# EMOTION TAGGING AND INTENSITY SCORING FOR SOCIAL MEDIA POST TEXTS

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# ABSTRACT

In the social media post analysis, the emotion analysis has been the most important topic. However, up to now very limited work has been done to automatically tag the emotion of a social media post with a per-defined list of emotions, such as anger, fear, joy and sadness. Meanwhile, the intensity of the corresponding emotion is hard to estimate from the content of the social media post. To fill this gap, this work targets to automatically tag emotion, and at the same time, estimate the intensity score of the emotion between a range of 0 and 1. A two-stage emotion tagging and intensity estimation pipeline is designed. For the emotion tagging and scoring, a convolutional neural network is designed and implemented by Keras open-source package. At the same time, it used the most popular language model BERT (Bidirectional Encoder Representations from Transformers) for the world binding purpose. The emotion and intensity scoring models are trained by a Twitter post data set, with a K-fold cross validation protocol. The system is implemented with the model trained and evaluated. The models accuracy and running time are tested, and the results are reported. The accuracy for four emotions are all be above 90% while the estimation score is below 0.14. According to the test result, it is concluded the effectiveness of the model for the purpose of emotion detection and intensity scoring.

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## LIST OF ABBREVIATIONS

| | |
|---|---|
| CNN | Convolutional neural network |
| MSE | Mean squared error |
| NLP | Natural Language Processing |
| DL | Deep Learning |
| AI | Artificial Intelligence |
| API | Application Programming Interface |
| ReLU | Rectified Linear Unit |
| GPT-3 | Generative Pre-trained Transformer 3 |

# CHAPTER 1

# INTRODUCTION

Social media data analysis has been a powerful tool for both political and commercial usages. Among the use cases, the emotion detection and intensity scoring have been the most important ones. In this project, a deep learning model-based in NLP tool is developed to automatically detect the emotions from the content of social media posts, and also score the intensity accordingly. In this section, the introduction of this project is provided by firstly giving the background of the study, then describe the aim and objectives of the project, followed by the research scope and significance. Finally, the structure of this report is given.

## 1.1 Background of the Study

With the rapid development of the Internet, social media has been a major channel for people to express their thoughts and exchange information. For example, currently, for every one second, there are over 6,000 tweets are posted over the social media channel of Twitter, while for each day, there are over 500 million tweet posts. Meanwhile, in another most popular social media channel of Facebook, more than 2.5 trillion posts have been posted by users (Perrin, 2015, Zhuravskaya et al. 2020, Seargeant and Tagg, 2014, Lenhart et al. 2010).

With such a large amount of social media posts, there is a great need to transform all those post texts into business values, for the applications of different sectors, such as the commercial, government, and security sectors. However, this transformation is not easy. The most important insight of those posts is about people's thoughts and their emotions, i.e., how they feel about some specific objects. The most useful and time-consuming process is to understand people's emotions from the content of the posts (Panger, 2017, De Choudhury et al. 2013).

The most popular emotions about people are joy, anger, sadness, and fear. Using those detected emotions, we can use the post more effectively.

- For example, in the commercial usage scenario, when one product is mentioned by a social media post, it is wanted to know how people feel about this product and then use this emotion detection result to recommend the product to most wanting consumers (Matsui and Yamada).

- Another application is for the Politics champion. When people mention a candidate, we also want to know how the people feel about him or her. With the emotion detection results, we can group social media users according to their emotions to some specific candidates and take different actions to improve the chance of some specific candidates to be selected (Brady et al. 2019).

There are two options for the purpose of emotion detection

- One is human processing. A group of people is asked to read the content they post and give a tag of the emotions.
- Another solution is to use a computer to read the content of the post automatically and the emotion for future usage.

Of course, human processing is more reliable and accurate sense. The posts are posted by humans, and then, if it is read by a human, the understanding will be close to the thought of the other humans. However, this process is very costly and time-consuming. Especially with today's large amount and fast-growing social media data, it is almost impossible to have humans read the content of all the people's social media posts. Imagine in this scenario, half of the people all over the world are reading the other half posts. This is not practical at all.
So we have to use the computer to automatically parse and extract the emotions from the text of the content of the social media. This will be the topic of this thesis.

Another important concept about social media content detection is the intensity of the emotions. With the same emotion expressed by the post of the social media. Intensity could be very different. For example, when people post something about one politician, assume they always have the same emotion of anger, but when time is passing by, their anger could be growing from time to time. The intensity can be changed. In this case, we need a measurement of the intensity of the emotion of anger. This measurement will be very important to show the trend of people's feelings about this politician. Of course, we can use people's manual effort to estimate this intensity. But unfortunately, different people have different standards of scoring. So, it is also better to use computers to calculate this intensity, both objectively and fast. The intensity is also another important topic of this thesis.

## 1.2 Aim and Objectives

The aims of this project are two folds.

1. Firstly, we want to develop a model of emotion tag for the input text of social media. It is the tagger that can tag and text with emotions of four types. Secondly, it is the intensity that can assign a score of a detected emotion between zero and one to indicate how strong is this emotion.

2. Secondly, we want to train this model in each database and evaluate quality in a test database to verify if this model is of good quality and for real-world usage. The purpose of the project is to give objective measures of the quality and risk of using this model. So that the users will be aware of the effectiveness and the risk of failure when they are using this model.

## 1.3 Research Questions

In this paper we study two-layer progressive problems.

1. The first layer research problem is how to tag the emotion of a social media post text. i.e., how to assign a tag of four emotions to a text. The four emotions are anger, sadness and fear. Of course, if this text has no emotions, we should also tag it by non-emotion. At this layer, the problem is how to design a system for the computer to take the input text and output a tag of four emotions. So, it is a typical classification problem from the view of machine learning.

2. The second layer research problem is the estimation of the intensity of the detected emotion. So, we define scores between zero and one. Zero means this emotion doesn't exist for this post, and one means the emotion for this post is extremely strong. A score between zero and one in decades how strong is this emotion detected from the content of the social media post. The second problem is to automatically get this score between zero and one. Since the score is continuing value, we want to define a system to automatically predict this value, this problem is a regression problem from the view of machine learning.

## 1.4 Scope of the Study

The scope of this project is to do two things.

1. Firstly, we want to explore the possibilities of building an AI model of emotion detection and intensity scoring by using deep learning models and NLP technology. This scope is about algorithm design and model training from the view of learning. It is including the database preparing model design and training parameter tuning.
2. The second scope is to build software for open-source usage purposes. For this purpose, we need to have a model and build an interface for the usage of this model. The usage should be user-friendly so that they can easily import the package and called the function to get the emotion of a text and the corresponding intensity score.

## 1.5 Significance of the Study

The significance of this study is it combines emotion tagging and intensity scoring problems together to give a practical and useful solution for real-world projects. In the traditional emotion detection solutions, they only consider one of the problems of emotion tagging or intensity regression. However, in real-world software, we need an end-to-end solution. This is the first time in the industry and academia to give an end-to-end solution. This solution has two stages, and it is smoothly connected to form a complete pipeline. After we developed this solution and publish it to the open-source website, the user will be gaining the ability to directly detect the emotion and its corresponding intensity from a social media text.

## 1.6 Structure of the Study

The structure of this study has two most important parts.

1. The first one is about the data, it includes data collection, data preparing and cleaning to make the data fit for the model training and prediction.
2. The second part is about the model, we need to design new models for the emotion detection are also its intensity scoring. After the model is designed, we need to train the model with data and evaluate performance.

# CHAPTER 2

# LITERATURE REVIEW

There are some related works like our work. However, some are not completed end-to-end solutions for emotion detection and intensity scoring. There are only some theoretical studies, not an industry-level application.

## 2.1 Related works

The literature of two topics are reviewed in this section: emotion tagging and emotion intensity estimation. We list some literature of the tow topics, and discuss the details of their implementation and the shortages of these works as follows.

### 2.1.1 Topic of emotion tagging

- Batbaatar et al. (2019) Proposed a semantic-emotion neural network for emotion recognition from text.

  **Detailed and methodical review:** This network is composed of two sub-networks. The first network is a network to the model language features from the text by using word embedding. The second network is using the emotional information from the text to extract features to represent the sentence. The networks are based on a bi-directional recurrent neural network and a convolutional network.

  **Limitation**: However, this network is not directly for the prediction of emotions from the text. Emotions are used as the input, not as the output of the neural network. So, it cannot be directly used to predict the emotion, and it cannot be used to estimate the intensity of emotions. To these limitations, it will not be useful for the purpose of this project, as it is claimed in the title of their article.

- Alhuzali and Ananiadou (2021) developed an emotion recognition model.

**Detailed and methodical review:** This model can do emotion tagging, but it can take one text with multiple emotions. The most impressive part of this work is it can embed the words and sentences to explore the relationship between different emotions.

**Limitation**: However, this is not appreciated because if we consider independent emotion tigers, they can also give us multiple motions. A more important problem is the assumption behind the work is that the different emotions are closely related, which might not be true. In real-world applications, by splitting a long sentence into short sentences, we can also find that different short sentences may have different emotions, but the overlapping is limited. Another shortage of this work is that it cannot estimate the intensity at all, so when we are using this model, it can only give us partial answers.

- Junianto and Rachman (2019) designed an emotion recognition model.

**Detailed and methodical review:** This work is only for emotion tagging, and it uses a very simple classification model called Naive Bayes, and the model parameters are trained by the particle swarm optimization algorithm.

**Limitation**: The novelty of this model is very poor. The data is the same as many other researchers. There is a very limited contribution to the community of emotion tagging, not to mention its missing part of the intensity estimation.

### 2.1.2 Topic of emotion intensity estimation

- Duppada and Hiray (2017) proposed a tweet emotion intensity estimator.

**Detailed and methodical review:** This work is only for the purpose of emotional intensity estimation. It is using the generalized models and the input features are the lexical, syntactic, and pre-trained word embedding features.

**Limitation**: The main shortages of this model are lack of novelty, but it combines the different regression models outputs. The main advantages of this model are two folds. Firstly, its accuracy is low, and secondly, it cannot detect the emotion before the intensity. So, when the user tries to use this model, they must manually tag the emotion. At least they will receive intensity scores of four emotions, which will be very confusing for the end-users.

## 2.2 Challenges

There are two challenges for the emotion tagging and intensity.

1. One challenge is the connection between the tagging and intensity are not studied very well and all the models are independently developed for the two problems.

2. The second challenge is the missing end-to-end solution for the intensity scoring and emotion tagging. There is no design to do the tagging and intensity jointly.

# CHAPTER 3

# RESEARCH METHODOLOGY

## 3.1 Introduction

In this section, we introduce the methodology of our research. The methodology has 4 most important parts. The first part is processing and preparing of data for the machine learning model. The second part is machine learning model building. The third part is the evaluation of the model and, the last part is the deployment of the models to let the user from the public Internet to use model.

## 3.2 Data Collection and Processing

### 3.2.1. Data Collection

Since we want to understand the emotions and the intention of the emotions from the content of the text, we need a database of text with the corresponding emotions and the intensity. For this purpose, we choose the database of Twitter text with emotions (Mohammad and Bravo-Marquez, 2017). This database is firstly Published by the researchers from the national research council Canada and The University of Waikato. This database is called the 2017 share task on emotion intensity. It is originally for a competition of emotion city. But now it's already open for public usage.

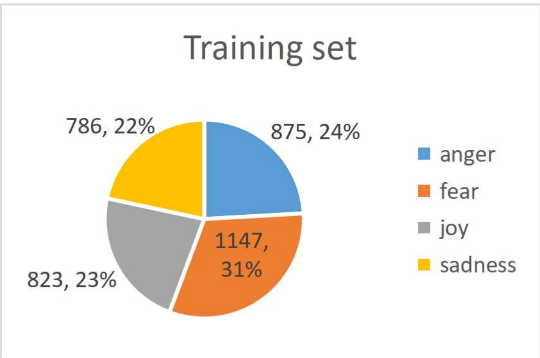


Figure 1. The number and percentage of texts of four emotions in the training set.

This data set has three subsets. The first subset is a training set. The second subset is a development set. The last subset is a test set.

a) For the training set, all the texts are from Twitter. Each text has an emotion tag of anger, fear, joy, or sadness. At the same time, each text has the intensity of the corresponding emotion between zero and one. The four emotions texts number and percentages are shown in Figure 1.
b) The development subset has the text and the tags. It is split into two parts. One part has the motion intensity, but the other part only has the tags of the emotion, but the intensity is missing.
c) The test subset also has two parts. It is similar to the development. Part of the intensity and another part has no intensity. Both of them have the tag of emotions.

### 3.2.2. Data Pre-Processing

To prepare the data we need to extract the data and transform the format of data to fit machine learning models.

**Emotion tagger data pre-processing**

For the first machine learning problem, which is text classification problem for emotion tagging, we need to prepare the input data and the label, the label is the binary label for four different emotions including fear, anger, and each so on. The following steps are used to prepare the data and processes to transform the format.

1. We first load the data from the text data, we used spark to do this. There are four columns in the data, one column is text, another column is a label. We dropped the two useless columns including the Twitter ID and the intensity, because in the classification problem, we don't want to include the intensity into the consideration.

2. For the text column we collect it as a list, and for the label column, if the label equals to the target level for such as fear, we will mark it as one, otherwise it will be zero.

3. And then we collect the levels and put them into a NumPy array.

**Emotion intensity scorer data pre-processing**

For the second problem, which is scoring of the intensity of emotions, it is a regression problem.

4. The same data is used, but at this time the intensity column is not dropped but used as a target -- the label of the regression problem. The emotion tag column is dropped.

5. Again, the text and the intensity are collected into two NumPy arrays.

### 3.2.3. Data Transformation

But the machine learning model only takes a list of word indices, which is not the original word, so we need to transform the text into a list of integers of the world indices. For this purpose, we use the Keras built-in word processing function, called one-hot encoding. The one hold including directly transform a string of sentence into a list of word indices. But different sentence has different numbers of words, but the machine model takes the same length of word index array, so we need to pad the sequence for this purpose, with the Keras pad sequence function.

## 3.3 Model Building

The second step is to build the **models** for the purpose of emotion tagging and intensity scoring. This step has two stages.

1) The first stage is to generate the tag of emotions from the content of the text. For this purpose, we want to do build a model to classify a text into four different classes, including the four emotions and one more class of no emotion detected.

2) The second stage is to build a model to output the intensity score for one detected emotion. For this purpose, we want to build another model to read the content and also. to generate the intensity for the corresponding emotion predicted by the previous model.

To build those models, we want to use two technologies, which are popular for natural language processing.

a) One technology is called the word embedding (Lai et al. 2016, Yin and Yin, 2018, Ghannay et al. 2016, Levy and Goldberg, 2014). It transforms one word into a continuous value vector to represent the meaning of this word. For this purpose, we try to use one word embedding method, the language mode BERT (Devlin, et al, 2018). This model is a deep learning model composed of bi-directional transformer and attention layers. It is pre-trained by large scale text data for the problems of work masking and next sentence prediction. It has been proven to be one of the most successful pre-trained word embedding models. This models is not a model to be trained, but a pre-trained model. For each word, it already has its unique vector. So, we don't need to train any model for the purpose of word embedding, but we can directly query the word embedding from the word embedding lookup table.

b) Another technique is the model of deep learning (LeCun et al. 2015, Goodfellow et al. 2016). We choose to use the model of a convolutional neural network (Albawi et al. 2017, Kalchbrenner et al. 2014, Kim, 2017). This model has many layers, and each layer has two sub-layers. The first sub-layer is the layer of convolution, and the next sub-layer is the max-pooling layer. This model is used for the purpose of both emotion tagging, and intensity scoring. For the two different tasks, the basic layers are the same, but the last layers are different. One is for classification purposes; another is for regression purposes.

### 3.3.1 Model Architecture

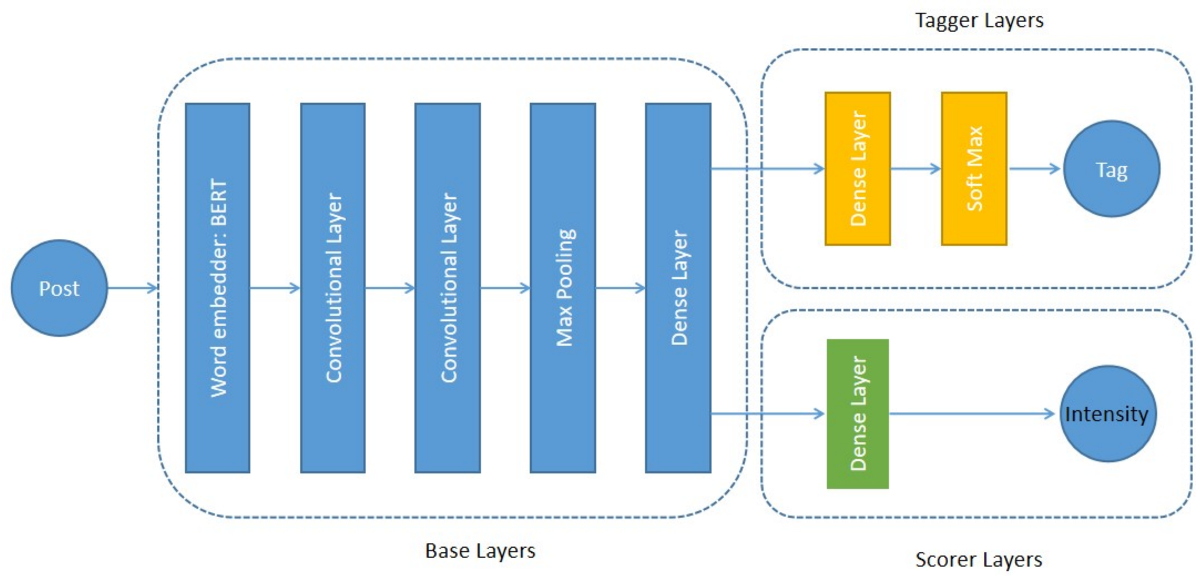


Figure 2. Model Architecture.

Two models are designed for the tagging and regression respectively. The two models share the same base layers, and the last layers are different. The architecture is shown in Figure 2.

### 3.3.2 Model Details

| Layer (type) | Output Shape | Param # | Connected to |
|---|---|---|---|
| input_ids (InputLayer) | [(None, 100)] | 0 | [] |
| attention_masks (InputLayer) | [(None, 100)] | 0 | [] |
| token_type_ids (InputLayer) | [(None, 100)] | 0 | [] |
| tf_bert_model (TFBertModel) | TFBaseModelOutputWithPoolingAndCrossAttentions(last_hidden_state=(None, 100, 768), pooler_output=(None, 768), past_key_values=None, hidden_states=None, attentions=None, cross_attentions=None) | 109482240 | ['input_ids[0][0]', 'attention_masks[0][0]', 'token_type_ids[0][0]'] |
| dropout_37 (Dropout) | (None, 100, 768) | 0 | ['tf_bert_model[0][0]'] |
| conv1d (Conv1D) | (None, 99, 128) | 196736 | ['dropout_37[0][0]'] |
| conv1d_1 (Conv1D) | (None, 98, 128) | 32896 | ['conv1d[0][0]'] |
| global_max_pooling1d (GlobalMaxPooling1D) | (None, 128) | 0 | ['conv1d_1[0][0]'] |
| dense (Dense) | (None, 128) | 16512 | ['global_max_pooling1d[0][0]'] |
| dropout_38 (Dropout) | (None, 128) | 0 | ['dense[0][0]'] |
| predictions (Dense) | (None, 2) | 258 | ['dropout_38[0][0]'] |

Total params: 109,728,642
Trainable params: 246,402
Non-trainable params: 109,482,240

Figure 3. Complete description of the layers and parameters of the deep learning model.

According to the marker's suggestions, the detail of the model is listed in Table 1. This model is solely contributed by this study and the model design is unique. The code is available in the contributor's GitHub https://github.com/yanliang12/deep_emotion_intensity as a proof of the contribution of the study. The innovation of this study is the model design and the implementation, and the very first end-to-end solution for both emotion tagging and intensity scoring, with a ready-to-use sets of models. The complete description of the model is given in Figure 3.

Table 1. Details of an example deep learning model of the study

| **Item** | **Value** |
| --- | --- |
| number of layers | 11 |
| activation function used | ReLU |
| training procedure | Standard 5-fold cross validation |
| Total Parameter Number | 109,728,642 |
| Trainable Parameter Number | 246,402 |

### 3.4 Summary

The information flowing chart is summarized shown in Figure 4.

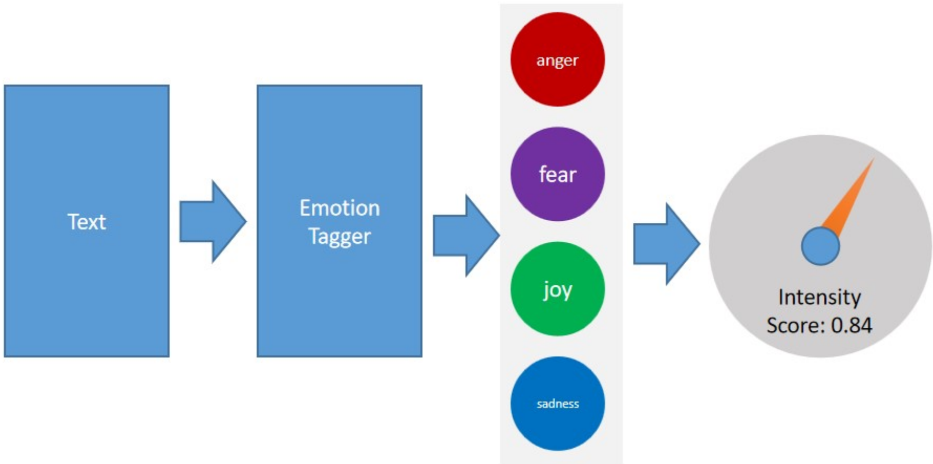


Figure 4. Information flowing of the proposed social media post text emotion tagging and intensity scoring system.

As can be seen from the figure, the different stages are not independent but related. The intensity scoring is only activated only when the first stage tagged a text with one specific emotion. For example, if one text is tagged with anger, then we will score the intensity of anger in the second stage. But if a text is not tagged with anger, then the anger intensity scoring will not be performed. A potential risk of this framework is the accumulation of errors. If the first stage fails, because the intensity of the emotion is not strong enough, then the intensity will never be estimated in the second stage.

# CHAPTER 4

# RESULTS

## 4.1 Introduction

In this chapter, the results are introduced, including the model training and testing results. The performance is evaluated regarding both accuracy and running time. The implementation results are also introduced.

## 4.2 Model Evaluation

### 4.2.1 Performance Metrics

The last step is to train the model and **evaluate** its quality. Our plan is to train the model with the training set, and then evaluate it over the development set and the test set. In the training process, we will use the cross-validation protocol to tune the parameters of the model. Then test the model over the development set to check the quality of the model until its performance is satisfying. Finally, we will perform the evaluation of the performance of the model over the test set independently to see how good the model is actually, and then report the performance metrics. Since our system is of two-stage processing, we need to evaluate the model at two stages.

- For the emotion tagging, we calculate the accuracy of the classification of the emotions.
- For the intensity scoring, we will calculate the mean squared error (MSE) of the scores outputted by the system and the actual intensity score.

### 4.2.2 K-fold Cross Validation

But to objectively measure the performance of the two types of models including the text tagging model and the test intensity scoring models, we need to have the cross-validation protocol. In this protocol, the entire training set is split into K different no-overlapping folds. For each fold, we will use it as a test set, and the other folds are combined as a training set. So, when we train the model, we only train it over the training set, but test it in the test set, so that the training set and the test set have no overlapping. When the model is trained, it will not see the tests as data. In this way, we guarantee the model is not cheating, because during the training model, it cannot see and memorize the test set.

In practice, we used the 5-fold cross validation method. The training side spread into 5 folds. We use each fold as a test set one by one, and the other 4 folds as the training set. So, we have five validation process. Accordingly, we have five performance measures.

- For the tagging method, we used the accuracy as the performance methods, we have five accuracy values. We calculate the average accuracy to represent the performance of the model.
- For the intensity scoring method, we use the MSE as performance method, so accordingly, we also have five different MSE values and we calculate the average of the five values to get the overall MSE to present the performance of the model.

Our 5-fold cross validation protocol is shown in Figure 5.


Figure 5. The 5-fold cross validation.

The results of our 5-fold cross validation for both the emotion tagger and the intensity scorer are showing in Table 2.

Table 2. Performance measures of Emotion Tagger and Intensity Scorers.

| Emotion | Accuracy of Emotion Tagger | MSE of Emotion Intensity Scoring |
|---|---|---|
| fear | 0.901010096 | 0.121590205 |
| sadness | 0.909343421 | 0.129784618 |
| joy | 0.942171729 | 0.139808434 |
| anger | 0.920202029 | 0.10980515 |

- As we can see from the table, the accuracy for the tagging is hihger than 0.9 for all emotions.

- For the intensity scoring, the MSE is usually smaller than the 0.13.

So, we can conclude the models' effectiveness are good.

### 4.2.3 Running Time

Another most important performance factor is the running time for the training process for both models of tagger and scorer of four emotions. We tested the training process for one single training. We use the entire desert for this testing. During the testing, 90% of the data are the training and the remaining 10% are used at the testing. Including the training and the testing process, the entire running time is showing in the following Table 3. According to the table, it is concluded that the tagger takes more time to do the training, but the scorer takes less time.

Table 3. Running time of tagger and scorer training and validation, in seconds.

| Emotion | tagger training time | scorer training time |
|---|---|---|
| fear | 46.9833684 | 15.46066403 |
| sadness | 45.32489204 | 10.91144252 |
| joy | 45.84551263 | 12.01507878 |
| anger | 45.95310903 | 13.10193324 |

## 4.3 Model Deployment

### 4.3.1 Pipeline

To deploy the model, we need to do two development works. The first work is to combine four different models for both tagger and intensity scores into one single function, and needed to design a pipeline on how to use this model to conclude with a final emotion and the concluded intensity scorer. Giving the fact that in each sentence, there be multiple emotions, for example including both fear and anger, we want to design the interface of API of function to produce whatever emotions detected by the four models, and then for each tagged emotion, we will then go to the scorer to calculate the intensity.

So, in this pipeline, this is the two stages. In the first stage we need to input the text into four models one by one, and for each model, if the output is positive, we will send the sentence to the corresponding emotions intensity scorer to get the scores and at the end of the program will output the detected emotions, and the corresponding an intensity score.

### 4.3.2 Interface Design

The second part is after we have this function, how do we use it to produce the output in the interface. For this purpose, we choose the flask open-source software. In the flask, we have a interface to the build the web page, and in the web page, we have an input text and a submit button. Once the user clicks the button, the input text will be sent to the function to tag the emotion and calculate the intensity of the emotion. At the same page, below the input, we will show the outputs, include emotion and the according scores. Of course, if there's multiple emotions, all of them will be shown on the page.

The interface design of the system is shown in Figure 6.

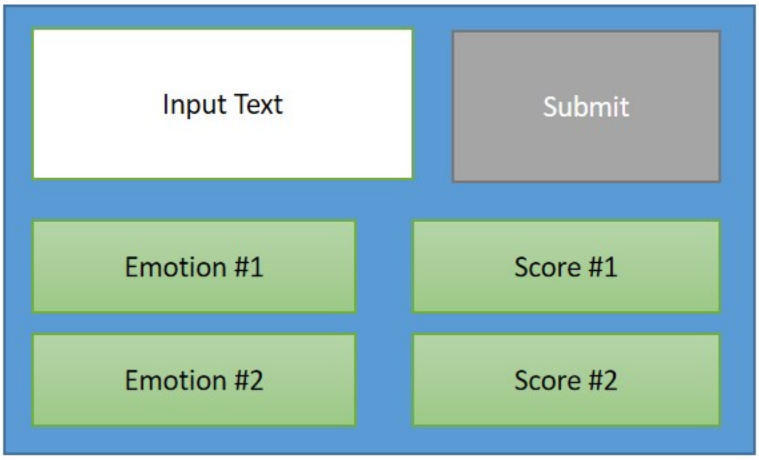


Figure 6. Interface design of deployed web page service.

### 4.3.3 Deployment to the cloud

All these functions, including the API and the interface will be built into the docker and the docker will be deployed into the cloud server. We chose to use the digital ocean to host this docker, so that the public users can be accepted to this interface to get the result from their own input.

## 4.4 Summary

In this chapter, the results and implementation of the system are introduced. the results are composed of two parts, one is the quality of the prediction of the models. We have developed two models, one is a classification model, another one is regression model. So we test them two models, and regarding classification model, we use the the accuracy as metric. Regarding the regression model we use the MSE. Four emotions are all tested, so there are eight test results for the classification and regression results, we use the accuracy percentage. all of the classification results are above 90%, which is good for the usage. All the regression results are is all below 0.14, which is also good. So we can conclude the accuracy of the model has a good quality.

The second part of the testing is the running time testing, especially for the modern training running time. The model training running time for both classification and regression have been recorded and presented in the tables. According to the running time test, the training for GPU machine is acceptable.

# CHAPTER 5

# CONCLUSIONS

In this report, a system is designed to automatically read the social media posts and detect the emotions. At the same time, the system can also estimate the intensity of the emotions. The applications of this study is the wide, from e-commerce, political usage, social monitoring, to economic analysis, even for the stock market prediction. We designed unique model based on the CNN layers and BERT word embedding.

Twitter data set is downloaded to train and test the model, the model shows good performance over the Twitter data. Four emotions are considered in the system, corresponding models for each emotion are trained. A tagger model and an intensity scoring model is built for each emotion. Based on the models, an end-to-end solution is designed for the users to test the emotion detection and intensity functions.

**Future works**: In the future, more advanced NLP models will considered, for example, the GPT-3 model. At the same time, we will also consider to have more emotions, not only the four emotions and train models together with some other learning and natural language processing tasks.

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# APPENDIX A: RESEARCH PROPOSAL

EMOTION TAGGING AND INTENSITY SCORING FOR SOCIAL MEDIA POST TEXTS

YAN LIANG

Research Proposal Report

OCTOBER 2021

## Abstract

In this project, we try to develop an AI model for the purpose of analysis of social media post text content. We have two targets for this project. The first target is to automatically tag the emotion expressed by the content of the text. The emotions are anger, fear, joy, and sadness. The second target of this project is to estimate the intensity of the detected emotions and give a score of the intensity between zero and one. We developed the AI models to solve the problems to meet the two targets. Two deep learning models are designed and trained over the Twitter text database. They are the classification and regression models for the emotion and intensity estimation separately. The evaluation of the models over the Twitter post texts shows the effectiveness of our model. We further build an end-to-end pipeline for emotion tagging and intensity and publish it as a project on GitHub. The users can download, install, and use it directly for the purpose of emotion analysis of social media text.

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## 1. Background

With the rapid development of the Internet, social media has been a major channel for people to express their thoughts and exchange information. For example, currently, for every one second, there are over 6,000 tweets are posted over the social media channel of Twitter, while for each day, there are over 500 million tweet posts. Meanwhile, in another most popular social media channel of Facebook, more than 2.5 trillion posts have been posted by users (Perrin, 2015, Zhuravskaya et al. 2020, Seargeant and Tagg, 2014, Lenhart et al. 2010).

With such a large amount of social media posts, there is a great need to transform all those post texts into business values, for the applications of different sectors, such as the commercial, government, and security sectors. However, this transformation is not easy. The most important insight of those posts is about people's thoughts and their emotions, i.e. how they feel about some specific objects. The most useful and time-consuming process is to understand people's emotions from the content of the posts (Panger, 2017, De Choudhury et al. 2013, Gaind et al. 2019, Dai et al. 2015, Sul et al. 2014, Sampson et al. 2018, Rout 2018).

The most popular emotions about people are joy, anger, sadness, and fear. Using those detected emotions, we are able to use the post more effectively.

- For example, in the commercial usage scenario, when one product is mentioned by a social media post, we want to know how people feel about this product and then use this emotion detection result to recommend the product to most wanting consumers (Matsui and Yamada, 2019, Jaiswal, et al. 2019, Lim and Kim, 2017).

- Another application is for the Politics champion. When people mention a candidate, we also want to know how the people feel about him or her. With the emotion detection results, we can group social media users according to their emotions to some specific candidates, and take different actions to improve the chance of some specific candidates to be selected (Brady et al. 2019, López et al. 2020, and Hasell, 2016).

There are two options for the purpose of emotion detection

- One is human processing. A group of people is asked to read the content they post and give a tag of the emotions.
- Another solution is to use a computer to read the content of the post automatically and the emotion for future usage.

Of course, human processing is more reliable and accurate sense. The posts are posted by humans, and then, if it is read by a human, the understanding will be close to the thought of the other humans. However, this process is very costly and time-consuming. Especially with today's large amount and fast-growing social media data, it is almost impossible to have humans read the content of all the people's social media posts. Imagine in this scenario, half of the people all over the world are reading the other half posts. This is not practical at all.

So we have to use the computer to automatically parse and extract the emotions from the text of the content of the social media. This will be the topic of this thesis.

Another important concept about social media content detection is the intensity of the emotions. With the same emotion expressed by the post of the social media. Intensity could be very different. For example. When people post something about Donald Trump, assume they always have the same emotion of anger. But when time is passing by, their anger could be growing from time to time. The intensity can be changed. In this case, we need a measurement of the intensity of the emotion of anger. And also, this measurement will be very important to show the trend of people's feelings about Donald Trump. Of course, we can use people's manual effort to estimate this intensity. But unfortunately, different people have different standards of scoring. So it is also better to use computers to calculate this intensity, both objectively and fast. The intensity is also another important topic of this thesis.

## 2. Related Works

There are some related works similar to our work. However, some are not completed end-to-end solutions for emotion detection and intensity scoring. There are only some theoretical studies, not an industry-level application. We list some of them and discuss the details of their implementation and the shortages of these works as follows.

- Batbaatar et al. (2019) Proposed a semantic-emotion neural network for emotion recognition from text. This network is composed of two sub-networks. The first network is a network to the model language features from the text by using word embedding. The second network is using the emotional information from the text to extract features to represent the sentence. The networks are based on a bi-directional recurrent neural network and a convolutional network. However, this network is not directly for the prediction of emotions from the text. Emotions are used as the input, not as the output of the neural network. So it cannot be directly used to predict the emotion, and it can not be used to estimate the intensity of emotions. To these limitations, it will not be useful for the purpose of this project, as it is claimed in the title of their article.

- Duppada and Hiray (2017) proposed a tweet emotion intensity estimator. This work is only for the purpose of emotional intensity estimation. It is using the generalized models and the input features are the lexical, syntactic, and pre-trained word embedding features. The main shortages of this model are lack of novelty, but it combines the different regression models outputs. The main advantages of this model are two folds. Firstly, its accuracy is low, and secondly, it can not detect the emotion before the intensity. So when the user tries to use this model, they have to manually tag the emotion. At least they will receive intensity scores of four emotions, which will be very confusing for the end-users.

- Alhuzali and Ananiadou (2021) developed a emotion recognition model. This model can do emotion tagging, but it can take one text with multiple emotions. The most impressive part of this work is it can embed the words and sentences to explore the relationship between different emotions. However, this is not appreciated because if we consider independent emotion tigers, they can also give us multiple motions. A more important problem is the assumption behind the work is that the different emotions are closely related, which might not be true. In real-world applications, by splitting a long sentence into short sentences, we can also find that different short sentences may have different emotions, but the overlapping is limited. Another shortage of this work is that it cannot estimate the intensity at all, so when we are using this model, it can only give us partial answers.

- Junianto and Rachman (2019) designed a emotion recognition model. This work is only for emotion tagging, and it uses a very simple classification model called Naive Bayes, and the model parameters are trained by the particle swarm optimization algorithm. The novelty of this model is very poor. The data is the same as many other researchers. There is a very limited contribution to the community of emotion tagging, not to mention its missing part of the intensity estimation.

## 3. Research Questions

In this paper we study two layer progressive problems.

3. The first layer research problem is how to tag the emotion of a social media post text. i.e., how to assign a tag of four emotions to a text. The four emotions are anger, sadness and fear. Of course, if this text have no emotions, we should also tag it by non-emotion. At this layer, the problem is how to design a system for the computer to take the input text and output a tag of four emotions. So it is a typical classification problem from the view of machine learning.
4. The second layer research problem is the estimation of the intensity of the detected emotion. So we define scores between zero and one. Zero means this emotion doesn't exist for this post, and one means the emotion for this post is extremely strong. A score between zero and one in decades how strong is this emotion detected from the content of the social media post. The second problem is to automatically get this score between zero and one. Since the score is continuing value, we want to define a system to automatically predict this value, this problem is a regression problem from the view of machine learning.

## 4. Aim and Objectives

The aims of this project are three folds.

- Firstly, we want to develop a model of emotion tag for the input text of social media. It is the tiger that can tag and text with emotions of four types. Secondly, it is the intensity that can assign a score of a detected emotion between zero and one to indicate how strong is this emotion.
- Secondly, we want to train this model in a given database and evaluate quality in a test database to verify if this model is of good quality and for real-world usage. The purpose of the project is to give objective measures of the quality and risk of using this model.

So that the users will be aware of the effectiveness and the risk of failure when they are using this model.

- Our last aim is to publish this model on an open-source website such as GitHub so that the users can easily download, install, and use it in their world project to solve their business problems.

### 5. Significance of the Study

The significance of this study is it combines emotion tagging and intensity scoring problems together to give a practical and useful solution for real-world projects. In the traditional emotion detection solutions, they only consider one of the problems of emotion tagging or intensity regression. However, in real-world software, we need an end-to-end solution. This is the first time in the industry and academia to give an end-to-end solution. This solution has two stages and it is smoothly connected to form a complete pipeline. After we developed this solution and publish it to the open-source website, the user will be gaining the ability to directly detect the emotion and its corresponding intensity from a social media text.

### 6. Scope of the Study

The scope of this project is to do two things.

- Firstly, we want to explore the possibilities of building an AI model of emotion detection and intensity scoring by using deep learning models and NLP technology. This scope is about algorithm design and model training from the view of learning. It is including the database preparing model design and training parameter tuning.

- The second scope is to build software for open-source usage purposes. For this purpose, we need to have a model and also build an interface for the usage of this model.

The usage should be user-friendly so that they can easily import the package and called the function to get the emotion of a text and also the corresponding intensity score.

## 7. Research Methodology

This research project, we have a few steps to follow up.

### 7.1 Database

The Firstly step is the **database**. Since we want to understand the emotions and the intention of the emotions from the content of the text, we need a database of text with the corresponding emotions and the intensity. For this purpose, we choose the database of Twitter text with emotions (Mohammad and Bravo-Marquez, 2017). This database is firstly Published by the researchers from The national research council Canada and The University of Waikato. This database is called the 2017 share task on emotion intensity. It is originally for a competition of emotion city. But now it's already open for public usage.

This data set has tree subsets. The first subset is a training set. The second subset is a development set. The last subset is a test set.

d) For the training set, all the texts are from Twitter. Each text has an emotion tag of anger, fear, joy, or sadness. At the same time, each text has the intensity of the corresponding emotion between zero and one. The four emotions texts number and percentages are shown in Figure 1.

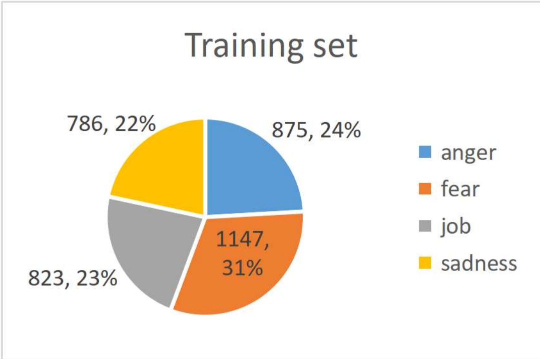


Figure 1. The number and percentage of texts of four emotions in the training set.

e) The development subset has the text and the tags. It is split into two parts. One part has the motion intensity, but the other part only has the tags of the emotion, but the intensity is missing.

f) The test subset also has two parts. It is similar to the development. Part of the intensity and another part has no intensity. Both of them have the tag of emotions.

### 7.2 Models

The second step is to build the **models** for the purpose of emotion tagging and intensity scoring. This step has two stages.

a) The first stage is to generate the tag of emotions from the content of the text. For this purpose, we want to do build a model to classify a text into four different classes, including the four emotions and one more class of no emotion detected.

b) The second stage is to build a model to output the intensity score for one detected emotion. For this purpose, we want to build another model to read the content and also. to generate the intensity for the corresponding emotion predicted by the previous model.

To build those models, we want to use two technologies, which are popular for natural language processing.

a) One technology is called the word embedding (Lai et al. 2016, Yin and Yin, 2018, Ghannay et al. 2016, Levy and Goldberg, 2014). It transforms one word into a continuous value vector to represent the meaning of this word. For this purpose, we try to use the word embeddings provided by an open-source NLP model called spaCy (Srinivasa-Desikan, 2018, Schmitt et al. 2019, Partalidou et al. 2019). This model is not a model to be trained, but a pre-trained model. For each word, it already has its unique vector. So we don't need to train any model for the purpose of word embedding, but we can directly query the word embedding from the word embedding lookup table.

b) Another technique is the model of deep learning (LeCun et al. 2015, Goodfellow et al. 2016). We choose to use the model of a convolutional neural network (Albawi et al. 2017, Kalchbrenner et al. 2014, Kim, 2017). This model has many layers and each layer has two sub-layers. The first sub-layer is the layer of convolution, and the next sub-layer is the max-pooling layer. This model is used for the purpose of both emotion tagging, and intensity scoring. For the two different tasks, the basic layers are the same, but the last layers are different. One is for classification purposes, another is for regression purposes.

The information flowing chart is shown in Figure 2.

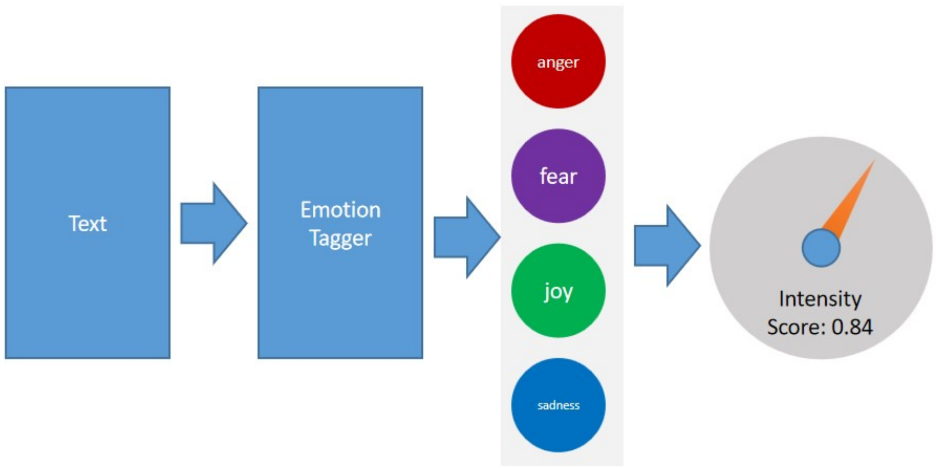


Figure 2. Information flowing of the proposed social media post text emotion tagging and intensity scoring system.

As you can see from the figure, the different stages are not independent but related. The intensity scoring is only activated only when the first stage tagged a text with one specific emotion. For example, if one text is tagged with anger, then we will score the intensity of anger in the second stage. But if a text is not tagged with anger, then the anger intensity scoring will not be performed. A potential risk of this framework is the accumulation of errors. If the first stage fails, because the intensity of the emotion is not strong enough, then the intensity will never be estimated in the second stage.

### 7.3 Evaluation

The last step is to train the model and **evaluate** its quality. Our plan is to train the model with the training set, and then evaluate it over the development set and the test set. In the training process, we will use the cross-validation protocol to tune the parameters of the model. And then test the model over the development set to check the quality of the model until its performance is satisfying. Finally, we will perform the evaluation of the performance of the model over the test set independently to see how good is the model actually and then report the performance metrics. Since our system is of two-stage processing, we need to evaluate the model at two stages.

- For the emotion tagging, we calculate the accuracy of the classification of the emotions.
- For the intensity scoring, we will calculate the mean squared error (MSE) of the scores outputted by the system and the actual intensity score.

## 8. Requirements Resources

In this research project, three types of resources are required.

1) The first requirement of resources is about the data. As we described in the above sections, we have the data source of the tweet emotions and their corresponding intensity scores.

2) The second required resource is the open-sourced packages of NLP and deep learning. For this part, we used the open-source NLP package called spaCy, and the deep learning package called Keras. The project is based on the project of Tensorflow. It is a wrapper for Tensorflow. It allows the users to build their own models.

3) The last part of the resources is the hardware. Because we are trying to train the deep learning models so better to have a GPU (Owens, 2007, Buck, 2007). It is the graphics processing unit which is originally used for computer games, but also later people found it very useful for matrix manipulation. Matrix manipulation is the most common processing unit in deep learning models. In our work, we use my laptop for the GPU. On my laptop, there is GPU from NVIDIA. It is a GeForce GPU with 6614 MiB memory. Its running is supported by the CUDA driver software with a version of 11.5, as shown in Figure 3.

```
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 496.49       Driver Version: 496.49       CUDA Version: 11.5     |
|-------------------------------+----------------------+----------------------+
| GPU  Name            TCC/WDDM | Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|                               |                      |               MIG M. |
|===============================+======================+======================|
|   0  NVIDIA GeForce ... WDDM  | 00000000:01:00.0  On |                  N/A |
| N/A   44C    P8     2W /  N/A |    969MiB /  6144MiB |      1%      Default |
|                               |                      |                  N/A |
+-------------------------------+----------------------+----------------------+
```

Figure 3. NVIDIA GPU configuration.

## 9. Research Plan

To complete this project, we need a research plan. In this plan, there are 26 weeks to complete the entire project. The number of activities in this plan is 8. It starts with a literature review, which takes 2 weeks, and ends with a documentation of all the works, which takes another 3 weeks.  Between these two activities, we have activities of literature review, data collection, and model building. Of course, there needs an algorithm choosing, and lastly, we test and verify the developed product and publish it on the open-source website GitHub. Detailed research is shown in the following Figure 4, with the different steps and the time duration.

*Select a period to highlight at right. A legend describing the charting follows.*

Period Highlight: 1 | Plan Duration | Actual Start | % Complete | Actual (beyond plan)

| ACTIVITY | PLAN START | PLAN DURATION | ACTUAL START | ACTUAL DURATION | PERCENT COMPLETE |
|---|---|---|---|---|---|
| Literature research | 1 | 1 | 1 | 2 | 100% |
| Literature review | 2 | 2 | 2 | 3 | 100% |
| Data collection | 4 | 4 | 4 | 6 | 90% |
| Data preparation | 8 | 2 | 8 | 3 | 50% |
| Algrithom choose | 11 | 4 | 11 | 4 | 0% |
| Model building | 16 | 4 | 16 | 4 | 0% |
| Testing and validating results | 20 | 4 | 20 | 4 | 0% |
| Documentation | 24 | 3 | 24 | 3 | 0% |

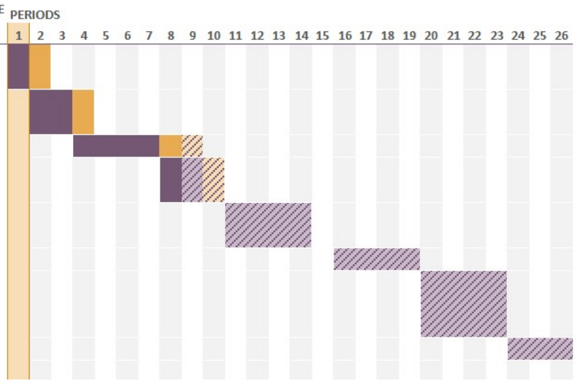


Figure 4. Research plan of activities, time duration and steps.

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