KAUNO TECHNOLOGIJOS UNIVERSITETAS

INFORMATIKOS FAKULTETAS

Intelektikos Pagrindai (P176B101)

Pirmojo laboratorinio darbo ataskaita

Atliko:

IFF – 6/8 gr. studentas

Tadas Laurinaitis

2019 m. balandžio 1 d.

Priėmė:

Lekt. Germanas Budnikas

KAUNAS 2019

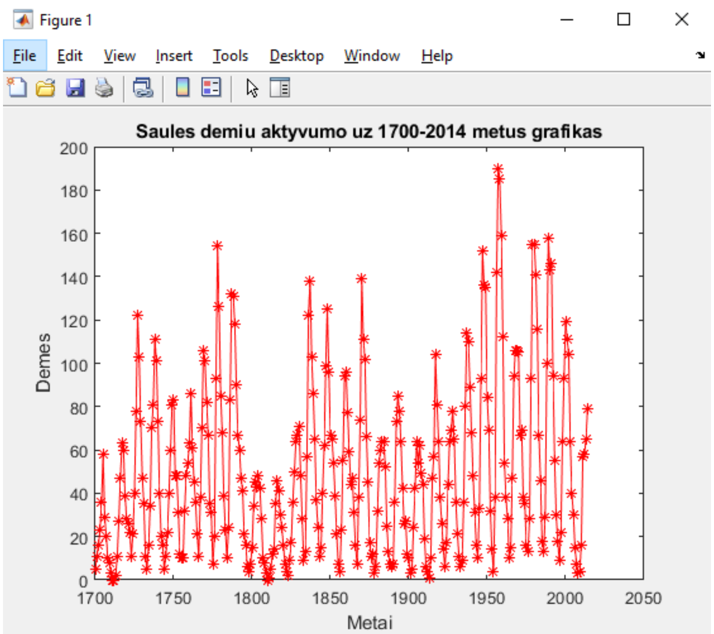
Scenarijus nr. 1 (1-14 užduotis)

Kodas:

```
% 1-3 uzduotis
load("sunspot.txt")
% 4 uzduotis
figure(1)
plot(sunspot(:,1), sunspot(:,2),'r-*')
xlabel("Metai")
ylabel("Demes")
title ("Saules demiu aktyvumo uz 1700-2014 metus grafikas")
% 5 uzduotis
L = length(sunspot);     % duomen? kiekis
P = [sunspot(1:L-2,2)'; % ?vesties duomen?
    sunspot(2:L-1,2)']; % matrica
T = sunspot(3:L,2)';     % išvesties duomen? vektorius
%duomenu isvedimas i console
disp('Matricos P dydis')
size(P)
disp('Matricos P elementai')
P
disp('Matricos T dydis')
size(T)
disp('Matricos T elementai')
T
% 6 uzduotis
figure(2)
plot3(P(1,:), P(2,:), T, 'bo')
xlabel('Demes n-2 metais');
ylabel('Demes n-1 metais');
zlabel('Demes  n  metais');
title("Matricu P ir T duomenys")
% 7 uzduotis
Pu = P(:, 1:200);
Tu = T(:, 1:200);
disp('Matricos Pu dydis')
size(Pu)
disp('Matrica Pu')
Pu
disp('Matricos Tu dydis')
size(Tu)
disp('Matrica Tu')
Tu
% 8 uzduotis
% sukuriam neurona ir apskaiciuojam jo svoriu reiksmes tiesioginiu metodu
net = newlind(Pu, Tu);
% 9 uzduotis
disp('neurono svorio koeficientai:' )
disp(net.IW{1})
disp(net.b{1})
%priskiriam svoriu reiksmes pagalbiniam kintamiesiems
w1 = net.IW{1}(1)
w2 = net.IW{1}(2)
b = net.b{1}
% 10 uzduotis
% neurono veikimo imitacija
Tsu = sim(net,Pu)
figure(3)
hold on;
grid on;
plot(sunspot(3:202, 1), Tu, 'r-o');
plot(sunspot(3:202, 1), Tsu, 'b-o');
```

```
xlabel('Metai');
ylabel('Demes');
legend('Tikrosios reiksmes', 'Prognozuojamos reiksmes');
title('Prognozavimo kokybes patikrinimas, prognozuojant 1702-1901 metais');
% 11 uzduotis
% neurono veikimo imitacija
Ts = sim(net,P)
figure(4)
hold on;
grid on;
plot(sunspot(3:315, 1), T, 'r-o')
plot(sunspot(3:315, 1), Ts, 'b-o')
xlabel('Metai');
ylabel('Demes');
legend('Tikrosios reiksmes', 'Prognozuojamos reiksmes');
title('Prognozavimo kokybes patikrinimas, prognozuojant 1702-2014 metais');
% 12 uzduotis
e = (T-Ts)';
figure(5)
grid on;
plot(sunspot(3:315), e, 'b-o')
xlabel('Metai');
ylabel('Tikrosios ir prognozuojamos prognozes skirtumas');
title('Prognozes klaidu grafikas');
% 13 uzduotis
figure(6);
hist(e);
xlabel('Prognozes klaidos reiksme');
ylabel('Daznis');
title('Prognozes klaidu histograma');
% 14 uzduotis
disp('Vidutinës kvadratinës prognozës klaidos reik?më')
mse_reiksme = mse(e)
clear()
```

Grafikai:



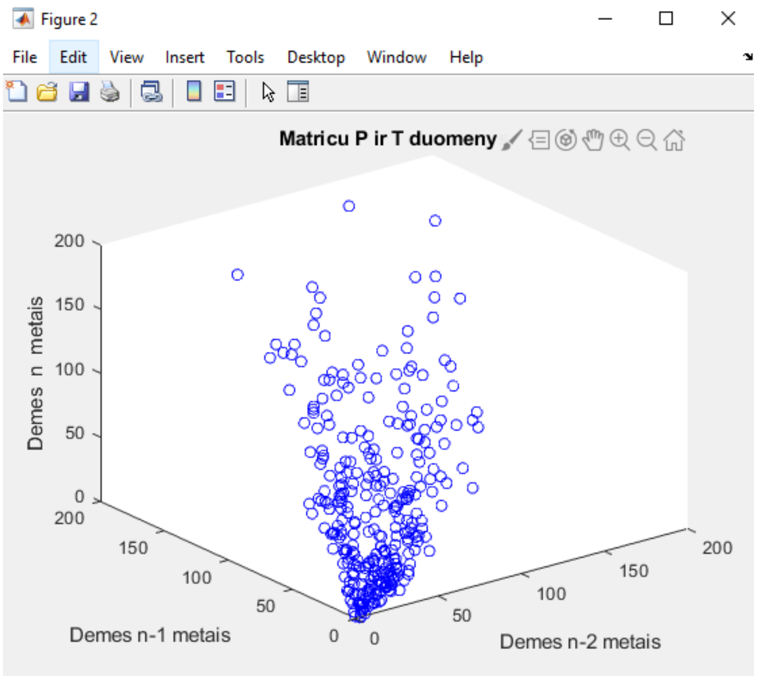


Figure 2
File Edit View Insert Tools Desktop Window Help
Matricu P ir T duomeny
Demes n metais
Demes n-1 metais
Demes n-2 metais

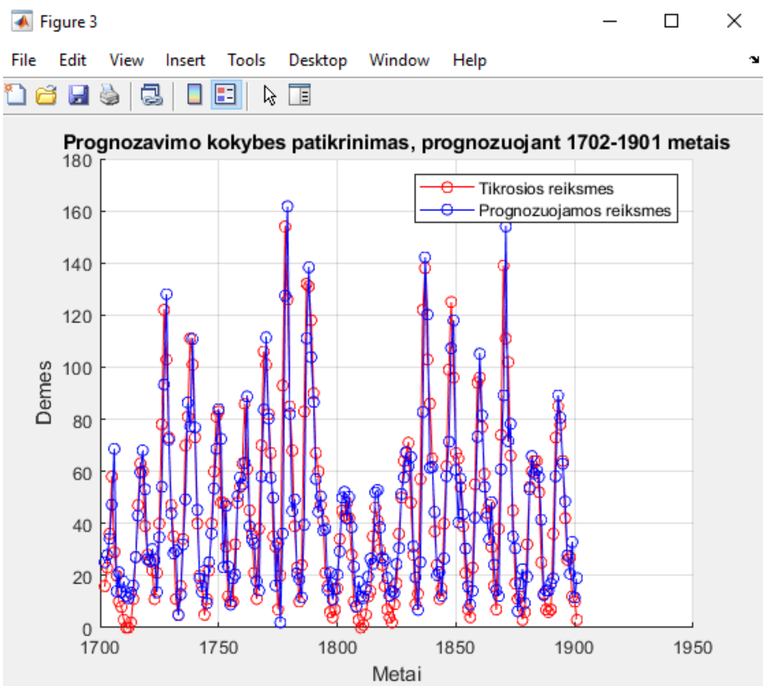


Figure 3
File Edit View Insert Tools Desktop Window Help
Prognozavimo kokybes patikrinimas, prognozuojant 1702-1901 metais
Tikrosios reiksmes
Prognozuojamos reiksmes
Demes
Metai

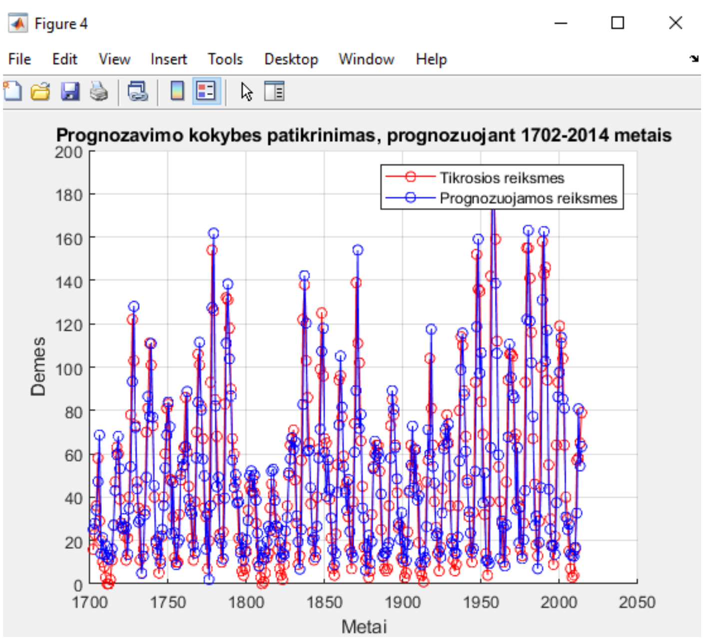
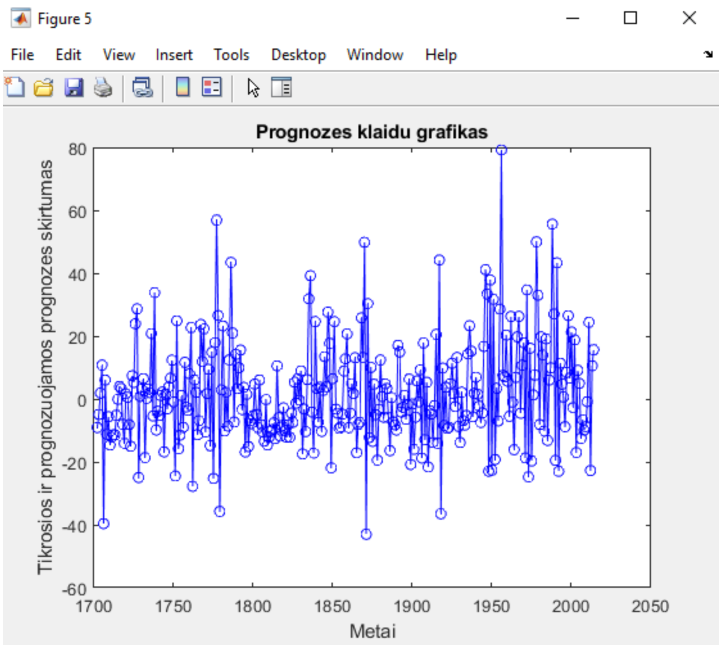
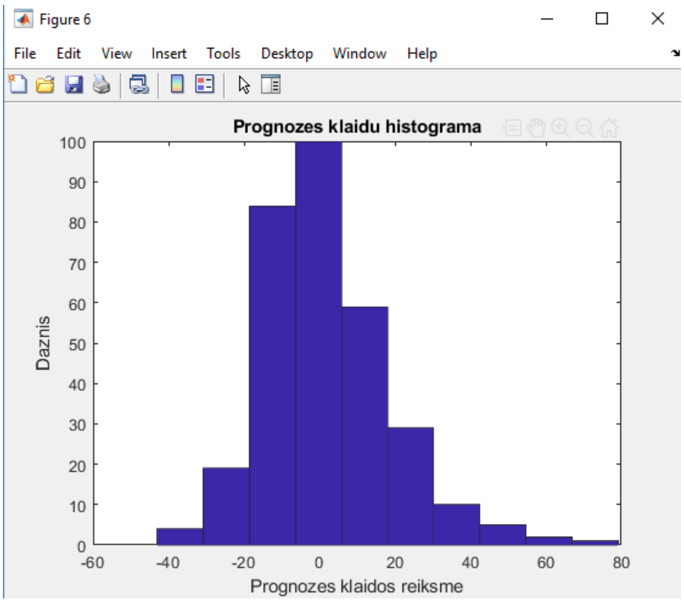


Figure 4
File Edit View Insert Tools Desktop Window Help
Prognozavimo kokybes patikrinimas, prognozuojant 1702-2014 metais
Tikrosios reiksmes
Prognozuojamos reiksmes
Demes
Metai





Scenarijus nr. 2 (15-19 užduotis)

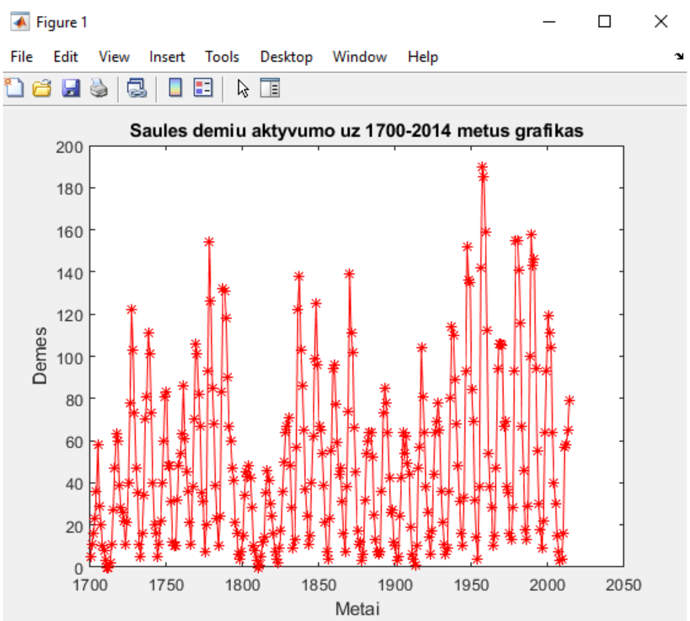
Kodas:

```
% 1-3 uzduotis
load("sunspot.txt")
% 4 uzduotis
figure(1)
plot(sunspot(:,1), sunspot(:,2),'r-*')
xlabel("Metai")
ylabel("Demes")
title ("Saules demiu aktyvumo uz 1700-2014 metus grafikas")
% 5 uzduotis
L = length(sunspot);     % duomen? kiekis
P = [sunspot(1:L-2,2)'; % ?vesties duomen?
    sunspot(2:L-1,2)']; % matrica
T = sunspot(3:L,2)';     % išvesties duomen? vektorius
%duomenu isvedimas i console
disp('Matricos P dydis')
```

```
size(P)
disp('Matricos P elementai')
P
disp('Matricos T dydis')
size(T)
disp('Matricos T elementai')
T
% 6 uzduotis
figure(2)
plot3(P(1,:), P(2,:), T, 'bo')
xlabel('Demes n-2 metais');
ylabel('Demes n-1 metais');
zlabel('Demes  n  metais');
title("Matricu P ir T duomenys")
% 7 uzduotis
Pu = P(:, 1:200);
Tu = T(:, 1:200);
disp('Matricos Pu dydis')
size(Pu)
disp('Matrica Pu')
Pu
disp('Matricos Tu dydis')
size(Tu)
disp('Matrica Tu')
Tu
% 8 uzduotis
% sukuriam neurona ir apskaiciuojam jo svoriu reiksmes tiesioginiu metodu
%net = newlind(Pu, Tu);
% 15 uzduotis
S = 1
lr = 0.0000001;
% 16 uzduotis
net = newlin(Pu,S,0,lr)
disp('neurono svorio koeficientai:' )
disp(net.IW{1})
disp(net.b{1})
%priskiriam svoriu reiksmes pagalbiniam kintamiesiems
w1 = net.IW{1}(1)
w2 = net.IW{1}(2)
b = net.b{1}
% 17 uzduotis
net.trainParam.goal = 100;
net.trainParam.epochs = 1000;
% 18 uzduotis
net = train(net, Pu, Tu)
disp('neurono svorio koeficientai:' )
disp(net.IW{1})
disp(net.b{1})
%svoriu reiksmiu priskyrimas
w3 = net.IW{1}(1)
w4 = net.IW{1}(2)
bb = net.b{1}
% 10 uzduotis
% neurono veikimo imitacija
Tsu = sim(net,Pu)
figure(3)
hold on;
grid on;
plot(sunspot(3:202, 1), Tu, 'r-o');
plot(sunspot(3:202, 1), Tsu, 'b-o');
xlabel('Metai');
ylabel('Demes');
legend('Tikrosios reiksmes', 'Prognozuojamos reiksmes');
title('Prognozavimo kokybes patikrinimas, prognozuojant 1702-1901 metais');
% 11 uzduotis
% neurono veikimo imitacija
```

```
Ts = sim(net,P)
figure(4)
hold on;
grid on;
plot(sunspot(3:315, 1), T, 'r-o')
plot(sunspot(3:315, 1), Ts, 'b-o')
xlabel('Metai');
ylabel('Demes');
legend('Tikrosios reiksmes', 'Prognozuojamos reiksmes');
title('Prognozavimo kokybes patikrinimas, prognozuojant 1702-2014 metais');
% 12 uzduotis
e = (T-Ts)';
figure(5)
grid on;
plot(sunspot(3:315), e, 'b-o')
xlabel('Metai');
ylabel('Tikrosios ir prognozuojamos prognozes skirtumas');
title('Prognozes klaidu grafikas');
% 13 uzduotis
figure(6);
hist(e);
xlabel('Prognozes klaidos reiksme');
ylabel('Daznis');
title('Prognozes klaidu histograma');
% 14 uzduotis
disp('Vidutines kvadratines prognozes klaidos reiksme')
mse_reiksme = mse(e)
clear()
% 19 uzduotis
% Klausimai:
% 1. Ka pavaizduoja diagrama,  kuri vaizduojama mokymosi proceso metu?
% Diagrama pavaizduoja dirbtinio neurono modeli
% 2. Ar mokymosi procesas yra konverguojantis? Jeigu ne, pamastyti kas gali b?ti
priezastimi ir pakeisti atitinkama parametra.
% Nekonveguojantis, galbut pavyzdziu kiekio pakeitimas???
% 3. Kokios yra naujos neurono svoriu koeficientu reiksm?s ?
% Naujos gautos reiksmes yra toliau 0 negu senos
% 4. Kokia yra neurono darbo kokybes ivercio – vidutinis kvadratinis nuokrypis –
reiksme ?
% 357.2350
```

Grafikai:



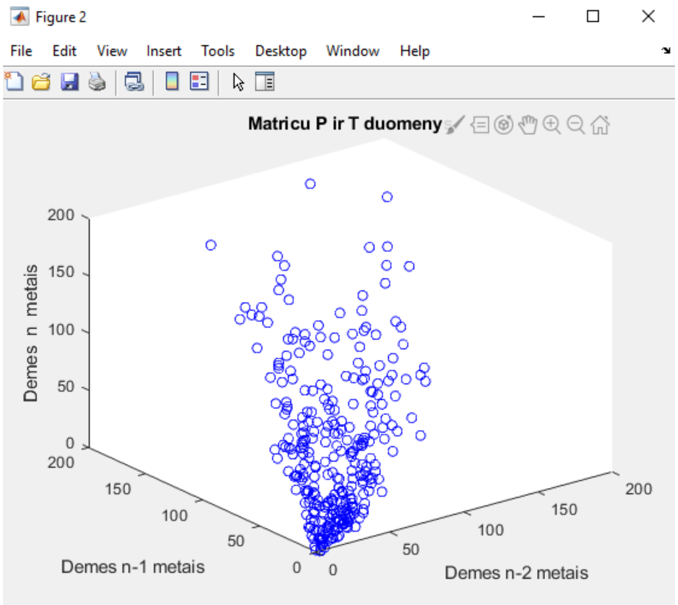


Figure 2
File Edit View Insert Tools Desktop Window Help
Matricu P ir T duomeny
Demes n metais
Demes n-1 metais
Demes n-2 metais
200
150
100
50
0

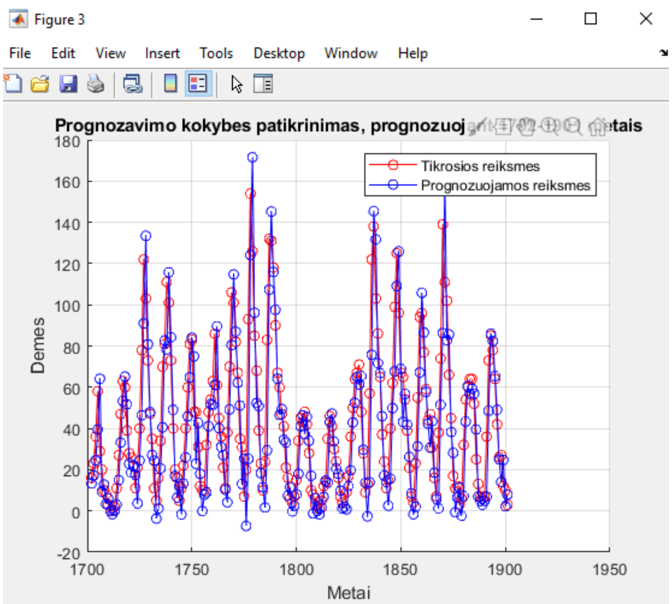


Figure 3
File Edit View Insert Tools Desktop Window Help
Prognozavimo kokybes patikrinimas, prognozuoj
etais
Tikrosios reiksmes
Prognozuojamos reiksmes
Demes
Metai
1700
1750
1800
1850
1900
1950

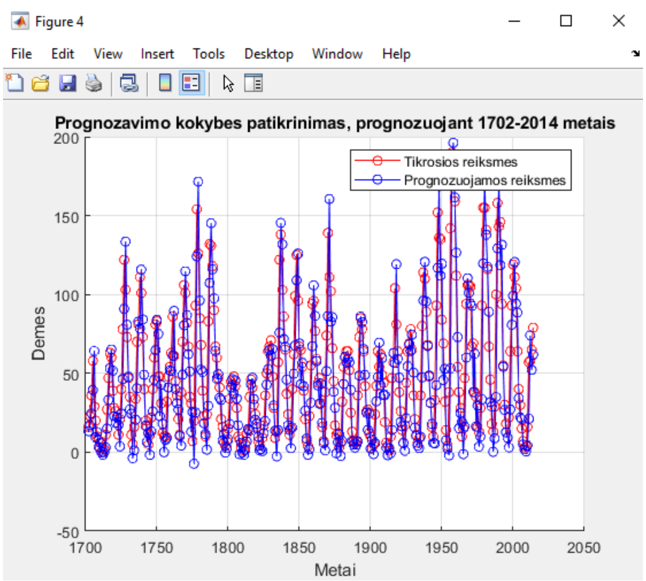
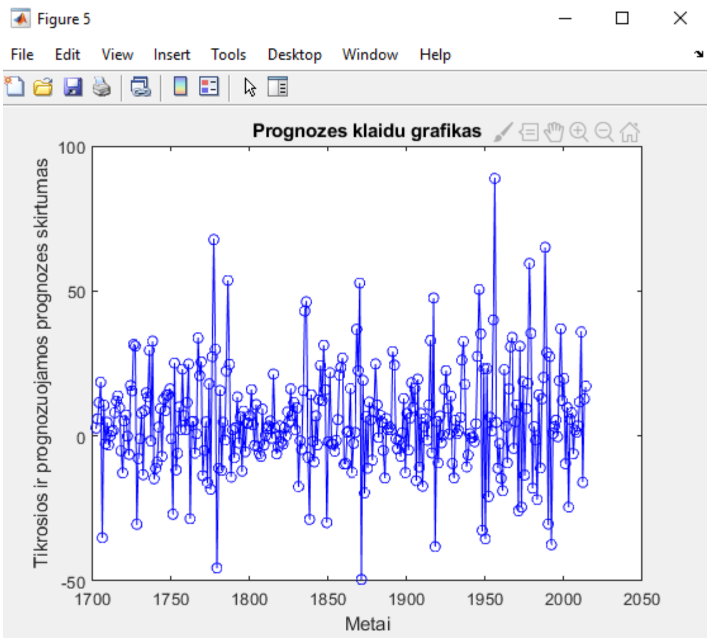
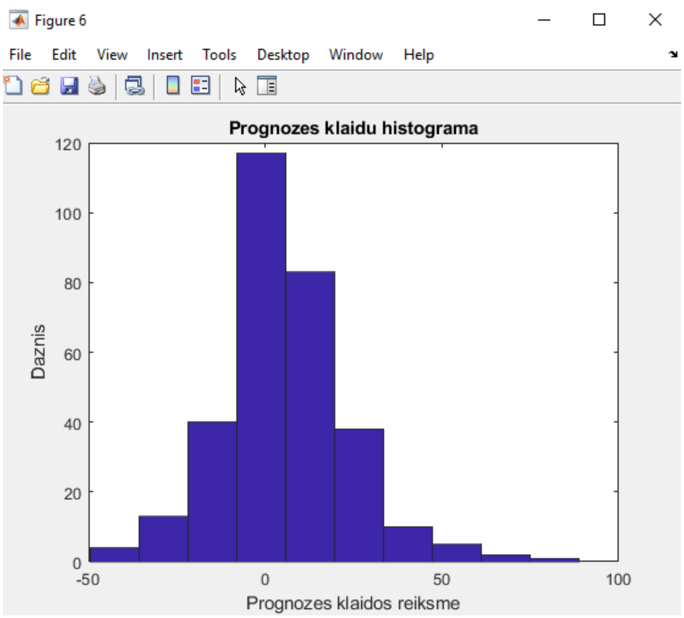


Figure 4
File Edit View Insert Tools Desktop Window Help
Prognozavimo kokybes patikrinimas, prognozuojant 1702-2014 metais
Tikrosios reiksmes
Prognozuojamos reiksmes
Demes
Metai
1700
1750
1800
1850
1900
1950
2000
2050





Scenarijus nr. 3 (21 užduotis)

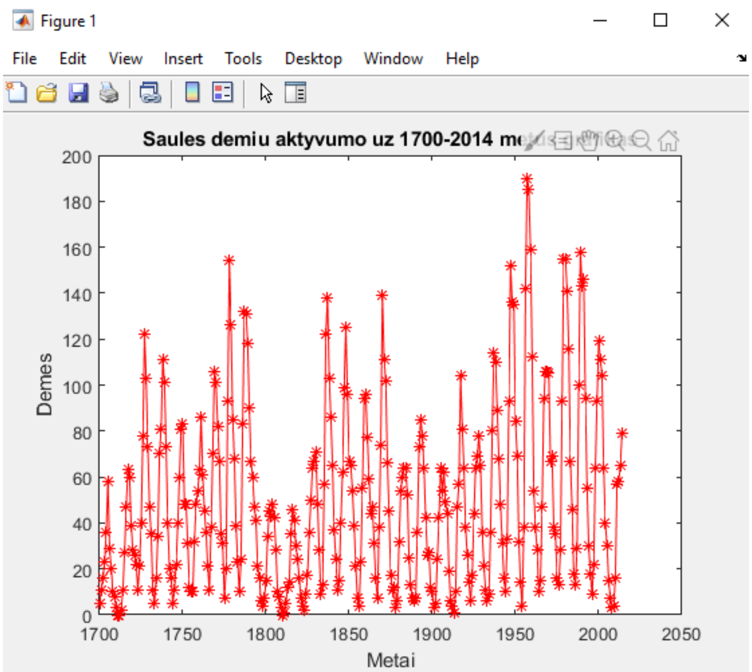
Kodas:

```
% 1-3 uzduotis
load("sunspot.txt")
% 4 uzduotis
figure(1)
plot(sunspot(:,1), sunspot(:,2),'r-*')
xlabel("Metai")
ylabel("Demes")
title ("Saules demiu aktyvumo uz 1700-2014 metus grafikas")
% 5 uzduotis
L = length(sunspot)     % duomen? kiekis
P = [sunspot(1:L-6,2)'; % n = 6
    sunspot(2:L-5,2)';
    sunspot(3:L-4,2)';
    sunspot(4:L-3,2)';
```

```
    sunspot(5:L-2,2)';
    sunspot(6:L-1,2)'];
T = sunspot(7:L,2)';
%duomenu isvedimas i console
disp('Matricos P dydis')
size(P)
disp('Matricos P elementai')
P
disp('Matricos T dydis')
size(T)
disp('Matricos T elementai')
T
% 7 uzduotis
Pu = P(:, 1:200);
Tu = T(:, 1:200);
disp('Matricos Pu dydis')
size(Pu)
disp('Matrica Pu')
Pu
disp('Matricos Tu dydis')
size(Tu)
disp('Matrica Tu')
Tu
% 8 uzduotis
% sukuriam neurona ir apskaiciuojam jo svoriu reiksmes tiesioginiu metodu
%net = newlind(Pu, Tu);
% 15 uzduotis
S = 1
lr = 0.0000001;
% 16 uzduotis
net = newlin(Pu,S,0,lr)
% 17 uzduotis
net.trainParam.goal = 100;
net.trainParam.epochs = 1000;
% 18 uzduotis
net = train(net, Pu, Tu)
disp('neurono svorio koeficientai:' )
disp(net.IW{1})
disp(net.b{1})
%svoriu reiksmiu priskyrimas
w1 = net.IW{1}(1)
w2 = net.IW{1}(2)
b = net.b{1}
% 10 uzduotis
% neurono veikimo imitacija
Tsu = sim(net,Pu)
figure(3)
hold on;
grid on;
plot(sunspot(7:206, 1), Tu, 'r-o');
plot(sunspot(7:206, 1), Tsu, 'b-o');
xlabel('Metai');
ylabel('Demes');
legend('Tikrosios reiksmes', 'Prognozuojamos reiksmes');
title('Prognozavimo kokybes patikrinimas, prognozuojant 1702-1901 metais');
% 11 uzduotis
% neurono veikimo imitacija
Ts = sim(net, P)
figure(4)
hold on;
grid on;
plot(sunspot(7:315, 1), T, 'r-o')
plot(sunspot(7:315, 1), Ts, 'b-o')
xlabel('Metai');
ylabel('Demes');
legend('Tikrosios reiksmes', 'Prognozuojamos reiksmes');
```

```
title('Prognozavimo kokybes patikrinimas, prognozuojant 1702-2014 metais');
% 12 uzduotis
e = (T-Ts)'
figure(5)
grid on;
plot(sunspot(7:315), e, 'b-o')
xlabel('Metai');
ylabel('Tikrosios ir prognozuojamos prognozes skirtumas');
title('Prognozes klaidos grafikass');
% 13 uzduotis
figure(6);
hist(e);
xlabel('Prognozes klaidos reiksme');
ylabel('Daznis');
title('Prognozes klaidu histograma');
% 14 uzduotis
disp('Vidutines kvadratines prognozes klaidos reiksme')
mse_reiksme = mse(e)
clear()
% 19 uzduotis
% Klausimai:
% 1. Ka pavaizduoja diagrama,  kuri vaizduojama mokymosi proceso metu?
% Diagrama pavaizduoja dirbtinio neurono modeli
% 2. Ar mokymosi procesas yra konverguojantis? Jeigu ne, pamastyti kas gali b?ti
priezastimi ir pakeisti atitinkama parametra.
% Nekonveguojantis, galbut pavyzdziu kiekio pakeitimas???
% 3. Kokios yra naujos neurono svoriu koeficientu reiksm?s ?
% Naujos gautos reiksmes yra toliau 0 negu senos
% 4. Kokia yra neurono darbo kokybes ivercio - vidutinis kvadratinis nuokrypis -
reiksme ?
% 357.2350
```

Grafikai:



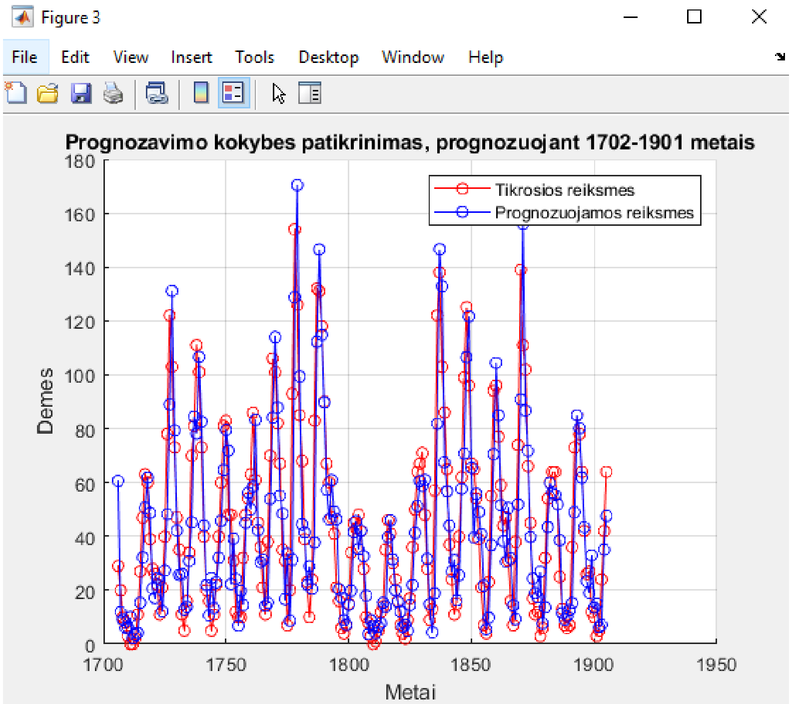


Figure 3
File Edit View Insert Tools Desktop Window Help
Prognozavimo kokybes patikrinimas, prognozuojant 1702-1901 metais
Tikrosios reiksmes
Prognozuojamos reiksmes
Demes
Metai
0
20
40
60
80
100
120
140
160
180
1700
1750
1800
1850
1900
1950

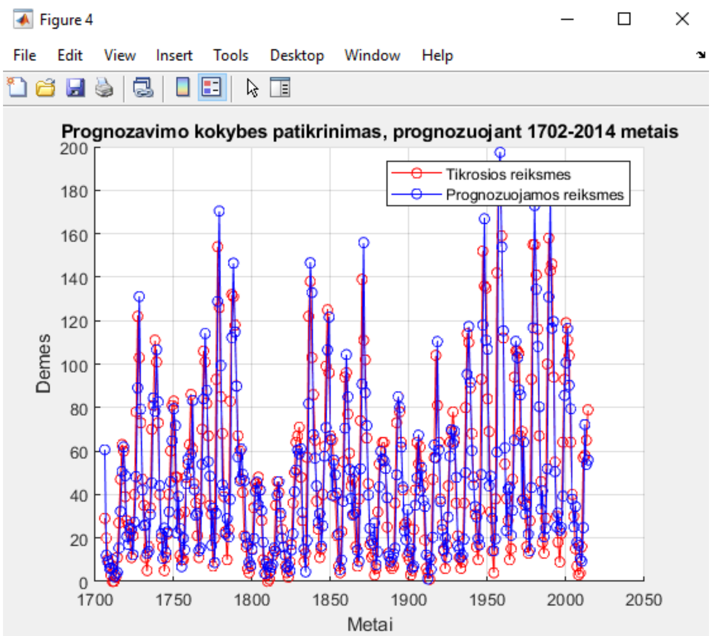


Figure 4
File Edit View Insert Tools Desktop Window Help
Prognozavimo kokybes patikrinimas, prognozuojant 1702-2014 metais
Tikrosios reiksmes
Prognozuojamos reiksmes
Demes
Metai
0
20
40
60
80
100
120
140
160
180
200
1700
1750
1800
1850
1900
1950
2000
2050

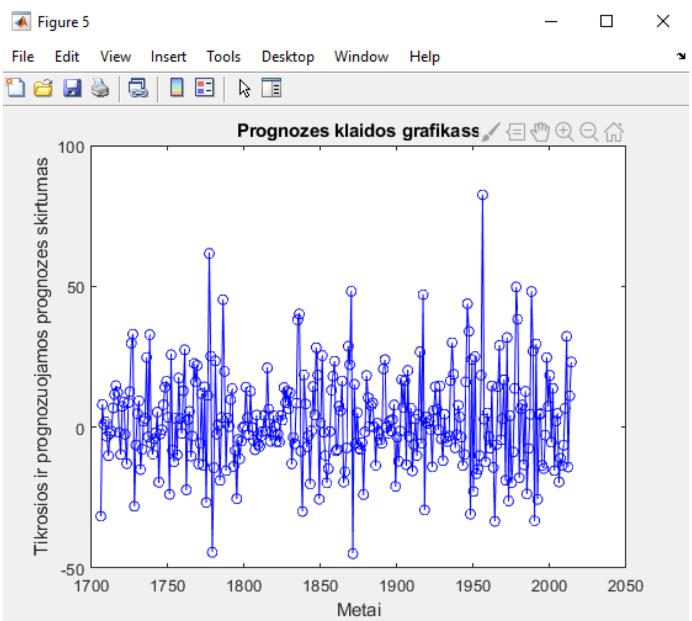
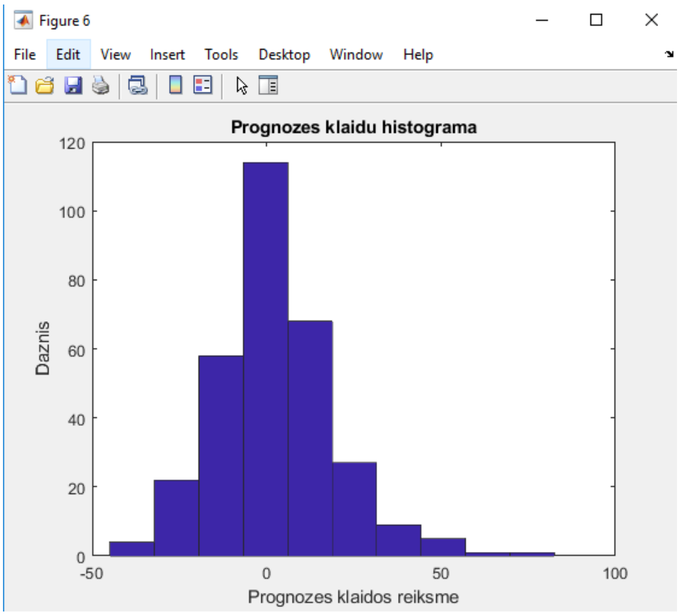


Figure 5
File Edit View Insert Tools Desktop Window Help
Prognozes klaidos grafikass
Tikrosios ir prognozuojamos prognozes skirtumas
Metai
-50
0
50
100
1700
1750
1800
1850
1900
1950
2000
2050



Scenarijus nr. 4 (Papildoma užduotis)

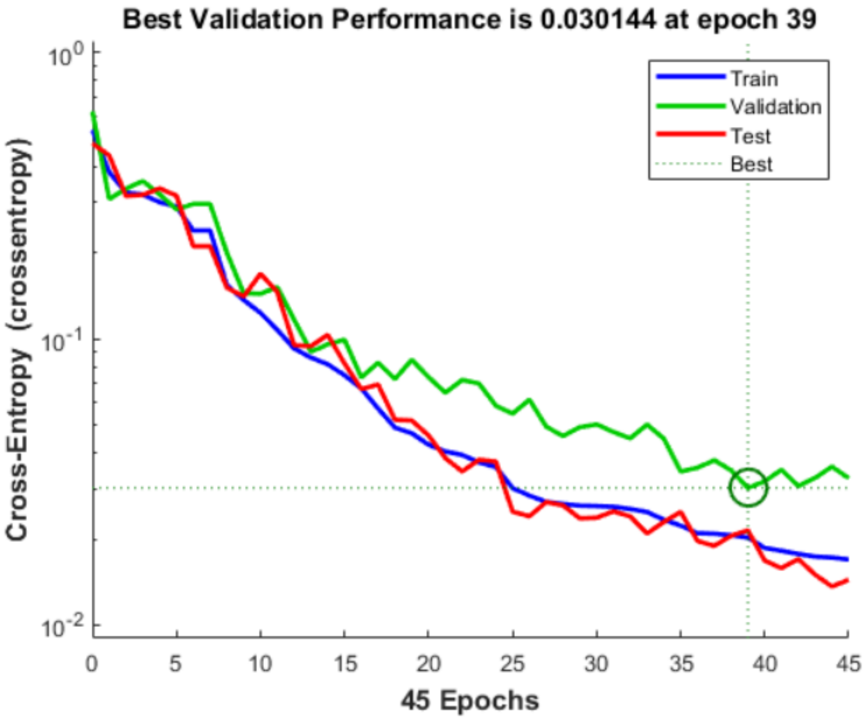
Kodas:

```
%% Crab Classification
% This example illustrates using a neural network as a classifier to
% identify the sex of crabs from physical dimensions of the crab.

%% The Problem: Classification of Crabs
% In this example we attempt to build a classifier that can identify the
% sex of a crab from its physical measurements. Six physical
% characteristics of a crab are considered: species, frontallip, rearwidth,
% length, width and depth. The problem on hand is to identify the sex of a
% crab given the observed values for each of these 6 physical
% characteristics.
%
%% Why Neural Networks?
% Neural networks have proven themselves as proficient classifiers and are
% particularly well suited for addressing non-linear problems. Given the
% non-linear nature of real world phenomena, like crab classification,
% neural networks are certainly a good candidate for solving the problem.
%
% The six physical characteristics will act as inputs to a neural network
% and the sex of the crab will be the target. Given an input, which
% constitutes the six observed values for the physical characteristics of a
% crab, the neural network is expected to identify if the crab is male or
% female.
%
% This is achieved by presenting previously recorded inputs to a neural
% network and then tuning it to produce the desired target outputs. This
% process is called neural network training.
%
%% Preparing the Data
% Data for classification problems are set up for a neural network by
% organizing the data into two matrices, the input matrix X and the target
% matrix T.
%
% Each ith column of the input matrix will have six elements representing a
% crab's species, frontallip, rearwidth, length, width, and depth.
%
```

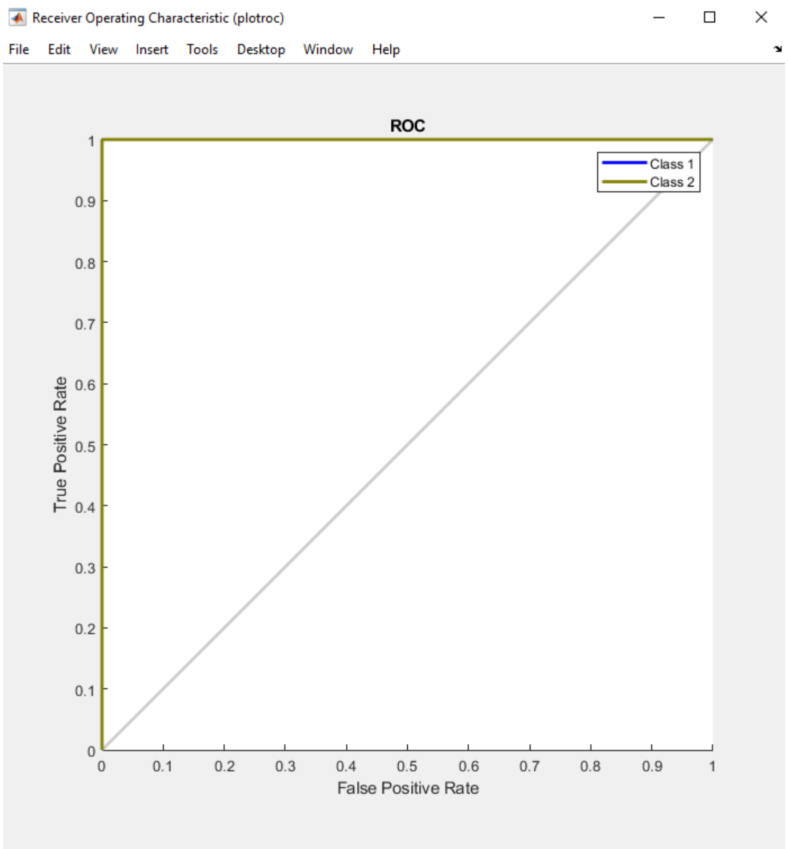
```
% Each corresponding column of the target matrix will have two elements.
% Female crabs are represented with a one in the first element, male crabs
% with a one in the second element. (All other elements are zero).
%
% Here the dataset is loaded.

[x,t] = crab_dataset;
size(x)
size(t)

%% Building the Neural Network Classifier
% The next step is to create a neural network that will learn to identify
% the sex of the crabs.
%
% Since the neural network starts with random initial weights, the results
% of this example will differ slightly every time it is run. The random
% seed is set to avoid this randomness. However this is not necessary for
% your own applications.

setdemorandstream(491218382)

%%
% Two-layer (i.e. one-hidden-layer) feed forward neural networks can learn
% any input-output relationship given enough neurons in the hidden layer.
% Layers which are not output layers are called hidden layers.
%
% We will try a single hidden layer of 10 neurons for this example. In
% general, more difficult problems require more neurons, and perhaps more
% layers.  Simpler problems require fewer neurons.
%
% The input and output have sizes of 0 because the network has not yet been
% configured to match our input and target data.  This will happen when the
% network is trained.

net = patternnet(10);
view(net)

%%
% Now the network is ready to be trained. The samples are automatically
% divided into training, validation and test sets. The training set is used
% to teach the network. Training continues as long as the network continues
% improving on the validation set. The test set provides a completely
% independent measure of network accuracy.

[net,tr] = train(net,x,t);
nntraintool

%%
% To see how the network's performance improved during training, either
% click the "Performance" button in the training tool, or call PLOTPERFORM.
%
% Performance is measured in terms of mean squared error, and is shown in a
% log scale.  It rapidly decreased as the network was trained.
%
% Performance is shown for each of the training, validation and test sets.

plotperform(tr)

%% Testing the Classifier
% The trained neural network can now be tested with the testing samples.
% This will give us a sense of how well the network will do when applied to
% data from the real world.
%
% The network outputs will be in the range 0 to 1, so we can use *vec2ind*
```

```
% function to get the class indices as the position of the highest element
% in each output vector.

testX = x(:,tr.testInd);
testT = t(:,tr.testInd);

testY = net(testX);
testIndices = vec2ind(testY)

%%
% One measure of how well the neural network has fit the data is the
% confusion plot.  Here the confusion matrix is plotted across all samples.
%
% The confusion matrix shows the percentages of correct and incorrect
% classifications.  Correct classifications are the green squares on the
% matrices diagonal.  Incorrect classifications form the red squares.
%
% If the network has learned to classify properly, the percentages in the
% red squares should be very small, indicating few misclassifications.
%
% If this is not the case then further training, or training a network with
% more hidden neurons, would be advisable.

plotconfusion(testT,testY)

%%
% Here are the overall percentages of correct and incorrect classification.

[c,cm] = confusion(testT,testY)

fprintf('Percentage Correct Classification   : %f%%\n', 100*(1-c));
fprintf('Percentage Incorrect Classification : %f%%\n', 100*c);

%%
% Another measure of how well the neural network has fit data is the
% receiver operating characteristic plot.  This shows how the false
% positive and true positive rates relate as the thresholding of outputs is
% varied from 0 to 1.
%
% The farther left and up the line is, the fewer false positives need to be
% accepted in order to get a high true positive rate.  The best classifiers
% will have a line going from the bottom left corner, to the top left
% corner, to the top right corner, or close to that.

plotroc(testT,testY)

%%
% This example illustrated using a neural network to classify crabs.
%
% Explore other examples and the documentation for more insight into neural
% networks and their applications.


%%
% Copyright 2012 The MathWorks, Inc.
```

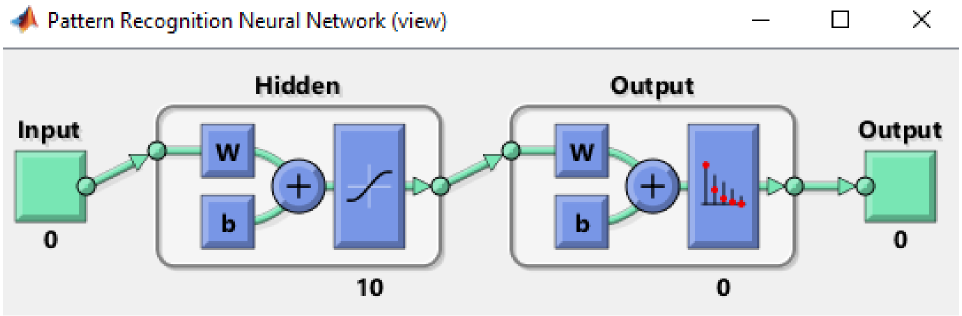
Grafikai:

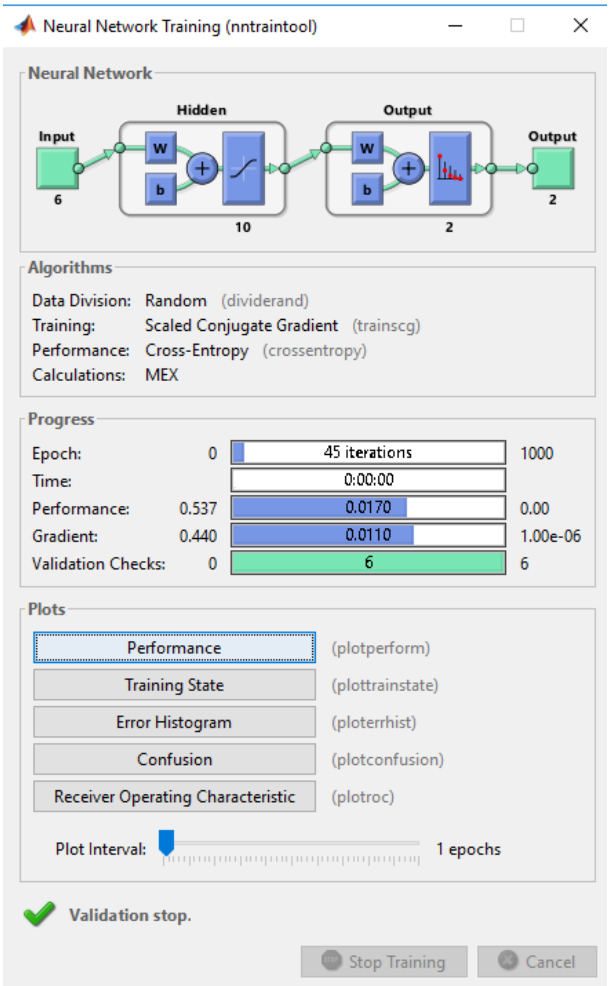


Best Validation Performance is 0.030144 at epoch 39
Train
Validation
Test
Best
Cross-Entropy (crossentropy)
45 Epochs



Receiver Operating Characteristic (plotroc)
File Edit View Insert Tools Desktop Window Help
ROC
Class 1
Class 2
True Positive Rate
False Positive Rate


Pattern Recognition Neural Network (view)
Hidden
Output
Input
W
b
W
b
Output
0
10
0
0


Neural Network Training (nntraintool)
Neural Network
Hidden
Output
Input
Output
6
10
2
2
Algorithms
Data Division: Random (dividerand)
Training: Scaled Conjugate Gradient (trainscg)
Performance: Cross-Entropy (crossentropy)
Calculations: MEX
Progress
Epoch: 0 45 iterations 1000
Time: 0:00:00
Performance: 0.537 0.0170 0.00
Gradient: 0.440 0.0110 1.00e-06
Validation Checks: 0 6 6
Plots
Performance (plotperform)
Training State (plottrainstate)
Error Histogram (ploterrhist)
Confusion (plotconfusion)
Receiver Operating Characteristic (plotroc)
Plot Interval: 1 epochs
Validation stop.
Stop Training
Cancel