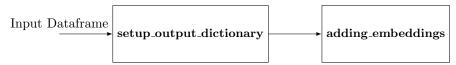
DMT HW3: Natural Language Processing

Alessandro Quattrociochi - 1609286 Tansel Simsek - 1942297

Part 1.1

Pre-processing and embeddings

In this part and in 2.1 we focus on text processing and some operations that led us to define the final form of the dataset on which, subsequently we applied the classification algorithms. We have three different datasets: train, test and dev, presented as list of dictionaries. For each dictionary, we considered only 3 fields: id, input, output while for the output we considered only the first dictionary (in case of multiples), particularly the key "answer" which had only two possible outcomes: SUPPORT and REFUTES. Although the initial form is, as mentioned, a list of dictionaries, we converted it to dataframe to have faster execution speed and to take advantage of the that structure. After the conversion to dataframe, we created two different functions: setup_output_dictionary, adding_embeddings. These functions, passed dataframe as input return as output a new one with the modification. The second function is the one of interest, as it exploits the SentenceTransformer library and the paraphrase-distilroberta-base-v1 model to return an array of 768 elements, indicating the logarithm of similarity probability. To increase effectiveness, we made extensive use of the map() function to avoid loops on every line, especially when fitting models.



At the end of step 1.2, the final table was saved in two formats .pickle to have a save checkpoint and as .jsonl as required by the assignment.

Below is a printout of the train dataset after applying the two functions.

	id	input	output	claim_embedding
0	75397	Nikolaj Coster-Waldau worked with the Fox Broa	[{'answer': 'SUPPORTS'}]	[-0.022804047912359238, 0.14688865840435028, 0
1	150448	Roman Atwood is a content creator.	[{'answer': 'SUPPORTS'}]	[0.020325791090726852,0.22245517373085022,0
2	214861	History of art includes architecture, dance, s	[{'answer': 'SUPPORTS'}]	[-0.12503863871097565,-0.11809630692005157,0
3	156709	Adrienne Bailon is an accountant.	[{'answer': 'REFUTES'}]	[0.04965561628341675,0.7739212512969971,0.24
4	129629	Homeland is an American television spy thrille	[{'answer': 'SUPPORTS'}]	[-0.24140028655529022,0.1532667875289917,0.2
5	33078	The Boston Celtics play their home games at TD	[{'answer': 'SUPPORTS'}]	[-0.10345622897148132, 0.029171394184231758,
6	6744	The Ten Commandments is an epic film.	[{'answer': 'SUPPORTS'}]	[-0.19420571625232697, -0.17690017819404602, 0
7	226034	Tetris has sold millions of physical copies.	[{'answer': 'SUPPORTS'}]	[0.19175095856189728, 0.22708220779895782, 0.1
8	40190	Cyndi Lauper won the Best New Artist award at	[{'answer': 'SUPPORTS'}]	[0.022759675979614258, 0.46901243925094604, -0
9	76253	There is a movie called The Hunger Games.	[{'answer': 'SUPPORTS'}]	[-0.38541746139526367, -0.20291005074977875,

Figure 1. Final dataset for 1.1

Part 1.2

We have picked 2 algorithms, 1st one as Logistic Regression and 2nd one as knn. The details about selected parameters and best parameters found after hyper-parameter tuning will be given below.

Grid Of Parameters

■ Logistic Regression

solver: ['newton-cg', 'lbfgs', 'liblinear'], penalty: ['l1', 'l2', 'elasticnet'], C: loguniform(1e-5, 100)

knn

n_neighbors : [13,15,17] weights : ['uniform', 'distance'] metric : ['euclidean', 'manhattan']

Best Configurations for Each Classifier

Logistic Regression

'C': 1.1700993456412832, 'penalty': 'l1', 'solver': 'liblinear'

knn

'weights': 'distance', 'n_neighbors': 17, 'metric': 'manhattan'

Confusion Matrices

Classifier	Predicted	Predicted	Recall
1	Refutes	Supports	
Actual	3735	1517	0.711
Refutes			
Actual	1339	3853	0.742
Supports			
Precision	0.736	0.718	0.727

Classifier	Predicted	Predicted	Recall
2	Refutes	Supports	
Actual	3332	1920	0.634
Refutes			
Actual	1510	3682	0.709
Supports			
Precision	0.688	0.657	0.672

From the results above, We can state that Logistic Regression performs much better than knn for all recall, precision and accuracy metrices.

Hyper-parameter optimisation

First of all, it is fundamental to mention about data preprocessing that lead to find the above results. Because of the unbalanced train dataset (73% as Supports, 27% as Refutes), We have decided to get only 27% of the 0 labeled train data to acquire fair precision. Randomized Search algorithm with 5-cross validation is applied in both Logistic Regression and knn algorithm. Additionally, number of iterations taken as 500 for the Logistic Regression. Because of the cost of computational time, different k values are tried in different small datasets then the most frequent values are picked to construct our parameter space for k in knn algorithm.

if the goal was to be sure to correctly catch all REFUTES claims (i.e. label them as REFUTES), which metric should you look at? And what trivial solution could be adopted?

In that case, we should look at the True Negative Recall rate and pick the classifier with the highest TNR rate which is Classifier 1 (Logistic Regression) for our setting while trial solution can be taken as to collect many REFUTES labeled classes with providing few labeled SUPPORTS classes to increase TNR rate for REFUTES.

Pre-processing and embeddings

This second part follows the same pattern as part 1.1 In fact, also in this case we have maintained the approach of writing functions that would take the dataset from part_1 output data folder and from those we have added the last three columns related to wikipedia pages, abtracts and finally embedding for the abstracts from wikipedia. In more detail, we used the pre-trained model "hf_e2e_entity_linking_wiki_abs" and from the outputs, after fitting GENRE library model, we selected only the predicted pages in square brackets. For each claim we created a list that contained all the resulting pages. After creating the column related to wikipedia pages, we used the file abstract_kilt_knowledgesource.json to query the abstract related to the previously found wikipedia pages, stored and finally ranked in descending order of length. At the end, we reapplied the function defined in Section 1.1 to compute the embeddings for each claim. For this last case, the maximum length of the input sequence was set equal to 256. As before, we appended to each row an array of size 768 containing the logarithm of the similarity probability. For this computationally intensive part of the homework, we used GPU accelerators and divided the datasets into batches of 1000 samples each. Nevertheless, in the final version of the code we report the driver code version without the split. Also in this case we report a screen of the final version of the dataset, subsequently converted in jsonl.

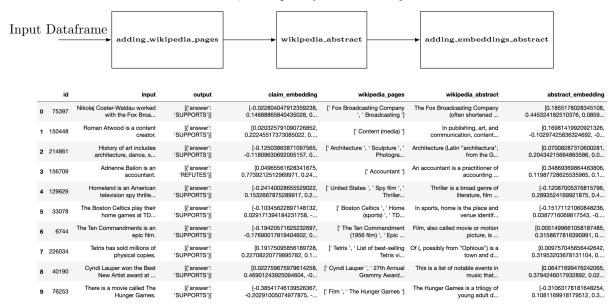


Figure 2. Final dataset for part 2.1

Part 2.2

We have picked 2 algorithms, 1st one as Logistic Regression and 2nd one as knn. The details about selected parameters and best parameters found after hyper-parameter tuning will be given below.

■ Grid Of Parameters

■ Logistic Regression

solver: ['newton-cg', 'lbfgs', 'liblinear'], penalty: ['l1', 'l2', 'elasticnet'], C: loguniform(1e-5, 100)

knn

n_neighbors: [13,15,17]
weights: ['uniform', 'distance']
metric: ['euclidean', 'manhattan']

Best Configurations for Each Classifier

■ Logistic Regression

'C': 0.4115283426435553, 'penalty': 'l1', 'solver': 'liblinear'

■ knn

'weights': 'distance', 'n_neighbors': 15, 'metric': 'manhattan'

Confusion Matrices

Classifier	Predicted	Predicted	Recall
1	Refutes	Supports	
Actual	3683	1569	0.701
Refutes			
Actual	1300	3892	0.750
Supports			
Precision	0.739	0.713	0.725

Classifier	Predicted	Predicted	Recall
2	Refutes	Supports	
Actual	3090	2162	0.588
Refutes			
Actual	1731	3461	0.667
Supports			
Precision	0.641	0.616	0.627

From the results above, We can state that Logistic Regression performs much better than knn for all recall, precision and accuracy metrices.

■ Hyper-parameter optimisation

Randomized Search algorithm with 5-cross validation is applied both Logistic Regression and knn algorithm. Additionally, number of iterations taken as 500 for the Logistic Regression. Because of the cost of computational time, different k values are tried in different small datasets then the most frequent values are picked to construct our parameter space for k in knn algorithm.

■ Bonus Part

■ Prediction file used

 $new_set_pred_1.jsonl$

Result

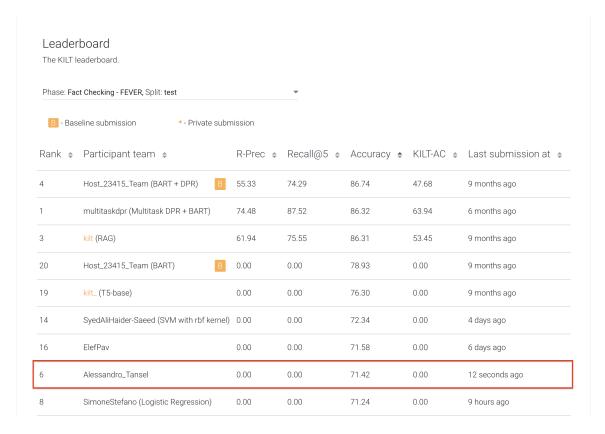


Figure 3. Ranking and score in the leader board