Spatial Role Labelling

Satvik Gupta(12633) and Garvit Pahal(12264)

Advisor : Prof. Amitabha Mukerjee

Introduction

The task involves labelling of words and phrases in a sentence with a set of roles such as Trajector, Landmark, Spatial Indicator, Location, Organization, Dates and Time. For example:

- Stanford[**Trajector, Organization**] is located in[**Spatial indicator**] California[**Landmark, Location**].
- The cat[**Trajector**] is sitting on[**Spatial indicator**] the table[**Landmark**] since morning[**Time**].

Motivation

Various applications of spatial labelling are:

- Controlling a robot by textual or audio instructions.
- Performing text-to-scene conversion.
- Providing directions on a map based on textual input.
- Building Geographic information systems.
- Query answering systems

Previous Work

- **SpatialML (Mani et al., 2008):** Focuses on geographical information
- **Pustejovsky and Moszkowicz (2009):** Considers pivot of the spatial information is the spatial verb.
- **O. Stock (1997)** Spatial and Temporal Reasoning.

In all these previous work very specific and application-dependent relations from text were extracted. None of them have covered spatial relation and role extraction using machine learning methods.

Methodology

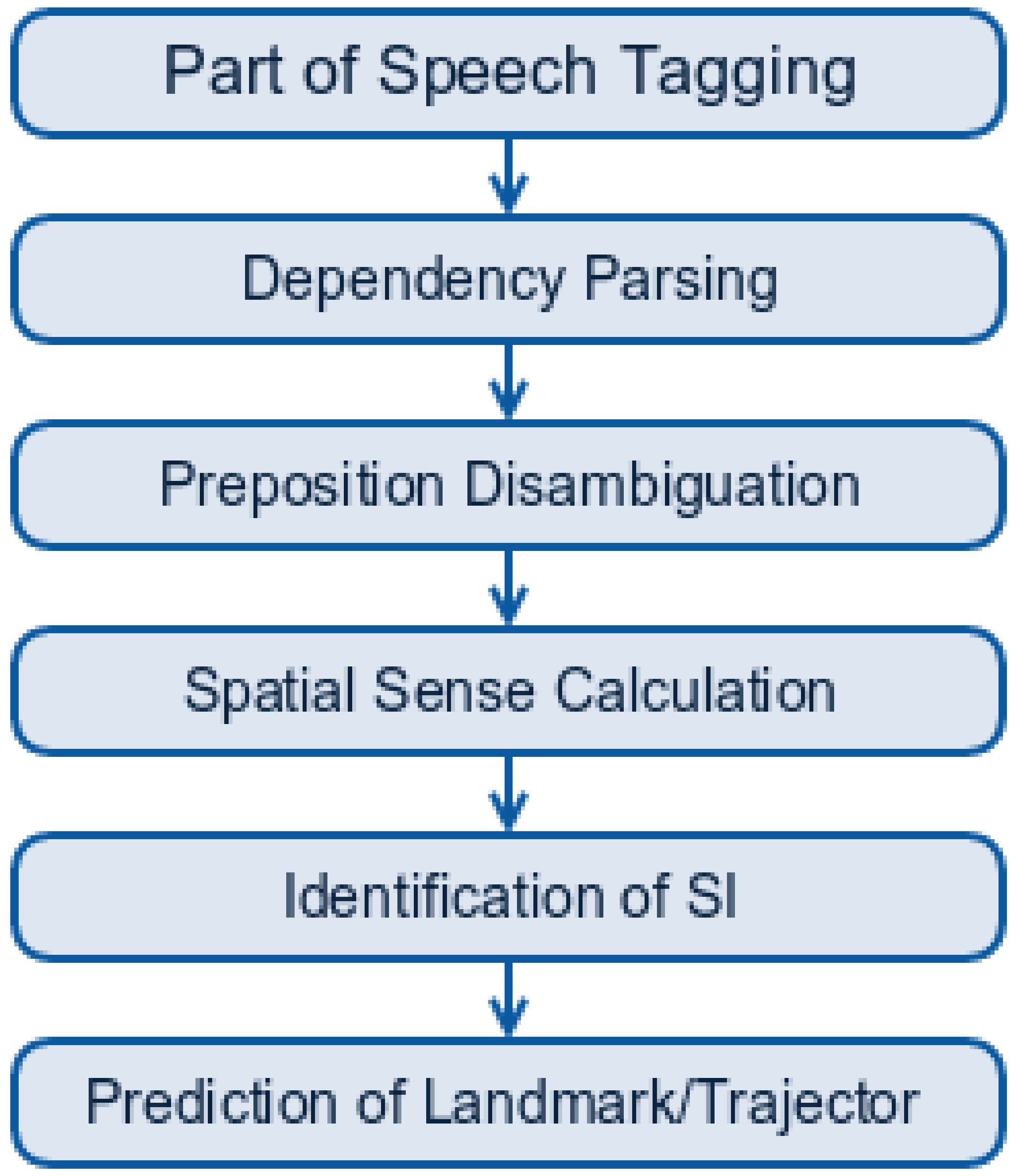

Figure 1: Methodology flowchart

Other feature detection (CRF)

Let $x_{1:N}$ be the observations (e.g., words in a document), and $z_{1:N}$ be the labels (e.g., tags), then a linear chain Conditional Random Field (CRF) defines a conditional probability

$$p(z_{1:N}|x_{1:N}) = \frac{exp(\sum_{n=1}^{N}\sum_{i=1}^{F}\lambda_i f_i(z_{n-1}, z_n, x_{1:N}))}{Z}$$

where Z is the normalization For each position, we sum over i = $1 \ldots F$ weighted features. The scalar λ_i is the weight for feature $f_i()$. Example of feature function can be

$$fi(z_{n-1}, z_n, x_{1:N}) = \begin{cases} 1, z_n\text{=PER \& } x_n\text{=John} \\ 0, \text{ o/w} \end{cases}$$

We have used the nltk library for Name Entity Tagging which is a trained CRF model based on CoNLL, MUC and ACE dataset.

Results

Spatial Role	Accuracy	Previous Best
Spatial Indicator	83%	88%
Trajector	76%	84%
Landmark	79%	91%

Figure 2: Spatial indicator identification results

Example result:

- Stanford[**Trajector**] is located in[**Spatial indicator**] California[**Landmark, Location**], United[**Location**] States[**Location**].

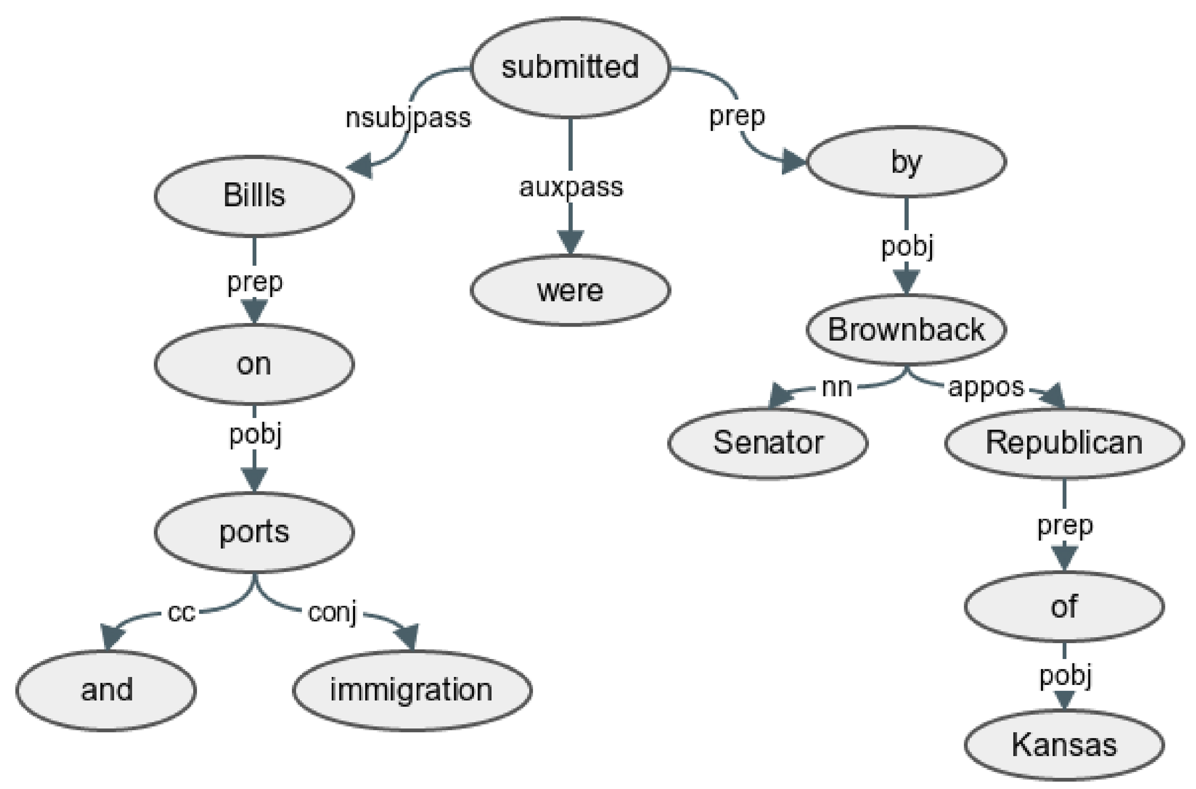

Figure 3: Basic dependencies

Future Work

- The feature set for the spacial indicator classification can be improved by using word2vec.
- Incorporate spatial relations such as path, direction, distance, motion etc.
- Develop a method to incorporate multi-word prepositions as spatial indicators.
- Incoperating linear chain conditional random field in the prediction of trajector and landmark

Acknowledgements

- Datasets: TPP, CoNLL, MUC-7, ACE and SemEval 2012 dataset
- Code adapted from: https://code.google.com/p/pln-pmt-pract/
- Python NLTK Library (nltk.pos_tag(), nltk.lemma(), Named Entity Recognizer of nltk stanford library)

References

[1] P. Kordjamshidi et.al. *Learning to Interpret Spatial Natural Language in terms of Qualitative Spatial Relations.* Oxford University Press, 2013.

[2] P. Kordjamshidi et.al. Spatial role labeling: Task definition and annotation scheme. *International Language Resources and Evaluation(LREC)*, 2010.

[3] P. Kordjamshidi et.al. Spatial role labeling: Towards extraction of spatial relations from natural language. *ACM Transactions on Speech and Language Processing*, pages 4–36, 2011.