```
from google.colab import files
uploaded = files.upload()
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to

```
Saving dummydata.csv to dummydata.csv
```

```
import pandas as pd
import numpy as np
df = pd.read_csv('dummydata.csv')
pd.DataFrame.from_records(df)
df.head()
```

| | Unnamed: 0 | age | self_employed | family_history | mh_treatment | interfere | company_size | remote | tech_company | mh_negati |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 3 | 1 | 1 | 0 | 3 | 1 | 1 | 1 | |
| **1** | 2 | 2 | 0 | 1 | 1 | 3 | 4 | 0 | 1 | |
| **2** | 3 | 2 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | |
| **3** | 4 | 3 | 0 | 0 | 1 | 4 | 3 | 1 | 1 | |
| **4** | 5 | 3 | 0 | 0 | 1 | 1 | 6 | 0 | 0 | |

```
df.describe
```

```
<bound method NDFrame.describe of      Unnamed: 0  age  ...  country_Ireland  country_India
0             1    3  ...                0              0
1             2    2  ...                0              0
2             3    2  ...                0              0
3             4    3  ...                0              0
4             5    3  ...                0              0
..          ...  ...  ...              ...            ...
891         892    2  ...                0              0
892         893    2  ...                0              0
893         894    2  ...                0              0
894         895    2  ...                0              0
895         896    3  ...                0              0

[896 rows x 51 columns]>
```

```
df.columns
```

```
Index(['Unnamed: 0', 'age', 'self_employed', 'family_history', 'mh_treatment',
       'interfere', 'company_size', 'remote', 'tech_company',
       'mh_negative_consequence_flag', 'ph_negative_consequence_flag',
       'mh_disscuss_coworker', 'mh_disscuss_supervisor',
       'interview_mh_bringup', 'interview_ph_bringup', 'witness_mh_nc',
       'anonymity_protected_Yes', 'anonymity_protected_No',
       'anonymity_protected_Don't know', 'awareness_mh_benefits_Not sure',
       'awareness_mh_benefits_Yes', 'awareness_mh_benefits_No', 'gender_M',
       'gender_F', 'gender_T', 'medical_leave_easy_Very easy',
       'medical_leave_easy_Somewhat difficult',
       'medical_leave_easy_Don't know', 'medical_leave_easy_Very difficult',
       'medical_leave_easy_Somewhat easy', 'mh_benefits_Yes', 'mh_benefits_No',
       'mh_benefits_Don't know', 'mh_discuss_Yes', 'mh_discuss_No',
       'mh_discuss_Don't know', 'mh_resources_Don't know', 'mh_resources_No',
       'mh_resources_Yes', 'mh_serious_ph_Yes', 'mh_serious_ph_No',
       'mh_serious_ph_Don't know', 'country_United States',
       'country_United Kingdom', 'country_Canada', 'country_Netherlands',
       'country_Australia', 'country_France', 'country_Germany',
       'country_Ireland', 'country_India'],
      dtype='object')
```

```
df.drop(df.columns[[0]], axis=1, inplace=True)
df.head()
```

| | age | self_employed | family_history | mh_treatment | interfere | company_size | remote | tech_company | mh_negative_consequ |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 3 | 1 | 1 | 0 | 3 | 1 | 1 | 1 | |
| **1** | 2 | 0 | 1 | 1 | 3 | 4 | 0 | 1 | |
| **2** | 2 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | |
| **3** | 3 | 0 | 0 | 1 | 4 | 3 | 1 | 1 | |
| **4** | 3 | 0 | 0 | 1 | 1 | 6 | 0 | 0 | |

```
df.shape
```

```
(896, 50)
```

Supervised ML

```
X=df.loc[:, df.columns != 'mh_treatment']
X.head()
```

| | age | self_employed | family_history | interfere | company_size | remote | tech_company | mh_negative_consequence_flag | ph_ |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 3 | 1 | 1 | 3 | 1 | 1 | 1 | 0 | |
| **1** | 2 | 0 | 1 | 3 | 4 | 0 | 1 | 1 | |
| **2** | 2 | 1 | 0 | 1 | 1 | 1 | 1 | 0 | |
| **3** | 3 | 0 | 0 | 4 | 3 | 1 | 1 | 1 | |
| **4** | 3 | 0 | 0 | 1 | 6 | 0 | 0 | 1 | |

```
X.columns
```

```
Index(['age', 'self_employed', 'family_history', 'interfere', 'company_size',
       'remote', 'tech_company', 'mh_negative_consequence_flag',
       'ph_negative_consequence_flag', 'mh_disscuss_coworker',
       'mh_disscuss_supervisor', 'interview_mh_bringup',
       'interview_ph_bringup', 'witness_mh_nc', 'anonymity_protected_Yes',
       'anonymity_protected_No', 'anonymity_protected_Don't know',
       'awareness_mh_benefits_Not sure', 'awareness_mh_benefits_Yes',
       'awareness_mh_benefits_No', 'gender_M', 'gender_F', 'gender_T',
       'medical_leave_easy_Very easy', 'medical_leave_easy_Somewhat difficult',
       'medical_leave_easy_Don't know', 'medical_leave_easy_Very difficult',
       'medical_leave_easy_Somewhat easy', 'mh_benefits_Yes', 'mh_benefits_No',
       'mh_benefits_Don't know', 'mh_discuss_Yes', 'mh_discuss_No',
       'mh_discuss_Don't know', 'mh_resources_Don't know', 'mh_resources_No',
       'mh_resources_Yes', 'mh_serious_ph_Yes', 'mh_serious_ph_No',
       'mh_serious_ph_Don't know', 'country_United States',
       'country_United Kingdom', 'country_Canada', 'country_Netherlands',
       'country_Australia', 'country_France', 'country_Germany',
       'country_Ireland', 'country_India'],
      dtype='object')
```

```
y=df.mh_treatment
y.head()
```

```
0    0
1    1
2    0
3    1
4    1
Name: mh_treatment, dtype: int64
```

```
np.random.seed(888)
#Split X and y into train (70%) and test (30%) sets.
from sklearn.model_selection import train_test_split
# Let 20% of the data to be a test set
train_x, test_x, train_y, test_y = train_test_split(X, y, test_size=0.30, random_state=0)
```

1. Linear Regression

```
#fit the model
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
model1 = LinearRegression()
model1.fit(train_x,train_y)
```

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

```
# coefficeints of the trained model
print('\nCoefficient of model :', model1.coef_)

# intercept of the model
print('\nIntercept of model',model1.intercept_)

# predict the target on the test dataset
```

```
predict_train1 = model1.predict(train_x)

# Root Mean Squared Error on training dataset
rmse_train1 = mean_squared_error(train_y,predict_train1)**(0.5)
print('\nRMSE on train dataset : ', rmse_train1)

```

```
Coefficient of model : [ 7.94394178e-02 -3.13073938e-02  1.35247094e-01  2.00005298e-01
  2.16494895e-03  6.28433680e-03 -3.96517007e-03  2.29191247e-02
 -9.32070297e-03  6.02567060e-02 -8.94607436e-03  9.01932694e-03
  1.84655909e-02  6.08269687e-03  2.47073445e+11  2.47073445e+11
  2.47073445e+11 -6.17962248e+11 -6.17962248e+11 -6.17962248e+11
 -2.39548373e+11 -2.39548373e+11 -2.39548373e+11 -3.63133064e+11
 -3.63133064e+11 -3.63133064e+11 -3.63133064e+11 -3.63133064e+11
 -4.70124964e+11 -4.70124964e+11 -4.70124964e+11 -5.22730142e+11
 -5.22730142e+11 -5.22730142e+11 -7.48774855e+11 -7.48774855e+11
 -7.48774855e+11 -1.77157781e+11 -1.77157781e+11 -1.77157781e+11
 -1.33097841e+11 -1.33097841e+11 -1.33097841e+11 -1.33097841e+11
 -1.33097841e+11 -1.33097841e+11 -1.33097841e+11 -1.33097841e+11
 -1.33097841e+11]

Intercept of model 3025455823032.587

RMSE on train dataset :  0.38898088972415895
```

```
# predict the target on the testing dataset
predict_test1 = model1.predict(test_x)

# Root Mean Squared Error on testing dataset
rmse_test1 = mean_squared_error(test_y,predict_test1)**(0.5)
print('\nRMSE on test dataset : ', rmse_test1)
```

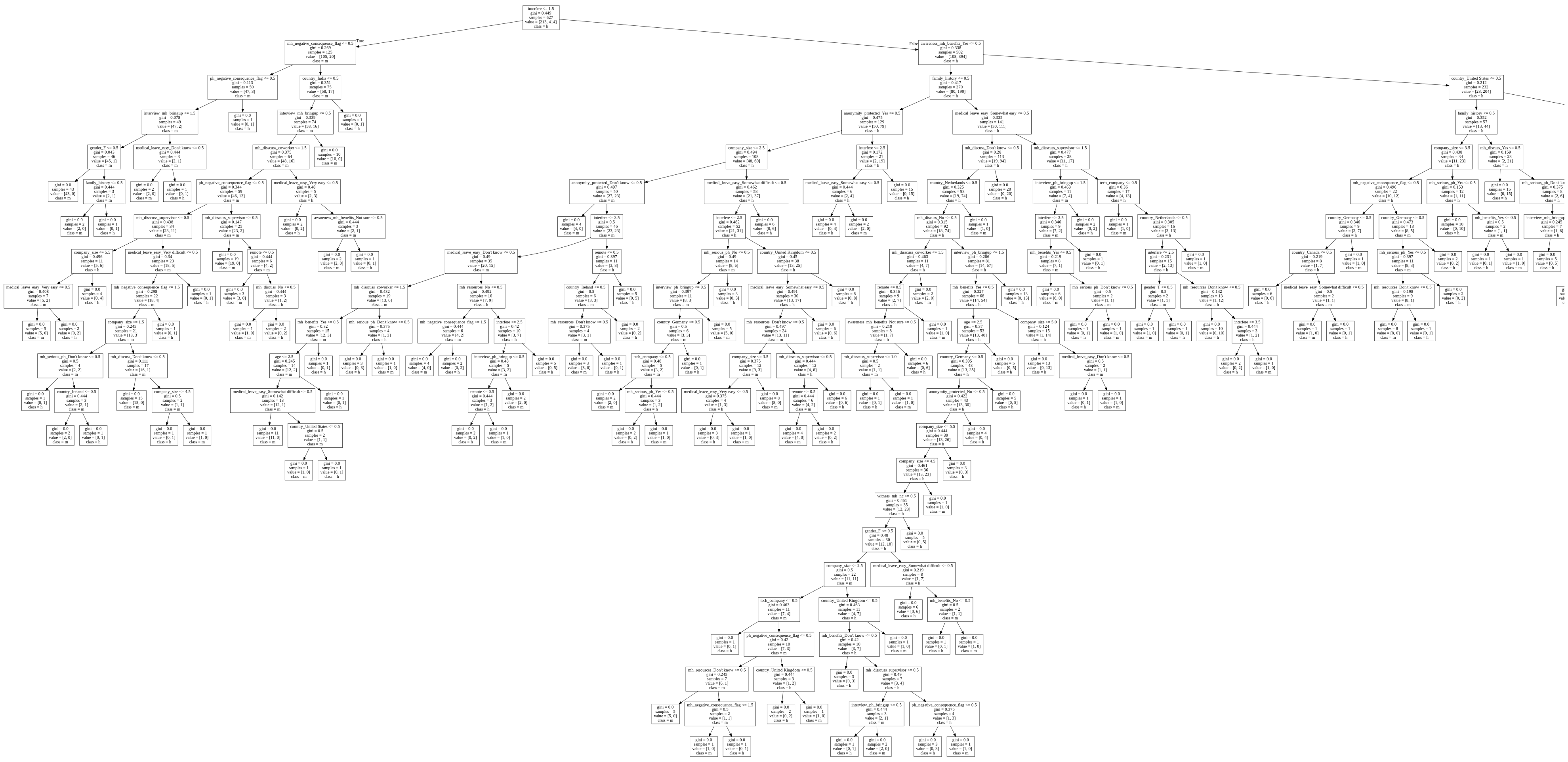
```
RMSE on test dataset :  0.3846918650527029
```

2. Tree

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
model2 = DecisionTreeClassifier()

# fit the model with the training data
model2.fit(train_x,train_y)

# depth of the decision tree
print('Depth of the Decision Tree :', model2.get_depth())

```

```
Depth of the Decision Tree : 21
```

```
from sklearn import datasets
from IPython.display import Image
from sklearn import tree
import pydotplus
# Create DOT data
dot_data = tree.export_graphviz(model2.fit(train_x,train_y), out_file=None,
                                feature_names=train_x.columns,
                                class_names=train_y.name)

# Draw graph
graph = pydotplus.graph_from_dot_data(dot_data)

# Show graph
Image(graph.create_png())
```



```
# predict the target on the train dataset
predict_train2 = model2.predict(train_x)

# Accuray Score on train dataset
accuracy_train2 = accuracy_score(train_y,predict_train2)
print('accuracy_score on train dataset : ', accuracy_train2)

```

```
accuracy_score on train dataset :  1.0
```

```
# predict the target on the test dataset
predict_test2 = model2.predict(test_x)

# Accuracy Score on test dataset
accuracy_test2 = accuracy_score(test_y,predict_test2)
print('accuracy_score on test dataset : ', accuracy_test2)
```

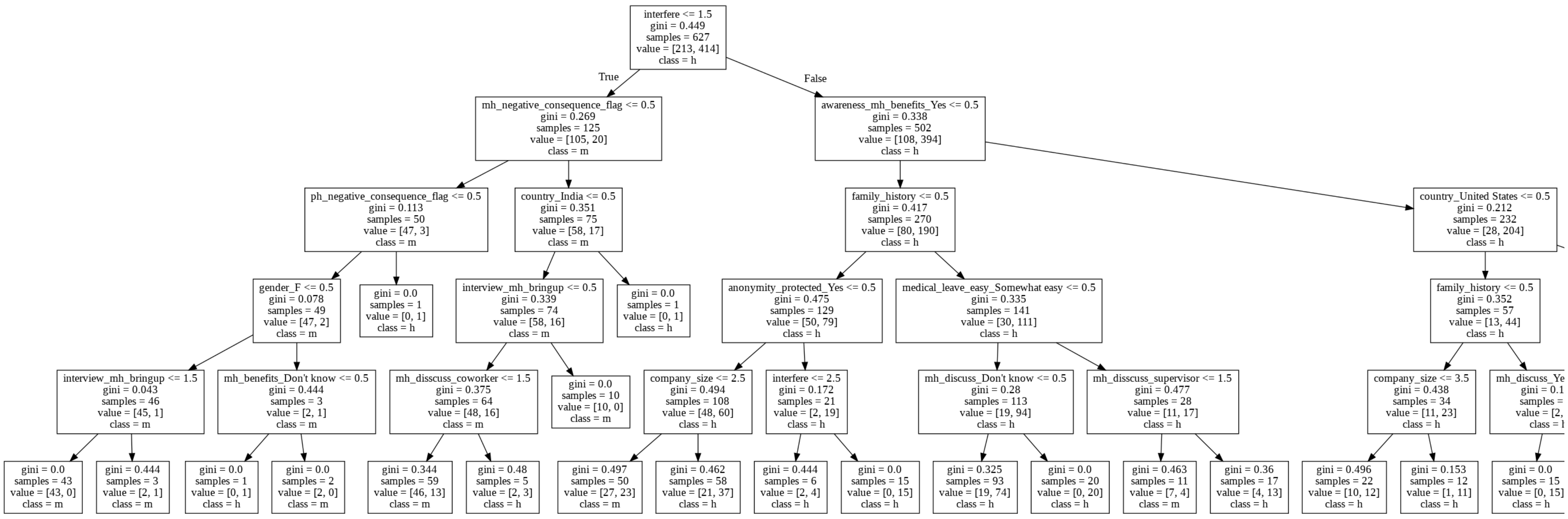
```
accuracy_score on test dataset :  0.7026022304832714
```

### 3. Decision Tree Calssifier

```
model3 = DecisionTreeClassifier(max_depth=5)

# fit the model with the training data
model3.fit(train_x,train_y)

# depth of the decision tree
print('Depth of the Decision Tree :', model3.get_depth())
```

```
Depth of the Decision Tree : 5
```

```
# Create DOT data
dot_data3 = tree.export_graphviz(model3.fit(train_x,train_y), out_file=None,
                                feature_names=train_x.columns,
                                class_names=train_y.name)

# Draw graph
graph3 = pydotplus.graph_from_dot_data(dot_data3)

# Show graph
Image(graph3.create_png())
```




```
# predict the target on the train dataset
predict_train3 = model3.predict(train_x)

# Accuray Score on train dataset
accuracy_train3 = accuracy_score(train_y,predict_train3)
print('accuracy_score on train dataset : ', accuracy_train3)
```

```
accuracy_score on train dataset :  0.8133971291866029
```

```
# predict the target on the test dataset
predict_test3 = model3.predict(test_x)

# Accuracy Score on test dataset
accuracy_test3 = accuracy_score(test_y,predict_test3)
print('accuracy_score on test dataset : ', accuracy_test3)
```

```
accuracy_score on test dataset :  0.758364312267658
```

### 4. SVM

```
from sklearn.svm import SVC
model4 = SVC()

# fit the model with the training data
model4.fit(train_x,train_y)
```

```
SVC(C=1.0, break_ties=False, cache_size=200, class_weight=None, coef0=0.0,
    decision_function_shape='ovr', degree=3, gamma='scale', kernel='rbf',
    max_iter=-1, probability=False, random_state=None, shrinking=True,
    tol=0.001, verbose=False)
```

```
# predict the target on the train dataset
predict_train4 = model4.predict(train_x)

# Accuray Score on train dataset
accuracy_train4 = accuracy_score(train_y,predict_train4)
print('accuracy_score on train dataset : ', accuracy_train4)
```

```
accuracy_score on train dataset :  0.8181818181818182
```

```
# predict the target on the test dataset
predict_test4 = model4.predict(test_x)

# Accuracy Score on test dataset
accuracy_test4 = accuracy_score(test_y,predict_test4)
print('accuracy_score on test dataset : ', accuracy_test4)
```

```
accuracy_score on test dataset :  0.8066914498141264
```

### 5. KNN

```
from sklearn.neighbors import KNeighborsClassifier
model5 = KNeighborsClassifier()

# fit the model with the training data
model5.fit(train_x,train_y)
```

```
model5.fit(train_x,train_y)

# Number of Neighbors used to predict the target
print('\nThe number of neighbors used to predict the target : ',model5.n_neighbors)
```

```
The number of neighbors used to predict the target :  5
```

```
# predict the target on the train dataset
predict_train5 = model5.predict(train_x)

# Accuray Score on train dataset
accuracy_train5 = accuracy_score(train_y,predict_train5)
print('accuracy_score on train dataset : ', accuracy_train5)
```

```
accuracy_score on train dataset :  0.8197767145135566
```

```
# predict the target on the test dataset
predict_test5 = model5.predict(test_x)

# Accuracy Score on test dataset
accuracy_test5 = accuracy_score(test_y,predict_test5)
print('accuracy_score on test dataset : ', accuracy_test5)
```

```
accuracy_score on test dataset :  0.7211895910780669
```

### 6. GBM

```
from sklearn.ensemble import GradientBoostingClassifier
model6 = GradientBoostingClassifier(n_estimators=100,max_depth=5)

# fit the model with the training data
model6.fit(train_x,train_y)
```

```
GradientBoostingClassifier(ccp_alpha=0.0, criterion='friedman_mse', init=None,
                           learning_rate=0.1, loss='deviance', max_depth=5,
                           max_features=None, max_leaf_nodes=None,
                           min_impurity_decrease=0.0, min_impurity_split=None,
                           min_samples_leaf=1, min_samples_split=2,
                           min_weight_fraction_leaf=0.0, n_estimators=100,
                           n_iter_no_change=None, presort='deprecated',
                           random_state=None, subsample=1.0, tol=0.0001,
                           validation_fraction=0.1, verbose=0,
                           warm_start=False)
```

```
# predict the target on the train dataset
predict_train6 = model6.predict(train_x)

# Accuray Score on train dataset
accuracy_train6 = accuracy_score(train_y,predict_train6)
print('\naccuracy_score on train dataset : ', accuracy_train6)
```

```
accuracy_score on train dataset :  0.9904306220095693
```

```
# predict the target on the test dataset
predict_test6 = model6.predict(test_x)

# Accuracy Score on test dataset
accuracy_test6 = accuracy_score(test_y,predict_test6)
print('\naccuracy_score on test dataset : ', accuracy_test6)
```

```
accuracy_score on test dataset :  0.724907063197026
```

### 7. XGBoost

```
from xgboost import XGBClassifier
model7 = XGBClassifier()

# fit the model with the training data
model7.fit(train_x,train_y)
```

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0,
              learning_rate=0.1, max_delta_step=0, max_depth=3,
              min_child_weight=1, missing=None, n_estimators=100, n_jobs=1,
              nthread=None, objective='binary:logistic', random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=None, subsample=1, verbosity=1)
```

```
# predict the target on the train dataset
predict_train7 = model7.predict(train_x)

# Accuray Score on train dataset
accuracy_train7 = accuracy_score(train_y,predict_train7)
print('\naccuracy_score on train dataset : ', accuracy_train7)
```

```
accuracy_score on train dataset :  0.8389154704944178
```

```
# predict the target on the test dataset
predict_test7 = model7.predict(test_x)

# Accuracy Score on test dataset
accuracy_test7 = accuracy_score(test_y,predict_test7)
print('\naccuracy_score on test dataset : ', accuracy_test7)
```

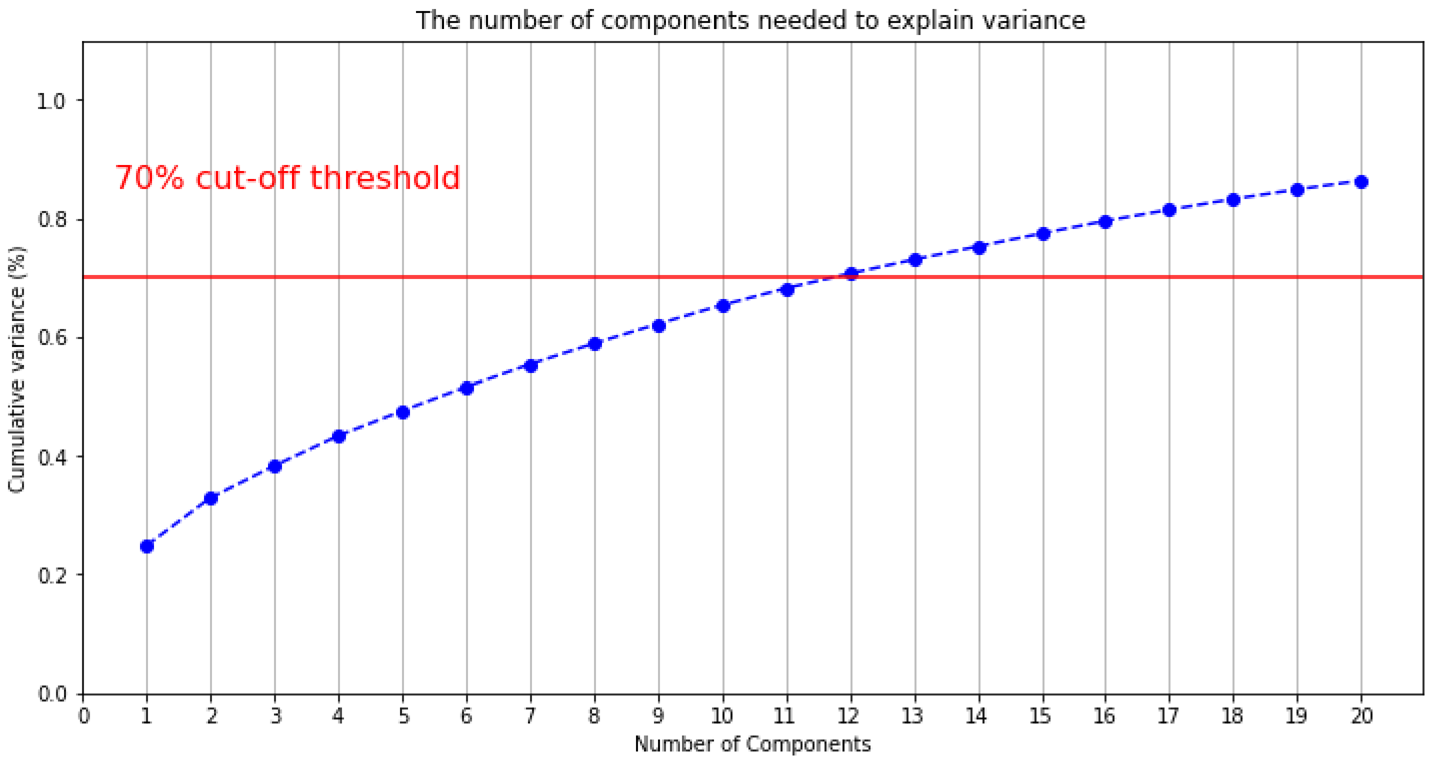
```
accuracy_score on test dataset :  0.7695167286245354
```

## Unsupervised ML

### PCA + kmeans

```
#scaler data
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
data_rescaled = scaler.fit_transform(df)
```

```
# find the suitable number of components
from sklearn.decomposition import PCA
pca = PCA().fit(data_rescaled)

% matplotlib inline
import matplotlib.pyplot as plt
plt.rcParams["figure.figsize"] = (12,6)

fig, ax = plt.subplots()
xi = np.arange(1, 21, step=1)
y = np.cumsum(pca.explained_variance_ratio_)[1:21]

plt.ylim(0.0,1.1)
plt.plot(xi, y, marker='o', linestyle='--', color='b')

plt.xlabel('Number of Components')
plt.xticks(np.arange(0, 21, step=1))
plt.ylabel('Cumulative variance (%)')
plt.title('The number of components needed to explain variance')

plt.axhline(y=0.70, color='r', linestyle='-')
plt.text(0.5, 0.85, '70% cut-off threshold', color = 'red', fontsize=16)

ax.grid(axis='x')
plt.show()
```



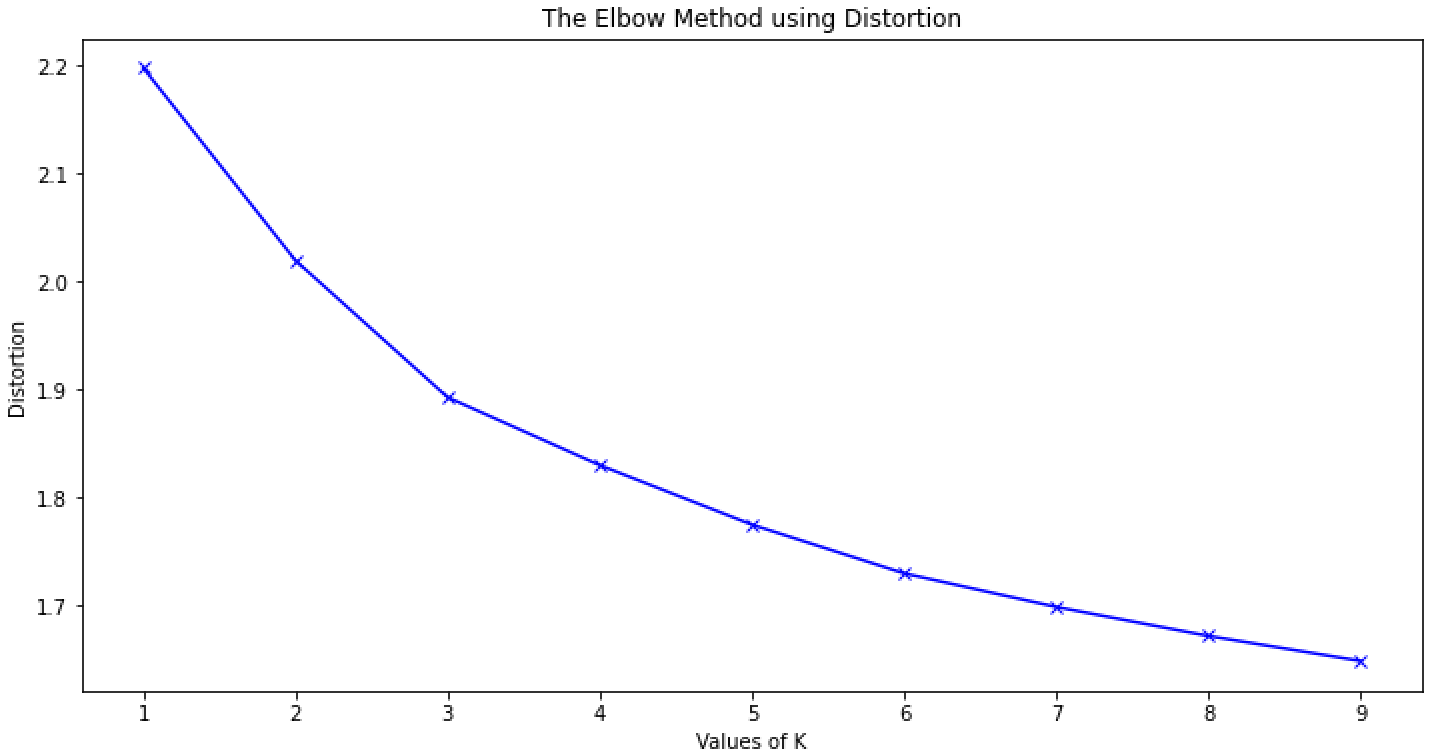

In order to get aroud 70%, we decided to choose the first 12 components.

```
#fit the model
pca_final = PCA(n_components = 12)
pca_final.fit(data_rescaled)
data_pca = pca_final.fit_transform(data_rescaled)
data_pca.shape
```

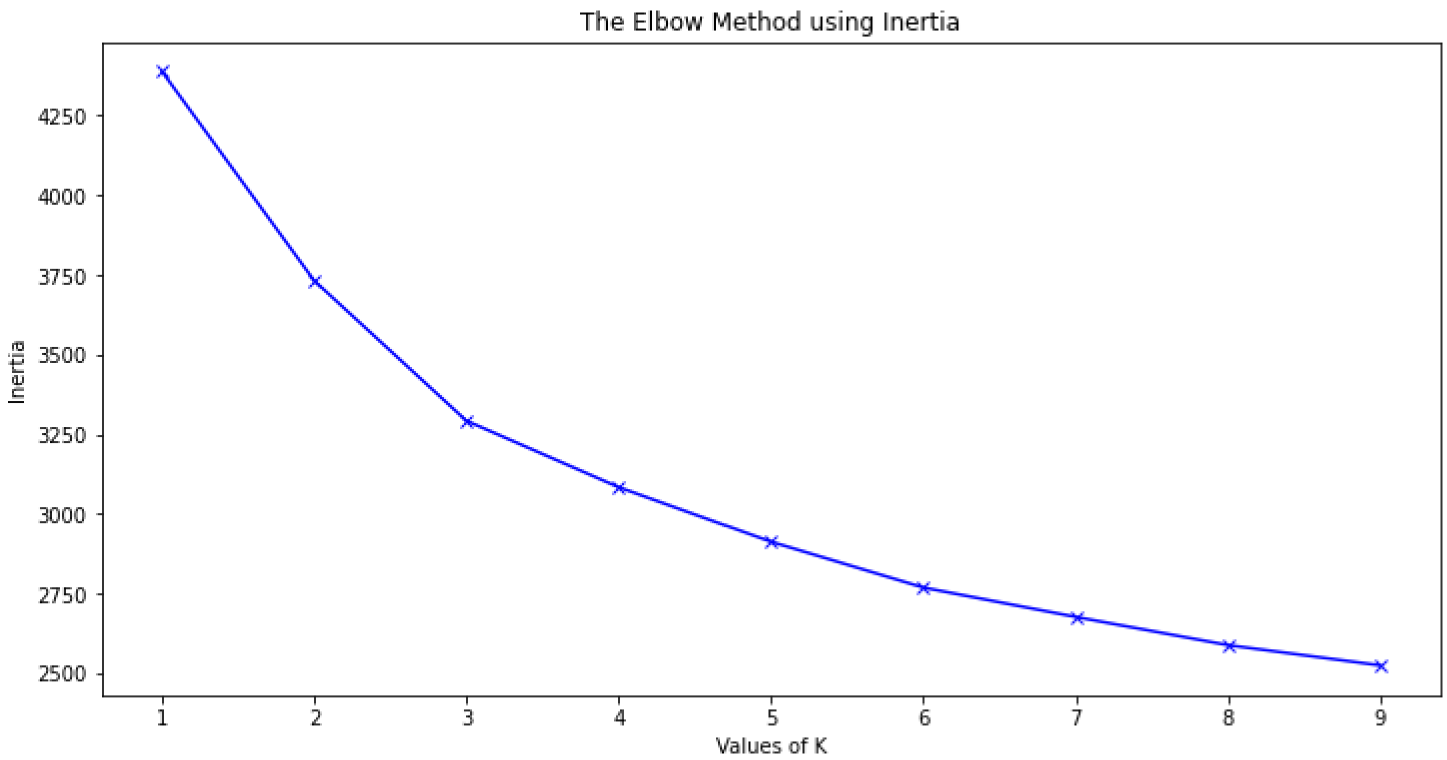
```
(896, 12)
```

```
#find reasonable number of k with elbow method
from sklearn.cluster import KMeans
from sklearn import metrics
from scipy.spatial.distance import cdist
import numpy as np
import matplotlib.pyplot as plt

distortions = []
inertias = []
mapping1 = {}
mapping2 = {}
K = range(1,10)

for k in K:
    #Building and fitting the model
    kmeanModel = KMeans(n_clusters=k).fit(data_pca)
    kmeanModel.fit(data_pca)

    distortions.append(sum(np.min(cdist(data_pca, kmeanModel.cluster_centers_,
                      'euclidean'),axis=1)) / data_pca.shape[0])
    inertias.append(kmeanModel.inertia_)

    mapping1[k] = sum(np.min(cdist(data_pca, kmeanModel.cluster_centers_,
                 'euclidean'),axis=1)) / data_pca.shape[0]
    mapping2[k] = kmeanModel.inertia_

```

```
plt.plot(K, distortions, 'bx-')
plt.xlabel('Values of K')
plt.ylabel('Distortion')
plt.title('The Elbow Method using Distortion')
plt.show()
```




```
plt.plot(K, inertias, 'bx-')
plt.xlabel('Values of K')
plt.ylabel('Inertia')
plt.title('The Elbow Method using Inertia')
plt.show()
```




Based on the results, we chose to use k=5.

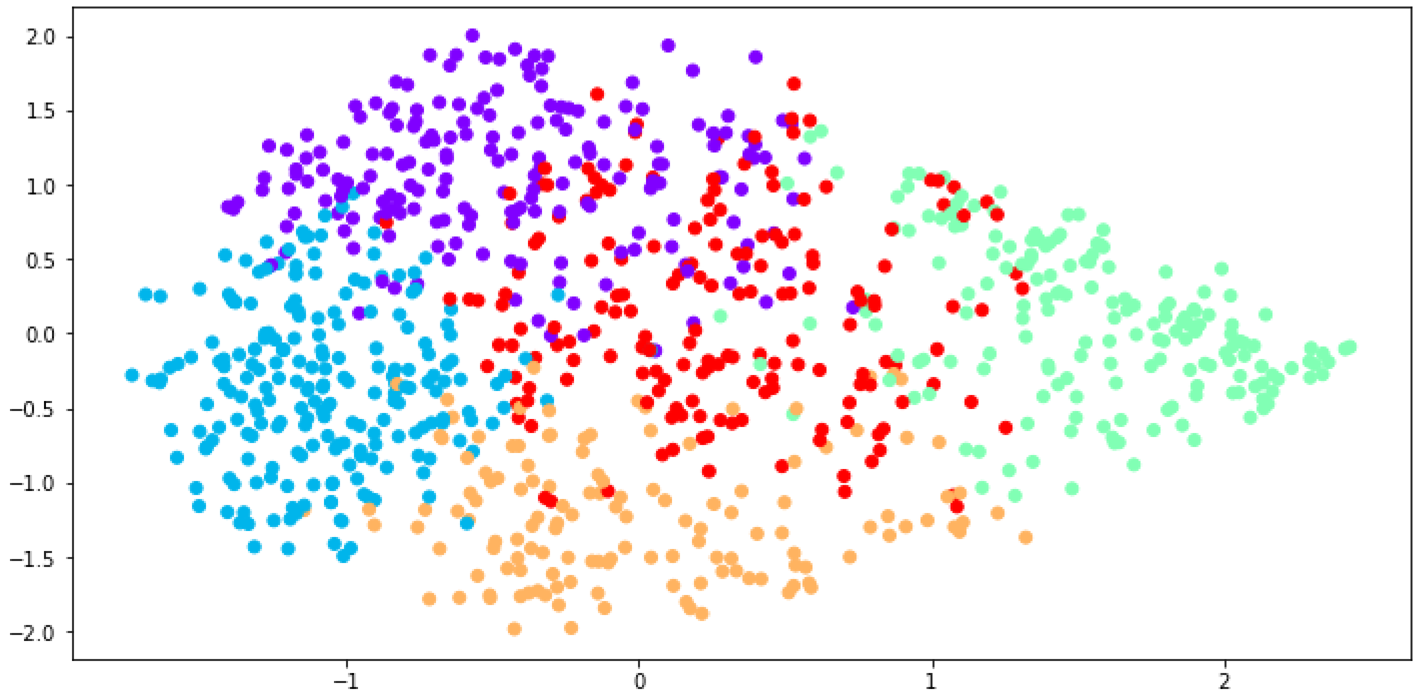
```
#fit the kmeans model
kmeans= KMeans(n_clusters=5)
kmeans5=kmeans.fit_predict(data_pca)
```

```
kmeans.cluster_centers_
```

```
array([[-0.4429739 ,  1.05666511,  0.43913159,  0.28931182,  0.11870278,
        -0.09887435, -0.00617988, -0.07980882, -0.07975342, -0.05690273,
         0.12475788,  0.15104256],
       [-1.07536002, -0.34658112, -0.08408743, -0.11913515,  0.10029392,
         0.18634079, -0.02428671,  0.00897236,  0.06673901,  0.05804446,
        -0.03544   , -0.17652532],
       [ 1.53302396,  0.07519759,  0.0984913 , -0.14740826,  0.2511941 ,
         0.16342133, -0.03881158, -0.01913487, -0.05577262,  0.09761498,
         0.04129115, -0.1241347 ],
       [-0.00363126, -1.22165991,  0.41078203,  0.09182208, -0.23131532,
        -0.18612103,  0.15502751, -0.00565208, -0.06049708, -0.10816998,
         0.06534425,  0.0312912 ],
       [ 0.26556962,  0.15832695, -0.79598708, -0.08762594, -0.33144407,
        -0.14719943, -0.04429081,  0.0998988 ,  0.10781135, -0.02589955,
        -0.18514208,  0.15876326]])
```

```
#visualizing clustering
plt.scatter(data_pca[:,0],data_pca[:,1],c=kmeans5,cmap="rainbow")
```

<matplotlib.collections.PathCollection at 0x7f457c7b1198>




```
1 # Get cluster assignment labels
2 labels = kmeans.labels_
3 df['Group']=labels
4 df.head()
```

| | age | self_employed | family_history | mh_treatment | interfere | company_size | remote | tech_company | mh_negative_consequ |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 3 | 1 | 1 | 0 | 3 | 1 | 1 | 1 | |
| 1 | 2 | 0 | 1 | 1 | 3 | 4 | 0 | 1 | |
| 2 | 2 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | |
| 3 | 3 | 0 | 0 | 1 | 4 | 3 | 1 | 1 | |
| 4 | 3 | 0 | 0 | 1 | 1 | 6 | 0 | 0 | |

```
1 df.groupby('Group').describe()
```

| | age | | | | | | | | self_employed | | | | | | | | family_history | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | count | mean | std | min | 25% | 50% | 75% | max | count | mean | std | min | 25% | 50% | 75% | max | count | mean |
| Group | | | | | | | | | | | | | | | | | | |
| 0 | 190.0 | 2.100000 | 0.378664 | 1.0 | 2.0 | 2.0 | 2.0 | 3.0 | 190.0 | 0.100000 | 0.300793 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 | 190.0 | 0.384211 |
| 1 | 218.0 | 2.059633 | 0.347637 | 1.0 | 2.0 | 2.0 | 2.0 | 3.0 | 218.0 | 0.114679 | 0.319367 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 | 218.0 | 0.371560 |
| 2 | 178.0 | 2.207865 | 0.433805 | 2.0 | 2.0 | 2.0 | 2.0 | 4.0 | 178.0 | 0.061798 | 0.241467 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 | 178.0 | 0.500000 |
| 3 | 136.0 | 2.080882 | 0.323297 | 1.0 | 2.0 | 2.0 | 2.0 | 3.0 | 136.0 | 0.367647 | 0.483947 | 0.0 | 0.0 | 0.0 | 1.0 | 1.0 | 136.0 | 0.433824 |
| 4 | 174.0 | 2.132184 | 0.339668 | 2.0 | 2.0 | 2.0 | 2.0 | 3.0 | 174.0 | 0.011494 | 0.106901 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 | 174.0 | 0.637931 |

5 rows × 400 columns

```
1 df.groupby('Group').mean()
```

| | age | self_employed | family_history | mh_treatment | interfere | company_size | remote | tech_company | mh_negativ |
|---|---|---|---|---|---|---|---|---|---|
| Group | | | | | | | | | |
| 0 | 2.100000 | 0.100000 | 0.384211 | 0.505263 | 2.257895 | 3.573684 | 0.315789 | 0.821053 | |
| 1 | 2.059633 | 0.114679 | 0.371560 | 0.481651 | 2.481651 | 2.834862 | 0.288991 | 0.834862 | |
| 2 | 2.207865 | 0.061798 | 0.500000 | 0.735955 | 2.477528 | 4.516854 | 0.224719 | 0.707865 | |
| 3 | 2.080882 | 0.367647 | 0.433824 | 0.727941 | 2.801471 | 2.066176 | 0.514706 | 0.897059 | |
| 4 | 2.132184 | 0.011494 | 0.637931 | 0.890805 | 2.816092 | 4.097701 | 0.229885 | 0.816092 | |

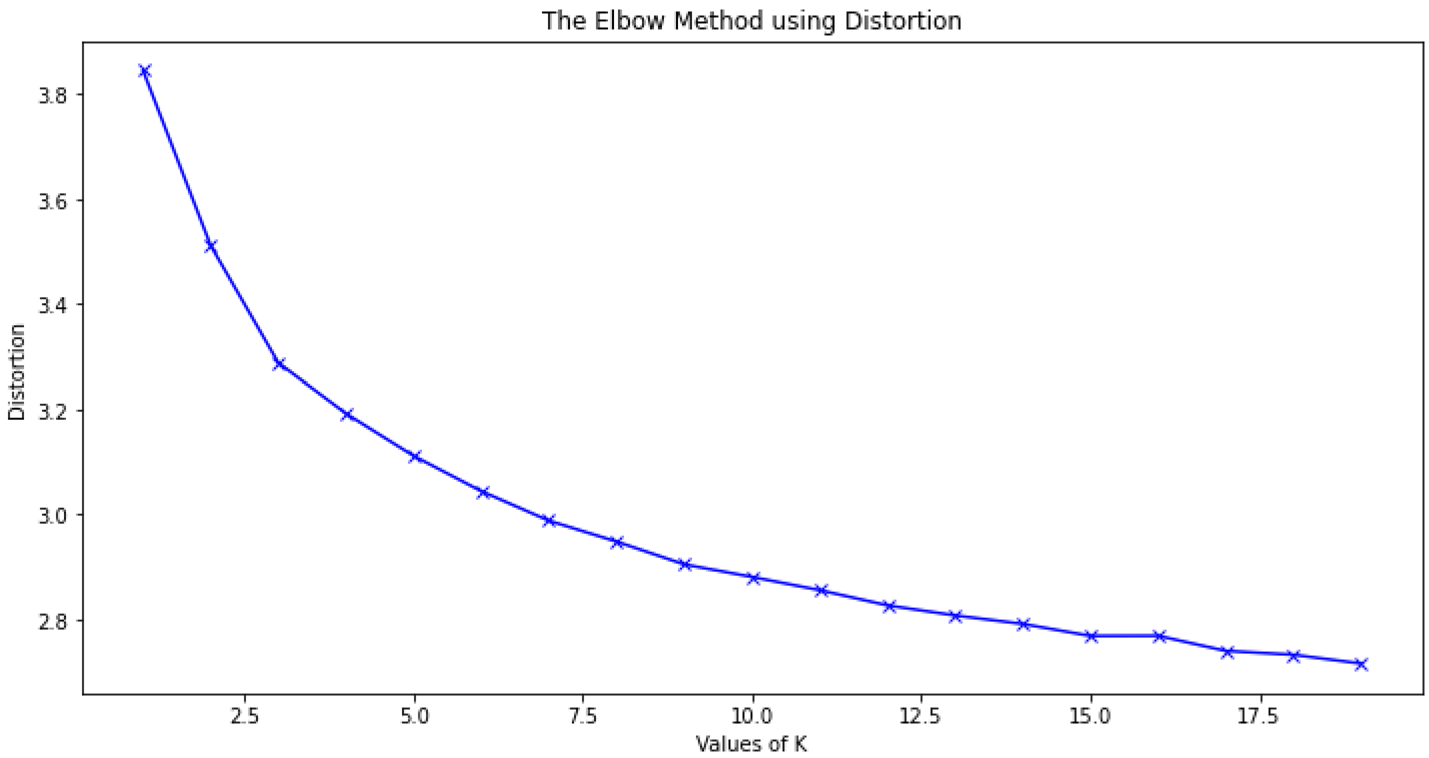
```
1 df.groupby('Group').mean().rank()
```

| Group | age | self_employed | family_history | mh_treatment | interfere | company_size | remote | tech_company | mh_negative_con |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 3.0 | 3.0 | 2.0 | 2.0 | 1.0 | 3.0 | 4.0 | 3.0 | |
| **1** | 1.0 | 4.0 | 1.0 | 1.0 | 3.0 | 2.0 | 3.0 | 4.0 | |
| **2** | 5.0 | 2.0 | 4.0 | 4.0 | 2.0 | 5.0 | 1.0 | 1.0 | |
| **3** | 2.0 | 5.0 | 3.0 | 3.0 | 4.0 | 1.0 | 5.0 | 5.0 | |
| **4** | 4.0 | 1.0 | 5.0 | 5.0 | 5.0 | 4.0 | 2.0 | 2.0 | |

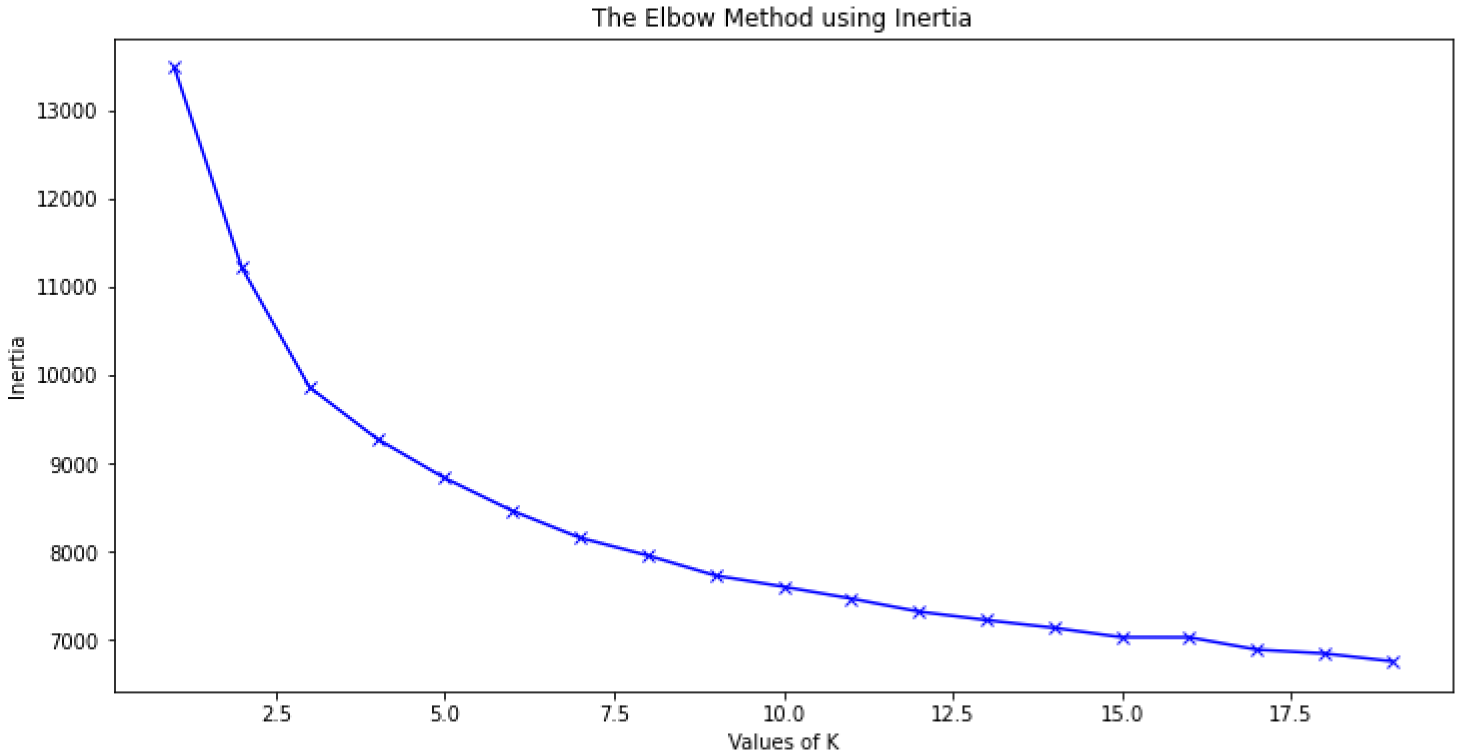
PCA

```
distortions = []
inertias = []
mapping3 = {}
mapping4 = {}
K2 = range(1,20)

for k in K2:
    #Building and fitting the model
    kmeanModel2 = KMeans(n_clusters=k).fit(df)
    kmeanModel2.fit(df)

    distortions.append(sum(np.min(cdist(df, kmeanModel2.cluster_centers_,
                      'euclidean'),axis=1)) / df.shape[0])
    inertias.append(kmeanModel2.inertia_)

    mapping3[k] = sum(np.min(cdist(df, kmeanModel2.cluster_centers_,
                 'euclidean'),axis=1)) / df.shape[0]
    mapping4[k] = kmeanModel2.inertia_
```

```
plt.plot(K2, distortions, 'bx-')
plt.xlabel('Values of K')
plt.ylabel('Distortion')
plt.title('The Elbow Method using Distortion')
plt.show()
```




```
plt.plot(K2, inertias, 'bx-')
plt.xlabel('Values of K')
plt.ylabel('Inertia')
plt.title('The Elbow Method using Inertia')
plt.show()
```



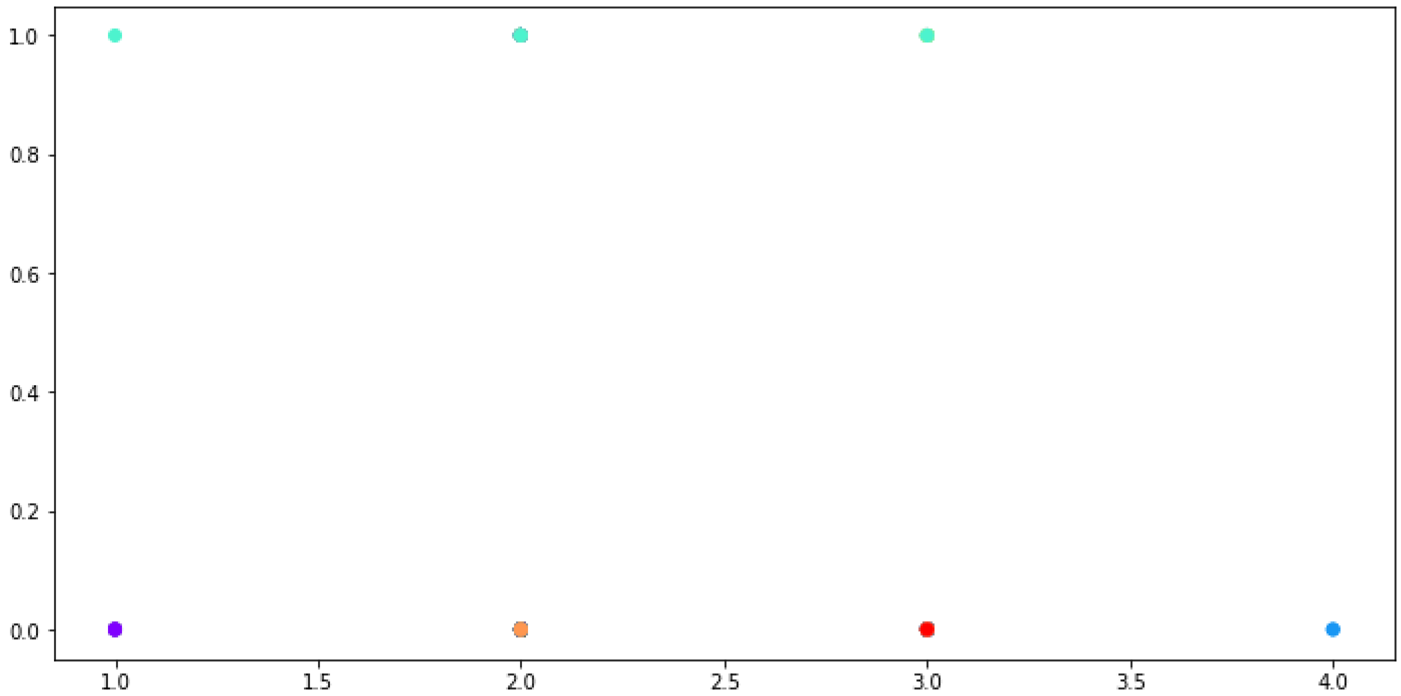

```
We decided to use 6 clusters.
```

```
#fit the kmeans model
kmeans2= KMeans(n_clusters=6)
kmeans6=kmeans2.fit_predict(df)
```

```
df=np.array(df)
```

```
#visualizing clustering
plt.scatter(df[:,0],df[:,1], c=kmeans6, cmap='rainbow')
```

```
<matplotlib.collections.PathCollection at 0x7f457c491da0>
```




The reason why we got imperfect plot is that there are two many dimensions here.