# l'IA au service de la formation en Médecine: retour d'expérience du projet SIDES 3.0

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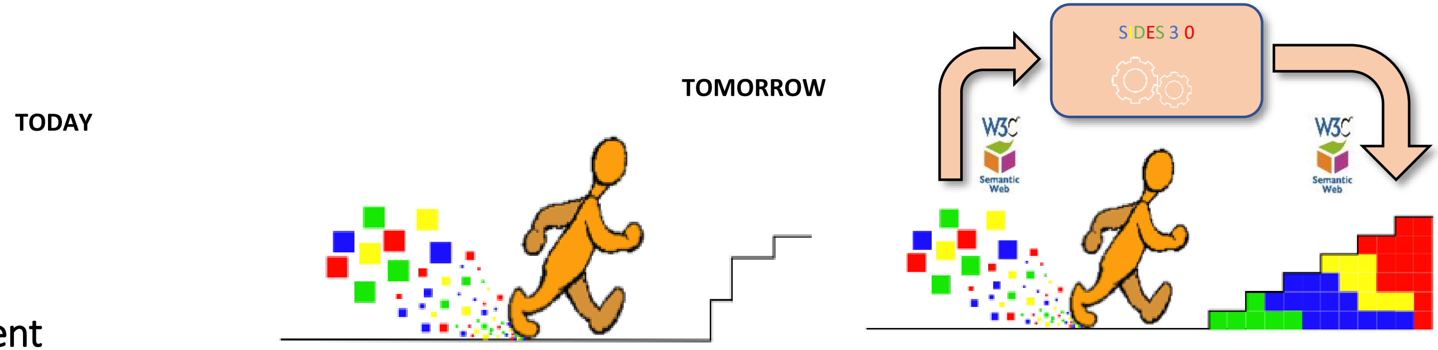
# SIDES 3.0 : DUNE project (August 2017-July 2021)

## Towards data-driven personalized self-assesment and training

A successful experience of online graduation, training and assessment for all medical students in France




**Produces a huge amount of low-level activity traces that are exploited by database administrators for predefined tasks**

**facilitates the empowerment of end-users in data analytics**

**by using Semantic Web technologies and Linked Data principles**

# Ontology-Based Data Access: OBDA

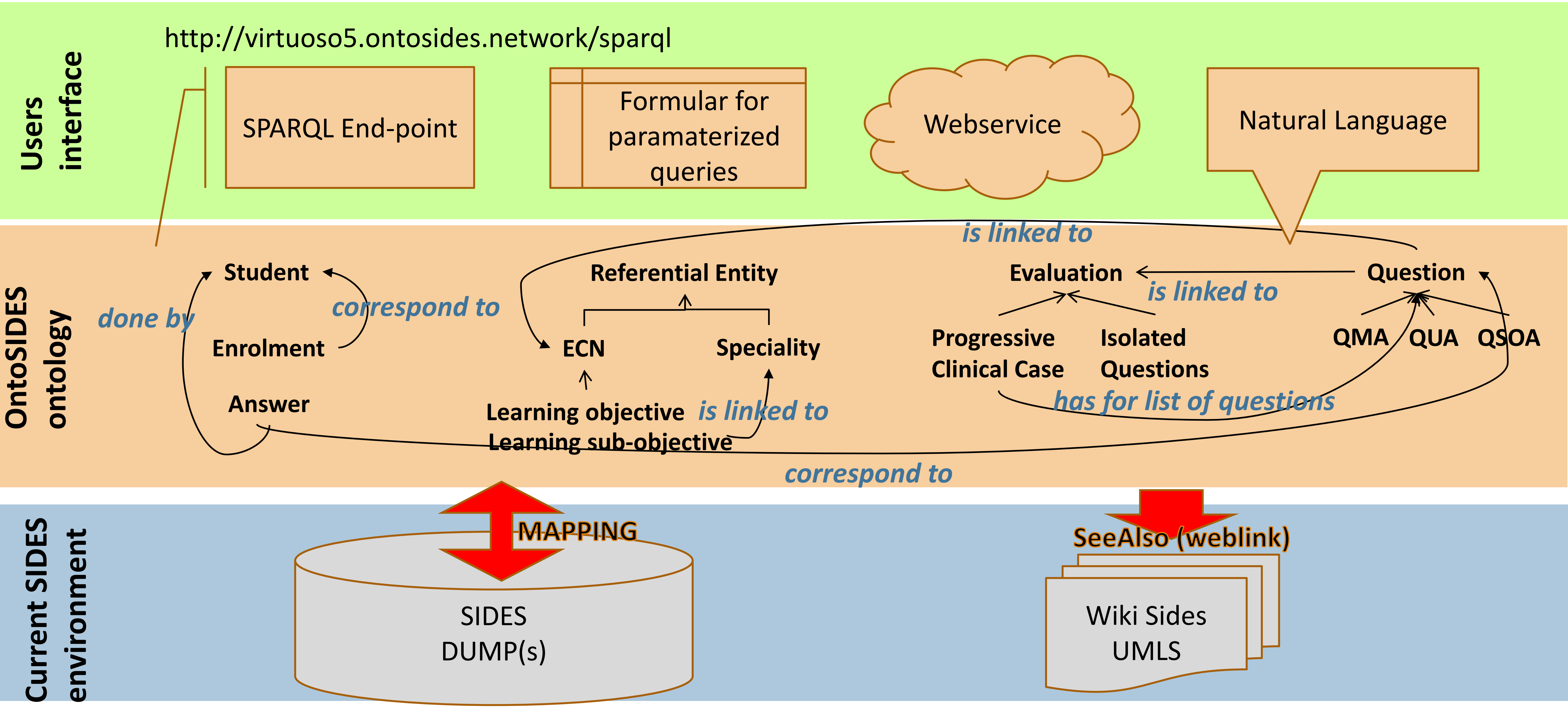
- A novel paradigm at the crossroad of Artificial Intelligence and Databases
  - a **domain ontology** serves as a **mediator** for expressing **users queries**

- Ontology: a formal specification of a domain of expertise
  - a structured vocabulary (classes and properties) meaningful for domain experts
  - a conceptual yet computational model of a domain

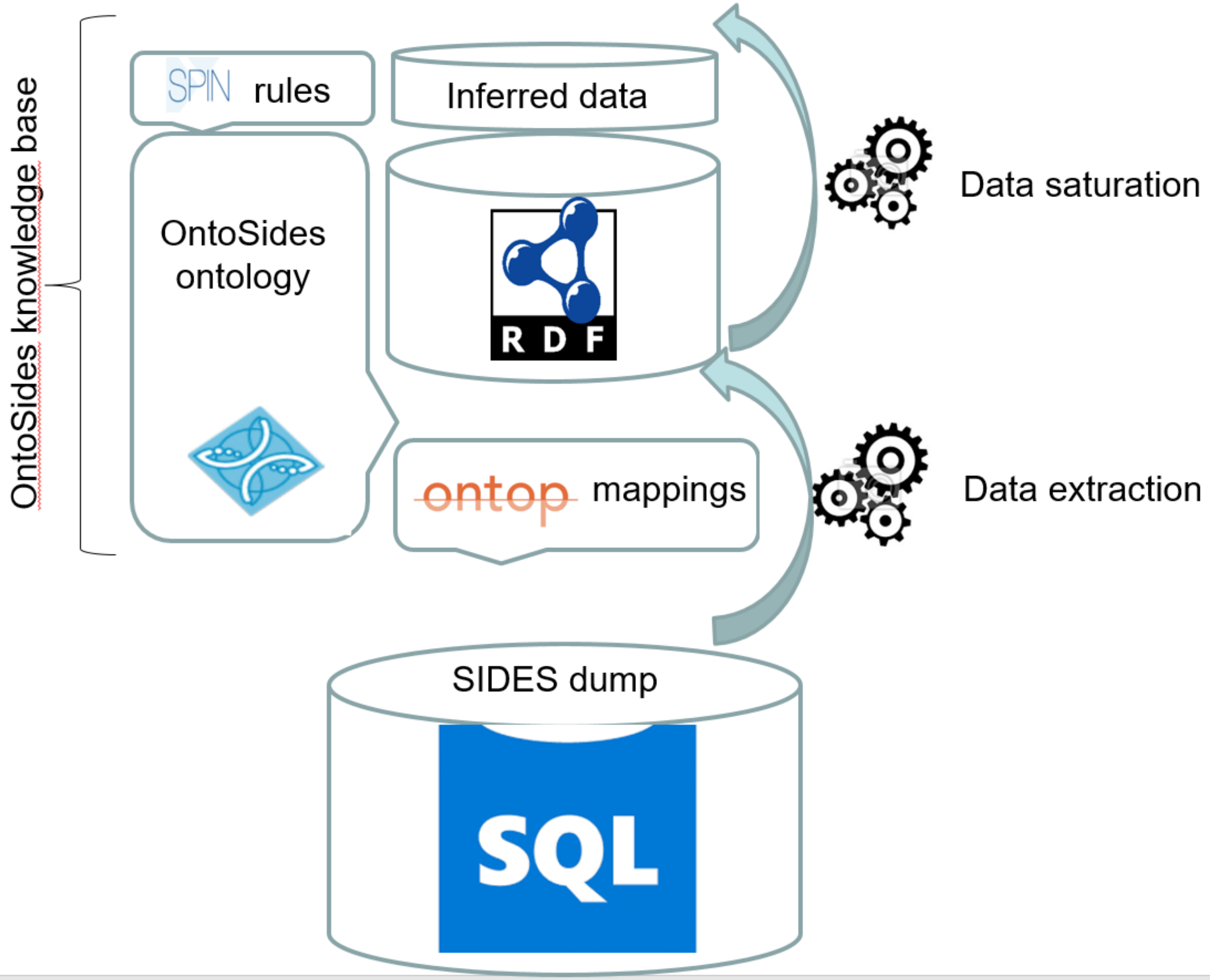
$\Rightarrow$ **humans** can express their data analysis needs using terms of a **shared vocabulary in their domain of interest or of expertise**

$\Rightarrow$ **computer systems** can base decisions on **reasoning on domain knowledge**

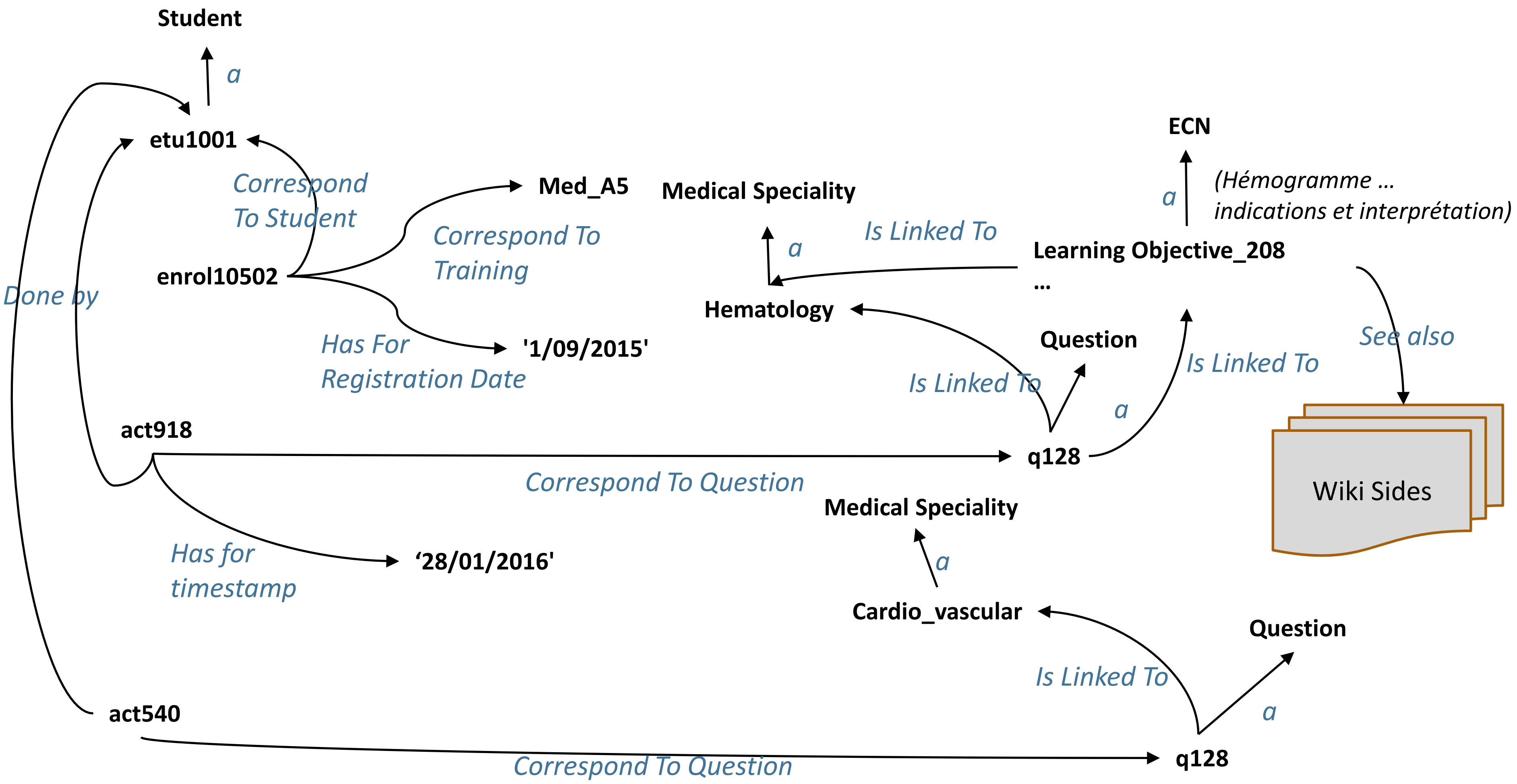
# OntoSIDES ontology: interface for data access and analytics



# Mapping-based automatic data extraction guided by the ontology



# Zoom on data linkage



# OntoSIDES knowledge graph

- the linked data layer of SIDES 3.0
  - describes **training** and **assessments activities** performed by more than **145,000 students** in Medicine **over almost 6 years**
    - exams and training tests are made of **multiple choices questions**
    - students **answers** are described at the granularity of **time-stamped clicks of answers** done by students for choosing among the proposals of answers (correct or distractors) associated to questions

⇒**7,8 billions triples** with almost **400 millions clicks** coming from the answers of students to almost **1,4 million questions.**

# Knowledge Graphs

- Modern knowledge representation formalism based on **RDF data model**
  - more flexible than the relational model
  - adapted to data/knowledge sharing between distributed data sources over the Web
- a set of triples <subject, property, object/value>
  - **subject, property** and **object** are URIs (http Uniform Resource Identifiers)
  - **dereferencable URIs** (pointers to Web pages) versus **local URIs**
  - **value** is a literal (string, integer, date, boolean)
- Tractable reasoning
  - Simple knowledge (OntoSides ontology: 52 classes, 50 properties, 1400 instances, 18 rules)
  - Big data associated with a powerful query language (SPARQL)

# Illustration : RDF modeling multiple choice questions in OntoSides

**Q30986** has_for_textual_content **"Concernant la péritonite appendiculaire, donnez la ou les propositions exactes :"** ;

is_linked_to_the_medical_speciality **digestive_surgery**

has_for_proposal_of_answer_ **prop98552 [** has_for_textual_content **"les signes infectieux sont présents d'emblée » ;**

has_for_correction **« true »]**

**prop98553** [ has_for_textual_content

**"il n'y a pas de défense abdominale ou de contracture" ;**

has_for_correction **« false »]**

**prop98604[** has_for_textual_content

**"elle peut se présenter comme une occlusion fébrile" ;**

has_for_correction **« true»]**

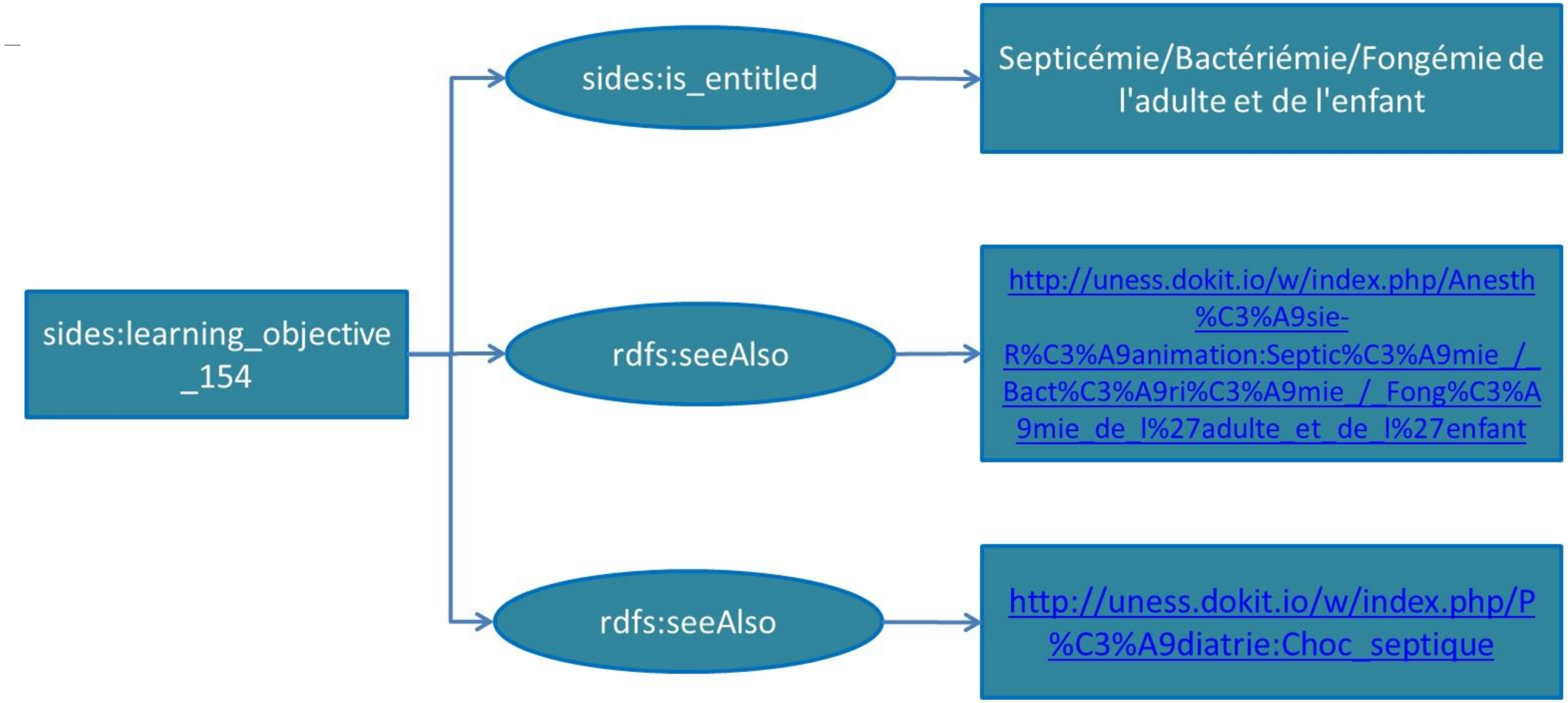
**prop98605[** has_for_textual_content **"il n'y a pas de pneumopéritoine" ;**

has_for_correction **« true»]**

**prop98606[** has_for_textual_content **« le traitement est chirurgical" ;**

has_for_correction **« true»]**

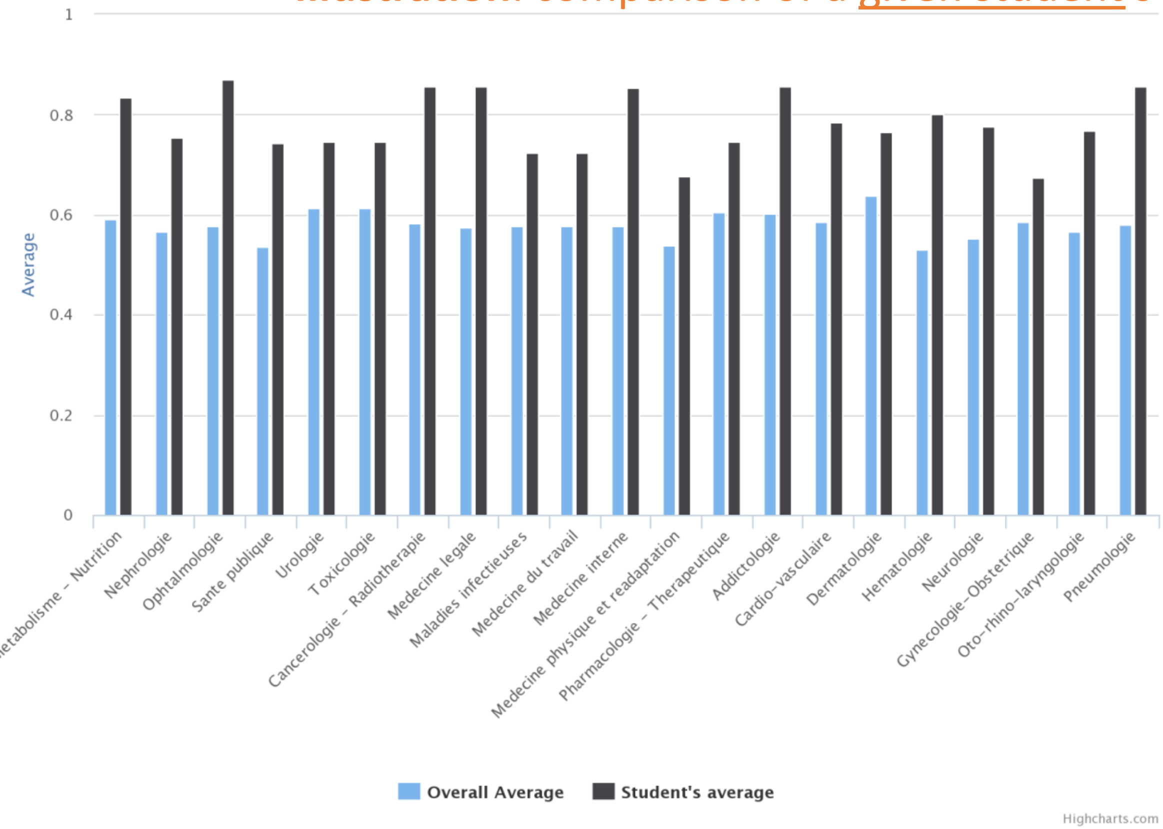
# Illustration: Learning objectives linked to web pages of the wiki SIDES (*)




(*) official educational content provided by the association of French Medical colleges covering the French pre-residency program examination

# Parametrized queries:
# a step towards personalized and explainable data analytics

**Illustration**: comparison of a given student's results with results of all students by medical specialty




```
SELECT ?specialty  ?globalAverage  ?studentAverage
WHERE  {
  {  SELECT ?specialty ( AVG(?result) AS ?globalAverage)
   WHERE { ?answer sides:has_for_result ?result .
              ?answer sides:done_by ?student .
              ?answer sides:correspond_to_a_question ?q .
              ?q sides:is_linked_to_the_medical_speciality ?specialty . }
     GROUP BY ?specialty } .
 { SELECT ?specialty (AVG(?result) AS ?studentAverage)
   WHERE { ?answer sides:has_for_result ?result .
               ?answer sides:done_by sides:etu12402 .
               ?answer sides:correspond_to_a_question ?q .
               ?q sides:is_linked_to_the_medical_speciality ?specialty .}
   GROUP BY ?specialty} .
}
```

## Aggregate queries (SPARQL 1.1)

- not supported by query rewriting approaches
- **requires data completeness**

# Data incompleteness

- Problematic for conducting **well-grounded learning analytics**
  - partial answers for basic Select From Where queries
  - **wrong results for aggregate or counting queries**

- This may occur on some specific properties likely to be involved in aggregate queries to define dimensions
  - is_linked_to_medical_specialty (from questions to medical specialties)
    - **13% questions** have been explicitly **linked** by their authors **to medical specialties**
  - is_linked_to_ECN_item (from questions to learning objectives)
    - **12% questions linked to learning objectives**

# Knowledge graph completion and enrichment

- Knowledge graph completion
  - automatically inferring missing facts from existing ones
    - between **questions** and **medical specialties** or **learning objectives**

- Knowledge graph enrichment
  - automatically discovering links with external reference knowledge graphs or standard ontologies
    - Standard **UMLS (Unified Medical Language System)** medical terminologies like **MeSH (Medical Subject Headings)** and **SNOMED CT (Systematized Nomenclature of Medicine Clinical Terms)**

=> Can be modeled as **classification** or **matching** problems

- depending on the availability of textual description of the target entities and of training data

# Inferring links between **questions** and **medical specialties**

- can be solved as a **multi-label** and **multi-class** classification problem
  - **multi-class**: 31 possible classes (the different medical specialties)
  - **multi-label**:  question can be linked to more than one medical specialty
  - **training set:** the 149,000 (13%) questions (with their textual description) for which the property is linked to the medical specialty is valued
- using several classifiers
  - Naive Bayes, Maximum Entropy, CNN (Convolutional Neural Network)

# Inferring links between **questions** and **learning objectives**

- a **multi-label** and **multi-class classification** problem
  - **multi-class:** 362 possible classes (the different learning objectives) and **multi-label**
  - **training set** : 144,000 (12%) questions for which the corresponding property is valued
- can be also solved as a **matching** problem between the textual descriptions of the questions and of the learning objectives
  - only for the **236 learning objectives** that have a textual description

using several variants of TF-IDF ranking function used in **Information Retrieval** to return the top-k learning objectives for each question

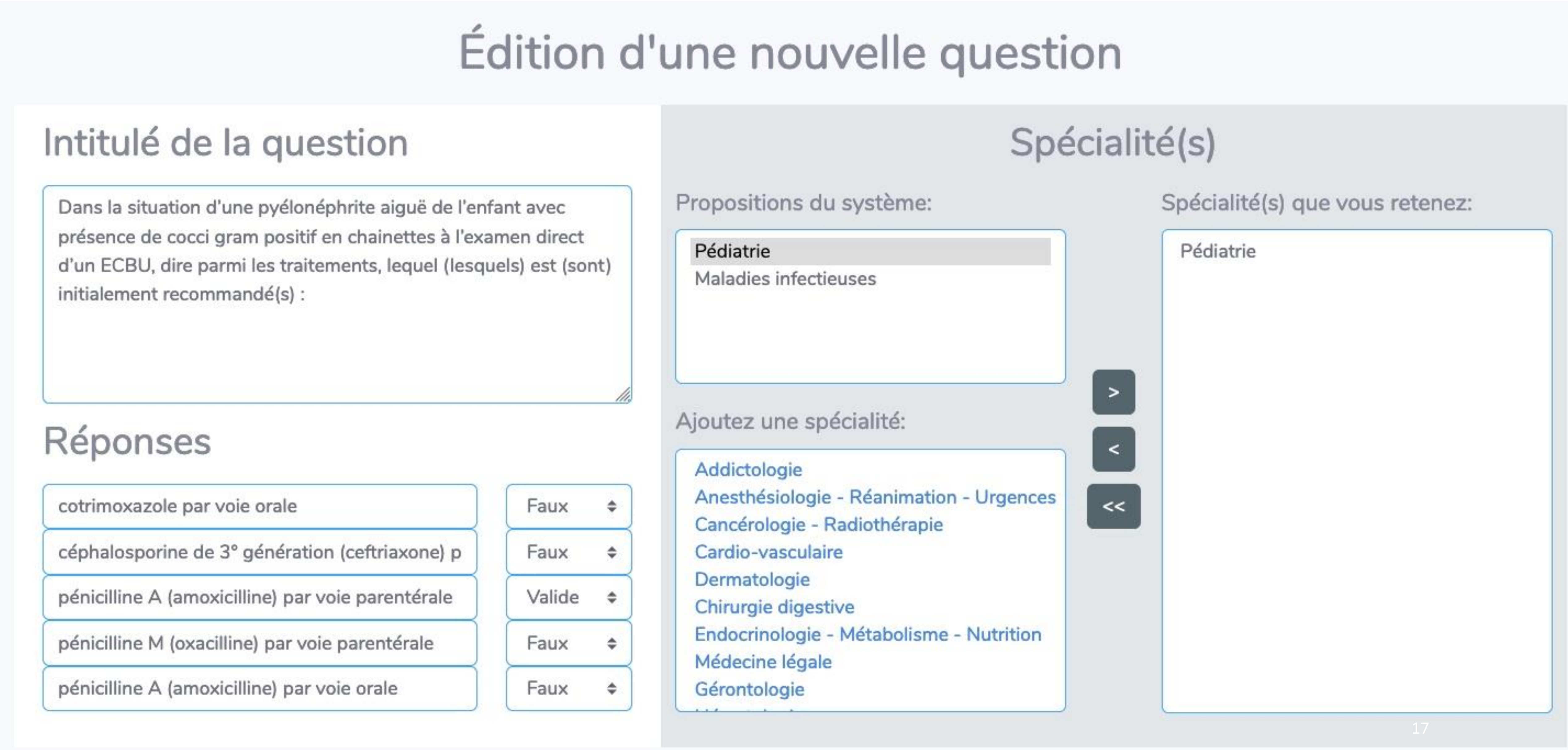
# Experimental results for classification

| Dataset | Classifier | Hits@1 | Hits@2 | Hits@5 | Hits@10 | MRR |
|---|---|---|---|---|---|---|
| Dataset1 | Naive Bayes classifier | 73.8% | 83.1% | 84.2% | 84.3% | 79.9% |
| | Maximum Entropy classifier | 75.1% | 88.9% | 95.4% | 96.8% | 84% |
| | CNN classifier | 76.4% | 89.4% | 96.3% | 98.5% | 85.2% |
| Dataset2 | Naive Bayes classifier | 56.4% | 64.8% | 67.8% | 67.9% | 61.5% |
| | Maximum Entropy classifier | 68% | 81.7% | 90.6% | 93.6% | 78.2% |
| | CNN classifier | 66.4% | 78.9% | 88.8% | 93.4% | 76% |

**Dataset1**: 149145 questions -> 31 medical specialties
**Dataset2**: 144708 questions -> 362 learning objectives
**Hits@k (Precision at k):** average number of times a correct result appears in the top-k answers
**MRR (Mean Reciprocal Rank)**: average of the rank inverses of the first correct answer

- **All the classifiers perform better on Dataset1 than on Dataset2**
  - the number of classes for Dataset2 is more than 10 times the number of classes for Dataset1 for almost the same number of items to classify
- **Naive Bayes outperformed by Maximum Entropy and CNN**
- Maximum Entropy gives slightly better results than CNN classifier on Dataset2
- **In more than 96% (93%) of the cases, the correct medical specialties (learning objectives) are returned in the top-10 answers**

# Application: suggestions to teachers while editing questions



# Application to OntoSides completion

- Focus on Hits@1
  - set up a threshold to obtain the desired balance between high precision and an acceptable recall.

| Dataset | Threshold | Hits@1 | % Questions |
|---|---|---|---|
| Dataset1 | 0 | 75.1% | 100% |
| | 0.3 | 78.2% | 96.5% |
| | 0.5 | 82.1% | 84.5% |
| | 0.7 | 86.6% | 66% |
| | 0.9 | 91% | 43% |
| | 0.95 | 92.6% | 33.3% |
| | 0.99 | 94.5% | 18.3% |

| | Threshold | Hits@1 | % Questions |
|---|---|---|---|
| Dataset2 | 0 | 67.5% | 100% |
| | 0.1 | 75.2% | 85% |
| | 0.3 | 81.3% | 61% |
| | 0.5 | 86% | 43% |
| | 0.7 | 89% | 29% |
| | 0.8 | 91% | 23% |
| | 0.9 | 92.4% | 16% |

- if we consider that **a precision more than 90% is acceptable** for adding reliable links from questions to medical specialties (Dataset1), and to learning objectives (Dataset2), it suffices to **fix the threshold to 0.9 for Dataset1 and 0.8 for Dataset2**.
- it decreases the percentage of questions for which such links can be added (**43% of links from questions to medical specialties**, and **23% of links from questions to learning objectives**).

# Comparative results of classification and matching

**Dataset3:** 108818 questions -> 236 learning objectives with textual description

| Method | | Hits@1 | Hits@2 | Hits@5 | Hits@10 | MRR |
|---|---|---|---|---|---|---|
| unsupervised | Jelinek-Mercer applied to bags of words | 44.5% | 58.2% | 72.2% | 80.9% | 57% |
| | BM25 applied to bags of semantic terms | 51.5% | 64% | 75.7% | 81.9% | 62.4% |
| supervised | Naive Bayes classifier | 56.2% | 64.6% | 67.5% | 67.7% | 61.3% |
| | Maximum Entropy classifier | 68.2% | 81.4% | 90.4% | 93.6% | 78% |
| | CNN classifier | 66.2% | 78.9% | 88.6% | 93% | 75.9% |

- **The "bag of semantic terms" representation** leads to more accurate results than **the "bag of words" representation**
  - **Semantic terms** are **medical concepts** that are **automatically extracted** from the textual descriptions **by** using the **SIFR BioPortal Annotator** (LIRMM, Clément Jonquet) applied to the French versions of the reference biomedical terminologies MESH and SNOMED
- Not surprisingly, **supervised classification methods outperform the unsupervised ones** (except Naïve Bayes at precision 5 and 10)
- However, **unsupervised methods provide good results (above 80%) at precision 10**

# Automatic Discovery of Links with External Ontologies

- From the 236 **learning objectives** with a textual description to standard **medical concepts** described in biomedical ontologies
  - UMLS concepts in MeSH and SNOMED CT (French and English version)
- Method overview
  - applied to the set of learning objectives, **seen as a corpus**, each learning objective being seen as a document described by a bag of medical concepts
    - Computation of the term frequency (TF) and the inverse document frequency (IDF) for each medical concept present in the corpus
    - Filtering out the medical concepts with a low IDF (below a certain threshold fixed experimentally )
    - For each learning objective, return the top-k medical concepts (ordered by decreasing TF): k is also fixed experimentally

# Two-step validation: method and results

No training dataset available

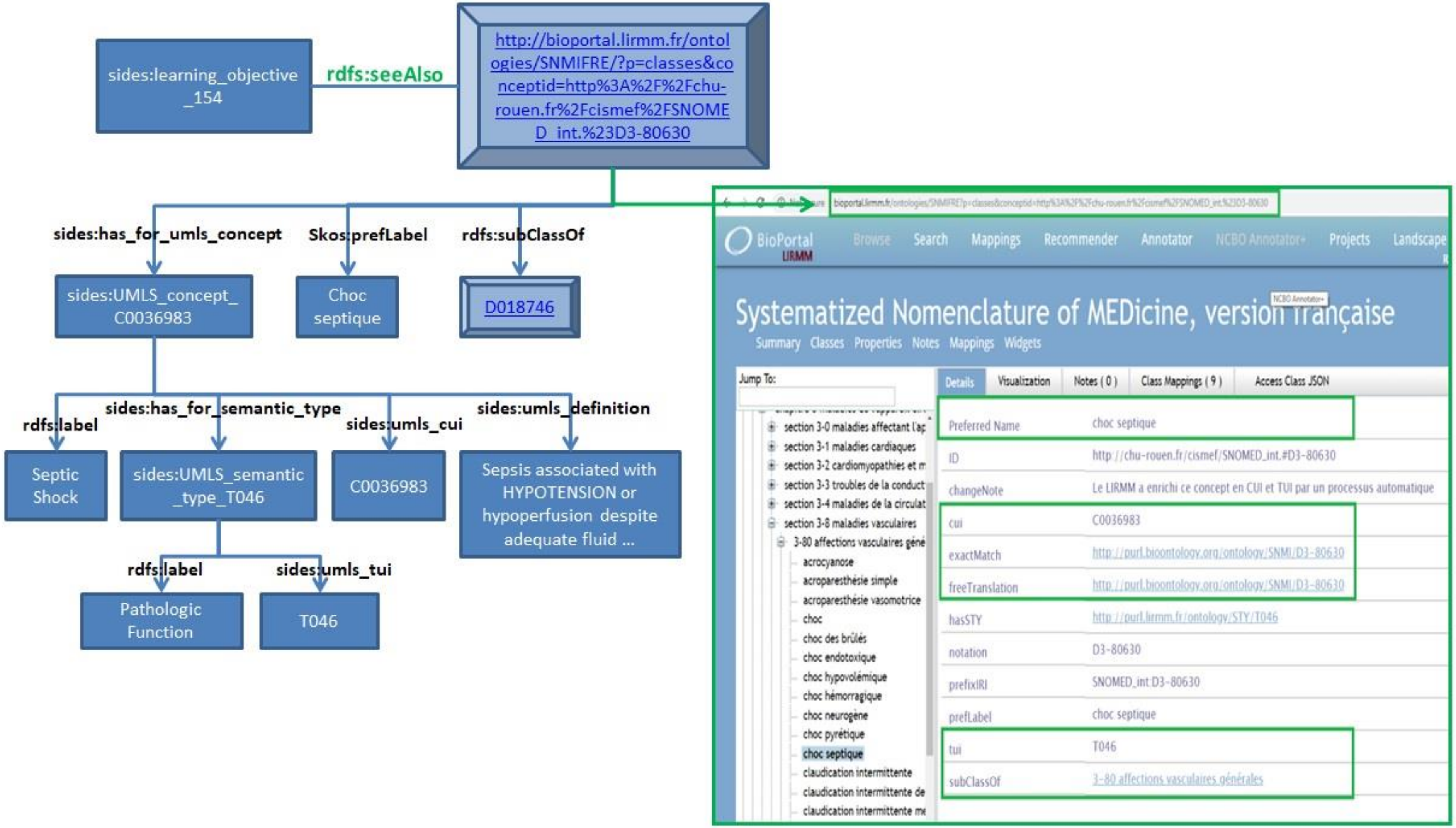
- First step of validation on 15 learning objectives with a domain expert (O.Palombi)
  - calibration of the parameters to get the best precision at precision k
- Second step of validation with medical experts through an online validation interface
  - answers of experts on 96 learning objectives

| #Evaluated Learning Objectives | #MSHFRE and SNMIFRE Semantic Terms | P@5 |
|---|---|---|
| 96 | 510 | 94.5% |

=> OntoSIDES enrichment by adding useful triples in addition to the discovered links

- 15371 triples added

# Example



sides:learning_objective_154
rdfs:seeAlso
http://bioportal.lirmm.fr/ontologies/SNMIFRE/?p=classes&conceptid=http%3A%2F%2Fchu-rouen.fr%2Fcismef%2FSNOMED_int.%23D3-80630
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Systematized Nomenclature of MEDicine, version française
Summary
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Properties
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Mappings
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Notes ( 0 )
Class Mappings ( 9 )
Access Class JSON
section 3-0 maladies affectant l'ap
section 3-1 maladies cardiaques
section 3-2 cardiomyopathies et m
section 3-3 troubles de la conduct
section 3-4 maladies de la circulat
section 3-8 maladies vasculaires
3-80 affections vasculaires géné
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choc des brûlés
choc endotoxique
choc hypovolémique
choc hémorragique
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choc pyrétique
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prefLabel
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T046
subClassOf
3-80 affections vasculaires générales

# In summary

## Specific completion and enrichment problems

- targeting property  of interest guided by the needs in data analytics of domain experts.

## Generic methodology

- exploiting textual information found in knowledge graphs through datatype properties or rdfs:seeAlso links to web pages.

## Experimental results

- demonstrated that it can effectively perform big knowledge graph completion and enrichment with a precision up to 95%

# Ongoing and future work

- Automatic generation of personalized Quizz
  - based on models that evaluate jointly the level of students and the difficulty of questions

    Inria Nice WIMMICS and ENS Ulm Cognitive Science partner

- Full deployment of SIDES NG as a moodle front-end on top of OntoSIDES

    UNESS

- SIDES LAB : new ANR project (starting in March 2022)
  - Large-scale in situ experimentation of several evidence-based strategies to enhance learning

=> continuously improve the learning platform to offer medical students **individually optimised learning paths based on the newly obtained results**.

# https://sides3.uness.fr/

**Artificial Intelligence In Medicine, Volume 96, May 2019, Pages 59-67**

OntoSIDES: Ontology-based student progress monitoring on the national evaluation system of French Medical Schools.

*Authors:* Olivier Palombi, Fabrice Jouanot, Nafissetou Nziengam, Behrooz Omidvar-Tehrani, Marie-Christine Rousset, Adam Sanchez.

https://doi.org/10.1016/j.artmed.2019.03.006

**AMEE 2019 Symposium: Understanding student behaviour: the role of digital data**

E-poster : https://my.ltb.io/#/viewStack/BHKJS