IR BONUS

Advanced Text Classification and Model Evaluation

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Github: https://github.com/shiffy01/IR_Bonus.git
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Part A:

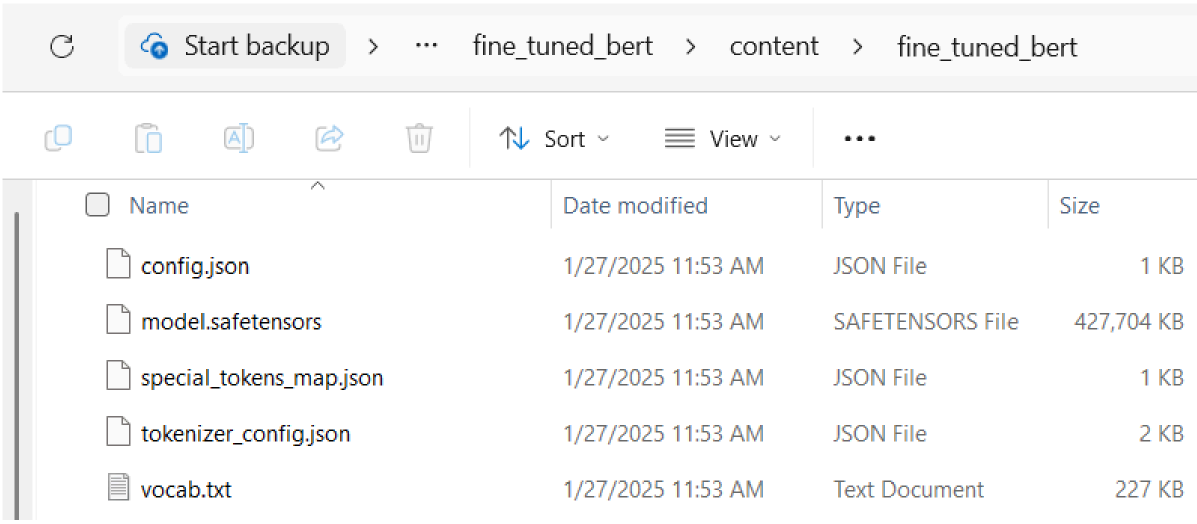
In hw3 we trained a model that predicts the sentiment of a sentence with words only from 1 list(Israeli **or** Palestinian word) . In this part we want to check the performance of the model with sentences that contain words from **both** lists. And then we Evaluated the model using precision, recall, F1 score, and accuracy.

From the file posts_first_targil we ran the same code from hw3 with a line difference, now we want the sentences with words from both lists (palestinian words and israeli words)

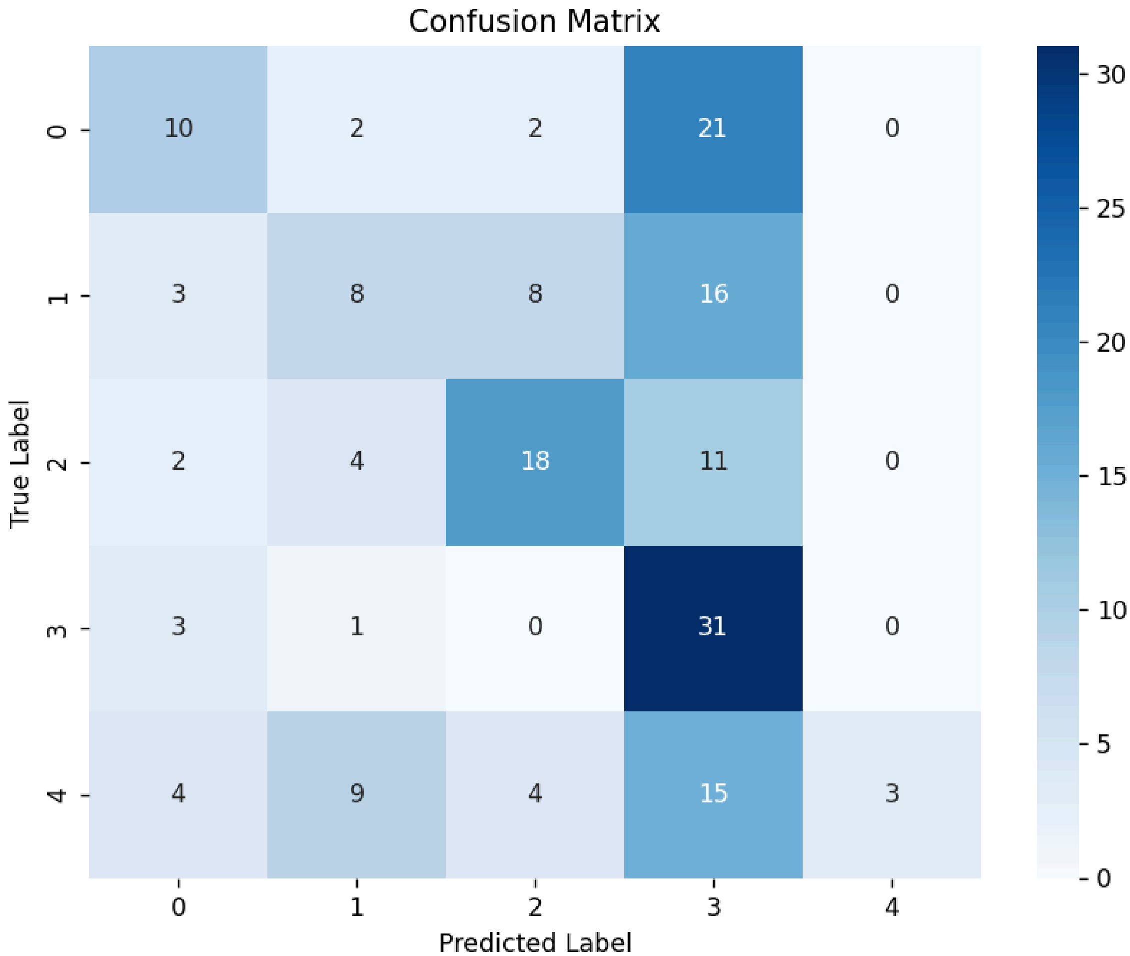
By hand we extracted 35 sentences from each of the 5 categories:
```
label_mapping = {
    "anti-i": 0,
    "pro-p": 1,
    "neutral": 2,
    "anti-p": 3,
```

"pro-i": 4
}

The model:



Results:



It seems like the model does not work so well for sentences with both types of words. It has a strong bias towards anti palestinian. It makes sense because the dataset is from the news of a war time. And most of the world thinks that Israel is the bad guy here and that they are hurting the Palestinians for no reason.

```
Classification Report:
              precision    recall  f1-score   support

           0       0.45      0.29      0.35        35
           1       0.33      0.23      0.27        35
           2       0.56      0.51      0.54        35
           3       0.33      0.89      0.48        35
           4       1.00      0.09      0.16        35

    accuracy                           0.40       175
   macro avg       0.54      0.40      0.36       175
weighted avg       0.54      0.40      0.36       175
```

Example of a sentence that can be labeled anti israeli(by hand), and anti palestine(model):

gaza's health ministry says nearly 31,000 people - mostly women and children - have been killed by israel's offensive.

If we did a model of pro-Israeli anti-israel and neutral it would work better because it looks like it is confusing the anti palestinian and pro palestine. Or pro Israel with anti palestine. So if it was 3 categories it would work better.

The output file:

	A	B	C	D	E	F	G
1	lewspape	ument Nur	tence Nun	Sentence	Label By Hand	Prediction	Score
2	al-j	217	1	tel aviv/west jerusalem –	4	4	0.526748
3	jpost	524	4	In response, the IDF stru	4	0	0.6215764
4	jpost	416	3	If a meeting between Abl	2	2	0.9358292
5	jpost	558	2	The Israeli military dropp	3	3	0.8538795
6	BBC	223	1	an israeli missile has hit	4	0	0.6565936
7	The New Y	2	5	the israeli military also sa	3	3	0.5182915
8	jpost	548	5	Hezbollah has linked wh	1	3	0.9733946
9	al-j	37	2	israel is using bureaucra	0	0	0.6667844
10	jpost	519	6	He blamed Hamas for th	3	3	0.9763172
11	BBC	49	1	"the war in gaza crushed	1	3	0.9635468
12	BBC	23	2	it comes a day after the	3	3	0.9758857
13	The New Y	22	1	iran seizes commercial s	1	3	0.944811
14	BBC	42	3	the welsh singer, who ha	1	1	0.9508616
15	al-j	29	1	this year, the shadow of	1	3	0.9506314

Part B:

We create 6 models. SVM, LoR and ANN. on bert and then on Sbert embedding.

First we embed the sentences from hw4.(the ones with words from one list) in hw4 we put in labels.
We used models:
Bert: bert-based-uncase
Sbert: `all-MiniLM-L6-v2`

For the Bert Model we tokenized the sentences, removed stop words and then summed up the vectors (without the stop words) to create one vector for each document.
Suggestions For Improvement:

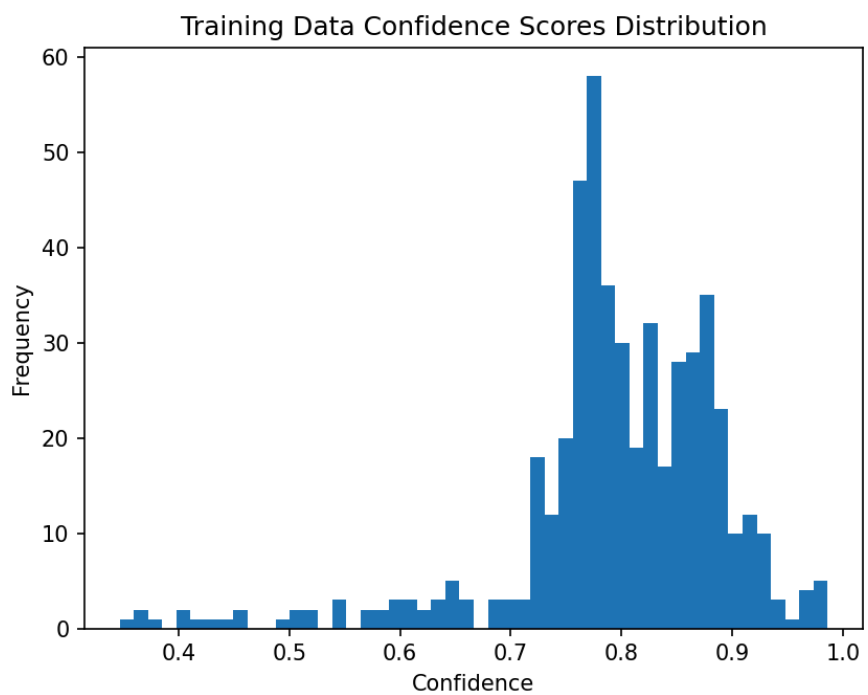
Removing stop words is a good start, but there are many other words that can be removed from our sentences before they are turned into vectors. Some words are expected with high probability to appear in proximity to each other. For example, if a document contains the word “starvation” we might expect to see the words: “strategy”, “policy”, “of [children, people, etc]” “as a weapon of war”, etc. These words do not help infer the meaning of the sentence and only distract (since we assume starvation is saying something negative about the people utilizing it) therefore those words can be removed. We could have a dictionary of words that have the connotation of war, and keep only those words.

Since we are dealing with sentences then we can assume that all of the sentences have less than 512 tokens/words. That's why we didnt take care of the limitation that Bert works with up to 512 tokens.

Support Vector Machine (SVM):

Perform 10-fold cross-validation to evaluate the model.
-Bert

```
Best Parameters: {'C': 10, 'gamma': 'scale'}
Accuracy: 0.5920
Precision: 0.6511
Recall: 0.5920
F1 Score: 0.5955
Confusion Matrix:
[[10  0  3  7  4]
 [ 1 22  4  1  9]
 [ 0  0  8  2  9]
 [ 3  4  2 18  0]
 [ 0  0  2  0 16]]
```



Sentences the model labeled successfully:

Sentence:preparing for elections is, sabri saidam believes, the biggest feasible step to restore faith in palestinian politics.

Label: Pro-Israel
Confidence score: 0.799

Sentence: these inaccuracies and errors may violate israel's obligation under international law to provide "effective advanced warnings", says janina dill, co-director of the oxford institute of ethics, law and armed conflict.
Label: Anti-Israel
Confidence score: 0.876

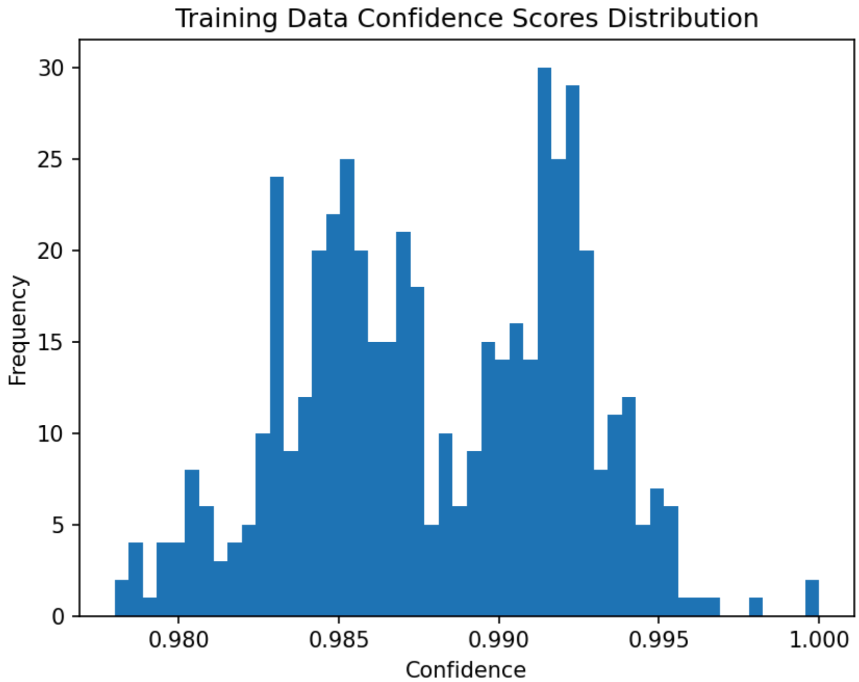
Sentences the model labeled unsuccessfully:

Sentence: israel does not want that war either.
Label: Anti-Israel
Predicted Label: Neutral
Confidence score: 0.372

Sentence: it is thought that arrow dealt with most of the ballistic missiles aimed at israel.
Label: Neutral
Predicted Label: Anti-Israel
Confidence score: 0.35

-Sbert

```
Best Parameters: {'C': 10, 'gamma': 'scale'}
Accuracy: 0.7200
Precision: 0.7531
Recall: 0.7200
F1 Score: 0.7214
Confusion Matrix:
[[17  0  5  2  0]
 [ 0 24  3  3  7]
 [ 2  0  9  3  5]
 [ 1  1  2 23  0]
 [ 0  1  0  0 17]]
```



Sentences the model labeled successfully:

Sentence: preparing for elections is, sabri saidam believes, the biggest feasible step to restore faith in palestinian politics.
Label: Pro-Israel
Confidence score: 0.984

Sentence: these inaccuracies and errors may violate israel's obligation under international law to provide "effective advanced warnings", says janina dill, co-director of the oxford institute of ethics, law and armed conflict.
Label: Anti-Israel
Confidence score: 0.986

Sentences the model labeled unsuccessfully:

Sentence: it said soldiers near the aid convoy had fired towards people who approached them and who they considered a threat.
Label: Anti-Israel
Predicted Label: Neutral
Confidence score: 0.503

Sentence: “Regret for shattering an entire division of the occupation army?” Hamden countered.
Label: Anti-Israel
Predicted Label: Neutral
Confidence score: 0.469

Logistic Regression (LoR):

Perform 10-fold cross-validation to evaluate the model.
-Bert

```
Cross-Validation Accuracy: 0.6400
Classification Report:
              precision    recall  f1-score   support

           0       0.66      0.66      0.66       125
           1       0.64      0.70      0.67       125
           2       0.58      0.55      0.57       125
           3       0.68      0.69      0.68       125
           4       0.63      0.59      0.61       125

    accuracy                           0.64       625
   macro avg       0.64      0.64      0.64       625
weighted avg       0.64      0.64      0.64       625

Predictions saved to BERT_file.xlsx
```

Sentences the model labeled successfully:

Sentence: these inaccuracies and errors may violate israel's obligation under international law to provide "effective advanced warnings", says janina dill, co-director of the oxford institute of ethics, law and armed conflict.
Label: Anti-Israel
Confidence score: 0.999

Sentence: Gaza is my life.
Label: Pro-Palestine
Confidence score: 0.98

Sentences the model labeled unsuccessfully:

Sentence: preparing for elections is, sabri saidam believes, the biggest feasible step to restore faith in palestinian politics.
Label: Pro-Israel
Predicted Label: Pro-Palestinian
Confidence score: 0.846

Sentence: we asked the idf how many tunnels, and what proportion of the total tunnel network, they had destroyed.
Label: Anti-Israel
Predicted Label: Anti-Palestine
Confidence score: 0.472

-Sbert

```
Cross-Validation Accuracy: 0.7392
Classification Report:
              precision    recall  f1-score   support

           0       0.73      0.70      0.71       125
           1       0.79      0.76      0.78       125
           2       0.69      0.65      0.67       125
           3       0.75      0.77      0.76       125
           4       0.74      0.82      0.78       125

    accuracy                           0.74       625
   macro avg       0.74      0.74      0.74       625
weighted avg       0.74      0.74      0.74       625
```

Sentences the model labeled successfully:

Sentence: these inaccuracies and errors may violate israel's obligation under international law to provide "effective advanced warnings", says janina dill, co-director of the oxford institute of ethics, law and armed conflict.
Label: Anti-Israel
Confidence score: 0.999

Sentence: Gaza is my life.
Label: Pro-Palestine

Confidence score: 0.566

Sentences the model labeled unsuccessfully:

Sentence: preparing for elections is, sabri saidam believes, the biggest feasible step to restore faith in palestinian politics.
Label: Pro-Israel
Predicted Label: Pro-Palestinian
Confidence score: 0.434

Sentence: we asked the idf how many tunnels, and what proportion of the total tunnel network, they had destroyed.
Label: Anti-Israel
Predicted Label: Neutral
Confidence score: 0.315

Artificial Neural Network (ANN):

ANN model with 4 hidden layers
-Bert

```
Epoch 1/15
14/16 [=========================>....] - ETA: 0s - loss: 3.2041 - accuracy: 0.2299
Epoch 1: val_accuracy improved from -inf to 0.29464, saving model to best_model_bert_2.h5
C:\Users\user\AppData\Roaming\Python\Python38\site-packages\keras\src\engine\training.py:3000: UserWarning: You are saving your mod
  saving_api.save_model(
16/16 [==============================] - 3s 63ms/step - loss: 3.0710 - accuracy: 0.2340 - val_loss: 1.9118 - val_accuracy: 0.2946
Epoch 2/15
11/16 [===================>..........] - ETA: 0s - loss: 1.6607 - accuracy: 0.3153
Epoch 2: val_accuracy did not improve from 0.29464
16/16 [==============================] - 0s 16ms/step - loss: 1.6235 - accuracy: 0.3140 - val_loss: 1.9959 - val_accuracy: 0.2946
Epoch 3/15
11/16 [===================>..........] - ETA: 0s - loss: 1.5070 - accuracy: 0.3665
Epoch 3: val_accuracy did not improve from 0.29464
16/16 [==============================] - 0s 10ms/step - loss: 1.4456 - accuracy: 0.4020 - val_loss: 1.9976 - val_accuracy: 0.2768
Epoch 4/15
15/16 [===========================>..] - ETA: 0s - loss: 1.2944 - accuracy: 0.4563
Epoch 4: val_accuracy improved from 0.29464 to 0.34821, saving model to best_model_bert_2.h5
16/16 [==============================] - 0s 13ms/step - loss: 1.2948 - accuracy: 0.4560 - val_loss: 1.8982 - val_accuracy: 0.3482
Epoch 5/15
14/16 [=========================>....] - ETA: 0s - loss: 1.2561 - accuracy: 0.4821
Epoch 5: val_accuracy did not improve from 0.34821
16/16 [==============================] - 0s 9ms/step - loss: 1.2724 - accuracy: 0.4700 - val_loss: 1.8104 - val_accuracy: 0.3393
Epoch 6/15
14/16 [=========================>....] - ETA: 0s - loss: 1.1996 - accuracy: 0.5335
```

```
Epoch 6: val_accuracy improved from 0.34821 to 0.36607, saving model to best_model_bert_2.h5
16/16 [==============================] - 0s 13ms/step - loss: 1.1797 - accuracy: 0.5380 - val_loss: 1.7270 - val_accuracy: 0.3661
Epoch 7/15
13/16 [=======================>......] - ETA: 0s - loss: 1.1007 - accuracy: 0.6034
Epoch 7: val_accuracy improved from 0.36607 to 0.41071, saving model to best_model_bert_2.h5
16/16 [==============================] - 0s 15ms/step - loss: 1.1175 - accuracy: 0.5800 - val_loss: 1.9347 - val_accuracy: 0.4107
Epoch 8/15
14/16 [=========================>....] - ETA: 0s - loss: 1.0197 - accuracy: 0.6362
Epoch 8: val_accuracy did not improve from 0.41071
16/16 [==============================] - 0s 10ms/step - loss: 1.0272 - accuracy: 0.6380 - val_loss: 1.9651 - val_accuracy: 0.3750
Epoch 9/15
14/16 [=========================>....] - ETA: 0s - loss: 0.9747 - accuracy: 0.6384
Epoch 9: val_accuracy did not improve from 0.41071
16/16 [==============================] - 0s 9ms/step - loss: 0.9783 - accuracy: 0.6400 - val_loss: 2.1654 - val_accuracy: 0.3750
Epoch 10/15
12/16 [=====================>........] - ETA: 0s - loss: 0.8977 - accuracy: 0.6823
Epoch 10: val_accuracy did not improve from 0.41071
16/16 [==============================] - 0s 11ms/step - loss: 0.8852 - accuracy: 0.6860 - val_loss: 1.9157 - val_accuracy: 0.4107
Epoch 11/15
16/16 [==============================] - ETA: 0s - loss: 0.7691 - accuracy: 0.7440
Epoch 11: val_accuracy improved from 0.41071 to 0.43750, saving model to best_model_bert_2.h5
16/16 [==============================] - 0s 14ms/step - loss: 0.7691 - accuracy: 0.7440 - val_loss: 1.9182 - val_accuracy: 0.4375
Epoch 12/15
```



```
16/16 [==============================] - ETA: 0s - loss: 0.7022 - accuracy: 0.7560
Epoch 12: val_accuracy improved from 0.43750 to 0.45536, saving model to best_model_bert_2.h5
16/16 [==============================] - 0s 14ms/step - loss: 0.7022 - accuracy: 0.7560 - val_loss: 1.8958 - val_accuracy: 0.4554
Epoch 13/15
 1/16 [>.............................] - ETA: 0s - loss: 0.6435 - accuracy: 0.7500
Epoch 13: val_accuracy did not improve from 0.45536
16/16 [==============================] - 0s 7ms/step - loss: 0.6360 - accuracy: 0.7880 - val_loss: 1.8538 - val_accuracy: 0.4196
Epoch 14/15
15/16 [===========================>..] - ETA: 0s - loss: 0.5870 - accuracy: 0.8083
Epoch 14: val_accuracy improved from 0.45536 to 0.49107, saving model to best_model_bert_2.h5
16/16 [==============================] - 0s 12ms/step - loss: 0.5877 - accuracy: 0.8000 - val_loss: 1.8959 - val_accuracy: 0.4911
Epoch 15/15
16/16 [==============================] - ETA: 0s - loss: 0.5080 - accuracy: 0.8460
Epoch 15: val_accuracy did not improve from 0.49107
16/16 [==============================] - 0s 8ms/step - loss: 0.5080 - accuracy: 0.8460 - val_loss: 1.7958 - val_accuracy: 0.4911
Best Epoch Used: 14
4/4 [==============================] - 0s 3ms/step
1/1 [==============================] - 0s 44ms/step - loss: 1.4133 - accuracy: 0.6154
Test Accuracy: 0.6153846383094788
```


Sentences the model labeled successfully:

Sentence: it said soldiers near the aid convoy had fired towards people who approached them and who they considered a threat.
Label: Anti-Israel
Confidence score: 0.957

Sentence: it is thought that arrow dealt with most of the ballistic missiles aimed at israel.
Label: Neutral
Confidence score: 0.543

Sentences the model labeled unsuccessfully:

Sentence: israel does not want that war either.
Label: Anti-Israel
Predicted Label: Neutral
Confidence score: 0.505

Sentence: Nearly half of its students are women, 20% are Israeli Arabs, and over 1,000 international students from 30 countries enrich the campus.
Label: Pro-Israel
Predicted Label: Neutral
Confidence score: 0.495

-Sbert

```
Epoch 1/15
 1/16 [>.............................] - ETA: 31s - loss: 1.6093 - accuracy: 0.1875
C:\Users\user\AppData\Roaming\Python\Python38\site-packages\keras\src\engine\training.py:3000: UserWarning: You are saving your model
  saving_api.save_model(
Epoch 1: val_accuracy improved from -inf to 0.26786, saving model to best_model_sbert_2.h5
16/16 [==============================] - 3s 35ms/step - loss: 1.6063 - accuracy: 0.2600 - val_loss: 1.5997 - val_accuracy: 0.2679
Epoch 2/15
 1/16 [>.............................] - ETA: 0s - loss: 1.5955 - accuracy: 0.3125
Epoch 2: val_accuracy improved from 0.26786 to 0.29464, saving model to best_model_sbert_2.h5
16/16 [==============================] - 0s 10ms/step - loss: 1.5801 - accuracy: 0.3300 - val_loss: 1.5592 - val_accuracy: 0.2946
Epoch 3/15
 1/16 [>.............................] - ETA: 0s - loss: 1.5274 - accuracy: 0.3750
Epoch 3: val_accuracy improved from 0.29464 to 0.32143, saving model to best_model_sbert_2.h5
16/16 [==============================] - 0s 9ms/step - loss: 1.5137 - accuracy: 0.3820 - val_loss: 1.4811 - val_accuracy: 0.3214
Epoch 4/15
 1/16 [>.............................] - ETA: 0s - loss: 1.4612 - accuracy: 0.4375
Epoch 4: val_accuracy improved from 0.32143 to 0.33036, saving model to best_model_sbert_2.h5
16/16 [==============================] - 0s 10ms/step - loss: 1.3992 - accuracy: 0.4020 - val_loss: 1.4000 - val_accuracy: 0.3304
Epoch 5/15
 1/16 [>.............................] - ETA: 0s - loss: 1.2759 - accuracy: 0.4375
Epoch 5: val_accuracy improved from 0.33036 to 0.38393, saving model to best_model_sbert_2.h5
16/16 [==============================] - 0s 9ms/step - loss: 1.2574 - accuracy: 0.4420 - val_loss: 1.3099 - val_accuracy: 0.3839
Epoch 6/15
```

```
 1/16 [>.............................] - ETA: 0s - loss: 1.2574 - accuracy: 0.5000
Epoch 6: val_accuracy improved from 0.38393 to 0.48214, saving model to best_model_sbert_2.h5
16/16 [==============================] - 0s 10ms/step - loss: 1.1003 - accuracy: 0.5340 - val_loss: 1.2054 - val_accuracy: 0.4821
Epoch 7/15
 1/16 [>.............................] - ETA: 0s - loss: 0.9903 - accuracy: 0.6562
Epoch 7: val_accuracy improved from 0.48214 to 0.60714, saving model to best_model_sbert_2.h5
16/16 [==============================] - 0s 12ms/step - loss: 0.9246 - accuracy: 0.6920 - val_loss: 1.0672 - val_accuracy: 0.6071
Epoch 8/15
 1/16 [>.............................] - ETA: 0s - loss: 0.7464 - accuracy: 0.7812
Epoch 8: val_accuracy improved from 0.60714 to 0.63393, saving model to best_model_sbert_2.h5
16/16 [==============================] - 0s 12ms/step - loss: 0.7467 - accuracy: 0.7940 - val_loss: 0.9830 - val_accuracy: 0.6339
Epoch 9/15
 1/16 [>.............................] - ETA: 0s - loss: 0.6246 - accuracy: 0.8750
Epoch 9: val_accuracy improved from 0.63393 to 0.64286, saving model to best_model_sbert_2.h5
16/16 [==============================] - 0s 11ms/step - loss: 0.5925 - accuracy: 0.8440 - val_loss: 0.9140 - val_accuracy: 0.6429
Epoch 10/15
 1/16 [>.............................] - ETA: 0s - loss: 0.4388 - accuracy: 0.8438
Epoch 10: val_accuracy did not improve from 0.64286
16/16 [==============================] - 0s 6ms/step - loss: 0.4703 - accuracy: 0.8700 - val_loss: 0.9330 - val_accuracy: 0.6429
Epoch 11/15
 1/16 [>.............................] - ETA: 0s - loss: 0.5322 - accuracy: 0.7188
Epoch 11: val_accuracy improved from 0.64286 to 0.66071, saving model to best_model_sbert_2.h5
16/16 [==============================] - 0s 11ms/step - loss: 0.3784 - accuracy: 0.8980 - val_loss: 0.9061 - val_accuracy: 0.6607
Epoch 12/15
```



```
 1/16 [>.............................] - ETA: 0s - loss: 0.3662 - accuracy: 0.9375
Epoch 12: val_accuracy did not improve from 0.66071
16/16 [==============================] - 0s 6ms/step - loss: 0.3078 - accuracy: 0.9220 - val_loss: 0.8735 - val_accuracy: 0.6607
Epoch 13/15
 1/16 [>.............................] - ETA: 0s - loss: 0.3055 - accuracy: 0.9688
Epoch 13: val_accuracy did not improve from 0.66071
16/16 [==============================] - 0s 7ms/step - loss: 0.2528 - accuracy: 0.9400 - val_loss: 0.9270 - val_accuracy: 0.6429
Epoch 14/15
 1/16 [>.............................] - ETA: 0s - loss: 0.1570 - accuracy: 1.0000
Epoch 14: val_accuracy did not improve from 0.66071
16/16 [==============================] - 0s 6ms/step - loss: 0.2100 - accuracy: 0.9520 - val_loss: 0.9425 - val_accuracy: 0.6607
Epoch 15/15
 1/16 [>.............................] - ETA: 0s - loss: 0.1469 - accuracy: 1.0000
Epoch 15: val_accuracy did not improve from 0.66071
16/16 [==============================] - 0s 6ms/step - loss: 0.1735 - accuracy: 0.9680 - val_loss: 0.9681 - val_accuracy: 0.6607
Best Epoch Used: 11
4/4 [==============================] - 0s 1ms/step
1/1 [==============================] - 0s 44ms/step - loss: 0.3887 - accuracy: 0.8462
Test Accuracy: 0.8461538553237915
```

Sentences the model labeled successfully:

Sentence: israel does not want that war either.
Label: Anti-Israel
Confidence score: 0.667

Sentence: it is thought that arrow dealt with most of the ballistic missiles aimed at israel.
Label: Neutral
Confidence score: 0.849

Sentences the model labeled unsuccessfully:

Sentence: it said soldiers near the aid convoy had fired towards people who approached them and who they considered a threat.
Label: Anti-Israel
Predicted Label: Neutral
Confidence score: 0.609

Sentence: “Regret for shattering an entire division of the occupation army?” Hamden countered.
Label: Anti-Israel
Predicted Label: Neutral
Confidence score: 0.484

Interesting insights:

1) Within each model When the score was 1. Then the prediction was correct. All the time. The model was very sure of its prediction and it was really correct. Those sentences were very straight forward.
2) Because we are using 10 cross folds for SVM and LoR then it splits the data so sometimes each line is in the train and sometimes it's in the test. That's how it knows how to predict the label and score without knowing the data beforehand.
3) Ann testing was only on some of the dataset so only some sentences had predictions. So we had to merge the files smartly.

Majority:

After we ran all models and combined them to 1 file we checked the majority label of the 6 models and if there was a tie we checked which average score was higher. We reached 92% accuracy (Accuracy: 0.9200). Which is very good. 🙂

Output file:

D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X
Sentence	label	bel encode	edicted La	t_embedd	rt_embed	ogreg_pre	_logreg_s	ogreg_pre	t_logreg_s	Bert_pred	l_Bert_sco	sBert_pred	_sBert_sc	Bert_pred	l_Bert_sco	sBert_pred	_sBert_sc	ajority_Lab	ect_Prediction	
We aim to	pro-i	4	4	[-9.626074	[-0.058555	4	1	4	0.800774	4	0.759235	4	0.984286					4	1	
preparing t	pro-i	4	1	[-1.606126	[0.004436	1	0.84604	1	0.434483	4	0.799867	4	0.984836					4	1	
Museums i	pro-p	1	1	[-3.128663	[-0.041235	1	1	4	0.595729	4	0.489269	4	0.937045	4	0.838838	4	0.891639	4	0	
• Soci	pro-i	4	4	[-1.123837	[0.106906	1	0.521777	4	0.577329	4	0.883172	4	0.983091					4	1	
these inac	anti-i	0	0	[0.547733	[0.017690	0	1	0	0.57826	0	0.87677	0	0.986308					0	1	
IN F	pro-p	1	1	[-5.069488	[0.016631	1	0.974182	1	0.480772	1	0.790343	1	0.991718					1	1	

Column names(in order):

Newspaper

Document Number

Sentence Number

Sentence

label

label encoded

Predicted Label

bert_embedded

sbert_embedded

Bert_logreg_prediction

Bert_logreg_score

sBert_logreg_prediction

sBert_logreg_score

SVM_Bert_prediction

SVM_Bert_scores

SVM_sBert_prediction

SVM_sBert_scores

ANN_Bert_prediction

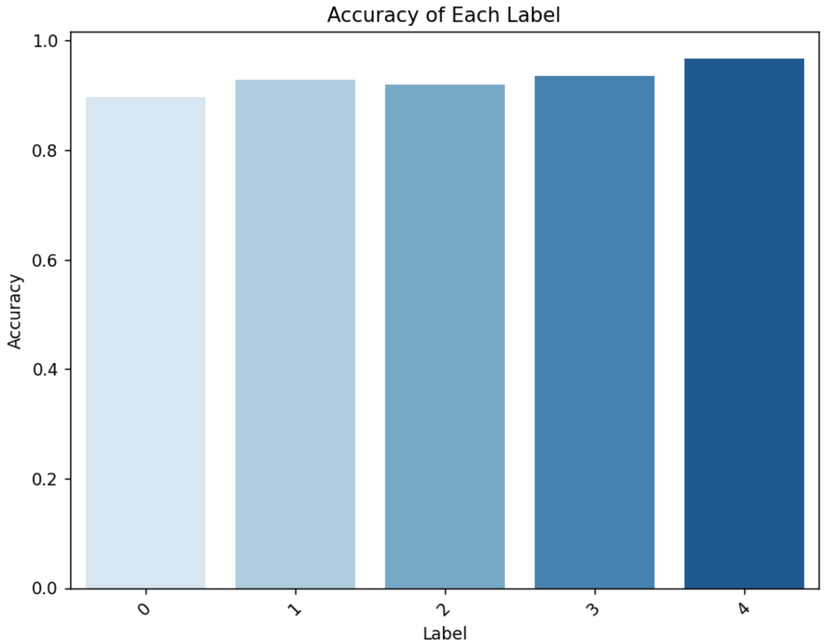
ANN_Bert_scores

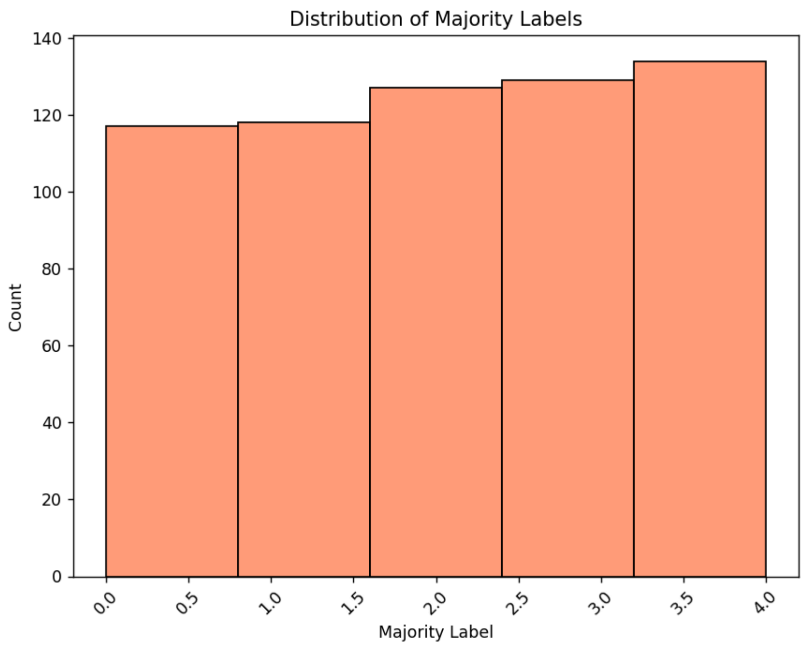
ANN_sBert_prediction

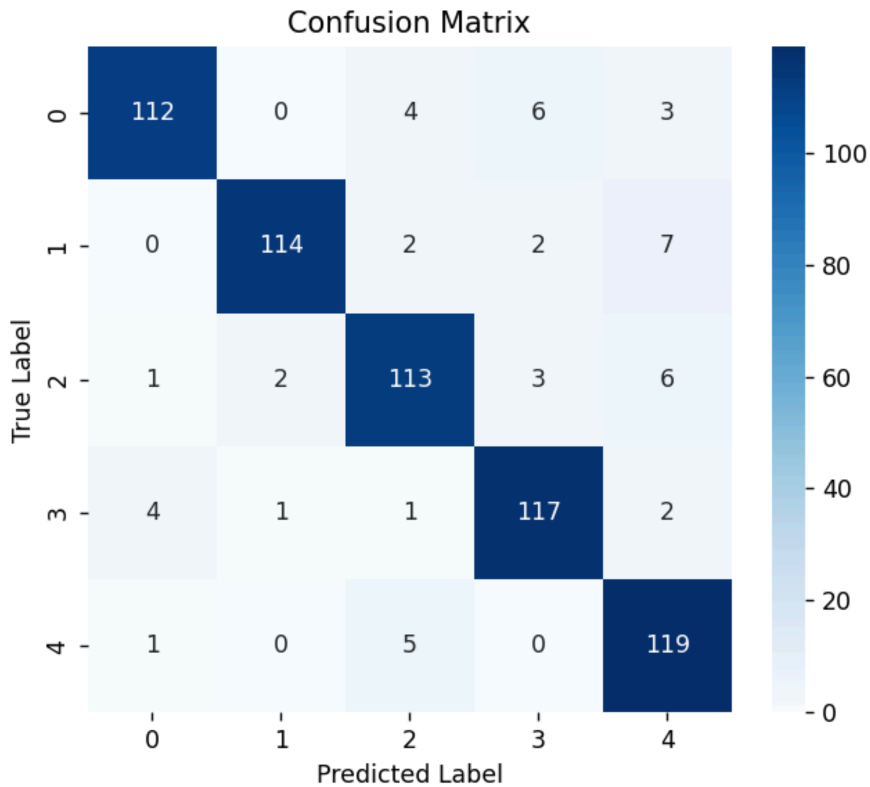
ANN_sBert_scores

Majority_Label

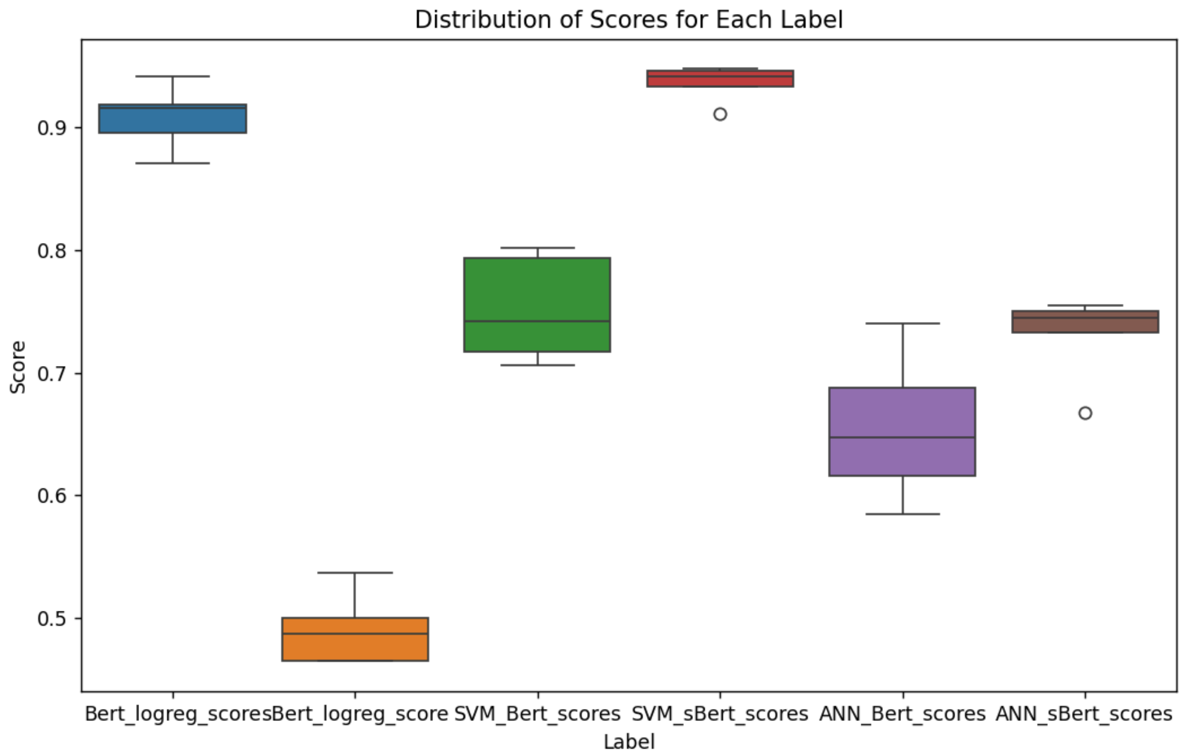
Correct_Prediction

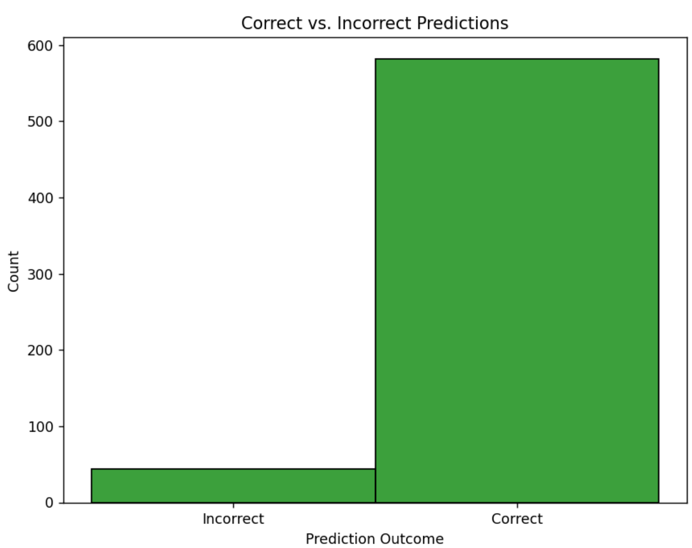

Accuracy of Each Label
Accuracy
Label
0
1
2
3
4
0.0
0.2
0.4
0.6
0.8
1.0

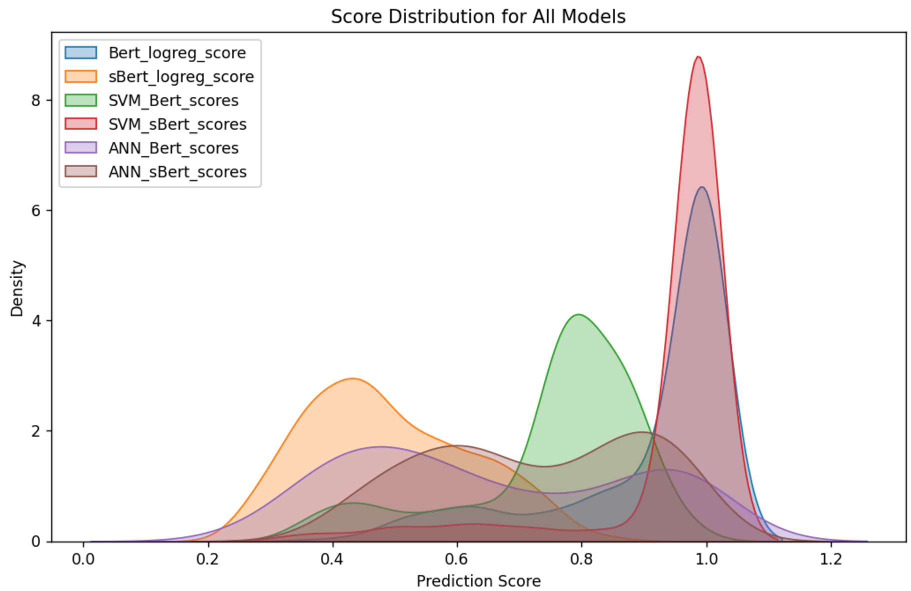

Distribution of Majority Labels
Count
Majority Label
0
20
40
60
80
100
120
140
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0



We managed to predict the labels very well. Ideal (100%) would be 125 of each label. 125 on the diagonal. But we came very close. It made the most mistakes with label 0 - anti israel. And the best with label 4 pro israel.

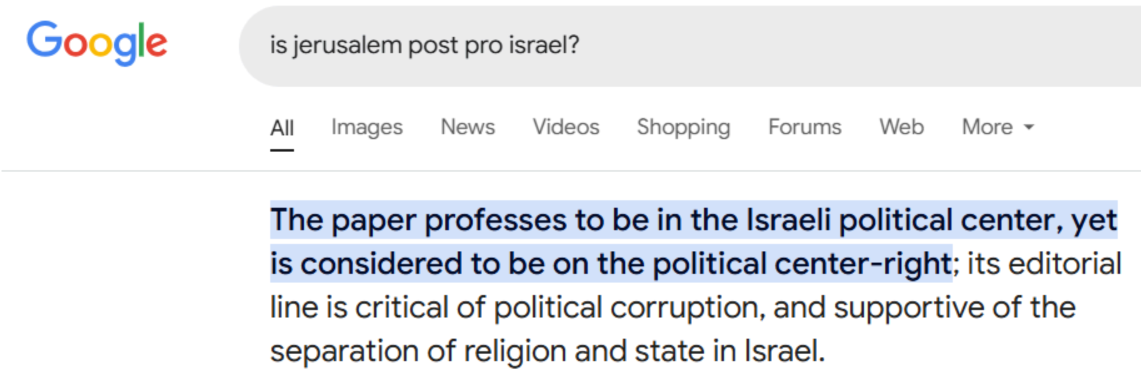

Distribution of Scores for Each Label
Score
0.9
0.8
0.7
0.6
0.5
Bert_logreg_scores
Bert_logreg_score
SVM_Bert_scores
SVM_sBert_scores
ANN_Bert_scores
ANN_sBert_scores
Label

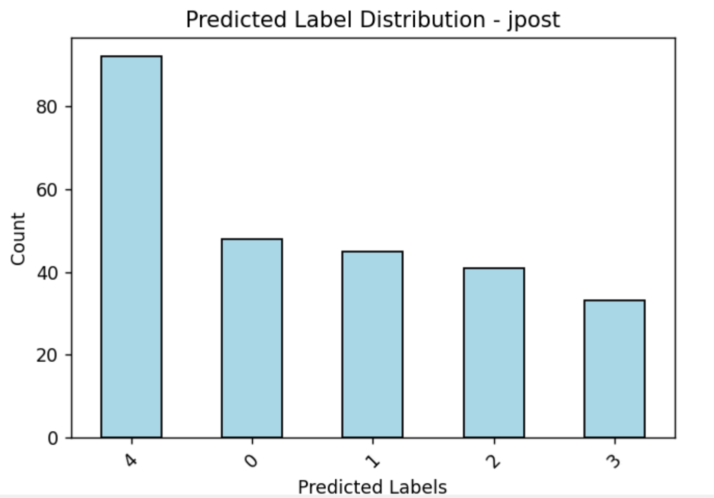

Correct vs. Incorrect Predictions
Count
600
500
400
300
200
100
0
Incorrect
Correct
Prediction Outcome

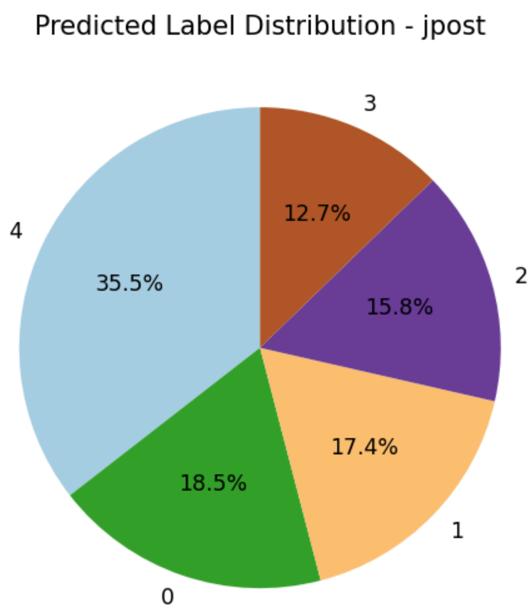



```
label_mapping = {
    "anti-i": 0,
    "pro-p": 1,
    "neutral": 2,
    "anti-p": 3,
    "pro-i": 4
}
```

JPost: prediction was good, the majority is pro israel-4. Just like we expected. Jerusalem post, is a pro israeli newspaper, owned by jews.

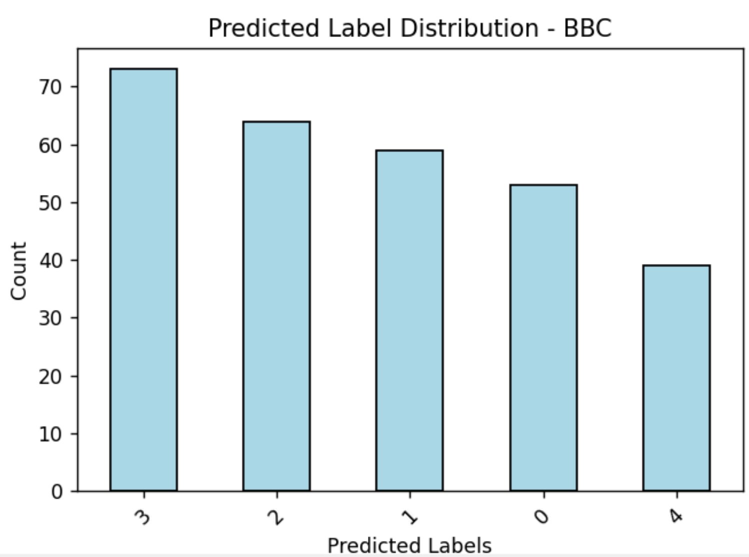

is jerusalem post pro israel?
All
Images
News
Videos
Shopping
Forums
Web
More
The paper professes to be in the Israeli political center, yet is considered to be on the political center-right; its editorial line is critical of political corruption, and supportive of the separation of religion and state in Israel.

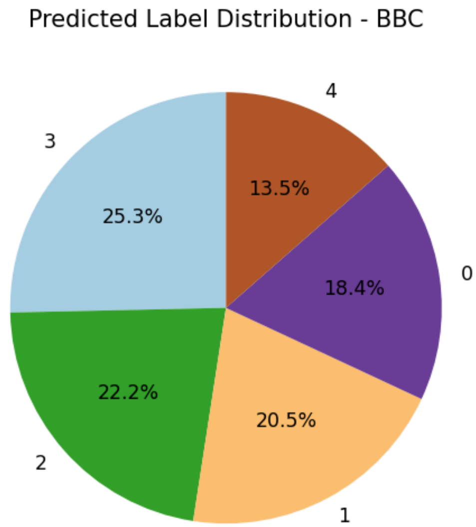

Predicted Label Distribution - jpost
Count
0
20
40
60
80
4
0
1
2
3
Predicted Labels



BBC:

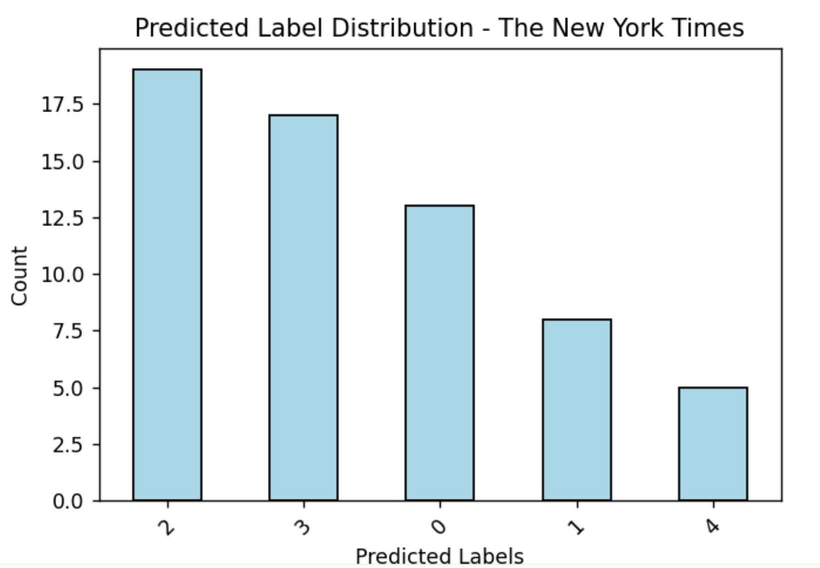
Its majority is anti palestine as in “poor palestine israel is doing bad stuff to them” but up close second in neutral towards both sides.

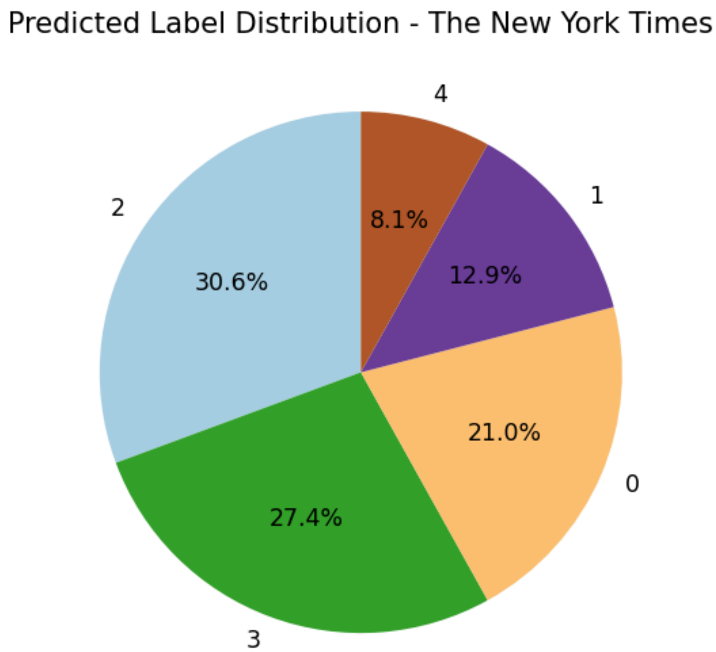




NEW YORK TIMES:

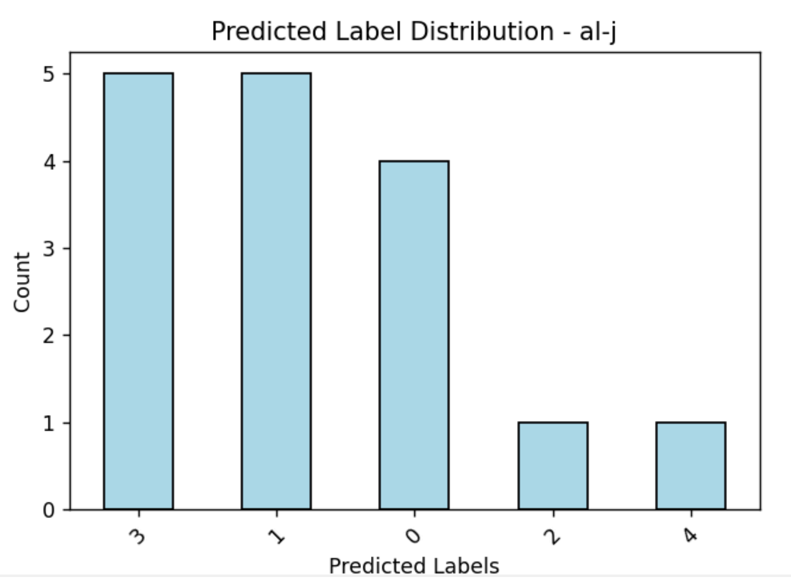
Its neutral with a strong closeup to anti palestine.

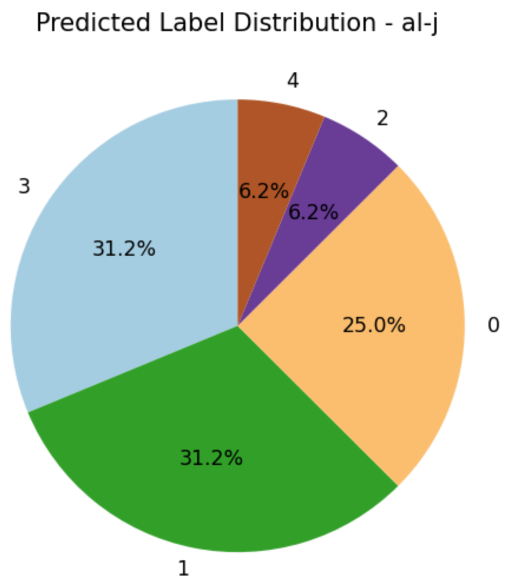




Al-J:

It's clearly a pro Palestine newspaper. 3-anti palestine, 1 pro-palestine, where it mentions palestine or how good they are or how bad stuff is happening to them.





=== Overall Accuracy Statistics ===

Overall Accuracy: 92.00%

--- Newspaper: jpost ---

Total Articles: 259

Correct Predictions: 237 (91.51%)

Predicted Labels Distribution:

Majority_Label

4   92

0   48

1   45

2   41

3   33

Name: count, dtype: int64

--- Newspaper: BBC ---

Total Articles: 288

Correct Predictions: 267 (92.71%)

Predicted Labels Distribution:

Majority_Label

3   73

2   64

1   59

0   53

4   39

Name: count, dtype: int64

--- Newspaper: The New York Times ---

Total Articles: 62

Correct Predictions: 56 (90.32%)

Predicted Labels Distribution:

Majority_Label

2   19

3   17

0   13

1   8

4   5

Name: count, dtype: int64

--- Newspaper: al-j ---

Total Articles: 16

Correct Predictions: 15 (93.75%)

Predicted Labels Distribution:

Majority_Label

3   5

1   5

0   4

2   1

4   1

Name: count, dtype: int64

Process finished with exit code 0

Ideas for improvement:

- One of the things we can do to improve our model is to use more accurate data. Our data is based on other models we built, and if we had labeled the data by hand we might be able to train it better.
- Another thing we can do is play around with the hidden layers of the ANN model, and with the attributes of the other models to try to reach optimal results.

- A third idea is the original words list to do more research and see what words really belong where. And experiment with different words.
- The label mapping isn't random numbers. It's organized from most against Israel to most pro israel. We did it that way because we might calculate the sentence using the label as a weight but we didn't end up needing it. It might be another way to improve results.

```
label_mapping = {
    "anti-i": 0,
    "pro-p": 1,
    "neutral": 2,
    "anti-p": 3,
    "pro-i": 4
}
```

THE END 🎉