HMM

December 8, 2021

[1]:
```python
import math
import random
import numpy
from collections import *
```

[2]:
```python
class HMM:
    """
    Simple class to represent a Hidden Markov Model.
    """
    def __init__(self, order, initial_distribution, emission_matrix,␣
 ↪transition_matrix):
        self.order = order
        self.initial_distribution = initial_distribution
        self.emission_matrix = emission_matrix
        self.transition_matrix = transition_matrix
```

[3]:
```python
def read_pos_file(filename):
    """
    Parses an input tagged text file.
    Input:
    filename --- the file to parse
    Returns:
    The file represented as a list of tuples, where each tuple
    is of the form (word, POS-tag).
    A list of unique words found in the file.
    A list of unique POS tags found in the file.
    """
    file_representation = []
    unique_words = set()
    unique_tags = set()
    f = open(str(filename), "r")
    for line in f:
        if len(line) < 2 or len(line.split("/")) != 2:
            continue

        word = line.split("/")[0].replace(" ", "").replace("\t", "").strip()
        tag = line.split("/")[1].replace(" ", "").replace("\t", "").strip()
```

```
        file_representation.append( (word, tag) )
        unique_words.add(word)
        unique_tags.add(tag)

    f.close()

    return file_representation, unique_words, unique_tags
```

[4]:
```
def read_pos_file_modified(training_data_file):
    """
    A modified verysion of read_pos that only returns the file representation
    Input: training data file, a text file
    Output: The file represented as a list of tuples, where each tuple
    is of the form (word, POS-tag).
    """
    file_representation = []

    #open file
    f = open(str(training_data_file), "r")
    for line in f:
        if len(line) < 2 or len(line.split("/")) != 2:
            continue

        #split the string up
        word = line.split("/")[0].replace(" ", "").replace("\t", "").strip()
        tag = line.split("/")[1].replace(" ", "").replace("\t", "").strip()
        file_representation.append( (word, tag) )

    # close the file
    f.close()
    return file_representation
```

[5]:
```
#################################### Testing RPOSFM
print (read_pos_file_modified("onesentence.txt"))
#expects The file represented as a list of tuples, where each tuple is of the␣
↪form (word, POS-tag).
#passes
```

```
[('The', 'DT'), ('New', 'NNP'), ('Deal', 'NNP'), ('was', 'VBD'), ('a', 'DT'),
('series', 'NN'), ('of', 'IN'), ('domestic', 'JJ'), ('programs', 'NNS'),
('enacted', 'VBN'), ('in', 'IN'), ('the', 'DT'), ('United', 'NNP'), ('States',
'NNPS'), ('between', 'IN'), ('1933', 'CD'), ('and', 'CC'), ('1936', 'CD'), (',',
','), ('and', 'CC'), ('a', 'DT'), ('few', 'JJ'), ('that', 'WDT'), ('came',
'VBD'), ('later', 'RB'), ('.', '.')]
```

[6]:
```
def parse_test_file(test_file):
    """
```

```
    Parses a test file into a list of lists, where the inner lists are sentences
    Input: A testing data file, test_file
    Outputs: a list of words in the file, and a list of lists as described above
    """

    # open the file
    f = open(test_file, "r")

    #split the file into a list
    list_of_words = f.read().split()
    testing_block = []
    L = len(list_of_words)
    count = 0

    while count < L:

        #container for each sentence
        sentence = []
        for word in list_of_words:

            #add word to the sentence
            sentence.append(word)
            count += 1
            if word == ".":

                # add sentence to the testing block
                testing_block.append(sentence)
                sentence = []

    return list_of_words, testing_block
```

[7]:
```
############################## TESTING PARSE ␣
↪####################################
# print (parse_test_file("testdata_untagged.txt"))
#expect the test data parsed into a list of list
#passes
```

[8]:
```
def wrangle_data(training_data_file, percent):
    """
    Inputs: training_data_file, a text file of tagged training data
            percent: a decimal represeting the amount of data you want to build␣
↪a model on
    Output: partitioned data, a sequence of (word, tag) tuples
    """
    #read in data
    data = read_pos_file_modified(training_data_file)
```

```
    #get the total length of the training data
    tokens = len(data)

    #get the amount of tokens you want to keep
    end_token = int(tokens*percent)

    partitioned_data = []

    #iterate until you read the end number of tokens
    for i in range(end_token):
        partitioned_data.append(data[i])

    return partitioned_data
```

[9]:
```
############################################ TESTING Wrangle Data␣
↪############################################
#print (wrangle_data("training.txt", 0.01))[1]
# expects 1 percent of the training data
# passes
```

[10]:
```
def get_unique_words_and_tags(data):
    """
    Gets the unique words and tags in a data set
    Input: Data in the representation returned by read pos
    Output: 2 sets, one that holds the unique words and one that holds the␣
↪unique tags
    """

    #init empty sets
    unique_words = set([])
    unique_tags = set([])


    for pair in data:

        #add the word if its not already been seen
        if pair[0] not in unique_words:
            unique_words.add(pair[0])

        #add the tag if its not already been seen
        if pair[1] not in unique_tags:
            unique_tags.add(pair[1])

    return unique_words, unique_tags
```

[11]:
```
########################## TESTING GET UNIQUE WORDS/TAGS␣
↪#########################
#fifty = wrangle_data("training.txt", 0.5)
#print (get_unique_words_and_tags(fifty))
# expects two sets with unique words and tags, on fifty percent of the training␣
↪data
# passes

fifty = wrangle_data("training.txt", 0.1)
#print (get_unique_words_and_tags(fifty))
# expects two sets with unique words and tags, on ten percent of the training␣
↪data
# passes
```

[12]:
```
def compute_counts(training_data, order):
    """
    Function that computes different relevant counts about the input file

    Input: Training data, a list of (word, POS-tag) pairs returned by the␣
↪function read_pos_file,
           Order, the order of the hidden markov model

    Output : If the HMM order is 2, the function returns a tuple consisting of:
                the number of tokens in training data
                dictionary that contains that contains C(ti,wi) for every␣
↪unique tag and unique word (keys correspond to tags)
                    The number of times word wi is tagged with ti
                a dictionary that contains  C(ti)
                    The number of times tag ti appears
                a dictionary that contains C(ti-1, ti)
                    The number of times the tag sequence ti-1, ti appears
             If the HMM order is 3, the function returns a tuple consisting of:
                the number of tokens in training data
                dictionary that contains that contains C(ti,wi) for every␣
↪unique tag and unique word (keys correspond to tags)
                a dictionary that contains  C(ti)
                a dictionary that contains  C(ti-1, ti)
                a dictionary that contains  C(ti-2, ti-1, ti)
                    The number of times the tag sequence ti-2, ti-1, ti appears


    """
    # get the number of tokens in the training set
    numtokens = len(training_data)

    # counts the number of times word wi is taked with tag ti
    word2tag_dict = defaultdict(lambda: defaultdict(int))
```

```
    # counts the number of times tag ti appears
    tag_count_dict = defaultdict(int)

    # counts the number of times the tag sequence ti-1, ti appears
    bigramdict = defaultdict(lambda: defaultdict(int))

    # counts the number of times the tag sequence ti-2, ti-1, ti appears
    trigramdict = defaultdict(lambda: defaultdict(lambda: defaultdict(int)))

    for i in range(0, numtokens):

        #increment the tag_count_dict
        tag_count_dict[training_data[i][1]] += 1

        #increment the word2tag_dict
        word2tag_dict[training_data[i][1]][training_data[i][0]]+=1

        if i > 0:

            if training_data[i-1][1] != ".":

                #increment the bigram dict
                bigramdict[training_data[i-1][1]][training_data[i][1]] += 1

        if order > 2:

            if i > 1:

                if (training_data[i-2][1] != ".") and (training_data[i-1][1] !=␣
↪"."):

                    #increment the trigram dict
                   ␣
↪trigramdict[training_data[i-2][1]][training_data[i-1][1]][training_data[i][1]]␣
↪+= 1



    if order == 2:
        return(numtokens, word2tag_dict, tag_count_dict, bigramdict)
    else:
        return(numtokens, word2tag_dict, tag_count_dict, bigramdict,␣
↪trigramdict)
```

[13]:
```
####### TESTING COMPUTE COUNTS #################
tinydata = read_pos_file('onesentence.txt')
```

```
#print(tinydata[0])
#Order 2 test on a single sentence
print(compute_counts(tinydata[0], 2)[0])
print(dict(compute_counts(tinydata[0], 2)[1]))
print(dict(compute_counts(tinydata[0], 2)[2]))




#expect a dictionary with the correct amount of words in the sentence
#passes

# Order 3 test on a single sentence
#print(dict(compute_counts(tinydata[0], 3)))
# expect a dictionary with the correct amount of words in the sentence
# passes
```

```
26
{'DT': defaultdict(<class 'int'>, {'The': 1, 'a': 2, 'the': 1}), 'NNP':
defaultdict(<class 'int'>, {'New': 1, 'Deal': 1, 'United': 1}), 'VBD':
defaultdict(<class 'int'>, {'was': 1, 'came': 1}), 'NN': defaultdict(<class
'int'>, {'series': 1}), 'IN': defaultdict(<class 'int'>, {'of': 1, 'in': 1,
'between': 1}), 'JJ': defaultdict(<class 'int'>, {'domestic': 1, 'few': 1}),
'NNS': defaultdict(<class 'int'>, {'programs': 1}), 'VBN': defaultdict(<class
'int'>, {'enacted': 1}), 'NNPS': defaultdict(<class 'int'>, {'States': 1}),
'CD': defaultdict(<class 'int'>, {'1933': 1, '1936': 1}), 'CC':
defaultdict(<class 'int'>, {'and': 2}), ',': defaultdict(<class 'int'>, {',':
1}), 'WDT': defaultdict(<class 'int'>, {'that': 1}), 'RB': defaultdict(<class
'int'>, {'later': 1}), '.': defaultdict(<class 'int'>, {'.': 1})}
{'DT': 4, 'NNP': 3, 'VBD': 2, 'NN': 1, 'IN': 3, 'JJ': 2, 'NNS': 1, 'VBN': 1,
'NNPS': 1, 'CD': 2, 'CC': 2, ',': 1, 'WDT': 1, 'RB': 1, '.': 1}
```

[14]:

```
def compute_initial_distribution(training_data, order):
    """
    Function that computes the intitial distributions of words, pi_1 and pi_2

    Input: Training data, a list of (word, POS-tag) pairs returned by the␣
 ↪function read_pos_file,
           Order, the order of the hidden markov model

    Output: If order = 2:
                Returns a one dim dictionary pi_1, that maps a tag to its␣
 ↪emission probability
            If order = 3:
                Returns a 2 dim dictionary pi_2 , that maps a bigram to its␣
 ↪emmission probabiliity

    """
```

```
numtokens = len(training_data)

# initialize the pi dictionaries
pi_1 = defaultdict(int)
pi_2 = defaultdict(lambda: defaultdict(int))

if order==2:

    # the first tag is the second element of the first tuple
    first_tag = training_data[0][1]

    # increment the total count by 1
    pi_1[first_tag] += 1

else:

    # access the first and second tags
    first_tag = training_data[0][1]
    second_tag = training_data[1][1]

    # increment the dictionary
    pi_2[first_tag][second_tag] += 1

# set the total counts to be 1, we will normalize later
order2count = 1
order3count = 1

for i in range(order -1, numtokens - order + 1):

    if order == 2:

        #if we encounter a period, we know we have the beginning of a␣
↪sentence
        if training_data[i-1][1] == ".":

            # increment the count by 1
            pi_1[training_data[i][1]] += 1
            order2count += 1

    if order == 3:

        # if two words ago was a period, then we have a bigram that is at␣
↪the begining of a word
        # will fail for 1 word sentences
        if training_data[i-2][1] == ".":
            pi_2[training_data[i-1][1]][training_data[i][1]] += 1
```

```
                order3count +=1

    if order == 2:

        for key, value in pi_1.items():

            #normalize by the order 2 count
            pi_1[key] = float(float(value)/float(order2count))

        return pi_1

    else:
        # iterate through the keys and values
        for key, value in pi_2.items():

            # value is a dict, whose "values" are counts
            for tag, count in value.items():

                #normalize by the order 3 count
                pi_2[key][tag] = float(float(count)/float(order3count))

        return pi_2
```

[15]:
```
######################## TESTING COMPUTE INTIAL DISTRIBUTION␣
 ↪###############################
littledata = read_pos_file('littledata.txt')
print(compute_initial_distribution(littledata[0], 3))
#expect DT-JJ to be 1/2 and NNP-NNPS to be 1/2
#passes

littledata = read_pos_file('littledata.txt')
print(compute_initial_distribution(littledata[0], 2))
# #expect DT to be 1/2 and NNP to be 1/2
# #passes
```

```
defaultdict(<function compute_initial_distribution.<locals>.<lambda> at
0x7fd19bed9700>, {'DT': defaultdict(<class 'int'>, {'JJ': 0.5}), 'NNP':
defaultdict(<class 'int'>, {'NNPS': 0.5})})
defaultdict(<class 'int'>, {'DT': 0.5, 'NNP': 0.5})
```

[16]:
```
def compute_emission_probabilities(unique_words, unique_tags, W, C):
    """
    Function computes the emmission matrix for different parts of speech given␣
 ↪training data

    Input: unique_words: a set of unique words returned by the read_pos function
           unique_tags : a set of unique tags returned by the read_pos function
```

```
        W : the C(ti, wi) dictionary returned by the function compute_counts
        C : the C(ti) dictionary returned by the function compute_counts

    Output: emission matrix, a 2d dict where the keys are parts of speech

    """

    #initialize the emission matrix
    emission_matrix = defaultdict(lambda: defaultdict(int))


    # tags are keys in the emission matrix
    for tag in unique_tags:
        for word in W[tag].keys():

            #caluculate emission prob
            emission_matrix[tag][word] = float(float(W[tag][word])/
↪float(C[tag]))

    return emission_matrix
```

[17]:

```
##################################### TESTING COMPUTE EMMISSION PROBABILITIES␣
↪######################
tinydata = read_pos_file('onesentence.txt')
unique_words2 = tinydata[1]
unique_tags2 = tinydata[2]
w1 = compute_counts(tinydata[0], 2)[1]
C1 = compute_counts(tinydata[0], 2)[2]
print(compute_emission_probabilities(unique_words2, unique_tags2, w1, C1))
# expect a dict with each word corresponding to its emmision prob
# passes

onethousand = read_pos_file("onethousandlines.txt")
unique_tags = onethousand[2]
unique_words = onethousand[1]
c1 = compute_counts(onethousand[0], 3)[1]
c2 = compute_counts(onethousand[0], 3)[2]
# print(compute_emission_probabilities(unique_words, unique_tags, c1, c2))
# # expect a dict with each word corresponding to its emmision prob
# # passes
```

```
defaultdict(<function compute_emission_probabilities.<locals>.<lambda> at
0x7fd1a441b160>, {'VBN': defaultdict(<class 'int'>, {'enacted': 1.0}), 'CD':
defaultdict(<class 'int'>, {'1933': 0.5, '1936': 0.5}), 'VBD':
defaultdict(<class 'int'>, {'was': 0.5, 'came': 0.5}), 'NN': defaultdict(<class
'int'>, {'series': 1.0}), 'JJ': defaultdict(<class 'int'>, {'domestic': 0.5,
'few': 0.5}), ',': defaultdict(<class 'int'>, {',': 1.0}), 'NNS':
```

```
defaultdict(<class 'int'>, {'programs': 1.0}), 'NNP': defaultdict(<class 'int'>,
{'New': 0.3333333333333333, 'Deal': 0.3333333333333333, 'United':
0.3333333333333333}), '.': defaultdict(<class 'int'>, {'.': 1.0}), 'CC':
defaultdict(<class 'int'>, {'and': 1.0}), 'IN': defaultdict(<class 'int'>,
{'of': 0.3333333333333333, 'in': 0.3333333333333333, 'between':
0.3333333333333333}), 'RB': defaultdict(<class 'int'>, {'later': 1.0}), 'DT':
defaultdict(<class 'int'>, {'The': 0.25, 'a': 0.5, 'the': 0.25}), 'WDT':
defaultdict(<class 'int'>, {'that': 1.0}), 'NNPS': defaultdict(<class 'int'>,
{'States': 1.0}))}
```

[18]:

```
def compute_lambdas(unique_tags, num_tokens, C1, C2, C3, order):
    """
    Function implements the Algorithm Compute_Lambdas

    Inputs: unique_tags: a set of unique tags returned by the read_pos function
            numtokens : number of words in the training corpus
            C1 : C(ti), The number of times tag ti appears
            C2: C(ti-1, ti), the Number of times the sequence ti -1, ti appears
            C3: C(ti-2, ti-1, ti) the number of times the sequence ti-2, ti-1,␣
 ↪ti appears

    Outputs: A list that contains lambda1, lambda2, lambda2

    """

    lambdas = [0.0,0.0,0.0]
    counter = 0
    # only if order is 3 do we consider trigrams
    if order == 3:

        # access ti -2
        for timinus2, value in C3.items():

            # access ti-1
            for timinus1, value2 in value.items():

                # access ti
                for ti, count in value2.items():

                    counter += 1

                    # initialize the argmax
                    argmax = 0
                    max_alpha = 0

                    # calculate the alpha scores
                    for i in range(3):
```

```
                        if i == 0:
                            if float(num_tokens) == 0:
                                alpha = 0
                            else:
                                alpha = float(float(C1[ti] - 1)/
↪float(num_tokens))

                        if i == 1:
                            if float(C1[timinus1] - 1) == 0:
                                alpha = 0
                            else:
                                #print "hey", C2[timinus1][ti]
                                #print C1[timinus1]
                                alpha = float(float(C2[timinus1][ti] - 1)/
↪float(C1[timinus1] - 1))

                        if i == 2:
                            if float(C2[timinus2][timinus1] - 1) == 0:
                                alpha = 0
                            else:
                                alpha = float(float(C3[timinus2][timinus1][ti]␣
↪- 1)/float(C2[timinus2][timinus1] - 1))

                        # find the biggest alpha
                        if alpha > max_alpha:
                            max_alpha = alpha
                            argmax = i

                    # increment alpha
                    lambdas[argmax] += C3[timinus2][timinus1][ti]

        # calculate the lambda values

        lambdas_sum = sum(lambdas)
        for i in range(order):
            lambdas[i] = float(float(lambdas[i])/float(lambdas_sum))

        return lambdas

    # if order is equal to 2
    else:

        #access ti- 1 and ti
        for timinus1, value2 in C2.items():
            for ti, count in value2.items():

                argmax = 0
```

```
                max_alpha = 0

                #calculate alpha scores
                for i in range(2):
                    if i == 0:
                        if float(num_tokens) == 0:
                            alpha = 0
                        else:
                            alpha = float(float(C1[ti] - 1)/float(num_tokens))
                    if i == 1:
                        if float(C1[timinus1] - 1) == 0:
                            alpha = 0
                        else:
                            alpha = float(float(C2[timinus1][ti] - 1)/
↪float(C1[timinus1] - 1))

                    if alpha > max_alpha:
                        max_alpha = alpha
                        argmax = i

                # increment lambda
                lambdas[argmax] += C2[timinus1][ti]

        # calculate the final lambda values
        lambdas_sum = sum(lambdas)

        for i in range(order):
            lambdas[i] = float(float(lambdas[i])/float(lambdas_sum))

        return lambdas
```

[19]:

```
####################################### TESTING COMPUTE LAMBDAS␣
↪#######################################################
alldata = read_pos_file("training.txt")
counts = compute_counts(alldata[0], 3)
unique_tags = alldata[2]
unique_words = alldata[1]
print(compute_lambdas(unique_tags, counts[0], counts[2], counts[3], counts[4],␣
↪2))
# expect 2 lambda values that are not 0 that sum to 1
# passes

tinydata = read_pos_file('onesentence.txt')
unique_tags = tinydata[2]
counts = compute_counts(tinydata[0], 3)
print(compute_lambdas(unique_tags, counts[0], counts[2], counts[3], counts[4],␣
↪3))
```

```
# expect 2 lambda values that are not 0 that sum to 1
# passes
```

```
[0.20472736536501893, 0.7952726346349811, 0.0]
[0.9583333333333334, 0.041666666666666664, 0.0]
```

[20]:
```
def compute_transition_matrix(training_data, unique_tags, order, use_smoothing):
    """
    Input: training_data, a file containing training data,
        unique tags, a set of unique tags in the data,
        order, the order of the HMM
        use smoothing: a boolean paramater

    Output: transistion matrix: a matrix that contains the transistion␣
↪probabiility between states
    """
    # order
    if order == 2:
        # get the counts
        # counts = compute_counts(training_data, 2)
        counts_trigram = compute_counts(training_data, 3)

        # get the number of tokens
        num_tokens = counts_trigram[0]

        # if smoothing is true, compute the appropriate lambda values
        if use_smoothing == True:
            lambdas = compute_lambdas(unique_tags, num_tokens,␣
↪counts_trigram[2], counts_trigram[3], counts_trigram[4], order)
        else:
            lambdas = [0, 1, 0]

        # compute the transition matrix
        transition_matrix = defaultdict(lambda: defaultdict(int))

        # obtain ti - 1
        for timinus1 in unique_tags:

            # obtain ti
            for ti in unique_tags:

                term1 =␣
↪(float(lambdas[1])*float(counts_trigram[3][timinus1][ti])/
↪float(counts_trigram[2][timinus1]))
                term2 = (float(lambdas[0])*float(counts_trigram[2][ti])/
↪float(num_tokens))
```

```
                transition_matrix[timinus1][ti] = float(term1) + float(term2)

        return transition_matrix


    else:

        #get your counts
        counts_trigram = compute_counts(training_data, 3)

        # get the number of tokens
        num_tokens = counts_trigram[0]

        # if smoothing is true, compute the appropriate lambda values
        if use_smoothing == True:
            lambdas = compute_lambdas(unique_tags, num_tokens,␣
↪counts_trigram[2], counts_trigram[3], counts_trigram[4], order)
        else:
            lambdas = [0.0, 0.0, 1.0]

        # compute the transition matrix
        transition_matrix = defaultdict(lambda: defaultdict(lambda:␣
↪defaultdict(int)))

        for timinus2 in unique_tags:

            # obtain ti - 1
            for timinus1 in unique_tags:

                # obtain ti
                for ti in unique_tags:

                    # calculate term 1 of the equation
                    if float(counts_trigram[3][timinus2][timinus1]) == 0:
                        term1 = 0
                    else:
                        term1 =␣
↪(float(lambdas[2])*float(counts_trigram[4][timinus2][timinus1][ti]))/
↪float(counts_trigram[3][timinus2][timinus1])

                    #caluculate term 2 of the equations
                    if float(counts_trigram[2][timinus1]) == 0:
                        term2 =0
                    else:
                        term2 =␣
↪(float(lambdas[1])*float(counts_trigram[3][timinus1][ti])/
↪float(counts_trigram[2][timinus1]))
```

```
                # calculate term 3 of the equation
                if float(num_tokens) == 0:
                    term3 =0
                else:
                    term3 = (float(lambdas[0])*float(counts_trigram[2][ti])/
↪float(num_tokens))

                #calculate the full probability
                transition_matrix[timinus2][timinus1][ti] = term1 + term2 +␣
↪term3

    return transition_matrix
```

[21]:

```
################################################ TESTING COMPUTE TRANSISTION␣
↪MATRIX ##########################################################

tinydata = read_pos_file('onesentence.txt')
unique_tags = tinydata[2]
print(compute_transition_matrix(tinydata[0], unique_tags, 2, False))
# EXPECTS a 2d dict of transistion probs from one state to another
# passes

tinydata = read_pos_file('onesentence.txt')
unique_tags = tinydata[2]
#print(compute_transition_matrix(tinydata[0], unique_tags, 3, True))
# EXPECTS a 3d dict of transistion probs from two state to another
# passes
```

```
defaultdict(<function compute_transition_matrix.<locals>.<lambda> at
0x7fd1803628b0>, {'VBN': defaultdict(<class 'int'>, {'VBN': 0.0, 'CD': 0.0,
'VBD': 0.0, 'NN': 0.0, 'JJ': 0.0, ',': 0.0, 'NNS': 0.0, 'NNP': 0.0, '.': 0.0,
'CC': 0.0, 'IN': 1.0, 'RB': 0.0, 'DT': 0.0, 'WDT': 0.0, 'NNPS': 0.0}), 'CD':
defaultdict(<class 'int'>, {'VBN': 0.0, 'CD': 0.0, 'VBD': 0.0, 'NN': 0.0, 'JJ':
0.0, ',': 0.5, 'NNS': 0.0, 'NNP': 0.0, '.': 0.0, 'CC': 0.5, 'IN': 0.0, 'RB':
0.0, 'DT': 0.0, 'WDT': 0.0, 'NNPS': 0.0}), 'VBD': defaultdict(<class 'int'>,
{'VBN': 0.0, 'CD': 0.0, 'VBD': 0.0, 'NN': 0.0, 'JJ': 0.0, ',': 0.0, 'NNS': 0.0,
'NNP': 0.0, '.': 0.0, 'CC': 0.0, 'IN': 0.0, 'RB': 0.5, 'DT': 0.5, 'WDT': 0.0,
'NNPS': 0.0}), 'NN': defaultdict(<class 'int'>, {'VBN': 0.0, 'CD': 0.0, 'VBD':
0.0, 'NN': 0.0, 'JJ': 0.0, ',': 0.0, 'NNS': 0.0, 'NNP': 0.0, '.': 0.0, 'CC':
0.0, 'IN': 1.0, 'RB': 0.0, 'DT': 0.0, 'WDT': 0.0, 'NNPS': 0.0}), 'JJ':
defaultdict(<class 'int'>, {'VBN': 0.0, 'CD': 0.0, 'VBD': 0.0, 'NN': 0.0, 'JJ':
0.0, ',': 0.0, 'NNS': 0.5, 'NNP': 0.0, '.': 0.0, 'CC': 0.0, 'IN': 0.0, 'RB':
0.0, 'DT': 0.0, 'WDT': 0.5, 'NNPS': 0.0}), ',': defaultdict(<class 'int'>,
{'VBN': 0.0, 'CD': 0.0, 'VBD': 0.0, 'NN': 0.0, 'JJ': 0.0, ',': 0.0, 'NNS': 0.0,
'NNP': 0.0, '.': 0.0, 'CC': 1.0, 'IN': 0.0, 'RB': 0.0, 'DT': 0.0, 'WDT': 0.0,
'NNPS': 0.0}), 'NNS': defaultdict(<class 'int'>, {'VBN': 1.0, 'CD': 0.0, 'VBD':
```

```
0.0, 'NN': 0.0, 'JJ': 0.0, ',': 0.0, 'NNS': 0.0, 'NNP': 0.0, '.': 0.0, 'CC':
0.0, 'IN': 0.0, 'RB': 0.0, 'DT': 0.0, 'WDT': 0.0, 'NNPS': 0.0}), 'NNP':
defaultdict(<class 'int'>, {'VBN': 0.0, 'CD': 0.0, 'VBD': 0.3333333333333333,
'NN': 0.0, 'JJ': 0.0, ',': 0.0, 'NNS': 0.0, 'NNP': 0.3333333333333333, '.': 0.0,
'CC': 0.0, 'IN': 0.0, 'RB': 0.0, 'DT': 0.0, 'WDT': 0.0, 'NNPS':
0.3333333333333333}), '.': defaultdict(<class 'int'>, {'VBN': 0.0, 'CD': 0.0,
'VBD': 0.0, 'NN': 0.0, 'JJ': 0.0, ',': 0.0, 'NNS': 0.0, 'NNP': 0.0, '.': 0.0,
'CC': 0.0, 'IN': 0.0, 'RB': 0.0, 'DT': 0.0, 'WDT': 0.0, 'NNPS': 0.0}), 'CC':
defaultdict(<class 'int'>, {'VBN': 0.0, 'CD': 0.5, 'VBD': 0.0, 'NN': 0.0, 'JJ':
0.0, ',': 0.0, 'NNS': 0.0, 'NNP': 0.0, '.': 0.0, 'CC': 0.0, 'IN': 0.0, 'RB':
0.0, 'DT': 0.5, 'WDT': 0.0, 'NNPS': 0.0}), 'IN': defaultdict(<class 'int'>,
{'VBN': 0.0, 'CD': 0.3333333333333333, 'VBD': 0.0, 'NN': 0.0, 'JJ':
0.3333333333333333, ',': 0.0, 'NNS': 0.0, 'NNP': 0.0, '.': 0.0, 'CC': 0.0, 'IN':
0.0, 'RB': 0.0, 'DT': 0.3333333333333333, 'WDT': 0.0, 'NNPS': 0.0}), 'RB':
defaultdict(<class 'int'>, {'VBN': 0.0, 'CD': 0.0, 'VBD': 0.0, 'NN': 0.0, 'JJ':
0.0, ',': 0.0, 'NNS': 0.0, 'NNP': 0.0, '.': 1.0, 'CC': 0.0, 'IN': 0.0, 'RB':
0.0, 'DT': 0.0, 'WDT': 0.0, 'NNPS': 0.0}), 'DT': defaultdict(<class 'int'>,
{'VBN': 0.0, 'CD': 0.0, 'VBD': 0.0, 'NN': 0.25, 'JJ': 0.25, ',': 0.0, 'NNS':
0.0, 'NNP': 0.5, '.': 0.0, 'CC': 0.0, 'IN': 0.0, 'RB': 0.0, 'DT': 0.0, 'WDT':
0.0, 'NNPS': 0.0}), 'WDT': defaultdict(<class 'int'>, {'VBN': 0.0, 'CD': 0.0,
'VBD': 1.0, 'NN': 0.0, 'JJ': 0.0, ',': 0.0, 'NNS': 0.0, 'NNP': 0.0, '.': 0.0,
'CC': 0.0, 'IN': 0.0, 'RB': 0.0, 'DT': 0.0, 'WDT': 0.0, 'NNPS': 0.0}), 'NNPS':
defaultdict(<class 'int'>, {'VBN': 0.0, 'CD': 0.0, 'VBD': 0.0, 'NN': 0.0, 'JJ':
0.0, ',': 0.0, 'NNS': 0.0, 'NNP': 0.0, '.': 0.0, 'CC': 0.0, 'IN': 1.0, 'RB':
0.0, 'DT': 0.0, 'WDT': 0.0, 'NNPS': 0.0})})
```

[22]:
```python
def build_hmm(training_data, unique_tags, unique_words, order, use_smoothing):
    """
    Creates a fully trained Hidden Markov Model

    Inputs: training_data : a full training corpus,
            unique_tags : a set of parts of speech found in the training corpus
            unique_words : a set of words found in the training corpus
            order : the order of the markov chain
            Use_smoothing : a boolean parameter
    Outputs: a fully trained HMM object

    """

    # build an order 2 markov model

    counts = compute_counts(training_data, order)

    #compute the initial distribution
    initial_distribution = compute_initial_distribution(training_data, order)

    #compute the emission matrix
```

```
    W_dict = counts[1]
    C_dict = counts[2]
    emission_matrix = compute_emission_probabilities(unique_words, unique_tags,␣
↪W_dict, C_dict)

    #build a transition matrix
    transition_matrix = compute_transition_matrix(training_data, unique_tags,␣
↪order, use_smoothing)

    #build the hmm
    my_hmm = HMM(order, initial_distribution, emission_matrix,␣
↪transition_matrix)

    return my_hmm
```

[23]:
```
########################################## Testing Build HMM␣
↪################################################################

onethousand = read_pos_file("onethousandlines.txt")
unique_tags = onethousand[2]
unique_words = onethousand[1]
#print(build_hmm(onethousand[0], unique_tags, unique_words, 2, True))
#expect am HMM object
#passes

tinydata = read_pos_file('onesentence.txt')
unique_tags = tinydata[2]
unique_words = tinydata[1]
model = build_hmm(tinydata[0], unique_tags, unique_words, 3, False)
#Expect an HMM Object
#View the HMM Attributes
#print( "Order", model.order)
#print( "Intial Dist", model.initial_distribution)
#print( "Emmission Matrix", model.emission_matrix)
#print( "trans mat", model.transition_matrix)
# pass
```

[24]:
```
def update_hmm(hmm, sentence):
    """
    Function updates HMM based on new words it encounters
    Input: an hmm object and a sentence, a list of strings ending with a period
    Output: An updated hmm object
    """
    #get the attributes of the hidden markov model
    order = hmm.order
    initial_distribution = hmm.initial_distribution
    emission_matrix = hmm.emission_matrix
```

```
    transition_matrix = hmm.transition_matrix


    # get all the words
    unique_words = []

    for pos in emission_matrix:

        for word in emission_matrix[pos]:


            # add each word that the model has seen into unique words

            unique_words.append(word)

    #bool flag for if any new words were encountered
    new_word = False

    for word in sentence:

        # if the word is new, we want to add update the HMM
        if word not in unique_words:

            # if we get to this line, we have a new word
            new_word = True

            for part_of_speech in emission_matrix:

                for seen_word in emission_matrix[part_of_speech]:

                    # increment the each word by the same amount

                    emission_matrix[part_of_speech][seen_word] +=  0.00001

                # add the new word to each part of speech with a small␣
↪probability

                emission_matrix[part_of_speech][word] =  0.00001


    if new_word == True:

        #begin the normalization process
        for tag in emission_matrix:

            # find the normalizing term
            normalizer = sum(emission_matrix[tag].values())
```

```
            # normalize each word

            for finalword in emission_matrix[tag]:

                emission_matrix[tag][finalword] =␣
↪float(emission_matrix[tag][finalword])/float(normalizer)

        # updated_model = HMM(order, initial_distribution, emission_matrix,␣
↪transition_matrix)

    return HMM(order, initial_distribution, emission_matrix, transition_matrix)
```

[25]:
```
############################################################## Testing Update␣
↪HMM
alldata = read_pos_file("training.txt")
unique_tags = alldata[2]
unique_words = alldata[1]
hiddenmarkovmodel = build_hmm(alldata[0], unique_tags, unique_words, 2, False)
print (hiddenmarkovmodel.order)
#expect a new hmm of order 2
#passes

alldata = read_pos_file("training.txt")
unique_tags = alldata[2]
unique_words = alldata[1]
hiddenmarkovmodel = build_hmm(alldata[0], unique_tags, unique_words, 3, False)
print (hiddenmarkovmodel.order)
#expect a new hmm of order 3
#passes
```

```
2
3
```

[26]:
```
def log(number):
    """
    Caluculates the Logarithm of a number, and returns -inf in the number is 0
    Inputs : number, a real number
    Output : The log of a number, whihc is a real number of -inf
    """

    # log of 0 is negative infinity

    if number == 0:
        return float("-inf")
    else:
        return float(math.log(number))
```

```
################################## Testing LOG
print( log(0))
# Expect - inf
# passes

print( log(69))
# expect 4.2
#passes
```

```
-inf
4.23410650459726
```

[27]:
```
def bigram_viterbi(hmm, sentence):
    """
    Implements the Viterbi algorithm for the bigram model on an input HMM and a␣
 ↪sentence (a list of words and the period at the end).

    Input : HMM, an HMM object, and sentence, a list of words with a period at␣
 ↪the end
    Output: Tagged Words : a list of words and their tags
    """
    #get the data from the HMM object
    initial_distribution = hmm.initial_distribution
    emission_matrix = hmm.emission_matrix
    transition_matrix = hmm.transition_matrix


    # init V and BP
    V = defaultdict(lambda: defaultdict(int))
    bp = defaultdict(lambda: defaultdict(int))

    # length of the input sentence.
    L = len(sentence)

    # init the first column of the V matrix
    for pos in emission_matrix:

        #caluclate the first column of the matrix
        pi_sub_l = log(initial_distribution[pos])
        emissison_prob_x0 = log(emission_matrix[pos][sentence[0]])
        V[pos][0] = pi_sub_l + emissison_prob_x0

    for i in range(1, L):

        # l is a part of speech, more generally, a markov state
```

```
        for l in emission_matrix:

            max_prob = -float("inf")
            argmax = None

            # find the different l_prime values that can be take, then␣
↪determine the argmax and the max
            for l_prime in emission_matrix:

                transition_probability = log(transition_matrix[l_prime][l])

                previous_prob = V[l_prime][i-1]
                possible_max = transition_probability + previous_prob

                #update l prime
                if possible_max > max_prob:
                    max_prob = possible_max
                    argmax = l_prime

            # if none
            if argmax == None:
                for l_prime in emission_matrix.keys():
                    if V[l_prime][i-1]>= max_prob:
                        max_prob = V[l_prime][i-1]
                        argmax = l_prime

            emission_prob = log(emission_matrix[l][sentence[i]])

            #update V and BP
            V[l][i] = emission_prob + max_prob
            bp[l][i] = argmax


    # begin traceback
    argmax2 = None
    max_val_holder = -float("inf")

    #access the first element in the Sequence
    for l_prime_pos in emission_matrix:
        v_mat_entry = V[l_prime_pos][L-1]

        #get highest entry
        if v_mat_entry > max_val_holder:
            max_val_holder = v_mat_entry
            argmax2 = l_prime_pos

    sentence[L-1] = (sentence[L-1], argmax2)
```

```
    #traceback
    for i in range(L-2, -1, -1):
        zi = bp[sentence[i+1][1]][i+1]
        sentence[i] = (sentence[i], zi)


    return sentence
```

[28]:
```
################################################################ TESTING BIGRAM␣
↪VITERBI

alldata = read_pos_file("training.txt")
unique_tags = alldata[2]
unique_words = alldata[1]
hiddenmarkovmodel = build_hmm(alldata[0], unique_tags, unique_words, 2, False)
print (bigram_viterbi(hiddenmarkovmodel, ["My", "hips", "do", "not", "lie", ".
↪"]))
# Expect Possesive, noun, verb, negator, verb, period
# Passes

alldata = read_pos_file("training.txt")
unique_tags = alldata[2]
unique_words = alldata[1]
hiddenmarkovmodel = build_hmm(alldata[0], unique_tags, unique_words, 2, False)
print (bigram_viterbi(hiddenmarkovmodel, ["I", "hope", "I", "pass", "this",␣
↪"class", "."]))
# Expect Pronoun, verb, Pronoun, verb, determiner, noun, perios
# Passes
```

```
[('My', 'PRP$'), ('hips', 'NNS'), ('do', 'VBP'), ('not', 'RB'), ('lie', 'VB'),
('.', '.')]
[('I', 'PRP'), ('hope', 'VBP'), ('I', 'PRP'), ('pass', 'VBP'), ('this', 'DT'),
('class', 'NN'), ('.', '.')]
```

[29]:
```
def trigram_viterbi(hmm, sentence):
    """
    Implements the Viterbi algorithm for the treigram model on an input HMM and␣
↪a sentence (a list of words and the period at the end).

    Input : HMM, an HMM object, and sentence, a list of words with a period at␣
↪the end
    Output: Tagged Words : a list of words and their tags
    """
    #get the data from the HMM object
    initial_distribution = hmm.initial_distribution
    emission_matrix = hmm.emission_matrix
```

```
    transition_matrix = hmm.transition_matrix

    # init V and BP
    V = defaultdict(lambda: defaultdict(lambda: defaultdict(int)))
    bp = defaultdict(lambda: defaultdict(lambda: defaultdict(int)))

    # length of the input sentence.
    L = len(sentence)

    #being building the V matrix

    # init the l prime of the V matrix
    for pos_l_prime in emission_matrix:

        #init the l state
        for pos_l in emission_matrix:

            #caucluate the first column/plane in the 3d matrix

            pi_sub_lprime_l = log(initial_distribution[pos_l_prime][pos_l])
            emissison_prob_x0 = log(emission_matrix[pos_l_prime][sentence[0]])
            emissison_prob_x1 = log(emission_matrix[pos_l][sentence[1]])

            # put the entry in the matrix
            V[pos_l_prime][pos_l][1] = pi_sub_lprime_l + emissison_prob_x0 +␣
↪emissison_prob_x1

    for i in range(2, L):

        # l is a part of speech, more generally, a markov state
        for l_prime in emission_matrix:

            # find the different l_prime values that can be take, then␣
↪determine the argmax and the max
            for l in emission_matrix:

                bestmax = -float("inf")
                argmax = None

                for l_double_prime in emission_matrix:

                    #calculate possible entries

                    transition_probability =␣
↪log(transition_matrix[l_double_prime][l_prime][l])
                    previous_prob = V[l_double_prime][l_prime][i-1]
                    possible_max = transition_probability + previous_prob
```

```
                # update l double prime
                if possible_max > bestmax:
                    bestmax = possible_max
                    argmax = l_double_prime

            #if none in matrix
            if argmax == None:
                for l_double_prime in emission_matrix.keys():
                    if V[l_double_prime][l_prime][i-1] >= bestmax:
                        bestmax = V[l_double_prime][l_prime][i-1]
                        argmax = l_double_prime

            emission_prob = log(emission_matrix[l][sentence[i]])

            #update V and BP

            V[l_prime][l][i] = emission_prob + bestmax
            bp[l_prime][l][i] = argmax


    # begin traceback
    ZL_minus_1 = None
    ZL_minus_2 = None
    max_val_holder= -float("inf")

    #access the first element in the Sequence
    for state_1 in emission_matrix:
        for state_2 in emission_matrix:
            v_mat_entry = V[state_1][state_2][L-1]

            #get highest entry
            if v_mat_entry > max_val_holder:
                max_val_holder = v_mat_entry
                ZL_minus_1 = state_2
                ZL_minus_2 = state_1

    #init last Z values
    sentence[L-1] = (sentence[L-1], ZL_minus_1)
    sentence[L-2] = (sentence[L-2], ZL_minus_2)

    #traceback
    for i in range(L-3, -1, -1):
        zi = bp[sentence[i+1][1]][sentence[i+2][1]][i+2]
        sentence[i] = (sentence[i], zi)

    return sentence
```

[30]:
```
######################################### TESTING TRIGRAM

alldata = read_pos_file("training.txt")
unique_tags = alldata[2]
unique_words = alldata[1]
hiddenmarkovmodel = build_hmm(alldata[0], unique_tags, unique_words, 3, False)
print (trigram_viterbi(hiddenmarkovmodel, ["I", "am", "the", "machine", "."]))
# expecg Pronoun, verb, det, noun, period
#passes

alldata = read_pos_file("training.txt")
unique_tags = alldata[2]
unique_words = alldata[1]
hiddenmarkovmodel = build_hmm(alldata[0], unique_tags, unique_words, 3, False)
print (trigram_viterbi(hiddenmarkovmodel, ["I", "am", "happy", "."]))
# expecg Pronoun, verb, adj, period
#passes
```

```
[('I', 'PRP'), ('am', 'VBP'), ('the', 'DT'), ('machine', 'NN'), ('.', '.')]
[('I', 'PRP'), ('am', 'VBP'), ('happy', 'JJ'), ('.', '.')]
```

0.1 ANALYSIS CODE

[31]:
```
def compute_accuracy(tagged_data, results):
    '''
    Computes similarity between the actual tagged data and the algorithm's tags
    Input: tagged data, a list of tuples, and results, a list of tuples
    '''

    #init a numerator and a denominator
    numerator = 0
    denominator = 0
    for i in range(len(tagged_data)):

            #add a denominator regardless
            denominator += 1
            if tagged_data[i] == results[i]:

                #if we get a match, increment the numerator
                numerator += 1

    #calculate the percent accuracy
    percent_accurate = float(numerator)/float(denominator)

    return percent_accurate
```

[32]:

```python
############################################ TESTING COMPUTE ACCURACY␣
↪############################
a = ["a", "a", "a", "a"]
b = ["a", "b", "a", "a"]
print (compute_accuracy(a,b))
# expect .75
#passes

a = ["a", "a", "a", "a"]
b = ["a", "a", "a", "a"]
print (compute_accuracy(a,b))
# expect 1.0
#passes
```

```
0.75
1.0
```

[33]:

```python
def bigram_validate(training_data, percent, testdata_untagged, testdata_tagged,␣
↪order, use_smoothing):
    """
    Computes the out of sample accuracy of the POS tagging algorithm for bigram␣
↪HMM
    Inputs: a file training data, a percentage of data, untagged test data,␣
↪tagged test data, the order of the markov chain,
            a boolean parameter use smoothing

    Output: Accuracy, a real number between 0 and 1
    """

    #wrangle the data
    my_data = wrangle_data(training_data, percent)
    unique_words, unique_tags = get_unique_words_and_tags(my_data)

    #build an HMM
    old_hmm = build_hmm(my_data, unique_tags, unique_words, order,␣
↪use_smoothing)
    list_of_words, test_data_parsed = parse_test_file(testdata_untagged)

    #update the HMM if need be
    new_hmm = update_hmm(old_hmm, list_of_words)

    # put the predidted tags into a master list
    full_results = []
    for sentence in test_data_parsed:
        results = bigram_viterbi(new_hmm, sentence)
        for tup in results:
            full_results.append(tup)
```

```
    # read in the validation data
    validation_data = read_pos_file_modified(testdata_tagged)


    #get the final accuracy
    return compute_accuracy(validation_data, full_results)
```

[34]:
```
######################################## TESTING BIGRAM Validate␣
↪######################################
print (bigram_validate("training.txt", 0.01, "testdata_untagged.txt",␣
↪"testdata_tagged.txt", 2, True))
print (bigram_validate("training.txt", 0.01, "testdata_untagged.txt",␣
↪"testdata_tagged.txt", 2, False))

#expect two decimals between 0-1 with the first value higher than the second
# Passes
```

```
0.7587268993839835
0.6919917864476386
```

[35]:
```
def trigram_validate(training_data, percent, testdata_untagged,␣
↪testdata_tagged, order, use_smoothing):
    """
    Computes the out of sample accuracy of the POS tagging algorithm for bigram␣
↪HMM
    Inputs: a file training data, a percentage of data, untagged test data,␣
↪tagged test data,
            the order of the markov chain, a boolean parameter use smoothing

    Output: Accuracy, a real number between 0 and 1
    """
    #wrangle the data
    my_data = wrangle_data(training_data, percent)
    unique_words, unique_tags = get_unique_words_and_tags(my_data)

    #build an hmm
    old_hmm = build_hmm(my_data, unique_tags, unique_words, order,␣
↪use_smoothing)
    list_of_words, test_data_parsed = parse_test_file(testdata_untagged)

    #update the HMM if any new words are encountered
    new_hmm = update_hmm(old_hmm, list_of_words)

    # put the algorithm's predictions into a master list
    full_results = []
    for sentence in test_data_parsed:
```

```
        results = trigram_viterbi(new_hmm, sentence)
        for tup in results:
            full_results.append(tup)

    #read in the validation data
    validation_data = read_pos_file_modified(testdata_tagged)

    #get an accuracy value
    return compute_accuracy(validation_data, full_results)
```

[36]:

```
#################################### TESTING TRIGRAM VALIDATE
print (trigram_validate("training.txt", 0.01, "testdata_untagged.txt",␣
 ↪"testdata_tagged.txt", 3, True))
print (trigram_validate("training.txt", 0.01, "testdata_untagged.txt",␣
 ↪"testdata_tagged.txt", 3, False))

# expect two decimals between 0-1 with the first value higher than the second
# Passes
```

```
0.7453798767967146
0.6468172484599589
```

0.2 EXPERIMENT CODE

[37]:

```
################################################# EXPERIMENT ONE␣
 ↪#####################################################

'''
In experiment one, we build seven bigram HMMs on the first 1%, 5%, 10%, 25%,␣
 ↪50%,
75%, and 100% of the training corpus without smoothing and obtain 7 accuracy␣
 ↪values
'''
onepercent_1 = bigram_validate("training.txt", 0.01, "testdata_untagged.txt",␣
 ↪"testdata_tagged.txt", 2, False)
fivepercent_1 = bigram_validate("training.txt", 0.05, "testdata_untagged.txt",␣
 ↪"testdata_tagged.txt", 2, False)
tenpercent_1 = bigram_validate("training.txt", 0.1, "testdata_untagged.txt",␣
 ↪"testdata_tagged.txt", 2, False)
twentyfivepercent_1 = bigram_validate("training.txt", 0.25, "testdata_untagged.
 ↪txt", "testdata_tagged.txt", 2, False)
fiftypercent_1 = bigram_validate("training.txt", 0.5, "testdata_untagged.txt",␣
 ↪"testdata_tagged.txt", 2, False)
seventyfivepercent_1 = bigram_validate("training.txt", 0.75, "testdata_untagged.
 ↪txt", "testdata_tagged.txt", 2, False)
```

```
onehundopercent_1 = bigram_validate("training.txt", 1, "testdata_untagged.txt",␣
↪"testdata_tagged.txt", 2, False)
experiment_1_results = [onepercent_1, fivepercent_1, tenpercent_1,
                        twentyfivepercent_1, fiftypercent_1,␣
↪seventyfivepercent_1, onehundopercent_1]
print(experiment_1_results)

"""
[0.6919917864476386, 0.8275154004106776, 0.8696098562628337, 0.
↪9055441478439425, 0.9271047227926078, 0.9496919917864476, 0.9579055441478439]
"""
```

```
[0.6919917864476386, 0.8275154004106776, 0.8696098562628337, 0.9055441478439425,
0.9271047227926078, 0.9496919917864476, 0.9579055441478439]
```

[37]:
```
'\n[0.6919917864476386, 0.8275154004106776, 0.8696098562628337,
0.9055441478439425, 0.9271047227926078, 0.9496919917864476,
0.9579055441478439]\n'
```

[38]:
```
################################################ EXPERIMENT TWO␣
↪#######################################################

'''
In experiment 2, we build 7 trigram HMMs on the first 1%, 5%, 10%, 25%, 50%,
75%, and 100% of the training corpus without smoothing and obtain 7 accuracy␣
↪values
'''
onepercent_2 = trigram_validate("training.txt", 0.01, "testdata_untagged.txt",␣
↪"testdata_tagged.txt", 3, False)
fivepercent_2 = trigram_validate("training.txt", 0.05, "testdata_untagged.txt",␣
↪"testdata_tagged.txt", 3, False)
tenpercent_2 = trigram_validate("training.txt", 0.1, "testdata_untagged.txt",␣
↪"testdata_tagged.txt", 3, False)
twentyfivepercent_2 = trigram_validate("training.txt", 0.25, "testdata_untagged.
↪txt", "testdata_tagged.txt", 3, False)
fiftypercent_2 = trigram_validate("training.txt", 0.5, "testdata_untagged.txt",␣
↪"testdata_tagged.txt", 3, False)
seventyfivepercent_2 = trigram_validate("training.txt", 0.75,␣
↪"testdata_untagged.txt", "testdata_tagged.txt", 3, False)
onehundopercent_2 = trigram_validate("training.txt", 1, "testdata_untagged.
↪txt", "testdata_tagged.txt", 3, False)
experiment_2_results = [onepercent_2, fivepercent_2, tenpercent_2,␣
↪twentyfivepercent_2, fiftypercent_2, seventyfivepercent_2, onehundopercent_2]
print(experiment_2_results)

'''
```

```
[0.6468172484599589, 0.7905544147843943, 0.8357289527720739, 0.
↪8593429158110883, 0.8952772073921971, 0.917864476386037, 0.9322381930184805]

'''
```

[0.6468172484599589, 0.7905544147843943, 0.8357289527720739, 0.8593429158110883, 0.8952772073921971, 0.917864476386037, 0.9322381930184805]

[38]: '\n[0.6468172484599589, 0.7905544147843943, 0.8357289527720739, 0.8593429158110883, 0.8952772073921971, 0.917864476386037, 0.9322381930184805]\n\n'

[39]:
```
############################################### EXPERIMENT 3
'''
In experiment three, we build seven bigram HMMs on the first 1%, 5%, 10%, 25%,␣
↪50%,
75%, and 100% of the training corpus with smoothing and obtain 7 accuracy values
'''
onepercent_3 = bigram_validate("training.txt", 0.01, "testdata_untagged.txt",␣
↪"testdata_tagged.txt", 2, True)
fivepercent_3 = bigram_validate("training.txt", 0.05, "testdata_untagged.txt",␣
↪"testdata_tagged.txt", 2, True)
tenpercent_3 = bigram_validate("training.txt", 0.1, "testdata_untagged.txt",␣
↪"testdata_tagged.txt", 2, True)
twentyfivepercent_3 = bigram_validate("training.txt", 0.25, "testdata_untagged.
↪txt", "testdata_tagged.txt", 2, True)
fiftypercent_3 = bigram_validate("training.txt", 0.5, "testdata_untagged.txt",␣
↪"testdata_tagged.txt", 2, True)
seventyfivepercent_3 = bigram_validate("training.txt", 0.75, "testdata_untagged.
↪txt", "testdata_tagged.txt", 2, True)
onehundopercent_3 = bigram_validate("training.txt", 1, "testdata_untagged.txt",␣
↪"testdata_tagged.txt", 2, True)
experiment_3_results = [onepercent_3, fivepercent_3, tenpercent_3,␣
↪twentyfivepercent_3, fiftypercent_3, seventyfivepercent_3, onehundopercent_3]
print (experiment_3_results)

'''
[0.7587268993839835, 0.8603696098562629, 0.8901437371663244, 0.919917864476386,␣
↪0.9394250513347022, 0.9548254620123203, 0.9599589322381931]

'''
```

[0.7587268993839835, 0.8603696098562629, 0.8901437371663244, 0.919917864476386, 0.9394250513347022, 0.9548254620123203, 0.9599589322381931]

[39]: '\n[0.7587268993839835, 0.8603696098562629, 0.8901437371663244,
0.919917864476386, 0.9394250513347022, 0.9548254620123203,
0.9599589322381931]\n\n'

[40]:
```
########################################################## EXPERIMENT 4
'''
In experiment 2, we build 7 trigram HMMs on the first 1%, 5%, 10%, 25%, 50%,
75%, and 100% of the training corpus with smoothing and obtain 7 accuracy values
'''

onepercent_4 = trigram_validate("training.txt", 0.01, "testdata_untagged.txt",␣
 ↪"testdata_tagged.txt", 3, True)
fivepercent_4 = trigram_validate("training.txt", 0.05, "testdata_untagged.txt",␣
 ↪"testdata_tagged.txt", 3, True)
tenpercent_4 = trigram_validate("training.txt", 0.1, "testdata_untagged.txt",␣
 ↪"testdata_tagged.txt", 3, True)
twentyfivepercent_4 = trigram_validate("training.txt", 0.25, "testdata_untagged.
 ↪txt", "testdata_tagged.txt", 3, True)
fiftypercent_4 = trigram_validate("training.txt", 0.5, "testdata_untagged.txt",␣
 ↪"testdata_tagged.txt", 3, True)
seventyfivepercent_4 = trigram_validate("training.txt", 0.75,␣
 ↪"testdata_untagged.txt", "testdata_tagged.txt", 3, True)
onehundopercent_4 = trigram_validate("training.txt", 1, "testdata_untagged.
 ↪txt", "testdata_tagged.txt", 3, True)
experiment_4_results = [onepercent_4, fivepercent_4, tenpercent_4,␣
 ↪twentyfivepercent_4, fiftypercent_4, seventyfivepercent_4, onehundopercent_4]
print(experiment_4_results)

'''
[0.7453798767967146, 0.86652977412731, 0.8993839835728953, 0.9281314168377823,␣
 ↪0.9496919917864476, 0.9640657084188912, 0.9691991786447639]

'''
```

[0.7453798767967146, 0.86652977412731, 0.8993839835728953, 0.9281314168377823,
0.9496919917864476, 0.9640657084188912, 0.9691991786447639]

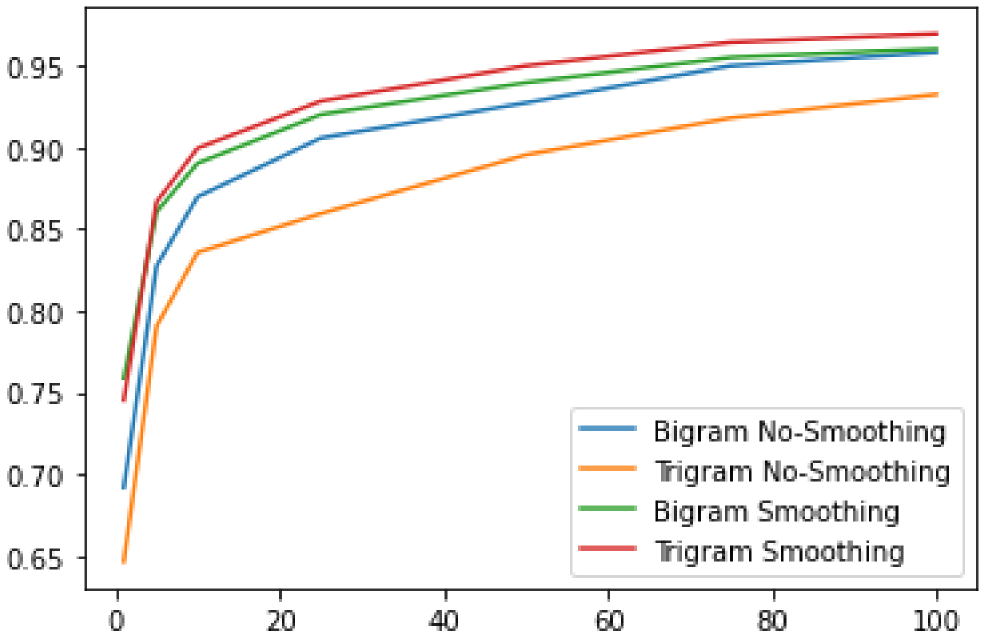
[40]: '\n[0.7453798767967146, 0.86652977412731, 0.8993839835728953,
0.9281314168377823, 0.9496919917864476, 0.9640657084188912,
0.9691991786447639]\n\n'

[41]:
```
# importing package
import matplotlib.pyplot as plt

# create data
x = [1,5,10,25,50, 75, 100]
y1 = experiment_1_results
```

```
y2 = experiment_2_results
y3 = experiment_3_results
y4 = experiment_4_results
# plot lines
plt.plot(x, y1, label = "Bigram No-Smoothing")
plt.plot(x, y2, label = "Trigram No-Smoothing")
plt.plot(x, y3, label = "Bigram Smoothing")
plt.plot(x, y4, label = "Trigram Smoothing")

plt.legend()
plt.show()
```



[ ]: