# Script Character Emotion Recognition

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## Abstract

*This task is to analyze and identify the emotions of each character involved in every dialogue and action description in the script scenes from multiple dimensions. Comparing with traditional sentimental classification task, there are more changes in this task. Emotions are multidimensional, and each emotion has a degree. For example, the degree of happiness ranges from 0 to 5, with 0 being none and 5 being the strongest. A sentence may have a variety of emotions, such as joy, surprise. Emotion classification is for a certain role in a sentence, rather than the whole sentence. A sentence may have multiple roles with different emotions. Considering the property of the task, we tried a few networks which different from what the multi-classifier does.*

## 1. Introduction and problem description

The importance of script to film and television industry is self-evident. A good script is not only the basis of good word of mouth and traffic, but also can bring higher commercial returns. Script analysis is the first link in the production chain of film and television content, in which the emotion identification of script characters is a very important task, which is mainly to analyze and identify the emotions of each character involved in every dialogue and action description in the script from multiple dimensions. Compared with the usual news and commentary text sentiment analysis, it has its unique business characteristics and challenges.

This project will use a part of film scripts as training sets, and the data of the training sets has been manually labeled. We need to analyze and identify the emotions of each character involved in every dialogue and action description in the script scenes from multiple dimensions.

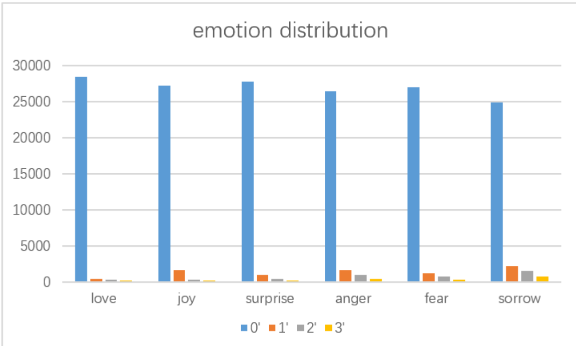
## 2. Description of the data used in the project

| id | id2 | content | character | 喜love | 乐joy | 惊surpris | 怒ange | 恐fear | 哀sorrow |
|---|---|---|---|---|---|---|---|---|---|
| 1460_0016_A_ | 189 | 全家人站成一排，拍了一张全家照。The whole family stood in a line for a family photo. | | | | | | | |
| 1460_0016_A_ | 190 | d1挽着p2走出照相馆，门口停着一辆婚车。D1 walked out of the studio with P2 on his arm. There was a wedding car parked at the gate. | p2 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1460_0016_A_ | 191 | d1挽着p2走出照相馆，门口停着一辆婚车。D1 walked out of the studio with P2 on his arm. There was a wedding car parked at the gate. | d1 | 0 | 1 | 0 | 0 | 0 | 0 |
| 1460_0016_A_ | 192 | 一x2称赞：哇，靓车啊！A X2 praise: Wow, beautiful car! | x2 | 0 | 2 | 3 | 0 | 0 | 0 |
| 1460_0016_A_ | 193 | p2不小心摔倒在地，d1连忙扶起p2。P2 accidentally fell to the ground, D1 quickly picked up P2. | p2 | 0 | 0 | 2 | 0 | 0 | 0 |
| 1460_0016_A_ | 194 | p2不小心摔倒在地，d1连忙扶起p2。P2 accidentally fell to the ground, D1 quickly picked up P2. | d1 | 0 | 0 | 2 | 0 | 0 | 0 |
| 1460_0016_A_ | 195 | d1：没事吧？D1: Are you all right? | d1 | 3 | 0 | 0 | 0 | 0 | 0 |
| 1460_0016_A_ | 196 | p2笑着：没事，没事。P2 smiled: Nothing, nothing. | p2 | 2 | 3 | 0 | 0 | 0 | 0 |

The above table is an example: The table content contains the script of a movie. The character column contains the specified character, that is mentioned in the script. The last 6 columns are the labels, which is in the training data but missing in the test data. The task is to identify the given character's six emotions: love, happiness, surprise, anger, fear, and sorrow, and numerically rank them according to the script. A sentence has multiple characters, such as p2, d1 and x2, and for each character, the type and degree of emotion needs to be identified. In the sample, there is one line: A X2 Praise: "Wow, beautiful car!", which contains two emotions: "joy" and "surprise", and they are in degree 2 and 3, respectively.

A total of 42896 labeled data were randomly shuffled and divided into training set and validation set in a ratio of 8:2. We have counted the label distribution on the training set, and it is obvious from the data distribution that emotion value 0 accounts for the vast majority. The higher the emotional value, the smaller the proportion.

| degree | love | joy | surprise | anger | fear | sorrow |
|---|---|---|---|---|---|---|
| 0' | 28434 | 27262 | 27735 | 26397 | 27048 | 24898 |
| 1' | 420 | 1645 | 1033 | 1612 | 1253 | 2259 |
| 2' | 328 | 370 | 458 | 981 | 815 | 1594 |
| 3' | 273 | 180 | 229 | 465 | 339 | 753 |
| percentage of 0 | 0.965337 | 0.925485 | 0.941606 | 0.896181 | 0.918282 | 0.843886 |
| percentage of 1 | 0.014259 | 0.055844 | 0.03507 | 0.054728 | 0.042539 | 0.076566 |
| percentage of 2 | 0.011136 | 0.012561 | 0.015549 | 0.033305 | 0.027669 | 0.054027 |
| percentage of 3 | 0.009268 | 0.006111 | 0.007775 | 0.015787 | 0.011509 | 0.025522 |




## 3. Our Work

This is an area for what we have done.
Preparation work(study papers, tools, libraries).
Build the environment.
Our baseline results.

### 3.1. Method

Our algorithm, including how to process the data, and turns to the problem of multi-label dichotomies of sentences.

We implemented the Baseline version the easiest way and got a score of 0.68. The methods are described below

1. By combining the character name and dialogue into one text, the emotion recognition of the role becomes a text classification problem, but because there are multiple emotions to be recognized, it is a multi-label classification problem. The category of each label has four values [0,1,2,3], but from the perspective of data distribution, category 2 and 3 account for a very small proportion. In order to simplify, multi-label dichotomy is adopted.

2. The difference between multi-label classification and multi-label classification is that:

   (a) Multi-label classification is the classification of multiple aspects or targets of a sample, usually dichotomies. These aspects are not mutually exclusive. For example, for a sample picture of a person, it is male or female in terms of gender, adult or child in terms of age, and East Asian or Western in terms of race. These aspects of the image can occur simultaneously, both gender, age, and race.

   (b) The multi-classification problem is to determine which category a sample belongs to, and there are more than two categories. These categories are mutually exclusive; belonging to category 1 cannot belong to category 2 or category 3. For example, if you look at a sample of faces, the difference is whose face it is.

3. Our task is a multi-label classification, because a sentence needs to be classified from multiple non-exclusive aspects (love, joy, surprise, anger, fear, sorrow). For simplicity, we only classify it into category 0 or 1, while category 2 and 3 are treated as category 1.

4. To convert text into vector, we use the current popular and better effect of bert-Base vector.

   (a) We take a batch of text samples with a batch size of 8, calculate the maximum text length

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   max_length_batch
   ```

   of this batch of data, convert each character of the text into character ID first, and transform a batch of text padding of different lengths into the sequence of

   ```
   max_length_batch
   ```

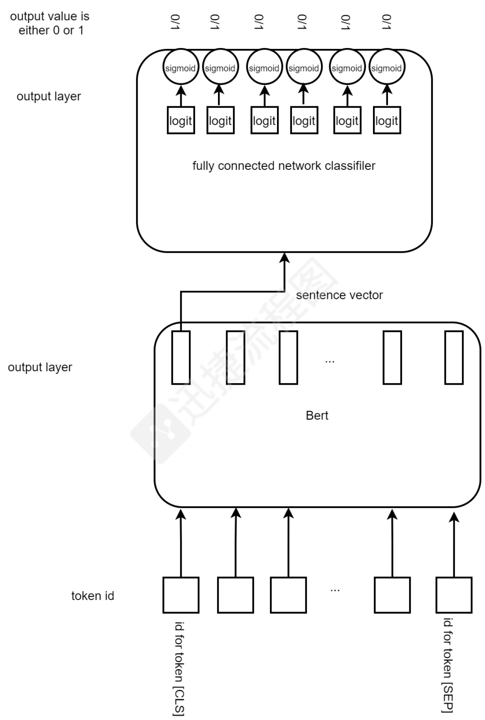
   of fixed length. Padding value is 0.

   (b) Input the character ID sequence of the sample into the Bert model, and extract the vector from the 0th unit of the last layer of the Bert model as the vector of the whole sentence.

   (c) Send the sentence vector obtained into the fully connected network for classification. Since there are 6 labels, the output is 6 neural units, and 6 logits are obtained.

   (d) Different from the multi-classification task, the multi-classification task is to make 6 logits as Softmax, while the multi-label classification task is to make 6 logits as sigmoid one by one, and each value activated with sigmoid represents the probability of this label as category 1.

   (e) Convert labels with probability greater than 0.5 to 1, and labels with probability less than or equal to 0.5 to 0.




### 3.2. Experiments

### 3.3. How to count the accuracy

The score of the algorithm in this competition is calculated by the common root mean square error (RMSE), and the emotion values corresponding to the six emotions identified by ”text content + character name” are counted:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\sum_{j=1}^{6}(y_{i,j}-x_{i,j})^2}{6n}}$$

score = 1/(1 + RMSE)

Where $y_{i,j}$ is the predicted emotion value, $x_{i,j}$ are the marked emotion value, and n is the total number of test samples. The final ranking is based on score.

### 3.4. Baseline score

### 3.5. The flaws of the method in baseline

## 4. What remains to be done

Next steps: This network has an obvious disadvantage: first, the original multi-label and multi-classification task is simplified into multi-label dichotomy task, which reduces the performance of the model to a certain extent. Second, the role to be identified is simply merged with the text, without explicitly telling the model which role the emotion to be identified is. Third, the emotional values of the characters depend not only on the current text, but sometimes also on the historical text, and the network does not use historical information for prediction. Our next step is to try to implement a multi-label multi-classification network. Since the category of classification has the relationship of degree and magnitude, we treat the classification problem as a regression problem, get the real value from 0 to 3, and then round it into an integer in 0,1,2,3, so as to get the classification result.

In the next step, we will refer to the question and answer task, regard the role as query, and conduct attention with text, so as to clearly tell the model which role's emotional value needs to be predicted.

## References

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