Report for Independent Study
Deep Learning and Part-of-speech Tagging

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August 3, 2018

Abstract

This is the report for an independent study with Prof. Damir Cavar at Indiana University Bloomington for the Summer Semester 2018. The independent study is conducted in several parts throughout the summer including reading groups led by Prof. Damir, guided reading over reference books, slides and papers, as well as hands-on coding for part-of-speech tagging using deep learning techniques.

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1 Introduction

Deep learning has been a hot topic in computer science especially artificial intelligence (AI) in recent years, especially after the five-game Go match between 18-time world champion Lee Sedol and AlphaGo, a computer Go program developed by Google DeepMind. Deep learning or more specifically, deep neural networks has been applied to most if not all AI applications such as computer vision and natural language processing.

Prof. Damir Cavar at Indiana University taught a course named Deep Learning and NLP in Spring 2017 and I did not have chance to participate. Since the techniques and applications of deep learning is so interesting and important, I decided to participate in an independent study with Prof. Cavar, focusing on deep learning with applications on natural language processing.

The whole process of independent study consists of several components:

1. Reading group regarding linear algebra and quantum algorithm
2. Project group regarding open information extraction (openIE)
3. Individual study and meeting with Prof. Cavar regarding deep learning basics and NLP applications

In this report, I will briefly summarize the knowledge and results from the last component listed, i.e. deep learning basics and NLP applications, in particular my experiments of part-of-speech tagging using deep learning techniques I learnt.

Outline The report is structured in the following way: Section 2 lists some basic knowledge and tools which are considered as preliminary to deep neural network models. The author spent two weeks reviewing materials regarding these preliminaries before actually started working on deep learning materials. Techniques and knowledge of deep neural networks that the author learnt are summarized in Section 3. Section 4 talks about word embeddings (word2vec), a warm up application of neural networks in natural language processing. This is also used in later sections as an input to train POS taggers. Section 5 focuses on using the machine learning library scikit-learn (in Python)for POS tagging on Brown Corpus and Part of the Penn Tree Bank. The author tried two methods. One uses basic token level features and the other uses word2vec. Section 6 discusses the use of Keras deep learning library and apply the model of Bidirectional Long Short-Term

Memory Recurrent Neural Network for POS tagging, which is more accurate and efficient than the previous attempts. Finally, Section 7 concludes and lists several questions for future research and discussion.

Materials and Resources There are several important sources that the author read and referenced when studying this topic and writing the report.

- The deep learning text book by Goodfellow, Bengio and Courville [3]. I also refers to the website links and youtube videos provided by Goodfellow regarding the materials of the book to get a better understanding.
- Course materials by Prof. Damir Cavar [2] including slides from the Stanford NLP course [9].
- Guidance on POS tagging with BLSTM-RNN including a paper [10], a github repository with code examples and explanation [1] and a blog explaining Long Short-Term Memory RNN [7].
- Other notes, materials and papers used, will be acknowledged and cited in later sections.

2 Deep Learning Preliminaries Summary

This section lists several of the preliminary piece of knowledge of deep learning models and techniques, which are reviewed in details by the author before step into the world of deep neural networks. The readings referenced including the first five chapters of the deep learning text book [3] and some of the pdf materials by Zico Kolter.

2.1 Probability Theory

Many machine learning algorithm including deep neural networks all have probability theory as the theoretic foundation. Some common distributions are widely used such as Bernoulli, Multinoulli, Guassian. For example, in a task of multi-class classification, we are trying to learn a Multinoulli distribution from the data.

Estimation theory is also applied when we try to maximize (or minimize) the objective functions, the core concepts involve maximum likelihood estimation, maximum a posteriori estimation, mean squared errors etc.

Finally, information theory especially Shannon entropy plays an important role defining the loss (objective) functions of machine learning models. In fact, cross-entropy, which is closely related to Kullback-Leibler divergence, is often used as the loss function for multi-classes classification. This could be treated as an interpretation for the maximum likelihood estimator. Suppose we are maximizing the log-likelihood function regarding some parameter θ, using data x_i's

$$\hat{\theta}_{ML} = \arg\max_{\theta} \sum_{i=1}^{m} \log P_{model}(x_i; \theta)$$

The summation could be viewed as an expectation with respect to the empirical distribution P_{data}. Hence we got the following equivalent expression:

$$\hat{\theta}_{ML} = \arg\max_{\theta} \mathop{\mathbb{E}}_{x \sim P_{data}} \log P_{model}(x; \theta)$$

If we use KL divergence to describe the dissimilarity between the empirical distribution P_{data} and the real underlying data generating process P_{model}, we have:

$$D_{KL}(P_{data} || P_{model}) = \mathop{\mathbb{E}}_{x \sim P_{data}} (\log P_{data}(x) - \log P_{model}(x))$$

Since $\mathbb{E}_{x \sim P_{data}} \log P_{data}(x)$ is constant, getting the maximum likelihood estimator is equivalent to minimize:

$$-\mathop{\mathbb{E}}_{x \sim P_{data}} \log P_{model}(x)$$

which is the cross-entropy between empirical distribution and the real underlying data generating process.

Goodfellow also noted that Any loss consisting of a negative log-likelihood is a cross-entropy between the empirical distribution defined by the training set and the probability distribution defined by the model. For example, mean squared error is the cross-entropy between the empirical distribution and a Gaussian model [3].

2.2 Linear Algebra

Linear Algebra is very important for machine learning especially deep neural networks. In fact, many neural network models are in essence just complex matrix multiplications. The word2vec model for word embeddings (explained in Section 4) is a good example.

To better understand the materials on deep learning, key concepts of linear algebra including matrix multiplication, linear dependence, norm, eigen-decomposition, trace and determinant need to be reviewed and well-understood.

While the topics listed above are typically covered in a standard course on linear algebra, one topic that does not seem to be covered very often (but used extensively in deep learning) is the extension of calculus to the vector setting. I referred to the paper by Terence Parr and Jeremy Howard to get a good summary of the core concept and notations of matrix calculus [8]. This piece of knowledge is very important for derivation of most of the theoretical models in neural networks as well as understanding the core concept of training them: gradient descent and back propagation.

Several formula that are useful for remembering:

- $\nabla_x b^T x = b$ (x and b are vectors)
- $\nabla_x x^A x = 2Ax$ (A is a symmetric matrix)
- $\nabla_x^2 x^A x = 2A$ (A is a symmetric matrix)
- Let f be some loss function and $\frac{\partial f}{\partial C} = G$ where $C = AB$ then the chain rule implies $\frac{\partial f}{\partial A} = \frac{\partial f}{\partial C} B^T = GB^T$.

2.3 Convex Optimization

Convex optimization is a very important area in optimization, economics and many other disciplines. In this part, I reviewed several general techniques/concepts: in unconstrained optimization problems, first-order gradient descent, second-order optimization (Newton's method using Hessian matrix). In constrained problems with equality and/or in-equality constraints, Lagrangian or Karush-Kun-Tucker method is used.

The importance of convexity is the guarantee of global minimum and fast convergence using gradient-based algorithms regardless of initial state. However, in general settings, we do not have global convexity or concavity. There may be many local maximum, local minimum, saddle points etc.

2.4 Machine Learning basics

In this part, the author reviewed several basic machine learning algorithms and general techniques in designing and training the models followed by Chapter 5 of the Deep Learning text book [3].

Basic algorithms include supervised learning algorithms such as support vector machines, decision trees, logistic regression, and unsupervised learning algorithms such as principle component analysis, and k-means clustering.

Useful techniques in design and training include concepts of capacity, over-fitting and under-fitting and use of hyper-parameters and validation sets. A key method in training is stochastic gradient descent, which is more efficient and less memory-consuming than the ”deterministic” version.

3 Deep Neural Network Summary

This section summarizes basic knowledge and practices in modern deep networks following the chapters 6 to 10 in Deep Learning book.

3.1 Deep Feedforward Networks

Deep feedforward network can be also referred to as feedforward neural networks or multilayer perceptrons (MLPs). There is no other obvious difference between deep forward network and the common neural network other than the fact that deep network may have more hidden layers (i.e. deeper).

Feedforward networks are typically represented by composing together many different functions, where the parameters to be learnt are often called weights. Back-propagation algorithm is used to train the model and learn the weights. The algorithm is basically a big chain rule calculating the partial derivatives of the loss function with respect to all the weights in previous layers.

The book [3] uses an entire chapter discussing regularization for deep learning and another chapter for optimization in training feedforward networks. These techniques are very practical and widely used in different deep learning libraries such as scikit-learn and keras.

3.2 Convolutional Neural Network

Convolutional neural networks (CNN) are a specialized kind of neural network for processing data that has a known grid-like topology. Examples include time-series data (1-D grid), image data (2-D grid of pixels) and volumetric data (3-D grid). There are three main types of layers that are often used to build CNN architectures: convolutional Layer, pooling Layer, and fully-connected Layer. However, since the author’s focus is on natural language processing, which is not grid-like but sequence-like data, the more relevant model is recurrent neural networks (RNN).

3.3 Recurrent Neural Network

A recurrent neural network (RNN) is specialized for processing a sequence of values. The extension for feedforward network to recurrent network involves the idea of parameter sharing, which makes it possible to apply the model to sequences of different length and generalize across them.

One simple illustration of RNN is in Figure 1, where A is some structure of network layers, for example a simple hidden layer or composition of several hidden layers. The model takes a sequence of inputs x_i, feed to the same network structure at each step and produce h_i as outputs. The left-hand side is a compact way of the RNN before unrolling.

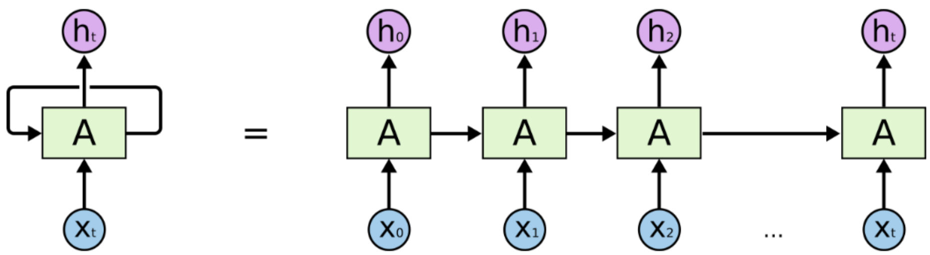


Figure 1: An Unrolled Recurrent Neural Network
[7]

In previous example, the network is one-directional, i.e. the state at time t captures only information from the past, $t-1$, $t-2$,... However, sometimes use a bidirectional RNN to allow the current state depends on both previous and post information. In particular: "using bidirectional will run inputs in two ways, one from past to future and one from future to past and what differs this approach from unidirectional is that in the RNN that runs backwards you preserve information from the future and using the two hidden states combined you are able in any point in time to preserve information from both past and future. Because of their ability to approach a unit from both the directions, they tend to understand context better" [1]. This could be illustrated in Figure 2, where $h^{(t)}$ are states moving forward through time and $g^{(t)}$ are states moving backward. The output at each time point is depending on both states.

For the Part-of-speech tagging in Section 6, a special RNN is used: Long Short-Term Memory Recurrent Neural Network. The details will be discussed in that section.

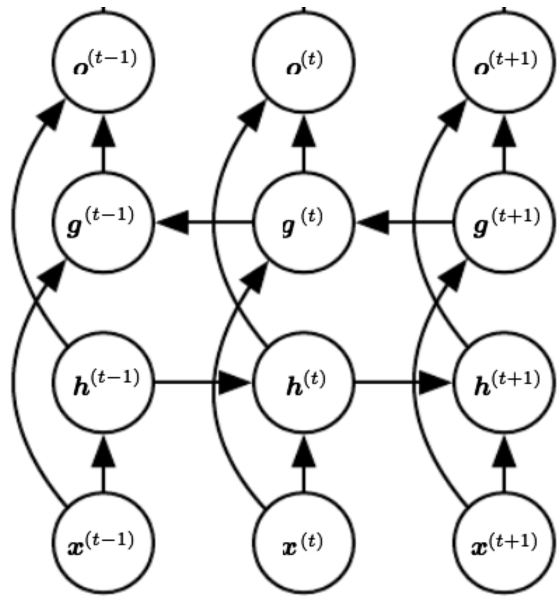


Figure 2: Bidirectional Recurrent Neural Network
[3]

4 Warm-up: Word Embeddings and Word2vec

This section talks about word embeddings, "which is the collective name for a set of language modeling and feature learning techniques in natural language processing (NLP) where words or phrases from the vocabulary are mapped to vectors of real numbers. Conceptually it involves a mathematical embedding from a space with one dimension per word to a continuous vector space with a much lower dimension" [11]. The word2vec is a model used to produce word embeddings. It is interesting in two ways. First, word2vec itself is a two-layer neural networks that are trained to reconstruct linguistic contexts of words, which can be think of as a simple application of feedforward networks. Second, using the resulting vectors as features for further NLP tasks is considered better in many cases due to less human supervised feature engineering.

4.1 Model

The model of word2vec is a two-layer neural networks with one hidden layer and one output layer. Given a specific word in the middle of a sentence (the input word), the network is going to predict the probability for every word in the vocabulary of being the context word i.e. within a certain window of the input word. A typical window size is 5, which means 5 words behind and 5 words ahead of the input word are considered as the context.

The network is trained by feeding word pairs found in training documents that are within the window size. Let us assume that the vocabulary is 10000. The structure of the network is illustrated in Figure 3.

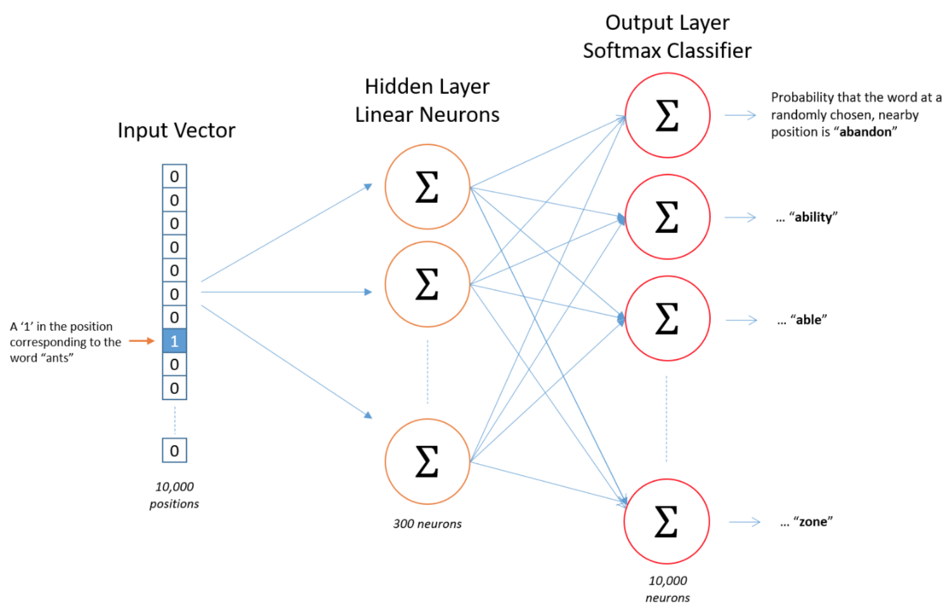


Figure 3: Structure of Word2vec Network
[5]

The input vector is an one-hot vector of length 10000, where only one entry is 1 and all others are 0. This vector indicates which input word it represents. (Notice there is a one-to-one relationship between the input vector and each word in the vocabulary). The hidden layer of size 300, is basically a 10000×300 matrix where each role is representing each word in the vocabulary in a form of a 300-length real-valued vector. Notice that this matrix is what we will save as the ultimate output of our word2vec task, since it is the word embeddings for each word. The output of the network is just used to tune the numbers in this matrix by comparing with the ground truth. (This is why some authors refers this neural network task as a fake task [5]). The output layer which contains the same number of neurons as the vocabulary size, is basically a matrix of dimension 300×10000. By a simple linear algebra calculation we know that taken one input vector, the network will output a vector of 10000. After a softmax activation function, which normalize these 10000 numbers to a discrete probability distribution, we get the probability that each word appear in the context of the input word. The loss function could be defined comparing the distance of this distribution with the one represented by the ground truth (as provided by the training data).

Training the network involves using techniques such as back propagation to minimize the loss function by alternating the weights in the two matrices discussed above.

4.2 Practical Techniques

The word2vec model with a large vocabulary could be very hard to train due to the extremely high dimensionality. Mikolov et al discussed several practical techniques on top of the basic model above [6]. There are three innovations in this second paper, also discussed by Chris McCormick in his online tutorial [5], the author will list them below without detailed explanation.

1. Treating common word pairs or phrases as single words in their model.
2. Subsampling frequent words to decrease the number of training examples.
3. Modifying the optimization objective with a technique they called Negative Sampling, which causes each training sample to update only a small percentage of the models weights.

4.3 Intuition and Implementation

Using word embeddings such as word2vect representing each word a vector provides the syntactic and semantic information about the words which in turn can be used for various other tasks. Words which are similar to each other are more likely to have similar context therefore the embedding vectors are closer in distance. This is the intuition of the model.

The author did not implement the word2vec model from scratch. Instead, the library gensim provides the word2vec model that one could train on his own corpus. The word vector for each token can be then provided. The sample code is attached here:

```python
import gensim

def train_w2v(sent_list, size=300):
    model = gensim.models.Word2Vec(sent_list, min_count=1,size=size)
    model.delete_temporary_training_data(replace_word_vectors_with_normalized=True)
    return model

def token2vec(token,w2vmodel):
    return w2vmodel.wv[token]
```

5 POS Tagging Using Scikit-learn

This section explains using the library scikit-learn to train a POS tagger with hand extracted feature and word embeddings. Different machine learning models are applied and the accuracy is around 95% for hand extracted features but relatively low for word embeddings (below 70%). These could be used as a baseline for advanced taggers introduced in Section 6.

5.1 Data

The data set I am using for this part is the Treebank tagged sentences included in the NLTK (Natural Language Toolkit) package. This is only a small fraction (10%) of the Penn Treebank corpus, which contains 3914 tagged sentences and 100676 tagged tokens. For only learning purpose, I did not try to purchase the full Penn Treebank. Another option is the Brown corpus, which contains 57340 tagged sentences and a vocabulary of 56057.

Another reason that I am using the Treebank tagged sentences but not the Brown corpus for this part is that due to some unknown limitation of scikit-learn (and perhaps my machines), training the neural network on 80% of the Treebank data already causes resource issues. Therefore I can only reduce the training proportion to 70%. In Section6, I used both Treebank and Brown because keras running tensorflow backend has no problem even handling Brown Corpus.

5.2 Method1: hand crafted features

As a baseline, I tried to extract some very simple features on each token as the input for various models. These features include:

- the token itself

- if the token is the start of the sentence
- if the token is the last of the sentence
- if the token is capitalized
- if the token has only capital letters
- if the token has only lower letters
- 3 prefix of the word
- 3 suffix of the word
- the previous word
- the next word
- if the word has hyphen
- if the word is numeric
- if the word has a capitalized word inside (not the first letter)

I used the machine learning models in scikit-learn to perform the training on 70% of the data and test on the rest. The models include decision tree, random forest and MLP (feedforward networks) with different number of hidden layers and units. After playing around with different parameters, based on these hand crafted features, all models could achieve accuracy around 94% to 95%.

For MLP in particular, using one hidden layer of 200 neurons achieve accuracy of 95.3%, using two hidden layers (50,50) achieve accuracy of 95.0% and using two hidden layers (800,30) achieve 95.2% accuracy. Varying different number of neurons in each layers, alternating activation functions, and playing around with other parameters do not seem to improve the results. Therefore I believe the limit of using this set of features are around 95% accuracy.

5.3 Method2: using word vectors

In the second method, instead of extracting features, I use the word vectors out of the word2vec model (trained on the same corpus) as the features. I chose the vector dimension to be 300 (as Google did) and concatenated the vector of the chosen word with the previous and next words. This results in a feature vector of 900 in length.

However, using this as the input to the same models yield very poor results. For decision tree and random forest, the accuracy is around 40%. Since the word2vec model is calculated from neural networks, I tried to test many different structures of feedforward networks, the results of accuracy are summarized in the Table 1, Table 2 and Table 3.

Table 1: Accuracy for Feedforward Network Using Word Vectors I

Model Number	Number of Hidden layers	Size of Hidden Layers	Accuracy
1	1	(100)	53.85%
2	1	(200)	55.25%
3	1	(500)	56.27%
4	1	(1000)	58.90%
5	1	(1500)	59.47%
6	1	(2000)	60.24%
7	1	(2500)	58.26%
8	1	(3000)	55.77%
9	1	(3500)	56.34%
10	1	(4000)	57.46%
11	1	(4500)	56.83%
12	1	(5000)	57.50%
13	1	(5500)	58.54%

Table 1 shows the results by using only 1 hidden layer. By increasing the number of neurons in that layer, the accuracy increases at first. After 2000 neurons, increasing the size of the layer does not increase accuracy any more. In all the accuracy is around or below 60%.

Table 2 shows accuracy of models with 2 hidden layers. The results are generally better than the ones with only one hidden layer. However there is no obvious patterns about how different number of neurons could affect the accuracy. The highest so far is to use two layers each having 3000 neurons.

Table 3 shows accuracy of models with 3 or more hidden layers. The results are not better than the ones with two hidden layer.

Remark 5.1. *The results of these model are in general performing much worse compared to the baseline with hand crafted features. The reason is probably that the word vector of three words may not be able to provide enough information for part of speech. Although the hand crafted features did not include more words in the sequence (also the previous and the next), they have more other features such as prefix, suffix, and word-shape. These*

Table 2: Accuracy for Feedforward Network Using Word Vectors II

Model Number	Number of Hidden layers	Size of Hidden Layers	Accuracy
1	2	(3000, 100)	58.78%
2	2	(3000, 200)	59.67%
3	2	(3000, 500)	63.61%
4	2	(3000, 1000)	64.72%
5	2	(3000, 1500)	61.60%
6	2	(3000, 2000)	62.38%
7	2	(3000, 2500)	65.28%
8	2	(3000, 3000)	68.72%
9	2	(3000, 3500)	65.40%
10	2	(3000, 4000)	60.81%
11	2	(3000, 4500)	59.43%
12	2	(4000, 3000)	59.70%
13	2	(4000, 4000)	61.86%
14	2	(4000, 5000)	65.29%
15	2	(5000, 3000)	64.63%
16	2	(5000, 4000)	62.99%
17	2	(5000, 5000)	66.13%

Table 3: Accuracy for Feedforward Network Using Word Vectors III

Model Number	Number of Hidden layers	Size of Hidden Layers	Accuracy
1	3	(3000, 3000, 3000)	63.68%
2	3	(3000, 3000, 4000)	54.90%
3	3	(3000, 3000, 5000)	69.44%
4	4	(3000, 3000, 3000, 3000)	51.80%
5	4	(3000, 3000, 3000, 4000)	57.62%

features may not be well-represented by the word vectors. Another possibility is that feedforward network is not well applied to this type of inputs. In Section 6, we can show that using RNN could achieve a much better result.

Remark 5.2. *The accuracy results in the previous three tables are only from one run of the corresponding model. More iterations or techniques like cross-validation are not used because the training process is very time-consuming. On average, each model takes more than 3 hours to train. I suppose the inefficiency is due to the implementation of scikit-learn, which is a machine learning library but not one specialized for deep learning. In fact, when using* *keras (with a scikit-learn wrapper), the same model runs within 30 minutes.*

Remark 5.3. *Another limitation of scikit-learn is that when handling more than 75000 training tokens, python will show errors with memory limitation. However, same model using keras (with a scikit-learn wrapper) can be executed without problems.*

6 POS Tagging Using Bidirectional Long Short-Term Memory Recurrent Neural Network

This section shows the steps and results for using a type of recurrent neural network: Long Short-Term Memory to tag part of speech. The library used for implementation is keras, which is "a high-level neural networks API, written in Python and capable of running on top of TensorFlow, CNTK, or Theano. It was developed with a focus on enabling fast experimentation. Being able to go from idea to result with the least possible delay is key to doing good research" [4].

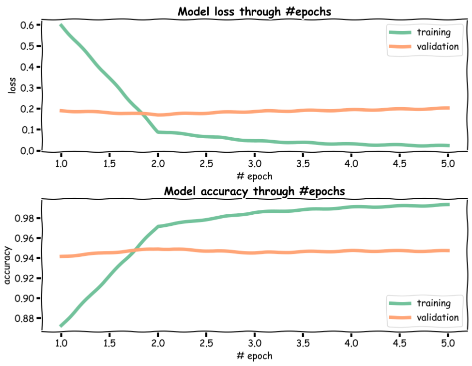
6.1 Previous Models Revisit Using Keras

All the models in Section 5 can be implemented in keras using a tensorflow backend. There are two ways for the implementation. The first is to use a wrapper for scikit-learn so that most of the code in previous scikit-learn implementation could be directly applied. The other is to rewrite code in keras, which allows more flexibility and options regarding deep neural networks. Both methods are tested (which gave similar results) and codes are included in the attached github repository.

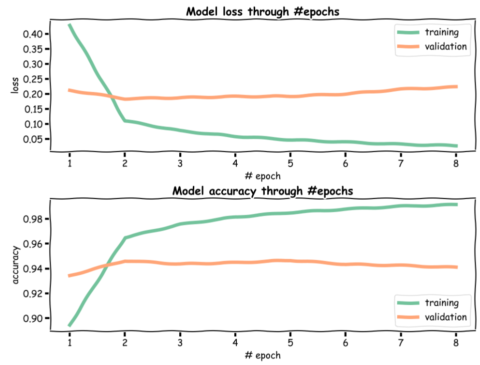
Further, when use keras, the more efficient backend allow us to train the model on much larger training sets, therefore, the analysis is also applied to Brown Corpus. The model performance (using same hand crafted features) are displayed in Figure 4. Note that I am using a two layer MLP with number of hidden units 400 and 300 respectively, details of which is shown in Figure 5

For both corpus, the model performances are very similar. First, the accuracy on validation sets is above 94%. Second, after two epochs, the model seems to start overfitting. The final accuracy on test sets (stopped after 3 epochs) are 95.17% and 95.68%.

Similar, using the word2vec embeding and feedfarward networks in keras yield similar results as before, no more than 70%. The details are omitted here since the performance is not good.



(a) Treebank corpus



(b) Brown corpus

Figure 4: Model Performance with Hand Crafted Features and FeedForward NN

```
model fitting sequential
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_1 (Dense)              (None, 400)               17694000
_________________________________________________________________
dense_2 (Dense)              (None, 300)               120300
_________________________________________________________________
dense_3 (Dense)              (None, 46)                13846
=================================================================
Total params: 17,828,146
Trainable params: 17,828,146
Non-trainable params: 0
_________________________________________________________________
Train on 61107 samples, validate on 19530 samples
```

(a) Treebank corpus

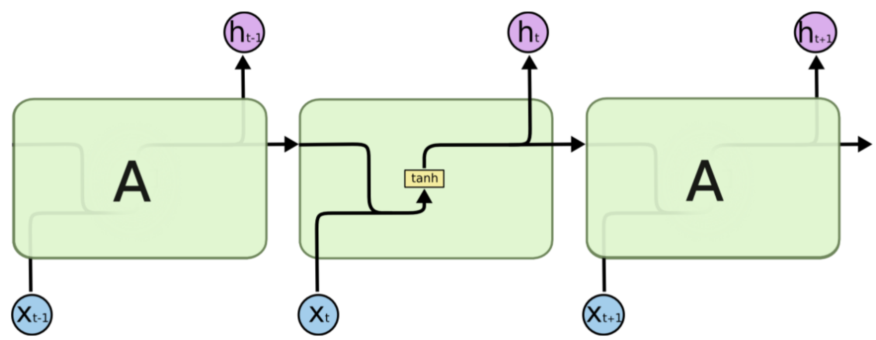
```
model fitting sequential
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_1 (Dense)              (None, 400)               71704400
_________________________________________________________________
dense_2 (Dense)              (None, 300)               120300
_________________________________________________________________
dense_3 (Dense)              (None, 472)               142072
=================================================================
Total params: 71,966,772
Trainable params: 71,966,772
Non-trainable params: 0
_________________________________________________________________
Train on 729286 samples, validate on 250360 samples
```

(b) Brown corpus

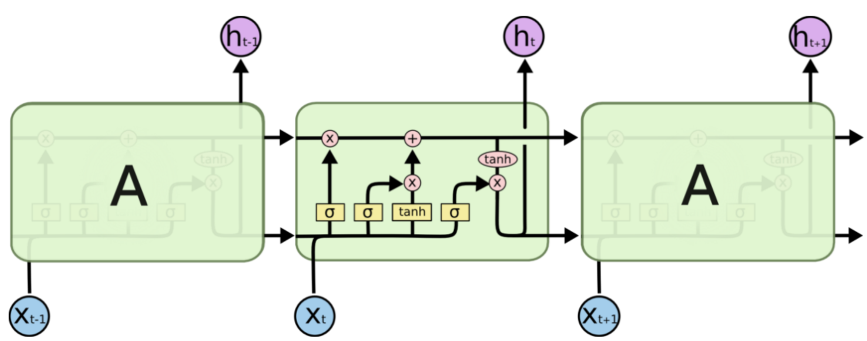
Figure 5: Model Used with Hand Crafted Features and FeedForward NN

6.2 Bidirectional Long Short-Term Memory Recurrent Neural Network

"In theory, RNNs are absolutely capable of handling long-term dependencies. Sadly, in practice, RNNs dont seem to be able to learn them" [7]. Therefore, some researchers have suggested using a special gated recurrent neural network to handle POS tagging [10]. In this subsection, the author summarized some of the main features of LSTM RNN, inspired by Christopher Olah [7]. The comparison can be illustrated by Figure 6.



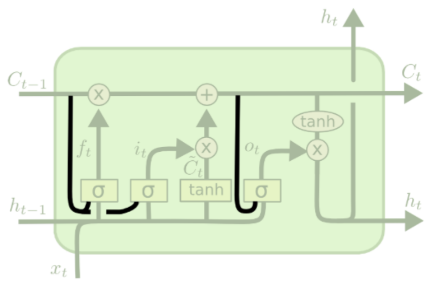
(a) Standard RNN contains a single layer



(b) LSTM contains four interacting layers

Figure 6: The repeating module in RNN
[7]

In standard RNNs, the repeating module will have a very simple structure, such as a single tanh layer, or relu layer etc. However, in LSTM, the repeating module consists of several gates that controls the probability of information flow thus deciding to keep or abandon long/short memories. The details of the structure within the repeating units is as in Figure 7 where the 3 equations on the right-hand side correspond to forget gate, input gate, and output gate respectively.



$$f_t = \sigma\left(W_f \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] \;+\; b_f\right)$$
$$i_t = \sigma\left(W_i \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] \;+\; b_i\right)$$
$$o_t = \sigma\left(W_o \cdot [\boldsymbol{C_t}, h_{t-1}, x_t] \;+\; b_o\right)$$

Figure 7: LSTM Repeating Module Gates in Details
[7]

- Forget gate: $f_t = \sigma(W_f \dot{[} C_{t-1}, h_{t-1}, x_t] + b_f)$, where the weights (W_f) are applied to previous hidden state (C_{t-1}), previous output h_{t-1}, and the current input (x_t), plus a bias term (b_f). After a sigmoid activation function (σ), f_t is transformed to a number between 0 and 1, representing the fraction of previous memory to keep.

- Input gate: $i_t = \sigma(W_i \dot{[} C_{t-1}, h_{t-1}, x_t] + b_i)$, where a new sets of weights and bias are applied to the same features as before, out put a fraction of current input to be taken into consideration.

- Output gate: $o_t = \sigma(W_o \dot{[} C_t, h_{t-1}, x_t] + b_o)$, where another new sets of weights and bias are applied to the same features as before (except using current cell state C_t), output a fraction of current output to be emit.

By using the three gates above, we can update the old cell state C_{t-1} to current cell state C_t by the following two steps. The step one is calculating the input (before input gate):

$$\tilde{C}_t = \tanh(W_C \dot{[} h_{t-1}, x_t] + b_C)$$

Then current cell state is updated according to input gate and forget gate:

$$C_t = f_t\, C_{t-1} + i_t\, \tilde{C}_t$$

The output of the current cell is then:

$$h_t = o_t \tanh(C_t)$$

Another illustration from Goodfellow's book is in Figure 8, "where an input feature is computed with a regular articial neuron unit. Its value can be accumulated into the state if the sigmoidal input gate allows it. The state unit has a linear self-loop whose weight is controlled by the forget gate. The output of the cell can be shut o by the output gate. All the gating units have a sigmoid nonlinearity, while the input unit can have any squashing nonlinearity. The state unit can also be used as an extra input to the gating units. The black square indicates a delay of a single time step" [3].

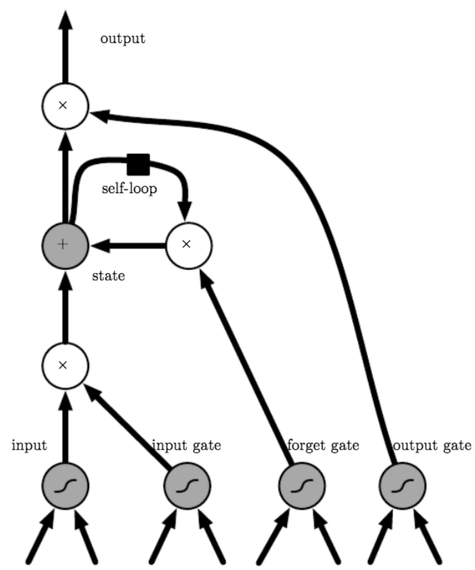


Figure 8: LSTM Repeating Module Gates in Deep Learning Text Book [3]

Furthermore, we use bidirectional LSTM RNN instead of unidirectional as suggested by Wang and his co-authors [10]. They also mentioned that: as a neural network model, it is awkward for BLSTM RNN to make use of conventional NLP features, such as morphological features. Word embeddings seem to be a better choice. Therefore, I used word2vec model as discussed in Section 4 as the input.

6.3 Network Structure and Implementation

The implementation includes adding three layers in keras model building to construct the network:

1. Embedding Layer: applying word2vec and transform the tokens into a real valued vector with a fixed length.
2. Bidirectional LSTM layer
3. Fully Connected Layer: a simple output layer using softmax to convert the vector to probability values for each tagging (similar as the output layer of word2vec network).

The structure is illustrated in Figure 9, in Aneesh's Github repository documentation [1].

Note that since all the sentences are not of the same length, it creates a lot of variability and creates a staggered matrix/tensor which isnt good for fast training in the TensorFlow paradigm. Therefore, Aneesh padded all the words with zeros in the beginning to make all the sentences have the same dimension and for sentences of length longer than 100, we just simply truncated the sentence and discard the tokens after 100.

The code for implementing the structure depicted in Figure 9 is extremely simple in keras. The sample code is attached as follows:

```
embedding_layer = Embedding(len(word2int) + 1,
                            EMBEDDING_DIM,
                            weights=[embedding_matrix],
                            input_length=MAX_SEQUENCE_LENGTH,
                            trainable=True)

sequence_input = Input(shape=(MAX_SEQUENCE_LENGTH,), dtype='int32')

embedded_sequences = embedding_layer(sequence_input)

l_lstm = Bidirectional(LSTM(64,
                      return_sequences=True))(embedded_sequences)

preds = TimeDistributed(Dense(len(tag2int) + 1, activation='softmax'))(l_lstm)

model = Model(sequence_input, preds)
model.compile(loss='categorical_crossentropy',
              optimizer='rmsprop',
              metrics=['acc'])
```

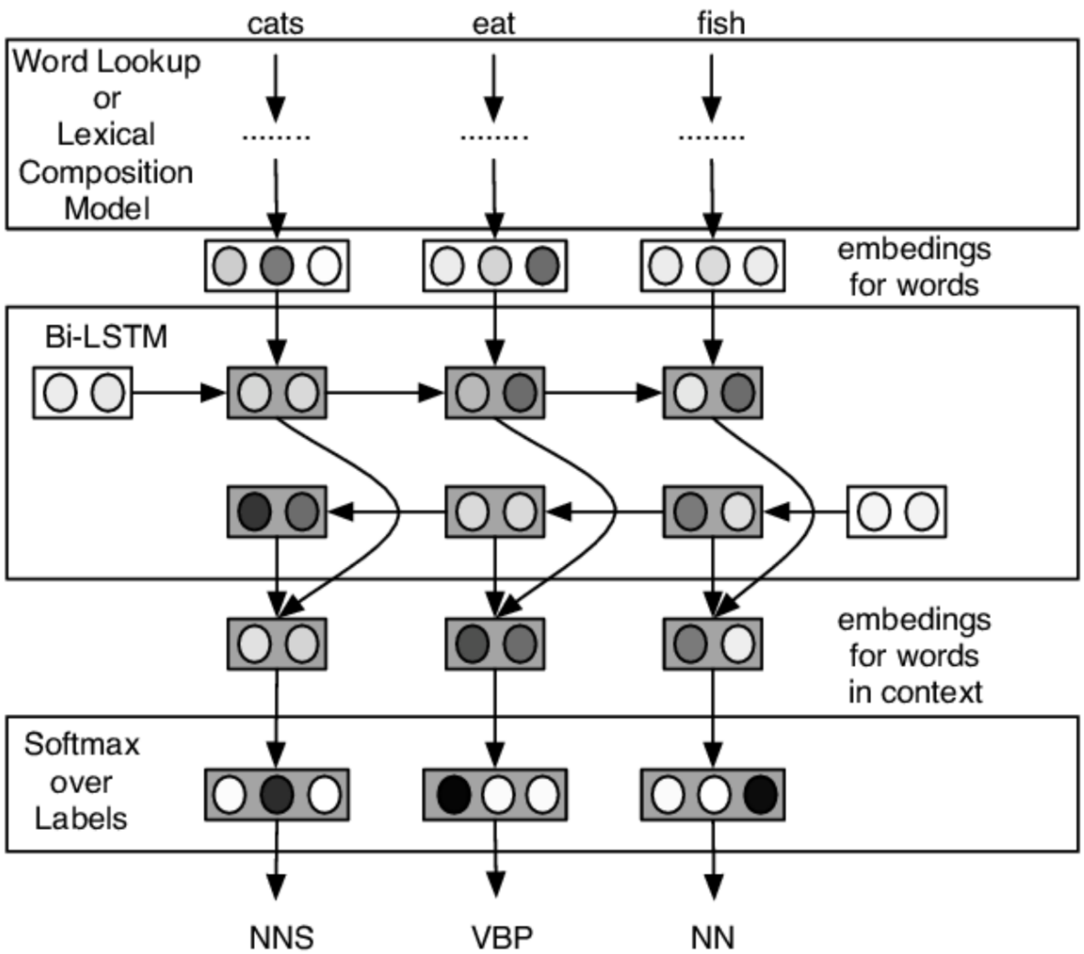
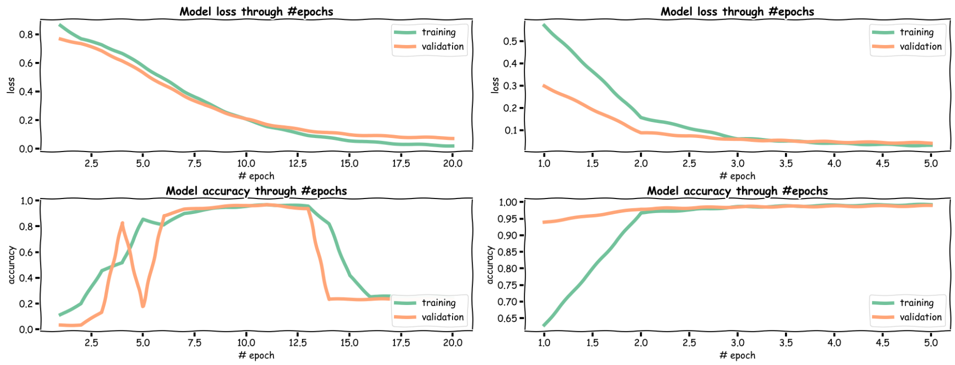


Figure 9: Structure of the Network
[1]

6.4 Results

The discussed BILSTM RNN structure is implemented in keras with TensorFlow backend. Again, the model is applied to the smaller Treebank corpus and the larger Brown corpus. Across the task, 60% of the data is used as training, with 20% validation and 20% testing. The model performance are displayed in Figure 10 with the detailed network model summarized in Figure 11

For the Treebank corpus, the model performance shows that the model



(a) Treebank corpus

(b) Brown corpus

Figure 10: Model Performance with Word2vec Embeddings and BI-LSTM RNN

```
model fitting - Bidirectional LSTM
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         (None, 100)               0
_________________________________________________________________
embedding_1 (Embedding)      (None, 100, 300)          3722700
_________________________________________________________________
bidirectional_1 (Bidirection (None, 100, 128)          186880
_________________________________________________________________
time_distributed_1 (TimeDist (None, 100, 47)           6063
=================================================================
Total params: 3,915,643
Trainable params: 3,915,643
Non-trainable params: 0
_________________________________________________________________
Train on 2348 samples, validate on 783 samples
```

(a) Treebank corpus

```
model fitting - Bidirectional LSTM
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         (None, 100)               0
_________________________________________________________________
embedding_1 (Embedding)      (None, 100, 300)          16817400
_________________________________________________________________
bidirectional_1 (Bidirection (None, 100, 128)          186880
_________________________________________________________________
time_distributed_1 (TimeDist (None, 100, 473)          61017
=================================================================
Total params: 17,065,297
Trainable params: 17,065,297
Non-trainable params: 0
_________________________________________________________________
Train on 34404 samples, validate on 11468 samples
```

(b) Brown corpus

Figure 11: Model Used with Word2vec Embeddings and BI-LSTM RNN

is underfitting before epoch 7 and overfitting after epoch 13. The accuracy on final test set, after stopping at the 13th epoch, is 97.31%.

For Brown corpus, the model performance looks more stable in terms of training and validation accuracy over epochs. The accuracy on validation sets is above 98% and after two epochs, the model seems to start overfitting. The final accuracy on test sets (stopped after 3 epochs) is 98.57%, which is consistent with the references: 98.79% from Aneesh [1]. Wang et al [10] showed a lower accuracy of 97.4% because they are training one one corpus and testing on another one, which requires higher generalization of the trained tagger. However, in my case, the Treebank corpus (46 different tags) and the Brown corpus (472 different tags) have different tagging convention, therefore I keep the training and testing within one corpus thus having a higher accuracy. Accuracy over 98% on a blind test set is very impressive and demonstrates the power of deep learning techniques used including word2vec, and BI-LSTM RNN.

7 Conclusion

In this independent study, the author followed the guidance of Prof. Damir Cavar and focused on basic knowledge of deep learning and possible application to natural language processing. A good fraction of study time is distributed to read the Goodfellow's deep learning text book and try to understand different deep neural network architecture and techniques. In application, the author chose part-of-speech tagging, the very basic component in NLP and experiment using different Python libraries (Scikit-learn, TensorFlow, Keras) with both hand crafted features and self-trained word embeddings using word2vec models.

It appears that the deep learning library Keras is more efficient and flexible for designing and training complicated neural network models with large data sets. For POS tagging, hand crafted features with various machine learning algorithms could achieve accuracy around 95%. Using word embeddings from word2vec as features tend to result in low accuracy (below 70%) when trained with feedforward networks. However, using a special kind of recurrent neural network: bidirectional long-short term memory recurrent neural network, the accuracy is very high, over 97% for part of the Treebank Corpora and over 98% for the Brown Corpus.

Future research areas Due to time constraint, the author did not have enough time to experiment through many options provided by the Keras library to improve or compare different architecture. Further, other than POS tagging, deep learning techniques have been applied to many other NLP tasks. The author would like to try different deep network structures to improve accuracy in areas such as parsing, co-reference resolution, sentiment analysis and applications with knowledge graph.

Acknowledgement The author would like to thank Prof. Damir Cavar for his support and suggestions throughout the independent study and illustrations and materials regarding deep learning.

A Code Files Index

The code for this project is included in the Github repository: https://github.com/minchen57/deeplearningNLP There are several Python source code in this folder and they correspond to the following tasks mentioned in this report:

Table 4: Source Code Files

File Name	Libraries	Features	Model
POS_scikitlearn.py	Scikit-learn	hand crafted	DT, RF, NN
POS_w2v_scikitlearn.py	Scikit-learn	word2vec	DT, RF,NN
POS_keras_scikitlearnwrapper.py	Keras, Scikit-learn	hand crafted	DT, RF, NN)
POS_keras.py—	Keras	hand crafted	NN
POS_w2v_keras.py	Keras	word2vec	NN
POS_LSTM_keras_w2v.py	Keras	word2vec	BI-LSTM RNN

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