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Course: SEAS 8414 — Security Analytics

Goal of this notebook

Train and audit detectors on the WUSTL-IIoT industrial testbed, where a false alarm can stop a process.

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 6: Digital Twins for Remediation Simulation** — Learning objective 2 (section 6.1) treats fidelity as a **promotion gate**. An in-distribution score is not a deployment estimate, which is the gate this notebook refuses to pass.
- **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.

Industrial-IoT Intrusion Detection on WUSTL-IIoT-2021

Model comparison + per-attack-family recall + validity audit (1.19M SCADA-testbed flows)

Abstract: WUSTL-IIoT-2021 (Zolanvari et al., 2021) is network telemetry from a real **Industrial IoT** testbed — a water-storage-tank SCADA process at Washington University.

It carries 1.19M flows labelled benign vs attack (DoS, Reconnaissance, command-injection, Backdoor). Unlike the consumer-IoT and enterprise-network datasets elsewhere in this series, this is an operational-technology (OT) setting. We compare four learners and report recall per attack family — where command-injection (CommInj) and Backdoor are vanishingly rare.

1. Research problem

Task: Flag an IIoT network flow as benign or attack in an OT environment. In that setting, a false positive can trip a physical process and a missed intrusion can damage equipment. The set is 93% benign and the malicious 7% is ~90% DoS. So the honest challenge is the **rare** families (command-injection and Backdoor (a few hundred flows each)), not the DoS flood.

2. Literature review

- **Zolanvari, Teixeira, Gupta, Khan & Jain (2021)** — the WUSTL-IIoT-2021 testbed and dataset for IIoT cyber-security research.
- **Zolanvari et al. (2019)** — an *earlier, separate* study (not this 2021 dataset): *Machine Learning-Based Network Vulnerability Analysis of IIoT* (IEEE IoT Journal): the ML-IDS motivation.
- **Morris & Gao (2014)** — industrial control-system attack datasets.
- **Sommer & Paxson (2010)** — the closed-world ML 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
Zolanvari et al. — ML-IDS on IIoT flows (2019 study; 2021 dataset release)	different corpus/protocol from this run; extreme imbalance, DoS dominates the attack class
Flow-based OT intrusion detectors	rare families (CommInj/backdoor) are the hard, safety-critical cases

3. Dataset provenance & honesty caveats

Property	Value
Source	Kaggle `annaamalaiu/wustl-iiot-2021-dataset` (Zolanvari et al., 2021)
Rows	1,194,464 flows. **The released CSV spans ~7 h** (2019-08-19, by its own StartTime/LastTime columns); the ~53 h figure quoted for WUSTL-IIoT-2021 refers to the raw collection campaign, not this flow product.
Label	`Target` 0/1 (~7% attack); family `Traffic` (DoS/Reconn/CommInj/Backdoor)

Property	Value
Access	Kaggle API token required

Honestly: the attack class is ~90% DoS, so aggregate accuracy is base-rate inflated. The rare command-injection (CommInj) and Backdoor families are the real test. Worst-first per-family recall makes them visible. IP/port/time identifiers are dropped so the model uses flow behaviour, not endpoint identity.

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 `annaamalaiu/wustl-iiot-2021-dataset` -> `/tmp/kg_wustl`. It is about **391 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:

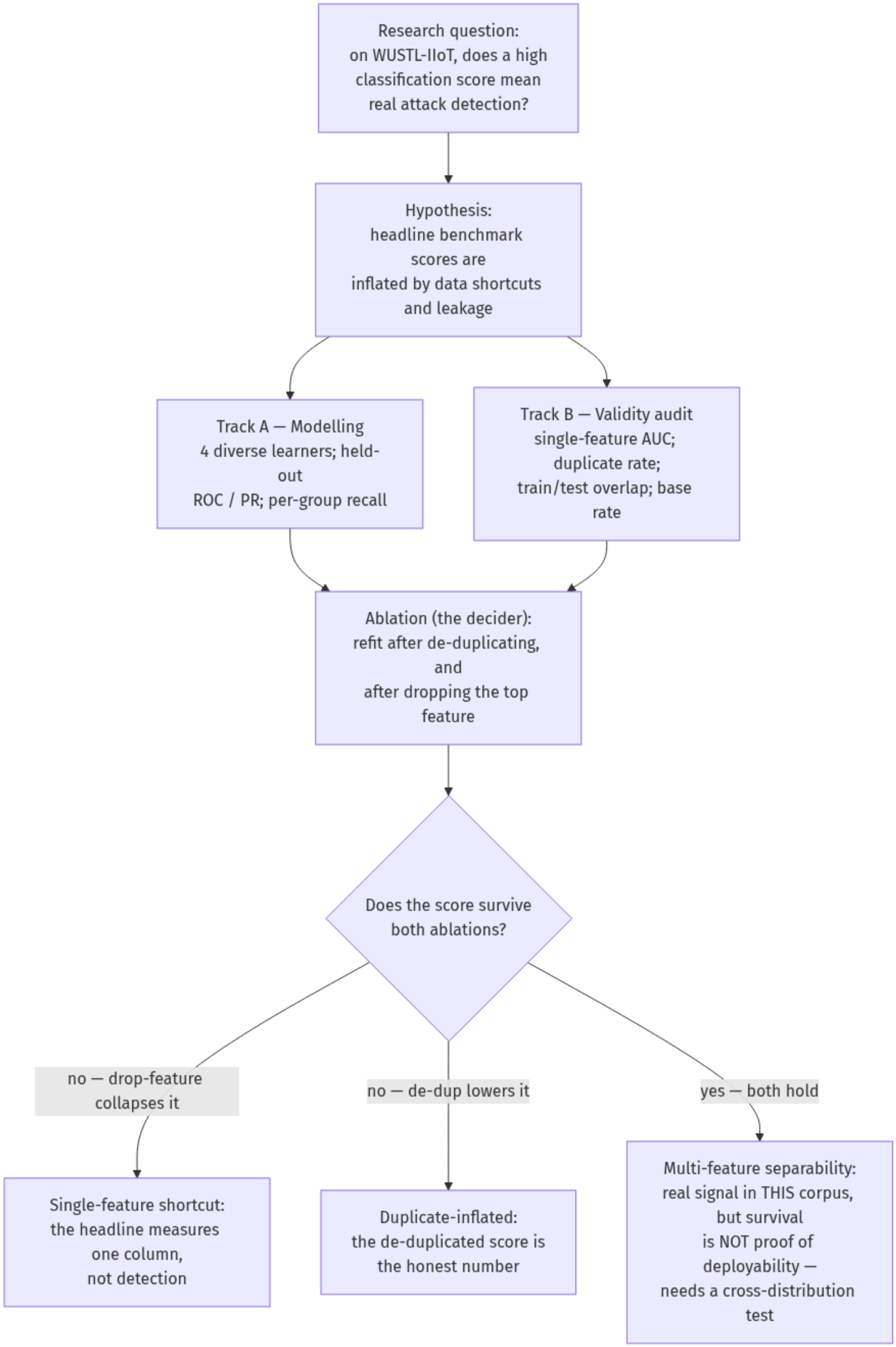
- `FileNotFoundError: ~/.kaggle/access_token` - you created `kaggle.json` but not the key file. Run the command above.
- `401 Unauthorized` - the key is wrong, or a trailing newline crept in.
- `403 Forbidden` - open the dataset page on Kaggle while signed in, accept its terms, then re-run the cell.

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.

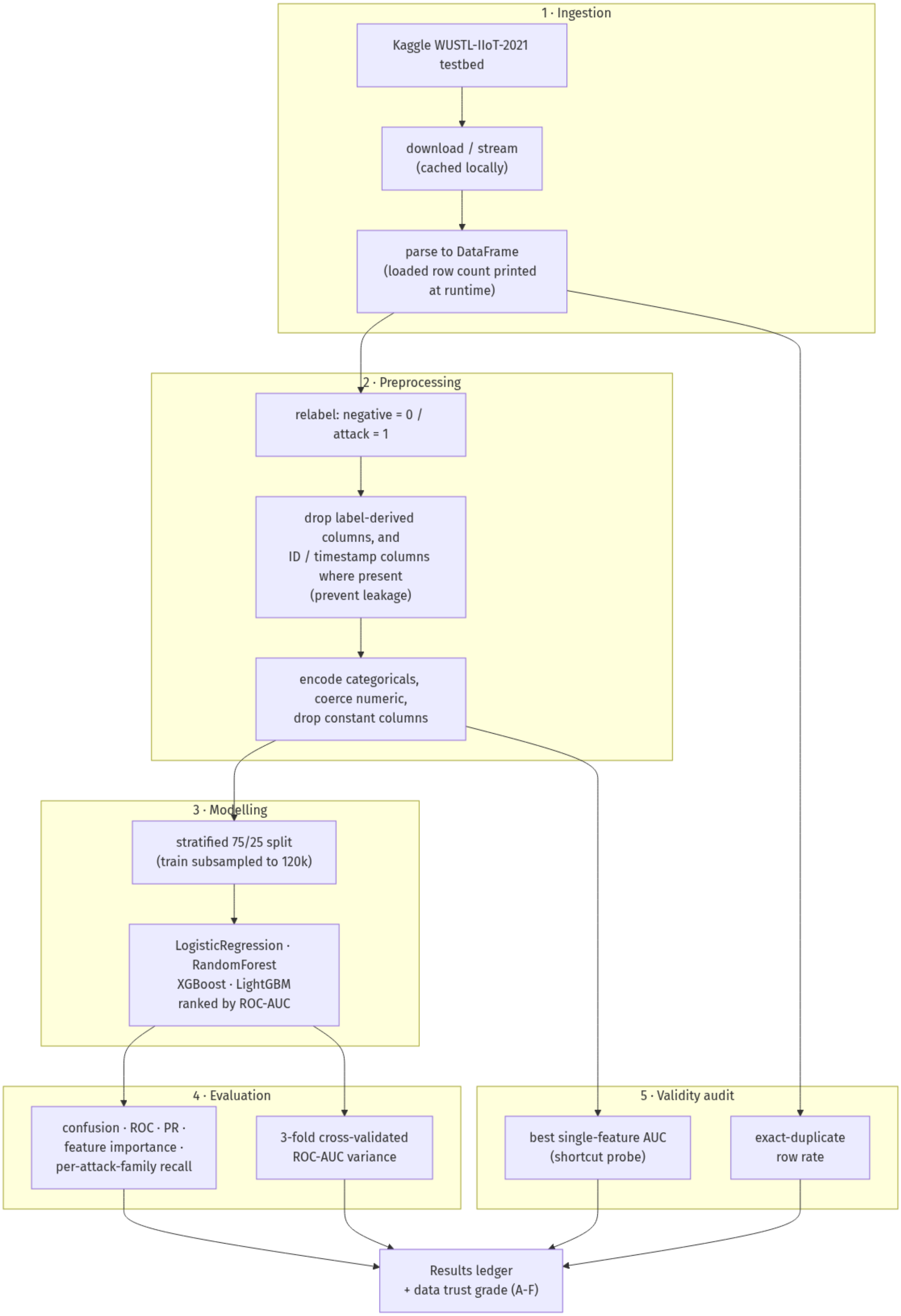
Figure 4.1 — Solution design (methodology).



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
# WUSTL-IIoT-2021 (Zolanvari et al., 2021): network telemetry from a
Washington University INDUSTRIAL
# IoT testbed (a real water-storage-tank SCADA process), 1.19M flows
labelled Target 0/1 with the
# attack family in `Traffic` (DoS / Reconnaissance / command-injection /
Backdoor). Self-contained.
os.environ.setdefault('KAGGLE_KEY',
open(os.path.expanduser('~/.kaggle/access_token')).read().strip())
DEST = '/tmp/kg_wustl'; os.makedirs(DEST, exist_ok=True)
if not glob.glob(DEST + '/**/*.csv', recursive=True):
    import kaggle; kaggle.api.authenticate()
    print('downloading WUSTL-IIoT-2021 (one-time)...')
    kaggle.api.dataset_download_files('annaamalaiu/wustl-iiot-2021-
dataset', path=DEST, unzip=True, quiet=True)
f = sorted(glob.glob(DEST + '/**/*.csv', recursive=True),
key=os.path.getsize, reverse=True)[0]
df = pd.read_csv(f, low_memory=False); df.columns = [str(c).strip() for c
in df.columns]
assert len(df) >= 1_000_000, f'floor not met: {len(df):,}'
df['y'] = df['Target'].astype(int)
df['family'] = df['Traffic'].astype(str).str.strip()          # normal /
DoS / Reconn / CommInj / Backdoor
# Drop labels and flow IDENTIFIERS (IP/port/time/ip-id) so only behaviour
features remain.
DROP = ['Target', 'Traffic', 'y', 'family', 'StartTime', 'LastTime',
'SrcAddr', 'DstAddr',
        'Sport', 'Dport', 'sIpId', 'dIpId']
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)]
```

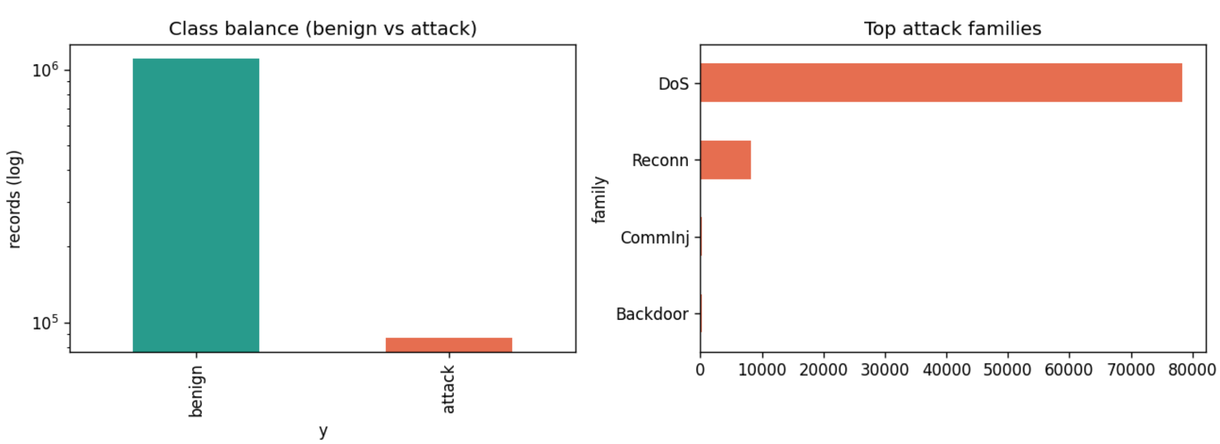
```
X = X.drop(columns=idlike)                                    # drop
id/timestamp-like leaky columns
for c in X.select_dtypes(include='object').columns:
    X[c] = LabelEncoder().fit_transform(X[c].astype(str))
X = X.apply(pd.to_numeric, errors='coerce').replace([np.inf,-
np.inf],np.nan).fillna(0.0)
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):,} IIoT flows x {len(feat)} features; attack rate
{y.mean():.4f}; families {sorted(set(family))}')
```

```
loaded 1,194,464 IIoT flows x 39 features; attack rate 0.0728; families
['Backdoor', 'CommInj', 'DoS', 'Reconn', 'normal']
```

7. Exploratory data analysis

In [3]:

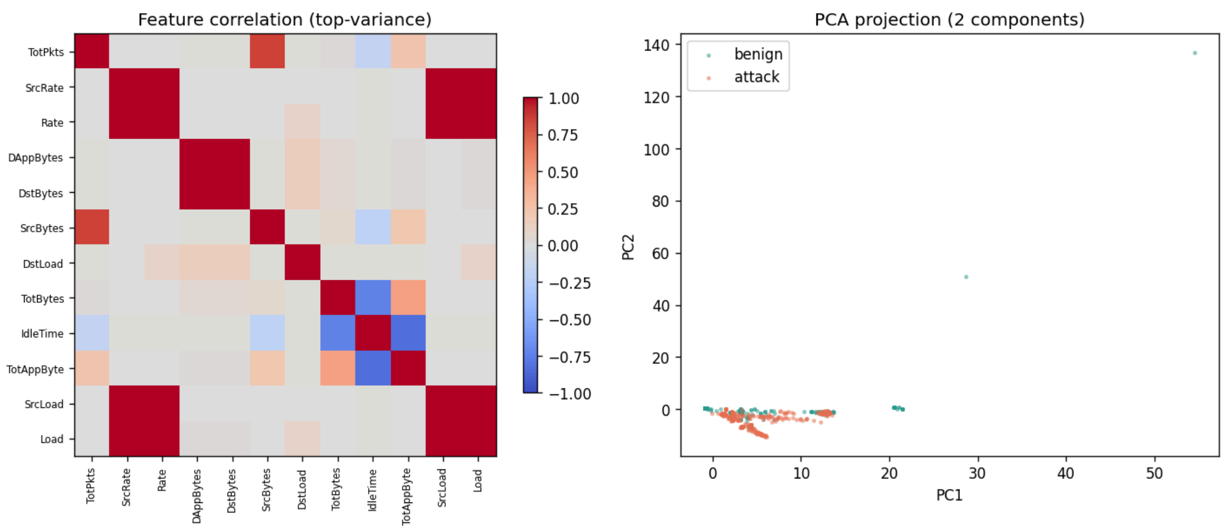
```
# --- EDA 1: class balance and the attack-family mix ---
fig, ax = plt.subplots(1, 2, figsize=(11, 4))
df['y'].map({0:NEG_WORD,1:POS_WORD}).value_counts().plot.bar(
# counts per class
    ax=ax[0], color=['#2a9d8f','#e76f51']); ax[0].set_yscale('log')
ax[0].set_title(f'Class balance ({NEG_WORD} vs {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 1,194,464 rows | trained on 120,000 (stratified subsample) |
held-out 298,616
MAJORITY-CLASS BASELINE accuracy = 0.9272  (any model must beat THIS, not
0.5, to be interesting)
best model: XGBoost
```

Out[5]:

	model	accuracy	roc_auc	train_s
0	XGBoost	0.999963	1.000000	0.3
1	LightGBM	0.999913	1.000000	1.1
2	RandomForest	0.999940	0.999977	0.6
3	LogisticRegression	0.994649	0.998680	0.3
4	MajorityBaseline	0.927200	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.

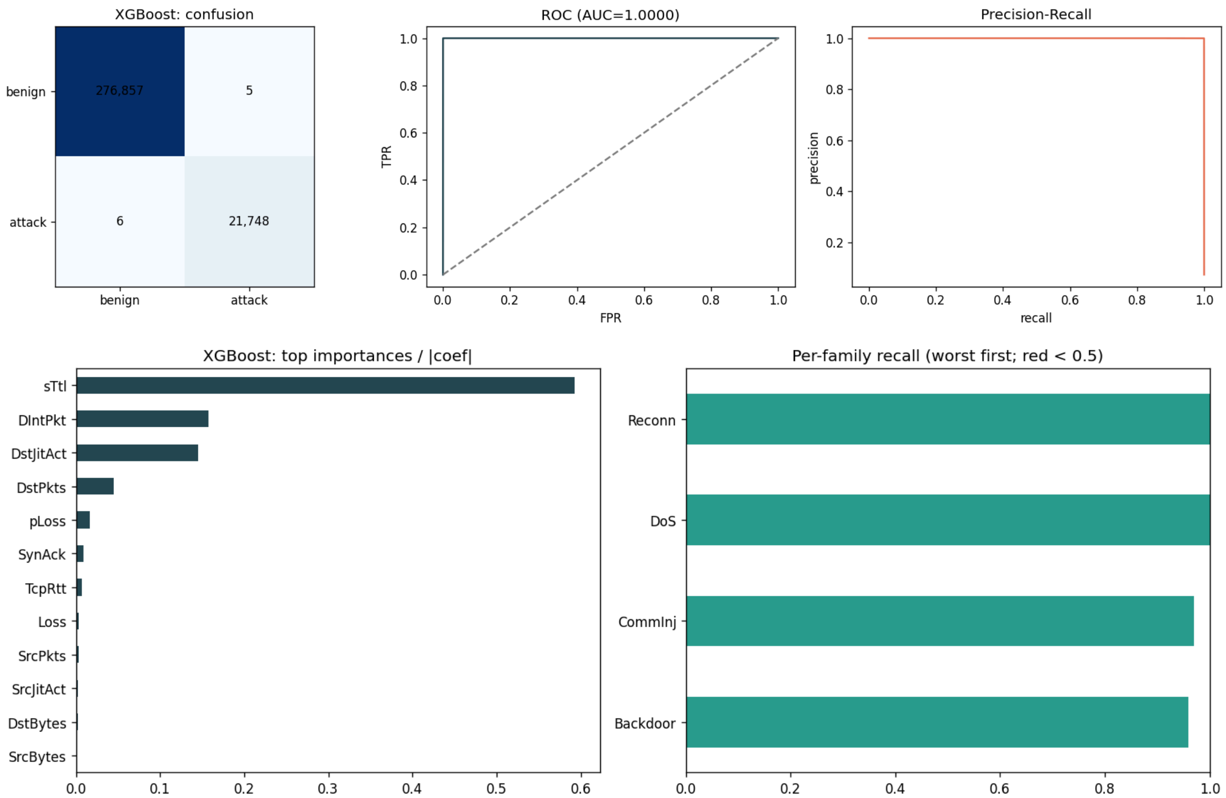
In [6]:

```
# --- 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])
```

```python
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  (5 benign flagged of 276,862)
worst per-family recalls: {'Backdoor': 0.96, 'CommInj': 0.971, 'DoS': 1.0,
'Reconn': 1.0}
```

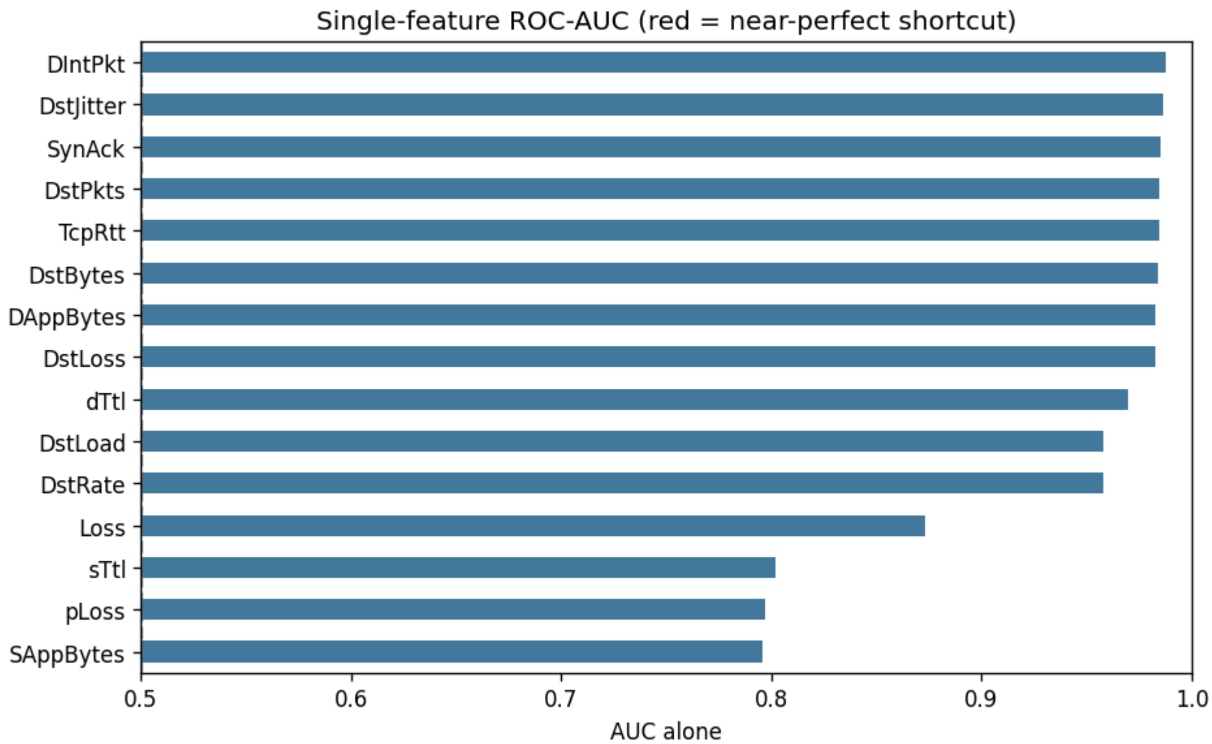
10. Validity audit — is the score real?

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 = 0.9879  (feature: DIntPkt)
   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       = 0.019  (single-feat grade C,
contam grade A)
==> data trust grade: C   (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)	1.0
1	de-duplicated (3% rows removed)	1.0
2	shortcut feature dropped (DIntPkt)	1.0

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

Flow features separate benign from attack IIoT traffic well above the 93%-benign baseline. But that number is carried by the dominant DoS flood. The honest, safety-relevant metrics are per-family recall on the rare command-injection (CommInj) and Backdoor flows, plus the benign false-positive rate. That rate matters because a false trip can halt a physical process.

Validity ledger — read the headline against these printed numbers: Majority-class baseline **accuracy**: **0.9272**. 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: `DIntPkt` at AUC **0.9879**. The ablation refutes a single-feature story. Dropping that feature barely moves the AUC: **1.000000 → 1.000000**. So the separability is **multi-feature**. That reflects how this corpus was generated, not one leaky column. De-duplication does **not** lower the score (**1.000000**). So duplicate rows are not what props it up. Train/test overlap is negligible too, so neither issue explains the result. Data-trust grade: **C**. It is the worse of two independent sub-checks. Single-feature AUC 0.9879 scores **C**. Train/test exact-row overlap 0.019 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: **0.0000**. Worst per-group recalls, exactly as printed: { `Backdoor` : 0.96, `CommInj` : 0.971, `DoS` : 1.0, `Reconn` : 1.0}. The weakest group sits at **0.960**, 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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