```
# Install necessary libraries
!pip install shap lime scikit-learn imbalanced-learn tensorflow pandas pyarrow polars

import os
import json
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.metrics import classification_report, roc_auc_score, precision_recall_fscore_support, roc_curve
from sklearn.ensemble import IsolationForest
from sklearn.inspection import permutation_importance
import shap
import tensorflow as tf
from tensorflow import keras

```

```
Requirement already satisfied: shap in /usr/local/lib/python3.12/dist-packages (0.48.0)
Requirement already satisfied: lime in /usr/local/lib/python3.12/dist-packages (0.2.0.1)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.12/dist-packages (1.6.1)
Requirement already satisfied: imbalanced-learn in /usr/local/lib/python3.12/dist-packages (0.14.0)
Requirement already satisfied: tensorflow in /usr/local/lib/python3.12/dist-packages (2.19.0)
Requirement already satisfied: pandas in /usr/local/lib/python3.12/dist-packages (2.2.2)
Requirement already satisfied: pyarrow in /usr/local/lib/python3.12/dist-packages (18.1.0)
Requirement already satisfied: polars in /usr/local/lib/python3.12/dist-packages (1.25.2)
Requirement already satisfied: numpy in /usr/local/lib/python3.12/dist-packages (from shap) (2.0.2)
Requirement already satisfied: scipy in /usr/local/lib/python3.12/dist-packages (from shap) (1.16.1)
Requirement already satisfied: tqdm>=4.27.0 in /usr/local/lib/python3.12/dist-packages (from shap) (4.67.1)
Requirement already satisfied: packaging>20.9 in /usr/local/lib/python3.12/dist-packages (from shap) (25.0)
Requirement already satisfied: slicer==0.0.8 in /usr/local/lib/python3.12/dist-packages (from shap) (0.0.8)
Requirement already satisfied: numba>=0.54 in /usr/local/lib/python3.12/dist-packages (from shap) (0.60.0)
Requirement already satisfied: cloudpickle in /usr/local/lib/python3.12/dist-packages (from shap) (3.1.1)
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.12/dist-packages (from shap) (4.15.0)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.12/dist-packages (from lime) (3.10.0)
Requirement already satisfied: scikit-image>=0.12 in /usr/local/lib/python3.12/dist-packages (from lime) (0.25.2)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.12/dist-packages (from scikit-learn) (1.5.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.12/dist-packages (from scikit-learn) (3.6.0)
Requirement already satisfied: absl-py>=1.0.0 in /usr/local/lib/python3.12/dist-packages (from tensorflow) (1.4.0)
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Requirement already satisfied: flatbuffers>=24.3.25 in /usr/local/lib/python3.12/dist-packages (from tensorflow) (25.2.10)
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Requirement already satisfied: google-pasta>=0.1.1 in /usr/local/lib/python3.12/dist-packages (from tensorflow) (0.2.0)
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Requirement already satisfied: opt-einsum>=2.3.2 in /usr/local/lib/python3.12/dist-packages (from tensorflow) (3.4.0)
Requirement already satisfied: protobuf!=4.21.0,!=4.21.1,!=4.21.2,!=4.21.3,!=4.21.4,!=4.21.5,<6.0.0dev,>=3.20.3 in /usr/local/lib
Requirement already satisfied: requests<3,>=2.21.0 in /usr/local/lib/python3.12/dist-packages (from tensorflow) (2.32.4)
Requirement already satisfied: setuptools in /usr/local/lib/python3.12/dist-packages (from tensorflow) (75.2.0)
Requirement already satisfied: six>=1.12.0 in /usr/local/lib/python3.12/dist-packages (from tensorflow) (1.17.0)
Requirement already satisfied: termcolor>=1.1.0 in /usr/local/lib/python3.12/dist-packages (from tensorflow) (3.1.0)
Requirement already satisfied: wrapt>=1.11.0 in /usr/local/lib/python3.12/dist-packages (from tensorflow) (1.17.3)
Requirement already satisfied: grpcio<2.0,>=1.24.3 in /usr/local/lib/python3.12/dist-packages (from tensorflow) (1.74.0)
Requirement already satisfied: tensorboard~=2.19.0 in /usr/local/lib/python3.12/dist-packages (from tensorflow) (2.19.0)
Requirement already satisfied: keras>=3.5.0 in /usr/local/lib/python3.12/dist-packages (from tensorflow) (3.10.0)
Requirement already satisfied: h5py>=3.11.0 in /usr/local/lib/python3.12/dist-packages (from tensorflow) (3.14.0)
Requirement already satisfied: ml-dtypes<1.0.0,>=0.5.1 in /usr/local/lib/python3.12/dist-packages (from tensorflow) (0.5.3)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.12/dist-packages (from pandas) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.12/dist-packages (from pandas) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.12/dist-packages (from pandas) (2025.2)
Requirement already satisfied: wheel<1.0,>=0.23.0 in /usr/local/lib/python3.12/dist-packages (from astunparse>=1.6.0->tensorflow)
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Requirement already satisfied: llvmlite<0.44,>=0.43.0dev0 in /usr/local/lib/python3.12/dist-packages (from numba>=0.54->shap) (0.
Requirement already satisfied: charset_normalizer<4,>=2 in /usr/local/lib/python3.12/dist-packages (from requests<3,>=2.21.0->ten
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Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.12/dist-packages (from requests<3,>=2.21.0->tensorflo
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Requirement already satisfied: networkx>=3.0 in /usr/local/lib/python3.12/dist-packages (from scikit-image>=0.12->lime) (3.5)
Requirement already satisfied: pillow>=10.1 in /usr/local/lib/python3.12/dist-packages (from scikit-image>=0.12->lime) (11.3.0)
Requirement already satisfied: imageio!=2.35.0,>=2.33 in /usr/local/lib/python3.12/dist-packages (from scikit-image>=0.12->lime)
Requirement already satisfied: tifffile>=2022.8.12 in /usr/local/lib/python3.12/dist-packages (from scikit-image>=0.12->lime) (20
Requirement already satisfied: lazy-loader>=0.4 in /usr/local/lib/python3.12/dist-packages (from scikit-image>=0.12->lime) (0.4)
Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.12/dist-packages (from tensorboard~=2.19.0->tensorflow)
Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0 in /usr/local/lib/python3.12/dist-packages (from tensorboard
Requirement already satisfied: werkzeug>=1.0.1 in /usr/local/lib/python3.12/dist-packages (from tensorboard~=2.19.0->tensorflow)
```

Loading the CIC-IoT 2023 Dataset

```python
# Load the CIC-IoT 2023 dataset
DATA_PATH_IOT_1 = "/content/drive/MyDrive/Datasets/CIC-IoT 2023/cic-iot_2023_1.csv"
DATA_PATH_IOT_2 = "/content/drive/MyDrive/Datasets/CIC-IoT 2023/cic-iot_2023_2.csv"
DATA_PATH_IOT_3 = "/content/drive/MyDrive/Datasets/CIC-IoT 2023/cic-iot_2023_3.csv"
DATA_PATH_IOT_4 = "/content/drive/MyDrive/Datasets/CIC-IoT 2023/cic-iot_2023_4.csv"
DATA_PATH_IOT_5 = "/content/drive/MyDrive/Datasets/CIC-IoT 2023/cic-iot_2023_5.csv"

df_iot_1 = pd.read_csv(DATA_PATH_IOT_1)
df_iot_2 = pd.read_csv(DATA_PATH_IOT_2)
df_iot_3 = pd.read_csv(DATA_PATH_IOT_3)
df_iot_4 = pd.read_csv(DATA_PATH_IOT_4)
df_iot_5 = pd.read_csv(DATA_PATH_IOT_5)

df_iot_combined = pd.concat([df_iot_1, df_iot_2, df_iot_3, df_iot_4, df_iot_5], ignore_index=True)
# Display the first few rows of the dataset
df_iot_combined.head()

```

	flow_duration	Header_Length	Protocol Type	Duration	Rate	Srate	Drate	fin_flag_number	syn_flag_number	rst_flag_nu
0	0.000000	53.46	5.94	63.36	1.145800	1.145800	0.0	0.0	1.0	
1	0.000000	54.00	6.00	64.00	1.027823	1.027823	0.0	0.0	0.0	
2	2.204616	93.96	6.00	64.00	0.671213	0.671213	0.0	0.0	1.0	
3	0.053618	12497.00	17.00	64.00	47647.897124	47647.897124	0.0	0.0	0.0	
4	0.000000	0.00	1.00	64.00	0.667744	0.667744	0.0	0.0	0.0	

5 rows × 47 columns

```python
df_iot_combined.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1617141 entries, 0 to 1617140
Data columns (total 47 columns):
 #   Column           Non-Null Count    Dtype
---  ------           --------------    -----
 0   flow_duration    1617141 non-null  float64
 1   Header_Length    1617141 non-null  float64
 2   Protocol Type    1617141 non-null  float64
 3   Duration         1617141 non-null  float64
 4   Rate             1617141 non-null  float64
 5   Srate            1617141 non-null  float64
 6   Drate            1617141 non-null  float64
 7   fin_flag_number  1617141 non-null  float64
 8   syn_flag_number  1617141 non-null  float64
 9   rst_flag_number  1617141 non-null  float64
 10  psh_flag_number  1617141 non-null  float64
 11  ack_flag_number  1617141 non-null  float64
 12  ece_flag_number  1617141 non-null  float64
 13  cwr_flag_number  1617141 non-null  float64
 14  ack_count        1617141 non-null  float64
 15  syn_count        1617141 non-null  float64
 16  fin_count        1617141 non-null  float64
 17  urg_count        1617141 non-null  float64
 18  rst_count        1617141 non-null  float64
 19  HTTP             1617141 non-null  float64
 20  HTTPS            1617141 non-null  float64
 21  DNS              1617141 non-null  float64
 22  Telnet           1617141 non-null  float64
 23  SMTP             1617141 non-null  float64
 24  SSH              1617141 non-null  float64
 25  IRC              1617141 non-null  float64
 26  TCP              1617141 non-null  float64
 27  UDP              1617141 non-null  float64
 28  DHCP             1617141 non-null  float64
 29  ARP              1617141 non-null  float64
 30  ICMP             1617141 non-null  float64
 31  IPv              1617141 non-null  float64
 32  LLC              1617141 non-null  float64
 33  Tot sum          1617141 non-null  float64
 34  Min              1617141 non-null  float64
```

```
 35  Max             1617141 non-null  float64
 36  AVG             1617141 non-null  float64
 37  Std             1617141 non-null  float64
 38  Tot size        1617141 non-null  float64
 39  IAT             1617141 non-null  float64
 40  Number          1617141 non-null  float64
 41  Magnitue        1617141 non-null  float64
 42  Radius          1617141 non-null  float64
 43  Covariance      1617141 non-null  float64
 44  Variance        1617141 non-null  float64
 45  Weight          1617141 non-null  float64
 46  label           1617141 non-null  object
dtypes: float64(46), object(1)
memory usage: 579.9+ MB
```

```
df = df_iot_combined.copy()
print("Shape:", df.shape)
print("Columns:", df.columns.tolist()[:8], "...", df.columns.tolist()[-8:])
```

```
Shape: (1617141, 47)
Columns: ['flow_duration', 'Header_Length', 'Protocol Type', 'Duration', 'Rate', 'Srate', 'Drate', 'fin_flag_number'] ... ['IAT', '
```

```
print("Exact duplicate rows:", df.duplicated().sum())
nan_cols = df.isna().sum()
print("Columns with NaNs:\n", nan_cols[nan_cols>0])

# Everything is numeric except 'label' (object); confirm:
print(df.dtypes.tail(10))

```

```
Exact duplicate rows: 0
Columns with NaNs:
 Series([], dtype: int64)
Std           float64
Tot size      float64
IAT           float64
Number        float64
Magnitue      float64
Radius        float64
Covariance    float64
Variance      float64
Weight        float64
label          object
dtype: object
```

Normalize labels into MainClass + Attack (no rows dropped)

```
# Clean label strings
df["label"] = df["label"].astype(str).str.strip()

# Subclass → MainClass mapping (only subclasses that actually appear will be used)
subclass_mapping_full = {
    "DDoS": ["DDoS-ICMP_Flood","DDoS-UDP_Flood","DDoS-TCP_Flood","DDoS-PSHACK_Flood",
             "DDoS-SYN_Flood","DDoS-RSTFINFlood","DDoS-SynonymousIP_Flood",
             "DDoS-ICMP_Fragmentation","DDoS-UDP_Fragmentation","DDoS-ACK_Fragmentation",
             "DDoS-HTTP_Flood","DDoS-SlowLoris"],
    "DoS": ["DoS-UDP_Flood","DoS-TCP_Flood","DoS-SYN_Flood","DoS-HTTP_Flood"],
    "Recon": ["Recon-HostDiscovery","Recon-OSScan","Recon-PortScan","Recon-PingSweep","VulnerabilityScan"],
    "Spoofing": ["MITM-ArpSpoofing","DNS_Spoofing"],
    "BruteForce": ["DictionaryBruteForce"],
    "Web-based": ["BrowserHijacking","XSS","Uploading_Attack","SqlInjection","CommandInjection","Backdoor_Malware"],
    "Mirai": ["Mirai-greeth_flood","Mirai-udpplain","Mirai-greip_flood"],
    "BENIGN": ["BenignTraffic"]
}

# Restrict to labels that exist in your file (robust to naming diffs)
present = set(df["label"].unique())
subclass_mapping = {m:[s for s in subs if s in present] for m,subs in subclass_mapping_full.items()}
# Drop empty families (no subclass present)
subclass_mapping = {m:subs for m,subs in subclass_mapping.items() if len(subs)>0}

# Build reverse map
sub2main = {s:m for m,subs in subclass_mapping.items() for s in subs}

# New columns
```

```
df["MainClass"] = df["label"].map(sub2main).fillna("OTHER_ATTACK")
df["Attack"]    = (df["MainClass"]!="BENIGN").astype(int)

print("Sample:\n", df[["label","MainClass","Attack"]].head())
print("\nMainClass counts:\n", df["MainClass"].value_counts())
print("\nAttack (0/1):\n", df["Attack"].value_counts())

```

```
Sample:
                       label MainClass  Attack
0           DDoS-SYN_Flood      DDoS       1
1           DDoS-TCP_Flood      DDoS       1
2  DDoS-SynonymousIP_Flood      DDoS       1
3           DDoS-UDP_Flood      DDoS       1
4          DDoS-ICMP_Flood      DDoS       1

MainClass counts:
 MainClass
DDoS          1177334
DoS            280040
Mirai           91710
BENIGN          37913
Spoofing        16797
Recon           12082
Web-based         787
BruteForce        478
Name: count, dtype: int64

Attack (0/1):
 Attack
1    1579228
0      37913
Name: count, dtype: int64
```

Define a proper zero-day protocol

```
# Choose unseen subclasses (one per main family) from those present
unseen_subclasses = []
for main, subs in subclass_mapping.items():
    if main == "BENIGN":
        continue
    vc = df[df["label"].isin(subs)]["label"].value_counts()
    if vc.empty:
        continue
    # Pick least frequent subclass to make generalization harder (deterministic)
    unseen_subclasses.append(vc.index[-1])

unseen_subclasses = sorted(set(unseen_subclasses))
print("Zero-day (UNSEEN) subclasses:", unseen_subclasses)

# Partition into SEEN (for tuning) and UNSEEN (for zero-day testing). Benign goes to both.
is_unseen = df["label"].isin(unseen_subclasses)
df_seen   = df[(~is_unseen) | (df["MainClass"]=="BENIGN")].copy()
df_unseen = df[(is_unseen)  | (df["MainClass"]=="BENIGN")].copy()

print("SEEN shape:", df_seen.shape, "UNSEEN shape:", df_unseen.shape)
print("SEEN attack ratio:", df_seen["Attack"].mean(), "UNSEEN attack ratio:", df_unseen["Attack"].mean())

```

```
Zero-day (UNSEEN) subclasses: ['DDoS-SlowLoris', 'DNS_Spoofing', 'DictionaryBruteForce', 'DoS-HTTP_Flood', 'Mirai-greip_flood', 'Re
SEEN shape: (1580977, 49) UNSEEN shape: (74077, 49)
SEEN attack ratio: 0.9760192589772021 UNSEEN attack ratio: 0.4881947163087058
```

Build splits: Train (benign-only), Validation (seen attacks), Test (unseen attacks)

```
from sklearn.model_selection import train_test_split

# Train = benign-only from SEEN (unsupervised fit benefits from more benign)
train_benign = df_seen[df_seen["Attack"]==0].copy()

# Validation (threshold/hyperparam selection) = mix of benign + SEEN attacks
# Keep a sizable, stratified validation subset
val_df, _ = train_test_split(
```

```
    df_seen, test_size=0.70, stratify=df_seen["Attack"], random_state=42
)

# Zero-day test = benign + UNSEEN families (no SEEN attacks)
test_df = df_unseen.copy()

print("Train_benign:", train_benign.shape, "| Val:", val_df.shape, "| Test:", test_df.shape)
print("Val attack ratio:", val_df["Attack"].mean(), "Test attack ratio:", test_df["Attack"].mean())

```

```
Train_benign: (37913, 49) | Val: (474293, 49) | Test: (74077, 49)
Val attack ratio: 0.9760190430809648 Test attack ratio: 0.4881947163087058
```

Create two test regimes for reporting

```
# 1) Realistic test: attacks are rare (e.g., target 10% attack prevalence)
target_prev = 0.10
ben_test = test_df[test_df["Attack"]==0]
atk_test = test_df[test_df["Attack"]==1]
n_b = len(ben_test)
n_a = min(len(atk_test), int(n_b * target_prev / (1 - target_prev)))
atk_down = atk_test.sample(n=n_a, random_state=42) if n_a>0 else atk_test
test_realistic = pd.concat([ben_test, atk_down]).sample(frac=1.0, random_state=42).reset_index(drop=True)

# 2) Stress test: keep original skew from UNSEEN
test_stress = test_df.sample(frac=1.0, random_state=42).reset_index(drop=True)

print("Realistic:", test_realistic.shape, "attack ratio:", test_realistic["Attack"].mean())
print("Stress   :", test_stress.shape,     "attack ratio:", test_stress["Attack"].mean())

```

```
Realistic: (42125, 49) attack ratio: 0.09998813056379822
Stress   : (74077, 49) attack ratio: 0.4881947163087058
```

Minimal Exploratory Data Analysis

```
def quick_eda(name, dfx):
    print(f"\n=== {name} ===")
    print("Shape:", dfx.shape, "| Attack ratio:", dfx["Attack"].mean())
    print("Top MainClass:\n", dfx["MainClass"].value_counts().head(10))
    # numeric snapshot
    num_cols = dfx.select_dtypes(include=[np.number]).columns.drop(["Attack"])
    print("Numeric cols:", len(num_cols))
    print(dfx[num_cols].describe(percentiles=[.01,.25,.5,.75,.99]).T.head(10))

quick_eda("Train (benign)", train_benign)
quick_eda("Validation (SEEN)", val_df)
quick_eda("Test REALISTIC (UNSEEN)", test_realistic)
quick_eda("Test STRESS (UNSEEN)", test_stress)

```

```
=== Train (benign) ===
Shape: (37913, 49) | Attack ratio: 0.0
Top MainClass:
 MainClass
BENIGN    37913
Name: count, dtype: int64
Numeric cols: 46
                   count          mean           std       min          1%  \
flow_duration    37913.0  3.886023e+01  5.203497e+01  0.000000    0.141755
Header_Length    37913.0  1.020668e+06  1.341055e+06  0.000000  851.092000
Protocol Type    37913.0  7.470203e+00  2.252745e+00  0.000000    4.800000
Duration         37913.0  1.151078e+02  5.145048e+01  0.000000   50.800000
Rate             37913.0  1.856269e+03  1.731521e+04  0.021591    1.466400
Srate            37913.0  1.856269e+03  1.731521e+04  0.021591    1.466400
Drate            37913.0  0.000000e+00  0.000000e+00  0.000000    0.000000
fin_flag_number  37913.0  0.000000e+00  0.000000e+00  0.000000    0.000000
syn_flag_number  37913.0  5.275235e-05  7.262986e-03  0.000000    0.000000
rst_flag_number  37913.0  0.000000e+00  0.000000e+00  0.000000    0.000000

                         25%            50%           75%           99%  \
flow_duration       9.987032      26.472649  5.260494e+01  2.485242e+02
Header_Length   76218.000000  510832.200000  1.402154e+06  6.242186e+06
```

```
Protocol Type        6.000000       6.500000  8.200000e+00  1.480000e+01
Duration            73.600000      99.100000  1.480000e+02  2.320000e+02
Rate                23.852218      52.999576  7.845009e+01  6.995490e+04
Srate               23.852218      52.999576  7.845009e+01  6.995490e+04
Drate                0.000000       0.000000  0.000000e+00  0.000000e+00
fin_flag_number      0.000000       0.000000  0.000000e+00  0.000000e+00
syn_flag_number      0.000000       0.000000  0.000000e+00  0.000000e+00
rst_flag_number      0.000000       0.000000  0.000000e+00  0.000000e+00

                          max
flow_duration    1.014878e+03
Header_Length    9.473703e+06
Protocol Type    1.700000e+01
Duration         2.487000e+02
Rate             8.388860e+05
Srate            8.388860e+05
Drate            0.000000e+00
fin_flag_number  0.000000e+00
syn_flag_number  1.000000e+00
rst_flag_number  0.000000e+00

=== Validation (SEEN) ===
Shape: (474293, 49) | Attack ratio: 0.9760190430809648
Top MainClass:
 MainClass
DDoS         352838
DoS           83323
Mirai         19596
BENIGN        11374
Recon          3604
Spoofing       3306
Web-based       252
Name: count, dtype: int64
Numeric cols: 46
                    count          mean            std  min     1%        25%  \
```

splits to disk

```
# Work dirs (adjust drive path if needed)
BASE = "/content/drive/MyDrive/colab_zero_day"
os.makedirs(f"{BASE}/splits", exist_ok=True)
```

```
split_dir = f"{BASE}/splits"
train_benign.to_parquet(f"{split_dir}/train_benign_seen.parquet", index=False)
val_df.to_parquet(        f"{split_dir}/val_seen.parquet",        index=False)
test_realistic.to_parquet(f"{split_dir}/test_unseen_realistic.parquet", index=False)
test_stress.to_parquet(   f"{split_dir}/test_unseen_stress.parquet",    index=False)

meta = {
  "unseen_subclasses": unseen_subclasses,
  "target_attack_prevalence_realistic": target_prev,
  "seed": 42
}
with open(f"{split_dir}/meta.json","w") as f:
    json.dump(meta, f, indent=2)

print("Saved splits to:", split_dir)

```

```
Saved splits to: /content/drive/MyDrive/colab_zero_day/splits
```

Preprocessing

```
import os, json, math, gc, numpy as np, pandas as pd
import matplotlib.pyplot as plt
from collections import Counter
from scipy import stats

BASE = "/content/drive/MyDrive/colab_zero_day"
EDA_DIR = f"{BASE}/eda"
os.makedirs(EDA_DIR, exist_ok=True)

def savefig(path):
    plt.tight_layout()
```

```
    plt.savefig(path, dpi=160, bbox_inches='tight')
    plt.close()

def mem_mb(df):
    return df.memory_usage(deep=True).sum()/1024**2

# Which columns are meta (not model features)
META_COLS = ["Label","MainClass","Attack"]

```

Basic dataset cards + class balance

```
def dataset_card(name, df):
    print(f"\n=== {name} ===")
    print("shape:", df.shape, "| mem MB:", f"{mem_mb(df):.2f}")
    print("columns:", len(df.columns))
    print("attack ratio:", df["Attack"].mean())
    print("MainClass (top 10):\n", df["MainClass"].value_counts().head(10))

for nm, d in [("Train (benign-only)", train_benign),
              ("Validation (SEEN)", val_df),
              ("Test REALISTIC (UNSEEN)", test_realistic),
              ("Test STRESS (UNSEEN)", test_stress)]:
    dataset_card(nm, d)

# Bar plots: MainClass counts per split
def bar_counts_mainclass(df, title, fname):
    counts = df["MainClass"].value_counts().sort_values(ascending=False)
    plt.figure(figsize=(8,4))
    counts.plot(kind="bar")
    plt.title(title); plt.ylabel("count"); plt.xlabel("MainClass")
    savefig(f"{EDA_DIR}/{fname}.png")

bar_counts_mainclass(val_df, "Validation MainClass distribution", "val_mainclass_counts")
bar_counts_mainclass(test_realistic, "Test REALISTIC MainClass distribution", "test_realistic_mainclass_counts")
bar_counts_mainclass(test_stress, "Test STRESS MainClass distribution", "test_stress_mainclass_counts")

# Attack vs Normal counts per split
def pie_attack(df, title, fname):
    plt.figure(figsize=(4,4))
    vals = df["Attack"].value_counts().reindex([0,1]).fillna(0)
    plt.pie(vals, labels=["Normal","Attack"], autopct="%1.1f%%", startangle=90)
    plt.title(title)
    savefig(f"{EDA_DIR}/{fname}.png")

pie_attack(val_df, "Validation Attack vs Normal", "val_attack_pie")
pie_attack(test_realistic, "Test REALISTIC Attack vs Normal", "test_realistic_attack_pie")
pie_attack(test_stress, "Test STRESS Attack vs Normal", "test_stress_attack_pie")

```

```
=== Train (benign-only) ===
shape: (37913, 49) | mem MB: 18.11
columns: 49
attack ratio: 0.0
MainClass (top 10):
 MainClass
BENIGN    37913
Name: count, dtype: int64

=== Validation (SEEN) ===
shape: (474293, 49) | mem MB: 226.78
columns: 49
attack ratio: 0.9760190430809648
MainClass (top 10):
 MainClass
DDoS         352838
DoS           83323
Mirai         19596
BENIGN        11374
Recon          3604
Spoofing       3306
Web-based       252
Name: count, dtype: int64

=== Test REALISTIC (UNSEEN) ===
```

```
shape: (42125, 49) | mem MB: 19.82
columns: 49
attack ratio: 0.09998813056379822
MainClass (top 10):
 MainClass
BENIGN        37913
Mirai          3035
Spoofing        718
DoS             271
DDoS            103
BruteForce       67
Recon            13
Web-based         5
Name: count, dtype: int64

=== Test STRESS (UNSEEN) ===
shape: (74077, 49) | mem MB: 34.91
columns: 49
attack ratio: 0.4881947163087058
MainClass (top 10):
 MainClass
BENIGN        37913
Mirai         26158
Spoofing       6141
DoS            2495
DDoS            791
BruteForce      478
Recon            69
Web-based        32
Name: count, dtype: int64
```

Numeric summary & missingness

```python
def numeric_columns(df):
    return df.select_dtypes(include=[np.number]).columns.difference(META_COLS)

num_cols_all = numeric_columns(val_df)  # use val_df to define feature set
print("Numeric feature count:", len(num_cols_all))

# Missingness table (should be tiny; if not, we'll impute later)
miss_tbl = pd.DataFrame({
    "train_benign": train_benign[num_cols_all].isna().sum(),
    "val": val_df[num_cols_all].isna().sum(),
    "test_realistic": test_realistic[num_cols_all].isna().sum(),
    "test_stress": test_stress[num_cols_all].isna().sum(),
})
miss_tbl.to_csv(f"{EDA_DIR}/missingness.csv")
print("Missingness saved -> missingness.csv")

# Quick numeric stats (validation)
desc = val_df[num_cols_all].describe(percentiles=[.01,.05,.25,.5,.75,.95,.99]).T
desc.to_csv(f"{EDA_DIR}/val_numeric_describe.csv")
desc.head()

```

```
Numeric feature count: 46
Missingness saved -> missingness.csv
```

	count	mean	std	min	1%	5%	25%	50%	75%	95%	99%	max
ARP	474293.0	0.000038	0.006160	0.0	0.0	0.0	0.0	0.0	0.000000	0.000000	0.000000	1.000000e+00
AVG	474293.0	115.785542	234.994619	42.0	42.0	42.0	50.0	54.0	54.015000	587.441335	1004.797783	1.165000e+04
Covariance	474293.0	30103.214257	358113.590216	0.0	0.0	0.0	0.0	0.0	0.910903	25292.212302	587493.689942	1.076490e+08
DHCP	474293.0	0.000002	0.001452	0.0	0.0	0.0	0.0	0.0	0.000000	0.000000	0.000000	1.000000e+00
DNS	474293.0	0.000093	0.009631	0.0	0.0	0.0	0.0	0.0	0.000000	0.000000	0.000000	1.000000e+00

Feature separation ranking (KS & Cohen's d)

```python
def feature_separation(df, cols, target="Attack"):
    rows=[]
    a = df[df[target]==1][cols]
    n = df[df[target]==0][cols]
```

```
    for c in cols:
        # Two-sample KS statistic (distributional difference)
        ks_stat, ks_p = stats.ks_2samp(a[c].values, n[c].values, alternative='two-sided', mode='auto')
        # Cohen's d (mean difference / pooled sd)
        mu1, mu0 = a[c].mean(), n[c].mean()
        s1, s0   = a[c].std(ddof=1), n[c].std(ddof=1)
        n1, n0   = a[c].shape[0], n[c].shape[0]
        sp = math.sqrt(((n1-1)*s1**2 + (n0-1)*s0**2) / max(n1+n0-2,1))
        d  = (mu1 - mu0) / (sp + 1e-12)
        rows.append((c, ks_stat, ks_p, d, mu0, mu1))
    out = pd.DataFrame(rows, columns=["feature","KS","KS_p","Cohen_d","mean_normal","mean_attack"])
    out["abs_d"] = out["Cohen_d"].abs()
    out.sort_values(["KS","abs_d"], ascending=[False, False], inplace=True)
    return out

sep_tbl = feature_separation(val_df, num_cols_all)
sep_tbl.to_csv(f"{EDA_DIR}/feature_separation_val.csv", index=False)
sep_tbl.head(10)

```

	feature	KS	KS_p	Cohen_d	mean_normal	mean_attack	abs_d
41	rst_count	0.970092	0.0	-3.734265	1079.206057	12.522938	3.734265
45	urg_count	0.959992	0.0	-1.654283	117.357471	3.321979	1.654283
31	Variance	0.894642	0.0	-4.134234	0.864167	0.072552	4.134234
15	Magnitue	0.884271	0.0	-2.324234	30.265314	12.288978	2.324234
28	Tot size	0.883263	0.0	-2.422983	636.306384	103.054970	2.422983
1	AVG	0.882726	0.0	-2.410241	634.458300	103.041663	2.410241
25	Std	0.861164	0.0	-3.402065	500.857297	20.361353	3.402065
20	Radius	0.860759	0.0	-3.397181	707.597746	28.781234	3.397181
16	Max	0.851222	0.0	-3.521473	1743.614360	131.890664	3.521473
2	Covariance	0.838170	0.0	-1.890230	664782.049875	14509.045350	1.890230

Histograms for the top 12 discriminative features

```
TOPK = 12
top_feats = sep_tbl["feature"].head(TOPK).tolist()
print("Top features by separation:", top_feats)

def plot_hist_by_class(df, cols, title_prefix, fname_prefix):
    for c in cols:
        plt.figure(figsize=(5,3))
        # Normal
        x0 = df[df["Attack"]==0][c].values
        x1 = df[df["Attack"]==1][c].values
        # Clip extremes for viz (1st–99th percentile)
        lo = np.nanpercentile(df[c].values, 1)
        hi = np.nanpercentile(df[c].values, 99)
        bins = 50
        plt.hist(np.clip(x0, lo, hi), bins=bins, alpha=0.6, label="Normal", density=True)
        plt.hist(np.clip(x1, lo, hi), bins=bins, alpha=0.6, label="Attack", density=True)
        plt.xlabel(c); plt.ylabel("density")
        plt.title(f"{title_prefix}: {c}")
        plt.legend()
        savefig(f"{EDA_DIR}/{fname_prefix}_{c.replace(' ','_')}.png")

plot_hist_by_class(val_df, top_feats, "Validation distributions", "val_hist")

```

```
Top features by separation: ['rst_count', 'urg_count', 'Variance', 'Magnitue', 'Tot size', 'AVG', 'Std', 'Radius', 'Max', 'Covarian
```

Correlation heatmap + highly correlated pairs

```
# Correlation on validation (only numeric)
corr = val_df[num_cols_all].corr().fillna(0.0)
```

```
plt.figure(figsize=(8,6))
plt.imshow(corr.values, aspect='auto', interpolation='nearest')
plt.colorbar(label="Pearson r")
plt.xticks(range(len(num_cols_all)), num_cols_all, rotation=90, fontsize=6)
plt.yticks(range(len(num_cols_all)), num_cols_all, fontsize=6)
plt.title("Validation correlation heatmap")
savefig(f"{EDA_DIR}/corr_heatmap_val.png")

# Extract high-corr pairs
pairs = []
thr = 0.98
for i in range(len(num_cols_all)):
    for j in range(i+1, len(num_cols_all)):
        r = corr.iat[i,j]
        if abs(r) >= thr:
            pairs.append((num_cols_all[i], num_cols_all[j], r))
high_corr_pairs = sorted(pairs, key=lambda x: -abs(x[2]))
pd.DataFrame(high_corr_pairs, columns=["feat_a","feat_b","r"]).to_csv(f"{EDA_DIR}/high_corr_pairs.csv", index=False)
print("High corr pairs (|r|>=0.98):", len(high_corr_pairs))

```

```
High corr pairs (|r|>=0.98): 7
```

Outlier analysis & tail heaviness

```
def tail_heaviness(df, cols):
    rows=[]
    for c in cols:
        x = df[c].values
        # robust metrics
        q1,q3 = np.nanpercentile(x, [25,75]); iqr = q3 - q1
        p01,p99 = np.nanpercentile(x, [1,99])
        kurt = stats.kurtosis(x, fisher=True, nan_policy='omit')
        skw  = stats.skew(x, nan_policy='omit')
        out_frac = np.mean((x < q1 - 3*iqr) | (x > q3 + 3*iqr))
        rows.append((c, skw, kurt, out_frac, p01, p99, q1, q3))
    T = pd.DataFrame(rows, columns=["feature","skew","kurtosis","outlier_frac","p01","p99","q1","q3"])
    T.sort_by = "outlier_frac"
    return T.sort_values("outlier_frac", ascending=False)

tails = tail_heaviness(val_df, num_cols_all)
tails.to_csv(f"{EDA_DIR}/tail_heaviness_val.csv", index=False)
tails.head(10)

# Plot outlier rate bar for top 20
plt.figure(figsize=(8,4))
top_out = tails.head(20)
plt.bar(range(len(top_out)), top_out["outlier_frac"])
plt.xticks(range(len(top_out)), top_out["feature"], rotation=90, fontsize=7)
plt.ylabel("fraction beyond 3*IQR")
plt.title("Top-20 heavy-tail/outlier features (validation)")
savefig(f"{EDA_DIR}/outlier_frac_bar.png")

# Heuristic recommendation
heavy_tail_frac = (tails["outlier_frac"] > 0.01).mean()  # >1% extreme
suggest_scaler = "RobustScaler" if heavy_tail_frac > 0.1 else "StandardScaler"
print(f"Suggested scaler based on tails: {suggest_scaler}  (heavy-tail features: {heavy_tail_frac*100:.1f}% )")

```

```
Suggested scaler based on tails: RobustScaler  (heavy-tail features: 71.7% )
```

Constant / near-constant features, zero variance

```
def constant_features(df, cols, thresh_unique=1):
    nun = df[cols].nunique(dropna=False)
    const = nun[nun <= thresh_unique].index.tolist()
    return const

const_feats = constant_features(train_benign, num_cols_all, 1)
print("Constant features in TRAIN (drop):", const_feats)
pd.Series(const_feats).to_csv(f"{EDA_DIR}/constant_features.csv", index=False)

```

```
Constant features in TRAIN (drop): ['DHCP', 'Drate', 'IRC', 'SMTP', 'SSH', 'Telnet', 'cwr_flag_number', 'ece_flag_number', 'fin_fla
```

Save a preprocessing plan for the next step

```
# Pick which feature to keep from each high-corr pair (keep the one with higher separation)
sep = sep_tbl.set_index("feature")
drop_due_corr = []
keep_due_corr = set()

for a,b,r in high_corr_pairs:
    if a in drop_due_corr or b in drop_due_corr:
        continue
    # Compare absolute Cohen's d (fallback to KS)
    da = abs(sep.loc[a, "Cohen_d"]) if a in sep.index else 0.0
    db = abs(sep.loc[b, "Cohen_d"]) if b in sep.index else 0.0
    if da >= db:
        drop_due_corr.append(b); keep_due_corr.add(a)
    else:
        drop_due_corr.append(a); keep_due_corr.add(b)

drop_due_corr = sorted(set(drop_due_corr))
print("Drop due to high correlation:", drop_due_corr[:15], f"... total={len(drop_due_corr)}")
pd.Series(drop_due_corr).to_csv(f"{EDA_DIR}/drop_due_to_corr.csv", index=False)

# Tail clipping suggestions (top 10 heaviest)
clip_suggestions = tails.head(10)[["feature","p01","p99"]].to_dict(orient="records")
with open(f"{EDA_DIR}/clip_suggestions.json","w") as f:
    json.dump(clip_suggestions, f, indent=2)

preproc_plan = {
    "suggested_scaler": suggest_scaler,
    "constant_features_drop": const_feats,
    "high_corr_drop": drop_due_corr,
    "top_sep_features": top_feats,
    "clip_suggestions": clip_suggestions,
    "feature_list_candidate": [c for c in num_cols_all if c not in set(const_feats) | set(drop_due_corr)]
}
with open(f"{EDA_DIR}/preprocessing_plan.json","w") as f:
    json.dump(preproc_plan, f, indent=2)

print("Saved preprocessing plan -> preprocessing_plan.json")

```

```
Drop due to high correlation: ['IAT', 'LLC', 'Radius', 'Srate', 'Weight', 'ack_count'] ... total=6
Saved preprocessing plan -> preprocessing_plan.json
```

Build the preprocessing transformer (winsorize + scale)

```
import os, json, numpy as np, pandas as pd
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.preprocessing import StandardScaler, RobustScaler
from sklearn.pipeline import Pipeline

BASE = "/content/drive/MyDrive/colab_zero_day"
PLAN_PATH = f"{BASE}/eda/preprocessing_plan.json"

with open(PLAN_PATH, "r") as f:
    preproc_plan = json.load(f)

features_keep = preproc_plan["feature_list_candidate"]  # numeric features we’ll keep
clip_suggestions = preproc_plan.get("clip_suggestions", [])
scaler_choice = preproc_plan.get("suggested_scaler", "RobustScaler")

# Map clip targets -> we will recompute percentiles from TRAIN BENIGN to avoid leakage
clip_targets = [d["feature"] for d in clip_suggestions]

class ColumnClipper(BaseEstimator, TransformerMixin):
    """
    Winsorize specified columns using percentiles computed on fit(X).
    thresholds_: dict {col: (lo, hi)}
```

```
    """
    def __init__(self, cols, lower=1.0, upper=99.0):
        self.cols = list(cols)
        self.lower = lower
        self.upper = upper
        self.thresholds_ = {}

    def fit(self, X, y=None):
        df = pd.DataFrame(X, columns=self.feature_names_in_) if hasattr(self, "feature_names_in_") else X
        # If X is DataFrame, use its columns; else assume previously set
        if isinstance(df, pd.DataFrame):
            for c in self.cols:
                if c in df.columns:
                    lo = np.nanpercentile(df[c].values, self.lower)
                    hi = np.nanpercentile(df[c].values, self.upper)
                    self.thresholds_[c] = (lo, hi)
        return self

    def transform(self, X):
        if isinstance(X, pd.DataFrame):
            df = X.copy()
            for c,(lo,hi) in self.thresholds_.items():
                if c in df.columns:
                    x = df[c].values
                    x = np.clip(x, lo, hi)
                    df[c] = x
            return df
        else:
            # If numpy array was passed, we need columns; prefer passing DataFrames
            return X

class ColumnSelector(BaseEstimator, TransformerMixin):
    def __init__(self, cols):
        self.cols = list(cols)
    def fit(self, X, y=None):
        return self
    def transform(self, X):
        return X[self.cols].copy()  # keep DataFrame for named columns

# Choose scaler
Scaler = RobustScaler if scaler_choice == "RobustScaler" else StandardScaler

# Build preprocessing pipeline:
#  1) select columns
#  2) winsorize tails for selected heavy-tail features (recomputed from train_benign)
#  3) scale
preprocess = Pipeline(steps=[
    ("select", ColumnSelector(features_keep)),
    ("winsor", ColumnClipper(cols=clip_targets, lower=1.0, upper=99.0)),
    ("scale", Scaler(with_centering=True, with_scaling=True))
])

# Fit on BENIGN TRAIN ONLY (no leakage)
preprocess.fit(train_benign)

# Transform all splits
X_train = preprocess.transform(train_benign)     # benign-only
X_val   = preprocess.transform(val_df)
X_tr    = preprocess.transform(test_realistic)
X_ts    = preprocess.transform(test_stress)

y_val = val_df["Attack"].astype(int).values
y_tr  = test_realistic["Attack"].astype(int).values
y_ts  = test_stress["Attack"].astype(int).values

print("Shapes -> X_train:", X_train.shape, "X_val:", X_val.shape, "X_tr:", X_tr.shape, "X_ts:", X_ts.shape)

```

```
Shapes -> X_train: (37913, 30) X_val: (474293, 30) X_tr: (42125, 30) X_ts: (74077, 30)
```

Thresholding utilities & metrics (F2 and FPR-controlled)

```
import numpy as np
from sklearn.metrics import precision_recall_curve, classification_report, roc_auc_score, confusion_matrix, roc_curve, precisi
```

```python

def pick_thresh_by_Fbeta(y_true, scores, beta=2.0):
    P, R, thr = precision_recall_curve(y_true, scores)
    P, R = P[:-1], R[:-1]  # last point has no threshold
    fbeta = (1+beta**2) * (P*R) / (beta**2 * P + R + 1e-12)
    i = np.nanargmax(fbeta)
    return float(thr[i]), float(P[i]), float(R[i]), float(fbeta[i])

def pick_thresh_at_fpr(y_true, scores, max_fpr=0.05):
    fpr, tpr, thr = roc_curve(y_true, scores)
    ok = np.where(fpr <= max_fpr)[0]
    if len(ok)==0:
        j = np.argmax(tpr - fpr)
        return float(thr[j]), float(fpr[j]), float(tpr[j])
    i = ok[np.argmax(tpr[ok])]
    return float(thr[i]), float(fpr[i]), float(tpr[i])

def summarize(y_true, y_pred, scores, name=""):
    P,R,F1,_ = precision_recall_fscore_support(y_true, y_pred, average='binary', zero_division=0)
    auc_ = roc_auc_score(y_true, scores) if len(np.unique(y_true))>1 else np.nan
    cm = confusion_matrix(y_true, y_pred)
    print(f"\n== {name} ==")
    print(f"Precision={P:.4f}  Recall={R:.4f}  F1={F1:.4f}  ROC-AUC={auc_:.4f}")
    print("Confusion matrix:\n", cm)
    print(classification_report(y_true, y_pred, digits=4))

```

Train & evaluate Isolation Forest

```python
from sklearn.ensemble import IsolationForest

iforest = IsolationForest(
    n_estimators=400, max_samples='auto',
    contamination='auto',  # we will set threshold from validation
    random_state=42, n_jobs=-1
).fit(X_train)  # benign only

# Anomaly scores (higher = more anomalous)
val_scores = -iforest.score_samples(X_val)
tr_scores  = -iforest.score_samples(X_tr)
ts_scores  = -iforest.score_samples(X_ts)

# Strategy A: F2-optimized threshold (recall-oriented)
th_f2, p_f2, r_f2, f2 = pick_thresh_by_Fbeta(y_val, val_scores, beta=2.0)
y_tr_f2 = (tr_scores >= th_f2).astype(int)
y_ts_f2 = (ts_scores >= th_f2).astype(int)

print(f"IForest threshold F2-opt: {th_f2:.6f} (val P={p_f2:.3f}, R={r_f2:.3f}, F2={f2:.3f})")
summarize(y_tr, y_tr_f2, tr_scores, "IForest | REALISTIC | F2-opt")
summarize(y_ts, y_ts_f2, ts_scores, "IForest | STRESS    | F2-opt")

# Strategy B: control FPR on validation (e.g., <= 5%)
th_fpr, fpr_sel, tpr_sel = pick_thresh_at_fpr(y_val, val_scores, max_fpr=0.05)
y_tr_fpr = (tr_scores >= th_fpr).astype(int)
y_ts_fpr = (ts_scores >= th_fpr).astype(int)

print(f"IForest threshold FPR<=5%: {th_fpr:.6f} (val FPR={fpr_sel:.3f}, TPR={tpr_sel:.3f})")
summarize(y_tr, y_tr_fpr, tr_scores, "IForest | REALISTIC | FPR<=5%")
summarize(y_ts, y_ts_fpr, ts_scores, "IForest | STRESS    | FPR<=5%")

```

```
IForest threshold F2-opt: 0.384001 (val P=0.978, R=1.000, F2=0.995)

== IForest | REALISTIC | F2-opt ==
Precision=0.1059  Recall=0.9945  F1=0.1914  ROC-AUC=0.9103
Confusion matrix:
 [[ 2538 35375]
 [   23  4189]]
              precision    recall  f1-score   support

           0     0.9910    0.0669    0.1254     37913
           1     0.1059    0.9945    0.1914      4212

    accuracy                         0.1597     42125
   macro avg     0.5484    0.5307    0.1584     42125
```

```
weighted avg     0.9025    0.1597    0.1320     42125


== IForest | STRESS    | F2-opt ==
Precision=0.5045  Recall=0.9960  F1=0.6698  ROC-AUC=0.9129
Confusion matrix:
 [[ 2538 35375]
 [  144 36020]]
              precision    recall  f1-score   support

           0     0.9463    0.0669    0.1250     37913
           1     0.5045    0.9960    0.6698     36164

    accuracy                         0.5205     74077
   macro avg     0.7254    0.5315    0.3974     74077
weighted avg     0.7306    0.5205    0.3910     74077

IForest threshold FPR<=5%: 0.525049 (val FPR=0.050, TPR=0.378)

== IForest | REALISTIC | FPR<=5% ==
Precision=0.6353  Recall=0.7602  F1=0.6922  ROC-AUC=0.9103
Confusion matrix:
 [[36075  1838]
 [ 1010  3202]]
              precision    recall  f1-score   support

           0     0.9728    0.9515    0.9620     37913
           1     0.6353    0.7602    0.6922      4212

    accuracy                         0.9324     42125
   macro avg     0.8040    0.8559    0.8271     42125
weighted avg     0.9390    0.9324    0.9350     42125


== IForest | STRESS    | FPR<=5% ==
Precision=0.9374  Recall=0.7612  F1=0.8402  ROC-AUC=0.9129
Confusion matrix:
 [[36075  1838]
 [ 8636 27528]]
              precision    recall  f1-score   support

           0     0.8068    0.9515    0.8732     37913
           1     0.9374    0.7612    0.8402     36164
```

Train & evaluate Autoencoder

```
import tensorflow as tf
from tensorflow import keras
tf.random.set_seed(42)

input_dim = X_train.shape[1]
inp = keras.Input(shape=(input_dim,))
x = keras.layers.Dense(256, activation='relu')(inp)
x = keras.layers.Dense(128, activation='relu')(x)
z = keras.layers.Dense(64,  activation='relu')(x)
x = keras.layers.Dense(128, activation='relu')(z)
x = keras.layers.Dense(256, activation='relu')(x)
out = keras.layers.Dense(input_dim, activation='linear')(x)

ae = keras.Model(inp, out)
ae.compile(optimizer=keras.optimizers.Adam(1e-3), loss='mse')
es = keras.callbacks.EarlyStopping(monitor='loss', patience=5, restore_best_weights=True)
hist = ae.fit(X_train, X_train, epochs=60, batch_size=1024, shuffle=True, callbacks=[es], verbose=0)

# Reconstruction error = anomaly score
val_rec = ae.predict(X_val, batch_size=4096, verbose=0)
tr_rec  = ae.predict(X_tr,  batch_size=4096, verbose=0)
ts_rec  = ae.predict(X_ts,  batch_size=4096, verbose=0)

val_err = np.mean((X_val - val_rec)**2, axis=1)
tr_err  = np.mean((X_tr  - tr_rec )**2, axis=1)
ts_err  = np.mean((X_ts  - ts_rec )**2, axis=1)

# Thresholds
th_f2_ae, p_f2_ae, r_f2_ae, f2_ae = pick_thresh_by_Fbeta(y_val, val_err, beta=2.0)
y_tr_f2_ae = (tr_err >= th_f2_ae).astype(int)
y_ts_f2_ae = (ts_err >= th_f2_ae).astype(int)

```

```
print(f"AE threshold F2-opt: {th_f2_ae:.6f} (val P={p_f2_ae:.3f}, R={r_f2_ae:.3f}, F2={f2_ae:.3f})")
summarize(y_tr, y_tr_f2_ae, tr_err, "AE | REALISTIC | F2-opt")
summarize(y_ts, y_ts_f2_ae, ts_err, "AE | STRESS    | F2-opt")

th_fpr_ae, fpr_sel_ae, tpr_sel_ae = pick_thresh_at_fpr(y_val, val_err, max_fpr=0.05)
y_tr_fpr_ae = (tr_err >= th_fpr_ae).astype(int)
y_ts_fpr_ae = (ts_err >= th_fpr_ae).astype(int)

print(f"AE threshold FPR<=5%: {th_fpr_ae:.6f} (val FPR={fpr_sel_ae:.3f}, TPR={tpr_sel_ae:.3f})")
summarize(y_tr, y_tr_fpr_ae, tr_err, "AE | REALISTIC | FPR<=5%")
summarize(y_ts, y_ts_fpr_ae, ts_err, "AE | STRESS    | FPR<=5%")

```

```
AE threshold F2-opt: 0.002784 (val P=0.982, R=0.999, F2=0.995)

== AE | REALISTIC | F2-opt ==
Precision=0.1258  Recall=0.9919  F1=0.2232  ROC-AUC=0.9312
Confusion matrix:
 [[ 8868 29045]
 [   34  4178]]
              precision    recall  f1-score   support

           0     0.9962    0.2339    0.3789     37913
           1     0.1258    0.9919    0.2232      4212

    accuracy                         0.3097     42125
   macro avg     0.5610    0.6129    0.3010     42125
weighted avg     0.9091    0.3097    0.3633     42125


== AE | STRESS    | F2-opt ==
Precision=0.5521  Recall=0.9899  F1=0.7088  ROC-AUC=0.9317
Confusion matrix:
 [[ 8868 29045]
 [  367 35797]]
              precision    recall  f1-score   support

           0     0.9603    0.2339    0.3762     37913
           1     0.5521    0.9899    0.7088     36164

    accuracy                         0.6030     74077
   macro avg     0.7562    0.6119    0.5425     74077
weighted avg     0.7610    0.6030    0.5386     74077

AE threshold FPR<=5%: 0.054767 (val FPR=0.050, TPR=0.562)

== AE | REALISTIC | FPR<=5% ==
Precision=0.6629  Recall=0.8170  F1=0.7319  ROC-AUC=0.9312
Confusion matrix:
 [[36163  1750]
 [  771  3441]]
              precision    recall  f1-score   support

           0     0.9791    0.9538    0.9663     37913
           1     0.6629    0.8170    0.7319      4212

    accuracy                         0.9402     42125
   macro avg     0.8210    0.8854    0.8491     42125
weighted avg     0.9475    0.9402    0.9429     42125


== AE | STRESS    | FPR<=5% ==
Precision=0.9441  Recall=0.8172  F1=0.8761  ROC-AUC=0.9317
Confusion matrix:
 [[36163  1750]
 [ 6610 29554]]
              precision    recall  f1-score   support

           0     0.8455    0.9538    0.8964     37913
           1     0.9441    0.8172    0.8761     36164
```

Save artifacts (preprocessor, models, thresholds)

```
import joblib, json, os
ART = f"{BASE}/models"; os.makedirs(ART, exist_ok=True)

joblib.dump(preprocess, f"{ART}/preprocess.joblib")
joblib.dump(iforest,   f"{ART}/iforest.joblib")
```

```
ae.save(f"{ART}/autoencoder_ae.keras")

thresholds = {
    "iforest": {"F2": float(th_f2), "FPR5": float(th_fpr)},
    "autoencoder": {"F2": float(th_f2_ae), "FPR5": float(th_fpr_ae)}
}
with open(f"{ART}/thresholds.json","w") as f:
    json.dump(thresholds, f, indent=2)

print("Saved ->", ART)

```

```
Saved -> /content/drive/MyDrive/colab_zero_day/models
```

```
import numpy as np, pandas as pd
from sklearn.metrics import average_precision_score, precision_recall_curve

def pr_summary(y_true, scores, name=""):
    ap = average_precision_score(y_true, scores)
    P,R,Thr = precision_recall_curve(y_true, scores)
    print(f"{name}  PR-AUC(AP) = {ap:.4f}")
    return ap

# Use your already computed scores: IForest (ts_scores) and AE (ts_err)
ap_if = pr_summary(y_ts, ts_scores, "IForest | STRESS")
ap_ae = pr_summary(y_ts, ts_err,   "AE      | STRESS")

# Per-MainClass recall on UNSEEN test at your FPR<=5% thresholds
def per_family_recall(df_test, y_pred, family_col="MainClass"):
    T = df_test[[family_col,"Attack"]].copy()
    T["pred"] = y_pred
    # Only attacks; benign don't have 'family'
    atk = T[T["Attack"]==1]
    rec = atk.groupby(family_col).apply(lambda g: (g["pred"]==1).mean()).sort_values(ascending=False)
    return rec

rec_if = per_family_recall(test_stress, (ts_scores >= th_fpr).astype(int))
rec_ae = per_family_recall(test_stress, (ts_err    >= th_fpr_ae).astype(int))
print("\nPer-family recall (IForest, FPR<=5%):\n", rec_if)
print("\nPer-family recall (AE, FPR<=5%):\n", rec_ae)

```

```
IForest | STRESS  PR-AUC(AP) = 0.8567
AE      | STRESS  PR-AUC(AP) = 0.9048

Per-family recall (IForest, FPR<=5%):
 MainClass
Mirai         0.949881
DoS           0.473347
Spoofing      0.234815
DDoS          0.059418
Recon         0.028986
BruteForce    0.018828
Web-based     0.000000
dtype: float64

Per-family recall (AE, FPR<=5%):
 MainClass
Mirai         0.981382
DoS           0.783166
DDoS          0.335019
Recon         0.260870
Spoofing      0.260707
BruteForce    0.089958
Web-based     0.062500
dtype: float64
```

```
# Rank-normalize scores to [0,1] then average (robust across scales)
def rank_norm(x):
    r = pd.Series(x).rank(method="average").values
    return (r - r.min()) / (r.max() - r.min() + 1e-12)

val_ens = 0.5*rank_norm(val_scores) + 0.5*rank_norm(val_err)
tr_ens  = 0.5*rank_norm(tr_scores)  + 0.5*rank_norm(tr_err)
ts_ens  = 0.5*rank_norm(ts_scores)  + 0.5*rank_norm(ts_err)

# Pick threshold on validation (again FPR<=5% and F2)
th_ens_f2, _, _, _     = pick_thresh_by_Fbeta(y_val, val_ens, beta=2.0)
```

```
th_ens_fpr, _, _       = pick_thresh_at_fpr(y_val, val_ens, max_fpr=0.05)

from sklearn.metrics import roc_auc_score
y_ts_f2   = (ts_ens >= th_ens_f2).astype(int)
y_ts_fpr5 = (ts_ens >= th_ens_fpr).astype(int)

summarize(y_ts, y_ts_f2,   ts_ens, "Ensemble | STRESS | F2-opt")
summarize(y_ts, y_ts_fpr5, ts_ens, "Ensemble | STRESS | FPR<=5%")

# Also report REALISTIC
y_tr_f2   = (tr_ens >= th_ens_f2).astype(int)
y_tr_fpr5 = (tr_ens >= th_ens_fpr).astype(int)
summarize(y_tr, y_tr_f2,   tr_ens, "Ensemble | REALISTIC | F2-opt")
summarize(y_tr, y_tr_fpr5, tr_ens, "Ensemble | REALISTIC | FPR<=5%")

```

```
== Ensemble | STRESS | F2-opt ==
Precision=0.4891  Recall=0.9999  F1=0.6569  ROC-AUC=0.9308
Confusion matrix:
 [[  135 37778]
 [    2 36162]]
              precision    recall  f1-score   support

           0     0.9854    0.0036    0.0071     37913
           1     0.4891    0.9999    0.6569     36164

    accuracy                         0.4900     74077
   macro avg     0.7372    0.5018    0.3320     74077
weighted avg     0.7431    0.4900    0.3243     74077


== Ensemble | STRESS | FPR<=5% ==
Precision=0.8666  Recall=0.8893  F1=0.8778  ROC-AUC=0.9308
Confusion matrix:
 [[32963  4950]
 [ 4003 32161]]
              precision    recall  f1-score   support

           0     0.8917    0.8694    0.8804     37913
           1     0.8666    0.8893    0.8778     36164

    accuracy                         0.8791     74077
   macro avg     0.8792    0.8794    0.8791     74077
weighted avg     0.8795    0.8791    0.8792     74077


== Ensemble | REALISTIC | F2-opt ==
Precision=0.1001  Recall=1.0000  F1=0.1821  ROC-AUC=0.9331
Confusion matrix:
 [[   67 37846]
 [    0  4212]]
              precision    recall  f1-score   support

           0     1.0000    0.0018    0.0035     37913
           1     0.1001    1.0000    0.1821      4212

    accuracy                         0.1016     42125
   macro avg     0.5501    0.5009    0.0928     42125
weighted avg     0.9100    0.1016    0.0214     42125


== Ensemble | REALISTIC | FPR<=5% ==
Precision=0.1970  Recall=0.9577  F1=0.3269  ROC-AUC=0.9331
Confusion matrix:
 [[21475 16438]
 [  178  4034]]
              precision    recall  f1-score   support

           0     0.9918    0.5664    0.7210     37913
           1     0.1970    0.9577    0.3269      4212

    accuracy                         0.6056     42125
   macro avg     0.5944    0.7621    0.5240     42125
```

Loading UNSW-2015 Dataset

```
import pandas as pd
NB15_1 = pd.read_csv('/content/drive/MyDrive/Datasets/UNSW-2015/UNSW-NB15_1.csv')
```

```
NB15_2 = pd.read_csv('/content/drive/MyDrive/Datasets/UNSW-2015/UNSW-NB15_2.csv')
NB15_3 = pd.read_csv('/content/drive/MyDrive/Datasets/UNSW-2015/UNSW-NB15_3.csv')
NB15_4 = pd.read_csv('/content/drive/MyDrive/Datasets/UNSW-2015/UNSW-NB15_4.csv')
NB15_features = pd.read_csv('/content/drive/MyDrive/Datasets/UNSW-2015/NUSW-NB15_features.csv', encoding='cp1252')
```

```
/tmp/ipython-input-1562369842.py:2: DtypeWarning: Columns (1,3,47) have mixed types. Specify dtype option on import or set low_memo
  NB15_1 = pd.read_csv('/content/drive/MyDrive/Datasets/UNSW-2015/UNSW-NB15_1.csv')
/tmp/ipython-input-1562369842.py:3: DtypeWarning: Columns (3,39,47) have mixed types. Specify dtype option on import or set low_mem
  NB15_2 = pd.read_csv('/content/drive/MyDrive/Datasets/UNSW-2015/UNSW-NB15_2.csv')
```

```
NB15_features
```

	No.	Name	Type	Description
0	1	srcip	nominal	Source IP address
1	2	sport	integer	Source port number
2	3	dstip	nominal	Destination IP address
3	4	dsport	integer	Destination port number
4	5	proto	nominal	Transaction protocol
9	10	sttl	Integer	Source to destination time to live value
11	12	sloss	Integer	Source packets retransmitted or dropped
12	13	dloss	Integer	Destination packets retransmitted or dropped
14	15	Sload	Float	Source bits per second
16	17	Spkts	integer	Source to destination packet count
18	19	swin	integer	Source TCP window advertisement value
20	21	stcpb	integer	Source TCP base sequence number
22	23	smeansz	integer	Mean of the ?ow packet size transmitted by the...
24	25	trans_depth	integer	Represents the pipelined depth into the connec...
25	26	res_bdy_len	integer	Actual uncompressed content size of the data t...
26	27	Sjit	Float	Source jitter (mSec)
27	28	Djit	Float	Destination jitter (mSec)
28	29	Stime	Timestamp	record start time
31	32	Dintpkt	Float	Destination interpacket arrival time (mSec)
32	33	tcprtt	Float	TCP connection setup round-trip time, the sum ...
33	34	synack	Float	TCP connection setup time, the time between th...
34	35	ackdat	Float	TCP connection setup time, the time between th...
35	36	is_sm_ips_ports	Binary	If source (1) and destination (3)IP addresses ...
36	37	ct_state_ttl	Integer	No. for each state (6) according to specific r...
37	38	ct_flw_http_mthd	Integer	No. of flows that has methods such as Get and ...
38	39	is_ftp_login	Binary	If the ftp session is accessed by user and pas...
39	40	ct_ftp_cmd	integer	No of flows that has a command in ftp session.
40	41	ct_srv_src	integer	No. of connections that contain the same servi...
41	42	ct_srv_dst	integer	No. of connections that contain the same servi...
42	43	ct_dst_ltm	integer	No. of connections of the same destination add...
43	44	ct_src_ ltm	integer	No. of connections of the same source address ...
44	45	ct_src_dport_ltm	integer	No of connections of the same source address (...
45	46	ct_dst_sport_ltm	integer	No of connections of the same destination addr...

Concating the dataset

```python
NB15_1.columns = NB15_features['Name']
NB15_2.columns = NB15_features['Name']
NB15_3.columns = NB15_features['Name']
NB15_4.columns = NB15_features['Name']

df_unsw = pd.concat([NB15_1, NB15_2, NB15_3, NB15_4], ignore_index=True)
```

```python
df_unsw
```

Name	srcip	sport	dstip	dsport	proto	state	dur	sbytes	dbytes	sttl	...	ct_ftp_cmd	ct_srv_src	ct_srv_
0	59.166.0.0	33661	149.171.126.9	1024	udp	CON	0.036133	528	304	31	...	0	2	
1	59.166.0.6	1464	149.171.126.7	53	udp	CON	0.001119	146	178	31	...	0	12	
2	59.166.0.5	3593	149.171.126.5	53	udp	CON	0.001209	132	164	31	...	0	6	
3	59.166.0.3	49664	149.171.126.0	53	udp	CON	0.001169	146	178	31	...	0	7	
4	59.166.0.0	32119	149.171.126.9	111	udp	CON	0.078339	568	312	31	...	0	2	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
2540038	59.166.0.5	33094	149.171.126.7	43433	tcp	FIN	0.087306	320	1828	31	...		1	
2540039	59.166.0.7	20848	149.171.126.4	21	tcp	CON	0.365058	456	346	31	...	2	2	
2540040	59.166.0.3	21511	149.171.126.9	21	tcp	CON	6.335154	1802	2088	31	...	2	2	
2540041	59.166.0.9	35433	149.171.126.0	80	tcp	CON	2.200934	3498	166054	31	...		1	
2540042	175.45.176.0	17293	149.171.126.17	110	tcp	CON	0.942984	574	676	62	...		1	

2540043 rows × 49 columns

Dataset Analysis

```python
print("dataset shape: ",df_unsw.shape)
print(f"Memory usage: {df_unsw.memory_usage(deep=True).sum() / (1024**2):.2f} MB")
df_unsw.info()
```

```
dataset shape:  (2540043, 49)
Memory usage: 1837.93 MB
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2540043 entries, 0 to 2540042
Data columns (total 49 columns):
 #   Column   Dtype
---  ------   -----
 0   srcip    object
 1   sport    object
 2   dstip    object
 3   dsport   object
 4   proto    object
 5   state    object
 6   dur      float64
 7   sbytes   int64
 8   dbytes   int64
 9   sttl     int64
 10  dttl     int64
 11  sloss    int64
 12  dloss    int64
 13  service  object
 14  Sload    float64
 15  Dload    float64
 16  Spkts    int64
 17  Dpkts    int64
 18  swin     int64
```

46	47	ct_dst_src_ltm	integer	No of connections of the same source (1) and t...
47	48	attack_cat	nominal	The name of each attack category. In this data...
48	49	Label	binary	0 for normal and 1 for attack records

```
 19  dwin              int64
 20  stcpb             int64
 21  dtcpb             int64
 22  smeansz           int64
 23  dmeansz           int64
 24  trans_depth       int64
 25  res_bdy_len       int64
 26  Sjit              float64
 27  Djit              float64
 28  Stime             int64
 29  Ltime             int64
 30  Sintpkt           float64
 31  Dintpkt           float64
 32  tcprtt            float64
 33  synack            float64
 34  ackdat            float64
 35  is_sm_ips_ports   int64
 36  ct_state_ttl      int64
 37  ct_flw_http_mthd  float64
 38  is_ftp_login      float64
 39  ct_ftp_cmd        object
 40  ct_srv_src        int64
 41  ct_srv_dst        int64
 42  ct_dst_ltm        int64
 43  ct_src_ ltm       int64
 44  ct_src_dport_ltm  int64
 45  ct_dst_sport_ltm  int64
 46  ct_dst_src_ltm    int64
 47  attack_cat        object
 48  Label             int64
dtypes: float64(12), int64(28), object(9)
memory usage: 949.6+ MB
```

Setup & work dir

```
import os, gc, math, json, numpy as np, pandas as pd
import matplotlib.pyplot as plt
from scipy import stats
from collections import Counter

BASE = "/content/drive/MyDrive/colab_zero_day_unsw"
EDA_DIR = f"{BASE}/eda"
os.makedirs(EDA_DIR, exist_ok=True)

def savefig(path):
    plt.tight_layout()
    plt.savefig(path, dpi=160, bbox_inches='tight')
    plt.close()

def mem_mb(df):
    return df.memory_usage(deep=True).sum()/1024**2

def numeric_columns(df, extra_drop=()):
    return df.select_dtypes(include=[np.number]).columns.difference(list(extra_drop))
```

dataset cards & class/attack category balance

```
def dataset_card(name, df):
    print(f"\n=== {name} ===")
    print("shape:", df.shape, "| mem MB:", f"{mem_mb(df):.2f}")
    if "Attack" in df.columns:
        print("attack ratio:", df["Attack"].mean())
    if "attack_cat" in df.columns:
        print("attack_cat top 10:\n", df["attack_cat"].value_counts().head(10))

for nm, d in [("UNSW full", df_unsw),
              ("Train (benign-only)", train_benign),
              ("Validation (SEEN)", val_df),
              ("Test REALISTIC (UNSEEN)", test_realistic),
              ("Test STRESS (UNSEEN)", test_stress)]:
    dataset_card(nm, d)

# Bars for attack categories (use full df attacks only to be representative)
if "attack_cat" in df_unsw.columns:
```

```
    atk_counts = df_unsw[df_unsw["Label"]==1]["attack_cat"].value_counts().sort_values(ascending=False)
    plt.figure(figsize=(8,4))
    atk_counts.plot(kind="bar")
    plt.title("UNSW-NB15 attack categories (full dataset)")
    plt.ylabel("count"); plt.xlabel("attack_cat")
    savefig(f"{EDA_DIR}/attack_cat_counts_full.png")

# Pies for splits
def pie_attack(df, title, fname):
    if "Attack" not in df.columns: return
    plt.figure(figsize=(4,4))
    vals = df["Attack"].value_counts().reindex([0,1]).fillna(0)
    plt.pie(vals, labels=["Normal","Attack"], autopct="%1.1f%%", startangle=90)
    plt.title(title)
    savefig(f"{EDA_DIR}/{fname}.png")

pie_attack(val_df, "Validation Attack vs Normal", "val_attack_pie")
pie_attack(test_realistic, "Test REALISTIC Attack vs Normal", "test_realistic_attack_pie")
pie_attack(test_stress, "Test STRESS Attack vs Normal", "test_stress_attack_pie")
```

```
=== UNSW full ===
shape: (2540043, 49) | mem MB: 1837.93
attack_cat top 10:
 attack_cat
Generic             215481
Exploits             44525
 Fuzzers             19195
DoS                  16353
 Reconnaissance      12228
 Fuzzers              5051
Analysis              2677
Backdoor              1795
Reconnaissance        1759
 Shellcode            1288
Name: count, dtype: int64

=== Train (benign-only) ===
shape: (2218760, 47) | mem MB: 285.67
attack ratio: 0.0
attack_cat top 10:
 attack_cat
 Fuzzers            0
 Fuzzers            0
 Reconnaissance     0
 Shellcode          0
Analysis            0
Backdoor            0
Backdoors           0
DoS                 0
Exploits            0
Generic             0
Name: count, dtype: int64

=== Validation (SEEN) ===
shape: (761893, 47) | mem MB: 98.11
attack ratio: 0.1263510755447287
attack_cat top 10:
 attack_cat
Generic             64724
Exploits            13349
 Fuzzers             5729
DoS                  4923
 Reconnaissance      3638
 Fuzzers             1528
Analysis              792
Reconnaissance        532
Backdoor              518
 Shellcode            376
Name: count, dtype: int64

=== Test REALISTIC (UNSEEN) ===
shape: (2219157, 47) | mem MB: 268.79
attack ratio: 0.00017889676124762692
attack_cat top 10:
 attack_cat
Shellcode           223
Worms               174
```

missingness & basic numeric describe (memory-aware)

```
# choose a representative sample for heavy describe (to reduce RAM)
SAMPLE_N = min(len(df_unsw), 500_000)
df_sample = df_unsw.sample(n=SAMPLE_N, random_state=42) if len(df_unsw)>SAMPLE_N else df_unsw

# missingness on sample (full missingness can be huge to compute)
miss = df_sample.isna().sum().sort_values(ascending=False)
miss = miss[miss>0]
miss.to_csv(f"{EDA_DIR}/missingness_sample.csv")
print("Missing columns in sample (top):\n", miss.head(20))

# numeric describe on validation (stable for thresholding)
num_cols_val = numeric_columns(val_df, extra_drop=["Attack"])
desc = val_df[num_cols_val].describe(percentiles=[.01,.05,.25,.5,.75,.95,.99]).T
desc.to_csv(f"{EDA_DIR}/val_numeric_describe.csv")
print("Saved val numeric describe.")

```

```
Missing columns in sample (top):
 Name
attack_cat          436655
is_ftp_login        281440
ct_flw_http_mthd    265283
dtype: int64
Saved val numeric describe.
```

categoricals overview (proto, state, service, plus ports)

```
def bar_top(series, top=20, title="", fname=""):
    vc = series.value_counts().head(top)
    plt.figure(figsize=(8,4))
    vc.plot(kind="bar")
    plt.title(title); plt.ylabel("count")
    savefig(f"{EDA_DIR}/{fname}.png")

for c in ["proto","state","service"]:
    if c in df_unsw.columns:
        bar_top(df_unsw[c], 20, f"{c} top-20 (full UNSW)", f"{c}_top20_full")

# Ports: ensure numeric
for pcol in ["sport","dsport"]:
    if pcol in df_unsw.columns and not np.issubdtype(df_unsw[pcol].dtype, np.number):
        df_unsw[pcol] = pd.to_numeric(df_unsw[pcol], errors="coerce")

for pcol in ["sport","dsport"]:
    if pcol in df_unsw.columns:
        bar_top(df_unsw[pcol], 20, f"{pcol} top-20 (full UNSW)", f"{pcol}_top20_full")

```

feature separation (KS & Cohen's d) on validation set

```
def feature_separation(df, cols, target="Attack"):
    rows=[]
    a = df[df[target]==1][cols]
    n = df[df[target]==0][cols]
    for c in cols:
        try:
            ks_stat, ks_p = stats.ks_2samp(a[c].values, n[c].values, alternative='two-sided', mode='auto')
            mu1, mu0 = a[c].mean(), n[c].mean()
            s1, s0   = a[c].std(ddof=1), n[c].std(ddof=1)
            n1, n0   = a[c].shape[0], n[c].shape[0]
            sp = math.sqrt(((n1-1)*s1**2 + (n0-1)*s0**2) / max(n1+n0-2,1))
            d  = (mu1 - mu0) / (sp + 1e-12)
            rows.append((c, ks_stat, ks_p, d, mu0, mu1))
        except Exception as e:
            rows.append((c, np.nan, np.nan, np.nan, np.nan, np.nan))
    out = pd.DataFrame(rows, columns=["feature","KS","KS_p","Cohen_d","mean_normal","mean_attack"])
    out["abs_d"] = out["Cohen_d"].abs()
    out.sort_values(["KS","abs_d"], ascending=[False, False], inplace=True)
```

```
    return out

num_cols_val = numeric_columns(val_df, extra_drop=["Attack"])
sep_tbl = feature_separation(val_df, num_cols_val)
sep_tbl.to_csv(f"{EDA_DIR}/feature_separation_val.csv", index=False)
print("Top 10 separating features:\n", sep_tbl.head(10))

```

```
Top 10 separating features:
          feature        KS  KS_p       Cohen_d   mean_normal   mean_attack  \
4          Label  1.000000   0.0  1.000000e+12  0.000000e+00      1.000000   
37          sttl  0.978912   0.0  6.397585e+00  3.706996e+01    240.080194   
19  ct_state_ttl  0.977707   0.0  5.442588e+00  3.365999e-02      1.830241   
2          Dload  0.801384   0.0 -6.769236e-01  2.799810e+06  11541.887695   
22       dmeansz  0.774339   0.0 -8.500083e-01  3.114549e+02     36.684364   
20        dbytes  0.708067   0.0 -2.208217e-01  4.124267e+04   5080.558640   
36    state_code  0.707914   0.0  1.076418e+00  4.363343e+00      5.811574   
3          Dpkts  0.707901   0.0 -3.409656e-01  4.821069e+01      6.275456   
0       Dintpkt  0.707664   0.0 -3.172701e-02  8.410172e+01     38.834361   
24          dttl  0.705257   0.0  4.061654e-01  2.854549e+01     45.753890   

           abs_d  
4   1.000000e+12  
37  6.397585e+00  
19  5.442588e+00  
2   6.769236e-01  
22  8.500083e-01  
20  2.208217e-01  
36  1.076418e+00  
3   3.409656e-01  
0   3.172701e-02  
24  4.061654e-01  
```

histograms for top 12 features (validation, clipped 1–99%)

```
TOPK = 12
top_feats = sep_tbl["feature"].head(TOPK).tolist()

def plot_hist_by_class(df, cols, title_prefix, fname_prefix):
    for c in cols:
        plt.figure(figsize=(5,3))
        x0 = df[df["Attack"]==0][c].values
        x1 = df[df["Attack"]==1][c].values
        lo = np.nanpercentile(df[c].values, 1)
        hi = np.nanpercentile(df[c].values, 99)
        bins = 50
        plt.hist(np.clip(x0, lo, hi), bins=bins, alpha=0.6, label="Normal", density=True)
        plt.hist(np.clip(x1, lo, hi), bins=bins, alpha=0.6, label="Attack", density=True)
        plt.xlabel(c); plt.ylabel("density")
        plt.title(f"{title_prefix}: {c}")
        plt.legend()
        savefig(f"{EDA_DIR}/{fname_prefix}_{c}.png")

plot_hist_by_class(val_df, top_feats, "Validation distributions", "val_hist")

```

correlation heatmap (numeric, on a sample to save RAM) + high-corr pairs

```
# sample from validation for correlation
VAL_CORR_N = min(len(val_df), 150_000)
val_samp = val_df.sample(n=VAL_CORR_N, random_state=42) if len(val_df)>VAL_CORR_N else val_df
num_cols_val = numeric_columns(val_samp, extra_drop=["Attack"])
corr = val_samp[num_cols_val].corr().fillna(0.0)

plt.figure(figsize=(8,6))
plt.imshow(corr.values, aspect='auto', interpolation='nearest')
plt.colorbar(label="Pearson r")
plt.title("Validation correlation heatmap (sampled)")
plt.xticks([], []); plt.yticks([], [])  # hide tick clutter for large matrices
savefig(f"{EDA_DIR}/corr_heatmap_val_sampled.png")

pairs = []
thr = 0.98
```

```python
cols = list(num_cols_val)
for i in range(len(cols)):
    for j in range(i+1, len(cols)):
        r = corr.iat[i,j]
        if abs(r) >= thr:
            pairs.append((cols[i], cols[j], float(r)))
pairs = sorted(pairs, key=lambda x: -abs(x[2]))
pd.DataFrame(pairs, columns=["feat_a","feat_b","r"]).to_csv(f"{EDA_DIR}/high_corr_pairs.csv", index=False)
print("High-corr pairs (|r|>=0.98):", len(pairs))

```

```
High-corr pairs (|r|>=0.98): 3
```

outlier/tail heaviness (validation)

```python
def tail_heaviness(df, cols):
    rows=[]
    for c in cols:
        x = df[c].values
        q1,q3 = np.nanpercentile(x, [25,75]); iqr = q3 - q1
        p01,p99 = np.nanpercentile(x, [1,99])
        kurt = stats.kurtosis(x, fisher=True, nan_policy='omit')
        skw  = stats.skew(x, nan_policy='omit')
        out_frac = np.mean((x < q1 - 3*iqr) | (x > q3 + 3*iqr))
        rows.append((c, skw, kurt, out_frac, p01, p99, q1, q3))
    T = pd.DataFrame(rows, columns=["feature","skew","kurtosis","outlier_frac","p01","p99","q1","q3"])
    return T.sort_values("outlier_frac", ascending=False)

tails = tail_heaviness(val_df, numeric_columns(val_df, extra_drop=["Attack"]))
tails.to_csv(f"{EDA_DIR}/tail_heaviness_val.csv", index=False)

plt.figure(figsize=(8,4))
top_out = tails.head(20)
plt.bar(range(len(top_out)), top_out["outlier_frac"])
plt.xticks(range(len(top_out)), top_out["feature"], rotation=90, fontsize=7)
plt.ylabel("fraction beyond 3*IQR")
plt.title("Top-20 heavy-tail/outlier features (validation)")
savefig(f"{EDA_DIR}/outlier_frac_bar.png")

heavy_tail_frac = (tails["outlier_frac"] > 0.01).mean()
suggest_scaler = "RobustScaler" if heavy_tail_frac > 0.1 else "StandardScaler"
print(f"Suggested scaler: {suggest_scaler}  (heavy-tail features: {heavy_tail_frac*100:.1f}% )")

```

```
/usr/local/lib/python3.12/dist-packages/scipy/stats/_stats_py.py:1231: RuntimeWarning: overflow encountered in square
  s = s**2
/usr/local/lib/python3.12/dist-packages/numpy/_core/_methods.py:127: RuntimeWarning: overflow encountered in reduce
  ret = umr_sum(arr, axis, dtype, out, keepdims, where=where)
Suggested scaler: RobustScaler  (heavy-tail features: 88.1% )
```

time profile (if Stime exists) + per-category rates

```
if "Stime" in df_unsw.columns:
    # Stime is epoch (seconds). Plot counts by hour on a sample to save RAM.
    S_N = min(len(df_unsw), 500_000)
    s = df_unsw.sample(n=S_N, random_state=42) if len(df_unsw)>S_N else df_unsw
    ts = pd.to_datetime(s["Stime"], unit="s", errors="coerce")
    hours = ts.dt.floor('H')
    counts = hours.value_counts().sort_index()
    plt.figure(figsize=(9,3))
    counts.plot()
    plt.title("Traffic volume over time (sampled, hourly)")
    plt.ylabel("flows/hour"); plt.xlabel("time")
    savefig(f"{EDA_DIR}/time_series_hourly.png")

# Attack rate per attack_cat (on full df)
if "attack_cat" in df_unsw.columns and "Label" in df_unsw.columns:
    grp = df_unsw.groupby("attack_cat")["Label"].agg(['count','mean']).sort_values('count', ascending=False)
    grp.rename(columns={'mean':'attack_ratio'}, inplace=True)
    grp.to_csv(f"{EDA_DIR}/attack_cat_stats.csv")
    print("Saved attack_cat_stats.csv")

```

```
/tmp/ipython-input-1388815498.py:6: FutureWarning: 'H' is deprecated and will be removed in a future version, please use 'h' instea
  hours = ts.dt.floor('H')
Saved attack_cat_stats.csv
```

EDA-driven preprocessing plan

```
#  drop ID/time/seq columns; keep ports and proto/state/service; use RobustScaler if many heavy tails
drop_cols_proposed = [c for c in ["srcip","dstip","Stime","Ltime","stcpb","dtcpb"] if c in df_unsw.columns]
cat_cols_proposed  = [c for c in ["proto","state","service"] if c in df_unsw.columns]

num_cols_proposed = df_unsw.select_dtypes(include=[np.number]).columns.tolist()
num_cols_proposed = [c for c in num_cols_proposed if c not in set(["Label","Attack"])]

preproc_plan_unsw = {
    "drop_cols": drop_cols_proposed,
    "categoricals": cat_cols_proposed,
    "numeric_candidates": num_cols_proposed,
    "scaler": suggest_scaler,
    "top_sep_features_val": sep_tbl["feature"].head(20).tolist(),
    "high_corr_pairs_thresh": 0.98
}
with open(f"{EDA_DIR}/preprocessing_plan_unsw.json","w") as f:
    json.dump(preproc_plan_unsw, f, indent=2)

print("Saved preprocessing_plan_unsw.json")

```

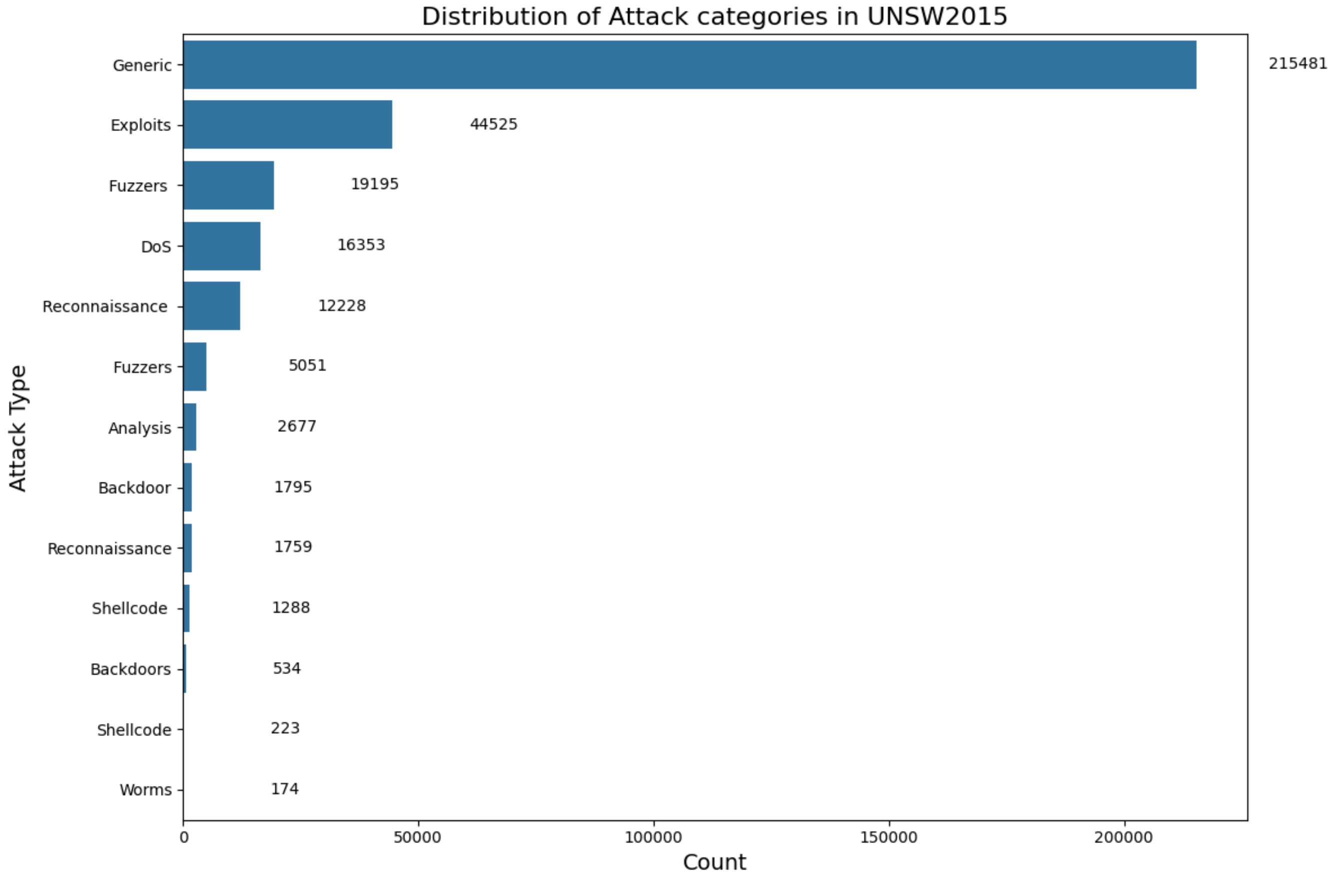
```
import matplotlib.pyplot as plt
import seaborn as sns

target_col = 'attack_cat'
plt.figure(figsize=(12, 8))
ax = sns.countplot(df_unsw, y=target_col, order=df_unsw[target_col].value_counts().index)

# 3. Add annotations and styling
plt.title('Distribution of Attack categories in UNSW2015', fontsize=16)
plt.xlabel('Count', fontsize=14)
plt.ylabel('Attack Type', fontsize=14)

# Add count values on each bar
for p in ax.patches:
    width = p.get_width()
    plt.text(width + 0.1 * max(df_unsw[target_col].value_counts()),
             p.get_y() + p.get_height()/2.,
             f'{int(width)}',
             ha='center', va='center')

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




```python
# 1.1 Fix odd column names (spaces, case)
df = df.rename(columns=lambda c: c.strip().replace(" ", "_"))
# e.g., 'ct_src_ ltm' -> 'ct_src__ltm' above; normalize further:
df = df.rename(columns={"ct_src__ltm": "ct_src_ltm"})

# 1.2 Coerce ports to numeric (often object in raw CSVs)
for col in ["sport", "dsport", "ct_ftp_cmd"]:
    if col in df.columns and df[col].dtype == "object":
        df[col] = pd.to_numeric(df[col], errors="coerce")

# 1.3 Convert low-cardinality text to category (saves RAM; fine for OneHot later)
for col in ["proto", "state", "service", "srcip", "dstip", "attack_cat"]:
    if col in df.columns and df[col].dtype == "object":
        # IPs are high-card; still set to category for cheaper memory even if we later drop them
        df[col] = df[col].astype("category")

# 1.4 Downcast numerics where safe
def downcast_df(dfx):
    for c in dfx.select_dtypes(include=["int64"]).columns:
        dfx[c] = pd.to_numeric(dfx[c], downcast="unsigned")  # counts/IDs are nonnegative in UNSW
    for c in dfx.select_dtypes(include=["float64"]).columns:
        dfx[c] = pd.to_numeric(dfx[c], downcast="float")
    return dfx

df = downcast_df(df)
print(df.dtypes.value_counts())
print("RAM (MB):", df.memory_usage(deep=True).sum()/1024**2)
```

```
uint8       15
float32     11
uint32       7
uint16       6
float64      4
category     1
category     1
category     1
```

```
category     1
category     1
category     1
Name: count, dtype: int64
RAM (MB): 334.309627532959
```

```
# 2.1 Normalize labels
assert "Label" in df.columns and "attack_cat" in df.columns, "Expected Label & attack_cat columns."
df["Attack"] = df["Label"].astype("int8")  # 1=attack, 0=normal

# 2.2 Pick UNSEEN zero-day categories (least frequent TWO, reproducibly)
atk_only = df[df["Attack"]==1]
vc = atk_only["attack_cat"].value_counts()
# Keep only valid strings
vc = vc[vc.index.notna()]
unseen_cats = list(vc.sort_values(ascending=True).head(2).index)  # e.g., ['Worms','Shellcode'] usually
print("Zero-day UNSEEN categories:", unseen_cats)

is_unseen = df["attack_cat"].isin(unseen_cats)
df_seen   = df[(~is_unseen) | (df["Attack"]==0)].copy()   # all benign + seen attacks
df_unseen = df[( is_unseen) | (df["Attack"]==0)].copy()   # all benign + unseen attacks

print("SEEN:", df_seen.shape, "UNSEEN:", df_unseen.shape)

```

```
Zero-day UNSEEN categories: ['Worms', 'Shellcode']
SEEN: (2539646, 50) UNSEEN: (2219157, 50)
```

```
from sklearn.model_selection import train_test_split

# 3.1 Train on benign-only from SEEN
train_benign = df_seen[df_seen["Attack"]==0].copy()

# 3.2 Validation (SEEN): stratified sample for stable thresholding
val_frac = 0.30
val_df, _ = train_test_split(
    df_seen, test_size=(1 - val_frac),
    stratify=df_seen["Attack"], random_state=42
)

# 3.3 Test sets from UNSEEN
test_df = df_unseen.copy()

# REALISTIC prevalence (e.g., 10% attacks)
target_prev = 0.10
ben = test_df[test_df["Attack"]==0]
atk = test_df[test_df["Attack"]==1]
n_b = len(ben)
n_a = min(len(atk), int(n_b * target_prev / (1 - target_prev)))
atk_down = atk.sample(n=n_a, random_state=42) if n_a>0 else atk
test_realistic = pd.concat([ben, atk_down]).sample(frac=1.0, random_state=42).reset_index(drop=True)

# STRESS: as-is
test_stress = test_df.sample(frac=1.0, random_state=42).reset_index(drop=True)

for nm, d in [("train_benign", train_benign), ("val_df", val_df),
              ("test_realistic", test_realistic), ("test_stress", test_stress)]:
    print(nm, d.shape, "attack ratio:", d["Attack"].mean())

# Save splits
split_dir = f"{BASE}/splits"
train_benign.to_parquet(f"{split_dir}/train_benign_seen.parquet", index=False)
val_df.to_parquet(        f"{split_dir}/val_seen.parquet",        index=False)
test_realistic.to_parquet(f"{split_dir}/test_unseen_realistic.parquet", index=False)
test_stress.to_parquet(   f"{split_dir}/test_unseen_stress.parquet",    index=False)
with open(f"{split_dir}/meta.json","w") as f:
    json.dump({"unseen_categories": [str(x) for x in unseen_cats],
               "target_attack_prevalence_realistic": target_prev}, f, indent=2)

```

```
train_benign (2218760, 50) attack ratio: 0.0
val_df (761893, 50) attack ratio: 0.1263510755447287
test_realistic (2219157, 50) attack ratio: 0.00017889676124762692
test_stress (2219157, 50) attack ratio: 0.00017889676124762692
```

```
drop_cols = [c for c in ["srcip","dstip","Stime","Ltime","stcpb","dtcpb"] if c in df.columns]
cat_cols  = [c for c in ["proto","state","service"] if c in df.columns]
label_cols = ["Label","attack_cat","Attack"]

# numeric candidates = all numeric minus drops & labels
num_cols = df.select_dtypes(include=["float32","float64","int16","int32","int64","uint8","uint16","uint32"]).columns.tolist()
num_cols = [c for c in num_cols if c not in set(drop_cols + label_cols)]

# remove ports if you choose not to use them
# num_cols = [c for c in num_cols if c not in ("sport","dsport")]

print("Drop cols:", drop_cols)
print("Categoricals:", cat_cols)
print("Numeric count:", len(num_cols))

```

```
Drop cols: ['srcip', 'dstip', 'Stime', 'Ltime', 'stcpb', 'dtcpb']
Categoricals: ['proto', 'state', 'service']
Numeric count: 38
```

```
import numpy as np, pandas as pd, gc

# Categoricals to keep (if present)
cat_cols  = [c for c in ["proto","state","service"] if c in train_benign.columns]
label_cols = ["Label","attack_cat","Attack"]

# Build code maps on TRAIN BENIGN ONLY (no leakage)
code_maps = {}
for c in cat_cols:
    cats = pd.Categorical(train_benign[c]).categories.tolist()
    code_maps[c] = {v:i for i,v in enumerate(cats)}

# FIXED encoder: map from object, allow -1 for unseen categories
def add_codes(df_in):
    df_out = df_in  # in-place to save RAM
    for c in cat_cols:
        cmap = code_maps[c]
        df_out[c + "_code"] = df_out[c].astype("object").map(cmap).fillna(-1).astype("int16")
    return df_out

# Apply to all splits
train_benign = add_codes(train_benign)
val_df       = add_codes(val_df)
test_realistic = add_codes(test_realistic)
test_stress    = add_codes(test_stress)

code_cols = [c+"_code" for c in cat_cols]

# Drop high-card/ID/leakage columns if present
drop_cols = [c for c in ["srcip","dstip","Stime","Ltime","stcpb","dtcpb"] if c in train_benign.columns]
for df_ in (train_benign, val_df, test_realistic, test_stress):
    for c in drop_cols:
        if c in df_.columns: df_.drop(columns=c, inplace=True)

# Numeric base features (we add code_cols later)
num_base_cols = train_benign.select_dtypes(include=[np.number]).columns.tolist()
num_base_cols = [c for c in num_base_cols if c not in set(label_cols + code_cols)]
print("num_base_cols:", len(num_base_cols), " | code_cols:", code_cols)
gc.collect();

```

```
num_base_cols: 38  | code_cols: ['proto_code', 'state_code', 'service_code']
```

```
def compute_clip_bounds(df_num, lower=1.0, upper=99.0):
    lo = df_num.quantile(lower/100.0)
    hi = df_num.quantile(upper/100.0)
    return lo.to_dict(), hi.to_dict()

train_benign_num = train_benign[num_base_cols].astype("float32", copy=False)
lo_b, hi_b = compute_clip_bounds(train_benign_num, 1.0, 99.0)
del train_benign_num; gc.collect()

def clip_numeric_block(df_in):
    Xn = df_in[num_base_cols].astype("float32", copy=True)
    for c in num_base_cols:
        Xn[c] = np.clip(Xn[c].values, lo_b[c], hi_b[c])
```

```
    return Xn

def build_matrix(df_in):
    # numeric (winsorized) + categorical codes (as float32)
    Xn = clip_numeric_block(df_in)
    Xc = df_in[code_cols].astype("float32", copy=False) if code_cols else None
    return Xn if Xc is None else pd.concat([Xn, Xc], axis=1)

```

```
from sklearn.preprocessing import RobustScaler, StandardScaler

# Sample benign for fitting scaler (keeps RAM/time low)
N_TRAIN_MAX = 400_000
rs = np.random.RandomState(42)
idx_fit = rs.choice(len(train_benign), size=min(N_TRAIN_MAX, len(train_benign)), replace=False)
train_sample = train_benign.iloc[idx_fit]

Scaler = RobustScaler  # robust to heavy tails
scaler = Scaler(with_centering=True, with_scaling=True)

X_train_sample_df = build_matrix(train_sample)
scaler.fit(X_train_sample_df.values)
del X_train_sample_df, train_sample; gc.collect()

def transform_split(df_in):
    Xdf = build_matrix(df_in)
    X = scaler.transform(Xdf.values).astype("float32", copy=False)
    del Xdf; gc.collect()
    return X

X_train = transform_split(train_benign)     # benign-only (you can subsample for fit below)
X_val   = transform_split(val_df)
X_tr    = transform_split(test_realistic)
X_ts    = transform_split(test_stress)

y_val = val_df["Attack"].astype(int).values
y_tr  = test_realistic["Attack"].astype(int).values
y_ts  = test_stress["Attack"].astype(int).values

print("Shapes -> X_train:", X_train.shape, "  X_val:", X_val.shape, "  X_tr:", X_tr.shape, "  X_ts:", X_ts.shape)
gc.collect();

```

```
Shapes -> X_train: (2218760, 41)   X_val: (761893, 41)   X_tr: (2219157, 41)   X_ts: (2219157, 41)
```

```
N_FIT_MAX = 400_000
if len(X_train) > N_FIT_MAX:
    idx_fit2 = rs.choice(len(X_train), size=N_FIT_MAX, replace=False)
    X_fit = X_train[idx_fit2]
else:
    X_fit = X_train
print("Fitting on:", X_fit.shape)

```

```
Fitting on: (400000, 41)
```

```
from sklearn.metrics import precision_recall_curve, classification_report, roc_auc_score, confusion_matrix, roc_curve, precisi
import numpy as np

def pick_thresh_by_Fbeta(y_true, scores, beta=2.0):
    P, R, thr = precision_recall_curve(y_true, scores)
    P, R = P[:-1], R[:-1]
    fbeta = (1+beta**2) * (P*R) / (beta**2 * P + R + 1e-12)
    i = np.nanargmax(fbeta)
    return float(thr[i]), float(P[i]), float(R[i]), float(fbeta[i])

def pick_thresh_at_fpr(y_true, scores, max_fpr=0.05):
    fpr, tpr, thr = roc_curve(y_true, scores)
    ok = np.where(fpr <= max_fpr)[0]
    if len(ok)==0:
        j = np.argmax(tpr - fpr)
        return float(thr[j]), float(fpr[j]), float(tpr[j])
    i = ok[np.argmax(tpr[ok])]
    return float(thr[i]), float(fpr[i]), float(tpr[i])

```

```
def summarize(y_true, y_pred, scores, name=""):
    P,R,F1,_ = precision_recall_fscore_support(y_true, y_pred, average='binary', zero_division=0)
    auc_ = roc_auc_score(y_true, scores) if len(np.unique(y_true))>1 else np.nan
    cm = confusion_matrix(y_true, y_pred)
    print(f"\n== {name} ==")
    print(f"Precision={P:.4f}  Recall={R:.4f}  F1={F1:.4f}  ROC-AUC={auc_:.4f}")
    print("Confusion matrix:\n", cm)
    print(classification_report(y_true, y_pred, digits=4))

```

Train and Evaluate Isolation Forest

```
from sklearn.ensemble import IsolationForest

iforest = IsolationForest(
    n_estimators=400, max_samples='auto', contamination='auto',
    random_state=42, n_jobs=-1
).fit(X_fit)

val_scores = -iforest.score_samples(X_val)
tr_scores  = -iforest.score_samples(X_tr)
ts_scores  = -iforest.score_samples(X_ts)

# F2-optimal threshold (recall-oriented)
th_f2, p_f2, r_f2, f2 = pick_thresh_by_Fbeta(y_val, val_scores, beta=2.0)
y_tr_f2 = (tr_scores >= th_f2).astype(int)
y_ts_f2 = (ts_scores >= th_f2).astype(int)
print(f"IForest F2 threshold: {th_f2:.6f} (val P={p_f2:.3f}, R={r_f2:.3f}, F2={f2:.3f})")
summarize(y_tr, y_tr_f2, tr_scores, "IForest | REALISTIC | F2-opt")
summarize(y_ts, y_ts_f2, ts_scores, "IForest | STRESS    | F2-opt")

# FPR-controlled threshold (≤5% on validation)
th_fpr, fpr_sel, tpr_sel = pick_thresh_at_fpr(y_val, val_scores, max_fpr=0.05)
y_tr_fpr = (tr_scores >= th_fpr).astype(int)
y_ts_fpr = (ts_scores >= th_fpr).astype(int)
print(f"IForest FPR<=5% threshold: {th_fpr:.6f} (val FPR={fpr_sel:.3f}, TPR={tpr_sel:.3f})")
summarize(y_tr, y_tr_fpr, tr_scores, "IForest | REALISTIC | FPR<=5%")
summarize(y_ts, y_ts_fpr, ts_scores, "IForest | STRESS    | FPR<=5%")

```

```
IForest F2 threshold: 0.505144 (val P=0.578, R=0.993, F2=0.868)

== IForest | REALISTIC | F2-opt ==
Precision=0.0017  Recall=0.9975  F1=0.0034  ROC-AUC=0.9615
Confusion matrix:
 [[1986445  232315]
 [      1     396]]
              precision    recall  f1-score   support

           0     1.0000    0.8953    0.9448   2218760
           1     0.0017    0.9975    0.0034       397

    accuracy                         0.8953   2219157
   macro avg     0.5009    0.9464    0.4741   2219157
weighted avg     0.9998    0.8953    0.9446   2219157


== IForest | STRESS    | F2-opt ==
Precision=0.0017  Recall=0.9975  F1=0.0034  ROC-AUC=0.9615
Confusion matrix:
 [[1986445  232315]
 [      1     396]]
              precision    recall  f1-score   support

           0     1.0000    0.8953    0.9448   2218760
           1     0.0017    0.9975    0.0034       397

    accuracy                         0.8953   2219157
   macro avg     0.5009    0.9464    0.4741   2219157
weighted avg     0.9998    0.8953    0.9446   2219157

IForest FPR<=5% threshold: 0.551726 (val FPR=0.050, TPR=0.479)

== IForest | REALISTIC | FPR<=5% ==
Precision=0.0022  Recall=0.6196  F1=0.0044  ROC-AUC=0.9615
Confusion matrix:
 [[2108237  110523]
```

```
 [    151     246]]
              precision    recall  f1-score   support

           0     0.9999    0.9502    0.9744   2218760
           1     0.0022    0.6196    0.0044       397

    accuracy                         0.9501   2219157
   macro avg     0.5011    0.7849    0.4894   2219157
weighted avg     0.9997    0.9501    0.9742   2219157


== IForest | STRESS    | FPR<=5% ==
Precision=0.0022  Recall=0.6196  F1=0.0044  ROC-AUC=0.9615
Confusion matrix:
 [[2108237  110523]
 [    151     246]]
              precision    recall  f1-score   support

           0     0.9999    0.9502    0.9744   2218760
           1     0.0022    0.6196    0.0044       397
```

```python
import numpy as np

def check_finiteness(X, name):
    n = X.shape[0]
    bad_nan = np.isnan(X).sum()
    bad_inf = np.isinf(X).sum()
    print(f"{name}: NaN={bad_nan}, Inf={bad_inf}, shape={X.shape}")

check_finiteness(X_train, "X_train")
check_finiteness(X_val,   "X_val")
check_finiteness(X_tr,    "X_tr")
check_finiteness(X_ts,    "X_ts")

```

```
X_train: NaN=3330904, Inf=0, shape=(2218760, 41)
X_val: NaN=1263517, Inf=0, shape=(761893, 41)
X_tr: NaN=3331234, Inf=0, shape=(2219157, 41)
X_ts: NaN=3331234, Inf=0, shape=(2219157, 41)
```

```python
import numpy as np, pandas as pd, gc
from sklearn.preprocessing import RobustScaler

# 1) Identify the columns we intend to use
label_cols = ["Label","attack_cat","Attack"]
code_cols  = [c for c in ["proto_code","state_code","service_code"] if c in train_benign.columns]

# Base numeric candidates = all numeric except labels & codes
num_base_cols = train_benign.select_dtypes(include=[np.number]).columns.tolist()
num_base_cols = [c for c in num_base_cols if c not in set(label_cols + code_cols)]

# 2) Drop columns that are ALL-NaN in train_benign
all_nan_cols = train_benign[num_base_cols].isna().all(axis=0)
drop_all_nan = all_nan_cols[all_nan_cols].index.tolist()
if drop_all_nan:
    print("Dropping all-NaN numeric cols:", drop_all_nan)
num_base_cols = [c for c in num_base_cols if c not in set(drop_all_nan)]

# 3) Compute clip bounds (1st/99th) on train_benign and FIX any NaN bounds by using the median
def compute_clip_bounds_safe(df_num, lower=1.0, upper=99.0):
    lo = df_num.quantile(lower/100.0)
    hi = df_num.quantile(upper/100.0)
    med = df_num.median()
    # Replace NaN lo/hi with median; if still NaN, use 0.0
    lo = lo.fillna(med).fillna(0.0)
    hi = hi.fillna(med).fillna(0.0)
    # Ensure lo <= hi
    bad = lo > hi
    if bad.any():
        # when inverted, set both to median
        lo[bad] = med[bad]
        hi[bad] = med[bad]
    return lo.to_dict(), hi.to_dict()

train_benign_num = train_benign[num_base_cols].astype("float32", copy=False)
lo_b, hi_b = compute_clip_bounds_safe(train_benign_num, 1.0, 99.0)
del train_benign_num; gc.collect()

```

```
# 4) Clip numerics and build matrices (numeric + code cols)
def clip_numeric_block(df_in, cols, lo_b, hi_b):
    Xn = df_in[cols].astype("float32", copy=True)
    for c in cols:
        lo, hi = lo_b[c], hi_b[c]
        # safe clip; if lo==hi, this becomes a constant column (we'll drop constants next)
        Xn[c] = np.clip(Xn[c].values, lo, hi)
    return Xn

def build_matrix(df_in):
    Xn = clip_numeric_block(df_in, num_base_cols, lo_b, hi_b)
    Xc = df_in[code_cols].astype("float32", copy=False) if code_cols else None
    X = Xn if Xc is None else pd.concat([Xn, Xc], axis=1)
    return X

X_train_df = build_matrix(train_benign)
X_val_df   = build_matrix(val_df)
X_tr_df    = build_matrix(test_realistic)
X_ts_df    = build_matrix(test_stress)

# 5) Drop constant columns (zero variance on TRAIN)
stds = X_train_df.std(axis=0, ddof=0)
const_cols = stds[~np.isfinite(stds) | (stds == 0)].index.tolist()
if const_cols:
    print("Dropping constant/invalid cols:", const_cols)
    X_train_df.drop(columns=const_cols, inplace=True, errors="ignore")
    X_val_df.drop(columns=const_cols, inplace=True, errors="ignore")
    X_tr_df.drop(columns=const_cols, inplace=True, errors="ignore")
    X_ts_df.drop(columns=const_cols, inplace=True, errors="ignore")

# 6) Scale with RobustScaler on benign sample
from sklearn.preprocessing import RobustScaler
rs = np.random.RandomState(42)
N_TRAIN_MAX = 400_000
idx_fit = rs.choice(len(X_train_df), size=min(N_TRAIN_MAX, len(X_train_df)), replace=False)
scaler = RobustScaler(with_centering=True, with_scaling=True)
scaler.fit(X_train_df.iloc[idx_fit].values)

def transform_df_to_array(Xdf):
    X = scaler.transform(Xdf.values).astype("float32", copy=False)
    # enforce finiteness just in case
    X = np.nan_to_num(X, nan=0.0, posinf=1e6, neginf=-1e6)
    return X

X_train = transform_df_to_array(X_train_df); del X_train_df
X_val   = transform_df_to_array(X_val_df);   del X_val_df
X_tr    = transform_df_to_array(X_tr_df);    del X_tr_df
X_ts    = transform_df_to_array(X_ts_df);    del X_ts_df
gc.collect()

# 7) Re-check finiteness
def check_finiteness(X, name):
    print(name, "NaN:", np.isnan(X).sum(), "Inf:", np.isinf(X).sum(), "shape:", X.shape)
check_finiteness(X_train, "X_train")
check_finiteness(X_val,   "X_val")
check_finiteness(X_tr,    "X_tr")
check_finiteness(X_ts,    "X_ts")

# 8) If you want to train on a subset of X_train (benign), pick it now
N_FIT_MAX = 400_000
if len(X_train) > N_FIT_MAX:
    idx_fit2 = rs.choice(len(X_train), size=N_FIT_MAX, replace=False)
    X_fit = X_train[idx_fit2]
else:
    X_fit = X_train
print("Fitting AE on:", X_fit.shape)
```

```
Dropping constant/invalid cols: ['is_sm_ips_ports']
X_train NaN: 0 Inf: 0 shape: (2218760, 40)
X_val NaN: 0 Inf: 0 shape: (761893, 40)
X_tr NaN: 0 Inf: 0 shape: (2219157, 40)
X_ts NaN: 0 Inf: 0 shape: (2219157, 40)
Fitting AE on: (400000, 40)
```

```
import tensorflow as tf
from tensorflow import keras
tf.random.set_seed(42)

input_dim = X_fit.shape[1]
inp = keras.Input(shape=(input_dim,))
x = keras.layers.Dense(256, activation='relu')(inp)
x = keras.layers.Dense(128, activation='relu')(x)
z = keras.layers.Dense(64,  activation='relu')(x)
x = keras.layers.Dense(128, activation='relu')(z)
x = keras.layers.Dense(256, activation='relu')(x)
out = keras.layers.Dense(input_dim, activation='linear')(x)

ae = keras.Model(inp, out)
ae.compile(optimizer=keras.optimizers.Adam(learning_rate=5e-4, clipnorm=1.0), loss='mse')
es = keras.callbacks.EarlyStopping(monitor='loss', patience=5, restore_best_weights=True)
_ = ae.fit(X_fit, X_fit, epochs=60, batch_size=1024, shuffle=True, callbacks=[es], verbose=0)

# Reconstructions
val_rec = ae.predict(X_val, batch_size=4096, verbose=0)
tr_rec  = ae.predict(X_tr,  batch_size=4096, verbose=0)
ts_rec  = ae.predict(X_ts,  batch_size=4096, verbose=0)

# Errors (now guaranteed finite)
val_err = np.mean((X_val - val_rec)**2, axis=1).astype("float32")
tr_err  = np.mean((X_tr  - tr_rec )**2, axis=1).astype("float32")
ts_err  = np.mean((X_ts  - ts_rec )**2, axis=1).astype("float32")

# Threshold selection & evaluation (same functions you already have)
th_f2_ae, p_f2_ae, r_f2_ae, f2_ae = pick_thresh_by_Fbeta(y_val, val_err, beta=2.0)
y_tr_f2_ae = (tr_err >= th_f2_ae).astype(int)
y_ts_f2_ae = (ts_err >= th_f2_ae).astype(int)
print(f"AE F2 threshold: {th_f2_ae:.6f} (val P={p_f2_ae:.3f}, R={r_f2_ae:.3f}, F2={f2_ae:.3f})")
summarize(y_tr, y_tr_f2_ae, tr_err, "AE | REALISTIC | F2-opt")
summarize(y_ts, y_ts_f2_ae, ts_err, "AE | STRESS    | F2-opt")

th_fpr_ae, fpr_sel_ae, tpr_sel_ae = pick_thresh_at_fpr(y_val, val_err, max_fpr=0.05)
y_tr_fpr_ae = (tr_err >= th_fpr_ae).astype(int)
y_ts_fpr_ae = (ts_err >= th_fpr_ae).astype(int)
print(f"AE FPR<=5% threshold: {th_fpr_ae:.6f} (val FPR={fpr_sel_ae:.3f}, TPR={tpr_sel_ae:.3f})")
summarize(y_tr, y_tr_fpr_ae, tr_err, "AE | REALISTIC | FPR<=5%")
summarize(y_ts, y_ts_fpr_ae, ts_err, "AE | STRESS    | FPR<=5%")
```