POLITECNICO
MILANO 1863

Semistructured data integration

Cinzia Cappiello
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These slides are based on Prof. Tanca slides.

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First part – mediators and wrappers

Again recall the new application context

- A (possibly large) number of data sources
- Heterogeneous data sources (use of wrappers)
- ➢ Different levels of data structure
  - Databases (relational, OO…)
  - Semi-structured data sources (XML, HTML, more markups …)
  - Unstructured data (text, multimedia etc…)
- Different terminologies and different operational contexts
- Time-variant data (e.g., WEB)
- Mobile, transient data sources

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A SEMISTRUCTURED DATA BASE IS SIMILAR TO A "CLASSIC" DATA BASE, BUT THE DATAS AND SCHEMAS INVOLVED CAN CHANGE (ATTRIBUTES, PROPERTIES..)

SEMISTRUCTURED DATA

FOR THIS DATA THERE IS SOME FORM OF STRUCTURE, BUT IT IS NOT AS

- PRESCRIPTIVE → IT CAN CHANGE
- REGULAR
- COMPLETE

DYNAMIC ENVIRONMENT

AS IN TRADITIONAL DBMSs

EXAMPLES

- WEB DATA JSON, NoSQL
- XML DATA
- BUT ALSO DATA DERIVED FROM THE INTEGRATION OF HETEROGENEOUS DATASOURCES

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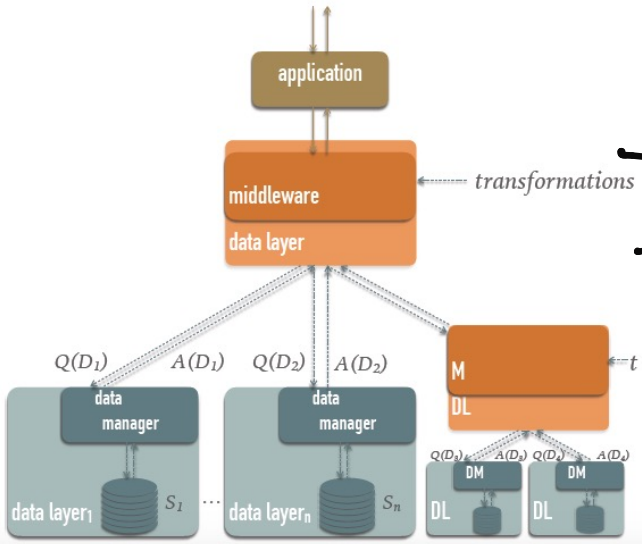
Our general framework for Data Integration



(Alvaro Fernandez, EDBT Summ. School 2017)

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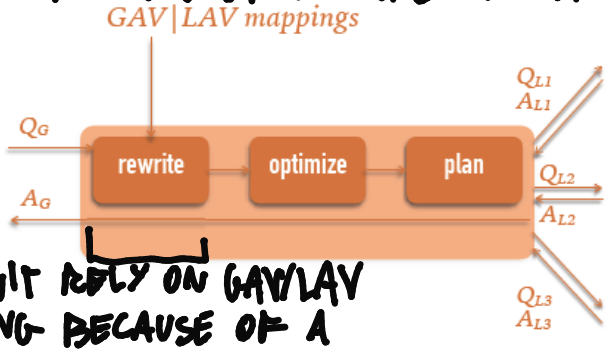
A closer look at the middleware

MAPPING OF THE GLOBAL SCHEMA WITH THE LOCAL SCHEMAS



WE CAN'T RELY ON GAV/LAV MAPPING BECAUSE OF A DYNAMIC ENVIRONMENT

(Alvaro Fernandez, EDBT Summ. School 2017)

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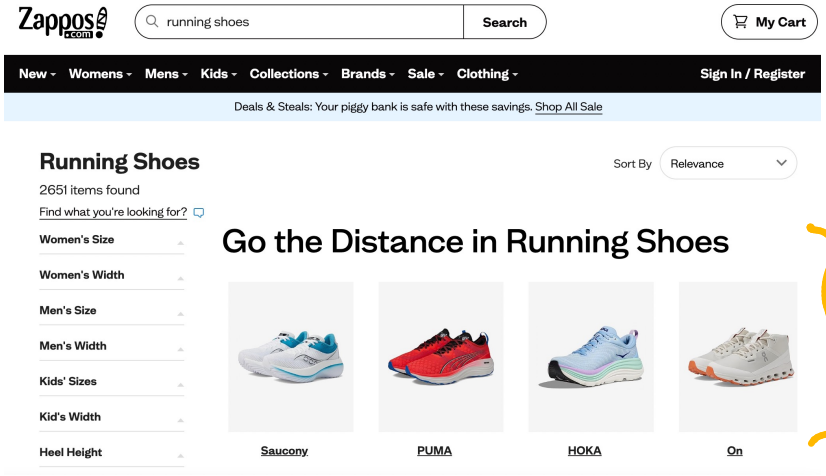
AN EXAMPLE OF SEMISTRUCTURED DATA

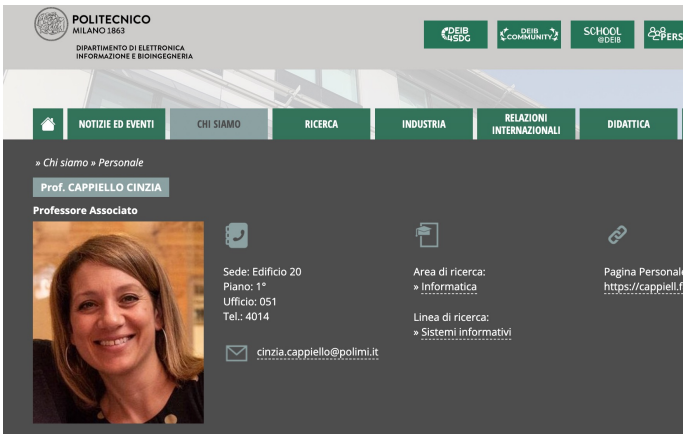
E-COMMERCE ENVIRONMENT



SET OF DATAS EXTRACTED BY AN/SOME EXTERNAL INFORMATION/S

SEMISTRUCTURED DATA:

a page produced from a database



SEMISTRUCTURED DATA MODELS

- BASED ON
  - TEXT
  - TREES
  - GRAPHS → NOWADAYS (AND FOR THE EARLY FUTURE) THE MOST COMMON
    - LABELED NODES
    - LABELED ARCS
    - BOTH
- THEY ARE ALL DIFFERENT AND DO NOT LEND THEMSELVES TO EASY INTEGRATION

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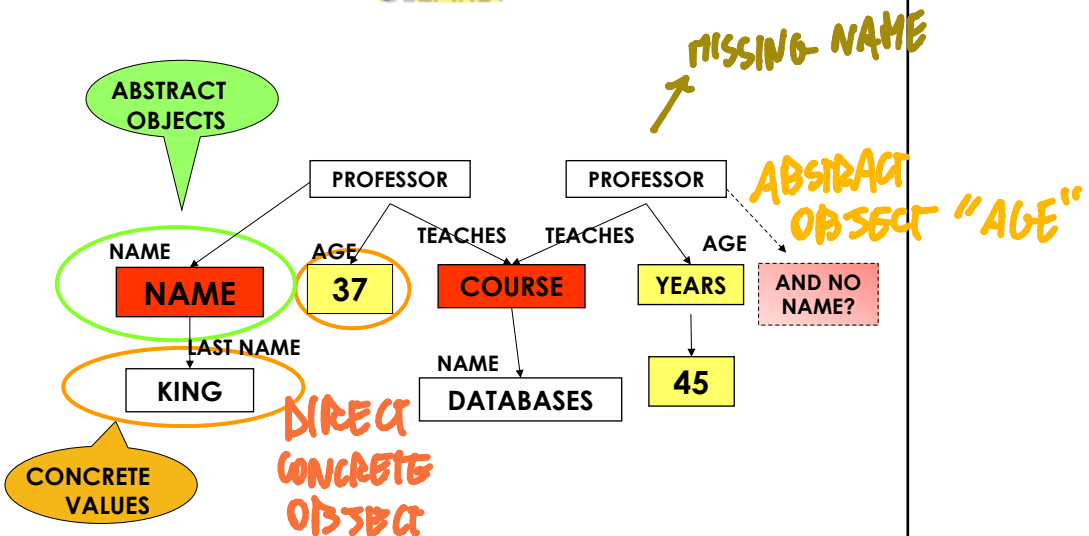
A GRAPH-BASED REPRESENTATION, WHERE THE IRREGULAR DATA STRUCTURE APPEARS VERY CLEARLY



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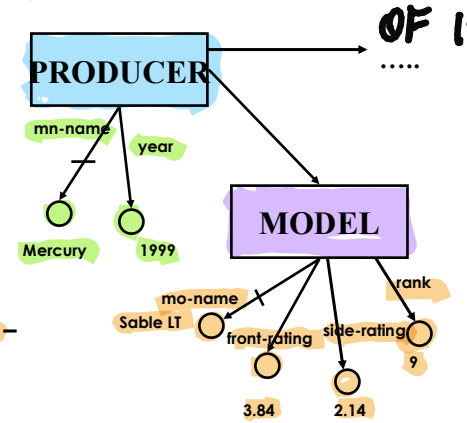
A SIMPLE XML DOCUMENT WITH ITS GRAPH BASED REPRESENTATION

GRAPHS ARE BASED ON THE DEFINING OF ISTANCES

```
<producer>
  <mn-name>Mercury</mn-name>
  <year>1999</year>
  <model>
  <mo-name>Sable LT</mo-name>
  <front-rating>3.84</front-rating>
  <side-rating>2.14</side-rating>
  <rank>9</rank>
  </model>
  .........
</producer>
```



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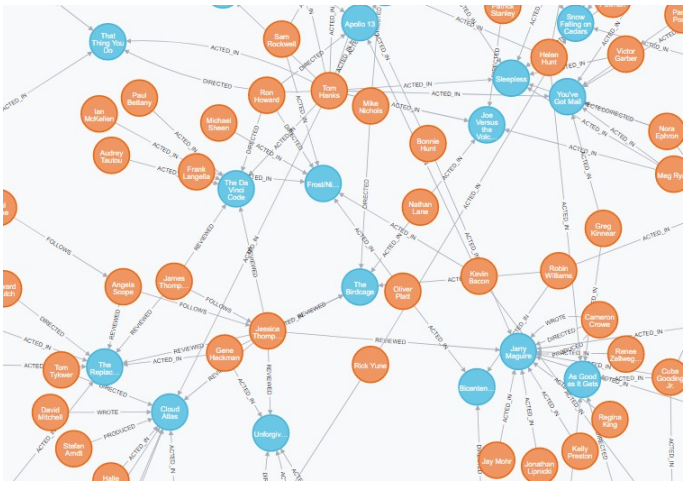
A Graph-based model:

Neo4j

MOVIES

ACTORS



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12 IT IS CLEAR THAT DATAS ARE NOT SCHEMAS

THEY ARE REPRESENTED AS NODES, AND ARCHS STAND FOR RELATIONS

INFORMATION SEARCH IN SEMISTRUCTURED DATABASES

BEING ABLE TO EXTRACT DATA FROM THEM

- WE WOULD LIKE TO:
  - INTEGRATE
  - QUERY
  - COMPARE

  DATA WITH DIFFERENT STRUCTURES ALSO WITH SEMISTRUCTURED DATA, JUST AS IF THEY WERE ALL STRUCTURED

  BEING ABLE TO EXTRACT DATAS FROM THEM
- AN OVERALL DATA REPRESENTATION SHOULD BE PROGRESSIVELY BUILT, AS WE DISCOVER AND EXPLORE NEW INFORMATION SOURCES

  GLOBAL SCHEMA HAS TO BE MANAGED THROUGH THE TIME.
- DESIGN HAS TO BE REGULARLY UPDATE

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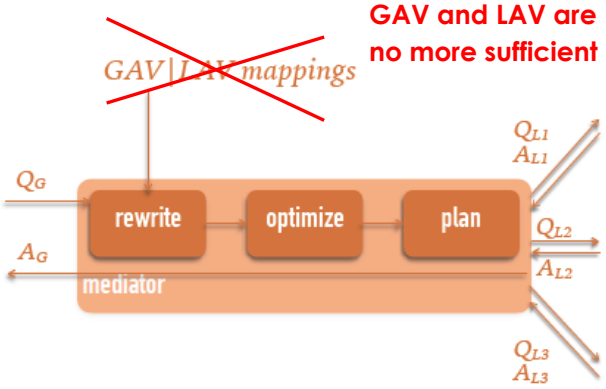
MEDIATORS

GAV and LAV are no more sufficient !!



- A **mediator** must do the same as the integration systems seen up to now, but this time the problem is much more complex

(Alvaro Fernandez, EDBT Summ. School 2017)

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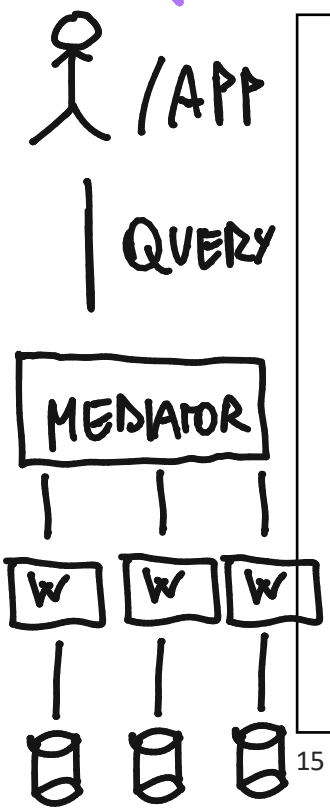
A MEDIATOR MANAGES THE FLOW FROM APP/USER TO THE SOURCES

W - WRAPPER



MEDIATORS must do many different things

The term mediation includes:

- the processing needed to make the interfaces work
- the knowledge structures that drive the transformations needed to transform data to information
- any intermediate storage that is needed (Wiederhold)

Problem:

each different domain needs a mediator appropriately designed to "understand" its semantics

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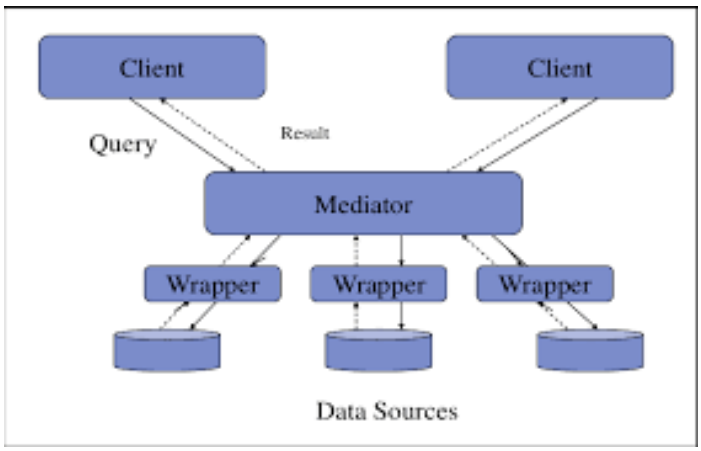
USUALLY, DATAS ARE PRESENT ONLY IN THE SOURCES

↓

SAVING RESULTS IN THE REPOSITORY IS NOT MANDATORY ANYMORE

Mediation-based systems



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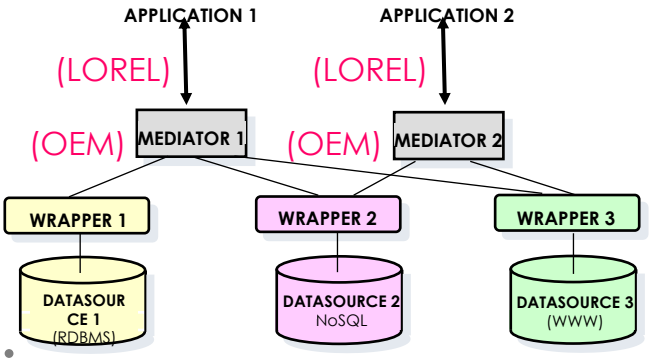
EXAMPLE: TSIMMIS

- first system based on the **mediator/wrapper paradigm**
- Proposed already in the 90's at Stanford university



Mediator-based approach

IN TSIMMIS:

- UNIQUE, GRAPH-BASED INTERNAL DATA MODEL: OEM (Object Exchange Model), MANAGED BY THE MEDIATOR
- WRAPPERS FOR THE MODEL-TO-MODEL TRANSLATIONS
- QUERY POSED TO THE MEDIATOR IN THE *LOREL (Lightweight Object REpository Language)* LANGUAGE
- MEDIATOR "KNOWS" THE SEMANTICS OF THE APPLICATION DOMAIN

OEM (Object Exchange Model) (TSIMMIS)

- Graph-based
- It does not represent the schema
- It directly represents the data : self-descriptive

WE HAVE ONLY ISTANCES

```
<temp-in-farenheit,int,80>
```

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Object structure in OEM

```
<(Object-id),label,type,value>
```

Nested structure

⟨set-of-temps, set, {cmp_1, cmp_2}⟩
cmp_1: ⟨temp-in-Fahrenheit, int, 80⟩
cmp_2: ⟨temp-in-Celsius, int, 20⟩

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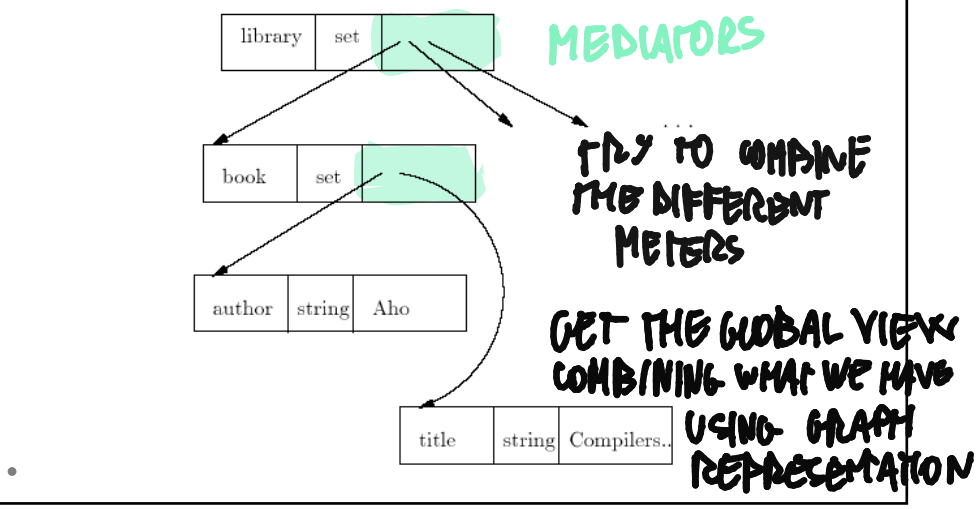
OEM (Object Exchange Model) (TSIMMIS)



Typical complications when integrating semi- or un-structured data

- Each mediator is specialized into a certain domain (e.g. weather forecast), thus
- Each mediator must know domain metadata , which convey the data semantics
- On-line duplicate recognition, reconciliation and removal (no designer to solve conflicts at design time here)
- If data source changes a little, the wrapper has to be modified → automatic wrapper generation (later)

The language of TSIMMIS is LOREL

- *L*ightweight *O*bject *RE*pository *L*anguage
- Object-based
- Similar to object oriented query languages, with some modifications appropriate for semistructured data:

EXAMPLE:

" Find books authored by Aho"

```
select library.book.title
where library.book.author = "Aho"
from library
```

USER HAS TO KNOW HOW THE GRAPH IS DEFINED

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Query formulation in the Lorel language

```
select library.book.title
where library.book.author = "Aho"
from library
```
(if more than one root is available)

OK, but if this query must be produced at run-time and there is no schema, how does the user (or the system, if a transformation has to be applied) know that a node *library* exists, which contains nodes *book*, which in turn contain the fields *author* and *title* ?

- The TSIMMIS system introduced the *Dataguide*: a kind of a-posteriori schema, progressively built by the Mediator while exploring the data sources. Again, strictly bound to the application !!!

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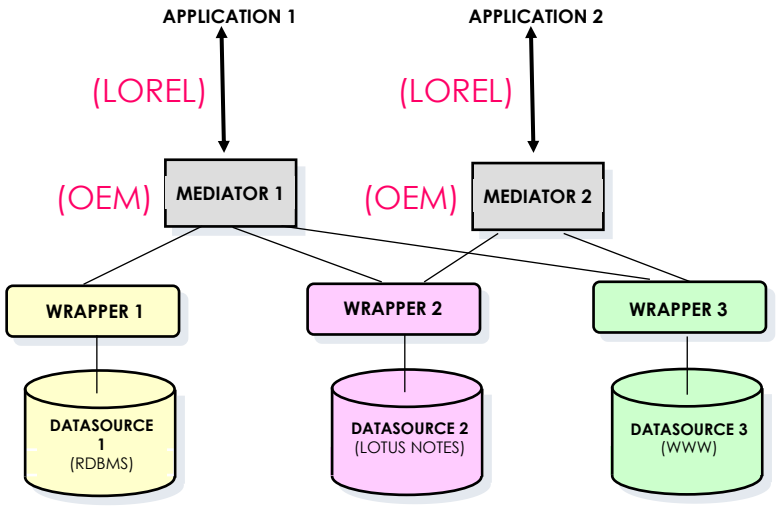
TSIMMIS SYSTEM



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LET'S GO BACK TO THE CONCEPT OF WRAPPER

- Convert queries into queries/commands which are understandable for the specific data source
  - they can extend the query possibilities of a data source
- Convert query results from the source's format to a format which is understandable for the application

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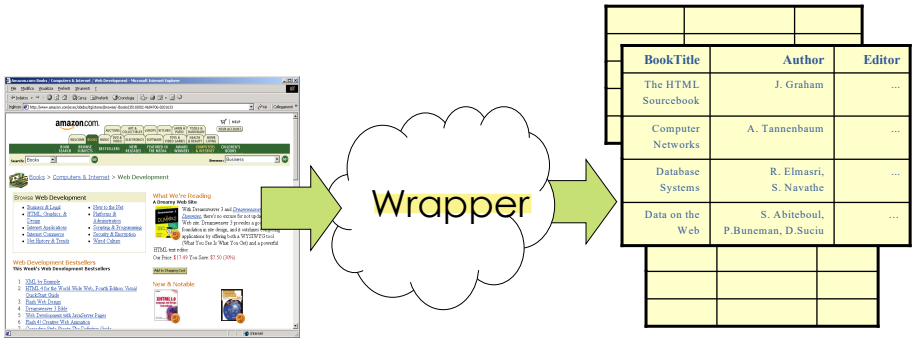
a WRAPPER for Web Pages



HTML page

database table(s) (or XML docs)

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Estraction of information from HTML docs

- Information extraction
  - Source Format: plain text with HTML tags (no semantics)
  - Target Format: e.g., relational table (possibly nested, NF^2) or XML, JSON, etc.(we add *structure*, i.e. *semantics*)
  - Much easier if the underlying page structure is derived from a DB
- Wrapper
  - Software module that performs an *extraction step*
  - Intuition: use extraction rules which exploit the *marking tags*

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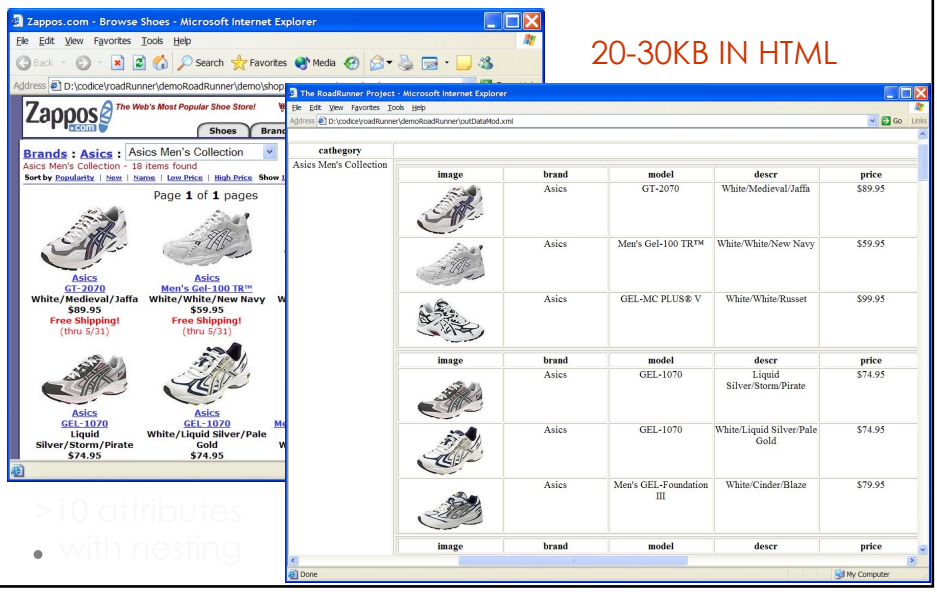
A complex extraction process



20-30KB IN HTML

- >10 attributes
- with nesting

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Problems

- Web sites change very frequently
- A layout change may affect the extraction rules
- Human-based maintenance of an ad-hoc wrapper is very expensive
- Better: ***automatic wrapper generation***

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Automatic wrapper generation

- We can only use it when pages are *regular* to some extent
- OK when:
  - Many pages sharing the same structure
  - e.g. pages are dynamically generated from a DB

→ *data intensive* web sites

PAGINATOR

ALESSANDRO CUCCHIARELLI

A VOLTE RITORNANO

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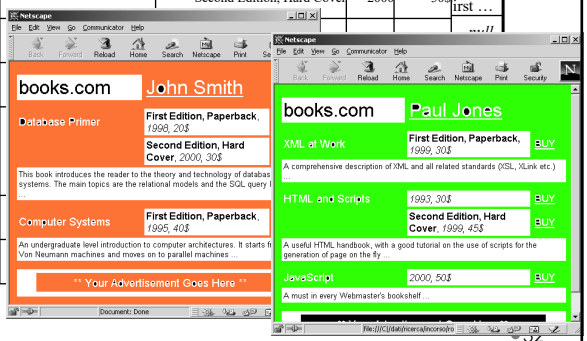
Online library

Name	Books				
	Title	Description	Editions		
			Details	Year	Price
John Smith	Database Primer	This book …	First Edition, Paperback	1998	20$
			Second Edition, Hard Cover	2000	30$
	Computer Systems				
Paul Jones	XML at Work				
	HTML and Scripts				
	JavaScripts				
…	…				



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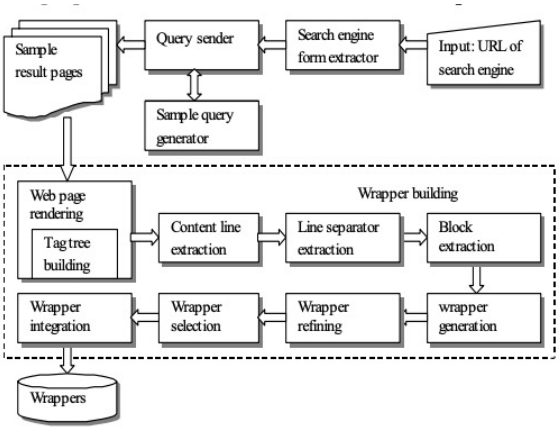
An example



Hongkun Zhao, Weiyi Meng, Zonghuan Wu, Vijay Raghavan, and Clement Yu. 2005. Fully automatic wrapper generation for search engines. In Proceedings of the 14th international conference on World Wide Web (WWW '05). Association for Computing Machinery, New York, NY, USA, 66-75. https://doi.org/10.1145/1060745.1060760

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- L. Dong, D. Srivastava, Big Data Integration, Morgan & Claypool Publishers, 2015
- Roberto De Virgilio, Fausto Giunchiglia, Letizia Tanca (Eds.): Semantic Web Information Management – A Model-Based Perspective. Springer 2009, ISBN 978-3-642-04328-4
- M. Lenzerini, Data Integration: A Theoretical Perspective, Proceedings of ACM PODS, pp. 233-246, ACM, 2002, ISBN: 1-58113-507-6
- Clement T. Yu, Weiyi Meng, Principles of Database Query Processing for Advanced Applications , Morgan Kaufmann, 1998, ISBN: 1558604340

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Second part – ontologies

A WAY TO MODEL DOMAINS. GOOD TOOL IN PARTICULAR DEALING WITH SEMANTIC MATCHING

Ontologies:
a way to solve the problem of automatic semantic matching

- A formal and shared definition of a vocabulary of terms and their inter-relationships
- Predefined relations:
  - *synonimy*
  - *omonimy*
  - *hyponimy*
  - *etc..*
- More complex, designer-defined relationships, whose semantics depends on the domain

FORMAL AND PRECISE
CONCEPTS AND RELATIONSHIPS
STATIC PART
DINAMIC PART

e.g. enrolled(*student*,*course*)

→ an ER diagram, a class diagram, any conceptual schema *is a kind of ontology!*

Definitions

- Ontology = formal specification of a conceptualization of a shared knowledge domain.
- An ontology is a controlled vocabulary that describes objects and the relationships between them in a formal way
- It has a grammar for using the terms to express something meaningful within a specified domain of interest.
- The vocabulary is used to express queries and assertions.
- Ontological commitments are agreements to use the vocabulary in a consistent way for knowledge sharing

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Aims...

TO ENABLE AUTOMATIC KNOWLEDGE SHARING

- A formal specification allows for use of a common vocabulary for *automatic knowledge sharing*
- Formally specifying a *conceptualization* means giving a unique meaning to the terms that define the knowledge about a given domain
- *Shared:* an ontology captures knowledge which is common, thus *over which there is a consensus* (objectivity is not an issue here)

≠ METHODS FOR DEFINING A SAME CONCEPT

AN ONTOLOGY CAN BE ACCESSED TO ALL USERS THROUGH CONSENS

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• TAXONOMIC → TREE ORGANIZATION

• DESCRIPTIVE → GRAPH ORGANIZATION

CONTEXT$_1$

|

CONTEXT$_2$

Ontology types

→ VOCABULARIES IN WHICH WE DEFINE A HIERARCHICAL ORGANIZATION AMONG TERMS

- **Taxonomic** ontologies
  - Definition of concepts through terms, their hierarchical organization, and additional (pre-defined) relationships (synonymy, composition,…)
  - To provide a reference vocabulary

(CONTEXT$_2$ ⊂ CONTEXT$_1$)

- **Descriptive** ontologies
  - Definition of concepts through data structures and their interrelationships
  - Provide information for "aligning" existing data structures or to design new, specialized ontologies (***domain ontologies***)
  - Closer to the database area techniques

MODELING MORE RELATIONS AND COMPLEX COMPONENTS

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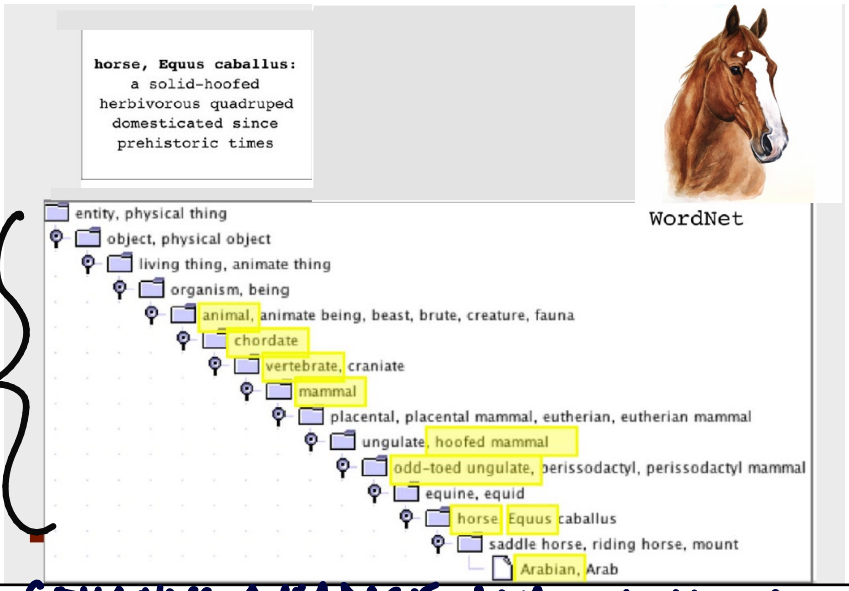
Wordnet

→ OFTEN USE IN UNIVERSITIES



HIERARCHICAL ORGANIZATION

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SEMANTIC DATABASE THAT ORGANIZES, DEFINES AND DESCRIBES THE GIVEN CONCEPTS (ENGLISH LANGUAGE)

An ontology consists of...

- Concepts:
  - Generic concepts, they express general world categories
  - Specific concepts, they describe a particular application domain (domain ontologies)
- Concept Definition
  - Via a formal language
  - In natural language
- Relationships between concepts:
  - Taxonomies (IS_A),
  - Meronymies (PART_OF),
  - Synonymies, homonymies, ...
  - User-defined associations,

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Formal Definitions

USE OF 4 CONCEPTS

O = (C, R, I, A)

O: ontology, *C:* concepts, *R:* relations, *A:* axioms,

I: Instances

- Specified in some logic-based language
- Organized in a ISA hierarchy → SUBSUMPTIVE RELATIONSHIP BETWEEN ABSTRACTIONS, WHERE A CLASS A IS A SUBCLASS OF ANOTHER CLASS B
- *I is an* instance collection, stored in the information source

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Formal Definitions

An ontology is (part of) a knowledge base, composed by:

- a ***T-Box***: contains all the concept and role definitions, and also contains all the axioms of our *logical theory* (e.g. "A father is a Man with a Child").
- an ***A-box***: contains all the basic assertions (also known as ground *facts*) of the logical theory (e.g. "Tom is a father" is represented as Father(Tom)). It describes the *instances*.

ABSTRACT REPRESENTATION

CONCRETE REPRESENTATION

↳ DEFINITIONS

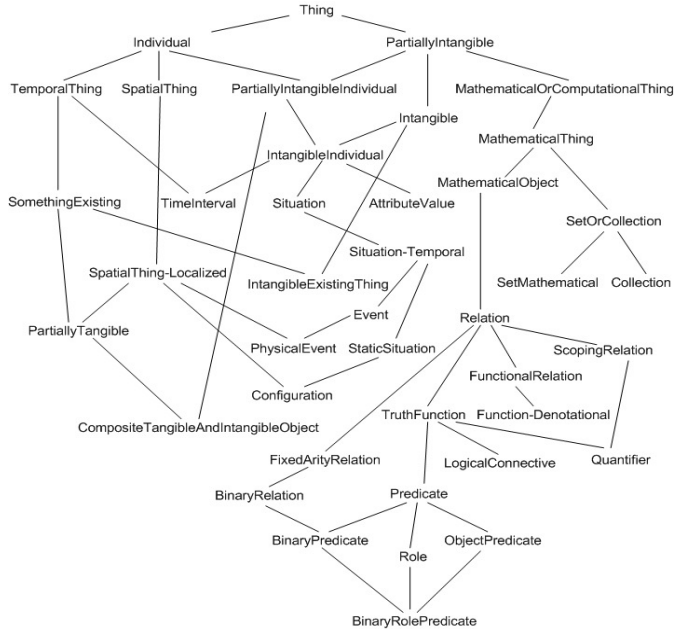
FUNCTIONS

OpenCyc

EXAMPLE OF A FAMOUS ONTOLOGY

- The open source version of the Cyc technology, started in 1984 at MCC.
- Available until early 2017 as OpenCyc under an open source (Apache) license.
- Later, Cyc was made available to AI researchers under a research-purpose license as ResearchCyc.
- Cyc is a long-term artificial intelligence project that aims to assemble a comprehensive ontology and knowledge base that spans the basic concepts and rules about how the world works.
- The entire Cyc ontology contains hundreds of thousands of terms and millions of assertions relating the terms to each other, forming an ontology whose domain is all of human consensus reality.

Top level concepts of Cyc



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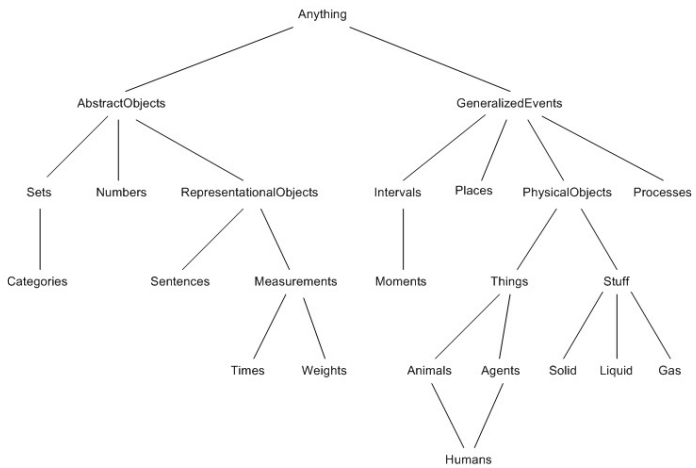
Top level concepts of the Russel and Norvig ontology



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semantic interoperability → *Semantic Web*

- A vision for the future of the Web in which information is given explicit meaning, making it easier for machines to automatically process and integrate information available on the Web.
- Built on XML's ability to define customized tagging schemes and RDF's flexible approach to representing data(*).
- The first level above RDF: OWL, an ontology language what can formally describe the meaning of terminology used in Web documents → beyond the basic semantics of RDF Schema.

(*) Also different implementations of RDF exist, not based on XML (e.g. Turtle)

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Linked Data

- Linked Data is a W3C-backed movement about connecting data sets across the Web. It describes a method of publishing structured data so that it can be interlinked and become more useful.
- It builds upon standard Web technologies such as HTTP, RDF and URIs, but extends them to share information in a way that can be read automatically by computers, enabling data from different sources to be connected and queried.
- A subset of the wider Semantic Web movement, which is about adding meaning to the Web (Tim Berners-Lee)
- Open Data describes data that has been uploaded to the Web and is accessible to all
- Linked Open Data: extend the Web with a data commons by publishing various open datasets as RDF on the Web and by setting RDF links among them

BASED ON WEB STANDARD TECHNOLOGIES THAT CONNECTS OPEN DATAS

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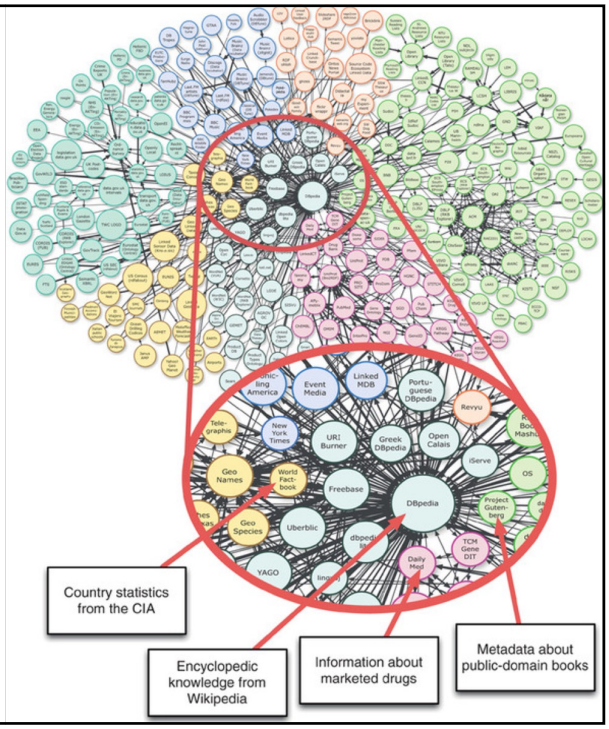
Linked Open Data



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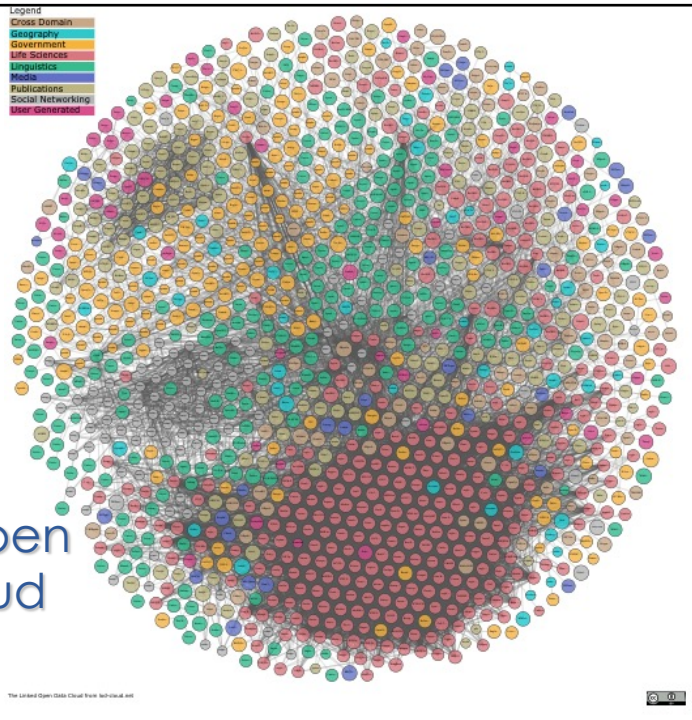
Linked Open Data Cloud Diagram

https://lod-cloud.net/



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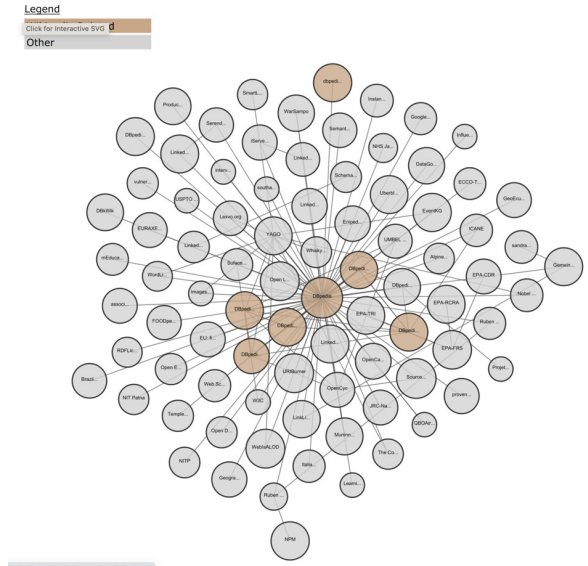
Cross-Domain Subcloud



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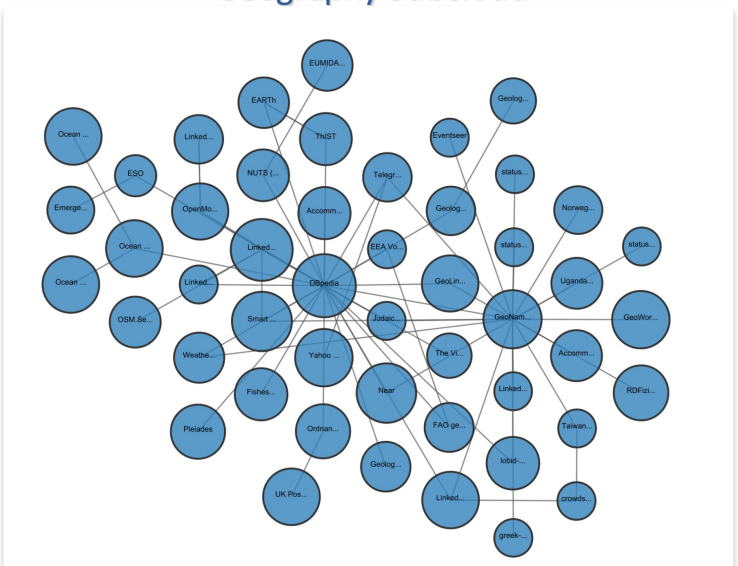
Geography Subcloud



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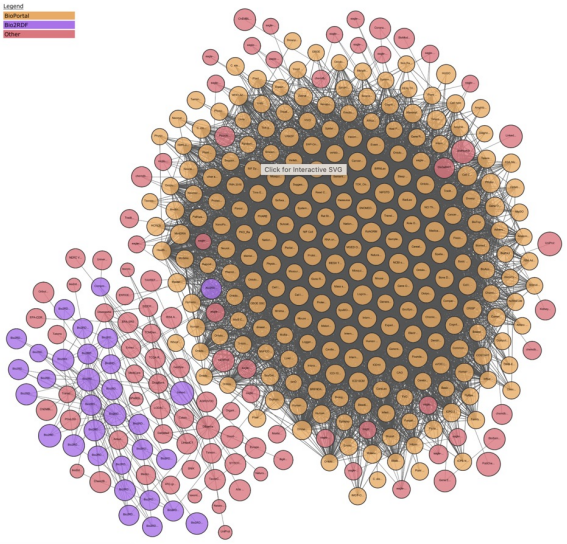
Life Sciences Subcloud



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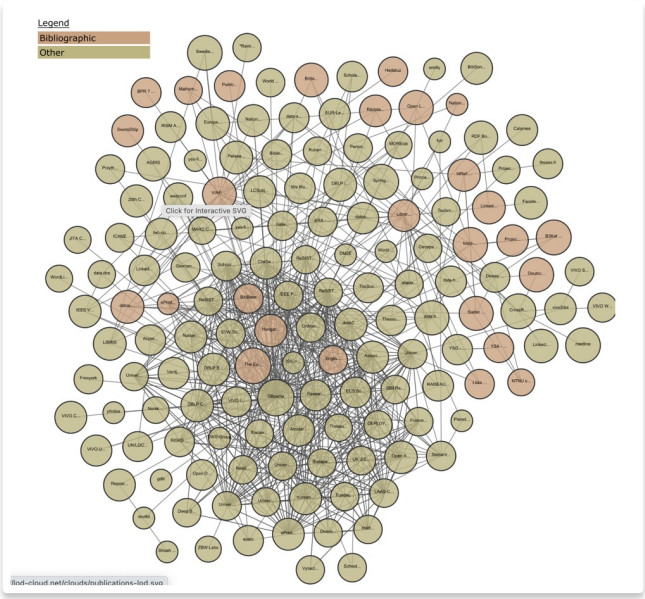
Publications Subcloud



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Some famous datasets

- CKAN – registry of open data and content packages provided by the Open Knowledge Foundation
- DBpedia – a dataset containing data extracted from Wikipedia; it contains about 4 million concepts described by some billion triples, including abstracts in 11 different languages
- GeoNames provides RDF descriptions of more than 7,500,000 geographical features worldwide.
- YAGO (Yet Another Great Ontology) is an ever-growing open source knowledge base developed at the Max Planck Institute for Computer Science in Saarbrücken. It is automatically extracted from Wikipedia and other sources.
- UMBEL – a lightweight reference structure of 20,000 subject concept classes and their relationships derived from OpenCyc, which can act as binding classes to external data; also has links to 1.5 million named entities from DBpedia and YAGO
- FOAF – a dataset describing persons, their properties and relationships

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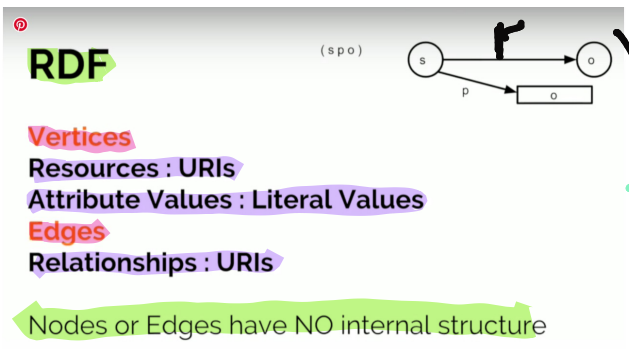
RESOURCE DESCRIPTION FRAMEWORK

RDF

A WWW TOOL FOR METADATA'S SHARING

At the core of RDF is this notion of a triple **subject-predicate-object,** a statement that represents two vertices connected by an edge:

- **Subject**: a resource, or a node in the graph
- **Predicate**: an edge – a relationship
- **Object**: another node or a literal value



VALUE, EVEN A URL

ANOTHER OBJECT INSIDE THE NETWORK

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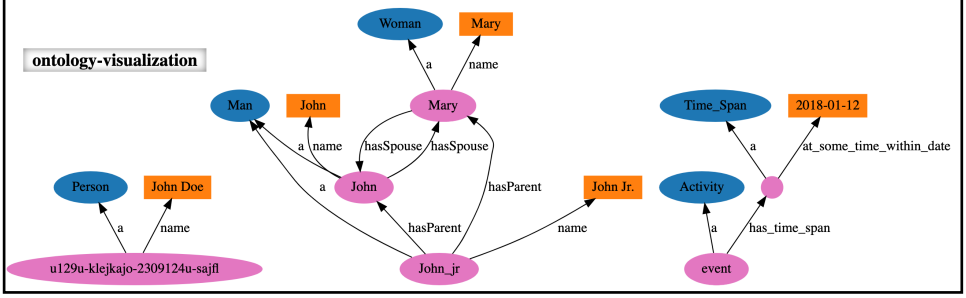
```
:John a :Man ;
    :name "John" ;
    :hasSpouse :Mary .
:Mary a :Woman ;
    :name "Mary" ;
    :hasSpouse :John .
:John_jr a :Man ;
    :name "John Jr." ;
    :hasParent :John, :Mary .
:Time_Span a owl:Class .
:event a :Activity ;
    :has_time_span [
        a :Time_Span ;
        :at_some_time_within_date "2018-01-12"^^xsd:date
        ] .
:u129u-klejkajo-2309124u-sajfl a :Person ;
    :name "John Doe" .
```

A sample RDF file



A fragment of an RDF (XML) document, describing an ontology.
The language is OWL
http://www.w3.org/TR/owl-ref/

```
<?xml version="1.0"?>
<rdf:RDF
xmlns:rdf="http://www.w3.org/1999/02/22-rdf-syntax-ns#"
xmlns:rdfs="http://www.w3.org/2000/01/rdf-schema#"
xmlns:owl="http://www.w3.org/2002/07/owl#"
xmlns:daml="http://www.daml.org/2001/03/daml+oil#"
xmlns="http://eng.it/ontology/tourism#"
xmlns:dc="http://purl.org/dc/elements/1.1/"
xml:base="http://eng.it/ontology/tourism">
<owl:Ontology rdf:about=""/>
<owl:Class rdf:ID="Church">
<rdfs:comment rdf:datatype="http://www.w3.org/2001/XMLSchema#string"
>Definition: Edificio sacro in cui si svolgono pubblicamente gli atti
di culto delle religioni cristiane.</rdfs:comment>
<rdfs:subClassOf>
<owl:Class rdf:about="#PlaceOfWorship"/>
</rdfs:subClassOf>
</owl:Class>
<owl:Class rdf:ID="Theatre">
<rdfs:comment rdf:datatype="http://www.w3.org/2001/XMLSchema#string"
>Definition: a building where theatrical performances or motion-
picture shows can be presented.</rdfs:comment>
<rdfs:subClassOf>
<owl:Class rdf:about="#SocialAttraction"/>
</rdfs:subClassOf>
</owl:Class>
<owl:Class rdf:ID="DailyCityTransportationTicket">
<rdfs:subClassOf>
<owl:Class rdf:about="#CityTransportationTicket"/>
</rdfs:subClassOf>
<rdfs:comment rdf:datatype="http://www.w3.org/2001/XMLSchema#string"
>Definition: Biglietto che consente di usufruire di un numero
illimitato di viaggi sui mezzi pubblici (autobus e metropolitana)
all'interno del centro urbano (o della regione, con un costo maggiore)
per un periodo di 24 ore.</rdfs:comment>
</owl:Class>
```

RDF and OWL

- Designed to meet the need for a Web Ontology Language, OWL is part of the growing stack of W3C recommendations related to the Semantic Web.
- XML provides a surface syntax for structured documents, but imposes no semantic constraints on the meaning of these documents.
- XML Schema is a language for restricting the structure of XML documents and also extends XML with data types.
- RDF is a data model for objects ("resources") and relations between them, provides a simple semantics for this data model, and can be represented in an XML syntax.
- RDF Schema is a vocabulary for describing properties and classes of RDF resources, with a semantics for generalization-hierarchies of such properties and classes.
- OWL adds more vocabulary for describing properties and classes: among others, relations between classes (e.g. disjointness), cardinality (e.g. "exactly one"), equality, richer typing of properties, characteristics of properties (e.g. symmetry), and enumerated classes.

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OWL

- The OWL Web Ontology Language is designed for use by applications that need to process the content of information instead of just *presenting* information to humans.
- OWL facilitates greater machine interpretability of Web content than that supported by XML, RDF, and RDF Schema (RDF-S) by providing additional vocabulary along with a formal semantics.
- OWL has three increasingly-expressive sublanguages: OWL Lite, OWL DL, and OWL Full.

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Reasoning services for ontologies

Services for the Tbox

- Subsumption: verifies if a concept C subsumes (is a subconcept of) another concept D
- Consistency: verifies that there exists at least one interpretation I which satisfies the given Tbox
- Local Satisfiability: verifies, for a given concept C, that there exists at least one interpretation in which C is true.

Services for the Abox

- Consistency: verifies that an Abox is consistent with respect to a given Tbox
- Instance Checking: verifies if a given individual x belongs to a particular concept C
- Instance Retrieval: returns the extension of a given concept C, that is, the set of individuals belonging to C.

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Comparison

- analysis of the features of a descriptive ontology (data structures, instance management, constraint definition, queries)
- compare these features with the functionality provided by current representation approaches from the database world

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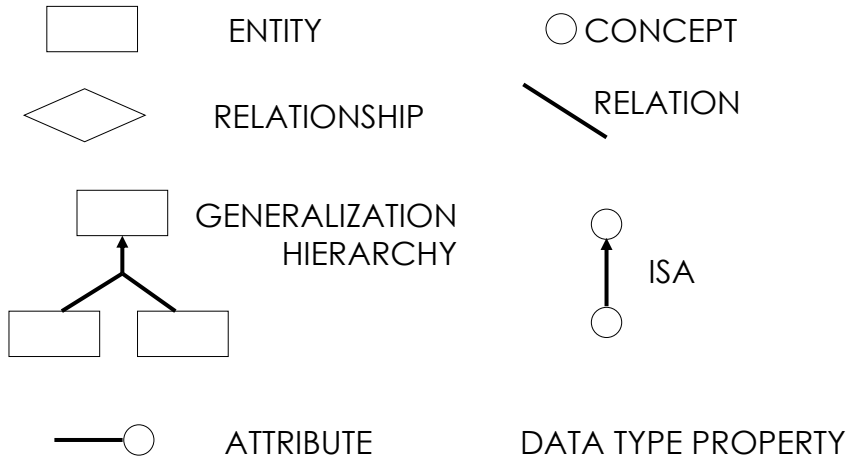
ER vs.ontology



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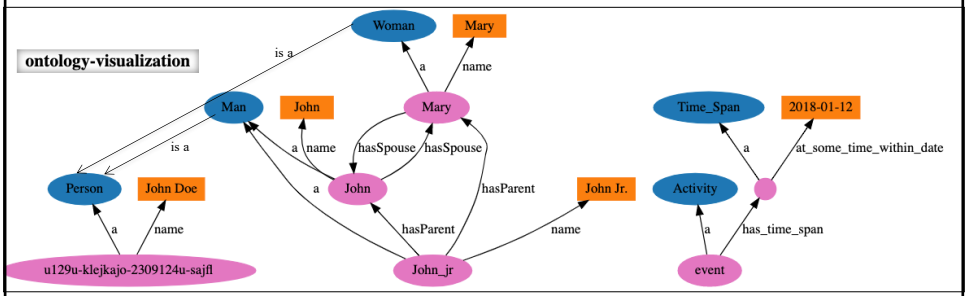
Let's see how this corresponds to an ER diagram



75 **Caution:** An ER schema does not have VALUES !

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Comparison

Descriptive ontologies require rich models to enable representations close to human perception

	Ont.	DB
Complex data structures	**No**	**yes**
Generalization/specialization hierarchies	**yes**	**yes**
Defined concepts	**yes**	**no**

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DB versus ontologies

How should we improve database conceptual models to fulfill ontology requirements ?

- Supporting defined concepts and adding the necessary reasoning mechanisms
- Managing missing and incomplete information: semantic differences between the two assumptions made w.r.t. missing information (*Closed World Assumption* vs. *Open World Assumption*)
- Databases are assumed to represent certain data: a tuple in the database is true, any tuple NOT in the database is false (Closed World Assumption)

Ontologies and integration problems

- Discovery of "equivalent" concepts (mapping)
  - What does equivalent mean? → again we look for some kind of similarity
- Formal representation of these mappings
  - How are these mappings represented?
- Reasoning on these mappings
  - How do we use the mappings within our reasoning and query-answering process?

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Ontology *matching*

- The process of finding pairs of resources coming from different ontologies which can be considered equal in meaning – *matching operators*
- Again we need some kind of *similarity measure.*
- Recall: a *similarity value* is usually a number in the interval [0,1]
- *Caution:* this time the similarity measure takes into account *semantics*, not only on the structure of the words as in the examples given in the previous lectures !!!!

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More on similarity

- The concept of similarity is a basic concept in human cognition.
- Similarity plays an essential role in taxonomy, recognition, case-based reasoning and many other fields. There are many aspects of the concept of similarity that have eluded formalization.
- According to Zadeh(*), "Formulation of a valid, general-purpose definition of similarity is a challenging problem".
- There do exist many special-purpose definitions which have been employed with success in cluster analysis, search, classification, recognition and diagnostics.

(*) The "inventor" of fuzzy sets and fuzzy logic

As already seen, *similarity* is strictly related to *distance*

Self-identity is the property which says that the distance between identical objects is zero. This translates to the following self-identity axiom:

Axiom 2.1.1. *For all x in S, $d(x,x) = 0$.*

Positivity is the property which says that distinct objects have a nonzero distance:

Axiom 2.1.2. *For all $x \neq y$ in S, $d(x,y) > 0$.*

Symmetry says that the order of two elements does not matter for the distance between them:

Axiom 2.1.3. *For all x and y in S, $d(x,y) = d(y,x)$.*

The *triangle inequality* says that the distance between y and z does not exceed the sum of the distance between y and x and the distance between x and z:

Axiom 2.1.4. *For all $x, y, z \in S$, $d(y,z) \leq d(y,x) + d(x,z)$.*

Similarity

- While dealing with distance-based similarity measures, examples have been constructed where every distance axiom is clearly violated by dissimilarity measures, and particularly *the triangle inequality*, consequently the corresponding similarity measure disobeys transitivity.

- For these cases a different attitude has been taken and more general concepts of distance have been proposed: a distinction is made between *perceived dissimilarity* and *judged dissimilarity*.

WE CAN'T RELATE TO ONE ONLY SIMILARITY MEASURE
↓
MORE AXPECTS TO ANALYZE
↓
FOCUS ON A SPECIFIC SIMILARITY AXPECT

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Ontology mapping

- The process of relating similar concepts or relations of two or more information sources using equivalence relations or order relations.

- These relations are commonly implemented in inference and reasoning softwares, so we can use the output ontology to perform complex tasks on them without extra effort.

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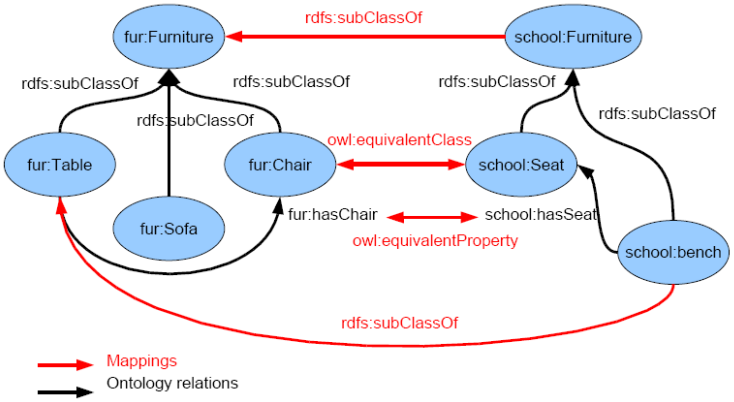
Ontology mapping

NEEDS TO FIND ≠ CLASS RELATED TO THE SAME TOPIC



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Reasons for ontology mismatches

→ SYNTAXES → ≠ NAMES FOR ≠ CONCEPTS

At the definition language level:

- Syntax
- Availability of different constructs (e.g. part-of, synonym, etc.)
- Linguistic primitives' semantics (e.g. union or intersection of multiple intervals)

→ Normalize by translating to the same language/ paradigm

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Reasons for ontology mismatches

At the ontology level:

- Scope: Two classes seem to represent the same concept, but do not have exactly the same instances
- Model coverage and granularity: a mismatch in the part of the domain that is covered by the ontology, or the level of detail to which that domain is modelled.
- Paradigm: Different paradigms can be used to represent concepts such as time. For example, one model might use temporal representations based on continuous intervals while another might use a representation based on discrete sets of time points.
- Encoding
- Concept description: e.g. a distinctions between two classes can be modeled using a qualifying attribute or by introducing a separate class, or the way in which is-a hierarchy is built
- Homonymies
- Synonymies

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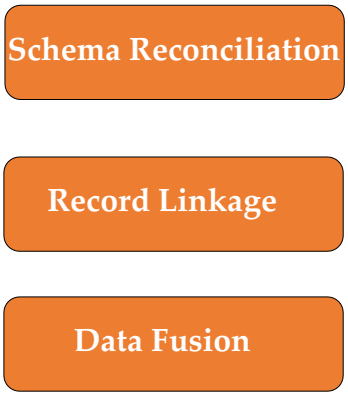
Recall the steps of Data Integration



Schema reconciliation: mapping the **data structure**

Record linkage: data matching based on **the same content**

Data fusion: reconciliation of **non-identical content**

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How can ontologies support integration ?

An ontology as a schema integration support tool

- Ontologies used to represent the semantics of schema elements (if the schema exists)
- Similarities between the source ontologies guide conflict resolution
  - At the schema level (if the schemata exist)
  - At the instance level (record linkage)

An ontology instead of a global schema:

- Schema-level representation only in terms of ontologies
- Ontology mapping, merging, etc. instead of schema integration
- Integrated ontology used as a schema for querying

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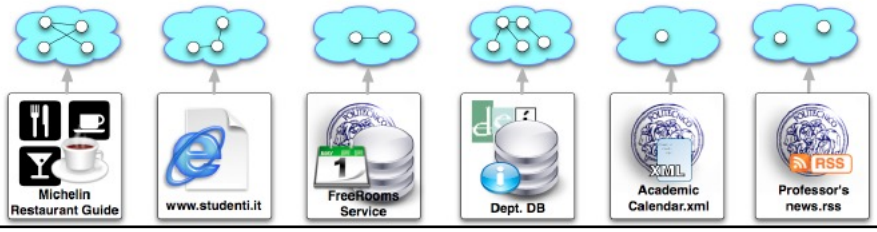
An ontology instead of a global schema

- Data-source heterogeneity is solved by extracting the semantics in an ontological format (potentially *at run-time*)
- Automatic Wrapper generation + Query translation will bridge among two models.
- Not an easy task:
  - several issues, e.g., impedance mismatch
  - unstructured data sources

Note:the impedance mismatch is the problem that occurs when the database model is different from the programming language model



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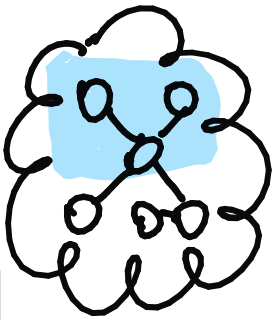
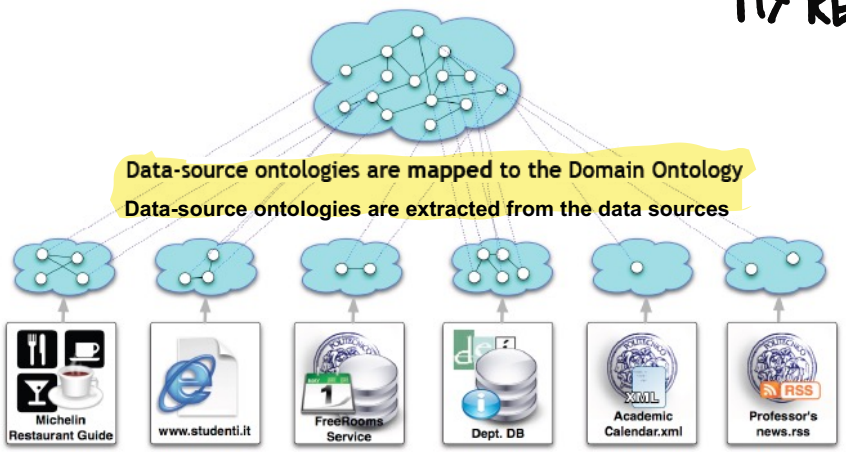
MY ONTOLOGY WITH VARIOUS CONCEPTS



An ontology instead of a global schema

Global Schema : Domain Ontology (*at design-time*)



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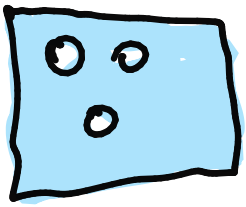
MY REPO



WE CAN TRY TO FIND, IF WE THINK OUR SET OF REPO IS FIXED, A SPECIFIC PART OF THE ONTOLOGY THAT IS USEFUL FOR OUR GOAL

More: how can ontologies support integration?

- An ontology as a support tool for content interpretation and wrapping (e.g. HTML pages)
- An ontology as a mediation support tool for content inconsistency detection and resolution (record linkage and data fusion)

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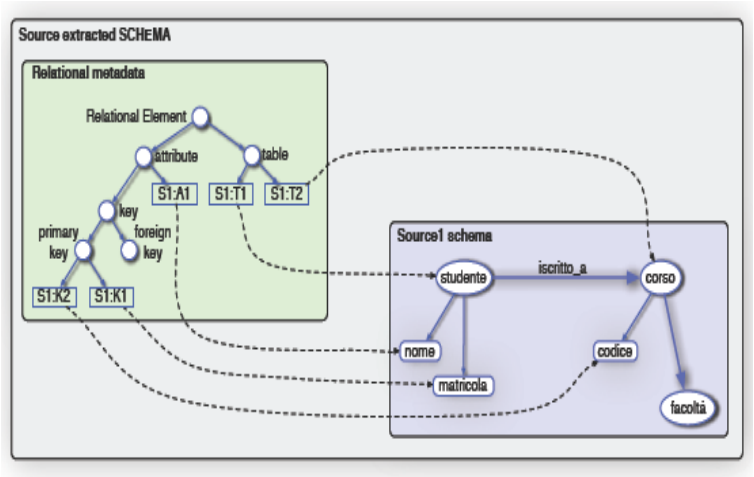
Ontology extraction from a relational schema: example



Ontology query processing

Ontologies require query languages as well, for:

- Schema exploration (when the schema is replaced by an ontology)
- Reasoning on the schema
- Instance querying (when the instance is contained in an ontology, like in the Semantic Web case)
- Example of ontology query language: SPARQL (W3C)

Examples of SPARQL queries

We can give an informal idea of **SPARQL** focusing on the SELECT queries. In particular we can say that a query *q* is a structure like:
SELECT ?X1 … ?Xn WHERE P
With *?X1 … ?Xn* as the set of variables and *P* as the graph pattern.

Let's consider this **example** where we have a simple SPARQL query which asks for all projects in which some PhD student is involved:
SELECT ?Y
WHERE { ?X rdf:type PhDStudent. ?X inProject ?Y }

This next **example** of query instead retrieves employees who are PhD students or professors together with their projects:
SELECT ?X ?Y
WHERE { { ?X rdf:type PhDStudent. UNION ?X rdf:type Professor. }
AND ?X inProject ?Y. }

Ontology query processing versus database query processing

When we use ontologies to interact with databases, we have to take care of:

- Transformation of ontological query into the language of the datasource, and the other way round
- Different semantics (CWA versus OWA)
- What has to be processed where (e.g. push of the relational operators to the relational engine)

The new application context (recall)

- A (possibly large) number of data sources
- Heterogeneous data sources
- Different levels of data structure
  - Databases (relational, OO…)
  - Semi-structured data sources (XML, HTML, more markups …)
  - Unstructured data (text, multimedia etc…)
- Different terminologies and different operational contexts
- ➢ Time-variant data (e.g. WEB and social media)
- ➢ Mobile, transient data sources (e.g. sensor values)

…..as you can see, everything becomes more and more dynamic.

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Next Lectures

From next lecture, we'll talk about the second important subject of this course:

Data Warehouses:
a fully consolidated paradigm for *business analytics*.

After that, we'll come back to the frontiers of Data Management and Integration, which at the moment still constitute hot research topics

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Data Quality

Cinzia Cappiello
cinzia.cappiello@polimi.it

1

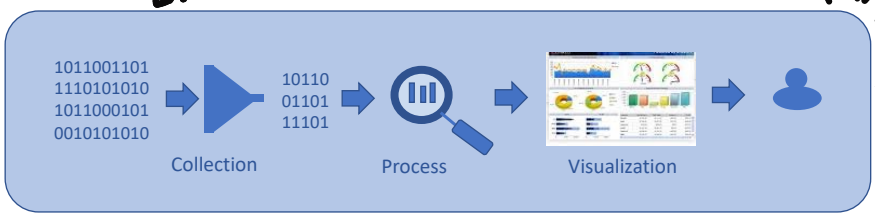
The importance of Data Quality

2

Data Driven Management

Data-driven Management is characterized by the practice of collecting data, analyzing it, and **basing decisions on** insights derived from the **information**.

ENTERPRICES FOCUS ON ANALYSIS OF DATAS FOR SUPPORT THEIR DECISION

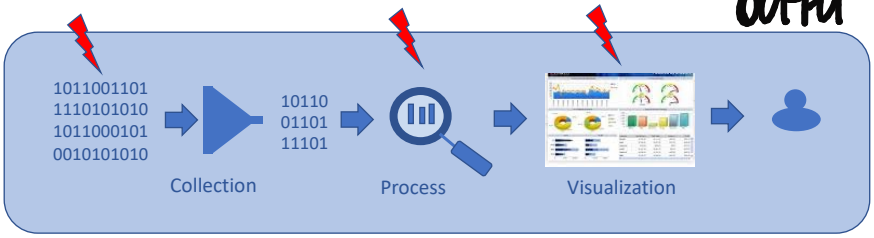


https://www.smartsheet.com/data-driven-decision-making-management

3

The Problem: GIGO (Garbage In – Garbage Out) Phenomenon

POSSIBLE ERRORS IN THE INPUT MIGHT AFFECT THE OUTPUT



The success of data-driven decision making depends on
- the **quality of data** collected
- the **methods** used to **analyze data**

4

even if it is a small error...you can have the snowball effect

QUANTITY MIGHT IMPLY SOME ERRORS. EVEN A SMALL ERROR CAN BRING TO SOME SERIOUS CONSEQUENCES

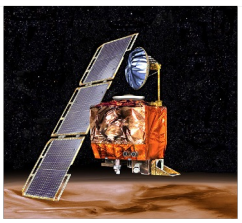
5

Data Quality Horror stories

The Mars *Climate Orbiter,* a key part of NASA's program to explore the planet Mars, vanished in September 1999 after rockets were fired to bring it into orbit of the planet. It was later discovered by an investigative board that NASA engineers failed to convert English measures of rocket thrusts to newtons, a metric system measuring rocket force, and that was the root cause of the loss of the spacecraft. The orbiter smashed into the planet instead of reaching a safe orbit.

This discrepancy between the two measures, which was relatively small, caused the orbiter to approach Mars at too low an altitude. The result was the loss of a $125 million spacecraft and a significant setback in NASA's ability to explore Mars.

Lost In Translation



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Data Quality Horror stories


Business

Why Britain has 17,000 pregnant men

By Sarah Kliff
April 7, 2012

https://www.washingtonpost.com/blogs/ezra-klein/post/why-britain-has-17000-pregnant-men/2012/04/06/gIQAC2oJ0S_blog.html


News > World > Americas

Workers demolish wrong house after relying on Google Maps for directions

Crew reportedly thought they had torn down the correct home - describing the situation as 'not a big deal'

Friday 25 March 2016 18:39 • Comments

https://www.independent.co.uk/news/world/americas/lindsay-diaz-google-maps-demolition-house-home-accident-a6952356.html


Spreadsheet error led to Edinburgh hospital opening delay

26 August 2020

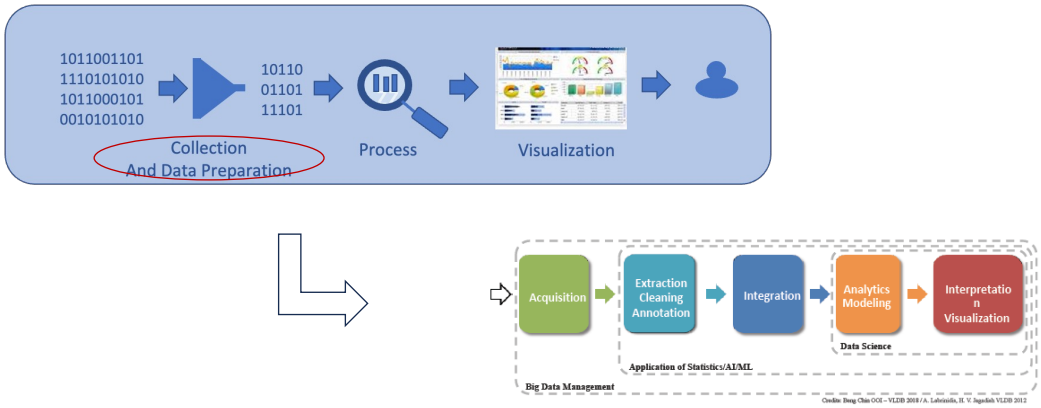
https://www.bbc.com/news/uk-scotland-edinburgh-east-fife-53893101

Data Quality Horror stories

Back in 1870," Arbesman explained, "Erich von Wolf, a German chemist, examined the amount of iron within spinach, among many other green vegetables. In recording his findings, von Wolf accidentally misplaced a decimal point when transcribing data from his notebook, changing the iron content in spinach by an order of magnitude. While there are actually only 3.5 milligrams of iron in a 100-gram serving of spinach, the accepted fact became 35 milligrams. Once this incorrect number was printed, spinach's nutritional value became legendary. So when Popeye was created, studio executives recommended he eat spinach for his strength, due to its vaunted health properties, and apparently Popeye helped increase American consumption of spinach by a third!"

http://www.ocdqblog.com/home/popeye-spinach-and-data-quality.html

We need an adequate architecture for analyze data



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Why is data preparation important?

- Real-word data is often incomplete, inconsistent, and contain many errors…
- Data preparation, cleaning, and transformation comprises the majority of the work in a data mining application (90%).

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Data Quality definition

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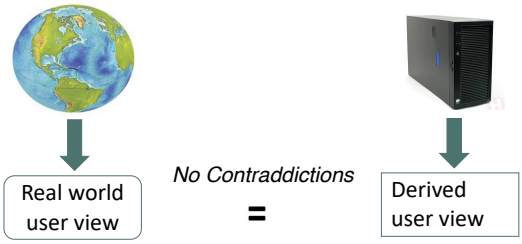
Data Quality definition

- Traditional definition YOU HAVE TO VERIFY THAT THE DATAS YOU HAVE ARE USEFUL FOR THE GIVEN PURPOSE

  "**Fitness for use** … *the ability of a data collection to meet user requirements*"

- From an Information System perspective



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Data Quality Management

- Quality dimensions definition
- Quality dimensions assessment
- Quality issues analysis
- Quality improvement

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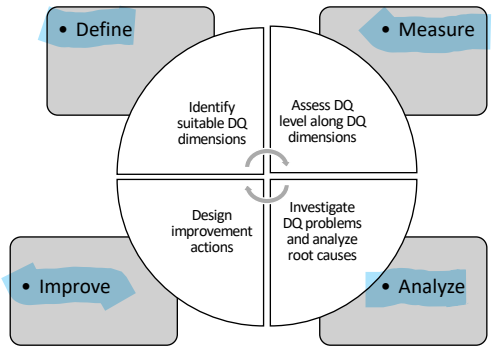
Data Quality methodology

4 PHASES THAT INTERACT CONTINUOUSLY BECAUSE THE CONTINUOUS CHANGE IN THE DATAS



Wang R.Y., A Product Perspective on Total Data Quality Management, Communications of the ACM, Volume 41, Number 2, 1998

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Data Quality dimensions

MULTIDIMENSIONAL CONCEPTS. WE HAVE LOTS OF CHECKS TO DO TO UNDERSTAND QUALITY PROBLEM

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Data Quality issues to consider in data preparation activities are mainly related to…

- Missing values
- Duplicate data
- Inconsistent data
- Outliers
- Noise

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Is Data Quality Measurable?

Data Quality dimensions & Metrics

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Data Quality Problems (single source) - example

ID	Name	Street and house number	Postcode	Town	Date of birth	Phone	e-mail
1	Janet Gordon	30 Fruit Street	75201	Dallas			
2	Kathy Robert	436 Devon Park Drive	94105	San Francisco	08.08.1969	215-367-2355	krob@robert.com
3	Sandra Powels	3349 North Ridge Avenue	33706	St. Pete Beach			
4	Johnstone, Jeffrey	3300 Sylvester Rd	92020	El Cajon			
5	Lowe Ruth-Hanna	25 Peachtree Lane	02112	Boston	10.10.50	(0617)-8845123	
6	Gordon Janet	30 Fruit Street	75201	Dallas			
7	NIck Goodman	Regional Campuses, 711	10020	New York	08/07/1975		n.good@goodman.com
8	Poweles Donna S.	3347 North Ridge	33706	Saint Pete Beach			
9	Cathy Robbert	436 Devon Park Drive	94105	San Francisco	08.03.1969		
10	Ruthanna Lowe	25 Peachtree Lane	02112	Boston		0617-8845123	
11	John Smith	10 Main Street	02112	New York			
12	Robert Katrin	434 Devon Park	94105	San Francisco			
13	Nick Goodman	56 Grafton Street	94105	San Francisco	08/07/1975		n.good@goodman.com
14	Sandro Powels	3349 North Ridge Av.	33706	Pete Beach			

PROBLEMS

- SOME MISSING DATAS
- REPETITIONS OF SAME DATAS IF WRITTEN IN ≠ FORMATS
- DIFFERENT VALUES FOR SAME INFORMATIONS
- INCORRECT DATAS
- FORMAT DATAS

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Data Quality problems in BI (multiple sources) - example

ID	Diagnosis	Hospital	Province	Date	Cost
1	Flu	SR	Milan	01/05/2008	200
2	Flu	SR	Milan	24/5/2008	180-220
3	Flu	SR	Milan	04/05/2008	9999
4	Influenza	SC	Trento	03.05.2008	
5	Influenza	SC	Trento	03.04.2008	230
6	Influenza	SC	Trento	10.07.2008	
7	Flu Type A	CG	Milano	04-04-2008	130
8	Flu	OS	Bolzano	2008/04/23	130
9	Flu	OS	Bolzano	2008/05/11	200

DATAS ARE MAINLY COLLECTED IN ORDER TO LET THE ENVIRONMENT OPERATE

ANALYSIS COMES SECONDLY

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Poor data quality is due mainly to

- Missing values
- Duplicates
- Inconsistencies
- Outliers
- Noise
- Out-of-date data

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DOMANDA ESAME FEBBRAIO 2018

Most used objective Dimensions

Accuracy
- the extent to which data are correct, reliable and certified

→ AND SEMANTIC → SYNTACTIC ACCURACY

Completeness
- the degree to which a given data collection includes the data describing the corresponding set of real-world objects

Consistency
- the satisfaction of semantic rules defined over a set of data items

Timeliness
- the extent to which data are sufficiently up-to-date for a task

DIMENSION

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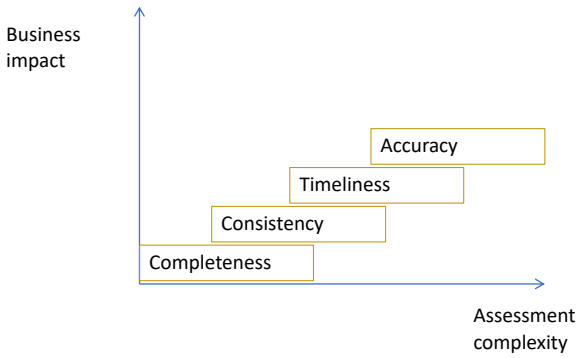
Assessment complexity



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Data Quality Improvement

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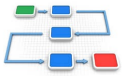
Data Quality improvement strategies

Data-based approaches

- They focus on data values and aim to identify and correct errors without considering the process and context in which they will be used

MORE USED

Process-based actions



- They are activated when an error occurs and aim to discover and eliminate the root cause of the error

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Data Based approach: data cleaning

Definition

"Data cleaning is the process of identifying and eliminating inconsistencies, discrepancies and errors in data in order to improve quality"

[Naumann 2000]

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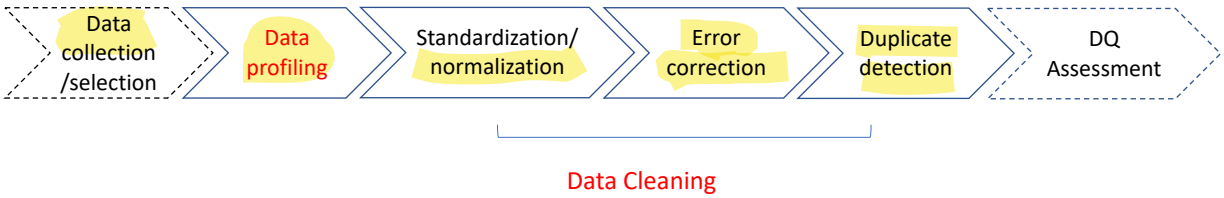
Steps of Data Cleaning



Felix Naumann, Kai-Uwe Sattler 2006

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Profiling

- Analysis of content and structure of attributes: Data type, domain, data distribution and variance, occurence of null values, uniqueness, format (e.g., mm/dd/yyyy)
- Analysis of dependencies between attributes of a single relation: E.g., Functional dependencies, primary key candidates
- Analysis of overlapping attributes from different relations: Redundancies, foreign keys
- Number of missing values or wrong values
  - current vs.expected cardinality
  - frequency of null values, minimum / maximum, variance
- Duplicates
  - Number of tuples vs. Cardinality of attribute domain

Felix Naumann, Kai-Uwe Sattler 2006

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Data Profiling with Python: Ydata profiling

```
In [23]: import pandas_profiling
         pandas_profiling.ProfileReport(ds)
```

Pandas Profiling Report | Overview | Variables | Correlations | Missing values | Sample

Overview

Dataset info

Number of variables	8
Number of observations	2410
Missing cells	1072 (5.6%)
Duplicate rows	0 (0.0%)
Total size in memory	150.8 KiB
Average record size in memory	64.1 B

Variables types

Numeric	6
Categorical	2
Boolean	0
Date	0
URL	0
Text (Unique)	0
Rejected	0
Unsupported	0

Warnings

abv	has 62 (2.6%) missing values	Missing
ibu	has 1005 (41.7%) missing values	Missing
name	has a high cardinality: 2305 distinct values	Warning
style	has a high cardinality: 100 distinct values	Warning

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Data Profiling with Python: Ydata profiling

Sample

First rows

	abv	brewery_id	ibu	id	name	ounces	style	U
0	0.050	408	NaN	1436	Pub Beer	12.0	American Pale Lager	0
1	0.066	177	NaN	2265	Devil's Cup	12.0	American Pale Ale (APA)	1
2	0.071	177	NaN	2264	Rise of the Phoenix	12.0	American IPA	2
3	0.090	177	NaN	2263	Sinister	12.0	American Double / Imperial IPA	3
4	0.075	177	NaN	2262	Sex and Candy	12.0	American IPA	4
5	0.077	177	NaN	2261	Black Exodus	12.0	Oatmeal Stout	5
6	0.045	177	NaN	2260	Lake Street Express	12.0	American Pale Ale (APA)	6
7	0.065	177	NaN	2259	Foreman	12.0	American Porter	7
8	0.055	177	NaN	2258	Jade	12.0	American Pale Ale (APA)	8
9	0.086	177	NaN	2131	Cone Crusher	12.0	American Double / Imperial IPA	9

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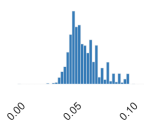
Data Profiling with Python: Ydata profiling

Variables

abv
Numeric

Distinct count	75
Unique (%)	3.1%
Missing (%)	2.6%
Missing (n)	62
Infinite (%)	0.0%
Infinite (n)	0

Mean	0.059773424
Minimum	0.001
Maximum	0.128
Zeros (%)	0.0%

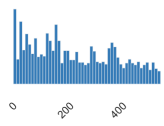


Toggle details

brewery_id
Numeric

Distinct count	558
Unique (%)	23.2%
Missing (%)	0.0%
Missing (n)	0
Infinite (%)	0.0%
Infinite (n)	0

Mean	231.7497925
Minimum	0
Maximum	557
Zeros (%)	0.2%



Toggle details

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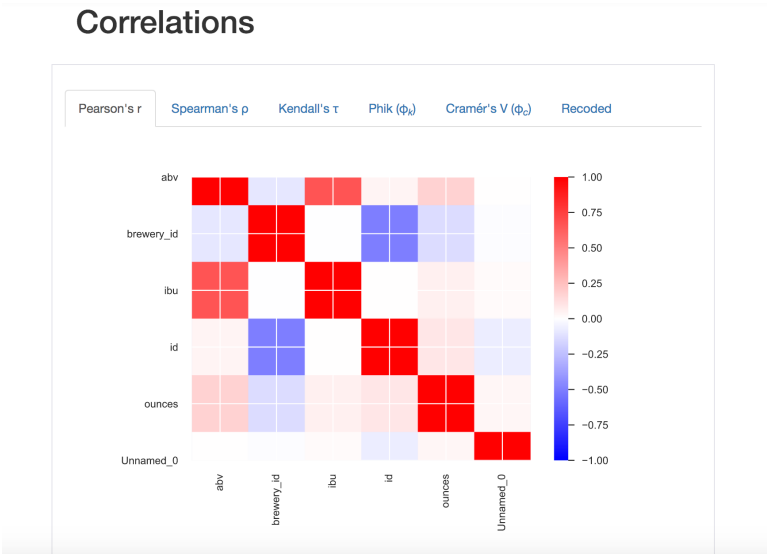
Data Profiling with Python: Ydata profiling



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Cleaning tasks

Normalization/standardization
- Datatype conversion
- Discretization
- Domain specific

Missing values
- Detection
- Imputing

Outlier detection
- Model
- Distance

Duplicate detection

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Data transformation and normalization

LOOK FOR ALL HOMOGENEOUS DATE AND LET THEM HAVE THE SAME FORMAT

Data type conversion: varchar → int

Normalization: mapping into a common format
- date: 03/01/15 → 01-MAR-2015
- currency: $ → €
- tokenizing: „Smith, Paul“→ „Smith“, „Paul“

Discretization of numerical values

Domain-specific transformations
- Surname, name→ Name surname
- St. → Street
- Address transformation using address databases
- Domain-specific product names/codes (e.g., in pharmacy)

Felix Naumann, Kai-Uwe Sattler 2006

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Error Localization and correction

MOST DIFFICULT PART

This activity can be seen as composed of:

- Localization and correction of inconsistencies
- Localize and correction of incomplete data
- Localization of outliers

FINDING THE CORRECT INFORMATION, EVEN LOOKING FOR EXTERNAL SOURCES

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Localize and correct inconsistencies

Once we have a valid, i.e., at least consistent, set of edits, we can use them to perform the activity of error localization.

In particular, we can check syntactic accuracy and inconsistencies

After the localization of erroneous records, in order to correct errors, we could perform the activity called *new data acquisition*

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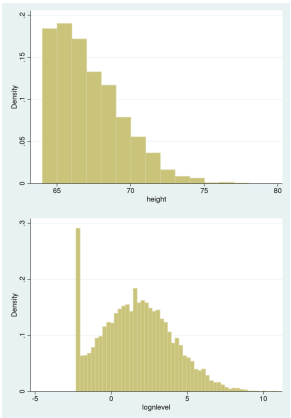
Missing data

Missing information on different levels

- Instance level: values, tuples, relation fragments, ...
- Schema level: Attributes, ...

Main Problems on instance level:

- Treating null values: missing value or default value?
- Data truncation and data censorization
- Biased data, e.g. caused by null values



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Imputing missing value

unbiased estimators“
- Estimating missing values without changing characteristics of existing dataset (mean, variance, ...)
- E.g.: 1, 2, 3, _, 5 → (median: 2.75; variance: 4.659)

Exploiting functional dependencies
- E.g.: #Bedrooms → Income

Techniques from statistics
- Linear regression:
  income = c • #Bedrooms
- techniques for non-linear dependencies:
  - Neural networks, ...

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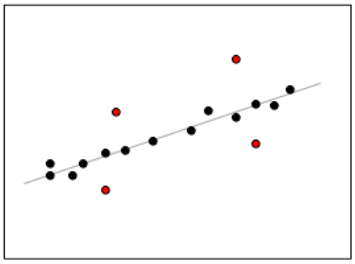
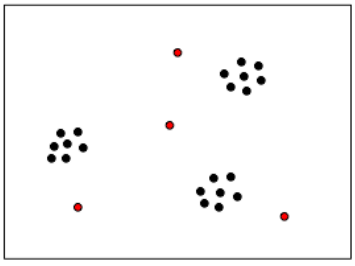
Outlier detection

Outlier: „suspicious“ observation that deviates too much from other observations. An outlier is then a value that is unusually larger or smaller in relation to other values in a set of data



issues:
- detection: distribution, „geometry“, time series
- interpretation: data or observation error vs. real event



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Duplicate detection Identify a good similarity measure

Duplicate detection (or entity reconciliation) is the discovery of multiple representations of the same real-world object.

- Main issues:
  - Identify a good similarity measure
  - Minimize the number of comparisons

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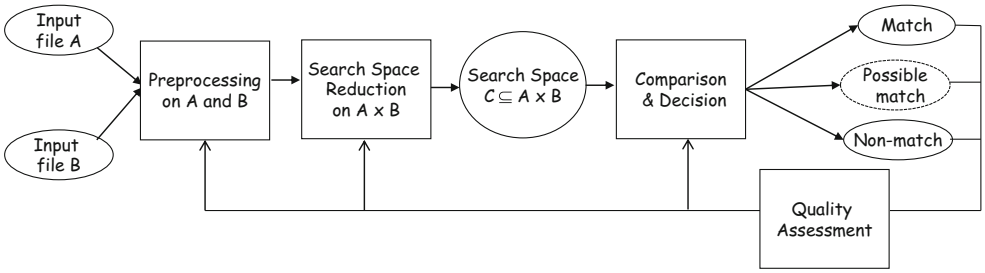
The high level process



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mailBatch for USA : Consumer-Comparison : Examples

Clustering: Individual person level / Household level

Duplicates: Only certain / All

Sandra Powels	3349 North Ridge Avenue	33706	St. Pete Beach		
Powells Sandra	3349 North Ridge Avenue	33706	Pete Beach		
Poweles Donna S.	3347 North Ridge	33706	Saint Pete Beach		
Lowe Ruth-Hanna	25 Peachtree Lane	02114	Boston	10.10.50	(0617)-8845342
Ruthanna Lowe	1201 Oak Street	02132	Boston		0617-8845342
Lowe Ruth Anna		02110	Boston		
Ruth Lowe	1 Becton Drive	21030	Cockeysville	10.10.50	
Johnstone, Jeffrey	3300 Sylvester Rd	92020	El Cajon		
Jeffrey Johnstane	3300 Sylversterroad	92020	El Cajon		
J.R. Johnstone	3302 Sylvester	92020	Cajon		
Jeff Johnston	3300 S. Road	92020	El Cajon		
Gray-David Richard Crewson	Mail Stop, 300 Constitution Drive	33186	Miami		
Richard Crawson	300 constitution drive	33186	Miami		
Crewson, Gray Dave	Mail Stop, Constitution Dr. 301	33186	Miami		
Graham Crewsons	30 Constitution Drive	33186	Miami		
Michael & Nicole Goodman	Regionel Campuses, 711 Lincoln Bldg	10022	New York		
Ph. D. M. Goodnam	711 Lincoln Bldg	10022	New York		
Nicole Goodman	Regional Campuses, 711 Lincoln Bldg	10020	New York		
Michael Goodman	Regional Campuses, 711 Lincoln Bldg	10010	New York		
Mike Goodnan	711 Bldg	10020	New York		
Haddou, Judith Ben	137 Victoriacourt	22153	Springfield		
Benhaddou, Judith	137 S. Viktoria Court	22153	Springfield		
Haddou, Ben	137 Vicctoria Court	22153	Springfield		

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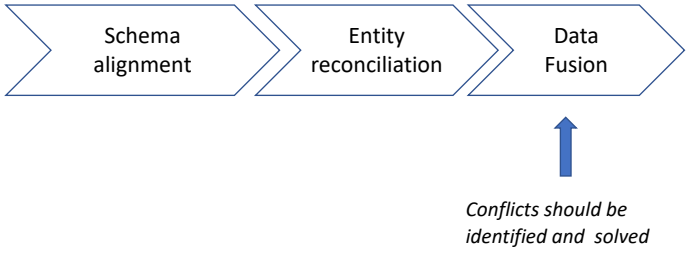
In case of multiple sources, data integration is also needed



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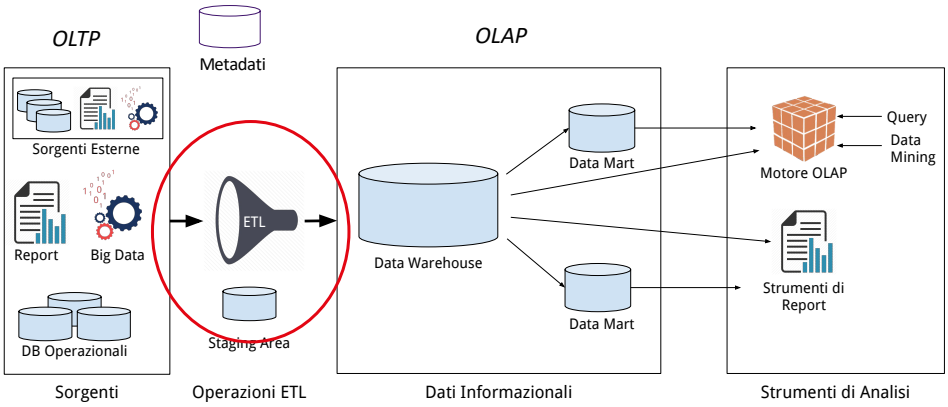
Data Quality improvement methods are also used in Data Warehouse



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Big data and data quality

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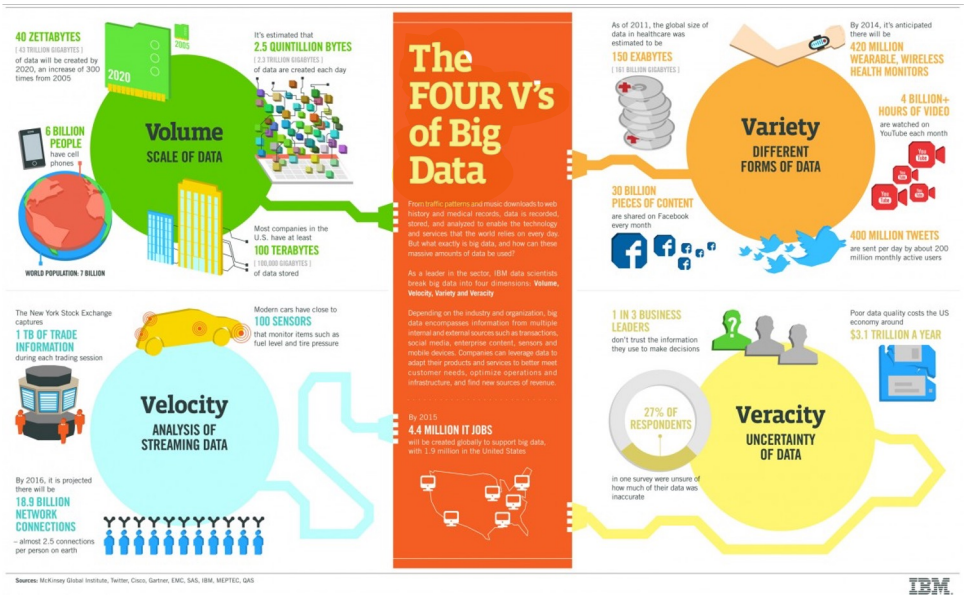
HIGH VOLUME : DIFFICULT TO GUARANTEE GOOD QUALITY

NOT ONLY RELATIONAL!

TEXT, SEMISTRUCTURED...



https://www.ibmbigdatahub.com/infographic/four-vs-big-data

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Big data and data quality

Big Data analysis allows to understand customer needs, improve service quality, and predict and prevent risks.

High quality data are the precondition for guaranteeing the quality of the results of Big Data analysis.

Big Data tried to overcome **Data Quality issues with Data Quantity. But quality is still an issue.**

Cai, Li, and Yangyong Zhu. "The challenges of data quality and data quality assessment in the big data era." *Data Science Journal* 14 (2015).

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Big data challenges

(1) Diversity of data sources (Variety)

Abundant data types - internal + external data sources

Complex data structures - structured, semi-structured, IoT

Difficult data integration - ETL and traditional approaches useless due to data volume and velocity

(2) Tremendous data volume (Volume)

Data quality profiling and assessment (collection, cleaning, and integration) is difficult to execute in a reasonable amount of time.

(3) Timeliness of data is very short (Velocity)

Data is updated continuously. If data is not collected and analysed in real time, information becomes outdated and invalid.

(4) Missing standard for Data Quality (Veracity)

Standards have been proposed for DQ of traditional data sources but not for big data.

Cai, Li, and Yangyong Zhu. "The challenges of data quality and data quality assessment in the big data era." *Data Science Journal* 14 (2015).

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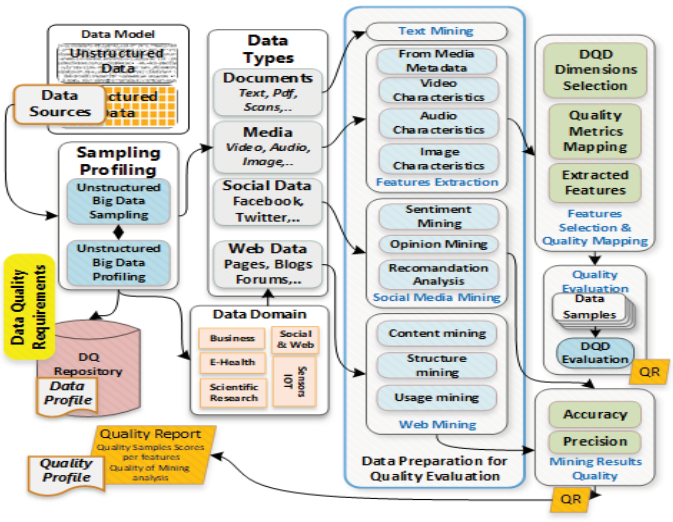
Unstructured Big Data Quality Assessment Model



I. Taleb, M. A. Serhani and R. Dssouli, "Big Data Quality Assessment Model for Unstructured Data," *2018 International Conference on Innovations in Information Technology (IIT)*, 2018, pp. 69-74, doi: 10.1109/INNOVATIONS.2018.8605945.

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To summarize: most common DQ issues in big data

- Not integrated data
- Incomplete data
- Incorrect data
- Data cleaning have to be frequently performed
- Inconsistent sources and issues in data integration
- Source reliability
- Data variety
- Human resources: find the right competencies
- Data provenance and lineage informatio should be available

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