Problem Statement

Context

AllLife Bank is a US bank that has a growing customer base. The majority of these customers are liability customers (depositors) with varying sizes of deposits. The number of customers who are also borrowers (asset customers) is quite small, and the bank is interested in expanding this base rapidly to bring in more loan business and in the process, earn more through the interest on loans. In particular, the management wants to explore ways of converting its liability customers to personal loan customers (while retaining them as depositors).

A campaign that the bank ran last year for liability customers showed a healthy conversion rate of over 9% success. This has encouraged the retail marketing department to devise campaigns with better target marketing to increase the success ratio.

You as a Data scientist at AllLife bank have to build a model that will help the marketing department to identify the potential customers who have a higher probability of purchasing the loan.

Objective

To predict whether a liability customer will buy personal loans, to understand which customer attributes are most significant in driving purchases, and identify which segment of customers to target more.

Data Dictionary

- `ID` : Customer ID
- `Age` : Customer's age in completed years
- `Experience` : #years of professional experience
- `Income` : Annual income of the customer (in thousand dollars)
- `ZIP Code` : Home Address ZIP code.
- `Family` : the Family size of the customer
- `CCAvg` : Average spending on credit cards per month (in thousand dollars)
- `Education` : Education Level. 1: Undergrad; 2: Graduate;3: Advanced/Professional
- `Mortgage` : Value of house mortgage if any. (in thousand dollars)
- `Personal_Loan` : Did this customer accept the personal loan offered in the last campaign? (0: No, 1: Yes)
- `Securities_Account` : Does the customer have securities account with the bank? (0: No, 1: Yes)
- `CD_Account` : Does the customer have a certificate of deposit (CD) account with the bank? (0: No, 1: Yes)
- `Online` : Do customers use internet banking facilities? (0: No, 1: Yes)
- `CreditCard` : Does the customer use a credit card issued by any other Bank (excluding All life Bank)? (0: No, 1: Yes)

Importing necessary libraries

In [ ]:
```
# Installing the libraries with the specified version.
!pip install numpy==1.25.2 pandas==1.5.3 matplotlib==3.7.1 seaborn==0.13.1 sci
kit-learn==1.2.2 sklearn-pandas==2.2.0 -q --user
```

Note:

1. After running the above cell, kindly restart the notebook kernel (for Jupyter Notebook) or runtime (for Google Colab), write the relevant code for the project from the next cell, and run all cells sequentially from the next cell.
2. On executing the above line of code, you might see a warning regarding package dependencies. This error message can be ignored as the above code ensures that all necessary libraries and their dependencies are maintained to successfully execute the code in this notebook.

In [16]:
```
import pandas as pd
import numpy as np

# to visualize data
import matplotlib.pyplot as plt
import seaborn as sns

# to split data into training and test sets
from sklearn.model_selection import train_test_split

# to build decision tree model
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree

# to tune different models
from sklearn.model_selection import GridSearchCV

# to compute classification metrics
from sklearn.metrics import (
    confusion_matrix,
    accuracy_score,
    recall_score,
    precision_score,
    f1_score,
)
```

Loading the dataset

In [2]:
```
from google.colab import drive
drive.mount('/content/drive')
file = r'/content/drive/MyDrive/AI Class/Projects/Project 2/Loan_Modelling.cs
v'
personal_loan_cmpgn = pd.read_csv(file)
```

```
Mounted at /content/drive
```

In [3]:
```
data = personal_loan_cmpgn.copy()
```

In [132]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 14 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   ID                  5000 non-null   int64  
 1   Age                 5000 non-null   int64  
 2   Experience          5000 non-null   int64  
 3   Income              5000 non-null   int64  
 4   ZIPCode             5000 non-null   int64  
 5   Family              5000 non-null   int64  
 6   CCAvg               5000 non-null   float64
 7   Education           5000 non-null   int64  
 8   Mortgage            5000 non-null   int64  
 9   Personal_Loan       5000 non-null   int64  
 10  Securities_Account  5000 non-null   int64  
 11  CD_Account          5000 non-null   int64  
 12  Online              5000 non-null   int64  
 13  CreditCard          5000 non-null   int64  
dtypes: float64(1), int64(13)
memory usage: 547.0 KB
```

In [5]:
```
data.shape
```

Out[5]:
```
(5000, 14)
```

In [6]:
```
data.head(5)
```

Out[6]:

	ID	Age	Experience	Income	ZIPCode	Family	CCAvg	Education	Mortgage	Personal_Loan
0	1	25	1	49	91107	4	1.6	1	0	0
1	2	45	19	34	90089	3	1.5	1	0	0
2	3	39	15	11	94720	1	1.0	1	0	0
3	4	35	9	100	94112	1	2.7	2	0	0
4	5	35	8	45	91330	4	1.0	2	0	0

In [7]:
```
data.tail(5)
```

Out[7]:

	ID	Age	Experience	Income	ZIPCode	Family	CCAvg	Education	Mortgage	Personal_
4995	4996	29	3	40	92697	1	1.9	3	0	
4996	4997	30	4	15	92037	4	0.4	1	85	
4997	4998	63	39	24	93023	2	0.3	3	0	
4998	4999	65	40	49	90034	3	0.5	2	0	
4999	5000	28	4	83	92612	3	0.8	1	0	

Data Overview

In [125]:
```
data.describe(include="all")
```

Out[125]:

	ID	Age	Experience	Income	ZIPCode	Family	CCA
count	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5000.000C
mean	2500.500000	45.338400	20.104600	73.774200	93169.257000	2.396400	1.9379
std	1443.520003	11.463166	11.467954	46.033729	1759.455086	1.147663	1.7476
min	1.000000	23.000000	-3.000000	8.000000	90005.000000	1.000000	0.000C
25%	1250.750000	35.000000	10.000000	39.000000	91911.000000	1.000000	0.700C
50%	2500.500000	45.000000	20.000000	64.000000	93437.000000	2.000000	1.500C
75%	3750.250000	55.000000	30.000000	98.000000	94608.000000	3.000000	2.500C
max	5000.000000	67.000000	43.000000	224.000000	96651.000000	4.000000	10.000C

In [130]:
```
data.isnull().sum()
```

Out[130]:

	0
ID	0
Age	0
Experience	0
Income	0
ZIPCode	0
Family	0
CCAvg	0
Education	0
Mortgage	0
Personal_Loan	0
Securities_Account	0
CD_Account	0
Online	0
CreditCard	0

dtype: int64

In [129]:
```
data.nunique()
```

Out[129]:

	0
ID	5000
Age	45
Experience	47
Income	162
ZIPCode	467
Family	4
CCAvg	108
Education	3
Mortgage	347
Personal_Loan	2
Securities_Account	2
CD_Account	2
Online	2
CreditCard	2

dtype: int64

- Observations
- Sanity checks

Exploratory Data Analysis.

- EDA is an important part of any project involving data.
- It is important to investigate and understand the data better before building a model with it.
- A few questions have been mentioned below which will help you approach the analysis in the right manner and generate insights from the data.
- A thorough analysis of the data, in addition to the questions mentioned below, should be done.

Questions:

1. What is the distribution of mortgage attribute? Are there any noticeable patterns or outliers in the distribution?
2. How many customers have credit cards?
3. What are the attributes that have a strong correlation with the target attribute (personal loan)?
4. How does a customer's interest in purchasing a loan vary with their age?
5. How does a customer's interest in purchasing a loan vary with their education?

In [ ]:
```
#1
plt.figure(figsize=(10, 5))
sns.histplot(data=data, x='Mortgage')
plt.title("Distribution of Mortgage Values")
plt.show()

# using histplot to show the distribution of the mortgages
# most either dont have one or paid it off
```

In [ ]:
```
#2
sns.countplot(data=data, x='CreditCard')
plt.xticks(ticks=[0, 1], labels=['No', 'Yes'])
plt.xlabel('Has Credit Card?')
plt.title("Number of Customers with a Credit Card")
plt.show()

cust_with_cc = (data['CreditCard'] == 1).sum()
print(f"Number of customers with Credit Card: {cust_with_cc}")

#simple countplot to show the numbers of customers with a credit card vs not h
aving one
```

In [ ]:
```
#3
plt.figure(figsize=(10, 6))
sns.heatmap(data.corr(), annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Correlation Matrix")
plt.show()
## Displaying the corr matrix with all the vars then narrowing it down to only
a few in the next corr matrix

post_correlation_matrix = data.corr()
selected_columns = ["Personal_Loan", "Income", "CCAvg", "CD_Account", "Experie
nce"]
post_personal_loan_corr = post_correlation_matrix.loc[selected_columns, select
ed_columns]
print(post_personal_loan_corr)
plt.figure(figsize=(6, 4))
sns.heatmap(post_personal_loan_corr, annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Selected Feature Correlations")
plt.show()
## only showing the correlation that matters in this scenario so its easier on
the eyes
## although experience doesnt have a favorable output, I believe it is importa
nt for the later half of the project

num_features = ['Experience', 'Income', 'Mortgage']
plt.figure(figsize=(12, 8))
sns.pairplot(data, vars=num_features, hue='Personal_Loan', diag_kind='kde');
## tried seeing if there is any correlation with the above 3 vars against pers
onal loan
## found a somewhat interesting correlation with experience and mortgage and i
ncome and experience
## that those with very little exp and high income are more likely to have a l
oan
## and that people with little exp and a mortgage of ~300 or higher are likely
to have a loan
```

In [ ]:
```
fig, axes = plt.subplots(1, 2, figsize=(16, 5))
# data.drop(columns=['Age_Binned'], inplace=True)


# Boxplot of Age & Personal Loan
sns.boxplot(
    data=data,
    x='Personal_Loan',
    y='Age',
    ax=axes[0],
    showmeans=True,
    meanprops={"marker":"o", "markerfacecolor":"white", "markeredgecolor":"bla
ck", "markersize":"8"}
)
axes[0].set_title("Boxplot of Age and Personal Loan")
axes[0].set_xticks([0, 1])
axes[0].set_xticklabels(['No', 'Yes'])

# Histogram of Binned Age & Personal Loan
bins = [20, 30, 40, 50, 60, 70]
labels = ['20-30', '30-40', '40-50', '50-60', '60-70']
data_copy = data.copy()
data_copy['Age_Binned'] = pd.cut(data_copy['Age'], bins=bins, labels=labels, r
ight=True)

sns.histplot(data_copy, x='Age_Binned', hue='Personal_Loan', palette='Set2', m
ultiple='stack', ax=axes[1])
axes[1].set_title("Histogram of Binned Age by Personal Loan")
axes[1].set_xticklabels(labels, rotation=45)

plt.tight_layout()
plt.show()

#fairly straightforward plots, was trying to spice it but little but given the
params needed only so much can be done
```

In [ ]:
```
fig, axes = plt.subplots(1, 2, figsize=(16, 5))

# Boxplot of Education & Personal Loan
sns.boxplot(data=data, x='Personal_Loan', y='Education', ax=axes[0])
axes[0].set_title("Boxplot of Education and Personal Loan")
axes[0].set_xticks([0, 1])
axes[0].set_xticklabels(['No', 'Yes'])
axes[0].set_yticks([1, 2, 3])
axes[0].set_yticklabels(["Undergrad", "Graduate", "Advanced/Professional"])

# Countplot of Education & Personal Loan
sns.countplot(data=data, x='Education', hue='Personal_Loan', palette='Set2', a
x=axes[1])
axes[1].set_title("Countplot of Education by Personal Loan")
axes[1].set_xticks([0, 1, 2])
axes[1].set_xticklabels(["Undergrad", "Graduate", "Advanced/Professional"])

plt.tight_layout()
plt.show()

#again another 2 fairly straightforward plots, only fun was seeing people with
higher degrees getting loans
```

Data Preprocessing

- Missing value treatment
- Feature engineering (if needed)
- Outlier detection and treatment (if needed)
- Preparing data for modeling
- Any other preprocessing steps (if needed)

In [12]:
```
#drop the customer id or any other var if it is not helping contribute to solv
ing problem statement --> feature engineering
```

In [ ]:
```
features = data.select_dtypes(include=['number']).columns.tolist()

n_cols = 4
n_rows = (len(features) // n_cols) + (1 if len(features) % n_cols != 0 else 0)

plt.figure(figsize=(n_cols * 5, n_rows * 4))

for i, variable in enumerate(features):
    plt.subplot(n_rows, n_cols, i + 1)
    plt.boxplot(data[variable], whis=1.5)
    plt.title(variable)
    plt.tight_layout()

plt.show()

#finding the outliers in the data using boxplots
#the attributes with 0 & 1 arent going to show much, fairly obvious why
#cant treat the outliers as this info would skew our findings on what people t
o target
#although we need to find liability customers so the only real outliers that m
ight be removed would be income as the other categories are favorable
```

Model Building

best accuracy and lowest over fit segmentation and classification

Model Evaluation Criterion

*

In [54]:
```
selected_features = ['Online', 'Securities_Account', 'Family', 'ZIPCode', 'I
D', 'Personal_Loan']
X = data.drop(selected_features, axis=1)
Y = data["Personal_Loan"]

X_train, X_test, y_train, y_test = train_test_split(
    X, Y, test_size=0.20, stratify=Y, random_state=30
)

print("Shape of training set:", X_train.shape)
print("Shape of test set:", X_test.shape, '\n')
print("Percentage of classes in training set:")
print(100*y_train.value_counts(normalize=True), '\n')
print("Percentage of classes in test set:")
print(100*y_test.value_counts(normalize=True))

## took out the selected features from the modeling since they werent much hel
p, I had experience on there but realized it was a factor in the above boxplot
so removed it
```

```
Shape of training set: (4000, 8)
Shape of test set: (1000, 8)

Percentage of classes in training set:
Personal_Loan
0    90.4
1     9.6
Name: proportion, dtype: float64

Percentage of classes in test set:
Personal_Loan
0    90.4
1     9.6
Name: proportion, dtype: float64
```

Model Building for decision tree

In [140]:
```
dtree1 = DecisionTreeClassifier(random_state=30)
dtree1.fit(X_train, y_train)
```

Out[140]:
```
▾ DecisionTreeClassifier
DecisionTreeClassifier(random_state=30)
```
(https://scikit-learn.org/1.6/modules/generated/sklearn.tree.Deci

In [141]:
```
def model_performance_classification(model, predictors, target):
    """
    Function to compute different metrics to check classification model perfor
mance

    model: classifier
    predictors: independent variables
    target: dependent variable
    """

    # predicting using the independent variables
    pred = model.predict(predictors)

    acc = accuracy_score(target, pred)  # to compute Accuracy
    recall = recall_score(target, pred)  # to compute Recall
    precision = precision_score(target, pred)  # to compute Precision
    f1 = f1_score(target, pred)  # to compute F1-score

    # creating a dataframe of metrics
    df_perf = pd.DataFrame(
        {"Accuracy": acc, "Recall": recall, "Precision": precision, "F1": f
1,},
        index=[0],
    )

    return df_perf

    ## got the code from the hands on notebooks
```

In [142]:
```
def plot_confusion_matrix(model, predictors, target):
    """
    To plot the confusion_matrix with percentages

    model: classifier
    predictors: independent variables
    target: dependent variable
    """
    # Predict the target values using the provided model and predictors
    y_pred = model.predict(predictors)

    # Compute the confusion matrix comparing the true target values with the p
redicted values
    cm = confusion_matrix(target, y_pred)

    # Create labels for each cell in the confusion matrix with both count and
percentage
    labels = np.asarray(
        [
            ["{0:0.0f}".format(item) + "\n{0:.2%}".format(item / cm.flatten().
sum())]
            for item in cm.flatten()
        ]
    ).reshape(2, 2)    # reshaping to a matrix

    # Set the figure size for the plot
    plt.figure(figsize=(6, 4))

    # Plot the confusion matrix as a heatmap with the labels
    sns.heatmap(cm, annot=labels, fmt="")

    # Add a label to the y-axis
    plt.ylabel("True label")

    # Add a label to the x-axis
    plt.xlabel("Predicted label")

  ## got the code from the hands on notebooks
```

In [ ]:
```
plot_confusion_matrix(dtree1, X_train, y_train)
```

In [59]:
```
dtree1_train_perf = model_performance_classification(
    dtree1, X_train, y_train
)
dtree1_train_perf
```

Out[59]:

	Accuracy	Recall	Precision	F1
0	1.0	1.0	1.0	1.0

In [ ]:
```
plot_confusion_matrix(dtree1, X_test, y_test)
```

In [143]:
```
dtree1_test_perf = model_performance_classification(
    dtree1, X_test, y_test
)
dtree1_test_perf

## thougth my model was wrong or something since the numbers returned were hig
her than what i had seen
## but apparently the testing material was off to a good star
```

Out[143]:

	Accuracy	Recall	Precision	F1
0	0.966	0.895833	0.781818	0.834951

In [ ]:
```
# list of feature names in X_train
feature_names = list(X_train.columns)

# set the figure size for the plot
plt.figure(figsize=(20, 20))

# plotting the decision tree
out = tree.plot_tree(
    dtree1,                         # decision tree classifier model
    feature_names=feature_names,    # list of feature names (columns) in the d
ataset
    filled=True,                    # fill the nodes with colors based on clas
s
    fontsize=5,                     # font size for the node text
    node_ids=False,                 # do not show the ID of each node
    class_names=None,               # whether or not to display class names
)

# add arrows to the decision tree splits if they are missing
for o in out:
    arrow = o.arrow_patch
    if arrow is not None:
        arrow.set_edgecolor("black")    # set arrow color to black
        arrow.set_linewidth(1)          # set arrow linewidth to 1

# displaying the plot
plt.show()

## got the code from the hands on notebooks
## very big tree, not a lot of conclusive end nodes, very few samples were in
there so need to prune to get better results
```

Model Performance Improvement for decision tree

In [145]:
```
max_depth_values = np.arange(3, 16, 2)
max_leaf_nodes_values = np.arange(10, 101, 15)
min_samples_split_values = np.arange(5, 31, 5)

best_estimator = None
best_score_diff = float('inf')

# iterate over all combinations of the specified parameter values
for max_depth in max_depth_values:
    for max_leaf_nodes in max_leaf_nodes_values:
        for min_samples_split in min_samples_split_values:

            # initialize the tree with the current set of parameters
            estimator = DecisionTreeClassifier(
                max_depth=max_depth,
                max_leaf_nodes=max_leaf_nodes,
                min_samples_split=min_samples_split,
                random_state=30
            )

            # fit the model to the training data
            estimator.fit(X_train, y_train)

            # make predictions on the training and test sets
            y_train_pred = estimator.predict(X_train)
            y_test_pred = estimator.predict(X_test)

            # calculate F1 scores for training and test sets
            train_f1_score = f1_score(y_train, y_train_pred)
            test_f1_score = f1_score(y_test, y_test_pred)

            # calculate the absolute difference between training and test F1 s
cores
            score_diff = abs(train_f1_score - test_f1_score)

            # update the best estimator and best score if the current one has
a smaller score difference
            if score_diff < best_score_diff:
                best_score_diff = score_diff
                best_estimator = estimator

## got the code from the hands on notebooks
## changed the top 3 lines of code to better fit my current situation for the
trees
## Setting max_depth between 3 and 15 allows a meaningful base model while all
owing deeper trees to capture complex patterns
## Expanding max_leaf_nodes to 100 provides more flexibility for complex decis
ion boundaries, while a larger step size of 15 balances thoroughness with comp
utational efficiency.
## Lowering min_samples_split to 5 allows for more smaller splits to capture d
ata patterns better, while stopping it at 30 to stop underfitting
```

```
## used chatgpt to help breakdown code and understanding and it helped me with
the above 3 lines explaining the first 3 lines of code
```

In [147]:

```
# creating an instance of the best model
dtree2 = best_estimator

# fitting the best model to the training data
dtree2.fit(X_train, y_train)
```

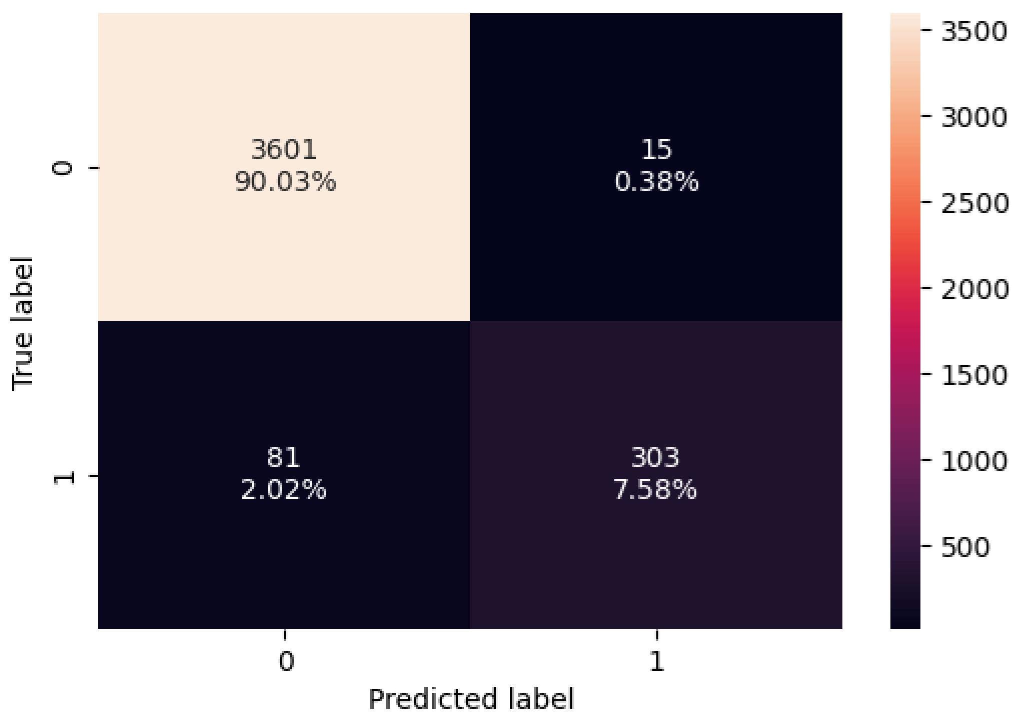
Out[147]:

```
DecisionTreeClassifier

DecisionTreeClassifier(max_depth=7, max_leaf_nodes=40, min_samples_split=30,
                       random_state=30)
```

(http
learn

In [148]:

```
plot_confusion_matrix(dtree2, X_train, y_train)
```



In [149]:

```
dtree2_train_perf = model_performance_classification(
    dtree2, X_train, y_train
)
dtree2_train_perf

## obviously the training will go down since I pruned it but results are good
thus far
```

Out[149]:

	Accuracy	Recall	Precision	F1
0	0.976	0.789062	0.95283	0.863248

In [ ]:

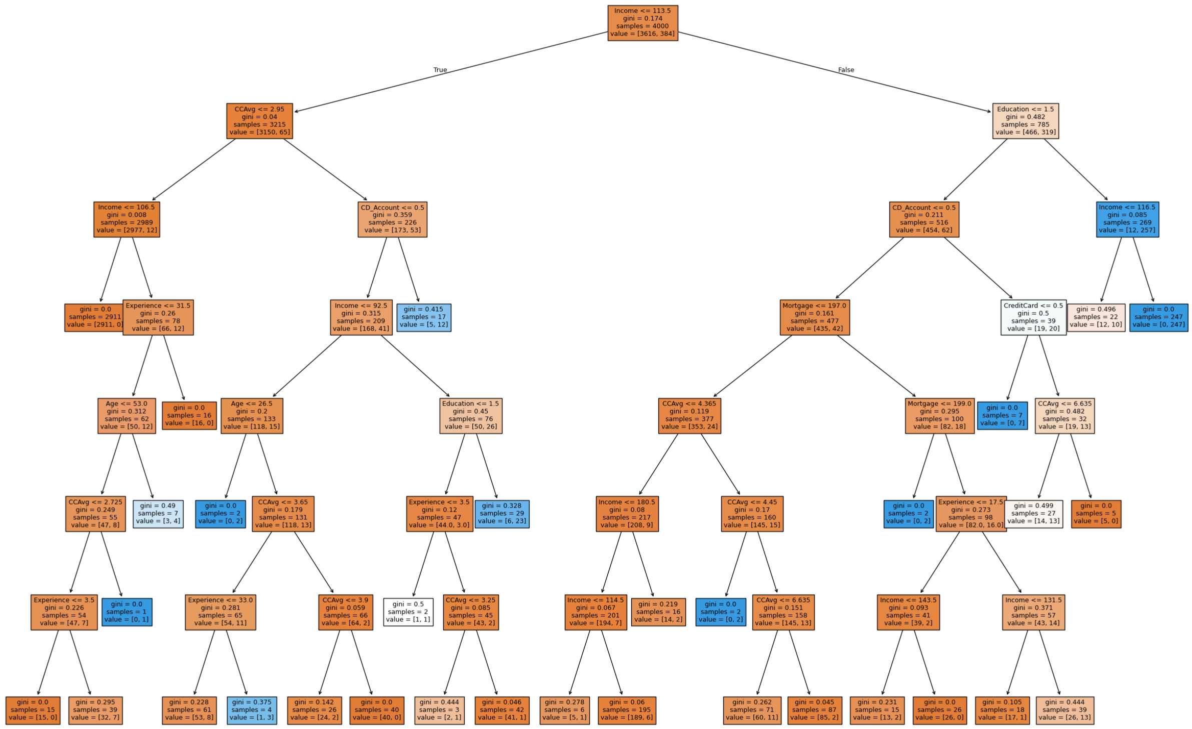
```
plot_confusion_matrix(dtree2, X_test, y_test)
```

In [150]:
```
dtree2_test_perf = model_performance_classification(
    dtree2, X_test, y_test
)
dtree2_test_perf
## acc went a tad, which was expected, recall went down as well, but precision and f1 both went up
## this means fewer FPs, and also means its capturing better info since the pruning, so getting more positives
```

Out[150]:

	Accuracy	Recall	Precision	F1
0	0.974	0.854167	0.87234	0.863158

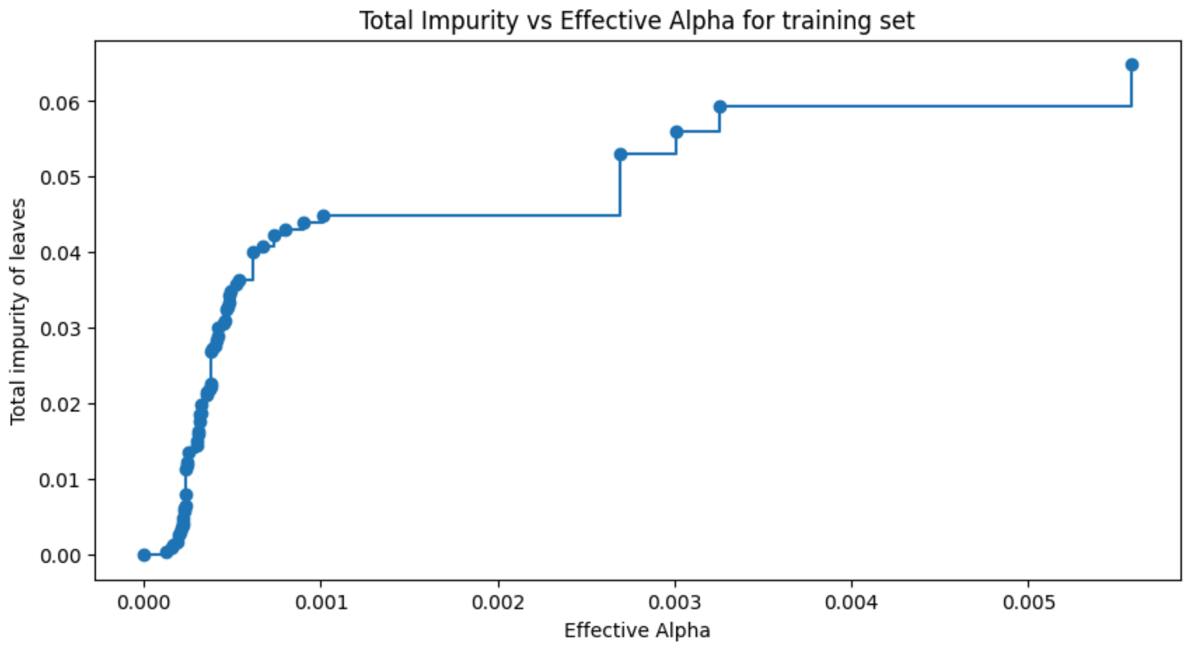
In [167]:
```
# list of feature names in X_train
feature_names = list(X_train.columns)

# set the figure size for the plot
plt.figure(figsize=(30, 20))

# plotting the decision tree
out = tree.plot_tree(
    dtree2,                            # decision tree classifier model
    feature_names=feature_names,       # list of feature names (columns) in the d
ataset
    filled=True,                       # fill the nodes with colors based on clas
s
    fontsize=9,                        # font size for the node text
    node_ids=False,                    # do not show the ID of each node
    class_names=None,                  # whether or not to display class names
)

# add arrows to the decision tree splits if they are missing
for o in out:
    arrow = o.arrow_patch
    if arrow is not None:
        arrow.set_edgecolor("black")    # set arrow color to black
        arrow.set_linewidth(1)          # set arrow linewidth to 1

# displaying the plot
plt.show()

## got the code from the hands on notebooks
## the avg gini value i got was 0.15, which is pretty pure
## the samples sum was 3980, so around %79.6
## meaning i am getting good results and there is a market for targetting the
liability customers for this project
```



In [153]:
```python
# Create an instance of the decision tree model
clf = DecisionTreeClassifier(random_state=30)

# Compute the cost complexity pruning path for the model using the training da
ta
path = clf.cost_complexity_pruning_path(X_train, y_train)

# Extract the array of effective alphas from the pruning path
ccp_alphas = abs(path.ccp_alphas)

# Extract the array of total impurities at each alpha along the pruning path
impurities = path.impurities
```

In [ ]:
```python
pd.DataFrame(path)
```

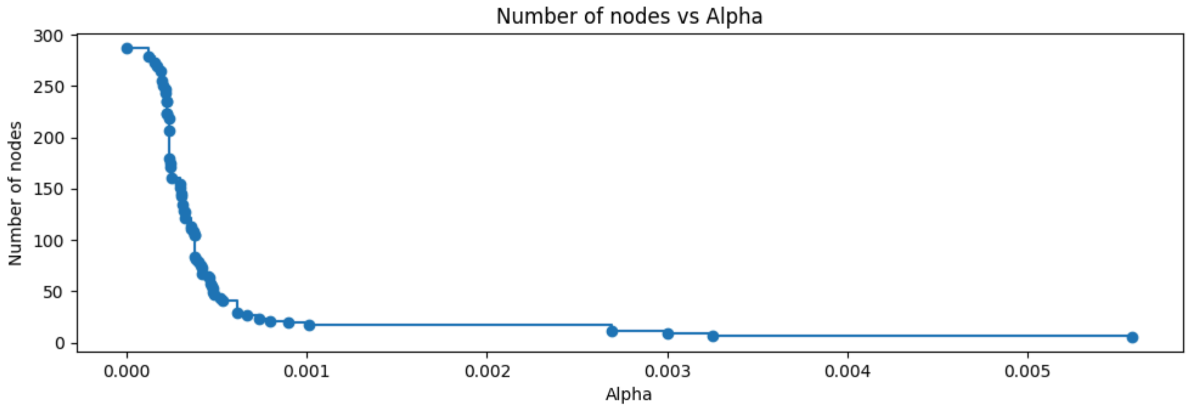
In [155]:
```
# Create a figure
fig, ax = plt.subplots(figsize=(10, 5))

# Plot the total impurities versus effective alphas, excluding the last value,
# using markers at each data point and connecting them with steps
ax.plot(ccp_alphas[:-1], impurities[:-1], marker="o", drawstyle="steps-post")

# Set the x-axis label
ax.set_xlabel("Effective Alpha")

# Set the y-axis label
ax.set_ylabel("Total impurity of leaves")

# Set the title of the plot
ax.set_title("Total Impurity vs Effective Alpha for training set");

## got the code from the hands on notebooks
## seeing a steep increase in the impurity and increase in the alpha, meaning
conclusive results
```

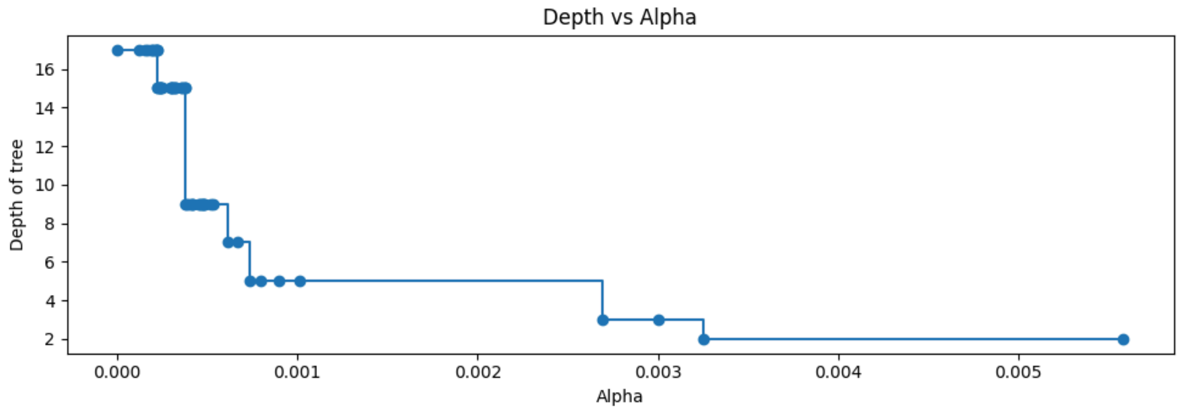


In [156]:
```
# Initialize an empty list to store the decision tree classifiers
clfs = []

# Iterate over each ccp_alpha value extracted from cost complexity pruning pat
h
for ccp_alpha in ccp_alphas:
    # Create an instance of the DecisionTreeClassifier
    clf = DecisionTreeClassifier(ccp_alpha=ccp_alpha, random_state=30)

    # Fit the classifier to the training data
    clf.fit(X_train, y_train)

    # Append the trained classifier to the list
    clfs.append(clf)

# Print the number of nodes in the last tree along with its ccp_alpha value
print(
    "Number of nodes in the last tree is {} with ccp_alpha {}".format(
        clfs[-1].tree_.node_count, ccp_alphas[-1]
    )
)
## got the code from the hands on notebooks
```

```
Number of nodes in the last tree is 1 with ccp_alpha 0.054358770199701534
```

In [157]:
```
# Remove the last classifier and corresponding ccp_alpha value from the lists
clfs = clfs[:-1]
ccp_alphas = ccp_alphas[:-1]

# Extract the number of nodes in each tree classifier
node_counts = [clf.tree_.node_count for clf in clfs]

# Extract the maximum depth of each tree classifier
depth = [clf.tree_.max_depth for clf in clfs]

# Create a figure and a set of subplots
fig, ax = plt.subplots(2, 1, figsize=(10, 7))

# Plot the number of nodes versus ccp_alphas on the first subplot
ax[0].plot(ccp_alphas, node_counts, marker="o", drawstyle="steps-post")
ax[0].set_xlabel("Alpha")
ax[0].set_ylabel("Number of nodes")
ax[0].set_title("Number of nodes vs Alpha")

# Plot the depth of tree versus ccp_alphas on the second subplot
ax[1].plot(ccp_alphas, depth, marker="o", drawstyle="steps-post")
ax[1].set_xlabel("Alpha")
ax[1].set_ylabel("Depth of tree")
ax[1].set_title("Depth vs Alpha")

# Adjust the layout of the subplots to avoid overlap
fig.tight_layout()

## got the code from the hands on notebooks
## number of nodes decreasing means it is finding the right customers to targe
t and higher and purer results, not too much noise
```



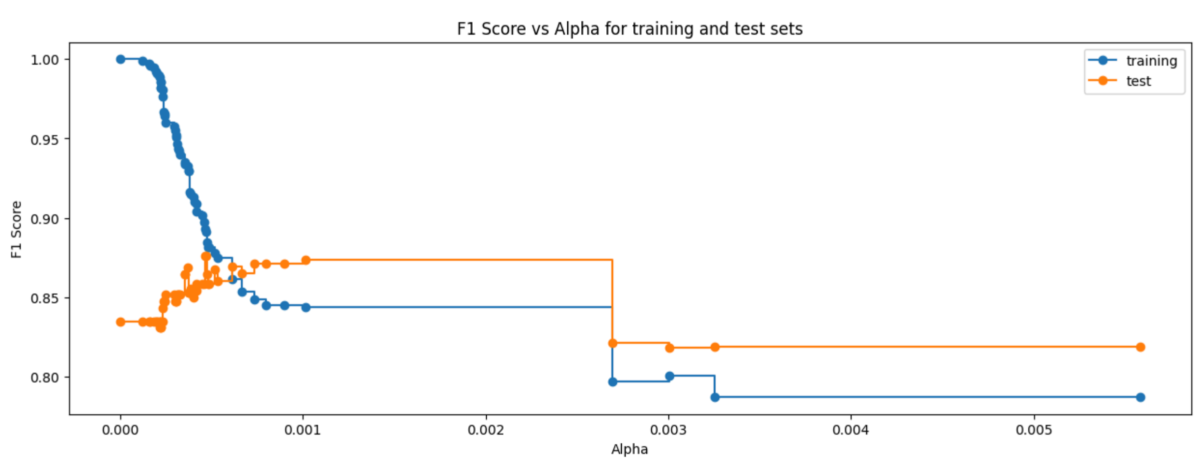


In [158]:

```
train_f1_scores = []  # Initialize an empty list to store F1 scores for traini
ng set for each decision tree classifier

# Iterate through each decision tree classifier in 'clfs'
for clf in clfs:
    # Predict labels for the training set using the current decision tree clas
sifier
    pred_train = clf.predict(X_train)

    # Calculate the F1 score for the training set predictions compared to true
labels
    f1_train = f1_score(y_train, pred_train)

    # Append the calculated F1 score to the train_f1_scores list
    train_f1_scores.append(f1_train)

## got the code from the hands on notebooks
```

In [159]:
```
test_f1_scores = []  # Initialize an empty list to store F1 scores for test se
t for each decision tree classifier

# Iterate through each decision tree classifier in 'clfs'
for clf in clfs:
    # Predict labels for the test set using the current decision tree classifi
er
    pred_test = clf.predict(X_test)

    # Calculate the F1 score for the test set predictions compared to true lab
els
    f1_test = f1_score(y_test, pred_test)

    # Append the calculated F1 score to the test_f1_scores list
    test_f1_scores.append(f1_test)

## got the code from the hands on notebooks
```

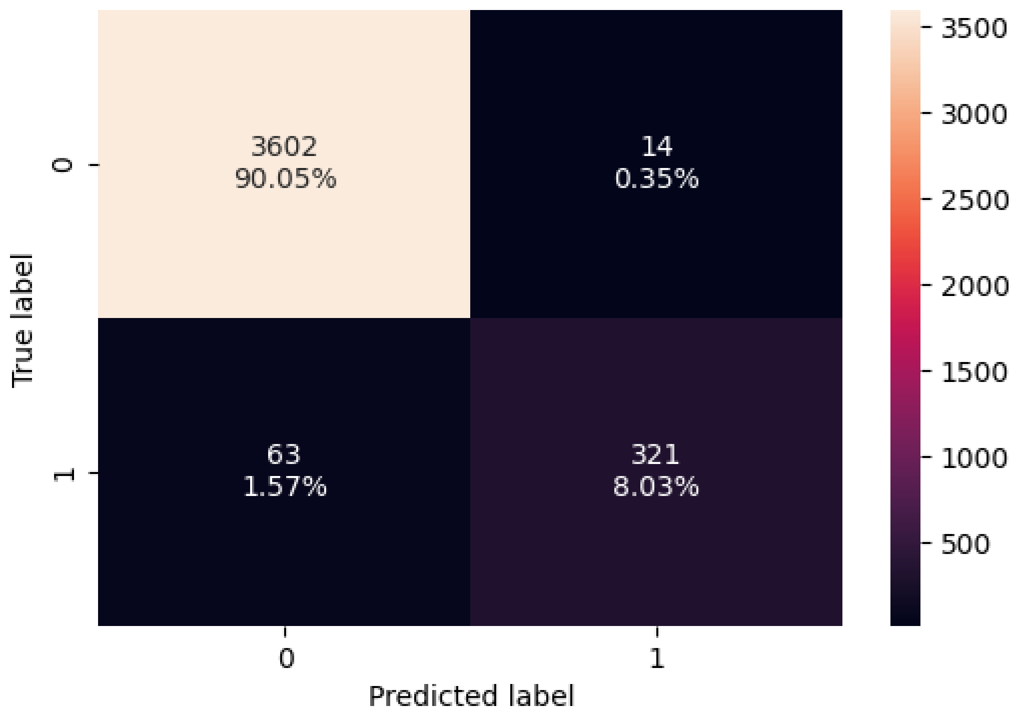
In [160]:
```
# Create a figure
fig, ax = plt.subplots(figsize=(15, 5))
ax.set_xlabel("Alpha")  # Set the label for the x-axis
ax.set_ylabel("F1 Score")  # Set the label for the y-axis
ax.set_title("F1 Score vs Alpha for training and test sets")  # Set the title
of the plot

# Plot the training F1 scores against alpha, using circles as markers and step
s-post style
ax.plot(ccp_alphas, train_f1_scores, marker="o", label="training", drawstyle
="steps-post")

# Plot the testing F1 scores against alpha, using circles as markers and steps
-post style
ax.plot(ccp_alphas, test_f1_scores, marker="o", label="test", drawstyle="steps
-post")

ax.legend();  # Add a legend to the plot

## got the code from the hands on notebooks
## although the test f1 score was higher, it being able to reach the same amou
nt of alpha score with only 1000 customer data means model is working right
```



In [161]:
```
# creating the model where we get highest test F1 Score
index_best_model = np.argmax(test_f1_scores)

# selcting the decision tree model corresponding to the highest test score
dtree3 = clfs[index_best_model]
print(dtree3)
```

```
DecisionTreeClassifier(ccp_alpha=0.0004632352941176471, random_state=30)
```

In [162]:
```
plot_confusion_matrix(dtree3, X_train, y_train)
```



In [164]:
```
dtree3_train_perf = model_performance_classification(
    dtree3, X_train, y_train
)
dtree3_train_perf

## from the training 2 data, the accuracy, recall, precision, and f1 went up
## this means the model is doing great at making predications, staying away fr
om FNs & FPs
```

Out[164]:

	Accuracy	Recall	Precision	F1
0	0.98075	0.835938	0.958209	0.892907

In [90]:
```
dtree3_test_perf = model_performance_classification(
    dtree3, X_test, y_test
)
dtree3_test_perf

## for the test data to improve too it means the model is not overfitting to t
he training data
## these are real improvements cementing this model as working
```

Out[90]:

	Accuracy	Recall	Precision	F1
0	0.976	0.885417	0.867347	0.876289

In [ ]:
```
# list of feature names in X_train
feature_names = list(X_train.columns)

# set the figure size for the plot
plt.figure(figsize=(25, 10))

# plotting the decision tree
out = tree.plot_tree(
    dtree3,                           # decision tree classifier model
    feature_names=feature_names,      # list of feature names (columns) in the d
ataset
    filled=True,                      # fill the nodes with colors based on clas
s
    fontsize=9,                       # font size for the node text
    node_ids=False,                   # do not show the ID of each node
    class_names=None,                 # whether or not to display class names
)

# add arrows to the decision tree splits if they are missing
for o in out:
    arrow = o.arrow_patch
    if arrow is not None:
        arrow.set_edgecolor("black")    # set arrow color to black
        arrow.set_linewidth(1)          # set arrow linewidth to 1

# displaying the plot
plt.show()

## got the code from the hands on notebooks
## now the gini was has dropped to less than 0.1 i believe
## and the samples size has gone down to 3174 meaning its eliminating customer
s
```

Model Performance Comparison and Final Model Selection for decision tree

In [169]:
```
# training performance comparison

models_train_comp_df = pd.concat(
    [
        dtree1_train_perf.T,
        dtree2_train_perf.T,
        dtree3_train_perf.T,
    ],
    axis=1,
)
models_train_comp_df.columns = [
    "Decision Tree (sklearn default)",
    "Decision Tree (Pre-Pruning)",
    "Decision Tree (Post-Pruning)",
]
print("Training performance comparison:")
models_train_comp_df

## got the code from the hands on notebooks
## so applying pruning methods really helps the model learn better and yield b
etter results
```

```
Training performance comparison:
```

Out[169]:

	Decision Tree (sklearn default)	Decision Tree (Pre-Pruning)	Decision Tree (Post-Pruning)
Accuracy	1.0	0.976000	0.980750
Recall	1.0	0.789062	0.835938
Precision	1.0	0.952830	0.958209
F1	1.0	0.863248	0.892907

In [98]:
```
# testing performance comparison

models_test_comp_df = pd.concat(
    [
        dtree1_test_perf.T,
        dtree2_test_perf.T,
        dtree3_test_perf.T,
    ],
    axis=1,
)
models_test_comp_df.columns = [
    "Decision Tree (sklearn default)",
    "Decision Tree (Pre-Pruning)",
    "Decision Tree (Post-Pruning)",
]
print("Test set performance comparison:")
models_test_comp_df

## got the code from the hands on notebooks
## model was overfitting but since pruning it has not
## it has the highest f1 score
## this is getting the best balance between training and test performance
```

```
Test set performance comparison:
```

Out[98]:

	Decision Tree (sklearn default)	Decision Tree (Pre-Pruning)	Decision Tree (Post-Pruning)
Accuracy	0.966000	0.974000	0.976000
Recall	0.895833	0.854167	0.885417
Precision	0.781818	0.872340	0.867347
F1	0.834951	0.863158	0.876289

Actionable Insights and Business Recommendations

- What recommedations would you suggest to the bank?

In [ ]:
```
# Primary High-Value Segments:

# Higher Income Customers
# Customers with annual incomes above $113,500 show significantly higher loan conversion rates
# This segment should be the highest priority target group


# Education & Income Combination
# Customers with advanced/professional degrees combined with higher income
# These customers likely have stable careers with growth potential and financial elegance, so theyll spend more


# Credit Card Power Users
# Customers with monthly credit card spending above $4.5K
# These customers are already comfortable with financial products and show spending capacity



# Secondary Opportunity Segments:

# Mortgage Holders with Moderate-to-High Income
# Customers who already have mortgages between $175K-$300K
# These customers are familiar with loan products and have established credit histories


# Family-Oriented Customers
# Customers with families of 3+ members and moderate-to-high income
# These customers may have more diverse financial needs including college planning


# Digital Banking Users
# Customers who use online banking services
# These customers are easier to reach through digital campaigns and typically more approachable



# Recommended Campaign Strategies

# Personalized Loan Offerings
# Create tiered loan products aligned with income brackets
# Tailor interest rates and terms based on customer profiles
# Emphasize benefits relevant to each segment's specific needs


# Multi-Channel Approach
# For digital banking users: targeted online promotions and app notifications
# For higher income/education segments: personalized banker consultations
# For credit card users: integrated offers with existing credit products
```

```
# Education-Based Marketing
# Develop educational content around smart borrowing and financial planning
# Host exclusive financial planning webinars for high-potential segments
# Position loans as strategic financial tools rather than just debt products


# Timing Optimization
# Target mortgage holders when they're approximately 2-3 years into their mort
gage
# Consider seasonal campaign timing for family-oriented customers
# Align with periods of higher credit card usage for the CCAvg segment
```