Web Data Integration

Data Quality Assessment and Data Fusion

The Data Integration Process

Data Collection / Extraction

Schema Mapping
Data Translation

Identity Resolution

Data Quality Assessment
Data Fusion

Outline

1. Introduction
2. Data Profiling
3. Data Provenance
4. Data Quality Assessment
5. Data Fusion
    1. Slot Filling and Conflict Resolution
    2. Conflict Resolution Functions
    3. Evaluation of Data Fusion Results
    4. Case Studies

1. Introduction

Information providers on the Web have

- different levels of knowledge
- different views of the world
- different intentions

Therefore,

1. information on the Web is partly wrong, biased, outdated, incomplete, and inconsistent.
2. every piece of information on the Web needs to be considered as a claim by somebody at some point in time and not as a fact.
3. the information consumer needs to make up her mind which claims to use for a certain task.

Example: Area and Population of Monaco

Area: Different claims and different conversions

en.wikipedia.org	2.02 sq km	0.78 sq miles
www.state.gov	1.95 sq km	0.8 sq miles
www.atlapedia.com	1.94 sq km	1 sq mile

(1.95 sq km = 0.753 sq miles)

Population: Different claims and vague meta-information

Value	Meta-information	Webpage
30,727	(July 2018 est.)	http://www.cia.gov/cia/publications/factbook/geos/mn.html
38,897	(2016 census)	https://en.wikipedia.org/wiki/Monaco, reference pointing at statistics from 2009
39,042	(2019 latest UN estimate)	https://www.worldometers.info/world-population/monaco-population/

Source: Peter Bunemann

Definition: Data Conflict

Multiple records that describe the same real-world entity provide different values for the same attribute.

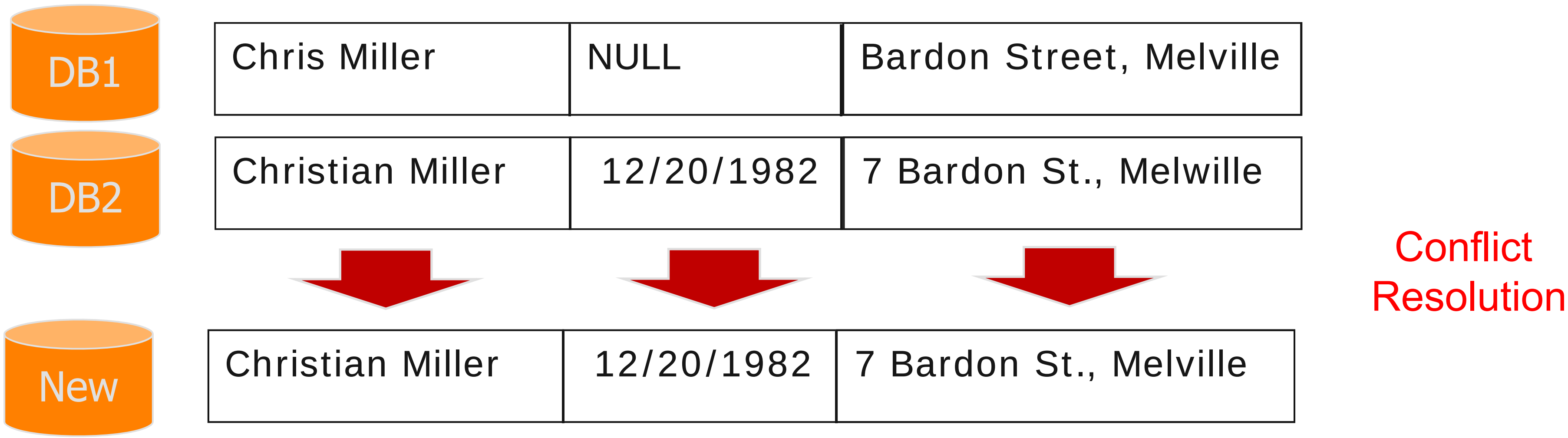
DB1	Chris Miller	12/20/1982	Bardon Street, Melville
DB2	Christian Miller	2/20/1982	7 Bardon St., Melwille

Reasons for data conflicts:

1. Data creation: Typos, measurement errors, erroneous information extraction
2. Data currency: Different points in time, missing updates
3. Data semantics: Different definitions of concepts (like population or GDP)
4. Data representation: Different coding of values (“Mrs.” vs. “2”)
5. Data integration: Wrong data translation or identity resolution
6. Actual disagreement of data providers: Subjective attributes (like cuteness)

Definition: Data Fusion

Given multiple records that describe the same real-world entity, create a single record by resolving data conflicts.



- **Goal:** Create a high quality record.
- But what does high data quality actually mean?

Data Quality

Data quality is a multi-dimensional construct which measures the fitness for use of data for a specific task.

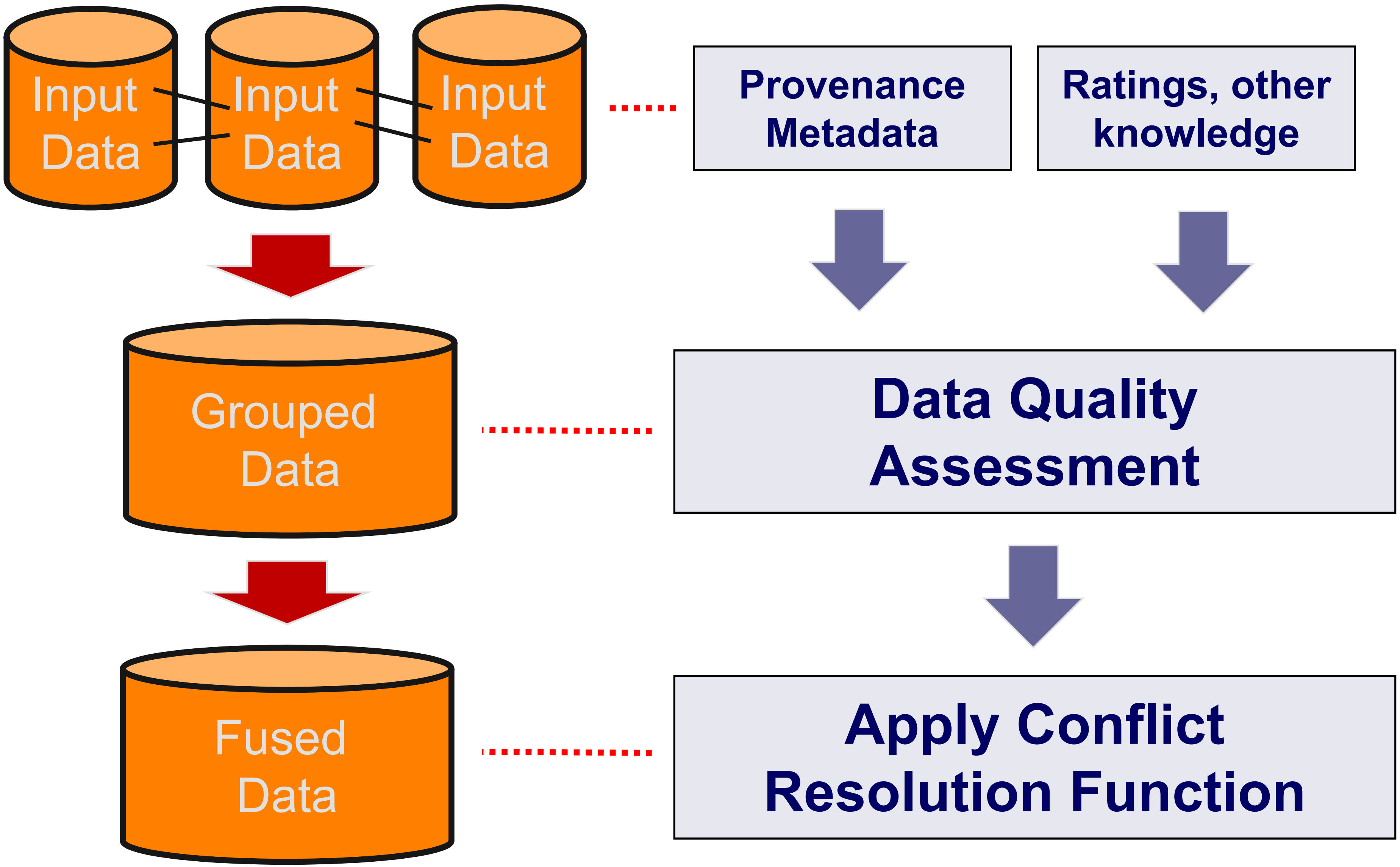
Fitness for use

1. has many dimensions
   - accuracy, timeliness, completeness, understandability, …
2. is task-dependent
   - higher quality requirements when you invest one million €
3. is subjective
   - some people are more paranoid than others

Data Quality Assessment

- Content-based Metrics
  - use information to be assessed itself as quality indicator
  - examples: voting, constraints and consistency rules, statistical outlier detection
- Provenance-based Metrics
  - employ provenance meta-information about the circumstances in which information was created as quality indicator
  - examples: “Disbelieve everything a vendor says about its competitor” or “Do not use information that is older than one week”
- Rating-based Metrics
  - rely on explicit or implicit ratings about information itself, information sources, or information providers
  - examples: “Only read news articles having at least 100 Facebook likes”, “Accept recommendations from a friend on restaurants, but distrust him on computers”, “Prefer content from websites having a high PageRank”

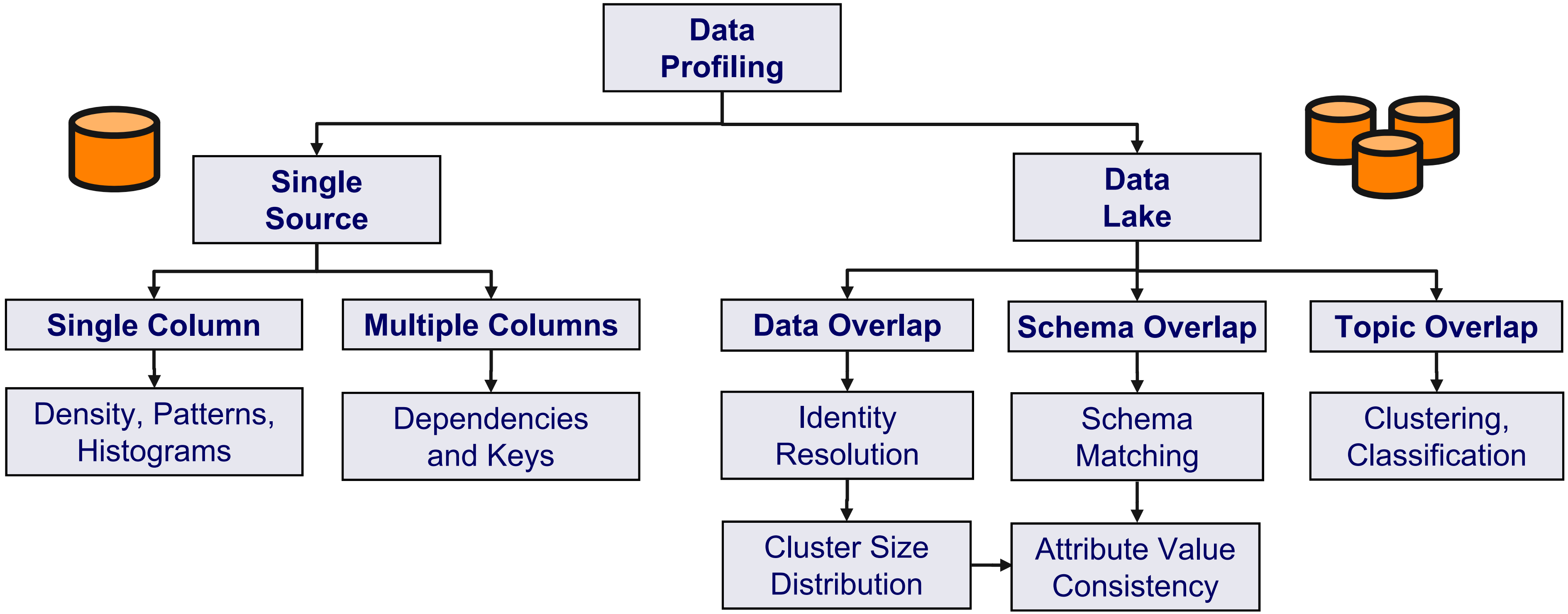
Summary: Elements of the Data Fusion Process



2. Data Profiling

Data profiling refers to the activity of calculating statistics and creating summaries of a data source or data lake.

- manual exploration (data gazing) should be supported with profiling results
- crucial when new data sets arrive or new people work with existing data lakes



Abedjan, et al.: Data Profiling. Morgan & Cleypool Synthesis Lecture in Computer Science, 2018.

2.1 Single Column Profiling: Metrics

Category	Task	Task Description
Cardinalities	num-rows	Number of rows
	null values	Number or percentage of null values
	distinct	Number of distinct values
	uniqueness	Number of distinct values divided by number of rows
Value Distributions	histogram	Frequency histograms (equi-width, equi-depth, etc.)
	extremes	Minimum and maximum values in a numeric column
	constancy	Frequency of most frequent value divided by number of rows
	quartiles	Three points that divide (numeric) values into four equal groups
	first digit	Distribution of first digit in numeric values; to check Benford's law
Data Types, Patterns, and Domains	basic type	Numeric, alphanumeric, date, time, etc.
	data type	DBMS-specific data type (varchar, timestamp, etc.)
	lengths	Minimum, maximum, median, and average lengths of values within a column
	size	Maximum number of digits in numeric values
	decimals	Maximum number of decimals in numeric values
	patterns	Histogram of value patterns (Aa9. . .)
	data class	Generic semantic data type, such as code, indicator, text, date/time, quantity, identier
	domain	Semantic domain, such as credit card, first name, city, phenotype

Central for judging the usefulness of attributes

A histogram says more than thousand averages
- outliers
- skewed distributions

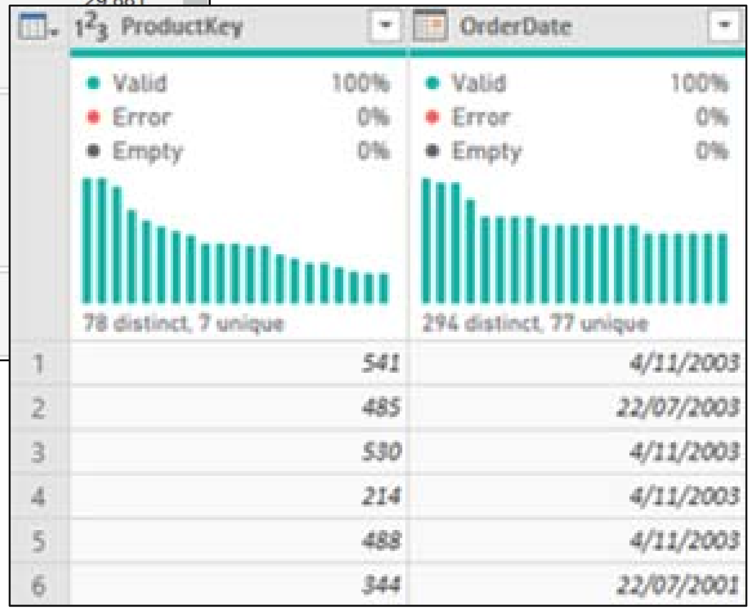
Data types and lengths should always be reported

Advanced column profiling

Single Column Profiling: Examples

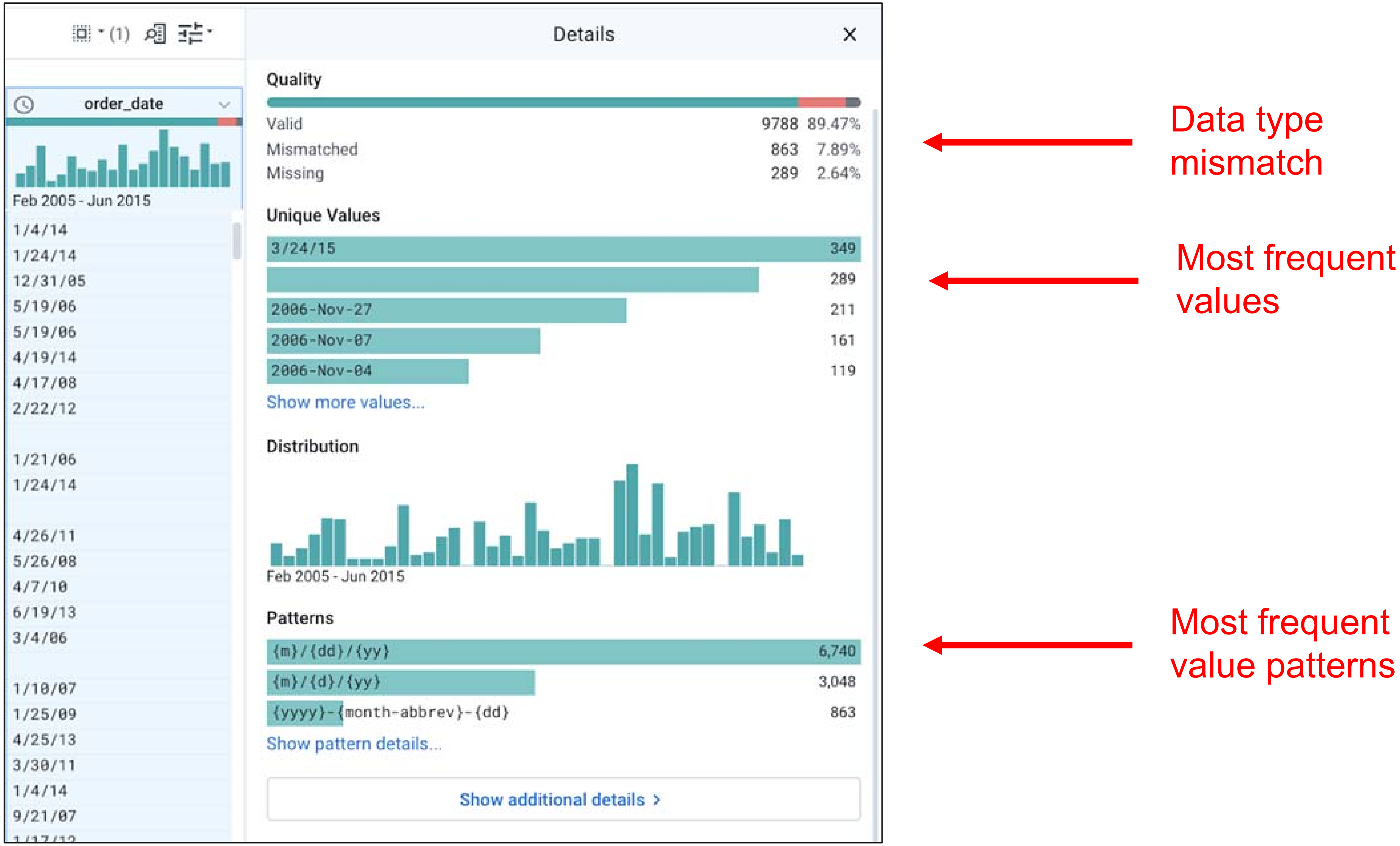
RapidMiner

Microsoft Power BI



Single Column Profiling: Examples

Goolge Cloud Dataprep by Trifacta



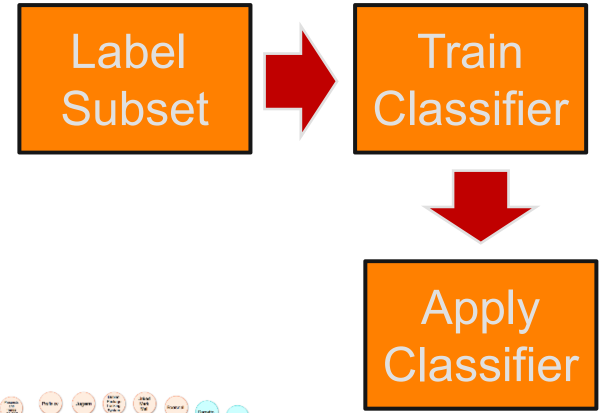
2.2 Data Lake Profiling: Data and Schema Overlap

– Approach: Match data to central database
– Example: Profiling a corpus of 33.3 million HTML tables by matching them to the DBpedia knowledge base
– Results
  - 301,000 tables (1%) have matching rows and matching columns
  - 8,000,000 million values for fusion
– Interpretation
  - topical bias of KB needs to be considered
  - product tables missed

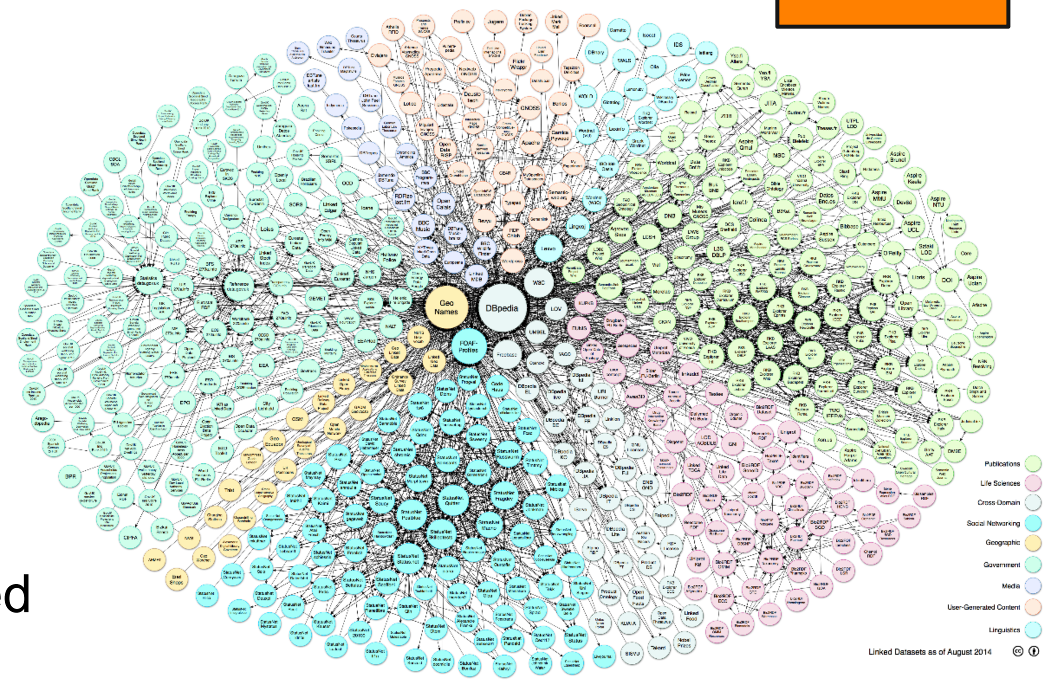
DBpedia Class	Number of Tables/Values			V_c Data Type			
	T_0	T_c	V_c	Numeric	Date	String	Reference
+ Person	265 685	103 801	4 176 370	2 117 793	1 588 475	266 628	203 474
|- Athlete	243 322	95 916	3 861 641	2 084 017	1 435 775	163 771	178 078
|- Artist	9 981	2 356	18 886	3	11 527	3 499	3 857
|- Politician	3 701	1 388	18 505	10	7 725	3 393	7 377
|- Office Holder	2 178	1 435	131 633	30	66 762	59 332	5 509
+ Organisation	194 317	36 402	573 633	99 714	187 370	100 710	185 839
|- Company	97 891	6 943	203 899	58 621	83 001	34 665	27 612
|- SportsTeam	50 043	2 722	31 866	2 206	22 368	43	7 249
|- Educational Institution	25 737	14 415	238 365	38 056	64 578	13 334	122 397
|- Broadcaster	14 515	11 315	93 042	564	13 095	52 186	27 197
Work	269 570	127 677	2 284 916	109 265	1 354 923	33 091	787 637
+ MusicalWork	138 676	80 880	1 131 167	64 545	396 940	7 610	662 072
+ Film	43 163	9 725	256 425	10 844	198 913	14 382	32 286
+ Software	39 382	23 829	486 868	418	414 092	9 194	63 164
Place	133 141	24 341	859 995	413 375	273 510	84 111	88 999
+ PopulatedPlace	119 361	21 486	787 854	405 406	257 780	57 064	67 604
|- Country	36 009	6 556	208 886	93 107	66 492	31 793	17 494
|- Settlement	17 388	2 672	17 585	4 492	6 662	2 444	3 987
Species	14 247	4 893	83 359	-	7 902	38 682	36 775
Σ	949 970	301 450	8 037 562	2 751 105	3 437 420	536 526	1 312 511

Hassanzadeh, et al.: Understanding a Large Corpus of Web Tables through Matching with Knowledge Bases. OM. 2015.
Ritze, et al. Profiling the Potential of Web Tables for Augmenting Cross-domain Knowledge Bases. WWW 2016.

Data Lake Profiling: Topic Overlap



- Approaches:
  1. Train supervised classifier to categorize data sources / tables into predefined categories using textual metadata, schema-level labels, or textual content
  2. Cluster sources / tables based on textual metadata and/or textual content



- Example:
  - 100 LOD data sources manually assigned to 9 categories
  - 1000 records sampled per data source
  - 900 additional data sources classified with F1 of 0.81

Böhm, Kasneci, Naumann: Latent topics in graph-structured data. CIKM 2012.
Meusel, Spahiu, Bizer, Paulheim: Towards automatic topical classification of LOD datasets. LDOW 2015.

3. Data Provenance

Provenance is information about entities, activities, and people involved in producing a piece of data or thing, which can be used to form assessments about its quality, reliability or trustworthiness.

Source: W3C PROV Specification

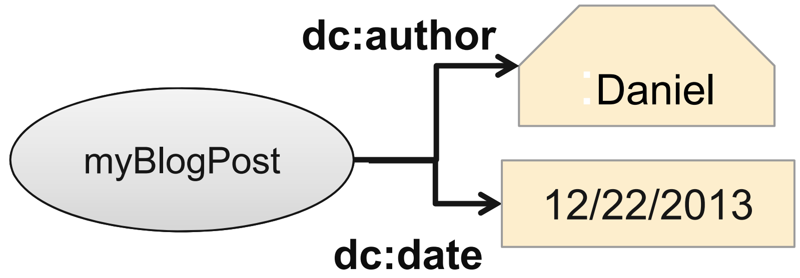
Provenance information = important data quality indicator

Outline of this Subsection

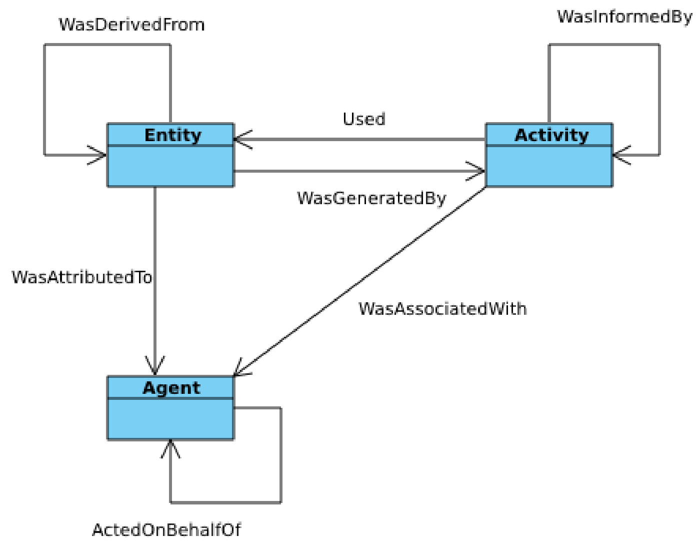
1. Simple Attribution versus Full Provenance Chains
2. Publishing Provenance Information on the Web
3. Representing Provenance Metadata together with Integrated Data

3.1 Simple Attribution versus Full Provenance Chains

1. Simple Attribution:
   - state who created a document/data item and when it was created
   - standard: Dublin Core vocabulary



2. Full Provenance Chains
   - Describe the full process of data creation / reuse / integration / aggregation
   - standard: W3C PROV Specification
   - alternative name: Data Lineage (explain why something is in a query result)



– Factors for the decision between both alternatives:
   - Will the users be interested in all the details?
     - Yes for science, investing, law suits. No for minor purchases in e-commerce
   - Can target applications understand/reason about all details?

3.2 Publishing Provenance Information on the Web

In the context of the Web, you always know the URL from which you downloaded things. Some sites also give you Last-Modified information.

HTTP-Response

```
HTTP/1.1 200 OK
Date: Mon, 18 Jan 2019 20:54:26 GMT
Server: Apache/1.3.6 (UNIX)
Last-Modified: Mon, 06 Dec 2018 14:06:11 GMT
Content-length: 6345
Content-Type: text/html

<html>
  <head><title>CB CD-Shop</title></head>
  <body><h1>Willkommen beim CB CD-Shop</h1> ....
```

Which vocabularies/schemata should websites use to publish more detailed provenance information?

Dublin Core

- The Dublin Core vocabulary defines terms for representing simple attribution information
  - creator, contributor, publisher, date, rights, format, language, …
- The terms are used in different technical contexts
  - HTML, Linked Data, proprietary library formats
  - Example of a Linked Data document:

http://dbpedia.org/data/Alec_Empire

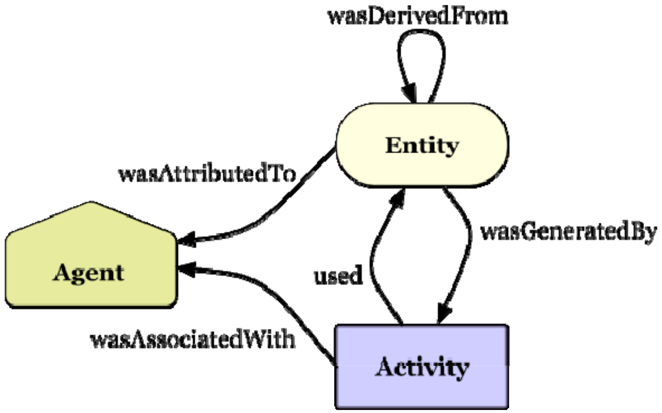
```
# Metadata and Licensing Information
<http://dbpedia.org/data/Alec_Empire>
    rdfs:label "RDF document describing Alec Empire" ;
    rdf:type foaf:Document ;
    dc:publisher <http://dbpedia.org/resource/DBpedia> ;
    dc:date "2019-07-13"^^xsd:date ;
    dc:rights <http://en.wikipedia.org/wiki/WP:GFDL> .

# The Document Content
<http://dbpedia.org/resource/Alec_Empire>
    foaf:name "Empire, Alec" ;
    rdf:type foaf:Person ;
    rdfs:comment "Alec Empire (born May 2, 1972) is a German musician..."@en ;
...
```

W3C PROV

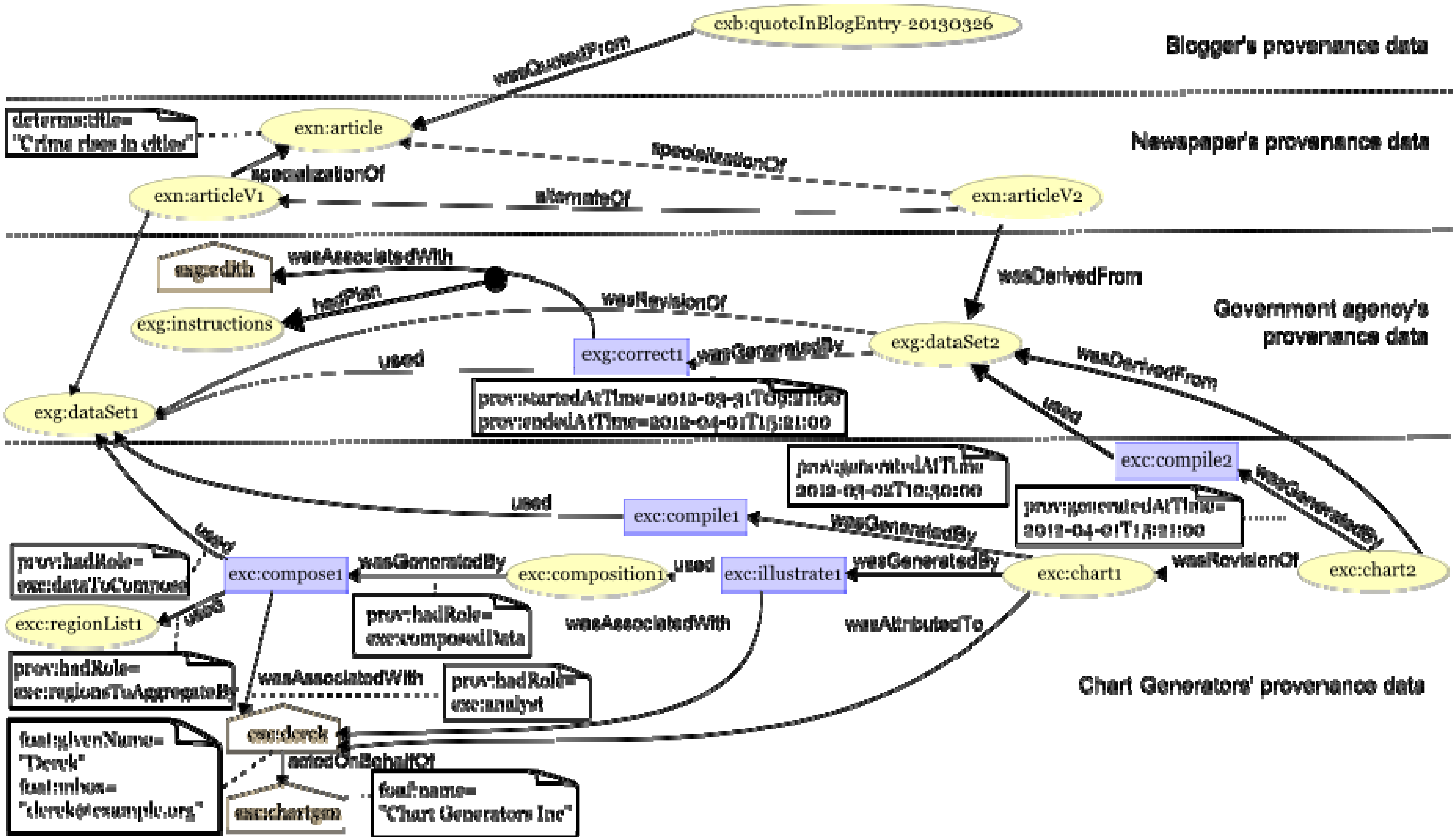
- The W3C PROV vocabulary defines terms for representing complex provenance chains
- Example of a PROV XML document:

```
<prov:document>
  <!-- Entities -->
  <prov:entity prov:id="exn:article">
        <dct:title>Crime rises in cities</dct:title>
  </prov:entity>
  <!-- Agents -->
  <prov:agent prov:id="exc:derek">
      <prov:type>prov:Person</prov:type>
      <foaf:givenName>Derek Smith</foaf:givenName>
      <foaf:mbox>mailto:derek@example.org</foaf:mbox>
  </prov:agent>
 <!-- Activities -->
  <prov:activity prov:id="exc:compile1"/>
 <!-- Usage and Generation -->
 <prov:wasGeneratedBy>
      <prov:entity prov:ref="exn:article"/>
      <prov:activity prov:ref="exc:compile1"/>
 </prov:wasGeneratedBy>
  <!–Agent‘s Responsibility -->
 <prov:wasAssociatedWith>
      <prov:activity prov:ref="exc:compile1"/>
      <prov:agent prov:ref="exc:derek"/>
 </prov:wasAssociatedWith>
...
```

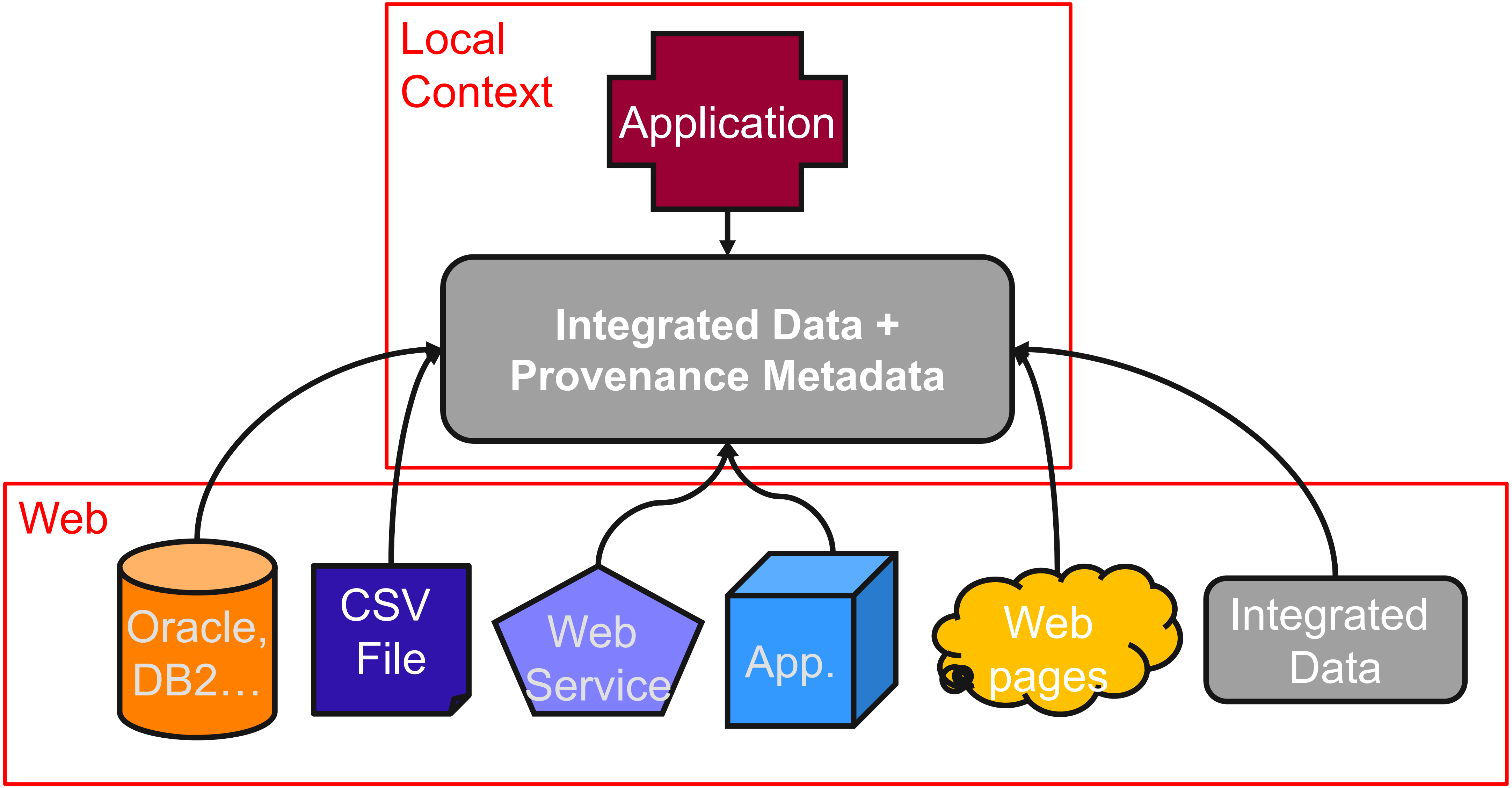
PROV



More Complex Example: W3C PROV



3.3 Representing Provenance Metadata together with Integrated Data



Relational Data Model

– Alternative 1: Record-Level Provenance (coarse grained, fast queries)
– Alternative 2: Value-Level Provenance (fine grained, but slow queries)
– Alternative 3: Employ special database engine which implements extended relational data model with a pointer to provenance information for each attribute value (e.g. Stanford Trio Database)

Physicians with Record-Level Provenance

Key	Name	Street	ProvID
1425	Dr. Mark Smith	14 Main Street	001
1425	Mark Smith	12 Main St.	002
…	…	…	…

Physicians with Value-Level Provenance

Key	Attribute	Value	ProvID
1425	Name	Dr. Mark Smith	001
1425	Name	Mark Smith	002
1425	Street	14 Main Street	001
…	…	…	…

Provenance Table

ProvID	Source	Date
001	www.mark-smith.com	12/6/2018 18:42:12
002	www.doc-find.com	12/1/2018 12:21:54
…	…	…

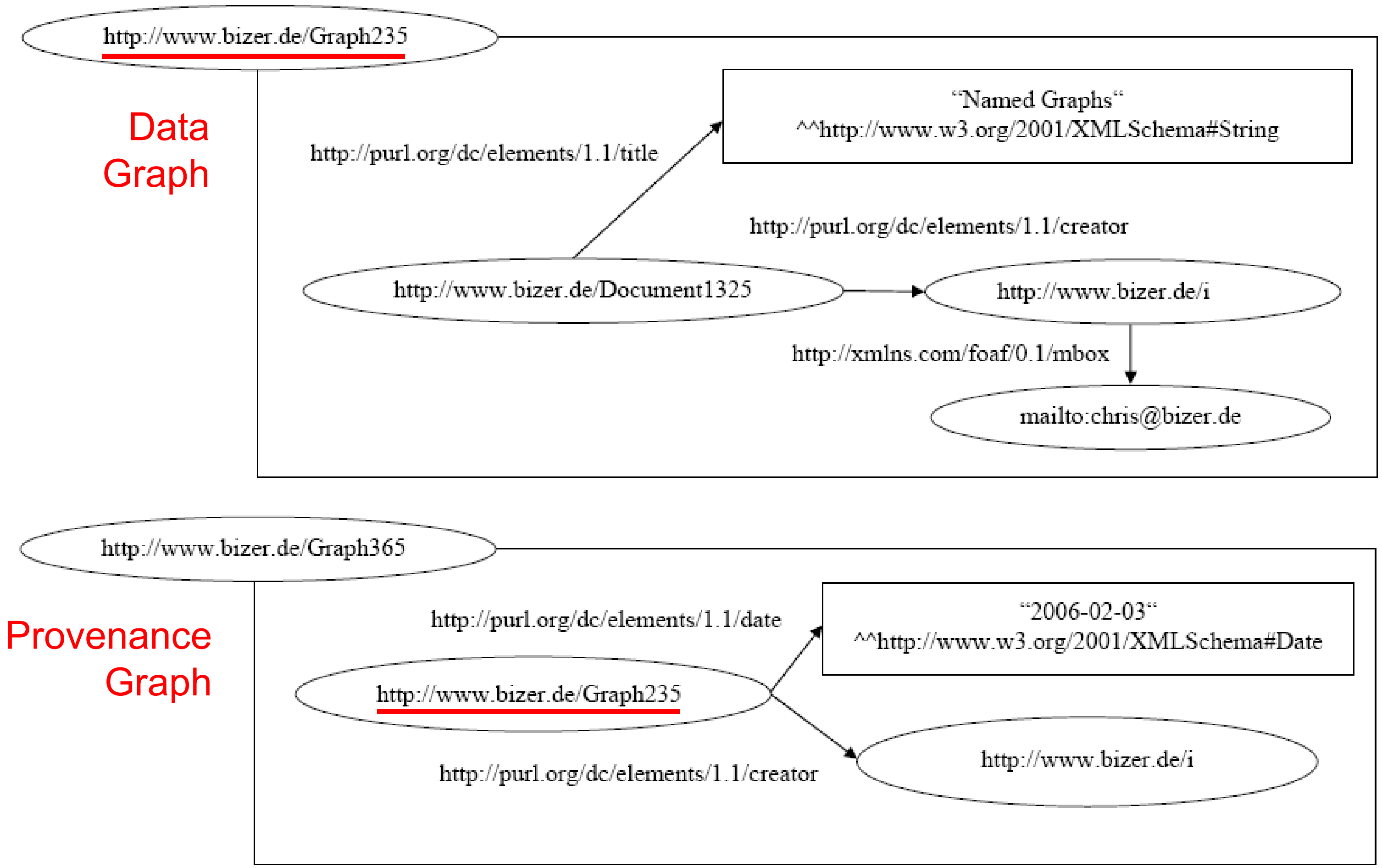
XML Data Model

Represent provenance using multiple value elements and references to provenance elements.

```
<physician>
  <name>
    <value prov=”prov01”>Dr. Mark Smith</value>
    <value prov=”prov02”>Mark Smith</value>
  </name>
  <address>
    <street>
      <value prov=”prov01”>14 Main Street</value>
      <value prov=”prov02”>12 Main St.</value>
    </street>
    <city> ... </city>
  </address>
</physician>
<provenance id=“prov01“>
    <source>http://www.marksmith.com/index.htm</source>
    <date>06 Nov 2018 14:06:11 GMT</date>
</provenance>
<provenance id=“prov02“>
     …
```

RDF Data Model

- Group triples into Named Graphs (= set of triples that is identified by a URI)
- Provide provenance information by talking about a graph in another graph
- Named Graphs can be queried using the SPARQL keyword GRAPH



Carroll, Bizer, Hayes, Stickler: Named Graphs. Journal of Web Semantics, 2005.

4. Data Quality

Data quality is a multi-dimensional construct which measures the "fitness for use" of data for a specific task.

- Which quality dimensions matter depends on the task
- The required level of quality depends on the task and the user

Outline of this Subsection

4.1 Data Quality Dimensions

4.2 Data Quality Assessment

Data Quality in the Enterprise and Web Context

– Enterprise Context

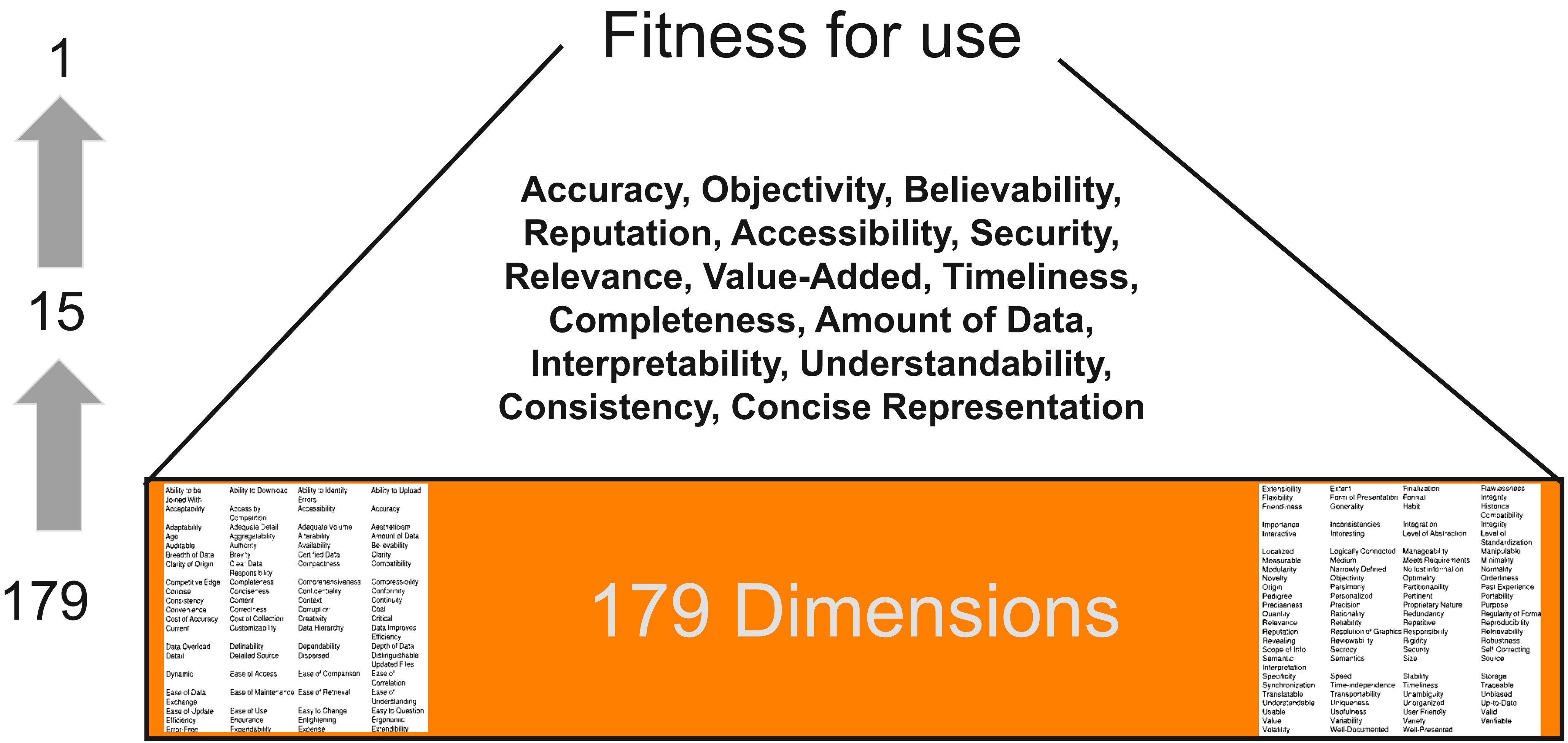
- the goal is to establish procedures and rules that guarantee high quality data production, quality monitoring, and regular data cleansing
- pioneering research by MIT Total Data Quality Management (TDQM) program
- consequences of low data quality:
  - US postal service: out of 100.000 mass-letters, 7.000 cannot be delivered because of wrong address
  - A.T. Kearny: 25%-40% of the operational costs result from low data quality as low quality data leads to wrong management decisions
  - SAS: Only 18% of all German companies trust their data

– Web Context

- large number of data sources, but no possibility to influence data providers
- thus, focus on identifying the high-quality subset of the available data
- challenge: quality indicators are often spare and unreliable

4.1 Data Quality Dimensions

As part of the MIT Total Data Quality Management (TDQM) program, [Wang/Strong1996] asked managers which data quality dimensions matter for their tasks:

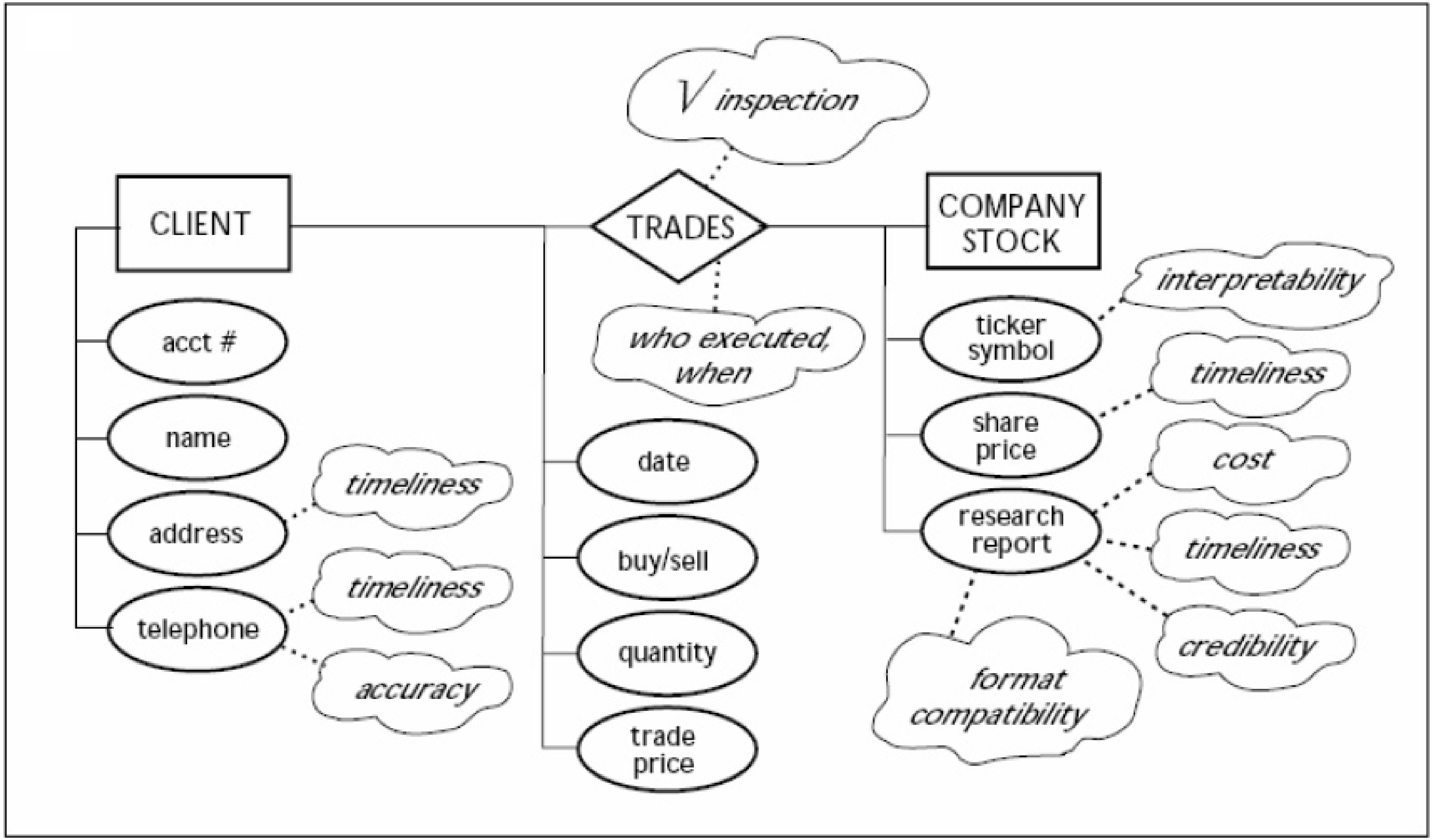


Category	IQ Criteria	TDQM	MBIS	Weikum	DWQ	SCOUG	Chen
Content-related Criteria	Accuracy	Yes	Yes	Yes	Yes	Yes	Yes
	Documentation					Yes	
	Relevancy	Yes	Yes		Yes		Yes
	Value-Added	Yes				Yes	
	Completeness	Yes	Yes	Yes	Yes	Yes	Yes
	Interpretability	Yes			Yes		
Technical Criteria	Timeliness	Yes	Yes	Yes	Yes	Yes	Yes
	Reliability			Yes			
	Latency			Yes			Yes
	Performability			Yes		Yes	
	Response time		Yes	Yes			Yes
	Security	Yes		Yes	Yes		
	Accessibility	Yes	Yes	Yes	Yes	Yes	
	Price		Yes	Yes		Yes	
	Customer Support					Yes	
Intellectual Criteria	Believability	Yes	Yes	Yes	Yes	Yes	
	Reputation	Yes	Yes		Yes		
	Objectivity	Yes					
Instantiation related Criteria	Verifiability			Yes			
	Amount of data	Yes	Yes				Yes
	Understandability	Yes	Yes				
	Concise represent.	Yes					
	Consistent represent.	Yes	Yes	Yes	Yes	Yes	

Source: Felix Naumann

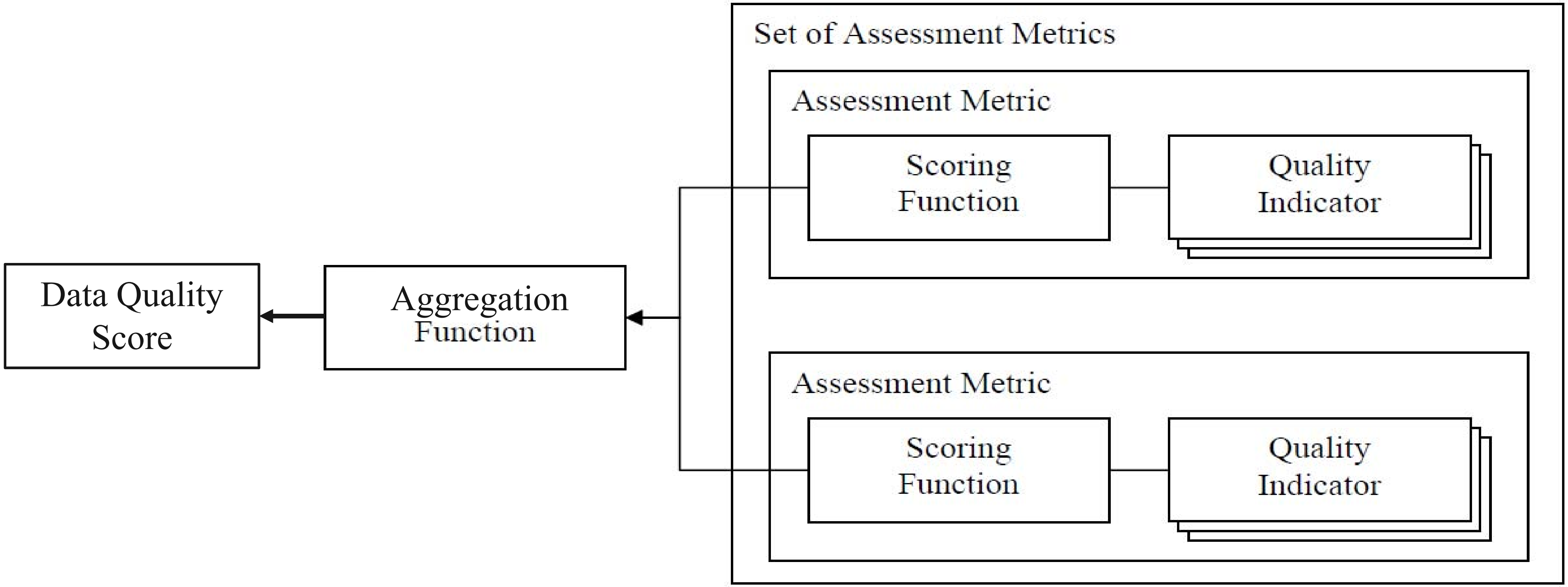
Relevancy of Data Quality Dimensions

Which quality dimensions matter depends on the task at hand.



4.2. Data Quality Assessment

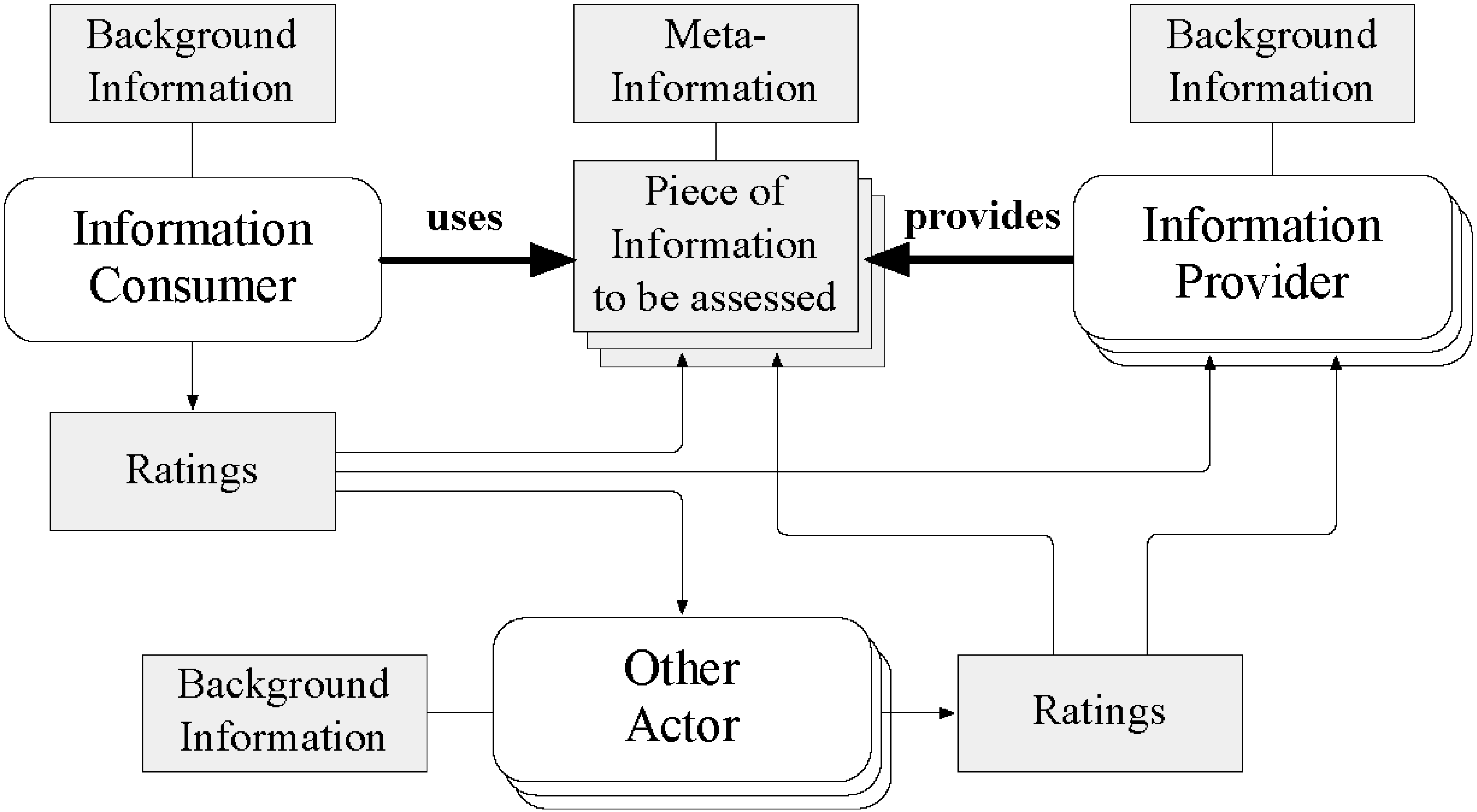
Various domain-specific heuristics are used to measure data quality.



The applicability of specific heuristics depends on

1. Availability of quality indicators (like provenance information or ratings)
2. Quality of quality indicators (fake ratings, sparse provenance information)

Quality Indicators in the Web Context



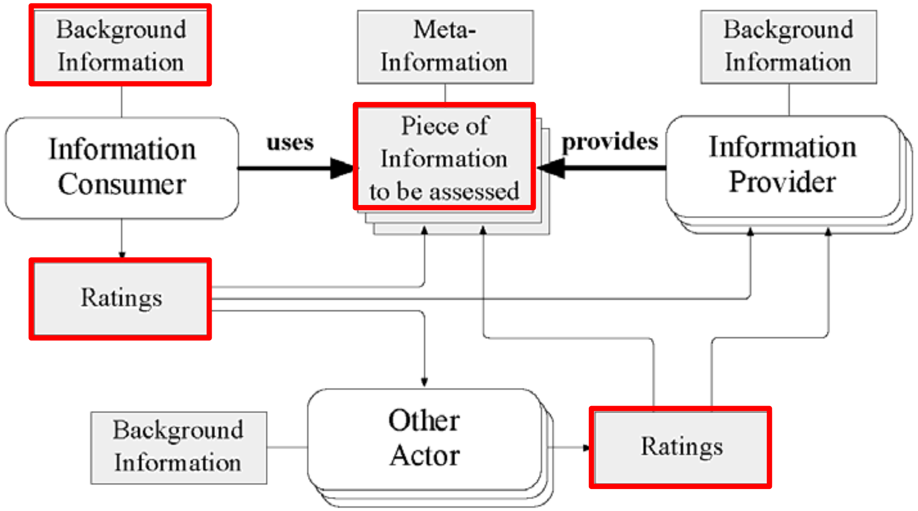
4.2.1 Assessing Data Accuracy

Definition Accuracy: The extent to which data is correct, reliable, and free of error.

– also called: Truth Discovery

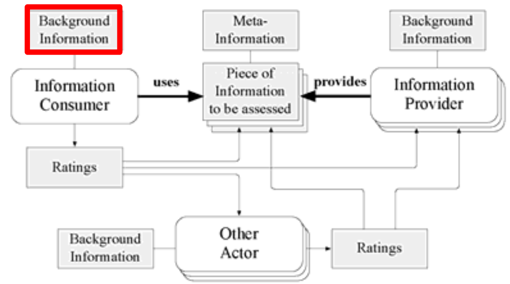
– Assessment Methods:
  1. Constraint testing
  2. Outlier detection
  3. Expert- or user ratings

– Relevant quality indicators:



Constraint Testing

Match data against constraints and consistency rules in order to detect errors.



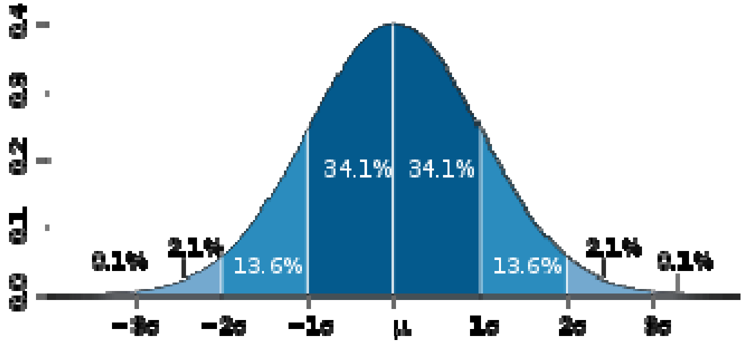
- Examples of constraints
  - the age of humans should be between 0 and 130
  - books must have at least one author
- Examples of consistency rules
  - if person is in middle school, then age is (likely) below 25
  - if area code is 131, then the city should be Edinburgh
- Rule and constraint acquisition
  - define rules and constraints manually
  - or learn from examples e.g. using association analysis (see lecture Data Mining)

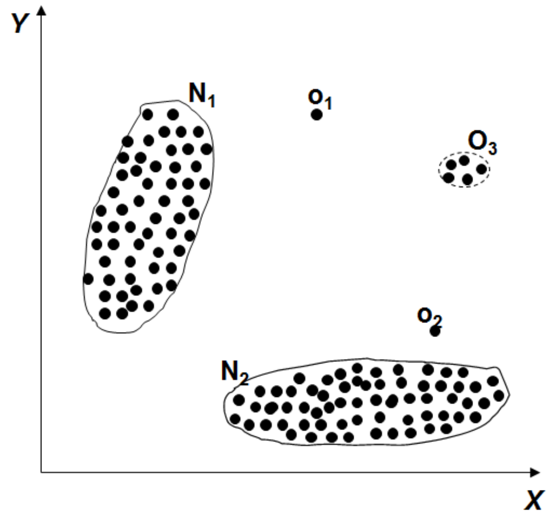
Fan, Geerts: Foundations of Data Quality Management. Morgan & Claypool, 2012.

Outlier Detection

An outlier is a individual data instance that is anomalous with respect to the rest of the data.

- Outliers can be considered as errors and be assigned a low quality score
- Techniques
  - statistical distributions, clustering, classification
- Challenges
  - the exact notion of an outlier is different for different application domains
  - an individual may be a outlier w.r.t. a single attribute or a combination of multiple attributes
  - natural outliers: population of Mexico City
  - normal behaviour keeps evolving over time

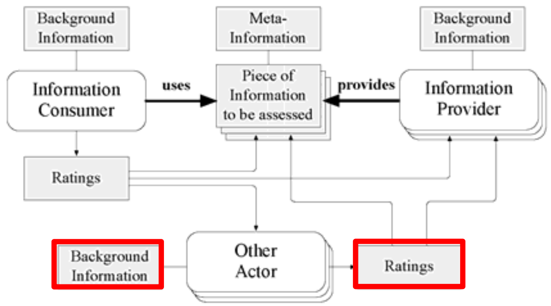




Chandola, et al.: Anomaly Detection: A Survey. ACM Computing Surveys, 2009.

Ratings

Data is often filtered or ranked based on ratings provided by users or experts.



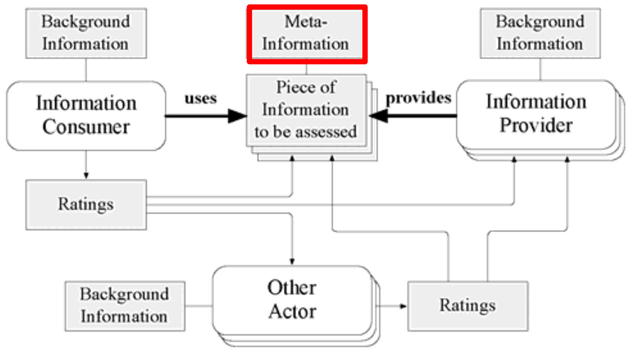
- Various scoring functions exist
  - practical systems often use simple, easily understandable functions
- Challenges:
  1. Motivate users to rate
     - data, data providers, data sources
  2. Quality of the ratings
     - fake ratings
     - clueless raters

- Events interpretable as positive ratings
  - clicks, page views
  - time spent on some page

4.2.2 Assessing Data Timeliness

Definition Timeliness: The extent to which the age of the data is appropriate for the task at hand.

- The assessment of the timeliness of data usually requires provenance data.

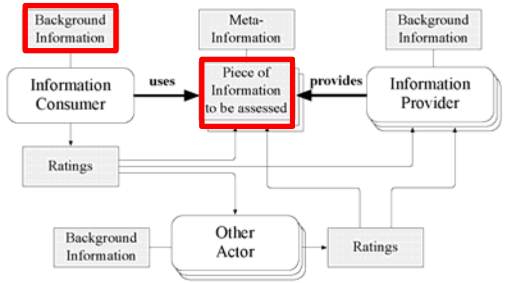


- Provenance metadata
  - HTTP Last-Modified
  - dc:date
- Fallbacks if no timestamps are available
  - propagate timestamps to data without timestamps
    - e.g. two tables provide same profit for a company, only one table has a timestamp
    - Zhang, Chakrabarti: InfoGather+, SIGMOD 2013.
  - use rules instead of timestamps
    - Number of children: Prefer higher value, as number of children of a person usually grows

4.2.3 Assessing Data Completeness

Definition Completeness: The extent to which data is not missing and is of sufficient breadth, depth, and scope for the task at hand.

– Two perspectives on completeness:
  - Density: Fraction of attributes filled
  - Coverage: Fraction of real-world objects represented

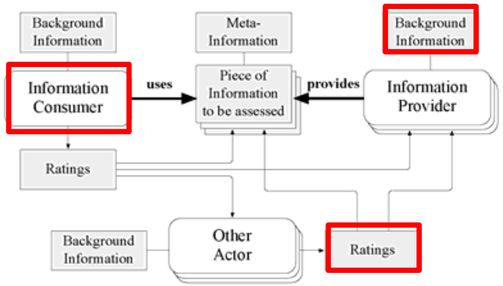


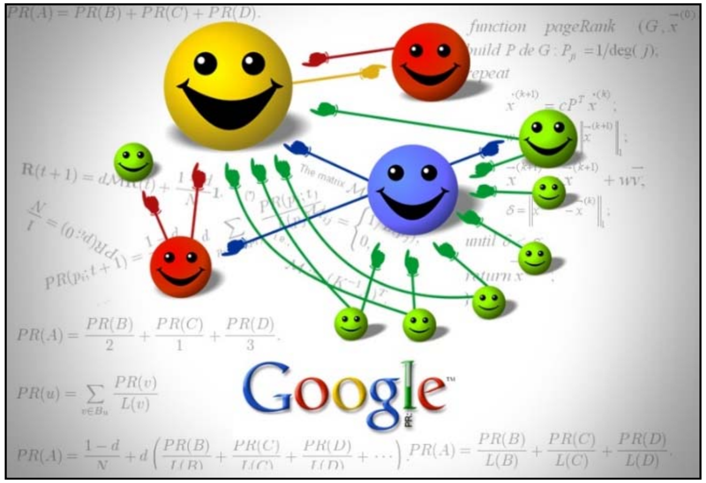
– Assessment:
  - Density
    - sample data source and calculate density from sample
  - Coverage
    - hard to calculate as overall number of real-world objects is unknown in many cases: countries fine; products or people problematic
    - fallback: prefer data sources that describe more entities

4.2.4 Assessing Data Relevancy

Definition Relevancy: The extent to which data is applicable and helpful for the task at hand.

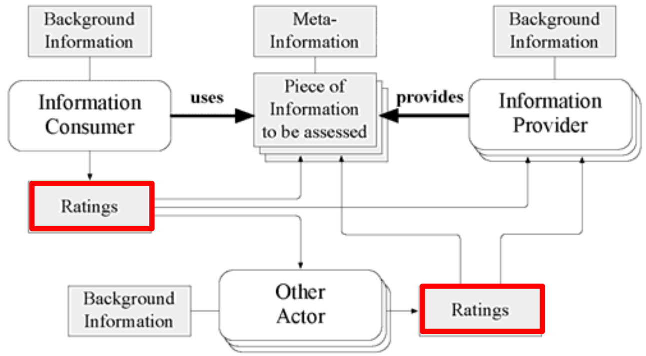
- Assessment:
  - Example: TripAdvisor
    - Filter reviews based on background information about information provider
  - Example: Google
    - Rank webpages based on search terms and PageRank score





4.2.5 Assessing Believability / Trustworthiness

Definition Believability / Trustworthiness: The extent to which data is regarded as true, real, and credible.



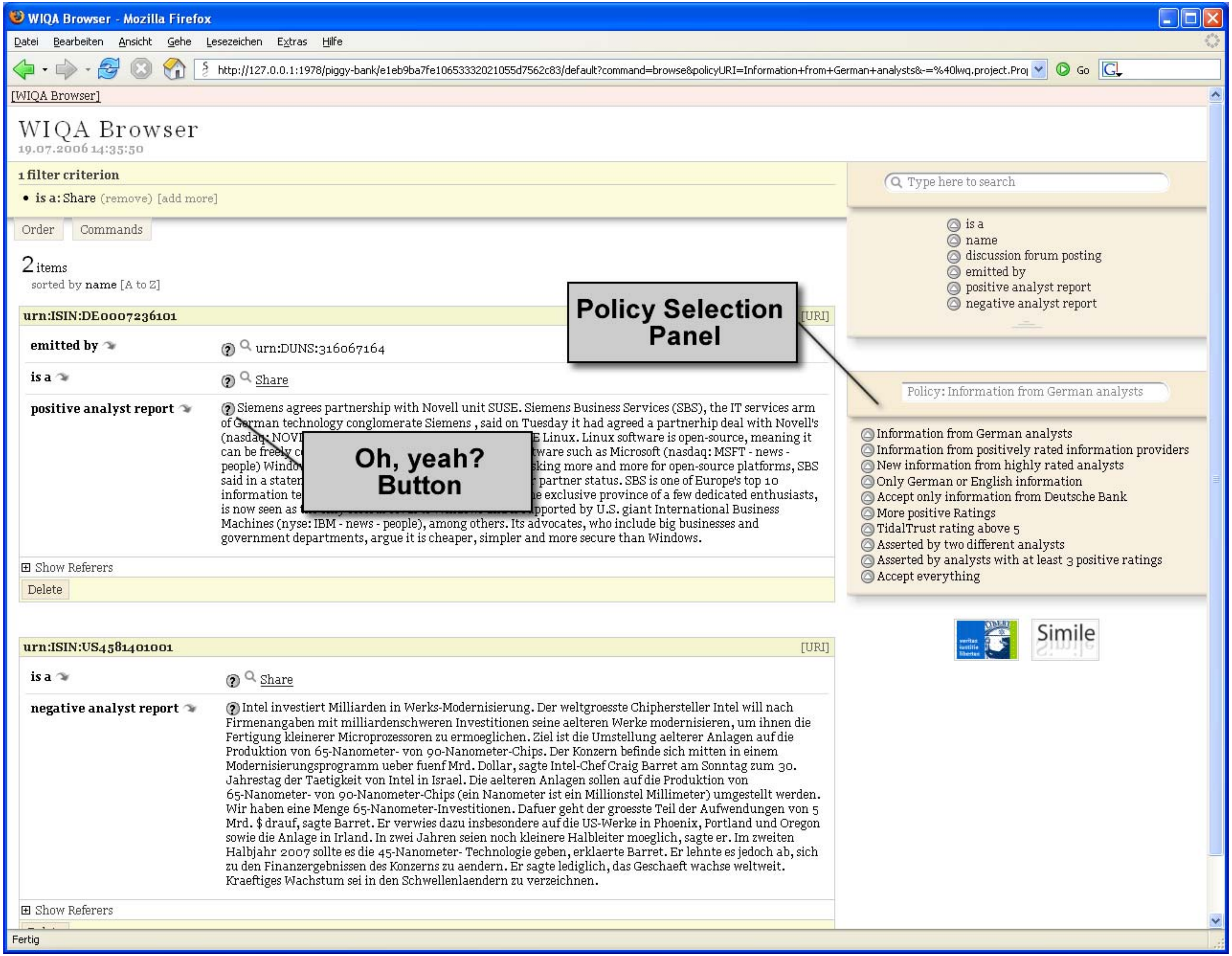
– Subjective dimension which depends on the individual user

– Assessment:
  - individual experience with the data
  - fallbacks:
    - corporate guidance about sources
    - trust networks

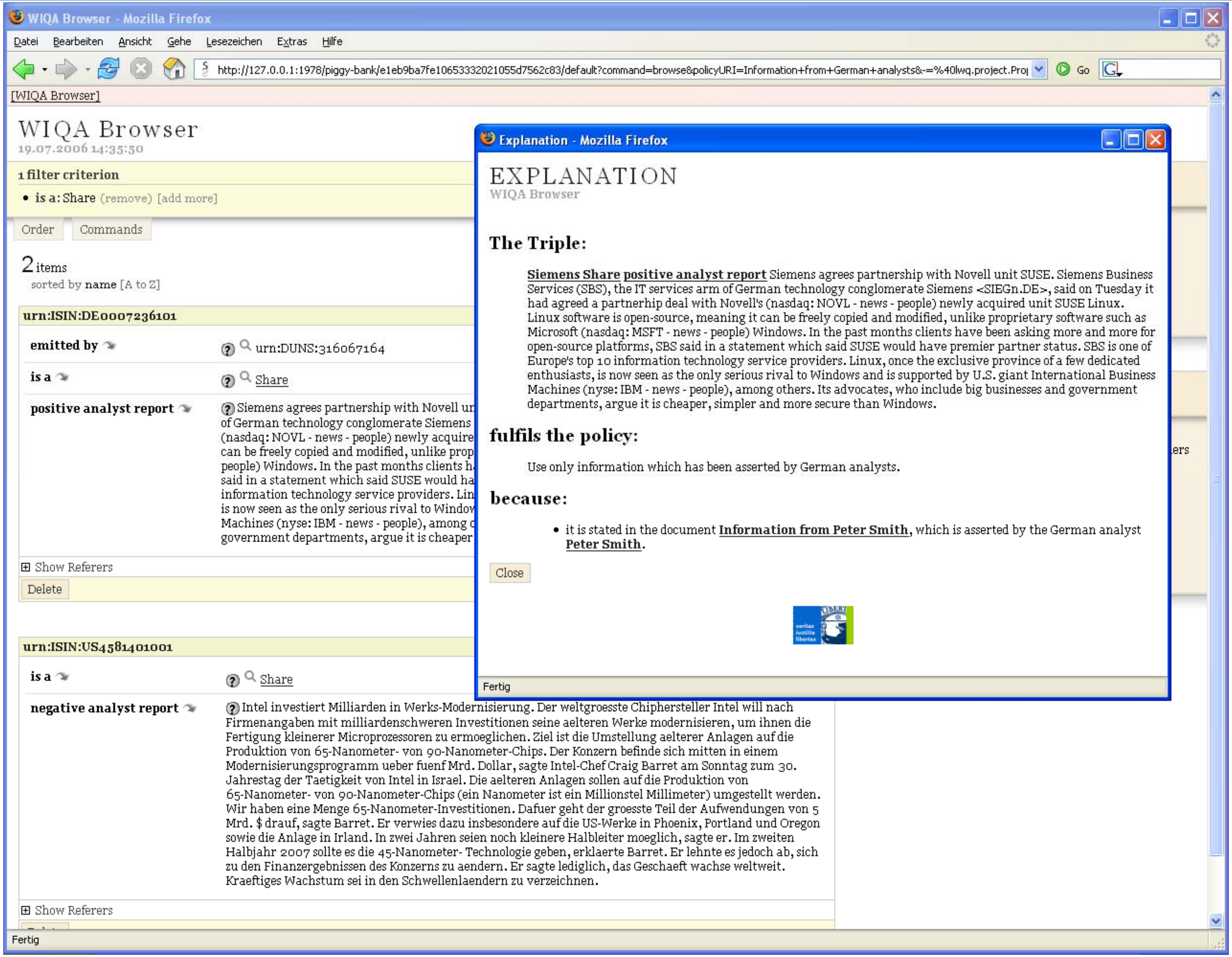
– Explanations about the data quality assessment process
  - in order to trust data, the users must understand why the system regards data to be high quality
  - Tim Berners-Lee’s “Oh, yeah?”-button

Prototype: The WIQA - Browser

- Enables users to employ different quality assess-ment policies
- Can explain assessment results



Explanation about an Assessment Decision



Example Explanation

The triple:

- Siemens AG has positive analyst report: "As Siemens agrees partnership with Novell unit SUSE ..."

fulfills the policy:

- Accept only information that has been asserted by people who have received at least 3 positive ratings.

because:

- it was asserted by Peter Smith and
- Peter Smith has received positive ratings from
  - Mark Scott who works for Siemens.
  - David Brown who works for Intel.
  - John Maynard who works for Financial Times.

Summary

- Data quality assessment is essential for web data integration as errors accumulate:
  1. Quality of the external data sources (everybody can publish on the Web)
  2. Quality of the integration process (wrong mappings, wrong identity resolution)
- Many data quality problems only become visible when we integrate data from multiple sources
- A wide range of different quality assessment heuristics can be used
  - content-based, provenance-based, rating-based metrics
- The applicability of the heuristics depends on
  - the availability of quality indicators (like provenance information or ratings)
  - quality of quality indicators (fake ratings, coarse grained provenance)
- Many systems only try to assess the accuracy and the timeliness of web data and ignore the other quality dimensions

5. Data Fusion

Given multiple records that describe the same real-world entity, create a single record while resolving conflicting data values.

DB1	Chris Miller	NULL	7 Bardon St., Melville
DB2	Christian Miller	12/20/1982	Bardon St., Melwille
New	Christian Miller	12/20/1982	7 Bardon St., Melville

– Goal: Create a single high quality record.

– Two basic fusion situations: Slot Filling and Conflict Resolution

5.1 Slot Filling and Conflict Resolution

Slot Filling: Fill missing values (NULLs) in one dataset with corresponding values from other datasets.

Result: increased dataset density

Conflict Resolution: Resolve contradictions between records by applying a conflict resolution function (heuristic).

Result: increased data quality

Complementary records

a, b, -, -
a, b, c, -
→ a, b, c, -

Conflicting records

a, b, c, -
a, e, -, -
→ a, *f*(b,e), c, -

a, -, c, -
a, b, -, -
a, e, -, d
→ a, *f*(b,e), c, d

Cluster Size Distribution, Matching Errors, and Data Fusion

- As final step of the identity resolution process, records are clustered using the discovered correspondences. Example with 3 data sources:

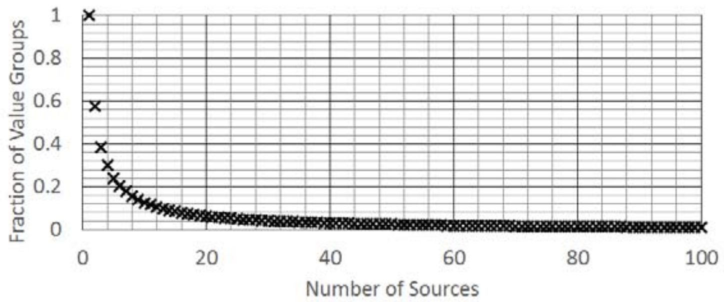
Cluster Size	Frequency
1	4256
2	939
3	503
4	75
5	14
35	3
61	1

No slot filling possible as single records with no overlap

Slot filling and conflict resolution allow the generation of improved records

Large cluster size indicates matching errors or duplicates in data sources

- Cluster size distribution from matching web tables to DBpedia
  - Out of 33.3 million web tables, 949,970 tables contain at least one matching row
  - 42% of the resulting clusters have a size of 1
  - 16% of the clusters have a size of 2
  - 39% of the clusters have a size of at least 3
  - 13% of the clusters have a size of at least 10



Ritze, et al.: Profiling the Potential of Web Tables for Augmenting Cross-domain Knowledge Bases. WWW 2016.

5.2 Conflict Resolution Functions

$$V_F = f\,(V_A, M_A, B)$$

Input Values
Background Knowledge
Fused Value
Meta-Information

- Conflict resolution functions are attribute-specific
  - you select or learn a specific function for each attribute that should be fused
- There is a wide range of different functions (heuristics) that fit different requirements
- Functions differ in regard to the data types, they can be applied for
  - numerical values (e.g. population of a place)
  - nominal values (e.g. name of a person)
  - value sets (e.g. actors performing in a movie)
- Two main groups of conflict resolution functions
  1. Instance-based functions that rely only on the data values to be fused
  2. Metadata-based functions that rely on provenance data, ratings, or quality scores

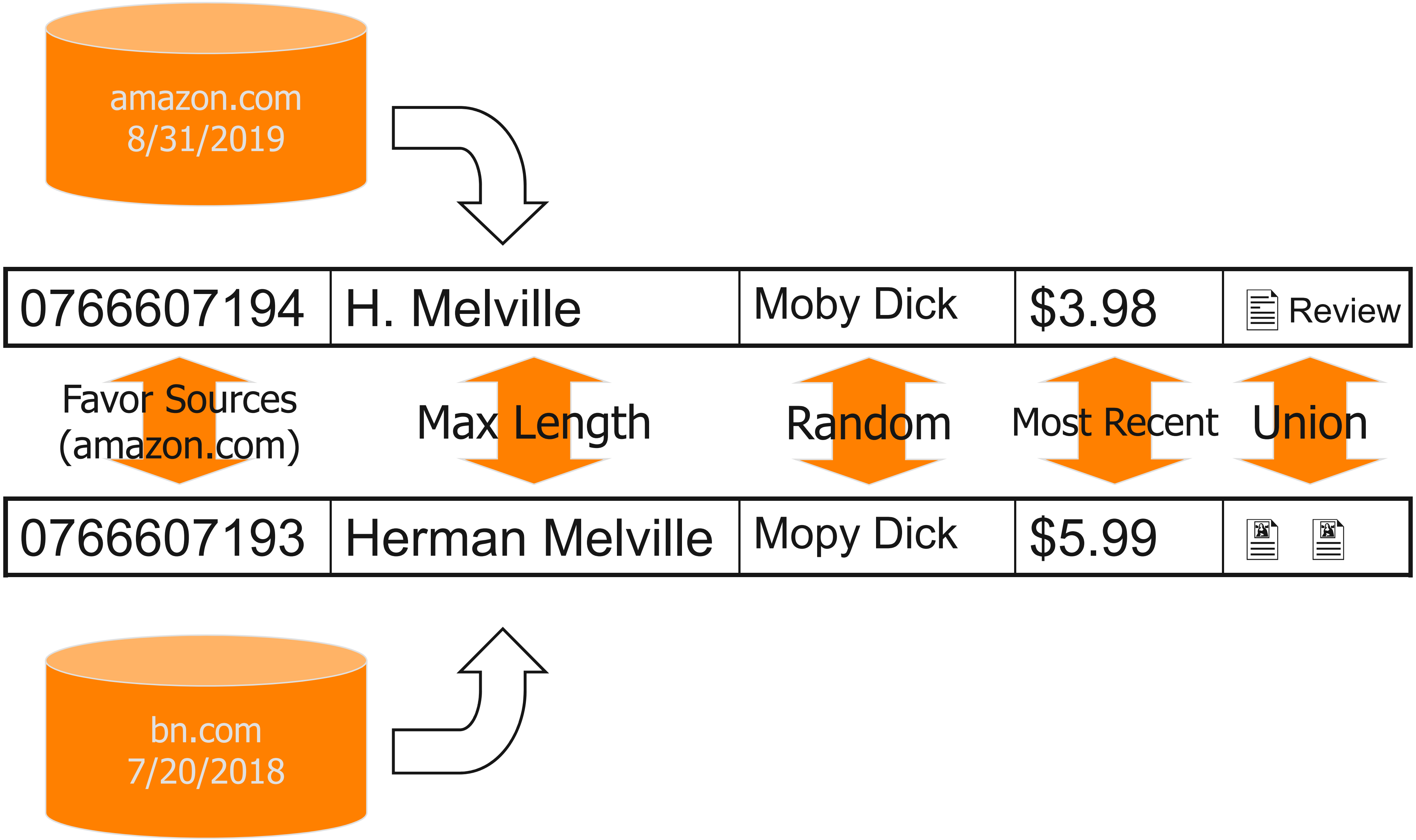
Instance-based Conflict Resolution Functions

Function	Explanation	Use Case
Average, Median	Calculate average/median of all values	Rating
Longest, Shortest	Choose longest / shortest value	First name
Max, Min	Take maximal, minimal value	Number of children
Vote	Majority decision (one vote per site or page?)	Capital city
Clustered Vote	Choose centroid / medoid of largest cluster	Population of city
Weighted Vote	Weight sources according to the fraction of true values they provided	Address of a shop
Union	Union of all values ($A \cup B \cup C$)	Product Reviews
Intersection	Intersection of all values ($A \cap B \cap C$)	Movie Actors
IntersectionKSources	Values must appear in at least k sources	Movie Actors
MostComplete	Choose value from record that is most complete	People's addresses
MostAbstract, MostSpecific	Use a taxonomy / ontology	Location
Random	Fallback: Choose random value	

Metadata-based Conflict Resolution Functions

Function	Explanation
FavorSources	Take first non-null value in particular order of sources Example: Use Eurostat for GDP, alternatively use Wikipedia
MostRecent	Choose most recent (up-to-date) value Example: Address, NumChildren
MostActive	Choose value that is most often accessed/edited Example: Prefer Wikipedia page with more edits
FavorSources basedOnRatings	Calculate quality of sources from ratings, take value from source with highest score or all values from sources with scores above specific threshold
MaxIQ	Choose the value with the highest quality score. Score might cover multiple quality dimensions, e.g. timeliness and believability of a source
TopkIQ	Choose the top K values with the highest quality scores
ClusterVoteAfter Filtering	Filter values using quality scores and apply clustered vote afterwards
….	….

Example: Complete Conflict Resolution Heuristic



5.3 Evaluation of Data Fusion Results

1. Data Centric Evaluation Measures
   - Density
   - Consistency
2. Ground Truth Based Evaluation Measures
   - Accuracy

Density

Density measures the fraction of non-NULL values.

$$density_{Column} = \frac{|non\text{–}NULL\ values\ in\ column|}{|rows\ in\ table|}$$

$$density_{Table} = \frac{|non\text{–}NULL\ values\ in\ table|}{|columns| * |rows|}$$

- As a result of schema integration, translated data sets often contain many null values (empty columns)
- We are interested in the density increase after fusion
  1. Measure density of table A or column C_1
  2. Fuse table A with table B
  3. Measure density of resulting table A' or column C_1'

Consistency

A data set is consistent if it is free of conflicting information.

$$consistency_{Column} = \frac{|non\text{-}conflicting\ values\ in\ column|}{|real\text{-}world\ entities\ described|}$$

$$consistency_{Table} = \frac{|non\text{-}conflicting\ values\ in\ table|}{|columns| * |real\text{-}world\ entities\ described|}$$

Measurement:

1. Combine multiple tables using record correspondences
   - group records that refer to same real-world entity
2. Calculate fraction of non-conflicting attribute values
   - same attribute value is provided by all data sources

Accuracy

Accuracy: Fraction of correct values selected by conflict resolution function.

$$accuracy = \frac{|correct\ values\ |}{|all\ values|}$$

$$error\ rate = \ 1 - accuracy$$

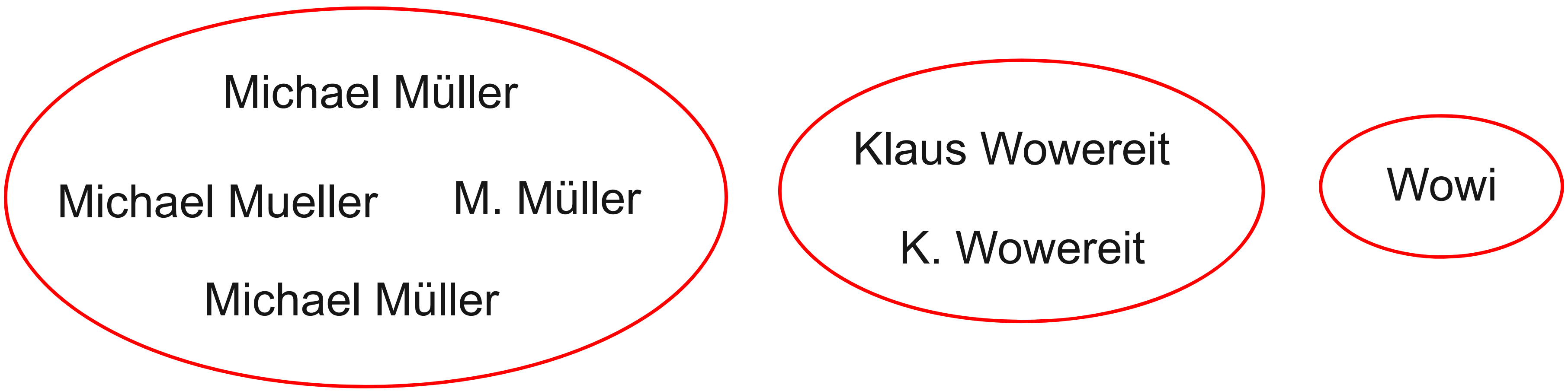
Measurement:

1. Build Ground Truth
   - Manually determine correct values for a subset of the records
   - Alternative: Use/buy correct data from external provider
   - Can be tricky as this requires you or external provider to know the truth!
2. Compare values selected by fusion function with true values

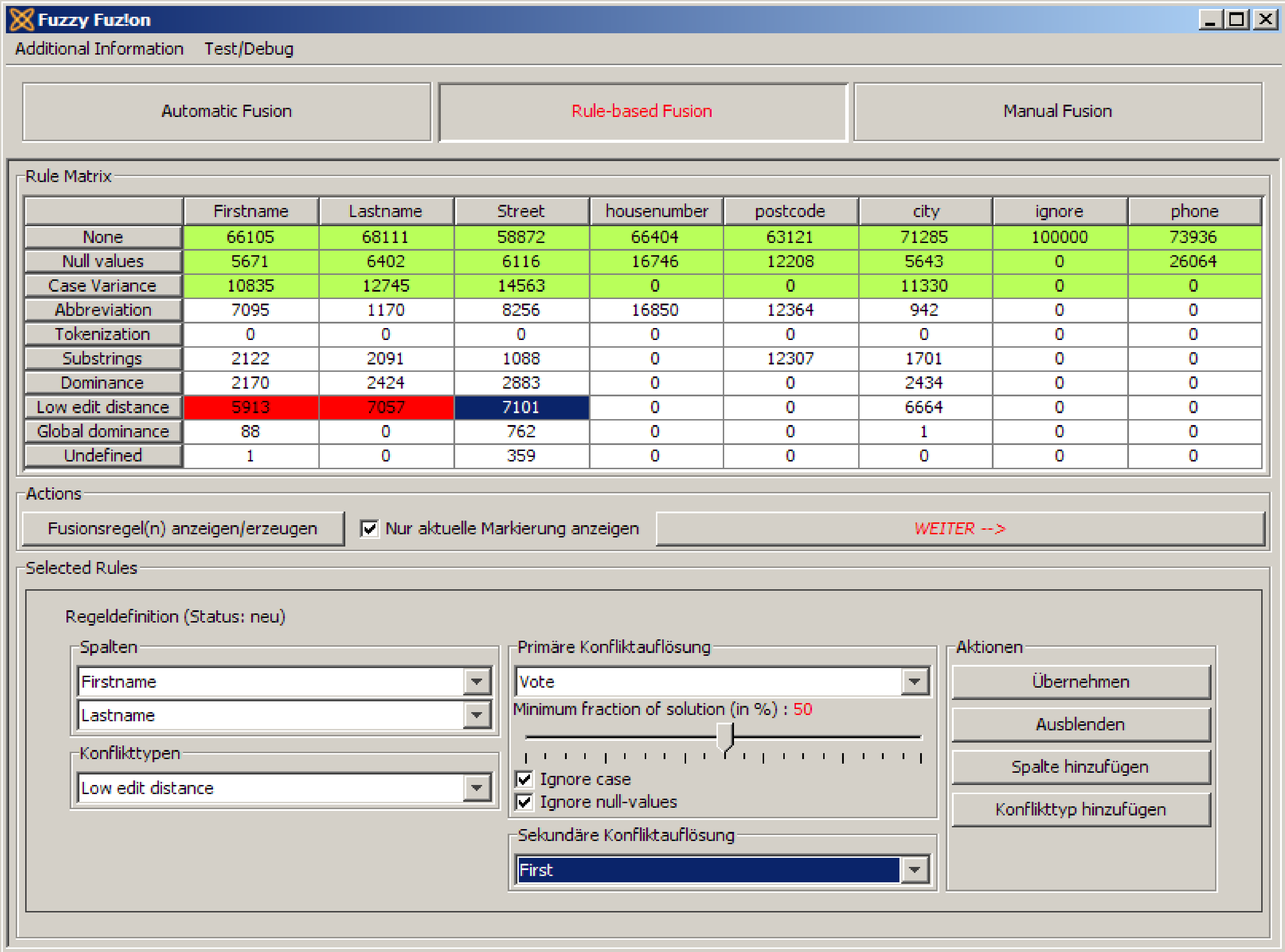
Gao, et al.: Efficient Knowledge Graph Accuracy Evaluation. VLDB Endowment, 2019.

How to Treat Similar Values?

– Treatment of similar values matters for calculating consistency and accuracy.
– Approach:
  1. Calculate similarity of values
     - using an appropriate similarity function (see Chapter Identity Resolution)
  2. Treat all values above threshold as equal
– Example: Mayor of Berlin



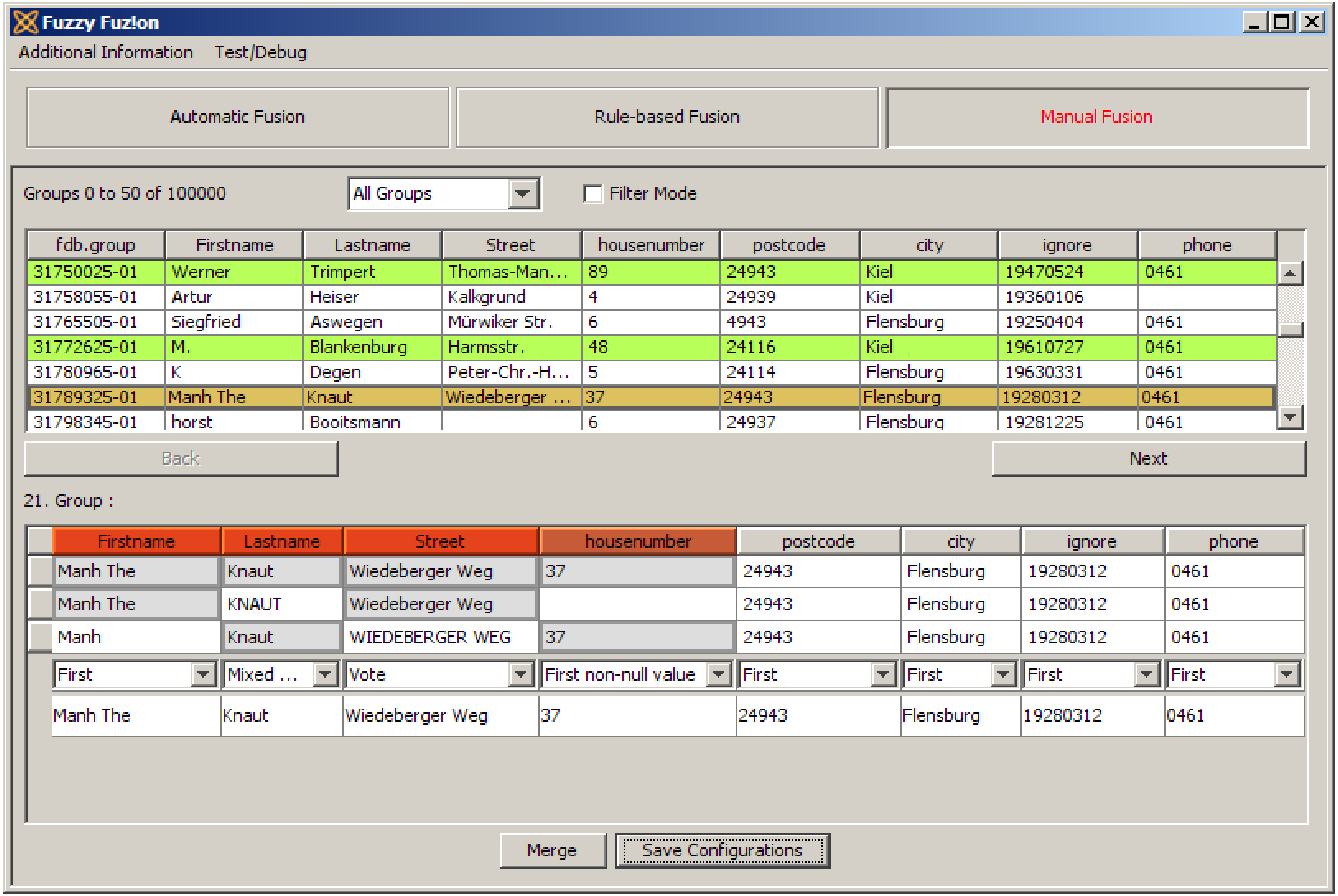
5.4. Example Data Fusion Tool: Fuz!on



	Firstname	Lastname	Street	housenumber	postcode	city	ignore	phone
None	66105	68111	58872	66404	63121	71285	100000	73936
Null values	5671	6402	6116	16746	12208	5643	0	26064
Case Variance	10835	12745	14563	0	0	11330	0	0
Abbreviation	7095	1170	8256	16850	12364	942	0	0
Tokenization	0	0	0	0	0	0	0	0
Substrings	2122	2091	1088	0	12307	1701	0	0
Dominance	2170	2424	2883	0	0	2434	0	0
Low edit distance	5913	7057	7101	0	0	6664	0	0
Global dominance	88	0	762	0	0	1	0	0
Undefined	1	0	359	0	0	0	0	0

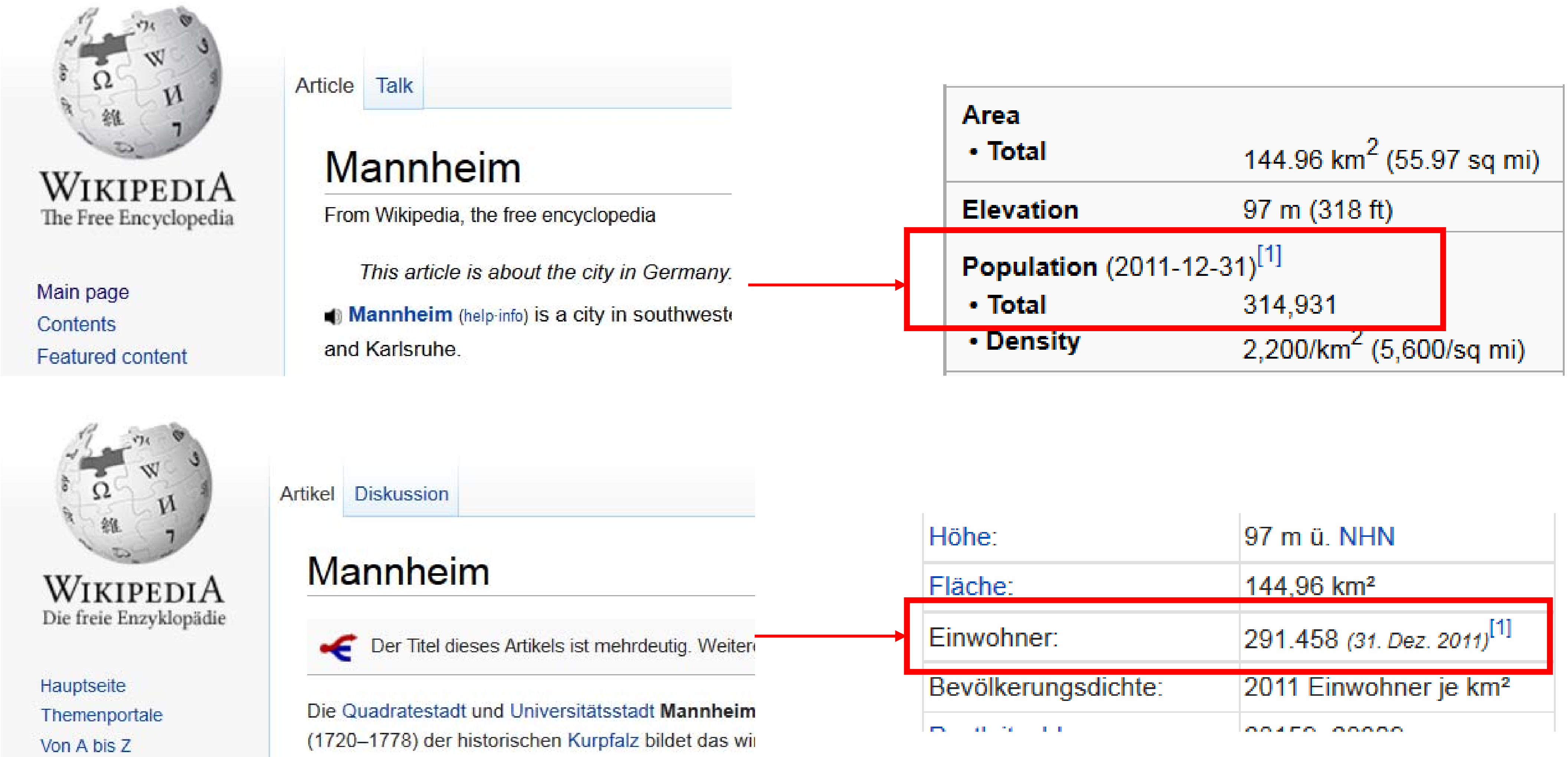
Prototype developed at Hasso Plattner Institute

Manual Fusion of Record Groups in Fuz!on



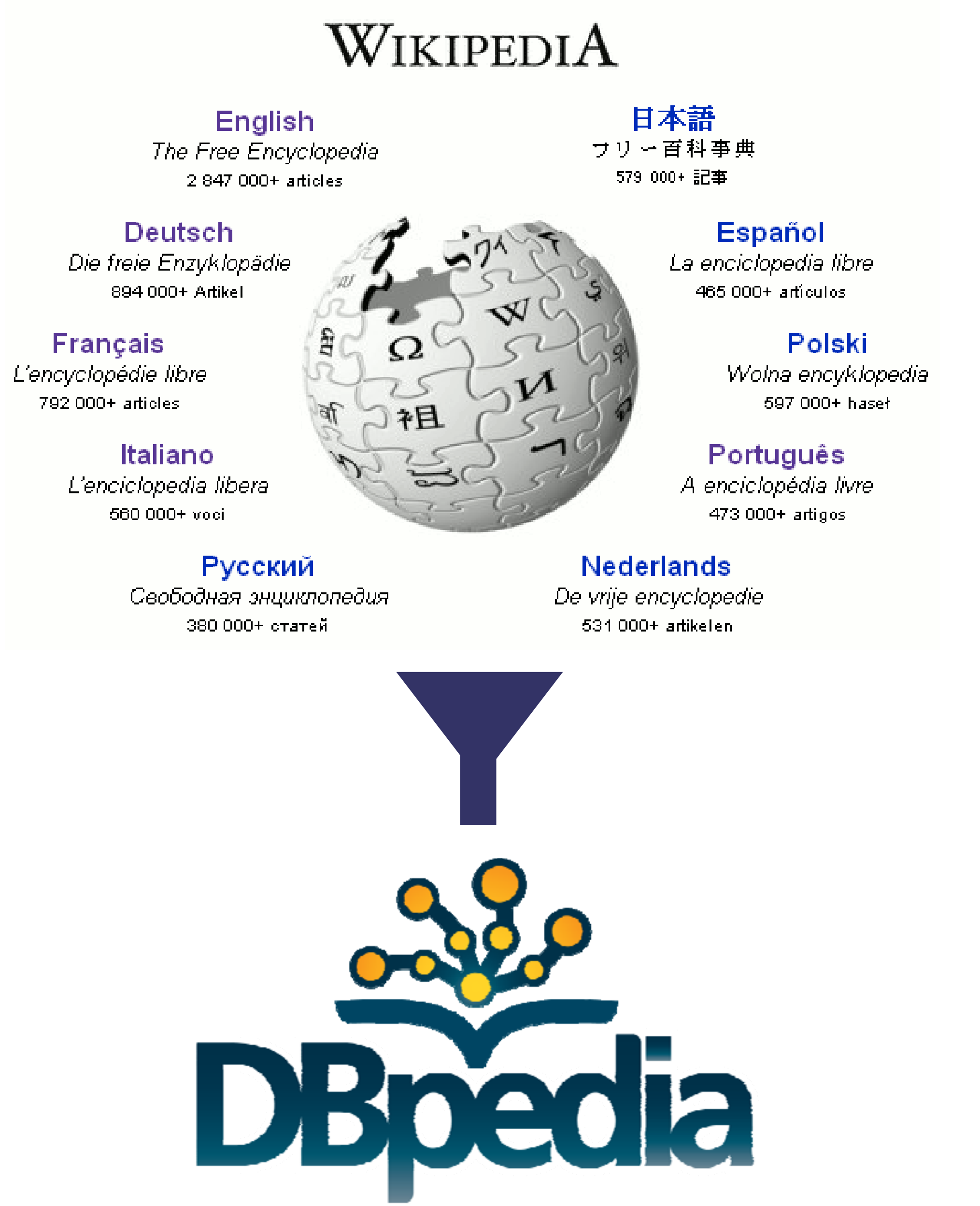
5.5 Case Study: DBpedia Cross Language Data Fusion

- **Infoboxes in different Wikipedia editions contain conflicting values.**
- **Which value to prefer?**



Cross-Lingual Data in DBpedia

- DBpedia extracts structured data from Wikipedia in **119 languages**.
- DBpedia contains **lots of data conflicts**, inherited from Wikipedia.
- **Identity resolution is solved** by Wikipedia inter-language links.
- **Schema heterogeneity problem is solved** by community-created mappings from infoboxes to DBpedia ontology.



Goal: Fuse Data between different Language Editions

Which value to prefer

- maximum?
- average?
- most frequent?
- from the specific language edition?
- most recent?
- inserted by most trusted author?
- edited most times?
- combination of the above?

data itself

prove nance

Population of Mannheim in 8 DBpedia language editions

```
Mannheim populationTotal
                     "314,931"@en
                     "291,458"@de
                     "311,969"@eu
                     "311,342"@fr
                     "308,676"@nl
                     "309,795"@pt
                     "313,174"@ru
                     "310,000"@sl
```

Provenance Metadata from the Wikipedia Revision Dumps

- We extract provenance metadata from the Wikipedia revision dumps of the Top10 languages
  - File size of revision dumps: > 6 TByte for English, >2 TByte for German
- Extracted metadata
  - Last edit timestamp of a fact
  - Number of edits of a fact
  - Author of the last edit
    - Author edit count
    - Author registration date

Provenance metadata

```
ru:Mannheim:populationTotal

        lastedit        2011-12-22T00:50:21Z
        propeditcnt     3
        autheditcnt     1136639
        authregdate     2009-12-18T02:08:09Z

nl:Mannheim:populationTotal

        lastedit        2007-12-09T16:41:06Z
        propeditcnt     1
        autheditcnt     73
        authregdate     2007-04-05T08:54:19Z
```

Learning Conflict Resolution Functions

- Ground Truth: Geonames, public geographical database
- Learning: Choose function with smallest mean absolute error with respect to gold standard.
- Tested conflict resolution functions
  1. *Maximum*
  2. *Average*
  3. *English* – prefer values from English DBpedia
  4. *Vote* – choose the most frequent value
  5. *MostRecent* fact – last edit timestamp
  6. *MostActive* fact – number of edits of a property
  7. *MostActive* author – author edit count
  8. *MostSenior* author – author registration date

DBpedia Case Study: Results

Property	Dataset	Count	Learned Fusion Function	Error, %	Error, %, en.dbpedia
populationTotal	cities1000-Germany *	7330	Vote (most frequent value)	0.3029	0.6796
populationTotal	cities1000-Netherlands	493	Maximum Value	2.1933	3.5714
populationTotal	countries	243	Maximum Value	2.1646	6.3485
country	cities1000-Italy	1078	Vote	0.0000	1.2060
country	cities1000-Brazil	1119	Max author edit count	9.8302	30.9205
country	cities1000-Germany	7638	Vote	0.0131	0.6415

** “cities1000” are cities with population >1000*

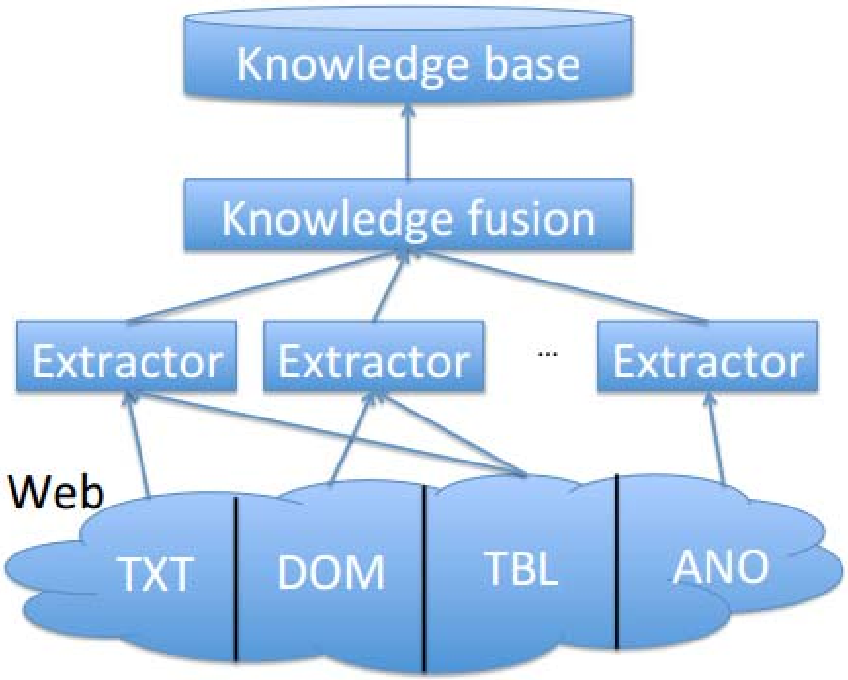
– **Error:** Mean absolute percentage error between chosen value and ground truth

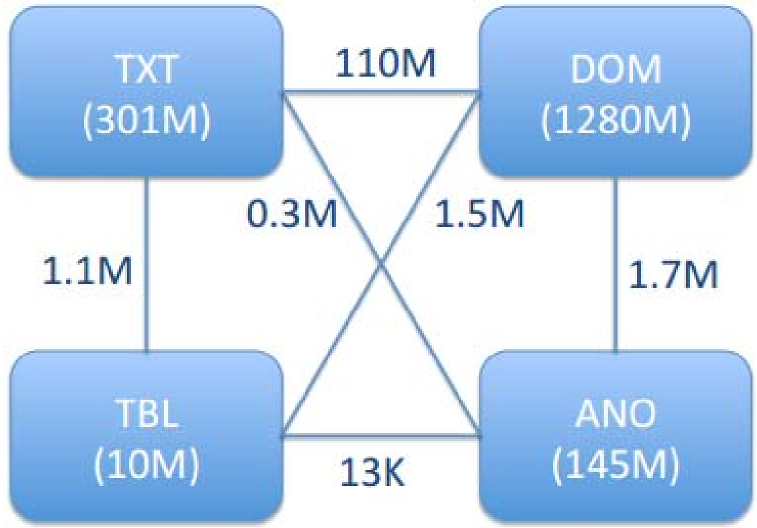
– **Error en.dbpedia:** Mean absolute percentage error between value in English DBpedia and gold standard

Volha Bryl, Christian Bizer: Learning Conflict Resolution Strategies for Cross-Language Wikipedia Data Fusion. 4th Workshop on Web Quality @ WWW 2014.

5.6 Case Study: Google Knowledge Vault

- uses 12 different extractors to extract 6.4 billion triples (1.6 billion unique triples) from 1 billion page Web crawl
- extracted data is fused to extend the Freebase knowledge base

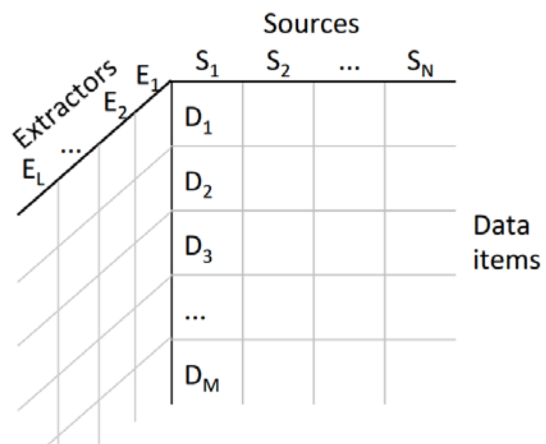




Luna Dong, et al.: From Data Fusion to Knowledge Fusion. VLDB 2014.

Google Knowledge Vault

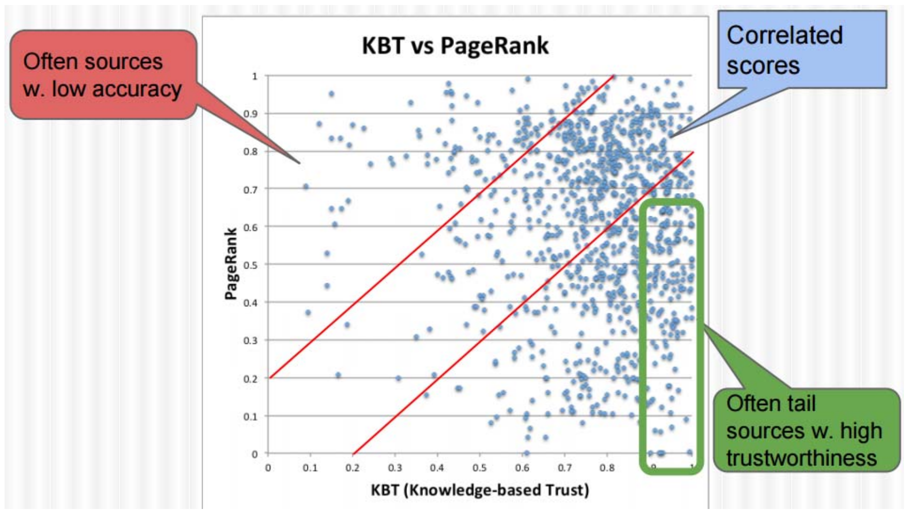
– uses probabilistic model to iteratively determine quality of triples, sources, and extractors



– result: 90 million triples with p>0.9 that were not in Freebase before

– Knowledge-based Trust

- determine trustworthiness of a data source by comparing its content with a knowledge base (ground truth)
- result: Better than PageRank in identifying
  - tail websites with high trustworthiness
  - gossip websites



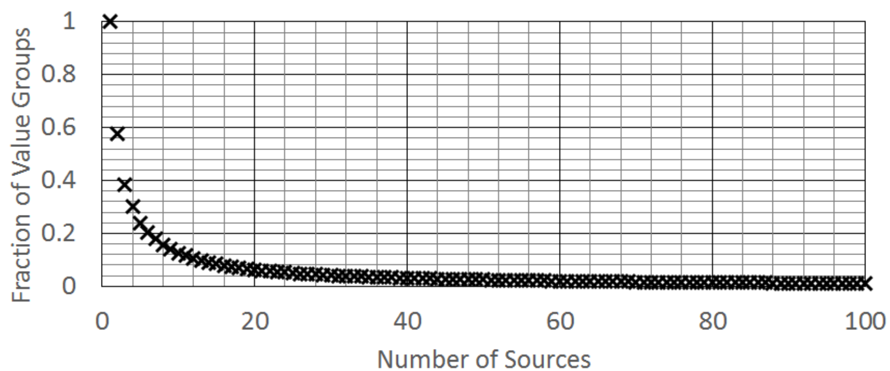
Luna Dong, et al.: Knowledge Vault: A Web-scale Approach to Probabilistic Knowledge Fusion. SIGKDD 2014.
Luna Dong, et al.: Knowledge-based Trust: Estimating the Trustworthiness of Web Sources. VLDB 2015.

Summary: Data Fusion

– Data Fusion addresses missing values (slot filling) as well as contradictions (conflict resolution)

– Appropriate conflict resolution function depends on
  - data type of the values
  - availability of quality-related metadata
  - availability of overlapping data

– On the Web, we often encounter long-tailed distributions
  - lots of overlapping data for head entities (New York)
  - hardly any data to fuse for tail entitles (some village)
  - example: Web tables matched to DBedia



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  - Wang, Strong: Beyond accuracy: What data quality means to data consumers. JMIS, 1996.
  - Naumann, Rolker: Assessment Methods for Information Quality Criteria. Conference on Information Quality, 2000.
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    Slides: http://dc-pubs.dbs.uni-leipzig.de/files/dataFusion_vldb.pdf
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  - Aggarwal: Managing and Mining Uncertain Data. Springer, 2010.

- Data Fusion Evaluation Datasets

  - Dong: Data Sets for Data Fusion Experiments
    http://lunadong.com/fusionDataSets.htm

Final Exam (IE670, 3 ECTS)

- Date and Time
  - Thursday, 12.12.2019, 8:30
- Room:
  - A5 B244. Please be at the room 10 minutes earlier.
- Duration
  - 60 minutes
- Format
  - 5-6 open questions that show that you have understood the content of the lecture
  - all lecture slide sets are relevant
    - including structured data on the Web and
    - data exchange formats
    - one question will require you to write XPath or SPARQL queries
  - we want precise answers, not all you know about the topic