# takehomeassessment (3)

### April 22, 2025

## Task 0: Make Relevant Imports

[]: !pip install transformers datasets sentence\_transformers

```
Requirement already satisfied: transformers in /usr/local/lib/python3.11/dist-
packages (4.51.3)
Collecting datasets
 Downloading datasets-3.5.0-py3-none-any.whl.metadata (19 kB)
Requirement already satisfied: sentence_transformers in
/usr/local/lib/python3.11/dist-packages (3.4.1)
Requirement already satisfied: filelock in /usr/local/lib/python3.11/dist-
packages (from transformers) (3.18.0)
Requirement already satisfied: huggingface-hub<1.0,>=0.30.0 in
/usr/local/lib/python3.11/dist-packages (from transformers) (0.30.2)
Requirement already satisfied: numpy>=1.17 in /usr/local/lib/python3.11/dist-
packages (from transformers) (2.0.2)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.11/dist-packages (from transformers) (24.2)
Requirement already satisfied: pyyaml>=5.1 in /usr/local/lib/python3.11/dist-
packages (from transformers) (6.0.2)
Requirement already satisfied: regex!=2019.12.17 in
/usr/local/lib/python3.11/dist-packages (from transformers) (2024.11.6)
Requirement already satisfied: requests in /usr/local/lib/python3.11/dist-
packages (from transformers) (2.32.3)
Requirement already satisfied: tokenizers<0.22,>=0.21 in
/usr/local/lib/python3.11/dist-packages (from transformers) (0.21.1)
Requirement already satisfied: safetensors>=0.4.3 in
/usr/local/lib/python3.11/dist-packages (from transformers) (0.5.3)
Requirement already satisfied: tqdm>=4.27 in /usr/local/lib/python3.11/dist-
packages (from transformers) (4.67.1)
Requirement already satisfied: pyarrow>=15.0.0 in
/usr/local/lib/python3.11/dist-packages (from datasets) (18.1.0)
Collecting dill<0.3.9,>=0.3.0 (from datasets)
  Downloading dill-0.3.8-py3-none-any.whl.metadata (10 kB)
Requirement already satisfied: pandas in /usr/local/lib/python3.11/dist-packages
(from datasets) (2.2.2)
Collecting xxhash (from datasets)
 Downloading
```

```
xxhash-3.5.0-cp311-cp311-manylinux 2_17_x86_64.manylinux2014_x86_64.whl.metadata
(12 kB)
Collecting multiprocess<0.70.17 (from datasets)
  Downloading multiprocess-0.70.16-py311-none-any.whl.metadata (7.2 kB)
Collecting fsspec<=2024.12.0,>=2023.1.0 (from
fsspec[http] <= 2024.12.0, >= 2023.1.0 -> datasets)
 Downloading fsspec-2024.12.0-py3-none-any.whl.metadata (11 kB)
Requirement already satisfied: aiohttp in /usr/local/lib/python3.11/dist-
packages (from datasets) (3.11.15)
Requirement already satisfied: torch>=1.11.0 in /usr/local/lib/python3.11/dist-
packages (from sentence_transformers) (2.6.0+cu124)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.11/dist-
packages (from sentence_transformers) (1.6.1)
Requirement already satisfied: scipy in /usr/local/lib/python3.11/dist-packages
(from sentence_transformers) (1.14.1)
Requirement already satisfied: Pillow in /usr/local/lib/python3.11/dist-packages
(from sentence_transformers) (11.1.0)
Requirement already satisfied: aiohappyeyeballs>=2.3.0 in
/usr/local/lib/python3.11/dist-packages (from aiohttp->datasets) (2.6.1)
Requirement already satisfied: aiosignal>=1.1.2 in
/usr/local/lib/python3.11/dist-packages (from aiohttp->datasets) (1.3.2)
Requirement already satisfied: attrs>=17.3.0 in /usr/local/lib/python3.11/dist-
packages (from aiohttp->datasets) (25.3.0)
Requirement already satisfied: frozenlist>=1.1.1 in
/usr/local/lib/python3.11/dist-packages (from aiohttp->datasets) (1.5.0)
Requirement already satisfied: multidict<7.0,>=4.5 in
/usr/local/lib/python3.11/dist-packages (from aiohttp->datasets) (6.4.3)
Requirement already satisfied: propcache>=0.2.0 in
/usr/local/lib/python3.11/dist-packages (from aiohttp->datasets) (0.3.1)
Requirement already satisfied: yarl<2.0,>=1.17.0 in
/usr/local/lib/python3.11/dist-packages (from aiohttp->datasets) (1.19.0)
Requirement already satisfied: typing-extensions>=3.7.4.3 in
/usr/local/lib/python3.11/dist-packages (from huggingface-
hub<1.0,>=0.30.0->transformers) (4.13.2)
Requirement already satisfied: charset-normalizer<4,>=2 in
/usr/local/lib/python3.11/dist-packages (from requests->transformers) (3.4.1)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.11/dist-
packages (from requests->transformers) (3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/usr/local/lib/python3.11/dist-packages (from requests->transformers) (2.3.0)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.11/dist-packages (from requests->transformers)
(2025.1.31)
Requirement already satisfied: networkx in /usr/local/lib/python3.11/dist-
packages (from torch>=1.11.0->sentence_transformers) (3.4.2)
Requirement already satisfied: jinja2 in /usr/local/lib/python3.11/dist-packages
(from torch>=1.11.0->sentence_transformers) (3.1.6)
Collecting nvidia-cuda-nvrtc-cu12==12.4.127 (from
```

```
torch>=1.11.0->sentence_transformers)
  Downloading nvidia_cuda_nvrtc_cu12-12.4.127-py3-none-
manylinux2014_x86_64.whl.metadata (1.5 kB)
Collecting nvidia-cuda-runtime-cu12==12.4.127 (from
torch>=1.11.0->sentence transformers)
  Downloading nvidia_cuda_runtime_cu12-12.4.127-py3-none-
manylinux2014_x86_64.whl.metadata (1.5 kB)
Collecting nvidia-cuda-cupti-cu12==12.4.127 (from
torch>=1.11.0->sentence_transformers)
 Downloading nvidia_cuda_cupti_cu12-12.4.127-py3-none-
manylinux2014_x86_64.whl.metadata (1.6 kB)
Collecting nvidia-cudnn-cu12==9.1.0.70 (from
torch>=1.11.0->sentence_transformers)
  Downloading nvidia_cudnn_cu12-9.1.0.70-py3-none-
manylinux2014_x86_64.whl.metadata (1.6 kB)
Collecting nvidia-cublas-cu12==12.4.5.8 (from
torch>=1.11.0->sentence_transformers)
  Downloading nvidia_cublas_cu12-12.4.5.8-py3-none-
manylinux2014_x86_64.whl.metadata (1.5 kB)
Collecting nvidia-cufft-cu12==11.2.1.3 (from
torch>=1.11.0->sentence_transformers)
 Downloading nvidia cufft cu12-11.2.1.3-py3-none-
manylinux2014_x86_64.whl.metadata (1.5 kB)
Collecting nvidia-curand-cu12==10.3.5.147 (from
torch>=1.11.0->sentence_transformers)
  Downloading nvidia_curand_cu12-10.3.5.147-py3-none-
manylinux2014_x86_64.whl.metadata (1.5 kB)
Collecting nvidia-cusolver-cu12==11.6.1.9 (from
torch>=1.11.0->sentence_transformers)
  Downloading nvidia_cusolver_cu12-11.6.1.9-py3-none-
manylinux2014_x86_64.whl.metadata (1.6 kB)
Collecting nvidia-cusparse-cu12==12.3.1.170 (from
torch>=1.11.0->sentence_transformers)
 Downloading nvidia_cusparse_cu12-12.3.1.170-py3-none-
manylinux2014 x86 64.whl.metadata (1.6 kB)
Requirement already satisfied: nvidia-cusparselt-cu12==0.6.2 in
/usr/local/lib/python3.11/dist-packages (from
torch>=1.11.0->sentence_transformers) (0.6.2)
Requirement already satisfied: nvidia-nccl-cu12==2.21.5 in
/usr/local/lib/python3.11/dist-packages (from
torch>=1.11.0->sentence_transformers) (2.21.5)
Requirement already satisfied: nvidia-nvtx-cu12==12.4.127 in
/usr/local/lib/python3.11/dist-packages (from
torch>=1.11.0->sentence_transformers) (12.4.127)
Collecting nvidia-nvjitlink-cu12==12.4.127 (from
torch>=1.11.0->sentence_transformers)
  Downloading nvidia_nvjitlink_cu12-12.4.127-py3-none-
manylinux2014_x86_64.whl.metadata (1.5 kB)
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Requirement already satisfied: triton==3.2.0 in /usr/local/lib/python3.11/dist-
packages (from torch>=1.11.0->sentence_transformers) (3.2.0)
Requirement already satisfied: sympy==1.13.1 in /usr/local/lib/python3.11/dist-
packages (from torch>=1.11.0->sentence_transformers) (1.13.1)
Requirement already satisfied: mpmath<1.4,>=1.1.0 in
/usr/local/lib/python3.11/dist-packages (from
sympy==1.13.1->torch>=1.11.0->sentence transformers) (1.3.0)
Requirement already satisfied: python-dateutil>=2.8.2 in
/usr/local/lib/python3.11/dist-packages (from pandas->datasets) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-
packages (from pandas->datasets) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-
packages (from pandas->datasets) (2025.2)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.11/dist-
packages (from scikit-learn->sentence_transformers) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in
/usr/local/lib/python3.11/dist-packages (from scikit-
learn->sentence_transformers) (3.6.0)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-
packages (from python-dateutil>=2.8.2->pandas->datasets) (1.17.0)
Requirement already satisfied: MarkupSafe>=2.0 in
/usr/local/lib/python3.11/dist-packages (from
jinja2->torch>=1.11.0->sentence_transformers) (3.0.2)
Downloading datasets-3.5.0-py3-none-any.whl (491 kB)
                         491.2/491.2 kB
10.5 MB/s eta 0:00:00
Downloading dill-0.3.8-py3-none-any.whl (116 kB)
                         116.3/116.3 kB
11.6 MB/s eta 0:00:00
Downloading fsspec-2024.12.0-py3-none-any.whl (183 kB)
                         183.9/183.9 kB
16.8 MB/s eta 0:00:00
Downloading multiprocess-0.70.16-py311-none-any.whl (143 kB)
                         143.5/143.5 kB
13.8 MB/s eta 0:00:00
Downloading nvidia_cublas_cu12-12.4.5.8-py3-none-manylinux2014_x86_64.whl
(363.4 MB)
                         363.4/363.4 MB
3.0 MB/s eta 0:00:00
Downloading nvidia_cuda_cupti_cu12-12.4.127-py3-none-
manylinux2014_x86_64.whl (13.8 MB)
                         13.8/13.8 MB
125.2 MB/s eta 0:00:00
Downloading nvidia_cuda_nvrtc_cu12-12.4.127-py3-none-
manylinux2014_x86_64.whl (24.6 MB)
                         24.6/24.6 MB
96.9 MB/s eta 0:00:00
Downloading nvidia_cuda_runtime_cu12-12.4.127-py3-none-
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manylinux2014_x86_64.whl (883 kB)
                         883.7/883.7 kB
59.3 MB/s eta 0:00:00
Downloading nvidia_cudnn_cu12-9.1.0.70-py3-none-manylinux2014_x86_64.whl
(664.8 MB)
                         664.8/664.8 MB
1.7 MB/s eta 0:00:00
Downloading nvidia_cufft_cu12-11.2.1.3-py3-none-manylinux2014_x86_64.whl
(211.5 MB)
                         211.5/211.5 MB
12.0 MB/s eta 0:00:00
Downloading nvidia_curand_cu12-10.3.5.147-py3-none-
manylinux2014_x86_64.whl (56.3 MB)
                         56.3/56.3 MB
44.6 MB/s eta 0:00:00
Downloading nvidia_cusolver_cu12-11.6.1.9-py3-none-
manylinux2014_x86_64.whl (127.9 MB)
                         127.9/127.9 MB
20.0 MB/s eta 0:00:00
Downloading nvidia cusparse cu12-12.3.1.170-py3-none-
manylinux2014_x86_64.whl (207.5 MB)
                         207.5/207.5 MB
3.8 MB/s eta 0:00:00
Downloading nvidia_nvjitlink_cu12-12.4.127-py3-none-
manylinux2014_x86_64.whl (21.1 MB)
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104.9 MB/s eta 0:00:00
Downloading
xxhash-3.5.0-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (194 kB)
                         194.8/194.8 kB
19.3 MB/s eta 0:00:00
Installing collected packages: xxhash, nvidia-nvjitlink-cu12, nvidia-
curand-cu12, nvidia-cufft-cu12, nvidia-cuda-runtime-cu12, nvidia-cuda-nvrtc-
cu12, nvidia-cuda-cupti-cu12, nvidia-cublas-cu12, fsspec, dill, nvidia-cusparse-
cu12, nvidia-cudnn-cu12, multiprocess, nvidia-cusolver-cu12, datasets
  Attempting uninstall: nvidia-nvjitlink-cu12
    Found existing installation: nvidia-nvjitlink-cu12 12.5.82
   Uninstalling nvidia-nvjitlink-cu12-12.5.82:
      Successfully uninstalled nvidia-nvjitlink-cu12-12.5.82
 Attempting uninstall: nvidia-curand-cu12
    Found existing installation: nvidia-curand-cu12 10.3.6.82
   Uninstalling nvidia-curand-cu12-10.3.6.82:
      Successfully uninstalled nvidia-curand-cu12-10.3.6.82
  Attempting uninstall: nvidia-cufft-cu12
    Found existing installation: nvidia-cufft-cu12 11.2.3.61
   Uninstalling nvidia-cufft-cu12-11.2.3.61:
      Successfully uninstalled nvidia-cufft-cu12-11.2.3.61
  Attempting uninstall: nvidia-cuda-runtime-cu12
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Found existing installation: nvidia-cuda-runtime-cu12 12.5.82 Uninstalling nvidia-cuda-runtime-cu12-12.5.82: Successfully uninstalled nvidia-cuda-runtime-cu12-12.5.82 Attempting uninstall: nvidia-cuda-nvrtc-cu12 Found existing installation: nvidia-cuda-nvrtc-cu12 12.5.82 Uninstalling nvidia-cuda-nvrtc-cu12-12.5.82: Successfully uninstalled nvidia-cuda-nvrtc-cu12-12.5.82 Attempting uninstall: nvidia-cuda-cupti-cu12 Found existing installation: nvidia-cuda-cupti-cu12 12.5.82 Uninstalling nvidia-cuda-cupti-cu12-12.5.82: Successfully uninstalled nvidia-cuda-cupti-cu12-12.5.82 Attempting uninstall: nvidia-cublas-cu12 Found existing installation: nvidia-cublas-cu12 12.5.3.2 Uninstalling nvidia-cublas-cu12-12.5.3.2: Successfully uninstalled nvidia-cublas-cu12-12.5.3.2 Attempting uninstall: fsspec Found existing installation: fsspec 2025.3.2 Uninstalling fsspec-2025.3.2: Successfully uninstalled fsspec-2025.3.2 Attempting uninstall: nvidia-cusparse-cu12 Found existing installation: nvidia-cusparse-cu12 12.5.1.3 Uninstalling nvidia-cusparse-cu12-12.5.1.3: Successfully uninstalled nvidia-cusparse-cu12-12.5.1.3 Attempting uninstall: nvidia-cudnn-cu12 Found existing installation: nvidia-cudnn-cu12 9.3.0.75 Uninstalling nvidia-cudnn-cu12-9.3.0.75: Successfully uninstalled nvidia-cudnn-cu12-9.3.0.75 Attempting uninstall: nvidia-cusolver-cu12 Found existing installation: nvidia-cusolver-cu12 11.6.3.83 Uninstalling nvidia-cusolver-cu12-11.6.3.83: Successfully uninstalled nvidia-cusolver-cu12-11.6.3.83 ERROR: pip's dependency resolver does not currently take into account all the packages that are installed. This behaviour is the source of the following dependency conflicts. gcsfs 2025.3.2 requires fsspec==2025.3.2, but you have fsspec 2024.12.0 which is incompatible. Successfully installed datasets-3.5.0 dill-0.3.8 fsspec-2024.12.0 multiprocess-0.70.16 nvidia-cublas-cu12-12.4.5.8 nvidia-cuda-cupti-cu12-12.4.127 nvidia-cuda-nvrtc-cu12-12.4.127 nvidia-cuda-runtime-cu12-12.4.127 nvidia-cudnncu12-9.1.0.70 nvidia-cufft-cu12-11.2.1.3 nvidia-curand-cu12-10.3.5.147 nvidiacusolver-cu12-11.6.1.9 nvidia-cusparse-cu12-12.3.1.170 nvidia-nvjitlinkcu12-12.4.127 xxhash-3.5.0

```
[]: import kagglehub
     # Download latest version
     path = kagglehub.dataset_download("kashishparmar02/
      ⇒social-media-sentiments-analysis-dataset")
     print("Path to dataset files:", path)
    Path to dataset files: /kaggle/input/social-media-sentiments-analysis-dataset
[]: import transformers
     import sentence_transformers
     import torch
     import torch.nn as nn
     import numpy as np
     import datasets
[]: device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
     device
[]: device(type='cuda')
    Task 1: Sentence Transformer Implementation
    Step 1: Load a standard SentenceTransformer model and generate embeddings
[]:|generic_model = sentence_transformers.SentenceTransformer("all-MiniLM-L6-v2")
     generic_model.to(device)
    /usr/local/lib/python3.11/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]
                                                       | 0.00/116 [00:00<?, ?B/s]
    config_sentence_transformers.json:
                                         0%1
                              | 0.00/10.5k [00:00<?, ?B/s]
    README.md:
                 0%1
    sentence_bert_config.json: 0%|
                                               | 0.00/53.0 [00:00<?, ?B/s]
                               | 0.00/612 [00:00<?, ?B/s]
    config.json: 0%
```

```
Xet Storage is enabled for this repo, but the 'hf_xet' package is not installed.
    Falling back to regular HTTP download. For better performance, install the
    package with: `pip install huggingface hub[hf xet]` or `pip install hf xet`
    WARNING: huggingface_hub.file_download: Xet Storage is enabled for this repo, but
    the 'hf xet' package is not installed. Falling back to regular HTTP download.
    For better performance, install the package with: `pip install
    huggingface_hub[hf_xet] or `pip install hf_xet`
    model.safetensors:
                                      | 0.00/90.9M [00:00<?, ?B/s]
                         0%|
                                           | 0.00/350 [00:00<?, ?B/s]
    tokenizer_config.json:
                             0%|
    vocab.txt:
                 0%1
                              | 0.00/232k [00:00<?, ?B/s]
                      0%|
                                   | 0.00/466k [00:00<?, ?B/s]
    tokenizer.json:
    special_tokens_map.json:
                               0%1
                                             | 0.00/112 [00:00<?, ?B/s]
                                | 0.00/190 [00:00<?, ?B/s]
    config.json:
                   0%1
[]: SentenceTransformer(
       (0): Transformer({'max_seq_length': 256, 'do_lower_case': False}) with
     Transformer model: BertModel
       (1): Pooling({'word_embedding_dimension': 384, 'pooling_mode_cls_token':
    False, 'pooling mode mean tokens': True, 'pooling mode max tokens': False,
     'pooling_mode_mean_sqrt_len_tokens': False, 'pooling_mode_weightedmean_tokens':
    False, 'pooling_mode_lasttoken': False, 'include_prompt': True})
       (2): Normalize()
     )
[]: # Some Input Sentences to Embed
     input_sentences = ["I hate this app.",
                        "I love how it works omg",
                        "it's alright, but i wish it was blue",
                        "i never will download this app.",
                        "i might have something else.",
                        "This is the best thing I've ever worked with."]
     # Labels representing sentiments attached to input sentences
     input_labels = ["negative negative", "positive positive", "neutral positive", u

¬"neutral neutral", "neutral negative", "positive positive"]

     generic_embeddings = generic_model.encode(input_sentences)
     generic_embeddings.shape
[]: (6, 384)
[]: generic_similarities = generic_model.similarity(generic_embeddings,_u
     →generic_embeddings)
     generic_similarities.to(device)
     # Direct Representation of Similarities
     print(generic similarities.shape)
```

# generic\_similarities torch.Size([6, 6]) []: tensor([[ 1.0000, 0.1785, 0.1557, 0.7266, 0.1313, 0.2293], [0.1785, 1.0000, 0.0757, 0.1144, -0.0487, 0.4011],[0.1557, 0.0757, 1.0000, 0.0581, 0.2297, 0.1269],[0.7266, 0.1144, 0.0581, 1.0000, 0.0976,0.2155],[ 0.1313, -0.0487, 0.2297, 0.0976, 1.0000, 0.1383], [0.2293, 0.4011, 0.1269, 0.2155, 0.1383,1.000011) []:|def display\_similarities(similarities, input\_sentences, input\_labels,\_ ⇔sentence\_indices, top\_n): Display the top-N most similar sentences (excluding self) for selected $\Box$ *⇔input sentences.* Parameters: similarities : torch 2D array (n\_sentences, n\_sentences) A square matrix where similarities[i][j] represents the $similarity_{\sqcup}$ *⇔score* between sentence i and sentence j. input\_sentences : list[str] The list of input sentences corresponding to the rows/columns of the $\sqcup$ *⇔similarity matrix.* input\_labels : list[str] Labels or categories associated with each input sentence (same order as $\sqcup$ $\hookrightarrow$ input\_sentences). sentence indices : list[int] Indices of the input sentences for which to display top-N most similar $\Rightarrow$ sentences. $top_n : int$ Number of most sentences to display for each. Returns: None for i in sentence\_indices: # Get indices sorted by similarity in descending order sorted\_indices = np.argsort(np.asarray(similarities[i]))[::-1] # Exclude the sentence itself top\_indices = [idx for idx in sorted\_indices if idx != i][:top\_n]

```
print(f"Top {top_n} similar sentences to \n '{input_sentences[i]}'\n_\u
      ⇔label = {input_labels[i]}:")
             for idx in top_indices:
                 print(f" - '{input_sentences[idx]}', label = {input_labels[idx]}__
      display_similarities(generic_similarities, input_sentences, input_labels,_
      (0,1,2], 4)
    Top 4 similar sentences to
     'I hate this app.'
     label = negative negative:
      - 'i never will download this app.', label = neutral neutral (Similarity:
    0.7266)
      - 'This is the best thing I've ever worked with.', label = positive positive
    (Similarity: 0.2293)
      - 'I love how it works omg', label = positive positive (Similarity: 0.1785)
      - 'it's alright, but i wish it was blue', label = neutral positive
    (Similarity: 0.1557)
    Top 4 similar sentences to
     'I love how it works omg'
     label = positive positive:
      - 'This is the best thing I've ever worked with.', label = positive positive
    (Similarity: 0.4011)
      - 'I hate this app.', label = negative negative (Similarity: 0.1785)
      - 'i never will download this app.', label = neutral neutral (Similarity:
    0.1144
      - 'it's alright, but i wish it was blue', label = neutral positive
    (Similarity: 0.0757)
    Top 4 similar sentences to
     'it's alright, but i wish it was blue'
     label = neutral positive:
      - 'i might have something else.', label = neutral negative (Similarity:
    0.2297)
      - 'I hate this app.', label = negative negative (Similarity: 0.1557)
      - 'This is the best thing I've ever worked with.', label = positive positive
    (Similarity: 0.1269)
      - 'I love how it works omg', label = positive positive (Similarity: 0.0757)
    Step 2: Custom SentenceTransformer Model: pre-trained HuggingFace Model + weighted pooling
[]: class SentenceTransformerModel_custom(nn.Module):
             Custom model for generating sentence embeddings using a pretrained \sqcup
      \hookrightarrow transformer.
             Architecture:
```

```
- Encoder: Pretrained transformer model (e.g., BERT) from Hugging Face.
       - Attention-Weighted Pooling: Softmax-weighted sum over token
\rightarrowembeddings (excluding [CLS]).
       - Projection: Linear layer to reduce to output dim.
       - Normalization: L2-normalizes the output embeddings.
      Parameters:
       _____
      model_name : str
           Pretrained transformer model name or path.
       output_dim : int, optional (default=384)
           Output embedding dimension.
      Inputs:
       input_ids : torch.Tensor
           Tokenized input IDs (batch_size, seq_len).
       attention\_mask : torch.Tensor
           Attention mask (batch_size, seq_len).
      Returns:
       torch. Tensor
           L2-normalized sentence embeddings (batch_size, output_dim).
  11 11 11
  def __init__(self, model_name, output_dim=384):
      super(SentenceTransformerModel_custom, self).__init__()
      self.model = transformers.AutoModel.from_pretrained(model_name)
      hidden_size = self.model.config.hidden_size
      self.pooling = nn.Linear(hidden_size, output_dim)
      self.normalize = nn.functional.normalize
      self.weights = nn.Parameter(torch.randn(hidden_size))
  def forward(self, input_ids, attention_mask):
      outputs = self.model(input_ids=input_ids, attention_mask=attention_mask)
      token_embeddings = outputs.last_hidden_state[:, 1:, :]
      softmaxed_embeddings = torch.nn.functional.softmax(token_embeddings,_
\rightarrowdim=1)
      weighted sum = torch.sum(token_embeddings * softmaxed_embeddings, dim=1)
      pooled_embeddings = self.pooling(weighted_sum)
      normalized_embeddings = nn.functional.normalize(pooled_embeddings, p=2,_
\rightarrowdim=1)
      return normalized_embeddings
```

```
custom_model = SentenceTransformerModel_custom('nlptown/
 ⇔bert-base-multilingual-uncased-sentiment')
custom_model.to(device)
tokenizer = transformers.AutoTokenizer.from pretrained('nlptown/
 ⇔bert-base-multilingual-uncased-sentiment')
#tokenizing the sample sentences such that they can be processed by the
 \hookrightarrow transformer
inputs = tokenizer(input_sentences, padding=True, truncation=True,__

→return tensors="pt")
inputs = inputs.to(device)
input_ids = inputs['input_ids']
attention_mask = inputs['attention_mask']
#encoding
with torch.no_grad():
    custom_embeddings = custom_model(input_ids, attention_mask)
    print(custom embeddings)
    print(custom_embeddings.shape)
```

```
| 0.00/953 [00:00<?, ?B/s]
config.json:
              0%1
                     0%1
model.safetensors:
                                  | 0.00/669M [00:00<?, ?B/s]
                        0%1
                                      | 0.00/39.0 [00:00<?, ?B/s]
tokenizer config.json:
vocab.txt:
            0%1
                          | 0.00/872k [00:00<?, ?B/s]
special_tokens_map.json:
                          0%1
                                        | 0.00/112 [00:00<?, ?B/s]
tensor([[-0.0796, 0.0016, 0.0671, ..., -0.0840, 0.0042, 0.0487],
        [0.0800, -0.0603, 0.0246, ..., -0.0221, 0.0251, -0.0101],
        [0.0030, -0.0131, -0.0099, ..., -0.0367, 0.0039, -0.0144],
        [-0.0045, -0.0495, 0.0478, ..., -0.0581, 0.0097, 0.0125],
        [0.0193, -0.0705, 0.0302, ..., -0.0687, 0.0588, 0.0222],
        [0.0809, -0.0392, 0.0596, ..., -0.0239, -0.0016, -0.0056]],
       device='cuda:0')
torch.Size([6, 384])
```

Step 3 : Comparing Similarity Scores generated by Generic and Custom Models

```
[]: from sklearn.metrics.pairwise import cosine_similarity

print(generic_embeddings.shape)

print(custom_embeddings.shape)

if generic_embeddings.device != 'cpu':
    generic_embeddings = generic_embeddings.cpu().numpy()

if custom_embeddings.device != 'cpu':
```

```
(6, 384)
torch.Size([6, 384])
Generic Model Similarity for first sentence: 0.40108969807624817
Custom Model Similarity for first sentence: 0.7373437881469727
```

Explanation: While I've kept much of the transformer architecture the same, I decided that I would add a custom pooling method outside the transformer backbone such that more semantic information could be captured. For this task, I used a pre-trained model from HuggingFace, and kept the backbone the same. However, as I was attempting to capture sentiment within the embeddings, and I wanted the model to be sensitive towards these aspects, I implemented a normalized, attention-based (with the softmax), weighted sum that generated fixed-length embeddings.

#### Task 2: Multi-task Learning Expansion

I have implemented both Task A and Task B in one MultiTaskLearning\_ClassificationandSentiment(nn.Module) class, so that the model is modular and can be used for both tasks.

```
- Sentiment Head: A two-layer feedforward neural network with ReLU_{\!\sqcup}
\hookrightarrow activation.
  Loss Computation:
   _____
   - Computes task-specific cross-entropy loss for both classification and
   - If only one task is active (i.e., its labels are provided), only that \sqcup
\hookrightarrow loss is used.
   - If both tasks are active, the final loss is the average of the two.
  Parameters:
   a_class_num : int
       Number of classes for the classification task.
   b_class_num : int
       Number of classes for the sentiment task.
   Inputs:
   _____
   input_ids : torch.Tensor
       Tokenized input IDs for the transformer encoder.
   attention mask: torch. Tensor, optional
       Attention mask for the encoder input.
   sentiment labels: torch. Tensor, optional
       Ground-truth sentiment labels for computing sentiment task loss.
   classification_labels : torch.Tensor, optional
       Ground-truth classification labels for computing classification task
\hookrightarrow loss.
  Returns:
   _____
   dict with keys:
       'classification' : torch.Tensor
           Logits for the classification task.
       'sentiment': torch.Tensor
           Logits for the sentiment task.
       'loss' : torch. Tensor
           Combined or individual task loss, depending on available labels.
   11 11 11
  def __init__(self, a_class_num, b_class_num):
       super(MultiTaskLearning ClassificationandSentiment, self). init ()
       # shared base encoder for both tasks
       self.shared_encoder = SentenceTransformerModel_custom('nlptown/
⇔bert-base-multilingual-uncased-sentiment')
       # output dim of the shared encoder
       hidden_size = self.shared_encoder.pooling.out_features
```

```
# head for the classification task
       self.classification_task = nn.Sequential(nn.Linear(hidden_size,_
⇔hidden_size // 2),
          nn.ReLU(),
          nn.Linear(hidden_size // 2, a_class_num))
       # head for the sentiment task
      self.sentiment_task = nn.Sequential(nn.Linear(hidden_size, hidden_size /
\hookrightarrow 2),
           nn.ReLU(),
           nn.Linear(hidden_size // 2, b_class_num))
  def forward(self, input_ids, attention_mask = None, sentiment_labels = __
→None, classification_labels = None):
       shared_embeddings = self.shared_encoder(input_ids, attention_mask)
       classification_logits = self.classification_task(shared_embeddings)
       sentiment_logits = self.sentiment_task(shared_embeddings)
      loss = 0
      num_losses = 0
       # If either of the task specific heads are frozen (so the task_labels_u
→are None)
       # then train normally for only one of them -> adjust loss fn_{\sqcup}
→accordingly.
       if classification_labels is not None:
           classification_loss = nn.CrossEntropyLoss()(classification_logits,__
⇔classification_labels)
           loss = loss + classification_loss
           num_losses += 1
       if sentiment_labels is not None:
           sentiment_loss = nn.CrossEntropyLoss()(sentiment_logits,__
⇔sentiment labels)
           loss = loss + sentiment_loss
           num_losses += 1
       # LOSS = 1/2(class_loss + sent_loss), adjusted appropriately if either_
⇔is None
       # for task-specific training.
      if num_losses > 0:
           loss = loss / num_losses
```

```
outputs = {
  'classification': classification_logits,
  'sentiment': sentiment_logits,
  'loss': loss}
return outputs
```

Explanation: In order to modify the the model such that it can handle multi-task learning, I created another class MultiTaskLearning\_ClassificationandSentiment(nn.Module) of Transformer model that took the original model as the "shared encoder" between the two tasks. Then, I added both a classification-specific head and a sentiment analysis-specific head so that the model could appropriately perform its downstream tasks.

I will train/fine-tune this model in Task 4 below.

#### Task 3: Training Considerations

The implications, advantages, and rationale for training the model based on the following criteria as it follows:

- 1. If the entire network is frozen, that means that no training can occur, and the network will default to the pre-trained model. This means that no learning can take place. Some advantages of this can include: fast deployment and preservation of pre-training not having to train the model frees up resources and would work well if the task at hand is similar to the pre-training task. This configuration, however, is not ideal for multi-task learning, or any "new" tasks.
- 2. If only the transformer backbone is frozen, then not only can the model take advantage of its pre-training, but one can also add task-specific heads that can fine-tune its understanding for new tasks. This configuration is preferable as it balances its pre-trained knowledge and its ability to learn. It is used in transfer learning, where a pre-trained model is leveraged for new tasks.
- 3. If only one task-specific head is frozen, then this leads to an unbalanced learning, where one head can learn from the data, while the other does not learn. Hence, the model becomes very task-specific. This is ideal for when there is asymmetrical pre-training, where one task is not represented as well, and thus needs to be focused on in fine-tuning.

Transfer learning can be beneficial where we want to leverage the language understanding of a pre-trained model, and then fine-tune on a specific task. For example, one could use a pre-trained NLP model and fine-tune it to perform sentiment analysis on product reviews.

- 1. The choice of pre-trained model would be something trained on an immense amount of language data, so either BERT or RoBERTa. That way, we can leverage its robust language capabilities to understand the product reviews, but also fine-tune it such that we can extract the sentiment.
- 2. In this case, we would need to freeze the transformer backbone and un-freeze the classification head. This is so that we can allow the model adapt to the specific task and "learn" patterns within the task. This way, it is efficient in its resource while also "learning" how to do the new task of extracting sentiment from product reviews.
- 3. As stated above, freezing the backbone would allow for the preservation of pre-trained knowl-

edge and the ability to learn new tasks. This way, we preserve computational resources but also get task-specific adaptation.

#### Task 4: Training Loop Implementation

```
[]: import pandas as pd
     #importing data to fine-tune the model
     df = pd.read_csv("/kaggle/input/social-media-sentiments-analysis-dataset/
      ⇔sentimentdataset.csv")
     df.drop(columns=['Unnamed: 0', 'Unnamed: 0.1'], inplace=True)
     df["Platform"] = df["Platform"].str.strip()
     df["Sentiment"] = df["Sentiment"].str.strip()
     df.head()
[]:
                                                     Text Sentiment \
        Enjoying a beautiful day at the park!
                                                      ... Positive
        Traffic was terrible this morning.
                                                      ... Negative
     1
                                                     ... Positive
     2
        Just finished an amazing workout!
        Excited about the upcoming weekend getaway! ... Positive
     3
        Trying out a new recipe for dinner tonight. ...
                                                          Neutral
                 Timestamp
                                              Platform \
                                       User
     0 2023-01-15 12:30:00
                              User123
                                               Twitter
     1 2023-01-15 08:45:00
                              CommuterX
                                               Twitter
     2 2023-01-15 15:45:00
                              FitnessFan
                                             Instagram
     3 2023-01-15 18:20:00
                            AdventureX
                                             Facebook
     4 2023-01-15 19:55:00
                              ChefCook
                                             Instagram
                                          Hashtags Retweets Likes
                                                                          Country \
        #Nature #Park
     0
                                                               30.0
                                                                        USA
                                                        15.0
                                                         5.0
     1
        #Traffic #Morning
                                                               10.0
                                                                        Canada
        #Fitness #Workout
                                                        20.0
                                                               40.0
     2
                                                                      USA
     3
        #Travel #Adventure
                                                         8.0
                                                               15.0
                                                                        UK
        #Cooking #Food
                                                        12.0
                                                               25.0
                                                                       Australia
       Year Month Day
                         Hour
     0 2023
                 1
                      15
                            12
     1 2023
                     15
                 1
                            8
     2 2023
                 1
                     15
                            15
     3 2023
                 1
                     15
                            18
     4 2023
                     15
                            19
[]: from sklearn.model_selection import train_test_split
     from transformers import AutoTokenizer, TrainingArguments, Trainer, __
      →DataCollatorWithPadding
     from datasets import Dataset, ClassLabel
     import numpy as np
```

```
def label_list_to_tensor(label_list : list[str]):
    Converts a list of string labels into a numerical tensor suitable for our
 \hookrightarrow PyTorch model.
    The function determines the unique label names, assigns an integer index to,
 ⇔each unique label,
    and converts the entire input list into a tensor of indices.
    Parameters:
    _____
    label list : list of str
        A list of string labels (e.g., ['Facebook', 'Instagram', 'Twitter', ...
 \hookrightarrow]) to be converted.
    Returns:
    _____
    torch. Tensor
        A tensor of shape (len(label_list),) containing integer valued labels.
    # qet unique label names -> sort for consistency across runs (hashing is \Box
 \hookrightarrow randomized)
    unique_labels = list(sorted(set(label_list))) # Get unique labels
    # enumerate label names -> these are the mappings
    label_to_index = {label: index for index, label in enumerate(unique_labels)}
    indexed_labels = [label_to_index[label] for label in label_list]
    # convert to torch.tensor for model
    label_tensor = torch.tensor(indexed_labels)
    return label_tensor
def preprocess_data(df):
    Preprocesses a DataFrame containing text reviews and their corresponding ∪
 ⇔sentiment and platform labels
    for multi-task learning.
    Parameters:
    df : pandas.DataFrame containing three required columns:
        - 'Text': review text (strings)
        - 'Sentiment': sentiment labels (strings, e.g., 'positive', 'neutral', __

        'negative')

        - 'Platform': classification labels (strings, e.g., 'web', 'ios', ⊔

    'android')
   Returns:
```

```
dict
        A dictionary containing:
        - tokenized inputs (e.g., 'input_ids', 'attention_mask', etc.)
        - 'sentiment_labels': torch. Tensor of numerical sentiment class indices
        - 'classification\_labels': torch.Tensor of numerical platform class_{\sqcup}
 \hookrightarrow indices
    Notes:
    - The tokenizer used must be initialized globally before calling this.
 \hookrightarrow function.
    11 11 11
    reviews = df['Text']
    # convert labels to numerical tensor
    sentiments = label_list_to_tensor(df['Sentiment'])
    classifications = label_list_to_tensor(df["Platform"])
    # encode input sentences/reviews as embeddings
    encoding =tokenizer(
              reviews,
              padding='max_length',
              max_length=128,
              truncation=True,
              return_tensors=None)
    # add labels to embeddings for the model
    encoding['sentiment_labels'] = sentiments
    encoding['classification_labels'] = classifications
    return encoding
# Globally initialize tokenizer
tokenizer = AutoTokenizer.from_pretrained('nlptown/
 ⇔bert-base-multilingual-uncased-sentiment')
# Split and Preprocess train/val data
full_dataset = Dataset.from_pandas(df)
train_dataset, val_dataset = full_dataset.train_test_split(test_size=0.2,_
⇒shuffle=True, seed=42).values()
train_dataset = train_dataset.map(preprocess_data, batched=True)
val_dataset = val_dataset.map(preprocess_data, batched=True)
# Compute number of sentiment and classification classes for initializing the
 →model
train_dataset.set_format(type='torch', columns=['input_ids', 'attention_mask',
                                                 'sentiment labels',,,
⇔'classification_labels'])
val_dataset.set_format(type='torch', columns=['input_ids', 'attention_mask',
                                               'sentiment_labels', u
```

```
num classification_classes = np.unique(df['Platform']).shape[0]
           num_sentiment_classes = np.unique(df['Sentiment']).shape[0]
         Map:
                         0%|
                                                       | 0/585 [00:00<?, ? examples/s]
                         0%1
                                                      | 0/147 [00:00<?, ? examples/s]
         Map:
[]: # Initialize Model
           model =
              -MultiTaskLearning_ClassificationandSentiment(num_classification_classes, المالية الم
              →num sentiment classes)
           model.to(device)
[]: MultiTaskLearning_ClassificationandSentiment(
                (shared_encoder): SentenceTransformerModel_custom(
                    (model): BertModel(
                         (embeddings): BertEmbeddings(
                              (word_embeddings): Embedding(105879, 768, padding_idx=0)
                              (position_embeddings): Embedding(512, 768)
                              (token_type_embeddings): Embedding(2, 768)
                             (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
                             (dropout): Dropout(p=0.1, inplace=False)
                         (encoder): BertEncoder(
                              (layer): ModuleList(
                                  (0-11): 12 x BertLayer(
                                       (attention): BertAttention(
                                           (self): BertSdpaSelfAttention(
                                                (query): Linear(in_features=768, out_features=768, bias=True)
                                               (key): Linear(in_features=768, out_features=768, bias=True)
                                               (value): Linear(in_features=768, out_features=768, bias=True)
                                               (dropout): Dropout(p=0.1, inplace=False)
                                           )
                                           (output): BertSelfOutput(
                                               (dense): Linear(in_features=768, out_features=768, bias=True)
                                               (LayerNorm): LayerNorm((768,), eps=1e-12,
           elementwise_affine=True)
                                               (dropout): Dropout(p=0.1, inplace=False)
                                           )
                                       (intermediate): BertIntermediate(
                                           (dense): Linear(in_features=768, out_features=3072, bias=True)
                                           (intermediate_act_fn): GELUActivation()
                                       (output): BertOutput(
                                           (dense): Linear(in_features=3072, out_features=768, bias=True)
                                           (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
```

```
)
             )
           )
           (pooler): BertPooler(
             (dense): Linear(in_features=768, out_features=768, bias=True)
             (activation): Tanh()
           )
         )
         (pooling): Linear(in_features=768, out_features=384, bias=True)
       (classification_task): Sequential(
         (0): Linear(in_features=384, out_features=192, bias=True)
         (1): ReLU()
         (2): Linear(in_features=192, out_features=3, bias=True)
       (sentiment_task): Sequential(
         (0): Linear(in_features=384, out_features=192, bias=True)
         (1): ReLU()
         (2): Linear(in_features=192, out_features=191, bias=True)
      )
     )
[]: from sklearn.metrics import accuracy_score, f1_score
     import os
     os.environ["WANDB_DISABLED"] = "true"
     training_args = TrainingArguments(
         output_dir='./results',
         num_train_epochs=10,
         per_device_train_batch_size=16,
         learning_rate=5e-4,
         weight_decay=0.01,
         optim='adamw_torch',
         lr_scheduler_type='linear',
         warmup_steps=500,
         eval_strategy='epoch',
         save_strategy='epoch',
         save steps=1000,
         load_best_model_at_end=True
     def compute_metrics(eval_pred):
         # Unpack predictions and labels
         logits, labels = eval_pred
```

(dropout): Dropout(p=0.1, inplace=False)

```
classification_logits, sentiment_logits = logits
  classification_labels, sentiment_labels = labels
  # For multi-task, logits and labels will be dictionaries
  classification_preds = np.argmax(classification_logits, axis = 1)
  sentiment_preds = np.argmax(sentiment_logits, axis = 1)
  print(classification_preds, sentiment_preds)
  # Calculate metrics for both tasks
  classification_acc = accuracy_score(classification_labels,__
→classification_preds)
  classification_f1 = f1_score(classification_labels, classification_preds,_
⇔average='weighted')
  sentiment_acc = accuracy_score(sentiment_labels, sentiment_preds)
  sentiment_f1 = f1_score(sentiment_labels, sentiment_preds,__
⇔average='weighted')
  # Calculate average metrics across tasks
  average_acc = (classification_acc + sentiment_acc) / 2
  average_f1 = (classification_f1 + sentiment_f1) / 2
  return {
       'classification_acc': classification_acc,
       'classification_f1': classification_f1,
       'sentiment_acc': sentiment_acc,
       'sentiment f1': sentiment f1,
       'average_acc': average_acc,
      'average_f1': average_f1
  }
```

Using the `WANDB\_DISABLED` environment variable is deprecated and will be removed in v5. Use the --report\_to flag to control the integrations used for logging result (for instance --report\_to none).

```
[]: from torch.utils.data import default_collate

def custom_collate(batch):
    return default_collate(batch)

# Initialize the trainer

trainer = Trainer(
    model=model,
    args=training_args,
    train_dataset=train_dataset,
    eval_dataset=val_dataset,
    compute_metrics=compute_metrics,
```

```
data_collator=custom_collate
)
```

#### []: trainer.train()

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107 107 107 134 107 107 107 69 107 107 147 107 45 107 107 147 107 107 107 107 107 107 69 69 107 107 107 107 107 107 45 45 107 107 69 107

107 107 134]

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134 134 134 134 134 107 134 134 45 134 45 134 134 134 69 134 134 134
134 134 134 134 134 107 134 45 134 134 134 134 134 107 134 134 134 134
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134 134 134]
```

```
134 134 134]
134 134 134]
107 107 107]
134 134 134]
```

[]: TrainOutput(global\_step=370, training\_loss=3.0135303394214525, metrics={'train\_runtime': 69.976, 'train\_samples\_per\_second': 83.6, 'train\_steps\_per\_second': 5.288, 'total\_flos': 0.0, 'train\_loss': 3.0135303394214525, 'epoch': 10.0})

```
[]: from datasets import load_dataset
     ds = load_dataset("stanfordnlp/imdb")
     ds_train = ds["train"]
     ds test = ds["test"]
     ds_train = ds_train.rename_column('label', 'sentiment_labels')
     ds_test = ds_test.rename_column('label', 'sentiment_labels')
     ds_train = ds_train.add_column('classification_labels', np.zeros(len(ds_train),_
      ⇒dtype=np.int64))
     ds_test = ds_test.add_column('classification_labels', np.zeros(len(ds_test),__
      ⇒dtype=np.int64))
     tokenizer = AutoTokenizer.from_pretrained('nlptown/
      ⇔bert-base-multilingual-uncased-sentiment')
     def tokenization(batch):
         return tokenizer(batch['text'], padding=True, truncation=True)
     ds_train = ds_train.map(tokenization, batched=True, batch_size=None)
     ds_test = ds_test.map(tokenization, batched=True, batch_size=None)
     ds_train.set_format('torch', columns=['input_ids', 'attention_mask', u
      ⇔'sentiment_labels', 'classification_labels'])
     ds test.set format('torch', columns=['input ids', 'attention mask', |
      ⇔'sentiment_labels', 'classification_labels'])
     sent_nums = 2
     model = MultiTaskLearning_ClassificationandSentiment(2, sent_nums)
     model.to(device)
     training_args = TrainingArguments(
         output_dir='./results',
         num_train_epochs=3,
         per_device_train_batch_size=16,
         learning_rate=5e-4,
         weight_decay=0.01,
         optim='adamw_torch',
         lr_scheduler_type='linear',
         warmup_steps=500,
         eval_strategy='epoch',
         save_strategy='epoch',
         save_steps=1000,
         load_best_model_at_end=True
     )
     trainer = Trainer(
         model=model,
```

```
args=training_args,
         train_dataset=ds_train,
         eval_dataset=ds_test,
         compute_metrics=compute_metrics,
         data_collator=custom_collate
         )
     trainer.train()
    R.F.ADMF..md:
                 0%1
                               | 0.00/7.81k [00:00<?, ?B/s]
    train-00000-of-00001.parquet:
                                     0%1
                                                  | 0.00/21.0M [00:00<?, ?B/s]
                                    0%|
    test-00000-of-00001.parquet:
                                                 | 0.00/20.5M [00:00<?, ?B/s]
    unsupervised-00000-of-00001.parquet:
                                            0%|
                                                          | 0.00/42.0M [00:00<?, ?B/s]
    Generating train split:
                               0%1
                                            | 0/25000 [00:00<?, ? examples/s]
                                           | 0/25000 [00:00<?, ? examples/s]
    Generating test split:
                              0%1
    Generating unsupervised split:
                                      0%|
                                                   | 0/50000 [00:00<?, ? examples/s]
    Map:
           0%1
                         | 0/25000 [00:00<?, ? examples/s]
                         | 0/25000 [00:00<?, ? examples/s]
    Map:
           0%1
    Using the `WANDB_DISABLED` environment variable is deprecated and will be
    removed in v5. Use the --report to flag to control the integrations used for
    logging result (for instance --report_to none).
    <IPython.core.display.HTML object>
    [0 0 0 ... 0 0 0] [1 1 1 ... 1 1 1]
    [0 0 0 ... 0 0 0] [1 1 1 ... 1 1 1]
    [0 0 0 ... 0 0 0] [0 0 0 ... 0 0 0]
[]: TrainOutput(global_step=4689, training_loss=0.3535468959177855,
    metrics={'train_runtime': 1978.3621, 'train_samples_per_second': 37.91,
     'train steps per second': 2.37, 'total flos': 0.0, 'train loss':
     0.3535468959177855, 'epoch': 3.0})
[]: !pip freeze > requirements.txt
[]: from google.colab import files
     files.download('requirements.txt')
```