Data Integration and Large-scale Analysis (DIA)
05 Entity Linking and Deduplication

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Big Data Engineering (DAMS Lab)

Last update: Nov 11, 2023

Announcements / Administrative Items

- **#1 Video Recording**
  - Hybrid lectures: in-person H 0107, zoom live streaming, video recording
  - https://tu-berlin.zoom.us/j/9529634787?pwd=R1ZsN1M3SC9BOU1OcFdmem9zT202UT09

- **#2 Lectures**
  - **Dec 07:** no lecture because blocked ADBS course Dec 04 - Dec 07 at TU Graz
  - Moved lecture **08 Cloud Fundamentals** to **Dec 14** and **09 Cloud Scheduling** to **Dec 21**

- **#3 Exam Registration**
  - Written exams **Feb 08, 4pm** and **Feb 15, 4pm** (both in **H 0107**)
  - Exam registration beginning of January

Agenda

- **Motivation and Terminology**
- **Entity Resolution Concepts**
- **Entity Resolution Tools**
- **Example Applications**

Motivation and Terminology

Recap: Corrupted/Inconsistent Data

- **Heterogeneity of Data Sources**
  - Update anomalies on denormalized data / eventual consistency
  - Changes of app/preprocessing over time (US vs us) → inconsistencies
- **Human Error**
  - Errors in semi-manual data collection, laziness (see default values), bias
  - Errors in data labeling (especially if large-scale: crowd workers / users)
- **Measurement/Processing Errors**
  - Unreliable HW/SW and measurement equipment (e.g., batteries)
  - Harsh environments (temperature, movement) → aging

No Global Keys

Uniqueness & duplicates

Contradictions & wrong values

Missing Values

Ref. Integrity

[**Credit:** Felix Naumann]

ID	Name	BDay	Age	Sex	Phone	Zip
3	Smith, Jane	05/06/1975	44	F	999-9999	98120
3	John Smith	38/12/1963	55	M	867-4511	11111
7	Jane Smith	05/06/1975	24	F	567-3211	98120

Zip	City
98120	San Jose
90001	Lost Angeles

Typos

Terminology

[Douglas Burdick, Ronald Fagin, Phokion G. Kolaitis, Lucian Popa, Wang-Chiew Tan: Expressive power of entity-linking frameworks. **J. Comput. Syst. Sci. 2019**]

- **Entity Linking**
  - "***Entity linking*** is the problem of creating links among records representing real-world entities that are related in certain ways."
  - "As an important special case, it includes **entity resolution**, which is the problem of **identifying or linking duplicate entities**
- **Other Terminology**
  - **Entity Linking** → Entity Linkage, Record Linkage
  - **Entity Resolution** → **Data Deduplication**, Entity/Record Matching

☺

- **Applications**
  - Named entity recognition and disambiguation
  - Archiving, knowledge bases and graphs
  - Recommenders / social networks
  - Financial institutions (persons and legal entities)
  - Travel agencies, transportation, health care

Barack Obama
Barack Hussein Obama II
The US president (2016)

Barack and **Michelle**
are married ….

Example Applications: Classical Deduplication

- **Example 1: DBLP, ACM, Google Scholar Publications**
  - `(title, authors, venue, year)`
  - Basic preprocessing via title capitalization, etc
  - How about leveraging the linked PDF papers?

In practice:
multi-modal data, and
feature engineering

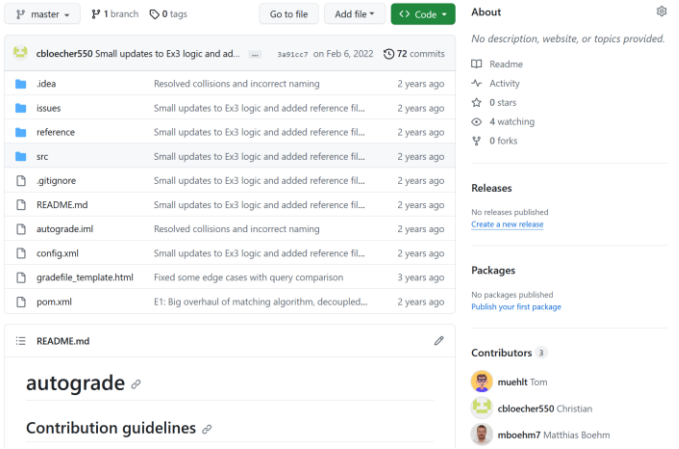
- **Example 2: Amazon, Google Products**
  - `(name, description, manufacturer, price)`
  - NLP for matching medium and long descriptions, e.g., word embeddings
  - How about leveraging the product images (different angles)

- **Benchmark Datasets**
  - Availability of ground truth

https://dbs.uni-leipzig.de/research/projects/object_matching/benchmark_datasets_for_entity_resolution

Example Applications: Plagiarism Detection for Autograding

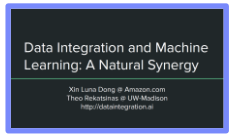
- **Background**
  - **WS20/21:** automatic grading system for Data Management exercises
  - **Overview:** export submissions, run ingestion programs, execute queries, compare results and test queries, auto comments/grades, upload
  - **Problem:** Increasing automation requires better plagiarism detection



- **Plagiarism Detection via Entity Resolution**
  - https://issues.apache.org/jira/browse/SYSTEMDS-3191 (DIA WiSe23/24)
  - **Data preparation:** file names/properties, runtime, correctness
  - **Blocking:** by programming language, results sets
  - **Matching**
    - Exact matches via basic diff + threshold
    - Code similarity via SotA embeddings
  - **Clustering**
    - Connected components within each block (min sim threshold)

[Fangke Ye et al: MISIM: An End-to-End Neural Code Similarity System. **CoRR 2020** arxiv.org/pdf/2006.05265.pdf]

Entity Resolution Concepts



[Xin Luna Dong, Theodoros Rekatsinas: Data Integration and Machine Learning: A Natural Synergy. Tutorials, **SIGMOD 2018**, **PVLDB 2018**, **KDD 2019**]

[Sairam Gurajada, Lucian Popa, Kun Qian, Prithviraj Sen: Learning-Based Methods with Human in the Loop for Entity Resolution, Tutorial, **CIKM 2019**]

[Felix Naumann, Ahmad Samiei, John Koumarelas: Master project seminar for Distributed Duplicate Detection. Seminar, **HPI WS 2016**]

Problem Formulation

[Ivan Fellegi, Alan Sunter: A Theory for Record Linkage, J. American. Statistical Assoc., pp. 1183-1210, **1969**]

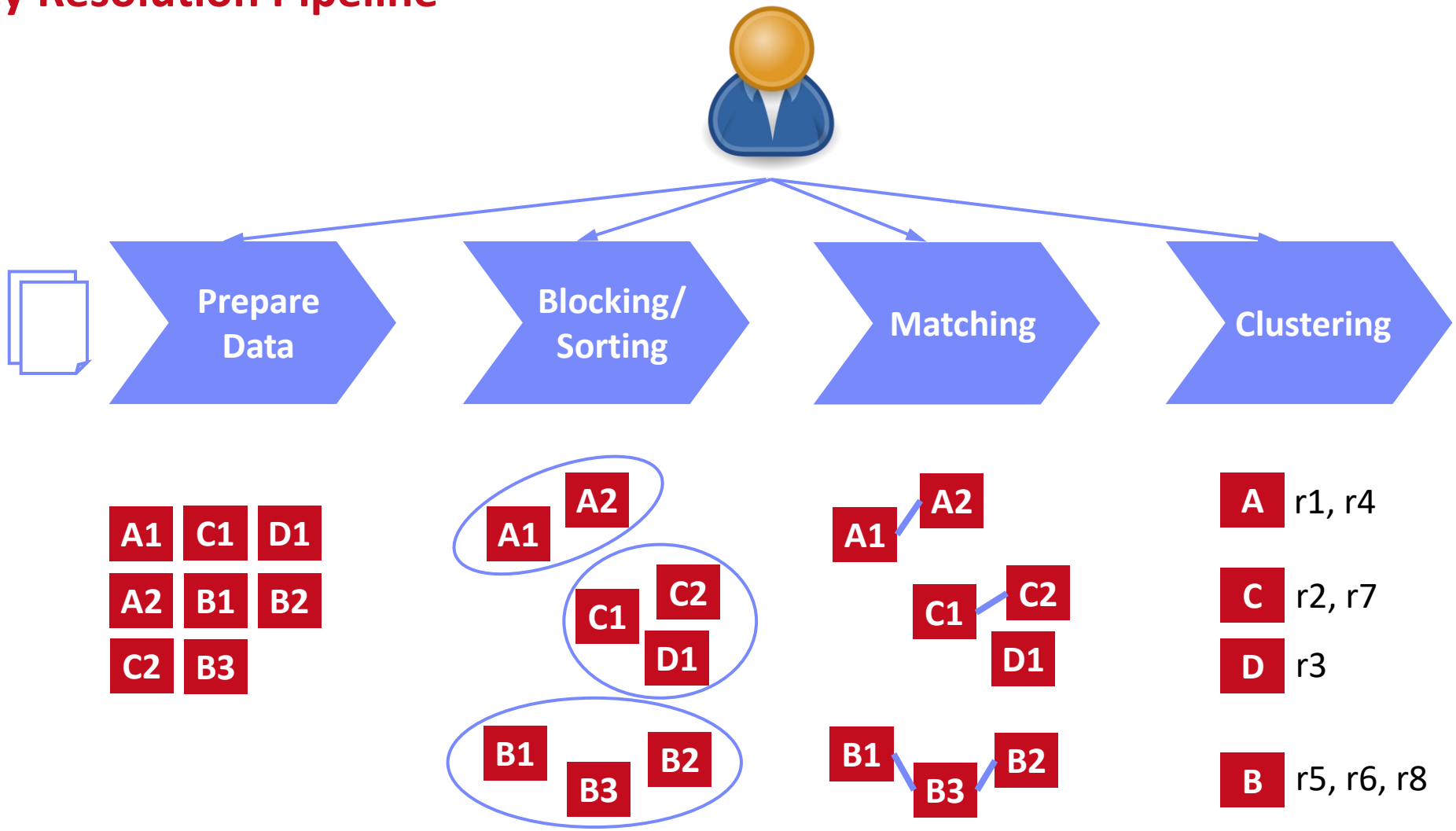
- **Entity Resolution**
  - "Recognizing those records in two files which represent identical persons, objects, or events"
  - Given two data sets A and B
  - Decide for all pairs of records a_i – b_j in A x B
    if match (**link**), no match (**non-link**), or not enough evidence (**possible-link**)

- **Naïve Deduplication**
  - `UNION DISTINCT`
    via hash group-by or sort group-by
  - **Problem:** only exact matches

Name	Position	Affiliation	Research
Matthias Boehm	RSM	IBM Research – Almaden	Apache SystemML
Matthias Böhm	Prof	TU Graz	Apache SystemDS
Matthias Böhm	Prof	TU Berlin	Apache SystemDS

➔ **Similarity Measures**
- Token-based: e.g., Jaccard J(A,B) = $|A \cap B| / |A \cup B|$
- Edit-based: e.g., Levenshtein lev(A,B) → min(replace, insert, delete)
- Phonetic similarity (e.g., soundex, metaphone), **Python lib Jellyfish**

Entity Resolution Pipeline



Entity Linking Approaches

[Xin Luna Dong, Theodoros Rekatsinas: Data Integration and Machine Learning: A Natural Synergy. **PVLDB 2018**]

50 Years of Entity Linkage

Rule-based and stats-based
- Blocking: e.g., same name
- Matching: e.g., avg similarity of attribute values
- Clustering: e.g., transitive closure, etc.

Supervised learning
- Random forest for matching
  F-msr: >95% w. ~1M labels
- Active learning for blocking & matching
  F-msr: 80%-98% w. ~1000 labels

1969 (Pre-ML) — **~2000 (Early ML)** — **~2015 (ML)** — **2018 (Deep ML)**

Sup / Unsup learning
- Matching: Decision tree, SVM
  F-msr: 70%-90% w. 500 labels
- Clustering: Correlation clustering, Markov clustering

Deep learning
- Deep learning
- Entity embedding

Step 1: Data Preparation

- **#1 Schema Matching and Mapping**
  - See lecture **04 Schema Matching and Mapping**
  - Create **homogeneous schema** for comparison
  - Split composite attributes

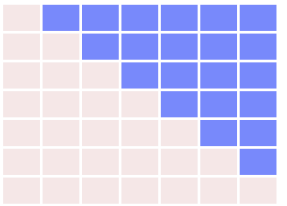
Autonomous, heterogeneous systems

- **#2 Normalization**
  - Removal of special characters and white spaces
  - **Stemming**
  - **Capitalization** (to upper/lower)
  - Remove redundant works, resolve abbreviations

likes/liked/likely/liking → like
Like / like → LIKE

- **#3 Data Cleaning**
  - See lecture **06 Data Cleaning and Data Fusion**
  - Correct data corruption and inconsistencies

Step 2: Blocking and Sorting



- **#1 Naïve All-Pairs**
  - Brute-force, naïve approach → n*(n-1)/2 pairs → **O(n^2) complexity**

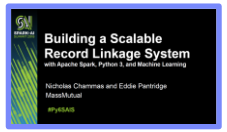
- **#2 Blocking / Partitioning**
  - Efficiently create small blocks of similar records for pair-wise matching
  - **Basic:** equivalent values on selected attributes (name)
  - **Predicates:** whole field, token field, common integer, same x char start, n-grams
  - **Hybrid:** disjunctions/conjunctions
  - Blocking Keys: → JR01111

John Roberts	20 Main St	Plainville	MA	01111

  - Learned: Minimal rule set via greedy algorithms

→ **Significant reduction:** 1M records → 1T pairs

→ 10K partitions w/ 100 records → 100M pairs (**10,000x**)



[Nicholas Chammas, Eddie Pantrige: Building a Scalable Record Linkage System, **Spark+AI Summit 2018**]

Step 2: Blocking, cont.

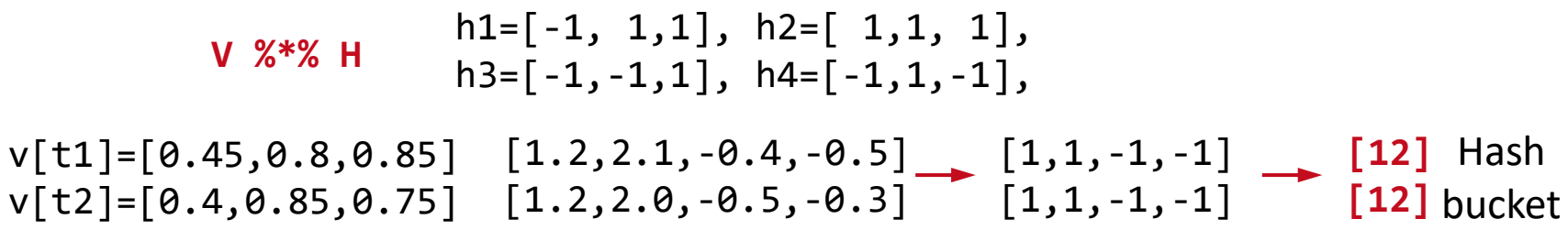
- **#3 Sorted Neighborhood**
  - Define **sorting keys** (similar to blocking keys; e.g., publication year)
  - Sort records by sorting keys
  - Define **sliding window of size m** (e.g., size 100, step 90) or **value range** (2 years) and compute all-pair **matching within sliding window**

- **#4 Blocking via Word Embeddings and LSH/DL**
  - Compute word/attribute embeddings + tuple embeddings
  - **Locality-Sensitive Hashing (LSH)** for blocking
  - K hash functions h(t) → k-dim hash-code
  - L hash tables, each k hash functions

Distributed Tuple Representation

[Muhammad Ebraheem et al: Distributed Representations of Tuples for Entity Resolution. **PVLDB 2018**]

[Saravanan Thirumuruganathan et al. Deep Learning for Blocking in Entity Matching […]. **PVLDB 2021**]



Step 3: Matching

- **#1 Basic Similarity Measures**
  - Pick similarity measure sim(r, r') and thresholds: high θ_h (and low θ_l)
  - **Record similarity:** avg attribute similarity; attribute similarity on token/n-gram/character-level
  - **Match:** sim(r, r') > θ_h **Non-match:** sim(r, r') < θ_l **possible match:** θ_l < sim(r, r') < θ_h

- **Examples** `sim("Matt Böhm", "Matt Boehm")`

Jaccard Similarity
(token-level, set semantics)

```
A: {Matt, Böhm}
B: {Matt, Boehm}
sim = |A ∩ B|/|A ∪ B|
    = 1 / 3 = 0.333
```

Trigram Similarity

```
A: {__M, _Ma, Mat, att, tt_, t_B,
    _Bö, Böh, öhm, hm_, m__}
B: {__M, _Ma, Mat, att, tt_, t_B,
    _Bo, Boe, oeh, ehm, hm_, m__}
sim = 2*|A ∩ B| / (|A|+|B|)
    = 2*8 / (11+12) = 0.696
```

Levenshtein Distance: 2

		M	a	t	t		B	o	e	h	m
	0	1	2	3	4	5	6	7	8	9	10
M	1	0	1	2	3	4	5	6	7	8	9
a	2	1	0	1	2	3	4	5	6	7	8
t	3	2	1	0	1	2	3	4	5	6	7
t	4	3	2	1	0	1	2	3	4	5	6
	5	4	3	2	1	0	1	2	3	4	5
B	6	5	4	3	2	1	0	1	2	3	4
ö	7	6	5	4	3	2	1	1	2	3	4
h	8	7	6	5	4	3	2	2	2	2	3
m	9	8	7	6	5	4	3	3	3	3	2

[https://phiresky.github.io/levenshtein-demo/]

Step 3: Matching - #2 Learned Matchers

- **Traditional ML for ER**
  - Phase 1: Learned string similarity measures for selected attributes
  - Phase 2: Training matching decisions from similarity metrics
  - Selection of samples for labeling (sufficient, suitable, **balanced**)
  - **Example ML Algorithms:** **SVM** and **decision trees**, **logistic regression**, **random forest**, XGBoost

[Mikhail Bilenko, Raymond J. Mooney: Adaptive duplicate detection using learnable string similarity measures. **KDD 2003**]

[Hanna Köpcke, Andreas Thor, Erhard Rahm: Evaluation of entity resolution approaches on real-world match problems. **PVLDB 2010**]

[Xin Luna Dong: Building a Broad Knowledge Graph for Products. **ICDE 2019**]

- **Deep Learning for ER**
  - Automatic representation learning from text (avoid feature engineering)
  - Leverage pre-trained word embeddings for semantics (no syntactic limitations)

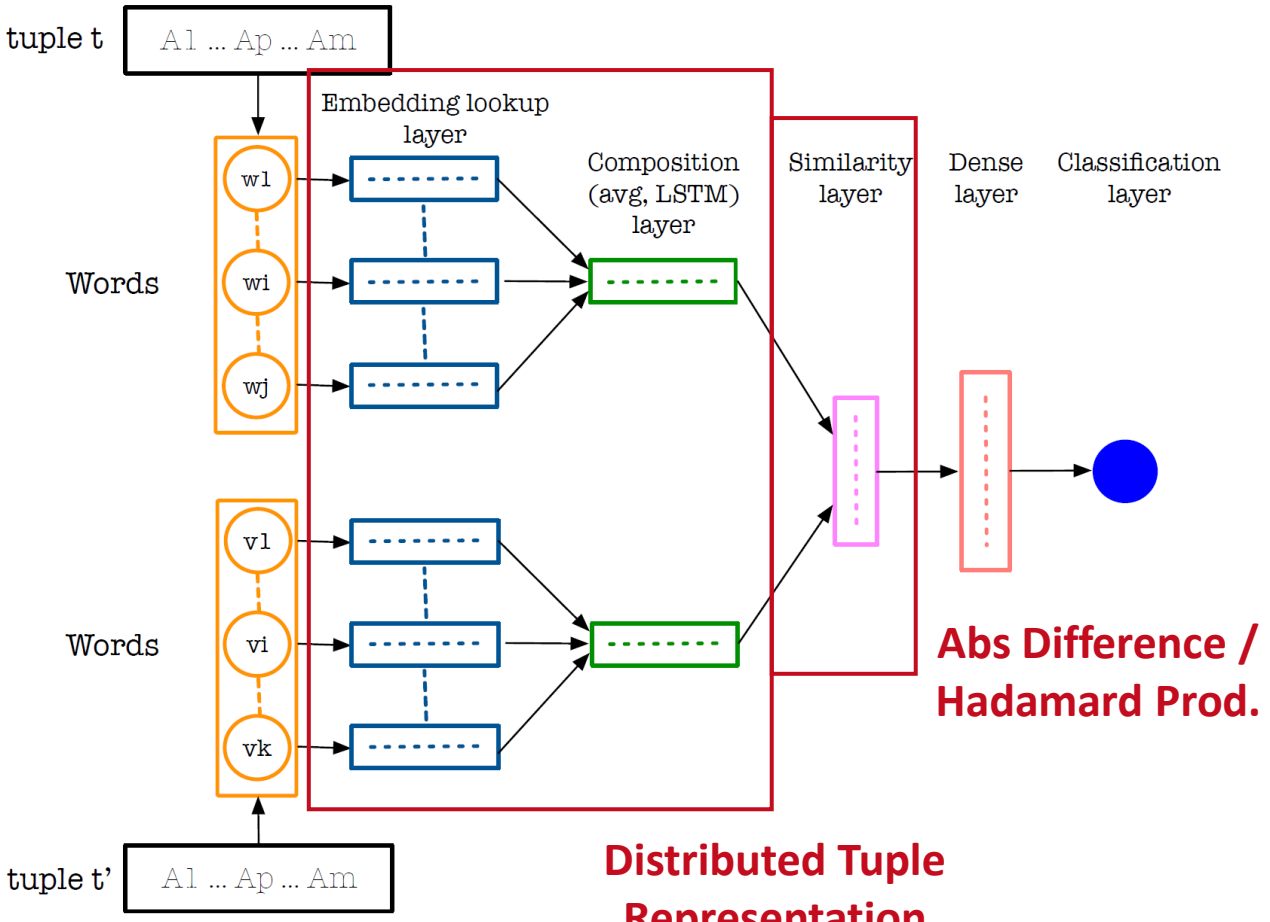
Step 3: Matching - #2 Learned Matchers, cont.

- **Example DeepER**

[Muhammad Ebraheem et al: Distributed Representations of Tuples for Entity Resolution. **PVLDB 2018**]

- **Example Magellan**
  - DL for **text and dirty data**

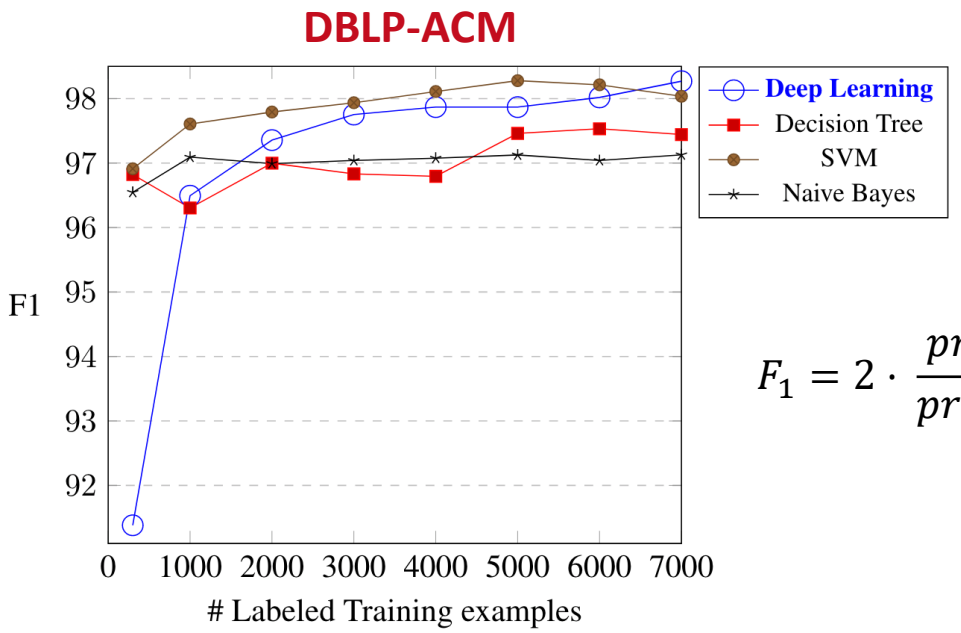
[Sidharth Mudgal et al: Deep Learning for Entity Matching: A Design Space Exploration. **SIGMOD 2018**]



Step 3: Matching - #2 Learned Matchers, cont.

[Sairam Gurajada, Lucian Popa, Kun Qian, Prithviraj Sen: Learning-Based Methods with Human in the Loop for Entity Resolution, Tutorial, **CIKM 2019**]

- **Labeled Data**
  - Scarce (experts)
  - **Class skew**



$$F_1 = 2 \cdot \frac{precision \cdot recall}{precision + recall}$$

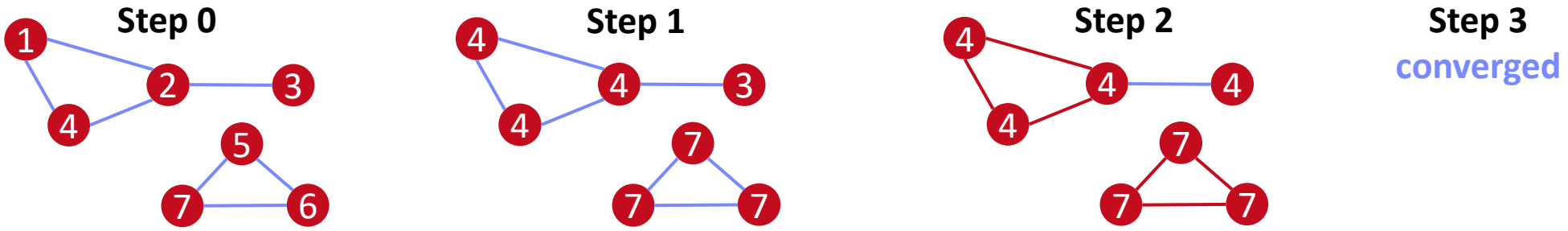
➔ **Transfer Learning**
- Learn model from high-resource ER scenario (w/ regularization)
- Fine-tune using low-resource examples

➔ **Active Learning**
- Select instances for tuning to min labeling

[Jungo Kasai et al: Low-resource Deep Entity Resolution with Transfer and Active Learning. **ACL 2019**]

Step 4: Clustering

- **Recap: Connected Components**
  - Determine connected components of a graph (subgraphs of connected nodes)
  - Propagate max(current, msgs) if != current to neighbors, terminate if no msgs



- **Clustering Approaches**
  - **Basic:** connected components (transitive closure) w/ edges sim > θ_h
    → Issues: **big clusters** and **dissimilar records**
  - **Correlation clustering:** +/- cuts based on sims → global opt NP-hard
  - **Markov clustering:** stochastic flow simulation via random walks

[Oktie Hassanzadeh, Fei Chiang, Renée J. Miller, Hyun Chul Lee: Framework for Evaluating Clustering Algorithms in Duplicate Detection. **PVLDB 2009**]

Incremental Data Deduplication

[Anja Gruenheid, Xin Luna Dong, Divesh Srivastava: Incremental Record Linkage. **PVLDB 2014**]

- **Goals**
  - Incremental stream of updates → previously **computed results obsolete**
  - Same or **similar results** AND **significantly faster** than batch computation

- **Approach**
  - End-to-end incremental record linkage for new and changing records
  - Incremental maintenance of similarity graph and incremental graph clustering
  - Initial graph created by **correlation clustering**
  - Greedy update approach in polynomial time
    - Directly connect components from increment ΔG into Q
    - **Merge** of **pairs of clusters** to obtain better result?
    - **Split** of **cluster into two** to obtain better result?
    - **Move** nodes **between two clusters** to obtain better result?

Entity Resolution Tools

Python Dedupe

https://docs.dedupe.io/en/latest/API-documentation.html
https://dedupeio.github.io/dedupe-examples/docs/csv_example.html

- **Overview**
  - Python library for data deduplication (entity resolution)
  - **By default:** logistic regression matching (and blocking)
- **Example**

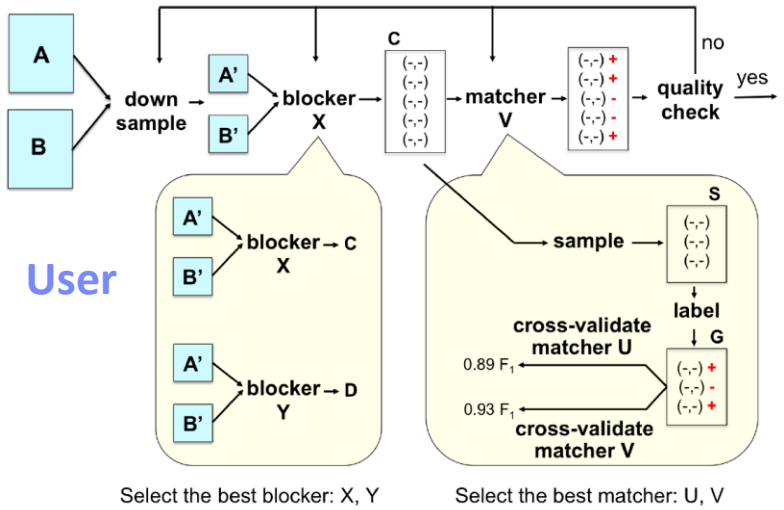
```
fields = [
  {'field':'Site name', 'type':'String'},
  {'field':'Address', 'type':'String'}]
deduper = dedupe.Dedupe(fields)

# sample data and active learning
deduper.sample(data, 15000)
dedupe.consoleLabel(deduper)

# learn blocking rules and pairwise classifier
deduper.train()

# Obtain clusters as lists of (RIDs and confidence)
threshold = deduper.threshold(data, recall_weight=1)
clustered_dupes = deduper.match(data, threshold)
```

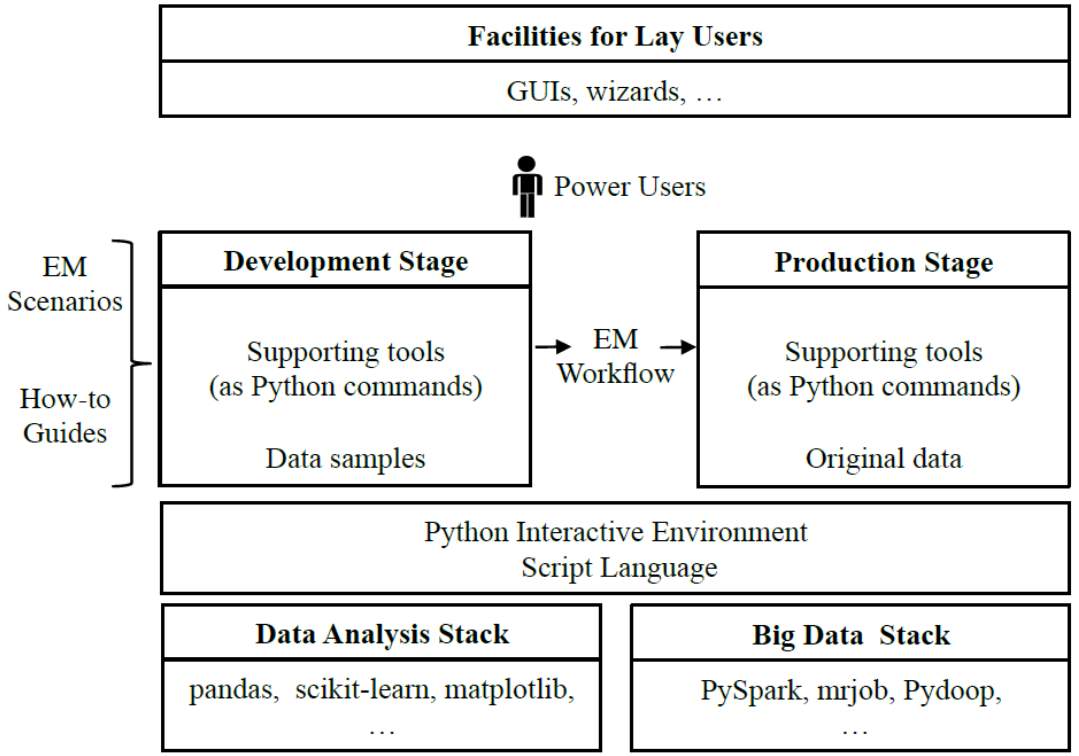
```
Do these records refer
to the same thing?
(y)es / (n)o /
(u)nsure / (f)inished
```

Magellan (University Wisconsin-Madison)

[Pradap Konda et al.: Magellan: Toward Building Entity Matching Management Systems. **PVLDB 2016**]

- **System Architecture**
  - **How-to guides for users**
  - Tools for individual steps of **entire ER pipeline**
  - Build on top of existing Python/big data stack
  - Scripting environment for power users

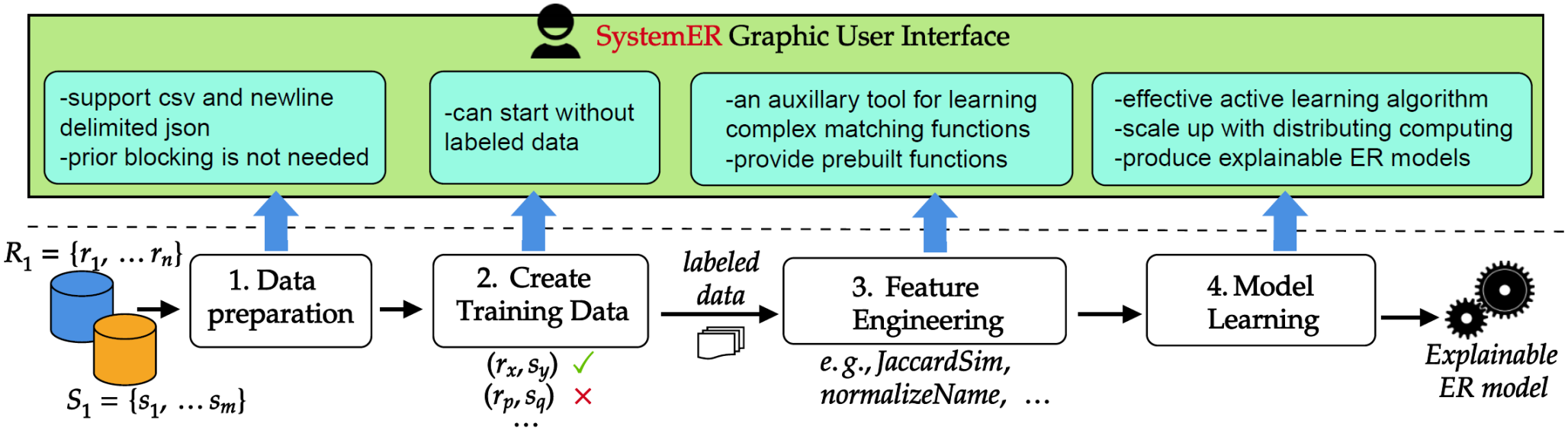




[Yash Govind et al: Entity Matching Meets Data Science: A Progress Report from the Magellan Project. **SIGMOD 2019**]

SystemER (IBM Research – Almaden)

[Kun Qian, Lucian Popa, Prithviraj Sen: SystemER: A Human-in-the-loop System for Explainable Entity Resolution. **PVLDB 2019**]



Learns explainable ER rules (in HIL)

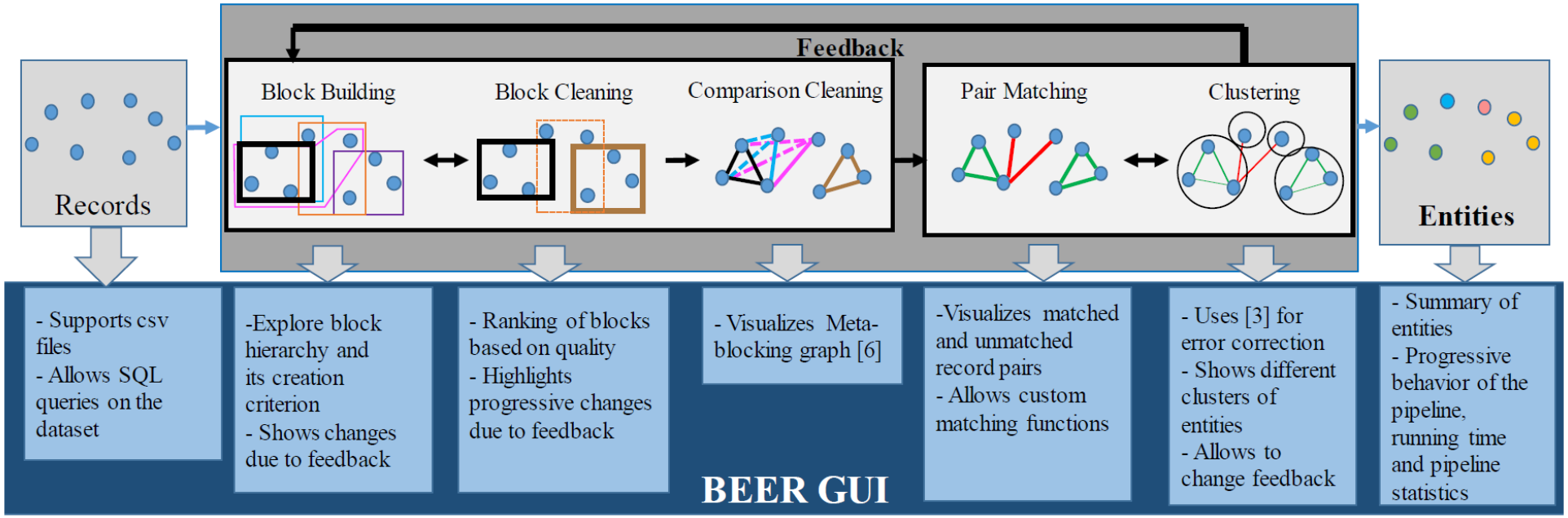
```
DBLP.title = ACM.title
AND DBLP.year = ACM.year
AND jaccardSim(DBLP.authors,ACM.authors)>0.1
AND jaccardSim(DBLP.venue,ACM.venue)>0.1
→ SamePaper(DBLP.id,ACM.id)
```

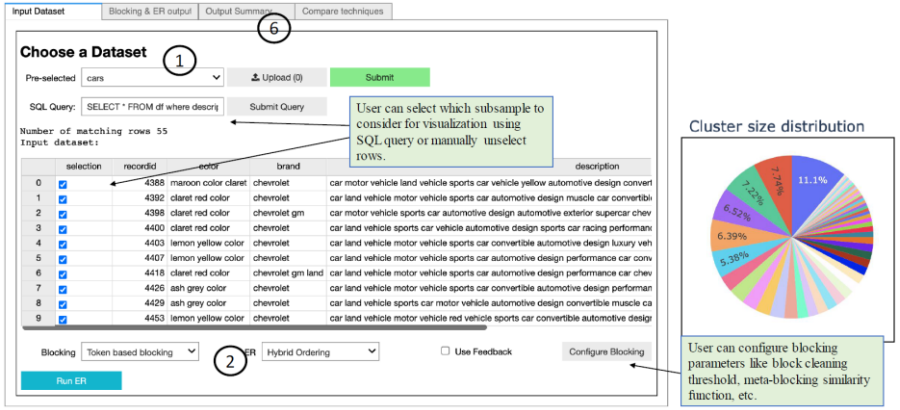
[Mauricio A. Hernández, Georgia Koutrika, Rajasekar Krishnamurthy, Lucian Popa, Ryan Wisnesky: HIL: a high-level scripting language for entity integration. **EDBT 2013**]

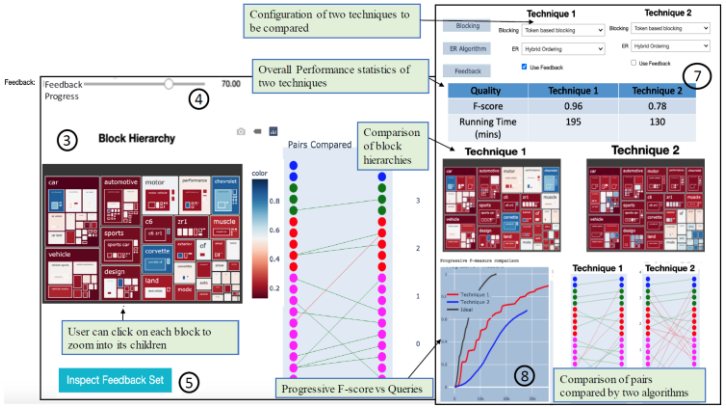
BEER (UMass/Roma/AT&T Labs)

[Sainyam Galhotra, Donatella Firmani, Barna Saha, and Divesh Srivastava: BEER: Blocking for Effective Entity Resolution, **SIGMOD 2021**]

Feedback after **1% sample**







Summary and Q&A

- **Motivation and Terminology**
- **Entity Resolution Concepts**
- **Entity Resolution Tools**

Fundamental Data Integration Technique
w/ lots of applications + remaining challenges

- **Next Lectures (Data Integration Architectures)**
  - **06** Data Cleaning and Data Fusion [Nov 23]
  - **07** Data Provenance and Catalogs [Nov 30]
  - **no lecture** → project work [Dec 07]