In [ ]:

```
!pip install --upgrade pip
#create a virtual environment
#!pip install virtualenv

#Create a virtual environment:
#Open Command Prompt
#Navigate to your project directory
#Run the following commands:
#
#!python3 -m venv myenv
#!source myenv/bin/activate
#!pip install seaborn
!pip install matplotlib
!pip install scikit-learn
#https://www.freecodecamp.org/news/python-requirementstxt-explained/
#!pip install -r requirements.txt

import pandas as pd
import sys
```

In [1]:

```
import pandas as pd
# Specify the file path
file_path = 'cleaned_benign_malicious_suspicious_service_installs_30days.csv'

# Read the CSV file into a pandas DataFrame
shuffled_df = pd.read_csv(file_path, low_memory=False)

# Display the DataFrame
display(shuffled_df)
```

	Timestamp	Event ID	ID	Account_Name	Service File Name	Service Name	Service Type	Service Start Type	Label
0	2024-08-04T17:58:19Z	7045.0	fc7deb2c-9f43-49de-aff0-e1d1080e871f	LocalSystem	C:\WINDOWS\sysmon.exe	sysmon	auto start	user mode service	benign
1	2024-08-04T17:58:26Z	7045.0	a91101ef-fe9a-4d65-b1d2-6479cee86eaf	LocalSystem	C:\WINDOWS\SysmonDrv.sys	SysmonDrv	boot start	kernel mode driver	benign
2	2024-08-04T18:00:18Z	7045.0	6bb5ea31-a7ba-4a3f-8ee6-694e57040b36	LocalSystem	C:\Windows\sysmon.exe	sysmon	auto start	user mode service	benign
3	2024-08-04T18:01:35Z	7045.0	1d62042f-5def-4338-8b51-eda4d6e0c2b9	LocalSystem	C:\Program Files (x86)\Microsoft Intune Manage...	Microsoft Intune Management Extension	auto start	user mode service	benign
4	2024-08-04T18:03:03Z	7045.0	6cdd1f43-8592-41bf-b3be-d9257c90ff9e	LocalSystem	C:\WINDOWS\sysmon.exe	sysmon	auto start	user mode service	benign
...	...	...	...	...	...	...	...	...	...
689339	2024-09-03T18:18:22Z	7045.0	e2897037-6042-4336-be2a-06464aa123f3	LocalSystem	C:\WINDOWS\sysmon.exe	sysmon	auto start	user mode service	benign
689340	2024-09-03T18:18:28Z	7045.0	837d494f-86b9-4a68-863b-33268450febb	LocalSystem	C:\WINDOWS\SysmonDrv.sys	SysmonDrv	boot start	kernel mode driver	benign
689341	2024-09-03T18:19:26Z	7045.0	f9a4d604-9a1b-4db5-ac35-ad33071df9d0	LocalSystem	C:\Windows\sysmon.exe	sysmon	auto start	user mode service	benign
689342	2024-09-03T18:19:28Z	7045.0	6639547f-83ec-4a85-9896-8bd5d84e41d1	LocalSystem	C:\Windows\sysmon.exe	sysmon	auto start	user mode service	benign
689343	2024-09-03T18:20:57Z	7045.0	6afa2345-f887-4447-a17f-a638f38d4665	LocalSystem	C:\Program Files (x86)\WK\ProSystem fx Suite\S...	CCH Axcess DCS Service	auto start	user mode service	benign

689344 rows × 9 columns

In [19]:

```
print(shuffled_df.columns)
```

```
Index(['Timestamp', 'Event ID', 'ID', 'Account_Name', 'Service File Name',
       'Service Name', 'Service Type', 'Service Start Type', 'Label'],
      dtype='object')
```

In [11]:

```
unique_values = shuffled_df['Label'].unique()
print(unique_values)
```

```
['benign' ' malicious' nan]
```

In [12]:

```
label_frequency =shuffled_df['Label'].isna().sum()
print(label_frequency)
```

```
2
```

In [2]:

```
#Remove any NaN values in the 'Label' column
#shuffled_df['Label'] = shuffled_df['Label'].dropna()
shuffled_df = shuffled_df.dropna()
unique_values2 = shuffled_df['Label'].unique()
print(unique_values2)
print( shuffled_df.shape)
```

```
['benign' ' malicious']
(689288, 9)
```

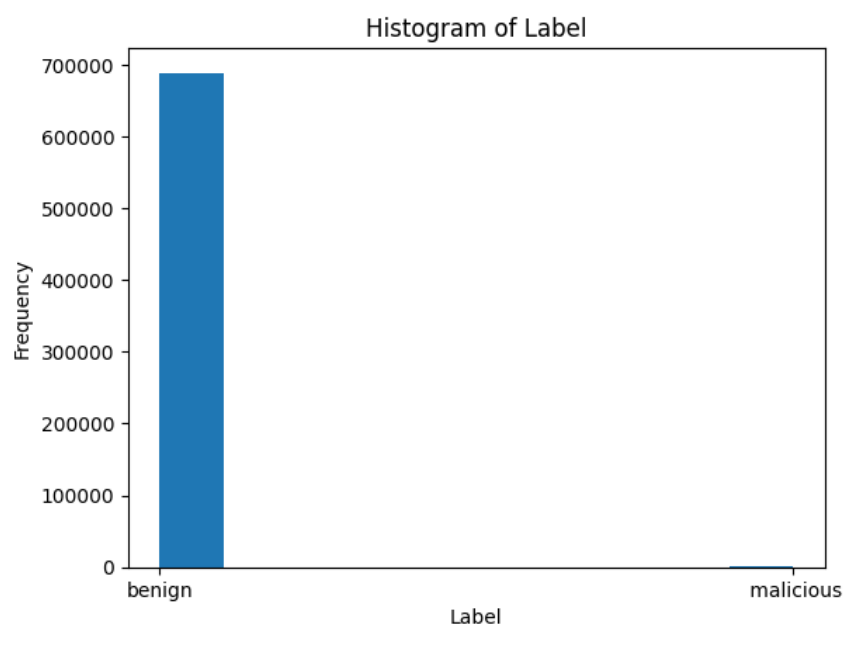
In [ ]:

```
#check number of row
print( shuffled_df.shape)
```

In [18]:

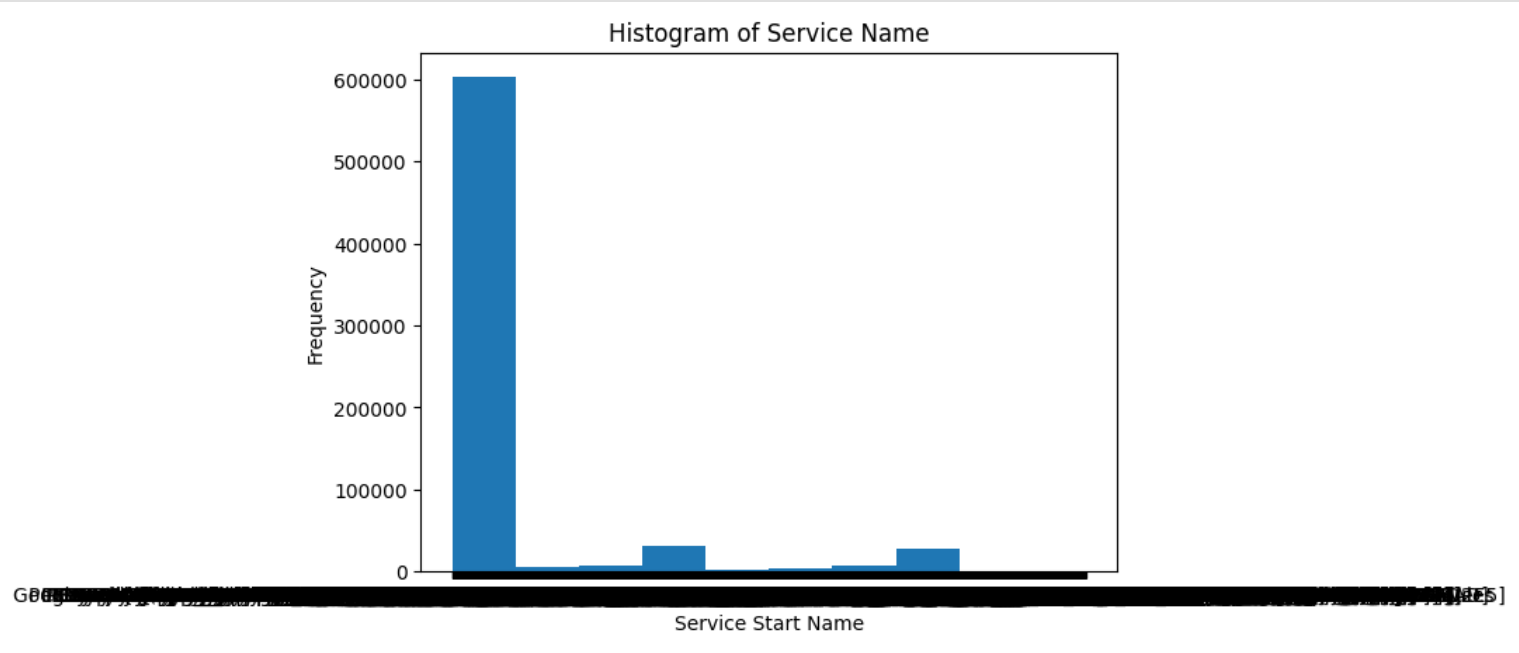
```
import matplotlib.pyplot as plt
# Check class distribution
class_distribution = shuffled_df['Label'].value_counts()
benign_count = class_distribution['benign']  # Adjust with your actual label for the benign class
malicious_count = class_distribution[' malicious']  # Adjust with your actual label for the malicious class

print(f"Benign count: {benign_count}")
print(f"Malicious count: {malicious_count}")

# Plot the histogram
plt.hist(shuffled_df['Label'].astype(str))  # Convert labels to strings if needed

# Add labels and title
plt.xlabel('Label')
plt.ylabel('Frequency')
plt.title('Histogram of Label')

# Show the plot
plt.show()
```

```
Benign count: 688688
Malicious count: 600
```



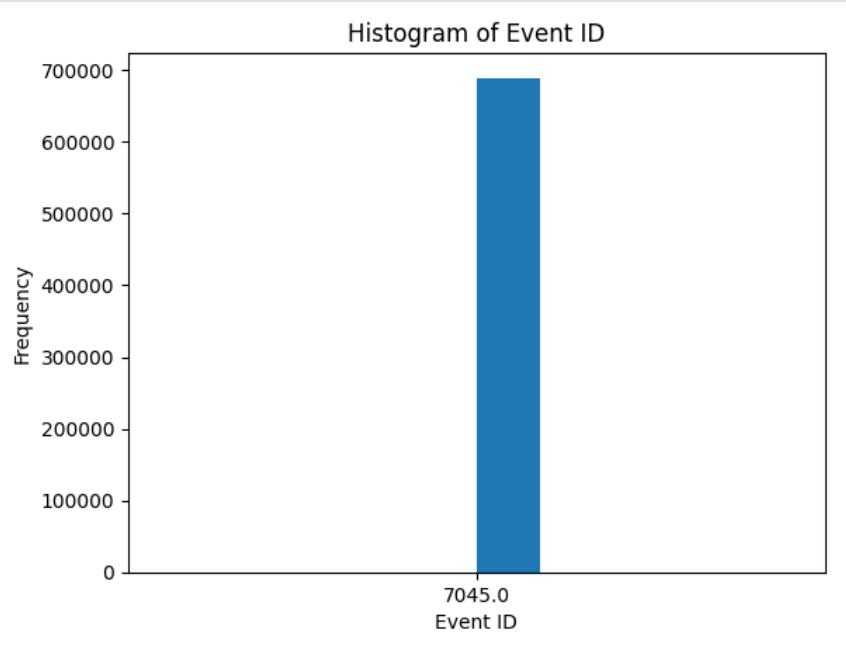
In [21]:

```
# Plot the histogram
plt.hist(shuffled_df['Service Name'].astype(str))  # Convert labels to strings if needed

# Add labels and title
plt.xlabel('Service Start Name')
plt.ylabel('Frequency')
plt.title('Histogram of Service Name')

# Show the plot
plt.show()
```



In [25]:

```
# Plot the histogram
plt.hist(shuffled_df['Event ID'].astype(str))  # Convert labels to strings if needed

# Add labels and title
plt.xlabel('Event ID')
plt.ylabel('Frequency')
plt.title('Histogram of Event ID')

# Show the plot
plt.show()
```



In [34]:

```
# List of columns to run frequency analysis
columns_to_analyze = ['Timestamp', 'Event ID', 'ID', 'Account Name', 'Service File Name',
       'Service Name', 'Service Type', 'Service Start Type', 'Label']

# Dictionary to store frequency counts
frequency_counts = {}

# Calculate frequency for each column
for column in columns_to_analyze:
    frequency_counts[column] = shuffled_df[column].value_counts().head(3)

# Display the frequency counts
for column, counts in frequency_counts.items():
    print(f"\nTop 3 frequencies for column '{column}':")
    print(counts)
```

```
Top 3 frequencies for column 'Timestamp':
Timestamp
2024-08-07T19:43:13Z    33
2024-08-07T16:36:15Z    31
2024-08-30T23:43:00Z    30
Name: count, dtype: int64

Top 3 frequencies for column 'Event ID':
Event ID
7045.0    689288
Name: count, dtype: int64

Top 3 frequencies for column 'ID':
ID
1a1f754a-ac85-4e7d-86b4-1013abea571e    13
cdc70203-499e-469d-87a7-35be4dca7826    10
c18efd8a-8a2c-47af-940d-7c6b09cb8a86     7
Name: count, dtype: int64

Top 3 frequencies for column 'Account Name':
Account Name
LocalSystem                  686799
NT AUTHORITY\LocalService      1033
.\localsystem                   436
Name: count, dtype: int64

Top 3 frequencies for column 'Service File Name':
Service File Name
C:\WINDOWS\sysmon.exe       150301
C:\WINDOWS\SysmonDrv.sys    145246
C:\Windows\sysmon.exe       123120
Name: count, dtype: int64

Top 3 frequencies for column 'Service Name':
Service Name
sysmon                                                                                327494
SysmonDrv                                                                             196445
GoogleUpdater InternalService 129.0.6651.0 (GoogleUpdaterInternalService129.0.6651.0)     15281
Name: count, dtype: int64

Top 3 frequencies for column 'Service Type':
Service Type
auto start      431391
boot start      198252
demand start     47499
Name: count, dtype: int64

Top 3 frequencies for column 'Service Start Type':
Service Start Type
user mode service                459237
kernel mode driver               223843
slu?ba v u?ivatelsk?m re?imu      1622
Name: count, dtype: int64

Top 3 frequencies for column 'Label':
Label
benign        688688
 malicious       600
Name: count, dtype: int64
```

We don't upsample malicious activities

In [ ]:

```
!pip install imblearn
from imblearn.over_sampling import RandomOverSampler

# Example DataFrame with labels 'malicious' and 'benign'
# Make sure you replace it with your actual data
# Assuming 'Label' column has 'malicious' and 'benign' values
X = shuffled_df.drop(columns='Label')  # Features
y = shuffled_df['Label']  # Target labels ('malicious' and 'benign')

# Set the sampling strategy for 20% malicious and 80% benign
sampling_strategy = {' malicious': int(0.25 * y.value_counts()['benign']), 'benign': y.value_counts()['benign']}

# Initialize RandomOverSampler with the custom strategy
ros = RandomOverSampler(sampling_strategy=sampling_strategy, random_state=42)

# Resample the dataset
X_resampled, y_resampled = ros.fit_resample(X, y)

# Combine the resampled features and labels into a new DataFrame
shuffled_df = pd.concat([pd.DataFrame(X_resampled, columns=X.columns), pd.Series(y_resampled, name='Label')], axis=1)

# Check the new class distribution
print(shuffled_df['Label'].value_counts())
```

In [29]:

```
# Get summary statistics of the numerical columns
print(shuffled_df.describe())
# Check for missing values
print(shuffled_df.isna().sum())
```

```
       Event ID
count  689288.0
mean     7045.0
std         0.0
min      7045.0
25%      7045.0
50%      7045.0
75%      7045.0
max      7045.0
Timestamp             0
Event ID              0
ID                    0
Account_Name          0
Service File Name     0
Service Name          0
Service Type          0
Service Start Type    0
Label                 0
dtype: int64
```

In [3]:

```
shuffled_df.columns = shuffled_df.columns.str.replace('_', ' ')
print(shuffled_df.columns)
```

```
Index(['Timestamp', 'Event ID', 'ID', 'Account Name', 'Service File Name',
       'Service Name', 'Service Type', 'Service Start Type', 'Label'],
      dtype='object')
```

Run frequency

Isolation Forest is an unsupervised machine learning algorithm for anomaly detection. This algorithm leverages an ensemble of decision trees, much like a random forest, to make its predictions. By averaging the results from multiple trees, Isolation Forest assigns a robust anomaly score to each data point, ensuring a more reliable detection of outliers.

Source: F. T. Liu, K. M. Ting and Z. -H. Zhou, "Isolation Forest," 2008 Eighth IEEE International Conference on Data Mining, Pisa, Italy, 2008, pp. 413-422, doi: 10.1109/ICDM.2008.17. keywords: {Application software;Credit cards;Detectors;Constraint optimization;Data mining;Information technology;Laboratories;Isolation technology;Performance evaluation;Astronomy;anomaly detection;outlier detection;novelty detection;isolation forest;binary trees;model based}, URL: https://ieeexplore.ieee.org/document/4781136

convert the datetime to a Unix timestamp

It's in an ISO 8601 formatted datetime string, which is a common format used in many systems and databases.

working on below

The final version

In [4]:

```
from sklearn.preprocessing import OneHotEncoder
from sklearn.model_selection import train_test_split
from sklearn.ensemble import IsolationForest
```

Feature extractions

In [5]:

```
# datetime conversion
shuffled_df['Timestamp'] = pd.to_datetime(shuffled_df['Timestamp'], errors='coerce')

# Feature Engineering: Extract date components from the Timestamp
# Extract year, month, day, and hour from the Timestamp
shuffled_df['year'] = shuffled_df['Timestamp'].dt.year
shuffled_df['year'] = shuffled_df['Timestamp'].dt.year
shuffled_df['month'] = shuffled_df['Timestamp'].dt.month
shuffled_df['day'] = shuffled_df['Timestamp'].dt.day
shuffled_df['day_of_week'] = shuffled_df['Timestamp'].dt.day_name()
shuffled_df['hour'] = shuffled_df['Timestamp'].dt.hour

# Drop the 'Timestamp' column
shuffled_df.drop(columns=['Timestamp'], inplace=True)
shuffled_df = shuffled_df.dropna()
```

Modeling

In [6]:

```
# Identify categorical columns to encode (excluding 'ID')
categorical_columns = ['Account Name', 'Service File Name', 'Service Name', 'Service Type', 'Service Start Type', 'hour', 'day_of_week']

# Initialize OneHotEncoder and encode categorical columns
encoder = OneHotEncoder(sparse_output=False, drop='first')
encoded_df = pd.DataFrame(encoder.fit_transform(shuffled_df[categorical_columns]),
                          columns=encoder.get_feature_names_out(categorical_columns))

#  Concatenate the encoded columns back to the original DataFrame
shuffled_df = pd.concat([shuffled_df.reset_index(drop=True), encoded_df.reset_index(drop=True)], axis=1)

# Step 8: Drop the original categorical columns
shuffled_df.drop(columns=categorical_columns, inplace=True)

# Step 9: Ensure the 'ID' column exists
# If you don't have an 'ID' column in your dataset, remove this part
id_column = shuffled_df['ID'] if 'ID' in shuffled_df.columns else pd.Series(range(len(shuffled_df)))

# Step 10: Extract features for the model (excluding 'Label' and 'ID')
features = shuffled_df.drop(columns=['Label', 'ID'] if 'ID' in shuffled_df.columns else ['Label'])
labels = shuffled_df['Label']

# Step 11: Split the data into training and testing sets
X_train, X_test, y_train, y_test, id_train, id_test = train_test_split(features, labels, id_column, test_size=0.3, random_state=42)

# Step 12: Initialize and fit the Isolation Forest model on the training data
model = IsolationForest(n_estimators=100, contamination='auto', random_state=50)
X_train_cleaned = X_train.dropna()
model.fit(X_train)

# Step 13: Predict on the testing set
test_scores = model.decision_function(X_test)
test_predictions = model.predict(X_test)

# Step 14: Combine predictions with the 'ID' column for identification
results_df = pd.DataFrame({
    'ID': id_test,
    'Test Scores': test_scores,
    'Test Predictions': test_predictions
})
```

Model evaluation # 1

In [7]:

```
# Create a DataFrame for the results
shuffled_df_test = shuffled_df.iloc[X_test.index].copy()

# Add the label, scores, and predictions back to the testing set for analysis
shuffled_df_test['Label'] = y_test
shuffled_df_test['Scores'] = test_scores
shuffled_df_test['Anomaly'] = test_predictions

# Display results
if 'ID' in shuffled_df_test.columns:
    print(shuffled_df_test[['ID', 'Label', 'Scores', 'Anomaly']])
else:
    print("Warning: '0: Indicates an anomaly & 1: Indicates that the point is not an anomaly.")
    print(shuffled_df_test[['Label', 'Scores', 'Anomaly']])
```

```
                                          ID   Label    Scores  Anomaly
93268   f69638f5-08a1-4fe5-b31b-a322ab874d8a  benign  0.169191        1
415865  af914061-225b-45c0-b3ed-c6d9f1d2a80b  benign  0.136105        1
503149  ac528e8e-76e6-4590-a41a-77fecc2706ea  benign  0.152184        1
215501  f20109ac-d7d2-43ca-943b-3bb835b7502d  benign  0.164312        1
664145  3355a030-9e9e-49c9-a652-adecbdc7f811  benign  0.139457        1
...                                      ...     ...       ...      ...
411876  de3da1f0-5821-49bd-85e7-7e44fb523c83  benign  0.140691        1
71441   dadfec06-d643-4e52-974d-8f6c62a6cb55  benign  0.152947        1
109644  fcd06ba4-c519-4956-aaca-c287f188ae9d  benign  0.143127        1
284425  321b7055-3cf5-47fb-a0ee-866efa50b1fa  benign  0.171291        1
374242  2fc0b52f-9df6-43dd-9721-13931c50434d  benign  0.154766        1

[206787 rows x 4 columns]
```

Model evaluation # 2

In [8]:

```
# Display frequency for 'Label' and 'Anomaly'
print("Frequency of Expert Opinion or Label ( 'benign' vs 'malicious'):")
print(shuffled_df_test['Label'].value_counts() )
```

```
Frequency of Expert Opinion or Label ( 'benign' vs 'malicious'):
Label
benign        206594
 malicious       193
Name: count, dtype: int64
```

Model evaluation # 3

In [9]:

```
# Relabel the 'Anomaly' column: 1 -> "not an anomaly", 0 -> "an anomaly"
shuffled_df_test['Anomaly'] = shuffled_df_test['Anomaly'].replace({1: "not an anomaly", 0: "an anomaly"})

# Print the frequency to check the new labels
print("Frequency of Model Result ('not an anomaly' vs 'an anomaly'):")
print(shuffled_df_test['Anomaly'].value_counts())
```

```
Frequency of Model Result ('not an anomaly' vs 'an anomaly'):
Anomaly
not an anomaly    206787
Name: count, dtype: int64
```

Accuracy is 100%! What's going on?

1 Adjusting the ratio of benign and malicious or using different datasets

2 Using supervised learning

3 Trying different models

4 Train test split does not matter much

5 Adding another dataset for enrichement