

# CSC 555 and DSC 333

## Mining Big Data

### Lecture 9

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# Tonight

- Clustering
  - Document matching
  - Running Spark
  - Recommender systems
- Map-side join*

# Canopy (Pre-)Clustering

- Used for pre-processing

- Initialize centroids

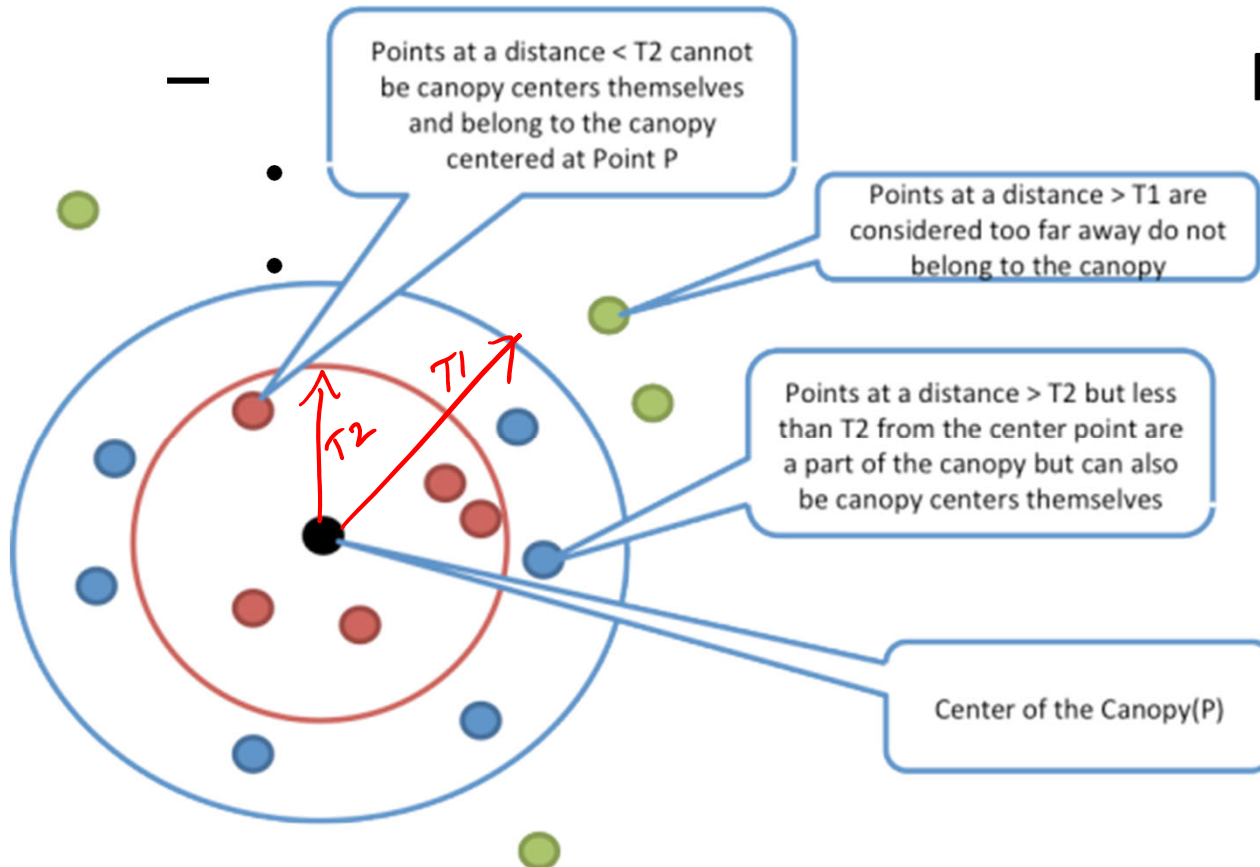
- 

Repeat

Pick random center

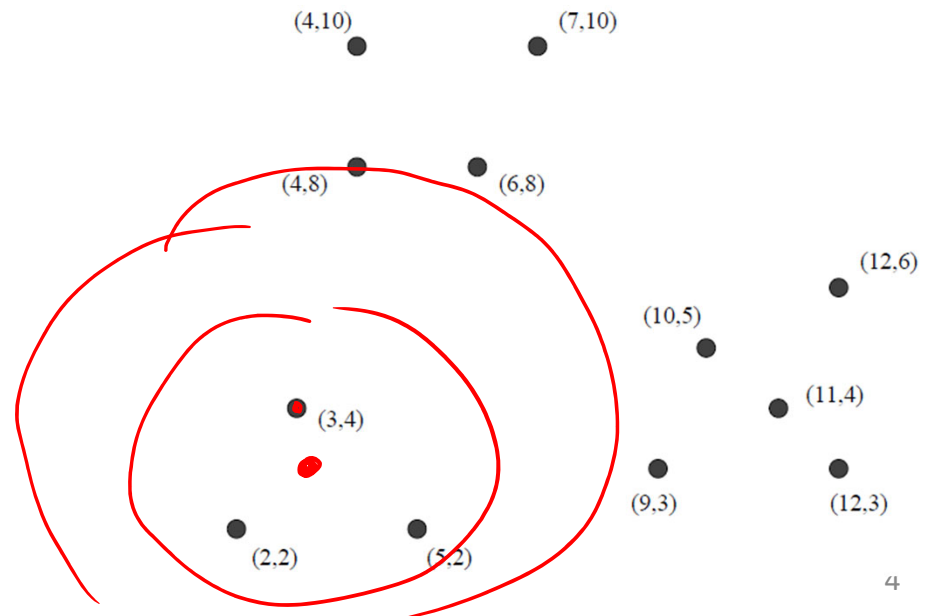
Build canopy

Remove points



# K-Means Clustering with Mahout

- Create a simple input file (12 points)
- `$MAHOUT_HOME/bin/mahout`  
`org.apache.mahout.clustering.syntheticcontrol.kmeans.Job --maxIter 8 --numClusters 3 --t1 5 --t2 3 --input testdata --output kmeansRes`



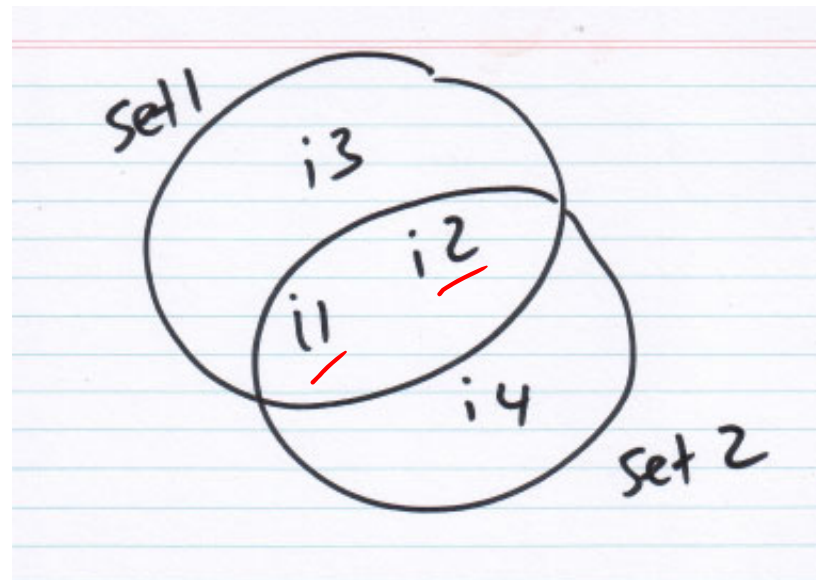
# Similarity of Sets

- How do you compare two sets?

$$\frac{2}{4}$$

- Items represented by sets

- Documents
- Homeworks
- Fingerprints
- SQL Queries



- Overlap = “Similarity”

# Jaccard Similarity Measure

- Clustering/recommender engines
- Find buyers with similar taste
  - Collaborative/content filtering
- Find movie-renters with similar taste
  - Netflix, Blockbuster
  - Ratings are 1-5, not boolean
    - Bag distance (minimum for intersection, sum for union)
    - $\{a,a,a,b\} \triangleleft \{a,a,b,b,c\} = 1/3$

# Shingling

- A mechanism to represent documents
- Pick value  $k$
- Generate  $k$ -shingles to represent the document
  - Document = abcdabd
  - 2-shingles = {ab, bc, cd, da, bd}
- Compute similarity
- White space? (' ', '\n', ...)

# Shingle Size

- What if we pick  $k=1$ ?
- $K$  large enough to keep shingle appearance probability low
- How many characters do you expect?
  - $30^2 = 900$
  - $30^3 = 27K$
  - $30^4 = \underline{810K}$
  - $30^5 = \sim 24M$  combinations

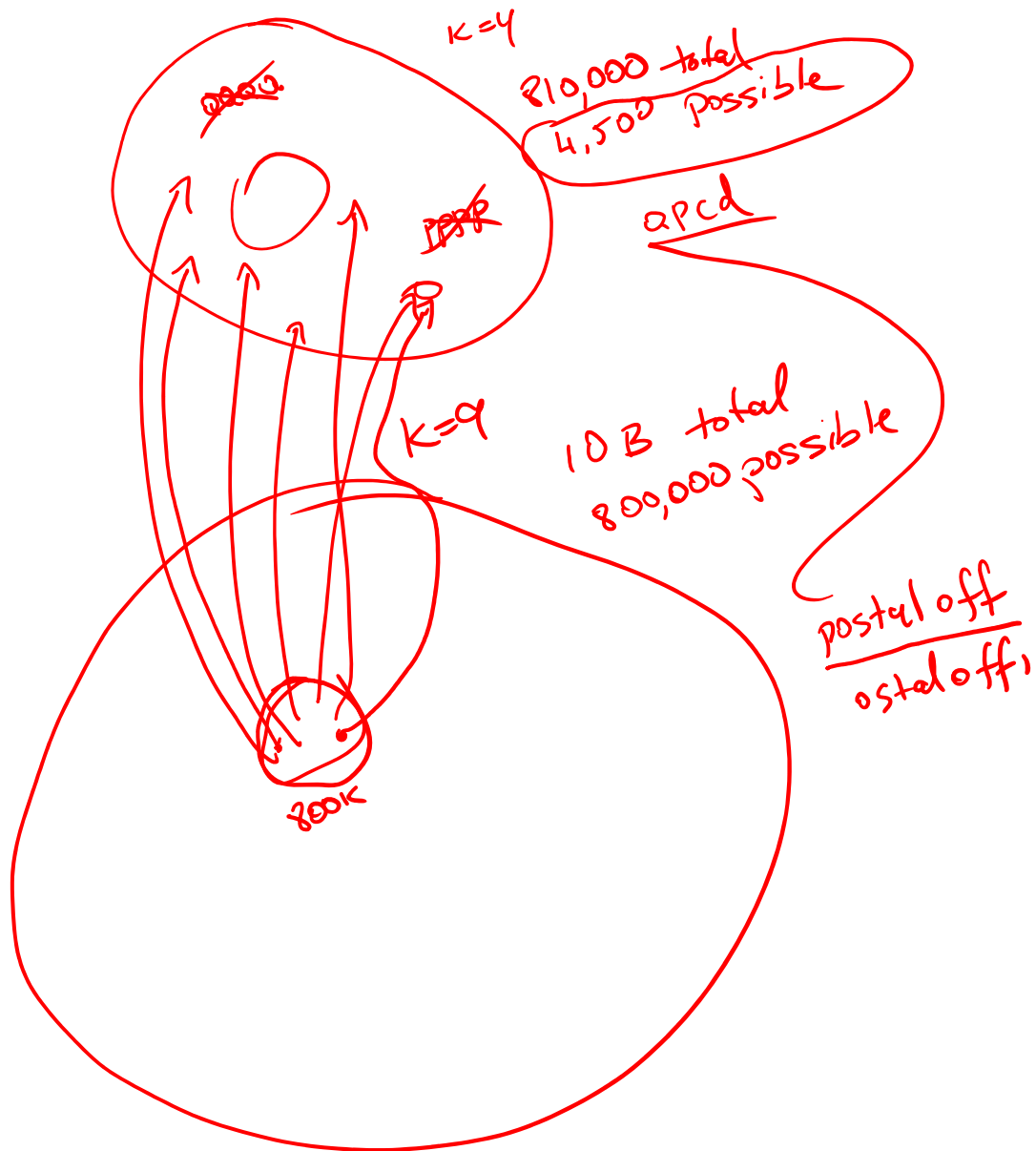


# Letter Distribution

- Letter distribution is not uniform
  - Scrabble values
- 810K combinations *zQzP*
- Common 4-letter combinations are a much smaller subset
  - Others are unusual or impossible

# String Overhead

- Comparing strings is expensive
  - For  $k=9$ , abcdefghi and abcdefghz
- One of the many uses of hashing
  - Similar to compression (lossy)
  - Represent each shingle by a code (hash)
- How much space does the hash require?
  - $k=9$ ,  $30^9$  different potential shingles
- $k=9$  hashed to 4 bytes better than  $k=4$ 
  - Effective space is much smaller



# Shingle Cost

- $k=9 \rightarrow 9X$  document size
  - Hash to 4 bytes, still 4X
  - Does not fit in memory
- Create signatures
  - Again, hashing
  - Lossy compression
  - Similarity-preserving

abcd  
bcde  
cdef

# Matrix Representation

- Each document = binary vector
  - # elements
  - # of documents
- Jaccard measure
- Sparse matrix


postal off  
↓  
zettot

<i>Element</i>	$S_1$	$S_2$	$S_3$	$S_4$
<i>a</i>	1	0	0	1
<i>b</i>	0	0	1	0
<i>c</i>	0	1	0	1
<i>d</i>	1	0	1	1
<i>e</i>	0	0	1	0

Figure 3.2: A matrix representing four sets

# Minhashing

- Select a permutation of the matrix rows
- The first occurrence of 1 in the vector

  $\begin{aligned} & - h(S_1) = a \\ & - h(S_2) = c \\ & - h(S_3) = b \\ & - h(S_4) = a \end{aligned}$

<i>Element</i>	$S_1$	$S_2$	$S_3$	$S_4$
$b$	0	0	1	0
$e$	0	0	1	0
$a$	1	0	0	1
$d$	1	0	1	1
$c$	0	1	0	1

Figure 3.3: A permutation of the rows of Fig. 3.2

- Similar to the Jaccard measure

# Minhash Signatures

*S rows* → *S rows*

- Permute and build a Minhash signature several times
- No need to build the permutation

Row	$S_1$	$S_2$	$S_3$	$S_4$	$x + 1 \bmod 5$	$3x + 1 \bmod 5$
0	1	0	0	1	1	1
1	0	0	1	0	2	4
2	0	1	0	1	3	2
3	1	0	1	1	4	0
4	0	0	1	0	0	3

Figure 3.4: Hash functions computed for the matrix of Fig. 3.2

- Final result (2)

→

	$S_1$	$S_2$	$S_3$	$S_4$
$h_1$	1	3	0	1
$h_2$	0	2	0	0

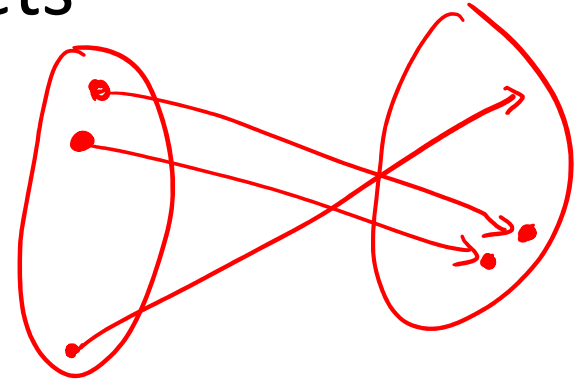
# Comparing Document Pairs

- The curse of the  $N^2$ 
  - 100,000 documents
  - Enough memory to store hash/signatures
  - $\sim 100,000 \times 100,000$  pairs =  $\sim 10,000,000,000$  comparisons
- This can take a long time
  - 1000 comparisons/second
  - 115 days
- (embarrassingly) Parallelizable



# Locality-Sensitive Hashing

- Assign documents into “buckets”
- 100K  $\Rightarrow$  50 buckets
  - 50 \*  $\overset{100K \times 100K}{2,000 * 2,000} = 200,000K$
  - (vs 10,000,000K)
  - 115 days  $\Rightarrow$  2.3 days
- Split the signature matrix into “bands”
- Hash each band

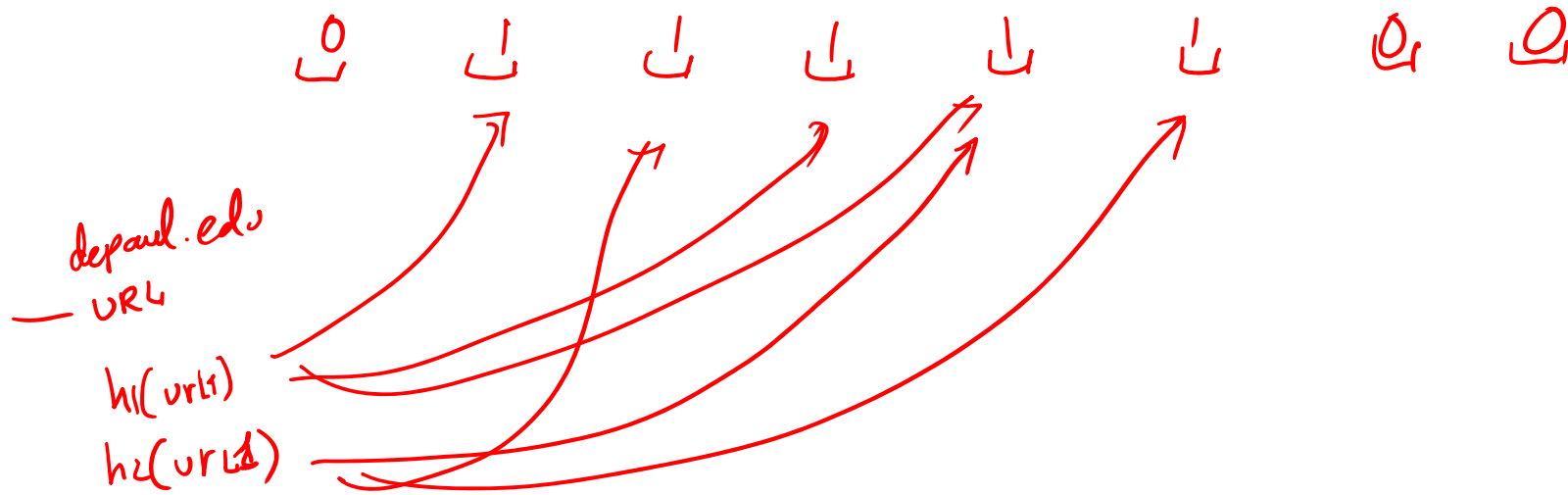


# Combining the Techniques

- Construct set of  $k$ -shingles (for some  $k$ )
  - Optionally hash shingles to  $n$ -bit values
- Arrange the documents by shingle value
- Pick a length for the minhash signatures
- Select a threshold  $t$  (false neg. vs speed)
- Construct candidate pairs by applying LSH
- Find the candidate matches
  - Optionally, look at the actual matched documents

# Bloom Filter

- Simple hashed approximation
- Find match (with false positives)
- Example
  - 10M URLs
  - 8bits/URL (~10MB)
    - ~2% false positive rate
  - 10bits/URL (~12.5MB)
    - ~0.8% false positive



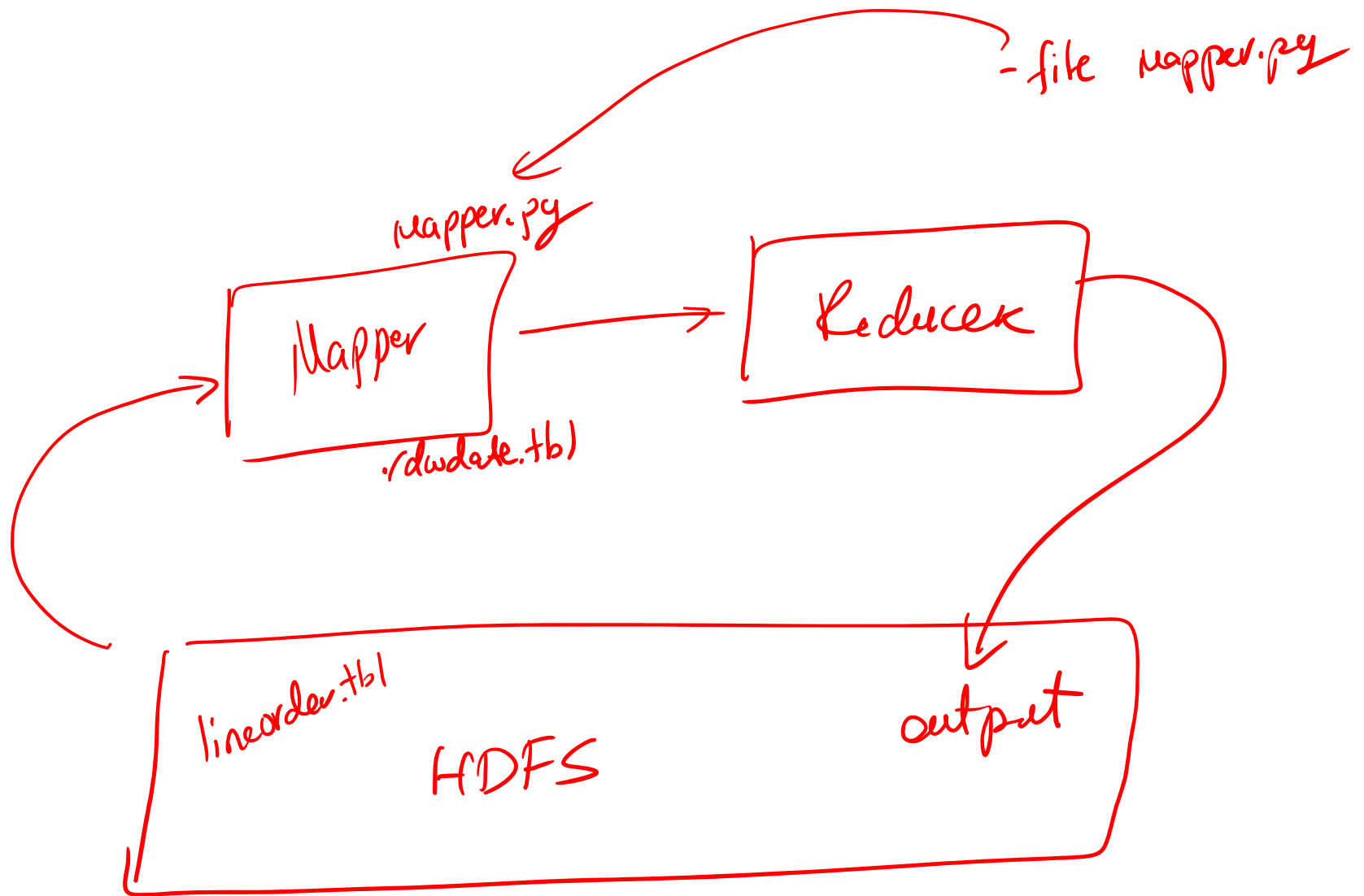
4:30

# A Break



# Map-join implementation

```
SELECT lo_quantity, AVG(lo_revenue)
FROM lineorder, dwdate
WHERE lo_orderdate = d_datekey AND d_year = 1994
AND lo_discount BETWEEN 6 AND 8
GROUP BY lo_quantity;
```



# Spark Principles

in HDFS/Map file = 8 blocks  
128 MB  
in spark file = 100M lines  
line

- Distributed datasets
  - data = [1, 2, 3, 4, 5]
  - distData = sc.parallelize(data)
  - distData.reduce(lambda a, b: a + b)
- distFile = sc.textFile("data.txt")
  - hdfs://... , s3n://
  - lengths = distFile.map(lambda s: len(s))
  - totalLength = lengths.reduce(lambda a, b: a + b)

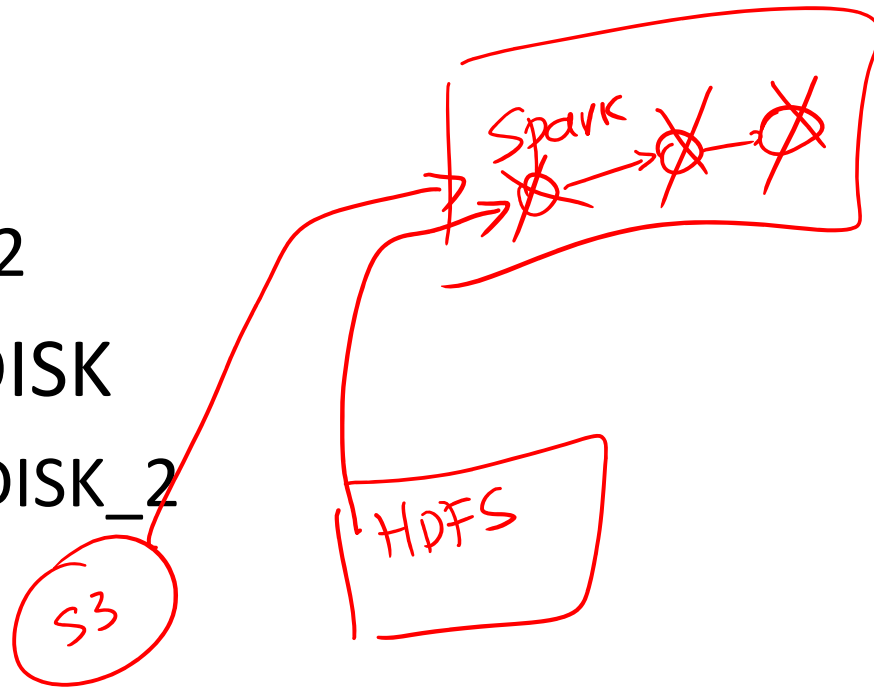


# Spark Storage

- As close to data as possible (HDFS nodes?)
- Uses local disk to store data
  - Recommended 4-8 disks per node w/out RAID
- Recommend allocating up to 75% of RAM
- When data in RAM, performance network-bound

# RDD Persistence

- MEMORY\_ONLY
  - MEMORY\_ONLY\_2
- MEMORY\_AND\_DISK
  - MEMORY\_AND\_DISK\_2
- DISK\_ONLY
- Unpersist



# Spark Example

```
# Read file from HDFS
```

```
text_file = sc.textFile("hdfs://ip-172-31-29-219.us-west-  
1.compute.internal/data/README.md")
```

```
lengths = text_file.map(lambda s: len(s))
```

```
print text_file.take(100)
```

```
lengths.foreach(myprint)
```

```
print lengths.take(100)
```

```
totalLength = lengths.reduce(lambda a, b: a + b)
```

# Spark Example

```
# Read file from HDFS
```

```
text_file = sc.textFile("hdfs://ec2-54-67-64-123.us-west-1.compute.amazonaws.com/data.txt")
```

```
counts = text_file.flatMap
```

```
  (lambda line: line.split(" ")).map(
```

```
    lambda word: (word, 1)).
```

```
    reduceByKey(lambda a, b: a + b)
```

SUM

```
counts.saveAsTextFile("hdfs://ip-172-31-29-219.us-west-1.compute.internal/data/output")
```

# Spark Example

```
import random
def sample(p):
    x, y = random.random(), random.random()
    return 1 if x*x + y*y < 1 else 0

count = sc.parallelize(xrange(0, 500000)).map(sample) \
    .reduce(lambda a, b: a + b)
print "Pi is roughly %f" % (4.0 * count / 500000)
```

# Recommender Systems

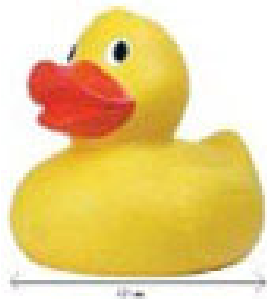
- Recommend
  - Movies/Purchases/News
- Content-based systems
  - Analyze user history
  - Find similar items
- Collaborative filtering
  - Similarity between users
  - Users like you also liked...

Search

All Departments 

## More to Explore

You looked at

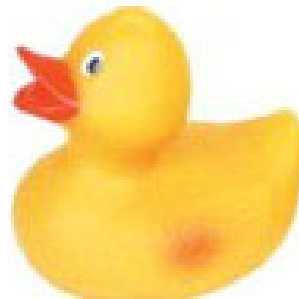


[Giant Bath Duck](#)

**£9.75**

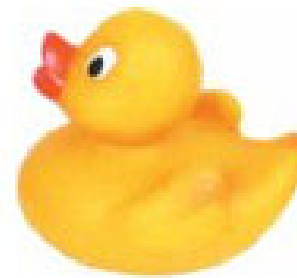
[Find similar items](#)

You might also consider



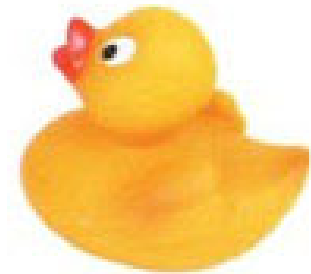
[Classic Bath Duck](#)

**£1.50**



[Medium Rubber Duck](#)

**£1.49**



[Small Rubber Duck](#)

**£0.56**



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20oz Cat Repellent  
Coyote / Fox Urine](#)

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[Coyote Urine Lure-32 oz](#)

★★★★★ (4)

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Ame...](#) by Ann Coulter

★★★★☆ (369)

**\$10.88**



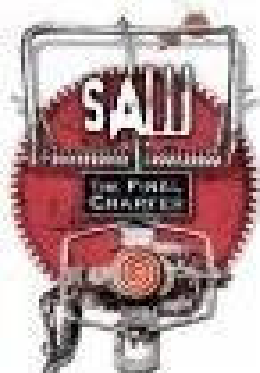


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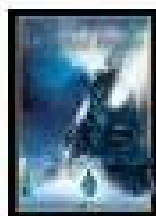
☐

I own it

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☐

This was a gift

☐

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## Large Crowbar

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**70%****Up to 70% Savings on Thousands of Products**Find great bargains on [thousands of products](#) in Sports & Outdoors orders. [Shop now.](#)[See larger image](#)[Share your own customer images](#)

## Frequently Bought Together

Customers buy this item with [The Zombie Survival Guide: Complete Protection from the Living Dead](#) by Max Brooks**Price For Both: \$22.04** **Add both to Cart****Add both to Wish List**These items are shipped from and sold by different sellers. [Show details](#)

# Utility Matrix

- Users/ratings
- Very sparse

	HP1	HP2	HP3	TW	SW1	SW2	SW3
<i>A</i>	4			5	1		
<i>B</i>	5	5	4				
<i>C</i>				2	4	5	
<i>D</i>		3					3

# Populating the Utility Matrix

- Determine the (relevant) features
- Populate the values
  - User purchase
  - User like/dislike
  - User rating

# Collaborative Filtering

- Jaccard measure loses information

$\frac{1}{5}$

	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	4			5	1		
B	5	5	4				
C				2	4	5	
D		3					3

- A $\leftrightarrow$ B
  - Jaccard similarity of 1/5 (distance of 4/5)
  - Yet they agree on HP1 (the only common movie)
- A $\leftrightarrow$ C
  - Jaccard distance of 1/2

# Rounding the Data

- Replace

- 1, 2 => No rating

- 3, 4, 5 => 1

	HP1	HP2	HP3	TW	SW1	SW2	SW3
<i>A</i>	1			1			
<i>B</i>	1	1	1				
<i>C</i>					1	1	
<i>D</i>		1					1

- Jaccard

- A to B distance => 3/4

- A to C distance => 1

# Normalizing Ratings

- Subtract the average from each value
  - How “different” is the rating

$\frac{14}{3} = 4\frac{2}{3}$

	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	$\frac{2}{3}$			$\frac{5}{3}$	$-\frac{7}{3}$		
B	$\frac{1}{3}$	$\frac{1}{3}$	$-\frac{2}{3}$				
C				$-\frac{5}{3}$	$\frac{1}{3}$	$\frac{4}{3}$	
D		0					0

# Clustering Users/Items

- Utility matrix is very sparse
  - Unlikely to find many matches
  - Cluster to unite attributes

	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	4			5	1		
B	5	5	4				
C				2	4	5	
D		3					3

	HP	TW	SW
A	4	5	1
B	4.67		
C		2	4.5
D	3		3



# Clustering Users/Items

- Hierarchical clustering
- Revised matrix is denser
- Can also cluster users in the same manner
- Can repeat the process

	HP	TW	SW
<i>A</i>	4	5	1
<i>B</i>	4.67		
<i>C</i>		2	4.5
<i>D</i>	3		3

# Collaborative Filtering

- MovieLens data
  - (User, Movie, Rating, Date)
  - Predict/recommend movies
- Netflix challenge
  - 480,000 users
  - 18,000 movies
  - 100M ratings
  - Minimize RMSE (2.8M testing set)
    - Netflix's CineMatch scored 0.9514

# Netflix Challenge

- Data had been removed
- Removing user info does not “anonymize”
  - Can reverse-engineer users
  - With 8 movie ratings and a up to 14 day error dates => 99% can be identified
  - Two ratings with 3 day error => 68% identified
  - 6 movies outside of top 500 (without dates) => 84% accuracy
- Can mine IMDB for data

# Matrix Decomposition Example

Users X Items		M1	M2	M3	M4
A	5.00	5.00	2.00	-?	
B	2.00	-?	3.00	5.00	
C	-	5.00	-	3.00	
D	3.00	-	-	5.00	

Users X Features			
	F1	F2	F3
A	1.12	1.49	0.48
B	1.31	-0.52	0.59
C	1.13	0.67	-0.52
D	1.39	0.05	0.45

Features X Items				
	M1	M2	M3	M4
F1	1.81	2.66	1.73	3.16
F2	1.62	1.71	-0.23	-0.24
F3	0.74	-1.08	0.78	0.90

4.78	5.01	1.97	3.61
1.97	1.96	2.85	4.80
2.75	4.71	1.40	2.94
2.93	3.30	2.74	4.79

# Root Mean Squared Error

- Evaluate error between estimator and actual values

– Vectors:

$$\theta_1 = \begin{bmatrix} x_{1,1} \\ x_{1,2} \\ \vdots \\ x_{1,n} \end{bmatrix} \quad \text{and} \quad \theta_2 = \begin{bmatrix} x_{2,1} \\ x_{2,2} \\ \vdots \\ x_{2,n} \end{bmatrix}.$$

$$\sqrt{\frac{\sum_{i=1}^n (x_{1,i} - x_{2,i})^2}{n}}$$

$$0.22^2 \quad 0.01^2$$

# Next Time:

- Larger Hadoop Ecosystem Overview
- Web advertising
- Mining Social Graphs