Response to Review #258643

The paper is not very well written, and it is quite difficult to read it. The most important section which introduces the method is not clearly written.

Thank for your valuable comments and the point-by-point responses to the comments are provided as follows.

Some phrases in the Introduction are extremely strange, such as "The two most commonly used feature extraction methods are traditional machine learning and deep leaning"; "Traditional machine leaning algorithms... can extract effective feature information contained in original data by simple calculations".

RESPONSE:

Thank for your valuable comments. To address your concern, we will make the descriptions clearer in the revised paper. For the first sentence, we would like to express that "Recently, when extracting features from original data, traditional machine learning and deep leaning are the two kinds of technologies that are often based on." For the second sentence, we would like to express that "Through some calculations in traditional machine leaning methods, such as eigen decomposition, more discriminative features can be extracted from the original data for better feature extraction." The traditional machine leaning methods in these sentences refer to the methods that do not include multi-layer networks, such as matrix factorization.

In my opinion, feature selection is an important domain in machine learning, with plenty of methods, and some of them are rather technical and elaborated. Another impressive sentence is "Traditional machine learning methods have poor performance in feature extraction...." It is quite a strange generalisation.

RESPONSE:

To address your concern, we revise the sentences as follows: For this sentence, we would like to express that "Some machine learning methods without multi-layer networks are technical and elaborated, but deep learning enables feature learning with multi-layer networks, which shows advantages in many problems, especially on large-scale data."

Figure 1: it is not very clear, why the architecture is focused on the error, and why the Figure is called "The total error of GDGCNN".

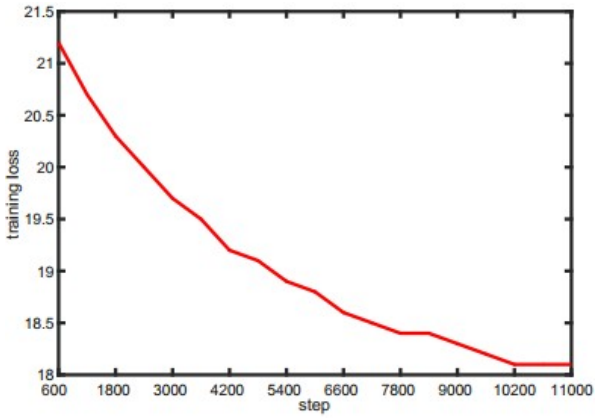
RESPONSE:

To address your concern, we will make the descriptions clearer in the revised paper. In our paper, GDGCNN mines feature information from the original data in both global and local aspects, which is mainly reflected in the constraint on the loss function. In Graph convolutional neural network model in [Defferrard et al., 2016], global feature information is well considered, but local feature information is ignored. Based on GCNN, the proposed algorithm improves GCNN with local structure information and discriminant information, which are the constraint on the loss function as the part of error. Therefore, the loss function of GDGCNN consists of three parts: global error in GCNN, local structure error, and discriminant error, and they are combined as the total error of GDGCNN.

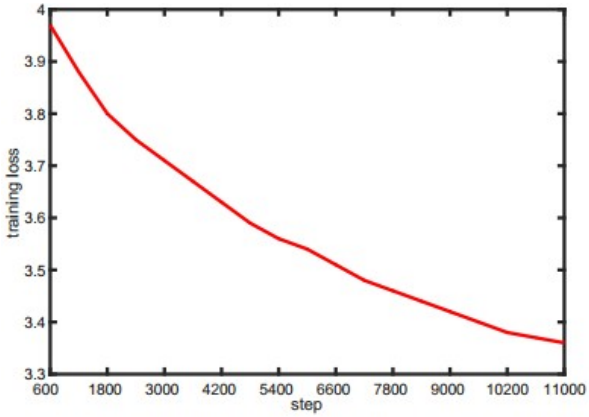
Convergence study (Section 3.5) is not really a study but just a plot of a training loss on one data set.

RESPONSE:

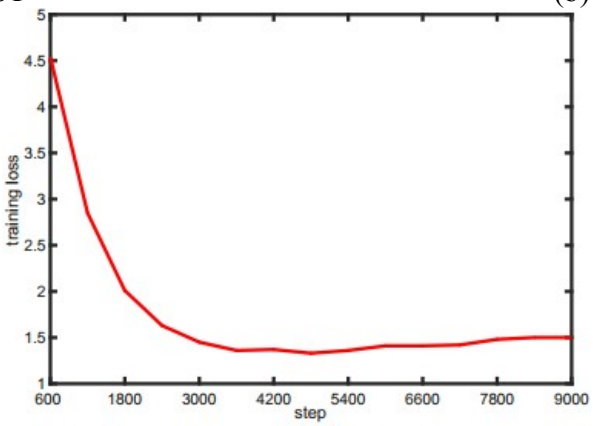
In fact, we have performed convergence experiments on all three datasets, but we only select one image to display in our paper due to the page limit. Here we mainly show the convergence of the proposed GDGCNN on the three datasets (MNIST, Fashion and CIFAR10) as follows:



(a) MNIST



(b) Fashion



(c) CIFAR10

For each image, the abscissa represents the number of iterations and the ordinate represents the training loss. It can be seen that the training loss of GDGCNN has a decreasing trend on all the three datasets, which can achieve convergence. The convergence speed is slow on MNIST and Fashion, which needs more than 10,000 iterations to converge. On CIFAR 10, it can converge only in about 3000 iterations.

Probably, a publicly available implementation would be beneficial to assure that the method indeed outperforms all other methods on the considered data sets.

RESPONSE:

Thank you very much for your constructive comment. We would like to post our code to our homepage as usual to discuss with the researchers.

Thank you very much for your insightful comments, which have greatly helped us in improving the quality of the paper. Thank you!