```
!pip install -q hvplot
# Install memory_profiler
%pip install memory_profiler

# Load memory_profiler extension
%load_ext memory_profiler
```

```
^C
Requirement already satisfied: memory_profiler in c:\users\fahad\
anaconda3\envs\sea600\lib\site-packages (0.58.0)
Requirement already satisfied: psutil in c:\users\fahad\anaconda3\
envs\sea600\lib\site-packages (from memory_profiler) (5.9.0)
Note: you may need to restart the kernel to use updated packages.
The memory_profiler extension is already loaded. To reload it, use:
  %reload_ext memory_profiler
```

```
import pandas as pd
import numpy as np
import seaborn as sns
from scipy import stats
import matplotlib.pyplot as plt
import hvplot.pandas
from IPython.display import display

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix
from sklearn.model_selection import cross_val_score
from sklearn.metrics import make_scorer, f1_score, roc_auc_score
from sklearn.model_selection import StratifiedKFold
from sklearn.metrics import roc_curve, auc, precision_recall_curve,
average_precision_score,RocCurveDisplay
from sklearn.model_selection import StratifiedKFold
from sklearn.base import clone
from sklearn.discriminant_analysis import
QuadraticDiscriminantAnalysis
from sklearn.svm import SVC
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.tree import DecisionTreeClassifier



import time

pd.set_option('display.float', '{:.2f}'.format)
pd.set_option('display.max_columns', 50)
pd.set_option('display.max_rows', 50)
```

```
""

""

""
```

Introduction

- LendingClub is a US peer-to-peer lending company, headquartered in San Francisco, California.
- What we are trying to do is to predict the loan approval of a person based on the data we have been given
- Lets now **load** the data and **describe** it.

```
data = pd.read_csv("train_lending_club.csv")
print("Data imported successfully")

data.head()

Data imported successfully

      issue_d sub_grade        term home_ownership  fico_range_low
total_acc  \
0  2014-01-01        D1   60 months       MORTGAGE          660.00
18.00
1  2014-01-01        C4   60 months       MORTGAGE          740.00
26.00
2  2014-01-01        A4   36 months           RENT          700.00
47.00
3  2014-01-01        D1   60 months       MORTGAGE          665.00
26.00
4  2014-01-01        C3   36 months       MORTGAGE          700.00
15.00

   pub_rec  revol_util  annual_inc  int_rate   dti             purpose
\
0     0.00       86.80    40440.00     16.99 15.16         credit_card

1     0.00      103.50    59000.00     15.61 16.74         credit_card

2     0.00       11.40    40000.00      7.90 20.34  debt_consolidation

3     0.00       56.20    70000.00     16.99 23.15  debt_consolidation

4     1.00       67.10   120000.00     14.98 17.88            vacation


   mort_acc  loan_amnt application_type  installment
verification_status  \
0      1.00   17775.00       Individual       441.66
Verified
```

```
1      4.00   29175.00       Individual       703.45
Verified
2      1.00    6000.00       Individual       187.75        Not
Verified
3      7.00   15600.00       Individual       387.62
Verified
4      1.00   10000.00       Individual       346.56
Verified

   pub_rec_bankruptcies addr_state initial_list_status
fico_range_high  \
0                  0.00         AR                   f
664.00
1                  0.00         VT                   f
744.00
2                  0.00         TX                   w
704.00
3                  0.00         IN                   f
669.00
4                  0.00         LA                   f
704.00

   revol_bal        id  open_acc  emp_length  loan_status  \
0   17264.00  11024793     11.00        2.00            1
1    6725.00  10596078      8.00        3.00            1
2    7613.00  10775616     27.00        1.00            1
3   14173.00  10765610      9.00       11.00            1
4    2549.00  10794837      8.00        2.00            1

   time_to_earliest_cr_line
0                 478656.00
1                 541728.00
2                 657590.40
3                 328838.40
4                 305164.80
```

Description of the data

```
data.describe()

       fico_range_low  total_acc   pub_rec  revol_util  annual_inc
int_rate  \
count       236846.00  236846.00 236846.00   236846.00   236846.00
236846.00
mean           694.35      25.57      0.24       52.85    77379.53
12.60
std             30.93      12.20      0.67       24.01    77290.67
4.48
min            660.00       2.00      0.00        0.00        0.00
5.32
```

```
25%             670.00      17.00       0.00       35.00    46000.00
9.17
50%             685.00      24.00       0.00       53.00    65000.00
12.29
75%             710.00      32.00       0.00       71.20    92000.00
15.31
max             845.00     169.00      86.00      182.80  9573072.00
30.99

            dti  mort_acc  loan_amnt  installment
pub_rec_bankruptcies  \
count 236846.00 236846.00  236846.00    236846.00
236846.00
mean      18.53      1.73   14626.43       441.92
0.14
std        9.21      2.04    8611.59       257.21
0.39
min        0.00      0.00    1000.00        14.77
0.00
25%       12.05      0.00    8000.00       254.07
0.00
50%       17.89      1.00   12450.00       378.20
0.00
75%       24.52      3.00   20000.00       588.37
0.00
max      999.00     47.00   40000.00      1534.88
9.00

       fico_range_high  revol_bal          id  open_acc  emp_length  \
count        236846.00  236846.00   236846.00 236846.00   236846.00
mean            698.35   16956.26 49269391.36     11.81        5.99
std              30.93   23829.01 20980382.07      5.59        4.24
min             664.00       0.00    56705.00      0.00        0.00
25%             674.00    6127.00 33191497.25      8.00        2.00
50%             689.00   11399.00 52979215.50     11.00        6.00
75%             714.00   20431.00 66645529.25     15.00       11.00
max             850.00 2560703.00 84363456.00     76.00       11.00

       loan_status  time_to_earliest_cr_line
count    236846.00                 236846.00
mean          0.83                 526420.51
std           0.37                 241312.11
min           0.00                  97113.60
25%           1.00                 360374.40
50%           1.00                 478483.20
75%           1.00                 647049.60
max           1.00                2240524.80

data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 236846 entries, 0 to 236845
Data columns (total 27 columns):
 #   Column                   Non-Null Count   Dtype  
---  ------                   --------------   -----  
 0   issue_d                  236846 non-null  object 
 1   sub_grade                236846 non-null  object 
 2   term                     236846 non-null  object 
 3   home_ownership           236846 non-null  object 
 4   fico_range_low           236846 non-null  float64
 5   total_acc                236846 non-null  float64
 6   pub_rec                  236846 non-null  float64
 7   revol_util               236846 non-null  float64
 8   annual_inc               236846 non-null  float64
 9   int_rate                 236846 non-null  float64
 10  dti                      236846 non-null  float64
 11  purpose                  236846 non-null  object 
 12  mort_acc                 236846 non-null  float64
 13  loan_amnt                236846 non-null  float64
 14  application_type         236846 non-null  object 
 15  installment              236846 non-null  float64
 16  verification_status      236846 non-null  object 
 17  pub_rec_bankruptcies     236846 non-null  float64
 18  addr_state               236846 non-null  object 
 19  initial_list_status      236846 non-null  object 
 20  fico_range_high          236846 non-null  float64
 21  revol_bal                236846 non-null  float64
 22  id                       236846 non-null  int64  
 23  open_acc                 236846 non-null  float64
 24  emp_length               236846 non-null  float64
 25  loan_status              236846 non-null  int64  
 26  time_to_earliest_cr_line 236846 non-null  float64
dtypes: float64(16), int64(2), object(9)
memory usage: 48.8+ MB
```

Data Preprocessing

- Remove or fill any missing data
- scaling
- convert categorical data into numeric

```python
print(f"The Length of the data: {data.shape}")
```

```
The Length of the data: (236846, 27)
```

```python
# Missing values
for column in data.columns:
    if data[column].isna().sum() != 0:
        missing = data[column].isna().sum()
        portion = (missing / data.shape[0]) * 100
```

```
        print(f"'{column}': number of missing values '{missing}' ==>
'{portion:.3f}%'")
```

```
data.emp_length.unique()
```

```
array([ 2.,  3.,  1., 11.,  9.,  8.,  6.,  4.,  0.,  5.,  7.])
```

```
for year in data.emp_length.unique():
    print(f"{year} years in this position:")
    print(f"{data[data.emp_length ==
year].loan_status.value_counts(normalize=True)}")
    print('==========================================')
```

```
2.0 years in this position:
loan_status
1   0.84
0   0.16
Name: proportion, dtype: float64
==========================================
3.0 years in this position:
loan_status
1   0.83
0   0.17
Name: proportion, dtype: float64
==========================================
1.0 years in this position:
loan_status
1   0.83
0   0.17
Name: proportion, dtype: float64
==========================================
11.0 years in this position:
loan_status
1   0.84
0   0.16
Name: proportion, dtype: float64
==========================================
9.0 years in this position:
loan_status
1   0.83
0   0.17
Name: proportion, dtype: float64
==========================================
8.0 years in this position:
loan_status
1   0.83
0   0.17
Name: proportion, dtype: float64
==========================================
6.0 years in this position:
```

```
loan_status
1    0.83
0    0.17
Name: proportion, dtype: float64
==========================================
4.0 years in this position:
loan_status
1    0.83
0    0.17
Name: proportion, dtype: float64
==========================================
0.0 years in this position:
loan_status
1    0.80
0    0.20
Name: proportion, dtype: float64
==========================================
5.0 years in this position:
loan_status
1    0.83
0    0.17
Name: proportion, dtype: float64
==========================================
7.0 years in this position:
loan_status
1    0.83
0    0.17
Name: proportion, dtype: float64
==========================================
```

Label Encoding

- Turning Categorical values into numerical

```
# List of categorical columns to convert
categorical_columns = ['sub_grade', 'term', 'home_ownership',
'purpose', 'application_type', 'verification_status',
'initial_list_status']

# One-hot encode these columns
data = pd.get_dummies(data, columns=categorical_columns)

# remove issue date because before hand we don't know when the loan
will be issued
# drop loan_status because it is the target
# drop id,addr_state because it is not useful


# Store 'loan_status' in a separate variable Y
y_train = data['loan_status']
```

```
# Now we can safely drop 'issue_d', 'sub_grade', 'loan_status', and
'id' from the dataset
data = data.drop(['issue_d', 'loan_status', 'id', 'addr_state'],
axis=1)
X_train = data

# 'X_train' now contains only the features, and 'y_train' is your
target variable

X_train.head()
```

```
   fico_range_low  total_acc  pub_rec  revol_util  annual_inc
int_rate   dti  \
0          660.00      18.00     0.00       86.80    40440.00
16.99 15.16
1          740.00      26.00     0.00      103.50    59000.00
15.61 16.74
2          700.00      47.00     0.00       11.40    40000.00
7.90 20.34
3          665.00      26.00     0.00       56.20    70000.00
16.99 23.15
4          700.00      15.00     1.00       67.10   120000.00
14.98 17.88

   mort_acc  loan_amnt  installment  pub_rec_bankruptcies
fico_range_high  \
0      1.00   17775.00       441.66                  0.00
664.00
1      4.00   29175.00       703.45                  0.00
744.00
2      1.00    6000.00       187.75                  0.00
704.00
3      7.00   15600.00       387.62                  0.00
669.00
4      1.00   10000.00       346.56                  0.00
704.00

   revol_bal  open_acc  emp_length  time_to_earliest_cr_line
sub_grade_A1  \
0   17264.00     11.00        2.00                 478656.00
False
1    6725.00      8.00        3.00                 541728.00
False
2    7613.00     27.00        1.00                 657590.40
False
3   14173.00      9.00       11.00                 328838.40
False
4    2549.00      8.00        2.00                 305164.80
False
```

```
   sub_grade_A2  sub_grade_A3  sub_grade_A4  sub_grade_A5
sub_grade_B1  \
0         False         False         False         False
False
1         False         False         False         False
False
2         False         False          True         False
False
3         False         False         False         False
False
4         False         False         False         False
False

   sub_grade_B2  sub_grade_B3  sub_grade_B4  ...  term_ 60 months  \
0         False         False         False  ...             True
1         False         False         False  ...             True
2         False         False         False  ...            False
3         False         False         False  ...             True
4         False         False         False  ...            False

   home_ownership_MORTGAGE  home_ownership_OWN  home_ownership_RENT  \
0                     True               False                False
1                     True               False                False
2                    False               False                 True
3                     True               False                False
4                     True               False                False

   purpose_car  purpose_credit_card  purpose_debt_consolidation  \
0        False                 True                       False
1        False                 True                       False
2        False                False                        True
3        False                False                        True
4        False                False                       False

   purpose_educational  purpose_home_improvement  purpose_house  \
0                False                     False          False
1                False                     False          False
2                False                     False          False
3                False                     False          False
4                False                     False          False

   purpose_major_purchase  purpose_medical  purpose_moving
purpose_other  \
0                   False            False           False
False
1                   False            False           False
False
2                   False            False           False
False
3                   False            False           False
```

```
False
4                    False            False          False
False

   purpose_renewable_energy  purpose_small_business  purpose_vacation
\
0                     False                   False             False

1                     False                   False             False

2                     False                   False             False

3                     False                   False             False

4                     False                   False              True


   purpose_wedding  application_type_Individual
application_type_Joint App  \
0            False                         True
False
1            False                         True
False
2            False                         True
False
3            False                         True
False
4            False                         True
False

   verification_status_Not Verified  verification_status_Source
Verified  \
0                             False
False
1                             False
False
2                              True
False
3                             False
False
4                             False
False

   verification_status_Verified  initial_list_status_f
initial_list_status_w
0                          True                   True
False
1                          True                   True
False
2                         False                  False
```

```
True
3                          True                      True
False
4                          True                      True
False

[5 rows x 77 columns]
```

Logistic Regression

```
# Scale the numeric features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)

logistic_classifier = LogisticRegression(max_iter=1000) # You can
adjust regularization parameters if needed
logistic_classifier.fit(X_train_scaled, y_train)

LogisticRegression(max_iter=1000)
```

KNN CLASSIFIER

```
# Train KNN Classifier
# in terminal set LOKY_MAX_CPU_COUNT= <number of cores you want to
use>

knn_classifier = KNeighborsClassifier(n_neighbors=5) # You can adjust
the number of neighbors (k) as needed
knn_classifier.fit(X_train_scaled, y_train)

KNeighborsClassifier()
```

Performance evaluation Milestone 1

```
# F1 Score for Logistic Regression
logistic_f1_scores = cross_val_score(logistic_classifier,
X_train_scaled, y_train, cv=5, scoring='f1')
print("Logistic Regression CV F1 Score:", logistic_f1_scores.mean())

# AUC for Logistic Regression
logistic_auc_scores = cross_val_score(logistic_classifier,
X_train_scaled, y_train, cv=5, scoring='roc_auc')
print("Logistic Regression CV AUC:", logistic_auc_scores.mean())

# Repeat for KNN
knn_f1_scores = cross_val_score(knn_classifier, X_train_scaled,
y_train, cv=5, scoring='f1')
print("KNN CV F1 Score:", knn_f1_scores.mean())

knn_auc_scores = cross_val_score(knn_classifier, X_train_scaled,
```

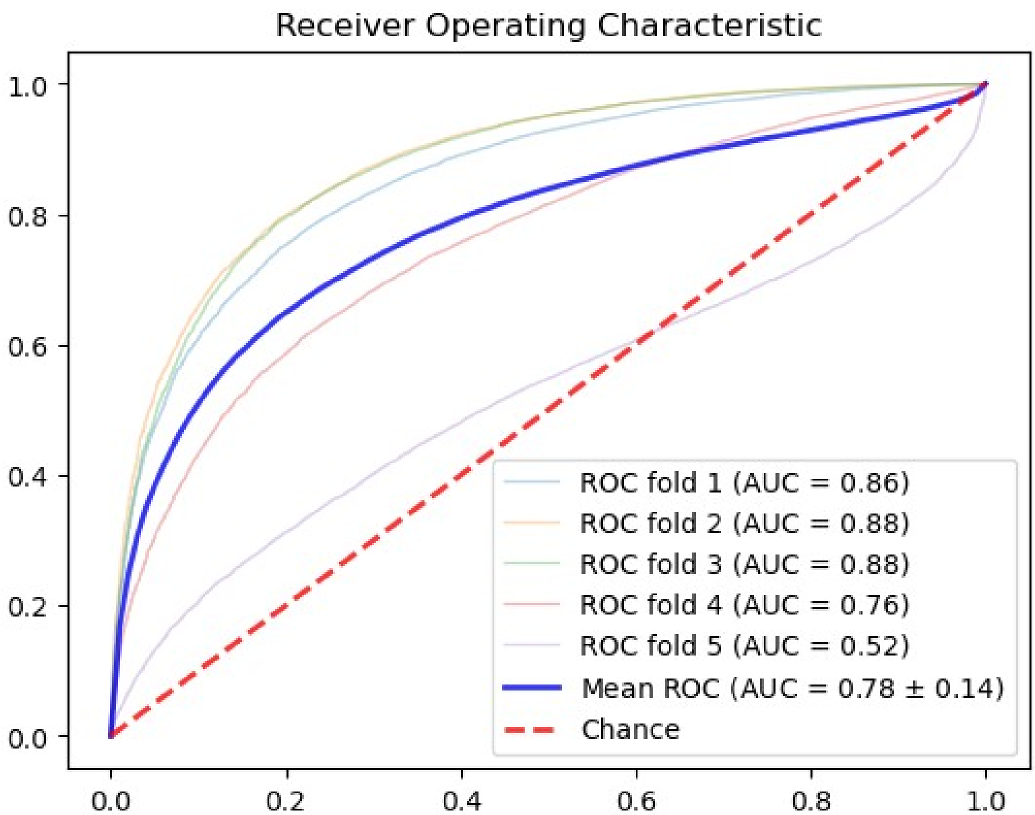
```
y_train, cv=5, scoring='roc_auc')
print("KNN CV AUC:", knn_auc_scores.mean())
```

```
Logistic Regression CV F1 Score: 0.9033793225069063
Logistic Regression CV AUC: 0.7789966094200176
KNN CV F1 Score: 0.8945972841418024
KNN CV AUC: 0.6943401702263249
```

ROC Curve for Logistic Regression

```
# Initialize StratifiedKFold
cv = StratifiedKFold(n_splits=5)

tprs = []
aucs = []
mean_fpr = np.linspace(0, 1, 100)

fig, ax = plt.subplots()
for i, (train, test) in enumerate(cv.split(X_train_scaled, y_train)):
    # Fit the logistic regression model on the training data
    logistic_classifier.fit(X_train_scaled[train], y_train[train])

    # Predict probabilities for the test set
    probas_ = logistic_classifier.predict_proba(X_train_scaled[test])

    # Compute ROC curve and area the curve
    fpr, tpr, thresholds = roc_curve(y_train[test], probas_[:, 1])
    tprs.append(np.interp(mean_fpr, fpr, tpr))
    tprs[-1][0] = 0.0
    roc_auc = auc(fpr, tpr)
    aucs.append(roc_auc)
    ax.plot(fpr, tpr, lw=1, alpha=0.3, label=f'ROC fold {i+1} (AUC =
{roc_auc:.2f})')

# Plot the mean ROC curve
mean_tpr = np.mean(tprs, axis=0)
mean_tpr[-1] = 1.0
mean_auc = auc(mean_fpr, mean_tpr)
std_auc = np.std(aucs)
ax.plot(mean_fpr, mean_tpr, color='b', label=r'Mean ROC (AUC = %0.2f
$\pm$ %0.2f)' % (mean_auc, std_auc),
        lw=2, alpha=.8)

# Plot the chance line
ax.plot([0, 1], [0, 1], linestyle='--', lw=2, color='r',
label='Chance', alpha=.8)

# Final plot adjustments
ax.set(xlim=[-0.05, 1.05], ylim=[-0.05, 1.05], title="Receiver
Operating Characteristic")
```

```
ax.legend(loc="lower right")
plt.show()
```




```
def plot_cv_roc_curve(classifier, X, y, cv_splits=5,
classifier_name='Classifier'):
    """
    Plots ROC curves for each fold in cross-validation and the mean
ROC curve.

    Parameters:
    - classifier: The classifier to use.
    - X: Feature set.
    - y: Target variable.
    - cv_splits: Number of cross-validation splits.
    - classifier_name: Name of the classifier (for legend labeling).
    """
    cv = StratifiedKFold(n_splits=cv_splits)
    tprs = []
    aucs = []
    mean_fpr = np.linspace(0, 1, 100)
    fig, ax = plt.subplots()

    for i, (train, test) in enumerate(cv.split(X, y)):
```

```
        classifier.fit(X[train], y[train])
        probas_ = classifier.predict_proba(X[test])
        fpr, tpr, thresholds = roc_curve(y[test], probas_[:, 1])
        tprs.append(np.interp(mean_fpr, fpr, tpr))
        tprs[-1][0] = 0.0
        roc_auc = auc(fpr, tpr)
        aucs.append(roc_auc)
        ax.plot(fpr, tpr, lw=1, alpha=0.3, label=f'Fold {i+1}
{classifier_name} (AUC = {roc_auc:.2f})')

    mean_tpr = np.mean(tprs, axis=0)
    mean_tpr[-1] = 1.0
    mean_auc = auc(mean_fpr, mean_tpr)
    std_auc = np.std(aucs)
    ax.plot(mean_fpr, mean_tpr, color='b', label=f'Mean
{classifier_name} (AUC = {mean_auc:.2f} $\pm$ {std_auc:.2f})', lw=2,
alpha=.8)
    ax.plot([0, 1], [0, 1], linestyle='--', lw=2, color='r',
label='Chance', alpha=.8)
    ax.set(xlim=[-0.05, 1.05], ylim=[-0.05, 1.05], title=f"Receiver
Operating Characteristic - {classifier_name}")
    ax.legend(loc="lower right")
    plt.show()

# Measure CPU time for training KNN Classifier
start_time = time.time()
knn_classifier.fit(X_train_scaled, y_train)
end_time = time.time()
print("Time taken for training KNN Classifier:", end_time -
start_time, "seconds")

# Measure memory usage for training KNN Classifier
%memit knn_classifier.fit(X_train_scaled, y_train)


# Measure CPU time for training Logistic Regression Classifier
start_time = time.time()
logistic_classifier.fit(X_train_scaled, y_train)
end_time = time.time()
print("Time taken for training Logistic Classifier:", end_time -
start_time, "seconds")

# Measure memory usage for training KNN Classifier
%memit logistic_classifier.fit(X_train_scaled, y_train)
```

```
Time taken for training KNN Classifier: 0.08687520027160645 seconds
peak memory: 763.15 MiB, increment: 142.79 MiB
Time taken for training Logistic Classifier: 1.1194474697113037
seconds
peak memory: 768.02 MiB, increment: 147.64 MiB
```

Linear Discriminant Analysis AND Desicion Trees

```
# Define the LDA model
lda_model = LinearDiscriminantAnalysis()
# Measure training time for LDA
start_time = time.time()
lda_model.fit(X_train_scaled, y_train)
lda_training_time = time.time() - start_time

print(f"LDA Training Time: {lda_training_time} seconds")

# Define the Decision Tree model
dt_model = DecisionTreeClassifier()

# Measure training time for Decision Trees
start_time = time.time()
dt_model.fit(X_train_scaled, y_train)
dt_training_time = time.time() - start_time

print(f"Decision Tree Training Time: {dt_training_time} seconds")
```

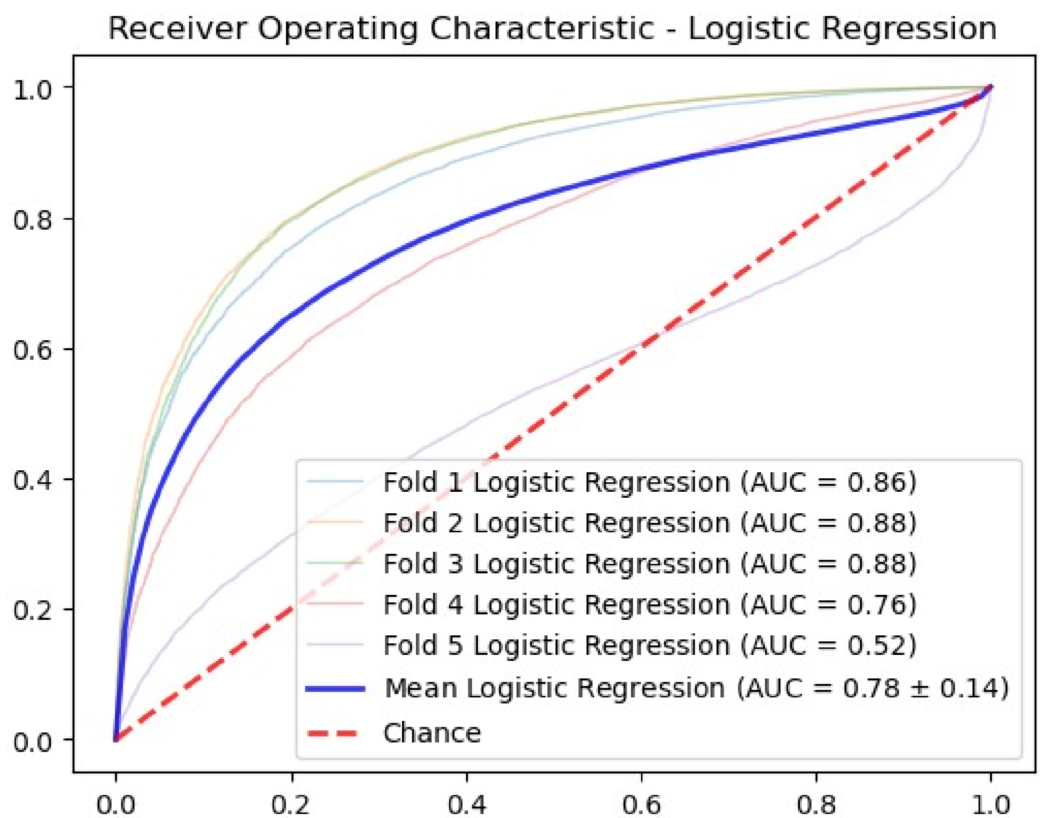
```
LDA Training Time: 2.908019542694092 seconds
Decision Tree Training Time: 15.742506742477417 seconds
```

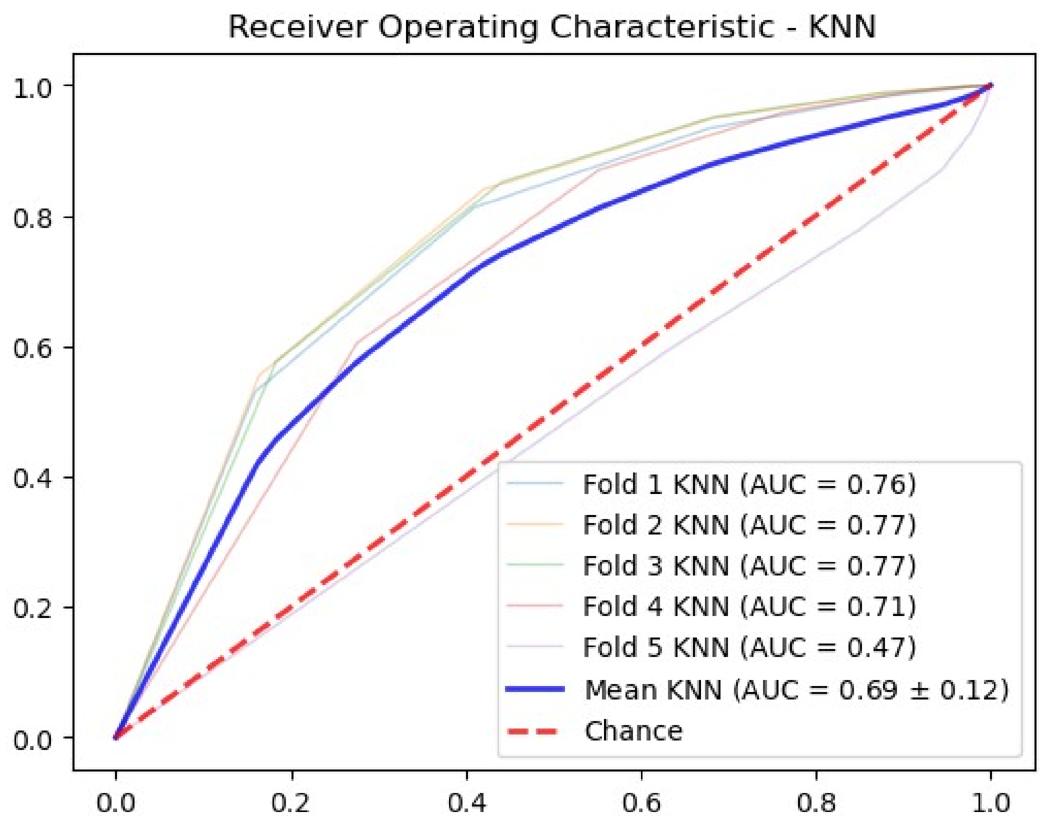
Performance and Resource Utilization

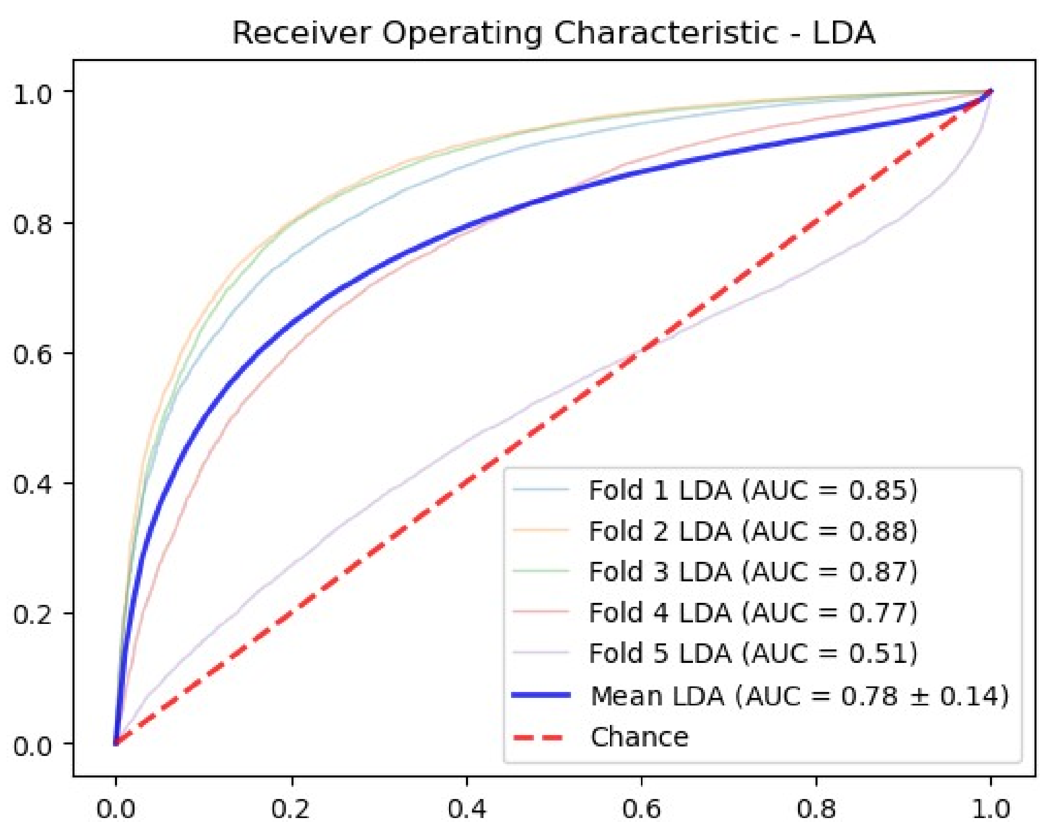
```
# AUC and F1 for LDA
lda_auc = cross_val_score(lda_model, X_train_scaled, y_train, cv=5,
scoring='roc_auc').mean()
lda_f1 = cross_val_score(lda_model, X_train_scaled, y_train, cv=5,
scoring='f1').mean()

print(f"LDA Mean AUC: {lda_auc}")
print(f"LDA Mean F1: {lda_f1}")

# AUC and F1 for Decision Trees
dt_auc = cross_val_score(dt_model, X_train_scaled, y_train, cv=5,
scoring='roc_auc').mean()
dt_f1 = cross_val_score(dt_model, X_train_scaled, y_train, cv=5,
scoring='f1').mean()

print(f"Decision Tree Mean AUC: {dt_auc}")
print(f"Decision Tree Mean F1: {dt_f1}")
```

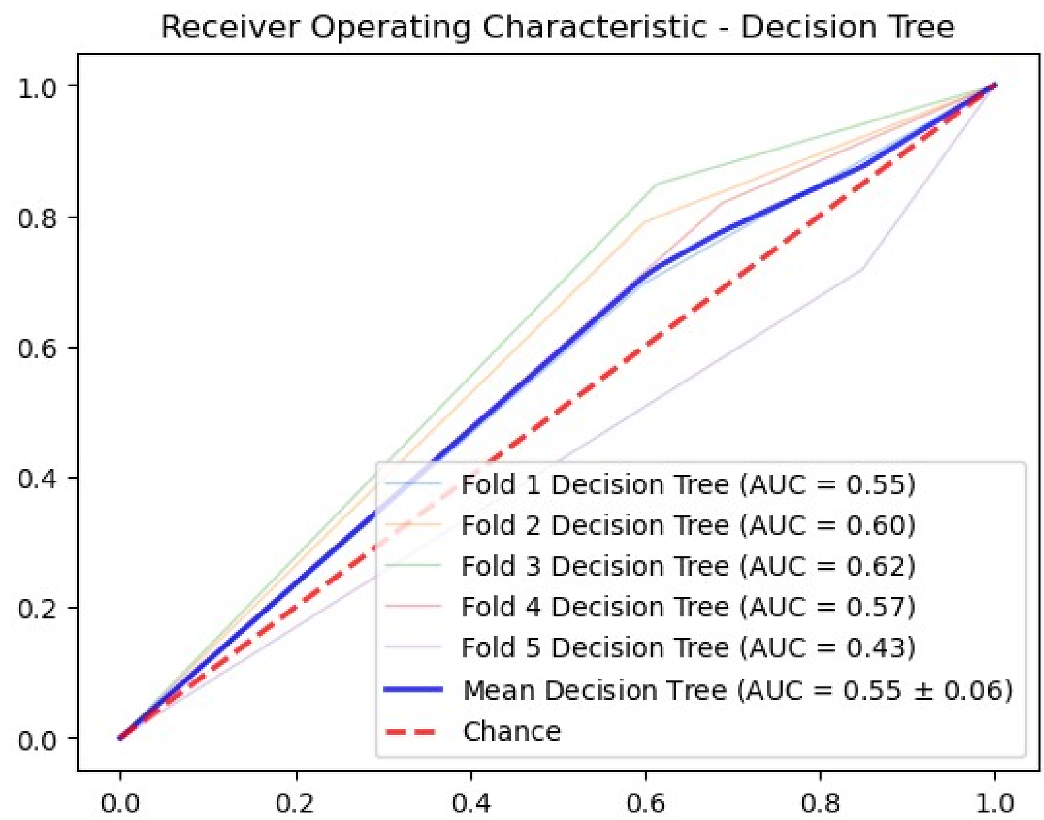
```
LDA Mean AUC: 0.7762112146124798
LDA Mean F1: 0.9008621176642944
Decision Tree Mean AUC: 0.5538783998959265
Decision Tree Mean F1: 0.8094133830039187
```

```python
# For Logistic Regression
plot_cv_roc_curve(logistic_classifier, X_train_scaled, y_train,
classifier_name='Logistic Regression')

# For KNN
plot_cv_roc_curve(knn_classifier, X_train_scaled, y_train,
classifier_name='KNN')

# For LDA
plot_cv_roc_curve(lda_model, X_train_scaled, y_train,
classifier_name='LDA')

# For Decision Trees
plot_cv_roc_curve(dt_model, X_train_scaled, y_train,
classifier_name='Decision Tree')
```




Receiver Operating Characteristic - KNN
Fold 1 KNN (AUC = 0.76)
Fold 2 KNN (AUC = 0.77)
Fold 3 KNN (AUC = 0.77)
Fold 4 KNN (AUC = 0.71)
Fold 5 KNN (AUC = 0.47)
Mean KNN (AUC = 0.69 ± 0.12)
Chance
0.0
0.2
0.4
0.6
0.8
1.0

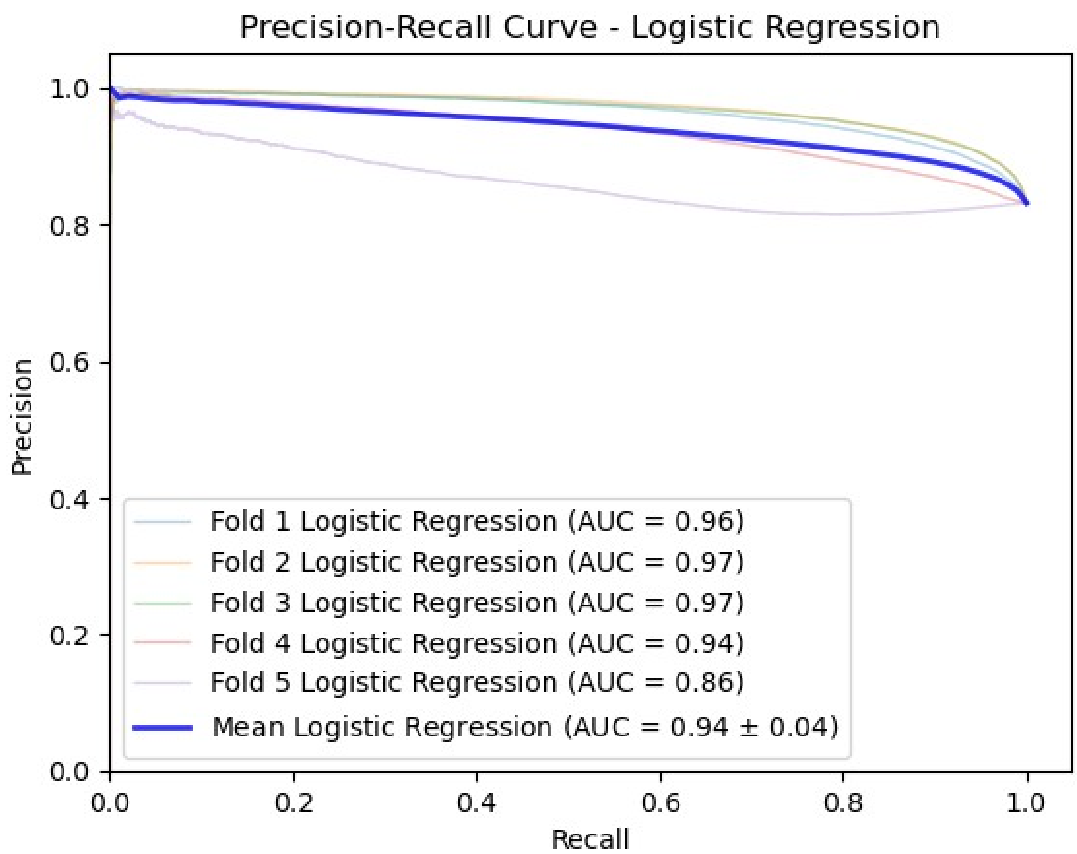

Receiver Operating Characteristic - LDA
Fold 1 LDA (AUC = 0.85)
Fold 2 LDA (AUC = 0.88)
Fold 3 LDA (AUC = 0.87)
Fold 4 LDA (AUC = 0.77)
Fold 5 LDA (AUC = 0.51)
Mean LDA (AUC = 0.78 ± 0.14)
Chance
0.0
0.2
0.4
0.6
0.8
1.0



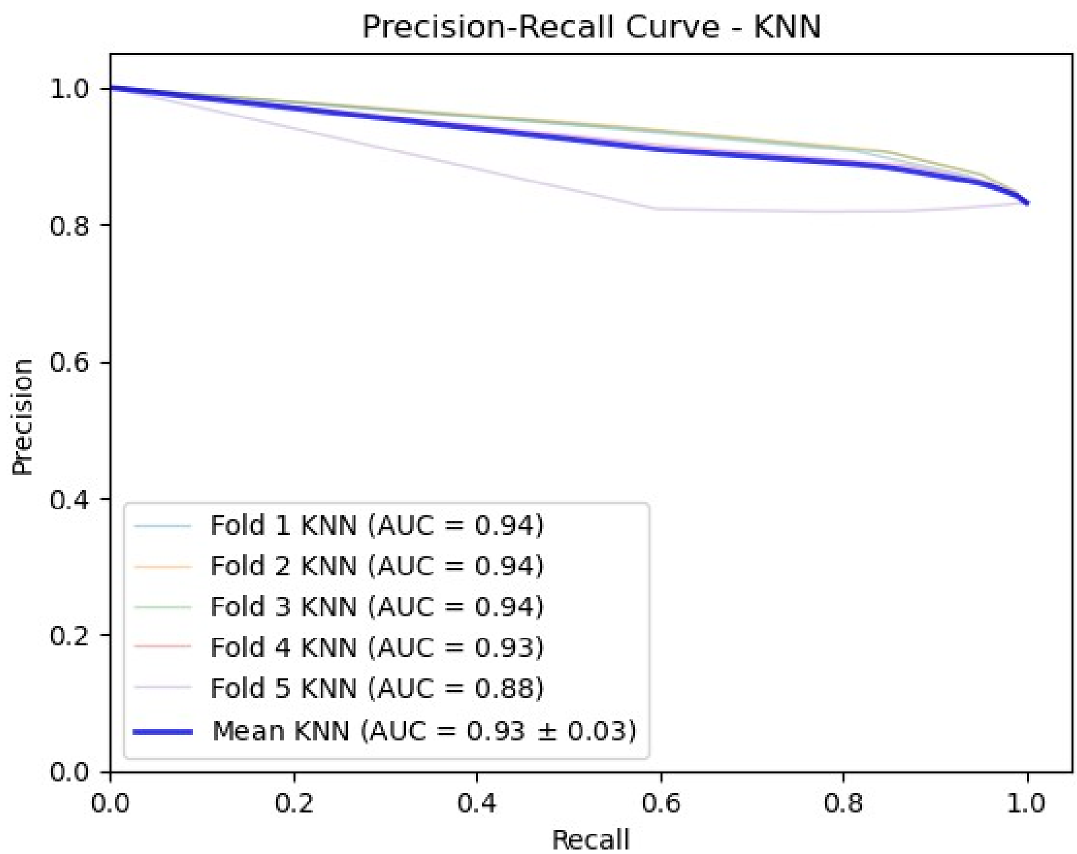
Precision Recall Curve

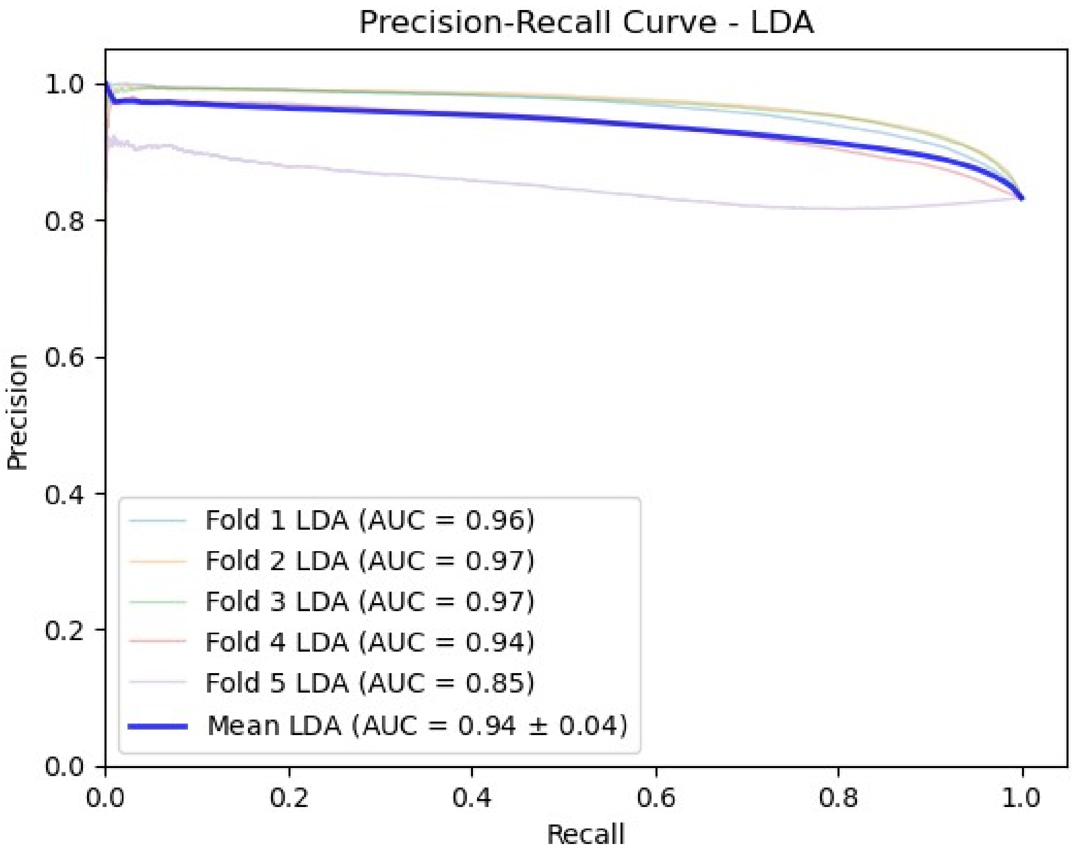
```
def plot_cv_precision_recall_curve(classifier, X, y, cv_splits=5,
classifier_name='Classifier'):
    """
    Plots Precision-Recall curves for each fold in cross-validation
and the mean Precision-Recall curve.

    Parameters:
    - classifier: The classifier to use.
    - X: Feature set.
    - y: Target variable.
    - cv_splits: Number of cross-validation splits.
    - classifier_name: Name of the classifier (for legend labeling).
    """
    cv = StratifiedKFold(n_splits=cv_splits)
    mean_recall = np.linspace(0, 1, 100)
    precisions = []
    aucs = []
    fig, ax = plt.subplots()

    for i, (train, test) in enumerate(cv.split(X, y)):
        classifier.fit(X[train], y[train])
        probas_ = classifier.predict_proba(X[test])
        precision, recall, thresholds =
```

```
precision_recall_curve(y[test], probas_[:, 1])
        rev_recall = recall[::-1]  # Reverse the recall array
        rev_precision = precision[::-1]  # Reverse the precision array
        precisions.append(np.interp(mean_recall, rev_recall,
rev_precision))
        precisions[-1][0] = 1.0
        pr_auc = auc(rev_recall, rev_precision)
        aucs.append(pr_auc)
        ax.plot(recall, precision, lw=1, alpha=0.3, label=f'Fold {i+1}
{classifier_name} (AUC = {pr_auc:.2f})')

    mean_precision = np.mean(precisions, axis=0)
    mean_auc = auc(mean_recall, mean_precision)
    std_auc = np.std(aucs)
    ax.plot(mean_recall, mean_precision, color='b', label=f'Mean
{classifier_name} (AUC = {mean_auc:.2f} $\pm$ {std_auc:.2f})', lw=2,
alpha=.8)
    ax.set(xlim=[0, 1.05], ylim=[0, 1.05], title=f"Precision-Recall
Curve - {classifier_name}")
    ax.legend(loc="lower left")
    plt.xlabel('Recall')
    plt.ylabel('Precision')
    plt.show()

# For Logistic Regression
plot_cv_precision_recall_curve(logistic_classifier, X_train_scaled,
y_train, classifier_name='Logistic Regression')

# For KNN
plot_cv_precision_recall_curve(knn_classifier, X_train_scaled,
y_train, classifier_name='KNN')

# For LDA
plot_cv_precision_recall_curve(lda_model, X_train_scaled, y_train,
classifier_name='LDA')

# For Decision Trees
plot_cv_precision_recall_curve(dt_model, X_train_scaled, y_train,
classifier_name='Decision Tree')
```

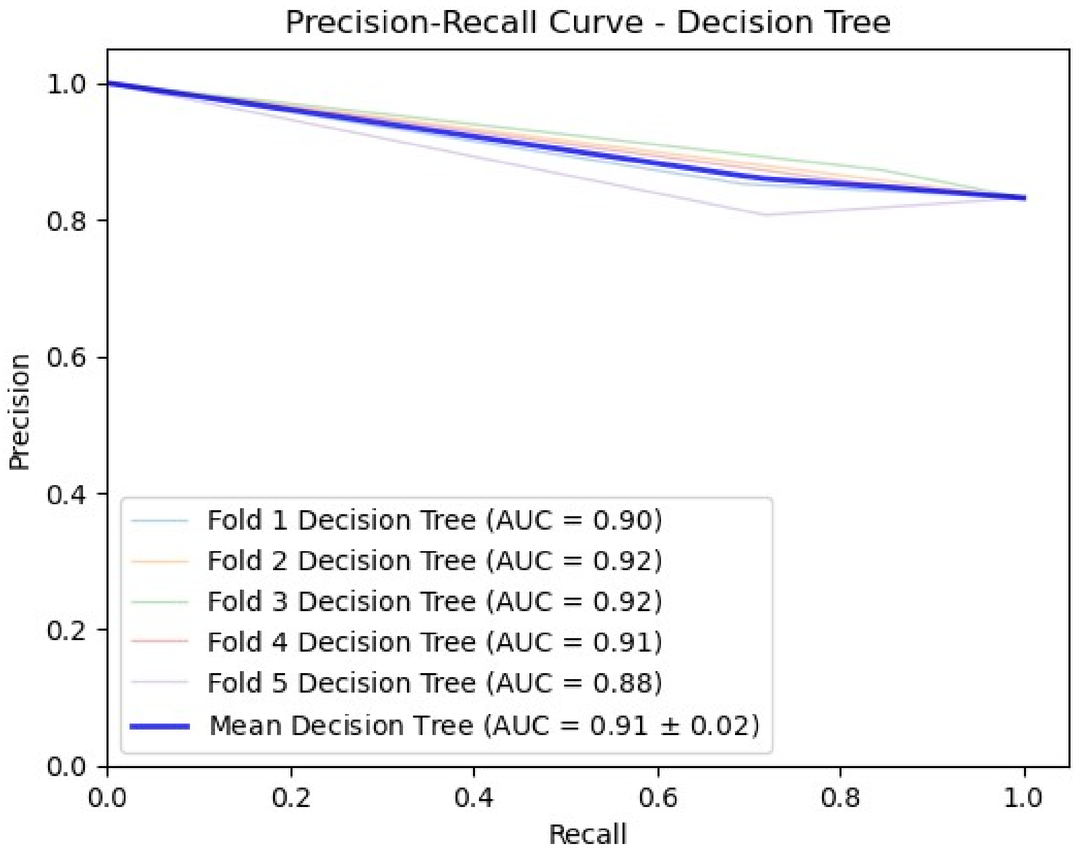


Precision-Recall Curve - Logistic Regression
Precision
Recall
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
Fold 1 Logistic Regression (AUC = 0.96)
Fold 2 Logistic Regression (AUC = 0.97)
Fold 3 Logistic Regression (AUC = 0.97)
Fold 4 Logistic Regression (AUC = 0.94)
Fold 5 Logistic Regression (AUC = 0.86)
Mean Logistic Regression (AUC = 0.94 ± 0.04)


Precision-Recall Curve - KNN
Precision
Recall
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
Fold 1 KNN (AUC = 0.94)
Fold 2 KNN (AUC = 0.94)
Fold 3 KNN (AUC = 0.94)
Fold 4 KNN (AUC = 0.93)
Fold 5 KNN (AUC = 0.88)
Mean KNN (AUC = 0.93 ± 0.03)



Precision-Recall Curve - LDA
Precision
Recall
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
Fold 1 LDA (AUC = 0.96)
Fold 2 LDA (AUC = 0.97)
Fold 3 LDA (AUC = 0.97)
Fold 4 LDA (AUC = 0.94)
Fold 5 LDA (AUC = 0.85)
Mean LDA (AUC = 0.94 ± 0.04)


Precision-Recall Curve - Decision Tree
Precision
Recall
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
Fold 1 Decision Tree (AUC = 0.90)
Fold 2 Decision Tree (AUC = 0.92)
Fold 3 Decision Tree (AUC = 0.92)
Fold 4 Decision Tree (AUC = 0.91)
Fold 5 Decision Tree (AUC = 0.88)
Mean Decision Tree (AUC = 0.91 ± 0.02)