Use logistic and softmax regression to classify facial expressions on CAFE Dataset

Shuo Xu
Computer Science and Engineering Department
UCSD
s3xu@ucsd.edu

Changhao Shi
Electrical and Computer Engineering
UCSD
cshi@ucsd.edu

Abstract

In this report, we focuses on using logistic regression and softmax regression to classify facial expressions over CAFE dataset. The logistic regressor is used for 2-class identification, and the softmax regressor performs identification task over 6 classes multi classification. We performed data centralization techniques and PCA algorithm over the dataset as data pre-processing methods. We carried out a set of experiments to explore the effect of hyperparameters, including learning rate, the number of principle components, and contrast the ability of batch gradient descent and SGD. In the end, we visualized the best weight vector.

1 Introduction

In this report, we focus on a set of classification tasks on California Facial Expresion(CAFE) dataset. Two tasks are solved, which are

- Two face classification: Use logistic regression to separate 2 kinds of facial expressions
- Six face classification: Use softmax regression to classify 6 emotional faces

The data pre-processing techniques we performed on the dataset are data centralization and principle component analysis. The reason we perform such techniques comes from the fact taht centralized and decomposited data can accelerate the speed of gradient descent.

2 Methods

In this section, we would show the basic pipeline of two task solutions.

2.1 Test methods and dataset building

In order to test the robustness of the algorithm and parameter selection, we test over all the subjects by making each one as testee once. And report the averaged 10 accuracies over the 10 runs.

Since different task require various facial expressions, we decide to build data in a dynamical way. This shall follow these two steps

- Screen out useless data: Filter out the facial expressions labeled by 'neutral' and 'happy'.
- Split data: Divide the dataset in terms of 10 subjects with ratio of 80%, 10%, 10% each for training, holdout and test dataset, respectively.
- Facial ecpression selection: Select task-related facial expressions according to the requirements

Specifically, in the second step, we iterate through all the 10 subjects and build test dataset from each subject exactly once. The holdout dataset is selected from the rest of the subjects, and all the other 8 subjects are used as training data.

Thus, we would have 10 randomly built dataset with different testee appeared exactly once.

To be specific, for each selection of testee, the numerical features of dataset constitution should be as in Table 1.

Table 1: Dataset constitution

Train	**Holdout**	**Test**
8 subjects	1 subject	1 subject
48 images	6 images	6 images

2.2 Data preprocessing

After loading all the images, we carry out following pre-processing methods.

- Centerize data: Calculate the mean over training dataset, and subtract this value from training, holdout and test dataset to get centerized data.
- PCA: Fit PCA model with centerized training data, and perform transformation(compression) over training, holdout and test dataset.

We describe some detailed implementation in PCA.

1 Avoid high dimentional matrix calculation

  By following the instruction in this article, we avoided the calculation of a matrix of size 91200 by 91200

2 Each principle vector is scaled by the standard diviation.

3 Only use the training data to compute the principle components

  Reason: To prevent overfitting, which means the model performs very well on training dataset but terrible on testing data. The test and validation data shouold only be used to measure the performance of the model trained on train dataset. If the test or holdout dataset are exposed to PCA algorithm, the final eigen vectors would have 'learned' from test / holdout, which would cause the performance to be falsely biased on validation and test dataset.

2.3 Two face logistic classification

We used logistic classification over 2 sets of facial expressions.

- Happy VS Maudlin
- Afraid VS Surprised

We performed SGD and batch gradient descent on both datasets. Here's the best parameters we used

$$learning\ rate = 0.4$$

$$epoches = 10$$

2.4 Six face softmax classification

We performed SGD and batch gradient descent on the dataset. Here's the parameters we used

$$learning\ rate = 0.2$$

$$epoches = 10$$

3 Results

In this part, we report the required results of the two tasks.

3.1 Load and preprocess the data

(a) Why is it important to only use the training data to compute the principal components?

To prevent overfitting, which means the model performs very well on training dataset but terrible on testing data. The test and validation data shouold only be used to measure the performance of the model trained on train dataset. If the test or holdout dataset are exposed to PCA algorithm, the final eigen vectors would have 'learned' from test / holdout, which would cause the performance to be falsely biased on validation and test dataset.

(b) Six emotions

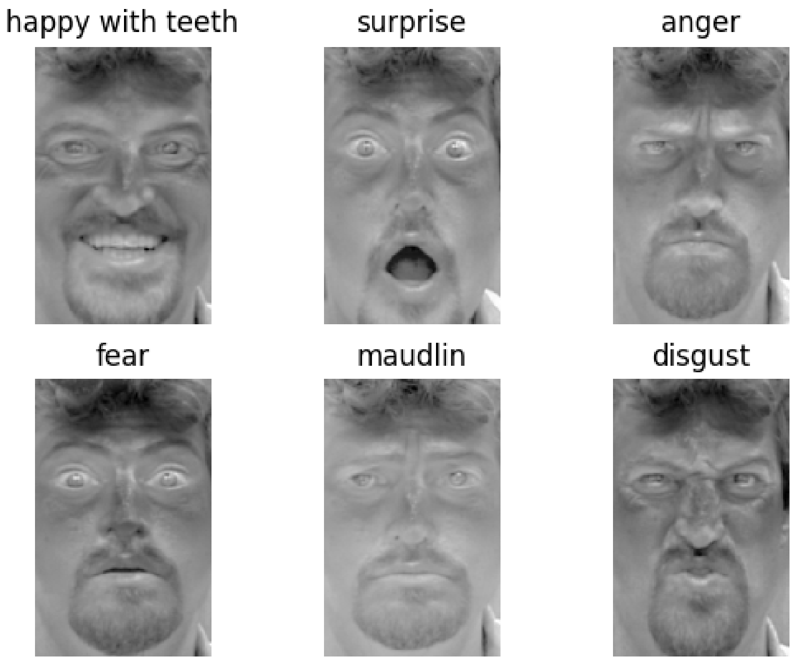


Figure 1: Six emotions

(c) First 6 eigenvectors

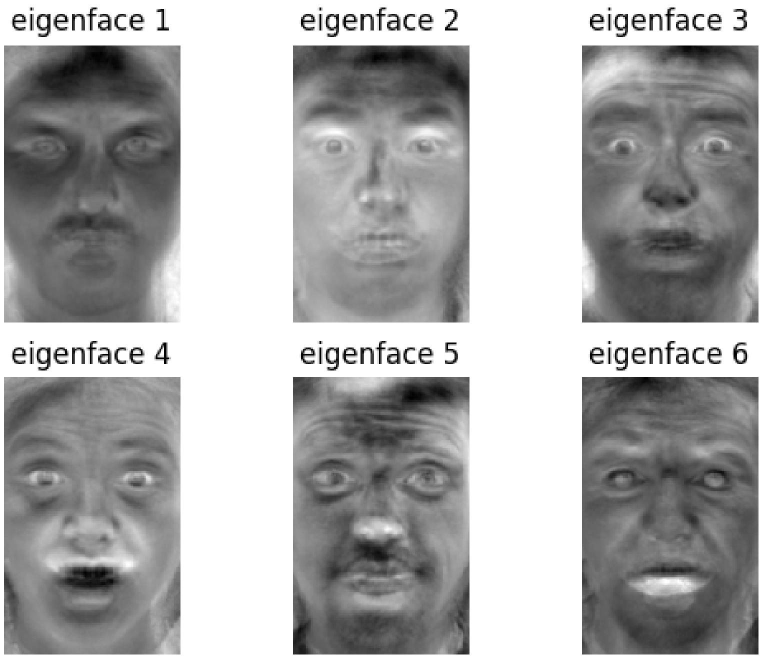


Figure 2: First 6 eigenvectors

3.2 Logistic Regression

3.2.1 Happy vs Maudlin

Question: Why we only need one if we're classifying two classes?

Say if the probability of one class is p, the other's probability could be simply calculated as 1-p.

Averaged error and deviation with the best learning rate

The best learning rate we've found is **0.4**
Here, we display the averaged error on training and holdout dataset with deviation of epoch 2, 4, 8 and 10. Note that principle components varies.

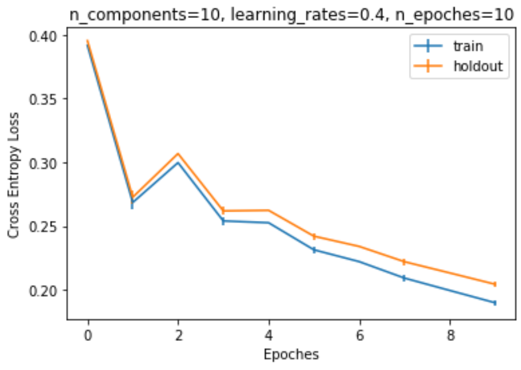
Averaged test accuracy

The averaged test accuracy over the 10 runs with best learning rate of 0.4 are shown as below.

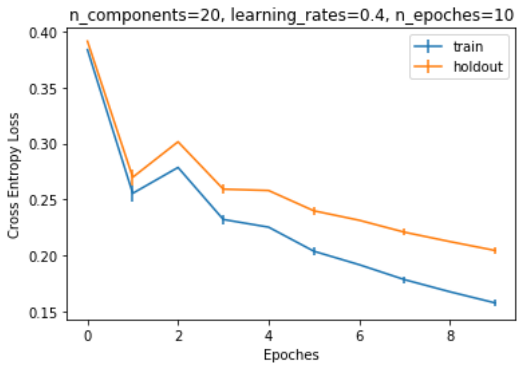
- number of components = 10, eccuracy = 0.955
- number of components = 20, eccuracy = 0.965
- number of components = 40, eccuracy = 0.860

Results of various learning rate

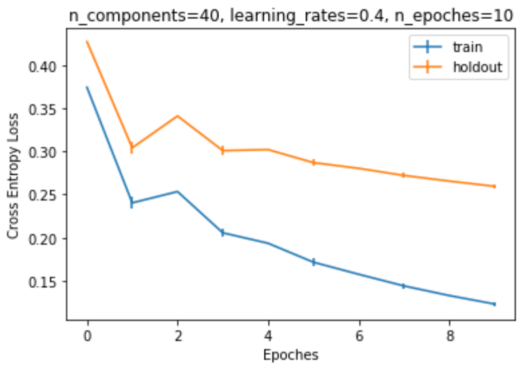
We've tried out 3 different learning rate in our experiments, which are **0.1, 0.4 and 0.8**. Here's a plot of the error of three different learning rates on the same training dataset.



(a) Averaged error with 10 principle components



(b) Averaged error with 20 principle components



(c) Averaged error with 40 principle components

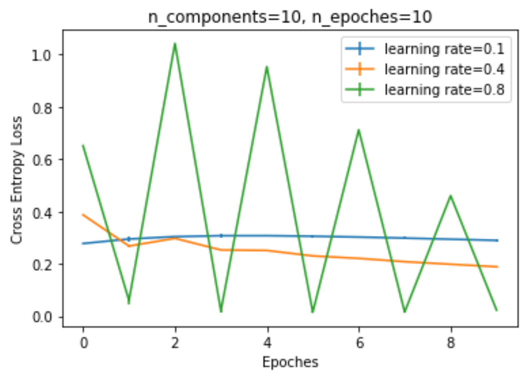
3.2.2 Afraid vs Surprised

Averaged error and deviation with the best learning rate

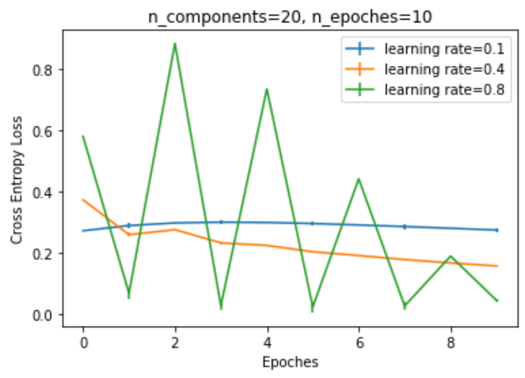
The best learning rate we've found is 0.4
Here, we display the averaged error on training and holdout dataset with deviation of epoch 2, 4, 8 and 10. Note that principle components varies.

Averaged test accuracy

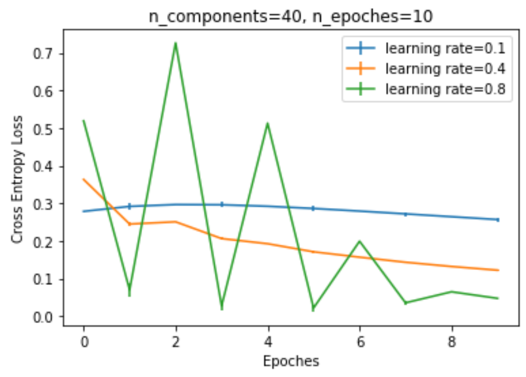
The averaged test accuracy over the 10 runs with learning rate of 0.4 are shown a below.



(d) Averaged error with 10 principle components



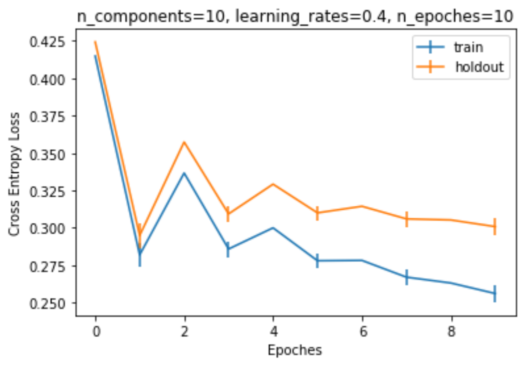
(e) Averaged error with 20 principle components



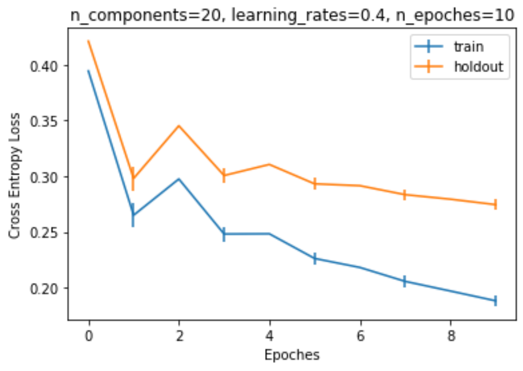
(f) Averaged error with 40 principle components

- number of components=10, accuracy = 0.690
- number of components=20, accuracy = 0.755
- number of components=40, accuracy = 0.640

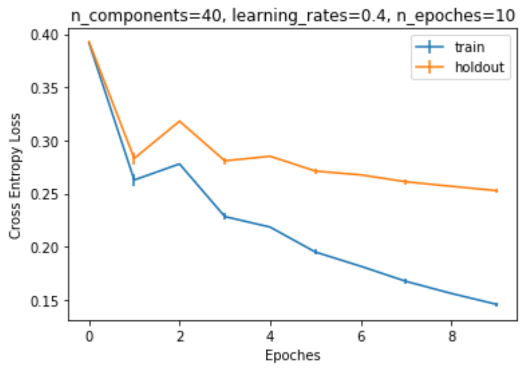
Comparison with Happy VS Maudlin



(g) Averaged error with 10 principle components



(h) Averaged error with 20 principle components



(i) Averaged error with 40 principle components

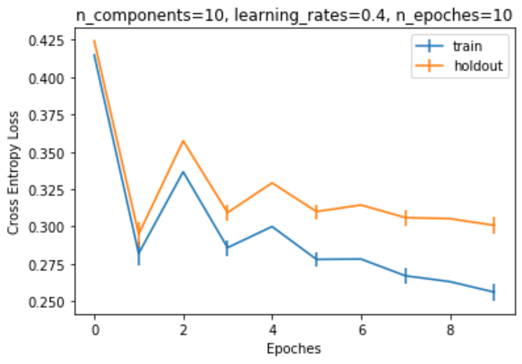
3.3 Softmax Regression

3.3.1 Evaluation on all six emotions

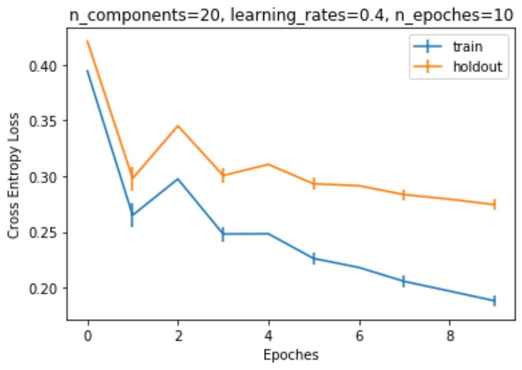
Question: What do you think would happen if we used all of the happy faces? The accuracy will be impaired. Because it's hard to discriminate between happy face and happy face with teeth??

Averaged error and deviation with the best learning rate

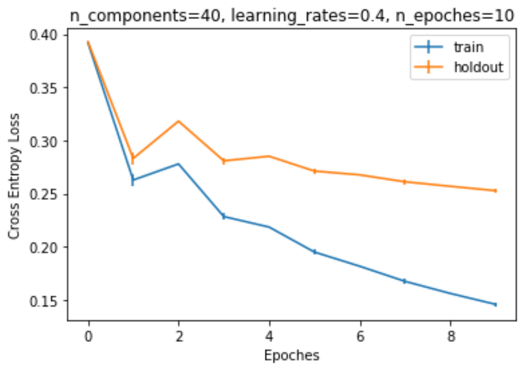
The best learning rate we've found is **0.2**
Here, we display the averaged error on training and holdout dataset. Note that principle components varies.



(j) Averaged error with 10 principle components



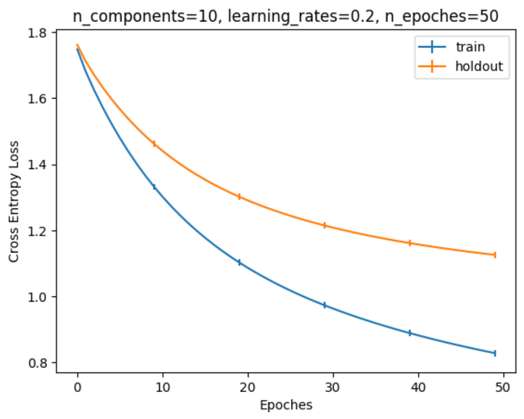
(k) Averaged error with 20 principle components



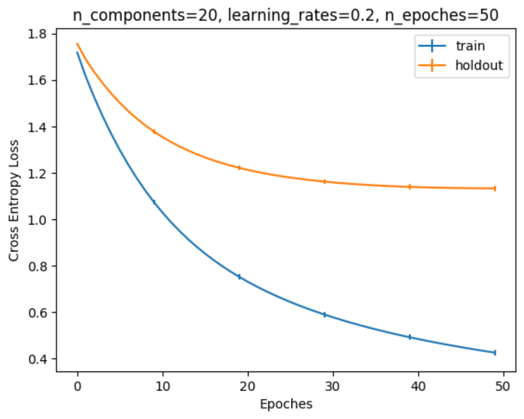
(l) Averaged error with 40 principle components

Averaged test accuracy In this part, we performed the softmax regression over dataset when learning rate = 0.2. And the results are shown as below.

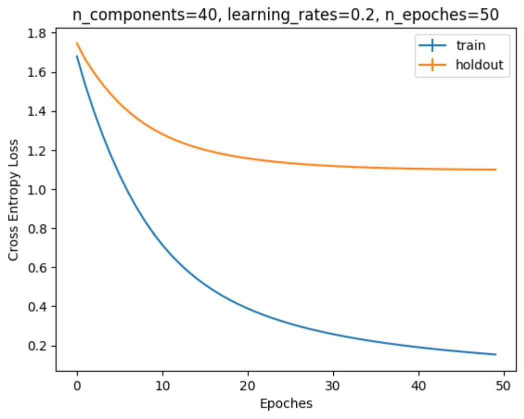
- number of components=10, accuracy = 0.607
- number of components=20, accuracy = 0.523
- number of components=40, accuracy = 0.592



(m) Averaged error with 10 principle components



(n) Averaged error with 20 principle components



(o) Averaged error with 40 principle components

Confusion Matrix

In this section, we display the confusion matrix on test dataest with the selection of different components numbers.

Table 2: number of principle components is 10, learning rate is 0.5, epoche is 50

	anger	fear	happy with teeth	disgust	surprise	maudlin
anger	0.4	0.01	0.04	0.23	0.0	0.32
fear	0.04	0.37	0.07	0.12	0.27	0.13
happy with teeth	0.0	0.02	0.72	0.26	0.0	0.0
disgust	0.12	0.05	0.24	0.5	0.0	0.09
surprise	0.01	0.25	0.0	0.02	0.68	0.04
maudlin	0.29	0.11	0.0	0.13	0.11	0.36

Table 3: number of principle components is 20, learning rate is 0.5, epoche is 50

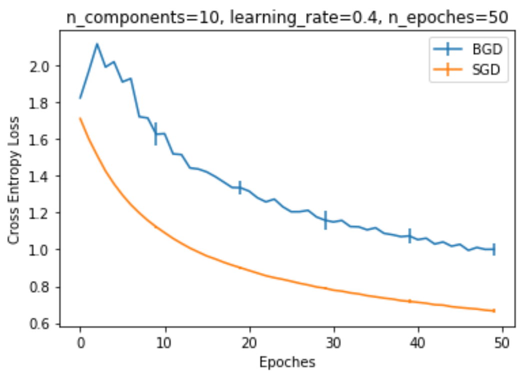
	anger	fear	happy with teeth	disgust	surprise	maudlin
anger	0.32	0.03	0.03	0.17	0.0	0.45
fear	0.07	0.41	0.1	0.01	0.2	0.21
happy with teeth	0.0	0.1	0.77	0.12	0.0	0.01
disgust	0.03	0.09	0.24	0.49	0.0	0.15
surprise	0.02	0.14	0.0	0.04	0.64	0.16
maudlin	0.29	0.12	0.0	0.2	0.05	0.34

Table 4: number of principle components is 40, learning rate is 0.5, epoche is 50

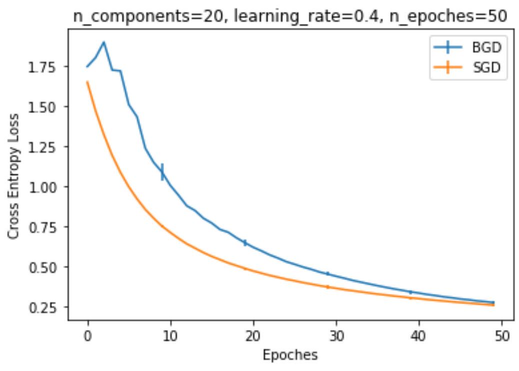
	fear	anger	disgust	maudlin	happy with teeth	surprise
fear	0.49	0.02	0.01	0.1	0.13	0.25
anger	0.01	0.65	0.16	0.18	0.0	0.0
disgust	0.14	0.13	0.56	0.03	0.14	0.0
maudlin	0.14	0.37	0.13	0.27	0.0	0.09
happy with teeth	0.12	0.0	0.04	0.0	0.84	0.0
surprise	0.26	0.0	0.0	0.09	0.0	0.65

Batch VS SGD

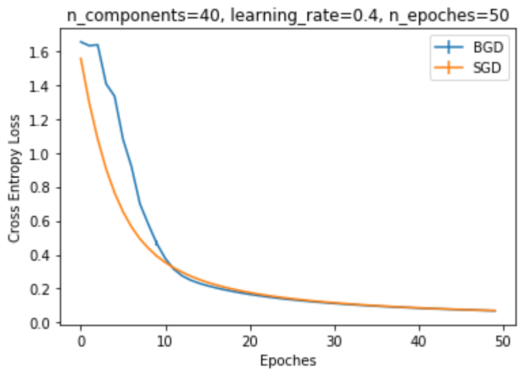
Here, we show the plot of error over training dataset using batch gradient and SGD.



(p) Averaged error with 10 principle components

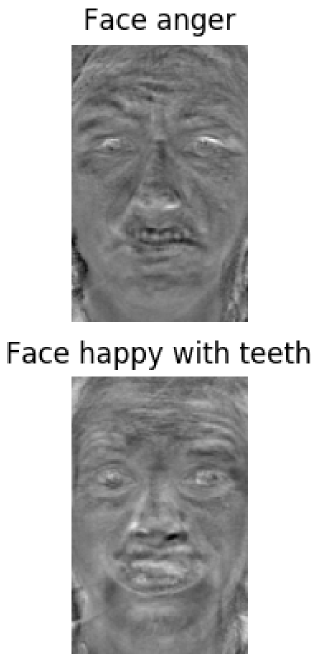


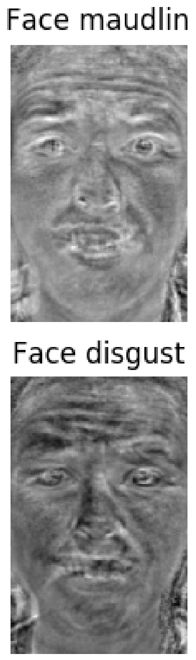
(q) Averaged error with 20 principle components



(r) Averaged error with 40 principle components

Visualize the weight





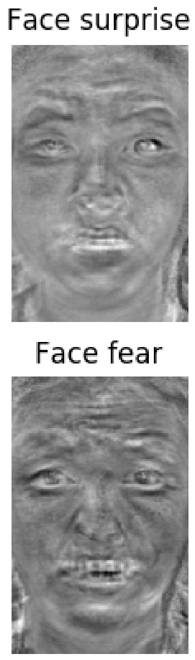


Figure 3: Visualized weight

3.4 Conclusion

In this assignment, we explore the influences of different hyperparameter on the emotion detection performance of logistic regression and softmax regression, for binary and multi-classes emotion classification tasks respectively. We first extract the eigenfaces, the principle components of face, from original images. We then train our networks, using thess new features, on the training set ,select the best network parameter (the weight of network) based on the loss of holdout set, and perform classification on the testing set to observe the network performance. We change the hyperparameter in of the network, including the number of eigenfaces, learning rates and batch size, and observe their influence on the performance of our network.

With the number of eigenfaces, we find that the cross entropy loss on the train set and holdout set goes down with the increasing of that number. However this does not always lead to the increase of classification accuracy on the test set. An interesting finding is that, with the number of eigenfaces increasing, the classification accuracy first goes down then goes up. This suggest that the number of features is not a determinant factor for classification performance.

With the learning rates, we find that there exist some ”right” learning rate for specific problems. When the learning rate is low, the loss on the train set and holdout set normally decrease in a slow way, which makes the loss hard to converge within a limit number of epoches. In this scenario, increase of learning rate can lead to a faster convergence of loss function on the train set. However, when learning rate is over a threshold, we observe an oscillation of loss on both train set and holdout set. This phenomenon illustrates that gradient descent steps over the local minimum. With that being said, the loss function can still converge if the learning rate is not too large.

With the batch size, we compare the network performance of softmax regression of full batch gradient descent and stochastic gradient descent. The results illustrate that the stochastic gradient descent can leads to a faster convergence, compared to the batch gradient descent. This is reasonable because the stochastic gradient descent compute the gradient only on one sample each time and thus the network weight can decrease faster.

Overall, logistic regression has a satisfying performance on the binary classification task between ”Happy with teeth” faces and ”Maudlin” faces. We can reach a 100% accuracy on test set which shows the strength of logistic regression on the simple tasks like this. On the other hand, softmax regression has a much lower accuracy on test set. This is because the multi-classification problem on six different labels is a much difficult problem compared to a binary classification task, while softmax regression is merely a generalization of logistic regression on multi-class problem. To achieve better performance, more powerful classifier might be necessary, like multi-layer neural network.

3.5 Individual Contribution

Declaration
For the coding part, we pair programmed. To be specific, we take turns to perform the role of driver and navigator. So almost every line of the code are co-authored by Shuo and Changhao.

Shuo Xu

- Co-designed classes and the structure of the project and implemented it with Changhao
- Wrote up the report
- Participated in the mathematical formula deduction

Changhao Shi

- Co-designed classes and the structure of the project and implemented it with Shuo
- Wrote up the report
- Participated in the mathematical formula deduction