

ArtGAN: Artwork synthesis with **Conditional Categorical GANs** Wei Ren Tan¹, Chee Seng Chan², Hernán E. Aguirre¹, and Kiyoshi Tanaka¹

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Motivations

- ► Recently, GAN showed significant promise in generating natural images, e.g. from MNIST, CIFAR-10, CUB-200, or LFW datasets.
- Subjects in these images have structured shape such as numeric, vehicles, birds, face, etc.
- Can GAN learn to draw based on more abstract classes?

Challenges

- ► Many paintings are non-representative nor figurative
- Some paintings are classified based on non-visual background knowledge, e.g. Renaissance paintings are artworks from Renaissance period.

Inspiration

- ▶ An artist teacher [1] pointed out that an effective learning in art domain requires one to focus on a particular skill.
- ► For instance, practice to draw one kind of movement at a time.
- ► To imitate this learning skill, ArtGAN is trained with additional information by training a classifier and backpropagate the class errors.

Goals

- End-to-end train ArtGAN to synthesize artworks based on *style*, *genre*, or artist.
- Investigate what kind of features GAN learnt from fine-art paintings.

Wikiart Paintings Dataset[2]

- \blacktriangleright Collection of > 80,000 fine-art paintings ranging from 15th century to modern times.
- ▶ 27 *styles* from **all** paintings.
- \blacktriangleright 10 genres with > 1,500 paintings $(\sim 65,000 \text{ samples}).$
- \blacktriangleright 23 artists with > 500 paintings $(\sim 20,000 \text{ samples}).$

References

[1] Paul Foxton. How to practise drawing effectly, 2011.

[2] Babak Saleh and Ahmed Elgammal. Large-scale classification of fine-art paintings: Learning the right metric on the right feature. arXiv preprint arXiv:1505.00855, 2015.



$$\mathcal{L}_{D} = -\mathbb{E}_{(\mathbf{x}_{r},k) \sim p_{data}} \big[y_{k} \log p(y_{k} | \mathbf{x}_{r}) + \sum_{i \neq k} \log(1 - p(y_{i} | \mathbf{x}_{r})) \big] - \mathbb{E}_{\hat{\mathbf{z}} \sim p_{noise}, \hat{k} \sim \mathbf{K}} \big[\log p(y_{\mathcal{K}+1} | G(\hat{\mathbf{z}}, \hat{\mathbf{y}}_{\hat{k}})) + \sum_{i < \mathcal{K}+1} \log(1 - p(y_{i} | G(\hat{\mathbf{z}}, \hat{\mathbf{y}}_{i}))) \big] \big] - \mathbb{E}_{\hat{\mathbf{z}} \sim p_{noise}, \hat{k} \sim \mathbf{K}} \big[\log p(y_{\mathcal{K}+1} | G(\hat{\mathbf{z}}, \hat{\mathbf{y}}_{\hat{k}})) + \sum_{i < \mathcal{K}+1} \log(1 - p(y_{i} | G(\hat{\mathbf{z}}, \hat{\mathbf{y}}_{i}))) \big] \big] \big] - \mathbb{E}_{\hat{\mathbf{z}} \sim p_{noise}, \hat{k} \sim \mathbf{K}} \big[\log p(y_{\mathcal{K}+1} | G(\hat{\mathbf{z}}, \hat{\mathbf{y}}_{\hat{k}})) \big] \big] \big] - \mathbb{E}_{\hat{\mathbf{z}} \sim p_{noise}, \hat{k} \sim \mathbf{K}} \big[\log p(y_{\mathcal{K}+1} | G(\hat{\mathbf{z}}, \hat{\mathbf{y}}_{\hat{k}})) \big] \big] \big] - \mathbb{E}_{\hat{\mathbf{z}} \sim p_{noise}, \hat{k} \sim \mathbf{K}} \big[\log p(y_{\mathcal{K}+1} | G(\hat{\mathbf{z}}, \hat{\mathbf{y}}_{\hat{k}})) \big] \big] \big] \big] - \mathbb{E}_{\hat{\mathbf{z}} \sim p_{noise}, \hat{k} \sim \mathbf{K}} \big[\log p(y_{\mathcal{K}+1} | G(\hat{\mathbf{z}}, \hat{\mathbf{y}}_{\hat{k}})) \big] \big] \big] \big] - \mathbb{E}_{\hat{\mathbf{z}} \sim p_{noise}, \hat{k} \sim \mathbf{K}} \big[\log p(y_{\mathcal{K}+1} | G(\hat{\mathbf{z}}, \hat{\mathbf{y}}_{\hat{k}})) \big] \big] \big] \big] \big] \big] \big] \big]$$

$$\mathcal{L}_{G} = -\mathbb{E}_{\hat{\mathbf{z}} \sim p_{noise}, \hat{k} \sim \mathbf{K}} \Big[\log p(y_{\hat{k}} | G(\hat{\mathbf{z}}, \hat{\mathbf{y}}_{\hat{k}})) + \sum_{i \neq \hat{k}} \log(1 - p(y_{i} | G(\hat{\mathbf{z}}, \hat{\mathbf{y}}_{\hat{k}}))) \Big] + \mathbb{E}_{\mathbf{x}_{r} \sim p_{data}} \Big[||Dec(Enc(\mathbf{x}_{r})) - \mathbf{x}_{r}||_{2}^{2} \Big]$$













