The Five Generations of Entity Resolution on Web Data

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Structure Outline

- Introduction
- Generations: 1^{st}, 2^{nd}, 3^{rd}, 4^{th}, 5^{th}
- Hands-on Session
- Challenges and Final Remarks

Part A – Introduction

  - Motivation
  - Preliminaries

- Generations: 1st, 2nd, 3rd, 4th, 5th
- Hands-on Session
- Challenges and Final Remarks

Motivation

- Entities invaluable asset for numerous current applications and systems
- Encode a large part of our **knowledge**

Matching, Linkage, Reconciliation, etc.

- Many names, descriptions, or IDs (URIs) are used for the same **real-world "entity"**

London 런던
ܠܘܢܕܘܢ लंडन
लंदन લંડન
ለንደን ロンド
ン লন্ডন
ลอนดอน
இலண்டன்
ლონდონი

Disambiguation, Deduplication, etc.

- Plethora of different "entities" have the same name

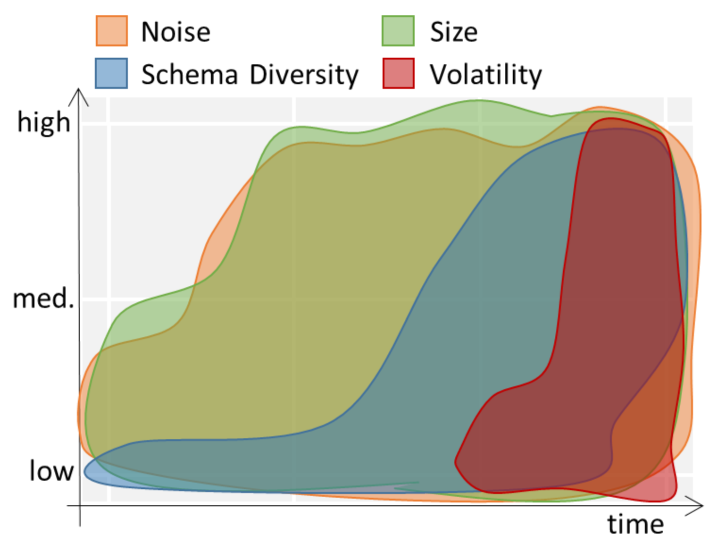
London Island, Chile

London, Jack
2612 Almes Dr
Montgomery, AL
(334) 272-7005

Motivation

Entity Resolution is required for data integration, link discovery, query answering, Web / object-oriented searching, etc.

- Goal remains the same for the last 50+ years
- BUT the challenges to be addressed are constantly evolving



cf. book: “The Four Generations of Entity Resolution”

Entity Resolution

- Identifies and aggregates the **different** entity profiles that describe the **same** objects [1, 2, 3, 4]
- Primary usefulness:
  - Improves data quality and integrity
  - Fosters re-use of existing data sources
- Example application domains:
  - Linked Data
  - Building Knowledge Graphs
  - Census data
  - Price comparison portals

Types of Entity Resolution

- The given entity collections can be of two types:
  clean + **dirty** [3,5]
- **Clean**:
  - Duplicate-free data
  - E.g., DBLP, ACM Digital Library, Wikipedia, Freebase
- **Dirty**:
  - Contain duplicate entity profiles
  - E.g., Google Scholar, CiteseerX

Types of Entity Resolution

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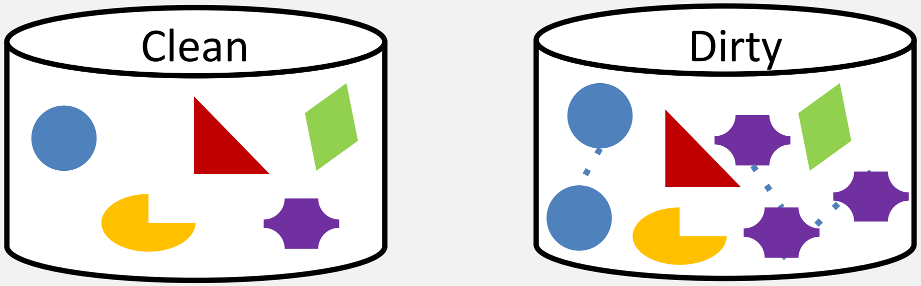
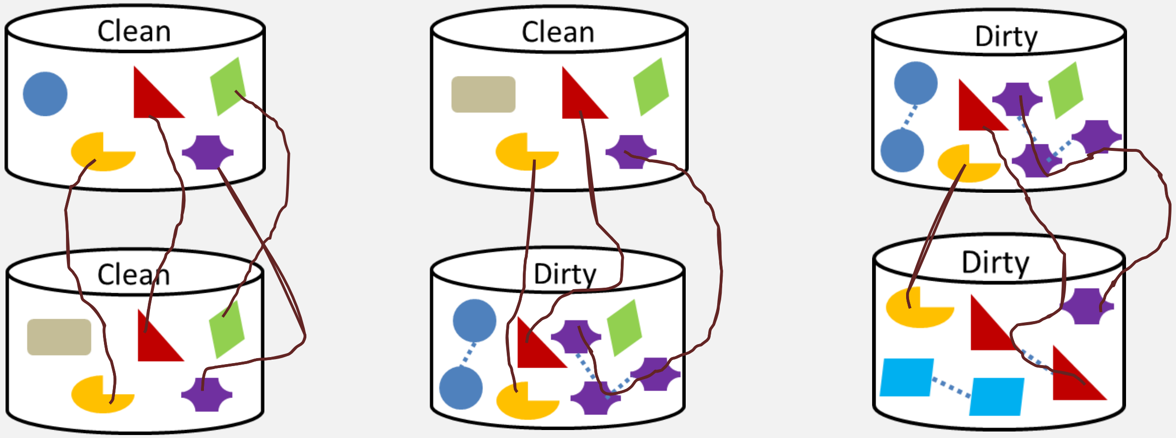


Types of Entity Resolution

- Based on the quality of input, we distinguish entity resolution into 3 sub-tasks:
  1. Clean-Clean ER (a.k.a. ***Record Linkage*** in databases)
  2. Dirty-Clean ER
  3. Dirty-Dirty ER

  Equivalent to **Dirty ER** (a.k.a. ***Deduplication*** in databases)



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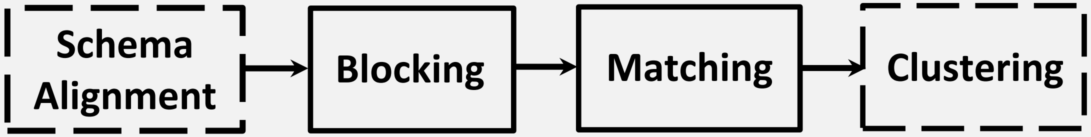
- Introduction

Part B – Generations

  - Generation 1: tackling Veracity
  - Generation 2: tackling Volume and Veracity
  - Generation 3: tackling Variety, Volume and Veracity
  - Generation 4: tackling Velocity, Variety, Volume and Veracity
  - Generation 5: Entity Resolution Revisited: Leveraging External Knowledge

- Hands-on Session
- Challenges and Final Remarks

Generation 1: Tackling Veracity



- Earliest approach
- Scope:
  - Structured data
- Goal:
  - Achieve **high accuracy** despite inconsistencies, noise, or errors in entity profiles
- Assumptions:
  - Known schema → custom, schema-based solutions

Step 1: Schema Alignment / Matching

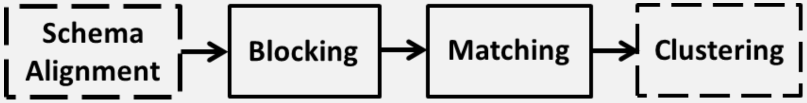
- Scope:
  - Record Linkage
- Goal:
  - Create **mappings between equivalent attributes** of the two schemata, e.g., *profession* ≡ *job*
- Types of Solutions:
  - Structure-based
  - Instance-based
  - Usage-based
  - Hybrid

Step 1: Schema Alignment / Matching

- Taxonomy of Main Schema Matching Methods (in chronological order)

Method	Category	Type of Evidence
Cupid [1]	Structure-based	Name similarity, Constraints, Contextual similarity
Similarity Flooding [2]	Structure-based	Name similarity, Contextual similarity
COMA [3]	Hybrid	Name similarity, Constraints, Contextual similarity
Distribution-based [4]	Instance-based	Value distribution

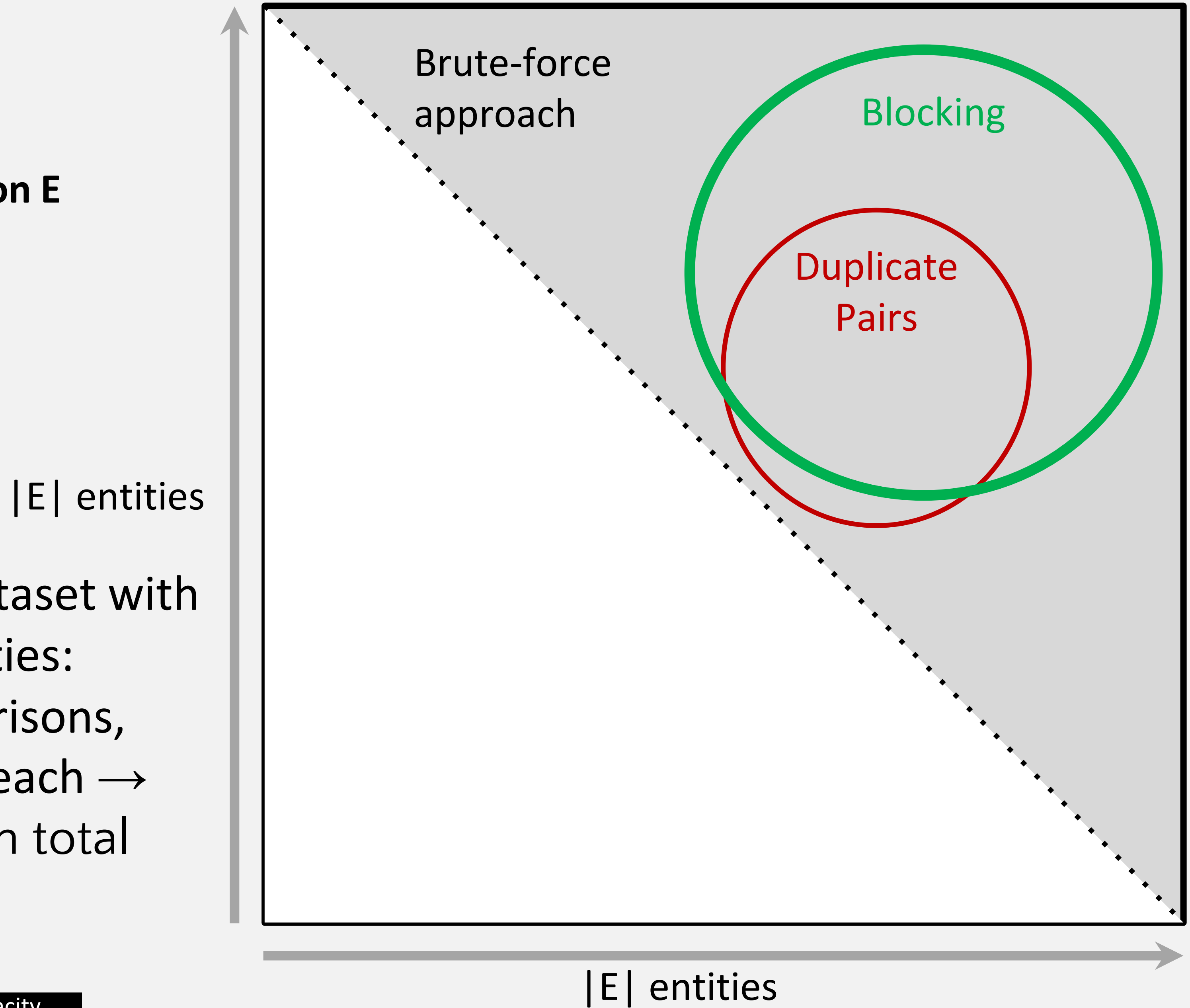
Step 2: Blocking



- <u>Scope</u>:
  - Both Deduplication and Record Linkage
- <u>Goal</u>:
  - ER is an inherently **quadratic** problem, $O(n^2)$: every entity has to be compared with all others
  - Blocking groups similar entities into **blocks**
    - Comparisons are executed **only inside** each block
    - Complexity is now quadratic to the size of the block (much smaller than dataset size!)

Computational cost

Input:
Entity Collection E



E.g.: For a dataset with 100,000 entities:
~10^{10} comparisons,
If 0.05 msec each → >100 hours in total

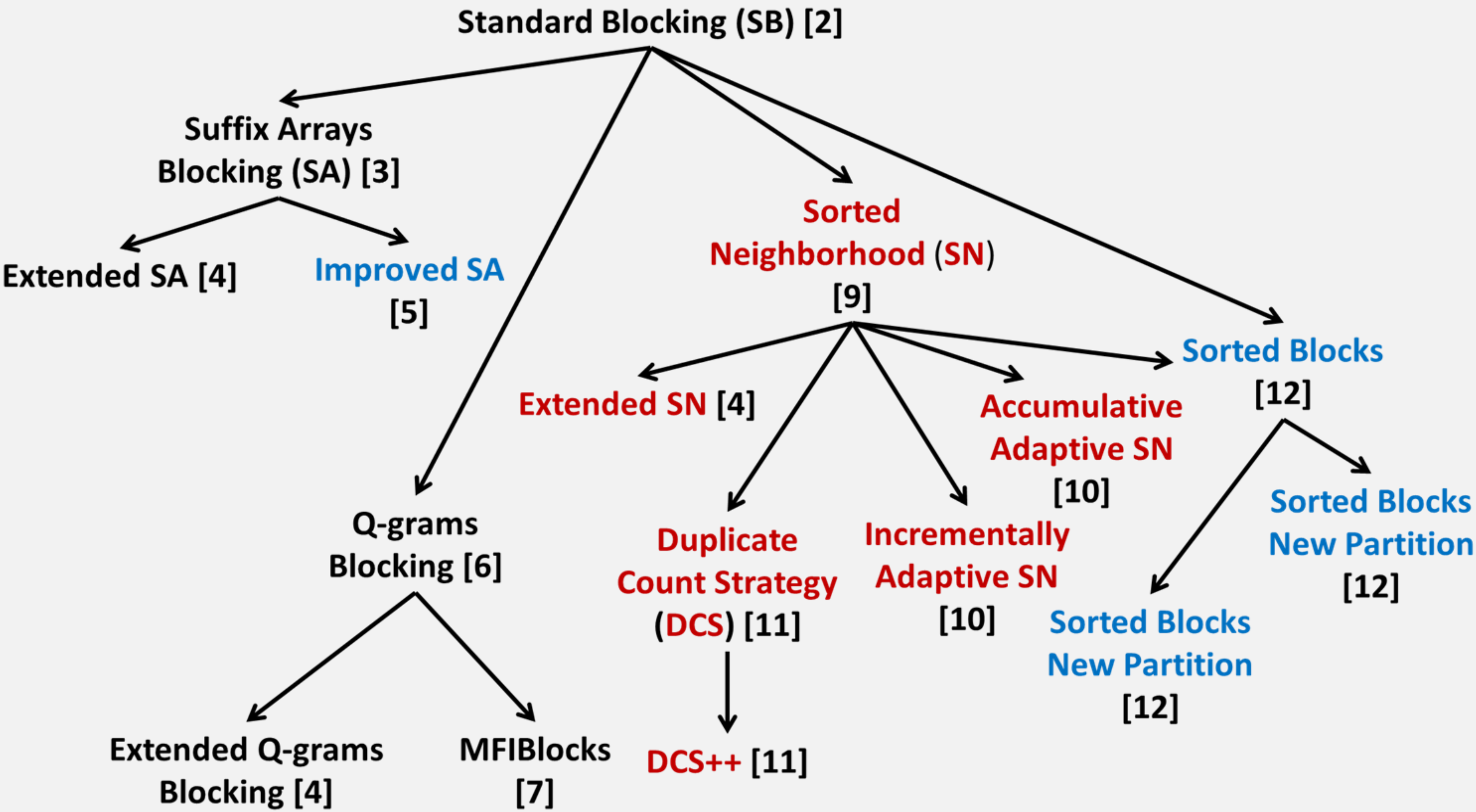
General Principles of Blocking

1. Represent each entity by *one or more* signatures called **blocking keys**
   - Focus on string values
2. Place into blocks all entities having the *same or similar* blocking key
3. Two matching profiles can be detected as long as they co-occur in at least one block
   - Trade-off between <u>recall</u> and <u>precision</u>!

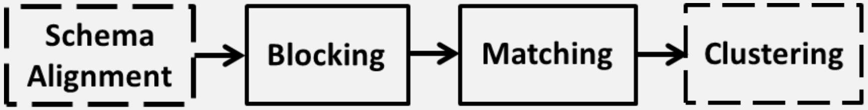
Taxonomy of Blocking Methods [1]

Method	Key Type	Redundancy awareness	Matching awareness	Key selection
Standard Blocking [2]	Hash-based	Red.-free	Static	Non-learning
Suffix Arrays [3] + [4,5]	Hash-based	Red.-positive	Static	Non-learning
Q-grams Blocking [6] + [4]	Hash-based	Red.-positive	Static	Non-learning
MFIBlocks [7]	Hash-based	Red.-positive	Static	Non-learning
Sorted Neighborhood [9] + [4,10]	Sort-based	Red.-neutral	Static	Non-learning
Duplicate Count Strategy [11]	Sort-based	Red.-neutral	Dynamic	Non-learning
Sorted Blocks [12]	Hybrid	Red.-neutral	Static	Non-learning
ApproxDNF [13]	Hash-based	Red.-positive	Static	Learning-based
Blocking Scheme Learner [14]	Hash-based	Red.-positive	Static	Learning-based
CBlock [15]	Hash-based	Red.-positive	Static	Learning-based
FisherDisjunctive [16]	Hash-based	Red.-positive	Static	Learning-based

Genealogy Tree of Non-learning Blocking Methods [1]

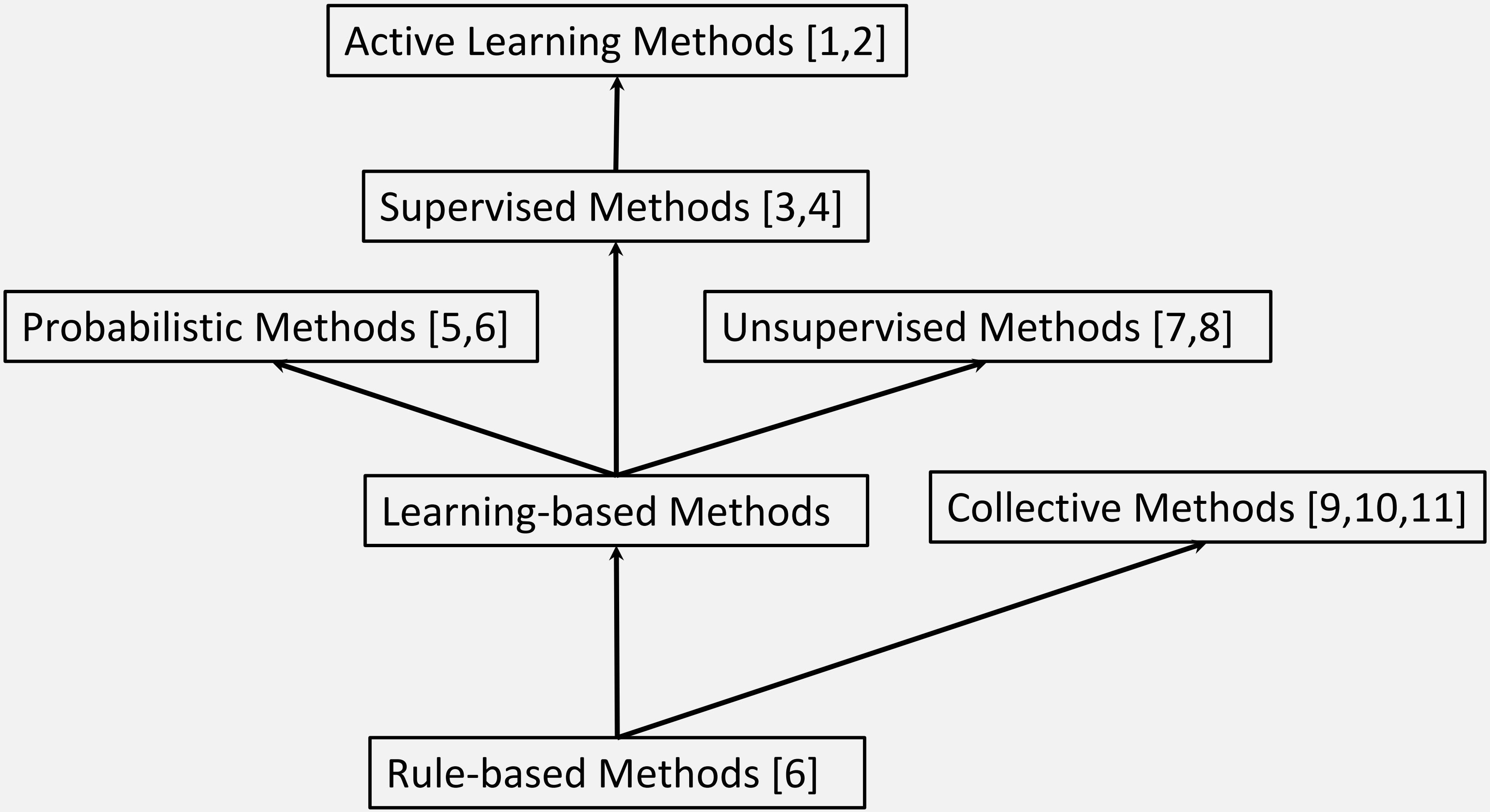


Step 3: Matching



- Estimates the **similarity** of candidate matches.
- Input
  - A set of blocks
    - Every distinct comparison in any block is a candidate match
- Output
  - Similarity Graph
    - Nodes → entities
    - Edges → candidate matches
    - Edge weights → matching likelihood (based on similarity score)

Evolution of Matching

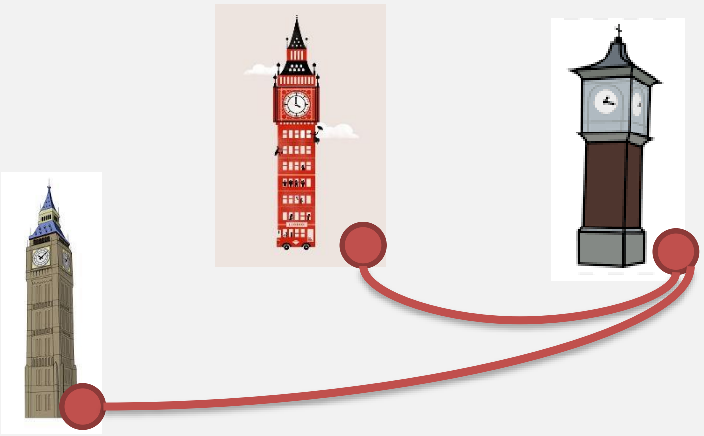


All are heavily based on string similarity measures [6].

Step 4: Clustering

Schema Alignment → Blocking → Matching → Clustering

- Partitions the matched pairs into equivalence clusters i.e., groups of entity profiles describing the same real-world object



- Input
  - Similarity Graph:
    - Nodes → entities
    - Edges → candidate matches
    - Edge weights → matching likelihood (based on similarity score)

- Output
  - Equivalence Clusters

Clustering Algorithms for **Record Linkage**

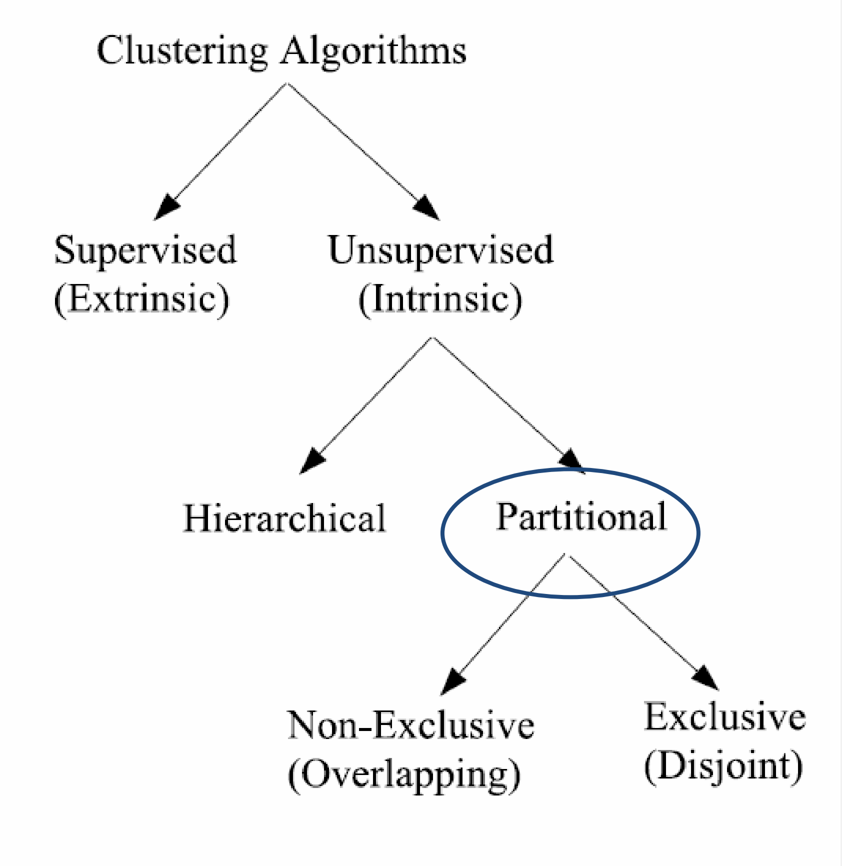
Relies on **1-1 constraint**

– 1 entity from source dataset matches to 1 entity from target dataset

1. Unique Mapping Clustering [1][2]
   – Sorts all edges in decreasing weight
   – Starting from the top, each edge corresponds to a pair of duplicates **if**:
     - None of the adjacent entities has already been matched
     - predefined threshold < edge weight
2. Row-Column Clustering [3]
   – efficient approximation of the Hungarian Algorithm
3. Best Assignment Clustering [4]
   – efficient, heuristic solution to the assignment problem in unbalanced bipartite graphs
4. Exact Clustering [7]
   – each entity is matched with its reciprocally most similar entity
5. Kiraly Clustering [7]
   – efficient solution to the stable marriage problem

Clustering Algorithms for **Deduplication**

- A wealth of literature on clustering algorithms
- Requirements:
  - Partitional and disjoint Algorithms
    - Sometimes overlapping may be desirable
  - <u>Goal</u>: Create sets of clusters that
    - maximize the intra-cluster weights
    - minimize the inter-cluster edge weights



Classification of clustering algorithms [6]

5gER
(courtesy of Oktie Hassanzadeh)

Dirty ER Clustering Algorithms Characteristics [3]

- Most important feature *"**Unconstrained algorithms**"*
  - Algorithms need to be able to *predict* the correct number of clusters

- Need to **scale** well
  - Time complexity < $O(n^2)$

- Need to be **robust** with respect to characteristics of the data
  - E.g., distribution of the duplicates

- Need to be capable of finding '**singleton**' clusters
  - Different from many clustering algorithms
    - E.g., algorithms proposed for image segmentation

5gER
(courtesy of Oktie Hassanzadeh)

Summary of Experimental Results [3]

	Scalability (Current Implementations)	Ability to find the correct number of clusters	Robustness Against		
			Choice of threshold	Amount of Errors	Distribution of errors
Partitioning	High	Low	Low	Low	High
CENTER	High	High	Low	Low	High
MERGE CENTER	High	High	Low	Low	High
Star	Medium	High	Low	Low	High
SR	Low	Medium	High	High	Low
BSR	Low	Low	High	High	Low
CR	Low	High	Medium	High	High
OCR	Low	High	Medium	High	Low
Correlation Clustering	Low	High	Low	Low	High
Markov Clustering	High	High	Medium	Medium	High
Cut Clustering	Low	Low	Low	Low	High
Articulation Point	High	Medium	Low	Low	High

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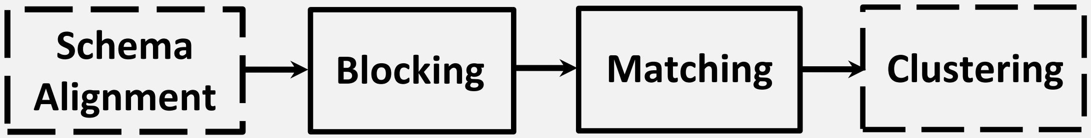
Generation 2: Tackling **Volume** and Veracity



- Same workflow as Generation 1
- <u>Scope</u>:
  - (tens of) millions of structured entity profiles
- <u>Goals</u>:
  - High accuracy despite noise
  - High time efficiency despite the size of data
- <u>Assumptions</u>:
  - Known schema → custom, schema-based solutions

Solution: Parallelization

Two types:

- Multi-core parallelization
  - Single system → shared memory
  - Distribute processing among available CPUs
- Massive parallelization
  - Cluster of independent systems
  - **Map-Reduce** paradigm [1]
    - Data partitioned across the nodes of a cluster
    - Fault-tolerant, optimized execution
    - Map Phase: transforms a data partition into (key, value) pairs
    - Reduce Phase: processes pairs with the same key

Parallelization Methods per Step

- Blocking
    - Dedoop [2]
    - MapReduce-based Sorted Neighborhood [3]
- Matching
    - Multi-core approaches [7][8]
    - MapReduce-based: Emphasis on **load balancing**
        - BlockSplit & PairRange [4][5]
        - Dis-Dedup [6]
        - Message-passing framework [9]
- Clustering
    - Fast Multi-source Entity Resolution (FAMER) framework [10][11]

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G3: Tackling **Variety**, Volume and Veracity

Schema Clustering → Block Building → Block Processing → Matching → Clustering

- Scope:
  - User-generated Web Data

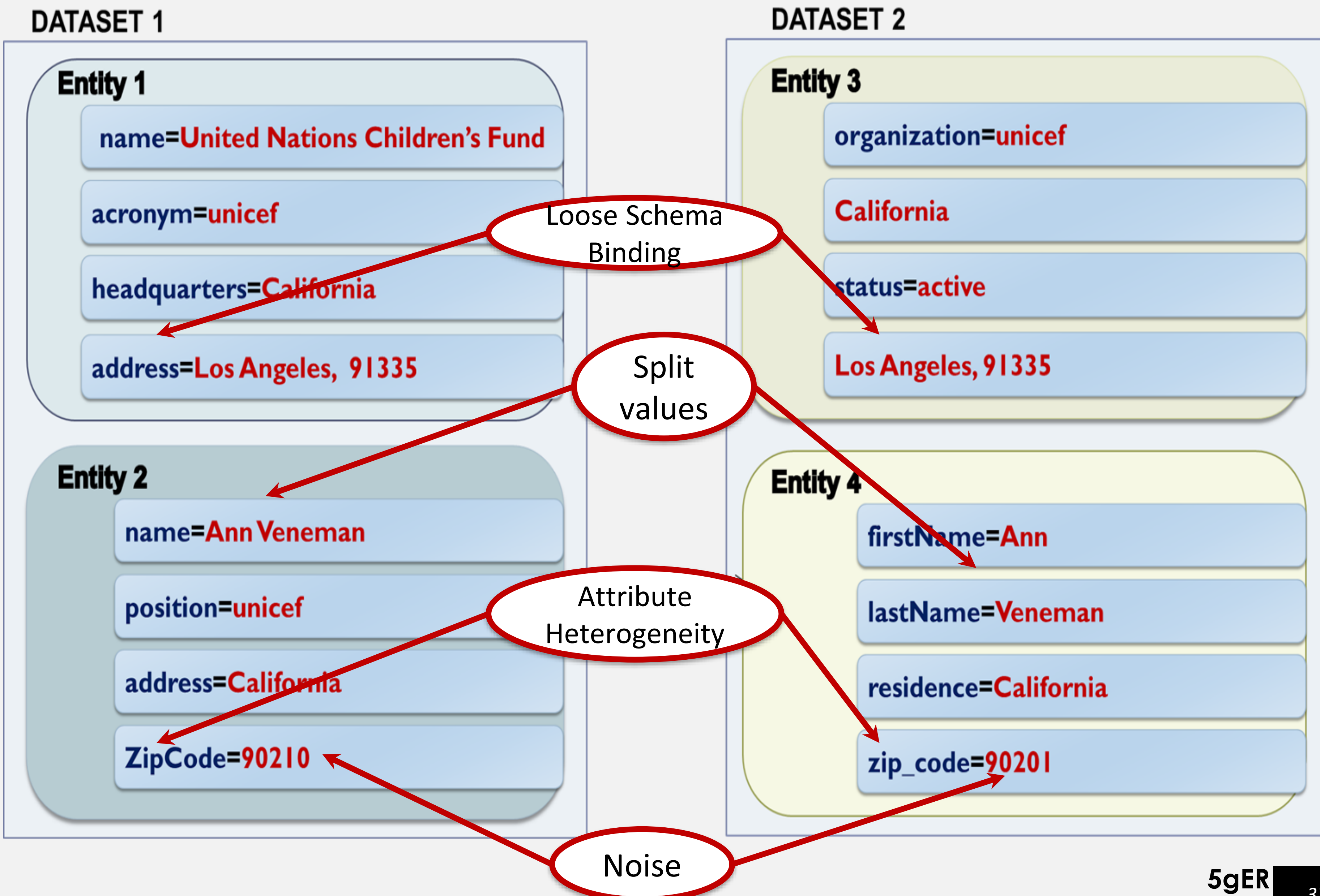
    Voluminous, **(semi-)structured datasets**.

    - BTC09: 1.15 billion triples, 182 million entities

    Users are free to add attribute values and/or attribute names unprecedented levels of schema heterogeneity.

    - Google Base: 100,000 schemata for 10,000 entity types
    - BTC09: 136,000 attribute names

Example of Web Data



Schema Clustering

- Schema Matching → **not applicable**
- Instead, partition attributes according to their syntactic similarity, regardless of their semantic relation
- Goal:
  - Facilitate next steps
- Scope:
  - Both Clean-Clean and Dirty ER
- Attribute Clustering [1][2][3]
  - Create a graph, where every node represents an attribute
  - For each attribute name/node n_i
    - Find the most similar node n_j
    - If **$sim(n_i,n_j) > 0$**, add an edge $<n_i,n_j>$
  - Extract connected components
  - Put all singleton nodes in a **"glue" cluster**

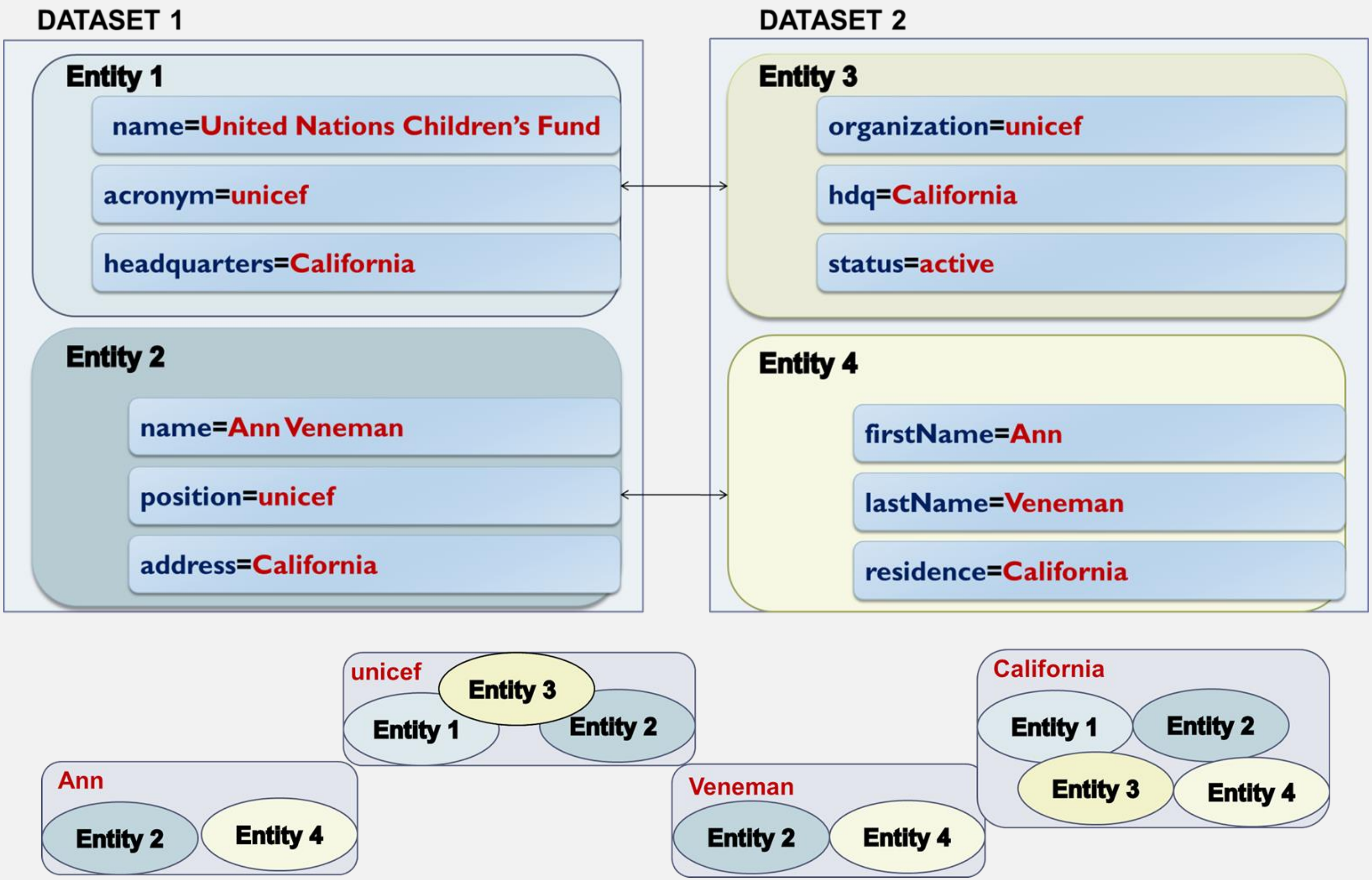
Block Building

- Unlike Blocking in G1/G2, it considers **all** attribute values and completely ignores all attribute names
  → **schema-agnostic functionality**

- Core approach: Token Blocking [1]
  1. Given an entity profile, extract all tokens that are contained in its attribute values.
  2. Create one block for every distinct token with frequency > 2 → each block contains all entities with the corresponding token.

     Pros:
     - Parameter-free
     - Efficient
     - Unsupervised

Example of Token Blocking



Genealogy of Block Building Techniques [8]

Token Blocking (TB) [1]

Attribute Clustering Blocking [2]

RDFKeyLearner [6]

Prefix-Infix(-Suffix) Blocking [3]

TYPiMatch [4]

Semantic Graph Blocking [5]

MapReduce-based parallelizations in [7]

Block Processing

- High **Recall** due to redundancy
- Low **Precision** due to:
  1. the blocks are overlapping → **redundant comparisons**
  2. high number of comparisons between irrelevant entities → **superfluous comparisons**

Solution:

restructure the original blocks so as to increase precision at no significant cost in recall

Block Processing Techniques

Generic approach

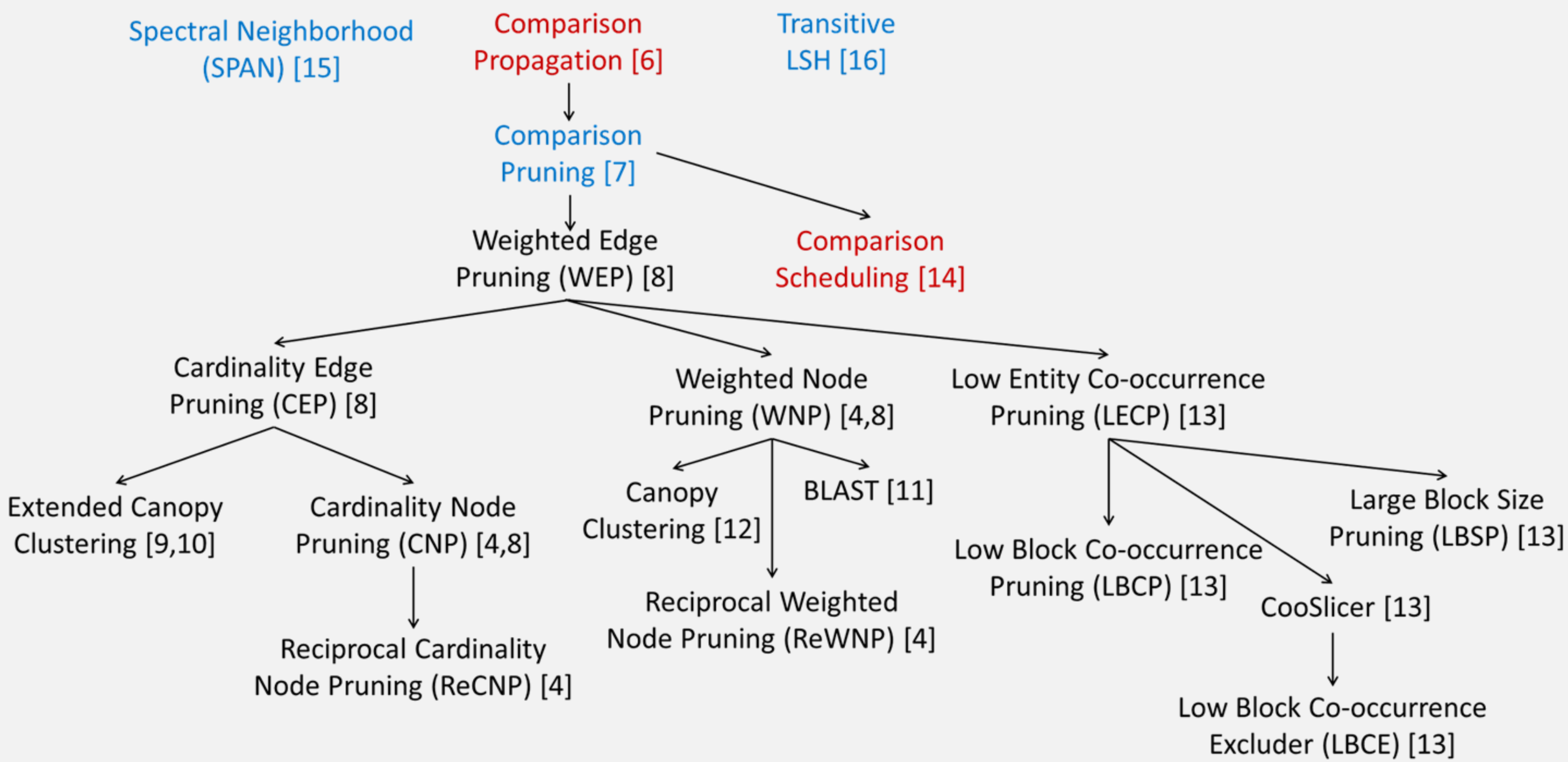
– Assign a matching likelihood score to each item

– Discard items with low costs

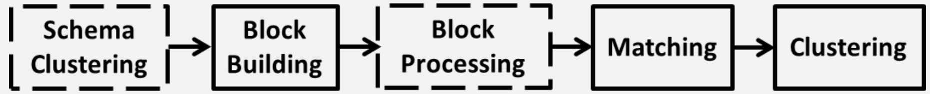
Block-centric methods

- Block Purging [1,2,3]
- Block Filtering [4]
- Block Clustering [5]

Comparison Cleaning Methods [17]

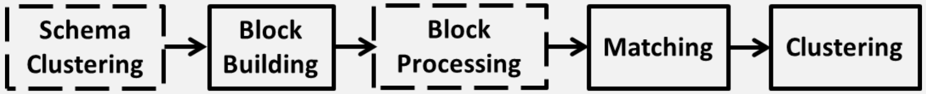


Entity Matching



- Collective approaches to **tackle Variety**
- Most methods crafted for Clean-Clean ER
- General outline of
  SiGMa [1], PARIS [2], LINDA [3], RiMOM-IM [4,5]
  - Bootstrap with a few reliable seed matches.
  - Using value and neighbor similarity, propagate initial matches to neighbors.
  - Order candidate matches in descending overall similarity
  - Iteratively mark the top pair as a match if it satisfies a constraint
  - Recompute the similarity of the neighbors
  - Update candidate matches order
- MinoanER [6] performs a specific number of steps, rather than iterating until convergence

Entity Clustering



- Methods of G1 & G2 are **still applicable**
  - Only difference: similarity scores extracted in a schema-agnostic fashion, not from specific attributes

- SplitMerge [1]
  - inherently capable of handling heterogeneous semantic types

[1] M. Nentwig, A. Groß, and E. Rahm. Holistic entity clustering for linked data. In ICDM Workshops, pages 194–201, 2016.

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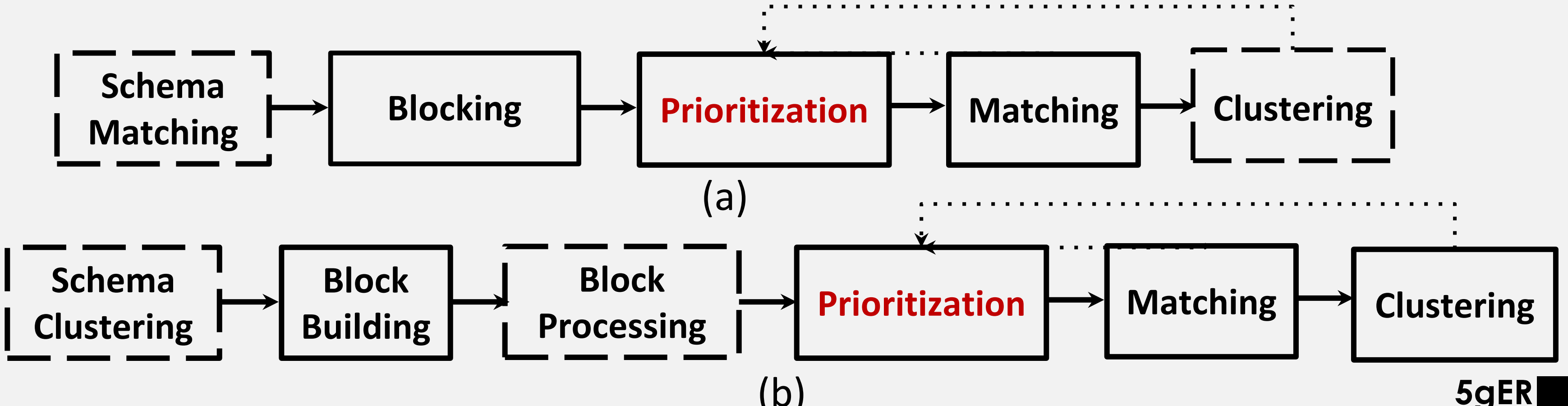
G4: Tackling **Velocity**, Variety, Volume and Veracity

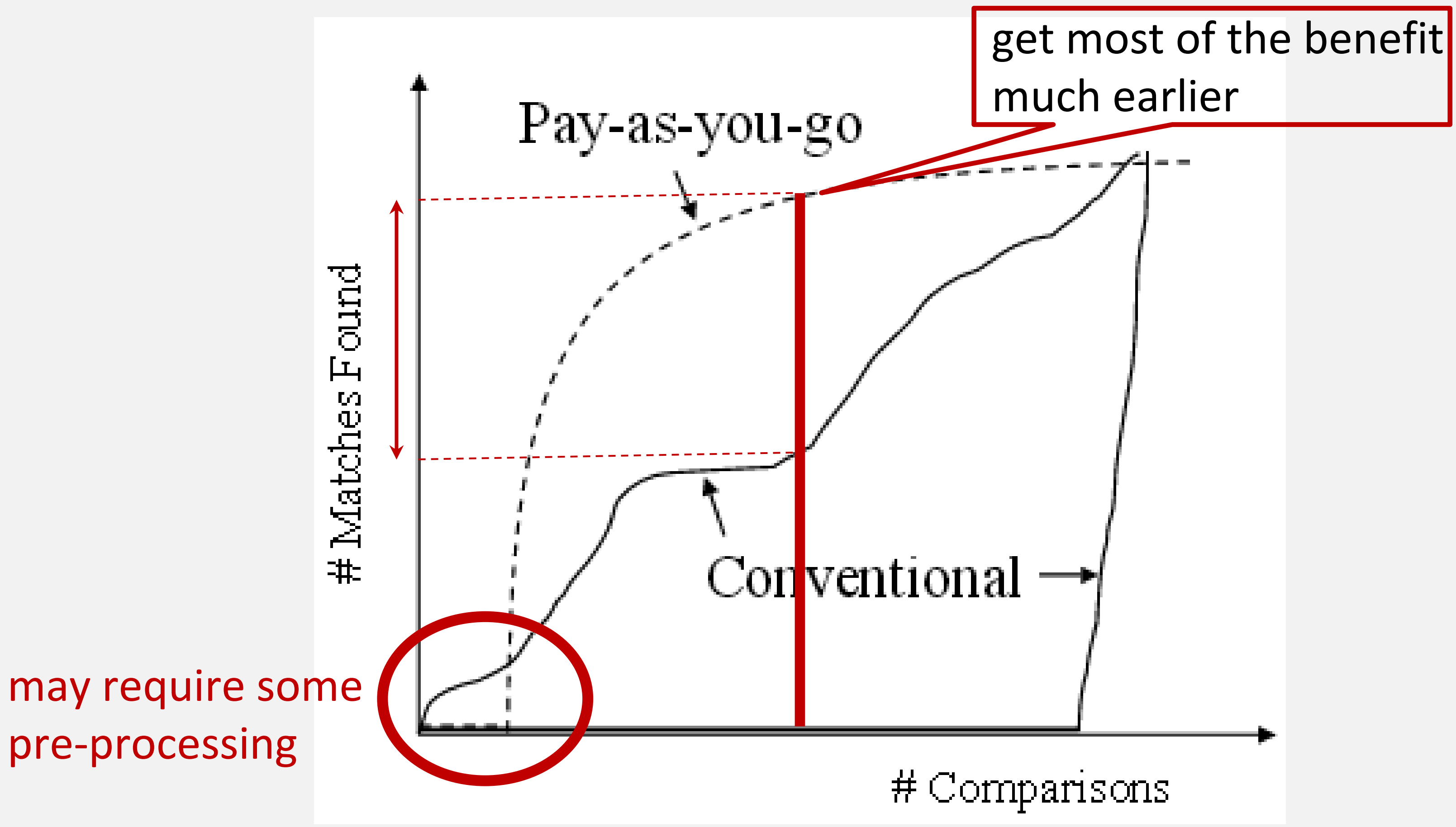
- Scope:
  - Applications with increasing data volume and time constraints
    - Loose ones (e.g., minutes, hours) → **Progressive ER**
    - Strict ones (i.e., seconds) → **Real-time (On-line) ER**

- End-to-end workflows for Progressive ER



Progressive Entity Resolution

Unprecedented, increasing volume of data → applications requiring partial solutions to produce useful results

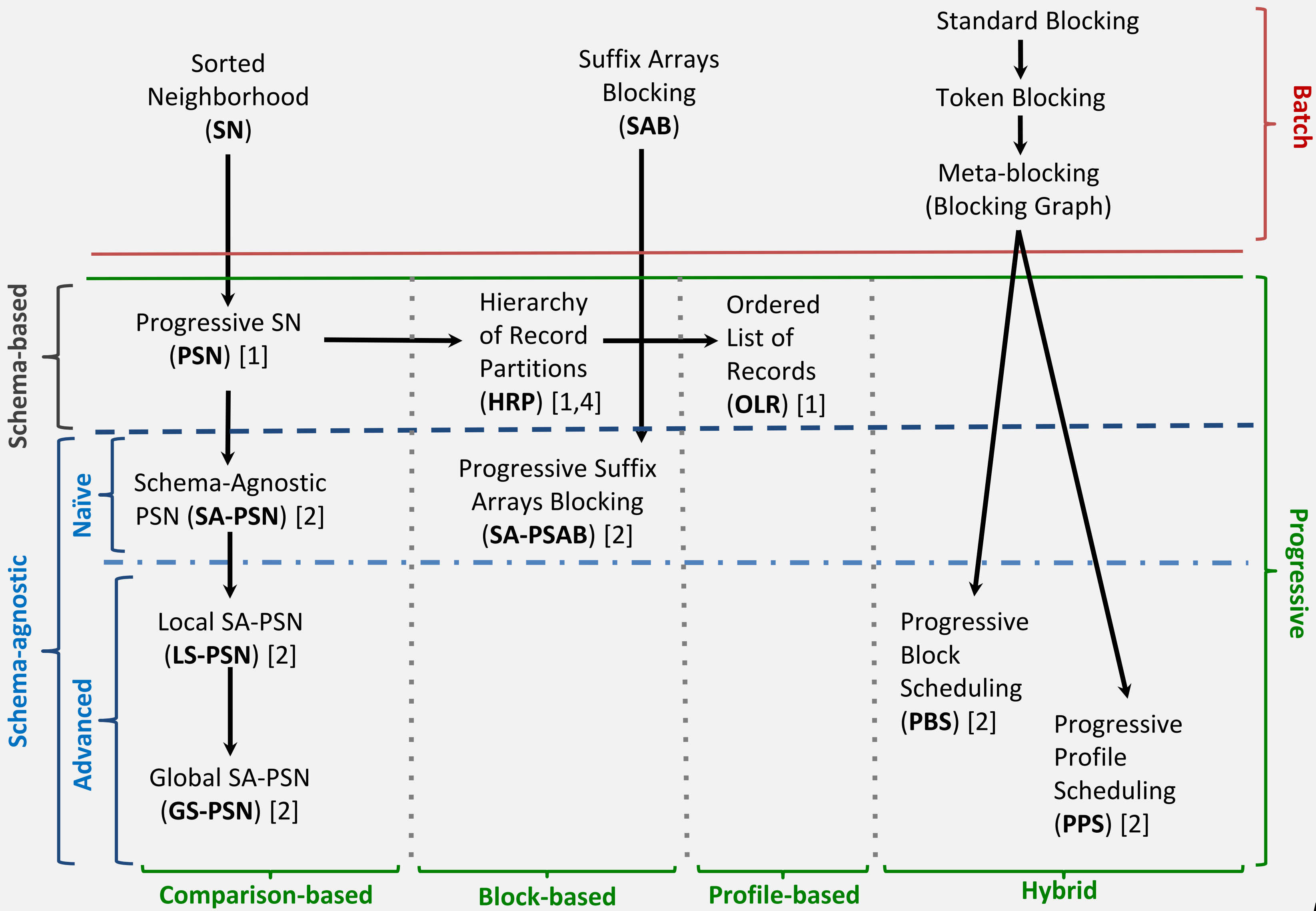


Outline Progressive ER

- Requires:
  - Improved Early Quality
  - Same Eventual Quality

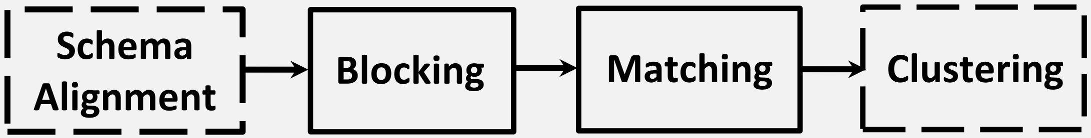
- **Prioritization**
  - **Defines optimal processing order for a set of entities**
  - Static Methods [1,2]:
    - Guide which records to compare first, **independently** of Entity Matching results
  - Dynamic Methods [3]:
    - If $c_{i,j}$ is a duplicate, then check $c_{i+1,j}$ and $c_{i,j+1}$ as well.
    - Assumption:
      - Oracle for Entity Matching

Taxonomy of Static Prioritization Methods



Real-time Entity Resolution

Same workflow as Generations 1 and 2:



Same scope (so far):

- Structured data

Different input:

- **stream** of query entity profiles

Different goal:

- resolve each query over a large dataset in the shorted possible time (& with the minimum memory footprint)

Techniques per workflow step

Incremental Blocking

- **DySimII** [1] - extends Standard Blocking
- **F-DySNI** [2,3] - extends Sorted Neighborhood
- **(S)BlockSketch** [4] - bounded matching time, constant memory footprint

Incremental Matching

- **QDA** [5] - SQL-like selection queries over a single dataset
- **QuERy** [6] - complex join queries over multiple, overlapping, dirty DSs
- **EAQP** [7] - queries under data
- Evolving matching rules [8]

Incremental Clustering

- Incremental Correlation Clustering [9]

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G5: Leveraging External Knowledge

- Applies to any of the previous generations
  - **No change** in the end-to-end workflows

- Performance improves by incorporating one of the three types of contextual information:
  1. **Human** common sense through crowd-sourcing
  - Open web data through:
    2. **Pre-trained** Language Models (PLMs)
    3. **Large** Language Models (LLMs)

- PLMs apply to **both** blocking and matching, unlike crowd-sourcing and LLMs, which apply **exclusively** to matching

Crowd-sourcing

- Process/work divided among a large number of people, either paid or unpaid
- Idea: tasks are simple for human intelligence, but complex for computers
- Approach:
  - Break a problem into microtasks, called Human Intelligence Tasks (**HITS**)
  - Choose an online community
    - Amazon Mechanical Turk
    - Figure Eight (former CrowdFlower)
  - Assign to every individual, called **worker**, a series of HITs
  - Each worker is paid per executed HIT → **monetary cost**
  - Popular for solving many tasks, e.g., CrowdDB

Crowd-sourcing for Entity Resolution

- Delegate the **entity matching decisions** to the workers
  i.e., transform pairwise comparisons into HITs
- Challenges:
  1. **Generating HITs**: CrowdER [8], ZenCrowd [9]
  2. **Formulating HITs**:
     Pair- & cluster-based [8], Hybrid [10], Crowdlink [14]
  3. **Balancing accuracy and monetary cost**:
     Random ordering [3], probabilistic question selection [2], Edge- and node-centric ordering [1], maximize progressive recall [4], adaptive crowd-based deduplication [12], attribute labeling and clustering [15], partial-order based framework [17], bDENSE [18], probabilistic ER with crowd errors [11, 16], and pair-wise error correction layer [13]
  4. **Restricting the labor cost**:
     Corleone [5], Falcon [6], and CloudMatcher [7]

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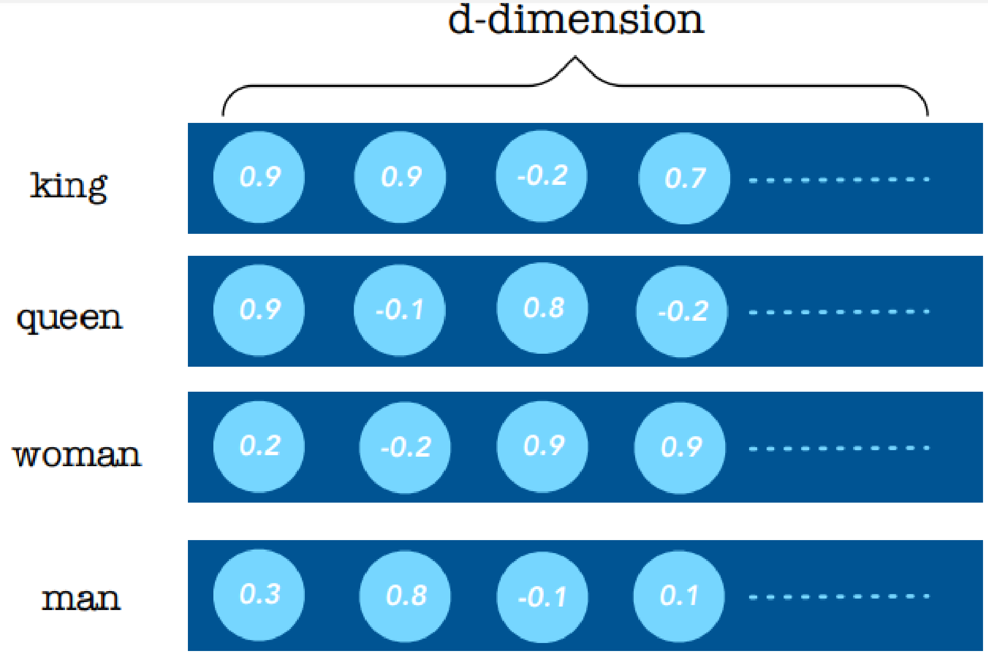
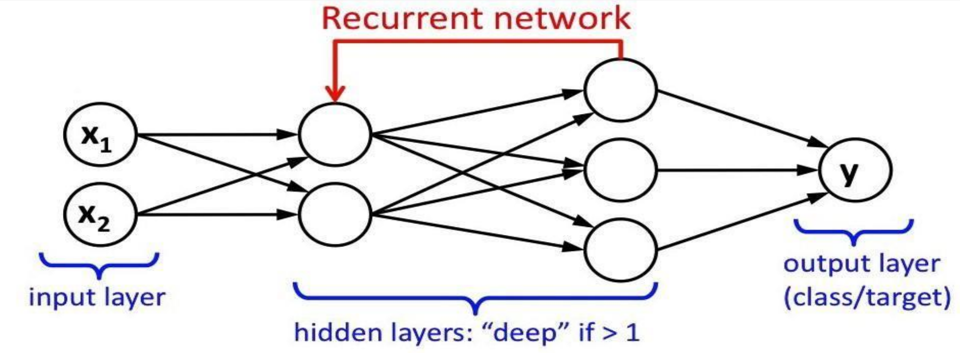
Embeddings

- Based on the distributional hypothesis
  i.e., words appearing in the same context **share meaning**
- Each word is represented as a distribution of weights (positive or negative) across specific dimensions
- <u>Goal</u>: capture semantic string similarities
- Popular embeddings pre-trained over huge corpora:
  - Word2Vec [5]
  - Glove [6]
  - fastText [7]



Deep Learning

- Specific class of Machine Learning / Data Mining
- Teaches computers to do what comes naturally to humans: learn by example
- Goal: learn a complicated function from the data
- Ideal for complex tasks involving multi-dimensional data like the embedding vectors of **PLMs**
- Has transformed many fields, e.g., computer vision, speech recognition, natural language processing, etc.
  - Similar performance, or even better, to human expert performance
- Details in [1]



Initial Approaches of Deep Learning

- SEMPROP [2] for schema matching
  - Semantic + syntactic matcher
- AutoBlock [3] for blocking
  - Combines similarity-preserving representation learning with nearest neighbor search
- DeepMatcher [8], Multi-Perspective Matching [9], and DeepER [4] for matching
  - Attribute embedding, summarization, and comparison
  - Deep Learning solutions
- Following approaches
  - Improve weaknesses

Architecture module		Options	
Attribute embedding		*Granularity:* (1) Word-based (2) Character-based	*Training:* (3) Pre-trained (4) Learned
Attribute similarity representation	(1) Attribute summarization	(1) Heuristic-based (2) RNN-based (3) Attention-based (4) Hybrid	
	(2) Attribute comparison	(1) Fixed distance (cosine, Euclidean) (2) Learnable distance (concatenation, element-wise absolute difference, element-wise multiplication)	
Classifier		NN (multi-layer perceptron)	

HierGAT [10]

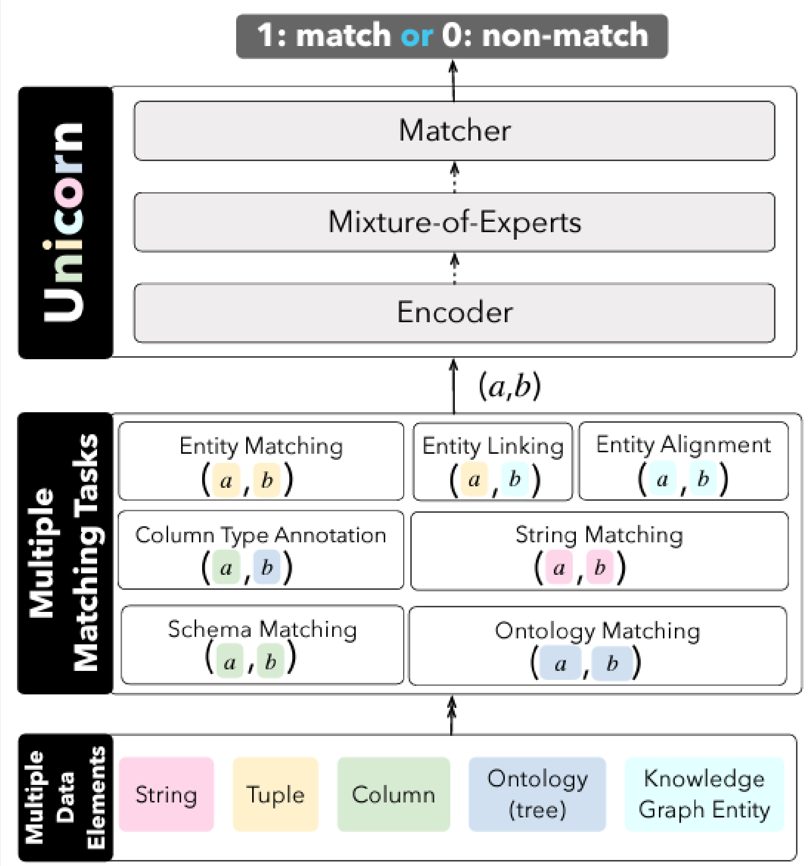
- Weaknesses of existing initial approaches
  - Assume all words / attributes are equally important
  - Don’t consider that words from different domains may have different meanings

- Create and process resolution using a Graph
- Encodes entities, attributes, and words
- Captures related relationships
- Assigns different weights given category

Unicorn [11]

- Weaknesses of existing initial approaches:
  - Task-specific solutions that disable the opportunities for generalization or sharing learnt knowledge

- Proposed a unified model for “data matching” task in data integration
  - Encoder: converts pair (a,b) into a learned representation
  - Mixture-of-Experts: enhances the learned representation into a better representation
  - Matcher: binary classifier



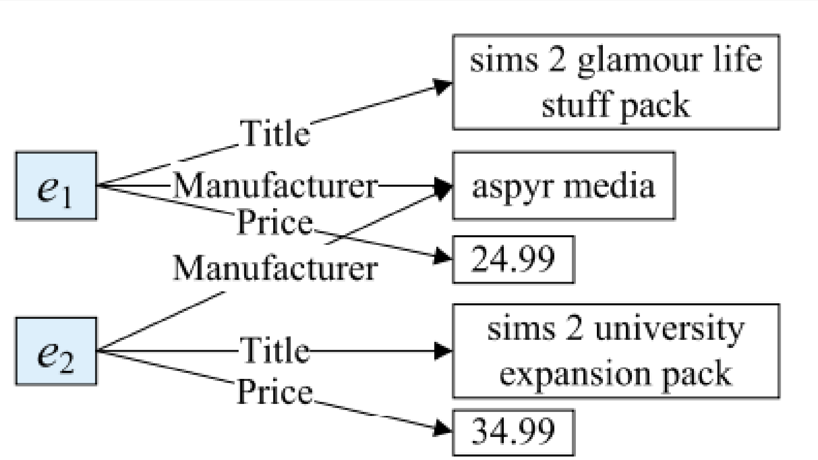
Sudowoodo [12]

- Weaknesses of existing initial approaches:
  - Require creating large-scale, high quality labeled datasets
  - Require separate modeling, annotation, and experimentation for each (sub) task of the process
- Contrastive learning: self-supervision approach that learns data representations where similar data items are close while different ones are far apart
  - Done by pre-training a representation model
- This fine-tuned model is used to generate the embeddings.
- The learned representations either directly used or facilitate fine-tuning to support different tasks.

CollaborEM [13]

- Weaknesses of existing initial approaches
  - Require a large number of labeled pairs
  - Insufficient feature discovery

- Generate labeled tuple pairs construct a graph that
  - Is the smallest, i.e., with fewer nodes and edges than graphs of other approaches
  - Preserves the semantic relationships between each tuple and its corresponding attribute values and between different tuples via shared value-level nodes



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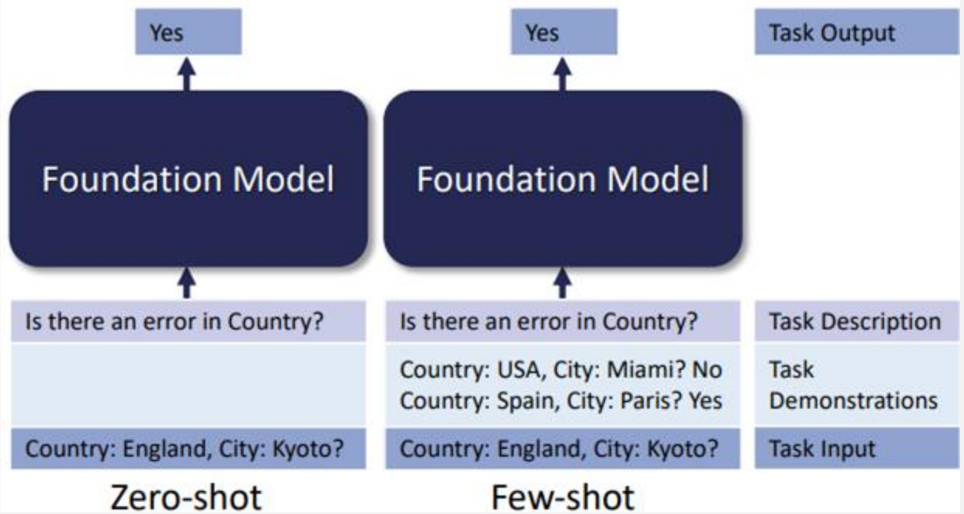
Large Language Models (LLMs)

- Core idea: ask a chatbot **whether a given pair** of entity descriptions **are matching or not**
  - each question is called "prompt"
- Challenge:
  - Unlike PLMs, the embedding representation is **transparent**
  - They constitute interactive approaches that are **sensitive** to the form of the **prompt**
- Solutions:
  - Prompt engineering!

Basic prompt engineering [1]

Three parameters that can be configured independently:

1. Problem definition:
   - "Are Product A and Product B the same?“ OR
   - "Are Product A and Product B equivalent?"
2. In-context learning:
   - zero shot OR
   - few shot
     - Random Selection OR
     - Manual Selection by experts
3. Entity serialization:
   - with all attributes OR
   - with a subset of attributes



Conclusions for **GPT3-175B**:

- Few shot outperforms zero shot to a significant extent
- Attribute selection is better than using all attributes
- Problem definition can have a large impact
- Comparable performance with DL-based matching algorithms

Fine-grained prompt engineering [2]

Three parameters that can be configured independently:

1. Problem definition
   - General (they refer to entities)
   - Domain specific (they refer to entity types, e.g., products)
2. Language
   - Simple (e.g., do two entities match?)
   - Complex (e.g., do two entities refer to the same real-world product?)
3. Output
   - Free (no output specifications)
   - Forced (e.g., reply "Yes" or "No")
4. Entity Serialization
   - Single attribute
   - Multiple attributes
5. In-context learning
   - Zero shot
   - Few shot
     - examples selection
       - at random, by expert or by context similarity
     - number of examples (e.g., 6, 10 or 20)
6. Instructions with matching rules
7. Fine-tuning

Task Desc.	Do the following two product descriptions match?
Demonstr-ations	Product 1: 'Title: DYMO D1 19 mm x 7 m' Product 2: 'Title: Dymo D1 (19mm x 7m – BoW)'
Answer	Yes.
Task Desc.	Do the following two product descriptions match?
Demonstr-ations	Product 1: 'Title: DYMO D1 Tape 24mm' Product 2: 'Title: Dymo D1 19mm x 7m'
Answer	No.
Task Desc.	Do the following two product descriptions match?
Task Input	Product 1: 'Title: DYMO D1 – Roll (1.9cm x 7m)' Product 2: 'Title: DYMO D1 Tape 12mm x 7m'

Fine-grained prompt engineering – Part II

Conclusions using 6 LLMs:

- 3 hosted:
  1. gpt3.5-turbo-0301
  2. gpt3.5-turbo-0613
  3. gpt4-0613
- 3 open-source:
  1. SOLAR 70B
  2. Beluga2
  3. Mixtral-8x7B

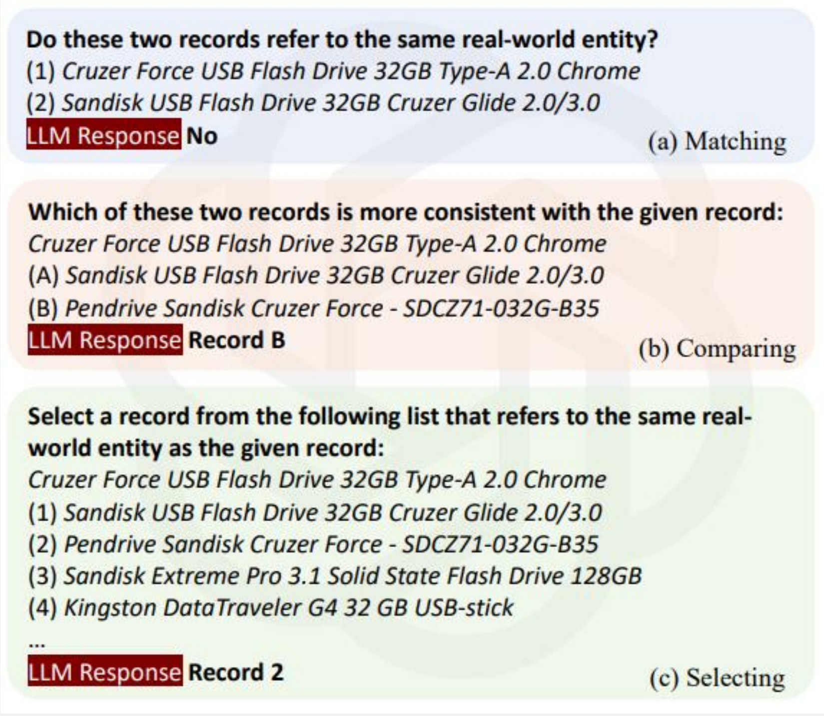
<u>Main takeaways:</u>

1. No prompt consistently outperforms all others
2. Open-source LLMs have similar effectiveness with hosted ones
3. LLMs comparable with DL-based matchers even in zero-shot settings
4. Few shot and instruction-based prompts outperform zero shot
5. Fine-tuning significantly improves effectiveness

Prompt strategies [3]

Three different approaches:

1. Match strategy:
   Pair-wise questions (as in previous works)
2. Comparison strategy:
   Given two entities, find the most similar to a specific entity.
3. Selection strategy:
   Given k candidates for a specific entity, identify the matching one or none of them.



Batch Prompting [4]

- Goal: **reduce the cost of hosted LLMs**, which charge in proportion to the number of input tokens, through batching, i.e., multiple pairwise questions with the same demonstrations.
- **BatchER** options:
  - Question Batching
    based on PLMs or structure-aware similarities like Jaccard similarity or edit distance
    - Random
    - Similarity-based (using clustering algorithms like DBScan and K-Means)
    - Diversity-based (using one pair from each similarity-based cluster)
  - Demonstration selection
    - Fixed
    - Top-k batch, i.e., the k most relevant demonstrations per batch
    - Top-k question, i.e., the most relevant demonstration per pair in the batch
    - Covering-based, i.e., for each pair in the batch, there is a demonstration with distance lower than a threshold
- Conclusions:
  - Batch prompting outperforms standard prompting both to effectiveness and cost
  - Best performance corresponds to Diversity-based Question Batching with Covering-based Demonstration Selection

LLMs References

1. Avanika Narayan, Ines Chami, Laurel J. Orr, Christopher Ré. Can Foundation Models Wrangle Your Data? Proc. VLDB Endow. 16(4): 738-746 (2022)
2. Ralph Peeters, Christian Bizer. Entity Matching using Large Language Models. CoRR abs/2310.11244 (2023)
3. T Wang, H Lin, X Chen, X Han, H Wang, Z Zeng, L Sun. Match, Compare, or Select? An Investigation of Large Language Models for Entity Matching. arXiv preprint arXiv:2405.16884, 2024.
4. Meihao Fan, Xiaoyue Han, Ju Fan, Chengliang Chai, Nan Tang, Guoliang Li, Xiaoyong Du. Cost-Effective In-Context Learning for Entity Resolution: A Design Space Exploration. CoRR abs/2312.03987 (2023)

- Introduction
- Generations: 1^{st}, 2^{nd}, 3^{rd}, 4^{th}, 5^{th}

Part C: Hands-on Session

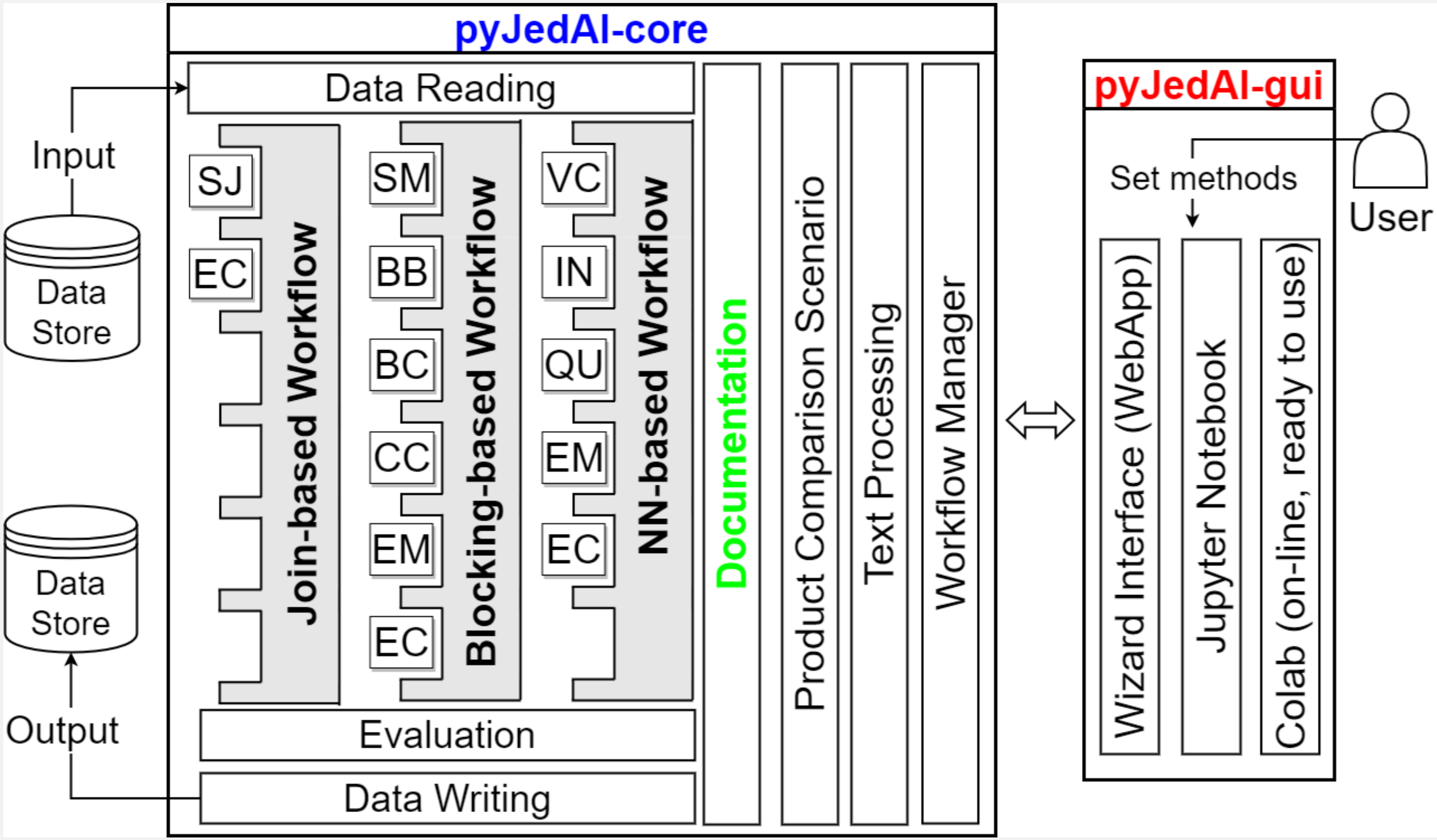
- Challenges and Final Remarks

Our tool for ER – pyJedAI!

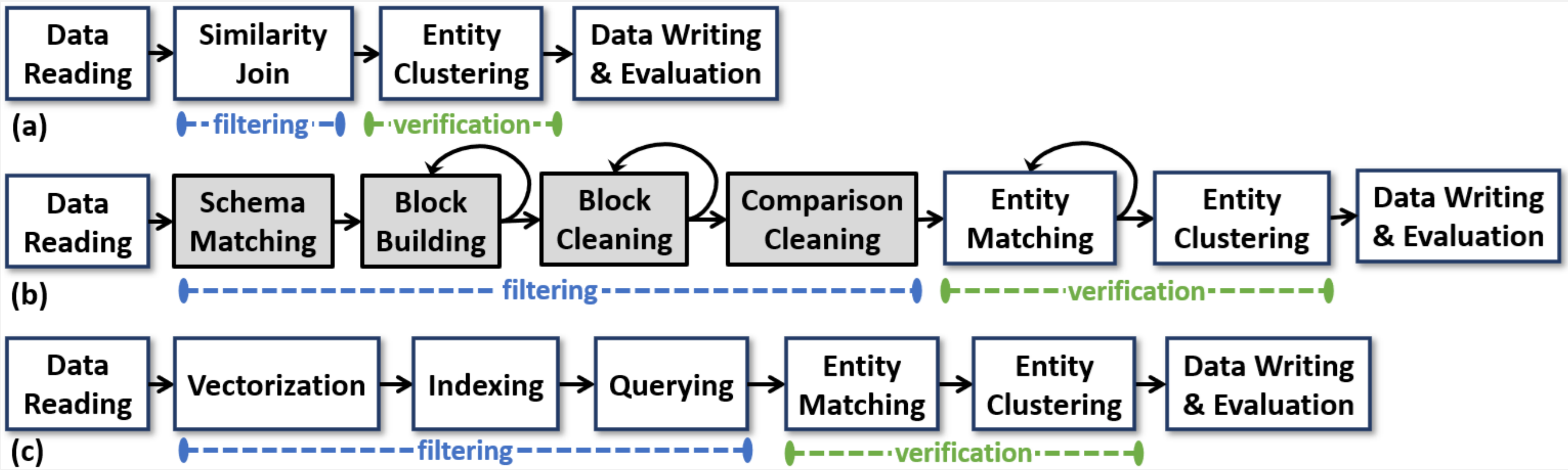
- A library of end-to-end ER workflows leveraging the Filtering-Verificaton framework
- ***pyJedAI*** *is an open-source Python framework, supporting both experts and novice users, that is leverages the latest breakthroughs in Deep Learning and NLP techniques, which are publicly available through the data science ecosystem*
- Available at: https://github.com/AI-team-UoA/pyJedAI,
- Extends the JedAI tool that is implemented in Java

  (available at: https://github.com/scify/JedAIToolkit)

pyJedAI Architecture

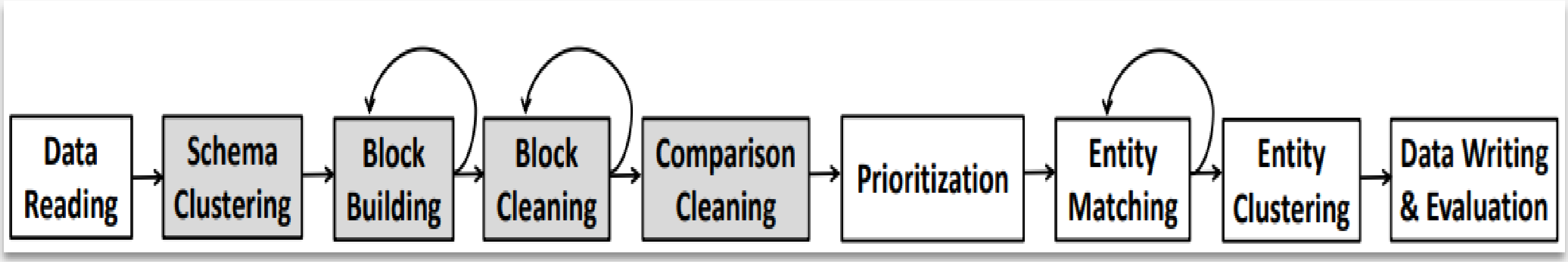


3 main Workflows



(a) Joins-based workflow
(b) Blocking-based workflow
(c) NN-based with embeddings workflow

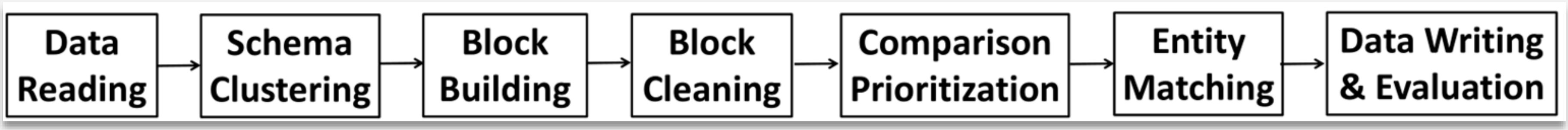
Blocking-based workflow



Link to tutorial:

https://pyjedai.readthedocs.io/en/latest/tutorials/CleanCleanER.html

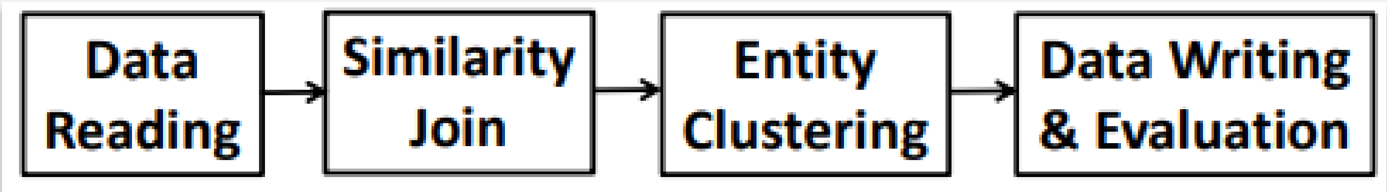
NN-based with embeddings workflow



Link to tutorial:

https://pyjedai.readthedocs.io/en/latest/tutorials/pyTorchWorkflow.html

Joins-based workflow



Link to tutorial:

https://pyjedai.readthedocs.io/en/latest/tutorials/SimilarityJoins.html

Install pyJedAI!

Scan QR and start entity-linking with **pyJedAI**!

- Introduction
- Generations: 1st, 2nd, 3rd, 4th, 5th
- Hands-on Session

Part D: Challenges & Final Remarks

Conclusions

Most promising works focus on:

1. Deep Learning
   - Pros:
     - High accuracy
   - Cons:
     - **High** training time
     - Too **many** training instances

2. Crowd-sourcing
   - Pros:
     - High accuracy
   - Cons:
     - High monetary **cost**
     - **Not scalable** to very large datasets

Challenges

Many challenges ahead

- Address shortcomings of Deep Learning
  - e.g., transfer learning for reducing labelling cost
- Cover gaps
  - e.g., incremental ER for semi-structured data
- New domains
  - e.g., adapt aforementioned techniques to **privacy-preserving** Entity Resolution

ER Systems

- Literature focuses on **stand-alone** methods
- More emphasis on **end-to-end** systems
  - Examples: **Magellan** [1], **JedAI** [2]
  - Partially cover the 4 generations
  - More efforts meeting the following requirements [1,3]:
    - **open-source**, **extensible** systems
    - process data of **any structuredness**
    - **no coding!** for users
    - guidelines for creating effective solutions
    - covers the entire end-to-end pipeline exploit
    - a wide range of techniques

Automatic Configuration

Facts:

- Several parameters in every method
  - Applies to all generations and workflow steps
- Performance sensitive to internal configuration
- Manual fine-tuning required

Open Research Directions:

- Plug-and-play methods
- Data-driven configuration

- Introduction
- Generations: 1st, 2nd, 3rd, 4th, 5th
- Hands-on Session
- Challenges &
  Final Remarks

time for additional questions

Thank you!

information & material
related to the tutorial
is available online

https://edu.nl/97b8v

References

1. P. Konda, S. Das, P. S. G. C., A. Doan, A. Ardalan, J. R. Ballard, H. Li, F. Panahi, H. Zhang, J. F. Naughton, S. Prasad, G. Krishnan, R. Deep, and V. Raghavendra. Magellan: Toward building entity matching management systems. PVLDB, 9(12):1197–1208, 2016.
2. G. Papadakis, L. Tsekouras, E. Thanos, G. Giannakopoulos, T. Palpanas, and M. Koubarakis. Domain- and structureagnostic end-to-end entity resolution with jedai. SIGMOD Record, 48(4):31, 2019.
3. B. Golshan, A. Y. Halevy, G. A. Mihaila, and W. Tan. Data integration: After the teenage years. In PODS, pages 101–106, 2017.