03_feature_engineering_and_baseline_models

December 14, 2025

1 Feature Engineering & Baseline Models

Objective: Extract advanced stylometric features and train a hybrid text classification model. **Crucially, this notebook implements a strict data splitting strategy to comply with project requirements regarding independent evaluation.**

Key Workflow: 1. **Load Data:** Import `final_merged_dataset.csv` (from Notebook 2). 2. **Strict Data Splitting (Project Compliance):** * **Test Set (Final Eval):** Composed *exclusively* of self-collected data (Wikipedia, ArXiv, News, ChatGPT) * **Training Set:** A mix of downsampled Kaggle data (for efficiency and diversity) and the remaining self-collected data. * **Validation Set:** Held-out Kaggle data for hyperparameter tuning. 3. **Feature Engineering (Stylometry):** * **Lexical Diversity:** Type-Token Ratio (vocabulary richness). * **Readability:** Flesch-Kincaid, Gunning Fog scores. * **Structure:** Sentence length variance, punctuation patterns. * **Linguistic Analysis:** Part-of-Speech (POS) tagging via spaCy. 4. **Hybrid Modeling:** * Combine **TF-IDF vectors** (content) with **Stylometric features** (style). * Train Baseline Models: Logistic Regression, Linear SVC, Random Forest. 5. **Evaluation:** Report Precision/Recall on the held-out Test set and analyze model coefficients to interpret "AI-like" writing markers.

[1]:
```python
from google.colab import drive
drive.mount("/content/drive")
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

[2]:
```python
# =========================
# Install all required libraries for this project
# =========================
!pip -q install -U \
  numpy pandas scipy \
  scikit-learn \
  matplotlib \
  tqdm \
  textstat \
  torch \
  transformers \
  datasets \
  accelerate
!python -m spacy download en_core_web_sm
```

```
Collecting en-core-web-sm==3.8.0
  Downloading https://github.com/explosion/spacy-
models/releases/download/en_core_web_sm-3.8.0/en_core_web_sm-3.8.0-py3-none-
any.whl (12.8 MB)
                                           12.8/12.8 MB
104.9 MB/s eta 0:00:00
  Download and installation successful
You can now load the package via spacy.load('en_core_web_sm')
  Restart to reload dependencies
If you are in a Jupyter or Colab notebook, you may need to restart Python in
order to load all the package's dependencies. You can do this by selecting the
'Restart kernel' or 'Restart runtime' option.
```

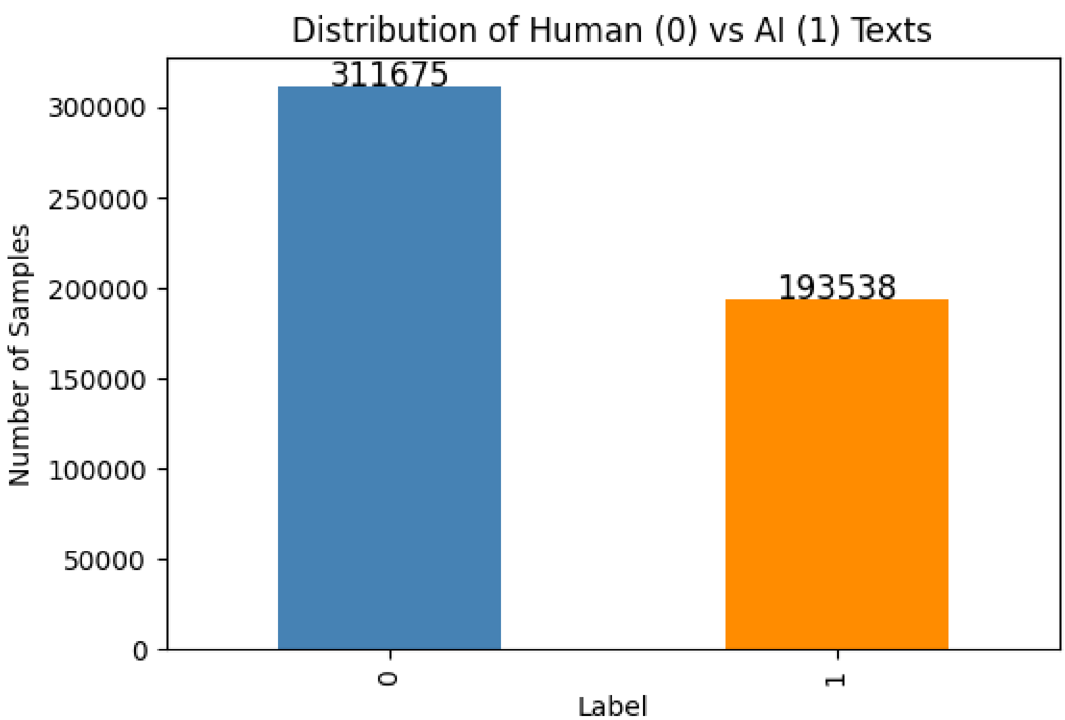
[3]:
```python
import re
import string
from collections import Counter

import numpy as np
import pandas as pd
from tqdm.notebook import tqdm
import re, math, hashlib, zlib
from collections import Counter

import textstat
import spacy

from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
from sklearn.feature_extraction.text import TfidfVectorizer

tqdm.pandas()  # enable progress bar on apply

# load lightweight spaCy model
nlp = spacy.load("en_core_web_sm", disable=["ner", "parser"])

RANDOM_SEED = 42
np.random.seed(RANDOM_SEED)
```

[4]:
```python
CSV_PATH = "/content/drive/MyDrive/final_merged_dataset.csv"
TEXT_COL = "text"
LABEL_COL = "label"

# Robust CSV load (handles quotes, bad lines)
```

```python
df = pd.read_csv(
    CSV_PATH,
    engine="python",
    escapechar="\\",
    on_bad_lines="skip"
)

# Drop rows with missing text/label
df = df.dropna(subset=[TEXT_COL, LABEL_COL]).copy()

# Clean label column: ensure numeric 0/1
df[LABEL_COL] = pd.to_numeric(df[LABEL_COL], errors="coerce")
df[LABEL_COL] = df[LABEL_COL].fillna(0).astype(int)

#additional fixes for NAN values
df["source"] = df["source"].fillna("kaggle")
nan_rows = df['doc_id'].isna()
df.loc[nan_rows, 'doc_id'] = "kaggle_" + df.loc[nan_rows].index.astype(str)


print("Columns:", df.columns)
print("First few rows:")
display(df.head())
print(f"\nDataset shape: {df.shape}")

print("\nLabel value counts:")
# Count class distribution
counts = df[LABEL_COL].value_counts().sort_index()
print(counts)


import matplotlib.pyplot as plt
# Plot
plt.figure(figsize=(6,4))
counts.plot(kind='bar', color=['steelblue', 'darkorange'])
plt.title("Distribution of Human (0) vs AI (1) Texts")
plt.xlabel("Label")
plt.ylabel("Number of Samples")

# Annotate bars with counts
for i, v in enumerate(counts):
    plt.text(i, v + 500, str(v), ha='center', fontsize=12)

plt.show()
```

```
Columns: Index(['text', 'label', 'doc_id', 'source'], dtype='object')
First few rows:
```

```
                                                text  label  \
0  Wlectoral College is a process that help the U…      0
1  Dear Principal Johnson, I AP writing to expres…      1
2  In the article, the author suggests studying c…      0
3  The usage of motor vehicles has been on a stea…      0
4  Sold 30 items on Vinted? Don't panic if you ge…      0

             doc_id  source
0          kaggle_0  kaggle
1          kaggle_1  kaggle
2          kaggle_2  kaggle
3          kaggle_3  kaggle
4  news_a6e189b87355    news


Dataset shape: (505213, 4)

Label value counts:
label
0    311675
1    193538
Name: count, dtype: int64
```



[5]:
```python
# ==========================
# FINAL FEATURE WRAPPER CELL
# ==========================

import re
from typing import Dict

# ---------- helpers ----------
def get_lines(text: str, max_lines: int):
    if not isinstance(text, str) or not text:
        return []
    return text.splitlines()[:max_lines]

def basic_counts(text: str):
    text = text or ""
    num_chars = len(text)

    # sentence split
    sentences = re.split(r"[.!?]+", text)
    sentences = [s.strip() for s in sentences if s.strip()]
    num_sent = len(sentences) if sentences else 1

    # word tokens
    words = re.findall(r"\w+", text)
    num_words = len(words) if words else 1

    avg_sent_len = num_words / num_sent
    return {
        "num_chars": num_chars,
        "num_words": num_words,
        "num_sentences": num_sent,
        "avg_sentence_length": avg_sent_len,
    }


def lexical_diversity(text: str):
    words = re.findall(r"\w+", str(text).lower())
    if not words:
        return {
            "type_token_ratio": 0.0,
            "unique_words": 0,
        }
    unique = set(words)
    ttr = len(unique) / len(words)
    return {
        "type_token_ratio": ttr,
        "unique_words": len(unique),
```

```python
    }


def punctuation_stats(text: str):
    text = text or ""
    if not text:
        return {
            "pct_punct": 0.0,
            "pct_upper": 0.0,
            "pct_digit": 0.0,
        }
    total = len(text)
    punct = sum(ch in string.punctuation for ch in text)
    upper = sum(ch.isupper() for ch in text)
    digit = sum(ch.isdigit() for ch in text)
    return {
        "pct_punct": punct / total,
        "pct_upper": upper / total,
        "pct_digit": digit / total,
    }


def readability_features(text: str):
    clean = text if isinstance(text, str) else ""
    if len(clean.split()) < 3:
        return {
            "flesch_reading_ease": 0.0,
            "flesch_kincaid_grade": 0.0,
            "gunning_fog": 0.0,
        }
    try:
        fre = textstat.flesch_reading_ease(clean)
        fkg = textstat.flesch_kincaid_grade(clean)
        gf  = textstat.gunning_fog(clean)
    except Exception:
        fre, fkg, gf = 0.0, 0.0, 0.0
    return {
        "flesch_reading_ease": fre,
        "flesch_kincaid_grade": fkg,
        "gunning_fog": gf,
    }


def repetition_features(text: str):
    tokens = re.findall(r"\w+", str(text).lower())
    if len(tokens) < 4:
        return {"bigram_repetition_ratio": 0.0}
```

```
    bigrams = list(zip(tokens, tokens[1:]))
    total_bigrams = len(bigrams)
    counts = Counter(bigrams)
    repeated = sum(c for c in counts.values() if c > 1)
    return {
        "bigram_repetition_ratio": repeated / total_bigrams
    }


def pos_features_spacy(text: str):
    doc = nlp(str(text))
    tokens = [t for t in doc if not t.is_space]
    total_tokens = len(tokens)
    if total_tokens == 0:
        return {
            "pos_ratio_NOUN": 0.0,
            "pos_ratio_VERB": 0.0,
            "pos_ratio_ADJ": 0.0,
            "pos_ratio_ADV": 0.0,
            "pos_ratio_PRON": 0.0,
            "pos_ratio_ADP": 0.0,
            "pos_ratio_DET": 0.0,
        }
    counts = Counter(tok.pos_ for tok in tokens)

    def ratio(tag):
        return counts.get(tag, 0) / total_tokens

    return {
        "pos_ratio_NOUN": ratio("NOUN"),
        "pos_ratio_VERB": ratio("VERB"),
        "pos_ratio_ADJ":  ratio("ADJ"),
        "pos_ratio_ADV":  ratio("ADV"),
        "pos_ratio_PRON": ratio("PRON"),
        "pos_ratio_ADP":  ratio("ADP"),
        "pos_ratio_DET":  ratio("DET"),
    }


def sentence_length_stats(text: str):
    sentences = re.split(r"[.!?]+", str(text))
    sentences = [s.strip() for s in sentences if s.strip()]
    if len(sentences) < 2:
        return {
            "sentence_length_std": 0.0,
            "sentence_length_mean": len(str(text).split()),
        }
```

```python
    lens = [len(s.split()) for s in sentences]
    return {
        "sentence_length_std": float(np.std(lens)),
        "sentence_length_mean": float(np.mean(lens)),
    }


def compute_all_features(text: str):
    feats = {}
    feats.update(basic_counts(text))
    feats.update(lexical_diversity(text))
    feats.update(punctuation_stats(text))
    feats.update(readability_features(text))
    feats.update(repetition_features(text))
    feats.update(pos_features_spacy(text))
    feats.update(sentence_length_stats(text))
    return feats

# ============================================================
# NEW FEATURES
# ============================================================

# --- A) Em-dash / emphasis punctuation ---
def emphasis_punctuation_features(text: str, max_lines: int = 5) -> Dict:
    lines = get_lines(text, max_lines)
    joined = "\n".join(lines)
    n = len(joined) if joined else 1

    return {
        "emdash_ratio": joined.count("-") / n,
        "double_dash_ratio": joined.count("--") / n,
        "colon_ratio_emphasis": joined.count(":") / n,
        "semicolon_ratio_emphasis": joined.count(";") / n,
        "emphasis_punctuation_ratio": (
            joined.count("-")
            + joined.count("--")
            + joined.count(":")
            + joined.count(";")
        ) / n,
    }


# --- B) Hedging / cautious language ---
HEDGE_PHRASES = [
    "some might argue",
    "it could be said",
    "it may be",
```

```python
    "it might be",
    "it is possible that",
    "it appears that",
    "it seems that",
    "may suggest",
    "could suggest",
    "is often considered",
    "is generally regarded",
]

def hedging_language_features(text: str, max_lines: int = 5) -> Dict:
    lines = get_lines(text.lower(), max_lines)
    if not lines:
        return {
            "hedge_phrase_count": 0,
            "hedge_phrase_ratio": 0.0,
            "hedge_line_ratio": 0.0,
        }

    hedge_count = 0
    hedge_lines = 0

    for ln in lines:
        c = sum(ln.count(p) for p in HEDGE_PHRASES)
        if c > 0:
            hedge_count += c
            hedge_lines += 1

    total = len(lines)

    return {
        "hedge_phrase_count": hedge_count,
        "hedge_phrase_ratio": hedge_count / total,
        "hedge_line_ratio": hedge_lines / total,
    }


# --- C) Vague / hallucination-proxy language ---
GENERIC_CLAIMS = [
    "studies suggest",
    "research shows",
    "experts believe",
    "it is believed",
    "it is widely accepted",
]

VAGUE_QUANTIFIERS = [
```

```python
    "various",
    "numerous",
    "several",
    "many",
    "a number of",
    "some",
]

FAKE_CITATION_PATTERNS = [
    r"\[\d+\]",        # [1], [23]
    r"\(\d{4}\)",      # (2021)
    r"et al\.",        # et al.
]

def vague_and_hallucination_features(text: str, max_lines: int = 5) -> Dict:
    lines = get_lines(text.lower(), max_lines)
    if not lines:
        return {
            "generic_claim_ratio": 0.0,
            "vague_quantifier_ratio": 0.0,
            "fake_citation_ratio": 0.0,
        }

    generic = 0
    vague = 0
    fake = 0

    for ln in lines:
        if any(p in ln for p in GENERIC_CLAIMS):
            generic += 1
        if any(q in ln for q in VAGUE_QUANTIFIERS):
            vague += 1
        if any(re.search(rx, ln) for rx in FAKE_CITATION_PATTERNS):
            fake += 1

    total = len(lines)

    return {
        "generic_claim_ratio": generic / total,
        "vague_quantifier_ratio": vague / total,
        "fake_citation_ratio": fake / total,
    }


# ============================================================
# FINAL WRAPPER
# ============================================================
```

```python
def compute_all_features_final(text: str, max_lines: int = 5) -> Dict:
    feats = {}
    feats.update(basic_counts(text))
    feats.update(lexical_diversity(text))
    feats.update(punctuation_stats(text))
    feats.update(readability_features(text))
    feats.update(repetition_features(text))
    feats.update(pos_features_spacy(text))
    feats.update(sentence_length_stats(text))
    feats.update(emphasis_punctuation_features(text, max_lines))
    feats.update(hedging_language_features(text, max_lines))
    feats.update(vague_and_hallucination_features(text, max_lines))

    return feats


# -------------------------
# quick sanity check
# -------------------------
print(compute_all_features_final(
    "Some might argue – it could be said that research shows various factors.
 ↪\n[1] et al. (2021)",
    max_lines=5
))
```

```
{'num_chars': 90, 'num_words': 16, 'num_sentences': 3, 'avg_sentence_length':
5.333333333333333, 'type_token_ratio': 1.0, 'unique_words': 16, 'pct_punct':
0.06666666666666667, 'pct_upper': 0.011111111111111112, 'pct_digit':
0.05555555555555555, 'flesch_reading_ease': 87.67750000000001,
'flesch_kincaid_grade': 3.017500000000002, 'gunning_fog': 5.7,
'bigram_repetition_ratio': 0.0, 'pos_ratio_NOUN': 0.08695652173913043,
'pos_ratio_VERB': 0.13043478260869565, 'pos_ratio_ADJ': 0.043478260869565216,
'pos_ratio_ADV': 0.0, 'pos_ratio_PRON': 0.043478260869565216, 'pos_ratio_ADP':
0.0, 'pos_ratio_DET': 0.043478260869565216, 'sentence_length_std':
5.2493385826745405, 'sentence_length_mean': 5.666666666666667, 'emdash_ratio':
0.011111111111111112, 'double_dash_ratio': 0.0, 'colon_ratio_emphasis': 0.0,
'semicolon_ratio_emphasis': 0.0, 'emphasis_punctuation_ratio':
0.011111111111111112, 'hedge_phrase_count': 2, 'hedge_phrase_ratio': 1.0,
'hedge_line_ratio': 0.5, 'generic_claim_ratio': 0.5, 'vague_quantifier_ratio':
0.5, 'fake_citation_ratio': 0.5}
```

[6]:
```python
import numpy as np
import pandas as pd
from tqdm.auto import tqdm

tqdm.pandas()
```

```
RANDOM_SEED = 42
MAX_LINES_FOR_NEW_FEATURES = 5
SAMPLE_N = 40000                #start here; increase later if needed

# ---- 1) Create a stratified sample (label-balanced + length-bin coverage) ----
# Length binning based on character length tertiles (computed on the full df,␣
↪but only uses text length)
char_len = df["text"].astype(str).str.len()

q1, q2 = char_len.quantile([1/3, 2/3]).values
length_bin = pd.cut(char_len, bins=[-np.inf, q1, q2, np.inf], labels=["short",␣
↪"medium", "long"])

# Add a temp bin column (small metadata, OK)
df_tmp = df.copy()
df_tmp["length_bin_tmp"] = length_bin.astype(str)

# Stratify by (label, length_bin)
group_cols = ["label", "length_bin_tmp"]
groups = df_tmp.groupby(group_cols, group_keys=False)

n_groups = groups.ngroups
per_group = SAMPLE_N // n_groups

# Sample per group (balanced across label + bins)
parts = []
for key, g in groups:
    take = min(per_group, len(g))
    parts.append(g.sample(n=take, random_state=RANDOM_SEED))

df_sample = pd.concat(parts, axis=0).sample(frac=1.0, random_state=RANDOM_SEED).
↪reset_index(drop=True)

# If rounding left us short, top up with label-stratified sampling
remaining = SAMPLE_N - len(df_sample)
if remaining > 0:
    df_rest = df_tmp.drop(df_sample.index, errors="ignore")
    topup = (
        df_rest.groupby("label", group_keys=False)
        .apply(lambda x: x.sample(n=min(remaining // 2, len(x)),␣
↪random_state=RANDOM_SEED))
    )
    df_sample = pd.concat([df_sample, topup], axis=0).sample(frac=1.0,␣
↪random_state=RANDOM_SEED).reset_index(drop=True)

# Keep only needed columns (avoid carrying temp column forward)
```

```python
df_sample = df_sample[["text", "label", "doc_id", "source"]].copy()

print("Sample shape:", df_sample.shape)
print("Label distribution:\n", df_sample["label"].value_counts())
print("Source distribution (top):\n", df_sample["source"].value_counts().head())

#2) Compute features on the sample only
#Returns one dict per row → DataFrame
features_series = df_sample["text"].progress_apply(
    lambda t: compute_all_features_final(t,␣
↪max_lines=MAX_LINES_FOR_NEW_FEATURES)
)

X_style = pd.DataFrame(list(features_series))

#cast to float32 to reduce memory
for c in X_style.columns:
    if X_style[c].dtype == "float64":
        X_style[c] = X_style[c].astype("float32")

print("Stylometric feature matrix:", X_style.shape)
display(X_style.head())
```

```
Sample shape: (40000, 4)
Label distribution:
 label
1    20000
0    20000
Name: count, dtype: int64
Source distribution (top):
 source
kaggle       38371
chatgpt       1249
wikipedia      221
news            97
arxiv           62
Name: count, dtype: int64
```

```
/tmp/ipython-input-3918048924.py:43: FutureWarning: DataFrameGroupBy.apply
operated on the grouping columns. This behavior is deprecated, and in a future
version of pandas the grouping columns will be excluded from the operation.
Either pass `include_groups=False` to exclude the groupings or explicitly select
the grouping columns after groupby to silence this warning.
  .apply(lambda x: x.sample(n=min(remaining // 2, len(x)),
random_state=RANDOM_SEED))
```

```
  0%|          | 0/40000 [00:00<?, ?it/s]
```

```
Stylometric feature matrix: (40000, 33)
```

```
   num_chars  num_words  num_sentences  avg_sentence_length  type_token_ratio  \
0       1407        182             13            14.000000          0.653846   
1       2747        469             28            16.750000          0.443497   
2       3365        596             28            21.285715          0.458054   
3       4093        616             30            20.533333          0.444805   
4       1304        260              8            32.500000          0.515385   

   unique_words  pct_punct  pct_upper  pct_digit  flesch_reading_ease  …  \
0           119   0.039090   0.034115   0.010661             7.023158  …   
1           208   0.019658   0.044776   0.000000            57.878223  …   
2           273   0.032987   0.012184   0.009212            58.330410  …   
3           274   0.023455   0.063034   0.000977            28.944954  …   
4           134   0.023006   0.032975   0.000000            63.030010  …   

   double_dash_ratio  colon_ratio_emphasis  semicolon_ratio_emphasis  \
0           0.002132              0.002843                       0.0   
1           0.000000              0.000000                       0.0   
2           0.000297              0.000000                       0.0   
3           0.000000              0.000244                       0.0   
4           0.000000              0.000000                       0.0   

   emphasis_punctuation_ratio  hedge_phrase_count  hedge_phrase_ratio  \
0                    0.004975                   0                 0.0   
1                    0.000000                   0                 0.0   
2                    0.000297                   0                 0.0   
3                    0.000244                   0                 0.0   
4                    0.000000                   0                 0.0   

   hedge_line_ratio  generic_claim_ratio  vague_quantifier_ratio  \
0               0.0                  0.0                     1.0   
1               0.0                  0.0                     1.0   
2               0.0                  0.0                     1.0   
3               0.0                  0.0                     1.0   
4               0.0                  0.0                     1.0   

   fake_citation_ratio  
0                  0.0  
1                  0.0  
2                  0.0  
3                  0.0  
4                  0.0  

[5 rows x 33 columns]
```

[7]:

```
# ========================
# FINAL: pipeline for TF-IDF(text) + Stylometry(features)
```

```python
# Trains LR, LinearSVC (full sparse), and KNN/RF (SVD-compressed but still
↪TF-IDF+style).
#
# Requires:
#   df_sample: has columns ["text","label", ...]
#   X_style:   DataFrame of your computed stylometric features, row-aligned
↪with df_sample
# =========================

import numpy as np
import pandas as pd

from sklearn.model_selection import train_test_split
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.decomposition import TruncatedSVD

from sklearn.linear_model import LogisticRegression
from sklearn.svm import LinearSVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier

from sklearn.metrics import classification_report

RANDOM_SEED = 42
TEST_SIZE = 0.20
VAL_SIZE  = 0.10  # of total df_sample

# -------------------------
# 0) Merge df_sample + X_style into one DataFrame (so ColumnTransformer can use
↪both)
# -------------------------
assert len(df_sample) == len(X_style), "df_sample and X_style must be
↪row-aligned and same length."
df_all = pd.concat([df_sample.reset_index(drop=True), X_style.
↪reset_index(drop=True)], axis=1)

text_col = "text"
y = df_all["label"].astype(int).values
style_cols = list(X_style.columns)

# -------------------------
# 1) Random, stratified train/val/test split
# -------------------------
idx = np.arange(len(df_all))
```

```
train_idx, temp_idx = train_test_split(
    idx,
    test_size=(TEST_SIZE + VAL_SIZE),
    random_state=RANDOM_SEED,
    stratify=y
)

val_frac_of_temp = VAL_SIZE / (VAL_SIZE + TEST_SIZE)

val_idx, test_idx = train_test_split(
    temp_idx,
    test_size=(1 - val_frac_of_temp),
    random_state=RANDOM_SEED,
    stratify=y[temp_idx]
)

train_df = df_all.iloc[train_idx].reset_index(drop=True)
val_df   = df_all.iloc[val_idx].reset_index(drop=True)
test_df  = df_all.iloc[test_idx].reset_index(drop=True)

y_train = train_df["label"].astype(int).values
y_val   = val_df["label"].astype(int).values
y_test  = test_df["label"].astype(int).values

print("Split sizes:", len(train_df), len(val_df), len(test_df))
print("Label dist train:", np.bincount(y_train))
print("Label dist val:  ", np.bincount(y_val))
print("Label dist test: ", np.bincount(y_test))

# -------------------------
# 2) Shared feature preprocessor: TF-IDF(text) + scaled style features
#    - TF-IDF output is sparse
#    - StandardScaler(with_mean=False) is required for sparse compatibility
# -------------------------
tfidf = TfidfVectorizer(
    analyzer="word",
    ngram_range=(1, 2),
    min_df=3,
    max_df=0.9,
    sublinear_tf=True
)

preprocessor = ColumnTransformer(
    transformers=[
        ("tfidf", tfidf, text_col),
        ("style", StandardScaler(with_mean=False), style_cols),
```

```python
    ],
    remainder="drop",
    sparse_threshold=0.3  # keep output sparse when possible
)

# -------------------------
# 3) Models
#    LR + LinearSVC can handle the full sparse matrix
#    KNN + RF will be trained on a compressed representation via TruncatedSVD
# -------------------------
def fit_eval(name, pipe):
    pipe.fit(train_df, y_train)
    print(f"\n==================== {name} ====================")
    print("VAL:")
    print(classification_report(y_val, pipe.predict(val_df), digits=4))
    print("TEST:")
    print(classification_report(y_test, pipe.predict(test_df), digits=4))
    return pipe

# 3A) Logistic Regression (FULL sparse TF-IDF + style)
lr_pipe = Pipeline([
    ("features", preprocessor),
    ("clf", LogisticRegression(max_iter=300, class_weight="balanced"))
])

# 3B) Linear SVM (FULL sparse TF-IDF + style)
svm_pipe = Pipeline([
    ("features", preprocessor),
    ("clf", LinearSVC(class_weight="balanced"))
])

# For KNN/RF: SVD makes it dense and manageable while still using TF-IDF info
SVD_DIM = 300  # 200-500 is a reasonable range;

# knn_pipe = Pipeline([
#     ("features", preprocessor),
#     ("svd", TruncatedSVD(n_components=SVD_DIM, random_state=RANDOM_SEED)),
#     ("scale_dense", StandardScaler()),  # now dense, safe to mean-center
#     ("clf", KNeighborsClassifier(n_neighbors=15, weights="distance"))
# ])

rf_pipe = Pipeline([
    ("features", preprocessor),
    ("svd", TruncatedSVD(n_components=SVD_DIM, random_state=RANDOM_SEED)),
    ("clf", RandomForestClassifier(
        n_estimators=300,
        max_depth=20,
```

```
        n_jobs=-1,
        class_weight="balanced_subsample",
        random_state=RANDOM_SEED
    ))
])

lr_pipe  = fit_eval("Logistic Regression (TF-IDF + Style)", lr_pipe)
svm_pipe = fit_eval("Linear SVM (TF-IDF + Style)", svm_pipe)
# knn_pipe = fit_eval("KNN (TF-IDF + Style via SVD)", knn_pipe)
rf_pipe  = fit_eval("Random Forest (TF-IDF + Style via SVD)", rf_pipe)

# -------------------------
# 4) Getting TF-IDF vector feature names (ngram vocabulary)
#    After fitting, you can inspect what TF-IDF "features" correspond to.
# -------------------------
tfidf_fitted = lr_pipe.named_steps["features"].named_transformers_["tfidf"]
tfidf_feature_names = tfidf_fitted.get_feature_names_out()

print("\nTF-IDF feature count:", len(tfidf_feature_names))
print("Example TF-IDF features:", tfidf_feature_names[:25])

#full hybrid feature names (TF-IDF + style)
hybrid_feature_names = np.concatenate([tfidf_feature_names, np.
 ↪array(style_cols, dtype=object)])
print("Total hybrid feature count:", len(hybrid_feature_names))
```

```
Split sizes: 27999 4000 8001
Label dist train: [13999 14000]
Label dist val:   [2000 2000]
Label dist test:  [4001 4000]
```

```
/usr/local/lib/python3.12/dist-packages/sklearn/linear_model/_logistic.py:406:
ConvergenceWarning: lbfgs failed to converge after 300 iteration(s) (status=1):
STOP: TOTAL NO. OF ITERATIONS REACHED LIMIT

Increase the number of iterations to improve the convergence (max_iter=300).
You might also want to scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

```
==================== Logistic Regression (TF-IDF + Style) ====================
VAL:
              precision    recall  f1-score   support
```

```
           0     0.9790    0.9775    0.9782      2000
           1     0.9775    0.9790    0.9783      2000

    accuracy                         0.9782      4000
   macro avg     0.9783    0.9783    0.9782      4000
weighted avg     0.9783    0.9782    0.9782      4000

TEST:
              precision    recall  f1-score   support

           0     0.9820    0.9823    0.9821      4001
           1     0.9822    0.9820    0.9821      4000

    accuracy                         0.9821      8001
   macro avg     0.9821    0.9821    0.9821      8001
weighted avg     0.9821    0.9821    0.9821      8001


/usr/local/lib/python3.12/dist-packages/sklearn/svm/_base.py:1258:
ConvergenceWarning: Liblinear failed to converge, increase the number of
iterations.
  warnings.warn(

==================== Linear SVM (TF-IDF + Style) ====================
VAL:
              precision    recall  f1-score   support

           0     0.9940    0.9900    0.9920      2000
           1     0.9900    0.9940    0.9920      2000

    accuracy                         0.9920      4000
   macro avg     0.9920    0.9920    0.9920      4000
weighted avg     0.9920    0.9920    0.9920      4000

TEST:
              precision    recall  f1-score   support

           0     0.9945    0.9935    0.9940      4001
           1     0.9935    0.9945    0.9940      4000

    accuracy                         0.9940      8001
   macro avg     0.9940    0.9940    0.9940      8001
weighted avg     0.9940    0.9940    0.9940      8001


==================== Random Forest (TF-IDF + Style via SVD) ====================
VAL:
              precision    recall  f1-score   support
```

```
           0     0.9806    0.9865    0.9835      2000
           1     0.9864    0.9805    0.9835      2000

    accuracy                         0.9835      4000
   macro avg     0.9835    0.9835    0.9835      4000
weighted avg     0.9835    0.9835    0.9835      4000

TEST:
              precision    recall  f1-score   support

           0     0.9809    0.9863    0.9835      4001
           1     0.9862    0.9808    0.9835      4000

    accuracy                         0.9835      8001
   macro avg     0.9835    0.9835    0.9835      8001
weighted avg     0.9835    0.9835    0.9835      8001


TF-IDF feature count: 334035
Example TF-IDF features: ['00' '00 57' '00 along' '00 am' '00 and' '00 pm' '00
voters' '000'
 '000 000' '000 001' '000 accidents' '000 along' '000 and' '000 annually'
 '000 are' '000 can' '000 car' '000 deaths' '000 defiantly'
 '000 different' '000 dollar' '000 dollars' '000 driver' '000 drivers'
 '000 each']
Total hybrid feature count: 334068
```

[8]:
```
#Simulating real world scenario by pre training on ML data and testing on
↪real-life data to see if model training fails



# =========================
# STRICT SPLIT: Train/Val on Kaggle ONLY, Test on Scraped ONLY (from df_sample)
# - Uses df_sample as the universe
# - Keeps X_style aligned
# - Removes any scraped rows whose normalized-text hash appears in Kaggle
↪(within df_sample)
#
# Outputs:
#   train_df, val_df, test_df
#   X_style_train, X_style_val, X_style_test
#   y_train, y_val, y_test
# =========================

import numpy as np
import pandas as pd
```

```python
import re, hashlib
from sklearn.model_selection import train_test_split

RANDOM_SEED = 42
VAL_SIZE = 0.15   # fraction of Kaggle portion used for validation (e.g., 15%)
np.random.seed(RANDOM_SEED)

#sanity checks
assert "source" in df_sample.columns, "df_sample must have a 'source' column."
assert "text" in df_sample.columns and "label" in df_sample.columns, "df_sample must have 'text' and 'label'."
assert len(df_sample) == len(X_style), "df_sample and X_style must be row-aligned and same length."

#helper: text hash for overlap removal
_ws = re.compile(r"\s+")
def norm_for_hash(s: str) -> str:
    s = "" if s is None else str(s)
    return _ws.sub(" ", s.strip().lower())

def text_hash(s: str) -> str:
    return hashlib.sha1(norm_for_hash(s).encode("utf-8")).hexdigest()

#1) Get Kaggle indices and Scraped indices (within df_sample)
all_idx = np.arange(len(df_sample))
k_idx = all_idx[df_sample["source"].astype(str).values == "kaggle"]
s_idx = all_idx[df_sample["source"].astype(str).values != "kaggle"]

print("Within df_sample:")
print("  Kaggle rows :", len(k_idx))
print("  Scraped rows:", len(s_idx))

if len(k_idx) == 0:
    raise ValueError("No Kaggle rows found inside df_sample. Cannot do Kaggle-only train/val.")
if len(s_idx) == 0:
    raise ValueError("No scraped rows found inside df_sample. Cannot do scraped-only test.")

# 2) Remove Kaggle Scraped overlaps (within df_sample)
# Hash Kaggle texts
k_text = df_sample.loc[k_idx, "text"].astype(str)
k_hash_set = set(k_text.map(text_hash).values)

#Hash scraped texts and keep only non-overlapping
s_text = df_sample.loc[s_idx, "text"].astype(str)
s_hash = s_text.map(text_hash)
```

```python
keep_scraped = ~s_hash.isin(k_hash_set)

test_idx = s_idx[keep_scraped.values]
dropped = int((~keep_scraped).sum())

print(f"  Dropped scraped overlaps vs Kaggle: {dropped}")
print(f"  Final TEST rows (scraped, deduped): {len(test_idx)}")

if len(test_idx) == 0:
    raise ValueError("After overlap removal, no scraped rows remain for TEST.␣
↪Increase df_sample size or change sampling.")

#3) Train/Val split ONLY on Kaggle (stratified by label)
k_labels = df_sample.loc[k_idx, "label"].astype(int).values

train_idx, val_idx = train_test_split(
    k_idx,
    test_size=VAL_SIZE,
    random_state=RANDOM_SEED,
    stratify=k_labels
)

#4) Slice df_sample + X_style together (keeps alignment)
train_df = df_sample.iloc[train_idx].reset_index(drop=True)
val_df   = df_sample.iloc[val_idx].reset_index(drop=True)
test_df  = df_sample.iloc[test_idx].reset_index(drop=True)

X_style_train = X_style.iloc[train_idx].reset_index(drop=True)
X_style_val   = X_style.iloc[val_idx].reset_index(drop=True)
X_style_test  = X_style.iloc[test_idx].reset_index(drop=True)

y_train = train_df["label"].astype(int).values
y_val   = val_df["label"].astype(int).values
y_test  = test_df["label"].astype(int).values

# Hash overlap checks
train_hashes = set(train_df["text"].astype(str).map(text_hash).values)
val_hashes   = set(val_df["text"].astype(str).map(text_hash).values)
test_hashes  = set(test_df["text"].astype(str).map(text_hash).values)

print("\nText-hash overlaps (should be 0):")
print("  TRAIN  VAL :", len(train_hashes & val_hashes))
print("  TRAIN  TEST:", len(train_hashes & test_hashes))
print("  VAL    TEST:", len(val_hashes & test_hashes))

print("\nSplit sizes:", len(train_df), len(val_df), len(test_df))
print("Label dist TRAIN:", np.bincount(y_train))
```

```
print("Label dist VAL:  ", np.bincount(y_val))
print("Label dist TEST: ", np.bincount(y_test))

#Kaggle-only TRAIN/VAL, Scraped-only TEST, with deduping and aligned X_style.
```

```
Within df_sample:
  Kaggle rows : 38371
  Scraped rows: 1629
  Dropped scraped overlaps vs Kaggle: 0
  Final TEST rows (scraped, deduped): 1629

Text-hash overlaps (should be 0):
  TRAIN   VAL : 23
  TRAIN   TEST: 0
  VAL     TEST: 0

Split sizes: 32615 5756 1629
Label dist TRAIN: [16677 15938]
Label dist VAL:   [2943 2813]
Label dist TEST:  [ 380 1249]
```

[9]:

```
# =========================
# Train + Evaluate models on STRICT split:
#   TRAIN/VAL = Kaggle only
#   TEST      = Scraped only
# Uses ALL features together:
#   TF-IDF(text) + precomputed stylometric X_style_*
#
# we have  the following from the split cell:
#   train_df, val_df, test_df
#   X_style_train, X_style_val, X_style_test
#   y_train, y_val, y_test
#
# Trains: Logistic Regression, Linear SVM, Random Forest (via SVD) all using␣
 ↪TF-IDF+Style "together".
# =========================

import numpy as np
import pandas as pd

from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.decomposition import TruncatedSVD

from sklearn.linear_model import LogisticRegression
```

```
from sklearn.svm import LinearSVC
from sklearn.ensemble import RandomForestClassifier

from sklearn.metrics import classification_report, accuracy_score,␣
↪precision_recall_fscore_support

RANDOM_SEED = 42

# -------------------------
# 0) Merge text+labels with precomputed style features (keeps alignment)
# -------------------------
assert len(train_df) == len(X_style_train)
assert len(val_df)   == len(X_style_val)
assert len(test_df)  == len(X_style_test)

train_all = pd.concat([train_df.reset_index(drop=True), X_style_train.
↪reset_index(drop=True)], axis=1) #Akanksha use this
val_all   = pd.concat([val_df.reset_index(drop=True),   X_style_val.
↪reset_index(drop=True)], axis=1)
test_all  = pd.concat([test_df.reset_index(drop=True),  X_style_test.
↪reset_index(drop=True)], axis=1)

text_col = "text"
style_cols = list(X_style_train.columns)

# -------------------------
# 1) Shared preprocessor: TF-IDF + scaled style (together)
# -------------------------
tfidf = TfidfVectorizer(
    analyzer="word",
    ngram_range=(1, 2),
    min_df=3,
    max_df=0.9,
    sublinear_tf=True
)

preprocessor = ColumnTransformer(
    transformers=[
        ("tfidf", tfidf, text_col),
        ("style", StandardScaler(with_mean=False), style_cols),
    ],
    remainder="drop",
    sparse_threshold=0.3
)

# -------------------------
# 2) Pipelines
```

```python
# -------------------------
lr_pipe = Pipeline([
    ("features", preprocessor),
    ("clf", LogisticRegression(max_iter=300, class_weight="balanced"))
])

svm_pipe = Pipeline([
    ("features", preprocessor),
    ("clf", LinearSVC(class_weight="balanced"))
])

# Random Forest needs dense input -> use SVD compression (still TF-IDF + style␣
↪together)
SVD_DIM = 300  # 200-500 reasonable
rf_pipe = Pipeline([
    ("features", preprocessor),
    ("svd", TruncatedSVD(n_components=SVD_DIM, random_state=RANDOM_SEED)),
    ("clf", RandomForestClassifier(
        n_estimators=300,
        max_depth=20,
        n_jobs=-1,
        class_weight="balanced_subsample",
        random_state=RANDOM_SEED
    ))
])

models = {
    "LR (TF-IDF + Style)": lr_pipe,
    "Linear SVM (TF-IDF + Style)": svm_pipe,
    f"RF (TF-IDF + Style via SVD={SVD_DIM})": rf_pipe,
}

# -------------------------
# 3) Compact results table (VAL + TEST)
# -------------------------
def eval_metrics(y_true, y_pred):
    p, r, f1, _ = precision_recall_fscore_support(
        y_true, y_pred, average="binary", zero_division=0
    )
    acc = accuracy_score(y_true, y_pred)
    return {"accuracy": acc, "precision": p, "recall": r, "f1": f1}

rows = []

for name, model in models.items():
    model.fit(train_all, y_train)
```

```
    val_pred = model.predict(val_all)
    test_pred = model.predict(test_all)

    rows.append({"model": name, "split": "VAL", **eval_metrics(y_val,␣
↪val_pred)})
    rows.append({"model": name, "split": "TEST", **eval_metrics(y_test,␣
↪test_pred)})

    print(f"\n==================== {name} ====================")
    print("VAL:")
    print(classification_report(y_val, val_pred, digits=4))
    print("TEST:")
    print(classification_report(y_test, test_pred, digits=4))

results_df = pd.DataFrame(rows).sort_values(["split", "f1"], ascending=[True,␣
↪False])
print("\n=== Compact Results Table ===")
display(results_df.round(4))

# -------------------------
# 4) LR coefficient interpretation (Top AI vs Human features)
# -------------------------
# Only for LR (interpretable). SVM coefficients are also available but less␣
↪nicely probabilistic.
tfidf_fitted = lr_pipe.named_steps["features"].named_transformers_["tfidf"]
tfidf_feature_names = tfidf_fitted.get_feature_names_out()

feature_names = np.concatenate([tfidf_feature_names, np.array(style_cols,␣
↪dtype=object)])
coef = lr_pipe.named_steps["clf"].coef_[0]

coef_df = pd.DataFrame({"feature": feature_names, "coefficient": coef})

TOPK = 25
top_ai = coef_df.sort_values("coefficient", ascending=False).head(TOPK)
top_human = coef_df.sort_values("coefficient", ascending=True).head(TOPK)

print(f"\n Top {TOPK} AI-indicative features (positive coef)")
display(top_ai)

print(f"\n Top {TOPK} Human-indicative features (negative coef)")
display(top_human)

# Stylometry-only interpretation (often the most report-friendly)
n_tfidf = len(tfidf_feature_names)
style_coef_df = coef_df.iloc[n_tfidf:].copy()
```

```python
print("\n Stylometric features pushing AI prediction")
display(style_coef_df.sort_values("coefficient", ascending=False).head(15))

print("\n Stylometric features pushing Human prediction")
display(style_coef_df.sort_values("coefficient", ascending=True).head(15))
```

```
/usr/local/lib/python3.12/dist-packages/sklearn/linear_model/_logistic.py:406:
ConvergenceWarning: lbfgs failed to converge after 300 iteration(s) (status=1):
STOP: TOTAL NO. OF ITERATIONS REACHED LIMIT

Increase the number of iterations to improve the convergence (max_iter=300).
You might also want to scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(


==================== LR (TF-IDF + Style) ====================
VAL:
              precision    recall  f1-score   support

           0     0.9771    0.9857    0.9814      2943
           1     0.9849    0.9758    0.9804      2813

    accuracy                         0.9809      5756
   macro avg     0.9810    0.9808    0.9809      5756
weighted avg     0.9809    0.9809    0.9809      5756

TEST:
              precision    recall  f1-score   support

           0     0.5259    0.1605    0.2460       380
           1     0.7892    0.9560    0.8646      1249

    accuracy                         0.7704      1629
   macro avg     0.6575    0.5582    0.5553      1629
weighted avg     0.7277    0.7704    0.7203      1629


/usr/local/lib/python3.12/dist-packages/sklearn/svm/_base.py:1258:
ConvergenceWarning: Liblinear failed to converge, increase the number of
iterations.
  warnings.warn(


==================== Linear SVM (TF-IDF + Style) ====================
VAL:
```

```
              precision    recall  f1-score   support

           0     0.9936    0.9963    0.9949      2943
           1     0.9961    0.9932    0.9947      2813

    accuracy                         0.9948      5756
   macro avg     0.9948    0.9948    0.9948      5756
weighted avg     0.9948    0.9948    0.9948      5756

TEST:
              precision    recall  f1-score   support

           0     0.8857    0.0816    0.1494       380
           1     0.7811    0.9968    0.8758      1249

    accuracy                         0.7833      1629
   macro avg     0.8334    0.5392    0.5126      1629
weighted avg     0.8055    0.7833    0.7064      1629


==================== RF (TF-IDF + Style via SVD=300) ====================
VAL:
              precision    recall  f1-score   support

           0     0.9724    0.9925    0.9823      2943
           1     0.9920    0.9705    0.9811      2813

    accuracy                         0.9818      5756
   macro avg     0.9822    0.9815    0.9817      5756
weighted avg     0.9820    0.9818    0.9818      5756

TEST:
              precision    recall  f1-score   support

           0     0.2682    0.1842    0.2184       380
           1     0.7734    0.8471    0.8086      1249

    accuracy                         0.6924      1629
   macro avg     0.5208    0.5156    0.5135      1629
weighted avg     0.6555    0.6924    0.6709      1629


=== Compact Results Table ===
                             model split  accuracy  precision  recall      f1
3      Linear SVM (TF-IDF + Style)  TEST    0.7833     0.7811  0.9968  0.8758
1              LR (TF-IDF + Style)  TEST    0.7704     0.7892  0.9560  0.8646
5  RF (TF-IDF + Style via SVD=300)  TEST    0.6924     0.7734  0.8471  0.8086
```

2	Linear SVM (TF-IDF + Style)	VAL	0.9948	0.9961	0.9932	0.9947
4	RF (TF-IDF + Style via SVD=300)	VAL	0.9818	0.9920	0.9705	0.9811
0	LR (TF-IDF + Style)	VAL	0.9809	0.9849	0.9758	0.9804

Top 25 AI-indicative features (positive coef)

	feature	coefficient
160248	important	3.949887
110230	essay	2.779738
160584	important to	2.722758
250608	potential	2.466024
155766	however	2.374525
304382	super	2.294504
365174	who	2.253059
175105	it like	2.152198
217318	number of	2.101647
304594	support	2.100790
175254	it not	2.062030
46614	believe that	2.049402
217273	number	2.029114
172102	is important	1.975613
7577	additionally	1.963188
183846	learn	1.956587
373811	writing	1.923050
183584	lead to	1.859386
261619	re	1.853206
378359	gunning_fog	1.833927
257767	provide	1.815205
183505	lead	1.800023
151443	hey	1.786165
314359	that it	1.777496
174982	it important	1.757589

Top 25 Human-indicative features (negative coef)

	feature	coefficient
43114	because	-5.918275
372669	would	-3.931982
352746	very	-3.331144
59560	car	-2.591493
60999	cars	-2.546151
352226	venus	-2.523459
196257	many	-2.489802
104596	electors	-2.471438
43332	because it	-2.438205
238107	paragraph	-2.422308
310095	technology	-2.369877
354860	vote for	-2.365622

375350	you	-2.248318
117074	extracurricular	-2.214957
99294	driving	-2.155884
74431	computer	-2.152534
378357	flesch_reading_ease	-2.078456
15229	although	-2.075022
242369	percent	-2.074867
43421	because of	-2.042330
283630	should	-1.991392
300740	students	-1.985410
372747	would be	-1.968150
355743	voting	-1.939500
156711	humans	-1.935855

Stylometric features pushing AI prediction

	feature	coefficient
378359	gunning_fog	1.833927
378360	bigram_repetition_ratio	1.531269
378352	type_token_ratio	1.093467
378354	pct_punct	0.878839
378370	emdash_ratio	0.863871
378353	unique_words	0.560544
378363	pos_ratio_ADJ	0.439509
378365	pos_ratio_PRON	0.321384
378372	colon_ratio_emphasis	0.185739
378366	pos_ratio_ADP	0.185077
378374	emphasis_punctuation_ratio	0.139275
378380	fake_citation_ratio	0.047860
378362	pos_ratio_VERB	0.026540
378376	hedge_phrase_ratio	0.017530
378375	hedge_phrase_count	0.017530

Stylometric features pushing Human prediction

	feature	coefficient
378357	flesch_reading_ease	-2.078456
378358	flesch_kincaid_grade	-1.927044
378368	sentence_length_std	-1.306341
378350	num_sentences	-0.851759
378351	avg_sentence_length	-0.748340
378369	sentence_length_mean	-0.497879
378356	pct_digit	-0.382851
378367	pos_ratio_DET	-0.230534
378373	semicolon_ratio_emphasis	-0.222932
378348	num_chars	-0.204868
378355	pct_upper	-0.159835
378371	double_dash_ratio	-0.060649

```
378377          hedge_line_ratio    -0.049512
378349                 num_words    -0.027030
378379    vague_quantifier_ratio    -0.009897
```

[10]:
```
import joblib
import json

ART_DIR = "artifacts_ml"
import os
os.makedirs(ART_DIR, exist_ok=True)

joblib.dump(lr_pipe, f"{ART_DIR}/lr_pipe.joblib")

with open(f"{ART_DIR}/style_cols.json", "w") as f:
    json.dump(style_cols, f)

print(" Saved ML artifacts to:", ART_DIR)
```

```
Saved ML artifacts to: artifacts_ml
```

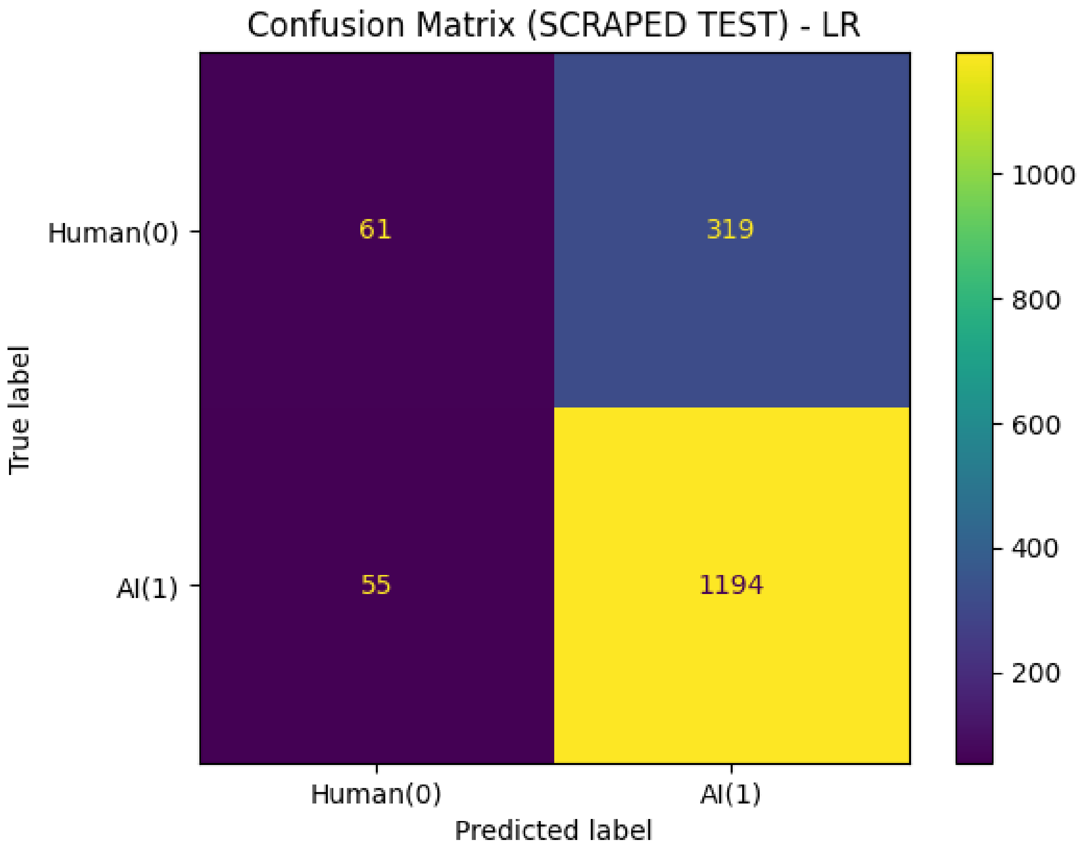
[11]:
```
# ========================
# DASHBOARD: LR (TF-IDF + Stylometry) interpretability
# No custom input here.
#
# Requires:
#   lr_pipe, val_all, test_all
#   val_df, test_df (must include 'text' and 'source')
#   y_val, y_test (numpy arrays)
#   style_cols (list)
# ========================

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

from sklearn.metrics import (
    accuracy_score, precision_recall_fscore_support,
    confusion_matrix, ConfusionMatrixDisplay,
    roc_auc_score, average_precision_score
)

def _metrics(y_true, y_pred, y_prob=None):
    p, r, f1, _ = precision_recall_fscore_support(y_true, y_pred,␣
 ↪average="binary", zero_division=0)
    out = {"acc": accuracy_score(y_true, y_pred), "prec": p, "rec": r, "f1": f1}
    if y_prob is not None:
        try: out["roc_auc"] = roc_auc_score(y_true, y_prob)
```

```
        except Exception: out["roc_auc"] = np.nan
        try: out["pr_auc"]  = average_precision_score(y_true, y_prob)
        except Exception: out["pr_auc"]  = np.nan
    return out

def prob_ai(model, X):
    if not hasattr(model, "predict_proba"):
        raise ValueError("Dashboard expects a model with predict_proba␣
↪(Logistic Regression).")
    return model.predict_proba(X)[:, 1]

def length_bins(texts: pd.Series, q=(0.33, 0.66)):
    lens = texts.astype(str).str.len()
    q1, q2 = lens.quantile(list(q)).values
    return pd.cut(lens, [-np.inf, q1, q2, np.inf],␣
↪labels=["short","medium","long"]).astype(str)

def plot_confidence_distributions(y_true, p_ai, title_suffix=""):
    p_h = p_ai[y_true == 0]
    p_a = p_ai[y_true == 1]

    bins = np.linspace(0, 1, 51)

    fig, ax = plt.subplots()
    ax.hist(p_h, bins=bins, alpha=0.6, density=True, label="True Human (0)")
    ax.hist(p_a, bins=bins, alpha=0.6, density=True, label="True AI (1)")
    ax.set_title(f"Prob(AI) distributions (SCRAPED TEST){title_suffix}")
    ax.set_xlabel("Predicted Prob(AI)")
    ax.set_ylabel("Density")
    ax.legend()
    plt.show()

    def cdf(vals):
        v = np.sort(vals)
        y = np.linspace(0, 1, len(v), endpoint=True)
        return v, y

    hx, hy = cdf(p_h)
    axx, ayy = cdf(p_a)

    fig, ax = plt.subplots()
    ax.plot(hx, hy, label="True Human (0)")
    ax.plot(axx, ayy, label="True AI (1)")
    ax.set_title(f"CDF of Prob(AI) (SCRAPED TEST){title_suffix}")
    ax.set_xlabel("Predicted Prob(AI)")
    ax.set_ylabel("Cumulative fraction")
    ax.legend()
```

```python
    plt.show()

def plot_length_bin_f1(df_text, y_true, p_ai, title):
    bins = length_bins(df_text["text"])
    y_pred = (p_ai >= 0.5).astype(int)

    labels = ["short","medium","long"]
    f1s, counts = [], []
    for b in labels:
        m = (bins == b).values
        counts.append(int(m.sum()))
        if m.sum() == 0:
            f1s.append(np.nan)
        else:
            _, _, f1, _ = precision_recall_fscore_support(y_true[m], y_pred[m],
 ↪average="binary", zero_division=0)
            f1s.append(float(f1))

    fig, ax = plt.subplots()
    ax.bar(labels, f1s)
    ax.set_ylim(0, 1)
    ax.set_ylabel("F1")
    ax.set_title(title)
    for i, c in enumerate(counts):
        ax.text(i, 0.02, f"n={c}", ha="center", va="bottom")
    plt.show()

def per_source_table(test_df, y_true, p_ai, min_n=20):
    y_pred = (p_ai >= 0.5).astype(int)
    rows = []
    for src, idx in test_df.groupby("source").indices.items():
        idx = np.array(list(idx))
        if len(idx) < min_n:
            continue
        m = _metrics(y_true[idx], y_pred[idx], p_ai[idx])
        rows.append({"source": src, "n": len(idx), **m})
    out = pd.DataFrame(rows).sort_values("f1", ascending=False)
    print(f"\n=== Per-source performance on SCRAPED TEST (min_n={min_n}) ===")
    display(out.round(4))
    return out

# ---- Compute probabilities ----
val_p = prob_ai(lr_pipe, val_all)
test_p = prob_ai(lr_pipe, test_all)

val_pred = (val_p >= 0.5).astype(int)
test_pred = (test_p >= 0.5).astype(int)
```

```python
# ---- Compact metrics ----
rows = [
    {"model":"LR (TF-IDF+Style)", "split":"VAL",  **_metrics(np.array(y_val), 
 ↪val_pred,  val_p)},
    {"model":"LR (TF-IDF+Style)", "split":"TEST", **_metrics(np.array(y_test),
 ↪test_pred, test_p)},
]
metrics_df = pd.DataFrame(rows)
print("\n=== Compact metrics ===")
display(metrics_df.round(4))

# ---- Confusion matrix (scraped test) ----
cm = confusion_matrix(np.array(y_test), test_pred, labels=[0,1])
disp = ConfusionMatrixDisplay(cm, display_labels=["Human(0)","AI(1)"])
fig, ax = plt.subplots()
disp.plot(ax=ax, values_format="d")
ax.set_title("Confusion Matrix (SCRAPED TEST) - LR")
plt.show()

# ---- Per-source table (scraped test) ----
per_source_table(test_df.reset_index(drop=True), np.array(y_test), test_p,
 ↪min_n=20)

# ---- Length-bin performance (scraped test) ----
plot_length_bin_f1(test_df.reset_index(drop=True), np.array(y_test), test_p,
                   "F1 by Length Bin (SCRAPED TEST) - LR")

# ---- Confidence distributions (scraped test) ----
plot_confidence_distributions(np.array(y_test), test_p)

# ---- Coefficient interpretability ----
# show_lr_top_features(lr_pipe, style_cols, topk=25)

# Expose test_p so Cell B can reuse it without recomputing
TEST_PROB_AI = test_p
```

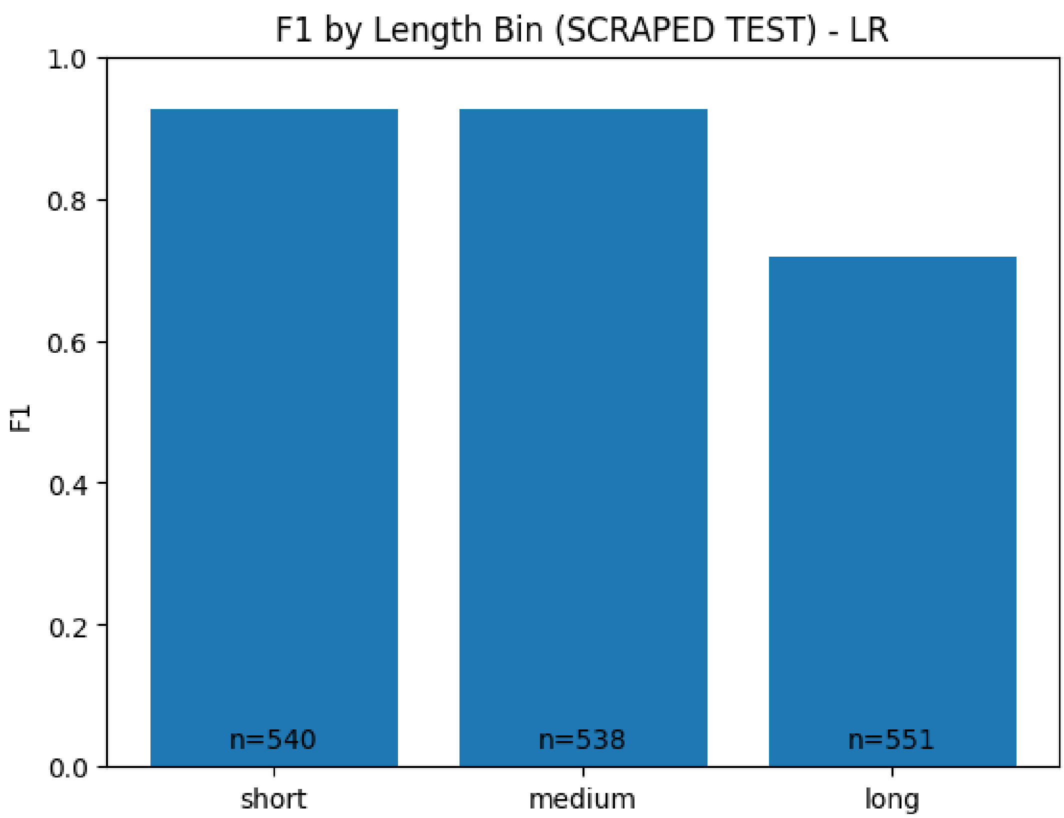
```
=== Compact metrics ===

               model split     acc    prec     rec      f1  roc_auc  pr_auc
0  LR (TF-IDF+Style)   VAL  0.9809  0.9849  0.9758  0.9804   0.9967  0.9973
1  LR (TF-IDF+Style)  TEST  0.7704  0.7892  0.9560  0.8646   0.8875  0.9647
```

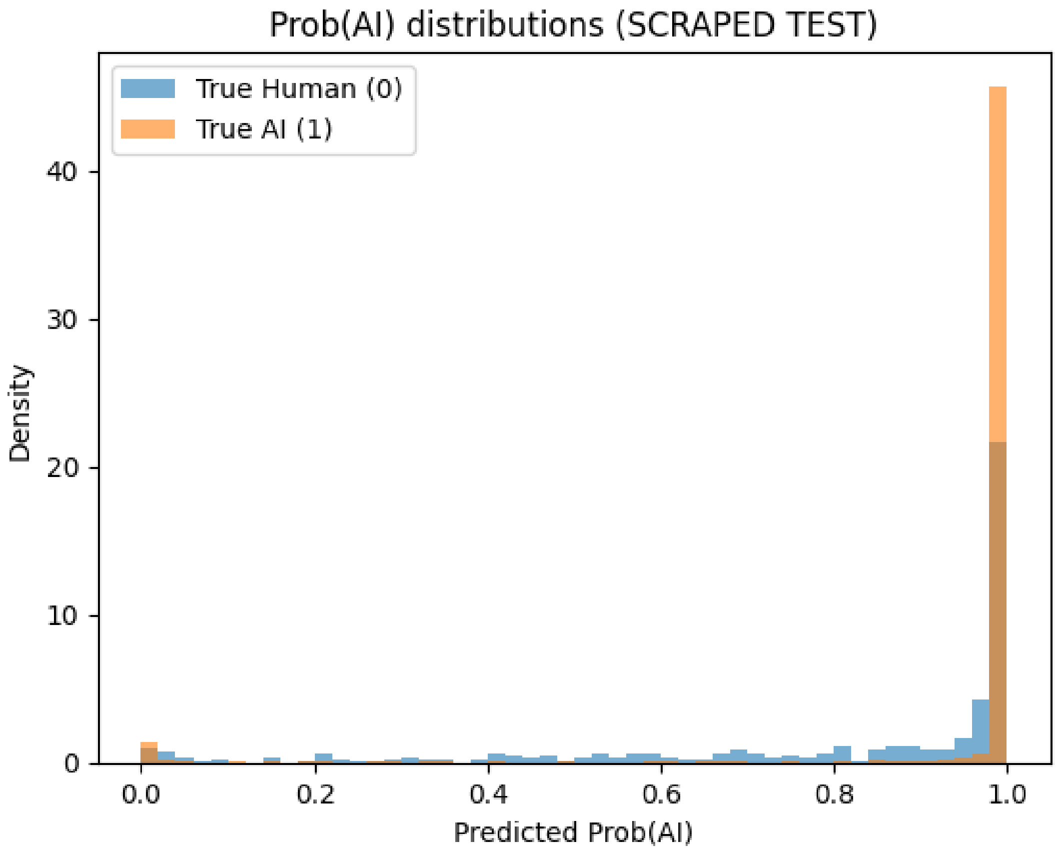



```
=== Per-source performance on SCRAPED TEST (min_n=20) ===

/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_ranking.py:442:
UndefinedMetricWarning: Only one class is present in y_true. ROC AUC score is
not defined in that case.
  warnings.warn(
/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_ranking.py:1131:
UserWarning: No positive class found in y_true, recall is set to one for all
thresholds.
  warnings.warn(
/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_ranking.py:442:
UndefinedMetricWarning: Only one class is present in y_true. ROC AUC score is
not defined in that case.
  warnings.warn(
/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_ranking.py:442:
UndefinedMetricWarning: Only one class is present in y_true. ROC AUC score is
not defined in that case.
  warnings.warn(
/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_ranking.py:1131:
UserWarning: No positive class found in y_true, recall is set to one for all
```

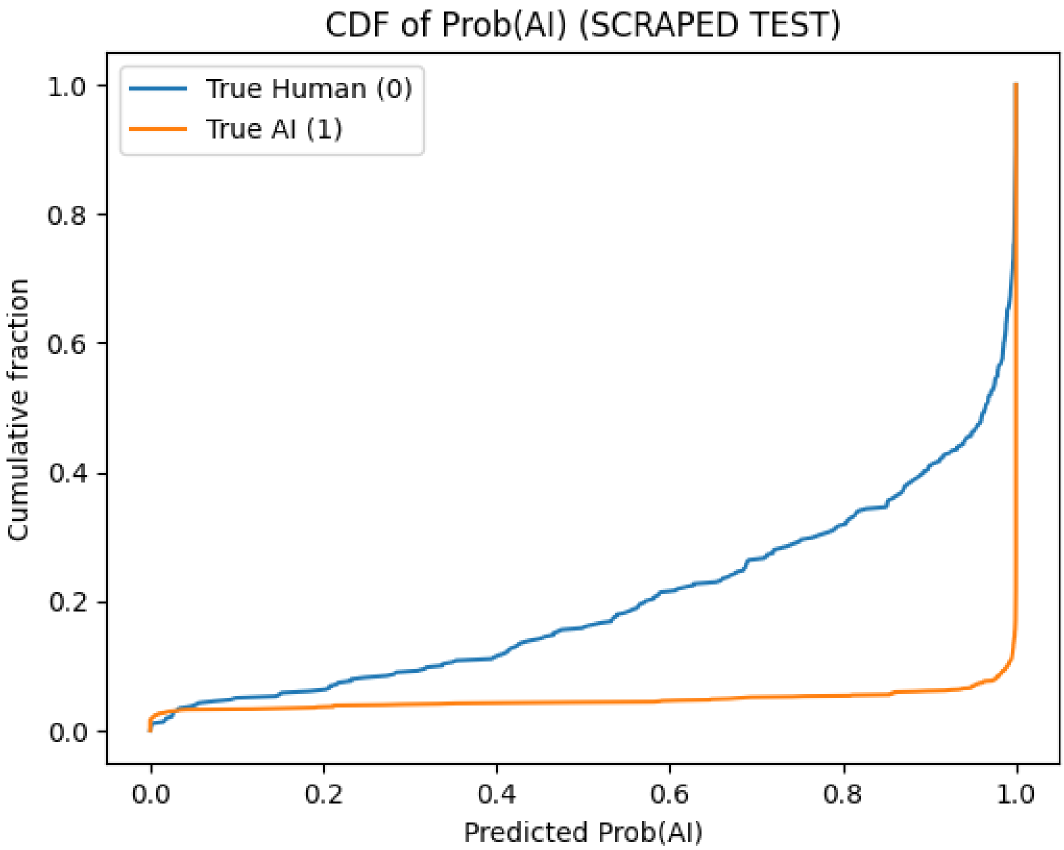
```
thresholds.
  warnings.warn(
/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_ranking.py:442:
UndefinedMetricWarning: Only one class is present in y_true. ROC AUC score is
not defined in that case.
  warnings.warn(
/usr/local/lib/python3.12/dist-packages/sklearn/metrics/_ranking.py:1131:
UserWarning: No positive class found in y_true, recall is set to one for all
thresholds.
  warnings.warn(
```

	source	n	acc	prec	rec	f1	roc_auc	pr_auc
1	chatgpt	1249	0.9560	1.0	0.956	0.9775	NaN	1.0
0	arxiv	62	0.0000	0.0	0.000	0.0000	NaN	0.0
2	news	97	0.3402	0.0	0.000	0.0000	NaN	0.0
3	wikipedia	221	0.1267	0.0	0.000	0.0000	NaN	0.0





Prob(AI) distributions (SCRAPED TEST)
True Human (0)
True AI (1)
Density
0
10
20
30
40
0.0
0.2
0.4
0.6
0.8
1.0
Predicted Prob(AI)



[12]:
```
# ========================
# INTERACTIVE CUSTOM INPUT TESTER (LogReg TF-IDF + Stylometry)
# Single-cell, notebook-friendly
#
# Requires (already defined in notebook):
#   lr_pipe
#   style_cols
#   compute_all_features_final()
#   TEST_PROB_AI        (from dashboard cell)
#   y_test              (scraped test labels)
#
# If widgets do not render:
#   pip install ipywidgets
# ========================

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

import ipywidgets as widgets
```

```python
from IPython.display import display, clear_output


# ---------- helper: overlay confidence marker ----------
def _plot_conf_dist_with_marker(y_true, p_ai, marker_prob):
    p_h = p_ai[y_true == 0]
    p_a = p_ai[y_true == 1]
    bins = np.linspace(0, 1, 51)

    fig, ax = plt.subplots()
    ax.hist(p_h, bins=bins, alpha=0.6, density=True, label="True Human (0)")
    ax.hist(p_a, bins=bins, alpha=0.6, density=True, label="True AI (1)")
    ax.axvline(marker_prob, linestyle="--", linewidth=2, color="black")
    ax.text(marker_prob, ax.get_ylim()[1]*0.95, "Custom input",
            rotation=90, va="top", ha="right")
    ax.set_title("Prob(AI) distribution on SCRAPED TEST")
    ax.set_xlabel("Predicted Prob(AI)")
    ax.set_ylabel("Density")
    ax.legend()
    plt.show()


# ---------- core prediction ----------
def _run_custom_prediction(text, max_lines, top_k, overlay):
    feats = compute_all_features_final(text, max_lines=max_lines)

    row = {c: float(feats.get(c, 0.0)) for c in style_cols}
    row["text"] = text
    X_one = pd.DataFrame([row])

    prob_ai = float(lr_pipe.predict_proba(X_one)[:, 1][0])
    pred = int(prob_ai >= 0.5)
    conf = prob_ai if pred == 1 else (1 - prob_ai)

    print("Prediction:", "AI (1)" if pred == 1 else "Human (0)")
    print(f"Prob(AI):   {prob_ai:.4f}")
    print(f"Confidence: {conf:.4f}")

    # ---- show key stylometry (interpretable) ----
    print("\n--- Stylometric summary ---")
    for k in [
        "num_words","num_sentences","avg_sentence_length",
        "type_token_ratio","pct_punct",
        "sentence_length_std","bigram_repetition_ratio"
    ]:
        if k in feats:
            print(f"{k}: {feats[k]}")
```

```
    # ---- per-sample LR contributions ----
    try:
        features = lr_pipe.named_steps["features"]
        tfidf_vec = features.named_transformers_["tfidf"]
        tfidf_names = tfidf_vec.get_feature_names_out()

        X_trans = features.transform(X_one).tocoo()
        coef = lr_pipe.named_steps["clf"].coef_[0]
        contrib = X_trans.data * coef[X_trans.col]

        feature_names = np.concatenate([tfidf_names, np.array(style_cols,
 ↪dtype=object)])
        order = np.argsort(np.abs(contrib))[::-1][:top_k]

        print(f"\n--- Top {top_k} feature contributions ---")
        for i in order:
            fname = feature_names[X_trans.col[i]]
            print(f"{fname}: {contrib[i]:+.6f}")
    except Exception as e:
        print("\n(Contribution breakdown skipped:", e, ")")

    # ---- overlay marker on TEST distribution ----
    if overlay:
        _plot_conf_dist_with_marker(np.array(y_test), TEST_PROB_AI, prob_ai)


# ---------- widgets UI ----------
text_box = widgets.Textarea(
    placeholder="Paste text here...",
    layout=widgets.Layout(width="100%", height="180px")
)

max_lines_slider = widgets.IntSlider(
    value=5, min=1, max=50, step=1,
    description="max_lines"
)

topk_slider = widgets.IntSlider(
    value=12, min=5, max=30, step=1,
    description="top_k"
)

overlay_checkbox = widgets.Checkbox(
    value=True,
    description="Overlay on TEST confidence plot"
)
```

```
run_button = widgets.Button(
    description="Predict",
    button_style="primary"
)

output = widgets.Output()

def on_run(_):
    with output:
        clear_output(wait=True)
        txt = text_box.value.strip()
        if not txt:
            print("Please paste some text.")
            return
        _run_custom_prediction(
            txt,
            max_lines_slider.value,
            topk_slider.value,
            overlay_checkbox.value
        )

run_button.on_click(on_run)

display(
    text_box,
    widgets.HBox([max_lines_slider, topk_slider, overlay_checkbox, run_button]),
    output
)
```

```
Textarea(value='', layout=Layout(height='180px', width='100%'),␣
↪placeholder='Paste text here…')
```

```
HBox(children=(IntSlider(value=5, description='max_lines', max=50, min=1),␣
↪IntSlider(value=12, description='to…
```

```
Output()
```

[13]:

```
# === SAVE FIXED SPLITS TO GOOGLE DRIVE (for reuse in LSTM) ===


from pathlib import Path
import json

ART_DIR = Path("/content/drive/MyDrive/artifacts/data_splits_v1")
ART_DIR.mkdir(parents=True, exist_ok=True)

#Make sure these exists
```

```python
# train_all, val_all, test_all  (DataFrames with 'text' + style feature columns)
# y_train, y_val, y_test
# style_cols (list of stylometry column names)

# --- sanity checks ---
for name, df in [("train_all", train_all), ("val_all", val_all), ("test_all",␣
↪test_all)]:
    missing = [c for c in ["text"] + style_cols if c not in df.columns]
    if missing:
        raise ValueError(f"{name} missing columns: {missing[:10]}{'...' if␣
↪len(missing)>10 else ''}")

# --- keep only what LSTM needs ---
train_export = train_all[["text"] + style_cols].copy()
val_export   = val_all[["text"] + style_cols].copy()
test_export  = test_all[["text"] + style_cols].copy()

train_export["label"] = y_train
val_export["label"]   = y_val
test_export["label"]  = y_test

# --- save datasets ---
try:
    train_export.to_parquet(ART_DIR / "train_all.parquet", index=False)
    val_export.to_parquet(ART_DIR / "val_all.parquet", index=False)
    test_export.to_parquet(ART_DIR / "test_all.parquet", index=False)
    fmt = "parquet"
except Exception:
    train_export.to_csv(ART_DIR / "train_all.csv", index=False)
    val_export.to_csv(ART_DIR / "val_all.csv", index=False)
    test_export.to_csv(ART_DIR / "test_all.csv", index=False)
    fmt = "csv"

# --- save metadata (style column order is critical) ---
meta = {
    "format": fmt,
    "style_cols": style_cols
}
with open(ART_DIR / "meta.json", "w") as f:
    json.dump(meta, f)

print(" Exported text+stylometry datasets to:", ART_DIR)
print("Format:", fmt)
print("Train shape:", train_export.shape, "Val shape:", val_export.shape, "Test␣
↪shape:", test_export.shape)
```

```
Exported text+stylometry datasets to:
```

```
/content/drive/MyDrive/artifacts/data_splits_v1
Format: parquet
Train shape: (32615, 35) Val shape: (5756, 35) Test shape: (1629, 35)
```

[13]:

```
[14]: # from https://gist.github.com/jonathanagustin/b67b97ef12c53a8dec27b343dca4abba
# install can take a minute

import os
# @title Convert Notebook to PDF. Save Notebook to given directory
NOTEBOOKS_DIR = "/content/drive/MyDrive/" # @param {type:"string"}
NOTEBOOK_NAME = "03_feature_engineering_and_baseline_models.ipynb" # @param␣
 ↪{type:"string"}
#------------------------------------------------------------------------------#
from google.colab import drive
drive.mount("/content/drive/", force_remount=True)
NOTEBOOK_PATH = f"{NOTEBOOKS_DIR}/{NOTEBOOK_NAME}"
assert os.path.exists(NOTEBOOK_PATH), f"NOTEBOOK NOT FOUND: {NOTEBOOK_PATH}"
!apt install -y texlive-xetex texlive-fonts-recommended texlive-plain-generic >␣
 ↪/dev/null 2>&1
!apt install pandoc > /dev/null 2>&1
!jupyter nbconvert "$NOTEBOOK_PATH" --to pdf > /dev/null 2>&1
NOTEBOOK_PDF = NOTEBOOK_PATH.rsplit('.', 1)[0] + '.pdf'
assert os.path.exists(NOTEBOOK_PDF), f"ERROR MAKING PDF: {NOTEBOOK_PDF}"
print(f"PDF CREATED: {NOTEBOOK_PDF}")
```

```
Mounted at /content/drive/
```

```
---------------------------------------------------------------------------
AssertionError                            Traceback (most recent call last)
/tmp/ipython-input-2634410530.py in <cell line: 0>()
     10 drive.mount("/content/drive/", force_remount=True)
     11 NOTEBOOK_PATH = f"{NOTEBOOKS_DIR}/{NOTEBOOK_NAME}"
---> 12 assert os.path.exists(NOTEBOOK_PATH), f"NOTEBOOK NOT FOUND:␣
 ↪{NOTEBOOK_PATH}"
     13 get_ipython().system('apt install -y texlive-xetex␣
 ↪texlive-fonts-recommended texlive-plain-generic > /dev/null 2>&1')
     14 get_ipython().system('apt install pandoc > /dev/null 2>&1')

AssertionError: NOTEBOOK NOT FOUND: /content/drive/MyDrive//
 ↪03_feature_engineering_and_baseline_models.ipynb
```

[13]:

[13]: