In [7]:
```
!pip install pandas
!pip install numpy
!pip install seaborn
!pip install matplotlib
!pip install xgboost
!pip install scikit-learn
```

```
Requirement already satisfied: pandas in ./.venv/lib/python3.10/site-packages (2.2.2)
Requirement already satisfied: numpy>=1.22.4 in ./.venv/lib/python3.10/site-packages (from pandas) (2.1.0)
Requirement already satisfied: python-dateutil>=2.8.2 in ./.venv/lib/python3.10/site-packages (from pandas) (2.9.0.p
ost0)
Requirement already satisfied: pytz>=2020.1 in ./.venv/lib/python3.10/site-packages (from pandas) (2024.1)
Requirement already satisfied: tzdata>=2022.7 in ./.venv/lib/python3.10/site-packages (from pandas) (2024.1)
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s) (1.16.0)
Requirement already satisfied: numpy in ./.venv/lib/python3.10/site-packages (2.1.0)
Requirement already satisfied: seaborn in ./.venv/lib/python3.10/site-packages (0.13.2)
Requirement already satisfied: numpy!=1.24.0,>=1.20 in ./.venv/lib/python3.10/site-packages (from seaborn) (2.1.0)
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(3.9.2)
Requirement already satisfied: contourpy>=1.0.1 in ./.venv/lib/python3.10/site-packages (from matplotlib!=3.6.1,>=
3.4->seaborn) (1.3.0)
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eaborn) (0.12.1)
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3.4->seaborn) (4.53.1)
Requirement already satisfied: kiwisolver>=1.3.1 in ./.venv/lib/python3.10/site-packages (from matplotlib!=3.6.1,>=
3.4->seaborn) (1.4.5)
Requirement already satisfied: packaging>=20.0 in ./.venv/lib/python3.10/site-packages (from matplotlib!=3.6.1,>=
3.4->seaborn) (24.1)
Requirement already satisfied: pillow>=8 in ./.venv/lib/python3.10/site-packages (from matplotlib!=3.6.1,>=3.4->seab
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Requirement already satisfied: pyparsing>=2.3.1 in ./.venv/lib/python3.10/site-packages (from matplotlib!=3.6.1,>=
3.4->seaborn) (3.1.4)
Requirement already satisfied: python-dateutil>=2.7 in ./.venv/lib/python3.10/site-packages (from matplotlib!=
3.6.1,>=3.4->seaborn) (2.9.0.post0)
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4.1)
Requirement already satisfied: tzdata>=2022.7 in ./.venv/lib/python3.10/site-packages (from pandas>=1.2->seaborn) (2
024.1)
Requirement already satisfied: six>=1.5 in ./.venv/lib/python3.10/site-packages (from python-dateutil>=2.7->matplotl
ib!=3.6.1,>=3.4->seaborn) (1.16.0)
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Requirement already satisfied: contourpy>=1.0.1 in ./.venv/lib/python3.10/site-packages (from matplotlib) (1.3.0)
Requirement already satisfied: cycler>=0.10 in ./.venv/lib/python3.10/site-packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in ./.venv/lib/python3.10/site-packages (from matplotlib) (4.53.1)
Requirement already satisfied: kiwisolver>=1.3.1 in ./.venv/lib/python3.10/site-packages (from matplotlib) (1.4.5)
```

```
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Requirement already satisfied: packaging>=20.0 in ./.venv/lib/python3.10/site-packages (from matplotlib) (24.1)
Requirement already satisfied: pillow>=8 in ./.venv/lib/python3.10/site-packages (from matplotlib) (10.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in ./.venv/lib/python3.10/site-packages (from matplotlib) (3.1.4)
Requirement already satisfied: python-dateutil>=2.7 in ./.venv/lib/python3.10/site-packages (from matplotlib)
(2.9.0.post0)
Requirement already satisfied: six>=1.5 in ./.venv/lib/python3.10/site-packages (from python-dateutil>=2.7->matplotl
ib) (1.16.0)
Collecting xgboost
  Downloading xgboost-2.1.1-py3-none-manylinux_2_28_x86_64.whl.metadata (2.1 kB)
Requirement already satisfied: numpy in ./.venv/lib/python3.10/site-packages (from xgboost) (2.1.0)
Collecting nvidia-nccl-cu12 (from xgboost)
  Downloading nvidia_nccl_cu12-2.23.4-py3-none-manylinux2014_x86_64.whl.metadata (1.8 kB)
Requirement already satisfied: scipy in ./.venv/lib/python3.10/site-packages (from xgboost) (1.14.1)
Downloading xgboost-2.1.1-py3-none-manylinux_2_28_x86_64.whl (153.9 MB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 153.9/153.9 MB 3.2 MB/s eta 0:00:00m eta 0:00:01[36m0:00:02
Downloading nvidia_nccl_cu12-2.23.4-py3-none-manylinux2014_x86_64.whl (199.0 MB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 199.0/199.0 MB 3.4 MB/s eta 0:00:00m eta 0:00:01[36m0:00:02
Installing collected packages: nvidia-nccl-cu12, xgboost
Successfully installed nvidia-nccl-cu12-2.23.4 xgboost-2.1.1
Requirement already satisfied: scikit-learn in ./.venv/lib/python3.10/site-packages (1.5.1)
Requirement already satisfied: numpy>=1.19.5 in ./.venv/lib/python3.10/site-packages (from scikit-learn) (2.1.0)
Requirement already satisfied: scipy>=1.6.0 in ./.venv/lib/python3.10/site-packages (from scikit-learn) (1.14.1)
Requirement already satisfied: joblib>=1.2.0 in ./.venv/lib/python3.10/site-packages (from scikit-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in ./.venv/lib/python3.10/site-packages (from scikit-learn)
(3.5.0)
```

Machine Learning Project: Bank Marketing Dataset

Loading Packages

In [8]:

```python
import os
```

In [9]:

```python
import numpy as np
import pandas as pd

import seaborn as sns
```

```
import matplotlib.pyplot as plt
```

In [10]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier

from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV,StratifiedKFold

from sklearn.metrics import accuracy_score,precision_score,recall_score,f1_score,roc_auc_score
from sklearn.metrics import confusion_matrix

from sklearn.preprocessing import LabelEncoder,StandardScaler
```

In [11]:
```
sns.set_theme(context='paper', style="darkgrid")
```

Loading Dataset

In [13]:
```
# Load the dataset
dir_path = './bank+marketing/bank-additional'
file_name = 'bank-additional-full.csv'
# file_name = 'bank-additional.csv'
file_path = os.path.join(dir_path, file_name)
print(f"Dataset: {file_path}")
data = pd.read_csv(file_path, sep=';')
data.head()
```

```
Dataset: ./bank+marketing/bank-additional/bank-additional-full.csv
```

Out[13]:

	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	may	mon	...	1	999	0	none
1	57	services	married	high.school	unknown	no	no	telephone	may	mon	...	1	999	0	none
2	37	services	married	high.school	no	yes	no	telephone	may	mon	...	1	999	0	none
3	40	admin.	married	basic.6y	no	no	no	telephone	may	mon	...	1	999	0	none
4	56	services	married	high.school	no	no	yes	telephone	may	mon	...	1	999	0	none

5 rows × 21 columns

Dataset Analysis

Initial analysis

In [14]:

```
print(data.columns)
```

```
Index(['age', 'job', 'marital', 'education', 'default', 'housing', 'loan',
       'contact', 'month', 'day_of_week', 'duration', 'campaign', 'pdays',
       'previous', 'poutcome', 'emp.var.rate', 'cons.price.idx',
       'cons.conf.idx', 'euribor3m', 'nr.employed', 'y'],
      dtype='object')
```

Dataset Summary

In [15]:

```
print("Summary of dataset:")
print(data.info())
```

```
Summary of dataset:
<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
None
<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
None
```

Missing values in table

In [16]:
```
print("Checking for missing values:")
print(data.isnull().sum())
```

```
Checking for missing values:
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
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
```

Dataset statistics

In [17]:
```python
print("\nDescriptive statistics:")
data.describe(include='all')
```

```
Descriptive statistics:
```

Out[17]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	...	campaign	
count	41188.00000	41188	41188	41188	41188	41188	41188	41188	41188	41188	...	41188.000000	4118
unique	NaN	12	4	8	3	3	3	2	10	5	...	NaN	
top	NaN	admin.	married	university.degree	no	yes	no	cellular	may	thu	...	NaN	
freq	NaN	10422	24928	12168	32588	21576	33950	26144	13769	8623	...	NaN	
mean	40.02406	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	2.567593	96
std	10.42125	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	2.770014	18
min	17.00000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	1.000000	
25%	32.00000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	1.000000	99
50%	38.00000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	2.000000	99
75%	47.00000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	3.000000	99
max	98.00000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	56.000000	99

11 rows × 21 columns

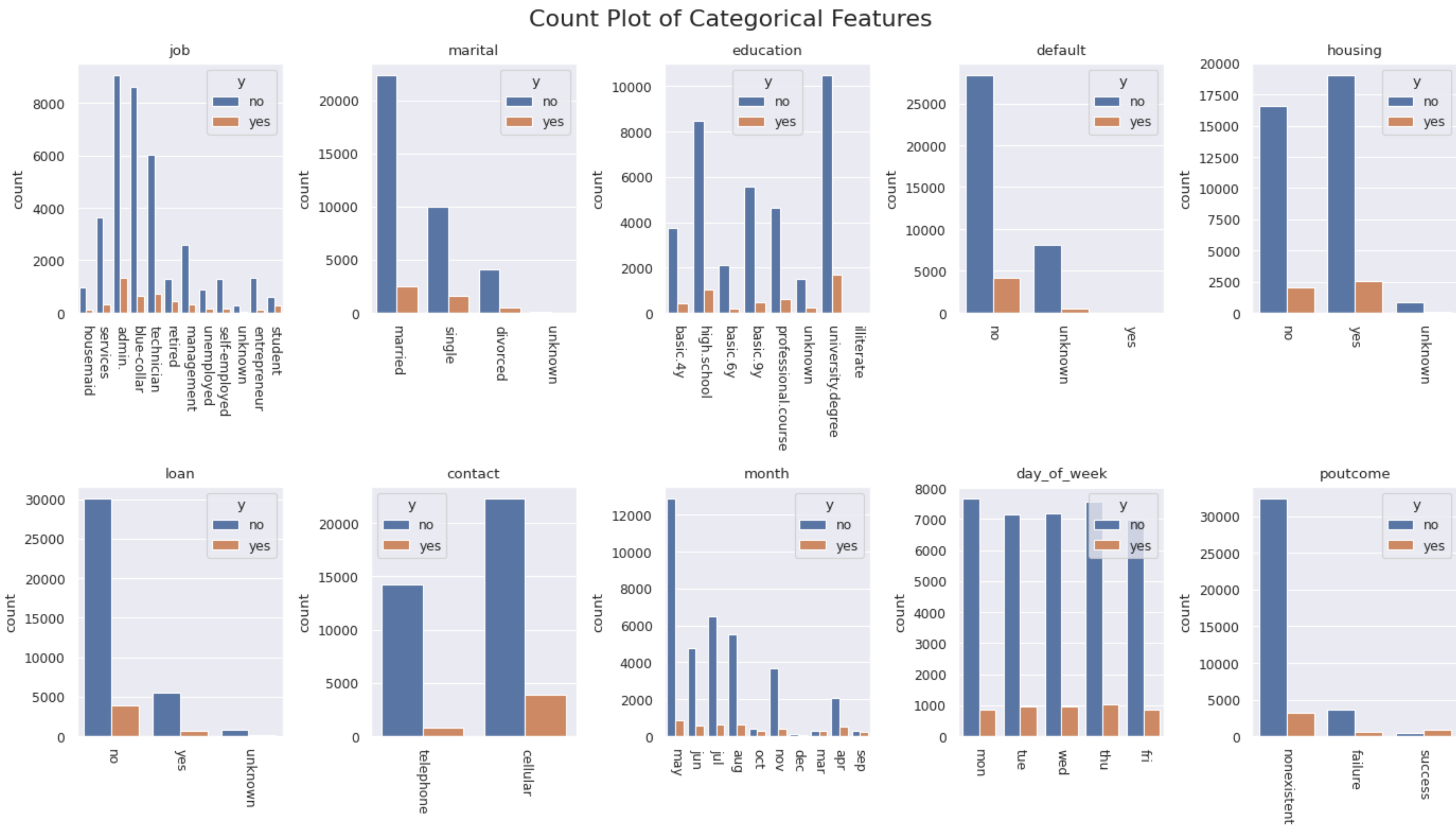
Data Visualization

Categorical features against target

In [18]:
```
categorical_feature_names = data.drop('y', axis=1).select_dtypes(include=['object']).columns
print(f"Number of categorical features: {categorical_feature_names.shape[-1]}")
```

```
Number of categorical features: 10
```

In [19]:
```
fig=plt.figure(figsize=(14, 8))
for i in range(categorical_feature_names.shape[-1]):
  plt.subplot(2,5,i+1)
  sns.countplot(data=data, x=categorical_feature_names[i], hue='y')
  plt.xticks(rotation=-90)
  plt.xlabel('')
  plt.title(categorical_feature_names[i])
fig.suptitle('Count Plot of Categorical Features', fontsize=16)
plt.tight_layout()
```



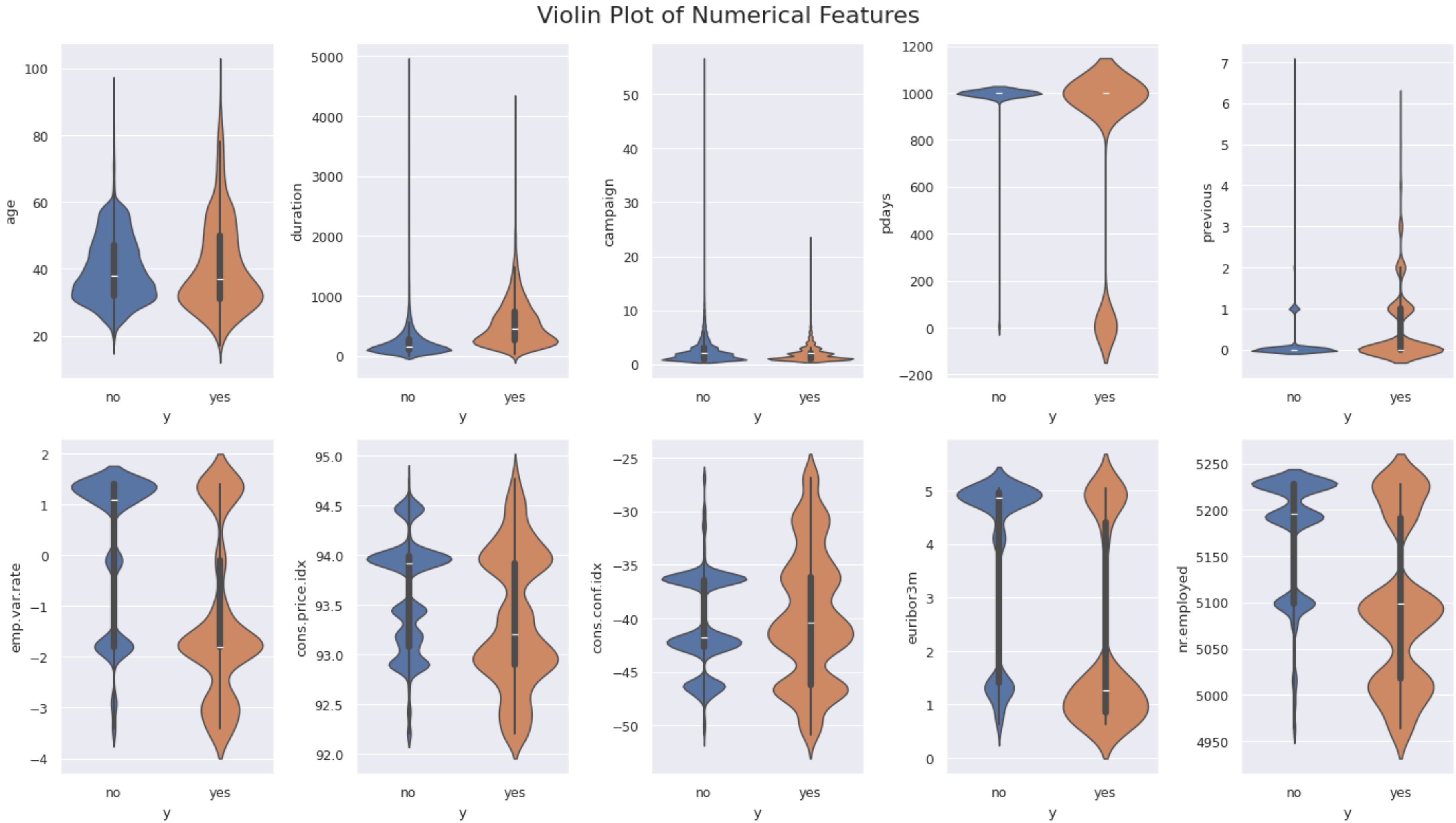
Numerical features against target variable

In [20]:
```
numerical_feature_names = data.drop('y', axis=1).select_dtypes(include=['int', 'float']).columns
print(f"Number of numerical features: {numerical_feature_names.shape[-1]}")
```

```
Number of numerical features: 10
```

In [21]:
```
fig=plt.figure(figsize=(14, 8))
for i in range(numerical_feature_names.shape[-1]):
```

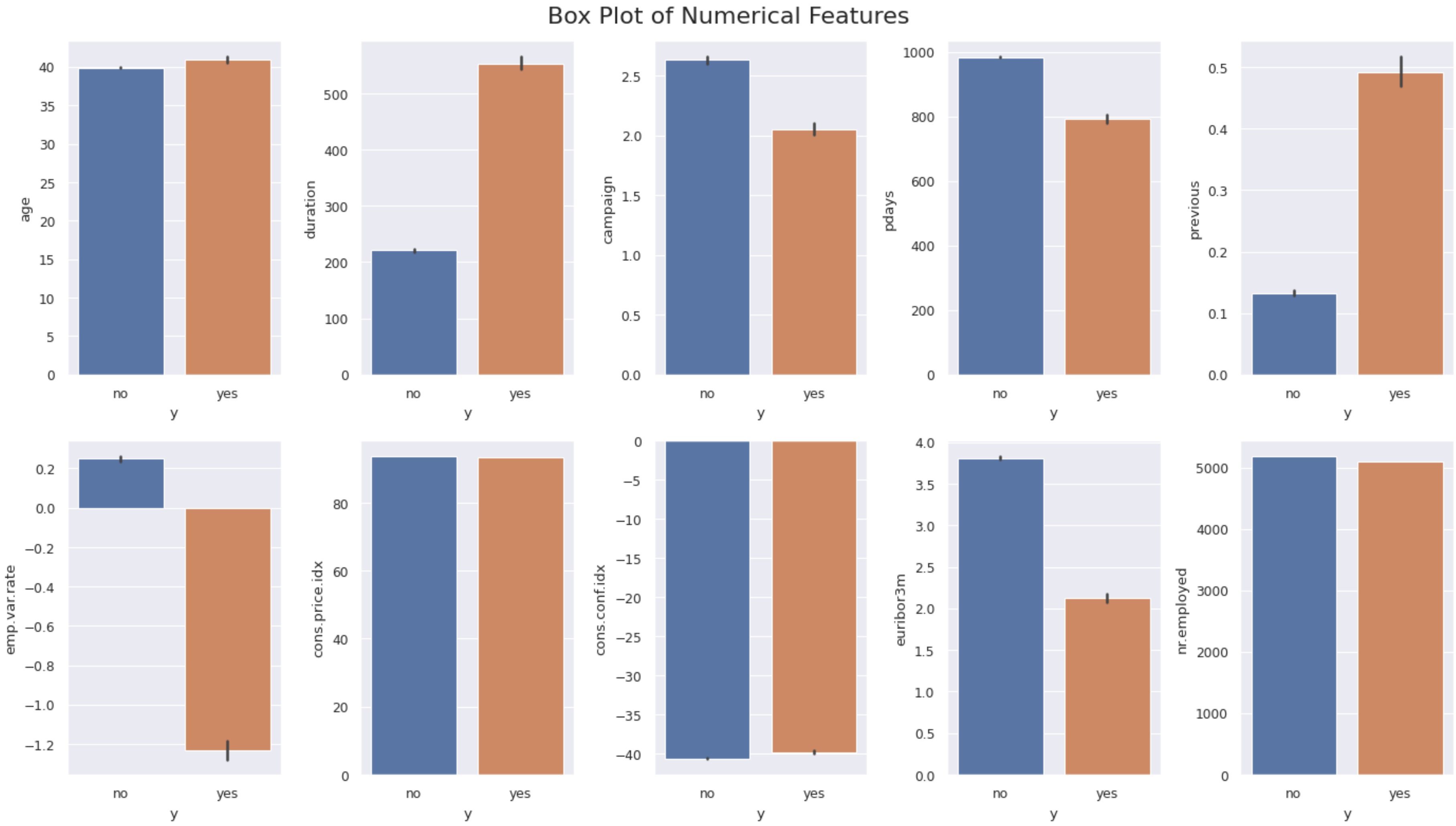
```
  plt.subplot(2,5,i+1)
  sns.violinplot(data=data,  x='y', y=numerical_feature_names[i], hue='y')
fig.suptitle('Violin Plot of Numerical Features', fontsize=16)
plt.tight_layout()
```



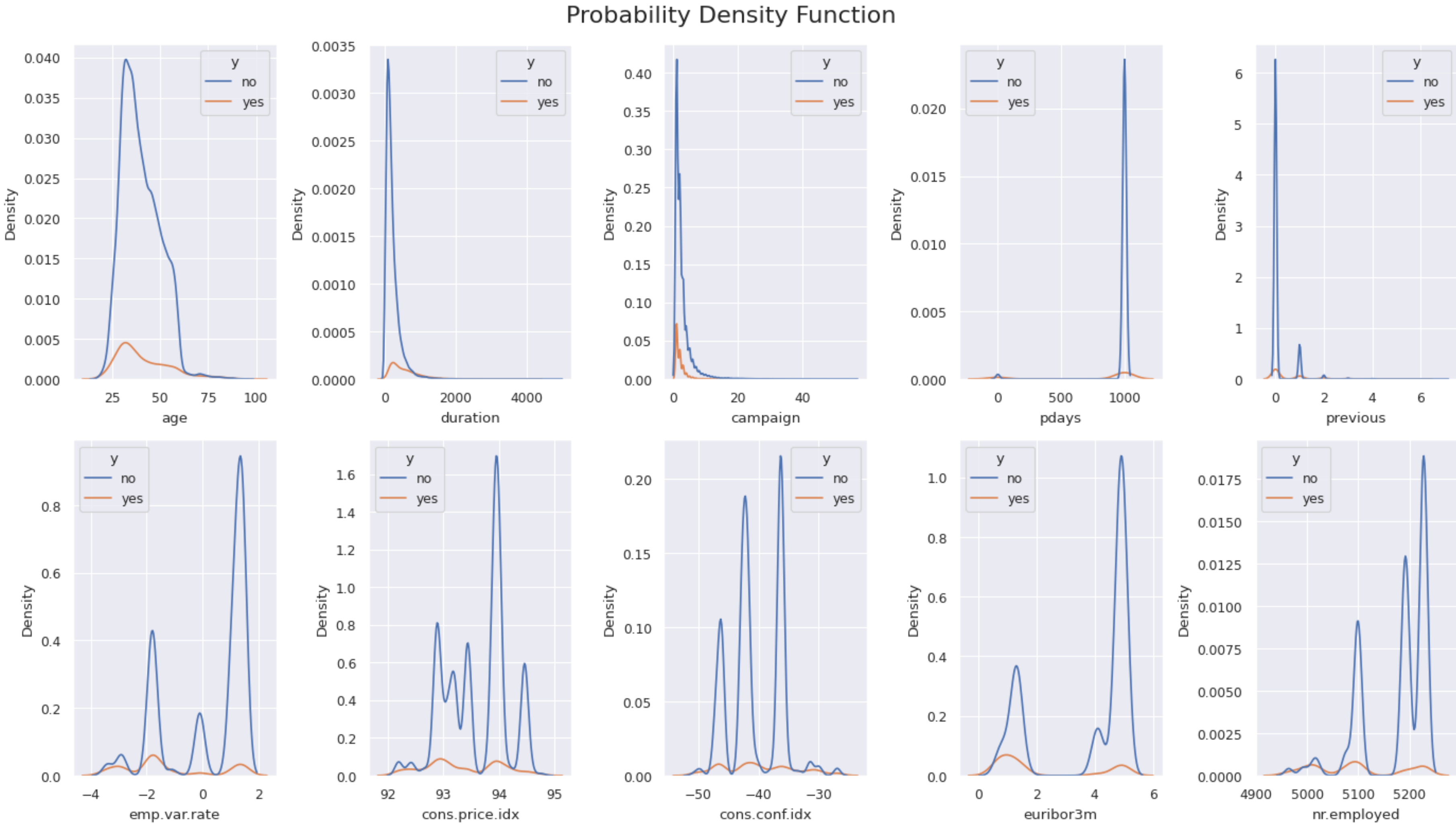
In [22]:

```
fig=plt.figure(figsize=(14, 8))
for i in range(numerical_feature_names.shape[-1]):
  plt.subplot(2,5,i+1)
  sns.barplot(data=data,  x='y', y=numerical_feature_names[i], hue='y')
```

```
fig.suptitle('Box Plot of Numerical Features', fontsize=16)
plt.tight_layout()
```



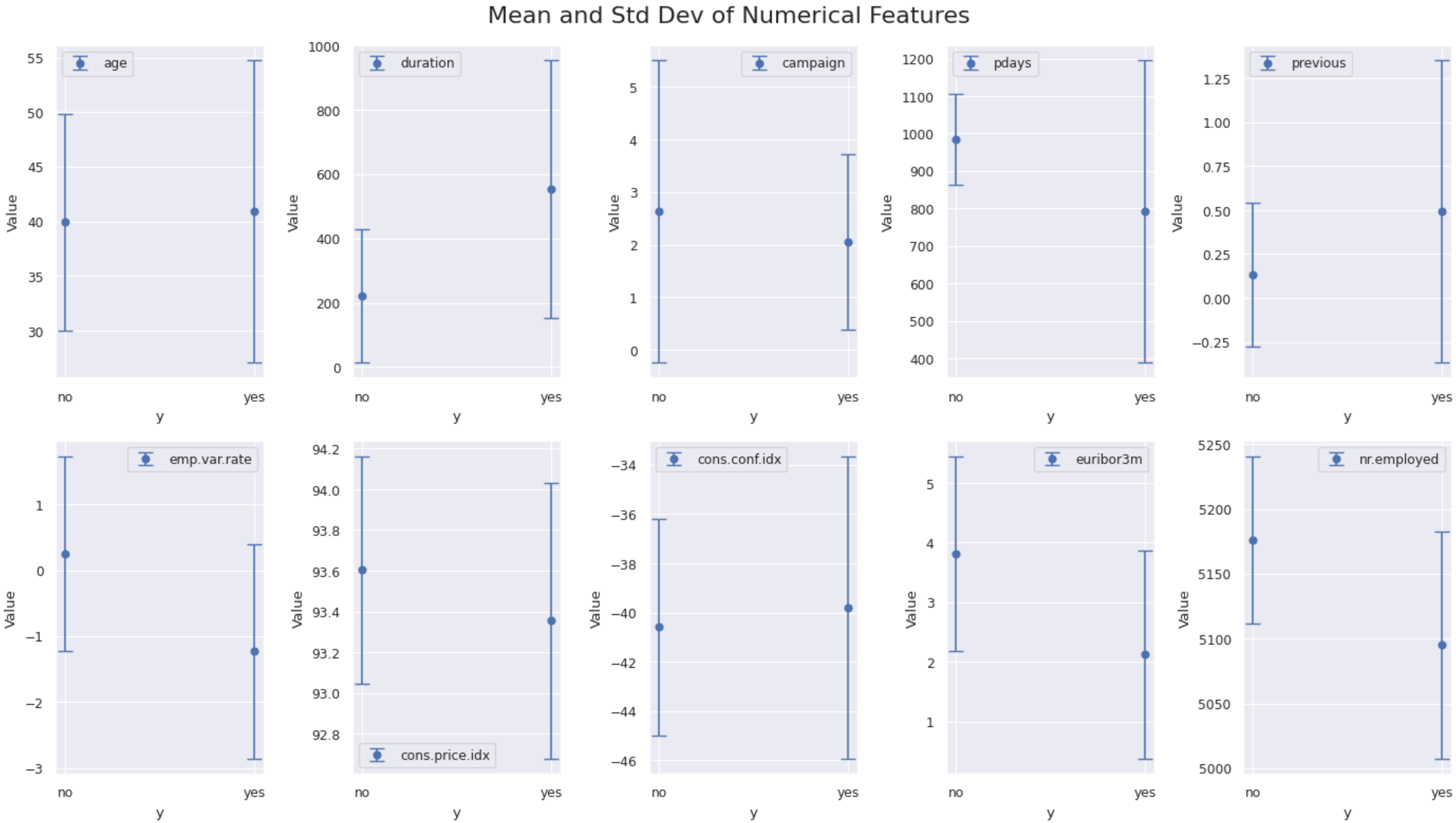
In [23]:
```
fig=plt.figure(figsize=(14, 8))
for i in range(numerical_feature_names.shape[-1]):
  plt.subplot(2,5,i+1)
  sns.kdeplot(data=data, x=numerical_feature_names[i], hue='y')
fig.suptitle('Probability Density Function', fontsize=16)
plt.tight_layout()
```




```
In [24]: grouped = data.drop(categorical_feature_names, axis=1).groupby('y').agg(['mean', 'std'])
grouped.columns = ['_'.join(col).strip() for col in grouped.columns.values]
grouped.reset_index(inplace=True)

fig=plt.figure(figsize=(14, 8))
for i in range(numerical_feature_names.shape[-1]):
  plt.subplot(2,5,i+1)
  plt.errorbar(grouped['y'], grouped[f'{numerical_feature_names[i]}_mean'], yerr=grouped[f'{numerical_feature_names
  plt.xlabel('y')
```

```
    plt.ylabel('Value')
    plt.legend()
fig.suptitle('Mean and Std Dev of Numerical Features', fontsize=16)
plt.tight_layout()
```



Class Balance

```
In [25]: plt.figure()
sns.countplot(data=data, x='y', hue='y')
```

```
plt.suptitle("Class Balance")
plt.tight_layout()
```

Binary Classification

Metrics evaluation function

In [26]:
```
def get_metrics(model_name:str, y_pred, y_true):
    accuracy  = accuracy_score(y_true, y_pred)
```

```
    precision = precision_score(y_true, y_pred, average='binary')
    recall    = recall_score(y_true, y_pred, average='binary')
    f1        = f1_score(y_true, y_pred, average='binary')
    roc_auc   = roc_auc_score(y_true, y_pred, average="macro")

    metrics_table = pd.DataFrame({'model': [model_name],
                                  'precision': [precision],
                                  'recall': [recall],
                                  'f1 score': [f1],
                                  'accuracy': [accuracy],
                                  'ROC AUC': [roc_auc]})

    cm = confusion_matrix(y_pred=y_pred, y_true=y_true)

    return metrics_table, cm
```

Categorical features encoding

In [27]:

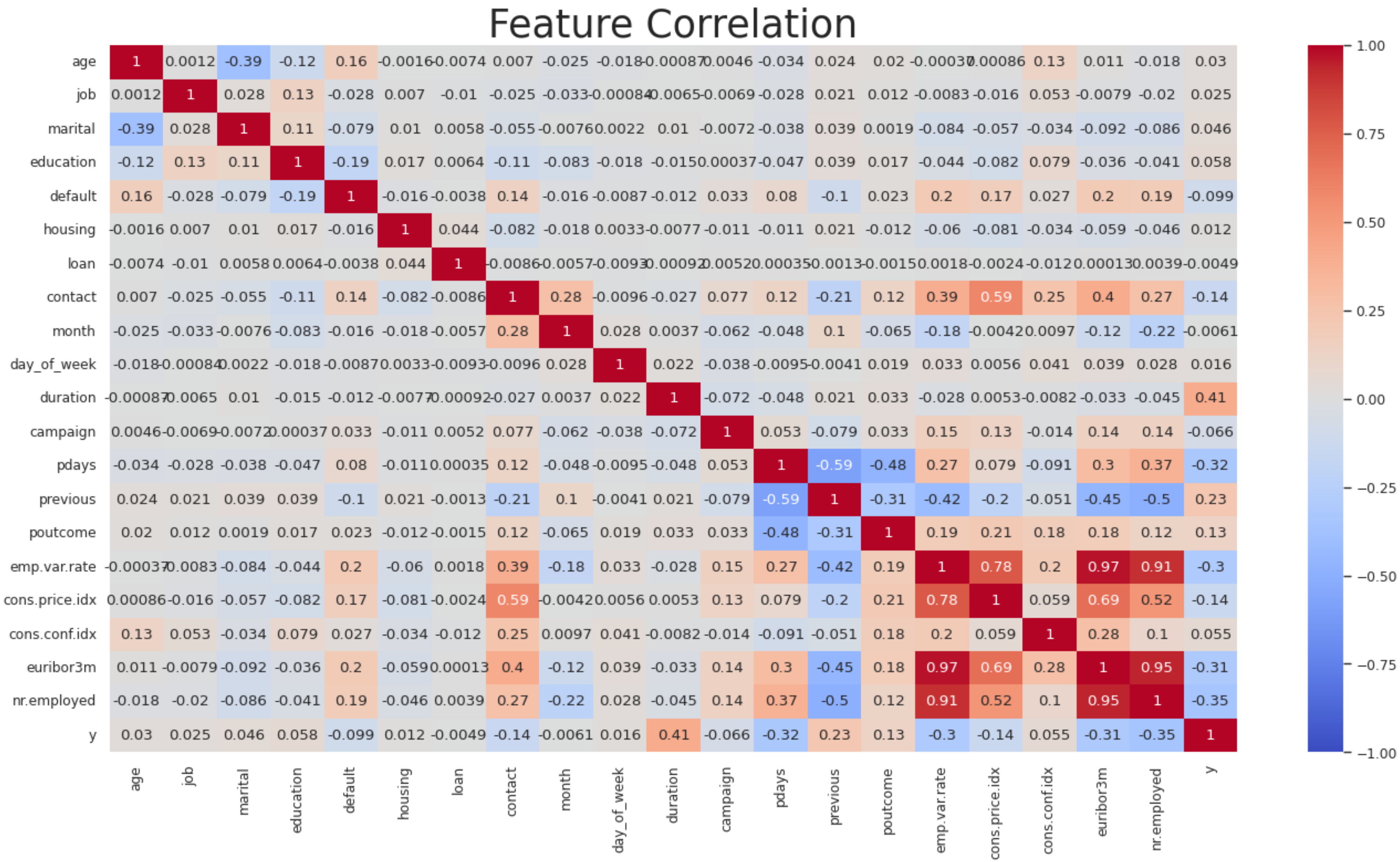
```
encoder = LabelEncoder()
for col in categorical_feature_names:
    data[col] = encoder.fit_transform(data[col])

data['y'] = encoder.fit_transform(data['y'])
```

Feature Correlation

In [28]:

```
plt.figure(figsize=(14,8))
sns.heatmap(data.corr(method='pearson'),vmin=-1,vmax=1,annot=True,cmap='coolwarm')
plt.title('Feature Correlation',fontsize=25)
plt.tight_layout()
plt.show()
```



In [29]:

```
ss_scaler = StandardScaler()
data[categorical_feature_names] = ss_scaler.fit_transform(data[categorical_feature_names])
data.head()
```

Out[29]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	...	campaign	pdays	previou
0	56	-0.201579	-0.283741	-1.753925	-0.513600	-1.087707	-0.452491	1.31827	0.762558	-0.718834	...	1	999	
1	57	0.911227	-0.283741	-0.349730	1.945327	-1.087707	-0.452491	1.31827	0.762558	-0.718834	...	1	999	
2	37	0.911227	-0.283741	-0.349730	-0.513600	0.942127	-0.452491	1.31827	0.762558	-0.718834	...	1	999	
3	40	-1.036184	-0.283741	-1.285860	-0.513600	-1.087707	-0.452491	1.31827	0.762558	-0.718834	...	1	999	
4	56	0.911227	-0.283741	-0.349730	-0.513600	-1.087707	2.311440	1.31827	0.762558	-0.718834	...	1	999	

5 rows × 21 columns

Train test split

In [30]:

```
TEST_SIZE = 0.2
feature_names = data.columns.drop('y')
X = data[feature_names]
y = data['y']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=TEST_SIZE, stratify=y, random_state=42)
```

Simple classifier based on class count

In [31]:
```
from collections import Counter

class ClassCountClassifier:
    def fit(self, y):
      class_counts = Counter(y)
      total_samples = len(y)
      self.class_probabilities = {cls: count / total_samples for cls, count in class_counts.items()}
      self.classes = list(self.class_probabilities.keys())
      self.probabilities = list(self.class_probabilities.values())
      return self.class_probabilities

    def predict(self, X):
        # np.random.seed(seed=42)
        return np.random.choice(self.classes, size=len(X), p=self.probabilities)
```

In [32]:
```
class_count_clf = ClassCountClassifier()
class_probabilities=class_count_clf.fit(y_train)
print(class_probabilities)
```

```
{0: 0.8873444613050075, 1: 0.11265553869499241}
```

In [33]:
```
y_pred = class_count_clf.predict(X_train)
class_count_clf_metrics, class_count_clf_cm = get_metrics("Class Count Classifier", y_pred, y_train)
```

In [34]:
```
fig, ax = plt.subplots()
ax=sns.heatmap(class_count_clf_cm,annot=True, ax=ax, fmt='.4g')
ax.xaxis.set_ticklabels(['No Deposit','Deposit'])
ax.yaxis.set_ticklabels(['No Deposit','Deposit'])
ax.set_title('Class Count Classifier-Train',fontsize=18)

print(class_count_clf_metrics.to_string(index=False))
```

```
                 model  precision   recall  f1 score  accuracy  ROC AUC
Class Count Classifier   0.109491 0.111261  0.110369  0.797936 0.498188
```

Logistic regression

In [37]:

```
lr = LogisticRegression(solver='liblinear', class_weight='balanced', random_state=42)

param_grid = {
    'C': [0.01, 0.1, 1, 10],
    'penalty': ['l1', 'l2']
}
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
grid_search = GridSearchCV(lr, param_grid, cv=cv, scoring='f1', refit=True, verbose=1, n_jobs=-1)
grid_search.fit(X_train, y_train)
lr_clf = grid_search.best_estimator_
print("Best parameters:", grid_search.best_params_)
```

```
print("Best score:", grid_search.best_score_)
```

```
Fitting 5 folds for each of 8 candidates, totalling 40 fits
```

```
/home/pc/Documents/MU projekat/.venv/lib/python3.10/site-packages/sklearn/svm/_base.py:1235: ConvergenceWarning: Lib
linear failed to converge, increase the number of iterations.
  warnings.warn(
/home/pc/Documents/MU projekat/.venv/lib/python3.10/site-packages/sklearn/svm/_base.py:1235: ConvergenceWarning: Lib
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  warnings.warn(
/home/pc/Documents/MU projekat/.venv/lib/python3.10/site-packages/sklearn/svm/_base.py:1235: ConvergenceWarning: Lib
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/home/pc/Documents/MU projekat/.venv/lib/python3.10/site-packages/sklearn/svm/_base.py:1235: ConvergenceWarning: Lib
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/home/pc/Documents/MU projekat/.venv/lib/python3.10/site-packages/sklearn/svm/_base.py:1235: ConvergenceWarning: Lib
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  warnings.warn(
/home/pc/Documents/MU projekat/.venv/lib/python3.10/site-packages/sklearn/svm/_base.py:1235: ConvergenceWarning: Lib
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  warnings.warn(
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  warnings.warn(
/home/pc/Documents/MU projekat/.venv/lib/python3.10/site-packages/sklearn/svm/_base.py:1235: ConvergenceWarning: Lib
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  warnings.warn(
/home/pc/Documents/MU projekat/.venv/lib/python3.10/site-packages/sklearn/svm/_base.py:1235: ConvergenceWarning: Lib
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  warnings.warn(
/home/pc/Documents/MU projekat/.venv/lib/python3.10/site-packages/sklearn/svm/_base.py:1235: ConvergenceWarning: Lib
```

```
linear failed to converge, increase the number of iterations.
  warnings.warn(
/home/pc/Documents/MU projekat/.venv/lib/python3.10/site-packages/sklearn/svm/_base.py:1235: ConvergenceWarning: Lib
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  warnings.warn(
/home/pc/Documents/MU projekat/.venv/lib/python3.10/site-packages/sklearn/svm/_base.py:1235: ConvergenceWarning: Lib
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  warnings.warn(
/home/pc/Documents/MU projekat/.venv/lib/python3.10/site-packages/sklearn/svm/_base.py:1235: ConvergenceWarning: Lib
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  warnings.warn(
/home/pc/Documents/MU projekat/.venv/lib/python3.10/site-packages/sklearn/svm/_base.py:1235: ConvergenceWarning: Lib
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  warnings.warn(
/home/pc/Documents/MU projekat/.venv/lib/python3.10/site-packages/sklearn/svm/_base.py:1235: ConvergenceWarning: Lib
linear failed to converge, increase the number of iterations.
  warnings.warn(
/home/pc/Documents/MU projekat/.venv/lib/python3.10/site-packages/sklearn/svm/_base.py:1235: ConvergenceWarning: Lib
linear failed to converge, increase the number of iterations.
  warnings.warn(
Best parameters: {'C': 0.1, 'penalty': 'l2'}
Best score: 0.5732759779610809
```
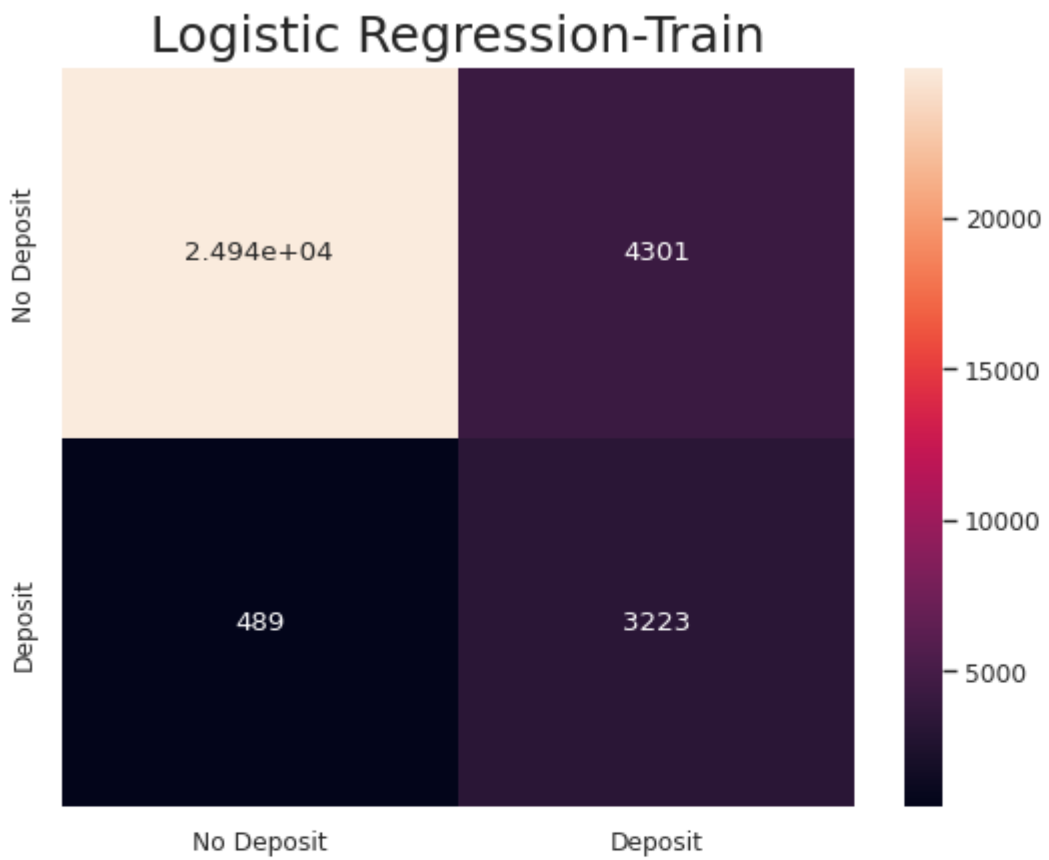

In [38]:

```
y_pred = lr_clf.predict(X_train)
lr_clf_metrics, lr_clf_cm = get_metrics("Logistic Regression", y_pred, y_train)
```

In [39]:

```
fig, ax = plt.subplots()
ax=sns.heatmap(lr_clf_cm,annot=True, ax=ax, fmt='.4g')
ax.xaxis.set_ticklabels(['No Deposit','Deposit'])
ax.yaxis.set_ticklabels(['No Deposit','Deposit'])
ax.set_title('Logistic Regression-Train',fontsize=18)

print(lr_clf_metrics.to_string(index=False))
```

```
              model  precision   recall  f1 score  accuracy  ROC AUC
Logistic Regression   0.428363 0.868265  0.573692  0.854628 0.860581
```



Support Vector Machine

In [40]:

```
svm = SVC(kernel='rbf', class_weight='balanced', random_state=42)

param_grid = {
    'C': [1, 10, 100],
    'gamma': ['scale', 0.1, 0.01, 0.001],
}

cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
grid_search = GridSearchCV(svm, param_grid, cv=cv, scoring='f1', refit=True, verbose=1, n_jobs=-1)
grid_search.fit(X_train, y_train)
svm_clf = grid_search.best_estimator_
```

```
print("Best parameters:", grid_search.best_params_)
print("Best score:", grid_search.best_score_)
```

```
Fitting 5 folds for each of 12 candidates, totalling 60 fits
Best parameters: {'C': 1, 'gamma': 0.001}
Best score: 0.573934420125766
```

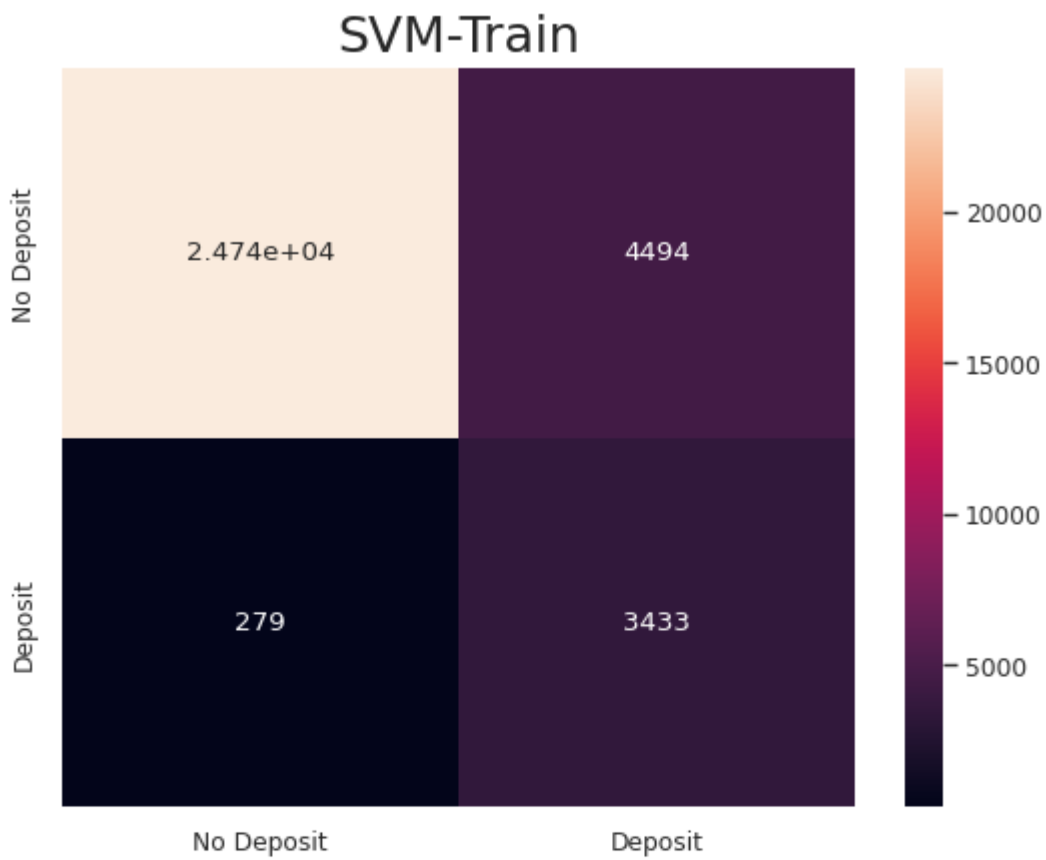
In [41]:

```
y_pred = svm_clf.predict(X_train)
svm_clf_metrics, svm_clf_cm = get_metrics("SVM Classifier", y_pred, y_train)
```

In [42]:

```
fig, ax = plt.subplots()
ax=sns.heatmap(svm_clf_cm,annot=True, ax=ax, fmt='.4g')
ax.xaxis.set_ticklabels(['No Deposit','Deposit'])
ax.yaxis.set_ticklabels(['No Deposit','Deposit'])
ax.set_title('SVM-Train',fontsize=18)

print(svm_clf_metrics.to_string(index=False))
```

```
         model  precision   recall  f1 score  accuracy  ROC AUC
SVM Classifier   0.433077 0.924838  0.589913  0.855144 0.885567
```



Decision Tree

In [43]:

```
dtree = DecisionTreeClassifier(class_weight='balanced', criterion='gini', random_state=42)
param_grid = {
    'max_depth': [5, 10, 20],
    'min_samples_split': [5, 10, 20],
    'min_samples_leaf': [2, 5, 10]
}

cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
grid_search = GridSearchCV(dtree, param_grid, cv=cv, scoring='f1', refit=True, verbose=1, n_jobs=-1)
grid_search.fit(X_train, y_train)
dt_clf = grid_search.best_estimator_
```

```
print("Best parameters:", grid_search.best_params_)
print("Best score:", grid_search.best_score_)
```

```
Fitting 5 folds for each of 27 candidates, totalling 135 fits
Best parameters: {'max_depth': 10, 'min_samples_leaf': 2, 'min_samples_split': 5}
Best score: 0.5801383257294856
```

In [44]:

```
y_pred = dt_clf.predict(X_train)
dt_clf_metrics, dt_clf_cm = get_metrics("Decision Tree Classifier", y_pred, y_train)
```

In [45]:

```
fig, ax = plt.subplots()
ax=sns.heatmap(dt_clf_cm,annot=True, ax=ax, fmt='.4g')
ax.xaxis.set_ticklabels(['No Deposit','Deposit'])
ax.yaxis.set_ticklabels(['No Deposit','Deposit'])
ax.set_title('Decision Tree-Train',fontsize=18)

print(dt_clf_metrics.to_string(index=False))
```

```
                   model  precision   recall  f1 score  accuracy  ROC AUC
Decision Tree Classifier   0.472839 0.975485  0.636939  0.874719 0.918706
```

Random Forest

In [46]:
```
rf = RandomForestClassifier(criterion='gini',
                            class_weight='balanced',
                            max_features='sqrt',
                            oob_score=True,
                            bootstrap=True,
                            random_state=42)

param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [5, 8, 10]
}
```

```
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
grid_search = GridSearchCV(rf, param_grid, cv=cv, scoring='f1', refit=True, verbose=1, n_jobs=-1)
grid_search.fit(X_train, y_train)
rf_clf = grid_search.best_estimator_
print("Best parameters:", grid_search.best_params_)
print("Best score:", grid_search.best_score_)
```

```
Fitting 5 folds for each of 9 candidates, totalling 45 fits
Best parameters: {'max_depth': 10, 'n_estimators': 50}
Best score: 0.6131917036193764
```

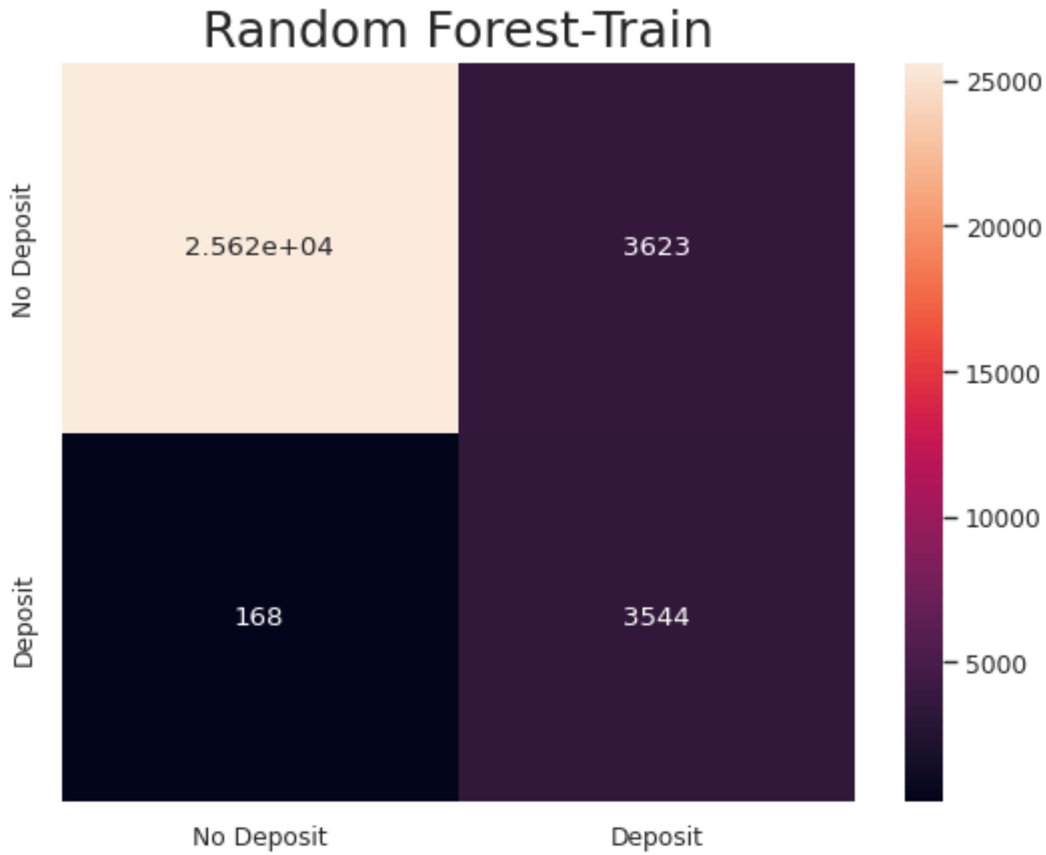
In [47]:

```
y_pred = rf_clf.predict(X_train)
rf_clf_metrics, rf_clf_cm = get_metrics("Random Forest Classifier", y_pred, y_train)
```

In [48]:

```
fig, ax = plt.subplots()
ax=sns.heatmap(rf_clf_cm,annot=True, ax=ax, fmt='.4g')
ax.xaxis.set_ticklabels(['No Deposit','Deposit'])
ax.yaxis.set_ticklabels(['No Deposit','Deposit'])
ax.set_title('Random Forest-Train',fontsize=18)

print(rf_clf_metrics.to_string(index=False))
print(f"Out Of Bag Score (OOB): {rf_clf.oob_score_}")
```

```
                   model  precision   recall  f1 score  accuracy  ROC AUC
Random Forest Classifier   0.494489 0.954741   0.65153  0.884947 0.915414
Out Of Bag Score (OOB): 0.8711684370257967
```



XGBoost

In [63]:
```
xgb = XGBClassifier(scale_pos_weight=(y_train == 0).sum() / (y_train == 1).sum(), random_state=42)

param_grid = {'n_estimators': [50, 100, 200],
              'learning_rate': [0.05, 0.1, 0.3], # eta in xgboost documentation - shrinkage
              'max_depth':[4, 6, 8, 10]
              }

cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
grid_search = GridSearchCV(xgb, param_grid, cv=cv, scoring='f1', refit=True, verbose=1, n_jobs=-1)
grid_search.fit(X_train, y_train)
xgb_clf = grid_search.best_estimator_
```

```
print("Best parameters:", grid_search.best_params_)
print("Best score:", grid_search.best_score_)
```

```
Fitting 5 folds for each of 36 candidates, totalling 180 fits
Best parameters: {'learning_rate': 0.05, 'max_depth': 10, 'n_estimators': 200}
Best score: 0.6302911493186312
```

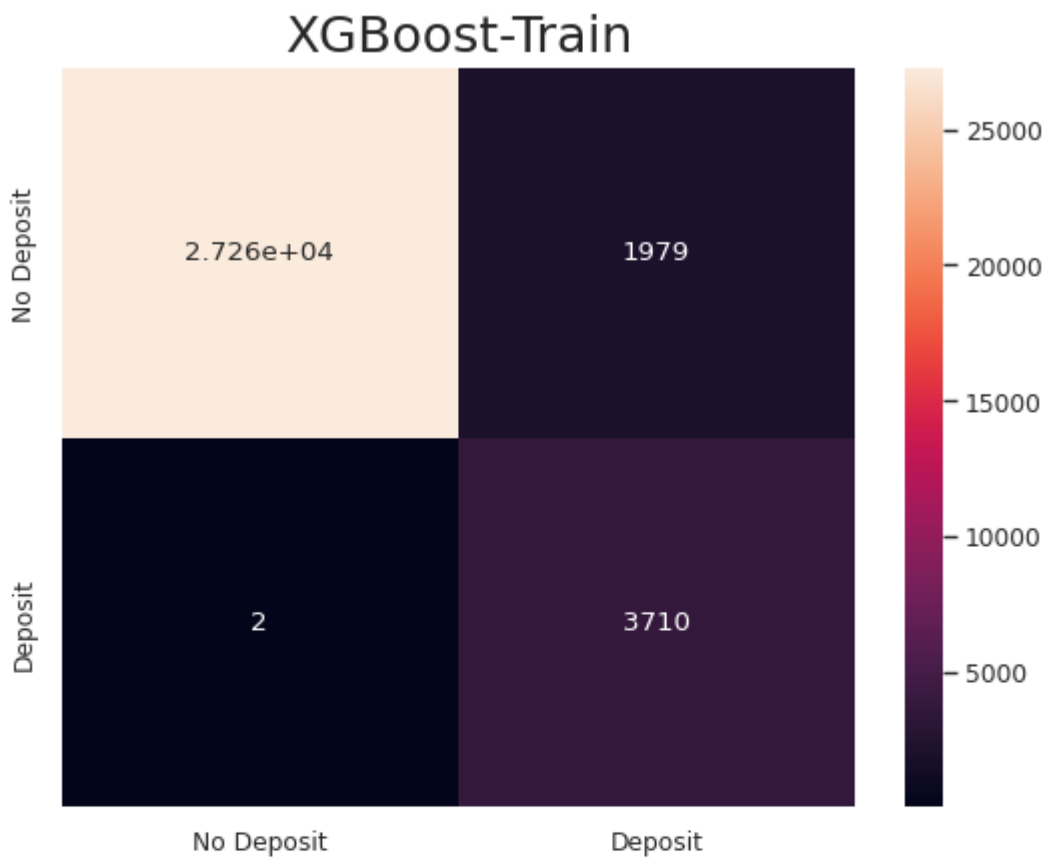
In [64]:

```
y_pred = xgb_clf.predict(X_train)
xgb_clf_metrics, xgb_clf_cm = get_metrics("XGBoost", y_pred, y_train)
```

In [65]:

```
fig, ax = plt.subplots()
ax=sns.heatmap(xgb_clf_cm,annot=True, ax=ax, fmt='.4g')
ax.xaxis.set_ticklabels(['No Deposit','Deposit'])
ax.yaxis.set_ticklabels(['No Deposit','Deposit'])
ax.set_title('XGBoost-Train',fontsize=18)

print(xgb_clf_metrics.to_string(index=False))
```

```
  model  precision   recall  f1 score  accuracy  ROC AUC
XGBoost   0.652136 0.999461  0.789278  0.939879 0.965888
```



Results on Test set

In [66]:

```
y_pred = class_count_clf.predict(X_test)
class_count_clf_metrics, class_count_clf_cm = get_metrics("Class Count Classifier", y_pred, y_test)

y_pred = lr_clf.predict(X_test)
lr_clf_metrics, lr_clf_cm = get_metrics("Logistic Regression", y_pred, y_test)

y_pred = svm_clf.predict(X_test)
svm_clf_metrics, svm_clf_cm = get_metrics("SVM Classifier", y_pred, y_test)

y_pred = dt_clf.predict(X_test)
```

```
dt_clf_metrics, dt_clf_cm = get_metrics("Decision Tree Classifier", y_pred, y_test)

y_pred = rf_clf.predict(X_test)
rf_clf_metrics, rf_clf_cm = get_metrics("Random Forest Classifier", y_pred, y_test)

y_pred = xgb_clf.predict(X_test)
xgb_clf_metrics, xgb_clf_cm = get_metrics("XGBoost", y_pred, y_test)
```

In [68]:

```
results = pd.concat([class_count_clf_metrics,
                     lr_clf_metrics,
                     svm_clf_metrics,
                     dt_clf_metrics,
                     rf_clf_metrics,
                     xgb_clf_metrics],axis=0)

results.reset_index(drop=True)
# print(results.to_string(index=False))
```

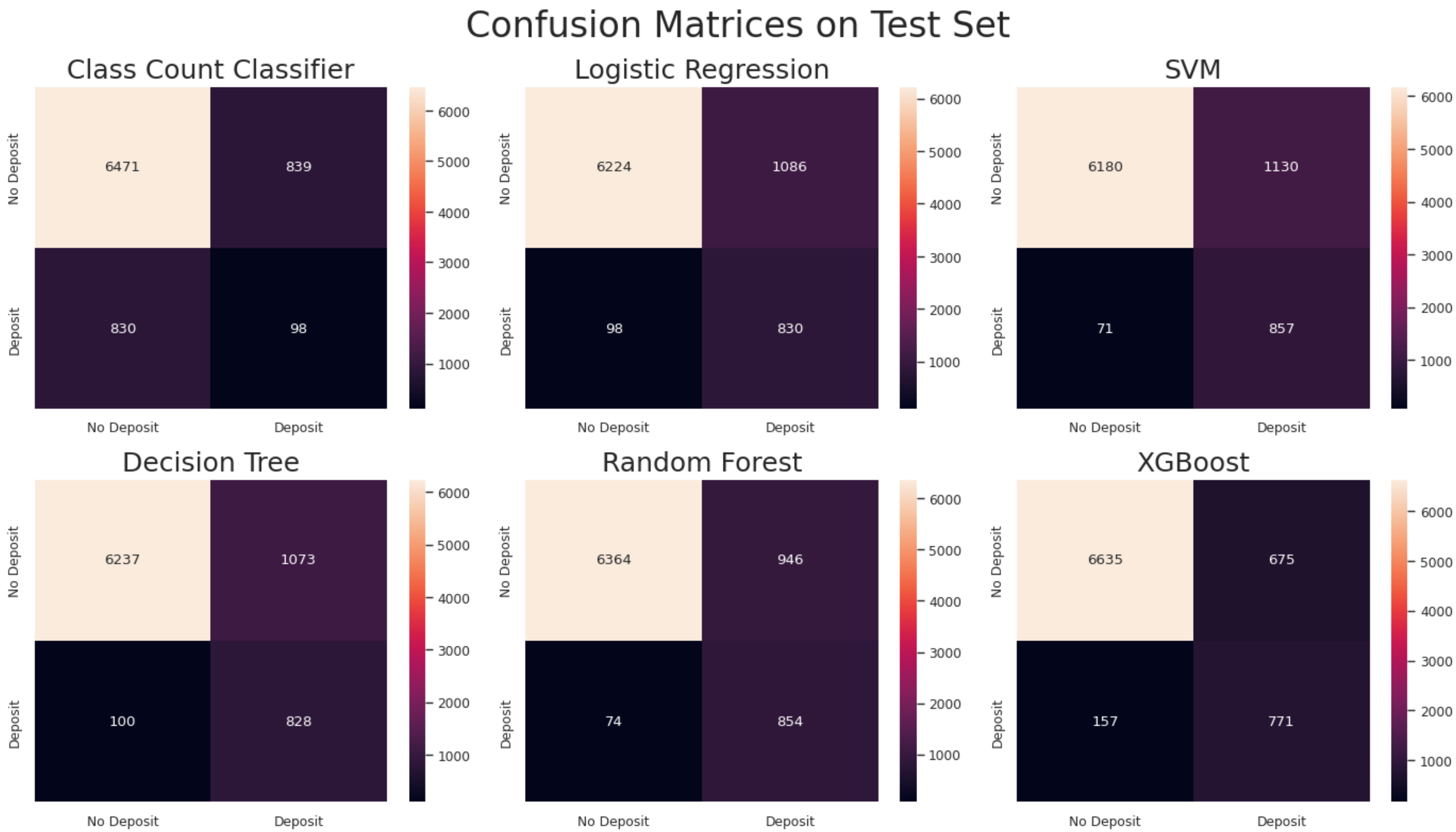
Out[68]:

	model	precision	recall	f1 score	accuracy	ROC AUC
0	Class Count Classifier	0.110521	0.112069	0.111289	0.798373	0.498784
1	Logistic Regression	0.433194	0.894397	0.583685	0.856276	0.872916
2	SVM Classifier	0.431303	0.923491	0.587993	0.854212	0.884454
3	Decision Tree Classifier	0.435560	0.892241	0.585366	0.857611	0.872728
4	Random Forest Classifier	0.474444	0.920259	0.626100	0.876184	0.895423
5	XGBoost	0.517173	0.843750	0.641278	0.893664	0.871875

In [61]:

```
fig, ax = plt.subplots(nrows=2, ncols=3, figsize=(14,8))
ax = ax.ravel()
ax[0]=sns.heatmap(class_count_clf_cm,annot=True, ax=ax[0], fmt='.4g')
ax[0].xaxis.set_ticklabels(['No Deposit','Deposit'])
ax[0].yaxis.set_ticklabels(['No Deposit','Deposit'])
ax[0].set_title('Class Count Classifier',fontsize=18)

ax[1]=sns.heatmap(lr_clf_cm,annot=True, ax=ax[1], fmt='.4g')
ax[1].xaxis.set_ticklabels(['No Deposit','Deposit'])
```

```
ax[1].yaxis.set_ticklabels(['No Deposit','Deposit'])
ax[1].set_title('Logistic Regression',fontsize=18)

ax[2]=sns.heatmap(svm_clf_cm,annot=True, ax=ax[2], fmt='.4g')
ax[2].xaxis.set_ticklabels(['No Deposit','Deposit'])
ax[2].yaxis.set_ticklabels(['No Deposit','Deposit'])
ax[2].set_title('SVM',fontsize=18)

ax[3]=sns.heatmap(dt_clf_cm,annot=True, ax=ax[3], fmt='.4g')
ax[3].xaxis.set_ticklabels(['No Deposit','Deposit'])
ax[3].yaxis.set_ticklabels(['No Deposit','Deposit'])
ax[3].set_title('Decision Tree',fontsize=18)

ax[4]=sns.heatmap(rf_clf_cm,annot=True, ax=ax[4], fmt='.4g')
ax[4].xaxis.set_ticklabels(['No Deposit','Deposit'])
ax[4].yaxis.set_ticklabels(['No Deposit','Deposit'])
ax[4].set_title('Random Forest',fontsize=18)

ax[5]=sns.heatmap(xgb_clf_cm,annot=True, ax=ax[5], fmt='.4g')
ax[5].xaxis.set_ticklabels(['No Deposit','Deposit'])
ax[5].yaxis.set_ticklabels(['No Deposit','Deposit'])
ax[5].set_title('XGBoost',fontsize=18)

fig.suptitle("Confusion Matrices on Test Set",fontsize=24)

plt.tight_layout()
```



Feature Importance

In [70]:
```
importance_rf = pd.DataFrame({
    'Features': feature_names,
    'Importance': rf_clf.feature_importances_
})
importance_xgb = pd.DataFrame({
```

```
    'Features': feature_names,
    'Importance': xgb_clf.feature_importances_
})

importance_rf = importance_rf.sort_values(by='Importance', ascending=False)
importance_xgb = importance_xgb.sort_values(by='Importance', ascending=False)

fig, ax = plt.subplots(ncols=2, figsize=(14,6))
ax[0]=sns.barplot(x='Importance', y='Features', data=importance_rf, ax=ax[0])
ax[0].set_title('Random Forest')

ax[1]=sns.barplot(x='Importance', y='Features', data=importance_xgb, ax=ax[1])
ax[1].set_title('XGBoost')

plt.suptitle('Feature Importance')
plt.tight_layout()
plt.show()
```