# developer-data-analysis

December 23, 2021

[ ]:
```
# importing packages
import numpy as np
import pandas as pd
from sklearn.preprocessing import␣
 ↪LabelEncoder,OneHotEncoder,OrdinalEncoder,StandardScaler
from collections import defaultdict
labelEncoder_dict = defaultdict(LabelEncoder)
from scipy import stats
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.pipeline import make_pipeline
from sklearn.metrics import mean_squared_error
from sklearn import svm
```

## 0.1 Data Cleaning

[ ]:
```
# Loading file data
df = pd.read_csv("stackoverflow_data.csv")
```

[ ]:
```
X = pd.DataFrame()
X['OpenSource'] = df['OpenSource'].eq('Yes').mul(1)
X['Hobby'] = df['Hobby'].eq('Yes').mul(1)
X['Student'] = df['Student'].str.contains('Yes').mul(1)
```

[ ]:
```
# YearsCoding
YearCodingMap = {
    '3-5 years':4,
    '30 or more years':30,
    '24-26 years':25,
    '18-20 years':19,
    '6-8 years':7,
    '9-11 years':10,
    '0-2 years':1,
```

```
    '15-17 years':16,
    '12-14 years':13,
    '21-23 years':22,
    '27-29 years':28,
}
X['YearsCoding'] = df['YearsCoding'].replace(YearCodingMap)
X['YearsCoding'].fillna(X['YearsCoding'].mean(),inplace=True)
```

[ ]:
```
companySizeMap = {
    '20 to 99 employees':60,
    '10,000 or more employees':10000,
    '100 to 499 employees':300,
    '10 to 19 employees':15,
    '500 to 999 employees':750,
    '1,000 to 4,999 employees':3000,
    '5,000 to 9,999 employees':7500,
    'Fewer than 10 employees':10
}
X['CompanySize'] = df['CompanySize'].replace(companySizeMap)
X.dropna(subset=["CompanySize"],inplace=True) #Droping NaN values
```

[ ]:
```
# Formal Education
dummy1 = pd.get_dummies(df['FormalEducation'], drop_first=True)
dummy1.drop(['I never completed any formal education','Primary/elementary␣
↪school','Secondary school (e.g. American high school, German Realschule or␣
↪Gymnasium, etc.)','Some college/university study without earning a␣
↪degree'],axis=1,inplace=True)
X.join(dummy1)
```

[ ]:
```
       OpenSource  Hobby Student  YearsCoding  CompanySize  \
0               0      1       0          4.0         60.0
1               1      1       0         30.0      10000.0
2               1      1       0         25.0         60.0
3               0      0       0         19.0        300.0
4               0      1       1          7.0      10000.0
…             …    …     …          …           …
71526           0      1       0          7.0         10.0
71527           0      1       1          4.0        750.0
71528           0      1       0         10.0         10.0
71529           1      1       0          7.0      10000.0
71530           0      1       0         16.0      10000.0

       Bachelor's degree (BA, BS, B.Eng., etc.)  \
0                                             1
1                                             1
2                                             0
3                                             1
```

```
4                                                   0
…                                                   …
71526                                               0
71527                                               1
71528                                               1
71529                                               1
71530                                               0

       Master's degree (MA, MS, M.Eng., MBA, etc.)  \
0                                                   0
1                                                   0
2                                                   0
3                                                   0
4                                                   0
…                                                   …
71526                                               0
71527                                               0
71528                                               0
71529                                               0
71530                                               1

       Other doctoral degree (Ph.D, Ed.D., etc.)  \
0                                                  0
1                                                  0
2                                                  0
3                                                  0
4                                                  0
…                                                  …
71526                                              0
71527                                              0
71528                                              0
71529                                              0
71530                                              0

       Professional degree (JD, MD, etc.)
0                                         0
1                                         0
2                                         0
3                                         0
4                                         0
…                                         …
71526                                     0
71527                                     0
71528                                     0
71529                                     0
71530                                     0
```

```
[71531 rows x 9 columns]
```

```
[ ]: # AssessJob and Benefits Added
df.fillna(df.iloc[:,17:38].mean(),inplace=True)
for col in df.iloc[:,17:38].columns:
    X[col] = df[col]
```

```
[ ]: # JobSatisfaction Mapping
SatisfactionMapping = {
    'Extremely satisfied':6,
    'Moderately satisfied':5,
    'Slightly satisfied':4,
    'Neither satisfied nor dissatisfied':3,
    'Moderately dissatisfied':2,
    'Slightly dissatisfied':1,
    'Extremely dissatisfied':0
}

df['JobSatisfaction'].replace(SatisfactionMapping,inplace=True)
df.fillna({'JobSatisfaction':3},inplace=True)
X['JobSatisfaction'] = df['JobSatisfaction']

# CareerSatisfaction
df['CareerSatisfaction'].replace(SatisfactionMapping,inplace=True)
df.fillna({'CareerSatisfaction':3},inplace=True)
X['CareerSatisfaction'] = df['CareerSatisfaction']
```

```
[ ]: # HackathonReasons
X['HackathonParticipated'] = df['HackathonReasons'].notna()*1

# ConvertedSalary
X['ConvertedSalary'] = df['ConvertedSalary']
X.dropna(subset=["ConvertedSalary"],inplace=True) #Droping NaN values
```

### 0.1.1 One Hot Encoding

```
[ ]: def CustomOneHotEncoding(data,X):
    temp = data.str.split(';', expand=True)
    new_columns = pd.unique(temp.values.ravel())
    for col in new_columns:
        if col is not None and col is not np.NaN:
            X[col] = data.str.contains(col, regex=False).fillna(False)*1
```

```
[ ]: # LanguageWorkedWith
CustomOneHotEncoding(df['LanguageWorkedWith'],X)
```

```
CustomOneHotEncoding(df['DevType'],X)

CustomOneHotEncoding(df['DatabaseWorkedWith'],X)

CustomOneHotEncoding(df['PlatformWorkedWith'],X)

CustomOneHotEncoding(df['FrameworkWorkedWith'],X)

CustomOneHotEncoding(df['IDE'],X)

# Methodology
CustomOneHotEncoding(df['Methodology'],X)

# RaceEthnicity
CustomOneHotEncoding(df['RaceEthnicity'],X)
```

[ ]:
```
# CheckInCode
CheckInCodeMapping = {
    'Multiple times per day':730,
    'A few times per week':156,
    'Weekly or a few times per month':52,
    'Never':0,
    'Less than once per month':12,
    'Once a day':365
}

X['CheckInCode'] = df['CheckInCode'].replace(CheckInCodeMapping)
X['CheckInCode'].fillna(X['CheckInCode'].mean(),inplace=True)
```

[ ]:
```
AgeMapping = {
    '25 - 34 years old':29.5,
    '35 - 44 years old':39.5,
    '18 - 24 years old':21,
    '45 - 54 years old':49.5,
    '55 - 64 years old':59.5,
    'Under 18 years old':18,
    '65 years or older':65
}
X['Age'] = df['Age'].replace(AgeMapping)
X.dropna(subset=["Age"],inplace=True) #Droping NaN values

X['MilitaryUS'] = (df['MilitaryUS']=='Yes')*1
X['Dependents'] = (df['Dependents']=='Yes')*1
X['Gender'] = (df['Gender']=='Female')*1
```

[ ]:
```
# Exercise
ExerciseFreqMap = {
```

```
    '3 - 4 times per week':((3+4)/2)*52,
    'Daily or almost every day':365,
    "I don't typically exercise":0,
    '1 - 2 times per week':52
}
X['Exercise'] = df['Exercise'].replace(ExerciseFreqMap)
X['Exercise'].fillna(X['Exercise'].mean(),inplace=True)

# HoursCompMap
HoursCompMap = {
    '9 - 12 hours':10.5,
    '5 - 8 hours':6.5,
    'Over 12 hours':12,
    '1 - 4 hours':2.5,
    'Less than 1 hour':1
}
X['HoursComputer'] = df['HoursComputer'].replace(HoursCompMap)
X['HoursComputer'].fillna(X['HoursComputer'].mean(),inplace=True)
```

[ ]:
```
# HypotheticalTools1-5
HypoToolMap = {
    'Extremely interested':5,
    'Very interested':4,
    'Somewhat interested':3,
    'A little bit interested':2,
    'Not at all interested':1
}
hypotheticalToolsList =␣
 ↪['HypotheticalTools1','HypotheticalTools2','HypotheticalTools3','HypotheticalTools4','Hypot
for col in hypotheticalToolsList:
    X[col] = df[col].replace(HypoToolMap)
    X[col].fillna(X[col].median(),inplace=True)
```

[ ]:
```
# EducationParents -> Higher Educated Parents
EducatedParentsMap = {
    "Bachelor's degree (BA, BS, B.Eng., etc.)":1,
    'Some college/university study without earning a degree':0,
    'Secondary school (e.g. American high school, German Realschule or␣
 ↪Gymnasium, etc.)':0,
    "Master's degree (MA, MS, M.Eng., MBA, etc.)":1,
    'Primary/elementary school':0,
    'Associate degree':1,
    'They never completed any formal education':0,
    'Other doctoral degree (Ph.D, Ed.D., etc.)':1,
    'Professional degree (JD, MD, etc.)':1
}
```

```
X['ParentsWithHighEducation'] = df['EducationParents'].
 ↪replace(EducatedParentsMap)
X.dropna(subset=["ParentsWithHighEducation"],inplace=True) #Droping NaN values
```

[ ]:
```
SelfTaughtValues = ['Some college/university study without earning a degree','I␣
 ↪never completed any formal education','Primary/elementary school','Secondary␣
 ↪school (e.g. American high school, German Realschule or Gymnasium, etc.)']
X['SelfTaught'] = df['FormalEducation'].isin(SelfTaughtValues)*1
```

[ ]:
```
InferiorityMap = {
    'Neither Agree nor Disagree':0,
    'Strongly disagree':0,
    'Strongly agree':1,
    'Disagree':0,
    'Agree':1
}
X['FeelingInferior'] = df['AgreeDisagree3'].replace(InferiorityMap)
X['FeelingInferior'].fillna(0,inplace=True)
```

# 1 Hypothesis Testing

[ ]:
```
X_dummy=X
```

[ ]:
```
#Age and Job and Career Satisfaction

#Null Hypothesis Career Satisfaction remains same at all Age level.

careerSatisfied = X_dummy[X_dummy['CareerSatisfaction']==1][['Age']]
careerNotSatisfied = X_dummy[X_dummy['CareerSatisfaction']==0][['Age']]

u,p=stats.mannwhitneyu(careerSatisfied,careerNotSatisfied)
print(p)
# Null Hypothesis Not Reject hence we cannot say that there is a career␣
 ↪satisfaction difference between older and younger people
```

```
[0.12159265]
```

[ ]:
```
# Null Hypothesis :- People who are self taught have no inferior complex␣
 ↪compared to people who had traditional degrees

self_inferior =X_dummy[X_dummy['SelfTaught']==1][['FeelingInferior']].sum()
self_non_inferior = X_dummy[X_dummy['SelfTaught']==1][['FeelingInferior']].
 ↪shape[0] - self_inferior


not_self_inferior =X_dummy[X_dummy['SelfTaught']==0][['FeelingInferior']].sum()
```

```
not_self_non_inferior = X_dummy[X_dummy['SelfTaught']==0][['FeelingInferior']].
 ↪shape[0] - self_inferior
cat_matrix = [
    [self_inferior,self_non_inferior],
    [not_self_inferior,not_self_non_inferior]
]
chi2, pchi, dof, ex = stats.chi2_contingency(cat_matrix)
pchi

# p-values is less than significance level (0.05) hence we safely reject null␣
 ↪hypothesis
# which means that there is a considerable number of self taught people who␣
 ↪feel that they are not as good as their peers.
```

[ ]:
```
1.4952279461561637e-20
```

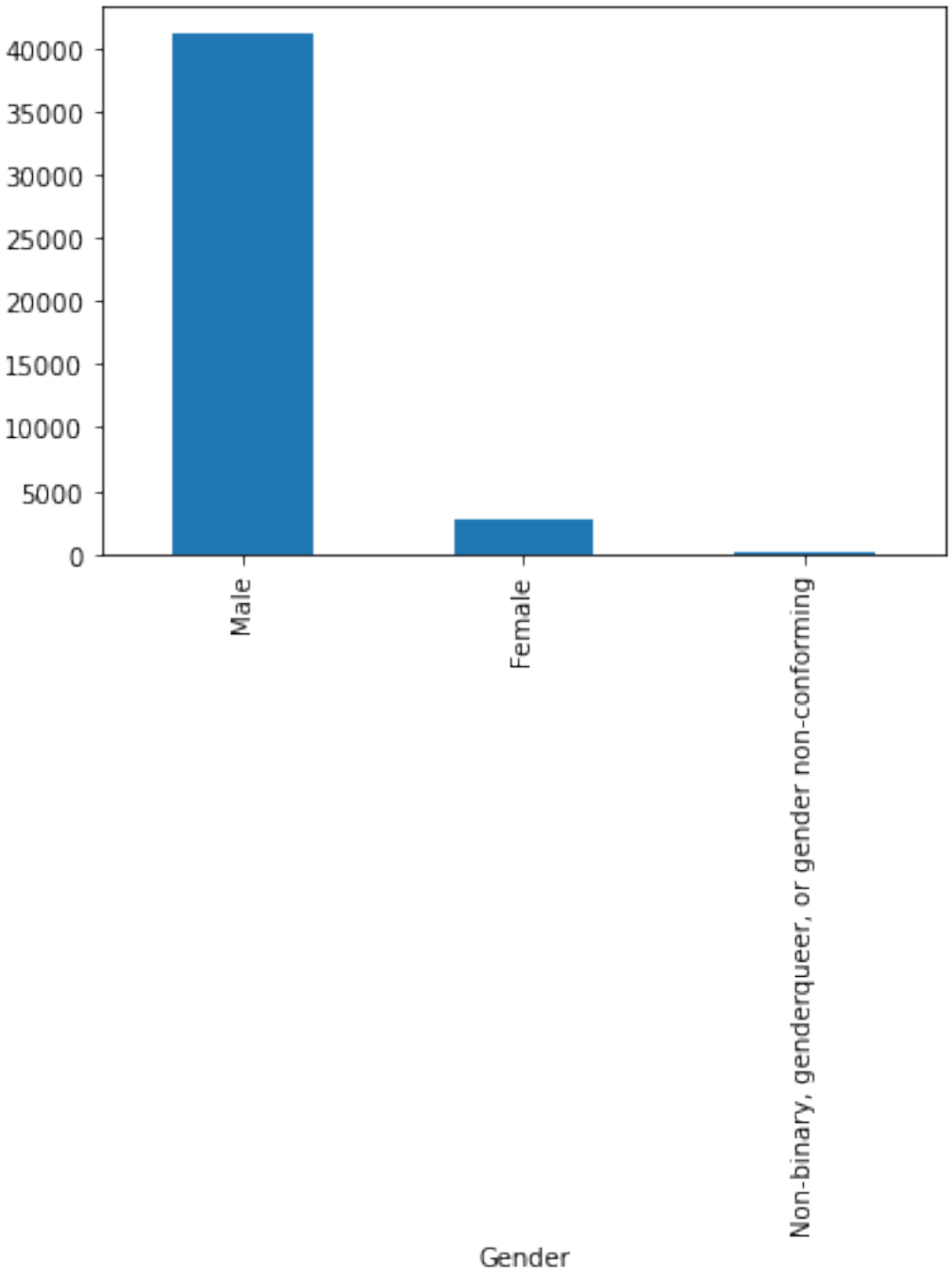
[ ]:
```
#Null Hypothesis Career Satisfaction remains same at all Age level.
M1=X_dummy['Age']
M2=X_dummy['CareerSatisfaction']

u,p=stats.mannwhitneyu(M1,M2)
print(p)
```

```
0.0
```

[ ]:
```
#%% Hypothesis for US male and female developers equally paid
#Code is designed in such way can compare for any country.

#Performing T test because assuming the sample is representative of actual␣
 ↪population parameters.

df.dropna(subset=['ConvertedSalary'], inplace=True)
df_allgender=df.groupby(['Gender']).count()
df_allgender.sort_values(by=['Respondent'], ascending=False, inplace=True)
df_allgender.iloc[0:3, 0].plot.bar()

df_allgender=df_allgender.T
df_gender= df_allgender[['Female', 'Male']]
df_gender=df_gender.iloc[0, :]

df_female= df[df['Gender']== 'Female']
df_male= df[df['Gender']== 'Male']
femaleSalaries_df= df_female[['ConvertedSalary']]
maleSalaries_df= df_male[['ConvertedSalary']]

t,p= stats.ttest_ind(femaleSalaries_df, maleSalaries_df)
print(p)
```

```
#As p<0.05, we can reject the Null Hypothesis, but we don't have enough␣
↪evidence to prove that male and female are equally paid.
```

```
[0.04068129]
```



## 2 PCA

[ ]:
```
# Calcuating zscore for normalizing the dataset
zscoredData = stats.zscore(X)
```

[ ]:
```
from sklearn.decomposition import PCA

pca = PCA().fit(zscoredData)
eigValues = pca.explained_variance_
loadings_v = pca.components_
u = pca.fit_transform(zscoredData)
covarExplained = (sum(eigValues[:10])/sum(eigValues))*100
covarExplained
```

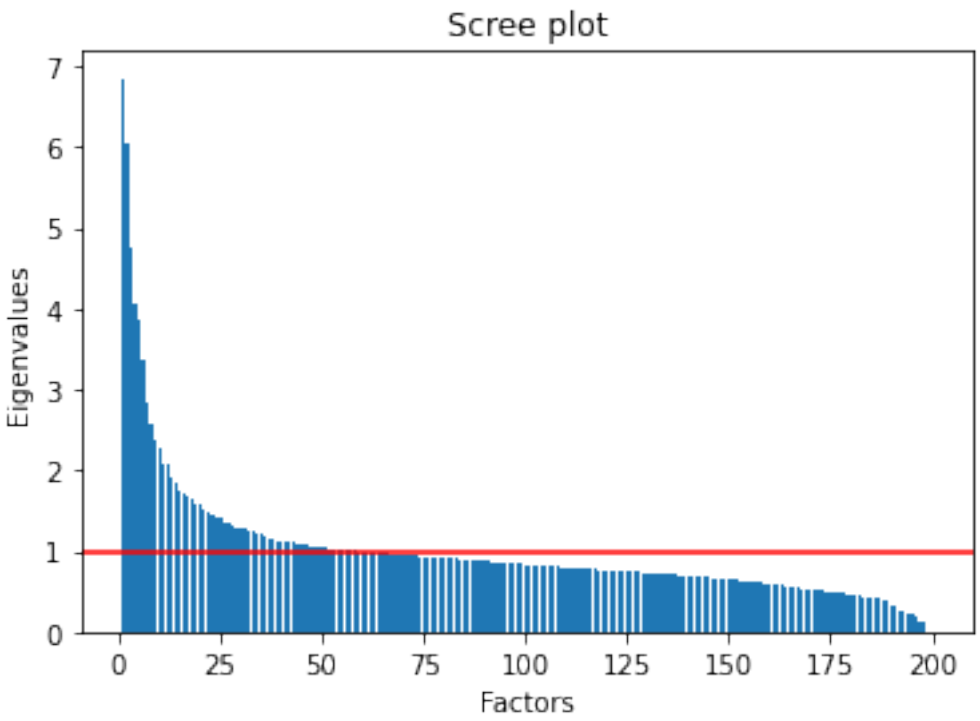
[ ]:
```
19.50572115100008
```

[ ]:
```
eigValues>1 #50 columns
X_transformed = u[:,0:50]
X_transformed.shape
```

[ ]:
```
(37268, 50)
```

[ ]:
```
import matplotlib.pyplot as plt

numPredictors = X.shape[1]
plt.bar(np.linspace(1,numPredictors,numPredictors),eigValues)
plt.axhline(y=1, color='r', linestyle='-')
plt.title('Scree plot')
plt.xlabel('Factors')
plt.ylabel('Eigenvalues')
```

[ ]:
```
Text(0, 0.5, 'Eigenvalues')
```




[ ]:
```
maxFeat=[]
for i in range(47):
    maxFeat.append(np.argmax(loadings_v[i,:]*-1))
set(maxFeat)
```

[ ]:
```
{3,
 5,
 6,
 8,
 10,
 11,
 12,
 13,
 17,
 19,
 22,
 23,
 26,
 30,
 35,
 49,
 51,
 92,
```

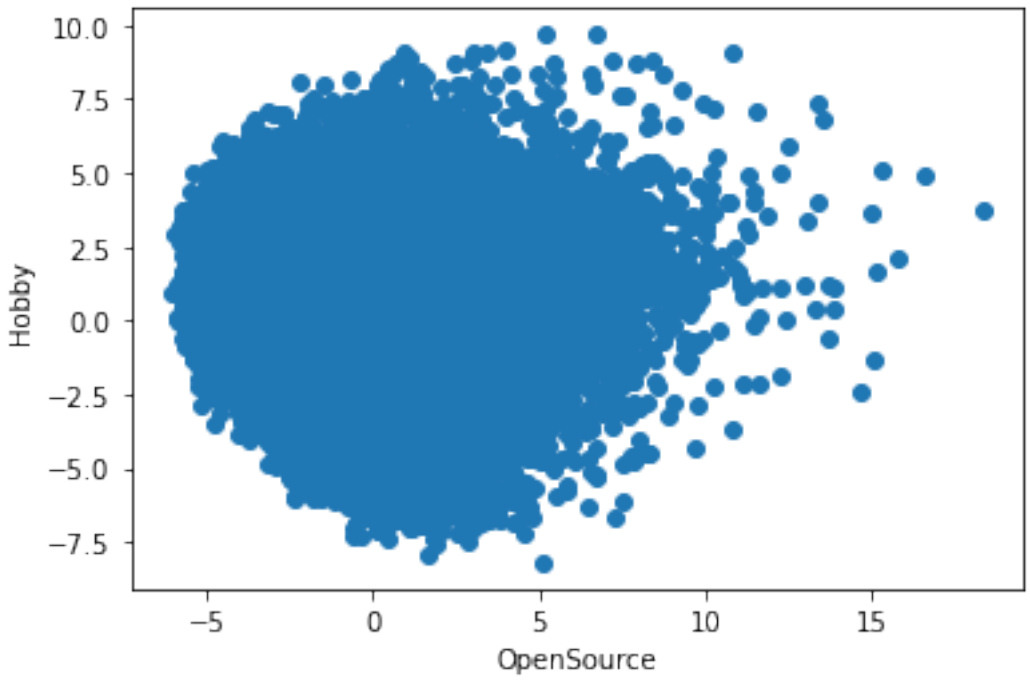
```
 97,
 98,
 121,
 125,
 128,
 129,
 134,
 142,
 145,
 148,
 149,
 152,
 153,
 154,
 169,
 176,
 180,
 183,
 190,
 191,
 192,
 197,
 199}
```

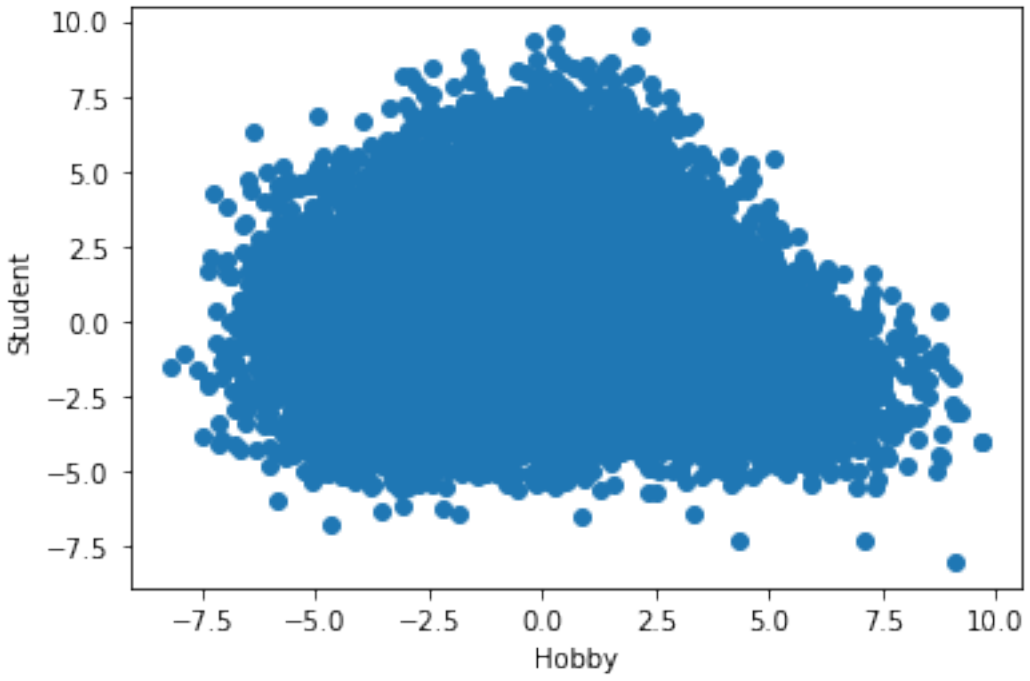
## 3 Clustering

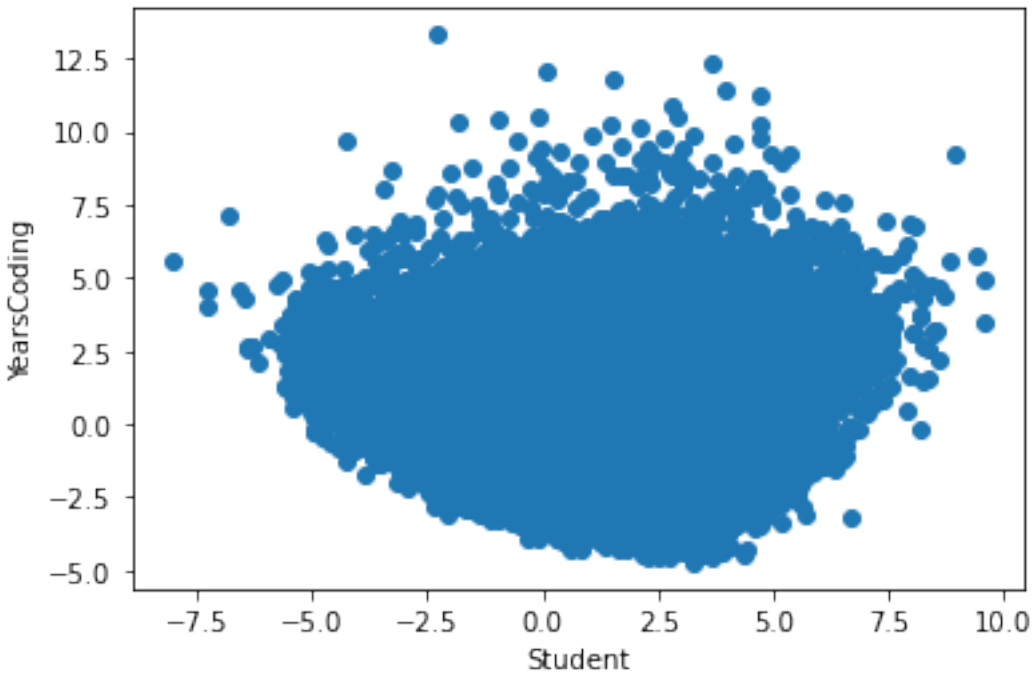
[ ]:
```
X.loc[X['JobSatisfaction'] <= 3.0, 'JobSatisfaction'] = 0
X.loc[X['JobSatisfaction'] > 3.0, 'JobSatisfaction'] = 1
X['JobSatisfaction'].value_counts()
```

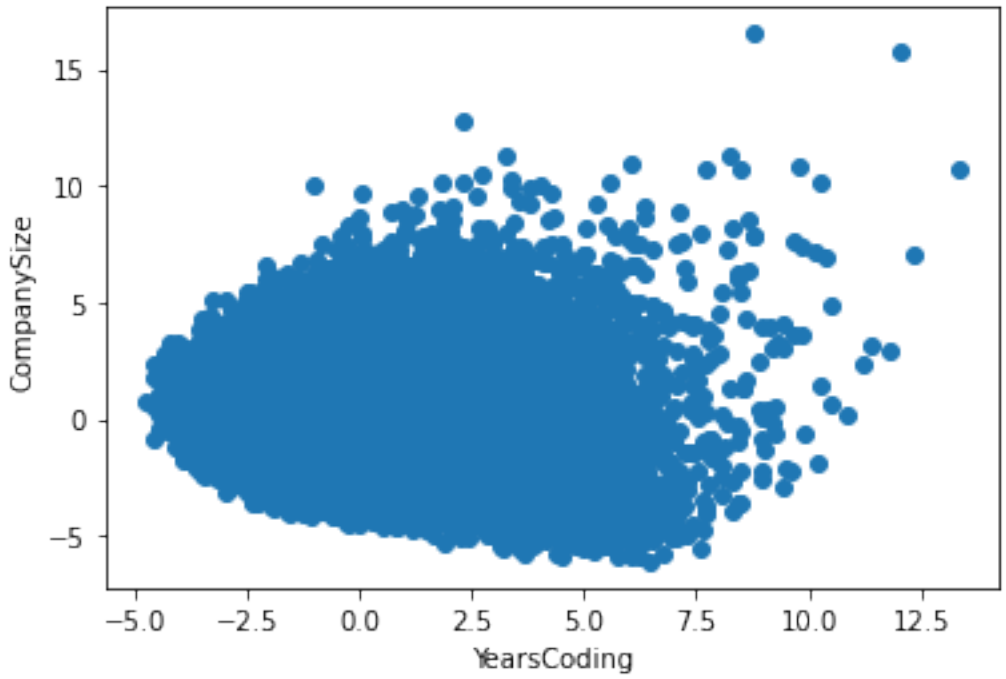
[ ]:
```
1.0    26184
0.0    11084
Name: JobSatisfaction, dtype: int64
```

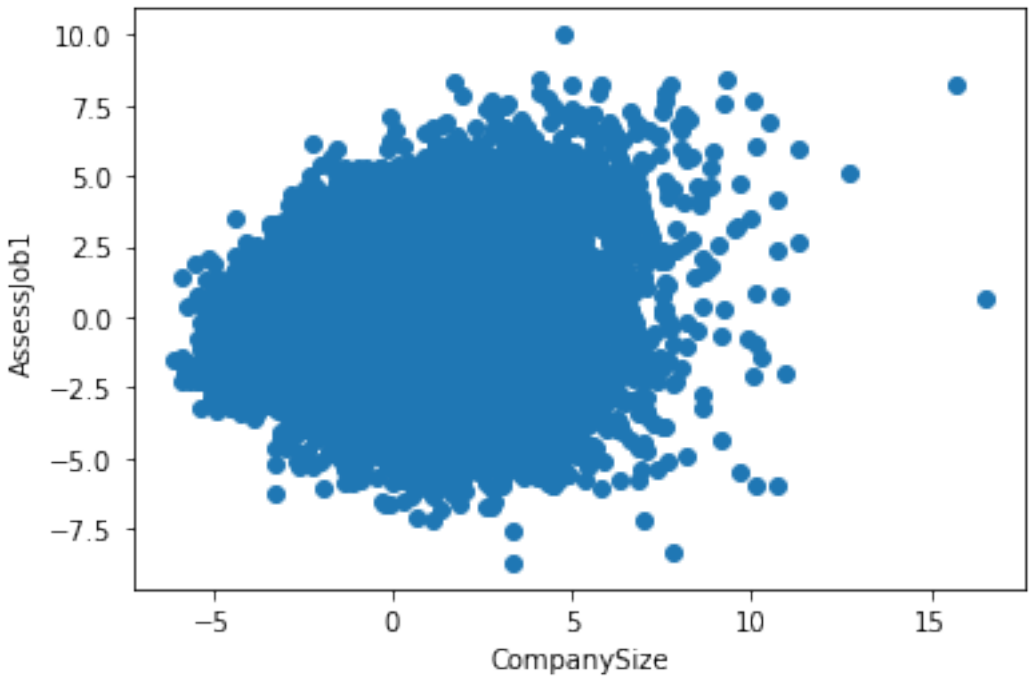
[ ]:
```
col=X.columns
for i in range(10):
    plt.figure()
    f1=col[i]
    f2=col[i+1]
    plt.scatter(X_transformed[:,i], X_transformed[:,i+1])
    plt.xlabel(f1)
    plt.ylabel(f2)
    plt.show()
```

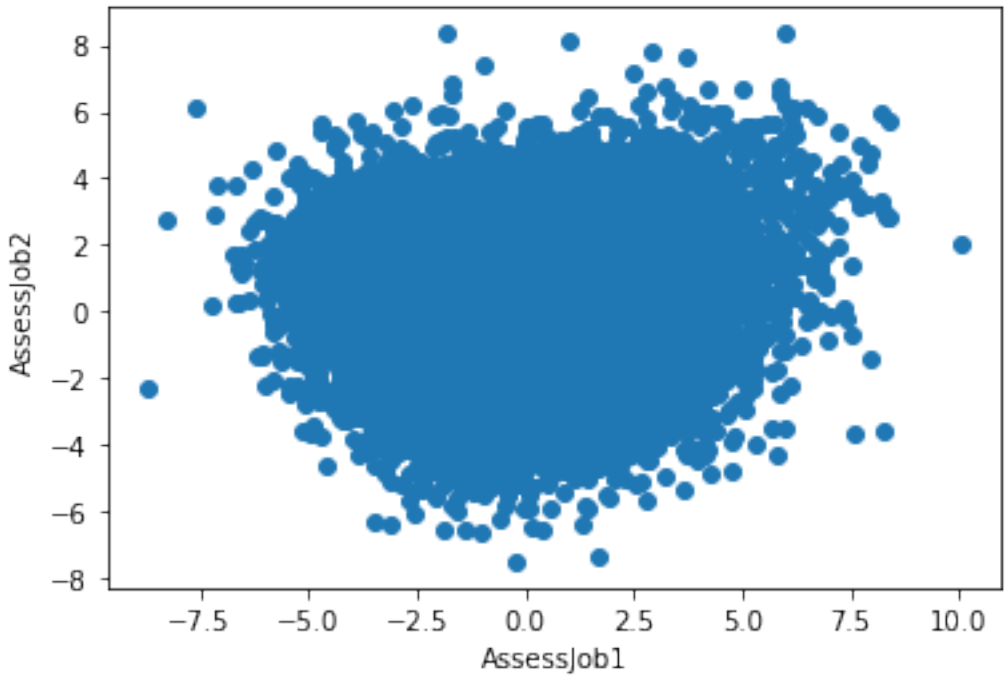

10.0
7.5
5.0
2.5
0.0
−2.5
−5.0
−7.5
Hobby
−5
0
5
10
15
OpenSource

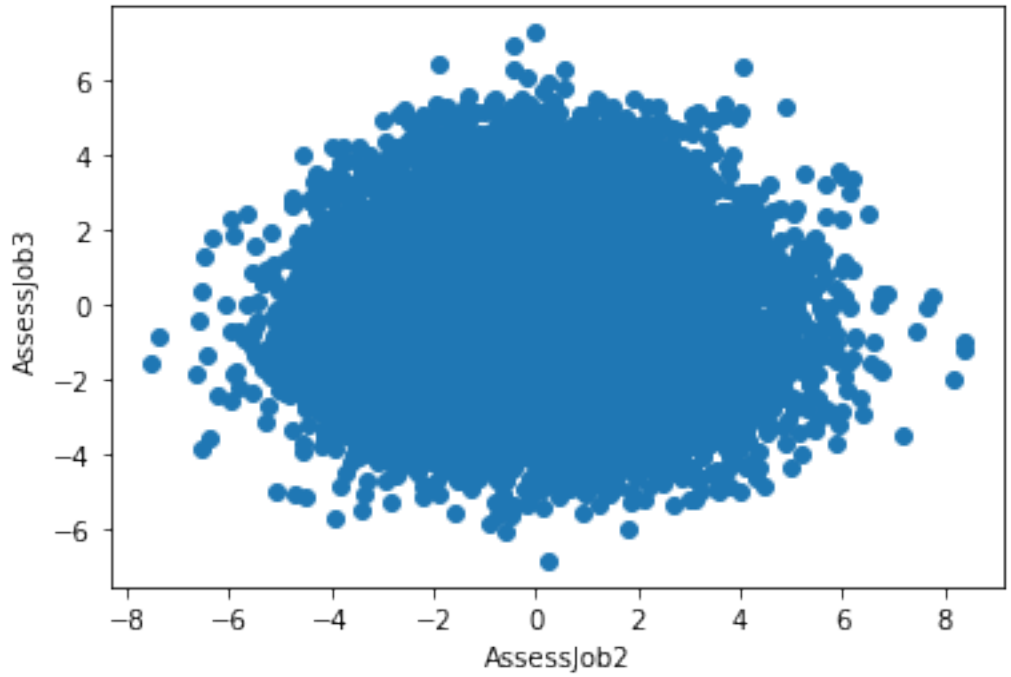

10.0
7.5
5.0
2.5
0.0
−2.5
−5.0
−7.5
Student
−7.5
−5.0
−2.5
0.0
2.5
5.0
7.5
10.0
Hobby

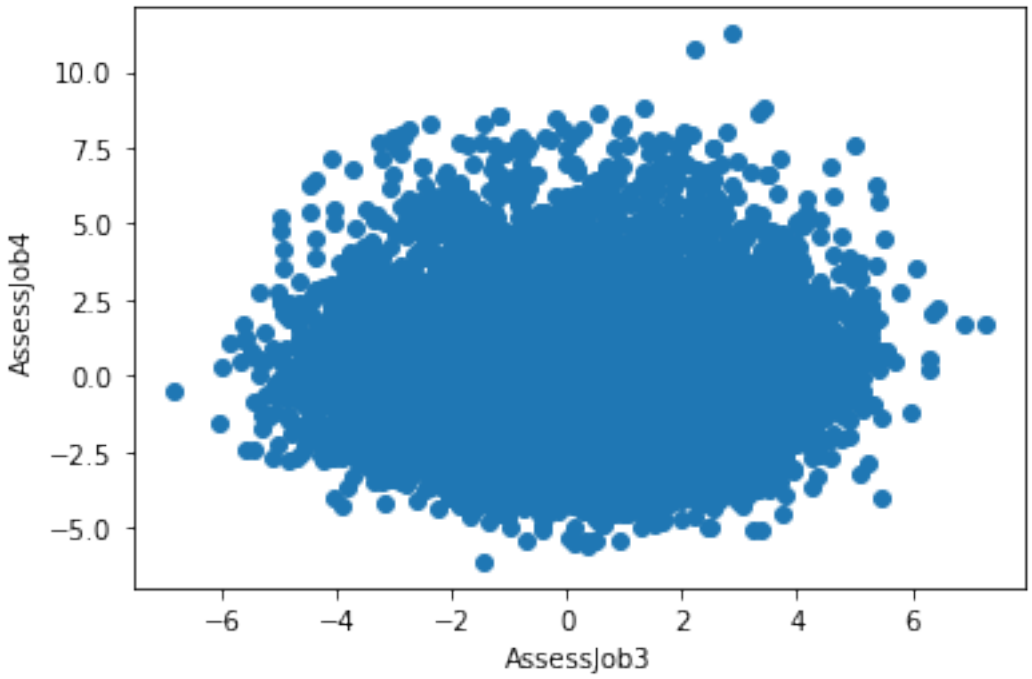

12.5
10.0
7.5
5.0
2.5
0.0
−2.5
−5.0
YearsCoding
−7.5
−5.0
−2.5
0.0
2.5
5.0
7.5
10.0
Student

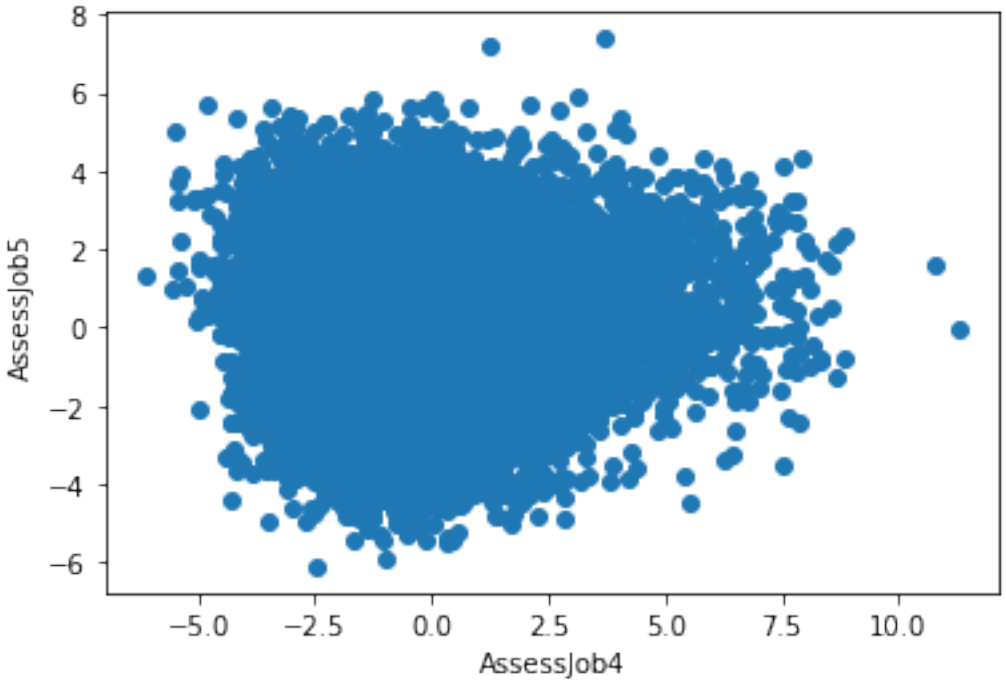

15
10
5
0
−5
CompanySize
−5.0
−2.5
0.0
2.5
5.0
7.5
10.0
12.5
YearsCoding

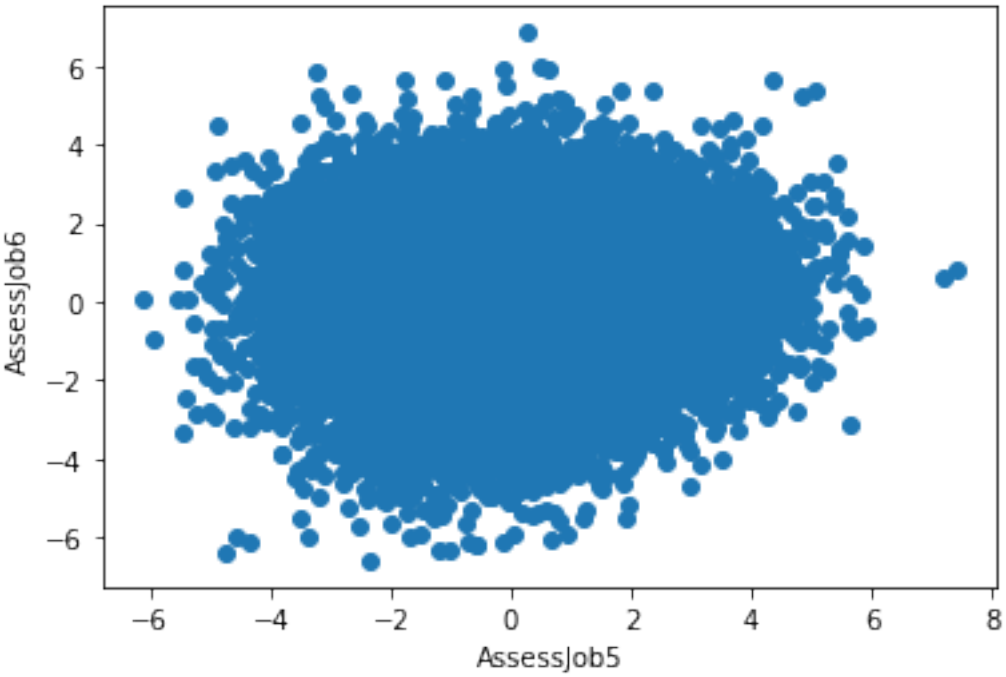

10.0
7.5
5.0
2.5
0.0
−2.5
−5.0
−7.5
AssessJob1
−5
0
5
10
15
CompanySize


8
6
4
2
0
−2
−4
−6
−8
AssessJob2
−7.5
−5.0
−2.5
0.0
2.5
5.0
7.5
10.0
AssessJob1

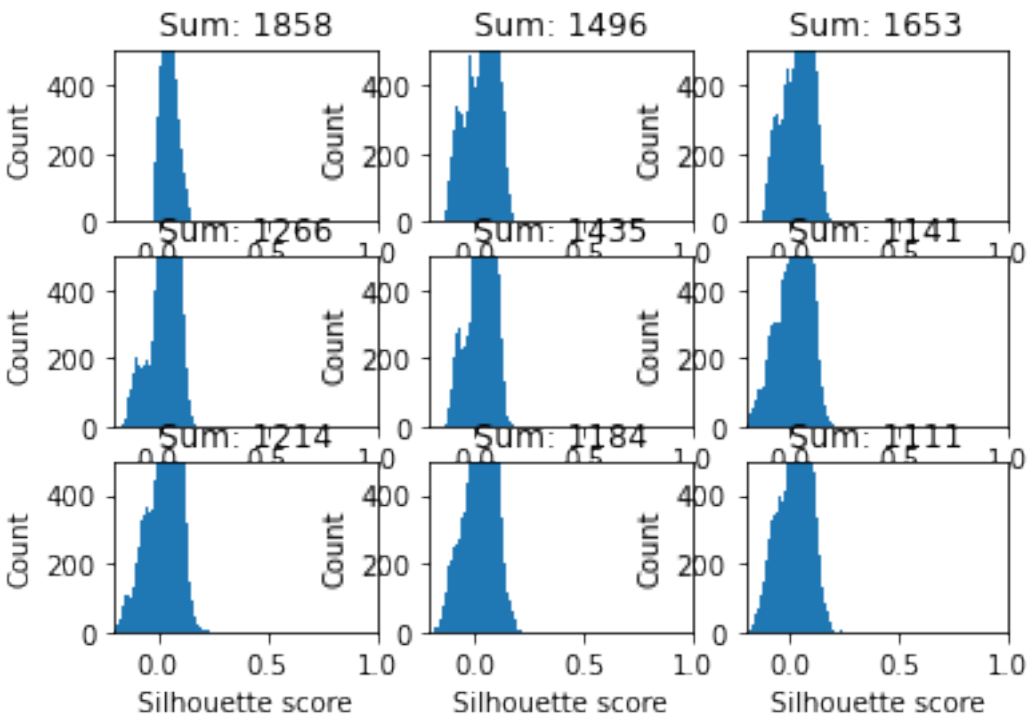

AssessJob3
AssessJob2
6
4
2
0
−2
−4
−6
−8
−6
−4
−2
0
2
4
6
8


AssessJob4
AssessJob3
10.0
7.5
5.0
2.5
0.0
−2.5
−5.0
−6
−4
−2
0
2
4
6

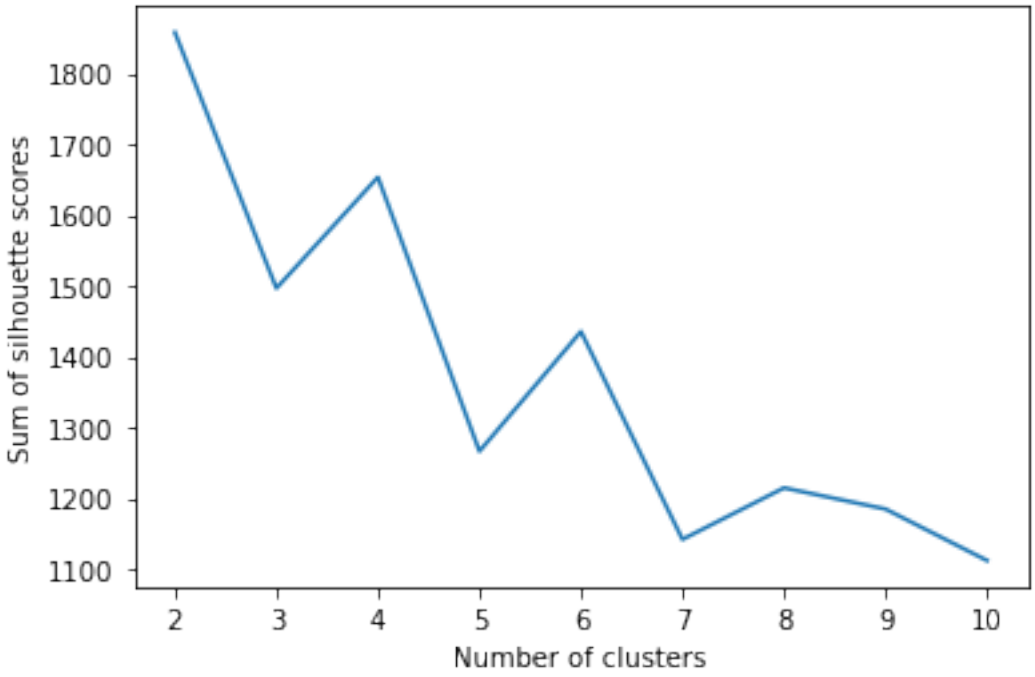

AssessJob5
AssessJob4
8
6
4
2
0
−2
−4
−6
−5.0
−2.5
0.0
2.5
5.0
7.5
10.0


AssessJob6
AssessJob5
6
4
2
0
−2
−4
−6
−6
−4
−2
0
2
4
6
8

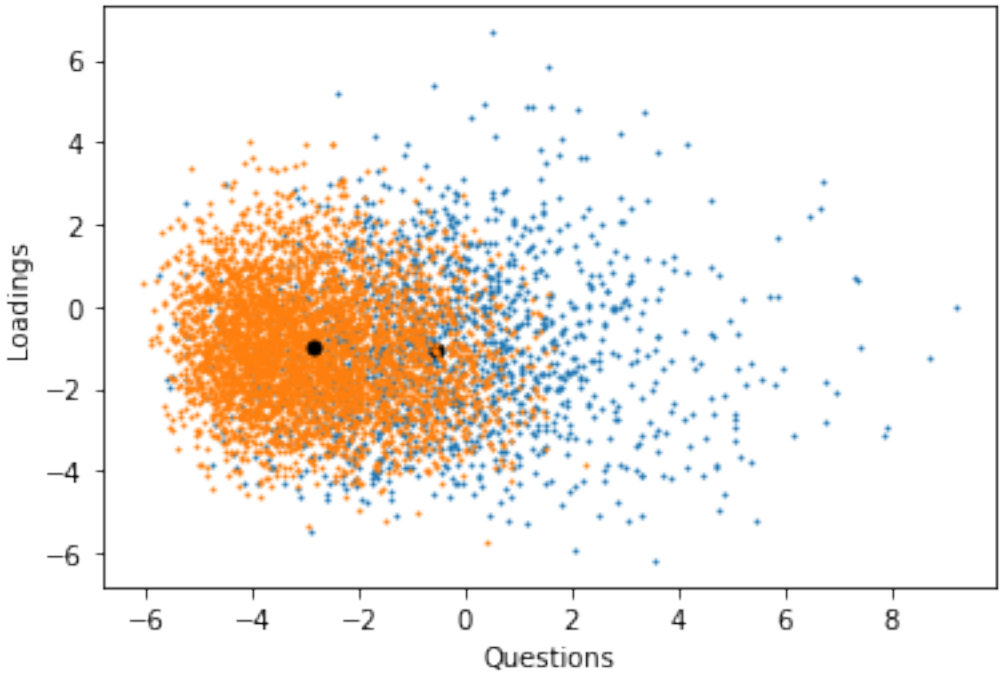
[ ]:
```
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_samples

numClusters = 9 # how many clusters are we looping over? (from 2 to 10)
Q = np.empty([numClusters,1]) # init container to store sums
Q[:] = np.NaN # convert to NaN

ans=[]
plt.figure()
# Compute kMeans:
for ii in range(2, 11): # Loop through each cluster (from 2 to 10!)
    kMeans = KMeans(n_clusters = int(ii)).fit(X_transformed) # compute kmeans
    cId = kMeans.labels_ # vector of cluster IDs that the row belongs to
    cCoords = kMeans.cluster_centers_ # coordinate location for center of each␣
 ↪cluster
    my_dict = {cCoords[i, 0]: np.where(cId== i)[0] for i in range(kMeans.
 ↪n_clusters)}
    ans.append(my_dict)
    s = silhouette_samples(X_transformed,cId) # compute the mean silhouette␣
 ↪coefficient of all samples
    # print(s.shape)
    Q[ii-2] = sum(s) # take sum
    # Plot data:
    plt.subplot(3,3,ii-1)
    plt.hist(s,bins=100)
    plt.xlim(-0.2,1)
    plt.ylim(0,500)
    plt.xlabel('Silhouette score')
    plt.ylabel('Count')
    plt.title('Sum: {}'.format(int(Q[ii-2])))
```




[ ]:
```
plt.figure()
plt.plot(np.linspace(2,10,numClusters),Q)
plt.xlabel('Number of clusters')
plt.ylabel('Sum of silhouette scores')
plt.show()
```




[ ]:
```
c= (np.argmax(Q)+2)
#Which two features do you want to visualize
v=[0,2]
plt.figure()
indexVector = np.linspace(1,c,c)
for ii in indexVector:
    plotIndex = np.argwhere(cId == int(ii-1))
    plt.plot(u[plotIndex,v[0]],u[plotIndex,v[1]],'o',markersize=1)
    plt.
 ↪plot(cCoords[int(ii-1),v[0]],cCoords[int(ii-1),v[1]],'o',markersize=5,color='black')
    plt.xlabel('Questions')
    plt.ylabel('Loadings')
```




[ ]:
```
kMeans = KMeans(n_clusters = 2).fit(X_transformed)
y_pred=kMeans.fit_predict(X_transformed)
y_pred
```

[ ]:
```
array([1, 1, 0, …, 0, 1, 0], dtype=int32)
```

## 4 Classification

[ ]:
```
X_transformed
```

[ ]:
```
array([[-0.68586667,  4.22211143, -2.90254614, …, -0.00794661,
        -0.03772511,  0.00446646],
       [-3.10485626, -0.90270874, -0.06370912, …,  1.35767865,
         1.61343151, -0.67296464],
       [ 0.05142156, -0.92866016,  0.11505253, …, -0.00682813,
        -0.23074653, -0.88473096],
       …,
       [ 3.01196229, -1.75566116,  1.95811169, …,  0.11183981,
        -0.16458308,  0.47807674],
       [-3.01564208,  2.60628849,  2.24644421, …,  0.22466506,
         0.48897615, -1.64088123],
       [-3.37623021, -2.01326199, -2.25656654, …,  0.21549133,
         0.28330975,  0.01061068]])
```

[ ]:
```
df=pd.DataFrame(X_transformed)
df['cluster']=y_pred
df['cluster'].value_counts()
```

[ ]:
```
0    24181
1    13087
Name: cluster, dtype: int64
```

[ ]:
```
Y=X['JobSatisfaction']
Y
```

[ ]:
```
1        0.0
4        1.0
5        1.0
6        1.0
8        1.0
        ...
71523    1.0
71524    1.0
71526    1.0
71529    1.0
71530    0.0
Name: JobSatisfaction, Length: 37268, dtype: float64
```

[ ]:
```
from sklearn.ensemble import RandomForestClassifier

X_train,X_test,y_train,y_test=train_test_split(X_transformed,Y)
clf=RandomForestClassifier()
clf.fit(X_train,y_train)
# y_hat=clf.predict(X_test,y_test)
print(clf.score(X_test, y_test))
```

```
0.8573575185145433
```

[ ]:
```
from sklearn.linear_model import LogisticRegression
clf=LogisticRegression()
clf.fit(X_train,y_train)
print(clf.score(X_test, y_test))
```

```
0.8994311473650317
```

[ ]:
```
from sklearn.svm import SVC
kernels = ['linear','rbf','poly']
for kernel in kernels:
    clf=SVC(kernel=kernel)
    clf.fit(X_train,y_train)
    print(kernel,clf.score(X_test, y_test))
```

```
linear 0.8988944939358162
```

```
rbf 0.8940646130728775
poly 0.8850488354620586
```

## 5 Regression

[ ]:
```
X_new=X
X_new.shape
```

[ ]:
```
(37268, 200)
```

[ ]:
```
Y=X['ConvertedSalary']
Y
```

[ ]:
```
1         70841.0
4         21426.0
5         41671.0
6        120000.0
8        250000.0
            ...
71523    134000.0
71524    165000.0
71526     64417.0
71529    160000.0
71530    107500.0
Name: ConvertedSalary, Length: 37268, dtype: float64
```

[ ]:
```
sc=StandardScaler()
sc.fit(X_new)
X_new=sc.transform(X_new)
X_train,X_test,y_train,y_test=train_test_split(X_new,Y)
```

[ ]:
```
alphas = [0.0, 1e-8, 1e-5, 0.1, 1, 10]
alphaErrMap = {}
for alpha in alphas:
    reg = Ridge(alpha=alpha)
    reg.fit(X_train,y_train)
    df_Y_test_pred = reg.predict(X_test)
    testing_error = mean_squared_error(y_test, df_Y_test_pred)
    # iI) testing error
    print("testing error",alpha, testing_error)
    alphaErrMap[alpha] = testing_error

optimal_alpha = min(alphaErrMap, key=alphaErrMap.get)
print("optimal_alpha",optimal_alpha,alphaErrMap[optimal_alpha])
pd.DataFrame(df_Y_test_pred, y_test)
```

```
testing error 0.0 3.5958916892151516e-09
testing error 1e-08 2.365465064397852e-09
```

```
testing error 1e-05 5.800764263944243e-09
testing error 0.1 0.5800262266436259
testing error 1 57.99854344635064
testing error 10 5795.77749828278
optimal_alpha 1e-08 2.365465064397852e-09
```

[ ]:
```
                              0
ConvertedSalary
90000.0           89993.811941
134627.0         134629.529397
180000.0         179979.840193
90000.0           90017.863829
200000.0         199989.057065
…                          …
124000.0         123995.460041
54173.0           54184.950735
1000000.0        999655.461548
38184.0           38214.135324
3792.0             3798.077237

[9317 rows x 1 columns]
```

[ ]:
```
alphas = [1e-3, 1e-2, 1e-1, 1]

for alpha in alphas:
    est=make_pipeline(Lasso(alpha=alpha))
    est.fit(X_train, y_train)
    Y_hat=est.predict(X_test)
    print(est.score(X_test, y_test))
```

```
0.9999999778132607
0.9999999779628922
0.9999999793861275
0.9999999901917171
```

[ ]:
```
from sklearn.ensemble import RandomForestRegressor

regr = RandomForestRegressor()
regr.fit(X_train, y_train)
Y_hat=est.predict(X_test)
print(regr.score(X_test, y_test))
pd.DataFrame(Y_hat, y_test)
```

```
0.9999751118451585
```

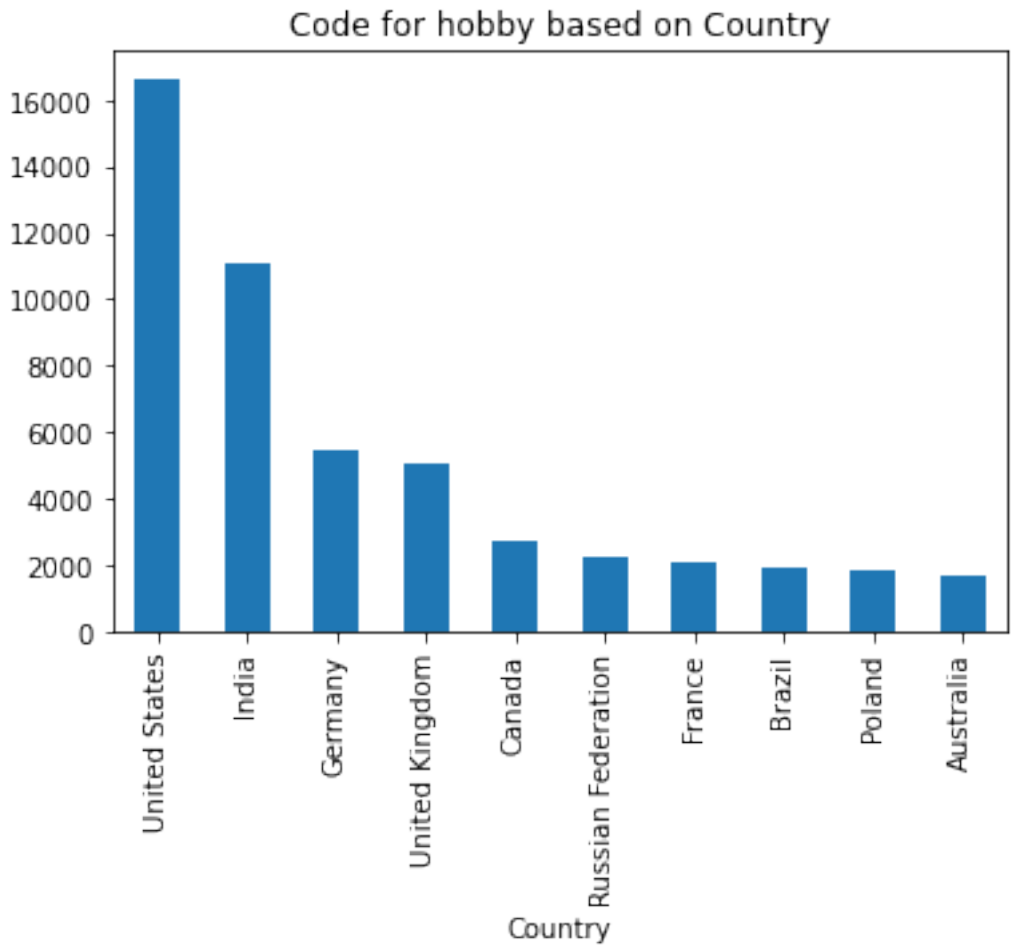
[ ]:
```
                              0
ConvertedSalary
90000.0           9.000796e+04
134627.0          1.346758e+05
```

```
180000.0          1.800376e+05
90000.0           8.999115e+04
200000.0          1.999874e+05
…                          …
124000.0          1.239851e+05
54173.0           5.418879e+04
1000000.0         1.000006e+06
38184.0           3.821488e+04
3792.0            3.780677e+03

[9317 rows x 1 columns]
```

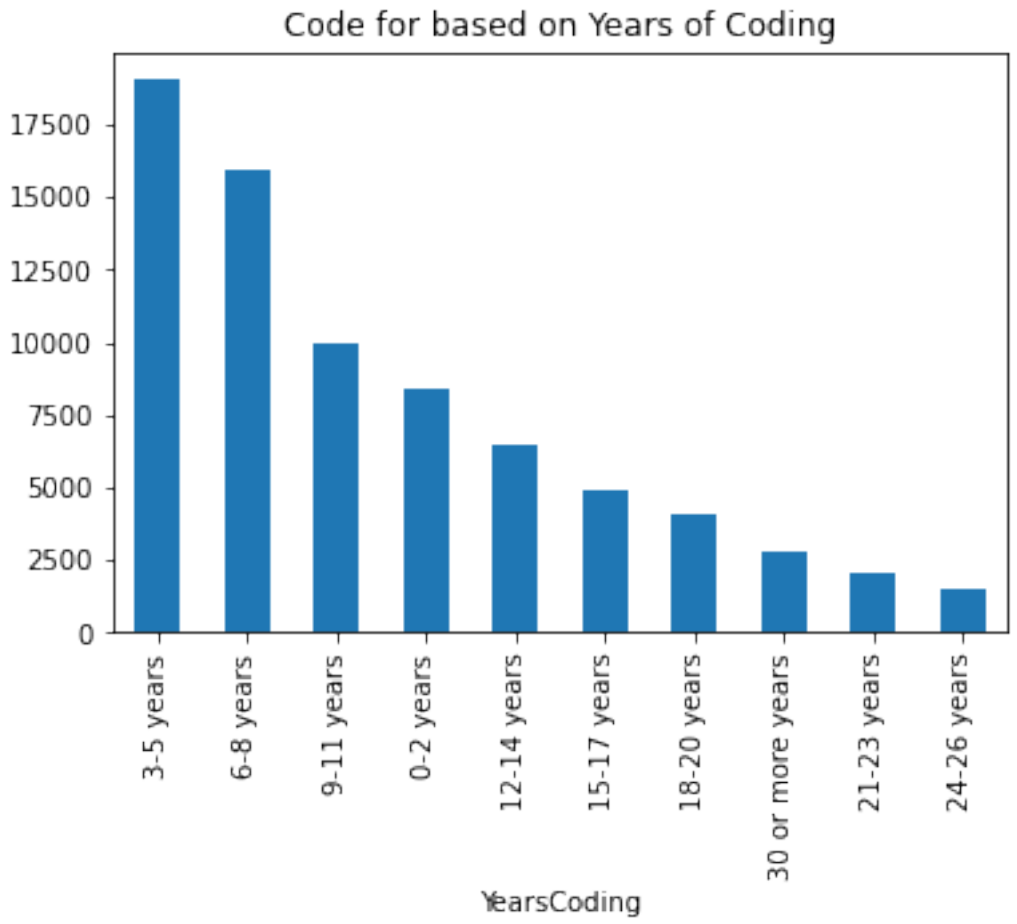
[ ]:
```
import xgboost as xgb
from sklearn.model_selection import KFold
from sklearn.model_selection import RepeatedKFold
from sklearn.model_selection import cross_val_score
from sklearn.metrics import auc, accuracy_score, confusion_matrix,␣
↪mean_squared_error

xg_reg = xgb.XGBRegressor(objective ='reg:linear', colsample_bytree = 0.3,␣
↪learning_rate = 0.1,
                max_depth = 10, alpha = 10, n_estimators = 10)
xg_reg.fit(X_train,y_train)
cv = RepeatedKFold(n_splits=10, n_repeats=3, random_state=1)
results = cross_val_score(xg_reg, X_train, y_train,␣
↪scoring='neg_mean_absolute_error', cv=cv, n_jobs=-1)
scores = np.absolute(results)
print('Mean MAE: %.3f (%.3f)' % (scores.mean(), scores.std()) )
# y_test_pred = xg_reg.predict(X_test)
# mse = mean_squared_error(y_test_pred, y_test)
# print(results, mse)
```

## 6 Summary and Conclusions(EDA)

[ ]:
```
df = pd.read_csv("stackoverflow_data.csv")
#Some facts about Does Developer Code For Hobby?
codeforHobby_df= df[df['Hobby']== 'Yes']

# Which country code for Hobby most?
codeforHobbyCountry_df= codeforHobby_df.groupby('Country').count()
codeforHobbyCountry_df.sort_values(by=['Respondent'], ascending=False,␣
↪inplace=True)

codeforHobbyCountry_df.iloc[0:10, 0].plot.bar()
plt.title('Code for hobby based on Country')
plt.show()
```

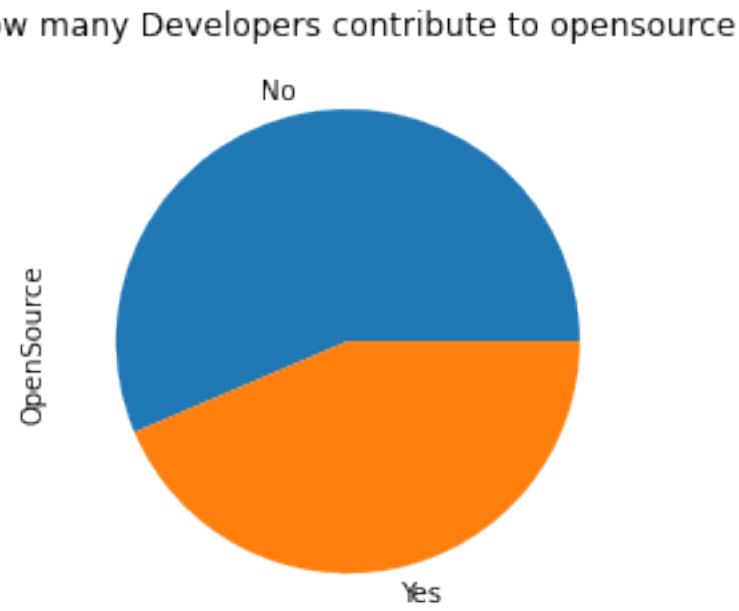



[ ]:
```
# How many years are developer coding for Hobby most?
codeforHobbyYearsCoding_df= codeforHobby_df.groupby('YearsCoding').count()
codeforHobbyYearsCoding_df.sort_values(by=['Respondent'], ascending=False,␣
 ↪inplace=True)

codeforHobbyYearsCoding_df.iloc[0:10, 0].plot.bar()
plt.title('Code for based on Years of Coding')
plt.show()
```



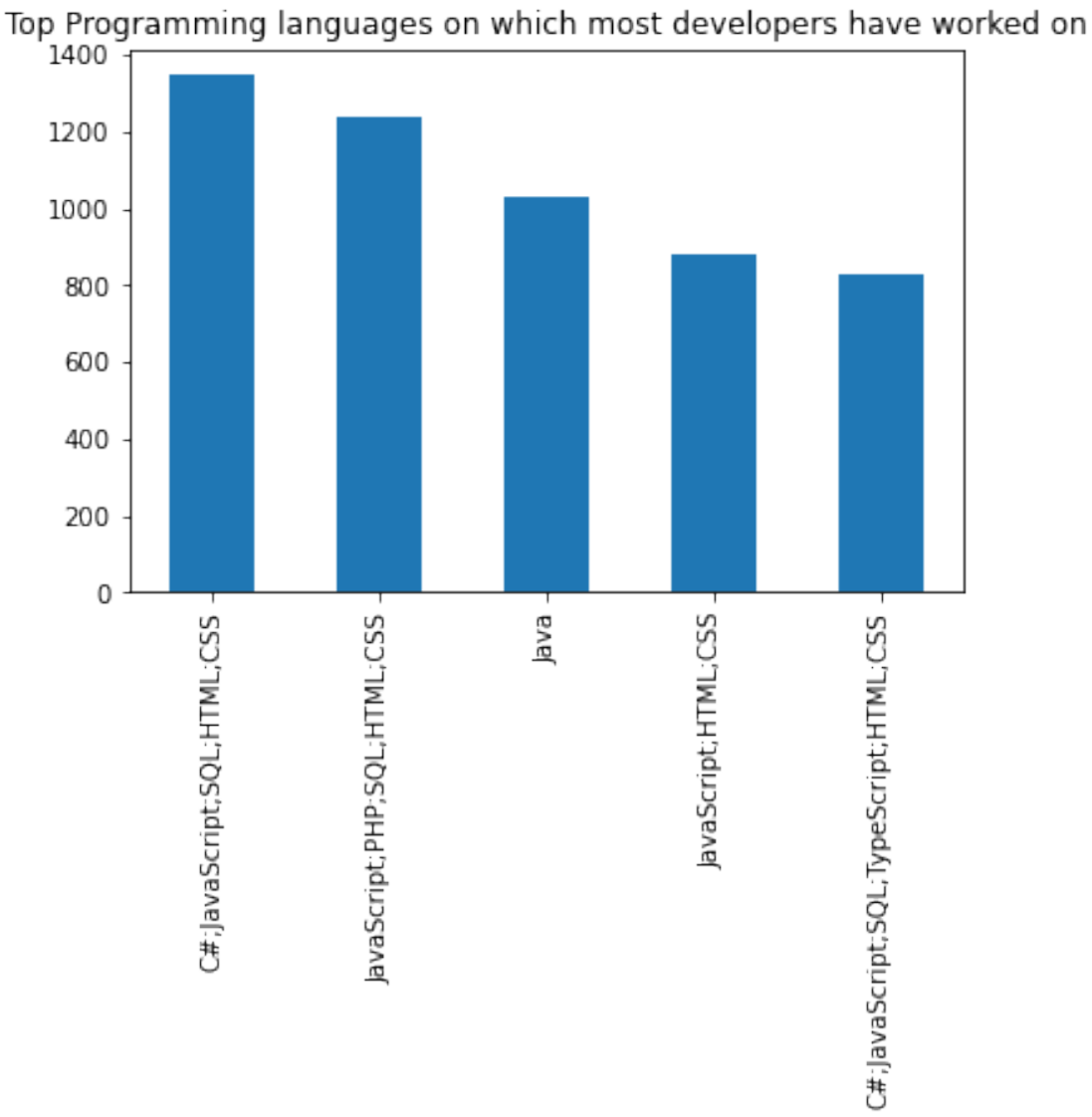

[ ]:
```
#How many Developers contribute to opensource

opensource_df= df['OpenSource'].value_counts()
opensource_df.plot.pie()
plt.title('How many Developers contribute to opensource')
```

[ ]: Text(0.5, 1.0, 'How many Developers contribute to opensource')



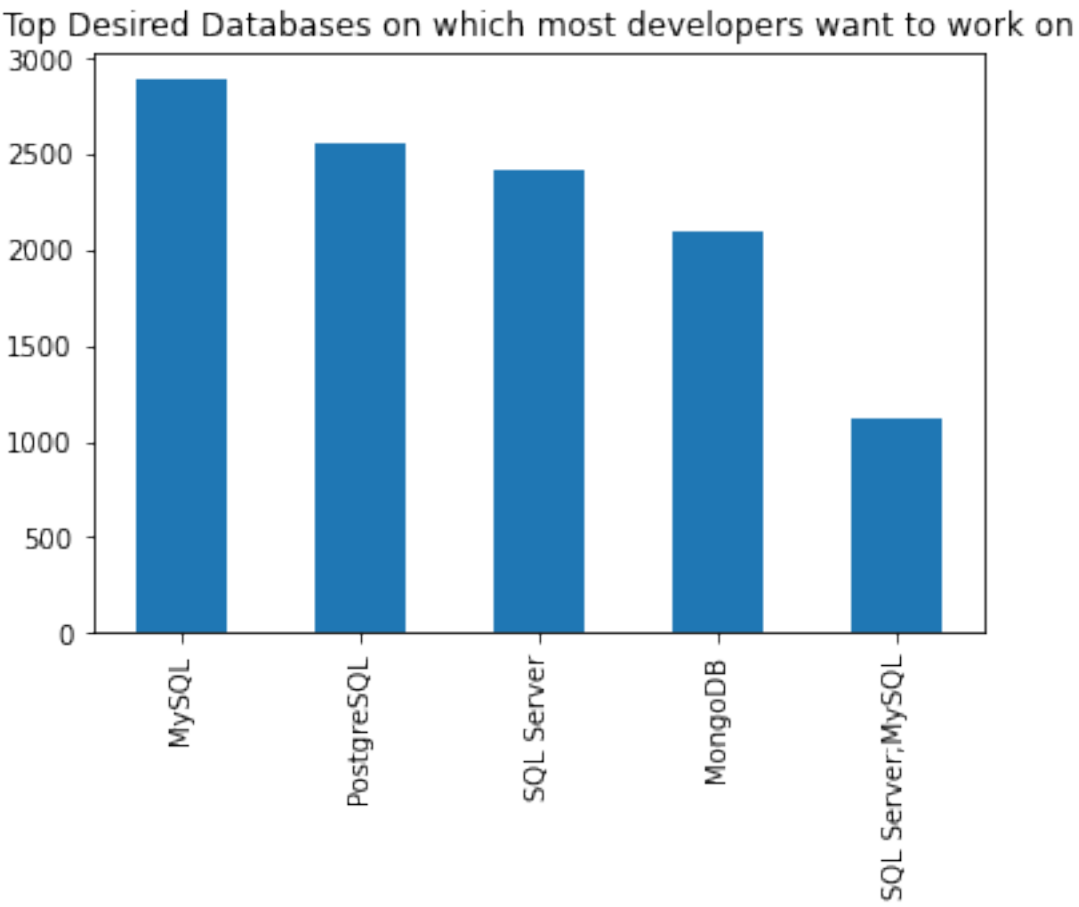

[ ]:
```
#Top Programming languages on which most developers have worked on
language_df= df['LanguageWorkedWith'].value_counts()
language_df.iloc[0:5].plot.bar()
plt.title('Top Programming languages on which most developers have worked on')
```

[ ]:
```
Text(0.5, 1.0, 'Top Programming languages on which most developers have worked
on')
```



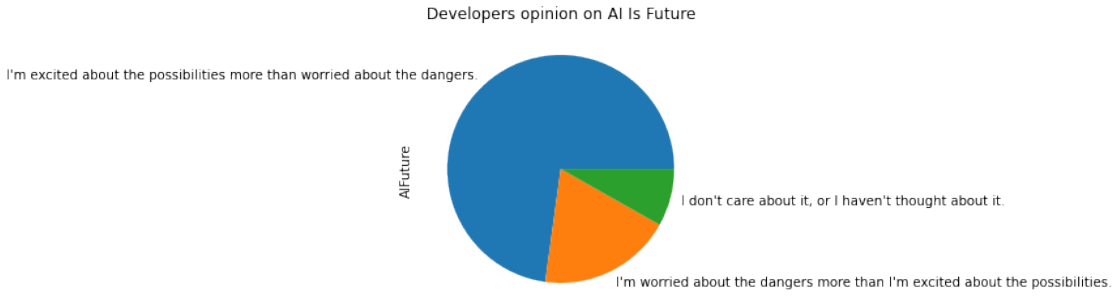

[ ]:
```
#Top Desired Databases on which most developers want to work on
desiredDatabase_df=df['DatabaseDesireNextYear'].value_counts()
desiredDatabase_df.iloc[0:5].plot.bar()
plt.title('Top Desired Databases on which most developers want to work on')
```

[ ]:
```
Text(0.5, 1.0, 'Top Desired Databases on which most developers want to work on')
```




[ ]:
```
#Something about AI
#What Does Developer think about 'AI is Future'?

AI_df= df['AIFuture'].value_counts()
AI_df.plot.pie()
plt.title('Developers opinion on AI Is Future')
```

[ ]:
```
Text(0.5, 1.0, 'Developers opinion on AI Is Future')
```



[ ]:
```
# Top countries with Female developers

female_df= df.groupby('Country')['Gender', 'Respondent'].count()
female_df.sort_values(by=['Gender'], ascending=False, inplace=True)

female_df.iloc[0:10, 0].plot.bar()
plt.title('Top countries with Female developers ')
plt.show()
```