import matplotlib.pyplot as plt import pandas as pd import numpy as np import fasttext import requests import skimage import shutil import torch import json import cv2 from PIL import Image from pathlib import Path from collections import Counter from tqdm.auto import trange, tqdm from torchvision import datasets, models, transforms Helper for downloading models from google drive import requests def download file from google drive(id, destination): def get confirm token(response): for key, value in response.cookies.items(): if key.startswith('download warning'): return value return None def save response content(response, destination): CHUNK SIZE = 32768 with open(destination, "wb") as f: for chunk in response.iter content(CHUNK SIZE): if chunk: f.write(chunk) URL = "https://docs.google.com/uc?export=download" session = requests.Session() response = session.get(URL, params = { 'id' : id }, stream = True) token = get confirm token(response) if token: params = { 'id' : id, 'confirm' : token } response = session.get(URL, params = params, stream = True) save response content (response, destination) Load test data import re def normalize text(t): without tags = re.sub(r"<.*?>|\[.*?\]|&([a-z0-9]+|#[0-9]{1,6}|#x[0-9a-f]{1,6});|\t|\n", " ", t) word list = without tags.strip().lower().split() without stop words = " ".join(word list) return without stop words Path("./test dataset").mkdir(parents=True, exist ok=True) def download image(url): response = requests.get(url) file path = f"./test dataset/{url.split('/')[-1]}" img bytes = np.frombuffer(response.content, np.uint8) cv2.imwrite(file path, cv2.imdecode(img bytes, cv2.IMREAD COLOR)) return file path test categories = pd.read csv("https://raw.githubusercontent.com/chenlh0/product-classification-challenge/maste test products df = pd.read json("https://raw.githubusercontent.com/chenlh0/product-classification-challenge/mas test categories = test categories.apply(normalize text) test_products_df["description"] = test_products_df["description"].apply(normalize_text) test_products_df["img_path"] = test_products_df.image url.apply(download image) test products df.drop duplicates("img path", inplace=True) Load models PRETRAINED LABEL TO ID = { 'accessories': 0, 'apparel set': 1, 'bags': 2, 'bath and body': 3, 'beauty accessories': 4, 'belts': 5, 'be 'dress': 8, 'eyes': 9, 'eyewear': 10, 'flip flops': 11, 'fragrance': 12, 'free gifts': 13, 'gloves': 14, '} 'innerwear': 18, 'jewellery': 19, 'lips': 20, 'loungewear and nightwear': 21, 'makeup': 22, 'mufflers': 23, 'saree': 27, 'scarves': 28, 'shoe accessories': 29, 'shoes': 30, 'skin': 31, 'skin care': 32, 'socks': 33, 'stoles': 36, 'ties': 37, 'topwear': 38, 'umbrellas': 39, 'vouchers': 40, 'wallets': 41, 'watches': 42, 'wa ID_TO_PRETRAINED_LABEL = {v: k for k, v in PRETRAINED_LABEL_TO_ID.items()} Image model device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu") image model = models.mobilenet v2().to(device) image model.classifier[-1] = torch.nn.Linear(1280, len(PRETRAINED LABEL TO ID)).to(device) file id = "1Fe DTre1Fr3osRDVGSR0zAzrtTJGkfHa" model destination = "trained models/image categorization.pt" download_file_from_google_drive(_file_id, _model_destination) image_model.load_state_dict(torch.load(_model_destination)) image model.eval() Out[8]: MobileNetV2((features): Sequential((0): ConvBNActivation((0): Conv2d(3, 32, kernel size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False) (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (1): InvertedResidual((conv): Sequential((0): ConvBNActivation((0): Conv2d(32, 32, kernel size=(3, 3), stride=(1, 1), padding=(1, 1), groups=32, bias=False) (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (1): Conv2d(32, 16, kernel size=(1, 1), stride=(1, 1), bias=False) (2): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): InvertedResidual((conv): Sequential((0): ConvBNActivation((0): Conv2d(16, 96, kernel size=(1, 1), stride=(1, 1), bias=False) (1): BatchNorm2d(96, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (1): ConvBNActivation((0): Conv2d(96, 96, kernel size=(3, 3), stride=(2, 2), padding=(1, 1), groups=96, bias=False) (1): BatchNorm2d(96, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (2): Conv2d(96, 24, kernel size=(1, 1), stride=(1, 1), bias=False) (3): BatchNorm2d(24, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (3): InvertedResidual((conv): Sequential((0): ConvBNActivation((0): Conv2d(24, 144, kernel_size=(1, 1), stride=(1, 1), bias=False) (1): BatchNorm2d(144, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (1): ConvBNActivation((0): Conv2d(144, 144, kernel size=(3, 3), stride=(1, 1), padding=(1, 1), groups=144, bias=False) (1): BatchNorm2d(144, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (2): Conv2d(144, 24, kernel_size=(1, 1), stride=(1, 1), bias=False) (3): BatchNorm2d(24, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (4): InvertedResidual((conv): Sequential((0): ConvBNActivation((0): Conv2d(24, 144, kernel_size=(1, 1), stride=(1, 1), bias=False) (1): BatchNorm2d(144, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (1): ConvBNActivation((0): Conv2d(144, 144, kernel size=(3, 3), stride=(2, 2), padding=(1, 1), groups=144, bias=False) (1): BatchNorm2d(144, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (2): Conv2d(144, 32, kernel size=(1, 1), stride=(1, 1), bias=False) (3): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (5): InvertedResidual((conv): Sequential((0): ConvBNActivation((0): Conv2d(32, 192, kernel_size=(1, 1), stride=(1, 1), bias=False) (1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (1): ConvBNActivation((0): Conv2d(192, 192, kernel size=(3, 3), stride=(1, 1), padding=(1, 1), groups=192, bias=False) (1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (2): Conv2d(192, 32, kernel size=(1, 1), stride=(1, 1), bias=False) (3): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (6): InvertedResidual((conv): Sequential((0): ConvBNActivation((0): Conv2d(32, 192, kernel_size=(1, 1), stride=(1, 1), bias=False) (1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (1): ConvBNActivation((0): Conv2d(192, 192, kernel size=(3, 3), stride=(1, 1), padding=(1, 1), groups=192, bias=False) (1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (2): Conv2d(192, 32, kernel size=(1, 1), stride=(1, 1), bias=False) (3): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (7): InvertedResidual((conv): Sequential((0): ConvBNActivation((0): Conv2d(32, 192, kernel_size=(1, 1), stride=(1, 1), bias=False) (1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (1): ConvBNActivation((0): Conv2d(192, 192, kernel size=(3, 3), stride=(2, 2), padding=(1, 1), groups=192, bias=False) (1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (2): Conv2d(192, 64, kernel size=(1, 1), stride=(1, 1), bias=False) (3): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (8): InvertedResidual((conv): Sequential((0): ConvBNActivation((0): Conv2d(64, 384, kernel_size=(1, 1), stride=(1, 1), bias=False) (1): BatchNorm2d(384, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (1): ConvBNActivation((0): Conv2d(384, 384, kernel size=(3, 3), stride=(1, 1), padding=(1, 1), groups=384, bias=False) (1): BatchNorm2d(384, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (2): Conv2d(384, 64, kernel_size=(1, 1), stride=(1, 1), bias=False) (3): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (9): InvertedResidual((conv): Sequential((0): ConvBNActivation((0): Conv2d(64, 384, kernel_size=(1, 1), stride=(1, 1), bias=False) (1): BatchNorm2d(384, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (1): ConvBNActivation((0): Conv2d(384, 384, kernel size=(3, 3), stride=(1, 1), padding=(1, 1), groups=384, bias=False) (1): BatchNorm2d(384, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (2): Conv2d(384, 64, kernel size=(1, 1), stride=(1, 1), bias=False) (3): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (10): InvertedResidual((conv): Sequential((0): ConvBNActivation((0): Conv2d(64, 384, kernel_size=(1, 1), stride=(1, 1), bias=False) (1): BatchNorm2d(384, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (1): ConvBNActivation((0): Conv2d(384, 384, kernel size=(3, 3), stride=(1, 1), padding=(1, 1), groups=384, bias=False) (1): BatchNorm2d(384, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (2): Conv2d(384, 64, kernel_size=(1, 1), stride=(1, 1), bias=False) (3): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (11): InvertedResidual((conv): Sequential((0): ConvBNActivation((0): Conv2d(64, 384, kernel_size=(1, 1), stride=(1, 1), bias=False) (1): BatchNorm2d(384, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (1): ConvBNActivation((0): Conv2d(384, 384, kernel size=(3, 3), stride=(1, 1), padding=(1, 1), groups=384, bias=False) (1): BatchNorm2d(384, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (2): Conv2d(384, 96, kernel size=(1, 1), stride=(1, 1), bias=False) (3): BatchNorm2d(96, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (12): InvertedResidual((conv): Sequential((0): Conv2d(96, 576, kernel_size=(1, 1), stride=(1, 1), bias=False) (1): BatchNorm2d(576, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (1): ConvBNActivation((0): Conv2d(576, 576, kernel size=(3, 3), stride=(1, 1), padding=(1, 1), groups=576, bias=False) (1): BatchNorm2d(576, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (2): Conv2d(576, 96, kernel size=(1, 1), stride=(1, 1), bias=False) (3): BatchNorm2d(96, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (13): InvertedResidual((conv): Sequential((0): ConvBNActivation((0): Conv2d(96, 576, kernel_size=(1, 1), stride=(1, 1), bias=False) (1): BatchNorm2d(576, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (1): ConvBNActivation((0): Conv2d(576, 576, kernel size=(3, 3), stride=(1, 1), padding=(1, 1), groups=576, bias=False) (1): BatchNorm2d(576, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (2): Conv2d(576, 96, kernel size=(1, 1), stride=(1, 1), bias=False) (3): BatchNorm2d(96, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (14): InvertedResidual((conv): Sequential((0): ConvBNActivation((0): Conv2d(96, 576, kernel_size=(1, 1), stride=(1, 1), bias=False) (1): BatchNorm2d(576, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (1): ConvBNActivation((0): Conv2d(576, 576, kernel size=(3, 3), stride=(2, 2), padding=(1, 1), groups=576, bias=False) (1): BatchNorm2d(576, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (2): Conv2d(576, 160, kernel size=(1, 1), stride=(1, 1), bias=False) (3): BatchNorm2d(160, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (15): InvertedResidual((conv): Sequential((0): ConvBNActivation((0): Conv2d(160, 960, kernel_size=(1, 1), stride=(1, 1), bias=False) (1): BatchNorm2d(960, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (1): ConvBNActivation((0): Conv2d(960, 960, kernel size=(3, 3), stride=(1, 1), padding=(1, 1), groups=960, bias=False) (1): BatchNorm2d(960, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (2): Conv2d(960, 160, kernel size=(1, 1), stride=(1, 1), bias=False) (3): BatchNorm2d(160, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (16): InvertedResidual((conv): Sequential((0): ConvBNActivation((0): Conv2d(160, 960, kernel_size=(1, 1), stride=(1, 1), bias=False) (1): BatchNorm2d(960, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (1): ConvBNActivation((0): Conv2d(960, 960, kernel size=(3, 3), stride=(1, 1), padding=(1, 1), groups=960, bias=False) (1): BatchNorm2d(960, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (2): Conv2d(960, 160, kernel size=(1, 1), stride=(1, 1), bias=False) (3): BatchNorm2d(160, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (17): InvertedResidual((conv): Sequential((0): Conv2d(160, 960, kernel size=(1, 1), stride=(1, 1), bias=False) (1): BatchNorm2d(960, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (1): ConvBNActivation((0): Conv2d(960, 960, kernel size=(3, 3), stride=(1, 1), padding=(1, 1), groups=960, bias=False) (1): BatchNorm2d(960, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (2): ReLU6(inplace=True) (2): Conv2d(960, 320, kernel size=(1, 1), stride=(1, 1), bias=False) (3): BatchNorm2d(320, eps=1e-05, momentum=0.1, affine=True, track running stats=True) (18): ConvBNActivation((0): Conv2d(320, 1280, kernel_size=(1, 1), stride=(1, 1), bias=False) (1): BatchNorm2d(1280, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True) (2): ReLU6(inplace=True) (classifier): Sequential((0): Dropout(p=0.2, inplace=False) (1): Linear(in features=1280, out features=45, bias=True) Load text model (it's big, this may take some time) _file_id = "1_Dbk5KPuVaCf8KD6DICzhA_QcSvxS8Lj" _model_destination = "trained_models/text_categorization.bin" download_file_from_google_drive(_file_id, _model_destination) text_model = fasttext.load_model(_model_destination) Warning: `load_model` does not return WordVectorModel or SupervisedModel any more, but a `FastText` object whi ch is very similar. Inference on the test set $TOP_K_PREDICTIONS = 3$ The test set has a different set of labels from what the models were trained, so, in order to infer the categories of products on the test set, we're going to **project** the test labels on the same label space the models were trained. After projecting the test labels, we're going to use the averaged pre-trained models predictions and compute the nearest neighbors with **KL-divergence** from the test labels. It goes as follows: I) Test set inferences, on their own "labels space" **Images first** from pathlib import Path from PIL import Image p = Path("test dataset/") class TestDataset(torch.utils.data.Dataset): def init (self, image path, transform): self.image paths = list(Path(image path).glob('*.jpg')) self.transform = transform def getitem (self, index): image path = self.image paths[index] x = Image.open(image path) x = self.transform(x)return x def len (self): return len(self.image paths) In [84]: test_img_transforms = transforms.Compose([transforms.Resize(256), transforms.CenterCrop(256), transforms.ToTensor(), transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])]) image model.eval() image model predictions = [] for img_path in tqdm(test_products_df["img_path"]): inputs = test img transforms(Image.open(img path)).to(device).unsqueeze(0) with torch.no grad(): outputs = torch.nn.Softmax(-1)(image model(inputs)) image model predictions.extend(outputs.cpu().numpy()) image model predictions = np.array(image model predictions) **Text inferences** text_model_predictions = [text model.predict(description, k=3) for description in test_products_df["description"] Ensemble both inferences with an average of the predictions def get_img_one_hot_prediction(img_prediction): top img probabilities = np.zeros(len(text model.get labels())) top_img_preds = np.argpartition(img_prediction, -TOP_K_PREDICTIONS)[-TOP_K_PREDICTIONS:] top_img_preds_probabilities = img_prediction[top_img_preds] / img_prediction[top_img_preds].sum() top_img_probabilities[top_img_preds] = top_img_preds_probabilities return top_img_probabilities def get_txt_one_hot_prediction(txt_prediction): top txt probabilities = np.zeros(len(text model.get labels())) top_txt_preds = list(map(lambda label: int(label.split("__")[-1]), txt_prediction[0])) top_txt_preds_probabilities = txt_prediction[1]/txt_prediction[1].sum() top_txt_probabilities[top_txt_preds] = top_txt_preds_probabilities return top_txt_probabilities ensembled preds = [] for (img_prediction, txt_prediction) in zip(image_model_predictions, text_model_predictions): # Get top k image predictions top_img_probabilities = get_img_one_hot_prediction(img_prediction) # Get top k text predictions top_txt_probabilities = get_txt_one_hot_prediction(txt_prediction) # Merge both predictions by summing up probabilities on the same class _ensembled_probabilities = top_txt_probabilities + top_img_probabilities _ensembled_probabilities /= _ensembled_probabilities.sum() ensembled_preds.append(_ensembled_probabilities) Assign the test class with lowest KL-divergence We'll project the test labels into the train labels distribution and then, with this new test label representation, we'll compute the KL-Divergence (it computes "distances" between probability distributions) between each test label and the predicted probabilities. The final inference will be that which holds the smallest the KL-divergence. def kl_divergence(p, q): EPS = 1e-8p = np.asarray(p)q = np.asarray(q)return np.sum(np.where(p != 0, p * np.log((p+EPS) / (q+EPS)), 0)) test labels probabilities = [get txt one hot prediction(text model.predict(label, k=3)) for label in test categories test_predictions = [] for idx, ensembled_prediction in enumerate(ensembled_preds): nearest_label = np.argmin([kl_divergence(ensembled_prediction, test_label_probabilities) for test_label_probabilities in test_labels_probabilities]) test_predictions.append(ID_TO_PRETRAINED_LABEL[nearest_label]) test_products_df["inferred_category"] = test_predictions Visual inspection of results and conclusions import matplotlib.image as mpimg f, axes = plt.subplots(10, 2, figsize=(18, 50)) for idx, (_, product) in enumerate(test_products_df.groupby("inferred_category").sample(2).iterrows()): current_axis = axes[idx//2][0 if idx%2==0 else 1] img = mpimg.imread(product["img_path"]) current_axis.imshow(img) current_axis.set_title(f'inferred category {product["inferred_category"].upper()}') inferred category ACCESSORIES inferred category ACCESSORIES 250 500 500 1000 750 1000 1500 1250 2000 1500 2500 1750 1000 1500 1000 1500 inferred category APPAREL SET inferred category APPAREL SET 500 500 1000 1000 1500 1500 2000 2000 2500 2500 3000 1000 1500 500 1000 1500 inferred category BAGS inferred category BAGS 0 100 500 200 1000 300 1500 400 2000 500 200 1500 inferred category BATH AND BODY inferred category BATH AND BODY 100 100 200 200 300 300 400 400 500 500 100 200 300 100 200 300 inferred category BEAUTY ACCESSORIES inferred category BEAUTY ACCESSORIES 250 250 500 500 750 750 1000 1000 1500 1500 1750 1750 2000 2000 500 1000 1500 500 1000 1500 inferred category BELTS inferred category BELTS 0 0 500 500 1000 1000 1500 1500 2000 2000 1500 1500 inferred category CUFFLINKS inferred category CUFFLINKS 500 500 1000 1000 1500 1500 2000 2000 1000 1500 2000 500 1000 1500 inferred category EYES inferred category EYES 100 200 1000 300 1500 400 2000 500 500 1000 1500 100 200 300 inferred category EYEWEAR inferred category EYEWEAR 0 100 500 200 1000 300 1500 400 2000 500 1000 500 1500 100 200 300 400 2000 inferred category FLIP FLOPS inferred category FLIP FLOPS 100 500 200 1000 300 1500 400 2000 500 100 Well, it didn't perform as good as one would expect. And that is due to fact that models weren't properly evaluated and tuned on the target distribution, but only on the dummy train dataset. With more time, I would: Try to better fit and evaluate both models indivudually, checking the error cases on the desired final dataset. Find a more representative dataset for the first training phase.