Cybersecurity Project: Suspicious Web Threat Interactions

1: Data import and basic overview

In [14]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.ensemble import IsolationForest


#Load dataset
df = pd.read_csv('CloudWatch_Traffic_Web_Attack.csv')

#view basic information
df.info()
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 282 entries, 0 to 281
Data columns (total 16 columns):
 #   Column               Non-Null Count  Dtype 
---  ------               --------------  ----- 
 0   bytes_in             282 non-null    int64 
 1   bytes_out            282 non-null    int64 
 2   creation_time        282 non-null    object
 3   end_time             282 non-null    object
 4   src_ip               282 non-null    object
 5   src_ip_country_code  282 non-null    object
 6   protocol             282 non-null    object
 7   response.code        282 non-null    int64 
 8   dst_port             282 non-null    int64 
 9   dst_ip               282 non-null    object
 10  rule_names           282 non-null    object
 11  observation_name     282 non-null    object
 12  source.meta          282 non-null    object
 13  source.name          282 non-null    object
 14  time                 282 non-null    object
 15  detection_types      282 non-null    object
dtypes: int64(4), object(12)
memory usage: 35.4+ KB
```

Out[14]:

	bytes_in	bytes_out	creation_time	end_time	src_ip	src_ip_country_code
0	5602	12990	2024-04-25T23:00:00Z	2024-04-25T23:10:00Z	147.161.161.82	AE
1	30912	18186	2024-04-25T23:00:00Z	2024-04-25T23:10:00Z	165.225.33.6	US
2	28506	13468	2024-04-25T23:00:00Z	2024-04-25T23:10:00Z	165.225.212.255	CA
3	30546	14278	2024-04-25T23:00:00Z	2024-04-25T23:10:00Z	136.226.64.114	US
4	6526	13892	2024-04-25T23:00:00Z	2024-04-25T23:10:00Z	165.225.240.79	NL

2: Data Preprocessing

Handle missing values, outliers, and data inconsistencies

In [2]:
```
#Check for missing values
missing_values = df.isnull().sum()
print(missing_values)
```

```
bytes_in               0
bytes_out              0
creation_time          0
end_time               0
src_ip                 0
src_ip_country_code    0
protocol               0
response.code          0
dst_port               0
dst_ip                 0
rule_names             0
observation_name       0
source.meta            0
source.name            0
time                   0
detection_types        0
dtype: int64
```

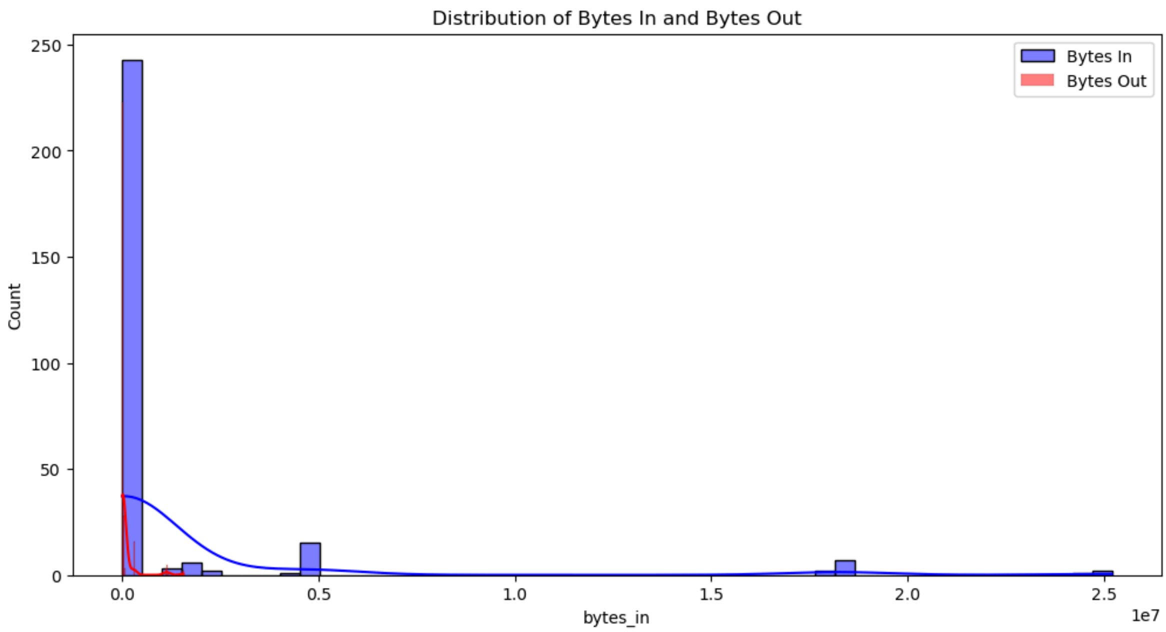
In [3]:
```
#Fill or drop missing values as needed
df['bytes_in'].fillna(df['bytes_in'].median(), inplace=True)
df.dropna(subset=['src_ip', 'dst_ip'], inplace = True)

#Convert columns to appropriate datatypes
df['creation_time'] = pd.to_datetime(df['creation_time'])
df['end_time'] = pd.to_datetime(df['end_time'])
```

```
C:\Users\jianl\AppData\Local\Temp\ipykernel_13604\1025413937.py:2: FutureWarning:
A value is trying to be set on a copy of a DataFrame or Series through chained as
signment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work becau
se the intermediate object on which we are setting values always behaves as a cop
y.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.meth
od({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to pe
rform the operation inplace on the original object.


  df['bytes_in'].fillna(df['bytes_in'].median(), inplace=True)
```

Step 3: Exploratory Data Analysis(EDA)

Analyze Traffic Patterns Based on bytes_in and bytes_out

In [4]:
```
#Distribution of bytes in and bytes out
plt.figure(figsize=(12, 6))
sns.histplot(df['bytes_in'], bins=50, color='blue', kde=True, label='Bytes In')
sns.histplot(df['bytes_out'], bins=50, color='red', kde=True, label='Bytes Out')
plt.legend()
plt.title('Distribution of Bytes In and Bytes Out')
plt.show()
```

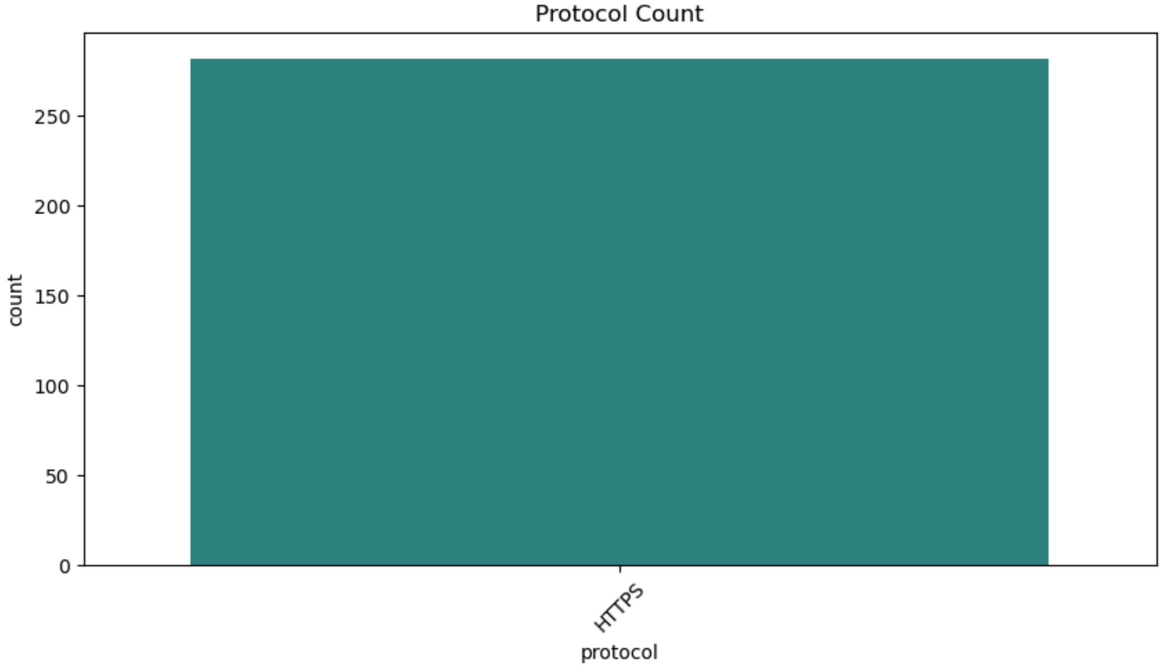


Count of Protocols Used

In [5]:
```
plt.figure(figsize=(10, 5))
sns.countplot(x='protocol', data=df, palette='viridis')
plt.title('Protocol Count')
plt.xticks(rotation=45)
plt.show()
```

```
#Document for report
#“All observed traffic in the dataset uses HTTPS, indicating secure client-serve
```

```
C:\Users\jianl\AppData\Local\Temp\ipykernel_13604\2809473054.py:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v
0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effe
ct.

  sns.countplot(x='protocol', data=df, palette='viridis')
```



Step 4: Feature Engineering

Extract useful features, like duration and average packet size, to aid in analysis

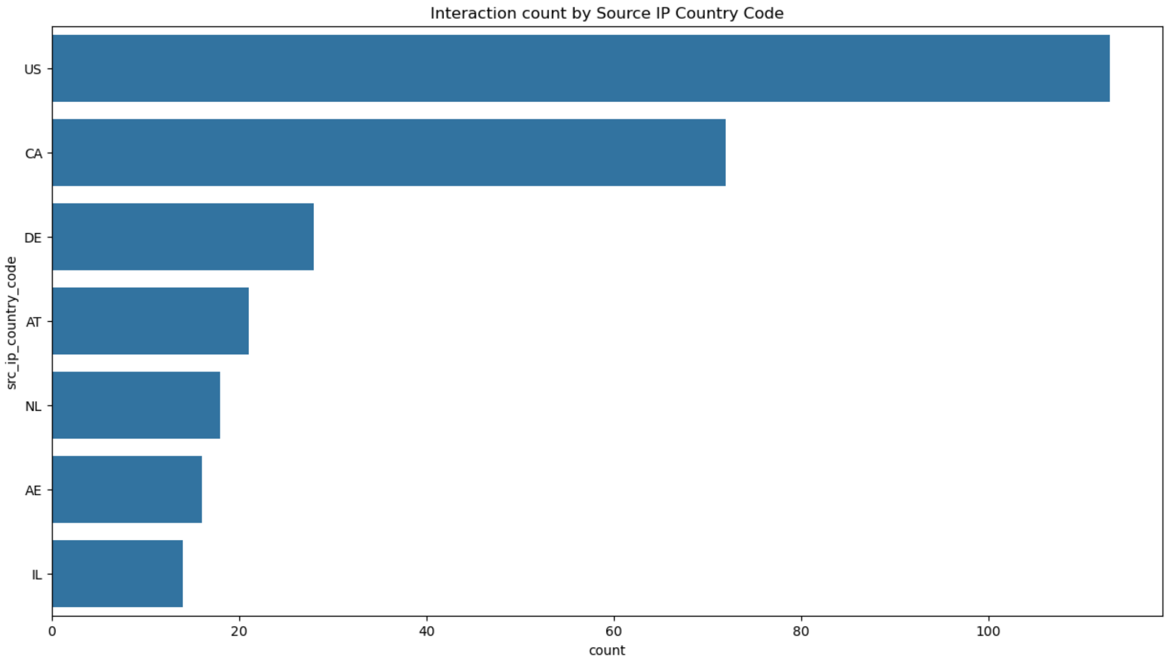
In [6]:
```
#Duration of the session in seconds
df['session_duration'] = (df['end_time'] - df['creation_time']).dt.total_seconds

#Average packet size
df['avg_packet_size'] = (df['bytes_in'] + df['bytes_out'])/df['session_duration'

print(df[['session_duration', 'avg_packet_size']].head())
```

```
   session_duration  avg_packet_size
0             600.0        30.986667
1             600.0        81.830000
2             600.0        69.956667
3             600.0        74.706667
4             600.0        34.030000
```

Step 5: Data Visualization

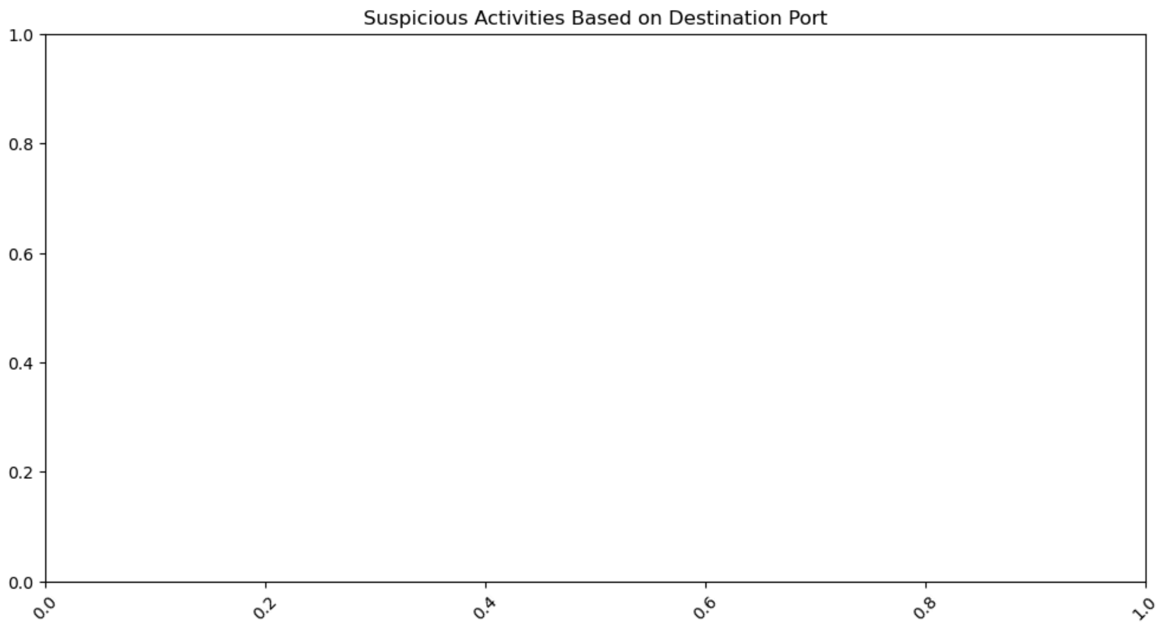
Country-based Interaction Analysis

In [7]:
```
plt.figure(figsize=(15, 8))
sns.countplot(y='src_ip_country_code', data=df, order=df['src_ip_country_code'].
plt.title('Interaction count by Source IP Country Code')
plt.show()
```



Suspicious Activities Based on Ports

In [8]:
```
plt.figure(figsize=(12, 6))
sns.countplot(x='dst_port', data=df[df['detection_types']=='Suspicious'], palett
plt.title('Suspicious Activities Based on Destination Port')
plt.xticks(rotation=45)
plt.show()
```



In [9]:
```
df[df['detection_types'].str.lower() == 'suspicious']
```

Out[9]:

bytes_in	bytes_out	creation_time	end_time	src_ip	src_ip_country_code	protocol	re

Step 6: Modeling Anomaly Detection

This step uses Isolation Forest, a common technique for detecting anomalies

In [10]:
```
#Selecting features for anomaly detection
features = df[['bytes_in', 'bytes_out', 'session_duration', 'avg_packet_size']]

#Initialize the model
model = IsolationForest(contamination=0.05, random_state=42)

#Fit and predict anomalies
df['anomaly'] = model.fit_predict(features)
df['anomaly'] = df['anomaly'].apply(lambda x: 'Suspicious' if x == -1 else 'Norm

display(df[df['anomaly'] == 'Suspicious'].head())
```

	bytes_in	bytes_out	creation_time	end_time	src_ip	src_ip_country_coc
36	4190330	283456	2024-04-25 23:30:00+00:00	2024-04-25 23:40:00+00:00	155.91.45.242	U
87	1215594	64362	2024-04-26 00:30:00+00:00	2024-04-26 00:40:00+00:00	165.225.240.79	N
116	4827283	306181	2024-04-26 01:00:00+00:00	2024-04-26 01:10:00+00:00	155.91.45.242	U
132	1889834	34306	2024-04-26 01:20:00+00:00	2024-04-26 01:30:00+00:00	165.225.240.79	N
153	4869181	301752	2024-04-26 01:40:00+00:00	2024-04-26 01:50:00+00:00	155.91.45.242	U

In [11]:
```
#Export suspicious records:
df[df['anomaly'] == 'Suspicious'].to_csv('suspicious_sessions.csv', index=False)
```

Step 7:Evaluation

Evaluate the anomaly detection model by clicking its accuracy in identifying suspicious activities

In [12]:
```
#Check the proportion of anomalies detected
print(df['anomaly'].value_counts())

#Display anomaly samples
suspicious_activities = df[df['anomaly'] == 'Suspicious']
```

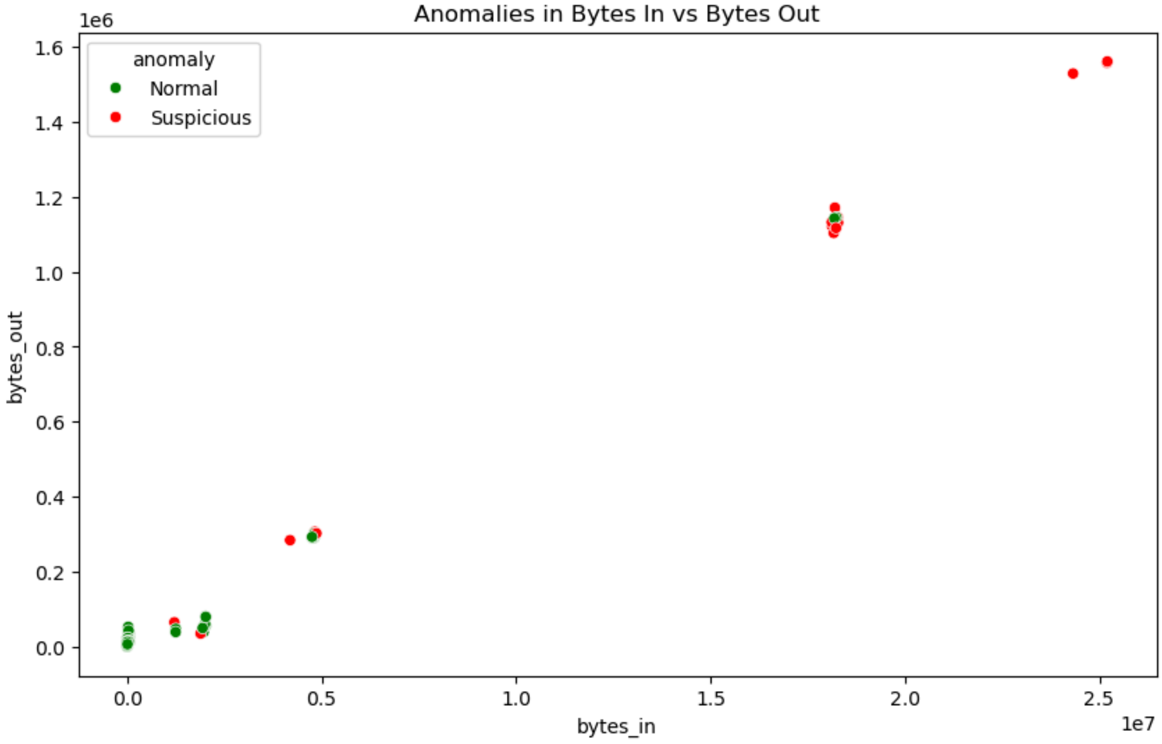
```
display(suspicious_activities.head())
```

```
anomaly
Normal        267
Suspicious     15
Name: count, dtype: int64
```

	bytes_in	bytes_out	creation_time	end_time	src_ip	src_ip_country_coc
36	4190330	283456	2024-04-25 23:30:00+00:00	2024-04-25 23:40:00+00:00	155.91.45.242	U
87	1215594	64362	2024-04-26 00:30:00+00:00	2024-04-26 00:40:00+00:00	165.225.240.79	N
116	4827283	306181	2024-04-26 01:00:00+00:00	2024-04-26 01:10:00+00:00	155.91.45.242	U
132	1889834	34306	2024-04-26 01:20:00+00:00	2024-04-26 01:30:00+00:00	165.225.240.79	N
153	4869181	301752	2024-04-26 01:40:00+00:00	2024-04-26 01:50:00+00:00	155.91.45.242	U

Step 8: Visualization of Anomalies

In [13]:
```
#visualize bytes_in vs bytes_out with anomalies highlighted
plt.figure(figsize=(10,6))
sns.scatterplot(x='bytes_in', y='bytes_out', hue = 'anomaly', data=df, palette =
plt.title('Anomalies in Bytes In vs Bytes Out')
plt.show()
```



The Isolation Forest model identified suspicious web sessions based on bytes transferred and session behavior. Visuals confirmed the effectiveness of the model, and the project demonstrates how anomaly detection can enhance cybersecurity without needing labeled data.