FYS-STK3155/4155 Applied Data Analysis and Machine Learning - Project 3

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`https://github.com/liseanh/FYS-STK4155-project3`

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Abstract

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1 Introduction

In popular culture the neural network is probably the most well known form of machine learning. In recent years many other statistical learning methods have proven themselves as well however. In this project we compare the performance of neural networks and gradient boosting in the case of binary classification. In addition to these, we also use the much simpler k-nearest neighbours method as a baseline for classification performance.

2 Data

The data set we will analyse in this project is the MAGIC Gamma Telescope data set retrieved from the UCI Machine Learning Repository, which was generated by a Monte Carlo (MC) program described by D. Heck et. al. [4] to simulate high energy gamma particle registration in a Cherenkov gamma telescope. The set consists of ten explanatory variables and a binary response variable `class` which specifies whether the measured photons resulted from a gamma particle (`class = g`) or a hadron (`class = h`). The entire data set consists of 19020 instances with no missing values, with outcome distribution as shown in Figure 1. The explanatory and response variables are defined as the following by the UCI Machine Learning Repository [2]:

1. `fLength`: continuous # major axis of ellipse [mm]
2. `fWidth`: continuous # minor axis of ellipse [mm]
3. `fSize`: continuous # 10-log of sum of content of all pixels [in #phot]
4. `fConc`: continuous # ratio of sum of two highest pixels over `fSize` [ratio]
5. `fConc1`: continuous # ratio of highest pixel over `fSize` [ratio]
6. `fAsym`: continuous # distance from highest pixel to center, projected onto major axis [mm]
7. `fM3Long`: continuous # 3rd root of third moment along major axis [mm]
8. `fM3Trans`: continuous # 3rd root of third moment along minor axis [mm]
9. `fAlpha`: continuous # angle of major axis with vector to origin [deg]
10. `fDist`: continuous # distance from origin

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to center of ellipse [mm]

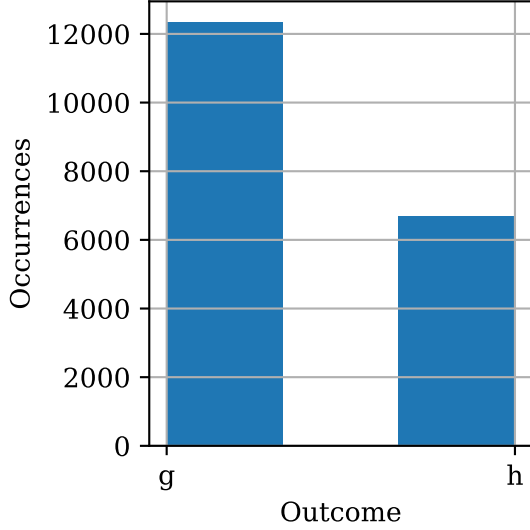11. `class:` g, h # gamma (signal), hadron (background)

Figure 1: Frequencies of the outcomes g and h in the data set. The numbers of instances for the categories were 12332 and 6688 for g and h respectively.

Preprocessing

To preprocess the data, we first split the data into a training set and a test set, with 2/3 of the total data set as training data and the remaining 1/3 as the test set, keeping the proportion of the two outcomes approximately equal. All the explanatory features are continuous, so each feature was centered by subtracting the mean of its values and scaled with respect to its standard deviation. The scaling and centering was executed with respect to each feature in the training set values.

The response `class` is a categorical variable with classes g (gamma particle) and h (hadron). These were onehot-encoded for our

k-nearest neighbour and multilayer perceptron procedures, whereas the extreme gradient boosting procedure managed this on its own.

3 Methods

3.1 k-Nearest Neighbour (kNN)

The k-nearest neighbour method is a nonparametric method that consists of using the k observations in the training set in feature space closest to a point x to form a model $\hat{y}$. For regression and binary classification, the method considers a point x and the k closest points x_i in the neighbourhood $N_k(x)$ defined by k, such that

$$\hat{y} = \frac{1}{k} \sum_{x_i \in N_k(x)} y_i, \qquad (1)$$

i.e. the model output is the average of the k closest points to x.

As we are using this method for binary classification, we assign the classes such that

$$\hat{Y} = \begin{cases} \text{g if } \hat{y} \leq 0.5 \\ \text{h if } \hat{y} > 0.5 \end{cases} \quad [3]. \qquad (2)$$

Alternatively, the observation can be assigned according to the majority class of its neighbours, such that the observation is classified as the most common class in its neighbourhood. This is the method used for multiclass classification.

To implement kNN and the hyperparameter optimisation in this project we use the Scikit-Learn library.

3.1.1 Hyperparameter tuning

The kNN method is a simple approach that only requires tuning of a single hyperparameter k. Using $k = 1$ results in a highly complex model with high variance, while using

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Figure 2: Correlation matrix of the features in the train set. Upper triangle excluded for readability.

$k = N$, where N is the total number of samples in the training set, results in a simple, highly biased model. To find the optimal value for k in our case, we use 5-fold cross-validation on the training set, keeping 1/3rd of the total data as test set.

3.2 Multilayer Perceptron (MLP)

A multilayer perceptron (MLP) is a feedforward neural network. It contains an input layer, one or more hidden layers, with tunable number of nodes and layers, and a final output layer. The information flows only in one direction from the input layer to the output layer. The input and output values of the nodes are determined by an activation function, in addition to the weights and biases of the nodes. For a more extensive explanation of how the different components of the MLP works, please refer to our previous work, *Project 2: Regression and Classification* [5].

We have chosen to use the Rectified Linear Unit (ReLU) function as our activation function $f(z)$ between the layers, which is given by

$$f(z) = \max(0, z), \tag{3}$$

and its gradient by

$$f'(z) = \begin{cases} 0, & z < 0 \\ 1, & z > 0 \end{cases}. \tag{4}$$

For the activation function of the final output layer, we use the softmax function to achieve the categorical outcomes,

$$f(z_i) = \frac{\exp(z_i)}{\sum_j \exp(z_j)} \tag{5}$$

For this project we will be using the TensorFlow library to implement the MLP with the addition of the Scikit-Optimize library to optimise the hyperparameters.

3.2.1 Hyperparameter tuning

In this project we choose to limit ourselves to two hidden layers for computational reasons, and tune the amount of nodes in both of those layers.

To counteract the high variance of the model, we introduce regularisation using dropout. Dropout is tuned for eachlayer, and is the chance of any node in the given layer to be ignored at an iteration in training. This reduces variance by forcing the other nodes to be able to work more independently from each other, lessening the chance for overfitting.

We also tune the batch size. This leaves us with five hyperparameters to tune. A grid search would be too expensive to perform, so instead we perform a random search. Ideally we would employ cross validation on the train set evaluate the candidate hyperparameters, but for computational reasons we have decided to instead set aside 0.10 of the training set for validation. After finding the tuning parameters that maximise F_1 on the validation set, we use these parameters to fit the model on the entire training data including the validation data. This is known as a refit.

3.3 Gradient Boosting and Extreme Gradient Boosting (XGB)

Boosting is a learning technique based on the idea of combining several weak learners b_m into a final strong learner $f_{m_{\text{stop}}}$, where each f_m is improved from the previous iteration f_{m-1} through the step h_m,

$$f_{m_{\text{stop}}} = \sum_{m=0}^{m_{\text{stop}}} h_m. \tag{6}$$

Gradient boosting is one such method. We consider a loss function $L(y, f(x))$, which is minimised by calculating the negative gradient of the loss function to obtain the minimisation direction. To prevent overfitting, the

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boosting step size, also referred to as learning rate, $\nu \in (0, 1)$ is introduced as a tuning parameter, with smaller values of ν resulting in larger shrinkage,

$$f_m(x) = f_{m-1}(x) + \nu h_m. \qquad (7)$$

The gradient boosting algorithm goes as follows: [1]

1. Initialize the estimate $f_0(x)$
2. for $m = 1, , \ldots, m_{\text{stop}}$:

   (a) Compute negative gradient vector

   $$u_m = -\left.\frac{\partial L(y, f(x))}{\partial f(x)}\right|_{f(x) = \hat{f}_{m-1}(x)}$$

   (b) Fit the base learner to the negative gradient vector, $b_m(u_m, x)$
   (c) Update the estimate

   $$f_m(x) = f_{m-1}(x) + \nu b_m(u_m, x)$$

3. Compute final estimate,

$$\hat{f}_{m_{\text{stop}}}(x) = \sum_{m=0}^{m_{\text{stop}}-1} \nu b_m(u_m, x)$$

For this project, we have chosen to boost decision trees using a variant of gradient boosting called extreme gradient boosting (XGB).

3.3.1 Hyperparameter tuning

The XGBoost package has many hyperparameters added on top of the ordinary gradient boosting algorithm.

The learning rate ν

As with the neural network model, we also do not use cross validation here. We use the same train-validation split as for the neural network. We also employ a randomised search instead of a grid search.

3.4 Model evaluation

For classification problems, one can visualise the performance of a model using the so-called confusion matrix. In our case it is defined as

$$\text{confusion matrix} = \begin{pmatrix} g_g & g_h \\ h_g & h_h \end{pmatrix}, \qquad (8)$$

with g_g indicating the amount of correctly classified gamma particles, g_h indicating the amount of incorrectly classified hadrons (false positives), h_g indicating the amount of incorrectly classified gamma particles (false negatives) and h_h indicating the amount of correctly classified hadrons. Mathematically, if $\hat{y}_i$ is our model output and y the true observations, this is expressed as

$$g_g = \sum_i^N I(y_i = g_i \text{ and } \hat{y}_i = g_i)$$

$$g_h = \sum_i^N I(y_i = g_i \text{ and } \hat{y}_i = h_i)$$

$$h_g = \sum_i^N I(y_i = h_i \text{ and } \hat{y}_i = g_i)$$

$$h_h = \sum_i^N I(y_i = h_i \text{ and } \hat{y}_i = h_i)$$

A perfect model will have $g_h = h_g = 0$, i.e. it would not misclassify any of the observations and only have non-zero elements on the diagonal.

A common way to evaluate classification models is the F_1-score. This is a metric quantifying the amount of diagonal and off-diagonal elements of the confusion matrix and is defined as

$$F_1 = \frac{2g_g}{2g_g + g_h + h_g} \qquad (9)$$

The F_1 score values can lie between 0 and 1, with 1 representing a perfect fit with no off-diagonal elements. We use the F_1 score to

evaluate the MLP and XGB models and select the hyperparameters that yield the models with the highest F$_1$ scores.

When considering the confusion matrix, the best performing model for this data set is the model which maximises F$_1$ and minimises g_h on the test set, as false negatives are worse than false positives in this case as they lead to loss of important data.

4   Results

Table 1: Estimated optimal hyperparameters found using randomised search for the multilayer perceptron model.

Hyperparameter	Optimal value
Batch size	109
Epochs	55
Dropout, first layer	0.13
Dropout, second layer	0.095
Nodes, first layer	17
Nodes, second layer	4

Table 2: Estimated optimal hyperparameters found using randomised search for the extreme gradient boosted tree model.

Hyperparameter	Optimal value
Learning rate	0.048
Epochs	125
Maximum tree depth	9
L1 shrinkage parameter	0.0074
L2 shrinkage parameter	0.0035
Minimum child weight	3

Figure 2 shows the correlation of the features in the training set. Some of the features are highly correlated to each other.

Figure 3 shows the result of the cross-validated grid search for the optimal k in the kNN model and the corresponding confusion matrix. The value of k that resulted in the highest F$_1$ score was $k = 5$. The F$_1$ scores for

Table 3: F$_1$ score for the training and test set for our k-nearest neighbour (kNN), multilayer perceptron (MLP) and extreme gradient boost (XGB) models .

F$_1$ score	kNN	MLP	XGB
Training set	0.88	0.87	0.95
Test set	0.83	0.87	0.88

Table 4: Classification rates for the k-nearest neighbour, multilayer perceptron and extreme gradient boosting models.

	kNN	MLP	XGB
True positives	0.607	0.611	0.613
False negatives	0.041	0.037	0.034
False positives	0.125	0.091	0.081
True negaties	0.227	0.260	0.270

the training and test set using this model can be found in Table 3. We see that the F$_1$ test score is lower than that of the training score, with values 0.83 and 0.88 respectively.

The optimal hyperparameters found using randomised search for the MLP model are shown in Table 1. The corresponding confusion matrix and the F$_1$ scores are shown in Figure 4 and Table 3 respectively. The F$_1$ score for the training and test set are both 0.87.

The results of the hyperparameter randomised search for the XGB model are shown in Table 2. Figure 5 shows the confusion matrix of the XGB model predictions and the F$_1$ scores for the training and test sets are shown in Table 3. The F$_1$ training score is 0.95, which is noticably higher than the test score at 0.88.

The true positive, true negative, false positive and false negative rates are shown in Table 4 for all three models.

When considering the F$_1$ scores in Table 3 for the three models , the highest test score value was obtained by the XGB model at 0.88, compared to 0.87 for the MLP and the 0.83. This corresponds to the values seen in the confusion matrices of the models in Fig-
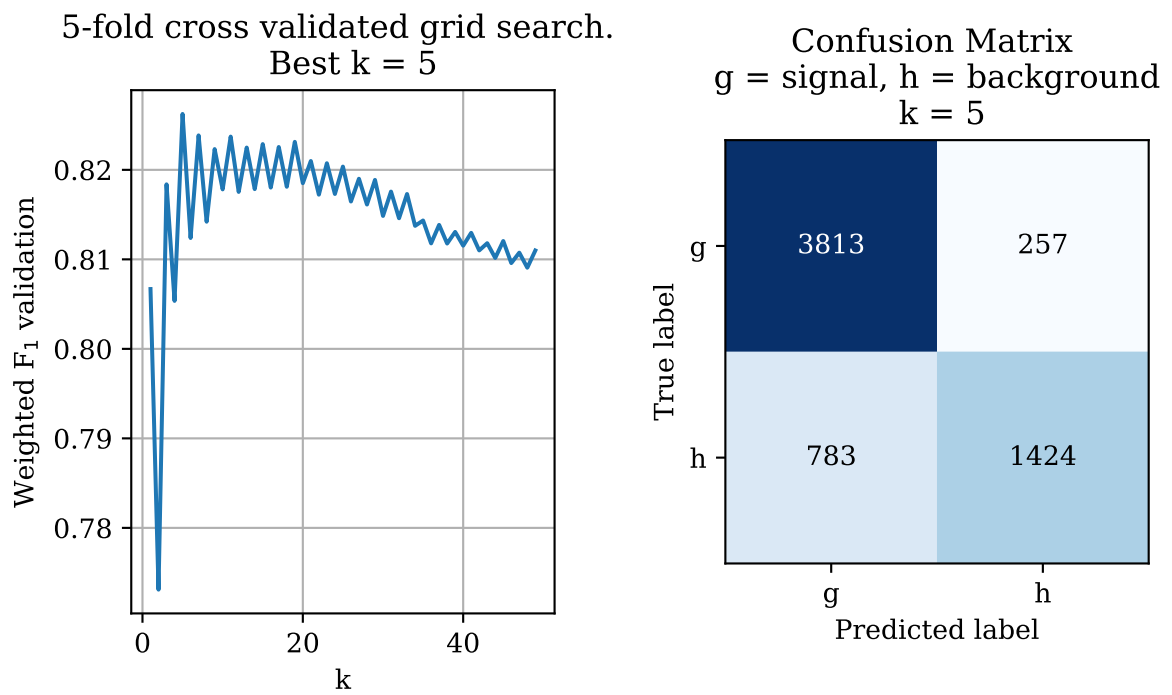
Figure 3: Results from tuned kNN using cross validation. The confusion matrix was found using the test set.
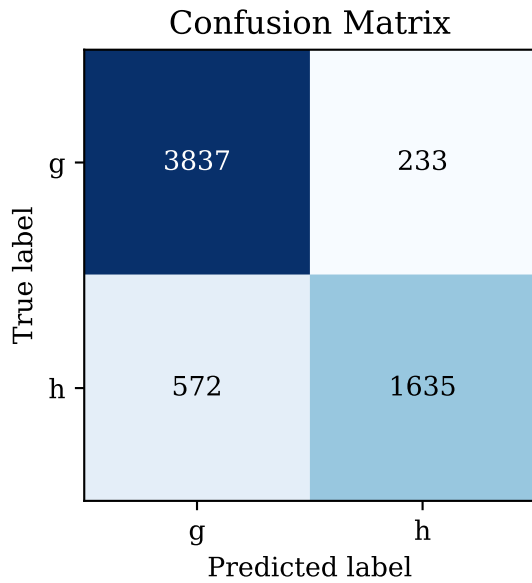
Confusion Matrix

Figure 4: Confusion matrix of the neural network model applied to the test set.
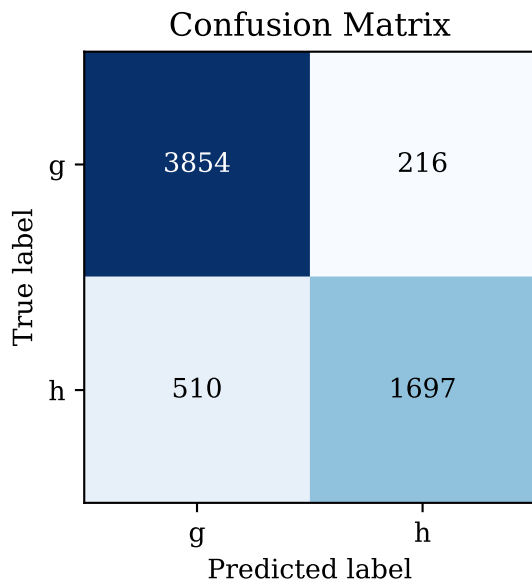
Confusion Matrix

Figure 5: Confusion matrix of the gradient boosted model applied to the test set.

ure 3, 4 and 5. Additionally, the rates of false positives and false negatives found in Table 4 show the lowest values for the XGB model, followed closely by the MLP, with the kNN model having the highest misclassification rates.

5 Discussion

6 Conclusion

Acknowledgements

References

[1] Riccardo De Bin. STK-IN4300 Statistical Learning Methods in Data Science: Lecture 10. `https://www.uio.no/studier/emner/matnat/math/STK-IN4300/h19/slides/lecture_10_ho.pdf`, 2019. Retrieved: 09-12-2019.

[2] Dheeru Dua and Casey Graff. UCI Machine Learning Repository. `http://archive.ics.uci.edu/ml`, 2017.

[3] Jerome Friedman, Trevor Hastie, and Robert Tibshirani. *The Elements of Statistical Learning*, volume 27. Springer Series in Statistics, 2009.

[4] Dieter Heck, G Schatz, J Knapp, T Thouw, and JN Capdevielle. CORSIKA: a Monte Carlo code to simulate extensive air showers. Technical report, 1998.

[5] Bernhard Nornes Lotsberg and Anh-Nguyet Lise Nguyen. *Project 2: Classification and Regression*. FYS-STK3155/4155 Applied Data Analysis and Machine Learning. 2019.