INTRODUCTION:

Predicting Customer Subscription to Term Deposits Using Bank Marketing Data

Summary

1.Business Understanding

2.Data Understanding

3.Data Preparation

4.Business Analysis

5.Modeling

6.Evaluation

7.Code Quality

1. Business Understanding

In this notebook, I am dealing with the data of a marketing campaign in our bank. .The primary goal is to predict whether a client will subscribe to a term deposit. This helps the bank focus its marketing efforts on clients with a higher probability of a positive response.

1.1 Problem Statement

The bank is running marketing campaigns to promote term deposit subscriptions, but the conversion rate is relatively low. Each campaign involves contacting thousands of clients, many of whom are not interested or eligible. This results in wasted resources, increased operational costs, and reduced marketing efficiency.

A successful predictive model enables the bank to:

- . Focus marketing efforts on customers most likely to convert.
- . Reduce operational costs by minimizing unnecessary calls.

1.2 Stakeholders for the Bank Marketing Campaign Project

Identifying stakeholders is important to ensure that the insights and models developed from the bank marketing dataset are aligned with business goals.

The key Stakeholders are:

- .Marketing Team: Optimize campaign targeting and messaging strategies.
- .Sales Executive: Increase conversion rates and ROI from outreach efforts.

- .Data Analysts: Build and evaluate predictive models; uncover meaningful customer

1.3 OBJECTIVES

- .Which customer attributes most strongly influence the likelihood of customers subscribing to a term deposit?
- .How do campaign related factors influence the likelihood of a customer subscribing to a term deposit?
- .Can we accurately predict whether a customer will subscribe using machine learning models?

2.Data Understanding

Dataset Overview

- .Source :The data source for this analysis is from **Kaggle** - Bank Marketing Campaign Dataset.
- .Features: 16 input features + 1 target (deposit)

2.1 Load The Dataset

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

```
C:\Users\user\anaconda3\envs\learn-env\lib\site-packages\scipy\__init__.p
y:138: UserWarning: A NumPy version >=1.16.5 and <1.23.0 is required for t
his version of SciPy (detected version 1.24.4)
  warnings.warn(f"A NumPy version >={np_minversion} and <{np_maxversion} i
s required for this version of "
```

In [2]:
```
df=pd.read_csv('bank.csv')
df.head()
```

Out[2]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month
0	59	admin.	married	secondary	no	2343	yes	no	unknown	5	may
1	56	admin.	married	secondary	no	45	no	no	unknown	5	may
2	41	technician	married	secondary	no	1270	yes	no	unknown	5	may
3	55	services	married	secondary	no	2476	yes	no	unknown	5	may
4	54	admin.	married	tertiary	no	184	no	no	unknown	5	may

2.2 Dataset Information

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11162 entries, 0 to 11161
Data columns (total 17 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   age        11162 non-null  int64 
 1   job        11162 non-null  object
 2   marital    11162 non-null  object
 3   education  11162 non-null  object
 4   default    11162 non-null  object
 5   balance    11162 non-null  int64 
 6   housing    11162 non-null  object
 7   loan       11162 non-null  object
 8   contact    11162 non-null  object
 9   day        11162 non-null  int64 
 10  month      11162 non-null  object
 11  duration   11162 non-null  int64 
 12  campaign   11162 non-null  int64 
 13  pdays      11162 non-null  int64 
 14  previous   11162 non-null  int64 
 15  poutcome   11162 non-null  object
 16  deposit    11162 non-null  object
dtypes: int64(7), object(10)
memory usage: 1.4+ MB
```

In [4]:
```
df.shape
```

Out[4]:
```
(11162, 17)
```

In [5]:
```
df.describe()
```

Out[5]:

	age	balance	day	duration	campaign	pdays	1
count	11162.000000	11162.000000	11162.000000	11162.000000	11162.000000	11162.000000	
mean	41.231948	1528.538524	15.658036	371.993818	2.508421	51.330407	
std	11.913369	3225.413326	8.420740	347.128386	2.722077	108.758282	
min	18.000000	-6847.000000	1.000000	2.000000	1.000000	-1.000000	
25%	32.000000	122.000000	8.000000	138.000000	1.000000	-1.000000	
50%	39.000000	550.000000	15.000000	255.000000	2.000000	-1.000000	
75%	49.000000	1708.000000	22.000000	496.000000	3.000000	20.750000	
max	95.000000	81204.000000	31.000000	3881.000000	63.000000	854.000000	

In [6]:
```
print(df.columns)
```

```
Index(['age', 'job', 'marital', 'education', 'default', 'balance', 'housin
g',
       'loan', 'contact', 'day', 'month', 'duration', 'campaign', 'pdays',
       'previous', 'poutcome', 'deposit'],
      dtype='object')
```

3.Data Preparation

3.1 Handling Missing Values and Duplicates

In [7]:
```
df.isnull().sum()
```

Out[7]:
```
age          0
job          0
marital      0
education    0
default      0
balance      0
housing      0
loan         0
contact      0
day          0
month        0
duration     0
campaign     0
pdays        0
previous     0
poutcome     0
deposit      0
dtype: int64
```

In [8]:
```
df.duplicated()
```

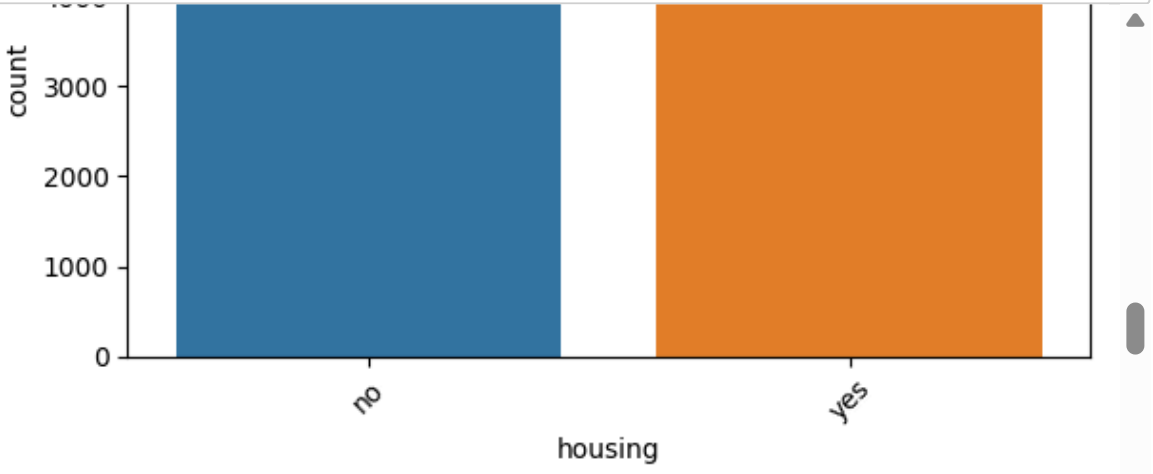
Out[8]:
```
0        False
1        False
2        False
3        False
4        False
         ...
11157    False
11158    False
11159    False
11160    False
11161    False
Length: 11162, dtype: bool
```

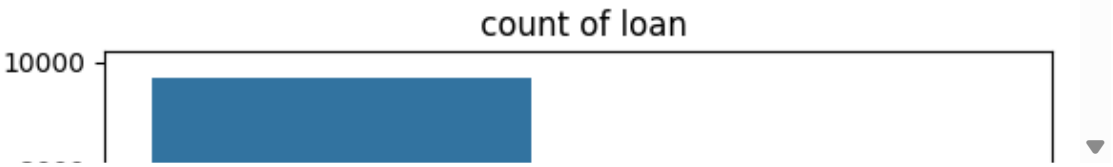
3.2. Handling Categorical Variables

In [9]:
```
# Categorical features:
categorical_features = df.select_dtypes(include=['object', 'bool']).columns.

# Numerical features:

numerical_features = df.select_dtypes(include=['int64', 'float64']).columns.


print("Numerical Features:", numerical_features)
print("Categorical Features:", categorical_features)
```

```
Numerical Features: ['age', 'balance', 'day', 'duration', 'campaign', 'pda
ys', 'previous']
Categorical Features: ['job', 'marital', 'education', 'default', 'housin
g', 'loan', 'contact', 'month', 'poutcome', 'deposit']
```

In [10]:
```
for col in categorical_features:
    plt.figure(figsize=(6, 4))
    sns.countplot(data=df, x=col, order=df[col].value_counts().index)
    plt.title(f" count of {col}")
    plt.xticks(rotation=45)
    plt.tight_layout()
    plt.show()
```





4. BUSINESS ANALYSIS

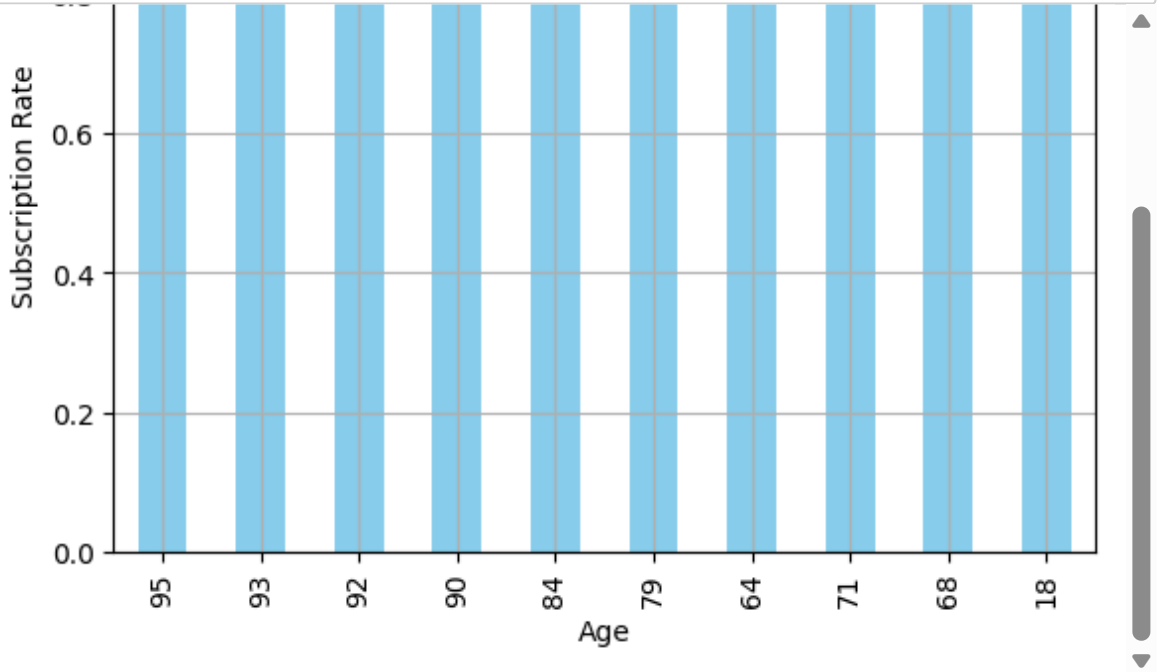
- In this section, we are going to look at the top reason why a cutomer is likely to Subscribe to Term Deposits. This analysis will help us create retention strategies

4.1 Customer Segmentation Objective

In [11]:
```
# Which customer attributes most strongly influence the likelihood of custom
# Group by age and count the number of 'yes' deposits

yes_counts = df[df['deposit'] == 'yes'].groupby('age').size()
total_counts = df.groupby('age').size()
age_yes_rate = (yes_counts / total_counts).sort_values(ascending=False)

print(age_yes_rate.head(10))
```

```
age
95    1.000000
93    1.000000
92    1.000000
90    1.000000
84    1.000000
79    1.000000
64    0.945946
71    0.925926
68    0.875000
18    0.875000
dtype: float64
```

In [12]:
```
#plotting
age_yes_rate.head(10).plot(kind='bar', color='skyblue')
plt.title('Top 10 Age Groups with Highest Deposit Subscription Rate')
plt.xlabel('Age')
plt.grid()
plt.ylabel('Subscription Rate')
plt.show()
```



Interpretation

- Ages 79, 84, 90, 92, 93, and 95 all have nearly 100% subscription rates.

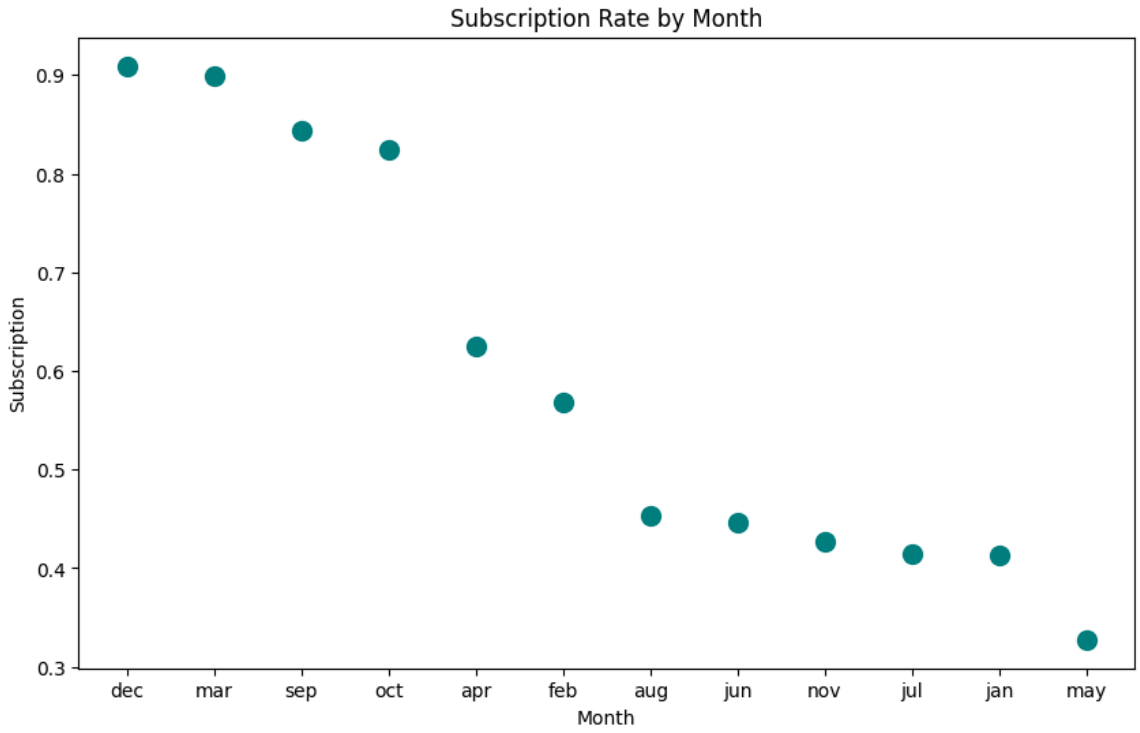
- This likely indicates that when customers in these older age groups are contacted,

4.2 Campaign Optimization Objective

In [13]:
```
#How do campaign related factors influence the likelihood of a customer subs
# Group by month and count the number of 'yes' deposits

yes_by_month = df[df['deposit'] == 'yes'].groupby('month').size()

total_by_month = df.groupby('month').size()

month_rate = (yes_by_month / total_by_month).sort_values(ascending=False)

print(month_rate)
```

```
month
dec    0.909091
mar    0.898551
sep    0.843260
oct    0.823980
apr    0.625135
feb    0.568299
aug    0.452930
jun    0.446809
nov    0.427359
jul    0.414135
jan    0.412791
may    0.327550
dtype: float64
```

In [14]:
```
#plotting

plt.figure(figsize=(10, 6))
plt.scatter(month_rate.index, month_rate.values, color='teal', s=100)
plt.title('Subscription Rate by Month')
plt.xlabel('Month')
plt.ylabel('Subscription')
plt.show()
```



Interpretation

- December,March and September are the months that show the strongest likelihood of customers subscribing to a term deposit which can be due to end of year financial planning.
- January and May, may see less subscribing rates.

5.Predictive Modeling

building and evaluating machine learning models to predict whether a customer will subscribe to a term deposit.I will begin with Logistic Regression as a baseline model due to its interpretability. I refine the predictions using a Decision Tree model, which captures complex patterns in customer behavior more effectively, leading to improved accuracy and performance in term deposit prediction.

In [15]:
```
#dealing with multi-categorical variables
multi_cat_cols = ['job', 'marital', 'education', 'month', 'poutcome','contac
df1 = pd.get_dummies(df, columns=multi_cat_cols, drop_first=True, dtype=int)
df1
```

Out[15]:

	age	default	balance	housing	loan	day	duration	campaign	pdays	previous	...	n
0	59	no	2343	yes	no	5	1042	1	-1	0	...	
1	56	no	45	no	no	5	1467	1	-1	0	...	
2	41	no	1270	yes	no	5	1389	1	-1	0	...	
3	55	no	2476	yes	no	5	579	1	-1	0	...	
4	54	no	184	no	no	5	673	2	-1	0	...	
...	...	...	...	...	...	...	...	...	...	...	...	
11157	33	no	1	yes	no	20	257	1	-1	0	...	
11158	39	no	733	no	no	16	83	4	-1	0	...	
11159	32	no	29	no	no	19	156	2	-1	0	...	
11160	43	no	0	no	yes	8	9	2	172	5	...	
11161	34	no	0	no	no	9	628	1	-1	0	...	

11162 rows × 43 columns

In [16]:
```
# Label Encoding for binary categories:

from sklearn.preprocessing import LabelEncoder

binary_cols = ['default', 'housing', 'loan', 'deposit']

le = LabelEncoder()
for col in binary_cols:
    df1[col] = le.fit_transform(df[col])
```

In [17]:
```
df1.columns
```

Out[17]:
```
Index(['age', 'default', 'balance', 'housing', 'loan', 'day', 'duration',
       'campaign', 'pdays', 'previous', 'deposit', 'job_blue-collar',
       'job_entrepreneur', 'job_housemaid', 'job_management', 'job_retire
d',
       'job_self-employed', 'job_services', 'job_student', 'job_technicia
n',
       'job_unemployed', 'job_unknown', 'marital_married', 'marital_singl
e',
       'education_secondary', 'education_tertiary', 'education_unknown',
       'month_aug', 'month_dec', 'month_feb', 'month_jan', 'month_jul',
       'month_jun', 'month_mar', 'month_may', 'month_nov', 'month_oct',
       'month_sep', 'poutcome_other', 'poutcome_success', 'poutcome_unknow
n',
       'contact_telephone', 'contact_unknown'],
      dtype='object')
```

5.0 Customer attributes Objective

To determine if customer attributes which strongly influence the likelihood of customers subscribing to a term deposit like age, job type,education, marital and balance

Regularization in Logistic Regression

TO build logistic models to predict deposit using customer attributes and to identify which attributes are most predictive on deposit subscription

In [18]:
```
# Define features and target
X1 = df1[['age','balance','job_blue-collar',
       'job_entrepreneur', 'job_housemaid', 'job_management', 'job_retired',
       'job_self-employed', 'job_services', 'job_student', 'job_technician',
       'job_unemployed', 'job_unknown', 'marital_married', 'marital_single',
       'education_secondary', 'education_tertiary', 'education_unknown','hou

y1 = df1['deposit']
```

In [19]:
```
# Splitting data
from sklearn.model_selection  import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X1, y1, test_size=0.3, r
```

In [20]:
```
from sklearn.linear_model import LogisticRegression

ridge = LogisticRegression(penalty='l2', solver='liblinear')
lasso = LogisticRegression(penalty='l1', solver='liblinear')

ridge.fit(X_train, y_train)
lasso.fit(X_train, y_train)

ridge_coefs = ridge.coef_.flatten()
lasso_coefs = lasso.coef_.flatten()
```

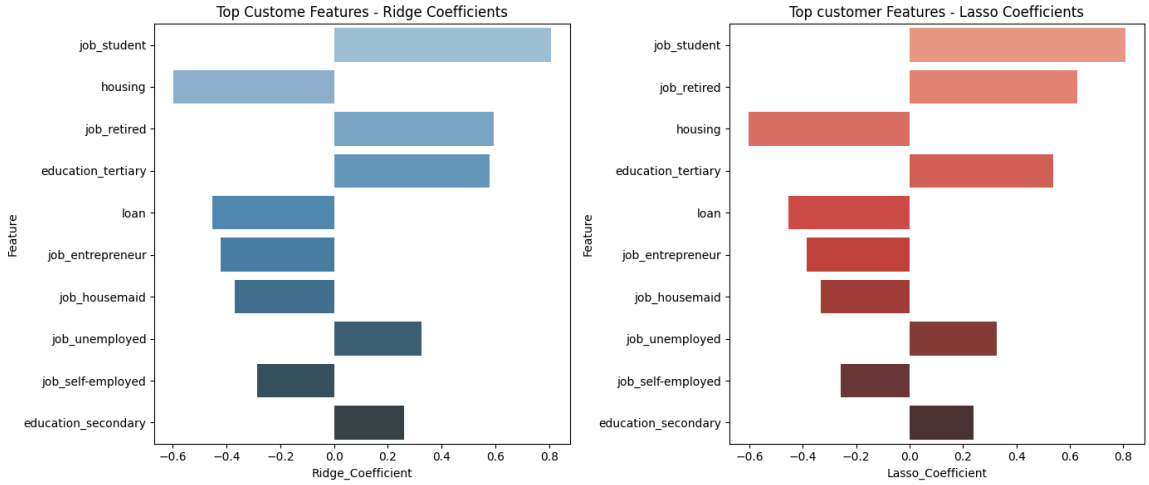
In [21]:
```
print(ridge_coefs.shape, X_train.columns.shape)
```

```
(20,) (20,)
```

In [22]:
```
# ridge and lasso coefficients
coefs_df = pd.DataFrame({'Feature': X_train.columns, 'Ridge_Coefficient': ri

coefs_df = coefs_df.sort_values(by='Lasso_Coefficient', key=abs, ascending=F

print(coefs_df)
```

	Feature	Ridge_Coefficient	Lasso_Coefficient
9	job_student	0.806083	0.809405
6	job_retired	0.593672	0.627679
18	housing	-0.597724	-0.604343
16	education_tertiary	0.577450	0.539576
19	loan	-0.452181	-0.454604
3	job_entrepreneur	-0.422010	-0.383742
4	job_housemaid	-0.368227	-0.331249
11	job_unemployed	0.324631	0.325304
7	job_self-employed	-0.284632	-0.257992
15	education_secondary	0.261959	0.239424
14	marital_single	0.220947	0.201953
5	job_management	-0.213405	-0.177577
2	job_blue-collar	-0.184567	-0.165665
17	education_unknown	0.161371	0.138559
8	job_services	-0.143219	-0.118609
13	marital_married	-0.100974	-0.113119
10	job_technician	-0.115164	-0.092455
0	age	0.004246	0.002989
1	balance	0.000042	0.000042
12	job_unknown	-0.034766	0.000000

In [23]:
```
top_n = 10
top_features = coefs_df.head(top_n)

ridge = top_features[['Feature', 'Ridge_Coefficient']].sort_values(by='Ridge
lasso = top_features[['Feature', 'Lasso_Coefficient']].sort_values(by='Lasso

fig, ax = plt.subplots(1, 2, figsize=(14, 6))

# Ridge plot
sns.barplot(x='Ridge_Coefficient', y='Feature', data=ridge, palette='Blues_d
ax[0].set_title("Top Custome Features - Ridge Coefficients")
ax[0].tick_params(axis='y', labelsize=10)

# Lasso plot
sns.barplot(x='Lasso_Coefficient', y='Feature', data=lasso, palette='Reds_d'
ax[1].set_title("Top customer Features - Lasso Coefficients")
ax[1].tick_params(axis='y', labelsize=10)

plt.tight_layout()
plt.show()
```



interpretation

- job_student : Students are highly likely to subscribe to term deposits.
- job_retired : Retired individuals also show strong interest in subscriptions.
- education_tertiary : Customers with tertiary education are more inclined to subscribe.
- housing : Customers with housing loans are less likely to subscribe.
- loan : Having a loan decreases the likelihood of subscription.
- job_entrepreneur, job_housemaid, job_self-employed : These types jobs have negative impact on subscription rates compared to others.

5.1 Campaign Optimization Objective:

To evaluate how do campaign-related factors like ['duration','day','campaign'] influence the likelihood of a customer subscribing to a term deposit

Logistic Regression Analysis

predict which customers are most likely to respond positively

In [24]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix,roc_auc_
```

In [25]:
```
# Define features and target
X = df1[['duration','day','campaign','contact_telephone', 'contact_unknown']
y = df1['deposit']
```

In [26]:
```
# Splitting data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rar
```

In [27]:
```
from sklearn.preprocessing import StandardScaler
#scaling data
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

In [28]:
```
#Handling imbalance using class weight, training and fitting

model = LogisticRegression(class_weight="balanced",max_iter= 2000 ,random_st
model.fit(X_train_scaled, y_train)
```

Out[28]:
```
LogisticRegression

LogisticRegression(class_weight='balanced', max_iter=2000, random_state=4
2)
```

In [29]:
```
#Evaluating the model

y_pred = model.predict(X_test_scaled)
y_proba = model.predict_proba(X_test_scaled)[:, 1]

# Evaluate
print(classification_report(y_test, y_pred))
print("ROC-AUC:", roc_auc_score(y_test, y_proba))
```

```
              precision    recall  f1-score   support

           0       0.74      0.78      0.76      1166
           1       0.75      0.70      0.72      1067

    accuracy                           0.74      2233
   macro avg       0.74      0.74      0.74      2233
weighted avg       0.74      0.74      0.74      2233

ROC-AUC: 0.8340070346798787
```

Interpratation

The model achieves 74% accuracy , meaning it correctly predicts whether a customer will subscribe to a term deposit .

0 means customers did not subscribe to a term deposit while 1 means customers subscribed.

Precision- 74% of customers did not subscribe, while 75% of the prediction did actually subscribe

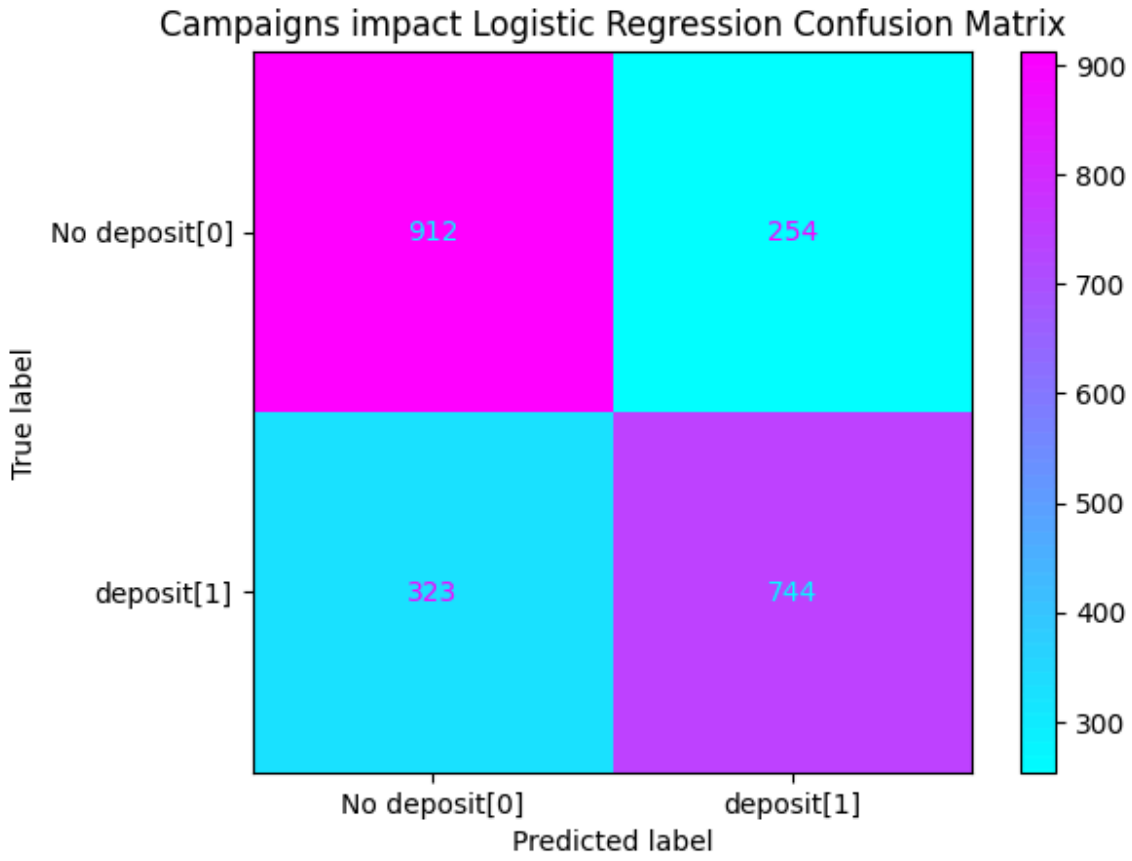
Recall - The model was able to identify 78% of non_subscribers and 70% of subscribers

Accuracy - this shows 74% of the prediction is correct

ROC-AUC - At 83.4%, indicates that the model has a very strong ability to distinguish between customers who will and won't subscribe to a term deposit.

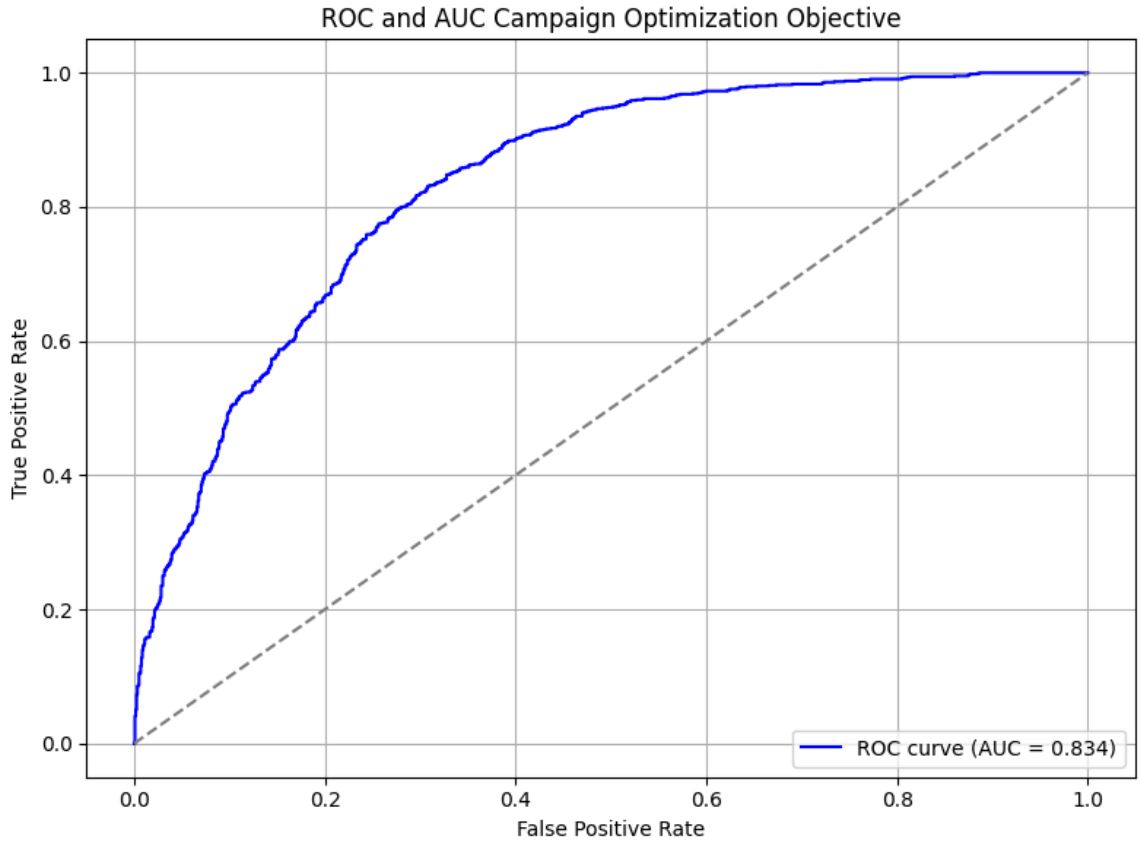
confusion matrix to see how many true positive and false positives we have on campaigns

In [30]:
```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

con_matrix = confusion_matrix(y_test, y_pred)

# Display it
disp = ConfusionMatrixDisplay(confusion_matrix=con_matrix, display_labels=['
disp.plot(cmap='cool')
plt.title("Campaigns impact Logistic Regression Confusion Matrix")
plt.show()
```



- True Negative (TN) = 912
- False Positive (FP) = 254
- False Negative (FN= 323
- True Positive (TP) = 744

In [31]:
```
# ROC and AUC Curve
from sklearn.metrics import roc_curve, auc

fpr, tpr, thresholds = roc_curve(y_test, y_proba)
roc_auc = auc(fpr, tpr)

# Plot ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', label=f'ROC curve (AUC = {roc_auc:.3f})')
plt.plot([0, 1], [0, 1], color='grey', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC and AUC Campaign Optimization Objective')
plt.legend(loc='lower right')
plt.grid(True)
plt.tight_layout()
plt.show()
```



Interpretation

The ROC curve and AUC value (0.834) indicate that the model using age , job ,Contact and education as features performs reasonably well in predicting term deposit subscriptions

5.2 Determine whether a customer will subscribe to a term deposit using machine learning models

Decision Tree Classification

In [32]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix, roc_auc
```

In [33]:
```
# Define features and target
X2 = df1.drop(['deposit'],axis=1)
y2 = df1['deposit']
```

In [34]:
```
#Split the data
X_train, X_test, y_train, y_test = train_test_split(X2, y2, test_size=0.2, r
```

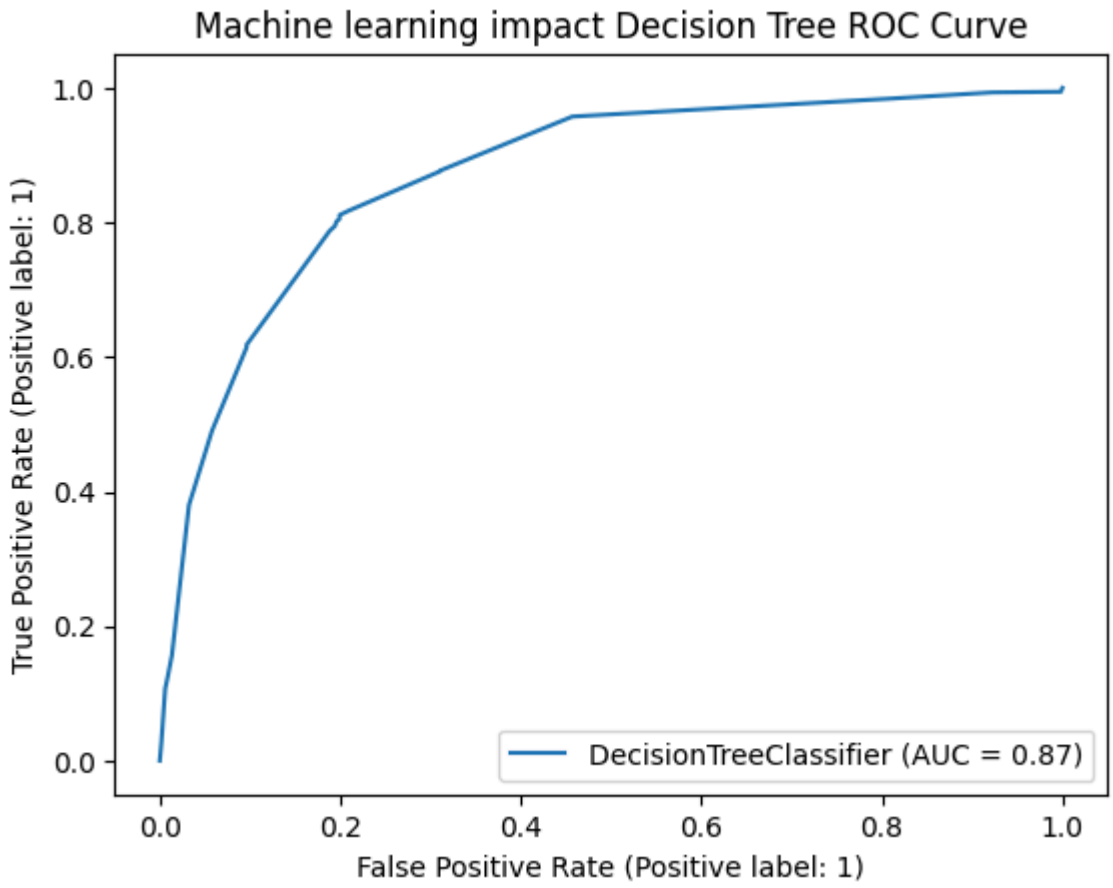
In [35]:
```
#Training the decision Tree
tree_clf = DecisionTreeClassifier(max_depth=5, random_state=42)
tree_clf.fit(X_train, y_train)
```

Out[35]:
```
DecisionTreeClassifier

DecisionTreeClassifier(max_depth=5, random_state=42)
```

In [36]:
```
#model evaluation
y_pred_2 = tree_clf.predict(X_test)
y_proba_2 = tree_clf.predict_proba(X_test)[:, 1]

print(classification_report(y_test, y_pred_2))
print("ROC-AUC:", roc_auc_score(y_test, y_proba_2))
```

```
              precision    recall  f1-score   support

           0       0.82      0.80      0.81      1175
           1       0.79      0.80      0.79      1058

    accuracy                           0.80      2233
   macro avg       0.80      0.80      0.80      2233
weighted avg       0.80      0.80      0.80      2233

ROC-AUC: 0.8713353175401198
```

In [37]:
```
RocCurveDisplay.from_estimator(tree_clf, X_test, y_test)
plt.title("Machine learning impact Decision Tree ROC Curve")
plt.show()
```



Interpretation

- Can machine learning models ,accurately predict whether a customer will subscribe to a term deposit ? **YES With an accuracy of 80% and a ROC-AUC of 0.87.**
- Precision- 82% of customers did not subscribe, while 79% of the prediction did actually subscribe
- Recall - The model was able to identify 80% of non_subscribers and 80% of subscribers

Conclusions

- predicting whether a customer will subscribe to a term deposit was successfully addressed using a Decision Tree model.
- The model was able to correctly predict customer behavior 79%(ROC-AUC) of the time, and it was very good at telling the difference between people who would and wouldn't subscribe to a term deposit.
- The precision and recall scores show that the model performs well in identifying both positive and negative classes.This helps avoid wasting time on the wrong people and increases the chances of getting real subscribers

RECCOMENDATIONS

Customer Segmentation Objective

- Target High-Value Groups : Retired individuals,Tertiary-educated professionals Customers with high balance and no existing loans
- Avoid Low-Response Groups :job_entrepreneur, job_housemaid, job_self-employed

Campaign Optimization

- Use past campaign data to improve the timing, message, and frequency of calls.
- Focus marketing campaigns in months with historically high subscription rates — especially December, March, and September.

Use of Machine learning models strategy

- Regularly update the models with new customer data to keep predictions accurate over time.
- Continue using machine learning models to predict customer responses.