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# Data Science(Classification)

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# Classification Trees

- ✓ Introduction
- ✓ Classification error rate
- ✓ Example study using R
- ✓ Example study using python



# Classification Trees

- A classification tree is used to predict a qualitative response
- For classifying examples, all of the features are assumed to have finite discrete domains
- Each element of the domain of the classification is called a **class**
- Algorithms for classification trees usually work top-down, by selecting a variable at each step that best splits the set of items



## Example study using R

- Data frame Carseats in ISLR package is a simulated data set containing sales of child car seats at 400 different stores
- It contains 400 observations on the following 11 variables
- Variables includes unit sales at each location, price charged by competitor, community income level, local advertising budget, population size in region, price company charges for car seats, the quality of the shelving location for the car seats, average age of the local population, education level, whether the store is an urban location and whether the store is in the US



## Example study using R

- Transform Sales into a binary variable High (Yes if Sales is greater than 8, otherwise, No)

```
library (ISLR)
attach (Carseats)
#Transform Sales variable to a binary variable
High=ifelse (Sales >8, "Yes ", " No ")
Carseats =data.frame(Carseats ,High)
head(Carseats)
```

	Sales	CompPrice	Income	Advertising	Population	Price	ShelveLoc	Age	Education	Urban	US	High
1	9.50	138	73	11	276	120	Bad	42	17	Yes	Yes	Yes
2	11.22	111	48	16	260	83	Good	65	10	Yes	Yes	Yes
3	10.06	113	35	10	269	80	Medium	59	12	Yes	Yes	Yes
4	7.40	117	100	4	466	97	Medium	55	14	Yes	Yes	No
5	4.15	141	64	3	340	128	Bad	38	13	Yes	No	No
6	10.81	124	113	13	501	72	Bad	78	16	No	Yes	Yes

See [ClassificationTrees.R](#)



## Example study using R

- To predict High variable, use the `tree()` function to fit a classification tree

```
> #Use all other variables except sales to fit a classification tree
> library(tree)
> tree = tree(High ~ . - Sales, Carseats)
> summary(tree)
```

```
Classification tree:
tree(formula = High ~ . - Sales, data = Carseats)
Variables actually used in tree construction:
[1] "ShelveLoc" "Price"      "Income"      "CompPrice"  "Population" "Advertising"
[7] "Age"      "US"
Number of terminal nodes: 27
Residual mean deviance: 0.4575 = 170.7 / 373
Misclassification error rate: 0.09 = 36 / 400
```

- The error rate is 9%

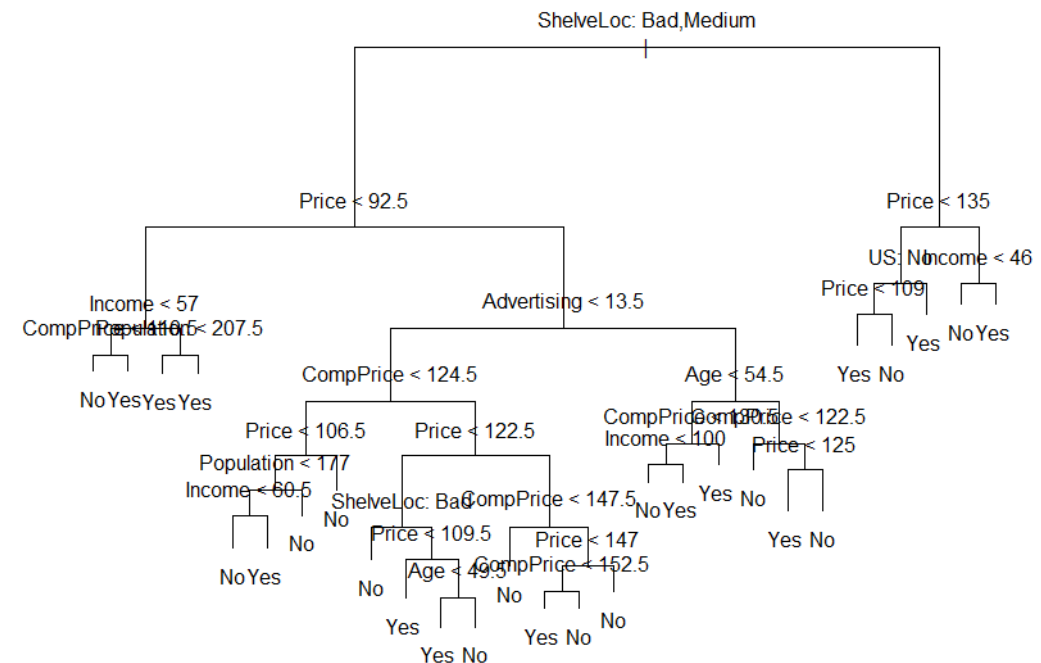
See [ClassificationTrees.R](#)



# Example study using R

- Use `plot()` function to display the tree structure
- Use `text()` function to display the node labels

```
#Display the tree structure and node labels
plot(tree)
text(tree, pretty = 0) #Pretty=0 includes the category names
```



See [ClassificationTrees.R](#)



## Example study using R

- predict() function can be used for evaluating the performance of a classification tree

```
#Split the dataset into a training set and a test set
set.seed(2)
train = sample(1:nrow(Carseats), 200)
Carseats.test = Carseats[-train,]
High.test = High[-train]
#Build the tree based on the training set
tree.train = tree(High ~ . - Sales, Carseats, subset = train)
#Evaluate its performance on the test data
tree.pred = predict(tree.train, Carseats.test, type = "class")
table(tree.pred, High.test)
```

	High.test	
tree.pred	No	Yes
No	86	27
Yes	30	57

- The error rate is  $(27+30)/200=28.5\%$

See [ClassificationTrees.R](#)





## Example study using R

- To determine the optimal level of tree complexity, use `cv.tree()` performs cross-validation

```
#Determine the optimal level
set.seed(3)
#FUN = prune.misclass indicate that classification error rate is used to
#guide the cross-validation and pruning process
cv.carseats = cv.tree(tree, FUN = prune.misclass)
names(cv.carseats)
cv.carseats
> names(cv.carseats)
[1] "size" "dev" "k" "method"
> cv.carseats
$size
[1] 27 26 24 22 19 17 14 12 7 6 5 3 2 1

$dev
[1] 107 105 109 109 109 103 103 106 116 118 116 117 119 165

$k
[1] -Inf 0.000000 0.500000 1.000000 1.333333 1.500000 1.666667 2.500000 3.800000
[10] 4.000000 5.000000 7.500000 18.000000 47.000000

$method
[1] "misclass"

attr(,"class")
[1] "prune" "tree.sequence"
```

size: number of terminal nodes of each tree considered  
 k: the value of the cost-complexity parameter used  
 dev: cross-validation error rate

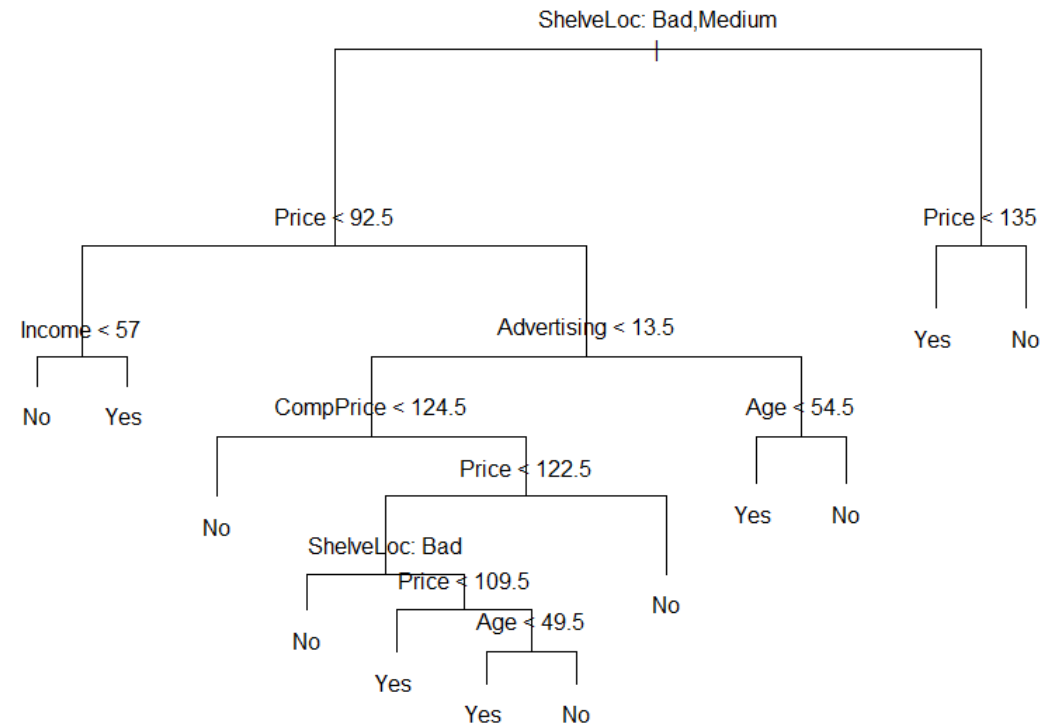
See [ClassificationTrees.R](#)



## Example study using R

- According to the cross-validation error rate dev, tree with 9 terminal nodes results in the lowest error rate
- Use `prune.misclass()` function in order to prune the tree

```
#Prune the tree
prune.carseats = prune.misclass(tree, best =9)
plot(prune.carseats)
text(prune.carseats, pretty =0)
```



See [\*ClassificationTrees.R\*](#)



## Example study using R

- According to the cross-validation error rate dev, tree with 9 terminal nodes results in the lowest error rate
- Use `prune.misclass()` function in order to prune the tree

```
> #The pruned tree performance
> prune.pred = predict(prune.carseats, Carseats.test, type = "class")
> table(prune.pred, High.test)
```

	High.test	
prune.pred	No	Yes
No	101	10
Yes	15	74

- The error rate is  $(15+10)/200=15\%$

See [ClassificationTrees.R](#)



# Example study using python

- Export Carseats dataset to an Excel spreadsheet

```
#Export dataset
data(Carseats, package="ISLR")
write.csv(Carseats, "Carseats.csv")
```

- Import data in python

```
In [1]: #Import Carseats from csv file
import pandas as pd
import numpy as np
carseats = pd.read_csv("Carseats.csv", header=0)
del carseats['Unnamed: 0']
carseats.head(10)
```

Out[1]:

	Sales	CompPrice	Income	Advertising	Population	Price	ShelveLoc	Age	Education	Urban	US
0	9.50	138	73	11	276	120	Bad	42	17	Yes	Yes
1	11.22	111	48	16	260	83	Good	65	10	Yes	Yes
2	10.06	113	35	10	269	80	Medium	59	12	Yes	Yes
3	7.40	117	100	4	466	97	Medium	55	14	Yes	Yes
4	4.15	141	64	3	340	128	Bad	38	13	Yes	No
5	10.81	124	113	13	501	72	Bad	78	16	No	Yes
6	6.63	115	105	0	45	108	Medium	71	15	Yes	No
7	11.85	136	81	15	425	120	Good	67	10	Yes	Yes
8	6.54	132	110	0	108	124	Medium	76	10	No	No
9	4.69	132	113	0	131	124	Medium	76	17	No	Yes

See [ClassificationTrees.ipynb](#)



# Example study using python

- Transform Sales into a binary variable High

```
In [2]: #Transform Sales into a binary factor called High
carseats['High'] = (carseats.Sales > 8).astype(bool)
carseats.head(10)
```

```
Out[2]:
```

	Sales	CompPrice	Income	Advertising	Population	Price	ShelveLoc	Age	Education	Urban	US	High
0	9.50	138	73	11	276	120	Bad	42	17	Yes	Yes	True
1	11.22	111	48	16	260	83	Good	65	10	Yes	Yes	True
2	10.06	113	35	10	269	80	Medium	59	12	Yes	Yes	True
3	7.40	117	100	4	466	97	Medium	55	14	Yes	Yes	False
4	4.15	141	64	3	340	128	Bad	38	13	Yes	No	False
5	10.81	124	113	13	501	72	Bad	78	16	No	Yes	True
6	6.63	115	105	0	45	108	Medium	71	15	Yes	No	False
7	11.85	136	81	15	425	120	Good	67	10	Yes	Yes	True
8	6.54	132	110	0	108	124	Medium	76	10	No	No	False
9	4.69	132	113	0	131	124	Medium	76	17	No	Yes	False

See [\*ClassificationTrees.ipynb\*](#)



# Example study using python

- Prepare the data

```
In [3]: carseats['Urban'] = (carseats.Urban == "Yes").astype(int)
carseats['US'] = (carseats.US == "Yes").astype(int)
carseats['ShelveLoc_'] = 0
carseats['ShelveLoc_'][carseats['ShelveLoc'] == "Good"] = 1
carseats['ShelveLoc_'][carseats['ShelveLoc'] == "Medium"] = 2
carseats['ShelveLoc_'][carseats['ShelveLoc'] == "Bad"] = 3
carseats.head(10)
```

```
Out[3]:
```

	Sales	CompPrice	Income	Advertising	Population	Price	ShelveLoc	Age	Education	Urban	US	High	ShelveLoc_
0	9.50	138	73	11	276	120	Bad	42	17	1	1	True	3
1	11.22	111	48	16	260	83	Good	65	10	1	1	True	1
2	10.06	113	35	10	269	80	Medium	59	12	1	1	True	2
3	7.40	117	100	4	466	97	Medium	55	14	1	1	False	2
4	4.15	141	64	3	340	128	Bad	38	13	1	0	False	3
5	10.81	124	113	13	501	72	Bad	78	16	0	1	True	3
6	6.63	115	105	0	45	108	Medium	71	15	1	0	False	2
7	11.85	136	81	15	425	120	Good	67	10	1	1	True	1
8	6.54	132	110	0	108	124	Medium	76	10	0	0	False	2
9	4.69	132	113	0	131	124	Medium	76	17	0	1	False	2

See [\*ClassificationTrees.ipynb\*](#)



# Example study using python

- Fit a classification tree using `DecisionTreeClassifier()` in scikit-learn

```
In [4]: #Select response y and training set X
y = carseats['High']
cols_to_keep = ['CompPrice', 'Income', 'Advertising', 'Population', 'Price', 'ShelveLoc_',
               'Age', 'Education', 'Urban']
X = carseats[cols_to_keep]
```

```
In [7]: from sklearn import tree
cltree = tree.DecisionTreeClassifier()
cltree = cltree.fit(X, y)
```

- Accuracy of this model

```
In [7]: #Evaluate the model
from sklearn.cross_validation import cross_val_score
scores = cross_val_score(cltree, X, y, cv=10)
print scores.mean()
```

0.737307692308

- Export the tree

```
In [11]: #Export the tree in Graphviz format using the export_graphviz
dotfile = open("E:/QuantUniversity/tree.dot", 'w')
tree.export_graphviz(cltree, out_file = dotfile, feature_names = X.columns)
dotfile.close()
```

See [ClassificationTrees.ipynb](#)



# KNN

- ✓ What is KNN
- ✓ KNN in R
- ✓ KNN in Python





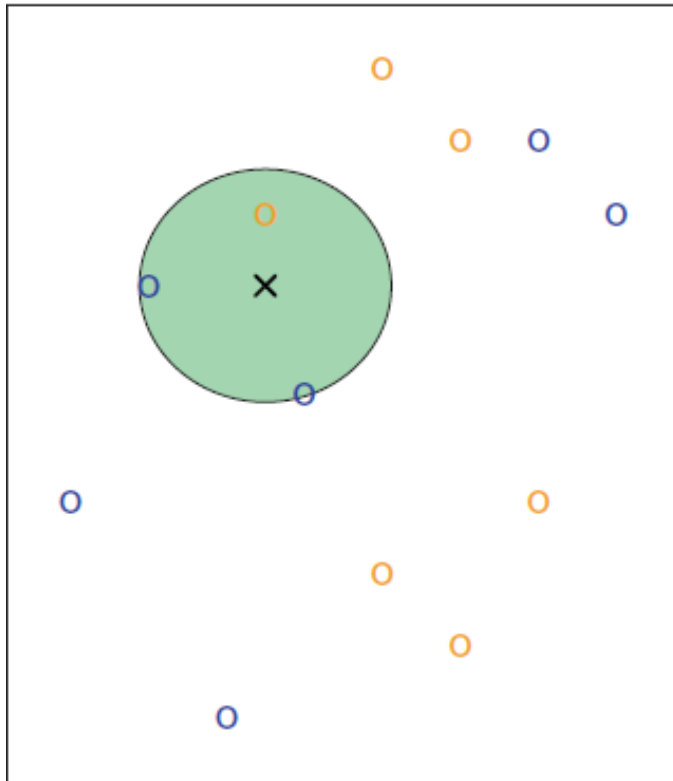
# What is KNN

- KNN means K-Nearest Neighbors, it is a very simple algorithm used for classification and regression.
- The KNN classifier first identifies the neighbors  $K$  points in the training data that are closest to a test observation  $x_0$ , amongst  $N_0$  points. It then estimates the conditional probability for  $Y = j$ , Finally, KNN applies Bayes rule and classifies the test observation  $x_0$  to the class with the largest probability.

$$\Pr(Y = j | X = x_0) = \frac{1}{N_0} \sum_{i \in N_0} I(y_i = j)$$



# What is KNN



Example:

- $K=3$  (three nearest neighbors of  $x$ )
- Class “orange o” and “blue o”.
- Find the class for  $x$

Result :

- Probabilities of  $2/3$  for the blue class
- Probabilities of  $1/3$  for the orange class



## KNN in R

- “Iris” dataset in R, it has 150 observations and 5 variables. Each observation represent a flower, and there are 5 features which recorded on those flowers. These 150 observations are collected from 3 different species. Based on knowing the first 4 features (Sepal.length, Sepal.width, Patel.length, Patel,width ) we can classifier a new observation into one of these 3 species.

```
> str(iris)
'data.frame':  150 obs. of  5 variables:
 $ Sepal.Length: num  5.1 4.9 4.7 4.6 5 5.4 4.6 5 4.4 4.9 ...
 $ Sepal.width : num  3.5 3 3.2 3.1 3.6 3.9 3.4 3.4 2.9 3.1 ...
 $ Petal.Length: num  1.4 1.4 1.3 1.5 1.4 1.7 1.4 1.5 1.4 1.5 ...
 $ Petal.width : num  0.2 0.2 0.2 0.2 0.2 0.4 0.3 0.2 0.2 0.1 ...
 $ Species      : Factor w/ 3 levels "setosa","versicolor",...: 1 1 1 1
```

```
> head(iris)
  Sepal.Length Sepal.width Petal.Length Petal.width Species
1          5.1          3.5          1.4          0.2  setosa
2          4.9          3.0          1.4          0.2  setosa
3          4.7          3.2          1.3          0.2  setosa
4          4.6          3.1          1.5          0.2  setosa
5          5.0          3.6          1.4          0.2  setosa
6          5.4          3.9          1.7          0.4  setosa
```

See [KNN.R](#)



# KNN in R

- Mix up data
- Since it is a very nice organized dataset, we need to mix the entire dataset up. To do this, we have to create a 150 random number dataset and make the original dataset re-organized follow the order of the random number dataset.

```
> group<- runif(nrow(iris))
> group
[1] 0.9882166183 0.5940190239 0.1337920092 0.1093714633
156312
[8] 0.6883584394 0.1238144503 0.1765312739 0.0513233980
005529
[15] 0.2526203436 0.0743994124 0.0132462864 0.8147595294
368890
[22] 0.0421418818 0.4482217485 0.9431283800 0.3041717457
944780
[29] 0.9930689118 0.0179640960 0.6333474671 0.3473129433
161311
[36] 0.3367951058 0.0606662470 0.8249456959 0.8221009444
111697
```

```
> iris
  Sepal.Length Sepal.width Petal.Length Petal.width  Species
66           6.7           3.1           4.4         1.4 versicolor
118          7.7           3.8           6.7         2.2 virginica
17           5.4           3.9           1.3         0.4 setosa
30           4.7           3.2           1.6         0.2 setosa
114          5.7           2.5           5.0         2.0 virginica
75           6.4           2.9           4.3         1.3 versicolor
150          5.9           3.0           5.1         1.8 virginica
22           5.1           3.7           1.5         0.4 setosa
45           5.1           3.8           1.9         0.4 setosa
115          5.8           2.8           5.1         2.4 virginica
11           5.4           3.7           1.5         0.2 setosa
```

See [KNN.R](#)



## KNN in R

- Re-scale data (Normalization)
- Normalization means adjusting values measured on different scales to a notionally common scale. In this case we adjust the range of first 4 features from 0 to 1 to minimize undue influence from the feature which has a larger range.

```
#Normalization#  
normalize<-function(x){return((x-min(x))/(max(x)-min(x)))}  
iris_n<-as.data.frame(lapply(iris[,c(1,2,3,4)],normalize))  
summary(iris_n)
```

```
> summary(iris_n)
```

Sepal.Length	Sepal.width	Petal.Length	Petal.width
Min. :0.0000	Min. :0.0000	Min. :0.0000	Min. :0.00000
1st Qu.:0.2222	1st Qu.:0.3333	1st Qu.:0.1017	1st Qu.:0.08333
Median :0.4167	Median :0.4167	Median :0.5678	Median :0.50000
Mean :0.4287	Mean :0.4406	Mean :0.4675	Mean :0.45806
3rd Qu.:0.5833	3rd Qu.:0.5417	3rd Qu.:0.6949	3rd Qu.:0.70833
Max. :1.0000	Max. :1.0000	Max. :1.0000	Max. :1.00000

See [\*KNN.R\*](#)



## KNN in R

- Training dataset & testing dataset
- Training dataset is what we used to learn the pattern, namely a KNN model. The test dataset is going to serve a way to test how well a model predicts. In this case we hold 20 observations for testing. We set the species feature as our training target as well as testing target. Separate

```
#Separate training&testing dataset
iris_train<-iris_n[1:129, ]
iris_test<-iris_n[130:150, ]
iris_train_target<-iris_n[1:129, 5]
iris_test_target<-iris_n[130:150, 5]
```

See [KNN.R](#)



## KNN in R

- Fit in KNN model
- We use knn() function to do the training, we need to fit in the training data frame, the test data frame and the training target variables. before that we have to choose a k value, as k is a place holder for how many nearest neighbor that you want the algorithm to use. The rule of thumb is to take the square root of the total number of observations you have, in this case should be 13.

```
# fit in knn algorithm
require(class)
m1<- knn(train= iris_train, test= iris_test, cl=iris_train_target, k=13)
```

See [KNN.R](#)



## KNN in R

- Results & comparison
- The predict results are present in a table.

```
> m1
[1] versicolor virginica versicolor virginica versicolor versicolor versicolor
[8] versicolor versicolor setosa versicolor setosa virginica virginica
[15] versicolor setosa setosa versicolor setosa versicolor virginica
Levels: setosa versicolor virginica
```

- To see how well the model predicted, we use table() to see the difference between predict result and what species they actually are.

```
> table(iris_test_target,m1)
      iris_test_target
      m1
      setosa versicolor virginica
setosa      5          0          0
versicolor  0         10          1
virginica   0          1          4
```

See [KNN.R](#)





# KNN in Python

- Create dataset
- First, create a dataset with four observations, each observation has a label. Our goal is to train a classifier to classify a new observation into one of these labels.

```
def createDataSet():  
    characters=array([[1.0,1.1],[1.0,1.0],[0,0],[0,0.1]])  
    labels=['A','A','B','B']  
    return characters,labels
```

See [KNN.ipynb](#)



# KNN in Python

- Train the classifier
- Train a classifier to count the distance between the sample and all the observations in training dataset. Choose k nearest observations then count their labels. The sample's label will be the same as the most label counted in the k nearest observations.

```
def classify(sample, dataSet, labels, k):
    dataSetSize=dataSet.shape[0]
    diffMat=tile(sample, (dataSetSize,1))-dataSet
    sqDiffMat=diffMat**2
    sqDistances=sqDiffMat.sum(axis=1)
    distances=sqDistances**0.5
    sortedDistIndicies=distances.argsort()

    classCount={}
    for i in range(k):
        voteIlabel=labels[sortedDistIndicies[i]]
        classCount[voteIlabel]=classCount.get(voteIlabel,0)+1

        sortedClassCount=sorted(classCount.items(),key=operator.itemgetter(1),reverse=True)
    return sortedClassCount[0][0]
```

See [KNN.ipynb](#)



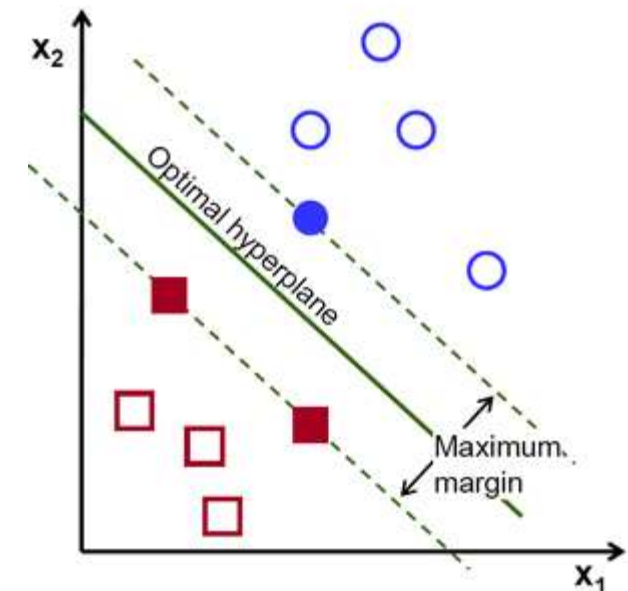
# Support Vector Machines

- ✓ Support vector machine
- ✓ Support vector classifier
- ✓ Example study using R
- ✓ Example study using python



# Support vector machine

- A **Support Vector Machine (SVM)** is a discriminative classifier formally defined by a separating hyperplane. In other words, given labeled training data (supervised learning), the algorithm outputs an optimal hyperplane which categorizes new examples.



Ref:

[http://docs.opencv.org/2.4/doc/tutorials/ml/introduction\\_to\\_svm/introduction\\_to\\_svm.html](http://docs.opencv.org/2.4/doc/tutorials/ml/introduction_to_svm/introduction_to_svm.html)



## Example study using R

- Data frame Khan in ILSR package consists of a number of tissue samples corresponding to four distinct types of small round blue cell tumors
- For each tissue sample, 2308 gene expression measurements are available
- The format is a list containing four components: xtrain, xtest, ytrain, and ytest



## Example study using R

- Examine the dimension of the data

```
> library(ISLR)
> names(khan)
[1] "xtrain" "xtest"  "ytrain" "ytest"
> dim(khan$xtrain)
[1] 63 2308
> dim(khan$xtest)
[1] 20 2308
> length(khan$ytrain)
[1] 63
> length(khan$ytest)
[1] 20
```

- The training and test sets consist of 63 and 20 observations respectively

See [SVM.R](#)



## Example study using R

- Use a support vector approach to predict cancer subtype using gene expression measurements
- Use svm() function in e1071 package

kernel: the kernel used in training and predicting  
cost: cost of constraints violation

```
> #Predict cancer subtype
> library(e1071)
> data = data.frame( x = Khan$xtrain, y = as.factor(Khan$ytrain))
> svm = svm(y ~., data=data, kernel = "linear", cost = 10)
> summary(svm)
```

```
call:
svm(formula = y ~ ., data = data, kernel = "linear", cost = 10)
```

```
Parameters:
  SVM-Type:  C-classification
SVM-Kernel:  linear
    cost:    10
   gamma:    0.0004332756
```

```
Number of Support Vectors:  58

( 20 20 11 7 )
```

```
Number of Classes:  4
```

```
Levels:
 1 2 3 4
```

See [SVM.R](#)



# Example study using R

```
> table(svm$fitted, data$y)
```

```

      1  2  3  4
1  8  0  0  0
2  0 23  0  0
3  0  0 12  0
4  0  0  0 20

```

- There is no training error
- Check support vector classifier's performance on the test observations

```

> #Support vector classifier's performance on the test observations
> data.test = data.frame(x = Khan$xtest, y = as.factor(Khan$ytest))
> pred = predict(svm, newdata = data.test)
> table(pred, data.test$y)

```

```

pred 1 2 3 4
1  3 0 0 0
2  0 6 2 0
3  0 0 4 0
4  0 0 0 5

```

See [SVM.R](#)





# Example study using python

- Import data

```
In [1]: #Import xtrain from csv file
import pandas as pd
import numpy as np
xtrain = pd.read_csv("Khan_xtrain.csv", header = None)
del xtrain[0]
xtrain = xtrain[1:]
```

```
In [2]: #Import ytrain from csv file
ytrain = pd.read_csv("Khan_ytrain.csv", header = None)
del ytrain[0]
ytrain = ytrain[1:]
```

```
In [4]: #Import xtest from csv file
xtest = pd.read_csv("Khan_xtest.csv", header = None)
del xtest[0]
xtest = xtest[1:]
```

```
In [5]: #Import ytest from csv file
ytest = pd.read_csv("Khan_ytest.csv", header = None)
del ytest[0]
ytest = ytest[1:]
```

See [SVM.ipynb](#)



## Example study using python

- Predict cancer subtype on train dataset
- Fit a SVM using svm() in scikit-learn

```
In [9]: from sklearn import svm  
X = xtrain  
y = ytrain  
clf = svm.SVC(kernel='linear')  
clf.fit(X, y)
```

```
Out[9]: SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0, degree=3, gamma=0.0,  
kernel='linear', max_iter=-1, probability=False, random_state=None,  
shrinking=True, tol=0.001, verbose=False)
```

See [SVM.ipynb](#)



## Example study using python

- Use the fitted SVM to predict test dataset
- Check the performance on the test observations

```
In [13]: #Make predictions on xtest dataset
pred = clf.predict(xtest)
pred
```

```
Out[13]: array(['3', '2', '4', '2', '1', '3', '4', '2', '3', '1', '3', '4', '1',
                '2', '2', '2', '4', '2', '4', '2'], dtype=object)
```

```
In [18]: #Performance on test dataset
pd.crosstab(pred,ytest[1],rownames=['pred'], colnames=['ytest'])
```

```
Out[18]:
```

ytest	1	2	3	4
pred				
1	3	0	0	0
2	0	6	2	0
3	0	0	4	0
4	0	0	0	5

See [SVM.ipynb](#)



# Neural Network Classification

- ✓ Neural network classification in R
- ✓ Neural network classification in python



## Example study using R

- Data frame **infert** is a matched case-control study dating from before the availability of conditional logistic regression
- It contains 248 observations on the following 8 variables
- The variables include education, age, parity, number of prior induced abortions, case status, number of prior spontaneous abortions, matched set number, stratum number



## Example study using R

- Fit the network classifying case variable using age, parity, induced, spontaneous
- The network has 3 hidden layers

```
attach(infert)
library(neuralnet)
neuralnet <- neuralnet(case ~ age + parity + induced + spontaneous, data=infert,
                        hidden=3, err.fct="ce", linear.output=FALSE)
neuralnet$result.matrix
plot(neuralnet)
```

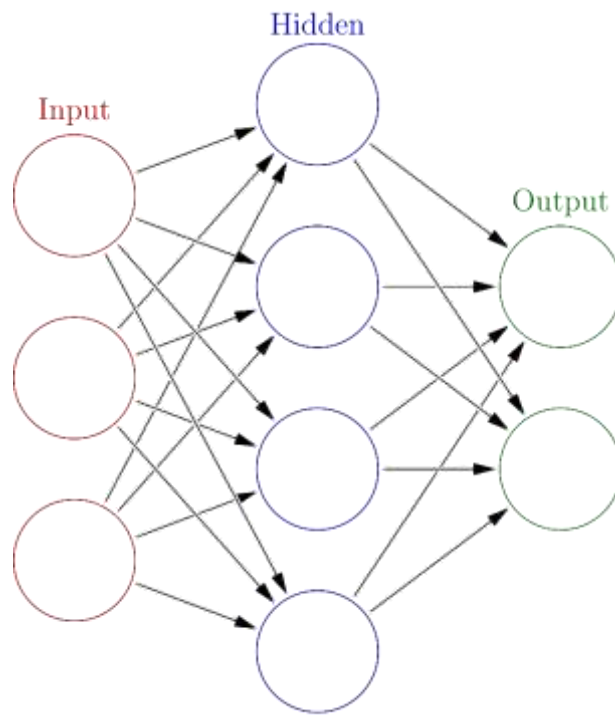
```
> neuralnet$result.matrix
1
error 113.73879260616
reached.threshold 0.00887480898
steps 64953.00000000000
Intercept.to.1layhid1 1.70749607309
age.to.1layhid1 23.17106882284
parity.to.1layhid1 11.96279868860
induced.to.1layhid1 -131.17641312579
spontaneous.to.1layhid1 -296.22131305983
Intercept.to.1layhid2 66.13485859737
age.to.1layhid2 -1.09159296623
parity.to.1layhid2 8.84059317974
induced.to.1layhid2 -19.40447872304
spontaneous.to.1layhid2 -25.28284597365
Intercept.to.1layhid3 -15.46184848858
age.to.1layhid3 0.58564168262
parity.to.1layhid3 -18.02353826644
induced.to.1layhid3 15.33660841139
spontaneous.to.1layhid3 20.89864632803
Intercept.to.case 20.41400808431
1layhid.1.to.case -6.50566456720
1layhid.2.to.case -15.58740034121
1layhid.3.to.case 2.27536828314
```

See [\*NeuralNet.R\*](#)

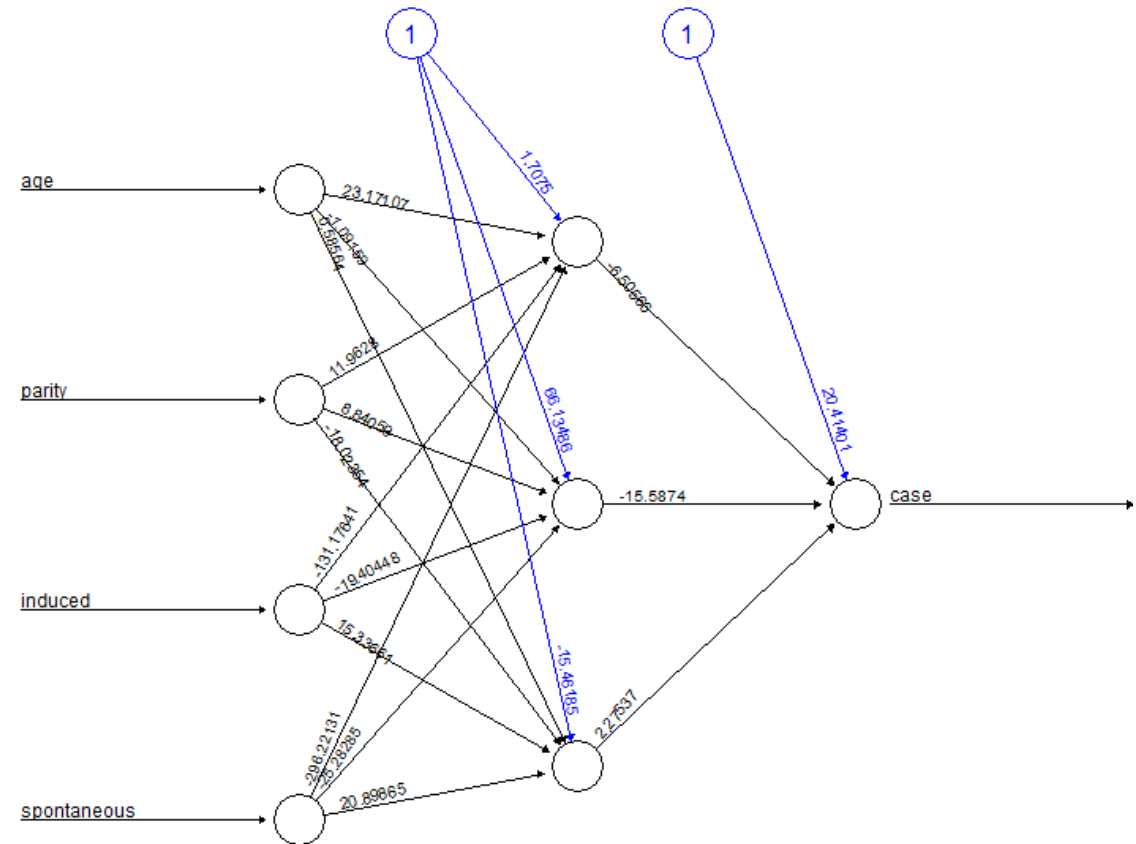


# Example study using R

- Neural network visualization



See [\*NeuralNet.R\*](#)



Error: 113.738793 Steps: 64953



# Example study using python

- Import data

```
In [1]: #Import xtrain from csv file
import pandas as pd
import numpy as np
infert = pd.read_csv("infert.csv", header = 0)
```

```
In [2]: del infert['Unnamed: 0']
infert.head(10)
```

```
Out[2]:
```

	education	age	parity	induced	case	spontaneous	stratum	pooled.stratum
0	0-5yrs	26	6	1	1	2	1	3
1	0-5yrs	42	1	1	1	0	2	1
2	0-5yrs	39	6	2	1	0	3	4
3	0-5yrs	34	4	2	1	0	4	2
4	6-11yrs	35	3	1	1	1	5	32
5	6-11yrs	36	4	2	1	1	6	36
6	6-11yrs	23	1	0	1	0	7	6
7	6-11yrs	32	2	0	1	0	8	22
8	6-11yrs	21	1	0	1	1	9	5
9	6-11yrs	28	2	0	1	0	10	19

See [NeuralNet.ipynb](#)





## Example study using python

- Create a network and load the data into the network

```
In [28]: columns = ['age', 'parity', 'induced', 'spontaneous']  
X = infert[columns]  
y = infert['case']
```

```
In [17]: from pybrain.datasets      import ClassificationDataSet  
from pybrain.utilities      import percentError  
from pybrain.tools.shortcuts import buildNetwork  
from pybrain.supervised.trainers import BackpropTrainer  
from pybrain.structure.modules import SoftmaxLayer  
from pybrain.tools.xml.networkwriter import NetworkWriter  
from pybrain.tools.xml.networkreader import NetworkReader
```

```
In [30]: ds = ClassificationDataSet(4, 1, nb_classes=2)  
for k in xrange(len(X)):  
    ds.addSample(X.iloc[k], y.iloc[k])
```

```
In [31]: ds._convertToOneOfMany( )
```

See [\*NeuralNet.ipynb\*](#)



# Example study using python

- Build the network and backpropagation trainer

```
In [33]: fnn = buildNetwork( ds.indim, 3 , ds.outdim, outclass=SoftmaxLayer )
```

```
In [34]: nn = BackpropTrainer( fnn, dataset=ds, momentum=0.1, verbose=True, weightdecay=0.01)
```

```
In [36]: print fnn
```

```
FeedForwardNetwork-8
```

```
Modules:
```

```
[<BiasUnit 'bias'>, <LinearLayer 'in'>, <SigmoidLayer 'hidden0'>, <SoftmaxLayer 'out'>]
```

```
Connections:
```

```
[<FullConnection 'FullConnection-4': 'bias' -> 'out'>, <FullConnection 'FullConnection-5': 'bias' -> 'hidden0'>, <FullConnection 'FullConnection-6': 'in' -> 'hidden0'>, <FullConnection 'FullConnection-7': 'hidden0' -> 'out'>]
```

See [NeuralNet.ipynb](#)



# Example study using python

- Evaluate the network

```
In [13]: result = percentError( nn.testOnClassData(), ds['class'] )  
         result
```

```
Out[13]: 33.46774193548387
```

See [\*NeuralNet.ipynb\*](#)



# Classification

We have covered	Key functionality
Classification tree	<ul style="list-style-type: none"> <li>✓ Introduction of classification tree and classification error rate</li> <li>✓ Use <code>tree()</code> function in <code>tree</code> library to construct classification trees in R</li> <li>✓ Use <code>DecisionTreeClassifier()</code> function in <code>sklearn.tree</code> module to construct classification trees in python</li> </ul>
KNN	<ul style="list-style-type: none"> <li>✓ Introduction of KNN</li> <li>✓ Use <code>knn()</code> function in <code>class</code> library to construct KNNs in R</li> <li>✓ How to construct KNNs in python</li> </ul>
SVM	<ul style="list-style-type: none"> <li>✓ Introduction of SVM</li> <li>✓ Use <code>svm()</code> function in <code>e1071</code> library to construct SVMs in R</li> <li>✓ Use <code>svm()</code> function in <code>scikit-learn</code> module to construct SVMs in python</li> </ul>
Neural network	<ul style="list-style-type: none"> <li>✓ Use <code>neuralnet()</code> function in <code>neuralnet</code> library to construct neural networks in R</li> <li>✓ Use <code>pybrain</code> module to construct neural networks in python</li> </ul>



## Reference

- Gareth James, Daniela Witten, Trevor Hastie, and Robert Tibshirani. An introduction to statistical learning. Springer, 2013
- Fritsch S, Günther F: neuralnet: Training of neural networks. R J 2010, 2:30-38
- brms: An R Package for Bayesian Generalized Linear Mixed Models using Stan. Paul-Christian Burkner.
- [scikit-learn.org](http://scikit-learn.org)
- [pybrain.org](http://pybrain.org)



## Q&A





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# Thank you!

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