```
import numpy as np
import pandas as pd
from sklearn.model_selection import GroupShuffleSplit
from hmmlearn import hmm
from sklearn.metrics import confusion_matrix, classification_report,__
accuracy_score, precision_score, recall_score, f1_score, roc_auc_score
```

### 0.0.3 Loading Data

```
[35]: data = pd.read_csv("ner_data.csv", encoding='latin1')
  data.head()
```

```
[35]:
          Sentence #
                                Word POS Tag
      0 Sentence: 1
                           Thousands NNS
      1
                 NaN
                                  of
                                       IN
      2
                 NaN
                     demonstrators NNS
      3
                 {\tt NaN}
                                have VBP
                                            0
                            marched VBN
                 NaN
                                            U
```

## 0.0.4 Data Cleaning

```
[36]: data = data.fillna(method="ffill")
data = data.rename(columns={'Sentence #': 'sentence'})
data.head(5)
```

```
[36]:
           sentence
                              Word POS Tag
     O Sentence: 1
                         Thousands
                                   NNS
     1 Sentence: 1
                               of
                                    IN
                                         0
     2 Sentence: 1 demonstrators NNS
                                         0
     3 Sentence: 1
                              have VBP
                                         0
     4 Sentence: 1
                          marched VBN
```

```
[38]: ' '.join(data[data['sentence'] == 'Sentence: 1'].Word.tolist())
```

[38]: 'Thousands of demonstrators have marched through London to protest the war in Iraq and demand the withdrawal of British troops from that country .'

```
[39]: tags = list(set(data.Tag.values))
words = list(set(data.Word.values))
```

```
[41]: print(f"Total Tags: {len(tags)}")
print()
print(tags)
```

Total Tags: 17

```
['O', 'I-geo', 'I-per', 'I-eve', 'B-gpe', 'B-art', 'B-per', 'I-gpe', 'I-nat', 'B-eve', 'I-org', 'I-tim', 'B-geo', 'I-art', 'B-org', 'B-nat', 'B-tim']
```

# 0.0.5 Data Preparation

We cannot split data normally with train\_test\_split because doing that makes some parts of a sentence in the training set while some others in the testing set. Instead, we use GroupShuffleSplit.

```
[42]: y = data.Tag
X = data.drop('Tag', axis=1)
```

```
[43]: gs = GroupShuffleSplit(n_splits=2, test_size=.33, random_state=42) train_ix, test_ix = next(gs.split(X, y, groups=data['sentence']))
```

```
[44]: data_train = data.loc[train_ix] data_test = data.loc[test_ix]
```

```
[45]: data_train
```

```
[45]:
                      sentence
                                     Word POS Tag
      24
                   Sentence: 2
                                 Families NNS
                                                  0
                   Sentence: 2
      25
                                       of
                                            ΙN
                                                  0
                   Sentence: 2
                                 soldiers NNS
                                                  0
      26
      27
                   Sentence: 2
                                   killed VBN
                                                  0
      28
                   Sentence: 2
                                       in
                                            IN
                                                  0
                                        . .
                                  ... ...
      1048570 Sentence: 47959
                                     they PRP
                                                  0
      1048571 Sentence: 47959
                                responded VBD
                                                  0
      1048572 Sentence: 47959
                                                  0
                                       to
                                            TO
      1048573 Sentence: 47959
                                       the
                                            DT
                                                  0
      1048574 Sentence: 47959
                                            NN
                                                  0
                                   attack
```

[702936 rows x 4 columns]

```
[46]: tags = list(set(data_train.Tag.values))
words = list(set(data_train.Word.values))
```

```
[47]: dfupdate = data_train.sample(frac=.15, replace=False, random_state=42) dfupdate.Word = 'UNKNOWN' data_train.update(dfupdate)
```

```
[48]: words = list(set(data_train.Word.values))
word2id = {w: i for i, w in enumerate(words)}
tag2id = {t: i for i, t in enumerate(tags)}
id2tag = {i: t for i, t in enumerate(tags)}
```

#### 0.0.6 Model Parameter Estimation

Hidden Markov Models can be trained by using the Baum-Welch algorithm. - startprob\_ - transmat\_ - emissionprob\_

```
[49]: count_tags = dict(data_train.Tag.value_counts())
count_tags_to_words = data_train.groupby(['Tag']).apply(lambda grp: grp.

→groupby('Word')['Tag'].count().to_dict())
count_init_tags = dict(data_train.groupby('sentence').first().Tag.

→value_counts())
```

```
[50]: count_tags_to_next_tags = np.zeros((len(tags), len(tags)), dtype=int)
    sentences = list(data_train.sentence)
    pos = list(data_train.Tag)
    for i in range(len(sentences)) :
        if (i > 0) and (sentences[i] == sentences[i - 1]):
            prevtagid = tag2id[pos[i - 1]]
            nexttagid = tag2id[pos[i]]
            count_tags_to_next_tags[prevtagid][nexttagid] += 1
```

#### Calculating Probablites

```
[52]: mystartprob
[52]: array([7.16419768e-01, 0.00000000e+00, 0.0000000e+00, 0.0000000e+00,
            6.27100710e-02, 3.42337856e-04, 8.25967882e-02, 0.00000000e+00,
            0.00000000e+00, 2.48972986e-04, 0.00000000e+00, 0.00000000e+00,
            6.89966389e-02, 0.00000000e+00, 5.80418275e-02, 2.17851363e-04,
             1.04257438e-021)
[53]: mytransmat
[53]: array([[8.89746990e-01, 0.00000000e+00, 0.0000000e+00, 0.0000000e+00,
             1.48244413e-02, 4.33193256e-04, 1.28715209e-02, 0.00000000e+00,
             0.00000000e+00, 3.00039591e-04, 0.00000000e+00, 0.00000000e+00,
             4.03011758e-02, 0.00000000e+00, 1.93978259e-02, 2.20147392e-04,
             2.19046655e-02],
             [8.70028124e-01, 1.05062274e-01, 0.00000000e+00, 0.00000000e+00,
             4.01767778e-04, 2.00883889e-04, 3.01325834e-03, 0.00000000e+00,
             0.0000000e+00, 0.0000000e+00, 0.0000000e+00, 0.0000000e+00,
             0.00000000e+00, 0.00000000e+00, 1.80795500e-03, 0.00000000e+00,
             1.94857372e-02],
             [7.18293954e-01, 0.00000000e+00, 2.71195274e-01, 0.00000000e+00,
             0.0000000e+00, 0.0000000e+00, 0.0000000e+00, 0.0000000e+00,
             0.0000000e+00, 0.0000000e+00, 0.0000000e+00, 0.0000000e+00,
             8.68658791e-05, 0.00000000e+00, 6.94927033e-04, 0.00000000e+00,
             9.72897846e-03],
             [6.95121951e-01, 0.00000000e+00, 0.0000000e+00, 2.92682927e-01,
             0.0000000e+00, 0.0000000e+00, 0.0000000e+00, 0.0000000e+00,
             0.0000000e+00, 0.0000000e+00, 0.0000000e+00, 0.0000000e+00,
             0.0000000e+00, 0.0000000e+00, 0.0000000e+00, 0.0000000e+00,
             1.21951220e-021.
             [8.69222097e-01, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
             0.00000000e+00, 9.39496430e-05, 8.25817362e-02, 1.28711011e-02,
             0.0000000e+00, 0.0000000e+00, 0.0000000e+00, 0.0000000e+00,
             7.70387073e-03, 0.00000000e+00, 2.57422022e-02, 0.00000000e+00,
             1.78504322e-03],
             [5.54716981e-01, 0.00000000e+00, 0.0000000e+00, 0.0000000e+00,
             0.00000000e+00, 0.00000000e+00, 3.77358491e-03, 0.00000000e+00,
             0.0000000e+00, 0.0000000e+00, 0.0000000e+00, 0.0000000e+00,
             0.00000000e+00, 4.11320755e-01, 1.13207547e-02, 0.00000000e+00,
             1.88679245e-02],
             [2.18449599e-01, 0.00000000e+00, 7.40717876e-01, 0.00000000e+00,
             3.35126554e-03, 0.00000000e+00, 0.0000000e+00, 0.00000000e+00,
             0.0000000e+00, 0.0000000e+00, 0.0000000e+00, 0.0000000e+00,
             1.47279302e-02, 0.00000000e+00, 2.01957845e-02, 8.81911985e-05,
```

mytransmat[tagid][tagid2] = count\_tags\_to\_next\_tags[tagid][tagid2] /\_\_

¬sum\_tags\_to\_next\_tags[tagid]

```
2.46935356e-03],
[8.74125874e-01, 0.00000000e+00, 0.0000000e+00, 0.0000000e+00,
0.00000000e+00, 0.00000000e+00, 7.69230769e-02, 4.19580420e-02,
0.0000000e+00, 0.0000000e+00, 0.0000000e+00, 0.0000000e+00,
6.99300699e-03, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
0.00000000e+00],
[9.00000000e-01, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
0.00000000e+00, 0.00000000e+00, 3.3333333e-02, 0.00000000e+00,
6.6666667e-02, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
0.0000000e+00, 0.0000000e+00, 0.0000000e+00, 0.0000000e+00,
0.0000000e+001.
[4.06091371e-01, 0.00000000e+00, 0.0000000e+00, 5.88832487e-01,
0.0000000e+00, 0.0000000e+00, 0.0000000e+00, 0.0000000e+00,
0.0000000e+00, 0.0000000e+00, 0.0000000e+00, 0.0000000e+00,
0.0000000e+00, 0.0000000e+00, 0.0000000e+00, 0.0000000e+00,
5.07614213e-03],
[5.27861848e-01, 0.00000000e+00, 0.0000000e+00, 0.0000000e+00,
2.49243368e-03, 0.00000000e+00, 1.98504540e-02, 0.00000000e+00,
0.00000000e+00, 0.00000000e+00, 4.32971337e-01, 0.00000000e+00,
1.42424782e-03, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
1.53996795e-02],
[6.90530131e-01, 0.00000000e+00, 0.0000000e+00, 0.0000000e+00,
1.58586316e-03, 0.00000000e+00, 2.49207068e-03, 0.00000000e+00,
0.00000000e+00, 1.58586316e-03, 0.00000000e+00, 2.94517444e-01,
7.92931581e-03, 0.00000000e+00, 1.35931128e-03, 0.00000000e+00,
0.00000000e+001.
[7.94497229e-01, 1.76484561e-01, 0.00000000e+00, 0.00000000e+00,
4.15676960e-03, 0.00000000e+00, 2.85035629e-03, 0.00000000e+00,
0.0000000e+00, 3.95882819e-05, 0.0000000e+00, 0.0000000e+00,
0.00000000e+00, 0.00000000e+00, 1.38558987e-03, 0.00000000e+00,
2.05859066e-02],
[6.06936416e-01, 0.00000000e+00, 0.0000000e+00, 0.0000000e+00,
0.00000000e+00, 0.00000000e+00, 1.15606936e-02, 0.00000000e+00,
0.0000000e+00, 0.0000000e+00, 0.0000000e+00, 0.0000000e+00,
0.00000000e+00, 3.69942197e-01, 0.00000000e+00, 0.00000000e+00,
1.15606936e-02],
[4.97683109e-01, 0.00000000e+00, 0.0000000e+00, 0.0000000e+00,
5.68011958e-03, 3.73692078e-04, 1.49476831e-02, 0.00000000e+00,
0.00000000e+00, 1.49476831e-04, 4.76457399e-01, 0.00000000e+00,
8.96860987e-04, 0.00000000e+00, 0.0000000e+00, 0.0000000e+00,
3.81165919e-03],
[7.80303030e-01, 0.00000000e+00, 0.0000000e+00, 0.0000000e+00,
0.0000000e+00, 0.0000000e+00, 0.0000000e+00, 0.0000000e+00,
2.12121212e-01, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
7.57575758e-03, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
0.00000000e+00],
[7.61915205e-01, 0.00000000e+00, 0.0000000e+00, 0.0000000e+00,
```

```
1.68128655e-03, 2.19298246e-04, 1.60818713e-03, 0.00000000e+00,
              0.00000000e+00, 7.30994152e-04, 0.00000000e+00, 2.27923977e-01,
              4.02046784e-03, 0.00000000e+00, 1.90058480e-03, 0.00000000e+00,
              0.0000000e+00]])
[54]: myemissionprob
[54]: array([[0.00000000e+00, 0.00000000e+00, 1.67972090e-06, ...,
              0.00000000e+00, 0.00000000e+00, 0.00000000e+00],
             [0.0000000e+00, 0.0000000e+00, 0.0000000e+00, ...,
              0.00000000e+00, 0.00000000e+00, 0.0000000e+00],
             [0.00000000e+00, 8.67980210e-05, 0.00000000e+00, ...,
              0.00000000e+00, 0.00000000e+00, 0.00000000e+00],
             [0.0000000e+00, 0.0000000e+00, 0.0000000e+00, ...,
             0.0000000e+00, 0.0000000e+00, 0.0000000e+00],
             [0.00000000e+00, 0.00000000e+00, 0.00000000e+00, ...,
              0.00000000e+00, 0.00000000e+00, 0.0000000e+00],
             [4.38500329e-04, 0.00000000e+00, 0.00000000e+00, ...,
              0.0000000e+00, 0.0000000e+00, 0.0000000e+00]])
     0.0.7 HMM
[55]: model = hmm.MultinomialHMM(n_components=len(tags), algorithm='viterbi',
       ⇒random state=42)
      model.startprob_ = mystartprob
      model.transmat_ = mytransmat
      model.emissionprob_ = myemissionprob
[56]: data_test.loc[~data_test['Word'].isin(words), 'Word'] = 'UNKNOWN'
[57]: word_test = list(data_test.Word)
      samples = []
      for i, val in enumerate(word_test):
          samples.append([word2id[val]])
[58]: len(samples)
[58]: 345639
[59]: lengths = []
      count = 0
      sentences = list(data_test.sentence)
      for i in range(len(sentences)) :
          if (i > 0) and (sentences[i] == sentences[i - 1]):
              count += 1
          elif i > 0:
```

```
lengths.append(count)
              count = 1
          else:
              count = 1
[60]: len(lengths)
[60]: 15826
     0.0.8 HMM - Prediction
[61]: ner_predict = model.predict(samples, lengths)
[62]: ner_predict
[62]: array([ 0, 0, ..., 12, 0, 0], dtype=int32)
     0.0.9 Testing
[64]: def reportTest(y_pred, y_test):
          print("The accuracy is {}".format(accuracy_score(y_test, y_pred)))
          print("The precision is {}".format(precision_score(y_test, y_pred,_
       ⇔average='weighted')))
          print("The recall is {}".format(recall_score(y_test, y_pred,__
       ⇔average='weighted')))
          print("The F1-Score is {}".format(f1_score(y_test, y_pred,__
       ⇔average='weighted')))
      min_length = min(len(pos_predict), len(pos_test))
      reportTest(pos_predict[:min_length], pos_test[:min_length])
     The accuracy is 0.9560956555705048
     The precision is 0.9544313510538452
     The recall is 0.9560956555705048
     The F1-Score is 0.9547968981401819
```