Machine Learning Project:

Members**:**

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Instructions on how to run our code:

First ensure that you are using Python 3.6.1 and above.

Using your terminal, Navigate to the /Code folder:

For part 2: >> python simple\_p2.py

For part 3: >> python viterbi\_p3.py

For part 4: >> python maxmarginal\_p4.py

For part 5: >> python ess\_p5.py

Our code will output results to the folder *EvalScript/\*Language\*.* For example, you can find the EN output for part 3 under *EvalScript/EN/dev.p3.out.* However, we have also created a folder Output\_Files, that contain our results in the format specified by the project handout.

Part 2

EvalScript Results

EN dataset:

#Entity in gold data: 226

#Entity in prediction: 981

#Correct Entity : 149

Entity precision: 0.1519

Entity recall: 0.6593

Entity F: 0.2469

#Correct Sentiment : 58

Sentiment precision: 0.0591

Sentiment recall: 0.2566

Sentiment F: 0.0961

CN dataset:

#Entity in gold data: 362

#Entity in prediction: 2608

#Correct Entity : 146

Entity precision: 0.0560

Entity recall: 0.4033

Entity F: 0.0983

#Correct Sentiment : 56

Sentiment precision: 0.0215

Sentiment recall: 0.1547

Sentiment F: 0.0377

FR dataset:

#Entity in gold data: 223

#Entity in prediction: 964

#Correct Entity : 176

Entity precision: 0.1826

Entity recall: 0.7892

Entity F: 0.2965

#Correct Sentiment : 65

Sentiment precision: 0.0674

Sentiment recall: 0.2915

Sentiment F: 0.1095

SG dataset:

#Entity in gold data: 1382

#Entity in prediction: 5112

#Correct Entity : 644

Entity precision: 0.1260

Entity recall: 0.4660

Entity F: 0.1983

#Correct Sentiment : 283

Sentiment precision: 0.0554

Sentiment recall: 0.2048

Sentiment F: 0.0872

Part 3

EvalScript Results

EN Dataset:

#Entity in gold data: 226

#Entity in prediction: 162

#Correct Entity : 104

Entity precision: 0.6420

Entity recall: 0.4602

Entity F: 0.5361

#Correct Sentiment : 64

Sentiment precision: 0.3951

Sentiment recall: 0.2832

Sentiment F: 0.3299

CN Dataset:

#Entity in gold data: 362

#Entity in prediction: 158

#Correct Entity : 64

Entity precision: 0.4051

Entity recall: 0.1768

Entity F: 0.2462

#Correct Sentiment : 47

Sentiment precision: 0.2975

Sentiment recall: 0.1298

Sentiment F: 0.1808

FR Dataset:

#Entity in gold data: 223

#Entity in prediction: 166

#Correct Entity : 112

Entity precision: 0.6747

Entity recall: 0.5022

Entity F: 0.5758

#Correct Sentiment : 72

Sentiment precision: 0.4337

Sentiment recall: 0.3229

Sentiment F: 0.3702

SG Dataset:

#Entity in gold data: 1382

#Entity in prediction: 723

#Correct Entity : 386

Entity precision: 0.5339

Entity recall: 0.2793

Entity F: 0.3667

#Correct Sentiment : 244

Sentiment precision: 0.3375

Sentiment recall: 0.1766

Sentiment F: 0.2318

Part 4

EvalScript Results

EN Dataset:

#Entity in gold data: 226

#Entity in prediction: 159

#Correct Entity : 83

Entity precision: 0.5220

Entity recall: 0.3673

Entity F: 0.4312

#Correct Sentiment : 53

Sentiment precision: 0.3333

Sentiment recall: 0.2345

Sentiment F: 0.2753

FR Dataset:

#Entity in gold data: 223

#Entity in prediction: 80

#Correct Entity : 41

Entity precision: 0.5125

Entity recall: 0.1839

Entity F: 0.2706

#Correct Sentiment : 25

Sentiment precision: 0.3125

Sentiment recall: 0.1121

Sentiment F: 0.1650

Our Algorithm

The execution of our max-marginal algorithm is done mainly in the *maximum\_marginal\_analysis()* function. We first read our training file as a list of sentences with its sequence of labels, and ran the *count()* function over it to count the number of occurrences of each label, word, emissions and transitions. We then use these counts to get our emission and transition parameters using the *get\_parameters()* function. These functions can be found in our external module.py file.

With our emission and transition parameters, we can estimate the most probable “current transition” by observing the current word and the previous label. When words appear less than a total of 3 times in our training set, we will modify the word into #UNK#, then calculate the emission and transition parameters accordingly.

Our training file is also read in as a list of sentences. Iterating through each sentence in the list, words in the sentence that do not appear in the training set are replaced with an #UNK#. The sentence, the emission parameters and the transition parameters are inputted into our max-marginal algorithm and the resulting word and label sequence of each sentence is appended/concatenated to our final output string. Our max-marginal algorithm is done in the *maximum\_marginal\_sentence()* function.

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To begin the algorithm, the alpha and beta lists are as matrices of zeroes with size n x T, where n refers to the length of the sentence, and T refers to the total number of labels. Alpha refers to our forward probabilities (the sum of scores of all the paths taken from “START” position to the input position with input state), while Beta refers to our backward probabilities (the sum of scores of all paths taken from the input position and input state to the “STOP” position). By multiplying Alpha and Beta, we are basically getting the sum scores for all the paths that pass through the input state and the input position. If we find the label that produces the best sum scores at the input position, we will predict that this label is the optimal label for the input position/word.

In our base case, we set the values of Alpha at position 0 of each label to be the transition probability from “START” to that label, with “START” as its parent node. We also set the values of Beta at position n-1 of each label to be the product of transition probability from that label to “STOP” and the emission probability of that label to the input word. The values of Alpha and Beta for the remaining positions are updated iteratively, summing the scores of all the paths leading to each label at each position.

After getting all our Alpha and Beta values, we multiply the corresponding values to find the label that gives the optimum score at each position. These optimal labels are then returned from our *maximum\_marginal\_sentence()* function. These optimal labels are then concatenated next to the words in the test data to give us our dev.p4.out.

Part 5

For part 5, we implemented Viterbi with modifications. The main execution of the code can be found in the *ess\_analysis()* function. We first read in the data using *read\_in\_file()*, then perform the count functions to get the respective counts of emissions, transitions, y and x. Note however, that we have two distinct count functions, as for *count\_sentiment\_only(train\_data, k)* function, we only count the labels related to sentiments and for *count\_entity\_only(train\_data, k)* function, we only count the labels related to entities. This results in two distinct counts of emissions, transitions, which we then use to run the function *get\_parameters()* over. These will give us our respective transition and emission parameters for entity (e\_a, e\_b) and sentiment (s\_a, s\_b). The motivation behind this is to get results that are more sensitive to entities and sentiments separately.

Once done with that, we read in the test data, using *read\_in\_file()* again. We then iterate through the test data, sentence by sentence and first check if the word can be found in our train data. If it is not, we replace the word by #UNK#, and get a modified sentence that replaces missing words with #UNK#.

Then we run the function *viterbi\_sentiment\_only(mod\_sentence, s\_a, s\_b),* in order to get our viterbi pi matrix. This Viterbi method performs Viterbi but only using the sentiment emission and transition parameters. Our Viterbi method has been modified to store the best parent node as well as the second best. From this, we can backtrack using *back\_propagation\_sentiment\_only()* and this returns us a state sequence array known as output\_states\_sentiment, with the best and second best parent node at each index of the array.

The output state sequence array will look something like:

**[[best\_state\_s1, second\_best\_state\_s1], [best\_state\_s2, second\_best\_state\_s2]…]**

Then we run the function *viterbi\_entity\_only(mod\_sentence, e\_a, e\_b)*, in order to get our viterbi pi matrix. This Viterbi method performs Viterbi but only using the entity emission and transition parameters. Our Viterbi method here stores the best parent node. From this, we can backtrack using *back\_propagation\_entity\_only()* and this returns us a state sequence array, known as output\_states\_sentiment, with the best parent node at each index of the array.

The output state sequence array will also look something like:

**[[best\_state\_e1], [best\_state\_e2]…]**

Now that we have two different state sequence arrays (one for sentiment only and the other for entity only), we can try to combine them together in order to get a final state sequence array. We iterate over the current sentence in the test data, and check if for a given position, output\_states\_entity has a value of ‘O’. If it does not, we also check if output\_states\_sentiment has a value of ‘O’ at that same position. If it also does not have an ‘O’, then we combine the results of the two together to give us the final label for the position. If output\_states\_entity does not have a value of ‘O’ but output\_states\_sentiment has a value of ‘O’, then we combine the result of output\_states\_entity with the second best result of output\_states\_sentiment (which will not be an ‘O’). We then append the result to the final output state sequence array, fixed\_output\_states.

Next, we iterate over the fixed\_output\_states to see check if there are any ‘I-‘ labels where there shouldn’t be, and modify the ‘I-‘s to ‘B-‘.

Finally, we have the fixed output state sequence array for the sentence and we can write it to file. We repeat this process till all sentences in the test data have been run through.

EvalScript Results

EN Dataset:

#Entity in gold data: 226

#Entity in prediction: 227

#Correct Entity : 135

Entity precision: 0.5947

Entity recall: 0.5973

Entity F: 0.5960

#Correct Sentiment : 79

Sentiment precision: 0.3480

Sentiment recall: 0.3496

Sentiment F: 0.3488

FR Dataset:

#Entity in gold data: 223

#Entity in prediction: 230

#Correct Entity : 141

Entity precision: 0.6130

Entity recall: 0.6323

Entity F: 0.6225

#Correct Sentiment : 85

Sentiment precision: 0.3696

Sentiment recall: 0.3812

Sentiment F: 0.3753