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Course: SEAS 8414 — Security Analytics

Goal of this notebook

Train and audit detectors on Edge-IIoTset, after excluding endpoint and payload columns that act as label proxies.

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. Read the loader's defence against a label proxy made by text formatting alone. The same numeric value can be serialised as `0`, `0.0` or `0x00000000`. If a capture spells it one way per class, label-encoding turns formatting into a class-tracking category. The loader coerces numeric-looking strings to numbers *before* any encoding, so the spellings collapse first. The defence is **applied** here, not demonstrated: no cell runs the pipeline without it. Untested hypothesis you can check: delete the `pd.to_numeric` coercion loop in the loader cell and rerun. Then compare section 10's best single-feature AUC.

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 2: Service Enrichment and Device Fingerprinting** — Learning objective 3 (section 2.1) compares evidence sources by strength and **spoofability**. Several features used here are protocol fields an attacker controls, which is the same concern.
- **Chapter 9: Supply-Chain Integrity and Counterfeit Detection** — Learning objective 3 (section 9.1) is to build **multi-signal** counterfeit detection (MAC OUI, firmware hash, TCP stack fingerprint, entropy, timing) rather than trusting one indicator, and the chapter's guardrails add that a single anomaly rarely settles a case and that a documentation gap is not evidence of tampering. Both cautions apply to artifact-derived features here.
- **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/IIoT Intrusion Detection: the Edge-IIoTset Dataset

Model comparison + validity audit on Edge-IIoTset (2.2M records, via Kaggle)

Abstract: Edge-IIoTset (Ferrag et al., 2022) is a large IoT/IIoT security dataset (~2M+ records, 14 attack types across MQTT/Modbus/HTTP). We compare four learners and audit the near-perfect scores.

1. Research problem

Task: Detect attacks (DoS/DDoS, injection, MITM, reconnaissance, malware) against IoT/IIoT devices from flow/protocol features. IIoT devices are constrained and long-lived, so a detector must generalize — exactly what an in-distribution score cannot show.

2. Literature review

- **Ferrag et al. (2022)** — Edge-IIoTset: realistic IoT/IIoT cyber-security dataset for centralized and federated learning.
- **Sommer & Paxson (2010)** — the closed-world critique.
- **Apruzzese et al. (2023)** — *The Role of Machine Learning in Cybersecurity* (ACM DTRAP): a broad survey of where ML is (and is not) deployed in practice. We cite it 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
Ferrag et al. (2022) — DNN / ML baselines	in-distribution; protocol fields can leak
Federated-learning studies	non-IID splits, optimistic

3. Dataset provenance & honesty caveats

Property	Value
Source	Kaggle `sibasispradhan/edge-iiotset-dataset`

Property	Value
Rows	~2M+ (DNN-EdgeIIoT-dataset.csv)
Label	`Attack_label` 0/1; family `Attack_type`
Access	Kaggle API token required

Honestly: `Attack_type` is dropped (it encodes the label). We also explicitly drop the **endpoint-identity and payload columns** — `ip.src_host`, `ip.dst_host`, the ARP IPv4 fields, and the HTTP/DNS/MQTT string payloads. In a testbed capture the attacker and victim addresses are fixed per role. So keeping those columns lets the model read *who* is talking instead of *what* the traffic does. The generic high-cardinality ID filter does not catch them, since testbed IPs take only a handful of values.

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 `sibasispradhan/edge-iiotset-dataset` -> `/tmp/kg_edge-iiotset-dataset`. It is about **1 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:

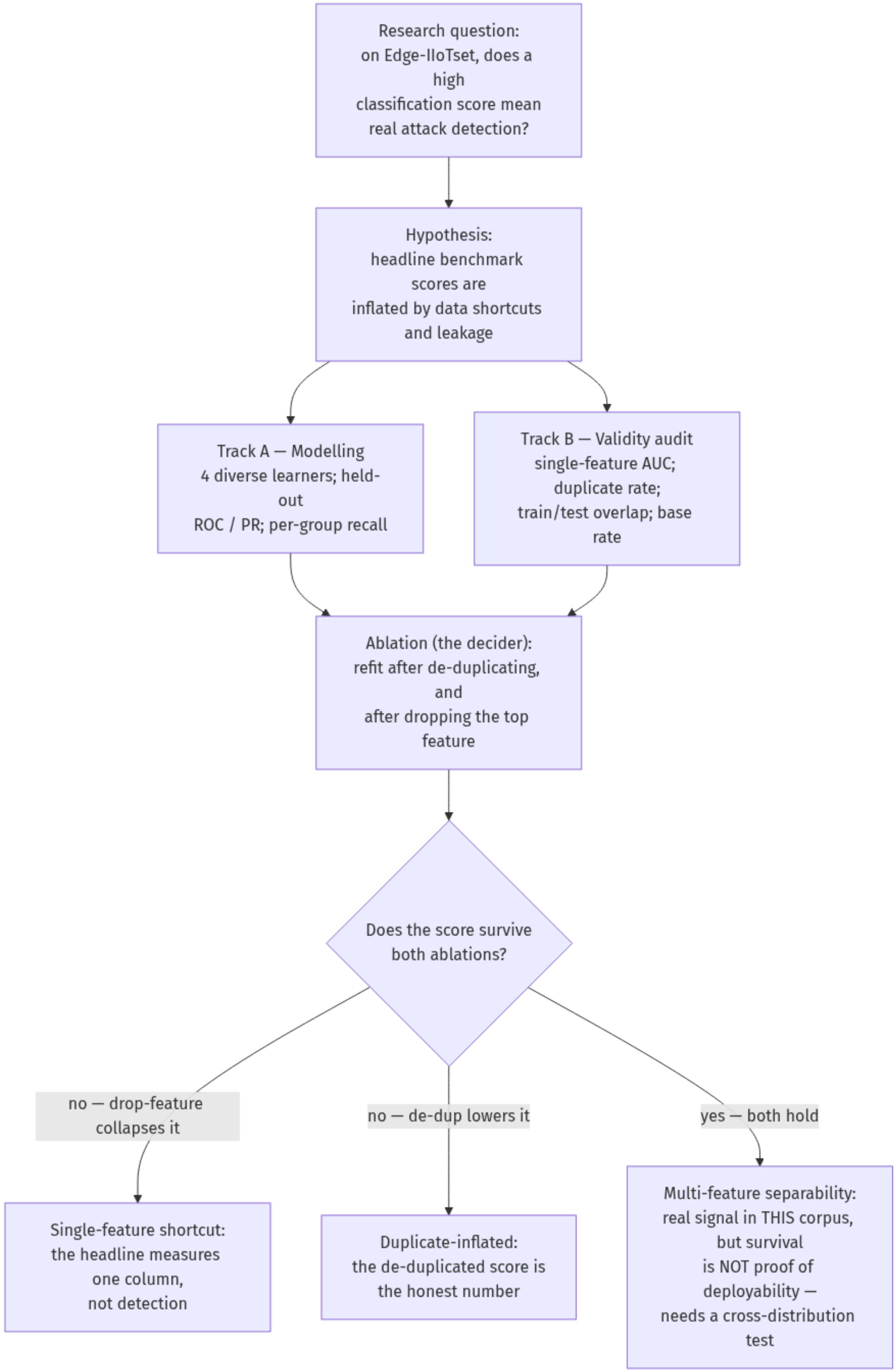
- `FileNotFoundError: ~/.kaggle/access_token` - you created `kaggle.json` but not the key file. Run the command above.
- `401 Unauthorized` - the key is wrong, or a trailing newline crept in.
- `403 Forbidden` - open the dataset page on Kaggle while signed in, accept its terms, then re-run the cell.

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.

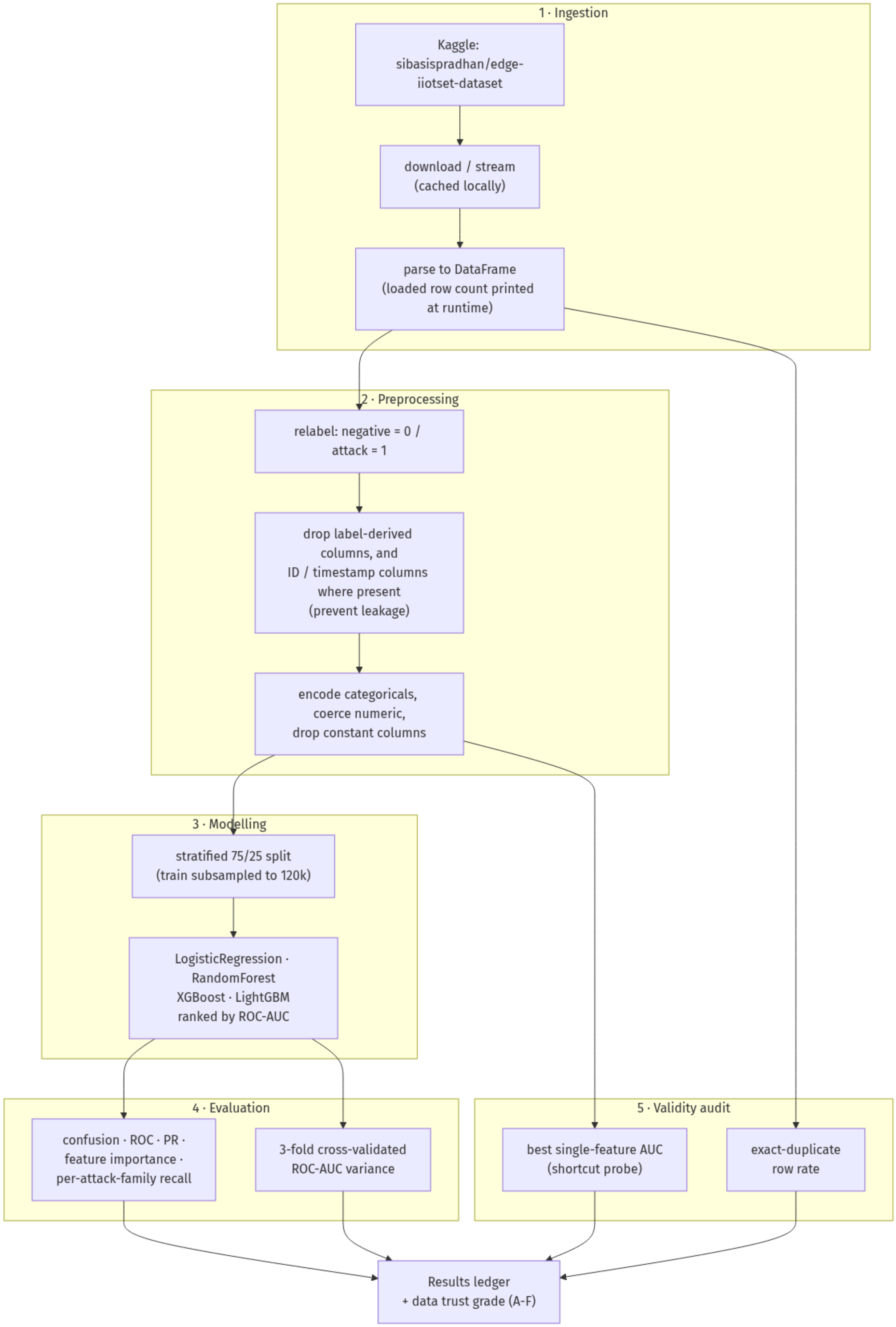
Figure 4.1 — Solution design (methodology).



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
# Kaggle auth: token read from ~/.kaggle/access_token (students supply
their own).
os.environ.setdefault('KAGGLE_KEY',
open(os.path.expanduser('~/.kaggle/access_token')).read().strip())
import kaggle; kaggle.api.authenticate()
REF = 'sibasispradhan/edge-iiotset-dataset'; DEST = '/tmp/kg_' +
REF.split('/')[-1]
if not os.path.exists(DEST):                                   # download +
unzip once (cached)
    kaggle.api.dataset_download_files(REF, path=DEST, unzip=True,
quiet=True)
NROWS = None                                                   # read the
file WHOLE: it is sorted by
#                                                               label, so
any head-cap would drop a class
files = sorted(glob.glob(DEST + '/**/*.csv', recursive=True))
ONLY = 'DNN-EdgeIIoT-dataset.csv'
# canonical file (others are variants)
files = [f for f in files if os.path.basename(f) == ONLY] or files
assert len(files) == 1, f'expected the canonical file {ONLY}, got {files}'
df = pd.concat([pd.read_csv(f, low_memory=False, nrows=NROWS) for f in
files], ignore_index=True)  # combine day/part files
df.columns = [str(c).strip() for c in df.columns]             # strip
header whitespace
LABEL = 'Attack_label'; FAMILY = 'Attack_type'
df['y'] = (df[LABEL].astype(str).str.strip().str.lower() !=
'0').astype(int)  # benign=0
df['family'] = df[FAMILY].astype(str).str.strip()             # descriptive
attack family
df = df.reset_index(drop=True)
assert len(df) >= 1_000_000, f'floor not met: {len(df):,}'    # honesty
gate: >= 1M rows
```

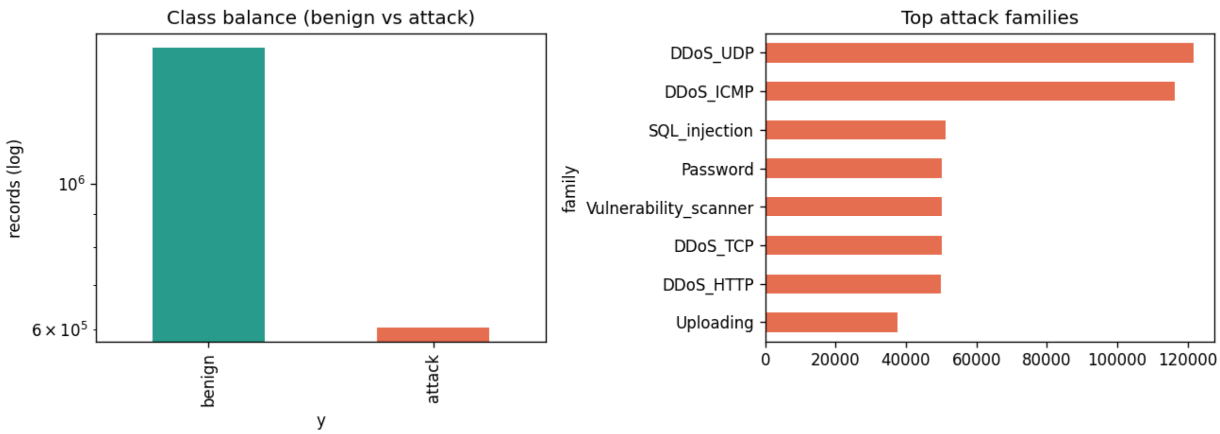
```
DROP = list({LABEL, FAMILY, 'y', 'family'} | set(['ip.src_host',
'ip.dst_host', 'arp.src.proto_ipv4', 'arp.dst.proto_ipv4',
'http.request.full_uri', 'http.request.uri.query', 'http.file_data',
'http.referer', 'http.request.version', 'http.response', 'tcp.payload',
'tcp.options', 'tcp.srcport', 'tcp.dstport', 'dns.qry.name',
'dns.qry.name.len', 'dns.qry.qu', 'mqtt.msg', 'mqtt.msg_decoded_as',
'mqtt.topic', 'mqtt.protoname', 'mbtcp.trans_id', 'mbtcp.unit_id',
'mqtt.conack.flags']))  # never leak label cols
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
# CRITICAL: coerce numeric-looking STRINGS *before* any label-encoding.
Some captures serialise
# the same numeric value differently per class ('0' vs '0.0' vs
'0x00000000'), which turns an
# innocuous protocol field into a PERFECT label proxy purely through text
formatting.
# Coercing first collapses those spellings; only genuinely non-numeric
columns are encoded.
for c in list(X.select_dtypes(include='object').columns):
    _num = pd.to_numeric(X[c].astype(str).str.strip(), errors='coerce')
    if _num.notna().mean() >= 0.95:                       #
essentially numeric -> keep numeric
        X[c] = _num
for c in X.select_dtypes(include='object').columns:       # encode
remaining categoricals
    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)                                   # clip huge
NetFlow counts (float32-safe)
X = X.loc[:, X.nunique() > 1]                             # drop
constants
import re                                                 # LightGBM
rejects special chars in names
_seen, _cols = {}, []
for _c in X.columns:                                      # sanitize
to unique, 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()                                    # STANDARD
CONTRACT
NEG_WORD, POS_WORD = 'benign', 'attack'            # class names for
plots
print(f'loaded {len(df):,} rows x {len(feat)} features; positive rate
{y.mean():.4f}')
```

```
loaded 2,219,201 rows x 32 features; positive rate 0.2720
```

7. Exploratory data analysis

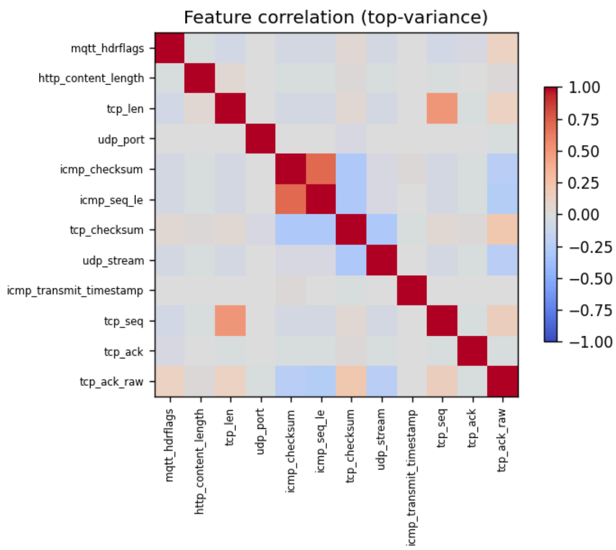
In [3]:

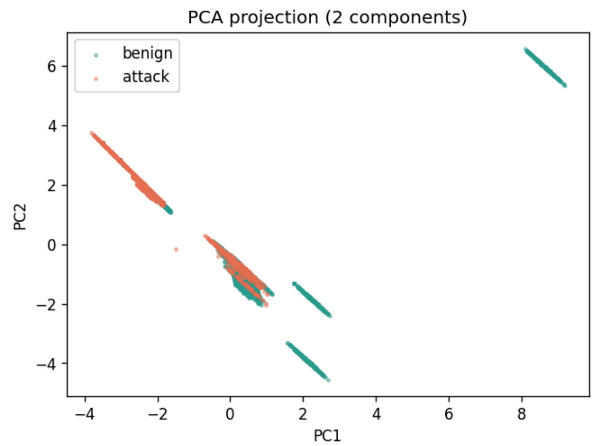
```
# --- EDA 1: class balance and the attack-family mix ---
fig, ax = plt.subplots(1, 2, figsize=(11, 4))
df['y'].map({0:NEG_WORD,1:POS_WORD}).value_counts().plot.bar(
# counts per class
    ax=ax[0], color=['#2a9d8f','#e76f51']); ax[0].set_yscale('log')
ax[0].set_title(f'Class balance ({NEG_WORD} vs {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 2,219,201 rows | trained on 120,000 (stratified subsample) |
held-out 554,801
MAJORITY-CLASS BASELINE accuracy = 0.7280  (any model must beat THIS, not
0.5, to be interesting)
best model: LightGBM
```

Out[5]:

	model	accuracy	roc_auc	train_s
0	LightGBM	0.969980	0.993167	1.7
1	XGBoost	0.969250	0.992720	0.5
2	RandomForest	0.962468	0.984829	0.6
3	LogisticRegression	0.898311	0.914780	0.4
4	MajorityBaseline	0.728000	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.

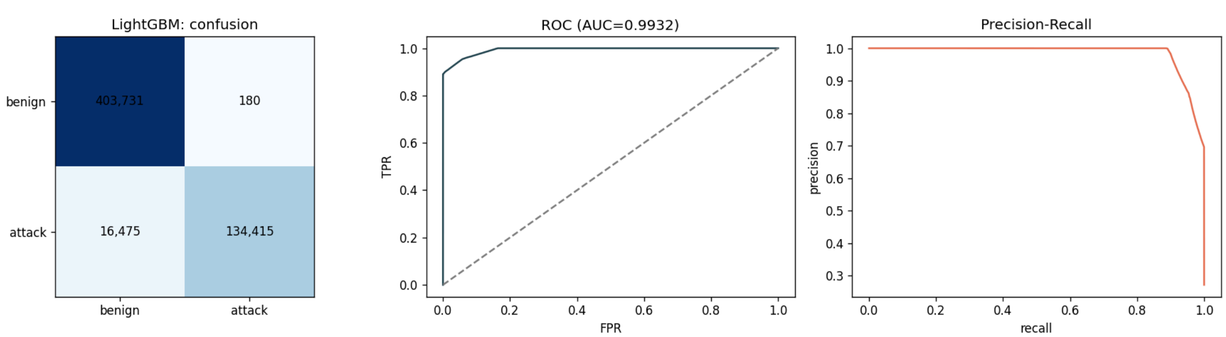
Read it accordingly. Where the groups are genuinely rare classes, they reveal whether detection is real. The dominant flood classes do not.

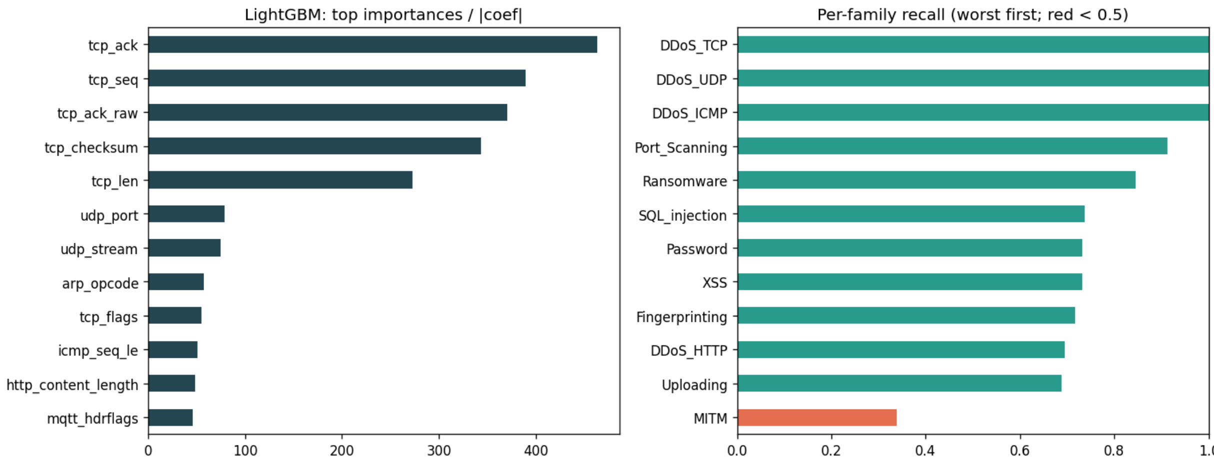
In [6]:

```
# --- 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 = 0.0004  (180 benign flagged of 403,911)
worst per-family recalls: {'MITM': 0.339, 'Uploading': 0.688, 'DDoS_HTTP': 0.694, 'Fingerprinting': 0.717, 'XSS': 0.731, 'Password': 0.732}
```

10. Validity audit — is the score real?

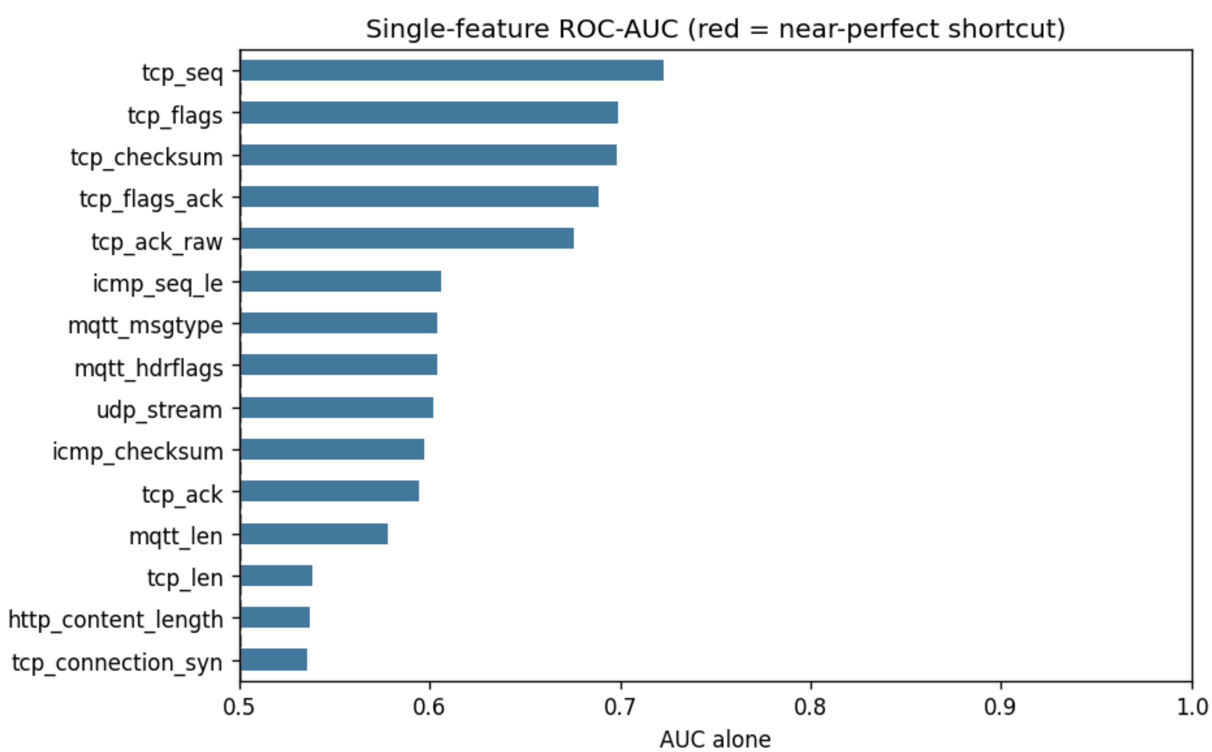
Three diagnostics. **(a)** How well can the *single best feature*, alone, separate the classes? A near-1.0 single-feature AUC means that feature is *near-sufficient* — a shortcut (which may be legitimate signal or an artifact), not the same as target leakage. **(b)** The exact-duplicate row rate. **(c)** 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.
```

```python
_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 = 0.7229  (feature: tcp_seq)
   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) = 0.151
TRAIN/TEST exact-row contamination       = 0.033  (single-feat grade A, contam grade A)
==> data trust grade: A   (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)	0.993167
1	de-duplicated (15% rows removed)	0.994870
2	shortcut feature dropped (tcp_seq)	0.991590

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
LightGBM 3-fold CV ROC-AUC = 0.9929 +/- 0.0002  (mean +/- std across 3
stratified folds; a small std means a stable estimate on this split)
```

13. Scientific conclusion

Four learners reach very high AUC on Edge-IIoTset. The audit quantifies how much is shortcut (a dominant single feature) versus separability that is spread across many protocol fields. The per-family recall breakdown is the honest metric for an IoT detector meant to see many device types.

Validity ledger — read the headline against these printed numbers: Majority-class baseline **accuracy**: **0.7280**. The accuracy column must clear that bar to mean anything. For ROC-AUC the trivial baseline is 0.5, not that figure. Winning learner: **LightGBM** (3-fold CV ROC-AUC **0.9929**). Strongest *single* feature: `tcp_seq` at AUC **0.7229**. The ablation refutes a single-feature story. Dropping that feature barely moves the AUC: **0.993167 → 0.991590**. So the separability is **multi-feature**. That reflects how this corpus was generated, not one leaky column. De-duplication **raises** the AUC, to **0.994870**. 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: **A**. It is the worse of two independent sub-checks. Single-feature AUC 0.7229 scores **A**. Train/test exact-row overlap 0.033 scores **A**. Neither check flags a problem, so nothing here explains the score away. Operational false-positive rate at threshold 0.5: **0.0004**. Worst per-group recalls, exactly as printed: {`MITM`: 0.339, `Uploading`: 0.688, `DDoS_HTTP`: 0.694, `Fingerprinting`: 0.717, `XSS`: 0.731, `Password`: 0.732}. The weakest group sits at **0.339**, 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. Ferrag, M.A. et al. (2022). Edge-IIoTset: A New Comprehensive Realistic Cyber Security Dataset of IoT and IIoT Applications. *IEEE Access*, 10.
2. Sommer, R. & Paxson, V. (2010). Outside the Closed World: On Using Machine Learning for Network Intrusion Detection. *IEEE S&P*.
3. Apruzzese, G. et al. (2023). The role of machine learning in cybersecurity. *ACM DTRAP*.