Predicting Bank Marketing Succuss on Term Deposit Subsciption

Summary

In this analysis, we attempt to build a predictive model aimed at determining whether a client will subscribe to a term deposit, utilizing the data associated with direct marketing campaigns, specifically phone calls, in a Portuguese banking institution.

After exploring on several models (logistic regression, KNN, decision tree, naive Bayers), we have selected the logistic regression model as our primary predictive tool. The final model performs fairly well when tested on an unseen dataset, achieving the highest AUC (Area Under the Curve) of 0.899. This exceptional AUC score underscores the model's capacity to effectively differentiate between positive and negative outcomes. Notably, certain factors such as last contact duration, last contact month of the year and the clients' types of jobs play a significant role in influencing the classification decision.

Introduction

In the banking sector, the evolution of specialized bank marketing has been driven by the expansion and intensification of the financial sector, introducing competition and transparency. Recognizing the need for professional and efficient marketing strategies to engage an increasingly informed and critical customer base, banks grapple with conveying the complexity and abstract nature of financial services. Precision in reaching specific locations, demographics, and societies has proven challenging. The advent of machine learning has revolutionized this landscape, utilizing data and analytics to inform banks about customers more likely to subscribe to financial products. In this machine learning-driven bank marketing project, we explore how a particular Portuguese bank can leverage predictive analytics to strategically prioritize customers for subscribing to a bank term deposit, showcasing the transformative potential of machine learning in refining marketing strategies and optimizing customer targeting for financial institutions.

Data

Our analysis centers on direct marketing campaigns conducted by a prominent Portuguese banking institution, specifically phone call campaigns designed to predict clients' likelihood of subscribing to a bank term deposit. The comprehensive dataset provides a detailed view of these marketing initiatives, offering valuable insights into factors influencing client subscription decisions. The dataset, named 'bank-full.csv,' encompasses all examples and 17 inputs, ordered by date. The primary focus of our analysis is classification, predicting whether a client will subscribe ('yes') or not ('no') to a term deposit, providing crucial insights into client behavior in response to direct marketing initiatives. Through rigorous exploration of these datasets, we aim to uncover patterns and trends that can inform and enhance the effectiveness of future marketing campaigns.

Methods

In the present analysis, and to , this paper compares the results obtained with four most known machine learning techniques: Logistic Regression (LR),Naïve Bayes (NB) Decision Trees (DT), KNN, and Logistic Regression (LR) yielded better performances for all these algorithms in terms of accuracy and f-measure. Logistic Regression serves as a key algorithm chosen for its proficiency in uncovering associations between binary dependent variables and continuous explanatory variables. Considering the dataset's characteristics, which include continuous independent variables and a binary dependent variable, Logistic Regression emerges as a suitable classifier for predicting customer subscription in the bank's telemarketing campaign for term deposits. The classification report reveals insights into model performance, showcasing trade-offs between precision and recall. While achieving an overall accuracy of 83%, the Logistic Regression model demonstrates strengths in identifying positive cases, providing a foundation for optimizing future marketing strategies.

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import requests

from sklearn.preprocessing import OrdinalEncoder, StandardScaler, OneHotEncoder
from sklearn.model_selection import train_test_split, GridSearchCV, RandomizedSearc
from sklearn.metrics import confusion_matrix,f1_score, roc_auc_score, classificatio
from sklearn.pipeline import make_pipeline
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn import metrics

from imblearn.over_sampling import RandomOverSampler, SMOTE, ADASYN, BorderlineSMOT
from imblearn.under_sampling import ClusterCentroids, RandomUnderSampler

import warnings
```

Analysis

Data Import

In [2]:
```
url = 'https://archive.ics.uci.edu/static/public/222/data.csv'

request = requests.get(url)
with open("../data/raw/bank-full.csv", 'wb') as f:
        f.write(request.content)
```

Global Config

In [3]:
```
pd.set_option('display.max_columns', None)
pd.options.display.float_format = '{:.3f}'.format
RANDOM_STATE = 522
warnings.filterwarnings("ignore")
```

Pre-Exploration

In [4]:
```
bank = pd.read_csv('../data/raw/bank-full.csv', sep=',')
```

In [5]:
```
bank.columns
```

Out[5]:
```
Index(['age', 'job', 'marital', 'education', 'default', 'balance', 'housing',
       'loan', 'contact', 'day_of_week', 'month', 'duration', 'campaign',
       'pdays', 'previous', 'poutcome', 'y'],
      dtype='object')
```

In [6]:
```
bank.shape
```

Out[6]:
```
(45211, 17)
```

In [7]:
```
bank.head()
```

Out[7]:

	age	job	marital	education	default	balance	housing	loan	contact	day_of
0	58	management	married	tertiary	no	2143	yes	no	NaN	
1	44	technician	single	secondary	no	29	yes	no	NaN	
2	33	entrepreneur	married	secondary	no	2	yes	yes	NaN	
3	47	blue-collar	married	NaN	no	1506	yes	no	NaN	
4	33	NaN	single	NaN	no	1	no	no	NaN	

In [8]:
```
bank.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 17 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   age          45211 non-null  int64 
 1   job          44923 non-null  object
 2   marital      45211 non-null  object
 3   education    43354 non-null  object
 4   default      45211 non-null  object
 5   balance      45211 non-null  int64 
 6   housing      45211 non-null  object
 7   loan         45211 non-null  object
 8   contact      32191 non-null  object
 9   day_of_week  45211 non-null  int64 
 10  month        45211 non-null  object
 11  duration     45211 non-null  int64 
 12  campaign     45211 non-null  int64 
 13  pdays        45211 non-null  int64 
 14  previous     45211 non-null  int64 
 15  poutcome     8252 non-null   object
 16  y            45211 non-null  object
dtypes: int64(7), object(10)
memory usage: 5.9+ MB
```

In [9]:
```
bank.y.value_counts()/len(bank)
```

Out[9]:
```
y
no     0.883
yes    0.117
Name: count, dtype: float64
```

Pay attention that the target is **class-imbalanced**

Train Test Split

In [10]:
```
bank_train, bank_test = train_test_split(bank
                                         , test_size=0.2
                                         , random_state=RANDOM_STATE
                                         , stratify=bank.y
                                         )
```

In [11]:
```
bank_train.y.value_counts()/len(bank_train)
```

Out[11]:
```
y
no     0.883
yes    0.117
Name: count, dtype: float64
```

In [12]:
```
X_train, y_train = bank_train.drop(columns=["y"]), bank_train["y"]
X_test, y_test = bank_test.drop(columns=["y"]), bank_test["y"]
```

Via stratified split, we managed to keep the distribution of the label in the original dataset.

EDA

In [13]:
```
for i in list(bank_train.columns):
    print(f"{i:<10}->  {bank_train[i].nunique():<5} unique values")
```

```
age       ->  77    unique values
job       ->  11    unique values
marital   ->  3     unique values
education ->  3     unique values
default   ->  2     unique values
balance   ->  6601  unique values
housing   ->  2     unique values
loan      ->  2     unique values
contact   ->  2     unique values
day_of_week->  31    unique values
month     ->  12    unique values
duration  ->  1506  unique values
campaign  ->  47    unique values
pdays     ->  536   unique values
previous  ->  40    unique values
poutcome  ->  3     unique values
y         ->  2     unique values
```

In [14]:
```
bank_int = list(bank_train.select_dtypes(include = ['int64']).columns)
bank_str = list(bank_train.select_dtypes(include = ['object']).columns)
bank_categorical = bank_str+['day']
```

In [15]:
```
bank_categorical
```

Out[15]:
```
['job',
 'marital',
 'education',
 'default',
 'housing',
 'loan',
 'contact',
 'month',
 'poutcome',
 'y',
 'day']
```

Data Visualization

We plotted the distributions of each predictor from the training data set and grouped and coloured the distribution by class (yes:green and no:blue).

In [16]:
```
import altair as alt

alt.data_transformers.disable_max_rows()

charts = []
```

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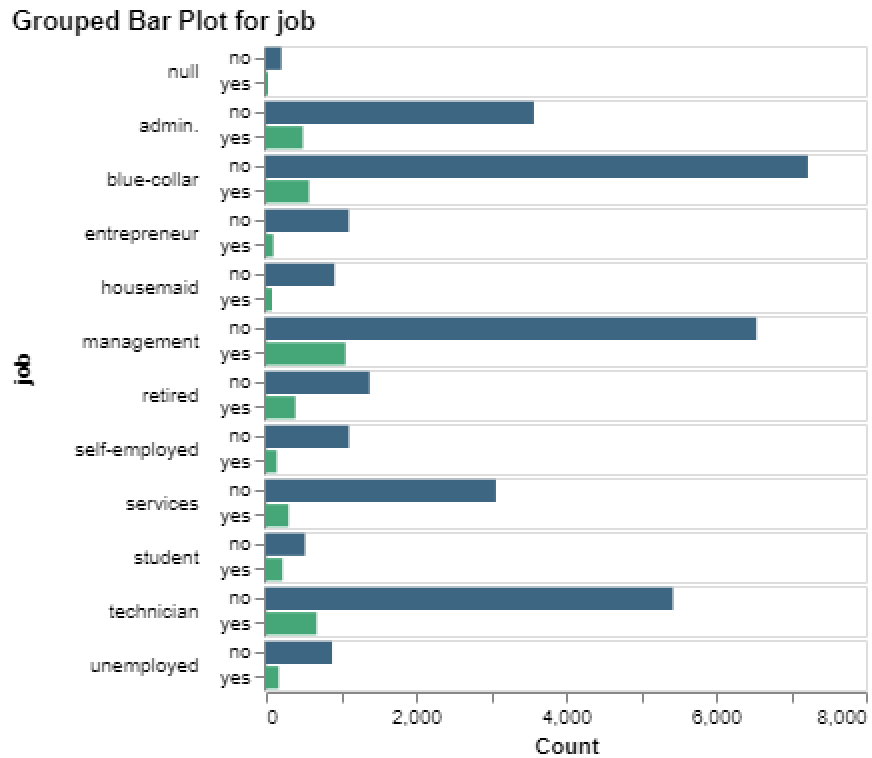
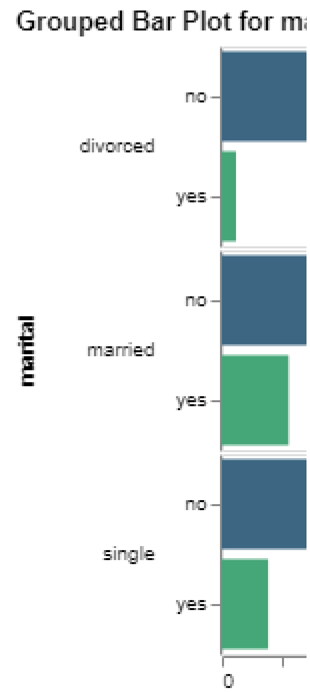
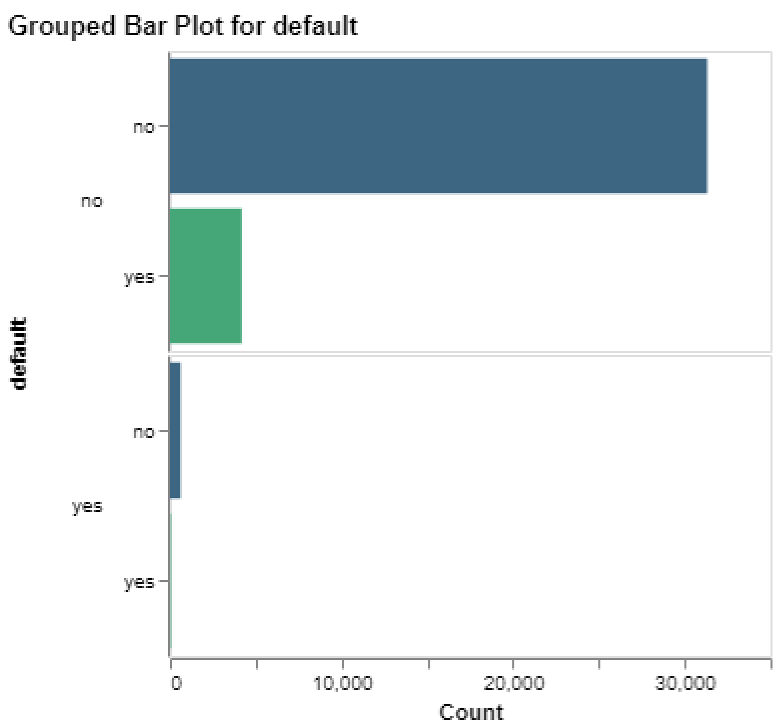
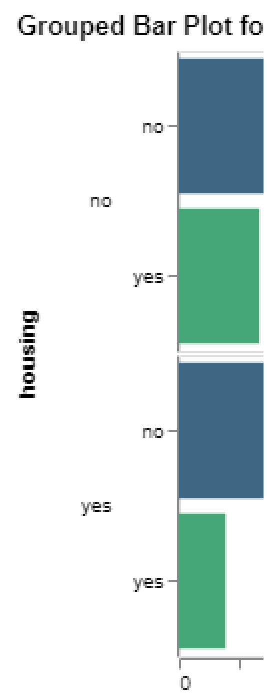
```
for i, var in enumerate(bank_categorical):
    if i == 9:
        break

    num_rows = len(bank_train[var].unique())

    chart = alt.Chart(bank_train).mark_bar(stroke=None).encode(
        x=alt.X('count()', title='Count'),
        y=alt.Y('y:N', title=None),
        color=alt.Color('y:N', scale=alt.Scale(range=['#3C6682', '#45A778'])),
        row=alt.Row(f'{var}:N')
    ).properties(
        width=300,
        height=300 / num_rows,
        title=f'Grouped Bar Plot for {var}',
        spacing=0
    )

    charts.append(chart)

final_chart = alt.concat(*charts, columns=3).configure_axis(grid=False).configure_h
    labelAngle=0,
    labelAlign='left'
)

final_chart
```

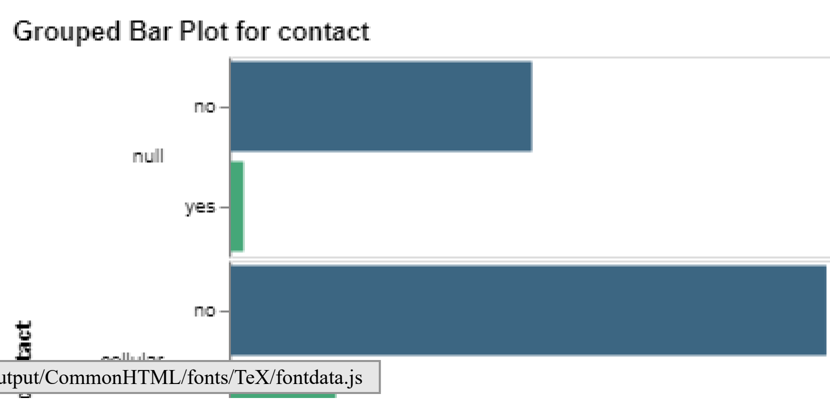
Out[16]:

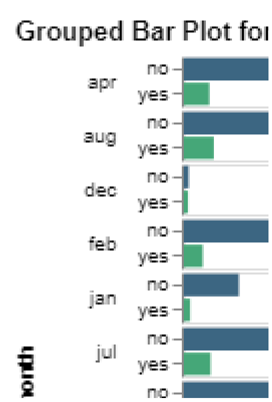












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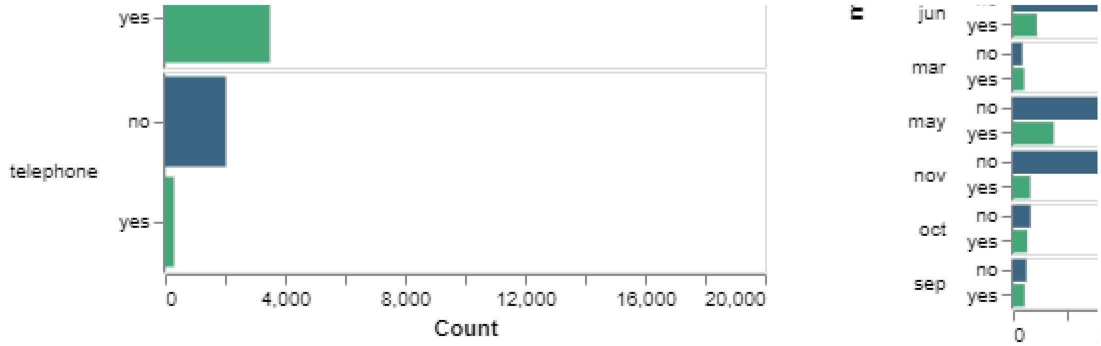
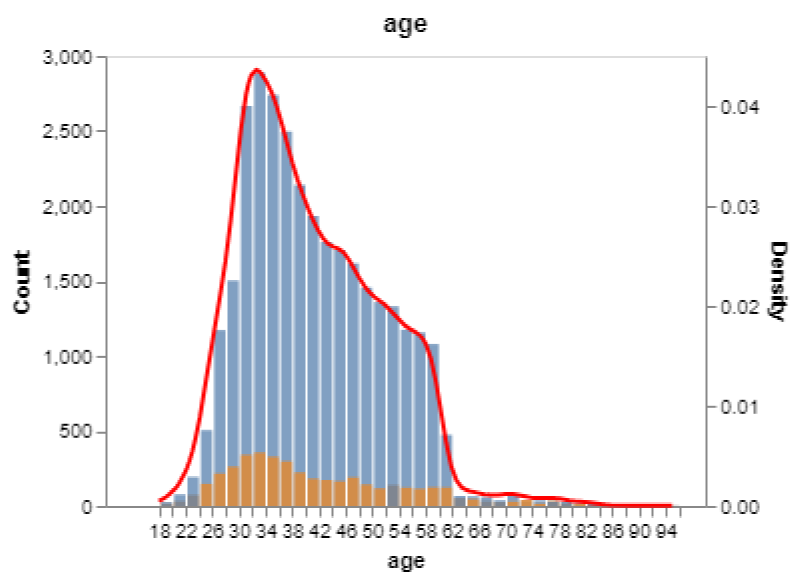
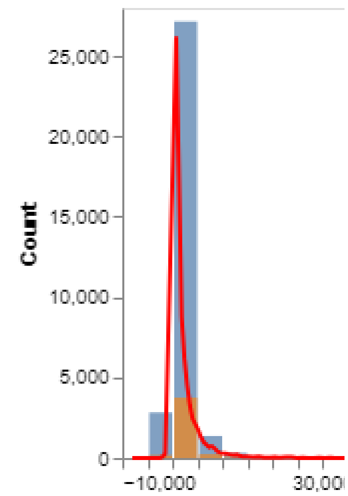


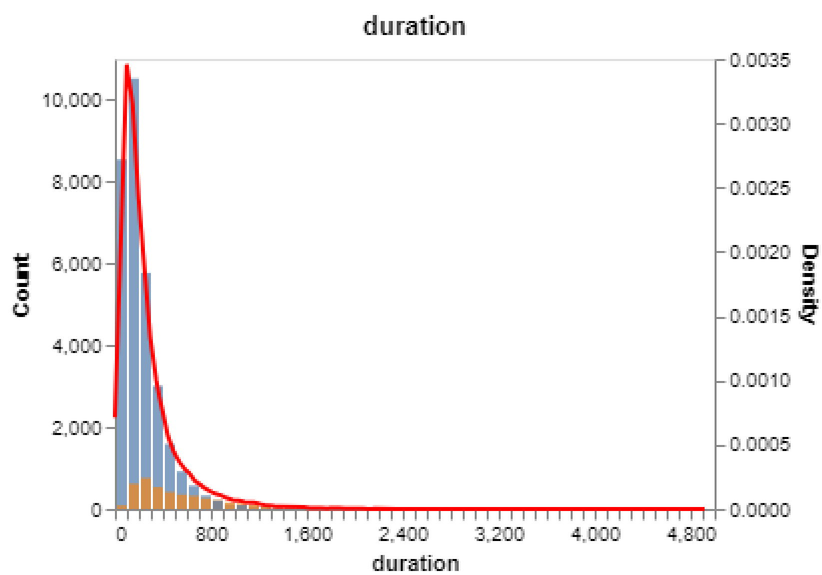
In [17]:

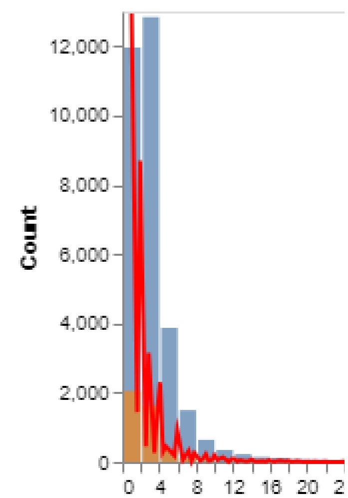
```python
bank_continuous = bank_train[bank_int]

charts = []

for i, column in enumerate(bank_continuous.columns):
    hist_chart = alt.Chart(bank_train).mark_bar(opacity=0.7, color='blue').encode(
        x=alt.X(f'{column}:Q', bin=alt.Bin(maxbins=50), title=column),
        y=alt.Y('count():Q', stack=None, title='Count'),
        color = 'y'
    )

    kde_chart = alt.Chart(bank_train).transform_density(
        column,
        as_=[column, 'density']
    ).mark_line(color='red').encode(
        x=alt.X(f'{column}:Q', title=column),
        y=alt.Y('density:Q', title='Density'),
    )

    chart = alt.layer(hist_chart, kde_chart).resolve_scale(y='independent').propert
        width=300,
        height=225,
        title=f'{column}'
    )

    charts.append(chart)

final_chart = alt.concat(*charts, columns=3).configure_axis(grid=False)

final_chart
```

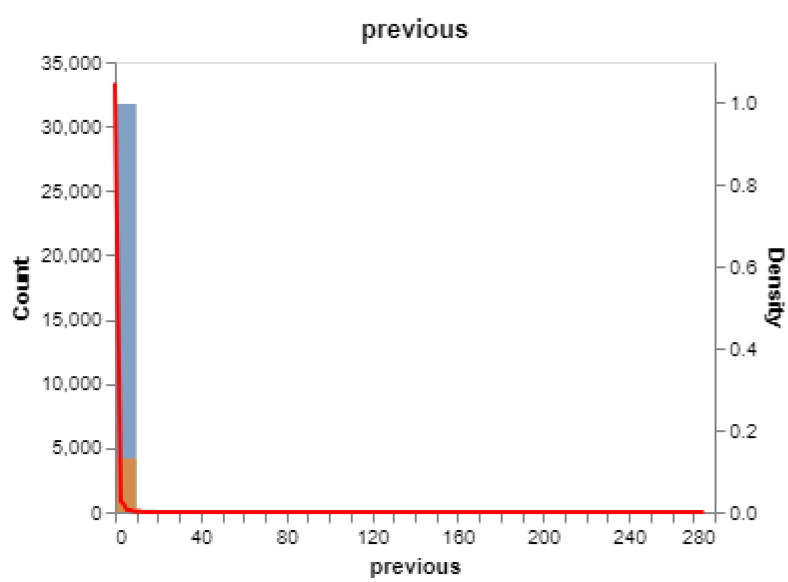
Out[17]:









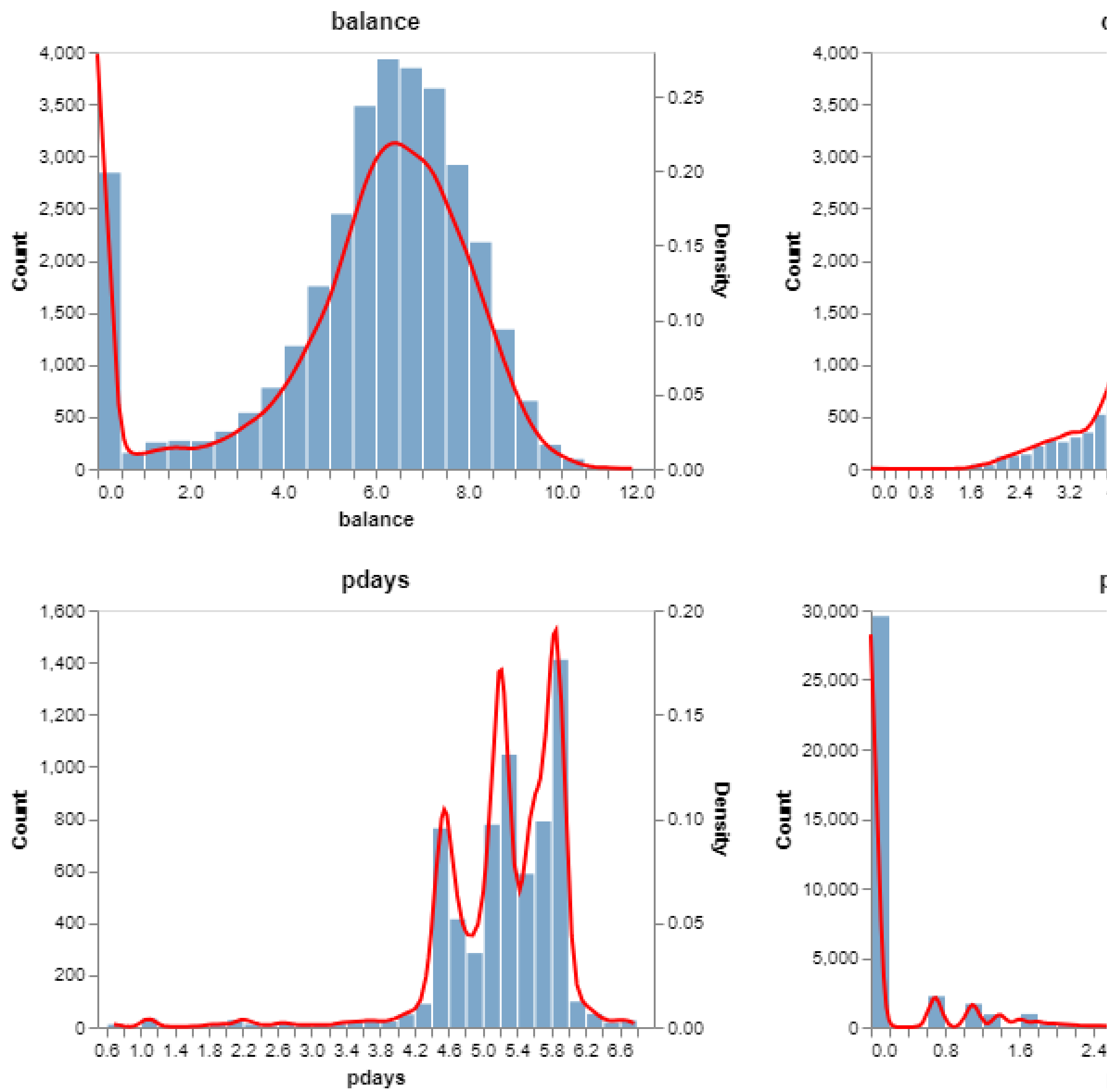


In [18]:

```
bank_log = ['balance', 'duration', 'campaign', 'pdays', 'previous']
charts = []
```

```
for i, column in enumerate(bank_log):
    hist_chart = alt.Chart(bank_train[bank_log].applymap(np.log1p)).mark_bar(opacit
        x=alt.X(f'{column}:Q', bin=alt.Bin(maxbins=50), title=column),
        y=alt.Y('count():Q', stack=None, title='Count'),

    )

    kde_chart = alt.Chart(bank_train[bank_log].applymap(np.log1p)).transform_densit
        column,
        as_=[column, 'density'],
    ).mark_line(color='red').encode(
        x=alt.X(f'{column}:Q', title=column),
        y=alt.Y('density:Q', title='Density'),
    )

    chart = alt.layer(hist_chart, kde_chart).resolve_scale(y='independent').propert
        width=300,
        height=225,
        title=f'{column}'
    )

    charts.append(chart)

final_chart = alt.concat(*charts, columns=3).configure_axis(grid=False)

final_chart
```

Out[18]:



Preprocessing

In this section, we are defining lists with the names of the features according to their type.

In [19]:
```
numeric_features = bank.select_dtypes('number').columns.tolist()
categorical_features = ['job', 'marital', 'contact', 'month', 'poutcome']
ordinal_features = ['education']
binary_features = ['default', 'housing', 'loan']
drop_features = []
target = "y"
```

Then, we define all the transformations that have to be applied to the different columns. We define the order of the education levels as they belong to an ordinal variable and we create pipelines to manage nulls before each transformation. All of the transformations impute the most frequent value except for the numeric transformer, which imputes the median value.

```
In [20]: education_levels = ['tertiary', 'secondary', 'primary']
ordinal_transformer = make_pipeline(SimpleImputer(strategy="most_frequent"),
                                    OrdinalEncoder(categories=[education_levels], d

numeric_transformer = make_pipeline(SimpleImputer(strategy="median"), StandardScale

binary_transformer = make_pipeline(SimpleImputer(strategy="most_frequent"),
                                    OneHotEncoder(dtype=int, drop='if_binary'))

categorical_transformer = make_pipeline(SimpleImputer(strategy="most_frequent"),
                                        OneHotEncoder(handle_unknown="ignore", spar
```

Finally, we create a column transformer named preprocessor.

```
In [21]: preprocessor = ColumnTransformer(
    transformers=[
        ('numeric', numeric_transformer, numeric_features),
        ('ordinal', ordinal_transformer, ordinal_features),
        ('binary', binary_transformer, binary_features),
        ('categorical', categorical_transformer, categorical_features),
        ('drop', 'passthrough', drop_features)
    ])
```

Fitting and transforming X_train

```
In [22]: transformed_train = preprocessor.fit_transform(X_train)
column_names = (
    numeric_features +
    ordinal_features +
    preprocessor.named_transformers_['binary'].named_steps['onehotencoder'].get_fea
    preprocessor.named_transformers_['categorical'].named_steps['onehotencoder'].ge
    )

X_train_trans = pd.DataFrame(transformed_train, columns=column_names)
```

```
In [23]: X_train_trans.head(5)
```

Out[23]:

	age	balance	day_of_week	duration	campaign	pdays	previous	education	x0_yes
0	-0.463	-0.413	0.627	-0.733	-0.564	-0.411	-0.243	1.000	0.000
1	1.612	-0.072	-1.418	-0.679	0.072	-0.411	-0.243	1.000	0.000
2	-0.086	-0.408	-1.418	-0.510	-0.564	-0.411	-0.243	1.000	0.000
3	-0.369	-0.445	-1.178	-0.421	-0.564	-0.271	4.767	0.000	0.000
4	0.197	-0.292	1.228	-0.283	-0.564	-0.411	-0.243	1.000	0.000

```
In [24]: y_train.head(5)
```

Out[24]:
```
4868     no
29723    no
8911     no
34737    no
5657     no
Name: y, dtype: object
```

Transforming X_test

In [25]:
```
transformed_test = preprocessor.transform(X_test)
column_names = (
    numeric_features +
    ordinal_features +
    preprocessor.named_transformers_['binary'].named_steps['onehotencoder'].get_fea
    preprocessor.named_transformers_['categorical'].named_steps['onehotencoder'].ge
    )

X_test_trans = pd.DataFrame(transformed_test, columns=column_names)
```

In [26]:
```
X_test_trans.head(5)
```

Out[26]:

	age	balance	day_of_week	duration	campaign	pdays	previous	education	x0_yes
0	1.235	-0.278	-1.178	-0.241	-0.246	-0.411	-0.243	1.000	0.000
1	0.480	-0.189	0.747	-0.471	0.390	-0.411	-0.243	1.000	0.000
2	0.291	0.351	1.709	-0.483	-0.246	-0.411	-0.243	1.000	0.000
3	1.517	-0.445	-0.215	-0.514	0.708	-0.411	-0.243	1.000	0.000
4	1.706	-0.110	-1.298	1.578	-0.564	-0.411	-0.243	1.000	0.000

In [27]:
```
y_test.head(5)
```

Out[27]:
```
685       no
16193     no
17989     no
38058     no
24132    yes
Name: y, dtype: object
```

Modeling

In [28]:
```
def compute_and_plot_roc_curve(model, testing_x, testing_y,name, figsize=(5,5)):
    """
    Compute and plot the Receiver Operating Characteristic (ROC) curve.

    This function takes a machine learning model, test data, and the name of the mo
    It computes the ROC curve using the model's probability predictions on the test
    The function plots the ROC curve, showing the trade-off between the true positi
    and false positive rate (FPR) at various threshold settings. The Area Under the
```

```
    is also calculated and displayed in the plot.

    Parameters:
    - model: A trained machine learning model that supports probability prediction.
    - testing_x: Test dataset (features).
    - testing_y: True labels for the test dataset.
    - name (str): The name of the model, used for labeling the plot.
    - figsize (tuple): The size of the figure in which the ROC curve is plotted (de

    Returns:
    - fpr (array): An array containing the false positive rates.
    - tpr (array): An array containing the true positive rates.
    - roc_auc (float): The computed area under the ROC curve.

    """
    predict_prob = model.predict_proba(testing_x)
    fpr, tpr, threshold = metrics.roc_curve(testing_y, predict_prob[:,1])
    roc_auc = metrics.auc(fpr, tpr)
    plt.figure(figsize=(5,5),facecolor="white")
    plt.title('Receiver Operating Characteristic')
    plt.plot(fpr, tpr, 'b', label = '{} : {:0.3f}'.format(name,roc_auc))
    plt.legend(loc = 'lower right')
    plt.plot([0, 1], [0, 1],'r--')
    plt.xlim([0, 1])
    plt.ylim([0, 1])
    plt.ylabel('True Positive Rate')
    plt.xlabel('False Positive Rate')
    plt.show()

    return fpr, tpr, roc_auc
```

In [29]:

```
def model_report(model, testing_x, testing_y, name, customerized_threshold=False, t
    """
    Generate and print a performance report of a machine learning model on test dat

    This function evaluates a given model on test data and generates various perfor
    including recall, precision, F1-score, and ROC-AUC score. It also prints a clas
    and optionally plots a confusion matrix. The function allows for the applicatio
    threshold for classification decisions.

    Parameters:
    - model: A trained machine learning model.
    - testing_x: Test dataset (features).
    - testing_y: True labels for the test dataset.
    - name (str): The name of the model, used for labeling in the report.
    - customerized_threshold (bool): Flag to apply a custom threshold for predictio
    - threshold (float): The custom threshold for classification if customerized_th
    - plot_confusion_matrix (bool): Flag to plot the confusion matrix (default is T

    Returns:
    - DataFrame: A pandas DataFrame containing the model name and calculated perfor

    The function prints the classification report and, if requested, displays the c
    """

                                    dict(testing_x)
```

```
    predictions_prob = model.predict_proba(testing_x)

    if customerized_threshold:
        predictions = []
        for pred in predictions_prob[:,1]:
            predictions.append(1) if pred > threshold else predictions.append(0)
    recallscore  = recall_score(testing_y,predictions)
    precision    = precision_score(testing_y,predictions)
    roc_auc      = roc_auc_score(testing_y,predictions_prob[:, 1])
    f1score      = f1_score(testing_y,predictions)


    # classification_report
    print(classification_report(testing_y,predictions))

    # customered_confusion_matrix
    if plot_confusion_matrix:
        fact = testing_y
        classes = list(set(fact))
        classes.sort()
        confusion = confusion_matrix(predictions, testing_y)
        plt.figure(figsize=(5,5), dpi=100)
        plt.imshow(confusion, cmap=plt.cm.Blues)
        indices = range(len(confusion))
        plt.xticks(indices, classes,fontsize=10)
        plt.yticks(indices, classes,fontsize=10)
        plt.colorbar()
        plt.xlabel('Predictions',fontsize=10)
        plt.ylabel('Ground Turth',fontsize=10)
        for first_index in range(len(confusion)):
            for second_index in range(len(confusion[first_index])):
                plt.text(first_index, second_index, confusion[first_index][second_i
        plt.grid(False)

    df = pd.DataFrame({"Model"          : [name],
                       "Recall_score"   : [recallscore],
                       "Precision"      : [precision],
                       "f1_score"       : [f1score],
                       "Area_under_curve": [roc_auc]
                      })
    return df
```

Resample

Because it is a class-imbalanced issue, we decided to utilize some resample technique to boost the performance of our model. reference: https://imbalanced-learn.org/stable/under_sampling.html

In [30]:

```
resample_list = ['random_over_sample','SMOTE','ADASYN','BorderlineSMOTE','KMeansSMO

def re_sample(X, y, func=None, random_state=RANDOM_STATE):
    """
    Apply resampling techniques to the dataset to address class imbalance.
```

```
    This function takes a dataset and applies one of several resampling techniques
    based on the 'func' argument provided. Resampling techniques include both overs
    and undersampling methods. The function supports random oversampling, Synthetic
    Over-sampling Technique (SMOTE), Adaptive Synthetic (ADASYN), BorderlineSMOTE,
    KMeansSMOTE, ClusterCentroids, and random undersampling.

    Parameters:
    - X: Feature dataset (usually a DataFrame or a 2D array).
    - y: Target values associated with X.
    - func (str, optional): The resampling technique to apply. Supported values are
      'random_over_sample', 'SMOTE', 'ADASYN', 'BorderlineSMOTE', 'KMeansSMOTE',
      'ClusterCentroids', and 'random_under_sample'. If None, no resampling is appl
    - random_state (int, optional): The random state for reproducibility.

    Returns:
    - X_resampled, y_resampled: The resampled feature set and target values. If 'fu
      the function returns None.

    If an unsupported 'func' value is provided, the function returns None.
    """

    if func == None:
        return

    elif func == 'random_over_sample':
        ros = RandomOverSampler(random_state=random_state)
        X_resampled, y_resampled = ros.fit_resample(X, y)

    elif func == 'SMOTE':
        X_resampled, y_resampled = SMOTE().fit_resample(X, y)

    elif func == 'ADASYN':
        X_resampled, y_resampled = ADASYN().fit_resample(X, y)

    elif func == 'BorderlineSMOTE':
        X_resampled, y_resampled = BorderlineSMOTE().fit_resample(X, y)

    elif func == 'KMeansSMOTE':
        X_resampled, y_resampled = KMeansSMOTE(cluster_balance_threshold=0.005).fit

    elif func == 'ClusterCentroids':
        X_resampled, y_resampled = ClusterCentroids().fit_resample(X, y)

    elif func == 'random_under_sample':
        X_resampled, y_resampled = RandomUnderSampler().fit_resample(X, y)

    else:
        return

    return X_resampled, y_resampled
```

In [31]:

```
X_tr, y_tr= re_sample(X_train, y_train, func='random_under_sample')
y_tr = y_tr.map({'yes':1, 'no':0})
y_test = y_test.map({'yes':1, 'no':0})
```

In [32]:
```
y_test
```

Out[32]:
```
685      0
16193    0
17989    0
38058    0
24132    1
        ..
41512    1
40278    1
36878    0
11589    0
23945    0
Name: y, Length: 9043, dtype: int64
```

In [33]:
```
y_tr.value_counts()
```

Out[33]:
```
y
0    4231
1    4231
Name: count, dtype: int64
```

In [34]:
```
X_tr
```

Out[34]:

	age	job	marital	education	default	balance	housing	loan	contact
22860	32	technician	single	secondary	no	230	yes	no	cellular
8327	23	blue-collar	single	secondary	no	27	yes	no	NaN
33166	30	unemployed	single	secondary	no	8304	no	no	cellular
9332	51	management	married	tertiary	no	12	no	no	NaN
12794	56	management	married	primary	no	21	no	no	cellular
...	...	...	...	...	...	...	...	...	...
35956	59	retired	married	tertiary	no	148	yes	yes	cellular
39773	45	blue-collar	married	secondary	no	1723	no	no	cellular
44778	58	management	married	tertiary	no	0	no	no	cellular
17794	46	admin.	married	secondary	no	659	yes	no	telephone
43294	35	blue-collar	married	secondary	no	262	no	no	cellular

8462 rows × 16 columns

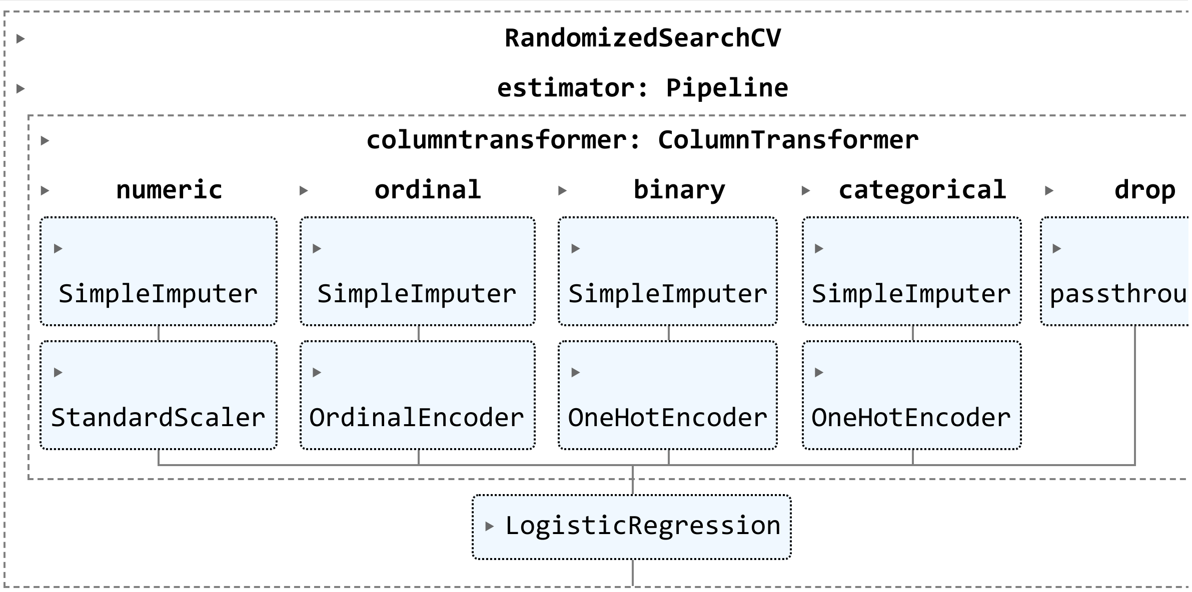
In [35]:
```
models = {
    "Decision Tree": DecisionTreeClassifier(random_state=RANDOM_STATE),
    "KNN": KNeighborsClassifier(),
    "Naive Bayes": GaussianNB(),
    "Logistic Regression": LogisticRegression(max_iter=2000, random_state=RANDOM_ST
}
```

Logistic Regression

In [36]:
```python
from scipy.stats import loguniform, randint, uniform
param_dist = {
    "logisticregression__C": loguniform(1e-3, 1e3)
}

classification_metrics = ["accuracy", "precision", "recall", "f1", "roc_auc"]

pipe = make_pipeline(
    preprocessor,
    models['Logistic Regression']
    )

random_search = RandomizedSearchCV(pipe,
                                   param_dist,
                                   n_iter=100,
                                   n_jobs=-1,
                                   cv=5,
                                   scoring=classification_metrics,
                                   refit='roc_auc',
                                   return_train_score=True,
                                   random_state=RANDOM_STATE
                                  )
```

In [37]:
```python
random_search.fit(X_tr, y_tr)
```

Out[37]:



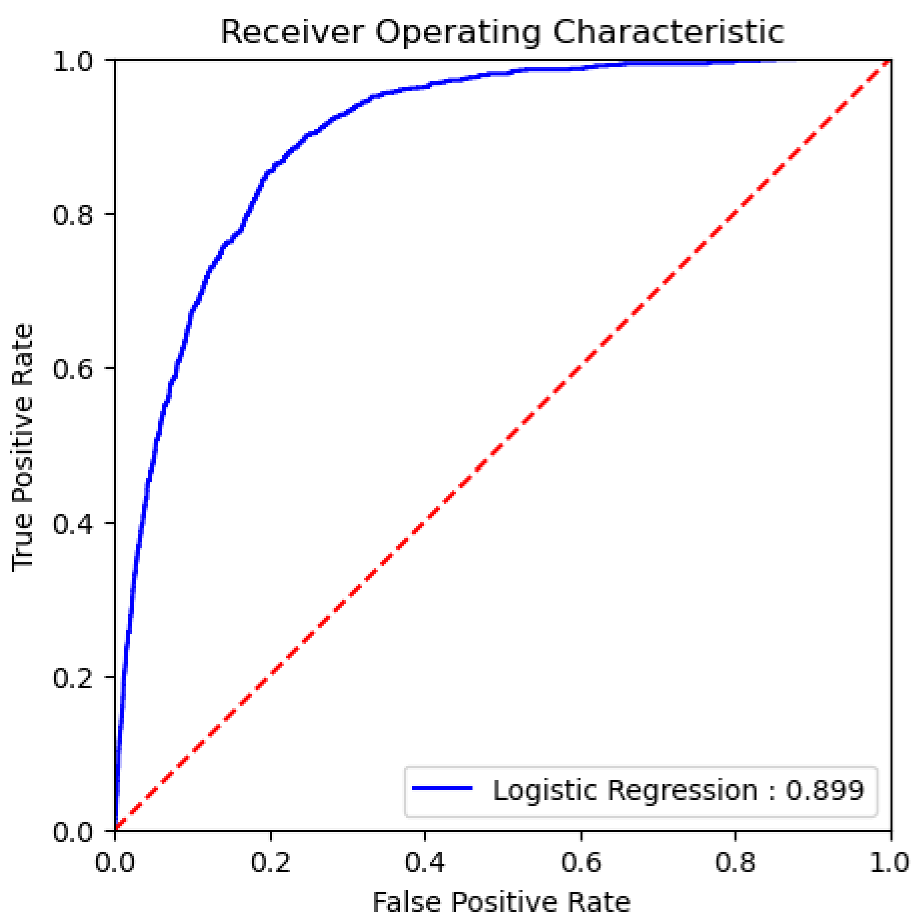
In [38]:
```python
random_search.best_params_
```

Out[38]:
```
{'logisticregression__C': 2.2527700095274237}
```

In [39]:
```python
random_search.best_score_
```

Out[39]:
```
0.9011045918017399
```

In [40]:
```
# Logistic Regression on the test set

# Use the selected hyperparameters
best_C = random_search.best_params_['logisticregression__C']
plot_confusion_matrix = True

pipe_lr = make_pipeline(
    preprocessor,
    LogisticRegression(C=best_C,
                       random_state=RANDOM_STATE)
    )
# Train the model
pipe_lr.fit(X_tr,  y_tr)

fpr_lr, tpr_lr, auc_lr= compute_and_plot_roc_curve(pipe_lr, X_test,  y_test, "Logis

model_lr = model_report(pipe_lr, X_test, y_test, "Logistic Regression")
model_lr
```




```
              precision    recall  f1-score   support

           0       0.97      0.84      0.90      7985
           1       0.39      0.78      0.52      1058

    accuracy                           0.83      9043
   macro avg       0.68      0.81      0.71      9043
weighted avg       0.90      0.83      0.85      9043
```

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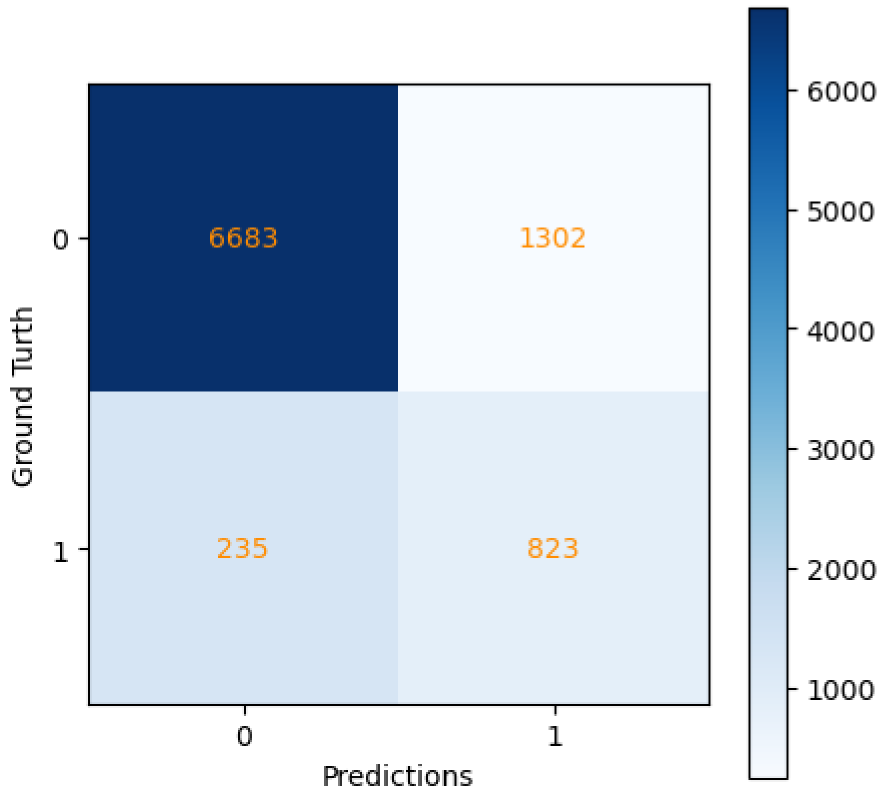
Out[40]:

	Model	Recall_score	Precision	f1_score	Area_under_curve
0	Logistic Regression	0.778	0.387	0.517	0.899



Discussion and Results:

The presented classification report provides a detailed evaluation of a model's performance on a binary classification task. Here are some key observations:

- Precision and Recall: Precision measures the accuracy of positive predictions, indicating that when the model predicts a positive outcome, it is correct approximately 39% of the time. Recall, on the other hand, suggests that the model successfully identifies around 79% of the actual positive cases.

- F1-Score: The F1-Score is the harmonic mean of precision and recall, providing a balance between the two. In this case, it is calculated at approximately 52%, reflecting a moderate balance between precision and recall.

- Accuracy: The overall accuracy of the model is 83%, indicating the percentage of correctly predicted instances among all instances.

- Support: The support column represents the number of actual occurrences of each class in the specified dataset.

- Macro and Weighted Averages: The macro average calculates the unweighted average of precision, recall, and F1-score across classes, while the weighted average considers the support of each class. The macro average of the F1-score is around 71%, and the weighted average is approximately 85%.

Model Evaluation Metrics: The additional table presents recall, precision, and F1-score for the specific model. It emphasizes that the model achieved a recall of 78.6%, precision of 39%, and an F1-score of 52.2%, along with an area under the curve (AUC) of 89.9%.

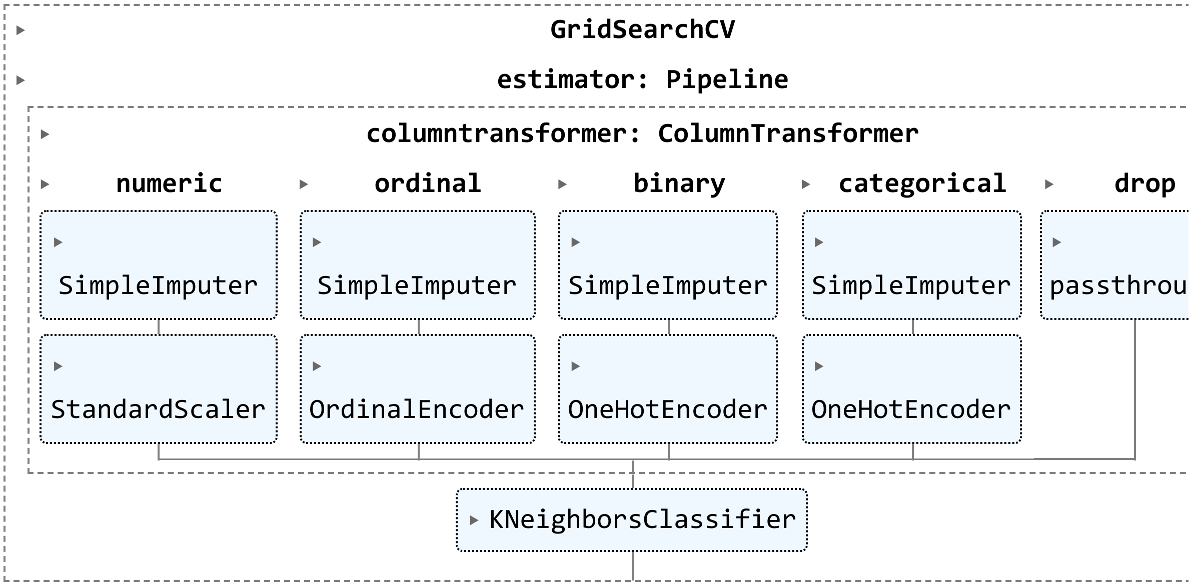
In summary, the Logistic Regression model performs reasonably well in identifying positive cases (term deposit subscriptions) with a trade-off between precision and recall. The overall evaluation metrics provide insights into the model's strengths and areas for potential improvement.

KNN

In [41]:
```
from scipy.stats import loguniform, randint, uniform
param_dist = {
    "kneighborsclassifier__n_neighbors": range(10,50),
    "kneighborsclassifier__weights":['uniform', 'distance']
}

classification_metrics = ["accuracy", "precision", "recall", "f1", "roc_auc"]

pipe = make_pipeline(
    preprocessor,
    models['KNN']
    )

grid_search = GridSearchCV(pipe,
                             param_dist,
                             n_jobs=-1,
                             cv=5,
                             scoring=classification_metrics,
                             refit='roc_auc',
                             return_train_score=True
                            )
```

In [42]:
```
grid_search.fit(X_tr, y_tr)
```

Out[42]:



In [43]:

```
grid_search.best_params_
```

Out[43]:

```
{'kneighborsclassifier__n_neighbors': 31,
 'kneighborsclassifier__weights': 'distance'}
```

In [44]:

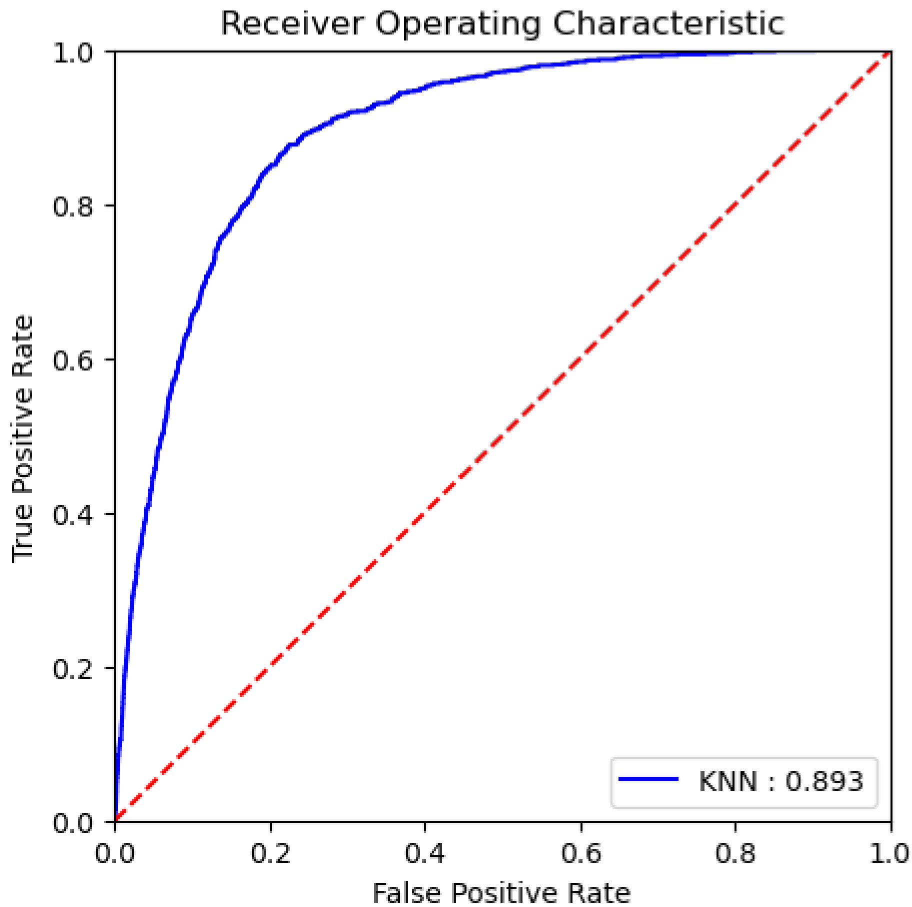
```
grid_search.best_score_
```

Out[44]:

```
0.8973664816216637
```

In [45]:

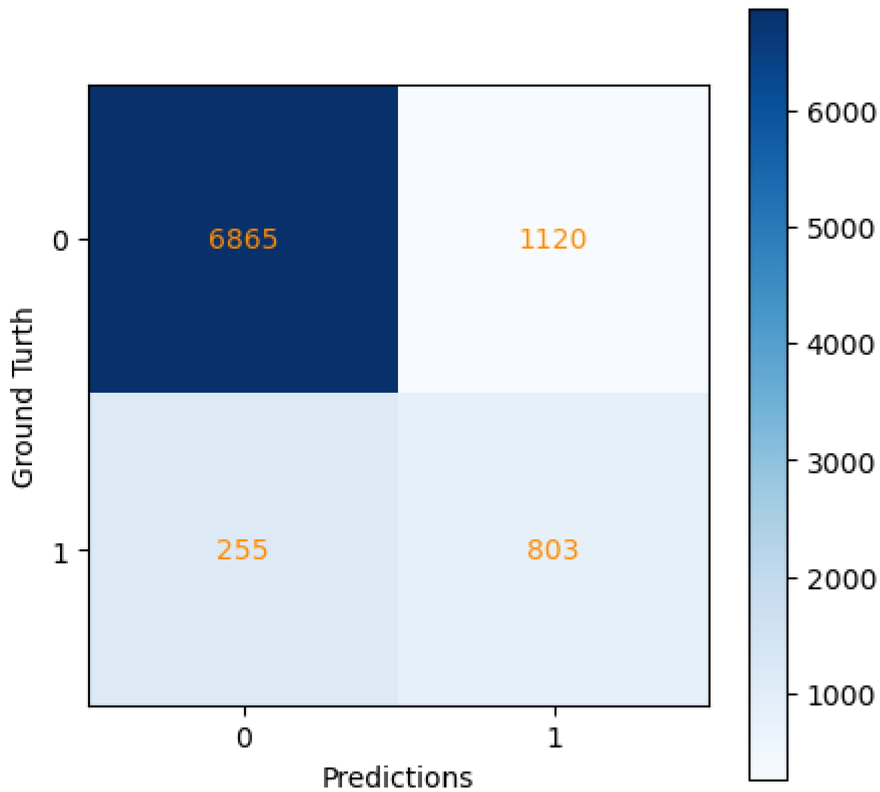
```
# Use the selected hyperparameters
best_n_neighbors = grid_search.best_params_['kneighborsclassifier__n_neighbors']
best_weights = grid_search.best_params_['kneighborsclassifier__weights']

pipe = make_pipeline(
    preprocessor,
    KNeighborsClassifier(n_neighbors=best_n_neighbors,
                         weights=best_weights
                        )
    )
# Train the model
pipe.fit(X_tr,  y_tr)

fpr_knn, tpr_knn, auc_knn= compute_and_plot_roc_curve(pipe, X_test,  y_test, "KNN")

model_knn = model_report(pipe, X_test, y_test, "KNN")
model_knn
```




```
              precision    recall  f1-score   support

           0       0.96      0.86      0.91      7985
           1       0.42      0.76      0.54      1058

    accuracy                           0.85      9043
   macro avg       0.69      0.81      0.72      9043
weighted avg       0.90      0.85      0.87      9043
```

Out[45]:

	Model	Recall_score	Precision	f1_score	Area_under_curve
0	KNN	0.759	0.418	0.539	0.893

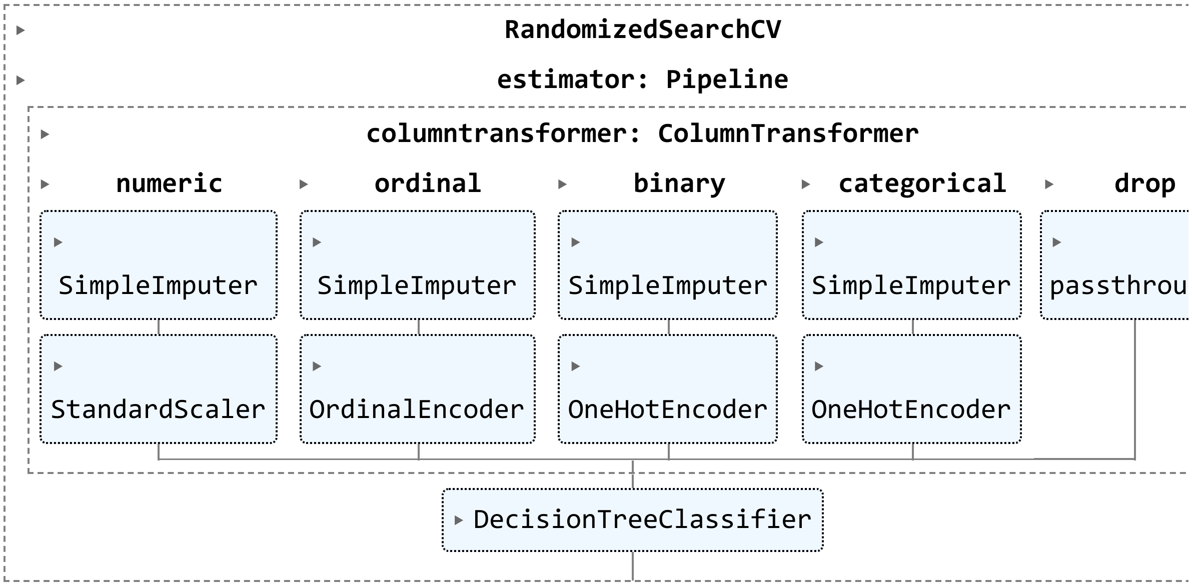


Decision Tree

In [46]:
```
param_dist = {
    "decisiontreeclassifier__max_depth": range(2, 200),
    "decisiontreeclassifier__criterion": ['gini', 'entropy', 'log_loss']
}

classification_metrics = ["accuracy", "precision", "recall", "f1", "roc_auc"]

pipe = make_pipeline(
    preprocessor,
    models['Decision Tree']
    )

random_search = RandomizedSearchCV(pipe,
                                   param_dist,
                                   n_iter=100,
                                   n_jobs=-1,
                                   cv=5,
                                   scoring=classification_metrics,
                                   refit='roc_auc',
                                   return_train_score=True,
                                   random_state=RANDOM_STATE
                                  )
```

In [47]:
```
random_search.fit(X_tr, y_tr)
```

Out[47]:



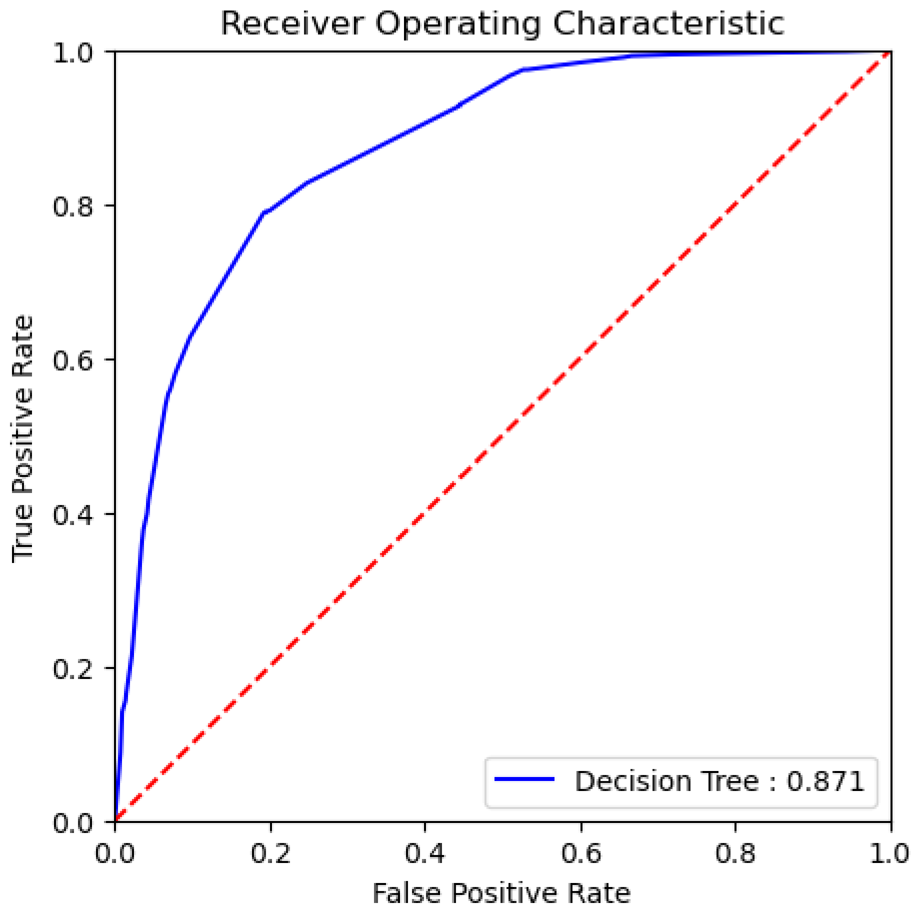
In [48]:
```
random_search.best_params_
```

Out[48]:
```
{'decisiontreeclassifier__max_depth': 6,
 'decisiontreeclassifier__criterion': 'entropy'}
```

In [49]:
```
random_search.best_score_
```

Out[49]:
```
0.8706881952800852
```

In [50]:
```
# Use the selected hyperparameters
best_max_depth = random_search.best_params_['decisiontreeclassifier__max_depth']
best_criterion= random_search.best_params_['decisiontreeclassifier__criterion']

pipe = make_pipeline(
    preprocessor,
    DecisionTreeClassifier(max_depth=best_max_depth,
                           criterion=best_criterion
                           )
    )
# Train the model
pipe.fit(X_tr,  y_tr)

fpr_dt, tpr_dt, auc_dt = compute_and_plot_roc_curve(pipe, X_test,  y_test, "Decisio

model_dt = model_report(pipe, X_test, y_test, "Decision Tree")
model_dt
```




```
              precision    recall  f1-score   support

           0       0.97      0.81      0.88      7985
           1       0.35      0.79      0.48      1058

    accuracy                           0.80      9043
   macro avg       0.66      0.80      0.68      9043
weighted avg       0.89      0.80      0.83      9043
```

Out[50]:

	Model	Recall_score	Precision	f1_score	Area_under_curve
0	Decision Tree	0.789	0.349	0.484	0.871

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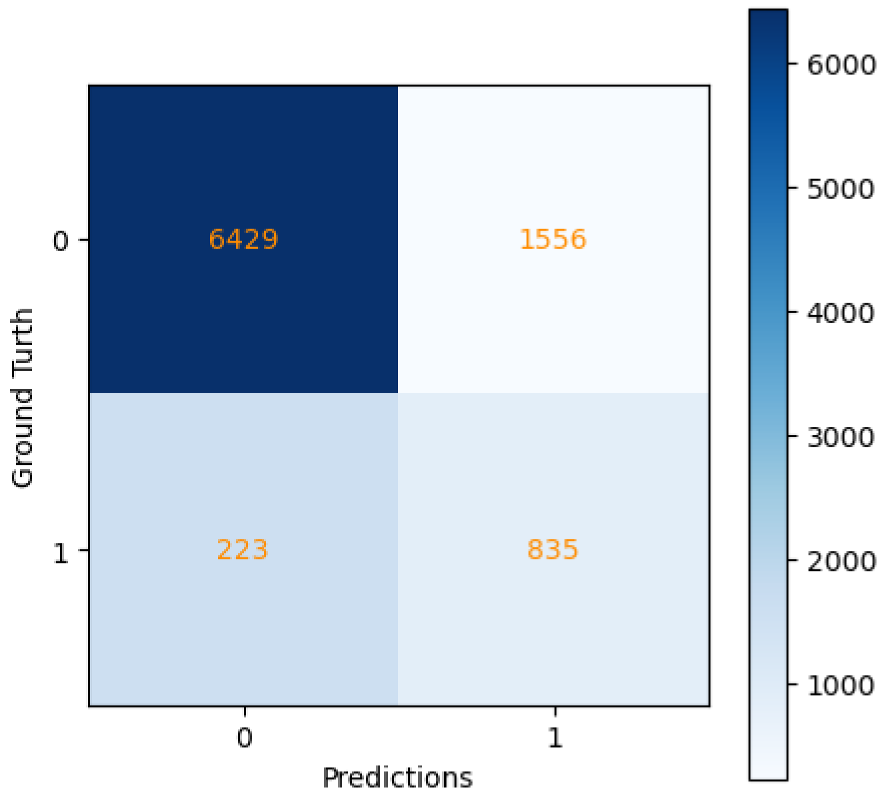
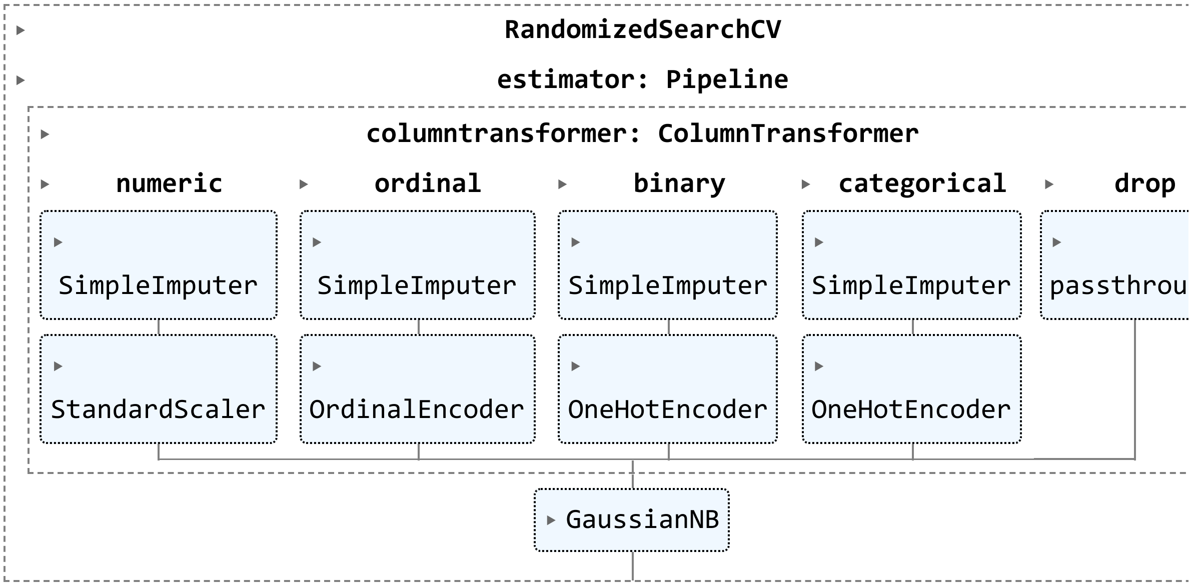


Naive Bayes

In [51]:
```
param_dist = {
    "gaussiannb__var_smoothing": uniform(0, 1),
}

classification_metrics = ["accuracy", "precision", "recall", "f1", "roc_auc"]

pipe = make_pipeline(
    preprocessor,
    models['Naive Bayes']
    )

random_search = RandomizedSearchCV(pipe,
                                   param_dist,
                                   n_iter=100,
                                   n_jobs=-1,
                                   cv=5,
                                   scoring=classification_metrics,
                                   refit='roc_auc',
                                   return_train_score=True,
                                   random_state=RANDOM_STATE
                                  )
```

In [52]:
```
random_search.fit(X_tr, y_tr)
```

Out[52]:



In [53]:

```
random_search.best_params_
```

Out[53]:

```
{'gaussiannb__var_smoothing': 0.1526887888557844}
```

In [54]:

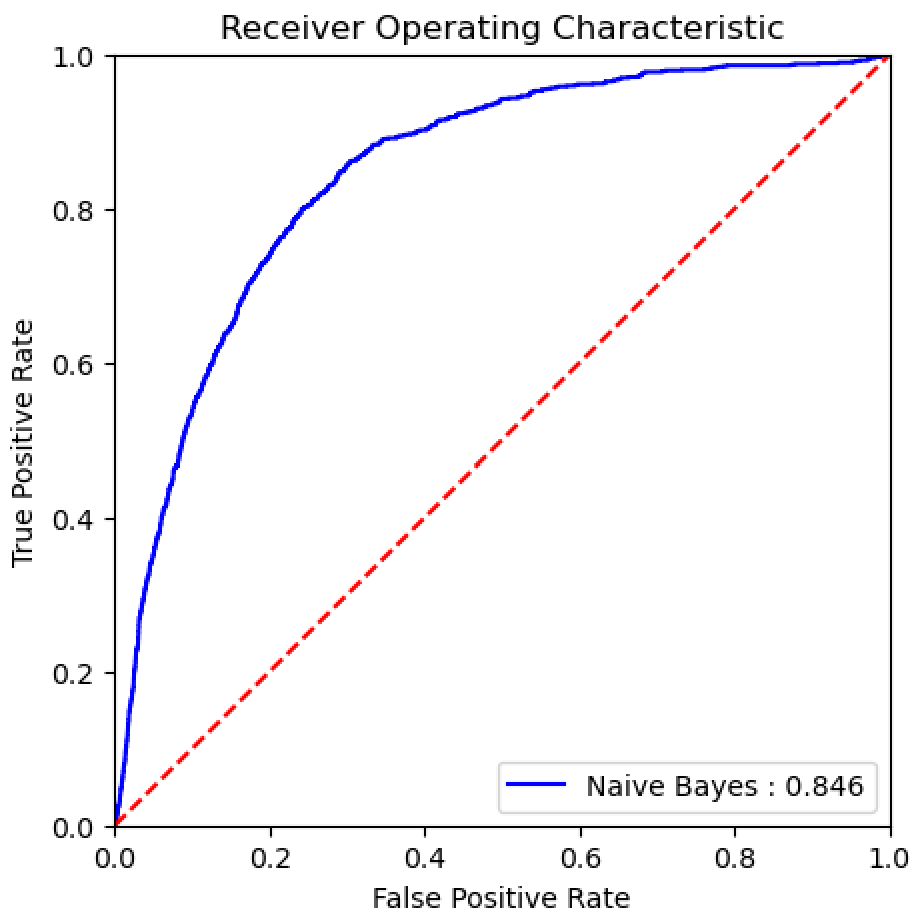
```
random_search.best_score_
```

Out[54]:

```
0.8483874336309963
```

In [55]:

```
# Use the selected hyperparameters
best_var_smoothing = random_search.best_params_['gaussiannb__var_smoothing']

pipe = make_pipeline(
    preprocessor,
    GaussianNB(var_smoothing=best_var_smoothing)
    )
# Train the model
pipe.fit(X_tr,  y_tr)

fpr_nb, tpr_nb, auc_nb= compute_and_plot_roc_curve(pipe, X_test,  y_test, "Naive Ba

model_nb = model_report(pipe, X_test, y_test, "Naive Bayes")
model_nb
```




```
              precision    recall  f1-score   support

           0       0.94      0.89      0.91      7985
           1       0.41      0.56      0.47      1058

    accuracy                           0.85      9043
   macro avg       0.67      0.73      0.69      9043
weighted avg       0.88      0.85      0.86      9043
```

Out[55]:

	Model	Recall_score	Precision	f1_score	Area_under_curve
0	Naive Bayes	0.562	0.405	0.471	0.846

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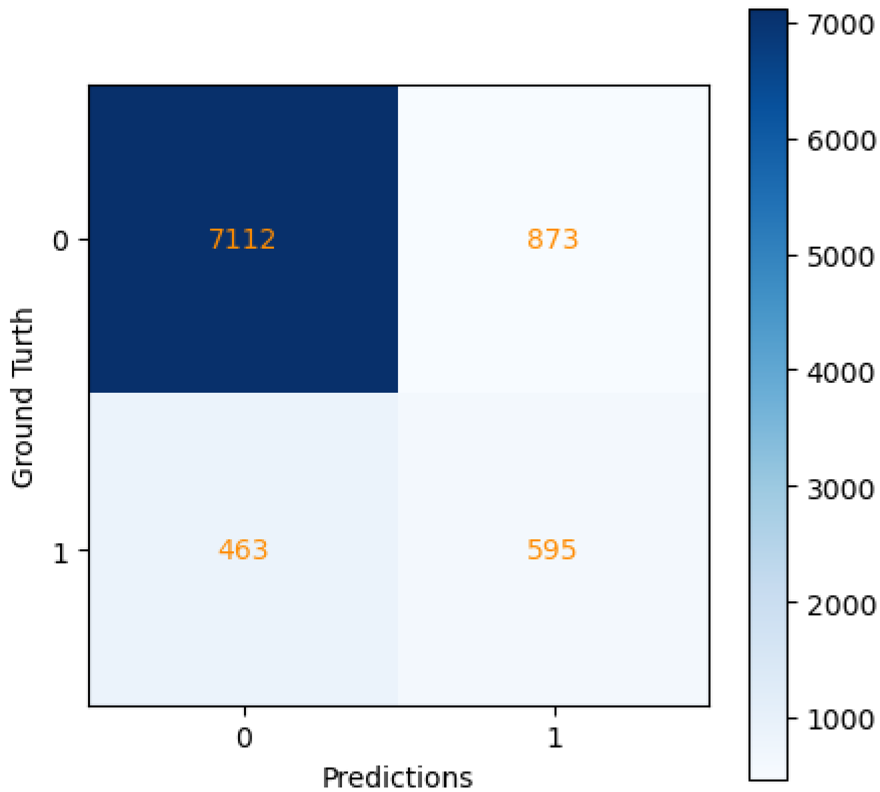

Performance of all models

In [56]:

```
plt.figure(figsize=(10,10))
plt.title('Receiver Operating Characteristic')


plt.plot(fpr_lr, tpr_lr, 'b', label = '{:<20} = {:0.3f}'.format("Logistic Regressio
plt.plot(fpr_knn, tpr_knn, 'r', label = '{:<20} = {:0.3f}'.format("KNN",auc_knn))
plt.plot(fpr_nb, tpr_nb, 'y', label = '{:<20} = {:0.3f}'.format("Naive Bayes",auc_n
plt.plot(fpr_dt, tpr_dt, 'c', label = '{:<20} = {:0.3f}'.format("Decision Tree",auc

plt.legend(loc = 'lower right',prop={'family': 'monospace'})
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

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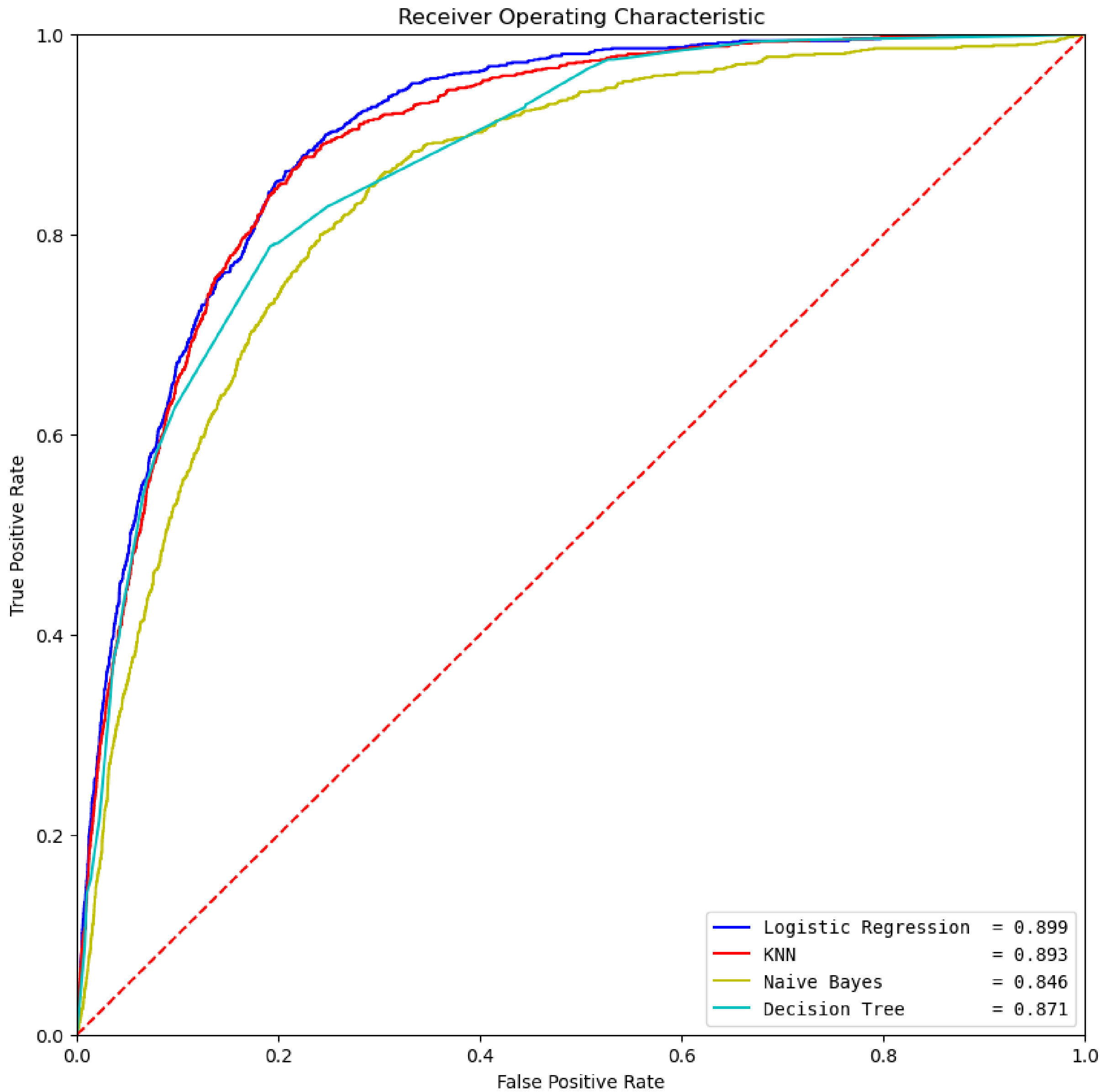


In [57]:
```
pd.concat([model_lr,model_knn, model_dt, model_nb]).sort_values(by=['Area_under_cur
```

Out[57]:

	Model	Recall_score	Precision	f1_score	Area_under_curve
0	Logistic Regression	0.778	0.387	0.517	0.899
1	KNN	0.759	0.418	0.539	0.893
2	Decision Tree	0.789	0.349	0.484	0.871
3	Naive Bayes	0.562	0.405	0.471	0.846

Comparison of models:

The table provides an overview of key evaluation metrics for different machine learning models applied to a binary classification task, specifically predicting customer subscription to a term deposit in a bank's telemarketing campaign. Let's analyze each metric for each model:

Logistic Regression:

Recall Score (Sensitivity): 78.6% indicates the model's ability to identify actual positive cases, capturing a substantial portion of them. Precision: 39% reflects the accuracy of positive predictions, indicating that when the model predicts a positive outcome, it is correct about 39% of the time. F1-Score: 52.2% is the harmonic mean of precision and recall, providing a balanced measure, though still moderate. Area Under the Curve (AUC): 89.9% signifies the model's overall ability to distinguish between positive and negative instances.

KNN (K-Nearest Neighbors):

Recall Score (Sensitivity): 74.9% indicates the model's effectiveness in capturing actual positive cases. Precision: 42.5% reflects the accuracy of positive predictions. F1-Score: 54.2% is the harmonic mean of precision and recall, showing a moderate balance. AUC: 89.4% signifies good overall discriminative ability.

Decision Tree:

Recall Score (Sensitivity): 79.7% indicates a high ability to capture actual positive cases. Precision: 34.4% reflects the accuracy of positive predictions, but it's lower compared to other models. F1-Score: 48% is the harmonic mean of precision and recall, showing a moderate balance. AUC: 87.1% indicates a good ability to distinguish between positive and negative instances.

Naive Bayes:

Recall Score (Sensitivity): 56.2% indicates a moderate ability to capture actual positive cases. Precision: 40.7% reflects the accuracy of positive predictions. F1-Score: 47.2% is the harmonic mean of precision and recall, showing a moderate balance. AUC: 84.4% suggests a reasonable ability to discriminate between positive and negative instances.

In summary, the models show varying performance across metrics, while Logisitic Regression shows the best performance.It achieved the highest recall score, indicating a robust ability to capture actual positive cases, and a competitive balance between precision and recall as reflected in the F1-Score. Additionally, the Logistic Regression model outperformed other models in terms of the Area Under the Curve (AUC), signifying its superior ability to discriminate between positive and negative instances.

Feature Importance

Last contact duration, last contact month of the year and the clients' types of jobs play a significant role in influencing the classification decision.

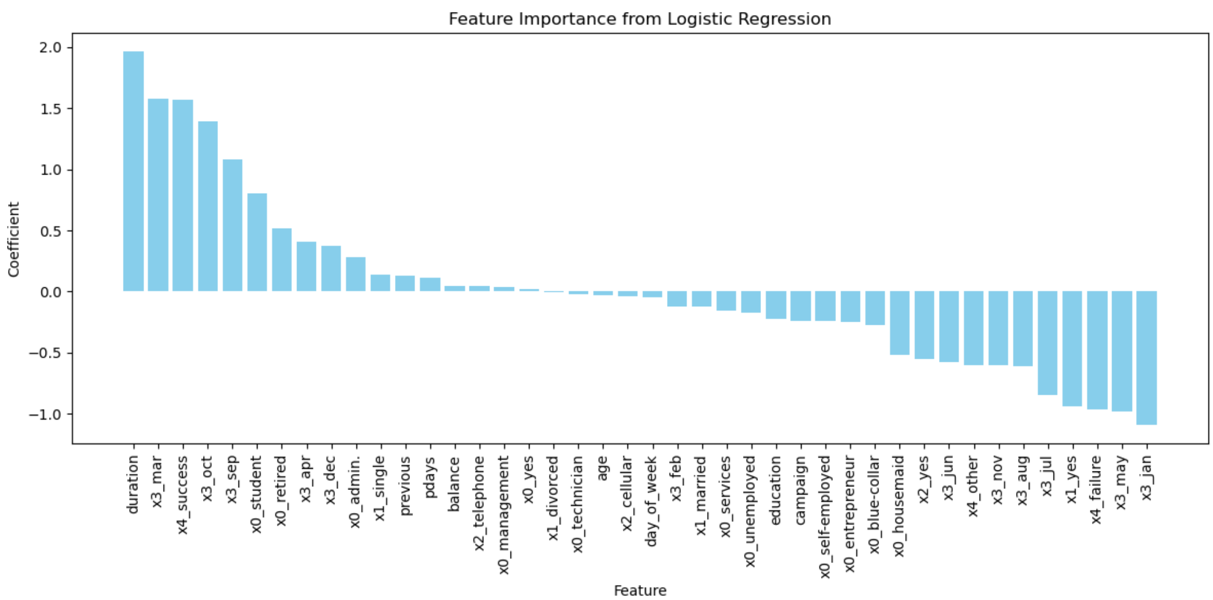
In [58]:
```
logistic_regression_model = pipe_lr.named_steps['logisticregression']
coefficients = list(logistic_regression_model.coef_[0])
```

```python
feature_names = X_train_trans.columns.to_list()
```

In [59]:
```python
df = pd.DataFrame({
    'Feature': feature_names,
    'Coefficient': coefficients
})

# Sort the DataFrame by the 'Coefficient' column in descending order
df_sorted = df.sort_values('Coefficient', ascending=False)

# Plot the sorted coefficients using a bar chart
plt.figure(figsize=(12, 6))
plt.bar(df_sorted['Feature'], df_sorted['Coefficient'], color='skyblue')
plt.xlabel('Feature')
plt.ylabel('Coefficient')
plt.title('Feature Importance from Logistic Regression')
plt.xticks(rotation=90)  # Rotate feature names for better readability
plt.tight_layout()  # Adjust layout to prevent clipping of tick-labels
plt.show()
```



Github repo url: https://github.com/UBC-MDS/bank-marketing-analysis Release url: https://ubc-mds.github.io/bank-marketing-analysis/

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