```
# Importing libraries
import nltk
import numpy as np
import pandas as pd
import random
from sklearn.model selection import train test split
import pprint, time
#download the treebank corpus from nltk
nltk.download('treebank')
#download the universal tagset from nltk
nltk.download('universal tagset')
# reading the Treebank tagged sentences
nltk_data = list(nltk.corpus.treebank.tagged_sents(tagset='universal'))
#print the first two sentences along with tags
print(nltk_data[:2])
      [nltk data] Downloading package treebank to /root/nltk data...
      [nltk data] Unzipping corpora/treebank.zip.
      [nltk_data] Downloading package universal_tagset to /root/nltk_data...
      [nltk_data] Unzipping taggers/universal_tagset.zip.
[[('Pierre', 'NOUN'), ('Vinken', 'NOUN'), (',', '.'), ('61', 'NUM'), ('years', 'NOUN'), ('old', 'ADJ'), (',', '.'), ('will', 'VERB')
#print each word with its respective tag for first two sentences
for sent in nltk_data[:2]:
  for tuple in sent:
    print(tuple)
      ('Pierre', 'NOUN')
('Vinken', 'NOUN')
      (',', '.')
('61', 'NUM')
      ('years', 'NOUN')
('old', 'ADJ')
(',',',')
      ('will', 'VERB')
('join', 'VERB')
('the', 'DET')
      ('board', 'NOUN')
      ('as', 'ADP')
('a', 'DET')
      ('nonexecutive', 'ADJ')
      ('director', 'NOUN')
      ('Nov.', 'NOUN')
('29', 'NUM')
('.', '.')
('Mr.', 'NOUN')
      ('Vinken', 'NOUN')
       'is', 'VERB')
      ('chairman', 'NOUN')
      ('of', 'ADP')
('Elsevier', 'NOUN')
      ('N.V.', 'NOUN')
(',',',')
('the', 'DET')
('Dutch', 'NOUN')
      ('publishing', 'VERB')
      ('group', 'NOUN')
# split data into training and validation set in the ratio 80:20
train_set,test_set =train_test_split(nltk_data,train_size=0.80, test_size=0.20, random_state= 101)
# create list of train and test tagged words
train_tagged_words = [tup for sent in train_set for tup in sent ]
test_tagged_words = [tup for sent in test_set for tup in sent ]
print(len(train_tagged_words))
print(len(test_tagged_words))
      80310
      20366
train_tagged_words[:5]
      [('Drink', 'NOUN'),
 ('Carrier', 'NOUN'),
 ('Competes', 'VERB'),
       ('With', 'ADP'),
       ('Cartons', 'NOUN')]
tags = {tag for word, tag in train_tagged_words}
print(len(tags))
print(tags)
```

```
vocab= {word tor word , tag in train_tagged_words}
     {'.', 'PRT', 'ADP', 'PRON', 'NOUN', 'ADV', 'X', 'CONJ', 'VERB', 'DET', 'NUM', 'ADJ'}
#compute Emission Probability
def word_given_tag(word, tag, train_bag = train_tagged_words):
 tag_list = [pair for pair in train_bag if pair[1]==tag]
 count_tag = len(tag_list)#total number of times the passed tag occurred in train_bag
 w_given_tag_list= [pair[0] for pair in tag_list if pair[0]==word]
#now calculate the total number of times the passed word occurred as the passed tag.
 count_w_given_tag = len(w_given_tag_list)
 return (count_w_given_tag, count_tag)
#compute Transition Probability
def t2_given_t1(t2, t1, train_bag = train_tagged_words):
    tags= [pair[1] for pair in train_bag]
    count_t1 = len([t for t in tags if t==t1])
   count_t2_t1 = 0
    for index in range(len(tags)-1):
     if tags[index]==t1 and tags[index+1] == t2:
       count t2 t1 += 1
    return (count_t2_t1, count_t1)
# creating t x t transition matrix of tags, t= no of tags
# Matrix(i, j) represents P(jth tag after the ith tag)
tags_matrix = np.zeros((len(tags), len(tags)), dtype='float32')
for i, t1 in enumerate(list(tags)):
 for j, t2 in enumerate(list(tags)):
    tags_matrix[i, j] = t2_given_t1(t2, t1)[0]/t2_given_t1(t2, t1)[1]
print(tags_matrix)
     [[9.23720598e-02 2.78940029e-03 9.29084867e-02 6.87694475e-02
       2.18538776e-01 5.25694676e-02 2.56410260e-02 6.00793920e-02
       8.96899477e-02 1.72191828e-01 7.82104954e-02 4.61323895e-02]
      [4.50097844e-02 1.17416831e-03 1.95694715e-02 1.76125243e-02
       2.50489235e-01 9.39334650e-03 1.21330721e-02 2.34833662e-03
       4.01174158e-01 1.01369865e-01 5.67514673e-02 8.29745606e-02]
      [3.87243740e-02 1.26550242e-03 1.69577319e-02 6.96026310e-02
       3.23588967e-01 1.45532778e-02 3.45482156e-02 1.01240189e-03
       8.47886596e-03 3.20931405e-01 6.32751212e-02 1.07061505e-01]
      [4.19134386e-02 1.41230067e-02 2.23234631e-02 6.83371304e-03
       2.12756261e-01 3.69020514e-02 8.83826911e-02 5.01138950e-03
      4.84738052e-01 9.56719834e-03 6.83371304e-03 7.06150308e-02]
      [2.40094051e-01 4.39345129e-02 1.76826611e-01 4.65906132e-03
       2.62344331e-01 1.68945398e-02 2.88252197e-02 4.24540639e-02
       1.49133503e-01 1.31063312e-02 9.14395228e-03 1.25838192e-02]
      [1.39255241e-01 1.47401085e-02 1.19472459e-01 1.20248254e-02
        3.21955010e-02 8.14584941e-02 2.28859577e-02 6.98215654e-03
       3.39022487e-01 7.13731572e-02 2.98681147e-02 1.30721495e-01]
      [1.60868734e-01 1.85085520e-01 1.42225638e-01 5.41995019e-02
       6.16951771e-02 2.57543717e-02 7.57255405e-02 1.03786280e-02
       2.06419379e-01 5.68902567e-02 3.07514891e-03 1.76821072e-02]
      [3.51262353e-02 4.39077942e-03 5.59824370e-02 6.03732169e-02
       3.49066973e-01 5.70801310e-02 9.33040585e-03 5.48847427e-04
       1.50384188e-01 1.23490669e-01 4.06147093e-02 1.13611415e-01]
      [3.48066315e-02 3.06629837e-02 9.23572779e-02 3.55432779e-02
       1.10589318e-01 8.38858187e-02 2.15930015e-01 5.43278083e-03
       1.67955801e-01 1.33609578e-01 2.28360966e-02 6.63904250e-02]
      [1.73925534e-02 2.87480245e-04 9.91806854e-03 3.30602261e-03
       6.35906279e-01 1.20741697e-02 4.51343954e-02 4.31220367e-04
       4.02472317e-02 6.03708485e-03 2.28546783e-02 2.06410810e-01]
      [1.19243130e-01 2.60621198e-02 3.74866128e-02 1.42806140e-03
       3.51660132e-01 3.57015361e-03 2.02427700e-01 1.42806144e-02
       2.07068902e-02 3.57015361e-03 1.84219927e-01 3.53445187e-02]
      [6.60194159e-02 1.14563107e-02 8.05825219e-02 1.94174761e-04
       6.96893215e-01 5.24271838e-03 2.09708735e-02 1.68932043e-02
       1.14563107e-02 5.24271838e-03 2.17475723e-02 6.33009672e-02]]
tags_df= pd.DataFrame(tags_matrix, columns = list(tags), index= list(tags))
display(tags_df)
```

```
PRT
                                                                                                                         ADP
                                                                                                                                                    PRON
                                                                                                                                                                                    NOUN
                                                                                                                                                                                                                       ADV
                                                                                                                                                                                                                                                            Х
                                                                                                                                                                                                                                                                                  CONJ
                                                                                                                                                                                                                                                                                                                 VERB
                                                                                                                                                                                                                                                                                                                                                                                  NUM
                                                                                                                                                                                                                                                                                                                                                                                                                  ADJ
                                          0.092372 \quad 0.002789 \quad 0.092908 \quad 0.068769 \quad 0.218539 \quad 0.052569 \quad 0.025641 \quad 0.060079 \quad 0.089690 \quad 0.172192 \quad 0.078210 \quad 0.046132 \quad 0.078210 \quad 0.088769 \quad 0.0887699 \quad 0
                                      0.045010 0.001174 0.019569 0.017613 0.250489 0.009393 0.012133 0.002348 0.401174 0.101370 0.056751 0.082975
                      ADP
                                          0.038724 \quad 0.001266 \quad 0.016958 \quad 0.069603 \quad 0.323589 \quad 0.014553 \quad 0.034548 \quad 0.001012 \quad 0.008479 \quad 0.320931 \quad 0.063275 \quad 0.107062 \quad 0.001012 
                    PRON 0.041913 0.014123 0.022323 0.006834 0.212756 0.036902 0.088383 0.005011 0.484738 0.009567 0.006834 0.070615
                    NOUN 0.240094 0.043935 0.176827 0.004659 0.262344 0.016895 0.028825 0.042454 0.149134 0.013106 0.009144 0.012584
def Viterbi (words, train bag = train tagged words):
       state = []
       T = list(set([pair[1] for pair in train_bag]))
       for key, word in enumerate(words):
            #initialise list of probability column for a given observation
            p = \lceil \rceil
             for tag in T:
                  if key == 0:
                       transition_p = tags_df.loc['.', tag]
                   else:
                        transition_p = tags_df.loc[state[-1], tag]
                    # compute emission and state probabilities
                    emission_p = word_given_tag(words[key], tag)[0]/word_given_tag(words[key], tag)[1]
                   state_probability = emission_p* transition_p
                   p.append(state_probability)
            pmax = max(p)
             # getting state for which probability is maximum
             state_max= T[p.index(pmax)]
             state.append(state_max)
       return list(zip(words, state))
#Let's test our Viterbi algorithm on a few sample sentences of test dataset
random.seed(1234) #define a random seed to get same sentences when run multiple times
#choose random 10 numbers
rndom = [random.randint(1, len(test_set)) for x in range(10)]
# list of 10 sents on which we test the model
test_run = [test_set[i] for i in rndom]
# list of tagged words
test_run_base = [tup for sent in test_run for tup in sent]
# list of untagged words
test_tagged_words = [tup[0] for sent in test_run for tup in sent]
#Here We will only test 10 sentences to check the accuracy
#as testing the whole training set takes huge amount of time
start = time.time()
tagged_seq= Viterbi (test_tagged_words)
end = time.time()
difference = end-start
print("Time taken in seconds: ", difference)
# accuracy
check = [i for i, j in zip(tagged_seq, test_run_base) if i == j]
accuracy = len(check)/len (tagged_seq)
print('Viterbi Algorithm Accuracy: ',accuracy*100)
                 Time taken in seconds: 50.37351584434509
                 Viterbi Algorithm Accuracy: 93.77990430622009
```