# ELECTROMYOGRAPHY (EMG) OF THE EXTRAOCULAR MUSCLES (EOM)

- Main Code: https://github.com/vasanza/EOG
- `IEEEDataPort:` https://dx.doi.org/10.21227/bhpj-mz94
- `More Matlab Examples:` https://github.com/Human-Machine-Interface
- Hardware: Instrumentation amplifier based on AD620
- Sampling Frequency = 120 Hz for approximately 2 seconds
- Electrical activity of EOG signals: Fmin=8 and Fmax=31
- Subjects: 10

## Raw dataset preparation

```
clear;clc;%clear all
addpath(genpath('./src'))%functions folders
datapath = fullfile('./data/');%data folder
folders = FindFolders(datapath);
allData=[];
```

## Raw dataset preprocessing

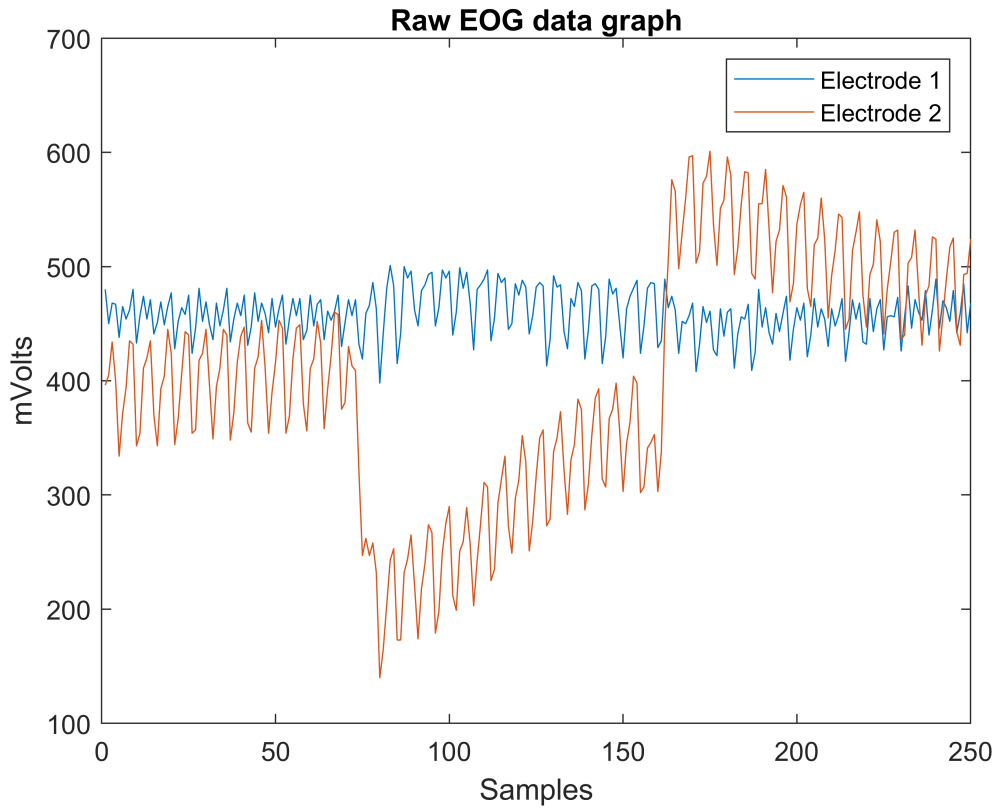
**% In this example no filtering was done, but it can be done**

```
for i=1:length(folders)% Through all folders
    folderpath=fullfile(datapath,folders(i).name);%Select i folder
    filenames = FindCSV(folderpath);%List All CSV files
    for j=1:length(filenames)% Through all files
        data=readtable(fullfile(folderpath,filenames(j).name));%Select i CSV file
        dataNew=table2array(data);% Array Double
        dataNew(isnan(dataNew)) = 0;%Remove NAN numbers
        DataNorm = fNormalization(dataNew);%Normalization
        Label = fLabelEOG(folders(i).name);%Name Folder to Label

        %max(EOG1,EOG2), min(EOG1,EOG2), mean(EOG1,EOG2), median(EOG1,EOG2),...
        %rms(EOG1,EOG2), std(EOG1,EOG2)
        DataFeatures = [max(DataNorm) min(DataNorm) mean(DataNorm)...
            median(DataNorm) rms(DataNorm) std(DataNorm) Label];%Feature extraction
        allData=[allData;DataFeatures];
    end
end
```

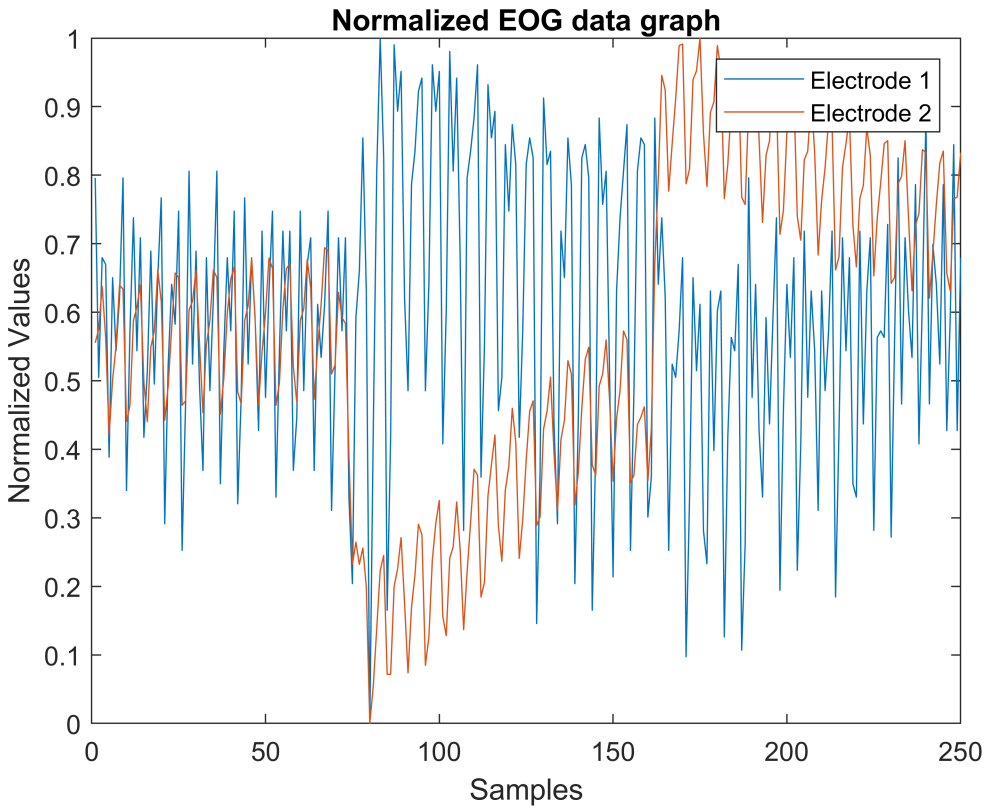
## Plot Raw EOG dataset

```
figure
plot(dataNew);xlabel('Samples');ylabel('mVolts');
title('Raw EOG data graph');
legend('Electrode 1','Electrode 2');
```




## Plot Normalization EOG dataset

```
figure
plot(DataNorm);xlabel('Samples');ylabel('Normalized Values');
title('Normalized EOG data graph');
legend('Electrode 1','Electrode 2');
```




# Feature Selection

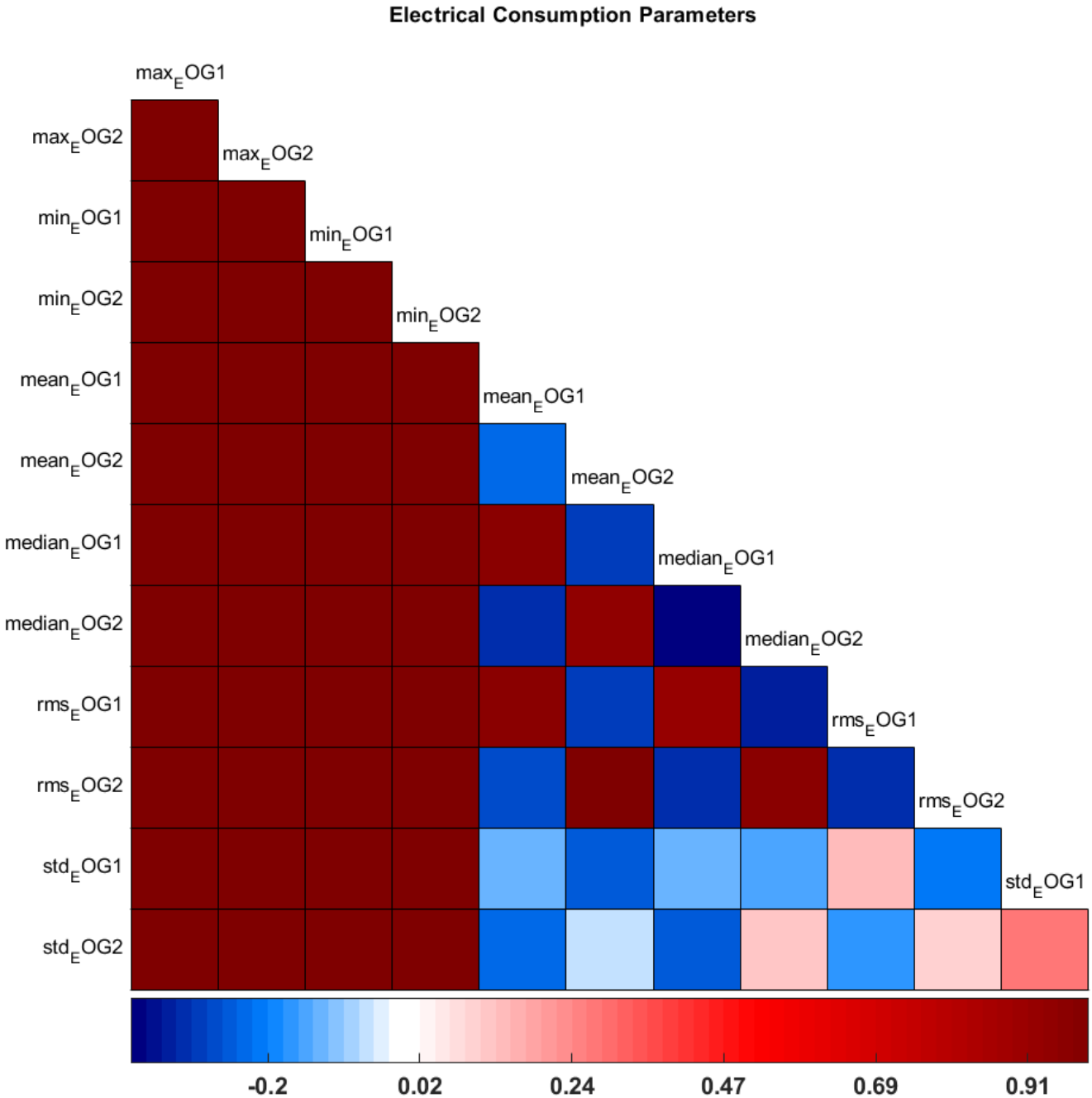
```
%max(EOG1,EOG2), min(EOG1,EOG2), mean(EOG1,EOG2), median(EOG1,EOG2),...
        %rms(EOG1,EOG2), std(EOG1,EOG2)
DataFeatureSelection=allData(1:end-1,1:end-1);%not including the label
R = corrcoef(DataFeatureSelection)
```

```
R = 12×12
       NaN       NaN       NaN       NaN       NaN       NaN       NaN       NaN ···
       NaN       NaN       NaN       NaN       NaN       NaN       NaN       NaN
       NaN       NaN       NaN       NaN       NaN       NaN       NaN       NaN
       NaN       NaN       NaN       NaN       NaN       NaN       NaN       NaN
       NaN       NaN       NaN       NaN    1.0000   -0.2582    0.9535   -0.3408
       NaN       NaN       NaN       NaN   -0.2582    1.0000   -0.3048    0.9415
       NaN       NaN       NaN       NaN    0.9535   -0.3048    1.0000   -0.4037
       NaN       NaN       NaN       NaN   -0.3408    0.9415   -0.4037    1.0000
       NaN       NaN       NaN       NaN    0.9597   -0.3195    0.9070   -0.3699
       NaN       NaN       NaN       NaN   -0.2929    0.9894   -0.3403    0.9546
     ⋮
```

```
% Labels:
SongSystem_labels = {'max_EOG1','max_EOG2','min_EOG1','min_EOG2','mean_EOG1','mean_EOG2','media
        'rms_EOG1','rms_EOG2','std_EOG1','std_EOG2'};
% Load 20x20 Fisher Z correlation matrix, stored as variable 'corrmat'
nROI = 20; % 20 regions of interest (ROIs)
sort_ind = [1:2:nROI,2:2:nROI]; % make all homotopic ROIs on 1 diagonal
[~, h_corrmat, h_colorbar] = plot_corrmat([],... % leave timeSeries input empty, since already
    'corrmat', R,... % the correlation matrix
```

```
    'title', 'Electrical Consumption Parameters',... % plot title
    'labels', SongSystem_labels,... % correlation matrix cell labels
    'sort_ind', sort_ind,... % sort ROIs for plotting
    'label_FontSize', 10,... % long labels get cutoff with larger fonts
    'outline', 1); % outline the cells (appearance improvement)
```

```
Warning: 'sort_ind' should be of length equal to the # of ROIs
```



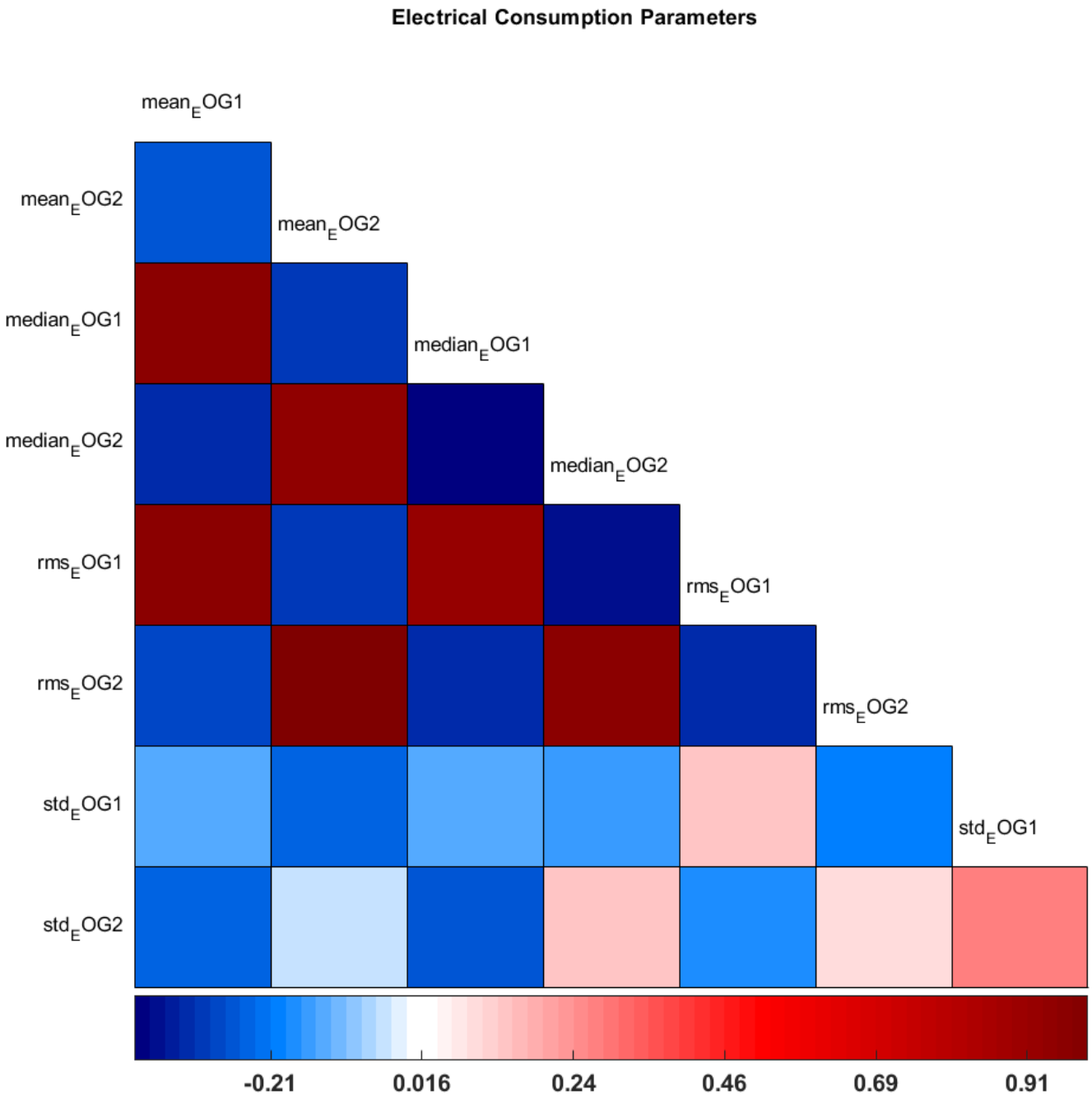

```
%Remove NaN results
%mean(EOG1,EOG2), median(EOG1,EOG2), rms(EOG1,EOG2), std(EOG1,EOG2)
DataFeatureSelection=allData(5:end-1,5:end-1);%not including the label
R = corrcoef(DataFeatureSelection)
```

```
R = 8×8
    1.0000   -0.2672    0.9536   -0.3481    0.9591   -0.3017   -0.1405   -0.2543
```

```
   -0.2672    1.0000   -0.3114    0.9407   -0.3272    0.9892   -0.2539   -0.0500
    0.9536   -0.3114    1.0000   -0.4089    0.9062   -0.3468   -0.1358   -0.2704
   -0.3481    0.9407   -0.4089    1.0000   -0.3755    0.9540   -0.1586    0.1213
    0.9591   -0.3272    0.9062   -0.3755    1.0000   -0.3487    0.1387   -0.1745
   -0.3017    0.9892   -0.3468    0.9540   -0.3487    1.0000   -0.2106    0.0913
   -0.1405   -0.2539   -0.1358   -0.1586    0.1387   -0.2106    1.0000    0.2631
   -0.2543   -0.0500   -0.2704    0.1213   -0.1745    0.0913    0.2631    1.0000
```

```
% Labels:
SongSystem_labels = {'mean_EOG1','mean_EOG2','median_EOG1','median_EOG2',...
        'rms_EOG1','rms_EOG2','std_EOG1','std_EOG2'};
% Load 20x20 Fisher Z correlation matrix, stored as variable 'corrmat'
nROI = 20; % 20 regions of interest (ROIs)
sort_ind = [1:2:nROI,2:2:nROI]; % make all homotopic ROIs on 1 diagonal
[~, h_corrmat, h_colorbar] = plot_corrmat([],... % leave timeSeries input empty, since already
    'corrmat', R,... % the correlation matrix
    'title', 'Electrical Consumption Parameters',... % plot title
    'labels', SongSystem_labels,... % correlation matrix cell labels
    'sort_ind', sort_ind,... % sort ROIs for plotting
    'label_FontSize', 10,... % long labels get cutoff with larger fonts
    'outline', 1); % outline the cells (appearance improvement)
```

```
Warning: 'sort_ind' should be of length equal to the # of ROIs
```



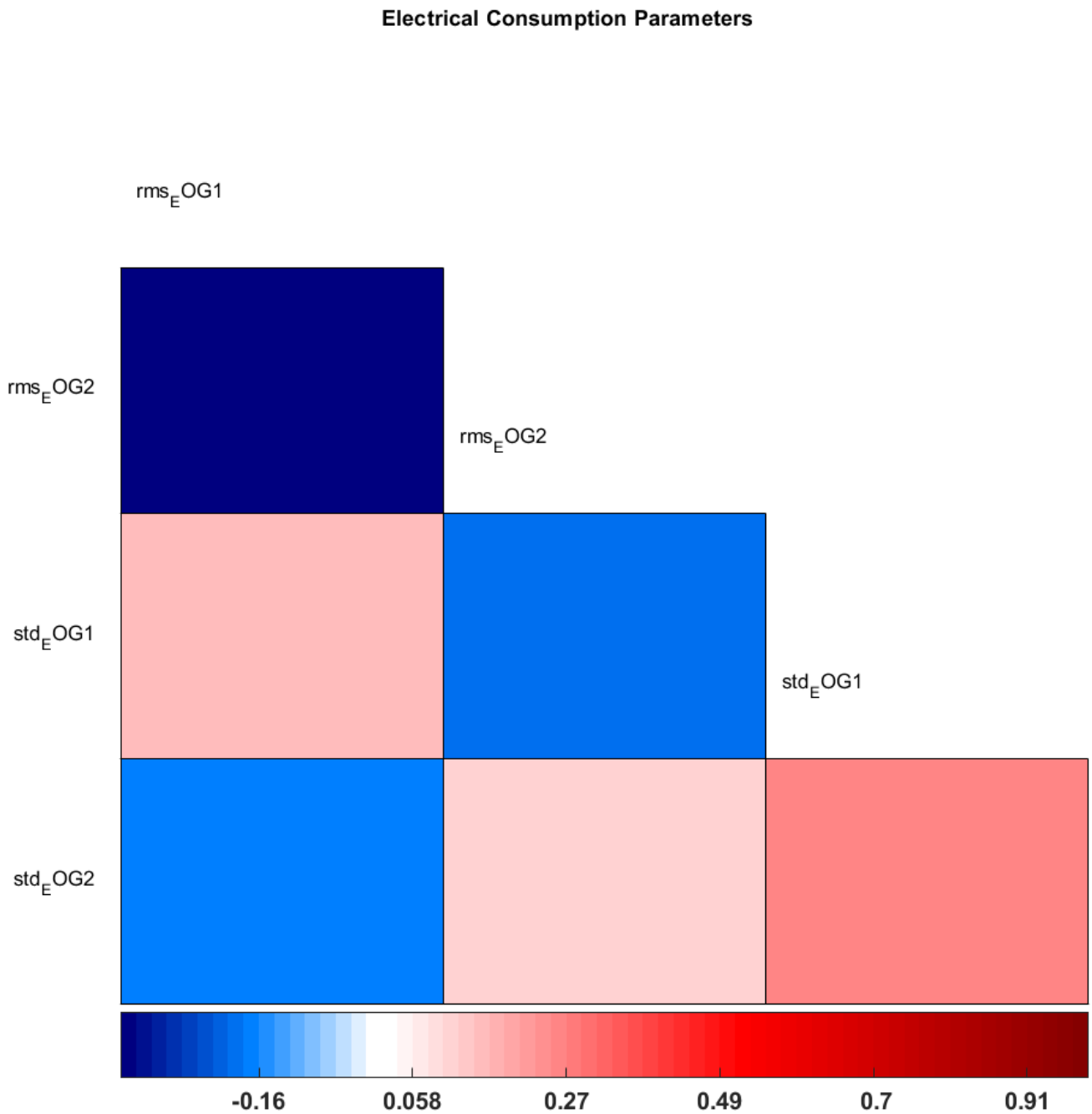

```
%Remove High correlation beatwen mean, meadian and rms
%rms(EOG1,EOG2), std(EOG1,EOG2)
DataFeatureSelection=allData(9:end-1,9:end-1);%not including the label
R = corrcoef(DataFeatureSelection)
```

```
R = 4×4
    1.0000   -0.3488    0.1381   -0.1756
   -0.3488    1.0000   -0.2031    0.0967
    0.1381   -0.2031    1.0000    0.2584
   -0.1756    0.0967    0.2584    1.0000
```

```
% Labels:
SongSystem_labels = {'rms_EOG1','rms_EOG2','std_EOG1','std_EOG2'};
% Load 20x20 Fisher Z correlation matrix, stored as variable 'corrmat'
nROI = 20; % 20 regions of interest (ROIs)
```

```
sort_ind = [1:2:nROI,2:2:nROI]; % make all homotopic ROIs on 1 diagonal
[~, h_corrmat, h_colorbar] = plot_corrmat([],... % leave timeSeries input empty, since already
    'corrmat', R,... % the correlation matrix
    'title', 'Electrical Consumption Parameters',... % plot title
    'labels', SongSystem_labels,... % correlation matrix cell labels
    'sort_ind', sort_ind,... % sort ROIs for plotting
    'label_FontSize', 10,... % long labels get cutoff with larger fonts
    'outline', 1); % outline the cells (appearance improvement)
```

```
Warning: 'sort_ind' should be of length equal to the # of ROIs
```




```
%Save .CSV file with all EOG file features
csvwrite(strcat(datapath,'AllDataFeatures.csv'),allData(:,9:end));%Including the label
```

# Motor Task Classification (Label + 8)

All Classifications Results:

- 1) CN, MR, ML, MU, MD, MP = "0", "1", "2", "3", "4", "5"
- 2) CN, MR, ML = "0", "1", "2"
- 3) CN, MP = "0", "5"
- 4) CN, MU, MD = "0", "3", "4"

```
clear;clc;
addpath(genpath('./src'))%functions folders
path = fullfile('./data/');%data folder
% Upload .CSV file with the features of all EOG files
allData = fLoad_csv(path,'AllDataFeatures');

[CN, MR, ML, MU, MD, MP] = fIdxLabel_EOG(allData);%Index of rows by task type

num = input('Enter a number: ');
switch num
    case 1 %all task
        idx = [CN(1:end);MR(1:end);ML(1:end);MU(1:end);MD(1:end);MP(1:end)];
        disp('All task')
    case 2 %Horizontal Movements
        idx = [CN(1:end);MR(1:end);ML(1:end)];
        disp('Horizontal Movements')
    case 3 %Blinking
        idx = [CN(1:end);MP(1:end)];
        disp('Blinking')
    case 4 %Vertical Movement
        idx = [CN(1:end);MU(1:end);MD(1:end)];
        disp('Vertical Movement')
    otherwise
        disp('other value')
end
```

```
All task
```

```
TaskData=allData(idx,:);
```

# Open the Classification Learner

```
%regressionLearner
classificationLearner
```

1) CN, MR, ML, MU, MD, MP = "0", "1", "2", "3", "4", "5"

| | | |
|---|---|---|
| **1.1** Tree | Accuracy (Validation): 85.5% | |
| Last change: Fine Tree | 4/4 features | |
| **1.2** Tree | Accuracy (Validation): 84.7% | |
| Last change: Medium Tree | 4/4 features | |
| **1.3** Tree | Accuracy (Validation): 69.8% | |
| Last change: Coarse Tree | 4/4 features | |
| **1.4** Linear Discriminant | Accuracy (Validation): 82.8% | |
| Last change: Linear Discriminant | 4/4 features | |
| **1.5** Quadratic Discriminant | Accuracy (Validation): 93.3% | |
| Last change: Quadratic Discriminant | 4/4 features | |
| **1.6** Naive Bayes | Accuracy (Validation): 90.5% | |
| Last change: Gaussian Naive Bayes | 4/4 features | |
| **1.7** Naive Bayes | Accuracy (Validation): 92.3% | |
| Last change: Kernel Naive Bayes | 4/4 features | |
| **1.8** SVM | Accuracy (Validation): 88.5% | |
| Last change: Linear SVM | 4/4 features | |
| **1.9** SVM | Accuracy (Validation): 93.3% | |
| Last change: Quadratic SVM | 4/4 features | |
| **1.10** SVM | Accuracy (Validation): **93.5%** | |
| Last change: Cubic SVM | 4/4 features | |

| | | |
|---|---|---|
| **1.11** SVM | Accuracy (Validation): 86.8% | |
| Last change: Fine Gaussian SVM | 4/4 features | |
| **1.12** SVM | Accuracy (Validation): 93.0% | |
| Last change: Medium Gaussian SVM | 4/4 features | |
| **1.13** SVM | Accuracy (Validation): 87.3% | |
| Last change: Coarse Gaussian SVM | 4/4 features | |
| **1.14** KNN | Accuracy (Validation): 92.0% | |
| Last change: Fine KNN | 4/4 features | |
| **1.15** KNN | Accuracy (Validation): 90.0% | |
| Last change: Medium KNN | 4/4 features | |
| **1.16** KNN | Accuracy (Validation): 73.3% | |
| Last change: Coarse KNN | 4/4 features | |
| **1.17** KNN | Accuracy (Validation): 86.2% | |
| Last change: Cosine KNN | 4/4 features | |
| **1.18** KNN | Accuracy (Validation): 89.2% | |
| Last change: Cubic KNN | 4/4 features | |
| **1.19** KNN | Accuracy (Validation): 91.0% | |
| Last change: Weighted KNN | 4/4 features | |
| **1.20** Ensemble | Accuracy (Validation): 89.2% | |
| Last change: Boosted Trees | 4/4 features | |

| | | |
|---|---|---|
| **1.21** | Ensemble | Accuracy (Validation): 90.8% |
| Last change: Bagged Trees | | 4/4 features |
| **1.22** | Ensemble | Accuracy (Validation): 82.0% |
| Last change: Subspace Discriminant | | 4/4 features |
| **1.23** | Ensemble | Accuracy (Validation): 85.5% |
| Last change: Subspace KNN | | 4/4 features |
| **1.24** | Ensemble | Accuracy (Validation): 84.7% |
| Last change: RUSBoosted Trees | | 4/4 features |
| **1.25** | Neural Network | Accuracy (Validation): 89.2% |
| Last change: Narrow Neural Network | | 4/4 features |
| **1.26** | Neural Network | Accuracy (Validation): 91.2% |
| Last change: Medium Neural Network | | 4/4 features |
| **1.27** | Neural Network | Accuracy (Validation): 91.3% |
| Last change: Wide Neural Network | | 4/4 features |
| **1.28** | Neural Network | Accuracy (Validation): 88.5% |
| Last change: Bilayered Neural Network | | 4/4 features |
| **1.29** | Neural Network | Accuracy (Validation): 91.3% |
| Last change: Trilayered Neural Network | | 4/4 features |

## Best Classification algorithm

**1.10** SVM | Accuracy (Validation): **93.5%**

Last change: Cubic SVM | 4/4 features

Current Model Summary

**Model 1.10**: Trained

**Training Results**

| | |
|---|---|
| Accuracy (Validation) | 93.5% |
| Total cost (Validation) | 39 |
| Prediction speed | ~4000 obs/sec |
| Training time | 2.7749 sec |

**Model Type**

Preset: Cubic SVM
Kernel function: Cubic
Kernel scale: Automatic
Box constraint level: 1
Multiclass method: One-vs-One
Standardize data: true

**Optimizer Options**

Hyperparameter options disabled

**Feature Selection**

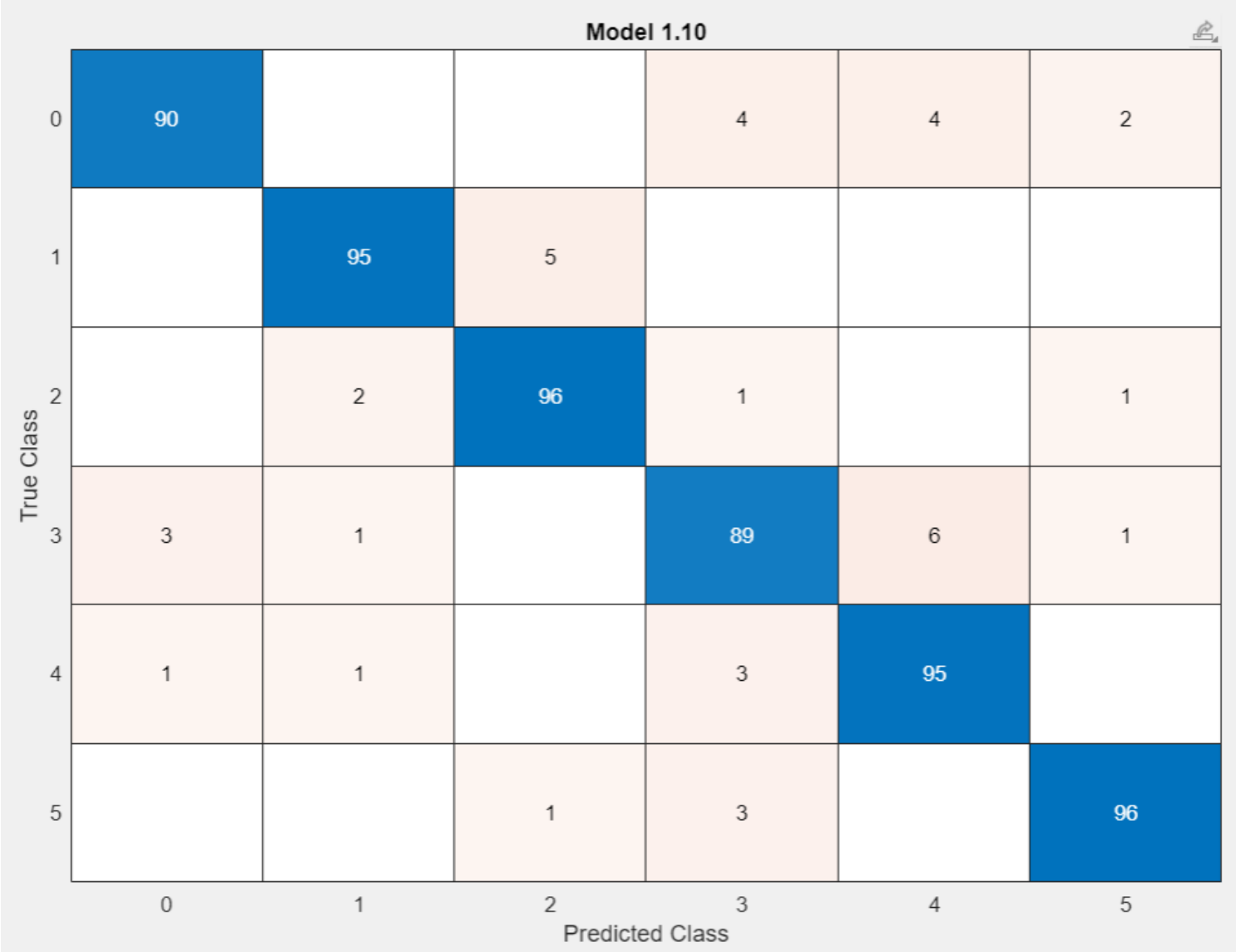
All features used in the model, before PCA

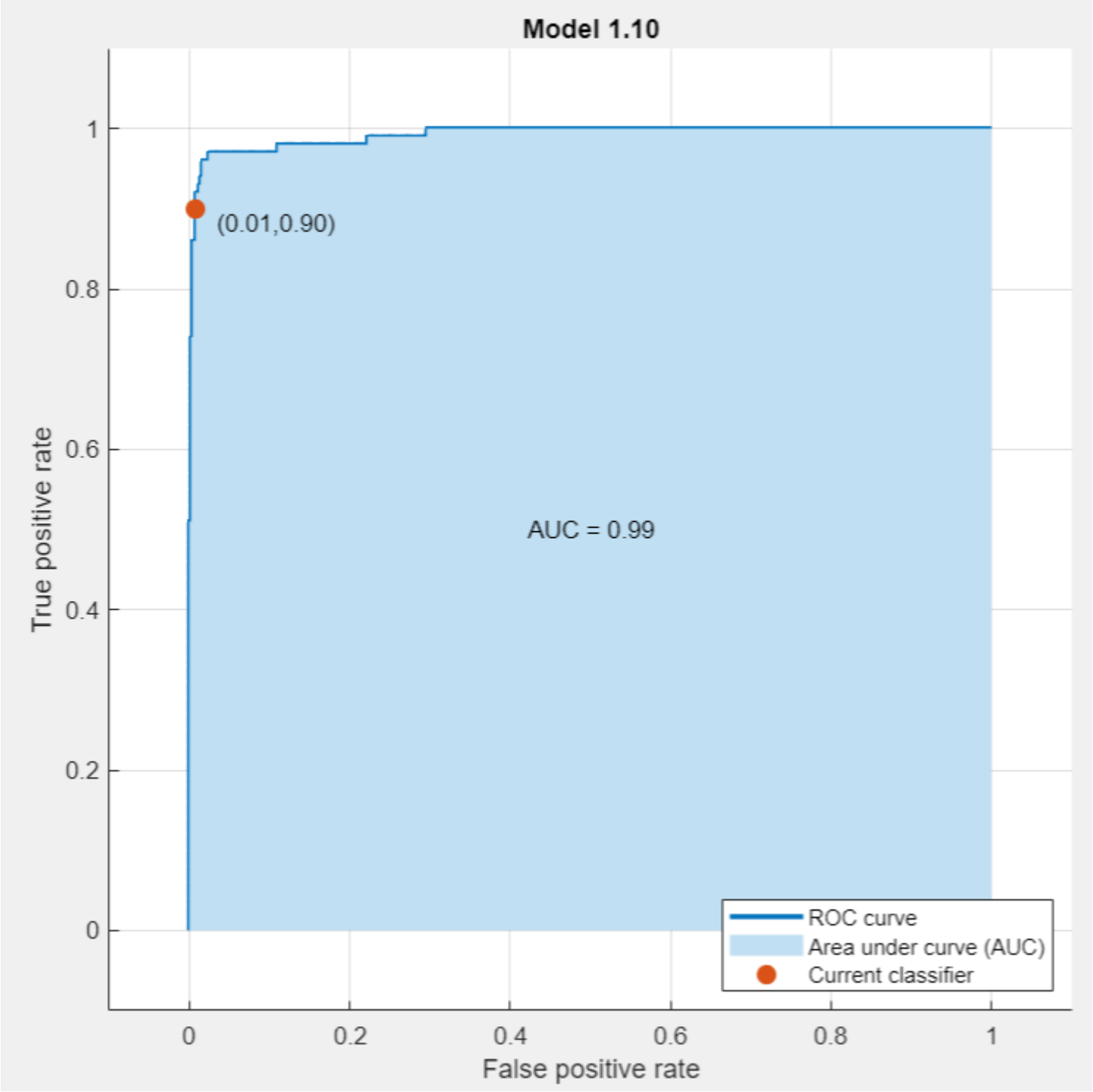
**PCA**

PCA disabled

**Misclassification Costs**

Cost matrix: default


Model 1.10
True Class
Predicted Class
0
1
2
3
4
5
90
4
4
2
95
5
2
96
1
1
3
1
89
6
1
1
1
3
95
1
3
96


Model 1.10
(0.01,0.90)
AUC = 0.99
True positive rate
False positive rate
ROC curve
Area under curve (AUC)
Current classifier
0
0.2
0.4
0.6
0.8
1