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A Note on IFS modifications and possible applications to machine translation

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Abstract In the present paper we consider some possible implementation of the Intuitionistic Fuzzy Sets as a tool for aiding machine translation.

Keywords: Intuitionistic Fuzzy Set (IFS), Metric, Machine Translation

1 Introduction.

The so-called Intuitionistic Fuzzy Sets (IFS) defined by K. Atanassov [1] are a generalization of the Fuzzy Sets (FS) proposed by Zadeh ([2]). The most common machine translation programs nowadays use statistical procedures for optimizing the output in the target language. The standard techniques for machine translation use the vast available databases of words and phrases like wordnet (developed by the Princeton University), a set of statistical procedures based on the translation model, and some restraints on the output. Syntax knowledge has not yet been introduced at the desired level. One idea we have is to use Intuitionistic fuzzy sets to represent better the relations between the words in a text, thus providing a basis for improvement of the machine translation.

2 d-IFS

Here we will briefly remind what $d - IFS$ are, since we will use some of their properties in the discussion below. Let $d\colon R^2 \times R^2 \to [0, +\infty)$ be an arbitrary metric on R^2 and $\mu\colon E \to I$, $\nu\colon E \to I$ be arbitrary mappings. Then we remind that the set

$$\{(\mu(x), \nu(x))|x \in E\}$$

is said to be d- Intuitionistic Fuzzy Set or abbreviated d-IFS, if it is fulfilled:

$$(\forall x \in E), (d((\mu(x), \nu(x)), (0, 0)) \leq 1)$$

A wide class of $d-IFS$ may be introduced with the help of any norm on R^2. For example, let $\varphi\colon R^2 \to [0,+\infty)$ be an arbitrary norm on R^2. Then as usual, φ represents a metric $d = d_\varphi$ on R^2, that is given by the formula:

$$(\forall(\mu_1,\nu_1),(\mu_2,\nu_2) \in R^2, d_\varphi((\mu_1,\nu_1),(\mu_2,\nu_2)) = \varphi(\mu_1-\mu_2,\nu_1-\nu_2)).$$

Thus the norm φ generates $d_\varphi - IFS$. When $\alpha \in (0,+\infty)$, the respective d_{φ_α}-IFS are introduced by:

$$\{(\mu(x),\nu(x))|x \in E, \mu\colon E \to I, \nu\colon E \to I\&((\mu(x))^\alpha + (\nu(x))^\alpha) \leq 1\}$$

Any d_{φ_∞}-IFS is a limit of d_{φ_α}-IFS, when $\alpha \to +\infty$.

We will consider only abstract languages marked A (source) and B (target) to present our idea. Let us assume that each word in the text that is to be translated has a set of different meanings in the target language, or if we denote the current word as x:

$$A \ni x \mapsto Y^n \subset B,$$

where n-denotes the number of meanings the word may take (it is reasonable to assume that some of these meanings will be rendered irrelevant by the context, or, if we are using a phrase-based approach, by the possible phrases that can be constructed). Let us denote them by $y_1,..,y_n$. For each of these n entities we define the functions

$$\mu(y_i), \nu(y_i), \pi(y_i) \text{ for } i = 1,...,n,$$

where μ- measures the degree with which the respective entity belongs to the correct translation, ν - the degree of non-membership, or level of contradiction with previously added entities, and π - the degree of uncertainty, or ambiguity of the resulting text. If we view the resulting text as a mapping we would also have for each word y a possible image $X^k \subset A$ with $\mu(x_i), \nu(x_i),$ and $\pi(x_i)$ being the respective values for possible preimage of y. If we construct a function that, based on the IFS values of $x(i)$, selects a preimage close to the original sequence, then we can improve the accuracy of the translation. In order to do so, we should define metrics over the languages A and B. In other words we would like to define "distance" between different words. To each word α from A we attribute the values $\mu_{A*_\alpha}(\alpha), \nu_{A*_\alpha}(\alpha), \pi_{A*_\alpha}(\alpha)$, and to each word β from B we attribute the values $\mu_{B*_\beta}(\beta), \nu_{B*_\beta}(\beta), \pi_{B*_\beta}(\beta)$, where $A*_\alpha$ and $B*_\beta$ are the set of words that are from the same gramatical category and refer to similar concepts as α. Or in other words $A*_\alpha$ and $B*_\beta$ are the domains in which α and β are comparable. A distance can then formally be defined as

$$d(\alpha_1,\alpha_2) = d((\mu_{A*_{\alpha_1}\cap A*_{\alpha_2}}(\alpha_1), \nu_{A*_{\alpha_1}\cap A*_{\alpha_2}}(\alpha_1)), (\mu_{A*_{\alpha_1}\cap A*_{\alpha_2}}(\alpha_2), \nu_{A*_{\alpha_1}\cap A*_{\alpha_2}}(\alpha_2))).$$

Thus we have assigned a $d - IFS$ to each of the target and source languages, which allows us to select and relate words better. Such metric can be created for any meaningful entities, though the domains in which they would be comparable will require some effort to find. Given a good database of examples, however, this is possible. What possible advantages might this offer? If we can easily verify that both the translated text is the most likely target outcome from the source text, and that for that source text the most likely ”preimage” is the target text we would have a basis for machine learning strategy that corrects its output as to satisfy both these conditions providing increased accuracy.

3 Conclusion

A possible way for handling lexical knowledge with the use of approprite IFS has been proposed. Such knowledge will be inherently embedded in the metrics corresponding to the target and source languages.

References

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