03_feature_engineering_and_baseline_models

December 15, 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
  Using cached 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)
 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)
df = pd.read_csv(
    CSV_PATH,
```

```python
    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()
```

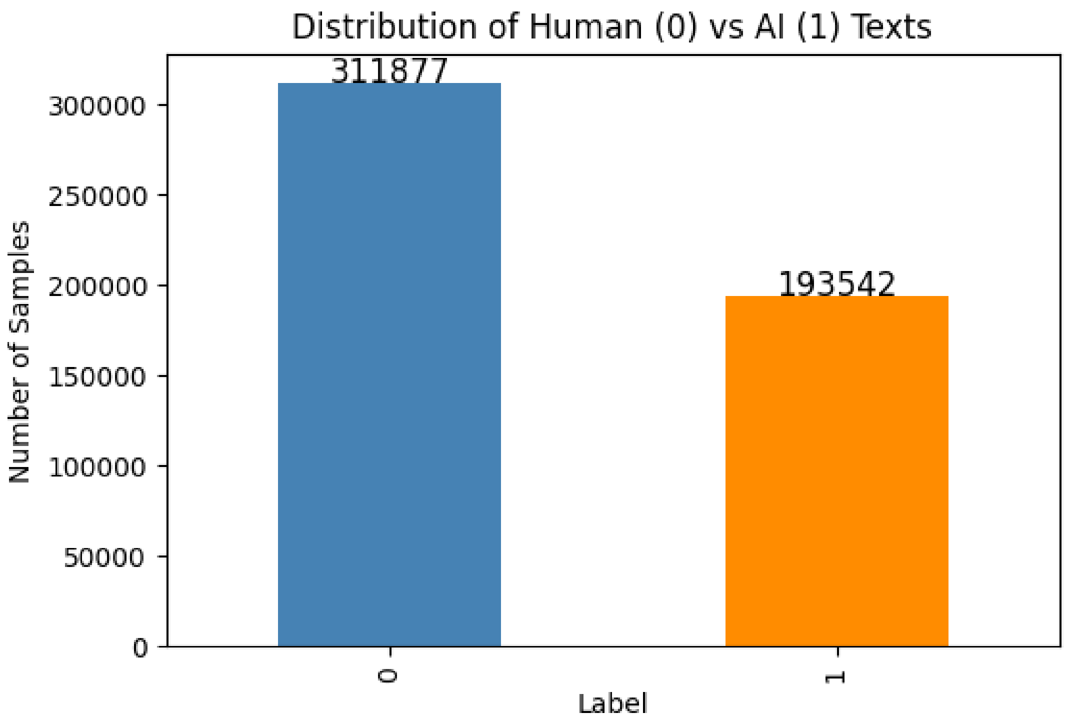
```
Columns: Index(['text', 'label', 'doc_id', 'source'], dtype='object')
First few rows:

                                                text  label    doc_id  source
0  Dear principal I agree with you with the extra…      0  kaggle_0  kaggle
```

```
1  Should or Shouldn't drivers USJ devices while …      0  kaggle_1  kaggle
2  My friend and I decided to take on the challen…      1  kaggle_2  kaggle
3  Dear Principal, I know that you are thinking o…      0  kaggle_3  kaggle
4  A think it is a good idea for students to iden…      0  kaggle_4  kaggle

Dataset shape: (505419, 4)

Label value counts:
label
0    311877
1    193542
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),
    }


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):
```

```python
    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()),
        }
    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))
```

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

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

FAKE_CITATION_PATTERNS = [
    r"\[\d+\]",        # [1], [23]
```

```python
    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
# ============================================================

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]:
```
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)
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       38354
chatgpt       1235
wikipedia      206
news           132
arxiv           73
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       1218        180             12            15.000000          0.700000
1       4201        686             26            26.384615          0.377551
2       5951       1056             36            29.333334          0.253788
3       2838        419             16            26.187500          0.584726
4       1434        272             22            12.363636          0.525735

   unique_words  pct_punct  pct_upper  pct_digit  flesch_reading_ease  …  \
```

```
0           126   0.089491   0.041051   0.005747             36.959293  …
1           259   0.025708   0.024994   0.001190             35.829475  …
2           268   0.012771   0.008234   0.000000             55.274792  …
3           245   0.023961   0.016561   0.003171             17.919603  …
4           143   0.025105   0.018828   0.000000             81.331154  …

   double_dash_ratio  colon_ratio_emphasis  semicolon_ratio_emphasis  \
0           0.001642              0.004105                       0.0
1           0.000000              0.000000                       0.0
2           0.000000              0.000000                       0.0
3           0.000000              0.000705                       0.0
4           0.000000              0.000000                       0.0

   emphasis_punctuation_ratio  hedge_phrase_count  hedge_phrase_ratio  \
0                    0.006568                   0                 0.0
1                    0.000000                   2                 2.0
2                    0.000000                   0                 0.0
3                    0.000705                   0                 0.0
4                    0.000000                   0                 0.0

   hedge_line_ratio  generic_claim_ratio  vague_quantifier_ratio  \
0               0.0                  0.0                     0.0
1               1.0                  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)
# 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
# =========================
```

```python
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)
```

```python
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),
    ],
    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
```

```python
# --------------------------
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     0.9755    0.9765    0.9760      2000
           1     0.9765    0.9755    0.9760      2000

    accuracy                         0.9760      4000
   macro avg     0.9760    0.9760    0.9760      4000
weighted avg     0.9760    0.9760    0.9760      4000

TEST:
              precision    recall  f1-score   support
```

```
           0     0.9768    0.9788    0.9778      4001
           1     0.9787    0.9768    0.9777      4000

    accuracy                         0.9778      8001
   macro avg     0.9778    0.9778    0.9778      8001
weighted avg     0.9778    0.9778    0.9778      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     0.9885    0.9910    0.9898      2000
           1     0.9910    0.9885    0.9897      2000

    accuracy                         0.9898      4000
   macro avg     0.9898    0.9898    0.9897      4000
weighted avg     0.9898    0.9898    0.9897      4000

TEST:
              precision    recall  f1-score   support

           0     0.9925    0.9928    0.9926      4001
           1     0.9927    0.9925    0.9926      4000

    accuracy                         0.9926      8001
   macro avg     0.9926    0.9926    0.9926      8001
weighted avg     0.9926    0.9926    0.9926      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     0.9830    0.9838    0.9834      4001
           1     0.9837    0.9830    0.9834      4000

    accuracy                         0.9834      8001
   macro avg     0.9834    0.9834    0.9834      8001
weighted avg     0.9834    0.9834    0.9834      8001


TF-IDF feature count: 335196
Example TF-IDF features: ['00' '00 am' '00 and' '00 expecting' '00 if' '00 or'
'00 pm' '00 to'
 '00 which' '000' '000 000' '000 accidents' '000 along' '000 alongside'
 '000 and' '000 are' '000 because' '000 being' '000 but' '000 car'
 '000 cr' '000 deaths' '000 dollar' '000 dollars' '000 driver']
Total hybrid feature count: 335229
```

[8]:

```python
#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
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."
```

```python
#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)
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)
```

```python
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 : 38354
  Scraped rows: 1646
  Dropped scraped overlaps vs Kaggle: 0
  Final TEST rows (scraped, deduped): 1646

Text-hash overlaps (should be 0):
  TRAIN   VAL : 28
```

```
  TRAIN   TEST: 0
  VAL     TEST: 0

Split sizes: 32600 5754 1646
Label dist TRAIN: [16650 15950]
Label dist VAL:   [2939 2815]
Label dist TEST:  [ 411 1235]
```

[ ]:
```
# 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
# -------------------------
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([
```

```python
    ("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("\nCompact 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()

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     0.9814    0.9881    0.9847      2939
           1     0.9875    0.9805    0.9840      2815

    accuracy                         0.9844      5754
   macro avg     0.9844    0.9843    0.9843      5754
weighted avg     0.9844    0.9844    0.9844      5754

TEST:
              precision    recall  f1-score   support

           0     0.5755    0.1484    0.2360       411
           1     0.7727    0.9636    0.8577      1235

    accuracy                         0.7600      1646
   macro avg     0.6741    0.5560    0.5468      1646
weighted avg     0.7235    0.7600    0.7024      1646
```

[ ]:
```
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)
```

[ ]:
```
# DASHBOARD: LR (TF-IDF + Stylometry) interpretability
#
# 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
```

```python
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()
    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)

#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
```

[ ]:
```
# =========================
# 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
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()
```

```python
# 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, ")")
```

```python
    # 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
)
```

[ ]:
```
# === 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
# 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"

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)
```

[ ]:
```
#Final Commit
```

[ ]:
```
# 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}")
```