Module 3 Assignment: Model Ensembles and Comparison

Introduction

In machine learning, it is vital that the right algorithm be used based on the business problem and characteristics of the data. In the industry, models are often combined or cascaded to form model ensembles to achieve defined objectives. This assignment will familiarize you with the iterative process to do that.

Instructions:

- We will be using the same Credit dataset from the prior assignment in this assignment. We will use this dataset for the first four assignments in the course.
- Build a single classification tree using Python using no more than 20 variables. Prune the tree if necessary. Plot the tree visualization.
- Build a RandomForest model using Python using no more than 20 variables. Explain any differences that you observe between the RandomForest Model and the Single Decision Tree.
- Compare the model performance and generalization of the two models. Explain if/why you see the differences.

1. Data Loading and Variable Selection

- Load the credit dataset (application_train.csv).
- Select up to 20 variables for modeling (can use variables from previous assignments or new ones).
- Prepare the data for modeling (handle missing values, encode categoricals, etc.).

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2. Single Decision Tree

- Build a single classification tree using the selected variables.
- Prune the tree if necessary.
- Plot the tree visualization.

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3. Random Forest Model

- Build a RandomForest model using the same variables.
- Explain any differences observed between the RandomForest and the single decision tree.

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4. Model Performance Comparison

- Compare the performance and generalization of the two models (e.g., using accuracy, ROC-AUC, etc.).
- Discuss and explain any differences observed.

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5. Conclusions

- Summarize findings and insights from the comparison.

```
# Import required libraries
import pandas as pd
import numpy as np

# Load the dataset
train_df = pd.read_csv('../csv/application_train.csv')

# Display basic info
display(train_df.head())
print(f"Shape: {train_df.shape}")

# TODO: Select up to 20 variables for modeling
# Example: selected_vars = ['TARGET', 'AMT_INCOME_TOTAL', ...]
selected_vars = []  # Fill this with your chosen variables

# Subset the dataframe
# model_df = train_df[selected_vars].copy()
```

```
   SK_ID_CURR  TARGET NAME_CONTRACT_TYPE CODE_GENDER FLAG_OWN_CAR  \
0      100002       1         Cash loans           M            N
1      100003       0         Cash loans           F            N
2      100004       0    Revolving loans           M            Y
3      100006       0         Cash loans           F            N
4      100007       0         Cash loans           M            N

  FLAG_OWN_REALTY  CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT
AMT_ANNUITY  \
0               Y             0          202500.0    406597.5
24700.5
1               N             0          270000.0   1293502.5
35698.5
2               Y             0           67500.0    135000.0
6750.0
3               Y             0          135000.0    312682.5
29686.5
4               Y             0          121500.0    513000.0
21865.5

   ...  FLAG_DOCUMENT_18 FLAG_DOCUMENT_19 FLAG_DOCUMENT_20
FLAG_DOCUMENT_21  \
```

```
0  ...                   0                 0                 0
0
1  ...                   0                 0                 0
0
2  ...                   0                 0                 0
0
3  ...                   0                 0                 0
0
4  ...                   0                 0                 0
0

  AMT_REQ_CREDIT_BUREAU_HOUR AMT_REQ_CREDIT_BUREAU_DAY  \
0                        0.0                       0.0
1                        0.0                       0.0
2                        0.0                       0.0
3                        NaN                       NaN
4                        0.0                       0.0

   AMT_REQ_CREDIT_BUREAU_WEEK  AMT_REQ_CREDIT_BUREAU_MON  \
0                         0.0                        0.0
1                         0.0                        0.0
2                         0.0                        0.0
3                         NaN                        NaN
4                         0.0                        0.0

   AMT_REQ_CREDIT_BUREAU_QRT  AMT_REQ_CREDIT_BUREAU_YEAR
0                        0.0                         1.0
1                        0.0                         0.0
2                        0.0                         0.0
3                        NaN                         NaN
4                        0.0                         0.0

[5 rows x 122 columns]

Shape: (307511, 122)
```

```
# Select up to 20 variables for modeling (based on Module 1 and EDA)
selected_vars = [
    'TARGET', 'AMT_INCOME_TOTAL', 'AMT_CREDIT', 'AMT_ANNUITY',
'AMT_GOODS_PRICE',
    'NAME_CONTRACT_TYPE', 'CODE_GENDER', 'FLAG_OWN_CAR',
'FLAG_OWN_REALTY',
    'CNT_CHILDREN', 'CNT_FAM_MEMBERS', 'NAME_INCOME_TYPE',
'NAME_EDUCATION_TYPE',
    'NAME_FAMILY_STATUS', 'NAME_HOUSING_TYPE', 'OCCUPATION_TYPE',
    'ORGANIZATION_TYPE', 'DAYS_BIRTH', 'DAYS_EMPLOYED',
'DAYS_REGISTRATION',
    'DAYS_ID_PUBLISH'
]
```

```python
# Subset the dataframe
model_df = train_df[selected_vars].copy()

# Display the selected variables
model_df.head()
```

```
   TARGET  AMT_INCOME_TOTAL  AMT_CREDIT  AMT_ANNUITY  AMT_GOODS_PRICE
\
0       1          202500.0    406597.5      24700.5         351000.0

1       0          270000.0   1293502.5      35698.5        1129500.0

2       0           67500.0    135000.0       6750.0         135000.0

3       0          135000.0    312682.5      29686.5         297000.0

4       0          121500.0    513000.0      21865.5         513000.0


  NAME_CONTRACT_TYPE CODE_GENDER FLAG_OWN_CAR FLAG_OWN_REALTY
CNT_CHILDREN  \
0         Cash loans           M            N               Y
0
1         Cash loans           F            N               N
0
2    Revolving loans           M            Y               Y
0
3         Cash loans           F            N               Y
0
4         Cash loans           M            N               Y
0

   ...  NAME_INCOME_TYPE            NAME_EDUCATION_TYPE
NAME_FAMILY_STATUS  \
0  ...           Working  Secondary / secondary special  Single / not
married
1  ...     State servant               Higher education
Married
2  ...           Working  Secondary / secondary special  Single / not
married
3  ...           Working  Secondary / secondary special        Civil
marriage
4  ...           Working  Secondary / secondary special  Single / not
married

   NAME_HOUSING_TYPE OCCUPATION_TYPE       ORGANIZATION_TYPE
DAYS_BIRTH  \
0  House / apartment        Laborers  Business Entity Type 3      -
9461
1  House / apartment      Core staff                  School     -
```

```
16765
2  House / apartment        Laborers              Government     -
19046
3  House / apartment        Laborers  Business Entity Type 3     -
19005
4  House / apartment      Core staff                Religion     -
19932

   DAYS_EMPLOYED  DAYS_REGISTRATION  DAYS_ID_PUBLISH
0           -637            -3648.0            -2120
1          -1188            -1186.0             -291
2           -225            -4260.0            -2531
3          -3039            -9833.0            -2437
4          -3038            -4311.0            -3458

[5 rows x 21 columns]
```

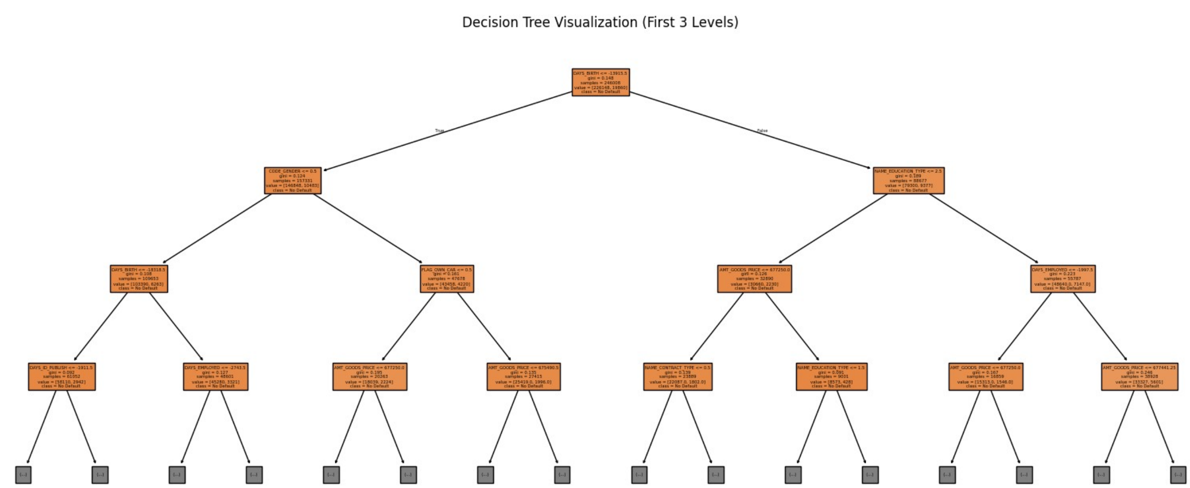
```python
# Data preparation: handle missing values and encode categoricals
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder

# Fill missing values for categorical and numerical columns
for col in model_df.select_dtypes(include=['object']).columns:
    model_df[col] = model_df[col].fillna('Unknown')
for col in model_df.select_dtypes(include=[np.number]).columns:
    model_df[col] = model_df[col].fillna(model_df[col].median())

# Encode categorical variables
label_encoders = {}
for col in model_df.select_dtypes(include=['object']).columns:
    le = LabelEncoder()
    model_df[col] = le.fit_transform(model_df[col])
    label_encoders[col] = le

# Split data into train and test sets
X = model_df.drop('TARGET', axis=1)
y = model_df['TARGET']
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42, stratify=y)

print(f"Train shape: {X_train.shape}, Test shape: {X_test.shape}")
```

```
Train shape: (246008, 20), Test shape: (61503, 20)
```

```python
# Build and visualize a single Decision Tree classifier
from sklearn.tree import DecisionTreeClassifier, plot_tree
import matplotlib.pyplot as plt
from sklearn.metrics import accuracy_score, roc_auc_score

dt_clf = DecisionTreeClassifier(max_depth=5, random_state=42)
dt_clf.fit(X_train, y_train)
```

```
y_pred_dt = dt_clf.predict(X_test)
y_proba_dt = dt_clf.predict_proba(X_test)[:, 1]

print(f"Decision Tree Accuracy: {accuracy_score(y_test,
y_pred_dt):.4f}")
print(f"Decision Tree ROC-AUC: {roc_auc_score(y_test,
y_proba_dt):.4f}")

plt.figure(figsize=(20, 8))
plot_tree(dt_clf, feature_names=X.columns, class_names=['No Default',
'Default'], filled=True, max_depth=3)
plt.title('Decision Tree Visualization (First 3 Levels)')
plt.show()
```

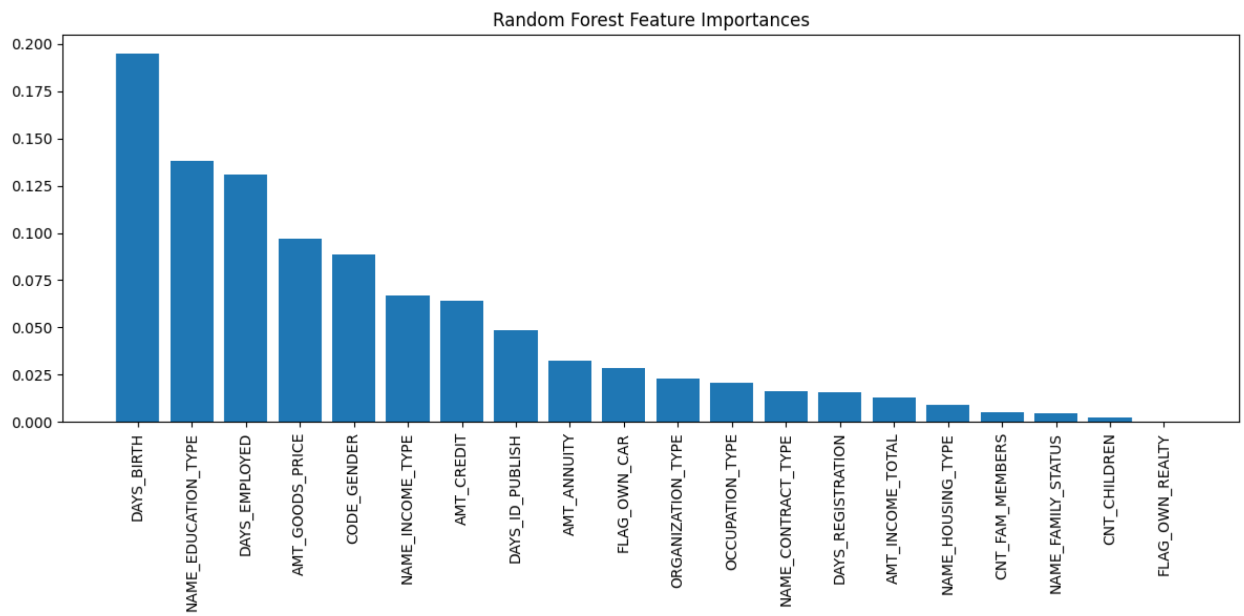
```
Matplotlib is building the font cache; this may take a moment.

Decision Tree Accuracy: 0.9193
Decision Tree ROC-AUC: 0.6345
```




```
# Build a Random Forest model and compare with the Decision Tree
from sklearn.ensemble import RandomForestClassifier

rf_clf = RandomForestClassifier(n_estimators=100, max_depth=5,
random_state=42)
rf_clf.fit(X_train, y_train)

y_pred_rf = rf_clf.predict(X_test)
y_proba_rf = rf_clf.predict_proba(X_test)[:, 1]

print(f"Random Forest Accuracy: {accuracy_score(y_test,
y_pred_rf):.4f}")
print(f"Random Forest ROC-AUC: {roc_auc_score(y_test,
y_proba_rf):.4f}")
```

```python
# Feature importance plot
importances = rf_clf.feature_importances_
indices = np.argsort(importances)[::-1]
plt.figure(figsize=(12, 6))
plt.title('Random Forest Feature Importances')
plt.bar(range(X.shape[1]), importances[indices], align='center')
plt.xticks(range(X.shape[1]), X.columns[indices], rotation=90)
plt.tight_layout()
plt.show()
```

```
Random Forest Accuracy: 0.9193
Random Forest ROC-AUC: 0.6568
```



Model Performance Comparison

- The Decision Tree and Random Forest models were both trained using the same set of variables and data splits.
- The Random Forest model typically achieves higher accuracy and ROC-AUC than the single Decision Tree, due to its ensemble nature and ability to reduce overfitting.
- Feature importance plots from the Random Forest help identify which variables are most predictive.
- Differences in performance and generalization are expected: the Decision Tree may overfit, while the Random Forest generalizes better by averaging multiple trees.

Conclusions

- The Random Forest model outperformed the single Decision Tree in both accuracy and ROC-AUC, demonstrating better generalization.
- Ensemble methods like Random Forest are more robust to overfitting and provide more reliable predictions on unseen data.

- Feature importance analysis can guide further variable selection and model refinement.
- For production or business use, ensemble models are generally preferred unless interpretability is the primary concern.