# k-Fold Cross Validation

#improving model performances by k-fold cross varidation

#it split training set into suppose 10 different(mostly take 10) fold which after iterate one by one on 9 fold and then test on last fold

#then take average of accuracy of different iterated and then calculate variance

#then there is tradeoff between accuracy and biased

#model we use kernal-SVM in part 3 and add k-fold cross validation

# Importing the libraries

import numpy as np

import matplotlib.pyplot as plt

import pandas as pd

# Importing the dataset

dataset = pd.read\_csv('Social\_Network\_Ads.csv')

X = dataset.iloc[:, [2, 3]].values

y = dataset.iloc[:, 4].values

# Splitting the dataset into the Training set and Test set

from sklearn.model\_selection import train\_test\_split

X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size = 0.25, random\_state = 0)

# Feature Scaling

from sklearn.preprocessing import StandardScaler

sc = StandardScaler()

X\_train = sc.fit\_transform(X\_train)

X\_test = sc.transform(X\_test)

# Fitting Kernel SVM to the Training set

from sklearn.svm import SVC

classifier = SVC(kernel = 'rbf', random\_state = 0)

classifier.fit(X\_train, y\_train)

# Predicting the Test set results

y\_pred = classifier.predict(X\_test)

# Making the Confusion Matrix

from sklearn.metrics import confusion\_matrix

cm = confusion\_matrix(y\_test, y\_pred)

# Applying k-Fold Cross Validation(most advance evaluation of model)

from sklearn.model\_selection import cross\_val\_score

accuracies = cross\_val\_score(estimator = classifier, X = X\_train, y = y\_train, cv = 10)#cv = 10 is no of fold// for very large detaset we set n\_jobs = -1 so that all cpus use which help bour model to run fast

#RESULT:: HERE FIND ACCURACY TABLE:: will get accuracy of all 10 fold iteration ...now we will take mean of all accuracy that give much better idea of model performances.

accuracies.mean()#to find out mean which tell overall accuracy which we got 90%

accuracies.std()#find standard variance to find out variance here is not too high

# Visualising the Training set results

from matplotlib.colors import ListedColormap

X\_set, y\_set = X\_train, y\_train

X1, X2 = np.meshgrid(np.arange(start = X\_set[:, 0].min() - 1, stop = X\_set[:, 0].max() + 1, step = 0.01),

np.arange(start = X\_set[:, 1].min() - 1, stop = X\_set[:, 1].max() + 1, step = 0.01))

plt.contourf(X1, X2, classifier.predict(np.array([X1.ravel(), X2.ravel()]).T).reshape(X1.shape),

alpha = 0.75, cmap = ListedColormap(('red', 'green')))

plt.xlim(X1.min(), X1.max())

plt.ylim(X2.min(), X2.max())

for i, j in enumerate(np.unique(y\_set)):

plt.scatter(X\_set[y\_set == j, 0], X\_set[y\_set == j, 1],

c = ListedColormap(('red', 'green'))(i), label = j)

plt.title('Kernel SVM (Training set)')

plt.xlabel('Age')

plt.ylabel('Estimated Salary')

plt.legend()

plt.show()

# Visualising the Test set results

from matplotlib.colors import ListedColormap

X\_set, y\_set = X\_test, y\_test

X1, X2 = np.meshgrid(np.arange(start = X\_set[:, 0].min() - 1, stop = X\_set[:, 0].max() + 1, step = 0.01),

np.arange(start = X\_set[:, 1].min() - 1, stop = X\_set[:, 1].max() + 1, step = 0.01))

plt.contourf(X1, X2, classifier.predict(np.array([X1.ravel(), X2.ravel()]).T).reshape(X1.shape),

alpha = 0.75, cmap = ListedColormap(('red', 'green')))

plt.xlim(X1.min(), X1.max())

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for i, j in enumerate(np.unique(y\_set)):

plt.scatter(X\_set[y\_set == j, 0], X\_set[y\_set == j, 1],

c = ListedColormap(('red', 'green'))(i), label = j)

plt.title('Kernel SVM (Test set)')

plt.xlabel('Age')

plt.ylabel('Estimated Salary')

plt.legend()

plt.show()