I drove by yester...	review	ljwgUJowB69klaR8A...	[0,0,0]
HZdLhv6COCleJMo7n...	2013-06-10	fBQ69-NU9ZyTjjS7T...	5	THANK YOU ROB! i ...	review	JbAeIYc89Sk8SwwrB...	[7,3,7]
HZdLhv6COCleJMo7n...	2014-09-04	UzMVimQZuSxOr5wrr...	4	I visited this st...	review	zo_soThZw8eVglPbC...	[0,0,0]
mVHrayjG3uZ_RLHKL...	2013-03-15	jVVv_DA5mCDB6medi...	5	Can't miss stop f...	review	m1FpV3EAeggaAdfPx...	[0,0,0]
mVHrayjG3uZ_RLHKL...	2014-09-29	5uyYmniYyIB_wtKty...	4	Wonderful reuben...	review	u9ULAsnYTdYH65Haj...	[0,0,0]
KayYbHCt-RkbGcPdG...	2010-10-11	v_uEDbK5fP1UJpkXN...	4	This would be my ...	review	ay9H1RpjbBkaiXGxf...	[2,2,2]
KayYbHCt-RkbGcPdG...	2011-12-22	UrukGX1emhSRe2fGd...	3	Good for cheap dr...	review	bcwr1bFov3PSa1FiG...	[0,0,0]



Data frames: select, filter

```
> reviews.select('stars', 'text').show()
```

▶ (1) Spark Jobs

```
+-----+-----+
|stars|          text|
+-----+-----+
|    5|dr. goldberg offe...|
|    5|Top notch doctor ...|
```

```
> reviews.filter(reviews['stars'] == 5).show()
```

▶ (1) Spark Jobs

```
+-----+-----+-----+-----+-----+-----+-----+-----+
|business_id|date|review_id|stars|text|type|user_id|votes|
+-----+-----+-----+-----+-----+-----+-----+-----+
|vcNAWiLM4dR7D2nww...|2007-05-17|15SdjuK7DmYqUAj6r...|5|dr. goldberg offe...|review|Xqd0DzHaiyRqVH3WR...|[1,0,2]|
|vcNAWiLM4dR7D2nww...|2014-01-02|kMu0knsSUFW2DZXqK...|5|Top notch doctor ...|review|jE5xVugujSaskAoh2...|[0,0,0]|
|vcNAWiLM4dR7D2nww...|2014-01-08|onDPFgNZpMk-bT1zl...|5|Dr. Eric Goldberg...|review|QnhQ8G51XbUpVEyWY...|[0,0,0]|
|vcNAWiLM4dR7D2nww...|2014-12-12|QzjRXUNSGk3PySEcg...|5|I love Dr. Goldbe...|review|GP-h9colXgkT79BW7...|[0,0,0]|
|HZdLhv6COCleJMo7n...|2013-06-10|fBQ69-NU9ZyTjS7T...|5|THANK YOU ROB! i ...|review|JbAeIYc89Sk8SWmrB...|[7,3,7]|
|mVHrayjG3uZ_RLHkL...|2013-03-15|jVVv_DA5mCDB6medi...|5|Can't miss stop f...|review|m1FpV3EAeggaAdfPx...|[0,0,0]|
|KayYbHCt-RkbGcPdG...|2014-02-16|0klMyorCLST8NYGJq...|5|Grew up near here...|review|h-A_xNeB_xSbc0psq...|[0,0,0]|
|fNGIbpazjTRdXgwRY...|2014-03-21|f5WKGxGq-XTJJPXh...|5|If you are search...|review|aOHQ9MlorpvL71Y6q...|[0,0,0]|
|4|I've been informe...|
|5|If you are search...|
|4|Rocky's has been ...|
+-----+-----+
only showing top 20 rows
```



Data Frames: groupBy

```
> reviews.groupBy('business_id').count().show()
```

► (1) Spark Jobs

business_id	count
FsY-8nYOCXyj9FoVx...	3
SzHTdZR3yY1WBYUxk...	2
3zgswf_NfBJpeAoWe...	13
SXvbOMPd7jNgTkY6p...	1
Lvk4P_Npmueqs-n1h...	3
oQJ4try-o-181bhsX...	1
vA8ed8BFvQxz4HFt8...	5
FqgotmZY0WcNjyDJh...	2
gZJmtLYGNLoAFU82X...	1
dLwTMpf63CxWGFRd8...	2



Data Frames => key-value

```
> def star_mapper(review):  
    return [(review.stars, review.text)]  
reviews.flatMap(star_mapper).take(10)
```

► (1) Spark Jobs

Out[25]:

```
[(5,  
  u"dr. goldberg offers everything i look for in a general practitioner. he's nice and  
  s patients; he's affiliated with a top-notch hospital (nyu) which my parents have expla  
  and you can get referrals to see specialists without having to see him first. really,  
  have about him, but i'm really drawing a blank."),  
  (5,  
    u"Top notch doctor in a top notch practice. Can't say I am surprised when I was refer  
    one of the best medical schools in the country. \nIt is really easy to get an appointme  
    (5,  
      u'Dr. Eric Goldberg is a fantastic doctor who has correctly diagnosed every issue tha  
      ry accessible and we have been able to schedule appointments with him and his staff ver  
      being his patients for many years to come.'),  
      (1,
```



DF => map => group => reduce

```
> def biz_mapper(review):  
    return [(review.business_id, 1)]  
counts = reviews.flatMap(biz_mapper).groupByKey().mapValues(sum)  
counts.take(10)
```

► (1) Spark Jobs

Out[27]:

```
[(u'0lpyp1EJ_c_hFxyand_Wxw', 14),  
 (u's0cZcXcNm8LmdoOYqEDqpg', 3),  
 (u'FFCkoA_L3cqYXtHtLyvxA', 24),  
 (u'A-y20kJLEs-FE7g_idjbPw', 5),  
 (u'FFd1PSZCGgTdg1CAfrlvlw', 6),  
 (u'pKp50rYh0iWZYKiWmWmLow', 2),  
 (u'MJtnKhA3l-2ZFzhneuSccw', 4),  
 (u'SNpVV5viJ2aPyLP6bkAx8Q', 10),  
 (u'fx4co000yW7Qe8vdLn1LiA', 2),  
 (u'j13Aby6-9ZyklpG_W7qsew', 2)]
```

Command took 5.54s

```
> counts.top(10, key=lambda x: x[1])
```

► (1) Spark Jobs

Out[28]:

```
[(u'4bEj0yTaDG24SY5TxsaUNQ', 823),  
 (u'zt1TpTuJ6y9n551sw9TaEg', 685),  
 (u'2e2e7WgqU1BnpxmQL5jbfw', 648),  
 (u'sIyHTizqAiGu12XMLX3N3g', 524),  
 (u'Xhg93cMdemu5pAMkDoEdt0', 521)]
```



Data Frame Operations

- `sqlContext.read.json(path=...)`
- `count()`, `distinct()`, `first()`
- `select(*cols)`, `drop(col)`,
- `flatMap(fun)`, `map(fun)`
- `filter(condition)`, `where(condition)`
- `groupBy(*cols)`
- `intersect(other)`, `join(other)`
- `orderBy(*cols)`, `sort(*cols)`
- `sample()`
- `stat`, `take`, `show`
- <https://spark.apache.org/docs/latest/api/python/pyspark.sql.html#pyspark.sql.DataFrame>



Summary

- **Performance is both about algorithmic “complexity” and implementation constants**
 - Make the common case fast
- **Parallelism**
 - Often the parallel work scales with the data
- **Master – Worker Model of Parallel data processing on clusters (in the cloud)**
- **RDDs of values, key-value**
- **Data Frame / SQL (like Tables)**
- **New concepts: flatMap, groupBy**

<https://databricks-prod-cloudfront.cloud.databricks.com/public/4027ec902e239c93eaaa8714f173bcfc/3044375856741396/398677364991930/1602914200610255/latest.html>