Machine Learning
Capacity and Performance Analysis
and R

Stephen O'Connell

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Introduction

Brief Introduction to Machine Learning and Data Mining

- What, Why and How

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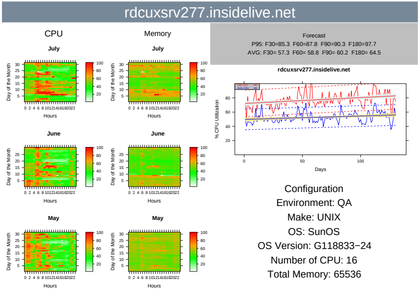
How can this be applied to Capacity and Performance Analysis

- Data driven
- Patterns



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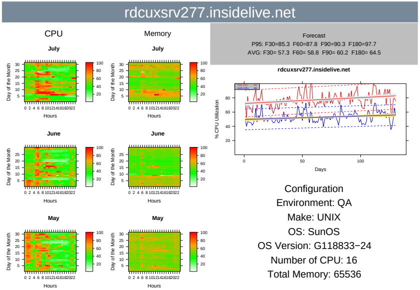
Example: Utilization Profiling in R

- Data Transformation
- Model Construction and Test
- Model Deployment



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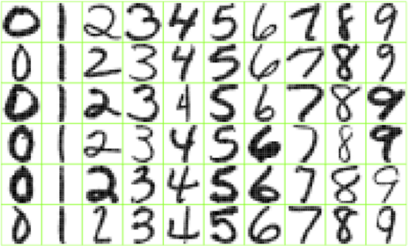
Definition:

The field of machine learning studies the design of computer programs able to induce patterns, regularities, or rules from past experiences. Learner (a computer program) processes data representing past experiences and tries to either develop an appropriate response to future data, or describe in some meaningful way the data seen. [2]

Example: Handwritten Digits

Elements of Machine Learning:



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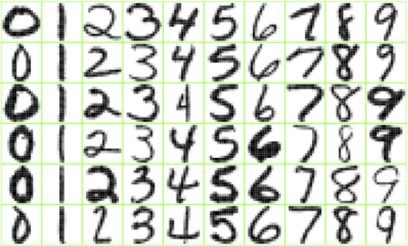
  - recognizing and classifying handwritten words within images



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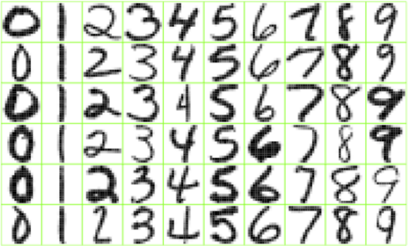

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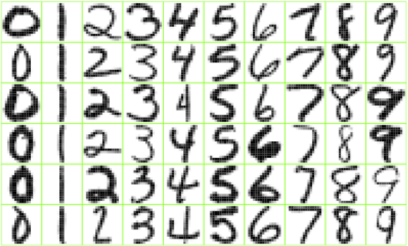
- Performance P
  - percent of words correctly classified
- Experience E
  - a database of handwritten words with given classifications



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- Use a labeled (known) set of data to build models to perform classification or regression
- Use the model on new data to make predictions or describe the data
- Supervised algorithms:
  - Linear Regression
  - Trees
  - Neural Networks
  - Support Vector Machines

Methods

Unsupervised learning[4]:

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Unsupervised learning[4]:

- Find hidden structure in unlabeled (unknown) data

Methods

Unsupervised learning[4]:

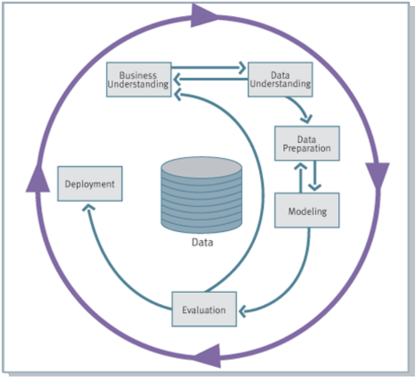
- Find hidden structure in unlabeled (unknown) data
- Unsupervised algorithms:
  - Kmeans
  - K Nearest Neighbor
  - Hierarchical Clustering
  - Association Rules
  - Principal Components

Machine Learning is a Process

Like application development

CRISP-DM, for example[3]:

- Business Understanding
- Data Understanding
- Data Preparation
- Modeling
- Evaluation
- Deployment
- REPEAT AS NEEDED



Applications

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And you can make money!

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- Heritage Health Prize - $3M

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Capacity Planning and Performance Analysis:

A simplified view of capacity planning:

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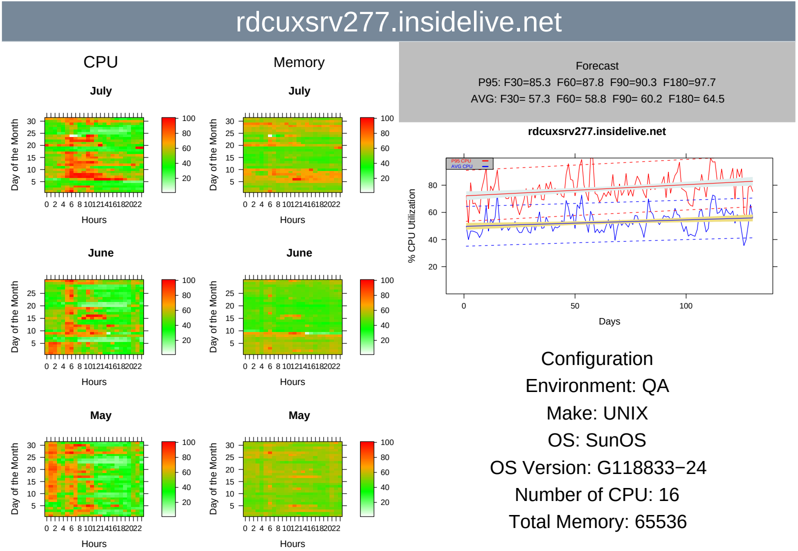
Capacity Planning and Performance Analysis:

A simplified view of capacity planning:

- Hourly and Daily, Monday thru Friday stats
- Peak and Average Daily Utilization
- Simple linear regression on peak and average utilization
- Extrapolate 30-60-90-180 days into the future.

Capacity Planning – Simplified View:



* One page Server Utilization, Forecast, and Configuration developed using R

Capacity Planning – Simplified View:

Put all forecasts into a spreadsheet and sort by 30, 60, 90, or 180 forecast to find top Utilized servers

	A	O	P	Q	R	S	T	U	V	W	X
1	***Host Capacity Forecast Report***		<0%	>80%	>90%						
2	server_name	days	avg_30_days	avg_60_days	avg_90_da	avg_180_c	p95_30_da	p95_60_da	p95_90_da	p95_180_c	avgm
3	rdclxsrv307.insidelive.net	129	145.44	169.73	194.02	266.89	140.25	161.71	183.18	247.56	5
4	calntmgt201.insidelive.net	129	131.69	146.18	160.68	204.16	132.62	147.04	161.46	204.73	3
5	rdclxsrv349.insidelive.net	126	117.36	132.64	147.91	193.73	117.97	133.18	148.4	194.05	5
6	sfouxsrv026.insidelive.net	129	112.19	135.61	159.03	229.29	116.24	139.45	162.66	232.3	3
7	sfouxsrv133.insidelive.net	129	98.66	116.56	134.47	188.17	103.55	121.31	139.06	192.33	6
8	yokuxsrv006.insidelive.net	129	93.27	110.22	127.17	178.01	107.51	122.72	137.94	183.57	8
9	calntscr001.insidelive.net	129	93.1	110.49	127.87	180.02	103.05	122.55	142.05	200.54	3
10	rdcuxsrv143.insidelive.net	129	89.35	92.05	94.75	102.85	95.98	97.89	99.79	105.52	3
11	rdcuxsrv161.insidelive.net	129	87.83	100.52	113.21	151.27	105.92	117.33	128.75	162.99	2
12	calntapp623.insidelive.net	42	75.69	106.86	138.02	231.53	85.12	118.05	150.97	249.75	5
13	rdcuxsrv017.insidelive.net	129	75.61	76.75	77.89	81.31	78.41	79.53	80.66	84.05	5
14	rmcuxsrv048.insidelive.net	129	75.29	75.96	76.62	78.62	100.03	100.06	100.09	100.19	1
15	rmcuxsrv099.insidelive.net	129	75.27	90.63	105.99	152.07	89.8	104.27	118.74	162.15	2
16	rdcuxsrv079.insidelive.net	129	74.61	85.59	96.57	129.52	102.6	119.14	135.68	185.31	4
17	rdcuxsrv134.insidelive.net	129	73.91	83.64	93.37	122.54	97.05	107.96	118.88	151.62	7
18	sfolxsrv085.insidelive.net	129	73.87	92.05	110.24	164.79	88.42	110.11	131.79	196.83	
19	sfolxsrv065.insidelive.net	115	73.36	83.59	93.82	124.51	73.87	83.81	93.74	123.56	
20	toklxsrv015.insidelive.net	129	73.24	82.98	92.72	121.94	74.12	83.93	93.75	123.2	4
21	rdcuxsrv276.insidelive.net	129	72.43	74.81	77.19	84.34	94.57	97.9	101.24	111.25	6
22	rdclxsrv267.insidelive.net	125	71.97	84.55	97.13	134.87	90.55	102.53	114.5	150.42	2
23	calntapp201.insidelive.net	129	71.85	78.5	85.15	105.11	88.94	95.47	101.99	121.57	7
24	calntesm412.insidelive.net	85	71.08	90.73	110.38	169.34	76.11	97.01	117.92	180.64	5
25	calntesm220.insidelive.net	26	70.72	105.89	141.06	246.58	87.74	127.98	168.21	288.92	6

Capacity Planning – Simplified View:

- Works well for stable business applications and environments.

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- Things are not stable and well formed – different applications have different utilization profiles, for different reasons.
- Exceptions occur

How can Machine Learning help?

- Lots and lots of data
  - System have many different components and each component has its own function and collection of metrics that determine performance
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- Lots of historical data (Capacity Database?)
- Many repeating and familiar patterns

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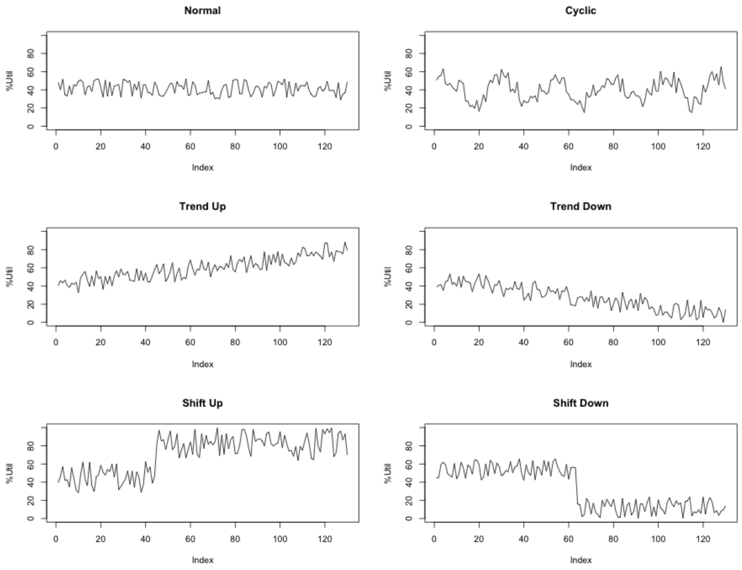

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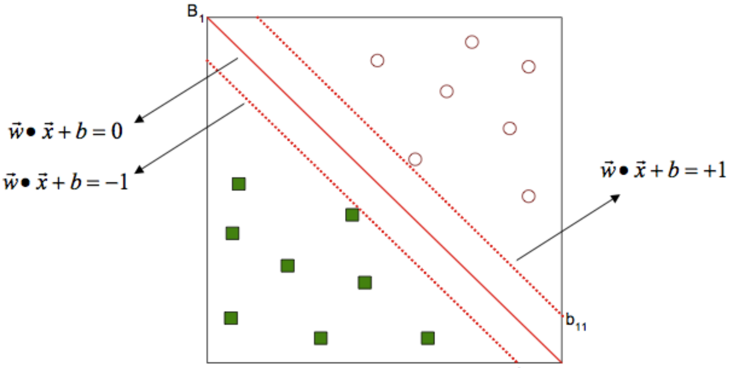
- Many different machine learning packages
- Almost a complete solution for building machine learning tools – scaling is an issue, i.e. the problem has to fit in memory.

Support Vector Machine



$$f(\vec{x}) = \begin{cases} 1 & \text{if } \vec{w} \bullet \vec{x} + b \geq 1 \\ -1 & \text{if } \vec{w} \bullet \vec{x} + b \leq -1 \end{cases}$$

$$\text{Margin} = \frac{2}{\|\vec{w}\|^2}$$

Data Considerations

- Performance and Utilization data is time series

```
DateTime      Server      AverageCPU
2011-05-01    webserver   95
2011-05-02    webserver   90
2011-05-03    webserver   85
2011-05-04    webserver   95
2011-05-05    webserver   94
```

- ML data format is a matrix with the general form Y, X1, X2,...Xn
- Need to convert time series to matrix

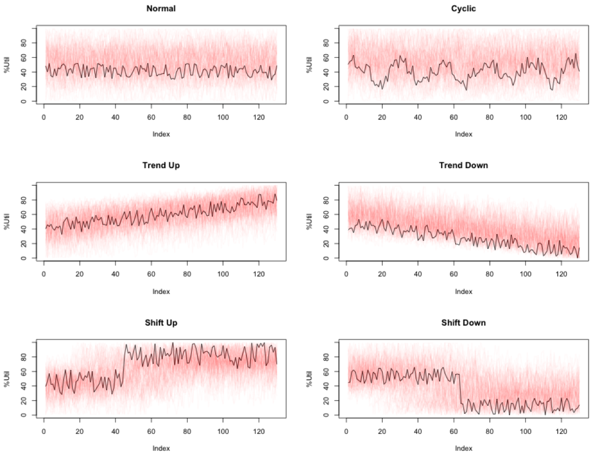
```
Y           X1   X2   X3   X4   X5
webserver   95   90   85   95   94
```

- Data needs to be consistent and well formed, no missing or bad data

SVM Demonstration

- Data is generated, `prototypes.R`
- `helperFunctions.R`
  - `createData`
  - `confusionM`
  - `printMissClassified`
- `demo_1.R` Builds an initial SVM model, tunes the model and classifies new data with the model
- `demo_2.R` Improves the accuracy of the initial model

Generated Data



- Datasets contain 100 of each type of pattern, i.e. 600 servers
- There are 130 X data points/features representing 180 days, Monday thru Friday
- Randomly generated...

First Predictive Model

Create the first model

```
###———————————————————— OUT OF THE BOX ————————————————————
## GET DATA
Ynew <- dget("Y_7")
data <- createData(Ynew)

## SPLIT TO x and Y
x <- subset(data, select = -class)
y <- data$class

## BUILD MODEL
model <- svm(class ~ ., data = data)
summary(model)

Call:
svm(formula = class ~ ., data = data)

Parameters:
   SVM-Type:  C-classification
 SVM-Kernel:  radial
       cost:  1
      gamma:  0.007692308

Number of Support Vectors:  545
 ( 95 100 89 80 88 93 )

Number of Classes:  6

Levels:
 Cyclic Normal ShiftDown ShiftUp TrendDown TrendUp
```

First Predictive Model

Check the models accuracy

```
> ## PREDICTIONS
pred <- predict(model, x)

# CHECK ACCURACY:
confusionM(pred, y)

Predicted Values:
Yp
   Cyclic    Normal ShiftDown   ShiftUp TrendDown   TrendUp
       94       109        90        92       108       107
Y values:
Y
   Cyclic    Normal ShiftDown   ShiftUp TrendDown   TrendUp
      100       100       100       100       100       100
Confusion Matrix:
            Yp
Y            Cyclic Normal ShiftDown ShiftUp TrendDown TrendUp
  Cyclic         90     10         0       0         0       0
  Normal          2     98         0       0         0       0
  ShiftDown       2      0        90       0         8       0
  ShiftUp         0      1         0      91         0       8
  TrendDown       0      0         0       0       100       0
  TrendUp         0      0         0       1         0      99
Accuracy =  0.9466667[1] 0.9466667
```

First Predictive Model

Model Tuning:

```
> obj <- tune.svm(class~., data = data, gamma = 2^(-1:1), cost = 2^(2:4))
> summary(obj)

Parameter tuning of svm :

- sampling method: 10-fold cross validation

- best parameters:
 gamma cost
   0.5    4

- best performance: 0.8883333

- Detailed performance results:
  gamma cost     error dispersion
1   0.5    4 0.8883333 0.03604695
2   1.0    4 0.9000000 0.03142697
3   2.0    4 0.9000000 0.03142697
4   0.5    8 0.8883333 0.03604695
5   1.0    8 0.9000000 0.03142697
6   2.0    8 0.9000000 0.03142697
7   0.5   16 0.8883333 0.03604695
8   1.0   16 0.9000000 0.03142697
9   2.0   16 0.9000000 0.03142697
```

First Predictive Model

Re-run the training data with tuned parameters

```
> ###----------------------------------- AFTER TUNING -----------------------------------
## NEW MODEL WITH COST AND GAMMA
model <- svm(class ~ ., data = data, cost=2.25, gamma=.01)

## RE-DO THE PREDICTION
pred <- predict(model, x)

# CHECK ACCURACY
confusionM(pred, y)

 Predicted Values:
Yp
   Cyclic    Normal ShiftDown   ShiftUp TrendDown   TrendUp
       98       102        98        98       102       102
Y values:
Y
   Cyclic    Normal ShiftDown   ShiftUp TrendDown   TrendUp
      100       100       100       100       100       100
 Confusion Matrix:
            Yp
Y             Cyclic Normal ShiftDown ShiftUp TrendDown TrendUp
  Cyclic          98      2         0       0         0       0
  Normal           0    100         0       0         0       0
  ShiftDown        0      0        98       0         2       0
  ShiftUp          0      0         0      98         0       2
  TrendDown        0      0         0       0       100       0
  TrendUp          0      0         0       0         0     100
 Accuracy =  0.99[1] 0.99
```

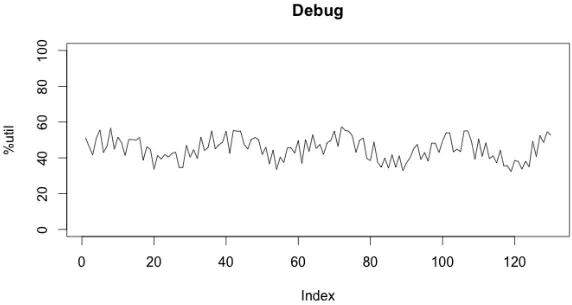
First Predictive Model

Missclassification Analysis

```
> printMissClassified(pred, y)

   Predicted    Actual  observation
1     Normal    Cyclic          156
2     Normal    Cyclic          177
3    TrendUp   ShiftUp          423
4    TrendUp   ShiftUp          452
5  TrendDown ShiftDown          553
6  TrendDown ShiftDown          586
```

```
> plot(t(data[156,2:131]), type='l',main="Debug",ylab="%util", ylim=c(0,100))
```



First Predictive Model

Use the model to classify new data

```
###---------------------------------------- NEW DATA ------------------------------------
## READ IN DATA THAT MODEL HAS NOT SEEN
Ynew <- dget("Y_6")
data <- createData(Ynew)
## SPLIT TO X and Y
x <- subset(data, select = -class)
y <- data$class
## PREDICT CLASS USING PREVIOUSLY CREATED MODEL
pred <- predict(model, x)

# CHECK ACCURACY
confusionM(pred, y)
Predicted Values:
Yp
   Cyclic    Normal ShiftDown   ShiftUp TrendDown   TrendUp
       96       107        99        86       102       110
Y values:
Y
   Cyclic    Normal ShiftDown   ShiftUp TrendDown   TrendUp
      100       100       100       100       100       100
Confusion Matrix:
           Yp
Y           Cyclic Normal ShiftDown ShiftUp TrendDown TrendUp
  Cyclic        69     23         6       0         2       0
  Normal        20     80         0       0         0       0
  ShiftDown      5      0        85       0        10       0
  ShiftUp        0      4         0      77         0      19
  TrendDown      2      0         8       0        90       0
  TrendUp        0      0         0       9         0      91
Accuracy =  0.82[1] 0.82
```

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- Are we using the right algorithm, the right way?

Improved Predictive Model

Add more data to the Model Build

```
> ###———————————————————— OUT OF THE BOX ————————————————————
## ADD MORE DATA TO THE MODEL BUILD
Ynew <- dget("Y_7")
d <- createData(Ynew)
data <- d
Ynew <- dget("Y_5")
d <- createData(Ynew)
data <- rbind(data, d)
Ynew <- dget("Y_4")
d <- createData(Ynew)
data <- rbind(data, d)
Ynew <- dget("Y_3")
d <- createData(Ynew)
data <- rbind(data, d)
Ynew <- dget("Y_2")
d <- createData(Ynew)
data <- rbind(data, d)
Ynew <- dget("Y_1")
d <- createData(Ynew)
data <- rbind(data, d)

## SPLIT TO x and Y
x <- subset(data, select = -class)
y <- data$class
```

Improved Predictive Model

Add more data to the Model Build, cont.

```
> ## BUILD MODEL
model <- svm(class ~ ., data = data)
summary(model)


Call:
svm(formula = class ~ ., data = data)


Parameters:
   SVM-Type:  C-classification
 SVM-Kernel:  radial
       cost:  1
      gamma:  0.007692308

Number of Support Vectors:  2475

 ( 479 550 361 346 374 365 )


Number of Classes:  6

Levels:
 Cyclic Normal ShiftDown ShiftUp TrendDown TrendUp
```

Improved Predictive Model

Add more data to the Model Build, cont.

```
> ## PREDICTIONS
pred <- predict(model, x)

# CHECK ACCURACY:
confusionM(pred, y)

 Predicted Values:
Yp
    Cyclic     Normal  ShiftDown    ShiftUp  TrendDown    TrendUp
       576        627        580        582        619        616
Y values:
Y
    Cyclic     Normal  ShiftDown    ShiftUp  TrendDown    TrendUp
       600        600        600        600        600        600
 Confusion Matrix:
            Yp
Y             Cyclic Normal ShiftDown ShiftUp TrendDown TrendUp
   Cyclic        529     61         4       0         6       0
   Normal         37    563         0       0         0       0
   ShiftDown       8      1       566       0        25       0
   ShiftUp         0      2         0     576         0      22
   TrendDown       2      0        10       0       588       0
   TrendUp         0      0         0       6         0     594
 Accuracy =  0.9488889[1] 0.9488889
```

Improved Predictive Model

Tune the new model

```
> ###———————————————————————— AFTER TUNING ————————————————————————
## NEW MODEL WITH COST AND GAMMA
model <- svm(class ~ ., data = data, cost=2.25, gamma=.01)

## RE-DO THE PREDICTION
pred <- predict(model, x)

# CHECK ACCURACY
confusionM(pred, y)
Predicted Values:
Yp
   Cyclic    Normal ShiftDown   ShiftUp TrendDown   TrendUp
      568       626       596       594       610       606
Y values:
Y
   Cyclic    Normal ShiftDown   ShiftUp TrendDown   TrendUp
      600       600       600       600       600       600
Confusion Matrix:
           Yp
Y            Cyclic Normal ShiftDown ShiftUp TrendDown TrendUp
  Cyclic        566     28         3       0         3       0
  Normal          2    598         0       0         0       0
  ShiftDown       0      0       593       0         7       0
  ShiftUp         0      0         0     593         0       7
  TrendDown       0      0         0       0       600       0
  TrendUp         0      0         0       1         0     599
Accuracy =  0.9858333[1] 0.9858333
```

Improved Predictive Model

Use the new model to classify new data

```
> ###---------------------------------- NEW DATA ----------------------------------
## READ IN DATA THAT MODEL HAS NOT SEEN
Ynew <- dget("Y_6")
data <- createData(Ynew)
## SPLIT TO X and Y
x <- subset(data, select = -class)
y <- data$class
## PREDICT CLASS USING PREVIOUSLY CREATED MODEL
pred <- predict(model, x)

# CHECK ACCURACY
confusionM(pred, y)
Predicted Values:
Yp
   Cyclic    Normal ShiftDown   ShiftUp TrendDown   TrendUp
       84       114        95        93       109       105
Y values:
Y
   Cyclic    Normal ShiftDown   ShiftUp TrendDown   TrendUp
      100       100       100       100       100       100
Confusion Matrix:
           Yp
Y           Cyclic Normal ShiftDown ShiftUp TrendDown TrendUp
  Cyclic        72     22         3       0         3       0
  Normal        10     90         0       0         0       0
  ShiftDown      2      0        89       0         9       0
  ShiftUp        0      2         0      88         0      10
  TrendDown      0      0         3       0        97       0
  TrendUp        0      0         0       5         0      95
Accuracy =  0.885[1] 0.885
```

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- Models are guides, not the answer.

Thank You!

E-mail: sao@saoconnell.com
Phone: 925-330-4350

Example code and slides available: ??

References:

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