Learning the Deep Emotional Intelligence of Artists
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Motivation
Creators of content attempt to evoke certain emotions in viewers. In this project we attempt to learn the mapping of pixel to emotion with deep learning. Our project has two goals:

1. Construct a classifier to predict emotion classes of art images.
2. Build GANs to generate art, which can be tested by our classifier.

Data and Problem Definition
Our data are 40k artistic images from a sponsor, ~3k of which have emotion labels and other tags. Most of the art is a medium with highly subjective labels. There are no ground truth labels for our data; a painting may transmit different emotions to different people. With this intuition, and some analysis of label distributions we grouped 16 emotion classes into 4. Nearly 39% of our data were labeled "neutral" or "NA". After some preliminary models we filtered our data to only portraits (further explanation in Approach). This filtered data left us with nearly 500 labeled artworks for our classifier which we augmented to 2k. For GANs, we used 7k unlabeled portraits.

GAN Models
The loss functions of the generator and discriminator are respectively:

\[ \mathcal{L}_{\text{GAN}} = -\mathbb{E}_{y \sim p_{data}} \log(D(y)) \]

\[ \mathcal{L}_{\text{GAN}} = -\mathbb{E}_{z \sim p_{z}} \log(D(G(z))) - \mathbb{E}_{z \sim p_{z}} \log(1 - D(G(z))) \]

Generator architectures:
1. Shallow network with Fully Connected (FC) layers: first we consider a network that receives a 100-dimensional input vector and generates an array of dimension \(w \times h \times c\) through 3 FC layers.
2. Deconvolution layers: the random code input, after going through a FC layer, is reshaped and goes through 3 deconvolutions.

Discriminator architectures:
1. Shallow network with FC layers: input image is flattened and fed to 3 FC layers.
2. CNN: network with 2 convolutional layers (with max pooling) and a FC layer.

Different combinations of generator and discriminator architectures are used, while varying parameters (filter sizes, channels, etc.) and hyperparameters.

Classifier Models with Attribution
We refined our classifiers based on their performance on the test set, as well as analyzing Class Activation Maps (CAM) and Class Model Visualization (CMV). We first attempted a shallow network with the same architecture used in our GANs. We used the adam optimizer with categorical cross-entropy loss. Performance was not satisfactory on the train and test sets, hence we attempted to train a FC layer appended to VGG-16 for feature extraction. This improved results but was still not satisfactory. By observing the CAMs from our Transfer Learning (TL) model, we concluded that many labels are driven by global features such as colour and texture rather than local ones such as shapes and objects that VGG was meant to learn.

To build on the above finding we examined the additional tags and ran our data through the YOLO pre-trained object detector, and found many images to have a “person” object, and also tags such as “portrait” that suggested a person in the artwork. We limited our data to only these art works.

We then built two models: a VGG feature extractor with a trained FC layer to classify based on the local features, and a shallow FC model to classify based on 13 global hand engineered features motivated by Computer Vision (CV) theory [3]. Since our data was now filtered we used data augmentation to increase it. Flips and rotations were used but not blur since it would impact texture.

Results and Analysis
We examine results on a 25% test set of our artworks. Below are the results of local and global feature models under different architectures and hyperparameters:

<table>
<thead>
<tr>
<th>Model</th>
<th>Train Acc</th>
<th>Test Acc</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shiffer-Arch1</td>
<td>29.0%</td>
<td>27.6%</td>
</tr>
<tr>
<td>Shiffer-Arch2</td>
<td>30.0%</td>
<td>25.4%</td>
</tr>
<tr>
<td>VGG16-1L-Arch1</td>
<td>45.1%</td>
<td>40.0%</td>
</tr>
<tr>
<td>VGG16-1L-Arch2</td>
<td>47.0%</td>
<td>48.1%</td>
</tr>
<tr>
<td>VGG16-TL-Arch1</td>
<td>56.1%</td>
<td>57.4%</td>
</tr>
<tr>
<td>CV-FC</td>
<td>55.2%</td>
<td>56.3%</td>
</tr>
</tbody>
</table>

For deep generators, the artworks are too noisy. We think more training epochs are needed, as there are many parameters. For our 3-deconvolutions model, although the generated images are not coherent, some patterns (face shape) are reproduced.

Discussion and Future Work
This task was challenging due to various reasons. The VGG models were pre-trained on real images (ImageNet), whereas here we are working with works of art. In addition, labeling tended to be ambiguous, with very similar images labeled as different emotions. Despite this we believe our classifier has managed to learn some utility.

Chez Mana, our sponsor, is a digital content creator. They aim to augment their content library using AI techniques. The high level goals of the project were developed jointly by our working team, CEO Mana Lewis, and science advisor Bill Jandoli.