```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import plot_tree
from sklearn.decomposition import PCA
import seaborn as sns

from ipywidgets import interact, FloatSlider, widgets

import plotly.express as px

pd.set_option('display.max_columns', None)
```

# HW:

The data set includes the churn of customers of a telecommunications company. The task is to create segments from customers based on their characteristics using the KMeans algorithm.

Do not use the following variables for grouping:

- churn?: has the customer dropped out?
- Contract_date: contract conclusion time
- Cust_ID: customer ID

```
file_path = "./telco_sampled.csv"
df = pd.read_csv(file_path, sep = ';')

df.head()

       Contract_date Package   Gender   Age Marital_Status
Living_Condition  \
0   9/20/04 12:00 AM  PACK_B    Male  42.0        Married
Owner
1   2/12/05 12:00 AM  PACK_B  Female  53.0        Married
Owner
2  10/19/04 12:00 AM  PACK_X    Male  43.0        Married
Owner
3  10/31/04 12:00 AM  PACK_B    Male  32.0        Married
Owner
4  11/19/04 12:00 AM  PACK_B  Female  31.0        Married
Owner

   Graduation         Job_Type     Income  Peak_minute_09
Weekend_minute_09   \
0  University           Leader     15_30k            0.55
0.28
```

```
1  University  Public_Employee  Below_15k           11.32
6.53
2  Highschool        Executive     30_60k           78.05
3.90
3  Highschool         Labourer     15_30k            0.08
0.00
4  Highschool  Public_Employee     30_60k           20.68
13.87

   Offpeak_minute_09  Offpeak_nr_09  Peak_nr_09  Weekend_nr_09  \
0               0.00            0.0         2.0            1.0
1               6.98           26.0        37.0           19.0
2               8.43            5.0       103.0            9.0
3               0.00            0.0         1.0            0.0
4              33.27           49.0        30.0           26.0

   Selfnet_minute_09  Fixed_minute_09  Othermob_minute_09
Voicemail_nr_09  \
0               0.83             0.00                0.00
3.0
1               6.70             8.02               10.12
21.0
2              19.67             2.83               67.88
116.0
3               0.08             0.00                0.00
1.0
4              37.90             0.53               23.02
79.0

   Voicemail_minute_09  SMS_09  Peak_minute_10  Weekend_minute_10  \
0                 0.83     0.0            0.00               0.00
1                21.90    58.0           25.70               5.28
2                90.38     1.0           24.30              15.53
3                 0.08     0.0            0.00               0.00
4                67.82    26.0           42.08              24.48

   Offpeak_minute_10  Offpeak_nr_10  Peak_nr_10  Weekend_nr_10  \
0               0.00            0.0         0.0            0.0
1              15.38           52.0        77.0           32.0
2               2.63            9.0        40.0           16.0
3               0.00            0.0         0.0            0.0
4              31.10           39.0        56.0           28.0

   Selfnet_minute_10  Fixed_minute_10  Othermob_minute_10
Voicemail_nr_10  \
0               0.00             0.00                0.00
0.0
1              11.07            12.80               22.50
30.0
2              17.15             1.68               23.35
```

```
65.0
3               0.00              0.00                0.00
0.0
4              65.58              1.53               26.10
100.0

   Voicemail_minute_10  SMS_10  Peak_minute_11  Weekend_minute_11  \
0                 0.00     0.0            0.00               0.00
1                37.33   128.0           25.33               0.00
2                42.47     0.0           55.27               1.27
3                 0.00     0.0            0.00               0.00
4                97.67    23.0           31.52              28.27

   Offpeak_minute_11  Offpeak_nr_11  Peak_nr_11  Weekend_nr_11  \
0               0.00            0.0         0.0            0.0
1               7.60           51.0        49.0           20.0
2               1.75            7.0        64.0            4.0
3               0.00            0.0         0.0            0.0
4              28.37           33.0        48.0           46.0

   Selfnet_minute_11  Fixed_minute_11  Othermob_minute_11
Voicemail_nr_11  \
0               0.00             0.00                0.00
0.0
1               1.83            14.52               16.58
36.0
2               6.63            15.45               36.20
74.0
3               0.00             0.00                0.00
0.0
4              50.80             0.62               31.17
103.0

   Voicemail_minute_11  SMS_11  Peak_minute_12  Weekend_minute_12  \
0                 0.00     0.0            0.00               0.00
1                32.93    83.0           11.95               3.60
2                58.28     1.0            9.97               8.65
3                 0.00     0.0            0.00               0.00
4                86.70    21.0           49.68              35.90

   Offpeak_minute_12  Offpeak_nr_12  Peak_nr_12  Weekend_nr_12  \
0               0.00            0.0         0.0            0.0
1               4.28           25.0        40.0           25.0
2               4.23            3.0        22.0           18.0
3               0.00            0.0         0.0            0.0
4              29.45           69.0        78.0           47.0

   Selfnet_minute_12  Fixed_minute_12  Othermob_minute_12
Voicemail_nr_12  \
0               0.00             0.00                0.00
```

```
0.0
1                0.93             6.20                  12.70
21.0
2                2.98             0.38                   9.40
31.0
3                0.00             0.00                   0.00
0.0
4               71.17             2.13                  31.05
121.0

   Voicemail_minute_12  SMS_12  churn?    Cust_ID
0                 0.00     0.0       0  ID0020614
1                19.83    66.0       0  ID0029505
2                22.07    12.0       0  ID0050206
3                 0.00     0.0       0  ID0050343
4               111.40    64.0       0  ID0050688
```

```
df['churn?'].value_counts()
```

```
churn?
0    1224
1     341
Name: count, dtype: int64
```

# 1. Subtask: (data preparation)

Use all variables except for the three variables above when creating the clusters. Perform data preparation so that the variables are input to the model in the appropriate form.

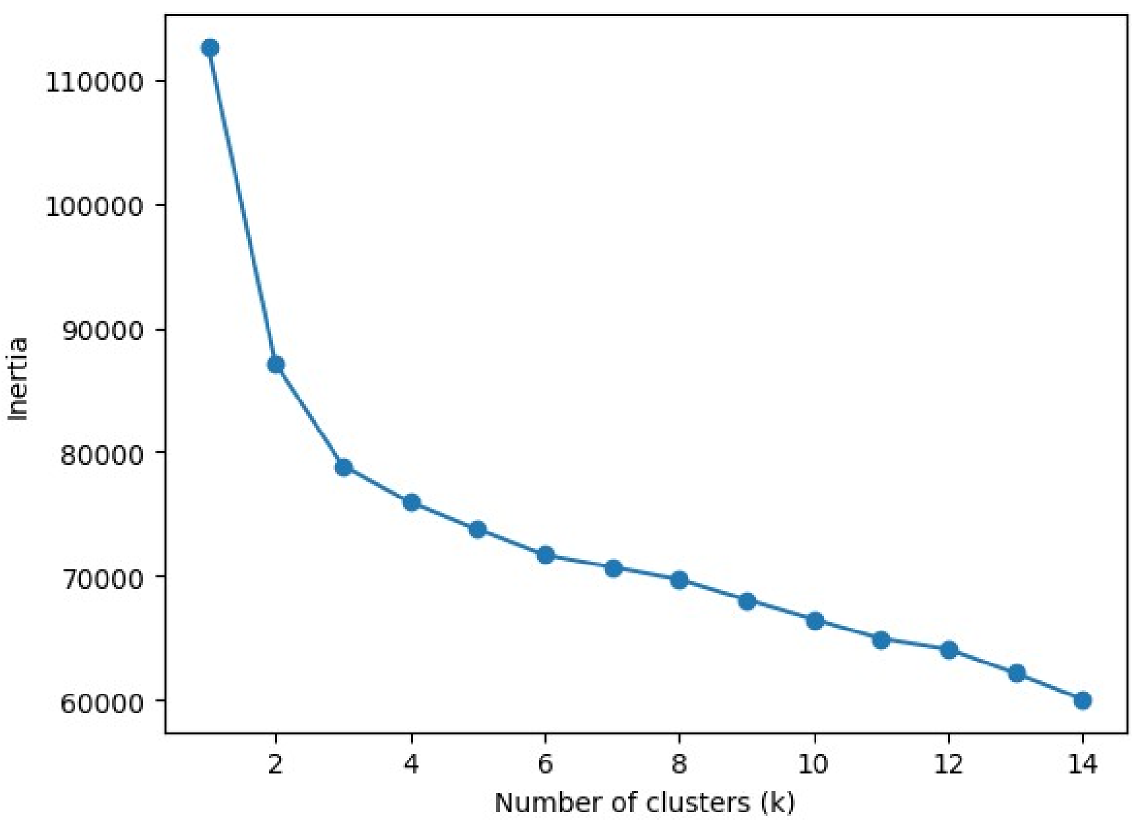
(hint: categorical variables, missing values, scaling, etc.)

```
# Exclude unnecessary columns
df = df.drop(['churn?', 'Contract_date', 'Cust_ID'], axis=1)

# Handle categorical variables
df = pd.get_dummies(df, drop_first=True)

# Identify and handle missing values
df.fillna(df.mean(), inplace=True)  # Numerical
df = df.apply(lambda x: x.fillna(x.mode()[0]) if x.dtype == 'object'
else x)  # Categorical

# Scaling
scaler = StandardScaler()
scaled_data = scaler.fit_transform(df)
```

# 2. Subtask: (clustering)

Find the optimal k value for the KMeans algorithm using the variables prepared in the previous task. Then group the customers.

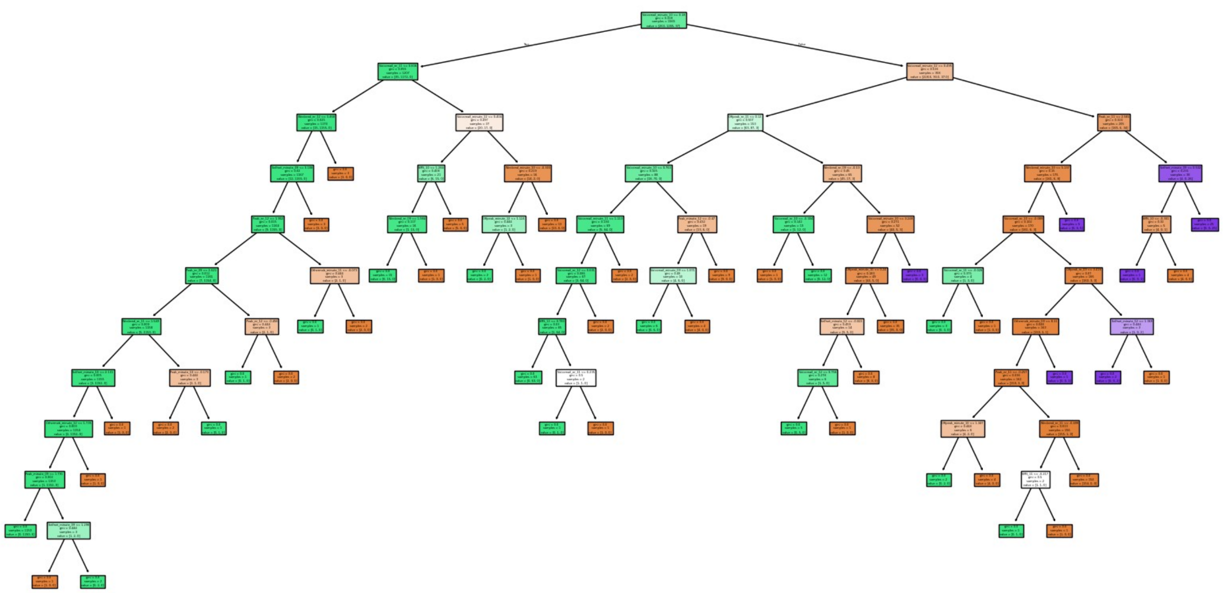
```
inertias = []
for k in range(1, 15):
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(scaled_data)
    inertias.append(kmeans.inertia_)

plt.plot(range(1, 15), inertias, marker='o')
plt.xlabel('Number of clusters (k)')
plt.ylabel('Inertia')
plt.show()



# Fromt the plot, we find that k = 3 or k = 4 is optimal
optimal_k = 3
kmeans = KMeans(n_clusters=optimal_k, random_state=42)
df['Cluster'] = kmeans.fit_predict(scaled_data)
```



# 3. Subtask: (explaination of clusters / conclusions)

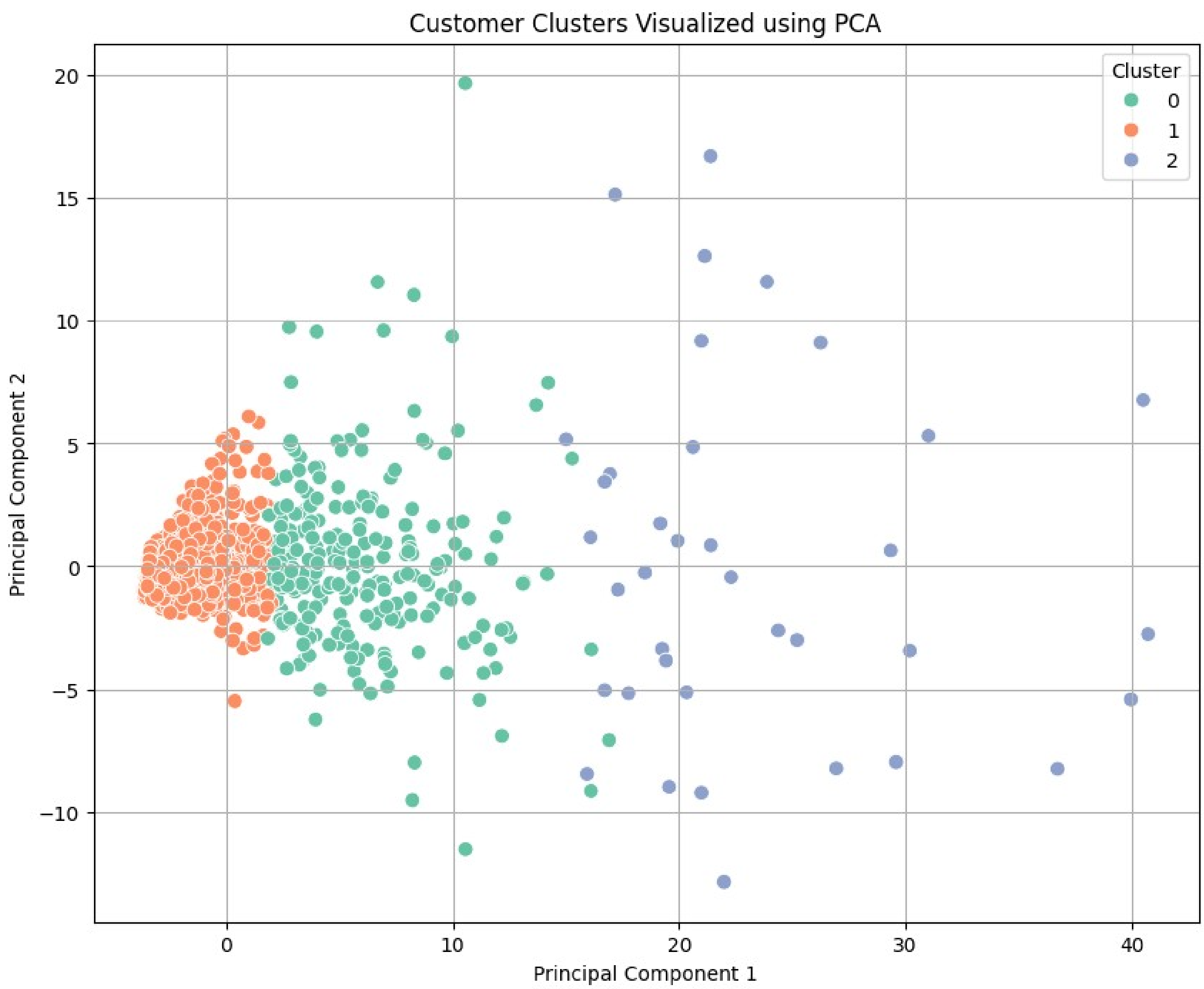
Try to find an explanation of what characterizes each group and what characteristics caused each customer to be in the given cluster.

```
# Analyze cluster characteristics
cluster_profiles = df.groupby('Cluster').mean()

# Decision tree to explain clusters
X = scaled_data
y = df['Cluster']
clf = DecisionTreeClassifier()
clf.fit(X, y)

plt.figure(figsize=(20, 10))
plot_tree(clf, feature_names=df.columns, filled=True)
plt.show()
```



```
# Reduce to 2 dimensions for visualization
pca = PCA(n_components=2)
pca_components = pca.fit_transform(scaled_data)

# Create a DataFrame for visualization
df_pca = pd.DataFrame(data=pca_components, columns=['PC1', 'PC2'])
df_pca['Cluster'] = df['Cluster']
```

```
# Visualize clusters in 2D
plt.figure(figsize=(10, 8))
sns.scatterplot(x='PC1', y='PC2', hue='Cluster', palette='Set2',
data=df_pca, s=60)
plt.title('Customer Clusters Visualized using PCA')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.legend(title='Cluster')
plt.grid(True)
plt.show()
```




```
# Step 1: Rebuild preprocessed_data without the 'Cluster' column
columns_to_use = [col for col in df.columns if col not in ['Cust_ID',
'churn?', 'Contract_date', 'Cluster']]
preprocessed_data = df[columns_to_use]

# Verify shapes again
print("Shape of preprocessed data:", preprocessed_data.shape)  #
```

```
Should now match (1565, 72)

# Step 2: Re-align columns and create centroids DataFrame
centroids = pd.DataFrame(kmeans.cluster_centers_,
columns=preprocessed_data.columns)

# Step 3: Re-run cluster profile examination
df['Cluster'] = kmeans.labels_
cluster_profiles = df.groupby('Cluster')
[preprocessed_data.columns].mean()

# Display the profiles
print(cluster_profiles)
```

```
Shape of preprocessed data: (1565, 72)
               Age  Peak_minute_09  Weekend_minute_09
Offpeak_minute_09  \
Cluster

0        31.551331       67.272015          39.894183
61.655817
1        34.744664       12.575723           7.228221
9.245723
2        31.567568      234.267838         109.141081
172.416486

         Offpeak_nr_09  Peak_nr_09  Weekend_nr_09
Selfnet_minute_09  \
Cluster

0            45.958175   78.353612      38.471483          74.593308

1            10.137549   18.182609       9.640316          11.558474

2           143.405405  249.648649     116.567568         180.965676


         Fixed_minute_09  Othermob_minute_09  Voicemail_nr_09  \
Cluster
0              11.723498           85.253308       122.357414
1               2.457747           14.477186        28.928063
2              14.503514          327.817297       377.374784

         Voicemail_minute_09      SMS_09  Peak_minute_10
Weekend_minute_10  \
Cluster

0                 169.521920   45.771863       62.413802
48.479734
1                  29.030798   10.349407       10.441953
7.135897
```

```
2                 531.712703  124.000000      203.726757
139.935946

         Offpeak_minute_10  Offpeak_nr_10  Peak_nr_10
Weekend_nr_10  \
Cluster

0                56.671065      42.775665   71.296578      46.186312

1                 6.776198       7.445059   14.755731       9.165217

2               138.285676     120.243243  221.378378     132.675676


         Selfnet_minute_10  Fixed_minute_10  Othermob_minute_10  \
Cluster
0                74.273042        15.008099           85.669392
1                10.207296         2.129043           12.068095
2               156.399730        15.503243          323.112432

         Voicemail_nr_10  Voicemail_minute_10      SMS_10
Peak_minute_11  \
Cluster

0             119.912548           176.123346   49.878327
62.027376
1              23.302767            24.740830    9.536759
10.233660
2             363.069486           501.939459  111.108108
229.897568

         Weekend_minute_11  Offpeak_minute_11  Offpeak_nr_11
Peak_nr_11  \
Cluster

0                41.664449          51.707110      38.304183
71.893536
1                 5.874640           6.400411       6.452174
13.591304
2               128.590541         141.060270     115.324324
246.729730

         Weekend_nr_11  Selfnet_minute_11  Fixed_minute_11  \
Cluster
0            40.140684          66.505399        13.362776
1             7.206324           9.773573         2.004379
2           129.216216         179.681622        17.124324

         Othermob_minute_11  Voicemail_nr_11  Voicemail_minute_11
SMS_11  \
```

```
Cluster

0                  76.274981       108.387833           157.029620
47.110266
1                  10.257905        19.879842            22.288798
7.688538
2                 309.457027       352.070471           486.814447
113.135135

         Peak_minute_12  Weekend_minute_12  Offpeak_minute_12
Offpeak_nr_12  \
Cluster

0              69.246996          44.492243          54.914006
43.562738
1              10.689542           5.479597           6.372087
7.938340
2             219.457297         114.304054         129.625405
111.459459

         Peak_nr_12  Weekend_nr_12  Selfnet_minute_12  Fixed_minute_12
\
Cluster

0         74.965779      42.642586          67.875987        12.844981

1         15.263241       8.241897           9.654522         2.048862

2        203.297297     101.459459         168.091081        18.497297


         Othermob_minute_12  Voicemail_nr_12  Voicemail_minute_12
SMS_12  \
Cluster

0                  92.358289       117.418251           171.191056
51.790875
1                  11.227684        21.312253            23.146174
10.912253
2                 256.085966       324.054054           444.153481
120.216216

         Package_PACK_B  Package_PACK_C  Package_PACK_E
Package_PACK_X  \
Cluster

0              0.391635        0.079848        0.041825
0.235741
1              0.433202        0.009486        0.038735
0.237945
```

```
2               0.243243        0.162162        0.081081
0.378378

         Package_PACK_Z  Gender_Male
Marital_Status_In_Relationship  \
Cluster

0               0.209125     0.642586                               0.015209

1               0.249802     0.577075                               0.023715

2               0.135135     0.729730                               0.054054


         Marital_Status_Married  Marital_Status_Single
Marital_Status_Widow  \
Cluster

0                       0.593156               0.296578
0.011407
1                       0.657708               0.223715
0.016601
2                       0.567568               0.324324
0.000000

         Living_Condition_Other  Living_Condition_Owner  \
Cluster
0                       0.076046                0.779468
1                       0.073518                0.850593
2                       0.054054                0.864865

         Living_Condition_Rent  Graduation_Primary_School  \
Cluster
0                      0.007605                   0.003802
1                      0.003162                   0.027668
2                      0.000000                   0.000000

         Graduation_University  Job_Type_Labourer  Job_Type_Leader  \
Cluster
0                      0.258555           0.380228         0.072243
1                      0.244269           0.374704         0.069565
2                      0.270270           0.270270         0.054054

         Job_Type_Other  Job_Type_Public_Employee  Job_Type_Retired  \
Cluster
0               0.000000                  0.387833          0.041825
1               0.002372                  0.365217          0.056126
2               0.000000                  0.486486          0.000000

         Income_30_60k  Income_Below_15k  Income_Over_60k
```

```
Cluster
0               0.380228          0.098859          0.121673
1               0.378656          0.142292          0.097233
2               0.324324          0.108108          0.135135

# Step 1: Prepare the dataset
# Assuming df is your DataFrame and the cluster labels are already
added
# Run PCA excluding the 'Cluster' column
pca = PCA(n_components=2)
pca_result = pca.fit_transform(df.drop(columns=['Cluster']))  # Adjust
to exclude the cluster column

# Add PCA results to DataFrame
df['PC1'] = pca_result[:, 0]
df['PC2'] = pca_result[:, 1]

# Step 2: Function to plot the scatter plot, adjusting color or size
by the chosen variable
def plot_pca(variable):
    plt.figure(figsize=(10, 6))

    # If variable is numeric, use it to adjust the point sizes
    if pd.api.types.is_numeric_dtype(df[variable]):
        sns.scatterplot(data=df, x='PC1', y='PC2', hue='Cluster',
size=variable, sizes=(20, 200), palette='viridis', alpha=0.6)
    else:
        # Use different colors for different values of the selected
categorical variable
        sns.scatterplot(data=df, x='PC1', y='PC2', hue=variable,
style='Cluster', palette='viridis', alpha=0.6)

    plt.title(f'PCA Scatter Plot - Colored/Scaled by {variable}')
    plt.xlabel('Principal Component 1 (PC1)')
    plt.ylabel('Principal Component 2 (PC2)')

    # Set x and y limits for consistency
    plt.xlim(df['PC1'].min() - 1, df['PC1'].max() + 1)
    plt.ylim(df['PC2'].min() - 1, df['PC2'].max() + 1)

    # Add horizontal and vertical lines at 0 for reference
    plt.axhline(y=0, color='k', linestyle='--', lw=0.8)
    plt.axvline(x=0, color='k', linestyle='--', lw=0.8)

    # Display the plot
    plt.legend(loc='best', title=variable)
    plt.grid(True)
    plt.show()

# Step 3: Use interact to create dropdown menu for variable selection
```

```
variable_dropdown = widgets.Dropdown(
    options=df.columns.drop(['Cluster', 'PC1', 'PC2']),
    value=df.columns[0],  # Default value
    description='Variable:'
)

# Interact function to update the plot based on the selected variable
interact(plot_pca, variable=variable_dropdown)
```

{"model_id":"b616e28cb80a4550bd0b00ccaee99728","version_major":2,"version_minor":0}

```
<function __main__.plot_pca(variable)>
```

```
# # Conclusion

# Cluster 0: Moderate Users
#   Age: Average age of around 31.5 years.
#   Usage Pattern: Moderate across all usage categories (peak, weekend, off-peak). They use around 67 minutes during peak times and 61 minutes during off-peak, with a balanced distribution across different times.
#   Voice Services: Moderate engagement with voicemail, around 169 minutes per month. Other mobile minutes are relatively average (85 minutes).
#   SMS: Average SMS usage (45-51 messages across different months).
#   Packages: Most common package is "PACK_B" (39%), with significant usage of "PACK_X" (24%).
#   Gender & Demographics: Predominantly male (64%) and married (59%). A majority own their living condition (78%).
#   Job & Income: High representation among public employees (38%) and laborers (38%). Around 38% have an income in the 30-60k range.
#       Conclusion: Cluster 0 represents moderately active users who have balanced usage across different services. They are typically working-class individuals, predominantly male, and inclined towards packages offering flexibility like "PACK_B."
#
# Cluster 1: Low Users
#   Age: Slightly older, average age of around 34.7 years.
#   Usage Pattern: Significantly lower usage across all metrics. For instance, peak minutes are just around 12, and off-peak minutes are also low (~9). Voicemail usage is similarly minimal (29 minutes).
#   Voice Services: Very low mobile and fixed-line minutes.
#   SMS: Low SMS usage (~10 messages).
#   Packages: High proportion using "PACK_B" (43%) and "PACK_X" (24%).
#   Gender & Demographics: A bit more evenly distributed by gender (58% male). Higher tendency to be married (66%) and own their residence (85%).
#   Job & Income: Broad range of jobs, with notable representation among public employees (36%) and a smaller proportion of retired
```

```
individuals (5%). Income tends to be in the 30-60k range (38%) but
with a higher-than-average percentage below 15k (14%).
#       Conclusion: Cluster 1 appears to capture low-usage customers.
They tend to be slightly older, stable (married, homeowners), and
economically varied, with many favoring basic and budget-friendly
packages.
#
# Cluster 2: Heavy Users
#   Age: Similar to Cluster 0, average age is around 31.6 years.
#   Usage Pattern: Significantly higher usage across all categories.
For example, 234 peak minutes, 172 off-peak minutes, and voicemail
minutes reaching over 500 in a month. This group makes extensive use
of their services.
#   Voice Services: Much higher mobile minutes (~327) and frequent use
of voicemail (~377).
#   SMS: Heavier SMS users, averaging over 100 messages per month.
#   Packages: Preference for "PACK_X" (37%) and "PACK_B" (24%), with
higher diversity across package usage than the other clusters.
#   Gender & Demographics: Predominantly male (73%) and, while married
(56%), have a higher proportion of single individuals (32%).
#   Job & Income: Higher presence among public employees (48%) and a
lower number of laborers. More diverse income range, with a notable
proportion earning over 60k (13%).
#       Conclusion: Cluster 2 represents high-usage customers who
frequently use voice and SMS services. These customers are
predominantly male, more likely to be single, and opt for packages
with broader services like "PACK_X." They show a more diverse economic
profile, including higher earners.
#
# General Observations
#   Age and Usage: The usage levels do not seem to vary dramatically
with age, suggesting that service engagement is more lifestyle-driven.
#   Gender Differences: Across clusters, males are predominant, but
the level of male dominance is highest among heavy users (Cluster 2).
#   Income: Higher earners are more present in Cluster 2, while
Cluster 1 has a mix that includes lower-income groups.
#   Service & Package Preferences: Heavy users lean toward packages
that provide extensive coverage or perks, whereas lighter users prefer
basic or more economical options.
```