In [5]:
```python
import numpy as np
import pandas as pd
from sklearn.decomposition import PCA
from sklearn.preprocessing import scale

from numpy import set_printoptions
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
from sklearn.feature_selection import RFE
from sklearn.linear_model import LogisticRegression
from sklearn.tree import  DecisionTreeClassifier

import warnings
warnings.filterwarnings('ignore')
```

In [6]:
```python
test = pd.read_csv('SalaryData_Test(1).csv')
test
```

Out[6]:

	age	workclass	education	educationno	maritalstatus	occupation	relationship	race	
0	25	Private	11th	7	Never-married	Machine-op-inspct	Own-child	Black	
1	38	Private	HS-grad	9	Married-civ-spouse	Farming-fishing	Husband	White	
2	28	Local-gov	Assoc-acdm	12	Married-civ-spouse	Protective-serv	Husband	White	
3	44	Private	Some-college	10	Married-civ-spouse	Machine-op-inspct	Husband	Black	
4	34	Private	10th	6	Never-married	Other-service	Not-in-family	White	
...	...	...	...	...	...	...	...	...	
15055	33	Private	Bachelors	13	Never-married	Prof-specialty	Own-child	White	
15056	39	Private	Bachelors	13	Divorced	Prof-specialty	Not-in-family	White	Fe
15057	38	Private	Bachelors	13	Married-civ-spouse	Prof-specialty	Husband	White	
15058	44	Private	Bachelors	13	Divorced	Adm-clerical	Own-child	Asian-Pac-Islander	
15059	35	Self-emp-inc	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	

15060 rows × 14 columns

In [7]:
```
test.head()
```

Out[7]:

	age	workclass	education	educationno	maritalstatus	occupation	relationship	race	sex	ca
0	25	Private	11th	7	Never-married	Machine-op-inspct	Own-child	Black	Male	
1	38	Private	HS-grad	9	Married-civ-spouse	Farming-fishing	Husband	White	Male	
2	28	Local-gov	Assoc-acdm	12	Married-civ-spouse	Protective-serv	Husband	White	Male	
3	44	Private	Some-college	10	Married-civ-spouse	Machine-op-inspct	Husband	Black	Male	
4	34	Private	10th	6	Never-married	Other-service	Not-in-family	White	Male	

In [8]:
```
train = pd.read_csv('SalaryData_Train(1).csv')
train
```

Out[8]:

	age	workclass	education	educationno	maritalstatus	occupation	relationship	race	s
0	39	State-gov	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	M
1	50	Self-emp-not-inc	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	M
2	38	Private	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	M
3	53	Private	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	M
4	28	Private	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Fem
...	...	...	...	...	...	...	...	...	
30156	27	Private	Assoc-acdm	12	Married-civ-spouse	Tech-support	Wife	White	Fem
30157	40	Private	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husband	White	M
30158	58	Private	HS-grad	9	Widowed	Adm-clerical	Unmarried	White	Fem
30159	22	Private	HS-grad	9	Never-married	Adm-clerical	Own-child	White	M
30160	52	Self-emp-inc	HS-grad	9	Married-civ-spouse	Exec-managerial	Wife	White	Fem

30161 rows × 14 columns

In [9]:
```
train.head()
```

Out[9]:

	age	workclass	education	educationno	maritalstatus	occupation	relationship	race	sex
0	39	State-gov	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male
1	50	Self-emp-not-inc	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male
2	38	Private	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male
3	53	Private	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male
4	28	Private	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female

In [10]:
```
#Checking for null values & data types
test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15060 entries, 0 to 15059
Data columns (total 14 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   age            15060 non-null  int64 
 1   workclass      15060 non-null  object
 2   education      15060 non-null  object
 3   educationno    15060 non-null  int64 
 4   maritalstatus  15060 non-null  object
 5   occupation     15060 non-null  object
 6   relationship   15060 non-null  object
 7   race           15060 non-null  object
 8   sex            15060 non-null  object
 9   capitalgain    15060 non-null  int64 
 10  capitalloss    15060 non-null  int64 
 11  hoursperweek   15060 non-null  int64 
 12  native         15060 non-null  object
 13  Salary         15060 non-null  object
dtypes: int64(5), object(9)
memory usage: 1.6+ MB
```

In [11]:
```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30161 entries, 0 to 30160
Data columns (total 14 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   age            30161 non-null  int64 
 1   workclass      30161 non-null  object
 2   education      30161 non-null  object
 3   educationno    30161 non-null  int64 
 4   maritalstatus  30161 non-null  object
 5   occupation     30161 non-null  object
 6   relationship   30161 non-null  object
 7   race           30161 non-null  object
 8   sex            30161 non-null  object
 9   capitalgain    30161 non-null  int64 
 10  capitalloss    30161 non-null  int64 
 11  hoursperweek   30161 non-null  int64 
 12  native         30161 non-null  object
 13  Salary         30161 non-null  object
dtypes: int64(5), object(9)
memory usage: 3.2+ MB
```

In [12]:
```
# one hot encoding
```

In [13]:
```
train1 = train.iloc[:,0:13]

train1 = pd.get_dummies(train1)
train1
```

Out[13]:

	age	educationno	capitalgain	capitalloss	hoursperweek	workclass_ Federal-gov	workclass_ Local-gov	workclas Priva
0	39	13	2174	0	40	0	0	
1	50	13	0	0	13	0	0	
2	38	9	0	0	40	0	0	
3	53	7	0	0	40	0	0	
4	28	13	0	0	40	0	0	
...	...	...	...	...	...	...	...	
30156	27	12	0	0	38	0	0	
30157	40	9	0	0	40	0	0	
30158	58	9	0	0	40	0	0	
30159	22	9	0	0	20	0	0	
30160	52	9	15024	0	40	0	0	

30161 rows × 102 columns

In [14]:
```
test1 = test.iloc[:,0:13]

test1 = pd.get_dummies(test1)
test1
```

Out[14]:

	age	educationno	capitalgain	capitalloss	hoursperweek	workclass_ Federal-gov	workclass_ Local-gov	workc Pr
0	25	7	0	0	40	0	0	
1	38	9	0	0	50	0	0	
2	28	12	0	0	40	0	1	
3	44	10	7688	0	40	0	0	
4	34	6	0	0	30	0	0	
...	...	...	...	...	...	...	...	
15055	33	13	0	0	40	0	0	
15056	39	13	0	0	36	0	0	
15057	38	13	0	0	50	0	0	
15058	44	13	5455	0	40	0	0	
15059	35	13	0	0	60	0	0	

15060 rows × 102 columns

PCA to decide best features

In [15]:
```
# min max scaler
from sklearn.preprocessing import MinMaxScaler
trans = MinMaxScaler()
train_scaler = pd.DataFrame(trans.fit_transform(train1))
test_scaler = pd.DataFrame(trans.fit_transform(test1))
```

In [16]:
```
pca_train = PCA(n_components = 102)
pca_train_values = pca_train.fit_transform(train_scaler)
var = pca_train.explained_variance_ratio_
var1 = np.cumsum(np.round(var,decimals = 4)*100)
var1
```

Out[16]:
```
array([19.42, 27.36, 34.3 , 40.13, 45.  , 49.69, 53.89, 57.2 , 60.27,
       62.99, 65.66, 68.19, 70.45, 72.53, 74.44, 76.26, 77.9 , 79.45,
       80.74, 81.95, 83.09, 84.15, 85.19, 86.17, 87.08, 87.91, 88.71,
       89.49, 90.23, 90.97, 91.68, 92.38, 93.04, 93.64, 94.12, 94.56,
       94.97, 95.37, 95.73, 96.06, 96.37, 96.67, 96.96, 97.24, 97.49,
       97.69, 97.88, 98.06, 98.19, 98.31, 98.42, 98.53, 98.62, 98.7 ,
       98.78, 98.85, 98.92, 98.99, 99.06, 99.12, 99.17, 99.22, 99.27,
       99.32, 99.37, 99.41, 99.45, 99.49, 99.53, 99.57, 99.6 , 99.63,
       99.66, 99.68, 99.7 , 99.72, 99.74, 99.76, 99.78, 99.8 , 99.82,
       99.83, 99.84, 99.85, 99.86, 99.87, 99.88, 99.89, 99.9 , 99.91,
       99.92, 99.93, 99.94, 99.94, 99.94, 99.94, 99.94, 99.94, 99.94,
       99.94, 99.94, 99.94])
```

In [17]:
```
pca_test = PCA(n_components = 102)
pca_test_values = pca_test.fit_transform(test_scaler)
```

Best Columns

In [18]:
```
finaltrain = pd.concat([pd.DataFrame(pca_train_values[:,0:50]),
                     train[['Salary']]], axis = 1)
finaltrain
```

Out[18]:

	0	1	2	3	4	5	6	7	
0	0.511884	-0.570399	0.985410	0.869147	0.301768	-0.160966	-0.069890	-0.248351	0.292
1	-1.186474	0.389451	0.805358	0.407706	0.380658	-0.302254	-0.106618	0.209061	0.920
2	0.327319	-0.448965	-0.614483	1.019098	-0.704198	0.351374	0.014607	0.297586	0.005
3	-0.872767	-0.017105	-0.213117	-0.454347	0.086417	0.047109	1.242660	-0.134197	-0.038
4	0.371012	1.147050	0.312747	-0.460719	0.180534	-1.024316	1.292872	-0.349665	-0.469
...	...	...	...	...	...	...	...	...	
30156	0.294538	0.952058	-0.098474	-0.531724	-0.213346	-0.469396	-0.279332	-0.316085	-0.179
30157	-1.001348	-0.091425	-0.831089	0.003952	-0.135485	-0.197470	-0.096730	-0.126849	-0.024
30158	0.942438	0.867860	-0.980524	-0.022298	-0.026156	-0.069330	-0.277006	0.235377	0.019
30159	0.532346	-1.046443	-0.611753	-0.193523	0.522283	-0.205924	-0.417356	0.253337	0.130
30160	0.105998	1.214254	-0.426850	0.260569	0.577362	-0.251165	-0.574298	-0.385188	0.809

30161 rows × 51 columns

In [19]:
```
finaltest = pd.concat([pd.DataFrame(pca_test_values[:,0:50]),
                       test[['Salary']]], axis = 1)
finaltest
```

Out[19]:

	0	1	2	3	4	5	6	7	
0	0.544139	-1.082697	0.043718	-0.638660	0.600414	-0.037211	1.117301	0.303058	0.08
1	-1.017577	-0.173468	-0.721000	0.034038	-0.051207	-0.169266	-0.173861	-0.133687	-0.01
2	-1.079069	0.331812	0.385397	0.156170	0.541402	0.179608	-0.124271	-0.014775	-0.09
3	-0.846450	-0.012312	-0.003005	-0.778263	-0.161833	0.679751	1.182308	-0.408033	0.06
4	0.613603	-0.980319	0.315324	0.309863	-0.254993	0.026711	0.039416	-0.213736	-0.16
...	...	...	...	...	...	...	...	...	
15055	0.392559	-0.799233	0.857450	-0.224953	0.264490	-0.949432	0.035834	0.698898	-0.38
15056	1.064367	0.803553	0.497037	0.719569	-0.820526	-0.579177	0.120411	0.287500	-0.51
15057	-1.022440	0.211868	0.552672	-0.053465	-0.327323	-0.844022	0.221308	0.212895	-0.48
15058	0.346779	-0.164803	0.224122	-0.087735	-0.083448	-0.185222	0.845949	0.963429	0.28
15059	-1.165265	0.443859	0.760096	0.275990	0.213953	-0.453195	-0.056964	0.127963	0.97

15060 rows × 51 columns

In [20]:
```
# will use some part of data as comands are taking really long time to execute wi
array = finaltrain.values
X = array[0:2000:,0:50]
Y = array[0:2000:,50]
```

KNN Model

In [21]:
```
# Grid search CV to find best value for K
```

In [22]:
```
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import GridSearchCV
```

In [23]:
```
n_neighbors = np.array(range(1,40))
param_grid = dict(n_neighbors=n_neighbors)
model = KNeighborsClassifier()
grid = GridSearchCV(estimator=model, param_grid=param_grid)
grid.fit(X, Y)
```

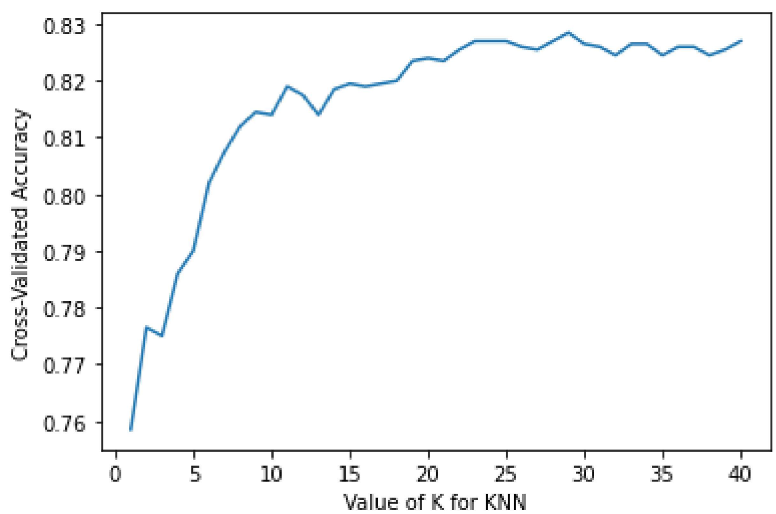
Out[23]:
```
GridSearchCV(estimator=KNeighborsClassifier(),
             param_grid={'n_neighbors': array([ 1,  2,  3,  4,  5,  6,  7,  8,
9, 10, 11, 12, 13, 14, 15, 16, 17,
       18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34,
       35, 36, 37, 38, 39])})
```

In [24]:
```
print(grid.best_score_)
print(grid.best_params_)
```

```
0.8284999999999998
{'n_neighbors': 29}
```

In [25]:
```
# Visualizing the CV results
```

In [26]:
```
import matplotlib.pyplot as plt
%matplotlib inline
# choose k between 1 to 41
k_range = range(1, 41)
k_scores = []
# use iteration to caclulator different k in models, then return the average accu
for k in k_range:
    knn = KNeighborsClassifier(n_neighbors=k)
    scores = cross_val_score(knn, X, Y, cv=5)
    k_scores.append(scores.mean())
# plot to see clearly
plt.plot(k_range, k_scores)
plt.xlabel('Value of K for KNN')
plt.ylabel('Cross-Validated Accuracy')
plt.show()
```



In [27]:
```
#KNN Classification
num_folds = 10
kfold = KFold(n_splits=10)
model = KNeighborsClassifier(n_neighbors=29)
results = cross_val_score(model, X, Y, cv=kfold)
print(results.mean())
```

```
0.8239999999999998
```

SVM Classification

In [28]:
```
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
from sklearn.preprocessing import StandardScaler

from sklearn import svm
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import classification_report
```

In [29]:
```
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.model_selection import train_test_split, cross_val_score
```

In [30]:
```
clf = SVC()
param_grid = [{'kernel':['rbf'],'gamma':[50,5,10,0.5],'C':[15,14,13,12,11,10,0.1,
gsv = GridSearchCV(clf,param_grid,cv=10)
gsv.fit(X,Y)
```

Out[30]:
```
GridSearchCV(cv=10, estimator=SVC(),
             param_grid=[{'C': [15, 14, 13, 12, 11, 10, 0.1, 0.001],
                          'gamma': [50, 5, 10, 0.5], 'kernel': ['rbf']}])
```

In [31]:
```
gsv.best_params_ , gsv.best_score_
```

Out[31]:
```
({'C': 11, 'gamma': 0.5, 'kernel': 'rbf'}, 0.7875)
```

In [32]:
```
# using some part of test data
array1 = finaltest.values
x = array1[0:2000:,0:50]
y = array1[0:2000:,50]
```

In [33]:
```
clf = SVC(C= 15, gamma = 50)
clf.fit(x , y)
y_pred = clf.predict(x)
acc = accuracy_score(y, y_pred) * 100
print("Accuracy =", acc)
confusion_matrix(y, y_pred)
```

```
Accuracy = 98.45
```

Out[33]:
```
array([[1500,    6],
       [  25,  469]], dtype=int64)
```

SVM gives higher accuracy i.e 98.45 than of knn

Bagging

In [35]:
```python
# Bagged Decision Trees for Classification
from sklearn.ensemble import BaggingClassifier
seed = 7
kfold = KFold(n_splits=15)
cart = DecisionTreeClassifier()
num_trees = 100
model = BaggingClassifier(base_estimator=cart, n_estimators=num_trees, random_sta
results = cross_val_score(model, x, y, cv=kfold)
print(results.mean())
```

```
0.8110013840571578
```

Random Forest

In [36]:
```python
from sklearn.ensemble import RandomForestClassifier
num_trees = 200
max_features = 4
kfold = KFold(n_splits=15)
model = RandomForestClassifier(n_estimators=num_trees, max_features=max_features)
results = cross_val_score(model, x, y, cv=kfold)
print(results.mean())
```

```
0.8115213406650956
```

Boosting

In [37]:
```python
# AdaBoost Classification
from sklearn.ensemble import AdaBoostClassifier
num_trees = 200
seed=7
kfold = KFold(n_splits=15)
model = AdaBoostClassifier(n_estimators=num_trees, random_state=seed)
results = cross_val_score(model, x, y, cv=kfold)
print(results.mean())
```

```
0.8150226312048778
```

Stacking

In [38]:
```python
# Stacking Ensemble for Classification
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.ensemble import VotingClassifier
```

In [39]:

```
# create the sub models
estimators = []
model1 = LogisticRegression(max_iter=500)
estimators.append(('logistic', model1))
model2 = DecisionTreeClassifier()
estimators.append(('cart', model2))
model3 = SVC()
estimators.append(('svm', model3))

# create the ensemble model
ensemble = VotingClassifier(estimators)
results = cross_val_score(ensemble, x, y, cv=kfold)
print(results.mean())
```

```
0.82600531178693
```

In [ ]: