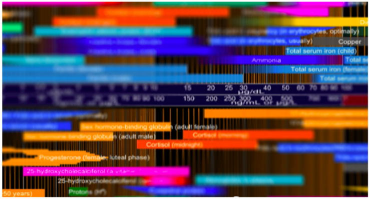
Preliminaries

Rebecca C. Steorts

August 27, 2024



Copper
Total serum iron (child)
Ammonia
Total serum iron (female
15 20 25 30 40 50 60 70 80 90 100
μg/dL
150 200 250 300 400 500
ng/mL or μg/L
Sex hormone-binding globulin (adult female)
n (adult male)
Cortisol (midnight)
Progesterone (female, luteal phase)
25-hydroxycholecalciferol
50 years)
Protons (H+)

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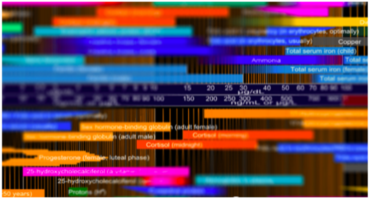
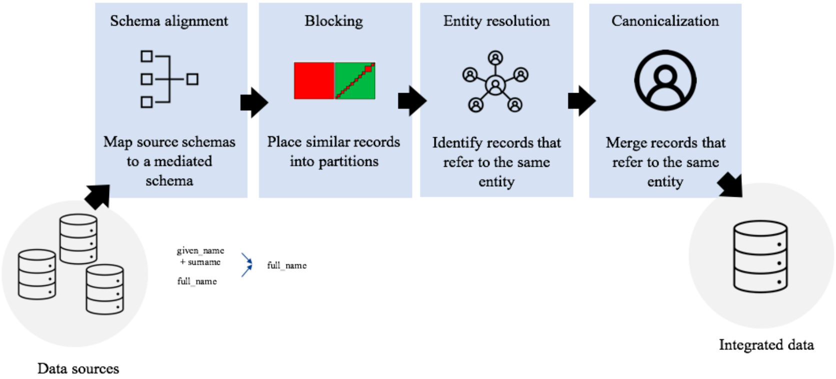

(in erythrocytes, optimally)
(in erythrocytes, usually)
Copper
Total serum iron (child)
Ammonia
Total se
Total serum iron (female)
Total serum iro
15 20 25 30 40 50 60 70
μg/dL
100 150 200 250 300 400 500
ng/mL or μg/L
Sex hormone-binding globulin (adult female)
Sex hormone-binding globulin (adult male)
Cortisol (morning)
Cortisol (midnight)
Progesterone (female, luteal phase)
25-hydroxycholecalciferol (a vitamin
25-hydroxycholecalciferol
-50 years)
Protons (H⁺)

What do these datasets have in common?

- There is duplication in the data.
- The amount of duplication is typically small.
- Before we can apply inferential or prediction methods, any duplicate records must be removed.

Data Cleaning Pipeline


Schema alignment
Map source schemas to a mediated schema
Blocking
Place similar records into partitions
Entity resolution
Identify records that refer to the same entity
Canonicalization
Merge records that refer to the same entity
given_name + surname
full_name
full_name
Data sources
Integrated data

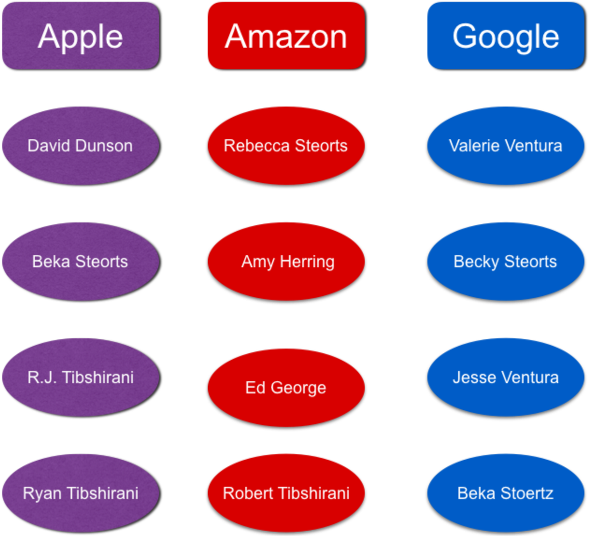
Entity resolution (ER) is the process of merging together noisy (structured) databases to remove duplicate entities, often in the absence of a unique identifier.

Other names for entity resolution:

record linkage, deduplication, duplicate detection, data matching, data integration, data cleansing.

Foundations and Terminology

A graph with no edges



Apple

David Dunson

Beka Steorts

R.J. Tibshirani

Ryan Tibshirani

Amazon

Rebecca Steorts

Amy Herring

Ed George

Robert Tibshirani

Google

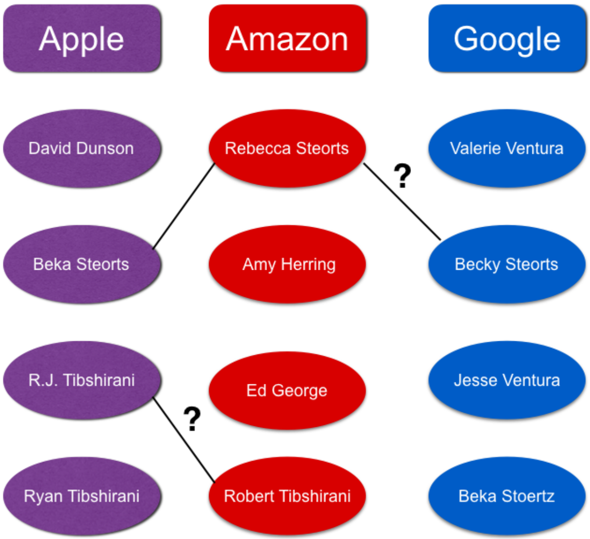
Valerie Ventura

Becky Steorts

Jesse Ventura

Beka Stoertz

The entity resolution graph



Entities are Real People (Objects, Businesses, Etc.)

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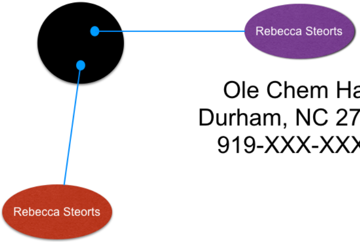
Goal of Entity Resolution

This is a cluster of size 2



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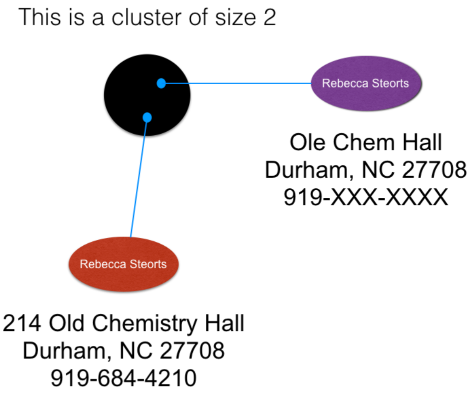
Goal of Entity Resolution


This is a cluster of size 2

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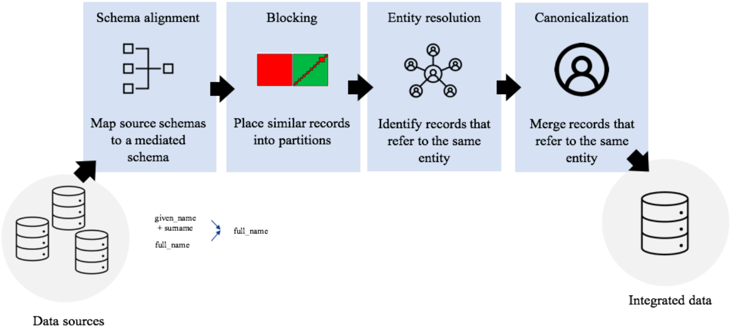
To find the most representative records after ER, one must perform canonicalization (data fusion or merging).

In this talk, I will focus on the entity resolution task of the data cleaning pipeline.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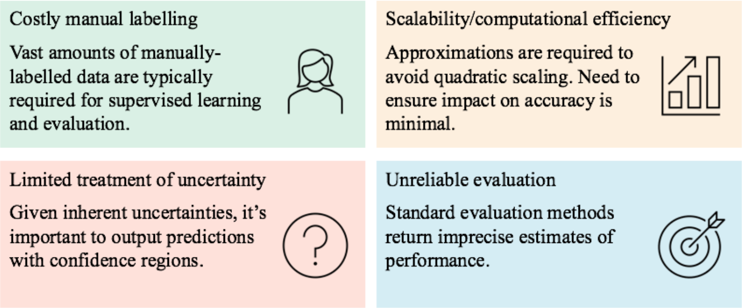
[Christen (2012), Christophides+ (2021), Papadakis+ (2021), Binette and Steorts (2022)]

Challenges

Challenges of Entity Resolution



Costly manual labelling

Vast amounts of manually-labelled data are typically required for supervised learning and evaluation.

Scalability/computational efficiency

Approximations are required to avoid quadratic scaling. Need to ensure impact on accuracy is minimal.

Limited treatment of uncertainty

Given inherent uncertainties, it’s important to output predictions with confidence regions.

Unreliable evaluation

Standard evaluation methods return imprecise estimates of performance.

Evaluation Metrics

How do we assess the effectiveness of entity resolution methods, where some ground truth is known?

Confusion Matrix

- No = Non-Match
- Yes = Match

Table: Confusion Matrix

N= Total Records	Actual Linkage		
		No	Yes
Predicted Linkage	No	true neg. (TN)	false neg. (FN)
	Yes	false pos. (FP)	true pos. (TP)

Confusion Matrix

Table: Confusion Matrix

	Predicted Linkage		
		Match	Non-Match
Actual Linkage	Match	true pos. (TP)	false pos. (FP)
	Non-Match	false neg. (FN)	true neg. (TN)

In the TP, FP, TN, FN terminology:

- “True” / “False” = prediction is correct/incorrect
- “Positive” / “Negative” = predicted class is positive/negative

Evaluation Metrics

$$\text{Accuracy (acc)} = \frac{TP + TN}{TP + FP + TN + FN}$$

- Commonly used in machine learning problems.
- Useful in situations where the data is balanced, i.e. matches and non-matches are roughly the same.
- The number of TN dominates, and leads to a class imbalance issue (and results that are misleading).

For an example, see page 167 of Christen (2012).

Evaluation Metrics

- False positive rate (FPR) $= \dfrac{FP}{FP + FN}$
  - Fraction of actual negatives that were predicted to be positive.
  - Specificity = Precision = 1 - FPR $= \dfrac{TP}{TP + FP}$
- True Positive Rate (TPR) $= \dfrac{TP}{TP + FN}$
  - Fraction of actual positives that were predicted to be positive.
  - Sensitivity = TPR.

- Useful in situations where the data is balanced, i.e. matches and non-matches are roughly the same.
- The number of TN dominates, and leads to a class imbalance issue (and results that are misleading).

Evaluation Metrics

$$\text{Precision} = \frac{TP}{TP + FP}$$

Measures how precise a method is in classifying true matches.

$$\text{Recall} = \frac{TP}{TP + FN}$$

Measures how accurately the actual true matching pairs of records are correctly classified as matches.

Observe these metrics do not include TN. They do not suffer from a class imbalance issue.

Evaluation Metrics

$$\text{F-Measure} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

- Harmonic mean of the precision and recall.
- Attempts to summarize all aspects of the effectiveness of an entity resolution method.