About the course

We are always trying to improve the course so would be very happy to hear any suggestions. The course has been run by using new method Project Based Learning (PBL). We remind you that:

(1) The course is run in its current configuration for the first time; the number of contact face-to-face hours has been dramatically increased. With the minimum required 12x3=36 hrs, we actually delivered more hours than this minimum: 4x3 + 8x4 = 12+32 = 44 hrs.

(2) Our qualified team has designed a modern and relevant context for this Course.

About the course

- (3) We have presented universal techniques to solve variety of problems; at the same time representative examples were provided from a range of engineering applications (mechanical, automotive, electrical, environmental engineering, etc.).
- (4) We have introduced computer-based hand-on tutorials and involved the team of best expert tutors.
- (5) We worked hard to take into account student's feedback and listen to the students suggestions.
- (6) We value their feedback and CES is important to us.
- (7) Please if you have any questions and issues contact your tutorial directly and cc Hamid (hamid.khayyam@rmit.edu.au) as well.

CES

10 Minutes to complete your feedback and CES please!!



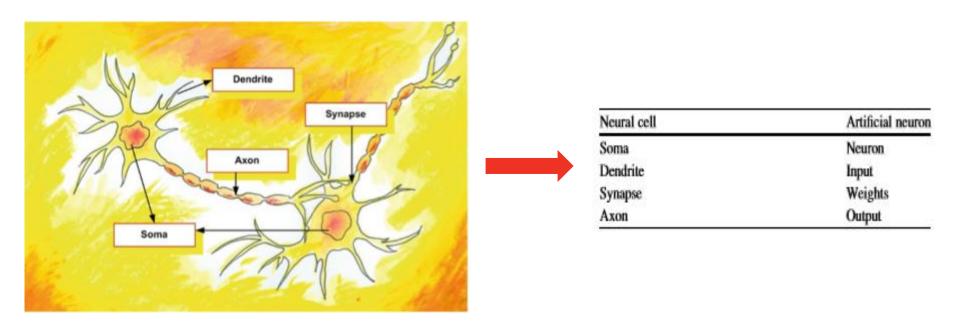
Machine Learning Practical Revision (ANN, SVM, NLR)

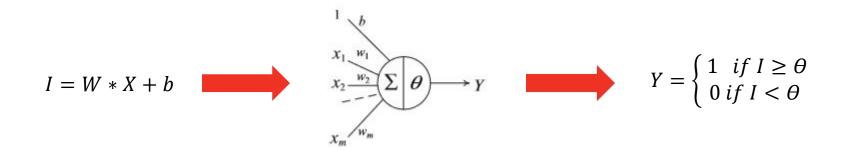
Lecturer:

Dr Hamid Khayyam (Australia) Email: hamid.khayyam@rmit.edu.au



Artificial Neural Network (ANN)





The mathematical relation of the functional process of an artificial neuron

The Steps of an application of ANN

1. Data pre-processing (check for missing data ,standardization)

2. Selecting network architecture

```
net = feedforwardnet();
```

3. Network training

```
[net,tr]= train(net,inputs,targets);
```

4. Simulation (validation)

```
a =net (inputs);
```

5. Performance(Post-processing)

MSE: Mean squared error performance function.

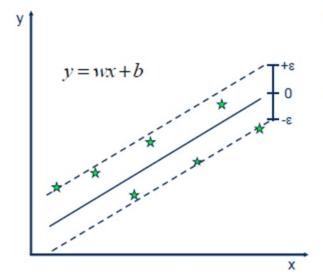
RMSE: Root Mean squared error performance function

R: Coefficient of correlation.

Support Vector Machine (SVM):



- +: data points of type 1
 -: data points of type -1
- Regression in SVM (SVR)



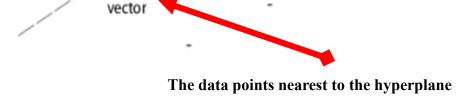
· Solution:

$$\min \frac{1}{2} ||w||^2$$

· Constraints:

$$y_i - wx_i - b \le \varepsilon$$

 $wx_i + b - y_i \le \varepsilon$



Support vector

Support

Support vector (

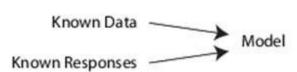
E: Margin of tolerance

Steps of An Application of SVR

1. Data pre-processing (check for missing data ,standardization)

2. Model development and training

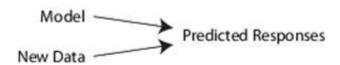
$$Mdl = fitrsvm(X, Y)$$
 (Regression)



3. Simulation (prediction)

Y_predicted= predict(Mdl,X) (Regression) %Y_predicted is the predicted responses

- 4. Post-processing
 - MSE,RMSE,R (Regression)



Nonlinear Regression (NLR):

A term used for all a wide range of regression models which all present a nonlinear relationship between input and output.

Model	Equation
Exponential	$y = ae^{bx} + ce^{dx}$
Fourier	$y = a_0 + a_1 \cos(x * w) + b_1 \sin(x * w) +$
	$\cdots a_n \cos(x*w) + b_n \sin(x*w)$
Gaussian	$y = a_1 e^{[(x-b_1)/c_1]^2} + \cdots + a_n e^{[(x-b_n)/c_n]^2}$
Polynomial	$y = a_1 x^n + a_2 x^{n-1} + \dots + a_n x + a_0$
Power	$y = ax^b + c$
Sin function	$y = a_1 \sin(b_1 x + c_1) + \cdots + a_n \sin(b_n x + c_n)$
Weibull	$y = abx^{b-1}e^{\left(-a*x^b\right)}$

Conventional nonlinear regression functions

Steps of An Application of NLR

- I. Data pre-processing (check for missing data ,standardization)
- II. Define the model function and coefficients initiation
- III. Model development and training

```
mdl = fitnlm(x,t,fun,beta);
```

IV. Simulation (prediction)

```
Y predicted= predict(Mdl,X);
```

V. Post-processing

MSE, RMSE, R

Example of ANN (1):

```
%prediction of Torque based on fuel rate and speed
clear; clc;
Filename='DataEngine.xlsx';
Sheetread='Training';
Input1='A1:B1194';
output1='C1:C1194';
Input=xlsread(Filename, Sheetread, Input1);
Target=xlsread(Filename, Sheetread, output1);
x=Input;
t=Target;
• Sheetread1='Newdata';
• Input2='A1:B3';
• Target2 = 'C1:C3';
Inputnew=xlsread(Filename, Sheetread1, Input2);
Targetnew=xlsread(Filename, Sheetread1, Target2);
```

Example of ANN (1): (cont.)

```
xnew=Inputnew;
tnew=Targetnew;
x=Input';
t=Target';
xnew=Inputnew';
tnew=Targetnew';
trainFcn = 'trainlm'; hiddenLayerSize = 10;
net = fitnet(hiddenLayerSize, trainFcn);
net.input.processFcns = {'mapminmax'}; % To standardize
the input
net.output.processFcns = {'mapminmax'}; % To standardize
the output
RandStream.setGlobalStream (RandStream ('mrg32k3a')); %
Just to get the same results; Set random number stream;
net.divideMode = 'sample';
```

Example of ANN (1): (cont.)

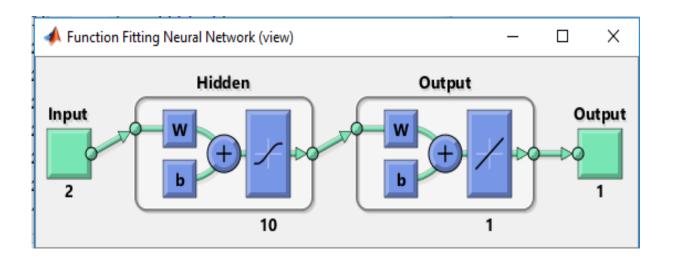
```
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 20/100;
net.divideParam.testRatio = 10/100;
net.performFcn = 'mse'; % Choose MSE for performance
[net, tr] = train(net, x, t);
y = net(x);
e = gsubtract(t, y);
performance = perform(net,t,y);
figure; plotperform(tr)
figure; plottrainstate (tr)
figure, plotregression(t,y)
trainTargets = t .* tr.trainMask{1};
```

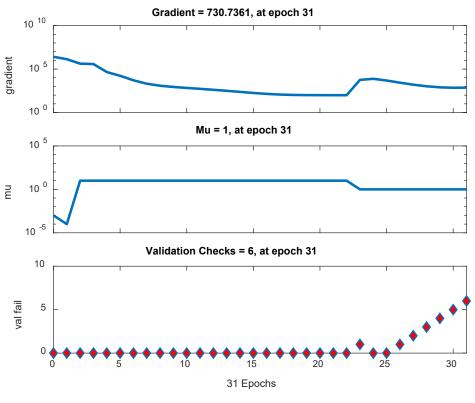
Example of ANN(1): (cont.)

```
valTargets = t .* tr.valMask{1}; %Select validation data
testTargets = t .* tr.testMask{1}; %select test data
trainPerformance = perform(net, trainTargets, y) % training
data performance
valPerformance = perform(net, valTargets, y)
                                                 90
validation data performance
testPerformance = perform(net, testTargets, y) % test data
performance
Ynew=net(xnew); %Test the net with new data to calculate
the performance and make predictions.
table (tnew (1: 3)', Ynew (1: 3)', 'VariableNames', ...
{'Actual Torque',' Predicted Torque'})
```

Example of ANN(1): (cont.)

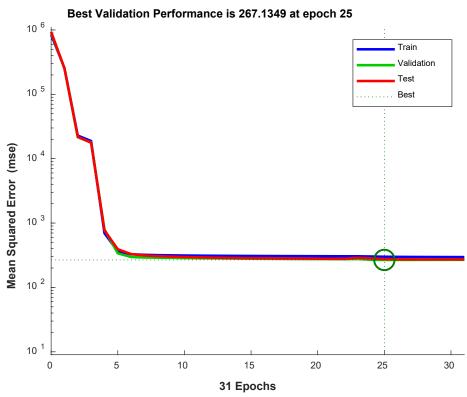
```
MSE_testing=sum((tnew-Ynew).^2)/numel(tnew); %
Calculate MSE for new data
RMSE_testing=sqrt(sum((tnew-Ynew).^2)/numel(tnew));
% Calculate RMSE for new data
```

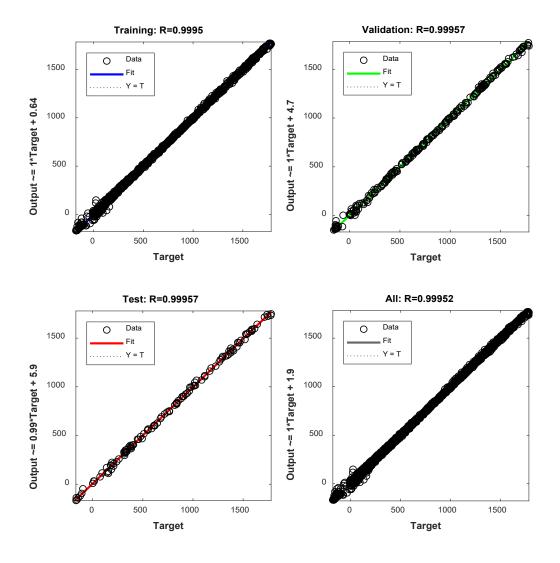




Plottrainstate

Plotperform





Plotregression

trainPerformance =		
299.7241		
valPerformance =		
267.1349		
testPerformance =	Actual_data_tnew	Predicted_data_Ynew
275.9776		
	58	50.023
	45.5	55.111
MSE_newdata=67.6933	57.6	50.739

RMSE_newdata=8.2278

Example of ANN, SVM, and NLR: (ANN)

```
clear; clc;
Filename='Datachemical.xlsx';
Sheetread='Training';
Input1='A1:C72';
output1='D1:D72';
Input=xlsread(Filename, Sheetread, Input1);
Target=xlsread(Filename, Sheetread, output1);
x=Input;
t=Target;
Sheetread1='Newdata';
Input2='A1:C3';
Target2 = 'D1:D3';
Inputnew=xlsread(Filename, Sheetread1, Input2);
Targetnew=xlsread(Filename, Sheetread1, Target2);
```

```
xnew=Inputnew;
tnew=Targetnew;
x=Input';
t=Target';
xnew=Inputnew';
tnew=Targetnew';
trainFcn = 'trainlm'; hiddenLayerSize = 10;
net.layers{1}.transferFcn = 'logsig'; %for hidden layer
net = fitnet(hiddenLayerSize, trainFcn);
net.input.processFcns = {'mapminmax'}; % To standardize
the input between -1 to 1.
net.output.processFcns = {'mapminmax'}; % To standardize
the output -1 to 1
RandStream.setGlobalStream (RandStream ('mrg32k3a')); %
Just to get the same results create random number streams;
net.divideMode = 'sample';
```

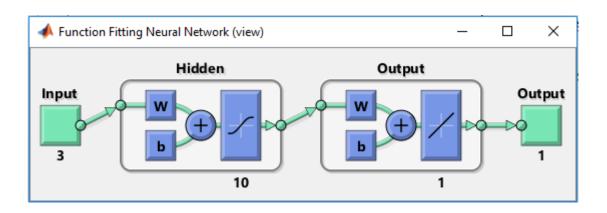
```
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 20/100;
net.divideParam.testRatio = 10/100;
net.performFcn = 'mse'; % Choose MSE for performance
[net, tr] = train(net, x, t);
y = net(x);
e = gsubtract(t,y); %Generalized subtraction
performance = perform(net,t,y);
figure; plotperform(tr)
figure; plottrainstate(tr) %Plot training state
valuesfigure, plotregression(t,y) % Regression plot
trainTargets = t .* tr.trainMask{1}; % Apply a mask (0's
and 1's to select the proper targets) to select train data
```

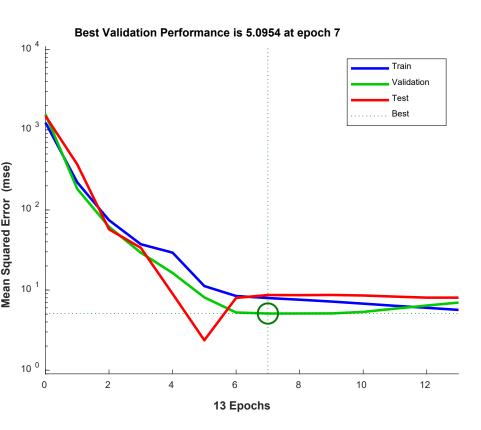
```
valTargets = t .* tr.valMask{1}; %Select validation data
testTargets = t .* tr.testMask{1}; %select test data
trainPerformance = perform(net, trainTargets, y) % training
data performance
valPerformance = perform(net, valTargets, y)
validation data performance
testPerformance = perform(net, testTargets, y) %test data
performance
Ynew=net(xnew); %Test the net with new data to calculate
the performance and make predictions.
Newperformance=mse(tnew, Ynew); %MSE for new data
table (tnew(1:10)', Ynew(1:10)', 'VariableNames',
{'Actual data tnew',' Predicted data Ynew'}) % Prediction
of thew and Ynew for first 10th data
```

MSE_testing=sum((tnew-Ynew).^2)/numel(tnew); %
Calculate MSE for new data

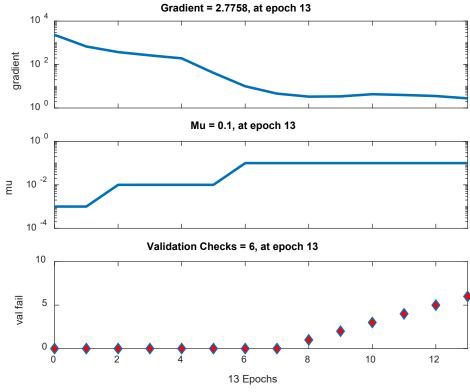
RMSE_testing=sqrt(sum((tnew-Ynew).^2)/numel(tnew)); %
Calculate RMSE for new data

Errorpercentage=((Ynew-tnew)./tnew)*100; % Calculate
error percentage for tnew and ynew

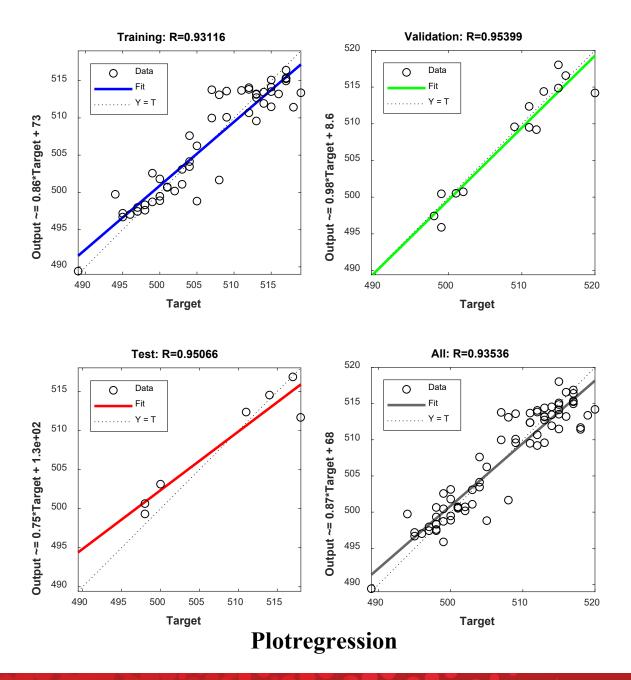




Plotperform



Plottrainstate



trainPerformance =

7.9503

valPerformance =

5.0954

testPerformance =

8.6680

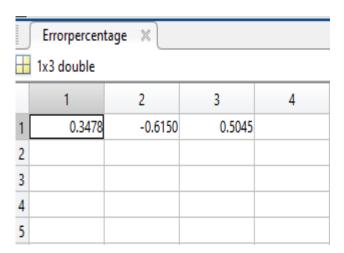
MSE_newdata=6.6460

 $RMSE_newdata = 2.5780$

3×2 <u>table</u>

Actual	data	tnew	Predicted	data	Ynew
_		-	_		_

514	515.79
516	512.83
512	514.58



```
clear; clc;
Filename='Datachemical.xlsx';
Sheetread='Training';
Input1='A1:C72';
output1='D1:D72';
Input=xlsread(Filename, Sheetread, Input1);
Target=xlsread(Filename, Sheetread, output1);
x=Input;
t=Target;
Sheetread1='Newdata';
Input2='A1:C3';
Target2 = 'D1:D3';
```

```
Inputnew=xlsread(Filename, Sheetread1, Input2);
Targetnew=xlsread(Filename, Sheetread1, Target2);
xnew=Inputnew;
tnew=Targetnew;
mdl = fitrsvm(x,t,'KernelFunction', 'qaussian', ...
     'Standardize', true); %standardize the data
%standardize the data and
conv = mdl.ConvergenceInfo.Converged; % Shows whether the
program reach an answer or not .
% smetimes it cannot find a solution and doesnot converge
iter = mdl.NumIterations; % number of iteration to reach
the answer
```

```
yfit=predict(mdl,x); % prediction based on the developed
SVR model and x as the input
table(t(1:10,:), yfit(1:10,:), 'VariableNames', { 'ObservedVal
ue', ' PredictedValue'}) % show 20th to 30th data in output
and predicted output
MSE training=sum((yfit-t).^2)/numel(t); % Calculate MSE
for data
% MSE training1=mse(yfit,t);
RMSE training=sqrt(sum((yfit-t).^2)/numel(t)); % Calculate
RMSE for data
ynew=predict(mdl, xnew);
table(tnew(:), ynew(:), 'VariableNames', { 'ObservedValue Newd
ata',' PredictedValue newdata'}) % show data in output and
predicted output
% MSE testing1=mse(tnew, ynew);
```

MSE_testing=sum((tnew-ynew).^2)/numel(tnew); % Calculate
MSE for new data

RMSE_testing=sqrt(sum((tnew-ynew).^2)/numel(tnew)); %
Calculate RMSE for new data

Errorpercentage=((ynew-tnew)./tnew)*100; % Calculate error percentage for tnew and ynew

ObservedValue	PredictedValue
511	511.9
504	505.17
512	514.62
505	506.05
507	510.81
501	502.04
500	500.05
505	498.23
502	500.96
508	502.33
502	500.95

3×2 table

ObservedValue_Newdata	PredictedValue_newdata
514	514.23
516	513.71
512	513.61

Errorpercentage × 3x1 double				
	1	2	3	4
1	0.0446			
2	-0.4444			
3	0.3150			
4				

Example of ANN, SVM, and NLR: (NLR)

```
clear; clc;
Filename='Datachemical.xlsx';
Sheetread='Training';
Input1='A1:C72';
output1='D1:D72';
Input=xlsread(Filename, Sheetread, Input1);
Target=xlsread(Filename, Sheetread, output1);
x=Input;
t=Target;
Sheetread1='Newdata';
Input2='A1:C3';
Target2 = 'D1:D3';
Inputnew=xlsread(Filename, Sheetread1, Input2);
Targetnew=xlsread(Filename, Sheetread1, Target2);
```

```
xnew=Inputnew;
tnew=Targetnew;
[xn, sxn] = mapminmax(x'); % Standardize x
[tn,stn] = mapminmax(t'); % Standardize t
xnewn = mapminmax('apply', xnew', sxn); % The same Process
setting of
%standardization for x should be applied for xnew as well
.%xnewn is the
%standardized xnew
xn=xn';% standardized x
tn=tn';% standardized t
```

```
xnewn=xnewn';%standardized xnew
beta = [1 1 1 1 1 1 1 1]; % coefficient initiation
fun=0 (b, xn) b (1) + b (2) *xn (:, 1) + b (3) *xn (:, 2) + b (4) *xn (:, 3) + b (5)
)*(xn(:,1).^2)+b(6)*((xn(:,1).*xn(:,2).*xn(:,3))+b(7).*exp
(b(8)*xn(:,3)); % nonlinear model with standardized x
mdl = fitnlm(xn,tn,fun,beta); % find coeffcients(beta) of
model(fun )using normalized x and t
yfitn = predict(mdl,xn); % make prediction based on
normalized x
yfit = mapminmax('reverse', yfitn,stn); % To reverse the
prediction to original state using the same process
setting of t
table( t( 40:50 ), yfit( 40:50 ), 'VariableNames',...
    {' TrueLabel', ' PredictedLabel'}) %Show the results of
40th to 50th
```

```
MSE training=sum((yfit-t).^2)/numel(t); % Calculate MSE
for data
RMSE training=sqrt(sum((yfit-t).^2)/numel(t)); % Calculate
RMSE for data
ynewn=predict(mdl, xnewn); % make prediction based on
normalized new data
ynew = mapminmax('reverse', ynewn, stn); % To reverse the
normalized ynew and use the processing setting of t
table(tnew(:), ynew(:), 'VariableNames', { 'ObservedValue Newd
ata',' PredictedValue newdata'}) % show data in output and
predicted output
MSE testing=sum((tnew-ynew).^2)/numel(tnew); % Calculate
MSE for new data
RMSE testing=sqrt(sum((tnew-ynew).^2)/numel(tnew)); %
Calculate RMSE for new data
Errorpercentage=((ynew-tnew)./tnew)*100; % Calculate error
percentage for thew and ynew
```

Tr	rueLabel	PredictedLabel
_		
51	1	512.76
50)4	509.69
51	.2	513.41
50)5	505.57
50	7	511.84
50)1	504.31
50	00	499.39
50)5	496.6
50)2	497.6
50	8	499.4
50)2	498.5
MSE_training =10	0.1974	RMSE_training =3.1933
MSE_testing =5.	.6746	RMSE_testing =2.3821

3×2 <u>table</u>

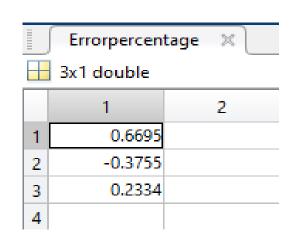
ObservedValue Newdata

${\tt PredictedValue_newdata}$

514	517.44
516	514.06
512	513.19

mdl.Coefficients

		1	
		Estimate	
1	b 1	-3.1592	
2	b2	0.5237	
3	b3	-0.0042	
4	b4	-1.7069	
5	b 5	-0.0952	
6	b 6	0.0679	
7	b 7	44.2546	
8	b 8	0.4503	



ANN

MSE_training =7.9503

MSE_testing =8.6680

SVR

MSE_training =5.7400

MSE_testing =2.6371

NLR

MSE_training =10.1974

MSE_testing =5.6746