Scaler DSML Portfolio Project - Network Anomaly Detection

by **Atharva Nitin Deshpande** (DSML August 2024 Batch)

1. Introduction

1.1 Problem Statement and Objective

In the realm of cybersecurity, network anomaly detection is a critical task that involves identifying unusual patterns or behaviors that deviate from the norm within network traffic. These anomalies could signify a range of security threats, from compromised devices and malware infections to large-scale cyber-attacks like DDoS (Distributed Denial of Service). The challenge lies in accurately detecting these anomalies in real-time, amidst the vast and continuous streams of network data, which are often noisy and heterogeneous.

In this project, the objective is to design an end-to-end machine learning pipeline for intrusion detection, covering the entire lifecycle: exploratory data analysis (EDA), hypothesis formulation and testing, model training, evaluation, and deployment considerations. The system follows a two-stage architecture:

1. Binary classification to detect whether a network connection is normal or malicious.
2. Multiclass classification to identify the specific attack category once an intrusion is detected.

1.2 Importing Required Libraries and Raw Data

In [2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import os
from datetime import datetime
import seaborn as sns
import warnings

from scipy import stats
import statsmodels.api as sm

from sklearn.feature_selection import mutual_info_classif
from sklearn.pipeline import Pipeline
from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline as ImbPipeline
from sklearn.preprocessing import (
    OneHotEncoder,
    StandardScaler,
    FunctionTransformer)
from sklearn.compose import ColumnTransformer

from sklearn.model_selection import (
    train_test_split,
    StratifiedKFold,
    RandomizedSearchCV)

from sklearn.linear_model import LogisticRegression
from sklearn.svm import LinearSVC

from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import (
    RandomForestClassifier,
    AdaBoostClassifier,
    GradientBoostingClassifier,
    StackingClassifier)

from sklearn.metrics import (
    roc_auc_score,
    classification_report,
    confusion_matrix,
    ConfusionMatrixDisplay)

from joblib import dump
```

```python
from IPython.display import Markdown, display

warnings.filterwarnings('ignore')
pd.set_option('display.float_format', '{:.4f}'.format)
```

Let us now import the raw data.

In [3]:
```python
raw_data = pd.read_csv(r'G:\00000 SCALER BUSINESS CASES\PORTFOLIO PROJECTS\Network-Anomaly-Detect
```

In [4]:
```python
raw_data.head().T
```

Out[4]:

	0	1	2	3	4
duration	0	0	0	0	0
protocoltype	tcp	udp	tcp	tcp	tcp
service	ftp_data	other	private	http	http
flag	SF	SF	S0	SF	SF
srcbytes	491	146	0	232	199
dstbytes	0	0	0	8153	420
land	0	0	0	0	0
wrongfragment	0	0	0	0	0
urgent	0	0	0	0	0
hot	0	0	0	0	0
numfailedlogins	0	0	0	0	0
loggedin	0	0	0	1	1
numcompromised	0	0	0	0	0
rootshell	0	0	0	0	0
suattempted	0	0	0	0	0
numroot	0	0	0	0	0
numfilecreations	0	0	0	0	0
numshells	0	0	0	0	0
numaccessfiles	0	0	0	0	0
numoutboundcmds	0	0	0	0	0
ishostlogin	0	0	0	0	0
isguestlogin	0	0	0	0	0
count	2	13	123	5	30
srvcount	2	1	6	5	32
serrorrate	0.0000	0.0000	1.0000	0.2000	0.0000
srvserrorrate	0.0000	0.0000	1.0000	0.2000	0.0000
rerrorrate	0.0000	0.0000	0.0000	0.0000	0.0000
srvrerrorrate	0.0000	0.0000	0.0000	0.0000	0.0000
samesrvrate	1.0000	0.0800	0.0500	1.0000	1.0000
diffsrvrate	0.0000	0.1500	0.0700	0.0000	0.0000
srvdiffhostrate	0.0000	0.0000	0.0000	0.0000	0.0900
dsthostcount	150	255	255	30	255
dsthostsrvcount	25	1	26	255	255
dsthostsamesrvrate	0.1700	0.0000	0.1000	1.0000	1.0000
dsthostdiffsrvrate	0.0300	0.6000	0.0500	0.0000	0.0000
dsthostsamesrcportrate	0.1700	0.8800	0.0000	0.0300	0.0000
dsthostsrvdiffhostrate	0.0000	0.0000	0.0000	0.0400	0.0000
dsthostserrorrate	0.0000	0.0000	1.0000	0.0300	0.0000
dsthostsrvserrorrate	0.0000	0.0000	1.0000	0.0100	0.0000
dsthostrerrorrate	0.0500	0.0000	0.0000	0.0000	0.0000
dsthostsrvrerrorrate	0.0000	0.0000	0.0000	0.0100	0.0000
attack	normal	normal	neptune	normal	normal

In [5]:

```
raw_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 125973 entries, 0 to 125972
Data columns (total 42 columns):
 #   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  float64
 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 
dtypes: float64(15), int64(23), object(4)
memory usage: 40.4+ MB
```

Let's check for any missing values or duplicate rows.

In [6]:
```
# Missing values check
print("Number of missing values in the dataset: ", raw_data.isna().sum().sum())

# Duplicate rows check
print("Number of duplicate rows in the dataset: ", raw_data.duplicated().sum())
```

```
Number of missing values in the dataset:  0
Number of duplicate rows in the dataset:  0
```

1.3 Defining The 4 Major Attack Types

The Network Attacks are widely classified into the following 4 categories:

- **Denial of Service (DoS)**

  These attacks aim to disrupt availability by overwhelming a target with excessive traffic or malformed requests, causing legitimate users to be unable to access services. E.g. These attacks try to shut down a website or service by flooding it with too many requests, making it unavailable to real users.

- **Probe**

  These attacks focus on reconnaissance, where attackers scan networks or hosts to discover open ports, running services, or potential vulnerabilities before launching more targeted attacks. E.g. These attacks are like digital scouting, where attackers quietly look for weak points or open doors in a system.

- **Remote to Local (R2L)**

  These attacks occur when an external attacker gains unauthorized local access by exploiting weaknesses such as weak passwords or misconfigurations, often without generating high traffic volumes. E.g. These attacks happen when someone outside the system manages to log in without permission, often by guessing or stealing credentials.

- **User to Root (U2R)**

  These attacks involve a local user escalating privileges to gain root or administrative access, typically through software vulnerabilities, and are rare but highly impactful. E.g. These attacks occur when a user with limited access manages to gain full control of a system, which is rare but very serious.

Let us define these types via new feature `attacktype`.

In [7]:

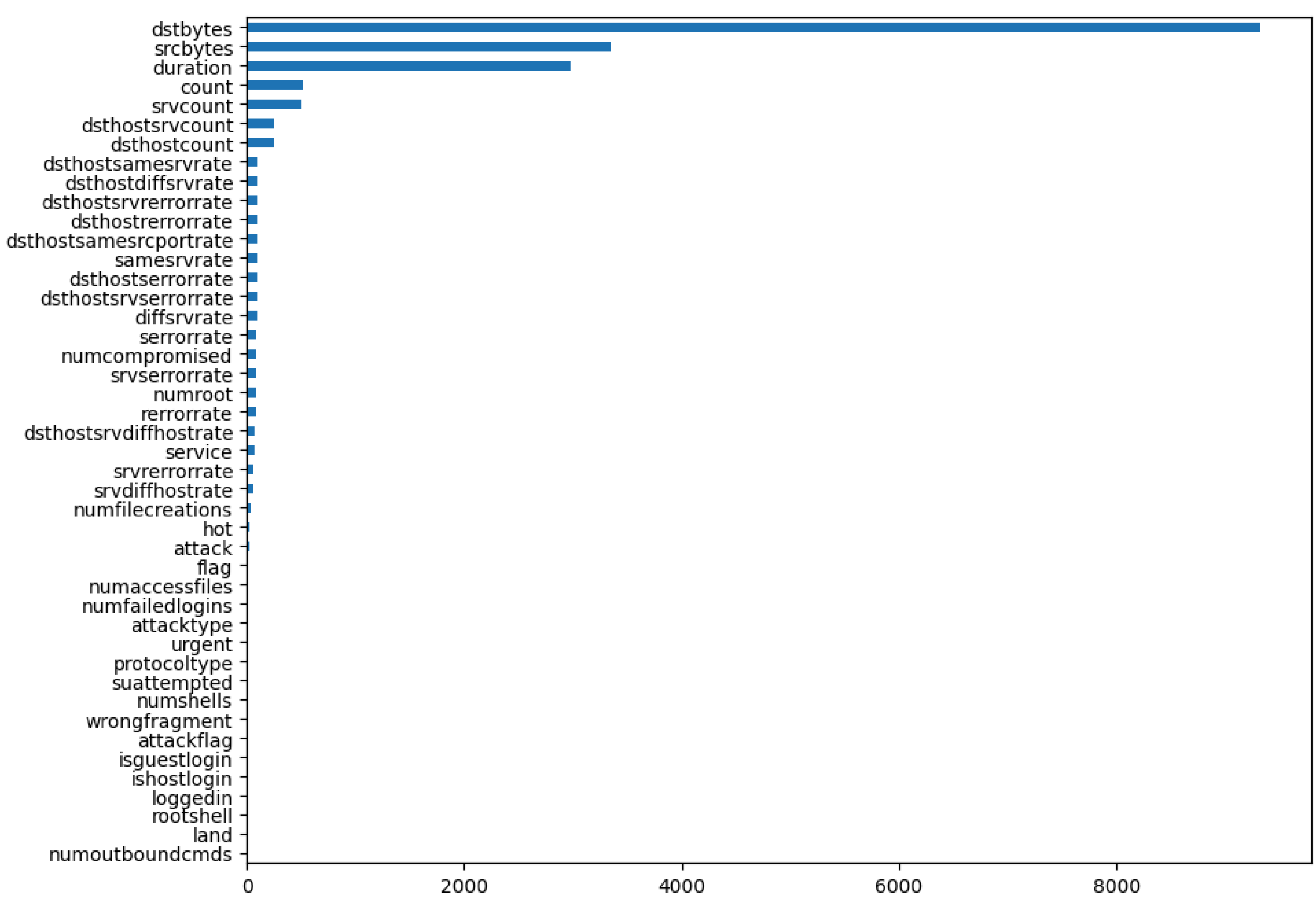
```
df = raw_data.copy(deep=True)
df['attackflag'] = raw_data['attack'].apply(lambda x: 0 if x=='normal' else 1)

def type_of_attack(attack):
    # Denial of Service (DoS) attacks
    DoS = [
        "back",
        "land",
        "neptune",
        "pod",
        "smurf",
        "teardrop",
        "mailbomb",
        "apache2",
        "processtable",
        "udpstorm"
    ]

    # Probe (surveillance / scanning) attacks
    Probe = [
        "satan",
        "ipsweep",
        "nmap",
        "portsweep",
        "mscan",
        "saint"
    ]

    # Remote to Local (R2L) attacks
    R2L = [
        "guess_passwd",
        "ftp_write",
        "imap",
        "phf",
        "multihop",
        "warezmaster",
        "warezclient",
        "spy",
        "xlock",
        "xsnoop",
        "snmpguess",
        "snmpgetattack",
        "httptunnel",
        "sendmail",
        "named"
    ]

    # User to Root (U2R) attacks
    U2R = [
        "buffer_overflow",
        "loadmodule",
        "rootkit",
        "perl",
        "sqlattack",
        "xterm",
        "ps"
    ]
    if attack == 'normal':
        return 'normal'
    elif attack in DoS:
```

```
        return 'DoS'
    elif attack in Probe:
        return 'Probe'
    elif attack in R2L:
        return 'R2L'
    elif attack in U2R:
        return 'U2R'

    return 'other'

df['attacktype'] = df['attack'].apply(type_of_attack)
attacks_DoS = df[df['attacktype']=='DoS']['attack']
attacks_Probe = df[df['attacktype']=='Probe']['attack']
attacks_R2L = df[df['attacktype']=='R2L']['attack']
attacks_U2R = df[df['attacktype']=='U2R']['attack']
attacks_all = df[df['attack'] != 'normal']['attack']

attacktypes = df['attacktype'].copy(deep=True)
attacktypes_within_attacks = df[df['attackflag']==1]['attacktype'].copy(deep=True)

attackflags_text = df['attackflag'].copy(deep=True).map({0:'normal',1:'attack'})
```

In [8]:
```
_original_show = plt.show

def auto_save_show(*args, **kwargs):
    os.makedirs('../plots', exist_ok=True)
    for num in plt.get_fignums():
        fig = plt.figure(num)
        ts = datetime.now().strftime("%Y%m%d_%H%M%S_%f")
        fig.savefig(f'../plots/fig_{ts}.png', dpi=600, bbox_inches='tight')
        _original_show(*args, **kwargs)

plt.show = auto_save_show
```

1.4 Check for Features with very high Modal Frequency (>99%)

In [ ]:
```
plt.figure(figsize=(10,8))
df.nunique().sort_values(ascending=True).plot(kind='barh')
plt.show()
```



In [10]:
```
pd.concat(
    [
        df.nunique(),
        df.dtypes,
        df.mode().T[0],
        df.apply(lambda col: col.value_counts(normalize=True).iloc[0])
        ],
        axis=1,
```

```
        keys=[
            'No. of Unique Values',
            'Data Type',
            'Mode',
            'Mode Frequency'
            ]
            ).sort_values(by=['Data Type','Mode Frequency', 'No. of Unique Values'], ascending=[
```

Out[10]:

	No. of Unique Values	Data Type	Mode	Mode Frequency
numoutboundcmds	1	int64	0	1.0000
ishostlogin	2	int64	0	1.0000
urgent	4	int64	0	0.9999
land	2	int64	0	0.9998
numshells	3	int64	0	0.9996
suattempted	3	int64	0	0.9994
numfailedlogins	6	int64	0	0.9990
rootshell	2	int64	0	0.9987
numfilecreations	35	int64	0	0.9977
numaccessfiles	10	int64	0	0.9971
numroot	82	int64	0	0.9948
wrongfragment	3	int64	0	0.9913
isguestlogin	2	int64	0	0.9906
numcompromised	88	int64	0	0.9898
hot	28	int64	0	0.9788
duration	2981	int64	0	0.9205
loggedin	2	int64	0	0.6043
dsthostcount	256	int64	255	0.5882
dstbytes	9326	int64	0	0.5395
attackflag	2	int64	0	0.5346
srcbytes	3341	int64	0	0.3921
dsthostsrvcount	256	int64	255	0.2857
count	512	int64	1	0.2204
srvcount	509	int64	1	0.2016
rerrorrate	82	float64	0.0000	0.8715
srvrerrorrate	62	float64	0.0000	0.8714
dsthostsrvrerrorrate	101	float64	0.0000	0.8463
dsthostrerrorrate	101	float64	0.0000	0.8190
srvdiffhostrate	60	float64	0.0000	0.7746
srvserrorrate	86	float64	0.0000	0.7045
dsthostsrvdiffhostrate	75	float64	0.0000	0.6899
serrorrate	89	float64	0.0000	0.6893
dsthostsrvserrorrate	100	float64	0.0000	0.6776
dsthostserrorrate	101	float64	0.0000	0.6461
samesrvrate	101	float64	1.0000	0.6097
diffsrvrate	95	float64	0.0000	0.6050
dsthostsamesrcportrate	101	float64	0.0000	0.5003
dsthostsamesrvrate	101	float64	1.0000	0.3894
dsthostdiffsrvrate	101	float64	0.0000	0.3730
protocoltype	3	object	tcp	0.8152
flag	11	object	SF	0.5949
attacktype	5	object	normal	0.5346
attack	23	object	normal	0.5346

	No. of Unique Values	Data Type	Mode	Mode Frequency
service	70	object	http	0.3202

For columns with modal frequency > 99%, we will first check the attack distribution for non-modal classes of each column.

In [11]:
```
for col in df.nunique().sort_values().index:
    if df[col].value_counts(normalize=True).iloc[0] >= 0.99:
        text = col + f' ({df.shape[0] - df[col].value_counts().iloc[0]} non-modal values)'
        l = len(text)
        print('-'*int(30-l/2),text.upper(),'-'*int(30-l/2))
        x = df[df[col] != df[col].mode().iloc[0]]['attack'].value_counts()
        print(x)
        print('\n')
```

```
------------ NUMOUTBOUNDCMDS (0 NON-MODAL VALUES) ------------
Series([], Name: count, dtype: int64)


----------------- LAND (25 NON-MODAL VALUES) -----------------
attack
land      18
normal     7
Name: count, dtype: int64


-------------- ROOTSHELL (169 NON-MODAL VALUES) --------------
attack
normal             137
buffer_overflow     18
phf                  4
loadmodule           3
perl                 3
rootkit              2
multihop             2
Name: count, dtype: int64


-------------- ISHOSTLOGIN (1 NON-MODAL VALUES) --------------
attack
normal    1
Name: count, dtype: int64


------------ ISGUESTLOGIN (1187 NON-MODAL VALUES) ------------
attack
normal          873
warezclient     306
ftp_write         2
warezmaster       2
multihop          2
satan             1
guess_passwd      1
Name: count, dtype: int64


----------- WRONGFRAGMENT (1090 NON-MODAL VALUES) -----------
attack
teardrop    892
pod         198
Name: count, dtype: int64


-------------- NUMSHELLS (47 NON-MODAL VALUES) --------------
attack
normal        39
perl           3
multihop       2
loadmodule     2
spy            1
Name: count, dtype: int64


------------- SUATTEMPTED (80 NON-MODAL VALUES) -------------
attack
normal    79
spy        1
Name: count, dtype: int64


---------------- URGENT (9 NON-MODAL VALUES) ----------------
attack
normal       6
ftp_write    2
rootkit      1
Name: count, dtype: int64


----------- NUMFAILEDLOGINS (122 NON-MODAL VALUES) -----------
attack
normal          68
guess_passwd    52
satan            1
rootkit          1
```

```
Name: count, dtype: int64


----------- NUMACCESSFILES (371 NON-MODAL VALUES) -----------
attack
normal        361
phf             4
ftp_write       3
multihop        1
spy             1
loadmodule      1
Name: count, dtype: int64


---------- NUMFILECREATIONS (287 NON-MODAL VALUES) ----------
attack
normal             253
buffer_overflow     13
multihop             4
loadmodule           4
perl                 3
rootkit              3
ftp_write            2
warezmaster          2
satan                1
ipsweep              1
spy                  1
Name: count, dtype: int64


--------------- NUMROOT (649 NON-MODAL VALUES) ---------------
attack
normal             630
rootkit              4
perl                 3
satan                3
multihop             2
buffer_overflow      2
ftp_write            2
ipsweep              1
loadmodule           1
imap                 1
Name: count, dtype: int64
```

We can see that, the non-modal rows are tiny fractions of the data. Moreover, we cannot see any significant association between a specific attack and column, even when conditioned on only non-modal values. Thus, these columns add very little-to-no informative value for ML modelling. Hence, these columns can be discarded as well.

Let us further verify this decision by checking the Mutual Information (MI) Scores. MI measures how much information the presence or absence of a feature contributes to making the correct prediction on the target (attack).

In [12]:
```python
print('MUTUAL INFORMATION SCORES:')
for col in df.drop(columns='attack'):
    X = df[[col]].apply(lambda x: pd.factorize(x)[0])
    y = df['attack']

    # For Classification
    mi_score = mutual_info_classif(X, y, discrete_features=[True])
    if mi_score <= 0.1:
        print(f"{col.upper()}{' '*(30-len(col)-6)}{round(mi_score[0],4)}")
```

```
MUTUAL INFORMATION SCORES:
DURATION                0.0844
LAND                    0.0013
WRONGFRAGMENT           0.0534
URGENT                  0.0002
HOT                     0.0619
NUMFAILEDLOGINS         0.0034
NUMCOMPROMISED          0.0403
ROOTSHELL               0.0021
SUATTEMPTED             0.0005
NUMROOT                 0.0039
NUMFILECREATIONS        0.0027
NUMSHELLS               0.0007
NUMACCESSFILES          0.0022
NUMOUTBOUNDCMDS         0.0
ISHOSTLOGIN             0.0
ISGUESTLOGIN            0.0116
```

The MI scores for the columns previously identified above for discarding are very low. Hence it is safe to discard these columns.

In [13]:
```
for col in raw_data:
    if df[col].value_counts(normalize=True).iloc[0]>=0.99:
        print(f'Dropping column: {col}')
        df.drop(columns=col, inplace=True)
```

```
Dropping column: land
Dropping column: wrongfragment
Dropping column: urgent
Dropping column: numfailedlogins
Dropping column: rootshell
Dropping column: suattempted
Dropping column: numroot
Dropping column: numfilecreations
Dropping column: numshells
Dropping column: numaccessfiles
Dropping column: numoutboundcmds
Dropping column: ishostlogin
Dropping column: isguestlogin
```

In [14]:
```
df.columns
```

Out[14]:
```
Index(['duration', 'protocoltype', 'service', 'flag', 'srcbytes', 'dstbytes',
       'hot', 'loggedin', 'numcompromised', 'count', 'srvcount', 'serrorrate',
       'srvserrorrate', 'rerrorrate', 'srvrerrorrate', 'samesrvrate',
       'diffsrvrate', 'srvdiffhostrate', 'dsthostcount', 'dsthostsrvcount',
       'dsthostsamesrvrate', 'dsthostdiffsrvrate', 'dsthostsamesrcportrate',
       'dsthostsrvdiffhostrate', 'dsthostserrorrate', 'dsthostsrvserrorrate',
       'dsthostrerrorrate', 'dsthostsrvrerrorrate', 'attack', 'attackflag',
       'attacktype'],
      dtype='object')
```

2. Exploratory Data Analysis (EDA)

2.1 Defining Numerical and Categorical Features

In [15]:
```
df_num = df.select_dtypes(exclude='object')
df_cat = df.select_dtypes(include='object')
df_cat['attackflag'] = df['attackflag'].copy(deep=True)
```

In [16]:
```
df_num.columns
```

Out[16]:
```
Index(['duration', 'srcbytes', 'dstbytes', 'hot', 'loggedin', 'numcompromised',
       'count', 'srvcount', 'serrorrate', 'srvserrorrate', 'rerrorrate',
       'srvrerrorrate', 'samesrvrate', 'diffsrvrate', 'srvdiffhostrate',
       'dsthostcount', 'dsthostsrvcount', 'dsthostsamesrvrate',
       'dsthostdiffsrvrate', 'dsthostsamesrcportrate',
       'dsthostsrvdiffhostrate', 'dsthostserrorrate', 'dsthostsrvserrorrate',
       'dsthostrerrorrate', 'dsthostsrvrerrorrate', 'attackflag'],
      dtype='object')
```

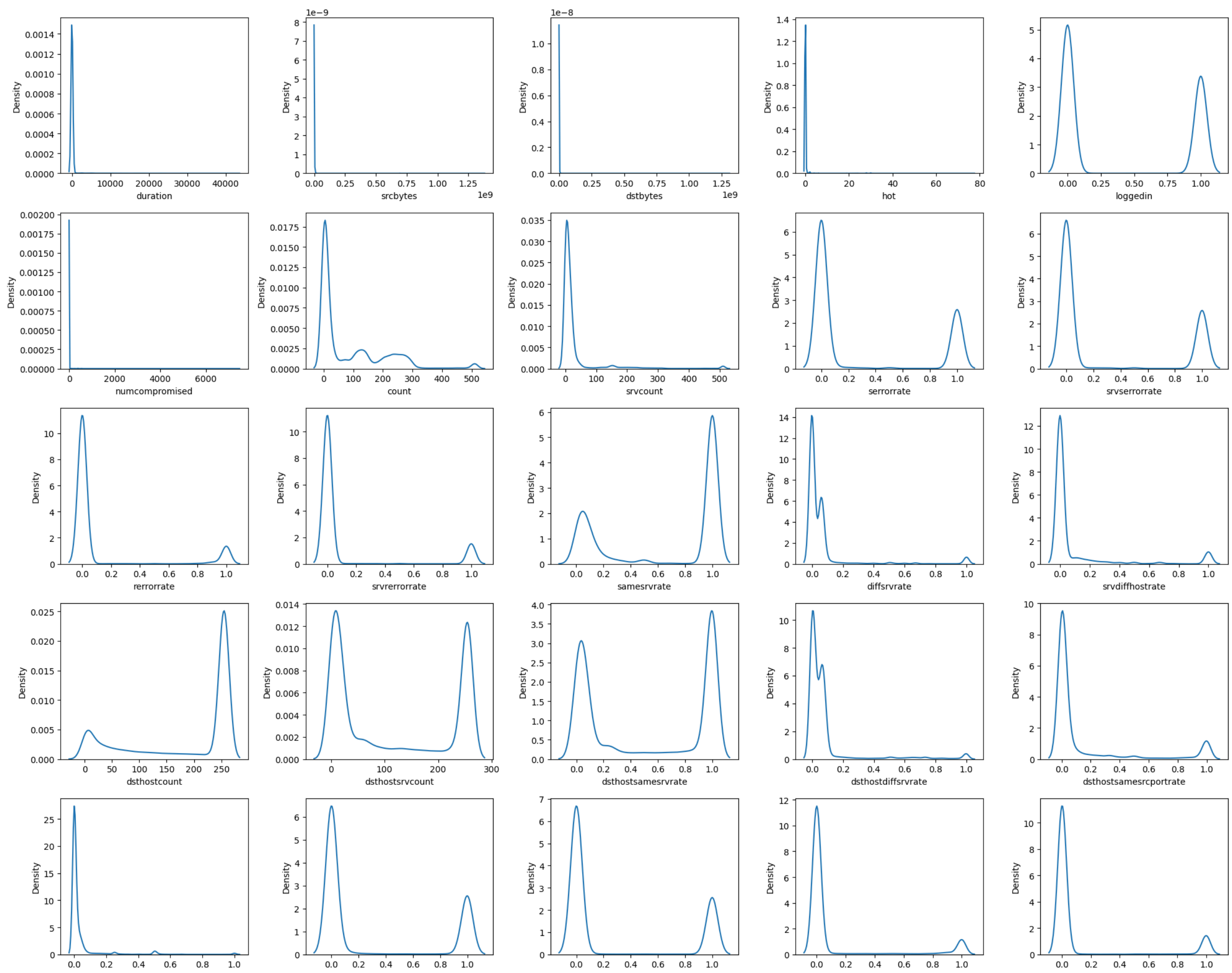
In [17]:
```
df_cat.columns
```

Out[17]:
```
Index(['protocoltype', 'service', 'flag', 'attack', 'attacktype',
       'attackflag'],
      dtype='object')
```

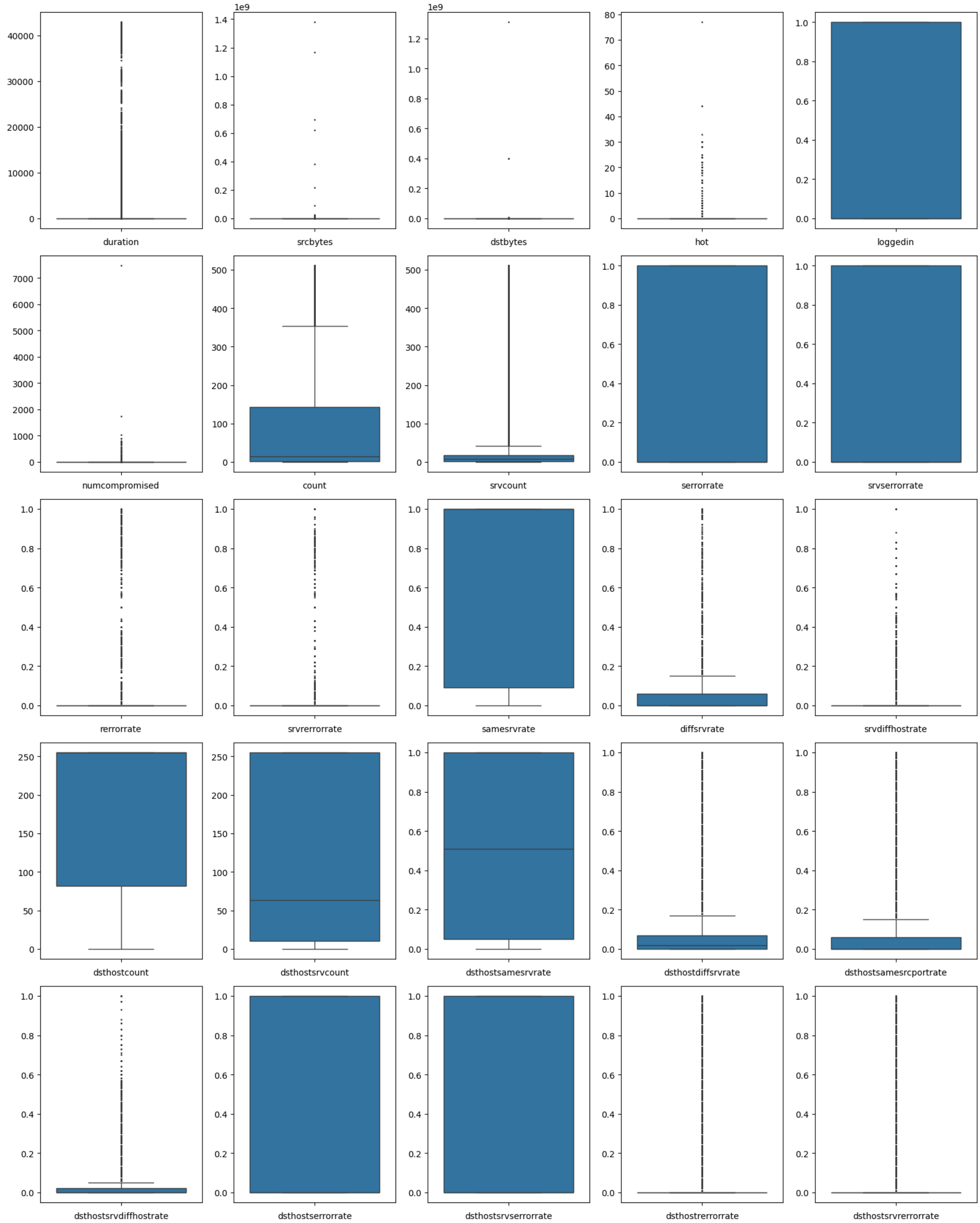
2.2 Univariate Analysis

2.2.1 Numerical Features

In [18]:
```
grid_size = int(np.ceil((df_num.shape[1]-1)**0.5))

plt.figure(figsize=(20,16))
for i,col in enumerate(df_num):
    if col != 'attackflag':
        plt.subplot(grid_size, grid_size, i+1)
        sns.kdeplot(data=df_num, x=col)
plt.tight_layout()
plt.show()
```



In [19]:
```
grid_size = int(np.ceil((df_num.shape[1]-1)**0.5))

plt.figure(figsize=(16,20))
for i,col in enumerate(df_num):
    if col != 'attackflag':
        plt.subplot(grid_size, grid_size, i+1)
        sns.boxplot(data=df_num, y=col, fliersize=1)
        plt.xlabel(col)
        plt.ylabel('')
plt.tight_layout()
plt.show()
```



Insights:

- Most features exhibit **strong right skewness**, with values concentrated near zero and a small number of extreme observations.
- **Duration, source bytes, and destination bytes show particularly heavy tails**, indicating mostly short, low-volume connections with a few very large transfers.
- Count-based variables (e.g., `count`, `srvcount`, `dsthostcount`, `dsthostsrvcount`) have long right tails, suggesting repetitive or bursty connection behavior in a minority of cases.
- Outliers are prevalent across many features, especially in traffic volume and connection count metrics, likely corresponding to anomalous or attack-related activity.
- `numcompromised` is mostly zero with rare large values, making it a sparse but potentially strong indicator of compromise.
- Binary or near-binary behavior is evident in loggedin, clearly separating logged-in and non-logged-in sessions.
- Many rate-based features (e.g., `serrorrate`, `srvserrorrate`, `rerrorrate`, `srvrerrorrate`) cluster near 0 with a secondary peak near 1, indicating sharp transitions between normal and abnormal

traffic.

- Host-based rate features (dsthost*rate) consistently show bimodal distributions, suggesting strong discriminative power for intrusion detection.

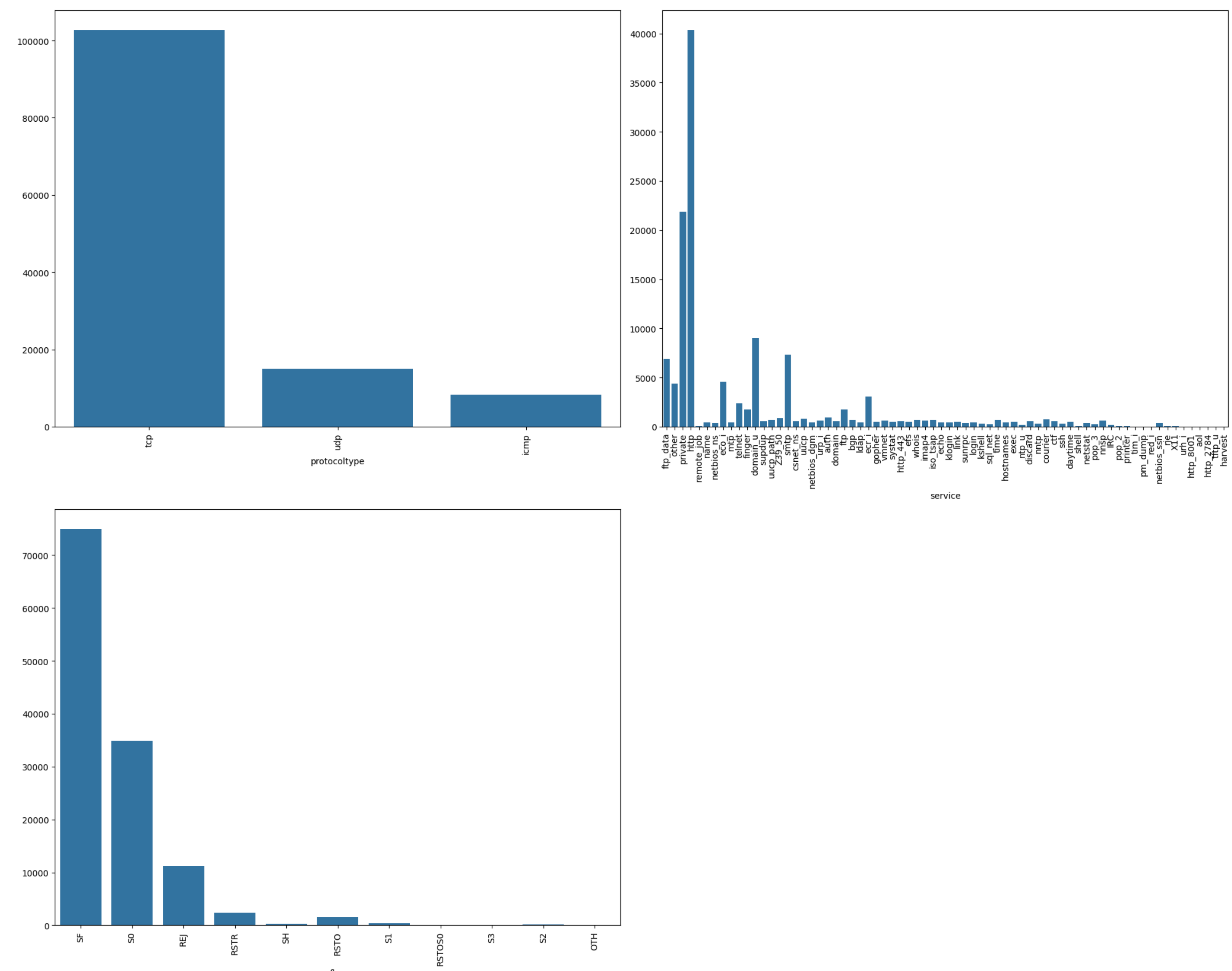
- Service similarity measures (`samesrvrate` , `dsthostsamesrvrate`) display clear separation between diverse-service normal traffic and repeated-service attack patterns.

- Difference-based service rates (`diffsrvrate` , `dsthostdiffsrvrate`) are mostly close to zero, indicating limited service switching in most connections.

- The dominance of extreme values implies a need for log scaling prior to modeling.

2.2.2 Categorical Features

In [20]:
```
grid_size = int(np.ceil((df_cat.shape[1]-3)**0.5))

plt.figure(figsize=(20,16))
for i,col in enumerate(df_cat):
    if 'attack' not in col:
        plt.subplot(grid_size, grid_size, i+1)
        sns.countplot(data=df_cat, x=col)
        plt.xlabel(col)
        plt.xticks(rotation=90)
        plt.ylabel('')
plt.tight_layout()
plt.show()
```



Insights:

- **TCP dominates the protocol distribution**, accounting for the majority of connections, while UDP is significantly less frequent and ICMP appears relatively rare.

- The **service feature is highly imbalanced**, with a small number of services (e.g., HTTP-related and common network services) accounting for most connections, and many services occurring very infrequently.

- The long tail in the service distribution indicates **high categorical sparsity**, which may require grouping rare services or using robust encoding techniques.

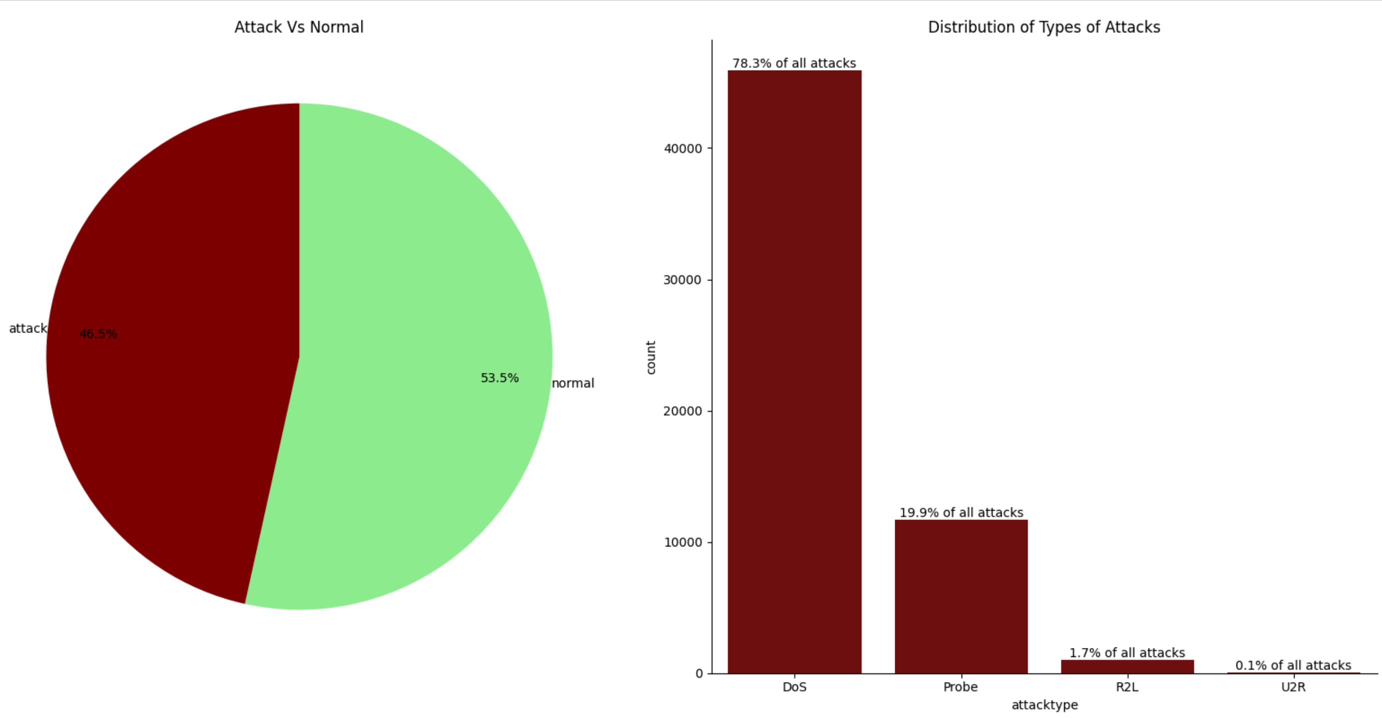
- **Connection flags are strongly skewed**, with `SF` being the most common state, followed by `S0`, while other flags occur much less frequently.
- The prevalence of `S0`, `REJ`, and other non-`SF` flags suggests a **substantial presence of failed or incomplete connections**, which can be indicative of scanning or attack behavior.
- Overall, the categorical features exhibit **class imbalance**, implying that careful encoding and imbalance-aware modeling strategies are necessary.

2.3 Bivariate Analysis (Normal vs. Attack)

2.3.1 Normal vs. Attack Distribution

In [21]:

```
plt.figure(figsize=(16,8))
plt.subplot(1,2,1)
plt.title('Attack Vs Normal')
plt.pie(attackflags_text.value_counts(),
        labels=attackflags_text.value_counts().index,
        explode=[0,0] + [0.5]*(attackflags_text.nunique()-2),
        autopct='%1.1f%%',
        counterclock=False,
        startangle=90,
        pctdistance=0.8,
        labeldistance=1,
        colors=['lightgreen','maroon'])

x = attacktypes_within_attacks.value_counts()

plt.subplot(1,2,2)
plt.title('Distribution of Types of Attacks')
ax = sns.countplot(x=attacktypes_within_attacks,
                   order=x.index,
                   color='maroon')
total=len(attacktypes_within_attacks)
for p in ax.patches:
    value = int(p.get_height())
    value = str(round(value/total*100,1)) + r"% of all attacks"
    ax.annotate(value,
                (p.get_x() + p.get_width() / 2, p.get_height()),
                ha='center', va='bottom')
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)

plt.tight_layout()
plt.show()
```



Insights:

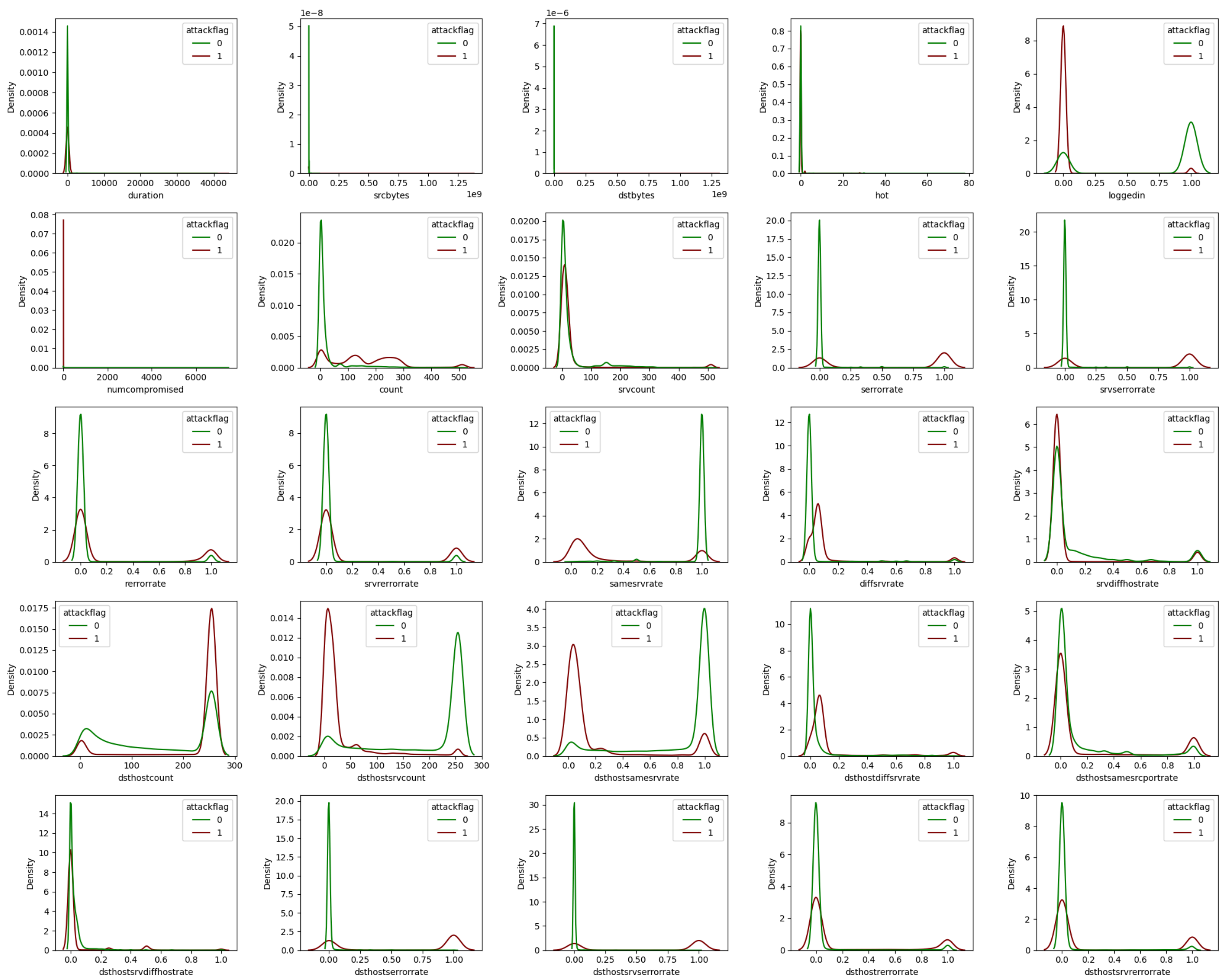
- **The dataset is fairly balanced between normal and attack traffic**, with normal connections making up ~53.5% and attacks ~46.5%, reducing severe class imbalance concerns for model training.
- **DoS attacks overwhelmingly dominate the attack landscape**, accounting for ~78% of all attacks, indicating the dataset is heavily biased toward availability-based attack patterns.

- **R2L and U2R attacks are extremely rare**, together contributing less than 2% of attacks, which may make them difficult to learn without resampling or specialized modeling techniques.

2.3.2 Numerical Features

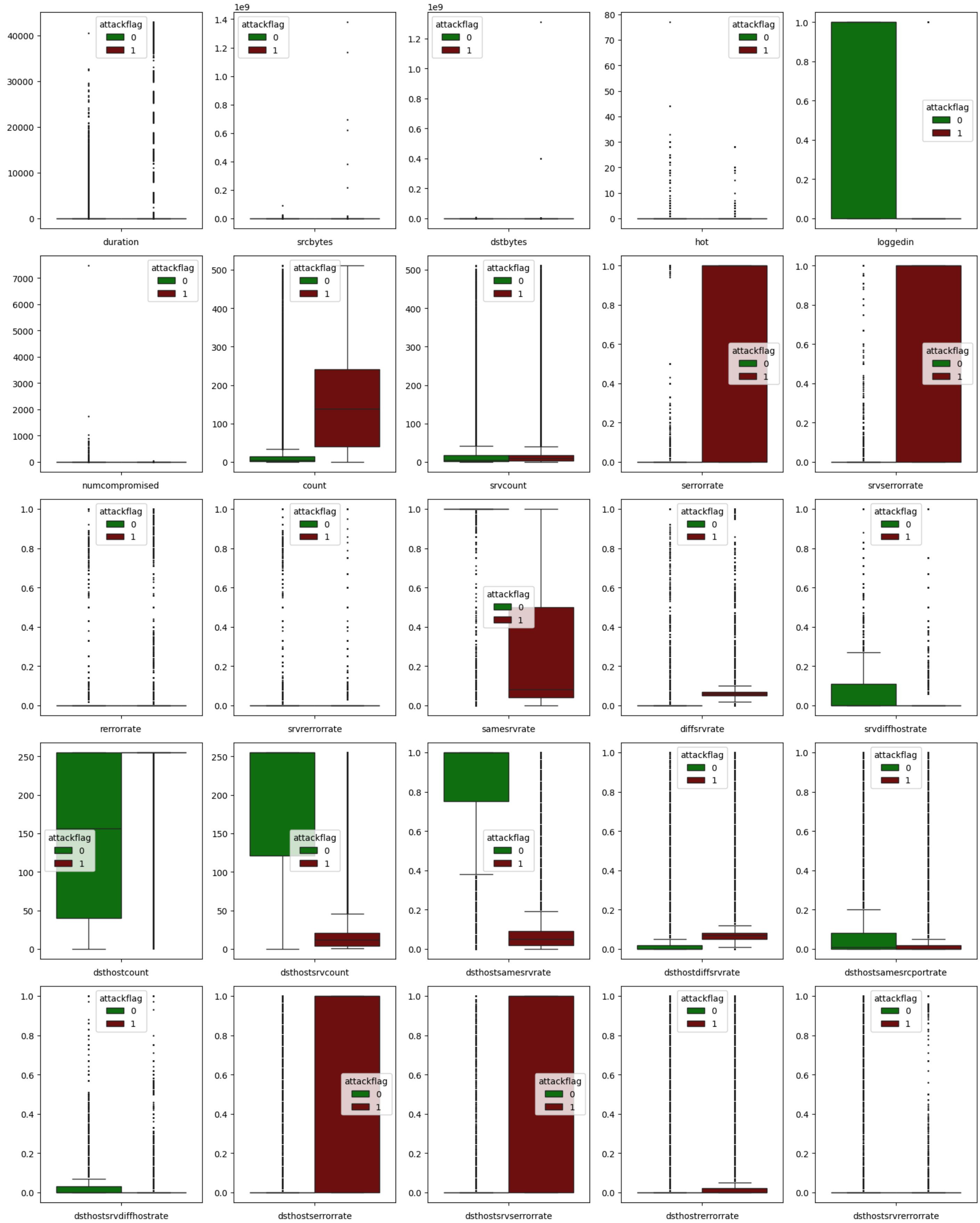
In [22]:

```
palette = {0:'green',1:'maroon'}
grid_size = int(np.ceil((df_num.shape[1]-1)**0.5))

plt.figure(figsize=(20,16))
for i,col in enumerate(df_num):
    if col != 'attackflag':
        plt.subplot(grid_size, grid_size, i+1)
        sns.kdeplot(data=df_num,
                    x=col,
                    hue='attackflag',
                    palette=palette)
plt.tight_layout()
plt.show()
```



In [23]:

```
grid_size = int(np.ceil((df_num.shape[1]-1)**0.5))

plt.figure(figsize=(16,20))
for i,col in enumerate(df_num):
    if col != 'attackflag':
        plt.subplot(grid_size, grid_size, i+1)
        sns.boxplot(data=df_num,
                    y=col,
                    hue='attackflag',
                    fliersize=1,
                    palette=palette)
        plt.xlabel(col)
        plt.ylabel('')
plt.tight_layout()
plt.show()
```



attackflag
0
1
1e9
duration
srcbytes
dstbytes
hot
loggedin
numcompromised
count
srvcount
serrorrate
srvserrorrate
rerrorrate
srvrerrorrate
samesrvrate
diffsrvrate
srvdiffhostrate
dsthostcount
dsthostsrvcount
dsthostsamesrvrate
dsthostdiffsrvrate
dsthostsamesrcportrate
dsthostsrvdiffhostrate
dsthostserrorrate
dsthostsrvserrorrate
dsthostrerrorrate
dsthostsrvrerrorrate

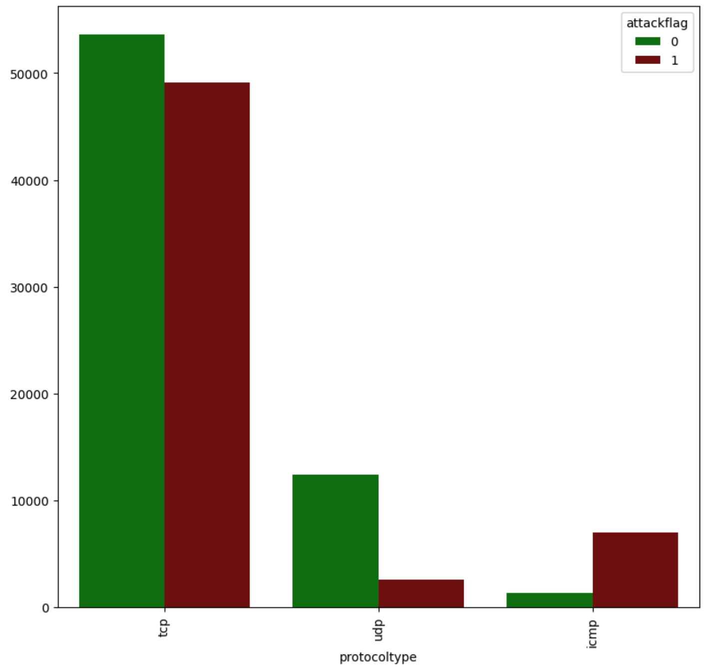
Insights:

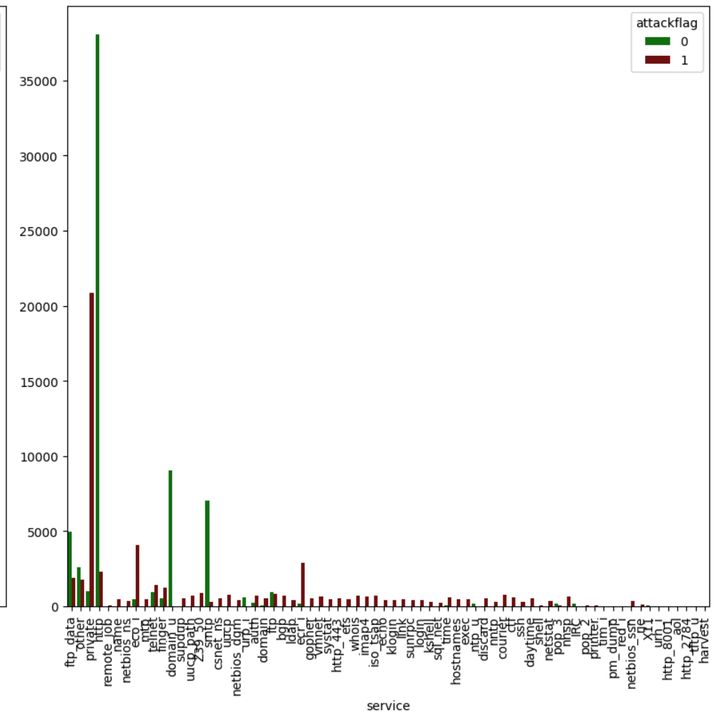
- **Attack traffic shows extreme skewness in connection behavior**, with much higher `count`, `srvcount`, and `dsthostcount` values compared to normal traffic, indicating repeated or bursty connection attempts typical of scanning and flooding attacks.
- **Rate-based features are the strongest discriminators**, especially `serrorrate`, `srvserrorrate`, `same_srv_rate`, and their dsthost variants, where attack connections cluster near extreme values (close to 0 or 1) while normal traffic remains more spread out.
- **Error-related metrics are heavily associated with attacks**, as attack-labeled flows exhibit significantly higher SYN error and service error rates, suggesting failed or half-open connections common in DoS and probing activities.
- **Login and privilege-related features are highly imbalanced**, with `loggedin` and `numcompromised` almost exclusively indicating normal behavior, while attacks rarely involve successful authentication.
- **Host-based aggregation features (`dsthost*`) amplify separation**, where attack traffic consistently shows abnormal consistency across hosts and services, reflecting coordinated or automated attack patterns.

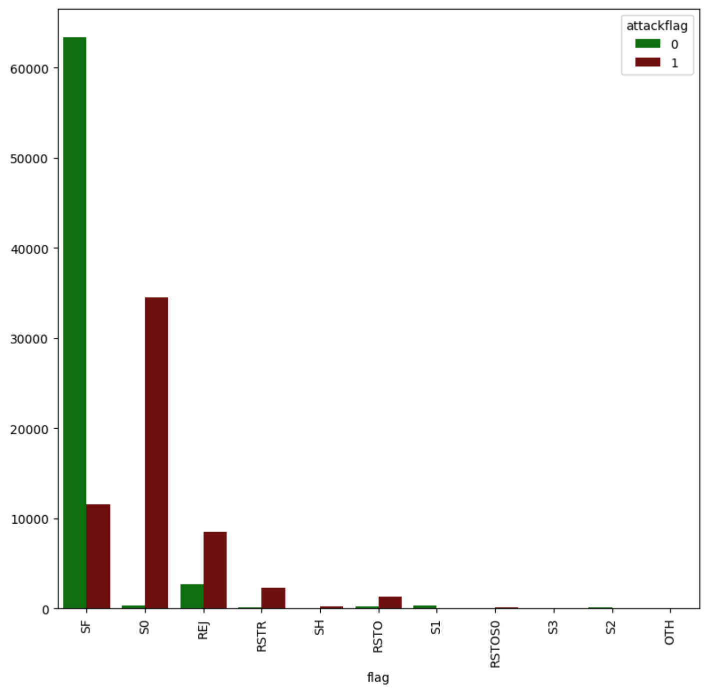
2.3.3 Categorical Features

In [ ]:

```
grid_size = int(np.ceil((df_cat.shape[1]-3)**0.5))

plt.figure(figsize=(16,16))
for i,col in enumerate(df_cat):
    if col not in ['attack','attacktype','attackflag']:
        plt.subplot(grid_size, grid_size, i+1)
        sns.countplot(data=df_cat,
                      x=col,
                      hue='attackflag',
                      palette=palette)
        plt.xlabel(col)
        plt.xticks(rotation=90)
        plt.ylabel('')
plt.tight_layout()
plt.show()
```







Insights:

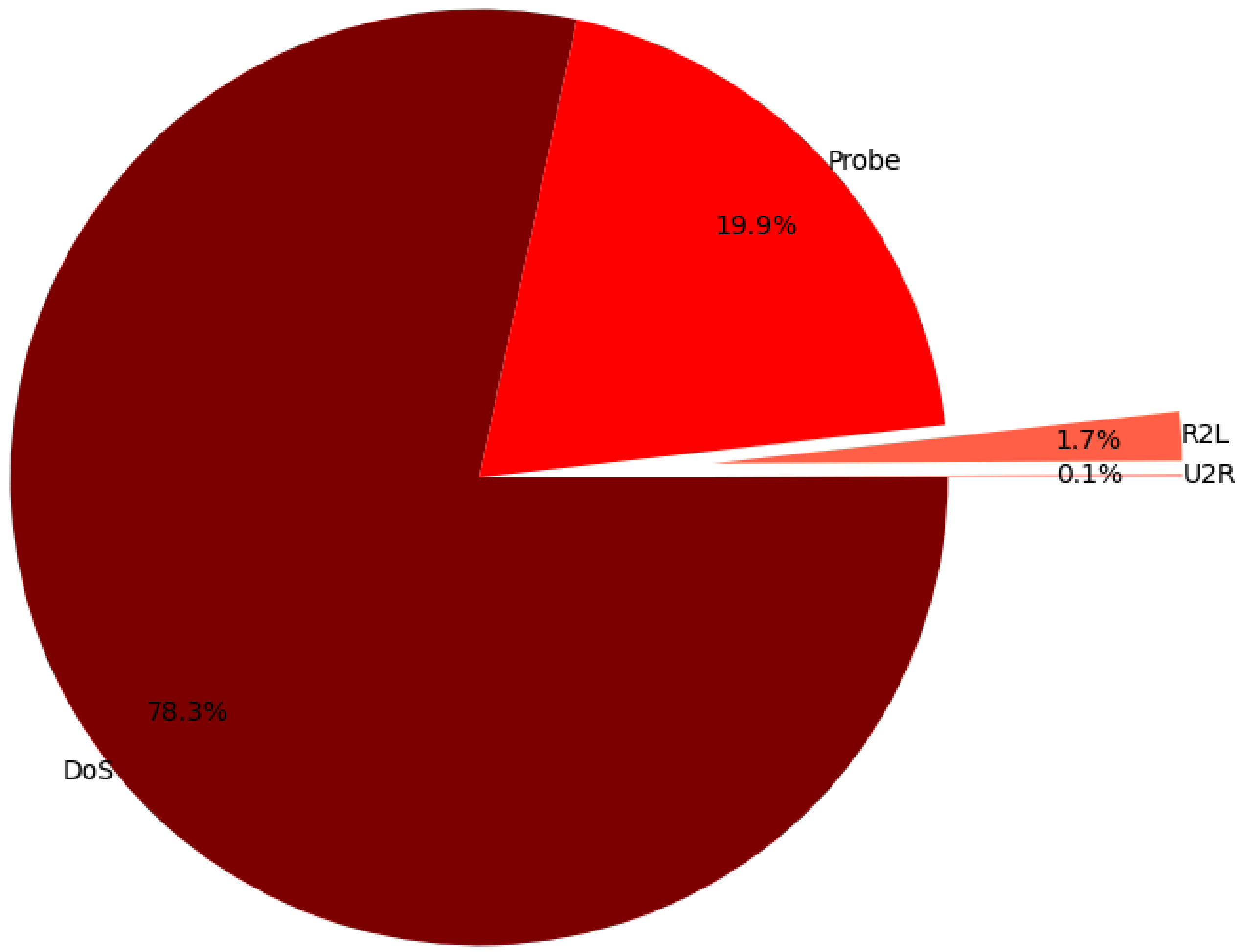
- **TCP is the most commonly used protocol** for both normal and attack traffic, indicating it is the primary communication channel and a major attack surface.
- **ICMP traffic shows a disproportionately high number of attacks** compared to normal usage, suggesting frequent use in reconnaissance and flooding activities.
- UDP traffic is largely associated with normal behavior, with relatively few attack instances observed in the dataset.
- Services such as **ftp_data, private, http, eco_i, ecr_i, etc.** exhibit higher attack frequencies, highlighting that publicly accessible services are more frequently targeted.
- Normal traffic is dominated by the SF flag (successful connections), while **attack traffic shows higher occurrences of S0, REJ, and RSTR flags**, reflecting failed or abnormal connection attempts.

2.4 Multivariate Analysis (Attack Types: DoS/Probe/R2L/U2R)

2.4.1 Distribution of Attack Types

In [110…

```
plt.figure(figsize=(8,8))
plt.pie(attacktypes_within_attacks.value_counts(),
        labels=attacktypes_within_attacks.value_counts().index,
        explode=[0,0] + [0.5]*(attacktypes_within_attacks.nunique()-2),
        autopct='%1.1f%%',
        counterclock=False,
        pctdistance=0.8,
        labeldistance=1,
        colors=['maroon','red','tomato','salmon'], )
plt.show()
```



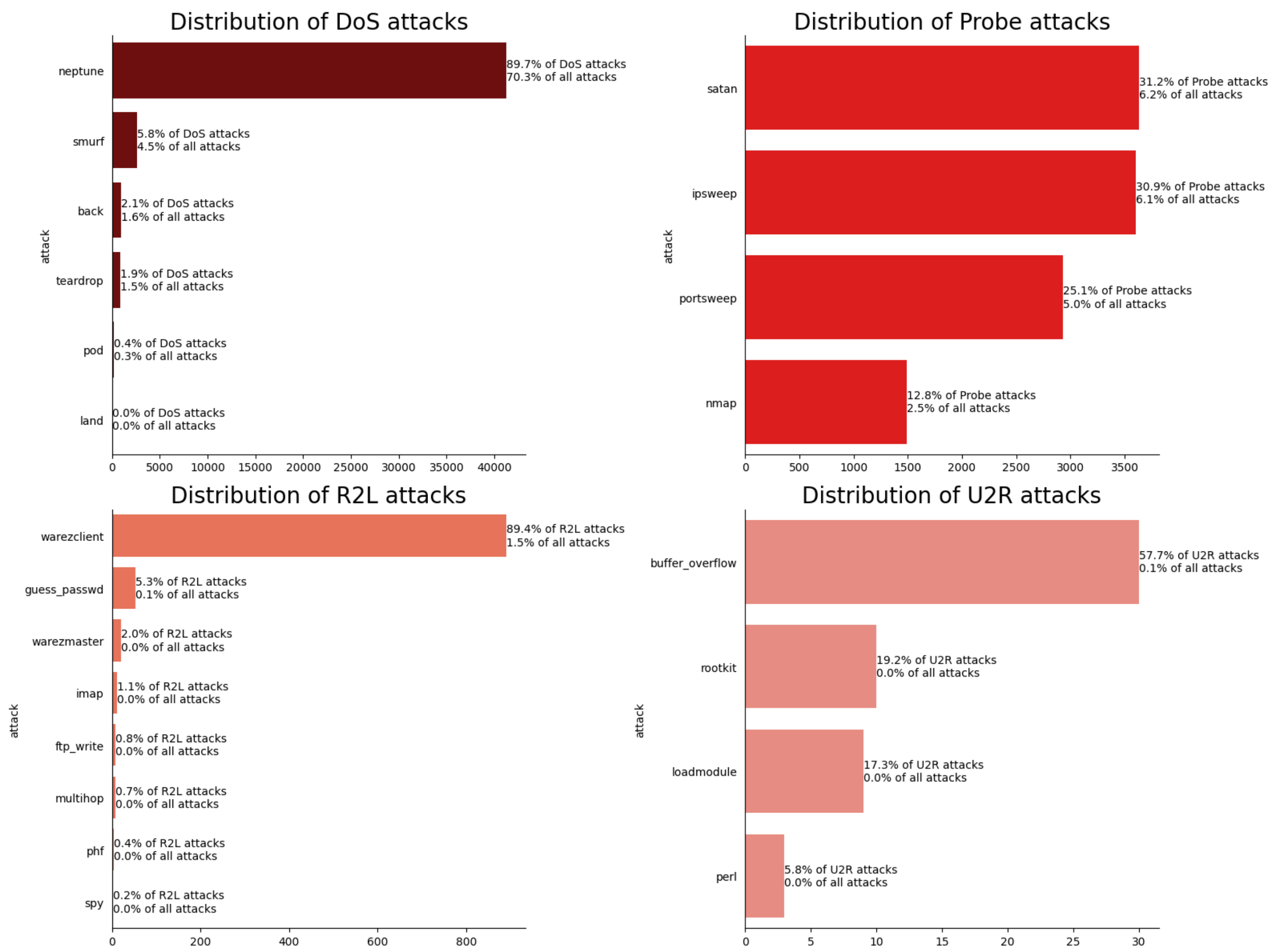
Insights:

- **DoS attacks dominate the dataset, accounting for approximately 78% of all attacks**, indicating that denial-of-service behavior is the primary threat pattern.
- Probe attacks form a significant secondary category at about 20%, reflecting extensive reconnaissance and scanning activity prior to exploitation.
- R2L and U2R attacks together make up less than 2% of all attacks, highlighting extreme class imbalance and the difficulty of detecting rare but high-impact intrusions.

2.4.2 Distribution of Attacks within each Attack Type

In [25]:
```
plt.figure(figsize=(16,12))

x = {
    'DoS':attacks_DoS,
    'Probe':attacks_Probe,
    'R2L':attacks_R2L,
    'U2R':attacks_U2R
}

i=1
colors = ['maroon','red','tomato','salmon']
total = len(attacktypes_within_attacks)
for k,s in x.items():
    vc = s.value_counts()
    plt.subplot(2,2,i)
    plt.title(f'Distribution of {k} attacks',size=20)
    ax = sns.countplot(y=s,
                       order=vc.index,
                       color=colors[i-1])
    subtotal = len(s)
    for p in ax.patches:
        count = int(p.get_width())
        text1 = str(round(count/subtotal*100,1)) + r"% of " + k + " attacks"
        text2 = str(round(count/total*100,1)) + r"% of all attacks"
        text = text1 + '\n' + text2
```

```
        ax.annotate(text,
                    (count, p.get_y() + p.get_height()/2),
                    ha='left',
                    va='center')
    ax.spines['top'].set_visible(False)
    ax.spines['right'].set_visible(False)
    ax.yaxis.set_ticks_position('none')
    plt.xlabel('')
    # plt.xticks(rotation=90)
    i+=1

plt.tight_layout()
plt.show()
```



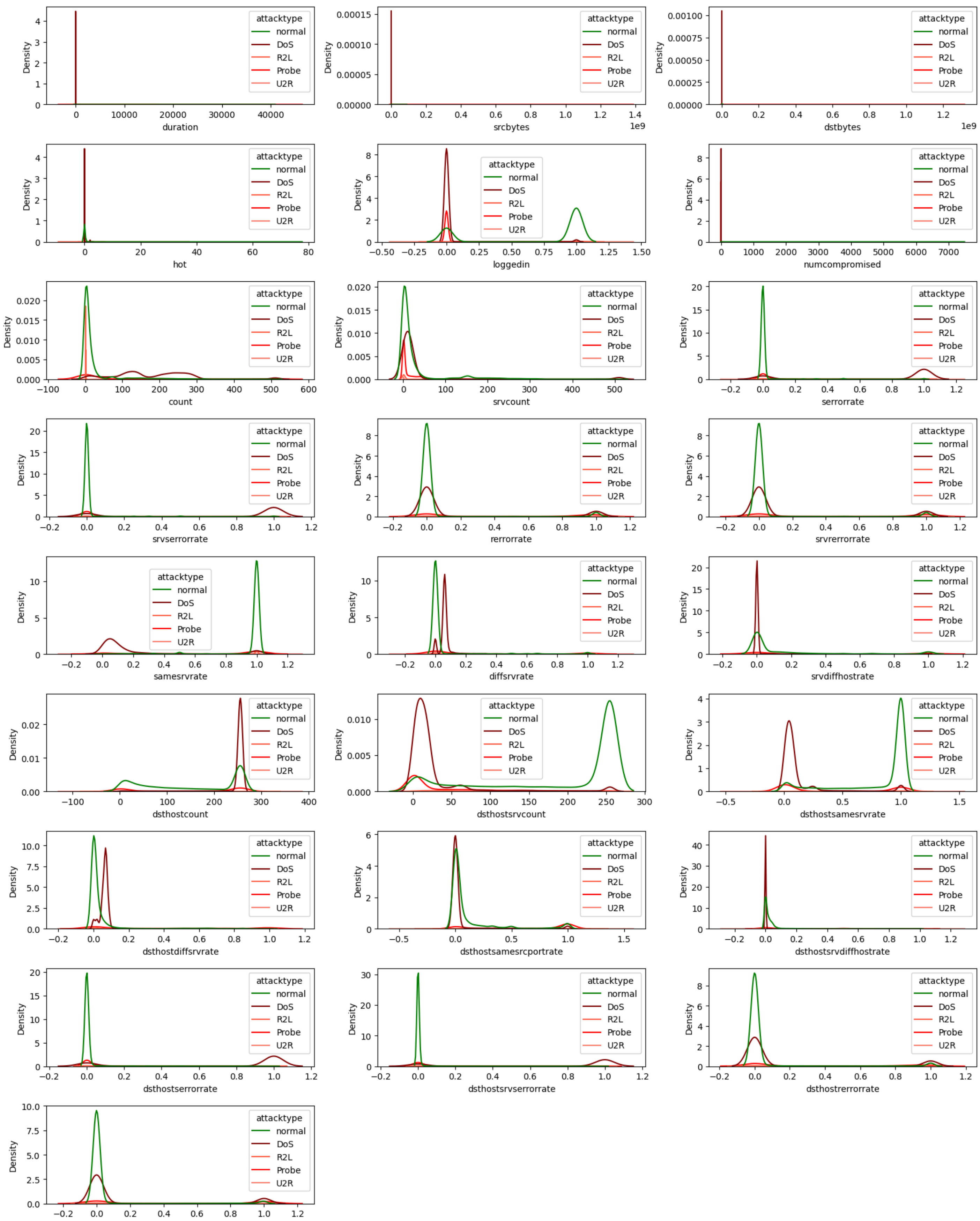
Insights:

- DoS attacks are overwhelmingly dominated by the **neptune** attack, accounting for nearly 90% of all DoS incidents and over 70% of total attacks, indicating a severe class imbalance.
- Probe attacks are more evenly distributed, with **satan, ipsweep, and portsweep** together forming the majority, suggesting diverse reconnaissance techniques.
- R2L attacks are highly concentrated, with **warezclient** making up almost 90% of R2L cases, while other R2L attack types occur very rarely.
- U2R attacks are extremely scarce overall, but **buffer_overflow** is the most prominent within this category, representing more than half of U2R attacks.
- The attack dataset is heavily skewed toward a few dominant attack types, which may bias machine learning models if not handled with resampling or class-weighting techniques.
- Rare attack classes (especially U2R and minor R2L types) are difficult to learn from due to low frequency, increasing the risk of false negatives in intrusion detection systems.

2.4.3 Numerical Features

In [26]:
```
df_num1 = df_num.copy(deep=True)
df_num1['attacktype'] = df['attacktype']

palette = {
    'normal':'green',
    'DoS':'maroon',
    'Probe':'red',
```

```
    'R2L':'tomato',
    'U2R':'salmon'
}

grid_ht = int(np.ceil((df_num1.shape[1]-2)/3))

plt.figure(figsize=(16,20))
i=1
for col in df_num1:
    if col not in ['attacktype','attackflag']:
        plt.subplot(grid_ht, 3, i)
        sns.kdeplot(data=df_num1,
                    x=col,
                    hue='attacktype',
                    palette=palette)

        i+=1
plt.tight_layout()
plt.show()
```



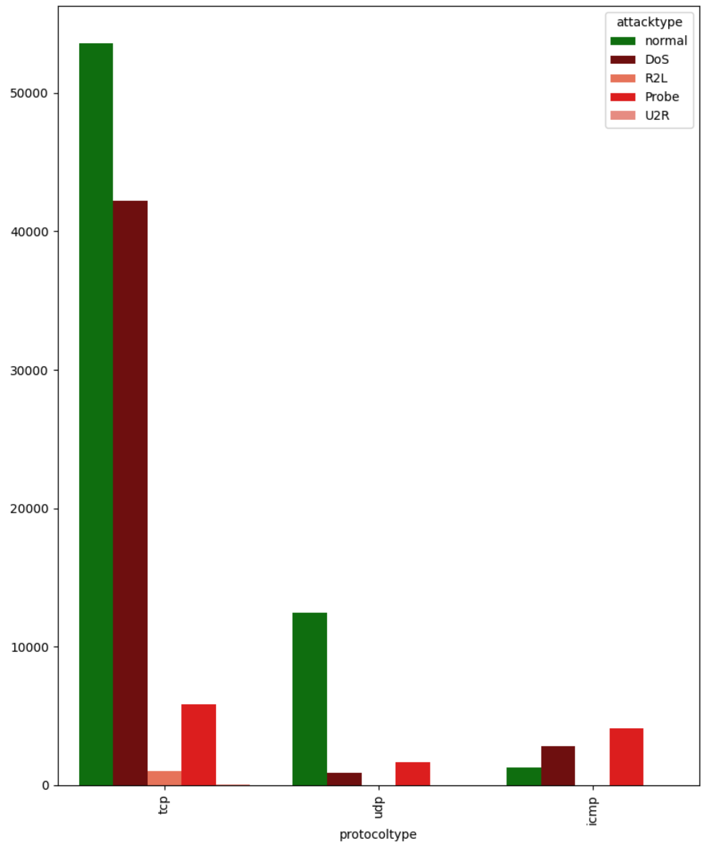
Insights:

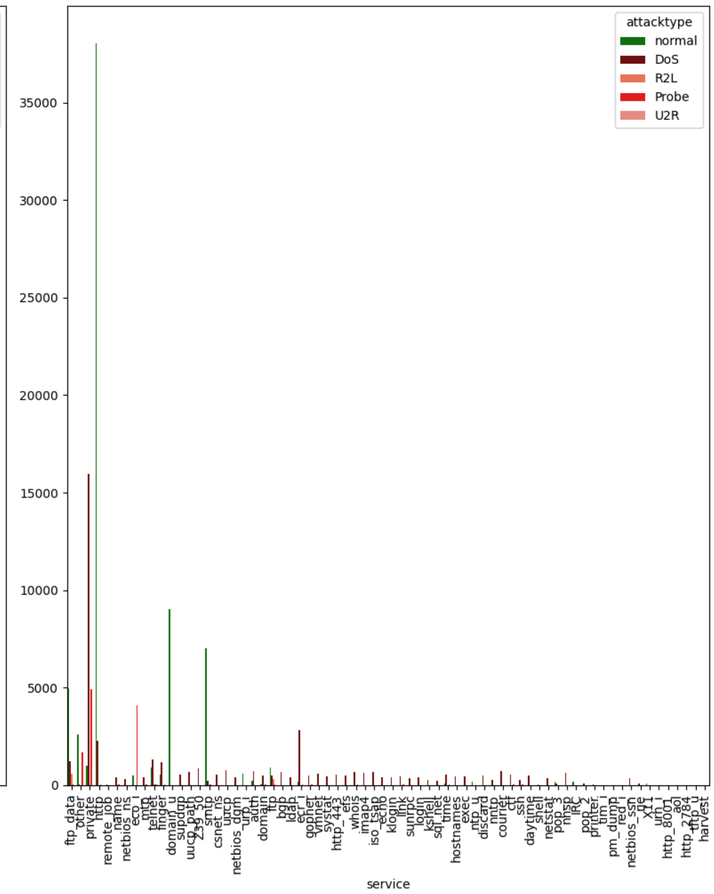
- Duration, srcbytes, and dstbytes show heavy right-skew; DoS traffic concentrates near zero duration with extreme byte outliers.

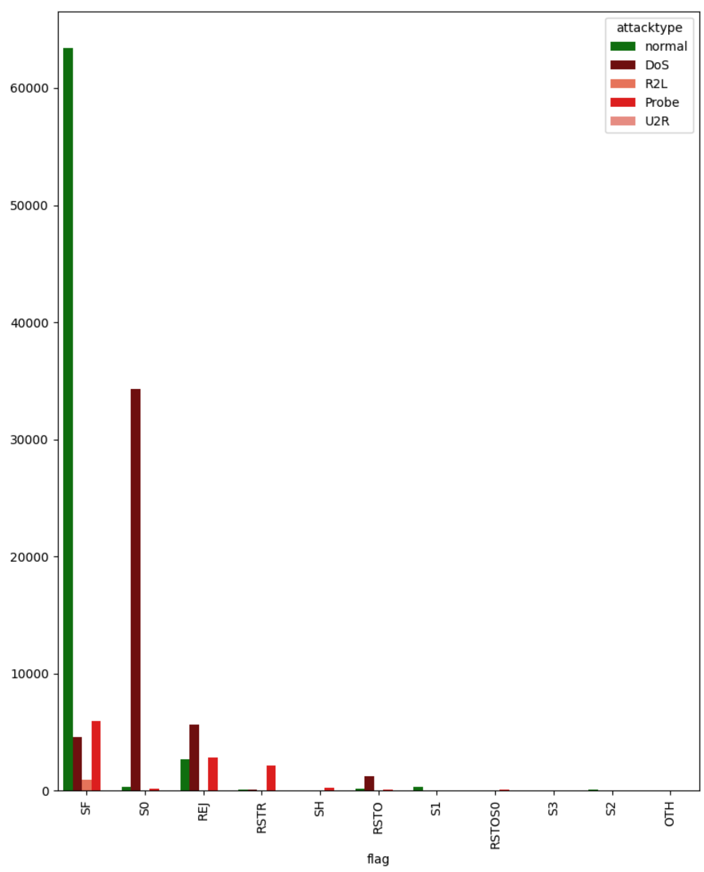
- Loggedin clearly separates classes: normal connections peak near 1, while most attack types cluster near 0.
- Count and srvcount are higher and more dispersed for DoS and Probe attacks, indicating repeated connection attempts.
- Error-rate features (serrorrate, srvserrorrate, rerrorrate) peak near 1 for DoS, while normal traffic stays near 0.
- Host-based features (dsthostcount, dsthostsrvcount) show strong separation, with attacks exhibiting higher densities at large values.
- R2L and U2R often overlap with normal in many distributions, suggesting they are harder to distinguish using single features.

2.4.4 Categorical Features

In [27]:
```
grid_ht = int(np.ceil((df_cat.shape[1]-3)/2))

plt.figure(figsize=(16,20))
i=1
for col in df_cat:
    if col not in ['attack','attacktype','attackflag']:
        plt.subplot(grid_ht, 2, i)
        sns.countplot(data=df_cat,
                      x=col,
                      hue='attacktype',
                      palette=palette)
        plt.xlabel(col)
        plt.xticks(rotation=90)
        plt.ylabel('')
        i+=1
plt.tight_layout()
plt.show()
```







Insights:

- TCP dominates across all classes, with normal and DoS traffic heavily concentrated on TCP, while ICMP is more associated with Probe attacks.
- A small subset of services (e.g., http, private) accounts for the majority of normal traffic, whereas attacks spread across more services.
- DoS traffic shows strong association with specific services and protocol combinations, indicating repetitive attack patterns.
- Flag distribution differs clearly: normal traffic is dominated by SF, while DoS and Probe attacks show higher counts of S0, REJ, and RSTR flags.

3. Hypothesis Testing

3.1 Effect of Unusually High or Low Traffic Volume (bytes transferred)

3.1.1 `srcbytes`

In [28]:
```
df1 = raw_data.copy(deep=True)
df1['attackflag'] = df1['attack'].apply(lambda x: 0 if x=='normal' else 1)
```

In [29]:
```
H0 = 'The mean srcbytes for normal connections IS EQUAL TO the mean srcbytes for attacked connect
Ha = 'The mean srcbytes for normal connections DIFFERS from the mean srcbytes for attacked connec

srcbytes_normal = df1[df1['attackflag']==0]['srcbytes']
srcbytes_attack = df1[df1['attackflag']==1]['srcbytes']

t_stat, p_value = stats.ttest_ind(srcbytes_normal, srcbytes_attack, equal_var=False)
print(f'T-statistic = {t_stat:.4f}')

if p_value < 0.05:
    # reject H0
    print(f'P-value = {p_value:.4f} < 0.05')
    print('Decision: Reject H0.')
    print('Conclusion:\n',Ha)
else:
    # Fail to reject H0
    print(f'P-value = {p_value:.4f} >= 0.05')
    print('Decision: Fail to reject H0')
    print('Conclusion:\nInsufficient evidence to conclude statistically significant difference ir
```

```
T-statistic = -1.9616
P-value = 0.0498 < 0.05
Decision: Reject H0.
Conclusion:
 The mean srcbytes for normal connections DIFFERS from the mean srcbytes for attacked connection
s.
```

3.1.2 `dstbytes`

In [30]:
```
H0 = 'The mean dstbytes for normal connections IS EQUAL TO the mean dstbytes for attacked connect
Ha = 'The mean dstbytes for normal connections DIFFERS from the mean dstbytes for attacked connec

dstbytes_normal = df1[df1['attackflag']==0]['dstbytes']
dstbytes_attack = df1[df1['attackflag']==1]['dstbytes']

t_stat, p_value = stats.ttest_ind(dstbytes_normal, srcbytes_attack, equal_var=False)
print(f'T-statistic = {t_stat:.4f}')
print(f'P-value = {p_value:.4f}')
if p_value < 0.05:
    # reject H0
    print('Decision: Reject H0.')
    print('Conclusion:\n', Ha)
else:
    # Fail to reject H0
    print('Decision: Fail to reject H0')
    print('Conclusion:\nInsufficient evidence to conclude statistically significant difference ir
```

```
T-statistic = -2.2117
P-value = 0.0270
Decision: Reject H0.
Conclusion:
 The mean dstbytes for normal connections DIFFERS from the mean dstbytes for attacked connection
s.
```

3.2 Impact of Protocol Type on Anomaly Detection

In [31]:
```
H0 = 'Attack status and protocol type are INDEPENDENT.'
Ha = 'Attack status and protocol type are ASSOCIATED.'

table = pd.crosstab(df1['attack'], df1['protocoltype'])

chi2, p_value, dof, expected_freq = stats.chi2_contingency(table)

if p_value < 0.05:
    # reject H0
    print(f'P-value = {p_value:.4f} < 0.05')
    print('Decision: Reject H0.')
    print('Conclusion:\n', Ha)
else:
    # Fail to reject H0
    print(f'P-value = {p_value:.4f} >= 0.05')
    print('Decision: Fail to reject H0')
    print('Conclusion:\nInsufficient evidence to conclude statistically significant association b
```

```
P-value = 0.0000 < 0.05
Decision: Reject H0.
Conclusion:
 Attack status and protocol type are ASSOCIATED.
```

3.3 Role of Service in Network Security

In [32]:
```python
H0 = 'Attack status and service type are INDEPENDENT.'
Ha = 'Attack status and service type are STATISTICALLY ASSOCIATED.'

table = pd.crosstab(df1['attack'], df1['service'])

chi2, p_value, dof, expected_freq = stats.chi2_contingency(table)

if p_value < 0.05:
    # reject H0
    print(f'P-value = {p_value:.4f} < 0.05')
    print('Decision: Reject H0.')
    print('Conclusion: ', Ha)
else:
    # Fail to reject H0
    print(f'P-value = {p_value:.4f} >= 0.05')
    print('Decision: Fail to reject H0')
    print('Conclusion:\nInsufficient evidence to conclude statistically significant association b
```

```
P-value = 0.0000 < 0.05
Decision: Reject H0.
Conclusion:  Attack status and service type are STATISTICALLY ASSOCIATED.
```

3.4 Connection Status and Anomalies

In [33]:
```python
X = pd.get_dummies(df1['flag'], drop_first=True, dtype=int)
X = sm.add_constant(X)
y = df1['attackflag']

model = sm.Logit(y, X)
result = model.fit_regularized(alpha=1.0)

print(result.summary())
```

```
Optimization terminated successfully    (Exit mode 0)
            Current function value: 0.3309826988360228
            Iterations: 204
            Function evaluations: 204
            Gradient evaluations: 204
                           Logit Regression Results
==============================================================================
Dep. Variable:             attackflag   No. Observations:               125973
Model:                          Logit   Df Residuals:                   125962
Method:                           MLE   Df Model:                           10
Date:                Sun, 28 Dec 2025   Pseudo R-squ.:                  0.5212
Time:                        07:59:36   Log-Likelihood:                -41666.
converged:                       True   LL-Null:                       -87016.
Covariance Type:            nonrobust   LLR p-value:                     0.000
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          1.1541      0.345      3.342      0.001       0.477       1.831
REJ             7e-16      0.346   2.02e-15      1.000      -0.678       0.678
RSTO           0.6543      0.353      1.854      0.064      -0.037       1.346
RSTOS0         3.5657      1.108      3.218      0.001       1.394       5.737
RSTR           1.5848      0.356      4.456      0.000       0.888       2.282
S0             3.4224      0.349      9.794      0.000       2.737       4.107
S1            -5.4308      0.568     -9.570      0.000      -6.543      -4.319
S2            -3.7267      0.489     -7.627      0.000      -4.684      -2.769
S3            -3.3248      0.584     -5.691      0.000      -4.470      -2.180
SF            -2.8565      0.346     -8.268      0.000      -3.534      -2.179
SH             3.3144      0.670      4.949      0.000       2.002       4.627
==============================================================================
```

In [34]:
```python
llr_p_value = result.llr_pvalue

if llr_p_value < 0.05:
    print(f"LLR p-value = {llr_p_value:.4f} < 0.05")
    print("Decision: Reject H0.")
    print("Conclusion: Error flag and attack status are STATISTICALLY ASSOCIATED.")
else:
    print(f"LLR p-value = {llr_p_value:.4f} >= 0.05")
```

```
    print("Decision: Fail to reject H0.")
    print("Conclusion:\nInsufficient evidence to conclude statistically significant association b
```

```
LLR p-value = 0.0000 < 0.05
Decision: Reject H0.
Conclusion: Error flag and attack status are STATISTICALLY ASSOCIATED.
```

3.5 Influence of Urgent Packets

In [35]:

```
urgent_flag = (df1['urgent'] > 0).astype(int)
X = sm.add_constant(pd.DataFrame(urgent_flag))
y = df['attackflag']

model = sm.Logit(y, X)
result = model.fit()

print(result.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.690751
         Iterations 4
                           Logit Regression Results
==============================================================================
Dep. Variable:             attackflag   No. Observations:               125973
Model:                          Logit   Df Residuals:                   125971
Method:                           MLE   Df Model:                            1
Date:                Sun, 28 Dec 2025   Pseudo R-squ.:               3.717e-06
Time:                        07:59:37   Log-Likelihood:                -87016.
converged:                       True   LL-Null:                       -87016.
Covariance Type:            nonrobust   LLR p-value:                    0.4212
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.1385      0.006    -24.522      0.000      -0.150      -0.127
urgent        -0.5546      0.707     -0.784      0.433      -1.941       0.831
==============================================================================
```

In [36]:

```
beta = result.params['urgent']
p_two_sided = result.pvalues['urgent']

if beta > 0:
    p_one_sided = p_two_sided / 2
else:
    p_one_sided = 1.0

alpha = 0.05

print(f"β_urgent = {beta:.4f}")
print(f"One-sided p-value = {p_one_sided:.4f}")

if p_one_sided < alpha:
    print("Decision: Reject H0.")
    print("Conclusion:\nConnections with urgent packets have higher odds of being anomalous.")
else:
    print("Decision: Fail to reject H0.")
    print("Conclusion:\nInsufficient evidence that urgent packets increase the odds of an anomaly
```

```
β_urgent = -0.5546
One-sided p-value = 1.0000
Decision: Fail to reject H0.
Conclusion:
Insufficient evidence that urgent packets increase the odds of an anomaly.
```

In [37]:

```
odds_ratio = np.exp(beta)
print(f"Odds ratio = {odds_ratio:.3f}")
if odds_ratio > 1:
    print(f'Connections with urgent packets have {odds_ratio:.2f}× higher odds of being anomalous
else:
    print(f'Connections with urgent packets have {odds_ratio:.2f}× lower odds of being anomalous
```

```
Odds ratio = 0.574
Connections with urgent packets have 0.57× lower odds of being anomalous.
```

Thus, Logistic regression provides no evidence that the presence of urgent packets increases the odds of an anomalous connection.

4. Pre-processing the Data for Modelling

4.1 Creating Preprocessing Pipelines for Linear and Tree-based Models

In [38]:
```
df.columns
```

Out[38]:
```
Index(['duration', 'protocoltype', 'service', 'flag', 'srcbytes', 'dstbytes',
       'hot', 'loggedin', 'numcompromised', 'count', 'srvcount', 'serrorrate',
       'srvserrorrate', 'rerrorrate', 'srvrerrorrate', 'samesrvrate',
       'diffsrvrate', 'srvdiffhostrate', 'dsthostcount', 'dsthostsrvcount',
       'dsthostsamesrvrate', 'dsthostdiffsrvrate', 'dsthostsamesrcportrate',
       'dsthostsrvdiffhostrate', 'dsthostserrorrate', 'dsthostsrvserrorrate',
       'dsthostrerrorrate', 'dsthostsrvrerrorrate', 'attack', 'attackflag',
       'attacktype'],
      dtype='object')
```

In [39]:
```
cat_cols = df.drop(columns=['attack','attackflag','attacktype']).select_dtypes('object').columns
num_cols = df.drop(columns=['attack','attackflag','attacktype']).select_dtypes(exclude='object')
num_nominal_cols = [col for col in num_cols if df[col].nunique()==2]
num_ordinal_cols = [col for col in num_cols if col not in num_nominal_cols]
```

In [40]:
```
cat_cols
```

Out[40]:
```
['protocoltype', 'service', 'flag']
```

In [41]:
```
num_nominal_cols
```

Out[41]:
```
['loggedin']
```

In [42]:
```
num_ordinal_cols
```

Out[42]:
```
['duration',
 'srcbytes',
 'dstbytes',
 'hot',
 'numcompromised',
 'count',
 'srvcount',
 'serrorrate',
 'srvserrorrate',
 'rerrorrate',
 'srvrerrorrate',
 'samesrvrate',
 'diffsrvrate',
 'srvdiffhostrate',
 'dsthostcount',
 'dsthostsrvcount',
 'dsthostsamesrvrate',
 'dsthostdiffsrvrate',
 'dsthostsamesrcportrate',
 'dsthostsrvdiffhostrate',
 'dsthostserrorrate',
 'dsthostsrvserrorrate',
 'dsthostrerrorrate',
 'dsthostsrvrerrorrate']
```

In [43]:
```
cat_pipeline = Pipeline([
    ('ohe', OneHotEncoder(
        handle_unknown='infrequent_if_exist',
        min_frequency=0.01
    ))
])

num_ordinal_pipeline_linear = Pipeline([
    ('log', FunctionTransformer(np.log1p, feature_names_out='one-to-one')),
    ('scale', StandardScaler())
])
```

In [44]:
```
preprocess_linear = ColumnTransformer([
    ('cat', cat_pipeline, cat_cols),
    ('num_ordinal', num_ordinal_pipeline_linear, num_ordinal_cols)
])

preprocess_tree = ColumnTransformer([
    ('cat', cat_pipeline, cat_cols)
])
```

4.2 Train-Test Split

We will essentially train two separate pipelines. The first pipeline is trained on full data, with target being `y_bin` i.e. binary classification task of Normal (0) vs Attack (1). The Second pipeline is trained on only the attack data, with target being `y_multi`, which is a multiclass classification task for detecting Attack Type.

In [45]:
```
X = df.drop(columns=['attack','attackflag','attacktype'])
y_bin = df['attackflag']
y_multi = df['attacktype']

X_train_bin, X_test_bin, y_train_bin, y_test_bin, y_train_multi_with_normals, y_test_multi_with_n
    X,
    y_bin,
    y_multi,
    test_size=0.2,
    stratify=y_bin,
    random_state=42
)
```

In [113…
```
y_train_multi_with_normals.shape
```

Out[113…
```
(100778,)
```

In [46]:
```
attacks_only_mask_train = y_train_bin == 1

X_train_multi = X_train_bin[attacks_only_mask_train]
y_train_multi = y_train_multi_with_normals[attacks_only_mask_train]
```

In [47]:
```
attacks_only_mask_test = y_test_bin == 1

X_test_multi = X_test_bin[attacks_only_mask_test]
y_test_multi = y_test_multi_with_normals[attacks_only_mask_test]
```

5. Modelling - Binary Classification (Normal/Attack)

5.1 Models

In [48]:
```
models_bin = {

    'logistic': Pipeline([
        ('preprocess', preprocess_linear),
        ('clf', LogisticRegression(
            max_iter=1000,
            class_weight='balanced',
            random_state=42,
            verbose=True,
            n_jobs=-1
        ))
    ]),

    'linear_svc': Pipeline([
        ('preprocess', preprocess_linear),
        ('clf', LinearSVC(
            class_weight='balanced',
            random_state=42,
            verbose=True
        ))
    ]),

    'rf':Pipeline([
        ('preprocess', preprocess_tree),
        ('clf', RandomForestClassifier(
            class_weight='balanced',
            random_state=42,
            n_jobs=-1,
            verbose=True
        ))
    ]),

    'adaboost':Pipeline([
        ('preprocess', preprocess_tree),
        ('clf', AdaBoostClassifier(
```

```
            estimator=DecisionTreeClassifier(),
            random_state=42
        ))
    ]),

    'gradboost':Pipeline([
        ('preprocess', preprocess_tree),
        ('clf', GradientBoostingClassifier(
            n_estimators=500,
            n_iter_no_change=10,
            random_state=42,
            verbose=True
        ))
    ]),

    'stacking':Pipeline([
        ('preprocess', preprocess_tree),
        ('clf', StackingClassifier(
            estimators=[
                (
                    'linear_svm',
                    LinearSVC(
                            class_weight='balanced',
                            random_state=42,
                            verbose=True
                    )
                ),
                (
                    'rf',
                    RandomForestClassifier(
                        n_estimators=300,
                        random_state=42,
                        n_jobs=-1,
                        verbose=True
                    )
                )
            ],
            final_estimator=LogisticRegression(max_iter=1000,
                                               random_state=42,
                                               n_jobs=-1,
                                               verbose=True),
            cv=5,
            n_jobs=-1,
            verbose=True
        ))
    ])
}
```

5.2 Distribution Grids for Randomized Search Cross-Validation (RSCV)

In [49]:
```
logreg_dist_bin = {
    'clf__C': stats.loguniform(1e-3, 1e2),
}

linear_svc_dist_bin = {
    'clf__C': stats.loguniform(1e-3, 1e2)
}

rf_dist_bin = {
    'clf__n_estimators': stats.randint(100, 500),
    'clf__max_depth': [10, 20, 30],
    'clf__min_samples_split': stats.randint(2, 20),
    'clf__min_samples_leaf': stats.randint(1, 10),
    'clf__max_features': ['sqrt', 'log2']
}

adaboost_dist_bin = {
    'clf__n_estimators': stats.randint(100, 500),
    'clf__learning_rate': stats.loguniform(1e-3, 1),
    'clf__estimator__max_depth': [1, 2, 3]
}

gradboost_dist_bin = {
    'clf__max_depth': stats.randint(2, 6),
    'clf__learning_rate': stats.loguniform(1e-3, 1),
    'clf__subsample': stats.uniform(0.6, 0.4)
}
```

```
stacking_dist_bin = {
    'clf__final_estimator__C': stats.loguniform(1e-3, 1e2)
}

param_dists_bin = {
    'logistic': logreg_dist_bin,
    'linear_svc': linear_svc_dist_bin,
    'rf': rf_dist_bin,
    'adaboost': adaboost_dist_bin,
    'gradboost': gradboost_dist_bin,
    'stacking': stacking_dist_bin
}
```

5.3 Defining Cross Validation and Scoring Functions

In [ ]:

```
skf = StratifiedKFold(
    n_splits=5,
    shuffle=True,
    random_state=42
)

scoring = {
    'accuracy':'accuracy',
    'precision':'precision',
    'recall':'recall',
    'f1':'f1'
}
```

5.4 RandomizedSearchCV

In [52]:

```
results_bin = {}

print('='*100)
t = 'RANDOMIZED SEARCH CV FOR BINARY CLASSIFICATION'
print(' '*int((100-len(t))/2),t,' '*int((100-len(t))/2))
print('='*100)

for name, model in models_bin.items():
    print('\n')
    print(f"Running RSCV for {name.upper()}...")
    rs = RandomizedSearchCV(
    estimator=model,
    param_distributions=param_dists_bin[name],
    n_iter=20,
    cv=skf,
    scoring=scoring,
    refit='f1',
    n_jobs=-1,
    random_state=42,
    verbose=3
    )

    rs.fit(X_train_bin, y_train_bin)

    results_bin[name] = {
    'best_estimator': rs.best_estimator_,
    'best_score': rs.best_score_,
    'best_params': rs.best_params_,
    'cv_results': {
        k: rs.cv_results_[k].mean()
        for k in rs.cv_results_
        if k.startswith('mean_test_')
    }}
    print('\n')
    print('-'*100)
```

```
===================================================================================================
===
                               RANDOMIZED SEARCH CV FOR BINARY CLASSIFICATION
===================================================================================================
===


Running RSCV for LOGISTIC...
Fitting 5 folds for each of 20 candidates, totalling 100 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.

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


Running RSCV for LINEAR_SVC...
Fitting 5 folds for each of 20 candidates, totalling 100 fits
[LibLinear]

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


Running RSCV for RF...
Fitting 5 folds for each of 20 candidates, totalling 100 fits
[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:    0.5s
[Parallel(n_jobs=-1)]: Done 184 tasks      | elapsed:    2.6s
[Parallel(n_jobs=-1)]: Done 330 out of 330 | elapsed:    4.8s finished

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


Running RSCV for ADABOOST...
Fitting 5 folds for each of 20 candidates, totalling 100 fits


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


Running RSCV for GRADBOOST...
Fitting 5 folds for each of 20 candidates, totalling 100 fits
      Iter       Train Loss      OOB Improve   Remaining Time 
         1           0.6102           0.7769           33.27s
         2           0.4059           0.1921           29.65s
         3           0.3320           0.0821           31.78s
         4           0.2961           0.0345           31.95s
         5           0.2793           0.0169           29.49s
         6           0.2671           0.0121           27.55s
         7           0.2583           0.0044           26.06s
         8           0.2522           0.0064           26.77s
         9           0.2484          -0.0025           26.84s
        10           0.2511           0.0118           27.59s
        20           0.2472           0.0050           24.61s


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


Running RSCV for STACKING...
Fitting 5 folds for each of 20 candidates, totalling 100 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.

----------------------------------------------------------------------------------------------------
---
```

In [53]:

```python
print('='*100)
t = 'BINARY CLASSIFICATION RESULTS'
print(' '*int((100-len(t))/2),t,' '*int((100-len(t))/2))
print('='*100)

for name, scores in results_bin.items():
    print('\n')
    print(f"{name.upper()}:")
    print('\t', 'Best F1 Score =', round(scores['best_score'],4))
    print('\t', 'Best Params:')
    for param, value in scores['best_params'].items():
        if isinstance(value, (int, float)):
            value = round(value,4)
        print('\t\t', param, ':', value)
    print('\t', 'CV Results:')
    print('\t\t', 'Mean Validation Accuracy = ', round(scores['cv_results']['mean_test_accuracy'
    print('\t\t', 'Mean Validation F1 Score = ', round(scores['cv_results']['mean_test_f1'],4))
    print('\t\t', 'Mean Validation Recall = ', round(scores['cv_results']['mean_test_recall'],4)
```

```
    print('\t\t', 'Mean Validation Precision = ', round(scores['cv_results']['mean_test_precisio
    print('\n')
    print('-'*100)
```

```
=====================================================================================
===
                                    BINARY CLASSIFICATION RESULTS
=====================================================================================
===


LOGISTIC:
        Best F1 Score = 0.9782
        Best Params:
                clf__C : 14.5282
        CV Results:
                Mean Validation Accuracy =  0.9748
                Mean Validation F1 Score =  0.9729
                Mean Validation Recall =  0.9717
                Mean Validation Precision =  0.9741


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


LINEAR_SVC:
        Best F1 Score = 0.9767
        Best Params:
                clf__C : 4.5706
        CV Results:
                Mean Validation Accuracy =  0.9774
                Mean Validation F1 Score =  0.9757
                Mean Validation Recall =  0.9746
                Mean Validation Precision =  0.9769


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


RF:
        Best F1 Score = 0.9585
        Best Params:
                clf__max_depth : 30
                clf__max_features : sqrt
                clf__min_samples_leaf : 1
                clf__min_samples_split : 6
                clf__n_estimators : 330
        CV Results:
                Mean Validation Accuracy =  0.9613
                Mean Validation F1 Score =  0.9584
                Mean Validation Recall =  0.9581
                Mean Validation Precision =  0.9587


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


ADABOOST:
        Best F1 Score = 0.9577
        Best Params:
                clf__estimator__max_depth : 2
                clf__learning_rate : 0.7025
                clf__n_estimators : 415
        CV Results:
                Mean Validation Accuracy =  0.9471
                Mean Validation F1 Score =  0.9418
                Mean Validation Recall =  0.9296
                Mean Validation Precision =  0.9557


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


GRADBOOST:
        Best F1 Score = 0.9585
        Best Params:
                clf__learning_rate : 0.6541
                clf__max_depth : 3
                clf__subsample : 0.6727
```

```
        CV Results:
                Mean Validation Accuracy =  0.956
                Mean Validation F1 Score =  0.9523
                Mean Validation Recall =  0.9461
                Mean Validation Precision =  0.9589


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


STACKING:
        Best F1 Score = 0.9586
        Best Params:
                clf__final_estimator__C : 0.0746
        CV Results:
                Mean Validation Accuracy =  0.9613
                Mean Validation F1 Score =  0.9584
                Mean Validation Recall =  0.9576
                Mean Validation Precision =  0.9592


-----------------------------------------------------------------------------------------------
---
```

In [54]:

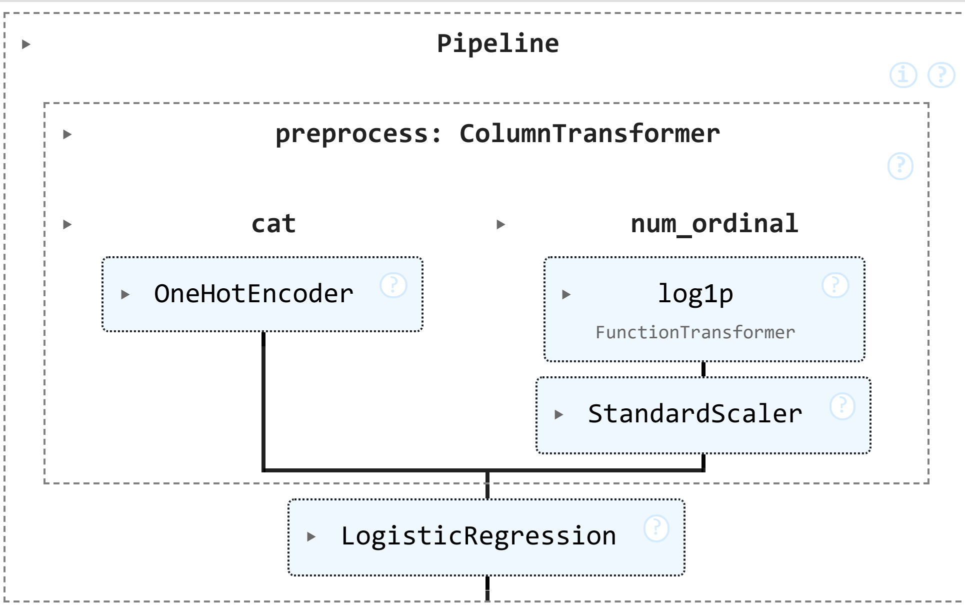
```
best_model_name_bin = max(
    results_bin,
    key=lambda name: results_bin[name]['best_score']
)

best_model_bin = results_bin[best_model_name_bin]['best_estimator']
best_score_bin = results_bin[best_model_name_bin]['best_score']

print("BEST MODEL (BINARY CLF):", best_model_name_bin)
print("Best CV F1 SCORE:", round(best_score_bin,4))
```

```
BEST MODEL (BINARY CLF): logistic
Best CV F1 SCORE: 0.9782
```

In [55]:

```
best_model_bin
```

Out[55]:



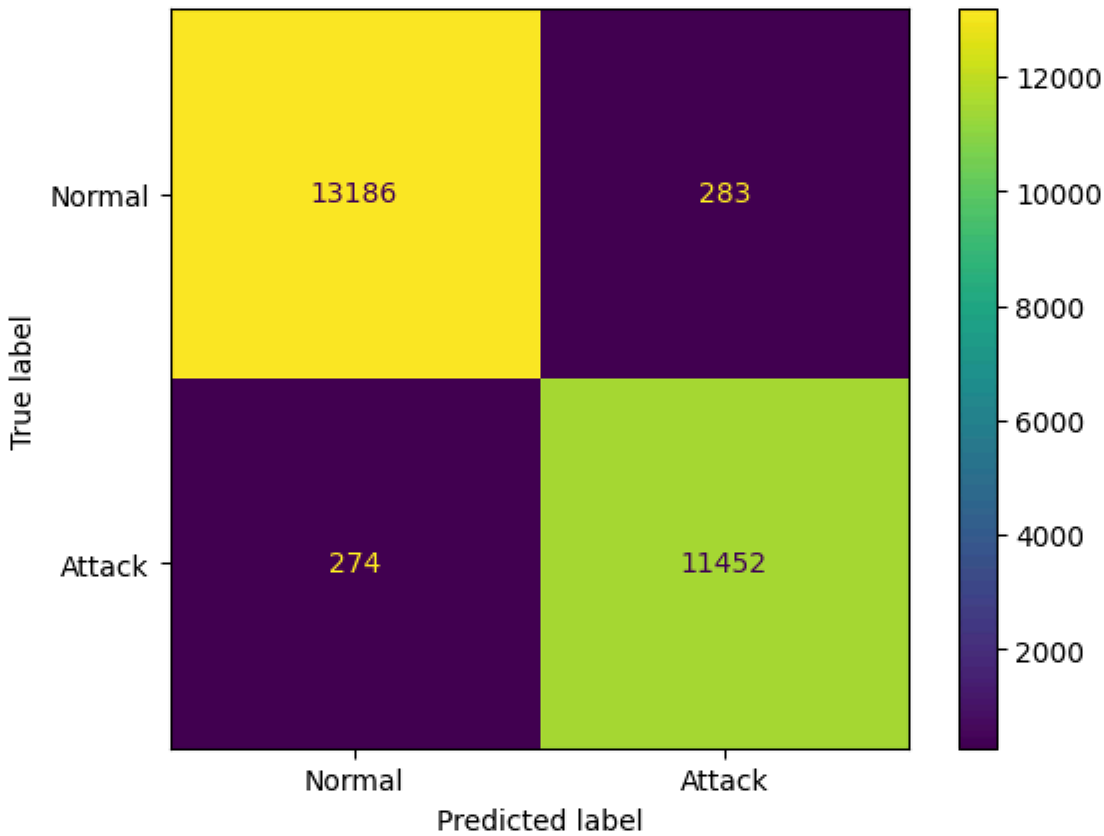
5.5 Performance of Best Model on Test Data

In [56]:

```
y_test_bin_pred = best_model_bin.predict(X_test_bin)

print(classification_report(
    y_test_bin,
    y_test_bin_pred,
    target_names=["Normal", "Attack"]
))

y_test_bin_proba = best_model_bin.predict_proba(X_test_bin)[:, 1]
roc_auc = roc_auc_score(y_test_bin, y_test_bin_proba)
print("ROC-AUC:", round(roc_auc,4))

cm = confusion_matrix(y_test_bin, y_test_bin_pred)

ConfusionMatrixDisplay(
    confusion_matrix=cm,
    display_labels=["Normal", "Attack"],
```

```
).plot(values_format='d')

plt.show()
```

```
              precision    recall  f1-score   support

      Normal       0.98      0.98      0.98     13469
      Attack       0.98      0.98      0.98     11726

    accuracy                           0.98     25195
   macro avg       0.98      0.98      0.98     25195
weighted avg       0.98      0.98      0.98     25195

ROC-AUC: 0.9969
```



Insights:

- The confusion matrix shows very low misclassification, with only 283 Normal and 274 Attack samples incorrectly predicted.
- Precision, recall, and F1-score are all 0.98 for both classes, indicating balanced and reliable classification performance.
- Overall accuracy of 98% suggests the model generalizes well without favoring either class.
- A high ROC-AUC of 0.9969 confirms excellent separability between Normal and Attack traffic.

5.6 Feature Importances

In [114…

```
ct = best_model_bin.named_steps['preprocess']
ohe = ct.named_transformers_['cat'].named_steps['ohe']
cat_input_features = ct.transformers_[0][2]
cat_feature_names = ohe.get_feature_names_out(cat_input_features)
num_feature_names = ct.transformers_[1][2]
feature_names = list(cat_feature_names) + list(num_feature_names)
feature_names
```

Out[114…

```
['protocoltype_icmp',
 'protocoltype_tcp',
 'protocoltype_udp',
 'service_domain_u',
 'service_eco_i',
 'service_ecr_i',
 'service_finger',
 'service_ftp',
 'service_ftp_data',
 'service_http',
 'service_other',
 'service_private',
 'service_smtp',
 'service_telnet',
 'service_infrequent_sklearn',
 'flag_REJ',
 'flag_RSTO',
 'flag_RSTR',
 'flag_S0',
 'flag_SF',
 'flag_infrequent_sklearn',
 'duration',
 'srcbytes',
 'dstbytes',
 'hot',
 'numcompromised',
 'count',
 'srvcount',
 'serrorrate',
 'srvserrorrate',
 'rerrorrate',
 'srvrerrorrate',
 'samesrvrate',
 'diffsrvrate',
 'srvdiffhostrate',
 'dsthostcount',
 'dsthostsrvcount',
 'dsthostsamesrvrate',
 'dsthostdiffsrvrate',
 'dsthostsamesrcportrate',
 'dsthostsrvdiffhostrate',
 'dsthostserrorrate',
 'dsthostsrvserrorrate',
 'dsthostrerrorrate',
 'dsthostsrvrerrorrate']
```

In [ ]:

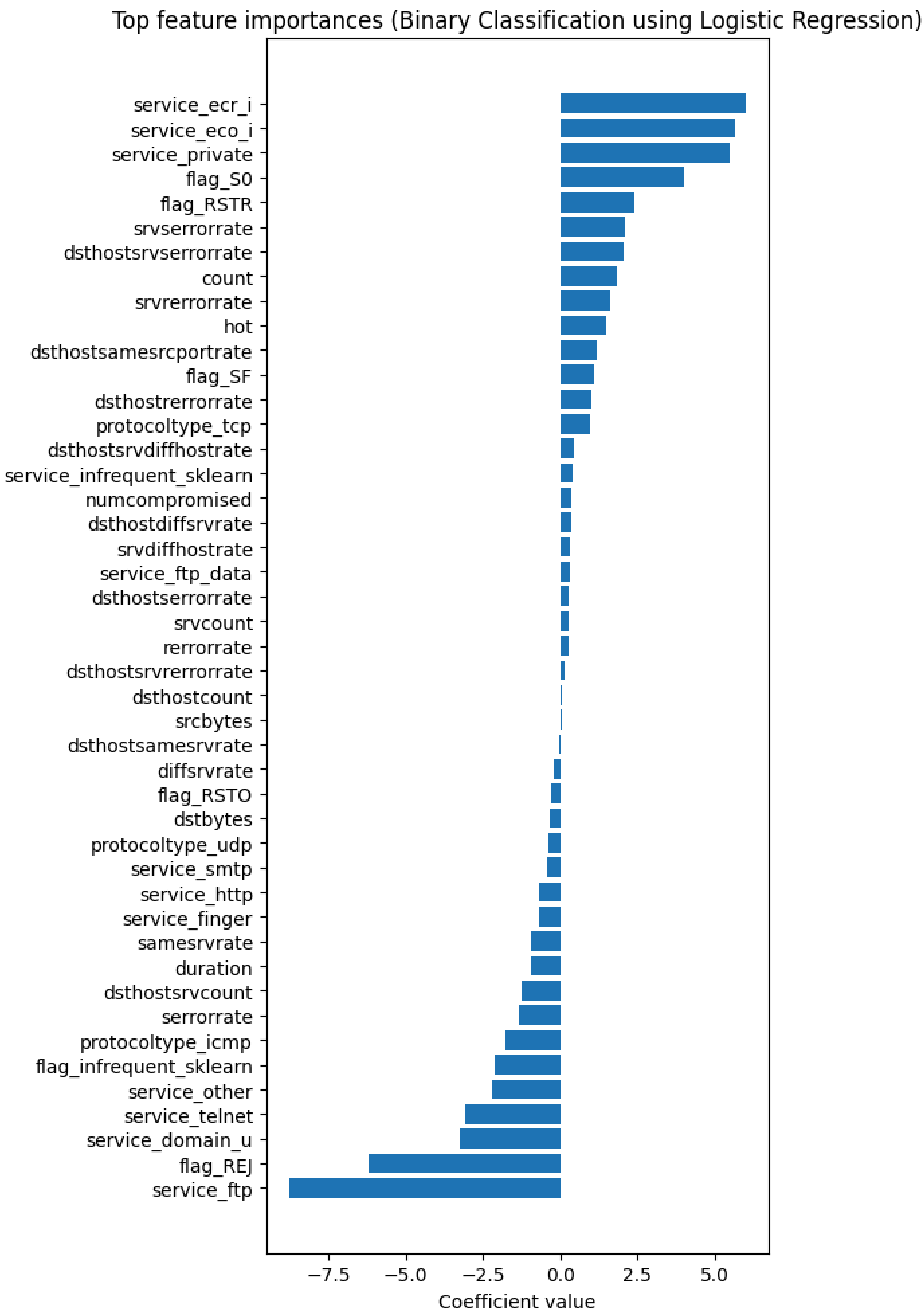
```
clf = best_model_bin.named_steps['clf']
coefs = clf.coef_[0]

importance = pd.DataFrame({
    'feature': feature_names,
    'coef': coefs,
}).sort_values('coef', ascending=True)

importance
```

Out[ ]:

	feature	coef
7	service_ftp	-8.7724
15	flag_REJ	-6.2029
3	service_domain_u	-3.2262
13	service_telnet	-3.0794
10	service_other	-2.1889
20	flag_infrequent_sklearn	-2.1359
0	protocoltype_icmp	-1.7807
28	serrorrate	-1.3448
36	dsthostsrvcount	-1.2570
21	duration	-0.9558
32	samesrvrate	-0.9302
6	service_finger	-0.6704
9	service_http	-0.6674
12	service_smtp	-0.4255
2	protocoltype_udp	-0.3601
23	dstbytes	-0.3194
16	flag_RSTO	-0.2982
33	diffsrvrate	-0.1955
37	dsthostsamesrvrate	-0.0194
22	srcbytes	0.0431
35	dsthostcount	0.0505
44	dsthostsrvrerrorrate	0.1339
30	rerrorrate	0.2587
27	srvcount	0.2858
41	dsthostserrorrate	0.2912
8	service_ftp_data	0.3125
34	srvdiffhostrate	0.3286
38	dsthostdiffsrvrate	0.3422
25	numcompromised	0.3501
14	service_infrequent_sklearn	0.4084
40	dsthostsrvdiffhostrate	0.4550
1	protocoltype_tcp	0.9737
43	dsthostrerrorrate	1.0102
19	flag_SF	1.0856
39	dsthostsamesrcportrate	1.1712
24	hot	1.5095
31	srvrerrorrate	1.6219
26	count	1.8235
42	dsthostsrvserrorrate	2.0521
29	srvserrorrate	2.1019
17	flag_RSTR	2.3824
18	flag_S0	4.0018
11	service_private	5.4823

	feature	coef
4	service_eco_i	5.6530
5	service_ecr_i	6.0069

In [61]:
```
plt.figure(figsize=(6, 10))
plt.barh(importance["feature"], importance["coef"])
plt.xlabel("Coefficient value")
plt.title("Top feature importances (Binary Classification using Logistic Regression)")
plt.tight_layout()
plt.show()
```



In [62]:
```
feature_categories = {
'basic_connection_features' : ['duration','srcbytes','dstbytes'] + [f for f in feature_names if
'content_related_features' : ['hot','numcompromised'],
'time_related_traffic_features' : ['count','serrorrate','rerrorrate','samesrvrate','diffsrvrate'
'host_based_traffic_features' : [f for f in feature_names if f[:3] == 'dst' and f != 'dstbytes']
}
```

```
assert sum([len(value) for key,value in feature_categories.items()]) == len(feature_names)
```

In [63]:
```
COEF_THRESHOLD = 1

markdown_text = f"""
**Insights:**

* Features with **Strong Positive Coefficients (>{COEF_THRESHOLD})**, indicating increased likel

    * Basic Connection Features:

        {sorted(['``'+f+'``' for f in feature_categories['basic_connection_features'] if importanc

    * Content-Related Features:

        {sorted(['``'+f+'``' for f in feature_categories['content_related_features'] if importance

    * Time-Related Traffic Features:

        {sorted(['``'+f+'``' for f in feature_categories['time_related_traffic_features'] if impor

    * Host-based Traffic Features:

        {sorted(['``'+f+'``' for f in feature_categories['host_based_traffic_features'] if importa
"""

display(Markdown(markdown_text))

markdown_text = f"""

* Features with **Strong Negative Coefficients (<{-COEF_THRESHOLD})**, indicating increased likel

    * Basic Connection Features:

        {sorted(['``'+f+'``' for f in feature_categories['basic_connection_features'] if importanc

    * Content-Related Features:

        {sorted(['``'+f+'``' for f in feature_categories['content_related_features'] if importance

    * Time-Related Traffic Features:

        {sorted(['``'+f+'``' for f in feature_categories['time_related_traffic_features'] if impor

    * Host-based Traffic Features:

        {sorted(['``'+f+'``' for f in feature_categories['host_based_traffic_features'] if importa

"""

display(Markdown(markdown_text))
```

Insights:

- Features with **Strong Positive Coefficients (>1)**, indicating increased likelihood of an **ATTACK**:
    - Basic Connection Features:

      [' `flag_RSTR` ', ' `flag_S0` ', ' `flag_SF` ', ' `service_eco_i` ', ' `service_ecr_i` ', ' `service_private` ']

    - Content-Related Features:

      [' `hot` ']

    - Time-Related Traffic Features:

      [' `count` ', ' `srvrerrorrate` ', ' `srvserrorrate` ']

    - Host-based Traffic Features:

      [' `dsthostrerrorrate` ', ' `dsthostsamesrcportrate` ', ' `dsthostsrvserrorrate` ']

- Features with **Strong Negative Coefficients (<-1)**, indicating increased likelihood of a **NORMAL ACTIVITY**:

  - Basic Connection Features:

    [' `flag_REJ` ', ' `flag_infrequent_sklearn` ', ' `protocoltype_icmp` ', ' `service_domain_u` ', ' `service_ftp` ', ' `service_other` ', ' `service_telnet` ']

  - Content-Related Features:

    []

  - Time-Related Traffic Features:

    [' `serrorrate` ']

  - Host-based Traffic Features:

    [' `dsthostsrvcount` ']

5.7 Saving the best model

In [65]:
```
dump(best_model_bin, '../artifacts/binary_model.joblib')
```

Out[65]:
```
['../artifacts/binary_model.joblib']
```

6. Multiclass Classification (Attack Type - DoS/Probe/R2L/U2R)

6.1 Models

In [66]:
```
y_train_multi.value_counts()
```

Out[66]:
```
attacktype
DoS      36822
Probe     9267
R2L        769
U2R         46
Name: count, dtype: int64
```

In [67]:
```
smote = SMOTE(sampling_strategy={'R2L':2000, 'U2R':500}, random_state=42)
```

In [68]:
```
models_multi = {

    'logistic_ovr': ImbPipeline([
        ('preprocess', preprocess_linear),
        ('smote', smote),
        ('clf', LogisticRegression(
            max_iter=2000,
            multi_class='ovr',
            class_weight='balanced',
            n_jobs=-1,
            random_state=42
        ))
    ]),

    'linear_svc_ovr': ImbPipeline([
        ('preprocess', preprocess_linear),
        ('smote', smote),
        ('clf', LinearSVC(
            class_weight='balanced',
            random_state=42
        ))
    ]),

    'rf': ImbPipeline([
        ('preprocess', preprocess_tree),
        ('smote', smote),
        ('clf', RandomForestClassifier(
            class_weight='balanced',
            n_jobs=-1,
```

```
            random_state=42
        ))
    ]),

    'adaboost': ImbPipeline([
        ('preprocess', preprocess_tree),
        ('smote', smote),
        ('clf', AdaBoostClassifier(
            estimator=DecisionTreeClassifier(),
            random_state=42
        ))
    ]),

    'gradboost': ImbPipeline([
        ('preprocess', preprocess_tree),
        ('smote', smote),
        ('clf', GradientBoostingClassifier(
            n_estimators=500,
            n_iter_no_change=10,
            random_state=42
        ))
    ])
}
```

6.2 Distribution Grids for Randomized Search Cross-Validation

In [69]:

```
logreg_dist_multi = {
    'clf__C': stats.loguniform(1e-3, 1e2)
}

linearsvc_dist_multi = {
    'clf__C': stats.loguniform(1e-3, 1e2)
}

rf_dist_multi = {
    'clf__n_estimators': stats.randint(100, 500),
    'clf__max_depth': [10, 20, 30],
    'clf__min_samples_split': stats.randint(2, 20),
    'clf__min_samples_leaf': stats.randint(1, 10),
    'clf__max_features': ['sqrt', 'log2']
}

adaboost_dist_multi = {
    'clf__n_estimators': stats.randint(100, 500),
    'clf__learning_rate': stats.loguniform(1e-3, 1),
    'clf__estimator__max_depth': [1, 2, 3]
}

gradboost_dist_multi = {
    'clf__max_depth': stats.randint(2, 6),
    'clf__learning_rate': stats.loguniform(1e-3, 1),
    'clf__subsample': stats.uniform(0.6, 0.4)
}

param_dists_multi = {
    'logistic_ovr': logreg_dist_multi,
    'linear_svc_ovr': linearsvc_dist_multi,
    'rf': rf_dist_multi,
    'adaboost': adaboost_dist_multi,
    'gradboost': gradboost_dist_multi
}
```

6.3 Defining Cross Validation and Scoring Functions

In [ ]:
```
skf = StratifiedKFold(
    n_splits=5,
    shuffle=True,
    random_state=42
)

scoring_multi = {
    'accuracy': 'accuracy',
    'f1': 'f1_macro',
    'precision': 'precision_macro',
    'recall': 'recall_macro'
}
```

6.4 RandomizedSearchCV

In [71]:
```
results_multi = {}

print('='*100)
t = 'RANDOMIZED SEARCH CV FOR MULTICLASS CLASSIFICATION'
print(' '*int((100-len(t))/2),t,' '*int((100-len(t))/2))
print('='*100)

for name, model in models_multi.items():
    print('\n')
    print(f"Running RSCV for {name.upper()}...")
    rs = RandomizedSearchCV(
        estimator=model,
        param_distributions=param_dists_multi[name],
        n_iter=10,
        cv=skf,
        scoring=scoring_multi,
        refit='f1',
        n_jobs=1,
        random_state=42,
        verbose=1
        )

    rs.fit(X_train_multi, y_train_multi)

    results_multi[name] = {
    'best_estimator': rs.best_estimator_,
    'best_score': rs.best_score_,
    'best_params': rs.best_params_,
    'cv_results': {
        k: rs.cv_results_[k].mean()
        for k in rs.cv_results_
        if k.startswith('mean_test_')
    }}
    print('\n')
    print('-'*100)
```

```
====================================================================================================
                          RANDOMIZED SEARCH CV FOR MULTICLASS CLASSIFICATION
====================================================================================================


Running RSCV for LOGISTIC_OVR...
Fitting 5 folds for each of 10 candidates, totalling 50 fits


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


Running RSCV for LINEAR_SVC_OVR...
Fitting 5 folds for each of 10 candidates, totalling 50 fits


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


Running RSCV for RF...
Fitting 5 folds for each of 10 candidates, totalling 50 fits


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


Running RSCV for ADABOOST...
Fitting 5 folds for each of 10 candidates, totalling 50 fits


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


Running RSCV for GRADBOOST...
Fitting 5 folds for each of 10 candidates, totalling 50 fits


----------------------------------------------------------------------------------------------------
```

In [72]:

```
print('='*100)
t = 'MULTICLASS CLASSIFICATION RESULTS'
print(' '*int((100-len(t))/2),t,' '*int((100-len(t))/2))
print('='*100)

for name, scores in results_multi.items():
    print('\n')
    print(f"{name.upper()}:")
    # print('\t', scores['best_estimator'])
    print('\t', 'Best F1 Score =', round(scores['best_score'],4))
    print('\t', 'Best Params:')
    for param, value in scores['best_params'].items():
        if isinstance(value, (int, float)):
            value = round(value,4)
        print('\t\t', param, ':', value)
    print('\t', 'CV Results:')
    print('\t\t', 'Mean Validation Accuracy = ', round(scores['cv_results']['mean_test_accuracy'
    print('\t\t', 'Mean Validation F1 Score = ', round(scores['cv_results']['mean_test_f1'],4))
    print('\t\t', 'Mean Validation Recall = ', round(scores['cv_results']['mean_test_recall'],4)
    print('\t\t', 'Mean Validation Precision = ', round(scores['cv_results']['mean_test_precisio
    print('\n')
    print('-'*100)
```

```
==================================================================================================
===
                                  MULTICLASS CLASSIFICATION RESULTS
==================================================================================================
===


LOGISTIC_OVR:
         Best F1 Score = 0.9217
         Best Params:
                 clf__C : 56.6985
         CV Results:
                 Mean Validation Accuracy =  0.9945
                 Mean Validation F1 Score =  0.8967
                 Mean Validation Recall =  0.9585
                 Mean Validation Precision =  0.8654


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


LINEAR_SVC_OVR:
         Best F1 Score = 0.931
         Best Params:
                 clf__C : 0.9847
         CV Results:
                 Mean Validation Accuracy =  0.9969
                 Mean Validation F1 Score =  0.9166
                 Mean Validation Recall =  0.9508
                 Mean Validation Precision =  0.8995


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


RF:
         Best F1 Score = 0.8006
         Best Params:
                 clf__max_depth : 30
                 clf__max_features : log2
                 clf__min_samples_leaf : 5
                 clf__min_samples_split : 3
                 clf__n_estimators : 443
         CV Results:
                 Mean Validation Accuracy =  0.9308
                 Mean Validation F1 Score =  0.7912
                 Mean Validation Recall =  0.8759
                 Mean Validation Precision =  0.7584


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


ADABOOST:
         Best F1 Score = 0.8528
         Best Params:
                 clf__estimator__max_depth : 3
                 clf__learning_rate : 0.2183
                 clf__n_estimators : 120
         CV Results:
                 Mean Validation Accuracy =  0.9077
                 Mean Validation F1 Score =  0.7252
                 Mean Validation Recall =  0.7041
                 Mean Validation Precision =  0.78


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


GRADBOOST:
         Best F1 Score = 0.8536
         Best Params:
                 clf__learning_rate : 0.0133
                 clf__max_depth : 2
                 clf__subsample : 0.6734
```

```
        CV Results:
                Mean Validation Accuracy =  0.9277
                Mean Validation F1 Score =  0.7414
                Mean Validation Recall =  0.7446
                Mean Validation Precision =  0.7784


-----------------------------------------------------------------------------------------------
---
```

In [73]:

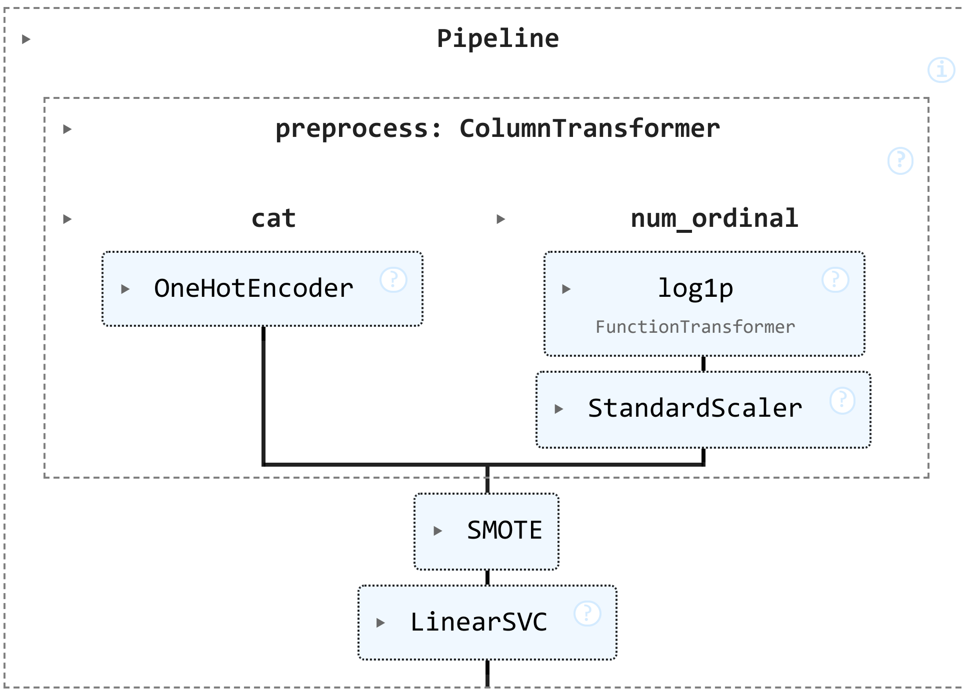
```python
best_model_multi_name = max(
    results_multi,
    key=lambda name: results_multi[name]['best_score']
)

best_model_multi = results_multi[best_model_multi_name]['best_estimator']
best_score_multi = results_multi[best_model_multi_name]['best_score']

print("BEST MODEL (MULTICLASS CLF):", best_model_multi_name)
print("BEST CV F1 SCORE:", round(best_score_multi,4))
```

```
BEST MODEL (MULTICLASS CLF): linear_svc_ovr
BEST CV F1 SCORE: 0.931
```

In [74]:

```python
best_model_multi
```

Out[74]:

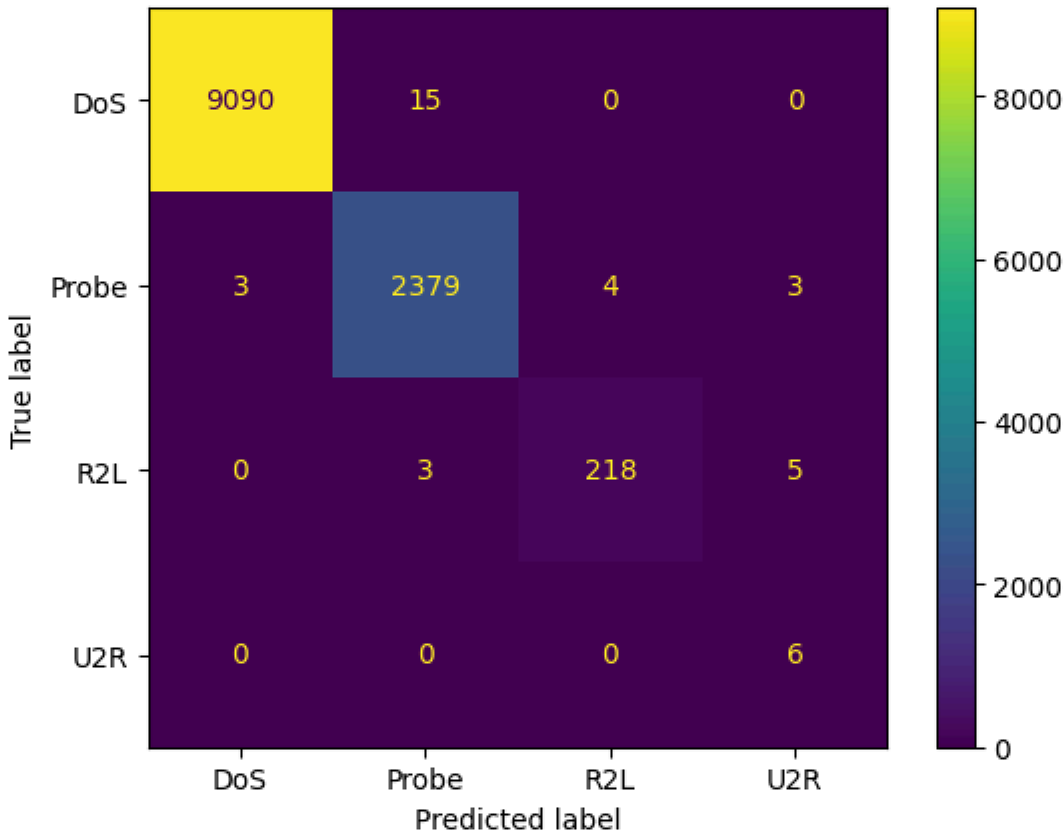


6.5 Performance of Best Model on Test Data

In [75]:

```python
y_test_multi_pred = best_model_multi.predict(X_test_multi)

print(classification_report(
    y_test_multi,
    y_test_multi_pred
))

cm = confusion_matrix(y_test_multi, y_test_multi_pred)

ConfusionMatrixDisplay(
    confusion_matrix=cm,
    display_labels=np.unique(y_test_multi)
).plot(values_format='d')

plt.show()
```

```
              precision    recall  f1-score   support

         DoS       1.00      1.00      1.00      9105
       Probe       0.99      1.00      0.99      2389
         R2L       0.98      0.96      0.97       226
         U2R       0.43      1.00      0.60         6

    accuracy                           1.00     11726
   macro avg       0.85      0.99      0.89     11726
weighted avg       1.00      1.00      1.00     11726
```



Insights from Classification Report:

- DoS and Probe achieve near-perfect precision, recall, and F1-score with very large support, indicating extremely reliable detection.
- R2L shows slightly lower recall (0.96), meaning some R2L attacks are missed, but overall performance remains high.
- U2R has perfect recall but very low precision (0.43), indicating many false positives despite detecting all true U2R samples.
- Macro averages are noticeably lower than weighted averages, highlighting the impact of severe class imbalance.

Insights from Confusion Matrix:

- DoS is classified with extremely high accuracy, with only 15 misclassifications out of 9,105 total DoS samples.
- Probe shows strong performance, but minor confusion exists with R2L and U2R, indicating some overlap in attack behavior.
- R2L has the weakest performance relative to its size, with noticeable misclassification into U2R and Probe.
- U2R has perfect precision in this matrix, but the very small sample size (6) limits confidence in robustness.
- Overall errors are rare and mostly occur between Probe, R2L, and U2R, suggesting these classes are harder to separate.
- The confusion matrix is highly imbalanced, so accuracy alone may be misleading without recall and F1-score analysis.

6.6 Feature Importances

6.6.1 Extracting Feature Names Used in the model

In [76]:
```
ct = best_model_multi.named_steps['preprocess']
ohe = ct.named_transformers_['cat'].named_steps['ohe']
cat_input_features = ct.transformers_[0][2]
cat_feature_names = ohe.get_feature_names_out(cat_input_features)
num_feature_names = ct.transformers_[1][2]
feature_names = list(cat_feature_names) + list(num_feature_names)
feature_names
```

```
Out[76]: ['protocoltype_icmp',
 'protocoltype_tcp',
 'protocoltype_udp',
 'service_Z39_50',
 'service_auth',
 'service_bgp',
 'service_courier',
 'service_eco_i',
 'service_ecr_i',
 'service_finger',
 'service_ftp',
 'service_ftp_data',
 'service_http',
 'service_imap4',
 'service_iso_tsap',
 'service_nnsp',
 'service_other',
 'service_private',
 'service_telnet',
 'service_uucp',
 'service_uucp_path',
 'service_vmnet',
 'service_whois',
 'service_infrequent_sklearn',
 'flag_REJ',
 'flag_RSTO',
 'flag_RSTR',
 'flag_S0',
 'flag_SF',
 'flag_infrequent_sklearn',
 'duration',
 'srcbytes',
 'dstbytes',
 'hot',
 'numcompromised',
 'count',
 'srvcount',
 'serrorrate',
 'srvserrorrate',
 'rerrorrate',
 'srvrerrorrate',
 'samesrvrate',
 'diffsrvrate',
 'srvdiffhostrate',
 'dsthostcount',
 'dsthostsrvcount',
 'dsthostsamesrvrate',
 'dsthostdiffsrvrate',
 'dsthostsamesrcportrate',
 'dsthostsrvdiffhostrate',
 'dsthostserrorrate',
 'dsthostsrvserrorrate',
 'dsthostrerrorrate',
 'dsthostsrvrerrorrate']
```

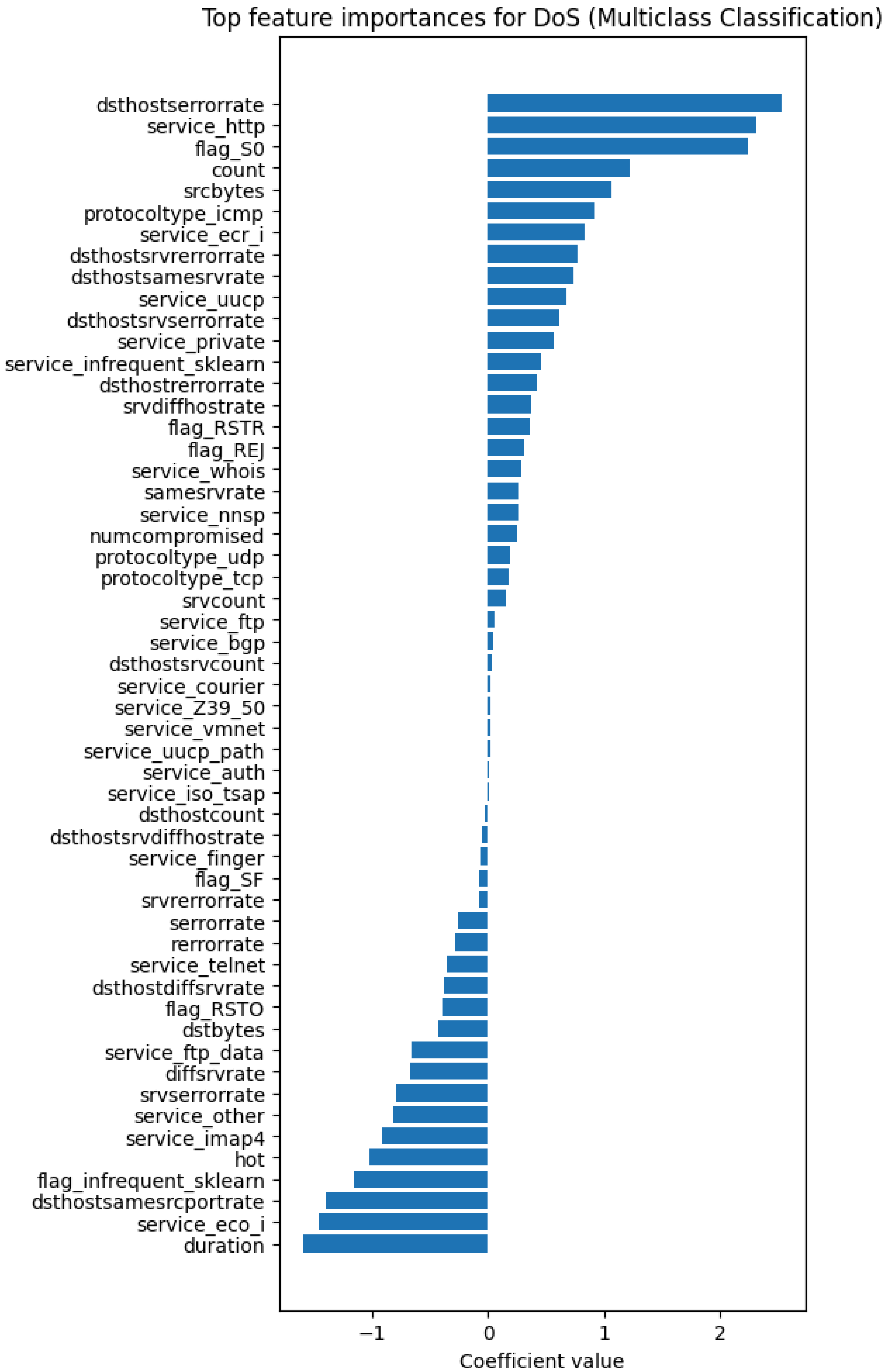
```
In [77]: feature_categories = {
'basic_connection_features' : ['duration','srcbytes','dstbytes'] + [f for f in feature_names if
'content_related_features' : ['hot','numcompromised'],
'time_related_traffic_features' : ['count','serrorrate','rerrorrate','samesrvrate','diffsrvrate'
'host_based_traffic_features' : [f for f in feature_names if f[:3] == 'dst' and f != 'dstbytes']
}

assert sum([len(value) for key,value in feature_categories.items()]) == len(feature_names)
```

```
In [87]: def feature_imp(attack, COEF_THRESHOLD=0):
    clf = best_model_multi.named_steps['clf']
    class_idx = list(clf.classes_).index(attack)
    coefs = clf.coef_[class_idx]

    imp = (
        pd.DataFrame({
            "feature": feature_names,
            "coef": coefs
        })
        .sort_values("coef", ascending=True)
    )

    plt.figure(figsize=(6, 10))
```

```python
    plt.barh(imp["feature"], imp["coef"])
    plt.xlabel("Coefficient value")
    plt.title(f"Top feature importances for {attack} (Multiclass Classification)")
    plt.tight_layout()
    plt.show()

    markdown_text = f"""
**Insights:**

* Features with **Strong Positive Coefficients (>{COEF_THRESHOLD})**, indicating increased likel

    * Basic Connection Features:

        {sorted(['``'+f+'``' for f in feature_categories['basic_connection_features'] if imp.loc[in

    * Content-Related Features:

        {sorted(['``'+f+'``' for f in feature_categories['content_related_features'] if imp.loc[im

    * Time-Related Traffic Features:

        {sorted(['``'+f+'``' for f in feature_categories['time_related_traffic_features'] if imp.lo

    * Host-based Traffic Features:

        {sorted(['``'+f+'``' for f in feature_categories['host_based_traffic_features'] if imp.loc
"""

    display(Markdown(markdown_text))
```

6.6.2 DoS

In [89]:
```python
feature_imp('DoS',0.5)
```


Top feature importances for DoS (Multiclass Classification)
dsthostserrorrate
service_http
flag_S0
count
srcbytes
protocoltype_icmp
service_ecr_i
dsthostsrvrerrorrate
dsthostsamesrvrate
service_uucp
dsthostsrvserrorrate
service_private
service_infrequent_sklearn
dsthostrerrorrate
srvdiffhostrate
flag_RSTR
flag_REJ
service_whois
samesrvrate
service_nnsp
numcompromised
protocoltype_udp
protocoltype_tcp
srvcount
service_ftp
service_bgp
dsthostsrvcount
service_courier
service_Z39_50
service_vmnet
service_uucp_path
service_auth
service_iso_tsap
dsthostcount
dsthostsrvdiffhostrate
service_finger
flag_SF
srvrerrorrate
serrorrate
rerrorrate
service_telnet
dsthostdiffsrvrate
flag_RSTO
dstbytes
service_ftp_data
diffsrvrate
srvserrorrate
service_other
service_imap4
hot
flag_infrequent_sklearn
dsthostsamesrcportrate
service_eco_i
duration
−1
0
1
2
Coefficient value

Insights:

- Features with **Strong Positive Coefficients (>0.5)**, indicating increased likelihood of a **DOS ATTACK**:
  - Basic Connection Features:

    [' `flag_S0` ', ' `protocoltype_icmp` ', ' `service_ecr_i` ', ' `service_http` ', ' `service_private` ', ' `service_uucp` ', ' `srcbytes` ']
  - Content-Related Features:

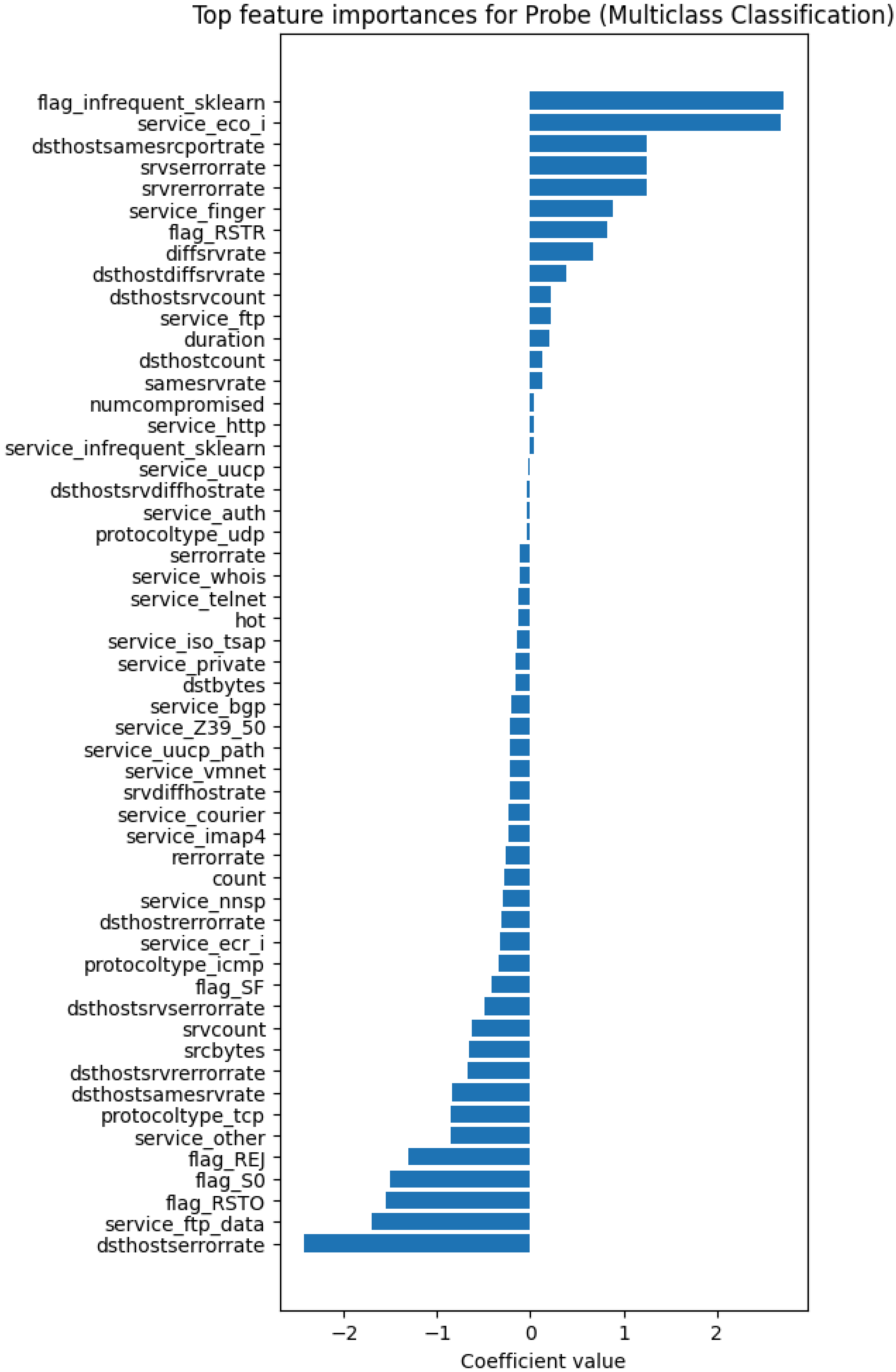
    []
  - Time-Related Traffic Features:

    [' `count` ']
  - Host-based Traffic Features:

    [' `dsthostsamesrvrate` ', ' `dsthostserrorrate` ', ' `dsthostsrvrerrorrate` ', ' `dsthostsrvserrorrate` ']

6.6.3 Probe

In [90]:
```
feature_imp('Probe',0.5)
```


Top feature importances for Probe (Multiclass Classification)
flag_infrequent_sklearn
service_eco_i
dsthostsamesrcportrate
srvserrorrate
srvrerrorrate
service_finger
flag_RSTR
diffsrvrate
dsthostdiffsrvrate
dsthostsrvcount
service_ftp
duration
dsthostcount
samesrvrate
numcompromised
service_http
service_infrequent_sklearn
service_uucp
dsthostsrvdiffhostrate
service_auth
protocoltype_udp
serrorrate
service_whois
service_telnet
hot
service_iso_tsap
service_private
dstbytes
service_bgp
service_Z39_50
service_uucp_path
service_vmnet
srvdiffhostrate
service_courier
service_imap4
rerrorrate
count
service_nnsp
dsthostrerrorrate
service_ecr_i
protocoltype_icmp
flag_SF
dsthostsrvserrorrate
srvcount
srcbytes
dsthostsrvrerrorrate
dsthostsamesrvrate
protocoltype_tcp
service_other
flag_REJ
flag_S0
flag_RSTO
service_ftp_data
dsthostserrorrate
−2
−1
0
1
2
Coefficient value

Insights:

- Features with **Strong Positive Coefficients (>0.5)**, indicating increased likelihood of a **PROBE ATTACK**:
    - Basic Connection Features:

      ['`flag_RSTR`', '`flag_infrequent_sklearn`', '`service_eco_i`', '`service_finger`']
    - Content-Related Features:

      []
    - Time-Related Traffic Features:

      ['`diffsrvrate`', '`srvrerrorrate`', '`srvserrorrate`']
    - Host-based Traffic Features:

      ['`dsthostsamesrcportrate`']

6.6.4 R2L

In [91]:
```
feature_imp('R2L',0.5)
```


Top feature importances for R2L (Multiclass Classification)
dsthostserrorrate
service_imap4
flag_RSTO
service_other
service_ftp_data
dsthostsrvserrorrate
dsthostsamesrvrate
flag_RSTR
flag_SF
protocoltype_tcp
service_infrequent_sklearn
hot
srcbytes
dsthostcount
duration
dsthostsrvrerrorrate
srvdiffhostrate
dsthostdiffsrvrate
service_courier
service_Z39_50
service_vmnet
service_uucp_path
rerrorrate
service_nnsp
service_uucp
service_bgp
service_iso_tsap
service_whois
numcompromised
service_finger
dstbytes
dsthostsrvdiffhostrate
dsthostrerrorrate
dsthostsrvcount
service_auth
srvrerrorrate
diffsrvrate
srvcount
service_eco_i
samesrvrate
service_ftp
flag_REJ
dsthostsamesrcportrate
serrorrate
service_private
flag_infrequent_sklearn
srvserrorrate
service_ecr_i
protocoltype_icmp
count
protocoltype_udp
service_telnet
service_http
flag_S0
−4
−2
0
2
Coefficient value

Insights:

- Features with **Strong Positive Coefficients (>0.5)**, indicating increased likelihood of a **R2L ATTACK**:

  - Basic Connection Features:

    [' `flag_RSTO` ', ' `flag_RSTR` ', ' `flag_SF` ', ' `protocoltype_tcp` ', ' `service_ftp_data` ', ' `service_imap4` ', ' `service_other` ']

  - Content-Related Features:

    []

  - Time-Related Traffic Features:

    []

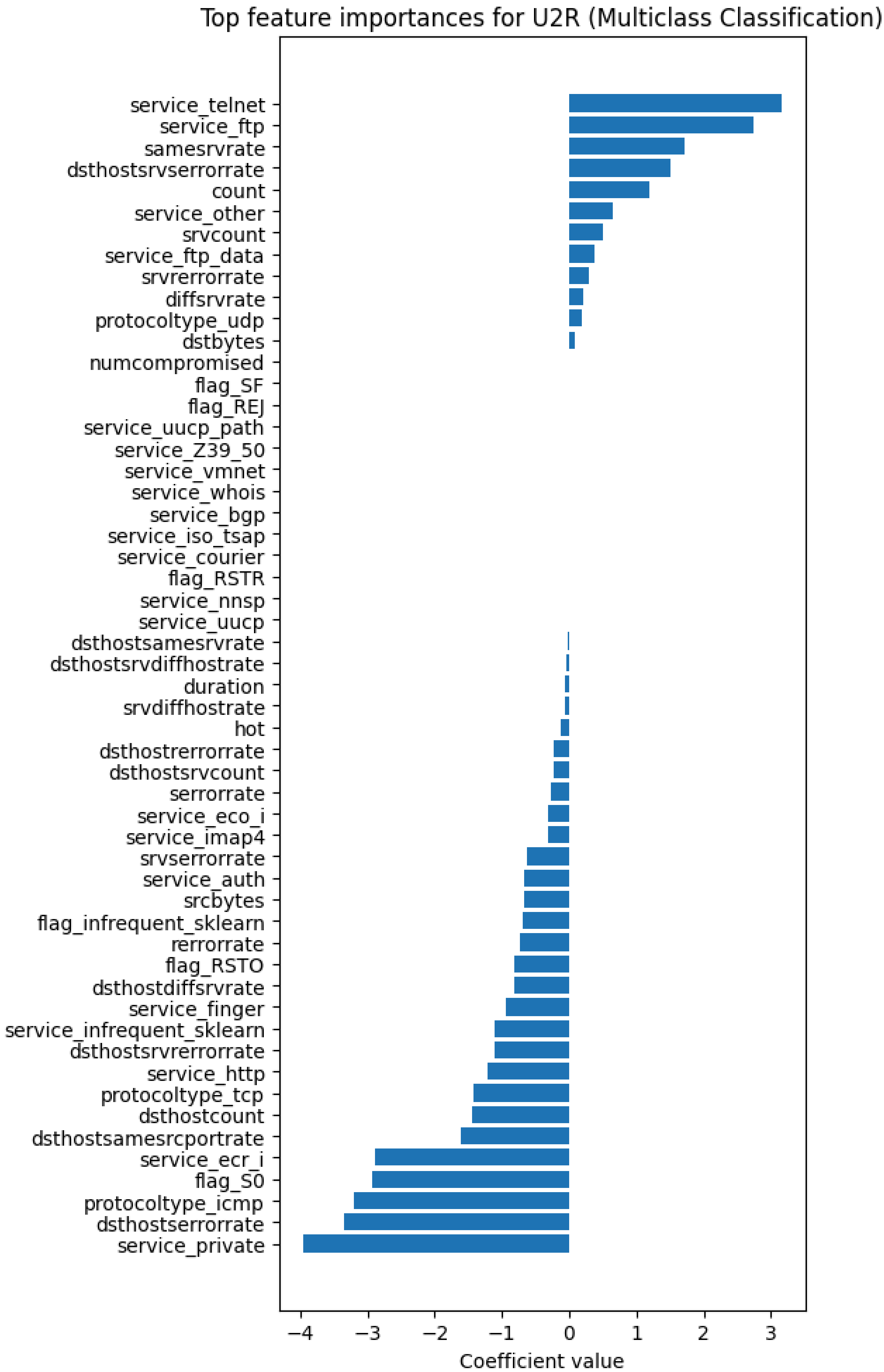
  - Host-based Traffic Features:

    [' `dsthostsamesrvrate` ', ' `dsthostserrorrate` ', ' `dsthostsrvserrorrate` ']

6.6.5 U2R

In [93]:

```
feature_imp('U2R',0.5)
```


Top feature importances for U2R (Multiclass Classification)
service_telnet
service_ftp
samesrvrate
dsthostsrvserrorrate
count
service_other
srvcount
service_ftp_data
srvrerrorrate
diffsrvrate
protocoltype_udp
dstbytes
numcompromised
flag_SF
flag_REJ
service_uucp_path
service_Z39_50
service_vmnet
service_whois
service_bgp
service_iso_tsap
service_courier
flag_RSTR
service_nnsp
service_uucp
dsthostsamesrvrate
dsthostsrvdiffhostrate
duration
srvdiffhostrate
hot
dsthostrerrorrate
dsthostsrvcount
serrorrate
service_eco_i
service_imap4
srvserrorrate
service_auth
srcbytes
flag_infrequent_sklearn
rerrorrate
flag_RSTO
dsthostdiffsrvrate
service_finger
service_infrequent_sklearn
dsthostsrvrerrorrate
service_http
protocoltype_tcp
dsthostcount
dsthostsamesrcportrate
service_ecr_i
flag_S0
protocoltype_icmp
dsthostserrorrate
service_private
−4
−3
−2
−1
0
1
2
3
Coefficient value

Insights:

- Features with **Strong Positive Coefficients (>0.5)**, indicating increased likelihood of a **U2R ATTACK**:
  - Basic Connection Features:

    [' `service_ftp` ', ' `service_other` ', ' `service_telnet` ']
  - Content-Related Features:

    []
  - Time-Related Traffic Features:

    [' `count` ', ' `samesrvrate` ']
  - Host-based Traffic Features:

    [' `dsthostsrvserrorrate` ']

6.7 Saving the best model

In [94]:
```
best_model_multi.named_steps
```

Out[94]:
```
{'preprocess': ColumnTransformer(transformers=[('cat',
                                  Pipeline(steps=[('ohe',
                                                   OneHotEncoder(handle_unknown='infrequent_if_e
xist',
                                                                 min_frequency=0.01))]),
                                  ['protocoltype', 'service', 'flag']),
                                 ('num_ordinal',
                                  Pipeline(steps=[('log',
                                                   FunctionTransformer(feature_names_out='one-to
-one',
                                                                       func=<ufunc 'log1p'>)),
                                                  ('scale', StandardScaler())]),
                                  ['duration', 'srcbytes', 'dstbytes', 'hot',
                                   'numcompromised', 'count', 'srvcount',
                                   'serrorrate', 'srvserrorrate', 'rerrorrate',
                                   'srvrerrorrate', 'samesrvrate', 'diffsrvrate',
                                   'srvdiffhostrate', 'dsthostcount',
                                   'dsthostsrvcount', 'dsthostsamesrvrate',
                                   'dsthostdiffsrvrate',
                                   'dsthostsamesrcportrate',
                                   'dsthostsrvdiffhostrate', 'dsthostserrorrate',
                                   'dsthostsrvserrorrate', 'dsthostrerrorrate',
                                   'dsthostsrvrerrorrate'])]),
 'smote': SMOTE(random_state=42, sampling_strategy={'R2L': 2000, 'U2R': 500}),
 'clf': LinearSVC(C=np.float64(0.9846738873614566), class_weight='balanced',
          random_state=42)}
```

In [95]:
```
preprocessor_multi = best_model_multi.named_steps['preprocess']
classifier_multi = best_model_multi.named_steps['clf']
```

In [96]:
```
deploy_pipeline = Pipeline(steps=[
    ('preprocess', preprocessor_multi),
    ('classifier', classifier_multi)
])
```

In [97]:
```
dump(deploy_pipeline, "../artifacts/multiclass_model.joblib")
```

Out[97]:
```
['../artifacts/multiclass_model.joblib']
```