Open Data Link

A dataset search engine for open data

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Open Data Link

- Dataset search engine for open data.
- Search methods:
  - Semantic keyword search
  - Joinable table search
  - Unionable table search

Motivation

- Governments and other organizations publish a lot of open data, but discovery is still difficult.
- Data scientists can identify ways to integrate datasets.
- Data publishers can see the wider context of their data.

Demo

Outline

System overview

Joinable table search

Unionable table search

Semantic Keyword Search

Future work

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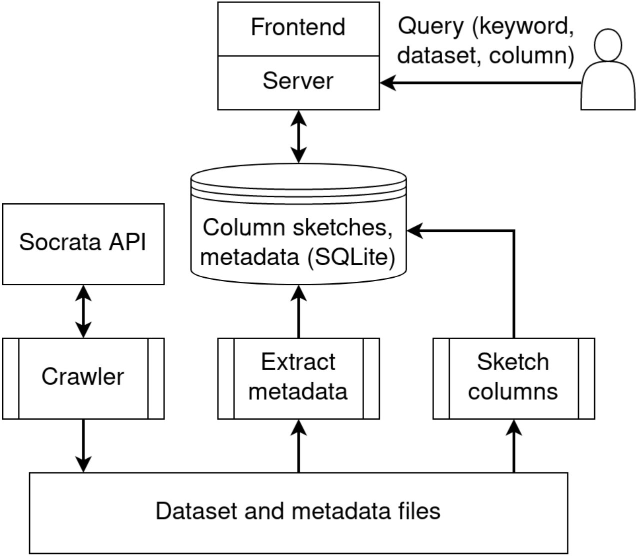
System overview



Dataset crawl

- 10k of 42k datasets on Socrata.
- 172k columns.
- Most datasets are small.
- Largest datasets have over 100 million rows.

Outline

Joinable table search

JOIN

ACTION_SOUGHT	DEPARTMENT	CLIENT_ID	CLIENT_NAME	LOBBYIST_ID
AMENDMENT TO PLANNED DEVELOPMENT	TRANSPORTATION	2201517748	FRIEDMAN PROPERTIES	6842
DISCUSSED FY 2020 BUDGET				
CONTRACT APPROVAL				
CONSTRUCTION RELATED				
LANDMARKING, CLASS L APPROVALS AND RIGHT OF WAY ISSUES				
EVENT APPROVA				
ZONING				

YEAR	LOBBYIST_ID	SALUTATION	FIRST_NAME	MIDDLE_INITIAL	LAST_NAME
2011	3958	MR	STEPHEN		FORTINO
2012	3789	MR	NEIL	A	PRITZ
2013	3773	MS.	ERICA	N.	BLAND
2012	3964	MRS	MARY KAY		BONOMA
2011	3764	MS	JENNIFER		CLARK
2013	4332	MR.	MICHAEL	J	PAULOS
2014	3802	MR.	JAMES	L	TERMAN

Joinable table search

- Attributes are treated as sets.
- Sets are encoded with minhash data sketches.
- A table T is joinable with the query U if $Containment(X \in T, Q \in U) \geq t$.
- We use an LSH index for fast querying.

Minhash[2]

- Data sketch for estimating Jaccard similarity of sets.

$$J(S, T) = \frac{|S \cap T|}{|S \cup T|}$$

- A minhash signature is composed of the results of a number of minhashes.
- The probability that the minhashes for two sets are the same equals the Jaccard similarity of the sets[1].
- Minhash LSH hashes similar signatures to the same bucket.

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[1] Mining of Massive Datasets, Chapter 3.

[2] A. Broder, "On the Resemblance and Containment of Documents", Compression and Complexity of Sequences 1997.

LSH Ensemble[3]

- Set containment is a better measure for computing joinability.

$$C(Q, X) = \frac{|Q \cap X|}{|Q|}$$

- We can convert Jaccard similarity to containment, given the sizes of the domains.
- The size of the indexed domain is not constant, so domains are partitioned by cardinality.
- A minhash LSH index is constructed for each partition.

[3] Erkang Zhu, Fatemeh Nargesian, Ken Q. Pu, Renée J. Miller, "LSH Ensemble: Internet-Scale Domain Search", VLDB 2016.

Outline

Unionable table search

Candidate Name	Source Type	Source Name	Date	Amount
Abbett, Richard	Candidate	Abbett, Richard	09/29/2016	20.00
Abercrombie, Neil	Other Entity	Facebook, Inc.	04/01/2014	65.16
Aiona, Sam	Candidate	Aiona, Sam	06/30/2015	6415.49

UNION

Candidate Name	Contributor Type	Contributor Name	Date	Amount
Ige, David	Individual	Ohori, Yoshiko	09/11/2014	99.05
Ige, David	Individual	Perry, Nolan	10/13/2014	50.00
Herkes, Robert	Individual	Nip, Celeste	02/04/2008	200.00
Hannemann, Mufi	Individual	Murakami, Ross R.	04/15/2008	500.00
Hannemann, Mufi	Individual	Dinsmore, Jeffrey C.	07/20/2009	1000.00
Hooser, Gary	Individual	SHERMAN, WENDY L.	06/10/2010	500.00
Hannemann, Mufi	Individual	Miyashiro, Alton K.	10/09/2014	2000.00
Hannemann, Mufi	Individual	Konishi, Glen S.	07/22/2010	150.00
Hong, Ted	Individual	Malasek, Vojtech	10/29/2008	4000.00
Hannemann, Mufi	Individual	Takara, Russell H.	09/08/2008	1000.00
Hokama, Riki	Individual	Matsuda, Eric	06/25/2013	225.00
Hannemann, Mufi	Individual	McIntyre, Gregory T.	06/30/2007	250.00
Ige, David	Individual	Lincoln, Faye	11/10/2014	500.00

Unionable table search

- The LSH Ensemble index is queried for each column of the query table.
- Candidate tables are those that appear in $\geq 40\%$ of the joinability queries.
- Candidates are ranked by alignment: the fraction of candidate columns that are unionable with a query column.

Outline

Semantic Keyword Search

- Problem: Given a list of keywords, return top-k similar datasets
- Motivation: Data scientists want a simple way to find new and insightful datasets

Our Approach

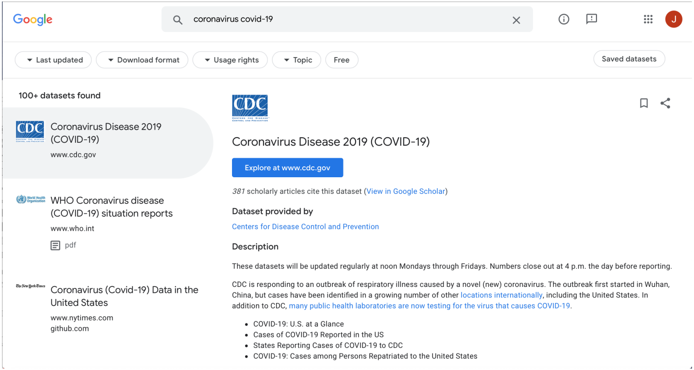
- Search on the metadata, not on the data in the dataset
  - Data in dataset is too noisy
- Metadata that we have:
  - Dataset description
  - Column description
  - Datasets tags

Our Approach (Cont.)

- Use semantic similarity
  - Example: Fish & Seafood
  - Example: Coronavirus & Respitory System

Others Approach

- Google Dataset Search



System Overview

- FastText: word in dataset's metadata -> embedding vector
- SimHash: embedding vector -> bit vector
- Locality Sensitive Hashing (LSH): build index on the bit vector of each word

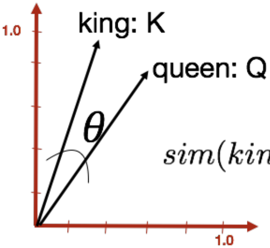
FastText[4]

- Word in dataset's metadata -> embedding vector
- Embedding vector represent the semantics of words
- Embedding vectors are learned from wikipedia articles

[4] A. Joulin, E. Grave, P. Bojanowski, T. Mikolov, *Bag of Tricks for Efficient Text Classification*

FastText (Cont.)

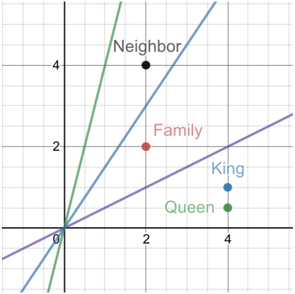
- closeness or similarity of vectors := Cosine-Similarity
- Closer a pair of vectors, closer the semantics of the two words
- Example: King and Queen have high cosine similarity



$$sim(king, queen) = Cosine(\theta) = \frac{\vec{K}.\vec{Q}}{\|\vec{K}\|.\|\vec{Q}\|}$$

Simhash

- Embedding Vector -> Bit Vector
- Word: [puple, blue, green]
  - Neighbor: [1, 1, 0]
  - Family: [1, 0, 0]
  - King: [0, 0, 0]
  - Queen: [0, 0, 0]



Locality Sensitive Hashing (LSH)

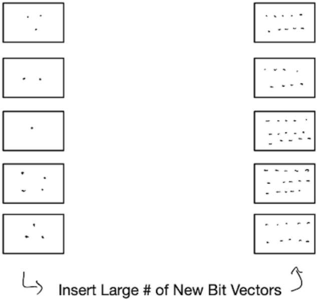
- Underlying data structure: Hash Table
  - Predefined # of buckets
- Insert SimHashed embedding vectors into hash table
- Collitions in hash table buckets are candidate pairs.

SimHash LSH (Cont.)

- Predefined # of hash tables
- Query each hash table for M candidates
  - $M \geq k$
- Order M candidates into a top-k list by the cosine similairty of embedding vectors

Problem with SimHash LSH

- The # of hash tables and # of buckets in each hash table must be **hand tuned**
- Must be retuned when data size significantly changes



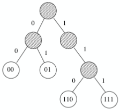
LSH Forest[5]

- Underlying data structure: Prefix Tree or Trie
- Similar to LSH
  - Predefined # of prefix trees
  - Ascend each prefix tree for M candidates
    - $M \geq k$

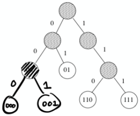
[5] Mayank Bawa, Tyson Condie, and Prasanna Ganesan. 2005. *LSH forest: self-tuning indexes for similarity search*

LSH Forest (Cont.)

- Variable length hashing in prefix tree solves LSH's problems



- Add Bit Vector: [0, 0, 1, . . .]



- Prefix Tree expands and contracts to account for # of embedding vectors
  - Thus, no hand tuning

Review

- FastText: Word in Metadata -> Embedding vector
- SimHash: Embedding Vector -> Bit Vector
- LSH Forest: Index on Bit Vectors

Answering Queries

- Query the index with each keyword in the keyword list
- Add the results to a list
- Rank datasets by how often they appear in the list

Problems

- No semantic relationships **between** words
  - Example: Keyword List := "traffic violations"
    - Produces good results for "traffic" and "violations", but not "traffic violations"

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Future work

Future work

- Improve ability to see semantic relationships between words
- Organize datasets into a directory structure
- Use semantic similarity of column names in unionable table search.
- Similar dataset search based on metadata similarity.
- Keyword search over data values.