# Introduction to Big Data and Data Science (CSCE 5300)\*

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7<sup>th</sup> November, 2024



- 1 Topics Covered So Far

### Topics Covered So Far

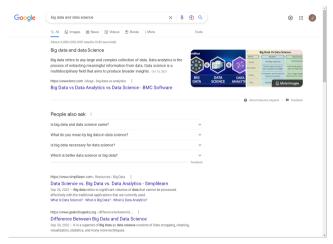
- Introduction to Python Programming
- Data Visualization Techniques
- Working with DataFrames, Pandas, and PySpark
- An Introduction to Machine Learning
- Logistic Regression and Confusion Matrix Analysis
- Deep Learning Using PyTorch
- Fundamentals of Image Processing
- K-Nearest Neighbors (KNN) Classification
- Hadoop for Distributed Computing
- Introduction to Parallel Computing

- 1 Topics Covered So Far
- 2 Special Topics: Finding Similar/Same Items in Big Data
- 3 Bloom Filter: A Probabilistic Data Structure for Membership Test
- 4 Assignment

### Finding Similar/Same Items Matters in Search Engines

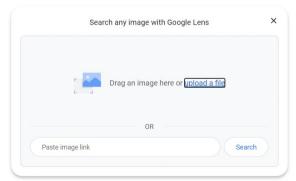


# Search by Text on Google

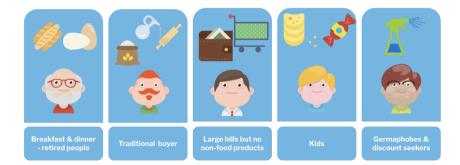


### Search by an Image on Google https://images.google.com/





### Finding Similar Items Matters in Recommender System



#### Recommendations on Amazon



### Recommendations on Google Scholar https://scholar.google.com/



		Q
	Articles	
Reco	Recommended articles	
☆	Fairness task assignment strategy with distance constraint in Mobile CrowdSensing X Song, E Wang, W Liu, Y Liu, Y Dong CCF Transactions on Pervasive Computing and Intera 2 days ago	~
☆	Stable Worker-Task Assignment in Mobile Crowdsensing Applications F Yucel, M Yuksel, E Bulut	~

<sup>\*</sup>Teaching materials are reorganized and reformed based on Dr. Jure Leskovec & Dr. Mina Ghashami's Stanford CS246: Mining Massive Data Sets Introduction to Big Data and Data Science (CSCE 5300)\*

### Similarity Metrics

Euclidean distance

$$d(p,q) = \sqrt{\sum_{i=1}^{n} (p_i - q_i)^2}$$

Cosine similarity

$$\cos_{-}\operatorname{sim}(\mathsf{p},\mathsf{q}) = \frac{\sum_{i=1}^{n} p_i \cdot q_i}{\sqrt{\sum_{i=1}^{n} p_i^2} \cdot \sqrt{\sum_{i=1}^{n} q_i^2}}$$

Jaccard index

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|}$$

## Question - Removing Duplicated Text in Big Data

Any cell values that repeat are highlighted						Only duplicate rows are highlighted					
м	A	В	C	D	al a	A	В	C	D		
1	Date	Sales Rep	Region	Amount	1	Date	Sales Rep	Region	Amount		
2	22-07-2015	John	China	\$ 16,543	2	22-07-2015	John	China	\$ 16,543		
3	22-07-2015	Jack	US	\$ 32,434	3	22-07-2015	Jack	US	\$ 32,434		
4	23-07-2015	Dill	Canada	\$ 534	4	23-07-2015	Jill	Canada	\$ 534		
5	22-07-2015	Joe	Brazil	\$ 5,243	5	22-07-2015	Joe	Brazil	\$ 5,243		
6	22-07-2015	Jinie	US	\$ 34,536	6	22-07-2015	Jinie	US	\$ 34,536		
7	22-07-2015	Jasmine	Canada	\$ 23,424	7	22-07-2015	Jasmine	Canada	\$ 23,424		
8	22-07-2015	John	Brazil	\$ 2,342	8	22-07-2015	John	Brazil	\$ 2,342		
9	23-07-2015	Jack	China	\$ 6,547	9	23-07-2015	Jack	China	\$ 6,547		
10	23-07-2015	Dill	US	\$ 5,000	10	24-07-2015	Dill	US	\$ 5,000		
11	23-07-2015	Joe	Canada	\$ 31,235	11	23-07-2015	Joe	Canada	\$ 31,235		
12	23-07-2015	Jinie	Brazil	\$ 6,465	12	23-07-2015	Jinie	Brazil	\$ 6,465		
13	23-07-2015	Dill	US	\$ 5,000	13	24-07-2015	Dill	US	\$ 5,000		
14	23-07-2015	Joe	Canada	\$ 4,325	14	23-07-2015	Joe	Canada	\$ 4,325		
15	22-07-2015	Jinie	Brazil	\$ 2,346	15	22-07-2015	Jinie	Brazil	\$ 2,346		
16	22-07-2015	John	China	\$ 16,543	16	22-07-2015	John	China	\$ 16,543		

### Question - Removing Duplicated Text in Big Data

- 1 Preprocessing and normalization (e.g., case normalization, and whitespace normalization)
- Mashing for quick comparison (e.g., SimHash or MinHash for near-duplicate detections)
- Scalable data structures and algorithms (e.g., Bloom Filters, Hadoop or Spark for distributed data processing)

### Question - Removing Duplicated Images in Big Data



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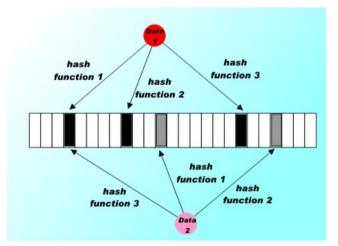
- 1 Preliminary sorting based on metadata (e.g., file size, creation date, and dimensions)
- 2 Hashing for quick comparison (e.g., Average Hash, Perceptual Hash, Difference Hash for near-duplicate detections)
- Detailed comparison for near-duplicates (e.g., structural similarity indexes (SSIM))

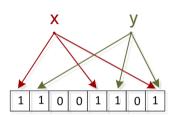
### Question - Removing Duplicated Videos in Big Data

- 1 Video fingerprinting (e.g., capturing key features such as color distribution, shape, motion patterns, and scene changes across frames)
- Kevframe extraction
- Process duplicated images

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#### What is Bloom Filter

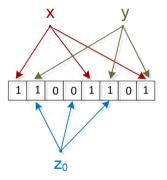




- m = 8• n = 2
- k = 3• t = 5

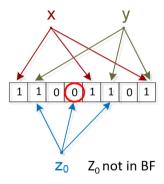
- m: the size (total number of bits) of the bloom filter;
- k: the number of hash functions:
- n: the number of elements inserted in the bloom filter:
- t: the number of bits flipped to one;
- p: the false positive probability of the bloom filter.





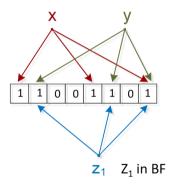
To query for  $z_0$ 

- *m*: the size (total number of bits) of the bloom filter:
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- t: the number of bits flipped to one:
- p: the false positive probability of the bloom filter.



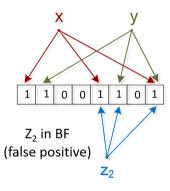
To query for  $z_0$ 

- m: the size (total number of bits) of the bloom filter:
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To query for z₁

- *m*: the size (total number of bits) of the bloom filter:
- k: the number of hash functions:
- n: the number of elements inserted in the bloom filter:
- t: the number of bits flipped to one:
- p: the false positive probability of the bloom filter.



To query for z<sub>2</sub>

- m: the size (total number of bits) of the bloom filter:
- k: the number of hash functions:
- n: the number of elements inserted in the bloom filter:
- t: the number of bits flipped to one:
- p: the false positive probability of the bloom filter.

• The probability of false positives p given a parameter setting (m; k; n) can be calculated as:

$$p \approx (1 - e^{\frac{-kn}{m}})^k$$

 For a given bloom filter size m and the number of inserted elements n, the number of hash functions k that minimizes the false positive is:

$$k = \frac{m}{n} \ln 2$$

• For a given number of inserted elements n and the desired false positive p, the required bloom filter size m is:

$$m = -\frac{n \ln p}{(\ln 2)^2}$$



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# Assignment-9 (2.0 pts.)

• Implement Bloom Filter (2.0 pts.)