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**Tutorial 1 for Chapter 3**

Case study 9: Telecom Plan Customization by K-means

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*Reference: 数据挖掘原理与应用*

For the course AMA546 Statistical Data Mining
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**Content:**



# 1 Objectives of the analysis

This case study looks at **clustering customers using their call records in a month** to customize different telecom plans for them. In this study, we will perform clustering using the **K-means** method. The attributes are call duration in different time periods, recorded in **minutes**.

# 2 Description of the data

There are **3395 rows (samples)** and 7 columns in the dataset. The `CustomerID` column is the unique identifier of each customer, which is useless in the clustering. Thus the **total number of attributes is 6**.

Note that:
`Workday_working_call_duration` : Duration of call made during working hours on weekdays.
`Workday_after_work_call_duration` : Duration of call made after working hours on weekdays.

In [1]:

```
import pandas as pd
import numpy as np

# Load the data
call_record = pd.read_csv('call_record.csv',engine='python')
print(call_record.shape)  # number of rows and columns
display(np.transpose(call_record.head()))  # display the table
```

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```
(3395, 7)
```

| | 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|
| **CustomerID** | K100050 | K100120 | K100170 | K100390 | K100450 |
| **Workday_working_call_duration** | 40.61 | 68.12 | 100.2 | 55.8 | 58.63 |
| **Workday_after_work_call_duration** | 18.82 | 33.88 | 31.5 | 18.0 | 9.09 |
| **Weekend_call_duration** | 1.23 | 8.33 | 9.0 | 19.2 | 11.31 |
| **International_call_duration** | 4.47 | 13.42 | 4.86 | 5.62 | 5.06 |
| **Total_call_duration** | 60.67 | 110.34 | 140.7 | 93.0 | 79.03 |
| **Average_call_duration** | 1.29 | 1.07 | 1.67 | 3.44 | 2.26 |

# 3 Exploratory data analysis

The original data set has been cleaned, so we'll **skip the data cleaning.** Firstly, we draw the **scatter plot matrx** of the dataset to observe the **correlation between features**, and explore whether observations can **achieve good clustering performance on certain dimension.**

## 3.1 Scatter plot matrix

According to the scatter plot matrix, we found that the **samples were evenly distributed**, and **no two feature dimensions** could **separate the samples into several clusters.** `Workday_working_call_duration` and `Total_call_duration` have a strong linear relationship. We will further determine their correlation through the **correlation coefficient matrix.**

In [2]:

```python
import seaborn as sns
import matplotlib. pyplot as plt

# Scatter plot matrices of explanatory variables
sns.set_theme(style="ticks")
plt.figure(figsize=(32, 54), dpi=1800)
sns.pairplot(call_record, corner=True)
plt.show()
```

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```
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```

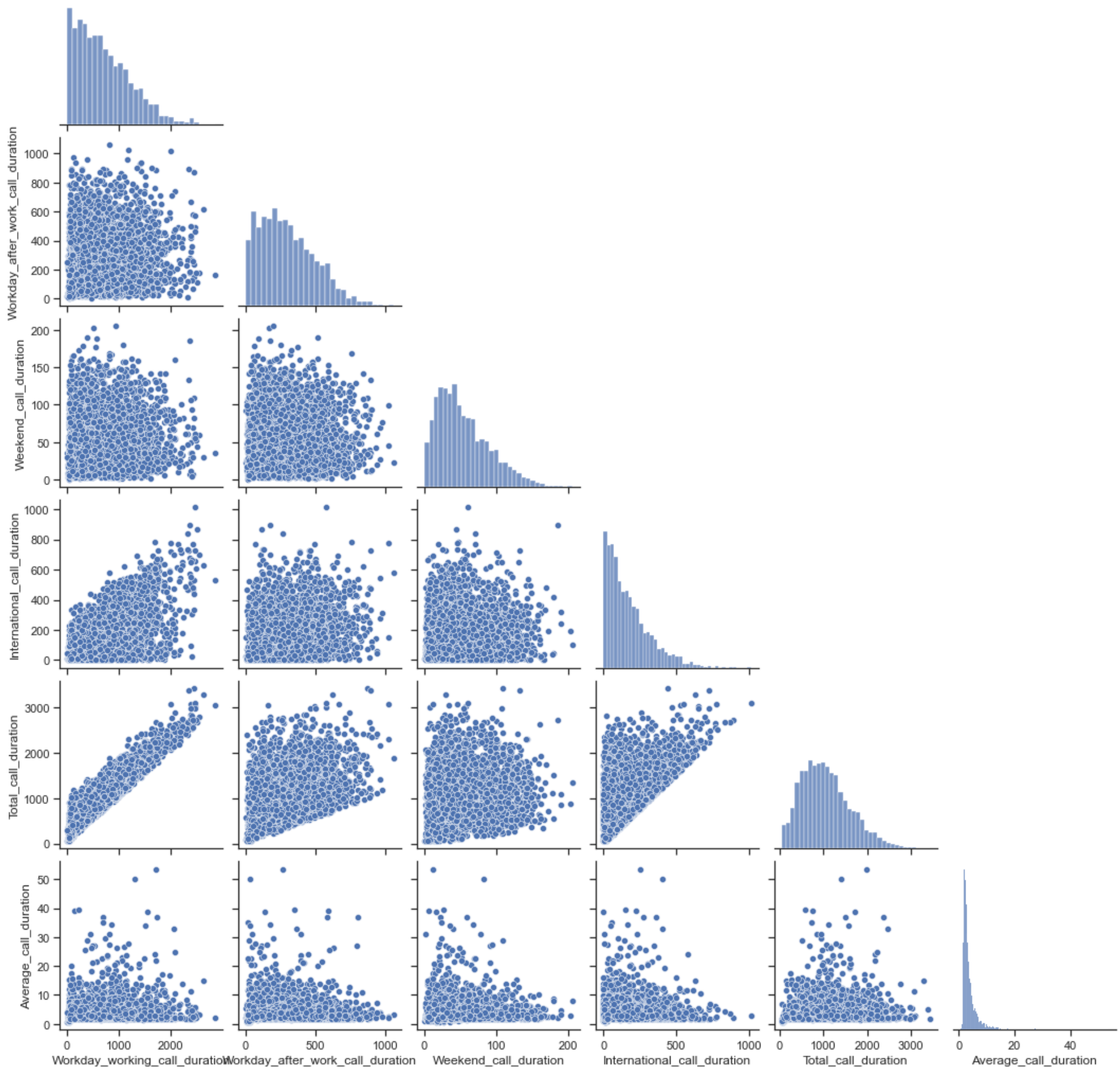


## 3.2 Correlation coefficient matrix

The following figure is the **heat map of the correlation coefficient matrix. Green** indicates **a large positive correlation**, while **red** indicates **a large negative correlation**. With a correlation coefficient of **0.3 as the boundary**, the correlation between most features was moderate. The correlation between `Total_call_duration` and `Workday_working_call_duration` , `Workday_after_work_call_duration` , `International_call_duration` is **0.935**, 0.39 and 0.606, respectively. Combined with the information from the Scatter plot matrix, this is because Total_call_duration represents the total call duration, which is equivalent to an upper bound of the other features. Therefore, **we will remove the feature `Total_call_duration` in the following analysis.**

In addition, the correlation between `Workday_working_call_duration` and

In [3]:

```python
dCorr = call_record.corr()
heatmap = sns.heatmap(dCorr, annot=True, fmt=".3f", vmin=-1, vmax=1, cmap='BrBG'
heatmap.set_title('Correlation Heatmap', fontdict={'fontsize':18}, pad=12)
plt.show()
```

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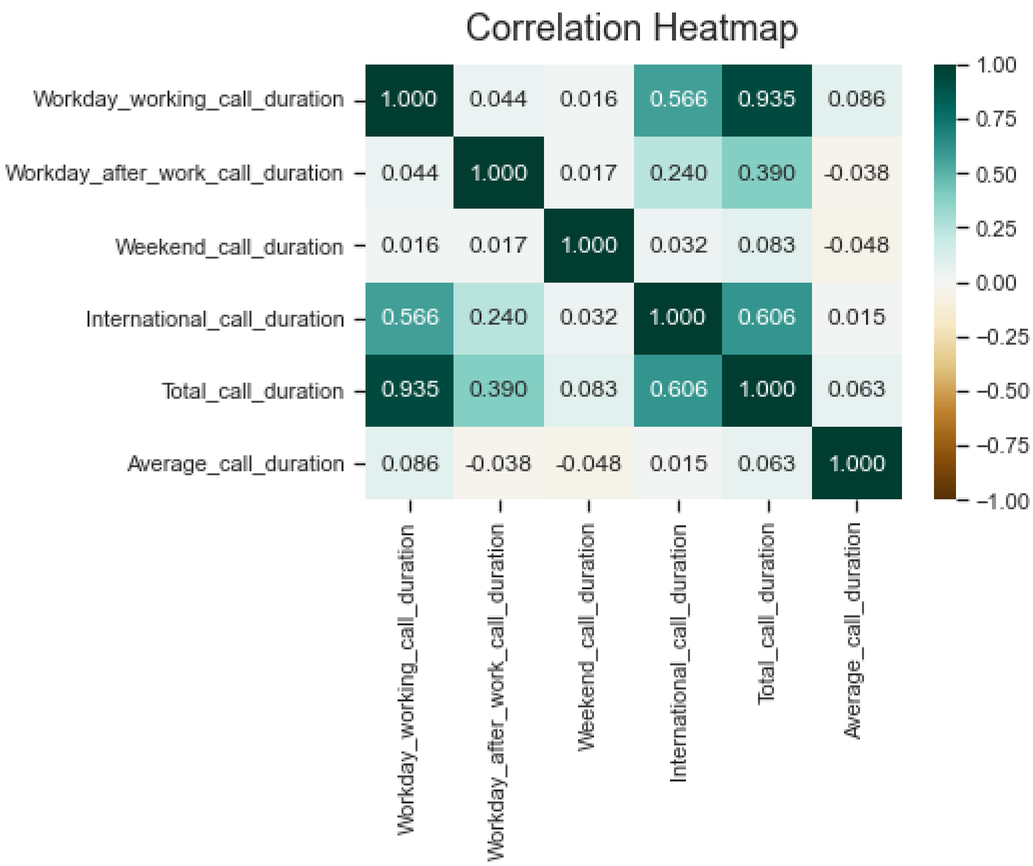


In [4]:

```python
# Remove the Total_call_duration column
attributes = ['Workday_working_call_duration',
              'Workday_after_work_call_duration',
              'Weekend_call_duration',
              'International_call_duration',
              'Average_call_duration']
```

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# 4 Model building

## 4.1 Find the optimal K

We use the **Elbow Method** to **determine the K value** of the k-means method. We have previously found that the **original data set is evenly distributed** in the low-dimensional space, and there is **no obvious clustering pattern**. That is to say, there is a high probability that there is **no underlying $k$ cluster structure in the**

**original data set**, which makes **WCSS drop significantly when $K = k$**. As you can imagine, there is **no obvious elbow point** in the elbow plot.

Below, we calculate the WCSS of the corresponding K-means model from $K = 1$ to $K = 10$, and draw the Elbow plot:

In [5]:

```
from sklearn.cluster import KMeans

distortions = []
K = range(1,10)
for k in K:
    kmeanModel = KMeans(n_clusters=k)
    kmeanModel.fit(call_record[attributes])
    distortions.append(kmeanModel.inertia_)

plt.figure(figsize=(8,4))
plt.plot(K, distortions, 'bx-')
plt.plot(3,distortions[2],'ro',label="point", markersize=12, linewidth=.5)
plt.text(3+.2,distortions[2]+.4,'Elbow point')
plt.xlabel('K')
plt.ylabel('WCSS')
plt.title('The Elbow Method showing the optimal k')
plt.show()
```

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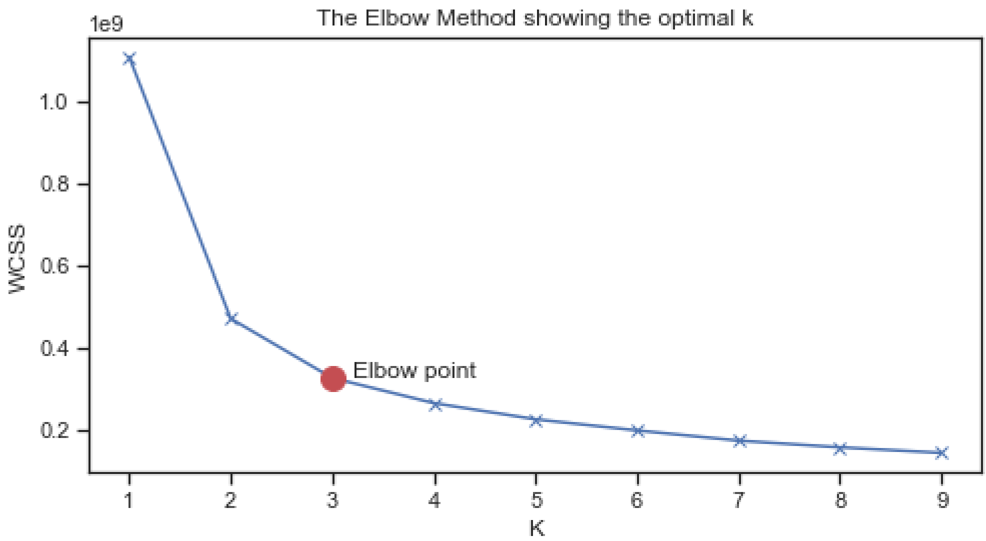


According to the Elbow plot, **either $k = 2$ or $k = 3$ is a suitable elbow point.** After $k = 3$, WCSS declines gently. Considering the **diversity of telecom plans**, we **select the number of cluster groups $k = 3$** in the following analysis.

## 4.2 Bulid K-means model with k=3

In [6]:

```
# bulid K-means model with k=3
kmModel = KMeans(n_clusters=3)
kmModel = kmModel.fit(call_record[attributes])
call_record['cluster'] = kmModel.predict(call_record[attributes])
```

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## 4.3 Model interpretation

### 4.3.1 Number of samples in each category

Let's first look at the **number of samples each category** after clustering. In general, we want a similar sample size for each category. (If our model has a **sample size that is significantly smaller** in some categories than in others, it is likely that the **model is overfitting** to group some outliers into one category. This affects the generalization ability of the model.

When **K=3, the sample numbers of each group are similar**, indicating that this is a good classification.

In [7]:

```
item_series = pd.Series(call_record['cluster'])  # Convert the list to a Pandas
item_counts = item_series.value_counts()  # Count the frequency of each item
table = item_counts.to_frame().reset_index().rename(columns={'index': 'Item', 0:
display(table.sort_values(by=['Item']))  # Output the table, sort by Item
```

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| | Item | cluster |
|---|---|---|
| **0** | 0 | 1614 |
| **1** | 1 | 1247 |
| **2** | 2 | 534 |

### 4.3.2 Scatter plot matrix colored by clustering results,

Then, we plotted the scatter plot matrix colored by the clustering results, aiming to study **which attribute K-means selected for clustering.** According to **density plots on the diagonal**, `Workday_working_call_duration` has the best clustering effect. The clients of cluster 1 has a shortest `Workday_working_call_duration` ($\leq 500$), followed by cluster 2. Cluster 3 has the longest `Workday_working_call_duration` ($\geq 1250$). `International_call_duration` also has some clustering effect. Similar to `Workday_working_call_duration` , clients of class 1 have a short duration, while those of class 3 have the longest duration. The clustering effect of other attributes is not obvious.

For the non-diagonal parts, the scatter plot in the first column shows that th K-means clustering is almost **carried out by stratifying `Workday_working_call_duration` .**

In [8]:

```python
attributes_2 = ['Workday_working_call_duration',
                'Workday_after_work_call_duration',
                'Weekend_call_duration',
                'International_call_duration',
                'Average_call_duration',
                'cluster']

plt.figure(figsize=(32, 54), dpi=1800)
sns.pairplot(call_record[attributes_2], corner=True, hue='cluster')
plt.show()
```

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```
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```

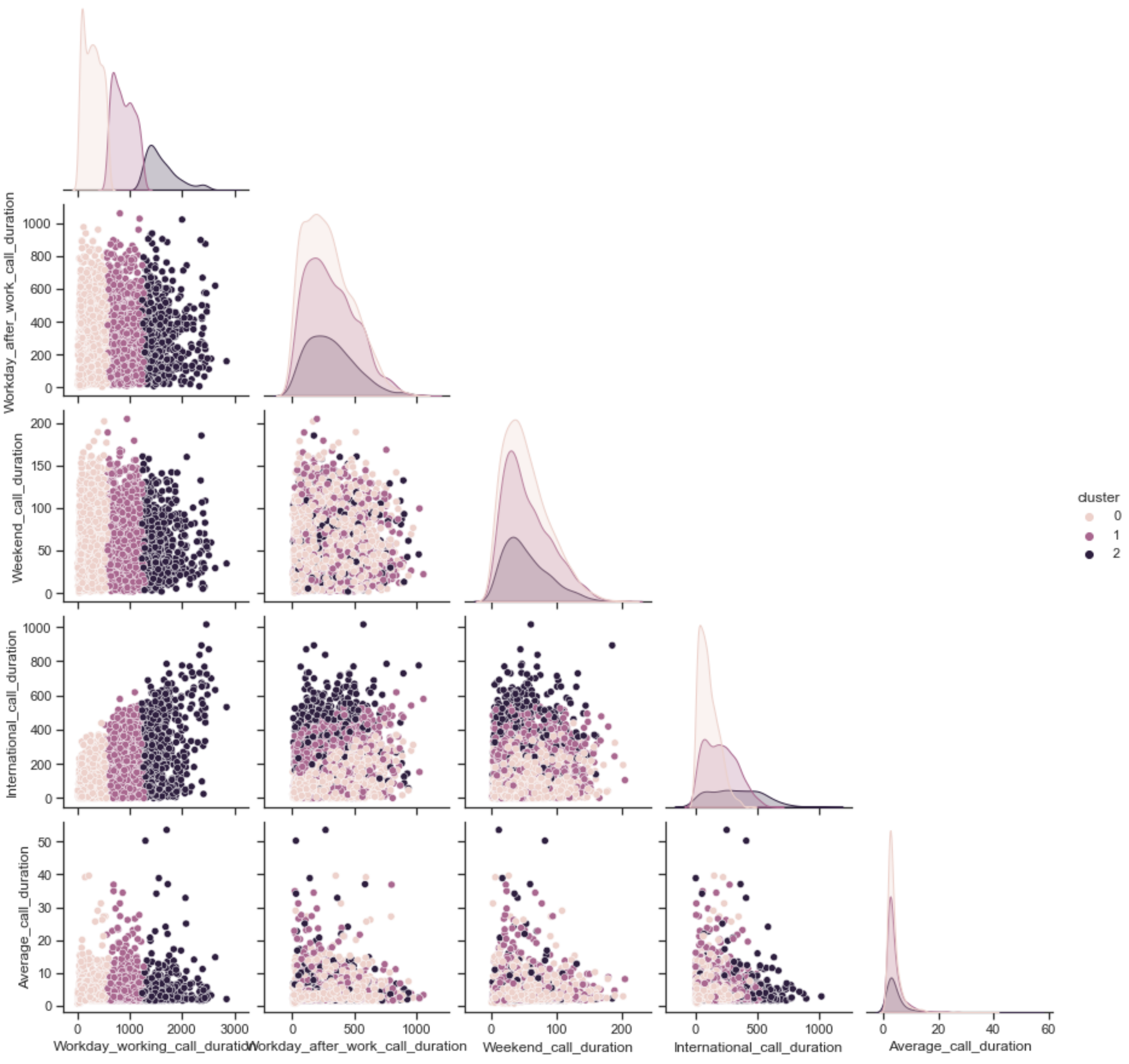


## 4.3.3 3D-plot

Finally, let's conclude the model interpretation section with a **3D-plot**. We chose two attributes with high clustering effects `Workday_after_work_call_duration` and `Workday_after_work_call_duration` and one attribute with poor clustering effect `Workday_after_work_call_duration`.

The three types of customers are classified by `Workday_working_call_duration` . The thresholds are about 500 and 1250. **As `Workday_working_call_duration` increases , `International call duration` gradually increases** (sounds reasonable), so

In [9]:

```
import plotly.express as px
fig = px.scatter_3d(call_record, x='Workday_working_call_duration',
                    y='Workday_after_work_call_duration',
                    z='International_call_duration',color=call_record['cluster']
fig.show()
```

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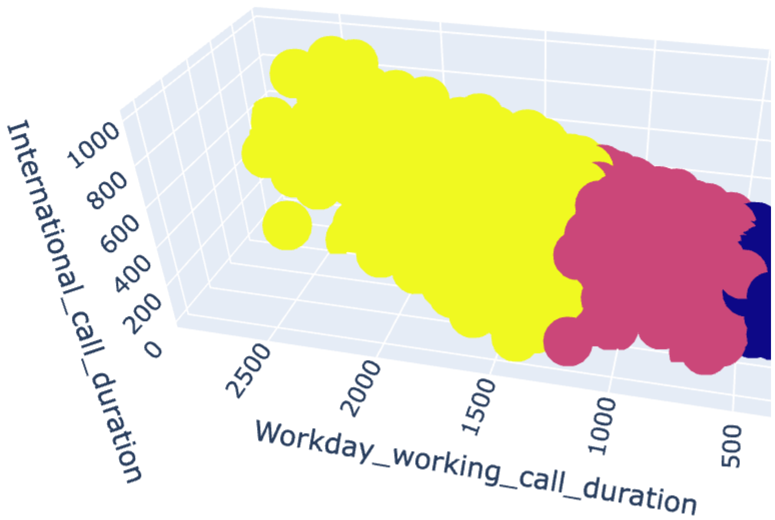


# 5 Conclusions

The goal of this case study is to **tailor different telecom plans** for different customers.

Based on the above analysis, we find that:

- `Total_call_duration` has a **strong positive correlation** with `Workday_working_call_duration` .
- `Workday_working_call_duration` and `International_call_duration` also have strong positive correlation.
- When K-means is used for clustering, **customers can be roughly divided into three clusters** according to `Workday_working_call_duration` , and the sample numbers of the three types of customers are relatively uniform.

| Item | Count | Workday_working_call_duration |
|---|---|---|
| 0 | 1247 | <500 |
| 1 | 1614 | [500, 1250] |
| 2 | 534 | >1250 |

- In addition, `International_call_duration` also has some clustering effect.

To sum up, `three different telecom plans` can be formulated according to the duration of `Workday_working_call_duration` and `International_call_duration` .

- The **first plan** is for customers whose `Workday_working_call_duration` and `International_call_duration` are both low, accounting for 36.7% of the total customers.
- The **second plan** is for customers with higher `Workday_working_call_duration` and `International_call_duration` , accounting for 47.5% of the total customers.
- The **third plan** is for clients with high `Workday_working_call_duration` and `International_call_duration` . Most of them are professionals who need to make frequent calls. Accounts for 15.7% of the total number of customers.

# 6 Discussion: Is it important to scale data before clustering?

## 6.1 Benefit of scaling:

The ‘benefit’ of scaling is measured by an increase in the metric. Let’s understand what scaling does to K-means model.

If we have two attribute, X, Y. The range of X is -30 to 30, and Y is -4 to 8. While computing the intracluster variances, **X will contribute more to the WCSS than Y**. Hence, the model tends to minimize this WCSS more by minimizing the span of the clusters in attribute X. Sometimes this property makes the classification of the K-means model counterintuitive. This won’t happen if you use standard scaling where you transform the feature as:

Let’s look at examples!

In [10]:

```
from matplotlib.pyplot import figure
import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = [10, 10]

rnorm = np.random.randn

x = rnorm(1000) * 10
y = np.concatenate([rnorm(500), rnorm(500) + 5])

fig, axes = plt.subplots(3, 1)

axes[0].scatter(x, y)
axes[0].set_title('Data (note different axes scales)')

km = KMeans(2)

clusters = km.fit_predict(np.array([x, y]).T)

axes[1].scatter(x, y, c=clusters, cmap='bwr')
axes[1].set_title('non-normalised K-means')

clusters = km.fit_predict(np.array([x / 10, y]).T)

axes[2].scatter(x, y, c=clusters, cmap='bwr')
axes[2].set_title('Normalised K-means')
plt.show()
```

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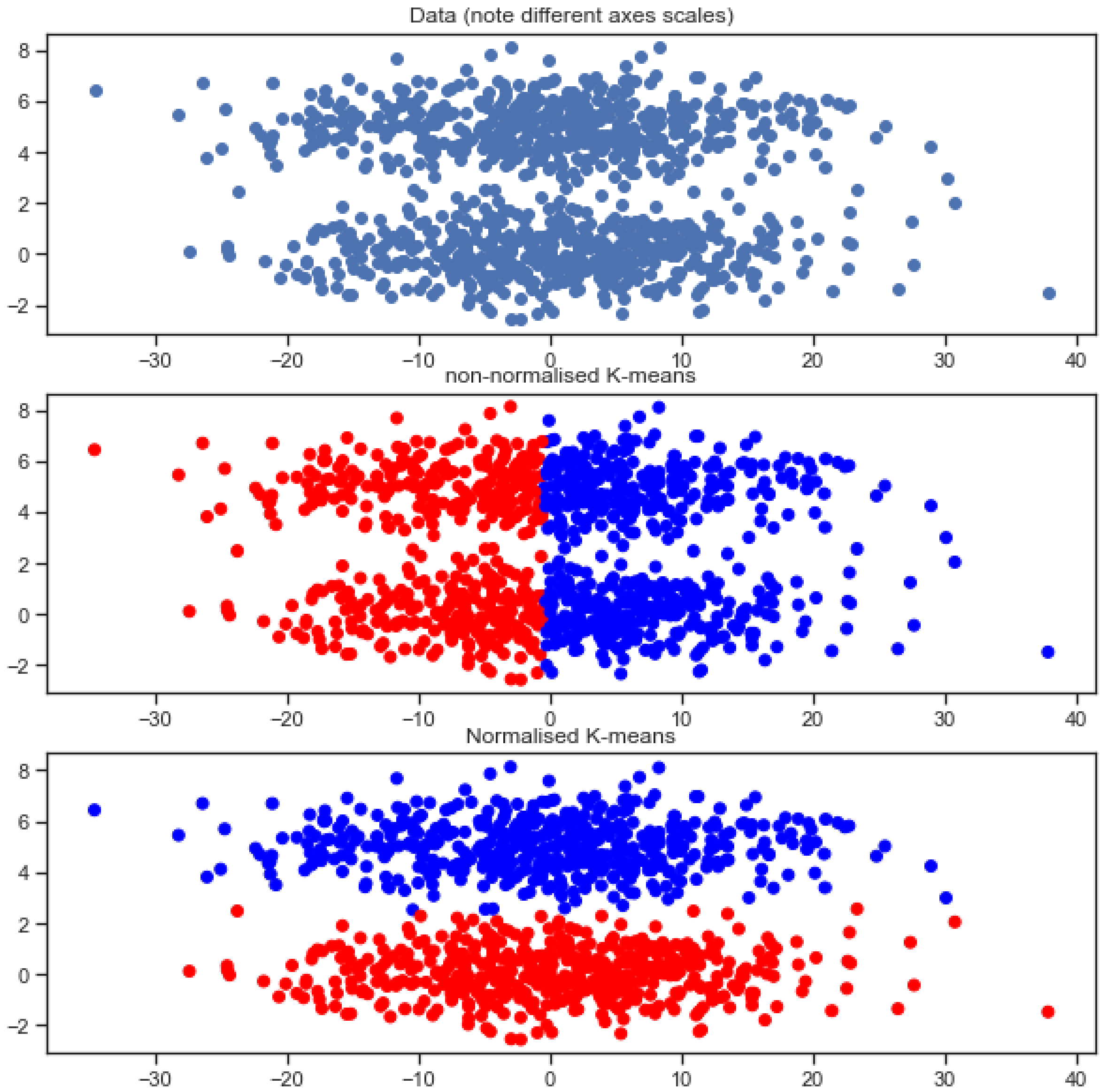


We **randomly generated two groups of normally distributed samples** with the same variance, and their **means differed by 5 in the Y direction**. An intuitive classification would be one cluster above and below. But the **WCSS for this classification is too large** without scale (because of the **span of clusters in the X direction is too large**). So **K-means converges to the result of the left and right clusters**. If the data is normalized, then this **non-uniformity in different directions is eliminated** and K-means converges to the ideal case of one cluster above and the other.

## 6.2 Cost of scaling:

Scaling will also bring many problems, for example, the **data after scale does not have clear meaning**, which will affect our interpretation of clustering results.

In addition, there's often a **nice elbow point** when I don't scale the data, but it **disappears when it's scaled**. In fact, this is **also the case with our data set.** Suppose we **max\min scaling** the data set and then plot the elbow plot:

In [11]:

```
from sklearn import preprocessing
from sklearn.cluster import KMeans

min_max_scaler = preprocessing.MinMaxScaler()
# scale function
def scaleColumns(df, cols_to_scale):
    df2 = pd.DataFrame()
    for col in cols_to_scale:
        df2[col] = pd.DataFrame(min_max_scaler.fit_transform(pd.DataFrame(df[col
    return df2
# scale the original dataset
scaled_call_record = scaleColumns(call_record, attributes)

# plot the elbow plot
scale_distortions = []
K = range(1,10)
for k in K:
    kmeanModel = KMeans(n_clusters=k)
    kmeanModel.fit(scaled_call_record[attributes])
    scale_distortions.append(kmeanModel.inertia_)

plt.figure(figsize=(8,4))
plt.plot(K, scale_distortions, 'bx-')
plt.xlabel('K')
plt.ylabel('WCSS')
plt.title('The Elbow Method showing the optimal k')
plt.show()
```

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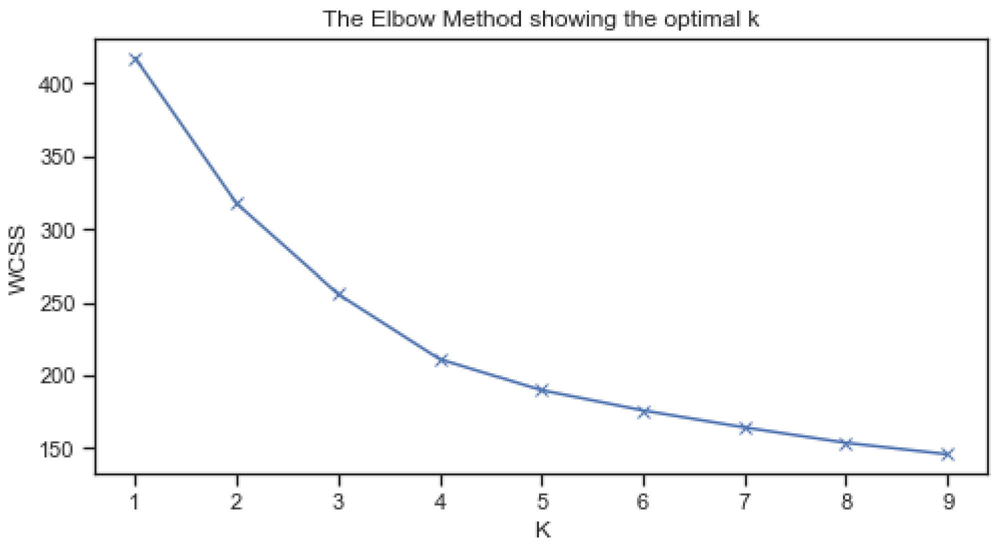


In short, whether you need scaling depends on the data.

- If **all the attributes have the same meaning** (call duration in minutes, in our case), you should not scale the data, as this causes distortion.
- If **each attribute is something completely different** (like shoe size and weight), there are different units (centimeters, kilometers, minutes, kilograms...) , then the **values are not really comparable. Scaling** them is the best practice for **giving them equal weight.**