CHEATSHEET

Machine Learning Algorithms

(Python and R Codes)

Types

Supervised Learning

- Decision Tree
- Random Forest
- kNN
- Logistic Regression

Unsupervised Learning

- Apriori algorithm
- k-means
- Hierarchical Clustering

Reinforcement Learning

- Markov Decision Process
- Q Learning

Python Code	R Code

Linear Regression

Python Code

```python
#Import Library
#Import other necessary libraries like pandas,
#numpy...
from sklearn import linear_model
#Load Train and Test datasets
#Identify feature and response variable(s) and
#values must be numeric and numpy arrays
x_train=input_variables_values_training_datasets
y_train=target_variables_values_training_datasets
x_test=input_variables_values_test_datasets
#Create linear regression object
linear = linear_model.LinearRegression()
#Train the model using the training sets and
#check score
linear.fit(x_train, y_train)
linear.score(x_train, y_train)
#Equation coefficient and Intercept
print('Coefficient: \n', linear.coef_)
print('Intercept: \n', linear.intercept_)
#Predict Output
predicted= linear.predict(x_test)
```

R Code

```r
#Load Train and Test datasets
#Identify feature and response variable(s) and
#values must be numeric and numpy arrays
x_train <- input_variables_values_training_datasets
y_train <- target_variables_values_training_datasets
x_test <- input_variables_values_test_datasets
x <- cbind(x_train,y_train)
#Train the model using the training sets and
#check score
linear <- lm(y_train ~ ., data = x)
summary(linear)
#Predict Output
predicted= predict(linear,x_test)
```

Logistic Regression

Python Code

```python
#Import Library
from sklearn.linear_model import LogisticRegression
#Assumed you have, X (predictor) and Y (target)
#for training data set and x_test(predictor)
#of test_dataset
#Create logistic regression object
model = LogisticRegression()
#Train the model using the training sets
#and check score
model.fit(X, y)
model.score(X, y)
#Equation coefficient and Intercept
print('Coefficient: \n', model.coef_)
print('Intercept: \n', model.intercept_)
#Predict Output
predicted= model.predict(x_test)
```

R Code

```r
x <- cbind(x_train,y_train)
#Train the model using the training sets and check
#score
logistic <- glm(y_train ~ ., data = x,family='binomial')
summary(logistic)
#Predict Output
predicted= predict(logistic,x_test)
```

Decision Tree

Python Code

```python
#Import Library
#Import other necessary libraries like pandas, numpy...
from sklearn import tree
#Assumed you have, X (predictor) and Y (target) for
#training data set and x_test(predictor) of
#test_dataset
#Create tree object
model = tree.DecisionTreeClassifier(criterion='gini')
#for classification, here you can change the
#algorithm as gini or entropy (information gain) by
#default it is gini
#model = tree.DecisionTreeRegressor() for
#regression
#Train the model using the training sets and check
#score
model.fit(X, y)
model.score(X, y)
#Predict Output
predicted= model.predict(x_test)
```

R Code

```r
#Import Library
library(rpart)
x <- cbind(x_train,y_train)
#grow tree
fit <- rpart(y_train ~ ., data = x,method="class")
summary(fit)
#Predict Output
predicted= predict(fit,x_test)
```

SVM (Support Vector Machine)

Python Code

```python
#Import Library
from sklearn import svm
#Assumed you have, X (predictor) and Y (target) for
#training data set and x_test(predictor) of test_dataset
#Create SVM classification object
model = svm.svc()
#there are various options associated
with it, this is simple for classification.
#Train the model using the training sets and check
#score
model.fit(X, y)
model.score(X, y)
#Predict Output
predicted= model.predict(x_test)
```

R Code

```r
#Import Library
library(e1071)
x <- cbind(x_train,y_train)
#Fitting model
fit <-svm(y_train ~ ., data = x)
summary(fit)
#Predict Output
predicted= predict(fit,x_test)
```

Naive Bayes

Python Code

```python
#Import Library
from sklearn.naive_bayes import GaussianNB
#Assumed you have, X (predictor) and Y (target) for
#training data set and x_test(predictor) of test_dataset
#Create SVM classification object model = GaussianNB()
#there is other distribution for multinomial classes
like Bernoulli Naive Bayes
#Train the model using the training sets and check
#score
model.fit(X, y)
#Predict Output
predicted= model.predict(x_test)
```

R Code

```r
#Import Library
library(e1071)
x <- cbind(x_train,y_train)
#Fitting model
fit <-naiveBayes(y_train ~ ., data = x)
summary(fit)
#Predict Output
predicted= predict(fit,x_test)
```

kNN (k- Nearest Neighbors)

Python Code

```python
#Import Library
from sklearn.neighbors import KNeighborsClassifier
#Assumed you have, X (predictor) and Y (target) for
#training data set and x_test(predictor) of test_dataset
#Create KNeighbors classifier object model
KNeighborsClassifier(n_neighbors=6)
#default value for n_neighbors is 5
#Train the model using the training sets and check score
model.fit(X, y)
#Predict Output
predicted= model.predict(x_test)
```

R Code

```r
#Import Library
library(knn)
x <- cbind(x_train,y_train)
#Fitting model
fit <-knn(y_train ~ ., data = x,k=5)
summary(fit)
#Predict Output
predicted= predict(fit,x_test)
```

k-Means

Python Code

```python
#Import Library
from sklearn.cluster import KMeans
#Assumed you have, X (attributes) for training data set
#and x_test(attributes) of test_dataset
#Create KNeighbors classifier object model
k_means = KMeans(n_clusters=3, random_state=0)
#Train the model using the training sets and check score
model.fit(X)
#Predict Output
predicted= model.predict(x_test)
```

R Code

```r
#Import Library
library(cluster)
fit <- kmeans(X, 3)
#5 cluster solution
```

Random Forest

Python Code

```python
#Import Library
from sklearn.ensemble import RandomForestClassifier
#Assumed you have, X (predictor) and Y (target) for
#training data set and x_test(predictor) of test_dataset
#Create Random Forest object
model= RandomForestClassifier()
#Train the model using the training sets and check score
model.fit(X, y)
#Predict Output
predicted= model.predict(x_test)
```

R Code

```r
#Import Library
library(randomForest)
x <- cbind(x_train,y_train)
#Fitting model
fit <- randomForest(Species ~ ., x,ntree=500)
summary(fit)
#Predict Output
predicted= predict(fit,x_test)
```

Dimensionality Reduction Algorithms

Python Code

```python
#Import Library
from sklearn import decomposition
#Assumed you have training and test data set as train and
#test
#Create PCA object pca= decomposition.PCA(n_components=k)
#default value of k =min(n_sample, n_features)
#For Factor analysis
#fa= decomposition.FactorAnalysis()
#Reduced the dimension of training dataset using PCA
train_reduced = pca.fit_transform(train)
#Reduced the dimension of test dataset
test_reduced = pca.transform(test)
```

R Code

```r
#Import Library
library(stats)
pca <- princomp(train, cor = TRUE)
train_reduced  <- predict(pca,train)
test_reduced  <- predict(pca,test)
```

Gradient Boosting & AdaBoost

Python Code

```python
#Import Library
from sklearn.ensemble import GradientBoostingClassifier
#Assumed you have, X (predictor) and Y (target) for
#training data set and x_test(predictor) of test_dataset
#Create Gradient Boosting Classifier object
model= GradientBoostingClassifier(n_estimators=100, \
        learning_rate=1.0, max_depth=1, random_state=0)
#Train the model using the training sets and check score
model.fit(X, y)
#Predict Output
predicted= model.predict(x_test)
```

R Code

```r
#Import Library
library(caret)
x <- cbind(x_train,y_train)
#Fitting model
fitControl <- trainControl( method = "repeatedcv",
+ number = 4, repeats = 4)
fit <- train(y ~ ., data = x, method = "gbm",
+ trControl = fitControl,verbose = FALSE)
predicted= predict(fit,x_test,type= "prob")[,2]
```