Ling 573: Project Report D#3
Predicting Human Empathy and Emotion

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Abstract

Building off of the WASSA 2022 Shared Task on Empathy Detection and Emotion Classification, we predict the level of empathic concern and personal distress displayed in essays. For the D#2 deliverable we implemented a Feed-Forward Neural Network using sentence-level embeddings as features. We experimented with four different embedding models for generating the inputs to the neural network. The D#3 deliverable builds upon the previous work and we have implemented three types of revisions. The first revision focuses on the enhancements to the model architecture and the training approach. The second revision focuses on handling class imbalance using stratified data sampling. The third revision focuses on leveraging lexical resources, where we apply four different resources to enrich the features associated with the dataset. We plan to further adapt these approaches in the deliverable D#4 to the WASSA 2023 Shared Task on Empathy Emotion and Personality Detection in Interactions, in which the empathic concern and personal distress in dyadic text conversations are predicted.

1 Introduction

As human-computer interactions increasingly integrate into our daily lives through applications, such as conversational agents where form is as critical as substance, it becomes paramount for computer systems to demonstrate natural interactions by recognizing and expressing affect. The field of Affective Computing, as proposed by Picard (2000), aims to endow computer systems with the capability to mimic our understanding of how emotions influence human perception and behavior. This is particularly relevant in light of the fact that a vast majority of U.S. adults (86%) receive news through digital devices such as smartphones, computers, or tablets (Shearer, 2021). This project focuses on predicting empathy and distress elicited from news stories.

2 Task Description

This project is organized to address a primary task and an adaptation task. The description of the primary task is provided in (Section 2.1) and the description of the adaptation task is provided in (Section 2.2)

2.1 Primary Task

The primary task in this project is based on the shared task from WASSA 2022 Shared Task on Empathy Detection and Emotion Classification (Buechel et al., 2018), organized at WASSA (2022) and whose final results are published at Barriere et al. (2022). The affect type of the task is emotion. The genre of the dataset is news articles, the modality is text, and the language is English.

The primary task for this project is the first subtask of the WASSA (2022) shared task, Empathy Prediction, which consists of predicting both the empathy concern and the personal distress at the essay-level. This is a regression task. The dataset used in this project is the same as the one used in the shared task, and can be downloaded from WASSA (2022). The dataset contains empathic essay reactions to news stories, with associated Batson empathic concern and personal distress scores for each response. In addition to these scores, each response in the dataset contains gold standard labels for emotion, demographic information (age, gender, education, race, income) of the person who submitted the response, as well as the personality type of the writer.

The training data for this task consists of 1860 responses with gold standards for Empathy Prediction subtask. The development data consists of 270 responses with gold standard labels, and the

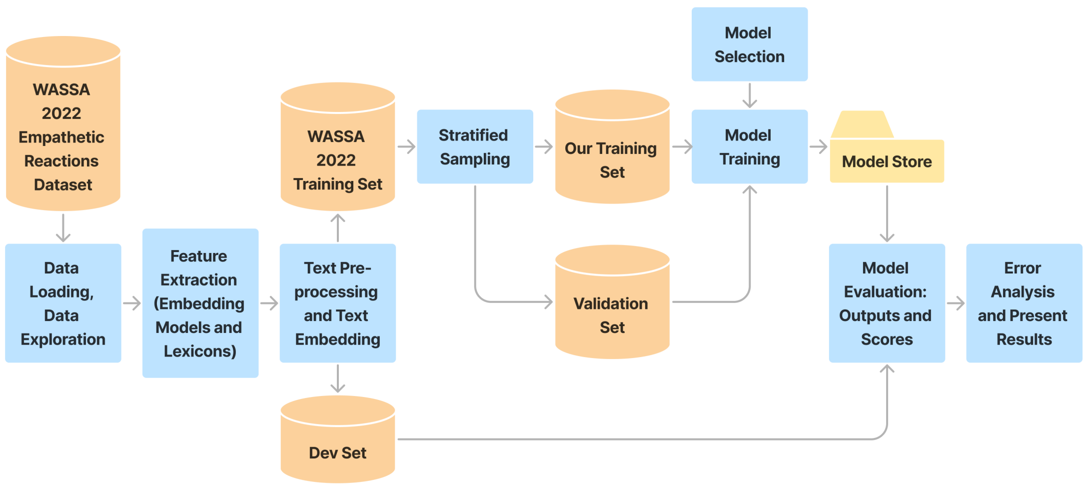


Figure 1: Architecture Overview.

test data contains 525 responses, but without gold standard labels.

The evaluation criteria for the Empathy Prediction task is the average Pearson correlation of the empathy scores and the distress scores.

2.2 Adaptation Task

The adaptation task for this project is based on the WASSA 2023 Shared Task on Empathy Emotion and Personality Detection in Interactions (WASSA, 2023). This shared task builds on the shared task from WASSA (2022) and includes dyadic (two person) text conversations about news articles. The dataset, described in Omitaomu et al. (2022), can be downloaded from the WASSA (2023) website. This dataset complements the Empathic Reactions dataset by Buechel et al. (2018) by providing conversational interactions rather than only first-person statements.

The selected adaptation task for this project is Empathy and Emotion Prediction in Conversations, which involves predicting the perceived empathy, emotion polarity and emotion intensity at the speech-turn-level in a conversation. This is a regression task. The affect type of this task is emotion, and the genre of the dataset is news articles. The modality is text, and the language is English. This adaptation task differs from the primary task in that the primary task focuses on first-person text while the adaptation task focuses on turn-by-turn conversations. One potential application for this adaptation task is to develop and evaluate conversational AI agents, such as ChatGPT, that are capable of producing and processing empathetic responses in human-AI interactions.

The training data for the adaptation task consists of 792 conversations with gold values for empathy and distress. Each of these conversations is further organized at the turn-level with 8,777 turns and has gold standard values for empathy, emotion, and emotional polarity.

The evaluation criteria for the Empathy and Emotion Prediction in Conversations task is the average of the three Pearson correlations: Pearson correlation of empathy, Pearson correlation of emotional polarity, and Pearson correlation of emotional intensity.

3 System Overview

3.1 Dataset repository and usage details

The dataset is part of the WASSA 2022 Shared Task on Empathy and Emotion Classification[1]. Training and Development dataset can be downloaded from the WASSA 2022 dataset link[2]. As part of the WASSA 2022 dataset usage guidelines, this dataset must only be used for scientific or research purposes and the paper Barriere et al. (2022) must be cited.

3.2 Data exploration

The training dataset is comprised of 1860 rows, each of which containing three columns for empathy, distress and the essay. The Dev set dataset contains 270 rows with the same three columns.

[1] https://codalab.lisn.upsaclay.fr/competitions/834#learn_the_details-overview

[2] https://codalab.lisn.upsaclay.fr/competitions/834#learn_the_details-datasets

The distribution of the training dataset is shown in Figure 2. We observe that the empathy and distress values in the training and dev datasets are imbalanced, with a higher concentration of density between values 1 and 2.

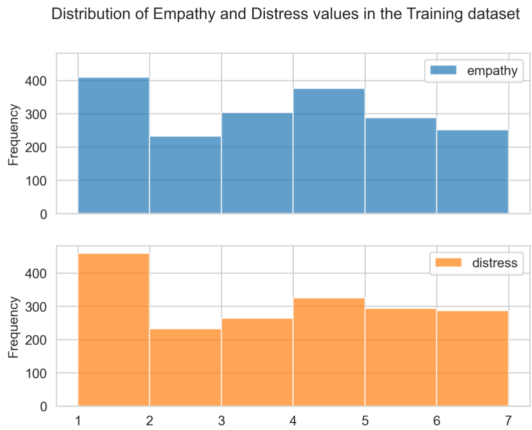


Figure 2: Distribution of Empathy and Distress values in the training dataset, indicating an imbalance in the distribution of samples

3.3 Architecture overview

The architecture diagram in Figure 1 shows an overview of the system. The first module in this system performs data loading, data exploration, and preprocessing. The training and development datasets are loaded into pandas dataframe. The golden values for the dev dataset are joined with the dev instances to facilitate comparison evaluation. The observations from data exploration are described in the previous section. From a preprocessing perspective, the text from the essays are encoded using BPE tokenization before calling the Azure OpenAI embedding model. The other embedding models do not need preprocessing and are therefore kept as is.

The essay text was the only feature used for the initial system during deliverable D#2. The text in the essay have been converted to dense vectors using the embedding models described in Section 4.2.

During deliverable D#3, three revisions have been made to this architecture. In the first revision, the Model Selection and Model Training portions of the architecture have been enhanced. The updates include updating the dropout method, adding more modern activation function, and finetuning the training process. These updates revision is further detailed in Section 4.3. The second revision focuses on addressing class imbalance using Stratified Sampling. This revision is further detailed in Section 4.4. The third revision focuses on the Feature Extraction portion of the architecture. Four lexical resources have been used to expand the number of features that are used during training. This revision is detailed in Section 4.5.

3.4 The hardware

The embeddings for sentence-transformer models were initially generated on CPU, but this was found to be very time consuming. Subsequent embeddings were generated on a NVIDIA Tesla T4 GPU hosted on Google Colab. The embeddings for the text-embedding-ada-002 model were generated using Azure OpenAI API. The values of the embedding vector are stored in a data store to allow efficient modeling. This NVIDIA Tesla T4 GPU-based hardware has been used to train the Neural Network models.

4 Approach

4.1 Initial system

For the initial system presented in deliverable D#2, a Feed-Forward Neural Network has been implemented. The PyTorch library has been used to create the Neural Network models. The implementation is based on the FFN architecture proposed in Buechel et al. (2018) with two hidden layers (256 and 128 units, respectively) with ReLU activation. The sentence-level embeddings are used as features for this model. Dropout layers with p=0.5 values have been added before every linear layer to help reduce overfitting. 20% of the training set is set aside to act as a validation set. MSE loss function has been used as the loss for the training and AdamW with learning rate of 1e-4 has been used as the optimizer. The seed value has been set for numpy and pytorch to help with reproducibility of the results. The validation set is used to select the model with the lowest MSE when running the training loop for 100 epochs. The model weights have been saved so that these weights can be used during the evaluation and scoring steps of the project.

4.2 Embedding models

For the initial system presented in deliverable D#2, we have used four different embedding models.

The all-MiniLM-L6-v2 is a sentence-transformer model (Wang et al., 2020). This model maps sentences and paragraphs to 384

	empathy	distress	essay	essay_emb
0	5.667	4.375	it is really diheartening to read about these ...	[0.04520609974861145, 0.058606069535017014, -0...
1	4.833	4.875	the phone lines from the suicide prevention li...	[-0.0877808928489685, 0.009987352415919304, 0....
2	5.333	3.500	no matter what your heritage, you should be ab...	[0.01799248717725277, 0.04691638424992561, -0....
3	4.167	5.250	it is frightening to learn about all these sha...	[0.056801456958055496, -0.0004722552839666605,...
4	5.333	4.625	the eldest generation of russians aren't being...	[0.013306875713169575, 0.04898981750011444, 0....

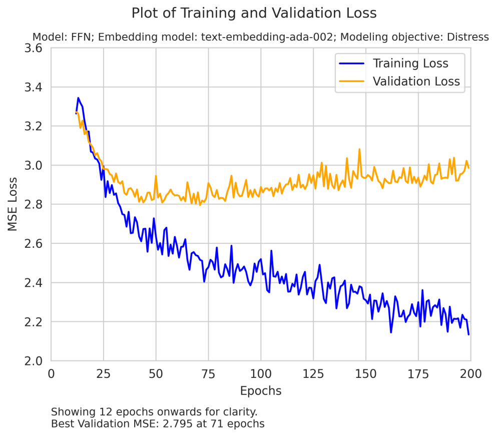
Figure 3: Samples from the Training Dataset with Embeddings (Sentence Transformer)

dimensional dense vector space which captures semantic information. By default, input text longer than 256 word pieces is truncated. The MiniLM is a six layer version of MiniLM model created by Microsoft (Wang et al., 2020). Figure 3 shows a snippet of the training dataset with a few values of the sentence-transformer embedding.

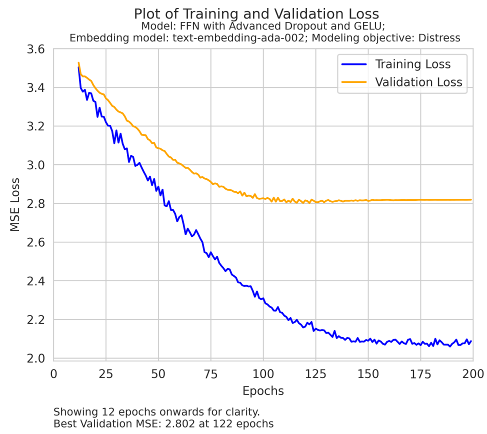
The all-mpnet-base-v2 is a sentence-transformer model that maps sentences and paragraphs to a 768 dimensional dense vector space. By default, input text longer than 384 word pieces is truncated. This model is based on the MPNet model created by Microsoft (Song et al., 2020).

The all-roberta-large-v1 is a sentence-transformer model that maps sentences and paragraphs to 1024 dimensional dense vector space. By default, input text longer than 128 word pieces is truncated. This model is based on RoBERTa developed by the University of Washington and Facebook AI (Liu et al., 2019).

The text-embedding-ada-002 is an embedding model created by OpenAI and served from Microsoft Azure (Neelakantan et al., 2022) (Azure-OpenAI, 2023). This model maps a list of tokens to a dense vector of 1536 dimensions and replaces five separate models for text search, text similarity, and code search tasks. This model uses cl100k_base tokenizer that uses BPE tokenization and has a limit of 8191 maximum tokens.



(a)



(b)

Figure 4: Training and validation losses: (a) Before hyperparameter tuning (b) After hyperparameter tuning

4.3 D#3 Revision #1: Hyperparameter tuning

Previously during the deliverable D#2 of this project, a Feed Forward Network was used with two hidden layers (of 256 and 128 neurons), RELU activation functions, and dropout layers with p=0.5. During deliverable D#3 multiple experiments were performed to finetune this model architecture.

The first set of experiments focused on the dropout layers and the activation function. As mentioned in the discussion section of deliverable D#2, the model tends to overfit the training dataset. One of the methods of mitigating overfitting is to use dropout. However, getting the values of the dropout rate (p) right requires hyperparameter tuning. Such tuning is generally very time consuming, requiring retraining the entire model with each option of the dropout rate. In an alternate approach, Xie et al. (2021) proposed an advanced dropout technique that adaptively adjusts the dropout rate, resulting in a stable convergence of dropout rate and superior ability of preventing overfitting.

The paper Hendrycks and Gimpel (2020) proposes a novel activation function, called Gaussian Error Linear Unit (GELU). This nonlinearity weights inputs by their value, rather than gates inputs by their sign as in ReLUs. Experiments in this paper indicates that GELU exceeds the accuracy of ReLU consistently, and therefore we have used GELU in the updated model architecture.

In addition to these updates to the model, a PyTorch Learning Rate Scheduler has been implemented during model training. This scheduler has been configured to reduce the learning rate on plateau, with a factor of 0.8 and a patience value of 3. The initial learning rate of the AdamW optimizer has been kept the same as during deliverable D#2 to allow for relative comparisons.

The results of these changes to the model architecture are shown in Table 2 and the associated plots of train and validation losses are show in Figure 4. The results of the Pearson correlation of empathy scores and distress scores are comparable to the best performing model from deliverable D#2. We can observe from the plots that overfitting has been mitigated from this model and we can further assert that even when the model is trained for double the number of epochs (200 epochs compared to 100 epochs from deliverable D#2) the model does not overfit. These changes to the architecture can allow for longer training resulting in a more stable training process.

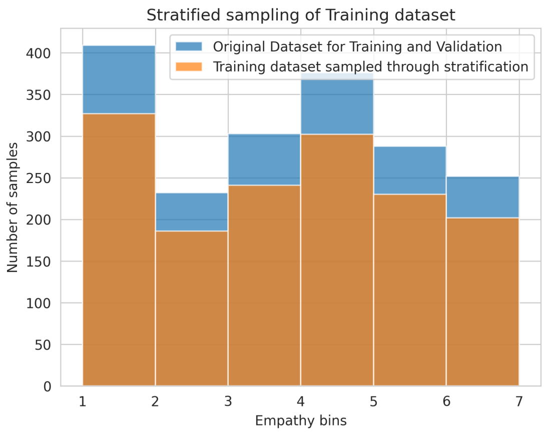


Figure 5: Distribution of the 80% Training dataset sampled from the original WASSA Dataset

4.4 D#3 Revision #2: Handling class imbalance using Stratified Data Sampling

Stratified Sampling approach has been used to address the class imbalance. This method of sampling preserves the same distribution of each target class in the training and validation sets as in the original dataset. This approach was implemented using Scikit-learn's `stratify` parameter in train_test_split method. The Figure 5 shows the distribution of the original dataset and the distribution of the training dataset after stratification. We can observe that the same proportion of the original dataset has been retained in the training dataset. Once the model is trained with this training dataset, we can observe that the Pearson correlation for the empathy score and distress score increases by 9.4% and 5.4% respectively over the results from Revision #1. These results show that stratified sampling has a significant impact to the performance scores. The results are updated in Table 2.

4.5 D#3 Revision #3: Lexicon features

For the revised system presented in deliverable D#3, we have created 48 additional features based on 4 different word-level lexicons. Essays were preprocessed via NLTK's tokenizer and WordNet's lemmatizer before applying the corresponding lexicons.

The NRC Word-emotion association lexicon (Mohammad and Turney, 2013) provides markers on word relations to the eight basic emotions of Plutchik's wheel of emotions, as well as association to general polarity (i.e. positive and negative feelings). The lexicon was built on the union of three datasets (Google top n-grams list, WordNet Affect Lexicon, and General Inquirer), totaling 14,154 words. Annotation for emotions was carried out through crowdsourcing via Mechanical Turk requests. Features derived from this lexicon include word counts by essay for each emotion and their corresponding ratio (normalized by essay length).

The MPQA subjectivity lexicon (Wilson et al., 2005) contains scores for prior polarity (i.e. positive, negative, neutral, both) as well as contextual information (i.e. whether the examined word has strong or weak subjectivity) and part-of-speech information over 6,886 words. The lexicon was constructed by combining existing subjectivity corpora (e.g. Multi-perspective Question Answering Opinion corpus) with additional dictionaries and thesaurus, as well as positive/negative word lists from the General Inquirer. Features generated from this lexicon included word counts and ratios for type of subjectivity, part-of-speech tags and polarity.

	Empathy	Distress	Mean
FNN baseline	.379	.401	.390
FNN with `all-MiniLM-L6-v2` embedding	.379	.370	.375
FNN with `all-mpnet-base-v2` embedding	.386	.324	.355
FNN with `all-roberta-large-v1` embedding	.395	.360	.378
FNN with `text-embedding-ada-002` embedding	.438	.426	.432

Table 1: Table of results for D#2.

	Empathy	Distress	Mean
FNN baseline	.379	.401	.390
FNN best performing model from D#2	.438	.426	.432
D#3 Revision #1: FNN, Advanced Dropout, GELU	.434	.425	.430
D#3 Revision #2: FNN, Advanced Dropout, GELU, and SDS	.475	.448	.462
D#3 Revision #3: FNN, Advanced Dropout, GELU, Lexicons, and SDS	.481	.456	.469

Table 2: Table of results for D#3: Advanced Dropout, GELU, Lexicons, and Stratified Data Sampling (SDS). All results beyond the baseline are with the `text-embedding-ada-002` embedding model

The NRC VAD lexicon (Mohammad, 2018) consists of 19,852 words which have been annotated for valence, arousal and dominance scores. The lexicon's dataset is comprised of terms from various sources including the NRC Emotion lexicon, General Inquirer, ANEW, amongst others. Annotation was carried out through a Best-Worst scaling approach, which asked annotators crowdsourced via the CrowdFlower platform to rank tuples of 4 words from least to most valence, arousal or dominance. Features created from this lexicon include the mean of the valence, arousal and dominance scores for each word in the essay.

The verbal polarity shifters lexicon (Schulder et al., 2018) contains annotations for words which can cause a shift in polarity (i.e. positive or negative feeling) or not. The lexicon consists of 10,577 lemmas sourced from WordNet (a lexicon at the lemma-sense level is also available but was not employed for this model). The annotation process was performed by an expert with experience in both linguistics and annotation, and a second annotator re-annotated 400 word senses for validation. Features derived from this lexicon include the count of shifter words that appear in the essay.

5 Result

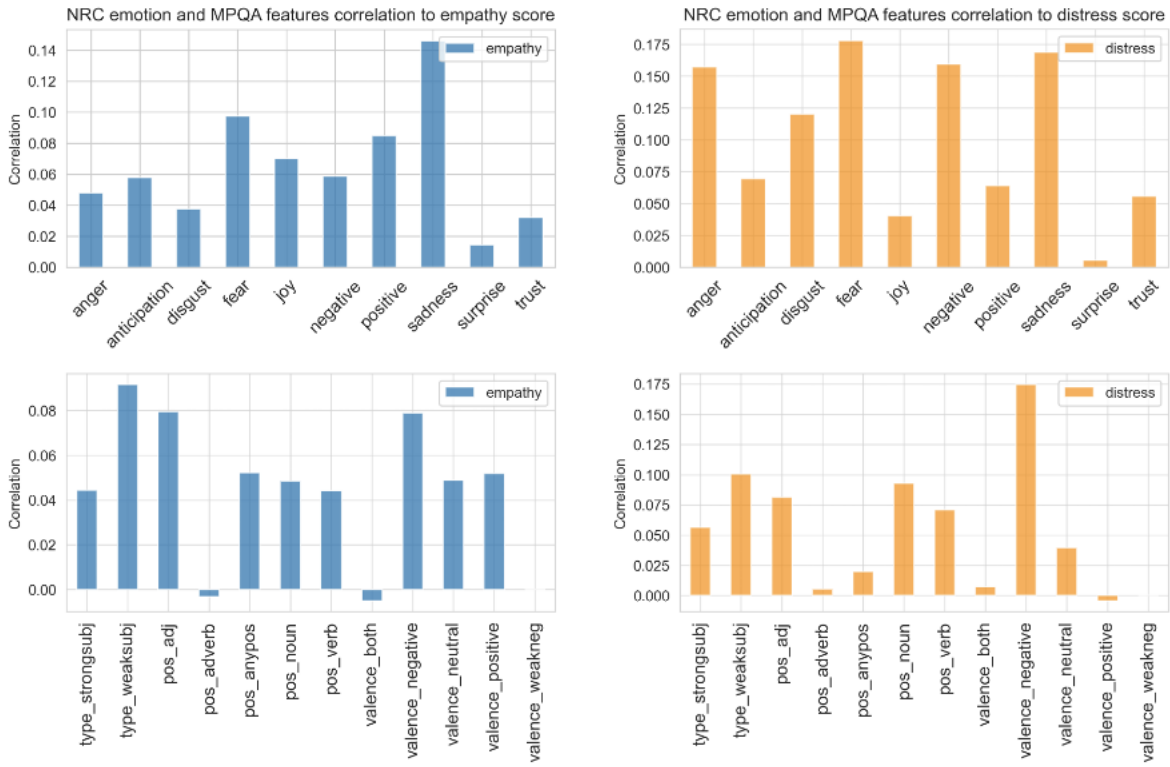
5.1 Initial system results

Model performance for predicting empathy and distress is reported in terms of Pearson correlation, including row-wise mean for the empathy and distress scores. Results are presented in Table 1, with the first row representing the FNN baseline based on the Buechel et al. (2018) model. All subsequent reported FNN's follow the same base network architecture, but vary the models used to generate the input embeddings. Similar correlations are observed for all models, with the exception of the `text-embedding-ada-002` model which achieved significantly higher scores. Figure 13 shows the training and validation loss for mpnet distress and empathy. Figure 14 shows the training and validation loss for MiniLM distress and empathy. Figure 15 shows the training and validation loss for OpenAI distress and empathy. Figure 12 shows the training and validation loss for RoBERTa distress and empathy. All these figures are part of Appendix section.

5.2 Revised system results

The results from the revised system are presented in Table 2. The first row presents the FNN baseline based on the Buechel et al. (2018) model, and the second row presents the evaluation scores for the best performing model from deliverable D#2, which was the FNN with `text-embedding-ada-002` embedding. Each of the following rows presents the evaluation scores after making incremental revisions to the system.

The Revision #1 uses the FNN model with the addition of Advanced Dropout layers and GELU activation units as described in the Section 4.3. This revision results in an increase of 10.3% in the mean score from the baseline and maintains the mean



(a) (b)

Figure 6: Correlation of lexicon features with: (a) empathy scores (b) distress scores

score at a similar level as from the initial system from D#2. The Revision #2 incrementally applies Stratified Data Sampling as described in Section 4.4. This revision leads to an 18.5% increase in the mean scores from the baseline, and 6.9% increase compared to the scores from the D#2 initial system. The Revision #3 incrementally applies lexical features as described in Section 4.5. This revision leads to an 20.3% increase in the mean scores from the baseline, and 8.6% increase compared to the scores from deliverable D#2. We can observe that each of the revisions incrementally builds on the previous work, resulting in an overall model that significantly outperforms both the baseline and the model from deliverable D#2.

5.3 Error analysis

The error analysis is similar to done in the paper Kuijper et al. (2018). We performed a manual error analysis on the data showing the maximum deviation as well as overall positive and negative deviation. Positive deviation is when the value of gold standard is higher than the predicted value. Negative deviation is when the value of the gold standard data is less than predicated value.

For D#2 the average positive deviation for empathy is 1.5 and for distress is 1.54. The average negative deviation for empathy is -1.33 and for distress is -1.41. Similarly, for D#3 the average positive deviation for empathy is 1.33 and for distress is 1.47. The average negative deviation for empathy is -1.40 and for distress is -1.41. So, we can observe that the average of both empathy and distress remains almost the same. We present the following key takeaways and reasons behind these observations. First, the overall prediction given by the gold standard depends a lot on the annotator demography. Another reason is when text is depicting empathy mixed with anger then the model may give a confused result and deviate from the gold standard value. The example shown in Figure 10 and Figure 11 gives few data examples for empathy and distress deviations from the gold standard.

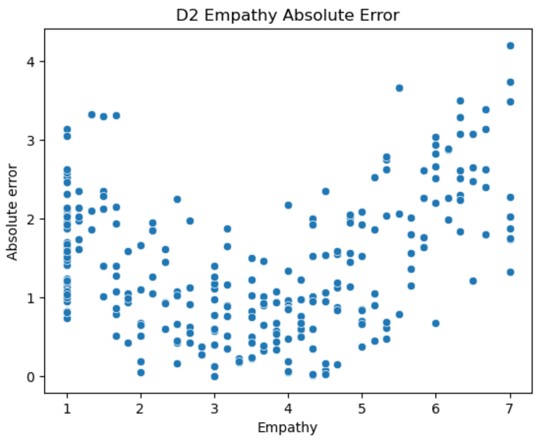
Error was also analyzed in relation to the distribution of values for empathy and distress. As seen in Figure 9, the distribution of our models' predictions varies from the distribution of the gold values for both empathy and distress. Table 3 gives

	True values	D#2 predictions	D#3 predictions
Empathy mean	3.558	3.412	3.603
Empathy standard deviation	1.861	0.848	0.960
Distress mean	3.773	3.707	3.722
Distress standard deviation	1.932	1.055	1.157

Table 3: Measures of center and spread for empathy and distress true values and D#2 and D#3 predictions.

	D#2 absolute error	D#3 absolute error
True empathy distance from center	0.540	0.550
True distress distance from center	0.527	0.468

Table 4: Pearson correlations of model prediction absolute error and distance of true label from the center of the 1-7 scale.



(a)

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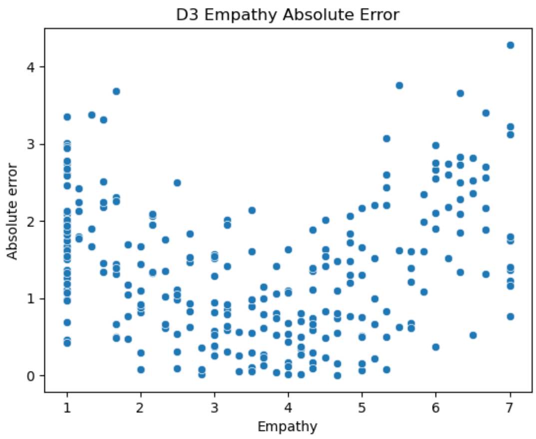
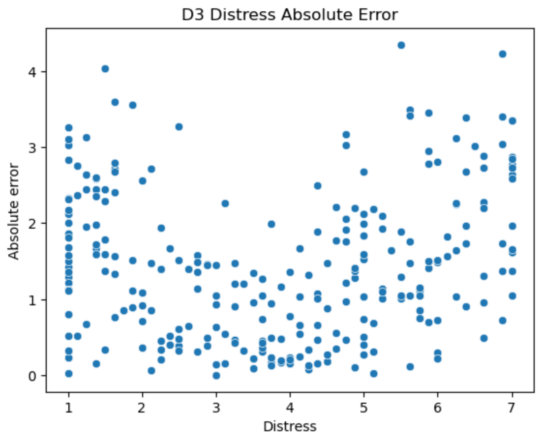


(c)



(d)

Figure 7: Absolute error of predictions with respect to true values of empathy and distress: (a) D#2 error for empathy (b) D#2 error for distress (c) D#3 error for empathy (d) D#3 error for distress.

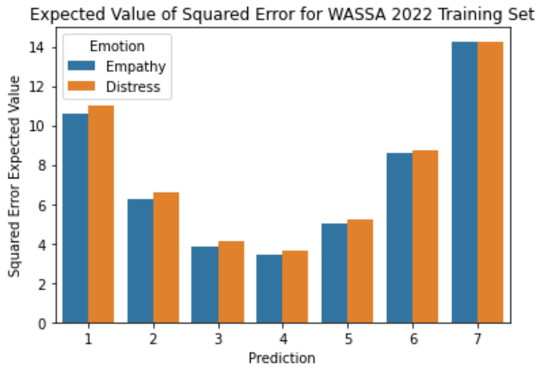


Figure 8: Average squared error for predicted integer values on our training and validation data.

the mean and standard deviation of the gold values and our models' predictions. While the center of our models' predictions are fairly close to the means of the true distributions (the means of our predictions from both D#2 and D#3 differ from the means of the gold values by less than 0.15), the standard deviations of our predictions are significantly smaller than the standard deviations of the gold values. Our models' predictions favor values close to the center of the 1-7 range more frequently than our gold values do. This suggests that essays with emotion values at either end of the range may be more likely to have high error in our models' predictions.

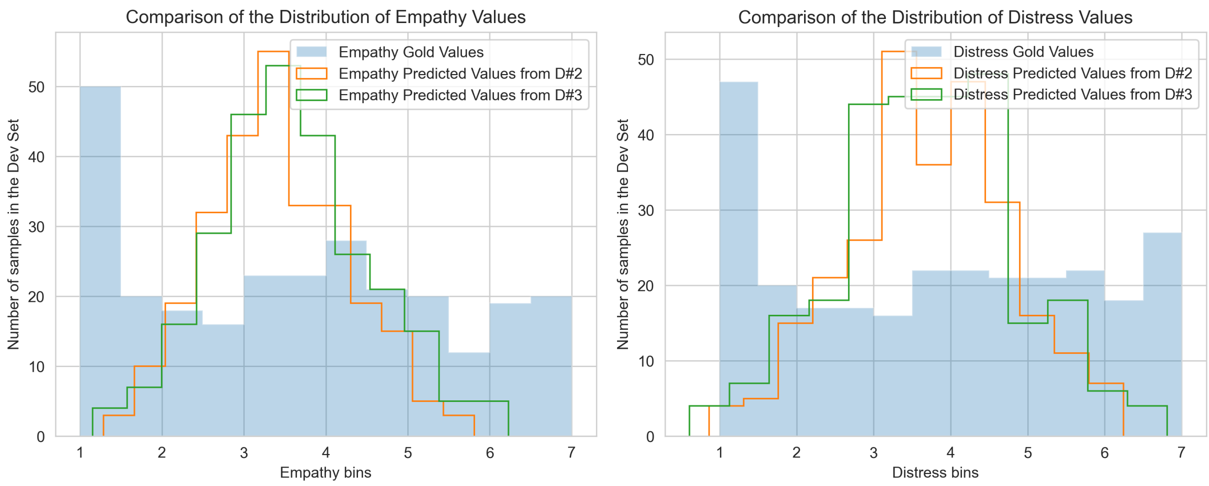
To test this hypothesis, absolute error was graphed with respect to true distress or empathy value in Figure 7. The graphs in Figure 7 show a wide spread of absolute error values when emotion values are close to either end of the scale. Relative to the ends of the scale, the error values in the center are consistently low. As an additional test, the distance of each true value from the center of the scale was calculated, followed by the Pearson correlation between these distances and the absolute error. The Pearson correlations are shown in Table 4. For both emotions and both deliverables, distance from the center of the emotional scale has a moderate or strong positive correlation with the absolute error of our models' predictions. Together, Figure 7 and Table 4 confirm that our models perform better on essays whose true empathy or distress values are close to 4, and worse when true values are closer to 1 or 7.

Our analysis is that the calculation of loss during training causes our models' differing performance on essays with true values at the center and ends of the scale. The expected value of squared error for integers 1 to 7 was calculated for the WASSA (2022) training data and graphed in Figure 8. The average value of the squared error calculation is 6-10 squared units higher at the ends of the scale than in the center. This indicates higher average loss for predicting empathy and distress values at the ends of the scale may have guided our model toward predicting values close to the center of the scale more frequently.

It is worth noticing in Table 3 that the center and spread of our D#3 models' predictions are closer to the true values' center and spread than was the case for our D#2 models. In particular, the standard deviation for both emotions for our D#3 models' predictions is higher than the standard deviations of the D#2 models' predictions by about 0.1. Compared to D#2, our D#3 models also have lower average absolute error on essays with true values within 1 unit of the ends of the scale (the average absolute error for empathy has improved by 0.049 and the average absolute error for distress has improved by 0.476, for essays where the relevant emotion has a true value less than 2 or greater than 6). This indicates that as we make improvements to our approach, the penalty for predicting values far from the center of the scale has less influence on our models' predictions.

6 Discussion

The features for the D#2 FFN models are high dimensional vectors of 384, 768, 1024, and 1536 dimensions for the different embedding models. During training we found that the models tended to overfit to the training data. Therefore, dropout layers and preserving the model weights using a validation set have been used to limit such effects. Although these changes resulted in a decrease in the rate at which the models overfitted, the issue remained prevalent at later epochs. These observa-



(a)

(b)

Figure 9: Comparison of gold and predicted values for: (a) Empathy (b) Distress

tions have been addressed in deliverable D#3 where an Advanced Dropout method has been used. The activation function has been updated and a learning rate scheduler has been implemented during the model training. These revisions are described in Section 4.3. We can observe from Figure 4, that these updates result in a stable training and validation loss. The plots of losses shows a smoother curve and the losses don't diverge even after training for over 100 epochs. We can also observe that the MSE loss values converge to stable levels and are still comparable to the best MSE losses obtained prior to hyperparameter tuning.

Furthermore, during deliverable D#3, lexicon features have been added as described in Section 4.5. As shown in the results in Section 5.2, lexicon features added for the upgraded models result in an increase in performance. Their positive effect (examined through the correlation between lexicon features and empathy/distress scores) appears to come from two main sources: the NRC emotion lexicon and the MPQA subjectivity lexicon. Among these sources, higher counts in features related to negative feelings (e.g. sadness, fear, disgust, etc.), use of adjectives and weak subjectivity showed the biggest correlation to empathy/distress scores, as observed in Figure 6.

In the report for deliverable D#2, we examined the distribution of the empathy and distress values in the designated development set, and we observed that the distribution is imbalanced, with a large spike for values between 1 and 2. However when we observed the distribution of empathy and distress values in the prediction, we find that the distributions appear to be Gaussian, peaking between 3 and 4. A comparative visual representation is shown in Figure 9. During deliverable D#3, we have revised the data sampling approach as detailed in Section 4.4.

Figure 9 shows the cumulative effect of all the revisions performed during D# on the predicted values. We can observe that although the predicted values retain a Gaussian distribution as we observed during D#2, the predicted values have a wider distribution with lower peaks. These observations are in alignment with the results discussed in Section 5.2.

7 Ethical considerations

7.1 Dataset Usage

The details of dataset and its license used in training of the model is updated in the dataset details in Section 3.2.

7.2 Essential elements for results reproducibility

All the components such as dataset, code, and software requirement to reproduce the results are updated at the GitHub repository[3].

8 Conclusion

In the previous deliverable D#2, we had created an end-to-end functioning affect recognition system

[3]https://github.com/manisha-Singh-UW/LING573_HUE-Human-Understanding-and-Empathy

Example	Gold standard Empathy	Predicted Empathy #D2	Predicted Empathy #D3	Anticipated Reason
When I first started reading this article it made me mad at heroin addicts and I thought it must be these forgetful types nodding off that was causing the crisis to occur. I'm pretty surprised that the name culprit seems to be parents that don't control their medicine cabinets. Somehow, I think that makes me even more angry.	7	2.799	2.71	Empathy with anger
I'm torn on the whole ivory trade situation. I get that farmers and people in their territory are often bothered by elephants (i.e. through crop destruction, etc.), but it doesn't seem fair to cause so much suffering to these animals. I feel bad that the locals are likely poor and feel that they have little choice, but I hate to think of elephants suffering.	1.33	4.65	4.71	Empathy with anger

Figure 10: Empathy data example for maximum deviation from gold standard

Example	Gold standard Distress	Predicted Distress #D2	Predicted Distress #D3	Anticipated Reason
I think people would have a field day over this in blogs and forums, especially the conspiracy theorist who thinks some cabal is somewhere controlling events and outcomes, the good news is the pilot survived and was recovered safely and maybe Russia should be more focused on ensuring safety of its military .	5.5	1.41	1.15	Empathy mixed with sarcasm
The way that the United Kingdom is treating its refugees within the camps is nothing short of barbaric. It is actually so sad seeing these people who ran from war get to countries just to be unwanted and hoarded up into camps. The children within the Calais camp in particular are just being neglected and abused and are lacking so many things required for growth	1.87	4.75	5.43	Annotators demography or sarcasm

Figure 11: Distress data example for maximum deviation from gold standard

based on the WASSA 2022 Shared Task on Empathy Detection and Emotion Classification. The affect recognition system and associated approach used for this task are based on the teachings discussed in class and in readings. The designated development set from the shared task has been used to generate the output results and the scores of these results are based on the shared task's evaluation metric. The scores from the implementation using multiple embedding models have been presented in this report. This deliverable D#3 builds upon the previous deliverable and presents three revisions, which have been described in the Approach section. The Results section describes the results of the revised system. The results also include the evaluation scores for the revised system, and compares them to the baseline system and also the results of the system presented during deliverable D#2.

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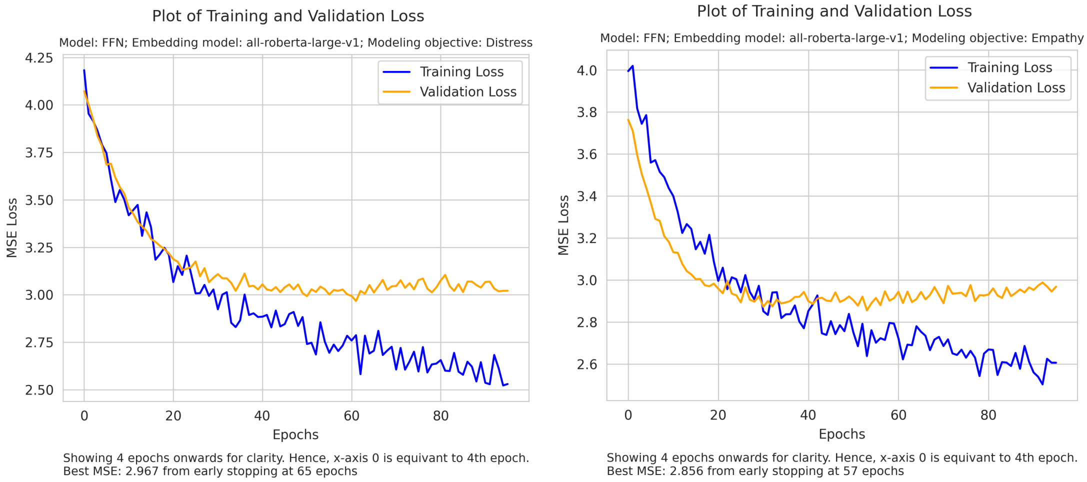
Appendix

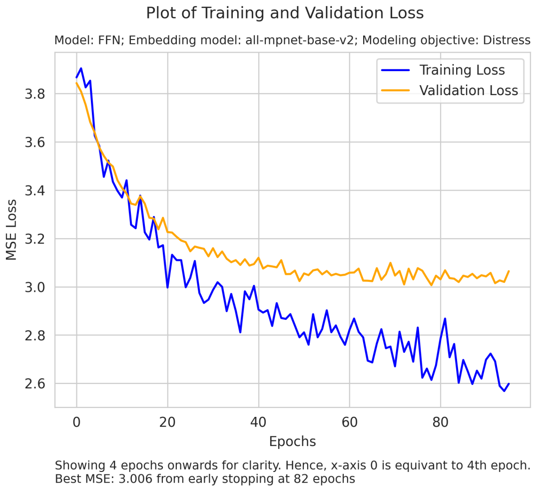


(a) (b)

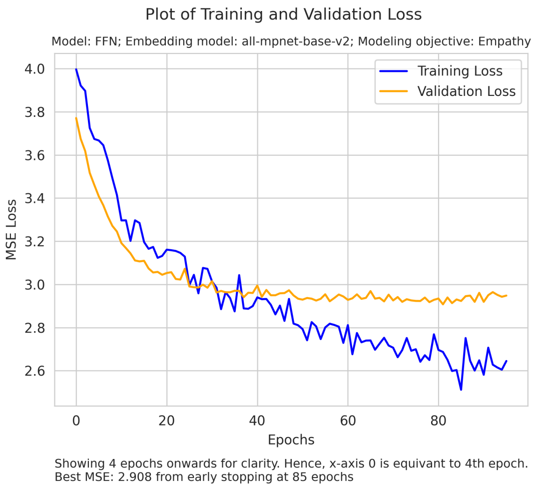
Figure 12: Training and Validation Loss: (a)roberta_distress (b)roberta_empathy

	Empathy	**Distress**	**Mean**
NN, Advanced Dropout, GELU, Lexicons and SDS (all-MiniLM-L6-v2)	.392	.334	.363
NN, Advanced Dropout, GELU, Lexicons and SDS (all-mpnet-base-v2)	.381	.351	.366
NN, Advanced Dropout, GELU,Lexicons and SDS (all-roberta-large-v1)	.330	.346	.338
FNN,Advanced Dropout, GELU, Lexicons and SDS (text-embedding-ada-002)	.481	.456	.469

Table 5: Additional results for D#3: Advanced Dropout, GELU, Lexicons, and Stratified Data Sampling (SDS) for the different embeddings

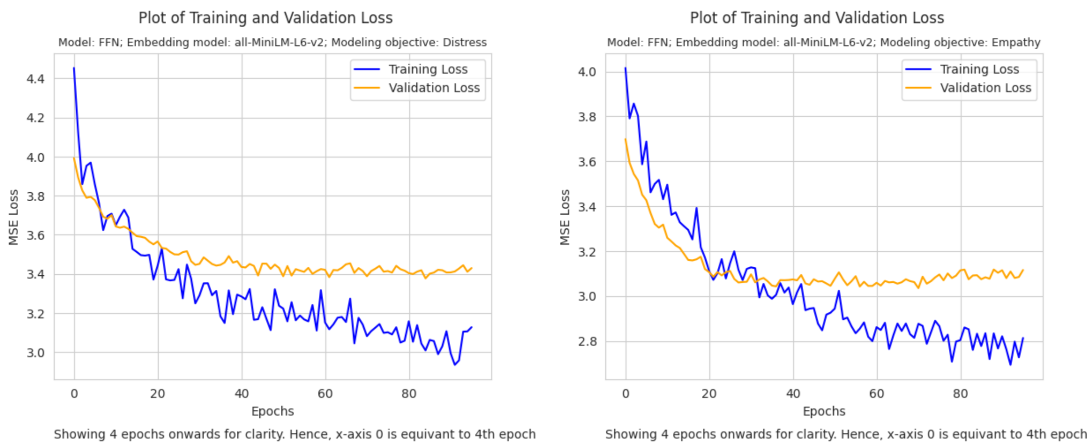


(a)



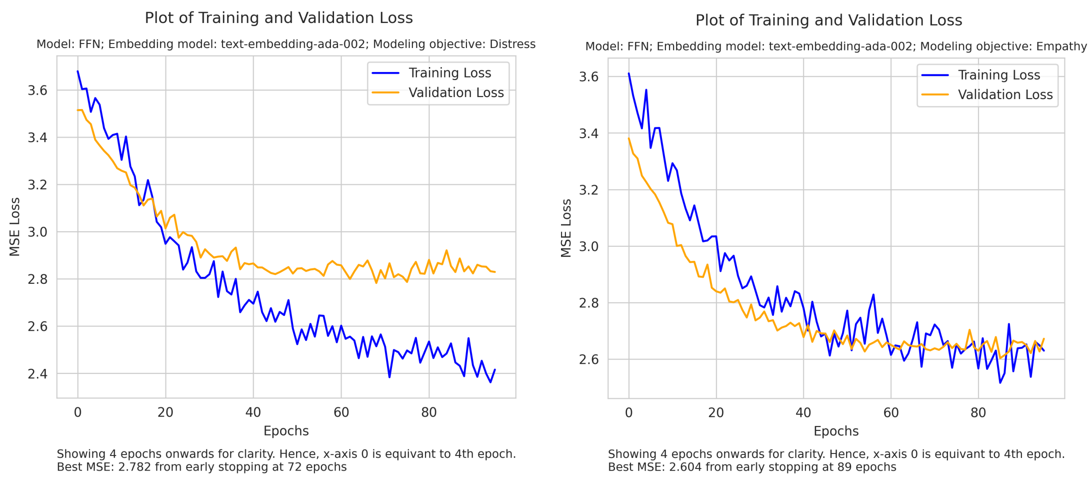
(b)

Figure 13: Training and Validation Loss: (a)mpnet_distress (b)mpnet_empathy



(a) (b)

Figure 14: Training and Validation Loss: (a)MiniLM_distress (b)MiniLM_empathy



(a) (b)

Figure 15: Training and Validation Loss: (a)openai_distress (b)openai_empathy