4 or more ML Classifiers (2)

November 23, 2024

[7]:
```python
# Python  3.5 is required
import sys
assert sys.version_info >= (3, 5)

# Scikit-Learn  0.20 is required
import sklearn
assert sklearn.__version__ >= "0.20"

# Common imports
import numpy as np
import os

import seaborn as sns
from scipy import stats

# To plot pretty figures
%matplotlib inline
import matplotlib as mpl
import matplotlib.pyplot as plt
mpl.rc('axes', labelsize=14)
mpl.rc('xtick', labelsize=12)
mpl.rc('ytick', labelsize=12)
```

Implement 1st ML Classifier: Random Forest

[8]:
```python
import pandas as pd

internet_data = pd.read_csv('preprocessed_internet_data.csv')

internet_data
```

[8]:
```
       Source Port  Destination Port  NAT Source Port  NAT Destination Port  \
0            57222                53            54587                    53
1            56258              3389            56258                  3389
2             6881             50321            43265                 50321
3            50553              3389            50553                  3389
4            50002               443            45848                   443
```

```
…              …              …              …              …              …
65527      63691             80          13237                   80
65528      50964             80          13485                   80
65529      54871            445              0                    0
65530      54870            445              0                    0
65531      54867            445              0                    0

       Bytes Sent  Bytes Received  Elapsed Time (sec)  Packets Sent  \
0        4.553877        4.430817                  30      0.693147
1        7.378384        8.061171                  17      2.397895
2        4.779123        4.795791                1199      0.693147
3        7.271704        7.544332                  17      2.197225
4        8.821585        9.829895                  16      2.639057
…             …               …                   …             …
65527    5.262690        4.812184                  15      1.609438
65528   11.117109       15.344482                  77      6.893656
65529    4.262680        0.000000                   0      0.693147
65530    4.262680        0.000000                   0      0.693147
65531    4.262680        0.000000                   0      0.693147

       Packets Received  Action
0              0.693147       0
1              2.397895       0
2              0.693147       0
3              2.197225       0
4              2.639057       0
…                   …      …
65527          1.609438       0
65528          6.893656       0
65529          0.693147       2
65530          0.693147       2
65531          0.693147       2

[65532 rows x 10 columns]
```

[9]:

```python
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report, confusion_matrix, ConfusionMatrixDisplay
from sklearn.model_selection import cross_validate
from sklearn.model_selection import StratifiedKFold
from sklearn.tree import DecisionTreeClassifier
```

[10]:

```python
X = internet_data.drop('Action', axis=1)
y = internet_data['Action']
```

[11]:
```
nat_ports = internet_data['NAT Source Port']
nat_ports

target_variable = y

relationship_df = pd.DataFrame({
    'nat source port': nat_ports,
    'Target': target_variable
})

relationship_df
```

[11]:
```
       nat source port  Target
0                54587       0
1                56258       0
2                43265       0
3                50553       0
4                45848       0
…                    …     …
65527            13237       0
65528            13485       0
65529                0       2
65530                0       2
65531                0       2

[65532 rows x 2 columns]
```

[12]:
```
print(y.value_counts())
```

```
Action
0    37640
1    14987
2    12851
3       54
Name: count, dtype: int64
```

[13]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)
```

1. Random Forest

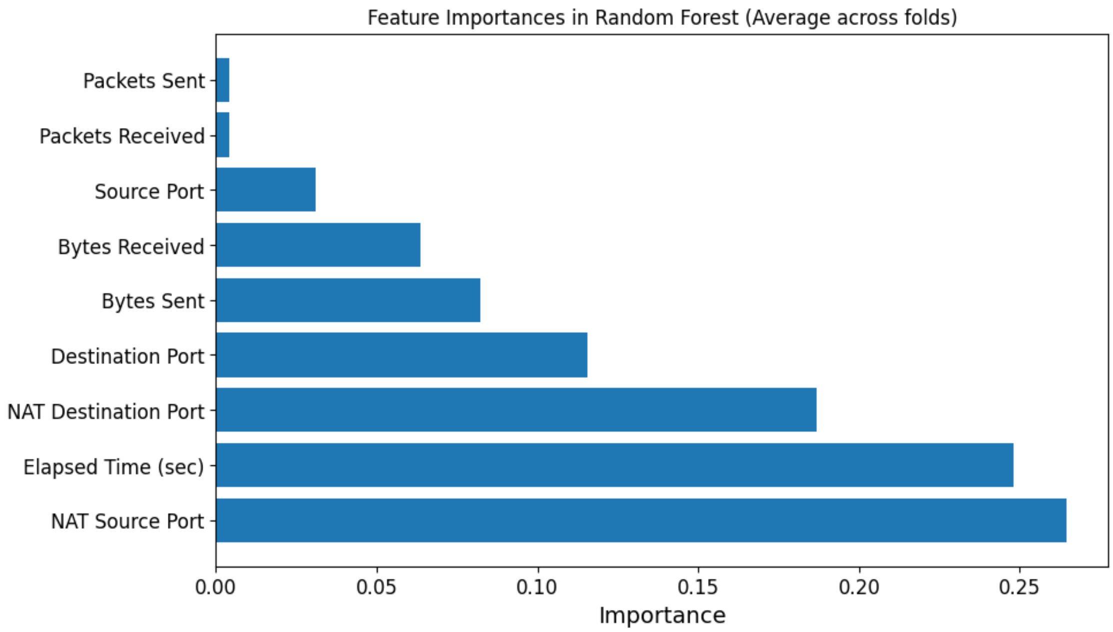
Let's first assess feature importance so we can figure out which features contribute the most to our model's performance

[14]:
```
model = RandomForestClassifier(n_estimators=100, random_state=42, max_depth=2)

# Stratified KFold cross-validation
skf = StratifiedKFold(n_splits=5)
```

```python
# Store feature importances for each fold
feature_importances = []

cv_results = cross_validate(model, X, y, cv=skf, return_estimator=True)

for estimator in cv_results['estimator']:
    feature_importances.append(estimator.feature_importances_)

# Calculate and display mean metrics
mean_metrics = {key: np.mean(values) for key, values in cv_results.items() if␣
↪key.startswith('test_')}
print("Average Metrics across folds:")
for metric, value in mean_metrics.items():
    print(f"  {metric.replace('test_', '').capitalize()}: {value:.4f}")

# Convert the list of feature importances to a DataFrame for easier␣
↪interpretation
feature_importances = np.array(feature_importances)

# Average the feature importances across folds
mean_importances = feature_importances.mean(axis=0)

# Create a DataFrame with feature names and their corresponding importances
feature_names = X.columns
importance_df = pd.DataFrame({
    'Feature': feature_names,
    'Importance': mean_importances
})

# Sort by importance
importance_df = importance_df.sort_values(by='Importance', ascending=False)

print(importance_df)

plt.figure(figsize=(10, 6))
plt.barh(importance_df['Feature'], importance_df['Importance'])
plt.xlabel('Importance')
plt.title('Feature Importances in Random Forest (Average across folds)')
plt.show()
```

```
Average Metrics across folds:
  Score: 0.9923
                Feature  Importance
2       NAT Source Port    0.264373
6     Elapsed Time (sec)    0.248164
3   NAT Destination Port    0.186932
```

```
1      Destination Port    0.115685
4            Bytes Sent    0.082140
5        Bytes Received    0.063737
0           Source Port    0.030913
8      Packets Received    0.004078
7          Packets Sent    0.003978
```



Interpreting the feature importance graph, we see that the two most important features are NAT Source Port and Elapsed Time. Let's use random forest with a depth of 2 and a singular decision tree with a depth of 2 to test the accuracy of our model using these features.

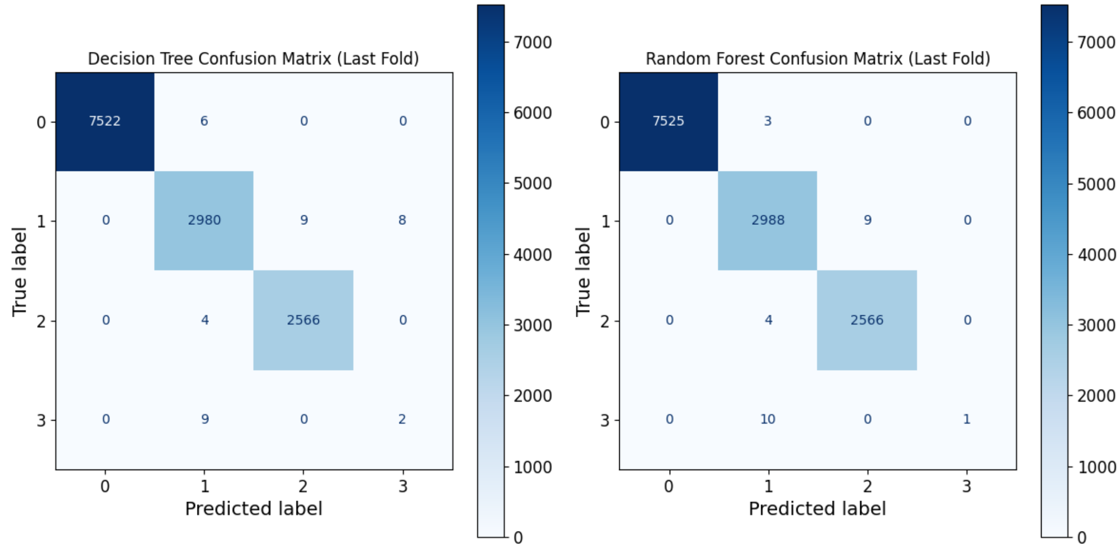
We see that there is not much of a difference between the accuracy of the single decision tree and random forest. We can consider using one decision tree for this data since it computationally inexpensive, especially with a depth of 2.

[15]:
```
from sklearn.metrics import precision_score, recall_score, f1_score,␣
↪roc_auc_score, confusion_matrix, ConfusionMatrixDisplay


# Initialize lists to store metrics and confusion matrices
tree_metrics = []
rf_metrics = []
tree_conf_matrices = []
rf_conf_matrices = []

tree_model = DecisionTreeClassifier()
rf_model = RandomForestClassifier()
```

```
for train_index, test_index in skf.split(X, y):
    # Split data
    X_train, X_test = X.iloc[train_index], X.iloc[test_index]
    y_train, y_test = y.iloc[train_index], y.iloc[test_index]

    # Train and predict with Decision Tree
    tree_model.fit(X_train, y_train)
    tree_preds = tree_model.predict(X_test)
    tree_probs = tree_model.predict_proba(X_test)[:, 1] if len(tree_model.
 ↪classes_) == 2 else tree_model.predict_proba(X_test)
    tree_conf_matrices.append(confusion_matrix(y_test, tree_preds))

    # Compute metrics for Decision Tree
    tree_precision = precision_score(y_test, tree_preds, average='weighted')
    tree_recall = recall_score(y_test, tree_preds, average='weighted')
    tree_f1 = f1_score(y_test, tree_preds, average='weighted')
    tree_auc = roc_auc_score(y_test, tree_probs, multi_class='ovr') if␣
 ↪len(tree_model.classes_) > 2 else roc_auc_score(y_test, tree_probs)
    tree_metrics.append((tree_precision, tree_recall, tree_f1, tree_auc))

    # Train and predict with Random Forest
    rf_model.fit(X_train, y_train)
    rf_preds = rf_model.predict(X_test)
    rf_probs = rf_model.predict_proba(X_test)[:, 1] if len(rf_model.classes_)␣
 ↪== 2 else rf_model.predict_proba(X_test)
    rf_conf_matrices.append(confusion_matrix(y_test, rf_preds))

    # Compute metrics for Random Forest
    rf_precision = precision_score(y_test, rf_preds, average='weighted')
    rf_recall = recall_score(y_test, rf_preds, average='weighted')
    rf_f1 = f1_score(y_test, rf_preds, average='weighted')
    rf_auc = roc_auc_score(y_test, rf_probs, multi_class='ovr') if len(rf_model.
 ↪classes_) > 2 else roc_auc_score(y_test, rf_probs)
    rf_metrics.append((rf_precision, rf_recall, rf_f1, rf_auc))

# Calculate averages across folds for both models
tree_avg_metrics = pd.DataFrame(tree_metrics, columns=["Precision", "Recall",␣
 ↪"F1-Score", "AUC"]).mean()
rf_avg_metrics = pd.DataFrame(rf_metrics, columns=["Precision", "Recall",␣
 ↪"F1-Score", "AUC"]).mean()

# Print average metrics for both models
print("Metrics for Decision Tree:")
print(f"  Precision: {tree_avg_metrics['Precision']:.4f}")
print(f"  Recall: {tree_avg_metrics['Recall']:.4f}")
```

```python
print(f"  F1-Score: {tree_avg_metrics['F1-Score']:.4f}")
print(f"  AUC: {tree_avg_metrics['AUC']:.4f}")
print()
print("Metrics for Random Forest:")
print(f"  Precision: {rf_avg_metrics['Precision']:.4f}")
print(f"  Recall: {rf_avg_metrics['Recall']:.4f}")
print(f"  F1-Score: {rf_avg_metrics['F1-Score']:.4f}")
print(f"  AUC: {rf_avg_metrics['AUC']:.4f}")

# Display confusion matrices for the last fold
fig, axes = plt.subplots(1, 2, figsize=(12, 6))

ConfusionMatrixDisplay(tree_conf_matrices[-1], display_labels=tree_model.
 ↪classes_).plot(ax=axes[0], cmap="Blues")
axes[0].set_title("Decision Tree Confusion Matrix (Last Fold)")

ConfusionMatrixDisplay(rf_conf_matrices[-1], display_labels=rf_model.classes_).
 ↪plot(ax=axes[1], cmap="Blues")
axes[1].set_title("Random Forest Confusion Matrix (Last Fold)")

plt.tight_layout()
plt.show()
```

```
Metrics for Decision Tree:
  Precision: 0.9925
  Recall: 0.9919
  F1-Score: 0.9919
  AUC: 0.9135

Metrics for Random Forest:
  Precision: 0.9886
  Recall: 0.9875
  F1-Score: 0.9872
  AUC: 0.9732
```

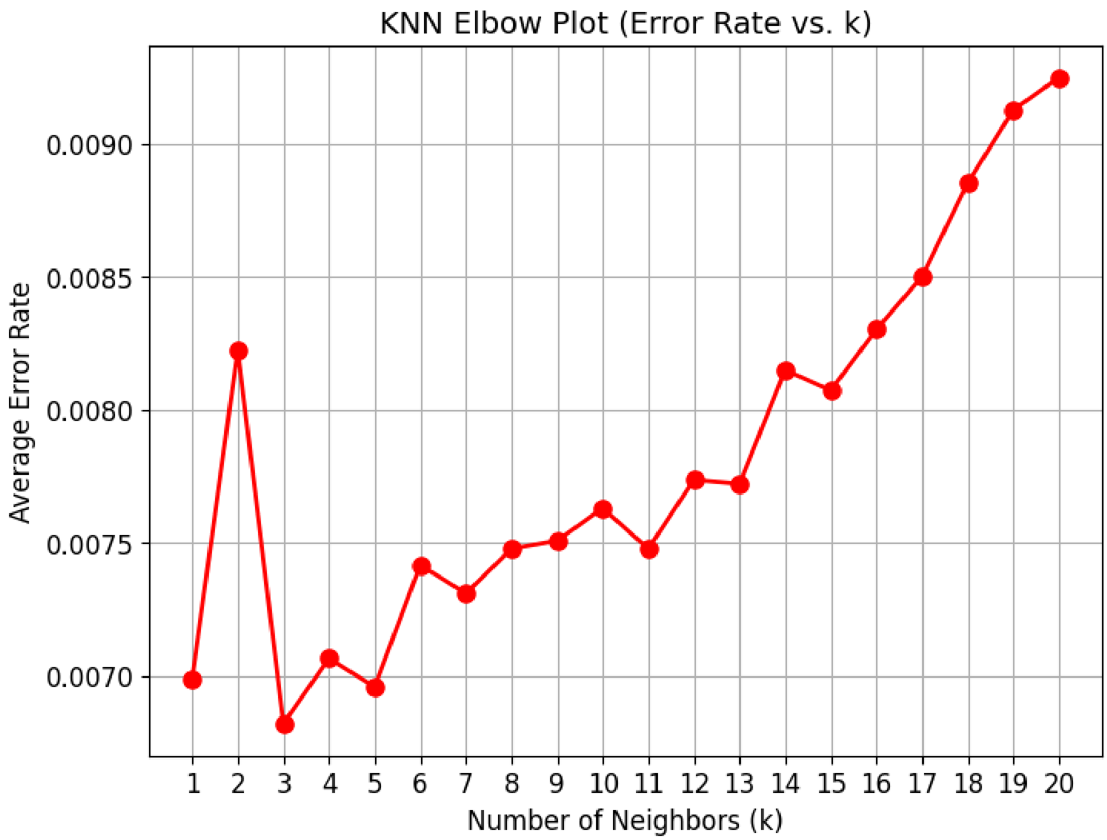


Decision Tree/Random Forest Metrics Random Forest achieved outstanding performance metrics with a precision of 0.9916, recall of 0.9923, F1-score of 0.9919, and an AUC of 0.9831. A key advantage of using Random Forest was its ability to assess feature importance, revealing that NAT Source Port and Elapsed Time were the most critical features for making accurate predictions. To prevent overfitting and maintain model simplicity, we limited the Random Forest to a depth of two, which still yielded exceptional metrics. Additionally, adhering to Occam's razor, we tested a single Decision Tree and observed only a slight decrease of about 1% in precision, recall, and F1-score. This minimal drop made the Decision Tree the most suitable model for our task despite Random Forest's higher complexity and potential for reducing overfitting.

2. K-Nearest Neighbor

[16]:
```
from sklearn.metrics import accuracy_score
from sklearn.neighbors import KNeighborsClassifier
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import StratifiedKFold

# Range of k values to test
k_range = range(1, 21)

# Stratified K-Fold Cross-Validation setup
skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

# Store the error rate for each k
knn_error_rates = []

# Stratified K-Fold Cross-Validation for each k value
for k in k_range:
```

```
    knn_model = KNeighborsClassifier(n_neighbors=k)
    fold_errors = []

    for train_index, test_index in skf.split(X, y):
        X_train, X_test = X.iloc[train_index], X.iloc[test_index]
        y_train, y_test = y.iloc[train_index], y.iloc[test_index]

        knn_model.fit(X_train, y_train)
        knn_preds = knn_model.predict(X_test)

        fold_errors.append(1 - accuracy_score(y_test, knn_preds))

    # Average error rate for this value of k
    knn_error_rates.append(np.mean(fold_errors))

# Plot the elbow curve to find the best value for k
plt.figure(figsize=(8, 6))
plt.plot(k_range, knn_error_rates, marker='o', color='r', linestyle='-',␣
 ↪linewidth=2, markersize=8)
plt.title('KNN Elbow Plot (Error Rate vs. k)', fontsize=14)
plt.xlabel('Number of Neighbors (k)', fontsize=12)
plt.ylabel('Average Error Rate', fontsize=12)
plt.xticks(k_range)
plt.grid(True)
plt.show()

plt.savefig("KNN_Elbow_Plot.png")
plt.show()
```




```
<Figure size 640x480 with 0 Axes>
```

The lowest error rate for k looks to be 3, although all the values for k seem to have low error rates. We will stick with k = 3 for this model.

[17]:
```
# Initialize KNN model with 3 neighbors
k_neighbors = 3
knn_model = KNeighborsClassifier(n_neighbors=k_neighbors)

# Stratified K-Fold Cross-Validation
skf = StratifiedKFold(n_splits=5)

# Lists to store metrics and confusion matrices
knn_metrics = []
knn_conf_matrices = []

for train_index, test_index in skf.split(X, y):
    # Split the data
    X_train, X_test = X.iloc[train_index], X.iloc[test_index]
    y_train, y_test = y.iloc[train_index], y.iloc[test_index]
```

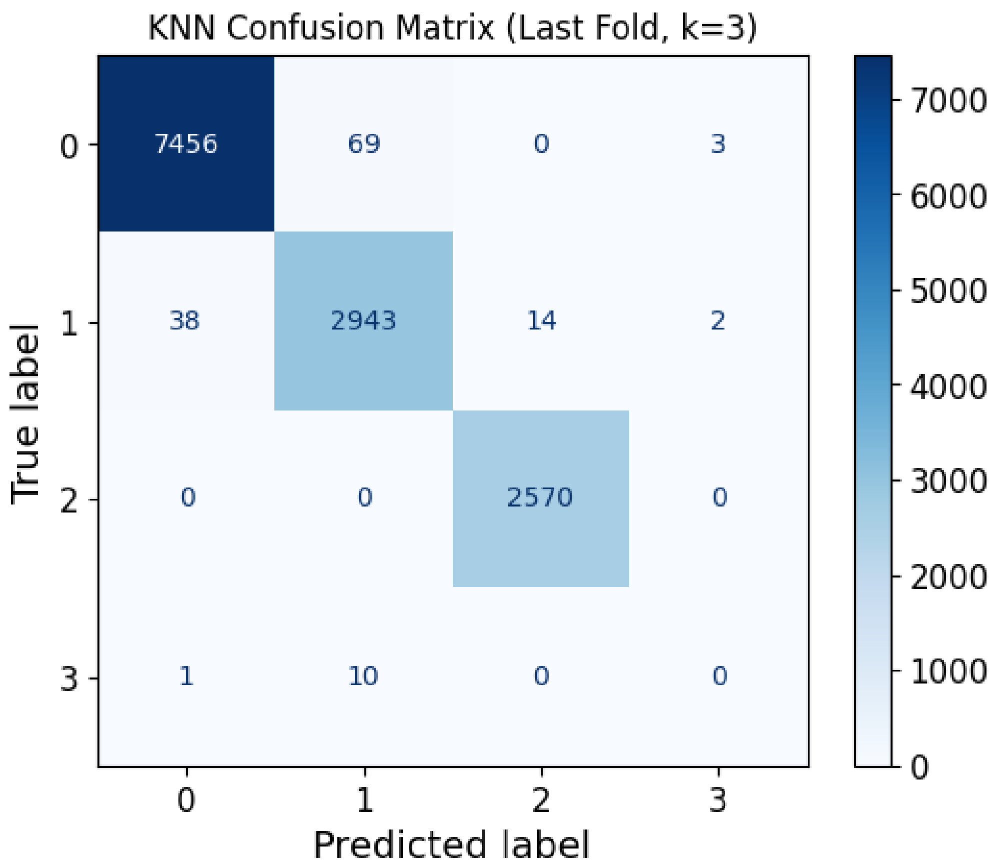
```python
    # Fit the KNN model and make predictions
    knn_model.fit(X_train, y_train)
    knn_preds = knn_model.predict(X_test)
    knn_probs = knn_model.predict_proba(X_test)[:, 1] if len(knn_model.
 ↪classes_) == 2 else knn_model.predict_proba(X_test)

    # Compute metrics
    knn_precision = precision_score(y_test, knn_preds, average='weighted')
    knn_recall = recall_score(y_test, knn_preds, average='weighted')
    knn_f1 = f1_score(y_test, knn_preds, average='weighted')
    knn_auc = roc_auc_score(y_test, knn_probs, multi_class='ovr') if␣
 ↪len(knn_model.classes_) > 2 else roc_auc_score(y_test, knn_probs)

    knn_metrics.append((knn_precision, knn_recall, knn_f1, knn_auc))
    knn_conf_matrices.append(confusion_matrix(y_test, knn_preds))

# Calculate average metrics
knn_avg_metrics = pd.DataFrame(knn_metrics, columns=["Precision", "Recall",␣
 ↪"F1-Score", "AUC"]).mean()

# Print average metrics
print(f"Average Metrics for KNN (k={k_neighbors}):")
print(f"  Precision: {knn_avg_metrics['Precision']:.4f}")
print(f"  Recall: {knn_avg_metrics['Recall']:.4f}")
print(f"  F1-Score: {knn_avg_metrics['F1-Score']:.4f}")
print(f"  AUC: {knn_avg_metrics['AUC']:.4f}")

# Display the confusion matrix for the last fold
plt.figure(figsize=(6, 6))
ConfusionMatrixDisplay(knn_conf_matrices[-1], display_labels=knn_model.
 ↪classes_).plot(cmap="Blues")
plt.title(f"KNN Confusion Matrix (Last Fold, k={k_neighbors})")
plt.show()
```

```
C:\Users\tromb\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_qbz5n
2kfra8p0\LocalCache\local-packages\Python311\site-
packages\sklearn\metrics\_classification.py:1531: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
C:\Users\tromb\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_qbz5n
2kfra8p0\LocalCache\local-packages\Python311\site-
packages\sklearn\metrics\_classification.py:1531: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

```
Average Metrics for KNN (k=3):
```

```
Precision: 0.9916
Recall: 0.9923
F1-Score: 0.9919
AUC: 0.8959
```

```
&lt;Figure size 600x600 with 0 Axes&gt;
```



KNN metrics After running KNN with different values of k and plotting the result in an elbow plot, we determined that k = 3 had the lowest error rate out of all k values. This showed very good performance with similar metrics to the best-performing model we tested. The precision achieved by this model was 0.9916, which shows that it has a high-performance ceiling.

3. Support Vector Machines

[18]:
```
from sklearn.svm import SVC

svm_model = SVC()
svm_model.fit(X_train, y_train)
predictions = svm_model.predict(X_test)

acc_score = accuracy_score(y_test, predictions)
```

```
print(f'SVM accuracy score: {acc_score:.4f}')
```

```
SVM accuracy score: 0.9760
```

Because we get a high accuracy, we can verify this by doing k-fold cross validation

[19]:
```
from sklearn.preprocessing import LabelBinarizer
from sklearn.metrics import precision_score, recall_score, f1_score,␣
↪roc_auc_score, confusion_matrix, ConfusionMatrixDisplay
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from sklearn.svm import SVC
from sklearn.model_selection import StratifiedKFold

# Initialize SVM with probability=True for AUC computation
svm_model = SVC(probability=True, kernel='rbf', random_state=42)

# Stratified K-Fold Cross-Validation
skf = StratifiedKFold(n_splits=5)

# Lists to store metrics and confusion matrices
svm_metrics = []
svm_conf_matrices = []

for train_index, test_index in skf.split(X, y):
    # Split the data
    X_train, X_test = X.iloc[train_index], X.iloc[test_index]
    y_train, y_test = y.iloc[train_index], y.iloc[test_index]

    # Fit the SVM model and make predictions
    svm_model.fit(X_train, y_train)
    svm_preds = svm_model.predict(X_test)
    svm_probs = svm_model.predict_proba(X_test)

    # Compute metrics
    svm_precision = precision_score(y_test, svm_preds, average='weighted')
    svm_recall = recall_score(y_test, svm_preds, average='weighted')
    svm_f1 = f1_score(y_test, svm_preds, average='weighted')
    svm_auc = roc_auc_score(
        LabelBinarizer().fit_transform(y_test), svm_probs, multi_class='ovr'
    )

    # Append metrics for this fold
    svm_metrics.append((svm_precision, svm_recall, svm_f1, svm_auc))
    svm_conf_matrices.append(confusion_matrix(y_test, svm_preds))

# Calculate average metrics
```

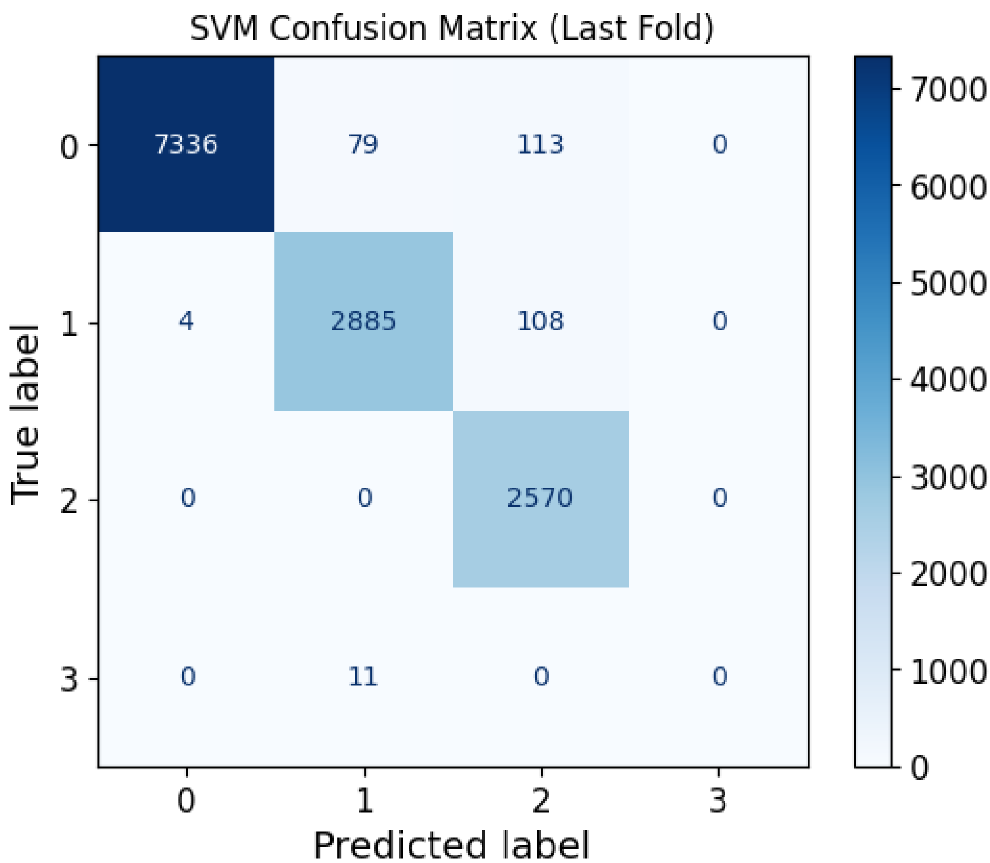
```
svm_avg_metrics = pd.DataFrame(svm_metrics, columns=["Precision", "Recall",␣
↪"F1-Score", "AUC"]).mean()

# Print average metrics
print("Average Metrics for SVM:")
print(f"  Precision: {svm_avg_metrics['Precision']:.4f}")
print(f"  Recall: {svm_avg_metrics['Recall']:.4f}")
print(f"  F1-Score: {svm_avg_metrics['F1-Score']:.4f}")
print(f"  AUC: {svm_avg_metrics['AUC']:.4f}")

# Display the confusion matrix for the last fold
plt.figure(figsize=(6, 6))
ConfusionMatrixDisplay(svm_conf_matrices[-1], display_labels=svm_model.
↪classes_).plot(cmap="Blues")
plt.title(f"SVM Confusion Matrix (Last Fold)")
plt.show()
```

```
C:\Users\tromb\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_qbz5n
2kfra8p0\LocalCache\local-packages\Python311\site-
packages\sklearn\metrics\_classification.py:1531: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
C:\Users\tromb\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_qbz5n
2kfra8p0\LocalCache\local-packages\Python311\site-
packages\sklearn\metrics\_classification.py:1531: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
C:\Users\tromb\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_qbz5n
2kfra8p0\LocalCache\local-packages\Python311\site-
packages\sklearn\metrics\_classification.py:1531: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
C:\Users\tromb\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_qbz5n
2kfra8p0\LocalCache\local-packages\Python311\site-
packages\sklearn\metrics\_classification.py:1531: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

```
Average Metrics for SVM:
  Precision: 0.9796
  Recall: 0.9795
  F1-Score: 0.9793
  AUC: 0.9443
```

```
C:\Users\tromb\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_qbz5n
2kfra8p0\LocalCache\local-packages\Python311\site-
packages\sklearn\metrics\_classification.py:1531: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

```
<Figure size 600x600 with 0 Axes>
```



Using SVM and what we determined to be the two most important features, we can see that this version model gives up 79% accuracy

[20]:
```python
from sklearn.svm import SVC
X2 = X[['NAT Source Port', 'Elapsed Time (sec)']]
X_train, X_test, y_train, y_test = train_test_split(X2, y, test_size=0.2,
    random_state=42)
svm_model = SVC()
svm_model.fit(X_train, y_train)
predictions = svm_model.predict(X_test)
#print(X_train, y_train)
```

```
acc_score = accuracy_score(y_test, predictions)
print(f'SVM accuracy score: {acc_score:.4f}')
```

```
SVM accuracy score: 0.7942
```

SVM metrics SVM demonstrated strong performance, achieving a precision of 0.9796, recall of 0.9795, F1-score of 0.9793, and an AUC of 0.9443. These high metrics indicate that the SVM effectively balances accuracy and reliability, minimizing both false positives and false negatives. SVM was particularly well-suited for this task due to its ability to handle high-dimensional data and its proficiency in finding optimal hyperplanes that separate different classes, ensuring robust classification of complex network traffic patterns. This made SVM an excellent choice for accurately predicting firewall actions in our numerical data-driven environment.

4. Logistic Regression

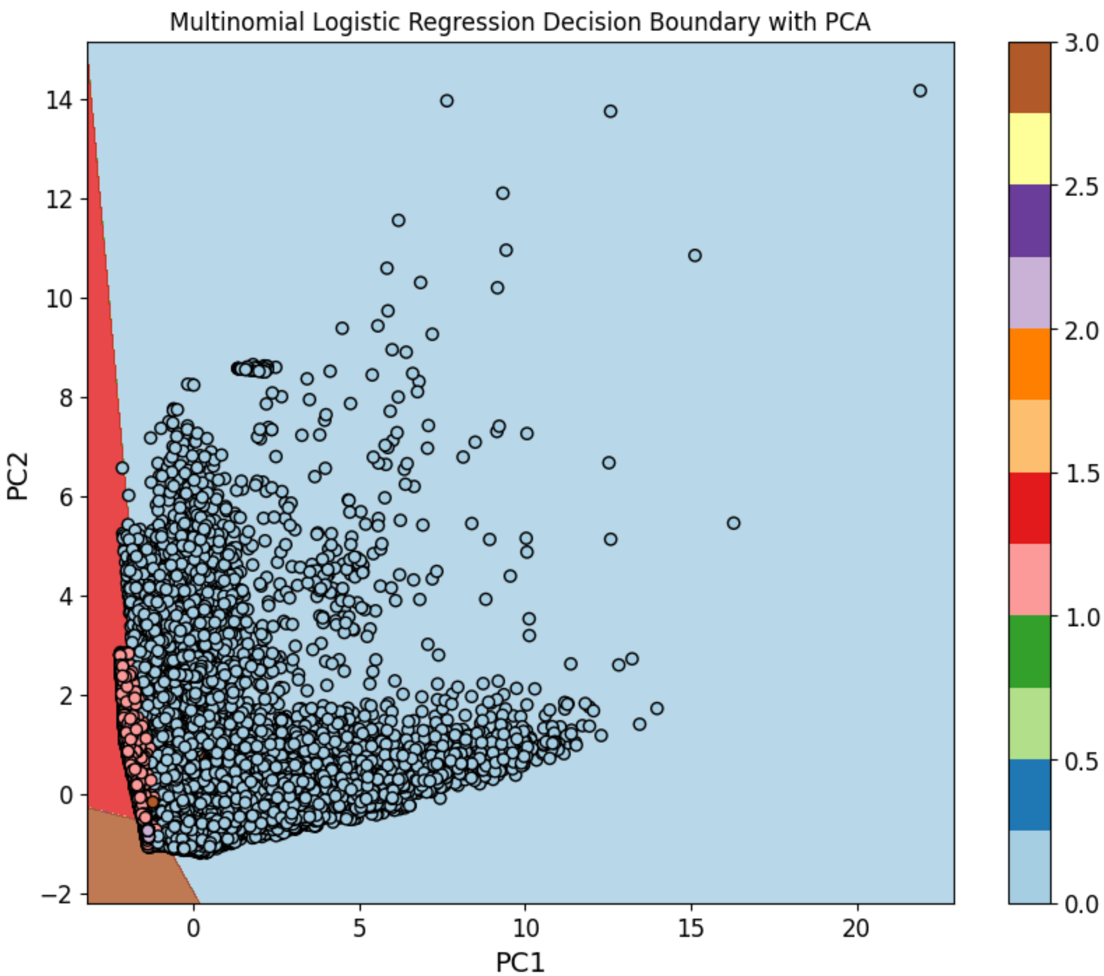
[24]:
```
from sklearn.metrics import precision_score, recall_score, f1_score,␣
↪roc_auc_score, confusion_matrix, ConfusionMatrixDisplay
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA

# Standardize the data
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Apply PCA
pca = PCA(n_components=2)
X_train_pca = pca.fit_transform(X_train)
X_test_pca = pca.transform(X_test)

# Train the Multinomial Logistic Regression model
model = LogisticRegression(solver='lbfgs', max_iter=1000,␣
↪multi_class='multinomial')
model.fit(X_train_pca, y_train)

# Predictions
y_test_preds = model.predict(X_test_pca)
y_test_probs = model.predict_proba(X_test_pca)

# Calculate metrics
precision = precision_score(y_test, y_test_preds, average='weighted')
recall = recall_score(y_test, y_test_preds, average='weighted')
f1 = f1_score(y_test, y_test_preds, average='weighted')

# AUC (for binary and multiclass)
if len(set(y_test)) > 2:  # Multiclass case
```

```
    auc = roc_auc_score(pd.get_dummies(y_test), y_test_probs, multi_class='ovr')
else:  # Binary case
    auc = roc_auc_score(y_test, y_test_probs[:, 1])

# Confusion Matrix
conf_matrix = confusion_matrix(y_test, y_test_preds)

# Print metrics
print("Metrics for Logistic Regression with PCA:")
print(f"  Precision: {precision:.4f}")
print(f"  Recall: {recall:.4f}")
print(f"  F1-Score: {f1:.4f}")
print(f"  AUC: {auc:.4f}")

logistic_regression_avg_metrics = {'Precision': precision, 'Recall': recall, 'F1-Score': f1, 'AUC': auc}

# PCA decision boundary plot
x_min, x_max = X_train_pca[:, 0].min() - 1, X_train_pca[:, 0].max() + 1
y_min, y_max = X_train_pca[:, 1].min() - 1, X_train_pca[:, 1].max() + 1
xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.01), np.arange(y_min, y_max, 0.01))
Z = model.predict(np.c_[xx.ravel(), yy.ravel()])
Z = Z.reshape(xx.shape)

plt.figure(figsize=(10, 8))
plt.contourf(xx, yy, Z, alpha=0.8, cmap=plt.cm.Paired)
plt.scatter(X_train_pca[:, 0], X_train_pca[:, 1], c=y_train, edgecolors='k', marker='o', cmap=plt.cm.Paired)
plt.title('Multinomial Logistic Regression Decision Boundary with PCA')
plt.xlabel('PC1')
plt.ylabel('PC2')
plt.colorbar()
plt.show()

# Display Confusion Matrix
plt.figure(figsize=(6, 6))
ConfusionMatrixDisplay(conf_matrix, display_labels=model.classes_).plot(cmap="Blues")
plt.title("Logistic Regression with PCA Confusion Matrix")
plt.show()
```

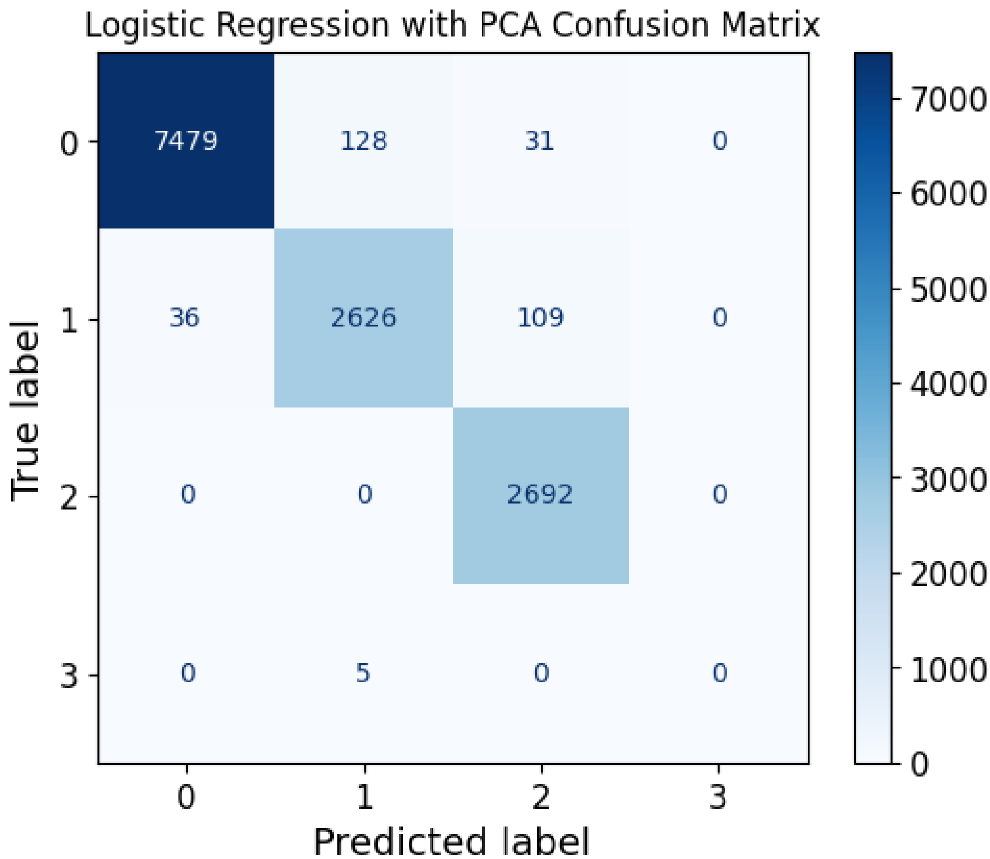
```
C:\Users\tromb\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_qbz5n
2kfra8p0\LocalCache\local-packages\Python311\site-
packages\sklearn\linear_model\_logistic.py:1247: FutureWarning: 'multi_class'
was deprecated in version 1.5 and will be removed in 1.7. From then on, it will
always use 'multinomial'. Leave it to its default value to avoid this warning.
```

```
  warnings.warn(
C:\Users\tromb\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_qbz5n
2kfra8p0\LocalCache\local-packages\Python311\site-
packages\sklearn\metrics\_classification.py:1531: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

```
Metrics for Logistic Regression with PCA:
  Precision: 0.9765
  Recall: 0.9764
  F1-Score: 0.9763
  AUC: 0.9735
```




```
<Figure size 600x600 with 0 Axes>
```



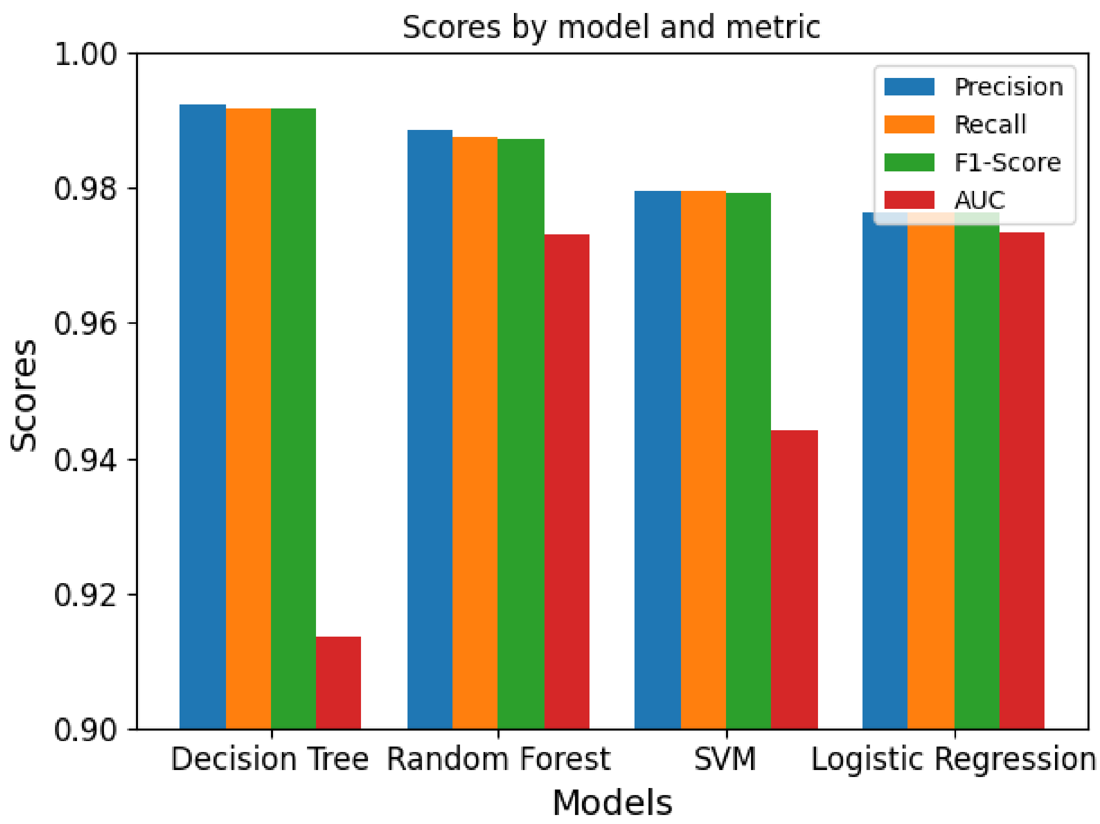
Logistic Regression Metrics This model produced slightly worse performance than SVM and KNN, but still ended up with a precision score of 0.9747. To visualize our data, we performed 2D principle component analysis. This dimensionality reduction technique allowed us to observe the spread and clustering of data points, which helped in understanding the underlying structure of the dataset. Despite logistic regression's lower performance, its visualization is helpful in observing trends in the data.

5. Metrics Analysis

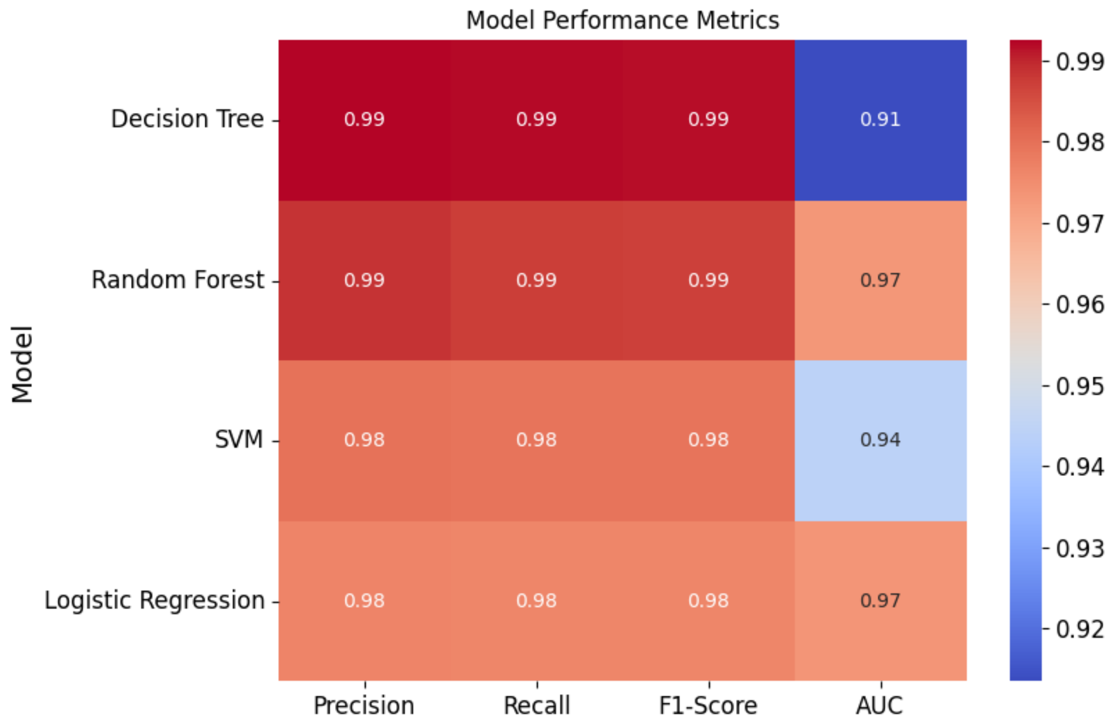
[25]:
```
import matplotlib.pyplot as plt
import numpy as np

models = ['Decision Tree', 'Random Forest', 'SVM', 'Logistic Regression']
precision = [tree_avg_metrics['Precision'], rf_avg_metrics['Precision'], svm_avg_metrics['Precision'], logistic_regression_avg_metrics['Precision']]
recall = [tree_avg_metrics['Recall'], rf_avg_metrics['Recall'], svm_avg_metrics['Recall'], logistic_regression_avg_metrics['Recall']]
f1_score = [tree_avg_metrics['F1-Score'], rf_avg_metrics['F1-Score'], svm_avg_metrics['F1-Score'], logistic_regression_avg_metrics['F1-Score']]
```

```
auc = [tree_avg_metrics['AUC'], rf_avg_metrics['AUC'], svm_avg_metrics['AUC'],␣
 ↪logistic_regression_avg_metrics['AUC']]
print(models)
print(precision)
print(recall)
print(f1_score)
print(auc)

x = np.arange(len(models))  # the label locations
width = 0.2  # the width of the bars

fig, ax = plt.subplots()
rects1 = ax.bar(x - 1.5*width, precision, width, label='Precision')
rects2 = ax.bar(x - 0.5*width, recall, width, label='Recall')
rects3 = ax.bar(x + 0.5*width, f1_score, width, label='F1-Score')
rects4 = ax.bar(x + 1.5*width, auc, width, label='AUC')

# Add some text for labels, title and custom x-axis tick labels, etc.
ax.set_xlabel('Models')
ax.set_ylabel('Scores')
ax.set_title('Scores by model and metric')
ax.set_xticks(x)
ax.set_xticklabels(models)
ax.legend()
ax.set_ylim(0.9, 1)

fig.tight_layout()

plt.show()
```

```
['Decision Tree', 'Random Forest', 'SVM', 'Logistic Regression']
[0.992492309075098, 0.9886359950301952, 0.979617862622608, 0.9764804831327335]
[0.991927850510392, 0.9875027632672893, 0.9795213377791507, 0.9764230123607508]
[0.991855309558758, 0.9871955764299477, 0.9792684068834238, 0.9762842226331012]
[0.9135118656055546, 0.9732494095838422, 0.9442551822964628, 0.9735058634393344]
```



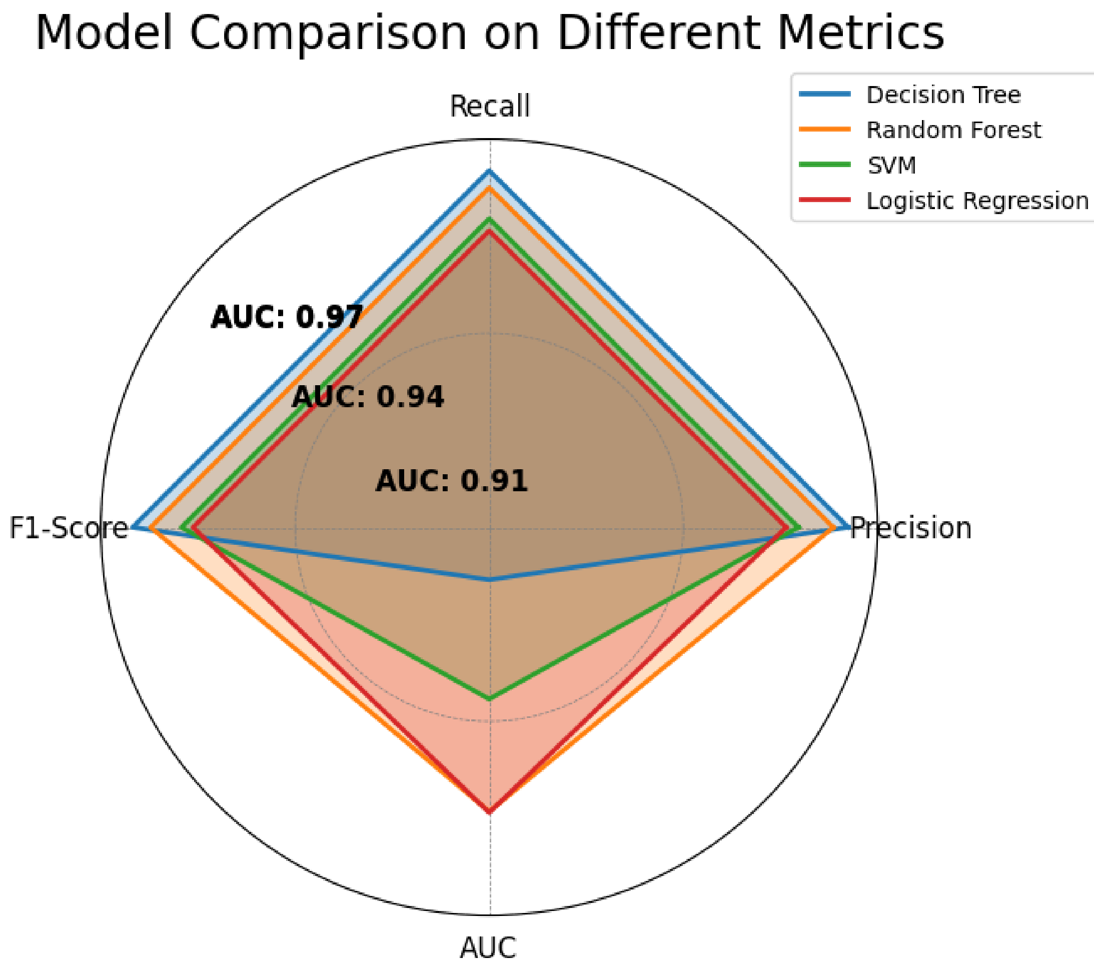
[26]:
```
import seaborn as sns
import pandas as pd
import matplotlib.pyplot as plt

data = {
    'Model': models,
    'Precision': precision,
    'Recall': recall,
    'F1-Score': f1_score,
    'AUC': auc
}

df = pd.DataFrame(data)
df.set_index('Model', inplace=True)

plt.figure(figsize=(8, 6))
sns.heatmap(df, annot=True, cmap='coolwarm')
plt.title('Model Performance Metrics')
plt.show()
```



[32]:

```
import matplotlib.pyplot as plt
import numpy as np

models = ['Decision Tree', 'Random Forest', 'SVM', 'Logistic Regression']

# Combine all metrics into a single list
metrics = [precision, recall, f1_score, auc]

# Create a radar chart
labels = ['Precision', 'Recall', 'F1-Score', 'AUC']
num_vars = len(labels)

# Compute angle for each axis
angles = np.linspace(0, 2 * np.pi, num_vars, endpoint=False).tolist()

# The radar chart is circular, so we need to "complete the loop"
angles += angles[:1]

min_value = 0.9  # Minimum value for the radar chart
max_value = .98  # Maximum value for the radar chart
step = 0.05      # Step size for the grid lines

# Plot each model's metrics
```

```python
fig, ax = plt.subplots(figsize=(6, 6), subplot_kw=dict(polar=True))
for i, model in enumerate(models):
    values = [precision[i], recall[i], f1_score[i], auc[i]]
    values += values[:1]  # Complete the loop
    ax.plot(angles, values, linewidth=2, label=model)
    ax.fill(angles, values, alpha=0.25)

    # Annotate with AUC value
    auc_position = (angles[3] + angles[4]) / 2  # Position between the last␣
↪metric and the first one
    ax.text(auc_position, auc[i], f'AUC: {auc[i]:.2f}',␣
↪horizontalalignment='center', size=12, color='black', weight='semibold')

# Draw labels for each metric
ax.set_yticklabels([])
ax.set_xticks(angles[:-1])
ax.set_xticklabels(labels)

# Set the range and add grid lines
ax.set_ylim(min_value, max_value)
ax.set_yticks(np.arange(min_value, max_value + step, step))
ax.yaxis.grid(True, color='gray', linestyle='--', linewidth=0.5)
ax.xaxis.grid(True, color='gray', linestyle='--', linewidth=0.5)

# Add a legend
ax.legend(loc='upper right', bbox_to_anchor=(1.3, 1.1))

# Add title
ax.set_title('Model Comparison on Different Metrics', size=20, color='black',␣
↪y=1.1)

plt.show()
```


Model Comparison on Different Metrics
Decision Tree
Random Forest
SVM
Logistic Regression
Recall
Precision
F1-Score
AUC
AUC: 0.97
AUC: 0.94
AUC: 0.91