CS7327-033-M01 Assignment 4

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Problem 1.

The dataset used in this homework is the SJTU Emotion EEG Dataset (SEED). Out of 37367 training data, the category label distribution are as follows: The EEG signals are from 15 experiment

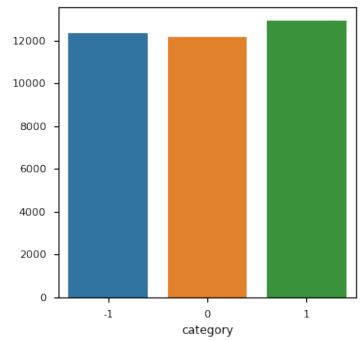

Fig. 1. Dataset distribution

subject, where 11 are used as training data and 4 are used as testing data. The data. The training data has the shape of (37367,310) where 310 is feature dimension of EEG data signals.

1.1 Baseline M3-SVM

The results of previous baseline svm for the problem is tabulated 3 as follows:

Table 1: Classification Report of one-vs-rest strategy and SVM

Class	Precision	Recall	F-score	Support
-1	0.52	0.38	0.44	4480
0	0.52	0.50	0.51	4416
1	0.63	0.81	0.71	4692
micro avg	0.56	0.56	0.55	13588
macro avg	0.56	0.56	0.55	13588
avg	0.56	0.57	0.55	13588
accuracy			0.57	13588

1.2 LSTM

1.2.1 Preprocessing

Both training set and testing set are preprocessed in a similar manner. First, we use the minmax scaler to keep scale the features within the [0,1] range to stabilize the learning process and also to prevent problems like gradient exploding or vanishing gradient.

Next, we transform the data so it is stationary so we can feed the signal into a LSTM network sequence by sequence. By dividing the time series data to a constant sequence length (s) with $t = 1$ as the smallest unit, we can feed a sequence to a LSTM cell sequentially.

A sliding window without overlap method is used to obtain the feature matrix of the data with a hyperparameter windows size w, which is used as the sequence input to the LSTM network. The feature vectors is divided such that w_i has the shape of (w $\times$ 310). For example, with $w = 10$, the training data becomes the shape of (3737, 10, 310). For the data label, the majority labels is chosen as the true label for that particular window.

1.3 LSTM network

A one layer Long Short Term Memory (LSTM) network with 128 hidden units is use for this problem. In this problem, we only require the hidden weights from the last LSTM unit, where it is connected with one fully connected layer to a 3 class output layer. The input sequence s_0 with the shape (b,w,310) and initial hidden state h_0 with all zeros and with the shape (1,b,h) is feed into the LSTM cell $t0$. At the following time step, the model outputs a hidden unit $h1$ with the shape of (1,h), which is then fed into the t_1 LSTM cell along with the sequence s_1. The process repeats from $1 \ldots t$, where $t = w$ until the end of sequence w.

Because this is a multi class classification problem, the cross entropy loss function is used to train the network. We also attempted to add another non-linear activation function in between the hidden layers, but this configuration negatively impacted the model performance due to the model is overfitting the training data.

As for the optimizer, we choose among the Adam, AdamW and SGD and find that model with Adam optimizer shows better performance.

1.4 Training

Using `pytorch.DataLoader`, the 3737 training data are fed into the LSTM network in batches b for 5 epochs. The hyperparameters for this network are window size w, batch size b, learning rate α and hidden unit size h.

1.4.1 Results

Model /Hyperparameter	window size w	batch size b	Accuracy (%)
A	8	10	53
B	20	10	47
C	30	10	52.21
D	50	10	54
E	80	10	42

Table 2: LSTM Results

We then train the model C for a longer period. With the early stopping technique, we find that model C can achieve 59.04% after 12 epochs of training. The classification report is tabulated at table 3 as follows:

Table 3: Classification Report of LSTM model

Class	Precision	Recall	F-score	Support
-1	0.60	0.6	0.61	84
0	0.20	0.67	0.31	27
1	0.94	0.56	0.70	160
macro avg	0.58	0.62	0.54	271
weighted avg	0.76	0.59	0.64	271
accuracy			0.59	271

Indeed, Recurrent Neural Network, specifically LSTM is suitable model to solve problems related to time series or sequential in nature. In this project, we manager to preprocess the EEG signals from 15 subjects and classify the emotions accordingly. However, the model has problems identifying the neutral mood, which it has only a low F1-score with 0.31. To solve this issue, we could possibly use a variable window size according to the labels instead of a fixed window size in the future.

The LSTM model shows better performance (4% increase) compared to SVM models. Besides, the training efficiency of LSTM is far superior compared to SVM. The experiment also showed that LSTM or other RNN models are suitable candidates to solve tasks to classify EEG Signals.