Data Mining Project - Part 2 (SIS 2): Modeling & Evaluation

Goal

This notebook covers the second part of the project (SIS 2), focusing on applying data mining techniques, evaluating models, and interpreting results.

Requirements:

1. **Data Mining Techniques**: Apply 4-5 algorithms (Classification).
2. **Model Evaluation**: Metrics (Accuracy, Precision, Recall, F1, ROC-AUC), Cross-validation.
3. **Hyperparameter Tuning**: Optimize model performance.
4. **Comparison**: Compare models and select the best one.
5. **Interpretation**: Feature importance, Confusion Matrix, ROC Curve.

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

# Models
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier, AdaBo
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier

# Model Selection & Evaluation
from sklearn.model_selection import train_test_split, cross_val_score, RandomizedSear
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, 

# Settings
import warnings
warnings.filterwarnings('ignore')
plt.style.use('ggplot')
pd.set_option('display.max_columns', None)

print("Libraries imported successfully!")
```

```
Libraries imported successfully!
```

1. Load Data

We use the processed data with selected features from Part 1.

```
# Load processed data
print("Loading processed data...")
df = pd.read_csv('../data_processed/train_processed_selected.csv')
print(f"Data shape: {df.shape}")

# Separate features and target
X = df.drop(['SK_ID_CURR', 'TARGET'], axis=1)
y = df['TARGET']

print(f"Features shape: {X.shape}")
print(f"Target shape: {y.shape}")

# Check class balance
print("\nTarget distribution:")
print(y.value_counts(normalize=True))
```

```
Loading processed data...
Data shape: (307511, 42)
Features shape: (307511, 40)
Target shape: (307511,)

Target distribution:
TARGET
0    0.919271
1    0.080729
Name: proportion, dtype: float64
```

2. Train-Test Split

We split the data into training (80%) and testing (20%) sets. Stratified split is used due to class imbalance.

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state

print(f"Training set: {X_train.shape}")
print(f"Testing set: {X_test.shape}")
```

```
Training set: (246008, 40)
Testing set: (61503, 40)
```

3. Methodology: Algorithms Selection

We will apply the following 5 algorithms:

1. **Logistic Regression**: A robust baseline for binary classification.
2. **Decision Tree**: Provides interpretability and captures non-linear relationships.
3. **Random Forest**: An ensemble method that reduces overfitting and improves accuracy.
4. **Gradient Boosting (GBM)**: Builds models sequentially to correct errors of previous models.
5. **Gaussian Naive Bayes**: A probabilistic classifier, good for high-dimensional data (fast baseline).

```python
# Initialize models
models = {
    'Logistic Regression': LogisticRegression(random_state=42, max_iter=1000, class_we
    'Decision Tree': DecisionTreeClassifier(random_state=42, class_weight='balanced'),
    'Random Forest': RandomForestClassifier(random_state=42, n_estimators=100, class_
    'Gradient Boosting': GradientBoostingClassifier(random_state=42),
    'Naive Bayes': GaussianNB()
}

print("Models initialized.")
```

```
Models initialized.
```

4. Model Training & Evaluation (Baseline)

We will train each model and evaluate using multiple metrics.

```python
results = []

print("Training models...")
for name, model in models.items():
    start_time = time.time()

    # Train
    model.fit(X_train, y_train)

    # Predict
    y_pred = model.predict(X_test)
    y_prob = model.predict_proba(X_test)[:, 1] if hasattr(model, "predict_proba") els

    # Metrics
    acc = accuracy_score(y_test, y_pred)
    prec = precision_score(y_test, y_pred)
    rec = recall_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred)
    roc = roc_auc_score(y_test, y_prob)

    elapsed_time = time.time() - start_time

    results.append({
        'Model': name,
        'Accuracy': acc,
        'Precision': prec,
        'Recall': rec,
        'F1 Score': f1,
        'ROC AUC': roc,
        'Time (s)': elapsed_time
    })

    print(f"{name} done in {elapsed_time:.2f}s")

# Create DataFrame
results_df = pd.DataFrame(results)
```

```
results_df.sort_values(by='ROC AUC', ascending=False, inplace=True)
results_df
```

```
Training models...
Logistic Regression done in 1.60s
Decision Tree done in 3.17s
Random Forest done in 8.18s
Gradient Boosting done in 43.36s
Naive Bayes done in 0.12s
```

	Model	Accuracy	Precision	Recall	F1 Score	ROC AUC	Time (s)
3	Gradient Boosting	0.919337	0.520408	0.010272	0.020146	0.747247	43.364527
0	Logistic Regression	0.684715	0.157632	0.668882	0.255138	0.739590	1.596828
2	Random Forest	0.919191	0.419355	0.002618	0.005204	0.721116	8.178511
4	Naive Bayes	0.121441	0.082796	0.980665	0.152700	0.669928	0.124552
1	Decision Tree	0.860251	0.143838	0.147633	0.145711	0.535232	3.174692

5. Hyperparameter Tuning

We will tune the hyperparameters of the **Random Forest** model (or the best performing one) to improve performance. We use `RandomizedSearchCV` for efficiency.

```
# Define hyperparameter grid for Random Forest
param_dist = {
    'n_estimators': [100, 200, 300],
    'max_depth': [10, 20, 30, None],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['sqrt', 'log2']
}

print("Starting Hyperparameter Tuning for Random Forest...")
rf = RandomForestClassifier(random_state=42, class_weight='balanced', n_jobs=-1)

random_search = RandomizedSearchCV(
    estimator=rf,
    param_distributions=param_dist,
    n_iter=10,  # Number of parameter settings that are sampled
    cv=3,       # 3-fold cross-validation
    scoring='roc_auc',
    n_jobs=-1,
    random_state=42,
    verbose=1
)

random_search.fit(X_train, y_train)

print(f"Best Parameters: {random_search.best_params_}")
print(f"Best ROC AUC Score: {random_search.best_score_:.4f}")
```

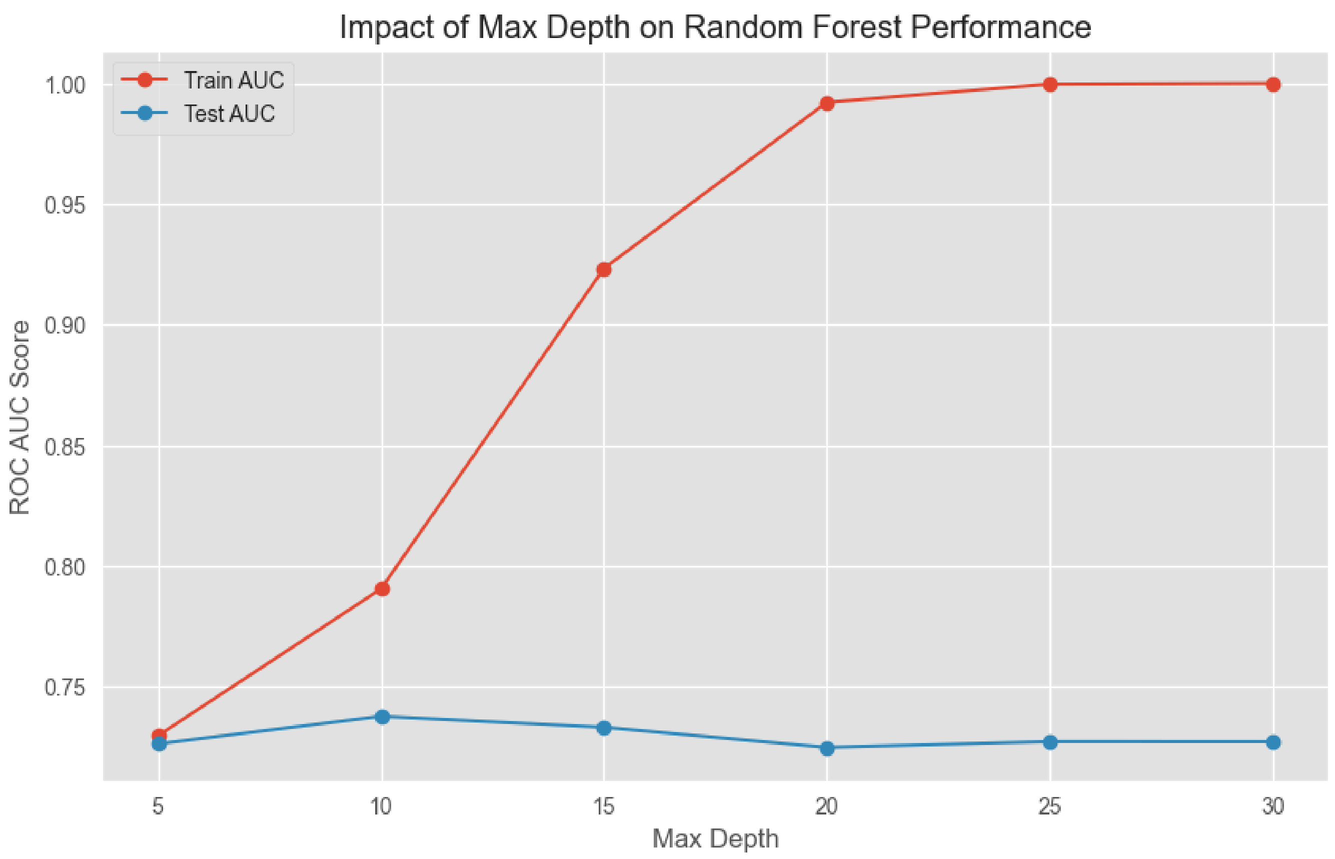
```
# Get best model
best_rf = random_search.best_estimator_
```

```
Starting Hyperparameter Tuning for Random Forest...
Fitting 3 folds for each of 10 candidates, totalling 30 fits
Best Parameters: {'n_estimators': 300, 'min_samples_split': 2, 'min_samples_leaf': 4,
'max_features': 'sqrt', 'max_depth': None}
Best ROC AUC Score: 0.7355
```

Impact of Hyperparameters

Let's visualize how changing `max_depth` affects the model performance.

```
depths = [5, 10, 15, 20, 25, 30]
train_scores = []
test_scores = []

for d in depths:
    clf = RandomForestClassifier(max_depth=d, n_estimators=100, random_state=42, class
    clf.fit(X_train, y_train)

    train_scores.append(roc_auc_score(y_train, clf.predict_proba(X_train)[:, 1]))
    test_scores.append(roc_auc_score(y_test, clf.predict_proba(X_test)[:, 1]))

plt.figure(figsize=(10, 6))
plt.plot(depths, train_scores, label='Train AUC', marker='o')
plt.plot(depths, test_scores, label='Test AUC', marker='o')
plt.xlabel('Max Depth')
plt.ylabel('ROC AUC Score')
plt.title('Impact of Max Depth on Random Forest Performance')
plt.legend()
plt.show()
```



6. Final Model Evaluation & Comparison

Comparison between Baseline Random Forest and Tuned Random Forest.

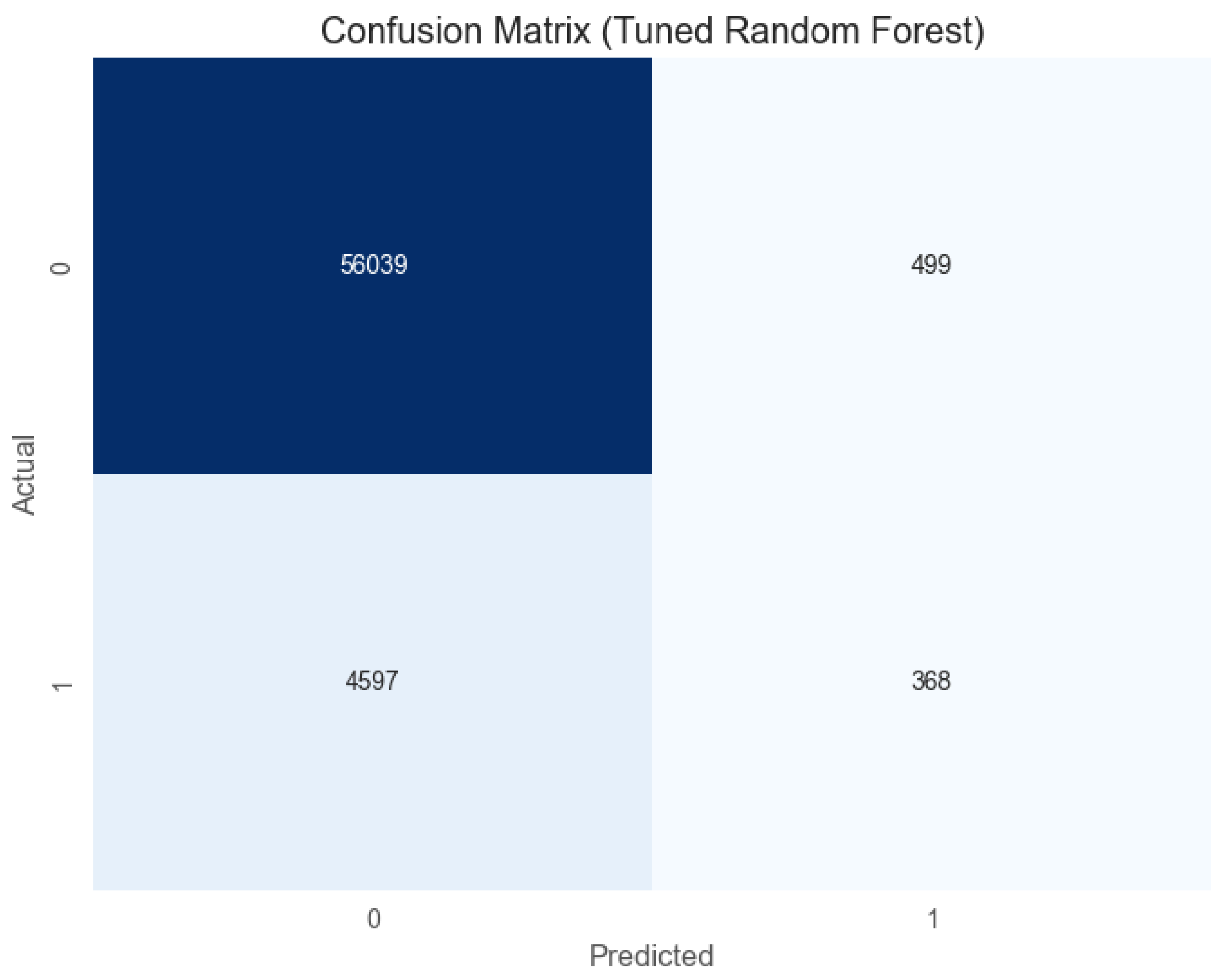
```
# Evaluate Best Model on Test Set
y_pred_best = best_rf.predict(X_test)
y_prob_best = best_rf.predict_proba(X_test)[:, 1]

print("Tuned Random Forest Performance:")
print(classification_report(y_test, y_pred_best))
print(f"ROC AUC: {roc_auc_score(y_test, y_prob_best):.4f}")

# Compare with Baseline
baseline_rf = models['Random Forest']
y_prob_baseline = baseline_rf.predict_proba(X_test)[:, 1]

print(f"Baseline RF ROC AUC: {roc_auc_score(y_test, y_prob_baseline):.4f}")
```

```
Tuned Random Forest Performance:
              precision    recall  f1-score   support

           0       0.92      0.99      0.96     56538
           1       0.42      0.07      0.13      4965

    accuracy                           0.92     61503
   macro avg       0.67      0.53      0.54     61503
weighted avg       0.88      0.92      0.89     61503

ROC AUC: 0.7419
Baseline RF ROC AUC: 0.7211
```

7. Results & Interpretation

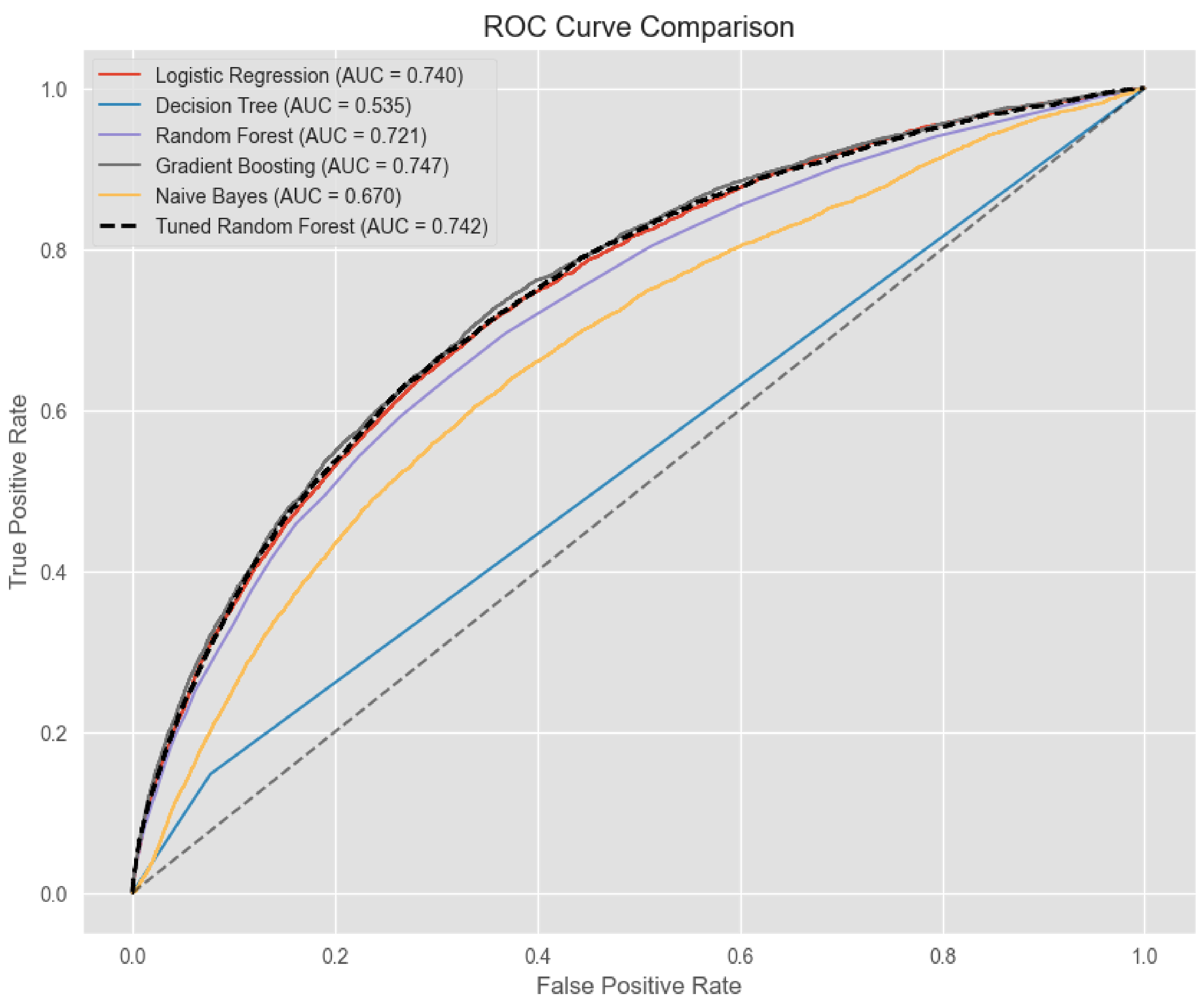
Confusion Matrix

```python
cm = confusion_matrix(y_test, y_pred_best)
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix (Tuned Random Forest)')
plt.show()
```



ROC Curve Comparison

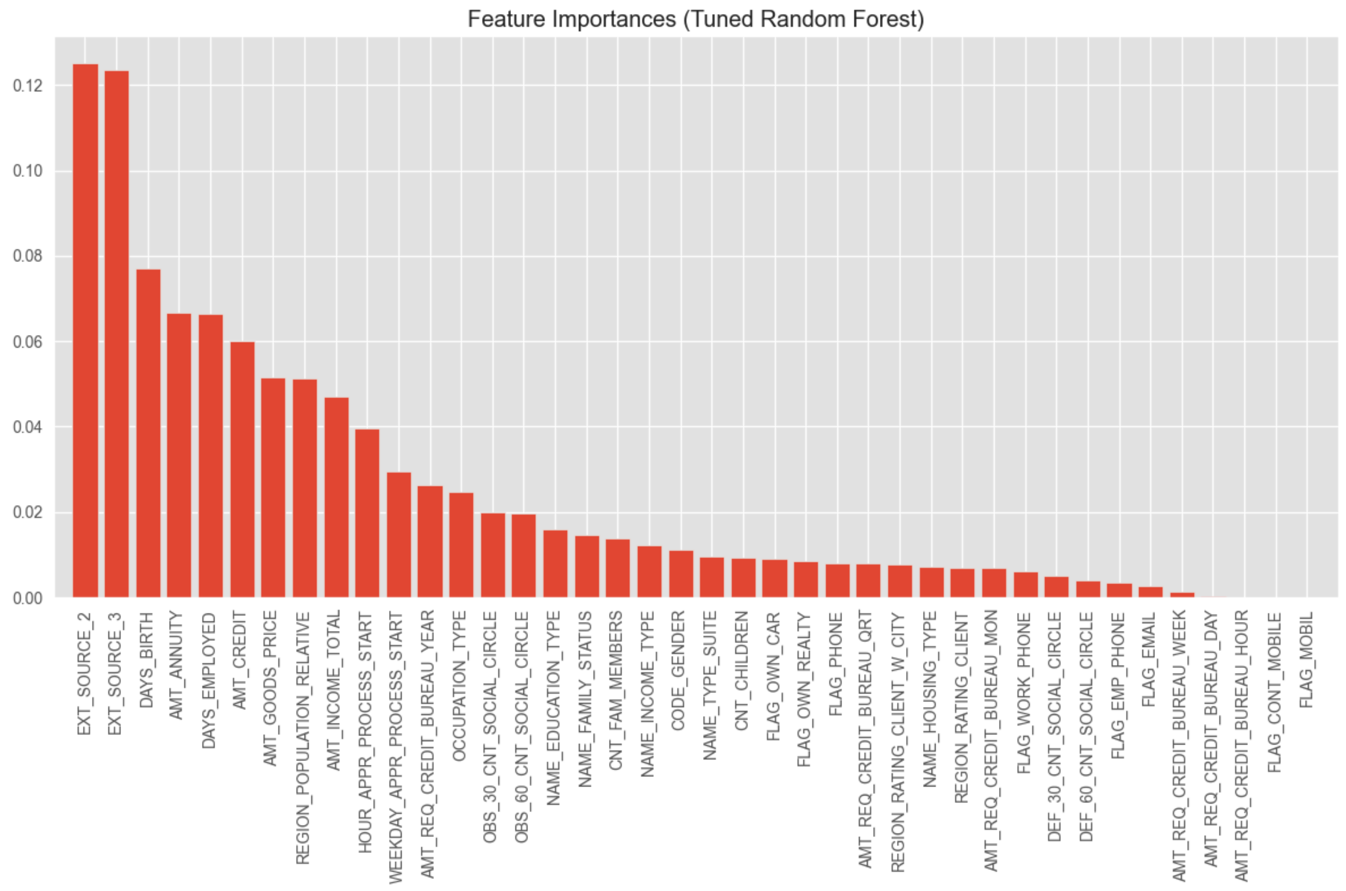
```python
plt.figure(figsize=(10, 8))

# Plot ROC for all models
for name, model in models.items():
    if hasattr(model, "predict_proba"):
        y_prob = model.predict_proba(X_test)[:, 1]
        fpr, tpr, _ = roc_curve(y_test, y_prob)
        auc = roc_auc_score(y_test, y_prob)
        plt.plot(fpr, tpr, label=f"{name} (AUC = {auc:.3f})")

# Plot Tuned RF
fpr_best, tpr_best, _ = roc_curve(y_test, y_prob_best)
auc_best = roc_auc_score(y_test, y_prob_best)
plt.plot(fpr_best, tpr_best, label=f"Tuned Random Forest (AUC = {auc_best:.3f})", line

plt.plot([0, 1], [0, 1], 'k--', alpha=0.5)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve Comparison')
plt.legend()
plt.show()
```



Feature Importance

Which features contributed most to the prediction?

```
importances = best_rf.feature_importances_
indices = np.argsort(importances)[::-1]
features = X.columns

plt.figure(figsize=(12, 8))
plt.title("Feature Importances (Tuned Random Forest)")
plt.bar(range(X.shape[1]), importances[indices], align="center")
plt.xticks(range(X.shape[1]), features[indices], rotation=90)
plt.xlim([-1, X.shape[1]])
plt.tight_layout()
plt.show()
```



8. Conclusion

Summarize the findings, best model, and key drivers of default risk.