AMAN ARPIT

In [116…
```python
# Importing the required Libraries
import pandas as pd
import numpy as np
from datetime import datetime as dt
from scipy import stats

# Visualization
import matplotlib.pyplot as plt
import seaborn as sns; sns.set()

# Data Preprocessing
from sklearn.model_selection import train_test_split
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OneHotEncoder, OrdinalEncoder
from sklearn.preprocessing import PowerTransformer

# Model
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn.model_selection import cross_val_score, GridSearchCV

from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
```

In [5]:
```python
#Loding the dataset
df = pd.read_csv(r"C:\Users\91700\Downloads\bank+marketing\bank-additional\bank-additional\bank-additional-full
df_raw = df.copy()
```

In [6]:
```python
df_raw.head()
```

Out[6]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	...	campaign	pdays	previous	poutcome
0	56	housemaid	married	basic.4y	no	no	no	telephone	may	mon	...	1	999	0	nonexistent
1	57	services	married	high.school	unknown	no	no	telephone	may	mon	...	1	999	0	nonexistent
2	37	services	married	high.school	no	yes	no	telephone	may	mon	...	1	999	0	nonexistent
3	40	admin.	married	basic.6y	no	no	no	telephone	may	mon	...	1	999	0	nonexistent
4	56	services	married	high.school	no	no	yes	telephone	may	mon	...	1	999	0	nonexistent

5 rows × 21 columns

In [7]:
```python
df_raw.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   age             41188 non-null  int64  
 1   job             41188 non-null  object 
 2   marital         41188 non-null  object 
 3   education       41188 non-null  object 
 4   default         41188 non-null  object 
 5   housing         41188 non-null  object 
 6   loan            41188 non-null  object 
 7   contact         41188 non-null  object 
 8   month           41188 non-null  object 
 9   day_of_week     41188 non-null  object 
 10  duration        41188 non-null  int64  
 11  campaign        41188 non-null  int64  
 12  pdays           41188 non-null  int64  
 13  previous        41188 non-null  int64  
 14  poutcome        41188 non-null  object 
 15  emp.var.rate    41188 non-null  float64
 16  cons.price.idx  41188 non-null  float64
 17  cons.conf.idx   41188 non-null  float64
 18  euribor3m       41188 non-null  float64
 19  nr.employed     41188 non-null  float64
 20  y               41188 non-null  object 
dtypes: float64(5), int64(5), object(11)
memory usage: 6.6+ MB
```

In [9]:
```python
df_raw.shape
```

Out[9]: (41188, 21)

In [11]:
```python
df_raw.isnull().sum()
```

Out[11]:
```
age               0
job               0
marital           0
education         0
default           0
housing           0
loan              0
contact           0
month             0
day_of_week       0
duration          0
campaign          0
pdays             0
previous          0
poutcome          0
emp.var.rate      0
cons.price.idx    0
cons.conf.idx     0
euribor3m         0
nr.employed       0
y                 0
dtype: int64
```

In [12]:
```python
df_raw.describe()
```

Out[12]:

	age	duration	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.e
count	41188.00000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	4118
mean	40.02406	258.285010	2.567593	962.475454	0.172963	0.081886	93.575664	-40.502600	3.621291	516
std	10.42125	259.279249	2.770014	186.910907	0.494901	1.570960	0.578840	4.628198	1.734447	7
min	17.00000	0.000000	1.000000	0.000000	0.000000	-3.400000	92.201000	-50.800000	0.634000	496
25%	32.00000	102.000000	1.000000	999.000000	0.000000	-1.800000	93.075000	-42.700000	1.344000	509
50%	38.00000	180.000000	2.000000	999.000000	0.000000	1.100000	93.749000	-41.800000	4.857000	519
75%	47.00000	319.000000	3.000000	999.000000	0.000000	1.400000	93.994000	-36.400000	4.961000	522
max	98.00000	4918.000000	56.000000	999.000000	7.000000	1.400000	94.767000	-26.900000	5.045000	522

Exploratory Data Analysis

In [14]:
```python
#checking for duplicate data
df_raw.duplicated().sum()
```

Out[14]: 12

In [19]:
```python
#As there are 12 duplicate values let's drop those values
print("Before : ",df_raw.shape)
df_n=df_raw.drop_duplicates()
df_n.reset_index(drop=True, inplace=True)
print("After : ",df_n.shape)

print("Number of duplicate data are: ",df_n.duplicated().sum())
```

```
Before :  (41188, 21)
After :  (41176, 21)
Number of duplicate data are:  0
```

In [20]:
```python
# Preliminary Check
# Variable : age
# Description : Customer's age

var ='age'
print('variable :', var)
print()
print('Descriptive stats:')
print(df[var].describe(percentiles=[0.5]))
```

```
variable : age

Descriptive stats:
count    41188.00000
mean        40.02406
std         10.42125
min         17.00000
50%         38.00000
max         98.00000
Name: age, dtype: float64
```

The minimum age is 17, max age is 98 and mean is around 40

The minimum age is 17 ,max age is 98 and mean is around 40

In [21]:
```
# Variable : job
# Description : types of job

var='job'
print('variable:', var)
print()
print('Unique Value Count:', df[var].nunique())
print(df[var].unique())
```

```
variable: job

Unique Value Count: 12
['housemaid' 'services' 'admin.' 'blue-collar' 'technician' 'retired'
 'management' 'unemployed' 'self-employed' 'unknown' 'entrepreneur'
 'student']
```

In [22]:
```
# Variable : marital
# Description : marital status

var = 'marital'

print('variable:', var)
print()
print('Unique Value Count:', df[var].nunique())
print(df[var].unique())
```

```
variable: marital

Unique Value Count: 4
['married' 'single' 'divorced' 'unknown']
```

In [23]:
```
# Variable : education

var = 'education'
print('variable:', var)
print()
print('Unique Value Count:', df[var].nunique())
print(df[var].unique())
```

```
variable: education

Unique Value Count: 8
['basic.4y' 'high.school' 'basic.6y' 'basic.9y' 'professional.course'
 'unknown' 'university.degree' 'illiterate']
```

In [24]:
```
# Variable : default

var = 'default'
print('variable:', var)
print()
print('Unique Value Count:', df[var].nunique())
print(df[var].unique())
```

```
variable: default

Unique Value Count: 3
['no' 'unknown' 'yes']
```

In [25]:
```
# Variable : housing


var ='housing'

print('variable:', var)
print()
print('Unique Value Count:', df[var].nunique())
print(df[var].unique())
```

```
variable: housing

Unique Value Count: 3
['no' 'yes' 'unknown']
```

In [26]:
```
# Preliminary Check
# Variable : month
# Description :last contact month of year
var = 'month'
print('variable:', var)
print()
print('Unique Value Count:', df[var].nunique())
print(df[var].unique())
print(df[var].dtype)
```

```
variable: month

Unique Value Count: 10
['may' 'jun' 'jul' 'aug' 'oct' 'nov' 'dec' 'mar' 'apr' 'sep']
object
```

In [27]:
```python
#converting months into numerical value
month_rename = {'may':5, 'jun':6, 'jul':7, 'aug':8, 'oct':10, 'nov':11, 'dec':12, 'mar':3, 'apr':4, 'sep':9}
df['month'] = df['month'].map(month_rename).astype(object)

print(df['month'].unique())
```

```
[5 6 7 8 10 11 12 3 4 9]
```

In [29]:
```python
var = 'day_of_week'

print('variable:', var)
print()
print('Unique Value Count:', df[var].nunique())
print(df[var].unique())
print(df[var].dtype)
```

```
variable: day_of_week

Unique Value Count: 5
['mon' 'tue' 'wed' 'thu' 'fri']
object
```

In [30]:
```python
days_rename = {'mon':1, 'tue':2, 'wed':3, 'thu':4, 'fri':5,}
df['day_of_week'] = df['day_of_week'].map(days_rename)

print(df['day_of_week'].unique())
```

```
[1 2 3 4 5]
```

In [31]:
```python
df.head()
```

Out[31]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	...	campaign	pdays	previous	poutcome
0	56	housemaid	married	basic.4y	no	no	no	telephone	5	1	...	1	999	0	nonexistent
1	57	services	married	high.school	unknown	no	no	telephone	5	1	...	1	999	0	nonexistent
2	37	services	married	high.school	no	yes	no	telephone	5	1	...	1	999	0	nonexistent
3	40	admin.	married	basic.6y	no	no	no	telephone	5	1	...	1	999	0	nonexistent
4	56	services	married	high.school	no	no	yes	telephone	5	1	...	1	999	0	nonexistent

5 rows × 21 columns

In [32]:
```python
# Description : last contact duration, in seconds (numeric).

var = 'duration'
print('variable:', var)
print()
print('Descriptive stats:')
print(df[var].describe().round())
```

```
variable: duration

Descriptive stats:
count    41188.0
mean       258.0
std        259.0
min          0.0
25%        102.0
50%        180.0
75%        319.0
max       4918.0
Name: duration, dtype: float64
```

As we can see here the difference between min and max value is to high,Here we may have outliers.

In [33]:
```python
 # Description : number of contacts performed during this campaign and for this client

var = 'campaign'

print('variable:', var)
print()
print('Descriptive stats:')
print(df[var].describe().round())
```

```
variable: campaign

Descriptive stats:
count    41188.0
mean         3.0
std          3.0
min          1.0
25%          1.0
50%          2.0
75%          3.0
max         56.0
Name: campaign, dtype: float64
```

In [34]:
```
# Description : number of days that passed by after the client was last contacted from a previous campaign

var = 'pdays'

print('variable:', var)
print()
print('Descriptive stats:')
print(df[var].describe().round())
```

```
variable: pdays

Descriptive stats:
count    41188.0
mean       962.0
std        187.0
min          0.0
25%        999.0
50%        999.0
75%        999.0
max        999.0
Name: pdays, dtype: float64
```

we may have outliers here also

In [35]:
```
# Description : number of contacts performed before this campaign and for this client (numeric)

var = 'previous'

print('variable:', var)
print()
print('Descriptive stats:')
print(df[var].describe().round())
```

```
variable: previous

Descriptive stats:
count    41188.0
mean         0.0
std          0.0
min          0.0
25%          0.0
50%          0.0
75%          0.0
max          7.0
Name: previous, dtype: float64
```

In [36]:
```
# Variable : poutcome
# Description : outcome of the previous marketing campaign
var = 'poutcome'

print('variable:', var)
print()
print('Unique Value Count:', df[var].nunique())
print(df[var].unique())
print(df[var].dtype)
```

```
variable: poutcome

Unique Value Count: 3
['nonexistent' 'failure' 'success']
object
```

In [37]:
```
# Description : employment variation rate

var = 'emp.var.rate'

print('variable:', var)
print()
print('Descriptive stats:')
print(df[var].describe().round())
```

```
variable: emp.var.rate

Descriptive stats:
count    41188.0
mean         0.0
std          2.0
min         -3.0
25%         -2.0
50%          1.0
75%          1.0
max          1.0
Name: emp.var.rate, dtype: float64
```

In [38]:
```
df.rename(columns={'emp.var.rate':'emp_var_rate'}, inplace=True)
```

In [39]:
```
# Description : consumer price index - monthly indicator (numeric)
```

```
var = 'cons.price.idx'

print('variable:', var)
print()
print('Descriptive stats:')
print(df[var].describe().round())
```

```
variable: cons.price.idx

Descriptive stats:
count    41188.0
mean        94.0
std          1.0
min         92.0
25%         93.0
50%         94.0
75%         94.0
max         95.0
Name: cons.price.idx, dtype: float64
```

In [41]:
```
df.rename(columns={'cons.price.idx':'cons_price_idx'}, inplace=True)
df.rename(columns={'cons.conf.idx':'cons_conf_idx'}, inplace=True)
df.rename(columns={'nr.employed':'nr_employed'}, inplace=True)
```

In [42]:
```
# Description :  Subscribed or not?
var = 'y'

print('variable:', var)
print()
print('Unique Value Count:', df[var].nunique())
print(df[var].unique())
print(df[var].dtype)
```

```
variable: y

Unique Value Count: 2
['no' 'yes']
object
```

In [43]:
```
#let's change it into numeric value that is 0 or 1
y_rename = {'yes':1, 'no':0}
df['y'] = df['y'].map(y_rename)

print(df['y'].unique())
```

```
[0 1]
```

In [44]:
```
df.rename(columns={'y':'subs_status'}, inplace=True)
```

In [48]:
```
df.head(10)
```

Out[48]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	...	campaign	pdays	previous	pou
0	56	housemaid	married	basic.4y	no	no	no	telephone	5	1	...	1	999	0	none
1	57	services	married	high.school	unknown	no	no	telephone	5	1	...	1	999	0	none
2	37	services	married	high.school	no	yes	no	telephone	5	1	...	1	999	0	none
3	40	admin.	married	basic.6y	no	no	no	telephone	5	1	...	1	999	0	none
4	56	services	married	high.school	no	no	yes	telephone	5	1	...	1	999	0	none
5	45	services	married	basic.9y	unknown	no	no	telephone	5	1	...	1	999	0	none
6	59	admin.	married	professional.course	no	no	no	telephone	5	1	...	1	999	0	none
7	41	blue-collar	married	unknown	unknown	no	no	telephone	5	1	...	1	999	0	none
8	24	technician	single	professional.course	no	yes	no	telephone	5	1	...	1	999	0	none
9	25	services	single	high.school	no	yes	no	telephone	5	1	...	1	999	0	none

10 rows × 21 columns

In [53]:
```
print(df['subs_status'].value_counts())
print()
print(df['subs_status'].value_counts(normalize=True)*100)
```

```
0    36548
1     4640
Name: subs_status, dtype: int64

0    88.734583
1    11.265417
Name: subs_status, dtype: float64
```

In [54]:
```
m= sns.countplot(df['subs_status'], palette='Set2')
m.set(xticklabels=['Not Subscribed', 'Subscribed'])
plt.show()
```

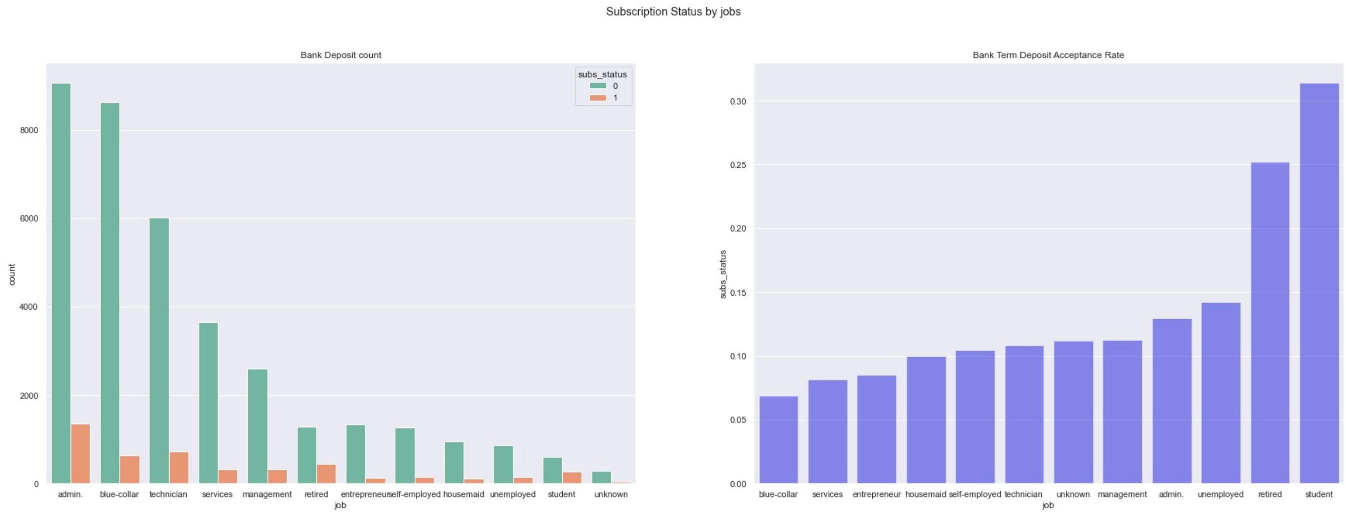
```
C:\Users\91700\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variabl
e as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

In [55]:
```
#Analyzing the marital status
fig, ax = plt.subplots(1,2, figsize=(30, 10))
plt.suptitle('Subscription Status by Marital Status')
sns.countplot(df['marital'], hue=df['subs_status'], palette='Set2', order=df['marital'].value_counts().index, a
ax[0].set_title('Bank Term Deposit count')
graph = df.groupby('marital')['subs_status'].mean().sort_values()
sns.barplot(x=graph.index, y=graph, color='blue', alpha=0.5, ax=ax[1])
ax[1].set_title('Bank Term Deposit Acceptance Rate')


plt.show()
```

```
C:\Users\91700\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variabl
e as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

In [59]:
```
fig,ax=plt.subplots(1,2, figsize=(30,10))
plt.suptitle('Subscription Status by jobs')
sns.countplot(df['job'], hue=df['subs_status'],palette='Set2', order=df['job'].value_counts().index,ax=ax[0])
ax[0].set_title('Bank Deposit count')

graph = df.groupby('job')['subs_status'].mean().sort_values()
sns.barplot(x=graph.index, y=graph, color='blue', alpha=0.5, ax=ax[1])
ax[1].set_title('Bank Term Deposit Acceptance Rate')

plt.show()
```

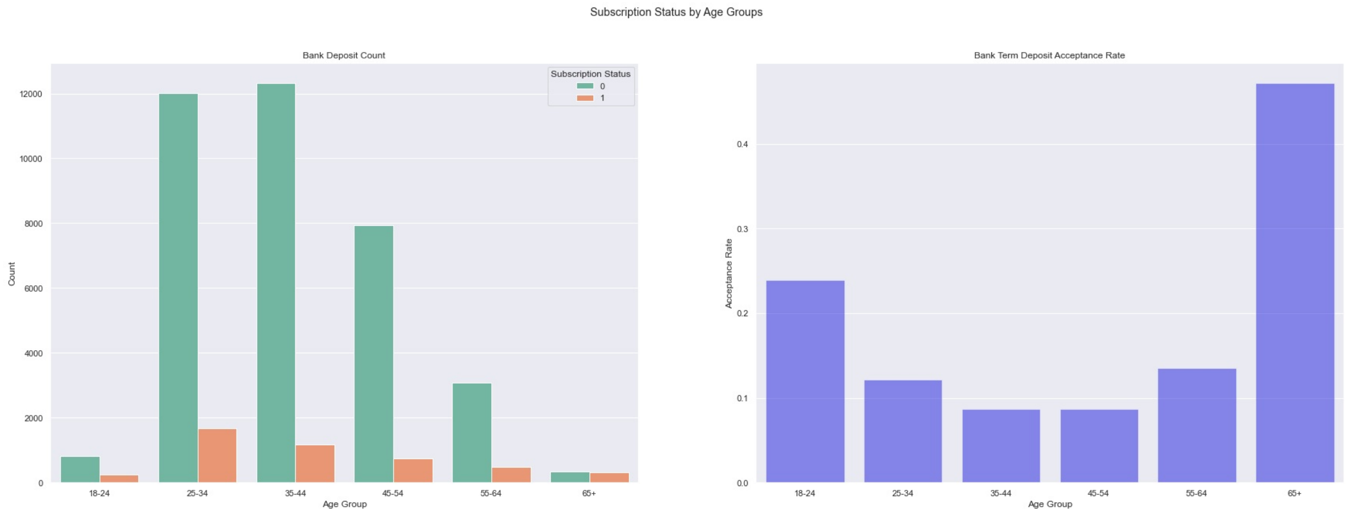
```
C:\Users\91700\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variabl
e as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```



Student and Retired people have high acceptance rate

Admin and blue collar are frequent clients of the company

In [62]:
```python
import seaborn as sns
import matplotlib.pyplot as plt


age_groups = ['18-24', '25-34', '35-44', '45-54', '55-64', '65+']
age_bins = [18, 25, 35, 45, 55, 65, 100]
df['age_group'] = pd.cut(df['age'], bins=age_bins, labels=age_groups, right=False)


fig, ax = plt.subplots(1, 2, figsize=(30, 10))
plt.suptitle('Subscription Status by Age Groups')

sns.countplot(x='age_group', hue='subs_status', palette='Set2', order=age_groups, data=df, ax=ax[0])
ax[0].set_title('Bank Deposit Count')
ax[0].set_xlabel('Age Group')
ax[0].set_ylabel('Count')
ax[0].legend(title='Subscription Status')

graph = df.groupby('age_group')['subs_status'].mean().sort_values()
sns.barplot(x=graph.index, y=graph, color='blue', alpha=0.5, ax=ax[1])
ax[1].set_title('Bank Term Deposit Acceptance Rate')
ax[1].set_xlabel('Age Group')
ax[1].set_ylabel('Acceptance Rate')

plt.show()
```

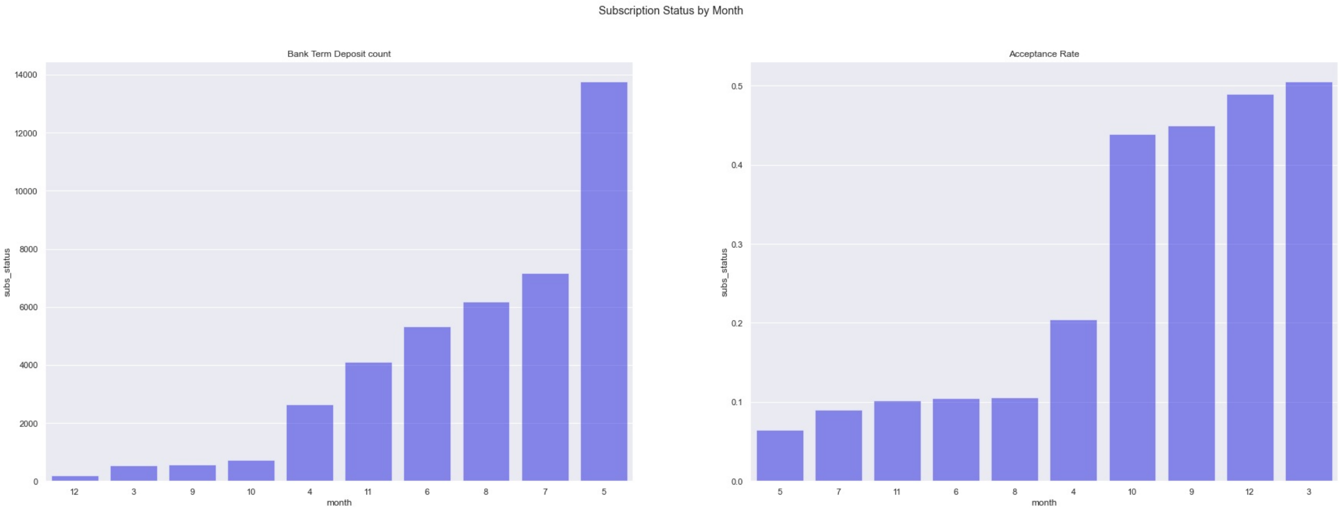


Age group between 25-34 are frequent clients

Age group between 25-64 are frequent clients

People above the age of 65 have higher acceptance rate

In [65]:
```
fig, ax = plt.subplots(1,2, figsize=(30, 10))
plt.suptitle('Subscription Status by Month')

graph = df.groupby('month')['subs_status'].count().sort_values()
sns.barplot(x=graph.index, y=graph, order=graph.index, color='blue', alpha=0.5, ax=ax[0])
ax[0].set_title('Bank Term Deposit count')

graph = df.groupby('month')['subs_status'].mean().sort_values()
sns.barplot(x=graph.index, y=graph, order=graph.index, color='blue', alpha=0.5, ax=ax[1])
ax[1].set_title('Acceptance Rate')

plt.show()
```



In May the clients are highest

.

Data Preprocessing

    16 Samples for inference set ,70% Train set and 30% Test set

In [66]:
```
random_state = 42
```

In [67]:
```
inf_set=df.sample(16,random_state=random_state)
```

In [73]:
```
inf_set.shape
```

Out[73]:
```
(16, 22)
```

In [72]:
```
#Dropping the inference data

train_test_data=df.drop(inf_set.index)
train_test_data.reset_index(drop=True,inplace=True)
train_test_data.shape
```

Out[72]:
```
(41172, 22)
```

In [75]:
```
df.shape
```

Out[75]:
```
(41188, 22)
```

In [77]:
```
# Splitting the data

# X input parameter only
X = train_test_data.drop(['subs_status'], axis=1)

# y target parameter only
y = train_test_data['subs_status']
```

In [106…
```
X_encoded = pd.get_dummies(X, drop_first=True)
X_train, X_test, y_train, y_test = train_test_split(X_encoded, y, test_size=0.2, random_state=42)
```

```
C:\Users\91700\Anaconda3\lib\site-packages\pandas\core\algorithms.py:798: FutureWarning: In a future version, t
he Index constructor will not infer numeric dtypes when passed object-dtype sequences (matching Series behavior
)
  uniques = Index(uniques)
```

In [107…

```python
print("Train set : ",X_train.shape)
print("Test set : ",X_test.shape)
print("Inference set : ",inf_set.shape)
```

```
Train set :  (32937, 55)
Test set :  (8235, 55)
Inference set :  (16, 22)
```

In [108…

```python
from scipy import stats

z_scores = stats.zscore(df['previous'])
df_no_outliers = df[(z_scores < 3) & (z_scores > -3)]
```

In [109…

```python
from scipy import stats

z_scores = stats.zscore(df['duration'])
df_no_outliers = df[(z_scores < 3) & (z_scores > -3)]
```

In [110…

```python
from scipy import stats

z_scores = stats.zscore(df['campaign'])
df_no_outliers = df[(z_scores < 3) & (z_scores > -3)]
```

In [111…

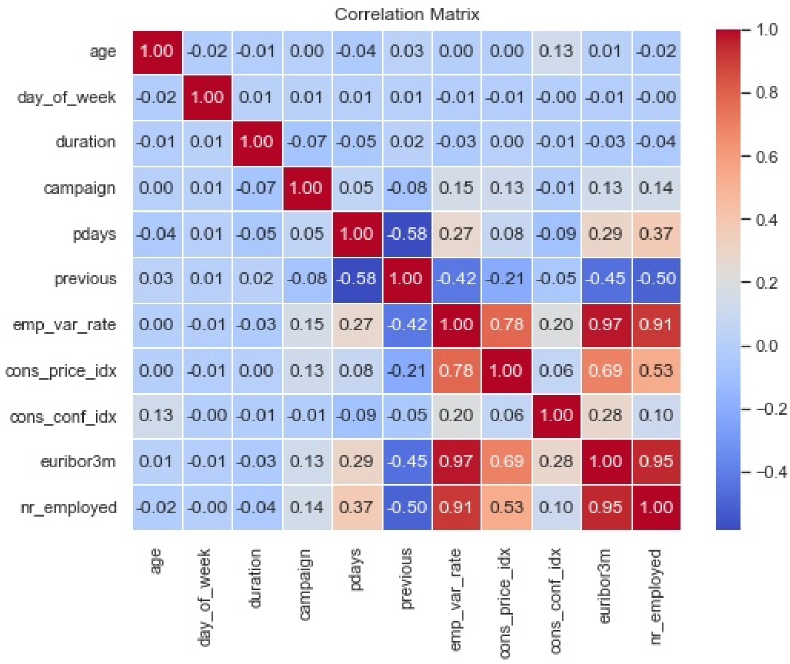
```python
from scipy import stats

z_scores = stats.zscore(df['pdays'])
df_no_outliers = df[(z_scores < 3) & (z_scores > -3)]
```

In [112…

```python
from scipy import stats

z_scores = stats.zscore(df['age'])
df_no_outliers = df[(z_scores < 3) & (z_scores > -3)]
```

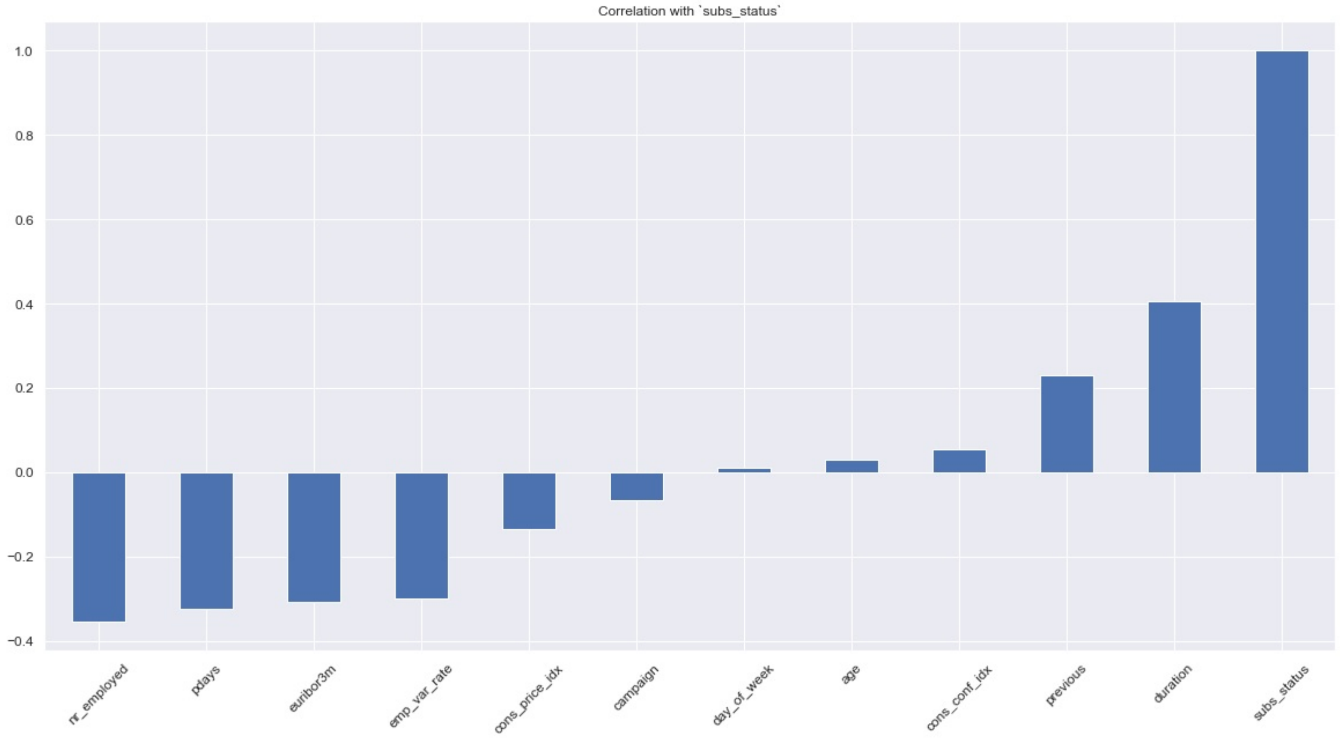
In [113…

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

numeric_columns = X_train.select_dtypes(include=['float64', 'int64']).columns

correlation_matrix = X_train[numeric_columns].corr()

plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f", linewidths=0.5)
plt.title("Correlation Matrix")
plt.show()
```



In [153…

```python
df.corrwith(df['subs_status']).sort_values().plot.bar(figsize=(20,10), title='Correlation with `subs_status`',
plt.show()
```



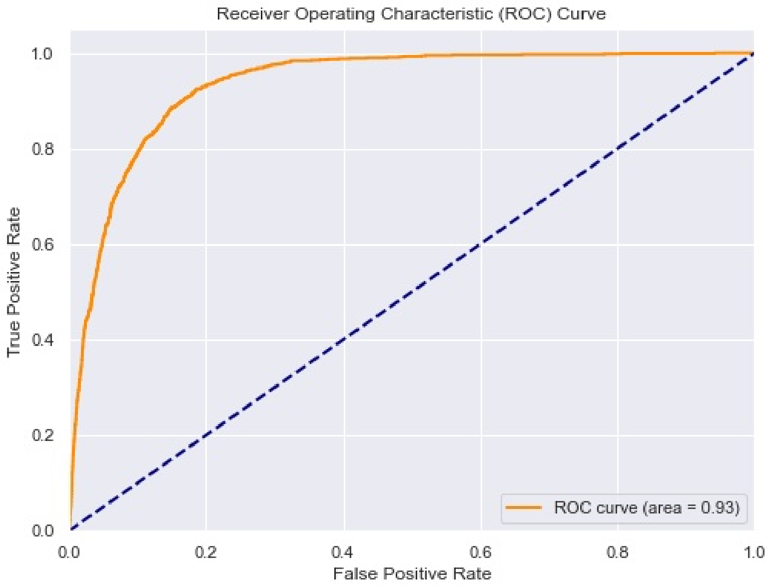
In [114…
```
print('X_train Before', X_train.shape)
print('y_train Before', y_train.shape)
print('X_train After', X_train.shape)
print('y_train After', y_train.shape)
```

```
X_train Before (32937, 55)
y_train Before (32937,)
X_train After (32937, 55)
y_train After (32937,)
```

Model Evaluation

In [150…
```
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix


scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

model = LogisticRegression(random_state=42)

model.fit(X_train_scaled, y_train)

y_pred = model.predict(X_test_scaled)


accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
classification_report_str = classification_report(y_test, y_pred)

print(f"Accuracy: {accuracy:.2f}")
print("\nConfusion Matrix:")
print(conf_matrix)
print("\nClassification Report:")
print(classification_report_str)

y_pred_prob = model.predict_proba(X_test_scaled)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)
roc_auc = auc(fpr, tpr)

# Plot ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area = {:.2f})'.format(roc_auc))
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```

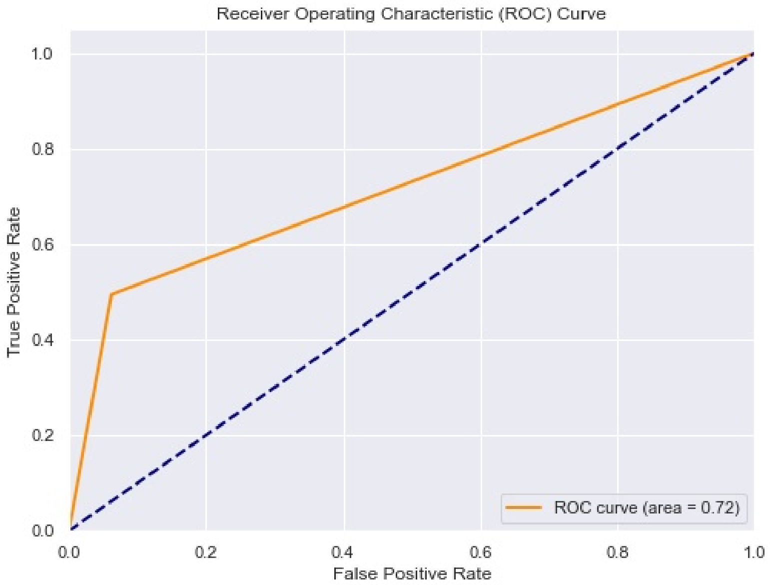
```
Accuracy: 0.91

Confusion Matrix:
[[7080  175]
 [ 555  425]]

Classification Report:
              precision    recall  f1-score   support

           0       0.93      0.98      0.95      7255
           1       0.71      0.43      0.54       980

    accuracy                           0.91      8235
   macro avg       0.82      0.70      0.74      8235
weighted avg       0.90      0.91      0.90      8235
```



In [146…

```python
from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt

model = DecisionTreeClassifier(random_state=42)
scaler = StandardScaler()
model.fit(X_train, y_train)

y_pred = model.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
classification_report_str = classification_report(y_test, y_pred)


print(f"Accuracy: {accuracy:.2f}")
print("\nConfusion Matrix:")
print(conf_matrix)
print("\nClassification Report:")
print(classification_report_str)

from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt

def plot_roc_curve(model, X, y):
    y_pred_prob = model.predict_proba(X)[:, 1]
    fpr, tpr, _ = roc_curve(y, y_pred_prob)
    roc_auc = auc(fpr, tpr)

    # Plot ROC curve
    plt.figure(figsize=(8, 6))
    plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area = {:.2f})'.format(roc_auc))
    plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver Operating Characteristic (ROC) Curve')
    plt.legend(loc='lower right')
    plt.show()

plot_roc_curve(model, X_test, y_test)
```

```
Accuracy: 0.89

Confusion Matrix:
[[6803  452]
 [ 495  485]]

Classification Report:
              precision    recall  f1-score   support

           0       0.93      0.94      0.93      7255
           1       0.52      0.49      0.51       980

    accuracy                           0.89      8235
   macro avg       0.72      0.72      0.72      8235
weighted avg       0.88      0.89      0.88      8235
```



In [118…

```python
model = RandomForestClassifier(n_estimators=100, random_state=42)

model.fit(X_train, y_train)


y_pred = model.predict(X_test)


accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
classification_report_str = classification_report(y_test, y_pred)

print(f"Accuracy: {accuracy:.2f}")
print("\nConfusion Matrix:")
print(conf_matrix)
print("\nClassification Report:")
print(classification_report_str)
```

```
Accuracy: 0.91

Confusion Matrix:
[[7049  206]
 [ 552  428]]

Classification Report:
              precision    recall  f1-score   support

           0       0.93      0.97      0.95      7255
           1       0.68      0.44      0.53       980

    accuracy                           0.91      8235
   macro avg       0.80      0.70      0.74      8235
weighted avg       0.90      0.91      0.90      8235
```

In [119…

```python
model = KNeighborsClassifier(n_neighbors=3)


model.fit(X_train, y_train)


y_pred = model.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
classification_report_str = classification_report(y_test, y_pred)
```

```python
print(f"Accuracy: {accuracy:.2f}")
print("\nConfusion Matrix:")
print(conf_matrix)
print("\nClassification Report:")
print(classification_report_str)
```

```
Accuracy: 0.90

Confusion Matrix:
[[6900  355]
 [ 502  478]]

Classification Report:
              precision    recall  f1-score   support

           0       0.93      0.95      0.94      7255
           1       0.57      0.49      0.53       980

    accuracy                           0.90      8235
   macro avg       0.75      0.72      0.73      8235
weighted avg       0.89      0.90      0.89      8235
```

In [120…

```python
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)


model = SVC(kernel='rbf', random_state=42)

model.fit(X_train_scaled, y_train)

y_pred = model.predict(X_test_scaled)

accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
classification_report_str = classification_report(y_test, y_pred)

print(f"Accuracy: {accuracy:.2f}")
print("\nConfusion Matrix:")
print(conf_matrix)
print("\nClassification Report:")
print(classification_report_str)
```

```
Accuracy: 0.90

Confusion Matrix:
[[7084  171]
 [ 629  351]]

Classification Report:
              precision    recall  f1-score   support

           0       0.92      0.98      0.95      7255
           1       0.67      0.36      0.47       980

    accuracy                           0.90      8235
   macro avg       0.80      0.67      0.71      8235
weighted avg       0.89      0.90      0.89      8235
```

In [121…

```python
model = GaussianNB()

model.fit(X_train, y_train)

y_pred = model.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
classification_report_str = classification_report(y_test, y_pred)

print(f"Accuracy: {accuracy:.2f}")
print("\nConfusion Matrix:")
print(conf_matrix)
print("\nClassification Report:")
print(classification_report_str)
```

```
Accuracy: 0.87

Confusion Matrix:
[[6665  590]
 [ 508  472]]

Classification Report:
              precision    recall  f1-score   support

           0       0.93      0.92      0.92      7255
           1       0.44      0.48      0.46       980

    accuracy                           0.87      8235
   macro avg       0.69      0.70      0.69      8235
weighted avg       0.87      0.87      0.87      8235
```

In [125…

```
print("LogisticRegression",0.91)
print("DecisionTreeClassifier",0.89)
print("RandomForestClassifier",0.91)
print("KNeighborsClassifier",0.90)
print("GaussianNB",0.87)
print("SVC",0.90)
```

```
LogisticRegression 0.91
DecisionTreeClassifier 0.89
RandomForestClassifier 0.91
KNeighborsClassifier 0.9
GaussianNB 0.87
SVC 0.9
```

Based on the above result , our best performing model is Logistic Regression and The most under performed model in this case is only Naive Bayes model.

Questions

1) What is the distribution of the customer ages?

Ans:- Using this we can easily evaluate

Descriptive stats: count 41188.00000 mean 40.02406 std 10.42125 min 17.00000 50% 38.00000 max 98.00000 Name: age, dtype: float64

The minimum age is 17 ,max age is 98 and mean age is around 40.

2) What is the relationship between customer age and subscription?

Ans:- By analyzing and visualizing the data and graph we can conclude that Age group between 25-34 are frequent clients and People above the age of 65 have higher acceptance rate.

3)Are there any other factors that are correlated with subscription?

Ans:- Based on graph above, we can conclude that:- top three negatively correlated : nr_employed, pdays, euribor3m, emp_var_rate top three positively correlated : duration, and previous

4)What is the accuracy of the logistic regression model?

Ans:- Logistic regression is having the heighest accuracy and it is our best performing model with an accuracy of 0.91.

```
                  Classification Report:
              precision    recall  f1-score   support

           0       0.93      0.98      0.95      7255
           1       0.71      0.43      0.54       980

    accuracy                           0.91      8235
```

5)What are the most important features for the logistic regression

5)What are the most important features for the logistic regression model?

Ans:- a) The logistic regression statistic modeling technique is used when we have a binary outcome variable. For example:will the student pass or fail? Will it rain or not? ,will he buy subscription or not? etc.

b) The logistic (or sigmoid) function transforms the log-odds into probabilities between 0 and 1.

c)Logistic regression predicts probabilities rather than class labels

6)What is the precision of the logistic regression model?

Ans:- Precision is a metric used in classification models to evaluate the accuracy of the positive predictions made by the model. It is the ratio of true positive predictions to the total number of positive predictions made by the model.

In our case the precision is around 0.93 for 0 and 0.71 for 1 for Logistic regression model .

7)What is the recall of the logistic regression model?

Ans:-It is used in classification models to evaluate the ability of the model to capture and correctly identify all the relevant instances of the positive class.

In our case recall value is 0.98 for 0 and 0.54 for 1 in logistic regression model.

8)What is the f1-score of the logistic regression model?

Ans:- The F1-score is the harmonic mean of precision and recall, providing a balance between the two metrics. In our case it is 0.95 for 0 and 0.54 for 1.

9)How can you improve the performance of the logistic regression model?

Ans:- Some common method or ideas to improve the performance of the logistic regression model are:-

a) Handle missing data appropriately

b)Encode categorical variables properly (one-hot encoding or label encoding)

c)Identify and handle outliers in the dataset

d)Apply regularization to prevent overfitting(L1, L2 regularization)

e)To Ensure that numerical features are on a similar scale(StandardScaler or MinMaxScaler)

f)Cleaning the data properly and dealing with the missing and duplicate data.

10)What are the limitations of the logistic regression model?

Ans:- a) If the number of observations is lesser than the number of features, Logistic Regression should not be used, otherwise, it may lead to overfitting.

b)The major limitation of Logistic Regression is the assumption of linearity between the dependent variable and the independent variables.

c)It constructs linear boundaries.

d)It is tough to obtain complex relationships using logistic regression. More powerful and compact algorithms such as Neural Networks can easily outperform this algorithm.

END

In [ ]:

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