Variational Style Transfer

Jan Schopohl, Dominik Fuchsgruber

Supervisor: Maxim Maximov

Department of Informatics, Technical University of Munich

December 3rd, 2019

Given a **content image** C
and an artistic **style image** S:

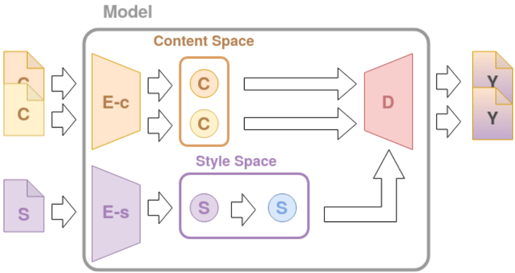
$\rightarrow$ **Stylization**: Image with content similar to C and a style similar to S

How to combine **different styles**?

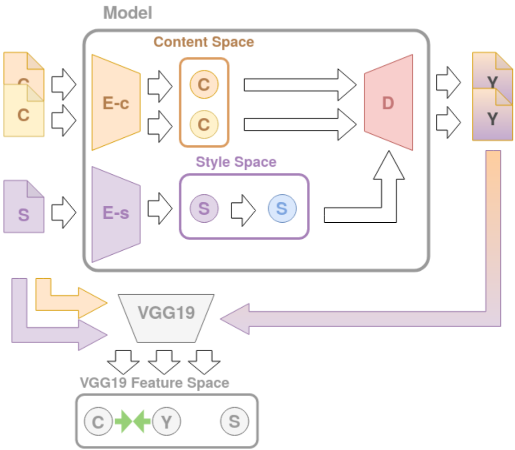
Related Work

- [1]: Optimize random image to fit C content-wise and S style-wise $\rightarrow$ **very slow!**
- [2]: **Autoencoders** to encode C and S, use Adaptive Instance Normalization (**AdaIn**) to transfer the style
- [5]: Separate Encoders for **content** and **style**
  $\rightarrow$ **Disentanglement**
- [4]: **Variational Autoencoders** encode into a **smooth latent space**
  $\rightarrow$ Good for **interpolation between encodings**
- [3]: **Perceptual losses** for style transfer

Our Approach - Pipeline

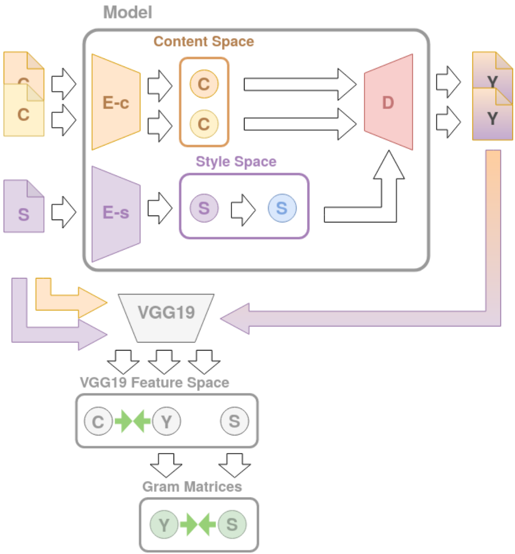


- **Content Encoder E-c** and **Style Encoder E-s**
- **Random sampling** from a Gaussian centered at **style encoding**



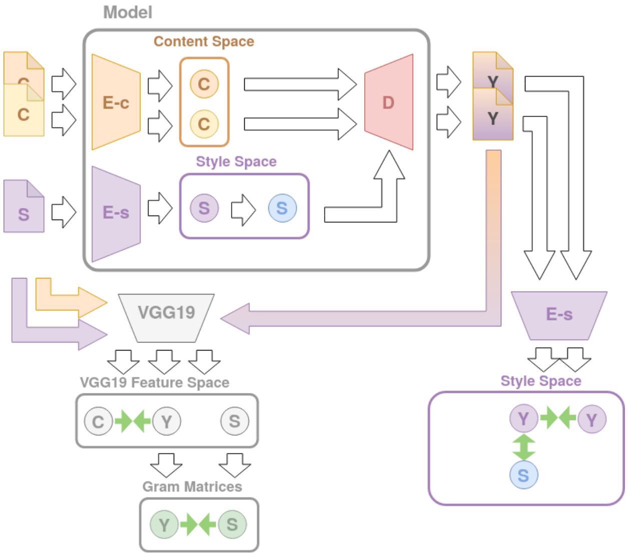
- **Content Loss**: Perceptual loss using pretrained **VGG19** loss network

Our Approach - Style Loss

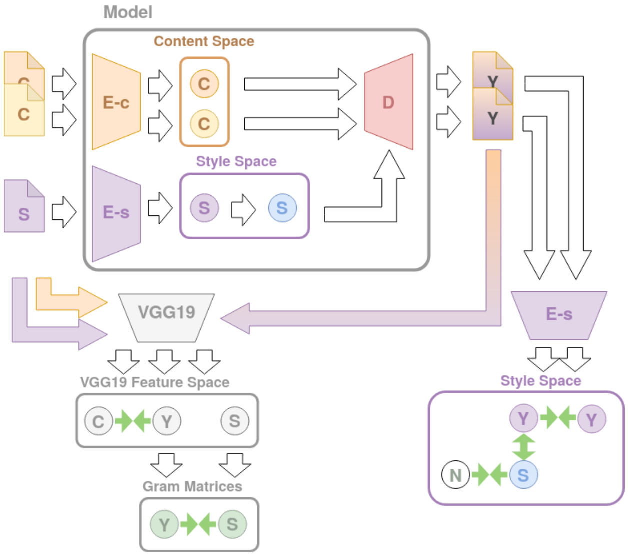


- **Style Loss**: Gram matrices of feature activations

Our Approach - Disentanglement Loss

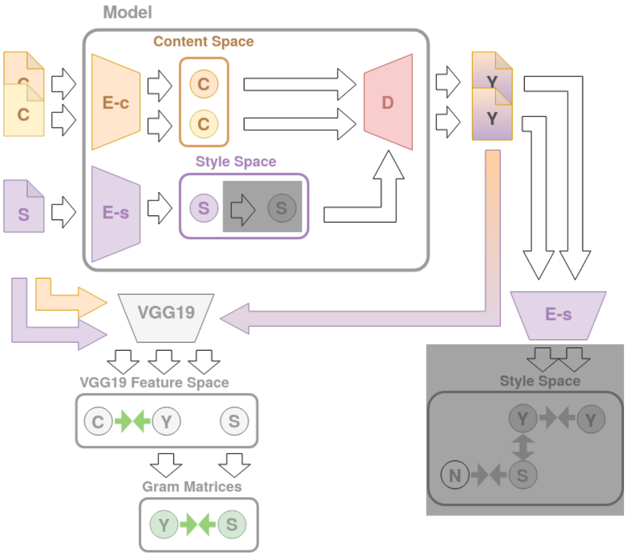


- **Disentanglement Loss**: Disentangles content and style



- **Regularization**: Regularizes style distribution

Our Approach - Implementation Progress



Gray components are not yet implemented.

Code

Available implementations:

- **Loss network**: **torchvision**'s[1] pretrained VGG19
- **Content** and **style** losses and **AdaIn**: Unofficial implementation[2] of [2]
- **Perceptual** and **style** losses pytorch implementation[3] of [1]

Unfortunately, for [5], **no implementation is available** so far.

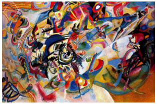
[1] `https://pytorch.org/docs/stable/torchvision/models.html`
[2] https://github.com/naoto0804/pytorch-AdaIN
[3] `https://github.com/leongatys/PytorchNeuralStyleTransfer`

Datasets

Content images: Places365[4] dataset with different sceneries



Style images: WikiArt[5] contains artistic images


Lack of large GPU resources: $\rightarrow$ **downsample** images to a **64x64** resolution and only **shallow** networks.

[4] `http://places2.csail.mit.edu/download.html`
[5] `https://github.com/cs-chan/ArtGAN`

Evaluation

To our best knowledge there is **no data-driven metric** to asses the quality of stylizations.

Common subjective assessment methods:

- **Preference Rate**: Probands **select most appealing** result among different stylizations
- **Deception Rate**: Probands try to **identify a real artistic image** mixed between stylizations

We focus on **interpolations between multiple styles**!

We would be glad if course participants and / or chair members could participate!

First Results

Milestones

What we want to achieve until the next presentation:

- Get the **style transfer** working
- Implement the **disentanglement loss**
- Implement **sampling** from a latent style distribution
- Fine-tune the architecture and train a final evaluation-ready model
- (Possibly) set up a **survey** and **participants** for our evaluation
  This includes getting **baselines** running as well

Baselines

Possible baselines for evaluation on **preference rate** include:

- The original style transfer paper [1]
- The **AdaIn** paper [2]: Same decoder for **content** and **style**
- Learning a **linear transformation** on an image embedding for style transfer [6]

Possibly problematic may be **model sizes** and **computation times** due to our limited resources.

References I

Leon A. Gatys, Alexander S. Ecker, and Matthias Bethge. "A Neural Algorithm of Artistic Style". In: *CoRR* abs/1508.06576 (2015). arXiv: 1508.06576. URL: http://arxiv.org/abs/1508.06576.

Xun Huang and Serge J. Belongie. "Arbitrary Style Transfer in Real-time with Adaptive Instance Normalization". In: *CoRR* abs/1703.06868 (2017). arXiv: 1703.06868. URL: http://arxiv.org/abs/1703.06868.

Justin Johnson, Alexandre Alahi, and Fei-Fei Li. "Perceptual Losses for Real-Time Style Transfer and Super-Resolution". In: *CoRR* abs/1603.08155 (2016). arXiv: 1603.08155. URL: http://arxiv.org/abs/1603.08155.

Diederik P Kingma and Max Welling. *Auto-Encoding Variational Bayes*. 2013. arXiv: 1312.6114 [stat.ML].

References II

Dmytro Kotovenko et al. "Content and Style Disentanglement for Artistic Style Transfer". In: *The IEEE International Conference on Computer Vision (ICCV)*. 2019.

Xueting Li et al. "Learning Linear Transformations for Fast Arbitrary Style Transfer". In: *CoRR* abs/1808.04537 (2018). arXiv: 1808.04537. URL: http://arxiv.org/abs/1808.04537.

Perceptual Loss

Instead of a pixel-wise loss between input and output:
$\rightarrow$ **error between feature activations** of layer(s) i provided by a pre-trained model Φ

$$\mathcal{L}_\Phi(y, \hat{y}) = \frac{1}{C_i \times H_i \times W_i} \sum_i \| f_\Phi^i(y) - f_\Phi^i(\hat{y}) \|_2^2$$

Where f^i are the **activation maps** of layer i with a dimensionality of $C_i \times H_i \times W_i$.

Penalizes **semantic discrepancies** between y and $\hat{y}$ (e.g. objects, composition, etc.)

Style Loss

Gram matrices G_i of feature activation maps f_i capture **correlations between channels**:

$$G_i(y) = \tilde{f}^i_\Phi(y)\tilde{f}^i_\Phi(y)^T$$

Where $\tilde{f}^i_\Phi$ are **flattened feature activation maps** of shape $C_i \times (H_i W_i)$.

$G_i(y)(c_1, c_2)$ captures how **strongly correlated** the features c_1 and c_2 are in the activation map f_i.

The **style loss** is given as the **error between Gram matrices of feature maps**:

$$\mathcal{L}_\Phi(y, \hat{y}) = \sum_i \frac{1}{C_i^2} \| G_i(y) - G_i(\hat{y}) \|_2^2$$

Style Loss

Try to **disentangle content and style**:
$\rightarrow$ Minimize influence of content on style representation

Let y_1 and y_2 denote stylizations of content images with style encoding s

$$\mathcal{L}(y_1, y_2, s) = max(0, \|y_1 - y_2\|_2^2 - \|y_1 - s\|_2^2) \tag{1}$$

Enforces two stylizations of **same style** to be **closer in style space** than a **stylization and the style source image**.

Instance Normalization is related to **Batch Normalization** but calculates **instance-wise** mean μ and variance σ^2, instead of using batch-wise statistics.

[2] showed that μ and σ **encapsulate style information**: $\rightarrow$

Adaptive Instance Normalization:

$$\mathrm{AdaIn}(x, y) = \sigma(y)\frac{x - \mu(x)}{\sigma(x)} + \mu(y)$$

transfers instance-wise statistics from y to x

No learnable parameters!

Autoencoders encode an input X to a latent space representation z and try to reconstruct X using only z.

$\rightarrow$ **neglects variations in input distribution** (e.g. noise)

$\rightarrow$ Latent space **may not be smooth**

Variational Autoencoders sample s from a **distribution parametrized by z** (usually Gaussian) instead

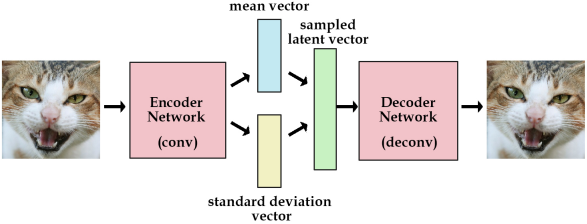


Figure: taken from
`http://kvfrans.com/variational-autoencoders-explained/`

Variational Autoencoders II

To enforce a **smooth latent space** the learned distribution is **regularized** using the KL-divergence:

$$\mathcal{L} = \mathbb{KL}(q_{\text{enc}}(s|X) \| p(z))$$

Where $q_{\text{enc}}(s|X)$ describes the distribution of latent representations s given an input X and $p(z)$ is set to be a standard normal distribution.

$\rightarrow$ forces **latent distribution** to be **close to a standard normal distribution**.