POS LSTM

April 15, 2020

1 Introduction

1.0.1 Due April 17th, 23:59

In this homework you will be implementing a LSTM model for POS tagging.

You are given the following files: - POS_NEMM.ipynb: Notebook file for NEMM model (Optional) - POS_LTML.ipynb: Notebook file for MTML model - train.txt: Training set to train your model - test.txt: Test set to report your model's performance - tags.csv: Treebank tag universe - sample_prediction.csv: Sample file your prediction result should look like - utils/: folder containing all utility code for the series of homeworks

1.0.2 Deliverables (zip them all)

- pdf or html version of your final notebook
- Use the best model you trained, generate the prediction for test.txt, name the output file prediction.csv (Be careful: the best model in your training set might not be the best model for the test set).
- writeup.pdf: summarize the method you used and report their performance. If you worked on the optional task, add the discussion. Add a short essay discussing the biggest challenges you encounter during this assignment and what you have learnt.

(You are encouraged to add the writeup doc into your notebook using markdown/html langauge, just like how this notes is prepared)

HW05 Write up

POS LSTM

This part is fairly straightforward mostly because the framework has already been done by the instructor.

The architechure is simple, just use two bidirectional LSTMs with 100 units, it already has a high prediction power.

The LSTM predicts a ignore_accuracy: 0.9627 sentence_accuracy: 0.5611 val_ignore_accuracy: 0.9451 val_sentence_accuracy: 0.4566

It can get 95% more of the tokens POS right and half of the whole sentence correct.

Optional POS MEMM

This part requires more coding and algorithm knowledge, so more challenging.

I spend few hours on the viter i algorithm implementation, and I think I learnt more about the dynamics programming

and I also found it is not only used in the POS tagging, but also a lot of other areas like DNA sequencing, also,

this notebook problem is not "hidden", it is pretty extensible to Hidden Markov Model, just adding another

probability matrix.

The training of MEMM takes a lot of time and it actually does not do as well as the LSTM one. It only uses

information in the context but not the whole history, and it is not optimized for speed.

2 Load data

```
In [1]: %load_ext autoreload
       %autoreload 2
       %matplotlib inline
       import os
       import sys
       import pandas as pd
       import numpy as np
       from sklearn.model_selection import train_test_split
       from scipy import sparse
       # add utils folder to path
       p = os.path.dirname(os.getcwd())
       if p not in sys.path:
           sys.path = [p] + sys.path
       from utils.hw5 import load_data, save_prediction, ignore_class_accuracy,
       whole_sentence_accuracy
       from utils.general import show_keras_model
Using TensorFlow backend.
/usr/local/lib/python3.6/site-packages/tensorflow/python/framework/dtypes.py:516:
FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a
future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint8 = np.dtype([("qint8", np.int8, 1)])
/usr/local/lib/python3.6/site-packages/tensorflow/python/framework/dtypes.py:517:
FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a
future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint8 = np.dtype([("quint8", np.uint8, 1)])
/usr/local/lib/python3.6/site-packages/tensorflow/python/framework/dtypes.py:518:
FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a
future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint16 = np.dtype([("qint16", np.int16, 1)])
/usr/local/lib/python3.6/site-packages/tensorflow/python/framework/dtypes.py:519:
FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a
future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  np quint16 = np.dtype([("quint16", np.uint16, 1)])
/usr/local/lib/python3.6/site-packages/tensorflow/python/framework/dtypes.py:520:
FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a
future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
```

```
_np_qint32 = np.dtype([("qint32", np.int32, 1)])
/usr/local/lib/python3.6/site-packages/tensorflow/python/framework/dtypes.py:525:
FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a
future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
 np_resource = np.dtype([("resource", np.ubyte, 1)])
/usr/local/lib/python3.6/site-
packages/tensorboard/compat/tensorflow_stub/dtypes.py:541: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy,
it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint8 = np.dtype([("qint8", np.int8, 1)])
/usr/local/lib/python3.6/site-
packages/tensorboard/compat/tensorflow_stub/dtypes.py:542: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy,
it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint8 = np.dtype([("quint8", np.uint8, 1)])
/usr/local/lib/python3.6/site-
packages/tensorboard/compat/tensorflow_stub/dtypes.py:543: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy,
it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint16 = np.dtype([("qint16", np.int16, 1)])
/usr/local/lib/python3.6/site-
packages/tensorboard/compat/tensorflow_stub/dtypes.py:544: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy,
it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint16 = np.dtype([("quint16", np.uint16, 1)])
/usr/local/lib/python3.6/site-
packages/tensorboard/compat/tensorflow_stub/dtypes.py:545: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy,
it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint32 = np.dtype([("qint32", np.int32, 1)])
/usr/local/lib/python3.6/site-
packages/tensorboard/compat/tensorflow stub/dtypes.py:550: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy,
it will be understood as (type, (1,)) / '(1,)type'.
 np_resource = np.dtype([("resource", np.ubyte, 1)])
tags is a dictionary that maps the Treebank tag to its numerical encoding. There are 45 tags in
total, plus a special tag START (tags[-1]) to indicate the beginning of a sentence.
In [2]: tags = list(pd.read_csv('tags.csv', index_col=0).tag_encode.keys())
       train, train_label = load_data("train.txt")
       train, dev, train_label, dev_label = train_test_split(train, train_label)
       test, _ = load_data("test.txt")
       print("Training set: %d" % len(train))
       print("Dev set: %d" % len(dev))
       print("Testing set: %d" % len(test))
Training set: 33539
Dev set: 11180
Testing set: 9955
```

3 LSTM

```
In [3]: from collections import Counter
    from keras.preprocessing.sequence import pad_sequences
```

```
from keras.models import Sequential
from keras.layers import Dense, LSTM, InputLayer, Bidirectional, TimeDistributed,
Embedding, Activation
from keras.optimizers import Adam
from keras.utils import to_categorical
class POS_LSTMM:
    To help you focus on the LSTM model, I have made most part of the code ready, make
    read all the parts to understand how the code works. You only need to modify the
prepare method
    to add the RNN model.
    def __init__(self, tag_vocab=tags, max_sent_len=40,
                 voc_min_freq=5, **kwargs):
        input:
            tag vocab: tag dictionary, you will less likely need to change this
            voc_min_freq: use this to truncate low frequency vocabulary
            max_sent_len: truncate/pad all sentences to this length
            kwarqs: Use as needed to pass extra parameters
        self.vocab = []
        self.reverse_vocab = {}
        self.tag_vocab = tag_vocab
        self.reverse_tag_vocab = {k:v for v, k in enumerate(tag_vocab)}
        self._voc_min_freq = voc_min_freq
        self._max_sent_len = max_sent_len
        Feel free to add code here as you need
    def collect_vocab(self, X):
        Create vocabulary from all input data
        input:
        X: list of sentences
        vocab = Counter([t for s in X for t in s])
        vocab = {k: v for k, v in vocab.items() if v > self._voc_min_freq}
        vocab = ["<PAD>", "<UNK>"] + sorted(vocab, key=lambda x: vocab[x], reverse=True)
        reverse_vocab = {k: v for v, k in enumerate(vocab)}
        return vocab, reverse_vocab
    def transform_X(self, X):
        Translate input raw data X into trainable numerical data
        X: list of sentences
        X_{out} = []
        for sent in X:
            X_out.append([self.reverse_vocab.get(t, 0) for t in sent])
        X_out = pad_sequences(sequences=X_out, maxlen=self._max_sent_len,
                              padding='post', truncating='post';
                              value=self.reverse_vocab['<PAD>'])
        return X_out
    def transform_Y(self, Y):
        Translate input raw data Y into trainable numerical data
```

```
input:
        y: list of list of tags
        Y_out = []
        for labs in Y:
            Y_out.append([self.reverse_tag_vocab[lab] for lab in labs])
        Y_out = pad_sequences(sequences=Y_out, maxlen=self._max_sent_len,
                              padding='post', truncating='post',
                              value=self.reverse_tag_vocab['<PAD>'])
        return Y_out
    def prepare(self, X, Y):
        input:
           X: list of sentences
            y: list of list of tags
        self.vocab, self.reverse_vocab = self.collect_vocab(X)
        X, Y = self.transform_X(X), self.transform_Y(Y)
        model = Sequential()
        Write your own model here
        Hints:
            - Rember to use embedding layer at the beginning
            - Use Bidrectional LSTM to take advantage of both direction history
        model.add(Embedding(input_dim=len(self.vocab),output_dim=100,input_length=self._
max sent len))
        model.add(Bidirectional(LSTM(100, return_sequences=True)))
        model.add(Bidirectional(LSTM(100, return_sequences=True)))
        model.add(TimeDistributed(Dense(len(self.tag_vocab),activation="softmax")))
        You can read the source code to understand how ignore\_class\_accuracy works.
        The reason of using this customized metric is because we have padded the
        data with lots of '<PAD>' tag. It's easy and useless to predict this tag, we
need
        to ignore this tag when calculate the accuracy.
        model.compile(loss='categorical_crossentropy',
                      optimizer=Adam(0.001),
                      metrics=['accuracy',
                               ignore_class_accuracy(self.reverse_tag_vocab['<PAD>']),
whole_sentence_accuracy(self.reverse_tag_vocab['<PAD>'])])
        self.model = model
        return self
    def fit(self, X, Y, batch_size=128, epochs=10):
        X, Y = self.transform_X(X), self.transform_Y(Y)
        self.model.fit(X, to_categorical(Y, num_classes=len(self.tag_vocab)),
                       batch_size=batch_size,
                       epochs=epochs, validation_split=0.2)
        return self
    def predict(self, X):
        results = []
        X_new = self.transform_X(X)
        Y_pred = self.model.predict_classes(X_new)
```

```
for i, y in enumerate(Y_pred):
    results.append(
        [self.tag_vocab[y[j]] for j in range(min(len(X[i]), len(X_new[i])))]
    )
```

return results

In [4]: lstm = POS_LSTMM().prepare(train, train_label)
 lstm.model.summary()
 show_keras_model(lstm.model)

WARNING: Logging before flag parsing goes to stderr. W0412 17:38:26.223311 4629745088 deprecation_wrapper.py:119] From /usr/local/lib/python3.6/site-packages/keras/backend/tensorflow_backend.py:74: The name tf.get_default_graph is deprecated. Please use tf.compat.v1.get_default_graph instead.

W0412 17:38:26.276912 4629745088 deprecation_wrapper.py:119] From /usr/local/lib/python3.6/site-packages/keras/backend/tensorflow_backend.py:517: The name tf.placeholder is deprecated. Please use tf.compat.v1.placeholder instead.

W0412 17:38:26.282796 4629745088 deprecation_wrapper.py:119] From /usr/local/lib/python3.6/site-packages/keras/backend/tensorflow_backend.py:4138: The name tf.random_uniform is deprecated. Please use tf.random.uniform instead.

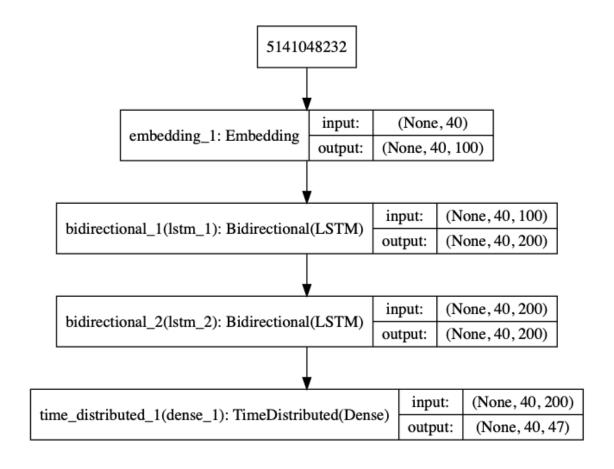
W0412 17:38:29.161601 4629745088 deprecation_wrapper.py:119] From /usr/local/lib/python3.6/site-packages/keras/optimizers.py:790: The name tf.train.Optimizer is deprecated. Please use tf.compat.v1.train.Optimizer instead.

W0412 17:38:29.186764 4629745088 deprecation_wrapper.py:119] From /usr/local/lib/python3.6/site-packages/keras/backend/tensorflow_backend.py:3295: The name tf.log is deprecated. Please use tf.math.log instead.

Layer (type)	Output Shape	Param #
embedding_1 (Embedding)	(None, 40, 100)	809100
bidirectional_1 (Bidirection	(None, 40, 200)	160800
bidirectional_2 (Bidirection	(None, 40, 200)	240800
time_distributed_1 (TimeDist	(None, 40, 47)	9447
Total params: 1,220,147		

Total params: 1,220,147 Trainable params: 1,220,147 Non-trainable params: 0

[4]:



```
In [5]: lstm = POS_LSTMM().prepare(train, train_label)
      lstm.fit(train, train_label)
W0412 17:38:38.322596 4629745088 deprecation.py:323] From
/usr/local/lib/python3.6/site-packages/tensorflow/python/ops/math_grad.py:1250:
add_dispatch_support.<locals>.wrapper (from tensorflow.python.ops.array_ops) is
deprecated and will be removed in a future version.
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where
W0412 17:38:46.296940 4629745088 deprecation_wrapper.py:119] From
/usr/local/lib/python3.6/site-packages/keras/backend/tensorflow_backend.py:986: The
name tf.assign_add is deprecated. Please use tf.compat.v1.assign_add instead.
Train on 26831 samples, validate on 6708 samples
Epoch 1/10
26831/26831 [============] - 178s 7ms/step - loss: 1.4483 - acc:
0.6135 - ignore_accuracy: 0.1679 - sentence_accuracy: 0.0059 - val_loss: 0.8909 -
val_acc: 0.7580 - val_ignore_accuracy: 0.4741 - val_sentence_accuracy: 0.0507
0.8948 - ignore_accuracy: 0.7730 - sentence_accuracy: 0.1496 - val_loss: 0.1690 -
val_acc: 0.9588 - val_ignore_accuracy: 0.9103 - val_sentence_accuracy: 0.2944
Epoch 3/10
26831/26831 [============= ] - 138s 5ms/step - loss: 0.1277 - acc:
0.9665 - ignore_accuracy: 0.9273 - sentence_accuracy: 0.3587 - val_loss: 0.1098 -
```

```
val_acc: 0.9695 - val_ignore_accuracy: 0.9336 - val_sentence_accuracy: 0.3939
Epoch 4/10
26831/26831 [============== ] - 144s 5ms/step - loss: 0.0952 - acc:
0.9724 - ignore_accuracy: 0.9402 - sentence_accuracy: 0.4201 - val_loss: 0.0943 -
val_acc: 0.9724 - val_ignore_accuracy: 0.9402 - val_sentence_accuracy: 0.4240
Epoch 5/10
0.9750 - ignore_accuracy: 0.9457 - sentence_accuracy: 0.4515 - val_loss: 0.0888 -
val_acc: 0.9736 - val_ignore_accuracy: 0.9427 - val_sentence_accuracy: 0.4366
Epoch 6/10
0.9770 - ignore_accuracy: 0.9501 - sentence_accuracy: 0.4763 - val_loss: 0.0836 -
val_acc: 0.9745 - val_ignore_accuracy: 0.9446 - val_sentence_accuracy: 0.4533
Epoch 7/10
0.9788 - ignore_accuracy: 0.9540 - sentence_accuracy: 0.4994 - val_loss: 0.0840 -
val_acc: 0.9742 - val_ignore_accuracy: 0.9441 - val_sentence_accuracy: 0.4477
0.9800 - ignore_accuracy: 0.9566 - sentence_accuracy: 0.5181 - val_loss: 0.0820 -
val_acc: 0.9748 - val_ignore_accuracy: 0.9456 - val_sentence_accuracy: 0.4539
Epoch 9/10
26831/26831 [============= ] - 132s 5ms/step - loss: 0.0580 - acc:
0.9814 - ignore_accuracy: 0.9597 - sentence_accuracy: 0.5373 - val_loss: 0.0824 -
val_acc: 0.9749 - val_ignore_accuracy: 0.9456 - val_sentence_accuracy: 0.4551
Epoch 10/10
0.9828 - ignore_accuracy: 0.9627 - sentence_accuracy: 0.5611 - val_loss: 0.0847 -
val_acc: 0.9747 - val_ignore_accuracy: 0.9451 - val_sentence_accuracy: 0.4566
```

[5]: <__main__.POS_LSTMM at 0x135f3f438>

3.1 Save your model prediction