Predicting TED Talk Ratings from Language and Prosody

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Abstract

We use the largest open repository of public speaking—TED Talks—to predict the ratings of the online viewers. Our dataset contains over 2200 TED Talk transcripts (includes over 200 thousand sentences), audio features and the associated meta information including about 5.5 Million ratings from spontaneous visitors of the website. We propose three neural network architectures and compare with statistical machine learning. Our experiments reveal that it is possible to predict all the 14 different ratings with an average AUC of 0.83 using the transcripts and prosody features only. The dataset and the complete source code is available for further analysis.

1 Introduction

Imagine you are a teacher, or a corporate employee, or an entrepreneur. Which soft skill do you think would be the most valuable in your daily life? According to an article in Forbes (Gallo, 2014), 70% of employed Americans agree that public speaking skills are critical to their success at work. Yet, it is one of the most dreaded acts. Many people rate the fear of public speaking even higher than the fear of death (Wallechinsky et al., 2005). As a result, several commercial products are being available nowadays to come up with automated tutoring systems for training public speaking. Predicting the viewer ratings is an essential component for the systems capable of tutoring oral presentations.

We propose a framework to predict the viewer ratings of TED talks from the transcript and prosody component of the speech. We use a dataset of 2233 public speaking videos accompanying over 5 million viewer ratings. The viewers rate each talk on 14 different categories. These are—Beautiful, Confusing, Courageous, Fascinating, Funny, Informative, Ingenious, Inspiring, Jaw-Dropping, Long-winded, Obnoxious, OK, Persuasive, and Unconvincing. Besides, the complete manual transcriptions of the talks are available. As a result, this dataset provides high-quality multimedia contents with rich ground truth annotations from a significantly large number of spontaneous viewers. We release the data and the complete source code for future scientific exploration\textsuperscript{1}.

TED talks are edited production videos. They contain numerous changes in the camera angles, clips from the presentation slides, reactions from the audience, etc. To avoid these extraneous features and to focus only on the speech, we remove the visual elements from the data. We use only the transcripts and the processed audio features (pitch, loudness etc.) in our experiments. However, the links to the original TED talks are preserved in the dataset. Therefore, it is possible to retrieve the visual elements if necessary.

We utilize three neural network architectures in our experiments. Our results show that the proposed solutions always outperform (AUC 0.83) the baseline approaches (AUC 0.78) for predicting the TED talk ratings.

2 Background Research

An example of behavioral prediction research is to automatically grade essays, which has a long history (Valenti et al., 2003). Recently, the use of deep neural network based solutions (Alikaniotis et al., 2016; Taghipour and Ng, 2016) are becoming popular in this field. Farag et al. (2018) proposed an adversarial approach for their task. Jin et al. (2018) proposed a two-stage deep neural network based solution. Predicting helpfulness (Martin and Pu, 2014; Yang et al., 2015;...
Research has been conducted on predicting various aspects of the TED talks. Chen and Lee (2017) analyzed the TED Talks for humor detection. Liu et al. (2017b) analyzed the transcripts of the TED talks to predict audience engagement in the form of applause. Haider et al. (2017) predicted user interest (engaging vs. non-engaging) from high-level visual features (e.g., camera angles) and audience applause. Pappas and Popescu-Belis (2013) proposed a sentiment-aware nearest neighbor model for a multimedia recommendation over the TED talks. Bertero and Fung (2016) proposed a combination of Convolutional Neural Network (CNN) and Long-short Term Memory (LSTM) based framework to predict humor in the dialogues. Jaech et al. (2016) analyzed the detection performance of phonological puns using various natural language processing techniques. Weniger et al. (2013) predicted the TED talk ratings from the linguistic features of the transcripts. This work is similar to ours. However, they did not use neural networks and thus obtained similar performance to our baseline methods.

### 3 Dataset

The data for this study was gathered from the ted.com website on November 15, 2017. We removed the talks published six months before the crawling date to make sure each talk has enough ratings for a robust analysis. More specifically, we filtered any talk that— 1. was published less than 6 months prior to the crawling date, 2. contained any of the following keywords: live music, dance, music, performance, entertainment, or, 3. contained less than 450 words in the transcript. This left a total of 2231 talks in the dataset.

We collect the manual transcriptions and the total view counts for each video. We also collect the “ratings” which is the counts of the viewer-annotated labels. The viewers can annotate a talk from a selection of 14 different labels provided in the website. The labels are not mutually exclusive. Viewers can choose at most 3 labels for each talk. If only one label is chosen, it is counted 3 times. We count the total number of annotations under each label as shown in Figure 1. The ratings are treated as the ground truth about the audience perception. A summary of the dataset characteristics is shown in Table 1.

The longer a TED talk remains in the web, the more views it gets. Large number of views also result in a large number of annotations. As a result, older TED talks contain more annotations per rating category. However, an old speech does not necessarily imply better quality. We normalize the rating counts of each individual talk as in the following equation:

$$ r_{i,\text{scaled}} = \frac{r_i}{\sum_i r_i} $$

(1)

Where $r_i$ represents the count of the $i^{th}$ label in a talk. Let us assume that in a talk, $f_i$ fractions of the total viewers annotate for the rating category $i$. Then the scaled rating, $r_{i,\text{scaled}}$ becomes $\frac{f_i}{\sum_i f_i}$. This process removes the effect of Total Views, $V$ as evident in Table 2. Scaling the rating counts removes the effects of Total Views by reducing the average correlation from 0.56 to −0.03. This also removes the effect of the Age of the Talks by reducing the average correlation from 0.15 to 0.06. Therefore, removing $V$ reduces the effect of the Age of the Talks in the ratings.

### Table 1: Dataset Properties

| Property                  | Quantity |
|---------------------------|----------|
| Number of talks           | 2,231    |
| Total length of all talks | 513.49   Hours |
| Total number of ratings   | 5,574,444 |
| Minimum number of ratings | 88       |
| Average ratings per talk  | 2498.6   |
| Total word count          | 5,489,628 |
| Total sentence count      | 295,338  |

Figure 1: Counts of all the 14 different rating categories (labels) in the dataset
In our experiments, we scale and binarize the rating counts by thresholding over the median value which results in a 0 and 1 class for each category of the ratings. The dataset contains the complete original information as well as the scaled and binarized versions of the ratings.

4 Network Architectures

We implemented three neural networks for comparison of their performance with the statistical machine learning techniques in predicting the viewer ratings. The architectures of these models are described in the following subsections. All these models are multi-label binary classifiers designed to capture sentence-wise patterns in the TED talks that contribute to the prediction of the rating labels.

4.1 Word Sequence Model

A pictorial illustration of this model is shown in Figure 2. Each sentence, $s_j$ in the transcript is represented by a sequence of words-vectors\(^2\), $w_1, w_2, w_3, \ldots, w_{n_j}$. Here, each $w$ represents the pre-trained, 300-dimensional GLOVE word vectors (Pennington et al., 2014) corresponding to the words in the sentence. We use a Long-Short-Term-Memory (LSTM) (Hochreiter and Schmidhuber, 1997) neural network to obtain an embedding vector, $h_{s_j}$, for the $j$th sentence in the talk transcript. These vectors ($h_{s_j}$) are averaged and passed through a feed-forward network to produce a 14-dimensional output vector corresponding to each category of the ratings. An element-wise sigmoid ($\sigma(x) = \frac{1}{1+e^{-x}}$) activation function is applied to the output vector. The mathematical description of the model can be given using the following equations:

$$h_{s_j} = \text{LSTM}(w_1, w_2, w_3, \ldots, w_{n_j}) \quad (2)$$

$$h = \frac{1}{N} \sum_{j=1}^{N} h_{s_j} \quad (3)$$

$$r = \sigma(W h + b_r) \quad (4)$$

Here, $h_{s_j}$ represents the the last recurrent state for the sentence $j$. $N$ represents the total number of the sentences in the transcript. We use zero vectors to initialize the memory cell ($c_0$) and the hidden state ($h_0$).

4.2 Dependency Tree-based Model

We are interested to represent the sentences as hierarchical trees of dependent words. We use a freely available dependency parser named SyntaxNet\(^3\) (Andor et al., 2016) to extract the dependency tree corresponding to each sentence. The child-sum TreeLSTM (Tai et al., 2015) is used to process the dependency trees. As shown in Figure 3, the parts-of-speech and dependency types of the words are used in addition to the GLOVE word vectors. We concatenate a parts-of-speech embedding ($p_i$) and a dependency type embedding ($d_i$) with the word vectors. These embeddings are learned through back-propagation along with other free parameters of the network. The

\(^2\)In this paper, we represent the column vectors as lowercase boldface letters; matrices or higher dimensional tensors as uppercase boldface letters and scalars as lowercase regular letters. We use a prime symbol ('$\prime$') to represent the transpose operation.

\(^3\)https://opensource.google.com/projects/syntaxnet

| Total Views | Age of Talks |
|-------------|-------------|
| Total Views | noscale     | scale      |
| Beaut.      | 0.52        | 0.01       | 0.03        | -0.14       |
| Conf.       | 0.39        | -0.12      | 0.27        | 0.20        |
| Cour.       | 0.52        | -0.003     | 0.01        | 0.15        |
| Fasc.       | 0.78        | 0.05       | 0.15        | 0.06        |
| Funny       | 0.57        | 0.14       | 0.10        | 0.15        |
| Info.       | 0.76        | -0.08      | 0.07        | -0.19       |
| Ingen.      | 0.59        | -0.06      | 0.18        | 0.10        |
| Insp.       | 0.79        | 0.1        | 0.05        | -0.15       |
| Jaw-Dr.     | 0.51        | 0.1        | 0.18        | 0.23        |
| Long.       | 0.44        | -0.17      | 0.36        | 0.31        |
| Obnox.      | 0.27        | -0.11      | 0.19        | 0.17        |
| OK          | 0.72        | -0.16      | 0.21        | 0.14        |
| Pers.       | 0.72        | -0.01      | 0.12        | 0.02        |
| Unconv.     | 0.29        | -0.14      | 0.18        | 0.15        |

Table 2: Correlation coefficients of each category of the ratings with the Total Views and the "Age" of Talks

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Figure 2: An illustration of the Word Sequence Model

Figure 3: An illustration of the Dependency Tree-based Model
The complete mathematical description of this model is as follows:

\[ x'_t = [w'_t, p'_t, d'_t] \] (5)

\[ \hat{h}_t = \sum_{k \in C(t)} h_k \] (6)

\[ i_t = \sigma(U_i x_t + V_i \hat{h}_t + b_i) \] (7)

\[ f_{tk} = \sigma(U_f x_t + V_f h_k + b_f) \] (8)

\[ u_t = \tanh(U_u x_t + V_u \hat{h}_t + b_u) \] (9)

\[ o_t = \sigma(U_o x_t + V_o \hat{h}_t + b_o) \] (10)

\[ c_t = f_{tk} \odot c_k + i_t \odot u_t \] (11)

\[ h_t = o_t \odot \tanh(c_t) \] (12)

\[ h_{s_j} = h_{\text{ROOT}} \] (13)

\[ h = \frac{1}{N} \sum_{j=1}^{N} h_{s_j} \] (14)

\[ r = \sigma(W_h + b_r) \] (15)

Here, equation (5) refers to the fact that the input to the treeLSTM nodes are constructed by concatenating the pre-trained GLOVE word-vectors with the embeddings of the parts of speech and the dependency type of a specific word. \( C(t) \) represents the set of all the children of node \( t \). The parent-child relation of the treeLSTM nodes come from the dependency tree. Notably, the memory cell and hidden states flow hierarchically from the children to the parent. Each node contains a forget gate (\( f \)) for each child. Zero vectors are used as the children of the leaf nodes and the sentence embedding vector is obtained from the root node.

4.3 Capturing the Patterns in Prosody

We align the TED talk audio with its corresponding transcriptions using forced alignment method \(^4\).

\(^4\)https://github.com/JoFrhwld/FAVE/wiki/FAVE-align

PRAAT \(^5\) is used to extract the pitch, loudness, and first three formants (frequency and bandwidth) sampled at a rate of 10Hz. We normalize these signals by subtracting the mean and dividing by the standard deviation over the whole video. These signals are then sentence-wise cropped based on the alignment data. We pad all the sentence-wise signal-clips to a length equal to the longest sentence in the transcript. This process constructs a signal of length \( M \); where \( M \) is the number of samples in the signal corresponding to the longest sentence. Each sample in the signal is an 8-dimensional vector.

We use one dimensional Convolutional Neural Network (CNN) (LeCun et al., 2015) to extract the patterns within the pitch, loudness and formant as follows:

\[ S_{\text{out}}[f_o, m] = \sum_{f_i=1}^{F} \sum_{k=1}^{K} W_{f_o, f_i, k} S_{\text{in}}[f_i, m - k] \]

\[ + b[f_o] \]

\[ \forall f_o \in 1, 2, ..., F_{\text{out}} \]

\[ \forall m \in 1, 2, ..., M \]

Here \( S_{\text{in}} \) is the input signal, \( S_{\text{out}} \) is the output signal, \( W_{f} \) is the filter weights, \( K \) is the receptive fields of the filters, \( F_{\text{in}} \) is the dimension of the input signal, \( F_{\text{out}} \) is the number of filters and \( M \) is the signal length. \( b \) is a bias term. Both \( W_{f} \) and \( b \) are learned in training time through back-propagation.

We use one dimensional Convolutional Neural Network (CNN) (LeCun et al., 2015) to extract the patterns within the prosody signal—i.e. pitch, loudness, and the first three formants computed over small segments of the audio. The network consists of four 1D convolutional layers, each having a receptive field of 3. We use element-wise RELU \( (R(x) = \max(0, x)) \) activation function to the output of each convolution layer. The lowest (closest to the input signal) two layers consist of 16 filters, and the upper two layers have 32 and 64 filters respectively. The second and third convolution layers are followed by max-pool layers of window size 2. The final convolution layer is followed by a max-pool layer having the window size equal to the length of the signal. Thus, the CNN outputs a 64-dimensional vector. This vector is concatenated with the sentence embedding vector obtained from the dependency tree-based

\(^5\)http://www.fon.hum.uva.nl/praat/
model discussed in section 4.2. The concatenated vector is passed through two layers of fully connected networks to produce the probabilities of the ratings.

5 Training the Networks

We implemented the networks in pyTorch \(^6\). Details of the training procedure are described in the following subsections.

5.1 Optimization

We use multi-label Binary Cross-Entropy loss as defined below for the backpropagation of the gradients:

\[
\ell(r, y) = -\frac{1}{n} \sum_{i=1}^{n} (y_i \log(r_i) + (1-y_i) \log(1-r_i))
\]

(16)

Here \( r \) is the model output and \( y \) is the ground truth label obtained from data. \( r_i \) and \( y_i \) represent the \( i \)th element of \( r \) and \( y \). \( n = 14 \) represents the number of the rating categories.

We randomly split the training dataset into 9:1 ratio and name them training and development subsets respectively. The networks are trained over the training subset. We use the loss in the development subset to tune the hyper-parameters, to adjust the learning rate and regularization strength, and to select the best model for final evaluation, etc. The training loop is terminated when the loss over the development subset saturates. The model parameters are saved only when the loss over the development subset is lower than any previous iteration.

We experiment with two optimization algorithms: Adam (Kingma and Ba, 2014) and Adagrad (Duchi et al., 2011). The learning rate is varied in an exponential range from 0.0001 to 1. The optimization algorithms are evaluated with mini-batches of size 10, 30, and 50. We obtain the best results using Adagrad with learning rate 0.01 and in Adam with a learning rate of 0.00066. The training loop ran for 50 iterations which mostly saturates the development set loss. We conducted around 100 experiments with various parameters. Experiments usually take about 48 hours to make 50 iterations over the dataset when running in an Nvidia K20 GPU.

5.2 Regularization

Neural networks are often regularized using Dropout (Hinton et al., 2012) to prevent overfitting—where the elements of a layer’s output are set to zero with a probability \( p \) during the training time. A naive application of dropout to LSTM’s hidden state disrupts its ability to retain long-term memory. We resolve this issue using the weight-dropping technique proposed by Merity et al. (2017). In this technique, instead of applying the dropout operation between time-steps, it is applied to the hidden-to-hidden weight matrices (Wan et al., 2013). The dropout probability, \( p \) is set to 0.2. Effect of the regularization is shown in Figure 4.

6 Baseline Methods

We compare the performance of the neural network models against several popular statistical classifiers.

6.1 Feature Extraction

We use language, prosody, and narrative trajectory features that are used in similar tasks in the relevant literature.

6.1.1 Language Features

We use a psycholinguistic lexicon named “Linguist Inquiry Word Count” (LIWC) (Pennebaker et al., 2001) for extracting language features. We count the total number of words under the 64 word categories provided in the LIWC lexicon and normalize these counts by the total number of words in the transcript. The LIWC categories include words describing function word categories (e.g., articles, quantifiers, pronouns), various content categories (e.g., anxiety, insight), positive emotions (e.g., happy, kind), negative emotions (e.g.,

\(^6\)pytorch.org
sad, angry), etc. These features have been used in several related works (Ranganath et al., 2009; Zechner et al., 2009; Naim et al., 2016; Liu et al., 2017b).

6.1.2 Prosodic Features

We extract several summary statistics from the pitch, loudness, and the first three formants extracted from the audio. These statistics are min, max, mean, 25th percentile, median, 75th percentile, standard deviation, kurtosis, and skewness. Additionally, we collect pause duration, the percentage of unvoiced frames, jitter (irregularities in pitch), shimmer (irregularities in vocal intensity), and percentage of breaks in speech. These features are used in several related works as well (Soman and Madan, 2009; Naim et al., 2016).

6.1.3 Narrative Trajectory

Tanveer et al. (2018) proposed a set of features that can capture the “narrative trajectory” of the TED Talks. These features are constructed by extracting sentence-wise emotion (anger, disgust, fear, joy, or sadness), language (analytical, confidence, and tentative) and personality (openness, conscientiousness, extraversion, emotional range, and agreeableness) scores from a standard machine learning toolbox and then interpolating the sentence-wise scores to a signal of fixed size (e.g., 100 samples). These signals form several interesting clusters that can capture patterns of storytelling. The summary statistics of these signals are found to be good predictors of the TED talk ratings as well. We use the min, max, mean, standard deviation, kurtosis, and skewness of these signals. We use IBM Tone Analyzer\(^7\) to extract the sentence-wise scores.

6.2 Baseline Classifiers

We use the Linear Support Vector Machine (SVM) (Vapnik and Chervonenkis, 1964) and LASSO (Tibshirani, 1996) as the baseline classifiers. In SVM, the following objective function is minimized:

\[
\min_{w, \xi_i, b} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{N} \xi_i \\
\text{subject to } y_i (w'x_i - b) \geq 1 - \xi_i, \forall i \\
\xi_i \geq 0, \forall i
\]

Where \(w\) is the weight vector and \(b\) the bias term. \(\|w\|\) refers to the \(\ell_2\) norm of the vector \(w\). In these equations, we assume that the “higher than median” and “lower than median” classes are represented by 1 and −1 values respectively.

We adapt the original Lasso (Tibshirani, 1996) regression model for classification purposes. It is equivalent to Logistic regression with \(\ell_1\) norm regularization. It works by solving the following optimization problem:

\[
\min_{w, b} \|w\|_1 + k \\
k = C \sum_{i=1}^{N} \log (\exp (-y_i (w'x_i + b)) + 1)
\]

where \(C > 0\) is the inverse of the regularization strength, and \(\|w\|_1 = \sum_{j=1}^{d} |w_j|\) is the \(\ell_1\) norm of \(w\). The \(\ell_1\) norm regularization is known to push the coefficients of the irrelevant features down to zero, thus reducing the predictor variance.

Finally, the Ridge regression is essentially same as logistic regression with \(\ell_2\) regularization. The objective function is as below:

\[
\min_{w, b} \frac{1}{2} \|w\|^2 + k \\
k = C \sum_{i=1}^{N} \log (\exp (-y_i (w'x_i + b)) + 1)
\]

7 Experimental Results

We allocated 150 randomly sampled TED talks from the dataset as a reserved test subset. All the

| Model            | Avg. AUC | Avg. F-sc. | Avg. Prec. | Avg. Recall |
|------------------|----------|------------|------------|-------------|
| Word Seq         | 0.83     | 0.76       | 0.76       | 0.76        |
| D.Tree           | 0.83     | 0.77       | 0.77       | 0.77        |
| D.Tree+Pr.       | 0.83     | 0.72       | 0.75       | 0.73        |
| Dep. Tree (Unscaled) | 0.76 | 0.70     | 0.68       | 0.68        |
| LinearSVM        | 0.78     | 0.71       | 0.71       | 0.71        |
| Ridge            | 0.78     | 0.71       | 0.71       | 0.71        |
| LASSO            | 0.77     | 0.70       | 0.70       | 0.70        |
| Weninger         | –        | 0.71       | –          | –           |

Table 3: Average of several prediction performance metrics over 14 different ratings of TED talks

\(^7\)https://www.ibm.com/watson/services/tone-analyzer/
results shown in this section are computed over this test subset. We evaluate the models by computing the values of four performance metrics—Area Under the ROC Curve (AUC), Precision, Recall, and F-score for all the 14 categories of the ratings. We compute averages of these metrics over all the rating categories that are shown in Table 3.

The first three rows represent the average performances of the Word Sequence model, the Dependency Tree based model, and the Dependency Tree model combined with CNN respectively. It is evident from the table that the neural networks outperform the baseline models in all the four metrics. These models were trained and tested on the scaled rating counts ($R^{scaled}$). We also trained and tested the dependency tree model with the unscaled rating counts (4th row in Table 3). Notably, the networks perform worse for predicting the unscaled ratings. We believe this is due to the fact that unscaled ratings are biased with the amount of time the TED talks remain online. This mixture of additional information makes it difficult for the neural networks to predict the ratings from transcript and prosody only.

We are surprised that adding the prosody does not improve the prediction performance. We think it is because TED Talks are highly rehearsed public speeches. It is likely that the change of prosody in most of the talks are acted, and therefore, it does not carry much information in addition to the talk transcripts. We believe it is a global artifact of the TED talk dataset.

Table 4 provides a clearer picture how the dependency tree based neural network performs better than the word sequence neural network. The former achieves a higher recall for most of the rating categories (9 out of 14). Only in three cases (Funny, Longwinded, and OK) the word sequence model achieved higher performance than the dependency tree model. Both these models performed equally well for the Obnoxious and Unconvincing rating category. It is important to realize that the dependency trees we extracted were not manually annotated. They were extracted using SyntaxNet which itself introduces some error. Andor et al. (2016) described their model accuracy to be approximately 0.95. We expected to notice an impact of this error in the results. However, the results show that the additional information (Parts of Speech tags and the dependency structure) benefited the prediction performance despite the error in annotating the dependency trees. We think the hierarchical tree structure resolves many ambiguities in the sentence semantics which is not available to the word sequence model.

We also compare our results with Weninger et al. (2013). However, this comparison is just an approximation because the number of TED talks are different in our experiment than in Weninger et al. (2013). The results show that the neural network models perform better for almost every rating category except Fascinating and Obnoxious.

A neural network is a universal function approximator (Cybenko, 1989; Hornik, 1991) and thus expected to perform better. Yet we think another reason for its excel is its ability to process a faithful representation of the transcripts. In the baseline methods, the transcripts are provided as words without any order. In the neural counterparts, however, it is possible to maintain a more natural representation of the words—either the sequence, or the syntactic relationship among them through a dependency tree. In addition, neural networks intrinsically capture the correlations among the rating categories. The baseline methods, on the other hand, considers each category as a separate classification problem. These are a few reasons why neural networks are a better choice for the TED talk prediction task.

| Ratings         | Word Seq. | Dep. Tree | Weninger et al. (SVM) |
|-----------------|-----------|-----------|-----------------------|
| Beautiful       | 0.88      | 0.91      | 0.80                  |
| Confusing       | 0.70      | 0.74      | 0.56                  |
| Courageous      | 0.84      | 0.89      | 0.79                  |
| Fascinating     | 0.75      | 0.76      | 0.80                  |
| Funny           | 0.78      | 0.77      | 0.76                  |
| Informative     | 0.81      | 0.83      | 0.78                  |
| Ingenious       | 0.80      | 0.81      | 0.74                  |
| Inspiring       | 0.72      | 0.77      | 0.72                  |
| Jaw-dropping    | 0.68      | 0.72      | 0.72                  |
| Longwinded      | 0.73      | 0.70      | 0.63                  |
| Obnoxious       | 0.64      | 0.64      | 0.61                  |
| OK              | 0.73      | 0.70      | 0.61                  |
| Persuasive      | 0.83      | 0.84      | 0.78                  |
| Unconvincing    | 0.70      | 0.70      | 0.61                  |
| Average         | 0.76      | 0.77      | 0.71                  |

Table 4: Recalls for various rating categories. The reason we choose recall is for making comparison with the results reported by Weninger et al. (2013).
8 Conclusion

In summary, we presented neural network architectures to predict the TED talk ratings from the speech transcripts and prosody. We provide domain specific information such as psycholinguistic language features, prosody and narrative trajectory features to the baseline classifiers. The neural networks, on the other hand, were designed to consume mostly the raw data with a few high-level assumptions on human cognition. The neural network architectures provide state of the art prediction performance, outperforming the competitive baseline method in the literature. The average AUC of the networks are 0.83 compared to the baseline method’s AUC of 0.78. The results also show that dependency tree based networks perform better in predicting the TED talk ratings. Furthermore, inclusion of prosody does not help as much as we expect it to be. The exact reason why this happens, however, remains to be explored in the future.

The dataset and the complete source code of this work will be freely available to the scientific community for further evaluation.

References

Dimitrios Alikaniotis, Helen Yannakoudakis, and Marek Rei. 2016. Automatic text scoring using neural networks. arXiv preprint arXiv:1606.04289.

Daniel Andor, Chris Alberti, David Weiss, Aliaksei Severyn, Alessandro Presta, Kuzman Ganchev, Slav Petrov, and Michael Collins. 2016. Globally normalized transition-based neural networks. In ACL.

Dario Bertero and Pascale Fung. 2016. A long short-term memory framework for predicting humor in dialogues. In NAACL-HLT, pages 130–135.

Cen Chen, Yinfei Yang, Jun Zhou, Xiaolong Li, and Forrest Sheng Bao. 2018. Cross-domain review helpfulness prediction based on convolutional neural networks with auxiliary domain discriminators. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers), volume 2, pages 602–607.

Lei Chen and Chong Mln Lee. 2017. Convolutional neural network for humor recognition. arXiv preprint arXiv:1702.02584.

Lei Chen, Ru Zhao, Chee Wee Leong, Blair Lehman, Gary Feng, and Mohammed Elsah Hoque. 2017. Automated video interview judgment on a large-sized corpus collected online. In ACH, pages 504–509.

George Cybenko. 1989. Approximation by superpositions of a sigmoidal function. Mathematics of control, signals and systems, 2(4):303–314.

John Duchi, Elad Hazan, and Yoram Singer. 2011. Adaptive subgradient methods for online learning and stochastic optimization. Journal of Machine Learning Research, 12(Jul).

Youmna Farag, Helen Yannakoudakis, and Ted Briscoe. 2018. Neural automated essay scoring and coherence modeling for adversarially crafted input. arXiv preprint arXiv:1804.06898.

Carmine Gallo. 2014. New survey: 70% say presentation skills are critical for career success. Forbes.

Fasih Haider, Fahim A Salim, Saturnino Luz, Carl Vogel, Owen Conlan, and Nick Campbell. 2017. Visual, laughter, applause and spoken expression features for predicting engagement within ted talks. Feedback, 10:20.

Geoffrey E Hinton, Nitish Srivastava, Alex Krizhevsky, Ilya Sutskever, and Ruslan R Salakhutdinov. 2012. Improving neural networks by preventing co-adaptation of feature detectors. arXiv preprint arXiv:1207.0580.

Sepp Hochreiter and Jrgen Schmidhuber. 1997. Long short-term memory. Neural Computation, 9(8):1735–1780.

Kurt Hornik. 1991. Approximation capabilities of multilayer feedforward networks. Neural networks, 4(2):251–257.

Aaron Jaech, Rik Koncel-Kedziorski, and Mari Ostendorf. 2016. Phonological pun-derstanding. In NAACL-HLT, pages 654–663.

CanCan Jin, Ben He, Kai Hui, and Le Sun. 2018. Tdnn: a two-stage deep neural network for prompt-independent automated essay scoring. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), volume 1, pages 1088–1097.

Diederik P Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.

Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. 2015. Deep learning. nature, 521(7553):436.

Haijing Liu, Yang Gao, Pin Lv, Mengxue Li, Shiqiang Geng, Minglan Li, and Hao Wang. 2017a. Using argument-based features to predict and analyse review helpfulness. arXiv preprint arXiv:1707.07279.
Zhe Liu, Anbang Xu, Mengdi Zhang, Jalal Mahmud, and Vibha Sinha. 2017b. Fostering user engagement: Rhetorical devices for applause generation learnt from ted talks. *arXiv preprint arXiv:1704.02362*.

Lionel Martin and Pearl Pu. 2014. Prediction of helpful reviews using emotions extraction. In *Proceedings of the 28th AAAI Conference on Artificial Intelligence (AAAI-14)*, EPFL-CONF-210749.

Stephen Merity, Nitish Shirish Keskar, and Richard Socher. 2017. Regularizing and optimizing lstm language models. *arXiv preprint arXiv:1708.02182*.

Iftekhar Naim, Md Iftekhar Tanveer, Daniel Gildea, and Ehsan Hoque. 2016. Automated analysis and prediction of job interview performance. *IEEE Transactions on Affective Computing*.

Laurent Son Nguyen and Daniel Gatica-Perez. 2016. Hirability in the wild: Analysis of online conversational video resumes. *IEEE Transactions on Multimedia*, 18(7):1422–1437.

Nikolaos Pappas and Andrei Popescu-Belis. 2013. Sentiment analysis of user comments for one-class collaborative filtering over ted talks. In *SIGIR*, *SIGIR ’13*, pages 773–776. ACM.

James W Pennebaker, Martha E Francis, and Roger J Booth. 2001. Linguistic Inquiry and Word Count: LIWC 2001. *Mahwah: Lawrence Erlbaum Associates*, 71.

Jeffrey Pennington, Richard Socher, and Christopher D. Manning. 2014. *Glove: Global vectors for word representation*. In *EMNLP*.

Rajesh Ranganath, Dan Jurafsky, and Dan McFarland. 2009. It’s not you, it’s me: detecting flirting and its misperception in speed-dates. In *EMNLP*, pages 334–342.

Vikrant Soman and Anmol Madan. 2009. Social signaling: Predicting the outcome of job interviews from vocal tone and prosody. In *ICASSP*.

Kaveh Taghipour and Hwee Tou Ng. 2016. A neural approach to automated essay scoring. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 1882–1891.

Kai Sheng Tai, Richard Socher, and Christopher D Manning. 2015. Improved semantic representations from tree-structured long short-term memory networks. In *ACL*, page 15561566.

M. Iftekhar Tanveer et al. 2018. Awe the audience: How the narrative trajectories affect audience perception in public speaking. In *CHI ’18*, pages 24:1–24:12, New York, NY, USA. ACM.

Robert Tibshirani. 1996. Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society*, pages 267–288.

Salvatore Valent, Francesca Neri, and Alessandro Cucchiarelli. 2003. An overview of current research on automated essay grading. *Journal of Information Technology Education: Research*, 2:319–330.

Vladimir Vapnik and Alexey Chervonenkis. 1964. A note on one class of perceptrons. *Automation and remote control*, 25(1).

David Wallechinsky, Amy Wallace, Jane Farrow, and Ira Basen. 2005. *The Book of Lists: The Original Compendium of Curious Information*. Knopf Canada.

Li Wan, Matthew Zeiler, Sixin Zhang, Yann Le Cun, and Rob Fergus. 2013. Regularization of neural networks using dropconnect. In *ICML*, pages 1058–1066.

Felix Weninger, Pascal Staudt, and Björn Schuller. 2013. Words that fascinate the listener: Predicting affective ratings of on-line lectures. *International Journal of Distance Education Technologies (IJDET)*, 11(2):110–123.

Yinfei Yang, Yaowei Yan, Minghui Qiu, and Forrest Bao. 2015. Semantic analysis and helpfulness prediction of text for online product reviews. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 2: Short Papers)*, volume 2, pages 38–44.

Klaus Zechner, Derrick Higgins, Xiaoming Xi, and David M Williamson. 2009. Automatic scoring of non-native spontaneous speech in tests of spoken english. *Speech Communication*, 51(10):883–895.