

Fuzzy Lemon: Making Lexical Semantic Relations More Juicy

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Abstract

The OntoLex-Lemon model provides a vocabulary to enrich ontologies with linguistic information that can be exploited by Natural Language Processing applications. The increasing uptake of Lemon illustrates the growing interest in combining linguistic information and Semantic Web technologies. In this paper, we present *Fuzzy Lemon*, an extension of Lemon that allows to assign an uncertainty degree to lexical semantic relations. Our approach is based on an OWL ontology that defines a hierarchy of data properties encoding different types of uncertainty. We also illustrate the usefulness of Fuzzy Lemon by showing that it can be used to represent the confidence degrees of automatically discovered translations between pairs of bilingual dictionaries from the Apertium family.

Keywords: linked data, ontologies, fuzzy logic, uncertainty

1. Introduction

Managing linguistic information is important in many real-world applications, in particular in those taking advantage of Natural Language Processing (NLP) techniques. For this reason, there is an increase in the interest in combining linguistic information and Semantic Web technologies (Cimiano et al., 2020). Such Semantic Web technologies include ontologies, or formal and shared specifications of the vocabulary of a domain of interest (Staab and Studer, 2004), usually expressed in OWL (Cuenca-Grau et al., 2008); and linked data, a set of best practices for publishing and connecting data on the Web (Bizer et al., 2009), usually expressed in RDF (Schreiber and Raimond, 2014).

A very good example is the *Ontolex-Lemon* model, which intends to provide a vocabulary to enrich ontologies with information about how ontology elements can be realized in natural languages (Cimiano et al., 2016; McCrae et al., 2017). Lemon includes support to represent lexical semantic relations (between pairs of lexical entries, pairs of lexical senses, or pairs of lexical concepts) by means of its *Vartrans* module, as illustrated in Figure 1, borrowed from (Cimiano et al., 2016).

One of the limitations of Lemon is its inability to represent and manage uncertainty in the linguistic information. To manage uncertainty, the literature includes many extensions of Semantic Web technologies, such as Description Logics (Bobillo et al., 2015; Lukasiewicz and Straccia, 2008), ontologies (Zhang et al., 2016), SPARQL (Pan et al., 2008), or RDF (Straccia, 2009). The objective of this paper is to propose *Fuzzy Lemon*, an extension of Lemon to assign an uncertainty degree to lexical semantic relations. We understand the term “uncertainty” in a wide sense, and it is intended to embrace a variety of aspects of imperfect knowledge, including incompleteness, inconclusiveness, vagueness, ambiguity, and others (Laskey et al., 2008).

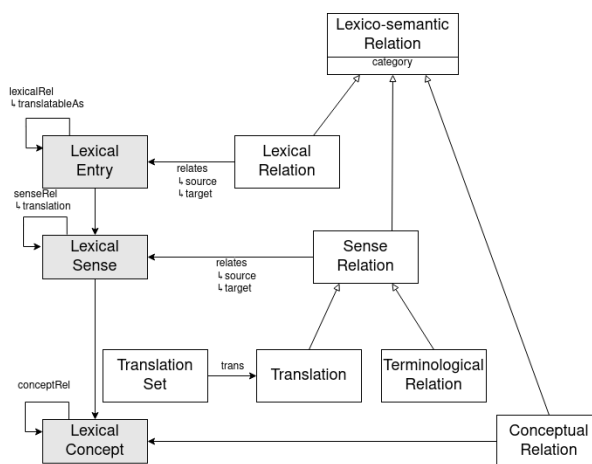


Figure 1: Scheme of the Lemon Vartrans module

The remainder of this paper is organized as follows. Section 2 discusses the need to support different types of uncertainty and some formalisms to do so. Section 3 presents Fuzzy Lemon ontology, enabling modeling uncertainty knowledge in lexical semantic data. Then, Section 4 discusses a use case: the representation of the confidence in automatically discovered translations between pairs of Apertium dictionaries. Finally, Section 5 ends up with some conclusions and ideas for future work.

2. Uncertainty in Lexical Semantic Relations

Current approaches to represent semantic relationships between pairs of lexical elements can be extended in several ways.

- Firstly, we might be interested in relations that partially hold, i.e., that hold to some *degree of*

truth. For example, there can be a translation between two terms in different languages that is imprecise or partially true, e.g., a Spanish “siesta” is slightly different than a “nap”. A more involved example, borrowed from (León-Araúz et al., 2012) is that a Spanish “dique” is similar to an English “breakwater” with degree 0.9. This also makes it possible to model the degree of semantic overlap between two meanings of two terms (in the same or different languages), or between two definitions of the same sense in different dictionaries with different granularity. For example, M. González et al. show different meanings of the senses of “fog” in an English monolingual dictionary and in an English-Spanish bilingual dictionary (González et al., 2021).

- Secondly, we might be interested in relations that we are not sure about, so we would attach a *confidence degree* to them. For example, there could be a term in a source language which can be perfectly translated as another term in a target language, but we are not sure if the translation is correct, i.e., if it is the right one. For example, the Spanish term “primo” has two senses and can be translated into English either as “prime” (number) or as “cousin”. This could be the case if we use an automatic software (e.g., Google Translate) to compute the translation of a term.

Both types of degrees require different formalisms to deal with them (Dubois and Prade, 2001).

- On the one hand, fuzzy logic can manage statements with an associated degree of truth (Zadeh, 1965; Klir and Yuan, 1995), expressing that the statement is partially true or, in other words, the extent to which the event described by such statement holds in the world. For example, “the bottle is full with fuzzy degree 0.5” means that the amount of liquid in the bottle is half of its total capacity. There can be completely full bottles (fuzzy degree 1) and completely empty bottles (fuzzy degree 0), but there are also bottles which are full up to some degree.
- On the other hand, possibilistic (Dubois and Prade, 1988) or probabilistic (Nilsson, 1986) logics can manage confidence degrees, which quantify our certainty about an event. In this case, there are several *worlds* or possible scenarios, but we are not sure which is the right one. The statement “the bottle is full with confidence degree 0.5” means that we are not sure about the status of the bottle, in some worlds it could be full, and in others it could be not full (but the amount of liquid does not need to be half of the total capacity).

Probability logic is a well known formalism that tries to quantify how likely an event is. Possibilis-

tic logic differs by the use of a pair of dual measures (possibility and necessity) rather than just one. A possibility degree quantifies how possible an event is (by taking the supremum value over all worlds), while the necessity degree quantifies how necessarily an event happens, by computing one minus the possibility of the negated event. For instance, “tomorrow it will rain with a possibility degree 1” means that there is a world where it will rain, but there could be other scenarios where it will not. Note also that if it is absolutely impossible that tomorrow will rain (the possibility degree is 0), it is necessarily true (the necessity degree is 1) that it will *not* rain.

Note that both approaches are actually orthogonal, and we might want to represent that we are partially confident on a statement being partially true.

3. Fuzzy Lemon Ontology

This section describes the elements of Fuzzy Lemon Ontology and how to use them to extend the Lemon model. We will also discuss how to populate and use the ontology, possible extensions, links to existing ontologies, and some reasoning strategies.

Elements of the Ontology. Fuzzy Lemon has been written in OWL 2 (Cuenca-Grau et al., 2008) and is publicly available¹. It includes data properties linking a lexical semantic relation with a numerical or textual data type value representing the degree of the relation. The main data property is `semanticRelationDegree`, and it has as domain the class `vartrans:LexicoSemanticRelation`. Note in particular that it is possible to consider other lexico-semantic relations different than translations, for instance equivalence or hyponymy relations between pairs of Wordnet synsets (or similar resources), as long as they are represented using lemon as already proposed by (McCrae et al., 2014).

Next, we built a hierarchy of subproperties of `semanticRelationDegree` to support different uncertainty types (see Figure 2). In particular, we propose to consider `fuzzyDegree` and `confidenceDegree`. The latter one has two subproperties `probabilisticDegree` and `possibilisticDegree`. The latter property has two subproperties `possibilityDegree` and `necessityDegree`. Properties `fuzzyDegree` and `confidenceDegree` have as range the decimal numbers in the interval $[0, 1]$. Properties `fuzzyDegree`, `probabilisticDegree`, `possibilityDegree`, and `necessityDegree` are functional. However, `semanticRelationDegree`, `confidenceDegree`, and `possibilisticDegree` are not. Therefore, it is possible to combine a single degree of truth with one or more confidence degrees, but we cannot combine several confidence degrees of the same type.

¹<http://sid.cps.unizar.es/ontology/fuzzyLemon.owl>

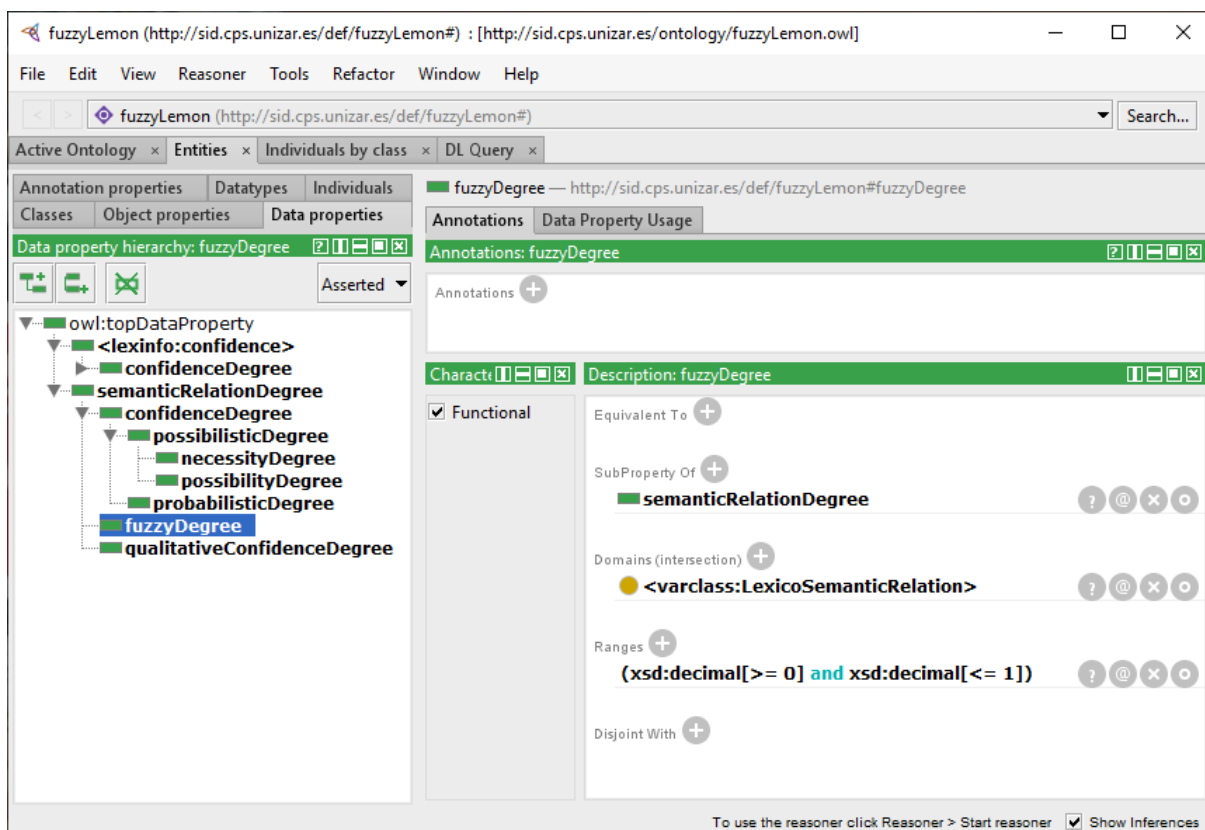


Figure 2: Subproperty hierarchy of the Fuzzy Lemon ontology

The default value of these semantic degrees is 1, making our extension backwards compatible. Therefore, if the value is 1, there is no need to represent it explicitly. Other authors have proposed using non-numerical (i.e., categorical) values to categorize the type of links between two lexical semantic elements. For example, possible values are *perfect*, *partial*, *unknown*, *narrowerThan* or *widerThan* (González et al., 2021). In order to support such non-numerical values, we have added a subproperty of `semanticRelationDegree`, called `qualitativeConfidenceDegree`, having as range an `xsd:string` value. Note that numerical values provide more information, e.g., two relations that hold with degrees 0.1 and 0.9 are both *partial*, but the second one is *truer* than the second one.

It is worth to mention that there is a previous ontology of uncertainty with more approaches to manage uncertainty, such as rough sets, belief functions, or random sets (Laskey et al., 2008). We have not reused it because uncertainty types are expressed as classes, but properties are more appropriate in our scenario. In particular, this allows to express domain and range restrictions, as well as non-numerical confidence degrees.

Using the Ontology. After having defined all these properties, we propose to extend the syntax of Lemon so that we can attach to a lexical semantic relationship (between senses, entries, or concepts) a degree via a subproperty of `semanticRelationDegree`. For exam-

ple, we could add a degree to a translation (i.e., to an instance of the `vartrans: Translation` class). Example 1 shows how to add a fuzzy degree to a translation involving two entities `ex:siesta` and `ex:nap`.

Populating the Ontology. A common problem when managing uncertainty is how to obtain the concrete values of the degrees. A first option is to ask a human expert, or a group of them, to assign the values. In some cases, the proportion of lexical semantic relations with an attached degree seems to be very small, so this could be a feasible solution. This could be the case, for example, if a human expert is encoding the translations, and only translations which do not fully hold are annotated. Another option is to use some automatic or semiautomatic machine learning procedure to obtain the degrees from examples. The problem here is the need to obtain large amounts of data to learn from. In Section 4 we will discuss in detail one of the many possible ways to do it: learning the confidence degrees of translations between pairs of terms in different languages based on the cycles density (Villegas et al., 2016; Lanau-Coronas and Gracia, 2020).

Extending the Ontology. We have restricted to three logics (fuzzy, possibilistic, and probabilistic) because there has been some previous work to extend ontology axioms with them (Lukasiewicz and Straccia, 2008). Clearly, our ontology could be extended with more sub-

properties of `semanticRelationDegree`.

In the case of fuzzy degrees, it would also be possible to further generalize our approach by replacing the interval $[0, 1]$ with a more general structure, such as another interval or a lattice. Despite these possibilities, we argue for a simple but flexible approach, which could be further extended in the future if there is need to.

Linking the Ontology. Lexinfo ontology (Cimiano et al., 2011)² has a data property `lexinfo:confidence` and a sub-property `lexinfo:translationConfidence`. Our properties `confidenceDegree` (with a numerical range) and `confidenceDegree` (with a textual range) are stated to be subproperties of `lexinfo:confidence`, which is more general as it does not restrict the domain or the range.

SKOS vocabulary (Miles et al., 2005)³ includes some object properties that are relevant to our work, such as `skos:exactMatch` or `skos:closeMatch`. `skos:exactMatch` could be used to represent relations without uncertainty, as in classical Lemon, whereas `skos:closeMatch` could be used to represent relations affected by uncertainty. However, our approach gives more information, as it makes it possible to specify the uncertainty type (e.g., probabilistic or fuzzy) and quantify the uncertainty (e.g., with a numerical degree), uses data properties rather than object properties, and make it possible to represent both exact (e.g., if the degree is 1) and close matches.

Reasoning with the Ontology. Another important problem is whether it is possible to infer new degrees from existing ones. In some cases, it is possible to exploit transitivity of the relationships. For example, if “siesta” can be translated as “nap” with degree α , and “nap” can be translated as “sonnellino” (in Italian) with degree β , can “siesta” be translated as “sonnellino” with degree γ ?

In fuzzy logic, given a transitive relation, one can infer that $\gamma \geq \alpha \otimes \beta$, where \otimes is a t-norm function that generalizes the classical conjunction to the fuzzy case (Klement et al., 2000). Examples of t-norm functions are the minimum and the product. Note in particular that the product is subidempotent, which means that $\alpha \otimes \alpha < \alpha, \forall \alpha \in (0, 1)$. Note also that a similar approach is not possible with possibility degrees, as possibilistic logic is not truth-compositional (Dubois and Prade, 2001).

In our scenario, we claim that the retrieved candidate relations should be revised by a human expert before incorporating them into our knowledge base. For example, given two relations that partially hold because there is an overlapping between lexical senses, we might not be able to infer a third relation because overlapping is not transitive, as Figure 3 shows (blue and

red squares overlap, red and green squares, but blue and green do not).

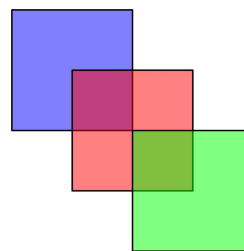


Figure 3: Example of non-transitivity of overlapping

4. Use case: Automatic translations

Apertium (Forcada et al., 2011) is a free open-source machine translation platform, initially created by Universitat d’Alacant and released under the terms of the GNU General Public License. In its core, Apertium relies on a set of bilingual dictionaries, developed by a community of contributors, which covers more than 50 languages pairs.

Apertium RDF (Gracia et al., 2018) is the result of publishing the Apertium bilingual dictionaries as linked data on the Web. The result groups the data of the (originally disparate) Apertium bilingual dictionaries in the same graph, interconnected through the common lexical entries of the monolingual lexicons that they share. In its current version, it contains 44 languages and 53 language pairs, with a total number of 1,540,996 translations between 1,750,917 lexical entries (Gracia et al., 2020).

Apertium RDF has been used in a number of campaigns of the Translation Inference Across Dictionaries (TIAD) initiative (Gracia et al., 2019; Kernerman et al., 2020)⁴. In this task, the participating systems were asked to generate new translations automatically among three languages, English, French, Portuguese, based on known translations contained in the Apertium RDF graph. As these languages (EN, FR, PT) are not directly connected in this graph, no translations can be obtained directly among them there. Based on the available RDF data, the participants applied their methodologies to derive translations, mediated by any other language in the graph, between the pairs EN/FR, FR/PT and PT/EN.

Motivated by the outcomes of this campaign, we are proposing in this work a way to semantically represent the inferred translations between pairs of senses resulting of such translation inference algorithms, which usually come with a confidence degree per translation pair.⁵ In that way, the new translations can be “materi-

⁴<http://tiad2021.unizar.es>

⁵Both the inferred data sets as well as their linked data representation are available at <https://github.com/sid-unizar/fuzzy-lemon-translations>.

²<https://www.lexinfo.net>

³<https://www.w3.org/2004/02/skos>

Example 1. Representation of the fact that siesta can be translated as nap with a fuzzyDegree 0.5.

```
@prefix dct: <http://purl.org/dc/terms/> .
@prefix ex: <http://example.org/> .
@prefix fuzzyLemon: <http://sid.cps.unizar.es/def/fuzzyLemon#> .
@prefix ontollex: <http://www.w3.org/ns/lemon/ontollex#> .
@prefix owl: <http://www.w3.org/2002/07/owl#> .
@prefix trcat: <http://purl.org/net/translation-categories#> .
@prefix rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#> .
@prefix rdfs: <http://www.w3.org/2000/01/rdf-schema#> .
@prefix vartrans: <http://www.w3.org/ns/lemon/vartrans#> .
@prefix xsd: <http://www.w3.org/2001/XMLSchema#> .

ex:siesta a ontollex:LexicalEntry ;
    dct:language <http://lexvo.org/id/iso639-1/es> ,
        <http://id.loc.gov/vocabulary/iso639-2/spa> ;
    ontollex:sense ex:siesta_sense .
ex:siesta_sense ontollex:reference <http://dbpedia.org/ontology/Nap> .
ex:nap a ontollex:LexicalEntry ;
    dct:language <http://lexvo.org/id/iso639-1/en> ,
        <http://id.loc.gov/vocabulary/iso639-2/eng> ;
    ontollex:sense ex:nap_sense .
ex:nap_sense ontollex:reference <http://es.dbpedia.org/resource/Siesta> .
ex:trans a vartrans:Translation ;
    vartrans:category trcat:directEquivalent ;
    fuzzyLemon:fuzzyDegree "0.5"^^xsd:decimal ;
    vartrans:source ex:siesta_sense ;
    vartrans:target ex:nap .
```

alized” in RDF and re-introduced in the overall Apertium RDF graph, with suitable provenance information and confidence degree, thus coexisting with human made translations from the original Apertium and enabling new ways of processing and enriching the Apertium data.

In particular, we focus on an algorithm that exploits the existence of cycles in the Apertium RDF graph structure in order to infer new translations, and computes their confidence degree based on the cycles density (Villegas et al., 2016; Lanau-Coronas and Gracia, 2020).

For the newly inferred translations we had thus three representation needs. We wanted to capture (1) the confidence score assigned for the translation, (2) the path followed in the Apertium RDF graph, that is, the entries making up the cycle leading to such a translation, and (3) their provenance as outcome from a specific translation inference software. For (1), we turned to the use of the property `fuzzyLemon:confidenceDegree`.

Figure 4 represents the inferred translation of *calendar* (English) into French (*calendrier*) as linked data. The inferred `vartrans:Translation` linking two senses, in English and French respectively, is given a confidence score of 0.83. For (2), note that we have kept the cycle information inside a comment linked to the translation: starting from English (*calendar*), and traversing through Spanish, French, and Esperanto, the cycle is closed with English again.

For aspect (3), the Prov Ontology (Belhajjame et al., 2012) has been used. In our case, the inferred translation belongs to a translation set (`vartrans:TranslationSet`) which is attributed to a `prov:SoftwareAgent` representing our inference system via the property `prov:wasAttributedTo`. This system is related to a `prov:Activity` representing the inference activity itself, which produces as output the translation set. This reflects the interplay between Agent-Activity-Entity accounted for in Prov-O.

The following pairs of dictionaries were inferred following the approach based on cycle density, and concern English, French, Esperanto, Italian and Sardinian (in parentheses, the number of inferred translations per dictionary): EN-FR (7772), EO-IT (7607), FR-IT (6497), SC-FR (4607), SC-EO (3473).

5. Conclusions

In this paper, we have presented *Fuzzy Lemon*, an extension of Lemon model that makes it possible to assign an uncertainty degree to lexical semantic relations. This can be achieved by means of an OWL ontology that defines a hierarchy of data properties supporting the management of different uncertainty types. The model has also been designed in such a way that future extensions to support more uncertainty types.

Because uncertainty is inherent to many real-world domains, Fuzzy Lemon can be useful in many Natural Language Processing or, more generally, Artificial Intelligence applications. To illustrate the usefulness of

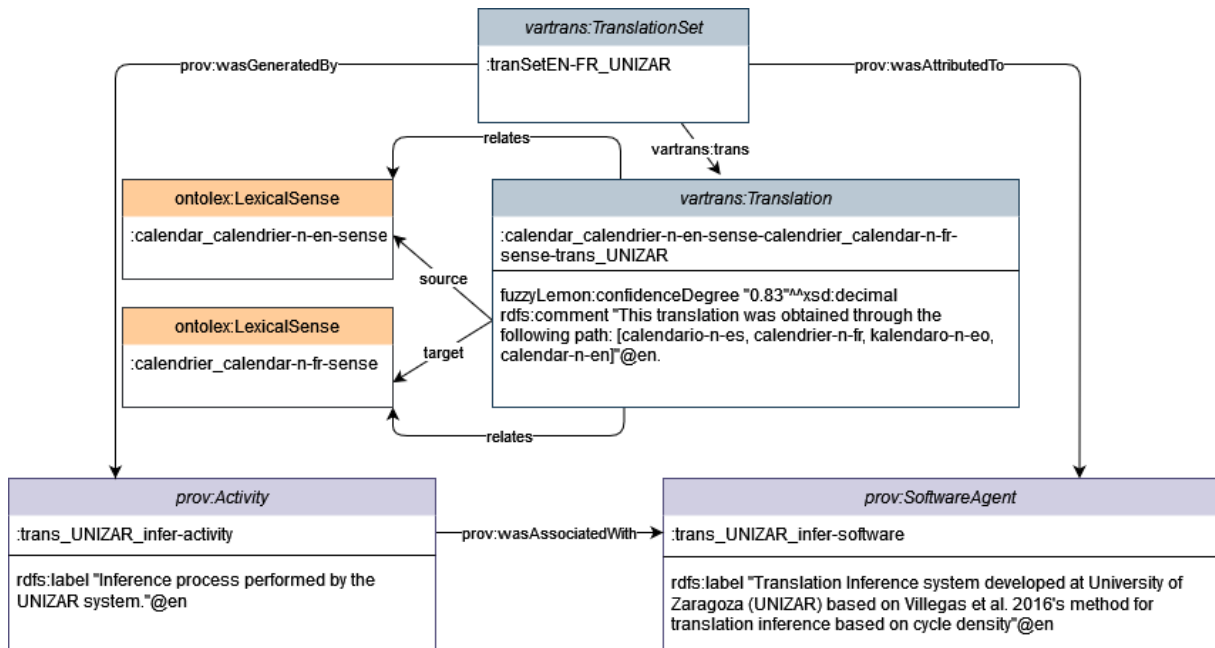


Figure 4: The inferred EN-FR translation *calendar-calendrier* represented as linked data with Fuzzy Lemon and Prov-O. The elements shaded in orange were already available in the Apertium graph, gray elements are inferred, and purple entities are common to all the inferred pairs and refer to the implemented system.

Fuzzy Lemon, we have shown how it can be used to represent the confidence degrees of automatically discovered translations between pairs of Apertium dictionaries.

As a next step, we plan to involve the broader W3C Ontolex community in order to gather feedback for our modelling proposal, to identify other possible use cases, and maybe to incorporate our proposed extension into the family of “official” Lemon modules in the future.

It would also be interesting adding to the model details about the creator of the uncertainty information, particularly when it comes from a machine learning software. A possible idea is to reuse the ideas behind the Internationalization Tag Set (ITS) tool annotation.⁶

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⁶<https://www.w3.org/TR/its20>

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