

## **Project Deliverable 3**

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## §1 Final Training Results

### §1.1 Preliminary Model

In my first deliverable, I have chosen to use a simple architecture of the following shape:

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	(None, 100)	0	
embedding_1 (Embedding)	(None, 100, 300)	6000000	input_1[0][0]
spatial_dropout1d_1 (SpatialDro	(None, 100, 300)	0	embedding_1[0][0]
lstm_layer (LSTM)	(None, 100, 60)	86640	spatial_dropout1d_1[0][0]
global_average_pooling1d_1 (Glo	(None, 60)	0	lstm_layer[0][0]
global_max_pooling1d_1 (GlobalM	(None, 60)	0	lstm_layer[0][0]
concatenate_1 (Concatenate)	(None, 120)	0	global_average_pooling1d_1[0][0] global_max_pooling1d_1[0][0]
dense_1 (Dense)	(None, 64)	7744	concatenate_1[0][0]
dense_2 (Dense)	(None, 1)	65	dense_1[0][0]
Total params: 6,094,449			
Trainable params: 6,094,449			
Non-trainable params: 0			
None			

however, this didn't give me quite good results as I obtained an f1 score of 0.98 for the sincere ones, but an f1 score of only 0.55 for the insincere ones, which is exactly what we are trying to see here. The reason why we are using the f1 score is because the f1 score is the average of the precision(True Positive/Predicted) and the recall(True Positive/Actual) in terms of the insincere class. Whereas the accuracy would be a faulty measure as there is class imbalance.

In my last deliverable, I didn't have time to properly include the different pre-trained word embeddings, hence I simply trained the word embeddings on my own data, I also used an LSTM layer since we are dealing with text data (we want to obtain the word dependencies) and finally both global average and max pooling which is another regularization method.

### §1.2 Some Models I have tried

While looking for a better solutions, I have both included the GloVe embeddings, wikinews embeddings as well as the Paragram embeddings. I have tried each of those with models to obtain the accuracies of each and have decided to make an ensemble of the GloVe and Paragram embeddings. I have tried to different preprocessing by taking more vocabulary, however it didn't really change as expected since i only let some stop words remain.

#### §1.2.1 CNN

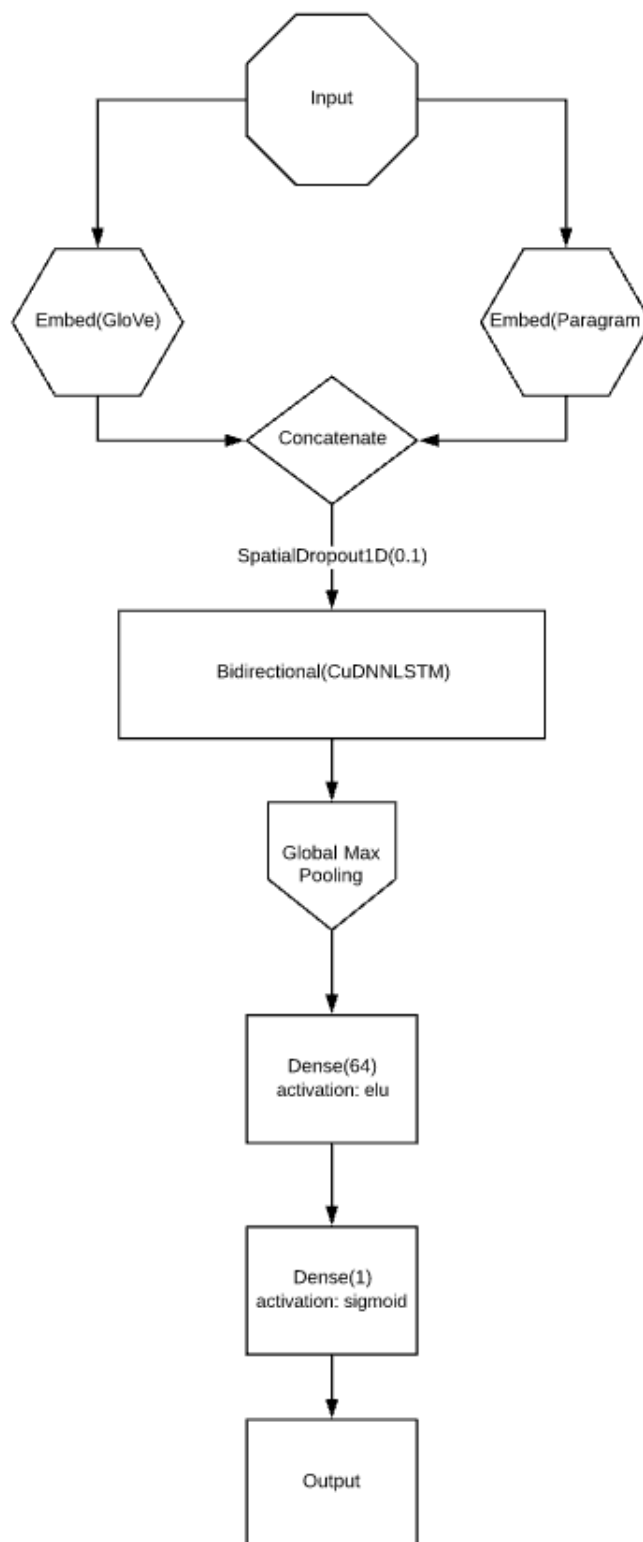
In one of the models I have explored, instead of using the traditional LSTM layer, I have used 4 one-dimensional convolutions which each had a different kernel size. The architecture was as follows:

Layer (type)	Output Shape	Param #	Connected to
input_3 (InputLayer)	(None, 100)	0	
embedding_3 (Embedding)	(None, 100, 300)	9000000	input_3[0][0]
dropout_1 (Dropout)	(None, 100, 300)	0	embedding_3[0][0]
conv1d_1 (Conv1D)	(None, 100, 128)	192128	dropout_1[0][0]
conv1d_2 (Conv1D)	(None, 100, 128)	153728	dropout_1[0][0]
conv1d_3 (Conv1D)	(None, 100, 128)	115328	dropout_1[0][0]
conv1d_4 (Conv1D)	(None, 100, 128)	76928	dropout_1[0][0]
concatenate_3 (Concatenate)	(None, 100, 512)	0	conv1d_1[0][0] conv1d_2[0][0] conv1d_3[0][0] conv1d_4[0][0]
global_max_pooling1d_3 (GlobalM	(None, 512)	0	concatenate_3[0][0]
global_average_pooling1d_3 (Glo	(None, 512)	0	concatenate_3[0][0]
concatenate_4 (Concatenate)	(None, 1024)	0	global_max_pooling1d_3[0][0] global_average_pooling1d_3[0][0]
dense_5 (Dense)	(None, 64)	65600	concatenate_4[0][0]
dense_6 (Dense)	(None, 1)	65	dense_5[0][0]
Total params: 9,603,777			
Trainable params: 603,777			
Non-trainable params: 9,000,000			
None			

This one gave me decent results although I was only using Paragram's embeddings. I had an f1 score of 0.6, however I wasn't very satisfied and through testing a few models, while fine tuning parameters, I opted for my final model which consists of the following:

### §1.2.2 Bidirectional LSTM

Here, I used both embeddings, a bidirectional LSTM layer and only global max pooling as I observed it performed better than both GMP and GAP together. Here, the most important hyper-parameters were the embedding layers, as they provide a huge jump from the initial 0.55 f1 score, the LSTM is important in this case since we are dealing with text data, and also the regularization layers. We use the binary cross-entropy loss since it is most efficient at capturing the a definite distinction between the 2 classes. I believe that although an f1 score of 0.65 seems low, it isn't that bad. What's left are the tfidf vectorizer for preprocessing, and possibly doing a k-fold validation and testing my prediction of the test data on the kaggle competition.



## §2 Final Demonstration Proposal

### §2.1 Application

I would like to make a web page using React or Angular, but I have no experience with either. So, if I do figure out, I'm probably going to keep it simple with a section where the user can input text which sends a request to a flask web app, converting the input using the same method as my preprocessing and using the same tokenizer.

### §2.2 Poster Presentation

Here, I would like to simply outline the process of my preprocessing/ model selection and about the potential usage of the model in industry. (filtering online blogs etc.)