SupervisedMatching

September 3, 2025

1 Supervised Learning with Synthetic Clients

1.1 Import

[1]:
```
import pandas as pd
import numpy as np
from scipy import sparse
import matplotlib.pyplot as plt

from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.compose import ColumnTransformer
from sklearn.linear_model import SGDClassifier
from sklearn.metrics import classification_report, roc_auc_score,␣
 ↪average_precision_score

SEED = 42

print("Libraries loaded. sklearn version check:")
import sklearn, sys
print("scikit-learn:", sklearn.__version__, "| Python:", sys.version.split()[0])
```

```
Libraries loaded. sklearn version check:
scikit-learn: 1.7.1 | Python: 3.12.11
```

1.2 Load synthetic pairs

[2]:
```
pairs_df = pd.read_csv("synth_pairs_large.csv")

print("Shape:", pairs_df.shape)
print("Label distribution:\n", pairs_df["label"].value_counts())
```

```
Shape: (24000, 7)
Label distribution:
 label
1    12000
```

```
0    12000
Name: count, dtype: int64
```

[3]:
```python
pairs_df.head()
```

[3]:
```
  first_name_left last_name_left country_left first_name_right  \
0            Luca        Colombo        Italy             Luca
1           Chloé          Petit       France             Lena
2           Elena         Müller  Switzerland             Hans
3          Maxime    Hugentobler  Switzerland         François
4           Lukas      Schneider      Germany             Nina

  last_name_right country_right  label
0         Colombo         Italy      1
1            Weiß       Germany      0
2           Weiss   Switzerland      0
3     Hugentobler   Switzerland      0
4         Kraemer       Germany      0
```

1.3 Train, Val, Test split

[4]:
```python
# Create short text fields for each side
def make_text_cols(df: pd.DataFrame) -> pd.DataFrame:
    df = df.copy()
    df["name_left"]  = (df["first_name_left"].astype(str)  + " " +␣
 ↪df["last_name_left"].astype(str))
    df["name_right"] = (df["first_name_right"].astype(str) + " " +␣
 ↪df["last_name_right"].astype(str))
    # Option A (no OHE): also feed country tokens into hashing
    df["country_left_txt"]  = df["country_left"].astype(str)
    df["country_right_txt"] = df["country_right"].astype(str)
    return df

pairs_df = make_text_cols(pairs_df)

# 70/30 first
train_df, temp_df = train_test_split(
    pairs_df, test_size=0.30, stratify=pairs_df["label"], random_state=SEED
)
# 15/15 from the remaining 30%
val_df, test_df = train_test_split(
    temp_df, test_size=0.50, stratify=temp_df["label"], random_state=SEED
)

print("Split sizes -> Train:", train_df.shape, "Val:", val_df.shape, "Test:",␣
 ↪test_df.shape)
```

```
print("Train label distribution:\n", train_df["label"].
    ↪value_counts(normalize=True).round(3))
print("Val   label distribution:\n", val_df["label"].
    ↪value_counts(normalize=True).round(3))
print("Test  label distribution:\n", test_df["label"].
    ↪value_counts(normalize=True).round(3))
```

```
Split sizes -> Train: (16800, 11) Val: (3600, 11) Test: (3600, 11)
Train label distribution:
 label
0    0.5
1    0.5
Name: proportion, dtype: float64
Val   label distribution:
 label
1    0.5
0    0.5
Name: proportion, dtype: float64
Test  label distribution:
 label
1    0.5
0    0.5
Name: proportion, dtype: float64
```

[5]:

```
train_df.head()
```

[5]:

```
      first_name_left last_name_left country_left first_name_right  \
6732            Pedro      Fernandes       Brazil         Fernanda
16403             Ana        Pereira       Brazil              Ana
9067           Chiara        Ferrari        Italy           Chiara
10522         Gustavo          Souza       Brazil            Luísa
15712             Ana        Pereira     Portugal             Inês

      last_name_right country_right  label        name_left  \
6732        Fernandes        Brazil      0  Pedro Fernandes
16403         Pereira        Brazil      1      Ana Pereira
9067          Ferrari         Italy      1   Chiara Ferrari
10522           Rcoha        Brazil      0    Gustavo Souza
15712         Almeida      Portugal      0      Ana Pereira

               name_right country_left_txt country_right_txt
6732   Fernanda Fernandes           Brazil            Brazil
16403         Ana Pereira           Brazil            Brazil
9067       Chiara Ferrari            Italy             Italy
10522         Luísa Rcoha           Brazil            Brazil
15712        Inês Almeida         Portugal          Portugal
```

[6]: `val_df.head()`

[6]:
```
      first_name_left last_name_left country_left first_name_right  \
53               José         García       Mexico             José
16923           Käthe        Schäfer      Germany            Käthe
5445            Laura          López        Spain             José
13570           Pedro      Rodrigues     Portugal            Pedro
4272             Théo        Laurent       France             Théo

      last_name_right country_right  label         name_left       name_right  \
53             Gacría        Mexico      1       José García      José Gacría
16923         Schäfer       Germany      1     Käthe Schäfer    Käthe Schäfer
5445            óGmez         Spain      0       Laura López       José óGmez
13570       Rodrigues      Portugal      1   Pedro Rodrigues  Pedro Rodrigues
4272          Laurent        France      1      Théo Laurent     Théo Laurent

      country_left_txt country_right_txt
53              Mexico            Mexico
16923          Germany           Germany
5445             Spain             Spain
13570         Portugal          Portugal
4272            France            France
```

[7]: `test_df.head()`

[7]:
```
      first_name_left last_name_left country_left first_name_right  \
17639             Ana        Pereira     Portugal              nAa
3652              Léa          Weiss  Switzerland           Matteo
15604          Chiara        Ferrari        Italy           Chiara
15585             Léa         Durand       France               La
14805           Pablo        Sánchez        Spain            Pablo

      last_name_right country_right  label        name_left      name_right  \
17639         Pereira      Portugal      1      Ana Pereira     nAa Pereira
3652          Mueller   Switzerland      0        Léa Weiss  Matteo Mueller
15604         Ferrari         Italy      1   Chiara Ferrari  Chiara Ferrari
15585          Durand        France      1       Léa Durand       La Durand
14805          Snchez         Spain      1    Pablo Sánchez    Pablo Snchez

      country_left_txt country_right_txt
17639         Portugal          Portugal
3652       Switzerland       Switzerland
15604            Italy             Italy
15585           France            France
14805            Spain             Spain
```

1.4 Pairwise TF-IDF transformation

[8]:
```python
# Step 3: Pairwise TF-IDF → cosine similarities (names + countries)
text_cols = ["name_left", "name_right", "country_left_txt", "country_right_txt"]

#  Fit TF-IDF encoders on TRAIN ONLY (concat left/right to build vocab) ---
tfidf_name = TfidfVectorizer(analyzer="char", ngram_range=(2,5),␣
 ↪sublinear_tf=True, lowercase=False)
tfidf_country = TfidfVectorizer(analyzer="char", ngram_range=(2,5),␣
 ↪sublinear_tf=True, lowercase=False)

tfidf_name.fit(pd.concat([train_df["name_left"], train_df["name_right"]],␣
 ↪axis=0))
tfidf_country.fit(pd.concat([train_df["country_left_txt"],␣
 ↪train_df["country_right_txt"]], axis=0))

def _pairwise_features_to_sparse(df: pd.DataFrame) -> sparse.csr_matrix:
    # Transform each side
    nl = tfidf_name.transform(df["name_left"])
    nr = tfidf_name.transform(df["name_right"])
    cl = tfidf_country.transform(df["country_left_txt"])
    cr = tfidf_country.transform(df["country_right_txt"])

    # Cosine similarities (as dense 1-D arrays)
    name_sim = cosine_similarity(nl, nr).diagonal()
    country_sim = cosine_similarity(cl, cr).diagonal()

    # Simple auxiliary signals
    fn_len_diff = (df["first_name_left"].astype(str).str.len() -␣
 ↪df["first_name_right"].astype(str).str.len()).abs().to_numpy()
    ln_len_diff = (df["last_name_left"].astype(str).str.len()  -␣
 ↪df["last_name_right"].astype(str).str.len()).abs().to_numpy()
    country_eq  = (df["country_left_txt"] == df["country_right_txt"]).
 ↪astype(int).to_numpy()

    # Stack into a sparse CSR (5 feature columns)
    M = np.column_stack([name_sim, country_sim, fn_len_diff, ln_len_diff,␣
 ↪country_eq]).astype(float)
    return sparse.csr_matrix(M)

# Build split matrices
X_train_sparse = _pairwise_features_to_sparse(train_df)
X_val_sparse   = _pairwise_features_to_sparse(val_df)
X_test_sparse  = _pairwise_features_to_sparse(test_df)

# Targets (unchanged)
y_train = train_df["label"].astype(int).to_numpy()
```

```
y_val   = val_df["label"].astype(int).to_numpy()
y_test  = test_df["label"].astype(int).to_numpy()

# Progress / troubleshooting printouts
def describe_sparse(name, X):
    nnz = X.nnz if sparse.issparse(X) else np.count_nonzero(X)
    total = X.shape[0] * X.shape[1]
    density = nnz / total if total else 0.0
    print(f"{name}: shape={X.shape}, nnz={nnz:,}, density={density:.6f}")

describe_sparse("X_train", X_train_sparse)
describe_sparse("X_val  ", X_val_sparse)
describe_sparse("X_test ", X_test_sparse)
print("Targets -> y_train:", y_train.shape, "y_val:", y_val.shape, "y_test:",␣
 ↪y_test.shape)
```

```
X_train: shape=(16800, 5), nnz=58,687, density=0.698655
X_val  : shape=(3600, 5), nnz=12,676, density=0.704222
X_test : shape=(3600, 5), nnz=12,571, density=0.698389
Targets -> y_train: (16800,) y_val: (3600,) y_test: (3600,)
```

1.5 Configure supervised model

[9]:
```
# Step 4: Build the supervised model (linear classifier suited for large sparse␣
 ↪features)

clf = SGDClassifier(
    loss="log_loss",       # logistic regression
    penalty="l2",
    alpha=1e-5,
    max_iter=10_000,
    tol=1e-3,
    random_state=SEED
)

print("Model prepared:", clf)
```

```
Model prepared: SGDClassifier(alpha=1e-05, loss='log_loss', max_iter=10000,
random_state=42)
```

1.6 Train supervised model

[10]:
```
# Step 5: Train
clf.fit(X_train_sparse, y_train)

# Quick training-set sanity check
train_probs = clf.predict_proba(X_train_sparse)[:, 1]
train_preds = (train_probs >= 0.5).astype(int)
```

```python
print("Training summary:")
print(classification_report(y_train, train_preds, digits=3))
print("Train ROC-AUC:", roc_auc_score(y_train, train_probs))
print("Train PR-AUC :", average_precision_score(y_train, train_probs))
```

```
Training summary:
              precision    recall  f1-score   support

           0      0.868     0.980     0.921      8400
           1      0.977     0.851     0.910      8400

    accuracy                          0.916     16800
   macro avg      0.923     0.916     0.915     16800
weighted avg      0.923     0.916     0.915     16800

Train ROC-AUC: 0.985876700680272
Train PR-AUC : 0.9826757872396451
```

1.7 Evaluate supervised model

[11]:
```python
# Step 6: Evaluate on validation and test
val_probs  = clf.predict_proba(X_val_sparse)[:, 1]
val_preds  = (val_probs >= 0.5).astype(int)

test_probs = clf.predict_proba(X_test_sparse)[:, 1]
test_preds = (test_probs >= 0.5).astype(int)

print("\n=== Validation ===")
print(classification_report(y_val, val_preds, digits=3))
print("ROC-AUC:", roc_auc_score(y_val, val_probs))
print("PR-AUC :", average_precision_score(y_val, val_probs))

print("\n=== Test ===")
print(classification_report(y_test, test_preds, digits=3))
print("ROC-AUC:", roc_auc_score(y_test, test_probs))
print("PR-AUC :", average_precision_score(y_test, test_probs))
```

```

=== Validation ===
              precision    recall  f1-score   support

           0      0.867     0.978     0.919      1800
           1      0.975     0.849     0.908      1800

    accuracy                          0.914      3600
   macro avg      0.921     0.914     0.913      3600
weighted avg      0.921     0.914     0.913      3600
```

```
ROC-AUC: 0.9866436728395063
PR-AUC : 0.9830909471493692

=== Test ===
              precision    recall  f1-score   support

           0      0.869     0.984     0.923      1800
           1      0.982     0.852     0.913      1800

    accuracy                          0.918      3600
   macro avg      0.926     0.918     0.918      3600
weighted avg      0.926     0.918     0.918      3600

ROC-AUC: 0.9883783950617284
PR-AUC : 0.987845710021069
```

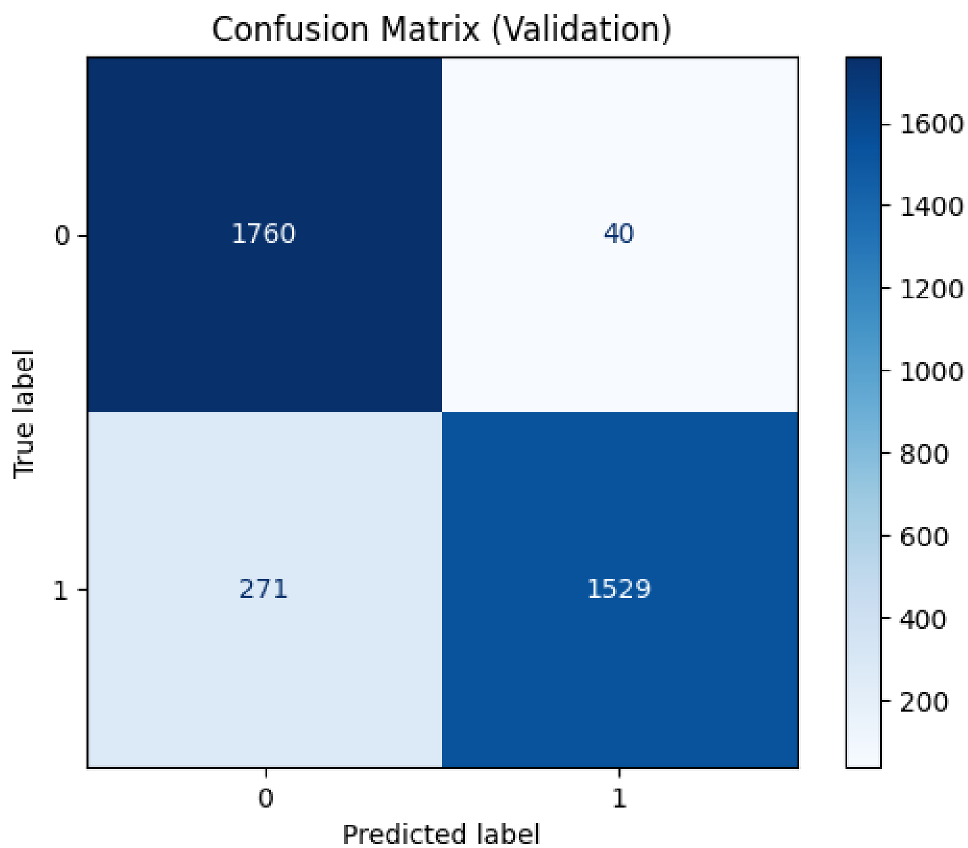
2 Human In the Loop

2.1 Confusion Matrix

[12]:

```
# HO - Confusion matrix on validation set

cm = confusion_matrix(y_val, val_preds, labels=[0,1])

print("Confusion Matrix (Validation):")
print(cm)

disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=[0,1])
disp.plot(cmap=plt.cm.Blues, values_format="d")
plt.title("Confusion Matrix (Validation)")
plt.show()
```

```
Confusion Matrix (Validation):
[[1760   40]
 [ 271 1529]]
```



271 “missed matches” (false negatives).
40 “wrongly flagged as matches” (false positives).

2.2 H1 — Extract misclassifications & show top 5

[13]:
```
# Get validation predictions (you already computed val_probs/val_preds in Step
↪6)
val_errors_mask = (val_preds != y_val)
val_errors_idx = np.where(val_errors_mask)[0]

# Build a dataframe for inspection
val_review_df = pd.DataFrame({
    "prob_1": val_probs,                 # P(y=1 | x)
    "pred": val_preds,
    "true": y_val
})
# attach original columns for context
columns_to_show = [
    "first_name_left","last_name_left","country_left",
    "first_name_right","last_name_right","country_right"
```

```
]
val_review_df = pd.concat([val_review_df, val_df.
↪reset_index(drop=True)[columns_to_show]], axis=1)

# Keep only errors
val_review_df = val_review_df.iloc[val_errors_idx].copy()

# Rank errors: "most confident but wrong" first (distance from 0.5 is large)
val_review_df["conf_dist"] = (val_review_df["prob_1"] - 0.5).abs()

# Show top-5 problematic cases
top5 = val_review_df.sort_values("conf_dist", ascending=False).head(5)
top5.reset_index(drop=True)
```

[13]:

```
      prob_1  pred  true first_name_left last_name_left country_left  \
0  0.009264     0     1         Mélanie         Grüter  Switzerland
1  0.988834     1     0          Miguel          Silva       Brazil
2  0.988834     1     0            René         Flores       Mexico
3  0.988834     1     0            Jürg    Hugentobler  Switzerland
4  0.988834     1     0          Andrés      Hernández       Mexico

  first_name_right last_name_right country_right  conf_dist
0            Mlani           Grter   Switzerland   0.490736
1           Miguel           Silva        Brazil   0.488834
2             René          Flores        Mexico   0.488834
3             Jürg     Hugentobler   Switzerland   0.488834
4           Andrés       Hernández        Mexico   0.488834
```

2.3 H2 — Map them to correct values (simulate human labels)

[14]:

```
# For the PoC, we use the ground-truth 'true' column as the "human-provided"␣
↪label.
# Build indices for errors and correct predictions
val_errors_mask = (val_preds != y_val)
val_errors_idx = np.where(val_errors_mask)[0]

val_correct_mask = (val_preds == y_val)
val_correct_idx = np.where(val_correct_mask)[0]

# Count errors by class to balance corrects
err_y = y_val[val_errors_idx]
n_err_0 = int((err_y == 0).sum())
n_err_1 = int((err_y == 1).sum())

# Sample the same number of correctly classified examples from each class (if␣
↪available)
rng = np.random.default_rng(42)
```

```
corr_0_pool = val_correct_idx[y_val[val_correct_idx] == 0]
corr_1_pool = val_correct_idx[y_val[val_correct_idx] == 1]

corr_0_pick = rng.choice(corr_0_pool, size=min(n_err_0, len(corr_0_pool)),␣
 ↪replace=False) if n_err_0 > 0 else np.array([], dtype=int)
corr_1_pick = rng.choice(corr_1_pool, size=min(n_err_1, len(corr_1_pool)),␣
 ↪replace=False) if n_err_1 > 0 else np.array([], dtype=int)

# Final batch = all errors + balanced corrects
human_idx = np.concatenate([val_errors_idx, corr_0_pick, corr_1_pick])
human_idx.sort()

X_human = X_val_sparse[human_idx]
y_human = y_val[human_idx]

print(f"Human batch size: {len(human_idx)} | errors: {len(val_errors_idx)} | "
      f"correct_0_added: {len(corr_0_pick)} | correct_1_added:␣
 ↪{len(corr_1_pick)}")
```

```
Human batch size: 622 | errors: 311 | correct_0_added: 40 | correct_1_added: 271
```

2.4 H3 — Feedback to the existing model

[15]:
```
# IMPORTANT: incremental update, not re-training from scratch.
# SGDClassifier supports partial_fit for warm updates.
# Optionally upweight human feedback to have a stronger effect:
HUMAN_WEIGHT = 5.0  # tweak as you like (>=1.0). Not in use, means human␣
 ↪feedback = learning insights

small_w = np.full(shape=len(y_human), fill_value=0.1, dtype=float)
clf.partial_fit(X_human, y_human, sample_weight=small_w)

print("Model updated with balanced human batch (small step).")
```

```
Model updated with balanced human batch (small step).
```

2.5 H4 — Validate again

[16]:
```
# Re-score validation (to see local effect)
val_probs2  = clf.predict_proba(X_val_sparse)[:, 1]
val_preds2  = (val_probs2 >= 0.5).astype(int)

print("\n=== Validation (after human update) ===")
print(classification_report(y_val, val_preds2, digits=3))
print("ROC-AUC:", roc_auc_score(y_val, val_probs2))
print("PR-AUC :", average_precision_score(y_val, val_probs2))

# Re-score test (unseen) to measure true generalization change
```

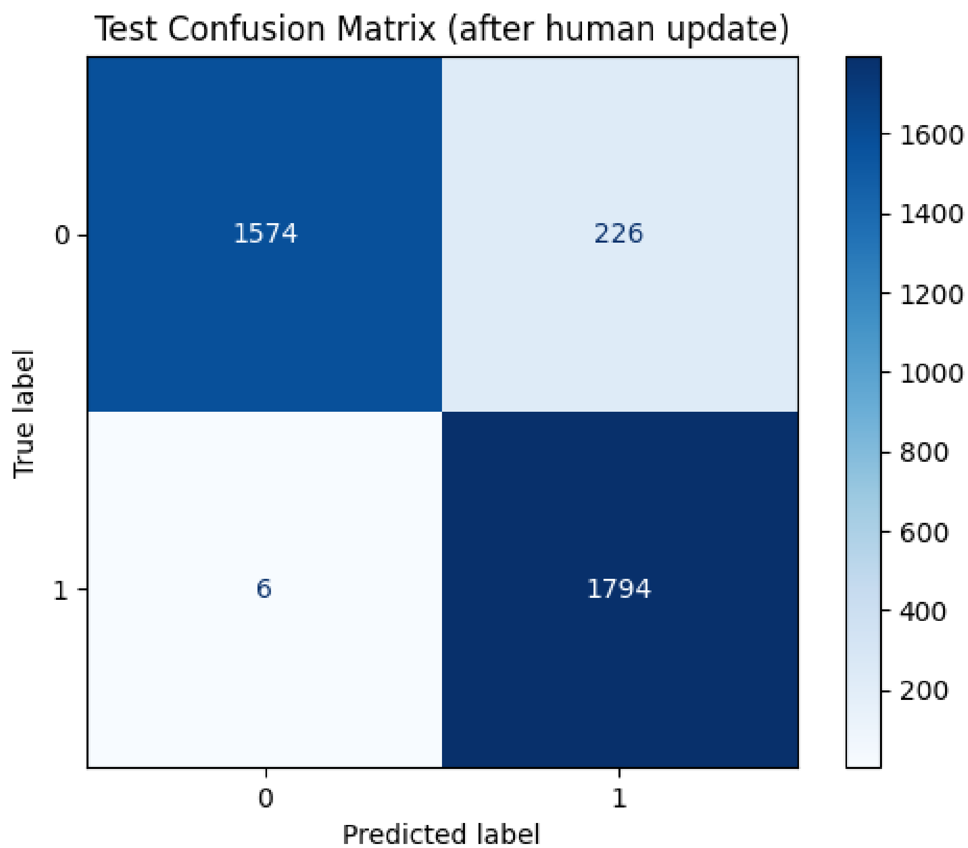
```
test_probs2 = clf.predict_proba(X_test_sparse)[:, 1]
test_preds2 = (test_probs2 >= 0.5).astype(int)

print("\n=== Test (after human update) ===")
print(classification_report(y_test, test_preds2, digits=3))
print("ROC-AUC:", roc_auc_score(y_test, test_probs2))
print("PR-AUC :", average_precision_score(y_test, test_probs2))
```

```
=== Validation (after human update) ===
              precision    recall  f1-score   support

           0      0.997     0.879     0.935      1800
           1      0.892     0.998     0.942      1800

    accuracy                          0.939      3600
   macro avg      0.945     0.939     0.938      3600
weighted avg      0.945     0.939     0.938      3600

ROC-AUC: 0.9856418209876543
PR-AUC : 0.9818731049232869

=== Test (after human update) ===
              precision    recall  f1-score   support

           0      0.996     0.874     0.931      1800
           1      0.888     0.997     0.939      1800

    accuracy                          0.936      3600
   macro avg      0.942     0.936     0.935      3600
weighted avg      0.942     0.936     0.935      3600

ROC-AUC: 0.9877938271604938
PR-AUC : 0.9867462629676667
```

[17]:

```
# H6 - Confusion Matrices after human feedback update

# Validation CM
cm_test = confusion_matrix(y_test, test_preds2, labels=[0,1])
print("Confusion Matrix (Test, after human update):")
print(cm_test)

disp_test = ConfusionMatrixDisplay(confusion_matrix=cm_test,␣
 ↪display_labels=[0,1])
disp_test.plot(cmap=plt.cm.Blues, values_format="d")
plt.title("Test Confusion Matrix (after human update)")
plt.show()
```

```
Confusion Matrix (Test, after human update):
[[1574  226]
 [   6 1794]]
```



Observations:
- Despite accuracy increased, it became less conservative which is not desired in our use case.
- This is highly dependant on the approach and training data.
- In this case it happened because the human in the loop biased the training towards the opposite direction, shifting toward predicting more matches (1) and produced lots of false positives.

- The error batch (which was validated by the human in the loop) had:
  - 311 errors (all misclassified),
  - 40 correctly classified 0s,
  - 271 correctly classified 1s.
- That means the update data was dominated by class 1 (matches):
  - Only ~12% of the batch was class 0 (40 / 311+40+271).
  - Almost 88% was class 1.
- When you `partial_fit` with this distribution, the model "learns" that class 1 is much more likely → it becomes overconfident in predicting matches.

Result:

- False negatives dropped (good),
- But false positives skyrocketed (bad).

3 LLM Matching

3.1 L1 — Imports & LLM config

[18]:
```
from langchain_openai import ChatOpenAI, OpenAIEmbeddings
from langchain_core.documents import Document
from langchain_community.vectorstores import FAISS
from langchain_core.output_parsers import JsonOutputParser
from langchain_core.prompts import PromptTemplate
import os
import json
import uuid
from textwrap import shorten
```

[19]:
```
llm = ChatOpenAI(
    model="gpt-5",
    temperature=0.1,
    openai_api_key=os.getenv("OPENAI_API_KEY"),
)
emb = OpenAIEmbeddings(openai_api_key=os.getenv("OPENAI_API_KEY"))
```

3.2 L2 — Build RAG index from train + val

[20]:
```
# L2 - Build RAG index (train + val only)
def row_to_case_text(r):
    # a compact canonical text for similarity search
    l = f"FIRST_LEFT:{r.first_name_left} LAST_LEFT:{r.last_name_left}␣
↪COUNTRY_LEFT:{r.country_left}"
    rt = f"FIRST_RIGHT:{r.first_name_right} LAST_RIGHT:{r.last_name_right}␣
↪COUNTRY_RIGHT:{r.country_right}"
    return f"{l} || {rt}"

def make_docs(df, split_name):
    docs = []
    for r in df.itertuples(index=False):
        text = row_to_case_text(r)
        meta = {
            "label": int(r.label),
            "split": split_name,
            "first_name_left": r.first_name_left,
            "last_name_left": r.last_name_left,
            "country_left": r.country_left,
            "first_name_right": r.first_name_right,
            "last_name_right": r.last_name_right,
```

```
            "country_right": r.country_right
        }
        docs.append(Document(page_content=text, metadata=meta))
    return docs

train_docs = make_docs(train_df, "train")
val_docs   = make_docs(val_df,   "val")

# Vector store (FAISS is simple & fast for local PoC)
vs = FAISS.from_documents(train_docs + val_docs, emb)
retriever = vs.as_retriever(search_kwargs={"k": 8})
print("RAG index built. #docs:", len(train_docs) + len(val_docs))
```

```
RAG index built. #docs: 20400
```

3.3 L3 — Prompt with strict JSON output and token estimator

[21]:

```
# L3 - Prompt, parser, retrieval config, and cache (for batched LLM evaluation)

# ---- Prompt (batched) ----
PROMPT_MULTI = """You are an entity-matching expert. You will receive multiple␣
 ↪independent items.
Each item contains two person records and some labeled exemplars (memory).␣
 ↪Decide if the two records
refer to the same person (1) or not (0), and produce probabilities and a short␣
 ↪rationale.

Rules:
- Respond with a SINGLE JSON array.
- For each input item, return an object:
  {{
    "id": "<the id we provided>",
    "match_label": 0 or 1,
    "match_probability": number in [0,1],
    "rationale": "one or two short sentences"
  }}
- Do not include any extra keys or extra text outside the JSON.

Consider:
- transliterations (ü→ue, ä→ae, ö→oe, ß→ss), diacritics (á/à/â),
- common typos/transpositions,
- country consistency (same country increases likelihood).

INPUT ITEMS:
{items}
"""
```

```python
# ---- JSON parser for outputs ----
parser = JsonOutputParser()  # robust JSON parsing

# ---- RAG + batching knobs (cost control) ----
BATCH_SIZE = 20       # number of pairs per LLM call
K_RETRIEVE = 3        # top-k exemplars per item (smaller -> cheaper)
MAX_EX_CHAR = 400     # truncate each exemplar line to control tokens

# ---- Simple in-memory cache for retrieval results ----
_retrieval_cache = {}

def cached_retrieve(query: str):
    """Retrieve labeled exemplars with caching (uses LangChain retriever)."""
    if query in _retrieval_cache:
        return _retrieval_cache[query]
    docs = retriever.invoke(query)  # modern LC API
    _retrieval_cache[query] = docs
    return docs

def format_exemplars_for_query(query: str) -> str:
    """Format and truncate retrieved exemplars for prompt inclusion."""
    docs = cached_retrieve(query)
    lines = []
    for d in docs[:K_RETRIEVE]:
        lbl = d.metadata.get("label", 0)
        txt = d.page_content
        lines.append(f"- LABEL:{lbl} | {shorten(txt, width=MAX_EX_CHAR,␣
↪placeholder='…')}")
    return "\n".join(lines) if lines else "- (no exemplars retrieved)"

    # Try to use tiktoken if available; otherwise fallback to a simple␣
↪heuristic (~4 chars per token)
try:
    import tiktoken
    _ENC = tiktoken.get_encoding("cl100k_base")  # good default for modern␣
↪GPT-family models
    def estimate_tokens(text: str) -> int:
        return len(_ENC.encode(text))
except Exception:
    def estimate_tokens(text: str) -> int:
        # Rough heuristic: ~4 chars per token (safe for budgeting)
        return max(1, int(len(text) / 4))

# Soft budget knobs (tune to your model/context window)
MAX_INPUT_TOKENS_PER_BATCH = 20000   # soft limit for prompt input tokens
TOKEN_BUDGET_VERBOSE = True          # print batch token estimates
```

```python
def estimate_batch_tokens(items_payload: list[str], prompt_template: str =␣
↪PROMPT_MULTI) -> int:
    """Estimate token count for the full batch prompt."""
    joined = "\n\n".join(items_payload)
    prompt_text = prompt_template.format(items=joined)
    return estimate_tokens(prompt_text)
```

3.4 L4 — Batch-pair classifier with retrieval

[22]:
```python
# L4 - Sampler (stratified/uncertainty) + batched classifier

import uuid
import numpy as np
import pandas as pd

def stratified_sample(df: pd.DataFrame, n_per_class: int = 100, seed: int = 42)␣
↪-> pd.DataFrame:
    """Take a balanced subset (n_per_class per label)."""
    out = []
    for y in (0, 1):
        block = df[df["label"].astype(int) == y]
        k = min(n_per_class, len(block))
        out.append(block.sample(n=k, random_state=seed))
    return pd.concat(out, axis=0).sample(frac=1.0, random_state=seed).
↪reset_index(drop=True)

def uncertainty_sample(df: pd.DataFrame, probs: np.ndarray, low: float = 0.4,␣
↪high: float = 0.6, max_n: int = 200, seed: int = 42) -> pd.DataFrame:
    """Select 'gray zone' items by probability in [low, high]. Falls back to␣
↪random if not enough."""
    mask = (probs >= low) & (probs <= high)
    sub = df.loc[mask]
    if len(sub) > max_n:
        sub = sub.sample(n=max_n, random_state=seed)
    elif len(sub) < max_n:
        # top-up with stratified random to reach max_n
        need = max_n - len(sub)
        rest = df.loc[~mask]
        add = rest.sample(n=min(need, len(rest)), random_state=seed)
        sub = pd.concat([sub, add], axis=0)
    return sub.sample(frac=1.0, random_state=seed).reset_index(drop=True)

def row_to_case_text(r):
    """Compact text used for retrieval similarity."""
    l = f"FIRST_LEFT:{r.first_name_left} LAST_LEFT:{r.last_name_left}␣
↪COUNTRY_LEFT:{r.country_left}"
```

```
    rt = f"FIRST_RIGHT:{r.first_name_right} LAST_RIGHT:{r.last_name_right}␣
↪COUNTRY_RIGHT:{r.country_right}"
    return f"{l} || {rt}"

def _format_single_item(item_id, row, exemplars_txt):
    return f"""
ID: {item_id}
PAIR:
  FIRST_LEFT: {row.first_name_left}
  LAST_LEFT: {row.last_name_left}
  COUNTRY_LEFT: {row.country_left}
  FIRST_RIGHT: {row.first_name_right}
  LAST_RIGHT: {row.last_name_right}
  COUNTRY_RIGHT: {row.country_right}
EXEMPLARS (labeled):
{exemplars_txt}
""".strip()

def llm_classify_batch(rows):
    """Classify a list of NamedTuple rows in one LLM call; returns list of␣
↪dicts with id/label/prob/rationale."""
    items_payload = []
    id_list = []
    for r in rows:
        item_id = str(uuid.uuid4())
        id_list.append(item_id)
        q = row_to_case_text(r)
        exemplars_txt = format_exemplars_for_query(q)
        items_payload.append(_format_single_item(item_id, r, exemplars_txt))

    # --- Token budgeting: estimate before sending ---
    est_tokens = estimate_batch_tokens(items_payload, PROMPT_MULTI)
    if TOKEN_BUDGET_VERBOSE:
        print(f"[Batch size={len(rows)}] Estimated input tokens  {est_tokens:
↪,} "
              f"(limit ~{MAX_INPUT_TOKENS_PER_BATCH:,}).")

    if est_tokens > MAX_INPUT_TOKENS_PER_BATCH:
        print("Estimated tokens exceed soft budget. Consider: "
              "lowering K_RETRIEVE, reducing MAX_EX_CHAR, or decreasing␣
↪BATCH_SIZE.")

    # Build and send the batch prompt
    prompt_text = PROMPT_MULTI.format(items="\n\n".join(items_payload))
    resp = llm.invoke([{"role": "user", "content": prompt_text}]).content

    # Parse strict JSON array (graceful fallback on parse error)
```

```
    try:
        data = json.loads(resp)
        id_to_obj = {
            str(o.get("id", "")): {
                "id": str(o.get("id", "")),
                "match_label": int(o.get("match_label", 0)),
                "match_probability": float(o.get("match_probability", 0.5)),
                "rationale": str(o.get("rationale", ""))[:500],
            }
            for o in data
        }
        return [id_to_obj.get(i, {"id": i, "match_label": 0,␣
↪"match_probability": 0.5, "rationale": "missing"}) for i in id_list]
    except Exception as e:
        return [{"id": i, "match_label": 0, "match_probability": 0.5,␣
↪"rationale": f"parse_error:{type(e).__name__}"} for i in id_list]
```

3.5 L5 — Run on test and evaluate

[23]:
```
# L5 - Choose subset, run batched evaluation, report metrics

# ---- Choose evaluation subset ----
EVAL_MODE = "uncertainty"   # "stratified" or "uncertainty"
N_PER_CLASS = 100           # used if EVAL_MODE="stratified"  -> total ~200
UNC_LOW, UNC_HIGH = 0.4, 0.6
UNC_MAX_N = 200             # used if EVAL_MODE="uncertainty"

test_supervised_probs = None  # set to array to use "uncertainty" mode
# We can provide the uncertain cases from the supervised model to have a side␣
↪to side comparison. Uncomment following line
# Note that here we will pass predictions after the Human in the Loop process.
test_supervised_probs = clf.predict_proba(X_test_sparse)[:, 1]


if EVAL_MODE == "uncertainty" and test_supervised_probs is None:
    print("Uncertainty mode selected but no supervised probs found; falling␣
↪back to stratified.")
    EVAL_MODE = "stratified"

if EVAL_MODE == "stratified":
    eval_df = stratified_sample(test_df, n_per_class=N_PER_CLASS, seed=SEED)
else:
    eval_df = uncertainty_sample(test_df, probs=test_supervised_probs,␣
↪low=UNC_LOW, high=UNC_HIGH, max_n=UNC_MAX_N, seed=SEED)

print(f"Evaluation subset size: {len(eval_df)} (mode={EVAL_MODE})")
```

```
# ---- Run LLM classifier in batches of 20 ----
rows = list(eval_df.itertuples(index=False))
pred_labels, pred_probs, rationales = [], [], []

for start in range(0, len(rows), BATCH_SIZE):
    chunk = rows[start:start+BATCH_SIZE]
    results = llm_classify_batch(chunk)
    for res in results:
        pred_labels.append(int(res["match_label"]))
        pred_probs.append(float(res["match_probability"]))
        rationales.append(res.get("rationale", ""))

y_true = eval_df["label"].astype(int).to_numpy()
y_pred = np.array(pred_labels, dtype=int)
y_prob = np.array(pred_probs, dtype=float)
```

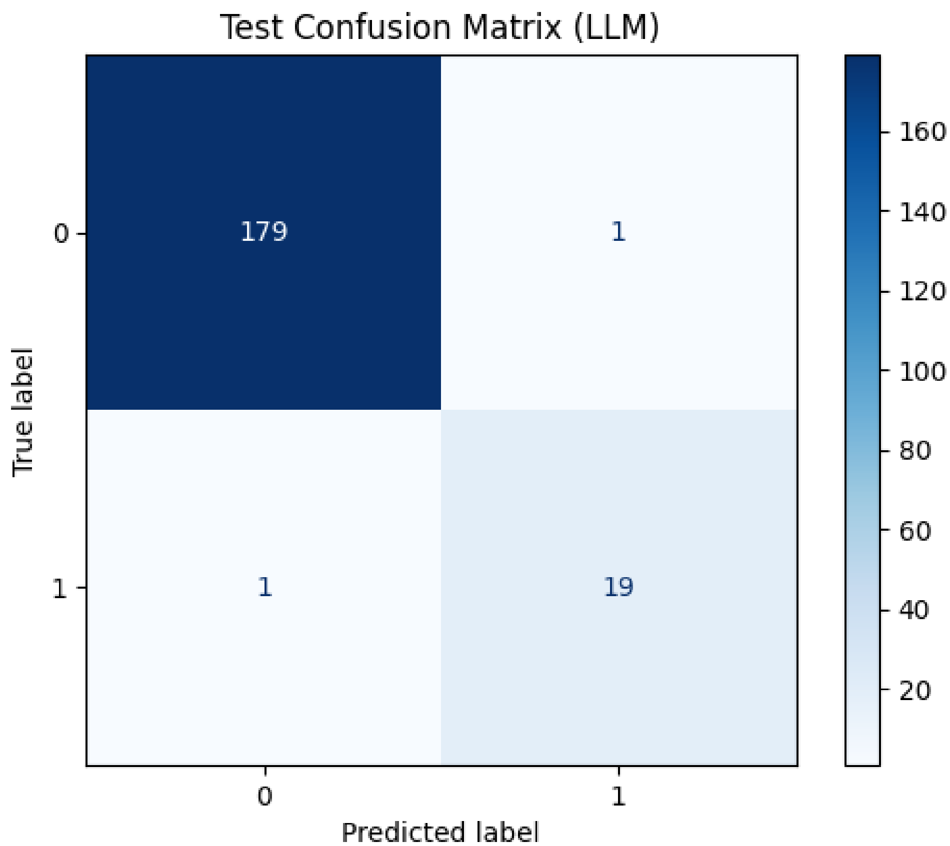
```
Evaluation subset size: 200 (mode=uncertainty)
[Batch size=20] Estimated input tokens  4,020 (limit ~20,000).
[Batch size=20] Estimated input tokens  3,983 (limit ~20,000).
[Batch size=20] Estimated input tokens  4,009 (limit ~20,000).
[Batch size=20] Estimated input tokens  4,017 (limit ~20,000).
[Batch size=20] Estimated input tokens  4,040 (limit ~20,000).
[Batch size=20] Estimated input tokens  3,997 (limit ~20,000).
[Batch size=20] Estimated input tokens  4,024 (limit ~20,000).
[Batch size=20] Estimated input tokens  3,990 (limit ~20,000).
[Batch size=20] Estimated input tokens  4,043 (limit ~20,000).
[Batch size=20] Estimated input tokens  4,005 (limit ~20,000).
```

[24]:

```
# ---- Report ----
print("=== LLM (RAG, batched) - Evaluation subset ===")
print(classification_report(y_true, y_pred, digits=3))
print("ROC-AUC:", roc_auc_score(y_true, y_prob))
print("PR-AUC :", average_precision_score(y_true, y_prob))

cm_llm = confusion_matrix(y_true, y_pred, labels=[0,1])
print("Confusion matrix:\n", cm_llm)

disp_test = ConfusionMatrixDisplay(confusion_matrix=cm_llm,␣
 ↪display_labels=[0,1])
disp_test.plot(cmap=plt.cm.Blues, values_format="d")
plt.title("Test Confusion Matrix (LLM)")
plt.show()
```

```
=== LLM (RAG, batched) - Evaluation subset ===
              precision    recall  f1-score   support

           0      0.994     0.994     0.994       180
           1      0.950     0.950     0.950        20
```

```
    accuracy                           0.990       200
   macro avg       0.972     0.972     0.972       200
weighted avg       0.990     0.990     0.990       200

ROC-AUC: 0.9969444444444444
PR-AUC : 0.9625203116456986
Confusion matrix:
 [[179   1]
 [  1  19]]
```



[ ]: