S223090226

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SIT719 5.1 D

▼ SECTION 1: DECLARE THE MODULES

```
import os
from collections import defaultdict
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy score, confusion matrix, f1 score, precision score, recall score, classification report
from sklearn.metrics import ConfusionMatrixDisplay
from sklearn.preprocessing import StandardScaler
import seaborn as sns
import time
import warnings
warnings.filterwarnings('ignore')
```

▼ SECTION 2: Data import and preprocess

Run this but dont worry if it does not make any sense Jump to SECTION 3 that is related to your HD task.

```
!pip install wget
import wget
```

```
link to data = 'https://raw.githubusercontent.com/shreyas-vivek/SIT719-5.1D/main/NSL KDD Dataset/training attack types.txt?raw=true'
DataSet = wget.download(link to data)
     Collecting wget
       Downloading wget-3.2.zip (10 kB)
       Preparing metadata (setup.py) ... done
     Building wheels for collected packages: wget
       Building wheel for wget (setup.py) ... done
       Created wheel for wget: filename=wget-3.2-py3-none-any.whl size=9655 sha256=102ebf644c635ca071d4da3899f2c8d6c21f9b05fd38ae23d66133d1fc9740bd
       Stored in directory: /root/.cache/pip/wheels/8b/f1/7f/5c94f0a7a505ca1c81cd1d9208ae2064675d97582078e6c769
     Successfully built wget
     Installing collected packages: wget
     Successfully installed wget-3.2
DataSet
     'training attack types.txt'
header names = ['duration', 'protocol type', 'service', 'flag', 'src bytes', 'dst bytes', 'land', 'wrong fragment', 'urgent', 'hot', 'num failed logins', 'logged in', 'num compromis
# Differentiating between nominal, binary, and numeric features
# root shell is marked as a continuous feature in the kddcup.names
# file, but it is supposed to be a binary feature according to the
# dataset documentation
# training_attack_types.txt maps each of the 22 different attacks to 1 of 4 categories
# file obtained from http://kdd.ics.uci.edu/databases/kddcup99/training attack types
col names = np.array(header names)
nominal_idx = [1, 2, 3]
binary_idx = [6, 11, 13, 14, 20, 21]
numeric idx = list(set(range(41)).difference(nominal idx).difference(binary idx))
nominal cols = col names[nominal idx].tolist()
binary cols = col names[binary idx].tolist()
numeric cols = col names[numeric idx].tolist()
# training attack types.txt maps each of the 22 different attacks to 1 of 4 categories
# file obtained from http://kdd.ics.uci.edu/databases/kddcup99/training attack types
category = defaultdict(list)
category['benign'].append('normal')
with open(DataSet, 'r') as f:
    for line in f.readlines():
        attack, cat = line.strip().split(' ')
        category[cat].append(attack)
```

```
attack mapping = dict((v,k) for k in category for v in category[k])
attack_mapping
     {'normal': 'benign',
      'apache2': 'dos',
      'back': 'dos',
      'mailbomb': 'dos',
      'processtable': 'dos',
      'snmpgetattack': 'dos',
      'teardrop': 'dos',
      'smurf': 'dos',
      'land': 'dos',
      'neptune': 'dos',
      'pod': 'dos',
      'udpstorm': 'dos',
      'ps': 'u2r',
      'buffer overflow': 'u2r',
      'perl': 'u2r',
      'rootkit': 'u2r'
      'loadmodule': 'u2r',
      'xterm': 'u2r',
      'sqlattack': 'u2r',
      'httptunnel': 'u2r',
      'ftp write': 'r21',
      'guess passwd': 'r21',
      'snmpguess': 'r21',
      'imap': 'r21',
      'spy': 'r21',
      'warezclient': 'r2l',
      'warezmaster': 'r21',
      'multihop': 'r2l',
      'phf': 'r21',
      'named': 'r21',
      'sendmail': 'r2l',
      'xlock': 'r21',
      'xsnoop': 'r21',
      'worm': 'probe',
      'nmap': 'probe',
      'ipsweep': 'probe',
      'portsweep': 'probe',
      'satan': 'probe',
      'mscan': 'probe',
      'saint': 'probe'}
#Processing Training Data
train file='https://raw.githubusercontent.com/shreyas-vivek/SIT719-5.1D/main/NSL KDD Dataset/KDDTrain%2B.txt'
train df = pd.read csv(train file, names=header names)
```

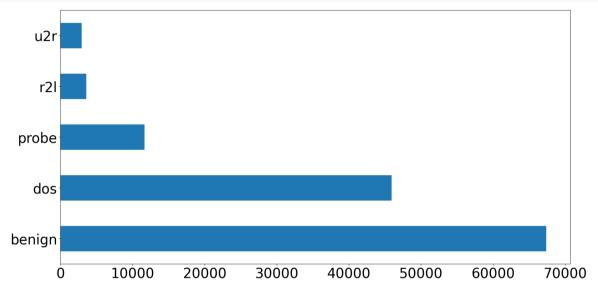
```
train df['attack category'] = train df['attack type'] \
                                .map(lambda x: attack mapping[x])
train_df.drop(['success_pred'], axis=1, inplace=True)
#Processing test Data
test file='https://raw.githubusercontent.com/shreyas-vivek/SIT719-5.1D/main/NSL KDD Dataset/KDDTest%2B.txt'
test_df = pd.read_csv(test_file, names=header_names)
test_df['attack_category'] = test_df['attack_type'] \
                                .map(lambda x: attack_mapping[x])
test_df.drop(['success_pred'], axis=1, inplace=True)
train attack types = train df['attack type'].value counts()
train_attack_cats = train_df['attack_category'].value_counts()
test_attack_types = test_df['attack_type'].value_counts()
test_attack_cats = test_df['attack_category'].value_counts()
train attack types.plot(kind='barh', figsize=(20,10), fontsize=20)
train_attack_cats.plot(kind='barh', figsize=(20,10), fontsize=30)
train df[binary cols].describe().transpose()
train df.groupby(['su attempted']).size()
train_df['su_attempted'].replace(2, 0, inplace=True)
test_df['su_attempted'].replace(2, 0, inplace=True)
train_df.groupby(['su_attempted']).size()
train df.groupby(['num outbound cmds']).size()
#Now, that's not a very useful feature - let's drop it from the dataset
train df.drop('num outbound cmds', axis = 1, inplace=True)
test_df.drop('num_outbound_cmds', axis = 1, inplace=True)
numeric cols.remove('num outbound cmds')
#Data Preparation
train_Y = train_df['attack_category']
train_x_raw = train_df.drop(['attack_category','attack_type'], axis=1)
test_Y = test_df['attack_category']
test_x_raw = test_df.drop(['attack_category','attack_type'], axis=1)
```

```
combined df raw = pd.concat([train x raw, test x raw])
combined df = pd.get dummies(combined df raw, columns=nominal cols, drop first=True)
train x = combined_df[:len(train_x_raw)]
test x = combined df[len(train x raw):]
# Store dummy variable feature names
dummy variables = list(set(train x)-set(combined df raw))
#execute the commands in console
train x.describe()
train x['duration'].describe()
# Experimenting with StandardScaler on the single 'duration' feature
from sklearn.preprocessing import StandardScaler
durations = train x['duration'].values.reshape(-1, 1)
standard scaler = StandardScaler().fit(durations)
scaled durations = standard scaler.transform(durations)
pd.Series(scaled_durations.flatten()).describe()
# Experimenting with MinMaxScaler on the single 'duration' feature
from sklearn.preprocessing import MinMaxScaler
min max scaler = MinMaxScaler().fit(durations)
min_max_scaled_durations = min_max_scaler.transform(durations)
pd.Series(min_max_scaled_durations.flatten()).describe()
# Experimenting with RobustScaler on the single 'duration' feature
from sklearn.preprocessing import RobustScaler
min_max_scaler = RobustScaler().fit(durations)
robust scaled durations = min max scaler.transform(durations)
pd.Series(robust scaled durations.flatten()).describe()
# Experimenting with MaxAbsScaler on the single 'duration' feature
from sklearn.preprocessing import MaxAbsScaler
max Abs scaler = MaxAbsScaler().fit(durations)
robust scaled durations = max Abs scaler.transform(durations)
pd.Series(robust scaled durations.flatten()).describe()
# Let's proceed with StandardScaler- Apply to all the numeric columns
standard scaler = StandardScaler().fit(train x[numeric cols])
train x[numeric cols] = \
    standard_scaler.transform(train_x[numeric_cols])
test_x[numeric_cols] = \
```

```
standard_scaler.transform(test_x[numeric_cols])

train_x.describe()

train_Y_bin = train_Y.apply(lambda x: 0 if x is 'benign' else 1)
test_Y_bin = test_Y.apply(lambda x: 0 if x is 'benign' else 1)
```



SECTION 3: Multi class classification

This is the section where you have to add other algorithms, tune algorithms and visualize to compare and analyze algorithms

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```
# 5-class classification version
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion matrix, zero one loss
classifier = DecisionTreeClassifier(random_state=17)
classifier.fit(train_x, train_Y)
pred_y = classifier.predict(test_x)
results = confusion_matrix(test_Y, pred_y)
error = zero_one_loss(test_Y, pred_y)
print(results)
print(error)
     [[9365 56 289
     [1541 5998 97
                             0]
     [ 677 220 1526 0
     [2278  1  14  277  4]
     [ 175 0 5 5 15]]
    0.2378903477643719
# ... (Previous code here)
# Define parameter grids for hyperparameter tuning (you can modify these)
param_grids = {
   "Decision Tree": {"max_depth": [None, 10, 20, 30]},
   "Random Forest": {"n_estimators": [10, 50, 100]},
   "SVC": {"C": [0.1, 1, 10], "kernel": ["linear", "rbf"]},
   "KNN": {"n_neighbors": [3, 5, 7]},
   "Logistic Regression": {"C": [0.1, 1, 10], "penalty": ["11", "12"]},
# Initialize an empty list to store results
results = []
# Classifier 1: Decision Tree
```

```
classifier name = "Decision Tree"
param grid = param grids[classifier name]
classifier = classifiers[classifier name]
result = perform classification(classifier name, classifier, param grid)
results.append(result)
# Classifier 2: Random Forest
classifier_name = "Random Forest"
param_grid = param_grids[classifier_name]
classifier = classifiers[classifier name]
result = perform classification(classifier name, classifier, param grid)
results.append(result)
# Classifier 3: Support Vector Classifier (SVC)
classifier name = "SVC"
param_grid = param_grids[classifier_name]
classifier = classifiers[classifier_name]
result = perform_classification(classifier_name, classifier, param_grid)
results.append(result)
     KevboardInterrupt
                                               Traceback (most recent call last)
     <ipython-input-28-6535eb368279> in <cell line: 5>()
           3 param_grid = param_grids[classifier_name]
           4 classifier = classifiers[classifier_name]
     ---> 5 result = perform_classification(classifier_name, classifier, param_grid)
           6 results.append(result)
                                       🗘 7 frames
     /usr/local/lib/python3.10/dist-packages/joblib/parallel.py in _retrieve(self)
        1705
                             (self._jobs[0].get_status(
                                 timeout=self.timeout) == TASK_PENDING)):
        1706
     -> 1707
                             time.sleep(0.01)
                             continue
        1708
        1709
     KeyboardInterrupt:
      SEARCH STACK OVERFLOW
print("hello")
     hello
```

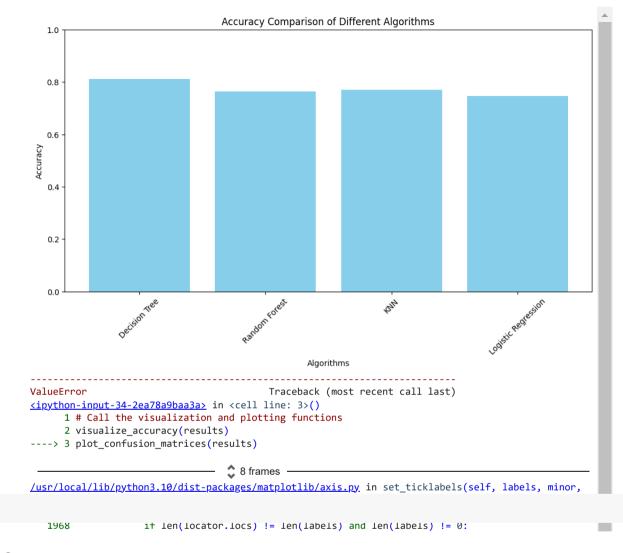
https://colab.research.google.com/drive/1fM07D6d8d6L0MZQIOAVPDklf6-m-6Oy8#scrollTo=uzOzvIVVMe2M&printMode=true

Double-click (or enter) to edit

```
# Classifier 4: K-Nearest Neighbors (KNN)
classifier name = "KNN"
param_grid = param_grids[classifier_name]
classifier = classifiers[classifier_name]
result = perform_classification(classifier_name, classifier, param grid)
results.append(result)
# Classifier 5: Logistic Regression
classifier name = "Logistic Regression"
param_grid = param_grids[classifier_name]
classifier = classifiers[classifier_name]
result = perform_classification(classifier_name, classifier, param_grid)
results.append(result)
# Define label names
label_names = ['normal', 'dos', 'probe', 'r2l', 'u2r']
# Define functions for visualization and plotting
def visualize_accuracy(results):
    plt.figure(figsize=(12, 6))
    plt.bar([result["Classifier"] for result in results], [result["Accuracy"] for result in results], color='skyblue')
    plt.xlabel("Algorithms")
    plt.ylabel("Accuracy")
    plt.title("Accuracy Comparison of Different Algorithms")
    plt.ylim([0, 1])
    plt.xticks(rotation=45)
    plt.show()
def plot_confusion_matrices(results):
    for result in results:
        classifier_name = result["Classifier"]
        confusion_matrix = result["Confusion Matrix"]
        plt.figure(figsize=(8, 6))
```

```
ConfusionMatrixDisplay(confusion_matrix, display_labels=label_names).plot(cmap='Blues', xticks_rotation='horizontal')
plt.title(f"Confusion Matrix - {classifier_name}")
plt.show()
```

Call the visualization and plotting functions
visualize_accuracy(results)
plot_confusion_matrices(results)



▼ C

```
ValueError: The number of FixedLocator locations (2), usually from a call to set ticks, does not
# ... (Previous code here)

# **Section 3: Benchmark Classification Algorithms**
from sklearn.model_selection import GridSearchCV

# Initialize the classifiers
classifiers = {
    "Decision Tree": DecisionTreeClassifier(),
```

```
"Random Forest": RandomForestClassifier(),
    "SVC": SVC(),
    "KNN": KNeighborsClassifier(),
    "Logistic Regression": LogisticRegression(),
                                                            # Define parameter grids for hyperparameter tuning (you can modify these)
param grids = {
    "Decision Tree": {"max_depth": [None, 10, 20, 30]},
    "Random Forest": {"n_estimators": [10, 50, 100]},
   "SVC": {"C": [0.1, 1, 10], "kernel": ["linear", "rbf"]},
    "KNN": {"n_neighbors": [3, 5, 7]},
    "Logistic Regression": {"C": [0.1, 1, 10], "penalty": ["l1", "l2"]},
# Lists to store results
results = {}
confusion_matrices = {}
# Iterate through classifiers
for classifier_name, classifier in classifiers.items():
   # Perform hyperparameter tuning using GridSearchCV
   param_grid = param_grids.get(classifier_name, {}) # Get the parameter grid for this classifier
   grid_search = GridSearchCV(classifier, param_grid, cv=5, n_jobs=-1, scoring="accuracy")
    # Fit the model to training data
   grid_search.fit(train_x, train_Y_bin)
    # Get the best model
    best_classifier = grid_search.best_estimator_
    # Make predictions on the test data
    predictions = best_classifier.predict(test_x)
   # Calculate performance metrics
    accuracy = accuracy score(test Y bin, predictions)
   precision = precision score(test Y bin, predictions)
   recall = recall score(test Y bin, predictions)
   f1 = f1_score(test_Y_bin, predictions)
    # Calculate the confusion matrix
    confusion = confusion matrix(test Y bin, predictions)
```

```
# Store results
results[classifier_name] = {"Accuracy": accuracy, "Precision": precision, "Recall": recall, "F1": f1}
confusion_matrices[classifier_name] = confusion

KeyboardInterrupt
Traceback (most recent call last)
```

```
KeyboardInterrupt
                                          Traceback (most recent call last)
<ipython-input-15-fd5c599f42fa> in <cell line: 2>()
      7
           # Fit the model to training data
----> 8
           grid search.fit(train x, train Y bin)
    10
           # Get the best model
                                  2 6 frames
/usr/local/lib/python3.10/dist-packages/joblib/parallel.py in retrieve(self)
   1705
                        (self. jobs[0].get status(
   1706
                           timeout=self.timeout) == TASK PENDING)):
-> 1707
                        time.sleep(0.01)
   1708
                        continue
   1709
```

KeyboardInterrupt:

SEARCH STACK OVERFLOW

```
# Define label names
label_names = ['normal', 'dos', 'probe', 'r2l', 'u2r']

# Visualize and compare the accuracy of different algorithms
plt.figure(figsize=(12, 6))
plt.bar(results.keys(), [result["Accuracy"] for result in results.values()], color='skyblue')
plt.xlabel("Algorithms")
plt.ylabel("Accuracy")
plt.title("Accuracy")
plt.title("Accuracy Comparison of Different Algorithms")
plt.ylin([0, 1])
plt.xticks(rotation=45)
plt.show()
```

```
# Plot the confusion matrix for each scenario
for classifier_name, confusion_matrix in confusion_matrices.items():
   plt.figure(figsize=(8, 6))
   ConfusionMatrixDisplay(confusion_matrix, display_labels=label_names).plot(cmap='Blues', xticks_rotation='horizontal')
   plt.title(f"Confusion Matrix - {classifier_name}")
   plt.show()
```