BigData

Iniciando meu estudo com Grandes Dados

email: susana.bouchardet@gmail.com

hadoop

jupyter

redis

ZooKeeper

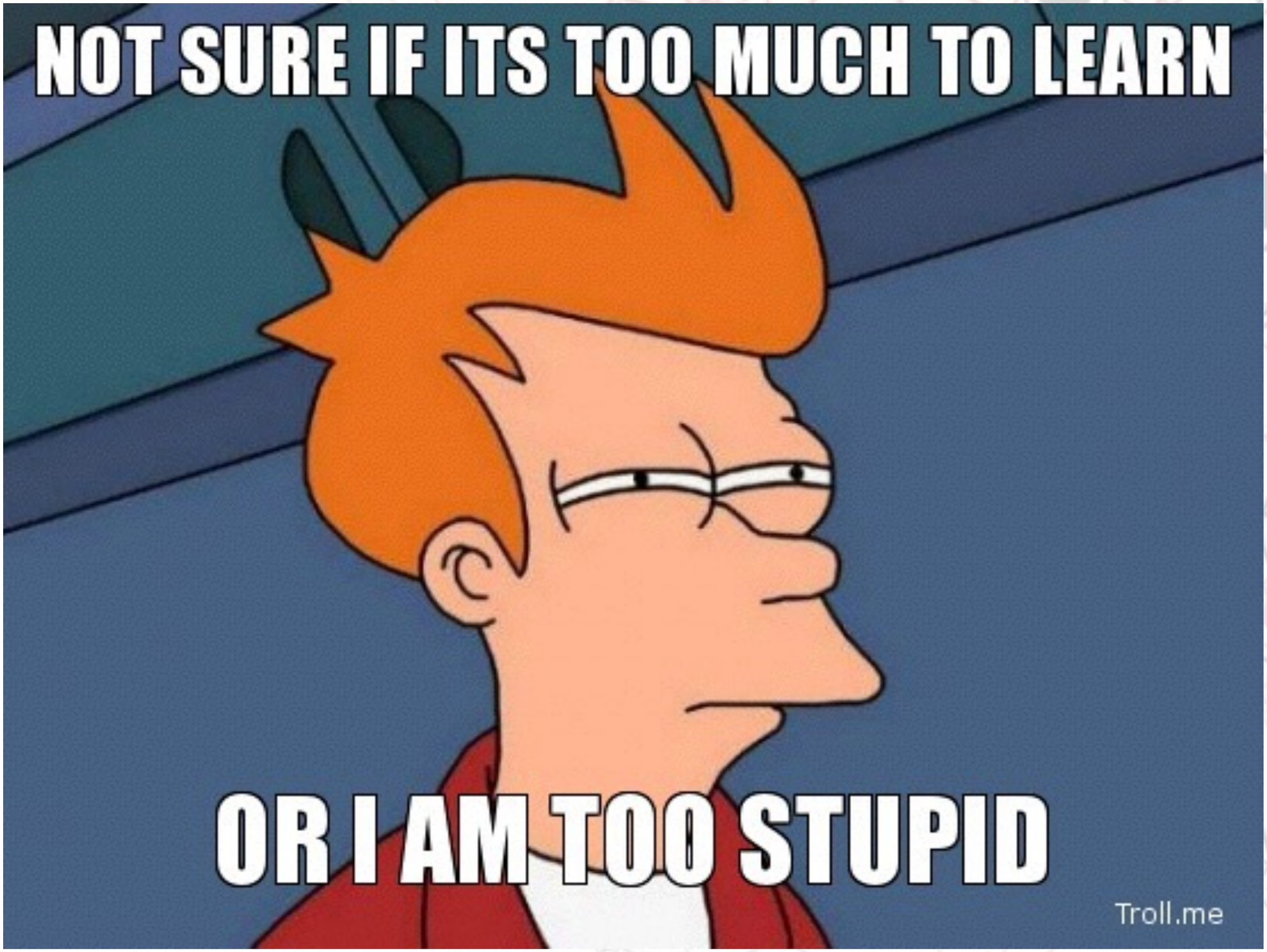
APACHE Spark™

Solr

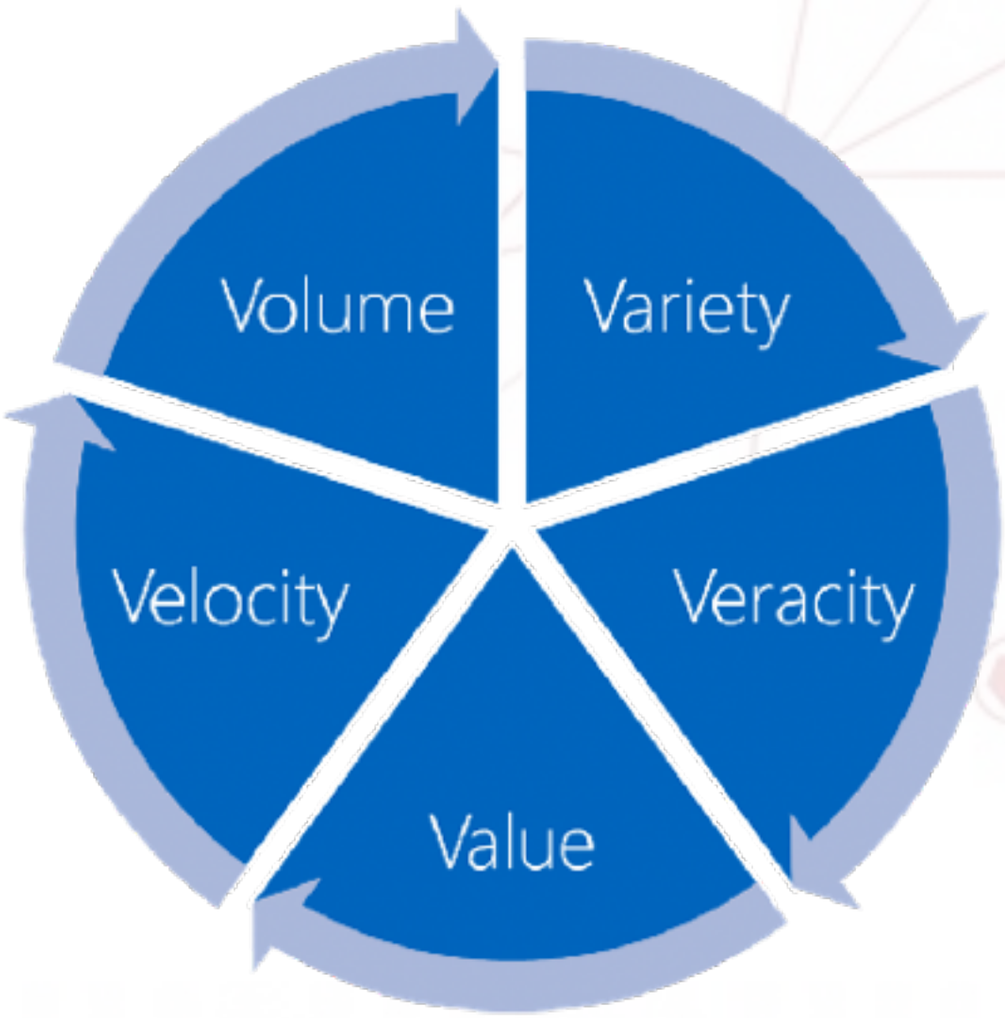
hadoop YARN

kafka

APACHE HBASE

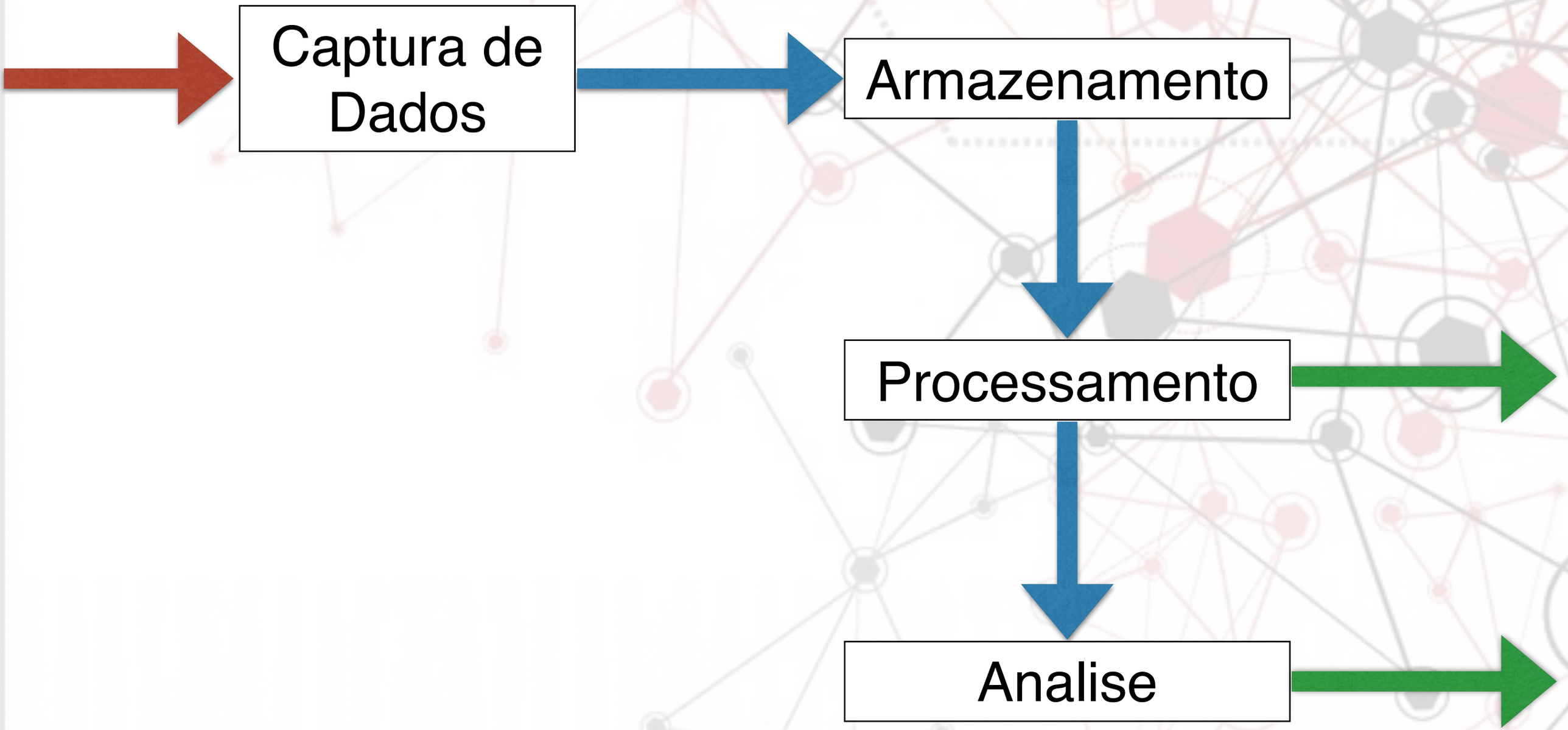

NOT SURE IF ITS TOO MUCH TO LEARN
OR I AM TOO STUPID
Troll.me

BigData 5V



- **Volume**: Muitos dados, desafio de armazenamento.
- **Variedade**: diferentes formatos de dados estruturados e/ou não.
- **Veracidade**: Acurácia e autenticidade.
- **Valor**: Retorno desses dados para o negócio.
- **Velocidade**: Tempo entre dado gerado e analisado.

Descrição do Problema



GFS

- Publicado em 2003
- Revolucionário
- arquivos em **chunks** de 64mb
- cada chunk esta no mínimo em 3 máquina

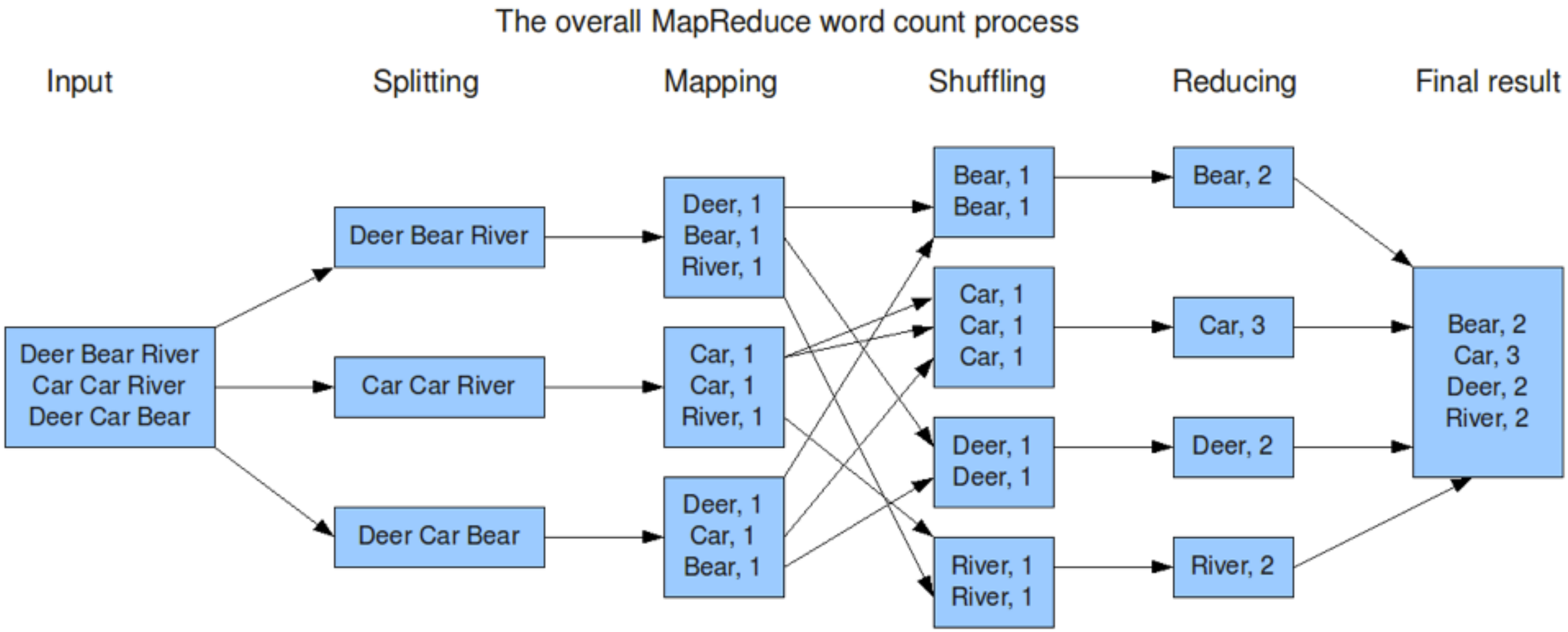
MapReduce

- Publicado em 2004
- modelo para processar **grandes volumes de dados**.
- Técnica muito usada em linguagens funcionais

MapReduce

```
1  map(String input_key, String input_value):
2      // input_key: document name
3      // input_value: document contents
4      for each word w in input_value:
5          EmitIntermediate(w, "1");
6
7  reduce(String output_key, Iterator intermediate_values):
8      // output_key: a word
9      // output_values: a list of counts
10     int result = 0;
11     for each v in intermediate_values:
12         result += ParseInt(v);
13     Emit(AsString(result));
```

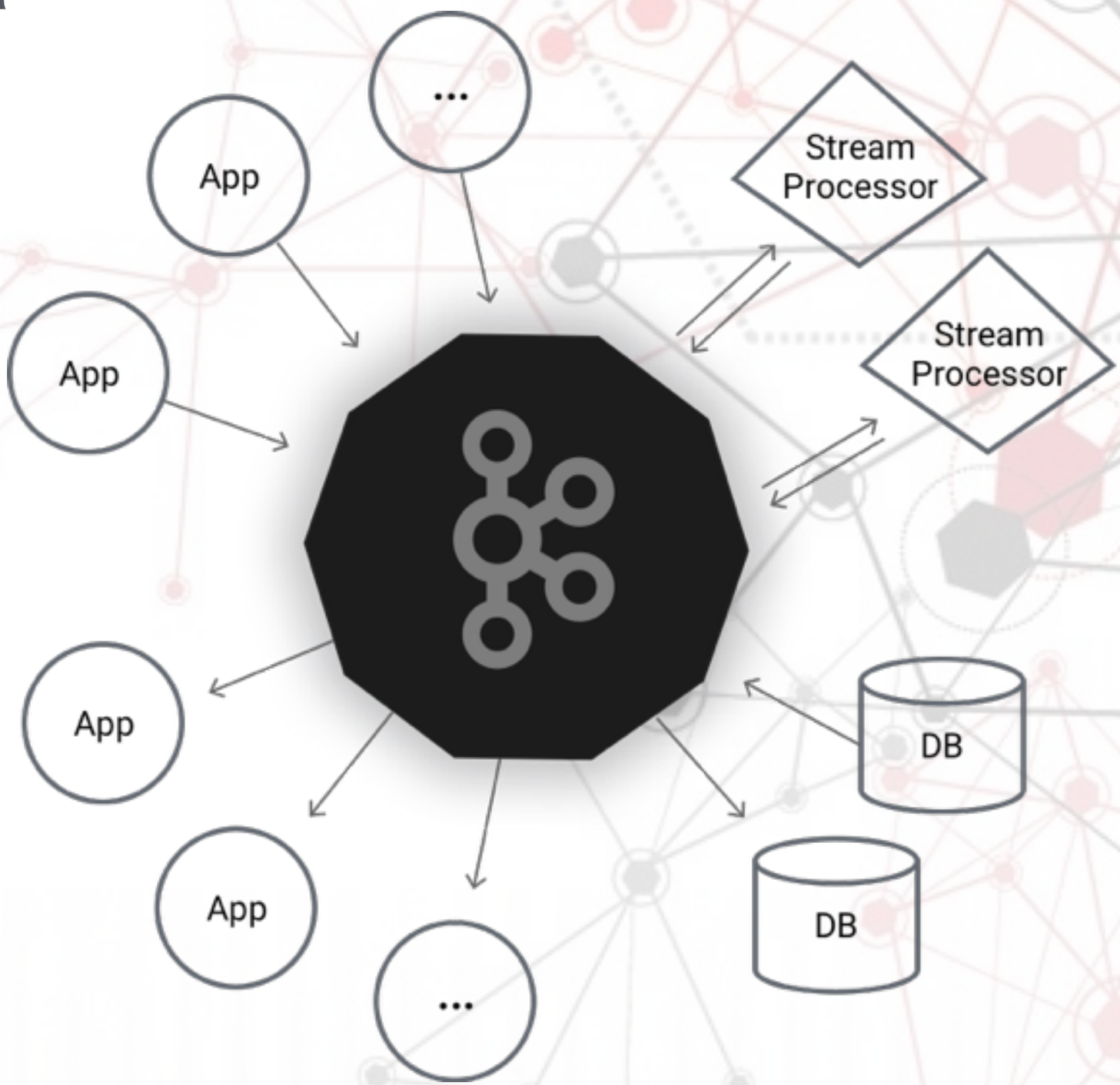
MapReduce


The overall MapReduce word count process
Input
Splitting
Mapping
Shuffling
Reducing
Final result
Deer Bear River
Car Car River
Deer Car Bear
Deer Bear River
Car Car River
Deer Car Bear
Deer, 1
Bear, 1
River, 1
Car, 1
Car, 1
River, 1
Deer, 1
Car, 1
Bear, 1
Bear, 1
Bear, 1
Car, 1
Car, 1
Car, 1
Deer, 1
Deer, 1
River, 1
River, 1
Bear, 2
Car, 3
Deer, 2
River, 2
Bear, 2
Car, 3
Deer, 2
River, 2

Hadoop

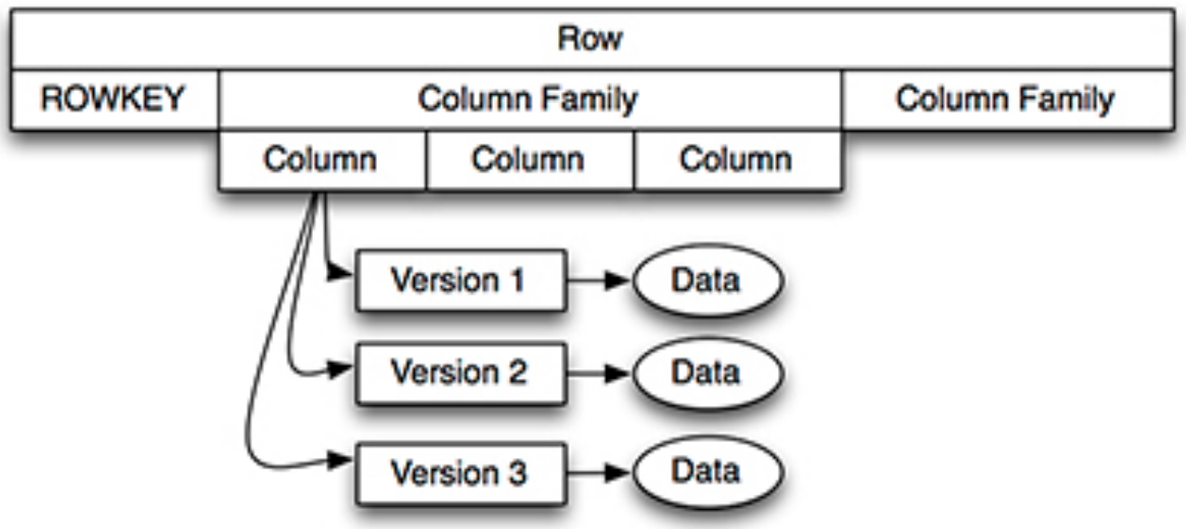
- Nasceu no Yahoo em 2006
- HDFS
- HadoopMapReduce
- HadoopYarn
- Bancos de dados e novos Frameworks surgiram baseados nele.

Kafka



HBase

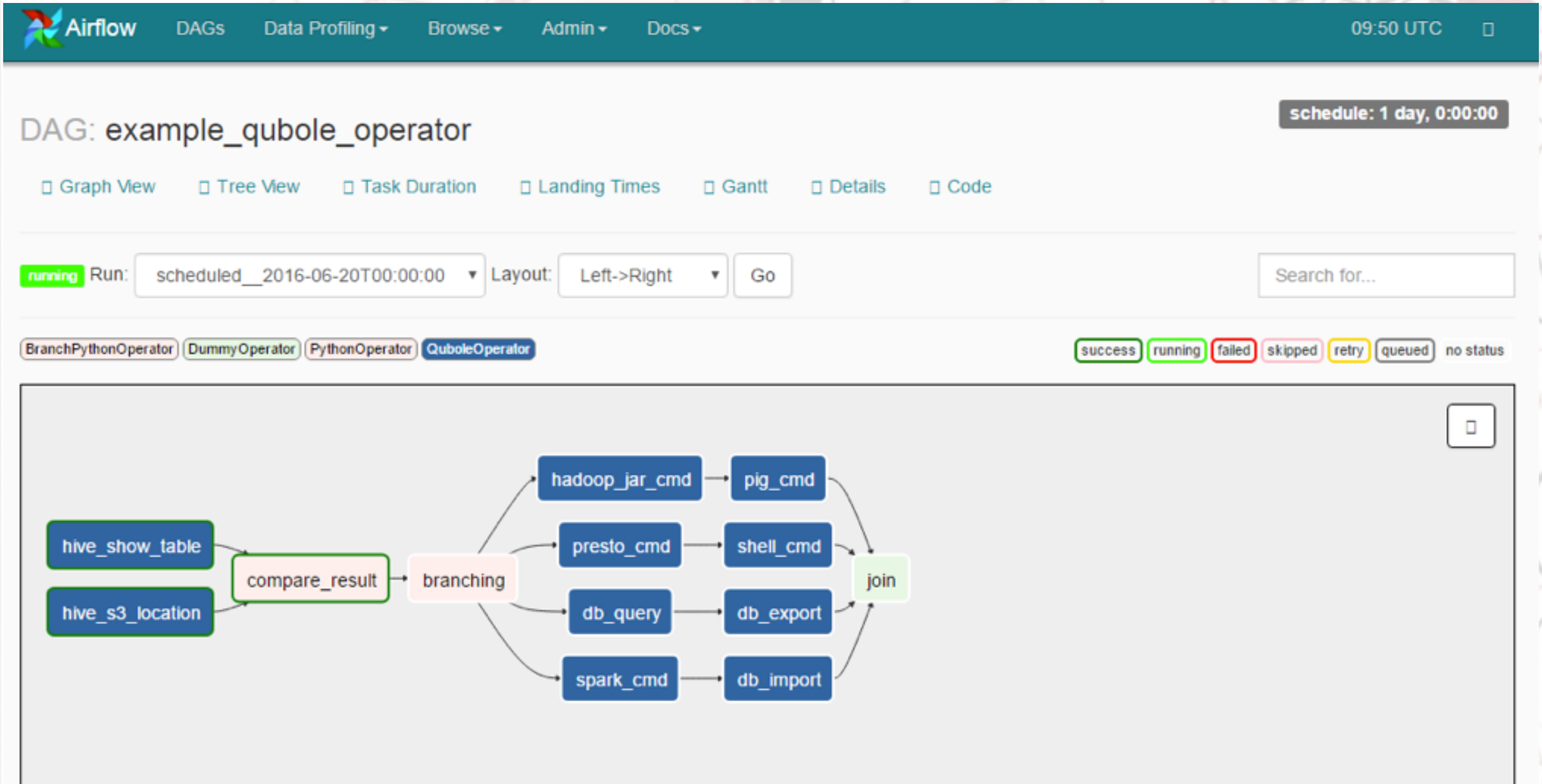
- Foi criado para ser usado com Hadoop
- Banco Distribuido
- Distribuído em Master > RegionServers > Regions
- Orientado por colunas



Airflow

- Criado em 2014 pelo AirBnB
- Conceit de DAG: sequencia de tarefas a serem executadas em ordem.
- Agendor de DAG's
- Divide a DAG em tasks

Airflow


Airflow
DAGs
Data Profiling
Browse
Admin
Docs
09:50 UTC
DAG: example_qubole_operator
schedule: 1 day, 0:00:00
Graph View
Tree View
Task Duration
Landing Times
Gantt
Details
Code
running
Run:
scheduled__2016-06-20T00:00:00
Layout:
Left->Right
Go
Search for...
BranchPythonOperator
DummyOperator
PythonOperator
QuboleOperator
success
running
failed
skipped
retry
queued
no status
hive_show_table
hive_s3_location
compare_result
branching
hadoop_jar_cmd
pig_cmd
presto_cmd
shell_cmd
db_query
db_export
spark_cmd
db_import
join

Será que a Globo.com precisa mesmo?

Números

3 Bilhões de eventos diários

2 Milhões de conexões **simultâneas**

50 Milhões de usuários únicos por mês

100 Mil novos conteúdos por mês

+20 algoritmos diferentes

100 Mil recomendações por minuto

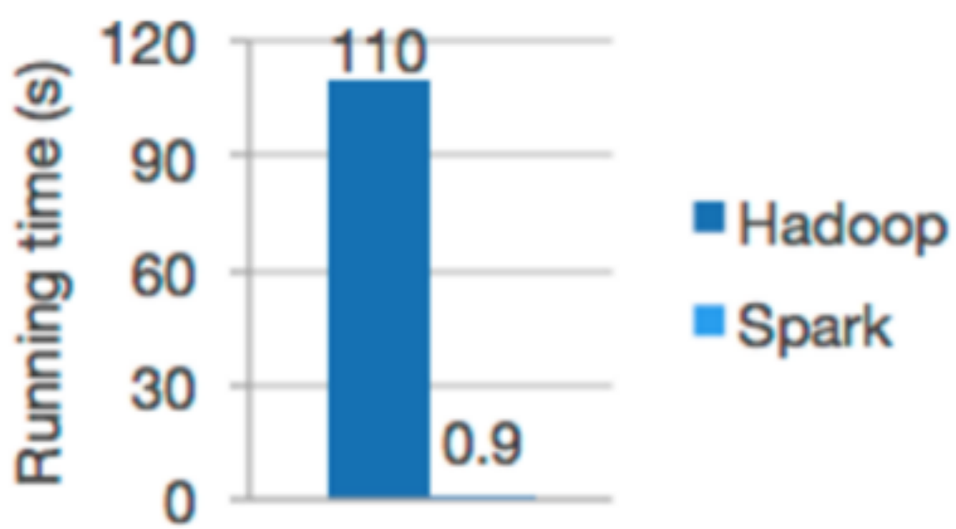
Pra que tudo isso?

Pra que tudo isso?

- Predição
- Personalização
- Saber mais sobre o público
- Distribuição mais inteligente de publicidade

Spark

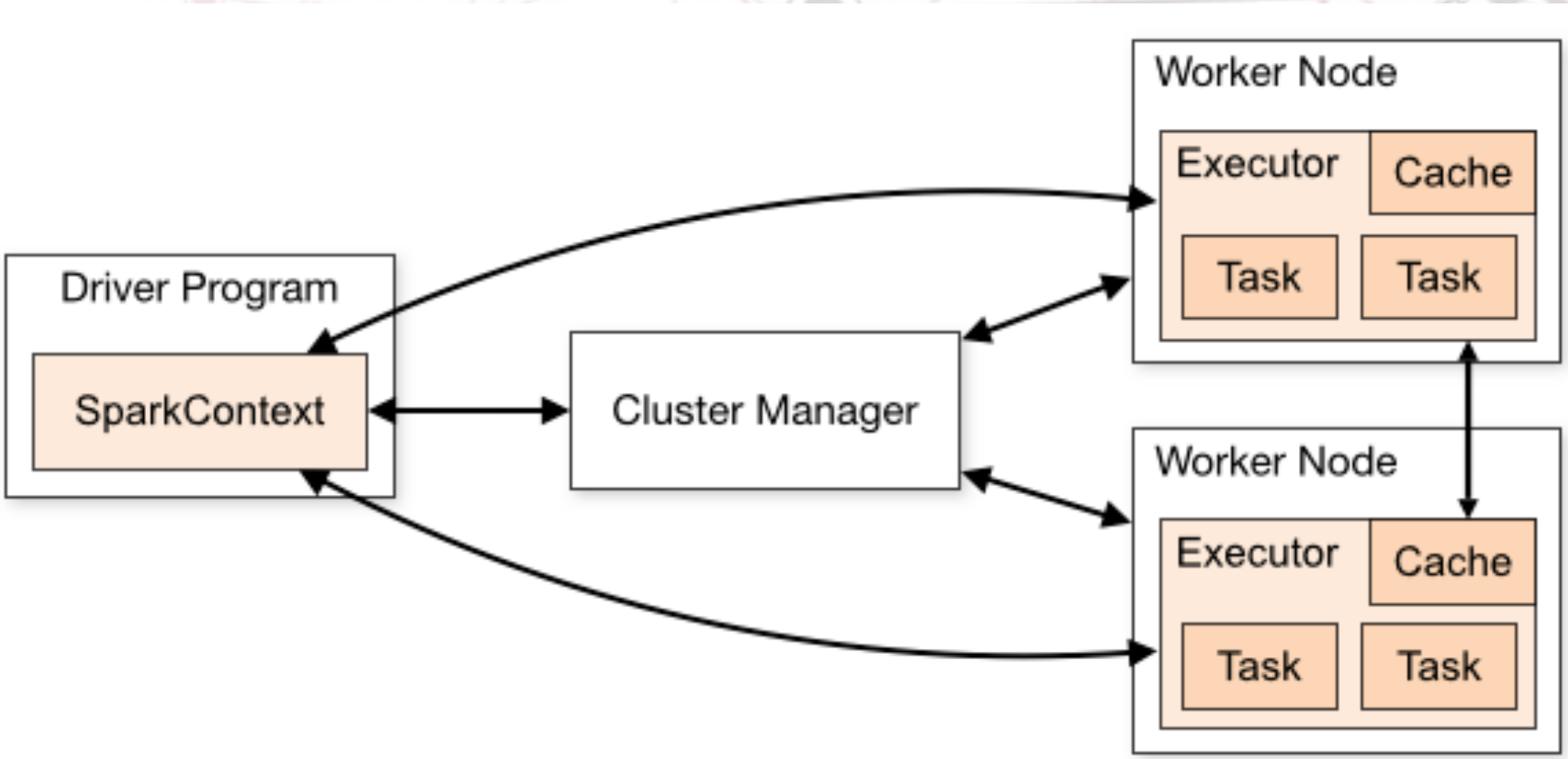
- Nasceu em 2014
- Foco em **velocidade**, facilidade de uso e análises sofisticadas



Logistic regression in Hadoop and Spark

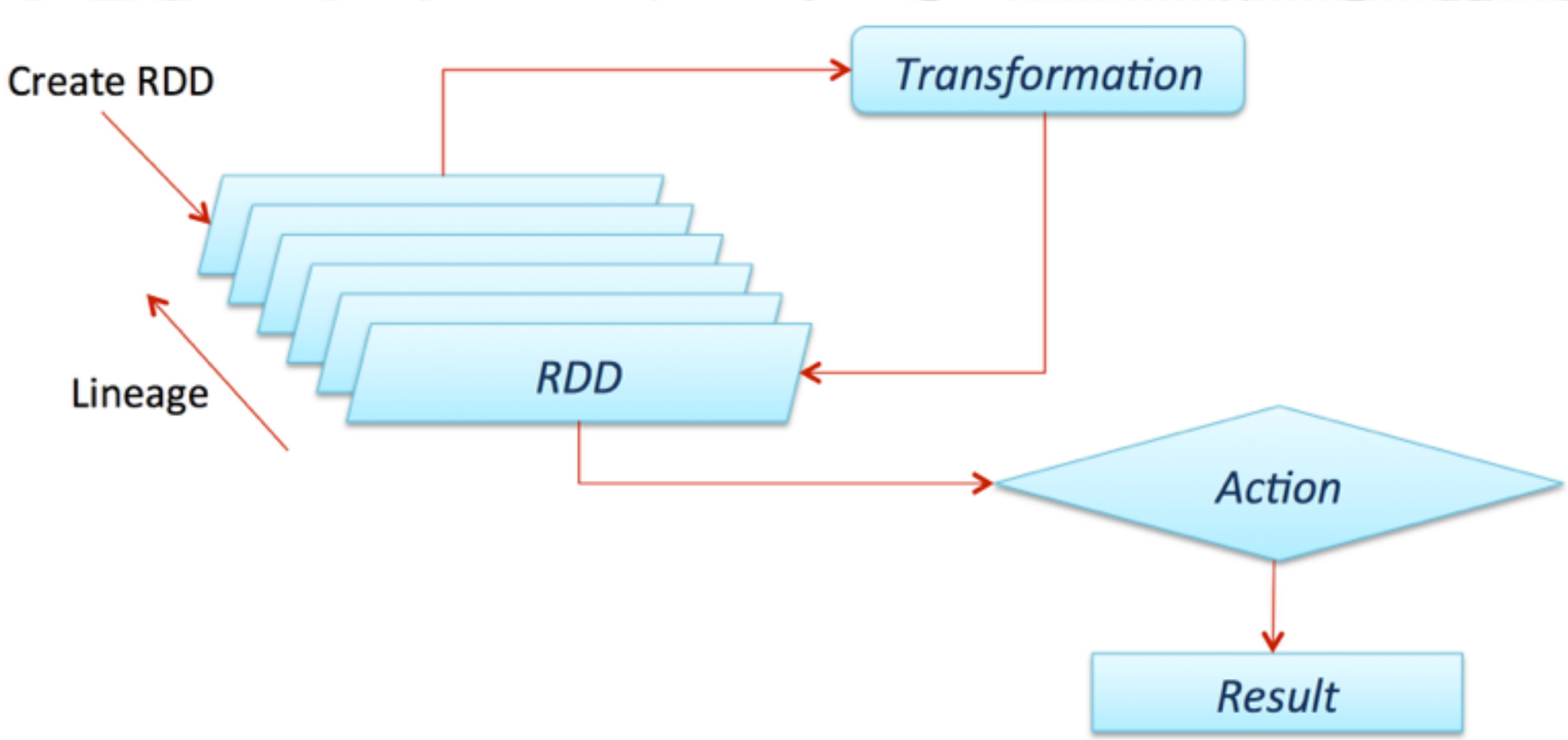
- Aplicações até **100 vezes** mais rápido em **memória** e até **10 vezes** mais rápido em **disco**

Spark


Worker Node
Executor
Cache
Task
Task
Driver Program
SparkContext
Cluster Manager
Worker Node
Executor
Cache
Task
Task

Spark

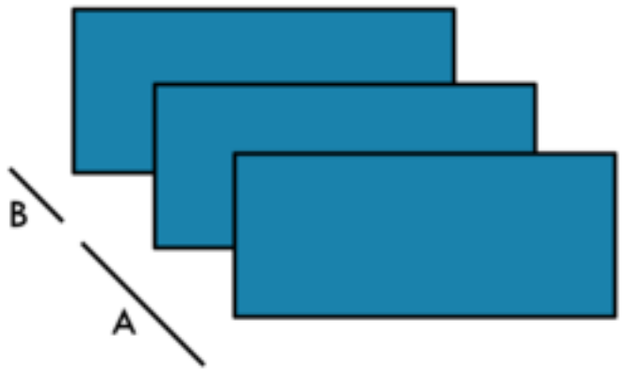
- **RDD** (**R**esilient **D**istributed **D**atasets)



Spark

- RDD

COLLECT

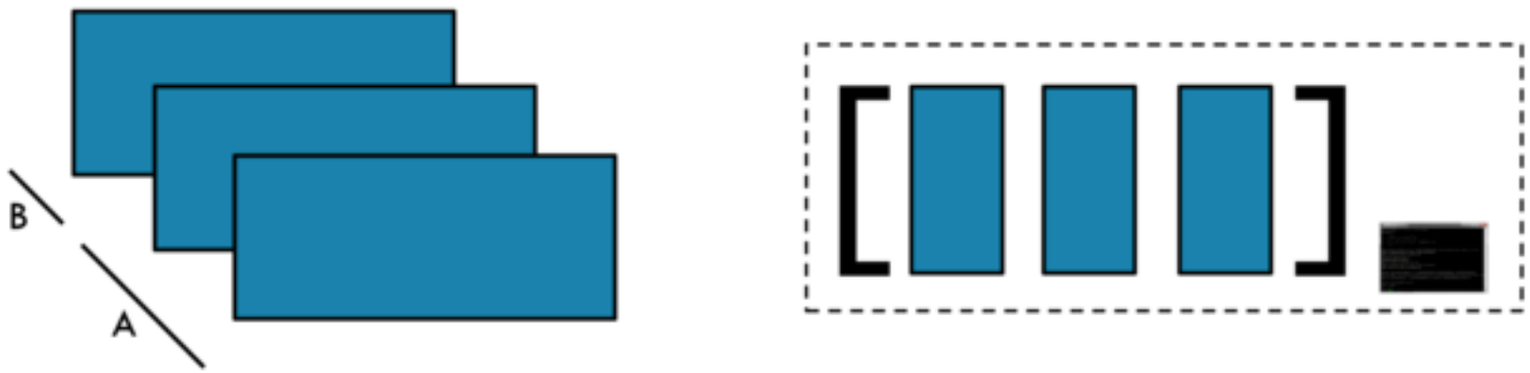


```
11    x = sc.parallelize([1,2,3],2)
12    y = x.collect()
13
14    print x.glom().collect()
15    print y
16
17    sc.stop()
```

Spark

- RDD

COLLECT



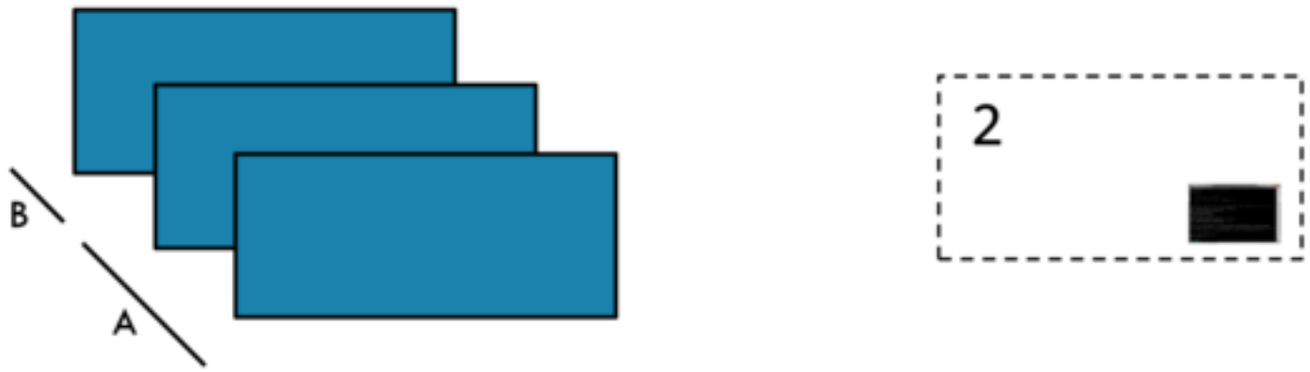

```
11    x = sc.parallelize([1,2,3],2)
12    y = x.collect()
13
14    print x.glom().collect()
15    print y
16
17    sc.stop()
```

```
x: [[1],[2,3]]
y:[1,2,3]
```

Spark

➤RDD

GETNUMPARTITIONS

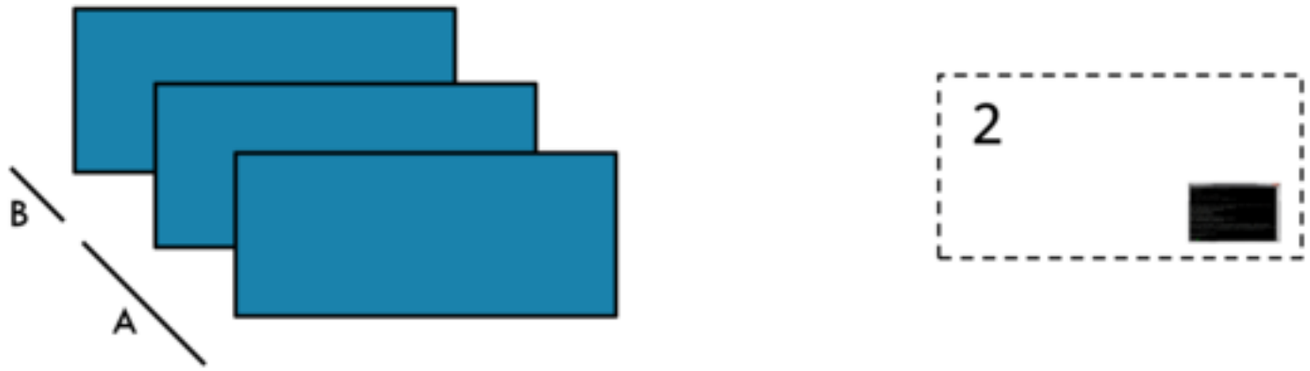



```
11    x = sc.parallelize([1,2,3],2)
12    y = x.getNumPartitions()
13
14    print x.glom().collect()
15    print y
16
```

Spark

➤RDD

GETNUMPARTITIONS



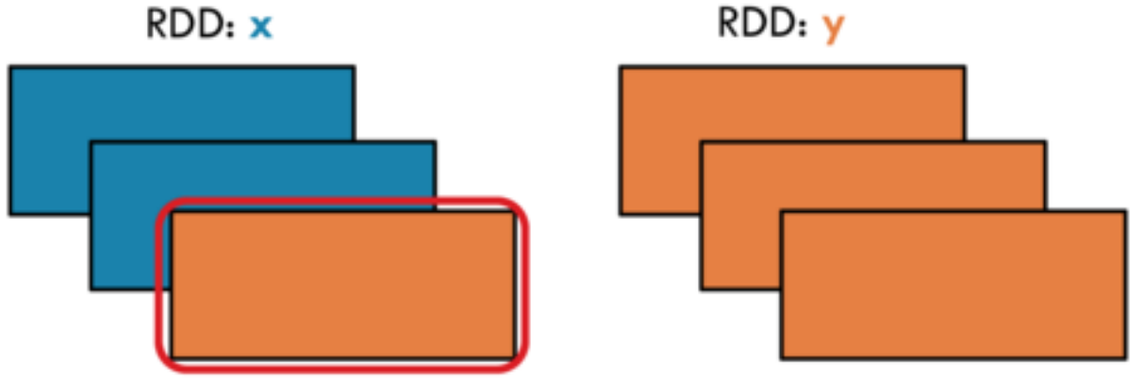

```
11    x = sc.parallelize([1,2,3],2)
12    y = x.getNumPartitions()
13
14    print x.glom().collect()
15    print y
16
```

```
x: [[1],[2,3]]
y: 2
```

Spark

➤RDD

MAP




```
map(f, preservesPartitioning=False)
```

Spark

- RDD

```
x = sc.parallelize(['a','b','c'])
y = x.map(lambda z:(z,1))

print x.collect()
print y.collect()
```

Spark

- RDD

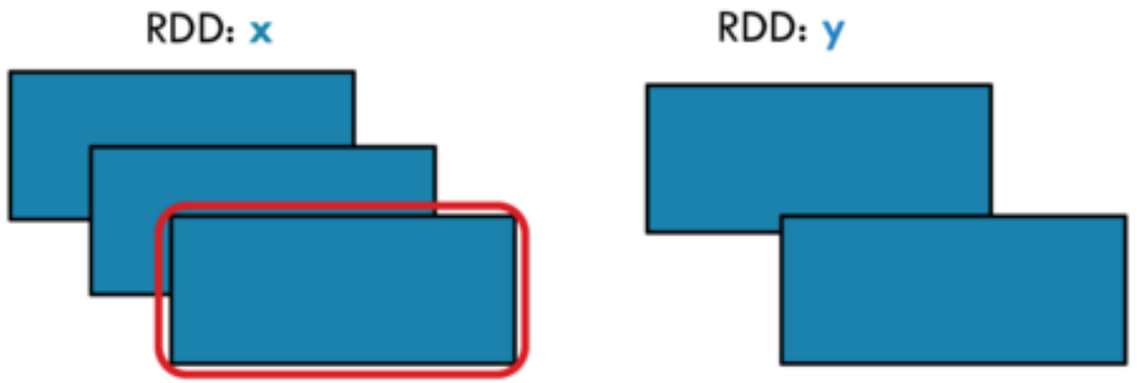
```
x = sc.parallelize(['a','b','c'])
y = x.map(lambda z:(z,1))

print x.collect()
print y.collect()
```

```
x: ['a','b','c']
y: [('a',1),
    ('b',1),
    ('c',1)]
```

Spark

- RDD

FILTER

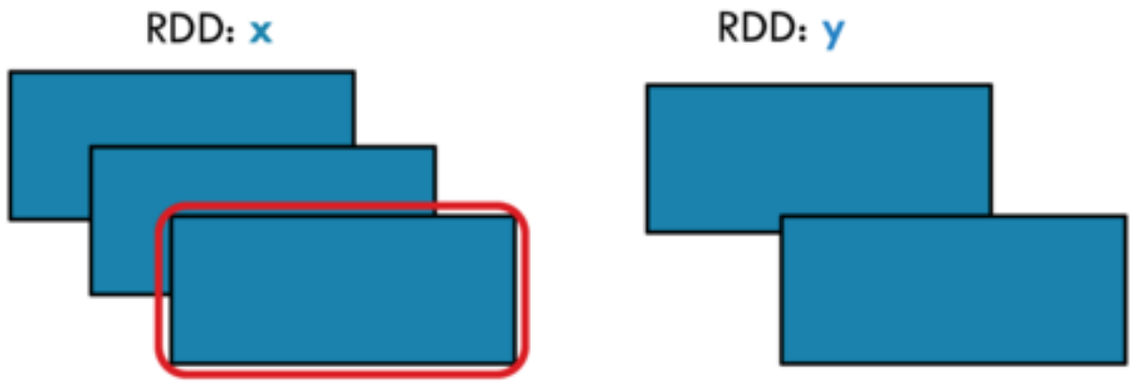



```
11    x = sc.parallelize([1,2,3])
12    y = x.filter(lambda x: x > 1)
13
14    print x.collect()
15    print y.collect()
16
```

Spark

- RDD

FILTER




```
11    x = sc.parallelize([1,2,3])
12    y = x.filter(lambda x: x > 1)
13
14    print x.collect()
15    print y.collect()
16
```

```
x: [1,2,3]
y: [2,3]
```

Spark

- RDD

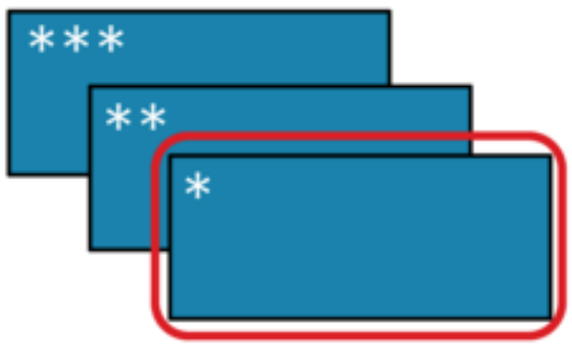
REDUCE


```
11    x = sc.parallelize([1,2,3,4])
12    y = x.reduce(lambda x,y: x + y)
13
14    print x.glom().collect()
15    print y
```

Spark

- RDD

REDUCE




```
11    x = sc.parallelize([1,2,3,4])
12    y = x.reduce(lambda x,y: x + y)
13
14    print x.glom().collect()
15    print y
```

```
x: [[1],[2],
    [3],[4]]
y: 10
```

Spark

- RDD

REDUCE

```
x = sc.parallelize([1,2,3],2)
y = x.reduce(lambda x,y: x - y)
```

==

```
x = sc.parallelize([1,2,3],3)
y = x.reduce(lambda x,y: x - y)
```

?

Spark

- RDD

REDUCE

```
x = sc.parallelize([1,2,3],2)
y = x.reduce(lambda x,y: x - y)
```

==

```
x = sc.parallelize([1,2,3],3)
y = x.reduce(lambda x,y: x - y)
```

?

y: 2

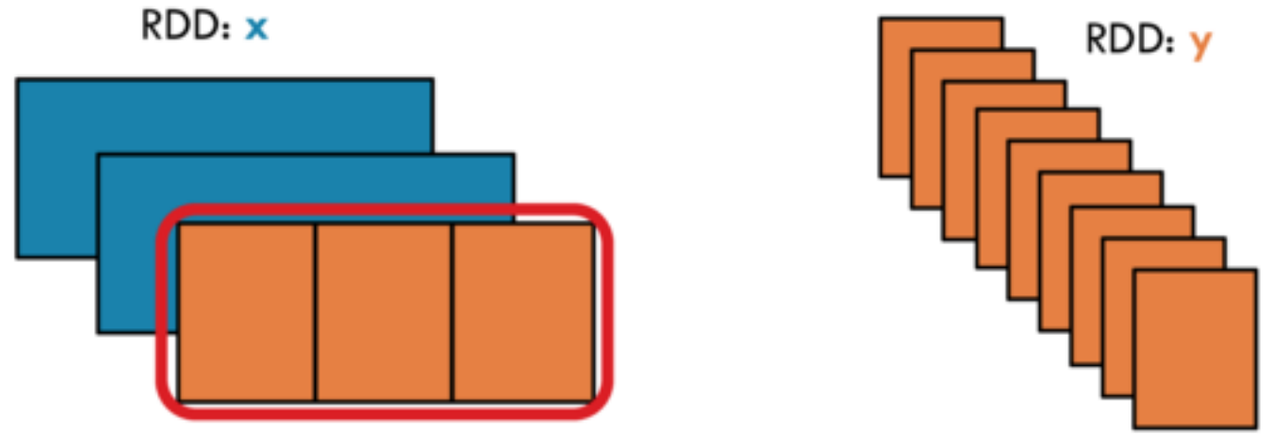
y: -4

Porque?

Spark

➤RDD

FLATMAP




```
flatMap(f, preservesPartitioning=False)
```

Spark

- RDD

```
11      x = sc.parallelize([1,2,3])
12      y = x.flatMap(lambda z:(z,z**2,42))
13
14      print x.collect()
15      print y.collect()
16
```

Spark

- RDD

```
11      x = sc.parallelize([1,2,3])
12      y = x.flatMap(lambda z:(z,z**2,42))
13
14      print x.collect()
15      print y.collect()
16
```

```
x:  [1,2,3]
y:  [1,1,42,
     2,4,42,
     3,9,42]
```

Spark

➤RDD

REDUCEBYKEY

```
11      x = sc.parallelize(['a','a','b','b'])
12      y = x.map(lambda z:(z,1)).reduceByKey(lambda x,y:x+y)
13
14      print x.collect()
15      print y.collect()
16
```

Spark

➤RDD

REDUCEBYKEY

```
11      x = sc.parallelize(['a','a','b','b'])
12      y = x.map(lambda z:(z,1)).reduceByKey(lambda x,y:x+y)
13
14      print x.collect()
15      print y.collect()
16
```

```
x: ['a','a','b','b']
y: [('a',2),
    ('b',2)]
```

Spark

➤RDD

GROUPBYKEY

```
11    x = sc.parallelize(['a','a','b','b']).map(lambda x:(x,1))
12    y = x.groupByKey().map(lambda x:(x[0],list(x[1])))
13
14    print x.collect()
15    print y.collect()
```

Spark

➤RDD

GROUPBYKEY

```
11    x = sc.parallelize(['a','a','b','b']).map(lambda x:(x,1))
12    y = x.groupByKey().map(lambda x:(x[0],list(x[1])))
13
14    print x.collect()
15    print y.collect()
```

```
x: [('a',1),
    ('a',1),
    ('b',1),
    ('b',1)]
y: [(‘a’,[1,1]),
    (‘b’,[1,1])]
```

Spark

Exemplo

```
import time
import pandas as pd
words_list = []

start_time= time.time()
with open('really_big_text.txt') as f:
    for i in f.readlines():
        words = i.split()
        words_list = words_list + map(lambda x:(x,1),words)

df = pd.DataFrame(words_list,columns=['word','count'])\
                        .groupby('word').sum()\
                        .sort('count',ascending=False)


print "TIME: %s"%(time.time()-start_time)
print df

```

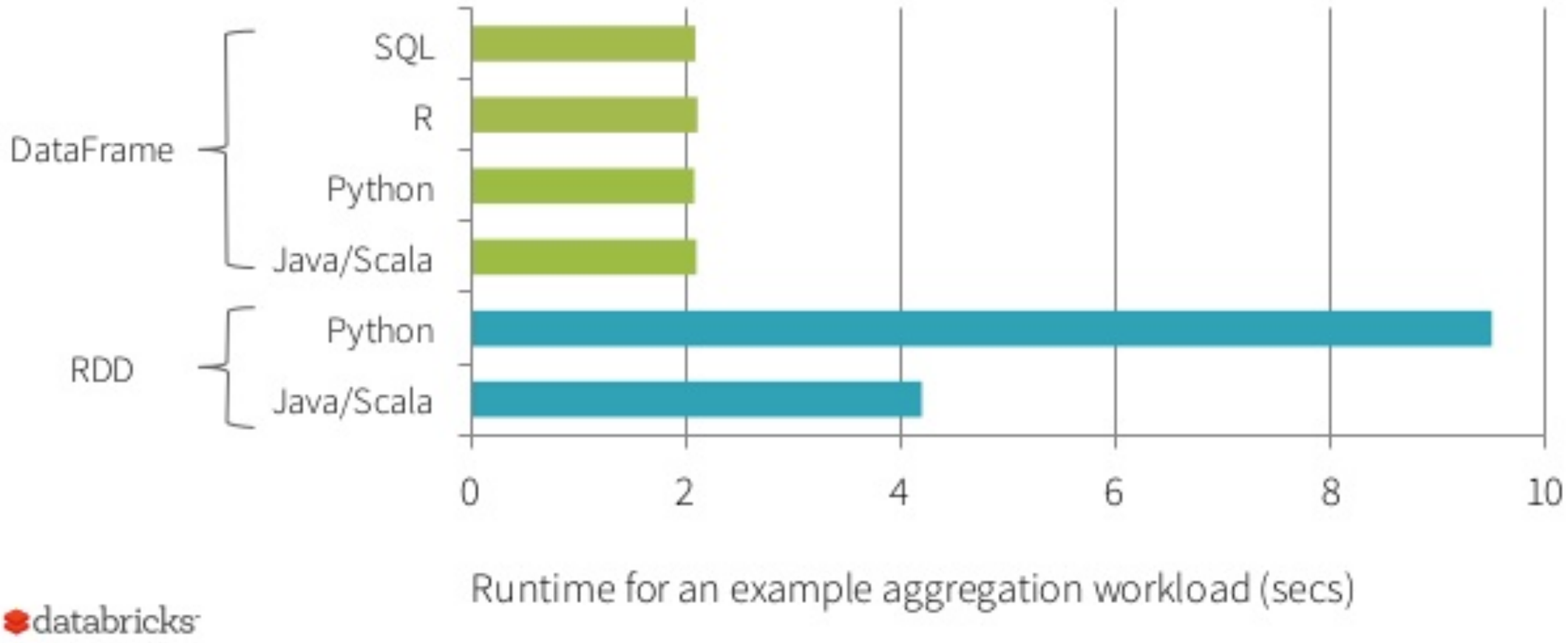
..ython_sudeste (zsh)

```
(.env) python_sudeste % python only_python.py
only_python.py:11: FutureWarning: sort(columns=...
  df = pd.DataFrame(words_list,columns=['word','co
TIME: 1506.24237919
                count
word
the             72271
and             46446
of              40346
to              16539
that            15553
in              14504
he              11377
shall           10872
```

```python
import time
from pyspark.sql import SQLContext
from pyspark import SparkConf, SparkContext

conf = (SparkConf()
         .setAppName("MyFirstApp")
         .set("spark.executor.memory", "12g"))

sc = SparkContext(conf = conf)
sqlContext = SQLContext(sc)

start_time = time.time()

text = sqlContext.read.text('really_big_text.txt').rdd
text_words = text.flatMap(lambda x: x['value'].split())
text_words.cache()

count_words = text_words\
                    .map(lambda x: (x,1))\
                    .reduceByKey(lambda x,y:x+y)\
                    .sortBy(lambda x:x[1],False)\
                    .toDF(schema=['word','count'])

print "TIME: %s"%(time.time()-start_time)
print "Top 100"
count_words.show(10)
print "Total : %s"%len(text_words.collect())
sc.stop()

```

```
(.env) python_sudeste % ./submit_job.sh
TIME: 10.1741509438
Top 100
+-----+-----+
| word|count|
+-----+-----+
|  the|72271|
|  and|46446|
|   of|40346|
|   to|16539|
| that|15553|
|   in|14504|
|   he|11377|
|shall|10872|
| unto|10056|
|  his|10017|
+-----+-----+
only showing top 10 rows

Total : 948432
```

Benefit of Logical Plan: Performance Parity Across Languages



databricks

OBRIGADA!


susana bouchardet


@s_bouchardet