Slides Credit: Matthias Boehm

SCIENCE
PASSION
TECHNOLOGY

Data Integration and Large Scale Analysis
05 Entity Linking and Deduplication

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Agenda

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

Motivation and Terminology

Recap: Corrupted/Inconsistent Data

- **#1 Heterogeneity of Data Sources**
  - Update anomalies on denormalized data / eventual consistency
  - Changes of app/prep over time (US vs us) → inconsistencies
- **#2 Human Error**
  - Errors in semi-manual data collection, laziness (see default values), bias
  - Errors in data labeling (especially if large-scale: crowd workers / users)
- **#3 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 Matching

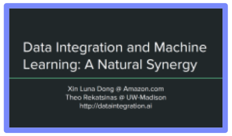
☺

- **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)

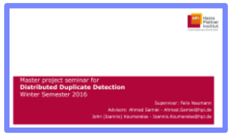
Barack and Michelle
are married ….

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

- **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**)

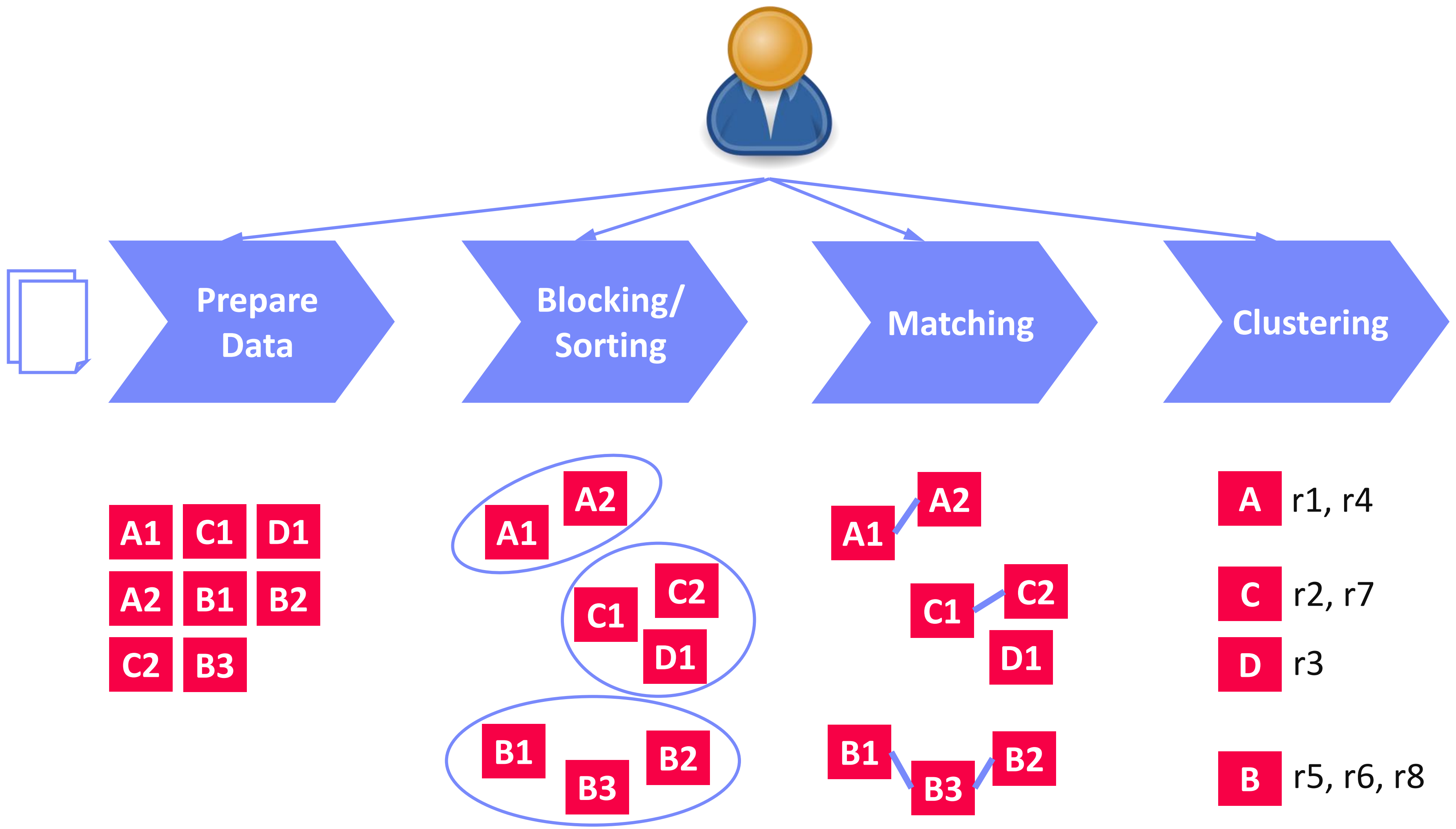
[Ivan Fellegi, Alan Sunter: A Theory for Record Linkage, J. American. Statistical Assoc., pp. 1183-1210, **1969**]

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

Name	Position	Affiliation	Department
Shafaq Siddiqui	Lecturer	Sukkur IBA	CS
Shafaq Siddiqi	TA	TU Graz	CSBME

→ **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**

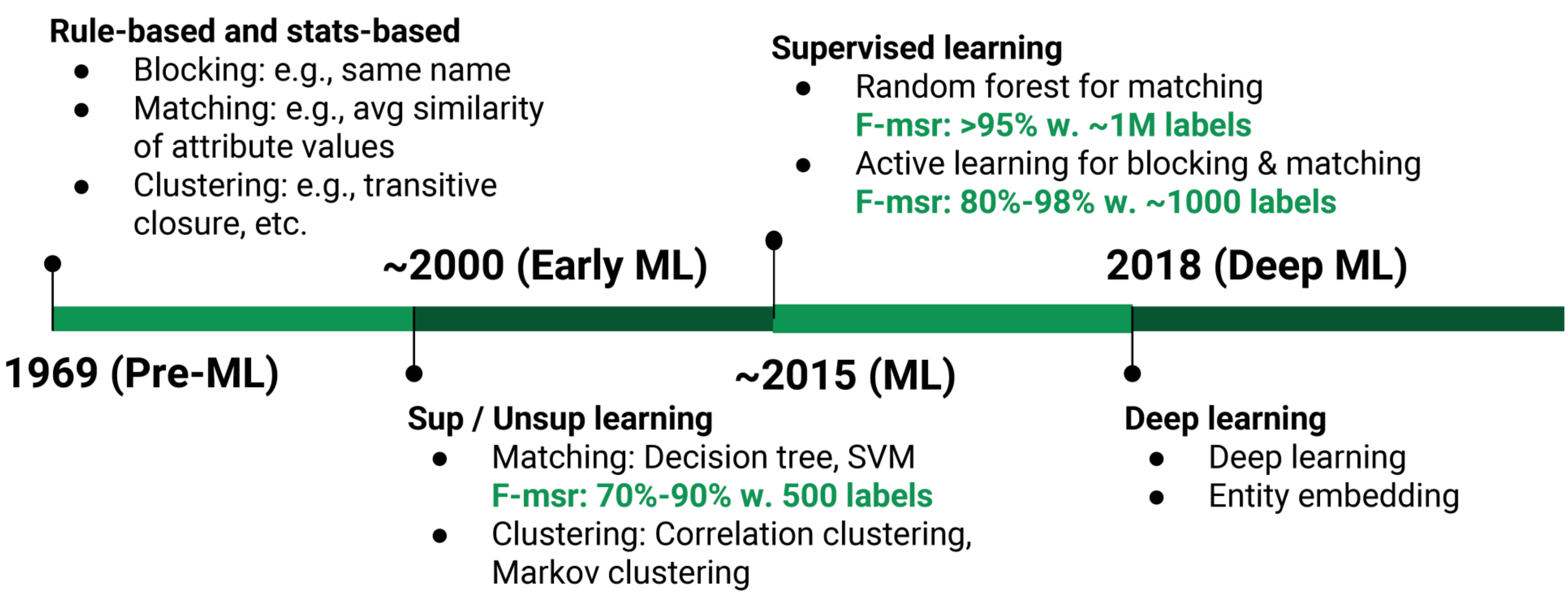
Entity Resolution Pipeline



Entity Linking Approaches

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

50 Years of Entity Linkage



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

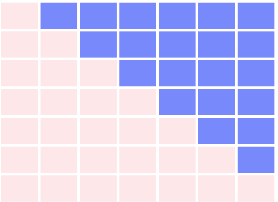
- **#2 Normalization**
  - Removal of special characters and white spaces
  - **Stemming**
  - **Capitalization** (to upper/lower)
  - Remove redundant works, resolve abbreviations

likes/liked/likely/liking → like

- **#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**

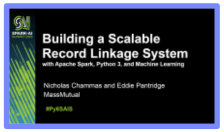


- **#2 Blocking / Partitioning**
  - Efficiently create small blocks of similar records for pair-wise matching
  - **Basic:** equivalent values on selected attributes (name)
  - **Predicates:** whole field, token field, common integer, same x char start, n-grams
  - **Hybrid:** disjunctions/conjunctions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

John Roberts	20 Main St	Plainville	MA	**01111**
Julia Ray	32 Main St	Plainville	MA	**01111**

  - Learned: Minimal rule set via greedy algorithms

→ **Significant reduction:** 1M records → 1T pairs
→ 1K partitions w/ 1K records → 1G pairs (**1000x**)



[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)
  - Sort records by sorting keys
  - Define **sliding window of size m** (e.g., 100) 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**]

V %*% H

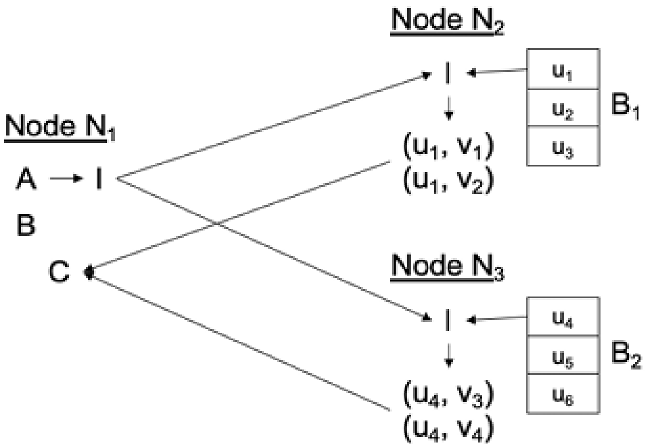
```
h1=[-1, 1,1], h2=[ 1,1, 1],
h3=[-1,-1,1], h4=[-1,1,-1],
```

```
v[t1]=[0.45,0.8,0.85]  [1.2,2.1,-0.4,-0.5] → [1,1,-1,-1] → [12]  Hash
v[t2]=[0.4,0.85,0.75]  [1.2,2.0,-0.5,-0.3]   [1,1,-1,-1]   [12]  bucket
```

Step 2: Blocking, cont.

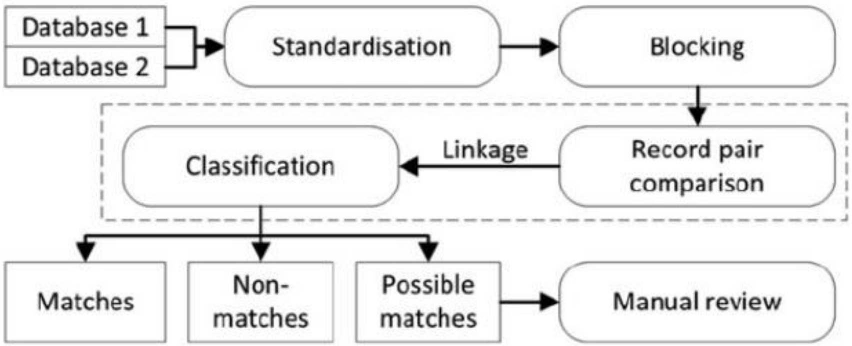
[Derek Paulsen et al: Sparkly: A Simple yet Surprisingly Strong TF/IDF Blocker for Entity Matching. **PVLDB 2023**]

- **#5 TF/IDF based blocking**
  - Build inverted index of smaller table A
  - Ship index and tuples of larger table B to other nodes in the cluster
  - Find **top-k** matches in table A for the tuples of table B



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
  - **Match:** sim(r, r') > θ_h **Non-match:** sim(r, r') < θ_l
    possible match: θ_l < sim(r, r') < θ_h
- **#2 Learned Matchers (Traditional ML)**
  - **Phase 1:** Model Generation
  - **Phase 2:** Model Application
  - Selection of samples for labeling (sufficient, suitable, **balanced**)
  - **SVM** and **decision trees**, **logistic regression**, **random forest**, XGBoost



[O'Hare, K.et.al. D. P., & A. Jurek-Loughrey,2019]

[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**]

Step 3: Matching, cont.

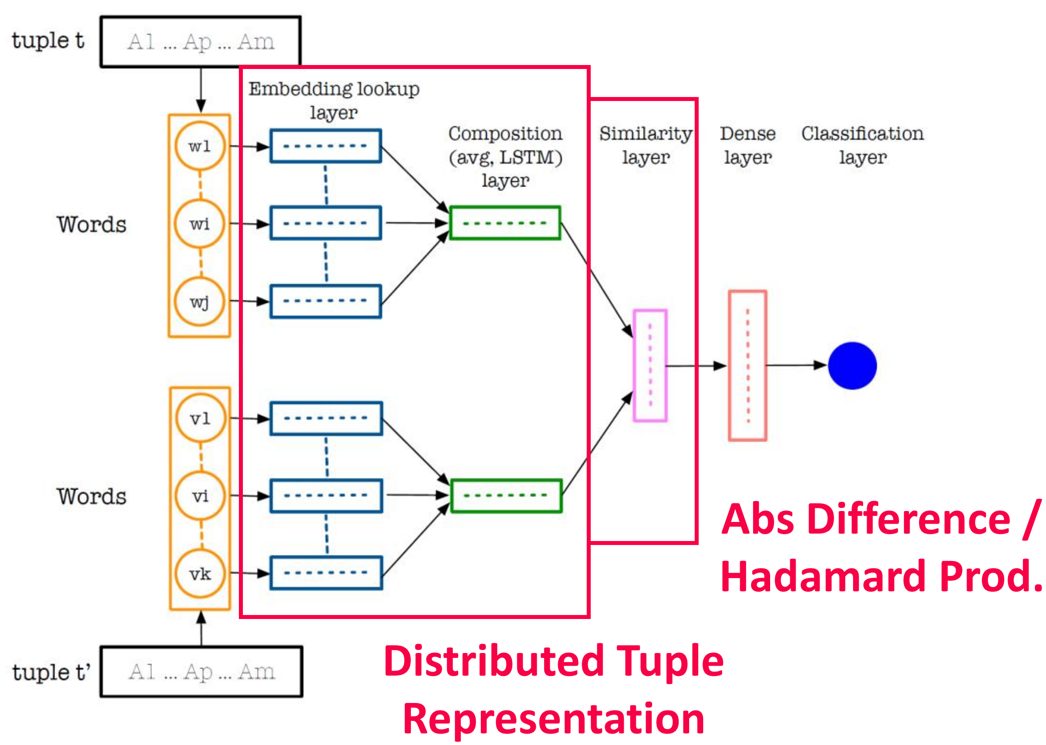
- **Deep Learning for ER**
  - Automatic **representation learning** from text (avoid feature engineering)
  - Leverage pre-trained **word embeddings for semantics** (no syntactic limitations)

- **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**]

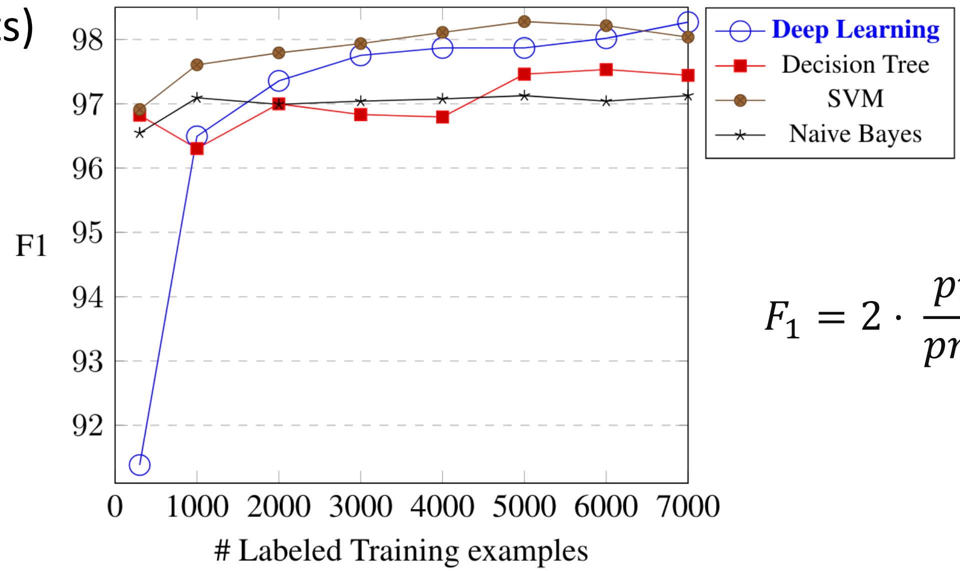


Step 3: Matching, cont.

[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

DBLP-ACM



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

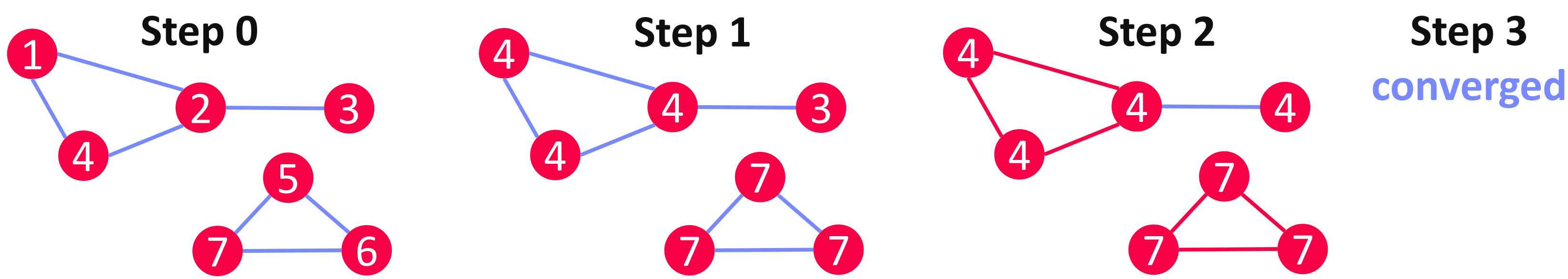
➔ **Transfer Learning**
  - Learn model from high-resource ER scenario (w/ regularization)
  - Fine-tune using low-resource examples

➔ **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**

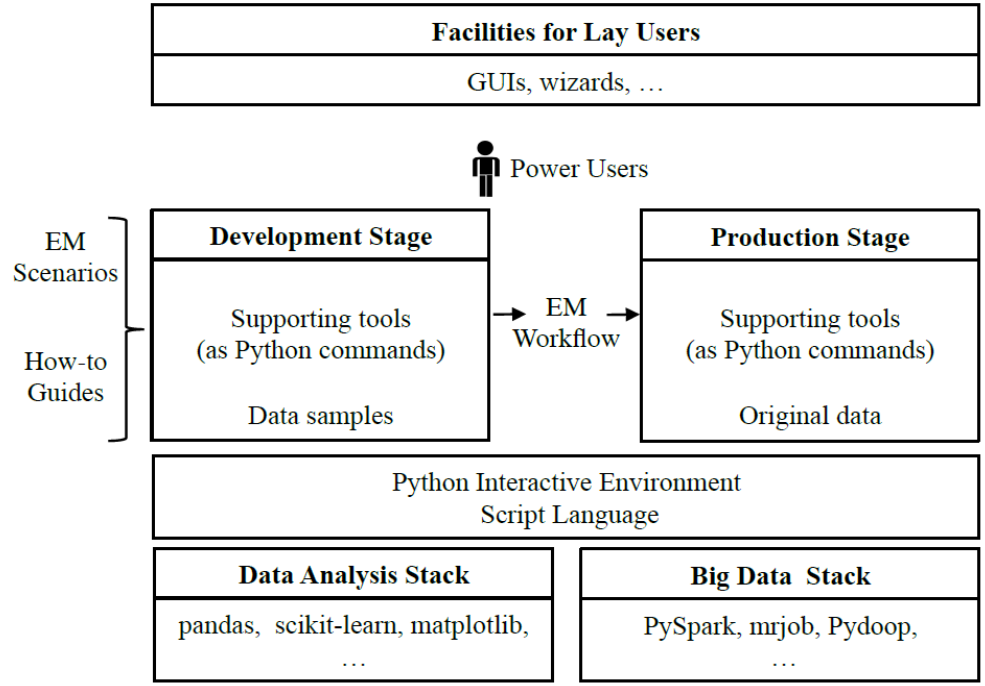
```
fields = [
  {'field':'Site name', 'type':'String'},
  {'field':'Address', 'type':'String'}]
deduper = dedupe.Dedupe(fields)

# 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)
```

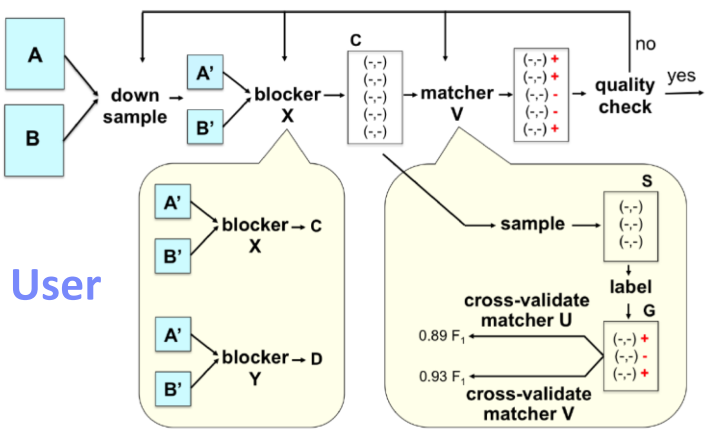
```
Do these records refer
 to the same thing?
  (y)es / (n)o /
(u)nsure / (f)inished
```

Magellan (UW-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





Select the best blocker: X, Y

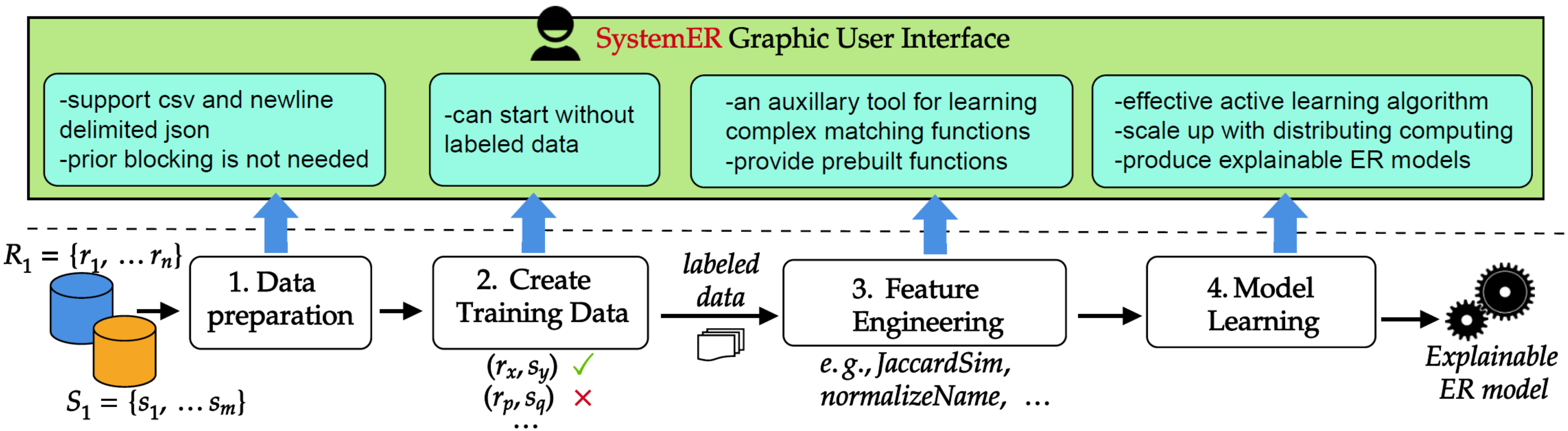
Select the best matcher: U, V

User

[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)

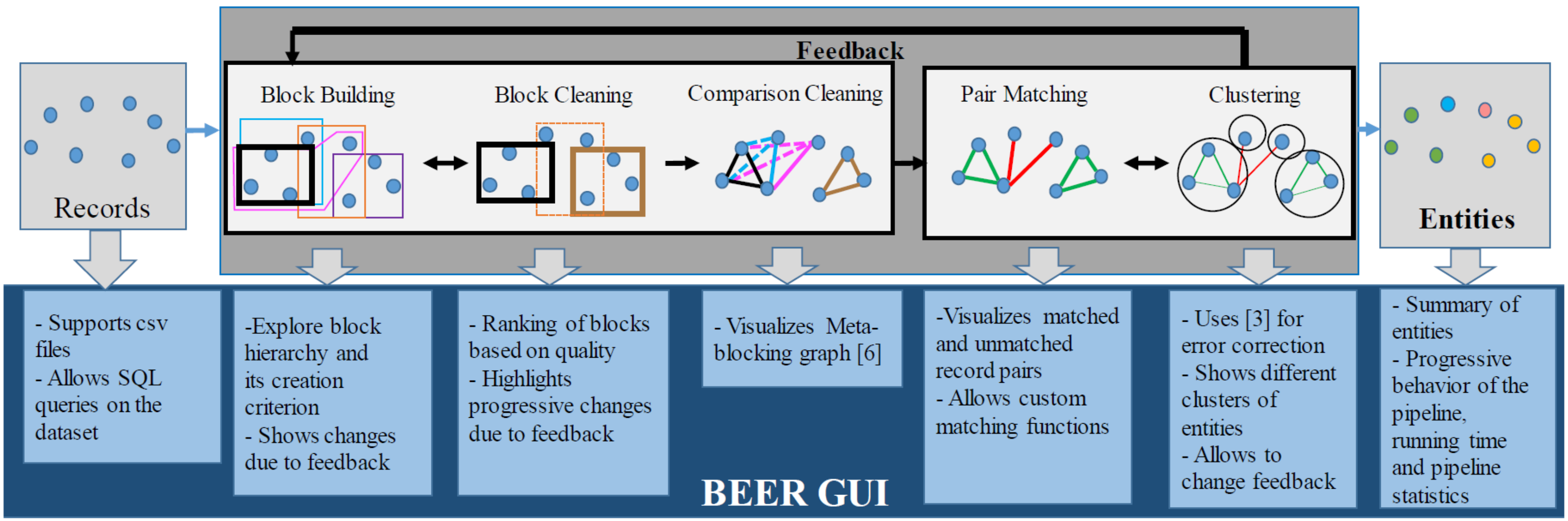
```
DBLP.title = ACM.title
AND DBLP.year = ACM.year
AND jaccardSim(DBLP.authors,ACM.authors)>0.1
AND jaccardSim(DBLP.venue,ACM.venue)>0.1
→ SamePaper(DBLP.id,ACM.id)
```

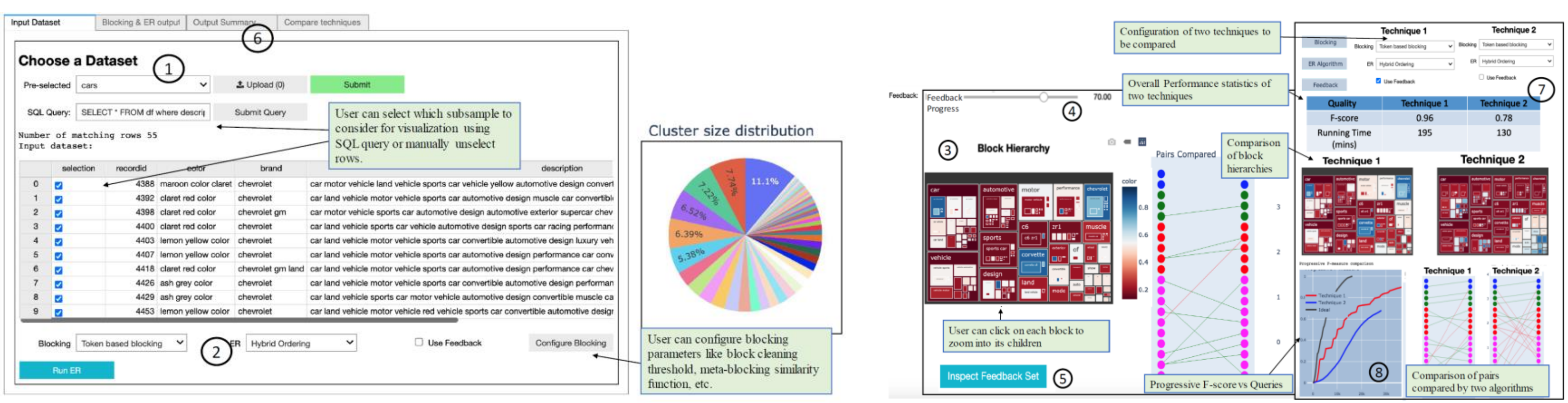
[Mauricio A. Hernández, Georgia Koutrika, Rajasekar Krishnamurthy, Lucian Popa, Ryan Wisnesky: HIL: a high-level scripting language for entity integration. **EDBT 2013**]

BEER (Blocking for Effective Entity Resolution)

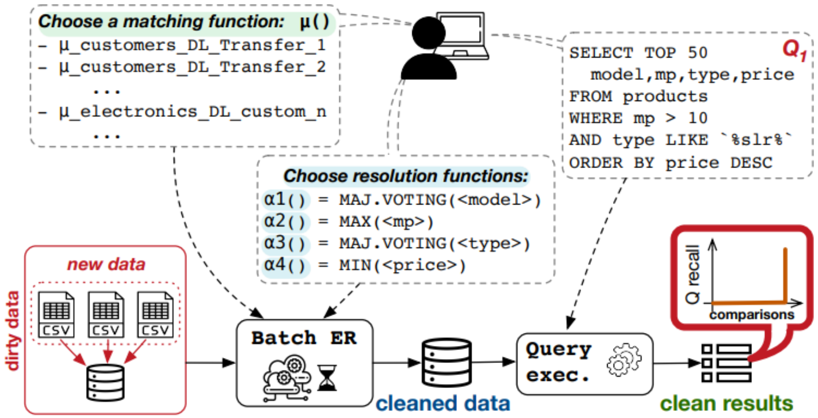
[Sainyam Galhotra, Donatella Firmani, Barna Saha, and Divesh Srivastava: BEER: Blocking for Effective Entity Resolution, **SIGMOD 2021**]

Feedback after **1% sample**

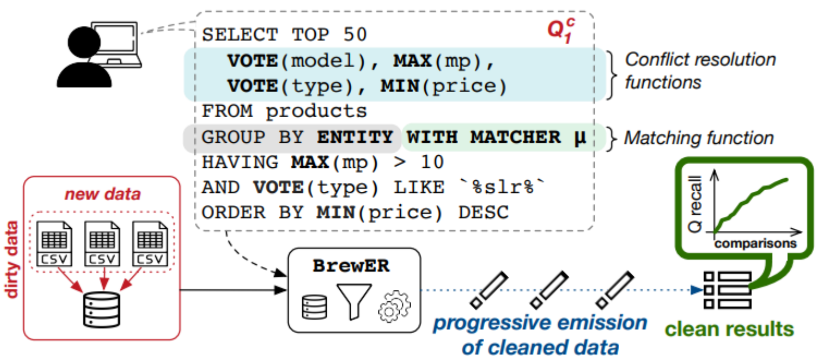




BrewER (Entity Resolution On-Demand)



(a) The traditional pipeline: the data scientist specifies how to clean the data with ER; once cleaned, she issues the query.



(b) The ER-on-demand pipeline: the data scientist specifies how to clean the data within the query.

[Giovanni Simonini, Luca Zecchini, Sonia Bergamaschi, Felix Naumann: Entity Resolution On-Demand. **PVLDB 2022**]

```
      SELECT [TOP k] ⟨α_j(A_j)⟩
        FROM 𝒟
      [WHERE φ]
    GROUP BY ENTITY WITH MATCHER μ
     [HAVING ⟨α_j(A_j) {LIKE|IN|<|≤|>|≥|=} const⟩]
   [ORDER BY α_j(A_j) [ASC|DESC]]
```

Figure 2: Query syntax in *BrewER*.

Example Applications

Record Linkage

- **Task: Distributed Entity Resolution on Apache Spark**
  - Uni Leipzig Benchmarks
- **Example 1: DBLP, ACM, Google Scholar Publications**
  - `(title, authors, venue, year)`
  - Basic preprocessing via title capitalization, etc
  - How about leveraging the linked PDF papers?

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

- **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)

In practice:
multi-modal data, and
feature engineering

- **SIGMOD Programming Contest 2022**
  - Design blocking scheme for Notebooks specifications dataset

https://dbgroup.ing.unimore.it/sigmod22contest/task.shtml?content=description

Data Management – Autograding

- **Plagiarism Detection via Entity Resolution**
  - https://issues.apache.org/jira/browse/SYSTEMDS-3191
  - **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]

Summary and Q&A

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

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

- **Next Lectures (Data Integration Architectures)**
  - **06 Data Cleaning and Data Fusion** [Nov 22]