FYS-STK4155: Project 3

Simen Nyhus Bastnes

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Abstract

In this project, we want to take a look at audio classification using different machine learning algorithms. The data set we will be looking at is a set of labeled audio files containing either cat or dog sounds. To reduce the complexity of the data set, we transform it into Fourier space, using the binned frequencies as our predictors. Principal component analysis (PCA) is employed to further reduce the predictor set. The classification methods we will be using is a feed-forward neural networks, random forests, and XGBoost. Cross-validation will be used in order to find the optimal hyperparameters. We find that all three methods classify the samples with an accuracy of over 90%, with XGBoost performing the best **at 95%**. For all methods there is a slightly lower accuracy rate for classifying dog samples compared to cats, possibly stemming from the larger variance in spectral characteristics between small and large dogs. **PCA**

1 Introduction

While image recognition with machine learning seems to have taken the spotlight in recent years when it comes to popularity, using machine learning for audio analysis is a field with a plethora of real world applications, both for supervised and unsupervised learning. Everything from speech recognition to make the lives of deaf individuals easier, to studying seismic data to detect earthquakes, or detect wear in critical machinery at a factory based on the sound or vibrations it makes.

In this project, we will be looking at a fairly simple supervised approach for classifying different audio events, namely looking at the Fourier transform of our audio samples. Under the assumption that different types of sound events has different spectral characteristics, we extract a number of features from each sample by binning the frequencies into 40 Hz bins. The methods used for the classification is a standard feed-forward neural network, random forests, and the XGBoost gradient boosting.

Since it is unlikely that all the different frequency bins are necessary for our analysis, we also test a common dimensionality reduction method, the principal component analysis (PCA), in order to see how much it affects both the results and run time of our code.

The data set we will be using is a set of audio files with cat and dog sounds from [1], consisting of 277 samples. As the data set is quite varied in terms of content and quality, this serves as a decent real world test case. First, in Chapter 2 we will go through the relevant theory, going briefly through feed-forward neural networks, and then decision trees/random forests, gradient boosting and finally PCA. A more in-depth description of the data sets can be found in Chapter 3. Then, in Chapter 4 we go through the results of performing the analysis on both the full data

set as well as the dimensionality reduced one, while discussing them. Finally, we conclude our findings in Chapter 5.

2 Theory

In this chapter we will be going through the fundamentals of the classification methods we will employ, as well as the dimensionality reduction and different metrics we use to gauge how well our models work. For the discussion on decision trees and random forests, we will follow chapter 6 and 7 of [2].

2.1 Feed-forward neural network

In this report, we will be using feed-forward neural networks to compare our results with the random forest and gradient boosting methods. A description of how FFNNs function and is trained can be found in [3]. Instead of using the neural net we created in project 2, we will be using Scikit-Learns `MLPClassifier` [4]. In addition to the hyperparameters we tested previously in [3], we will be testing the different solvers SKL has for weight optimization. Besides the stochastic gradient descent, `MLPClassifier` has a solver in the family of quasi-Newton methods, which is claimed to converge faster and perform better for small datasets.

2.2 Decision trees

Decision trees is a powerful machine learning algorithm that can be used for both regression and classification. One of the strengths of decision trees is the inherent simplicity when it comes to when it comes to understanding how it works. Unlike ANNs or other black box models, decision trees are white boxes, making it easy to interpret why the model makes the prediction. Decision trees are also the fundamental building blocks for both of the ensemble methods (random forest and XGBoost) that we will use later.

The base concept of decision trees is that the data set is split into two based on some question/"decision", which can for example be whether or not a person is male or female, or if their height is above or below some 1.7 meters. This process is repeated until all samples are correctly classified or you reach some specified stopping criteria.

Figure 1 shows an example of a decision tree attempting to classify iris flowers based on the sepal and petal length/width. The starting point is the *root node* (depth=0), and the method tries to find the question that separates the data the best. In this case, the question whether or not the petal width is less than or equal to 0.8 cm separates the data best. The left child node (at depth=1) is *pure*, as only samples of a single class is included. Thus, this is a *leaf node*, and there is no reason to split further. The right child node only correctly classifies 50% of the samples, and needs to be branched again. With a split at petal width <= 1.75 cm, the tree separates the data almost fully.

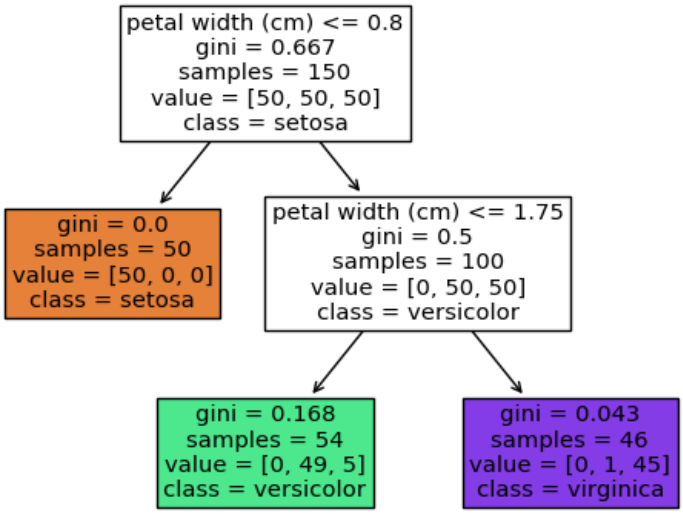


Figure 1: Decision tree example using the Iris data set. Corresponds to figure 6-1 in [2].

In order to quantify how pure a node is, we compute the *impurity* of each of the nodes. One of the common ways to do this for classification trees is the so-called Gini score/impurity

$$G_i = 1 - \sum_{k=1}^{n} p_{i,k}^2$$

where $p_{i,k}$ is the ratio of class k instances among the training instances in the i^{th} node. A fully pure node will have a gini score of 0.

To train/grow the decision tree, we will look at the CART[1] algorithm as it is the one that Scikit-Learn uses. The algorithm splits the data set into two subsets using a single feature k and a threshold t_k, and searches for the pair of (k, t_k) that yields the purest subsets. The cost function that it tries to minimize is the following

$$J(k, t_k) = \frac{m_{\text{left}}}{m} G_{\text{left}} + \frac{m_{\text{right}}}{m} G_{\text{right}}$$

where $G_{\text{left/right}}$ is the impurity of the left/right subset, and $m_{\text{left/right}}$ is the amount of instances in the left/right subset, meaning that the impurity is weighted by the size of each subset. It then splits each subset in two following the same logic, continuing until it either cannot find any splits that decrease the impurity, or some stopping criterion is met. One of these criteria is the maximum depth, limiting how deep the tree can go. Some of the hyperparameters that Scikit-Learn has that can be used to tweak how the tree grows is

[1] "*Classification and Regression Tree*"

- `max_depth`: maximum depth of the tree
- `max_features`: maximum amount of features to consider when looking for the best split
- `max_leaf_nodes`: maximum number of leaf nodes
- `min_samples_split`: minimum number of samples required to split
- `min_samples_leaf`: minimum number of samples required to be a leaf node

As decision trees make very few assumptions about the training data, it can easily end up overfitting, and give very poor results for the test data. Thus, using the different hyperparameters discussed above can help regularize the model and reduce the overfitting. Decision trees are also very sensitive to small variations in the training set, making just small variations in the train/test split enough to change your model. This brings us to the next topic, ensemble methods, which attempts to limit this instability aggregating multiple predictions.

2.3 Ensemble methods

Ensemble learning is a machine learning method where you combine the results of multiple methods to obtain better predictive power than each of the methods alone. While you could combine the results from all kinds of different machine learning algorithms, we will focus on methods based on decision trees, namely random forests as well as look at gradient boosting via the XGBoost library.

With ensemble methods even if the classifiers are weak learners (as in a classifier that is only slightly better than random guesses), the ensemble can still be a strong learner, provided there is a large enough and diverse set of classifiers.

2.3.1 Random forests

The Random Forest is an ensemble method where we train a set of decision trees, and combine the predictions from all the trees to get our final predictions. In order to make our ensemble method as good as possible, we can train each of the decision trees on a different random subset of the training data. Using bootstrap for this is referred to as *bagging* (bootstrap aggregating), while sampling without replacement is referred to as *pasting*.

When making the predictions, one can use either *hard* or *soft* voting. Hard voting is simply majority rule, where the class that has the most predictions/votes is the final prediction. Soft voting on the other hand, takes the average of the prediction probabilities for each of the decision trees, and makes the largest one the final prediction. This can give better results than hard voting as it gives more weight to highly confident predictions.

The random forest has mostly the same hyperparameters as decision trees, but also how many decision trees to grow, as well as other ensemble parameters. Another benefit with random forests is that instead of searching for the best feature to split at for each node, one can consider a random subset of the features, resulting in greater diversity among the trees and lower variance, producing better results.

2.3.2 Gradient boosting / XGBoost

Gradient boosting is another ensemble method where you sequentially add more predictors to the ensemble, with each one correcting the predecessor. The way this is done is that we initialize

an estimate to our targets. Given a cost function, we compute the negative gradient vector with respect to the previous prediction. Then, we fit our model to the negative gradient, and update the estimate by adding the gradient to the previous estimate. This is done for however long we want, and return our final estimate.

In this report, we will be using the XGBoost library [5] to perform gradient boosting. XGBoost is an optimized distributed gradient boosting library designed to be highly efficient, flexible and portable. It has become an extremely popular library, and has been used to win many machine learning competitions.

2.4 Principal component analysis

At its core, dimensionality reduction involves transforming data to a space with lower dimensionality than the original. Ideally, this new representation of the data retains as much of the information in the data set as possible, however some loss will always occur. Technically, when defining our data set, as described later in Chapter 3, we perform a somewhat arbitrary dimensionality reduction when binning the audio frequencies, hoping it works okay. To further reduce the number of dimensions, we employ a much used dimensionality reduction method, namely the principal component analysis (PCA).

Principal component analysis works by finding the hyperplane that lies closest to the data, and then projects the data onto it. First, it finds the axis that accounts for the largest amount of variance in the data (the first principal component). Then, the second is the axis orthogonal to the first that maximizes the variance, and so on for the amount of dimensions in the data set (or for as many dimensions you want to compute / reduce the data set to).

To compute the principal components, one can for example use singular value decomposition (SVD) to decompose the data matrix into

$$\mathbf{X} = U\Sigma V^{\mathsf{T}}$$

where V contains the principal components. The data set can then be projected down to D dimensions by transforming $\mathbf{X}$ using the first D components of V

$$\mathbf{T}_D = \mathbf{X}V_D$$

When determining the amount of dimensions to reduce down to, we can determine how much of the variance to keep, and then set D as the number of principal components needed to retain for example 95% of the data set variance.

One of the issues with this method of performing PCA is that the entire data set $\mathbf{X}$ needs to fit into memory, which while is not a big problem for our data set, can be difficult with larger data sets. To circumvent this issue, one can for example use an incremental PCA (IPCA) algorithm where the data set is split into mini-batches, or a stochastic approach where an approximation of the principal components is found.

2.5 Performance metrics

To measure the performance of our classifiers, we use a couple of different metrics. First of all, the **accuracy** gives us the number of correctly guessed targets t_i divided by the total number of

targets.

$$\text{Accuracy} = \frac{\sum_{i=1}^{n} I(t_i = y_i)}{n}$$

where I is the indicator function, and y_i is the output from our classifier.

For a 2-class classification problem, the correct guesses (for a positive result) can be expressed as the true positive (TN), while the samples incorrectly guessed as positive is the false positive (FP). Likewise with negative results, we have the true negative (TN) and false negative (FN). With this, the accuracy can be written as

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{n}$$

where n is the total amount of samples. To more closely study how our model performs for each class, we plot the **confusion matrix**

$$\text{confusion matrix} = \begin{pmatrix} \text{TP} & \text{FP} \\ \text{FN} & \text{TN} \end{pmatrix}$$

for practicality, we can normalize each row, making the values the ratio of true and false positives/negatives. Finally, we can plot the true positive rate (TPR)

$$\text{TPR} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

against the false positive rate (FPR)

$$\text{FPR} = \frac{\text{FP}}{\text{FP} + \text{TN}}$$

at various thresholds to get the so-called **receiver operating characteristic** (**ROC**) curve. The area under the ROC curve (**AUC**) is often used for comparing different methods, but it is worth keeping in mind that it is not a perfect estimator, especially not for small sample sizes [6].

3 Data sets

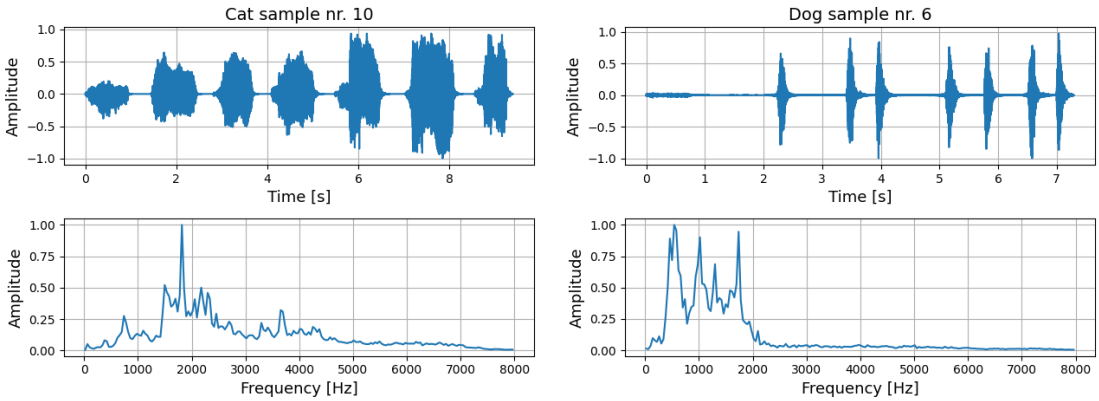
The data set we will be using in this project is a data set consisting of 277 audio files of various cat meows and dog barks, taken from [1]. There are 164 files labeled cat, containing 22 minutes of audio, and 113 files labeled dog, containing 10 minutes of audio. The audio files are originally harvested from `freesound.org`, as described in [7], which leads to quite big differences between the samples, both in length and quality (however all files are 16 KHz). Since the samples were recorded with different types of devices under different conditions, the noise level varies between the samples, and some of them contain other events such as footsteps, or for example many dogs barking at once. Some of the samples are also apparently synthesized. This gives us an opportunity to gain some insight into how machine learning algorithms manages smaller and less robust data sets.

Given the sound files, we need to define how the data will be represented when fed into our classification methods. When it comes to sound files, there are three main approaches one could take, working in either the time domain, the frequency domain, or even wavelet domain. Depending on the specific methods used for the analysis, different approaches may be more optimal.

For example, using recurrent neural networks [8]. In wavelet space one could for example use a convolutional neural network to classify based on the spectrogram images. In [7] convolutional neural networks was used on a larger audio data set (of which our data set is two of the different classes of audio events studied), achieving roughly 93% accuracy.

However, in order to keep this report as a simple demonstration, we will restrict ourselves to the frequency space, making a simple data matrix with the frequencies as our predictors. Since the nearby frequencies are highly correlated, we bin the frequencies, reducing the size of the data set. The Fourier transform of each of the files are computed, and the the frequencies are binned into 200 bins of size 40 Hz[2]

Figure 2 shows the time and frequency signal for one of the cat and one of the dog samples. We see that for at least this dog sample, the dominating frequencies are a lot lower than for the cat, which is the kind of difference we hope our methods will be able to detect.



(a) Cat sample nr. 10

(b) Dog sample nr. 6

Figure 2: Time and frequency signal for one of the cat (left panel) samples, and one of the dog (right panel) samples. The amplitudes are normalized.

We also use PCA to create a dimensionally reduced data set to test our classification methods with. As the data set is fairly small, there is no problem using the full PCA, and we perform the reduction by keeping 95% of the variance. This reduces our 200 frequency bins down to only 35 predictors, giving an 83% reduction in the dimensionality of our data set.

4 Results and discussion

1. only best params, confusion matrix (+ roc/auc) in results.
2. heatmaps and parameter combinations in appendices

In this section we will go through the results from analyzing the data set described in Chapter 3, using different classification methods and dimensionality reduction. The code used to generate the results can be found in the GitHub repository [9], and is implemented using Scikit-Learn [10]

[2]The number of bins and bin size here is chosen somewhat arbitrarily.

in order to be able to parallelize the hyperparameter search[3]. Cross-validation is employed during the hyperparameter search in order to more properly evaluate the results.

4.1 Neural networks

We find our optimal hyperparameters for the neural net by performing grid search using the hyperparameter sets found in appendix A. For simplicity, we set use a constant learning rate, and set all hidden layers to have the same amount of nodes, however a more proper analysis would be useful.

4.1.1 Full data set

Table 1 shows our best-fit hyperparameters for the neural net. Some of the hyperparameter heatmaps can be found in appendix A, figure 15. We note that yes

Table 1: Best-fit hyperparameters for feed-forward neural network. Full data set.

Parameter	Value
n hidden neurons	5
n hidden layers	100
activation	logistic
λ/α	0.0
learning rate	0.01
max iterations	500

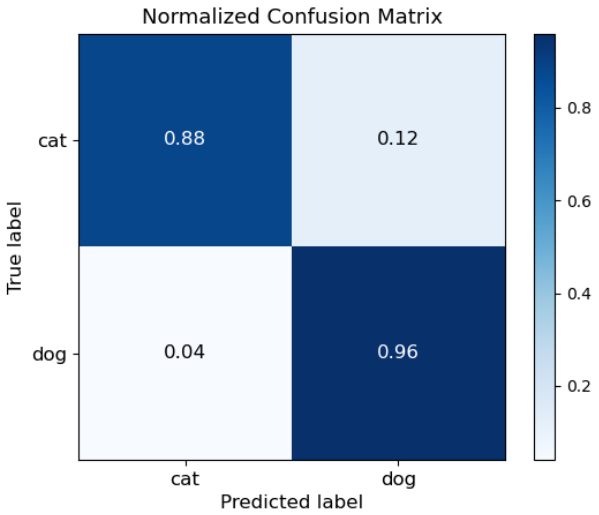


Figure 3: Confusion matrix for the neural net, full data set. The rows are normalized, showing the ratio of correctly/incorrectly labeled samples for each class.

[3]In the previous project [3], one of the grid searches took over 15 hours. Even though this data set is smaller, allowing the code to use more cores/threads (in the authors case, 12 threads) should reduce the run time significantly, allowing us to evaluate a larger part of the hyperparameter space.

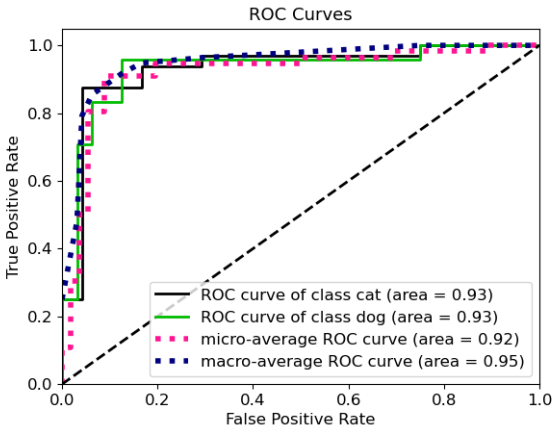


Figure 4: ROC curve for the neural net, full data set. The AUC is given in the legend.

4.1.2 PCA reduced data set

Table 2: Best-fit hyperparameters for feed-forward neural network. PCA reduced data set.

Parameter	Value
n hidden neurons	5
n hidden layers	100
activation	logistic
λ/α	0.0
learning rate	0.01
max iterations	500

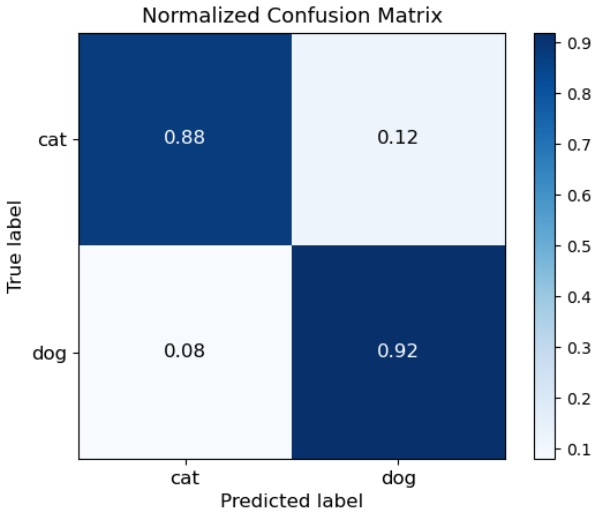


Figure 5: Confusion matrix for the neural net, PCA reduced data set. The rows are normalized, showing the ratio of correctly/incorrectly labeled samples for each class.

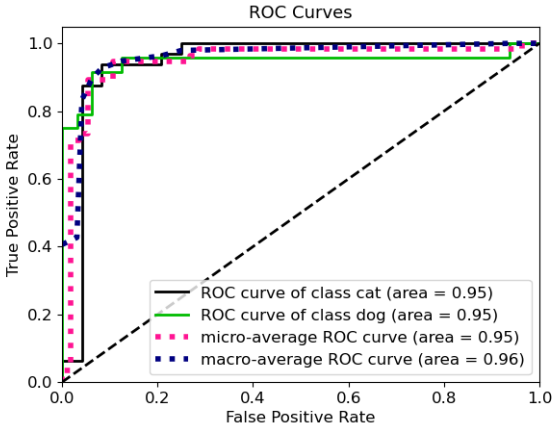


Figure 6: ROC curve for the neural net, PCA reduced data set. The AUC is given in the legend.

4.2 Random forests

4.2.1 Full data set

Table 3: Best-fit hyperparameters for random forests. Full data set.

Parameter	Value
n estimators	5
max depth	100
min samples split	1
min samples leaf	0.0
max features	10
max leaf nodes	0.1

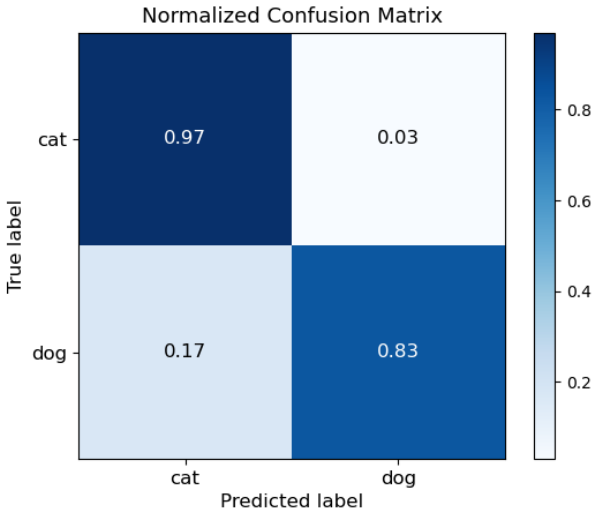


Figure 7: Confusion matrix for random forests, full data set. The rows are normalized, showing the ratio of correctly/incorrectly labeled samples for each class.

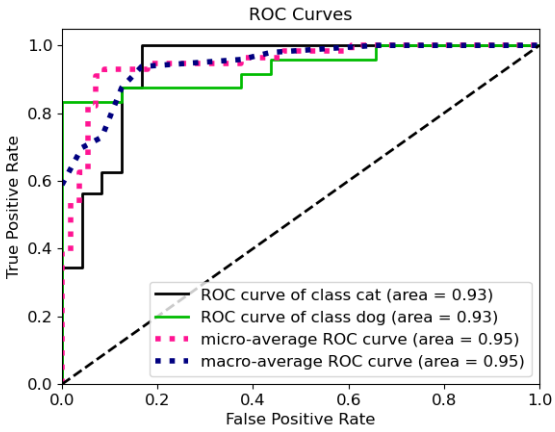


Figure 8: ROC curve for random forests, full data set. The AUC is given in the legend.

4.2.2 PCA reduced data set

Table 4: Best-fit hyperparameters for random forests. PCA reduced data set.

Parameter	Value
n estimators	5
max depth	100
min samples split	1
min samples leaf	0.0
max features	10
max leaf nodes	0.1

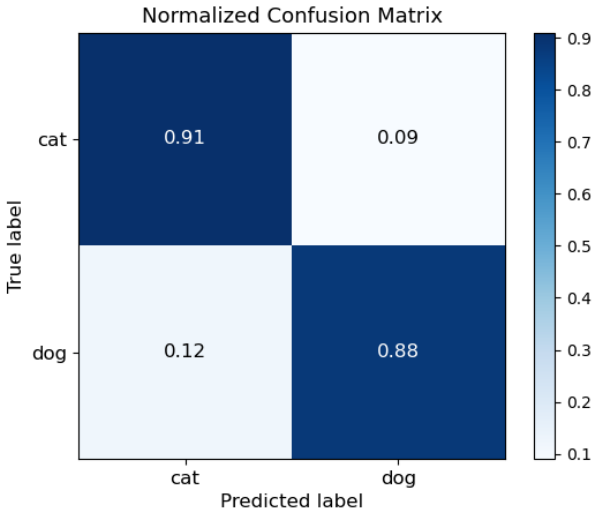


Figure 9: Confusion matrix for random forests, PCA reduced data set. The rows are normalized, showing the ratio of correctly/incorrectly labeled samples for each class.

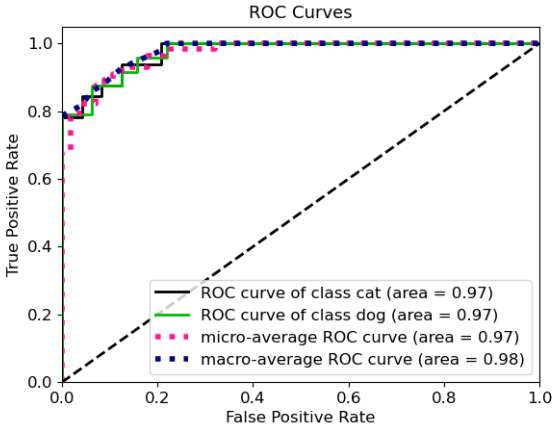


Figure 10: ROC curve for random forests, PCA reduced data set. The AUC is given in the legend.

4.3 XGBoost

4.3.1 Full data set

Table 5: Best-fit hyperparameters for XGBoost. Full data set.

Parameter	Value
learning rate	0.0
n estimators	5
max depth	100
min child weight	1
lambda	10

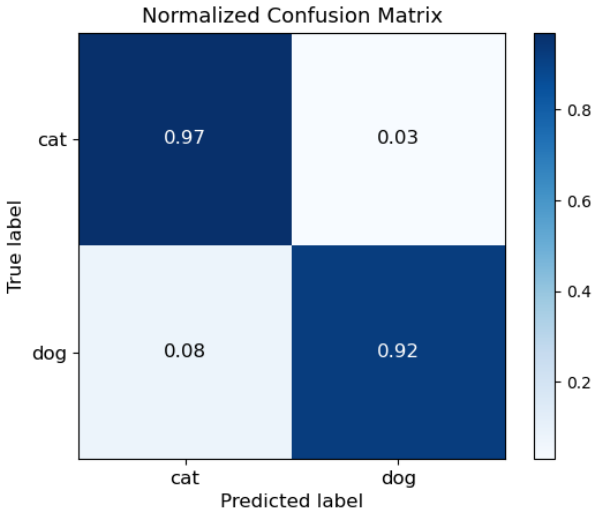


Figure 11: Confusion matrix for XGBoost, full data set. The rows are normalized, showing the ratio of correctly/incorrectly labeled samples for each class.

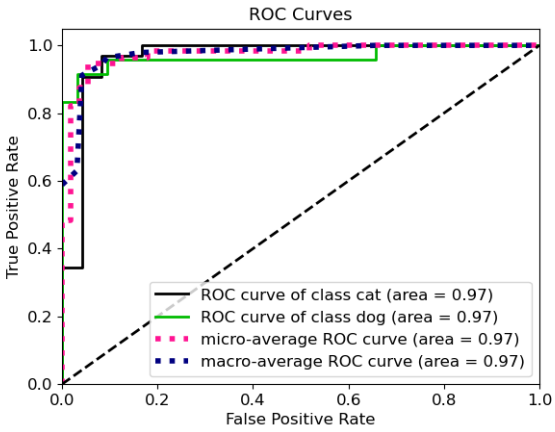


Figure 12: ROC curve for XGBoost, full data set. The AUC is given in the legend.

4.3.2 PCA reduced data set

Table 6: Best-fit hyperparameters for XGBoost. PCA reduced data set.

Parameter	Value
learning rate	0.0
n estimators	5
max depth	100
min child weight	1
lambda	10

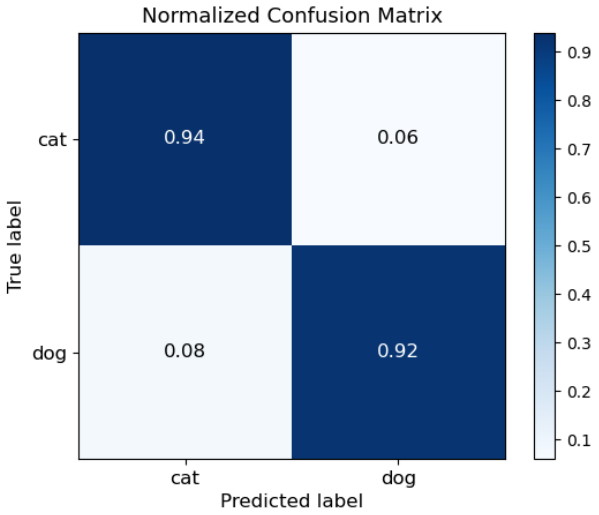


Figure 13: Confusion matrix for XGBoost, PCA reduced data set. The rows are normalized, showing the ratio of correctly/incorrectly labeled samples for each class.

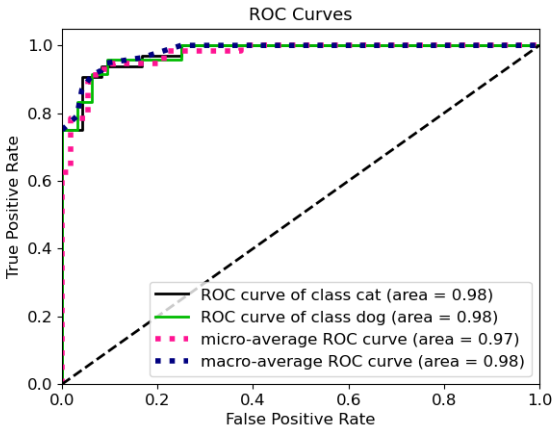


Figure 14: ROC curve for XGBoost, PCA reduced data set. The AUC is given in the legend.

SEEMS TO PERFORM BETTER AT PREDICTING CAT SOUNDS THAN DOG WOOFS, WHICH MAY EITHER BE A RESULT OF THE LOW AMOUNT OF SAMPLES, AND THE FACT THAT THE NUMBER OF DOG SAMPLES ARE LOWER. OR POTENTIALLY THE FACT THAT THERE IS MORE VARIATION IN THE ACTUAL SOUNDS THAT DOGS MAKE, AND MAKING JUST A DIRECT FREQUENCY ANALYSIS INSUFICCIENT TO PREDICT REALLY GOOD RESULTS, AND THAT A WAVELET APPROACH COULD POTENTIALLY SOLVE THIS ISSUE.

DATA SET QUALITY IS KINDA SPOTTY THOUGH, WITH SOME SAMPLES CONSISTING OF MANY DOGS, MANY CATS, OTHER NOISE, LOW VOLUME MEOWS, SYNTHETIC MEOW/BARKS

COULD LOOK AT THE MISCLASSIFIED DOG SOUNDS AND SEE THEIR FOURIER SPECTRUM TO SEE IF THERE IS SOME CONSISTENCY.

4.4 Time

Table 7 shows the average time the training/fit process took for each of the three classification methods, for both versions of the data set. **LBFGS is fast, SGD is not, took 420 ms on average.**

Table 7: Average fit/training time for the three different methods examined, given in milliseconds. (lbfgs solver for NN)

Method	Time without PCA $[ms]$	Time with PCA $[ms]$
Neural net (lbfgs)	69.8	32.6
Random forest	28.5	29.0
XGBoost	91.6	21.8

4.5 Summary of results

The results are summarized in table 8, showing the total accuracy and the ROC AUC for each of the three methods.

Table 8: Summary of the accuracy and AUC scores for each of the classification methods.

Method	Accuracy	ROC AUC	Accuracy (PCA)	ROC AUC (PCA)
Neural net	0.10	0.10	0.10	0.10
Random forest	0.10	0.10	0.10	0.10
XGBoost	0.10	0.10	0.10	0.10

Table of the ROC AUC or gain AUC for both methods (and both data set variations)

Issues with data set. At one point, the data set analyzed was messed up and contained 3 dog samples with the label cat. Causing the predictive power for classifying dogs to be much lower than the results here.

4.6 Future work

more preprocessing of audio, like noise reduction methods

5 Conclusion

In this project, we set out to investigate how a frequency-space approach to classifying different animal sounds performs when using feed-forward neural nets, random forests, and the gradient

boosting method XGBoost. The data set was a set of audio files containing cat and dog sounds, that were transformed into frequency space using Fourier transform, and then binned into 40 Hz bins. We also tested PCA to see if further reducing the amount of dimensions yielded improvements to either accuracy or run time. **Future, look at data with more classes, like the original set. FUTURE, LOOK AT RANDOM SEARCH FOR PARAMETERS INSTEAD OF grid saercarh**

References

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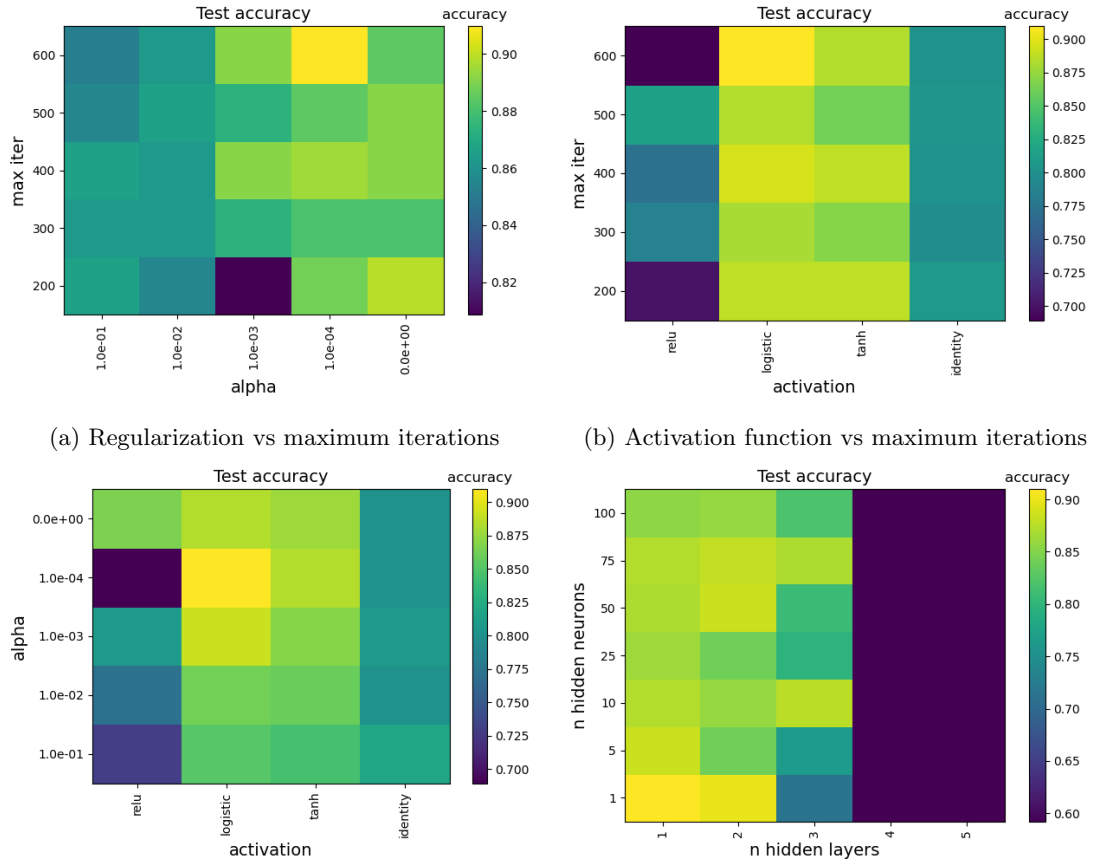
Appendix

A Neural Net Heatmaps

The following hyperparameter sets were used for finding best fit parameters as well as heatmaps below.

$$
\begin{aligned}
N_{\text{epochs}} &\in \{10, 25, 50, 100\} \\
\text{batch size} &\in \{1, 5, 10, 50\} \\
\eta_0 &\in \{0.1, 0.01, 0.001\} \\
\lambda &\in \{0.0, 0.1, 0.01, 0.001\} \\
N_{h,\text{nodes}} &\in \{10, 25, 50\} \\
N_{h,\text{layers}} &\in \{1, 2, 3, 4\}
\end{aligned}
$$

A.1 Without PCA



(a) Regularization vs maximum iterations

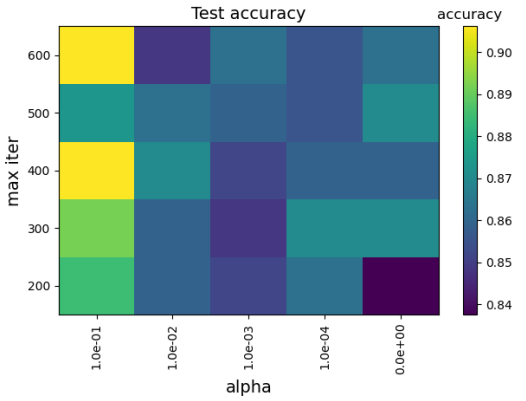
(b) Activation function vs maximum iterations

(c) Activation function vs regularization

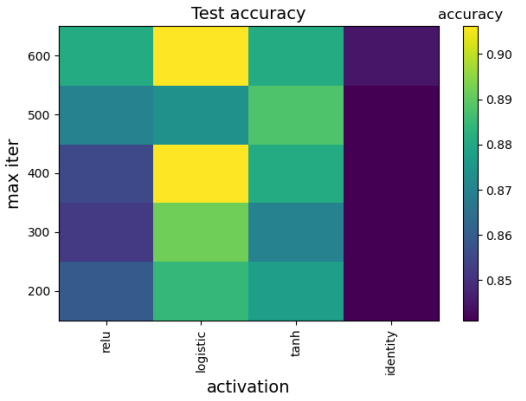
(d) Number of layers vs number of hidden neurons

Figure 15: Accuracy heatmaps for different hyperparameters. Neural net, full data set. All other hyperparameters set to the best-fit from table 1.

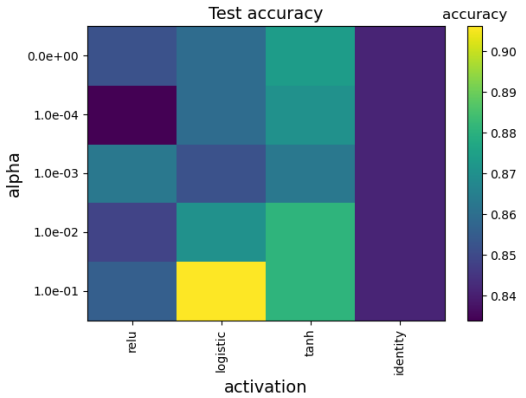
A.2 With PCA



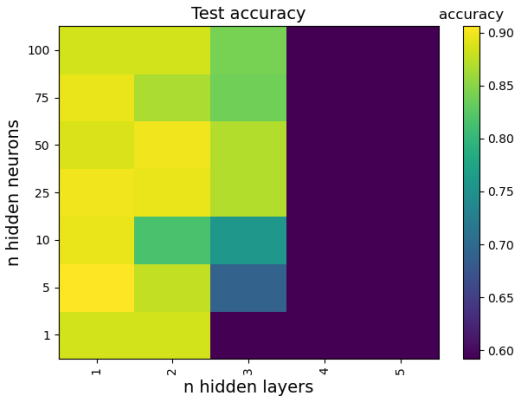
(a) Regularization vs maximum iterations



(b) Activation function vs maximum iterations



(c) Activation function vs regularization



(d) Number of layers vs number of hidden neurons

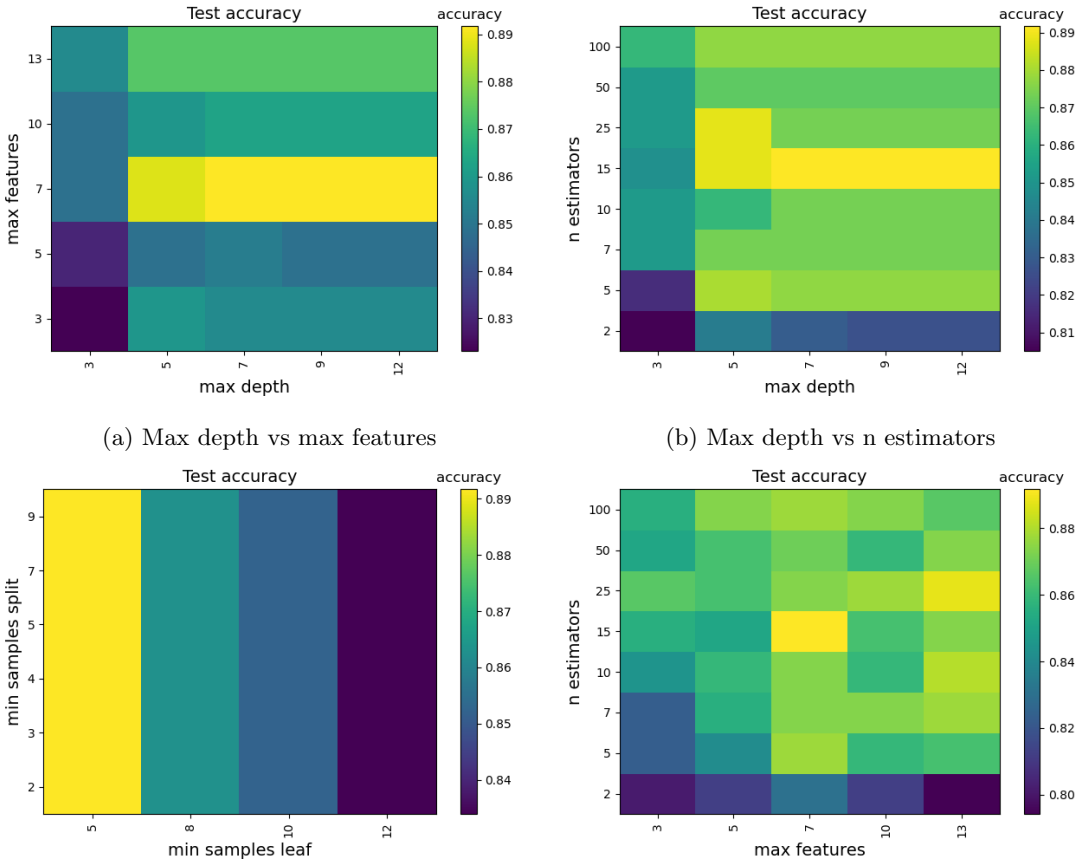
Figure 16: Accuracy heatmaps for different hyperparameters. Neural net, reduced data set. All other hyperparameters set to the best-fit from table 2.

B Random Forests Heatmaps

The following hyperparameter sets were used for finding best fit parameters as well as heatmaps below.

$$\begin{aligned}
\text{max depth} &\in \{10, 25, 50, 100\} \\
\text{max features} &\in \{1, 5, 10, 50\} \\
\text{min samples leaf} &\in \{0.1, 0.01, 0.001\} \\
\text{min samples split} &\in \{0.0, 0.1, 0.01, 0.001\} \\
N_{\text{estimators}} &\in \{10, 25, 50\} \\
\text{max leaf nodes} &\in \{1, 2, 3, 4\}
\end{aligned}$$

B.1 Without PCA



(a) Max depth vs max features

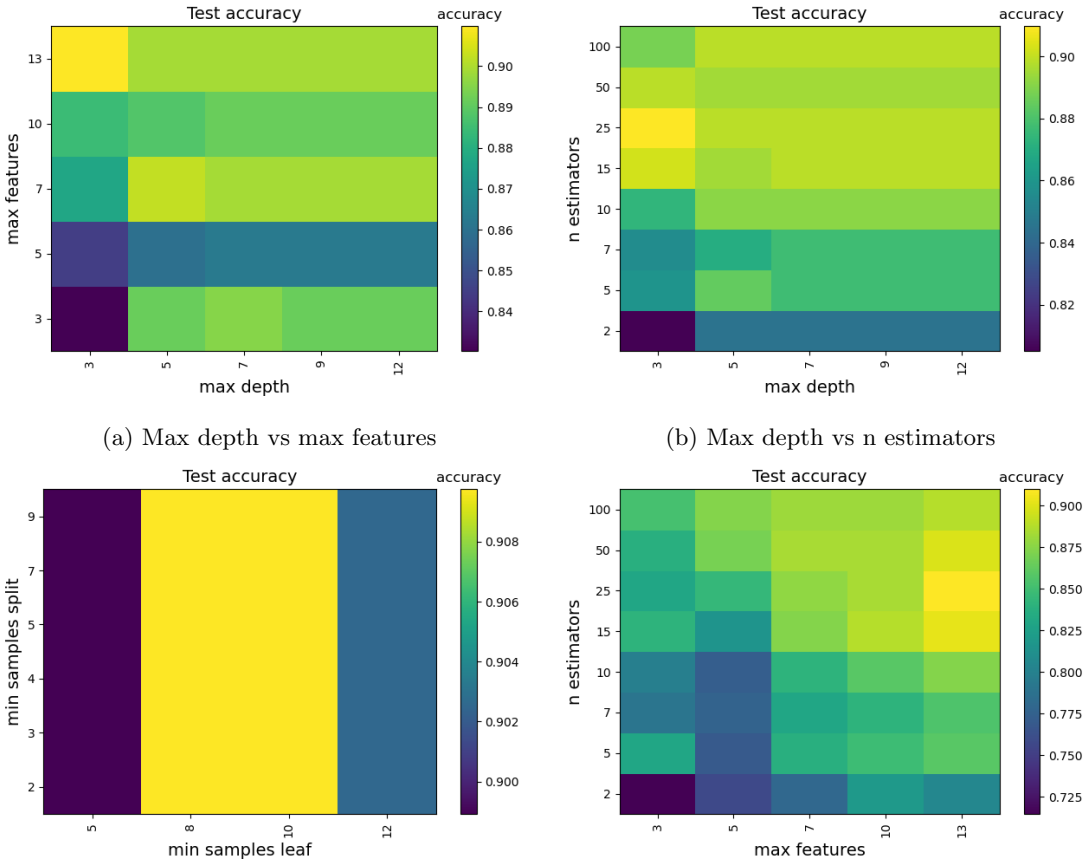
(b) Max depth vs n estimators

(c) Min samples leaf vs min samples split

(d) Max features vs n estimators

Figure 17: Accuracy heatmaps for different hyperparameters. Random forest, full data set. All other hyperparameters set to the best-fit from table 3.

B.2 With PCA



(a) Max depth vs max features

(b) Max depth vs n estimators

(c) Min samples leaf vs min samples split

(d) Max features vs n estimators

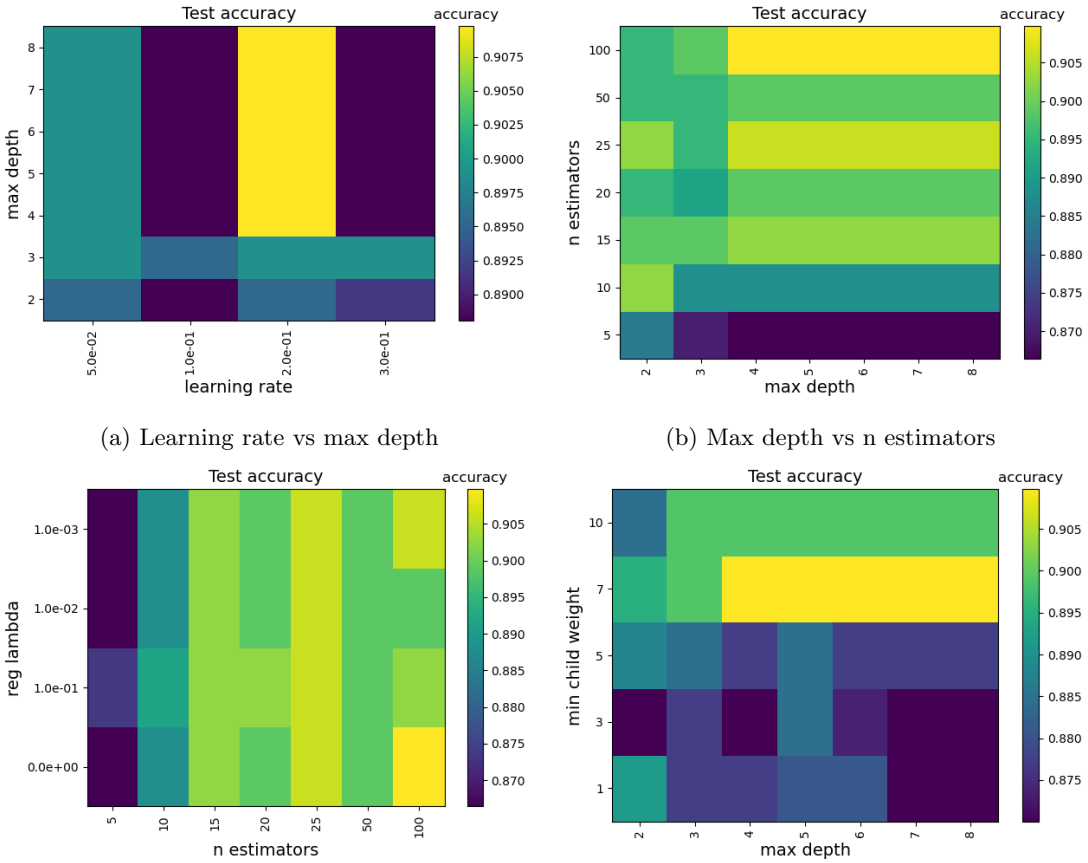
Figure 18: Accuracy heatmaps for different hyperparameters. Random forest, reduced data set. All other hyperparameters set to the best-fit from table 4.

C XGBoost Heatmaps

The following hyperparameter sets were used for finding best fit parameters as well as heatmaps below.

$$
\begin{aligned}
N_{\text{epochs}} &\in \{10, 25, 50, 100\} \\
\text{batch size} &\in \{1, 5, 10, 50\} \\
\eta_0 &\in \{0.1, 0.01, 0.001\} \\
\lambda &\in \{0.0, 0.1, 0.01, 0.001\} \\
N_{h,\text{nodes}} &\in \{10, 25, 50\} \\
N_{h,\text{layers}} &\in \{1, 2, 3, 4\}
\end{aligned}
$$

C.1 Without PCA



(a) Learning rate vs max depth

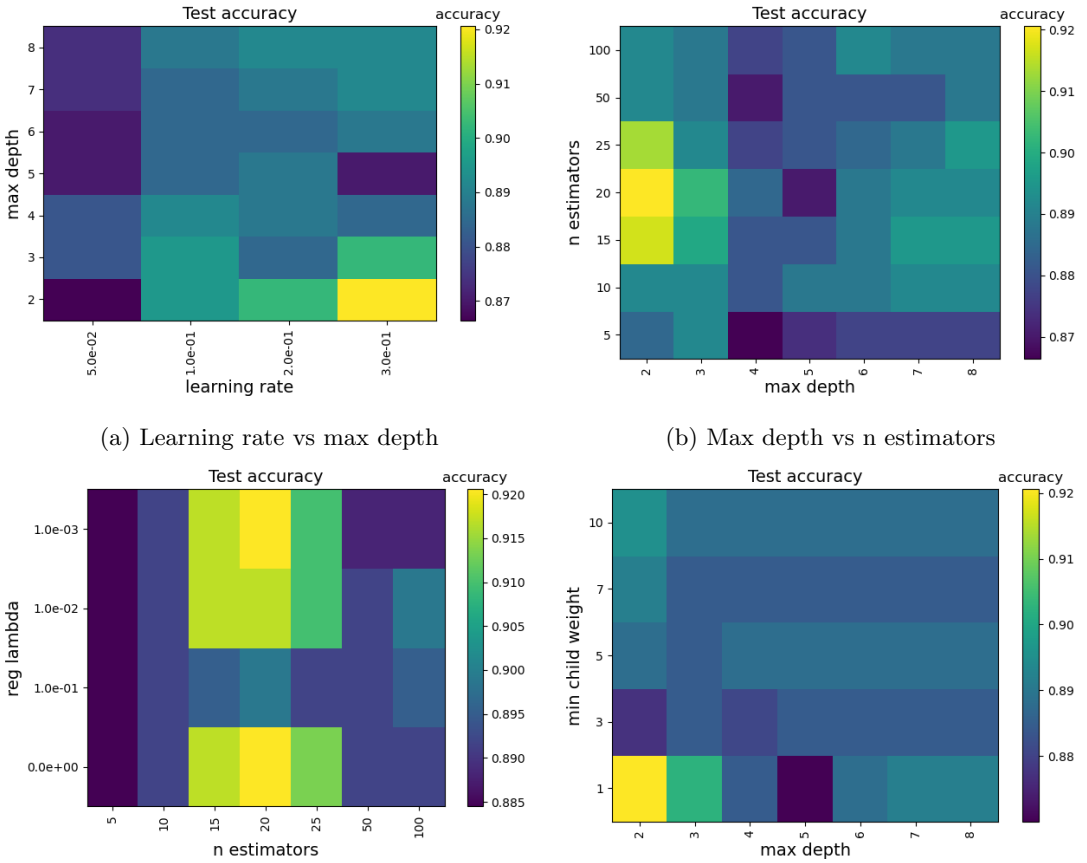
(b) Max depth vs n estimators

(c) Regularization vs n estimators

(d) Max depth vs min child weight

Figure 19: Accuracy heatmaps for different hyperparameters. XGBoost, full data set. All other hyperparameters set to the best-fit from table 5.

C.2 With PCA



(a) Learning rate vs max depth

(b) Max depth vs n estimators

(c) Regularization vs n estimators

(d) Max depth vs min child weight

Figure 20: Accuracy heatmaps for different hyperparameters. XGBoost, reduced data set. All other hyperparameters set to the best-fit from table 6.