**Datasets**

The datasets are downloaded from the link <https://archive.ics.uci.edu/ml/index.php> which was posted by a student in Ed. The two datasets chosen are Car Evaluation and Adult. The car evaluation dataset was chosen as it was interesting to see the effects of the various parameters across the general population. However, the data size was a little unsatisfactory. The adult dataset was chosen to look at the impact of race and sex on income earned for the same occupation. This dataset also had a relatively large number of records to play around with. For both datasets, the features were limited to be able to run effective experiments.

1. Car Evaluation [1]

The dataset is derived from a simple hierarchical decision model originally developed for the demonstration of DEX, M. Bohanec, V. Rajkovic: Expert system for decision making. Sistemica 1(1), pp. 145-157, 1990.).

This dataset will be referred to as dataset 1.

1. Adult [1]

The dataset extraction was done by Barry Becker from the 1994 Census database. A set of reasonably clean records was extracted using the following conditions: ((AAGE>16) && (AGI>100) && (AFNLWGT>1)&& (HRSWK>0)).

This dataset will be referred to as dataset 2.

Dataset 1 does not have as good results in the experiments as dataset 2 due to the lesser source data available for processing.

**Decision Tree**

The following links were used as references to code for the decision tree model:

1. <https://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeClassifier.html>
2. <https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.learning_curve.html>
3. <https://scikit-learn.org/stable/auto_examples/model_selection/plot_learning_curve.html>
4. <https://www.projectpro.io/recipes/plot-learning-curve-in-python>
5. <https://www.dataquest.io/blog/learning-curves-machine-learning/>
6. <https://ai.plainenglish.io/hyperparameter-tuning-of-decision-tree-classifier-using-gridsearchcv-2a6ebcaffeda>
7. <https://towardsdatascience.com/how-to-find-decision-tree-depth-via-cross-validation-2bf143f0f3d6>

As the training sample increases, there is marked improvement in the accuracy of the model and a reduction in bias. This is captured in the graphs depicting the Learning Curves of the decision tree model. This corresponds to a lower mean squared error as captured in the middle two graphs with MSE in the y-axis. The impact of overfitting along with the quality of split by adding gini (gini impurity) and entropy (information gain) as the hyper parameter in the decision tree is captured in the Validation Curves.

1. For dataset 1, the best two parameters are max depth of 7 and entropy as the criterion.
2. For dataset 2, the best two parameters are max depth of 7 and gini as the criterion.
3. For tree depth < 7, the model underfits.
4. Tree depth > 7 it starts to overfit. The training accuracy increases a lot for greater tree depths.

**Dataset 2 Dataset 1**

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**AdaBoost**

The following links were used as references to code for the adaboost implementation:

1. <https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.AdaBoostClassifier.html>
2. <https://www.datacamp.com/community/tutorials/adaboost-classifier-python>

As the training sample increases, the accuracy of the training set decreases and that of the validation set increases along with a reduction in bias. Gradually, they converge. This is captured in the graphs depicting the Learning Curves of the decision tree model after being boosted via the Adaboost classifier. This corresponds to the lower mean squared error in validation and increasing mean squared error in training as captured in the middle two graphs with MSE in the y-axis.

The two parameters with respect to hyper tuning the model considered here are the number of estimators and the learning rate. The number of estimators determines the number of weak learners and the learning rate determines the contribution of each classifier. The base estimator is defaulted to the decision tree.

As the number of estimators increase, the model is prone to overfitting. This can be seen in the validation curve of dataset 1. It is interesting to note that in dataset 2, the accuracy starts to drop at estimators around 130. The graph does not reflect that of dataset 1 and am unable to plot the downward trend of accuracy for even higher number of estimators similar to dataset 1.

1. For dataset 1, the best two parameters are learning rate = 0.25 and number of estimators = 11.
2. For dataset 2, the best two parameters are learning rate = 1.5 and number of estimators = 128.

**Dataset 2 Dataset 1**

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**Neural Network**

The following links were used as references to code for the neural network MLP model:

1. <https://scikit-learn.org/stable/modules/generated/sklearn.neural_network.MLPClassifier.html>
2. <https://www.tensorflow.org/api_docs/python/tf/keras/wrappers/scikit_learn>
3. <https://www.kaggle.com/residentmario/using-keras-models-with-scikit-learn-pipelines>
4. <https://machinelearningmastery.com/grid-search-hyperparameters-deep-learning-models-python-keras/>
5. <https://machinelearningmastery.com/display-deep-learning-model-training-history-in-keras/>

The MLP model is defined using the Keras wrapper for scikit learn. The number of input layers is set to the number of data points. The hidden layer size is defaulted to 100. The input and hidden layers are defaulted with relu activation and the output layer is defaulted to sigmoid activation. The output units are also set to 1.

The accuracy of the validation set increases as the training sample increases. As the epoch increases, the losses are reduced for the training set. However, for the validation set, the loss decreases and then increases. This is captured in the graphs depicting the Loss Curves of the MLP model. The impact of increase in epochs vs accuracy is captured in the Validation Curve plots.

1. For dataset 1, the best two parameters are epochs = 20 and batch size = 80.
2. For dataset 2, the best two parameters are epochs = 30 and batch size = 100.

**Dataset 2 Dataset 1**

Chart

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Chart

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Description automatically generated with low confidenceChart, scatter chart

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**KNN**

The following links were used as references to implement the KNN model:

1. <https://scikit-learn.org/stable/modules/generated/sklearn.neighbors.KNeighborsClassifier.html>
2. <https://www.datacamp.com/community/tutorials/k-nearest-neighbor-classification-scikit-learn>

As the training sample increases, the accuracy score increases. This is shown in the Learning curves of both datasets. The means squared error reduces as well as the training sample increases and is shown in the middle two plots. The effect of increasing k is shown in the validation curves. The grid search function returned the best k as 1 for dataset 1 which doesn’t seem to be right as it indicates overfitting.

1. For dataset 1, the best two hyper parameters are k = 1 and p =
2. For dataset 2, the best two hyper parameters are k = 16 and p =

**Dataset 2 Dataset 1**

**Chart

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**Chart

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**SVM**

The following links were used as references to implement SVM model:

1. <https://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.html>
2. <https://www.datacamp.com/community/tutorials/svm-classification-scikit-learn-python>

**Kernel = Linear**

As the training sample increases, there is marked improvement in the accuracy of the model and a reduction in bias for dataset 1. For dataset 2, the accuracy score is the almost the same for both the training and validation set and seems to be all over the place. This is captured in the graphs depicting the Learning Curves of the decision tree model. This corresponds to a lower mean squared error as captured in the middle two graphs with MSE in the y-axis.

There are two validation curves for dataset 2. One with a max iteration of 5000 and another with a max iteration as derived using Grid Search. To generate the 5000 plot, the value of iter will need to be set manually in the runCurves function in SVMLinera.py

1. For dataset 1, the best two parameters are max iteration = 1000 and C = 0.75.
2. For dataset 2, the best two parameters are max iteration = 10 and C = 0.25.
3. For both datasets, the best class weight option is balanced.

**Dataset 2 Dataset 1**

Chart, line chart

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**Kernel = rbf**

**Model Evaluation**

Below are the accuracy scores for the experiments. From the results, for the features and hyperparameter chosen, decision tree does well on dataset 1 and AdaBoost gives the best results for dataset 2.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Dataset 1** |  |  |  |  |
| **Model** | **Accuracy Score Without Hypertuning** | | **Accuracy Score With Hypertuning** | |
| **In Sample** | **Out Sample** | **In Sample** | **Out Sample** |
| Decision Tree | 0.808105873 | 0.76300578 | 0.799007444 | 0.784200385 |
| AdaBoost | 0.277915633 | 0.298651252 | 0.711331679 | 0.701348748 |
| KNN |  |  |  |  |
| Neural Network - MLP | 0.730355666 | 0.736030829 | 0.730355666 | 0.741811175 |
| SVM - Linear | 0.713813069 | 0.697495183 | 0.744416873 | 0.753371869 |
| SVM - rbf |  |  |  |  |
|  |  |  |  |  |
| **Dataset 2** |  |  |  |  |
| **Model** | **Accuracy Score Without Hypertuning** | | **Accuracy Score With Hypertuning** | |
| **In Sample** | **Out Sample** | **In Sample** | **Out Sample** |
| Decision Tree | 0.901325026 | 0.820247722 | 0.842664093 | 0.83437404 |
| AdaBoost | 0.83950509 | 0.838878084 | 0.847139347 | 0.844917596 |
| KNN |  |  |  |  |
| Neural Network - MLP | 0.795015795 | 0.753813082 | 0.781370656 | 0.779916061 |
| SVM - Linear | 0.231002106 | 0.234210257 | 0.35499298 | 0.349472822 |
| SVM - rbf |  |  |  |  |

**References**

1. Dua, D. and Graff, C. (2019). UCI Machine Learning Repository [http://archive.ics.uci.edu/ml]. Irvine, CA: University of California, School of Information and Computer Science.