Financial Aspect and Sentiment Predictions with Deep Neural Networks: An Ensemble Approach

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ABSTRACT
In this paper, we describe our ensemble approach for sentiment and aspect predictions in the financial domain for a given text. This ensemble approach uses Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) with a ridge regression and a voting strategy for sentiment and aspect predictions, and therefore, does not rely on any handcrafted feature. Based on 5-cross validation on the released training set, the results show that CNNs overall perform better than RNNs on both tasks, and the ensemble approach can boost the performance further by leveraging different types of deep learning approaches.

KEYWORDS
Sentiment Analysis; Financial Aspect Prediction; Deep Learning

1 INTRODUCTION
Deep learning [10] techniques such as Convolutional Neural Networks (CNNs) [11] for processing data in the form of multiple arrays, or Recurrent Neural Networks (RNNs) such as Long Short-Term Memory neural networks (LSTMs) [5] for tasks with sequential inputs, have been widely adopted in various research domains such as computer vision [4, 9], natural language processing (NLP) [6, 7] including sentiment analysis [3], recommender systems [14] etc.

More recently, [2] proposed an ensemble approach using several deep neural networks (DNNs) such as CNNs and LSTMs for one of the tasks at the sentiment analysis challenge SemEval20171, and their approach outperforms other methods for the sentiment analysis task on Twitter2. Deep learning approaches have also been applied to the sentiment analysis in the financial domain which plays a significant role in predicting the market reaction [3]. Motivated by the state-of-the-art results on different tasks including sentiment analysis, we introduce our ensemble approach with different types of DNNs for tackling the first task at the Financial Opinion Mining and Question Answering (FIQA) challenge3, which is co-located with the Web Conference 2018.

1.1 Task1: Sentiment and Aspect Predictions in the Financial Domain
Given a text \( t \) and a target as an input, the task is to predict its sentiment score \( y_s \) and its aspect labels \( y_a \) at the level two of an financial aspect tree. An example of a training instance is shown as below:

"55": {
    "sentence": "Tesco Abandons Video-Streaming Ambitions in Blinkbox Sale",
    "info": [
        {
            "snippets": "['Video-Streaming Ambitions']",
            "target": "Blinkbox",
            "sentiment_score": "+0.195",
            "aspects": "(['Corporate/Strategy'])"
        },
        {
            "snippets": "['Tesco Abandons Video-Streaming Ambitions ']",
            "target": "Tesco",
            "sentiment_score": "-0.335",
            "aspects": "(['Corporate/Strategy'])"
        }
    ]
}

Table 1 shows the details of the dataset for task 1. There are two types of text; one is Twitter posts and the other is news headlines in the financial domain. Overall, there are 28 distinct aspects for all posts and headlines in the released training dataset.

<table>
<thead>
<tr>
<th></th>
<th>Posts</th>
<th>Headlines</th>
</tr>
</thead>
<tbody>
<tr>
<td># of examples</td>
<td>675</td>
<td>436</td>
</tr>
<tr>
<td># of multi-labeled</td>
<td>0</td>
<td>30</td>
</tr>
<tr>
<td>max length</td>
<td>40</td>
<td>19</td>
</tr>
<tr>
<td>distinct aspects</td>
<td>28</td>
<td></td>
</tr>
</tbody>
</table>
2 DEEP NEURAL NETWORKS

In order to feed into DNNs such as CNNs, we first convert each text as a sequence of words, and map each word to its corresponding embedding. Therefore, a text is represented as a matrix of size $m' \times d$, where $m'$ is the number of words in the text and $d$ is the dimension of the word embedding space. We used the zero-padding strategy in order to make all texts have the same length $m$. The final matrix of a given text $T \in \mathbb{R}^{m \times d}$ ($m = 50$ for our approach) is used as an input to one of the DNNs which we will describe below.

2.1 Convolutional Neural Networks

CNNs apply convolutional filters to the input matrix with a filtering matrix $f \in \mathbb{R}^{h \times d}$, where $h$ is the filter size which denotes the number of words it spans. This operation can be defined as follows:

$$c_t = a \cdot \sum_{j,k} f_{j,k}(T_{[i:i+h-1]}, j, k + b)$$

where $b \in \mathbb{R}$ denotes the bias term, and $a(\cdot)$ is a non-linear activation function. We used the well-known ReLu activation here. Different filter sizes such as $[1, 2, 3]$ or $[3, 4, 5]$ can be used for CNNs, and there can be multiple filters for each filter size.

Next, CNNs can apply a pooling operation to each convolution with the hope to extract the most important feature for each convolution. For example, the max-pooling $\epsilon_{\text{max}} = \text{max}(\epsilon)$ retains the maximum value for each convolution. Finally, the output from each convolution is concatenated into a single vector which can be seen as the text embedding for a given text learned by CNNs.

For CNNs, we used the following settings for their hyperparameters for training:

<table>
<thead>
<tr>
<th>Hyperparameter</th>
<th>Settings</th>
</tr>
</thead>
<tbody>
<tr>
<td>pooling</td>
<td>max pooling</td>
</tr>
<tr>
<td>filter sizes</td>
<td>$[1, 2, 3], [3, 4, 5]$ or $[5, 6, 7]$</td>
</tr>
<tr>
<td># of filters</td>
<td>200 - 300</td>
</tr>
</tbody>
</table>

2.2 Long-Short Term Memory Networks

The first step in LSTM is going through a forget gate layer. This layer decides what information to keep from the cell state by looking at $h_{t-1}$ and $x_t$, as shown in Equation 2:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

where $[h_{t-1}, x_t]$ denotes the concatenated vector of $h_{t-1}$ and $x_t$, $\sigma$ is a sigmoid function: $\sigma(x) = \frac{1}{1 + e^{-x}}$, and $b_f$ denotes a bias term. $W_f$ is a weight vector to be learned for the forget gate layer.

Next, LSTM decides what new information to store in the cell state, which consists of two parts. The first part is an input gate layer, which is defined as below:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i).$$

The second part is a tanh layer (Equation 4), which creates a vector of new candidate values, $\tilde{C}_t$, that could be added into the cell state.

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

Finally, the new cell state $C_t$ will be created based on linear interactions of the previous cell state $C_{t-1}$, $f_t$, $i_t$, and $\tilde{C}_t$ as follows.

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$$

The last step is filtering the cell state to generate the final output, which can be formulated as below:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o),$$

$$h_t = o_t \cdot \tanh(C_t)$$

Here, $o_t$ decides what parts of the cell state to keep for the final output, and the cell state goes through a tanh layer before multiplying by $o_t$.

Another RNNs we used for Gated Recurrent Unit (GRU) [1] is a variant of LSTMs which has less parameters to tune.

For DNNs, we used the following hyperparameter settings for training:

<table>
<thead>
<tr>
<th>Hyperparameter</th>
<th>Settings</th>
</tr>
</thead>
<tbody>
<tr>
<td>embedding dimension</td>
<td>200</td>
</tr>
<tr>
<td>dropout rate</td>
<td>0.5</td>
</tr>
<tr>
<td>batch size</td>
<td>40</td>
</tr>
<tr>
<td>epochs</td>
<td>100 - 300</td>
</tr>
</tbody>
</table>

2.3 Regularization and Training

For regularization, we use the dropout [12] in the same way as [13]. Dropout, which refers to dropping out units in a neural network, is one of the widely used regularization techniques for preventing overfitting in training neural networks. Individual nodes are either “disabled” with probability $1 - p$ or kept with probability $p$. The “thinned” outputs of a hidden layer are then used as an input to the next layer. In this way, it prevents units from co-adapting and forces them to learn useful features individually.

We also constrain $l_2$-norms of the weight vectors to a threshold $\epsilon$ as below, which normalizes a word vector $w$ so that its $l_2$-norm is equal to $\epsilon$, and will be performed whenever the $l_2$-norm of $w$ is bigger than $\epsilon$ ($\epsilon = 3$ for our approach).

$$\|w\|_2 = \epsilon, \text{ if } \|w\|_2 > \epsilon.$$  (7)

To learn the parameters for minimizing the loss, we use a Stochastic Gradient Descent (SGD) with the Adam update rule [8] to train the model until the loss has converged.

3 PROPOSED APPROACH

In this section, we describe our proposed approach for the Financial Aspect and Sentiment Prediction task with Deep neural networks (Deep-FASP).

Figure 1 shows an overview of our proposed approach for predicting the aspects and the sentiment score of a given text. It consists of five steps from an input to the predicted output.

- Input. Each headline and post is a sequence of words.
Deep-FASP.

- **Look up.** Those words are represented as word embeddings.

- **DNNs.** The sequence of word embeddings is used as an input to multiple DNNs such as CNNs, LSTMs, and GRUs. Each DNN outputs their predicted labels for the aspect classification task, and outputs their measured sentiment scores for the task of sentiment prediction.

- **Prediction.** Finally, the outputs from multiple DNNs are aggregated for predicting the final results. The output of aspect classification is the predicted label with the highest votes based on the votes from all DNNs. For sentiment score prediction, we use a ridge regression to combine the outputs from different DNNs to produce the final sentiment score.

For both tasks, each DNN model (e.g., CNNs or LSTMs) has the same architecture for retrieving the representation of a given text. Given the text representation learned by a DNN, we design a customized fully connected and output layer for each task, which will be described in the following.

### 3.1 Sentiment Prediction

Figure 2 illustrates the model architecture for predicting the sentiment score of a given text. The fully connected layer for this task has 30 units as the settings in [2], and the final sentiment score is predicted with a linear regression on those 30 units.

We use the mean squared error as below for the loss function of sentiment prediction.

$$ L_s = \frac{1}{n} \sum_{i=1}^{n} (y'_s(i) - y_s(i))^2 $$  \hspace{1cm} (8)

where \( n \) is the number of training instances, \( y'_s(i) \) and \( y_s(i) \) denote the predicted and ground truth sentiment scores for \( i \)-th instance, respectively.

### 3.2 Aspect Prediction

Figure 3 shows the architecture for predicting aspect labels. As we can see from the figure, the fully connected layer for this task has 80 units, and the final output layer has the same number of units as the distinct aspect labels.

For the aspect prediction task, we use the cross-entropy loss as our loss function to optimize, which is defined as below:

$$ L_a = \frac{1}{n} \sum_{i=1}^{n} - \sum_{a} y_a(i) \log(y_a(i)) $$
Approach & Bi-GRU & 0.1076 & -0.0984 & 0.3196 & 0.0996 \\
CNN [3, 4, 5] & PredictZero & 0.3841 & 0.3278 \\
CNN [1, 2, 3] & CNN [5, 6, 7] & 0.4144 & 0.0926 & GRU & 0.1110 & 0.0973 & 0.1737 & R2 & 0.1067 & 0.3705 & 0.3262 & 0.0115 & MSE & 0.1064 \\

We pre-process the raw data (headlines and posts) as follows before words in terms of sentiment are nearby each other in the latent space. These embeddings were used to initialize the word embeddings. We used a CNN with the filter sizes [1, 2, 3] to pre-train these word embeddings. Figure 4 shows nearest words of the word “good” based on pre-trained word embeddings. As we can see from the figure, similar words in terms of sentiment are nearby each other in the latent space. These embeddings were used to initialize the word embeddings for both sentiment and aspect prediction tasks.

3.4 Pre-trained Word Embeddings
Considering the training set is not large for the given task, we used a Twitter corpus for sentiment analysis to pre-train word embeddings. We used a CNN with the filter sizes [1, 2, 3] to pre-train these word embeddings.

Table 4 shows the results for predicting sentiment scores based on DNNs and two simple baselines using Ridge Regression and Random Forest for aspect classification where each word is denoted as a boolean feature. The results are obtained by using 5-cross validation.

Table 5 shows the results for aspect prediction based on DNNs and two simple baselines using Ridge Regression and Random Forest for aspect classification where each word is denoted as a boolean feature. The results are obtained by using 5-cross validation.

4.2 Aspect Prediction
Table 5 shows the results for aspect prediction based on DNNs and two simple baselines using Ridge Regression and Random Forest for aspect classification where each word is denoted as a boolean feature. The results are obtained by using 5-cross validation.

Finally, we trained this ensemble model based on the whole training dataset in order to predict the aspect labels for the texts in the test dataset.

5 CONCLUSIONS AND FUTURE WORK
This paper described Deep-FASP which is an ensemble approach for sentiment and aspect prediction tasks in the financial domain using deep learning approaches such as CNNs without handcrafted features. The results based on 5-cross validation on the training dataset show that CNNs perform better than RNNs such as LSTMs or GRUs, and the ensemble approach provides the best performance in both tasks compared to any single model. As the final results of the challenge is not available at the time of writing, more details of
our approach and the performance compared to other participated teams will be updated on https://github.com/parklize/FIQA.

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