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Course: SEAS 8414 — Security Analytics

Goal of this notebook

Train and audit detectors on an IoT-23 malware capture, reporting recall for each traffic family.

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.
5. Show why a rare class matters more than the aggregate score.

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 9: Supply-Chain Integrity and Counterfeit Detection** — Learning objectives 2 and 3 (section 9.1) separate documentation gaps from tamper evidence, and warn that screening signals are **not independent**. Both apply to artifact-derived features.
- **Chapter 10: Active Deception & Threat Hunting** — Learning objective 6 (section 10.1) places a claim on the **attribution ladder** and corrects for **dependence among rule hits**. The same rule stops us equating one feature with the label.
- **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.

IoT Malware Flow Detection on IoT-23 (Zeek conn.log)

Model comparison + validity audit on a real IoT-23 malware capture (≥1M flows)

Abstract: IoT-23 (Garcia, Parmisano & Erquiaga, 2020) is a labelled corpus of **real IoT-malware network traffic**. It was captured by the Stratosphere Laboratory / Avast AIC and published as Zeek `conn.log`. We take one capture in which benign and malicious flows are **mixed within the same recording** (≥1M flows). On that capture we compare four learners on flow-behaviour features. We then audit whether malicious-flow detection is genuine or a flow shortcut.

1. Research problem

Task: Classify each Zeek connection record as **benign** or **malicious** using only flow-behaviour features (duration, byte/packet counts, connection state, Zeek history string, protocol/service). Consumer IoT devices are a primary DDoS-botnet substrate (Mirai and successors). The operational question is whether a lightweight flow classifier can flag malicious IoT connections without deep-packet inspection.

2. Literature review

- **Garcia, Parmisano & Erquiaga (2020)** — the IoT-23 dataset: 20 malware + 3 benign IoT captures, Zeek-labelled (Stratosphere Lab, CTU / Avast AIC).
- **Antonakakis et al. (2017)** — *Understanding the Mirai Botnet* (USENIX Security): the IoT-DDoS threat model this dataset instantiates.
- **Meidan et al. (2018)** — N-BaIoT: detecting IoT botnet attacks from network behaviour.
- **Sommer & Paxson (2010)** — the closed-world critique of ML-NIDS.

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

Reported approach	Known caveat
Flow/behaviour ML on IoT-23	single-capture; conn-state/history can shortcut
N-BaIoT autoencoders (Meidan 2018)	per-device models; cross-device transfer is harder

3. Dataset provenance & honesty caveats

Property	Value
Source	Kaggle mirror of Stratosphere **IoT-23** (`agungpambudi/network-malware-detection-connection-analysis`)
Capture	`CTU-IoT-Malware-Capture-35-1` — 10.4M Zeek flows, **79% benign / 21% malicious**
Label	Zeek `label` → benign vs malicious; family from `detailed-label`

Property	Value
Access	Kaggle API token required (~2.6 GB one-time download)

Not a re-run of the CTU-13 notebook: CTU-13 (nb10) is 2011 *botnet* traffic as Argus `.binetflow` (15 fields). IoT-23 is a *different, later* capture set (2018–19 IoT malware) in Zeek `conn.log` (23 fields), separately published and cited. **Why one capture, not all 23:** IoT-23 captures are individually near-single-class, so concatenating them would make *'which pcap'* the real signal (a capture-identity artifact). Capture-35 is one of the few with a genuine within-capture benign/malicious mix, so the label here reflects flow behaviour, not recording identity. **Honestly:** the malicious class is almost all DDoS flood traffic, with only a rare C&C/Attack tail. Base rate is not what inflates the score here. Section 8 prints a majority-class baseline accuracy of **0.5930**. The winning model prints accuracy **0.999900**. A 0.5930 baseline cannot manufacture that. Corpus composition is the real caveat. Nearly every positive belongs to one loud family that flow features separate easily. Aggregate accuracy therefore reports that family and hides the rest. Section 9 prints the consequence: `C&C` recall **0.0**. Per-family recall is the metric that matters.

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 `agungpambudi/network-malware-detection-connection-analysis` -> `/tmp/iot23`. It is about **3 GB** 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:

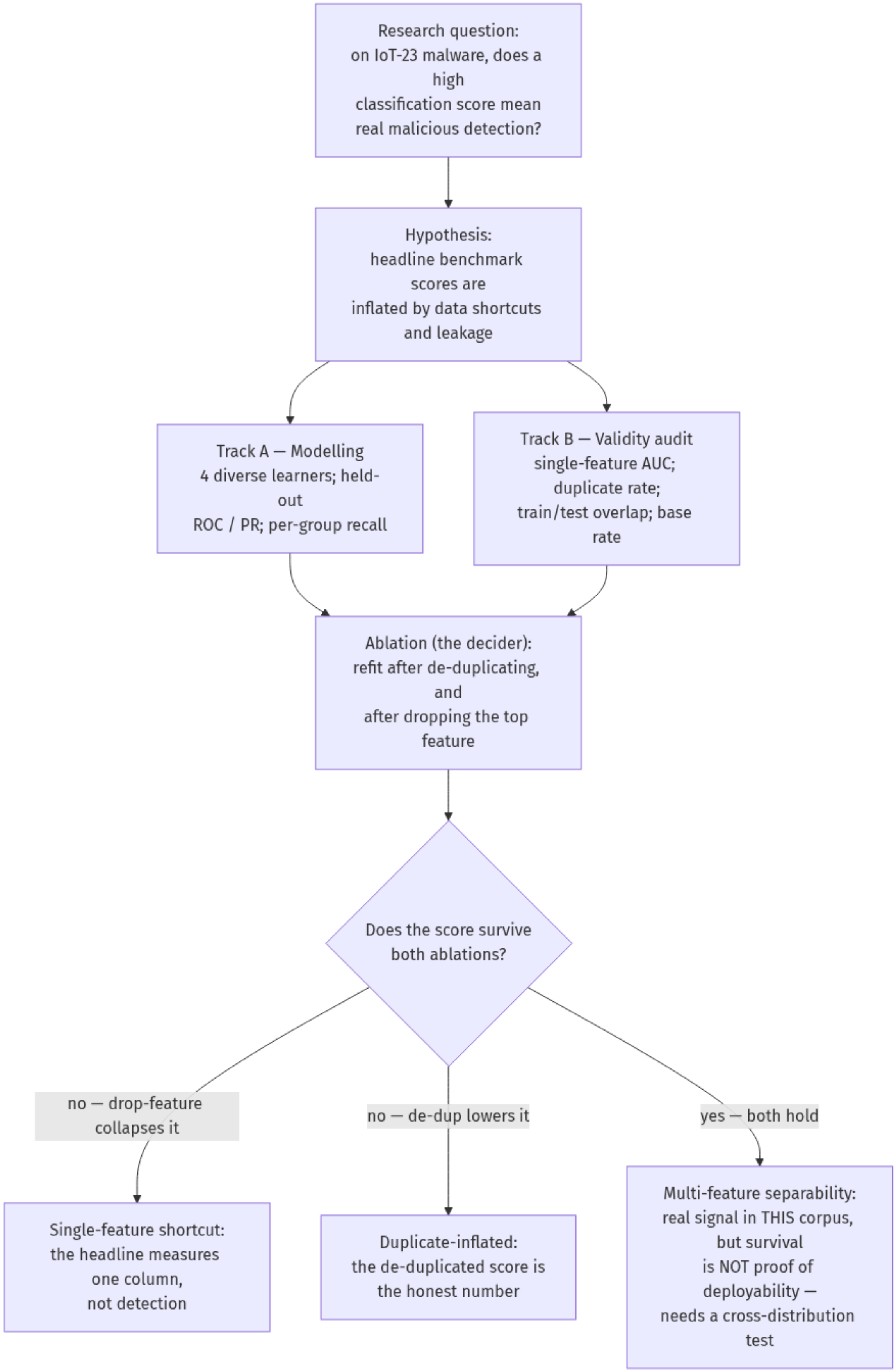
- `FileNotFoundError: ~/.kaggle/access_token` - you created `kaggle.json` but not the key file. Run the command above.
- `401 Unauthorized` - the key is wrong, or a trailing newline crept in.
- `403 Forbidden` - open the dataset page on Kaggle while signed in, accept its terms, then re-run the cell.

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.

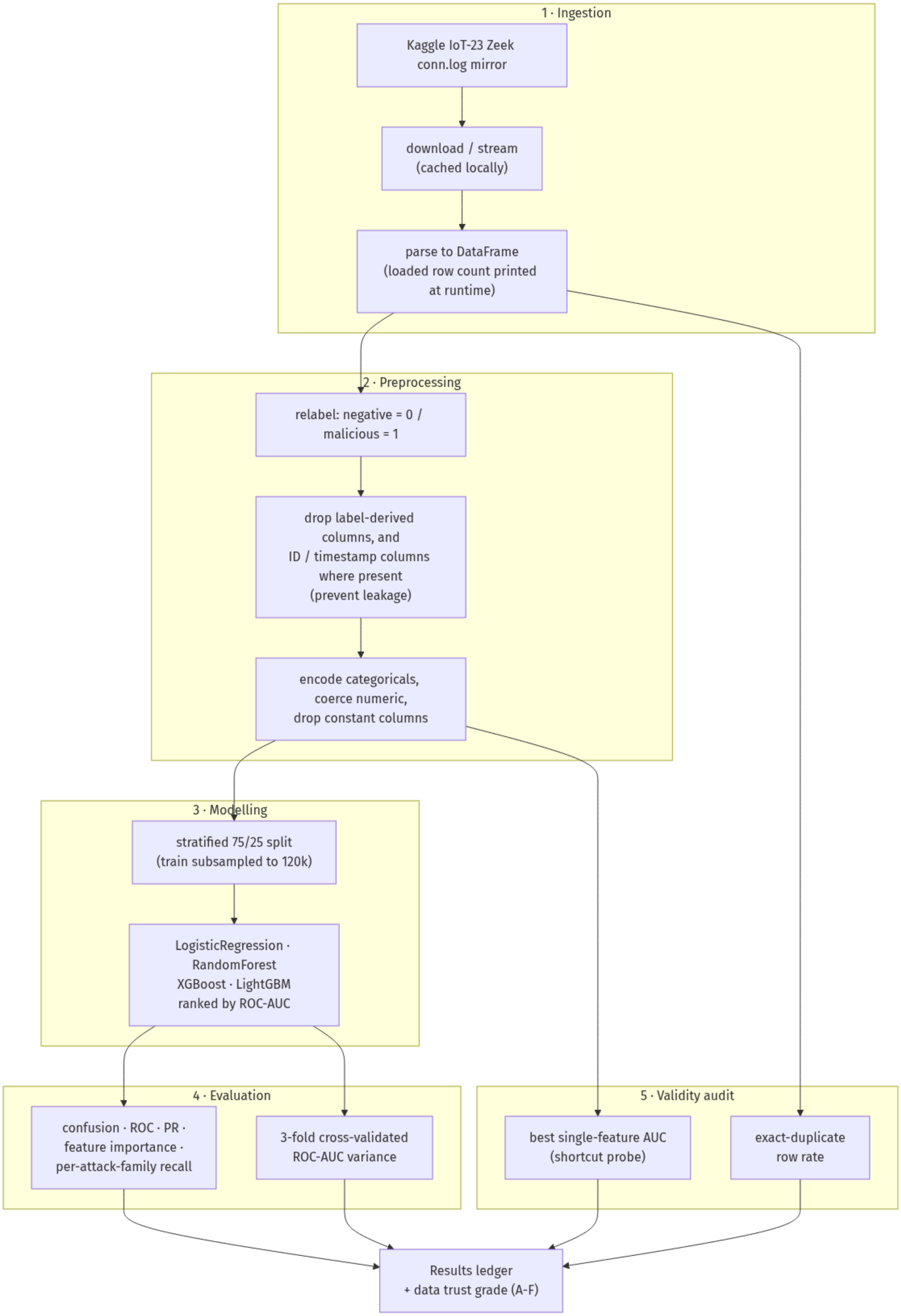
Figure 4.1 — Solution design (methodology).



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
# IoT-23 (Garcia, Parmisano & Erquiaga, 2020; Stratosphere Lab / Avast AIC): 20 real IoT-malware
# captures + 3 benign, published as Zeek conn.log. This is the Kaggle pipe-delimited mirror.
# Self-contained: download once (~2.6 GB, needs a Kaggle token) and cache under /tmp/iot23.
os.environ.setdefault('KAGGLE_KEY',
open(os.path.expanduser('~/.kaggle/access_token')).read().strip())
IOT_DIR = '/tmp/iot23'; os.makedirs(IOT_DIR, exist_ok=True)
CAP = 'CTU-IoT-Malware-Capture-35-1conn.log.labeled.csv'   # one capture, benign+malicious MIXED
hits = glob.glob(IOT_DIR + '/**/' + CAP, recursive=True)
if not hits:
    import kaggle; kaggle.api.authenticate()
    print('downloading IoT-23 captures (~2.6 GB, one-time)...')
    kaggle.api.dataset_download_files('agungpambudi/network-malware-detection-connection-analysis',
                                      path=IOT_DIR, unzip=True, quiet=True)
    hits = glob.glob(IOT_DIR + '/**/' + CAP, recursive=True)
f = hits[0]; assert os.path.exists(f), f'capture not found: {f}'
# Zeek conn.log fields; '-' is Zeek's null token. Keep flow-BEHAVIOUR features only; drop IP/port/
# uid/time identifiers so the model cannot memorise 'which host' instead of learning malicious behaviour.
KEEP =
['proto','service','duration','orig_bytes','resp_bytes','conn_state','missed_bytes',

'history','orig_pkts','orig_ip_bytes','resp_pkts','resp_ip_bytes','label']
raw = pd.read_csv(f, sep='|', usecols=KEEP, low_memory=False, na_values=['-'])
# The Kaggle pipe-conversion merged Zeek's `label` and `detailed-label`
```

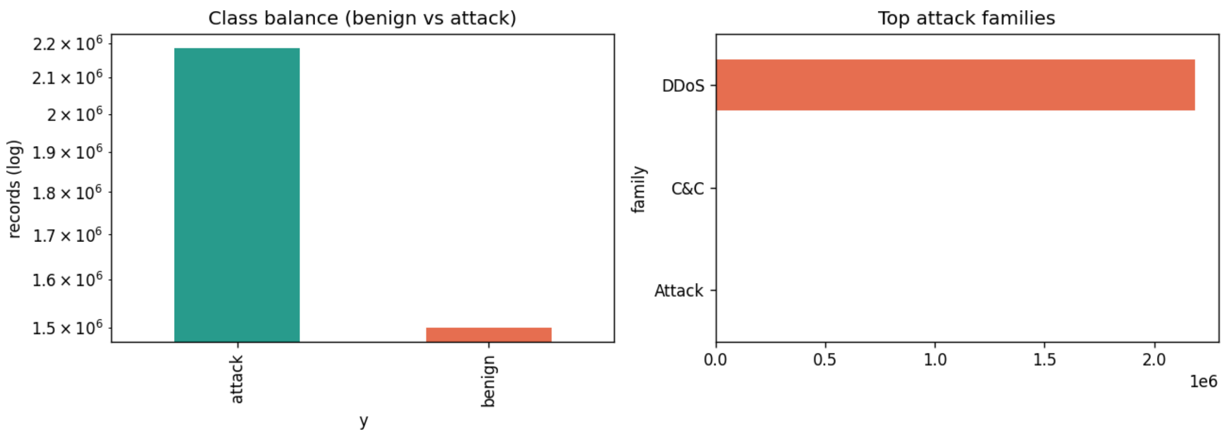
```
into ONE whitespace field:
# 'Benign   -' or 'Malicious   DDoS'. Split it — token0 = binary class,
token1 = attack family.
parts = raw['label'].astype(str).str.split(n=1)
binl = parts.str[0].str.strip()
fam  = parts.str[1].str.strip().replace('-', 'benign').fillna('benign')
ismal = binl.str.lower().eq('malicious')
# Malicious flows (DDoS-dominated) are time-clustered in the MIDDLE of the
capture (the head/tail are
# ~100% benign), so we KEEP EVERY malicious flow and SUBSAMPLE benign to a
bound — the CTU-13 recipe.
# The malicious rate printed below is therefore a bounded-sample rate, not
the natural base rate.
BENIGN_CAP = 1_500_000
ben = raw.index[~ismal]
ben = pd.Index(np.random.RandomState(0).choice(ben, size=min(len(ben),
BENIGN_CAP), replace=False))
keep = raw.index[ismal].union(ben)
df = raw.loc[keep].reset_index(drop=True)
df['y'] = ismal.loc[keep].astype(int).to_numpy()
df['family'] = fam.loc[keep].to_numpy()
assert len(df) >= 1_000_000, f'floor not met: {len(df):,}'
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()
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.loc[:, X.nunique() > 1]; feat = list(X.columns)
y = df['y'].to_numpy(); family = df['family'].to_numpy()
print(f'loaded {len(df):,} flows x {len(feat)} features from one capture; '
      f'malicious rate (bounded sample) {y.mean():.4f}; families
{sorted(set(family))}')
```

```
loaded 3,685,398 flows x 12 features from one capture; malicious rate
(bounded sample) 0.5930; families ['Attack', 'C&C', 'DDoS', 'benign']
```

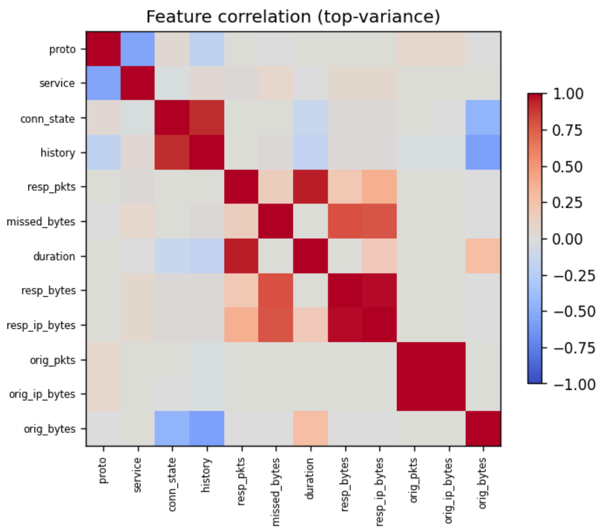
7. Exploratory data analysis

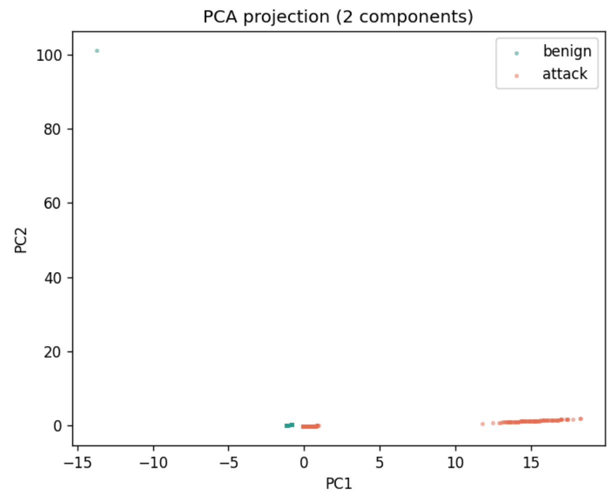
In [3]:

```
# --- 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]:
```python
# --- 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 3,685,398 rows | trained on 120,000 (stratified subsample) |
held-out 921,350
MAJORITY-CLASS BASELINE accuracy = 0.5930  (any model must beat THIS, not
0.5, to be interesting)
best model: RandomForest
```

Out [5]:

	model	accuracy	roc_auc	train_s
0	RandomForest	0.999900	0.999952	0.4
1	XGBoost	0.999902	0.999939	0.2
2	LightGBM	0.999903	0.999935	0.8
3	LogisticRegression	0.999903	0.999927	0.2
4	MajorityBaseline	0.593000	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.

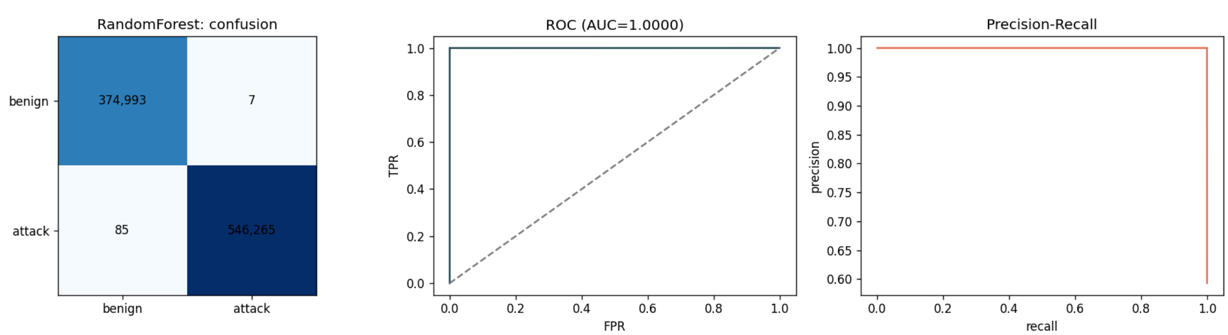
Read it accordingly. Where the groups are genuinely rare classes, they reveal whether detection is real. The dominant flood classes do not.

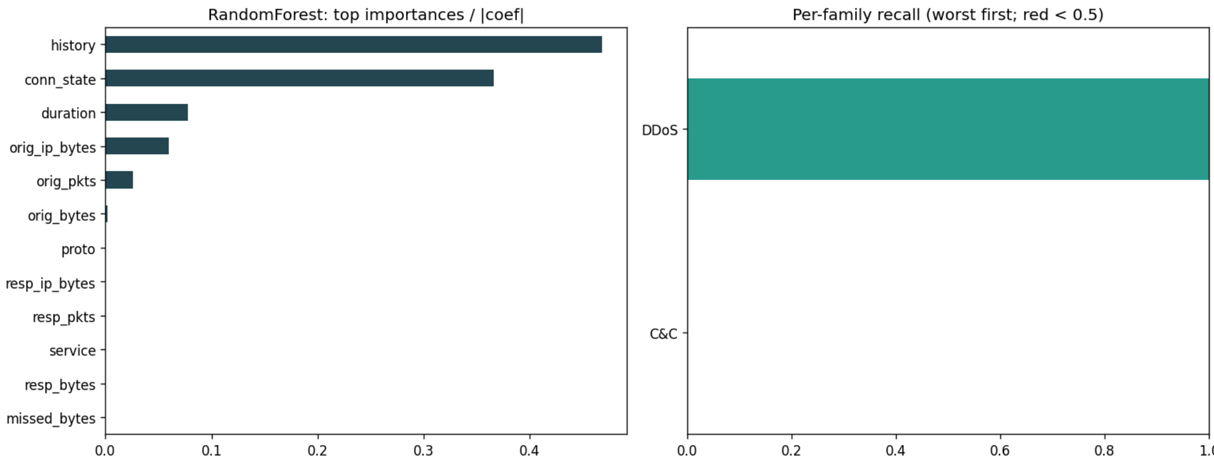
In [6]:

```
# --- 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 = 0.0000  (7 benign flagged of 375,000)
worst per-family recalls: {'C&C': 0.0, 'DDoS': 1.0}
```

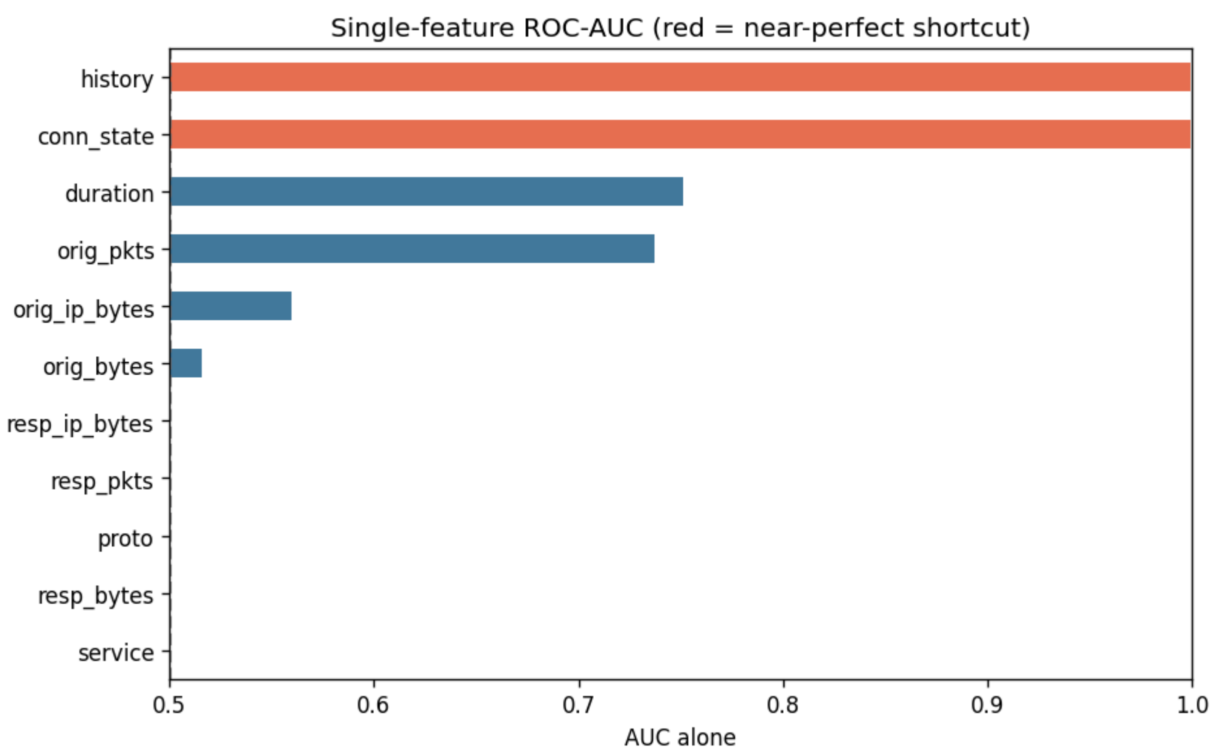
10. Validity audit — is the score real?

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]:
```python
# --- 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 = 0.9996  (feature: history)
   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) = 0.565
TRAIN/TEST exact-row contamination       = 0.422  (single-feat grade F,
contam grade D)
==> data trust grade: F   (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)	0.999952
1	de-duplicated (57% rows removed)	0.999996
2	shortcut feature dropped (history)	0.999949

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
RandomForest 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

The headline AUC on this capture is **not trustworthy as a detector**, and the notebook's own audit says why. The Zeek `history` string alone reaches near-perfect single-feature AUC — it encodes the DDoS flood pattern. It is that single-feature check, not the overlap check, that drives the overall grade to F. The contamination sub-grade is D, and de-duplication does **not** lower the AUC — see the ledger. The decisive evidence is the per-family recall. The model recovers essentially **all DDoS** flows but **almost none of the rare C&C** flows. That is precisely the stealthy compromise a real IoT monitor must catch. So the honest reading is that flow features detect the loud DDoS flood (which barely needs ML) while missing the quiet command-and-control. A deployable claim would require deduplicated, per-family evaluation and a cross-capture test, which we did not run here (Sommer & Paxson, 2010).

Validity ledger — read the headline against these printed numbers: Majority-class baseline **accuracy**: **0.5930**. The accuracy column must clear that bar to mean anything. For ROC-AUC the trivial baseline is 0.5, not that figure. Winning learner: **RandomForest** (3-fold CV ROC-AUC **1.0000**). Strongest *single* feature: `history` at AUC **0.9996**. The ablation refutes a single-feature story. Dropping that feature barely moves the AUC: **0.999952 → 0.999949**. So the separability is **multi-feature**. That reflects how this corpus was generated, not one leaky column. De-duplication does **not** lower the score (**0.999996**). So duplicate rows are not what props it up. The overlap above is a caveat about the *random split*, not proof the score is fabricated. Data-trust grade: **F**. It is the worse of two independent sub-checks. Single-feature AUC 0.9996 scores **F**. Train/test exact-row overlap 0.422 scores **D**. The single-feature check drives the grade, not the overlap check. Train/test overlap separately scores D, so overlap is not the issue here. On this A-best / F-worst scale, a D or F means the headline is optimistic. Treat it as a benchmark number, not a deployment estimate. Operational false-positive rate at threshold 0.5: **0.0000**. Worst per-group recalls, exactly as printed: {`C&C`: 0.0, `DDoS`: 1.0}. The weakest group sits at **0.000**, so the model misses most of it. That gap, not the aggregate score, is the operationally important result. **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

1. García, S., Parmisano, A. & Erquiaga, M.J. (2020). *IoT-23: A labeled dataset with malicious and benign IoT network traffic*. Stratosphere Lab, CTU University / Avast AIC.
2. Antonakakis, M. et al. (2017). Understanding the Mirai Botnet. *USENIX Security*.
3. Meidan, Y. et al. (2018). N-BaIoT: Network-based detection of IoT botnet attacks. *IEEE Pervasive Computing*.
4. Sommer, R. & Paxson, V. (2010). Outside the Closed World: On Using Machine Learning for Network Intrusion Detection. *IEEE S&P*.