Dimensionality reduction methods and deep learning approach

SEOYOUNG OH
Department of Mathematics, GNU

JIHYE HEO
Department of Statistics , GNU

YEONSEOK CHOI
Department of Mathematics, GNU

Background

Dimensionality reduction is using for classification. A widely used method is principal components analysis (PCA), which finds the directions of greatest variance in the dataset and represents each data point by its coordinates along each of these directions.

A nonlinear generalization of PCA that uses encoder to transform the high-dimensional code and decoder to recover the data from the code. However, with large initial weights, it is difficult to optimize the weights. We can solve this problem by using Restricted Boltzmann Machine (RBM).

RBM is a generative stochastic artificial neural network that can learn a probability distribution over its set of inputs and were rose to prominence after Geoffrey Hinton [1]. We can see that autoencoder using RBMs produces a better visualization of the data than do the first two principal components [1]. In other words, autoencoder produces a much more distinct separation of digits than PCA. Therefore, we can expect that RBM has a greater effect on the classification problem than PCA.

GoogLeNet is a deep neural network with 22 layers and is known as an efficient neural network. We can reduce the amount of computation by using 1 x 1 Conv of the inception module and the number of weights by using average pooling layer at the end.

GRU is a deep learning model to improve the structure of the LSTM. It has a slightly simpler structure, and reduces the amount of computation. It receives input sequentially and compresses the knowledge in the form of a vector of a fixed size.

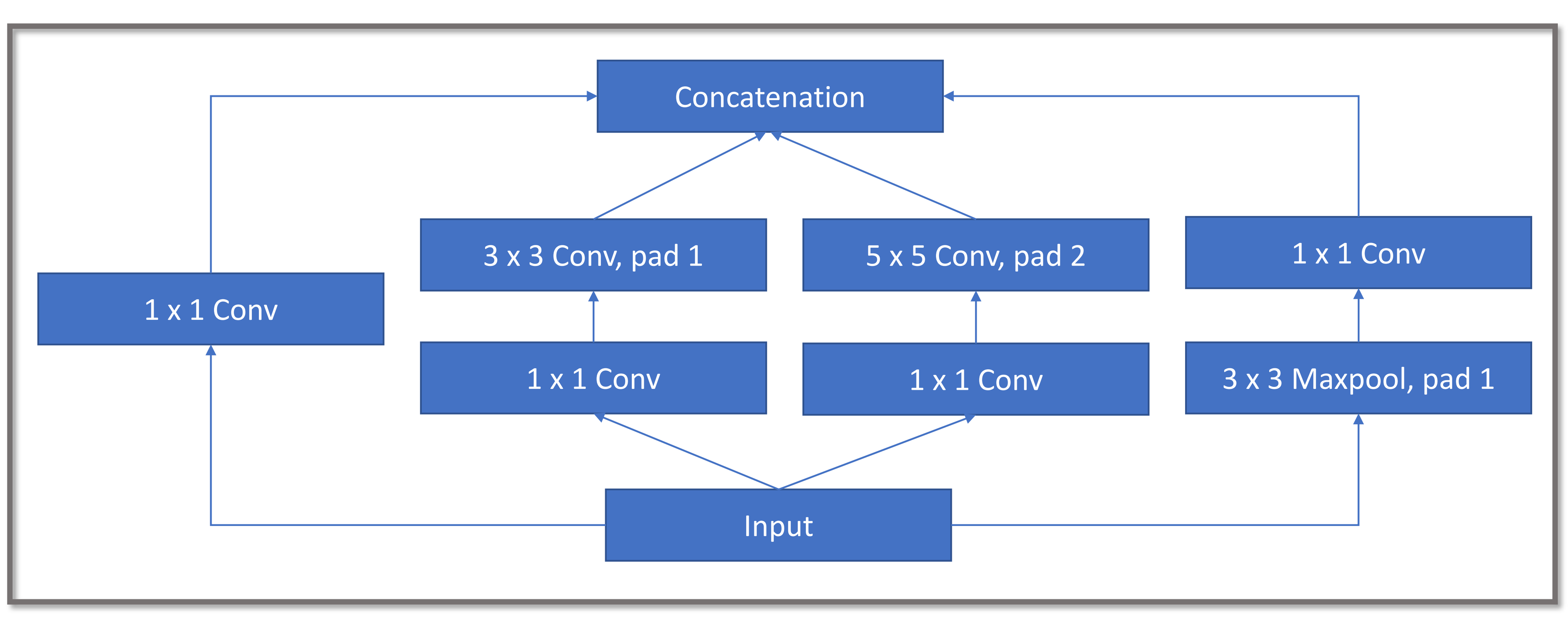


Fig 1. Inception block of GoogleNet

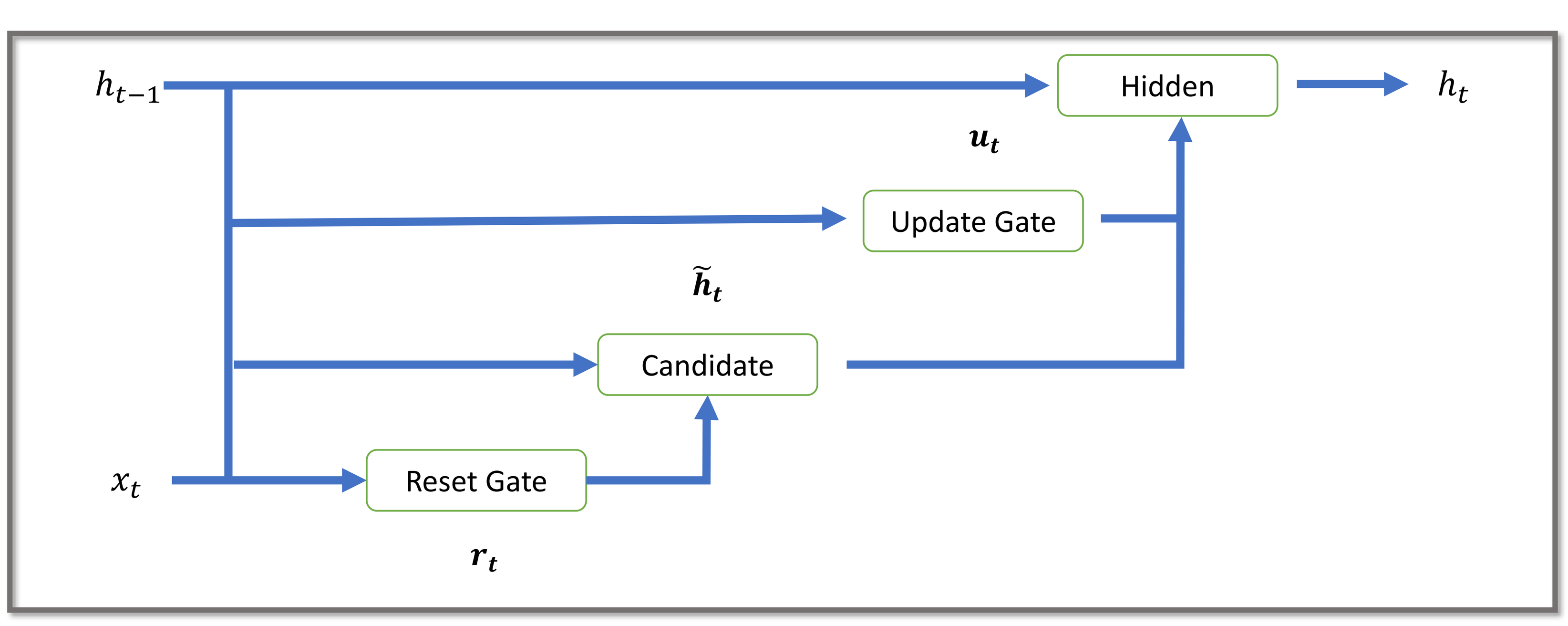


Fig 2. GRU model structure

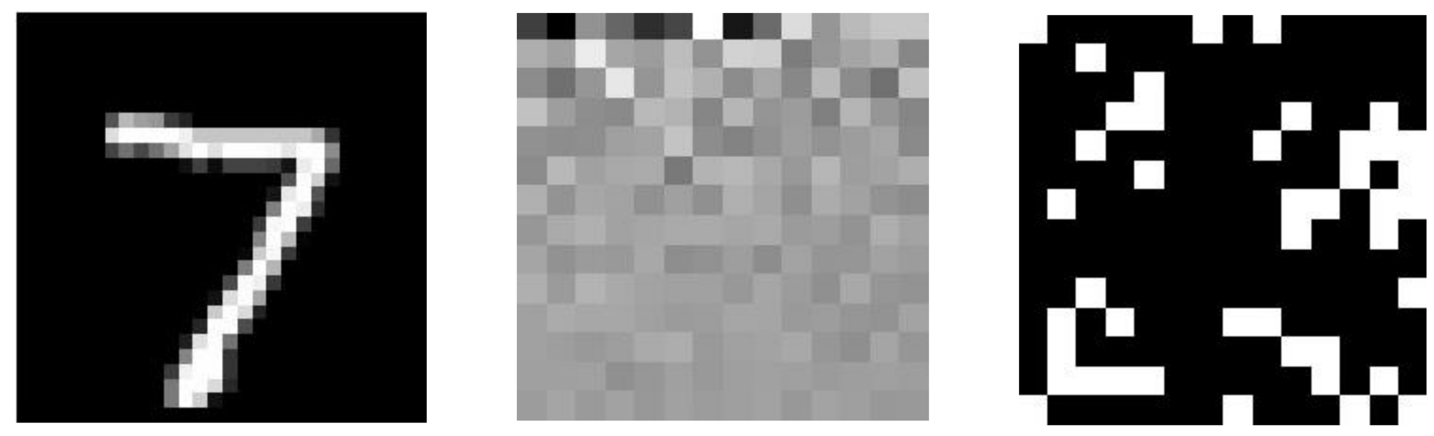
Aims

- Development of effective classification method for reducing computational costs.
- Comparison of dimensionality reduction methods to improve classification accuracy.

Methods

1. Dimensionality Reduction using PCA, RBM

By using PCA and RBM, MNIST images of 784 (28*28) size are reduced to 196 (14*14) size, resulting in a 75% reduction.



(a) (b) (c)

Fig 3. (a) Original, (b) PCA, and (c) RBM

RBM algorithm is repeated for 100 epochs with 256 batch size.

2. Classification (Googlenet, GRU)

We train GoogleNet on 60000 mnist images for 10 epochs with 64 batch sizes and GRU for 5 epochs with 16 batch sizes.

Results

As a result, we obtain 98.50% ~ 99.50% accuracy by using GoogleNet and GRU with original Mnist dataset, and 84.85% ~ 94.40% with PCA, and 10.70% ~ 11.31% with RBM.

It is true that RBM extracts more distinct features than PCA when dimensionally reducing the MNIST images [1], but applying them to deep learning cannot have a positive effect on improving accuracy. This is also because deep learning can extract important features from original data. However, I think that it is necessary to continue this study to reduce the costs. This study would be a pre-step for reducing computational costs for Big data

References

[1] Hinton, Geoffrey E., and Ruslan R. Salakhutdinov. "Reducing the dimensionality of data with neural networks." science 313.5786 (2006): 504-507.
[2] Szegedy, Christian, et al. "Going deeper with convolutions." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2015.
[3] Cho, Kyunghyun, et al. "Learning phrase representations using RNN encoder-decoder for statistical machine translation." *arXiv preprint arXiv:1406.1078* (2014).