

Recommendation System Optimization based on Spark

Insight Data Engineering Fellow Project

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Motivation



Dataset

- Yelp Dataset
 - Started with a small subset of Yelp Dataset.
 - Scale up to Whole dataset
 - Simulated more data



The Dataset



5,200,000 reviews



174,000 businesses



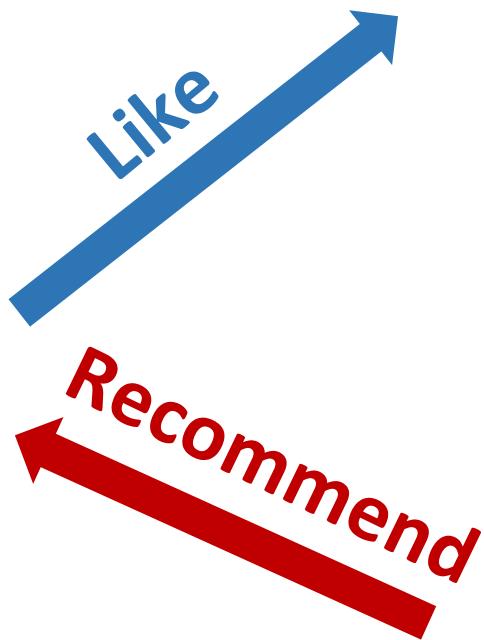
200,000 pictures



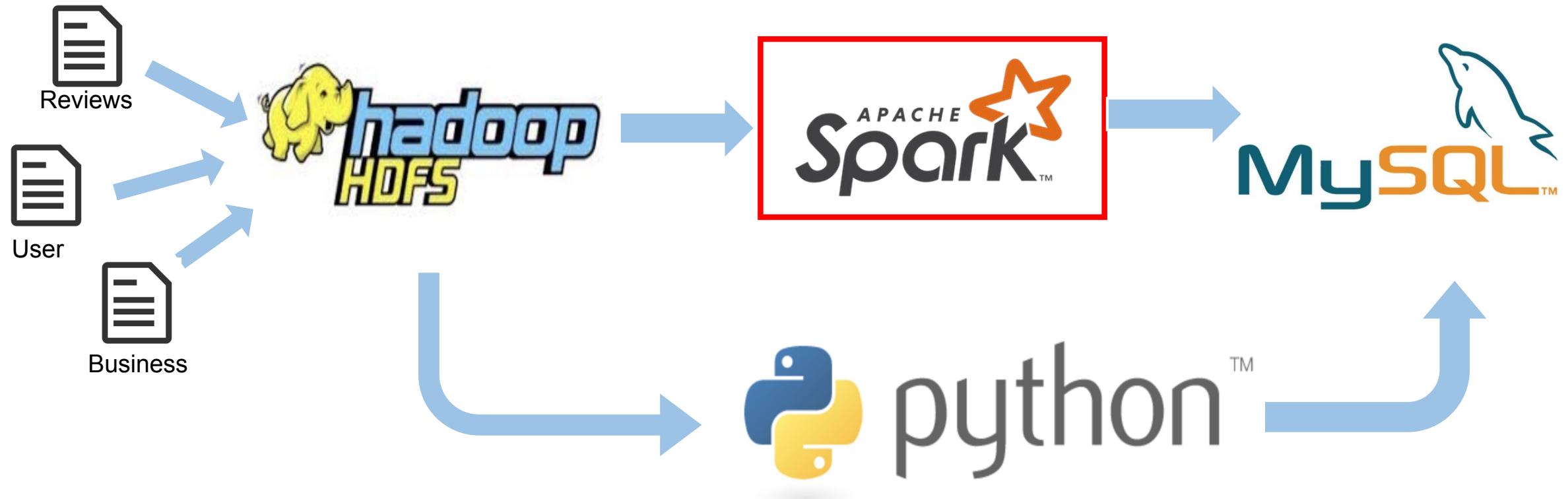
11 metropolitan areas

Algorithm

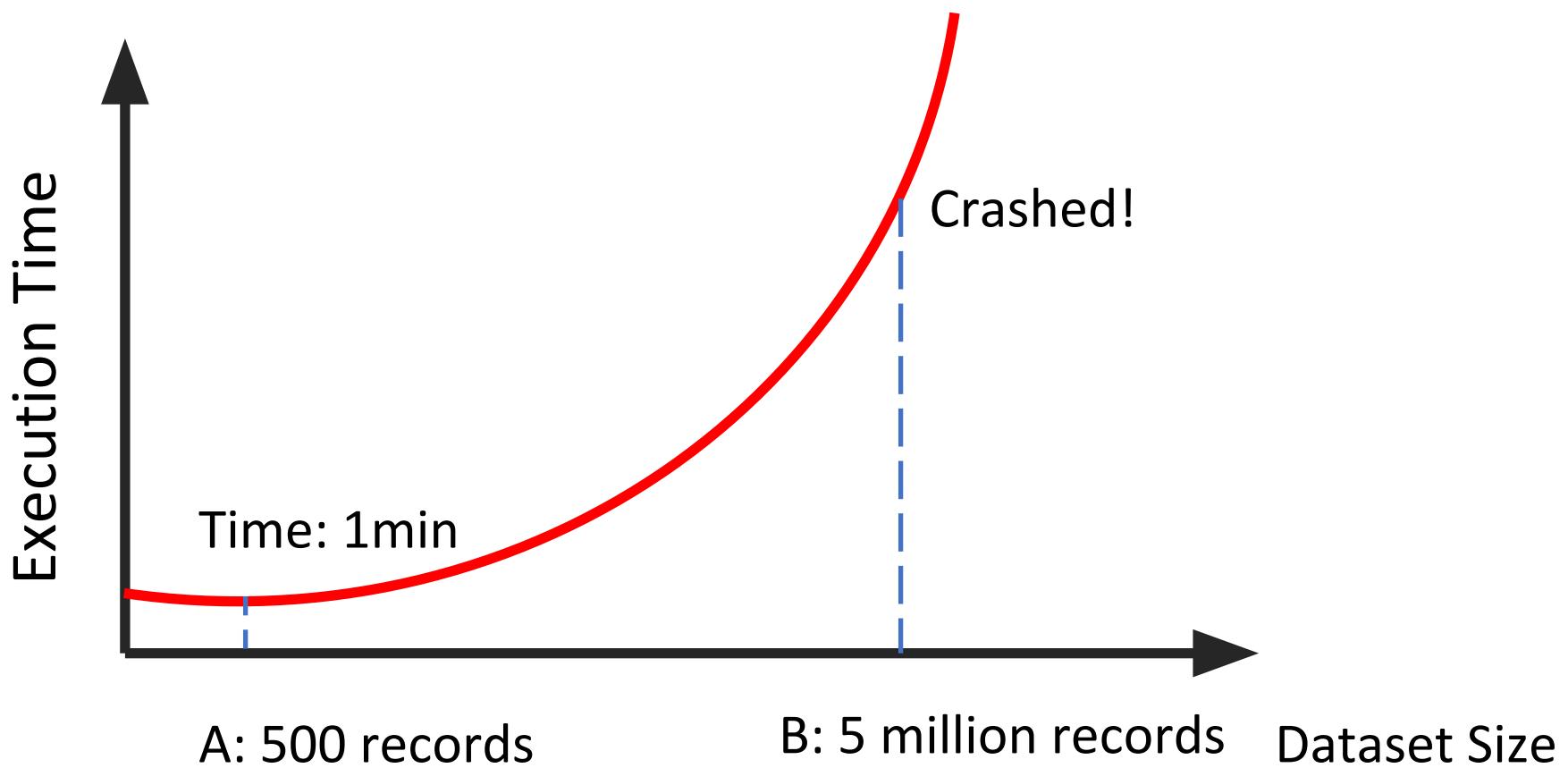
- Item-based Collaborative Filtering



Data Flow



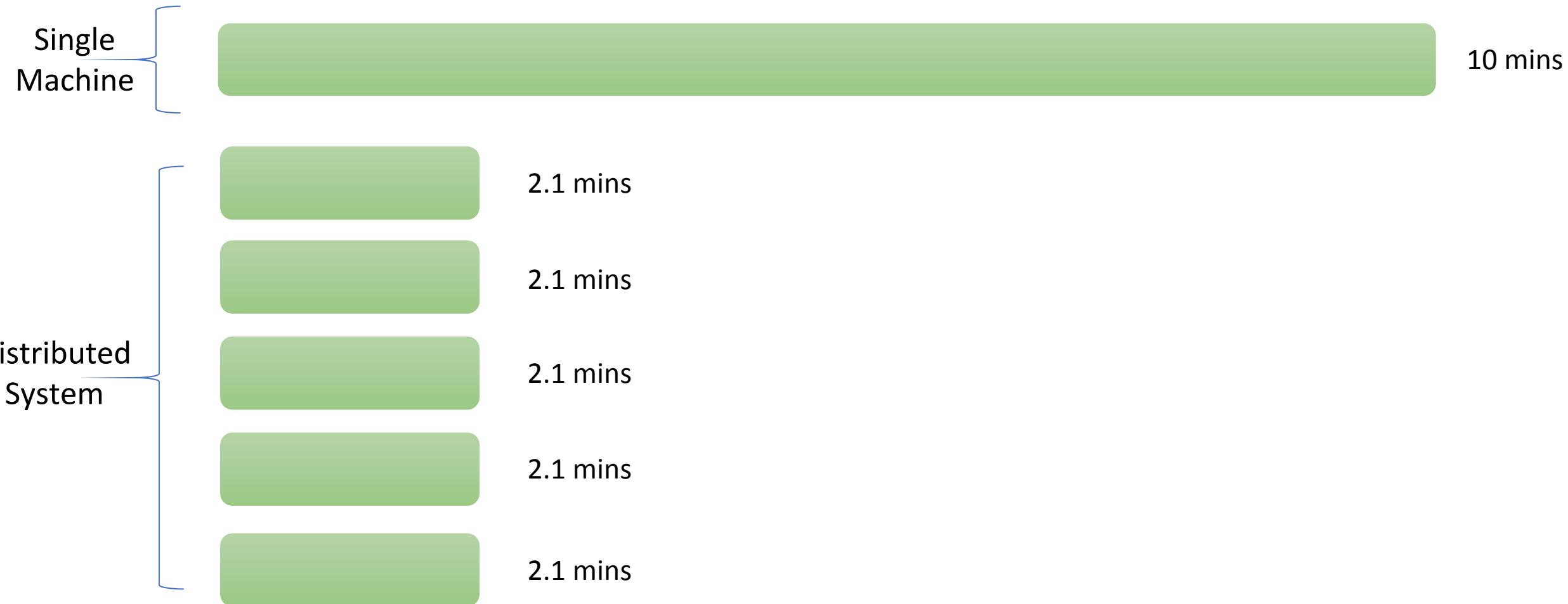
Data Engineering Challenge



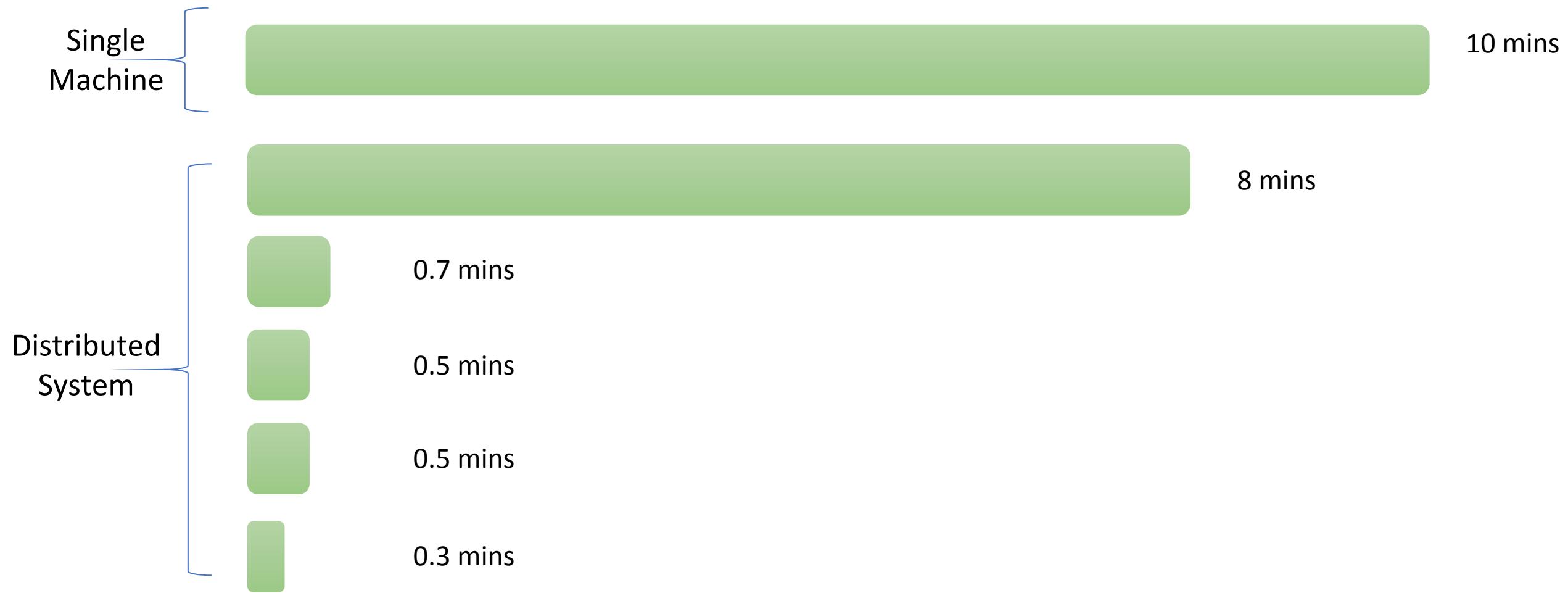
Optimization – Step One

- Data Preprocessing
 - Change business_id and user_id from string to Integer.
- Tuning Spark
 - Increased the value of “Spark.memory.fraction” from 0.6(default) to 0.75 to reduce disk spill.
 - Decreased the value of “spark.memory.storageFraction” from 0.5 to 0.35, save memory for spark execution.

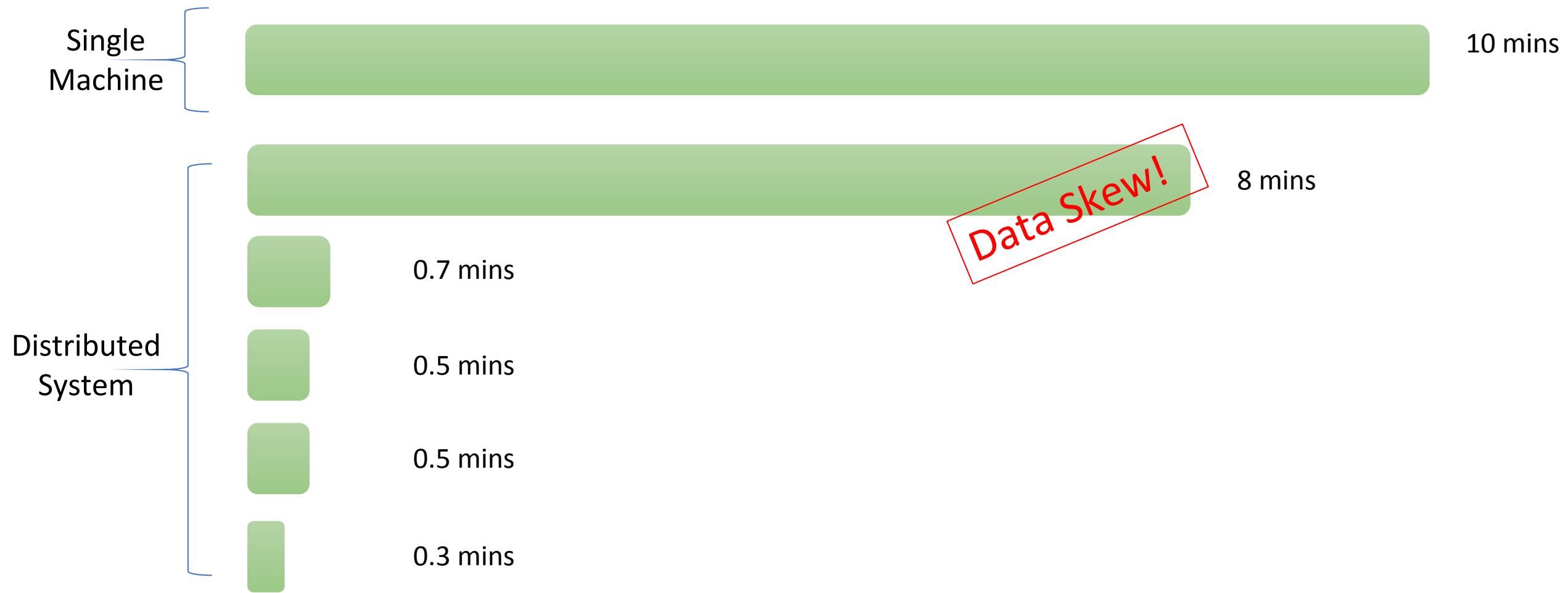
Ideal execution time of distributed system



Real execution time of distributed system



Real execution time of distributed system



Why Data Skew?

-- 20% business provide 80% reviews

Key	Value	
Business	User	Star
Starbucks	Tom	5
Five Guys	Tom	4
Starbucks	Jim	3
Qdoba	John	2
Five Guys	Alice	5
Starbucks	Romia	2
Starbucks	Juliet	5
Qdoba	Sam	3
Starbucks	Carl	5
Starbucks	Wendy	3
Starbucks	Kate	4
Starbucks	Vivian	5



Key	Value
Business	Avg_Star
Starbucks	4.5
Five Guys	3.8
Qdoba	3.5

Why Data Skew?

-- 20% business provide 80% reviews

Key	Value	
Business	User	Star
Starbucks	Tom	5
Five Guys	Tom	4
Starbucks	Jim	3
Qdoba	John	2
Five Guys	Alice	5
Starbucks	Romia	2
Starbucks	Juliet	5
Qdoba	Sam	3
Starbucks	Carl	5
Starbucks	Wendy	3
Starbucks	Kate	4
Starbucks	Vivian	5



Key	Value
Business	Avg_Star
Starbucks	4.5
Five Guys	3.8
Qdoba	3.5

Send the data to different partitions by hash code of the key

Executor I

Key	Value A	
Starbucks	4.5	
Key	Value B	
Starbucks	Tom	5
Starbucks	Jim	3
Starbucks	Romia	2
Starbucks	Juliet	5
Starbucks	Carl	5
Starbucks	Wendy	3
Starbucks	Kate	4
Starbucks	Vivian	5

Executor II

Key	Value A	
Five Guys	3.8	
Key	Value B	
Five Guys	Tom	4
Five Guys	Alice	5

Executor III

Key	Value A	
Qdoba	3.5	
Key	Value B	
Qdoba	John	2
Qdoba	Sam	3

Executor I

Key	Value A	
Starbucks	4.5	
Key	Value B	
Starbucks	Tom	5
Starbucks	Jim	3
Starbucks	Romia	2
Starbucks	Juliet	5
Starbucks	Carl	5
Starbucks	Wendy	3
Starbucks	Kate	4
Starbucks	Vivian	5

Executor II

Key	Value A	
Five Guys	3.8	
Key	Value B	
Five Guys	Tom	4
Five Guys	Alice	5

Executor III

Key	Value A	
Qdoba	3.5	
Key	Value B	
Qdoba	John	2
Qdoba	Sam	3

Execute “join” on different partitions parallelly

Executor I

Key	Value A
Starbucks	4.5
Key	Value B
Starbucks	Tom
Starbuck	5
Starbuck	3
Starbuck	2
Starbuck	5
Starbuck	5
Starbuck	3
Starbuck	4
Starbucks	Rate
Starbucks	Vivian



Running!

!

Executor II

Key	Value B	Value A
Five Guys	Tom	4
Five Guys	Alice	5

Finished!

Executor III

Key	Value B	Value A
Qdoba	John	2
Qdoba	Sam	3

Finished!

Executor I

Key	Value B	Value A
Starbucks	Tom	5 4.5
Starbucks	Jim	3 4.5
Starbucks	Romia	2 4.5
Starbucks	Juliet	5 4.5
Starbucks	Carl	5 4.5
Starbucks	Wendy	3 4.5
Starbucks	Kate	4 4.5
Starbucks	Vivian	5 4.5

Finished!

Executor II

Key	Value B	Value A
Five Guys	Tom	4 3.8
Five Guys	Alice	5 3.8

Finished!

Executor III

Key	Value B	Value A
Qdoba	John	2 3.5
Qdoba	Sam	3 3.5

Finished!

Data Skew Solution – Broadcast Small Table

Key	Value	
Business	User	Star
Starbucks	Tom	5
Five Guys	Tom	4
Starbucks	Jim	3
Qdoba	John	2
Five Guys	Alice	5
Starbucks	Romia	2
Starbucks	Juliet	5
Qdoba	Sam	3
Starbucks	Carl	5
Starbucks	Wendy	3
Starbucks	Kate	4
Starbucks	Vivian	5

Table Join



Key	Value
Business	Avg_Star
Starbucks	4.5
Five Guys	3.8
Qdoba	3.5

Broadcast to
each executor

Data Skew Solution – Broadcast Small Table

Key	Value	
Business	User	Star
Starbucks	Tom	5
Five Guys	Tom	4
Starbucks	Jim	3
Qdoba	John	2
Five Guys	Alice	5
Starbucks	Romia	2
Starbucks	Juliet	5
Qdoba	Sam	3
Starbucks	Carl	5
Starbucks	Wendy	3
Starbucks	Kate	4
Starbucks	Vivian	5

Table Join

Key	Value
Business	Avg_Star
Starbucks	4.5
Five Guys	3.8
Qdoba	3.5

Divide in 3 parts evenly

Broadcast to each partition

Data Skew Solution – Broadcast Small Table

Executor I

Key	Value
Business	Avg_Star
Starbucks	4.5
Five Guys	3.8
Qdoba	3.5

Executor II

Key	Value
Business	Avg_Star
Starbucks	4.5
Five Guys	3.8
Qdoba	3.5

Executor III

Key	Value
Business	Avg_Star
Starbucks	4.5
Five Guys	3.8
Qdoba	3.5

Key Value

Business	User	Star
Starbucks	Tom	5
Five Guys	Tom	4
Starbucks	Jim	3
Qdoba	John	2

Key Value

Business	User	Star
Five Guys	Alice	5
Starbucks	Romia	2
Starbucks	Juliet	5
Qdoba	Sam	3

Key Value

Business	User	Star
Starbucks	Carl	5
Starbucks	Wendy	3
Starbucks	Kate	4
Starbucks	Vivian	5

Data Skew Solution – Broadcast Small Table

Executor I

Key	Value
Business	Avg_Star
Starbucks	4.5
Five Guys	3.8
Qdoba	3.5

Running!

Executor II

Key	Value
Business	Avg_Star
Starbucks	4.5
Five Guys	3.8
Qdoba	3.5

Running!

Executor III

Key	Value
Business	Avg_Star
Starbucks	4.5
Five Guys	3.8
Qdoba	3.5

Running!

Key		
Business	User	Star
Starbucks	Tom	5
Five Guys	Tom	4
Starbucks	Jim	3
Qdoba	John	2

Key		
Business	User	Star
Five Guys	Alice	5
Starbucks	Romia	2
Starbucks	Juliet	5
Qdoba	Sam	3

Key		
Business	User	Star
Starbucks	Carl	5
Starbucks	Wendy	3
Starbucks	Kate	4
Starbucks	Vivian	5

Data Skew Solution – Broadcast Small Table

Executor I

Key	Value B	Value A	
Business	User	Star	Avg_Star
Starbucks	Tom	5	4.5
Five Guys	Tom	4	3.8
Starbucks	Jim	3	4.5
Qdoba	John	2	3.5

Finished!

Executor II

Key	Value B	Value A	
Business	User	Star	Avg_Star
Five Guys	Alice	5	3.8
Starbucks	Romia	2	4.5
Starbucks	Juliet	5	4.5
Qdoba	Sam	3	3.5

Finished!

Executor III

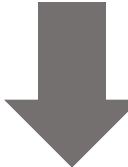
Key	Value	Value A	
Business	User	Star	Avg_Star
Starbucks	Carl	5	4.5
Starbucks	Wendy	3	4.5
Starbucks	Kate	4	4.5
Starbucks	Vivian	5	4.5

Finished!

Data Skew Solution

```
reviews = sc.textFile(args.reviews) \
    .map(lambda x: tuple(x.split(','))) \
    .map(lambda (u, i, riu):(int(u), (int(i), float(riu)))).partitionBy(args.N).cache()

rating_pairs = reviews.join(reviews).filter(lambda (x,y) : y[0][0] < y[1][0]) \
    .map(lambda (x,y) : (y[0][0], (y[1][0], y[0][1], y[1][1]))) \
    .join(avg_star).map(lambda (i,(j, ri, rj), avg_i) : (j, (i, avg_i, ri, rj))) \
    .join(avg_star).map(lambda (j, ((i, avg_i, ri, rj), avg_j)) : ((i,j),(ri, rj, avg_i, avg_j))) \
    .mapValues(lambda (ri, rj, avg_i, avg_j) : (ri - avg_i, rj - avg_j)) \
    .reduceByKey(lambda x,y : x+y) \
    .mapValues(list).mapValues(similarity_cal).filter(lambda (x,y) : y < 0.9999 and y > -0.9999)
```

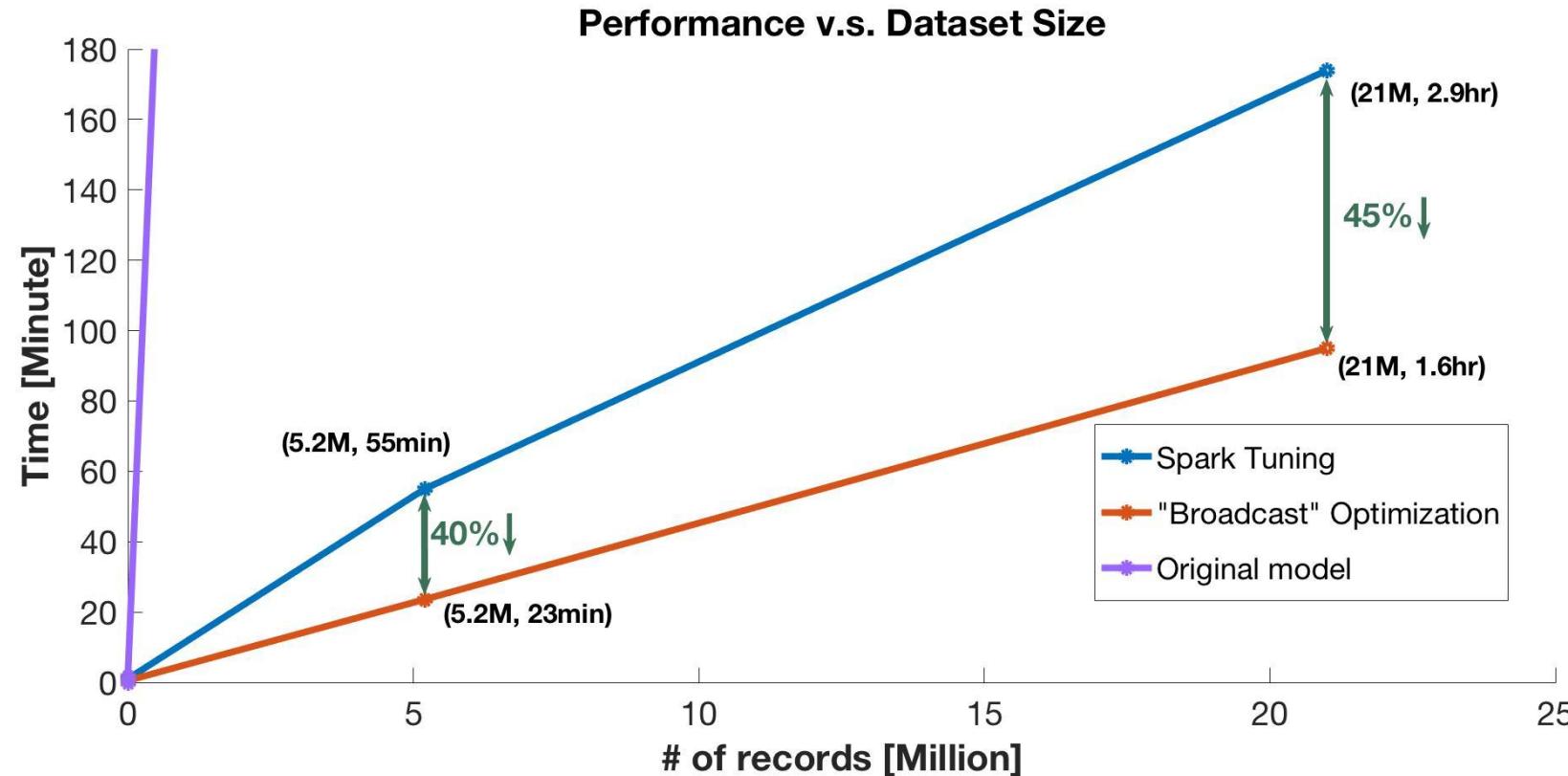


```
broadcast_avg_star = sc.broadcast(avg_star.collect())
avg_star.unpersist()
reviews = sc.textFile(args.reviews) \
    .map(lambda x: tuple(x.split(','))) \
    .map(lambda (u, i, riu):(int(u), (int(i), float(riu)))).partitionBy(args.N).cache()

rating_pairs = reviews.join(reviews).filter(lambda (x,y) : y[0][0] < y[1][0]) \
    .map(lambda (x,y) : ((y[0][0],y[1][0]), (y[0][1], y[1][1]))) \
    .map(lambda (x,y) : (x,(y[0],y[1],broadcast_avg_star.value[x[0]][1],broadcast_avg_star.value[x[1]][1]))) \
    .mapValues(lambda (ri, rj, avg_i, avg_j) : (ri - avg_i, rj-avg_j)) \
    .partitionBy(args.N) \
    .reduceByKey(lambda x,y : x+y) \
    .mapValues(list).mapValues(similarity_cal) \
    .filter(lambda (x,y) : y<0.9999 and y > -0.9999) \
    .saveAsTextFile(args.output)
```

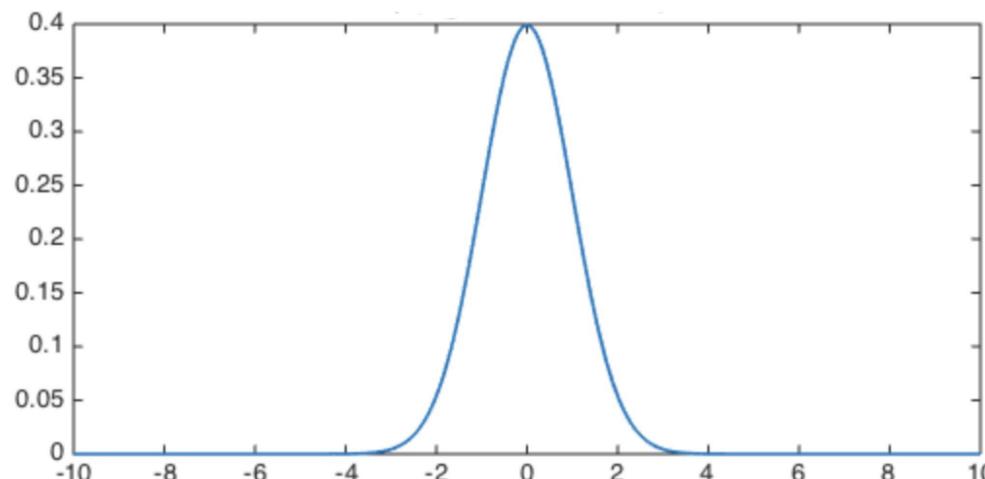
Performance

- System: 1 master node, 3 worker nodes.
- Memory: 6GB/node.



Application

- Transaction data processing
 - 20% companies provide 80% transaction data
- Traffic data processing
 - 20% geographic locations provide 80% traffic data
- Any data follows normal distribution with small sigma value.



Ruby Liu



**Master in Computer Engineering,
@ Northeastern University**



- Ballet
- Swimming

- Travelling
- Debug



Q&A

Thank you!

Further work

- Joined two big tables in Spark
 - Add a column “index” to the balanced table
 - Iteratively broadcast part of the balanced table according to the index value.