

# Detecting Bias in Online News Articles using Deep Neural Networks

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## 1 Introduction

Recent global events including the attack on the US capital building in January 2021, the mass imprisonment and reeducation of the Uyghur people in China as well as the rampant suppression of the pro-democratic movement as well as the Democratic pushes in Malaysia have shown how governments and well-funded private groups can influence public opinion through mass media have shown that it is vital to differentiate between biased media sources and unbiased media sources. There have been many academic papers published in recent years that attempt to provide solutions to this topic such as Aires et al. [2] and Mokherian et al. [12] have proposed approaches to this that utilize Moral Foundation Theory and Information Theory respectively. The bias towards a particular frame of reference is known as *framing bias* and is what this paper examines.

This paper seeks to provide a solution this problem based on Deep Learning and Neural Networks. As a baseline, this paper will analyze the neural network implementation in terms of three ensemble classifiers: Adaboost, Gradient Boosting and Extremely Random Forests. The neural network presented in this paper will be considered successful if it can outperform the best performing ensemble method. The comparison between the ensemble methods and the neural network will be performed using classification accuracy, F1 score, precision and recall. Noting that: F1 score measures the accuracy of testing, precision measures how many selected instances are relevant and recall measures how many relevant instances were selected. While precision and recall seem like they are the same measurement, they are in fact different from a statistical perspective.

## 2 Background

An embedding for a particular word  $w$  is an  $n$ -dimensional vector of real-valued components where each value specifies the distance between other words in a corpus or collection of words. Past methods of computing vectors such as the

Bag-of-Words model and Word2Vec utilize sliding window mechanisms over a document to generate word vectors. While these methods are extremely effective at doing so, they are inefficient in terms of run-time. Modern NLP sentence representations have moved onto the WordPiece embedding model first introduced by Wu et al. in their paper "Google's Neural Machine Translation System: Bridging the Gap between Human and Machine Translation" [20]. WordPiece seeks to provide an answer to an NLP optimization problem by breaking each word into two pieces - "Given a corpus and a number of desired tokens  $D$ , the goal of the optimization problem is to select  $D$  word pieces such that the resulting corpus is minimal in the number of wordpieces when segmented according to the chosen wordpiece model." WordPiece is used liberally in the state-of-the-art NLP architecture BERT introduced by Devlin et al. [4], in their work "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding". This paper utilizes the Word2Vec model to generate word embeddings as the primary advantage of BERT is that it incorporates both left-to-right and right-to-left context into the embeddings which is not needed by the model presented in this paper.

As stated by Simpson in their work, Moral Foundations Theory [16], Moral Foundations Theory (MFT) is an approach to measuring human values, judgments and morality in light of opposing moral categories. In MFT, a person's morals can be summed up to how far they align towards vices or virtues of the Harm, Fairness, Ingroup, Authority, Purity, and General Morality MFT categories. A person's leanings towards the virtues or vices of both categories can be determined mathematically through the use of semantic axes as presented by An et al. in their 2018 work "SemAxis: A Lightweight Framework to Characterize Domain-Specific Word Semantics Beyond Sentiment".

Let a semantic axis  $S$  be defined as two vectors of  $n$  word embeddings for a single MFT category such that  $S^+ = \{s_0, s_1, \dots, s_{n-2}, s_{n-1}\}$  and  $S^- = \{s_0, s_1, \dots, s_{n-2}, s_{n-1}\}$ . Then a semantic axis for a given MFT axis  $m$  can be computed as:

$$V_m = V^+ - V^- \quad (1)$$

where  $V^+$  and  $V^-$  are the average values of the  $S^+$  and  $S^-$  vectors respectively. Utilizing a given semantic axis  $m$ , Mokherian et al. [12] define the *framing bias* for a given document  $D$  as:

$$B_m^D = \frac{\sum_{d \in D} f_d * s(V_m, d)}{\sum_{d \in D} f_d} \quad (2)$$

Where  $s(V_m, d)$  is the cosine similarity between the semantic axis and the embedding for word  $d$  and  $f_d$  is the frequency of word  $d$  in the document  $D$ . Lastly, the *framing intensity* of a document along a specific moral axis  $m$  can be compute as:

$$I_m^D = \frac{\sum_{d \in D} f_d * (s(V_m, d) - B_m^T)^2}{\sum_{d \in D} f_d} \quad (3)$$

where  $B_m^T$  is the baseline *framing bias* for the entire corpus  $T$  along a given semantic axis  $m$ .  $B_m^D$  and  $I_m^D$  are generated per semantic axis per document

in my corpus and make up one of the embeddings that are fed into the neural network,  $E_{mft}$ .

Aires et al. [2] propose an information theoretic approach to determining framing bias in their work, "An Information Theory Approach to Detect Media Bias in News Websites". In their work, the authors propose a solution to classifying the bias of online news articles based on entropy, mutual information, Cosine Distance, Jaccard Distance and Jensen-Shannon Divergence.

As it relates to the model presented in this paper, let the entire corpus  $D$  be represented by a probability mass function  $p^{(D)}$  such that  $p^{(D)} = (p_1^{(d)}, p_2^{(d)}, \dots, p_n^{(d)})$  maps every word in every document in the corpus to the probability of it appearing in any given document in the corpus. Furthermore, let a given document  $d$  be represented by a probability mass function  $p^{(d)}$  that maps every word  $w$  in the document to its probability of appearing in the document such that  $p^{(d)} = (p_1^{(w)}, p_2^{(w)}, \dots, p_n^{(w)})$ . These probability mass functions are then used to calculate the Cosine Distance, Jaccard Distance and Jensen-Shannon Divergence to serve as embeddings for the neural network.

Given a discrete random variable  $X$  with possible outputs  $x_1, x_2, \dots, x_n$ , the entropy of  $X$  is defined as  $H(X) = -\sum_{i=1}^n P(x_i) \log(P(x_i))$ . Given this, the Jensen-Shannon Divergence which is used to measure the similarity between two probability distributions can be determined by:

$$jsd(p, q) = \frac{H(p) + H(q)}{2} - H\left(\frac{p+q}{2}\right) \quad (4)$$

noting that in this case,  $p$  is the overall pmf for the entire corpus and  $q$  is the pmf for a specific document from the corpus.

The next metric, cosine distance is equivalent to the Pearson correlation and represents the proportional angle between two points in a vector space. The cosine distance is determined as:

$$cos(p, q) = 1 - \frac{\sum_{i=1}^n p_i q_i}{\sqrt{\sum_{i=1}^n p_i^2} \sqrt{\sum_{i=1}^n q_i^2}} \quad (5)$$

The last information theory metric is the jaccard distance. Utilized in Computer Science to measure the difference between vectors in  $\mathbf{R}^n$  spaces, the jaccard distance is calculated as:

$$jac(p, q) = 1 - \frac{\sum_{i=1}^n \min(p_i, q_i)}{\sum_{i=1}^n \max(p_i, q_i)} \quad (6)$$

These three metrics are calculated on a per-document basis and make up  $E_{it}$  for purposes of being fed into the neural network.

Lastly, sentiment analysis is a branch of NLP that looks at determining the relationships between words and using these relationships to determine the cardinality of the sentence containing the words. Here cardinality is also known as valence and can be rated in terms of positive, negative or neutral valence indicating how emotionally positive, negative or neutral a sentence is respectively.

Again, as mentioned earlier, Google BERT by Devlin et al. [4] is the current state-of-the-art in this area. However, due to time constraints, I decided to not utilize Google BERT and instead use VADER from Hutto and Gilbert [10] instead.

First presented in "VADER: A Parsimonious Rule-based Model for Sentiment Analysis of Social Media Text" by Hutto and Gilbert [10], VADER is "... a simple rule-based model for general sentiment analysis ... [that combines] gold standard lexical features [with] five general rules that embody grammatical and syntactical conventions for expressing and emphasizing sentiment intensity." Vader utilizes a configurable lexicon of annotated English words to construct a semantic model for determining the valence-based intensity of English sentences. Because VADER was built to handle English in a social media context (i.e. a very noisy environment), VADER is extremely flexible in the sentences it can analyze. This makes it a perfect candidate for generating sentiment analysis features for use as embeddings (referred to as  $E_{sa}$ ) for the neural network presented in this paper.

### 3 Data Acquisition and Preprocessing

This paper utilizes the *All the News* dataset from kaggle.com [17]. Consisting of 200,000 news articles from 15 different online news outlets, *All the News* incorporates articles from a variety of political bias leanings including: Far-Left, Left, Moderate, Right and Far-Right. In its raw form, each article consists of an articleid, title, publication, authors, date of publication, year of publication, month (as an integer), url (which is an empty field), and the content of the article. For the purposes of this paper, features are only generated from the content of the article.

Now, the goal of the neural network and the other models I employ in this paper is to correctly classify the articles bias from one of: Far-Left, Left, Moderate, Right and Far-Right. Now, it is important to note that the dataset does not come with bias labels. Utilizing mediabiasfactcheck.com, a reputable (it has been utilized by published academic papers) website that lists the bias of major news outlets, I looked up the bias of each news outlet in the dataset and assigned this bias to the corresponding articles by each publication. For instance, all of the articles that were published under the New York Times were labelled as having a Left bias. This was a compromise, as I did not have the time to manually annotate all 200k articles with bias labels. It is very possible that some articles were mislabelled as it is known that some publications host articles with biases that fall outside the bias of the overall publication however, for the majority of the articles in the dataset, assigning them the bias label of the publication should be fine.

This dataset was downloaded as three separate comma separated value (CSV) files. To process this dataset for use by my classification models, I wrote several scripts that first cleaned the text of each article and then generated  $E_{mft}$ ,  $E_{it}$  and  $E_{sa}$  for each of them. It's important to note that as I describe

this process, it's not something you can do on a normal computer. My machine has 32 Gigabytes of RAM, of which pre-processing the entire dataset takes 11.5 Gigabytes of RAM because I load the entire dataset at once all into memory using a Pandas dataframe. This is done because Pandas in combination with Numpy [9] and SciPy [18] allow me to apply transformation operations to the text of each article in parallel, therefore resulting in shorter processing time overall.

Feature generation requires the use of word vectors as described in the background section. Aires et al. [2] and Mokherian et al. [12] utilize a reference corpus in addition to the dataset they are analyzing - the Stanford Global Vectors for Word Representation (GloVe) dataset [14]. I utilize the same reference corpus in this paper (Common Crawl 42B) which consists of word embeddings generated from uncased 42B tokens, 1.9M token unique vocabulary sourced from a combination of Wikipedia pages and Twitter data. The reference corpus is utilized by both Aires et al. and Mokherian et al. to provide a generalized high-quality corpus to leverage in key calculations of metrics from both papers. To represent the GloVe and All the News word vectors in a format that my pre-processor scripts can work with I utilize the well-known Gensim vector space modelling library [15] which implements functionality for generating word vectors and modelling them in memory.

$E_{mft}$  and  $E_{it}$  are generated per article from my own implementation of the corresponding Moral Framing and Information Theory metrics mentioned in the *Background* section.  $E_{sa}$  is generated utilizing the VADER implementation provided by the Natural Language Toolkit [3]. I utilize the GloVe word vectors and All the News word vectors where appropriate.

$E_{mft}$  is an embedding consisting of 12 features (2 features for each moral axis defined by the Moral Foundations Theory framework). The first feature is framing bias. This indicates how biased an article is w.r.t. a specific moral axis. Values closer to zero indicate less biased, while values further from zero along the positive or negative axis indicate a positive (virtue) or negative (vice) bias towards the axis respectively. The second feature is the framing intensity which attempts to capture how passionate the article is when speaking to the vices or virtues of a specific moral axis.

$E_{it}$  is an embedding consisting of 3 features generated for each article. The features generated for this embedding utilized what is known as a vocabulary of reference. To generate the vocabulary of reference, I generate the pmf of all the words in the entire *All the News* dataset. Utilizing this pmf, I then calculate the Shannon entropy for each word in the dataset. Sorting the words by entropy in ascending order and taking the top-n words yields the vocabulary of reference. A Shannon entropy metric as close to zero as possible indicates that the information gain from that particular word is high. In essence, the vocabulary of reference is the top-n most important words in the *All the News* dataset. I then utilize this vocabulary of reference along with the word vectors for the GloVe and *All the News* dataset to generate the cosine distance, Jaccard distance and Jensen-Shannon divergence for each article in the dataset thus yielding  $E_{it}$ .

$E_{sa}$  is generated by applying the VADER algorithm from Hutto et al. [10] to all the articles in the dataset. The embedding consists of 24 metrics that describe the compound, negative, neutral and positive sentence valences for each sentence in each article. For each article, I compute the minimum, maximum, median, mean, standard deviation and variance valence. These metrics describe the overall shape of the compound, negative, neutral and positive sentence valence distributions for each article and are the metrics utilized by the  $E_{sa}$  embedding.

Prior to being fed into the classifiers, I perform min-max normalization on each embedding to bring each feature from each embedding into the  $[0, 1]$  range. This is especially important for the neural net architecture proposed in this paper, as neural nets expect input features to be in the range  $[0, 1]$ . Feeding data into a neural network outside of this range will prevent the neural network from properly learning the weights for each feature.

## 4 Model

### 4.1 AdaBoost Ensemble Learning

As described by Freund and Schapire in their 1999 article "A Short Introduction to Boosting" [6], AdaBoost is a meta-estimator that repeatedly fits copies of the same classifier on-top of the input dataset adjusting for incorrectly classified instances such that their weights are given higher preference in the underlying classifier. According to Freund and Schapire, AdaBoost takes as input a training set  $(x_1, y_1), \dots, (x_m, y_m)$  where each  $x_i$  belongs to some domain or instance space  $X$ , and each label  $y_i$  is in some label set  $Y$ . AdaBoost functions by repeatedly calling a weak learner (a classifier that needs boosted) in a series of  $t = 1, \dots, T$  rounds. AdaBoost thus maintains a distribution of weights  $D_t(i)$  over the course of training, which are initially equal, but are adjusted each round such that the weights of incorrectly classified examples are increased so the weak learner is forced to focus on hard examples from the training set. Overall, the goal of AdaBoost is to make a weak learner less prone to outliers in a dataset – a challenge many classifiers must deal with in some way.

According to Freund and Schapire [6], the weak learner must find a *weak hypothesis*  $h_t : X \rightarrow \{-1, +1\}$  for the distribution  $D_t$  in the binary classification task. Noting that AdaBoost does generalize well to the multi-class classification task as presented by the problem in this paper. A *weak hypothesis* is measured by the error function defined in equation 7.

$$\epsilon_t = Pr_{i \sim D_t}[h_t(x_i) \neq y_i] = \sum_{i: h_t(x_i) \neq y_i} D_t(i) \quad (7)$$

Given:  $(x_1, y_1), \dots, (x_m, y_m)$  where  $x_i \in X$ ,  $y_i \in Y = \{-1, +1\}$

Initialize  $D_1(i) = 1/m$ .

For  $t = 1, \dots, T$ :

- Train weak learner using distribution  $D_t$ .
- Get weak hypothesis  $h_t : X \rightarrow \{-1, +1\}$  with error

$$\epsilon_t = \Pr_{i \sim D_t} [h_t(x_i) \neq y_i].$$

- Choose  $\alpha_t = \frac{1}{2} \ln \left( \frac{1 - \epsilon_t}{\epsilon_t} \right)$ .
- Update:

$$\begin{aligned} D_{t+1}(i) &= \frac{D_t(i)}{Z_t} \times \begin{cases} e^{-\alpha_t} & \text{if } h_t(x_i) = y_i \\ e^{\alpha_t} & \text{if } h_t(x_i) \neq y_i \end{cases} \\ &= \frac{D_t(i) \exp(-\alpha_t y_i h_t(x_i))}{Z_t} \end{aligned}$$

where  $Z_t$  is a normalization factor (chosen so that  $D_{t+1}$  will be a distribution).

Output the final hypothesis:

$$H(x) = \text{sign} \left( \sum_{t=1}^T \alpha_t h_t(x) \right).$$

Figure 1: The AdaBoost Algorithm as described by [6]

The AdaBoost algorithm is defined in figure 1.  $\alpha_t$  can be likened to the learning rate in a traditional classification algorithm. Within the context of AdaBoost,  $\alpha_t$  measures the importance that is assigned to the hypothesis  $h_t$ . The algorithm iterates the weights each round by increasing the weights for incorrectly classified instances and decreasing the weights for correctly classified instances. The final hypothesis  $H_t$  is determined by majority vote of the ensemble. Thus AdaBoost overall is an ensemble learner that focuses a weak learner on hard or outlier training instances. Note that this paper employs the `AdaboostClassifier` from the `sklearn` scientific computing library with default parameters.

## 4.2 Gradient Boosting

First proposed by Jerome H. Friedman in his seminal article "Greedy Function Approximation: A Gradient Boosting Machine" [5], gradient boosting, as the name implies, is a greedy approach to function approximation where the goal is to apply gradient descent based boosting to fitting criterion such as least-squares and mean-squared error. Friedman developed this as a general approach and thus it is applicable to areas such as logistic regression, binary classification, multi-class classification and anywhere else loss functions are applied.

Gradient boosting breaks down into three components:

1. A loss function.
2. A weak learner.
3. An additive model.

The loss function depends on the problem being solved and it must be differentiable as it will have gradient descent applied to it during the optimization step. Any standard statistical loss function can be applied with gradient boosting and in fact, as long as it is differentiable, users of gradient boosting can even define their own on a per-problem basis.

The weak learner is always a decision tree in gradient boosting. Similar to how AdaBoost repeatedly changes the weights on classification instances from a weak learner, gradient boosting repeatedly applies a greedy optimization algorithm to find the best splits in the input decision tree. Specifically, gradient boosting will utilize the additive model to add the outputs of subsequent models together and correct the residuals leftover in predictions.

While gradient boosting is running, it will repeatedly add one decision tree at a time to the model, leaving existing trees unchanged. Gradient descent is then applied during the additive process to minimize the results of the loss function when taken across trees. After determining the loss, the gradient descent procedure parameterizes all of the candidate trees that could be added and determines the best tree to add that would move the overall model in the right direction that best minimizes the residual loss. The new best tree is then added to the ensemble. This process repeats until either a fixed number of trees have been added or a certain number of iterations has been reached or a certain training criteria has been reached.

Algorithmically, the Gradient Boosting algorithm is defined in figure 2.



Input: training set  $\{(x_i, y_i)\}_{i=1}^n$ , a differentiable loss function  $L(y, F(x))$ , number of iterations  $M$ .

Algorithm:

1. Initialize model with a constant value:

$$F_0(x) = \arg \min_{\gamma} \sum_{i=1}^n L(y_i, \gamma).$$

2. For  $m = 1$  to  $M$ :

1. Compute so-called *pseudo-residuals*:

$$r_{im} = - \left[ \frac{\partial L(y_i, F(x_i))}{\partial F(x_i)} \right]_{F(x)=F_{m-1}(x)} \quad \text{for } i = 1, \dots, n.$$

2. Fit a base learner (or weak learner, e.g. tree)  $h_m(x)$  to pseudo-residuals, i.e. train it using the training set  $\{(x_i, r_{im})\}_{i=1}^n$ .

3. Compute multiplier  $\gamma_m$  by solving the following [one-dimensional optimization](#) problem:

$$\gamma_m = \arg \min_{\gamma} \sum_{i=1}^n L(y_i, F_{m-1}(x_i) + \gamma h_m(x_i)).$$

4. Update the model:

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x).$$

3. Output  $F_M(x)$ .

Figure 2: The Gradient Boosting Algorithm as described by the Wikipedia page on Gradient Boosting.

I utilized the algorithm as presented on the Wikipedia page because this algorithm describes what is going on in a fashion that is more comprehensible than the version presented in [5]. The two algorithms are in fact identical. Note that this paper employs the GradientBoostingClassifier class from the sklearn scientific computing library with default parameters.

### 4.3 Extremely Random Forests

First proposed by Pierre Geurts, Damien Ernst and Lousi Wehenkel in their article "Extremely Randomized Trees" [7], an extremely randomized tree is a decision tree that utilizes a stochastic process to create tree splits. An extremely randomized forest is constructed in the same way that a random forest is in that a subset of candidate features is utilized. Instead of looking for the most discriminative thresholds that classify instances for each candidate feature, an extremely random tree will instead draw thresholds at random for each candidate feature and the best thresholds are thus utilized as the split criterion. This process is in fact quite similar to a Monte-Carlo process and in general is proven to reduce the classification variance of a random forest at the expense of slightly increased bias.

An extremely random forest is a meta-estimator that attempts to fit a number of extremely random tree classifiers on top a various samples of a dataset. The construction of the extremely random forest classifier is guided by averaging in order to improve accuracy and control over-fitting wherein a classifier learns an inherent bias towards a particular training instance and as a result biases towards classifying instances as the over-fitted instance. Extremely random trees are controlled via appropriate choice of a randomization parameter. This parameter is of course situation dependent.

Per Geurts et al. [7], the primary extremely random tree algorithms can be summarized in figure 3. Because the focus of this paper is on the neural network model presented in the next subsection, I will not describe in detail what a decision tree is or how the splits are normally computed.

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**Split\_a\_node( $S$ )**  
*Input:* the local learning subset  $S$  corresponding to the node we want to split  
*Output:* a split  $[a < a_c]$  or nothing  
– If **Stop\_split**( $S$ ) is TRUE then return nothing.  
– Otherwise select  $K$  attributes  $\{a_1, \dots, a_K\}$  among all non constant (in  $S$ ) candidate attributes;  
– Draw  $K$  splits  $\{s_1, \dots, s_K\}$ , where  $s_i = \mathbf{Pick\_a\_random\_split}(S, a_i)$ ,  $\forall i = 1, \dots, K$ ;  
– Return a split  $s_*$  such that  $\text{Score}(s_*, S) = \max_{i=1, \dots, K} \text{Score}(s_i, S)$ .

**Pick\_a\_random\_split( $S, a$ )**  
*Inputs:* a subset  $S$  and an attribute  $a$   
*Output:* a split  
– Let  $a_{\max}^S$  and  $a_{\min}^S$  denote the maximal and minimal value of  $a$  in  $S$ ;  
– Draw a random cut-point  $a_c$  uniformly in  $[a_{\min}^S, a_{\max}^S]$ ;  
– Return the split  $[a < a_c]$ .

**Stop\_split( $S$ )**  
*Input:* a subset  $S$   
*Output:* a boolean  
– If  $|S| < n_{\min}$ , then return TRUE;  
– If all attributes are constant in  $S$ , then return TRUE;  
– If the output is constant in  $S$ , then return TRUE;  
– Otherwise, return FALSE.

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Figure 3: Extremely random trees as presented in Geurts et al. [7].

Note that the splitting procedure has two parameters:  $K$  which represents the number of attributes randomly selected at each extremely random tree node and  $n_{\min}$  which represents the minimum sample size for splitting a node. This sample size is used to generate an ensemble model. When the classifier must make a prediction, all of the trees in the forest simultaneously come to a prediction regarding an input instance and the output classification is decided by majority vote as is common with ensemble methods.

#### 4.4 The Proposed Model

The model presented in this section underwent extensive redesign as I tested each architecture with various parameters. While the architecture changed, the input and output from the model did not change. Let the political bias classification problem presented in this paper be a multi-class classification problem. Furthermore, let the dataset be split into two sets: a training set  $T$  and a validation set  $V$  consisting of  $n$  and  $m$  labelled instances respectively. Additionally, let  $T$  and  $V$  be split into a number of inputs and outputs,  $(X_T, Y_T)$  and  $(X_V, Y_V)$  respectively. The overall goal is to train a supervised model on  $(X_T, Y_T)$  such that the model can correctly classify all instances of  $(X_V, Y_V)$ .

As a reminder, input for each classification instance consists of three embeddings:  $E_{mft}$ ,  $E_{it}$  and  $E_{sa}$  which correspond to vectors containing metrics for Moral Foundation Theory, information theory and sentiment analysis respectively. Please see the *Background* section for information on how each of these vectors are calculated. Output for each classification instance consists of one of five bias labels:  $B = \{\text{Left-Center, Left, Moderate, Right-Center, RightFar-Right}\}$ . The classifier must learn the individual aspects of each bias class from  $(X_T, Y_T)$  and correctly apply these characteristics during validation of  $(X_V, Y_V)$ . Note that there is an imbalance in the dataset in that it does not contain any examples from the Far-Left.

The models presented in the subsequent subsections were constructed using PyTorch [13] and Tensorflow [1]. The implementation is highly parallelized and is setup to utilize the Compute Unified Device Architecture (CUDA) if the device running the model has a dedicated Nvidia graphics card. Each of these models utilize Cross-Entropy Loss as the loss criterion. They also utilize the Adam optimizer to guide weight updates. Cross-Entropy loss is applicable in situations with either multi-class classification (the problem proposed in this paper) as well as multi-label classification (when a single input instance can be multiple outputs).

Cross-Entropy loss is defined in equation 8 as stated in [8]. Note that  $t$  is the target vector, and  $C$  are the classification classes.

$$CE = - \sum_i^C t_i \log(f(s_i)) \quad (8)$$

In equation 8,  $t_i$  and  $s_i$  represent the ground-truth and the score calculated by the classifier respectively. Note that the models presented in the subsequent functions do not apply softmax or log softmax to the prediction logits because internally cross-entropy loss within the PyTorch framework applies softmax to them before calculating the loss. Applying the softmax or log softmax function to the output logits of the model before determining loss would result in improper training. Note that in a multi-class classification environment, the output labels from the ground-truth as well as the output labels from the classifier are one-hot encoded (PyTorch constructs the one-hot encoding for the classifier output on the fly when you give the cross-entropy loss function the truth index). This results in equation 9 which is the cross-entropy loss adjusted for a multi-class environment.

$$CE = -\log\left(\frac{e^{s_p}}{\sum_j^C e^{s_j}}\right) \quad (9)$$

In equation 9,  $S$  are the classification scores for all classes and  $S_p$  is the classification score determined by the classifier for the positive class.

Note that the gradient for the cross-entropy loss function in a multi-class environment is different for both the positive and negative classes. Remember that PyTorch automatically applies softmax before determining cross-entropy

loss. This yields equation 10 for the normal corss-entropy loss, equation 11 for the positive class gradient and equation 12 for the negative class gradient as stated by Raúl Gómez in [8]. These two gradients are fed into the optimizer so the weights of each neuron can be properly adjusted.

$$CE = \frac{1}{M} \sum_p^M (-\log(\frac{e^{s_p}}{\sum_j^C(e_j^s)})) \quad (10)$$

$$\frac{\partial}{\partial s_p} (\frac{1}{M} \sum_p^M (-\log(\frac{e^{s_p}}{\sum_j^C(e_j^s)}))) = \frac{1}{M} ((\frac{e^{s_p}}{\sum_j^C(e_j^s)} - 1) + (M - 1) \frac{e^{s_p}}{\sum_j^C(e_j^s)}) \quad (11)$$

$$\frac{\partial}{\partial s_n} (\frac{1}{M} \sum_p^M (-\log(\frac{e^{s_p}}{\sum_j^C(e_j^s)}))) = \frac{e^{s_n}}{\sum_j^C(e_j^s)} \quad (12)$$

In equations 11 and 12,  $s_p$  and  $s_n$  represent the score for any positive class and the score for any negative class respectively. In equations 10, 11 and 12,  $M$  represents the number of possible output classes. In this model,  $M = 5$ .

First introduced by Diederik P. Kingma and Jimmy Lei Ba in 2014, the Adam optimization algorithm is a first-order gradient-based optimizer capable of optimizing stochastic objective functions based on adaptive estimates of lower-order moments [11]. Adam computes individual adaptive learning rates for different parameters from both first and second moments of the gradients of the objective functions it is optimizing. This model utilizes the Adam optimizer to optimize the Cross-Entropy loss function defined above to train the weights of the proposed neural networks. Adam's algorithm can be seen in figure 4.

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**Algorithm 1:** *Adam*, our proposed algorithm for stochastic optimization. See section 2 for details, and for a slightly more efficient (but less clear) order of computation.  $g_t^2$  indicates the elementwise square  $g_t \odot g_t$ . Good default settings for the tested machine learning problems are  $\alpha = 0.001$ ,  $\beta_1 = 0.9$ ,  $\beta_2 = 0.999$  and  $\epsilon = 10^{-8}$ . All operations on vectors are element-wise. With  $\beta_1^t$  and  $\beta_2^t$  we denote  $\beta_1$  and  $\beta_2$  to the power  $t$ .

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**Require:**  $\alpha$ : Stepsize  
**Require:**  $\beta_1, \beta_2 \in [0, 1)$ : Exponential decay rates for the moment estimates  
**Require:**  $f(\theta)$ : Stochastic objective function with parameters  $\theta$   
**Require:**  $\theta_0$ : Initial parameter vector  
 $m_0 \leftarrow 0$  (Initialize 1<sup>st</sup> moment vector)  
 $v_0 \leftarrow 0$  (Initialize 2<sup>nd</sup> moment vector)  
 $t \leftarrow 0$  (Initialize timestep)  
**while**  $\theta_t$  not converged **do**  
 $t \leftarrow t + 1$   
 $g_t \leftarrow \nabla_{\theta} f_t(\theta_{t-1})$  (Get gradients w.r.t. stochastic objective at timestep  $t$ )  
 $m_t \leftarrow \beta_1 \cdot m_{t-1} + (1 - \beta_1) \cdot g_t$  (Update biased first moment estimate)  
 $v_t \leftarrow \beta_2 \cdot v_{t-1} + (1 - \beta_2) \cdot g_t^2$  (Update biased second raw moment estimate)  
 $\hat{m}_t \leftarrow m_t / (1 - \beta_1^t)$  (Compute bias-corrected first moment estimate)  
 $\hat{v}_t \leftarrow v_t / (1 - \beta_2^t)$  (Compute bias-corrected second raw moment estimate)  
 $\theta_t \leftarrow \theta_{t-1} - \alpha \cdot \hat{m}_t / (\sqrt{\hat{v}_t} + \epsilon)$  (Update parameters)  
**end while**  
**return**  $\theta_t$  (Resulting parameters)

---

Figure 4: The Adam objective function optimization algorithm as described in [11]

Adam accepts four parameters. First,  $\alpha$  is the step size and it determines how the first and second moments are calculated.  $\beta_1$  and  $\beta_2$  are exponential decay rates that are used to apply decay to the exponential moving averages from the first and second moments (a configurable parameter in PyTorch’s implementation of Adam).  $f(\theta)$  is the objective function being optimized with parameters  $\theta$ . Lastly,  $\theta_0$  is the initial parameter vector for use by Adam.

At each time-step, Adam first computes the first and second moment gradients of the objective function. Adam then computes a biased first and second moment estimate. This estimate is then corrected to produce an unbiased first and second moment estimate. These estimates are then used to update Adam’s parameter list. The entire point of Adam is to build an exponential moving average of the gradient and squared gradient of the objective function w.r.t. Adam’s hyper-parameters. At each time step, these gradients are applied to optimize the parameters of the objective function. Noting that the objective function in a classification context is generally a loss function, this results in a loss function that can overall guide the classification algorithm to produce less and less loss as it’s neural network weights are adjusted based on instances from the training space  $(X_T, Y_T)$ . W.r.t this model, the loss function being optimized is the multi-class cross-entropy loss.

In the following sections it is important to note that I utilized the entire dataset for training and validation. Training and validation was performed on a 80/20 split and running each network consisted of running 100 training

iterations followed by a single validation instance. Any input examples in the dataset that contained null or NaN values were dropped from the dataset before it was fed into the neural network model. Note that Adam optimization was only performed on the Linear/Bilinear/Dropout layers. Optimization was not performed on the ReLU activation layers as it does not make sense to optimize an activation function.

## 4.5 Iteration One

The first iteration of the neural network in presented in this paper was based on the work conducted by Clemen Winter in "Mastering Real-Time Strategy Games with Deep Reinforcement Learning: Mere Mortal Edition" [19] where he rigorously developed a DNN capable of playing a simplified real-time strategy game CodeCraft. The architecture is presented in figure 5.

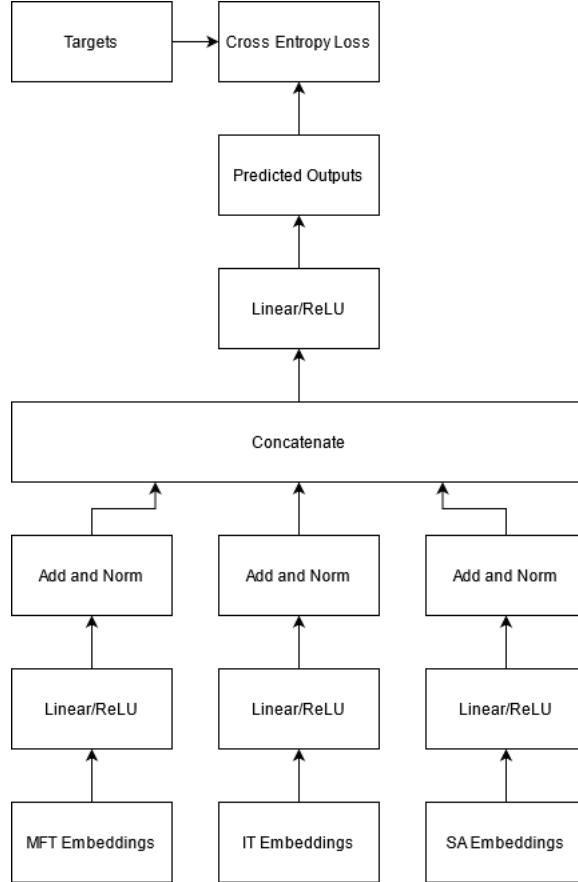


Figure 5: The first iteration of the proposed model.

I designed this model such that the input was still split into the three separate embeddings  $E_{mft}$ ,  $E_{it}$  and  $E_{sa}$ . This architecture consisted of a fully connected deep neural network with four hidden layers. The first hidden layer consists of three Linear/ReLU modules that accepted as input 12, 3 and 24 features respectively (for the three embeddings). This layer output the same amount of output to the next layer consisting of a tensor addition and normalization operation. The addition of this layer consists of adding the output of the first hidden layer to the original embeddings (though it is not shown in the figure). This produced output of 24, 6, and 48 values tensors respectively. The next hidden layer just concatenates the three tensor it receives from the previous layers into a single 1D tensor consisting of 78 values. This is then passed as input to the next hidden layer consisting of a Linear/ReLU activation function that outputs a single 1D tensor consisting of 78 values. These values are then argmaxed to retrieve the classification index for use in the cross-entropy function.

## 4.6 Iteration Two

The second iteration of this model was a stripped down variant of the first model. In this model I attempted to reduce complexity of the network and therefore increase accuracy as it can be shown that for many classification problems, even complex problems, you only need a single hidden layer. This model is shown in figure 6.

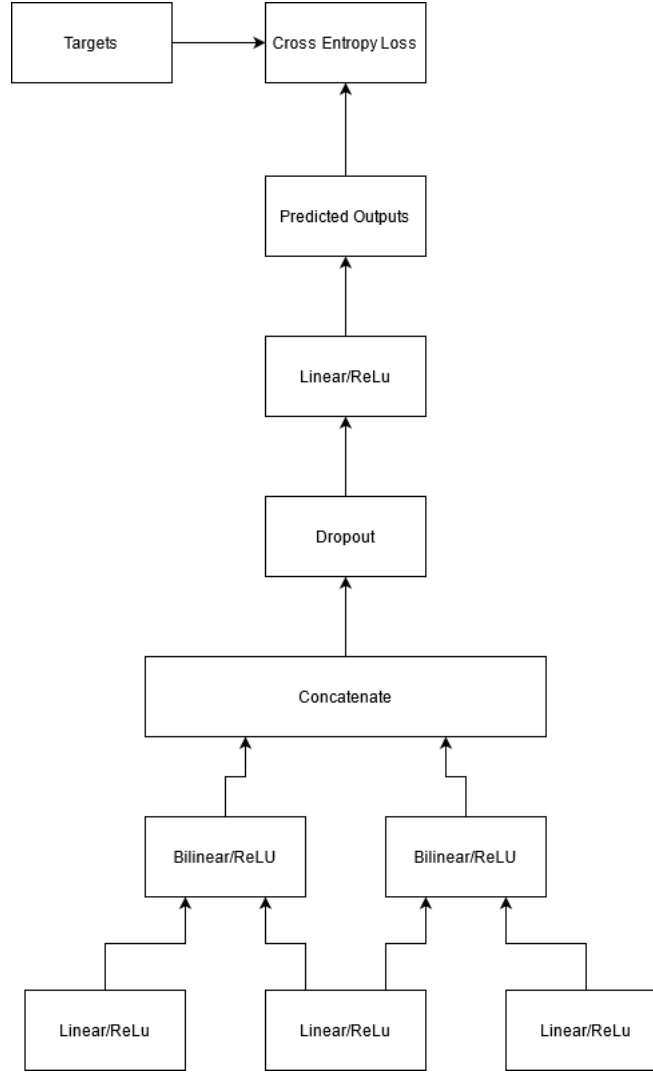


Figure 6: The second iteration of the proposed model.

This iteration still treats the embeddings as separate inputs to three different Linear/ReLU activation functions. However, this iteration saw the replacement of the Add/Norm layer with two Bilinear/ReLU layers that accept as input the output of the MFT/IT and IT/SA Linear/ReLU activation layer respectively. The first hidden layer accepted as input 12/3/24 features respectively and output 100/100/100 features respectively. The Bilinear/ReLU layer accepted as input 200/200 input features respectively and output 100/100 features respectively. The concatenation layer accepts 100/100 features as input and outputs a single 200 feature tensor. The dropout layer accepts a 200 feature tensor and



was configured to randomly drop inputs with a probability of 0.25% and outputs 100 features. The next Linear/ReLU layer accepts 100 features and outputs 5 features.

## 4.7 Iteration Three

The third iteration feeds all features into the neural network as a single embedding of 39 features. Likewise, the first layer has been replaced by a single Linear/ReLU activation function that accepts as input 39 features and outputs 300 features. The next layer is a Linear function that accepts as input 300 features and outputs 6 features. This simplistic model, as will be seen in the results section, outperforms the other two models by a strong margin. The model itself can be seen in figure 7.

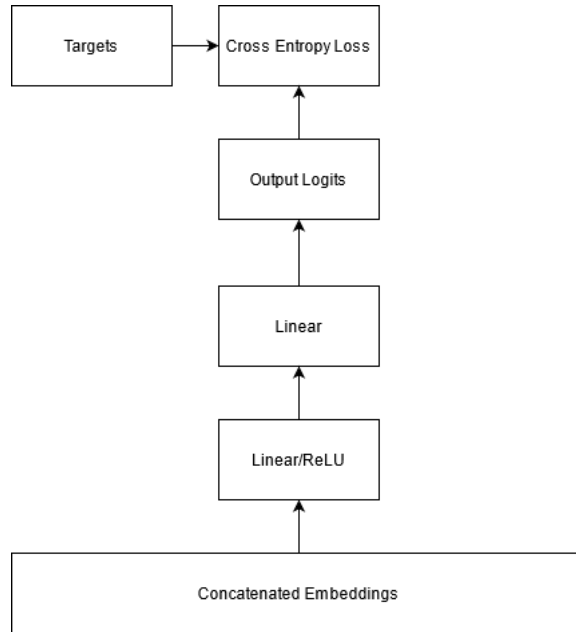


Figure 7: The third iteration of the proposed model.

This model, as I hinted to earlier, performed the best because it is the least complicated. For a majority of classification problems, even tough problems, they can be solved with a single hidden layer neural network.

## 5 Experimental Results

This section discusses the results of running the benchmark ensemble classifiers as well as all three models. Note that the ensemble classifiers and models are

best compared from a holistic viewpoint. While accuracy is certainly important for any classifier, precision, f1 score and recall are all also important metrics. These metrics are layed out in tables 1 and 2.

All training and validation was performed on a machine with the following parameters (all at stock, factory settings): 8-Core AMD Ryzen 7 3700X, 32GB DDR4 RAM 3200Mhz, Asus RTX 3080 FTW3 Ultra, 1TB Samsung EVO 970 Pro NVMe SSD, 1TB Samsung 860 EVO SATA SSD. Training and validation hardware is presented here for reproducability of this study.

<u>Classifier</u>	<u>Accuracy</u>	<u>F1-Score</u>	<u>Precision</u>	<u>Recall</u>
<b>AdaBoost</b>	0.4315	0.4315	0.4315	0.4315
<b>Grad. Boos.</b>	0.4935	0.4935	0.4935	0.4935
<b>Extr. Rand. Fore.</b>	0.9005	0.9005	0.9005	0.9005

Table 1: Metrics for the Ensemble Classifiers

As can be seen in tables 1 and 2, the AdaBoost and Gradient Boosting classifiers perform roughly similar to the best performing model. I did not expect this outcome especially since the AdaBoost and Gradient Boosting in sklearn utilize a decision tree as the weak classifier. The accuracy of the extremely random trees classifier was kind of expected. This is because decision trees in general tend to be excellent classifiers for both binary classification problems and multi-class classification problems. There is a reason that despite their age and simplicity, they remain one of the most popular choices for supervised learning problems.

<u>Model</u>	<u>Accuracy</u>	<u>Loss</u>	<u>F1-Score</u>	<u>Precision</u>	<u>Recall</u>
<b>Model 1</b>	30.2256	2243.4432	0.302268	0.302268	0.302268
<b>Model 2</b>	34.5446	1856.22	0.3458	0.3458	0.3458
<b>Model 3</b>	51.8426	544.7666	0.5188	0.5188	0.5188

Table 2: Metrics for the Neural Network Models

The results presented in table 2 showcases the principle that I have stated multiple times in this paper that simpler neural networks often work better for classification problems. Loss can be interpreted as how well the model is doing w.r.t. learning the weights needed to model the dataset. Generally, the lower the loss value, the better. It should be made known that the more complicated a DNN is (the more layers there are), the harder it is for gradient descent or any other optimization algorithm to optimize the weights across the network. A neural network with a single hidden layer works well with this task because there is only one layer of weights to update and as a result the optimization function knows exactly which parameters affect the learning process. Effectively, the more layers there are in a network, the more parameters the optimization algorithm has to optimize, this is known to reduce the overall effectiveness of the optimization algorithm.

It should be noted that with both the ensemble learners and the neural network models, the precision, recall and f1-scores are all the same. F1-score is essentially a combination of both precision and recall. To the best of my ability, I want to say that this oddity is due to the way the computation of these metrics are performed by the sklearn library.

## 6 Conclusion

This was an extremely challenging task for me to complete. As stated in my proposal, this was intended as a mini-application of the research I was intending to conduct as a part of my dissertation research. Overall, this project yielded mixed results towards determining if this is a good approach or not. On one hand, the neural network models vastly underperformed from what I expected. On the other hand, the extremely random forests classifier proved that this task could be accomplished with a much simpler (yet still stochastic) model.

My best guess as to why the neural network models underperformed was either because a.) I implemented the calculation of the MFT, IT and SA metrics incorrectly or b.) I did not design the architecture of the models correctly in the first place. I double-checked my implementation of the metrics, so I do not believe (a) is the problem. So, I strongly suspect that it the cause of the poor performance was due to issues with the model. This was my first time working with PyTorch and Tensorflow and I had to figure everything out on the fly with what is an extremely complicated library. I'm actually surprised I was able to get the models implemented at all as there was a point where I had considered dropping the neural network portion of the project altogether and instead using just the ensemble classifiers.

For future work, I would like to find more multi-class classification models in the literature and apply what they have done to my work. I am of the opinion that implementing a custom loss function that incorporates the three categories of metrics would also greatly assist the classification process. I would have done so for this project but frankly, I ran out of time.

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