Reading the Data and Observations on Dataset

```
#Importing necessary libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

```
cd sample_data
```

```
[Errno 2] No such file or directory: 'sample_data'
/content/sample_data
```

```
import pandas as pd
data = pd.read_excel('customer_churn_large_dataset.xlsx')

data.head(5)
```

	CustomerID	Name	Age	Gender	Location	Subscription_Length_Mont
0	1	Customer_1	63	Male	Los Angeles	
1	2	Customer_2	62	Female	New York	
2	3	Customer_3	24	Female	Los Angeles	

```
print(len(data))
```

```
100000
```

```
# Display basic information about the dataset
print(data.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 9 columns):
 #   Column                      Non-Null Count   Dtype  
---  ------                      --------------   -----  
 0   CustomerID                  100000 non-null  int64  
 1   Name                        100000 non-null  object 
 2   Age                         100000 non-null  int64  
 3   Gender                      100000 non-null  object 
 4   Location                    100000 non-null  object 
 5   Subscription_Length_Months  100000 non-null  int64  
 6   Monthly_Bill                100000 non-null  float64
 7   Total_Usage_GB              100000 non-null  int64  
 8   Churn                       100000 non-null  int64  
dtypes: float64(1), int64(5), object(3)
memory usage: 6.9+ MB
None
```

```
print(data.describe())
```

```
          CustomerID            Age  Subscription_Length_Months  \
count  100000.000000  100000.000000               100000.000000   
mean    50000.500000      44.027020                   12.490100   
std     28867.657797      15.280283                    6.926461   
min         1.000000      18.000000                    1.000000   
25%     25000.750000      31.000000                    6.000000   
50%     50000.500000      44.000000                   12.000000   
75%     75000.250000      57.000000                   19.000000   
max    100000.000000      70.000000                   24.000000   

        Monthly_Bill  Total_Usage_GB          Churn  
count  100000.000000   100000.000000  100000.000000  
mean       65.053197      274.393650       0.497790  
std        20.230696      130.463063       0.499998  
```

```
min       30.000000      50.000000      0.000000
25%       47.540000     161.000000      0.000000
50%       65.010000     274.000000      0.000000
75%       82.640000     387.000000      1.000000
max      100.000000     500.000000      1.000000
```

```
data.isna().sum()
```

```
CustomerID                    0
Name                          0
Age                           0
Gender                        0
Location                      0
Subscription_Length_Months    0
Monthly_Bill                  0
Total_Usage_GB                0
Churn                         0
dtype: int64
```

Great! There are no missing values.

Data preprocessing and cleaning

Decided to remove the CustomerID, Name columns as they won't making any impact on model.

```
data.drop(["CustomerID"], inplace = True, axis = 1)
```

```
data.drop(["Name"], inplace = True, axis = 1)
```

```
data
```

	Age	Gender	Location	Subscription_Length_Months	Monthly_Bill	To
0	63	Male	Los Angeles	17	73.36	
1	62	Female	New York	1	48.76	
2	24	Female	Los Angeles	5	85.47	
3	36	Female	Miami	3	97.94	
4	46	Female	Miami	19	58.14	
...	...	...	...	...	...	
99995	33	Male	Houston	23	55.13	
99996	62	Female	New York	19	61.65	
99997	64	Male	Chicago	17	96.11	

```
# Handling missing data
data.dropna(inplace=True)

# Handling outliers (you can use appropriate methods depending on the distribution of your data)
# For example, using z-score for numerical columns
from scipy.stats import zscore
z_scores = zscore(data[['Age', 'Subscription_Length_Months', 'Monthly_Bill', 'Total_Usage_GB']])
data = data[(z_scores < 3).all(axis=1)]
```

```
data
```

	Age	Gender	Location	Subscription_Length_Months	Monthly_Bill	To
0	63	Male	Los Angeles	17	73.36	
1	62	Female	New York	1	48.76	
2	24	Female	Los Angeles	5	85.47	
3	36	Female	Miami	3	97.94	
4	46	Female	Miami	19	58.14	
...	...	...	...	...	...	
99995	33	Male	Houston	23	55.13	
99996	62	Female	New York	19	61.65	
99997	64	Male	Chicago	17	96.11	

```
# Example: Remove outliers using IQR
Q1 = data['Total_Usage_GB'].quantile(0.25)
Q3 = data['Total_Usage_GB'].quantile(0.75)
IQR = Q3 - Q1
data = data[(data['Total_Usage_GB'] >= Q1 - 1.5 * IQR) & (data['Total_Usage_GB'] <= Q3 + 1.5 * IQR)]
```

```
# Let's say 'Gender' is a categorical column you want to encode
data= pd.get_dummies(data, columns=['Gender'], drop_first=True)
```

```
# Example: Min-Max Scaling
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
data[['Age', 'Monthly_Bill']] = scaler.fit_transform(data[['Age', 'Monthly_Bill']])
```

```
data
```

	Age	Location	Subscription_Length_Months	Monthly_Bill	Total
0	0.865385	Los Angeles	17	0.619429	
1	0.846154	New York	1	0.268000	
2	0.115385	Los Angeles	5	0.792429	
3	0.346154	Miami	3	0.970571	
4	0.538462	Miami	19	0.402000	
...	...	...	...	...	
99995	0.288462	Houston	23	0.359000	
99996	0.846154	New York	19	0.452143	
99997	0.884615	Chicago	17	0.944429	

feature engineering

```
# Example: Create a feature for the ratio of Monthly_Bill to Total_Usage_GB
data['Bill_to_Usage_Ratio'] = data['Monthly_Bill'] / data['Total_Usage_GB']
```

```
# Example: Create an interaction feature
data['Subscription_Bill_Interaction'] = data['Subscription_Length_Months'] * data['Monthly_Bill']
```

```
# Example: Calculate the average Monthly_Bill by Location
average_bill_by_location = data.groupby('Location')['Monthly_Bill'].mean().reset_index()
average_bill_by_location.rename(columns={'Monthly_Bill': 'Avg_Monthly_Bill_Location'}, inplace=True)
data = data.merge(average_bill_by_location, on='Location', how='left')
```

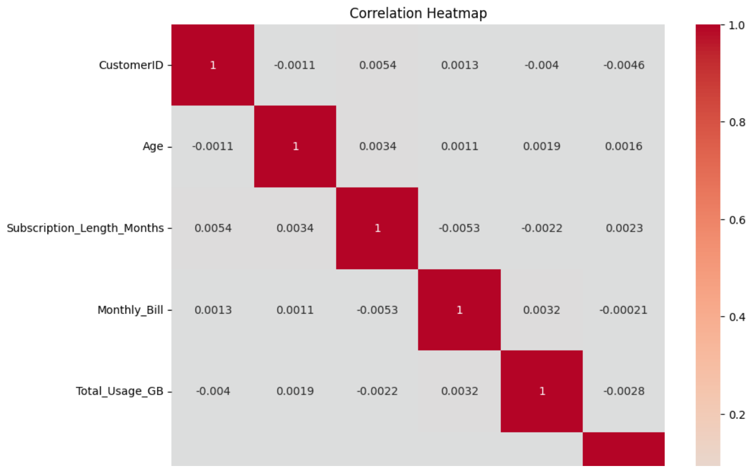
```
# Example: If you know that certain Age ranges are more likely to churn, create an Age_Group feature
data['Age_Group'] = pd.cut(data['Age'], bins=[0, 25, 35, 50, 100], labels=[0, 1,2,3])
```

```
data
```

	Age	Location	Subscription_Length_Months	Monthly_Bill	Total
0	0.865385	Los Angeles	17	0.619429	
1	0.846154	New York	1	0.268000	
2	0.115385	Los Angeles	5	0.792429	
3	0.346154	Miami	3	0.970571	
4	0.538462	Miami	19	0.402000	
...	...	...	...	...	
99995	0.288462	Houston	23	0.359000	
99996	0.846154	New York	19	0.452143	
99997	0.884615	Chicago	17	0.944429	
99998	0.634615	New York	20	0.275000	
99999	0.173077	Los Angeles	19	0.665286	

```
data = pd.read_excel('customer_churn_large_dataset.xlsx')
correlation_matrix = data.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', center=0)
plt.title('Correlation Heatmap')
plt.show()
```

```
<ipython-input-127-929b20b3ec89>:2: FutureWarning: The default value of nu
  correlation_matrix = data.corr()
```



Customer churn is highly correlated with Age and Subscription_Lenght_Month

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder

# Encode categorical variables
encoder = LabelEncoder()
data['Gender'] = encoder.fit_transform(data['Gender_Male'])
data['Location'] = encoder.fit_transform(data['Location'])

# Split the data into features (X) and target (y)
X = data.drop('Churn', axis=1)
y = data['Churn']

# Split into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
# Feature engineering
X_train['Bill_to_Usage_Ratio'] = X_train['Monthly_Bill'] / X_train['Total_Usage_GB']
X_test['Bill_to_Usage_Ratio'] = X_test['Monthly_Bill'] / X_test['Total_Usage_GB']
```

```
X_train
```

	Age	Location	Subscription_Length_Months	Monthly_Bill	Total
75220	0.692308	4	5	0.778571	
48955	0.192308	4	24	0.743714	
44966	0.750000	0	12	0.318429	
13568	0.019231	1	19	0.036714	
92727	0.730769	3	8	0.050286	
...	...	...	...	...	
6265	0.326923	3	21	0.533286	
54886	0.730769	0	13	0.791429	
76820	0.980769	1	2	0.660571	
860	0.711538	0	12	0.845571	
15795	0.153846	2	17	0.577286	

```
import pandas as pd
from sklearn.preprocessing import StandardScaler
```

```
# Apply feature scaling
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Print the first few rows of the scaled dataset
print(X_train_scaled)
```

```
[[ 6.53446686e-01  1.41703505e+00 -1.08272837e+00 ...  8.41406774e-01
   0.00000000e+00 -9.95534968e-01]
 [-1.04827574e+00  1.41703505e+00  1.66388226e+00 ...  8.41406774e-01
   0.00000000e+00  1.00448506e+00]
 [ 8.49799274e-01 -1.41806277e+00 -7.08191867e-02 ... -1.61937346e+00
   0.00000000e+00  1.00448506e+00]
 ...
 [ 1.63520963e+00 -7.09288318e-01 -1.51640373e+00 ...  5.15808394e-01
   0.00000000e+00  1.00448506e+00]
 [ 7.18897549e-01 -1.41806277e+00 -7.08191867e-02 ... -1.61937346e+00
   0.00000000e+00  1.00448506e+00]
 [-1.17917747e+00 -5.13861481e-04  6.51973084e-01 ...  9.61784624e-01
   0.00000000e+00 -9.95534968e-01]]
```

Model selection and optimization.

```
import pandas as pd
from sklearn.impute import SimpleImputer
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score


from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

imputer = SimpleImputer(strategy='mean')  # You can use other strategies as well

# Impute missing values in the feature matrix
X_imputed = imputer.fit_transform(X_train)
X_test_imputed= imputer.transform(X_test)
# Initialize the model
model = RandomForestClassifier(random_state=42)
# Train the model
model.fit(X_imputed, y_train)
```

```
▾        RandomForestClassifier
RandomForestClassifier(random_state=42)
```

```
y_pred=model.predict(X_test_imputed)
```

+ Code + Text

```
# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

print(f"Accuracy: {accuracy:.2f}")
print(f"Precision: {precision:.2f}")
print(f"Recall: {recall:.2f}")
print(f"F1 Score: {f1:.2f}")
```

```
Accuracy: 0.50
Accuracy: 0.50
Precision: 0.50
Recall: 0.47
F1 Score: 0.48
```

```
from sklearn.model_selection import GridSearchCV

# Define hyperparameters to tune
param_grid = {
    'n_estimators': [10, 20, 30],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

# Initialize GridSearchCV
grid_search = GridSearchCV(estimator=model, param_grid=param_grid, cv=3, scoring='f1')

# Perform grid search
grid_search.fit(X_imputed, y_train)

# Get the best model
best_model = grid_search.best_estimator_

# Make predictions using the best model
y_pred_best = best_model.predict(X_test_imputed)

# Evaluate the best model
f1_best = f1_score(y_test, y_pred_best)
print(f"Best F1 Score: {f1_best:.2f}")
```

```
Best F1 Score: 0.49
```