Assignment 2: Ensemble Methods and Calibration

Instructions

Please push the .ipynb, .py, and .pdf to Github Classroom prior to the deadline. Please include your UNI as well.

Make sure to use the dataset that we provide in CourseWorks/Classroom.

There are a lot of applied questions based on the code results. Please make sure to answer them all. These are primarily to test your understanding of the results your code generate (similar to any Data Science/ML case study interviews).

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Dataset Description: Bank Marketing Dataset

This dataset contains information about direct marketing campaigns (phone calls) of a banking institution. The goal is to predict whether the client will subscribe to a term deposit. The details of the features and target are listed below:

Features:

- `age` : Age of the client
- `job` : Type of job
- `marital` : Marital status
- `education` : Education level
- `default` : Has credit in default?
- `balance` : Average yearly balance
- `housing` : Has housing loan?
- `loan` : Has personal loan?
- `contact` : Contact communication type
- `day` : Last contact day of the month
- `month` : Last contact month of year
- `duration` : Last contact duration in seconds
- `campaign` : Number of contacts performed during this campaign
- `pdays` : Number of days since the client was last contacted from a previous campaign
- `previous` : Number of contacts performed before this campaign

- `poutcome` : Outcome of the previous marketing campaign
- `deposit` : Has the client subscribed to a term deposit? (target)

Objective: The target variable (`deposit`) is binary (yes/no), and the goal is to predict whether a client will subscribe to a term deposit based on the given features.

In [139…

```
## Use this cell to import necessary packages

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.preprocessing import OrdinalEncoder, OneHotEncoder, StandardScale
from sklearn.compose import make_column_transformer
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_s
from sklearn.model_selection import GridSearchCV

from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.ensemble import RandomForestClassifier, HistGradientBoostingClass
import xgboost as xgb

import time
```

Question 1: Decision Trees

1.1: Load the Bank Marketing Dataset and inspect its structure.

- Hint: Inspect columns and types.

In [5]:

```
bank_df = pd.read_csv("bank (1).csv")
```

In [6]:

```
bank_df
```

Out[6]:

	age	job	marital	education	default	balance	housing	loan	contact	day	mon
0	59	admin.	married	secondary	no	2343	yes	no	unknown	5	ma
1	56	admin.	married	secondary	no	45	no	no	unknown	5	ma
2	41	technician	married	secondary	no	1270	yes	no	unknown	5	ma
3	55	services	married	secondary	no	2476	yes	no	unknown	5	ma
4	54	admin.	married	tertiary	no	184	no	no	unknown	5	ma
...	...	...	...	...	...	...	...	...	...	...	
11157	33	blue-collar	single	primary	no	1	yes	no	cellular	20	a
11158	39	services	married	secondary	no	733	no	no	unknown	16	ju
11159	32	technician	single	secondary	no	29	no	no	cellular	19	au
11160	43	technician	married	secondary	no	0	no	yes	cellular	8	ma
11161	34	technician	married	secondary	no	0	no	no	cellular	9	j

11162 rows × 17 columns

In [7]:

```
cols = bank_df.columns
for col in bank_df[cols]:
  print(bank_df[col].value_counts, bank_df[col])
```

```
<bound method IndexOpsMixin.value_counts of 0        59
1        56
2        41
3        55
4        54
         ..
11157    33
11158    39
11159    32
11160    43
11161    34
Name: age, Length: 11162, dtype: int64> 0        59
1        56
2        41
3        55
4        54
         ..
11157    33
11158    39
11159    32
11160    43
11161    34
Name: age, Length: 11162, dtype: int64
<bound method IndexOpsMixin.value_counts of 0             admin.
1             admin.
2         technician
3           services
4             admin.
            ...
11157    blue-collar
11158       services
11159     technician
11160     technician
11161     technician
Name: job, Length: 11162, dtype: object> 0             admin.
1             admin.
2         technician
3           services
4             admin.
            ...
11157    blue-collar
11158       services
11159     technician
11160     technician
11161     technician
Name: job, Length: 11162, dtype: object
<bound method IndexOpsMixin.value_counts of 0        married
1        married
2        married
3        married
4        married
          ...
11157     single
11158    married
11159     single
11160    married
11161    married
Name: marital, Length: 11162, dtype: object> 0        married
1        married
2        married
```

```
3        married
4        married
          ...
11157     single
11158    married
11159     single
11160    married
11161    married
Name: marital, Length: 11162, dtype: object
<bound method IndexOpsMixin.value_counts of 0        secondary
1        secondary
2        secondary
3        secondary
4         tertiary
           ...
11157      primary
11158    secondary
11159    secondary
11160    secondary
11161    secondary
Name: education, Length: 11162, dtype: object> 0        secondary
1        secondary
2        secondary
3        secondary
4         tertiary
           ...
11157      primary
11158    secondary
11159    secondary
11160    secondary
11161    secondary
Name: education, Length: 11162, dtype: object
<bound method IndexOpsMixin.value_counts of 0        no
1        no
2        no
3        no
4        no
         ..
11157    no
11158    no
11159    no
11160    no
11161    no
Name: default, Length: 11162, dtype: object> 0        no
1        no
2        no
3        no
4        no
         ..
11157    no
11158    no
11159    no
11160    no
11161    no
Name: default, Length: 11162, dtype: object
<bound method IndexOpsMixin.value_counts of 0        2343
1          45
2        1270
3        2476
4         184
```

```
        ...
11157      1
11158    733
11159     29
11160      0
11161      0
Name: balance, Length: 11162, dtype: int64> 0        2343
1          45
2        1270
3        2476
4         184
        ...
11157      1
11158    733
11159     29
11160      0
11161      0
Name: balance, Length: 11162, dtype: int64
<bound method IndexOpsMixin.value_counts of 0        yes
1         no
2        yes
3        yes
4         no
        ...
11157    yes
11158     no
11159     no
11160     no
11161     no
Name: housing, Length: 11162, dtype: object> 0        yes
1         no
2        yes
3        yes
4         no
        ...
11157    yes
11158     no
11159     no
11160     no
11161     no
Name: housing, Length: 11162, dtype: object
<bound method IndexOpsMixin.value_counts of 0         no
1         no
2         no
3         no
4         no
        ...
11157     no
11158     no
11159     no
11160    yes
11161     no
Name: loan, Length: 11162, dtype: object> 0         no
1         no
2         no
3         no
4         no
        ...
11157     no
11158     no
```

```
11159     no
11160    yes
11161     no
Name: loan, Length: 11162, dtype: object
<bound method IndexOpsMixin.value_counts of 0         unknown
1         unknown
2         unknown
3         unknown
4         unknown
           ...
11157    cellular
11158     unknown
11159    cellular
11160    cellular
11161    cellular
Name: contact, Length: 11162, dtype: object> 0         unknown
1         unknown
2         unknown
3         unknown
4         unknown
           ...
11157    cellular
11158     unknown
11159    cellular
11160    cellular
11161    cellular
Name: contact, Length: 11162, dtype: object
<bound method IndexOpsMixin.value_counts of 0         5
1         5
2         5
3         5
4         5
         ..
11157    20
11158    16
11159    19
11160     8
11161     9
Name: day, Length: 11162, dtype: int64> 0         5
1         5
2         5
3         5
4         5
         ..
11157    20
11158    16
11159    19
11160     8
11161     9
Name: day, Length: 11162, dtype: int64
<bound method IndexOpsMixin.value_counts of 0        may
1        may
2        may
3        may
4        may
        ...
11157    apr
11158    jun
11159    aug
11160    may
```

```
11161    jul
Name: month, Length: 11162, dtype: object> 0        may
1        may
2        may
3        may
4        may
        ...
11157    apr
11158    jun
11159    aug
11160    may
11161    jul
Name: month, Length: 11162, dtype: object
<bound method IndexOpsMixin.value_counts of 0        1042
1        1467
2        1389
3         579
4         673
         ...
11157     257
11158      83
11159     156
11160       9
11161     628
Name: duration, Length: 11162, dtype: int64> 0        1042
1        1467
2        1389
3         579
4         673
         ...
11157     257
11158      83
11159     156
11160       9
11161     628
Name: duration, Length: 11162, dtype: int64
<bound method IndexOpsMixin.value_counts of 0        1
1        1
2        1
3        1
4        2
        ..
11157    1
11158    4
11159    2
11160    2
11161    1
Name: campaign, Length: 11162, dtype: int64> 0        1
1        1
2        1
3        1
4        2
        ..
11157    1
11158    4
11159    2
11160    2
11161    1
Name: campaign, Length: 11162, dtype: int64
<bound method IndexOpsMixin.value_counts of 0         -1
```

```
1        -1
2        -1
3        -1
4        -1
        ...
11157    -1
11158    -1
11159    -1
11160   172
11161    -1
Name: pdays, Length: 11162, dtype: int64> 0         -1
1        -1
2        -1
3        -1
4        -1
        ...
11157    -1
11158    -1
11159    -1
11160   172
11161    -1
Name: pdays, Length: 11162, dtype: int64
<bound method IndexOpsMixin.value_counts of 0        0
1        0
2        0
3        0
4        0
        ..
11157    0
11158    0
11159    0
11160    5
11161    0
Name: previous, Length: 11162, dtype: int64> 0        0
1        0
2        0
3        0
4        0
        ..
11157    0
11158    0
11159    0
11160    5
11161    0
Name: previous, Length: 11162, dtype: int64
<bound method IndexOpsMixin.value_counts of 0        unknown
1        unknown
2        unknown
3        unknown
4        unknown
          ...
11157    unknown
11158    unknown
11159    unknown
11160    failure
11161    unknown
Name: poutcome, Length: 11162, dtype: object> 0        unknown
1        unknown
2        unknown
3        unknown
```

```
4        unknown
          ...
11157    unknown
11158    unknown
11159    unknown
11160    failure
11161    unknown
Name: poutcome, Length: 11162, dtype: object
<bound method IndexOpsMixin.value_counts of 0        yes
1        yes
2        yes
3        yes
4        yes
        ...
11157     no
11158     no
11159     no
11160     no
11161     no
Name: deposit, Length: 11162, dtype: object> 0        yes
1        yes
2        yes
3        yes
4        yes
        ...
11157     no
11158     no
11159     no
11160     no
11161     no
Name: deposit, Length: 11162, dtype: object
```

In [8]:
```
bank_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 [9]:
```
bank_df.describe()
```

Out[9]:

	age	balance	day	duration	campaign	pdays	11
count	11162.000000	11162.000000	11162.000000	11162.000000	11162.000000	11162.000000	11
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 [7]:
```
bank_df.head()
```

Out[7]:

	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

In [10]:
```
bank_df.tail()
```

Out[10]:

	age	job	marital	education	default	balance	housing	loan	contact	day	mon
11157	33	blue-collar	single	primary	no	1	yes	no	cellular	20	a
11158	39	services	married	secondary	no	733	no	no	unknown	16	ju
11159	32	technician	single	secondary	no	29	no	no	cellular	19	au
11160	43	technician	married	secondary	no	0	no	yes	cellular	8	ma
11161	34	technician	married	secondary	no	0	no	no	cellular	9	j

1.2: Are there any missing values in the dataset? If yes, how do you plan to handle them?

- No, there are no missing values in the dataset. In the occurence of missing values, they would be dealt with depending on their variable type.
- For numeric variables, the median is a good estimate and the missing values would be replaced by the mean of all the other values in that variable.
- For categorical variables, the mode is used for imputation, since it replaces the missing value with the most common value.

In [11]:
```
bank_df.isnull().sum()
```

Out[11]:

	0
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

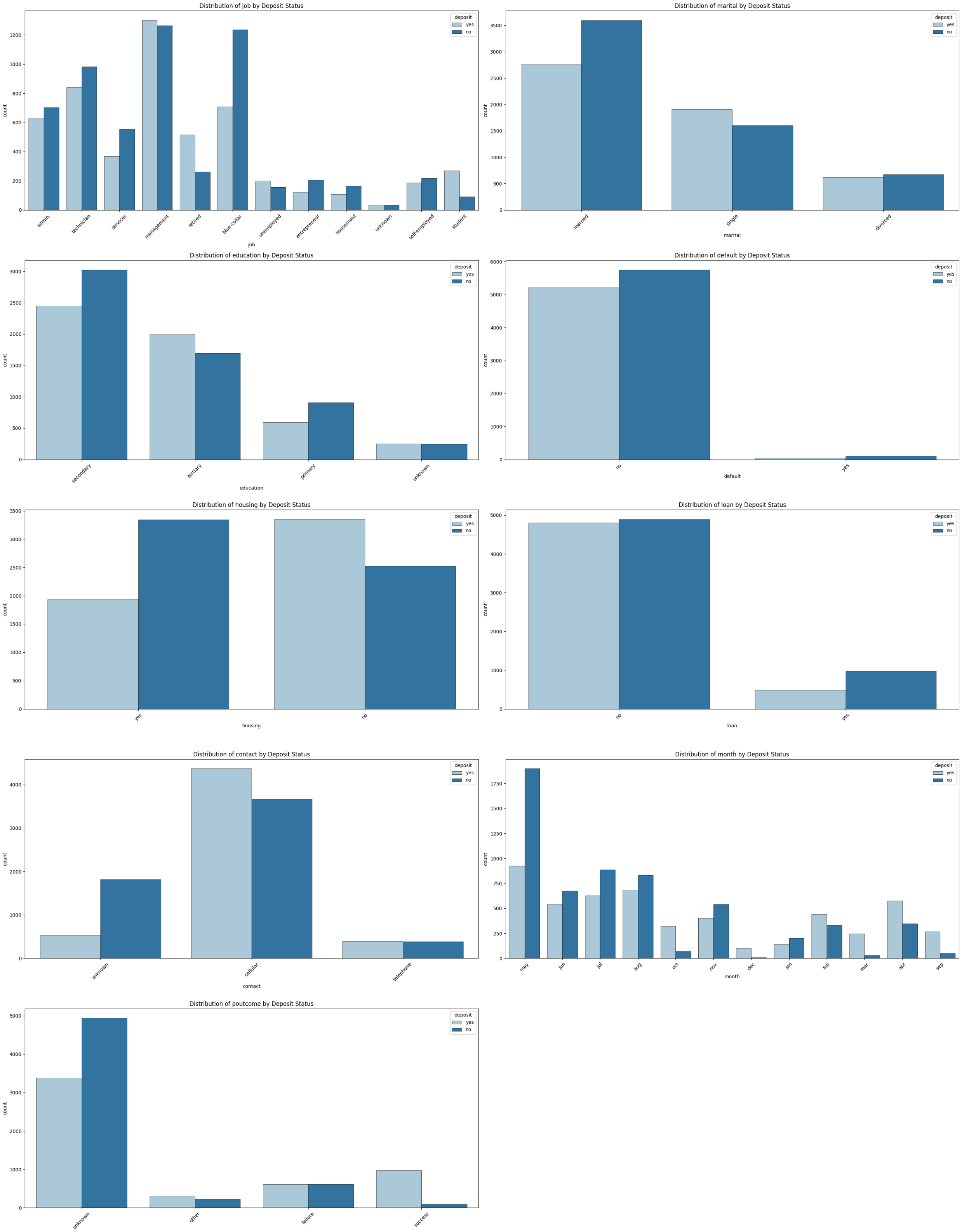
1.3: Plot side-by-side bars of class distribution for each categorical feature in the dataset with respect to the target variable (e.g., `job`, `marital`, `education`, etc.).

In [12]:
```
categorical_features = ['job', 'marital', 'education', 'default', 'housing', ''
```

In [13]:
```
plt.figure(figsize=(28, 36))

for i, feature in enumerate(categorical_features, 1):
    plt.subplot(5, 2, i)  # Adjust the grid size (5 rows, 2 columns)
    sns.countplot(data = bank_df, x = feature, hue = 'deposit', palette='Paire
    plt.title(f'Distribution of {feature} by Deposit Status')
    plt.xticks(rotation=45)  # Rotate the x-axis labels for better readability
    plt.tight_layout()  # Adjust spacing between plots

# Show the plots
plt.show()
```



1.4: Explain the distribution of the target variable and the dataset.

- By 'job' category, 'blue collar' and 'management' jobs have overall higher counts.
- Married people tend to have fewer subscriptions.
- May had the largest month for subscription rejections.
- The 'poutcome' variable has the highest counts for the 'unknown' class compared to other classes.

- The mode of contact was via 'cellular' for most of the calls made.

1.5: Split the data into development and test datasets. Which splitting methodology did you choose and why?

Hint: Based on the distribution of the data, try to use the best splitting strategy.

In [14]:
```
print("Class Distribution:",bank_df["deposit"].value_counts())
```

```
Class Distribution: deposit
no     5873
yes    5289
Name: count, dtype: int64
```

In [15]:
```
# Split the dataset into features and labels
bank_X = bank_df.drop(columns=['deposit'])
bank_y = bank_df['deposit']
```

In [16]:
```
dev_X, test_X, dev_y, test_y = train_test_split(bank_X, bank_y, test_size = 0.:
```

1.6: Would you drop any column? Justify your reasoning.

Preprocess the data (Handle the Categorical Variable). Would you consider a mix of encoding techniques? Justify. Do we need to apply scaling? Briefly Justify

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

Out[17]:
```
Index(['age', 'job', 'marital', 'education', 'default', 'balance', 'housing',
       'loan', 'contact', 'day', 'month', 'duration', 'campaign', 'pdays',
       'previous', 'poutcome', 'deposit'],
      dtype='object')
```

In [18]:
```
dev_X
```

Out[18]:

	age	job	marital	education	default	balance	housing	loan	contact	day	m
3955	28	student	single	tertiary	no	5741	no	no	cellular	10	
11150	34	management	married	secondary	no	355	no	no	cellular	21	
5173	48	unemployed	divorced	secondary	no	201	no	no	cellular	10	
3017	53	entrepreneur	married	tertiary	no	1961	no	no	cellular	15	
2910	53	management	married	tertiary	no	1624	no	no	cellular	11	
...	...	...	...	...	...	...	...	...	...	...	
5734	47	management	married	tertiary	no	761	yes	no	cellular	11	
5191	28	self-employed	single	tertiary	no	159	no	no	cellular	16	
5390	35	technician	married	secondary	no	1144	no	no	cellular	20	
860	51	retired	married	tertiary	no	746	no	no	cellular	25	
7270	30	management	single	tertiary	no	2	no	no	cellular	23	

8929 rows × 16 columns

In [19]:

```
dev_y
```

Out[19]:

	deposit
3955	yes
11150	no
5173	yes
3017	yes
2910	yes
...	...
5734	no
5191	yes
5390	no
860	yes
7270	no

8929 rows × 1 columns

dtype: object

In [20]:

```
#One Hot Encoding for Categorical Variables
ohe_features = ['job', 'marital', 'default', 'housing', 'loan', 'contact', 'mo
dev_X = pd.get_dummies(dev_X, columns=ohe_features, drop_first=True)
test_X = pd.get_dummies(test_X, columns = ohe_features, drop_first = True)
```

In [21]:
```
# Label Encoding for Target Variable
label_encoder = LabelEncoder()
dev_y = label_encoder.fit_transform(dev_y)
test_y = label_encoder.fit_transform(test_y)
```

In [22]:
```
#Standard Scaling for Numerical Variables
numerical = ['age', 'balance', 'campaign', 'pdays', 'previous', 'day', 'durati
scaler = StandardScaler()
dev_X[numerical] = scaler.fit_transform(dev_X[numerical])
test_X[numerical] = scaler.fit_transform(test_X[numerical])
```

In [24]:
```
# Ordinal Encoding
ordinal = ['education']
ordinal_encoder = OrdinalEncoder()
dev_X[ordinal] = ordinal_encoder.fit_transform(dev_X[ordinal])
test_X[ordinal] = ordinal_encoder.fit_transform(test_X[ordinal])
```

In [25]:
```
##Feature Importance Graph To Decide If Dropping Any Columns Is Necessary
test_X
```

Out[25]:

	age	education	balance	day	duration	campaign	pdays	previous
5527	1.981436	1.0	-0.229177	-1.294430	-0.560307	-0.543810	-0.501127	-0.352622
4541	-0.265498	1.0	0.018618	0.027611	2.683794	2.325245	-0.501127	-0.352622
1964	-0.515158	1.0	0.954793	-0.212760	0.218732	-0.543810	2.255387	0.031665
5007	0.483480	1.0	1.871325	-0.933873	1.151305	-0.185178	-0.501127	-0.352622
8928	-0.515158	2.0	-0.024599	-0.453131	-0.838941	0.173454	-0.501127	-0.352622
...	...	...	...	...	...	...	...	...
376	0.400260	1.0	-0.178102	-1.054059	0.016864	0.890717	-0.501127	-0.352622
5544	0.649919	0.0	-0.373420	-0.933873	-0.804823	-0.543810	-0.501127	-0.352622
10749	0.982798	2.0	-0.317013	-1.294430	-0.921394	-0.543810	2.511807	0.031665
3881	0.566699	1.0	-0.178102	-0.453131	0.355206	-0.185178	1.138129	3.490254
6786	-0.598377	2.0	0.021144	-1.174244	-0.691095	-0.543810	4.279272	0.415953

2233 rows × 40 columns

Here, a mix of encoding techniques have been considered depending on the datatype of the features.

- For categorical features, one hot encoding is the preferred form of encoding.
- Ordinal encoder is used for 'education' since it has an inherent order (primary < secondary < tertiary).

Scaling is applied to the numerial features so that we have a uniform scale for all the features. The numerical features in the dataset have different ranges (e.g. age ranges from 18 to 95 whereas 'balance' ranges from -6784 to 81204).

1.7: Fit a Decision Tree on the development data until all leaves are pure. Which scoring metric will you prefer, and why? What is the performance of the tree on the development set and test set? Evaluate test and train accuarcy on F-1 score and accuracy.

In [42]:
```
bank_df["deposit"].value_counts()
```

Out[42]:

deposit	count
no	5873
yes	5289

dtype: int64

Since the dataset, specifically the target variable, is fairly balanced, both accuracy and F1-score can be used as scoring metrics.

In a scenario where the variables are imbalanced, instead of accuracy, other scoring metrics like precision, recall, or F1-score are preferred.

In [36]:
```
#Instantiating the model
decision_tree_classifier = DecisionTreeClassifier(max_depth = None, min_sample:
```

In [37]:
```
#Fitting the model
decision_tree_classifier.fit(dev_X, dev_y)
```

Out[37]:
```
▾ DecisionTreeClassifier
DecisionTreeClassifier(random_state=42)
```

In [38]:
```
#Predictions
y_dev_pred = decision_tree_classifier.predict(dev_X)
y_test_pred = decision_tree_classifier.predict(test_X)
```

In [39]:
```
#Calculating accuracy and F1-score
train_accuracy = accuracy_score(dev_y, y_dev_pred)
test_accuracy = accuracy_score(test_y, y_test_pred)

f1_train = f1_score(dev_y, y_dev_pred)
f1_test = f1_score(test_y, y_test_pred)
```

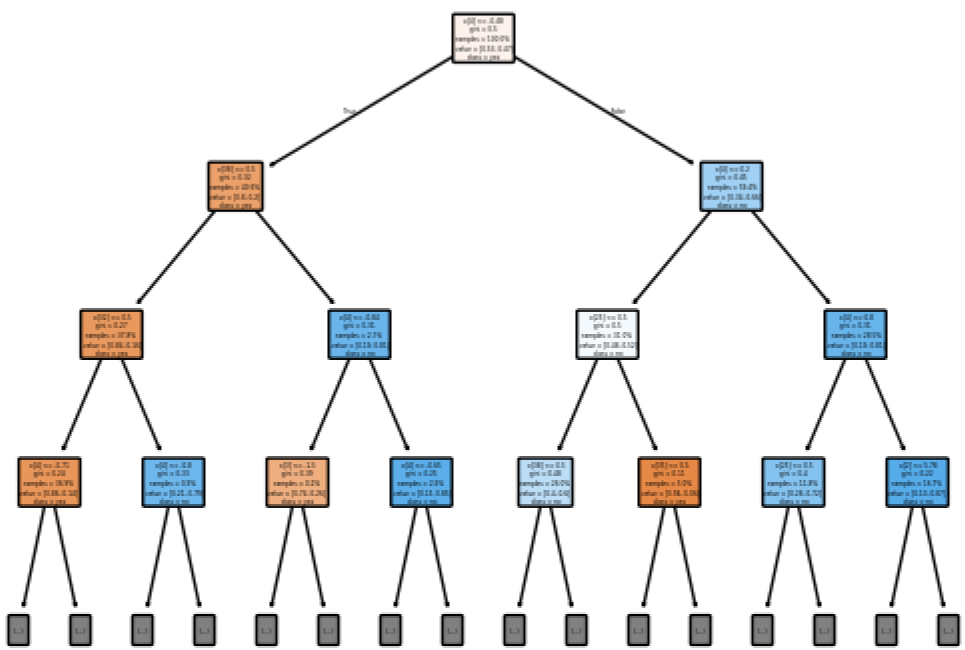
In [40]:
```
#Printing Results
print("Training Accuracy:", train_accuracy)
print("Testing Accuracy:", test_accuracy)
print("Training F1-Score:", f1_train)
print("Testing F1-Score:", f1_test)
```

```
Training Accuracy: 1.0
Testing Accuracy: 0.793551276309897
Training F1-Score: 1.0
Testing F1-Score: 0.7822390174775626
```

- The training accuracy and the training F1-score is 1.0 indicating that the model perfectly classifies all the training data points.
- It also suggests that the tree might've overfitted on the training data.
- The testing accuracy and F1-score indicate decent performance. The performance can be improved by tuning the parameters of the model.

1.8: Visualize the trained tree until the suitable max_depth.

In [49]:
```
tree_plot = plot_tree(decision_tree_classifier, filled = True, proportion = Tr
                      class_names = bank_df["deposit"].unique().tolist(), prec
```



1.9: Prune the tree using one of the techniques discussed in class and evaluate the performance.

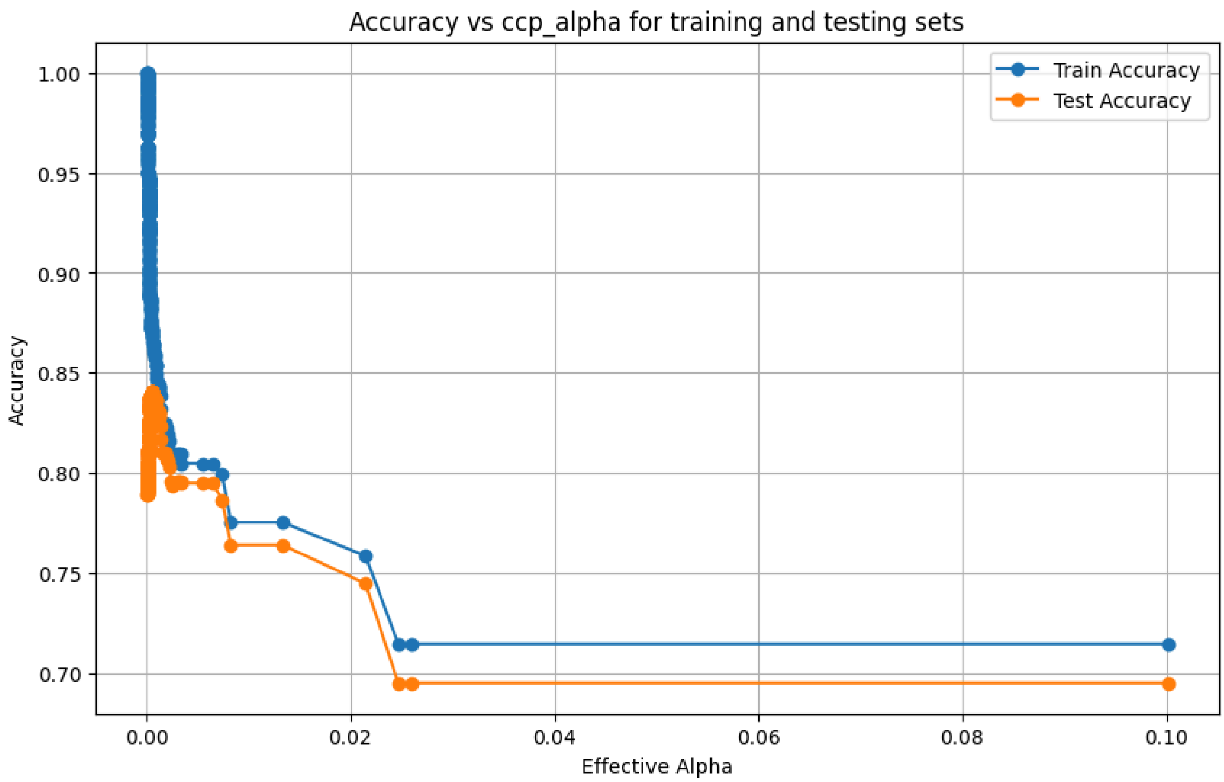
Print the optimal value of the tuned parameter.

In [ ]:
```
path = decision_tree_classifier.cost_complexity_pruning_path(dev_X, dev_y)  #G
ccp_alphas, impurities = path.ccp_alphas, path.impurities
```

In [52]:
```
trees = []
for ccp_alpha in ccp_alphas:
    clf = DecisionTreeClassifier(ccp_alpha=ccp_alpha, random_state=0)
    clf.fit(dev_X, dev_y)
    trees.append(clf)
```

In [53]:
```
# Training and Testing Scores for Each Tree
train_scores = [accuracy_score(dev_y, clf.predict(dev_X)) for clf in trees]
test_scores = [accuracy_score(test_y, clf.predict(test_X)) for clf in trees]
```

In [54]:
```
# Plotting the Results
plt.figure(figsize=(10, 6))
plt.plot(ccp_alphas, train_scores, label='Train Accuracy', marker='o')
plt.plot(ccp_alphas, test_scores, label='Test Accuracy', marker='o')
plt.xlabel('Effective Alpha')
plt.ylabel('Accuracy')
plt.title('Accuracy vs ccp_alpha for training and testing sets')
plt.legend()
plt.grid()
plt.show()
```



In [55]:
```
# Selecting the Optimal ccp_alpha
optimal_alpha_index = np.argmax(test_scores)
optimal_ccp_alpha = ccp_alphas[optimal_alpha_index]

print("Optimal ccp_alpha:", optimal_ccp_alpha)
```

```
Optimal ccp_alpha: 0.0005408204174315572
```

In [56]:
```
# Fitting the Decision Tree with The Optimal ccp_alpha
pruned_tree_classifier = DecisionTreeClassifier(ccp_alpha=optimal_ccp_alpha, ra
pruned_tree_classifier.fit(dev_X, dev_y)
```

Out[56]:

▾ DecisionTreeClassifier

```
DecisionTreeClassifier(ccp_alpha=0.0005408204174315572, random_state=
0)
```

In [113…

```
# Evaluating the Performance
train_pred_pruned = pruned_tree_classifier.predict(dev_X)
test_pred_pruned = pruned_tree_classifier.predict(test_X)

train_accuracy_pruned = accuracy_score(dev_y, train_pred_pruned)
test_accuracy_pruned = accuracy_score(test_y, test_pred_pruned)
train_f1_pruned = f1_score(dev_y, train_pred_pruned)
test_f1_pruned = f1_score(test_y, test_pred_pruned)

print("Pruned Training Accuracy:", train_accuracy_pruned)
print("Pruned Testing Accuracy:", test_accuracy_pruned)
print("Pruned Training F1 Score:", train_f1_pruned)
print("Pruned Testing F1 Score:", test_f1_pruned)
```

```
Pruned Training Accuracy: 0.8694142681151305
Pruned Testing Accuracy: 0.8410210479175997
Pruned Training F1 Score: 0.8675
Pruned Testing F1 Score: 0.8376771833561957
```

1.10: List the top 3 most important features for this trained tree? How would you justify these features being the most important?

In [115…

```
importances = pruned_tree_classifier.feature_importances_
importances_df = pd.DataFrame({'Feature': dev_X.columns, 'Importance': importa
top_features = importances_df.sort_values(by = 'Importance', ascending = False
```

In [117…

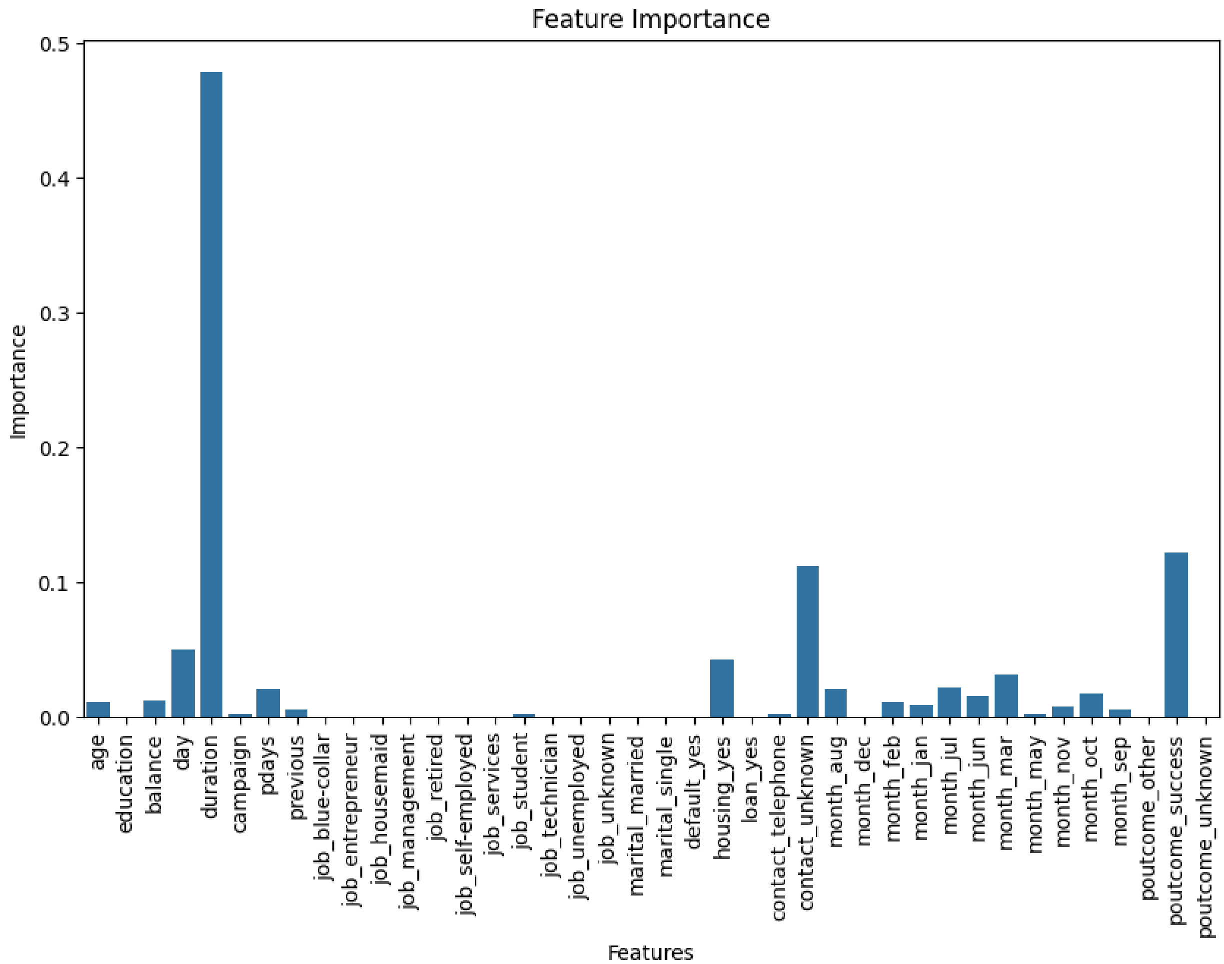
```
top_features
```

Out[117]:

	Feature	Importance
4	duration	0.478773
38	poutcome_success	0.122164
25	contact_unknown	0.111873

In [116…

```
#Plotting
plt.figure(figsize=(10, 6))
ax = sns.barplot(x = dev_X.columns, y = importances)
ax.tick_params(axis='x', rotation=90)
plt.title("Feature Importance")
plt.xlabel("Features")
plt.ylabel("Importance")
plt.show()
```



The top 3 most important features:

1. **poutcome(success)** - A succesful outcome in the previous marketing campaign is a key indicator for success in the current marketing campaign.
2. **contact(unknown)** - An unknown form of contact communication is impacting the outcome. Finding out more details about this would be beneficial to accelerate subscription growth.
3. **duration** - The duration of the call is a key feature in identifying whether a person will subscribe for a term deposit or not. Longer call durations suggest higher level of interest.

Question 2: Random Forests

2.1: Train a Random Forest model on the development dataset using RandomForestClassifier class in sklearn. Use the default parameters. Evaluate the performance of the model on test dataset. Use accuracy and F1 score to evaluate. Does this perform better than Decision Tree on the test dataset (compare to results in Q 1.7)?

In [79]:
```
random_forest_classifier = RandomForestClassifier()
random_forest_classifier.fit(dev_X, dev_y)
```

Out[79]:
```
▾ RandomForestClassifier
RandomForestClassifier()
```

In [80]:
```
y_dev_pred_rf = random_forest_classifier.predict(dev_X)
train_accuracy_rf = accuracy_score(dev_y, y_dev_pred_rf)
print("Training Accuracy for Random Forests:", train_accuracy_rf)
train_f1score_rf = f1_score(dev_y, y_dev_pred_rf)
print("Training F1-Score for Random Forests:", train_f1score_rf)

y_test_pred_rf = random_forest_classifier.predict(test_X)
test_accuracy_rf = accuracy_score(test_y, y_test_pred_rf)
print("Testing Accuracy for Random Forests:", test_accuracy_rf)
test_f1score_rf = f1_score(test_y, y_test_pred_rf)
print("Testing F1-Score for Random Forests:", test_f1score_rf)
```

```
Training Accuracy for Random Forests: 1.0
Training F1-Score for Random Forests: 1.0
Testing Accuracy for Random Forests: 0.8360949395432155
Testing F1-Score for Random Forests: 0.8324175824175825
```

The Random Forest model demonstrates improved predictive performance (0.83 as compared to 0.78 in Decision Trees), likely due to its ensemble nature, which helps reduce overfitting and increases generalization.

2.2: Do all trees in the trained random forest model have pure leaves? How would you verify that all trees have pure leaves? Print the score (mean accuracy) values of your choosen method

In [82]:
```
def check_pure_leaves(forest):
    pure_status = []
    for tree in forest.estimators_:
        tree_ = tree.tree_
        leaves = np.where(tree_.children_left == -1)[0]
        is_pure = np.all(tree_.impurity[leaves] == 0)
        pure_status.append(is_pure)
    return pure_status

# Check for pure leaves in the model
pure_leaves = check_pure_leaves(random_forest_classifier)

print("All trees have pure leaves:", all(pure_leaves))

# Mean accuracy calculation on test dataset
mean_accuracy = random_forest_classifier.score(test_X, test_y)
print("Mean accuracy of the random forest model:", mean_accuracy)
```

```
All trees have pure leaves: True
Mean accuracy of the random forest model: 0.8360949395432155
```

2.3: Assume you want to improve the performance of this model. Also, assume that you had to pick two hyperparameters that you could tune to improve its performance.

Which hyperparameters would you choose and why?

'n_estimators' and 'max_depth' are two key hyperparameters to improve the performance of the model.

- **n_estimators** controls the number of trees in the forest. Increasing the number of trees generally leads to improved performance, but it also increases the likelihood of the model overfitting to the training data.
- **max_depth** controls the depth of each tree in the forest. Controlling the depth helps prevent overfitting, by avoiding capturing noise in the data.

2.4: Now, assume you had to choose up to 5 different values (each) for these two hyperparameters. How would you choose these values that could potentially give you a performance lift?

By using a combination of Grid Search and Random Search strategies, a range over which these strategies can be applied could be defined.

For example,

n_estimators = [100, 200, 300, 400, 500]

max_depth = [2, 3, 5, 7, 10]

A combination of Grid Search and Random Search can be used to find the optimal set of hyperparameters for the Random Forest model.

2.5: Perform model selection using the chosen values for the hyperparameters. Use out-of-bag (OOB) error for finding the optimal hyperparameters. Report on the optimal hyperparameters. Estimate the performance of the optimal model (model trained with optimal hyperparameters) on train and test dataset? Has the performance improved over your plain-vanilla random forest model trained in Q2.1?

In [99]:
```
n_estimators = [100, 200, 300, 400, 500]
max_depth = [3, 6, 9, 12, 15, 18, 21, 24, 27, 30]

oob_scores = []  #To store the out-of-bag error

for n_estimator in n_estimators:
  for max_d in max_depth:
    random_forest_classifier_tuned = RandomForestClassifier(n_estimators = n_e
                                                           oob_score = True)
    random_forest_classifier_tuned.fit(dev_X, dev_y)
    oob_scores.append((n_estimator, max_d, random_forest_classifier_tuned.oob_
```

In [100…
```
best_params = max(oob_scores, key = lambda x:x[2])
```

In [101…
```
print("Optimal Hyperparameters:")
print("n_estimator:", best_params[0])
print("max_d:", best_params[1])
print("OOB Score:", best_params[2])
```

```
Optimal Hyperparameters:
n_estimator: 400
max_d: 24
OOB Score: 0.8598947250531974
```

In [102…

```
#Fitting a model with the best set of hyperparameters

rf_tuned = RandomForestClassifier(n_estimators = 400, max_depth = 21, random_s
rf_tuned.fit(dev_X, dev_y)
```

Out[102]:

```
RandomForestClassifier

RandomForestClassifier(max_depth=21, n_estimators=400, random_state=
0)
```

In [103…

```
# Evaluating the Performance
train_pred_pruned = pruned_tree_classifier.predict(dev_X)
test_pred_pruned = pruned_tree_classifier.predict(test_X)

train_accuracy_pruned = accuracy_score(dev_y, train_pred_pruned)
test_accuracy_pruned = accuracy_score(test_y, test_pred_pruned)

train_f1_pruned = f1_score(dev_y, train_pred_pruned)
test_f1_pruned = f1_score(test_y, test_pred_pruned)

print("Pruned Training Accuracy:", train_accuracy_pruned)
print("Pruned Testing Accuracy:", test_accuracy_pruned)
print("Pruned Training F1 Score:", train_f1_pruned)
print("Pruned Testing F1 Score:", test_f1_pruned)
```

```
Pruned Training Accuracy: 0.8694142681151305
Pruned Testing Accuracy: 0.8410210479175997
Pruned Training F1 Score: 0.8675
Pruned Testing F1 Score: 0.8376771833561957
```

2.6: Can you find the top 3 most important features from the model trained in Q2.5? How do these features compare to the important features that you found from Q1.10? If they differ, which feature set makes more sense?

In [108…

```
importances = rf_tuned.feature_importances_
importances_df = pd.DataFrame({'Feature': dev_X.columns, 'Importance': importa
top_features = importances_df.sort_values(by = 'Importance', ascending = False
```

In [109…

```
top_features
```

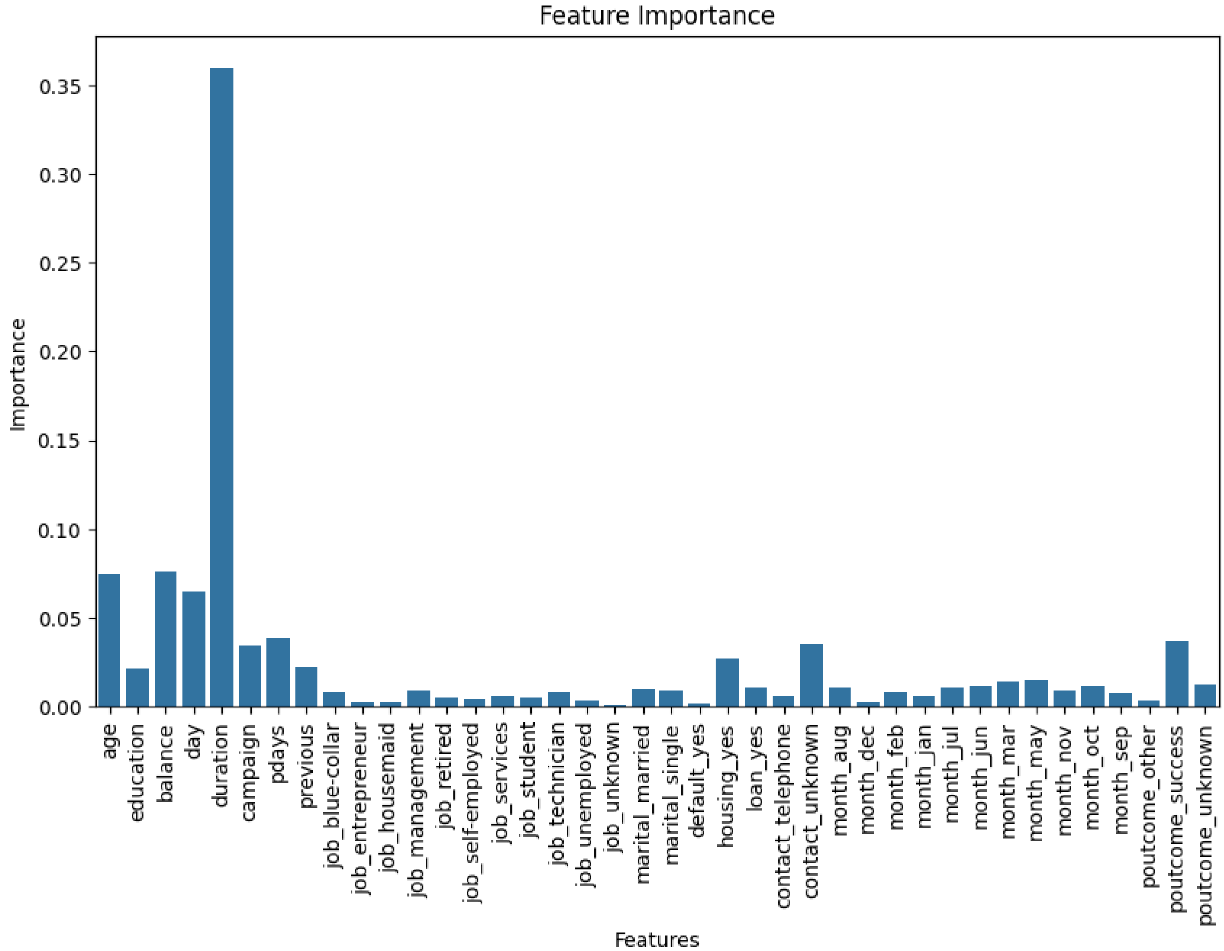
Out[109]:

	Feature	Importance
4	duration	0.359864
2	balance	0.076277
0	age	0.074242

In [111…

```
#Plotting
plt.figure(figsize=(10, 6))
ax = sns.barplot(x = dev_X.columns, y = importances)
```

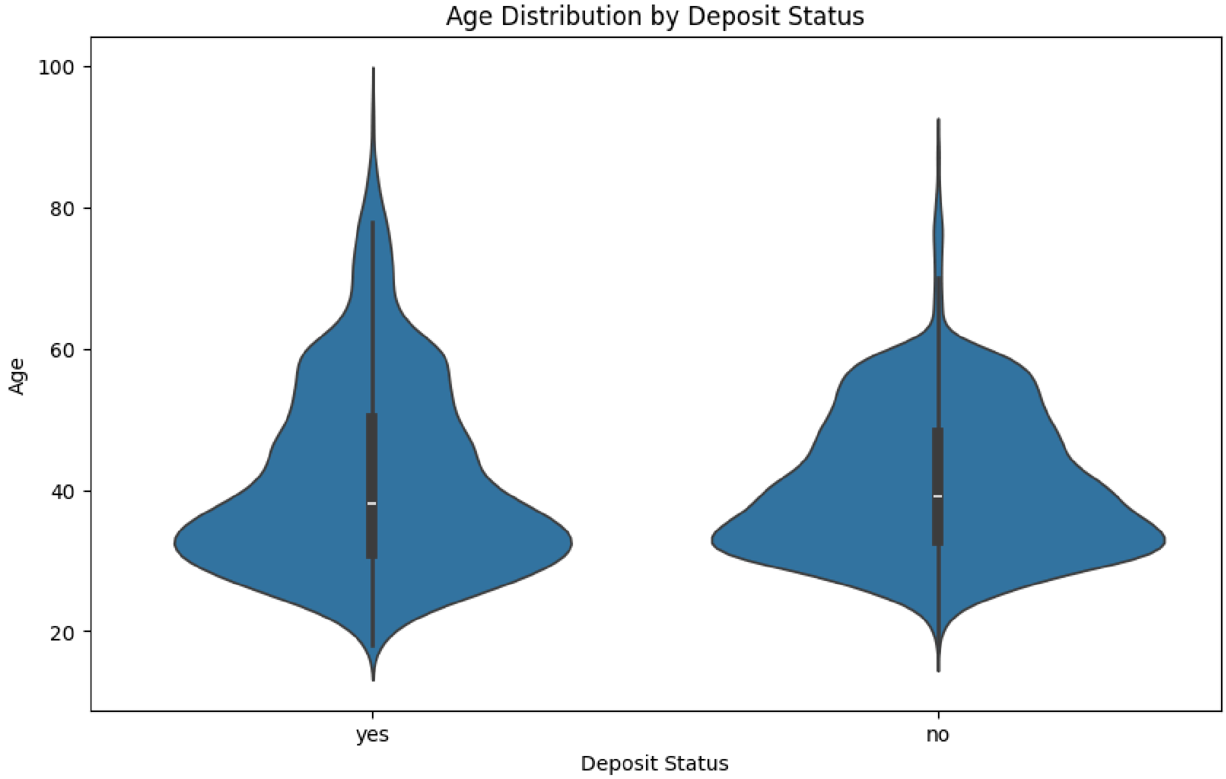
```
ax.tick_params(axis='x', rotation=90)
plt.title("Feature Importance")
plt.xlabel("Features")
plt.ylabel("Importance")
plt.show()
```



In [123…

```
plt.figure(figsize=(10, 6))
sns.violinplot(x='deposit', y='age', data=bank_df)
plt.title('Age Distribution by Deposit Status')
plt.xlabel('Deposit Status')
plt.ylabel('Age')
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/seaborn/_base.py:949: FutureWarning: W
hen grouping with a length-1 list-like, you will need to pass a length-1 tuple
to get_group in a future version of pandas. Pass `(name,)` instead of `name` t
o silence this warning.
  data_subset = grouped_data.get_group(pd_key)
/usr/local/lib/python3.10/dist-packages/seaborn/_base.py:949: FutureWarning: W
hen grouping with a length-1 list-like, you will need to pass a length-1 tuple
to get_group in a future version of pandas. Pass `(name,)` instead of `name` t
o silence this warning.
  data_subset = grouped_data.get_group(pd_key)
```



The three most important features are:

1. **duration** - The duration of the call is a key feature in identifying whether a person will subscribe for a term deposit or not. Longer call durations suggest higher level of interest
2. **balance** - High average yearly balance indicates that the clients would have more disposable income to invest, compared to low average yearly balance.
3. **age** - Younger clients and those in their early middle age are more likely to subscribe to deposits, while older clients may be less inclined to do so.

The features from the Decision Tree Model were:

1. **poutcome(success)**
2. **contact(unknown)**
3. **duration**

The set of features from the random forest model make more sense in determining the kind of factors (age, balance, duration) directly influencing customer decisions. Whereas, the factors poutcome, contact, and duration give more idea into the indiredct, marketing aspect of it.

Question 3: Gradient Boosted Trees

3.1: Choose three hyperparameters to tune HistGradientBoostingClassifier on the development dataset using 5-fold cross validation. For each hyperparmeter, give it 3

potential values. Report on the time taken to do model selection for the model. Also, report the performance of the test dataset from the optimal models.

In [135…
```
param_grid = {
    'learning_rate': [0.01, 0.1, 0.2],
    'max_depth': [3, 5, 7],
    'max_iter': [100, 200, 300]
}
```

In [136…
```
hgb_classifier = HistGradientBoostingClassifier()
grid_search = GridSearchCV(estimator = hgb_classifier, param_grid = param_grid
```

In [137…
```
start_time = time.time()
grid_search.fit(dev_X, dev_y)
end_time = time.time()
```

In [138…
```
# Report the time taken
time_taken = end_time - start_time

# Get optimal hyperparameters
optimal_hyperparameters = grid_search.best_params_

# Evaluate on test dataset
test_score = grid_search.score(test_X, test_y)

# Print results
print(f"Time taken for model selection: {time_taken:.2f} seconds")
print(f"Optimal hyperparameters: {optimal_hyperparameters}")
print(f"Test dataset performance (accuracy): {test_score:.2f}")
```

```
Time taken for model selection: 119.79 seconds
Optimal hyperparameters: {'learning_rate': 0.1, 'max_depth': 5, 'max_iter': 20
0}
Test dataset performance (accuracy): 0.85
```

3.2: Repeat 3.1 for XGBoost.

Note: For XGBoost, you **DO NOT HAVE TO** choose the same hyperparameters as HistGradientBoostingClassifier.

In [141…
```
param_grid_xgb = {
    'learning_rate': [0.01, 0.1, 0.3],  # Learning rate
    'max_depth': [3, 5, 7],             # Maximum depth of trees
    'n_estimators': [100, 200, 300]     # Number of boosting rounds
}
```

In [146…
```
xgb_classifier = xgb.XGBClassifier(use_label_encoder=False, eval_metric='mlogl
grid_search_xgb = GridSearchCV(estimator=xgb_classifier, param_grid=param_grid_
```

In [143…
```
start_time_xgb = time.time()
grid_search_xgb.fit(dev_X, dev_y)
end_time_xgb = time.time()
```

```
/usr/local/lib/python3.10/dist-packages/xgboost/core.py:158: UserWarning: [01:
34:01] WARNING: /workspace/src/learner.cc:740:
Parameters: { "use_label_encoder" } are not used.

  warnings.warn(smsg, UserWarning)
/usr/local/lib/python3.10/dist-packages/xgboost/core.py:158: UserWarning: [01:
34:02] WARNING: /workspace/src/learner.cc:740:
Parameters: { "use_label_encoder" } are not used.

  warnings.warn(smsg, UserWarning)
/usr/local/lib/python3.10/dist-packages/xgboost/core.py:158: UserWarning: [01:
34:02] WARNING: /workspace/src/learner.cc:740:
Parameters: { "use_label_encoder" } are not used.

  warnings.warn(smsg, UserWarning)
/usr/local/lib/python3.10/dist-packages/xgboost/core.py:158: UserWarning: [01:
34:03] WARNING: /workspace/src/learner.cc:740:
Parameters: { "use_label_encoder" } are not used.

  warnings.warn(smsg, UserWarning)
```

In [144…

```
time_taken_xgb = end_time_xgb - start_time_xgb

# Get optimal hyperparameters
optimal_hyperparameters_xgb = grid_search_xgb.best_params_

# Evaluate on test dataset
test_score_xgb = grid_search_xgb.score(test_X, test_y)

# Print results
print(f"Time taken for XGBoost model selection: {time_taken_xgb:.2f} seconds")
print(f"Optimal hyperparameters for XGBoost: {optimal_hyperparameters_xgb}")
print(f"Test dataset performance (accuracy) for XGBoost: {test_score_xgb:.2f}"
```

```
Time taken for XGBoost model selection: 91.26 seconds
Optimal hyperparameters for XGBoost: {'learning_rate': 0.3, 'max_depth': 5, 'n
_estimators': 100}
Test dataset performance (accuracy) for XGBoost: 0.84
```

In [150…

```
xgb_tuned = xgb.XGBClassifier(use_label_encoder=False, eval_metric='mlogloss',
xgb_tuned.fit(dev_X, dev_y)
```

```
/usr/local/lib/python3.10/dist-packages/xgboost/core.py:158: UserWarning: [01:
45:15] WARNING: /workspace/src/learner.cc:740:
Parameters: { "use_label_encoder" } are not used.

  warnings.warn(smsg, UserWarning)
```

Out[150]:

▾ XGBClassifier

```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_roun
ds=None,
              enable_categorical=False, eval_metric='mlogloss',
              feature_types=None, gamma=None, grow_policy=None,
              importance_type=None, interaction_constraints=None,
              learning_rate=0.3, max_bin=None, max_cat_threshold=Non
e,
              max_cat_to_onehot=None, max_delta_step=None, max_depth=
5,
```

3.3: Compare the results on the test dataset of XGBoost and HistGradientBoostingClassifier. Which model do you prefer and why?

Both models are similar in terms of accuracy. XGBoost is faster and has a shorter running time than HistGradient Boosting Classifier.

3.4: Can you list the top 3 important features from the trained XGBoost model? How do they differ from the features found from Random Forest and Decision Tree?

In [154…

```
importances = xgb_tuned.feature_importances_
importances_df = pd.DataFrame({'Feature': dev_X.columns, 'Importance': importa
top_features = importances_df.sort_values(by = 'Importance', ascending = False
```

In [155…

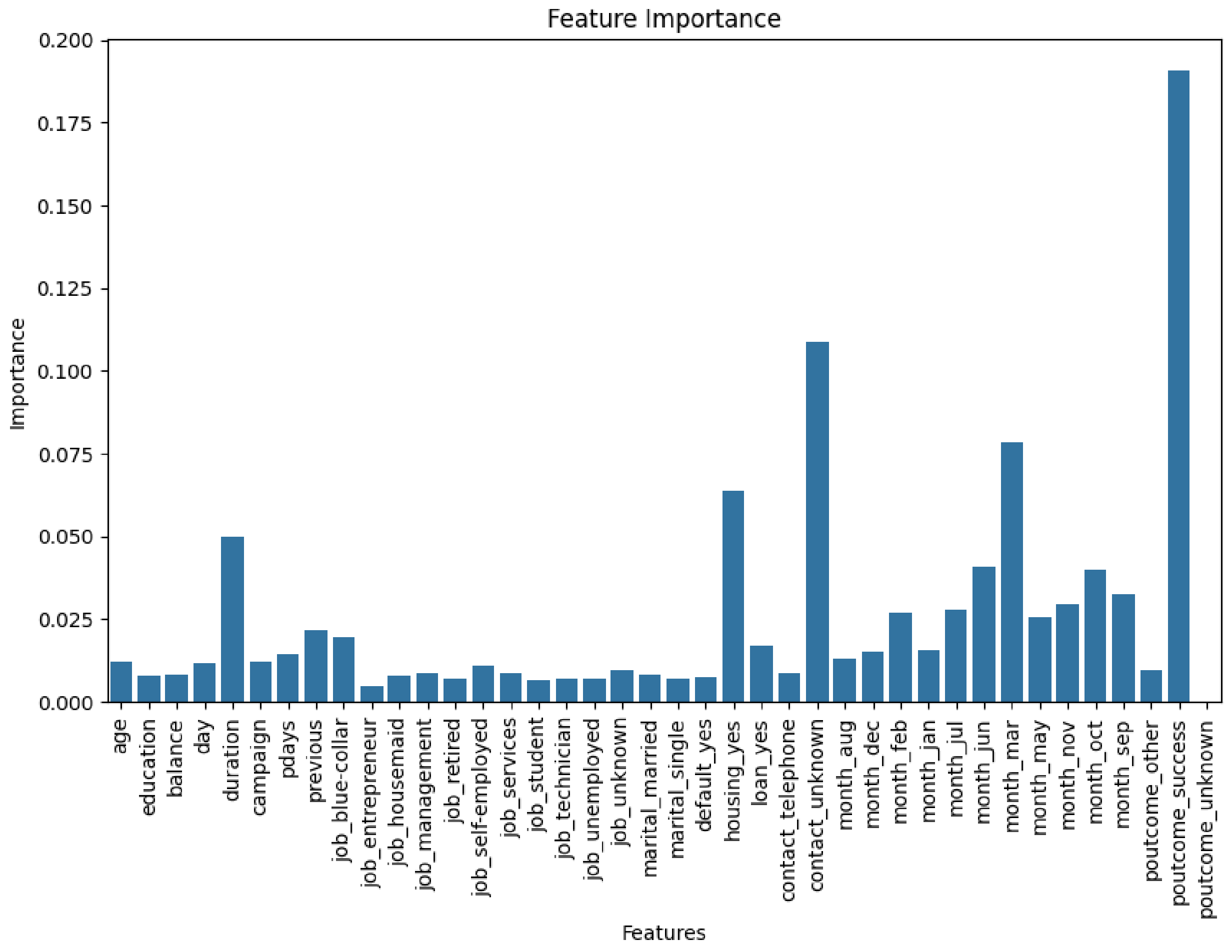
```
top_features
```

Out[155]:

	Feature	Importance
38	poutcome_success	0.190751
25	contact_unknown	0.108740
32	month_mar	0.078447
22	housing_yes	0.063727
4	duration	0.049939

In [153…

```
#Plotting
plt.figure(figsize=(10, 6))
ax = sns.barplot(x = dev_X.columns, y = importances)
ax.tick_params(axis='x', rotation=90)
plt.title("Feature Importance")
plt.xlabel("Features")
plt.ylabel("Importance")
plt.show()
```



The top 3 features are:

1. **poutcome(success)**
2. **contact(unknown)**
3. **month (mar)**

They are similar to the features in the Decision Tree model (with the exception of month, which was duration).

The features are different from the ones in the Random Forest Classifier (duration, age, and balance).

3.5: Can you choose the top 5 features (as given by feature importances from XGBoost) and repeat Q3.2? Does this model perform better than the one trained in Q3.2? Why or why not is the performance better?

In [156…
```
top_5_features = ['poutcome_success', 'contact_unknown', 'month_mar', 'housing_
```

In [159…
```
X_train_top5 = dev_X[top_5_features]
X_test_top5 = test_X[top_5_features]

# Train XGBoost with the top 5 features
xgb_top5_model = xgb.XGBClassifier()

# Fit the model on the training data
```

```python
xgb_top5_model.fit(X_train_top5, dev_y)

# Evaluate on the test data
test_accuracy_top5 = xgb_top5_model.score(X_test_top5, test_y)
print(f'Test Accuracy with Top 5 Features: {test_accuracy_top5}')
```

```
Test Accuracy with Top 5 Features: 0.7913121361397224
```

In [161…

```python
xgb_model = xgb.XGBClassifier()

# Define the hyperparameters and their potential values
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [3, 6, 9],
    'learning_rate': [0.01, 0.1, 0.2]
}

# Set up GridSearchCV
grid_search = GridSearchCV(estimator=xgb_model, param_grid=param_grid, cv=5, s

# Record the start time
start_time = time.time()

# Fit the model
grid_search.fit(X_train_top5, dev_y)

# Record the end time
end_time = time.time()

# Print the best hyperparameters and performance on the training set
print(f"Best Parameters: {grid_search.best_params_}")
print(f"Best CV Score: {grid_search.best_score_}")
```

```
Fitting 5 folds for each of 27 candidates, totalling 135 fits
[CV] END ..learning_rate=0.01, max_depth=3, n_estimators=100; total time=   0.
1s
[CV] END ..learning_rate=0.01, max_depth=3, n_estimators=100; total time=   0.
1s
[CV] END ..learning_rate=0.01, max_depth=3, n_estimators=100; total time=   0.
1s
[CV] END ..learning_rate=0.01, max_depth=3, n_estimators=100; total time=   0.
1s
[CV] END ..learning_rate=0.01, max_depth=3, n_estimators=100; total time=   0.
1s
[CV] END ..learning_rate=0.01, max_depth=3, n_estimators=200; total time=   0.
1s
[CV] END ..learning_rate=0.01, max_depth=3, n_estimators=200; total time=   0.
1s
[CV] END ..learning_rate=0.01, max_depth=3, n_estimators=200; total time=   0.
1s
[CV] END ..learning_rate=0.01, max_depth=3, n_estimators=200; total time=   0.
2s
[CV] END ..learning_rate=0.01, max_depth=3, n_estimators=200; total time=   0.
1s
[CV] END ..learning_rate=0.01, max_depth=3, n_estimators=300; total time=   0.
2s
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6s
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Best Parameters: {'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 300}
Best CV Score: 0.8083780791151847
```

In [166…

```
# Use the best estimator found in grid search
best_xgb_model = grid_search.best_estimator_

# Evaluate the model on the test set
test_accuracy = best_xgb_model.score(X_test_top5, test_y)
print(f"Test Accuracy: {test_accuracy}")
```

```
Test Accuracy: 0.7989252127183162
```

In [167…

```
# Calculate and print the time taken for model selection
time_taken = end_time - start_time
print(f"Time taken for model selection: {time_taken} seconds")
```

```
Time taken for model selection: 33.62224864959717 seconds
```

Question 4: Calibration

4.1: Estimate the brier score for the XGBoost model (trained with optimal hyperparameters from Q3.2) scored on the test dataset.

In [ ]:

```
## YOUR CODE HERE
```

4.2: Calibrate the trained XGBoost model using isotonic regression. Print the brier score after calibration and plot predicted v.s. actual on test datasets from the calibration method.

In [ ]:
```
## YOUR CODE HERE
```

4.3: Compare the brier scores from 4.1 and 4.2. Do the calibration methods help in having better predicted probabilities?

Your Comments Here