

# 05\_linear\_probe\_pretrained\_encoder

December 14, 2025

## 1 Linear Probe on a Pretrained Encoder

Goal: Evaluate how well a **frozen pretrained text encoder** separates human-written vs LLM-generated text using a **linear classifier** on top.

- Encoder is frozen (no fine-tuning).
- Only a lightweight classifier is trained.
- Uses the fixed `splits_v1` created in notebook 03.

```
[2]: import numpy as np
import pandas as pd
from pathlib import Path
from tqdm.auto import tqdm
import json
from datetime import datetime
```

```
[3]: !pip -q install sentence-transformers scikit-learn pandas numpy tqdm
```

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

Mounted at /content/drive

```
[4]: # === LOAD FIXED SPLITS (exported from baseline notebook) ===

# from google.colab import drive
# drive.mount("/content/drive")

import json
from pathlib import Path
import pandas as pd
import numpy as np

ART_DIR = Path("/content/drive/MyDrive/artifacts/data_splits_v1") # same ↵
folder used in baseline

# --- load metadata ---
with open(ART_DIR / "meta.json") as f:
```

```

meta = json.load(f)

fmt = meta["format"]
style_cols = meta["style_cols"]

# --- load datasets ---
if fmt == "parquet":
    train_df = pd.read_parquet(ART_DIR / "train_all.parquet")
    val_df   = pd.read_parquet(ART_DIR / "val_all.parquet")
    test_df  = pd.read_parquet(ART_DIR / "test_all.parquet")
else:
    train_df = pd.read_csv(ART_DIR / "train_all.csv")
    val_df   = pd.read_csv(ART_DIR / "val_all.csv")
    test_df  = pd.read_csv(ART_DIR / "test_all.csv")

# --- sanity checks (text + label + style columns) ---
required_cols = ["text", "label", "source"] + style_cols

for name, df in [("train", train_df), ("val", val_df), ("test", test_df)]:
    missing = [c for c in required_cols if c not in df.columns]
    if missing:
        raise ValueError(f"{name} split missing columns: {missing[:15]}{' ... '}" if len(missing) > 15 else '')
    print(f"Loaded splits from: {ART_DIR}")
    print(f"Format: {fmt}")
    print(f"Sizes: {len(train_df)} {len(val_df)} {len(test_df)}")
    print(f"Label dist train: {np.bincount(y_train)}")
    print(f"Label dist val: {np.bincount(y_val)}")
    print(f"Label dist test: {np.bincount(y_test)}")
    print(f"Num stylometry features: {len(style_cols)}")

```

Loaded splits from: /content/drive/MyDrive/artifacts/data\_splits\_v1  
 Format: parquet  
 Sizes: 32615 5756 1629  
 Label dist train: [16677 15938]  
 Label dist val: [2943 2813]  
 Label dist test: [ 380 1249]  
 Num stylometry features: 33

[5]: `from sentence_transformers import SentenceTransformer`

```

ENCODER_NAME = "sentence-transformers/all-MiniLM-L6-v2"

encoder = SentenceTransformer(ENCODER_NAME)
encoder.max_seq_length = 256
print("Loaded encoder:", ENCODER_NAME)

```

```

/usr/local/lib/python3.12/dist-packages/huggingface_hub/utils/_auth.py:94:
UserWarning:
The secret `HF_TOKEN` does not exist in your Colab secrets.
To authenticate with the Hugging Face Hub, create a token in your settings tab
(https://huggingface.co/settings/tokens), set it as secret in your Google Colab
and restart your session.
You will be able to reuse this secret in all of your notebooks.
Please note that authentication is recommended but still optional to access
public models or datasets.

    warnings.warn(
modules.json: 0%|          0.00/349 [00:00<?, ?B/s]
config_sentence_transformers.json: 0%|          0.00/116 [00:00<?, ?B/s]
README.md: 0.00B [00:00, ?B/s]
sentence_bert_config.json: 0%|          0.00/53.0 [00:00<?, ?B/s]
config.json: 0%|          0.00/612 [00:00<?, ?B/s]
model.safetensors: 0%|          0.00/90.9M [00:00<?, ?B/s]
tokenizer_config.json: 0%|          0.00/350 [00:00<?, ?B/s]
vocab.txt: 0.00B [00:00, ?B/s]
tokenizer.json: 0.00B [00:00, ?B/s]
special_tokens_map.json: 0%|          0.00/112 [00:00<?, ?B/s]
config.json: 0%|          0.00/190 [00:00<?, ?B/s]

Loaded encoder: sentence-transformers/all-MiniLM-L6-v2

```

[6]: # Cache embeddings so we don't re-encode every time

```

CACHE_DIR = Path("/content/drive/MyDrive/artifacts/linear_probe/cache")
CACHE_DIR.mkdir(parents=True, exist_ok=True)

def embed_texts(texts, cache_path: Path, batch_size: int = 64):
    if cache_path.exists():
        return np.load(cache_path)
    emb = encoder.encode(
        texts,
        batch_size=batch_size,
        show_progress_bar=True,
        convert_to_numpy=True,

```

```

        normalize_embeddings=True
    )
np.save(cache_path, emb)
return emb

X_train = embed_texts(train_df["text"].tolist(), CACHE_DIR / "X_train.npy")
X_val   = embed_texts(val_df["text"].tolist(),   CACHE_DIR / "X_val.npy")
X_test  = embed_texts(test_df["text"].tolist(),  CACHE_DIR / "X_test.npy")

print(" Embeddings shapes:", X_train.shape, X_val.shape, X_test.shape)

```

```

Batches:  0%| 0/510 [00:00<?, ?it/s]
Batches:  0%| 0/90 [00:00<?, ?it/s]
Batches:  0%| 0/26 [00:00<?, ?it/s]

Embeddings shapes: (32615, 384) (5756, 384) (1629, 384)

```

```

[7]: from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, f1_score, classification_report

clf = LogisticRegression(max_iter=2000, n_jobs=-1)
clf.fit(X_train, y_train)

val_pred = clf.predict(X_val)
val_prob = clf.predict_proba(X_val)[:, 1]

test_pred = clf.predict(X_test)
test_prob = clf.predict_proba(X_test)[:, 1]

val_acc = accuracy_score(y_val, val_pred)
val_f1  = f1_score(y_val, val_pred)

test_acc = accuracy_score(y_test, test_pred)
test_f1  = f1_score(y_test, test_pred)

print("VAL acc/f1:", val_acc, val_f1)
print("TEST acc/f1:", test_acc, test_f1)

report = classification_report(y_test, test_pred, output_dict=True)
report_df = pd.DataFrame(report).transpose()
report_df.round(4)

```

```

VAL acc/f1: 0.9279013203613621 0.9256938227394808
TEST acc/f1: 0.7562922038060159 0.8566269411339834

```

	precision	recall	f1-score	support
0	0.4220	0.1211	0.1881	380.0000

```

1          0.7803  0.9496   0.8566  1249.0000
accuracy      0.7563  0.7563   0.7563      0.7563
macro avg      0.6011  0.5353   0.5224  1629.0000
weighted avg    0.6967  0.7563   0.7007  1629.0000

```

```
[9]: def summarize_results(val_acc, val_f1, test_acc, test_f1):
    df = pd.DataFrame({
        "Split": ["Validation", "Test"],
        "Accuracy": [val_acc * 100, test_acc * 100],
        "F1": [val_f1*100, test_f1*100],
    })
    return df.round(2)

summarize_results(val_acc, val_f1, test_acc, test_f1)
```

```
[9]:      Split  Accuracy     F1
0  Validation    92.79  92.57
1       Test      75.63  85.66
```

The below confusion matrix shows that the linear probe correctly identifies most AI-generated texts, but frequently misclassifies human-written text as AI. This explains the high F1 for class 1 and low recall for class 0.

```
[10]: from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, test_pred)
cm_df = pd.DataFrame(
    cm,
    index=["Human (0)", "AI (1)"],
    columns=["Pred Human", "Pred AI"]
)

cm_df
```

```
[10]:      Pred Human  Pred AI
Human (0)        46      334
AI (1)         63     1186
```

##Qualitative Analysis

```
[11]: test_results = test_df.copy()
test_results["pred"] = test_pred
test_results["prob_ai"] = test_prob

false_positives = test_results[
    (test_results["label"] == 0) & (test_results["pred"] == 1)
]

false_negatives = test_results[
```

```
(test_results["label"] == 1) & (test_results["pred"] == 0)  
]
```

```
[12]: false_positives[["text", "prob_ai"]].head(3)
```

```
[12]:  
          text      prob_ai  
1  in Seoul If you want to test yourself, here's ...  0.990763  
2  Admissibility of solution estimators for stoch...  0.924783  
9  as well as putting them at risk of becoming ta...  0.999874
```

```
[13]: false_negatives[["text", "prob_ai"]].head(3)
```

```
[13]:  
          text      prob_ai  
8  PIL_AVAILABLE = False # MolScribe for image->SM...  0.496338  
21  "We model salary as ( mathcal{N}(\mu_k + \beta c...  0.249398  
24  of all trades the model predicted as violation...  0.291505
```

Observation: Many false positives (human text predicted as AI) are highly structured, neutral in tone, and lack personal context. These stylistic traits resemble LLM-generated text, causing the encoder to overgeneralize.

False negatives (AI predicted as human) often contain informal phrasing or personal language, which reduces stereotypical AI patterns.

```
[14]: false_positives["prob_ai"].describe()
```

```
[14]: count    334.000000  
mean     0.911384  
std      0.114466  
min      0.502408  
25%     0.878895  
50%     0.963300  
75%     0.989214  
max      0.999973  
Name: prob_ai, dtype: float64
```

```
[15]: false_negatives["prob_ai"].describe()
```

```
[15]: count    63.000000  
mean     0.340110  
std      0.129131  
min      0.027534  
25%     0.257143  
50%     0.374614  
75%     0.440502  
max      0.499187  
Name: prob_ai, dtype: float64
```

[ ]:

[ ]:

[ ]:

[ ]:

```
[16]: # 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 = "05_linear_probe_pretrained_encoder.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}")
```

```
KeyboardInterrupt                                     Traceback (most recent call last)
```

```
/tmp/ipython-input-3056652466.py in <cell line: 0>()
```

```
    8
    ↪#-----#
    9 from google.colab import drive
---> 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}"
```

```
/usr/local/lib/python3.12/dist-packages/google/colab/drive.py in_
    ↪mount(mountpoint, force_remount, timeout_ms, readonly)
```

```
    95     def mount(mountpoint, force_remount=False, timeout_ms=120000,_
    ↪readonly=False):
    96         """Mount your Google Drive at the specified mountpoint path."""
```

```

---> 97     return _mount(
98         mountpoint,
99         force_remount=force_remount,
100
101     /usr/local/lib/python3.12/dist-packages/google/colab/drive.py in _mount(mountpoint, force_remount, timeout_ms, ephemeral, readonly)
102         250
103         251     while True:
104 --> 252         case = d.expect([
105             253             success,
106             254             prompt,
107
108     /usr/local/lib/python3.12/dist-packages/pexpect/spawnbase.py in expect(self, pattern, timeout, searchwindowsize, async_, **kw)
109         352
110         353     compiled_pattern_list = self.compile_pattern_list(pattern)
111 --> 354     return self.expect_list(compiled_pattern_list,
112             355             timeout, searchwindowsize, async_)
113             356
114
115     /usr/local/lib/python3.12/dist-packages/pexpect/spawnbase.py in expect_list(self, pattern_list, timeout, searchwindowsize, async_, **kw)
116         381             return expect_async(exp, timeout)
117         382         else:
118 --> 383             return exp.expect_loop(timeout)
119         384
120         385     def expect_exact(self, pattern_list, timeout=-1, searchwindowsize=-1):
121
122     /usr/local/lib/python3.12/dist-packages/pexpect/expect.py in expect_loop(self, timeout)
123         169             incoming = spawn.read_nonblocking(spawn.maxread, timeout)
124         170             if self.spawn.delayafterread is not None:
125 --> 171                 time.sleep(self.spawn.delayafterread)
126         172             idx = self.new_data(incoming)
127             # Keep reading until exception or return.

```

KeyboardInterrupt: