Hands-on tutorial – CLIP for multimodal analysis

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Agenda

- Introduction to the dataset to be used in this session
- Setting up our Computing Infrastructure (Kaggle in this case)
- Hands-on Session with OpenAI's CLIP
  - Loading CLIP model
  - Generating Embeddings
  - Performing Information Retrieval using CLIP
  - Performing Zero-Shot Classification using CLIP
  - Demonstrating relationships in CLIP embeddings

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Dataset

Dataset

Exploring Hate Speech Detection in Multimodal Publications

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- 150K image and text pairs
- Manually annotated as Racist, Homophobic, Sexist, Religion-based, other hate and no-hate

Figure 1. Tweets from MMHS150K where the visual information adds relevant context for the hate speech detection task.

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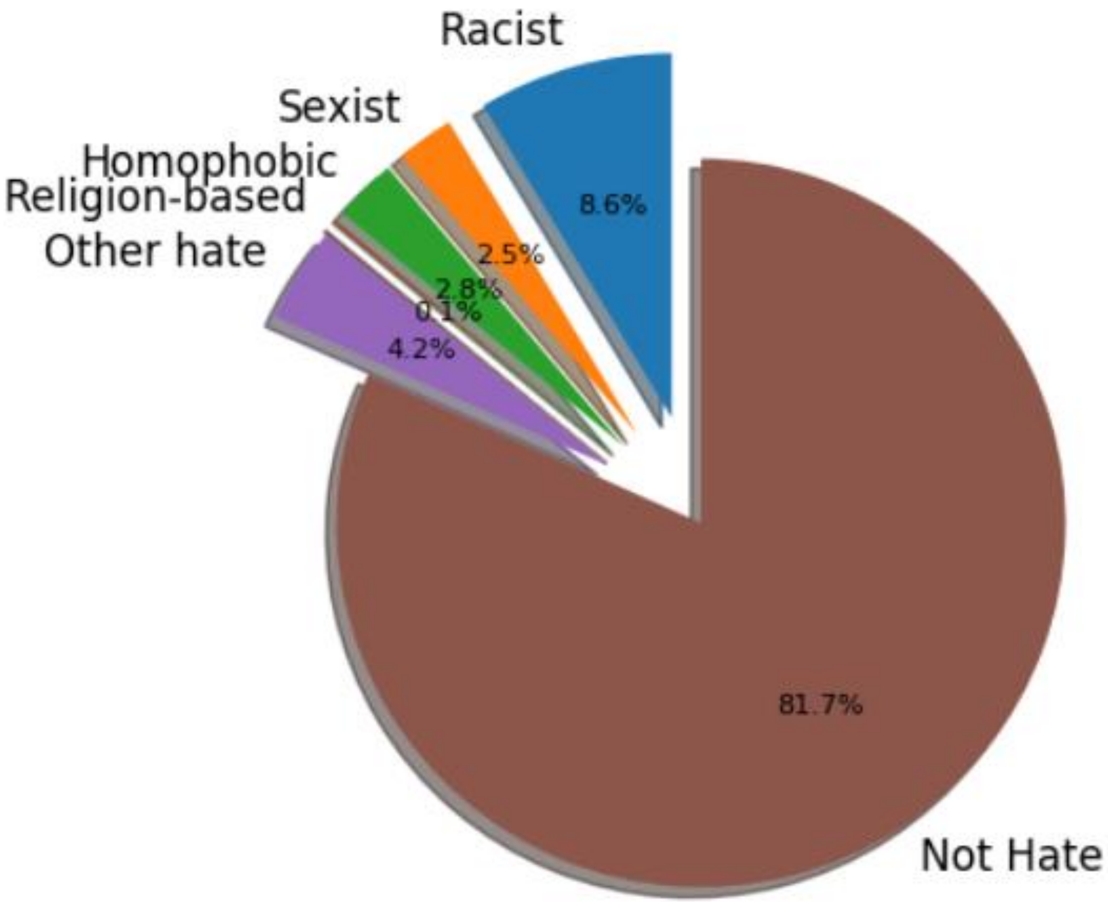
Data Collection Procedure

1. 51 terms included in the Hatebase dictionary
2. Collected tweets including these terms (Sep. 2018 – Feb. 2019)
3. Filtered tweets that include images
4. Annotated images using Mechanical Turk Workers

Data Annotation

- **Six classes:**
  - No attacks on any community
  - Racist
  - Sexist
  - Homophobic
  - Religion-based attacks
  - Other Hate



- Three annotators per tweet considering both text and image

An additional filtering step from my side

- Upon inspection of the dataset, I noticed that there were some images that were sexually explicit
  - E.g., showing human genitals
- Run a lightweight nudity detection model in Python (i.e., nudenet)
- Identified and removed from the dataset 1.2K images that include explicit sexually explicit content

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Warning on the dataset

- This dataset contains **hate speech, offensive language, and harmful stereotypes**.
- Also, while I made a best effort to remove sexually explicit images, some sexually explicit images might still be in the dataset
- These materials are used **solely for research and educational purposes**.
- **We do not endorse or support** the views, language, or imagery included.

→ If you are not comfortable with working with this dataset for this hand-on session, please let me know and we can find an alternative dataset

Hands-on session

Setting up the Computing Infrastructure (Kaggle)

Using Kaggle

- Visit https://www.kaggle.com/ and create a free account
  - Creating with Google account is the fastest way

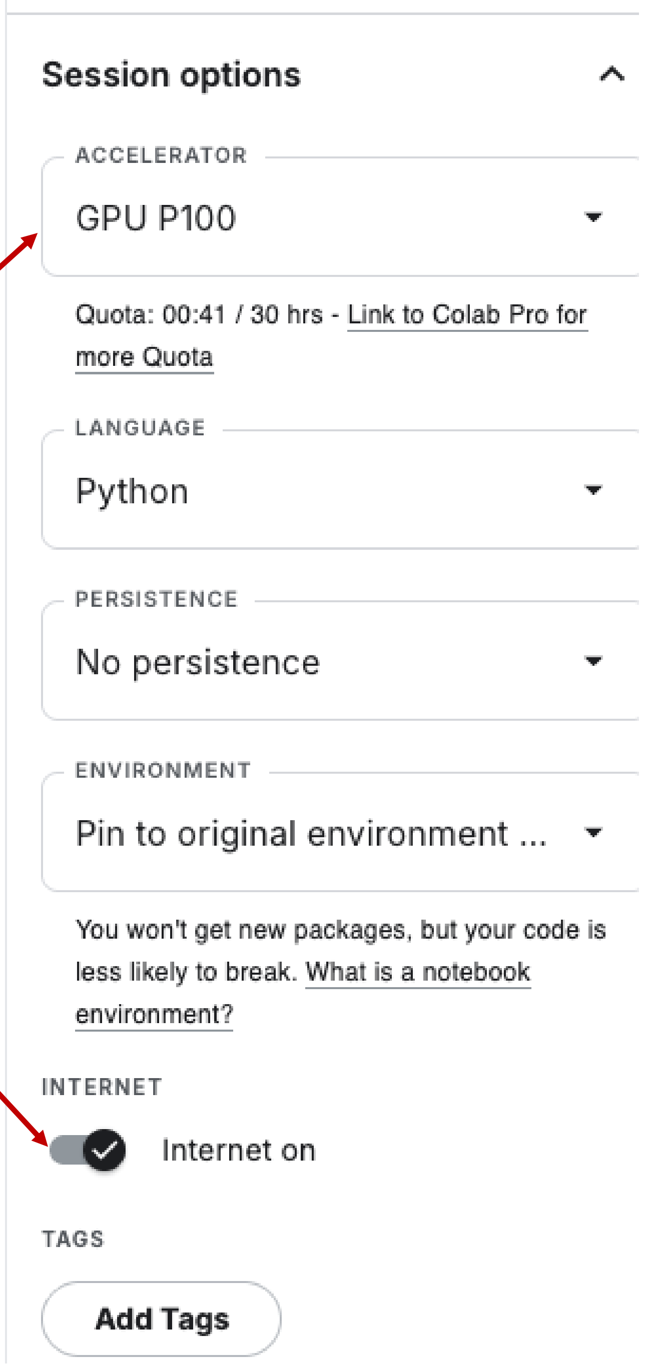
- Verify your account with your phone number so you get access to GPU resources
  - Press the top right profile icon
  - Go to “Settings”
  - Then “phone verify”
  - Input your phone number and follow the on-screen instructions

Using Kaggle

- Click here to get access to the Jupyter Notebook with the code
  - Press ”Copy and Edit” to see the code

- Change the session options (right hand side) so that:
  - You have a GPU accelerator (P100)
  - Internet is on (needed to install necessary Python packages)

- Then, you can run all the cells by clicking “Run all” on the top



Procedure

1. Loading CLIP model

2. Use pretrained OpenAI CLIP model to
   - Generate image and text embeddings (for a small sample of the dataset ~20K)

3. Demonstrate three use-cases
   - Information Retrieval
   - Zero-Shot Classification
   - Relationships between embeddings (text + text, text + image, weighted text+image)

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Loading CLIP model and Basic Demo

```python
import torch
from PIL import Image
import open_clip
from pathlib import Path
from typing import List, Tuple
import numpy as np
import json
import pandas as pd
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')

model, _, preprocess = open_clip.create_model_and_transforms('ViT-B-32', pretrained='openai')
model.eval()
tokenizer = open_clip.get_tokenizer('ViT-B-32')

image = preprocess(Image.open("/kaggle/input/clip-example/CLIP.png")).unsqueeze(0)
text = tokenizer(["a diagram", "a dog", "a cat"])

with torch.no_grad(), torch.autocast("cuda"):
    image_features = model.encode_image(image)
    text_features = model.encode_text(text)
    image_features /= image_features.norm(dim=-1, keepdim=True)
    text_features /= text_features.norm(dim=-1, keepdim=True)

    text_probs = (100.0 * image_features @ text_features.T).softmax(dim=-1)

print("Label probs:", text_probs)  # prints: [[1., 0., 0.]]
```

1. Load OpenAI's CLIP model

2. Define image (CLIP's diagram in this case) and textual prompts

3. Generate Embeddings for the image + text prompts

4. Calculate probabilities based on image and text embeddings

```
open_clip_model.safetensors: 100%  605M/605M [00:02<00:00, 257MB/s]
Label probs: tensor([[0.9940, 0.0040, 0.0020]])
```

"a diagram" received a probability of 0.994

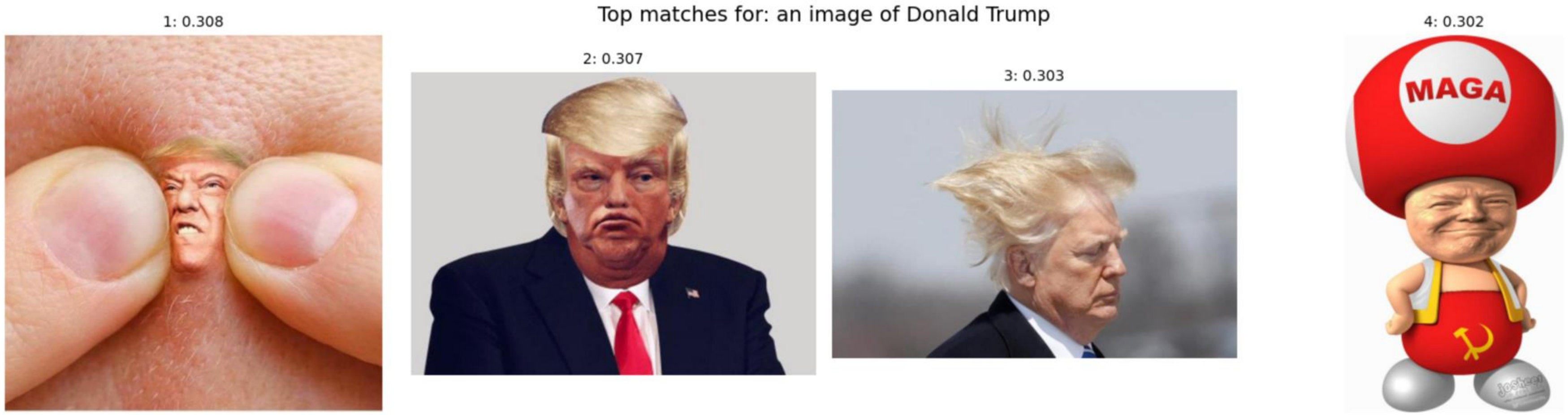
Use-Case Information Retrieval

```python
"""Rank images by similarity to a text prompt. Returns (idx, paths, scores)."""
@torch.no_grad()
def topn_for_text(prompt: str,
                  img_emb: np.ndarray,
                  image_paths: List[Path],
                  model, tokenizer,
                  topn: int = 4) -> Tuple[np.ndarray, List[Path], np.ndarray]:
    device = next(model.parameters()).device
    # text → embedding (normalized)
    toks = tokenizer([prompt]).to(device)
    t = model.encode_text(toks)
    q = (t / t.norm(dim=-1, keepdim=True)).detach().cpu().float().numpy()  # [1, D]

    # (re)normalize images for safety; then cosine via dot product
    img = img_emb / (np.linalg.norm(img_emb, axis=1, keepdims=True) + 1e-9)
    scores = (img @ q.T).squeeze(1)  # [N]

    idx = np.argsort(-scores)[:topn]
    return idx, [image_paths[i] for i in idx], scores[idx]

"""Simple grid viz of top-N images + scores."""
def show_topn(paths: List[Path], scores: np.ndarray, cols: int = 4, title: str = None):
    import math
    n = len(paths); rows = math.ceil(n / cols)
    fig, axes = plt.subplots(rows, cols, figsize=(4*cols, 4*rows))
    if title: fig.suptitle(title, fontsize=14)
    axes = np.atleast_2d(axes)
    for i in range(rows * cols):
        r, c = divmod(i, cols)
        ax = axes[r, c]; ax.axis("off")
        if i < n:
            ax.imshow(Image.open(paths[i]).convert("RGB"))
            ax.set_title(f"{i+1}: {scores[i]:.3f}", fontsize=10)
    plt.tight_layout(); plt.show()
```

Method to find top-n images based on text embedding

Helper to visualize results

Information Retrieval - Results



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Use Case – Zero Shot Classification

```python
# 1) Build text features for a list of people (prompt ensemble + mean)
@torch.no_grad()
def build_people_text_features(
    names: List[str],
    model,
    tokenizer,
    templates: List[str] = None
) -> Tuple[List[str], torch.Tensor]:
    device = next(model.parameters()).device
    if templates is None:
        templates = [
            "a photo of {}",
            "an image of {}",
            "a portrait of {}",
        ]
    feats = []
    for name in names:
        prompts = [t.format(name) for t in templates]
        toks = tokenizer(prompts).to(device)
        t = model.encode_text(toks)
        t = t / t.norm(dim=-1, keepdim=True)      # normalize each prompt
        f = t.mean(dim=0, keepdim=True)           # ensemble → mean
        f = f / f.norm(dim=-1, keepdim=True)      # re-normalize
        feats.append(f)
    text_feats = torch.cat(feats, dim=0)          # [C, D]
    return names, text_feats
```

Build a small ensemble with 3 text prompts for classification

```python
# 2) Turn image embeddings + text features into probabilities with CLIP
@torch.no_grad()
def probs_for_subset(
    img_emb_subset: np.ndarray,      # [M, D] (L2-normalized)
    text_feats: torch.Tensor,        # [C, D] (L2-normalized)
    model
) -> np.ndarray:                     # [M, C] probabilities
    # cosine = dot product for normalized vectors
    img_t = torch.from_numpy(img_emb_subset).float()          # CPU is fine for M=8
    cls_t = text_feats.float()
    logits = img_t @ cls_t.T                                  # [M, C]
    # apply CLIP temperature (logit_scale)
    logit_scale = model.logit_scale.exp().item()
    logits = logits * logit_scale
    probs = torch.softmax(logits, dim=-1).cpu().numpy()
    return probs
```

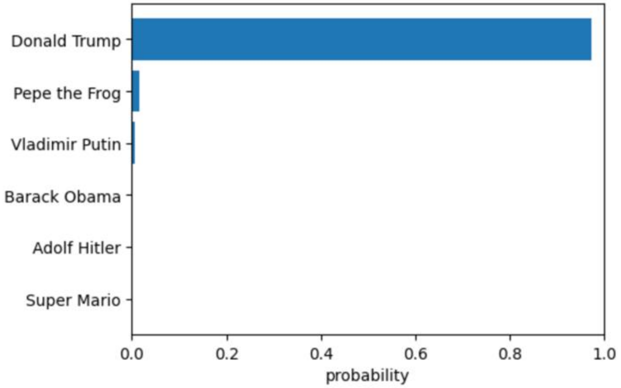
Calculate probabilities

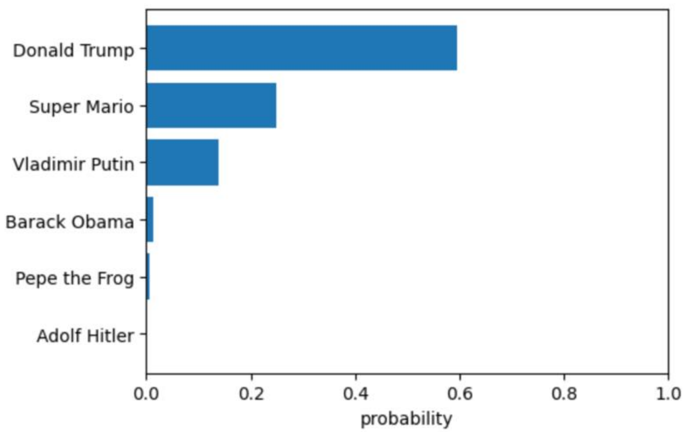
```python
# 3) Plot: each row = image, right column = horizontal bar chart of top-k classes
def plot_images_with_probs(
    paths: List[str],
    probs: np.ndarray,              # [M, C]
    classnames: List[str],
    topk: int = 5,
    figsize_per_row: float = 3.5
):
    M, C = probs.shape
    fig, axes = plt.subplots(M, 2, figsize=(10, figsize_per_row * M))
    if M == 1:
        axes = np.expand_dims(axes, 0)
    for i in range(M):
        # left: image
        ax_img = axes[i, 0]
        ax_img.axis("off")
        try:
            ax_img.imshow(Image.open(paths[i]).convert("RGB"))
        except Exception as e:
            ax_img.text(0.5, 0.5, f"load error\n{e}", ha="center", va="center")

        # right: top-k bar chart
        ax_bar = axes[i, 1]
        p = probs[i]
        order = np.argsort(-p)[:min(topk, C)]
        labels = [classnames[j] for j in order]
        vals = p[order]
        ax_bar.barh(range(len(order)), vals)
        ax_bar.set_yticks(range(len(order)))
        ax_bar.set_yticklabels(labels)
        ax_bar.invert_yaxis()
        ax_bar.set_xlim(0, 1)
        ax_bar.set_xlabel("probability")
    plt.tight_layout()
    plt.show()
```

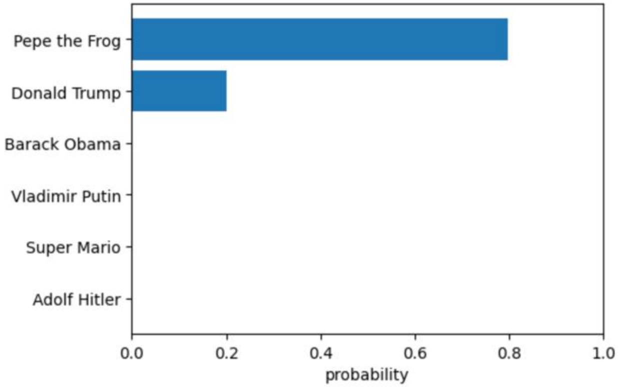
Helper method to visualize results

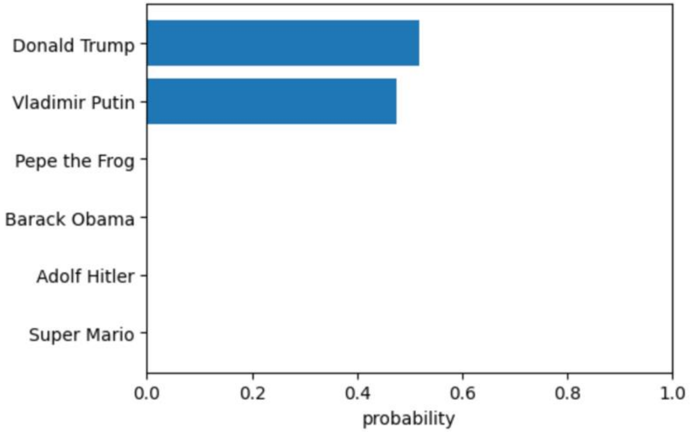
```python
# 1) Choose classes
people = [
    "Donald Trump", "Vladimir Putin", "Pepe the Frog", "Barack Obama", "Super Mario", "Adolf Hitler"
]

classnames, text_feats = build_people_text_features(people, model, tokenizer)

# 2) Get probabilities for the 8 selected images (use the precomputed embeddings)
img_emb_subset = img_emb[idx]      # shape [8, D], already L2-normalized
probs = probs_for_subset(img_emb_subset, text_feats, model)   # [8, 8]

# 3) Visualize: image + top-k class bars
plot_images_with_probs(paths, probs, classnames, topk=20)
```

Use Case - Zero-Shot Classification Results









Use Case – Relationships between CLIP Embeddings

Main method to compose query and identify top-n

```python
@torch.no_grad()
def topn_composed_query(
    base_emb: np.ndarray,
    add_text: str = None,
    sub_text: str = None,
    add_img_emb: np.ndarray = None,
    sub_img_emb: np.ndarray = None,
    weight_base: float = 1.0,
    weight_add_text: float = 1.0,
    weight_sub_text: float = 1.0,
    weight_add_img: float = 1.0,
    weight_sub_img: float = 1.0,
    img_emb: np.ndarray = None,
    image_paths=None,
    model=None, tokenizer=None,
    topn: int = 4
):
    device = next(model.parameters()).device

    # start from base embedding
    q = torch.from_numpy(_ensure_2d(base_emb)).to(device) * weight_base

    # add/sub text
    if add_text:
        t = torch.from_numpy(text_emb_for(add_text, model, tokenizer, device))
        q += weight_add_text * t
    if sub_text:
        t = torch.from_numpy(text_emb_for(sub_text, model, tokenizer, device))
        q -= weight_sub_text * t

    # add/sub image
    if add_img_emb is not None:
        q += weight_add_img * torch.from_numpy(_ensure_2d(add_img_emb)).to(device)
    if sub_img_emb is not None:
        q -= weight_sub_img * torch.from_numpy(_ensure_2d(sub_img_emb)).to(device)

    # normalize query
    q = q / (q.norm(dim=-1, keepdim=True) + 1e-9)
    q_np = q.detach().cpu().float().numpy()

    # cosine with gallery
    img = img_emb.astype(np.float32)
    img = img / (np.linalg.norm(img, axis=1, keepdims=True) + 1e-9)
    scores = (img @ q_np.T).squeeze(1)

    idx = np.argsort(-scores)[:topn]
    return idx, [image_paths[i] for i in idx], scores[idx]
```

```python
@torch.no_grad()
def text_emb_for(prompt: str, model, tokenizer, device=None, normalize=True) -> np.ndarray:
    """Return a [1, D] numpy embedding for a single text prompt."""
    if device is None:
        device = next(model.parameters()).device
    toks = tokenizer([prompt]).to(device)
    t = model.encode_text(toks)
    if normalize:
        t = t / (t.norm(dim=-1, keepdim=True) + 1e-9)
    return t.detach().cpu().float().numpy()  # [1, D]

@torch.no_grad()
def image_emb_for(path, model, preprocess, device=None, normalize=True) -> np.ndarray:
    """Return a [1, D] numpy embedding for a single image path."""
    if device is None:
        device = next(model.parameters()).device
    x = preprocess(Image.open(path).convert("RGB")).unsqueeze(0).to(device)  # [1, 3, H, W]
    e = model.encode_image(x)
    if normalize:
        e = e / (e.norm(dim=-1, keepdim=True) + 1e-9)
    return e.detach().cpu().float().numpy()  # [1, D]


def _ensure_2d(a: np.ndarray) -> np.ndarray:
    """Make sure array is [1, D] (accepts [D] or [1, D])."""
    a = np.asarray(a, dtype=np.float32)
    if a.ndim == 1:
        a = a[None, :]
    return a
```

Helper functions (extracting embeddings + normalizing arrays)

Relationships in CLIP Embeddings

Text + Text →
"An image of Donald Trump"
+ "Pepe the Frog"

Image + Text →
Donald Trump Image +
"Vladimir Putin"

Weighted Image(0.2) + Text(0.8) →
Donald Trump Image + "Vladimir
Putin"

Next Steps – Hands on Exercises

1. Prompt engineering for retrieval

- Pick 5–10 simple queries (e.g., "a crowd", "a protest sign", "a cartoon character", "a politician at a podium"). For each, retrieve top-k images with topn_for_text, then slightly vary the prompt (add/remove adjectives like "close-up", "outdoor", "old photo") and and compare the grids.

2. Build a tiny "hateful vs. benign" zero-shot probe

- MMHS150K has a labels_str column; construct a tiny balanced subset (e.g., 100 "likely hateful" vs 100 "likely benign" based on labels_str). Create two prompts like "an image that conveys hateful content" vs "an image that does not convey hateful content" (or a small template set). Compute the softmax probabilities and report a simple AUC or accuracy using a threshold on the hateful prompt's probability.

3. "Targeted retrieval" with vector composition

- Pick a base image (image_emb_for) and steer it with text, e.g., base = an image with Donald Trump + add_text = "wearing sunglasses". Compare results across weights (weight_base, weight_add_text ∈ {0.2,0.5,0.8}).

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Thank you for your attention

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