

Speed versus Accuracy in Neural Sequence Tagging for Natural Language Processing

by

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Abstract

Sequence Tagging including part of speech tagging and named entity recognition is an important task in NLP. Recurrent neural network models such as Bidirectional LSTMs have produced impressive results on sequence tagging. In this work, we first present a simple and fast greedy sequence tagging system using different types of feedforward neural network models. Then we show the speed and accuracy comparison between Bidirectional LSTMs and feedforward models. Besides the feedforward and the Bidirectional LSTM models, we propose two new models based on Mention2Vec by Stratos (2016): Feedforward-Mention2Vec for Named Entity Recognition and BPE-Mention2Vec for Part-of-Speech Tagging. Feedforward-Mention2Vec predicts named entity boundaries first and then predicts types of named entities. BPE-Mention2Vec uses the Byte Pair Encoding algorithm to segment words in the sequence first and then predicts the Part-of-Speech tags for the subword spans. We carefully design the experiments to demonstrate the speed and accuracy trade-off in different models. The empirical results reveal that feedforward models can achieve comparable accuracy and faster speed than recurrent models for Part-of-Speech tagging, and Feedforward-Mention2Vec is competitive with the fully structured BiLSTM model for Named Entity Recognition while being more scalable in the number of named entity types.

Keywords: Natural Language Processing; Sequence Tagging, Deep Learning

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Chapter 1

Introduction

In this chapter, we first describe sequence tagging tasks and introduce the motivation of this thesis. Then, we summarize our major contributions and describe the structure of the thesis.

1.1 Sequence Tagging Task

1.1.1 Part-of-Speech Tagging (POS)

Part-of-Speech Tagging (POS) is a basic sequence tagging task, which assigns each word with a unique tag that indicates its syntactic role, such as noun, adverb, verb ... Figure 1.1 illustrates a typical POS task.

Most POS systems are evaluated on the English Penn TreeBank data set (Marcus et al., 1993), which contains 45 part-of-speech tags. The standard split uses section 1-18 of the Treebank for training, section 19-21 for tuning, and section 22-24 for testing (Toutanova et al., 2003). The experimental data are summarized in Table 1.1. A lot of existing models are linear models, such as Maximum entropy Markov models (MEMMs) which obtains 96.46% per word accuracy (McCallum et al., 2000); and the averaged perception discriminative model which obtains 97.11% per word accuracy (Collins, 2002). More recently, neural network models are proposed to improve the state-of-the-art score. The Bidirectional LSTM network model proposed by Huang et al. (2015) reaches 97.55% per word accuracy. Ling et al. (2015) presents the compositional character-to-word LSTM model which reaches the state-of-the-art performance: 97.78% per word accuracy. The performance of existing POS models is reported in Table 1.2.

1.1.2 Named Entity Recognition (NER)

Named Entity Recognition (NER) is a more complex sequence tagging task than POS, which identifies expressions that refer to named entities, such as peoples, places, organizations and

Table 1.1: Number of Sentences (words) and Labels in Each Training, Validation and Test Section of Different Data Sets

	Training	Validation	Test	labels
Penn Treebank	39831(950011)	1699(40068)	2415(56671)	45
CoNLL2003	14987(204567)	3466(51578)	3684(46666)	9
OntoNotes	75187(1088503)	9479(147724)	9603(152728)	18

Table 1.2: Performance of Different POS and NER Systems

POS Systems	Accuracy	NER Systems	F1
McCallum et al. (2000)	96.46%	Florian et al. (2003)	88.76
Collins (2002)	97.11%	Huang et al. (2015)	88.83
Huang et al. (2015)	97.55%	Lample et al. (2016) with CRF	90.94
Ling et al. (2015)	97.78%	Lample et al. (2016) with Stack LSTM	90.33

others. The main difference between NER and POS is that each named entity label can span multiple words while each part-of-speech tag is only for one word. A popular convention in NER is to use the "IOB" label scheme (Inside, Outside, Beginning): if the word is the beginning of a named entity label, it is marked as B-label; if the word is inside a named entity tag but not the first one, it is marked as I-label; if the token is outside the named entity, it is labeled as O. An example of NER is shown in Figure 1.2. There are different number of named entity types in different NER tasks. For example, the shared task of CoNLL 2003 (Tjong Kim Sang and De Meulder, 2003) contains 4 types of named entities: locations (LOC), persons (PER), organizations (ORG), and miscellaneous (MISC); and the OntoNotes English data set (Hovy et al., 2006) contains 18 types of named entities shown in Table 1.3. The predefined training, development, and testing split of the data sets are shown in Table 1.1.

Most NER models are evaluated on CoNLL 2003 data set and are measured by the F1 score, which is the harmonic mean of precision and recall.

$$F_1 = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \quad (1.1)$$

Since CoNLL 2003 has a relatively smaller size of training data, most of the existing models make use of pretrained word embeddings along with the training data. A commonly used pretrained word embeddings is GloVe (Pennington et al., 2014) which contains 40K words. The best system presented at the NER CoNLL 2003 challenge by Florian et al. (2003) obtains 88.76 F1 score. The model using Bidirectional LSTM by Huang et al. (2015) reaches 88.83 F1 score. Both of these two models use a lot of external features along with gazetteer¹. Lample et al. (2016) proposed two NER models with no external features or a gazetteer: the first one makes structured prediction uses Bidirectional LSTM, Character

¹Gazetteers are language-specific knowledge resources

Table 1.3: Name Entity Types in OntoNotes

Types	Named Entities
PERSON	People, including fictional
NORP	Nationalities or religious or political groups
FACILITY	Buildings, airports, highways, bridges, etc.
ORG	Companies, agencies, institutions
GPE	Countries, cities, states
LOC	Non-GPE locations, mountain ranges, bodies of water
PRODUCT	Vehicles, weapons, foods, etc. (Not services)
EVENT	Named hurricanes, battles, wars, sports events
WORK OF ART	Titles of books, songs
LAW	Named documents made into laws
LANGUAGE	Any named language
DATE	Absolute or relative dates or period
TIME	Times smaller than a day
PERCENT	Percentage
MONEY	Monetary values, including unit
QUANTITY	Measurements, as of weight or distance
ORDINAL	â€œfirstâ€œ, â€œsecondâ€œ
CARDINAL	Numerals that do not fall under another type

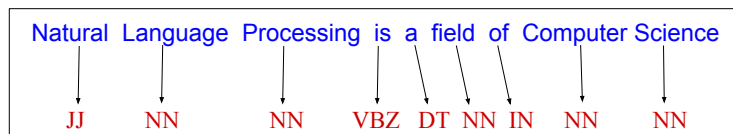


Figure 1.1: An example of POS

Embeddings (Ling et al., 2015) and Conditional Random Field (CRF) (Lafferty et al., 2001); and the second one uses a Shift-Reduce framework with Stack-LSTM (Dyer et al., 2015). The first model achieves the state-of-the-art F1 score, while the second one performs slightly worse. The performance of existing NER models is reported in Table 1.2.

1.2 Motivation

Recurrent Neural Networks (RNNs) have obtained impressive results in many NLP tasks, such as speech recognition (Graves et al., 2013) and machine translation (Cho et al., 2014). Bidirectional Long Short Term Memory (BiLSTM) (Hochreiter and Schmidhuber, 1997; Graves and Schmidhuber, 2005) is one of the RNN architectures that can maintain long-

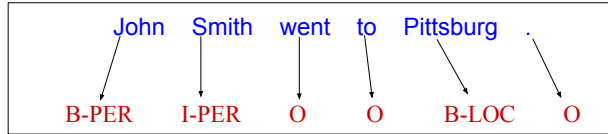


Figure 1.2: An example of NER

distance information from the past and future data in a input sequence. Based on the existing work (POS system by Ling et al. (2015) and NER system by Lample et al. (2016)), state-of-the-art results on POS and NER can be obtained by using a BiLSTM network with Character Embeddings and CRF. Some work has also shown that feedforward neural networks can achieve comparable accuracy with recurrent models in tasks such as POS and Dependency Parsing (Andor et al., 2016). One approach presented in this thesis is to employ a greedy transition system with a feedforward network to make independent classification decision on each word. However, the greedy system is limiting when there are strong correlations between output labels. NER is one of such tasks which have grammar constrains on output label sequences. For example, "I-PER" cannot follow "B-LOC" in NER. In order to take into account the strong dependencies among output labels, a CRF layer is added to model the output label sequence jointly. Since the CRF-based models focus on the sentence level and compute the score of every possible sequence, they take more time in training and decoding. Since we are interested in the decoding speed and performance trade-off in different neural network models, we re-implement variants of feedforward models and BiLSTM models using Tensorflow (Abadi et al., 2016) and systematically compare the performance and decoding speed between them on sequence tagging tasks, such as POS and NER.

Since the named entity labels in NER often span multiple tokens, most neural architectures for NER predict the boundaries and types of entities together using the the "IOB" label scheme. Mention2Vec (Stratos, 2016) is proposed to address the natural segment-level representation in NER by separating the NER task into boundary detection (I, O, B) and type prediction (PER, LOC, etc.). While Mention2Vec employs two BiLSTMs for each sub-task, we replace the BiLSTM layer for boundary detection with a feedforward network in order to obtain a simpler model and accelerate the decoding process. This new model is denoted as Feedforward-Mention2Vec in this thesis.

We use Byte Pair Encoding (BPE) (Gage, 1994) to deal with rare words in sentences for machine translation(Sennrich et al., 2015), and we propose a new model combining BPE and Mention2Vec for POS, which is denoted as BPE-Mention2Vec in this thesis. We use BPE

to segment the input words in the hope of capturing the orthographic evidence of the words without using spelling features (like prefixes and suffixes) or Character Embeddings. After we segment input words, POS becomes a NER-like task. Then, we can use Mention2Vec to solve the rest of the problem. Since boundaries of output tags are known in POS, we only need to use a BiLSTM network for type prediction in BPE-Mention2Vec.

1.3 Contribution

The three main contributions of this thesis are:

1. We implement two greedy tagging systems with two different feedforward network models, Feedforward-History and Feedforward-CRF.

Feedforward-History takes word features in context, spelling features, and history tag features as input. Feedforward-CRFmodel uses word features in context and CRF to model the output sequences jointly. There are few work measuring the decoding time using feedforward networks on sequence tagging, so We conduct the experiments on NER and POS and record the performance and decoding speed on Penn Treebank data for POS and CoNLL 2003 data for NER. To test the robustness of the feedforward networks, we also conduct experiments using a feedforward network with only word features, which also serves as the baseline. We compare different feedforward models and provide analysis on the results.

2. In addition to the greedy tagging systems with different feedforward networks, we build a tagging system using the fully structured BiLSTM model, which makes use of Character Embeddings and CRF.

There is few work examining how the configurations of the fully structured BiLSTM model affect the decoding speed, such as if the model is using Character Embeddings or if the model is using CRF. We conduct experiments to compare the performance and decoding time of different configurations on POS and NER. We also benchmark the BiLSTM models against the feedforward models.

3. Last but not least, we introduce two new neural architectures based on Mention2Vec: Feedforward-Mention2Vec for NER and BPE-Mention2Vec for POS.

Originally, Mention2Vec is designed for NER which uses BiLSTMs to detect named entity boundaries and predict corresponding types separately. We propose Feedforward-Mention2Vec for NER, in which we use a feedforward network with CRF to predict named entity boundaries instead of using a BiLSTM. We denote this new model for NER as Feedforward-Mention2Vec. We also adapt Mention2Vec for POS by combining Byte Pair Encoding (BPE) with BiLSTM in the model. BPE is used to segment the input words in our model, and it converts POS into a NER-like task. We denote

this new model for POS as BPE-Mention2Vec. In BPE-Mention2Vec, we use a feed-forward network to compute the hidden embeddings of the input segmented words. Since the boundaries of subword units are known, BPE-Mention2Vec does not need to predict the boundaries. It takes the hidden embeddings, tag boundaries, and a BiLSTM network to predict the actual POS tags. We benchmark these two multitasking models against the feedforward models and the BiLSTM models on POS and NER. Since different NER tasks have different number of named entity types, the decoding time of fully structured BiLSTM model grows quadratically in the number of types. In Mention2Vec and Feedforward-Mention2Vec, we only apply CRF on boundary labels (I, O, B), so the decoding time grows linearly in the number of types. To show the time difference on different NER tasks, we conduct the NER experiments on CoNLL 2003 which contains 4 different named entity types and OntoNotes which contains 18 different named entity types.

1.4 Overview

The thesis is organized as follows:

In **Chapter 2** we present three different feedforward network models: feedforward network with only word features (denoted as Feedforward); feedforward network with spelling features and history features (denoted as Feedforward-History); and feedforward network with CRF (denoted as Feedforward-CRF). We explain the training and decoding process of the feedforward models, demonstrate the experiment design, and compare the performance and decoding time between different feedforward models.

In **Chapter 3** we present the fully structured BiLSTM model (a combination of BiLSTM, Character Embeddings and CRF), denoted as the BiLSTM-Char-CRF model. We explain the training and decoding process of BiLSTM-Char-CRF, and conduct experiments using three different configurations: BiLSTM with word features only, BiLSTM with Character Embeddings, and BiLSTM model with Character Embeddings and CRF.

In **Chapter 4** we present two new new multitasking models based on Mention2Vec: Feedforward-Mention2Vec for NER and BPE-Mention2Vec for POS. We explain the architectures of these two models and benchmark them against the feedforward models and the BiLSTM models in terms of performance and speed.

In **Chapter 5** we discuss the empirical results from the previous chapters. We also analyze the trade-off between performance and speed in different neural network models.

In **Chapter 6** we summarize the contributions of this thesis and discuss the ongoing and related future work.

Chapter 2

Feedforward Neural Network Models

In this chapter, we describe two feedforward network models: Feedforward-History and Feedforward-CRF. Then, we show the performance and decoding speed of different feedforward models on POS and NER.

2.1 Network Architecture

2.1.1 Feedforward-History Model

Inspired by the greedy parser system by Chen and Manning (2014), we present a similar greedy transition system for sequence tagging in this thesis. The greedy parser system employs a basic arc-standard system (Nivre and Scholz, 2004), which consists of three types of transitions (LEFT-ARC, RIGHT-ARC, and SHIFT), a stack, and a buffer. While the greedy parser system has three types of actions, the sequence tagging system only needs SHIFT action which predicts the tag of the current word in the buffer and shifts the word to the stack.

In this greedy tagging system, we use a feedforward network to make decisions on individual words, and we assume that the word to be labeled depends mainly on its neighbor words instead of the whole sentence. Besides the word features, the system also takes into account the lexical composition of the words (spelling features), and the previous tagging decisions (history features). Thereby, we represent this architecture as the Feedforward-History model. The way Feedforward-History incorporates word features is the same with the window approach proposed in Collobert et al. (2011). The difference between these two models is that Feedforward-History uses spelling features and history features while the model in Collobert et al. (2011) only uses word features.

Figure 2.1 illustrates the process of how a greedy tagging system uses Feedforward-History to decode a POS example. Since the current word only depends on its neighbors in

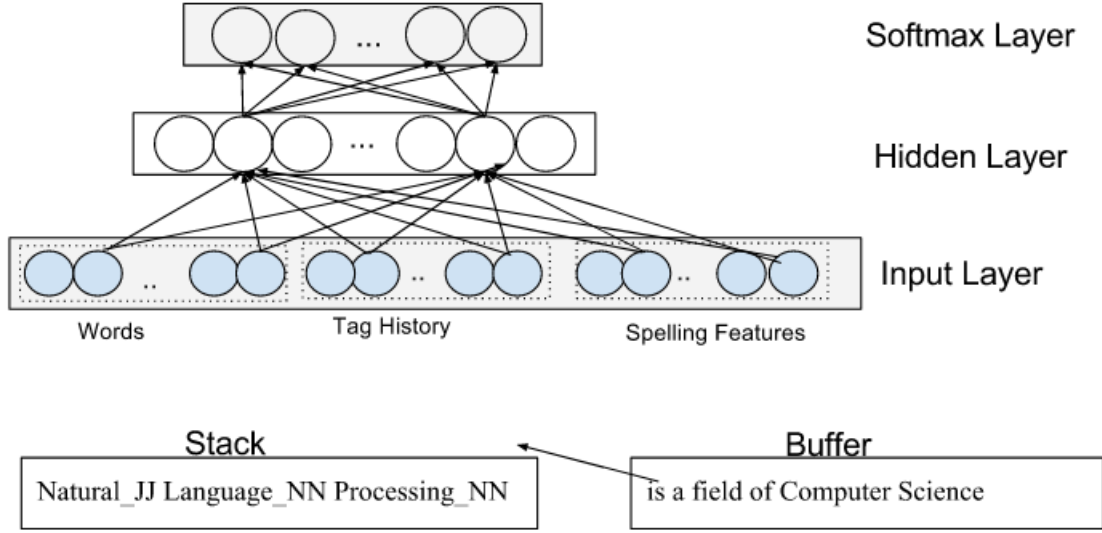


Figure 2.1: The architecture of a greedy tagging system using the Feedforward-History model.

this greedy tagging system, we use a fixed size window around the current word to generate features. In order to generate features for the words at the beginning and at the end of the sentence, we add special padding word at the beginning and at the end. To generate dense word features, we convert each word in the input sequence to a d -dimensional vector representation e_{w_i} . Meanwhile, we have a full vocabulary embedding dictionary E_w . Given a word w_i , we look up its embedding e_{w_i} in E_w . According to Ratnaparkhi et al. (1996), spelling features of a word can help predict the part-of-speech tag. The examples of spelling features are upper and lower case features, prefix and suffix features, digit features, etc. Each spelling feature of a word is also associate with an embedding vector e_{s_i} , and it can be looked up from a embedding vector dictionary E_s . Besides word features and spelling features, we incorporate the history tag features in this model. Since the greedy sequence tagging system makes decision word by word in a sequence, we can only use the previous tags as input features for predicting the current tag. Each history tag feature is represented as e_{ht_i} and can be looked up from a tag dictionary represented as E_{HT} .

The input layer $X = (x_1, x_2, \dots, x_n)$ to the feedforward network is obtained by concatenating the word feature vectors, spelling feature vectors, and history feature vectors. In general, generating a lot of hand-engineered features for sequence tagging is expensive: selecting useful features is an empirical process based on trials and errors, and computing features vectors requires searching feature strings in huge dictionaries and concatenating them together. We try to use hand-engineered features as little as possible to save the time from feature generation while keeping the model accurate. In our implementation, we

extract the word and spelling features on a window size of 8 centered on the current focused word. We extract the following spelling features of each word: whether it starts with a capital letter; whether it has all capital letters; whether it has a mix of letters and digits; whether it has punctuation; letter prefixes and suffixes of length two and three. We also extract the history tag features from the previous four predicted tags.

The input layer is the concatenation of the feature vectors of the focused word, and the output layer is a probability distribution over tags. In order to build a simple and fast neural network model, we only use one hidden layer in this model. The input unit x_i is mapped to a hidden unit h_i through the rectifier activation function (ReLU):

$$ReLU(x) = \ln[1 + \exp(x)] \quad (2.1)$$

$$h_i = ReLU(W_1^w x_i^w + W_1^s x_i^s + W_1^l x_i^l + b_1), \quad (2.2)$$

where x^w represents the word features, x^s represents the spelling features, x^l represents history tag features, W_1 is the weight parameters in the hidden layer, and b_1 is the bias of in the hidden layer. The output of the network is a probability distribution over tags, and its dimension is the size of the possible tags. Tag probability distribution is modeled by a softmax layer:

$$p_i = softmax(W_2 h_i + b_2), \quad (2.3)$$

where W_2 is the weight parameter in the softmax layer and b_2 is the bias in the softmax layer.

The network is trained by minimizing a negative log likelihood over the training data. The embedding vectors are trained together with the weight vectors and bias in the network. We denote all trainable parameters as θ . Given a sequence predictions, $Y = (y_1, y_2, \dots, y_n)$, the score of the output sequence is the sum of the probability of each decision y_i :

$$S(Y) = \sum_i^n p_i(y_i), \quad (2.4)$$

and the loss function is:

$$L(\theta) = -\log\left(\sum_i^n p_i(y_i)\right), \quad (2.5)$$

2.1.2 Feedforward-CRF

There are two ways to incorporate the output tags in the model: the first one is to use the previous predicted tags as input features to be fed into the feedforward network layer, as in Feedforward-History; the second one is to use CRF on sentence level output tags instead of

individual tags as in the following model. Feedforward-CRF shares the same architecture with Feedforward-History except using CRF to model the output sequence after computing tag probability distribution for each individual word. Feedforward-History can perform well on some sequence tagging tasks in which output labels do not have strong correlations, such as POS. Some tasks have grammar constraints on the output tags so that the tags depend on their neighbors, such as NER. While Feedforward-History fails to take into account the grammar constraints on output tag sequence, Feedforward-CRF can make final decisions on the sentence level. Since the first part of the architecture is the same with Feedforward-History, we skip this part. We describe how to apply CRF to model the sequence in detail here.

Given a sequence of output predictions $y = (y_1, y_2, \dots, y_n)$, The score of the output sequence is:

$$S(y) = \sum_i^n T_{i,i+1} + \sum_i^n p_i(y_i) \quad (2.6)$$

where T is a matrix of transition scores such that $T_{i,j}$ represents the score of a transition from the label i to label j , $p_i(y_i)$ is the probability of y_i being the label of word i .

During training, we score every possible output sequences, and use a softmax layer to generate the probability distribution of output sequences, shown in Equation 2.7. Then, we minimize the negative log likelihood over the training sentences. During decoding, we can recover the tag sequences of the test data using dynamic programming.

$$P(y) = \text{softmax}(S(y)) \quad (2.7)$$

2.2 Experiments and Results

In the POS experiments, we train the models using the Penn Treebank training data and development data. Then, we decode the Penn Treebank test data with trained models and record the per word accuracy and decoding time. In the NER experiments, we train the models using the CoNLL 2003 training data and development data. Then we decode the test data with the trained models, and record the F1 score and decoding time. The details of the data set are shown in Table 1.1. The performance of POS is measured by the per word accuracy, and the performance of NER is measured by the F1 score. The speed is measured by the average number of sentences and words decoded per second. We conduct the experiments using the Feedforward-History model and Feedforward-CRF model. We also want to show the robustness of the feedforward network models, so we build a model using a feedforward network with only word features, which serves as the baseline in our experiments. The tagging system using feedforward network with only word features is denoted as the Feedforward model in this thesis.

Table 2.1: Feedforward Models Accuracy and F1 Score

Model	POS (Accuracy)	NER (F1 Score)
Feedforward	95.89	84.12
Feedforward-History	97.28	86.54
Feedforward-CRF	97.30	87.85

Table 2.2: Feedforward Models Decoding Speed

Model	POS (sentences, words/sec)	NER (sentences, words/sec)
Feedforward	1319(30967)	2117(26819)
Feedforward-History	829(19474)	1390(17609)
Feedforward-CRF	761(17877)	1374(17412)

We implement the models using Python and the Tensorflow 1.0 library. In NER experiments, because of the lack of training data, we use the GloVE pretrained word embedding where each word corresponds to a 100-dimensional embedding vector. We tune the hyperparameters for training. Specifically we use Adam (Kingma and Ba, 2014) for stochastic optimization, and set the learning rate to be 0.001. We set the hidden layer size to be 128 in feedforward network. We have the batch implementation which can process multiple sentences at the same time, and we set the batch size to be 32 in the experiments. We run all the experiments in this thesis on a GeForce GTX 1080 GPU.

Table 2.1 and Table 2.2 demonstrate our final benchmark results of three feedforward models on POS and NER. Figure 2.2 illustrates the performance of the three models in a bar chart. In POS, Feedforward is 1.39% less accurate than Feedforward-History. In NER, the F1 score of Feedforward is 2.42 lower than Feedforward-History. Since the model with only word features does not decrease the performance dramatically, we can conclude that our greedy tagging systems with feedforward models do not heavily rely on spelling features. It also reveals that the spelling features are more helpful in NER than in POS. In both POS and NER, Feedforward-CRF has better performance than Feedforward-History, but it improves the NER performance more because of the dependencies between the output tags in NER. Feedforward-CRF is slower than Feedforward-History since the CRF model computes the scores of every possible output sequences.

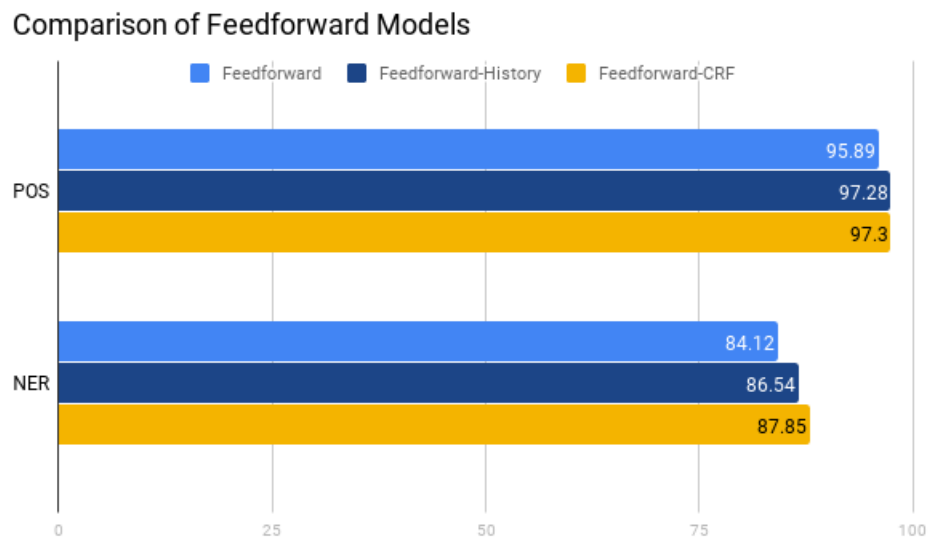


Figure 2.2: Performance comparison between Feedforward Models on POS and NER

Chapter 3

Bidirectional Long Short Term Memory Network Models

In this chapter, we first describe the Bidirectional Long Short Term Memory network (BiLSTM) and Character Embeddings. Then, we show the performance and decoding speed of the sequence tagging systems with different BiLSTM configurations.

3.1 Model Description

3.1.1 Bidirectional Bidirectional Long Short Term Memory

One major disadvantage of feedforward neural networks is that they cannot keep the past and future data of a sequence when predicting the current output. Recurrent neural networks (RNNs) (Mikolov et al., 2010) can keep the data to persist by using memory cells with loops in them. However, RNNs is biased towards the most recent data in practice. Long Short Term Memory Networks (LSTMs), special RNNs with Long Short Term memory cells (Graves and Schmidhuber, 2005), are designed to combat the bias problem. LSTMs learn long dependencies in a sequence with help of the structure of Gates (Graves and Schmidhuber, 2005). Gates control how much of the input is given to the next LSTM cell, and how much of the previous information to forget.

Given a sentence with n words each of which is represented as a dense vector x_i , a LSTM makes use of $x_{1:n}$ to compute a forward representation \vec{h}_i for the i th word. In general, computing a backward representation \overleftarrow{h}_i would be useful for sequence tagging. Bidirectional LSTM (BiLSTM) is an extension to LSTM which take into account both the past data and the future data in a sequence. A BiLSTM generates both \vec{h}_i and \overleftarrow{h}_i for the i th word in the sequence. The hidden embedding h_i is the concatenation of \vec{h}_i and \overleftarrow{h}_i . The BiLSTM mapping is defined as $BiLSTM_\theta: h_i = BiLSTM_\theta(x_{1:n}, i)$ where θ represents trainable parameters in BiLSTM.

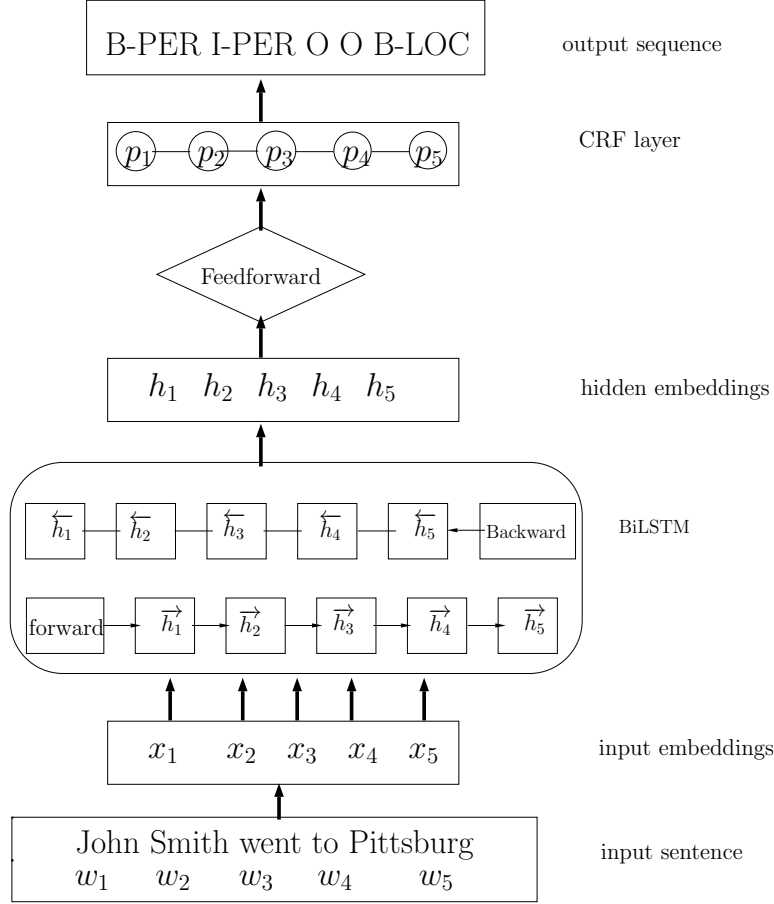


Figure 3.1: The architecture of the tagging system using BiLSTM with CRF

We can combine BiLSTM with CRF to make use of sentence level tag information. As in the Feedforward-CRF model, we introduce a transition matrix T to keep the transition score from y_i to y_{i+1} . Given an output sequence Y , the score of the output sequence is given by:

$$S(X|Y) = \sum_i^n T_{i,i+1} + \sum_i^n P_i \quad (3.1)$$

We can use dynamic program to compute the transition matrix and find the optimal output tag sequence. Figure 3.1 illustrates the BiLSTM model with CRF on a NER example.

3.1.2 Character Embeddings

Instead of using hand-engineered features listed in Chapter 2 (like the prefixes and the suffixes of a word), we can use a BiLSTM network to construct word representations from

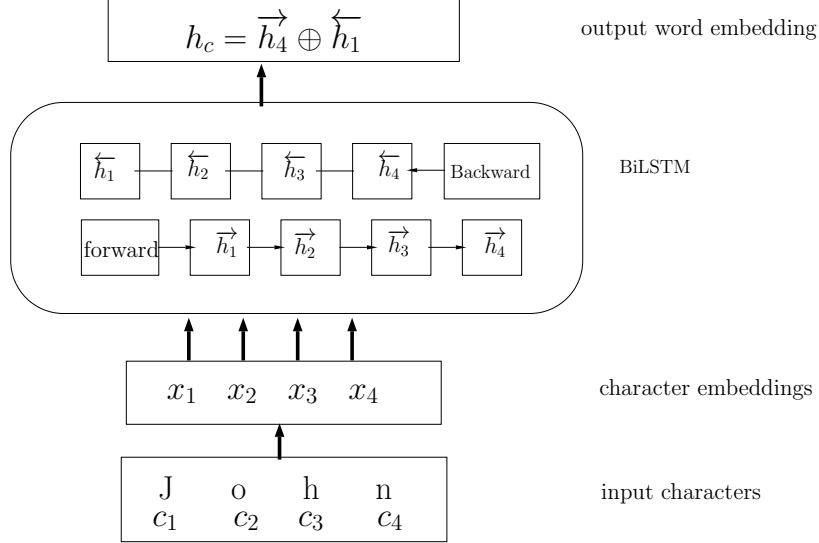


Figure 3.2: The word embedding derived from the character embeddings

the characters in it (Lample et al. 2016). This architecture is denoted as Character Embeddings. It’s been shown that learning character embeddings has been found useful for capturing morphological evidence (Ling et al., 2015). Figure 3.2 describes the architecture of the using Character Embeddings and BiLSTM to generate word embeddings. The input to the BiLSTM in Character Embeddings is the letter sequence of a word. We define a character dictionary which maps each character to a d -dimensional vector representation. The English character dictionary contains uppercase and lowercase letters, numbers, and punctuation. We look up each c_i of the input letter sequence from the dictionary and get the input character vectors $X : \{x_1, x_2, \dots, x_n\}$. Then, the input character vectors X is fed into BiLSTM to generate forward and backward hidden embeddings of the character sequence. We concatenate the last forward hidden embedding \vec{h}_n and the last backward hidden embedding \overleftarrow{h}_1 with the embedding from the word vector dictionary to obtain the final word embedding.

We add Character Embeddings into the tagging system by concatenating the output of Character Embeddings and the word embeddings from lookup to form the input embeddings. Then, we feed the input embeddings to BiLSTM and CRF, and we get the fully structured BiLSTM model (BiLSTM-Char-CRF) for sequence tagging. The character embeddings and word embeddings are learned together during training.

Table 3.1: BiLSTM Models Accuracy and F1 Score

Model	POS (Accuracy)	NER (F-Score)
BiLSTM	96.01	84.78
BiLSTM-Char	97.21	88.32
BiLSTM-Char-CRF	97.34	90.11

3.2 Experiments and Results

To evaluate the BiLSTM models, we run the BiLSTM with three configurations on POS and NER: the BiLSTM model with word features only (BiLSTM); the BiLSTM model with Character Embeddings (BiLSTM-Char); the BiLSTM model with Character Embeddings and a CRF layer (BiLSTM-Char-CRF). We report the performance and decoding speed of the models on Penn Treebank data set for POS, and on CoNLL 2003 data set for NER.

As the implementation for feedforward models, we implement the BiLSTM models using Python and the Tensorflow 1.0 library. The hidden layer size in the BiLSTM of Character Embeddings is set to 25, and the hidden layer size in word sequence BiLSTM is set to 100. The rest of the hyperparameters are the same as the ones in the experiments in Chapter 2.

Since dropout training (Hinton et al., 2012) can improve the performance by encouraging the model to depend on both character embeddings and word embeddings, we apply a dropout mask on the input embeddings before the BiLSTM layer. The dropout rate is set to 0.5 in the experiments.

Figure 3.3 illustrates the performance of BiLSTM, BiLSTM-Char, BiLSTM-Char-CRF. As expected, the fully structured BiLSTM model outperforms the other two. Character Embedding increases the POS accuracy by 1.17, and increases the NER F1 score by 3.34. It reveals that the BiLSTM networks do not heavily depend on features other than words, and Character Embeddings can help improve the performance of the models. Compared to BiLSTM-Char, BiLSTM-Char-CRF improves the POS performance by 0.13, and improves the NER performance by 1.79. CRF layer is more helpful for NER for the reason that there are grammar constraints on NER tags.

Table 3.1 and Table 3.2 describe the final results of the performance and decoding speed of the BiLSTM models on the POS and NER. It is obvious that the more features the model has, the slower it would be. Adding a CRF layer will increase the performance but decrease the decoding time. Table 3.3 benchmarks the fully structured BiLSTM-Char-CRF model against Feedforward-History and Feedforward-CRF.

Comparison of different Bi-LSTM Models

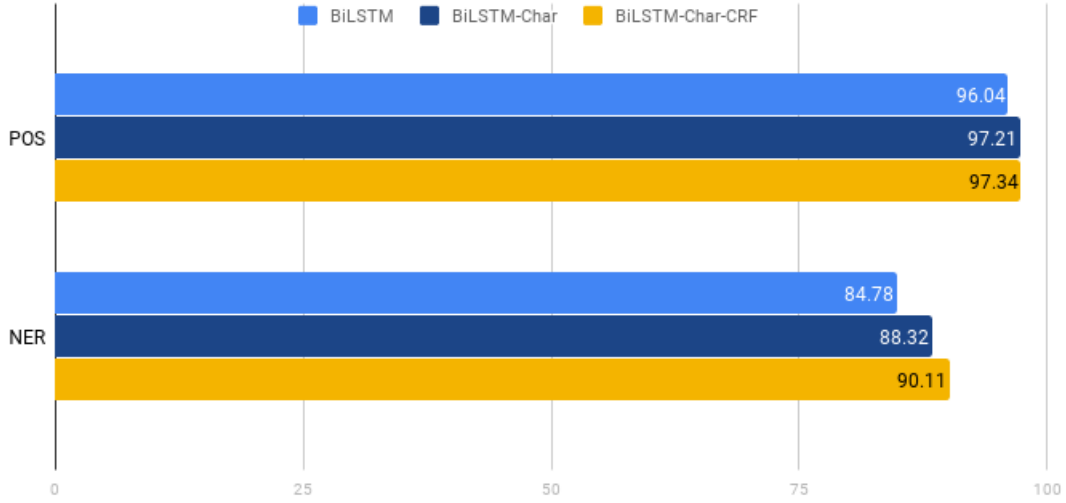


Figure 3.3: Performance comparison between BiLSTM models on POS and NER

Table 3.2: BiLSTM Models Decoding Speed

Model	POS (sentences, words/sec)	NER (sentences, words/sec)
BiLSTM	981(23036)	1637(20740)
BiLSTM-Char	596(13992)	889(11271)
BiLSTM-Char-CRF	383(9009)	795(10100)

Table 3.3: Decoding Speed Comparison between BiLSTM Models and Feedforward Models on POS and NER

Model	POS (sentences, words/sec)	NER (sentences, words/sec)
Feedforward-History	829(19474)	1390(17609)
Feedforward-CRF	761(17877)	1374(17412)
BiLSTM-Char-CRF	383(9009)	795(10100)

Chapter 4

Mention2Vec Models

In this chapter, we introduce two new multitasking models for POS and NER respectively. The multitasking model are based on the Mention2Vec model which is originally proposed for NER. We conduct experiments using the multitasking models on POS and NER and compare their performance and decoding speed with other neural network models.

4.1 Model Description

4.1.1 Feedforward-Mention2Vec for NER

Mention2Vec is a neural network model for NER, which uses BiLSTMs to predict boundaries and entity types separately (Stratos, 2016). We summarize the Mention2Vec model into three steps. The first step is using a BiLSTM to generate hidden embeddings the same way in the BiLSTM-Char-CRF model. Figure 4.1 illustrates the first step of Mention2Vec on a NER example. We denote the input sentence as $W : \{w_1, w_2, \dots, w_n\}$, vector concatenation operation as \oplus , input embedding as $X : \{x_1, x_2, \dots, x_n\}$ which are the concatenations of the character embeddings and the word embeddings, the hidden embeddings as $H : \{h_1, h_2, \dots, h_n\}$

The second step of Mention2Vec is the boundary detection which is predicting $\{I, O, B\}$ labels for each word in a sequence. Mention2Vec takes the hidden embeddings produced in step 1, and feed them in to a feedforward network to get the boundary label probability distribution for each word. Since the boundary labels has strong correlations, Mention2Vec uses CRF to capture the correlations and produce the boundary label sequence. Figure 4.2 illustrates the second step of Mention2Vec. The output boundary label probability distribution is denoted as p_i for word w_i , and the gold boundary label sequence is denoted as Y_{label} . In each training step, the boundary detection loss is given by the negative log likelihood of the gold boundary label sequence, shown in 4.1

$$L_1(\theta, \theta_1) = -\log(p(Y_{label}|h_1, h_2 \dots h_n)) \quad (4.1)$$

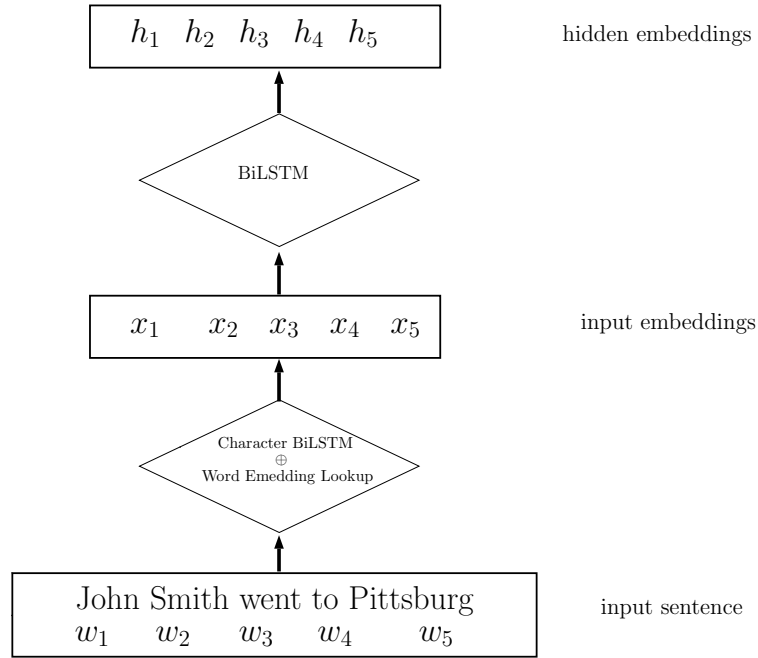


Figure 4.1: The first step of Mention2Vec for NER

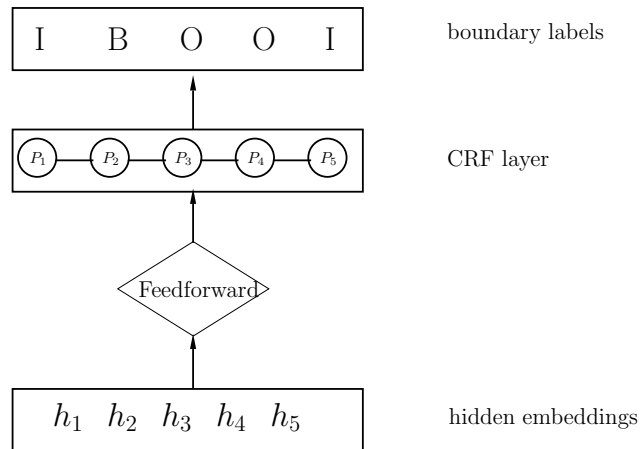


Figure 4.2: The second step of Mention2Vec for NER

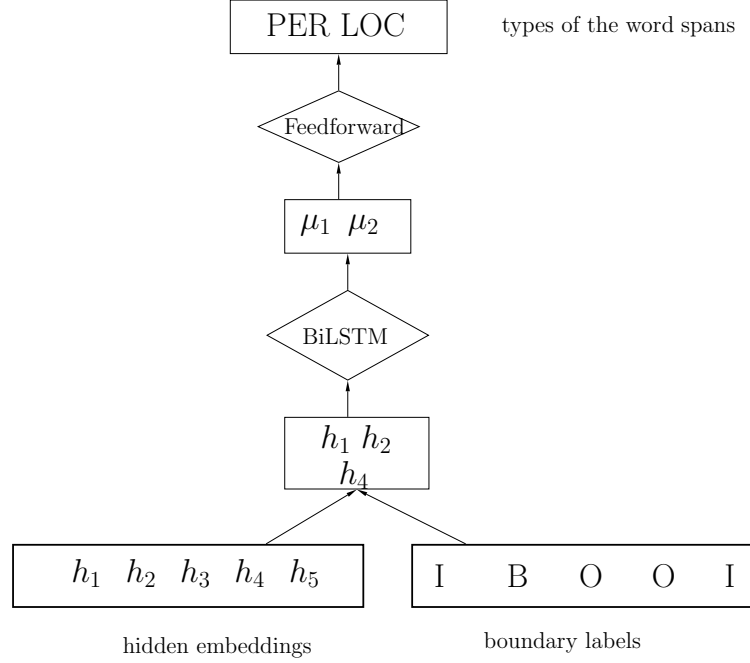


Figure 4.3: The third step of Mention2Vec for NER

The third step of Mention2Vec is the type prediction which is finding the actual types for each named entity span in the sequence. It makes use of the hidden embeddings and the entity boundaries from the previous two steps. The model first looks up the hidden embeddings for the words in entity spans. Then, it feeds the word span hidden embeddings into an additional BiLSTM and obtains the corresponding vector representations for the word span μ by concatenating the final forward and the backward states produced by the BiLSTM. A feedforward network, at the end, is used to map the word span vector representations μ to type probability distributions. Figure 4.3 illustrates the third step of Mention2Vec.

The gold type label sequence of an input sentence is denoted as Y_{type} . Assuming there are l named entities in a sentence, and the index of the first word in a named entity is represented as s , and the index of the last word in a named entity is represented as e , the type prediction loss is computed by 4.2:

$$L_2(\theta, \theta_2) = - \sum_l \log P(r^l | h_s^l \dots h_e^l) \quad (4.2)$$

During training, the model uses the gold boundaries and gold types to compute the boundary detection and the type prediction loss. In each training step, the boundary detection loss and the type prediction loss are minimized jointly: the training objective is to find the boundary sequence and type sequence that minimize the sum of L_1 and L_2 .

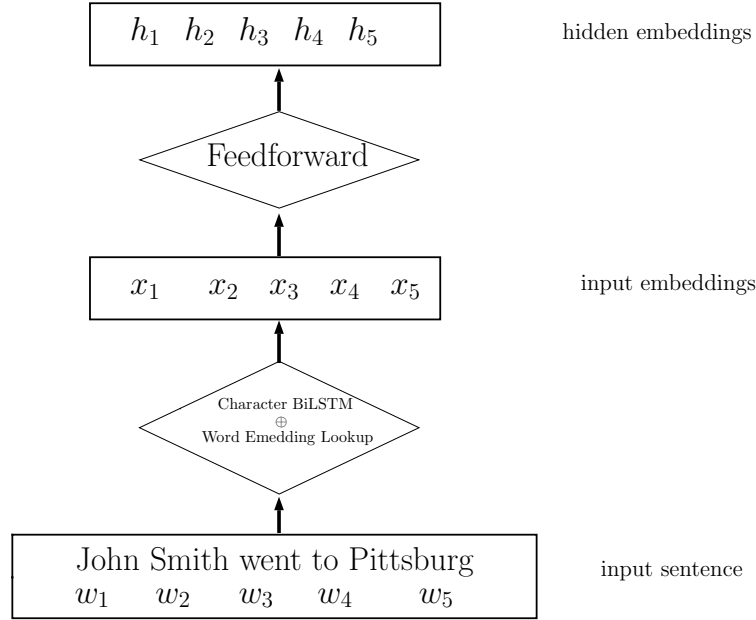


Figure 4.4: The first step of Feedforward-Mention2Vec for NER

In order to further speed up the tagging system as well as capture the correlation between boundary tags, we consider using a different network for boundary detection. Shown in Chapter 2 and Chapter 3, Feedforward-CRF produces relatively good performance on NER with faster speed than BiLSTM. We then replace the BiLSTM in the first step of Mention2Vec with a feedforward network. We denote this new model for NER as Feedforward-Mention2Vec. Feedforward-Mention2Vec still has three steps, the second step and the third step are the same as the ones in Mention2Vec. The first step uses a feedforward network to produce the hidden embeddings, which is illustrated in Figure 4.4.

The run time of decoding the boundaries is constant in both Feedforward-Mention2Vec and Mention2Vec, since there are only three types of boundaries ("I", "O", "B") to decode in the CRF layer. In other CRF based models, like BiLSTM-Char-CRF, the decoding time grows quadratically in the number of named entity types.

4.1.2 BPE-Mention2Vec for POS

In POS, each word in the input sentence is assigned a unique part-of-speech tag. Since there is no part-of-speech span existing in POS, it's not necessary to use a multitasking model on POS. However, we come up a way to convert POS into a NER-like task through the help of Byte Pair Encoding. Inspired by the successful results obtained by using BPE in machine translation (Sennrich et al., 2015), we initially wanted to use BPE to capture morphological

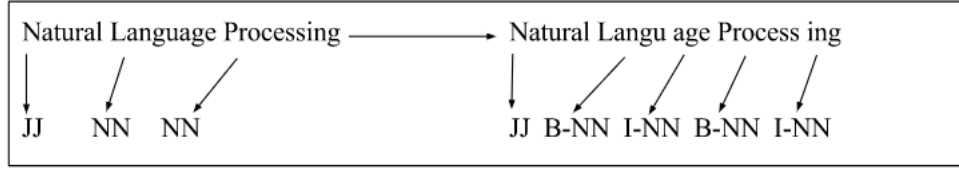


Figure 4.5: An example of using BPE for word segmentation

evidences of the words and replace the spelling features like prefix and suffix. BPE is a compression algorithm which replaces frequent pairs with an unused byte. Sennrich et al. (2015) presents a way to adapt BPE for word segmentation: using BPE to segment words into subword units of different length, and building a vocabulary dictionary using word frequency. In the POS tagging system, we first learn BPE merge operations on the training data. To segment training data and test data, we first split each word in characters and then apply BPE to merge the characters into larger chunks. In order to restore the words, we use the "IOB" label scheme to label the subword units. Since there can be multiple subword units sharing the same tag, POS becomes a task similar with NER. Figure 4.5 shows an example result after using BPE to segment a sequence with POS tags.

In our proposed BPE-Mention2Vec model for POS, there are three main steps. In the first step, given a sequence, we use BPE to segment the words and convert the corresponding tags using the "IOB" label scheme. After the first step, we have a NER-like task with known boundary of each entity span, so we can apply the same methods in Feedforward-Mention2Vec to predict the POS types for entity spans. In the second step, we use a feedforward network to produce the hidden embeddings of the input words. CRF is not used here because that the boundary labels are known in both training and decoding. The third step of BPE-Mention2Vec uses a BiLSTM to predict the POS tags for each entity span based on the hidden embeddings and the known boundaries. Figure 4.6 describes the process of using BPE-Mention2Vec to find POS tags for a sequence.

4.2 Experiments and Results

We empirically evaluate the Mention2Vec model and the Feedforward-Mention2Vec model for NER, and the BPE-Mention2Vec model for POS. We implement these models in Python and Tensorflow 1.0. The experiments in this section use the same set of hyperparameters in the previous experiments.

In the NER experiments, we compare the Feedforward-Mention2Vec model with the original Mention2Vec model on the CoNLL 2003 data set. We use the BiLSTM-Char-CRF model as the baseline model since it achieves the highest F1 score among the previous models we built, and it is recognized as the state-of-the-art model for NER. Table 4.1

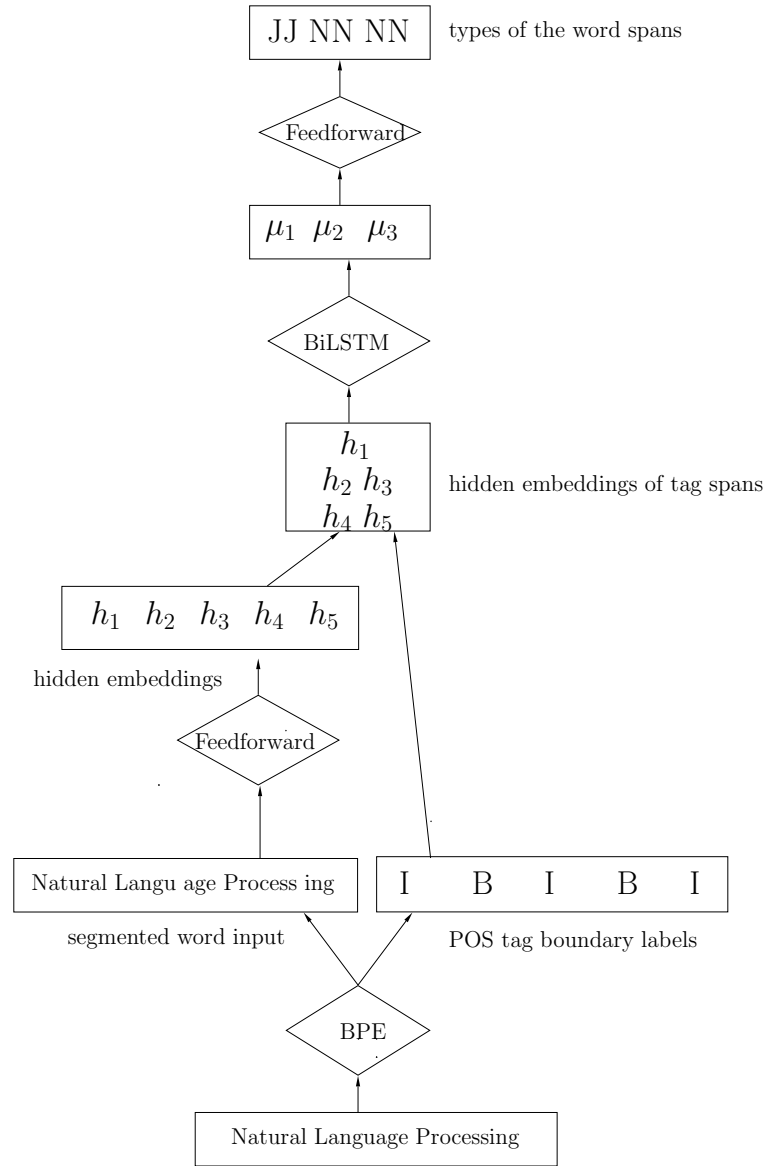


Figure 4.6: An example of using BPE-Mention2Vec to find POS tags

Table 4.1: F1 Score and Decoding Speed Comparison on CoNLL 2003

Model	F1	Speed(Sentences/sec)
BiLSTM-Char-CRF	90.11	795(10100)
Mention2Vec	89.51	765(9701)
Feedforward-Mention2Vec	88.97	1059(13445)

Table 4.2: F1 Score and Decoding Speed Comparison on OntoNotes

Model	F1	Speed(Sentences/sec)
BiLSTM-Char-CRF	86.84	481(7667)
Mention2Vec	85.31	530(8433)
Feedforward-Mention2Vec	84.48	658(10812)

demonstrates the NER performance and decoding speed of these three neural network models on CoNLL 2003 data set. Mention2Vec achieves 89.51 F1 score which is lower than the 90.11 F1 score of BiLSTM-CRF, and it is slightly slower than BiLSTM-Char-CRF. Feedforward-Mention2Vec achieves 88.79 F1 score compared to 89.51 of Mention2Vec and 90.11 of BiLSTM-Char-CRF, but it is 1.4 times faster than Mention2Vec and 1.3 times faster than BiLSTM-Char-CRF. The empirical results demonstrate that the Feedforward-Mention2Vec model performs competitively on the CoNLL 2003 NER tagging task while being faster than original Mention2Vec model and the state-of-the-art model.

Since we have known that Feedforward-Mention2Vec and Mention2Vec scale linearly in the number of named entity types while BiLSTM-Char-CRF grows quadratically. We want to show the time difference of the same model on NER data sets with different numbers of named entity type. Now we have the performance and decoding speed of these models on CoNLL 2003 which has 4 types of named entity. We conduct the experiments on the OntoNotes English data set which has 18 types of named entity. Table 4.2 reports the final results of the experiments. While Feedforward-Mention2Vec is 1.3 times faster than the BiLSTM-Char-CRF model on the data set with 4 named entity types, Feedforward-Mention2Vec is 1.4 times faster on the data set with 18 named entity types. Mention2Vec is slightly slower than BiLSTM-Char-CRF on CoNLL 2003, but it’s faster than BiLSTM-Char-CRF on OntoNotes.

In the POS experiments, we compare the BPE-Mention2Vec model with the BiLSTM-Char-CRF model which is the state-of-the-art model for POS. Table 4.3 demonstrates the performance and decoding speed of BiLSTM-Char-CRF and BPE-Mention2Vec on the Penn

Table 4.3: POS Tagging System Accuracy and Decoding Speed

Model	Accuracy	Speed(sentences(words)/sec)
BILSTM-Char-CRF	97.34	383(9009)
BPE-Mention2Vec	96.04	209(4923)

Treebank data set. BPE-Mention2Vec obtains less accurate result than the BiLSTM-Char-CRF model. Since using word segmentation increases the number of words to be processed and introduces more preprocess time, BPE-Mention2Vec is slower than the BiLSTM-Char-CRF. The empirical results conclude that BiLSTM-Char-CRF is a better model than BPE-Mention2Vec on POS.

Chapter 5

Discussion

In this Chapter, we put together the final experiment results of all the network models presented in this thesis, and provide analysis over the results.

Table 5.1 records the performance of the neural network models on POS and NER. The POS performance is measured on the Penn Treebank data set, and the NER performance is measured on the CoNLL 2003 data set. It also includes the results from other systems including Syntaxnet (Alberti et al., 2017) and NeuroNet (Dernoncourt et al., 2017), which can produce the state-of-the-art results on POS and NER respectively. Syntaxnet has a POS tagger using a similar model with the Feedforward-History model, and NeuroNet implements the fully structured BiLSTM model (BiLSTM-Char-CRF) for NER. While our re-implementation obtains slightly lower accuracy score and F1 score than the state-of-art results, we emphasize that our main goal of this thesis is to compare different neural networks, and to present to new multitasking models.

Table 5.2 records the average decoding speed of different neural network models on the Penn Treebank and CoNLL 2003 test data. All experiments are conducted on a GPU. It's obvious that the less features used in the same model the faster the decoding speed of the model will be. In general, the greedy tagging systems using feedforward models are faster than the systems using BiLSTM models. Since the CRF based models introduce a transition matrix and uses dynamic programming algorithm to decode the sequence, they are slower than the systems without the CRF layer.

Figure 5.1 illustrates the trade-off between performance and decoding speed in POS systems using different neural network models. Among the neural network models for POS systems, BiLSTM-Char-CRF achieves the best per word accuracy 97.34%, and Feedforward-CRF obtains the second best per word accuracy 97.30%. Feedforward model achieves the fastest decoding speed since it employs a simple neural network without extra features: the POS greedy system using the Feedforward model decodes 1319 sentences per second. The line in Figure 5.1 connects the BiLSTM-Char-CRF model which is the most accurate model and the Feedforward model which is the fastest model. The models above the line

Table 5.1: Neural Network Models Accuracy and F1 Score

Model	POS (Accuracy)	NER (F-Score)
Syntaxnet *	97.44	—
NeuroNet *	—	90.5
Feedforward-word	95.89	84.12
Feedforward-history	97.28	86.54
Feedforward-CRF	97.30	87.85
BiLSTM	96.04	84.78
BiLSTM-Char	97.21	88.32
BiLSTM-Char-CRF	97.34	90.11
Feedforward-Mention2Vec	—	88.97
BPE-Mention2Vec	96.04	—

Table 5.2: Neural Network Models Decoding Speed

Model	POS (sentences, words/sec)	NER (sentences, words/sec)
Feedforward-word	1319(30967)	2117(26819)
Feedforward-history	829(19474)	1390(17609)
Feedforward-CRF	761(17877)	1374(17412)
BiLSTM	981(23036)	1637(20740)
BiLSTM-Char	596(13992)	889(11271)
BiLSTM-Char-CRF	383(9009)	795(10100)
Feedforward-Mention2Vec	—	1059(13445)
BPE-Mention2Vec	209(4923)	—

are faster but performs slightly worse than BiLSTM-Char-CRF, such as Feedforward-CRF and BiLSTM-Char. Models below the line such as BPE-Mention2Vec are slower and less accurate, which makes them less ideal for POS. Feedforward-History model is the fastest model with competitive performance on POS, and it is about 2 times faster than BiLSTM-Char-CRF.

Figure 5.2 illustrates the trade-off between performance and speed in NER systems using different neural network models. BiLSTM-Char-CRF achieves the highest F1 Score 90.11, and Feedforward-Mention2Vec obtains the second best F1 Score 88.79. Feedforward achieves the fastest decoding speed since it employs a simple neural network with no extra features: the NER greedy system using the Feedforward model decodes 2177 sentences per second. The line in Figure 5.2 connects the BiLSTM-Char-CRF model which is the most accurate model and the Feedforward model which is the fastest model. The models above the line are faster but perform slightly worse than BiLSTM-Char-CRF, such as Feedforward-CRF and Feedforward-Mention2Vec. Models below the line are slower and less accurate, which makes them less ideal for NER. Feedforward-Mention2Vec model is the fastest model with competitive performance. Feedforward-Mention2Vec obtains 88.79 F1 score which is close to the best performance, and it is 1.3 times faster than the fully structured BiLSTM model.

As illustrated in Figure 5.1 and Figure 5.2, the greedy sequence tagging systems using feedforward networks can achieve comparable performance and faster speed than the systems using recurrent models on POS; the multitasking model (Feedforward-Mention2Vec) performs competitively with the state-of-the-art model (BiLSTM-Char-CRF) on NER.

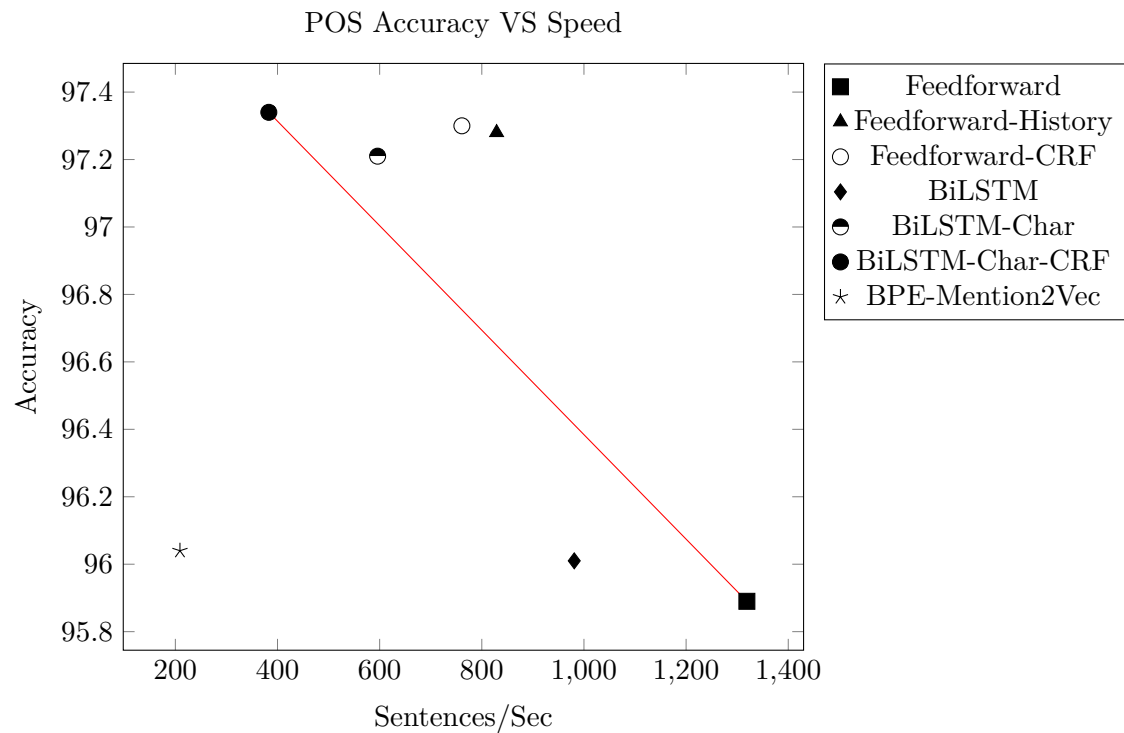


Figure 5.1: Results of the POS system using different Neural Network Models

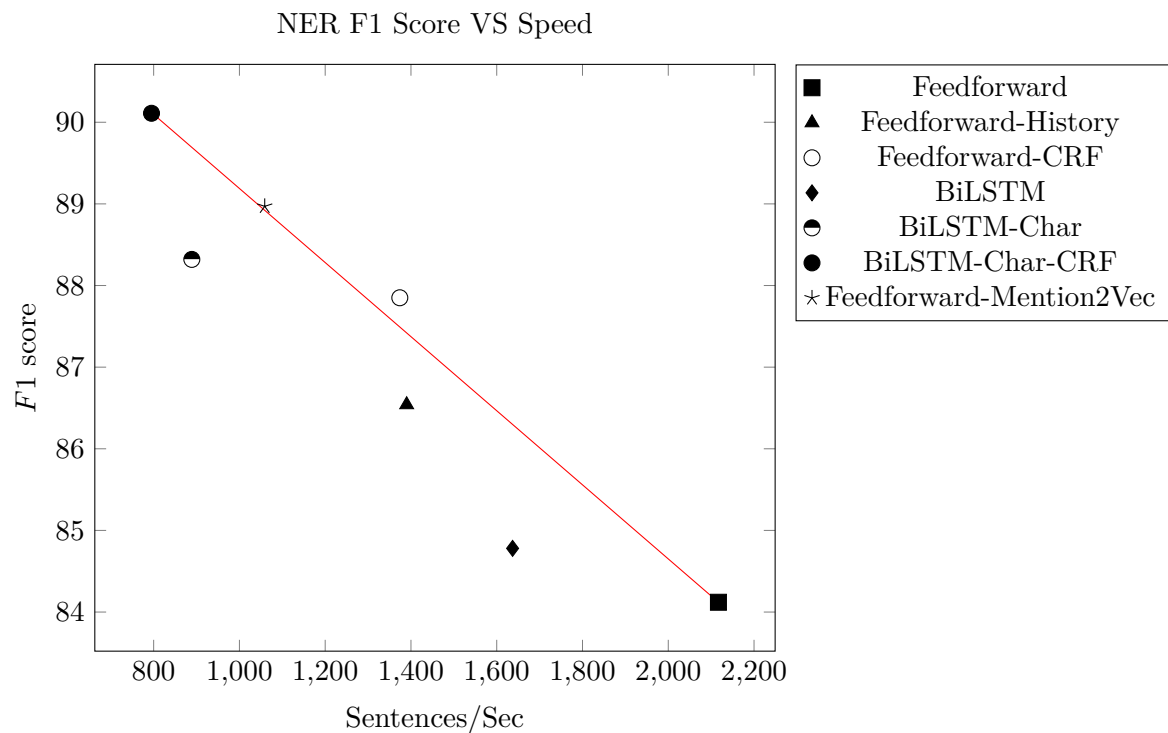


Figure 5.2: Results of the NER system using different Neural Network Models

Chapter 6

Conclusion and Future Work

This thesis presents and compares different neural network models for sequence tagging tasks. The empirical result reveals that simple feedforward networks can achieve competitive results while being significantly faster than the BiLSTM networks on POS. The empirical results also demonstrate that Feedforward-Mention2Vec performs well on NER, and it is more scalable in the number of named entity types.

6.1 Contribution

In this thesis, we first built three feedforward neural network models for POS and NER: Feedforward, Feedforward-History, and Feedforward-CRF. We conducted experiments to compare the decoding speed and performance between them. Experimental evaluations show that the feedforward models are not strongly dependent on hand engineered features, and the models are able to automatically learn the useful features for making decisions. Compared to Feedforward-CRF, Feedforward-History achieves similar per-word accuracy score on POS, but it is less accurate on NER.

Then, we re-implemented the state-of-the-art model for sequence tagging: BiLSTM-Char-CRF. We ran the BiLSTM model with different configurations on POS and NER, and we compared the decoding speed and performance between BiLSTM models and feedforward models. As the experiments show, BiLSTM models are robust and are more accurate than feedforward models in general. Since feedforward models have a simpler architecture and less parameters, feedforward models are faster than BiLSTM models.

In addition to feedforward models and BiLSTM models, we presented Feedforward-Mention2Vec for NER which is a combination of Feedforward-CRF and Mention2Vec, and BPE-Mention2Vec for POS which is based on BPE and Mention2Vec. Both of these two models are multitasking models. Feedforward-Mention2Vec predicted boundaries of named entity labels and types of named entity labels separately using a feedforward network, a BiLSTM network, and CRF. BPE-Mention2Vec first segmented words using BPE, and pre-

dicted the part-of-speech tags for the subword units using a BiLSTM network. Feedforward-Mention2Vec performs slight worse than the state-of-the-art model (BiLSTM-Char-CRF) on CoNLL 2003, but it’s decoding speed is 1.3 times faster. As the number of named entity types grows, the decoding speed of Feedforward-Mention2Vec grows linearly while the decoding speed of BiLSTM-Char-CRF grows quadratically. For example, Feedforward-Mention2Vec is 1.4 times faster than BiLSTM-Char-CRF on OntoNotes which has 18 named entity types.

Lastly, we summarized all the experiment results and compared the performance and decoding speed of all the models presented in this thesis. We provided analysis on the speed and accuracy trade-off in different models. Feedforward is the fastest among all models, since it includes no extra features and employs a simple network architecture. Our re-implementation of BiLSTM-Char-CRF achieves near state-of-the-art performance on POS and NER. Feedforward-History performs better on POS then on NER with a faster decoding speed than BiLSTM-Char-CRF. Feedforward-Mention2Vec performs slightly worse than BiLSTM-Char-CRF on NER, but it’s decoding speed is faster and grows linearly in the number of named entity types.

6.2 Future Work

There are several potential extensions of this thesis we would like to work on in the future:

First, Shallow Parsing, often referred as Chunking, is another classic sequence tagging task which can be solved using neural network models proposed in this thesis. We would like to compare different neural network models on Shallow Parsing and find the speed and accuracy relationship between these models.

Second, we would like to explore multitasking models which combine POS and NER. We can build a neural network tagging system to train and predict POS tags and NER tags jointly. The intermediate representations would benefit from considering linguistic hierarchies in the training process.

Third, in order to improve the performance of our sequence tagging system, we would like to combine the neural network models presented in this thesis. The easiest way to combine them is to use a voting method in post-process. During tagging, each model will predict a label for the input word, and we will take a majority vote on the output of the three models. The input word will be tagged with the label with the highest vote.

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