MATLAB
MACHINE LEARNING
ONRAMP
Data science assignment

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Unit 3

Improving Predictive Models

Task 1:

Create a five-fold cross-validation partition named `cvpt` of the data in the table `groupData`. The response is the table variable `group`.

Task 2:

Create a discriminant analysis model named `mdl` for the data in the table `groupData`. Use the cross-validation partition `cvpt`.

Task 3:

Save the loss to `kfLoss`.

Task 4:

Create a discriminant analysis model named `mdl2` for the data in the table `groupData` that uses leave-one-out validation. Then calculate and save the loss of the leave-one-out model to `kfLoss2`.

```
load data
cvpt = cvpartition(groupData.group,"HoldOut",0.3);
trainData = groupData(training(cvpt),:);
testData = groupData(test(cvpt),:);
holdoutMdl = fitcdiscr(trainData,"group");
holdoutLoss = loss(holdoutMdl,testData)
```

Task 1

```
cvpt=cvpartition(groupData.group,"KFold",5);
```

Task 2

```
mdl=fitcdiscr(groupData,"group","CVPartition",cvpt)
```

Task 3

```
kfLoss=kfoldLoss(mdl);
disp("k fold loss :" + kfLoss);
```

Task 4

```
mdl2=fitcdiscr(groupData,"group","Leaveout","on");
kfLoss2=kfoldLoss(mdl2);
disp("k fold loss :" + kfLoss2)
```

Further Practice

```
mdl3=fitcdiscr(groupData,"group","KFold",10);
kfLoss3=kfoldLoss(mdl3);
disp("k fold loss :" + kfLoss3);
```

```
holdoutLoss = 0.0379
```

```
mdl =
  ClassificationPartitionedModel
    CrossValidatedModel: 'Discriminant'
         PredictorNames: {'x'  'y'}
           ResponseName: 'group'
        NumObservations: 92
                  KFold: 5
              Partition: [1×1 cvpartition]
             ClassNames: [A    B    C]
         ScoreTransform: 'none'

  Properties, Methods
k fold loss :0.076087
```

```
k fold loss :0.086957
```

```
k fold loss :0.097826
```

4.2 Cross Validation: (7/8) Heart Health

Task 1:

Using the data stored in the table `heartData`, create the following models in order. Use seven-fold cross-validation and calculate their loss values.

Classifier	Model Variable Name	Loss Variable Name
k-Nearest Neighbor	`mdlKnn`	`lossKnn`
Discriminant Analysis	`mdlDa`	`lossDa`

What happens to the loss values if you use leave-one-out validation?

This code loads the data.

```
rng(0)
heartData = readtable("heartdataNumMulti.txt");
```

The script `holdoutAnalysis` calculates the loss for different models using holdout validation.

```
holdoutAnalysis
```

Task 1

Create models and calculate loss

```
cvpt=cvpartition(heartData.HeartDisease,"KFold",7);
```

```
mdlKnn=fitcknn(heartData,"HeartDisease","CVPartition",cvpt);
lossKnn=kfoldLoss(mdlKnn)
disp("knn k fold loss:" + lossKnn);


mdlDa=fitcdiscr(heartData,"HeartDisease","CVPartition",cvpt);
lossDa=kfoldLoss(mdlDa)
disp("da k fld loss :" + lossDa);
```

Display the results.

```
KFoldLoss = [lossKnn;lossDa];
results = table(KFoldLoss);
results.Properties.RowNames = ["kNN" "Discriminant Analysis"];
disp("Seven-fold cross-validated results")
disp(results)
```

```
30% holdout results
                               Loss
                              _______

    kNN                        0.625
    Discriminant Analysis    0.53125
```

```
lossKnn = 0.6347
knn k fold loss:0.63466


lossDa = 0.5222
da k fld loss :0.52225

Seven-fold cross-validated results
                             KFoldLoss
                             _________

    kNN                       0.63466
    Discriminant Analysis     0.52225


lossKnn1 = 0.6557
knn k fold loss:0.65574


lossDa1 = 0.5222
da k fld loss :0.52225
```

4.3 Hyperparameter Optimization: (3/4) Optimize kNN Hyperparameters

Task :
In the script, a kNN model is trained on `dataTrain` using the default property values.

Train another kNN model `mdl`, and tune the hyperparameters by setting `"OptimizeHyperparamters"` to `"auto"`. Use the training data `dataTrain` with response variable `group`.

Run the script by clicking **Run** in the MATLAB Toolstrip. This optimization takes approximately 1 to 2 minutes to run.

What did the optimization select for the property values?

```
mdl.NumNeighbors
mdl.Distance
```

To view a solution and see the output, enter the following command:

```
open optimizeknnSoln.mlx
```

Optimize k-NN Parameters

This code loads and partitions data.

```
load data
groupData
rng(1234)
pt = cvpartition(groupData.group,"Holdout",0.2);
dataTrain = groupData(training(pt),:);
dataTest = groupData(~training(pt),:);
```

This code fits a k-NN model and calculates the loss.

```
m = fitcknn(dataTrain,"group");
trainLoss = resubLoss(m)
testLoss = loss(m,dataTest)
```

Optimize hyperparameters

```
mdl=fitcknn(dataTrain,"group","OptimizeHyperparameters","auto");
```

Calculate the loss.

```
trainLossOpt = resubLoss(mdl)
testLossOpt = loss(mdl,dataTest)
```

4.3 Hyperparameter Optimization: (4/4) Heart Health

Task 1:

Create a 10-fold cross-validation partition named `cvpt` of the training data `heartTrain`.

Then use the **`struct`** function to create a structure named `opt` which sets the following optimization options:

- Set `"CVPartition"` to `cvpt`.
- Set `"MaxObjectiveEvaluations"` to 20.

Heart Disease Analysis

This code loads and partitions the data.

```
heartData = readtable("heartdataNumMulti.txt")
rng(1234)
pt = cvpartition(heartData.HeartDisease,"Holdout",0.2);
heartTrain = heartData(training(pt),:);
heartTest = heartData(~training(pt),:);
```

This code fits a *k*-NN model to the training data and calculates the loss.

```
m = fitcknn(heartTrain,"HeartDisease");
trainLoss = resubLoss(m)
testLoss = loss(m,heartTest)
```

Task 1

```
cvpt = cvpartition(heartTrain.HeartDisease,"KFold",10);
opt = struct("CVPartition",cvpt,"MaxObjectiveEvaluations",20);
```

Optimize hyperparameters

```
mdl=fitcknn(heartTrain,"HeartDisease","OptimizeHyperparameters","NumNei
ghbors");
```

4.4 Reducing Predictors - Feature Transformation: (4/6) PCA

Task1:

Perform PCA on the predictive variables of the table `dataOrig` and save transformed data in `scrs`. Save the percentage explained as `pexp`.

Task 2:

Create a Pareto chart of the percent variance explained values.

Task 3;

Create a new variable named `dataRed` that contains only the first three columns of `scrs`.

Task 4:

Fit a 10-fold cross-validated Naive Bayes model to the data containing only the first three principal components. Name the result `mdl`. Then calculate the loss of `mdl` and save it as `mdlLoss`.

```
rng(0)
load data
dataOrig
```

This code fits a 10-fold cross-validated Naive Bayes model to the original data and calculates the loss.

```
mdlOrig = fitcnb(dataOrig,"R","KFold",10);
kfoldLoss(mdlOrig)
```

Task 1

```
[~,scrs,~,~,pexp]=pca(dataOrig{:,1:end-1})
```

Task 2

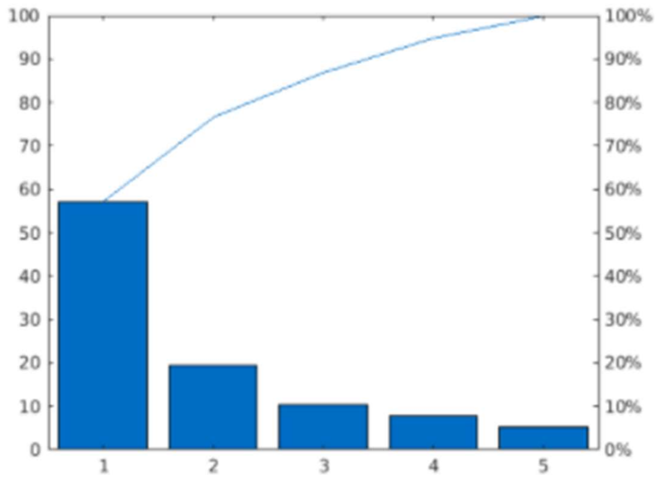
```
pareto(pexp)
```

Task 3

```
dataRed=scrs(:,1:3)
```

Task 4

```
mdl=fitcnb(dataRed,dataOrig.R,"KFold",10);
mdlLoss=kfoldLoss(mdl)
```




```
dataRed = 154x3
    -4.8124   -0.9437    0.8996
     0.3857   -2.2156   -0.6676
    -4.9675    0.5215    0.2417
     1.0857    4.2905    0.8709
    -1.9240   -1.6357    0.5774
    -0.0118    3.9925   -3.2267
    -5.0296   -0.5866    0.0800
    -3.1472    0.9471   -0.3543
     5.4659   -0.9839    1.7438
     1.5640    0.2460    1.3518
       :

mdlLoss = 0.0455
```

4.4 Reducing Predictors - Feature Transformation: (6/6) Heart Health

Task 1:

Use PCA to transform your data. Save the principal component coefficients as `pcs`, the transformed data as `scrs`, and the percent explained as `pexp`.

Create a Pareto chart of the percent variance explained values.

Task2:

Create a heat map of the absolute values of the first eight columns of the principal component coefficients.

Task 3:

Create a 10-fold cross-validated Naive Bayes model named `mdl` using the kernel distribution. Use only the first eight features returned from PCA.

Calculate the loss of this model and save it to `pcaLoss`.

This code loads the data and splits the data into predictors (`numData`) and response (`resp`).

```
rng(0)
heartData = readtable("heartDataNum.txt");
vars = heartData.Properties.VariableNames(1:end-1)
numData = heartData{:,1:end-1};
resp = categorical(heartData.HeartDisease);
```

This code fits a 10-fold cross-validated Naive Bayes model using the kernel distribution to the original data and calculates the loss.

```
mdlOrig = fitcnb(numData,resp,"DistributionNames","kernel","KFold",10);
lossOrig = kfoldLoss(mdlOrig)
```

Task 1

```
[pcs,scrs,~,~,pexp] = pca(numData);
pareto(pexp)
```

Task 2

```
heatmap(abs(pcs(:,1:8)),"YDisplayLabels",vars)
```

Task 3

```
mdl = fitcnb(scrs(:,1:8),resp,"DistributionNames","kernel","KFold",10);
pcaLoss = kfoldLoss(mdl)
```

4.5 Reducing Predictors - Feature Selection: (2/12) Built-in Feature Selection

Task 1:

Create a classification tree model named `mdl` without cross-validation. Then calculate the importance of each predictor and store the result in `p`.

Task 2:

Visualize the values in `p` using the `bar` function.

Task 3:

Create a logical vector `toKeep` whose values are true if the corresponding values of `p` are greater than 0.005 and false otherwise. Use `toKeep` to create a table `dataPart` which contains only the predictors with `p` greater than 0.005 and the response `R`.

Task 4:

Create a seven-fold cross-validated classification tree model named `mdlPart` which uses only the selected predictors. Calculate the loss and save it to `partLoss`.

```
rng(0)
load data.mat
data
```

This code fits a 7-fold cross-validated classification tree model to the original data and calculates the loss.

```
mdlFull = fitctree(data,"R","KFold",7);
fullLoss = kfoldLoss(mdlFull)
```

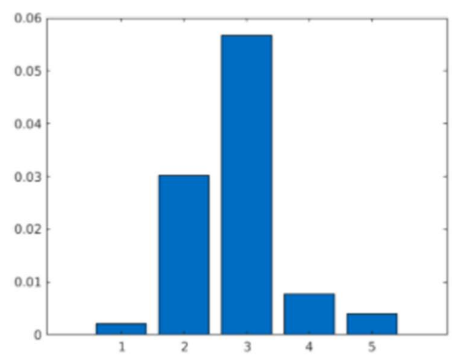
Task 1

```
mdl=fitctree(data,"R");
p= predictorImportance(mdl)
```

Task 2

```
bar(p)
```

```
fullLoss = 0.0844
p = 1x5
     0.0021    0.0302    0.0566    0.0077 ...
```



Task 3

```
toKeep = p > 0.005
dataPart = data(:,[toKeep true])
```

Task 4

```
mdlPart=fitctree(dataPart,"R","KFold",7)
partLoss=kfoldLoss(mdlPart)
```

```
toKeep = 1×5 logical array
     0   1   1   1   0
```

dataPart = 154×4 table

	P2	P3	P4	R
1	-1.1178	-4.1511	1.2458	B
2	-1.7874	-0.4522	-2.1508	C
3	-0.0593	-3.3889	2.7783	B
4	2.6283	2.2820	1.6122	A
5	-1.3114	-1.6471	-0.8356	B
6	1.4592	2.0335	3.8287	A
7	-1.2603	-4.4747	1.9510	B
8	-1.4930	-1.5366	1.9835	B
9	3.8282	3.0187	-4.7132	A

```
mdlPart =
  ClassificationPartitionedModel
    CrossValidatedModel: 'Tree'
         PredictorNames: {'P2'  'P3'  'P4'}
           ResponseName: 'R'
        NumObservations: 154
                  KFold: 7
              Partition: [1×1 cvpartition]
             ClassNames: [A    B    C]
         ScoreTransform: 'none'


  Properties, Methods
partLoss = 0.0909
```

4.5 Reducing Predictors - Feature Selection: (5/12) Sequential Feature Selection

Task 1:

Create an anonymous function named `ferror` that takes four inputs: `XTrain`, `yTrain`, `XTest`, and `yTest`, and returns the number of inaccurate predictions for `yTest`. Use a *k*-Nearest Neighbor classification model.

Task 2:

Use feature selection to create a logical vector named `toKeep`. The predictors are in the first five columns of the `data` table. The response is the last column, `R`.

Use `toKeep` to create a table `dataPart` which contains only the selected predictors and the response `R`.

Task 3:

Create a 7-fold cross-validated *k*-nearest neighbor model named `mdlPart` with only the selected predictors. Calculate the loss and save it to `partLoss`.

This code loads and displays the data.

```
rng(0)
load data.mat
data
```

This code fits a 7-fold cross-validated *k*-NN model to the original data and calculates the loss.

```
mdlFull = fitcknn(data,"R","KFold",7);
fullLoss = kfoldLoss(mdlFull)
```

Task 1

```
ferror = @(XTrain,yTrain,XTest,yTest) nnz(yTest ~=
predict(fitcknn(XTrain,yTrain),XTest))
```

Task 2

```
toKeep = sequentialfs(ferror,data{:,1:end-1},data.R)
dataPart=data(:,[toKeep true])
```

Task 3

```
mdlPart=fitcknn(dataPart,"R","KFold",7)
partLoss = kfoldLoss(mdlPart)
```

```
toKeep = 1×5 logical array
     0   1   1   1   1
```

dataPart = 154×5 table

	P2	P3	P4	P
3	-0.0593	-3.3889	2.7783	
4	2.6283	2.2820	1.6122	
5	-1.3114	-1.6471	-0.8356	
6	1.4592	2.0335	3.8287	
7	-1.2603	-4.4747	1.9510	
8	-1.4930	-1.5366	1.9835	
9	3.8282	3.0187	-4.7132	
10	1.3721	0.8799	-1.7261	
11	1.0084	0.6663	0.4765	

```
mdlPart =
  ClassificationPartitionedModel
    CrossValidatedModel: 'KNN'
         PredictorNames: {'P2'  'P3'  'P4'  'P5'}
           ResponseName: 'R'
        NumObservations: 154
                  KFold: 7
              Partition: [1×1 cvpartition]
             ClassNames: [A    B    C]
         ScoreTransform: 'none'


  Properties, Methods
partLoss = 0.0649
```

4.5 Reducing Predictors - Feature Selection: (7/12) Creating Dummy Variables

Task 1:

Create an anonymous function named `ferror` that takes four inputs: `XTrain`, `yTrain`, `XTest`, and `yTest`, and returns the number of inaccurate predictions for `yTest`. Use a *k*-Nearest Neighbor classification model.

Task 2:

Use feature selection to create a logical vector named `toKeep`. The predictors are in the first five columns of the `data` table. The response is the last column, `R`.

Use `toKeep` to create a table `dataPart` which contains only the selected predictors and the response `R`.

Task 3:

Create a 7-fold cross-validated *k*-nearest neighbor model named `mdlPart` with only the selected predictors. Calculate the loss and save it to `partLoss`.

This code loads and displays the data.

```
rng(0)
load data.mat
data
```

This code fits a 7-fold cross-validated *k*-NN model to the original data and calculates the loss.

```
mdlFull = fitcknn(data,"R","KFold",7);
fullLoss = kfoldLoss(mdlFull)
```

Task 1

```
ferror = @(XTrain,yTrain,XTest,yTest) nnz(yTest ~=
predict(fitcknn(XTrain,yTrain),XTest))
```

Task 2

```
toKeep = sequentialfs(ferror,data{:,1:end-1},data.R)
dataPart = data(:,[toKeep true])
```

Task 3

```
mdlPart = fitcknn(dataPart,"R","KFold",7);
partLoss = kfoldLoss(mdlPart)
```

```
fullLoss = 0.0519
```

```
ferror = function_handle with value:
    @(XTrain,yTrain,XTest,yTest)nnz(yTest~=predict(
```

```
toKeep = 1×5 logical array
     0   1   1   1   1
```

dataPart = 154×5 table

	P2	P3	P4	P
1	-1.1178	-4.1511	1.2458	
2	-1.7874	-0.4522	-2.1508	
3	-0.0593	-3.3889	2.7783	
4	2.6283	2.2820	1.6122	
5	-1.3114	-1.6471	-0.8356	
6	1.4592	2.0335	3.8287	
7	-1.2603	-4.4747	1.9510	
8	-1.4930	-1.5366	1.9835	
9	3.8282	3.0187	-4.7132	

```
partLoss = 0.0649
```

4.5 Reducing Predictors - Feature Selection: (12/12) Heart Health – Feature Selection with Categorical Data

Task :

The open live script performs feature selection on a Naive Bayes classifier for the heart disease data set. You can look at the local function `cattable2mat` to see how dummy variables are created.

Click **Run** in the MATLAB Toolstrip to execute the script. The feature selection is computationally intensive, and may take a long time to run. Thus, it may not complete.

Load the data.

```
heartData = readtable("heartDataAll.txt");
heartData = convertvars(heartData,12:22,"categorical");
```

Extract the response variable and make a partition for evaluation.

```
HD = heartData.HeartDisease;
rng(1234)
cvpt = cvpartition(HD,"KFold",10);
```

Convert categorical predictors to numeric dummy variables

```
[X,XNames] = cattable2mat(heartData(:,1:end-1))
```

Fit a Naive Bayes model to the full data

```
dists = [repmat("kernel",1,11),repmat("mvmn",1,10)];
mFull =
fitcnb(heartData,"HeartDisease","DistributionNames",dists,"CVPartition"
,cvpt);
```

Perform sequential feature selection

```
rng(1234)
fmodel = @(X,y) fitcnb(X,y,"DistributionNames","kernel");
ferror = @(Xtrain,ytrain,Xtest,ytest)
nnz(predict(fmodel(Xtrain,ytrain),Xtest) ~= ytest);
toKeep =
sequentialfs(ferror,X,HD,"cv",cvpt,"options",statset("Display","iter"))
;


% Which variables are in the final model?
XNames(toKeep)


% Fit a model with just the given variables
mPart =
fitcnb(X(:,toKeep),HD,'Distribution','kernel','CVPartition',cvpt);


% Display loss values
lossFull = kfoldLoss(mFull)
lossPart = kfoldLoss(mPart)
```

Local function: `cattable2mat`

```
function [dummymat,dummyvarnames] = cattable2mat(data)
    % Makes a matrix from a table, with categorical variables
    % replaced by (numeric) dummy variables

    vars = string(data.Properties.VariableNames);
    idxCat = varfun(@iscategorical,data,"OutputFormat","uniform");

    for k = find(idxCat)
        % get list of categories
        c = categories(data.(vars(k)));

        % replace variable with matrix of dummy variables
        data = convertvars(data,vars(k),@dummyvar);

        % split dummy variable and make new variable names (by
appending
        % the category value to the categorical variable name)
        varnames = vars(k) + "_" + replace(c," ","_");
        data = splitvars(data,vars(k),"NewVariableNames",varnames);
    end
```

```
    % return the numeric values
    dummymat = data.Variables;
    dummyvarnames = string(data.Properties.VariableNames);
end
```

```
X = 427×35
    0.7083    0.3715    0.4865    0.6875  ...
    0.7917    0.5196    0.4324    0.6875
    0.7917    0.3603    0.3784    0.5000
    0.1667    0.4190    0.6216    0.9375
    0.2500    0.2905    0.2973    0.4375
    0.5625    0.3799    0.5297    0.8750
    0.6875    0.4693    0.2432    0.3125
    0.5833    0.7095    0.4054    0.5000
    0.7083    0.4302    0.3514    0.4375
    0.5000    0.2877    0.2162    0.3125
      ⋮

XNames = 1×35 string
   "Age"      "Cholesterol"   "ExerciseDuratic ...

Start forward sequential feature selection:
Initial columns included:  none
Columns that can not be included:  none
Step 1, added column 14, criterion value 0.234192
Step 2, added column 8, criterion value 0.222482
Step 3, added column 11, criterion value 0.213115
Step 4, added column 17, criterion value 0.208431
Step 5, added column 25, criterion value 0.203747
Step 6, added column 2, criterion value 0.199063
Step 7, added column 12, criterion value 0.194379
Step 8, added column 31, criterion value 0.185012
Step 9, added column 1, criterion value 0.18267
Final columns included:  1 2 8 11 12 14 17 25 31
ans = 1×9 string
   "Age"      "Cholesterol"   "MaxHeartRate"   ...

lossFull = 0.2131

lossPart = 0.1827
```

4.6 Ensemble Learning: (5/7) Fit an Ensemble

Task 1:

Create an ensemble named `mdlEns` for the data in `data` with response `"R"`. Use classification tree learners and `"Bag"` as the ensemble creation method.

Calculate the resubstitution loss and save it to a variable named `lossEns`.

Task 2:

Create another ensemble of bagged trees named `mdlEns2`. Use 30 learners and the cross-validation partition `cvpt`. Calculate the *k*-fold loss and name it `lossEns2`.

This code loads and displays the data.

```
rng(1234)
load data
data
```

This code fits a classification tree and calculates the loss.

```
cvpt = cvpartition(data.R,"KFold",3);
mdlTree = fitctree(data,"R","CVPartition",cvpt);
lossTree = kfoldLoss(mdlTree)
```

Task 1

```
mdlEns = fitcensemble(data,"R","Method","Bag");
lossEns = resubLoss(mdlEns)
```

Task 2

```
mdlEns2 = fitcensemble(data,"R","Method","Bag",...
    "NumLearningCycles",30,"CVPartition",cvpt);
lossEns2 = kfoldLoss(mdlEns2)
```

Further Practice

```
mdlEns3 =
fitcensemble(data,"R","Method","Bag","Learners","discriminant","NumLear
ningCycles",30,"CVPartition",cvpt);
lossEns2 = kfoldLoss(mdlEns3)
```

data = 154x6 table

	P1	P2	P3	P
1	-1.2539	-1.1178	-4.1511	
2	1.1176	-1.7874	-0.4522	
3	-2.0149	-0.0593	-3.3889	
4	2.0259	2.6283	2.2820	
5	-0.6001	-1.3114	-1.6471	
6	0.9108	1.4592	2.0335	
7	-0.6914	-1.2603	-4.4747	
8	0.8586	-1.4930	-1.5366	
9	-0.5116	3.8282	3.0187	

```
lossTree = 0.0714
lossEns = 0
```

```
lossEns2 = 0.0455
```

```
lossEns2 = 0.0584
```

4.6 Ensemble Learning: (6/7) Use Learner Templates

Task 1:

Create an ensemble named `mdlEns` for the data in `data` with response `"R"`. Use kNN learners and the cross-validation partition `cvpt`.

Calculate the loss and save it to a variable named `lossEns`.

Task 2:

Create a template kNN learner `knnmodel` with the following properties:

Property Name	Property Value
"NumNeighbors"	5
"DistanceWeight"	"inverse"

Then create another ensemble named `mdlEns2` using the template kNN learners and the cross-validation partition `cvpt`. Calculate the *k*-fold loss and name it `lossEns2`.

This code loads and displays the data.

```
rng(1234)
load data
data
```

This code partitions the data, fits a *k*-NN model and calculates the loss.

```
cvpt = cvpartition(data.R,"KFold",3);
mdlKNN = fitcknn(data,"R","NumNeighbors",5,...
    "DistanceWeight","inverse","CVPartition",cvpt);
lossKNN = kfoldLoss(mdlKNN)
```

Task 1

```
mdlEns= fitcensemble(data,"R","Learners","knn","CVPartition",cvpt)
lossEns = kfoldLoss(mdlEns)
```

Task 2

```
knnmodel = templateKNN("NumNeighbors",5,"DistanceWeight","inverse")
mdlEns2= fitcensemble(data,"R","Learners",knnmodel,"CVPartition",cvpt)
lossEns2 = kfoldLoss(mdlEns2)
```

```
lossEns = 0.1753
knnmodel =
Fit template for classification KNN.

       NumNeighbors: 5
           NSMethod: ''
           Distance: ''
         BucketSize: ''
        IncludeTies: []
     DistanceWeight: 'inverse'
          BreakTies: []
           Exponent: []
                Cov: []
              Scale: []
    StandardizeData: []
            Version: 1
             Method: 'KNN'
               Type: 'classification'
mdlEns2 =
  ClassificationPartitionedEnsemble
    CrossValidatedModel: 'Subspace'
         PredictorNames: {'P1'  'P2'  'P3'  'P4'  'P
           ResponseName: 'R'
        NumObservations: 154
                  KFold: 3
              Partition: [1×1 cvpartition]
      NumTrainedPerFold: [100 100 100]
             ClassNames: [A    B    C]
         ScoreTransform: 'none'


  Properties, Methods
lossEns2 = 0.1104
```

4.6 Ensemble Learning: (7/7) Heart Health

Task 1:

Create an ensemble named `mdlEns` of 50 seven-fold cross-validated classification trees for the data in `heartDataNum` with response `"HeartDisease"`. Use the cross-validation partition `cvpt`. Calculate the loss and name it `lossEns`.

Task 2:

Modify your tree ensemble `mdlEns` so that the seven-fold loss is below 0.3.

This code loads and displays the data.

```
heartData = readtable("heartDataAll.txt");
heartData = convertvars(heartData,12:22,"categorical");
heartDataNum = heartData(:,[1:11 end])
```

This code partitions the data and fits a tree model.

```
rng(0)
cvpt = cvpartition(heartDataNum.HeartDisease,"KFold",7);
mdlTree = fitctree(heartDataNum,"HeartDisease","CVPartition",cvpt);
lossTree = kfoldLoss(mdlTree)
```

Tasks 1 & 2

Fit tree ensemble and calculate loss.

```
t=templateTree("Prune","on")
mdlEns =
fitcensemble(heartDataNum,"HeartDisease","Learners",t,"CVPartition",cvp
t,"NumLearningCycles",50)
lossEns = kfoldLoss(mdlEns)
```

```
lossTree = 0.3396
t =
Fit template for Tree.
    Prune: 'on'
```

```
mdlEns =
  ClassificationPartitionedEnsemble
    CrossValidatedModel: 'LogitBoost'
         PredictorNames: {'Age'  'Cholesterol'
           ResponseName: 'HeartDisease'
        NumObservations: 427
                  KFold: 7
              Partition: [1×1 cvpartition]
      NumTrainedPerFold: [50 50 50 50 50 50 50]
             ClassNames: [false    true]
         ScoreTransform: 'none'

  Properties, Methods
```

```
lossEns = 0.2693
```

4.7 Project - Improving Predictive Models: (1/2) Wine Quality

Task 1:

Reduce the number of predictors in `redData`. You may use feature selection and/or feature transformation.

Create a cross-validated model of any type with the reduced data. Name the model `mdl`, and calculate the loss `mdlLoss`.

Try different models to see if you can get the loss value below 0.45, that of the full quadratic discriminant analysis model.

This code loads and displays the wine data and a trained 7-fold cross-validated quadratic DA model of `redData`.

```
rng(0)
load wineDataRed
redData
mdlFull
fullLoss = kfoldLoss(mdlFull)
```

Reduce Predictors

Fit model with fewer predictors. Target loss value less than 0.45.

```
dataset = redData(:,1:end)
cvpt = cvpartition(dataset.QCLabel,"KFold",7);

ferror = @(XTrain,yTrain,XTest,yTest) nnz(yTest ~=
predict(fitcknn(XTrain,yTrain),XTest))
toKeep = sequentialfs(ferror,redData{:,1:end-1},redData.QCLabel)
dataPart = redData(:,[toKeep true])
mdlPart = fitcknn(dataPart,"QCLabel","KFold",7);
partLoss = kfoldLoss(mdlPart)


mdl =
fitcensemble(dataPart,"QCLabel","CVPartition",cvpt,"Learners","discrimi
nant")
mdlLoss= kfoldLoss(mdl)
```

```
    0    1    0    1    1    1    1    1    0    1    1
```

dataPart = 1593×9 table

	VolatileAcidity	ResidualSugar
1	0.397260273972603	0.068493150684932
2	0.520547945205479	0.116438356164384
3	0.438356164383562	0.095890410958904
4	0.109589041095890	0.068493150684932
5	0.397260273972603	0.068493150684932
6	0.369863013698630	0.061643835616438
7	0.328767123287671	0.047945205479452
8	0.363013698630137	0.020547945205479
9	0.315068493150685	0.075342465753425

```
partLoss =
   0.347143753923413
mdl =
  ClassificationPartitionedEnsemble
    CrossValidatedModel: 'Subspace'
         PredictorNames: {'VolatileAcidity'  'Resi
           ResponseName: 'QCLabel'
        NumObservations: 1593
                  KFold: 7
              Partition: [1×1 cvpartition]
      NumTrainedPerFold: [100 100 100 100 100 100
             ClassNames: [A     B     C     D     E]
         ScoreTransform: 'none'


  Properties, Methods

mdlLoss =
   0.448838669177650
```

4.7 Project - Improving Predictive Models: (2/2) Credit Ratings

Task 1:

Create a reduced data set with three or fewer predictor variables. You may use feature selection and/or feature transformation. Then, create a seven-fold cross-validated tree model named `mdl` and calculate the loss, `mdlLoss`.

Task 2:

Create an ensemble of 50 seven-fold cross-validated classification trees using the bag method. Create your model with three or fewer predictors selected from the previous task. Name the ensemble `mdlEns`. Calculate the loss and name it `lossEns`.

```
rng(0)
```

```
load creditData
creditRatings
mdlFull
fullLoss = kfoldLoss(mdlFull)
```

Task 1

Fit model with 3 or fewer predictors.

```
ferror = @(XTrain,yTrain,XTest,yTest) nnz(yTest
~=predict(fitcknn(XTrain,yTrain),XTest))
toKeep = sequentialfs(ferror,creditRatings{:,1:end-
1},creditRatings.Rating)
dataPart = creditRatings(:,[toKeep true])
mdl = fitctree(dataPart,"Rating","KFold",7)
mdlLoss= kfoldLoss(mdl)
```

Task 2

Fit ensemble with 3 or fewer predictors.

```
cvpt = cvpartition(creditRatings.Rating,"KFold",7)
mdlEns =
fitcensemble(dataPart,"Rating","Method","Bag","NumLearningCycles",50,"C
VPartition",cvpt)
lossEns = kfoldLoss(mdlEns)
```

Unit 4

Regression Methods

5.2 Linear Models: (4/11) Fit a Line

Task 1:

Create a regression model named `mdl` using the training data.

Task 2:

Use `mdl` to predict the response on the test data. Name the predicted response `yPred`.

```
load data
whos data dataTrain dataTest
plot(data.x,data.y,".")
```

Task 1

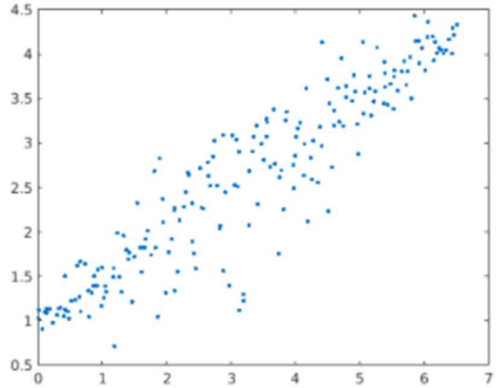
```
mdl=fitlm(dataTrain);
```

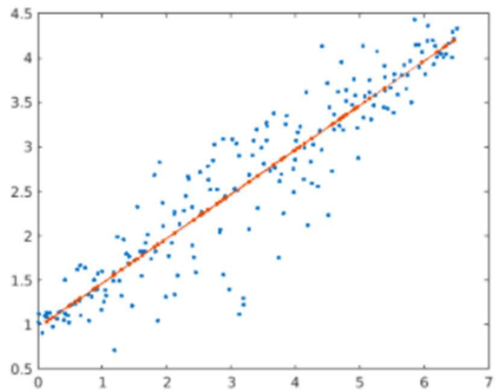
Task 2

```
yPred=predict(mdl,dataTest);
```

Further Practice

```
hold on
plot(dataTest.x,yPred,".-")
hold off
```





5.2 Linear Models: (6/11) Fit a Polynomial

Task 1:

Create a linear regression model named `mdl` which fits a line to the training data. Then, use the model to predict the response on the test data and name it `yPred`.

Task 2:

Modify your code so that `mdl` fits a quadratic polynomial to the training data.

Task 3:

Modify your code so that the influence of the outliers on the model `mdl` is reduced.

```
load data
whos data dataTrain dataTest
```

Tasks 1, 2, 3

```
mdl=fitlm(dataTrain)
yPred=predict(mdl,dataTest);
mdl=fitlm(dataTrain,"quadratic","RobustOpts","on");
yPred=predict(mdl,dataTest);
```

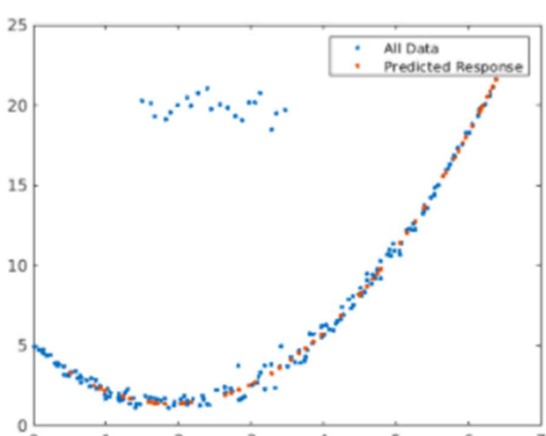
Plot the results.

```
plot(data.x,data.y,".")
hold on
plot(dataTest.x,yPred,".")
hold off
legend("All Data","Predicted Response")
```

Further Practice

```
mdl=fitlm(dataTrain,"quadratic","RobustOpts","cauchy");
yPred=predict(mdl,dataTest);


plot(data.x,data.y,".")
hold on
plot(dataTest.x,yPred,".")
hold off
legend("All Data","Predicted Response")
```

```
  Name              Size              Bytes  Class

  data             200x2               4388  table
  dataTest          60x2               2148  table
  dataTrain        140x2               3428  table

mdl =
Linear regression model:
    y ~ 1 + x

Estimated Coefficients:
                   Estimate      SE       tStat
                   ________    _______    ______

    (Intercept)     1.8546     0.88246    2.1016
    x               2.0153     0.25216    7.9924


Number of observations: 140, Error degrees of freed
Root Mean Squared Error: 5.47
R-squared: 0.316,  Adjusted R-Squared: 0.311
F-statistic vs. constant model: 63.9, p-value = 4.7
```



5.2 Linear Models: (8/11) Multivariable Linear Regression

TASK 1:

Create a regression model named `mdl` fitting the training data. Use a linear combination of the predictor variables for the model. Then predict the response on the test data and name it `yPred`.

Task2 :

Modify your code so that `mdl` fits a model where the response `Y` is a function of `X1`, `X1^2`, and `X3`.

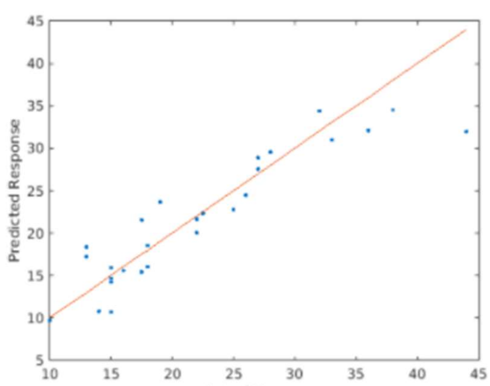
```
load data
whos data dataTrain dataTest
data.Properties.VariableNames
```

Tasks 1 & 2

```
mdl=fitlm(dataTrain)
yPred=predict(mdl,dataTest);
mdl=fitlm(dataTrain,"Y~X1+(X1^2)+X3")
```

```
plot(dataTest.Y,yPred,".")
hold on
plot(dataTest.Y,dataTest.Y)
hold off
xlabel("Actual Response")
ylabel("Predicted Response")
```

```
mdl =
Linear regression model:
    Y ~ 1 + X1 + X3 + X1^2

Estimated Coefficients:
                    Estimate        SE          tSt
                   __________    __________    _____

    (Intercept)      -0.38043        8.3718    -0.04
    X1              -0.014043     0.0037879      -3.
    X3                0.71314      0.081914       8.
    X1^2           1.1953e-06    5.9868e-07       1.


Number of observations: 66, Error degrees of freedon
Root Mean Squared Error: 2.85
R-squared: 0.872,  Adjusted R-Squared: 0.866
F-statistic vs. constant model: 141, p-value = 1.18e
```



5.2 Linear Models: (10/11) Multivariable Linear Regression with Numeric Arrays

Task 1:

Create a regression model named `mdl` fitting the training data. Use a linear combination of the predictor variables for the model.

Task 2:

Create a matrix `XTrain13` to represent a regression formula for the training data with terms x_1, x_3, and $x_1 \cdot x_3$.
Then create a regression model named `mdl13` which fits the training data, using the model.

This code loads the data.

```
load data
whos
```

Task 1

```
mdl=fitlm(XTrain,yTrain);
```

Task 2

```
XTrain13=[XTrain(:,1) XTrain(:,3) XTrain(:,1).*XTrain(:,3)]
mdl13=fitlm(XTrain13,yTrain);
```

```
  Name            Size             Bytes  Class

  X             100x3              2400  double
  XTest          30x3               720  double
  XTest13        30x3               720  double
  XTrain         70x3              1680  double
  XTrain13       70x3              1680  double
  mdl             1x1             12948  LinearModel
  mdl13           1x1             12948  LinearModel
  y             100x1               800  double
  yPred          30x1               240  double
  yTest          30x1               240  double
  yTrain         70x1               560  double
```

```
XTrain13 = 70x3
          4732          70      331240
          4615          70      323050
          4382          70      306740
          4055          76      308180
          3870          76      294120
          4312          70      301840
          4425          70      309750
          3609          70      252630
          3086          70      216020
          4215          76      320340
        ⋮
```

5.2 Linear Models: (11/11) Predict Fuel Economy

Task 1:

Create a multivariate linear model named `mdl` with the training data. Then, use the model to predict the values, `econPred`.

Task 2:

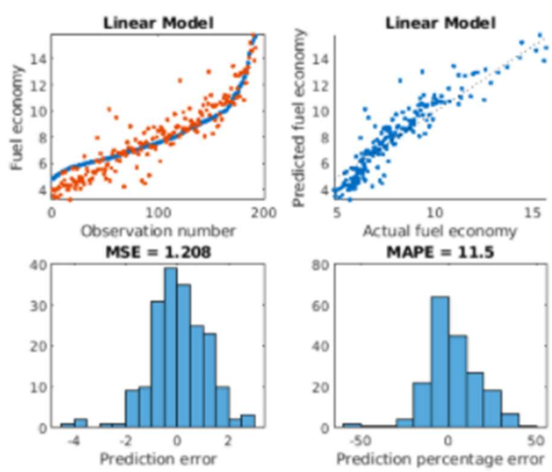
Modify your code so that the model `mdl` uses `"cauchy"` for the `"RobustOpts"` property value.

```
load carEcon
whos carData carTrain carTest
```

Tasks 1 and 2

```
mdl=fitlm(carTrain);
econPred=predict(mdl,carTest);
mdl=fitlm(carTrain,"RobustOpts","cauchy")
econPred=predict(mdl,carTest);
evaluateFit(carTest.FuelEcon,econPred,"Linear Model")
```

```
mdl =
Linear regression model (robust fit):
    FuelEcon ~ 1 + Car_Truck + EngDisp + RatedHP +

Estimated Coefficients:
                         Estimate        SE
                        __________    ________

    (Intercept)             7.9143        1.70
    Car_Truck_truck        0.63915       0.213
    EngDisp                0.11665       0.181
    RatedHP              0.0071033     0.00169
    Transmission_A6        0.64693         1.5
    Transmission_AV         -1.969        1.33
    Transmission_C6      -0.099603         1.7
    Transmission_L4       -0.59948        1.27
    Transmission_L5       -0.46086        1.26
    Transmission_L6        -1.1532        1.27
```



5.3 Stepwise Fitting: (4/6) Stepwise Feature Selection

Task 1:

Perform a stepwise linear fit of the training data and name it `mdl`. Predict the response on the test data and name the predicted response `yPred`.

Task 2:

Extract the model formula and name it `formula`.

Task 3:

Modify your stepwise linear fit from Task 1. Provide the model spec value `"purequadratic"` so that the initial model has pure quadratic terms.

Code:

This code loads the data.

```
load data
whos data dataTrain dataTest
```

Tasks 1 & 3

```
mdl = stepwiselm(dataTrain,"purequadratic");
yPred = predict(mdl,dataTest);
```

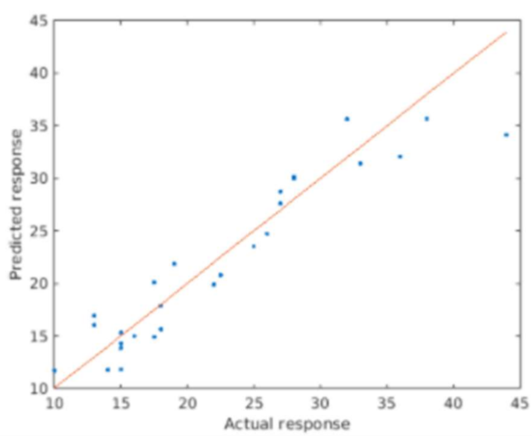
Task 2

```
formula=mdl.Formula
```

Compare predicted and actual responses.

```
plot(dataTest.Y,yPred,".")
hold on
plot(dataTest.Y,dataTest.Y)
hold off
xlabel("Actual response")
ylabel("Predicted response")
```

```
formula = Y ~ 1 + X1 + X3 + X1^2 + X3^2
```



5.3 Stepwise Fitting: (6/6) Predict Fuel Economy – Stepwise

Task 1:

Perform a stepwise linear fit of the training data to create `mdl`. Limit the model to use at most a constant plus linear terms. Predict the response on the test data and name the predicted response `econPred`.

Task 2:

Extract the root mean squared error (RMSE) of the model and name it `RMSE`.

Task 3:

Modify your stepwise linear fit from Task 1. Add an optional property so the model is chosen using the `"aic"` criterion.

Code:

Tasks 1 & 3

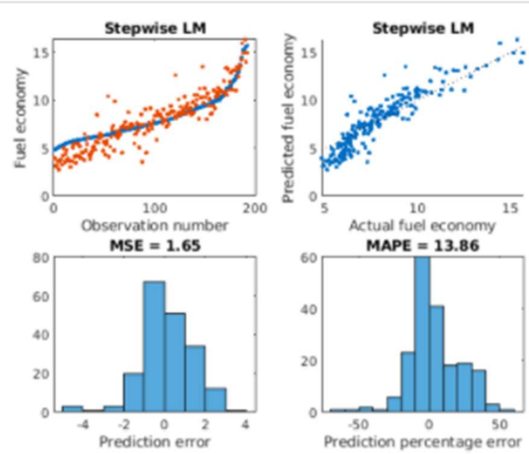
```
mdl = stepwiselm(carTrain,"Upper","linear","Criterion","aic");
econPred = predict(mdl,carTest);
```

Task 2

```
RMSE = mdl.RMSE
evaluateFit(carTest.FuelEcon,econPred,"Stepwise LM"
```

Name	Size	Bytes	Class
carData	600x15	48238	table
carTest	192x15	20086	table
carTrain	408x15	34990	table

```
1. Adding City_Highway, AIC = 1971.415
2. Adding EngDisp, AIC = 1553.9728
3. Adding Drive, AIC = 1509.3128
4. Adding AC, AIC = 1492.5695
5. Adding Valves_Cyl, AIC = 1480.9471
6. Adding Car_Truck, AIC = 1460.7706
7. Adding Transmission, AIC = 1445.2154
8. Adding FuelType, AIC = 1438.4181
9. Adding Comp, AIC = 1427.3403
10. Adding RatedHP, AIC = 1419.1872
11. Adding Weight, AIC = 1414.2136
12. Adding PRP, AIC = 1410.1785
13. Removing EngDisp, AIC = 1410.2
RMSE = 1.3195
```



5.4 Regularized Linear Models: (5/10) Fit a Ridge Regression Model

Task 1:

Create a vector `lambda` of integers from 0 to 100. Then perform ridge regression on the training data for the values in `lambda`. Return the coefficients in the scale of the original data, and name the coefficients `b`.

Task2:

Plot `b` against `lambda` to see how the coefficients change as λ increases.

This plot is called the *ridge trace*.

Task 3:

Predict the response for the test data `XTest`. Name the result `yPred`.

Task 4:

Calculate mean squared error and name the result `mdlMSE`. Plot `mdlMSE` against `lambda`

Task5:

Find the smallest MSE and the index where it occurs. Name the results `minMSE` and `idx`, respectively.

This code loads and plots the data.

```
load data
whos data XTrain XTest yTrain yTest
scatter3(data.X1,data.X2,data.Y)
```

Task 1

```
lambda = 0:100;
b = ridge(yTrain,XTrain,lambda,0);
```

Task 2

```
plot(lambda,b)
```

Task 3

```
yPred = XTest*b(2:end,:) + b(1,:)
```

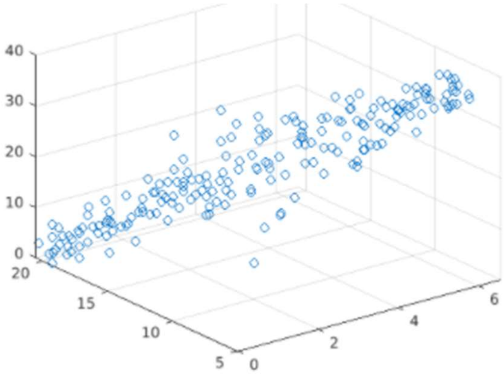
Task 4

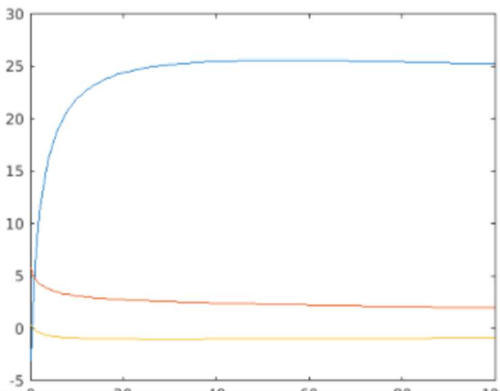
```
err = yPred - yTest;
mdlMSE = mean(err.^2);
plot(lambda,mdlMSE)
xlabel("\lambda")
ylabel("MSE")
```

Task 5

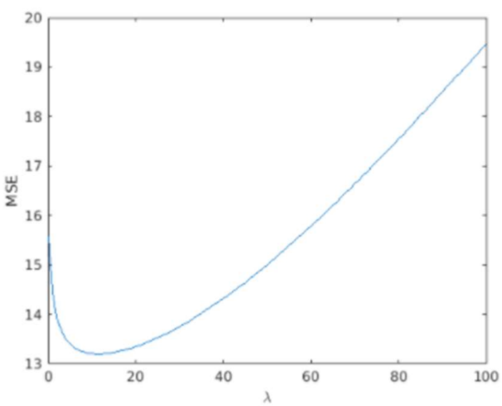
Find smallest MSE

```
[minMSE,idx] = min(mdlMSE)
```





```
yPred = 60×101
     2.5185     2.9354     3.1907     3.3727     3.5149  ...
     7.0816     6.6153     6.3786     6.2458     6.1687
     7.8270     7.1148     6.7419     6.5227     6.3859
     2.8752     3.3661     3.6615     3.8681     4.0268
     9.7136     8.8701     8.4221     8.1533     7.9806
     6.6538     6.6975     6.7415     6.7853     6.8289
     7.0665     7.5109     7.7741     7.9550     8.0914
     8.2191     8.1901     8.1915     8.2066     8.2290
     7.2292     6.9453     6.8084     6.7380     6.7033
    15.5827    15.6498    15.6922    15.7233    15.7484
       ⋮
```




```
minMSE = 13.1973
idx = 12
```

5.4 Regularized Linear Models: (8/10) Fit Lasso and Elastic Net Models

Task1 :

Perform lasso regression on the training data. For λ values, create a vector `lambda` of integers from 0 to 100 scaled by the number of observations. Name the fit coefficients `b`, and save information about the model fit as `fitInfo`.

Task 2:

Predict the response `yPred` for the test data `XTest`.

Calculate the mean squared error `mdlMSE`, and plot `mdlMSE` against `lambda`.

Find the smallest MSE and the index where it occurs. Name the results `minMSE` and `idx`, respectively.

Task 3:

Modify the call to the `lasso` function to use an alpha value of `0.4`. This will perform elastic net regression.

```
load data
whos data XTrain XTest yTrain yTest
scatter3(data.X1,data.X2,data.Y)
```

Tasks 1 & 3

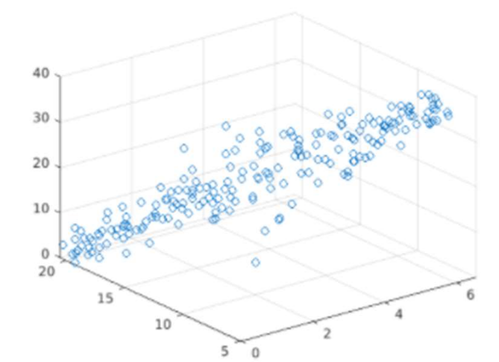
```
lambda = (0:100)/length(yTrain);
[b,fitInfo]= lasso(XTrain,yTrain,"Lambda",lambda,"Alpha",0.4)
```

Plot coefficients

```
plot(lambda,[fitInfo.Intercept;b],"LineWidth",2)
legend("intercept","X1","X2")
xlabel("\lambda")
```

Task 2

```
yPred = fitInfo.Intercept + XTest*b;
mdlMSE=mean((yPred - yTest).^2);
plot(lambda,mdlMSE)
[minMSE,idx]=min(mdlMSE)
```



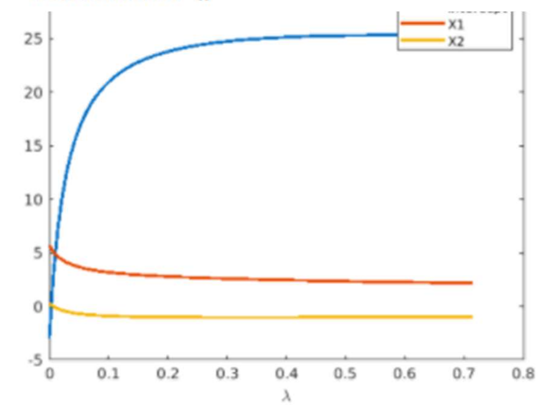
Code ^

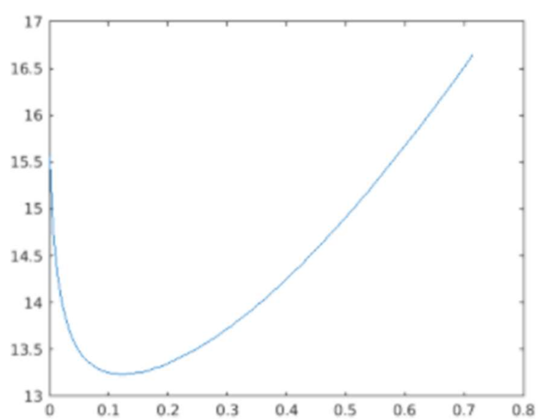
```
xlim([-0.01 6.55])
ylim([5.0 20.6])
zlim([0.0 40.0])
```

Update Code

```
b = 2x101
      5.7077    5.0956    4.6779    4.3750 ...
      0.2913   -0.0095   -0.2128   -0.3585
```

```
fitInfo = struct with fields:
         Intercept: [1×101 double]
            Lambda: [1×101 double]
             Alpha: 0.4000
                DF: [2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
               MSE: [1×101 double]
    PredictorNames: {}
```





```
minMSE = 13.2366
idx = 18
```

5.4 Regularized Linear Models: (10/10) Predict Fuel Economy – Regularized Model

Task 1:

Perform ridge regression on the training data. Create a vector `lambdaR` with values `0:300` to use as λ values. Return the coefficients in the scale of the original data, and name the coefficients `bR`.

Task 2:

Predict the response `econPredR` for the test data `XTest`, then calculate the MSE and name it `MSER`. Plot `MSER` against `lambdaR`.

Find the smallest MSE and the index where it occurs, and name the results `minMSER` and `idxR`, respectively.

Task 3:

Now perform lasso regression on the training data. For λ values, create a vector `lambdaL` with values `0:300` scaled by the number of observations.

Name the coefficients `bL`, and save information about the model fit as `fitInfo`.

Task 4:

For your lasso model, predict the response `econPredL` for the test data `XTest`, then calculate the MSE and name it `MSEL`. Plot `MSEL` against `lambdaL`.

Find the smallest MSE and the index where it occurs, and name the results `minMSEL` and `idxL`, respectively.

This code loads the data.

```
load carEcon
whos XTrain XTest econTrain econTest
```

Task 1

Fit ridge model

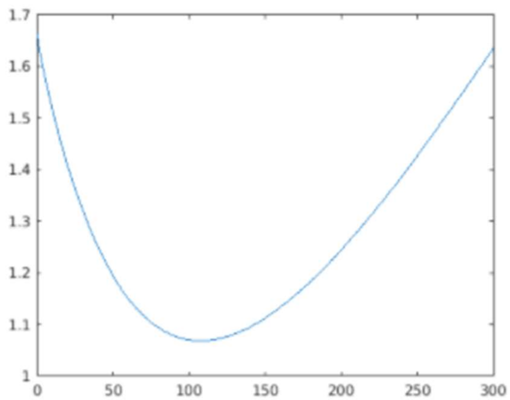
```
lambdaR = 0:300
bR = ridge(econTrain,XTrain,lambdaR,0)
```

Task 2

Calculate and plot MSE. Find smallest MSE.

```
econPredR = XTest*bR(2:end,:) + bR(1,:)
MSER = mean((econPredR-econTest).^2);
plot(lambdaR,MSER)
[minMSER,idxR]=min(MSER)
```

```
econPredR = 192x301
      3.5862    3.6012    3.6159    3.6304  ...
      3.0152    3.0307    3.0454    3.0595
      2.9775    2.9922    3.0075    3.0231
      3.8502    3.8626    3.8748    3.8868
      2.3020    2.3187    2.3359    2.3533
      3.5469    3.5624    3.5779    3.5935
      3.8199    3.8327    3.8449    3.8566
      3.2614    3.2730    3.2845    3.2959
      4.0350    4.0493    4.0631    4.0768
      4.7063    4.7177    4.7298    4.7422
        ⋮
```




```
minMSER = 1.0683
idxR = 109
```

Task 3

Fit lasso model

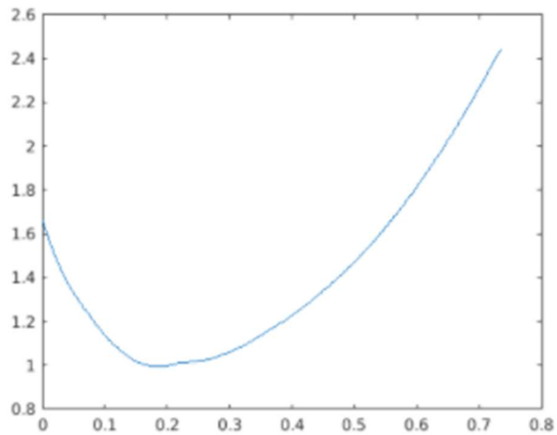
```
lambdaL = (0:300)/length(econTrain);
[bL,fitInfo] = lasso(XTrain,econTrain,"Lambda",lambdaL)
```

Task 4

Calculate and plot MSE. Find smallest MSE.

```
econPredL = fitInfo.Intercept + XTest*bL;
MSEL = mean((econPredL-econTest).^2);
plot(lambdaL,MSEL)
[minMSEL,idxL]=min(MSEL)
```

```
fitInfo = struct with fields:
         Intercept: [1×301 double]
            Lambda: [1×301 double]
             Alpha: 1
                DF: [1×301 double]
               MSE: [1×301 double]
    PredictorNames: {}
```




```
minMSEL = 0.9954
idxL = 77
```

5.5 SVMs and Trees: (2/6) Fit Tree and SVM Models

Task 1:

Create a decision tree model named `treeMdl` using the training data.

Calculate the model loss for the test data and name it `treeLoss`.

Then, use the model to predict the response for the test data and name it `yPred`.

Task 2:

Create an SVM model named `svmMdl` using the training data. Calculate the loss `svmLoss` and find the predicted response `yPred` for the test data.

Task 3:

Create another SVM model named `svmMdl2` which uses a `"polynomial"` kernel function. Calculate the loss `svmLoss2`. Again, find the predicted response `yPred` for the test data.

This code loads the data.

```
load data
whos data dataTrain dataTest
```

Task 1

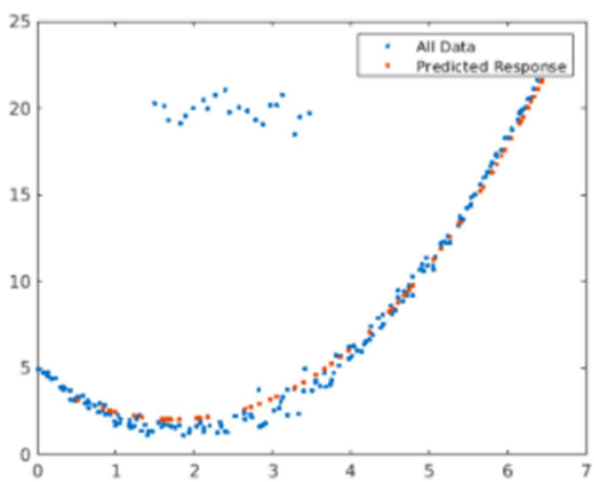
```
treeMdl = fitrtree(dataTrain,"y");
treeLoss=loss(treeMdl,dataTest);
disp(treeLoss)
yPred = predict(treeMdl,dataTest)
```

Task 2

```
svmMdl= fitrsvm(dataTrain,"y");
svmLoss = loss(svmMdl,dataTest);
disp(svmLoss)
yPred = predict(svmMdl,dataTest)
```

Task 3

```
svmMdl2= fitrsvm(dataTrain,"y","KernelFunction","polynomial");
svmLoss2 = loss(svmMdl2,dataTest);
disp(svmLoss2)
yPred = predict(svmMdl2,dataTest)
```



Task 1:

Create either a tree or SVM regression model fitting the training data, name it `mdl`. Try to get the loss value below 0.15.

This code loads and plots the data.

```
load data
whos data dataTrain dataTest
plot(data.x,data.y,".")
```

Fit a model

Fit a model

```
mdl = fitrsvm(dataTrain,"y","KernelFunction","gaussian");
```

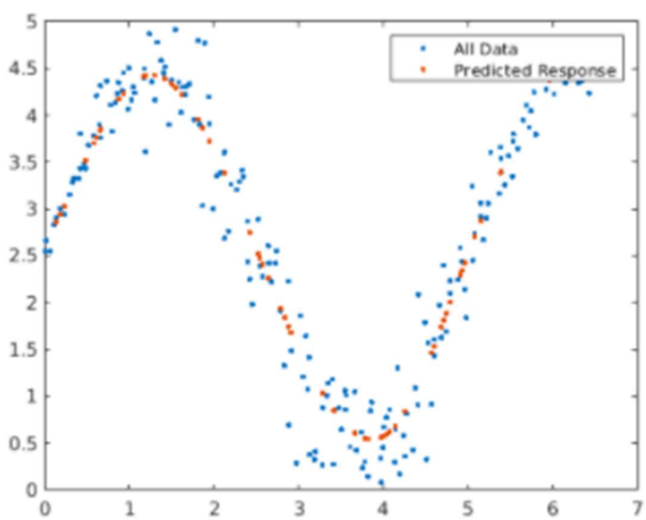
Evaluate at test values.

```
mdlLoss = loss(mdl,dataTest)
yPred = predict(mdl,dataTest);
```

Plot the response.

```
plot(data.x,data.y,".")
hold on
plot(dataTest.x,yPred,".")
hold off
legend("All Data","Predicted Response")
```

```
mdlLoss = 0.1251
```



5.5 SVMs and Trees: (5/6) Predict Fuel Economy – Tree

Task 1:

Create a decision tree regression model with the training data and name it `mdl`. Calculate the loss of the model and name it `mdlLoss`.

Use the model to predict the test values and store the predictions in a variable named `econPred`.

Task 2:

Modify your code to prune `mdl` to level 10.

Task 3:

Modify your code again. Remove the pruning step, and instead update `mdl` to set the `"MinLeafSize"` property to 5.

This code loads the data.

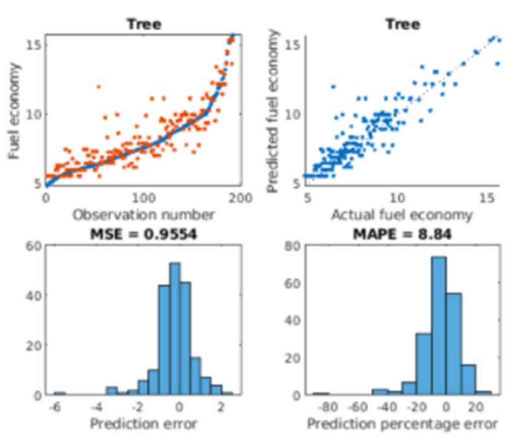
```
load carEcon
whos carData carTrain carTest
```

Tasks 1,2,3 - Fit the model

Fit a model and evaluate at test values.

```
mdl = fitrtree(carTrain,"FuelEcon","MinLeafSize",5)
mdlLoss = loss(mdl,carTest)
econPred = predict(mdl,carTest)
evaluateFit(carTest.FuelEcon,econPred,"Tree")
```

```
mdlLoss = 0.9554
econPred = 192×1
      5.5494
      5.5494
      5.5494
      5.5494
      5.5494
      5.5494
      5.5494
      5.5494
      5.5494
      5.9911
        ⋮
```



5.5 SVMs and Trees: (6/6) Predict Fuel Economy – SVM

Task 1:

Create an SVM regression model with the training data and name it `mdl`. Use a polynomial kernel function.

Calculate the loss of the model and name it `mdlLoss`. Use the model to predict the response for the test values, and store the predictions in a variable named `econPred`.

Task 2:

Modify your code to set an option in `fitrsvm` which will standardize the variables in `carTrain` before fitting the regression model.

This code loads the data.

```
load carEcon
whos carData carTrain carTest
```

Tasks 1 and 2 - Fit the model

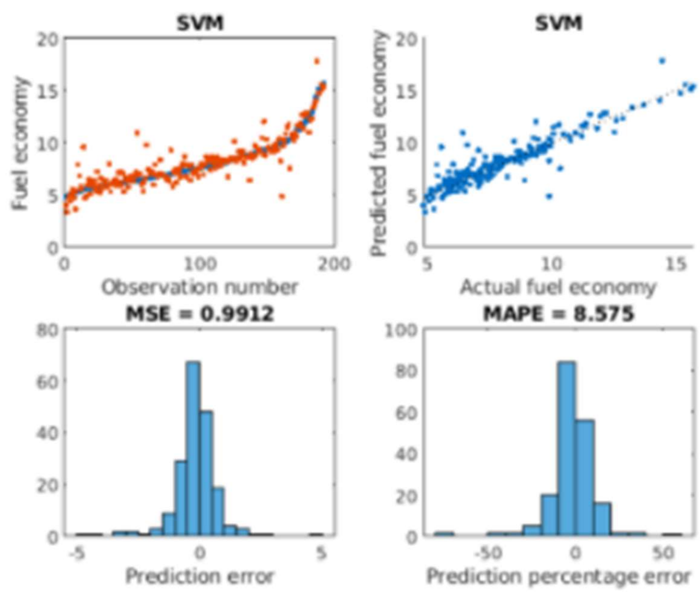
Fit a model and evaluate at test values.

```
mdl =
fitrsvm(carTrain,"FuelEcon","KernelFunction","polynomial","Standardize"
,true)
mdlLoss = loss(mdl,carTest)
econPred = predict(mdl,carTest)
```

Plot the results.

```
evaluateFit(carTest.FuelEcon,econPred,"SVM")
```

```
mdlLoss = 0.9912
```



5.6 Gaussian Process Regression: (4/6) Fit a GPR Model

Task :

Create a GPR model named `mdl` using the training data. Then, use the model to predict the response for the test data and name it `yPred`. Calculate the loss, or mean squared error, of the predictions and name it `mdlMSE`.

```
load data
whos data dataTrain dataTest
```

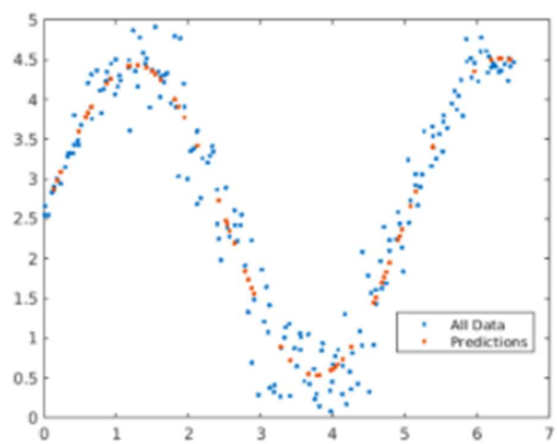
Task 1

Fit model and evaluate at test values.

```
mdl = fitrgp(dataTrain,"y");
yPred = predict(mdl,dataTest)
mdlMSE = loss(mdl,dataTest)
```

```
plot(data.x,data.y,".")
hold on
plot(dataTest.x,yPred,".")
hold off
legend("All Data","Predictions","Location","Best")
```

```
yPred = 60×1
       2.8789
       2.9872
       3.0903
       3.5996
       3.7809
       3.8343
       3.9098
       3.9176
       4.2049
       4.2637
         ⋮

mdlMSE = 0.1185
```



5.6 Gaussian Process Regression: (6/6) Predict Fuel Economy – GPR

Task 1:

Create a Gaussian process regression model with the training data and name it `mdl`.

This code loads the data.

```
load carEcon
whos carData carTrain carTest
```

Task 1

Fit a model.

```
mdl= fitrgp(carTrain,"FuelEcon");
```

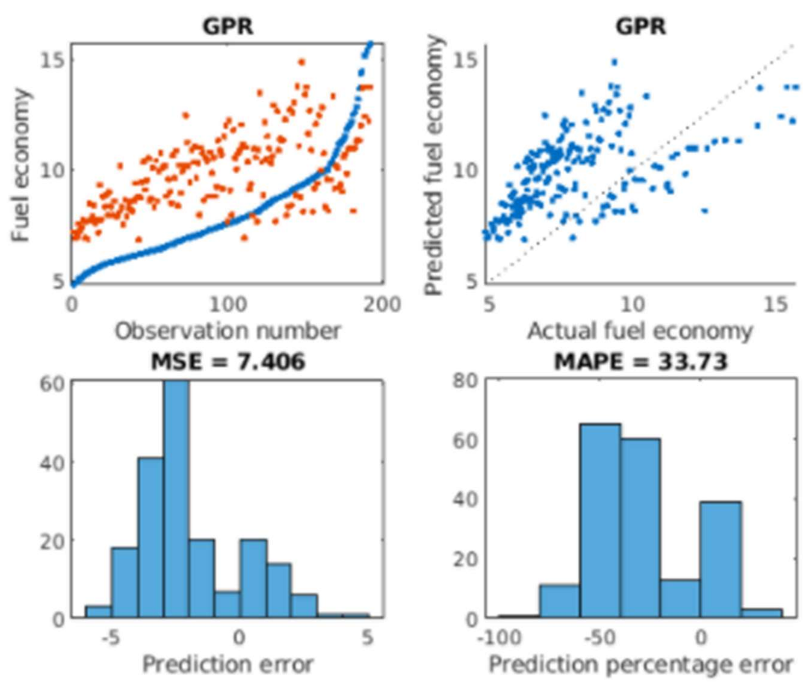
Evaluate at test values.

```
MSE = loss(mdl,carTest)
econPred = predict(mdl,carTest);
```

Plot the results.

```
evaluateFit(carTest.FuelEcon,econPred,"GPR")
```

```
MSE = 7.4062
```



5.7 Project - Regression

Task :

Use any regression technique with the training set to predict the outcome for the test set. Name the predictions `yPred`. Find a model where the MSE for the test set is less than 20.

Note Some models take longer to fit than others. Run your script to try different models. Your script should run in **under 30 seconds**. Submit your script after you have found a sufficient model.

This code loads the data.

```
load parkinsons
whos data dataTrain dataTest
```

Fit regression model

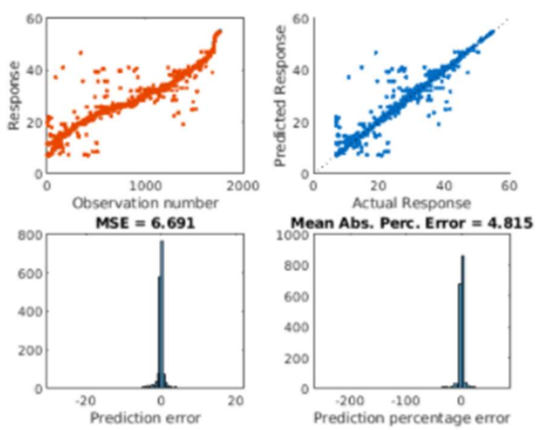
Fit model then predict response for test data.

```
mdl = fitrtree(dataTrain,"total_UPDRS");
yPred = predict(mdl,dataTest)
mdlMSE = loss(mdl,dataTest)
```

Compare predicted and actual responses.

```
evaluateFit(dataTest.total_UPDRS,yPred,"")
```

```
yPred = 1762x1
     19.8747
      7.0147
     11.4139
     11.7530
      7.0147
      7.0147
      7.0147
     18.4900
      7.0147
      7.0147
        ⋮

mdlMSE = 6.6906
```



Unit 5

Neural Networks

6.3 Feed-Forward Networks: (7/9) Use Commands to Create a Feed-Forward Classification Network

TASK 1:

Initialize a classification neural network named `net` with one hidden layer containing 15 neurons.

Divide the data so that 70% is for training, 10% is for testing, and 20% is for validation.

Task 2:

Train the network `net` with the data in `heartData` and the target values in `HDC`. Save the training record to `tr`.

Note that the target values are stored as categorical data, and samples for the data should be along the matrix columns rather than rows.

Task 3:

Make predictions on the test data. Store the predicted values in a variable named `scoreTest`.

Then, create a vector named `yPred` which contains the row index value with the largest value for each column in the predicted matrix.

Task 4:

Plot the confusion matrix for the test data.

Task 5:

Calculate the percentage of misclassified predicted test values and save the value in a variable named `validErr`.

This code loads and displays the heart disease data set.

```
load heartDisease
whos HDC heartData
```

Task 1

Initialize neural network

```
net = patternnet(15);
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 20/100;
net.divideParam.testRatio = 10/100;
```

Task 2

Train the network

```
heartData = heartData';   % transpose samples
HD = dummyvar(HDC)';      % convert categorical to dummy variable
[net,tr] = train(net,heartData,HD);
```

Task 3

Predict response

```
scoreTest = net(heartData(:,tr.testInd));
[~,yPred] = max(scoreTest);
```

Task 4

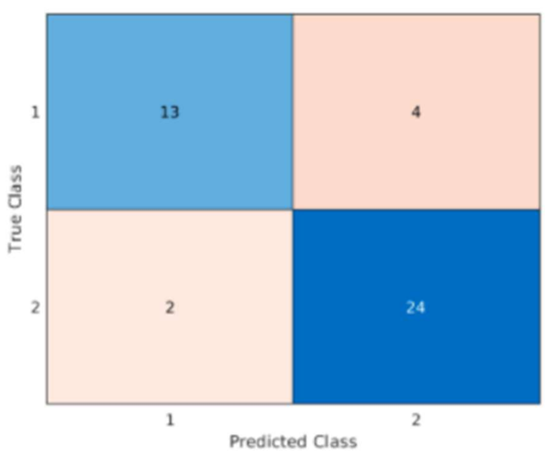
Evaluate classification with confusion matrix

```
HDtest = HDC(tr.testInd);
yTrue = double(HDtest);
confusionchart(yTrue,yPred');
```

Task 5

Determine validation error

```
HDtest = HDC(tr.testInd);
validErr = 100*nnz(yPred' ~= double(HDtest))/length(HDtest)
```




```
validErr = 13.9535
```

6.3 Feed-Forward Networks: (9/9) Use Commands to Create a Feed-Forward Regression Network

Task 1:

Initialize a neural network named `net` with one hidden layer containing 15 neurons.

Train the network with the data in `carData` and use the target values in `econ`. Save the training record in a structure named `tr`.

Note that the samples for the data should be along the matrix columns rather than rows as input to the `train` function.

Task 2:

Make predictions named `econPred` on the test set.

Then, you may use `plotregression` to show how well the predictions do.

Task 3:

Update `net` so there are two layers where the first layer has eight neurons and the second layer has 12 neurons.

Task 4:

Update `net` so the first layer uses the `'logsig'` transfer function, and the second layer uses the `'radbas'` transfer function.

```
load fuel
whos econ carData
```

Tasks 1, 3, & 4

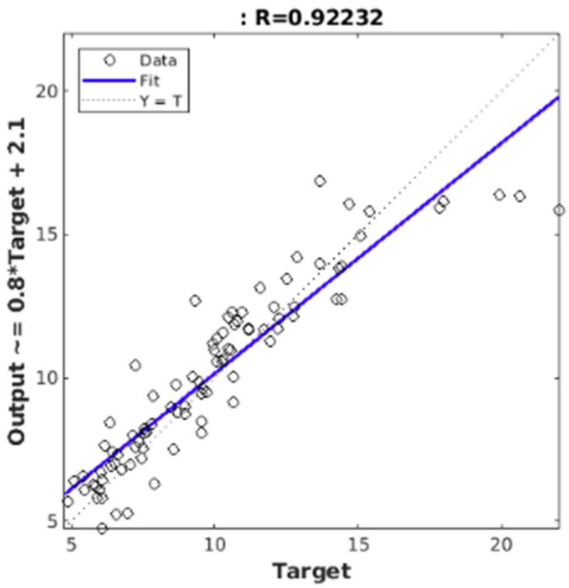
Initialize and train the neural network

```
net = fitnet([8 12]);
net.layers{1}.transferFcn = "logsig";
net.layers{2}.transferFcn = "radbas";
carData = carData';
econ = econ';
[net,tr] = train(net,carData,econ);
```

Task 2

Predict response and evaluate network performance

```
econPred = net(carData(:,tr.testInd));
plotregression(econ(tr.testInd),econPred)
```


: R=0.92232
Data
Fit
Y = T
Output ~= 0.8*Target + 2.1
Target
5
10
15
20
5
10
15
20