Project 2: A Comparative Study Between Traditional and Information Theoretic Neural Network Models for Fashion-MNIST Classification

Connor McCurley
Deep Learning, Fall 2019
University of Florida
Gainesville, FL, USA 32611
Email: cmccurley@ufl.edu

***Abstract*—**

***Index Terms*—Fashion MNIST, Autoencoder, Information Theoretic Learning, Support Vector Machine**

I. Introduction

II. Methodology

This section describes the methodology implemented in this work. Analysis of the data is performed, dimensionality reduction and classification procedures are described, various network architectures under analysis are elaborated on and experimental procedures are outlined.

A. Data Analysis

The following data analysis was originally described in [1], but is pertinent to this work and is thus re-analyzed here. The data was plotted as shown in Figure 1 to gain an understanding of the format. Each sample in the Fashion-MNIST dataset is a 28x28, gray-scale image of a clothing item belonging to one of ten classes [2]. This translates to 784 length feature vectors with values ranging between 0-255. There were exactly 60000 training images included in the training dataset and 10000 which were held-out for test. The 60000 samples were later sub-divided in the experimentation for cross-validation. As with Project 1, dimensionality reduction(DR) was incorporated to reduce data complexity. This DR was employed through the use of stacked autocoder neural networks (SAE). Elaboration on the SAE networks is provided in the following section.

B. Autoencoder

Description: An autoencoder is a specific taxonomy of artificial neural network which learns how to compress and de-compress representations of data [3], [4]. The first half of an autoencoder typically performs dimensionality reduction through non-linear transformations until the middle layer, known as the *bottleneck* or *latent* layer. The goal of the *encoder* is to learn efficient representations of the factors which govern variation in the data, or in terms of compression, *codes* which can be used to reconstruct the input data with high accuracy. The second half of an SAE (which is called the *decoder*) projects the data back into its original dimensionality in attempt to reconstruct the original sample.(See Figure 2.) Reconstruction loss is between the input and output is used to update the network's parameters. In practice, samples can be passed through the encoder to perform dimensionality reduction.

SAE Architecture: The SAE architecture tested in this work consisted of 5 hidden layers, along with the input and output. The layers were selected as $784 \rightarrow 500 \rightarrow 200 \rightarrow k \rightarrow 200 \rightarrow 500 \rightarrow 784$, where k is the arbitrarily chosen dimensionality of the bottleneck. In this work, k was tested at $[10, 25, 50, 75, 100]$ in order to provided a reasonable comparison of performance changes resulting from dimensionality reduction. ReLU activation functions were used to apply nonlinearity. A sigmoid activation, however, was used at the output layer to enforce image value constraints between $[0-1]$. This was done because the images were normalized between $[0-1]$ before passing through the network. An initial learning rate of $\eta = 0.01$ was selected, and was updated using the Adamax optimizer through training.

SAE Experiments: The SAE network was trained for 20 epochs using mini-batch sizes of 200 samples. The bottleneck layer's dimensionality was varied between $[10, 25, 50, 75, 100]$. Each network configuration was trained 5 times, and the model which provided the lowest reconstruction Mean-Squared Error (MSE) on the hold-out validation set was selected for further use in classification. Results are shown in section III-A.

C. Support Vector Machines

Description: A Support Vector Machine (SVM) is a specific class of sparse kernel machines whose objective is to learn a decision boundary which can adequately discriminate between classes in a high-dimensional space [5]. Because of its sparsity constraints, a SVMs' predictions rely only on a subset of the training data known as *support vectors*. By design, support vectors tend to be examples in the training data which lie

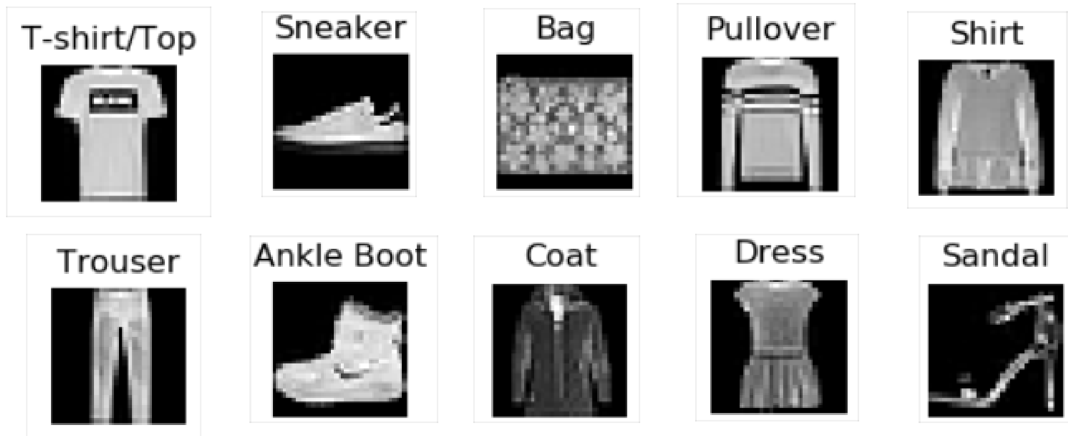


Fig. 1: Samples from the Fashion-MNIST dataset. One sample from each class was randomly chosen for visualization. The gray-scale images are size 28x28, each representing an article of clothing.

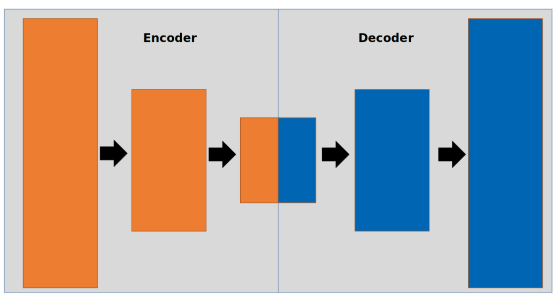


Fig. 2: Block diagram of an autoencoder neural network. The layers consecutively reduce dimensionality until the middle (bottleneck) layer. The second half of the network transforms the data back to the size of the input. The desired value of the network is the original image.

closest to the decision boundary, and are thus the most prone to incorrect classification. A primary difference between SVM and methods relying on Information Theory is that vanilla SVM classification predictions are not probabilistic. In other words, hard labels are assigned which do not capture the uncertainty of the prediction results.

Parameters:

Experiments:

D. Baseline CNN

E. Information Theoretic Learning (Minimum Cross-Entropy)

F. Experiments

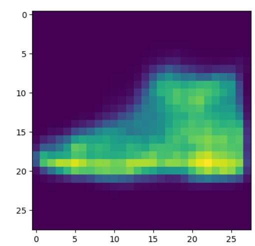
Experiments

III. Results

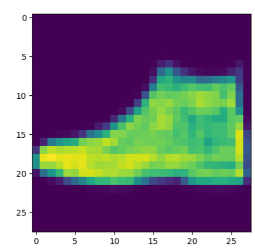
A. Autoencoder Reconstruction

B. Confusion Matrices

In this section, classification results for each experimental method tested are presented in the form of confusion matrices. A confusion matrix demonstrates the discrepancies between predicted and true class values for groups of samples. Essentially, it is a way to measure how accurate a classifier is, while providing insight into how the network confuses samples. A diagonal matrix signifies zero mis-classifications among all categories.



(a)



(b)

Fig. 3: Reconstructed images of a shoe after passing through an SAE with bottleneck dimensionality 10 (a) and 100 (b). The images' original dimensionality was 784.

TABLE I: Classification Accuracies for Different Neural Model/ Classification Systems

Classification Model	Accuracy
Baseline CNN	0.90
SVM 100D	0.86
SVM 75D	0.85
SVM 50D	0.84
SVM 25D	0.81
SVM 10D	0.76

TABLE II: Classification Accuracies for Different XEnt Kernel Bandwidths

Bottleneck Size	Bandwidth	Accuracy
Baseline CNN	0.90	
SVM 100D	0.86	
SVM 75D	0.85	
SVM 50D	0.84	
SVM 25D	0.81	
SVM 10D	0.76	

C. Comparison of Cost Functions

D. Comparison of XEnt Kernel Bandwidths

IV. Discussion

In this sections, observations are made on results and insight is given to potential influences.

A. Results

B. Potential Improvements

In

V. Conclusions

Three

Future research endeavors toward this topic include,

Honor Statement

* I confirm that this assignment is my own work, it is not copied from any other person's work (published or unpublished), and has not been previously submitted for assessment either at University of Florida or elsewhere.

References

[1] C. H. McCurley, "Project 1: Manifold learning for fashion-mnist classification with multi-layer perceptrons," 2019.

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[5] K. P. Murphy, *Machine Learning: A Probabilistic Perspective*. The MIT Press, 2012.