Emotion Recognition using Logistic Regression

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Abstract

The task of classifying a facial expression is quite an important task in Computer Vision and machine learning. It has multiple uses from allowing a robot to infer your mood in order to do or say something to interactive applications and others between others. In this paper we'll use a logistic regression to detect facial expressions on the fer2013 dataset. We obtained an ACA of 0,658 when classifying between happy and the rest, and an ACA of ?? when classifying among all classes. A way to improve the algorithm would be to start using a Convolutional Neural Network (CNN) in order to make a more descrive representation space for the image and get better results.

1. Introduction

The logistic Regression is a widely used method for classification. In it's original form, it's used to "teach" the model to differentiate between two classes. In order to do so, a loss function (L2) is optimized using the stochastic gradient decent algorithm to update important model parameters. One can also find a Multi-class Logistic regression, which instead of a sigmoid function, it uses a softmax function and instead of a L2 loss, it uses a Cross-Entropy loss function. In this paper we'll use the fer2013 dataset for facial expression recognition and implement two functions, one that will use the binary logistic regression, differentiating images of people smiling vs all other classes, and one that classifies an image in the seven classes presented in the dataset.

2. Methodology

2.1. Dataset Description

The fer2013 dataset was a challange originally posted on kaggle.com. It consists of 28709 Train samples and 3589 test samples. All of the images are 48x48.

Figure 1. Random Images of the aforementioned Dataset with their respective Label

In figure 1, it can be visuzalized how the train and test sets are configured.

2.2. Logistic Regression

Given a training set, $(\{x_i, y_i)\}\ with\ x_i\ \in R^p\ and\ y_i \in \{+1, -1\}$ a logistic regression model hypothesizes that

$$p(y_i = 1|x_i) = \sigma(\beta^T x_i)) \tag{1}$$

Where $\sigma(x)$ denotes a sigmoid function. Also, according to the maximum likelihood estimation principle, one can estimate β by maximizing $\prod_{i=1}^{n} p(y_i|x_i)$. Although there is no close solution, one can approximate it by iterating using a loss function and a stochasic gradient until a minimum is reached. [1]

3. Results

Running the training algorithm over the test and train sets, one obtains the following graph (figure 3) representing how the model actually improves with every epoch passed.

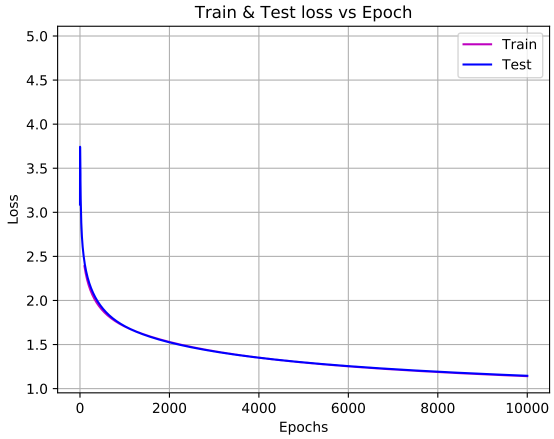

Figure 2. Train & Test loss for binary regression

Also, Evaluating the model over the test set, we obtained the following Results:

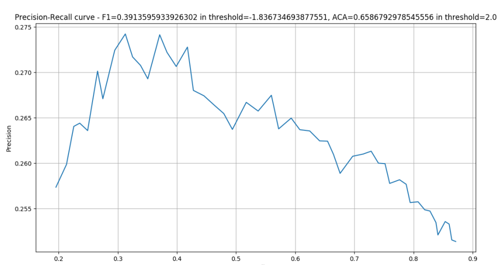

Figure 3. Precision-Recall curve (F1=0.39, ACA=0.658)

When we used the multinominal logistic regression the aim was accuracy the 7 different expression, the first tried using a the happiness faces like 1 and the other face like 0, the accuracy obteined was over 0.76, but when we used the whole emotions this value change to 0.36, the library used was the sklearn, and first we tried use in each iteration but the system became very slow, then we used this variable en database with the extracted dates

3.1. Extra Results

Running the algorithm over a new set of images we obtained the following results:

Figure 4. Images Classified using our classifier

We can see in figure 4 that our algorithm doesn't perform perfectly, as some images portraying neutral, scared and disgust facial expressions were classified as Happy. However, this is most probably due to this images portraying people with mouths opened, which was very stereotypical of the happy category of the train set.

4. Conclusions

In conclusion, we could improve our results by implementing a CNN (convolutional neural network) instead of a simple regression, as this would increase the descriptive capacity representation space in this task. to main_emmotion the time process was too much, this we improve using GPU instead, so the another problem viewed is the use of library of sklearn that was a bit of slow more when we used multype emotion facess, try use with iteration was a dificult work.

References

[1] *D. Hosmer, S. Lemeshow and R. Sturdivant, Applied logistic regression. Hoboken, N.J.: Wiley, 2013.*

[2]

[3]