Data Integration, Data Warehousing, and Entity Resolution

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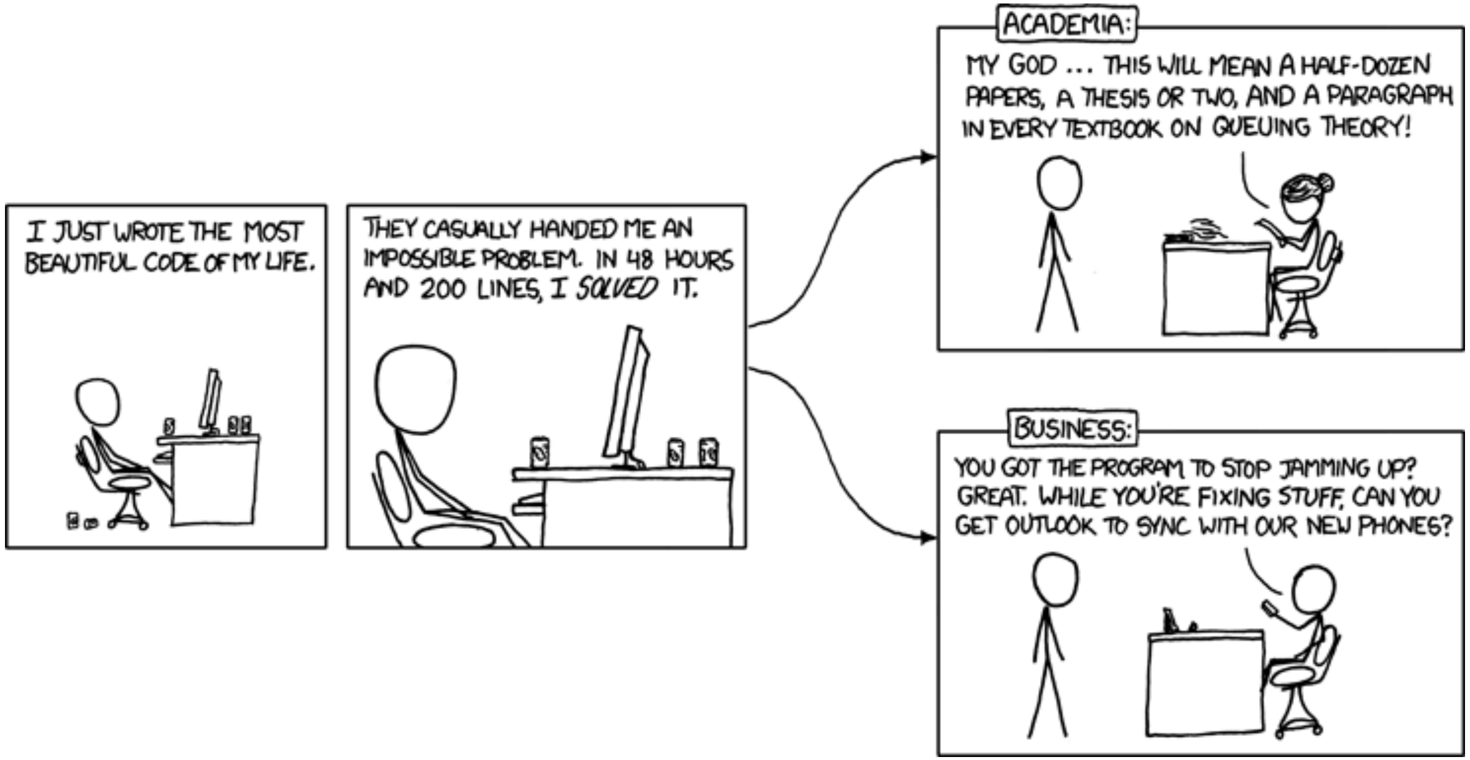
CMPS3660 – Introduction to Data Science – Fall 2019

https://rebrand.ly/TUDataScience

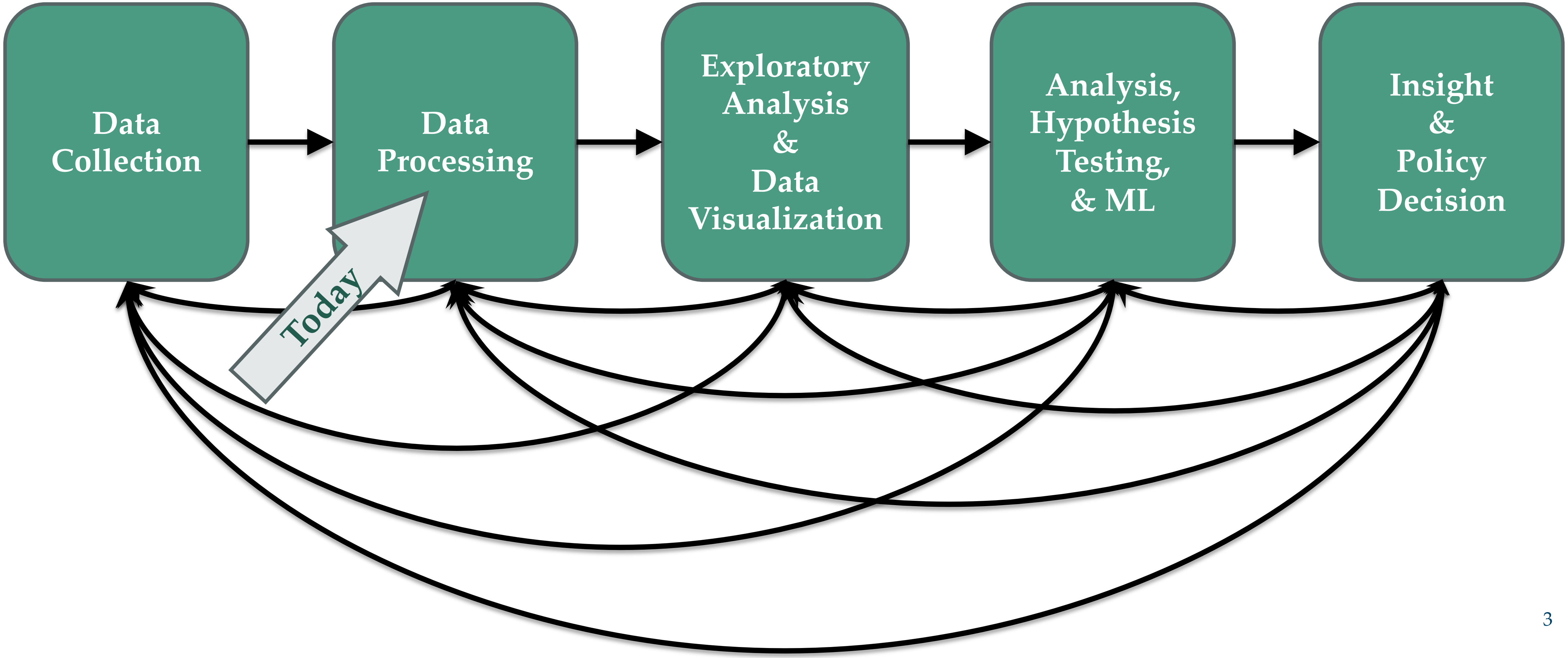
Many Thanks
Slides based off Introduction to Data Science from John P. Dickerson - https://cmsc320.github.io/

Announcements

- Milestone 1 Recap
  - Milestone 2 is Out!
- Lab 6+7 Recap
- Project 1 Due Tonight!



The Data LifeCycle

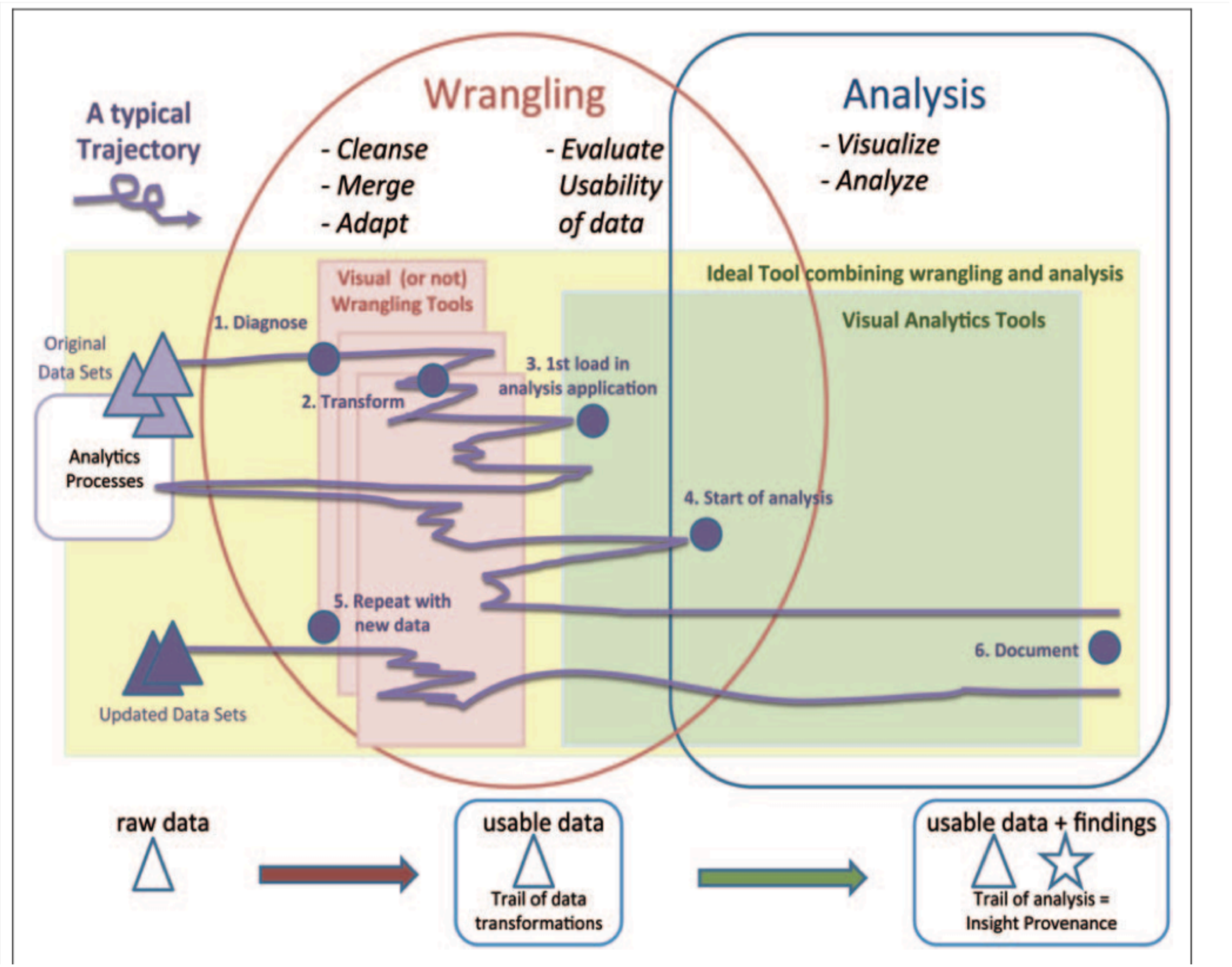


Overview

- **Goal: Get data into a structured form suitable for analysis!**
  - Variously called: data preparation, data munging, data curation.
  - Also often called ETL (Extract-Transform-Load) process.
- **Often the step where majority of time (80-90%) is spent.**
- Key Steps:
  - **Scraping:** extracting information from e.g., webpages, spreadsheets.
  - **Data Transformation:** to get it into the right structure.
  - **Data Integration:** combine information from multiple sources.
  - **Information Extraction:** extracting structured information from unstructured/text sources.
  - **Data Cleaning:** remove inconsistencies/errors.

Milestone 2!

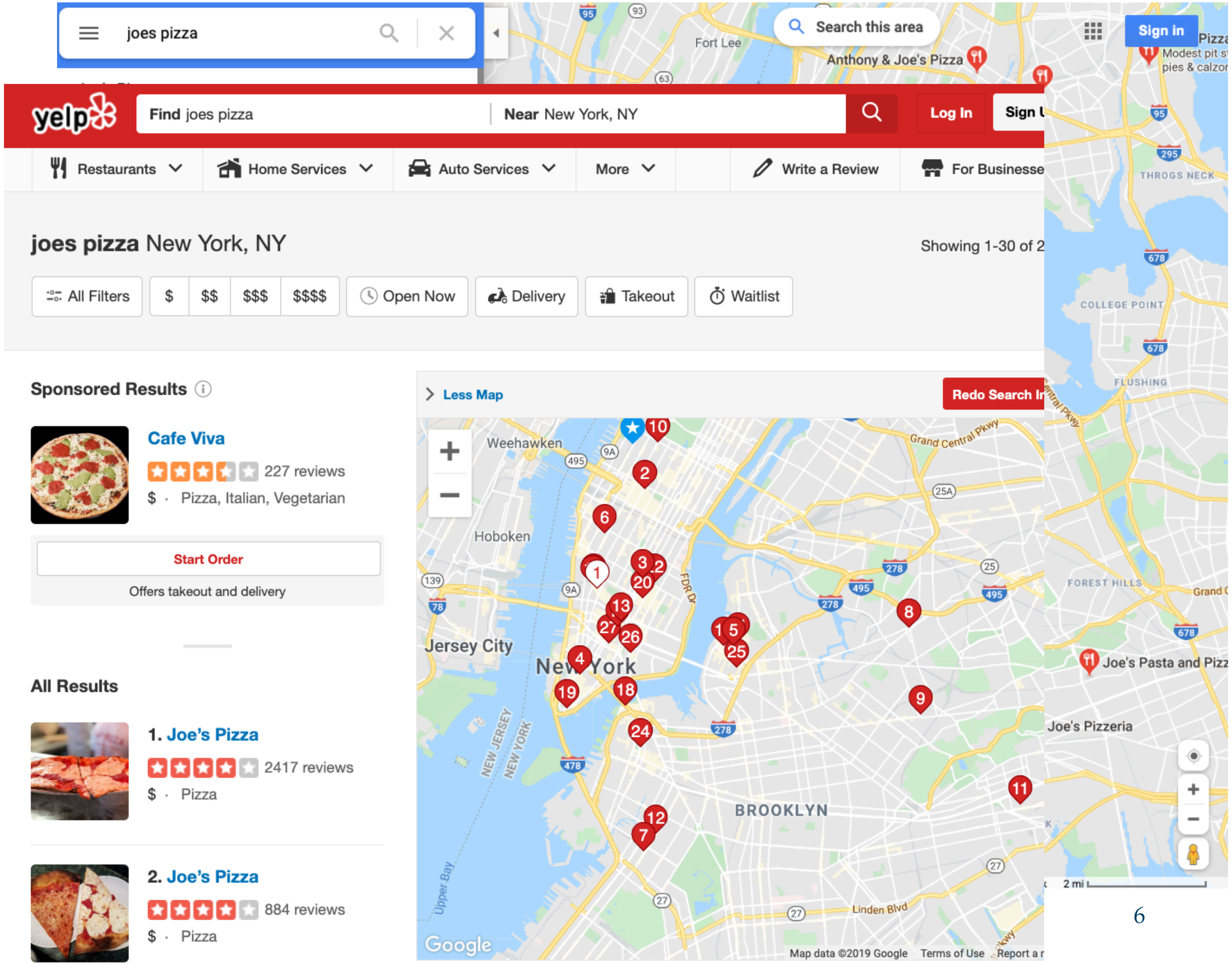
Data Science In Practice…



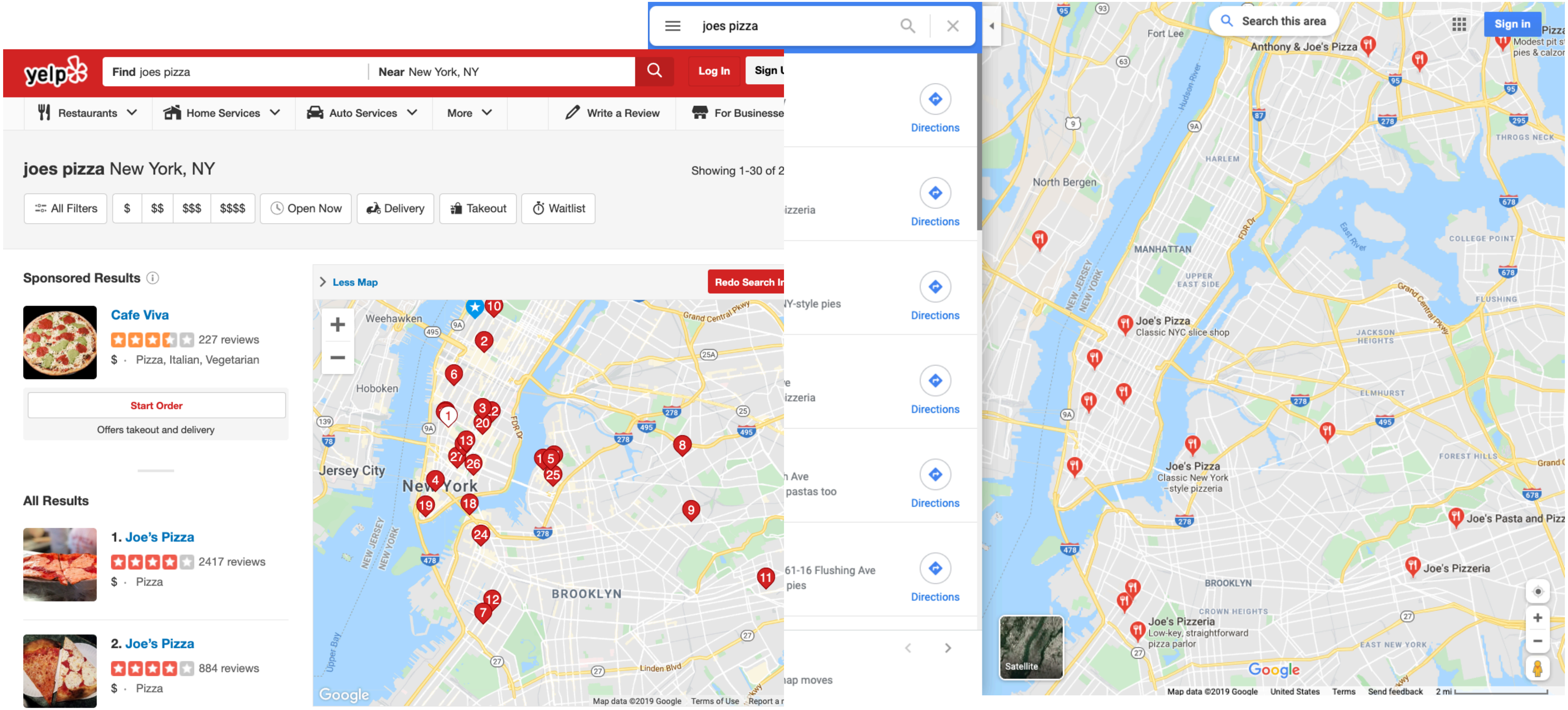
A Motivating Example

- I'm back in NYC for a visit.
- Pizza in New Orleans is awful, and I want Pizza.

- A friend told me to go to Joe's Pizza, because it's the best.
- Search away…

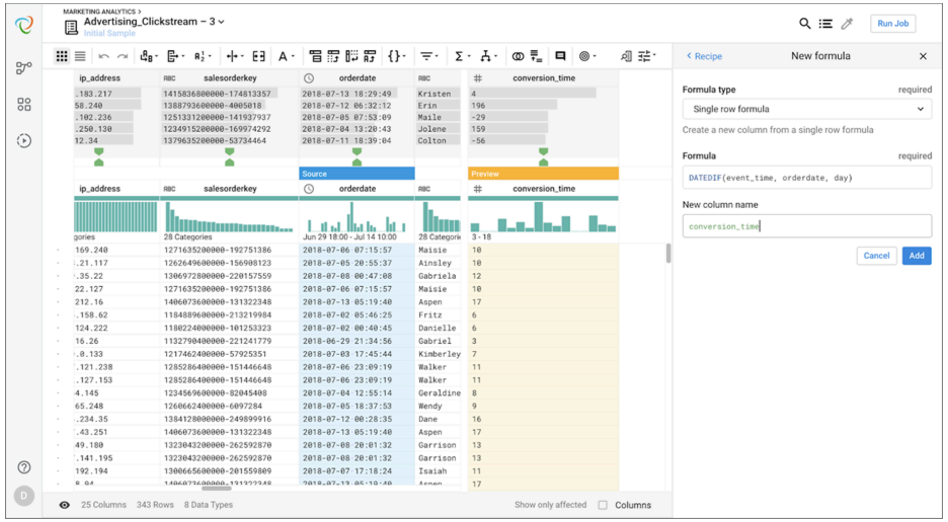


Not Even the Same Set!

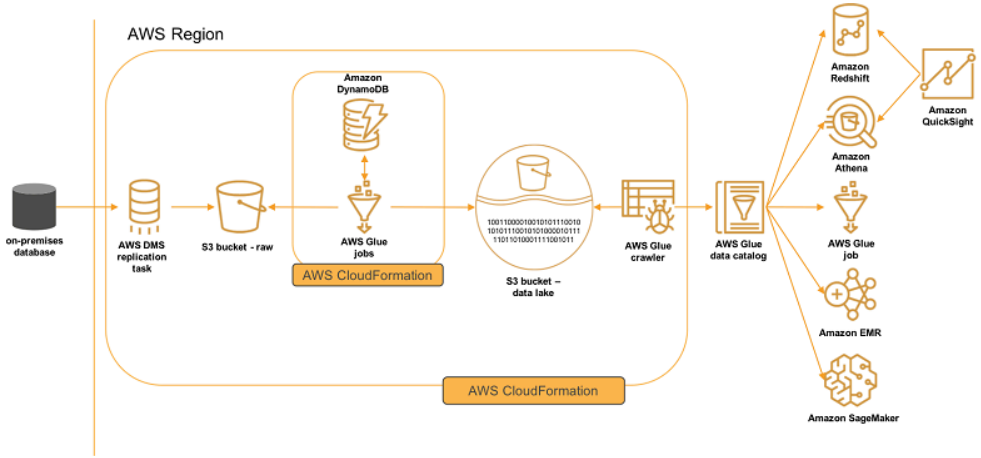


Overview

- Many of the problems ETL stack are hard to formalize, e.g., Data Cleaning.
- Others aspects have been studied in depth, e.g., schema matching and entity resolution
  - VLDB Tutorial on Entity Resolution



- A mish-mash of tools typically used:
  - Visual (e.g., Trifacta), or not (grep/sed/awk, Pandas).
  - Ad hoc programs for cleaning data, depending on the exact type of errors.
  - Different types of transformation tools.
  - Visualization and exploratory data analysis to understand and remove outliers/noise.
  - Several tools for setting up the actual pipelines, assuming the individual steps are setup (e.g., Talend, AWS Glue).



Outline

- **Data Integration**
- Data Quality Issues
- Data Cleaning
    - Outlier Detection
    - Entity Resolution

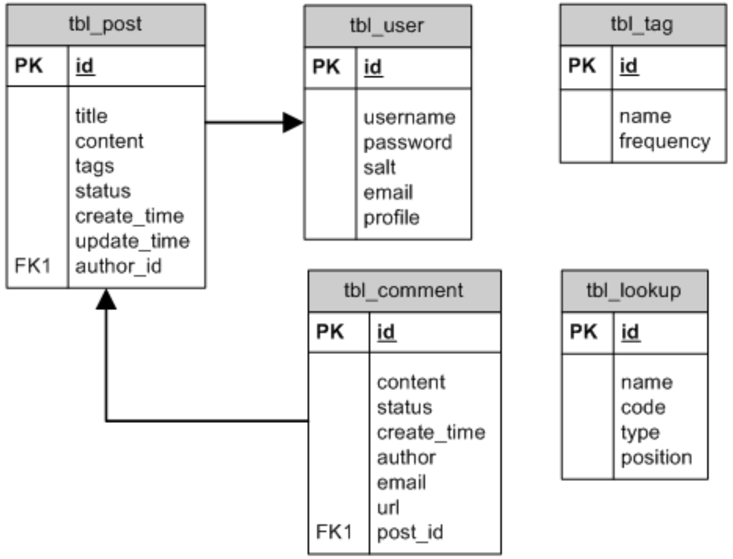
A Few Words to Remember…

- **Schema.** The organization of data within a database or table.
  - i.e., how you data is setup in either a table or RDBMS.

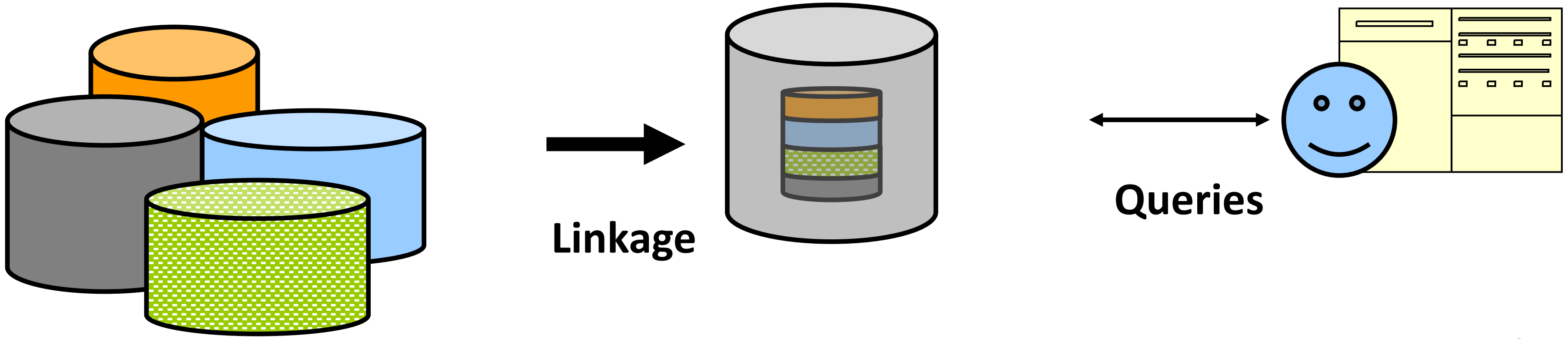
- **Instance.** A single record or element of your data.
  - e.g., Joe's Pizza, our 2nd athlete.

- What follows is from [Data Cleaning: Problems and Current Approaches]() – IEEE Big Data, 2000.
  - Somewhat old: data is mostly coming from structured sources.
  - For a data scientist, the data scraping is equally important.

ID	age	wgt_kg	hgt_cm
1	12.2	42.3	145.1
2	11.0	40.8	143.8
3	15.6	65.3	165.3
4	35.1	84.2	185.8



Data Integration: The Goal!



- **Discovering** information sources (e.g. web modeling, schema learning, …)
- **Gathering** data (e.g., wrapper learning & information extraction, federated search, …)

- **Cleaning** data (e.g., de-duping and **linking records**) to form a single [virtual] database

- **Querying** integrated information sources (e.g. queries to views, execution of web-based queries, …)
- **Data mining & analyzing** integrated information (e.g., collaborative filtering/classification learning using extracted data, …)

Data Integration

- **Goal:** Combine data residing in different sources and provide users with a unified view of these data for querying or analysis.
  - Each data source has its own schema called **local schemas**
    - Most work assumes relational schemas, but some work on XML and others.
  - The unified schema is often called **mediated schema** or **global schema.**

- Traditionally Two Approaches.
  1. **Data Warehousing:** bring the data together into a single repository.

  2. **In-Place Integration:** Keep the data where it is, and send queries back and forth.

1. Data Warehousing

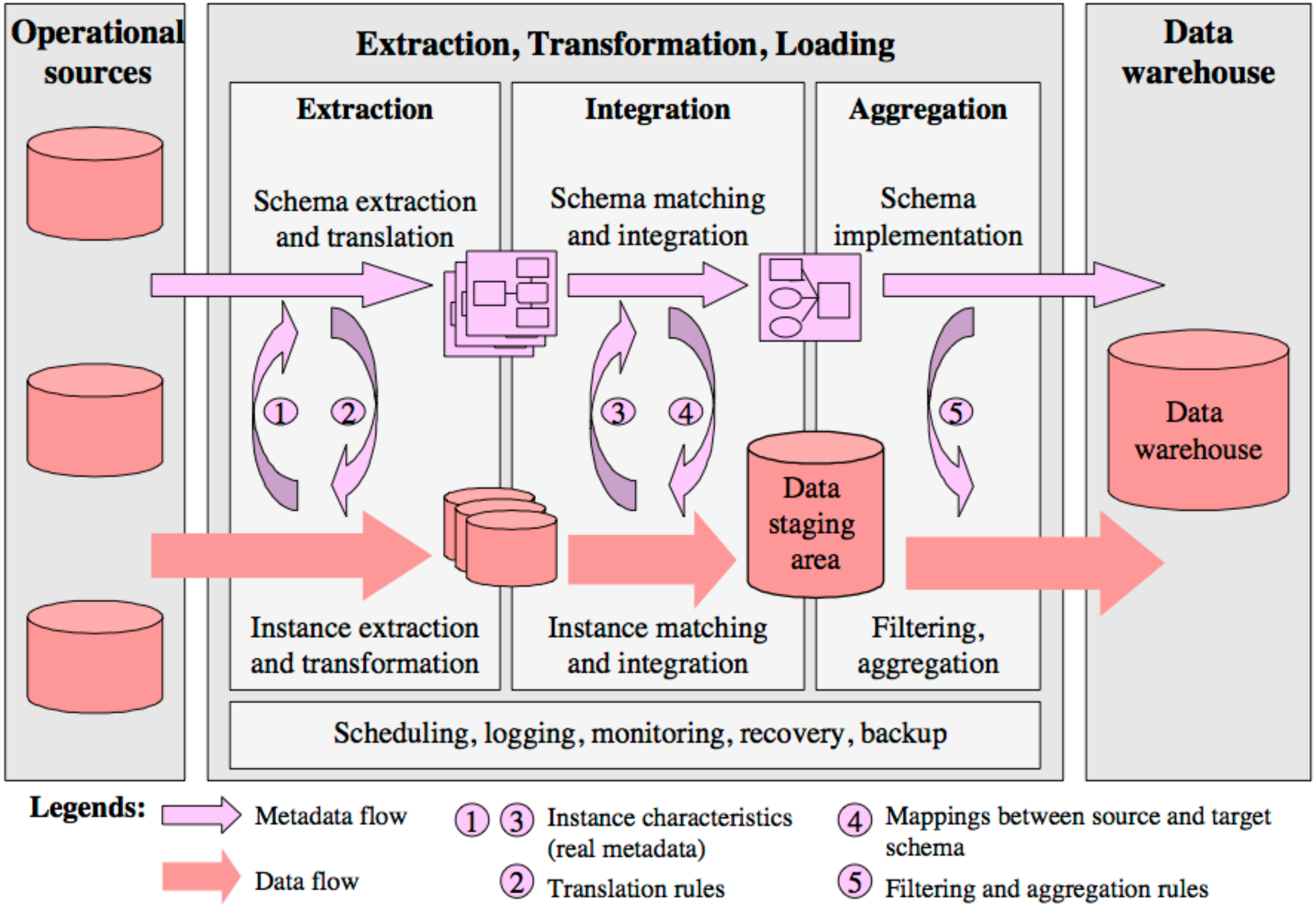
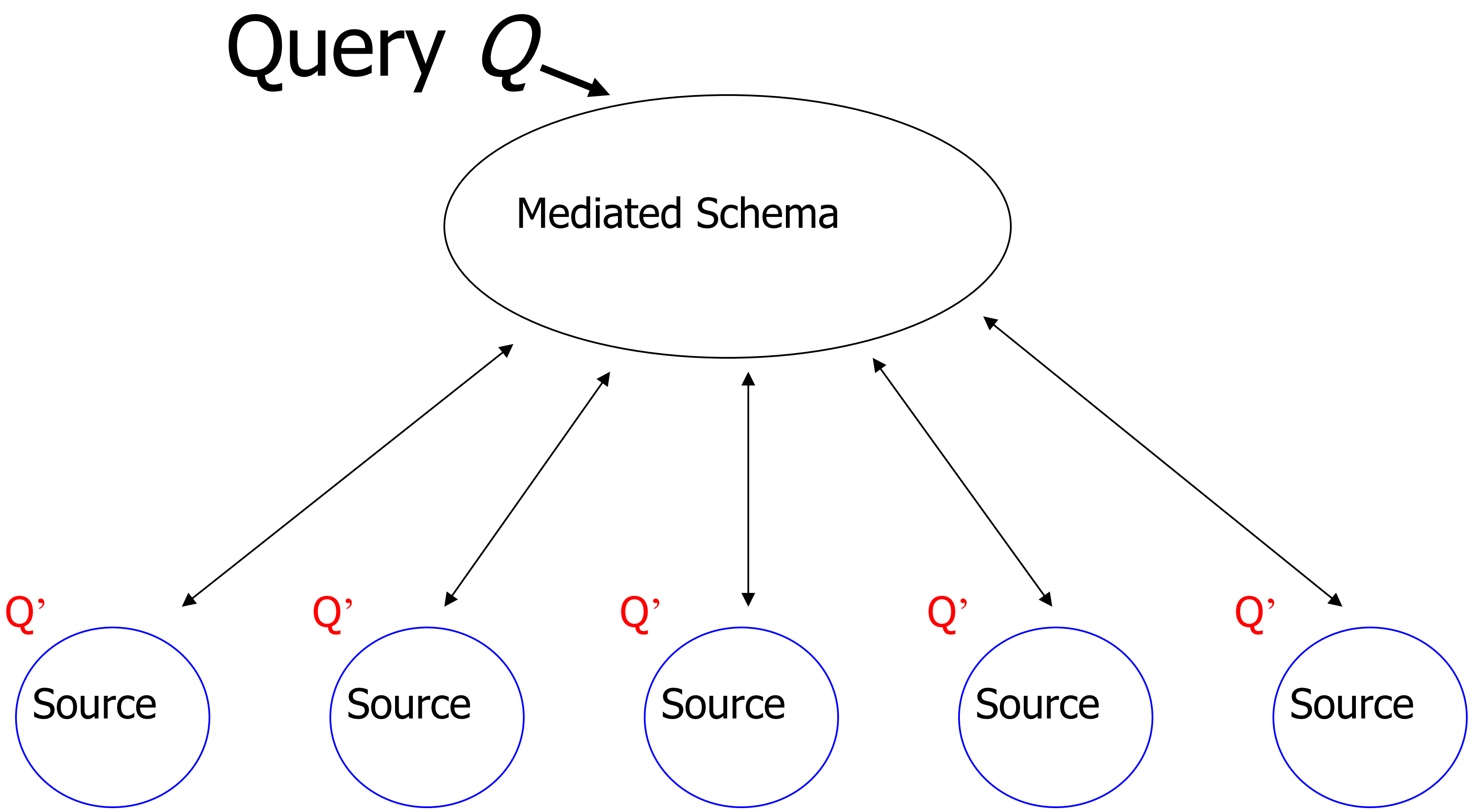


Figure 1. Steps of building a data warehouse: the ETL process

In-place Integration



Data Integration

- Two different setups:

1. **Data Warehousing:** bring the data together into a single repository.
   - Relatively easier problem - only need one-way-mappings.
   - Query performance predictable and under your control.
   - Hard to integrate changes as we have to reprocess.

2. **In-Place Integration:** Keep the data where it is, and send queries back and forth.
   - Need two-way mappings -- a query on the mediated schema needs to be translated into queries over data source schemas.
   - Not as efficient and clean as data warehousing, but a better fit for dynamic data.
   - Or when data warehousing is not feasible.

Data Integration: Key Challenges

- **Data extraction, reconciliation, and cleaning.**
  - Get the data from each source in a structured form.
  - Need to use wrappers to extract data and define local schema.

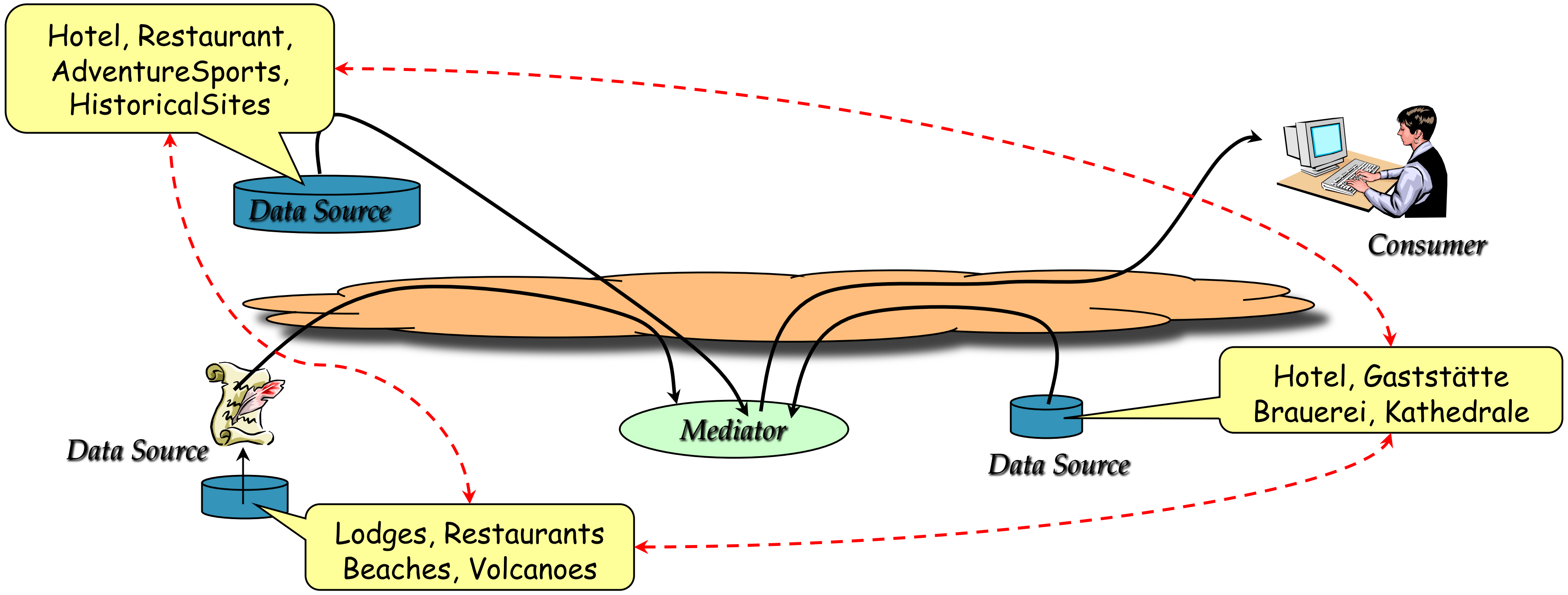
- **Schema alignment and mapping.**
  - Figure out mappings / matchings between schemas.
  - Decide on the best mediated schema.

- **Answer queries over the global schema.**
  - Decide mapping a query on global schema onto queries over local schemas
  - Also need to decide which sources contain relevant data

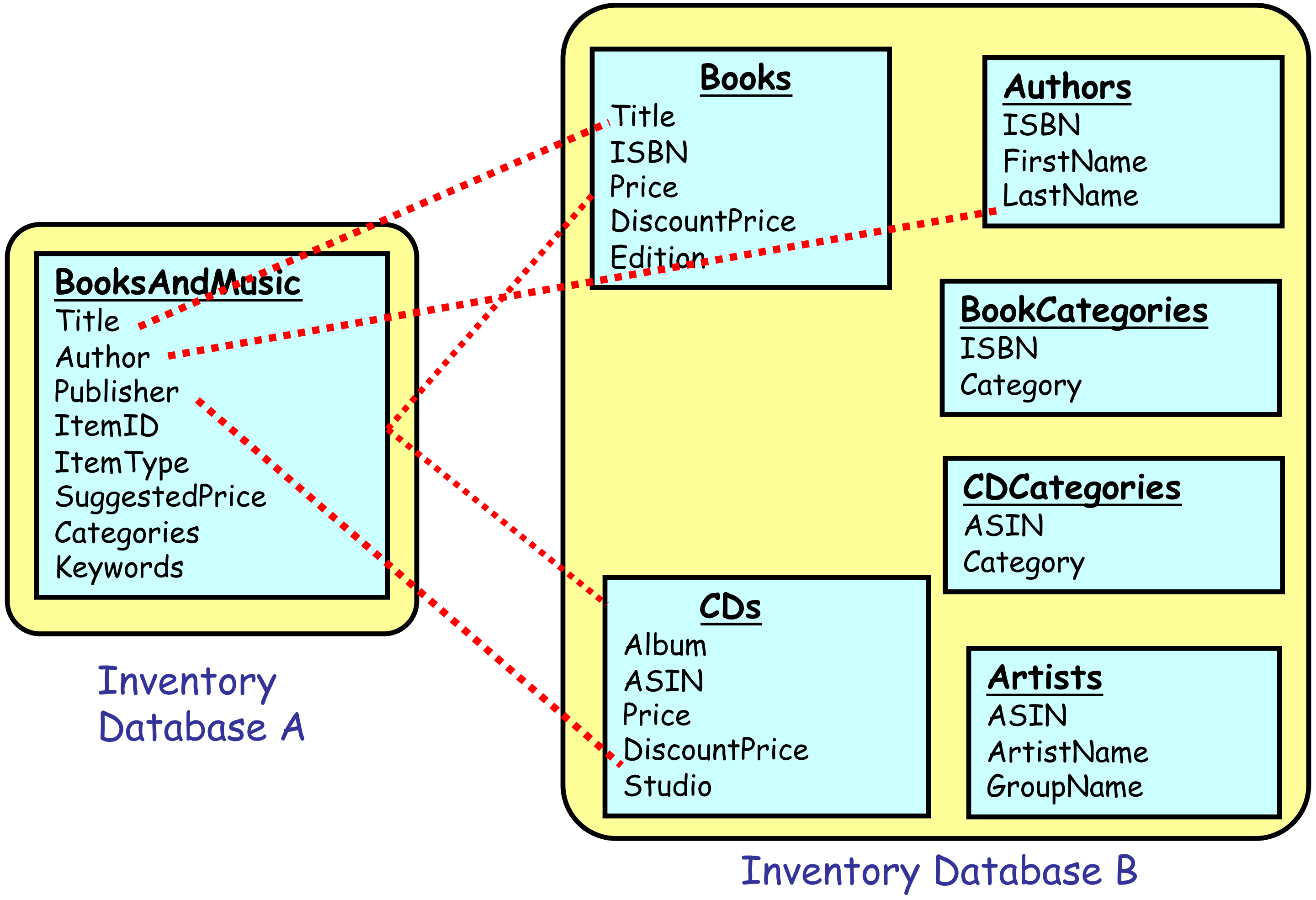
- **Limitations in mechanisms for accessing sources.**
  - Many sources have limits on how you can access them!
  - Limits on the number of queries you can issues (say 100 per min)
  - Limits on the types of queries
    - e.g., must enter a zipcode to get information from a web source.

Schema Matching or Alignment

- **Goal:** Identify corresponding elements in two schemas.
  - As a first step toward constructing a global schema.
  - Schema heterogeneity is a key roadblock.
    - Different data sources speak their own schema.



Schema Matching or Alignment



Summary

- Data integration continues to be a very active area in research and increasingly industry.
  - E.g, how do we automatically extract and query open / competitor databases.
- Solutions still somewhat ad hoc and manual, although tools beginning to emerge.
  - AWS Glue, Watson Data Pipe, etc.
- Goal: minimize the time needed to integrate a new data source!
  - Crucial opportunities may be lost otherwise.
  - Can take weeks to do it properly.
- Dealing with changes to the data sources a major headache.
  - Especially for data sources not under your control.
  - As Project 1 is showing you…

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- **Data Quality Issues**
- Data Cleaning
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Data Quality Problems

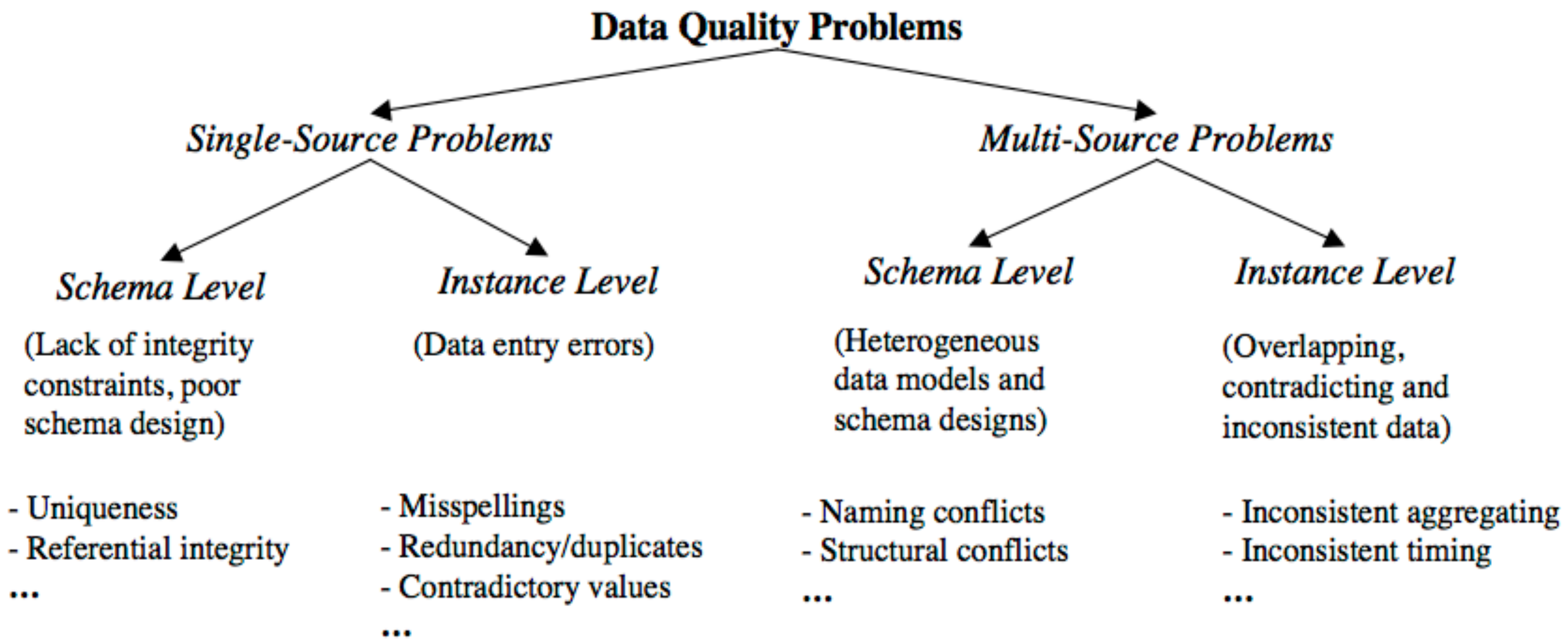

Figure 2. Classification of data quality problems in data sources

From Data Cleaning: Problems and Current Approaches

Single Source Problems

- Depends largely on the source – is it reliable or not?

- Databases can enforce constraints, whereas data extracted from files or spreadsheets, or scraped from webpages is much more messy.

- **Types of Problems:**
  - Ill-formatted data, especially from webpages or files or spreadsheets.
  - Missing or illegal values, Misspellings.
  - Use of wrong fields, Extraction issues (not easy to separate out different fields).
  - Duplicated records, Contradicting Information, Referential Integrity Violations.
  - Unclear/confusing default values.
  - Evolving/changing schemas or classification schemes (for categorical attributes).
  - Outliers.

Single Source Problems

Scope/Problem		Dirty Data	Reasons/Remarks
Attribute	Missing values	phone=9999-999999	unavailable values during data entry (dummy values or null)
	Misspellings	city="Liipzig"	usually typos, phonetic errors
	Cryptic values, Abbreviations	experience="B"; occupation="DB Prog."	
	Embedded values	name="J. Smith 12.02.70 New York"	multiple values entered in one attribute (e.g. in a free-form field)
	Misfielded values	city="Germany"	
Record	Violated attribute dependencies	city="Redmond", zip=77777	city and zip code should correspond
Record type	Word transpositions	$name_1$= "J. Smith", $name_2$="Miller P."	usually in a free-form field
	Duplicated records	emp_1=(name="John Smith",...); emp_2=(name="J. Smith",...)	same employee represented twice due to some data entry errors
	Contradicting records	emp_1=(name="John Smith", bdate=12.02.70); emp_2=(name="John Smith", bdate=12.12.70)	the same real world entity is described by different values
Source	Wrong references	emp=(name="John Smith", deptno=17)	referenced department (17) is defined but wrong

Table 2. Examples for single-source problems at instance level

Multi-Source Problems

- Different sources are developed separately, and maintained by different people.

- Issue 1: Mapping information across sources (schema mapping/transformation).
  - Same issues as in data integration we saw before.
  - Naming conflicts: same name used for different objects.
  - Structural conflicts: different representations across sources.

- Issue 2: Entity Resolution: Matching entities across sources!

- Issue 3: Data quality issues.
  - Contradicting information, Mismatched information, etc.

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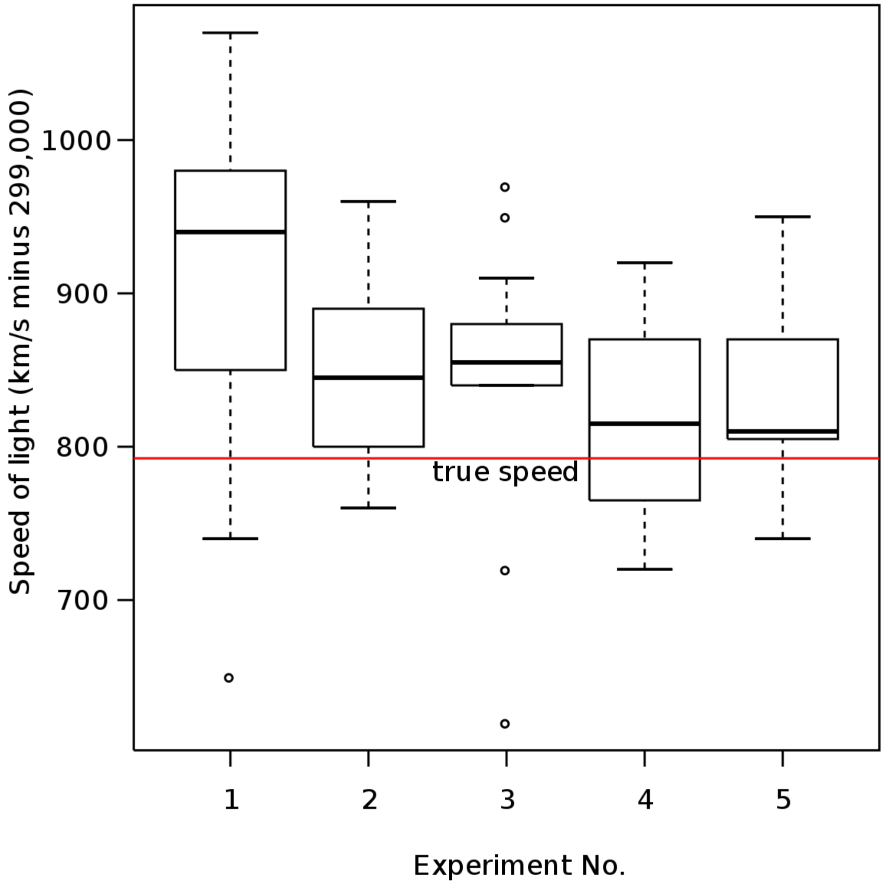
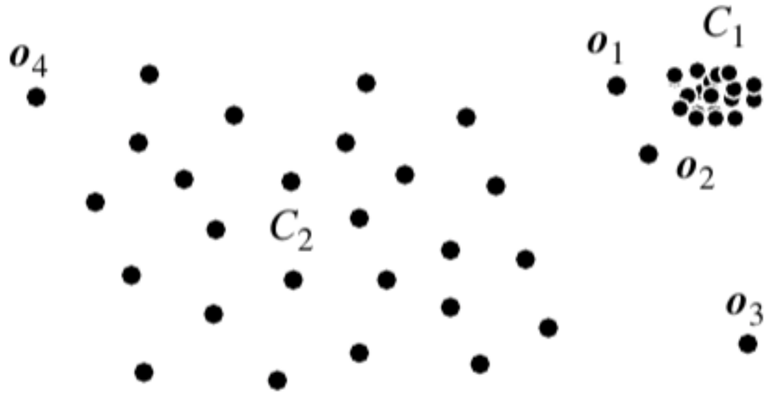
Dealing with Univariate Outliers

- Set of values can be characterized by metrics: center (e.g., mean), dispersion (e.g., standard deviation), and skew.
- Used to identify outliers:
  - Watch out for "masking": one extreme outlier may alter the metrics sufficiently to mask other outliers.
  - Should use **robust statistics**: considers effect of corrupted data values on distributions (next week!)
    - **Robust center metrics:** median, k% trimmed mean (discard lowest/highest k% values)
    - **Robust dispersion:** Median Absolute Deviation (MAD): median distance of all the values from the median value



- A reasonable approach: discard any data points 1.4826x MAD away from median.
  - The above assumes that data follows a **normal** distribution.
  - May need to eyeball the data (e.g., plot a histogram) to decide if this is true.

Univariate Outliers



- Wikipedia Article on Outliers lists several other normality-based tests for outliers.
- If data appears to be not normally distributed:
  - Distance-based methods: look for data points that do not have many neighbors.
  - Density-based methods:
    - Define *density* to be average distance to *k* nearest neighbors.
    - *Relative density* = density of node/average density of its neighbors.
    - Use relative density to decide if a node is an outlier

- Many techniques start breaking down as the dimensionality of the data increases:
  - *Curse of dimensionality* – too many different dimensions to look for outliers!
  - Can project data into lower-dimensional space and look for outliers there
    - PCA / Embeddings / Fun Machine Learning Stuff!

Other Types of Outliers

- Timeseries outliers:
  - Often the data is in the form of a timeseries
  - Can use the historical values/patterns in the data to flag outliers.
  - Rich literature on *forecasting* in timeseries data.

- Frequency-based outliers:
  - Item is called a "heavy hitter" if it is much more frequent than other items.
  - In relational tables, can be found using a simple *groupby-count.*
  - Often the volume of data may be too much (e.g., internet routers).
    - Approximation techniques often used.

- Things generally not as straightforward with other types of data.
  - What about Networks, Images, or other datasets?
  - Outlier detection continues to be a major research area

Wrap-up

- Data wrangling/cleaning are a key component of data science pipeline
- Still largely ad hoc although much tooling in recent years
- Specifically, we covered:
  - Schema mapping and matching
  - Outliers
- Next up:
  - Constraint-based Cleaning
  - Entity Resolution/Record Linkage/Data Matching

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  - **Entity Resolution**

Data Cleaning: Entity Resolution (ER)

- Content from: Entity Resolution Tutorial, VLDB 2012.

- **Goal: Identify different manifestations of the same real world object**.
  - Also called: identity reconciliation, record linkage, deduplication, fuzzy matching, Object consolidation, Coreference resolution, and several others (ER has an ER problem…).

- Motivating Examples ????
  - Postal addresses
  - Entity recognition in NLP/Information Extraction
  - Identifying companies in financial records
  - Comparison shopping
  - Author disambiguation in citation data
  - Connecting up accounts on online networks
  - Crime/Fraud Detection
  - Census
  - ...

Data Cleaning: Entity Resolution

- Important to correctly identify references.
  - Often actions taken based on extracted data.
  - Cleaning up data by entity resolution can show structure that may not be apparent before.

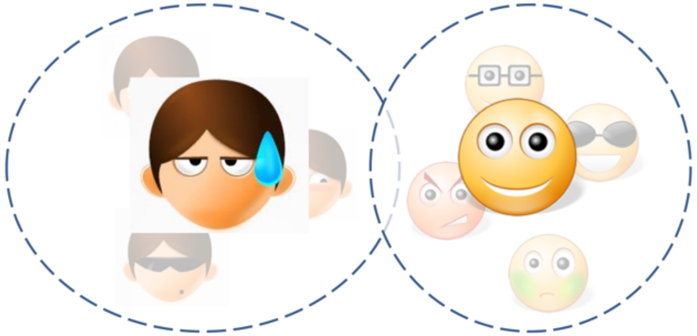
- **Challenges.**
  - Such data is naturally ambiguous (e.g., names, postal addresses).
  - Abbreviations/data truncation.
  - Data entry errors, Missing values, Data formatting issues complicate the problem.
  - Heterogeneous data from many diverse sources.

- **No magic bullet here !!**
  - Approaches fairly domain-specific.
  - Be prepared to do a fair amount of manual work.

Entity Resolution: Three Slightly Different Problems

- **Setup.**
  - Real world: there are entities (people, addresses, businesses).
  - We have a large collection of noisy, ambiguous "references" to those entities (also called "mentions").
  - Somewhat different techniques, but a lot of similarities.

- **Deduplication.**
  - Cluster records/mentions that correspond to the same entity
  - Choose/construct a cluster representative
    - This is in itself a non-trivial task (e.g., averaging may work for numerical attributes, but what about string attributes?)



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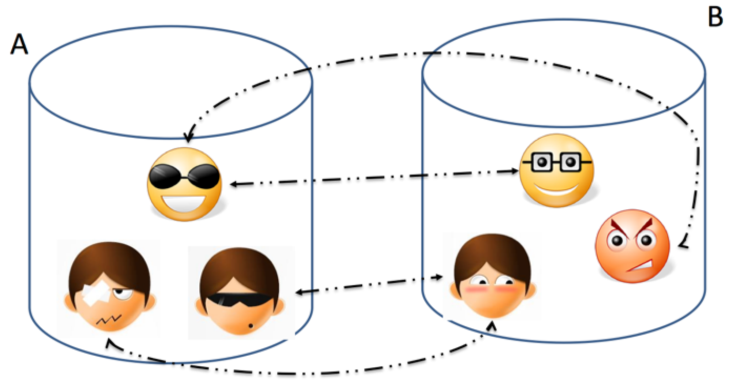
- **Record Linkage.**
  - Match records across two different databases (e.g., two social networks, or financial records w/ campaign donations).
  - Typically assume that the two databases are fairly clean.



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Entity Resolution: Three Slightly Different Problems

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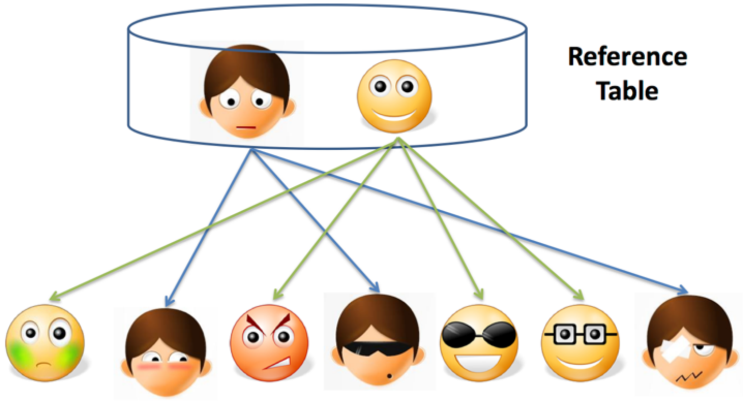
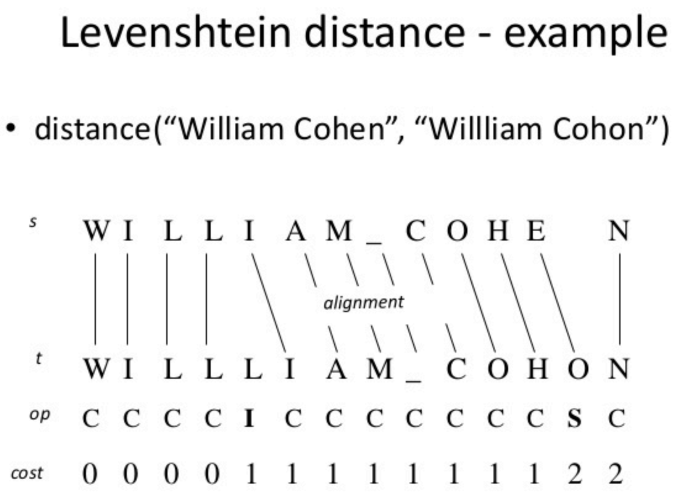
  - Somewhat different techniques, but a lot of similarities.

- **Reference Matching.**
  - Match "references" to clean records in a reference table.
  - Commonly comes up in "entity recognition" (e.g., matching newspaper article mentions to names of people).

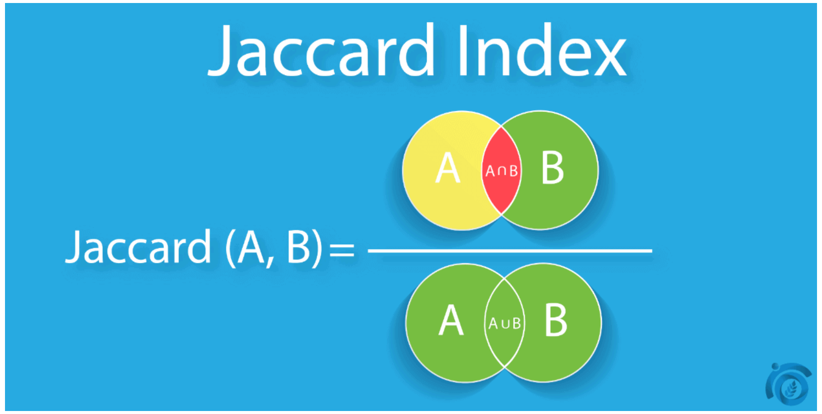


Entity Resolution: Data Matching

- **Book Ref: Data Matching; P. Christen; 2012 (Springer).**
- Key issues is finding similarities between two references – **but what function?**

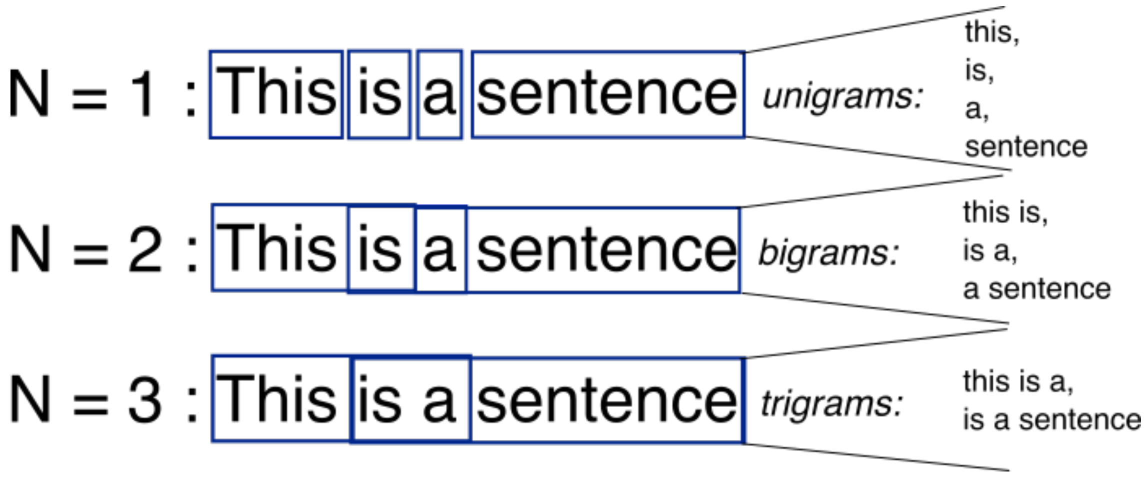


- Edit Distance Functions:
  - **Levenstein Distance**. min number of changes to go from one reference to another.
  - Lots of variants (weights) and not cheap to compute.
- Set Similarity:
  - Some function of intersection size and union size.
  - **Jaccard Distance** = size of intersection/size of union



- Vector Similarity
  - Cosine similarity – we'll talk about this much more in NLP lectures

Entity Resolution: Data Matching



- For Words: n-grams
  - Find all length-n substrings in each string.
  - Use set/vector similarity on the resulting set.
  - Combine with edit-distance metrics.
- May need to use Translation Tables.
  - To handle abbreviations, nicknames, other synonyms

- Soundex: Phonetic Similarity Metric.
  - Homophones should be encoded the same so spelling errors can be handled, e.g., Robert and Rupert get assigned the same code (R163), but Rubin yields R150.

- Different types of data requires more domain-specific functions
  - E.g., geographical locations, postal addresses, XML documents, etc.

Entity Resolution: Algorithms

- **Threshold Method.**
  - If the distance below some number, the two references are assumed to be equal
  - May review borderline matches manually

- Can be generalized to rule-based:
  - Example from Christen, 2012

$$(s(\text{GivenName})[r_i,r_j] \geq 0.9) \land (s(\text{Surname})[r_i,r_j] = 1.0) \land (s(\text{BMonth})[r_i,r_j] = 1.0) \land (s(\text{BYear})[r_i,r_j] = 1.0) \Rightarrow [r_i,r_j] \rightarrow \text{Match}$$

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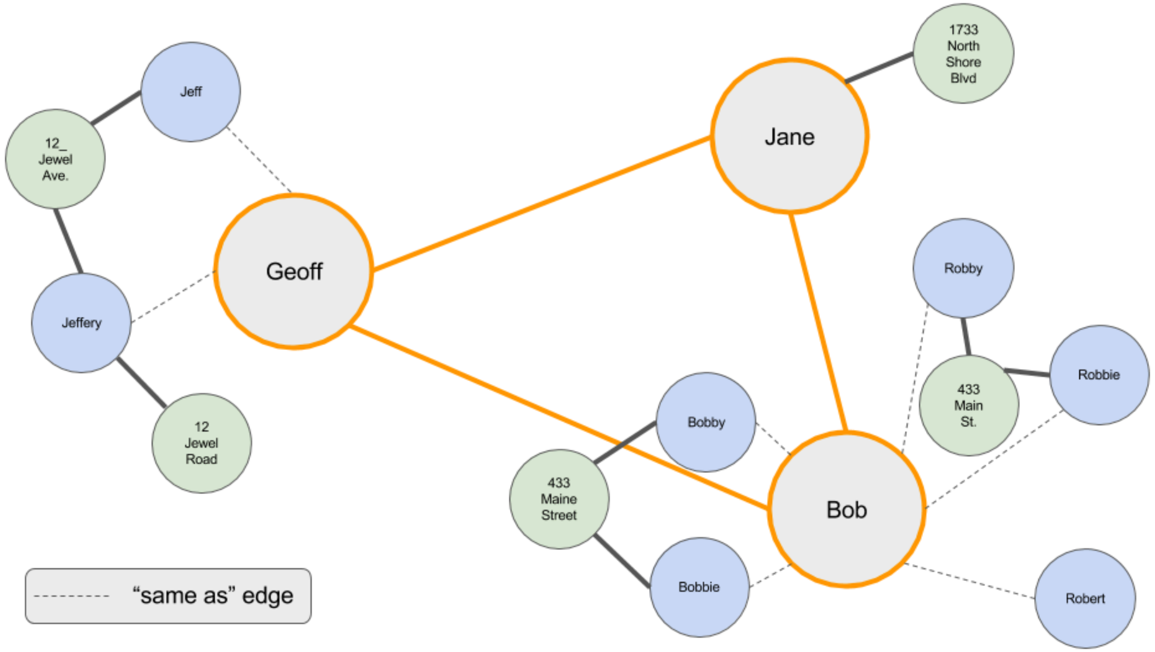
Entity Resolution: Algorithms

- **Threshold + Weights:** May want to give more weight to matches involving rarer words.
  - More naturally applicable to record linkage problem.
  - If two records match on a rare name like "Machanavajjhala", they are likely to be a match.
  - Can formalize this as "probabilistic record linkage".

- **Constraints:** May need to be satisfied, but can also be used to find matches.
  - We often have constraints on the matching possibilities:
  - **Transitivity:** M1 and M2 match, and M2 and M3 match, and M1 and M3 must match
  - Exclusivity: M1 and M2 match --> M3 cannot match with M2
  - Other types of constraints:
    - E.g., if two papers match, their venues must match

Entity Resolution: Algorithms

- **Clustering-based ER Techniques.**
  - Deduplication is basically a clustering problem.
  - Can use clustering algorithms for this purpose.
  - But most clusters are very small (in fact of size = 1).
  - Some clustering algorithms are better suited for this, especially Agglomerative Clustering
    - Unlikely K-Means would work here.



Entity Resolution: Algorithms

- **Crowdsourcing.**
  - Humans are often better at this task.
  - Can use one of the crowdsourcing mechanisms (e.g., Mechanical Turk) for getting human input on the difficult pairs.
  - Quite heavily used commercially (e.g., to disambiguate products, restaurants, etc.).

Entity Resolution: Scaling to Big Data

- One immediate problem:
  - There are $O(N^2)$ possible matches!
  - Must reduce the search space

- Use some easy-to-evaluate criterion to restrict the pairs considered further
  - May lead to false negative (i.e., missed matches) depending on how noisy the data is

- Much work on this problem as well, but domain-specific knowledge likely to be more useful in practice

- One useful technique to know: min-hash signatures
  - Can quickly find potentially overlapping sets
  - Turns up to be very useful in many domains (beyond ER)