Project 2 Report: Machine Learning on handwritten digits

Executive Summary

Introduction

Machine Learning is a method of data analysis which automates analytical model building. It is a category algorithm that can predict outcomes without being explicitly programmed. Machine learning algorithms may even be more efficient than a person on the same task. Even though a machine learning algorithm may not be perfect, a person can also make human error, which concludes that a machine learning doing some some errors might be acceptable having time and resource in mind.

Target Audience

Using machine learning in a postal office may be very beneficial. It faster and less time consuming and does not require much resources as it exist API, libraries and data to implement such algorithm. The only time consuming is implementing the algorithm but will be rewarded.

Risk/Opportunity

The risk with using machine learning is that it may do some errors, for example recognizing a digit wrong. This is also possible to do as a human. If the machine learning algorithm is well trained and even continuously training, the algorithm might never predict wrong.

Other opportunities that comes with such algorithm is it possible to extend it to do some other task, e.g., recognizing name and address. If the postal office has such database, the algorithm can recognize name and address, lookup in the database and forward the post/package more easily.

Conclusion

Use of machine learning algorithm is beneficial for time and resource, because can perform much faster than a human would on the same task, in this case recognizing handwritten digits. It might make some mistakes, but if it learns from it mistakes, the algorithm can perform even better next time. The system can also be extended to do some other task that is suitable for machine learning, e.g., name and address lookup.

Technical report

Introduction

This report contains observations and explanations on three different types of classification algorithms to recognizes different handwritten digits, and the goal is to classify handwritten digits correctly based on the training that is done for each classifier.

The code used for this report uses data from MNIST containing handwritten digits. The data is split into a training set and a test set. The training set is used to train the algorithms. This is necessary process as they will be able to predict a handwritten digit to an actual digit. At the end of the training, the algorithms are going to predict handwritten digits in the test data. This confirms the learning process of the algorithms to see if the algorithms are doing what it is supposed to do. In the middle of the process we also use validation to find the best model, which then gives us the best accuracy.

Preprocessing steps

The steps needed to start the project was to install the necessary program, in this case, Python. Necessary libraries and imports must also be installed to use the machine learning algorithms and other features.

```
import numpy as np
import random as rn
import tensorflow as tf
from sklearn.model_selection import ParameterGrid, GridSearchCV
from sklearn.svm import SVC
import matplotlib.pyplot as plt
import seaborn as sns

# Classifiers
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB, MultinomialNB, BernoulliNB

# Tools for measure performance
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
import time

# Functions from local files
from readhandwrittendigits import readhandwrittendigits
from neuralnet import neural_network_training
```

Figure 1 Some necessary imports

The data used is downloaded from MittUiB, which is from the MNIST database. The data contains 70,000 examples. The data is split into training and test with sklearn 'training_and_test_split()'.

The handwritten files are saved in a folder 'data' and are accessed by python file 'readhandwrittendigits.py'.
The python file uses relative path to access the data which is to avoid use of absolute path. This is achieved by using 'os.path' and having 'data' in the same folder as the python file.

```
7  def readhandwrittendigits():
8      image_path = os.path.join(os.path.dirname(__file__), "data/handwritten_digits_images.csv")
9      labels_path = os.path.join(os.path.dirname(__file__) ,"data/handwritten_digits_labels.csv")
```

Figure 2 Relative path of the files

A Python version 3.6 (specific 3.6.5) was installed instead of the newest version 3.7, because the version 3.7 were not compatible with the library tensorflow which is used to run neural network algorithm from keras.

Candidate algorithms and choice of candidate

In this project, the chosen classifications are Naive Bayes, Random Forest and Neural Network. Each of these classifications are very different from each other and where picked based on their advantages.

Naive Bayes

Naive Bayes is more lightweight which means it is quicker and faster than the other two classifiers. It is quicker because it requires less model training time relative to the two other algorithms and performs well when we have multiple classes and are working with text classification. Naive Bayes also converges quicker if the conditional independence holds, resulting in less training data needed.

Naive Bayes also doesn't need hyperparameters because it doesn't need lot of data to perform well. It only needs enough data to understand the probabilistic relationship of each attribute with the output variable.

There are different types of Naive Bayes models that uses different formulas to calculate the likelihood, and since Naive Bayes are fast the program uses three types of Naive Bayes algorithms: Gaussian, Multinomial and Bernoulli.

Gaussian Naïve Bayes

Gaussian is the easiest algorithm to work with because you only need to estimate the mean and the standard deviation from the given training data.

The formula used in Gaussian Naive Bayes to find the likelihood of the features:

$$P(x_i \mid y) = \frac{1}{\sqrt{2\pi\sigma_y^2}} \exp\left(-\frac{(x_i - \mu_y)^2}{2\sigma_y^2}\right)$$

Multinomial Naive Bayes

Multinomial Naive Bayes are used in text classification and estimate each parameter with a smoothed version of maximum likelihood:

$$\hat{\theta}_{yi} = \frac{N_{yi} + \alpha}{N_y + \alpha n}$$

Bernoulli Naive Bayes

There may be multiple features but each one is assumed to be binary-valued variable, according to Bernoulli Boolean. Therefore, the algorithm requires samples to be represented as binary-valued features vectors, which is handled by the BernoulliNB classifier.

The decision rule for this classifier is based on:

$$P(x_i \mid y) = P(i \mid y)x_i + (1 - P(i \mid y))(1 - x_i)$$

Random Forest

Random Forest is a flexible algorithm. It doesn't require much hyperparameter tuning to output a good result. By the name, the Random Forest is essentially a collection of Decision Trees and was therefore chosen instead of Decision Tree (see more about Decision Tree under). The Random Forest is a form for Bagging method, because the algorithm takes *n* Decision Trees and trains each of them separately. At the end, the algorithm then takes the average of the predictions to get a result. With Random Forest there is less chance for overfitting, because bagging reduces variance which helps to avoid overfitting.

Neural Network

Neural network is a machine learning algorithm used to model complex patterns in datasets using layers such as input, hidden and output layers and activation functions. Each layer has many neurons where the neurons are use for feature-detecting. If we have enough number of layers and neurons, the network can perform very well as image recognition. The training in neuron network uses labeled dataset of inputs that are tagged with their intended output response. In each layer, the data is calculated with a weight and an activation function.

Neural networks are good model with images and is reliable for tasks involving many features because of the splitting it does to layered network.

Neural network will perform better when given a large dataset, making it more accurate when predicting data, and once a network is trained, it can predict data very fast.

Other classifications

Support Vector Machine

There are other classifications that were considered, like Support Vector Machine and Decision Tree Classifier. The SVM is are great machine learning algorithm for image recognition. SVM is fast and accurate with a small dataset and few classifications, but performs poorly when given a large dataset. SVM are also poor for multiclass classification which we have in our case with ten classifiers.

My observation with SVM is that it took too long time to finish with the given dataset. It never finished training the model and therefore was not chosen as my candidate.

Decision Tree Classifier

Decision Trees are easy to interpret and visualize and can handle both numerical and categorical data. Decisions Trees can also perform well on large datasets while being fast. With that said, Decision Trees tend to overfit, especially when the data is large because the tree may become very deep. That is why Random Forest was chosen over Decision Tree, because Random Forest reduces the chance for overfitting.

Choice of hyperparameters

The choice of hyperparameters was a bit of random. In Random Forest Classification, '*n_estimators'* and '*max_features*' are the hyperparameters in this algorithm. Started with these parameters because they had a big impact on the accuracy and have only used these parameters so far in the project. The values for these parameters are ascending, starting with a low value to a high value.

The same thing is done for Neural Network, where the hyperparameters for this is '*epoch*' and '*batch_size'*. Number of inputs and activation function was also random selected. It is difficult to find the optimal values for Neural Network but came to a solution which gave the best accuracy with help from Google and other students.

No hyperparameters were chosen for Naive Bayes classifiers. The advantage with Naive Bayes is it does not require hyperparameters to perform well.

Conclusion

The three candidates for this project are Naive Bayes, Random Forrest and Neural Network. Naive Bayes was picked as a candidate, because it is fast and doesn't need to build a new model each time it receives new data. Since the Naive Bayes is fast, we allow to try out three different types of Naive Bayes Classes; Gaussian, Multinomial and Bernoulli.

While Decision Tree being a powerful classification, Random Forrest was picked as a candidate because it uses bagging method to reduce the chance for overfitting.

Neural network can become very accurate when given lot of training data and are also easy to experiment with (layers, neurons and activation function).

All three classifiers work very well with large datasets, which useful for this task.

Model selection schemes

The models from each classifier was created with sklearn's libraries, and each classifier has method .fit() which is used to train the models on the training set. The models are then given a testset it is going to predict on. The result we are interested in is how well they are predicting.
It is difficult to determine the best classifier based on a single run and nothing more. That is why the program uses GridSearchCrossValidation to run each model several times. It is running several times because the program test different values of hyperparameters. In other words, the Grid Search Cross Validation creates several new models with different hyperparameter values, use the model to predict on the test size, and output an accuracy score.

```
54  def gridSearchRandomForest(clf, X_train, X_test, y_train, y_test):
55      grid = [{
56          "n_estimators": [150, 300, 400, 500, 700],
57          "max_features": [25, 35, 45, 55, 70]
58      }]
```

Figure 3 Grid Search for Random Forest

For RandomForestClassifier, the hyperparameters *n_estimators* and *max_features* are given different values, in this case [150, 300, 400, 500, 700] and [25, 35, 45, 55, 70] respectively.

The observation concludes that the best parameter for *n_estimator* is 400 and for *max_features* is 45. These parameters for Random Forest Classifier give the highest accuracy.

```
65  def gridSearchNeuralNetwork(clf, X_train, X_test, y_train, y_test):
66      grid = [{
67          "epochs": [5, 10, 15, 20, 25],
68          "batch_size": [500, 750, 1000, 1250, 1500]
69      }]
```

Figure 4 Grid Seach for Neural Network

For Neural Network Classifier, *epochs* and *batch_size* are given [5, 10, 15, 20, 25] and [500, 750, 1000, 1250, 1500] respectively.
When running these parameter values, the GridSearchCV gives 20 for *epochs* and 1500 for *batch_size*.

How many layers, inputs and what activation function to use was more of trial-and-error, because it is difficult to find the optimal features for Neural Network. But trying different number of hidden layers and activation function gave more or less the same accuracy.

GirdSearchCV is not ran each time the program starts. It is run only when we are interested in finding the best model.

After finding the best value for the hyperparameters, the models are set to have these values when execution the program.

Performance measure

The performance of these chosen algorithms was based on time, accuracy, recall and specificity.
For each model, we train the classification model with .fit() on dataset X containing the handwritten images and dataset y containing the classifier. Afterward, we use .predict() on the testset X to get the predicted digits. At the end, we calculate the accuracy score by seeing how many predicted digits from .predict() were predicted correctly with regard to the testset y.

Each algorithm produces a classification report which contains different metrics, e.g., precision and recall.
Precision is the accuracy of positive predictions while recall is the fraction of positives that were correctly identified, while recall is a measure of how truly relevant results are returned.

In other words, we want high accuracy and high recall, because high precision relates to a low false positive rate, and high recall relates to a low false negative rate.

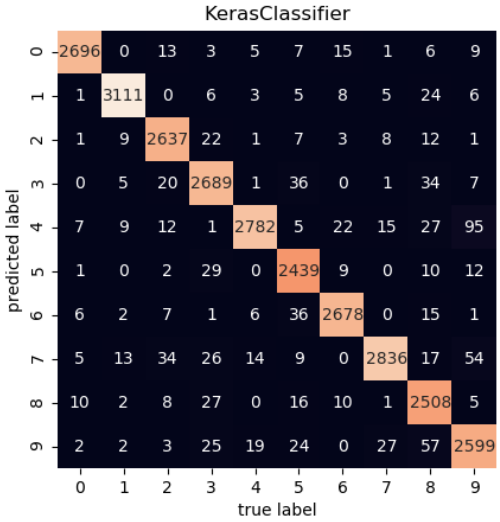
Performance from each classifier

Neural Network

```
Time KerasClassifier : 616.1103143692 seconds
Accuracy: 0.9634
              precision    recall  f1-score   support

           0       0.98      0.99      0.98      2729
           1       0.98      0.99      0.98      3153
           2       0.98      0.96      0.97      2736
           3       0.96      0.95      0.96      2829
           4       0.94      0.98      0.96      2831
           5       0.97      0.94      0.96      2584
           6       0.97      0.98      0.97      2745
           7       0.94      0.98      0.96      2894
           8       0.97      0.93      0.95      2710
           9       0.94      0.93      0.94      2789

   micro avg       0.96      0.96      0.96     28000
   macro avg       0.96      0.96      0.96     28000
weighted avg       0.96      0.96      0.96     28000
```



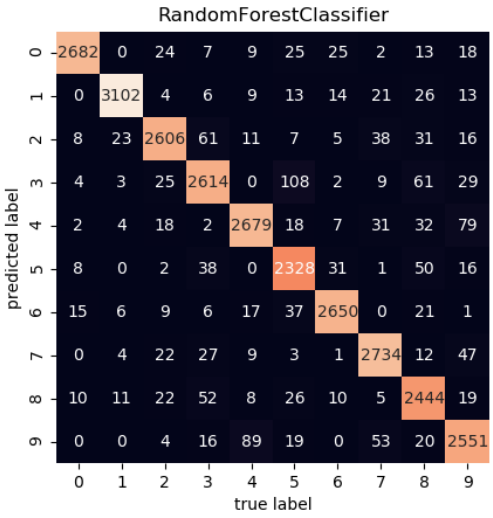
Running the Neural Network classifier takes approximately 10 minutes. It takes a long time to train, but the tradeoff is that the algorithm gets a high accuracy, which is around 96%. We can see on the confusion matrix that this accuracy is true, because it almost got all prediction right. Some noticeable observation is that it predicted ‘4’ as ‘9’ 95 times. ‘9’ and ‘4’ is very similar in handwriting, and that it got only 95 wrong is very good. Giving the Neural Network more training, we can get near perfect with the prediction.

Random Forest

```
Time RandomForestClassifier : 163.2274158001 seconds
Accuracy: 0.9606
              precision    recall  f1-score   support

           0       0.96      0.99      0.97      2729
           1       0.97      0.99      0.98      3153
           2       0.94      0.97      0.95      2736
           3       0.97      0.94      0.95      2829
           4       0.96      0.96      0.96      2831
           5       0.95      0.95      0.95      2584
           6       0.97      0.97      0.97      2745
           7       0.97      0.96      0.97      2894
           8       0.95      0.95      0.95      2710
           9       0.95      0.94      0.95      2789

   micro avg       0.96      0.96      0.96     28000
   macro avg       0.96      0.96      0.96     28000
weighted avg       0.96      0.96      0.96     28000
```



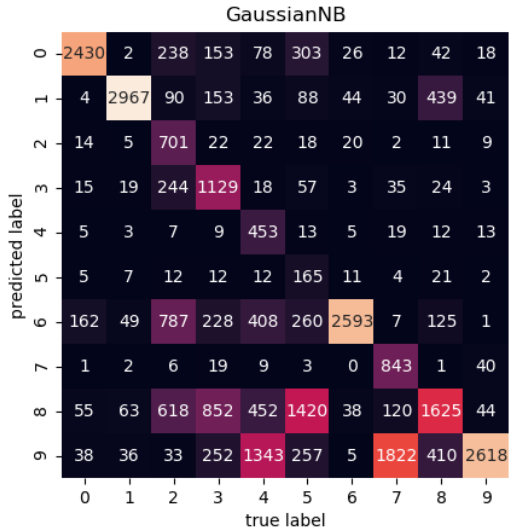
The Random Forest classifier is also very good, almost same accuracy as Neural Network. The same case applies for Random Forest where it also predicts ‘4’ and ‘9’ wrong, but it also predicts ‘8’ as ‘3’ and vice versa. Despite having lower accuracy than Neural Network, it is much faster than the former classifier. It only takes 167 seconds to train the classifier with 96% in accuracy as result.

Naive Bayes

```
Time GaussianNB : 5.5231282711 seconds
Accuracy: 0.5544
              precision    recall  f1-score   support

           0       0.74      0.89      0.81      2729
           1       0.76      0.94      0.84      3153
           2       0.85      0.26      0.39      2736
           3       0.73      0.40      0.52      2829
           4       0.84      0.16      0.27      2831
           5       0.66      0.06      0.12      2584
           6       0.56      0.94      0.70      2745
           7       0.91      0.29      0.44      2894
           8       0.31      0.60      0.41      2710
           9       0.38      0.94      0.55      2789

   micro avg       0.55      0.55      0.55     28000
   macro avg       0.67      0.55      0.50     28000
weighted avg       0.68      0.55      0.51     28000
```

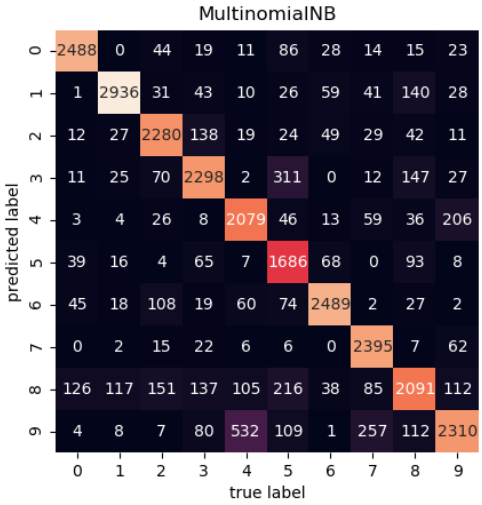


The Gaussian Naive Bayes is not good at all as a classifier for this dataset based on the observation. The precisions for ‘8’ and ‘9’ are very low, which means the classifier predicted these digits almost wrong all the time.

```
Time MultinomialNB : 0.3802218437 seconds
Accuracy: 0.8233
              precision    recall  f1-score   support

           0       0.91      0.91      0.91      2729
           1       0.89      0.93      0.91      3153
           2       0.87      0.83      0.85      2736
           3       0.79      0.81      0.80      2829
           4       0.84      0.73      0.78      2831
           5       0.85      0.65      0.74      2584
           6       0.88      0.91      0.89      2745
           7       0.95      0.83      0.89      2894
           8       0.66      0.77      0.71      2710
           9       0.68      0.83      0.74      2789

   micro avg       0.82      0.82      0.82     28000
   macro avg       0.83      0.82      0.82     28000
weighted avg       0.83      0.82      0.82     28000
```

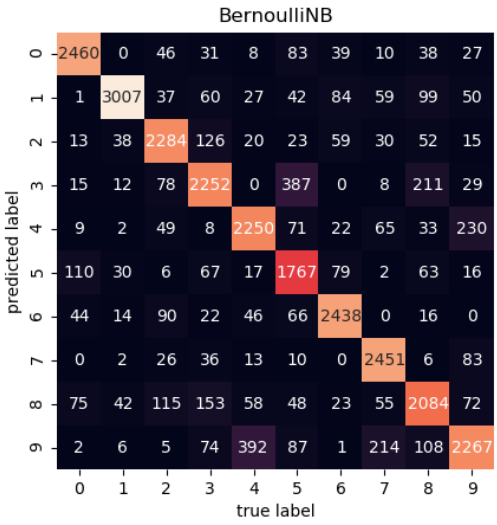


The Multinomial Naive Bayes classifier is much better than the previous one, also it much faster with only 0.3 seconds. Getting an accuracy on 82% is very good for having only 0.3 seconds of training.

```
Time BernoulliNB : 1.3539500237 seconds
Accuracy: 0.8307
              precision    recall  f1-score   support

           0       0.90      0.90      0.90      2729
           1       0.87      0.95      0.91      3153
           2       0.86      0.83      0.85      2736
           3       0.75      0.80      0.77      2829
           4       0.82      0.79      0.81      2831
           5       0.82      0.68      0.75      2584
           6       0.89      0.89      0.89      2745
           7       0.93      0.85      0.89      2894
           8       0.76      0.77      0.77      2710
           9       0.72      0.81      0.76      2789

   micro avg       0.83      0.83      0.83     28000
   macro avg       0.83      0.83      0.83     28000
weighted avg       0.83      0.83      0.83     28000
```



Bernouilli Naive Bayes is almost similar as Multinomial in accuracy and time. It takes a little bit more time, but the accuracy is the same.

Conclusion

From the confusion matrix, we can see some digits get predicted wrong in all classifiers, specifics ‘3’ for ‘8’, and ‘4’ for ‘9’ and vice versa for both. This is because the digits are very similar in written form, and having the classifiers predicting wrong is understandable.

The prediction made by these classifiers is overall very good. Naive Bayes classifiers have lower accuracy than Neural Network and Random Forest, but their running time is incredible fast, with some of them having under six seconds and even one. The two Naive Bayes classifier are very good, and with hyperparameter tuning, they might get even better score overall, but this observation was made without having hyperparameters on the Naive Bayes classifiers.

Random Forest and Neural Network are very similar in accuracy, and the confusion matrixes are almost the same. The only thing that is different is the training time. Random Forest is much faster than Neural Network, and if time and resource are important factors for deciding a classifier, Random Forest would have been chosen. Since time and resource was available for this project, the Neural Network was chosen over Random Forest. In practical, the Neural Network would be more beneficial because it doesn't need to build the learning process all over again with new data, versus the Random Forest which need to create new Decision Trees again when receiving new data.

Final classifier

The deciding classifier for this project was Neural Network. The reason for this classifier is that it got the highest accuracy of the candidates despite having the longest training time in training.
All three Naive Bayes Classifiers did not perform very well. This may be because the classifiers make a strong assumption on the shape of the data distribution. The result can be potentially very bad, therefore "naive" classifier.
While Random Forest Classifier got relatively high accuracy, even sometimes more than Neural Network given some specific hyperparameters, it is easier to use Neural Network. When more training data is observed, the Random Forest must build a new model from scratch versus Neural Network doesn't need to do this. Since we aim to use our machine learning algorithm on a real-life task, Neural Network has an advantage here over Random Forest.

Expected performance in production

Neural Network is expected to perform well in production. The reason for this is the accuracy it got from the training and testset was relatively high, or at least enough to be used in real life tasks.
An advantage with Neural Network is the more training data it gets, the more accurate it becomes. If there comes any new data, the Neural Network doesn't

need to be built again from the scratch, but rather building on the existing training.
Even though the classifier did not get 100% accuracy, which is ideal, a 97% accuracy is good enough. This means that it has 3% chance of predicting wrong, but we must also take human error in consideration for a task such as recognizing handwritten digits. If we allow human error, then we must also allow the machine learning algorithm to do at least 3% of the prediction wrong.

Improvement

With more time and/or computing resources, the neural network classifier will be more accurate if the number of epochs and the size of batch are increased. The computing time will get affected heavily, but the accuracy will at least increase which is a trade we can afford. If we are satisfied with 97% accuracy, the machine learning algorithm may become more efficient than a human doing the same job, with more time and resources.