In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
```

In [2]:
```
data = pd.read_csv("RT_IOT2022.csv")
data = pd.DataFrame(data)
data.head()
```

Out[2]:

	no	id.orig_p	id.resp_p	proto	service	flow_duration	fwd_pkts_tot	bwd_pkts_tot	fwd
0	0	38667	1883	tcp	mqtt	32.011598	9	5	
1	1	51143	1883	tcp	mqtt	31.883584	9	5	
2	2	44761	1883	tcp	mqtt	32.124053	9	5	
3	3	60893	1883	tcp	mqtt	31.961063	9	5	
4	4	51087	1883	tcp	mqtt	31.902362	9	5	

5 rows × 85 columns

In [3]:
```
data = data.set_index("no")
```

In [4]:
```
data.head()
```

Out[4]:

	id.orig_p	id.resp_p	proto	service	flow_duration	fwd_pkts_tot	bwd_pkts_tot	fwd_da
no								
0	38667	1883	tcp	mqtt	32.011598	9	5	
1	51143	1883	tcp	mqtt	31.883584	9	5	
2	44761	1883	tcp	mqtt	32.124053	9	5	
3	60893	1883	tcp	mqtt	31.961063	9	5	
4	51087	1883	tcp	mqtt	31.902362	9	5	

5 rows × 84 columns

In [5]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 123117 entries, 0 to 2009
Data columns (total 84 columns):
 #   Column                    Non-Null Count   Dtype  
---  ------                    --------------   -----  
 0   id.orig_p                 123117 non-null  int64  
 1   id.resp_p                 123117 non-null  int64  
 2   proto                     123117 non-null  object 
 3   service                   123117 non-null  object 
 4   flow_duration             123117 non-null  float64
 5   fwd_pkts_tot              123117 non-null  int64  
 6   bwd_pkts_tot              123117 non-null  int64  
 7   fwd_data_pkts_tot         123117 non-null  int64  
 8   bwd_data_pkts_tot         123117 non-null  int64  
 9   fwd_pkts_per_sec          123117 non-null  float64
 10  bwd_pkts_per_sec          123117 non-null  float64
 11  flow_pkts_per_sec         123117 non-null  float64
 12  down_up_ratio             123117 non-null  float64
 13  fwd_header_size_tot       123117 non-null  int64  
 14  fwd_header_size_min       123117 non-null  int64  
 15  fwd_header_size_max       123117 non-null  int64  
 16  bwd_header_size_tot       123117 non-null  int64  
 17  bwd_header_size_min       123117 non-null  int64  
 18  bwd_header_size_max       123117 non-null  int64  
 19  flow_FIN_flag_count       123117 non-null  int64  
 20  flow_SYN_flag_count       123117 non-null  int64  
 21  flow_RST_flag_count       123117 non-null  int64  
 22  fwd_PSH_flag_count        123117 non-null  int64  
 23  bwd_PSH_flag_count        123117 non-null  int64  
 24  flow_ACK_flag_count       123117 non-null  int64  
 25  fwd_URG_flag_count        123117 non-null  int64  
 26  bwd_URG_flag_count        123117 non-null  int64  
 27  flow_CWR_flag_count       123117 non-null  int64  
 28  flow_ECE_flag_count       123117 non-null  int64  
 29  fwd_pkts_payload.min      123117 non-null  float64
 30  fwd_pkts_payload.max      123117 non-null  float64
 31  fwd_pkts_payload.tot      123117 non-null  float64
 32  fwd_pkts_payload.avg      123117 non-null  float64
 33  fwd_pkts_payload.std      123117 non-null  float64
 34  bwd_pkts_payload.min      123117 non-null  float64
 35  bwd_pkts_payload.max      123117 non-null  float64
 36  bwd_pkts_payload.tot      123117 non-null  float64
 37  bwd_pkts_payload.avg      123117 non-null  float64
 38  bwd_pkts_payload.std      123117 non-null  float64
 39  flow_pkts_payload.min     123117 non-null  float64
 40  flow_pkts_payload.max     123117 non-null  float64
 41  flow_pkts_payload.tot     123117 non-null  float64
 42  flow_pkts_payload.avg     123117 non-null  float64
 43  flow_pkts_payload.std     123117 non-null  float64
 44  fwd_iat.min               123117 non-null  float64
 45  fwd_iat.max               123117 non-null  float64
 46  fwd_iat.tot               123117 non-null  float64
 47  fwd_iat.avg               123117 non-null  float64
 48  fwd_iat.std               123117 non-null  float64
 49  bwd_iat.min               123117 non-null  float64
 50  bwd_iat.max               123117 non-null  float64
```

```
 51  bwd_iat.tot               123117 non-null  float64
 52  bwd_iat.avg               123117 non-null  float64
 53  bwd_iat.std               123117 non-null  float64
 54  flow_iat.min              123117 non-null  float64
 55  flow_iat.max              123117 non-null  float64
 56  flow_iat.tot              123117 non-null  float64
 57  flow_iat.avg              123117 non-null  float64
 58  flow_iat.std              123117 non-null  float64
 59  payload_bytes_per_second  123117 non-null  float64
 60  fwd_subflow_pkts          123117 non-null  float64
 61  bwd_subflow_pkts          123117 non-null  float64
 62  fwd_subflow_bytes         123117 non-null  float64
 63  bwd_subflow_bytes         123117 non-null  float64
 64  fwd_bulk_bytes            123117 non-null  float64
 65  bwd_bulk_bytes            123117 non-null  float64
 66  fwd_bulk_packets          123117 non-null  float64
 67  bwd_bulk_packets          123117 non-null  float64
 68  fwd_bulk_rate             123117 non-null  float64
 69  bwd_bulk_rate             123117 non-null  float64
 70  active.min                123117 non-null  float64
 71  active.max                123117 non-null  float64
 72  active.tot                123117 non-null  float64
 73  active.avg                123117 non-null  float64
 74  active.std                123117 non-null  float64
 75  idle.min                  123117 non-null  float64
 76  idle.max                  123117 non-null  float64
 77  idle.tot                  123117 non-null  float64
 78  idle.avg                  123117 non-null  float64
 79  idle.std                  123117 non-null  float64
 80  fwd_init_window_size      123117 non-null  int64
 81  bwd_init_window_size      123117 non-null  int64
 82  fwd_last_window_size      123117 non-null  int64
 83  Attack_type               123117 non-null  object
dtypes: float64(56), int64(25), object(3)
memory usage: 79.8+ MB
```

In [6]:

```
data_rvst = data.iloc[:, [2, 3, 4, 9, 10, 59, 83]]
data_rvst
```

Out[6]:

	proto	service	flow_duration	fwd_pkts_per_sec	bwd_pkts_per_sec	payload_bytes_pe
no						
0	tcp	mqtt	32.011598	0.281148	0.156193	
1	tcp	mqtt	31.883584	0.282277	0.156821	
2	tcp	mqtt	32.124053	0.280164	0.155647	
3	tcp	mqtt	31.961063	0.281593	0.156440	
4	tcp	mqtt	31.902362	0.282111	0.156728	
...	...	...	...	...	...	
2005	tcp	-	0.000006	167772.160000	167772.160000	
2006	tcp	-	0.000007	144631.172414	144631.172414	
2007	tcp	-	0.000006	167772.160000	167772.160000	
2008	tcp	-	0.000006	167772.160000	167772.160000	
2009	tcp	-	0.000006	167772.160000	167772.160000	

123117 rows × 7 columns

1. What is the distribution of the Attack_type classes (normal vs. various attacks), and what percentage of the 123,117 instances does each class comprise?

In [7]:

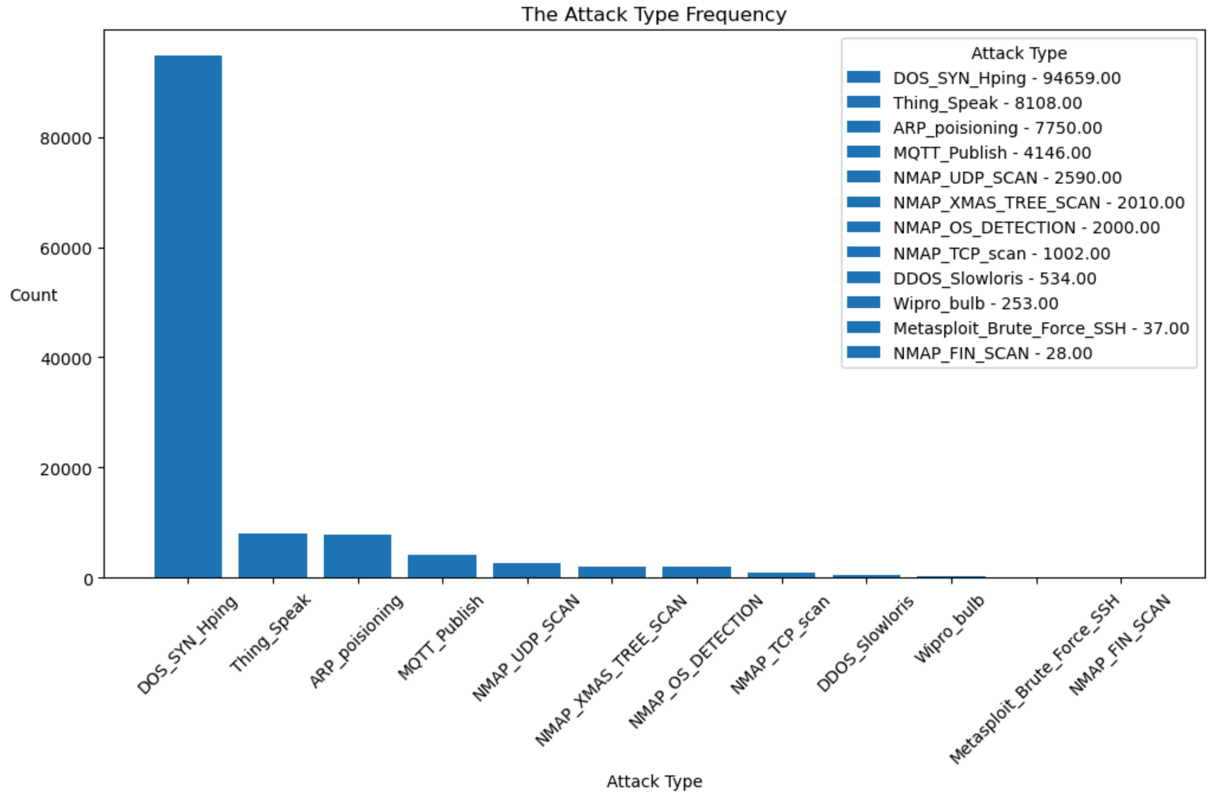
```
data_attack = data["Attack_type"].value_counts()
data_attack = pd.DataFrame(data_attack)
data_attack
```

Out[7]:

	count
Attack_type	
DOS_SYN_Hping	94659
Thing_Speak	8108
ARP_poisioning	7750
MQTT_Publish	4146
NMAP_UDP_SCAN	2590
NMAP_XMAS_TREE_SCAN	2010
NMAP_OS_DETECTION	2000
NMAP_TCP_scan	1002
DDOS_Slowloris	534
Wipro_bulb	253
Metasploit_Brute_Force_SSH	37
NMAP_FIN_SCAN	28

In [8]:

```
plt.figure(figsize = (12, 6))
labels = ["{0} - {1:1.2f}".format(i,j) for i,j in zip(data_attack.index, data_attac
bars = plt.bar(data_attack.index, data_attack["count"].values)

plt.xlabel("Attack Type")
plt.xticks(rotation = 45)
plt.ylabel("Count", rotation = 0)

plt.title("The Attack Type Frequency")
for bar, label in zip(bars, labels):
    bar.set_label(label)
plt.legend(title = "Attack Type", loc = "upper right")
plt.show()
```



In [9]:

```
data_attack["percentage"] = (data_attack["count"]/data_attack["count"].sum()) * 100
data_attack
```

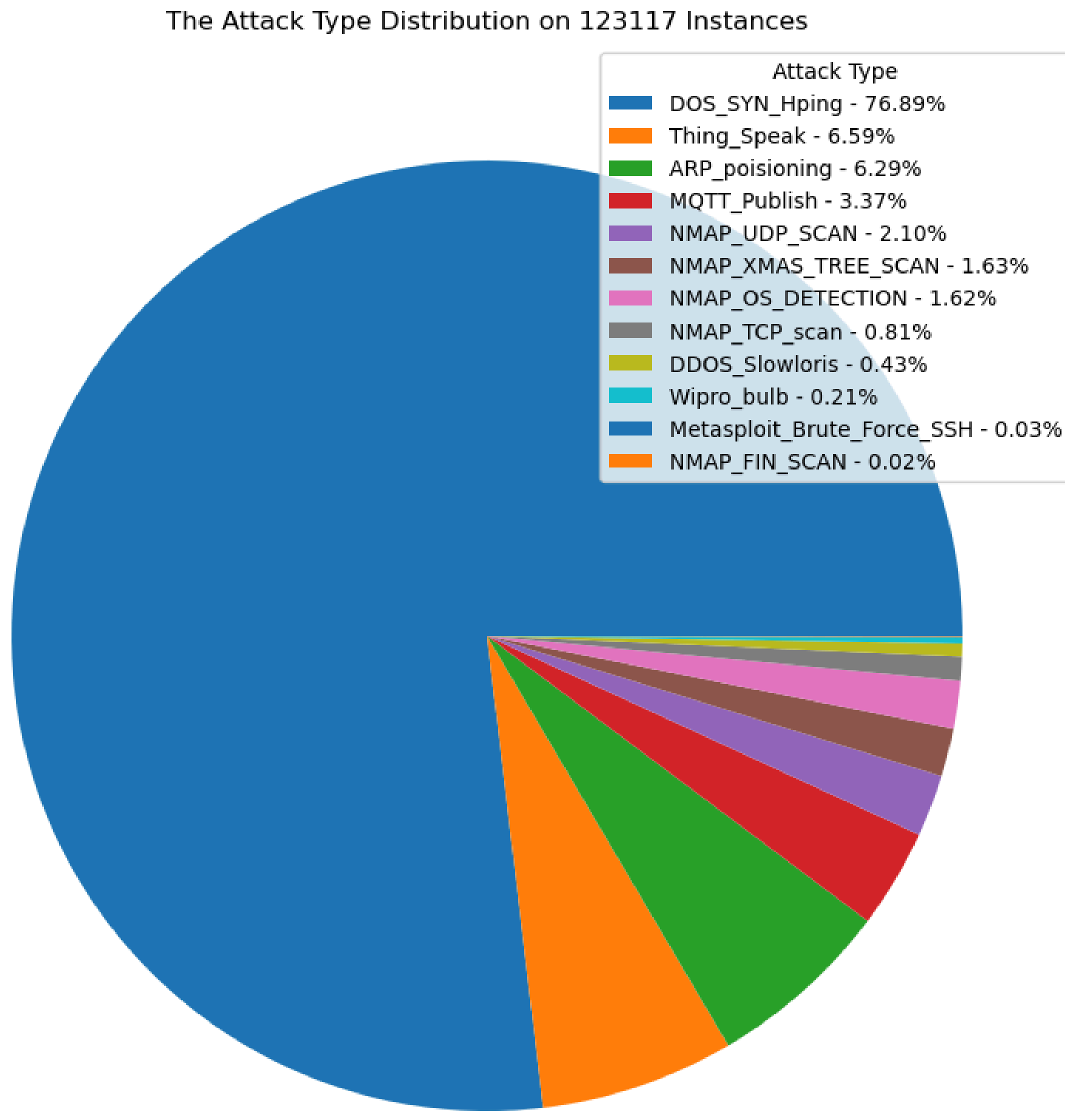
Out[9]:

Attack_type	count	percentage
DOS_SYN_Hping	94659	76.885402
Thing_Speak	8108	6.585606
ARP_poisioning	7750	6.294825
MQTT_Publish	4146	3.367528
NMAP_UDP_SCAN	2590	2.103690
NMAP_XMAS_TREE_SCAN	2010	1.632593
NMAP_OS_DETECTION	2000	1.624471
NMAP_TCP_scan	1002	0.813860
DDOS_Slowloris	534	0.433734
Wipro_bulb	253	0.205496
Metasploit_Brute_Force_SSH	37	0.030053
NMAP_FIN_SCAN	28	0.022743

In [10]:

```
labels = ["{0} - {1:1.2f}%".format(i,j) for i,j in zip(data_attack["percentage"].in
plt.figure(figsize = (10, 10))
```

```python
plt.pie(data_attack["percentage"].values)
plt.title("The Attack Type Distribution on 123117 Instances")
plt.legend(title = "Attack Type", labels = labels, loc = "upper right")
plt.show()
```



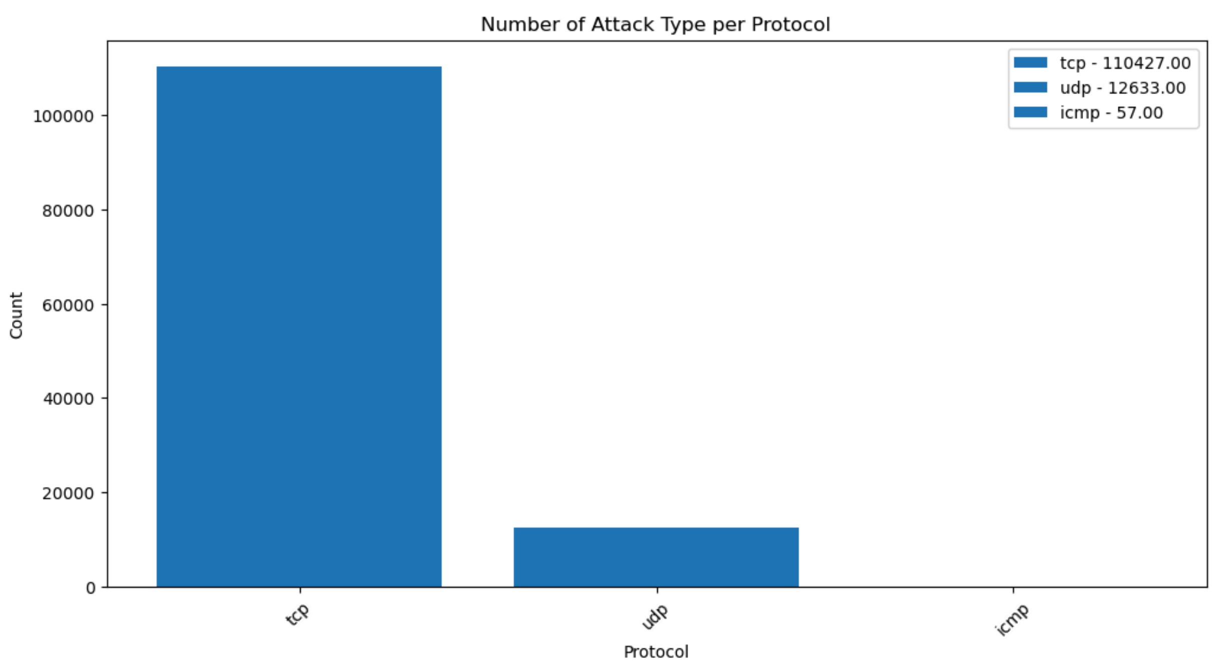
2. How do the categorical features proto (protocol) and service vary across different attack types and normal traffic patterns?

In [11]:
```python
data["service"].replace({
    "-": "None"
}, inplace = True)
```

```
C:\Users\TIPQC\AppData\Local\Temp\ipykernel_36600\1427060069.py:1: FutureWarning: A
value is trying to be set on a copy of a DataFrame or Series through chained assignm
ent using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because
the intermediate object on which we are setting values always behaves as a copy.

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


  data["service"].replace({
```

In [12]:

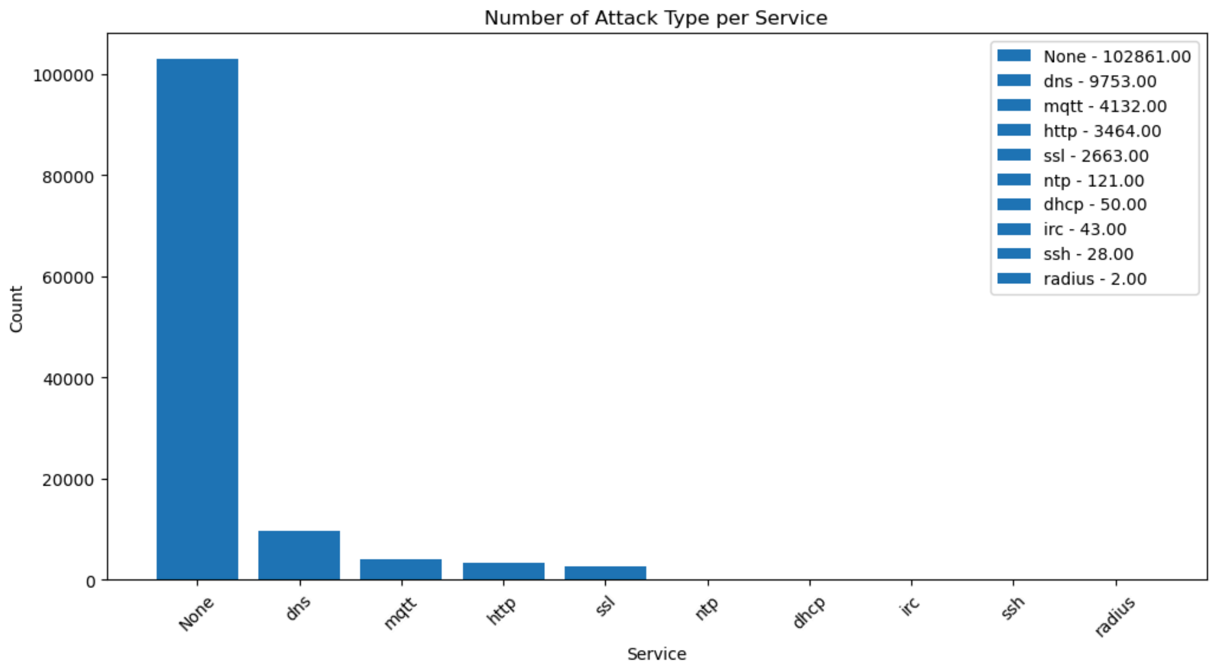
```
data_cat_1 = data.groupby("proto")["Attack_type"].count()
data_cat_1 = pd.DataFrame(data_cat_1)
data_cat_1 = data_cat_1.sort_values(["Attack_type"], ascending = False)

plt.figure(figsize = (12, 6))
labels = ["{0} - {1:1.2f}".format(i,j) for i,j in zip(data_cat_1.index, data_cat_1[
bars = plt.bar(data_cat_1.index, data_cat_1["Attack_type"].values)

plt.xlabel("Protocol")
plt.xticks(rotation = 45)
plt.ylabel("Count", rotation = 90)
plt.title("Number of Attack Type per Protocol")
for bar, label in zip(bars, labels):
    bar.set_label(label)
plt.legend()
plt.show()
```



In [13]:

```
data_cat_2 = data.groupby("service")["Attack_type"].count()
data_cat_2 = pd.DataFrame(data_cat_2)
data_cat_2 = data_cat_2.sort_values(["Attack_type"], ascending = False)

plt.figure(figsize = (12, 6))
```

```
labels = ["{0} - {1:1.2f}".format(i,j) for i,j in zip(data_cat_2.index, data_cat_2[
bars = plt.bar(data_cat_2.index, data_cat_2["Attack_type"].values)

plt.xlabel("Service")
plt.xticks(rotation = 45)
plt.ylabel("Count", rotation = 90)
plt.title("Number of Attack Type per Service")
for bar, label in zip(bars, labels):
    bar.set_label(label)
plt.legend()
plt.show()
```



3. What are the mean and standard deviation of flow_duration for each Attack_type, and are differences statistically significant?

In [14]:
```
data_stat_sig = data.groupby(["Attack_type"])["flow_duration"].mean()
data_stat_sig = pd.DataFrame(data_stat_sig)
```

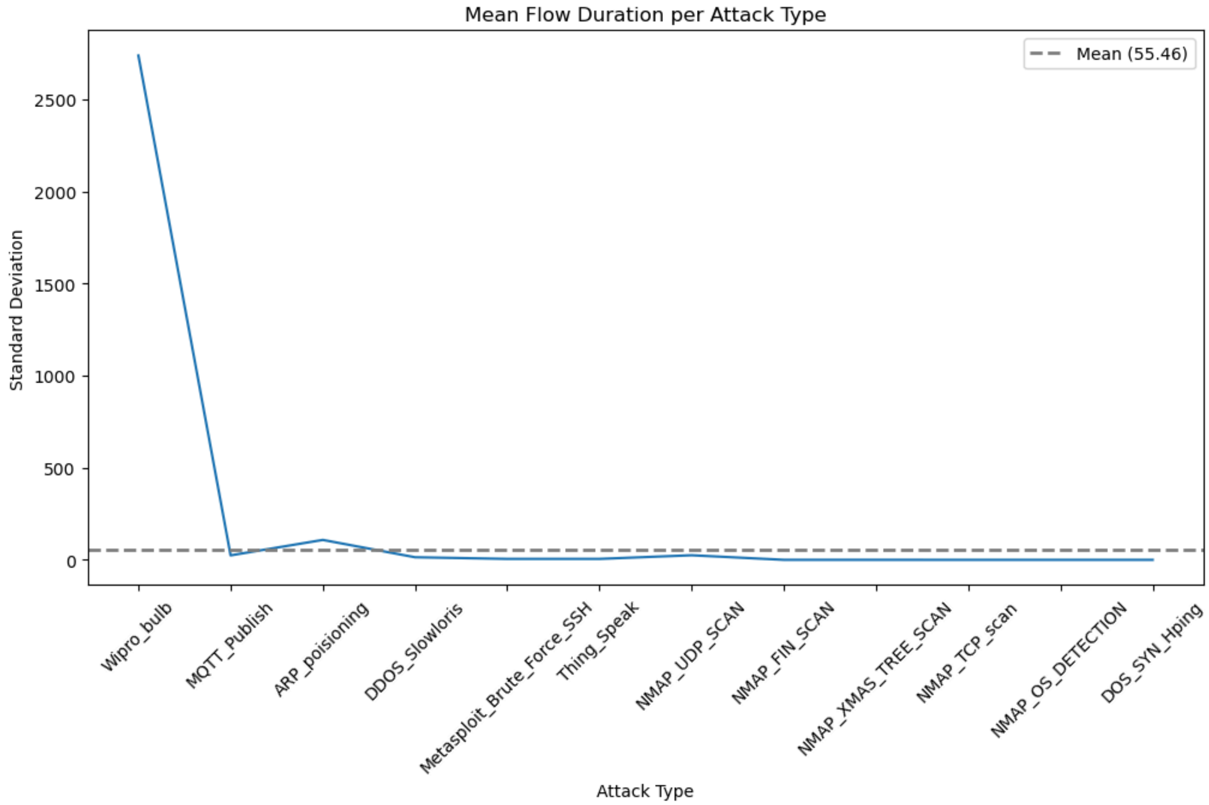
In [15]:
```
data_stat_sig["Standard Deviation"] = data.groupby("Attack_type")["flow_duration"].
data_stat_sig = data_stat_sig.rename(columns = {
    "flow_duration": "Mean"
})
data_stat_sig.index = data_stat_sig.index.set_names(["Attack Type"])
data_stat_sig = data_stat_sig.sort_values(["Mean", "Standard Deviation"], ascending
data_stat_sig
```

Out[15]:

Attack Type	Mean	Standard Deviation
Wipro_bulb	586.845727	2738.891637
MQTT_Publish	43.397013	24.341563
ARP_poisioning	15.893538	108.261070
DDOS_Slowloris	14.699148	14.124797
Metasploit_Brute_Force_SSH	3.006557	5.210286
Thing_Speak	0.934471	5.251602
NMAP_UDP_SCAN	0.737766	24.909755
NMAP_FIN_SCAN	0.023614	0.108791
NMAP_XMAS_TREE_SCAN	0.001171	0.050426
NMAP_TCP_scan	0.000019	0.000269
NMAP_OS_DETECTION	0.000008	0.000007
DOS_SYN_Hping	0.000003	0.000002

In [16]:

```
plt.figure(figsize = (12, 6))
plt.plot(data_stat_sig.index, data_stat_sig["Standard Deviation"].values)
plt.xlabel("Attack Type")
plt.xticks(rotation = 45)
plt.ylabel("Standard Deviation")
plt.axhline(y = data_stat_sig["Mean"].mean(), color = "gray", linestyle = "--", lin
plt.title("Mean Flow Duration per Attack Type")
plt.legend()
plt.show()
```



4. Which continuous features (e.g., fwd_pkts_per_sec, bwd_pkts_per_sec, payload_bytes_per_second) exhibit the highest correlation with specific attack classes?

In [17]:
```
data_rvst.head()
```

Out[17]:

no	proto	service	flow_duration	fwd_pkts_per_sec	bwd_pkts_per_sec	payload_bytes_per_s
0	tcp	mqtt	32.011598	0.281148	0.156193	3.3
1	tcp	mqtt	31.883584	0.282277	0.156821	3.3
2	tcp	mqtt	32.124053	0.280164	0.155647	3.2
3	tcp	mqtt	31.961063	0.281593	0.156440	3.2
4	tcp	mqtt	31.902362	0.282111	0.156728	3.3

In [18]:
```
data_rvst
```

Out[18]:

	proto	service	flow_duration	fwd_pkts_per_sec	bwd_pkts_per_sec	payload_bytes_pe
no						
0	tcp	mqtt	32.011598	0.281148	0.156193	
1	tcp	mqtt	31.883584	0.282277	0.156821	
2	tcp	mqtt	32.124053	0.280164	0.155647	
3	tcp	mqtt	31.961063	0.281593	0.156440	
4	tcp	mqtt	31.902362	0.282111	0.156728	
...	...	...	...	...	...	
2005	tcp	-	0.000006	167772.160000	167772.160000	
2006	tcp	-	0.000007	144631.172414	144631.172414	
2007	tcp	-	0.000006	167772.160000	167772.160000	
2008	tcp	-	0.000006	167772.160000	167772.160000	
2009	tcp	-	0.000006	167772.160000	167772.160000	

123117 rows × 7 columns

In [19]:
```
data_rvst_corr = data_rvst.groupby("Attack_type")[["fwd_pkts_per_sec", "bwd_pkts_pe
round(data_rvst_corr, 4)
```

Out[19]:

Attack_type		fwd_pkts_per_sec	bwd_pkts_per_sec
ARP_poisioning	fwd_pkts_per_sec	1.0000	0.4813
	bwd_pkts_per_sec	0.4813	1.0000
	payload_bytes_per_second	0.4289	0.8931
DDOS_Slowloris	fwd_pkts_per_sec	1.0000	-0.1848
	bwd_pkts_per_sec	-0.1848	1.0000
	payload_bytes_per_second	0.9991	-0.1422
DOS_SYN_Hping	fwd_pkts_per_sec	1.0000	1.0000
	bwd_pkts_per_sec	1.0000	1.0000
	payload_bytes_per_second	1.0000	1.0000
MQTT_Publish	fwd_pkts_per_sec	1.0000	0.9823
	bwd_pkts_per_sec	0.9823	1.0000
	payload_bytes_per_second	0.0370	0.2229
Metasploit_Brute_Force_SSH	fwd_pkts_per_sec	1.0000	1.0000
	bwd_pkts_per_sec	1.0000	1.0000
	payload_bytes_per_second	0.9983	0.9983
NMAP_FIN_SCAN	fwd_pkts_per_sec	1.0000	1.0000
	bwd_pkts_per_sec	1.0000	1.0000
	payload_bytes_per_second	0.9999	0.9999
NMAP_OS_DETECTION	fwd_pkts_per_sec	1.0000	1.0000
	bwd_pkts_per_sec	1.0000	1.0000
	payload_bytes_per_second	NaN	NaN
NMAP_TCP_scan	fwd_pkts_per_sec	1.0000	1.0000
	bwd_pkts_per_sec	1.0000	1.0000
	payload_bytes_per_second	-0.0599	-0.0621
NMAP_UDP_SCAN	fwd_pkts_per_sec	1.0000	-0.0030
	bwd_pkts_per_sec	-0.0030	1.0000
	payload_bytes_per_second	0.9998	0.0182
NMAP_XMAS_TREE_SCAN	fwd_pkts_per_sec	1.0000	1.0000
	bwd_pkts_per_sec	1.0000	1.0000

		fwd_pkts_per_sec	bwd_pkts_per_sec
Attack_type			
	payload_bytes_per_second	-0.0261	-0.0261
Thing_Speak	**fwd_pkts_per_sec**	1.0000	0.7215
	bwd_pkts_per_sec	0.7215	1.0000
	payload_bytes_per_second	0.7758	0.7213
Wipro_bulb	**fwd_pkts_per_sec**	1.0000	-0.0106
	bwd_pkts_per_sec	-0.0106	1.0000
	payload_bytes_per_second	0.8457	0.5202

In [20]:
```
data_rvst_corr = pd.DataFrame(data_rvst_corr)

# Get the highest correlated feature for each attack type
highest_corr_feature = data_rvst_corr.idxmax(axis = 1)
highest_corr_value = data_rvst_corr.max(axis = 1)

# Combine
data_rvst_corr = pd.DataFrame({
    "Most Correlated Feature": highest_corr_feature,
    "Correlation Value": highest_corr_value
})

data_rvst_corr
```

```
C:\Users\TIPQC\AppData\Local\Temp\ipykernel_36600\3970150690.py:4: FutureWarning: Th
e behavior of DataFrame.idxmax with all-NA values, or any-NA and skipna=False, is de
precated. In a future version this will raise ValueError
  highest_corr_feature = data_rvst_corr.idxmax(axis = 1)
```

Out[20]:

Attack_type		Most Correlated Feature	Correlation Value
ARP_poisioning	fwd_pkts_per_sec	fwd_pkts_per_sec	1.0
	bwd_pkts_per_sec	bwd_pkts_per_sec	1.0
	payload_bytes_per_second	payload_bytes_per_second	1.0
DDOS_Slowloris	fwd_pkts_per_sec	fwd_pkts_per_sec	1.0
	bwd_pkts_per_sec	bwd_pkts_per_sec	1.0
	payload_bytes_per_second	payload_bytes_per_second	1.0
DOS_SYN_Hping	fwd_pkts_per_sec	payload_bytes_per_second	1.0
	bwd_pkts_per_sec	payload_bytes_per_second	1.0
	payload_bytes_per_second	fwd_pkts_per_sec	1.0
MQTT_Publish	fwd_pkts_per_sec	fwd_pkts_per_sec	1.0
	bwd_pkts_per_sec	bwd_pkts_per_sec	1.0
	payload_bytes_per_second	payload_bytes_per_second	1.0
Metasploit_Brute_Force_SSH	fwd_pkts_per_sec	fwd_pkts_per_sec	1.0
	bwd_pkts_per_sec	bwd_pkts_per_sec	1.0
	payload_bytes_per_second	payload_bytes_per_second	1.0
NMAP_FIN_SCAN	fwd_pkts_per_sec	fwd_pkts_per_sec	1.0
	bwd_pkts_per_sec	bwd_pkts_per_sec	1.0
	payload_bytes_per_second	payload_bytes_per_second	1.0
NMAP_OS_DETECTION	fwd_pkts_per_sec	fwd_pkts_per_sec	1.0
	bwd_pkts_per_sec	fwd_pkts_per_sec	1.0
	payload_bytes_per_second	NaN	NaN
NMAP_TCP_scan	fwd_pkts_per_sec	fwd_pkts_per_sec	1.0
	bwd_pkts_per_sec	bwd_pkts_per_sec	1.0
	payload_bytes_per_second	payload_bytes_per_second	1.0
NMAP_UDP_SCAN	fwd_pkts_per_sec	fwd_pkts_per_sec	1.0
	bwd_pkts_per_sec	bwd_pkts_per_sec	1.0
	payload_bytes_per_second	payload_bytes_per_second	1.0
NMAP_XMAS_TREE_SCAN	fwd_pkts_per_sec	fwd_pkts_per_sec	1.0
	bwd_pkts_per_sec	bwd_pkts_per_sec	1.0

		Most Correlated Feature	Correlation Value
Attack_type			
	payload_bytes_per_second	payload_bytes_per_second	1.0
Thing_Speak	**fwd_pkts_per_sec**	fwd_pkts_per_sec	1.0
	bwd_pkts_per_sec	bwd_pkts_per_sec	1.0
	payload_bytes_per_second	payload_bytes_per_second	1.0
Wipro_bulb	**fwd_pkts_per_sec**	fwd_pkts_per_sec	1.0
	bwd_pkts_per_sec	bwd_pkts_per_sec	1.0
	payload_bytes_per_second	payload_bytes_per_second	1.0

5. How do time-based features like fwd_iat.avg and bwd_iat.avg (mean inter-arrival times) differ between various attack types and normal traffic?

In [21]:
```
data_iat = data.iloc[:, [47, 52, 83]]
data_iat.head()
```

Out[21]:

	fwd_iat.avg	bwd_iat.avg	Attack_type
no			
0	4.001450e+06	506597.757339	MQTT_Publish
1	3.985448e+06	469065.248966	MQTT_Publish
2	4.015507e+06	503442.466259	MQTT_Publish
3	3.995133e+06	470946.013927	MQTT_Publish
4	3.987795e+06	483996.033669	MQTT_Publish

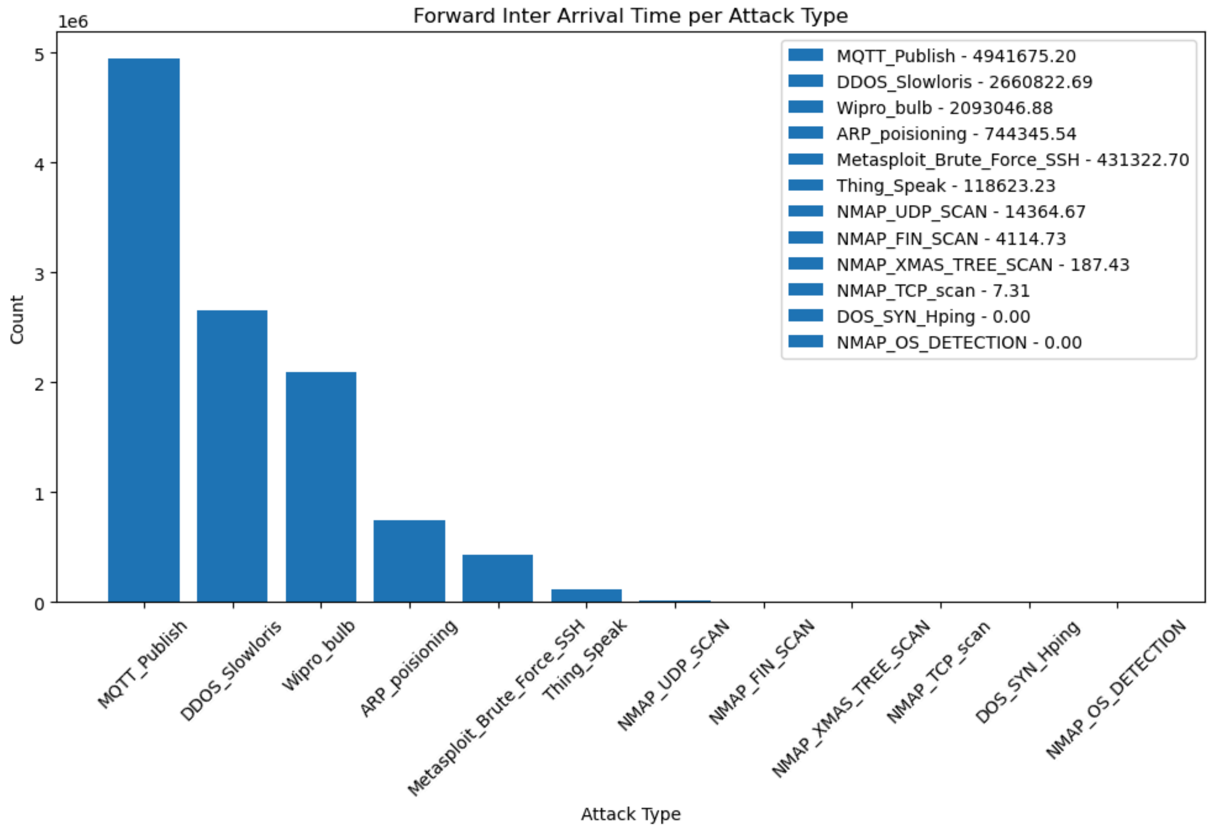
In [22]:
```
data_iat = data_iat.groupby("Attack_type")[["fwd_iat.avg", "bwd_iat.avg"]].mean()
data_iat = data_iat.sort_values(["fwd_iat.avg", "bwd_iat.avg"], ascending = [False,
data_iat.index = data_iat.index.set_names(["Attack Type"])
data_iat = pd.DataFrame(data_iat)
round(data_iat, 2)
```

Out[22]:

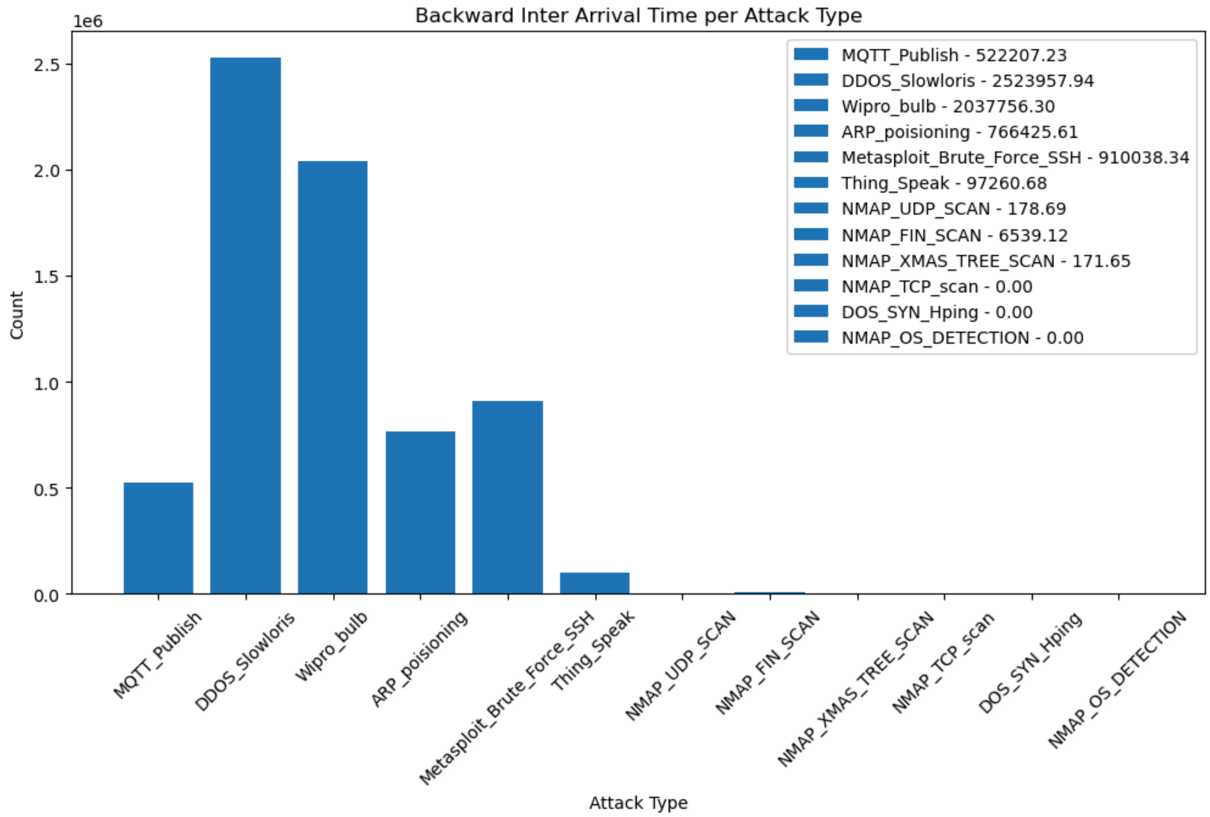
Attack Type	fwd_iat.avg	bwd_iat.avg
MQTT_Publish	4941675.20	522207.23
DDOS_Slowloris	2660822.69	2523957.94
Wipro_bulb	2093046.88	2037756.30
ARP_poisioning	744345.54	766425.61
Metasploit_Brute_Force_SSH	431322.70	910038.34
Thing_Speak	118623.23	97260.68
NMAP_UDP_SCAN	14364.67	178.69
NMAP_FIN_SCAN	4114.73	6539.12
NMAP_XMAS_TREE_SCAN	187.43	171.65
NMAP_TCP_scan	7.31	0.00
DOS_SYN_Hping	0.00	0.00
NMAP_OS_DETECTION	0.00	0.00

In [23]:

```
plt.figure(figsize = (12, 6))
labels = ["{0} - {1:1.2f}".format(i,j) for i,j in zip(data_iat.index, data_iat["fwd
bars = plt.bar(data_iat.index, data_iat["fwd_iat.avg"].values)

plt.xlabel("Attack Type")
plt.xticks(rotation = 45)
plt.ylabel("Count", rotation = 90)
plt.title("Forward Inter Arrival Time per Attack Type")
for bar, label in zip(bars, labels):
    bar.set_label(label)
plt.legend()
plt.show()
```



In [24]:
```
plt.figure(figsize = (12, 6))
labels = ["{0} - {1:1.2f}".format(i,j) for i,j in zip(data_iat.index, data_iat["bwd
bars = plt.bar(data_iat.index, data_iat["bwd_iat.avg"].values)

plt.xlabel("Attack Type")
plt.xticks(rotation = 45)
plt.ylabel("Count", rotation = 90)
plt.title("Backward Inter Arrival Time per Attack Type")
for bar, label in zip(bars, labels):
    bar.set_label(label)
plt.legend()
plt.show()
```



6. Which network flag counts (e.g., flow_SYN_flag_count, flow_RST_flag_count, fwd_PSH_flag_count) are most indicative of specific intrusion patterns?

In [25]:
```
data_ind = data.iloc[:, [20, 21, 22, 83]]
data_ind.head()
```

Out[25]:

no	flow_SYN_flag_count	flow_RST_flag_count	fwd_PSH_flag_count	Attack_type
0	2	1	3	MQTT_Publish
1	2	1	3	MQTT_Publish
2	2	1	3	MQTT_Publish
3	2	1	3	MQTT_Publish
4	2	1	3	MQTT_Publish

In [26]:
```
data_ind = data_ind.groupby("Attack_type")[["flow_SYN_flag_count", "flow_RST_flag_c
data_ind = data_ind.sort_values(["flow_SYN_flag_count", "flow_RST_flag_count", "fwd
data_ind.index = data_ind.index.set_names(["Attack Type"])
```

In [27]:
```
max_col_per_row = data_ind.idxmax(axis = 1)
max_val_per_row = data_ind.max(axis=1)
data_ind_max = pd.DataFrame({
    "Attack Type": data_ind.index,
    "Highest Network Flag": max_col_per_row,
```

```
    "Highest Mean Value": max_val_per_row
})

data_ind_max = data_ind_max.set_index("Attack Type")
data_ind_max = data_ind_max.sort_values(["Highest Mean Value"], ascending = 0)
round(data_ind_max, 2)
```

Out[27]:

	Highest Network Flag	Highest Mean Value
Attack Type		
Wipro_bulb	fwd_PSH_flag_count	10.58
Metasploit_Brute_Force_SSH	fwd_PSH_flag_count	5.03
MQTT_Publish	fwd_PSH_flag_count	2.99
DDOS_Slowloris	fwd_PSH_flag_count	2.95
ARP_poisioning	fwd_PSH_flag_count	1.95
Thing_Speak	fwd_PSH_flag_count	1.11
NMAP_TCP_scan	flow_SYN_flag_count	1.00
DOS_SYN_Hping	flow_SYN_flag_count	1.00
NMAP_OS_DETECTION	flow_RST_flag_count	1.00
NMAP_XMAS_TREE_SCAN	fwd_PSH_flag_count	1.00
NMAP_UDP_SCAN	flow_SYN_flag_count	0.11
NMAP_FIN_SCAN	flow_SYN_flag_count	0.07