UNSW SYDNEY | Australia's Global University

COMP9321

Data Services Engineering

Term 1, 2019

Week 2 Lecture 2

Data Cleansing and Integration

COMP9321 2019T1

Credit to ***Washington University, Carnegie Mellon University The University of Manchester***

Data Cleaning Activities

1. Extraction from sources
 Technical and syntactic obstacles
2. Transformation
 Schematic obstacles
3. Standardization
 Syntactic and semantic obstacles
4. Duplicate detection
 Similarity functions
 Algorithms
5. Data fusion / consolidation /integration
 Semantic obstacles
6. Loading into warehouse / presenting to user

Data Standardization / Normalization Terminology

Transformation

- Applying a function to each point z in the data: $y_i = f(z_i)$

Scaling

- Converting data to a different scale (like Celsius and Fahrenheit). Typically linear: $y = ax + b$

Normalization

- Either applying a transformation so that you transformed data is roughly normally distributed
- Or it can also mean putting different variables on a common scale (in this case it is a.k.a scaling)

Reasons to normalize and transformation

Easy comparison of values

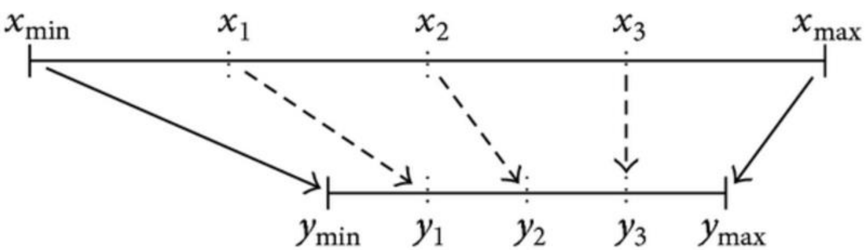
In some algorithms, objective functions will not work properly (or quickly) without it

Can create complex features that may improve the model (or make it non-linear)

Min-Max normalization

- Min/Max normalization to [0,1]

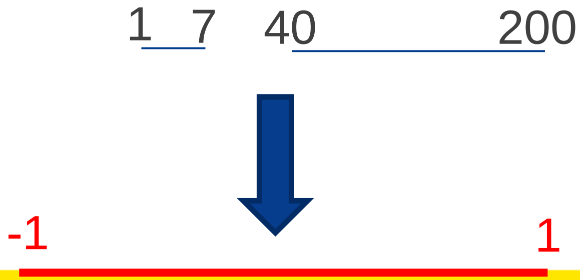
$$X_{i,\,0\text{ to }1} = \frac{X_i - X_{Min}}{X_{Max} - X_{Min}}$$



- Min/Max normalization to [-1,1]

  (if we want 0 to be the central point)

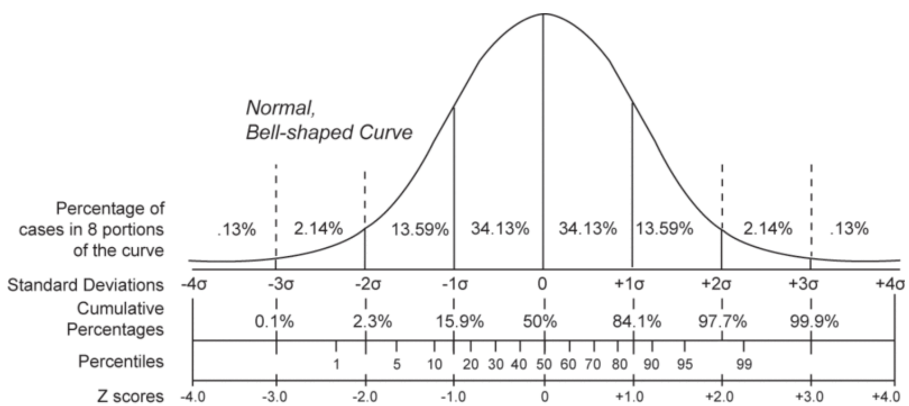
$$X_{i,-1\text{ to }1} = \frac{2X_i - X_{Min} - X_{Max}}{X_{Max} - X_{Min}}$$



Z-normalization

- Subtracting the mean and dividing by the standard deviation
- Mean becomes 0, units are s.d.

$$X_{i,\,1\sigma} = \frac{X_i - \bar{X}_S}{\sigma_{X,\,S}}$$



Log normalization

Used when values are ranged over several orders of magnitude.

$$X' = a*\log_b(X)$$

Choosing normalization method

Large range of data: (i.e. $4 to $120,000,000)

- Log transformation is often good

Skewed data (often large range)

- Log transformation is often good

If entropy is high → usually normalizing to [-1,1] is good

If entropy is low → often z-standardization is good

If near normally distributed → z-standardization is good

Transformations for increasing model complexity

- Can transform features in various ways
- log(X), 1/X, X^2 etc….

- Can lead us to non-linear models

- The more complex your model, the higher the likelihood of overfitting (next lesson)

For nature languages…

- Abstract concepts are **difficult to represent**

- **“Countless” combinations** of subtle, abstract relationships among concepts

- **Many ways** to represent similar concepts

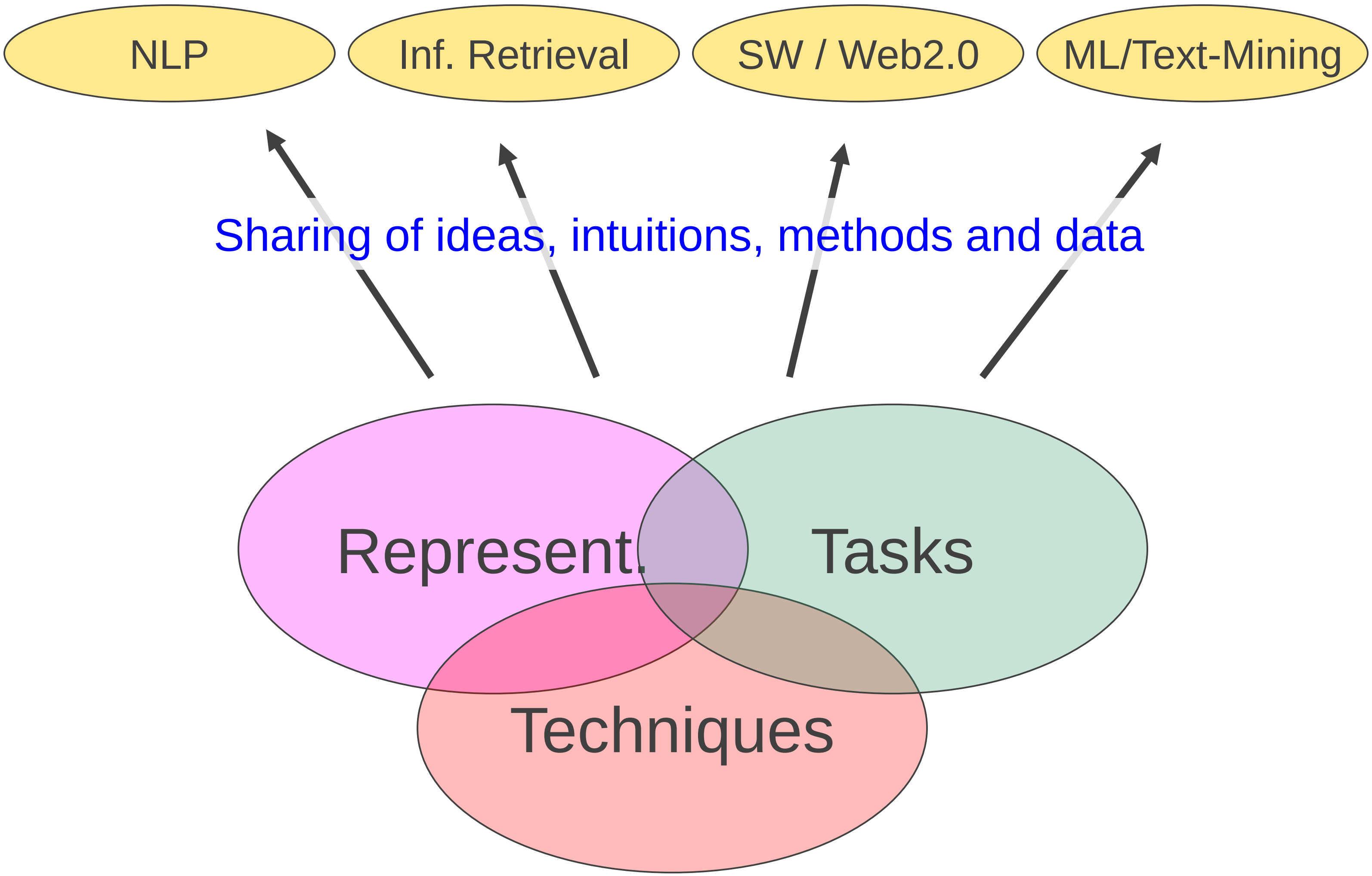
For nature languages…

For example…

- **Sant Martí** and **Sant Marti**
- **Meridiana** and **Av Meridiana**
- **Spaceship** and **Spacecraft**
- **International Business Machines** and **IBM**

We need a more consistent representation

The complex story…



Levels of text representations

Character (character n-grams and sequences)
Words (stop-words, stemming, lemmatization)
Phrases (word n-grams, proximity features)
Part-of-speech tags
Taxonomies / thesauri

Lexical

Vector-space model
Language models
Full-parsing
Cross-modality

Syntactic

Collaborative tagging / Web2.0
Templates / Frames
Ontologies / First order theories

Semantic

Tokenization

The protein is activated by IL2.

The protein is activated by IL2 .

Tokenizing general English sentences is relatively straightforward.

Use spaces as the boundaries

Use some heuristics to handle exceptions

Tokenization

The protein is activated by IL2.

The protein is activated by IL2 .

Convert a sentence into a sequence of tokens

Why do we tokenize?

Because we do not want to treat a sentence as a sequence of characters!

Tokenisation issues

separate possessive endings or abbreviated forms from preceding words:

- Mary’s $\rightarrow$ Mary ‘s
  Mary’s $\rightarrow$ Mary is
  Mary’s $\rightarrow$ Mary has

separate punctuation marks and quotes from words :

- Mary. $\rightarrow$ Mary .
- “new” $\rightarrow$ “ new “

Tokenization

Tokenizer.sed: a simple script in sed

- –http://www.cis.upenn.edu/~treebank/tokenization.html

Undesirable tokenization

- original: “1,25(OH)2D3”
- tokenized: “1 , 25 (OH) 2D3”

Tokenization for biomedical text

- Not straight-forward
- Needs dictionary? Machine learning?

Normalization

Need to "normalize" terms

- Information Retrieval: indexed text & query terms must have same form.
  - –We want to match ***U.S.A.*** and ***USA***

We implicitly define equivalence classes of terms

- e.g., deleting periods in a term

Alternative: asymmetric expansion:

- Enter: ***window***Search: ***window, windows***
- Enter: ***windows*** Search: ***Windows, windows, window***
- Enter: ***Windows*** Search: ***Windows***

Potentially more powerful, but less efficient

Case folding

Applications like IR: reduce all letters to lower case

- Since users tend to use lower case
- Possible exception: upper case in mid-sentence?
  - e.g., ***General Motors***
  - ***Fed*** vs. ***fed***
  - ***SAIL*** vs. ***sail***

For sentiment analysis, MT, Information extraction

- Case is helpful (***US*** versus ***us*** is important)

Lemmatization

Reduce inflections or variant forms to base form

- *am, are, is* → *be*
- *car, cars, car's*, *cars'* → *car*

the boy's cars are different colors → *the boy car be different color*

Lemmatization: have to find correct dictionary headword form

Machine translation

- Spanish quiero (‘I want’), quieres (‘you want’) same lemma as querer ‘want’

Morphology

Morphemes:

- The small meaningful units that make up words
- **Stems**: The core meaning-bearing units
- **Affixes**: Bits and pieces that adhere to stems
  - Often with grammatical functions

Stemming

Reduce terms to their stems in information retrieval

Stemming is crude chopping of affixes

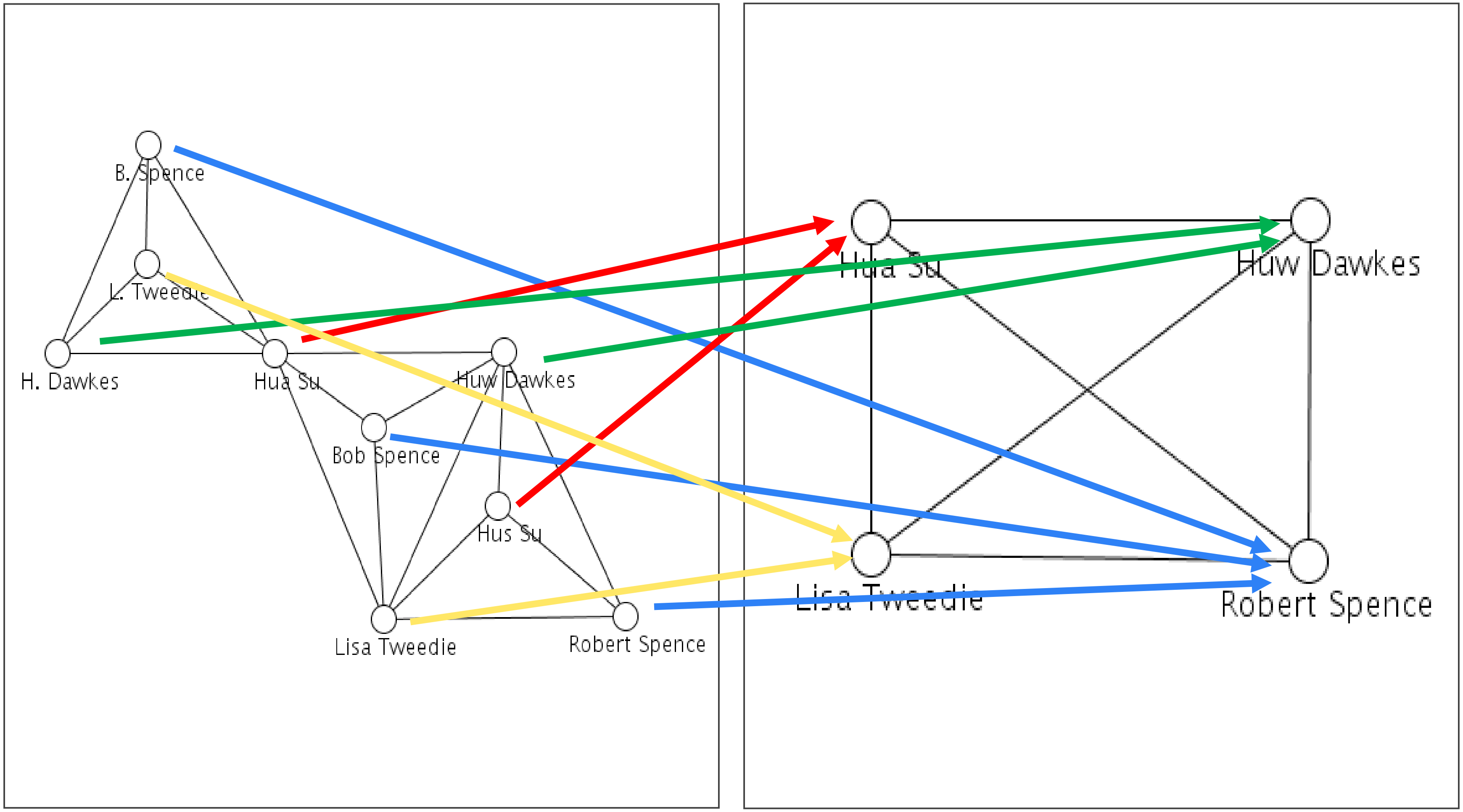
- language dependent
- e.g., ***automate(s), automatic, automation*** all reduced to ***automat***.

for example compressed and compression are both accepted as equivalent to compress.

→

for exampl compress and compress ar both accept as equival to compress

Example: Network Analysis



before after

What is Duplicates Detection?

Problem of identifying and linking/grouping different manifestations of the same real world object.

Examples of manifestations and objects:

Different ways of addressing (names, email addresses, FaceBook accounts) the same person in text.

Web pages with differing descriptions of the same business.

Different photos of the same object.

…

Ironically, Entity Resolution has many duplicate names

Record linkage

Duplicate detection

Coreference resolution

Reference reconciliation

Fuzzy match

Object consolidation

Object identification

Deduplication

Entity clustering

Approximate match

Identity uncertainty

Merge/purge

Household matching

Hardening soft databases

Householding

Reference matching

Doubles

Common Methods

- Pairwise Comparison Algorithms
- Algorithms for Complex Relationships
- Clustering

Pairwise Match Score

Problem: Given a vector of component-wise similarities for a pair of records (x,y), compute P(x and y match).

Solutions:

1. Weighted sum or average of component-wise similarity scores. Threshold determines match or non-match.
   - 0.5*1st-author-match-score + 0.2*venue-match-score + 0.3*paper-match-score.
   - Hard to pick weights.
     - Match on last name match *more predictive* than login name.
     - Match on “Smith” *less predictive* than match on “Getoor” or “Machanavajjhala”.
   - Hard to tune a threshold.

Pairwise Match Score

Problem: Given a vector of component-wise similarities for a pair of records (x,y), compute P(x and y match).

Solutions:

1. Weighted sum or average of component-wise similarity scores. Threshold determines match or non-match.
2. Formulate rules about what constitutes a match.
   - (1st-author-match-score > 0.7 AND venue-match-score > 0.8) OR (paper-match-score > 0.9 AND venue-match-score > 0.9)
   - Manually formulating the right set of rules is hard.

Basic Machine Learning Rules

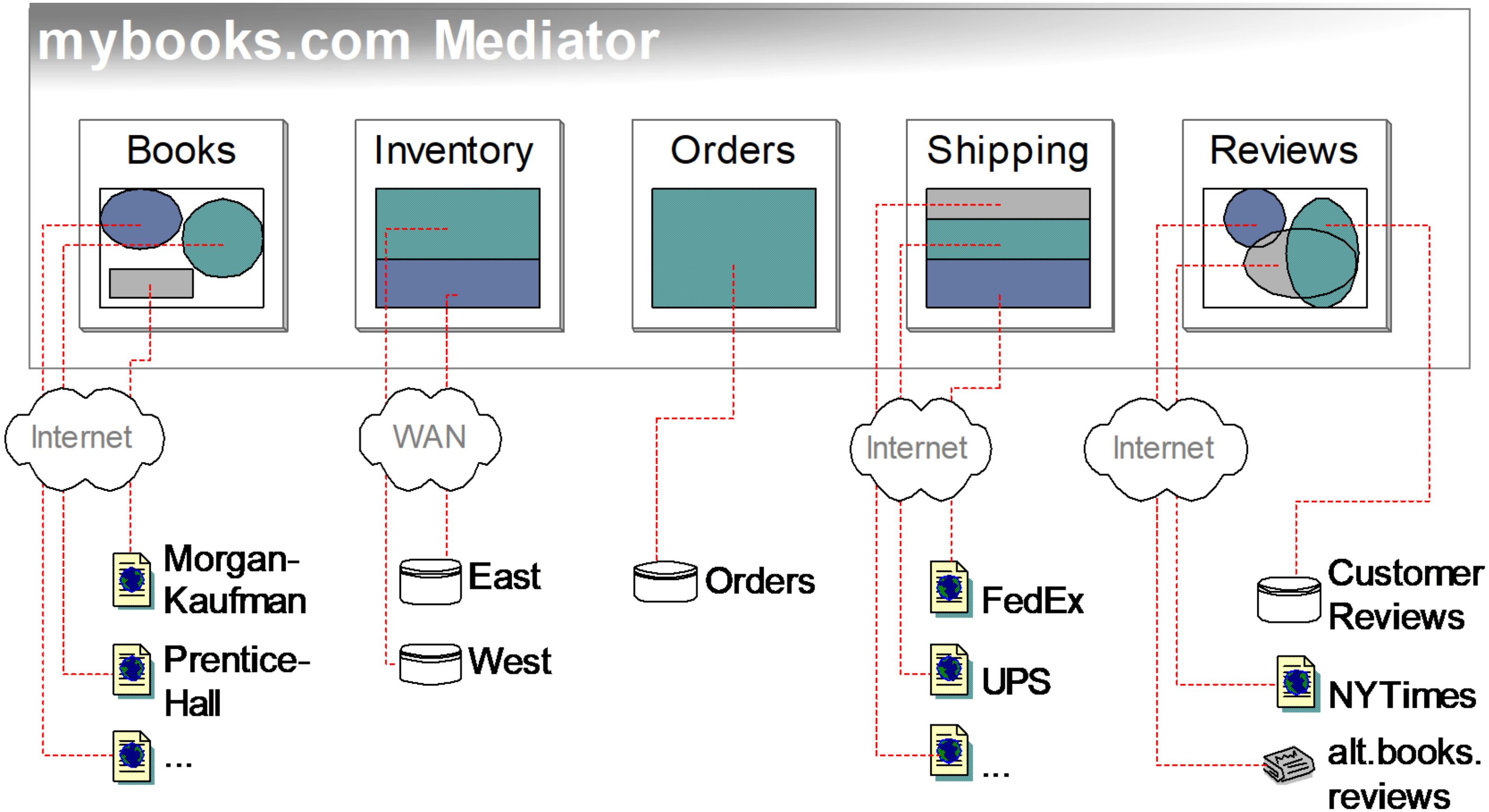
- *r = (x,y)* is record pair, γ is comparison vector, *M* matches, *U* non-matches

- Decision rule $$R = \frac{P(\gamma \mid r \in M)}{P(\gamma \mid r \in U)}$$

$$R > t \quad \Rightarrow r \rightarrow \text{Match}$$

$$R \leq t \quad \Rightarrow r \rightarrow \text{Non-Match}$$

Data Integration



Provide **uniform access** to data available in **multiple**, **autonomous**, **heterogeneous** and **distributed** data sources

Goals of Data Integration

Provide

- Uniform (same query interface to all sources)
- Access to (queries; eventually updates too)
- Multiple (we want many, but 2 is hard too)
- Autonomous (DBA doesn’t report to you)
- Heterogeneous (data models are different)
- Distributed (over LAN, WAN, Internet)
- Data Sources (not only databases).

Motivation

WWW

- Website construction
- Comparison shopping
- Portals integrating data from multiple sources
- B2B, electronic marketplaces

Science and culture

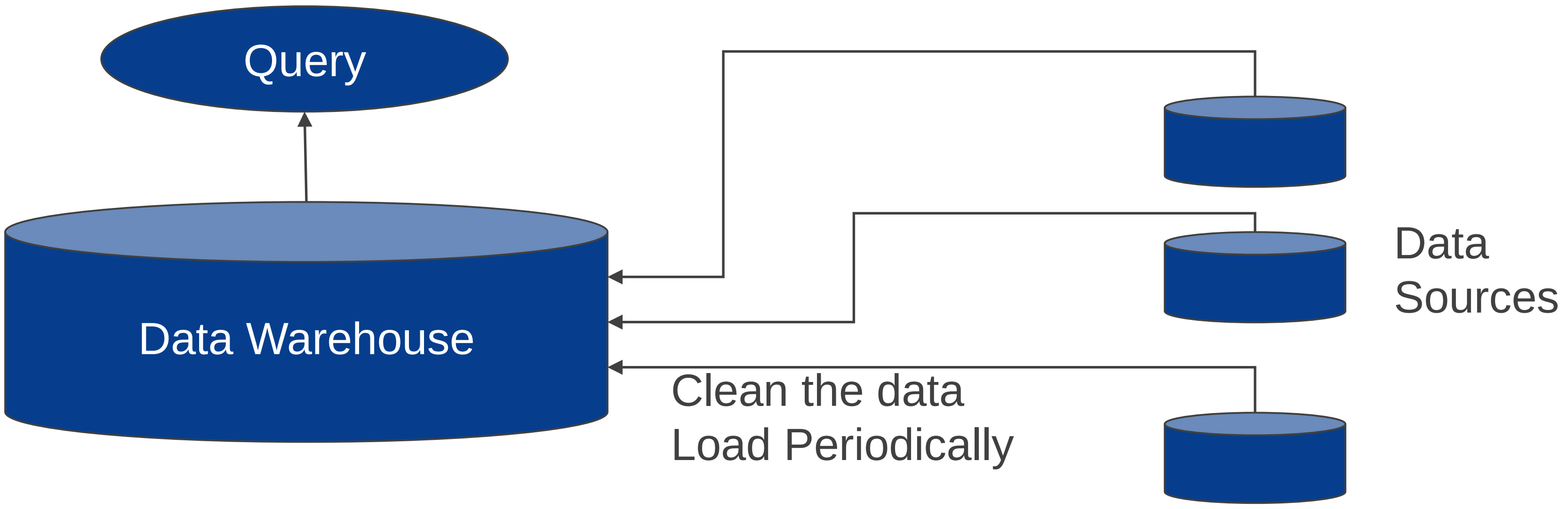
- Medical genetics: integrating genomic data
- Astrophysics: monitoring events in the sky.
- Culture: uniform access to all cultural databases produced by countries in Europe.

Current Solutions

Ad-hoc programming: Create custom solutions for each application.

Data Warehouse

- Extract all the data into a single data source



Problems with DW Approach

Data has to be cleaned – different formats

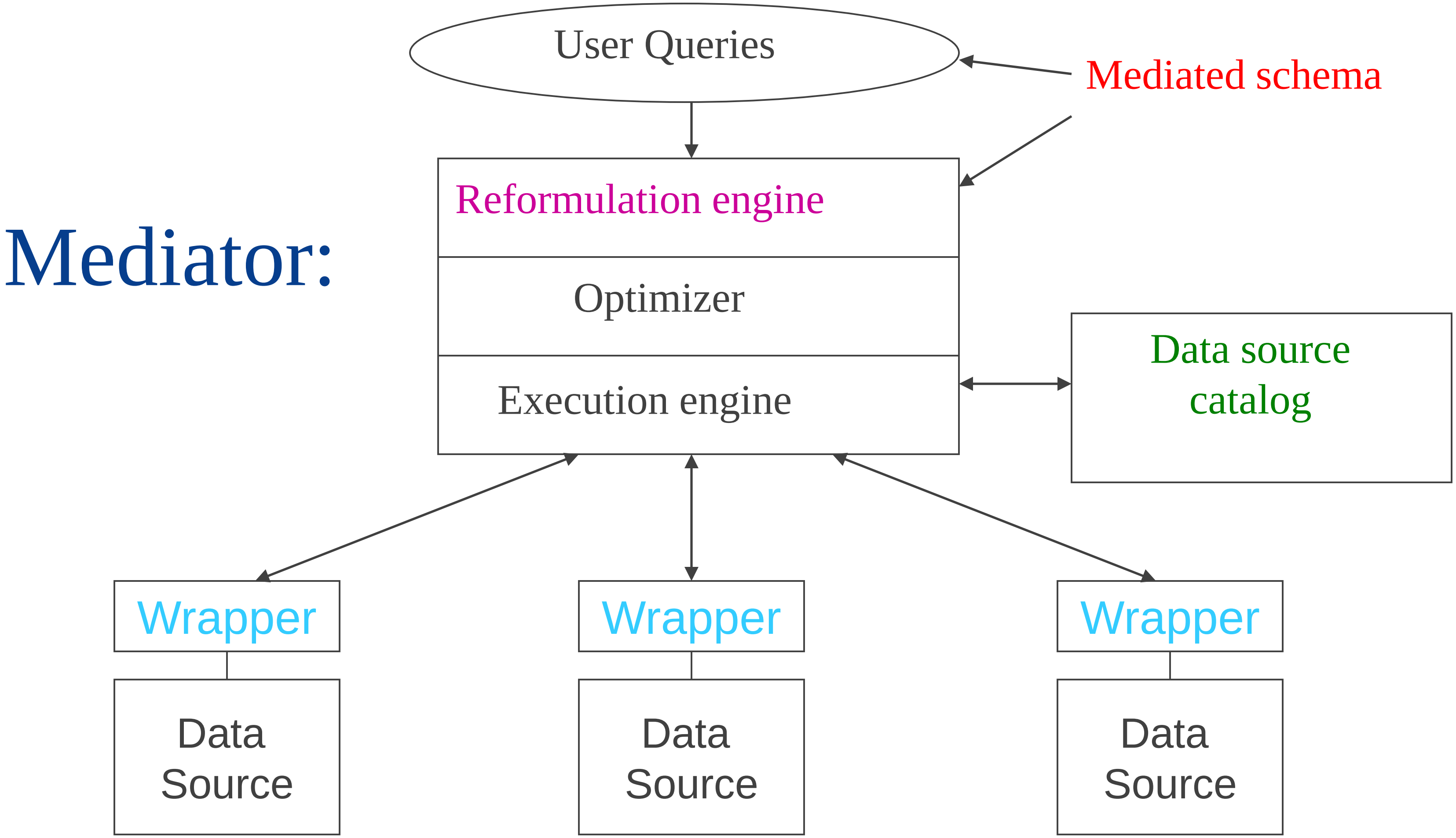
Needs to store all the data in all the data sources that will ever be asked for

- Expensive due to data cleaning and space requirements

Data needs to be updated periodically

- Data sources are autonomous – content can change without notice
- Expensive because of the large quantities of data and data cleaning costs

Virtual Integration



Architecture Overview

Leave the data in the data sources

For every query over the mediated schema

- Find the data sources that have the data (probably more than one)
- Query the data sources
- Combine results from different sources if necessary

Breaks

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Challenges

Designing a single mediated schema

- Data sources might have different schemas, and might export data in different formats

Translation of queries over the mediated schema to queries over the source schemas

Query Optimization

- No/limited/stale statistics about data sources
- Cost model to include network communication cost
- Multiple data sources to choose from

Challenges (2)

Query Execution

- Network connections unreliable – inputs might stall, close, be delayed, be lost
- Query results can be cached – what can be cached?

Query Shipping

- Some data sources can execute queries – send them sub-queries
- Sources need to describe their query capability and also their cost models (for optimization)

Challenges (3)

Incomplete data sources

- Data at any source might be partial, overlap with others, or even conflict
- Do we query all the data sources? Or just a few? How many? In what order?

Wrappers

Sources export data in different formats

Wrappers are custom-built programs that transform data from the source native format to something acceptable to the mediator

HTML

 Introduction to DB
<i> Phil Bernstein </i>
<i> Eric Newcomer </i>
Addison Wesley, 1999

XML

<book>
<title> Introduction to DB </title>
<author> Phil Bernstein </author>
<author> Eric Newcomer </author>
<publisher> Addison Wesley </publisher>
<year> 1999 </year>
</book>

Wrappers(2)

Can be placed either at the source or at the mediator

Maintenance problems – have to change if source interface changes

Data Source Catalog

Contains meta-information about sources

- Logical source contents (books, new cars)
- Source capabilities (can answer SQL queries)
- Source completeness (has *all* books)
- Physical properties of source and network
- Statistics about the data (like in an RDBMS)
- Source reliability
- Mirror sources
- Update frequency

Schema Mediation

Users pose queries over the mediated schema

The data at a source is visible to the mediator is its local schema

Reformulation: Queries over the mediated schema have to be rewritten as queries over the source schemas

How would we do the reformulation?

Global-as-View

Mediated schema as a view over the local schemas

Mediated Schema: Movie(title, dir, year, genre)

Data Sources and local schemas:

S1[Movie(title,dir,year,genre)]

S2[Director(title,dir), Movie(title,year,genre)]

```
Create View Movie As
Select * from S1.Movie
Union
Select * from S2.Director, S2.Movie
where S2.Director.title = S2.Movie.title
```

Global-as-View(2)

Simply unfold the user query by substituting the view definition for mediated schema relations

Difficult to add new sources – All existing view definitions might be affected

Subtle issues – some information can be lost

Local-as-View

Local schemas as views over the mediated schema

Mediated Schema: Movie(title, dir, year, genre)

Data Sources and local schemas:

S1[Movie(title,dir,year,genre)]

S2[Director(title,dir), Movie(title,year,genre)]

Create Source S1.Movie As
Select * from Movie

Create Source S2.Movie As
Select title, year, genre from Movie

Create Source S2.Director As
Select title,dir from Movie

Local-as-View(2)

Query Reformulation

- Given a query Q over the mediated schema, and view definitions (sources) over the mediated schema, can we answer Q?
- Answering Queries Using Views
- Great Survey written by Alon

Which would you use?

Mediated Schema:

Movie(title, dir, year, genre)

Schedule(cinema, title, time)

Data Source

S3[Genres(cinema,genre)]

How would you do schema mediation using Global-as-View? Local-as-View?

Can you answer this query in each case

Give me the cinema halls playing comedy movies

Query Optimization

Sources specify their capabilities if possible

- Transformation rules define the operations they can perform
- Sources might also specify cost models of their own

Cost model might be parametrized

- Mediator can estimate cost of transferring data by accumulating statistics from earlier transfers

Adaptive Query Processing

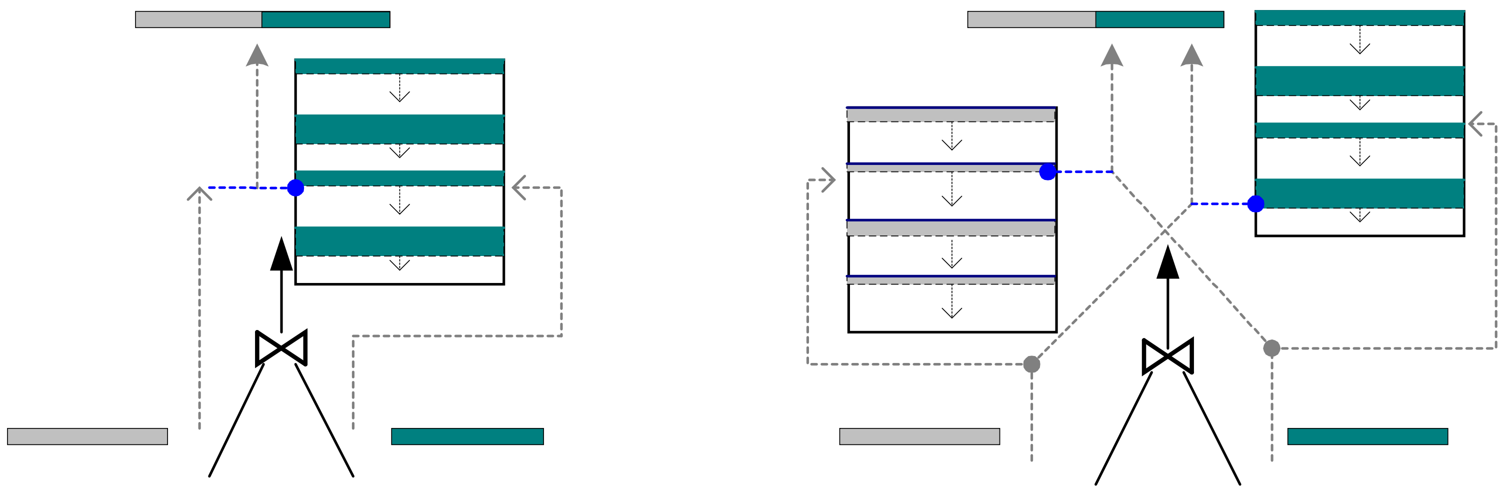
Adaptive query operators

- Aware that network communication might fail

Interleave Query Optimization and Execution

- Optimize query once with available limited statistics
- Execute the query for some time, collect statistics
- Re-optimize query again with improved statistics
- Resume execution… repeat

Double Pipelined Hash Join



Hash Join

- Partially pipelined: no output until inner read
- Asymmetric (inner vs. outer) — optimization requires source behavior knowledge

Double Pipelined Hash Join

- Outputs data immediately
- Symmetric — requires less source knowledge to optimize

Other Problems

Automatic Schema Matching

- How do I know what the view definitions are?
- Can I learn these definitions automatically?

Streaming Data

- The data is not stored in a data source, but is streaming across the network
- How do we query a data stream?

Other Problems(2)

Peer-to-Peer databases

- No clear mediator and data source distinction
- Each peer can both have data and fetch the rest of it
- Similar to Napster, Gnutella – except we want to share data that is not necessarily a single file

Examples - Cleaning

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