Language Understanding Systems Mid-Term Project 2017
FST GRM Tools for SLU

Nicola Garau (189086)
nicola.garau@studenti.unitn.it

Abstract

The aim of this project is to develop a SLU (Spoken Language Understanding) module capable to tag words with tags from a Movie Domain and to analyse its performance with different configurations.
To achieve these goals, a language model was trained to predict unseen utterances from a testing dataset. For both the training and testing phase, a set of natural language utterances for movie domain was used. The results show that, in this context, training the SLU on n-grams of order greater than five tend to overfit the data, leading to a lower Accuracy and F1-Score.

1 Introduction

A Concept Tagger is a model that assigns a token, called tag, to different words belonging to sentences. In order for it to work, it needs to be trained with several training data composed of couples word-tag.

For the purposes of this project, the following were given

- A data set for movie domain, split into train and test set
- A data set with additional features, split into train and test set
- A Perl script to analyse the tagger performances and give different scores as output (like Accuracy, Precision, Recall and F1-Score)

2 Data Analysis

As said before, a data set for the Concept Tagger training and testing was used. The given dataset is the Microsoft NL-SPARQL data set (Hakkani-Tur et al., 2014). All the data was already split into train (3338 utterances) and test (1084 utterances). Four files were given:

- NLSPARQL.train.data, containing training utterances composed of tab-separated couples of word-concept tag
- NLSPARQL.train.feats.txt, containing training utterances com-posed of tab-separated triples of word-POS tag-lemma
- NLSPARQL.test.data, containing, containing test utterances composed of tab-separated couples of word-concept tag
- NLSPARQL.test.feats.txt, containing test utterances composed of tab-separated triples of word-POS tag-lemma

Each utterance in the files is separated by the others with an empty line.

Here is an example of utterance from the given data set:

- From the data file

```
who             O
’s              O
in              O
star            B-movie.name
wars            I-movie.name
episode I-movie.name
four            I-movie.name
```

- From the feats file

```
who             WP      who
’s              VBZ     be
in              IN      in
star            NN      star
wars            NNS     war
episode NN      episode
four            CD      four
```

2.1 Data Distribution

As expected, movie.name is the most popular tag found (Zipf's Law). A graphic represented the concept distribution ban be found below. 2
It is interesting to notice that more than 80% of the tags are out of span concept tags.

2.2 Concept Tags

Concept tags are defined using an IOB Notation. The notation (the prefix notation B-NP is the one used in the dataset) is used to label multi-word spans in token-per-line format.

The prefixes are:

- B : beginning of a span
- E : end of a span
- I : inside of a span
- O : outside of span

2.3 POS (Part Of Speech) tags and lemmas

Both POS tags and lemmas in the feats files are additional features that can be used to improve the training of the concept tagger. They didn't really improve the performance of the tagger in this solution.

2.4 Dataset Issues

During the development phase there were three main misunderstandings with respect to the additional features data sets.
The first was that it was not clear how to cope with the fact that the same word could be mapped to different lemmas (s-be and s-s for example) in the transduction from word to lemma. Then it was clear that that transduction was not necessary because it led to a worst training performance.

The second issue was that was not clear how to take advantage of the test set NLSPARQL.test.feats.txt. The fact is, proba-bly it cant be exploited during the training phase without cheating.

The third issue was that it seemed like that the additional features could help improve the performance by calculating the cost of each transition with the following formula:

$$P = \frac{C(word, lemma, POS_{tag}, Concept_{tag})}{C(Concept_{tag})}$$

But, in the end, it always led to a worst performance.

3 Development, Structure and Imple-mentation

The whole system was entirely developed using a combination of Bash and Python 2.7. No third party libraries were used, apart from:

- OpenFST library (Ope, a)
- OpenGrm NGram library (Ope, b)

The main script, called conceptTagger.sh, can be split into 6 parts:

1. Variables definition and clearing of the previous computations files and folders
2. Pre-processing: the training data set was augmented by appending the words whenever an out of scope concept tag was found. The preprocessing script is called preTraining.py. By doing so, the overall best F1 score was increased because some out of span tags that before were mapped as inside the span were now mapped correctly as out of span
3. Utterances and tags sets extraction: two lists of sentences and of the associated concept tags were needed in order to create a far archive and extract FSTs for every single utterance later. The sets can be found inside the data folder. The script responsible for the extraction is called extractSets.py.
4. Lexicon creation: a lexicon (list of coupes element-index) was created, where each element was chosen amongst (training set):
   - Words
   - POS tags
   - Concept tags

   The lexicon can be found inside the data folder. The script responsible for the lexicon creation is called createLexicon.py.
5. Word-To-Concept transducer creation: a transducer which maps words into Movie Domain concept tags was created using a Python script called wordToLemma.py and then compiled using OpenFsts command fstcompile. During this phase, the cost of the

transition from a word to the corresponding concept tag was calculated as follows:

$$Cost = -log(P)$$

Where P is the probability of the word given the concept. It was calculated by taking into account the lemmas and POS-tags occurrences other than the words and concept tags ones:

$$P = \frac{C(word, Concept_{tag})}{C(Concept_{tag})}$$

Where C stands for counts. With this probability calculation, the best F1 score was reached with a 9-gram or 10-gram, Kneser Ney smoothing method.

6. Methods and n-gram orders iterations, tagging and evaluation: for each smoothing method offered by OpenFst (witten_bell, absolute, katz, kneser_ney, presmoothed and unsmoothed) and for each n-gram order from 1 to 10, the following pipeline was applied for each utterance in the dataset, using the appropriate generated language model:

    - Composition of the current utterance FST with the Word-To-Concept FST
    - Composition of the FST from the previous point with the language model (for the m-th method and the i-th n-gram order)
    - Epsilon removal
    - Shortest path calculation
    - Topological sort
    - Creation of the input file for the Perl script and evaluation of all the utterances for the m-th method and i-th n-gram order

    Each result for all the combinations methods-n-gram order were saved in a file. All the re-sults can be found in the folder results/outputData. The points 2,3 and 4 are de-fined by calls of Python scripts from the main Bash script. To call the main script is necessary to execute the command bash conceptTagger.sh from inside the scripts folder.

4 Failed attempts

Different method were tested before reaching the best result. Among them, two are worth mentioning:

1. Creation of intermediate transducers, like Word-To-Lemma and Lemma-To-Concept or Word-To-POS and POS-To-Concept. All those transducers only led to a loss of information and there-fore of performance, especially when trying to map a Part-Of-Speech infor-mation into a Concept tag (intuitively, because are two unlinked kind of in-formation). The creation of a Word-To-Lemma seemed like a good way to generalise and therefore improve the over-all performance but instead led to a worst F1 score for each combination.

2. Taking into account prior probabilities and assigning non-uniform probabilities to the transitions from ¡unk¿ words to con-cept tags. In the end, assigning cost ze-ro to all the unknown transitions pro-duced better results overall. Also, taking into consideration the additional features did improve the F1 score, but not when applying the preprocessing phase

5 Evaluation

As mentioned before, the Perl script conlleval.pl gives as output a text file containing different evaluation measures, some of which are:

$$Accuracy = 100 * \frac{TP + TN}{FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F = (1 + {}^2) * \frac{Precision * Recall}{(\beta^2 * Precision) + Recall}$$

In particular, in the script, with =1,

$$F_1 = 2 * \frac{Precision * Recall}{Precision + Recall}$$

In the diagram 1 is it possible to see all the best obtained F1 scores of the possible combinations method - n-gram order for the first 5 orders of n-grams

6 Conclusion

The method provided by this document describes a method for Movie Domain concept tagging given a training data set, which allows to obtain a high F1 score even for higher order n-grams by taking into account just the words and concepts, but not additional feature sets like POS tags and lemmas. It was possible to achieve these results by applying a pre-processing phase in which each word was appended to each out of span concept tag before the training.

Figure 1: F1 score for different smoothing methods and n-grams

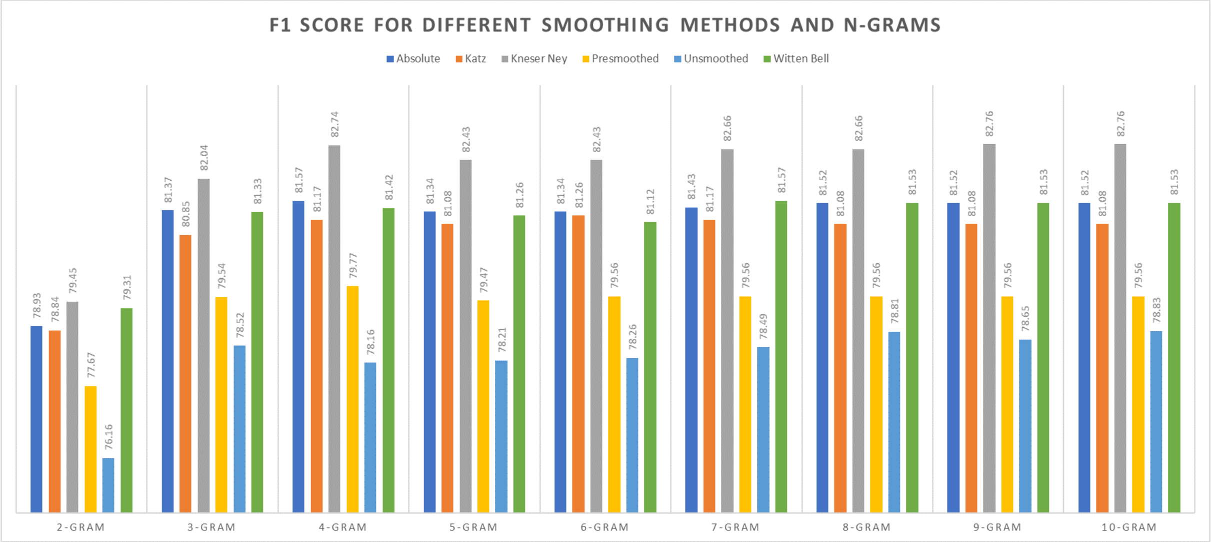

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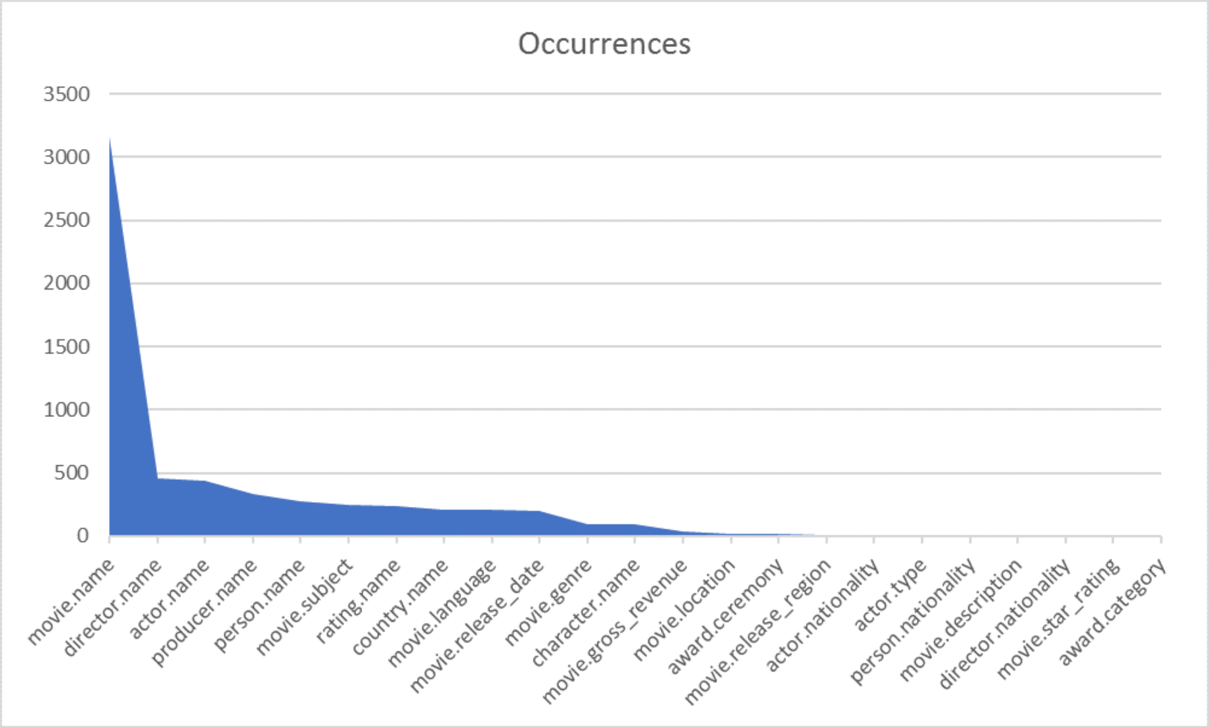
Figure 2: Concept occurrences



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