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Goal of this notebook

Train and audit detectors on the CSE-CIC-IDS2018 web-attack day, where the attack class is a fraction of a percent.

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. Explain why a 0.9995 accuracy can mean the model found nothing.

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 3: Vulnerability Assessment** — Learning objective 1 (section 3.1) frames assessment as **evidence grading**, not output collection. The A-F data-trust grade in section 10 is exactly that move, applied to a model score.
- **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.

CIC-IDS2018 Case Study — Web Attacks (Brute Force / XSS / SQLi)

Model comparison + validity audit on the web attacks (brute force / xss / sqli) day of CSE-CIC-IDS2018

Abstract: We study one day of the CSE-CIC-IDS2018 flow corpus. Its attack traffic is the day's **web attacks**, which carry three labels — `Brute Force -Web`, `Brute Force -XSS` and `SQL Injection`. All three are reported separately in the per-family recall breakdown in section 9. Benign flows still dominate the day numerically. The attack is the

minority class, and the loader prints the exact rate. We load ≥1,000,000 real CICFlowMeter records. The four learners then fit a **120,000-row stratified subsample**, so every score below is a subsample number. The question is whether the near-perfect in-distribution scores reflect detection, or a defect in the features. Engelen et al. (2021) found bugs in CICFlowMeter itself. That tool built this day's features too, so their tool-level findings are a live suspicion here. Their label corrections are specific to CICIDS2017 and do not carry over to this 2018 capture.

1. Research problem

Task: Detect Brute-Force-Web, XSS, and SQL-Injection among benign traffic on the 2018-02-23 capture. Web attacks are **extremely rare here (0.05% of flows, i.e. a 0.9995 majority baseline)**, making this a severe class-imbalance problem where aggregate accuracy is meaningless — the interesting question is recall on the rare attack families.

2. Literature review

- **Sharafaldin, Lashkari & Ghorbani (2018)** — the **CIC-IDS2017** dataset paper (*ICISSP 2018*, pp. 108–116): realistic profiled benign traffic plus a labeled attack schedule, with 80 CICFlowMeter flow features. It documents the **2017** capture, not the CSE-CIC-IDS2018 corpus studied here. The CIC’s 2018 dataset page lists no dataset paper of its own for the 2018 capture. It offers this one as the write-up of a *similar* dataset and its generation principles.
- **Engelen, Rimmer & Joosen (2021)** — *Troubleshooting an Intrusion Detection Dataset: the CICIDS2017 Case Study* — found labeling errors and CICFlowMeter feature bugs that inflate scores.
- **Rosay, Cheval, Carlier & Leroux (2022)** — *Network Intrusion Detection: A Comprehensive Analysis of CIC-IDS2017* (ICISSP): documents CICFlowMeter implementation flaws affecting these flow features.
- **Sommer & Paxson (2010)** — closed-world ML scores rarely survive deployment.
- **Apruzzese et al. (2023)** — *The Role of Machine Learning in Cybersecurity* (ACM DTRAP): a survey of where ML is and is not actually deployed in security practice. Cited for that framing, not as a study of dataset shortcuts.

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. (2018) — RF among seven learners on CIC-IDS**2017** (not the 2018 day studied here)	in-distribution; CICFlowMeter features later shown buggy
Engelen et al. (2021) — re-labeled CICIDS2017	original labels/features partly wrong

Reported approach	Known caveat
Typical DL-NIDS papers	benign-majority base rate inflates accuracy; per-family recall varies

3. Dataset provenance & honesty caveats

Property	Value
Source	CSE-CIC-IDS2018, AWS Open Data `s3://cse-cic-ids2018/` (no credentials)
File	`Friday-23-02-2018_TrafficForML_CICFlowMeter.csv`
Rows	≥ 1,000,000 flow records (bounded S3 slice)
Features	80 CICFlowMeter columns in the file → **68 used** after dropping label/ID and constant columns (the loader prints the exact count)
Label	`Benign` vs the day's attack families

Honestly: CICFlowMeter's feature implementation has documented bugs (Engelen et al. 2021; Rosay et al. 2022), and accuracy is inflated by the benign-majority base rate. We report per-attack-family recall and audit single-feature shortcuts for this reason.

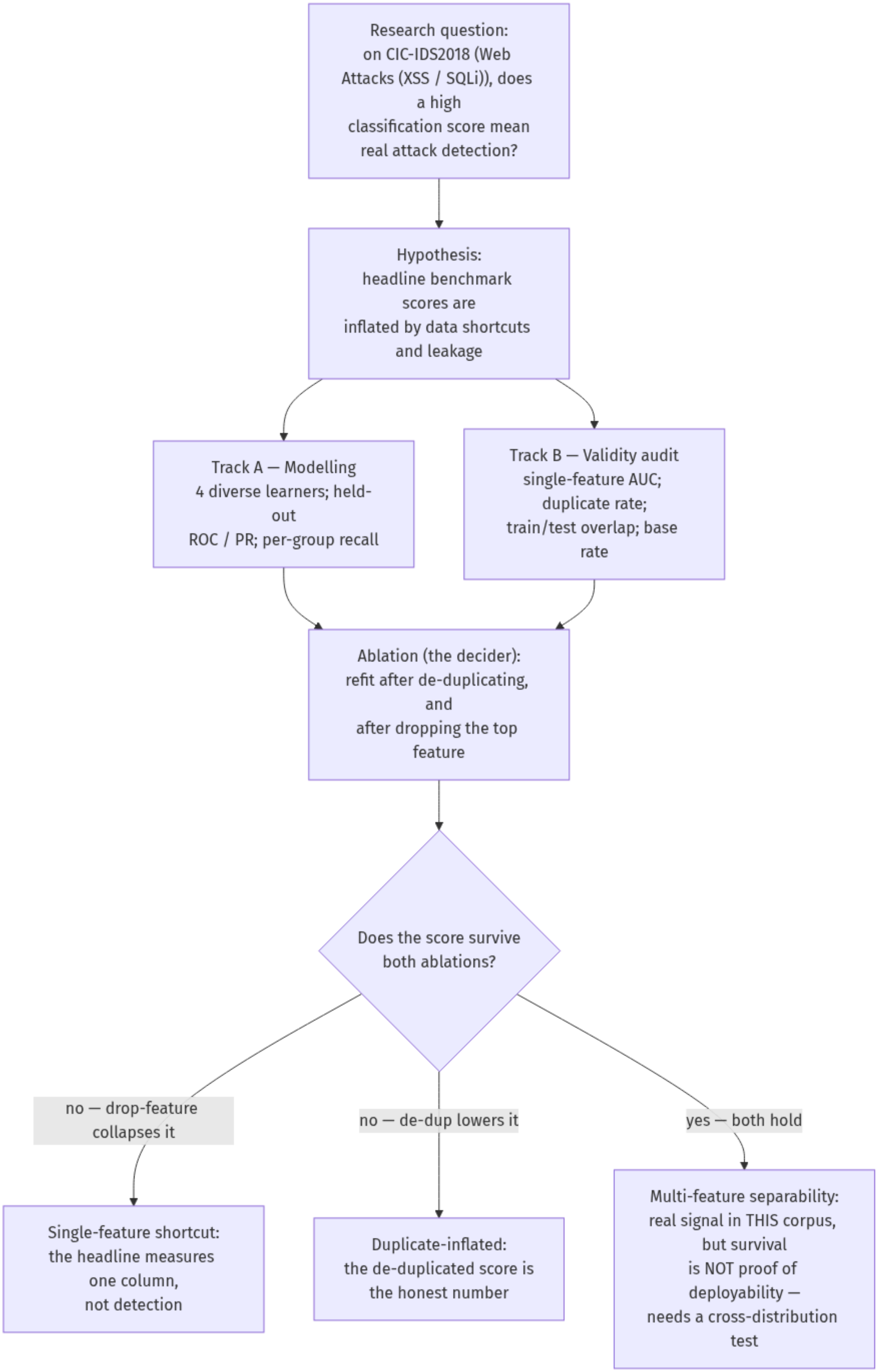
Before you run this: getting the data

This notebook downloads its own data on the first run, then caches it. **No Kaggle account and no credentials are needed** - the source is the public AWS Open Data bucket `s3://cse-cic-ids2018/`.

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.

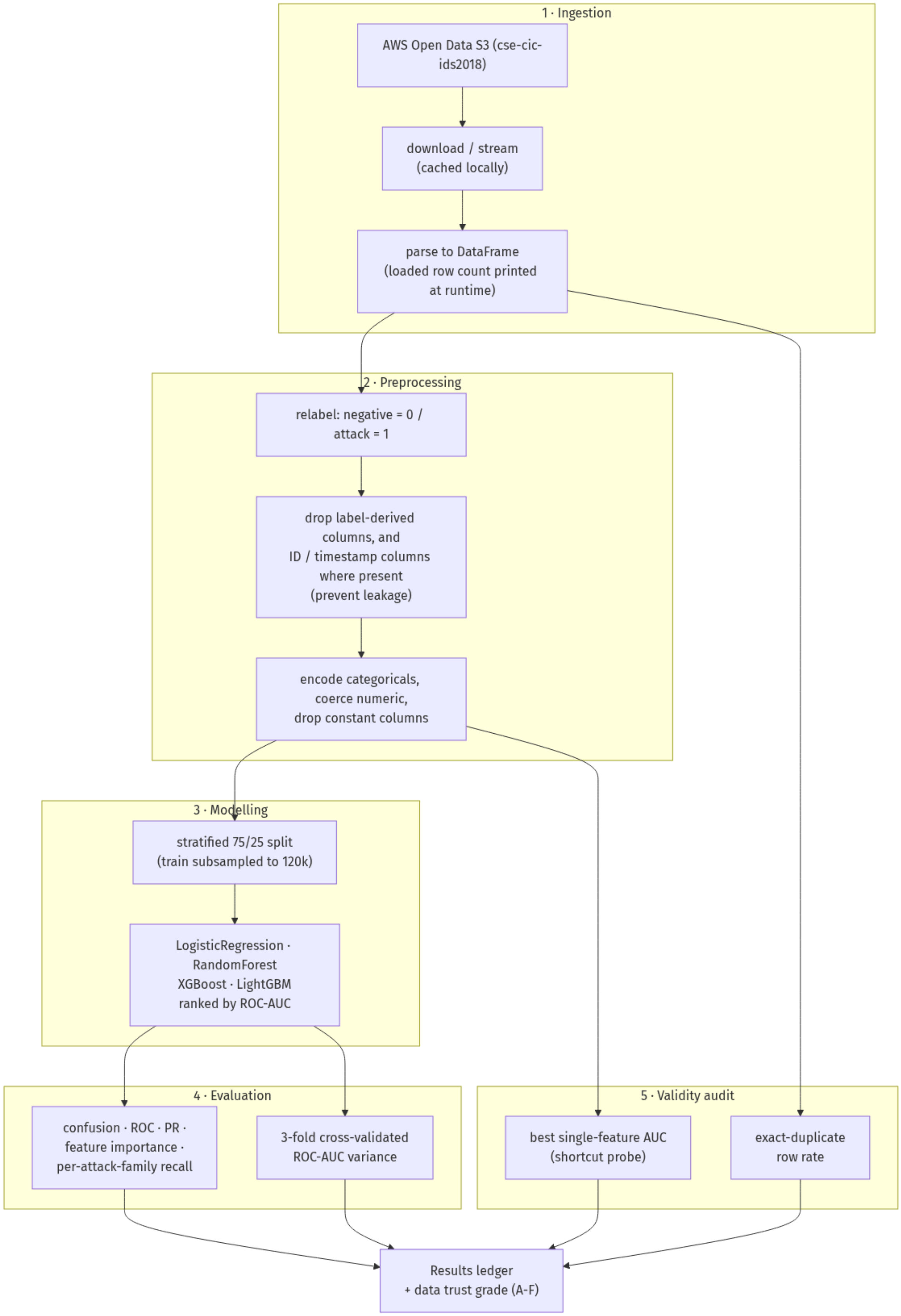
Figure 4.1 — Solution design (methodology).



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.

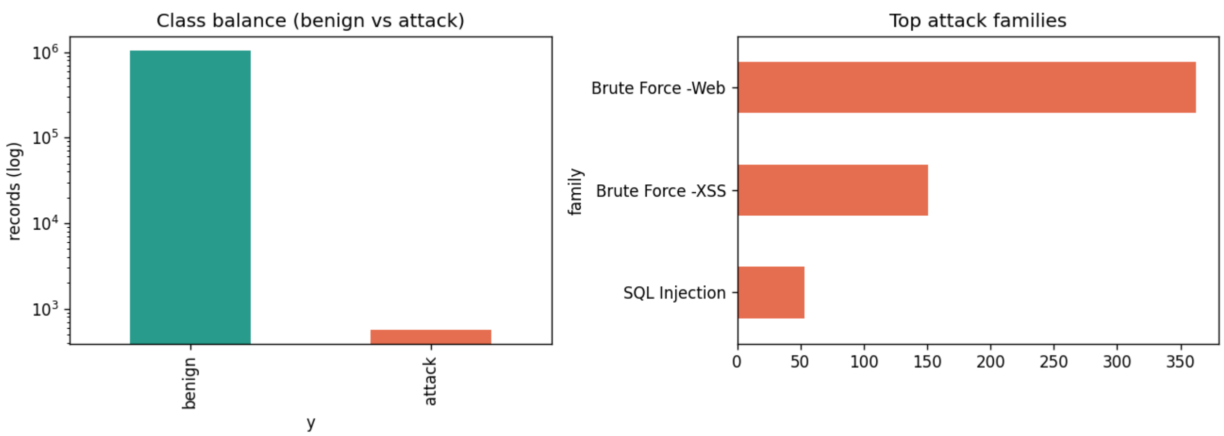
In [1]:
```
%matplotlib inline
import time, warnings; warnings.filterwarnings('ignore')   # keep output clean
import numpy as np, pandas as pd                            # numerics + dataframes
import matplotlib.pyplot as plt                             # static plots (embed in HTML+PDF)
plt.rcParams['figure.dpi'] = 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
FILE = 'Friday-23-02-2018_TrafficForML_CICFlowMeter.csv'; SHORT = 'webattacks'
PREFIX = 's3://cse-cic-ids2018/Processed Traffic Data for ML Algorithms/'
CACHE = f'/tmp/cic_{SHORT}.csv'
if not os.path.exists(CACHE):                                # bounded S3 download, no credentials
    os.system(f'aws s3 cp "{PREFIX}{FILE}" - --no-sign-request 2>/dev/null | head -n 1200000 > "{CACHE}"')
df = pd.read_csv(CACHE, low_memory=False)                    # parse the day's flow records
df = df[pd.to_numeric(df['Dst Port'], errors='coerce').notna()].reset_index(drop=True)  # drop repeated-header junk
df['Label'] = df['Label'].astype(str).str.strip()           # clean labels
df['y'] = (df['Label'] != 'Benign').astype(int)             # 1 = attack, 0 = benign
df['family'] = df['Label']                                   # attack type doubles as family
assert len(df) >= 1_000_000, f'floor not met: {len(df):,}'   # honesty gate: >= 1M rows
DROP = ['Label','Timestamp','y','family']
feat = [c for c in df.columns if c not in DROP]
X = df[feat].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)       # drop constants; align feat
y = df['y'].to_numpy()                                       # STANDARD CONTRACT: binary label
print(f'loaded {len(df):,} flows x {len(feat)} features; attack rate {y.mean():.4f}')
```

```
loaded 1,048,575 flows x 68 features; attack rate 0.0005
```

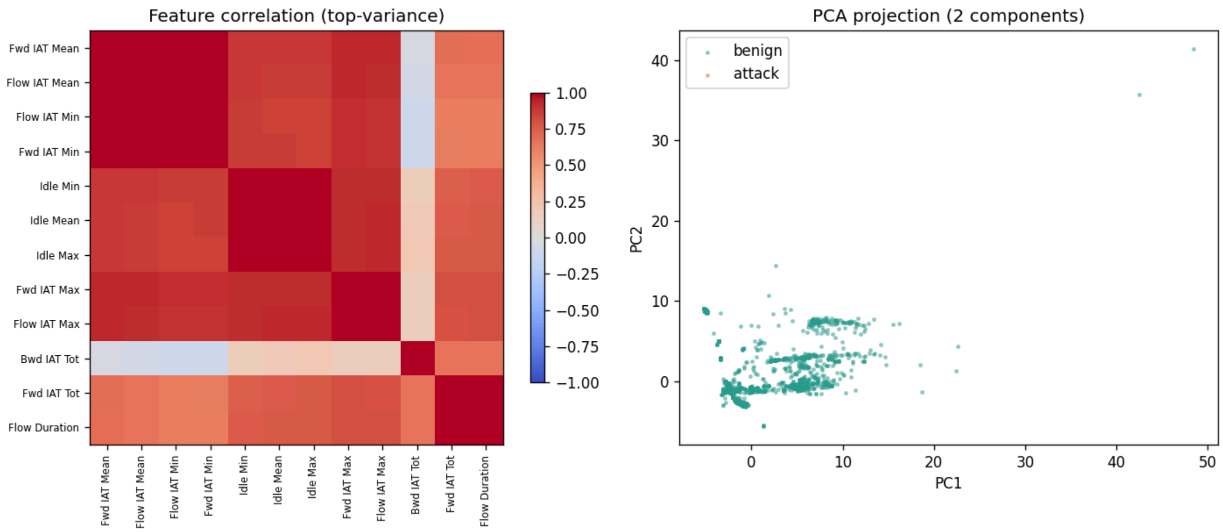
7. Exploratory data analysis

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 1,048,575 rows | trained on 120,000 (stratified subsample) |
held-out 262,144
MAJORITY-CLASS BASELINE accuracy = 0.9995  (any model must beat THIS, not
0.5, to be interesting)
best model: XGBoost
```

Out[5]:

	model	accuracy	roc_auc	train_s
0	XGBoost	0.999710	0.996349	0.6
1	LogisticRegression	0.999565	0.972244	0.2
2	RandomForest	0.999729	0.964414	0.7
3	LightGBM	0.996037	0.514258	1.2
4	MajorityBaseline	0.999500	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.

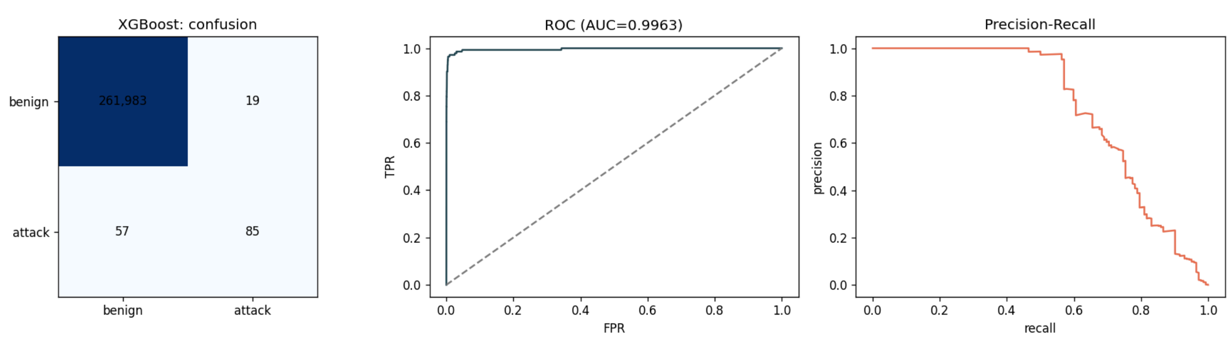
Read it accordingly. Where the groups are genuinely rare classes, they reveal whether detection is real. The dominant flood classes do not.

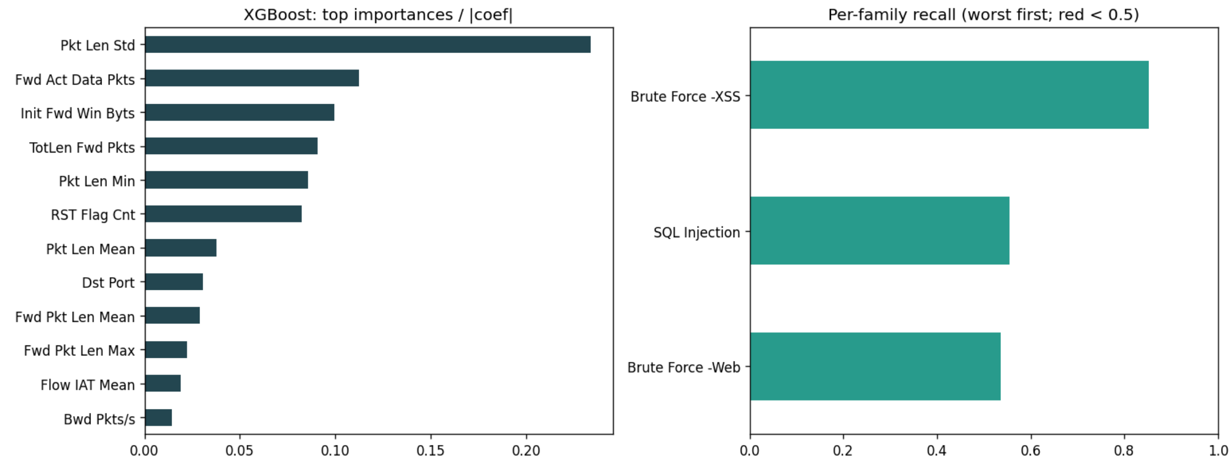
In [6]:

```
# --- 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 = 0.0001  (19 benign flagged of 262,002)
worst per-family recalls: {'Brute Force -Web': 0.536, 'SQL Injection': 0.556,
'Brute Force -XSS': 0.852}
```

10. Validity audit — is the score real?

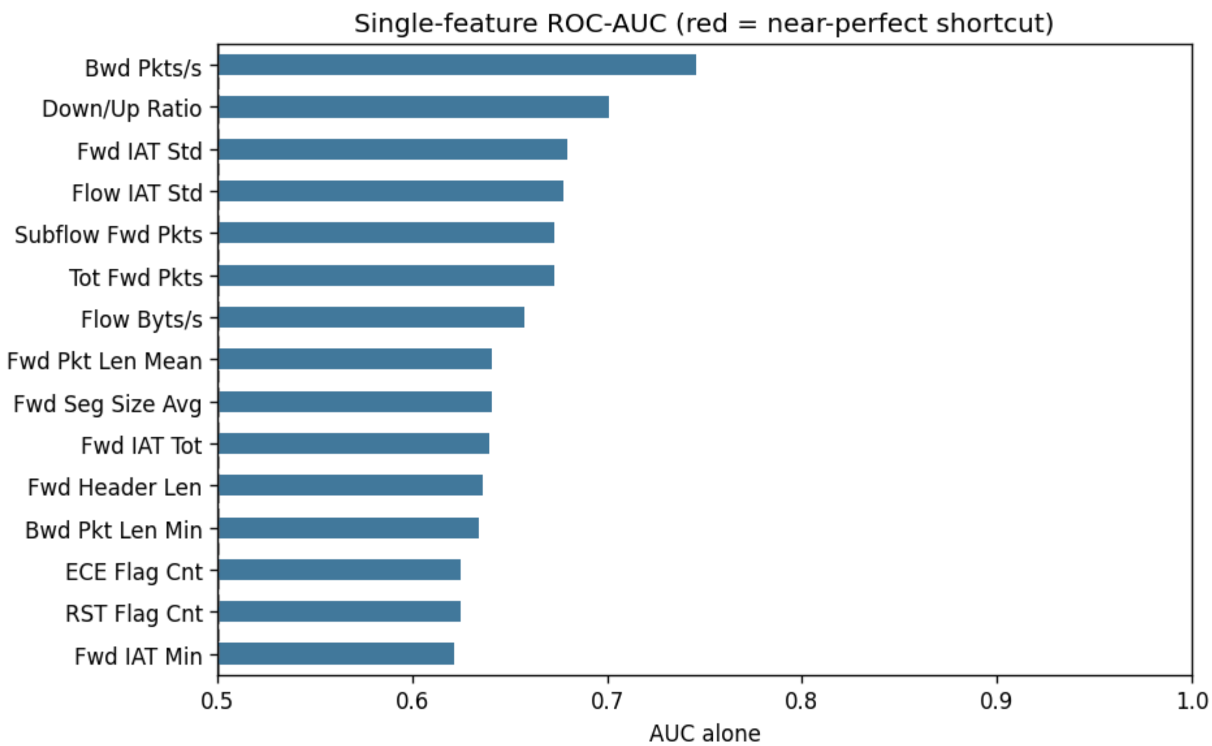
Three diagnostics. **(a)** How well can the *single best feature*, alone, separate the classes? A near-1.0 single-feature AUC means that feature is *near-sufficient* — a shortcut (which may be legitimate signal or an artifact), not the same as target leakage. **(b)** The exact-duplicate row rate. **(c)** 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 = 0.7457  (feature: Bwd Pkts/s)
   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) = 0.132
TRAIN/TEST exact-row contamination       = 0.088  (single-feat grade A,
contam grade B)
==> 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)	0.996349
1	de-duplicated (13% rows removed)	0.999049
2	shortcut feature dropped (Bwd Pkts/s)	0.994340

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 = 0.9746 +/- 0.0352  (mean +/- std across 3
stratified folds; a small std means a stable estimate on this split)
```

13. Scientific conclusion

With attacks at just **0.05%** of flows (majority baseline accuracy 0.9995), a model can reach >0.99 accuracy by predicting 'benign' almost always. That is why we report per-family recall and PR curves, not accuracy. The honest metric is whether the rare web-attack families are recalled at all. The accuracy figure is flattered by the benign base rate, though the model here is *not* useless. See the held-out AUC and the per-family recalls in the ledger below. This is the imbalance lesson every NIDS practitioner must internalize (Sommer & Paxson, 2010).

Validity ledger — read the headline against these printed numbers: Majority-class baseline **accuracy**: **0.9995**. 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 **0.9746**). Strongest *single* feature: `Bwd Pkts/s` at AUC **0.7457**. The ablation refutes a single-feature story. Dropping that feature barely moves the AUC: **0.996349 → 0.994340**. So the separability is **multi-feature**. That reflects how this corpus was generated, not one leaky column. De-duplication **raises** the AUC, to **0.999049**. That is not evidence the headline is safe. Collapsing duplicates removes the hardest rows. Identical feature vectors carrying conflicting labels get resolved to one label. The de-duplicated task is therefore *easier*, not cleaner. Data-trust grade: **B**. It is the worse of two independent sub-checks. Single-feature AUC 0.7457 scores **A**. Train/test exact-row overlap 0.088 scores **B**. The overlap check drives the grade, not the single-feature check. That says the split leaks, not that features are clean; the single-feature check separately scores A. Operational false-positive rate at threshold 0.5: **0.0001**. Worst per-group recalls, exactly as printed: {`Brute Force -Web`: 0.536, `SQL Injection`: 0.556, `Brute Force -XSS`: 0.852}. The weakest group sits at **0.536**, which is where detection is thinnest. **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.

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