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Course: SEAS 8414 — Security Analytics

Goal of this notebook

Train and audit detectors on CIC-DDoS2019, reporting recall for each DDoS type.

What you will learn

1. Read a majority-class baseline before trusting any accuracy figure.
2. Find the strongest single feature, then test it by dropping it and refitting.
3. Tell duplicate inflation apart from genuine signal.
4. Report per-group recall, because the rare classes carry the risk.

Where this connects to the course text

The text builds a defence pipeline; this notebook trains a classifier and audits it. The links below are to specific chapter objectives that share an *analytic move*, not to matching subject matter.

- **Chapter 4: Attack Graph Analytics** — Learning objective 5 (section 4.1) separates a **one-at-a-time** perturbation from the smallest perturbation that reverses a ranking, and warns the first **overstates stability**. Dropping only the top feature and refitting is exactly that weaker test, so read it as a floor.
- **Chapter 11: Formal Protocol Verification** — Section **11.1.2**, titled *Proved, tested, and hoped*, asks you to separate exactly those three. (Chapter 11 lists its objectives in §11.0, not §11.1 as the other chapters do.) The ablation does that job here: it tests whether the headline survives.
- **Chapter 12: Autonomous Remediation and Safety Verification** — Learning objective 1 (section 12.1) assembles evidence into a **safety case** with stated assumptions. Section 13 is that safety case for a model score.

DDoS Detection with Per-Type Recall on CIC-DDoS2019

Model comparison + per-DDoS-type recall + validity audit (~431k flows)

Abstract: CIC-DDoS2019 (Sharafaldin et al., 2019) is a modern DDoS dataset with a fine attack **taxonomy**. The taxonomy spans reflective/amplification floods (NTP, TFTP, LDAP,

MSSQL, SNMP, DNS) and volumetric floods (UDP, SYN), described by CICFlowMeter features. We use dhoogla's cleaned parquet (~431k flows). We compare four learners and, crucially, report recall **per DDoS type** so the rare attack classes are visible, not just the dominant floods.

1. Research problem

Task: detect DDoS flows from CICFlowMeter features. The label this notebook trains on is **binary** — benign versus attack.

The notebook does **not** name the attack type. No multi-class model is ever fitted. The taxonomy enters only as a *stratifier*: the binary detector's recall is reported separately inside each DDoS type. That answers "which types does the detector miss?", not "which type is this flow?".

DDoS is volumetric, so aggregate accuracy is easy and misleading. The operational questions are per-type recall and the false-positive rate on benign traffic. Those decide whether legitimate users get collateral-blocked.

2. Literature review

- **Sharafaldin, Lashkari, Hakak & Ghorbani (2019)** — *Developing Realistic Distributed Denial of Service (DDoS) Attack Dataset and Taxonomy* (IEEE ICCST). It covers the dataset, its taxonomy, and CICFlowMeter features.
- **Mirkovic & Reiher (2004)** — the classic DDoS attack/defense taxonomy.
- **Jonker, King, Krupp, Rossow, Sperotto & Dainotti (2017)** — *Millions of Targets Under Attack: a Macroscopic Characterization of the DoS Ecosystem* (IMC). It is an Internet-scale measurement of DoS **events and their victims**. It fuses network-telescope backscatter (randomly spoofed attacks) with amplification-honeypot logs, and adds DNS data on adoption of DDoS Protection Services. It measures attacks observed in the wild. It is **not** a study of booter/stresser "DDoS-as-a-service" markets, and not a detection method.
- **Sommer & Paxson (2010)** — the closed-world critique.

Related approaches and their known caveats — drawn from the wider literature; these are **not** measurements reproduced on this exact corpus:

Reported approach	Known caveat
Sharafaldin et al. (2019) — ID3/RF/NB on CICFlowMeter features	flow features near-separate floods; benign is a small minority
Flow-based DDoS detectors	high accuracy is base-rate-driven; FPR on benign is the real metric

3. Dataset provenance & honesty caveats

Property	Value
Source	Kaggle `dhoogla/cicddos2019` (cleaned parquet)
Rows	~431k flows (dhoogla deduplicated the raw 50M+)
Label	`Label` = Benign or a DDoS type (18 classes)
Access	Kaggle API token required

Honestly: benign is only ~23% of the cleaned set, so accuracy is inflated by the attack-heavy mix. Per-type recall and the benign false-positive rate are the honest metrics. Flow-count features can act as shortcuts for volumetric floods, which the audit probes.

Before you run this: getting the data

This notebook downloads its own data on the first run, then caches it. You do not fetch anything by hand.

Dataset: Kaggle `dhoogla/cicddos2019` -> `/tmp/kg_cicddos2019`. It is about **34 MB** on disk.

One-time setup. Sign in at kaggle.com, open **Settings**, and under **API** choose **Create New Token**. Kaggle hands you a `kaggle.json` file. This notebook does *not* read that file. It reads a plain key file, so convert it once:

```
mkdir -p ~/.kaggle
python3 -c "import json;print(json.load(open('kaggle.json'))
['key'],end='')" > ~/.kaggle/access_token
chmod 600 ~/.kaggle/access_token
```

Never paste the token into a cell, a commit, or a screenshot. If it leaks, revoke it from the same Settings page.

If the loader fails:

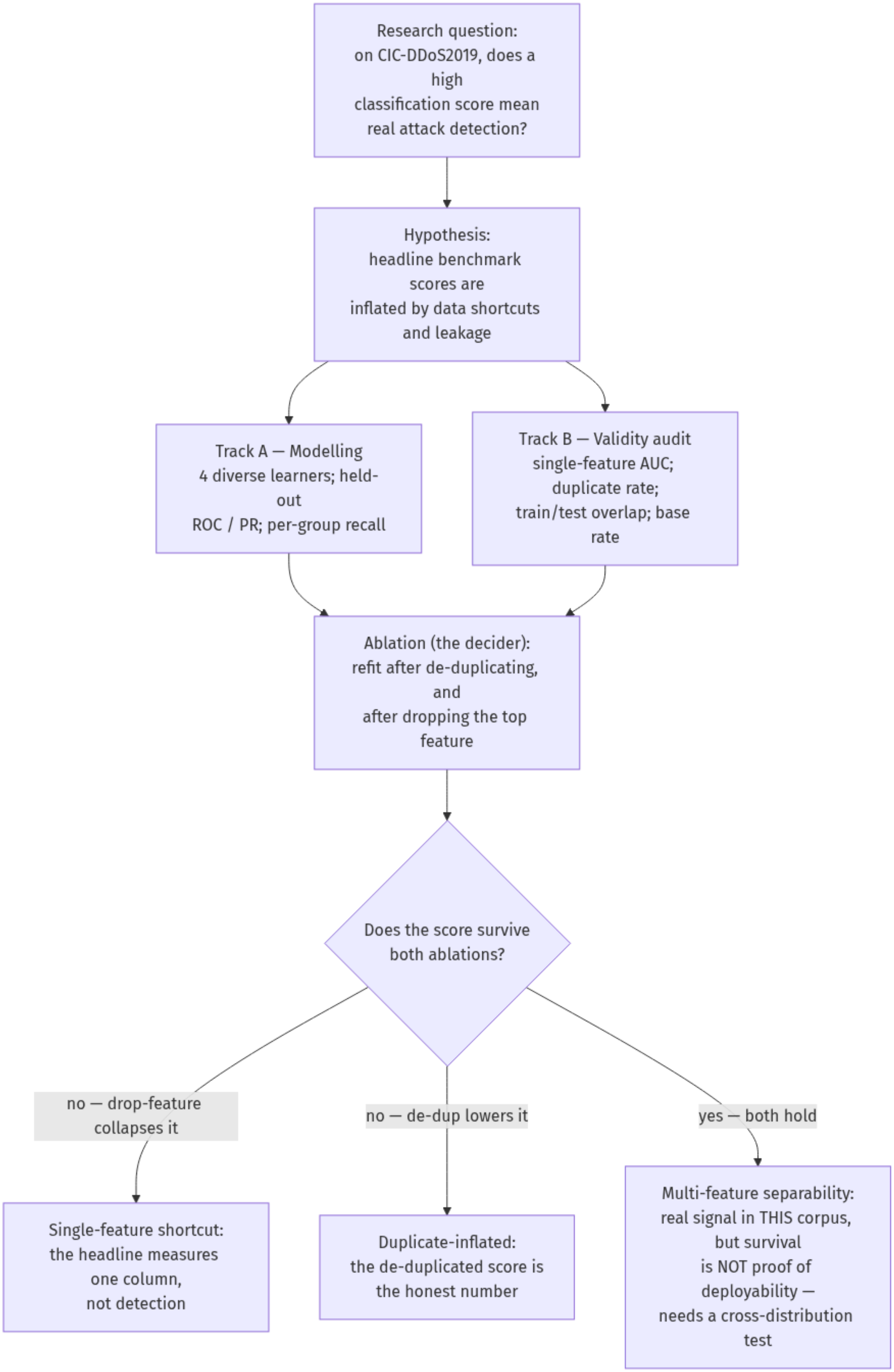
- `FileNotFoundError: ~/.kaggle/access_token` - you created `kaggle.json` but not the key file. Run the command above.
- `401 Unauthorized` - the key is wrong, or a trailing newline crept in.
- `403 Forbidden` - open the dataset page on Kaggle while signed in, accept its terms, then re-run the cell.

The cache sits under `/tmp`, which macOS clears on reboot. To keep it, move the folder somewhere durable and symlink it back. Do **not** edit the path in the code cell below: that changes a code cell and invalidates the stored outputs you are reviewing.

4. Solution design

The methodology is deliberately two-track. We *earn* a headline score with standard modelling, then *interrogate* it with a validity audit. Only a verdict that survives both is reported. The diagram below is the shape of every notebook in this series.

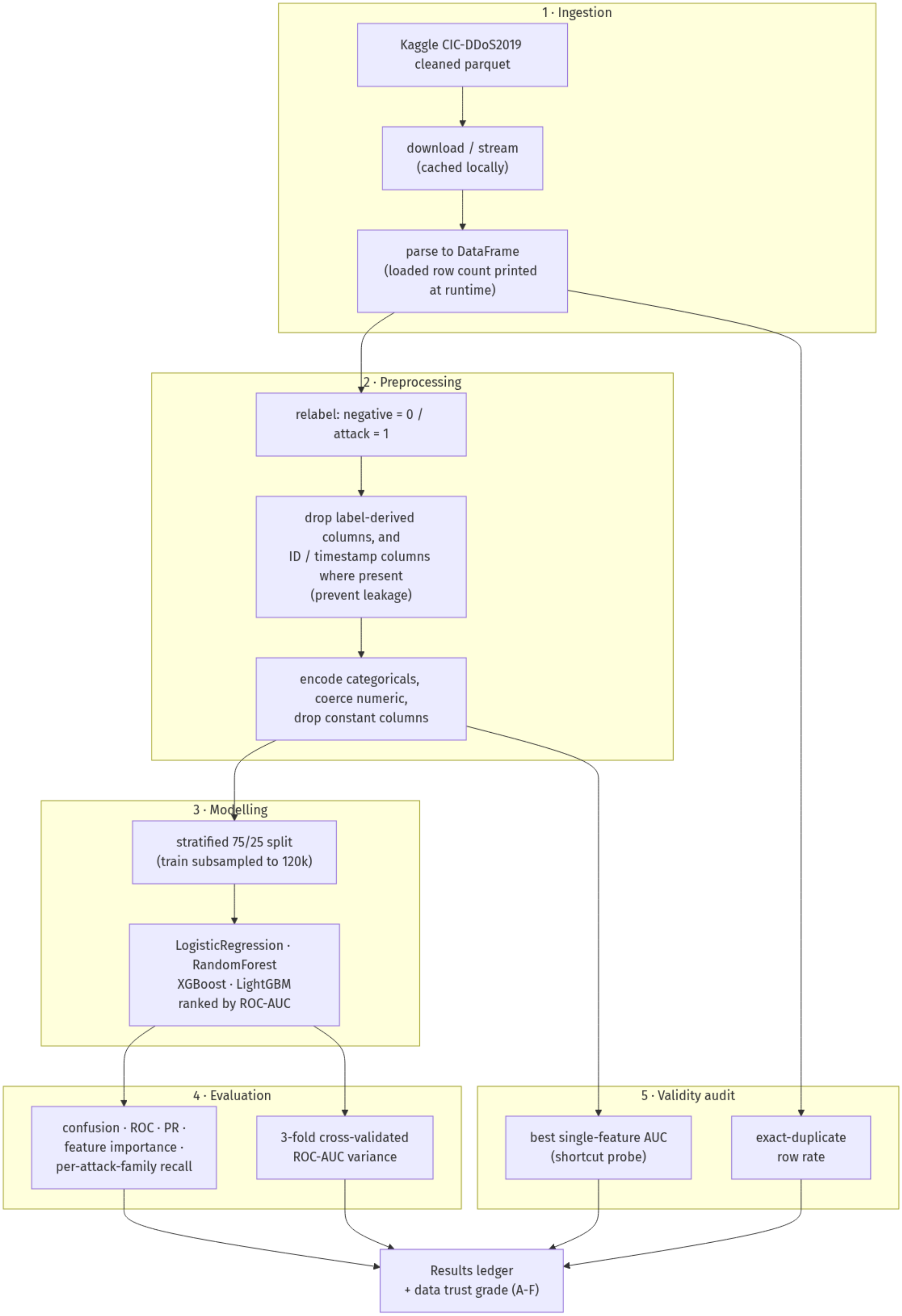
Figure 4.1 — Solution design (methodology).



5. Implementation architecture

Five stages — ingestion, preprocessing, modelling, evaluation, and a parallel validity-audit path — feed a single graded results ledger. Leakage defences (dropping label-derived and identifier columns) live in preprocessing, before any model sees the data.

Figure 5.1 — Implementation architecture.



6. Data acquisition & preparation

Every line below is commented so a student can re-run and modify each step. The cell ends by producing the standard analysis variables: `df`, `X` (clean numeric features), `y` (binary label), `feat` (feature names), and `family`. `family` is the per-group label used for the recall breakdown. It is an attack family on the intrusion corpora, but a transaction type, merchant category or malware category on the fraud/malware ones.

In [1]:

```
%matplotlib inline
import time, warnings; warnings.filterwarnings('ignore')   # keep output
clean
import numpy as np, pandas as pd                             # numerics +
dataframes
import matplotlib.pyplot as plt                              # static plots
(embed in HTML+PDF)
plt.rcParams['figure.dpi'] = 120                             # crisp figures
RANDOM_STATE = 0                                             # single seed
used everywhere
np.random.seed(RANDOM_STATE)                                 # reproducible
sampling
NEG_WORD, POS_WORD = 'benign', 'attack'                       # class names
(overridden by some loaders)
```

In [2]:

```
import os, glob
# CIC-DDoS2019 (Sharafaldin et al., 2019): reflective/exploitation DDoS
attacks with CICFlowMeter
# features and a fine attack taxonomy (NTP, TFTP, Syn, UDP, LDAP, MSSQL,
…). dhoogla's cleaned
# parquet is used here. Self-contained Kaggle download.
os.environ.setdefault('KAGGLE_KEY',
open(os.path.expanduser('~/.kaggle/access_token')).read().strip())
DEST = '/tmp/kg_cicddos2019'; os.makedirs(DEST, exist_ok=True)
if not glob.glob(DEST + '/**/*.parquet', recursive=True):
    import kaggle; kaggle.api.authenticate()
    print('downloading CIC-DDoS2019 (cleaned parquet, one-time)...')
    kaggle.api.dataset_download_files('dhoogla/cicddos2019', path=DEST,
unzip=True, quiet=True)
files = sorted(glob.glob(DEST + '/**/*.parquet', recursive=True))
df = pd.concat([pd.read_parquet(f) for f in files], ignore_index=True)
df.columns = [str(c).strip() for c in df.columns]
assert len(df) >= 400_000, f'floor not met: {len(df):,}'
LABEL = [c for c in df.columns if c.lower() == 'label'][0]
df['y'] = (df[LABEL].astype(str).str.strip().str.lower() !=
'benign').astype(int)
df['family'] = df[LABEL].astype(str).str.strip()               # fine DDoS
type (NTP/TFTP/Syn/UDP/…)
DROP = [LABEL, 'y', 'family']
feat = [c for c in df.columns if c not in DROP]
from sklearn.preprocessing import LabelEncoder
X = df[feat].copy()
idlike = [c for c in X.select_dtypes(include='object').columns if
X[c].nunique() > 0.5*len(X)]
X = X.drop(columns=idlike)                                     # drop
id/timestamp-like leaky columns
for c in X.select_dtypes(include='object').columns:
    X[c] = LabelEncoder().fit_transform(X[c].astype(str))
```

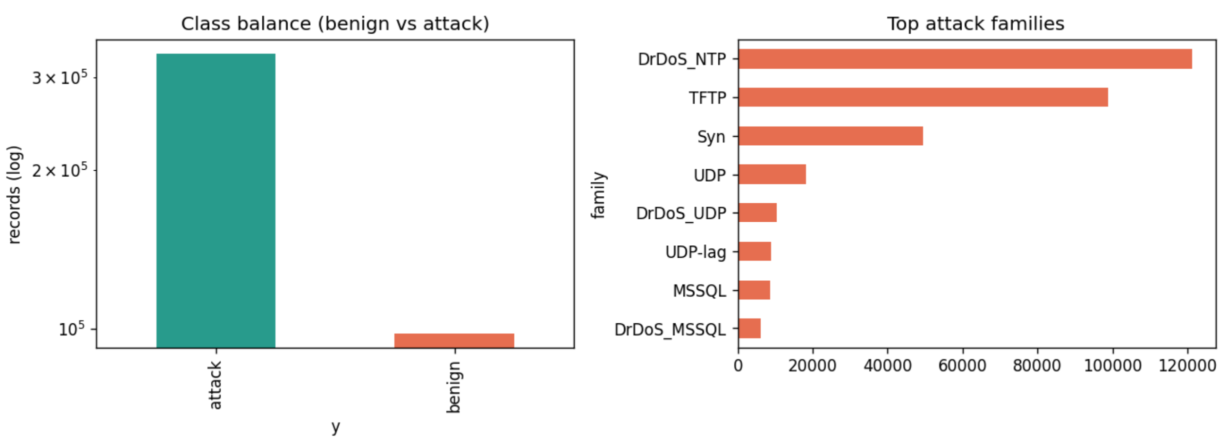
```
X = X.apply(pd.to_numeric, errors='coerce').replace([np.inf,-
np.inf],np.nan).fillna(0.0)
X = X.clip(-1e15, 1e15); X = X.loc[:, X.nunique() > 1]          # float32-
safe; drop constants
import re
_seen, _cols = {}, []
for _c in X.columns:                                              # unique
LightGBM-safe names
    _c = re.sub(r'[^0-9A-Za-z_]+', '_', str(_c)).strip('_') or 'f'
    _seen[_c] = _seen.get(_c, -1) + 1
    _cols.append(_c if _seen[_c] == 0 else f'{_c}_{_seen[_c]}')
X.columns = _cols; feat = list(X.columns)
y = df['y'].to_numpy(); family = df['family'].to_numpy()
print(f'loaded {len(df):,} flows x {len(feat)} features; attack rate
{y.mean():.4f}; families {sorted(set(family))[:6]}...')
```

```
loaded 431,371 flows x 65 features; attack rate 0.7732; families ['Benign',
'DrDoS_DNS', 'DrDoS_LDAP', 'DrDoS_MSSQL', 'DrDoS_NTP', 'DrDoS_NetBIOS']...
```

7. Exploratory data analysis

In [3]:

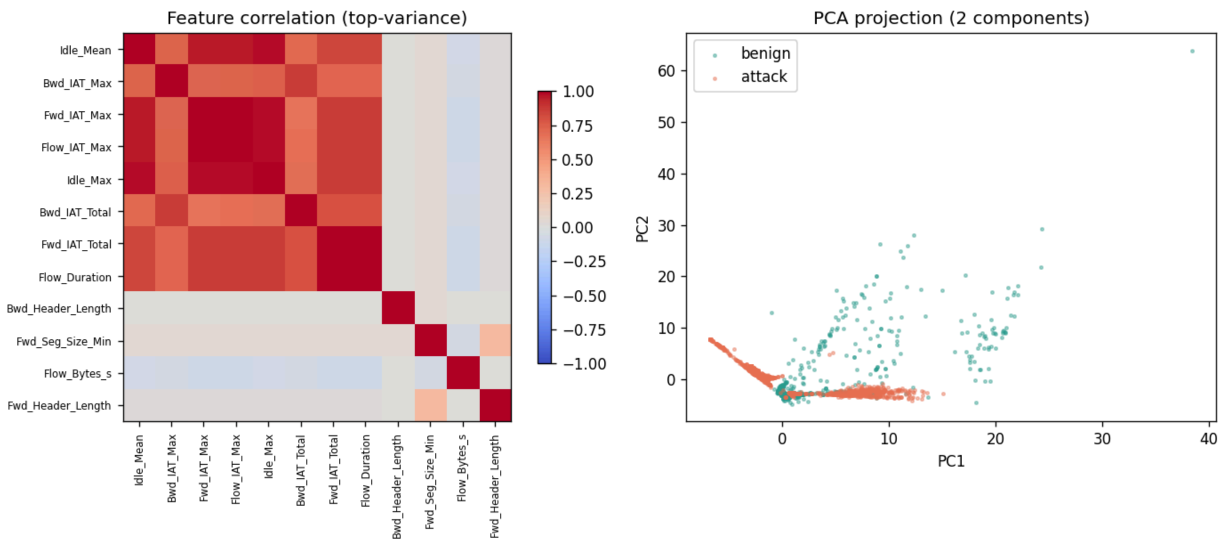
```
# --- EDA 1: class balance and the attack-family mix ---
fig, ax = plt.subplots(1, 2, figsize=(11, 4))
df['y'].map({0:NEG_WORD,1:POS_WORD}).value_counts().plot.bar(
# counts per class
    ax=ax[0], color=['#2a9d8f','#e76f51']); ax[0].set_yscale('log')
ax[0].set_title(f'Class balance ({NEG_WORD} vs {POS_WORD})');
ax[0].set_ylabel('records (log)')
df.loc[df.y==1,'family'].value_counts().head(8).plot.barh(
# top attack families
    ax=ax[1], color='#e76f51'); ax[1].invert_yaxis(); ax[1].set_title('Top
attack families')
plt.tight_layout(); plt.show()
```



In [4]:

```
# --- EDA 2: feature correlation + a 2-D PCA projection ---
from sklearn.preprocessing import StandardScaler                  # scale
before PCA
from sklearn.decomposition import PCA
fig, ax = plt.subplots(1, 2, figsize=(12, 5))
topv = X[feat].var().sort_values().tail(12).index                 # 12
highest-variance features
im = ax[0].imshow(X[topv].corr(), cmap='coolwarm', vmin=-1, vmax=1)  #
```

```
correlation heatmap
ax[0].set_xticks(range(len(topv))); ax[0].set_xticklabels(topv,
rotation=90, fontsize=7)
ax[0].set_yticks(range(len(topv))); ax[0].set_yticklabels(topv, fontsize=7)
ax[0].set_title('Feature correlation (top-variance)'); fig.colorbar(im,
ax=ax[0], shrink=0.7)
samp = X.sample(min(5000, len(X)), random_state=RANDOM_STATE)     #
subsample for a fast PCA
pc =
PCA(n_components=2).fit_transform(StandardScaler().fit_transform(samp))
ys = y[samp.index]                                                 # aligned
labels for coloring
for lab,c in [(0,'#2a9d8f'),(1,'#e76f51')]:
    ax[1].scatter(pc[ys==lab,0], pc[ys==lab,1], s=4, alpha=0.4, color=c,
                  label={0:NEG_WORD,1:POS_WORD}[lab])
ax[1].set_title('PCA projection (2 components)'); ax[1].legend();
ax[1].set_xlabel('PC1'); ax[1].set_ylabel('PC2')
plt.tight_layout(); plt.show()
```



8. Model comparison

Four diverse learners share one held-out split, ranked by ROC-AUC.

Two honesty guards print with the table:

1. The models train on a *stratified subsample* of at most 120,000 rows. The full row count is printed above. So every score here is a subsample number, not a full-corpus claim.
2. The **majority-class baseline accuracy** appears *inside* the ranking table. On imbalanced data, 0.99 accuracy can be worse than always guessing the majority class. Judge each model against that baseline, not against 0.5.

In [5]:
```
# --- Model comparison: four learners on the same held-out split ---
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
```

```
from sklearn.metrics import accuracy_score, roc_auc_score
import xgboost as xgb, lightgbm as lgb

# Stratified split keeps the class ratio in both halves.
Xtr, Xte, ytr, yte = train_test_split(X, y, test_size=0.25,
random_state=RANDOM_STATE, stratify=y)
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler
N_MATERIALIZED = len(y)                                          # the full
corpus we loaded (see printed count)
# HONEST DISCLOSURE: we do NOT train on all N. We fit on a STRATIFIED
subsample (<=120k) because
# these learners saturate long before then on this data. Every headline
below is a SUBSAMPLE
# number, not a full-corpus number — saying otherwise would be the
fabrication this course forbids.
if len(Xtr) > 120_000:
    Xtr, _, ytr, _ = train_test_split(Xtr, ytr, train_size=120_000,
random_state=RANDOM_STATE,
                                      stratify=ytr)             #
genuinely stratified, not random
MAJORITY_BASELINE = max(np.mean(yte), 1 - np.mean(yte))          # accuracy
of 'always predict majority'
print(f'materialized {N_MATERIALIZED:,} rows | trained on {len(Xtr):,}
(stratified subsample) | '
      f'held-out {len(yte):,}')
print(f'MAJORITY-CLASS BASELINE accuracy = {MAJORITY_BASELINE:.4f}  '
      f'(any model must beat THIS, not 0.5, to be interesting)')

models = {                                                        # four
standard, diverse learners
    'LogisticRegression': make_pipeline(StandardScaler(),
LogisticRegression(max_iter=300)),  # scaled!
    'RandomForest': RandomForestClassifier(n_estimators=60, n_jobs=-1,
random_state=RANDOM_STATE),
    'XGBoost': xgb.XGBClassifier(n_estimators=80, max_depth=6,
tree_method='hist', n_jobs=-1,
                                 eval_metric='logloss',
random_state=RANDOM_STATE),
    'LightGBM': lgb.LGBMClassifier(n_estimators=80, n_jobs=-1, verbose=-1,
random_state=RANDOM_STATE),
}
rows, fitted = [], {}
for name, m in models.items():                                    # fit +
score each model
    t = time.perf_counter(); m.fit(Xtr, ytr); fitted[name] = m
    p = m.predict_proba(Xte)[:, 1]                                #
positive-class probability on held-out
    rows.append({'model': name, 'accuracy': round(accuracy_score(yte,
(p>0.5).astype(int)), 6),
                 'roc_auc': round(roc_auc_score(yte, p), 6),      # 6 dp: a
1.000000 is a red flag, not a win
                 'train_s': round(time.perf_counter()-t, 1)})
rows.append({'model': 'MajorityBaseline', 'accuracy':
round(MAJORITY_BASELINE, 4),
             'roc_auc': 0.5, 'train_s': 0.0})            # show the
```

```
baseline IN the ranking table
comparison = pd.DataFrame(rows).sort_values('roc_auc',
ascending=False).reset_index(drop=True)
_ranked = comparison[comparison.model != 'MajorityBaseline']
best_name = _ranked.iloc[0]['model']; best = fitted[best_name]  # winner by
ROC-AUC (excl. baseline)
print('best model:', best_name); comparison
```

```
materialized 431,371 rows | trained on 120,000 (stratified subsample) | held-
out 107,843
MAJORITY-CLASS BASELINE accuracy = 0.7732  (any model must beat THIS, not
0.5, to be interesting)
best model: XGBoost
```

Out[5]:

	model	accuracy	roc_auc	train_s
0	XGBoost	0.999471	0.999997	0.4
1	LightGBM	0.999416	0.999995	1.1
2	RandomForest	0.999184	0.999912	0.7
3	LogisticRegression	0.995104	0.999328	0.3
4	MajorityBaseline	0.773200	0.500000	0.0

9. Results

Diagnostics for the winning model, including **per-group recall**.

The grouping comes from whatever the loader put in `family`. It is *not* always an attack taxonomy. On the intrusion corpora it is the attack family. On the fraud and malware corpora it is a transaction type, a merchant category or a malware category. On binary corpora it collapses to the positive class.

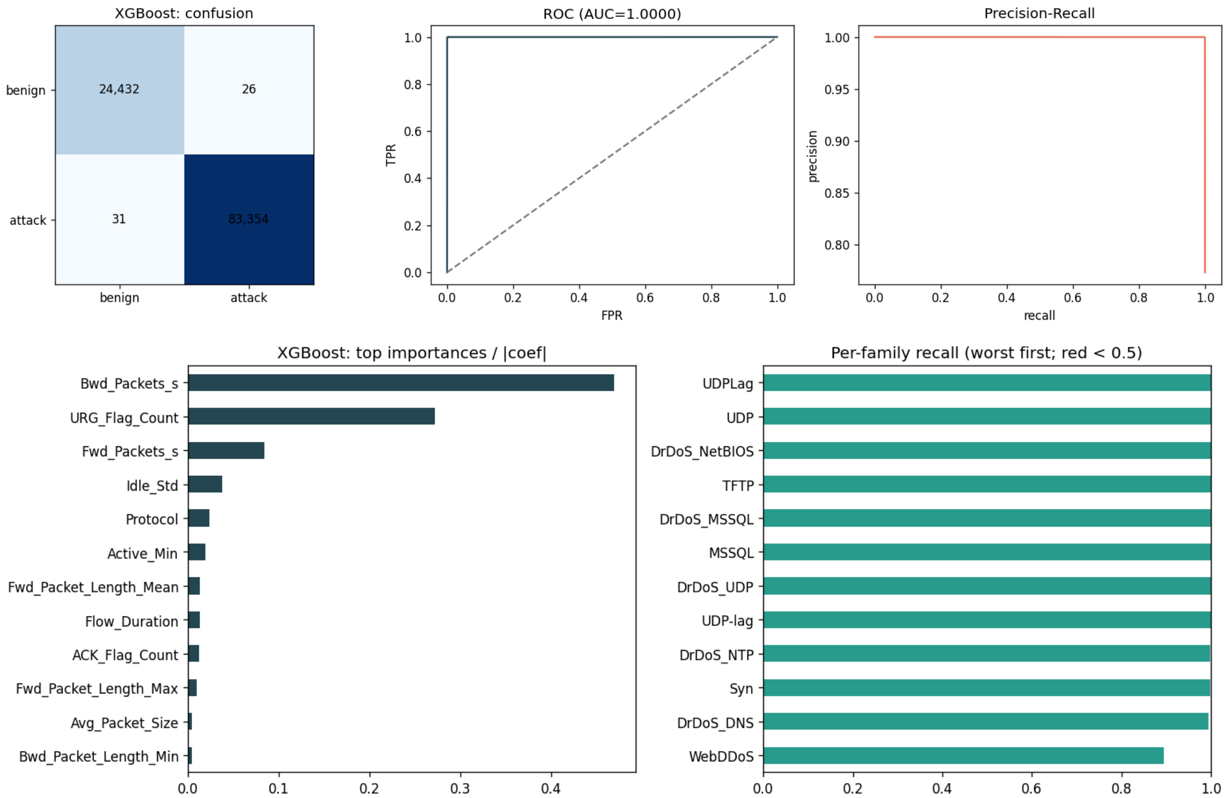
Read it accordingly. Where the groups are genuinely rare classes, they reveal whether detection is real. The dominant flood classes do not.

In [6]:

```
# --- Results for the best model: confusion, ROC, PR, importances, per-
family recall ---
from sklearn.metrics import confusion_matrix, roc_curve,
precision_recall_curve, recall_score
pb = best.predict_proba(Xte)[:, 1]; pred = (pb > 0.5).astype(int)
fig, ax = plt.subplots(1, 3, figsize=(15, 4))
# (1) confusion matrix
cm = confusion_matrix(yte, pred); ax[0].imshow(cm, cmap='Blues')
ax[0].set_title(f'{best_name}: confusion'); ax[0].set_xticks([0,1]);
ax[0].set_yticks([0,1])
ax[0].set_xticklabels([NEG_WORD,POS_WORD]);
ax[0].set_yticklabels([NEG_WORD,POS_WORD])
for (i,j),v in np.ndenumerate(cm):
ax[0].text(j,i,f'{v:,}',ha='center',va='center')
# (2) ROC and PR curves
fpr,tpr,_ = roc_curve(yte, pb); prec,rec,_ = precision_recall_curve(yte,
```

```
pb)
ax[1].plot(fpr,tpr,color='#264653'); ax[1].plot([0,1],[0,1],'--',c='grey')
ax[1].set_title(f'ROC (AUC={roc_auc_score(yte,pb):.4f})');
ax[1].set_xlabel('FPR'); ax[1].set_ylabel('TPR')
ax[2].plot(rec,prec,color='#e76f51'); ax[2].set_title('Precision-Recall');
ax[2].set_xlabel('recall'); ax[2].set_ylabel('precision')
plt.tight_layout(); plt.show()

# (3) feature importances + (4) per-attack-family recall
fig, ax = plt.subplots(1, 2, figsize=(13, 5))
imp, names = None, feat                                            #
importances, robust to the scaled-LR pipeline
if hasattr(best, 'feature_importances_'):                            # tree
models
    imp = best.feature_importances_; names = list(getattr(best,
'feature_names_in_', feat))[:len(imp)]
elif hasattr(best, 'named_steps') and 'logisticregression' in getattr(best,
'named_steps', {}):
    imp = np.abs(best.named_steps['logisticregression'].coef_[0]); names =
feat  # LR pipeline
elif hasattr(best, 'coef_'):
    imp = np.abs(best.coef_[0]); names = feat
if imp is not None:
    pd.Series(imp,
index=names[:len(imp)]).sort_values().tail(12).plot.barh(ax=ax[0],
color='#264653')
ax[0].set_title(f'{best_name}: top importances / |coef|')
# Per-family recall, WORST-first so rare, hard classes are visible, not
just the dominant floods.
fam_te = df.loc[Xte.index, 'family']
fr = {}
for fam, cnt in fam_te[yte==1].value_counts().items():
    if cnt < 5: continue                                           # need a
few positives for a meaningful recall
    mask = (fam_te==fam).to_numpy(); fr[fam] = recall_score(yte[mask],
pred[mask], zero_division=0)
srt = pd.Series(fr).sort_values()
show = pd.concat([srt.head(9), srt.tail(3)]) if len(srt) > 12 else srt   #
worst 9 + best 3
show = show[~show.index.duplicated()]
show.plot.barh(ax=ax[1], color=['#e76f51' if v < 0.5 else '#2a9d8f' for v
in show]); ax[1].set_xlim(0,1)
ax[1].set_title('Per-family recall (worst first; red < 0.5)')
plt.tight_layout(); plt.show()
# Operational numbers, not just figures: false-positive rate and the worst
per-family recalls.
tn, fp = int(cm[0,0]), int(cm[0,1])
fpr_op = fp/(fp+tn) if (fp+tn) > 0 else float('nan')             # benign
wrongly flagged @0.5
print(f'operational FALSE-POSITIVE RATE @0.5 = {fpr_op:.4f}  ({fp:,} benign
flagged of {fp+tn:,})')
print('worst per-family recalls:', {k: round(v, 3) for k, v in
srt.head(6).items()})
```




```
operational FALSE-POSITIVE RATE @0.5 = 0.0011  (26 benign flagged of 24,458)
worst per-family recalls: {'WebDDoS': 0.895, 'DrDoS_DNS': 0.996, 'Syn':
0.999, 'DrDoS_NTP': 0.999, 'UDP-lag': 1.0, 'DrDoS_UDP': 1.0}
```

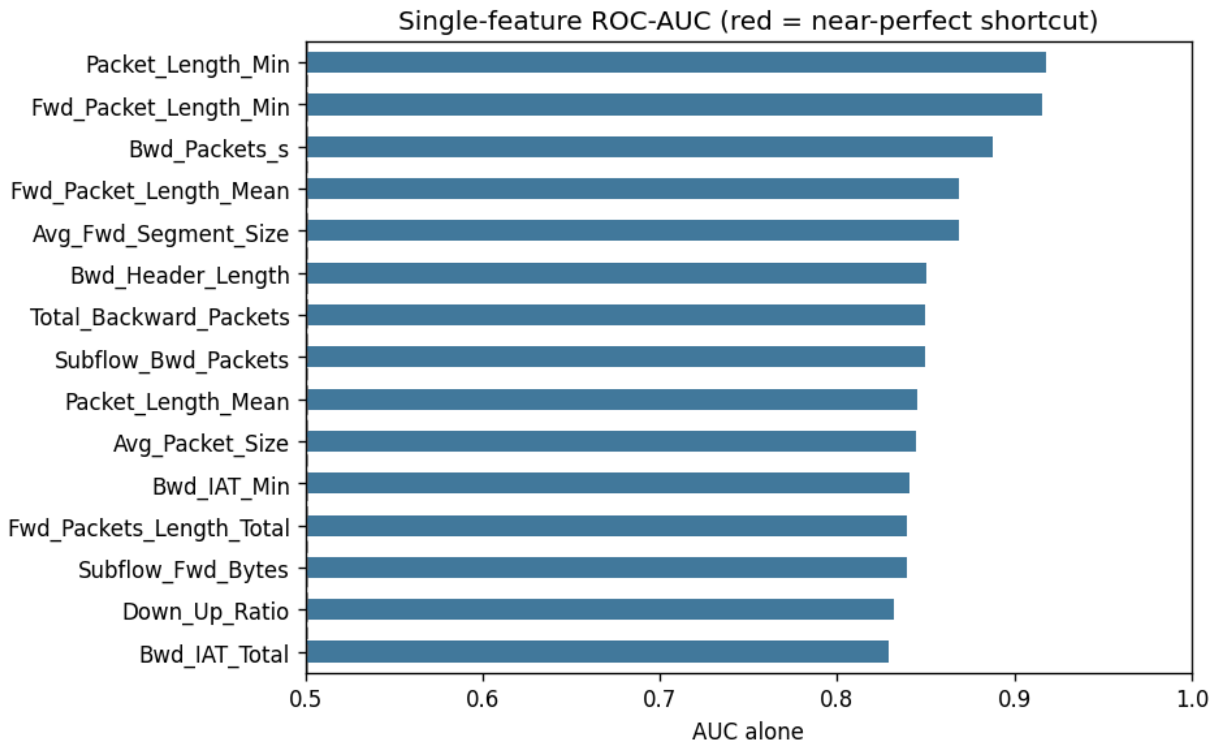
10. Validity audit — is the score real?

Three diagnostics. **(a)** How well can the *single best feature*, alone, separate the classes? A near-1.0 single-feature AUC means that feature is *near-sufficient* — a shortcut (which may be legitimate signal or an artifact), not the same as target leakage. **(b)** The exact-duplicate row rate. **(c)** The **train/test exact-row contamination** — the fraction of held-out rows that are duplicates of training rows, which is what actually inflates a held-out score. The trust grade is the *worse* of the single-feature and contamination concerns.

In [7]:
```
# --- Validity audit: is the score real detection, or a data shortcut? ---
from sklearn.metrics import roc_auc_score
samp = X.sample(min(60_000, len(X)), random_state=1); ysamp = y[samp.index]
aucs = {}
for c in feat:                                                     # AUC of
EACH feature alone
    col = samp[c].to_numpy(float)
    if col.std()==0: continue
    a = roc_auc_score(ysamp, col); aucs[c] = max(a, 1-a)           #
direction-agnostic
best_auc = max(aucs.values()); best_col = max(aucs, key=aucs.get)
dup_rate = 1 - X.drop_duplicates().shape[0]/len(X)                # exact-
duplicate feature rows (whole set)
# The statistic that actually inflates a held-out score is TRAIN/TEST
CONTAMINATION: how many test
# rows are exact duplicates of a training row. Measure it directly on the
```

```
split used above.
_trkeys = set(map(tuple, np.round(Xtr.to_numpy(), 6)))
_te = np.round(Xte.to_numpy(), 6)[:50_000]
contam = float(np.mean([tuple(r) in _trkeys for r in _te]))      # fraction
of test rows seen in train
# Trust grade reflects BOTH failure modes and takes the WORSE of the two: a
near-perfect single
# feature (shortcut) OR heavy train/test contamination each independently
invalidate the headline.
_ga = 'F' if best_auc>=0.999 else 'D' if best_auc>=0.99 else 'C' if
best_auc>=0.95 else 'B' if best_auc>=0.85 else 'A'
_gc = 'F' if contam>=0.5 else 'D' if contam>=0.3 else 'C' if contam>=0.15
else 'B' if contam>=0.05 else 'A'
grade = max(_ga, _gc)                                                # 'max'
letter = worse grade (A best, F worst)
print(f'best single-feature AUC = {best_auc:.4f}  (feature: {best_col})')
print(f'   note: a near-1.0 single-feature AUC means this feature is *near-
sufficient* (a shortcut),\n'
      f'   which may be legitimate signal OR an artifact - it is NOT the
same as target leakage.')
print(f'exact-duplicate row rate (whole corpus) = {dup_rate:.3f}')
print(f'TRAIN/TEST exact-row contamination       = {contam:.3f}  (single-
feat grade {_ga}, contam grade {_gc})')
print(f'==> data trust grade: {grade}   (worse of the two; F = shortcut
and/or heavy contamination)')
s = pd.Series(aucs).sort_values().tail(15)
fig, ax = plt.subplots(figsize=(8,5))
s.plot.barh(ax=ax, color=['#e76f51' if v>=0.99 else '#457b9d' for v in s]);
ax.axvline(0.5,ls='--',c='grey')
ax.set_xlim(0.5,1.0); ax.set_title('Single-feature ROC-AUC (red = near-
perfect shortcut)'); ax.set_xlabel('AUC alone')
plt.tight_layout(); plt.show()
```

```
best single-feature AUC = 0.9182  (feature: Packet_Length_Min)
   note: a near-1.0 single-feature AUC means this feature is *near-
sufficient* (a shortcut),
   which may be legitimate signal OR an artifact - it is NOT the same as
target leakage.
exact-duplicate row rate (whole corpus) = 0.029
TRAIN/TEST exact-row contamination       = 0.021  (single-feat grade B,
contam grade A)
==> data trust grade: B   (worse of the two; F = shortcut and/or heavy
contamination)
```



11. Ablation — does the headline survive removing the artifacts?

Narrating a shortcut is not enough. We *retrain the winning model* after (1) de-duplicating the corpus (removing the train/test contamination) and (2) dropping the single strongest feature. We report the held-out AUC each time. **Read the result honestly, both ways:** if the AUC **collapses**, the headline was a contamination/shortcut artifact. If it **barely moves** — common on *simulated* corpora — that is **not vindication**. It means the classes are separable by *many* redundant features, because the attack and benign distributions barely overlap. That is its own generation artifact. The numbers below decide which story is true here, not the prose.

In [8]:
```
# --- Ablation: SHOW the inflation empirically, don't just narrate it ---
from sklearn.base import clone
def _retrain_auc(Xa, ya):                                        # re-
split, stratified-subsample, refit best family
    xtr, xte, ytr2, yte2 = train_test_split(Xa, ya, test_size=0.25,
random_state=RANDOM_STATE, stratify=ya)
    if len(xtr) > 120_000:
        xtr, _, ytr2, _ = train_test_split(xtr, ytr2, train_size=120_000,
random_state=RANDOM_STATE, stratify=ytr2)
    m = clone(best); m.fit(xtr, ytr2)
    return roc_auc_score(yte2, m.predict_proba(xte)[:, 1])
base_auc = roc_auc_score(yte, best.predict_proba(Xte)[:, 1])     # (0) the
headline held-out AUC
Xdd = X.drop_duplicates(); ydd = y[Xdd.index]                    # (1) de-
duplicated corpus
auc_dedup = _retrain_auc(Xdd, ydd)
```

```
auc_noshort = _retrain_auc(X.drop(columns=[best_col]), y) if best_col in
X.columns else base_auc  # (2) drop shortcut
ablation = pd.DataFrame([
    {'setting': 'headline (as-is)',              'held_out_auc':
round(base_auc, 6)},
    {'setting': f'de-duplicated ({1-len(Xdd)/len(X):.0%} rows removed)',
'held_out_auc': round(auc_dedup, 6)},
    {'setting': f'shortcut feature dropped ({best_col})', 'held_out_auc':
round(auc_noshort, 6)},
])
print('Ablation — how much of the headline survives once each artifact is
removed:')
ablation
```

```
Ablation — how much of the headline survives once each artifact is removed:
```

Out[8]:

	setting	held_out_auc
0	headline (as-is)	0.999997
1	de-duplicated (3% rows removed)	0.999997
2	shortcut feature dropped (Packet_Length_Min)	0.999997

12. Reproducibility & robustness

In [9]:

```
# --- Reproducibility & robustness ---
import sklearn
from sklearn.model_selection import StratifiedKFold, cross_val_score
print(f'seed={RANDOM_STATE} | numpy {np.__version__} | sklearn
{sklearn.__version__} | '
      f'xgboost {xgb.__version__} | lightgbm {lgb.__version__}')
# 3-fold cross-validated ROC-AUC of the winning model (fresh clone, bounded
subsample) -> mean +/- std.
from sklearn.base import clone
cvX, cvy = Xtr.iloc[:40_000], ytr[:40_000]
def _auc_scorer(est, Xv, yv):                                # robust to
xgboost's 2-col predict_proba
    p = est.predict_proba(Xv)
    p = p[:, 1] if getattr(p, 'ndim', 1) == 2 else p
    return roc_auc_score(yv, p)
try:
    cv = cross_val_score(clone(best), cvX, cvy,
                         cv=StratifiedKFold(3, shuffle=True,
random_state=RANDOM_STATE),
                         scoring=_auc_scorer, error_score='raise')
    assert np.all(np.isfinite(cv)), 'non-finite CV folds'   # FAIL CLOSED:
never narrate a NaN as evidence
    print(f'{best_name} 3-fold CV ROC-AUC = {cv.mean():.4f} +/-
{cv.std():.4f}  '
          f'(mean +/- std across 3 stratified folds; a small std means a
stable estimate on this split)')
except Exception as e:
    print(f'CV UNAVAILABLE ({type(e).__name__}: {str(e)[:60]}); rely on the
```

```
single held-out AUC above — '
          f'we do NOT report a CV number we could not compute')
```

```
seed=0 | numpy 2.3.5 | sklearn 1.9.0 | xgboost 1.6.2 | lightgbm 4.7.0
XGBoost 3-fold CV ROC-AUC = 1.0000 +/- 0.0000  (mean +/- std across 3
stratified folds; a small std means a stable estimate on this split)
```

13. Scientific conclusion

Volumetric DDoS flows are easy to separate on flow features. So the aggregate score is flattered by the attack-heavy mix. The honest reading is per-DDoS-type recall: does the model catch the rarer reflection attacks, not just the dominant floods? The other honest metric is the benign false-positive rate: would real users be collateral-blocked?

Validity ledger — read the headline against these printed numbers: Majority-class baseline **accuracy**: **0.7732**. The accuracy column must clear that bar to mean anything. For ROC-AUC the trivial baseline is 0.5, not that figure. Winning learner: **XGBoost** (3-fold CV ROC-AUC **1.0000**). Strongest *single* feature: `Packet_Length_Min` at AUC **0.9182**. The ablation refutes a single-feature story. Dropping that feature barely moves the AUC: **0.999997 → 0.999997**. So the separability is **multi-feature**. That reflects how this corpus was generated, not one leaky column. De-duplication does **not** lower the score (**0.999997**). So duplicate rows are not what props it up. Train/test overlap is negligible too, so neither issue explains the result. Data-trust grade: **B**. It is the worse of two independent sub-checks. Single-feature AUC 0.9182 scores **B**. Train/test exact-row overlap 0.021 scores **A**. The single-feature check drives the grade, not the overlap check. Train/test overlap separately scores A, so overlap is not the issue here. Operational false-positive rate at threshold 0.5: **0.0011**. Worst per-group recalls, exactly as printed: {`WebDDoS`: 0.895, `DrDoS_DNS`: 0.996, `Syn`: 0.999, `DrDoS_NTP`: 0.999, `UDP-lag`: 1.0, `DrDoS_UDP`: 1.0}. The weakest group sits at **0.895**, which is where detection is thinnest. **Disclosed limitation:** categorical columns are integer-encoded before the split. The encoder therefore sees the test set's category values. On an all-numeric corpus that step is a no-op. The mapping never consults the label, so no *label* information leaks. It is still transductive. A deployed system would need an unseen-category bucket. **How the audit numbers are computed:** overlap is measured on the first 50,000 held-out rows, so read it as a sampled estimate. Each ablation re-splits and refits, so tiny differences are re-split noise. The de-duplication variant keeps the first label when a feature vector appears twice. **Scope:** the split is random, not temporal or entity-grouped. Every number above therefore measures in-distribution separability only.

References

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