CSE6242/CX4242: Data & Visual Analytics

# Data Integration

Duen Horng (Polo) Chau Professor, College of Computing Associate Director, MS Analytics Machine Learning Area Leader, College of Computing Georgia Tech

Partly based on materials by Professors Guy Lebanon, Jeffrey Heer, John Stasko, Christos Faloutsos

# What is Data Integration?

Combining data from multiple sources to provide the user with a unified view.

## Why is it important? Think about the apps, websites, and services that you use every day.

Businesses **derive value** through data integration.

### Google

#### atlanta

Tools

#### **6**3

Norci

#### ⊘ Maps News 🔝 Images

About 1,650,000,000 results (0.96 seconds)

#### ■ Top stories ÷ News about grand jury



INSIDER Atlanta DA: Trump grand jury report should be secret 7 hours ago

Protests in Atlanta over police shooting of activist >



: More

1 hour ago

A Axios

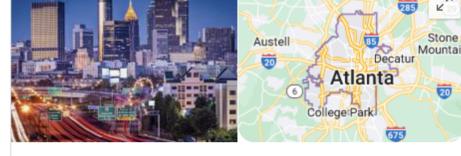
2 hours ago

7 hours ago

Videos

Atlanta district attorney pushes to keep Trump 2020 election report secret





Atlanta City in Georgia

Atlanta is the capital of the U.S. state of Georgia. It played an important part in both the Civil War and the 1960s Civil Rights Movement. Atlanta History Center chronicles the city's past, and the Martin Luther King Jr. National Historic Site is dedicated to the African-American leader's life and times. Downtown, Centennial Olympic Park, built for the 1996 Olympics, encompasses the massive Georgia Aquarium. — Google

#### Mayor: Andre Dickens Trending

#### Elevation: 738'

Weather: 52°F (11°C), Wind SE at 8 mph (13 km/h), 37% Humidity More on weather.com

Local time: Tuesday 4:57 PM

Population: 496,461 (2021)

**11** ALIVE

All but 1 arrested during protest that turned violent in Downtown Atlanta are from...

2 days ago

Also in the news



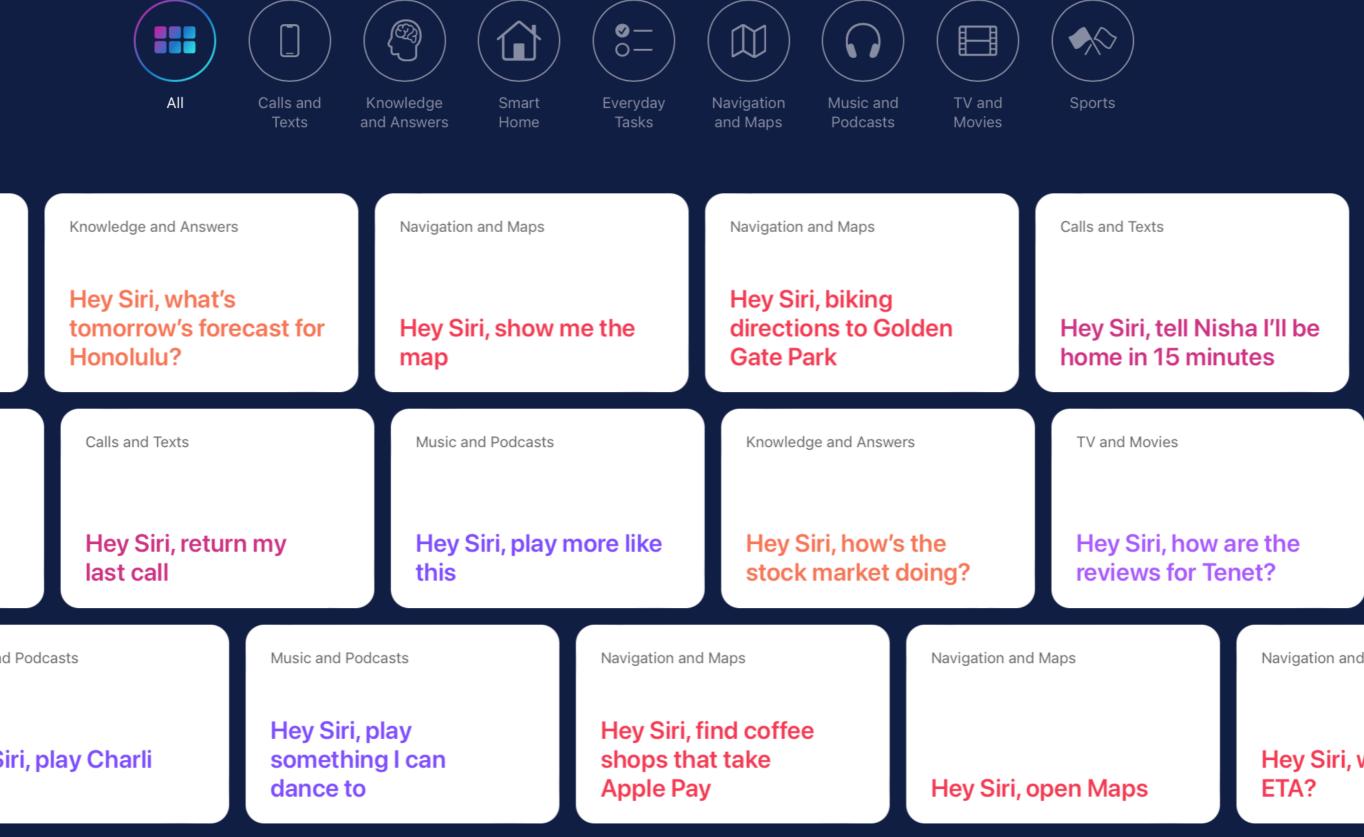
**FOX NEWS** Two Atlanta riot suspects granted bond, 4 others denied after domestic...







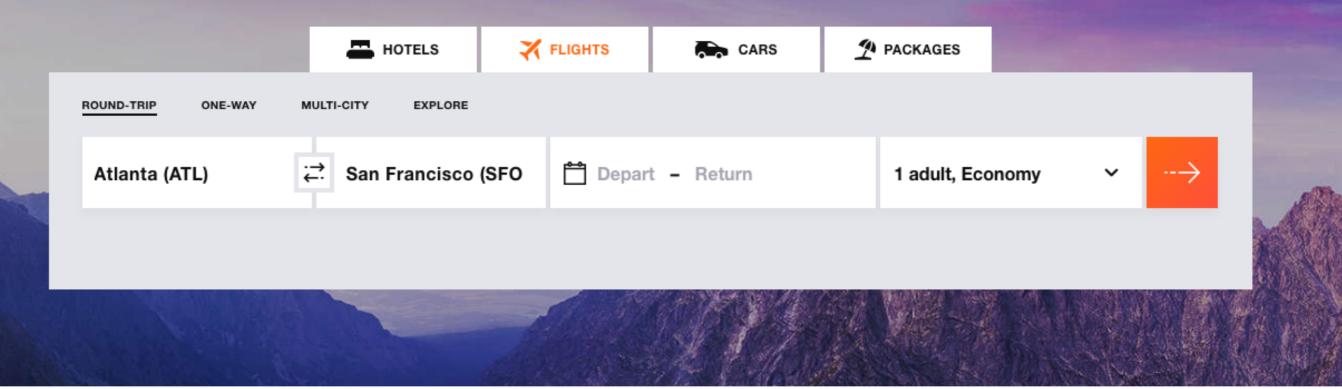








## Search hundreds of travel sites at once.



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		<b>—</b> Š

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# More Examples?

- Social media (data from users, businesses)
  - Facebook: your posts, advertisements, review
- Search engine: Google, Bing, Yahoo, etc.
- Smart assistants: Siri, Cortana, Alexa
- Price comparison: Kayak
- Uber, Lyft: drivers, traffic data, customers
- google maps: users, restaurants, traffic....

# How to do data integration?

# "Low" Effort Approaches

## 1. Use database's "Join"! (e.g., SQLite)

When does this approach work? (Or, when does it NOT work?)

id	name	id	salary	id	name	salary
111	Smith	111	\$40k	111	Smith	\$40k
222	Johnson	222	\$60k	222	Johnson	\$60k
333	Lee	333	\$50k	333	Lee	\$50k

## 2. Open Refine

http://openrefine.org (Video #3 "Reconcile and Match Data")

# **IDs** are really important, and can simplify data integration!

# But who creates the IDs?

## Crowd-sourcing Approaches: Freebase

Freebase Find...

Browse Query

Query Help

Sign In or Sign Up

How can you get started?

English 👻

Important! Freebase is read-only and will be shut-down. More.

3,179,263,202 Facts (and counting)

A community-curated database of well-known people, places, and things

Users	Review Tasks	Loads	Apps	Queries	Schema	Data
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**Explore Freebase Data** 

Domain	ID	Topics	Facts	Learn how it works
Music	/music	33M	240M	Discover what kind of information Freebase contains, how it's organized,
Books	/book	6M	15M	and how Freebase allows you to
Media	/media_common	6M	17M	uniquely identify identities anywhere on the web
People	/people	4M	20M	Keep reading »
Film	/film	2M	22M	Use Freebase data
Location	/location	2M	20M	Freebase data is free to use under an open license. You can:
т	/tv	2M	19M	Query Freebase using our Search,
Business	/business	1M	4M	Topic, or MQL APIs
Fictional Universes	/fictional_universe	1M	1M	<ul> <li>Download our weekly data dumps</li> </ul>
Organization	/organization	996K	4M	Join the Community
Biology	/biology	966K	5M	Follow Freebase on G+

## Freebase intro video: https://youtu.be/TJfrNo3Z-DU

Learn more about Freebase at https://en.wikipedia.org/wiki/Freebase

# **Freebase** (a graph of entities)

"...a large collaborative knowledge base consisting of metadata composed mainly by its community members..."

Wikipedia.

# So what? What can you do with the

# Freebase knowledge graph?

Hint: Google acquired it in 2010.

## Google Inside Search

Home Tips & Tricks Features Search Stories Playground Blog Help





Ginevra de' Benci

The Virgin a...

#### rdo da Vinci

Leonardo di ser Piero da Vinci y Renaissance polymath: painter architect, musician, scientist, r engineer, inventor, anatomist, g cartographer, botanist, and writ

Born: April 15, 1452, Anchiano Died: May 2, 1519, Clos Lucé Buried: Château d'Amboise Parents: Caterina da Vinci, Pie

Structures: Vebjørn Sand Da

See it in

Discover answers to q thought to ask, and ex

## The Knowledge Graph

Learn more about one of the key breakthroughs behind the future of search.

Google Knowledge Graph video: https://youtu.be/mmQl6VGvX-c

# Freebase replaced by Google Knowledge Graph API



Example: What does Google know about Taylor Swift?

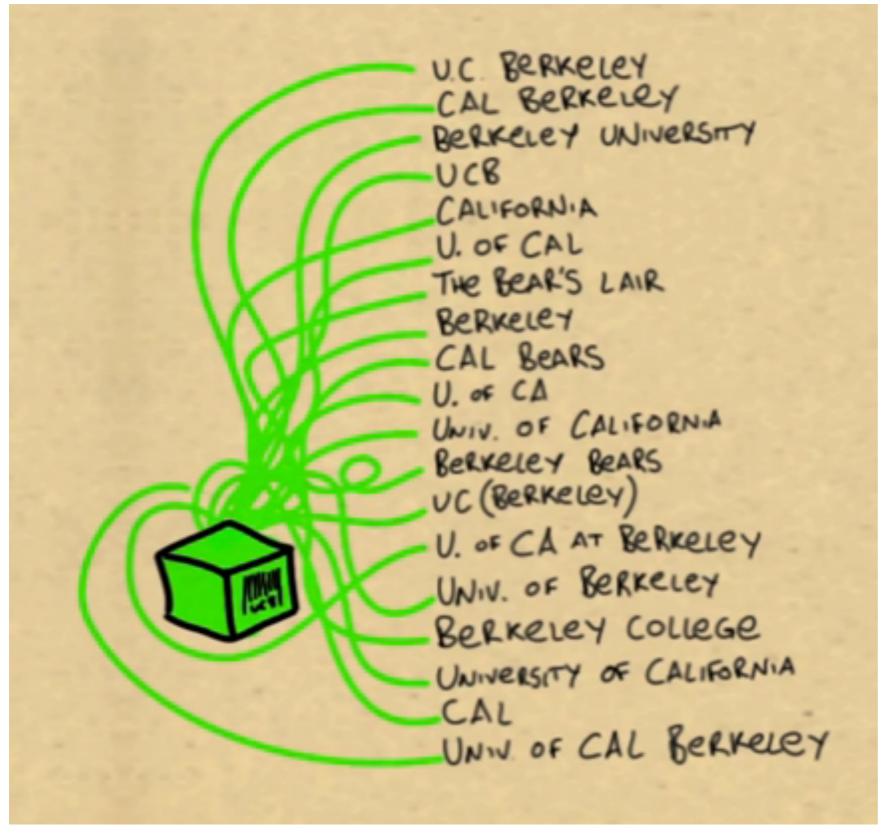
https://developers.google.com/ knowledge-graph/



## What does Google know about Taylor Swift? https://developers.google.com/knowledge-graph/

```
"@type": "ItemList",
"itemListElement": [
    "@type": "EntitySearchResult",
   "result": {
      "@id": "kg:/m/0dl567",
     "name": "Taylor Swift",
      "@type": [
        "Thing",
        "Person"
      "description": "Singer-songwriter"
      "image": {
        "contentUrl": "https://t1.gstatic.com/images?q=tbn:ANd96cQmVDAhjhWnN20Wys2ZM03PGAhu
        "url": "https://en.wikipedia.org/wiki/Taylor_Swift",
        "license": "http://creativecommons.org/licenses/by-sa/2.0
      }.
      "detailedDescription": {
        "articleBody": "Taylor Alison Swift is an American singer-songwriter and actress. R
        "url": "http://en.wikipedia.org/wiki/Taylor_Swift",
        "license": "https://en.wikipedia.org/wiki/Wikipedia:Text_of_Creative_Commons_Attrib
      "url": "http://taylorswift.com/"
```

## What if we don't have the luxury of having IDs ?



A common problem in academia:

Polo Chau Duen Horng Chau Duen Chau D. Chau

(Screenshot from FreeBase video)

# Then you need to do... **Entity Resolution** (A hard problem in data integration)

# Why is entity resolution so difficult?

Let's understand it through shopping for an iPhone on Apple and eBay

	Mac	iPa	ad i	iPhone	Watch	Vision	AirPods	Т	V & Home	Entertainm	ent	Accessories	Support	Q	
See all deals → after trade-in. <sup>△</sup> Trade-in. <sup>°</sup> V trade				t Apple			75/mo	Ŧ		60 after	✓	Pay as low as \$0 a trade-in. <sup>∆∆</sup>	fter		

# New Buy iPhone 15

From \$799 or \$33.29/mo. for 24 mo.\*

Get \$30–\$620 for your trade-in.  $\oplus$   $\oplus$ 

Get 3% Daily Cash back with Apple Card.  $\oplus$ 



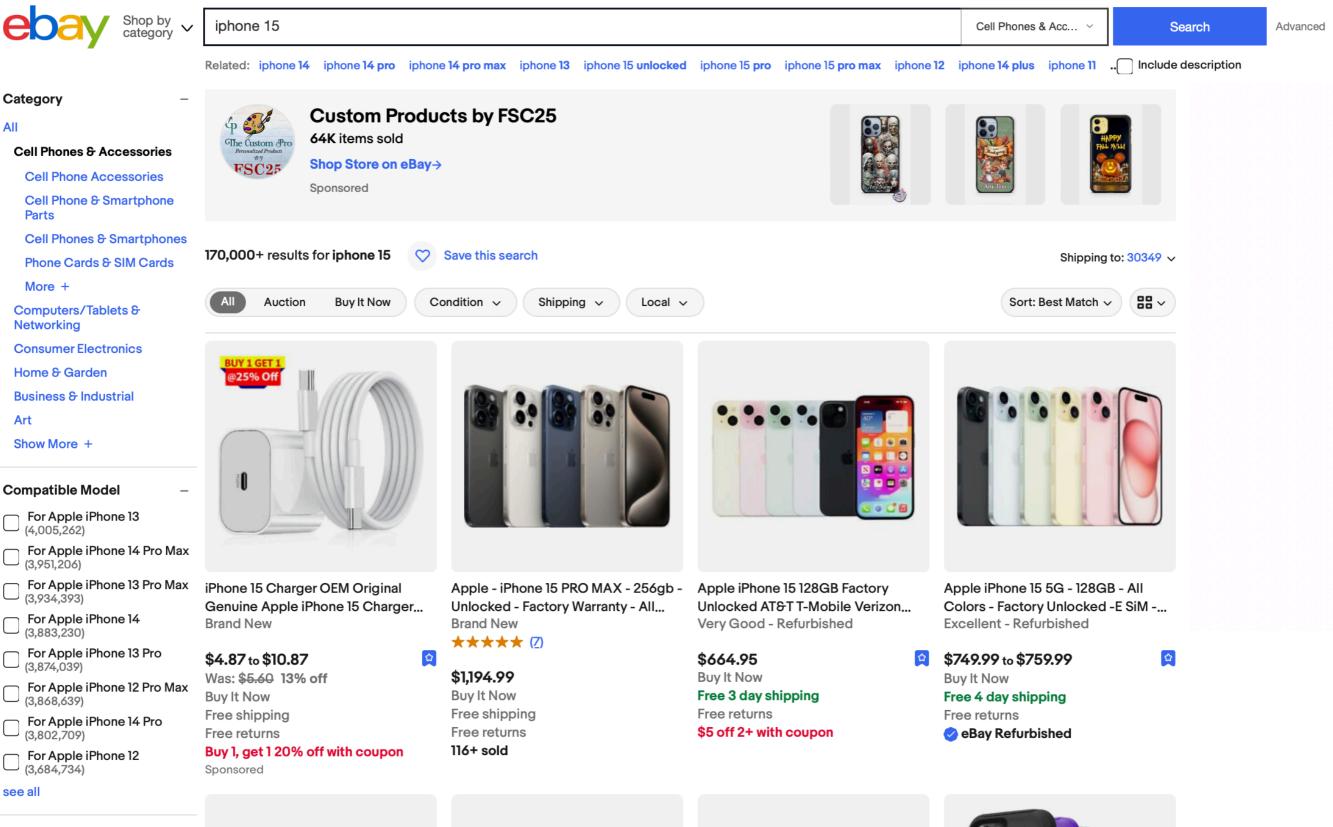
## Model. Which is best for you?

<b>iPhone 15</b> 6.1-inch display <sup>1</sup>	From \$799 or \$33.29/mo. for 24 mo.*

**iPhone 15 Plus** 6.7-inch display<sup>1</sup> From \$899 or \$37.45/mo. for 24 mo.\*



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#### Brand

All

Unbranded (4,840,340) Apple (313,402) Samsung (82,575)









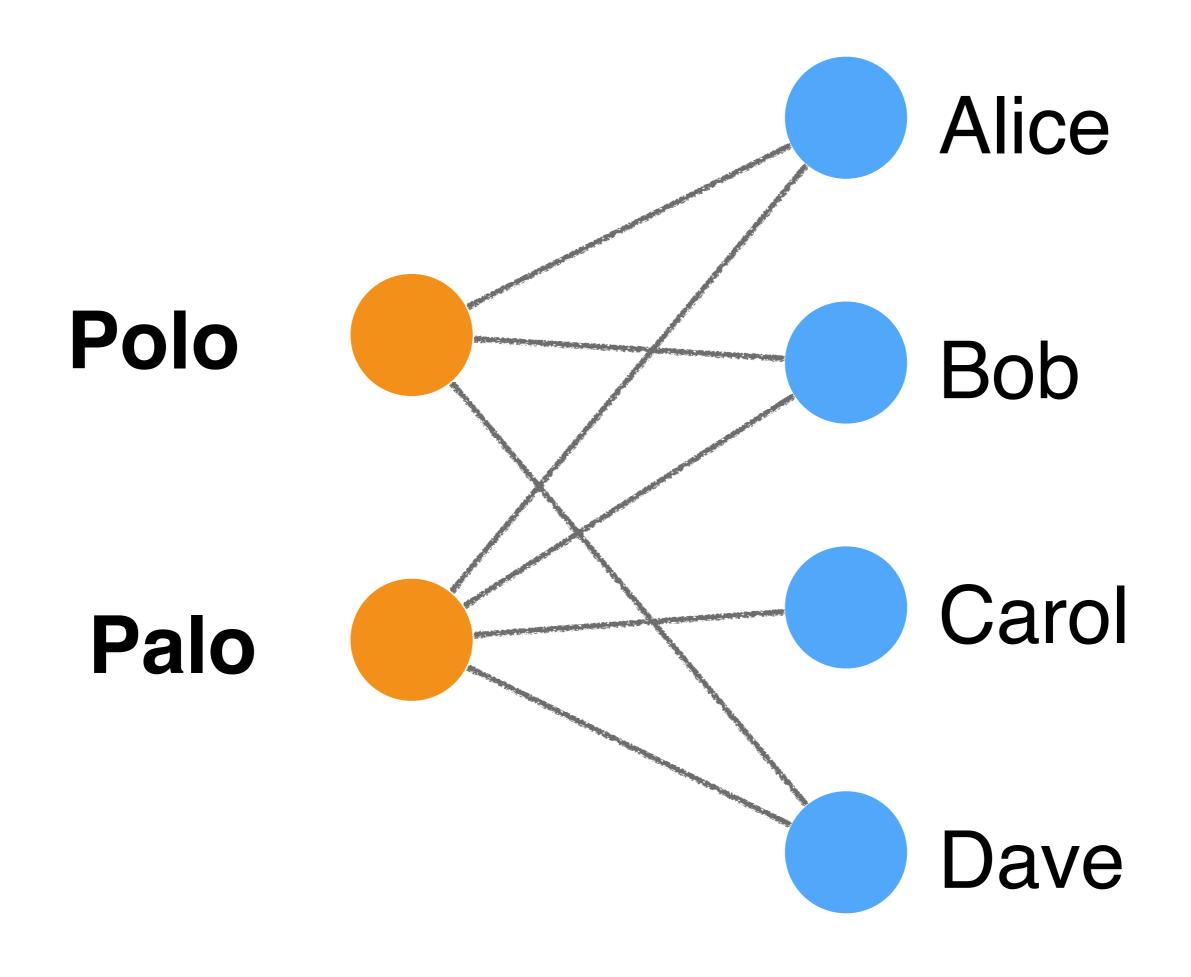
# **D-Dupe**

# Interactive Data Deduplication and Integration TVCG 2008

University of Maryland Bilgic, Licamele, Getoor, Kang, Shneiderman

https://linqspub.soe.ucsc.edu/basilic/web/Publications/2006/bilgic:vast06/

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## Core components: Similarity functions

Determine how two entities are similar.

D-Dupe's approach: Attribute similarity + relational similarity

 $sim(e_i, e_j) = (1 - \alpha) \times sim_A(e_i, e_j) + \alpha \times sim_R(e_i, e_j),$  $0 \le \alpha \le 1,$ 

Similarity score for a pair of entities

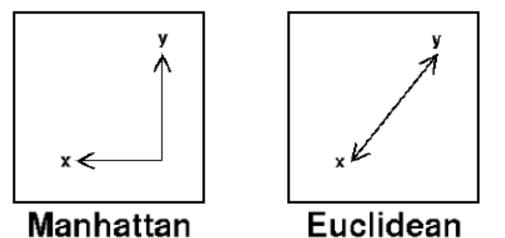
Attribute similarity (a weighted sum)  

$$sim_A(e_i, e_j) = \sum_{k=1}^n w_k \times sim_fun_k(e_i \cdot a_k, e_j \cdot a_k),$$
  
 $-1 \le w_k \le 1$  and  $\sum_{k=1}^n |w_k| = 1,$ 

# Numerous similarity functions

Excellent read: http://infolab.stanford.edu/~ullman/mmds/ch3a.pdf

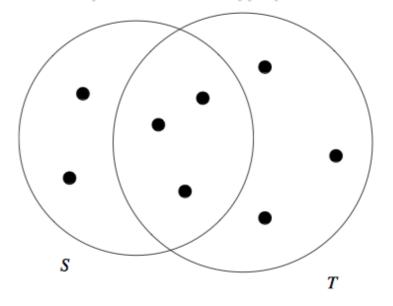
- Euclidean distance Euclidean norm / L2 norm
- TaxiCab/Manhattan distance



Jaccard Similarity (e.g., used with w-shingles)
 e.g., overlap of nodes' #neighbors

Jaccard similarity of sets S and T is  $|S \cap T|/|S \cup T|$ 

• String edit distance e.g., "Polo Chau" vs "Polo Chan"



## **Distance and Similarity Measures**

Different measures of distance or similarity are convenient for different types of analysis. The Wolfram Language provides built-in functions for many standard distance measures, as well as the capability to give a symbolic definition for an arbitrary measure.

Reference

#### Numerical Data

EuclideanDistance SquaredEuclideanDistance NormalizedSquaredEuclideanDistance	-
ManhattanDistance • ChessboardDistance • BrayCurtisDistance • CanberraDistance •	
CosineDistance  CorrelationDistance BinaryDistance TimeWarpingDistance	

#### Boolean Data

```
HammingDistance = JaccardDissimilarity = MatchingDissimilarity = DiceDissimilarity =
RogersTanimotoDissimilarity = RussellRaoDissimilarity = SokalSneathDissimilarity =
YuleDissimilarity
```

#### String Data

EditDistance • DamerauLevenshteinDistance • HammingDistance • SmithWatermanSimilarity • NeedlemanWunschSimilarity

#### Images & Colors

ImageDistance • ColorDistance

https://reference.wolfram.com/language/guide/ DistanceAndSimilarityMeasures.html

**Geospatial & Temporal Data** 

GeoDistance 

DateDifference

# **Excellent Tutorial on Entity Resolution**

http://www.umiacs.umd.edu/~getoor/Tutorials/ ER KDD2013.pdf

by Lise Getoor and Ashwin Machanavajjhala