Importing Libraries In [1]: import os import pandas as pd import math from collections import defaultdict Problem 1- Reading the data In [2]: data\_dir = "SST-2" file\_name = "train.tsv" file\_path = os.path.join(data\_dir, file\_name) df\_sst = pd.read\_csv(file\_path, delimiter="\t") df\_sst.head(3) sentence label Out[2]: 0 hide new secretions from the parental units 0 1 contains no wit , only labored gags 2 that loves its characters and communicates som... In [3]: validationSize = 100 testSize = 100 df\_sst = df\_sst.sample(frac=1, random\_state=42).reset\_index(drop=True) val = df\_sst[:validationSize] test = df\_sst[validationSize:validationSize + testSize] train = df\_sst[validationSize + testSize:] print("Validation dataset size:", len(val)) print("Test dataset size:", len(test)) print("Training dataset size:", len(train)) Validation dataset size: 100 Test dataset size: 100 Training dataset size: 67149 In [4]: positiveClassCount = (train['label'] == 1).sum() negativeClassCount = (train['label'] == 0).sum() totalLength = len(train)priorPositiveProbability = (positiveClassCount / totalLength) \* 100 priorNegativeProbability = (negativeClassCount / totalLength) \* 100 print("Positive Probability: {:.2f}%".format(priorPositiveProbability)) print("Negative Probability: {:.2f}%".format(priorNegativeProbability)) Positive Probability: 55.77% Negative Probability: 44.23% Problem 2- Tokenizing data In [5]: def tokenize(df, column): tokenizedSequences = df[column].apply(lambda sentence: ['<s>'] + sentence.split() + ['</s>']) return tokenizedSequences tokenizedSequences = tokenize(train, 'sentence') print(tokenizedSequences.head()) [<s>, more, measured, or, polished, production... 200 201 [<s>, a, child, 's, interest, and, an, adult, ... 202 [<s>, delivered, dialogue, and, a, heroine, wh... 203 [<s>, as, inept, as, big-screen, remakes, of, ... [<s>, ,, crocodile, hunter, has, the, hurried,... 204 Name: sentence, dtype: object In [6]: vocabulary = set() for tokenizedSequence in train['sentence']: tokens = tokenizedSequence.split() vocabulary.update(tokens) vocabulary.add('<s>') vocabulary.add('</s>') vocabularySize = len(vocabulary) #print(vocabulary) print("Vocabulary size :", vocabularySize) Vocabulary size : 14817 Problem 3- Bigram Counts def countBigramFrequencies(tokenizedSequences): In [7]: bigramCounts = defaultdict(lambda: defaultdict(int)) for sequence in tokenizedSequences: for i in range(len(sequence) - 1): wi = sequence[i] wj = sequence[i + 1]bigramCounts[wi][wj] += 1 return bigramCounts bigramCounts = countBigramFrequencies(tokenizedSequences) frequency = bigramCounts['<s>']['the'] print("Frequency of the bigram ('<s>', 'the') in the training set:", frequency) Frequency of the bigram ('<s>', 'the') in the training set: 4451 Problem 4- Smoothing In [8]: def smoothingLogProbability(wm, wm1, bigramCounts, alpha, vocabularySize): countWmWm1 = bigramCounts.get(wm1, {}).get(wm, 0) + alpha countWm1 = sum(bigramCounts.get(wm1, {}).values()) + (alpha \* vocabularySize) logProb = math.log(countWmWm1 / countWm1) return logProb wordWm1 = "academy" wordWm = "award" alpha1 = 0.001alpha2 = 0.5logProb1 = smoothingLogProbability(wordWm, wordWm1, bigramCounts, alpha1, vocabularySize) logProb2 = smoothingLogProbability(wordWm, wordWm1, bigramCounts, alpha2, vocabularySize) print(f"Log Probability with alpha={alpha1}: {logProb1}") print(f"Log Probability with alpha={alpha2}: {logProb2}") Log Probability with alpha=0.001: -1.0251860898691059 Log Probability with alpha=0.5: -6.173181082203538 Problem 5- Sentence Log-Probability In [9]: def logProbability(sentence, bigramCounts, alpha, vocabularySize): sentence\_tokens = sentence.split() logProb = 0.0for i in range(1, len(sentence\_tokens)): wm1 = sentence\_tokens[i - 1] wm = sentence\_tokens[i] logProb += math.log( (bigramCounts.get(wm1,  $\{\}$ ).get(wm, 0) + alpha) / (sum(bigramCounts.get(wm1, {}).values()) + (alpha \* vocabularySize)) return logProb alpha = 0.001vocabularySize = len(vocabulary) sentence1 = "this was a really great movie but it was a little too long." sentence2 = "long too little a was it but movie great really a was this." logProb1 = logProbability(sentence1, bigramCounts, alpha, vocabularySize) logProb2 = logProbability(sentence2, bigramCounts, alpha, vocabularySize) print(f"Log Probability of Sentence 1: {logProb1}") print(f"Log Probability of Sentence 2: {logProb2}") Log Probability of Sentence 1: -71.27052642123148 Log Probability of Sentence 2: -145.60202109372278 Problem 6- Tuning Alpha alphaValues = [0.001, 0.01, 0.1]In [10]: logLikelihoods = {} for alpha in alphaValues: logLikelihood = 0.0 for sentence in val['sentence']: logLikelihood += logProbability(sentence, bigramCounts, alpha, vocabularySize) logLikelihoods[alpha] = logLikelihood bestAlpha = max(logLikelihoods, key = logLikelihoods.get) for alpha, logLikelihood in logLikelihoods.items(): print(f"Alpha = {alpha}: Log-Likelihood = {logLikelihood}") print(f"Selected Alpha: {bestAlpha}") selectedAlpha = bestAlpha Alpha = 0.001: Log-Likelihood = -4060.954140773797 Alpha = 0.01: Log-Likelihood = -4564.418451383303Alpha = 0.1: Log-Likelihood = -5571.937644465253Selected Alpha: 0.001 Problem 7- Applying Language Models In [11]: def tokenize\_and\_pad\_sentence(sentence): tokens = ['<s>'] + sentence.split() + ['</s>']return tokens priorPositiveProbability = (train['label'] == 1).mean() priorNegativeProbability = (train['label'] == 0).mean() positive\_tokenized = train[train['label'] == 1]['sentence'].apply(tokenize\_and\_pad\_sentence) negative\_tokenized = train[train['label'] == 0]['sentence'].apply(tokenize\_and\_pad\_sentence) positive\_bigramCounts = countBigramFrequencies(positive\_tokenized) negative\_bigramCounts = countBigramFrequencies(negative\_tokenized) selectedAlpha = bestAlpha def sentiment\_score(sentence, bigramCounts, alpha, vocabularySize): return logProbability(sentence, bigramCounts, alpha, vocabularySize) def classify\_sentiment(sentence): positive\_score = sentiment\_score(sentence, positive\_bigramCounts, selectedAlpha, vocabularySize) negative\_score = sentiment\_score(sentence, negative\_bigramCounts, selectedAlpha, vocabularySize) if positive\_score > negative\_score: return 1 else: return 0 test['predicted\_label'] = test['sentence'].apply(classify\_sentiment) predicted\_distribution = test['predicted\_label'].value\_counts() positive\_predictions = test[test['label'] == 1] negative\_predictions = test[test['label'] == 0] correct\_predictions = (test['predicted\_label'] == test['label']).sum() positive\_correct = (positive\_predictions['predicted\_label'] == positive\_predictions['label']).sum() negative\_correct = (negative\_predictions['predicted\_label'] == negative\_predictions['label']).sum() total\_sentences = len(test) accuracy = correct\_predictions / total\_sentences positive\_accuracy = positive\_correct / len(positive\_predictions) negative\_accuracy = negative\_correct / len(negative\_predictions) print("Class Distribution of Predicted Labels:") print(predicted\_distribution) print("\nAccuracy of the Experiment: {:.2f}%".format(accuracy \* 100)) print("Accuracy of Positive Predictions: {:.2f}%".format(positive\_accuracy \* 100)) print("Accuracy of Negative Predictions: {:.2f}%".format(negative\_accuracy \* 100)) Class Distribution of Predicted Labels: 1 0 Name: predicted\_label, dtype: int64 Accuracy of the Experiment: 88.00% Accuracy of Positive Predictions: 86.36% Accuracy of Negative Predictions: 91.18% /var/folders/qz/8\_cb5kss6j909hn7j1mwr93c0000gn/T/ipykernel\_26106/80856143.py:27: SettingWithCopyWarning: A value is trying to be set on a copy of a slice from a DataFrame. Try using .loc[row\_indexer,col\_indexer] = value instead See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user\_guide/indexing.html#returning-a-view-versus-a-copy test['predicted\_label'] = test['sentence'].apply(classify\_sentiment) Problem 8- Markov Assumption Where in this homework did you apply the Markov assumption? Imagine you applied the 2nd-order Markov assumption, using trigrams. Do you think your accuracy results would increase or decrease? Why? Or, if you are not sure, give a benefit or drawback of using trigrams for this experiment. (Note: You do not need to rerun this experiment with trigrams to answer this question.) Answer: I applied the Markov Assumption when calculating the log probability of a sentence using bigrams. Each word's probability is conditioned on the previous word, which is a first-order Markov assumption. If we were to apply a 2nd-order Markov assumption using trigrams, it would mean that each word's probability would be conditioned on the previous two words. This approach would result in a more complex model. The accuracy of the model could potentially increase or decrease. One thing that would determine what happens to the accuracy would be the size of the dataset. If the dataset is small, the model might overfit which would result in bad accuracy, but if the dataset is larger, then the model provide more context and gain more information about the relationships between words which could lead to an increase in accuracy.