
# Open Data Integration

**Renée J. Miller**
**miller@northeastern.edu**


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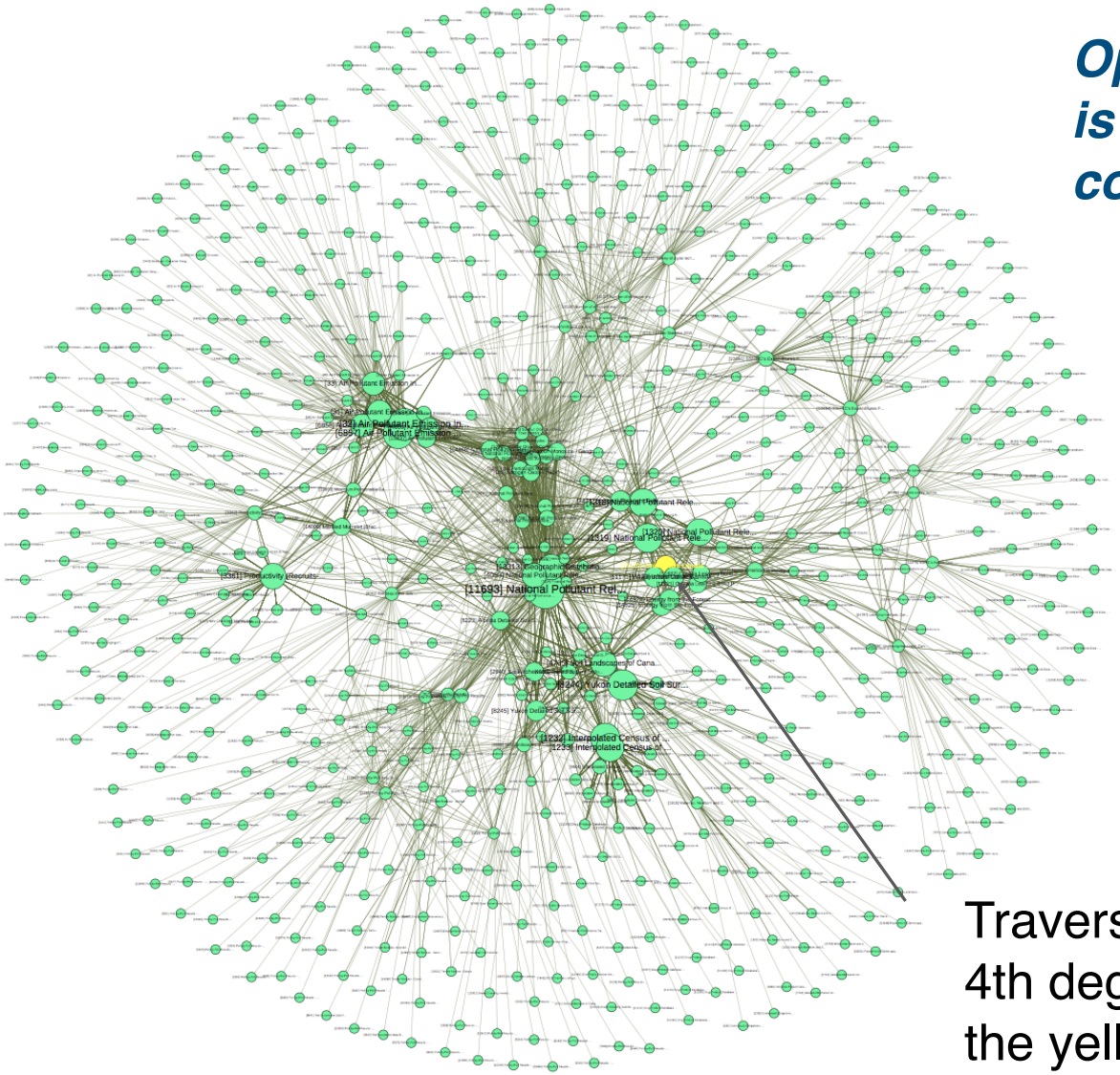
# Open Data Principles

- Timely & Comprehensive
- Accessible and Usable
- Complete
  - All public data is made available. Public data is data that is not subject to valid privacy, security or privilege limitations
- Primary
  - Including the original data & metadata on how it was collected

***Invaluable for data science***

***Open Data is deeply connected***

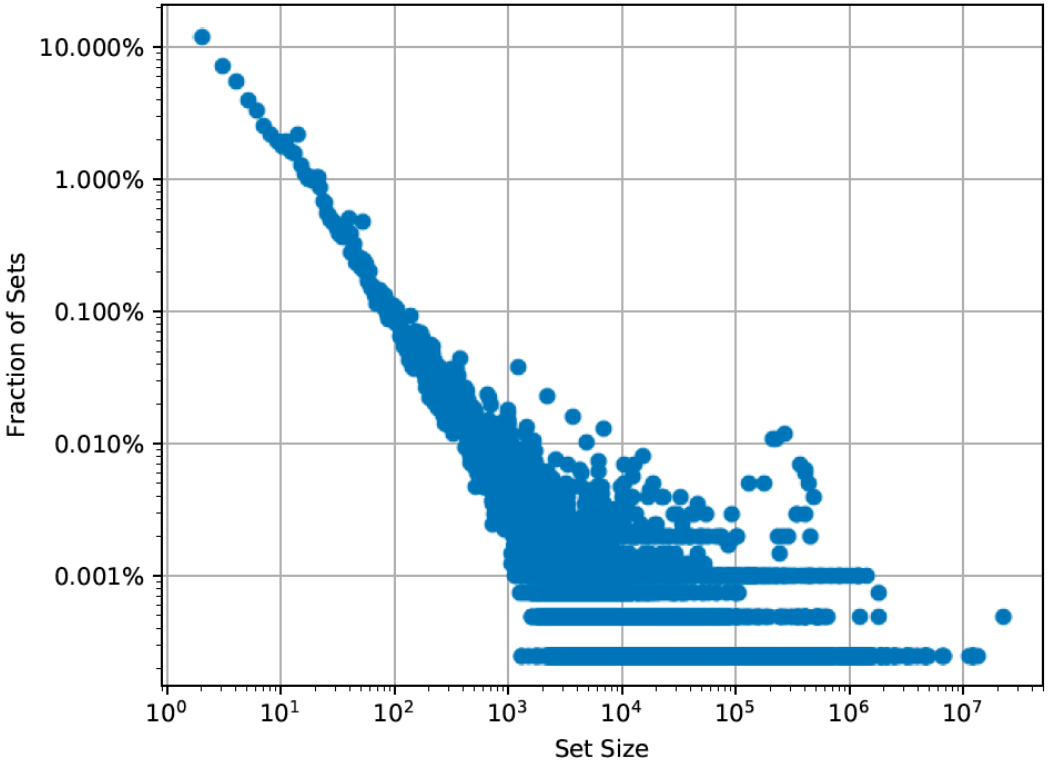


Each edge is an inclusion dependency

Traverse to the 4th degree from the yellow table

# Open Data

- Open Data
  - Wide (avg >16 attributes)
  - Deep (avg > 1500 values)
  - Often with **no or incomplete headers** (attribute names)
    - Published as CSV, JSON, …
  - Growing exponentially

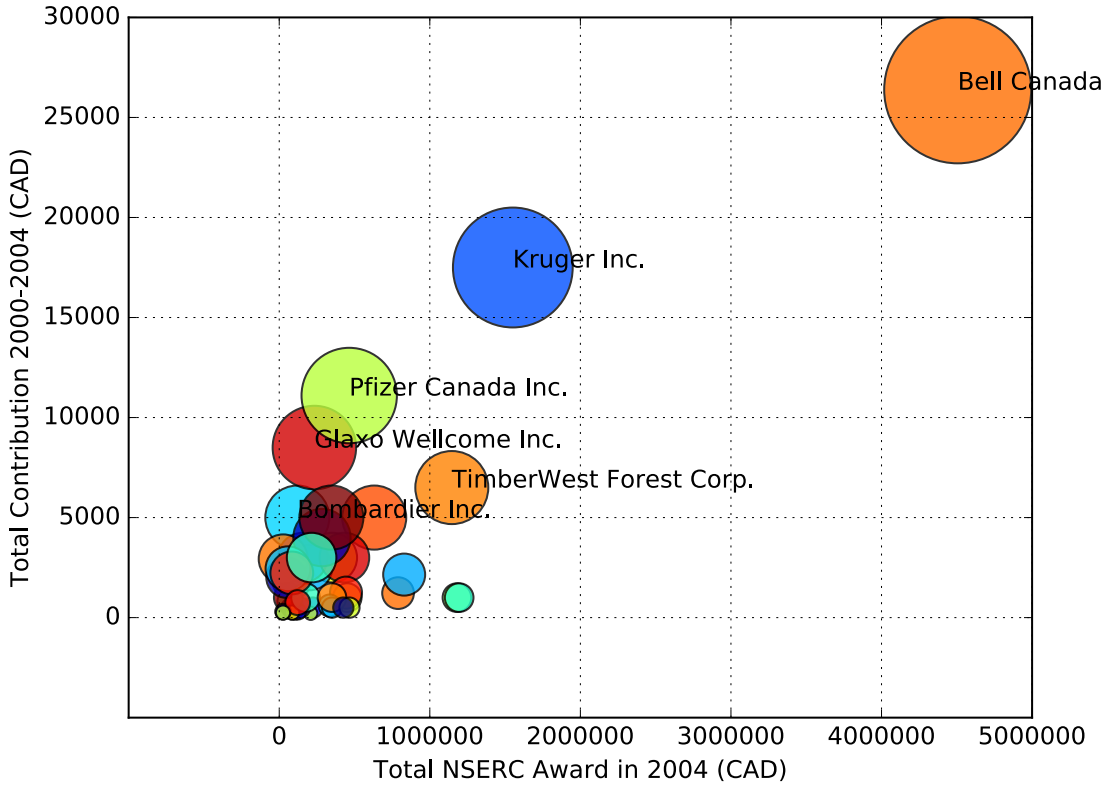



**Attribute Cardinalities [Zhu+VLDB2016]**

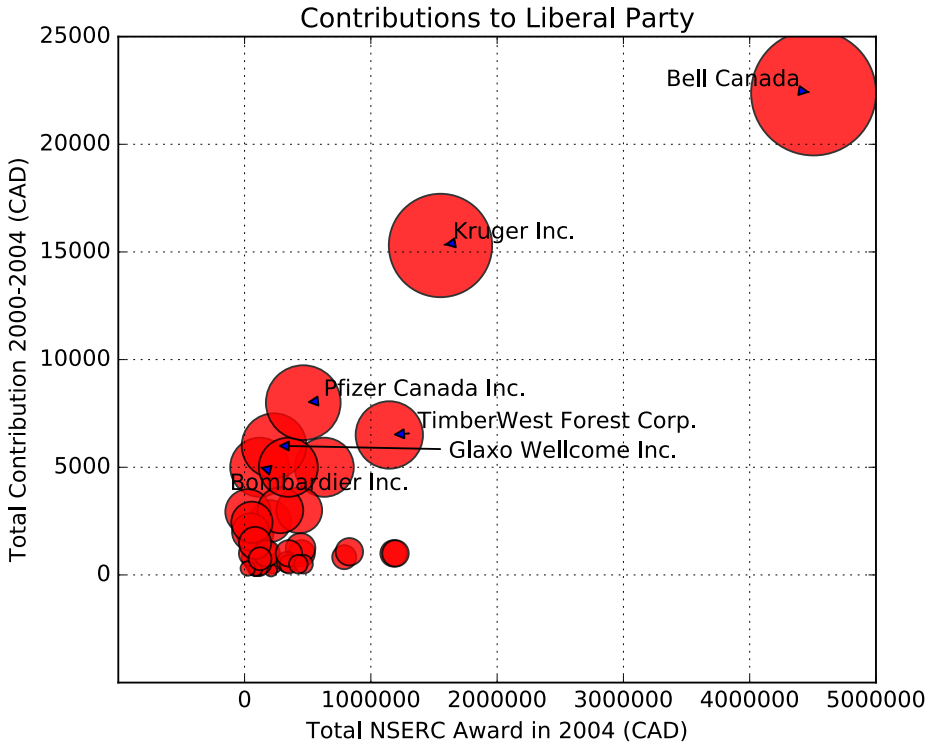
# Interactive Navigation of Open Data Linkages

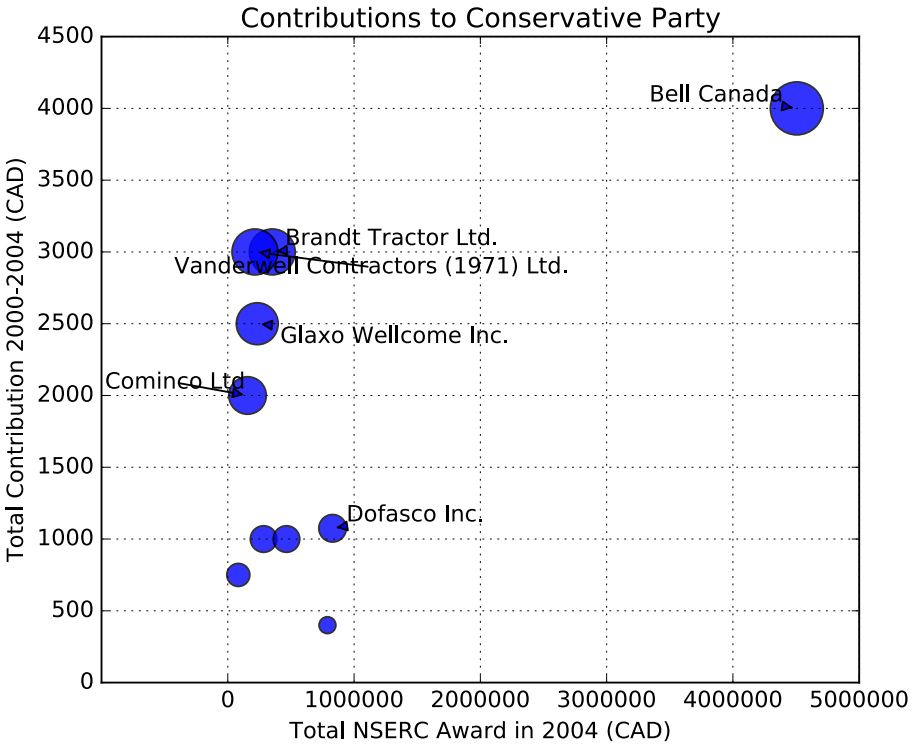
Three minute video of PVLDB2017 System Demonstration:
Erkang Zhu, Ken Q. Pu, Fatemeh Nargesian, Renée J. Miller:
Interactive Navigation of Open Data Linkages. PVLDB 10(12):
1837-1840 (2017) (received Best Demo Award)

# Goal:  Enable Data Science



# Goal: Enable Data Science



# Data Science Over Open Data

**In data science, it is increasingly the case that the main challenge is not in *integrating known data*, rather it is in *finding the right data to solve a given data science problem*.**

How can we facilitate data science over Open Data?

***Vision for Analysis-Driven Data Discovery***

# Example Open Government Data

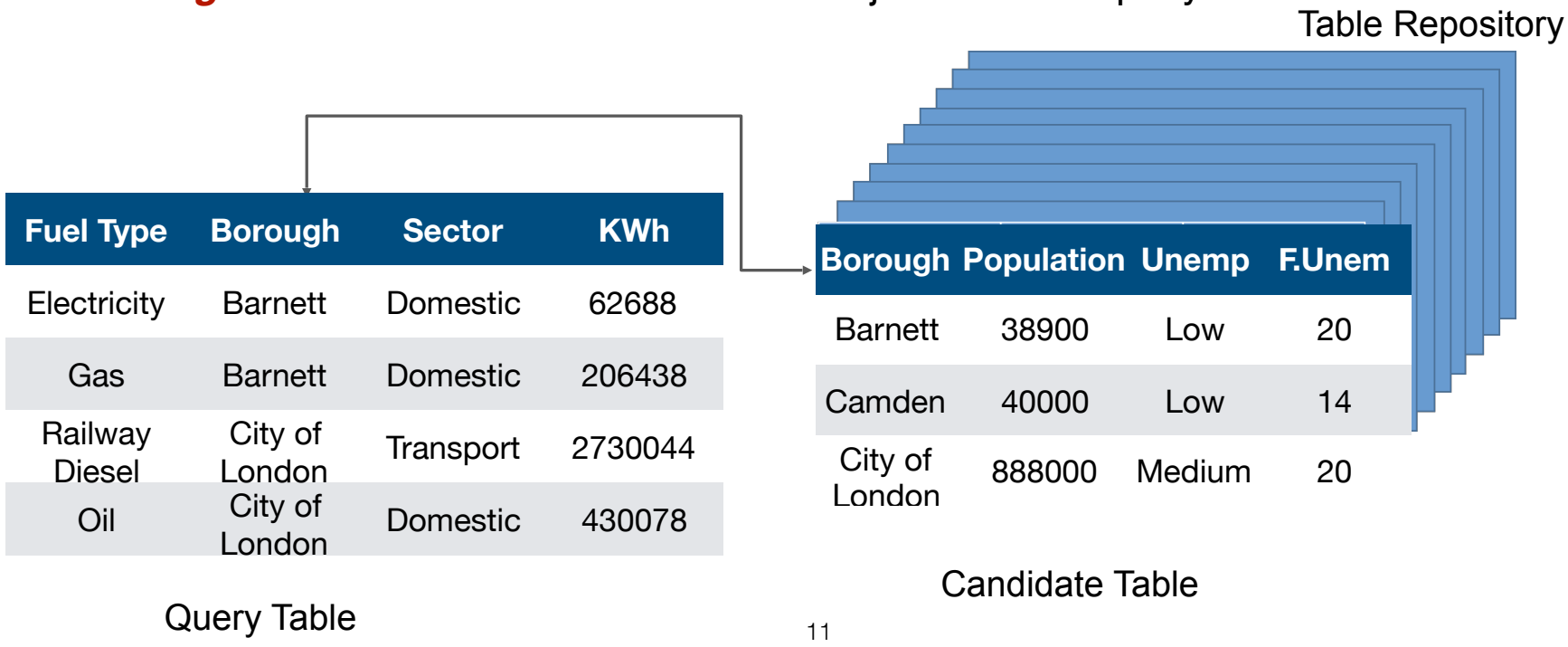

| Fuel Type | Borough | Sector | KWh | Year | … |
|---|---|---|---|---|---|
| Electricity | Barnett | Domestic | 62688 | 2015 | |
| Gas | Barnett | Domestic | 206438 | 2015 | |
| Railway Diesel | City of London | Transport | 2730044 | 2014 | |
| Oil | City of London | Domestic | 430078 | 2015 | |

- One example table
  - Greenhouse gas emissions in/around London
  - May have many attributes and tens/hundreds of thousands of tuples

# Join Table Search

***Data Science Question:*** How can I find more features for my model C02 emission?

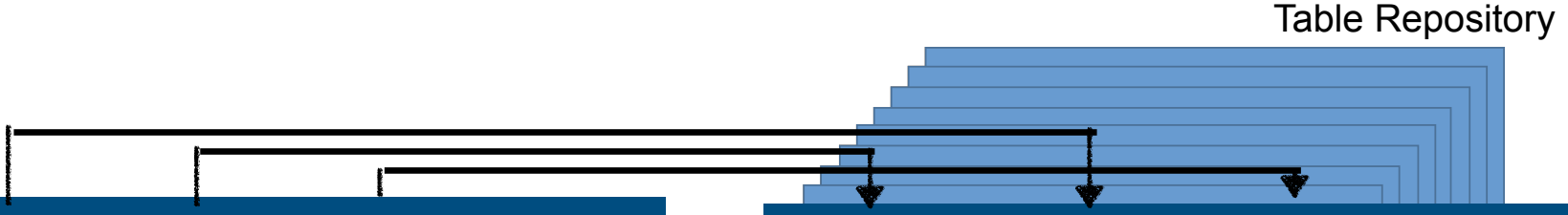
***Data Management Task***: Find tables that can be joined with a query table.



# Union Table Search

***Data Science Question:*** Does my analysis generalize? To new regions, new sectors, …

***Data Management Task***: Find tables that can be union with a query table.




| Fuel Type | Borough | Sector | KWh |
|---|---|---|---|
| Electricity | Barnett | Domestic | 62688 |
| Gas | Barnett | Domestic | 206438 |
| Railway Diesel | City of London | Transport | 2730044 |
| Oil | City of London | Domestic | 430078 |

Query Table

| County | Commodity | SecTyp | TotEmissions (MT CO2e |
|---|---|---|---|
| Benton | Gasoline | Transport | 20 |
| Kittitas | Fuel oil (1, 2..) | Hydro | 14 |
| Grays Harbor | Aviation Fuels | Domestic | 20 |
| Skagit | Liquified petroleum | Transport | 30 |

Candidate Table

# Outline

- Open Data
  - What is it and why is it important?
  - Motivating examples
- Analysis-driven Data Discovery
  - **Table Join**
  - Table Union
- Impact & Open Questions

# Join Table Search

**Query Q**

| | | | |
|---|---|---|---|
| Electricity | Barnett | Domestic | 62688 |
| Gas | Barnett | Domestic | 206438 |
| Railway Diesel | City of London | Transport | 2730044 |
| Oil | City of London | Domestic | 430078 |

Query Table

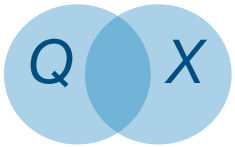
**Potential Answer X**

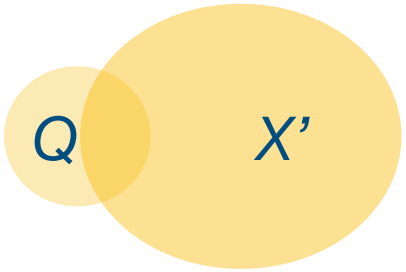
| | | | |
|---|---|---|---|
| Barnett | 38900 | Low | 20 |
| Camden | 40000 | Low | 14 |
| City of London | 888000 | Medium | 20 |
| … | | | |

Candidate Table

# Measuring Join Goodness?

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

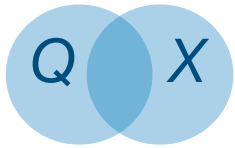


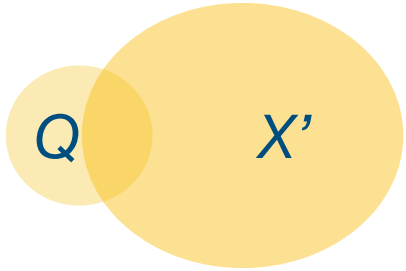




***Jaccard(Q,X)*** >> ***Jaccard(Q, X')***

Same intersection size, but the Jaccard similarity is much smaller on the right

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

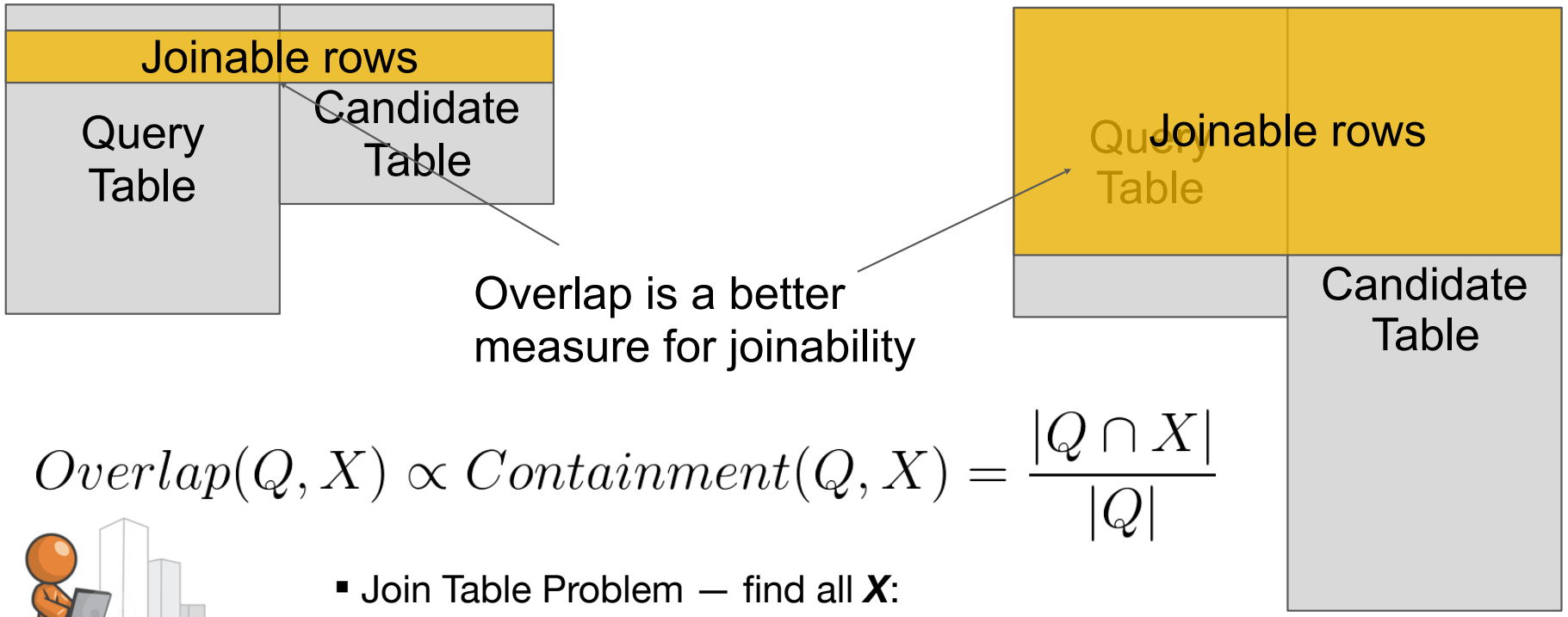



***Containment(Q,X)*** =***Containment(Q, X')***

Containment is the same for both, independent of the size of X and X'

# What is a good measure for joinability?




$$Overlap(Q, X) \propto Containment(Q, X) = \frac{|Q \cap X|}{|Q|}$$

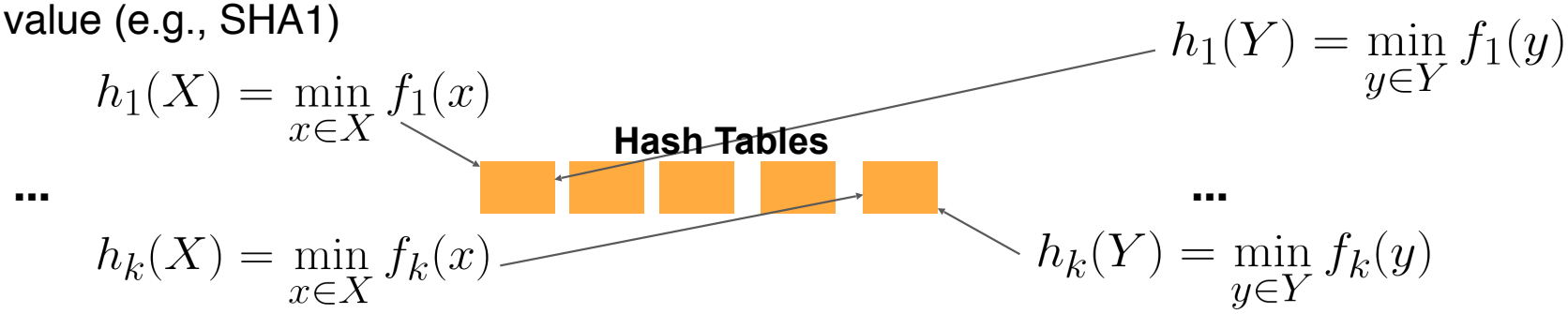
- Join Table Problem — find all ***X***:
  - ***Containment(Q,X) >= t****
- User specifies tolerance for error **t***

# MinHash LSH (Broder SEQ97)

$X = \{x_1, x_2, ..., x_m\}$ $Y = \{y_1, y_2, ..., y_m\}$

$$h_0(X) = \min_{x \in X} f_0(x) \qquad h_0(Y) = \min_{y \in Y} f_0(y) \qquad P(h_0(X) = h_0(Y)) = \frac{|X \cap Y|}{|X \cup Y|}$$

Define a hash function for set, where $f_i$ is a hash function for value (e.g., SHA1)

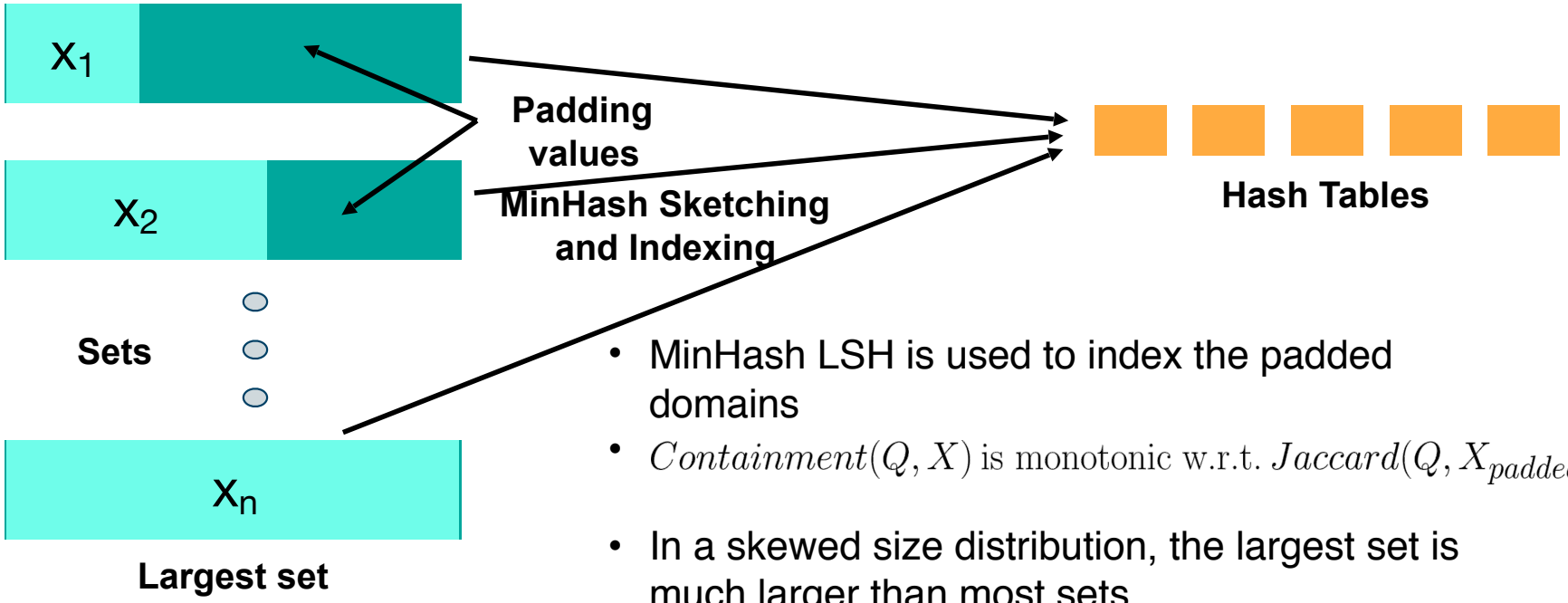



**Indexing:** generate k such hash functions and insert sets into k respective hash tables

**Query:** hash the query set with k hash functions, and retrieve candidates from the k hash tables

$$\frac{|X \cap Y|}{|X \cup Y|} \approx \frac{Count(h_i(X) = h_i(Y))}{k}$$

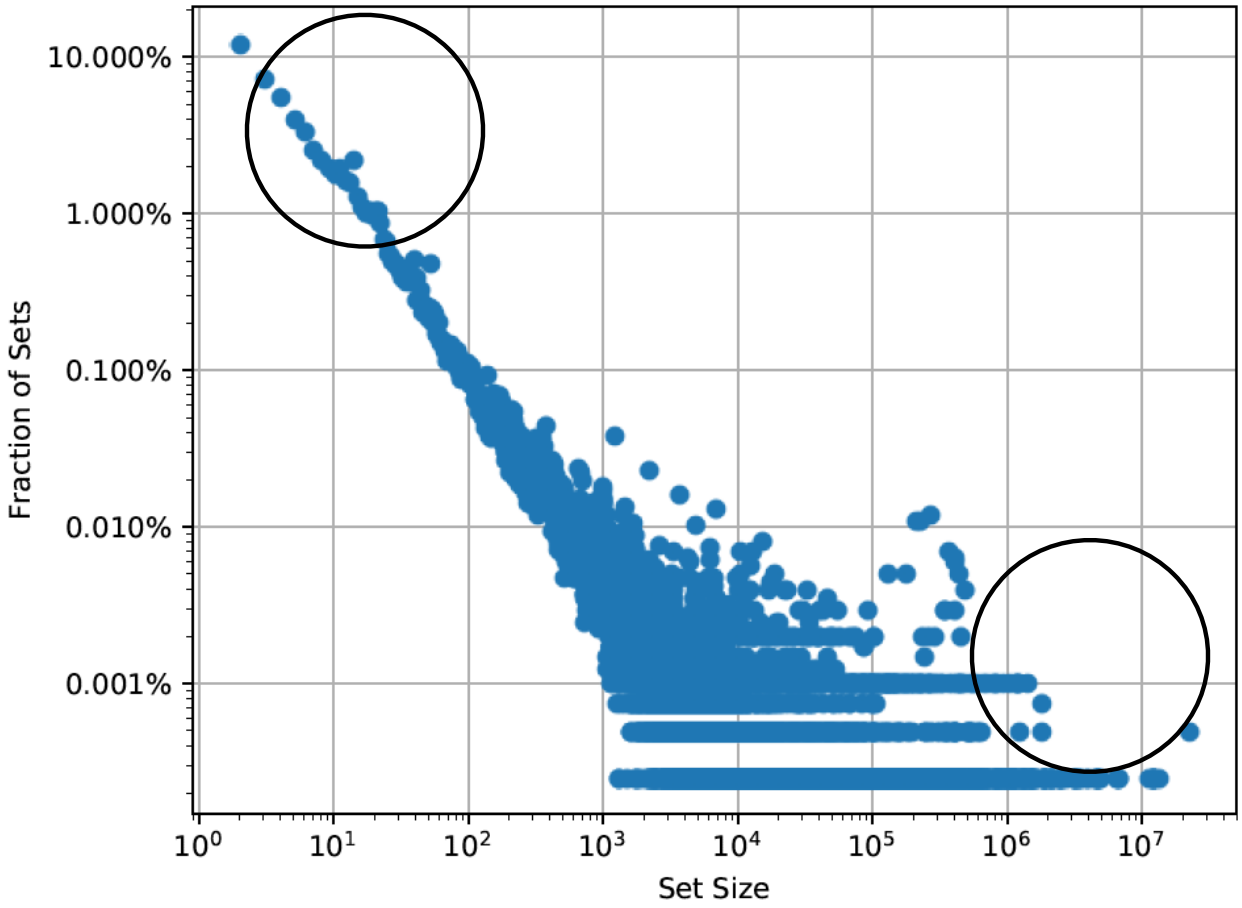
# Asymmetric MinHash (Shrivastava&Li WWW15)



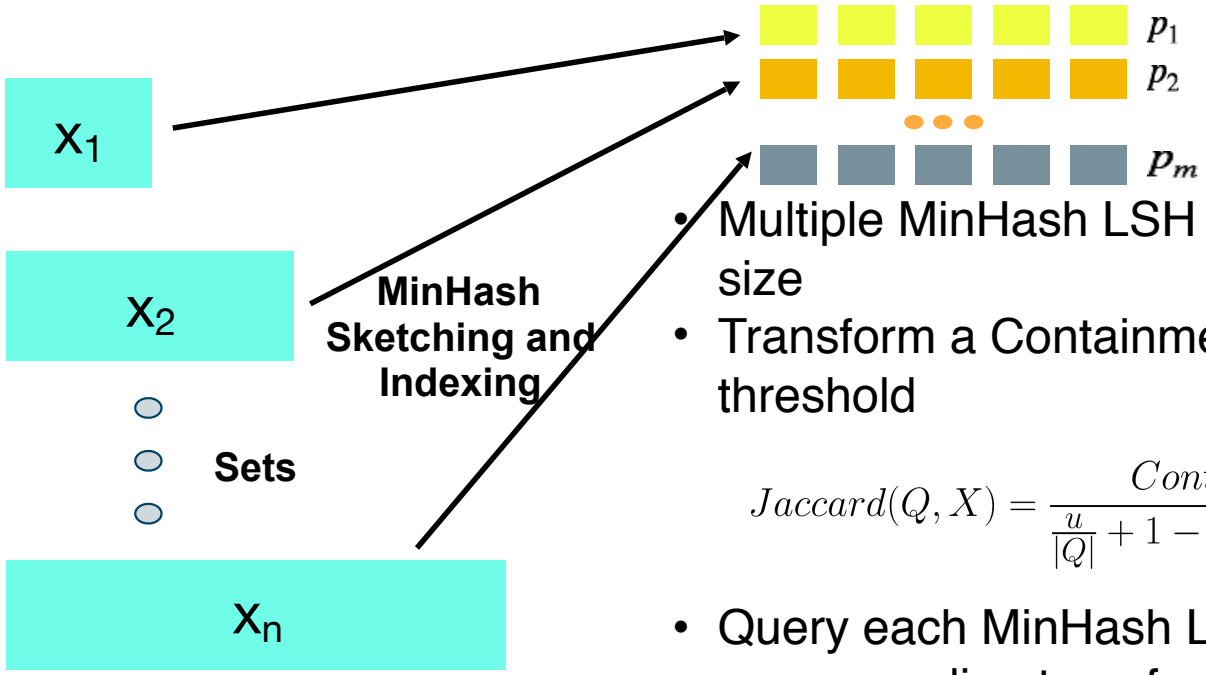

- MinHash LSH is used to index the padded domains
- $Containment(Q, X)$ is monotonic w.r.t. $Jaccard(Q, X_{padded})$

- In a skewed size distribution, the largest set is much larger than most sets
- Sketches contain mostly padding values — less likely to match a similar query set
- Hurts recall

# Open Data Attribute Cardinality Sizes



# LSH Ensemble (Zhu+ PVLDB16)

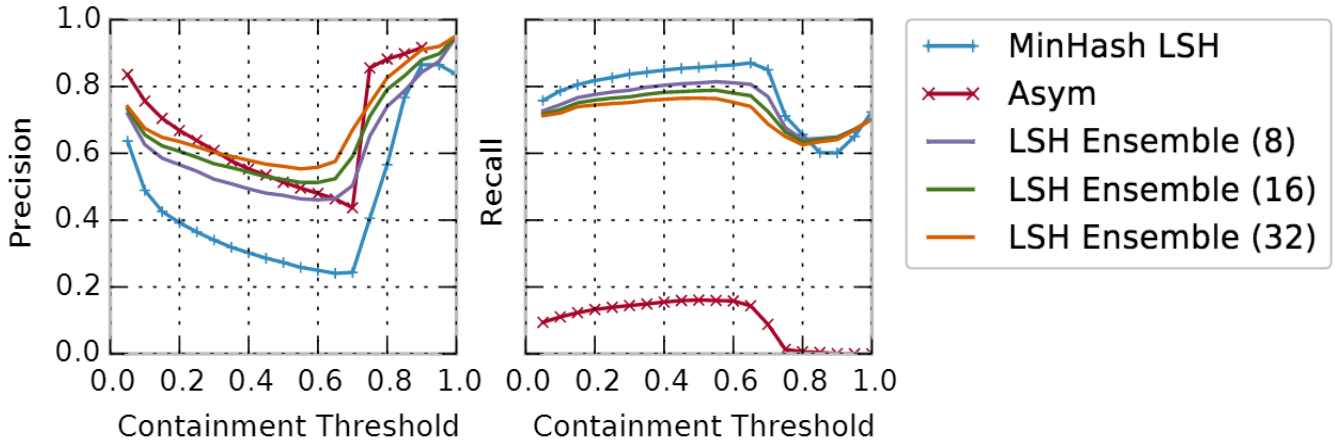



- Multiple MinHash LSH partitioned by increasing set size
- Transform a Containment threshold to a Jaccard threshold

$$Jaccard(Q, X) = \frac{Containment(Q, X)}{\frac{u}{|Q|} + 1 - Containment(Q, X)}$$

- Query each MinHash LSH index with the corresponding transformed threshold, in parallel
- Increasing number of partitions improves precision and speed
- **Optimal partitioning** strategy for power-law set size distribution (Zhu+ PVLDB16)

# LSH Ensemble Accuracy




- Creating more ***partitions*** leads to fewer false positives, while maintaining recall
- ***Asymmetric MinHash*** LSH has high precision, but low recall due to padding

# LSH Ensemble Query Performance

| Search Index | Mean Query (sec) | Precision (threshold=0.5) |
|---|---|---|
| MinHash LSH | 45.13 | 0.27 |
| LSH Ensemble (8) | 7.55 | 0.48 |
| LSH Ensemble (16) | 4.26 | 0.53 |
| LSH Ensemble (32) | 3.12 | 0.58 |

- Fewer false positive attributes to process (higher precision)
- Parallel querying over partitions

# Related Work

- Set Similarity Search
  - Prefix Filter
    - ✳[Chaudhuri+ICDE06,Bayardo+WWW07,Xiao+ICDE09]
  - Position Filter
    - ✳[Xiao+WWW08]
  - Cost Models
    - ✳[Behm+ICDE11,Wang+SIGMOD12]
  - Comparison
    - ✳[Mann+PVLDB16]

| DataSet | Avg Set Size | Max Set Size | Dictionary Size |
|---|---|---|---|
| AOL | 3 | 245 | 3.9M |
| ENRON | 135 | 3,162 | 1.1M |
| DBLP | 86 | 1,625 | 7K |
| WebTables | 10 | 17,030 | 184M |
| Open Data | 1.5K | 22M | 562M |

- Mass Collaboration Data Search
  - Linked Data/Microdata
    - ✳[Bizer+JSWIS09,Meusel+ISWC14]
  - Web Tables
    - ✳[Cafarella+ PVLDB08]
    - ✳[Bhagavatula+IDEA13]
    - ✳[Eberius+SSDBM15]
    - ✳**[Lehmberg+WWW16]**
  - Table extension
    - ✳Infogather [Yakout+SIGMOD12]
    - ✳[Cafarella+PVLDB09]
    - ✳[DasSarma+SIGMOD12]
    - ✳Mannheim Search Join [Lehmberg+JWebSem15]

# Outline

- Open Data
  - What is it and why is it important?
  - Motivating examples
- Analysis-driven Data Discovery
  - Table Join
  - **Table Union**
- Impact & Open Questions

# Table Union

| | | | | |
|---|---|---|---|---|
| Electricity | Barnett | Domestic | 240.99 | … |
| Gas | Brent | Transport | 164.44 | |
| Coal | Camden | Transport | 134.90 | |
| Railways diesel | City of London | Domestic | 10.52 | |
| Gas | Brent | Domestic | 169.69 | |
| Coal | Brent | Transport | 120.01 | |

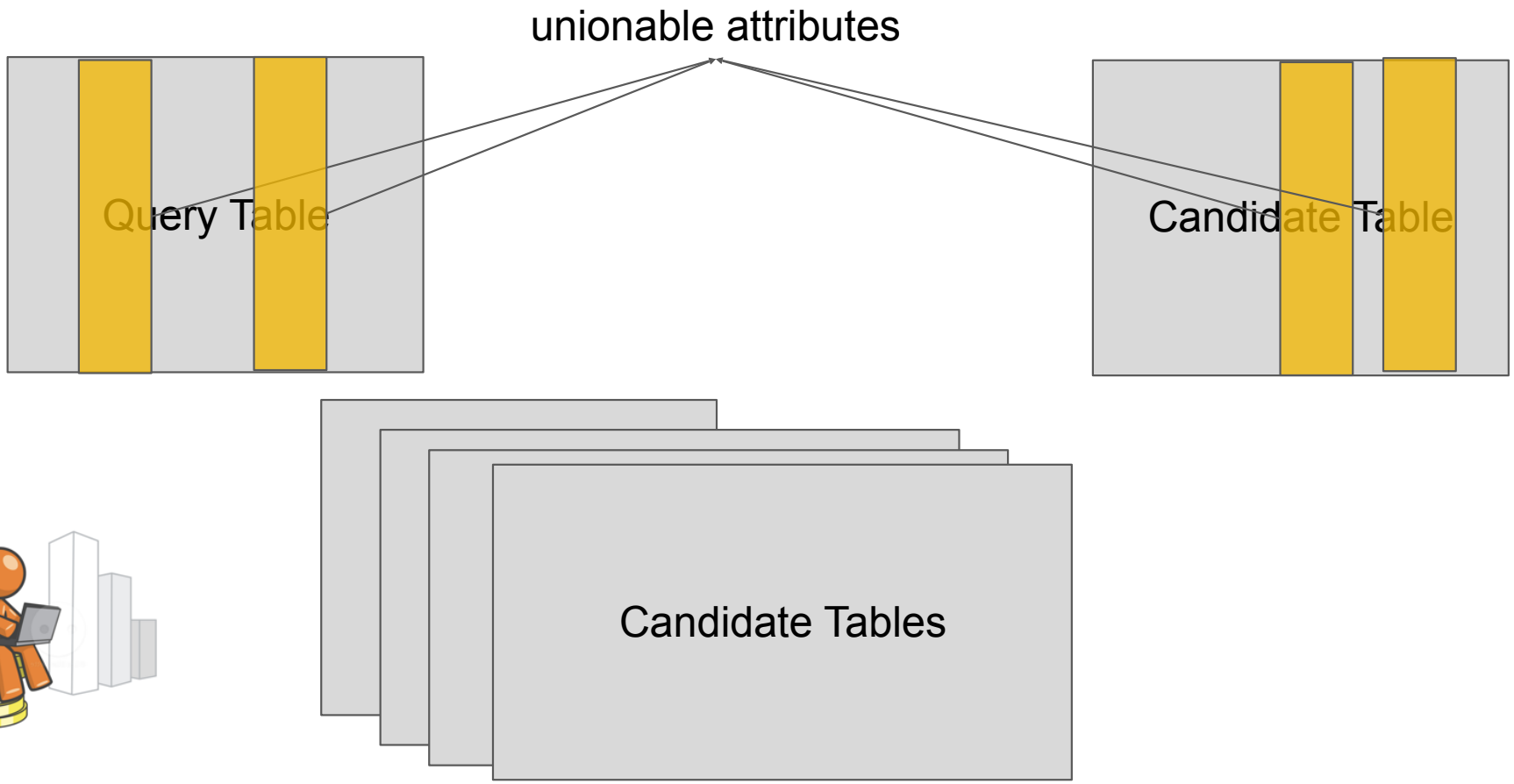
Query Table

| | | | | |
|---|---|---|---|---|
| Benton | Transport | Gasoline | 64413 | 62.9 |
| Kittitas | Hydro | Fuel oil (1,2,… | 12838 | 66.0 |
| Grays | Domestic | Aviation fuels | 1170393 | 66.1 |
| Skagit | Transport | Liquified | 59516 | 60.1 |

Candidate Table

- Some attributes may overlap
- Some may refer to entities of common type
- Some may use semantically similar words

# Unionable Attribute Search



# Attribute Unionability

| Natural Language | Semantic | Set | | |
|---|---|---|---|---|
| Electricity | Barnett | Domestic | 240.99 | … |
| Gas | Brent | Transport | 164.44 | |
| Coal | Camden | Transport | 134.90 | |
| Railways diesel | City of | Domestic | 10.52 | |
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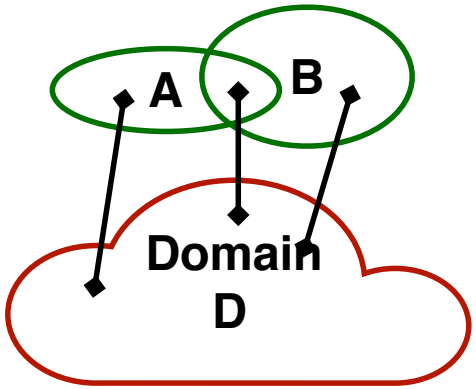
- Probabilistic Model
  - Attributes are samples drawn from the same domain
- Three types of attribute unionability/domains
  - Set, semantic, natural language

# Attribute Unionability

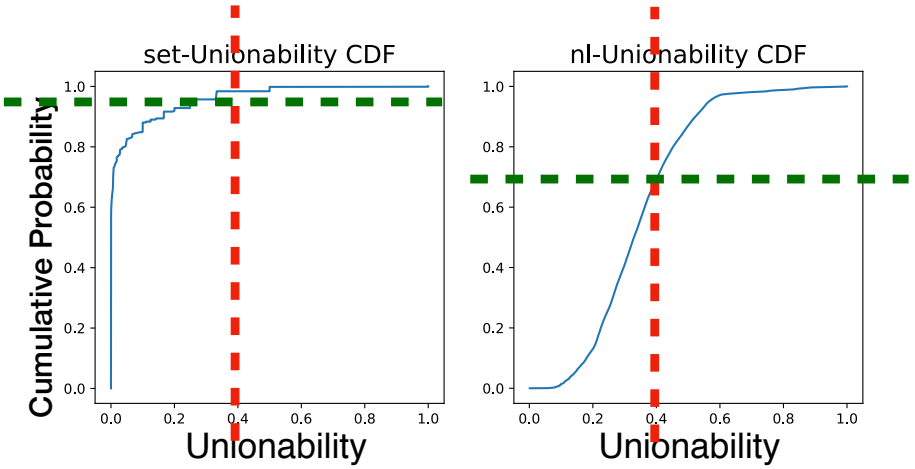



- Set and Semantic
  - D is set of values or set of ontology classes
- Natural Language
  - Convert values to word embeddings
  - Measure how likely the word embeddings are drawn from the same domain

## Ensemble unionability

Measures are incomparable so define based on the corpus. How unexpected is a score given the corpus?

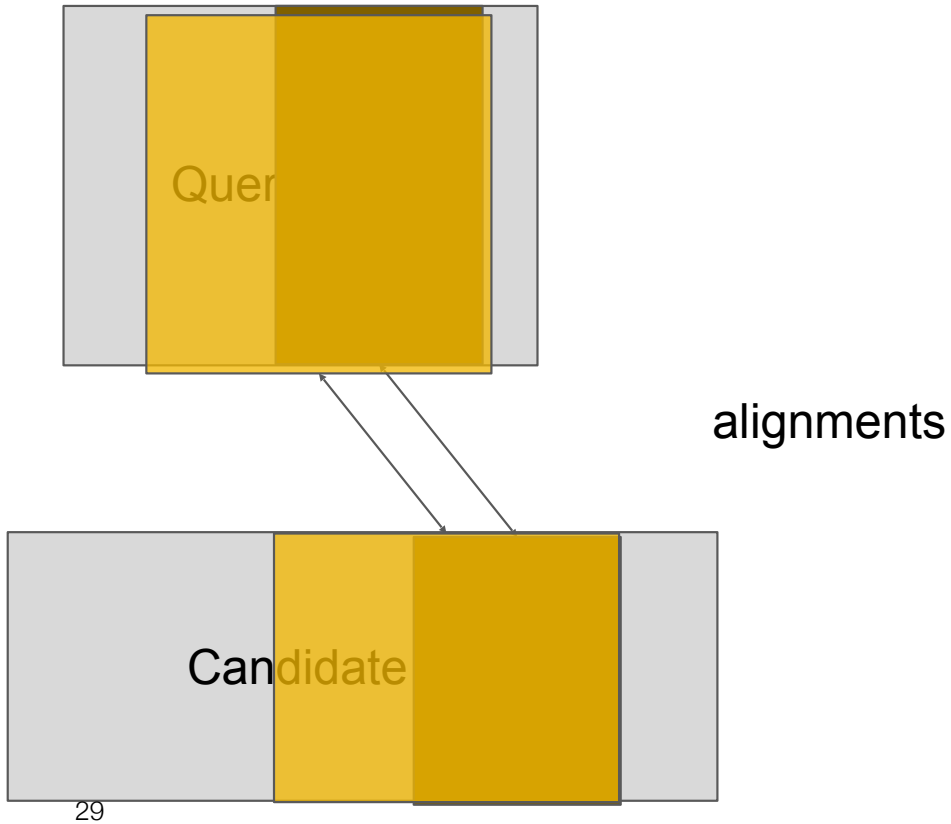
✳Full Paper Thursday 11am Segovia III



# Table Alignment

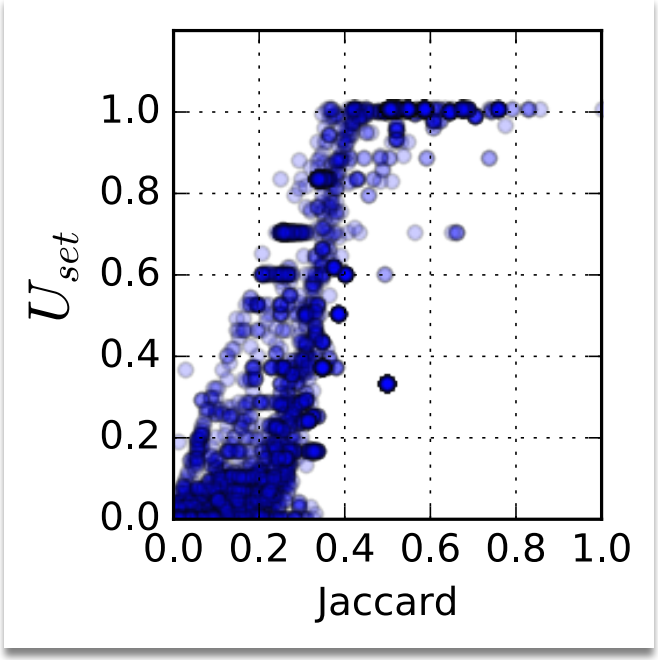
Given set of unionable attributes

when is an alignment of size *n* better than an alignment of size *n+1* attributes?



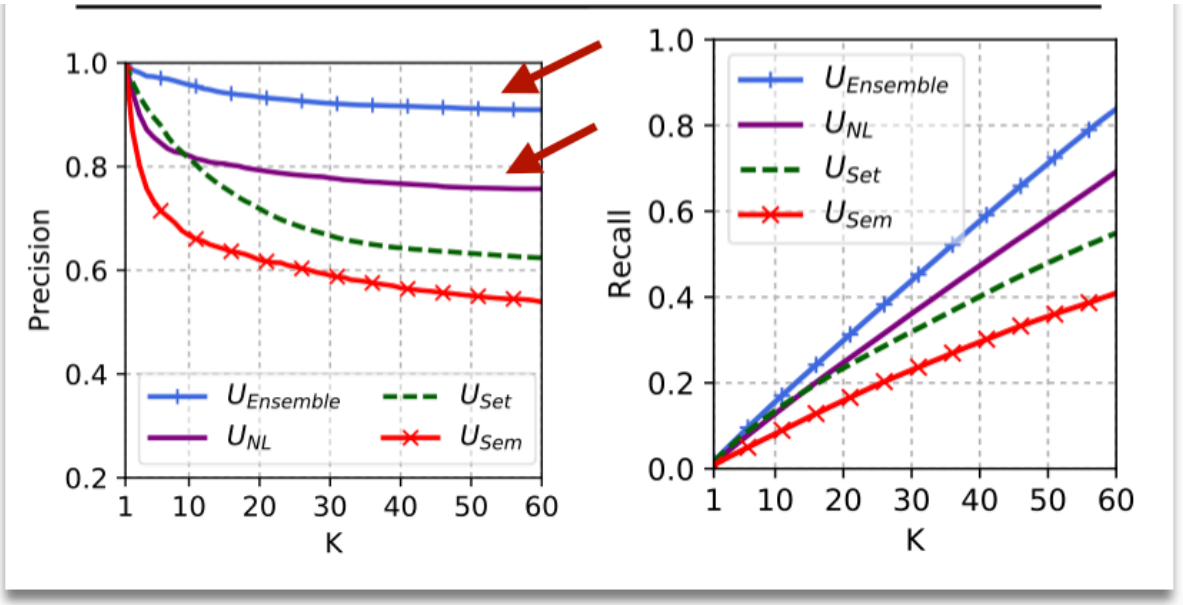
# Scaling Unionable Attribute Search

- Set and Semantic Unionability
  - Correlated with Jaccard
- Natural Language Unionability
  - Correlated with Cosine of topic vectors
- Use LSH indices to efficiently retrieve candidate attributes



# Evaluation Table Union on Open Data

- NL Unionability outperforms set and semantic (individually)
- Ensemble Unionability (uses all 3) best in accuracy
- Defined as top-K search
  - User defined threshold for unionability is not intuitive




- Semantic Unionability
  - Uses Open Ontology: YAGO
    - ✳[Suchenek+WWW07]

- Public Table Union Search Benchmark

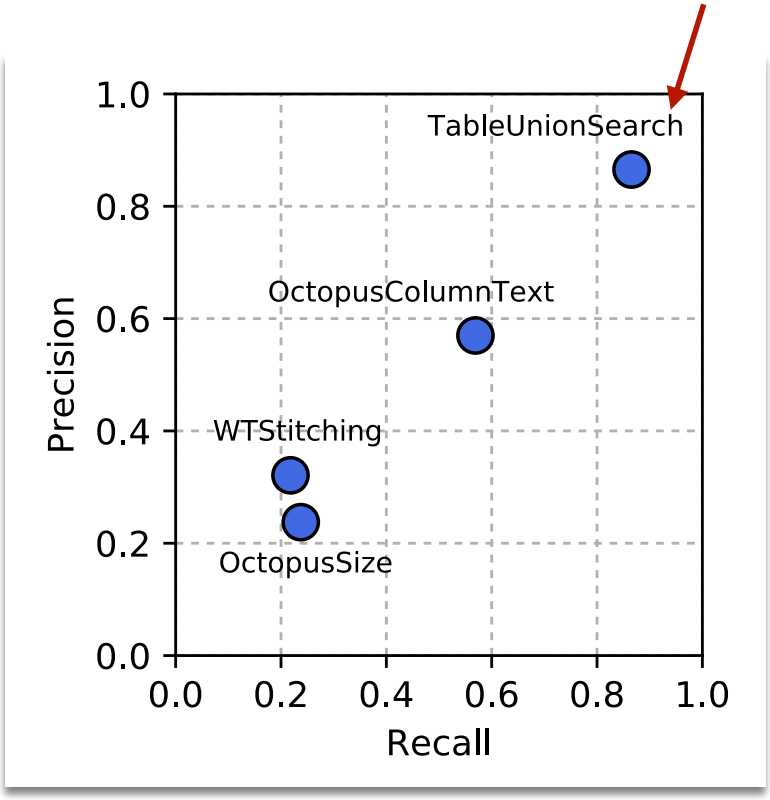
**https://github.com/RJMillerLab/table-union-search-benchmark**

# Using Search on Mass Collaboration Data

- Search on metadata
  - Schema Matching — attributes that matched can be “unioned”
    - ✳ [Ling+IJCAI13], [Lehmberg and BizerPVLDB17]
  - Schema plus keyword description of each attribute
    - ✳ [Pimplikar&SarawagiPVLDB12]
- Keyword Search and Clustering of Tables
  - Tables in the same cluster are “unionable”
    - ✳Octopus [Cafarella+PVLDB09]
- Entity-table search
  - Union tables that share a subject attribute (entities of same type)
    - ✳[Das Sarma+SIGMOD12]

# Comparison to WebTable Union

- Octopus [Cafarella+PVLDB09]
  - Keyword search; cluster result
  - Attribute Similarity (using instance only)
    - Size: avg length values
    - ColumnText: tf-idf of values
- Stitching [Lehmberg&BizerPVLDB17]
  - Instance-based schema matching
- Entity-Complement [DasSarma+SIGMOD12]
  - Union entity tables w/ same subject attribute
  - This comparison in paper



# Outline

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  - What is it and why is it important?
  - Motivating examples
- Analysis-driven Data Discovery
  - Table Join
  - Table Union
- Impact & Open Questions

# Open Data vs. Enterprise

| | Avg #Attr | Max Cardinality | Avg Cardinality | #UniqVal |
|---|---|---|---|---|
| OpenData | 16 | 22M | 1.5K* | 609M |
| Enterprise✤ | 12 | 900K | 4.0K | 4M |

- Enterprise data lakes
  - Can be massive
  - Maintaining join graphs can be expensive/inpractical
  - Data scientists may not know/understand all data available

✴***Need Analysis-Driven Data Discovery***

✤*From 167 table subset of MIT's 2400 table data warehouse [Deng+CIDR17]*
✤*Note that operational databases and corporate data lakes can be much wider and larger*
** Attributes containing string values*

# Open Problems

- Near-term:  analysis-driven data discovery
  - Bags vs. Sets
  - Multi-attribute join search
  - Finding tables that join and contain new information
  - Incorporating entity-resolution into scalable search
  - Search over quantities (with different measures)
  - Schema inference

# Vision

- ***Query discovery*** over massive data lakes
  - Finding not only the tables that can be integrated but also the best way to transform and integrate them meaningfully
  - Lessons from mapping discovery
- Data Quality over Open Data
  - Are "*Principles of Open Data"* being achieved?
    - ✳Truth finding has been studied over mass collaboration data [Pochampally+SIGMOD14]
    - ✳Can we quantify when open data is accurate, complete, primary?
  - Shazia Sadiq+, "Data Quality: The Role of Empiricism", SIGMOD Record 2018

# Acknowledgments


- This work was done in collaboration with Professor Ken Q. Pu, UOIT and
  - Erkang (Eric) Zhu
    - ✳Table Join and Open Data Search
    - ✳PhD expected December 2018
  - Fatemeh Nargesian
    - ✳Table Union Search
    - ✳PVLDB2018:  Paper will be presented this Thursday 11am Segovia III
    - ✳PhD expected December 2018


# Data Curation Lab

Database Systems Research

*Bringing data to life*

- Hiring ***Postdocs*** and PhD students
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Scalable Management and Analysis of Big Data