```
In [1]: import pandas as pd
       import matplotlib.pyplot as plt
       import seaborn as sns
       from scipy stats import zscore
       from sklearn.preprocessing import MinMaxScaler, OneHotEncoder
       from sklearn.decomposition import PCA
       import numpy as np
       from sklearn.ensemble import RandomForestClassifier
       from sklearn.feature selection import SelectFromModel
       from sklearn.preprocessing import StandardScaler
       from sklearn.ensemble import RandomForestClassifier
       from sklearn.feature_selection import SelectFromModel
       from scipy import stats
       from sklearn.decomposition import PCA
       from scipy.stats import chi2 contingency
       from sklearn.model selection import train test split
       from sklearn.linear_model import LogisticRegression
       from sklearn.preprocessing import LabelEncoder
       from sklearn.metrics import classification_report, accuracy_score
       from sklearn.preprocessing import PolynomialFeatures
       from sklearn.tree import DecisionTreeClassifier
       from sklearn.ensemble import RandomForestClassifier, GradientBoostin
       from sklearn.svm import SVC
       from sklearn.neural_network import MLPClassifier
       from sklearn.metrics import accuracy_score, classification_report
       from sklearn.model_selection import cross_val_score
       from xgboost import XGBClassifier
       from sklearn.preprocessing import StandardScaler
       from sklearn.decomposition import PCA
       from sklearn.cluster import KMeans, DBSCAN
       from sklearn.metrics import silhouette_score
       from sklearn.ensemble import IsolationForest
       from sklearn.neighbors import LocalOutlierFactor
       import warnings
       from sklearn.neighbors import NearestNeighbors
       from sklearn.manifold import TSNE
       from sklearn.preprocessing import StandardScaler
       from sklearn.metrics import pairwise distances argmin min
       import joblib
```

```
In [2]: # Suppress warnings
warnings.filterwarnings("ignore")
```

```
In [3]: # Load the cleaned dataset
    df = pd.read_csv("Network_anomaly_data.csv")

# Check the first few rows of the data
    print(df.head())

# Get general information about the dataset
    print(df.info())
```

1										
	ation	proto	coltype	se	rvice	flag	srcbytes	dstbyt	es	land
0	0		tcp	f+n	_data	SF	491		0	0
1	0		udp		_uata	SF	146		0	0
2	0		tcp		ivate	S0	0		0	0
2	0		tcp	P	http	SF	232	81		0
4	0		tcp		http	SF	199		20	0
ıonw	ngfra	gment	urgent	hot		dsth	nostsamesr	vrate d	sth	ostdif
fsrvrat 0	te \	0	0	0				0.17		
0.03 1		0	0	0				0.00		
0.60 2		0	0	0				0.10		
0.05					•••					
3 0.00		0	0	0	• • • •			1.00		
4 0.00		0	0	0	•••			1.00		
	nosts	amesro	portrate	e ds	thost	srvdif	fhostrate	dsthos	tse	rrorra
te \ 0			0.17	7			0.00			0.
00 1 00			0.88	3			0.00			0.
2 00			0.00)			0.00			1.
3 03			0.03	3			0.04			0.
4 00			0.00)			0.00			0.
		rvserr	orrate	dsth	ostre	rrorra	ate dstho	stsrvrer	ror	rate
attack 0	\		0.00			0.	05			0.00
normal 1			0.00			0.	00			0.00
normal 2	_		1.00			0.	00			0.00
neptune 3	2		0.01			0.	00			0.01
normal 4 normal			0.00			0.	00			0.00
	tflag 20									
1	15 19									
2 3 4	21 21									

[5 rows x 43 columns]

<class 'pandas.core.frame.DataFrame'> RangeIndex: 125973 entries, 0 to 125972

Data columns (total 43 columns):

#	Column (total 43 Column	Non-Null Count	Dtype
0	 duration	125973 non-null	 int64
1	protocoltype	125973 non-null	object
2	service	125973 non-null	object
3	flag	125973 non-null	object
4	srcbytes	125973 non-null	int64
5	dstbytes	125973 non-null	int64
6	land	125973 non-null	int64
7	wrongfragment	125973 non-null	int64
8	urgent	125973 non-null	int64
9	hot	125973 non-null	int64
10	numfailedlogins	125973 non-null	int64
11	loggedin	125973 non-null	int64
12	numcompromised	125973 non-null	int64
13	rootshell	125973 non-null	int64
14	suattempted	125973 non-null	int64
15	numroot	125973 non-null	int64
16	numfilecreations	125973 non-null	int64
17	numshells	125973 non-null	int64
18	numaccessfiles	125973 non-null	int64
19	numoutboundcmds	125973 non-null	int64
20	ishostlogin	125973 non-null	int64
21	isguestlogin	125973 non-null	int64
22	count	125973 non-null	int64
23	srvcount	125973 non-null	int64
24	serrorrate	125973 non-null	float64
25	srvserrorrate	125973 non-null	float64
26	rerrorrate	125973 non-null	
27	srvrerrorrate	125973 non-null	float64
28	samesrvrate	125973 non-null	float64
29	diffsrvrate	125973 non-null	float64
30	srvdiffhostrate	125973 non-null	float64
31	dsthostcount	125973 non-null	int64
32	dsthostsrvcount	125973 non-null	int64
33	dsthostsamesrvrate	125973 non-null	float64
34	dsthostdiffsrvrate	125973 non-null	float64
35	dsthostsamesrcportrate	125973 non-null	float64
36	dsthostsrvdiffhostrate	125973 non-null	float64
37	dsthostserrorrate	125973 non-null	float64
38	dsthostsrvserrorrate	125973 non-null	float64
39	dsthostrerrorrate	125973 non-null	float64
40	dsthostsrvrerrorrate	125973 non-null	float64
41	attack	125973 non-null	object
42	lastflag	125973 non-null	int64
dtype	es: float64(15), int64(24	4) , object(4)	
memo	ry usage: 41.3+ MB		

In [4]: # Display missing values before handling print("Missing values before handling:") print(df.isnull().sum())

Missing values before	
duration	0
protocoltype	0
service	0
flag	0 0
srcbytes dstbytes	0
land	0
wrongfragment	0
urgent	ø
hot	ő
numfailedlogins	ø
loggedin	0
numcompromised	0
rootshell	0
suattempted	0
numroot	0
numfilecreations	0
numshells	0
numaccessfiles	0
numoutboundcmds	0
ishostlogin	0
isguestlogin	0
count	0
srvcount	0
serrorrate	0
srvserrorrate	0
rerrorrate	0
srvrerrorrate	0
samesrvrate	0
diffsrvrate	0
srvdiffhostrate	0
dsthostcount dsthostsrvcount	0 0
dsthostsamesrvrate	0
dsthostdiffsrvrate	0
dsthostsamesrcportrate	
dsthostsrvdiffhostrate	
dsthostserrorrate	0
dsthostsrvserrorrate	ő
dsthostrerrorrate	ø
dsthostsrvrerrorrate	0
attack	0
lastflag	0
dtype: int64	

```
In [5]: # Separate numerical and categorical columns
    numerical_columns = df.select_dtypes(include=['float64', 'int64']).
    categorical_columns = df.select_dtypes(include=['object']).columns

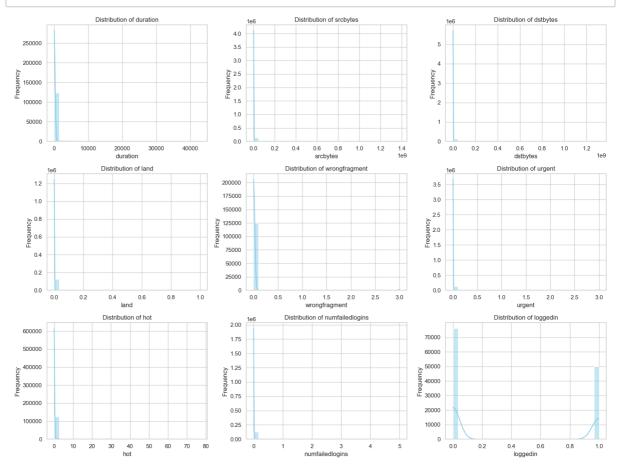
# Replace missing values in numerical columns with the median
    for col in numerical_columns:
        df[col].fillna(df[col].median(), inplace=True)

# Replace missing values in categorical columns with the most frequ
    for col in categorical_columns:
        df[col].fillna(df[col].mode()[0], inplace=True)
```

```
In [6]: # Display missing values after handling
print("\nMissing values after handling:")
print(df.isnull().sum())
```

Missing values after	handling:
duration	0
protocoltype	0
service	0
flag	ø
srcbytes	0
dstbytes	0
land	0
wrongfragment	0
urgent	0
hot	0
numfailedlogins	0
loggedin	0
numcompromised	0
rootshell	0
suattempted	0
numroot	0
numfilecreations	0
numshells	0
numaccessfiles	0
numoutboundcmds	0
ishostlogin	0
isguestlogin	0
count	0
srvcount	0
serrorrate	0
srvserrorrate	0
rerrorrate	0
srvrerrorrate	0
samesrvrate	0
diffsrvrate	0
srvdiffhostrate	0
dsthostcount	0
dsthostsrvcount	0
dsthostsamesrvrate	0
dsthostdiffsrvrate	0
dsthostsamesrcportrat	e 0
dsthostsrvdiffhostrat	
dsthostserrorrate	0
dsthostsrvserrorrate	0
dsthostrerrorrate	0
dsthostsrvrerrorrate	ø
attack	0
lastflag	0
dtype: int64	U
deyper file04	

```
In [7]: # Set plot style
        sns.set(style="whitegrid")
        # Function to plot the distribution of numeric features
        def plot_feature_distributions(data, feature_columns):
            n cols = 3
            n_rows = (len(feature_columns) + n_cols - 1) // n_cols
            plt.figure(figsize=(16, n_rows * 4))
            for i, feature in enumerate(feature columns, 1):
                plt.subplot(n_rows, n_cols, i)
                sns.histplot(data[feature], kde=True, bins=30, color="skybl
                plt.title(f"Distribution of {feature}")
                plt.xlabel(feature)
                plt.ylabel("Frequency")
            plt.tight_layout()
            plt.show()
        # Select numeric columns for distribution analysis
        numeric_columns = df.select_dtypes(include=['int64', 'float64']).co
        plot_feature_distributions(df, numeric_columns[:9]) # Plot for the
```



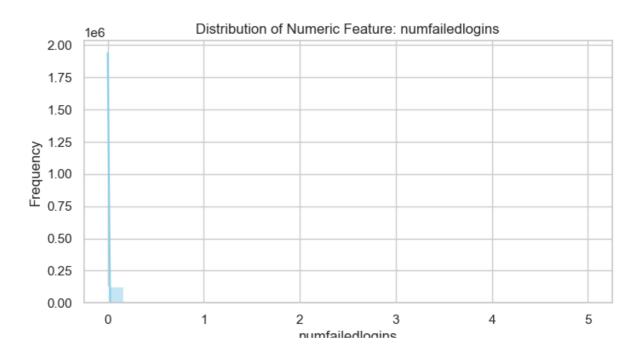
Observations:

Features like duration, srcbytes, and dstbytes have highly skewed distributions, likely influenced by extreme outliers or infrequent high values. Binary features such as land and urgent show a discrete distribution. Some features, like wrongfragment, have a significant number of zero entries, indicating sparsity.

```
In [8]: def plot distributions(data):
            # Separate numeric and categorical columns
            numeric_columns = data.select_dtypes(include=['int64', 'float64']
            categorical_columns = data.select_dtypes(include=['object', 'ca
            # Plot distributions for numeric features
            for column in numeric columns:
                plt.figure(figsize=(8, 4))
                sns.histplot(data[column], kde=True, bins=30, color="skyblu")
                plt.title(f"Distribution of Numeric Feature: {column}")
                plt.xlabel(column)
                plt.ylabel("Frequency")
                plt.show()
            # Plot distributions for categorical features
            for column in categorical_columns:
                plt.figure(figsize=(8, 4))
                sns.countplot(data=data, x=column, palette="viridis")
                plt.title(f"Distribution of Categorical Feature: {column}")
                plt.xlabel(column)
                plt.ylabel("Count")
                plt.xticks(rotation=45)
                plt.show()
```

In [9]: # Call the function to visualize all feature distributions
plot_distributions(df)

hot



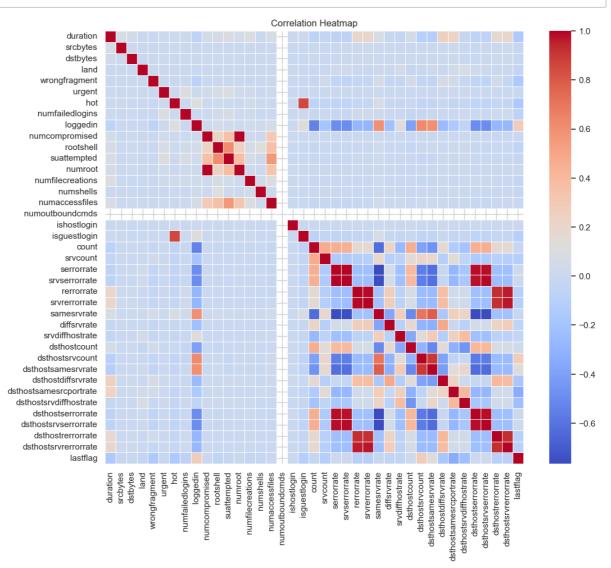
Corelation

To identify highly correlated features in your dataset and drop the ones that are redundant, we can calculate the correlation matrix and use a threshold to decide which features to drop.

```
In [10]: def correlation_analysis(data):
    # Compute the correlation matrix
    # Identify numerical columns to scale/normalize
    numerical_columns = data.select_dtypes(include=['float64', 'int corr_matrix = data[numerical_columns].corr()

# Plot the heatmap
    plt.figure(figsize=(12, 10))
    sns.heatmap(corr_matrix, annot=False, cmap="coolwarm", fmt='.2f
    plt.title("Correlation Heatmap")
    plt.show()

# Return the correlation matrix for further analysis
    return corr_matrix
```

```
In [12]: # Check for duplicates
    print(f"Number of duplicates before removal: {df.duplicated().sum()}

# Remove duplicates
    df_cleaned = df.drop_duplicates()

# Verify if duplicates are removed
    print(f"Number of duplicates after removal: {df_cleaned.duplicated()
```

Number of duplicates before removal: 0 Number of duplicates after removal: 0

```
In [13]: | categorical_columns = ['protocoltype', 'service', 'flag']
         # Dictionary to store mappings
         label encoders = {}
         label_mappings = \{\}
         # Apply Label Encoding and store mappings
         for col in categorical_columns:
              le = LabelEncoder()
             df[col] = le.fit transform(df[col])
              label encoders[col] = le
              label_mappings[col] = {index: label for index, label in enumera
         # Print the mappings for each column
         for col, mapping in label_mappings.items():
              print(f"Mapping for {col}:")
              for encoded, original in mapping.items():
                  print(f" {encoded} -> {original}")
              print()
         # Display the first few rows of the dataset
         print("\nEncoded Dataset:")
         print(df.head())
            51 -> remote_job
           52 -> rie
            53 -> shell
            54 -> smtp
            55 -> sql_net
            56 -> ssh
            57 -> sunrpc
            58 -> supdup
            59 -> systat
            60 -> telnet
            61 -> tftp_u
            62 -> tim i
            63 -> time
            64 \rightarrow urh i
            65 -> urp_i
            66 -> uucp
            67 -> uucp_path
            68 -> vmnet
            69 \rightarrow \text{whois}
In [14]: # Identify numerical columns to scale/normalize
         numerical_columns = df.select_dtypes(include=['float64', 'int64']).
         \# Standardization: Mean = 0, Std Dev = 1
         standard scaler = StandardScaler()
         df standardized = df.copy()
         df_standardized[numerical_columns] = standard_scaler.fit_transform(
```

```
# Normalization: Scale to range [0, 1]
minmax scaler = MinMaxScaler()
df_normalized = df.copy()
df_normalized[numerical_columns] = minmax_scaler.fit_transform(df[n
# Display the transformed datasets
print("Standardized Dataset (first 5 rows):")
print(df standardized.head())
print("\nNormalized Dataset (first 5 rows):")
print(df normalized.head())
Standardized Dataset (first 5 rows):
                                          flag srcbytes dstbytes
   duration protocoltype
                             service
land
     \
0 - 0.110249
                -0.124706 - 0.686785
                                     0.751111 -0.007679 -0.004919
-0.014089
1 - 0.110249
                 2.219312 0.781428 0.751111 -0.007737 -0.004919
-0.014089
2 - 0.110249
                -0.124706 1.087305 -0.736235 -0.007762 -0.004919
-0.014089
3 - 0.110249
                -0.124706 - 0.442083 0.751111 - 0.007723 - 0.002891
-0.014089
4 -0.110249
                -0.124706 -0.442083 0.751111 -0.007728 -0.004814
-0.014089
   wrongfragment
                    urgent
                                  hot
                                            dsthostsamesrvrate
0
       -0.089486 -0.007736 -0.095076
                                                      -0.782367
1
       -0.089486 - 0.007736 - 0.095076
                                                      -1.161030
2
       -0.089486 - 0.007736 - 0.095076
                                                      -0.938287
       -0.089486 - 0.007736 - 0.095076
3
                                                       1.066401
       -0.089486 - 0.007736 - 0.095076
                                                       1.066401
   dsthostdiffsrvrate dsthostsamesrcportrate dsthostsrvdiffhostr
ate
            -0.280282
                                      0.069972
                                                              -0.289
0
103
             2.736852
                                      2.367737
                                                              -0.289
1
103
            -0.174417
                                     -0.480197
                                                              -0.289
2
103
3
            -0.439078
                                     -0.383108
                                                               0.066
252
            -0.439078
                                     -0.480197
4
                                                              -0.289
103
   dsthostserrorrate dsthostsrvserrorrate
                                             dsthostrerrorrate
0
           -0.639532
                                  -0.624871
                                                      -0.224532
1
           -0.639532
                                  -0.624871
                                                      -0.387635
2
            1.608759
                                   1.618955
                                                      -0.387635
3
           -0.572083
                                  -0.602433
                                                      -0.387635
           -0.639532
                                  -0.624871
                                                      -0.387635
   dsthostsrvrerrorrate
                           attack lastflag
```

0	-0.376387	normal	0.216426
1	-0.376387	normal	-1.965556
2	-0.376387	neptune	-0.219970
3	-0.345084	normal	0.652823
4	-0.376387	normal	0.652823

[5 rows x 43 columns]

Norm	Normalized Dataset (first 5 rows):									
d	uration	protocoltype	service	flag	srcbytes	dstby				
tes	land \									
0	0.0	0.5	0.289855	0.9	3.558064e-07	0.000000e				
+00	0.0									
1	0.0	1.0	0.637681	0.9	1 . 057999e-07	0.000000e				
+00	0.0									
2	0.0	0.5	0.710145	0.5	0.000000e+00	0.000000e				
+00	0.0									
3	0.0	0.5	0.347826	0.9	1.681203e-07	6.223962e				
-06	0.0									
4	0.0	0.5	0.347826	0.9	1.442067e-07	3.206260e				
-07	0.0									

wrongfragment		urgent	hot	 dsthostsamesrvrate	dsthostdif
fsrvrate	\	_			
0	0.0	0.0	0.0	 0.17	
0.03					
1	0.0	0.0	0.0	 0.00	
0.60					
2	0.0	0.0	0.0	 0.10	
0.05					
3	0.0	0.0	0.0	 1.00	
0.00					
4	0.0	0.0	0.0	 1.00	
0.00					

	dsthostsamesrcportrate	dsthostsrvdiffhostrate	dsthostserrorra
te	\		
0	0.17	0.00	0.
00			
1	0.88	0.00	0.
00			
2	0.00	0.00	1.
00			
3	0.03	0.04	0.
03			
4	0.00	0.00	0.
00			

dsthostsrvserrorrate dsthostrerrorrate dsthostsrvrerrorrate attack \ 0 & 0.00 & 0.05 & 0.00 \\ normal & 0.00 & 0.00 & 0.00 \\ \end{tabular}

```
normal
                                                                0.00
                    1.00
                                        0.00
neptune
                    0.01
                                        0.00
                                                                0.01
3
normal
4
                    0.00
                                        0.00
                                                                0.00
normal
   lastflag
   0.952381
1
  0.714286
2
   0.904762
3 1.000000
4 1.000000
```

[5 rows x 43 columns]

Explanation of Changes:

Dropping Only One Feature from Each Pair:

For each correlated pair, only the first feature (i.e., pair[0]) is added to the correlated_features set, ensuring that only one feature from each correlated pair is dropped.

Set Data Structure for Features to Drop:

A set is used to ensure that each feature is only added once, even if it appears in multiple correlated pairs.

```
In [15]: # Select only numeric fields
         numeric_df = df.select_dtypes(include=[np.number])
         # Calculate the correlation matrix
         correlation matrix = numeric df.corr()
         # Set a threshold for correlation (e.g., 0.9)
         threshold = 0.9
         # Initialize a list to store correlated column pairs
         correlated pairs = []
         # Find highly correlated features
         for i in range(len(correlation_matrix.columns)):
             for j in range(i):
                 if abs(correlation_matrix.iloc[i, j]) > threshold: # Check
                     colname1 = correlation matrix.columns[i]
                     colname2 = correlation_matrix.columns[j]
                     correlated_pairs.append((colname1, colname2))
         # Print correlated column pairs
```

```
if correlated_pairs:
    print("Highly correlated column pairs (correlation > 0.9):")
    for pair in correlated_pairs:
        print(f"{pair[0]} and {pair[1]}")
else:
    print("No highly correlated column pairs found.")

# Initialize a set to keep track of features to drop
correlated_features = set()

# Keep only the first feature of each correlated pair (drop the sec
for pair in correlated_pairs:
        correlated_features.add(pair[0]) # Add only the first feature

# Drop the selected features from the original dataframe
df = df.drop(columns=correlated_features)

# Output the dropped features
print(f"\nDropped features due to high correlation: {correlated_fea
```

```
Highly correlated column pairs (correlation > 0.9):
numroot and numcompromised
srvserrorrate and serrorrate
srvrerrorrate and rerrorrate
dsthostserrorrate and srvserrorrate
dsthostsrvserrorrate and serrorrate
dsthostsrvserrorrate and srvserrorrate
dsthostsrvserrorrate and srvserrorrate
dsthostsrvserrorrate and dsthostserrorrate
dsthostrerrorrate and rerrorrate
dsthostrerrorrate and rerrorrate
dsthostsrvrerrorrate and rerrorrate
dsthostsrvrerrorrate and srvrerrorrate
dsthostsrvrerrorrate and srvrerrorrate
dsthostsrvrerrorrate and dsthostrerrorrate
```

Dropped features due to high correlation: {'dsthostrerrorrate', 'n umroot', 'dsthostsrvrerrorrate', 'dsthostserrorrate', 'srvrerrorrate', 'dsthostsrvserrorrate', 'srvserrorrate'}

In [16]: df.head()

Out [16]:

	duration	protocoltype	service	flag	srcbytes	dstbytes	land	wrongfragment	urgent	I
0	0	1	20	9	491	0	0	0	0	
1	0	2	44	9	146	0	0	0	0	
2	0	1	49	5	0	0	0	0	0	
3	0	1	24	9	232	8153	0	0	0	
4	0	1	24	9	199	420	0	0	0	

5 rows × 36 columns

```
In [17]: # Creating Interaction Features (combining numerical features)
df['src_dst_bytes_interaction'] = df['srcbytes'] * df['dstbytes']
df['num_failed_logins_hot_interaction'] = df['numfailedlogins'] * d
df['num_compromised_su_interaction'] = df['numcompromised'] * df['s

# Aggregated Features: Summary statistics over groups of features
df['total_data_transfer'] = df['srcbytes'] + df['dstbytes'] # Tota
df['total_access_operations'] = df['numfilecreations'] + df['numshe

# Drop any features that you may not need
df = df.drop(columns=['srcbytes', 'dstbytes', 'attack']) # Droppin
```

In [18]: df.head()

Out[18]:

	duration	protocoltype	service	flag	land	wrongfragment	urgent	hot	numfailedlogins
0	0	1	20	9	0	0	0	0	0
1	0	2	44	9	0	0	0	0	0
2	0	1	49	5	0	0	0	0	0
3	0	1	24	9	0	0	0	0	0
4	0	1	24	9	0	0	0	0	0

5 rows × 38 columns

```
In [19]: # Preprocessing
    scaler = StandardScaler()
    scaled_data = scaler.fit_transform(df)
```

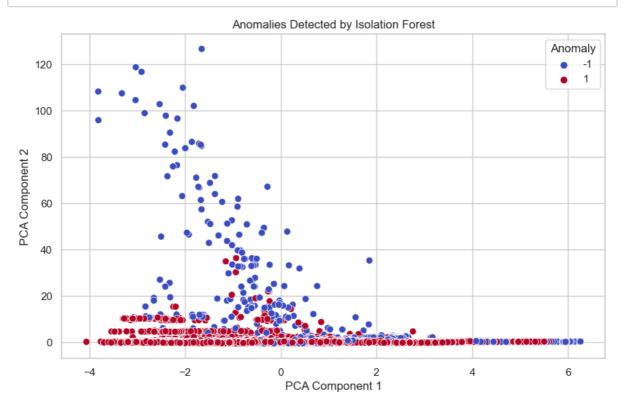
```
In [20]: # Dimensionality Reduction (PCA)
pca = PCA(n_components=0.95) # Retain 95% variance
reduced_data = pca.fit_transform(scaled_data)
print(f"Reduced data shape: {reduced_data.shape}")
```

Reduced data shape: (125973, 27)

```
In [21]: # Visualize Results (PCA-reduced 2D data)
    tsne = PCA(n_components=2)
    data_2d = tsne.fit_transform(reduced_data)
```

> Number of clusters (Isolation Forest): 1 Number of anomalies detected: 6298

In [23]: # Plot Anomalies Detected by Isolation Forest plt.figure(figsize=(10, 6)) sns.scatterplot(x=data_2d[:, 0], y=data_2d[:, 1], hue=anomaly_label plt.title("Anomalies Detected by Isolation Forest") plt.xlabel("PCA Component 1") plt.ylabel("PCA Component 2") plt.legend(title="Anomaly") plt.show()



```
In [24]: # Save the model to a file
   joblib.dump(iso_forest, "isolation_forest_model.joblib")
   print("Model saved successfully.")
```

Model saved successfully.

```
In [27]: # Load the model from the file
    iso_forest_loaded = joblib.load("isolation_forest_model.joblib")
    print("Model loaded successfully.")

# Predict anomalies
    anomaly_labels = iso_forest_loaded.predict(scaled_data)

# Count and summarize anomalies
    num_anomalies = (anomaly_labels == -1).sum()
    num_normal = (anomaly_labels == 1).sum()

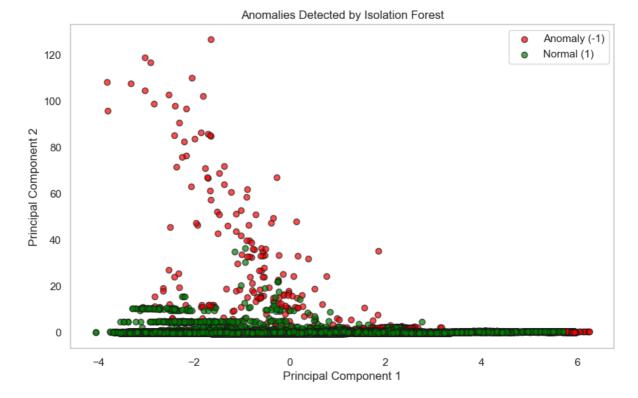
print(f"Total anomalies detected: {num_anomalies}")
    print(f"Total normal instances: {num_normal}")
```

Model loaded successfully.
Total anomalies detected: 6298
Total normal instances: 119675

```
In [34]: # Separate anomalies and normal instances
    anomalies = reduced_data[anomaly_labels == -1]
    normal = reduced_data[anomaly_labels == 1]

# Plot anomalies and normal instances separately
    plt.figure(figsize=(10, 6))
    plt.scatter(anomalies[:, 0], anomalies[:, 1], c='red', label='Anoma
    plt.scatter(normal[:, 0], normal[:, 1], c='green', label='Normal (1)

# Add title, labels, and legend
    plt.title("Anomalies Detected by Isolation Forest")
    plt.xlabel("Principal Component 1")
    plt.ylabel("Principal Component 2")
    plt.legend(loc="best") # Proper legend
    plt.grid()
    plt.show()
```



In []: