A Multi-task Ensemble Framework for Emotion, Sentiment and Intensity Prediction

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Abstract

In this paper, through multi-task ensemble framework we address three problems of emotion and sentiment analysis i.e. “emotion classification & intensity”, “valence, arousal & dominance for emotion” and “valence & arousal for sentiment”. The underlying problems cover two granularities (i.e. coarse-grained and fine-grained) and a diverse range of domains (i.e. tweets, Facebook posts, news headlines, blogs, letters etc.). The ensemble model aims to leverage the learned representations of three deep learning models (i.e. CNN, LSTM and GRU) and a hand-crafted feature representation for the predictions. Experimental results on the benchmark datasets show the efficacy of our proposed multi-task ensemble frameworks. We obtain the performance improvement of 2-3 points on an average over single-task systems for most of the problems and domains.

1 Introduction

Emotion (Picard, 1997) and sentiment (Pang et al., 2005) are closely related and are often been used interchangeably. However, according to Munezero et al. (2014), emotions and sentiments differ on the scale of duration on which they are experienced. These have applications in a diverse set of real-world problems such as stock market predictions, disaster management systems, health management systems, feedback systems for an organization or individual user w.r.t. a product or service to take an informed decision (Hawn, 2009; Bollen et al., 2011; Neubig et al., 2011). Any organization does not wish to lose their valuable customers. They can keep track of varying emotions and sentiments of their customers over a period of time. If the unpleasant emotions or sentiments of the customer are increasing day-by-day, the organization can act in a timely manner to address his/her concerns.

On the other hand, if the emotions and sentiments are pleasant the organization can ride on the positive feedbacks of their customers to analyze and forecast their economic situation with more confidence.

The classification of emotions and sentiments into coarse-grained classes does not always reflect exact state of mood or opinion of a user, hence, do not serve the purpose completely. Recently, the attention has been shifted towards fine-grained analysis on the continuous scale (Strapparava and Mihalcea, 2007; Preoţiuc-Pietro et al., 2016; Buechel and Hahn, 2017; Mohammad and Bravo-Marquez, 2017; Kiritchenko et al., 2016). Arousal or intensity defines the degree of emotion and sentiment felt by the user and often differs on a case-to-case basis. Within a single class (e.g. Sadness) some emotions are gentle (e.g. ‘I lost my favorite pen today.’) while others can be severe (e.g. ‘my uncle died from cancer today...RIP’). Similarly, some sentiments are gentler than others within the same polarity, e.g. ‘happy to see you again’ v/s ‘can’t wait to see you again’.

In our current research, we aim to solve these inter-related problems i.e. “emotion classification & intensity” for coarse-grained emotion classification, “valence, arousal & dominance” for fine-grained emotion analysis and “valence & arousal” for fine-grained sentiment analysis1. We propose an efficient multi-task ensemble framework that tackles all these problems concurrently.

Multi-task learning framework targets to achieve generalization by leveraging the inter-relatedness of multiple problems/tasks (Caruana, 1997). The intuition behind multi-task learning is that if two or more tasks are correlated then the

1Fine-grained refers to the prediction on a continuous scale, whereas coarse-grained refers to the prediction on a discrete level (Strapparava and Mihalcea, 2007; Buechel and Hahn, 2017).
joint-model can learn effectively from the shared representations. In comparison to the single-task framework, where different tasks are solved separately, a multi-task framework offers three main advantages i.e. a) achieves better generalization; b) improves the performance of each task through shared representation; and c) requires only one unified model in contrast to separate models for each task in single-task setting, resulting in reduced complexity.

Our proposed multi-task framework is greatly inspired from this, and it jointly performs multiple tasks. Our framework is based on an ensemble technique. At first, we learn hidden representations through three deep learning models, i.e. Convolutional Neural Network (CNN), Long Short Term Memory (LSTM) and Gated Recurrent Unit(GRU). We subsequently feed the learned representations of three deep learning systems along with a hand-crafted feature vector to a Multi-Layer Perceptron (MLP) network to construct an ensemble. The objective is to leverage four different representations and capture the relevant features among them for the predictions. The proposed network aims to predict multiple outputs from the input representations in one-shot.

We evaluate the proposed approach for three problems i.e. coarse-grained emotion analysis, fine-grained emotion analysis and fine-grained sentiment analysis. For coarse-grained emotion analysis, we aim to predict emotion class and its intensity value as the two tasks. The first task (i.e. emotion classification) classifies the incoming tweet into one of the predefined classes (e.g. joy, anger, sadness, fear etc.) and subsequently the second task (i.e. emotion intensity prediction) predicts the associated degree of emotion expressed by the writer in a continuous range of 0 to 1. In fine-grained emotion analysis, we aim to predict the valence, arousal and dominance scores in parallel, whereas, in the third problem, i.e. fine-grained sentiment analysis, our goal is to predict valence and arousal scores in a multi-task framework. The range of each task of the second and third problems is on the continuous scale of 1 to 5 and 1 to 9, respectively. In total, we apply the proposed multi-task approach for three configurations: a) multi-tasking for classification (emotion classification) and regression (emotion intensity prediction) together; b) multi-tasking for two regression tasks together (sentiment valence & arousal prediction); and c) multi-tasking for three regression tasks together (emotion valence, arousal & dominance).

The main contributions of our proposed work are summarized below: a) we effectively combine deep learning representations with manual features via an ensemble framework; and b) we develop a multi-task learning framework which attains overall better performance for different tasks related to emotion, sentiment and intensity.

2 Related Works

Literature suggests that multi-task learning has been successfully applied in a multitude of machine learning (including natural language processing) problems (Collobert and Weston, 2008; Søgaard and Goldberg, 2016; Balikas et al., 2017; Xia and Liu, 2017). Authors in (Balikas et al., 2017) employed recurrent neural network for their multi-task framework where they treated 3-way classification and 5-way classification as two separate tasks for sentiment analysis. One of the earlier works on emotion detection looks at emotion bearing words in the text for classification (Ekman, 1999). In another work, Ho and Cao (2012) studied human mental states w.r.t. an emotion for training a Hidden Markov Model (HMM). These systems concentrated on emotion classification, whereas, the works reported in (Mohammad and Bravo-Marquez, 2017; Jain et al., 2017; Köper et al., 2017) focus only on intensity prediction. Jain et al. (2017) used an ensemble of five different neural network models for predicting the emotion intensity. They also explored the idea of multi-task learning in one of the models, where they treated four different emotions as the four tasks. The final predictions were generated by a weighted average of the base models. Köper et al. (2017) employed a random forest regression model on the concatenated lexicon features and CNN-LSTM features. Authors in (Akhtar et al., 2017c) employed LSTM and SVR in cascade for predicting the emotion intensity. Recently, Xia and Liu (2017) have proposed VA (Valence-Activation) model for emotion recognition in 2D continuous space. Following the trends of emotion intensity prediction, researchers have also focused on predicting the intensity score for sentiment (Kabadjoj et al., 2011; Kiritchenko et al., 2016; Sharma et al., 2017; Akhtar et al., 2017b).

Traditional techniques e.g. Boosting (Freund
and Schapire, 1996), Bagging (Breiman, 1996), Voting (Weighted, Majority) (Kittler et al., 1998) etc. are some of the common choices for constructing ensemble (Ekbal and Saha, 2011; Xiao et al., 2013; Remya and Ramya, 2014). Recently, Akhtar et al. (2017a) proposed an ensemble technique based on Particle Swarm Optimization (PSO) to solve the problem of aspect based sentiment analysis.

Our proposed approach differs with these existing systems in terms of the following aspects: a) MLP based ensemble addresses both classification and regression problems; b) multi-task framework handles diverse set of tasks (i.e. classification & regression problems, 2 regression problems and 3 regression problems); and c) our proposed approach covers two granularities (i.e. coarse-grained & fine-grained) and a diverse set of domains (i.e. tweets, fb posts, news headlines, blogs, letters etc.).

3 Proposed Methodology

Ensemble is an efficient technique in combining the outputs of various candidate systems. The basic idea is to leverage the goodness of several systems to improve the overall performance. Motivated by this, we propose a multi-task ensemble learning framework built on top of learned representations of three deep learning models and a hand-crafted feature vector. We separately train all three deep learning models, i.e. a CNN, a LSTM and a GRU network in a multi-task framework (Figure 1a). Once the network is trained, we extract an intermediate layer activation from these CNN, LSTM and GRU models. These three task-aware deep representations are concatenated with a feature vector before feeding into the multi-task ensemble model. The multi-task ensemble model is a MLP network which comprises of four hidden layers. The first two hidden layers are shared for all the tasks and the final two hidden layers are specific for each individual task. The idea is to exploit the goodness of different feature representations and to learn a combined representation for solving multiple tasks. Consequently, we show that the ensemble model performs better than each of the individual models. A high-level outline of the proposed approach is depicted in Figure 1. Figure 1a shows the multi-task framework for the individual CNN, LSTM and GRU models. After training, the respective task-aware intermediate representations (color coded green in Figure 1a) and the hand-crafted feature vector are used as input for the ensemble in Figure 1b.

3.1 Deep Learning Models

We employ the architecture of Figure 1a to train and tune all the deep learning models using pre-trained GloVe (common crawl 840 billion) word embeddings (Pennington et al., 2014). In our CNN model, we use two convolution layers followed by two max-pool layers (conv-pool-conv-pool). Each convolution layer has 100 filters sliding over 2, 3 and 4 words in parallel. For LSTM/GRU models, we use two stacked LSTM/GRU layers, each having 128 neurons. The CNN, LSTM and GRU layers are followed by two fully connected layers and the output layer. We use 128 (color coded green in Figure 1a) and 100 (color coded blue ‘Dense Layer’ in Figure 1a) neurons in the fully connected layers for all the models. The output layer has multiple neurons depending on the number of tasks in the multi-task framework. The fully connected layer activation is set to rectified linear (Glorot et al., 2011), and the output layer activation is set according to the task - softmax for classification.
& sigmoid for regression. We apply 25% Dropout (Hinton et al., 2012) in the fully-connected layers as a measure of regularization. The Adam (Kingma and Ba, 2014) optimizer with default parameters is used for gradient based training.

3.2 Hand-Crafted Feature Vector

- **Word and Character Tf-Idf**: Word Tf-Idf weighted counts of 1, 2, 3 grams and character Tf-Idf weighted counts of 3, 4 and 5 grams.
- **TF-Idf Weighted Word Vector Averaging**: Word embeddings models are generally good at capturing semantic information of a word. However, every word is not equally significant for a specific problem. Tf-Idf assigns weights to the words according to their significance in the document. We scale the embeddings of words in the text w.r.t. their Tf-Idf weights and use this weighted embedding average of words to create a set of features.
- **Lexicon Features**:
  - count of positive and negative words using the MPQA subjectivity lexicon (Wiebe and Mihalcea, 2006) and Bing Liu lexicon (Ding et al., 2008).
  - positive, negative scores from Sentiment140, Hashtag Sentiment lexicon (Mohammad et al., 2013), AFINN (Nielsen, 2011) and Sentiwordnet (Baccianella et al., 2010).
  - aggregate scores of hashtags from NRC Hashtag Sentiment lexicon (Mohammad et al., 2013).
  - count of the number of words matching each emotion from the NRC Word-Emotion Association Lexicon (Mohammad and Turney, 2013).
  - Sum of emotion associations in NRC-10 Expanded lexicon (Bravo-Marquez et al., 2016), Hashtag Emotion Association Lexicon (Mohammad and Kiritchenko, 2015) and NRC Word-Emotion Association Lexicon (Mohammad and Turney, 2013).
  - Positive and negative scores of the emoticons obtained from the AFINN project (Nielsen, 2011).
- **Vader Sentiment**: We use Vader sentiment (Gilbert, 2014) which generates a compound sentiment score for a sentence between -1 (extreme negative) and +1 (extreme positive). It also produces ratio of positive, negative and neutral tokens in the sentence. We use the score and the three ratios as features in our feature based model.

Since the feature vector dimension is too large in comparison with DL representation during ensemble, we project the feature vector to smaller dimension (i.e. 128) through a small MLP network.

4 Datasets, Experiments and Analysis

4.1 Dataset

We evaluate our proposed model on the benchmark datasets of WASSA-2017 shared task on emotion intensity (EmoInt-2017) (Mohammad and Bravo-Marquez, 2017), EmoBank (Buechel and Hahn, 2017) and Facebook posts (Preoțiuc-Pietro et al., 2016) for the coarse-grained emotion analysis, fine-grained emotion analysis and fine-grained sentiment analysis, respectively. The dataset of EmoInt-2017 (Mohammad and Bravo-Marquez, 2017) contains generic tweets representing four emotions i.e. anger, fear, joy and sadness and their respective intensity scores. It contains 3613, 347 & 3142 generic tweets for training, validation and testing, respectively. The EmoBank dataset (Buechel and Hahn, 2017) comprises of 10,062 tweets across multiple domains (e.g. blogs, new headlines, fiction etc.). Each tweet has three scores representing valence, arousal and dominance of emotion w.r.t. the writer’s and reader’s perspective. Each score has continuous range of 1 to 5. For experiments, we adopt 70-10-20 split for training, validation and testing, respectively. The Facebook posts dataset (Preoțiuc-Pietro et al., 2016) has 2895 social media posts. Posts are annotated on a nine-point scale with valence and arousal score for sentiment analysis by two psychologically trained annotators. We perform 10-fold cross-validation for the evaluation.

Few example scenarios for the problems of emotion analysis (coarse-grained & fine-grained) and sentiment analysis (fine-grained) are depicted in Table 1. In the first example shown in Table 1a, emotion ‘joy’ is derived from the phrase ‘died from laughter’ which is intense. However, the emotion associated with the second example which contains similar phrase ‘died from cancer’ is ‘sadness’. The third example expresses ‘fear’ with mild intensity, whereas, the fourth example conveys ‘anger’ emotion with relatively lesser intensity.

Examples of fine-grained emotion analysis are listed in Table 1b. Each text is associated with psychologically motivated VAD (Valence, Arousal & Dominance) scores. Valence is defined by pleasantness (positive) or unpleasantness (negative) of the situations. Arousal reflects the degree of emotion, whereas, Dominance suggests the degree of
(a) Coarse-grained emotion analysis: Intensity is on the scale of 0 to 1 (Mohammad and Bravo-Marquez, 2017).

| Text                                           | Emotion | Intensity |
|------------------------------------------------|---------|-----------|
| Just died from laughter after seeing that.     | Joy     | 0.92      |
| My uncle died from cancer today...RIP.          | Sadness | 0.87      |
| Still salty about that fire alarm at 2am this morning. | Fear    | 0.50      |
| Happiness is the best revenge.                 | Anger   | 0.25      |

(b) Fine-grained emotion analysis: Valence, arousal & dominance are on the scale of 1 to 5 (Buechel and Hahn, 2017).

| Text                                           | Valence | Arousal | Dominance |
|------------------------------------------------|---------|---------|-----------|
| I am thrilled with the price.                   | 4.4     | 4.4     | 4.0       |
| I hate it, despise it, abhor it!               | 1.0     | 4.4     | 2.2       |
| Collision on icy road kills 7.                  | 1.2     | 4.2     | 2.2       |
| I was feeling calm and private that night.     | 3.2     | 1.6     | 3.0       |
| I just hope they keep me here.                 | 2.7     | 2.7     | 2.0       |
| James Brown’s 5-year-old son left out of will. | 1.0     | 2.6     | 2.2       |

(c) Fine-grained sentiment analysis: Valence and arousal are on the scale of 1 to 9 (Preotciuc-Pietro et al., 2016).

| Text                                           | Valence | Arousal |
|------------------------------------------------|---------|---------|
| I bought my wedding dress Monday and I cant wait to have it on again!!!! its sooo beautiful. | 8.0     | 8.0     |
| Happy, got new friends, and lifes getting smoother. | 8.0     | 1.5     |
| At least 15 dead as Israeli forces attack Gaza aid ships!!!!!!!! i hhhhhate israil | 1.5     | 8.0     |
| The worst way to miss someone is when they r right beside u and yet u know u can never have them. | 2.5     | 1.5     |

Table 1: Multi-task examples of emotion analysis and sentiment analysis from benchmark datasets. Valence ⇒ Concept of polarity (pleasant / unpleasant); Arousal or Intensity ⇒ Degree of emotion/sentiments; Dominance ⇒ Control over a situation;

control over a particular situation. Similarly, Table 1c depicts the example scenarios for fine-grained sentiment analysis.

4.2 Experimental Setup and Results

We use Python based libraries, Keras and Scikit-learn for implementation. For evaluation, we compute accuracy for the classification (emotion class) and pearson correlation coefficient for the regression (e.g. intensity, valence, arousal & dominance). Pearson correlation coefficient measures the linear correlation between the actual and predicted scores. The choice of these metrics was inspired from (Mohammad and Bravo-Marquez, 2017) and (Preotciuc-Pietro et al., 2016). We normalize the valence, arousal and dominance scores on a 0 to 1 scale. For prediction, we use softmax for classification and sigmoid for regression.

Table 2 shows the results on the test set for coarse-grained emotion analysis. In multi-task framework, we predict emotion class and intensity together, whereas in single-task framework we build two separate models, one for classification and one for intensity prediction. We follow a dependent evaluation\(^2\) technique where we compute the scores of only those instances which are correctly predicted by the emotion classifier. Such evaluation is informative and realistic as predicting intensity scores for the misclassified instances would not convey the correct information. For direct comparison, we also adopted a similar approach for intensity prediction evaluation in the single-task framework. The first half of Table 2 reports the evaluation results for three deep learning models. In multi-task framework, CNN reports 80.52% accuracy for classification and 0.578 Pearson score for intensity prediction. The multi-task LSTM and GRU models obtain 84.69% & 84.94% accuracy values and 0.625 & 0.606 Pearson scores, respectively. The corresponding models in single-task framework report 79.56%, 84.02% & 83.45% accuracy values and 0.493, 0.572 & 0.522 Pearson scores for CNN, LSTM & GRU models, respectively. It is evident that multi-task models perform better than the single-task models by a convincingly good margin for intensity prediction, and better for class prediction. On further analysis, we observe that these models obtain quite similar performance numerically. However, they are quite contrasting on a qualitative side. Figure 2 shows the contrasting nature of different individual models for emotion intensity. In some cases, prediction of one model is closer to the gold intensity than the other models and vice-versa. We observe similar trends for the other tasks

\(^2\)Please note that we adopted dependent evaluation strategy as this is commonly used for the evaluation of related-tasks in multi-task framework.
Table 2: **Coarse-grained Emotion Analysis**: Experimental results for multi-task (i.e. single model for both tasks in parallel) and single-task (i.e. first a tweet is classified to an emotion class and then intensity is predicted ) learning framework for EmoInt-2017 datasets (Mohammad and Bravo-Marquez, 2017). Significance $T$-test (p-values) are w.r.t. single task learning.

| Models              | Multi-task learning | Single-task learning |
|---------------------|---------------------|----------------------|
|                     | Emotion Class       | Intensity*            | Emotion Class       | Intensity*            |
|                     | Accuracy % Pearson  |                      | Accuracy % Pearson  |                      |
| CNN (C)             | 80.52 0.578         |                      | 79.56 0.493         |                      |
| LSTM (L)            | 84.69 0.625         |                      | 84.02 0.572         |                      |
| GRU (G)             | 84.94 0.606         |                      | 83.45 0.522         |                      |
| Ensemble (C, L & G) | 85.93 0.657         |                      | 85.77 0.596         |                      |
| Ensemble (C, L, G & Feat) | **89.88 0.670** |                      | 89.52 0.603         |                      |
| Significance $T$-test (p-values)$^3$ | 0.073 0.001 | -                     | -                     | -                     |

We report the results for **fine-grained emotion & sentiment analysis** in Table 3. Similar to coarse-grained emotion analysis we observe that multi-task models achieve the improved Pearson scores (0.635, 0.375 & 0.277) as compared to the single-task based models (0.616, 0.355 & 0.234) for the three tasks, i.e. valence, arousal and dominance, respectively. The ensemble approach also achieves better performance compared to each of the base models for all the tasks. For fine-grained sentiment analysis, deep learning based models i.e. CNN, LSTM & GRU obtain Pearson scores of 0.678, 0.671 & 0.668 for valence in multi-task environment. The ensemble of these three models and hand-crafted feature representation via MLP obtains an increased Pearson score of 0.727. The proposed approach also achieves the best Pearson score of 0.355 for arousal.

We observe two phenomenon from these results: a) use of multi-task framework for related tasks indeed helps in achieving generalization; and b) the ensemble network leverages the learned representations of three base models & the feature vector and produces superior results.

4.3 Comparative Analysis

For **coarse-grained sentiment analysis**, we compare our proposed approach with Prayas system (Jain et al., 2017), which was the top performing system at EmoInt-2017 (Mohammad and Bravo-Marquez, 2017) shared task on Emotion Intensity. Prayas (Jain et al., 2017) used an ensemble of five different neural network models including a multitasking feed-forward model. Although the final model was built for each emotion type separately, in multi-task model the authors treated four emotion classes as the four tasks. However, our proposed approach treats emotion classification and emotion intensity prediction as two separate tasks, and then learns jointly (a completely different setup than Prayas). Prayas reported the Pearson score of 0.662 for emotion intensity. In comparison, our proposed approach obtains a Pearson score of 0.670 for dependent evaluation, and 0.647 for independent evaluation. Statistical $T$-test shows that the value (0.679) is statistically significant over the model of Prayas.

Similarly, we do not compare our proposed approach with other systems of EmoInt-2017 (Mohammad and Bravo-Marquez, 2017) because of the following two reasons: a) those systems are of single-task nature as compared to our proposed multi-task; and b) separate models were trained for each of the emotions and an average score was reported as compared to a unified single model that addressed all the emotions and their intensity values altogether. The baseline system for emotion intensity prediction in Table 4 is taken from Mohammad and Bravo-Marquez (2017), which also differs from our proposed approach w.r.t. the above two points, and hence does not provide an ideal
Figure 2: Contrasting nature of the individual models and improved scores after ensemble for emotion intensity prediction. **X-axis**: 30 random samples from the test set. **Y-axis**: Intensity values.

| Models                          | Emotion Analysis - EmoBank | Sentiment Analysis - FB post |
|---------------------------------|-----------------------------|------------------------------|
|                                 | Multi-task | Single-task | Multi-task | Single-task |
| CNN (C)                         | Val   | Aro  | Dom | Val   | Aro  | Dom | Val   | Aro  | Dom |
| 0.567                           | 0.347 | 0.234 | 0.552 | 0.334 | 0.222 | 0.678 | 0.290 | 0.666 | 0.283 |
| LSTM (L)                        | 0.601 | 0.337 | 0.245 | 0.572 | 0.318 | 0.227 | 0.671 | 0.324 | 0.655 | 0.315 |
| GRU (G)                         | 0.569 | 0.315 | 0.243 | 0.553 | 0.306 | 0.227 | 0.668 | 0.313 | 0.657 | 0.294 |
| Ensemble (C, L & G)             | 0.618 | 0.365 | 0.263 | 0.603 | 0.351 | 0.234 | 0.695 | 0.336 | 0.684 | 0.324 |
| Ensemble (C, L, G &Feat)        | **0.635** | **0.375** | **0.277** | 0.616 | 0.355 | 0.237 | **0.727** | **0.355** | 0.713 | 0.339 |
| Significance T-test (p-values)² | 0.048 | 0.027 | 0.310 | -    | -    | -    | 0.033 | 0.024 | -    | -    |

Table 3: **Fine-grained Emotion and Sentiment Analysis**: Experimental results for multi-task and single-task learning framework on EmoBank datasets (Buechel and Hahn, 2017) & FB post datasets (Preotiu-Pietro et al., 2016). **Val**: Valence, **Aro**: Arousal & **Dom**: Dominance. Significance T-test (p-values) are w.r.t. single task learning.

| Models                          | Emotion Class | Emotion Intensity   | Pearson correlation |
|---------------------------------|---------------|---------------------|---------------------|
|                                 | Dependent Evaluation | Independent Evaluation |                           |
| Baseline*                       | -             | -                   | 0.648               |
| Prayas (Multi-task)*            | -             | -                   | 0.662               |
| Proposed (Single-task)          | 89.52         | 0.603               | -                   |
| Proposed (Multi-task)           | **89.88**     | **0.670**           | 0.647               |

Table 4: **Coarse-grained Emotion Analysis**: Comparative results. *Prayas (Jain et al., 2017) was the top system at EmoInt-2017. They treated intensity prediction of four emotion classes as multi tasks; **Dependent evaluation**: Intensity was evaluated following emotion classification; **Independent evaluation**: Intensity score is evaluated independent of the emotion class; +Baseline system is taken from (Mohammad and Bravo-Marquez, 2017). Please note that both the Prayas and baseline systems have different setups than the proposed method and do not provide an ideal scenario for direct comparison.

| Models                          | Valence | Arousal |
|---------------------------------|---------|---------|
| System (Preotiu-Pietro et al., 2016) | 0.650   | **0.850** |
| System - X*                     | 0.390   | 0.105   |
| Proposed (Single-task)          | 0.713   | 0.339   |
| Proposed (Multi-task)           | **0.727** | 0.355   |

Table 5: **Fine-grained Sentiment Analysis**: Comparative results for Facebook posts dataset. **System - X**: Google search lists this paper in the citation list of (Preotiu-Pietro et al., 2016), however, the publication details are not available. The pdf is available at [www.goo.gl/DcdaHF](http://www.goo.gl/DcdaHF).

We do not compare emotion classification tasks with other systems as we could not find any related candidate for direct comparison.

We do not compare emotion classification tasks with other systems as we could not find any related works on the same dataset. A comparative analysis is presented in Table 4. It is evident that solving both the tasks together in a multi-task setting produces better performance than solving these two tasks separately in a single-task setting.

The datasets for **fine-grained emotion analysis** and **fine-grained sentiment analysis** problems i.e. EmoBank (Buechel and Hahn, 2017) and Facebook posts (Preotiu-Pietro et al., 2016) are relatively recent datasets and limited studies are...
available on these. We did not find any existing system that evaluated Pearson score for these datasets except the resource paper of Facebook posts (Preotiuc-Pietro et al., 2016). For valence in fine-grained sentiment analysis a Pearson score of 0.650 has been reported in (Preotiuc-Pietro et al., 2016) using a Bag-of-Words (BoW) model. In comparison, our proposed approach reports the Pearson score of 0.727, an improvement of 7 points. For arousal Preotiuc-Pietro et al. (2016) reported a Pearson score of 0.850 as compared to 0.355 of ours. It should be noted that we tried to re-produce the scores of (Preotiuc-Pietro et al., 2016) using the same BoW model. We obtained the similar Pearson score of 0.645 for valence, however, we could not reproduce the reported results for arousal (we obtained Pearson score of 0.27)4. In Table 5, we demonstrate the comparative results for fine-grained sentiment analysis.

### 4.4 Error Analysis

We perform qualitative error analysis on the predictions of our best performing multi-task models. At first, we identify the most commonly occurring errors and then we analyze 15 test instances for each such error to detect the common error patterns. A number of frequently occurring error cases along with their possible reasons are shown in Table 7. We observe that the main sources of errors are metaphoric sentences, strong expressions, implicit emotions and idiomatic expressions.

We also compare the predictions of multi-task models against single-task models. We observe that in many case multi-task learning performs better (correct or closer w.r.t. gold labels) than single-task learning. For the emotion classification problem we analyze the confusion matrix and observe that the proposed model often confuses between fear and sadness class. In total 80 tweets (∼8%) representing fear are misclassified as sadness, whereas, 40 instances (∼6.5%) of sadness are misclassified as fear. The confusion matrix is depicted in Figure 6. We also perform statistical significance test (T-test) on the 10 runs of the proposed approach and observe that the obtained results are significant with p-values < 0.05.

### 5 Conclusion

In this work, we have proposed a multi-task ensemble framework for emotion analysis, sentiment analysis and intensity prediction. For ensemble we employed a MLP network that jointly learns multiple related tasks. First, we have developed three individual deep learning models (i.e. CNN, LSTM and GRU) to extract the learned representations. The multi-task ensemble network was further assisted through a hand-crafted feature vector. We evaluate our proposed approach on three benchmark datasets related to sentiment, emotion and intensity. Experimental results show that the multi-task framework is comparatively better than the single-task framework. Emotion detection can also be projected as multi-labeling task. However, due to absence of multi-emotion dataset we do not evaluate the proposed method on multi-emotion task. It should be noted that our model can easily be adapted to multi-label emotion classification.

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### Table 6: Confusion matrix for EmoInt-2017 emotion classification problem.

| EmoInt-2017 Emotion Classification | Actual | Predicted |
|-----------------------------------|--------|-----------|
| Going back to blissful ignorance.  | Sad    | Joy       | Metaphoric sentence. |
| Never let the sadness of your past ruin your future. | Sad/0.29 | Sad/0.64 | Strong expression. |

Table 7: Error Analysis: Frequent error cases for the best performing multi-task models.

| Text Actual | Predicted | Possible Reason |
|-------------|-----------|-----------------|
| EmoBank     |           |                 |
| Valence Prediction |        |                 |
| It’s summertime, so it must be time for CAMP! | 4.4 | 3.1 | Implicit emotion. |
| Arousal Prediction |          |                 |
| The company is on a roll. | 4.0 | 2.8 | Implicit emotions. |
| Dominance Prediction |          |                 |
| Three days later, another B-29 from the 509th bombed Nagasaki. | 2.0 | 3.3 | Numerical entities. |
| FB Posts |           |                 |
| Valence Prediction |        |                 |
| I am on cloud nine right now. | 7.5 | 4.3 | Idiomatic expressions. |
| Arousal Prediction |          |                 |
| Thank you all for wishing me a happy birthday. | 1.5 | 8.1 | Strong expressions. |
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