NLP MINI PROJECT

POS Tagging using NLTK

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2018103005

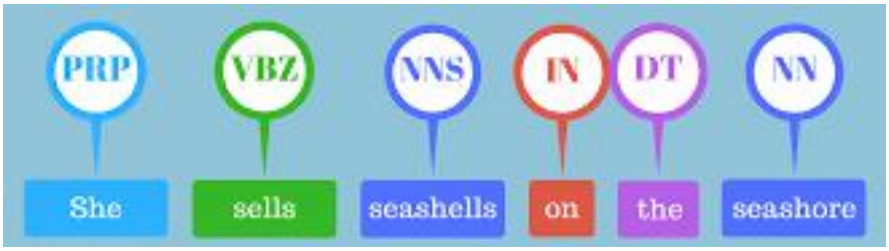
CSE - Batch-P

Introduction :

In this mini project we are going to train a Bidirectional LSTM on NLTK's treebank corpus to perform Part Of Speech tagging with high accuracy.

POS Tagging :

Part-of-speech (POS) tagging is a popular Natural Language Processing process which refers to categorizing words in a text (corpus) in correspondence with a particular part of speech, depending on the definition of the word and its context.



Part-of-speech tags describe the characteristic structure of lexical terms within a sentence or text, therefore, we can use them for making assumptions about semantics. Other applications of POS tagging include:

- Named Entity Recognition
- Co-reference Resolution
- Speech Recognition

When we perform POS tagging, it's often the case that our tagger will encounter words that were not within the vocabulary that was used. Consequently, augmenting your dataset to include unknown word tokens will aid the tagger in selecting appropriate tags for those words.

A set of all POS tags used in a corpus is called a tagset. Tagsets for different languages are typically different. They can be completely different for unrelated languages and very similar for similar languages, but this is not always the rule. Tagsets can also go to a different level of detail. Basic tagsets may only include tags for the most common parts of speech (N for noun, V for verb, A for adjective etc.). It is, however, more common to go into more detail and distinguish between nouns in singular and plural, verbal conjugations, tenses, aspect, voice and much more. Individual researchers might even develop their own very specialized tagsets to accommodate their research needs.

Module Split :

1. Preparing the dataset
2. Encoding and Padding
3. Model creation and training
4. Results

Module Explanation :

1. Preparing the dataset :

We first import nltk and make use of its 'treebank' corpus for preparing the dataset.

```
#Import nltk corpus and tag each sentence
import nltk

pos_tagged = nltk.corpus.treebank.tagged_sents()

print(pos_tagged[0])
print("Tagged sentences: ", len(pos_tagged))
print("Tagged words:", len(nltk.corpus.treebank.tagged_words()))
```

```
[1] ✓ 3.6s                                                                    Python
... [('Pierre', 'NNP'), ('Vinken', 'NNP'), (',', ','), ('61', 'CD'), ('years', 'NNS'), ('old', 'JJ'), (',', ','), ('will', 'MD'), ('join', 'VB'), ('the', 'DT'),
('board', 'NN'), ('as', 'IN'), ('a', 'DT'), ('nonexecutive', 'JJ'), ('director', 'NN'), ('Nov.', 'NNP'), ('29', 'CD'), ('.', '.')]
Tagged sentences:  3914
Tagged words: 100676
```

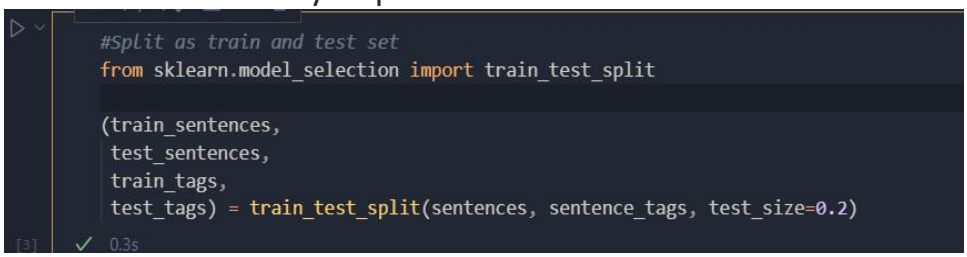
```
import numpy as np

sentences, sentence_tags =[], []
for sent in pos_tagged:
    sentence, tags = zip(*sent)
    sentences.append(np.array(sentence))
    sentence_tags.append(np.array(tags))

# Printing a Sequence
print(sentences[5])
print(sentence_tags[5])
```

```
[2] ✓ 1.3s
... ['Lorillard' 'Inc.' ',' 'the' 'unit' 'of' 'New' 'York-based' 'Loews'
 'Corp.' 'that' '*T*-2' 'makes' 'Kent' 'cigarettes' ',' 'stopped' 'using'
 'crocidolite' 'in' 'its' 'Micronite' 'cigarette' 'filters' 'in' '1956'
 '.']
['NNP' 'NNP' ',' 'DT' 'NN' 'IN' 'JJ' 'JJ' 'NNP' 'NNP' 'WDT' '-NONE-' 'VBZ'
 'NNP' 'NNS' ',' 'VBD' 'VBG' 'NN' 'IN' 'PRP$' 'NN' 'NN' 'NNS' 'IN' 'CD'
 '.']
```

Now we have a list of sentences and their corresponding POS tags in two different arrays. Split them as test and train sets.



```
#Split as train and test set
from sklearn.model_selection import train_test_split

(train_sentences,
 test_sentences,
 train_tags,
 test_tags) = train_test_split(sentences, sentence_tags, test_size=0.2)
```

```
[3] ✓ 0.3s
```

Create two dictionaries which associates each word / tag with its corresponding index. (OOV = Out of Vocabulary words)

```
#Word to index dictionary and Tag to index dictionary
words, tags = set([]), set([])

for s in train_sentences:
    for w in s:
        words.add(w.lower())

for ts in train_tags:
    for t in ts:
        tags.add(t)

w_to_i = {w: i + 2 for i, w in enumerate(list(words))}
w_to_i['-PAD-'] = 0  # The special value used for padding
w_to_i['-OOV-'] = 1  # The special value used for OOVs

t_to_i = {t: i + 1 for i, t in enumerate(list(tags))}
t_to_i['-PAD-'] = 0  # The special value used to padding
```

[4] ✓ 0.1s

2. Encoding and Padding :

After creating the dictionary we can now encode the datasets to its index values in the dictionary.

```
#Encode train and test sentences

X_train, X_test, Y_train, Y_test = [], [], [], []

for s in train_sentences:
    s_int = []
    for w in s:
        try:
            s_int.append(w_to_i[w.lower()])
        except KeyError:
            s_int.append(w_to_i['-OOV-'])

    X_train.append(s_int)

for s in test_sentences:
    s_int = []
    for w in s:
        try:
            s_int.append(w_to_i[w.lower()])
        except KeyError:
            s_int.append(w_to_i['-OOV-'])

    X_test.append(s_int)
```

```
for s in train_tags:
    Y_train.append([t_to_i[t] for t in s])

for s in test_tags:
    Y_test.append([t_to_i[t] for t in s])

print(X_train[0])
print(X_test[0])
print(Y_train[0])
print(Y_test[0])
```

✓ 0.1s

```
[7905, 8306, 8928, 5947, 10023, 5827, 466, 4181, 4926, 10023, 6444, 1300, 6528, 7696, 5597, 2207, 2876, 29, 7905, 10167, 7574, 8236]
[1826, 1, 2938, 6391, 3412, 1, 2390, 8318, 1826, 1, 6877, 7052, 8010, 3412, 1, 461, 7052, 8236]
[42, 41, 20, 6, 42, 41, 20, 46, 6, 42, 41, 20, 4, 1, 13, 21, 6, 41, 42, 41, 20, 12]
[3, 15, 27, 20, 30, 21, 27, 21, 3, 27, 6, 3, 38, 30, 21, 27, 3, 12]
```

After encoding we find the maximum length of a sentence and perform padding to make all sentences of same length.

```
MAX_LENGTH = len(max(X_train, key=len))
print(MAX_LENGTH)
```

✓ 0.4s

```
271
```

```
from keras.preprocessing.sequence import pad_sequences

X_train = pad_sequences(X_train, maxlen=MAX_LENGTH, padding='post')
X_test = pad_sequences(X_test, maxlen=MAX_LENGTH, padding='post')
Y_train = pad_sequences(Y_train, maxlen=MAX_LENGTH, padding='post')
Y_test = pad_sequences(Y_test, maxlen=MAX_LENGTH, padding='post')

print(X_train[0])
print(X_test[0])
print(Y_train[0])
print(Y_test[0])
```

✓ 10.5s

```
[ 7905  8306  8928  5947 10023  5827   466  4181  4926 10023  6444  1300
  6528  7696  5597  2207  2876    29  7905 10167  7574  8236     0     0
     0     0     0     0     0     0     0     0     0     0     0     0
     0     0     0     0     0     0     0     0     0     0     0     0
     0     0     0     0     0     0     0     0     0     0     0     0
     0     0     0     0     0     0     0     0     0     0     0     0
     0     0     0     0     0     0     0     0     0     0     0     0
     0     0     0     0     0     0     0     0     0     0     0     0
     0     0     0     0     0     0     0     0     0     0     0     0
     0     0     0     0     0     0     0     0     0     0     0     0
     0     0     0     0     0     0     0     0     0     0     0     0
```

```
[1826    1 2938 6391 3412    1 2390 8318 1826    1 6877 7052 8010 3412
    1  461 7052 8236    0    0    0    0    0    0    0    0    0    0

show more (open the raw output data in a text editor) ...

  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
  0  0  0  0  0  0  0]
```

3. Model creation and training :

Since this is a sequence processing problem, we will use a Bi-directional LSTM in our model since it is very efficient and gives good accuracy. A BiLSTM consists of two LSTMs: one taking the input in a forward direction, and the other in a backwards direction. BiLSTMs effectively increase the amount of information available to the network, improving the context available to the algorithm.

Hyperparameters :

Hyper Parameter	Value
LSTM units	256
Optimizer	Adam
Loss	Categorical Cross-Entropy
Metrics	Categorical Accuracy
Learning Rate	0.001
Activation	Softmax
Epochs	25

```
from keras.models import Sequential
from keras.layers import Dense, LSTM, InputLayer, Bidirectional, TimeDistributed, Embedding, Activation
from keras.optimizers import Adam


model = Sequential()
model.add(InputLayer(input_shape=(MAX_LENGTH, )))
model.add(Embedding(len(w_to_i), 128))
model.add(Bidirectional(LSTM(256, return_sequences=True)))
model.add(TimeDistributed(Dense(len(t_to_i))))
model.add(Activation('softmax'))

model.compile(loss='categorical_crossentropy',
              optimizer=Adam(0.001),
              metrics=['categorical_accuracy'])

model.summary()
```

[8] ✓ 2.8s

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding (Embedding)        (None, 271, 128)          1305088
_________________________________________________________________
bidirectional (Bidirectional (None, 271, 512)          788480
_________________________________________________________________
time_distributed (TimeDistri (None, 271, 47)           24111
_________________________________________________________________
activation (Activation)      (None, 271, 47)           0
=================================================================
Total params: 2,117,679
Trainable params: 2,117,679
Non-trainable params: 0
_________________________________________________________________
```

Performing one-hot encoding on the Y values:

```
def to_categorical(sequences, categories):
    cat_sequences = []
    for s in sequences:
        cats = []
        for item in s:
            cats.append(np.zeros(categories))
            cats[-1][item] = 1.0
        cat_sequences.append(cats)
    return np.array(cat_sequences)
```

[9] ✓ 0.2s

```
cat_Y_train = to_categorical(Y_train, len(t_to_i))
print(cat_Y_train[0])
```

[10] ✓ 1.6s

```
[[0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]
 ...
 [1. 0. 0. ... 0. 0. 0.]
 [1. 0. 0. ... 0. 0. 0.]
 [1. 0. 0. ... 0. 0. 0.]]
```

Training the model for 25 epochs :

```
history = model.fit(X_train, to_categorical(Y_train, len(t_to_i)), batch_size=128, epochs=25, validation_split=0.2)
```

✓ 1m 51.7s Python

```
Epoch 1/25
20/20 [==============================] - 4s 225ms/step - loss: 1.2358 - categorical_accuracy: 0.8582 - val_loss: 0.3753 - val_categorical_accuracy: 0.9070
Epoch 2/25
20/20 [==============================] - 4s 198ms/step - loss: 0.3350 - categorical_accuracy: 0.9069 - val_loss: 0.3224 - val_categorical_accuracy: 0.9042
Epoch 3/25
20/20 [==============================] - 4s 196ms/step - loss: 0.3148 - categorical_accuracy: 0.9090 - val_loss: 0.3107 - val_categorical_accuracy: 0.9164
Epoch 4/25
20/20 [==============================] - 4s 196ms/step - loss: 0.3045 - categorical_accuracy: 0.9170 - val_loss: 0.3021 - val_categorical_accuracy: 0.9168
Epoch 5/25
20/20 [==============================] - 4s 197ms/step - loss: 0.2966 - categorical_accuracy: 0.9171 - val_loss: 0.2947 - val_categorical_accuracy: 0.9167
Epoch 6/25
20/20 [==============================] - 4s 198ms/step - loss: 0.2886 - categorical_accuracy: 0.9173 - val_loss: 0.2871 - val_categorical_accuracy: 0.9183
Epoch 7/25
```

```
show more (open the raw output data in a text editor) ...
20/20 [==============================] - 4s 212ms/step - loss: 0.0461 - categorical_accuracy: 0.9911 - val_loss: 0.0585 - val_categorical_accuracy: 0.9867
Epoch 24/25
20/20 [==============================] - 4s 211ms/step - loss: 0.0382 - categorical_accuracy: 0.9927 - val_loss: 0.0529 - val_categorical_accuracy: 0.9878
Epoch 25/25
20/20 [==============================] - 4s 211ms/step - loss: 0.0322 - categorical_accuracy: 0.9938 - val_loss: 0.0488 - val_categorical_accuracy: 0.9886
```

4. Results :

After successfully training the model we get a final accuracy of 98.89 %

```
scores = model.evaluate(X_test, to_categorical(Y_test, len(t_to_i)))
print(f"{model.metrics_names[1]}: {scores[1] * 100}")
```

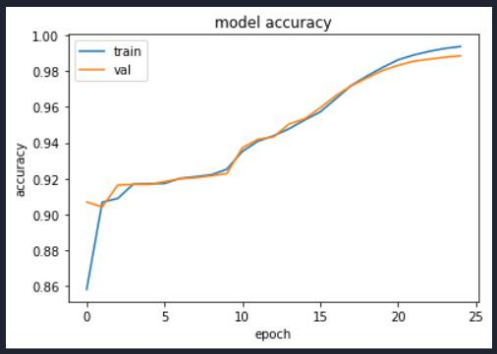
[18] ✓ 1.5s

```
25/25 [==============================] - 1s 27ms/step - loss: 0.0480 - categorical_accuracy: 0.9889
categorical_accuracy: 98.89251589775085
```

Accuracy and Loss plot :

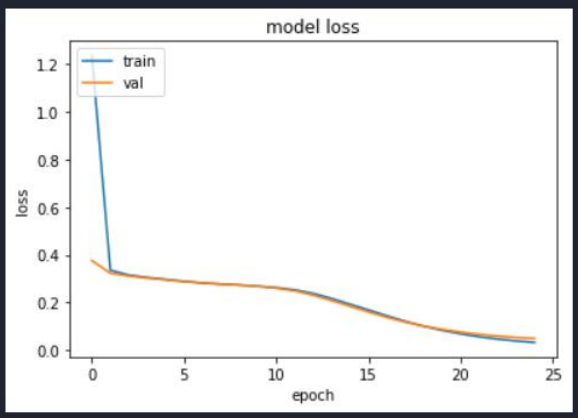
```
from matplotlib import pyplot as plt
plt.plot(history.history['categorical_accuracy'])
plt.plot(history.history['val_categorical_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='upper left')
plt.show()
```

[16] ✓ 0.2s




```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='upper left')
plt.show()
```

[17] ✓ 0.1s



Testing the model on custom input :

```
test_samples = [
    "The food is really good .".split(),
    "We will eat today .".split()
]
print(test_samples)
```

[61] ✓ 0.3s

```
[['The', 'food', 'is', 'really', 'good', '.'], ['We', 'will', 'eat', 'today', '.']]
```

```
test_samples_X = []
for s in test_samples:
    s_int = []
    for w in s:
        try:
            s_int.append(w_to_i[w.lower()])
        except KeyError:
            s_int.append(w_to_i['-OOV-'])
    test_samples_X.append(s_int)

test_samples_X = pad_sequences(test_samples_X, maxlen=MAX_LENGTH, padding='post')
print(test_samples_X)
```

[62] ✓ 0.6s

```
predictions = model.predict(test_samples_X)
print(predictions, predictions.shape)
```

[63] ✓ 0.3s

```
[[[7.83455289e-06 1.30391697e-06 1.84788700e-08 ... 1.98012776e-06
   2.87363264e-06 3.43013426e-07]
  [5.77143946e-05 1.04593906e-04 3.26638343e-03 ... 2.14479132e-06
   6.87002830e-05 3.51357194e-05]
  [1.18854325e-04 1.09395257e-03 1.32058412e-02 ... 4.99920025e-05
   6.96663558e-03 8.60003471e-01]
  ...
  [9.99962568e-01 1.04540702e-10 3.30660470e-07 ... 1.02411306e-08
   5.83800706e-08 2.66582734e-09]
  [9.99938369e-01 1.32127212e-10 2.85692835e-07 ... 2.12502442e-08
   6.79524206e-08 4.37604486e-09]
```

Since the predictions are in numerical values we define a function to convert them into their original values.

```
def original_val(sequences, index):
    token_sequences = []
    for categorical_sequence in sequences:
        token_sequence = []
        for categorical in categorical_sequence:
            token_sequence.append(index[np.argmax(categorical)])

        token_sequences.append(token_sequence)

    return token_sequences
```

✓ 0.4s

```
print(original_val(predictions, {i: t for t, i in t_to_i.items()}))
```

✓ 0.4s

Result for **“The food is really good”** :

```
[['DT', 'NN', 'VBZ', 'RB', 'JJ', '.', '-PAD-'
'-PAD-', '-PAD-', '-PAD-', '-PAD-', '-PAD-',
PAD-', '-PAD-', '-PAD-', '-PAD-', '-PAD-', '-
PAD-', '-PAD-', '-PAD-', '-PAD-', '-PAD-', '-
```

Result for **“We will eat today”** :

```
['PRP', 'MD', 'VB', 'NN', '.',
 '-PAD-', '-PAD-', '-PAD-', '-
'-PAD-', '-PAD-', '-PAD-', '-
'-PAD-', '-PAD-', '-PAD-', '-
```

-PAD- stands for padding values (0) which can be ignored.