Assignment 3: K-means Clustering Algorithm with Python

Section: ZBB
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Clustering

The purpose of this assignment is to use Python to learn how to perform K-means clustering in Python, and find the optimal value of K.

Instructions

Using Python, you are to complete the following questions. Please submit your answers (CODE USED AND OUTPUT) as PDF files.

Please answer following questions:

1. Find your preferred dataset from Kaggle which is appropriate for an unsupervised learning problem. https://www.kaggle.com/

   Dataset used for this assignment is from IBM HR Analytics Attrition.

1. Explore the dataset and provide information about that. You are free to use any preprocessing tools that you want. You can explain the problem and the purpose of the dataset. Visualizing is the best approach to exploring the dataset.

   This dataset contains the details of 1,470 IBM employees which includes seniority level, satisfaction rates as well as their attrition data. This dataset could be used by Human Resource department to analyze the performance and satisfaction of employees. It could also help in identifying contributing factors that lead to employees leaving the organization. Kmeans clustering will aim to identify groups of employees with similar attributes. This classification model could be used for further analysis and model building to better predict employee attrition rate.

1. Perform K-means clustering algorithm on your dataset with a range of values for K to choose the optimal value with Elbow method.

   - Import K-means from sklearn.cluster.
   - Apply K-means on the dataset and get y_pred.
   - Calculate the WSS. You can write your own function or get the inertia_ attribute from the fitted model.
   - Calculate the silhouette score by using: silhouette_score(X(actual), y_kmeans(predicted)).
   - Plot the values of K vs WSS.
   - Plot the output clusters with the optimal K.
   - Plot the centers of the clusters on the previous plot and show the centroids with a larger size.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
```

Data Importing

In [2]:
```
# Importing the IBM HR Analytics Attrition dataset
Attr_df = pd.read_csv("Attrition.csv")
Attr_df.head()
```

Out[2]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeNumber	...	Rela
0	41	Yes	Travel_Rarely	1102	Sales	1	2	Life Sciences	1	1	...	
1	49	No	Travel_Frequently	279	Research & Development	8	1	Life Sciences	1	2	...	
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	Other	1	4	...	
3	33	No	Travel_Frequently	1392	Research & Development	3	4	Life Sciences	1	5	...	
4	27	No	Travel_Rarely	591	Research & Development	2	1	Medical	1	7	...	

5 rows × 35 columns

Data Preprocessing

In [3]:

```
Attr_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1470 entries, 0 to 1469
Data columns (total 35 columns):
 #   Column                    Non-Null Count  Dtype 
---  ------                    --------------  ----- 
 0   Age                       1470 non-null   int64 
 1   Attrition                 1470 non-null   object
 2   BusinessTravel            1470 non-null   object
 3   DailyRate                 1470 non-null   int64 
 4   Department                1470 non-null   object
 5   DistanceFromHome          1470 non-null   int64 
 6   Education                 1470 non-null   int64 
 7   EducationField            1470 non-null   object
 8   EmployeeCount             1470 non-null   int64 
 9   EmployeeNumber            1470 non-null   int64 
 10  EnvironmentSatisfaction   1470 non-null   int64 
 11  Gender                    1470 non-null   object
 12  HourlyRate                1470 non-null   int64 
 13  JobInvolvement            1470 non-null   int64 
 14  JobLevel                  1470 non-null   int64 
 15  JobRole                   1470 non-null   object
 16  JobSatisfaction           1470 non-null   int64 
 17  MaritalStatus             1470 non-null   object
 18  MonthlyIncome             1470 non-null   int64 
 19  MonthlyRate               1470 non-null   int64 
 20  NumCompaniesWorked        1470 non-null   int64 
 21  Over18                    1470 non-null   object
 22  OverTime                  1470 non-null   object
 23  PercentSalaryHike         1470 non-null   int64 
 24  PerformanceRating         1470 non-null   int64 
 25  RelationshipSatisfaction  1470 non-null   int64 
 26  StandardHours             1470 non-null   int64 
 27  StockOptionLevel          1470 non-null   int64 
 28  TotalWorkingYears         1470 non-null   int64 
 29  TrainingTimesLastYear     1470 non-null   int64 
 30  WorkLifeBalance           1470 non-null   int64 
 31  YearsAtCompany            1470 non-null   int64 
 32  YearsInCurrentRole        1470 non-null   int64 
 33  YearsSinceLastPromotion   1470 non-null   int64 
 34  YearsWithCurrManager      1470 non-null   int64 
dtypes: int64(26), object(9)
memory usage: 402.1+ KB
```

In [4]:

```
# drop unneccessary variables: EmployeeCount, EmployeeNumber, StandardHours, Over18
Attr_df.drop(['EmployeeCount','EmployeeNumber', 'StandardHours', 'Over18'], axis=1, inplace=True)

Attr_df.shape
```

Out[4]:

```
(1470, 31)
```

In [5]:

```
# check if there are any Missing data points
Attr_df.isna().sum()
```

Out[5]:
```
Age                         0
Attrition                   0
BusinessTravel              0
DailyRate                   0
Department                  0
DistanceFromHome            0
Education                   0
EducationField              0
EnvironmentSatisfaction     0
Gender                      0
HourlyRate                  0
JobInvolvement              0
JobLevel                    0
JobRole                     0
JobSatisfaction             0
MaritalStatus               0
MonthlyIncome               0
MonthlyRate                 0
NumCompaniesWorked          0
OverTime                    0
PercentSalaryHike           0
PerformanceRating           0
RelationshipSatisfaction    0
StockOptionLevel            0
TotalWorkingYears           0
TrainingTimesLastYear       0
WorkLifeBalance             0
YearsAtCompany              0
YearsInCurrentRole          0
YearsSinceLastPromotion     0
YearsWithCurrManager        0
dtype: int64
```

In [6]:
```python
# Transform categorical into numerical variable using label encoder
from sklearn.preprocessing import LabelEncoder
label_encoder = LabelEncoder()

categorical = Attr_df.select_dtypes(include='object').columns

print('Transforming the following {} Categorical variables into numerical:'.format(len(categorical)))

for i in categorical:
    print(i)
    Attr_df[i]=label_encoder.fit_transform(Attr_df[i]).astype('int64')

Attr_df[categorical].head().style.hide_index()
```

```
Transforming the following 8 Categorical variables into numerical:
Attrition
BusinessTravel
Department
EducationField
Gender
JobRole
MaritalStatus
OverTime
```

Out[6]:

Attrition	BusinessTravel	Department	EducationField	Gender	JobRole	MaritalStatus	OverTime
1	2	2	1	0	7	2	1
0	1	1	1	1	6	1	0
1	2	1	4	1	2	2	1
0	1	1	1	0	6	1	1
0	2	1	3	1	2	1	0

In [7]:
```python
Attr_df.dtypes
```

Out[7]:

```
Age                         int64
Attrition                   int64
BusinessTravel              int64
DailyRate                   int64
Department                  int64
DistanceFromHome            int64
Education                   int64
EducationField              int64
EnvironmentSatisfaction     int64
Gender                      int64
HourlyRate                  int64
JobInvolvement              int64
JobLevel                    int64
JobRole                     int64
JobSatisfaction             int64
MaritalStatus               int64
MonthlyIncome               int64
MonthlyRate                 int64
NumCompaniesWorked          int64
OverTime                    int64
PercentSalaryHike           int64
PerformanceRating           int64
RelationshipSatisfaction    int64
StockOptionLevel            int64
TotalWorkingYears           int64
TrainingTimesLastYear       int64
WorkLifeBalance             int64
YearsAtCompany              int64
YearsInCurrentRole          int64
YearsSinceLastPromotion     int64
YearsWithCurrManager        int64
dtype: object
```

In [8]:

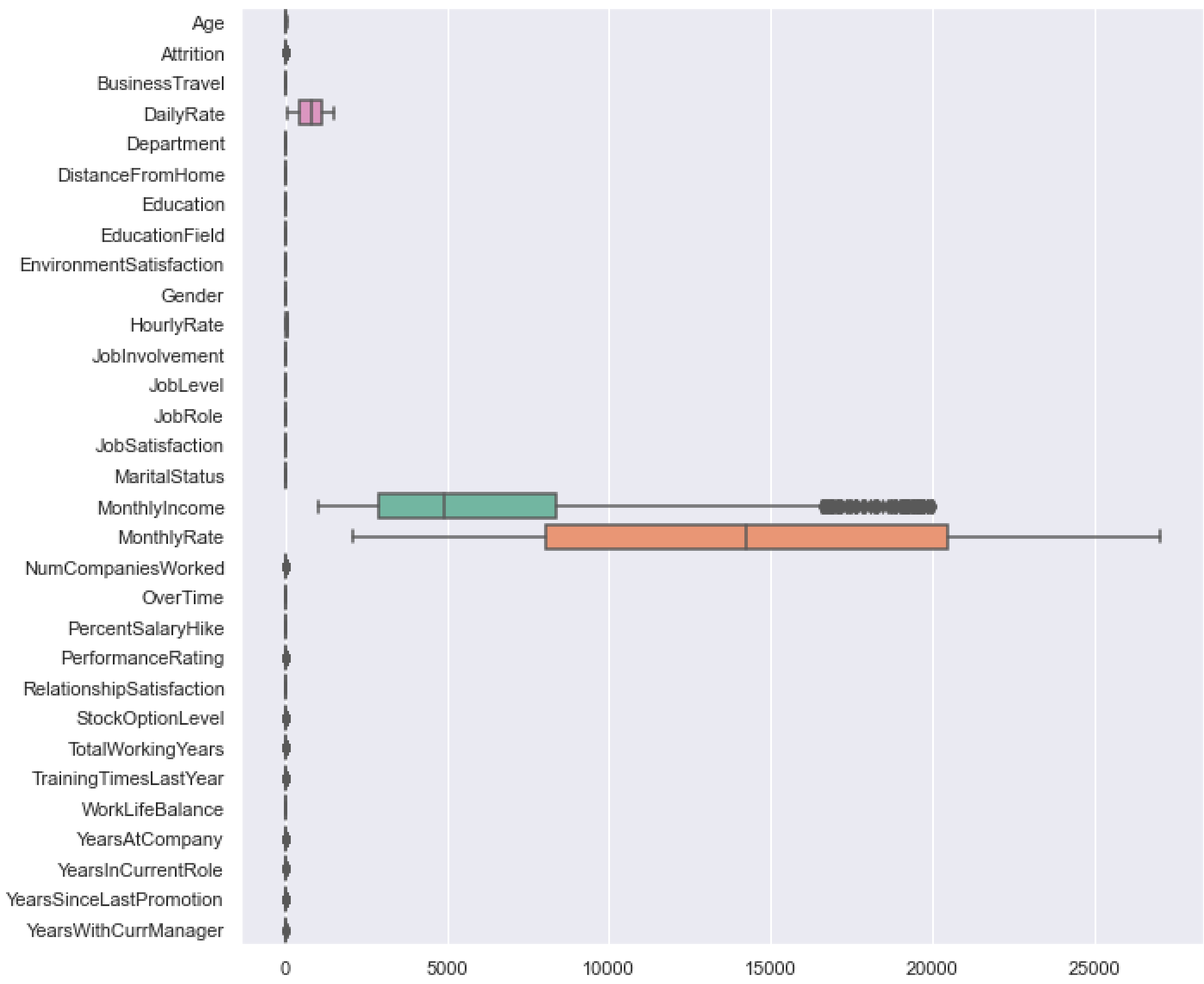
```
# check unique values per column
Attr_df.nunique()
```

Out[8]:

```
Age                           43
Attrition                      2
BusinessTravel                 3
DailyRate                    886
Department                     3
DistanceFromHome              29
Education                      5
EducationField                 6
EnvironmentSatisfaction        4
Gender                         2
HourlyRate                    71
JobInvolvement                 4
JobLevel                       5
JobRole                        9
JobSatisfaction                4
MaritalStatus                  3
MonthlyIncome               1349
MonthlyRate                 1427
NumCompaniesWorked            10
OverTime                       2
PercentSalaryHike             15
PerformanceRating              2
RelationshipSatisfaction       4
StockOptionLevel               4
TotalWorkingYears             40
TrainingTimesLastYear          7
WorkLifeBalance                4
YearsAtCompany                37
YearsInCurrentRole            19
YearsSinceLastPromotion       16
YearsWithCurrManager          18
dtype: int64
```

In [9]:

```
# boxplot
df_1= Attr_df.loc[:, Attr_df.columns]

sns.set(rc={'figure.figsize':(10,10)})
sns.boxplot(data=df_1, orient="h", palette="Set2");
```



Data Scaling

In [10]:

```
# Scaling
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
scaler.fit(df_1)
scaled_df1 = pd.DataFrame(scaler.transform(df_1),columns= df_1.columns)
scaled_df1.head()
```

Out[10]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EnvironmentSatisfaction	Gender	...
0	0.446350	2.280906	0.590048	0.742527	1.401512	-1.010909	-0.891688	-0.937414	-0.660531	-1.224745	...
1	1.322365	-0.438422	-0.913194	-1.297775	-0.493817	-0.147150	-1.868426	-0.937414	0.254625	0.816497	...
2	0.008343	2.280906	0.590048	1.414363	-0.493817	-0.887515	-0.891688	1.316673	1.169781	0.816497	...
3	-0.429664	-0.438422	-0.913194	1.461466	-0.493817	-0.764121	1.061787	-0.937414	1.169781	-1.224745	...
4	-1.086676	-0.438422	0.590048	-0.524295	-0.493817	-0.887515	-1.868426	0.565311	-1.575686	0.816497	...

5 rows × 31 columns

Feature Selection

In [11]:

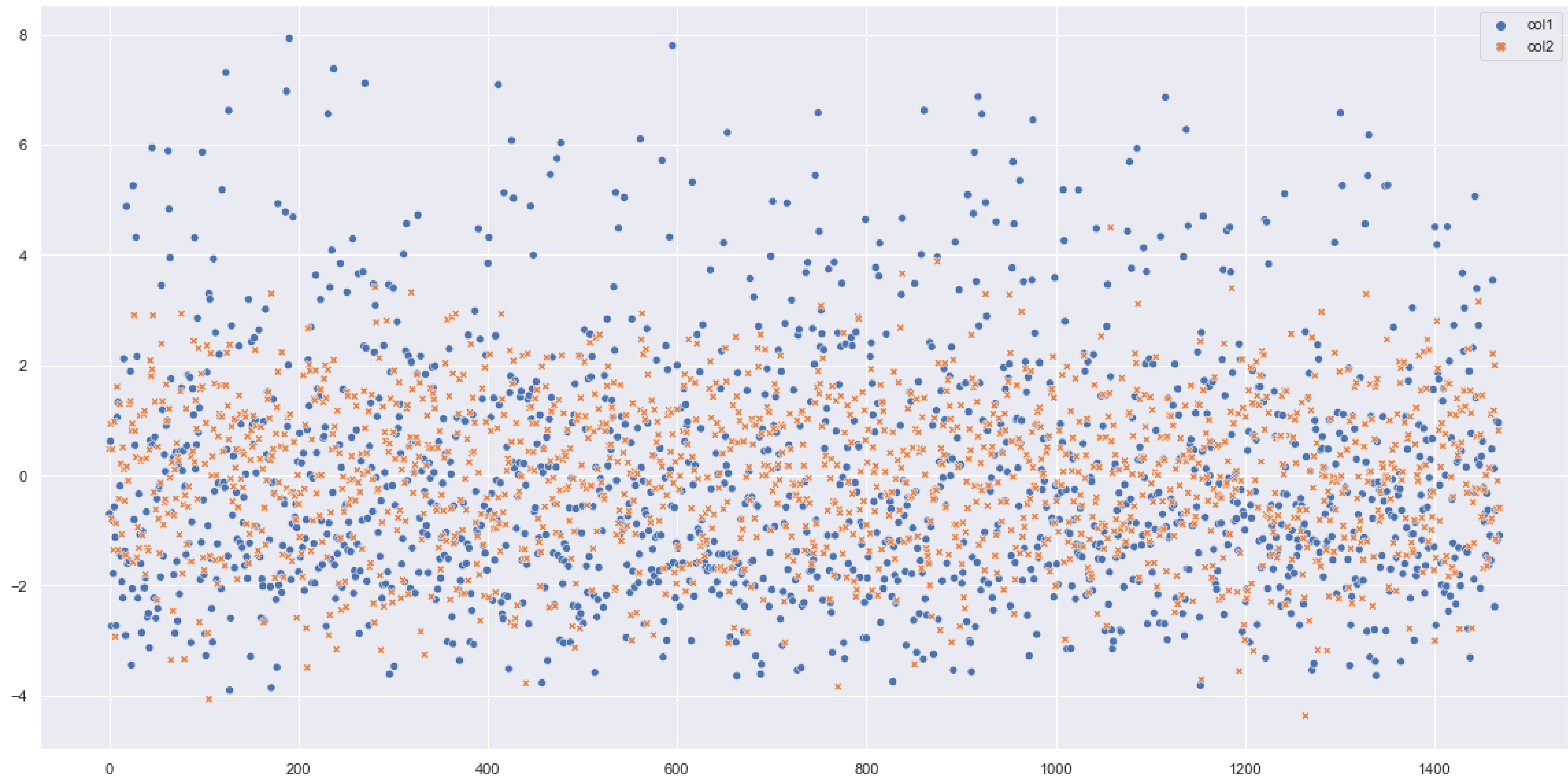
```
#PCA: reduce features to 2 dimension only
from sklearn.decomposition import PCA

pca_attr = PCA(n_components=2)
pca_attr.fit(scaled_df1)
PCA_df1 = pd.DataFrame(pca_attr.transform(scaled_df1), columns=(["col1","col2"]))
PCA_df1.describe().T
```

Out[11]:

	count	mean	std	min	25%	50%	75%	max
col1	1470.0	7.099385e-18	2.176639	-3.901737	-1.586664	-0.400616	1.097578	7.927667
col2	1470.0	-5.452932e-17	1.382002	-4.368912	-0.981629	0.034401	1.030095	4.495623

In [12]:

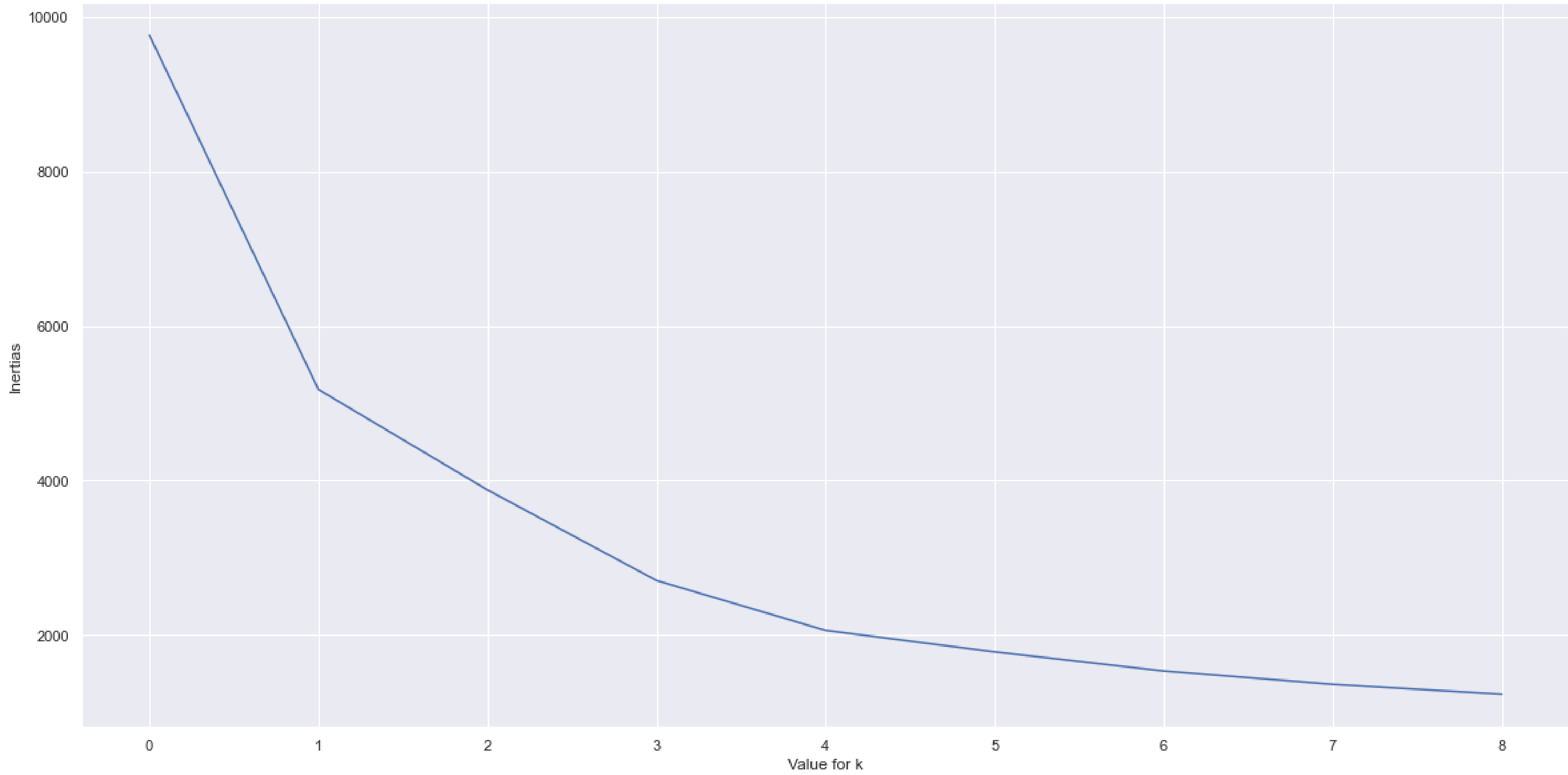
```
# original data set but reduced dimension scatter plot
sns.set(rc={'figure.figsize':(20,10)})
sns.scatterplot(data=PCA_df1);
```



Data Clustering

In [13]:
```
inertia = {}

for i in range(1, 10):
    kmeans = KMeans(n_clusters=i, max_iter=1000)
    kmeans.fit(PCA_df1)
    inertia[i] = kmeans.inertia_

for k, v in inertia.items():
    print(str(k), ': ', str(round(v,2)))


# Plot for each K value
plt.subplots()
plt.plot(list(inertia.values()))
plt.xlabel("Value for k")
plt.ylabel("Inertias")
plt.show()
```

```
1 :  9765.46
2 :  5178.18
3 :  3877.85
4 :  2705.24
5 :  2059.29
6 :  1781.74
7 :  1534.08
8 :  1361.41
9 :  1233.85
```



In [14]:
```
kmeans = KMeans(n_clusters=4 , n_init=15, random_state=10)
kmeans.fit(PCA_df1)
```

Out[14]: KMeans(n_clusters=4, n_init=15, random_state=10)

In [15]:
```
centroids = kmeans.cluster_centers_
labels = kmeans.labels_
pred_clusters = kmeans.predict(PCA_df1)
```

In [16]:
```
# inertia score
print('\nInertia in the K-means clustering',round(kmeans.inertia_,2))

#silhoutte score
print('\nSilhoutte score for K-means clustering',round(silhouette_score(PCA_df1,pred_clusters),4))
```

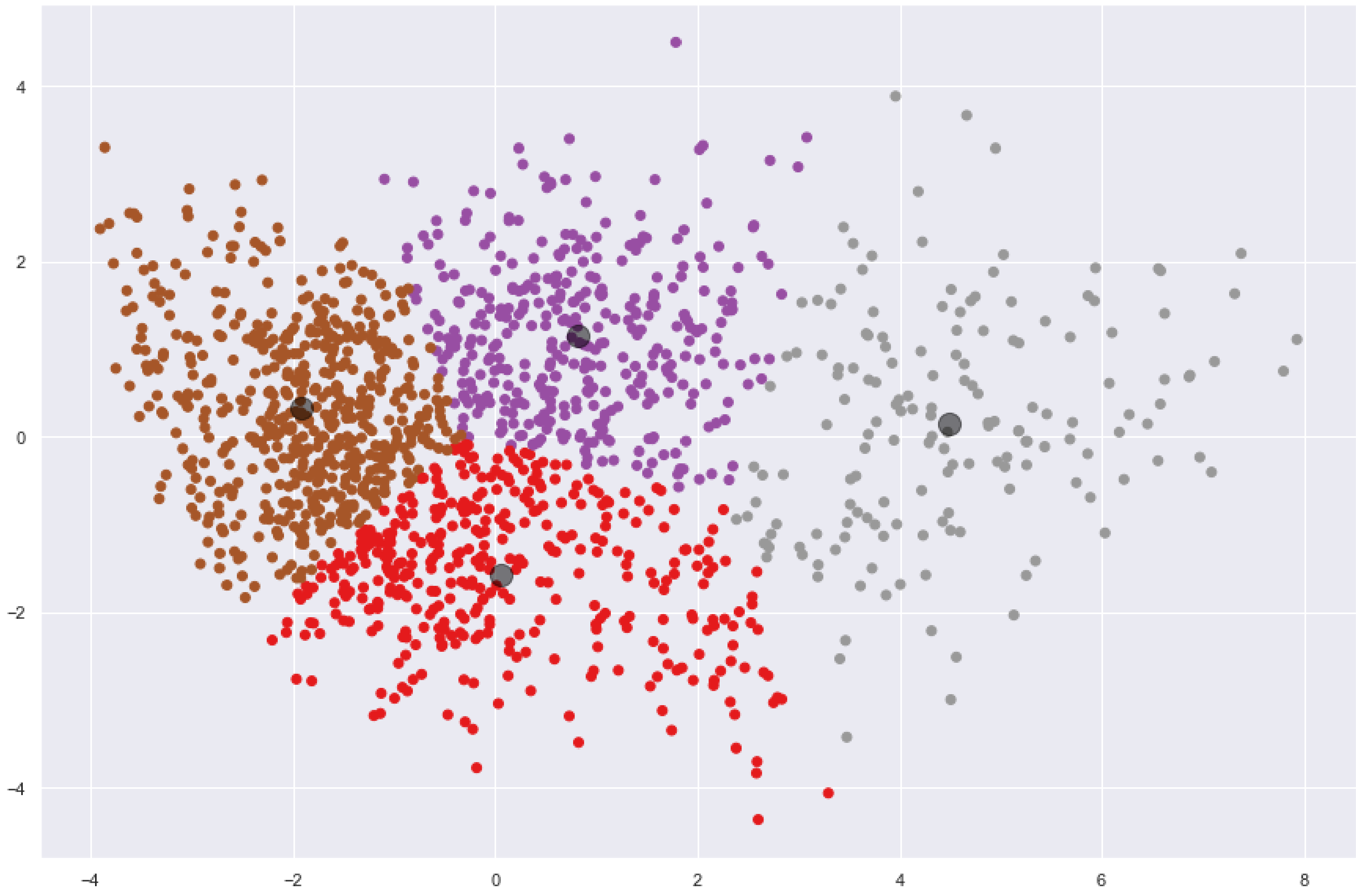
```
Inertia in the K-means clustering 2705.24

Silhoutte score for K-means clustering 0.3835
```

In [17]:
```
# dataframe with label attached for kmeans clustering
Attr_dfkmean = PCA_df1.copy()
Attr_dfkmean['label'] = labels
Attr_dfkmean.head()
```

Out[17]:

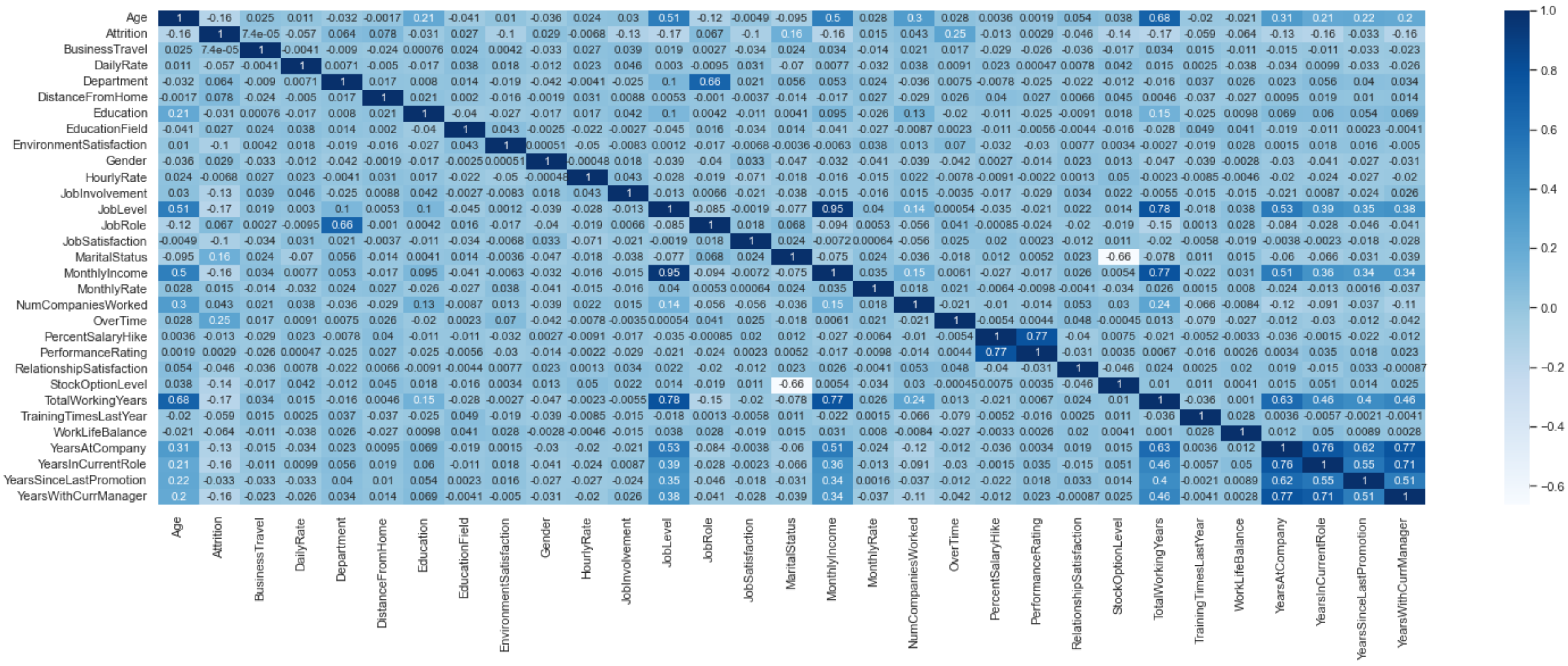
	col1	col2	label
0	-0.696076	0.478191	2
1	0.616857	0.929435	1
2	-2.735275	-0.788440	2
3	-0.822928	0.469346	2
4	-1.786719	-1.355992	2

In [18]:
```
plt.figure(figsize=(15,10))
plt.scatter(Attr_dfkmean[Attr_dfkmean.columns[0]],Attr_dfkmean[Attr_dfkmean.columns[1]],c=kmeans.labels_ , cmap=plt.cm.Set1)
plt.scatter(centroids[:, 0], centroids[:, 1], c='black', s=200, alpha=0.5)
plt.show()
```



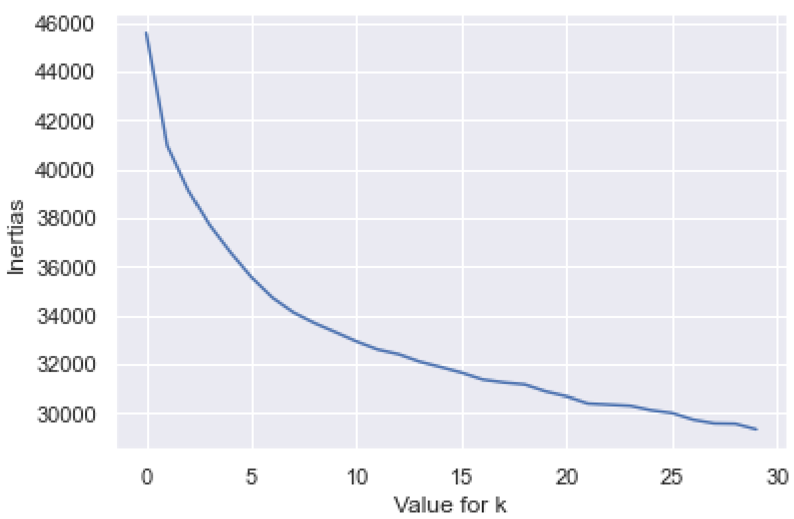
KMeans without PCA

In [19]:
```
%matplotlib inline
plt.figure(figsize=(25,8))
sns.heatmap(scaled_df1.corr(),annot=True,cmap='Blues');
```



In [20]:
```python
inertia = {}

for i in range(1, 31):
    kmeans = KMeans(n_clusters=i, max_iter=1000)
    kmeans.fit(scaled_df1)
    inertia[i] = kmeans.inertia_

for k, v in inertia.items():
    print(str(k), ': ', str(round(v,2)))


# Plot for each K value
plt.subplots()
plt.plot(list(inertia.values()))
plt.xlabel("Value for k")
plt.ylabel("Inertias")
plt.show()
```

```
1 :  45570.0
2 :  40965.41
3 :  39119.87
4 :  37702.47
5 :  36567.85
6 :  35545.92
7 :  34709.66
8 :  34102.06
9 :  33669.48
10 :  33294.31
11 :  32913.86
12 :  32585.57
13 :  32391.24
14 :  32084.9
15 :  31864.9
16 :  31634.6
17 :  31351.17
18 :  31232.45
19 :  31151.88
20 :  30865.84
21 :  30666.56
22 :  30385.04
23 :  30337.12
24 :  30291.81
25 :  30107.95
26 :  29994.41
27 :  29719.03
28 :  29569.76
29 :  29554.96
30 :  29325.69
```



In [21]:
```python
kmeans = KMeans(n_clusters=11 , n_init=15, random_state=10)
kmeans.fit(scaled_df1)
```

Out[21]:
```
KMeans(n_clusters=11, n_init=15, random_state=10)
```

In [22]:
```
centroids = kmeans.cluster_centers_
pred_clusters = kmeans.predict(scaled_df1)
labels = kmeans.labels_
```

In [23]:
```
# inertia score
print('\nInertia in the K-means clustering',round(kmeans.inertia_,2))

# silhoutte score
print('\nSilhoutte score for K-means clustering',round(silhouette_score(scaled_df1,pred_clusters),4))
```

```
Inertia in the K-means clustering 32879.26

Silhoutte score for K-means clustering 0.0466
```

In [24]:
```
scaled_df1['cluster_kmeans'] = labels
scaled_df1.head()
```

Out[24]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EnvironmentSatisfaction	Gender	...	I
0	0.446350	2.280906	0.590048	0.742527	1.401512	-1.010909	-0.891688	-0.937414	-0.660531	-1.224745	...	
1	1.322365	-0.438422	-0.913194	-1.297775	-0.493817	-0.147150	-1.868426	-0.937414	0.254625	0.816497	...	
2	0.008343	2.280906	0.590048	1.414363	-0.493817	-0.887515	-0.891688	1.316673	1.169781	0.816497	...	
3	-0.429664	-0.438422	-0.913194	1.461466	-0.493817	-0.764121	1.061787	-0.937414	1.169781	-1.224745	...	
4	-1.086676	-0.438422	0.590048	-0.524295	-0.493817	-0.887515	-1.868426	0.565311	-1.575686	0.816497	...	

5 rows × 32 columns

In [25]:
```
fig, axs = plt.subplots(1,3, figsize = (20,5))

plt.subplot(1,3,1)
sns.scatterplot(data=scaled_df1, x="MonthlyIncome", y="JobLevel", hue="cluster_kmeans");

plt.subplot(1,3,2)
sns.scatterplot(data=scaled_df1, x="PercentSalaryHike", y="PerformanceRating", hue="cluster_kmeans");

plt.subplot(1,3,3)
sns.scatterplot(data=scaled_df1, x="TotalWorkingYears", y="JobLevel", hue="cluster_kmeans");
```