Monsoon 2020 - NLP ReadMe File

NOTE:-

- The Output.pdf file contains the sample outputs along with screenshots wherever required.
- Theory answers are written in the ReadMe.pdf file.
- Both .py and .ipynb are attached in the zipped folder.

Q1)

- Importing the required libraries.
- Reading the given file.
 - Extracting sentences based on the next line character.
 - Extract word-tag pairs based on space as delimiter.
 - Extract words and tags separately based on underscore as delimiter.
- Calculating the statistics of sentences.
 - Minimum length of sentence
 - Maximum length of sentence
- Creating a list of tuples for the entire file. Each tuple contains (word, tag).
- 'Vocab' is a set of unique words.
- 'Tag set' is the set of unique tags.
- 'Tag_count' is the dictionary of tag and corresponding count of occurrences of tag in the given corpus.
- Emission Probabilities:-
 - For calculating the emission probabilities, initially calculating word-to-tag count which says about the count of a word given the tag.
 - Using these word-to-tag counts, emission probabilities are calculated.
- Transition Probabilities:-
 - Calculating Tag2-to-Tag1 count which says the count of tag2 given tag1.
 - With these Tag2-to-Tag1 counts, transition probabilities are calculated.
 - While calculating these probabilities, Laplace smoothing is used to handle the values of zeros.
- Viterbi Algorithm:
 - Initially, creating a predict proba list with size of input word file.
 - For every word,
 - Creating a list for storing the probabilities that a particular tag can set to this word.
 - This probability is calculated using the product of emission probability and transition probability.

- Extract the max probability from this list, indicating that the tag with maximum probability is correct for the current word.
- Append the tag with max probability to predict_proba list.
- Now, this predict_proba list contains the corresponding tags for the list of words.
- A function is written to calculate the confusion-matrix which takes the predicted tags and ground-truth tags and returns the matrix.
 - The same function is used to calculate the confusion matrix in all cases.
- Function for accuracy:-
 - Takes predicted tags and true tags as arguments and returns the accuracy for this prediction.
- Function for precision, recall and F1-score:-
 - Takes the Confusion matrix as an argument for this function.
 - For every tag,
 - Calculating True Positives, True Negatives, False Positives and False Negatives.
 - Using these values, precision,recall and f1-score is calculated for that particular tag.
 - Using the values for individual tags, the overall precision, recall and f1-score is calculated.

3 - fold Cross Validation:-

- Dividing the given set of sentences into three parts.
- For each fold, we consider one part as a validation set and the other two as training data.
- For every fold:-
 - Obtaining predicted tags for the validation data using Viterbi Algorithm.
 - Obtain the wrongly predicted words in particular fold.
 - Calculating Confusion Matrix with Predicted tags and True tags.
 - Calculating Accuracy.
 - Calculating Precision, Recall and F1-score for every tag in the validation data and for the overall validation data.

TRIGRAMS

- Emission Probabilities
 - These are the same for any n-grams as these are just the probability of a word given tag.
- Transition Probabilities
 - These are the probabilities of a tag3 given that the previous two tags are tag2 and tag1.

- For computational purposes, I am combining the tag2 and tag1 with '!' (exclamation) in the middle.
- For eg:- if tag2='NN' and tag1='AT', I will store them as 'NN!AT'.
- Whenever I need these tags separately, I will split them based on '!' as a delimiter.
 - While calculating these probabilities, we will be using the probability of bigrams, i.e., probability of tag2 given tag1.
- Laplace smoothing is used to handle all the cases.
- All the steps followed for each fold in 3-fold cross validation for HMM of length 1, are also followed here.

Observations:-

- There is not much difference in the accuracy values of bigrams and Trigrams.
- As the data is imbalanced, the evaluation metric cannot be the accuracy in this
 case.
- So, if we compare the precision, recall and F1-score values of bigrams language model and trigrams language model,
 - We can conclude that, for the given corpus 'BIGRAM LANGUAGE MODEL' will work better comparatively.

Q2) HMM for Markov Assumption length 2

HMM:

Goal! Maximize P(S/O) tag sequence by choosing best sequene s.

0 -> Observation; sastates.

->Apply Markor Assumption

Prior :-

$$P(S) = P(S_1) \cdot P(S_2|S_1) \cdot P(S_3|S_2S_1) \cdot P(S_4|S_3 \cdot S_2) - \cdots$$

Likelihood:

→ For probability of tag3 given that previous two tags are tag2 and tag1, We will be using the probability of tag2 given tag1.

- For every set of validation, I printed the wrongly predicted words as a list of lists which contain [word,true-tag,predicted-tag].
- If we observe true-tags in this list, some of those tags are AT,NN,IN,VBD.
- In the given corpus, these tags have more frequency and wrongly predicted words are also mapped to different types of tags.
- Due to this there will be more probability of assigning wrong labels to the word

References used:-

- → https://github.com/shikhinmehrotra/NLP-POS-tagging-using-HMMs-and-Viterbi-heuristic/blob/master/NLP-POS%20tagging%20using%20HMMs%20and%20Viterbi%20heuristic.ipynb
- → https://youtu.be/68hmUltbPnw
- → Textbook posted in google classroom for Viterbi Algo.
- → https://stackoverflow.com/questions/2148543/how-to-write-a-confusion-matrix-in-python
- → https://stackoverflow.com/questions/31324218/scikit-learn-how-to-obtain-true-positive-true-negative-false-positive-and-fal
- → https://machinelearningmastery.com/precision-recall-and-f-measure-for-imbalanc ed-classification/
- → Slides for solving Q2.
