Machine Learning Engineer Nanodegree

Capstone Proposal

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Proposal

Domain Background

My project will examine the MNIST database of handwritten digits. This is a very well known dataset having attracted a great deal of academic attention since its inception. More broadly, the analyis of automated handwriting recognition has applications for fields where it is important to quickly and securely process handwritten documents at scale. For instance, this can be useful in processing historical documents, input to handheld devices via a stylus or pen, or determining authorship of incriminating documents.

Over the years, it has proved fruitful territory for examining a range of machine learning classifiers, such as linear classifiers, svm, k-nearest neighbours, and a range of neural network implementations. There have therefore been a number of different approaches shown to be suitable to classify the dataset correctly. A paper by Hartwick is particularly relevant for this projet as he has provided a clear analysis of the dataset without any further preprocessing with an SVM classifier. For these reasons, I will focus on this paper later on in this proposal.

Problem Statement

The capstone should attempt to train and tune a classifier that is able to correctly determine the number intended from the supplied image of a handwritten sample. The model produced will be trained, tested and validated against the supplied dataset. The success of the classifier will be measured using the Scikit-Learn metric's module `metrics.recall_score` function, in particular I will focus on the recall ratio, which gives the error rate of the classifier. In this the case the proportion of wrongly classified images.

Datasets and Inputs

The MNIST dataset contatins 70000 samples of handwritten digits, labelled from 0 to 9. These are split into subsamples of 60000 and 10000 for training and testing respectively. The samples themselved contains have been centred and normalised to a grid size of 28-by-28 pixels, with each training entry composed of 784 features, corresponding the greyscale level for each pixel. The MNIST dataset in this case will be the MNIST original dataset obtained via the mldata repository using SciKit-Learn's `datasets.fetch_mldata` method. A sample of the dataset is given below.

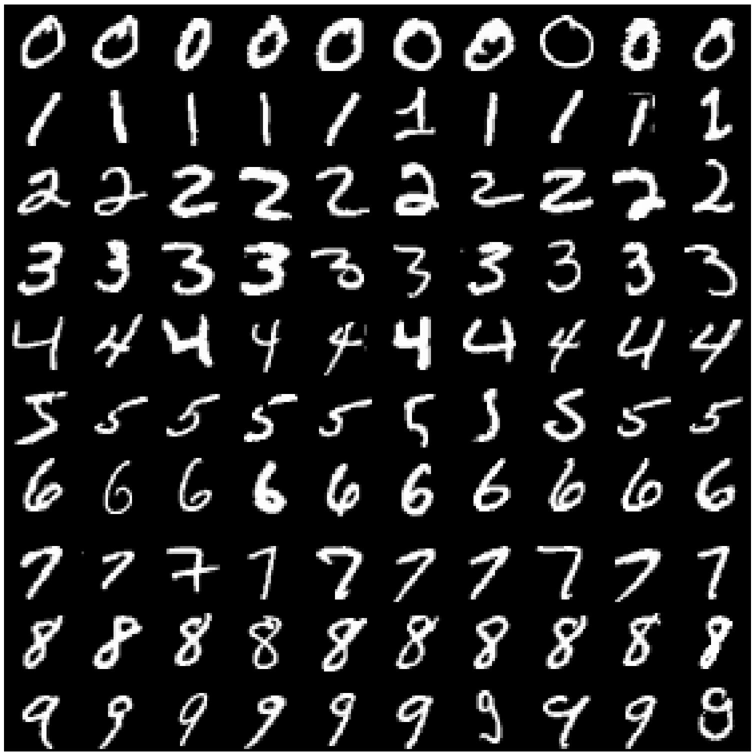

Figure 1: Sample of MNIST Dataset

The class labels in the testing set are roughly uniformly distributed, with the number of occurences of each label ranging from around 6300 and 7900. The distribution is shown graphically below. This distribution of labels means that no special sampling needs to take place to train and test correctly.

On a historical note,this dataset is the result of subsampling the original NIST dataset so that is was overall more consistent, and more suitable for machine learning: mixing together the original training and testing sets. The samples were collected from a combination of American Census Bureau employees and American high school students.

This dataset contains both training and testing samples, so no further data is needed to evaluate the classifier.

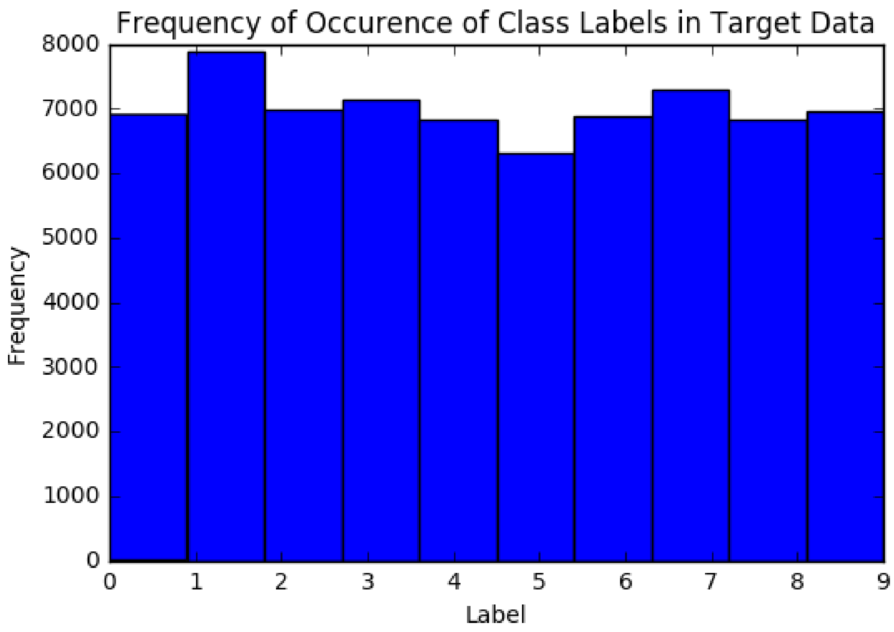

Figure 2: Frequency of Occurence of Class Labels

Solution Statement

suggestion: when you mention something like the following it is often advisable that you provide some citations to back up your claim.

"THERE ARE ALSO A NUMBER OF ACADEMIC STUDIES, MENTIONED ABOVE, THAT HAVE HAD SUCCESS WITH SVM CLASSIFIERS"

suggestion: you should mention the need for image preprocessing here.

I propose using a SVM classifier to train a solution that, with a reasonable level of accuracy, correctly map a handwritten sample to the correct digit. A supervised classifier should be an appropriate solution to the problem as we have training data. There are also a number of academic studies, mentioned above, that have had success with SVM classifiers. The trained classifier can be evaluated using a confusion matrix, and derived metrics such as f1 score, to determine its degree of success. To evaluate the trained model thoroughly, k-fold cross validation will be used to get a representative performance score of the model. Furthermore, we can consider a number of previous models7 of the datasets using a SVM classifier, which have accuracies around 99%.

Benchmark Model

This dataset is very well studied and as such, there are many comparable studies to check against. For the project, I will make direct comparison to the paper referenced above by Hartwick. This paper produces results for a SVM classifier with Guassian kernel, with parameters,

```
C = 10^6
gamma = (1/len(features)) * 10^-3.5 (approx. 4 * 10^-7)
```

The model in this paper achieves a error of around 1.4% against the MNIST testing set. Given all these results and the availability of the identical testing set, a direct comparison with this paper's results is possible.

Evaluation Metrics

The evaluation metric for this model will be the error rate, this is to enable a direct comparison with the benchmark, which calculates this value in the paper. We noted above that the error rate can be derived from the recall rate. A supervised classfier such as SVM has known labelled data, so we can determine the number of true positives, false positives, and false negatives these are ultimately derived from the confusion matrix. To be clear, these terms are defined as follows:

- True positives: Entries that are correctly labelled
- False positives: Entries that a wrongly identified with a given label
- False negatives: Entries for a given label that are wrongly identified with other labels

In the general case, a confusion matrix is simply a matrix illustrating the mapping from the true labels to the predicted labels. Elements along the diagonal represent a correct classification, whereas the off-diagonal represent a misclassification. In general, a confusion matrix can be a useful check to see what digits in particular are most likely confused for one another. From here we can derive both the recall and precision.

Precision is the result of the number of true positives divided by the sum of true positives and false negatives. This can be given by the following equation,

```
precision = tp / (tp + fp)
```

where tp and fp stand for true positive and false positive respectively.

Recall is the result of dividing the true positives by the sum of true positives with false negatives. This can be given as follows,

```
recall = tp / (tp + fn)
```

where tp and fn stand for true positive and false negative respectively. From this, the error rate or rate at which the classifier wrongly classifies the samples can be derived,

```
error rate = 1 - (tp / (tp + fn)) = fn / (tp + fn)
```

which is is also known as the false negative rate. The error rate per digit could be derived similarly, but on a digit-by-digit basis, as given by the confusion matrix above.

These metrics altogether will give us a means to determine how well the classifier correctly labels the digits as well the error rate per digit.The error rate as well as all the other metrics discussed in this section will be calculated using the SciKit-Learn `metrics.classification_report` and `metrics.confusion_matrix` methods.

Project Design

required: the following is not a valid justification

"SECONDLY, TO FORM A MEANINGFUL COMPARISON WITH THE BENCHMARK STUDY, WE WANT A COMPARATIVE DATASET TO BEGIN WITH AND IN THIS CASE THE PARTICULAR STUDY PERFORMED NO PREPROCESSING EITHER."

You will lose a lot of learning opportunities by not trying to preprocess the data, remember that you are using SVM and not a CNN (which can do pretty well without further preprocessing), so it would make more sense to do some preprocessing (such as feature extraction from MNIST). Take a look on these works:

- Feature Extraction of Handwritten Characters Using Supervised and Unsupervised Independent Component Analysis by OZAWA, SAKAGUCHI and KOTANI
- Simple Method for High-Performance Digit Recognition Based on Sparse Coding by Lausch, Barth and Martinetz
- Also, you can try several simple methods available from SKLearn directly, such as PCA. Also, scikit-image has lots of interesting algorithms already implemented.

This project will follow a typical machine workflow, starting from the dataset acquisition, then the model generation, and then an evaluation and optimisation process. There will be no preprocessing applied to the dataset for the two reasons. The first is that this dataset is already in a form understandable to SciKit-Learn, as it will be downloaded using SciKit-Learn `fetch_mldata` method. Secondly, to form a meaningful comparison with the benchmark study, we want a comparative dataset to begin with and in this case the particular study performed no preprocessing either. Feature engineering will not be used either as the dataset is not permitting of additional feature analysis - the features are just a pixel-by-pixel greyscale score.

Due to the previous success of such classifiers and the wealth of related former studies, this project will use a SVM classifier. To both optimise and evaluate the classifier a test-training split will be done on both the training lables and test labels. I would like to recover some of the same results as the benchmark study i.e. SVM with Guassian kernel, as well as another kernel for comparison. Using the training and testing data, I will use grid search cross-validation during the optimisation step. Discussed at greater length above, I will use the error rate or false negative rate to both determine the accuracy of the derived models and make a direct comparison with the benchmark study.

References

1 http://yann.lecun.com/exdb/publis/pdf/lecun-98.pdf "Gradient-Based Learning Applied to Document Recognition"

2 https://people.eecs.berkeley.edu/~malik/cs294/decoste-scholkopf.pdf "Training Invariant Support Vector Machines"

3 http://citeseerx.ist.psu.edu/viewdoc/download;jsessionid=E0F3BDC7642FBA1D8E2811526BD0E596?doi=10. "Deformation Models for Image Recognition"

4 https://www.microsoft.com/en-us/research/publication/best-practices-for-convolutional-neural-networks-applied-to-visual-document-analysis/ "Best Practices for Convolutional Neural Networks Applied to Visual Document Analysis"

5 https://cseweb.ucsd.edu/~jmcauley/cse190/reports/fa15/025.pdf "Reproducing Results of Guassian Kernel SVM classifers on the MNIST Dataset"

6 http://mldata.org/repository/data/viewslug/mnist-original/ "MNIST (original)"

7 http://yann.lecun.com/exdb/mnist/ "The MNIST Database of Handwritten Digits"

8 http://softclassval.r-forge.r-project.org/2013/2013-01-03-ChemomIntellLabSystTheorypaper.html "Validation of Soft Classification Models using Partial Class Memberships: An Extended Concept of Sensitivity & Co. applied to Grading of Astrocytoma Tissues"