Report of ArtExtract Evaluation Tasks

Task 1: Convolutional-Recurrent Architectures

For Task 1, I used this link to download the images and this link to download the labels.

This dataset categorizes images by **artist (23 classes)**, **genre (10 classes)**, and **style (27 classes)**. Thus, my goal for this task was to develop a multitask model capable of predicting the artist, genre, and style associated with each image.

Outlier Detection

To identify outliers, I initially computed the Z-score for each image across each class, encompassing artist, genre, and style. Despite the potential need for manual review, constrained by time, I designated images with a Z-score exceeding 3 as outliers, as they deviate three standard deviations from the class mean.

Model:

For model, I used ResNet-50 image net pretrained model, with an added LSTM layer to make it Convolutional-Recurrent model. After that, linear layers were added to classify artist, genre and style. Details of the model can be found in, ***"Task1/model.py"*** file.

Training

For training, I tried two approaches, first I tried to combine all three datasets into one dataset by only taking images with all three labels. Training code for this part is available in "***Task1/train.py"*** file. The performance of the model after 50 epochs is shown in the screenshot below,

```
Artist accuracy: 0.7867157378198387
Genre accuracy: 0.5571328426218016
Style accuracy: 0.3617245005257624
```

While the accuracy for artist classification in this model is commendable, it falls short for genre and style. One contributing factor is the absence of training images for certain genre and style classes when considering only images with all three labels. To address this, I approached training each classification task separately for each dataset, focusing on artists, genres, and styles individually, utilizing their respective image sets. The details of the code for this section can be found in "***Task1/Task1.ipynb"*** file. Training the model for 70 epochs produces the following result,

```
Artist accuracy: 0.6808622502628812
Genre accuracy: 0.6090080616894497
Style accuracy: 0.4032597266035752
```

I was training it longer because the loss was still higher comparatively. In this procedure model requires more time to converge, even after 70 epochs the loss was high compared to the previous approach. But the performance for genre and style improved while for artist it was worse. I think training it longer might improve the score for all three tasks.

Task 2: Similarity

For downloading dataset, I used this github repo. To download the images, I used script named ***“Task2/opendata-main/downloader.py”***.

I was always interested to find out if there is any similarity between arts of specific time frame and if there is, can an AI model be able to classify it effectively.

In this dataset, we can find which image is displayed in which timeframe. There are **20 timeframes available**, classifying images based on timeframe can be considered as a good indication of similarity. Therefore, I decided to try out classifying the image’s display timeframe. Details of the dataset creation is available in **“Task2/*opendata-main/*Task2.ipynb”** file.

Model and Training

For model, I tried imagenet pretrained ResNet-50 model. After training it for 70 epochs, the model was able to classify ~64% of test images were classified correctly. To improve the performance, maybe more sophisticated model is required.