Deliverable D2.4

Report on Query Answering under Uncertainty

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Abstract: This deliverable describes the progress of the X-Media consortium with respect to uncertain reasoning with very large ontologies, in particular A-Boxes. We recall the main requirements for reasoning derived in the context of deliverable D10.6. Further, we present the results of our empirical analysis of an approach to fuzzy reasoning which reduces the fuzzy ontologies to OWL-DL ontologies, thus allowing to use standard OWL reasoners for fuzzy query answering. Then we describe our progress with respect to expressive query answering with Fuzzy DL Lite. Finally, we describe our progress with using the Fire reasoner for fuzzy reasoning.

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Report on Query Answering under Uncertainty

D2.4

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Contents

1 Introduction

This deliverable describes the progress of the X-Media consortium with respect to uncertain reasoning with very large ontologies, in particular large A-Boxes. The structure of the deliverable is as follows: in Chapter 2 we recall the main requirements for reasoning derived in the context of deliverable D10.6 [1]. In Chapter 3 we present the results of our empirical analysis of an approach to fuzzy reasoning which reduces the fuzzy ontologies to OWL-DL ontologies, thus allowing to use standard OWL reasoners for fuzzy query answering. This idea was already described in deliverable D2.1 [4]. Then we describe our progress with respect to expressive query answering with Fuzzy DL Lite in Chapter 4. Further, in Chapter 5 we describe our progress with using the Fire reasoner for fuzzy reasoning. Finally, Chapter 6 describes the work carried out in the context of providing fuzzy reasoning functionality for the F-Logic language.

2 Reasoning Requirements

Deliverable D10.6 [1] strived at learning more about the factual reasoning needs within X-Media, asking questions like: Which subset of OWL (e.g. OWL DL, OWL Lite, OWL DLP) do the partners currently use? Which compromises would we have to make if we would agree on subsets of OWL-DL (like OWL DLP, OWL Lite) instead of relying on the complete OWL-DL fragment? Are there possibly needs for more sophisticated reasoning facilities, i.e fuzzy reasoning?

Many partners did not report any specific needs w.r.t. the expressivity of the domain ontologies. Their position can be summarized easily: *"If you can provide us with OWL DL reasoning support, it is fine. If there are more serious constraints we have to evaluate in detail what the implications are."* This observation clearly reflects the main findings of D10.6. On the one hand, partners would like to have reasoning services supporting expressive ontology languages. On the other hand, they are well aware of the problems involved with expressive ontology languages and are willing to trade-off expressiveness for efficient reasoning services such as required by the uses cases in X-Media.

As a result of D10.6 several complementary strategies of reasoning support are suggested:

1. Providing one general purpose reasoner which (ideally) strives for fulfilling all reasoning requirements at the same time doesn't fit to the large scale requirements of X-Media. Instead there is no chance but working with different reasoners, each one providing the very specific capabilities needed for a specific reasoning task in question.

2. Surely the domain ontologies play a key role with respect to defining reasoning requirements. An important finding of D10.6 was that it is a reasonable option for X-Media to provide reasoning support for various fragments of expressive ontology languages such as OWL-DL, i.e. OWL-Lite, OWL DLP or even DL-Lite.

Both decisions perfectly fit to the approach of X-Media to provide rather a generic and common architecture into which different reasoners can be plugged-in.

With respect to reasoning with uncertainty, ID 10.6 didn't report much specific requirements directly from the users. This is not astonishing, since dealing with uncertainty in ontologies raises even far more challenging demands than semantic modeling as such. Even if the theory of reasoning with uncertainty (like e.g. fuzzy reasoning) is well known since years, there are no well established semantic use cases around until today. Nevertheless there is hope in X-Media that representing axiom metadata such as their certainty does not only add important background information necessary at least for ranking query results, but also contributes to more complex operations like finding a path from a set of effects to their most probable cause, such as needed in the issue resolution use case. With respect to reasoning with uncertainty, the findings of deliverable D10.6 allow us to conclude that we will also have to support query answering for imperfect ontologies formulated in different fragments of OWL-DL. In this deliverable we thus present our progress supporting reasoning for f-SHIN (fuzzy OWL-DL without nominals) [11] as well as fuzzy DL-Lite [14], a fuzzy version of the DL Lite language [2].

3 Reasoning with Large Fuzzy A-Boxes using DL Reasoners

In order to provide functionality for fuzzy query answering with large A-Boxes, we have analyzed in detail the time performance of the fuzzy reasoning approach based on Straccia's idea of reducing fuzzy description logic to crisp description logics [13]. In particular, we examine the logic f-$\mathcal{SHIN}$, a fuzzy version of $\mathcal{SHIN}$, i.e. OWL-DL without nominals, which can be reduced to OWL-DL as described in deliverable D2.1 [4]. Our focus of research has been to verify if such an approach can scale to the large A-Boxes we expect within the X-Media consortium. Thus, we have examined the time performance for such an approach using the KAON2 reasoner varying the size of the A-Box from 100 to 1.000.000 individuals. Further, we have also varied the number of fuzzy degrees considered (from 3 over 6 to 11) in order to study their effect on the overall performance.

In particular, we have tested the approach with four ontologies: VICODI, LUBM, Semintec as well as the well-known Wine ontology. A paper about our results has been submitted to the European Semantic Web Conference ([Cimiano et al. 2008], attached as appendix). The detailed results of our experiments can be found there. Summarizing, our results show that the approach to fuzzy query answering can be feasible if we restrict ourselves to slightly axiomatized ontologies and we consider only 3 degrees. In these cases the query time doubles compared to the crisp version of the ontologies. This is a modest increase in time complexity which could be still feasible for practical applications. Considering more axiomatized ontologies (such as the Wine ontology in our experiments) as well as considering more fuzzy degrees yields either ontologies which are completely intractable (as is the case for the Wine ontology) or considerably increases query time beyond what seems feasible. In fact, considering more degrees than 3 yields time increases of a factor between 10 and 100.

Our research results are very innovative as the approach to fuzzy query answering based on reduction to crisp description logics has not been systematically analysed before with respect to performance for ontologies with very large A-Boxes. In fact, ours is the first approach known to us providing time measurements for ontologies with a size which is clearly beyond toy examples.

The approach developed has clear applications within the X-Media project with respect to supporting conjunctive threshold queries (CTQs) as described in D2.2 [10]. Such a query could look as follows:

$$q(v) \leftarrow Sportscar(v) \geq 0.8, hasLength(v, large) \geq 0.7, hasMaker(v, fiat) \geq 0.9$$

and can be translated into the following query formulated with respect to the reduced ontology:

$$q(v) \leftarrow Sportscar_{\geq 0.8}(v), hasLength_{\geq 0.7}(v, large), hasMaker_{\geq 0.9}(v, fiat)$$

With our experimental evaluation we have shown that, under certain restrictions, such an approach to fuzzy query answering can be feasible.

4 Expressive Query Answering with Fuzzy DL Lite

Straccia proposed Fuzzy DL-Lite as a fuzzy extension of the DL-Lite lightweight ontology language proposed by Calvanese et. al. [3]. Straccia used the conjunctive query language of Calvanese et. al. to perform query services. Then, Pan et. al. [6] extended the conjunctive query language and proposed a number of very expressive fuzzy conjunctive query languages inspired by the field of fuzzy databases and fuzzy information retrieval. Pan et. al. provided detailed algorithms for providing query answering over these languages, while they also presented an implementation based on an extension of the ONTOSEARCH2 DL-Lite reasoner [7]. Finally, they provided an extensive evaluation using a fuzzy version of the LUBM benchmark [5]. First results showed that although we are considering very expressive languages over fuzzy knowledge bases, the extended system performs as robustly as the classical DL-Lite system.

As a representative example consider the following extended fuzzy queries:

$$
\begin{aligned}
\text{f-LUBM-Q15}(v) \leftarrow\ & \mathit{Famous}(v) \geq 0.5 \\
\text{f-LUBM-Q16}(v) \leftarrow\ & \mathit{Famous}(v) : 0.5 \\
\text{f-LUBM-Q17}\ (v1) \leftarrow\ & \mathit{Student}(v1), \mathit{Buzy}(v1) \geq 0.5, \mathit{Staff}(v2), \\
& \mathit{Famous}(v2) \geq 0.5, \mathit{teacherOf}(v2, v3), \\
& \mathit{takesCourse}(v1, v3) \\
\text{f-LUBM-Q18}\ (v1) \leftarrow\ & \mathit{Student}(v1), \mathit{Buzy}(v1) : 0.5, \mathit{Staff}(v2), \\
& \mathit{Famous}(v2) : 0.5, \mathit{teacherOf}(v2, v3), \\
& \mathit{takesCourse}(v1, v3)
\end{aligned}
$$

To test the f-DL-Lite query engine, we created datasets containing 1, 10 and 50 universities, with the largest data set (for 50 universities) containing 6,888,642 individuals. We used fuzzy aggregation queries as representatives for *Generalized Fuzzy Conjunctive Queries* (GFCQs) (see Deliverable D2.2 [10]) in our test. In order to investigate the overhead of fuzzy queries, we compare the performance in the f-DL-Lite query engine with the DL-Lite query engine, which is used to answer the following two crisp queries.

$$
\begin{aligned}
\text{crisp-1}(v) \leftarrow\ & \mathit{Famous}(v) \\
\text{crisp-2}(v1) \leftarrow\ & \mathit{Student}(v1), \mathit{Buzy}(v1), \mathit{Staff}(v2), \\
& \mathit{Famous}(v2), \mathit{teacherOf}(v2, v3), \\
& \mathit{takesCourse}(v1, v3)
\end{aligned}
$$

Table 4.1: Results of some f-LUBM queries

Query	$T[1]$ (ms)	$T[10]$ (ms)	$T[50]$ (ms)
f-LUBM-Q15 (TQ)	179	536	1061
f-LUBM-Q16 (GFCQ)	220	683	1887
crisp-1	152	422	891
f-LUBM-Q17 (TQ)	532	845	2922
f-LUBM-Q18 (GFCQ)	520	973	3654
crisp-2	494	892	2523

The results are shown in Table 4.1

In the context of X-Media we have implemented the algorithms for answering fuzzy conjunctive queries over fuzzy-DL-Lite ontologies. The system is called F^2OQ (Fast Fuzzy Ontology Querying) and currently an experimental evaluation is under way. The first results are quite impressive and the system can answer within seconds for fuzzy queries over a knowledge base containing about 500.000 fuzzy assertions (not counting the TBox). The detailed results can be found in [Pan et al. 2008] (attached as Appendix).

Our work in fuzzy-DL-Lite contributes to the state-of-the-art in fuzzy query answering in the following ways.

- It proposes a family of very expressive fuzzy conjunctive queries, like threshold queries, fuzzy threshold queries, fuzzy aggregations queries and weighted t-norm queries.
- It presents reasoning algorithms and implements them on top of f-DL-Lite in order to answer such expressive fuzzy queries.
- It provides the very first report on scalable and expressive fuzzy querying over fuzzy ontologies that is able to scale up to millions of fuzzy assertions.

5 Reasoning with Fire

FiRE is a JAVA implementation of a fuzzy reasoning engine for imperfect knowledge currently supporting f-$\mathcal{SHIN}$. In this section the graphical user interface, the syntax and the inference services of FiRE are introduced.

FiRE can be found at `http://www.image.ece.ntua.gr/~nsimou` together with installation instructions and examples (**Fig** 5.1). Its user interface consists of the editor panel, the inference services panel and the output panel. The user can create or edit an existing fuzzy knowledge base using the editor panel. The inference services panel allows the user to make different kinds of queries to the knowledge base (entailment, subsumption and greatest lower bound queries (glb)) and also to query a Sesame repository using expressive fuzzy conjunctive queries, like *conjunctive threshold queries* (CTQs) and *general fuzzy conjunctive queries* (GFCQs) [6]. Finally, the output panel consists of four different tabs, each one displaying information depending on the user operation.

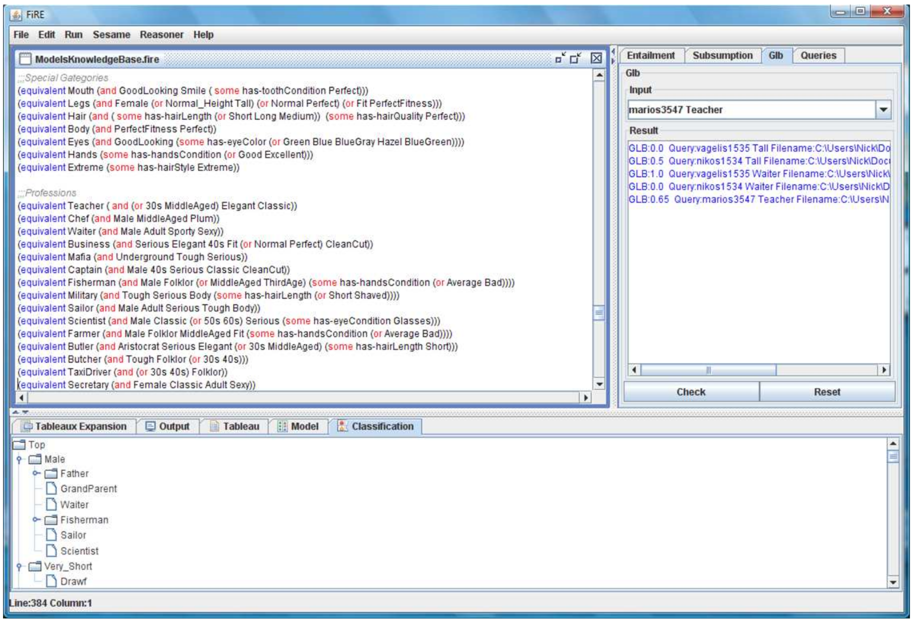

Figure 5.1: The FiRE user interface consists of the editor panel (upper left), the inference services panel (upper right) and the output panel (bottom)

FiRE implements the tableaux reasoning algorithm for the fuzzy DL f_{KD}-$\mathcal{SHIN}$

Query	Sesame Native			Sesame Memory		
	100.000	250.000	500.000	100.000	250.000	500.000
$x \leftarrow Scientist(x)$	1042	2461	3335	894	2364	3332
$x \leftarrow Father(x) \geq 1 \wedge Teacher(x) \geq 0.8$ $\wedge Normal\_Height(x) \geq 0.5.$	1068	2694	3935	994	2524	3732
$x \leftarrow Legs(x) \geq 1 \wedge Eyes(x) \geq 0.8 \wedge 20s(x) \geq 0.5$ $\wedge has - hairLength(x, y) : 1 \wedge Long(y) : 0.8$	3667	8752	21348	4267	18348	-
$x \leftarrow Scientist(x) : 0.8$	2562	4173	5235	3042	4543	6027
$x \leftarrow Father(x) : 0.6 \wedge Teacher(x) : 0.7$ $\wedge Normal\_Height(x) : 0.8.$	4318	6694	8935	4341	7896	9306
$x \leftarrow Legs(x) : 0.8 \wedge Eyes(x) : 1 \wedge 20s(x) : 0.6$ $\wedge has - hairLength(x, y) \wedge Long(y)$	9906	29831	66251	15164	-	-

Table 5.1: Fuzzy queries evaluation. Queries performed on repositories of size 100.000 250.000 and 500.000. The response time is in milliseconds

presented in [12]. On the other hand FiRE is able to communicate with the Sesame RDF triple store[1], serialize a fuzzy knowledge to RDF triples and store it to Sesame in order to provide persistent storage functionalities and querying. Before storing a fuzzy KB, users are able to perform a *global glb* reasoning service in order to deduce new inferred fuzzy knowledge using the f_{KD}-$\mathcal{SHIN}$ reasoning module. The architecture of the storing and querying system is described in more detail in [9].

The proposed architecture was applied and evaluated using a real world use case. We consider a casting scenario where an end-user is looking for actors to play in commercials or TV spots. For those reasons he/she wants to query a knowledge base containing information about actors, like body characteristics (height, weight, hair quality and length, etc) and appearance characteristics (sexy, mafia looking, teacher, etc). This knowledge was used to build high level concepts using the f_{KD}-$\mathcal{SHIN}$ language, while on the other hand fuzzy assertions (fuzzy data) were created by fuzzifing the age and height fields of each model defining new fuzzy concepts such as “Tall”, “VeryTall”, “20s”, “MiddleAged”, and more. Then the FiRE tool was used to perform a global glb service and the inferred knowledge was stored in sesame. Finally a number of expressive fuzzy conjunctive queries were issued over the Sesame repository and the response times was measured. Table 5.1 summarizes our main results. The results can be found in more detail in [Simou et al. 2008] (attached in the Appendix).

Our proposed architecture for connecting FiRE with Sesame contributes to the state-of-the-art in the following ways.

- It specifies a format for serializing fuzzy-OWL knowledge to RDF triples in order to be able to persistently store fuzzy knowledge using current RDF store technologies.

[1] http://www.openrdf.org/

- It extends Sesame's query language SeRQL by implementing expressive fuzzy conjunctive queries, like threshold queries, fuzzy threshold queries, fuzzy aggregations queries and weighted t-norm queries.

6 Fuzzy F-Logic

One possibility to associate meta information to statements, in particular (un-)certainty information, is to group the statements into collections, representing a reification of the set of statements, and then associate the information to this whole collection (of statements). This is essentially the idea of named graphs and is exploited for representing metaknowledge in the approach of Schüler et al. [8].

The essential idea is to identify groups of statements which somehow below to together, giving them an explicit name which can be referenced, and attach provenance data to the whole group of statements. This is a generic modeling pattern which is general enough to be applied to other knowledge representation formalisms other than RDF.

In F-Logic [**?**], the notion of a module directly maps to the notion of a named RDF graph. Ontoprise has provided resources during the last year in order to become compliant with the notion of named graphs and is in a position now to deal with named graphs natively in OntoBroker. In particular, when importing RDF data, URIs are interpreted as the names of a graph containing all the imported RDF spaces with the same URI. This allows a straightforward translation from RDF named graphs to F-Logic modules.

Complementary to the named graph approach, we also strived for a modeling of uncertainty which is more narrowly related to ontologies for the used cases considered in X-Media. In order to allow for uncertain reasoning using OntoBroker, we represent certainty (and other provenance information) specifically only at those places where it is really needed from the point of view of our use cases. This means in particular that we only associated provenance (and uncertainty) information to those relationships which require it.

For example, the fact that it “Ben loves Anna can be represented as a triple as follows (in N3 syntax):

```
graph_7890 { Ben loves Anna .}
```

Not surprisingly, in practice there is often the need to model n-ary relationships for n >= 3 (like “Ben probably gives a book to Anna). We represent a relation like this relying on a modeling paradigm we call *nominalization* of the predicate. We lift the predicate ”gives” up to the concept level, thus yielding a ”giving” which can be represented in RDF as follows (namespaces are omitted):

```
graph_7891 {
    _:giving1234 rdf:type gives-Nominal.
    _:giving1234 donator Ben .
    _:giving1234 adressee Anna .
    _:giving1234 what book .
    _:giving1234 certainty 0.7 .
}
```

Translated to F-Logic this RDF graphs would read as following (namespaces omitted):

```
giving1234:gives-Nominal[
    donator  -> ex:Ben ;
    adressee -> ex:Anna ;
    what     -> ex:book ;
    certainty -> 0.7
] @graph_7890 .
```

In order to make this modeling work, some drawbacks have to be taken into account:

1. While nominalization works perfectly for RDF, we have to be more careful when considering OWL. Transforming an OWL property to its nominalization yields an additional OWL class, thus modifying the ontology. OWL reasoning (e.g. A-Box classification) cannot rely any more on axioms concerning this property. Reasoning with nominalized relationships has to be performed with respect to a transformed rule base, by adding additional inferencing rules. However, the resulting inferencing rules exceed the expressivity of OWL. A rule enabled reasoner has thus to be used to in such scenarios, e.g. the OntoBroker. In D10.6 it is shown how this OWL DL to F-Logic move can be achieved manually. Additionally, ontoprise has implemented an automatic OWL DLP to F-Logic translation. This translation is available in the OntoBroker F-Logic edition.

2. The semantics of the predicates involved in a nominalization differ crucially. While “domain-properties (in the example e.g. domain:donator etc.) represent domain level knowledge, other properties (in the example e.g. provenance:certainty) describe meta-properies of the instance itself. In order to consider the appropriate semantics, inofficial agreements on how to interpret a property are needed – e.g. by evaluating the namespace of a relationship, thus giving it an implicit semantics.

In order to show how to perform reasoning in F-Logic with nominalized relationships we would like to discuss an example which is better aligned with the X-Media bike brake dissemination ontology. Suppose we want to model a transitive causation chain like *"If oil shows symptom heat then it will show symptom boil"* and *"If oil shows symptom boil then it will show symptom vapor"*. Inferencing then could infer *"If oil shows symptom heat it will show symptom vapor"*. Even if there might not be many readers familiar with F-Logic code we provide a minimal example how to model this state of affairs in F-Logic (see Appendix).

Summarizing, we have presented how to integrate two important approaches of X-Media how to represent (and inference with) uncertainty in F-Logic: the named graphs approach allows for attaching provenance information at each F-Logic module. The ontology modeling pattern called nominalization allows for maintaining provenance information on class level. While the former approach is more generic, we recommend the latter approach as it benefits from being less expressive and generic, thus allowing for a faster and more specific representation and reasoning with uncertainty in an F-Logic enhanced RDF store.

7 Conclusion

In this deliverable we have described our progress with fuzzy query answering in the context of the X-Media project. We have so far in particular focused on supporting various language fragments of different complexity, focusing in particular on efficient reasoning with large A-Boxes such as required for X-Media use cases. We have presented work on fuzzy reasoning with respect to f-$\mathcal{SHIN}$, a fuzzy version $\mathcal{SHIN}$, i.e. OWL-DL without nominals. Further, we have also presented first results obtained using the Fire tableaux reasoner which also supports f-$\mathcal{SHIN}$. We have also described an approach and presented first empirical results for our approach to answering more expressive fuzzy queries in DL Lite.

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8 Appendix

Attached documents:

- [Cimiano et al. 2008] – P. Cimiano, P. Haase, Q. Ji, T. Mailis, G. Stamou, G. Stoilos, T. Tran, V. Tzouvaras, ”Reasoning with Large A-Boxes in Fuzzy Description Logics using DL reasoners: An experimental evaluation”, submitted to the European Semantic Web Conference (ESWC)
- [Simou et al. 2008] – N. Simou, G. Stoilos, K. Pardalis, V. Tzouvaras, G. Stamou, S. Kollias, ”Storing and Querying Fuzzy Knowledge in the Semantic Web, submitted to the European Semantic Web Conference (ESWC)”
- [Pan et al. 2008] – J.Z. Pan, G. Stamou, G. Stoilos, S. Taylor, E. Thomas, ”Scalable Querying Services over Fuzzy Ontologies”, accepted for publication at the World Wide Web Conference, 2008.

8.1 A worked F-Logic example

```
// schema
symptom.
fluid.
contribution[
    antecedent => symptom;
    consequent => symptom;
    certainty  => xsd:number].

// modelling the causation chain with instances of the
// class causation c123:contribution[
    antecedent -> heat;
    consequent -> boil;
    certainty-> 0.7 ].
c234:contribution[
```

```
    antecedent -> boil;
    consequent -> vapor;
    certainty-> 0.6 ].
c345:contribution[
    antecedent -> heat;
    consequent -> smoke;
    certainty-> 0.5 ].

// schema
// for the reification of the relationship ‘‘shows’’:
showing [
    has_subject => fluid;
    has_symptom => symptom;
    certainty   => xsd:number].

// facts on heated oil
s123: showing [
    has_subject -> oil;
    has_symptom -> heat;
    certainty -> 1.0 ].

// transitivity rule for symptoms,
// taking into account the reification ‘‘showing:
forall ?F, ?SA, ?SB, ?C1, ?C2, ?C3

  s(?S,?SB):showing // skolemization
         [has_subject -> ?F:fluid;
          has_symptom -> ?SB:symptom
          certainty   -> ?C3 ]
  <-
      ?S:showing[has_subject -> ?F:fluid;
                 has_symptom -> ?SA:symptom;
         certainty   -> ?C1]
      AND ?C:contribution [antecedent -> ?SA:symptom;
                   consequent -> ?SB:symptom;
               certainty -> ?C2]
      AND min(C1, C2, C3).
```

This yields:

```
s(s123,boil):showing
[has_subject -> oil; has_symptom -> boil; certainty -> 0.7 ].
```

```
s(s(s123,boil),vapor):showing
[has_subject -> oil; has_symptom -> vapor; certainty -> 0.6 ].

s(s123,smoke):showing
[has_subject -> oil; has_symptom -> smoke; certainty -> 0.5 ].
```