CS 372

Assignment 2 - Decision Trees

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- Brandon L'Abbe
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Exploratory Data Analysis (Grace Biggs)

We begin this Decision Tree assignment by parsing the provided XLSX file into a Pandas dataframe for future modification. Our target feature is the binary Personal Loan field, denoting whether a customer accepted a personal loan offer during the bank's last campaign. Besides that, our other features are:

- Binary: Personal Loan, Securities Account, CD Account, Online, Credit Card
- Continuous: Age, Experience, Income, CCAvg, Mortgage
- Ordinal: Family
- Categorical: Education
- Other: ZIP Code

We drop the ID column per the assignment instructions as it contains no useful information. Similar to the ID, the ZIP Code feature is also of dubious use in constructing a Decision Tree - while it may encode some useful information regarding a customer's geoeconomic status, we would need to treat it as a broad categorical feature with dozens if not hundreds of sparsely-populated categories that may not generalize well. As we'll see later, there is also an extremely high correlation between the Age and Experience features, and we could theoretically drop one or the other from our dataframe safely, but will leave them in for the sake of posterity.

There are no duplicates in the dataframe, and just 6 missing values. Because only 6 rows out of 5000 (0.12%) are missing data, we can safely drop the rows with missing values.

In [1]:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

df = pd.read_excel('Personal Loan Data_DT.xlsx', sheet_name='Data')
df = df.drop(columns=['ID']) # Drop ID column - provides no useful info.
# df = df.drop(columns=['Age']) # Extremely high correlation between Age and Experience. Drop Age?

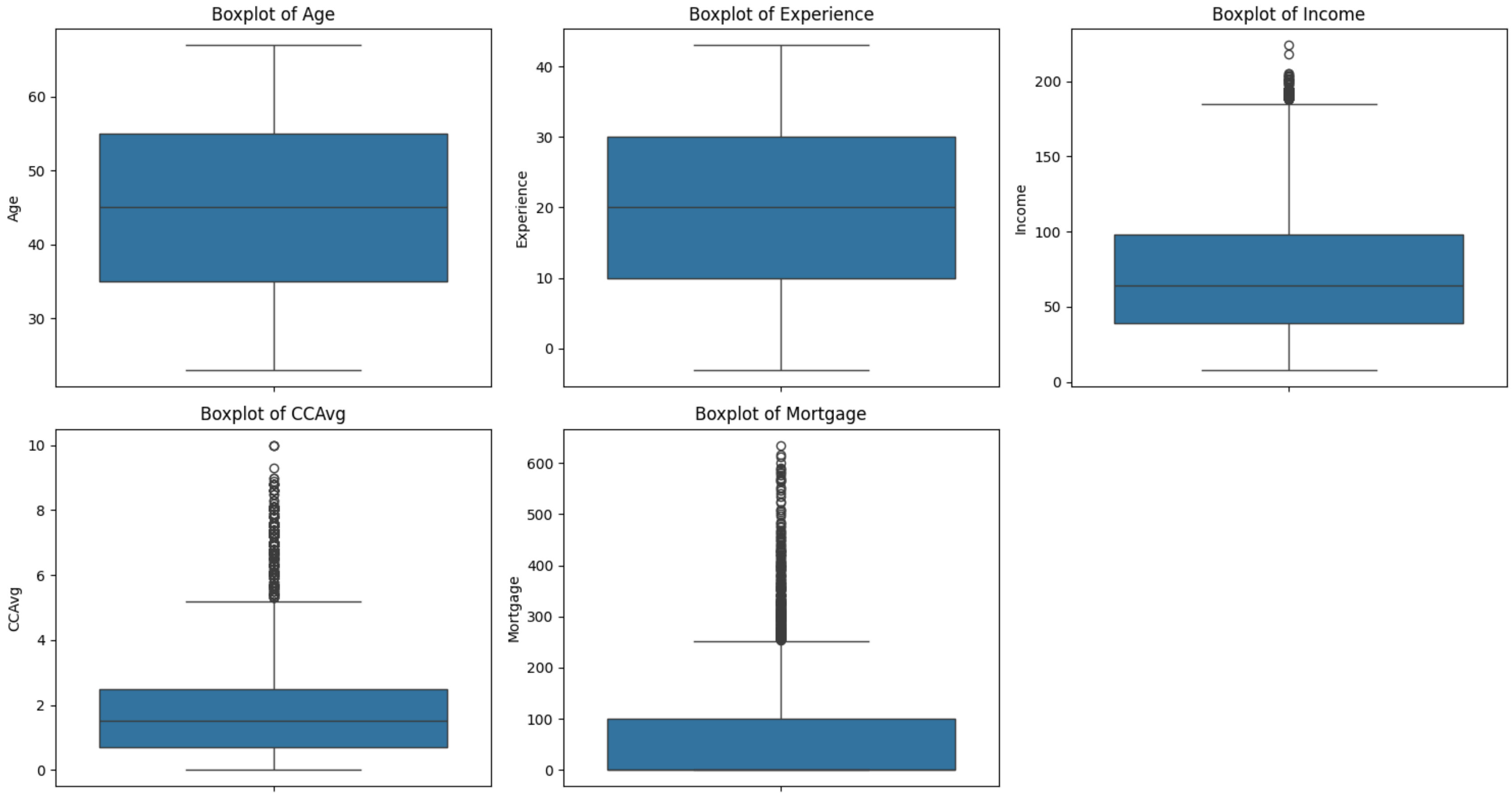
print("First 10 rows in Dataframe: ")
print(df.head(10))
print("Number of Duplicates: ")
print(df.duplicated().sum()) # 0 duplicates.
print("Number of missing values: ")
print(df.isnull().sum()) # 2 missing experience, 4 missing education
# We're making a Decision Tree from this dataset of 5000 rows. Because only 6 rows (0.12%) are missing data, we can s
df = df.dropna()
```

```
First 10 rows in Dataframe:
   Age  Experience  Income  ZIP Code  Family  CCAvg  Education  Mortgage  \
0   47        23.0     148     94551       2    7.5  Undergrad         0
1   48        24.0      71     93117       2    1.7  Undergrad       145
2   62        37.0      58     91320       4    1.7  Undergrad         0
3   57        32.0      28     95831       3    0.2  Undergrad         0
4   51        26.0      70     90089       1    1.2  Undergrad       169
5   41        17.0      78     94025       4    0.8  Undergrad        78
6   55        29.0      99     92121       2    1.4  Undergrad       264
7   65        40.0      53     91711       3    2.2  Undergrad         0
8   47        21.0     138     94583       1    0.0  Undergrad         0
9   66        41.0      18     92691       3    0.5  Undergrad         0

   Personal Loan  Securities Account  CD Account  Online  CreditCard
0              0                   0           1       1           1
1              0                   0           0       0           1
2              0                   0           0       1           0
3              0                   0           0       1           1
4              0                   0           0       0           0
5              0                   0           0       1           0
6              0                   0           0       1           1
7              0                   0           0       0           1
8              0                   0           0       0           0
9              0                   0           0       0           1
Number of Duplicates:
0
Number of missing values:
Age                   0
Experience            2
Income                0
ZIP Code              0
Family                0
CCAvg                 0
Education             4
Mortgage              0
Personal Loan         0
Securities Account    0
CD Account            0
Online                0
CreditCard            0
dtype: int64
```

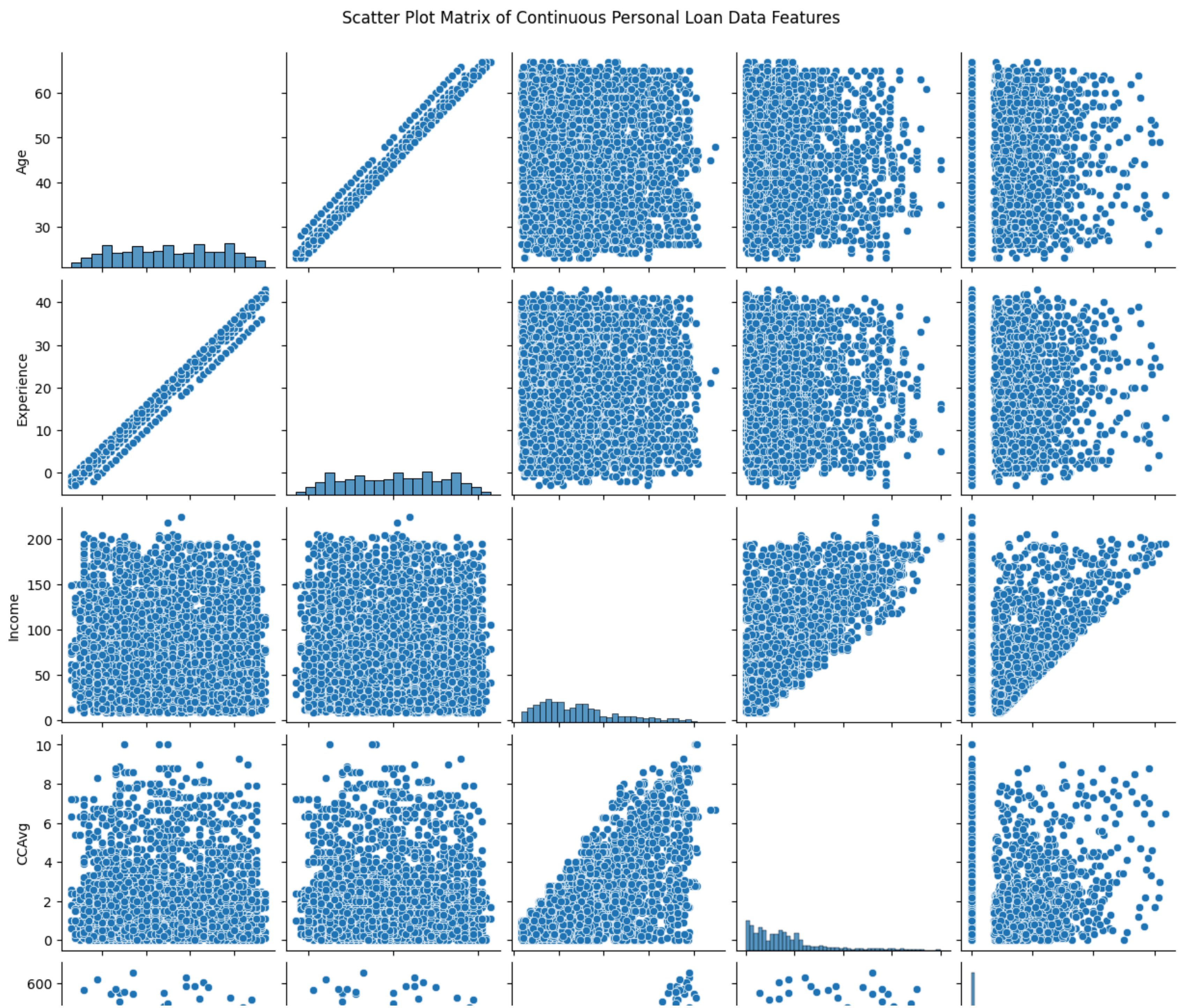
Next up, we check for outliers by creating boxplots of the continuous variables in the dataframe. Age and Experience do not contain outliers, while Income, CCAvg, and Mortgage predictably contain wealthy/indebted outliers as their values grow further from 0. Because we split the decision tree based on purity and not the distance between feature values, we don't need to do anything special as far as preprocessing for outliers goes. What we *do* need to be conscious of later is overfitting and pruning, but for now that's not an issue, and so we'll leave the outliers alone.

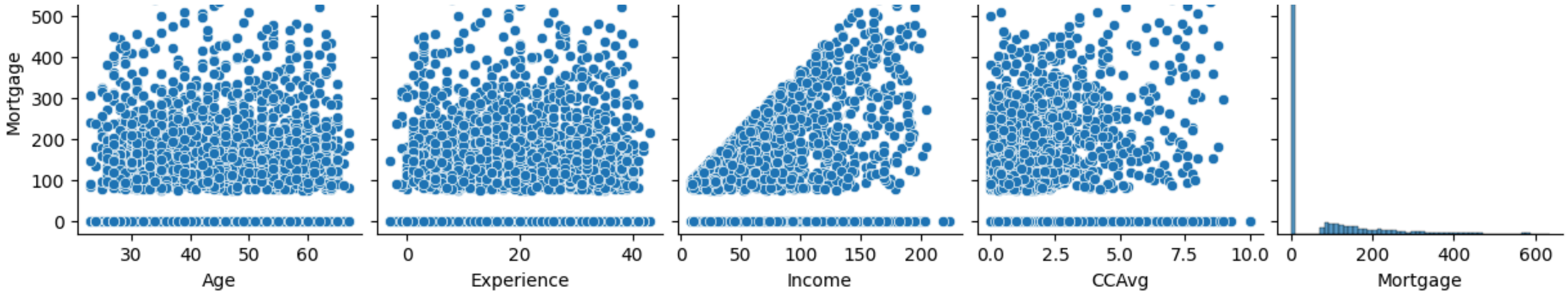
In [2]:
```
# Check for outliers with Boxplots.
continuous_vars = ['Age', 'Experience', 'Income', 'CCAvg', 'Mortgage']
plt.figure(figsize=(15,8))
for i, col in enumerate(continuous_vars, 1):
    plt.subplot(2, 3, i)
    sns.boxplot(y=df[col])
    plt.title(f'Boxplot of {col}')
plt.tight_layout()
plt.show()
```



Next, a scatter plot matrix of the continuous variables. As mentioned earlier, Age and Experience are *very* linearly correlated and we could probably drop one or the other from the dataframe without issue, but won't for posterity. Income seems moderately correlated to CCAvg and Mortgage. Everything else looks too noisy to draw strong conclusions about.

In [3]:
```
# Draw scatter plot matrix for all features. Comment.
sns.pairplot(df[continuous_vars])
plt.suptitle('Scatter Plot Matrix of Continuous Personal Loan Data Features', y=1.02)
plt.show()
```


Scatter Plot Matrix of Continuous Personal Loan Data Features
Age
Experience
Income
CCAvg
60
50
40
30
40
30
20
10
0
200
150
100
50
0
10
8
6
4
2
0
600



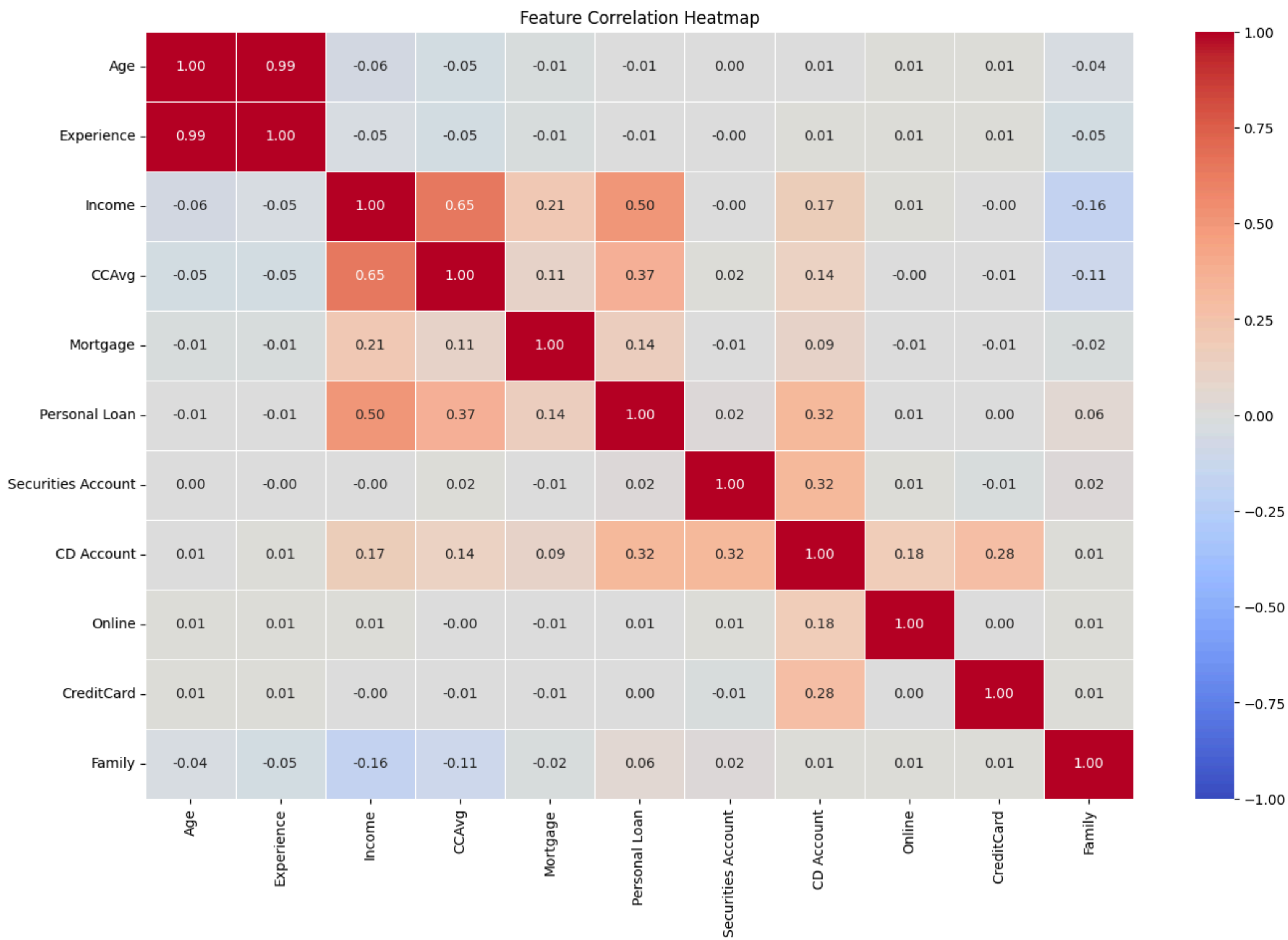
Finally, a heatmap plot between all of our continuous, binary, and ordinal features. Besides the obvious correlation between Age and Experience, the next-hottest correlation is between Income and CCAvg. Looking at the Personal Loan correlations, we can see that the most important features influencing whether a customer accepts a loan are their Income, CCAvg, CD Account, and Mortgage. CD Account in particular is in turn positively correlated with other features like Securities Account, Online, and CreditCard. On the flip side, Family has the chilliest relationship with other features out of any of them, with the most notable negative correlation being between Family and Income.

By this heatmap, we should expect our Decision Tree to look at the Income, CCAvg, Mortgage, and CD Account features when predicting if a customer will accept a Personal Loan, and by extension, it may also look closely at features associated with CD Accounts as well.

In [4]:

```
# Draw a heatmap plot between features. Comment.
binary_vars = ['Personal Loan', 'Securities Account', 'CD Account', 'Online', 'CreditCard']
ordinal_vars = ['Family']
numeric_vars = continuous_vars + binary_vars + ordinal_vars

plt.figure(figsize=(16,10))
sns.heatmap(df[numeric_vars].corr(), annot=True, fmt=".2f",
            cmap='coolwarm', vmin=-1, vmax=1, linewidths=0.5)
plt.title('Feature Correlation Heatmap')
plt.show()
```



Decision Trees (Brandon L'Abbe, Lane Thompson)

In [5]:

```
import sklearn.compose
import sklearn.model_selection
import sklearn.tree

import time

X = df.drop(columns=['Personal Loan'])
y = df['Personal Loan']
# Convert categorical columns into one-hots with ColumnTransformer()
ct = sklearn.compose.ColumnTransformer(
    transformers=[('cat', sklearn.preprocessing.OneHotEncoder(drop='first'), ['Education'])],
    remainder='passthrough'
)
state_value = 42
# Apply the transformation to the features
X_processed = ct.fit_transform(X)
# split the data into training and validation sets
data_train, data_test, label_train, label_test = sklearn.model_selection.train_test_split(X_processed, y, test_size=(

# Build and compare two Decision Trees, based on Gini Impurity and Entropy.
start = time.time()
gini_tree = sklearn.tree.DecisionTreeClassifier(criterion='gini',random_state=state_value)
gini_tree.fit(data_train, label_train)
end = time.time()
gini_train_time = end - start
print("Time taken to train Gini Tree: ", gini_train_time)
print("Gini Tree Score: ", gini_tree.score(data_test, label_test))
start = time.time()
entropy_tree = sklearn.tree.DecisionTreeClassifier(criterion='entropy',random_state=state_value)
entropy_tree.fit(data_train, label_train)
end = time.time()
entropy_train_time = end - start
print("Time taken to train Entropy Tree: ", entropy_train_time)
print("Entropy Tree Score: ", entropy_tree.score(data_test, label_test))


# Visualize the fully-grown Decision Trees you built with a tree graph.
# Include the feature name in the visualization of the trees, not the index of the feature.
plt.figure(figsize=(35,15))
sklearn.tree.plot_tree(gini_tree, fontsize=7, feature_names=df.columns, class_names=["Decline", "Accept"], label='roo
```

```
plt.figure(figsize=(35,18))
sklearn.tree.plot_tree(entropy_tree, fontsize=10, feature_names=df.columns, class_names=["Decline", "Accept"], label=
```

```
Time taken to train Gini Tree:  0.006129264831542969
Gini Tree Score:  0.974974974974975
Time taken to train Entropy Tree:  0.005070924758911133
Entropy Tree Score:  0.972972972972973
```

```
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```
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```

```
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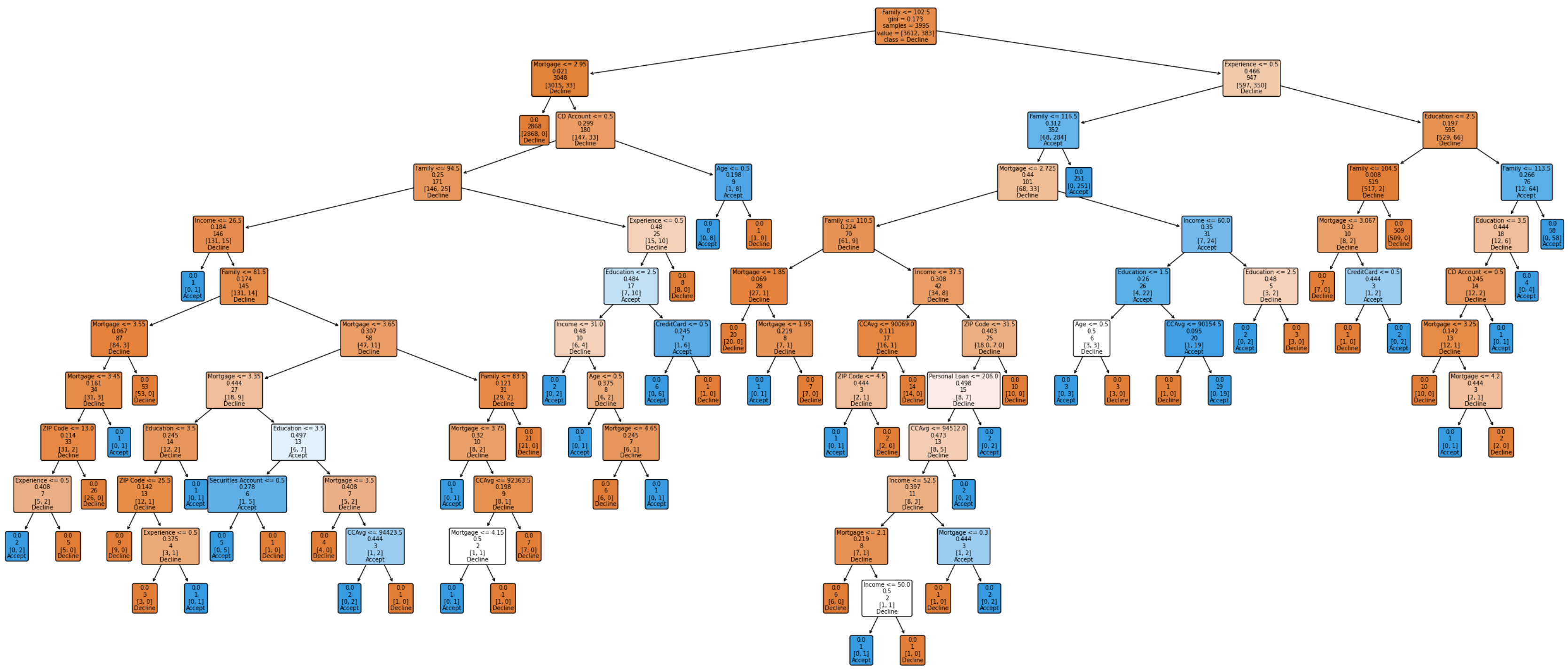
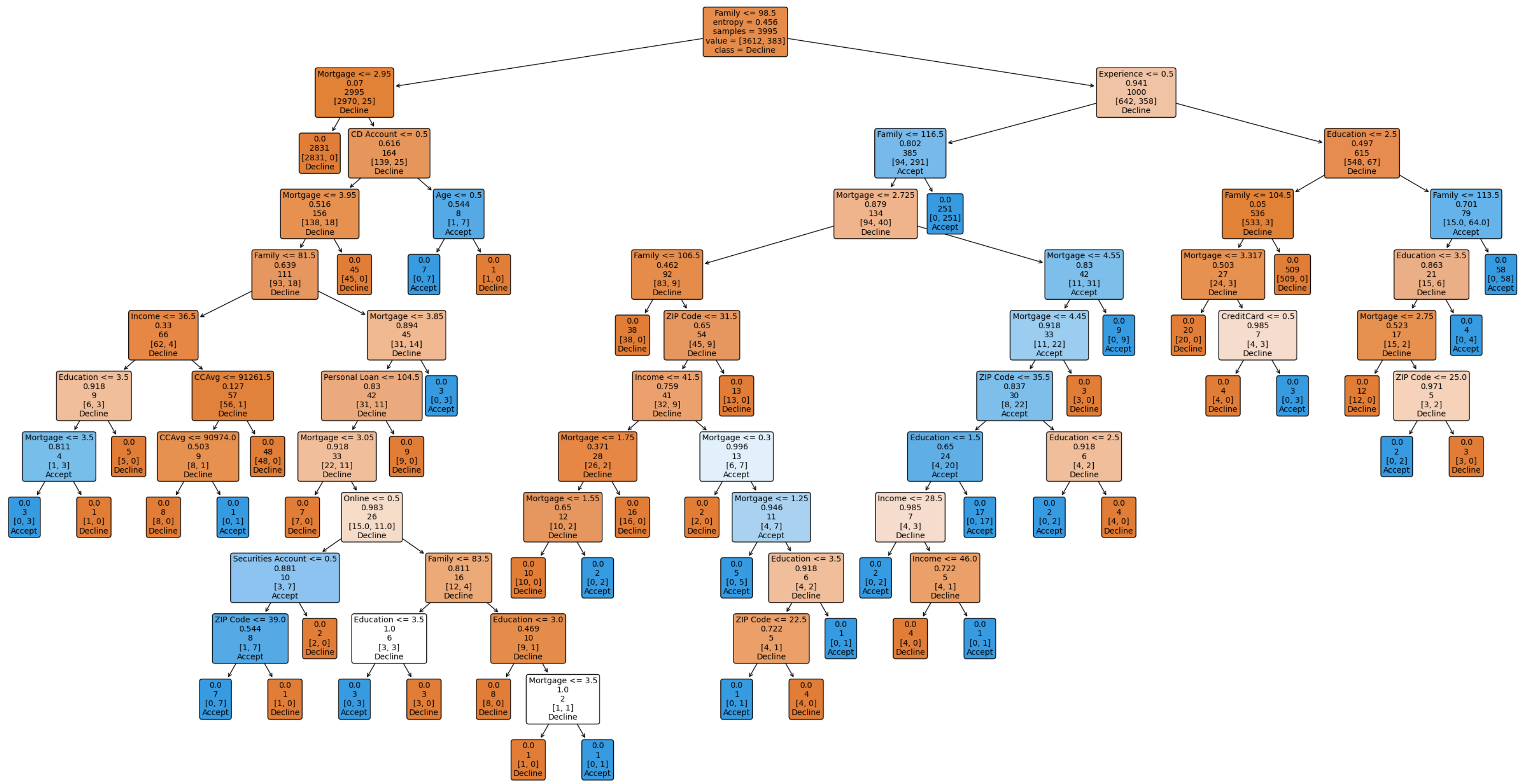
```





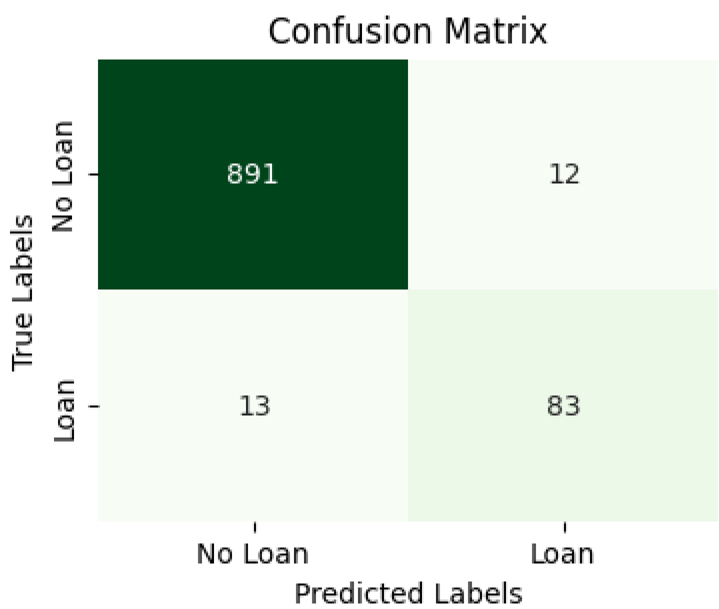
Model Evaluation (Lane Thompson)

- Evaluate the performance of your classifier using:
  - execution time
  - accuaracy
  - confusion matrix (comment on the results)
- Analyze, explain, and comment on the evaluation results
- How does the Number of training sample affect performance (accuracy, time, etc.)? Explain and draw graphs to support your claims.

Gini Impurity

In [6]:
```python
## Evaluate the performance of your classifier using:
# execution time
import time
import sklearn

start = time.time()
label_prediction = gini_tree.predict(data_test)
end = time.time()
gini_test_time = end - start
print(f"Execution time: {gini_test_time:.4f} seconds")
# accuracy
accuracy = sklearn.metrics.accuracy_score(label_test, label_prediction)
print(f"Accuracy: {accuracy:.4f}")
# confusion matrix
confusion_matrix = sklearn.metrics.confusion_matrix(label_test, label_prediction)
print("Confusion Matrix:")
plt.figure(figsize=(4, 3))
sns.heatmap(sklearn.metrics.confusion_matrix(label_test, label_prediction),
            annot=True, fmt='d', cmap='Greens', cbar=False,
            xticklabels=['No Loan', 'Loan'], yticklabels=['No Loan', 'Loan'])
plt.xlabel("Predicted Labels")
plt.ylabel("True Labels")
plt.title("Confusion Matrix")
plt.show()
```

```
Execution time: 0.0006 seconds
Accuracy: 0.9750
Confusion Matrix:
```

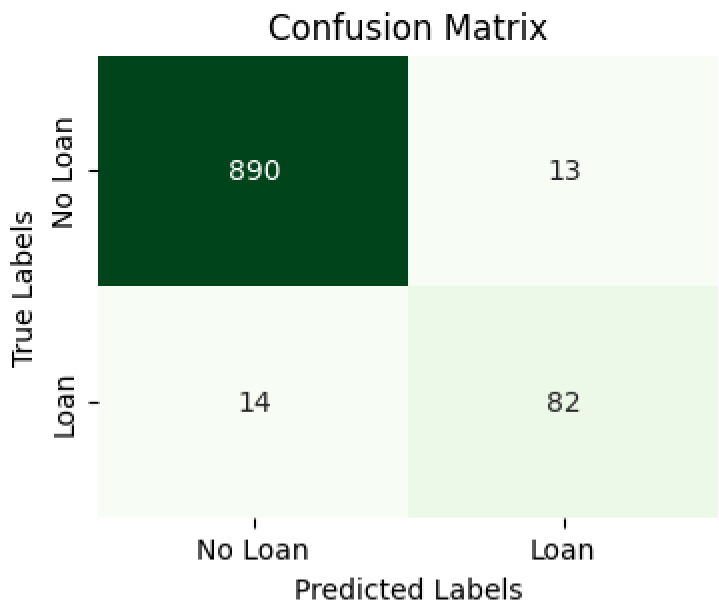


Entropy

In [7]:
```
## Evaluate the performance of your classifier using:
# execution time
import time
import sklearn

start = time.time()
label_prediction = entropy_tree.predict(data_test)
end = time.time()
entropy_test_time = end - start
print(f"Execution time: {entropy_test_time:.4f} seconds")
# accuracy
accuracy = sklearn.metrics.accuracy_score(label_test, label_prediction)
print(f"Accuracy: {accuracy:.4f}")
# confusion matrix
confusion_matrix = sklearn.metrics.confusion_matrix(label_test, label_prediction)
print("Confusion Matrix:")
plt.figure(figsize=(4, 3))
sns.heatmap(sklearn.metrics.confusion_matrix(label_test, label_prediction),
            annot=True, fmt='d', cmap='Greens', cbar=False,
            xticklabels=['No Loan', 'Loan'], yticklabels=['No Loan', 'Loan'])
```

```python
plt.xlabel("Predicted Labels")
plt.ylabel("True Labels")
plt.title("Confusion Matrix")
plt.show()
```

```
Execution time: 0.0010 seconds
Accuracy: 0.9730
Confusion Matrix:
```



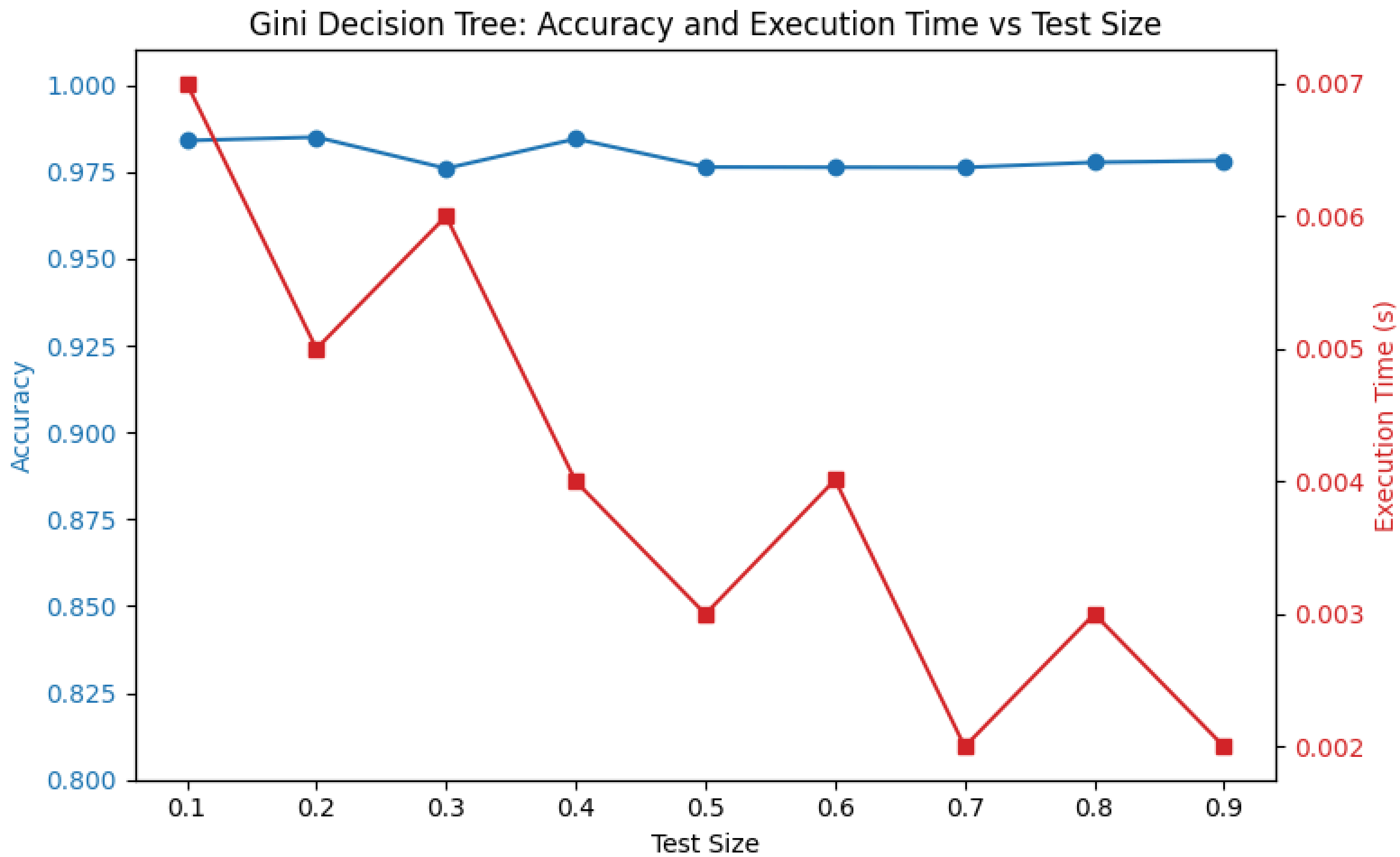
In [8]:
```python
from sklearn.model_selection import train_test_split

def split_and_test(X, y, test_size=0.5, random_state=None, tree_type='gini'):
    X_train, X_test = train_test_split(X, test_size=test_size, random_state=random_state)
    y_train, y_test = train_test_split(y, test_size=test_size, random_state=random_state)

    start = time.time()
    tree = sklearn.tree.DecisionTreeClassifier(criterion=tree_type, random_state=random_state)
    tree.fit(X_train, y_train)
    score = sklearn.metrics.accuracy_score(tree.predict(X_test), y_test)
    end = time.time()
    test_time = end - start

    return test_time, score
```

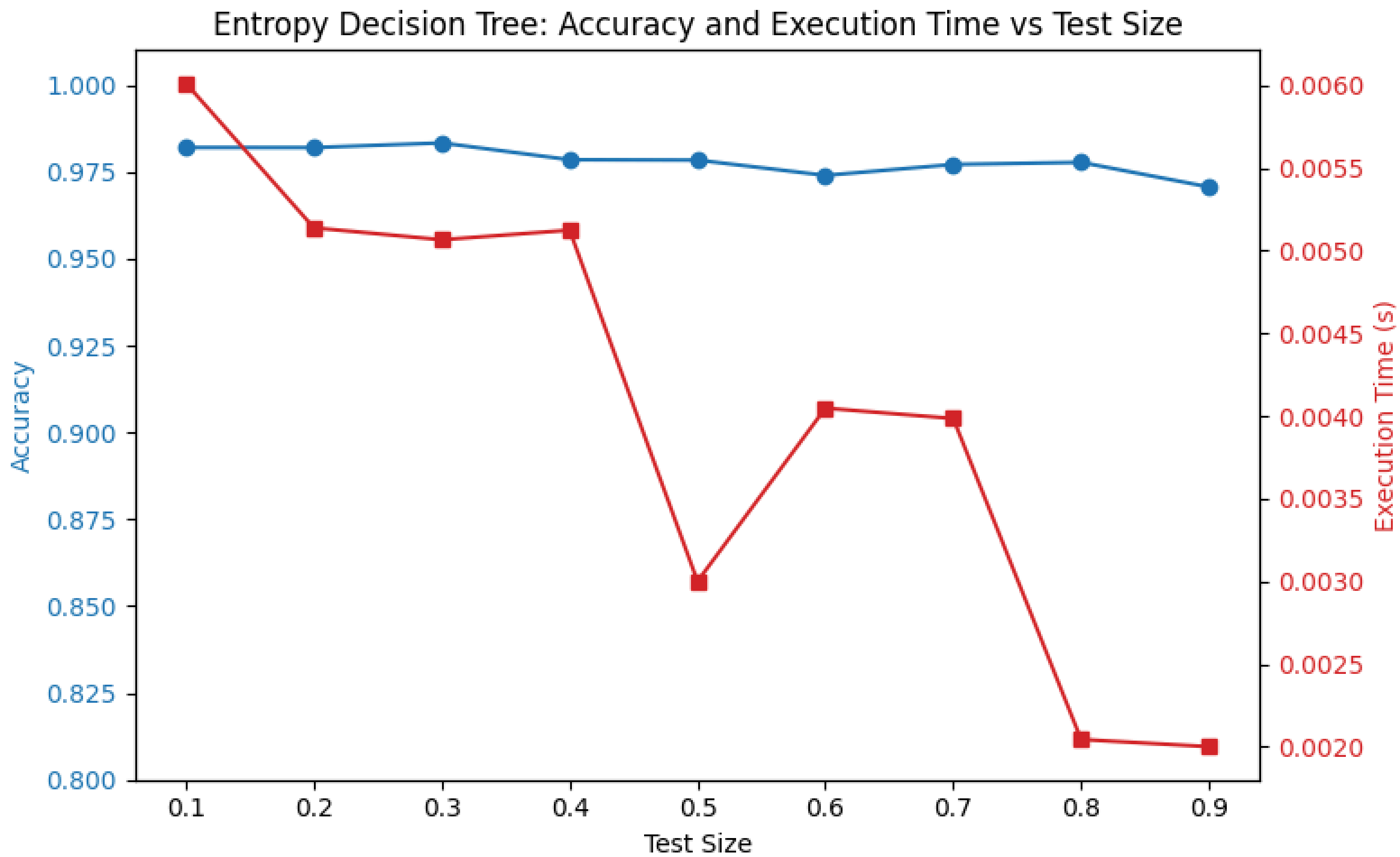
```python
class tests:
    def __init__(self, data, labels, test_sizes, random_state, tree_type):
        self.data = data
        self.labels = labels
        self.test_sizes = test_sizes
        self.random_state = random_state
        self.tree_type = tree_type
        self.results = []

        for test_size in self.test_sizes:
            train_time, score = split_and_test(data, labels, test_size=test_size, random_state=self.random_state, tre
            self.results.append((train_time, score))

test_sizes = [0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9]
random_state = 42
gini_tests = tests(X_processed, y, test_sizes, random_state, 'gini')
entropy_tests = tests(X_processed, y, test_sizes, random_state, 'entropy')
```

In [9]:

```python
# Plot the accuracy and execution time of the gini decision tree for different test sizes
gini_times = [result[0] for result in gini_tests.results]
gini_scores = [result[1] for result in gini_tests.results]

fig, ax1 = plt.subplots(figsize=(8, 5))

color = 'tab:blue'
ax1.set_xlabel('Test Size')
ax1.set_ylabel('Accuracy', color=color)
ax1.plot(test_sizes, gini_scores, marker='o', color=color, label='Accuracy')
ax1.tick_params(axis='y', labelcolor=color)
ax1.set_ylim(0.8, 1.01)

ax2 = ax1.twinx()
color = 'tab:red'
ax2.set_ylabel('Execution Time (s)', color=color)
ax2.plot(test_sizes, gini_times, marker='s', color=color, label='Execution Time')
ax2.tick_params(axis='y', labelcolor=color)

plt.title('Gini Decision Tree: Accuracy and Execution Time vs Test Size')
fig.tight_layout()
plt.show()
```

```python
# Plot the accuracy and execution time of the entropy decision tree for different test sizes
entropy_times = [result[0] for result in entropy_tests.results]
entropy_scores = [result[1] for result in entropy_tests.results]

fig, ax1 = plt.subplots(figsize=(8, 5))

color = 'tab:blue'
ax1.set_xlabel('Test Size')
ax1.set_ylabel('Accuracy', color=color)
ax1.plot(test_sizes, entropy_scores, marker='o', color=color, label='Accuracy')
ax1.tick_params(axis='y', labelcolor=color)
ax1.set_ylim(0.8, 1.01)

ax2 = ax1.twinx()
color = 'tab:red'
ax2.set_ylabel('Execution Time (s)', color=color)
ax2.plot(test_sizes, entropy_times, marker='s', color=color, label='Execution Time')
ax2.tick_params(axis='y', labelcolor=color)

plt.title('Entropy Decision Tree: Accuracy and Execution Time vs Test Size')
fig.tight_layout()
plt.show()
```

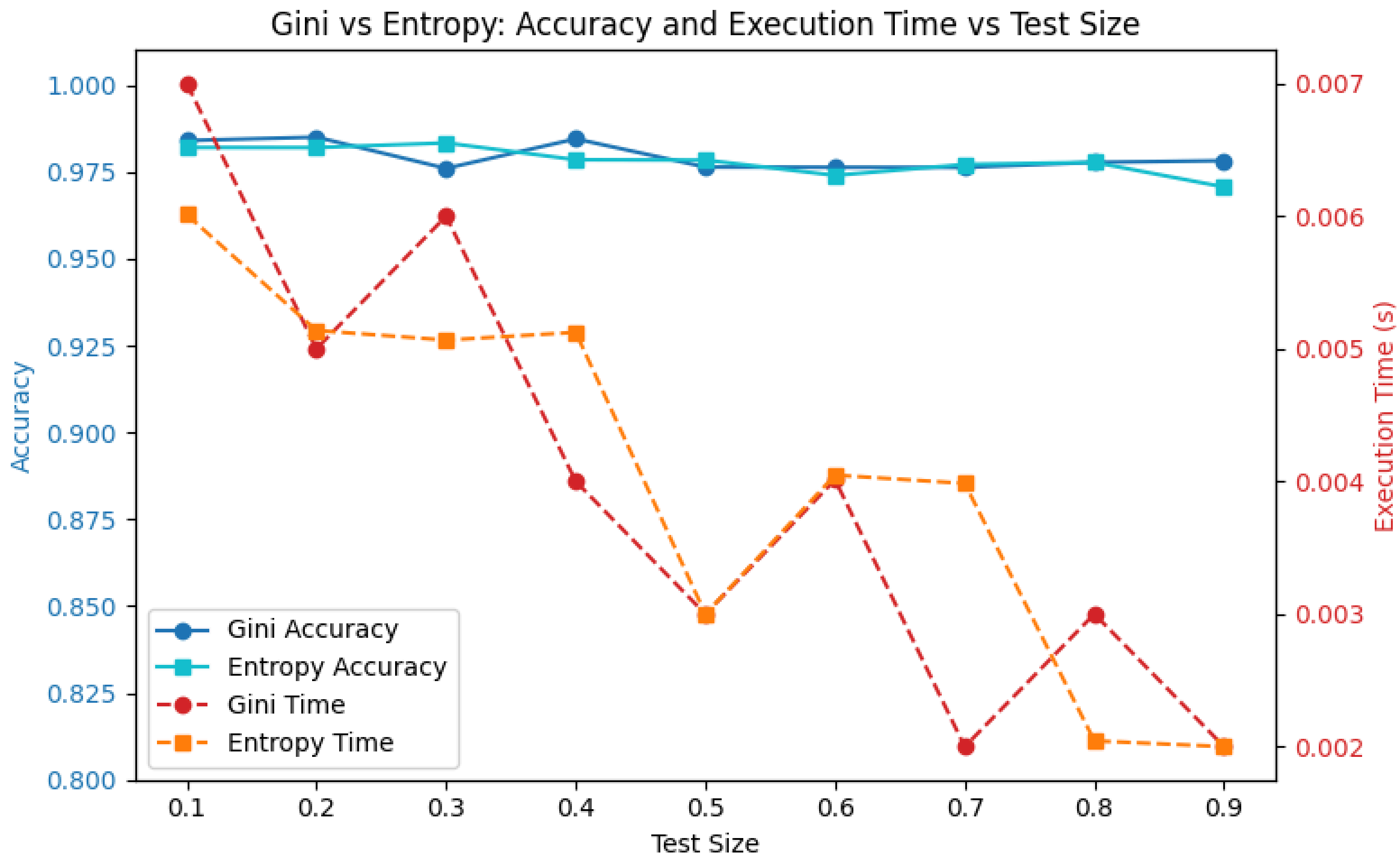

Gini Decision Tree: Accuracy and Execution Time vs Test Size
Accuracy
Execution Time (s)
Test Size
1.000
0.975
0.950
0.925
0.900
0.875
0.850
0.825
0.800
0.007
0.006
0.005
0.004
0.003
0.002
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9



In [10]:

```
fig, ax1 = plt.subplots(figsize=(8, 5))

# Accuracy plot
ax1.set_xlabel('Test Size')
ax1.set_ylabel('Accuracy', color='tab:blue')
ax1.plot(test_sizes, gini_scores, marker='o', color='tab:blue', label='Gini Accuracy')
ax1.plot(test_sizes, entropy_scores, marker='s', color='tab:cyan', label='Entropy Accuracy')
ax1.tick_params(axis='y', labelcolor='tab:blue')
ax1.set_ylim(0.8, 1.01)

# Execution time plot
ax2 = ax1.twinx()
```

```python
ax2.set_ylabel('Execution Time (s)', color='tab:red')
ax2.plot(test_sizes, gini_times, marker='o', linestyle='--', color='tab:red', label='Gini Time')
ax2.plot(test_sizes, entropy_times, marker='s', linestyle='--', color='tab:orange', label='Entropy Time')
ax2.tick_params(axis='y', labelcolor='tab:red')

# Legends
lines_1, labels_1 = ax1.get_legend_handles_labels()
lines_2, labels_2 = ax2.get_legend_handles_labels()
ax1.legend(lines_1 + lines_2, labels_1 + labels_2, loc='lower left')

plt.title('Gini vs Entropy: Accuracy and Execution Time vs Test Size')
fig.tight_layout()
plt.show()
```


Gini vs Entropy: Accuracy and Execution Time vs Test Size
Accuracy
Execution Time (s)
Test Size
1.000
0.975
0.950
0.925
0.900
0.875
0.850
0.825
0.800
0.007
0.006
0.005
0.004
0.003
0.002
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
Gini Accuracy
Entropy Accuracy
Gini Time
Entropy Time

Analyze, explain, and comment on the evaluation results

How does the Number of training sample affect performance (accuracy, time, etc.)? Explain and draw graphs to support your claims.

Changing the percentage of the test-train split has an interesting performance effect. While I would have expected Gini to be a more faster, it took longer to train and predict than entropy in almost all cases.

The difference in accuracy between the two models seems non-significent. Looking at the confusion matrices, it shows that both models were accurate with little difference between them. Additionally, there was little difference in the number of false negatives to false positives, and each model leaned in opposite directions for their incorrect classifications.

Tree Pruning (Grace Biggs)

Below, we take our Gini and Entropy trees and post-prune them with a few different techniques - limiting the maximum depth, setting the minimum number of samples needed to split on a node, and cost complexity pruning to remove nodes with low alpha values. To find the best depth limit, the minimum number of samples, and the ideal alpha value we should use, we take advantage of 5-fold cross validation - more specifically, scikit-learn's GridSearchCV function, which performs cross validation on models based on parameters you give it to iterate through and find the best value for.

In [16]:

```
# Model training
from sklearn.tree import DecisionTreeClassifier # https://scikit-learn.org/stable/modules/generated/sklearn.tree.Deci
from sklearn.model_selection import GridSearchCV, cross_val_score # https://scikit-learn.org/stable/modules/generated
# GridSearchCV is a function that performs Cross Validation on models based on some parameters you
#  give it to iterate through and find the best value for (e.g., max depth, min samples).
# https://stackoverflow.com/questions/35097003/cross-validation-decision-trees-in-sklearn
# gini_tree and entropy_tree
# data_train/data_test/label_train/label_test

# Max Depth 5-fold Cross Validation
params = {'max_depth': range(1, 21)}
grid_search = GridSearchCV(
    DecisionTreeClassifier(criterion='gini', random_state=state_value),
    params,
    cv=5,
    scoring='accuracy'
)
grid_search.fit(data_train, label_train) # Best to do CV on training set.
```

```
depth_gini = grid_search.best_estimator_
print(depth_gini)

grid_search = GridSearchCV(
    DecisionTreeClassifier(criterion='entropy', random_state=state_value),
    params,
    cv=5,
    scoring='accuracy'
)
grid_search.fit(data_train, label_train) # Best to do CV on training set.
depth_entropy = grid_search.best_estimator_
print(depth_entropy)

# Minimum-Sample 5-fold Cross Validation
params = {'min_samples_leaf': range(1, 101, 5)}
grid_search = GridSearchCV(
    DecisionTreeClassifier(criterion='gini', random_state=state_value),
    params,
    cv=5,
    scoring='accuracy'
)
grid_search.fit(data_train, label_train)
minsamp_gini = grid_search.best_estimator_
print(minsamp_gini)

grid_search = GridSearchCV(
    DecisionTreeClassifier(criterion='entropy', random_state=state_value),
    params,
    cv=5,
    scoring='accuracy'
)
grid_search.fit(data_train, label_train)
minsamp_entropy = grid_search.best_estimator_
print(minsamp_entropy)

# Cost Complexity Pruning
# https://scikit-learn.org/stable/auto_examples/tree/plot_cost_complexity_pruning.html#sphx-glr-auto-examples-tree-pl
ccp_base_gini = DecisionTreeClassifier(criterion='gini', random_state=state_value)
path = ccp_base_gini.cost_complexity_pruning_path(data_train, label_train)
ccp_alphas, impurities = path.ccp_alphas[:-1], path.impurities[:-1] # Remove the max-effective alpha value since it's
params = {'ccp_alpha': ccp_alphas}
grid_search = GridSearchCV(
```

```python
    DecisionTreeClassifier(criterion='gini', random_state=state_value),
    params,
    cv=5,
    scoring='accuracy'
)
grid_search.fit(data_train, label_train)
ccp_gini = grid_search.best_estimator_
print(ccp_gini)

ccp_base_entropy = DecisionTreeClassifier(criterion='entropy', random_state=state_value)
path = ccp_base_entropy.cost_complexity_pruning_path(data_train, label_train)
ccp_alphas, impurities = path.ccp_alphas[:-1], path.impurities[:-1] # Remove the max-effective alpha value since it's
params = {'ccp_alpha': ccp_alphas}
grid_search = GridSearchCV(
    DecisionTreeClassifier(criterion='entropy', random_state=state_value),
    params,
    cv=5,
    scoring='accuracy'
)
grid_search.fit(data_train, label_train)
ccp_entropy = grid_search.best_estimator_
print(ccp_entropy)
```

```
DecisionTreeClassifier(max_depth=5, random_state=42)
DecisionTreeClassifier(criterion='entropy', max_depth=4, random_state=42)
DecisionTreeClassifier(random_state=42)
DecisionTreeClassifier(criterion='entropy', min_samples_leaf=21,
                       random_state=42)
DecisionTreeClassifier(ccp_alpha=0.0003960995200044014, random_state=42)
DecisionTreeClassifier(ccp_alpha=0.00237996980608475, criterion='entropy',
                       random_state=42)
```

Model Accuracy (Grace Biggs)

After building our pruned trees, we compare their accuracy and training and evaluation times against the fully-grown trees'. There are only negligible differences between each tree's accuracy - each at 97% - and all prediction times were so fast they've seemingly been confused for floating point errors and rounded down to 0. This leaves the training time as the only real metric that lets us glean information about the models' performance with the new pruning. Indeed, there's a major difference with the full entropy tree taking 0.006s to train, compared to the pruned entropy trees which average 0.0046s - nearly 25% faster. Of these, the minimum-sample entropy tree had the best performance of .004s, followed closely by the depth entropy tree. Looking at Gini, it seems the original tree was faster than any others, though the pruned trees aren't quite out of the running by virtue of being just *slightly* more accurate by fractions of a percent.

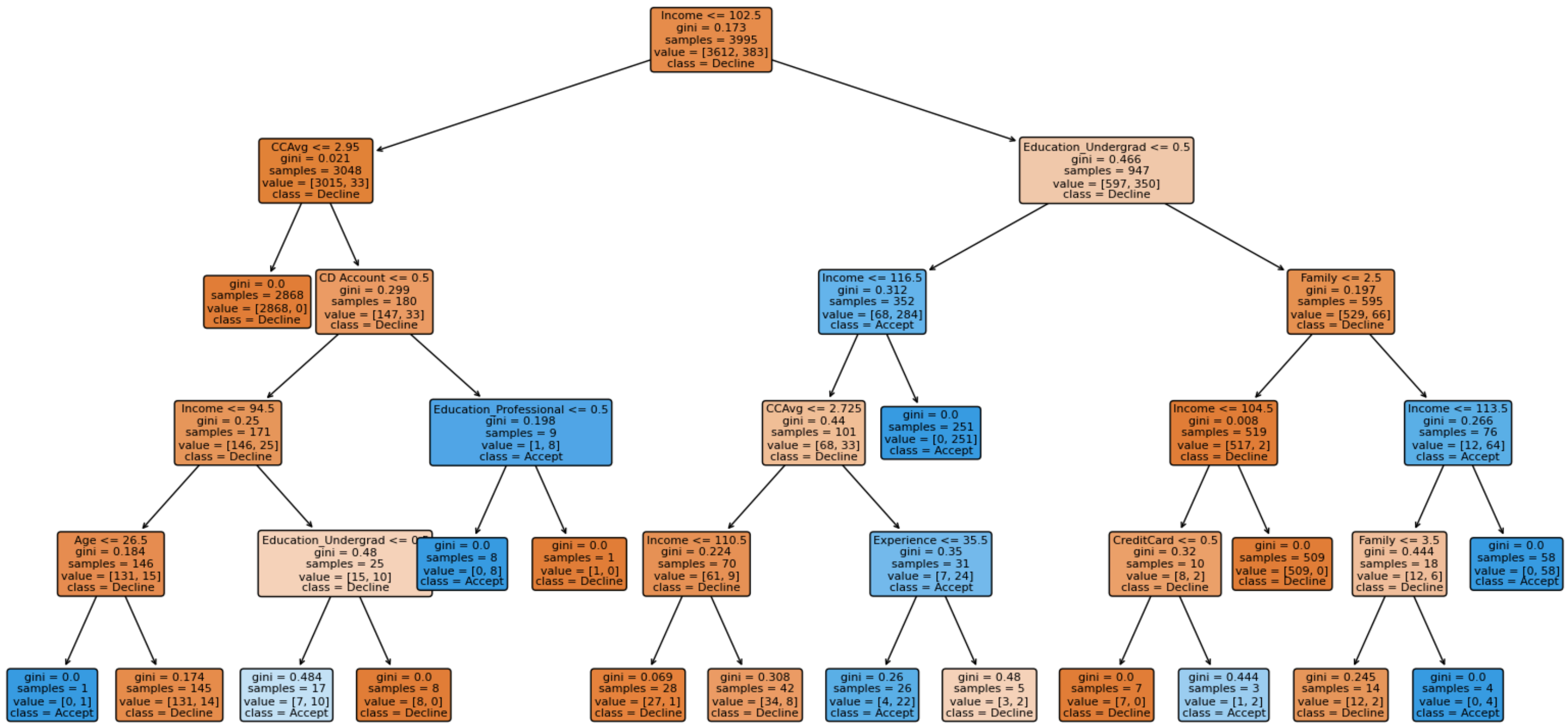
In [20]:
```python
models = {'depth_gini': depth_gini,
          'depth_entropy': depth_entropy,
          'minsamp_gini': minsamp_gini,
          'minsamp_entropy': minsamp_entropy,
          'ccp_gini': ccp_gini,
          'ccp_entropy': ccp_entropy,
          'gini_tree': gini_tree,
          'entropy_tree': entropy_tree
         }
metrics = {}

for label, model in models.items():
    start = time.time()
    model.fit(data_train, label_train)
    train_time = time.time() - start

    start = time.time()
    label_pred = model.predict(data_test)
    pred_time = time.time() - start

    accuracy = sklearn.metrics.accuracy_score(label_test, label_pred)

    metrics[label] = {'train_time': train_time,
                      'pred_time': pred_time,
                      'accuracy': accuracy
                     }

print(metrics)
```

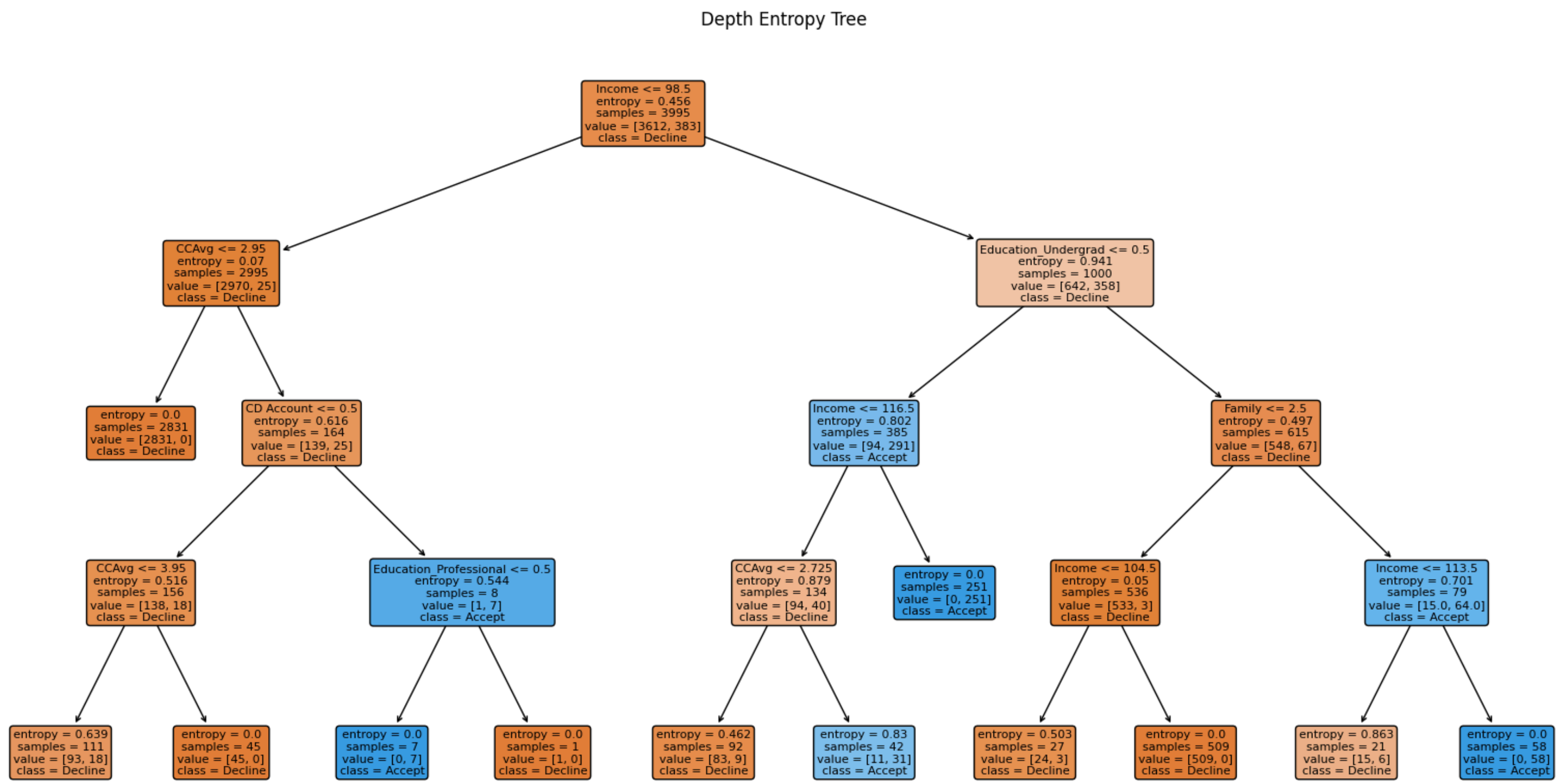

```
{'depth_gini': {'train_time': 0.004802703857421875, 'pred_time': 0.0, 'accuracy': 0.978978978978979}, 'depth_entrop
y': {'train_time': 0.004169940948486328, 'pred_time': 0.0, 'accuracy': 0.9769769769769769}, 'minsamp_gini': {'train_t
ime': 0.004183769226074219, 'pred_time': 0.0, 'accuracy': 0.974974974974975}, 'minsamp_entropy': {'train_time': 0.004
001617431640625, 'pred_time': 0.0, 'accuracy': 0.975975975975976}, 'ccp_gini': {'train_time': 0.004670619964599609,
'pred_time': 0.0, 'accuracy': 0.978978978978979}, 'ccp_entropy': {'train_time': 0.005681276321411133, 'pred_time': 0.
0, 'accuracy': 0.978978978978979}, 'gini_tree': {'train_time': 0.0039997100830078125, 'pred_time': 0.0, 'accuracy':
0.974974974974975}, 'entropy_tree': {'train_time': 0.00605320930480957, 'pred_time': 0.0, 'accuracy': 0.9729729729729
73}}
```

Finally, we plot our trees. The most immediate observation is that pruned Entropy trees tend to be significantly smaller than their Gini counterparts. Particularly, CCP Entropy is the smallest tree of them all, even compared to Gini Entropy. Minsamp Gini also resembes the original Gini tree closely, in a way that the Minsamp and Original Entropy trees don't, and it's also just way busier than Minsamp Entropy. Overall, Entropy seems to encourage aggressive pruning in a way that Gini doesn't, CCP Entropy is the smallest tree at the cost of a few fractions of a second of training time, and all the trees' test performance is comparable. Seems Entropy is the winner here!

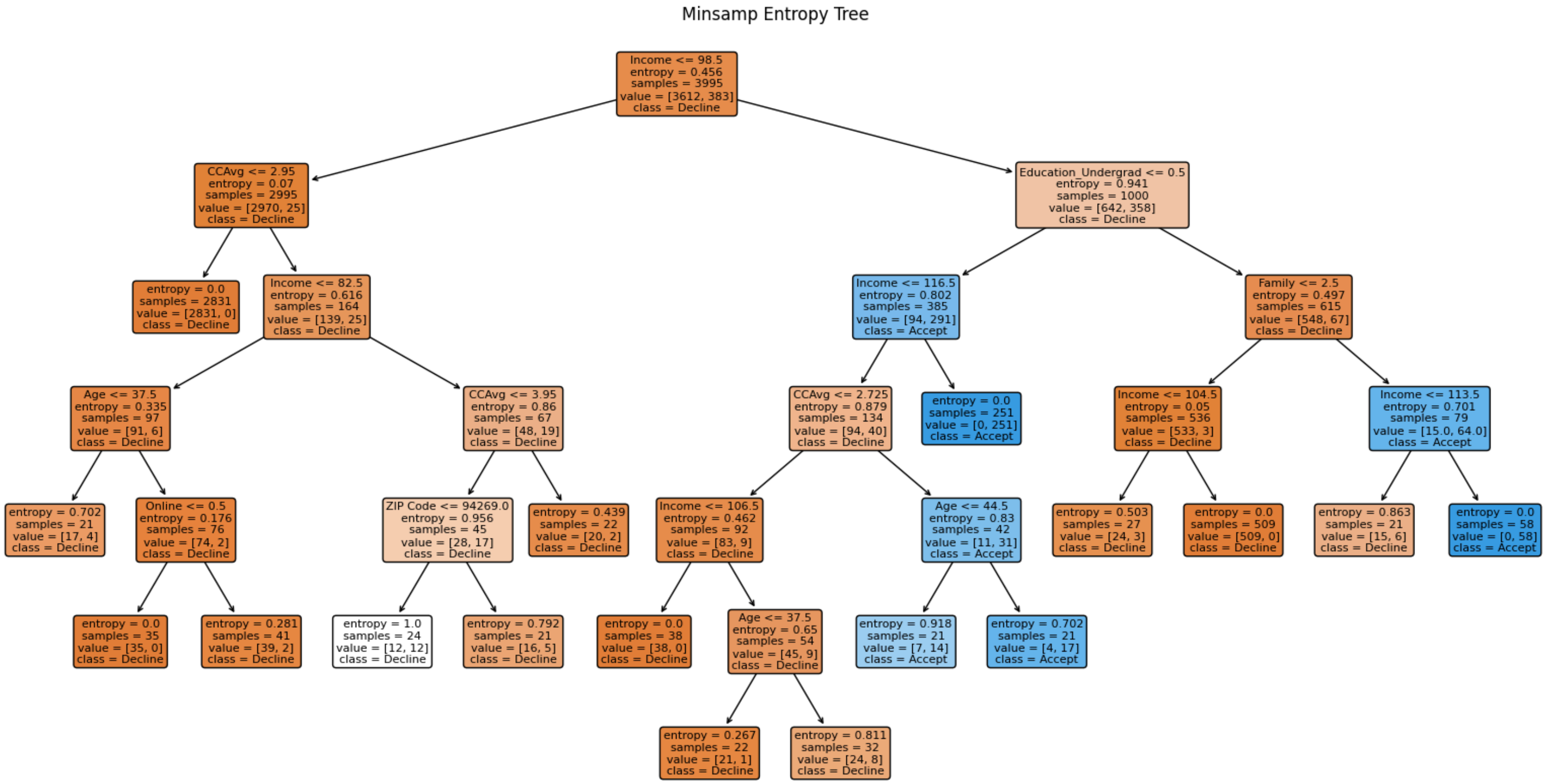
In [22]:
```
feature_names = list(ct.named_transformers_['cat'].get_feature_names_out(['Education']))
feature_names += [col for col in X.columns if col != 'Education']

for label, model in models.items():
    plt.figure(figsize=(20,10))
    sklearn.tree.plot_tree(model, filled=True, feature_names=feature_names,
                           class_names=["Decline", "Accept"], fontsize=8, rounded=True)
    plt.title(f"{label.capitalize().replace('_', ' ').title()} Tree")
    plt.show()
```

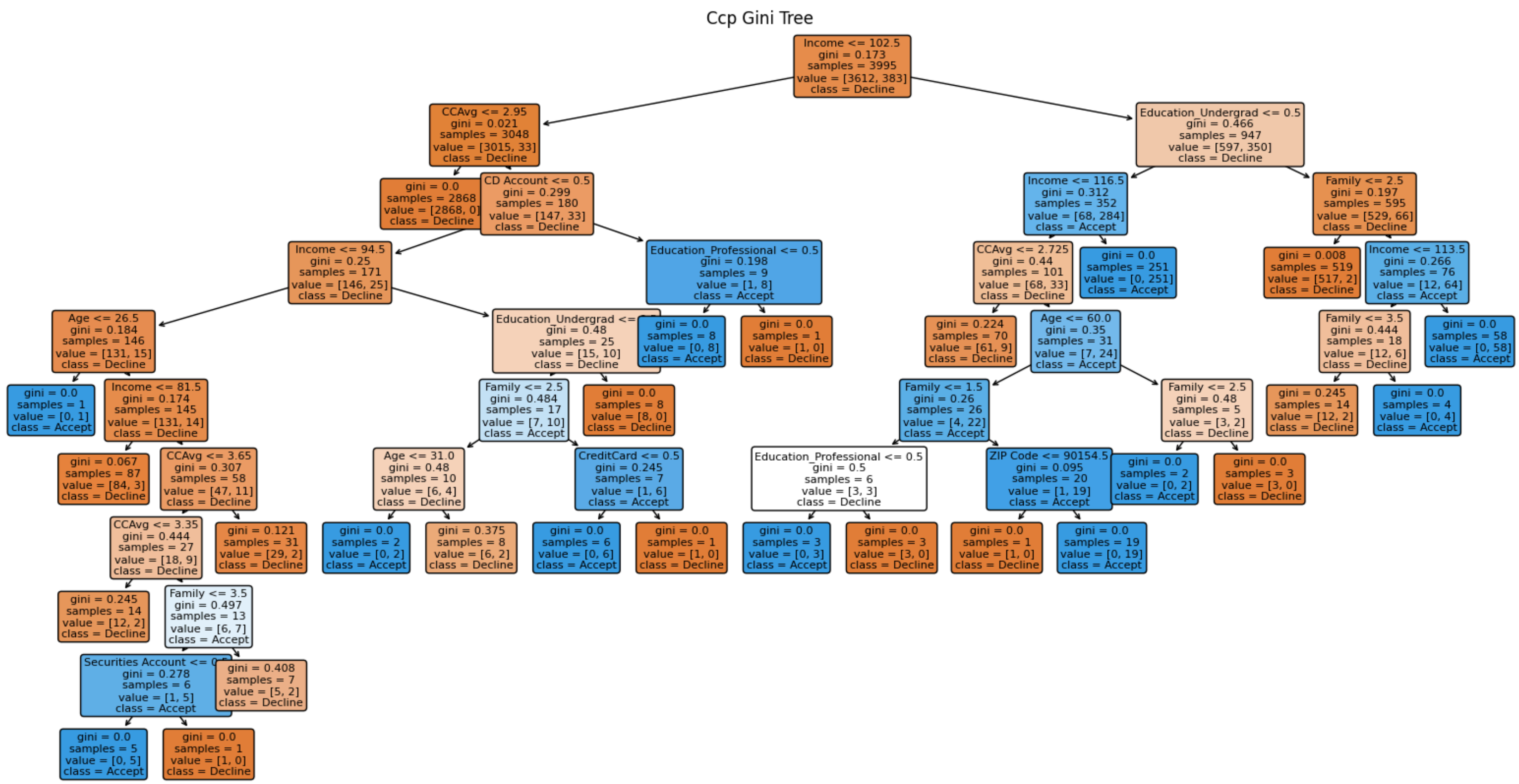
Depth Gini Tree




Depth Entropy Tree
Income <= 98.5
entropy = 0.456
samples = 3995
value = [3612, 383]
class = Decline
CCAvg <= 2.95
entropy = 0.07
samples = 2995
value = [2970, 25]
class = Decline
Education_Undergrad <= 0.5
entropy = 0.941
samples = 1000
value = [642, 358]
class = Decline
entropy = 0.0
samples = 2831
value = [2831, 0]
class = Decline
CD Account <= 0.5
entropy = 0.616
samples = 164
value = [139, 25]
class = Decline
Income <= 116.5
entropy = 0.802
samples = 385
value = [94, 291]
class = Accept
Family <= 2.5
entropy = 0.497
samples = 615
value = [548, 67]
class = Decline
CCAvg <= 3.95
entropy = 0.516
samples = 156
value = [138, 18]
class = Decline
Education_Professional <= 0.5
entropy = 0.544
samples = 8
value = [1, 7]
class = Accept
CCAvg <= 2.725
entropy = 0.879
samples = 134
value = [94, 40]
class = Decline
entropy = 0.0
samples = 251
value = [0, 251]
class = Accept
Income <= 104.5
entropy = 0.05
samples = 536
value = [533, 3]
class = Decline
Income <= 113.5
entropy = 0.701
samples = 79
value = [15.0, 64.0]
class = Accept
entropy = 0.639
samples = 111
value = [93, 18]
class = Decline
entropy = 0.0
samples = 45
value = [45, 0]
class = Decline
entropy = 0.0
samples = 7
value = [0, 7]
class = Accept
entropy = 0.0
samples = 1
value = [1, 0]
class = Decline
entropy = 0.462
samples = 92
value = [83, 9]
class = Decline
entropy = 0.83
samples = 42
value = [11, 31]
class = Accept
entropy = 0.503
samples = 27
value = [24, 3]
class = Decline
entropy = 0.0
samples = 509
value = [509, 0]
class = Decline
entropy = 0.863
samples = 21
value = [15, 6]
class = Decline
entropy = 0.0
samples = 58
value = [0, 58]
class = Accept

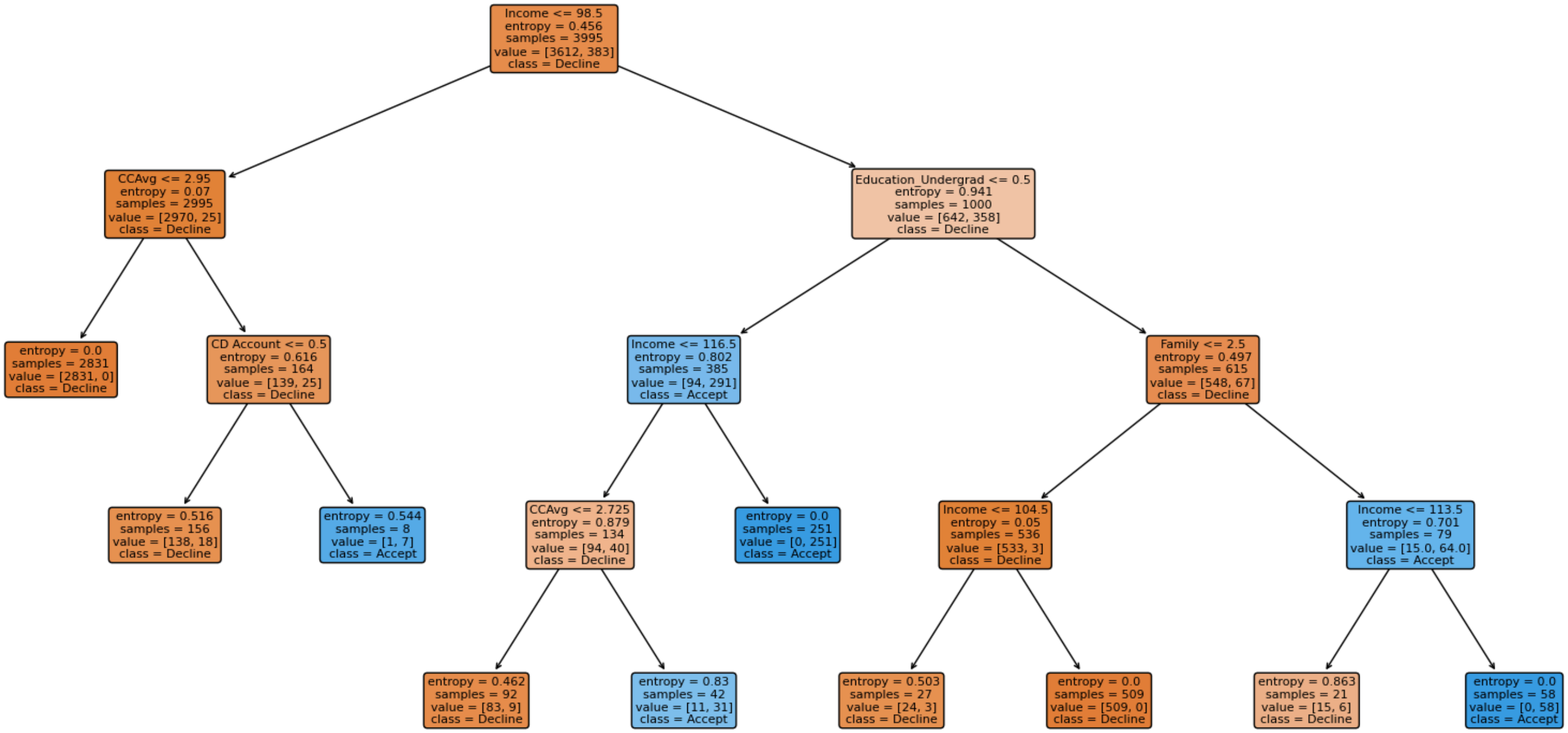

Minsamp Gini Tree
Income <= 102.5
gini = 0.173
samples = 3995
value = [3612, 383]
class = Decline
CCAvg <= 2.95
gini = 0.021
samples = 3048
value = [3015, 33]
class = Decline
Education_Undergrad <= 0.5
gini = 0.466
samples = 947
value = [597, 350]
class = Decline
CD Account <= 0.5
gini = 0.299
samples = 180
value = [147, 33]
class = Decline
Income <= 116.5
gini = 0.312
samples = 352
value = [68, 284]
class = Accept
Family <= 2.5
gini = 0.197
samples = 595
value = [529, 66]
class = Decline
Income <= 94.5
gini = 0.25
samples = 171
value = [146, 25]
class = Decline
Education_Professional <= 0.5
gini = 0.198
samples = 9
value = [1, 8]
class = Accept
gini = 0.0
samples = 251
value = [0, 251]
class = Accept
Income <= 104.5
gini = 0.008
samples = 519
value = [517, 2]
class = Decline
Income <= 113.5
gini = 0.266
samples = 76
value = [12, 64]
class = Accept
Age <= 26.5
gini = 0.184
samples = 146
value = [131, 15]
class = Decline
Income <= 110.5
gini = 0.224
samples = 70
value = [61, 9]
class = Decline
Age <= 60.0
gini = 0.35
samples = 31
value = [7, 24]
class = Accept
gini = 0.0
samples = 509
value = [509, 0]
class = Decline
gini = 0.0
samples = 58
value = [0, 58]
class = Accept
Income <= 81.5
gini = 0.174
samples = 145
value = [131, 14]
class = Decline
CCAvg <= 1.85
gini = 0.069
samples = 28
value = [27, 1]
class = Decline
Age <= 37.5
gini = 0.308
samples = 42
value = [34, 8]
class = Decline
Family <= 1.5
gini = 0.26
samples = 26
value = [4, 22]
class = Accept
CreditCard <= 0
gini = 0.444
samples = 3
value = [1, 2]
class = Accept
gini = 0.0
samples = 4
value = [0, 4]
class = Accept
CCAvg <= 3.55
gini = 0.067
samples = 87
value = [84, 3]
class = Decline
CCAvg <= 3.65
gini = 0.307
samples = 58
value = [47, 11]
class = Decline
Age <= 31.0
gini = 0.48
samples = 10
value = [6, 4]
class = Decline
gini = 0.219
samples = 8
value = [7, 1]
class = Decline
gini = 0.111
samples = 17
value = [16, 1]
class = Decline
gini = 0.5
samples = 6
value = [3, 3]
class = Decline
gini = 0.0
samples = 1
value = [0, 1]
class = Accept
gini = 0.0
samples = 53
value = [53, 0]
class = Decline
CCAvg <= 3.35
gini = 0.444
samples = 27
value = [18, 9]
class = Decline
gini = 0.0
samples = 19
value = [0, 19]
class = Accept
CCAvg <= 4.2
gini = 0.444
samples = 3
value = [2, 1]
class = Decline
Family <= 3.5
gini = 0.245
samples = 14
value = [12, 2]
class = Decline
Family <= 3.5
gini = 0.497
samples = 13
value = [6, 7]
class = Accept
CCAvg <= 4.65
gini = 0.245
samples = 7
value = [6, 1]
class = Decline
gini = 0.0
samples = 2
value = [0, 2]
class = Accept
gini = 0.0
samples = 2
value = [2, 0]
class = Decline
Securities Account <=
gini = 0.278
samples = 6
value = [1, 5]
class = Accept
CCAvg <= 3.5
gini = 0.408
samples = 7
value = [5, 2]
class = Decline
ZIP Code <= 92363
gini = 0.198
samples = 9
value = [8, 1]
class = Decline
gini = 0.0
samples = 1
value = [0, 1]
class = Accept
gini = 0.0
samples = 2
value = [0, 2]
class = Accept
ZIP Code <= 94423
gini = 0.444
samples = 3
value = [1, 2]
class = Accept
gini = 0.0
samples = 7
value = [7, 0]
class = Decline
CCAvg <= 2.1
gini = 0.219
samples = 8
value = [7, 1]
class = Decline
CCAvg <= 0.3
gini = 0.444
samples = 3
value = [1, 2]
class = Accept
gini = 0.0
samples = 1
value = [0, 1]
class = Accept
gini = 0.0
samples = 1
value = [1, 0]
class = Decline
gini = 0.0
samples = 2
value = [0, 2]
class = Accept
gini = 0.0
samples = 1
value = [1, 0]
class = Decline


Minsamp Entropy Tree
Income <= 98.5 entropy = 0.456 samples = 3995 value = [3612, 383] class = Decline
CCAvg <= 2.95 entropy = 0.07 samples = 2995 value = [2970, 25] class = Decline
Education_Undergrad <= 0.5 entropy = 0.941 samples = 1000 value = [642, 358] class = Decline
entropy = 0.0 samples = 2831 value = [2831, 0] class = Decline
Income <= 82.5 entropy = 0.616 samples = 164 value = [139, 25] class = Decline
Income <= 116.5 entropy = 0.802 samples = 385 value = [94, 291] class = Accept
Family <= 2.5 entropy = 0.497 samples = 615 value = [548, 67] class = Decline
Age <= 37.5 entropy = 0.335 samples = 97 value = [91, 6] class = Decline
CCAvg <= 3.95 entropy = 0.86 samples = 67 value = [48, 19] class = Decline
CCAvg <= 2.725 entropy = 0.879 samples = 134 value = [94, 40] class = Decline
entropy = 0.0 samples = 251 value = [0, 251] class = Accept
Income <= 104.5 entropy = 0.05 samples = 536 value = [533, 3] class = Decline
Income <= 113.5 entropy = 0.701 samples = 79 value = [15.0, 64.0] class = Accept
entropy = 0.702 samples = 21 value = [17, 4] class = Decline
Online <= 0.5 entropy = 0.176 samples = 76 value = [74, 2] class = Decline
ZIP Code <= 94269.0 entropy = 0.956 samples = 45 value = [28, 17] class = Decline
entropy = 0.439 samples = 22 value = [20, 2] class = Decline
Income <= 106.5 entropy = 0.462 samples = 92 value = [83, 9] class = Decline
Age <= 44.5 entropy = 0.83 samples = 42 value = [11, 31] class = Accept
entropy = 0.503 samples = 27 value = [24, 3] class = Decline
entropy = 0.0 samples = 509 value = [509, 0] class = Decline
entropy = 0.863 samples = 21 value = [15, 6] class = Decline
entropy = 0.0 samples = 58 value = [0, 58] class = Accept
entropy = 0.0 samples = 35 value = [35, 0] class = Decline
entropy = 0.281 samples = 41 value = [39, 2] class = Decline
entropy = 1.0 samples = 24 value = [12, 12] class = Decline
entropy = 0.792 samples = 21 value = [16, 5] class = Decline
entropy = 0.0 samples = 38 value = [38, 0] class = Decline
Age <= 37.5 entropy = 0.65 samples = 54 value = [45, 9] class = Decline
entropy = 0.918 samples = 21 value = [7, 14] class = Accept
entropy = 0.702 samples = 21 value = [4, 17] class = Accept
entropy = 0.267 samples = 22 value = [21, 1] class = Decline
entropy = 0.811 samples = 32 value = [24, 8] class = Decline

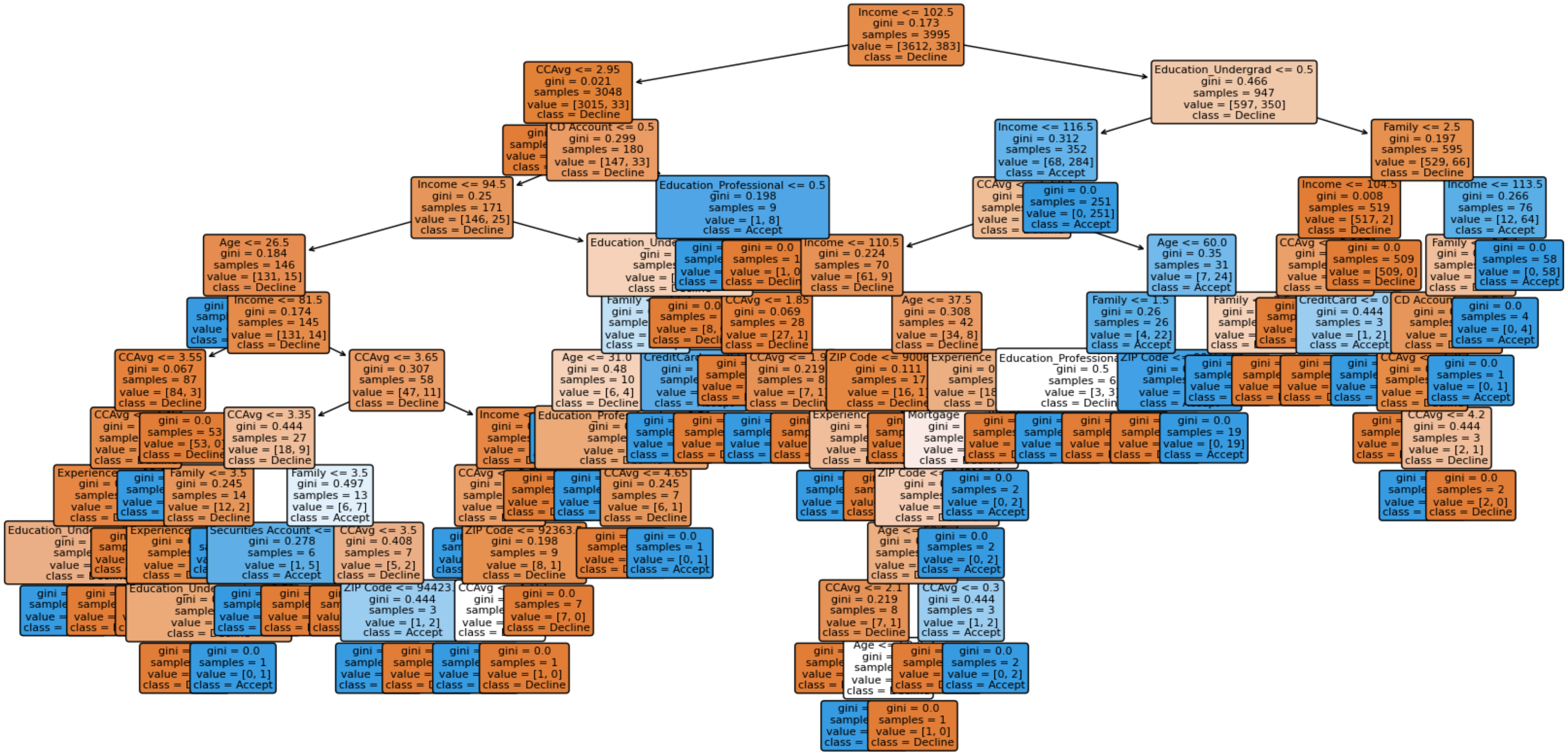


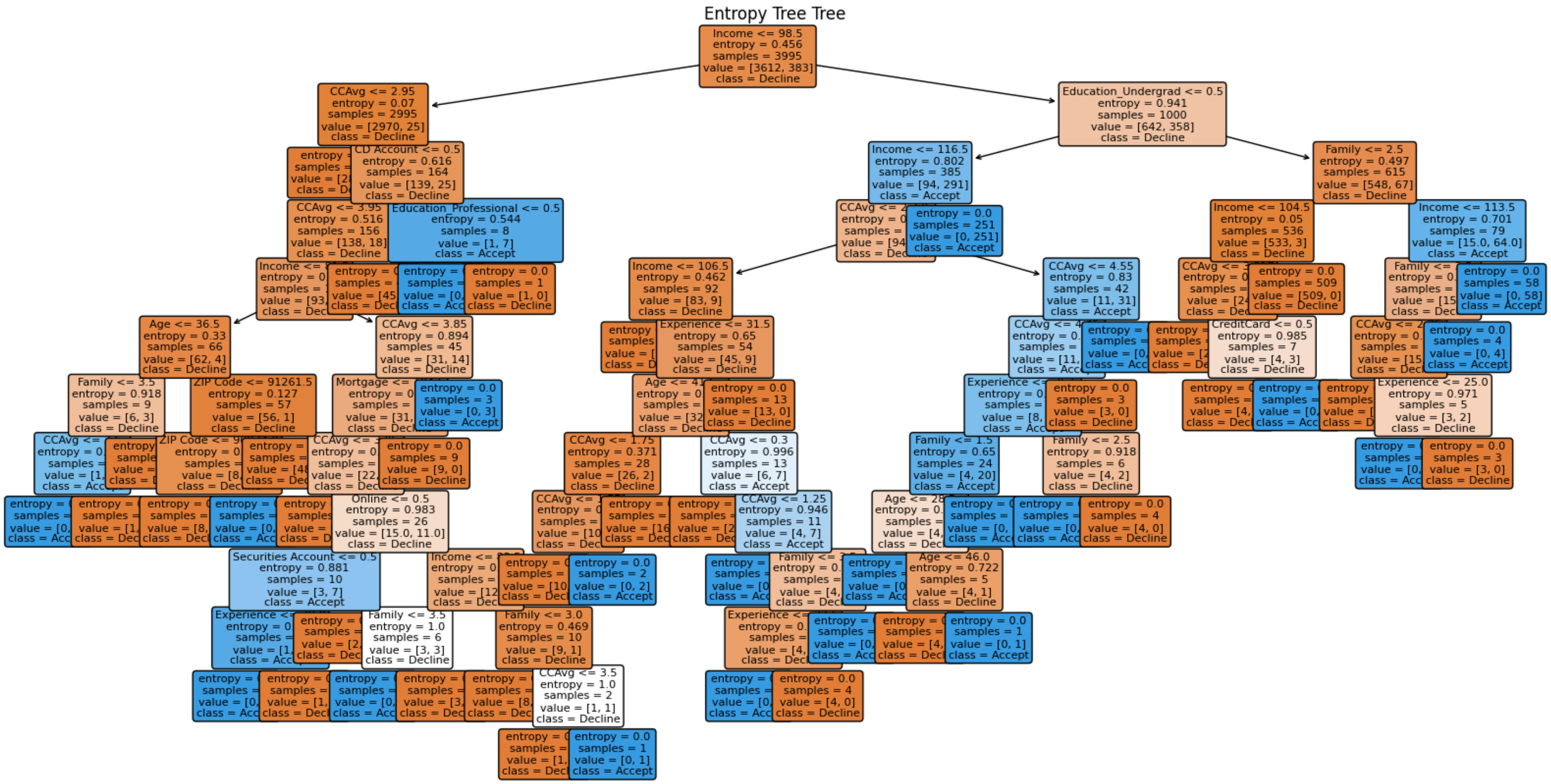
Ccp Gini Tree
Income <= 102.5
gini = 0.173
samples = 3995
value = [3612, 383]
class = Decline
CCAvg <= 2.95
gini = 0.021
samples = 3048
value = [3015, 33]
class = Decline
Education_Undergrad <= 0.5
gini = 0.466
samples = 947
value = [597, 350]
class = Decline

Ccp Entropy Tree



Gini Tree Tree





Conclusion/Summary (Grace Biggs)

Overall, our Decision Trees all seem to work just fine on the data provided. Gini and Entropy both had comparable performance and accuracy, but pruned Entropy seemed to result in smaller, slightly-faster trees. Our heatmap and scatter plot matrix illustrated that Income and CCAvg are the most important continuous features for predicting the Personal Loan feature, and our Decision Trees revealed that possessing an Undergrad degree also plays a big role.