# Symbolic Artificial Intelligence

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Oct. 2018

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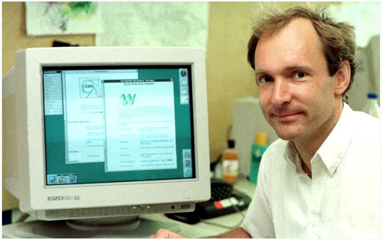
**IA301 Logique et IA - 3A - Master (2018/2019)**
https://perso.telecom-paristech.fr/bloch/OptionIA/Logics-SymbolicAI.html

# The Semantic Web Vision:

*I have a dream for the Web to become capable of analyzing all the data on the Web - the content, links, and transactions between people and computers. A Semantic Web, which should make this possible, has yet to emerge, but when it does, the day-to-day mechanisms of trade, bureaucracy and our daily lives will be handled by machines talking to machines. The intelligent agents people have touted for ages will finally materialize.*




Tim Berners Lee, CERN, 1999[1]

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[1] *Weaving the Web: The Original Design and Ultimate Destiny of the World Wide Web*. T. Berners-Lee with Mark Fischetti. Harper San Francisco, 1999.

# OWL vs Other Languages[2]

| | DTD | XSD | RDF(S) | OWL |
|---|---|---|---|---|
| Bounded lists ("X is known to have exactly 5 children") | | | | X |
| Cardinality constraints (Kleene operators) | X | X | | X |
| Class expressions (unionOf, complementOf) | | | | X |
| Data types | | X | | X |
| Enumerations | X | X | | X |
| Equivalence (properties, classes, instances) | | | | X |
| Formal semantics (model-theoretic & axiomatic) | | | | X |
| Inheritance | | | X | X |
| Inference (transitivity, inverse) | | | | X |
| Qualified contraints ("all children are of type person" | | | | X |
| Reification | | | X | X |

[2] **Document Type Definition**: Markup declarations that define a document type for an SGML-family markup language (SGML, XML, HTML). Defines the legal building blocks of an XML document through a list of legal elements and attributes. **XML Schema Definition**: W3C recommendation to formally describe the elements in an XML document and verify each piece of item content in a document [Lagoze].

# Knowledge Graphs

# Knowledge Graphs [8, 5]

What is a Knowledge Graph (KB)[3]?:

- a set of interconnected typed entities and their attributes
- has an ontology as schema defining its vocabulary

[3] originating from Pierce's existential graphs and Quillian' Semantic Networks [10] (semantic memory -fact, concept, relationship- models)[8].

# Why Knowledge Graphs (KG)? [8] IBM Watson: 1, Humans: 0


- 10% of Watson's winning performance in *Jeopardy* TV quiz game came from represented knowledge
- Explainability

# Explainability: important since the 1st expert system MYCIN [14]

Model of Inexact Reasoning in Medicine

It is useful to consider the advantages provided by a rule-based system for computer use of judgmental knowledge. It should be emphasized that we see these advantages as being sufficiently strong in certain environments that we have devised an alternative and approximate approach that parallels the results available from using Bayes' Theorem. I do not argue against the use of Bayes' theory in those medical environments in which sufficient data are available to permit adequate use of the theorem.

The advantages of rule-based systems for diagnostic consultations include:

(1) the use of general knowledge (from textbooks or experts) for consideration of a specific patient; even well-indexed books may be difficult for a nonexpert to use when considering a patient whose problem is not quite the same as those of patients discussed in the text;
(2) the use of judgmental knowledge for consideration of very small classes of patients with rare diseases about which good statistical data are not available;
(3) ease of modification; since the rules are not explicitly related to one another and there need be no prestructured decision tree for such a system, rule modifications and the addition of new rules need not require complex considerations regarding interactions with the remainder of the system's knowledge;
(4) facilitated search for potential inconsistencies and contradictions in the knowledge base; criteria stored explicitly in packets such as rules can be searched and compared without major difficulty;
(5) straightforward mechanisms for explaining decisions to a user by identifying and communicating the relevant rules;
(6) an augmented instructional capability; a system user may be educated regarding system knowledge in a selective fashion, i.e., only those portions of the decision process that puzzle him need be examined.

One of MYCIN's rules, which I shall use for illustrative purposes throughout this chapter, is the following:

IF: 1) THE STAIN OF THE ORGANISM IS GRAM POSITIVE, AND
2) THE MORPHOLOGY OF THE ORGANISM IS COCCUS, AND
3) THE GROWTH CONFORMATION OF THE ORGANISM IS CHAINS
THEN: THERE IS SUGGESTIVE EVIDENCE (.7) THAT THE IDENTITY OF THE ORGANISM IS STREPTOCOCCUS

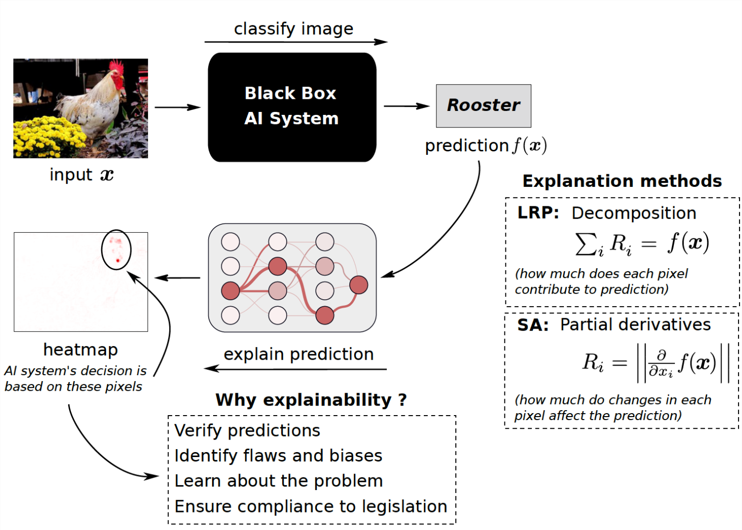
165

# Explainability (and comprehensibility): Today

- DARPA XAI Initiative (Explainable AI)
- IJCAI federation of workshops:
  - FAT ML
  - WHI-Human Interpretabililty in ML
  - IReDLia-Interpret. & Reasonable Deep Learning and Applications
- ICAPS XAI Planning/NIPS Interpretable ML
- GDPR *Right to explanation* does not exist yet[4]

[4] [18] Art. 13,14, (on notification duties) as it stands, only provides a limited (secret of affairs, etc) right to obtain ex-ante explanations about the model (which they call "right to be informed")

# Explaining predictions of an AI system[5]: Why?

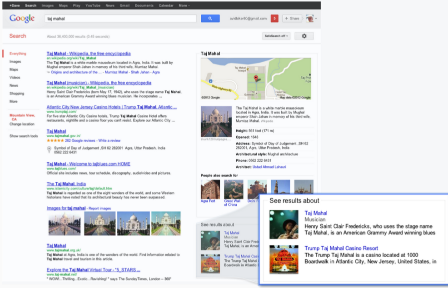



[5] SA: Sensitivity Analysis. LRP: Layer-wise Relevance Propagation [13]

# Introducing the Knowledge Graph: *Things, not strings*[6]

Objectives:

- Find the right thing
- Get the best summary
- Go deeper and broader




[6] Google, 2012, `https://www.blog.google/products/search/introducing-knowledge-graph-things-not/`[7, 8]

# Knowledge Graphs: Brief history

- Semantic Networks [10]: analyze the meaning of word concepts and the organization of human semantic memory (*nodes*: entities, situations; *arcs*: relations: *is-a, part-of, instance, has*) (no formal syntax and semantics).
  **Ex**: `Bird` ← *is-instance* - `Penguin` - *eats* → `Fish`
- Frames [6]: represent knowledge as collections of separate, simple fragments: 1 (entity and class) slot: 1 record-like fragment defining relationships, constraints intersections, unions, negations, FOL. **Ex**:
```
Bird
    subclass-of:  Animal
    member-slot:  has-part     value-class:  Wing
Penguin      subclass-of:  Bird
    colour:  black and white
```
- No standard frame language until 2004 (OWL)

# Knowledge Graphs: Brief history (II)

- KL-ONE [2]: Most well known KR frame system
  - 1st supporting DL.
  - 1st using deductive classifier for computing subsumption relations
  - Difference with previous frame systems (with *asserted* classes): class hierarchies are *inferred*.
- Semantic Web *stack*:
  - RDF: the modern W3C recommendation (std) graph-based data model for semantic networks to describe entities[7].
  - OWL: W3C std to define vocabularies for RDF graph data annotation. Allows concept descriptions and datatypes.
  - Linked Data: Framework to publish, share and link (via RDF and OWL mappings) data across applications and domains[8].
  - SPARQL: the SQL for RDF/OWL graphs (supporting conjunctive and navigational queries)[9].

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[7] RDF, as semantic networks, does not allow users to define concepts; this is addressed by OWL.

[8] RDF graphs can be linked together via schema-level (e.g., *rdfs:subClassOf*) and entity-level (e.g. *owl:sameAs*) mappings

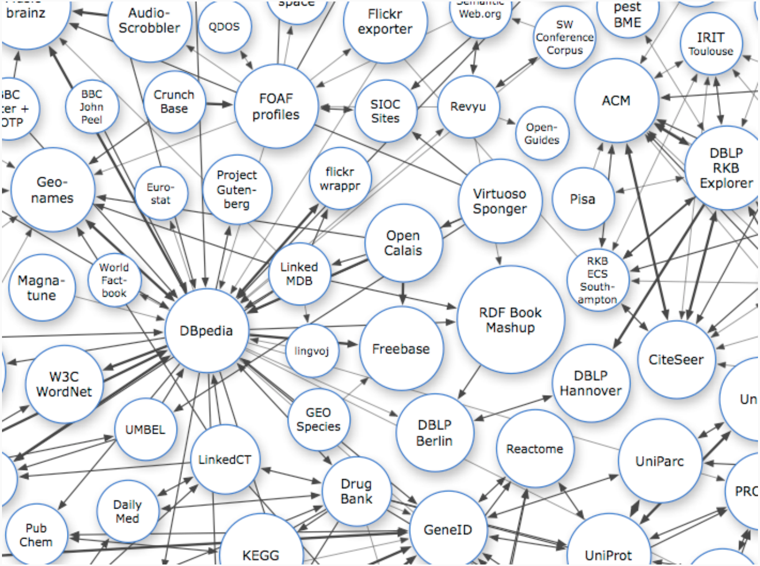
[9] Other pattern matching languages look for small subgraphs of interests (e.g. look for a clique of 3 individuals that are friends with each other) or navigational queries (when conditions are between nodes that are not necessarily adjacent), RPQ (Regular Path Queries, use RE)

# Knowledge Graphs: Brief history (II)

- Knowledge Graph: a set of interconnected typed entities and their attributes that has an ontology as its schema defining the vocabulary used in the KG.
- Today's largest KGs: Linked Open Data (LOD), NELL, Google KG, Microsoft Satori, Watson, the Facebook Graph, YAGO, DBpedia and BBC

Let's put these onto Knowledge Engineering context

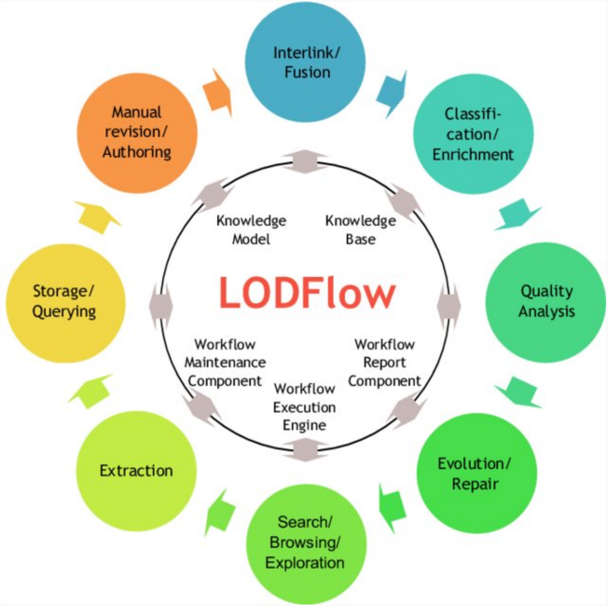
# Largest KGs: Linked Open Data (LOD)



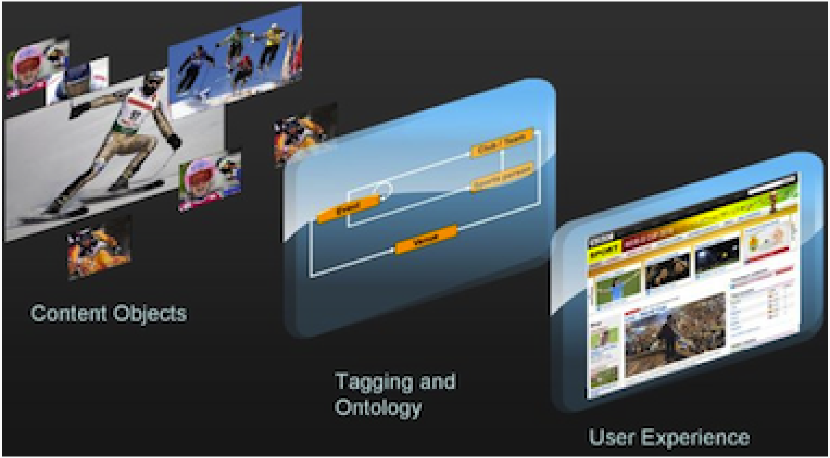
# Largest KGs: Linked Open Data (LOD)

- Aim: avoid data silos
- "Datasets that don't have this LOD ontology logic or interconnection capability (such as DBpedia) are data *feudalism*–data that's limited in its scope. Beyond that scope, it *lacks contextual relevance*. We have data manors with well-manicured lawns, but elsewhere lots of impoverished, underdescribed, underconnected data that machines can't help us much with. That's why *information overload is so pervasive*. $\rightarrow$ LOD logic allows data *globalism*".

# Largest KGs: Linked Open Data (LOD) Lifecycle [Auer]

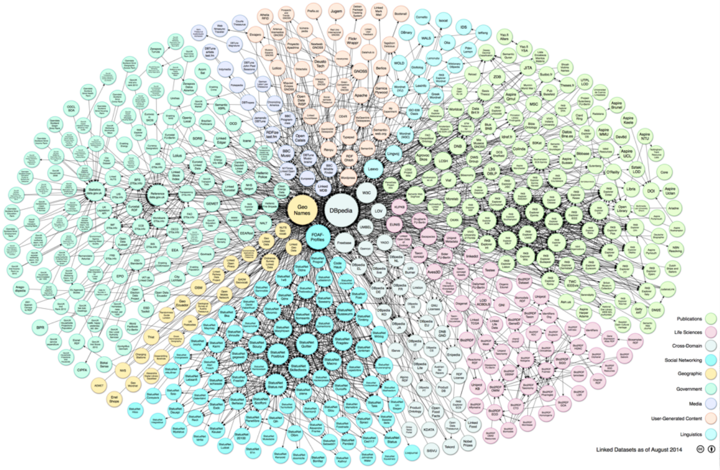


# KB examples: BBC User Experience [Source: Ontotext]

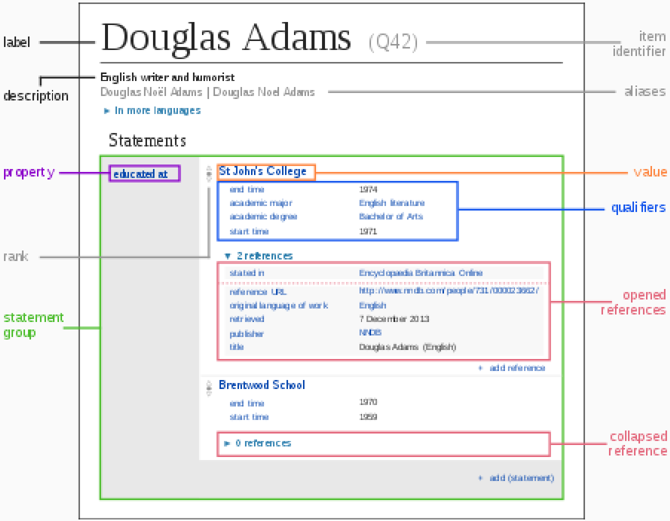


# Largest KGs examples: DBPedia Project

Aim: extract structured content from the information created in the Wikipedia and make it available on the WWW

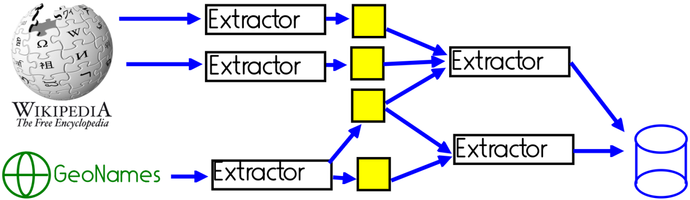


# KB examples: and more general: Wikidata




WIKIDATA

# Example: YAGO




YAGO is a knowledge base that was automatically constructed from Wikipedia and other sources:

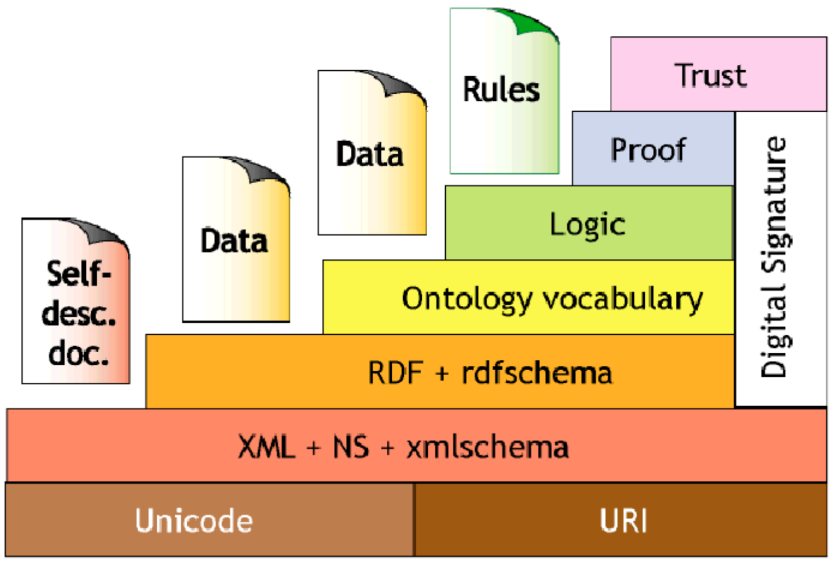
- 10m entities, 100m facts
- 95% accuracy
- 1700+ citations on WWW 2007 paper
- 10 languages
- used by IBM Watson, Bloomberg, DBpedia,...

yago select knowledge

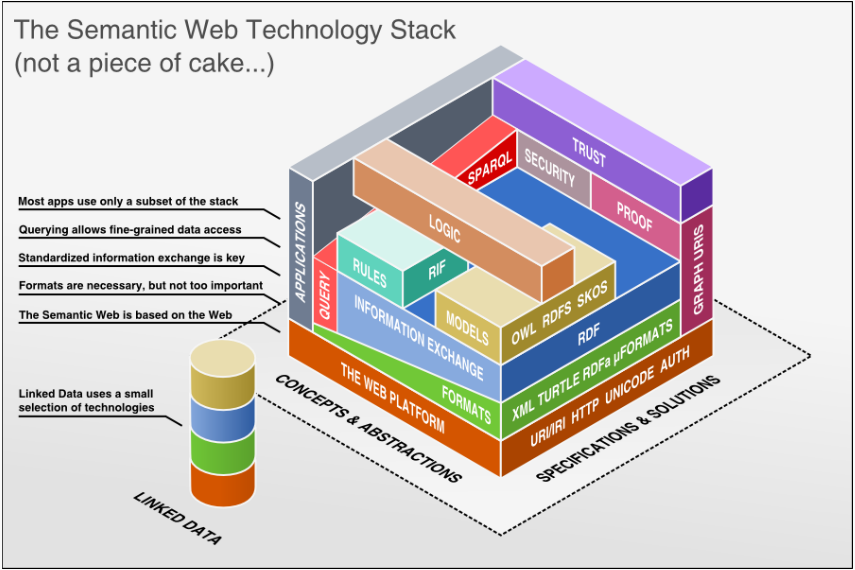
http://yago-knowledge.org

# Every good AI has a good cake

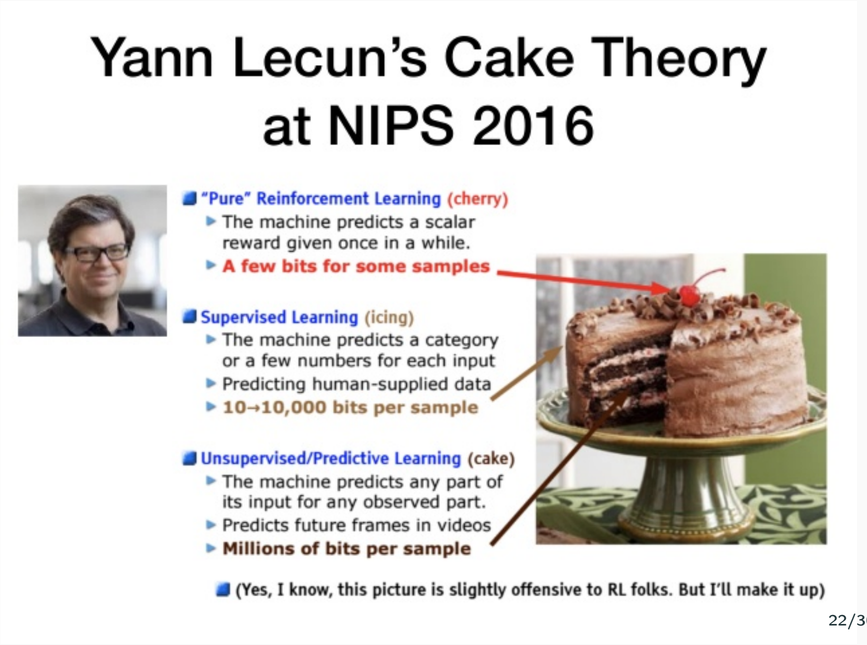
From Tim Berners-Lee Semantic Web (2001)...



# Every good AI has a good cake [B. Nowack]



# Every good AI has a good cake



# Ontology Engineering Methodologies

# Building KGs: bottlenecks [7]

Main challenges in ontology design:

- GUI of authoring tools unable to handle KGs complexity
- Reasoners and debuggers unable to deal with such complexity efficiently

# Ontology Building Methodologies

- TDKGC (Test Driven KG Construction): requirements expressed in form of query-answer pairs T = <q, a> and competency questions [7]
- OOPS! (OntOlogy Pitfall Scanner): structural ontology evaluation [9] wrt. number of pitfalls[10]
- Defining inconsistency-tolerant semantics [12]:
  - Able to derive meaningful conclusions from inconsistent ontologies (as a formal basis for an automated treatment of inconsistency)
  - *Repair*: a max. subset of the ABox that is consistent with the TBox

[10] See OOPS! Catalogue: `http://oeg-lia3.dia.fi.upm.es/oops/catalogue.jsp`, includes creating unconnected ontology elements, missing annotations, domain or range in properties, using different naming criteria in the ontology, or recursive definitions. See Pitfall Rate evaluation parameter in [4]

- What kind of questions the ontology could answer? *Given an application scenario where a KG is required, how suitable is a given graph for the purposes of this scenario?*[11].
- NeON Methodology [17, 15]
- CQOA (Competency Questions Ontology Authoring)[11]
- OMQA (Ontology Mediated Question Answering)[1]

[11] CQs: Question expressions that an ontology must be able to answer (functional req.) [8]

# Ontology Design Methods: CQOA (Competency Questions Ontology Authoring)[12]

| ID | Pattern | Example | PA | RT | M | DE |
|---|---|---|---|---|---|---|
| 1 | Which [CE1] [OPE] [CE2]? | Which pizzas contain pork? | 2 | obj. | | |
| 2 | How much does [CE] [DP]? | How much does Margherita Pizza weigh? | 2 | data. | | |
| 3 | What type of [CE] is [I]? | What type of software (API, Desktop application etc.) is it? | 1 | | | |
| 4 | Is the [CE1] [CE2]? | Is the software open source development? | 2 | | | |
| 5 | What [CE] has the [NM] [DP]? | What pizza has the lowest price? | 2 | data. | num. | |
| 6 | What is the [NM] [CE1] to [OPE] [CE2]? | What is the best/fastest/most robust software to read/edit this data? | 3 | both | num. | |
| 7 | Where do I [OPE] [CE]? | Where do I get updates? | 2 | obj. | | spa. |
| 8 | Which are [CE]? | Which are gluten free bases? | 1 | | | |
| 9 | When did/was [CE] [PE]? | When was the 1.0 version released? | 2 | data. | | tem. |
| 10 | What [CE1] do I need to [OPE] [CE2]? | What hardware do I need to run this software? | 3 | obj. | | |
| 11 | Which [CE1] [OPE] [QM] [CE2]? | Which pizza has the most toppings? | 2 | obj. | quan. | |
| 12 | Do [CE1] have [QM] values of [DP]? | Do pizzas have different values of size? | 2 | data. | quan. | |

[12] [11]. CQ Archetypes (PQ: Predicate Arity, RT= Relation Type, M= Modifier, DE=Domain-independent Element; obj. and data = object and data prop. relation resp., num. = numeric modifier, quan. = quantitative modifier, term. = temporal element, spa. = spatial element; CE = class expression, OPE = object property expression, DP = datatype property, I = individual, NM = numeric modifier, PE= property expression, QM = quantity modifier)

# Ontology Design Methodologies: Diagnosis based approaches [7]

- Inconsistency or unsatisfiability ontology *defect* detection tools
- Correctness and scalability
- Diagnosis tools: ECCO[13], ORE (Ontology Repair and Enrichment)[14], inference inspector and Protégé.
- More Ontology Engineering Methodologies: Ch. 9 [3], [16]

[13] A diff tool for OWL 2 `https://github.com/rsgoncalves/ecco`
[14] Allows validation of OWL KBs `aksw.org/Projects/ORE.html`

## That's a wrap

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