

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

import warnings

warnings.filterwarnings('ignore')

df = pd.read_csv("log2.csv")
df
```

	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				

	Action	Bytes	Bytes Sent	Bytes Received	Packets	\
0	allow	177	94	83	2	
1	allow	4768	1600	3168	19	
2	allow	238	118	120	2	
3	allow	3327	1438	1889	15	
4	allow	25358	6778	18580	31	
...	
65527	allow	314	192	122	6	
65528	allow	4680740	67312	4613428	4675	
65529	drop	70	70	0	1	
65530	drop	70	70	0	1	
65531	drop	70	70	0	1	

	Elapsed Time (sec)	pkts_sent	pkts_received
0	30	1	1
1	17	10	9
2	1199	1	1
3	17	8	7
4	16	13	18
...
65527	15	4	2
65528	77	985	3690
65529	0	1	0
65530	0	1	0
65531	0	1	0

[65532 rows x 12 columns]

Data Inspection

```
print("Dataset shape:", df.shape)
```

```
print("\nFirst 5 rows:")
```

```
print(df.head())
```

```
print("\nSummary statistics:")
```

```
print(df.describe())
```

```
print("\nMissing values per column:")
```

```
print(df.isnull().sum())
```

Dataset shape: (65532, 12)

First 5 rows:

	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
---	-------	-----	-------	-----

	Action	Bytes	Bytes Sent	Bytes Received	Packets	Elapsed Time (sec)
--	--------	-------	------------	----------------	---------	--------------------

0	allow	177	94	83	2	30
---	-------	-----	----	----	---	----

1	allow	4768	1600	3168	19	
---	-------	------	------	------	----	--

```

17
2 allow      238          118          120          2
1199
3 allow      3327         1438         1889         15
17
4 allow      25358        6778         18580        31
16

```

```

      pkts_sent  pkts_received
0           1           1
1          10           9
2           1           1
3           8           7
4          13          18

```

Summary statistics:

	Source Port	Destination Port	NAT Source Port	NAT
Destination Port \				
count	65532.000000	65532.000000	65532.000000	
mean	49391.969343	10577.385812	19282.972761	
std	15255.712537	18466.027039	21970.689669	
min	0.000000	0.000000	0.000000	
25%	49183.000000	80.000000	0.000000	
50%	53776.500000	445.000000	8820.500000	
75%	58638.000000	15000.000000	38366.250000	
max	65534.000000	65535.000000	65535.000000	

	Bytes	Bytes Sent	Bytes Received	Packets \
count	6.553200e+04	6.553200e+04	6.553200e+04	6.553200e+04
mean	9.712395e+04	2.238580e+04	7.473815e+04	1.028660e+02
std	5.618439e+06	3.828139e+06	2.463208e+06	5.133002e+03
min	6.000000e+01	6.000000e+01	0.000000e+00	1.000000e+00
25%	6.600000e+01	6.600000e+01	0.000000e+00	1.000000e+00
50%	1.680000e+02	9.000000e+01	7.900000e+01	2.000000e+00
75%	7.522500e+02	2.100000e+02	4.490000e+02	6.000000e+00
max	1.269359e+09	9.484772e+08	3.208818e+08	1.036116e+06

	Elapsed Time (sec)	pkts_sent	pkts_received
count	65532.000000	65532.000000	65532.000000
mean	65.833577	41.399530	61.466505
std	302.461762	3218.871288	2223.332271
min	0.000000	1.000000	0.000000

25%	0.000000	1.000000	0.000000
50%	15.000000	1.000000	1.000000
75%	30.000000	3.000000	2.000000
max	10824.000000	747520.000000	327208.000000

Missing values per column:

Source Port	0
Destination Port	0
NAT Source Port	0
NAT Destination Port	0
Action	0
Bytes	0
Bytes Sent	0
Bytes Received	0
Packets	0
Elapsed Time (sec)	0
pkts_sent	0
pkts_received	0

dtype: int64

Cleaning Data

df = df.dropna()

df

Port \	Source Port	Destination Port	NAT Source Port	NAT Destination
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				

	Action	Bytes	Bytes Sent	Bytes Received	Packets	\
0	allow	177	94	83	2	
1	allow	4768	1600	3168	19	
2	allow	238	118	120	2	
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...	
65527	allow	314	192	122	6	
65528	allow	4680740	67312	4613428	4675	
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65530	drop	70	70	0	1	
65531	drop	70	70	0	1	

	Elapsed Time (sec)	pkts_sent	pkts_received
0	30	1	1
1	17	10	9
2	1199	1	1
3	17	8	7
4	16	13	18
...
65527	15	4	2
65528	77	985	3690
65529	0	1	0
65530	0	1	0
65531	0	1	0

[65532 rows x 12 columns]

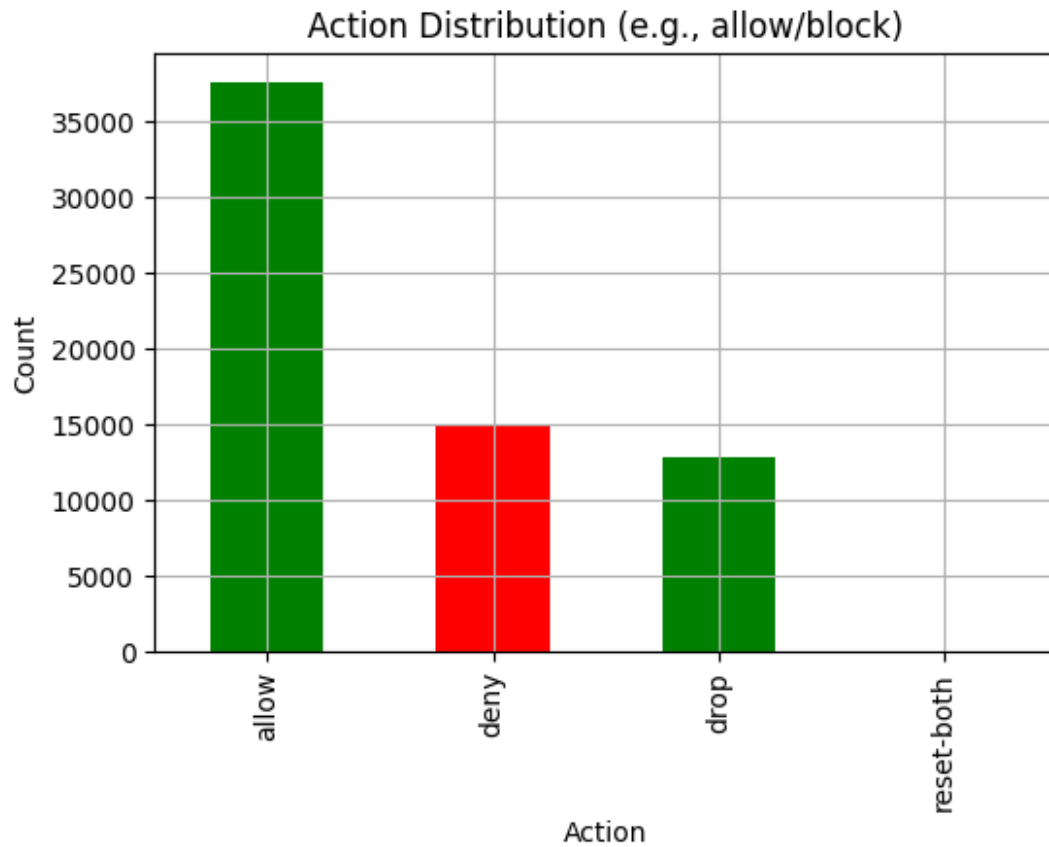
```
print("\nValue counts of Action (Target variable):")
print(df['Action'].value_counts())
```

Value counts of Action (Target variable):

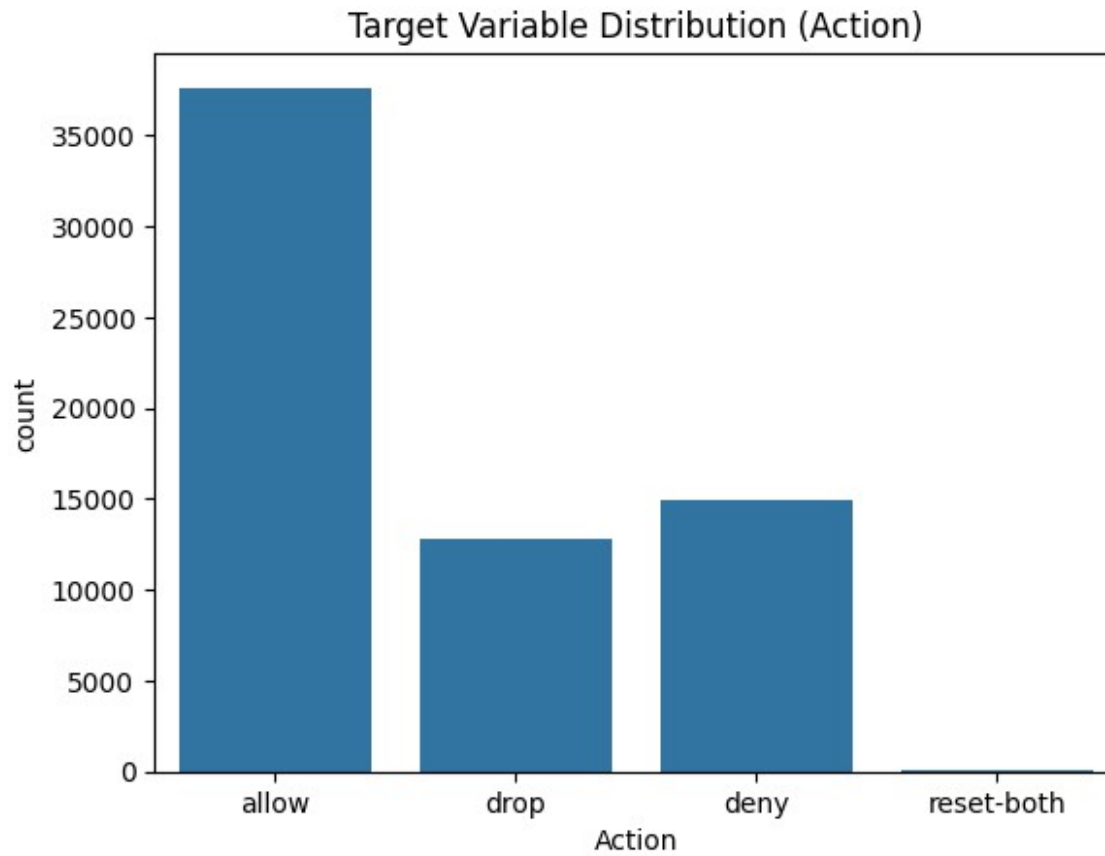
```
Action
allow      37640
deny       14987
drop       12851
reset-both    54
Name: count, dtype: int64
```

Bar plot of target variable

```
plt.figure(figsize=(6,4))
df['Action'].value_counts().plot(kind='bar', color=['green', 'red'])
plt.title('Action Distribution (e.g., allow/block)')
plt.xlabel('Action')
plt.ylabel('Count')
plt.grid()
plt.show()
```



```
##### Count plot using seaborn #####  
sns.countplot(x='Action', data=df)  
plt.title('Target Variable Distribution (Action)')  
plt.show()
```



Corelatio HeatMap

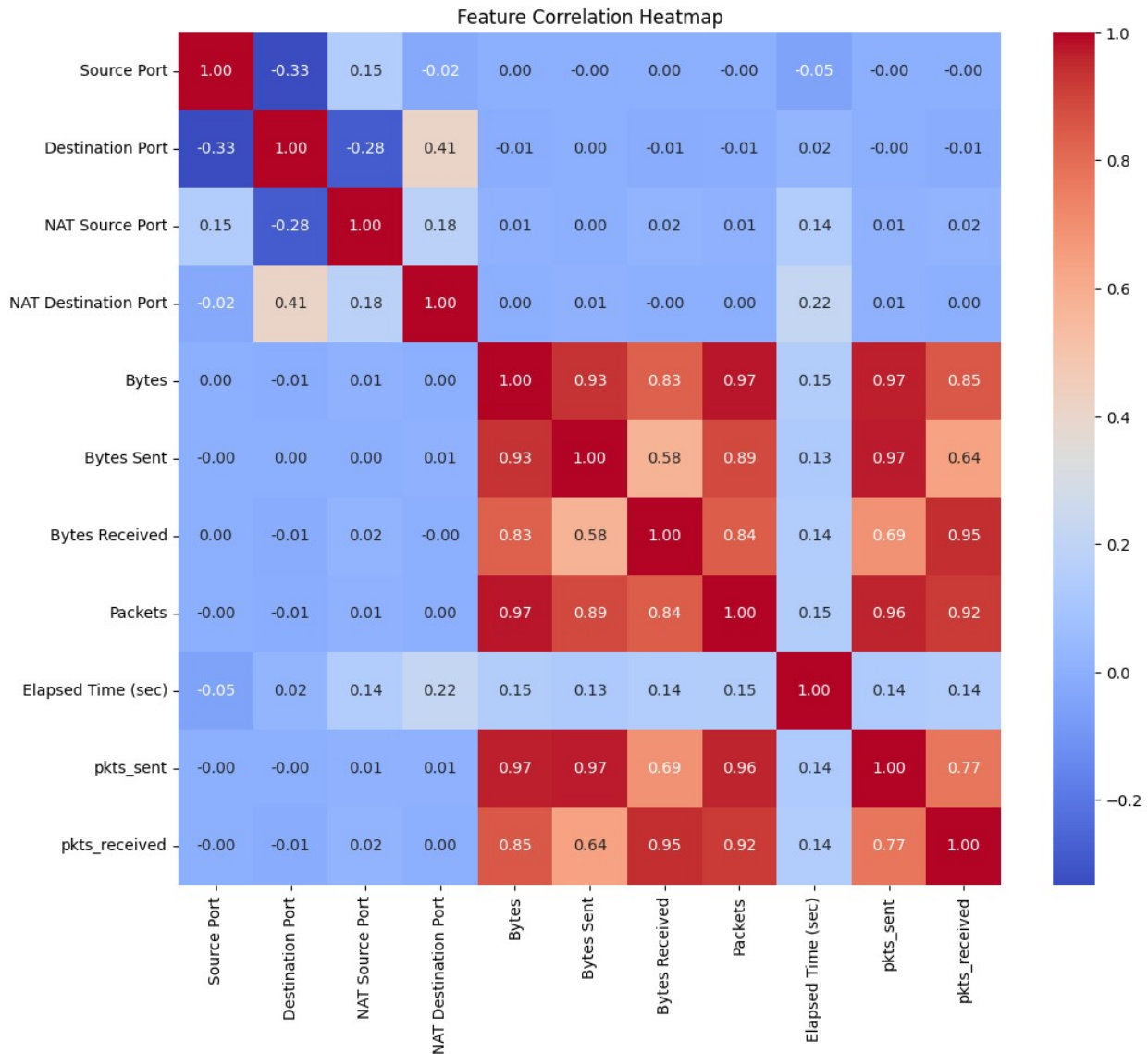
```
numeric_df = df.select_dtypes(include=[np.number])
```

```
plt.figure(figsize=(12,10))
```

```
sns.heatmap(numeric_df.corr(), cmap='coolwarm', annot=True, fmt='.2f')
```

```
plt.title('Feature Correlation Heatmap')
```

```
plt.show()
```



```
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA

features = numeric_df.columns.tolist()

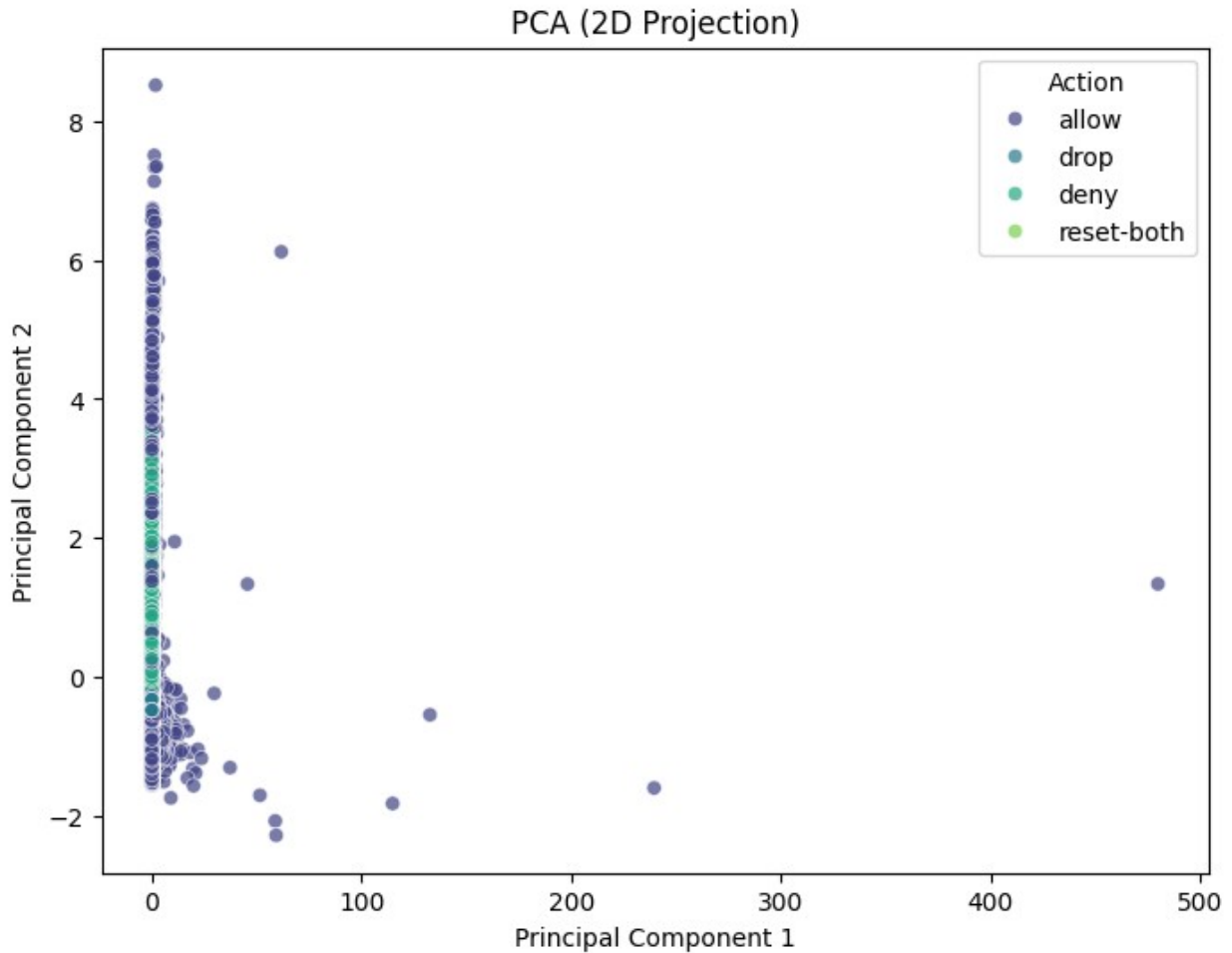
scaler = StandardScaler()
X_scaled = scaler.fit_transform(df[features])

pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)

plt.figure(figsize=(8,6))
sns.scatterplot(x=X_pca[:,0], y=X_pca[:,1], hue=df['Action'],
palette='viridis', alpha=0.7)
plt.title('PCA (2D Projection)')
```



```
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.legend(title='Action')
plt.show()
```



```
skewness = numeric_df.skew().sort_values(ascending=False)
print("\nSkewness of numeric columns:")
print(skewness)
```

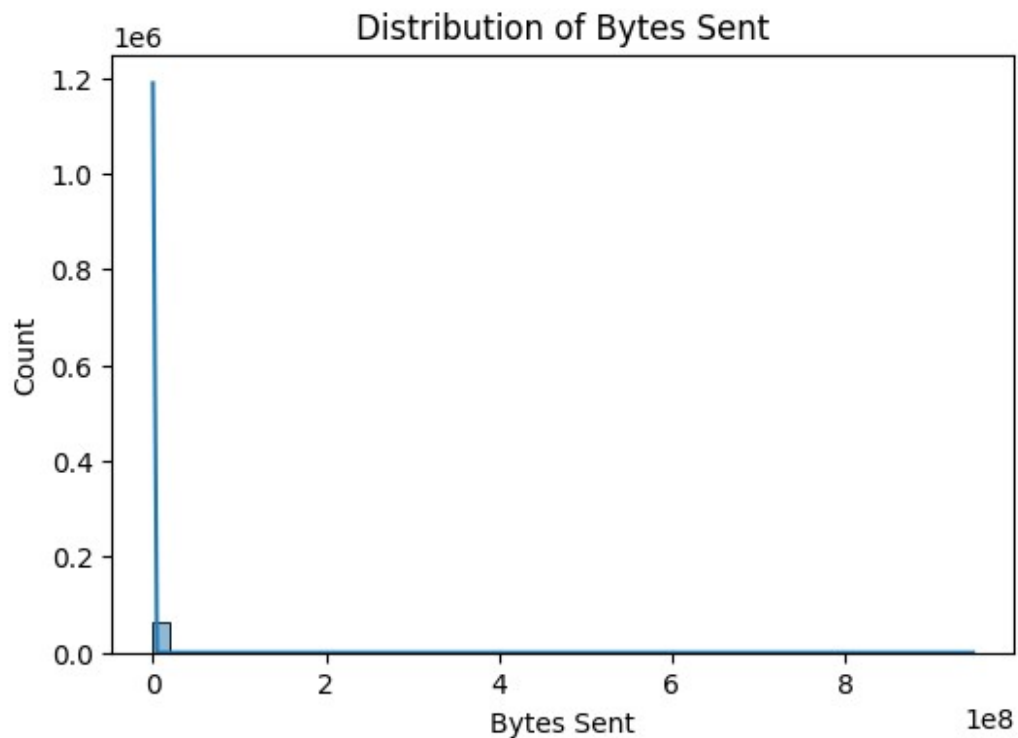
```
Skewness of numeric columns:
Bytes Sent          235.234612
pkts_sent           205.202114
Bytes               187.285581
Packets             158.891434
pkts_received       106.714701
Bytes Received       93.647470
Elapsed Time (sec)   12.445199
NAT Destination Port 4.193862
Destination Port     1.603034
```

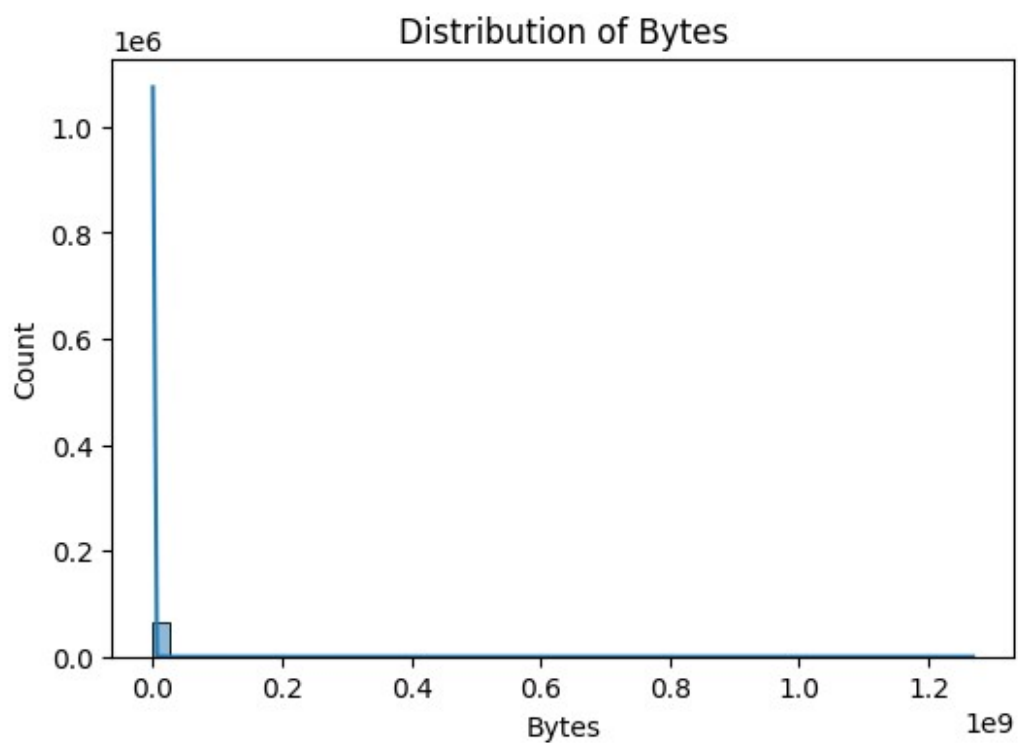
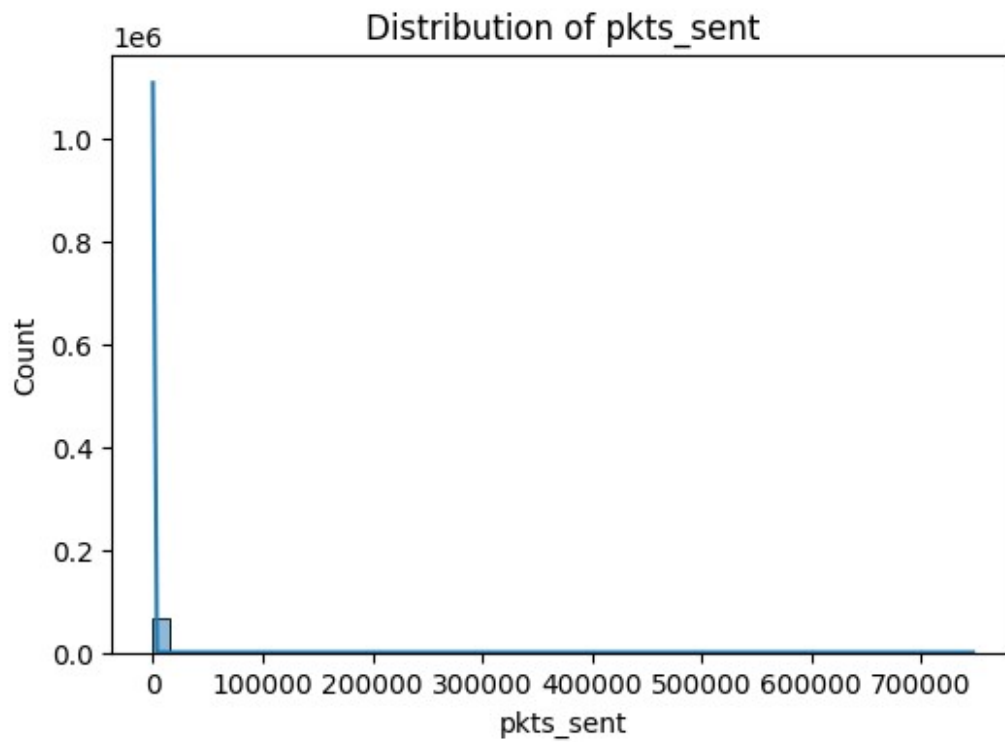
```
NAT Source Port      0.683319
Source Port          -1.708305
dtype: float64
```

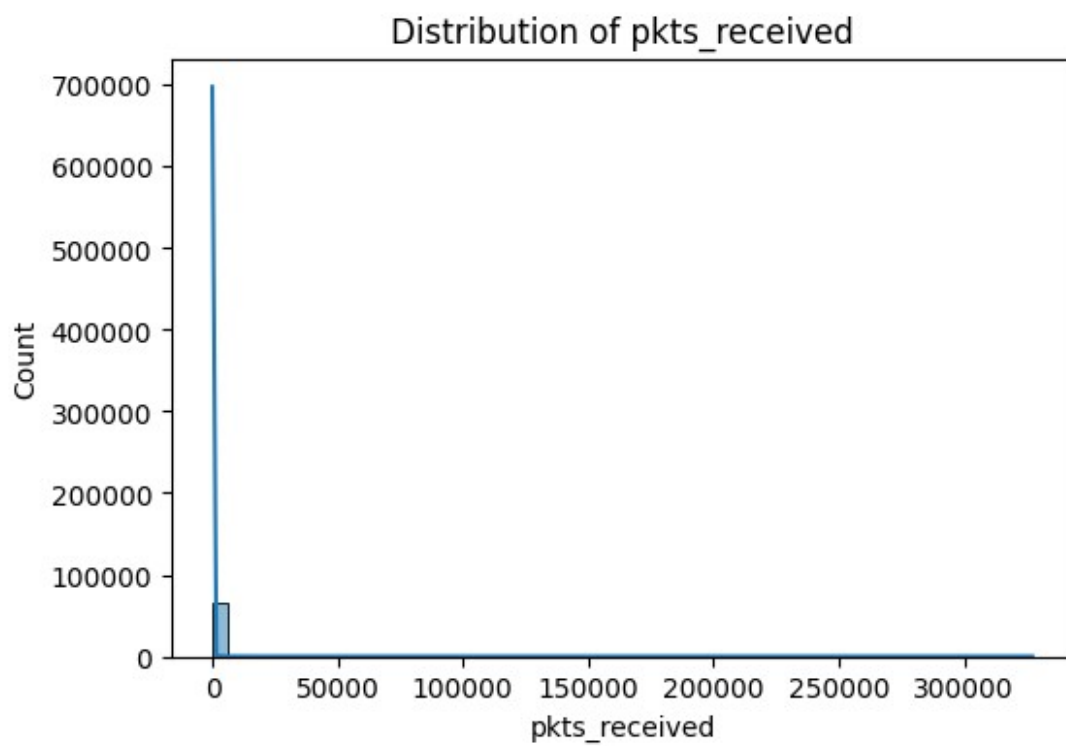
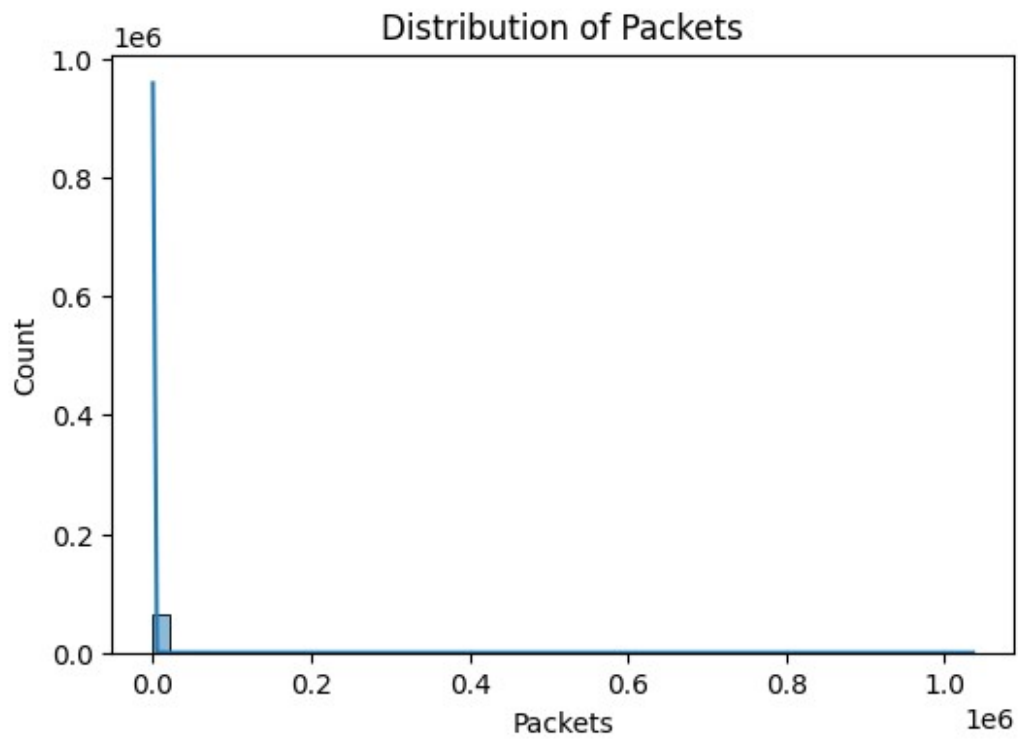
```
high_skew_cols = skewness[abs(skewness) > 1].index.tolist()
print("\nHighly skewed columns:", high_skew_cols)
```

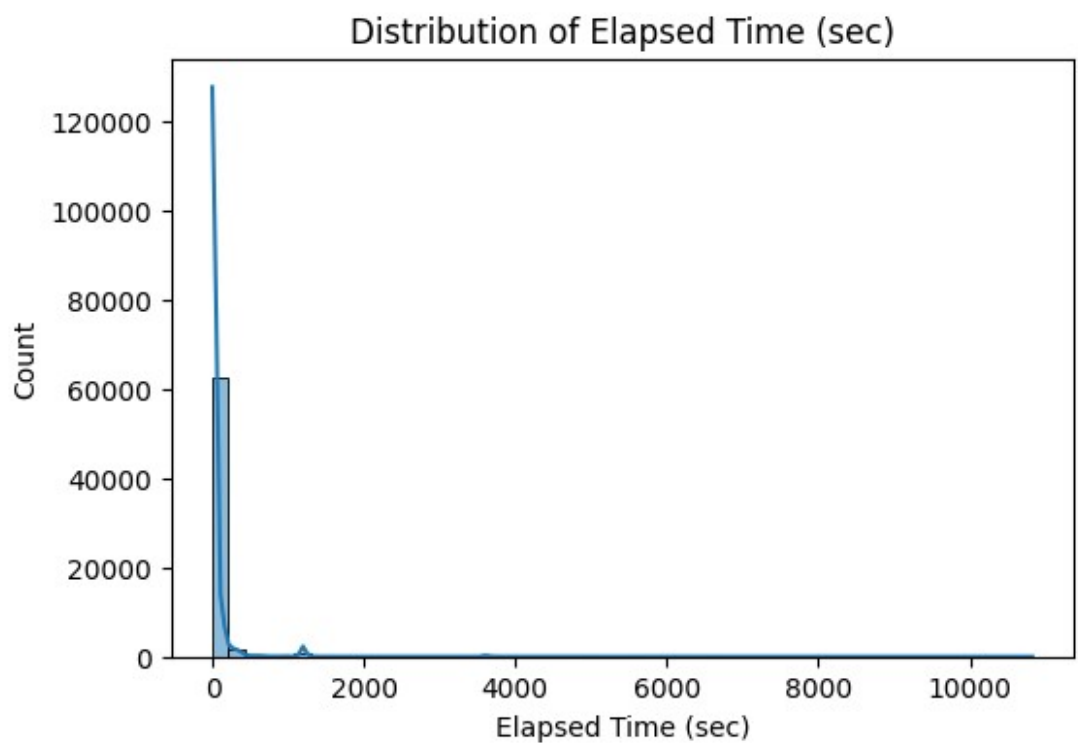
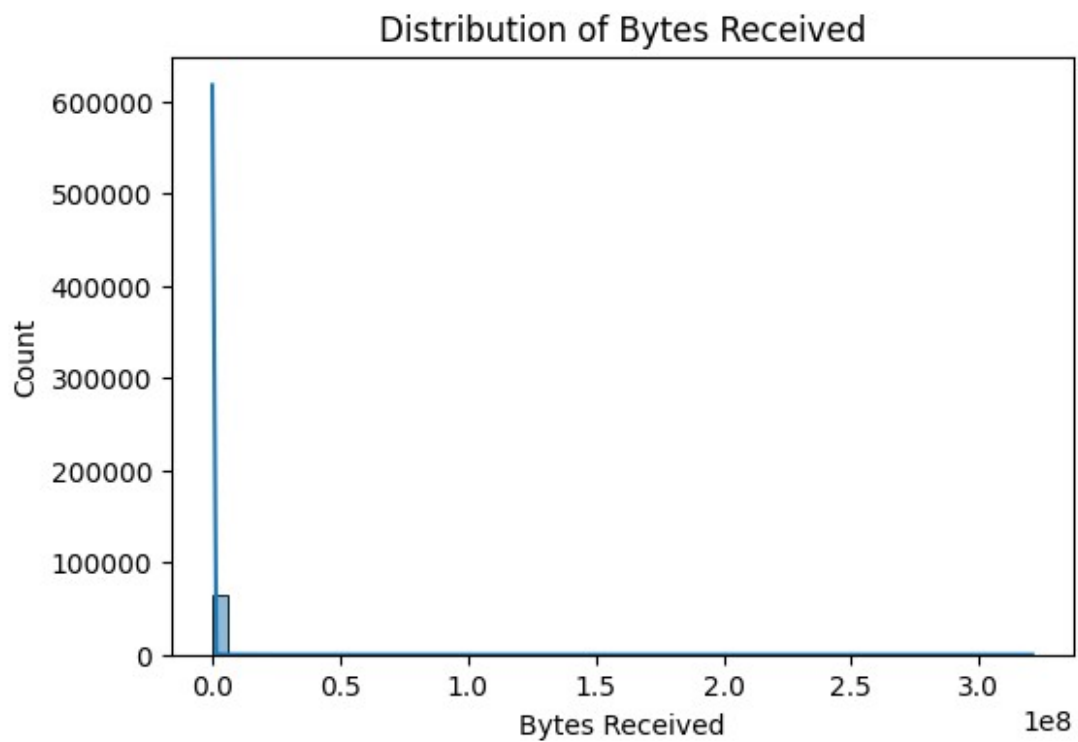
```
Highly skewed columns: ['Bytes Sent', 'pkts_sent', 'Bytes', 'Packets',
'pkts_received', 'Bytes Received', 'Elapsed Time (sec)', 'NAT
Destination Port', 'Destination Port', 'Source Port']
```

```
for col in high_skew_cols:
    plt.figure(figsize=(6,4))
    sns.histplot(df[col], bins=50, kde=True)
    plt.title(f'Distribution of {col}')
    plt.show()
```

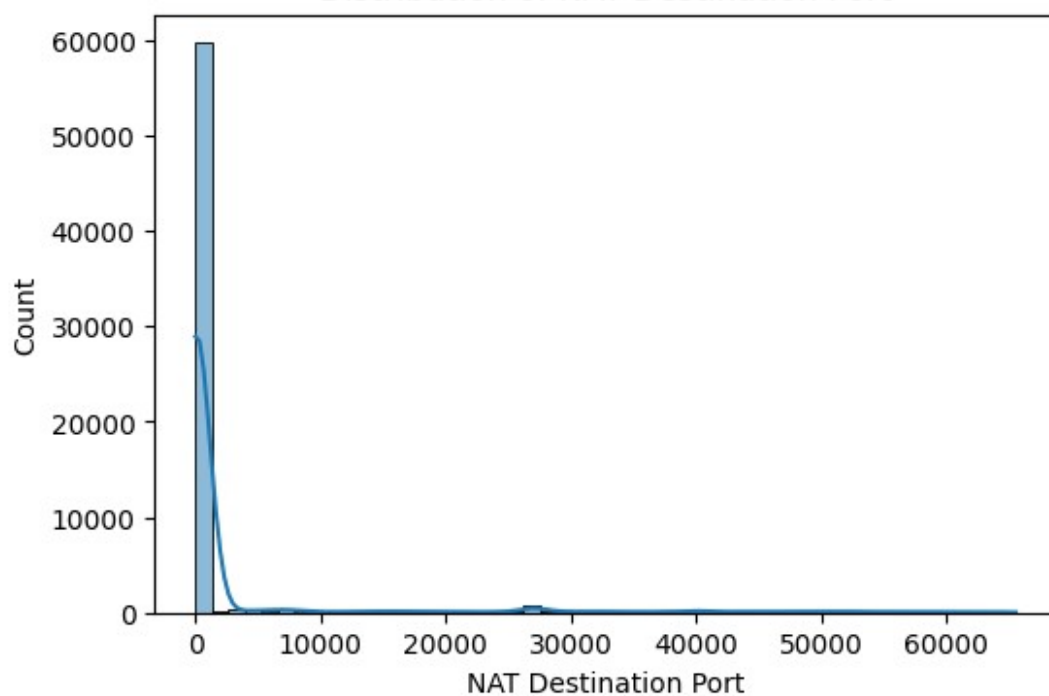




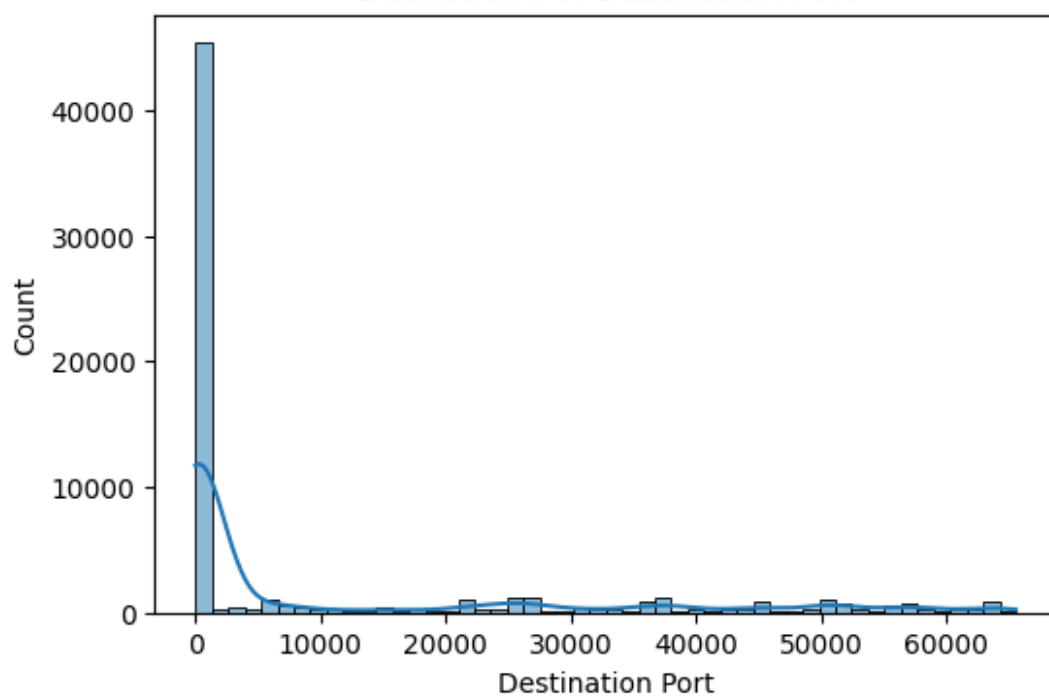


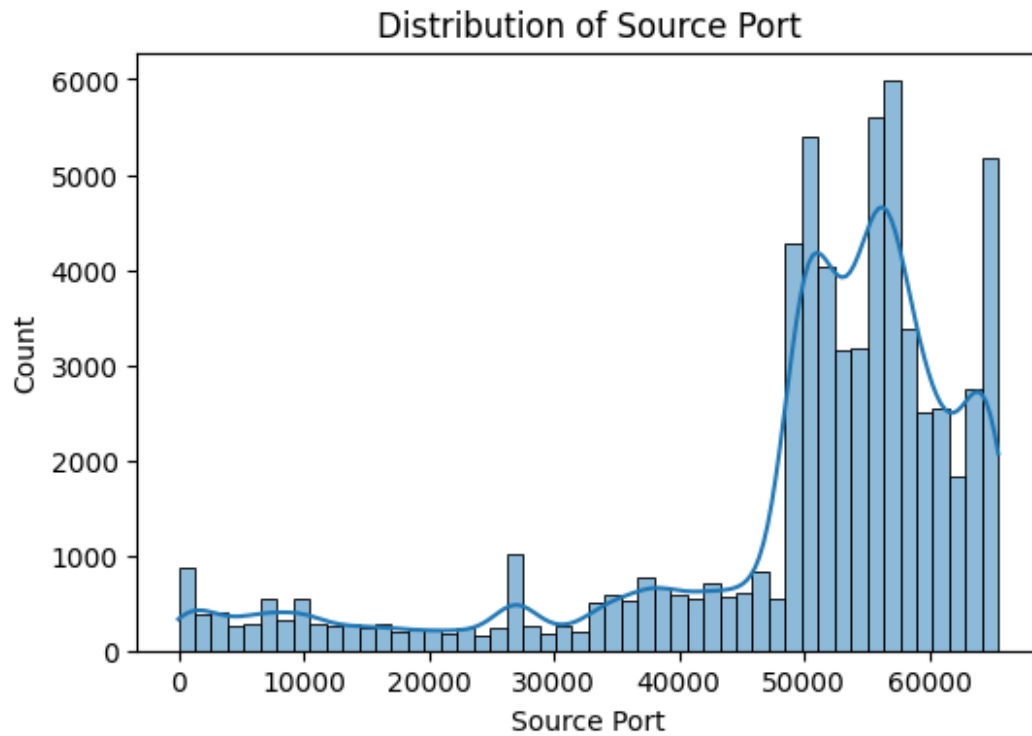


Distribution of NAT Destination Port



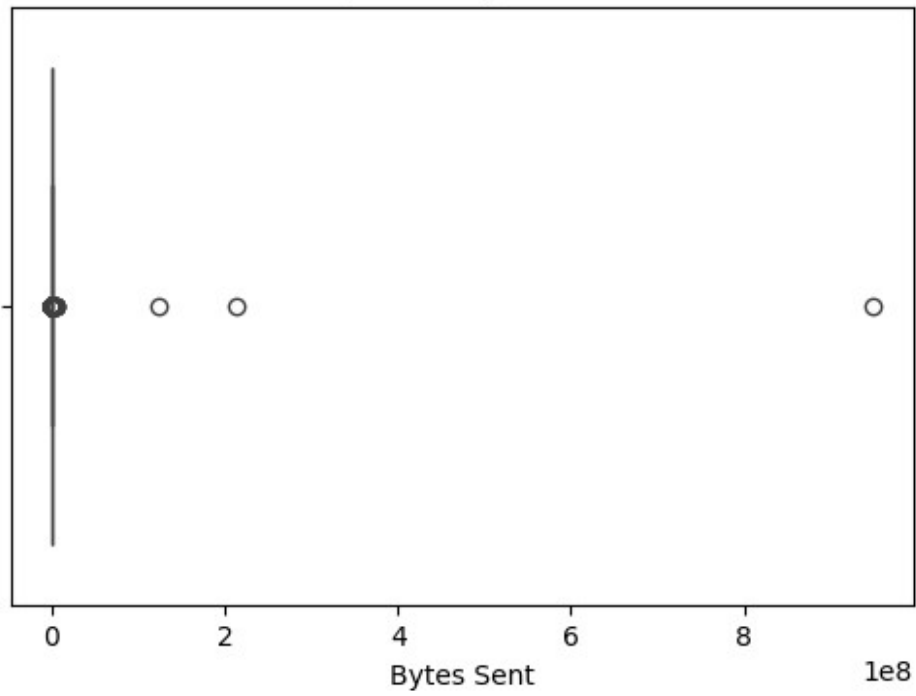
Distribution of Destination Port



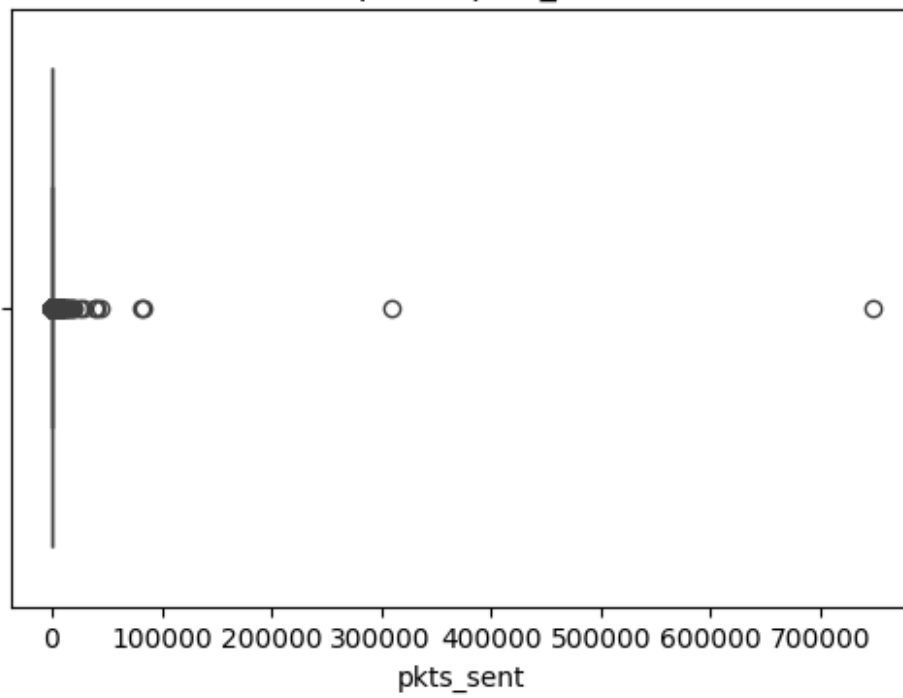


```
for col in high_skew_cols:  
    plt.figure(figsize=(6,4))  
    sns.boxplot(x=df[col])  
    plt.title(f'Boxplot of {col}')  
    plt.show()
```

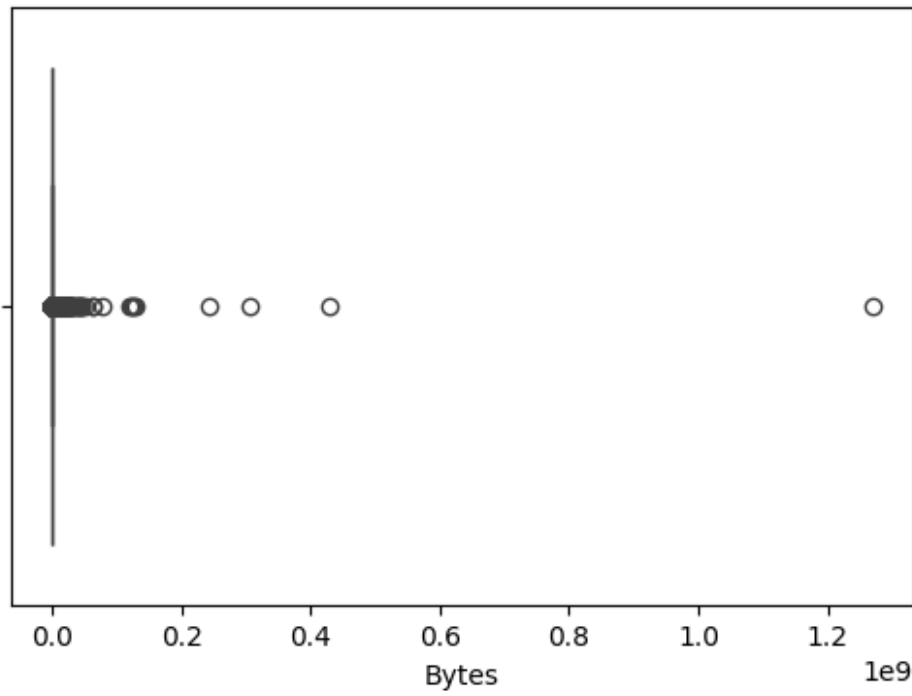
Boxplot of Bytes Sent



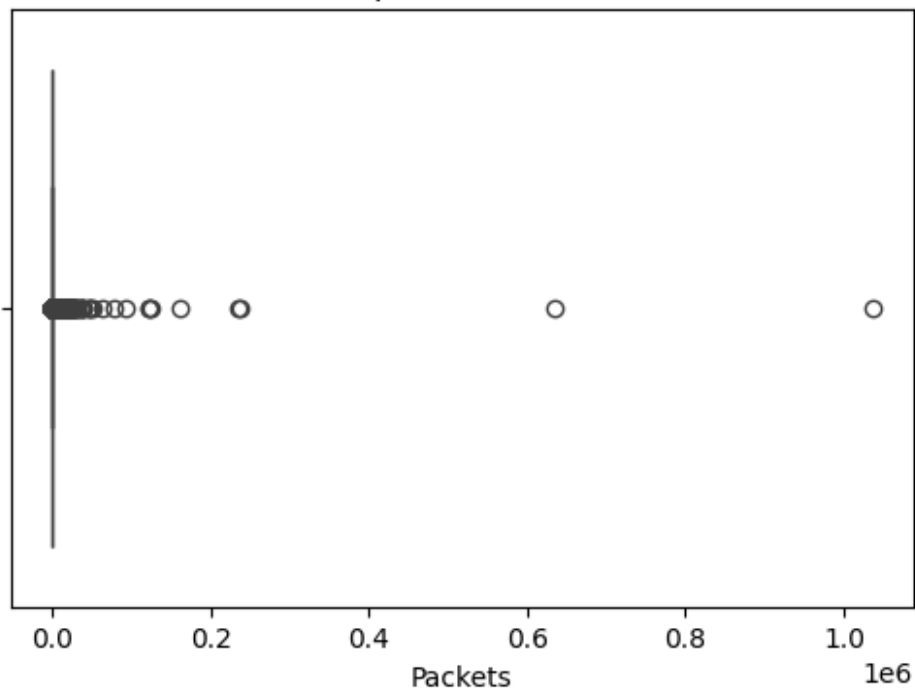
Boxplot of pkts_sent



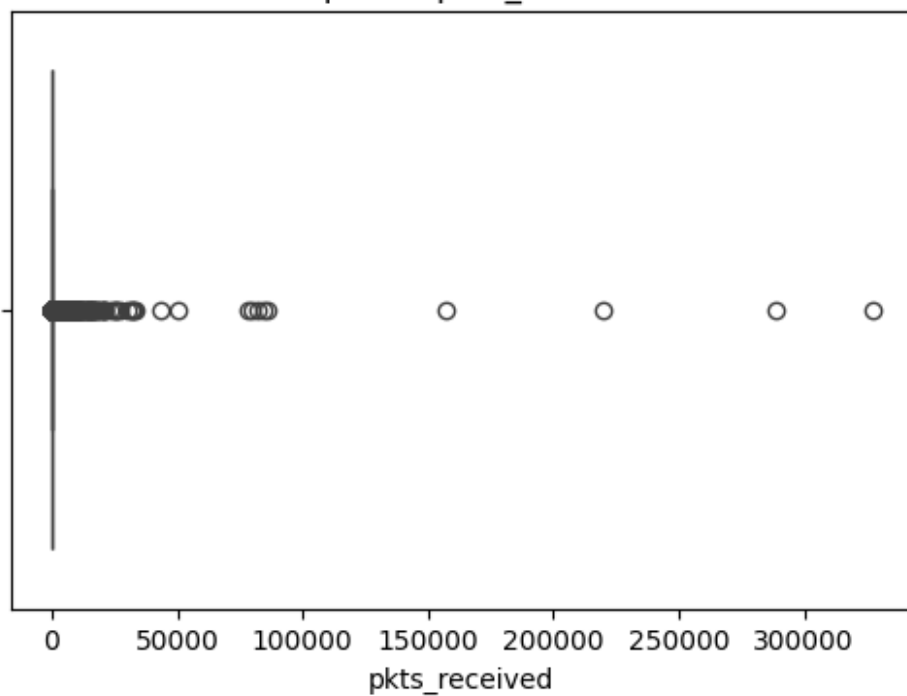
Boxplot of Bytes



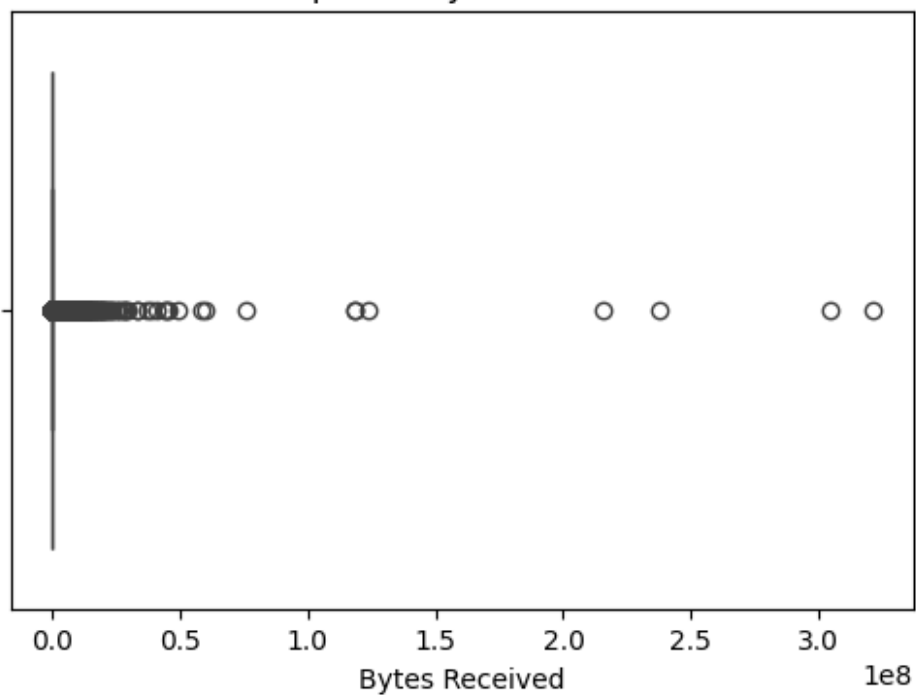
Boxplot of Packets



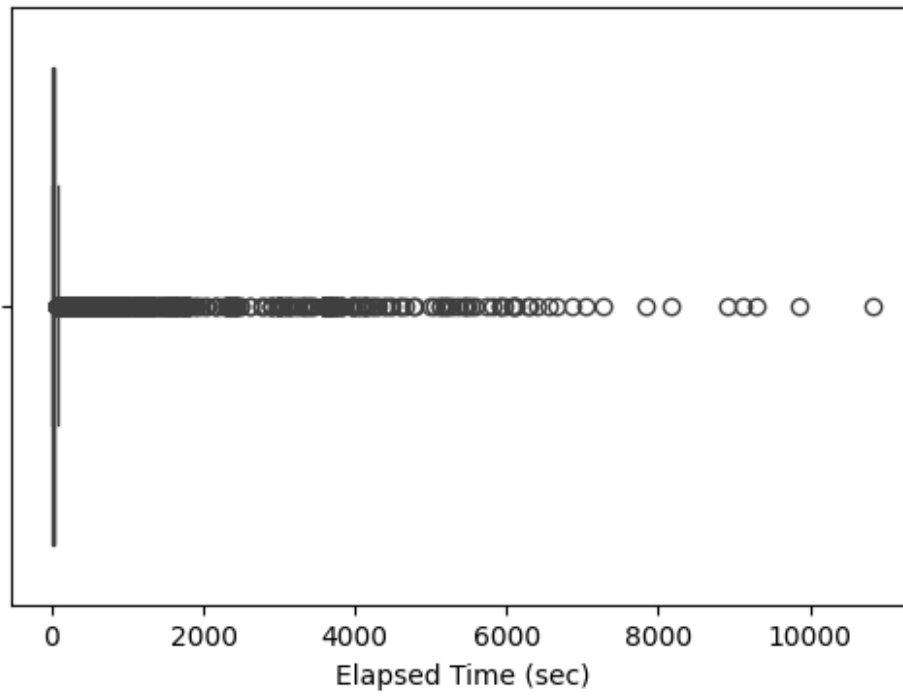
Boxplot of pkts_received



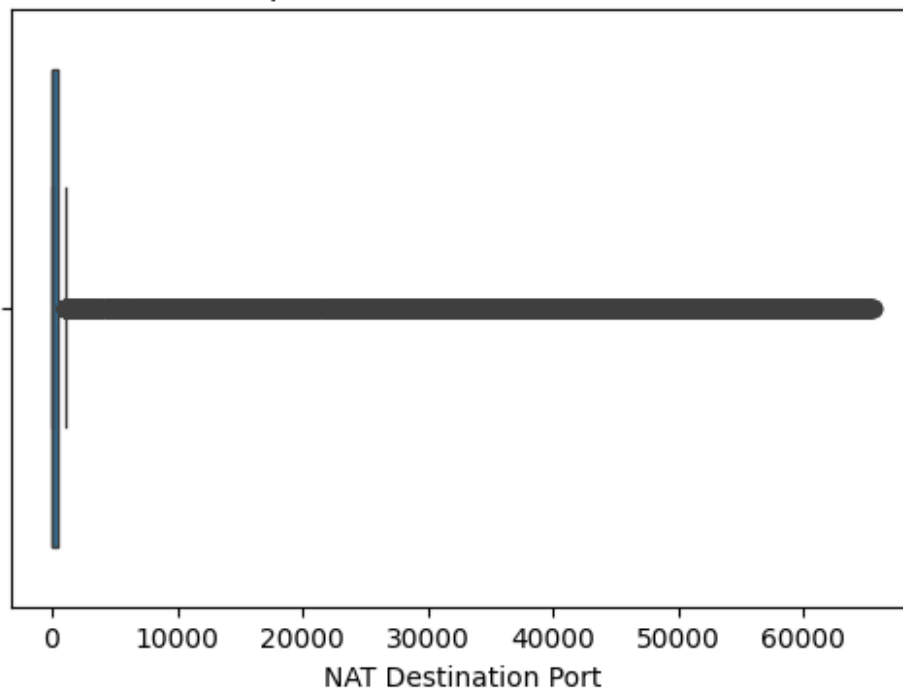
Boxplot of Bytes Received

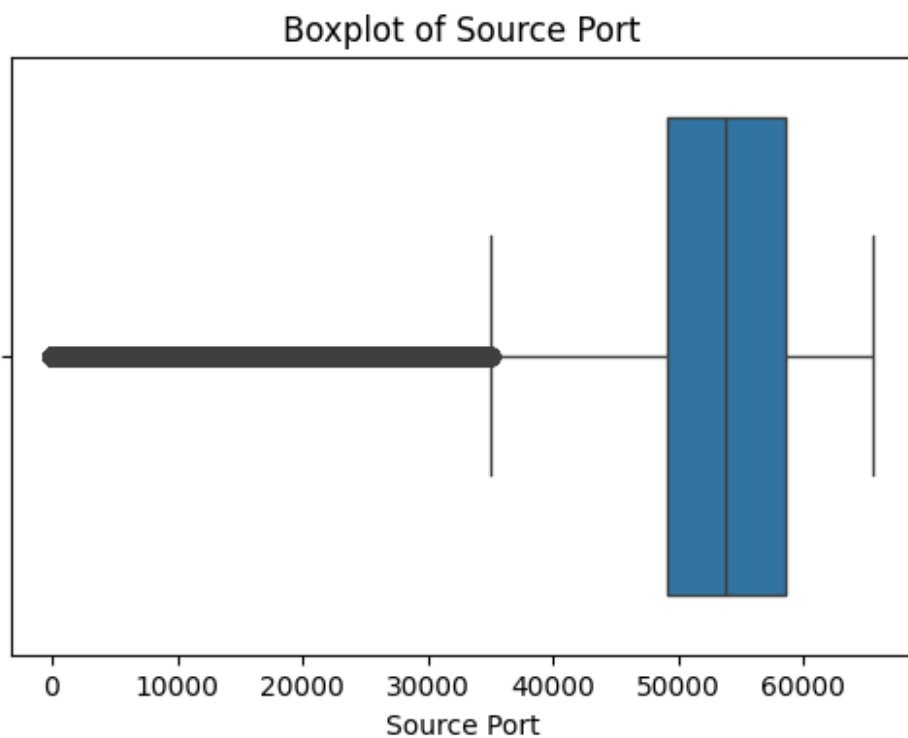
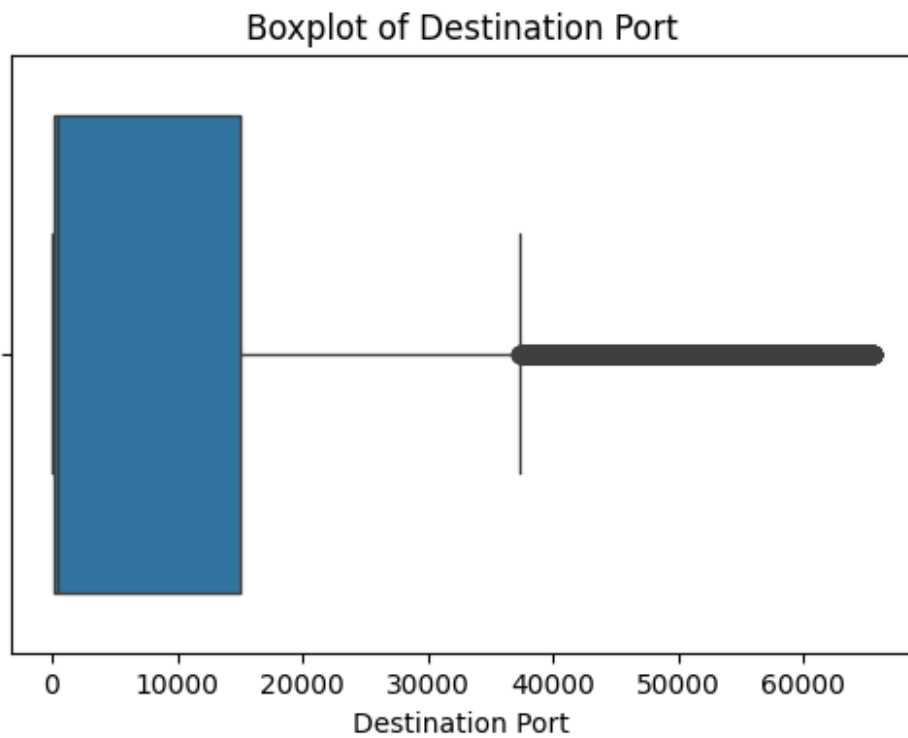


Boxplot of Elapsed Time (sec)



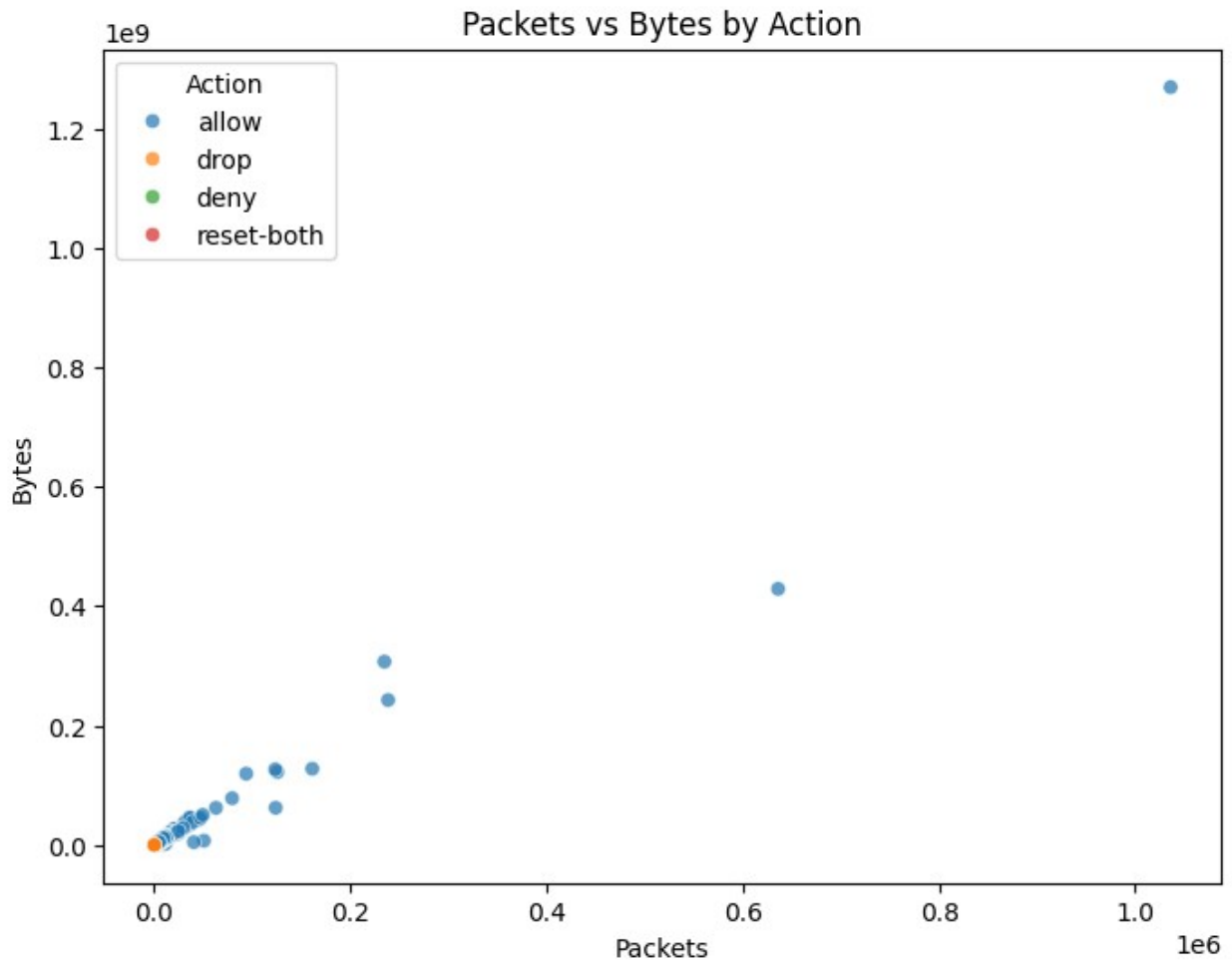
Boxplot of NAT Destination Port





```
plt.figure(figsize=(8,6))
sns.scatterplot(data=df, x='Packets', y='Bytes', hue='Action',
alpha=0.7)
```

```
plt.title('Packets vs Bytes by Action')
plt.show()
```



```
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix,
accuracy_score
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix,
accuracy_score, roc_curve, auc
%matplotlib inline
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
```

```
df['Action_encoded'] = df['Action'].apply(lambda x: 1 if x == 'allow'
else 0)
```

```
features = ['Bytes', 'Bytes Sent', 'Bytes Received', 'Packets',
'Elapsed Time (sec)', 'pkts_sent', 'pkts_received']
```

```
X = df[features]
```

```
y = df['Action_encoded']
```

```
X
```

	Bytes	Bytes Sent	Bytes Received	Packets	Elapsed Time
(sec) \					
0	177	94	83	2	
30					
1	4768	1600	3168	19	
17					
2	238	118	120	2	
1199					
3	3327	1438	1889	15	
17					
4	25358	6778	18580	31	
16					
...
.					
65527	314	192	122	6	
15					
65528	4680740	67312	4613428	4675	
77					
65529	70	70	0	1	
0					
65530	70	70	0	1	
0					
65531	70	70	0	1	
0					
	pkts_sent	pkts_received			
0	1	1			
1	10	9			
2	1	1			
3	8	7			
4	13	18			
...			
65527	4	2			
65528	985	3690			
65529	1	0			
65530	1	0			
65531	1	0			

```
[65532 rows x 7 columns]
```

```
y
```

```
0      1
1      1
2      1
3      1
4      1
```

```
..
65527   1
65528   1
65529   0
65530   0
65531   0
```

```
Name: Action_encoded, Length: 65532, dtype: int64
```

```
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.3, random_state=42, stratify=y)
```

```
scaler = StandardScaler()
```

```
X_train_scaled = scaler.fit_transform(X_train)
```

```
X_test_scaled = scaler.transform(X_test)
```

```
X_train_scaled
```

```
array([[ -0.01709844, -0.00674561, -0.02953929, ..., -0.21872727,
        -0.01280991, -0.02703282],
       [ -0.0163104 , -0.00653208, -0.02801914, ...,  0.02296643,
        -0.01020356, -0.02277993],
       [ -0.0167084 , -0.00641952, -0.02914625, ...,  2.49025631,
        -0.0112461 , -0.02277993],
       ...,
       [ -0.01706086, -0.00673031, -0.02947515, ..., -0.19858613,
        -0.01228864, -0.02587294],
       [ -0.01703817, -0.00673905, -0.02940709, ..., -0.07102557,
        -0.01254927, -0.02625956],
       [ -0.01709844, -0.00674561, -0.02953929, ..., -0.21872727,
        -0.01280991, -0.02703282]])
```

```
X_test_scaled
```

```
array([[ -0.01664558, -0.00634586, -0.02911738, ..., -0.16501756,
        -0.01046419, -0.02393981],
       [ -0.01708236, -0.00673949, -0.02951114, ..., -0.12137842,
        -0.01280991, -0.02664619],
       [ -0.01704613, -0.00670146, -0.02948727, ..., -0.11130785,
        -0.01254927, -0.02664619],
       ...,
       [ -0.01709784, -0.00674474, -0.02953929, ..., -0.21872727,
```

```

        -0.01280991, -0.02703282],
        [-0.01709904, -0.00674648, -0.02953929, ..., -0.21872727,
        -0.01280991, -0.02703282],
        [-0.01707319, -0.00673971, -0.02948905, ..., -0.11802156,
        -0.01280991, -0.02664619]])

results = {}

# Logistic Regression
lr = LogisticRegression()
lr.fit(X_train_scaled, y_train)
y_pred_lr = lr.predict(X_test_scaled)
results['Logistic Regression'] = {
    'accuracy': accuracy_score(y_test, y_pred_lr),
    'report': classification_report(y_test, y_pred_lr)
}

# SVM
svm = SVC(kernel='rbf', C=1)
svm.fit(X_train_scaled, y_train)
y_pred_svm = svm.predict(X_test_scaled)
results['SVM'] = {
    'accuracy': accuracy_score(y_test, y_pred_svm),
    'report': classification_report(y_test, y_pred_svm)
}

# Random Forest
rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(X_train, y_train) # RF doesn't need scaling
y_pred_rf = rf.predict(X_test)
results['Random Forest'] = {
    'accuracy': accuracy_score(y_test, y_pred_rf),
    'report': classification_report(y_test, y_pred_rf)
}

for model_name, metrics in results.items():
    print(f"\n==== {model_name} ====")
    print(f"Accuracy: {metrics['accuracy']:.4f}")
    print(metrics['report'])

```

==== Logistic Regression ====

Accuracy: 0.9465

	precision	recall	f1-score	support
0	0.89	1.00	0.94	8368
1	1.00	0.91	0.95	11292
accuracy			0.95	19660
macro avg	0.94	0.95	0.95	19660
weighted avg	0.95	0.95	0.95	19660

==== SVM ====

Accuracy: 0.9465

	precision	recall	f1-score	support
0	0.89	1.00	0.94	8368
1	1.00	0.91	0.95	11292
accuracy			0.95	19660
macro avg	0.94	0.95	0.95	19660
weighted avg	0.95	0.95	0.95	19660

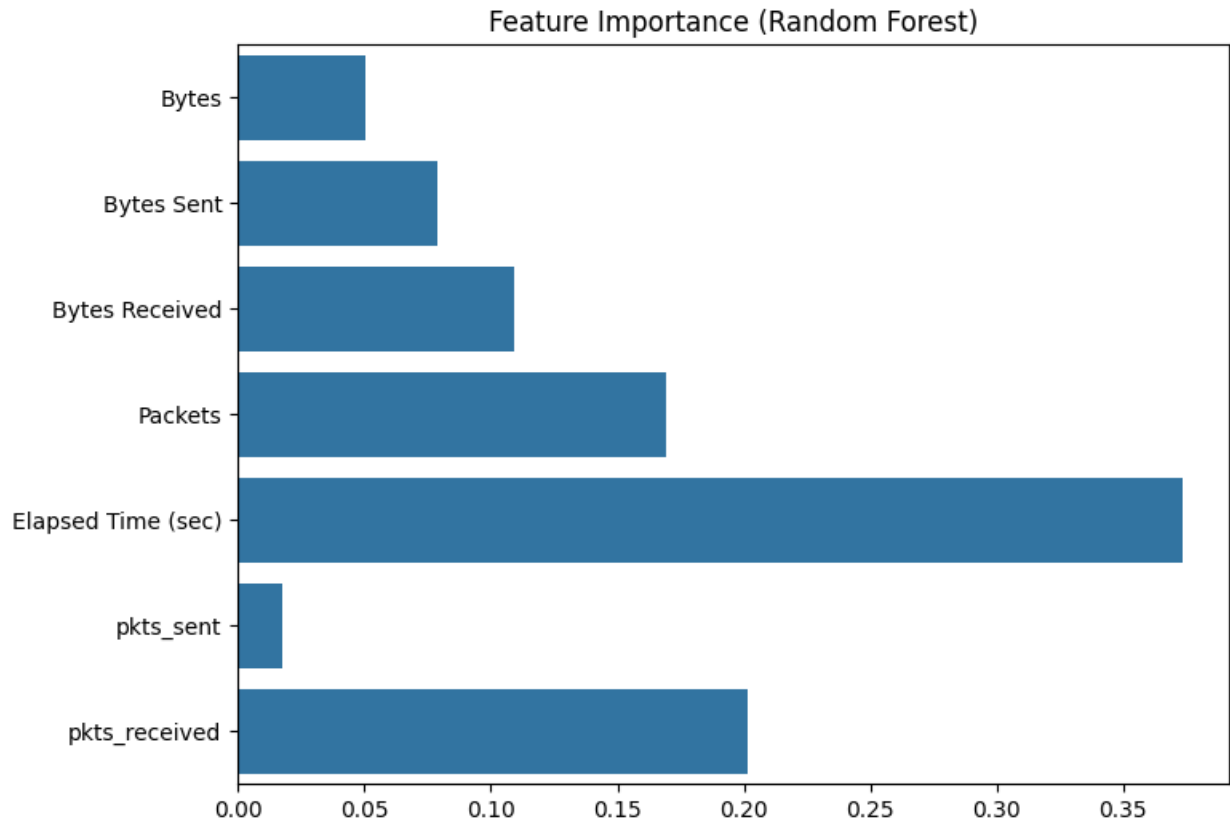
==== Random Forest ====

Accuracy: 0.9997

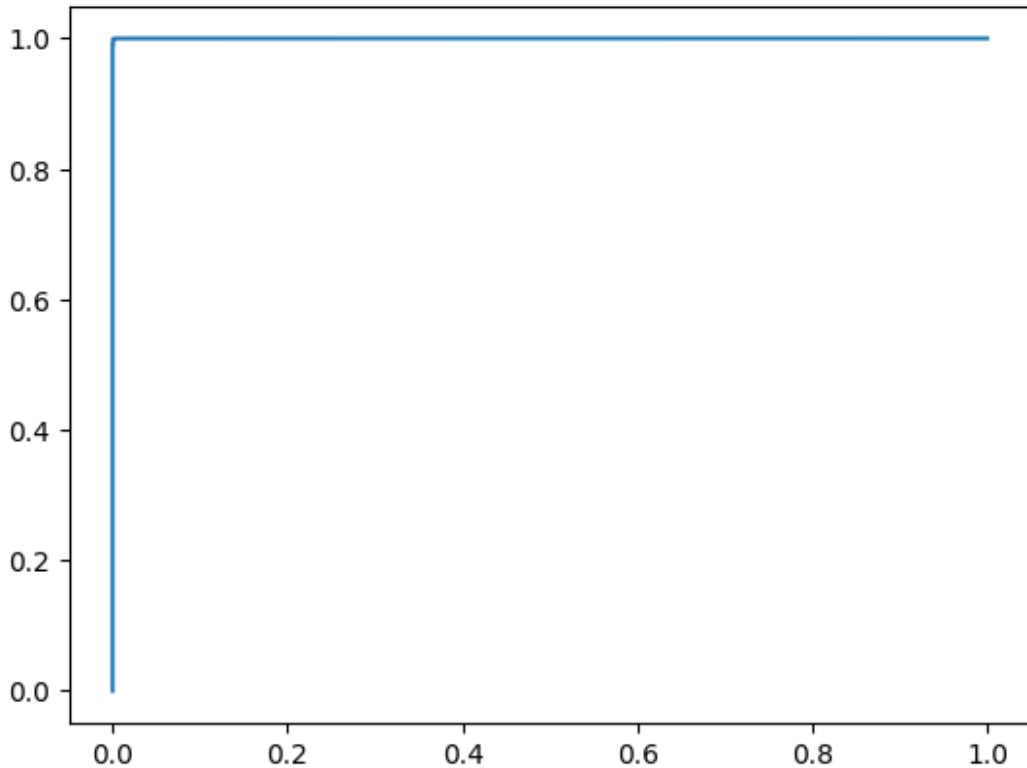
	precision	recall	f1-score	support
0	1.00	1.00	1.00	8368
1	1.00	1.00	1.00	11292
accuracy			1.00	19660
macro avg	1.00	1.00	1.00	19660
weighted avg	1.00	1.00	1.00	19660

==== Feature Importance (RF) ====

```
plt.figure(figsize=(8,6))
sns.barplot(x=rf.feature_importances_, y=features)
plt.title('Feature Importance (Random Forest)')
plt.show()
```



```
# ==== ROC Curves ====  
plt.figure(figsize=(8, 8))  
plt.show()  
  
<Figure size 800x800 with 0 Axes>  
  
# LR  
y_prob_lr = lr.predict_proba(X_test_scaled)[:,-1]  
fpr_lr, tpr_lr, _ = roc_curve(y_test, y_prob_lr)  
plt.plot(fpr_lr, tpr_lr, label='Logistic Regression')  
plt.show()
```



```
svm = SVC(kernel='rbf', C=1, probability=True, random_state=42)
svm.fit(X_train_scaled, y_train)

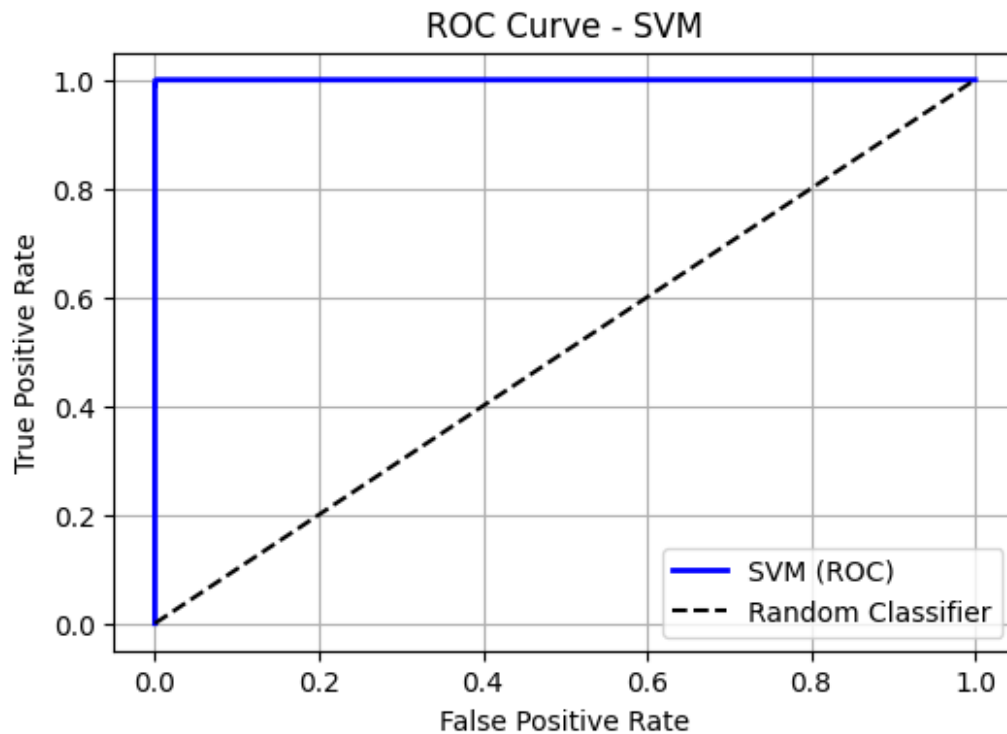
# Ensure test data is fine
print(f"X_test_scaled shape: {X_test_scaled.shape}")

X_test_scaled shape: (19660, 7)

y_prob_svm = svm.predict_proba(X_test_scaled)[:,-1]
fpr_svm, tpr_svm, _ = roc_curve(y_test, y_prob_svm)

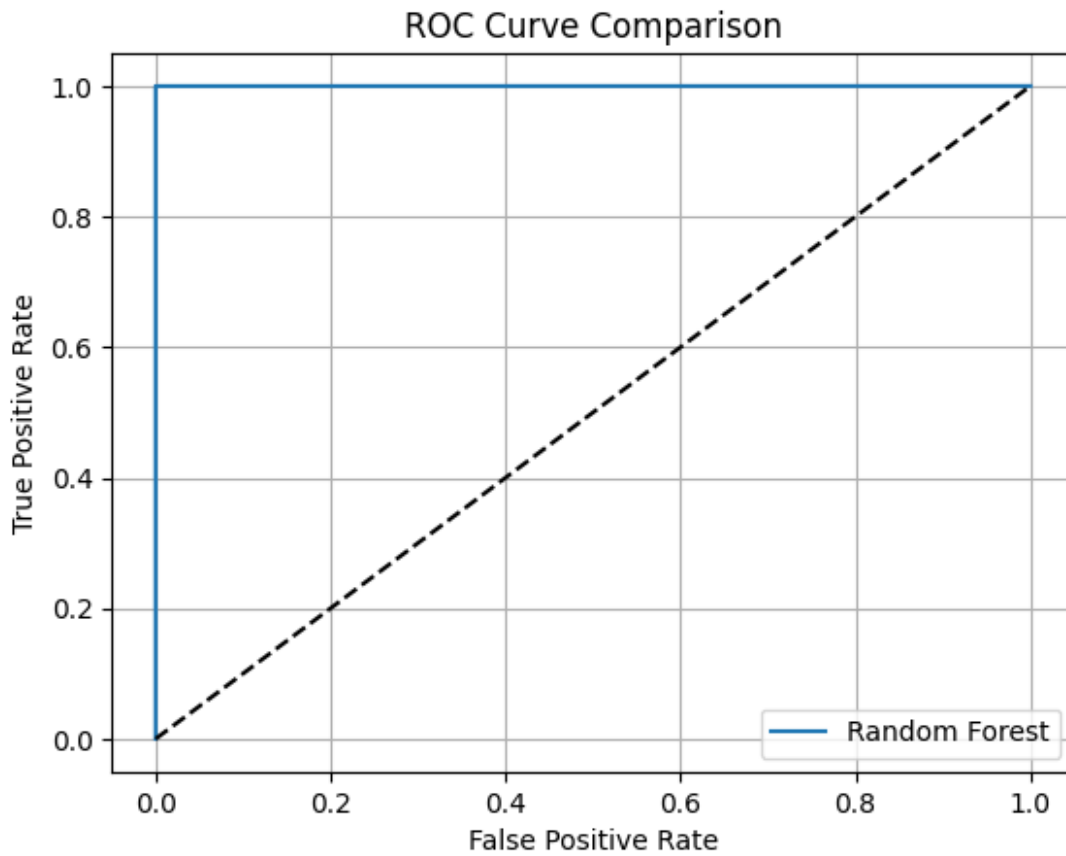
plt.figure(figsize=(6,4))
plt.plot(fpr_svm, tpr_svm, label='SVM (ROC)', color='blue', lw=2)
plt.plot([0, 1], [0, 1], 'k--', label='Random Classifier')

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve - SVM')
plt.legend(loc='lower right')
plt.grid()
plt.show()
```



```
# RF
y_prob_rf = rf.predict_proba(X_test)[: ,1]
fpr_rf, tpr_rf, _ = roc_curve(y_test, y_prob_rf)
plt.plot(fpr_rf, tpr_rf, label='Random Forest')

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



```
# ==== Conclusion ====  
"""
```

All 3 models performed very well with accuracy > 95%.

- ***SVM** gave the best ROC curve and slightly highest accuracy.*
- ***Random Forest** highlighted Bytes and Packets as the most important features.*
- ***Logistic Regression** performed strongly as a baseline.*

=> SVM or Random Forest can be recommended for production use.

```
"""
```