# Named Entity Recognition for Resumes

# Introduction





Thrun started working on self-driving cars at Google org in 2007 DATE, few people outside of the company took him seriously.

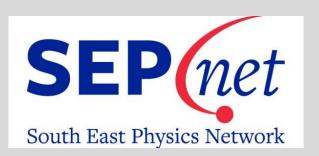
(Degree level)

Noun

Bsc

[0, 0]

Preposition



(Course name)

Noun

Computer

E.g.

[0, 0]

Verb

Required

No

Start

Does UniName

contain  $word_i$ ?

Last Word?

No

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#### What is Named Entity Recognition? //-

When Sebastian NORP

NER is a task in natural language processing, where the aim is to classify a words in text into predefined categories.

Fig.0: E.g. of an output of a NER

Fig.1: A diagram showing

used for NER tasks.

Where:

Yes

how a LSTM model can be

Fig.2: Flow chart of

labelled training data

SET: UniName = {Oxford,

program used to generate

Cambridge, ..., RHUL}

Label  $word_i$ 

as University

Stop

AIM //

- MeVitae is a company that provides services for automatically shortlisting CVs for organisations.
- There was a need for a NER to extract the key features of a resume for scoring.
- Therefore the aim was to write a NER program that classify, and extract words required for scoring CVs. E.g. University names and courses

**Entity Class Output:** 

POS Input:

Sentence:

#### Why Not Use Pre-Existing NER?

E.g.

- Publicly available named entity recognition programs are trained on commonly found text corpus such as news articles.
- Sentences found in resumes have different structure to theses. Hence, publicly available NERs did not perform well on resumes.

# Method

### Neural Network Based Method //-

- The NER was made by training a **bidirectional LSTM** model.
- LSTM is a recurrent neural network. When trained, it can output sequential predictions from sequential input.
- The network takes a sequence of **part of speech** as an input and return a sequence of predefined class as an output.

## Generating Training Data /

- Automated approach was used to label the training data to save time.
- The program labels sentences from CVs using a predefined set of words that belongs to a class.
- Problem: resulted in many false positives and false negatives in the generated training data.

The Causes of FPs and FNs:

E.g.

- 1. False negatives: The set of words do not contain all words that should belongs to the class
- 2. False positives: Context in use of the word is not taken into account (E.g. synonyms)

#### Use of Part of Speech as Input for the Model //-

We used part of speech of the sentence as an input for the RNN. This was done to counter the issues in generated training data.

If a set of words, "Course names" contained the word "Physics" but not "Management"

#### Sentence 1 Words Bachelor's **Physics** degree in Automatically **True Positive** 0 Generated Labels **PROPN** NOUN RNN Input **PROPN ADP** RNN Output 0 0 **Identical** (Indistinguishable) Sentence 2 Bachelor's Words degree Management Automatically 0 **False Negative** 0 Generated Labels RNN Input NOUN **ADP PROPN PROPN Correct Output** RNN Output 0 0 0

#### Why would using POS as input solve the problem?

If we used words as an input, e.g. word vectors, then the model will learn to make the same mistakes made on the generated labelled training data.

\* E.g. For Sentence 2, the model would memorise the word "Management" and incorrectly predict it as 0.

If POS is used as an input instead, then the incorrectly labelled sentence and correctly labelled sentence becomes indistinguishable, provided that they have the same sentence structure.

The cases where a sentence structure is labelled incorrectly is a minority, hence the model can predict the incorrectly labelled sentences correctly. Since the model learns to make predictions using sentence structures and not words.

It can not tell apart words that did or did not belong to the set of words used to generate the labelled training data.

### Result

- We successfully developed a NER tagger using a bidirectional LSTM.
- Labelled data was generated automatically, but contained false positives and false negatives.
- As shown on Fig.3, our LSTM model was able to give correct predictions, even when the labelled data is incorrect.
- This was achieved by using POS as input instead of word vectors.

