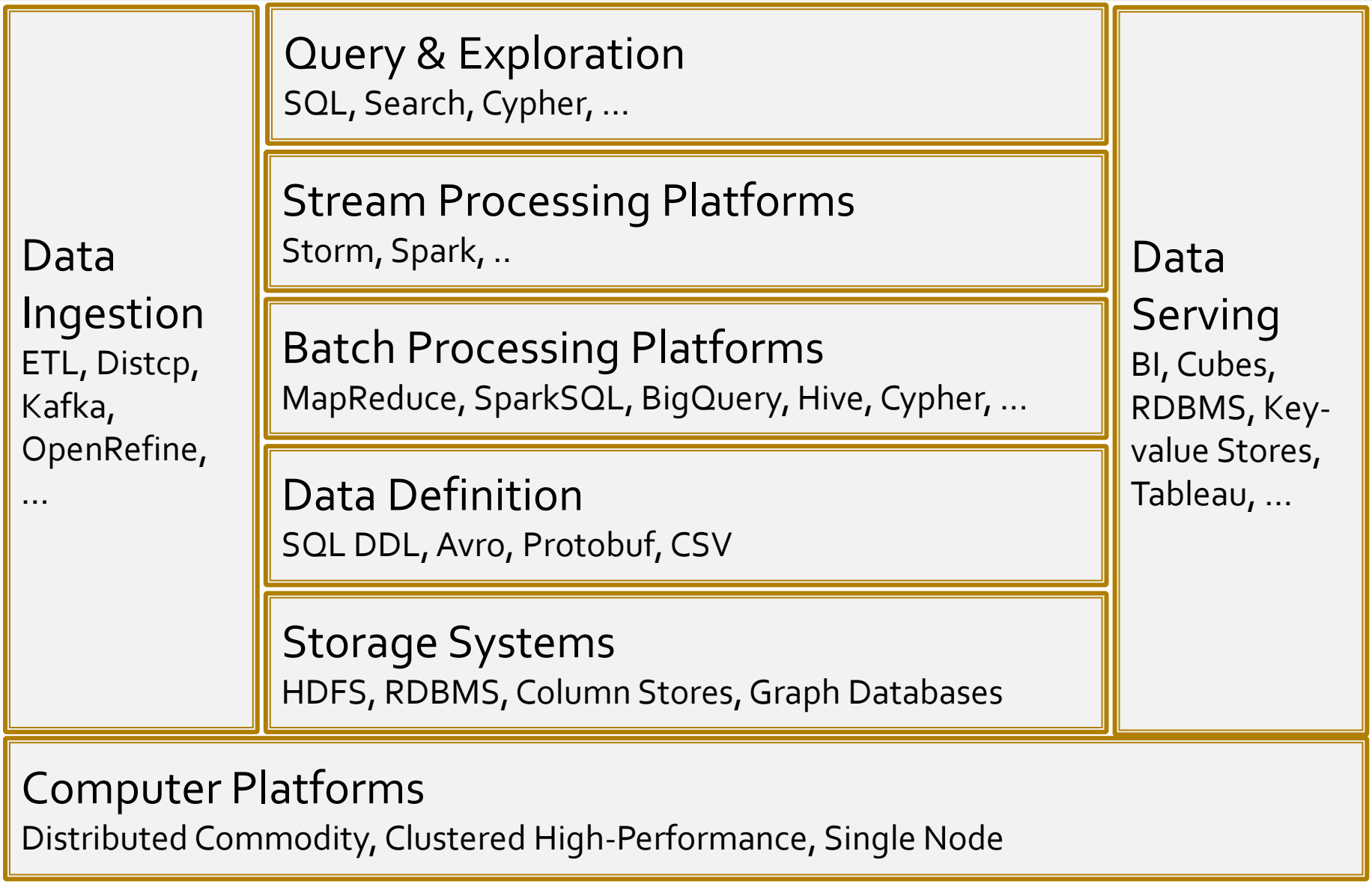
EECS6414:
Data Analytics & Visualization

Data Ingestion and Data Quality

Big Data Technology & Analytics



Data Ingestion

Bottom Line

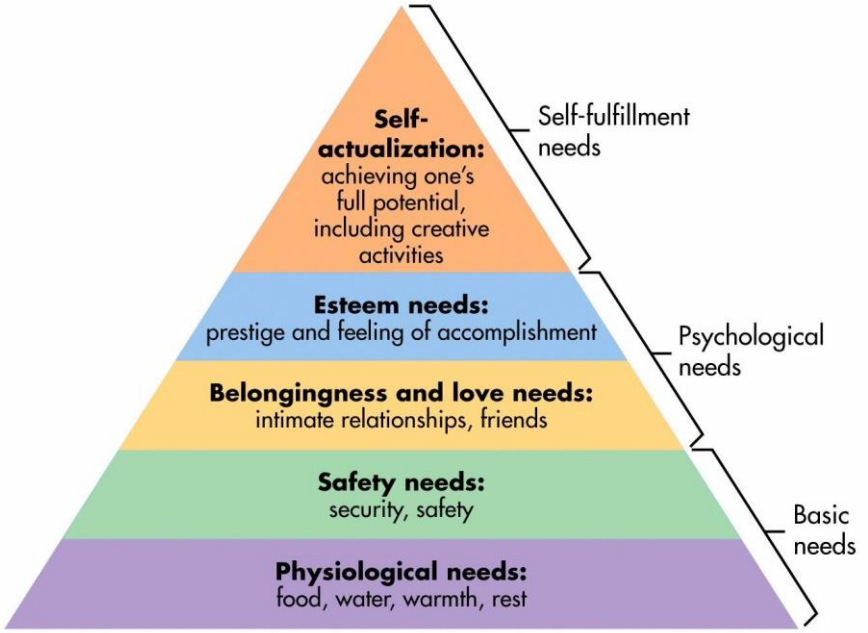
Analytics solutions start with **data ingestion**

Data integration challenges:

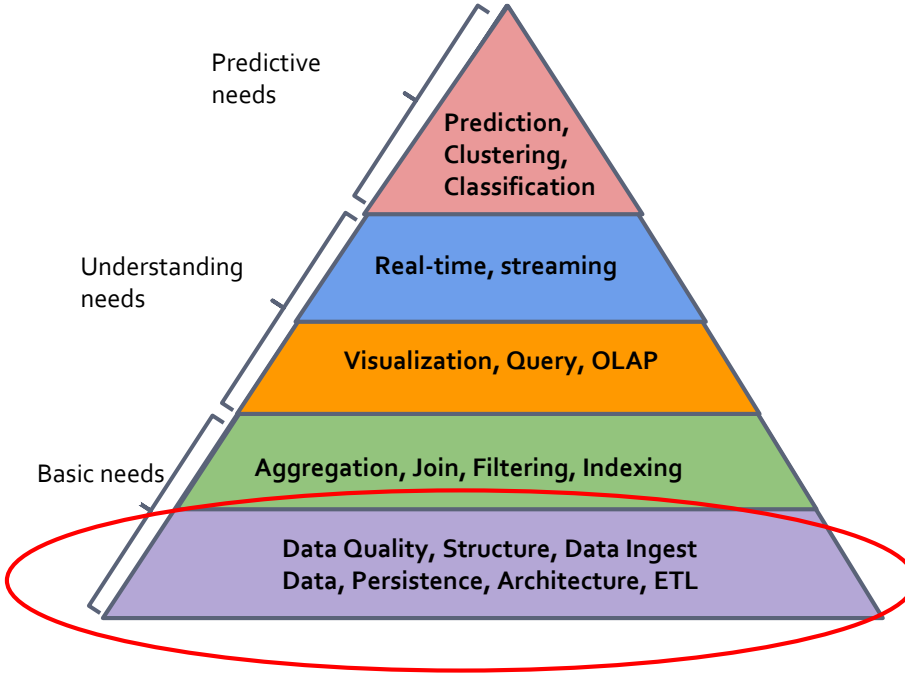
- **volume** (many similar integrations)
- **variety** (many different integrations)
- **velocity** (batch v.s real-time)
- (or all of the above)

Needs of Data Analytics

Maslow's hierarchy of needs*

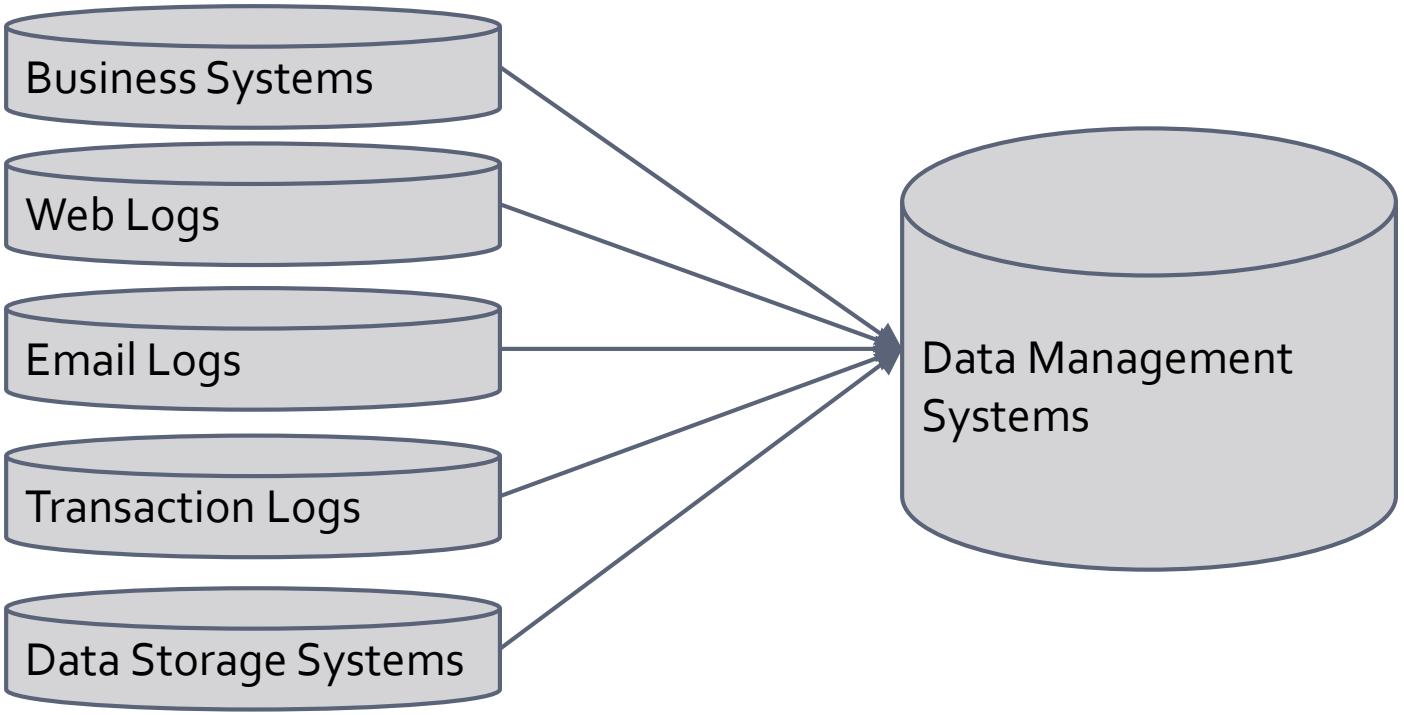


Hierarchy of effective analytics

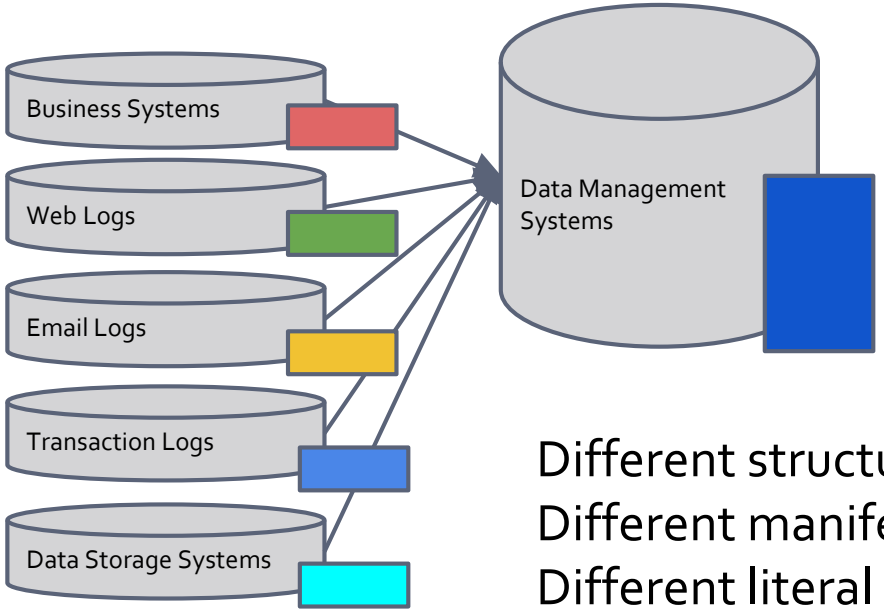


* A theory in psychology proposed by Abraham **Maslow** in 1943. Needs lower down in the hierarchy must be satisfied before individuals can attend to needs higher up.

Challenge: Many Sources

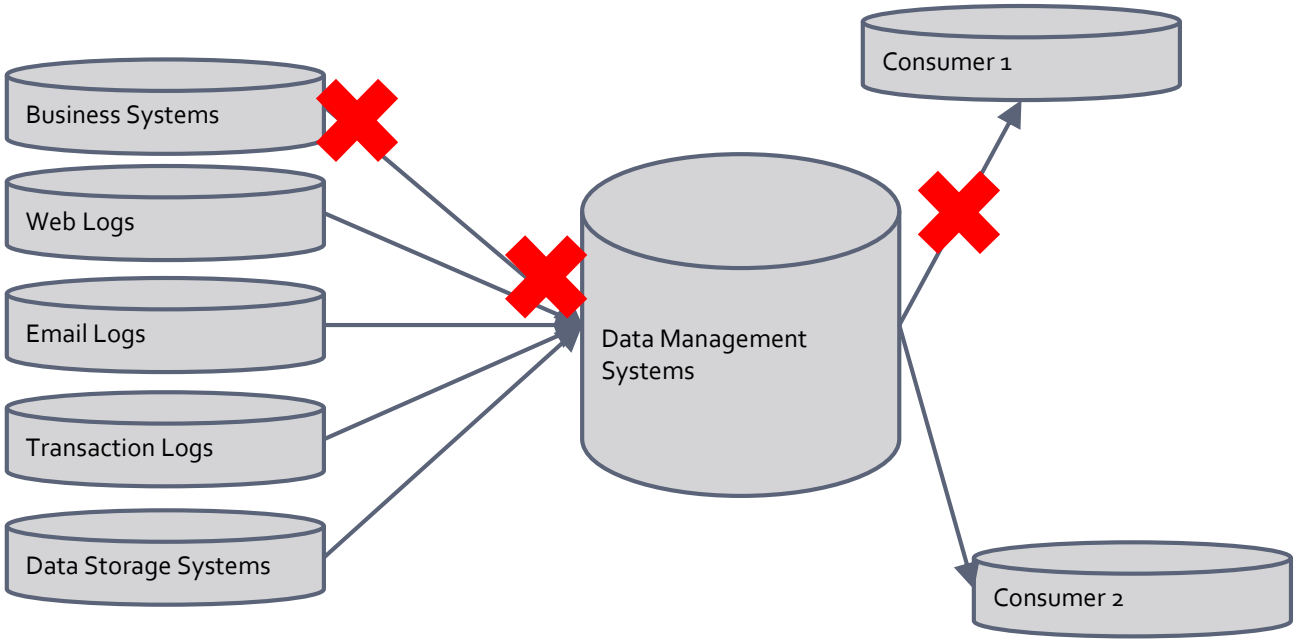


Challenge: Many Schemas



Different structures
Different manifest data types
Different literal for same data type
Different Keys

Challenge: Failures

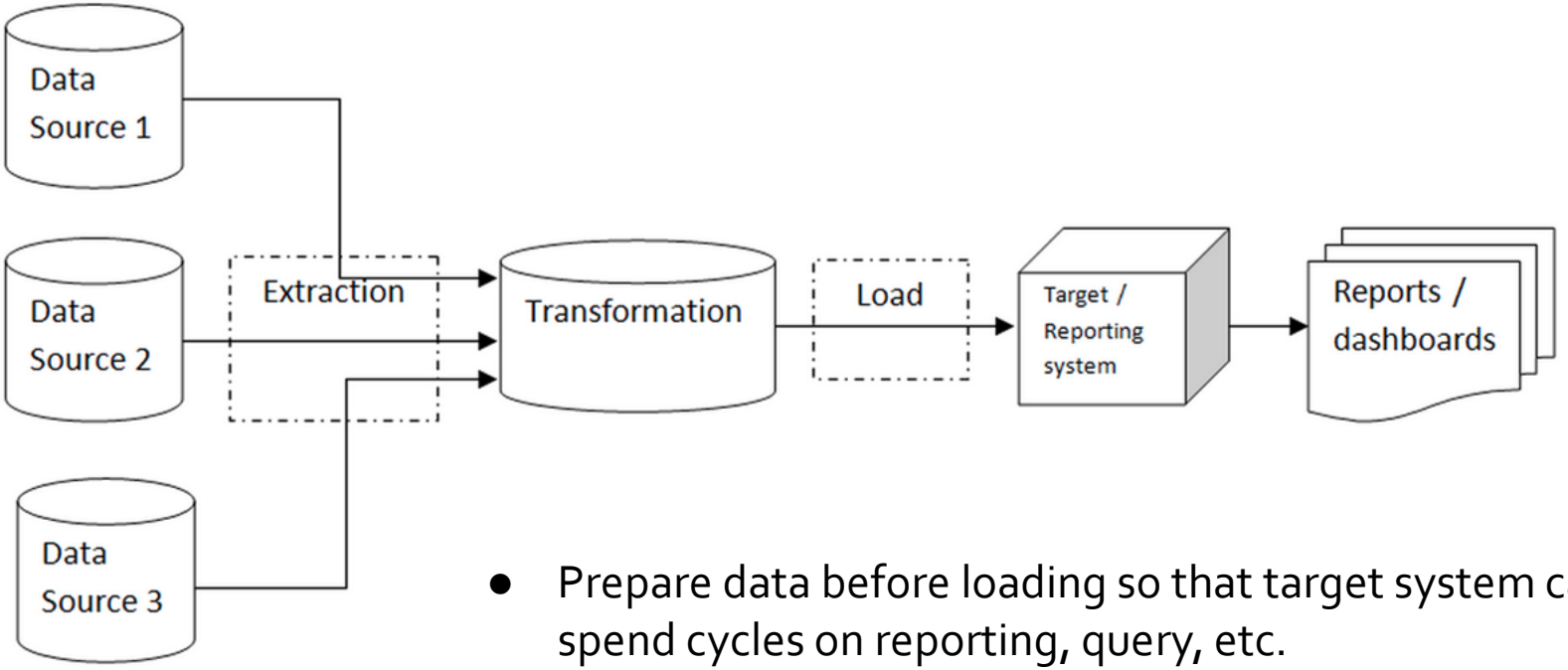


Failures when producers push data
Failures storing received data
Failures while transferring data over network

Data Bundle Semantics Examples

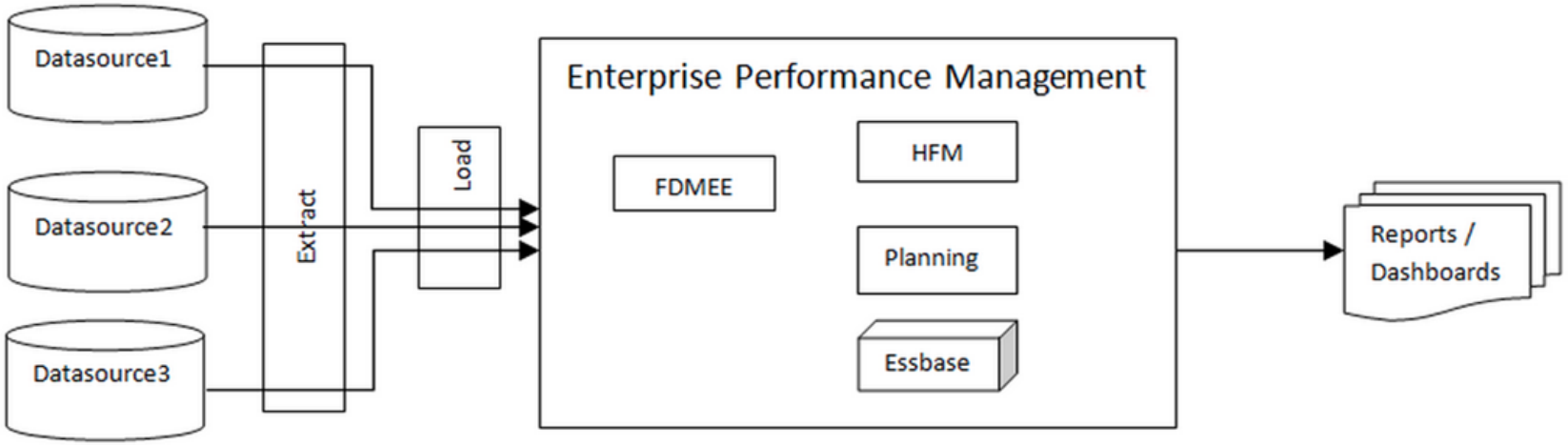
Full dumps	All data is provided at once and replaces all previous data.
Incremental	Increments are provided in any order, data interval in an increment is provided as metadata. On an hourly, daily or weekly cadence.
Append	Always appended at the end of the dataset. Order is assumed to be correct.
Stream	Stream of incoming data as individual rows or in small batches. On a second, minute or hourly cadence.

ETL: Extract, Transform, Load



- Prepare data before loading so that target system can spend cycles on reporting, query, etc.
- Requires transforms to know what reporting, query to enable

ELT: Extract, Load, Transform

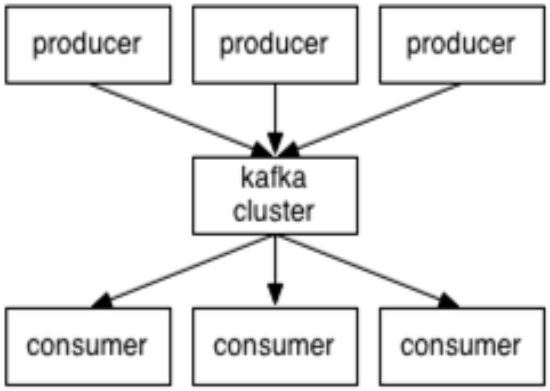


- Made possible by more powerful target systems
- Provides more flexibility at later stages than ETL

High Velocity Technologies

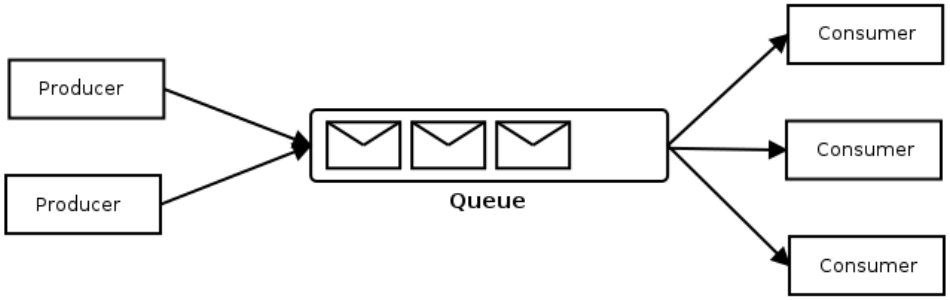
Kafka	Kafka is a distributed, partitioned, replicated commit log service. It provides the functionality of a messaging system, but with a unique design.
Kinesis	Amazon Kinesis is a fully managed, cloud-based service for real-time data processing over large, distributed data streams. Amazon Kinesis can continuously capture and store terabytes of data per hour from hundreds of thousands of sources.
S4	S4 is a general-purpose, distributed, scalable, fault-tolerant, pluggable platform that allows programmers to easily develop applications for processing continuous unbounded streams of data.
Storm	Apache Storm is a distributed realtime computation system. Storm makes it easy to reliably process unbounded streams of data, doing for realtime processing what Hadoop did for batch processing.
Samza	Apache Samza is a distributed stream processing framework. It uses Apache Kafka for messaging, and Apache Hadoop YARN to provide fault tolerance, processor isolation, security, and resource management.

Kafka Approach

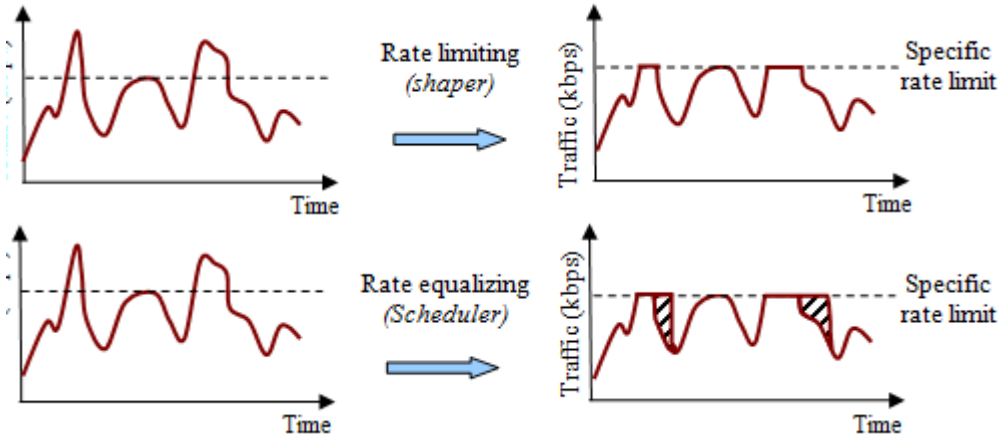


Scalability	Allows many producers and consumers. Partitions are the unit of scale.
Schema Variety	Does not really solve this.
Network Bottlenecks	Can handle some variability without losing messages.
Consumer Bottlenecks	Kafka acts as a buffer allowing producers and consumers to work at different speeds.
Bursts	Handles buffering of messages between producers and consumers.
Reliability, Fault Tolerance	Allows reading of messages if a consumer fails.

Bursts



- Data is produced in Bursts
- Consumers can only consume at a certain rate
- Dropping data can be a problem



Data Quality

Bad Data

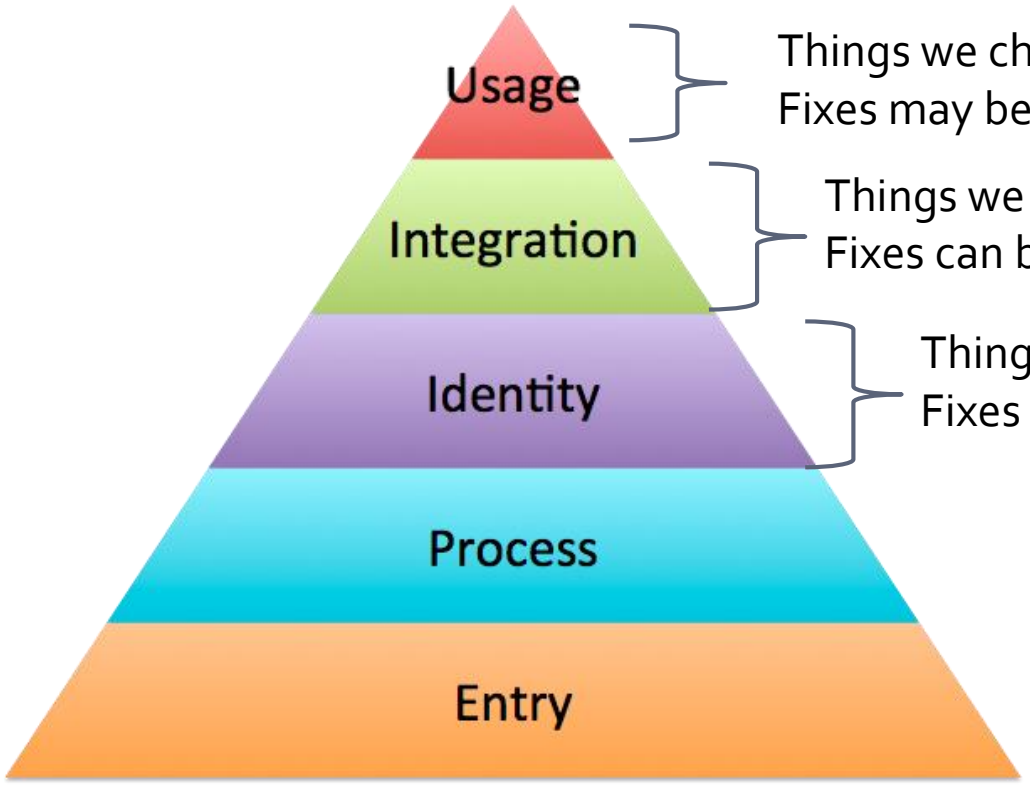
- Misspellings {Montgromery street}
- Outliers {1,2,4,2,4,123,3,4}
- Incorrect values {invalid zip, neg number}
- Missing values {6,7,4,3,,4,5,6}
- Incorrect values {94025, -345,96066,…}

So, What is Data Quality?

It depends!

- **Entry Quality**: Is the record entered correctly?
- **Process Quality**: Was the record correct throughout the system?
- **Identity Quality**: Are similar entities resolved to be the same?
- **Integration Quality**: Is the data sufficiently integrated to answer relevant questions?
- **Usage Quality**: Is the data being used correctly?
  - *Age Quality*: Is the data new-enough to be trusted?

Data Quality as a Hierarchy



Things we check **in the organization**.
Fixes may be non-technical.

Things we check **in architecture**.
Fixes can be costly!

Things we check across **many data sets**.
Fixes may need extra intelligence.

Things we check **in single record sets** and **data streams**.
Fixes can be automatic and independent.

Data Quality Framework

Quality Evaluation Framework

Observation

- It's too expensive to clean **all** the data **every** way
- How do we decide what to clean?

We need **a framework** that helps to:

- Determine what issues might occur in the data
- Weight the criticality of the issues
- Profile the data to score quality

The framework allows:

- to approach quality as an ever-increasing **standard**
- To **prioritize** data cleaning activities

Quality Issues for Single Streams

Definitional

Constants
Definition Mismatches
Filler Containing Data
Inconsistent Cases
Inconsistent Data Types
Inconsistent Null Rules

Incorrect

Invalid Keys
Invalid Values
Miscellaneous
Missing Values
Orphans
Out of Range

Too-Soon-to-Tell

Pattern Exceptions
Potential Constants
Potential Defaults
Potential Duplicates
Potential Invalids
Potential Redundant Values
Potential Unused Fields
Rule Exceptions
Unused Fields

Weighting Issues

Weight Factor	Issue Type
1	Constants
2	Definition Mismatches
2	Filler Containing Data
1	Inconsistent Cases
2	Inconsistent Data Types
3	Inconsistent Null Rules
5	Invalid Keys
5	Invalid Values

- Issues should be weighted in the context of our system
- Invalid or missing data is most problematic
- Potentially issues can be weighted lower

Assessing Quality

Weight	Issue Type	Discovered	Possible
1	Constants	1	59
2	Definition Mismatches	4	59
2	Filler Containing Data	1	59
1	Inconsistent Cases	3	59
2	Inconsistent Data Types	15	59
3	Inconsistent Null Rules	6	59
5	Invalid Keys	1	3
5	Invalid Values	5	59

- Any issue has a possible maximum
- This can be cardinality of
  - Rows
  - Keys
  - etc.

Quality Score

Raw Score	91.3%
Weighted Score	90.4%

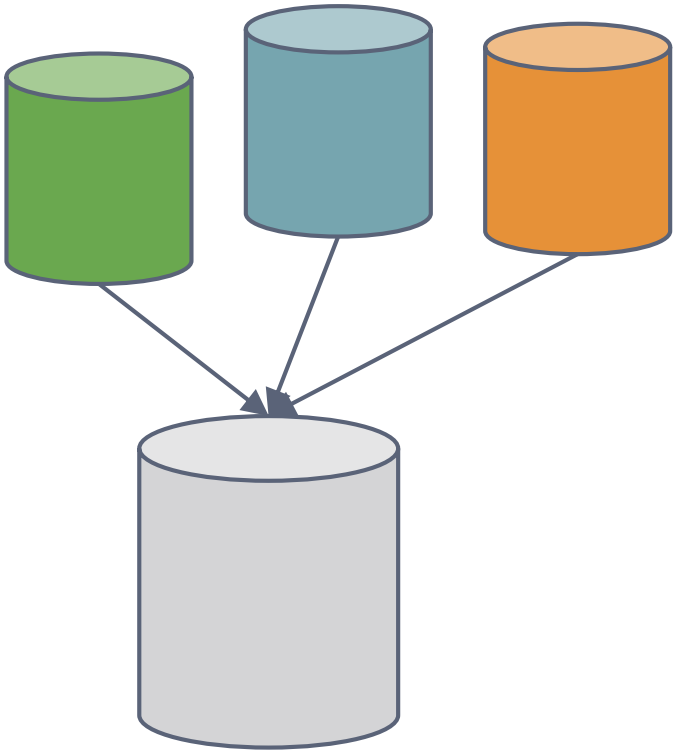
Missing Values

Approaches

- Nuclear Option: Listwise Removal
  - If a record has a missing value → Ignore the entire record in analyses
- Softer Option: Pairwise Removal
  - If a record has a missing value → Ignore the record iff the missing value is in the analyzed set
- Infer Substitute Values
  - *Statistical* (*Interpolation):* predict new data points in the range of a set (Simple linear, Splines, Kriging)
  - *Model-based*: Impute missing values based on a model (EM algorithm, etc.)

Entity Resolution/ Record Linkage

Entity Resolution/Record Lineage



What is it?

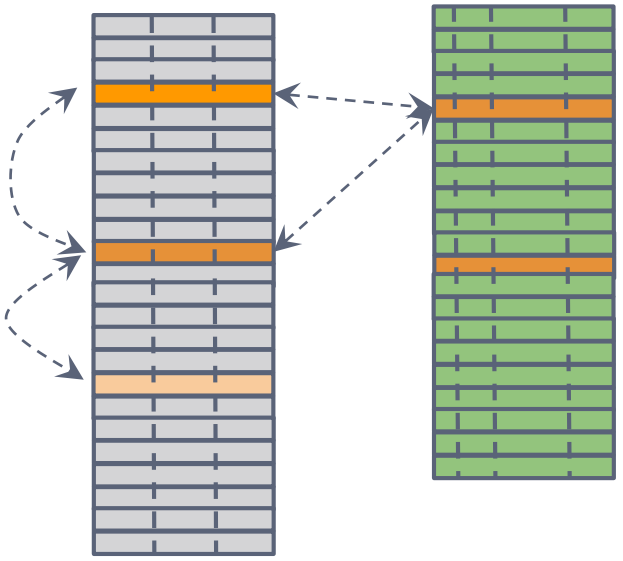
The task of finding records in a data set that refer to the same entity across different data sources

Problems

- Attributes/records not matching 100%
- How to apply to different/ changing data sets
- Missing values
- Data quality, errors etc.
- Semantic relations

Core Problems (to address)

- Normalize data
- Link records on a table
- Link records cross tables



Customer (source 1)

CID	*Name*	*Street*	*City*	*Sex*
11	Kristen Smith	2 Hurley Pl	South Fork, MN 48503	0
24	Christian Smith	Hurley St 2	S Fork MN	1

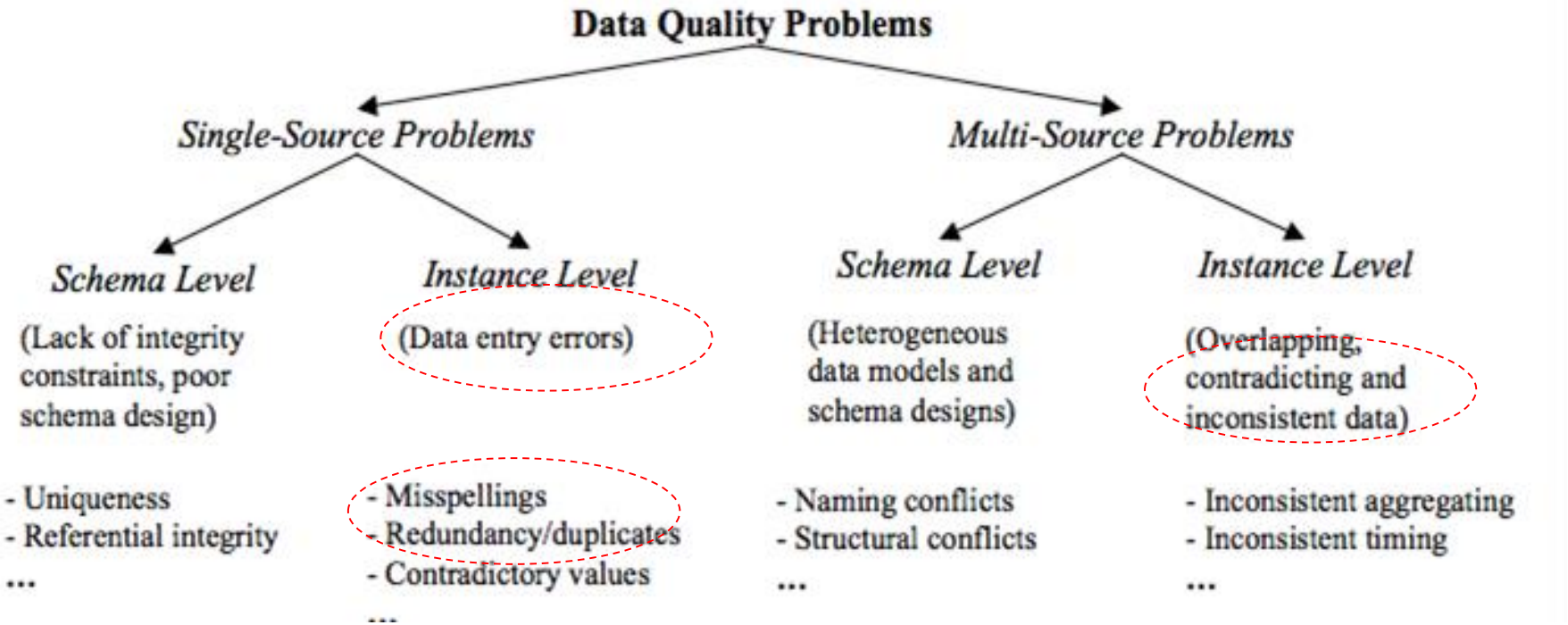
Client (source 2)

Cno	*LastName*	*FirstName*	*Gender*	*Address*	*Phone/Fax*
24	Smith	Christoph	M	23 Harley St, Chicago IL, 60633-2394	333-222-6542 / 333-222-6599
493	Smith	Kris L.	F	2 Hurley Place, South Fork MN, 48503-5998	444-555-6666

Customers (integrated target with cleaned data)

No	*LName*	*FName*	*Gender*	*Street*	*City*	*State*	*ZIP*	*Phone*	*Fax*	*CID*	*Cno*
1	Smith	Kristen L.	F	2 Hurley Place	South Fork	MN	48503-5998	444-555-6666		11	493
2	Smith	Christian	M	2 Hurley Place	South Fork	MN	48503-5998			24	
3	Smith	Christoph	M	23 Harley Street	Chicago	IL	60633-2394	333-222-6542	333-222-6599		24

Types of Problems



Single-source Cleaning

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

Scope/Problem		Dirty Data	Reasons/Remarks
Attribute	Illegal values	bdate=30.13.70	values outside of domain range
Record	Violated attribute dependencies	age=22, bdate=12.02.70	age = (current date – birth date) should hold
Record type	Uniqueness violation	emp_1=(name="John Smith", SSN="123456") emp_2=(name="Peter Miller", SSN="123456")	uniqueness for SSN (social security number) violated
Source	Referential integrity violation	emp=(name="John Smith", deptno=127)	referenced department (127) not defined

Deterministic vs. Fuzzy Methods

Deterministic

- rules + record level match

Fuzzy

- Match similar values and records and attempt to determine if *match*, *no match* or *possible match*

Deterministic Approach

Deterministic: rules + attribute level match

Data Set	#	SSN	Name	DOB	Sex	ZIP
Set A	1	000956723	Smith, William	1973/01/02	Male	94701
	2	000956723	Smith, William	1973/01/02	Male	94703
	3	000005555	Jones, Robert	1942/08/14	Male	94701
	4	123001234	Sue, Mary	1972/11/19	Female	94109
Set B	1	000005555	Jones, Bob	1942/08/14		
	2		Smith, Bill	1973/01/02	Male	94701

if **a.SSN** == **b.SSN** => match
if (missing(**a.SSN**) or missing(**b.SSN**)) =>
if ((**a.dob** == **b.dob**) and (**a.zip** == **b.zip**) and (**a.sex** == **b.sex**)) => match

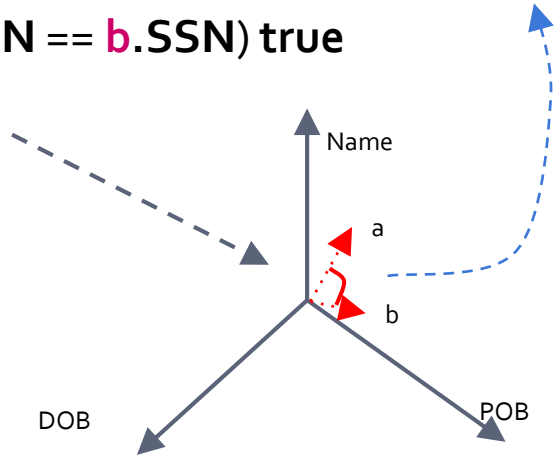
Fuzzy Approach

Fuzzy: similarity of attribute + distance of record + match thresholds + learning

SSN	Name	DOB	Place of Birth
605782877	Nilsson	1/14/76	Sainte-Paul
<missing>	Smith	8/8/68	Barstow
762009827	Smyth	<m>/8/68	Barstow
720384793	Carlson	8/8/68	Barstow
<missing>	Nilson	1/14/76	Minnesota
<missing>	Nilsson	1/13/76	Saint-Paul

match,
non-match,
possible match

if (**a**.**SSN** == **b**.**SSN**) **true**
else

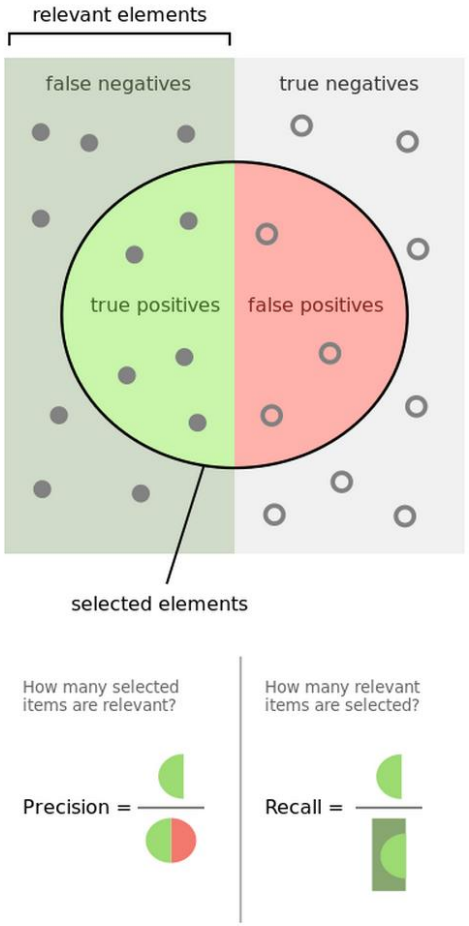


Fuzzy Approach

Recall vs Precision

Fuzzy + rules => practice

“Generate rules” by using machine learning



Similarity Metrics

- Levenshtein Distance (Edit Distance)
- Jaro Distance
- Jaro-Winkler Distance

Levenshtein Distance/ Edit Dist.

- Minimum number of single character edits:
  - Insert
  - Delete
  - Substitute

Stokcholm -> Stockholm *{Distance = 2}*

sanfransicso-> san francisco *{Distance = 4}*

sanfransicso-> San Francisco *{Distance = 6}*

Levenshtein

Step	Description
1	Set n to be the length of s. Set m to be the length of t. If n = 0, return m and exit. If m = 0, return n and exit. Construct a matrix containing 0..m rows and 0..n columns.
2	Initialize the first row to 0..n. Initialize the first column to 0..m.
3	Examine each character of s (i from 1 to n).
4	Examine each character of t (j from 1 to m).
5	If s[i] equals t[j], the cost is 0. If s[i] doesn't equal t[j], the cost is 1.
6	Set cell d[i,j] of the matrix equal to the minimum of: a. The cell immediately above plus 1: d[i-1,j] + 1. b. The cell immediately to the left plus 1: d[i,j-1] + 1. c. The cell diagonally above and to the left plus the cost: d[i-1,j-1] + cost.
7	After the iteration steps (3, 4, 5, 6) are complete, the distance is found in cell d[n,m].

Steps 1 and 2

		G	U	M	B	O
	0	1	2	3	4	5
G	1					
A	2					
M	3					
B	4					
O	5					
L	6					

Steps 3 to 6 When i = 1

		G	U	M	B	O
	0	1	2	3	4	5
G	1	0				
A	2	1				
M	3	2				
B	4	3				
O	5	4				
L	6	5				

Steps 3 to 6 When i = 2

		G	U	M	B	O
	0	1	2	3	4	5
G	1	0	1			
A	2	1	1			
M	3	2	2			
B	4	3	3			
O	5	4	4			
L	6	5	5			

Steps 3 to 6 When i = 3

		G	U	M	B	O
	0	1	2	3	4	5
G	1	0	1	2		
A	2	1	1	2		
M	3	2	2	1		
B	4	3	3	2		
O	5	4	4	3		
L	6	5	5	4		

Steps 3 to 6 When i = 4

		G	U	M	B	O
	0	1	2	3	4	5
G	1	0	1	2	3	
A	2	1	1	2	3	
M	3	2	2	1	2	
B	4	3	3	2	1	
O	5	4	4	3	2	
L	6	5	5	4	3	

Steps 3 to 6 When i = 5

		G	U	M	B	O
	0	1	2	3	4	5
G	1	0	1	2	3	4
A	2	1	1	2	3	4
M	3	2	2	1	2	3
B	4	3	3	2	1	2
O	5	4	4	3	2	1
L	6	5	5	4	3	2

distance

Other Algorithms

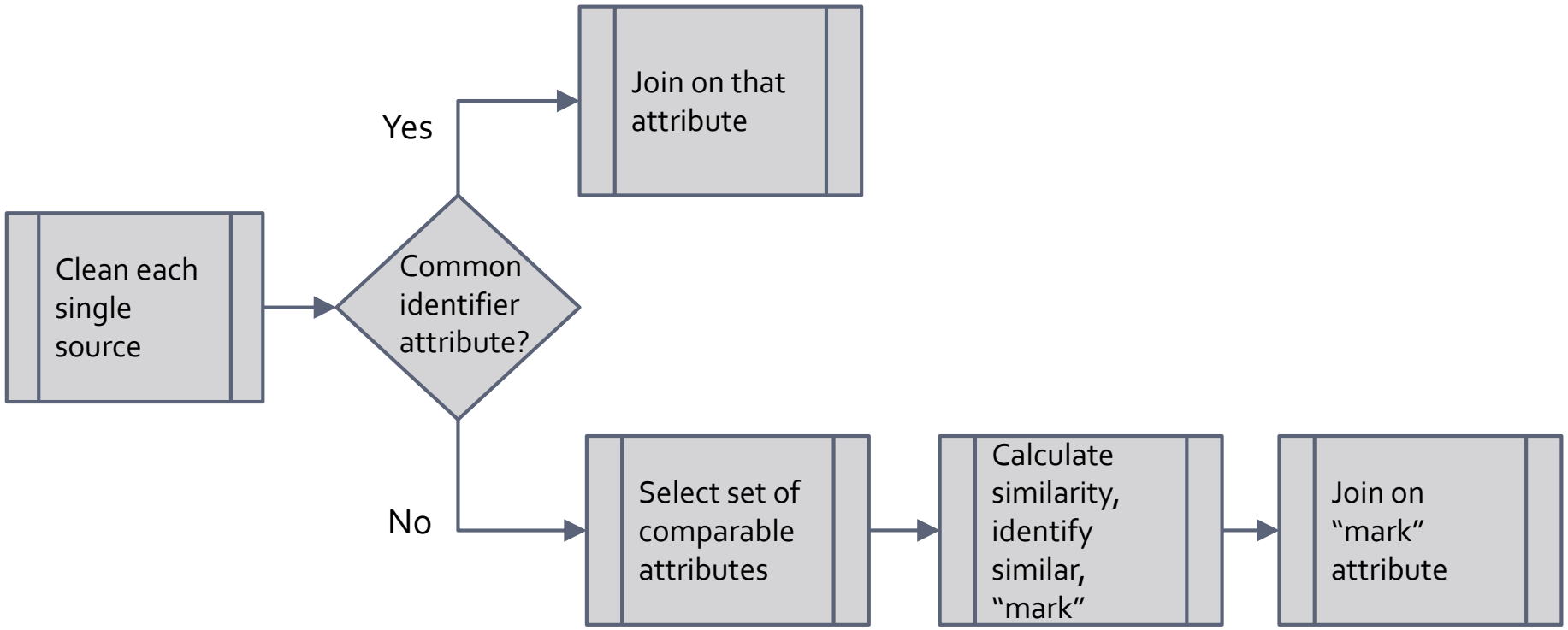
- Hamming Distance
- Damerau-Levenshtein Distance
- Longest Common Substring Distance
- Cosine Distance
- Jaccard Distance
- Jaro Distance
- N-grams

Multi-source Cleaning

Summary of problem

- Assume you want to link records across sources that do not share a common record key
  - These records may have data quality issues
- How would you create such **linkage** using fuzzy and deterministic methods?

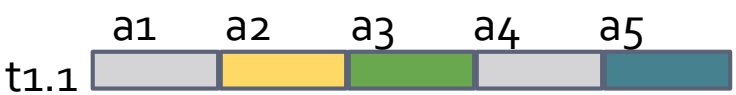
Multi Source Approach

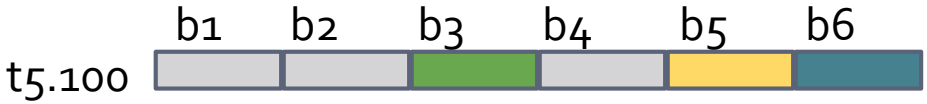


Fuzzy Methods, Multi-records

- Defining similarity is application specific
- Assume you have no common, unique key
- What can you do to identify similar record in different (or the same) source
- Example:
  - Cosine similarity for numeric /continuous attributes
  - Edit distance for strings
  - Jaccard for binary or categorical values

Principle (No unique key)





We map columns:

a2<->b5

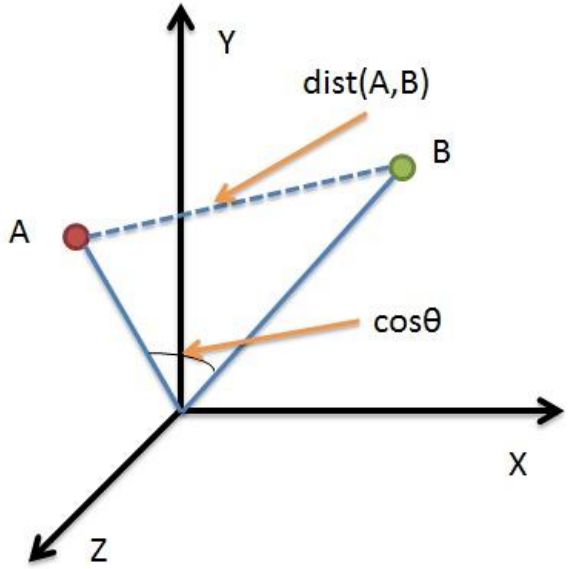
a3<->b3

a5<->b6

Compare record 1 from table 1, with record 100 from table 5.
Are they representing the same entity?
Are the attributes continuous, categorical, string, etc.?

Continuous Attributes

For **continuous attributes** we can calculate cosine distance




```
Let d1 = 20 30 40
Let d2 = 10 30 50
Cosine Similarity (d1, d2) =  dot(d1, d2) / ||d1|| ||d2||dot(d1, d2

||d1|| = sqrt((20)^2 + (30)^2 + (40)^2) = 53.8516480713

||d2|| = sqrt((10)^2 + (30)^2 + (50)^2) = 59.160797831

Cosine Similarity (d1, d2) = 3100 / (53.8516480713) * (59.160797831
                           = 3100 / 3185.90646441
                           = 0.97303547189
```

Strings and Categorical Attrib.

String: calculate an {edit} distance.

Categorical: bit vectors (0/1) for *different/same*

For sets of binary or categorical

The **Jaccard distance**, which measures *dis*similarity between sample sets, is complementary to the Jaccard coefficient and is obtained by subtracting the Jaccard coefficient from 1, or, equivalently, by dividing the difference of the sizes of the union and the intersection of two sets by the size of the union:

$$d_J(A,B) = 1 - J(A,B) = \frac{|A \cup B| - |A \cap B|}{|A \cup B|}.$$

Example Record Similarity

Score = cosine distance of **continuous attributes** +
normalized score of **string similarities** +
weighted score of **categorical values**

score = w_1*(cd(cont(r_1,r_5)))+w_2*(ed($r_1.a_n$,ry.by))+w_3*(compare($r_1.a_k$,$r_5.a_l$))

Cosine distance

Ps. this just an illustration, how to model similarity is application specific.

You define *score* ranges for ***same***, ***possibly same***, ***not same*** using **thresholds**

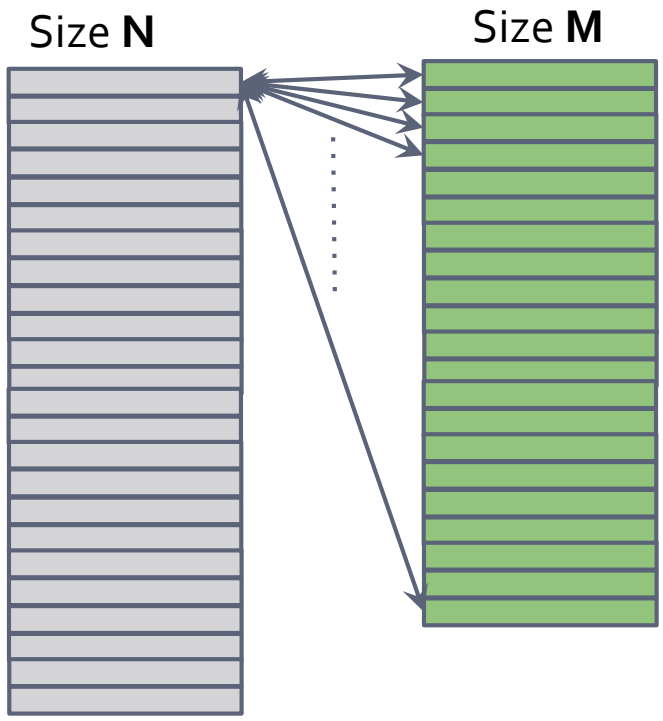
Scaling Record Linkage

Goal

Entity matching can be very computationally intensive. How to scale it?

- Understand basic **scaling techniques**
- Understand the techniques **pros** and **cons**

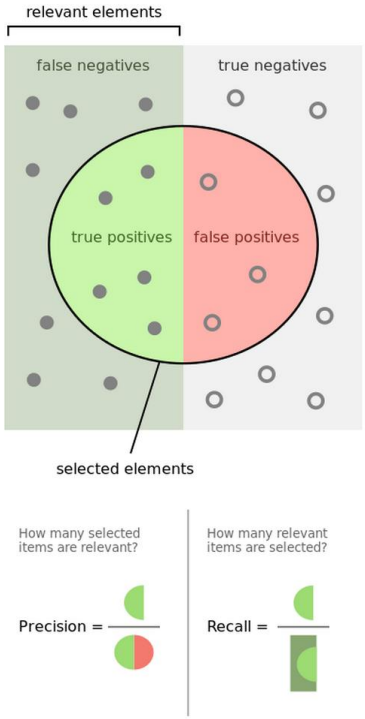
Scale/Efficiency Issues



- Polynomial complexity
- **N*M** record comparisons
- Expensive comparison operations
- May require multiple passes over the data

Concerns

Precision and Recall

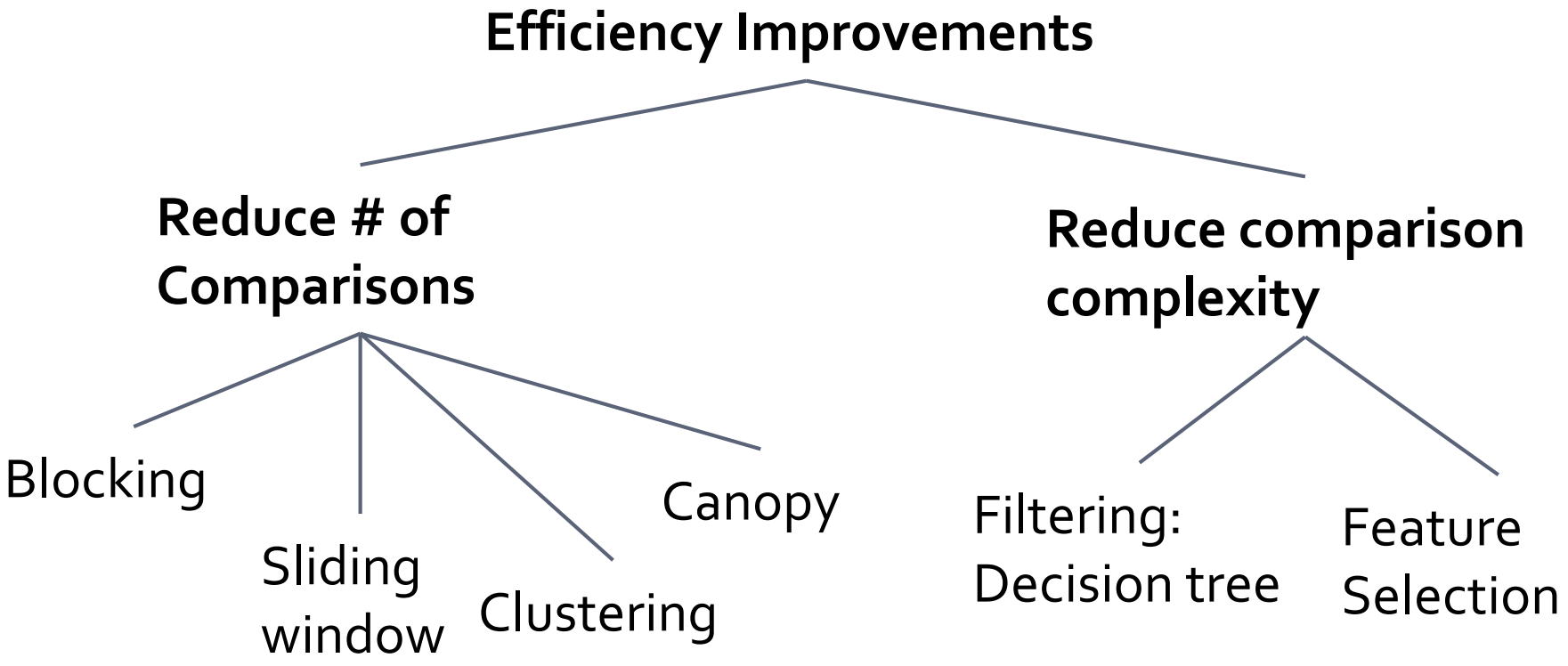


Efficiency

MB of processed data/
cost of infrastructure

Processing Time

Ways to Cope With Complexity



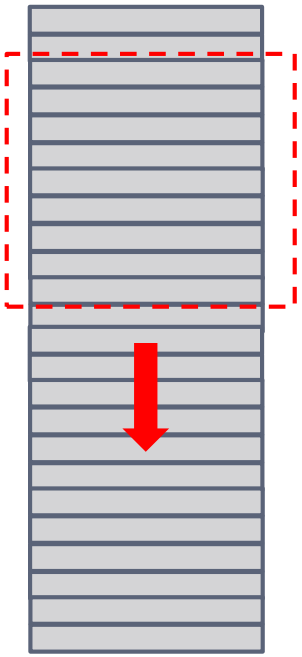
Reduce # of Comparisons

Sliding Window

- Create key from relevant data
- Sort on key
- Compare records in sliding window

Pros: Fewer comparison

Cons: Sensitivity to key selection, missed matches



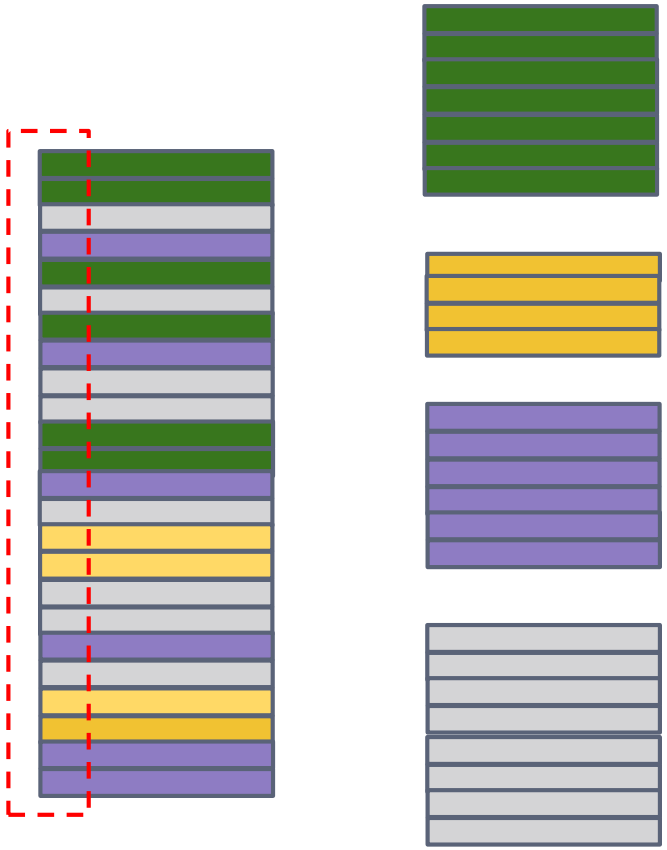
Reduce # of Comparisons

Blocking

- Define a blocking key
- Create blocks
- Compare within blocks

Pros: fewer comparisons

Cons: missed matches



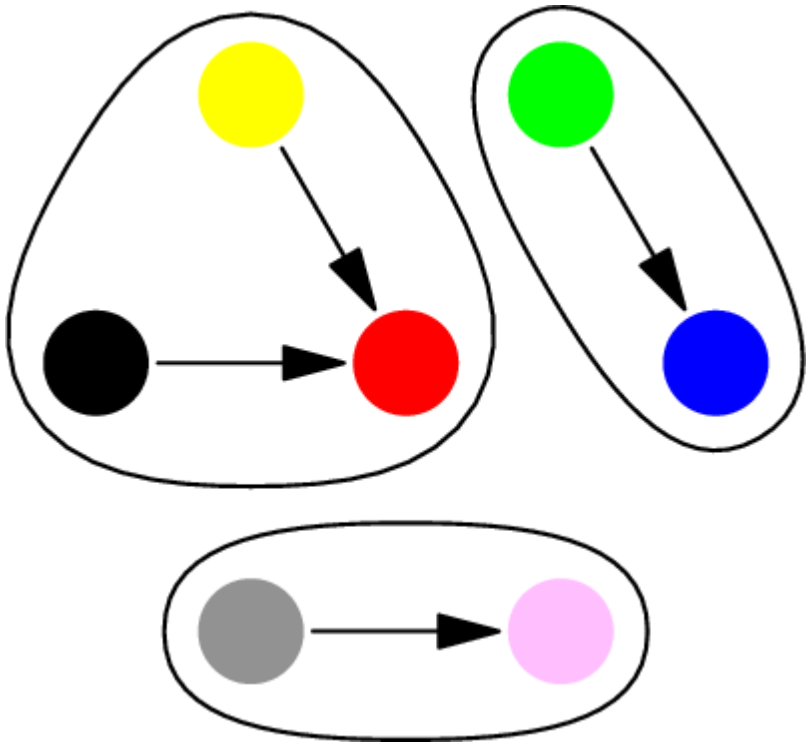
Reduce # of Comparisons

Clustering

- Similarity is transitive
- a->b->c
- Union-find algorithm

Pros: Fewer comparison

Cons: Potentially complex computation



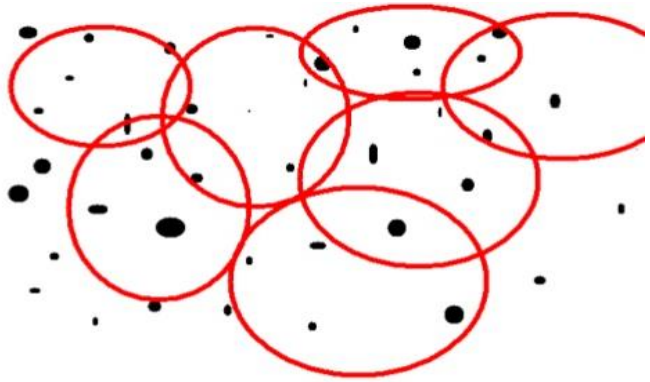
Reduce # of Comparisons

Canopy Clustering

- Records can belong to multiple canopies
- Cluster into canopies using "cheap" algorithm

Pros: Fewer comparison

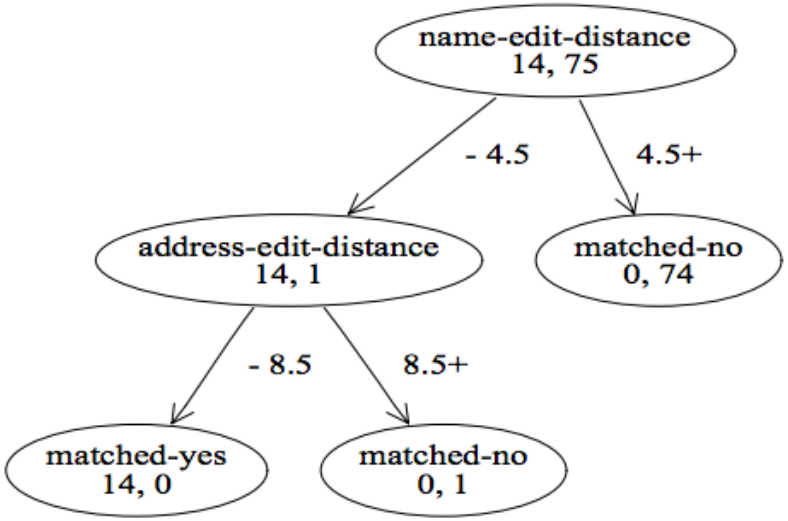
Cons: Sensitivity to key selection, missed matches



1. Begin with the set of data points to be clustered.
2. Remove a point from the set, beginning a new 'canopy'
3. For each point left in the set, assign it to the new canopy if the distance less than the loose distance
4. If the distance of the point is additionally less than the tight distance , remove it from the original set
5. Repeat from step 2 until there are no more data points in the set to cluster
6. Clustered canopies are sub-clustered using an expensive but accurate algorithm

Reduce Comparison Complexity

Decision Tree



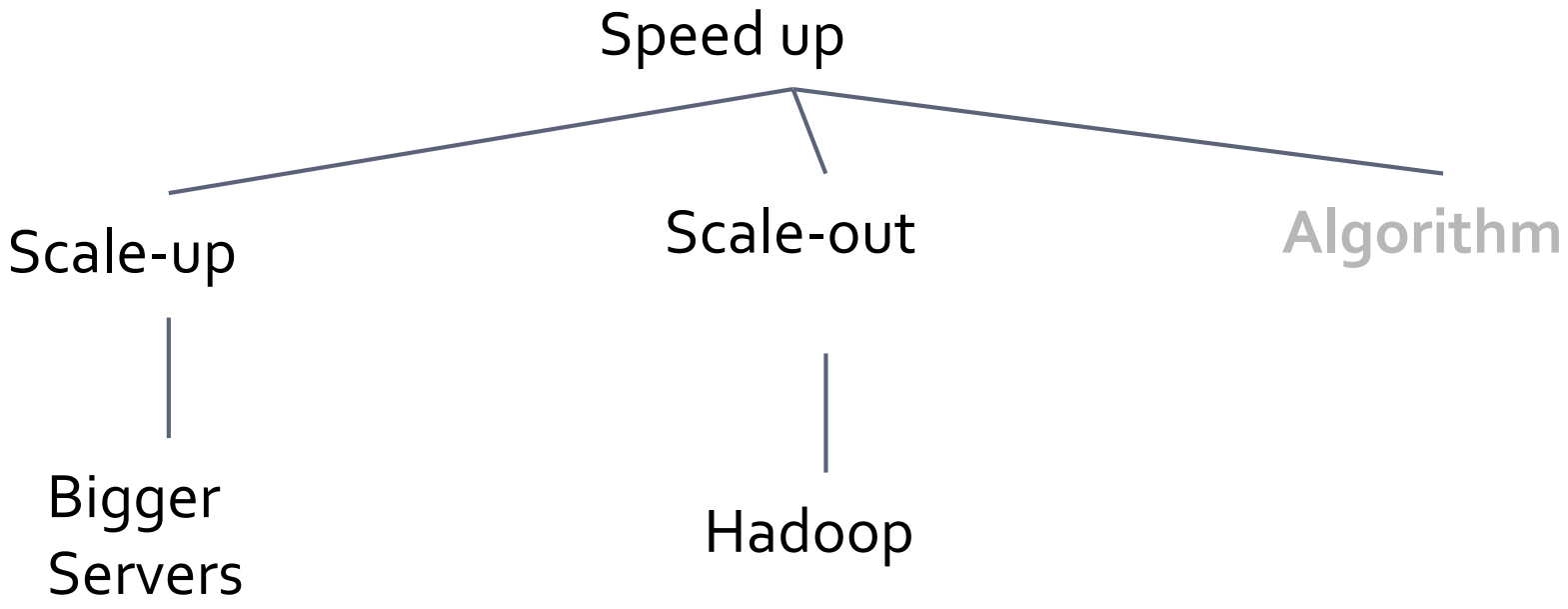

```
if  name-edit-distance < 4.5 and address-edit-distance < 8.5
   then class=matched-yes with certainty factor 1.0
if  name-edit-distance < 4.5 and address-edit-distance >= 8.5
   then class=matched-no with certainty factor 1.0
if  name-edit-distance >= 4.5
   then class=matched-no with certainty factor 1.0
```

Figure 2: The rule set produced by translating the information in the induced decision tree.

```
if  name-edit-distance < 4.5
   then class=matched-yes with certainty factor 0.933
if  name-edit-distance >= 4.5
   then class=matched-no with certainty factor 1.0
```

Figure 3: The rule set produced by simplifying the initial rule set.

Processing Time



Data cleaning
Hands-on Activity

Cleaning Tools

- OpenRefine (ex Google Refine)
  - Watch Introduction (6:48)
    - https://www.youtube.com/watch?v=B70J_H_zAWM
  - Install Open Refine (and Java if needed)
    - http://openrefine.org/
  - Download a data set
    - City of Berkeley Employee Salaries - 2013 Data from the link: https://data.cityofberkeley.info/Economic-Data/City-of-Berkeley-Employee-Salaries-2013/ifen-52iq
  - Create a new OpenRefine Project and load the data
  - Try to answer a few Questions below

Questions/Queries

Q1: Who gets the highest base pay in the city?

Q2: Who gets the highest 'total pay + benefits' in the city?

Q3: Group all police related job titles to a 'Police' job title

Q4: Export all information related to 'Police' jobs to a new CSV file