# Variational Style Transfer

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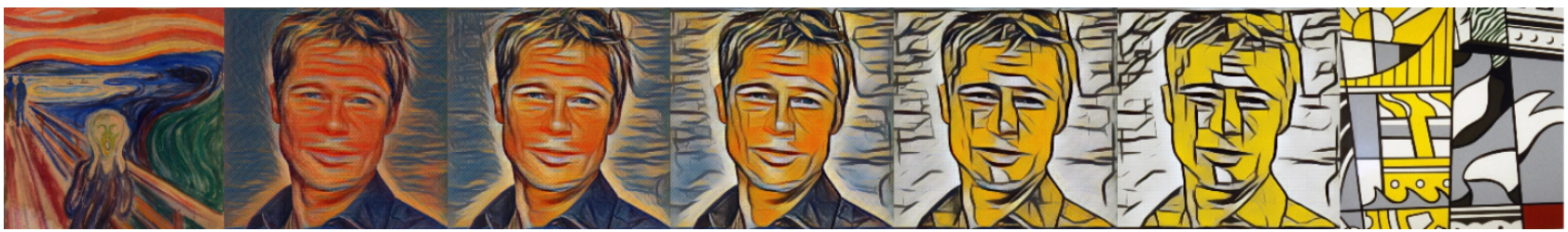
December 3rd, 2019

# Artistic Style Transfer

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

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

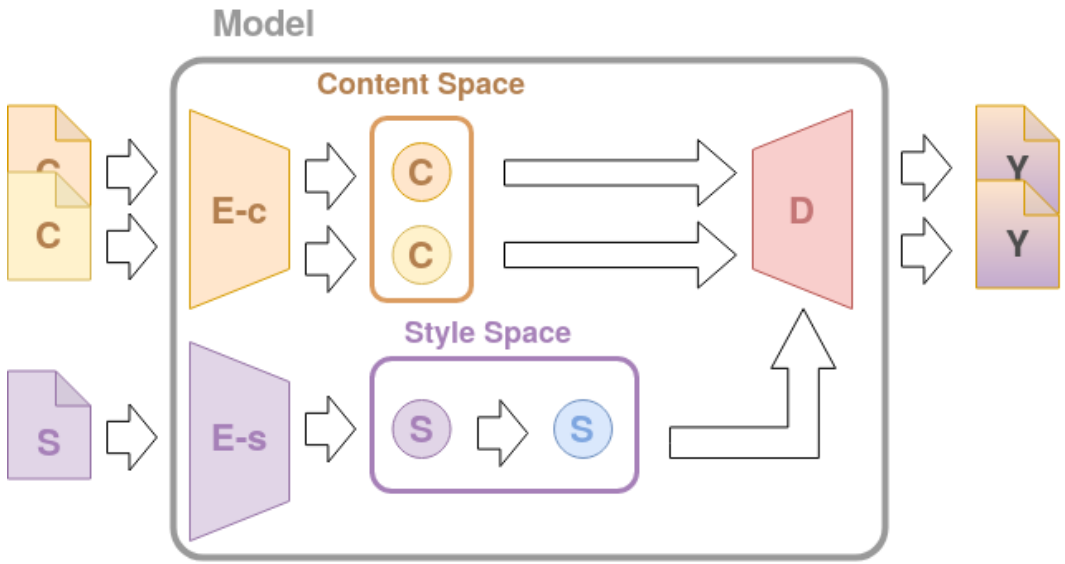
How to combine **different styles**?



# Related Work

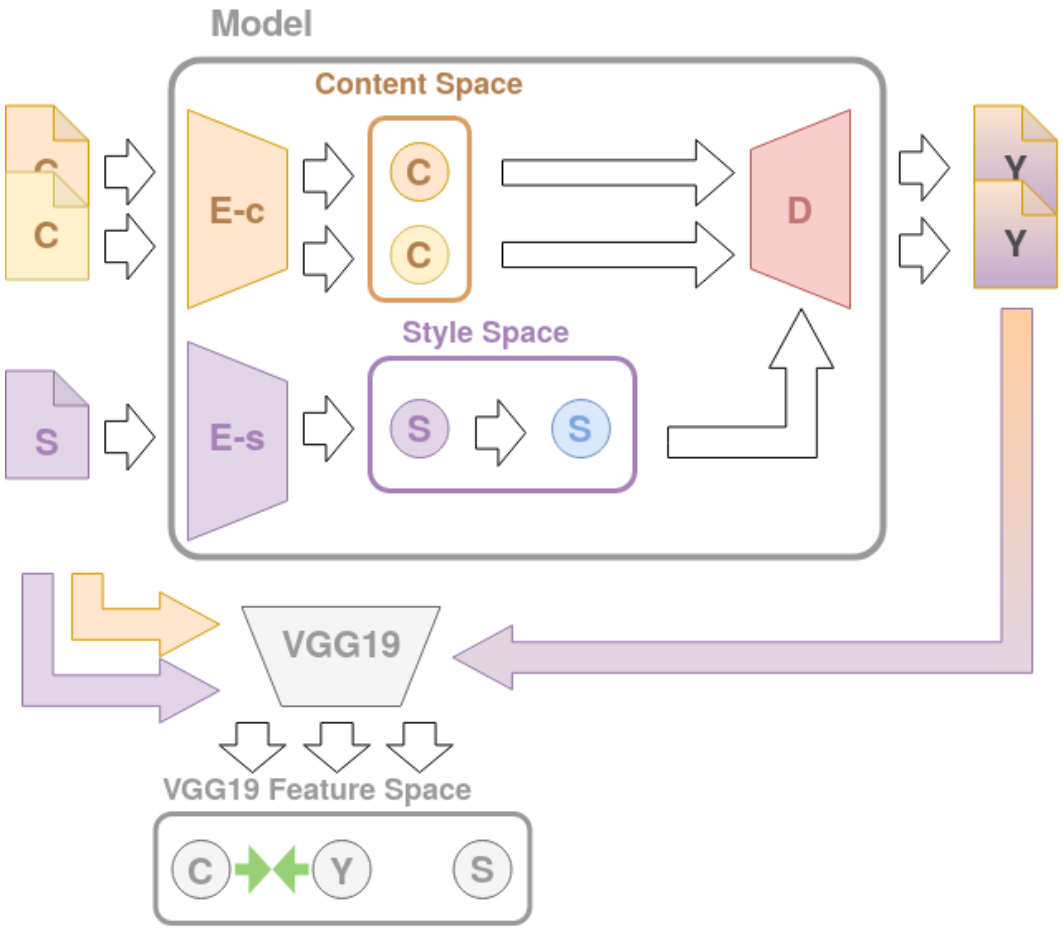
- [1]: Optimize random image to fit $C$ content-wise and $S$ style-wise $\rightarrow$ **very slow!**
- [2]: **Autoencoders** to encode $C$ and $S$, use Adaptive Instance Normalization (**AdaIn**) to transfer the style
- [5]: Separate Encoders for **content** and **style**
  $\rightarrow$ **Disentanglement**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

# Our Approach - Pipeline



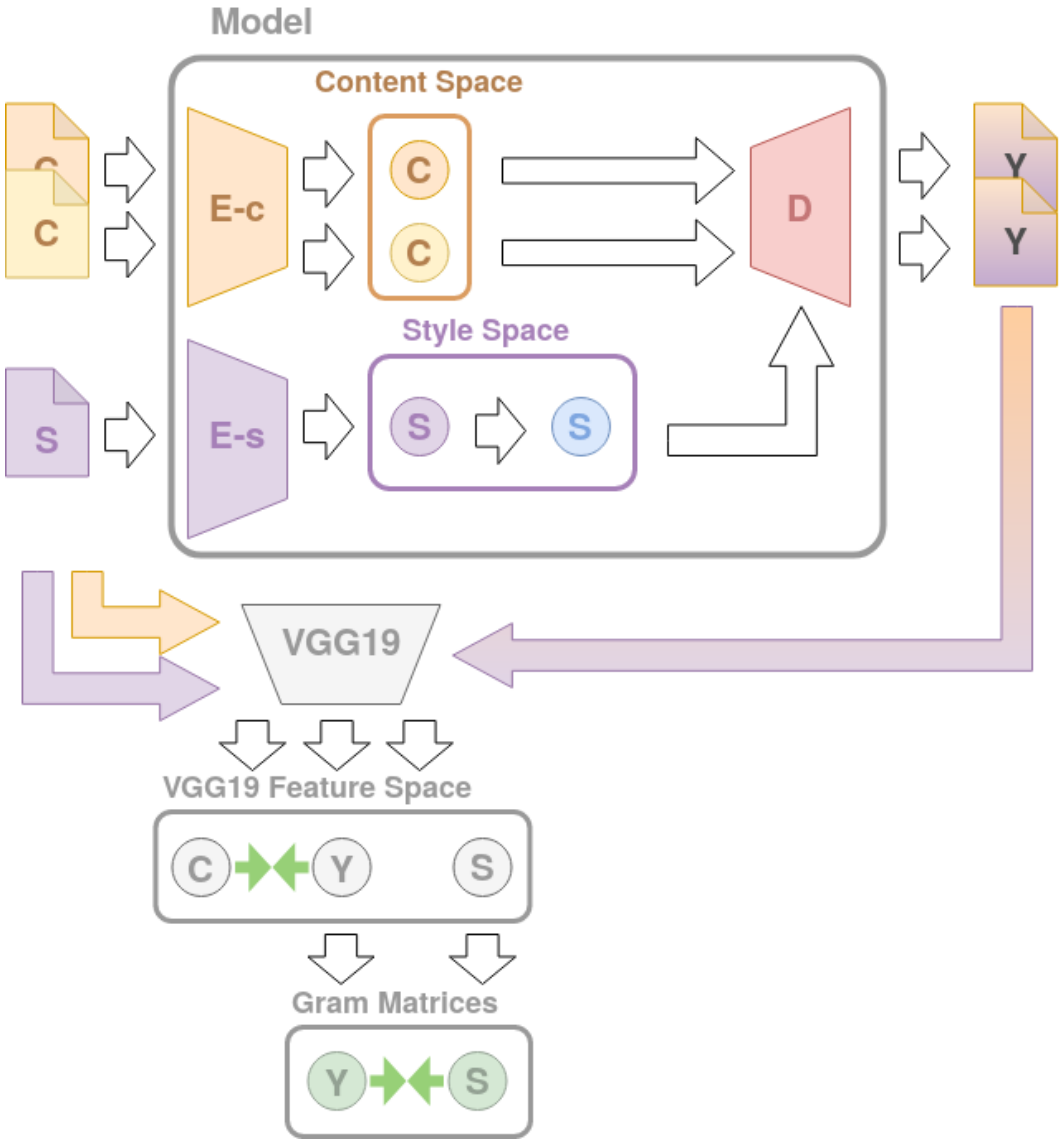

- **Content Encoder E-c** and **Style Encoder E-s**
- **Random sampling** from a Gaussian centered at **style encoding**

# Our Approach - Content Loss



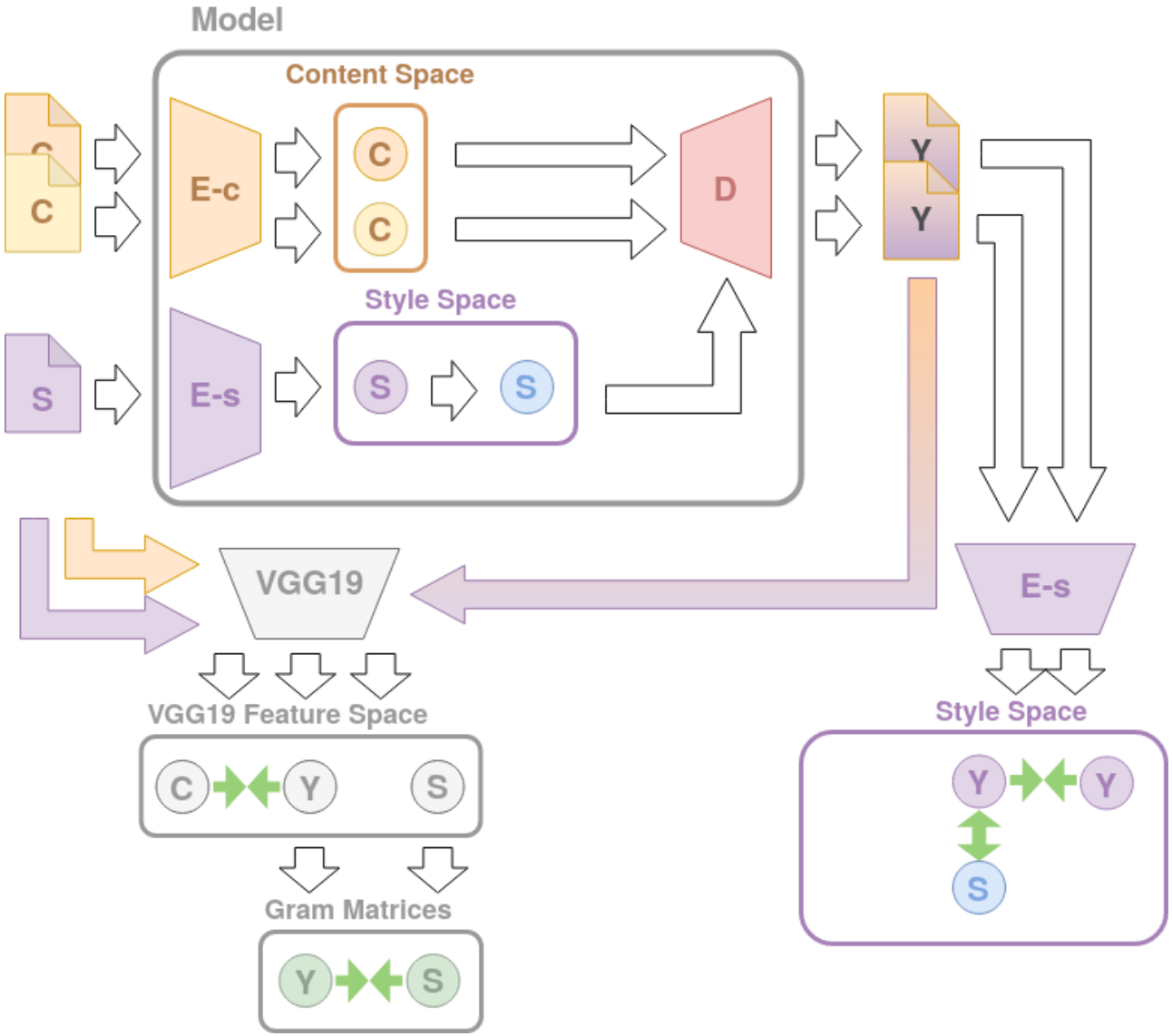

- **Content Loss**: Perceptual loss using pretrained **VGG19** loss network

# Our Approach - Style Loss



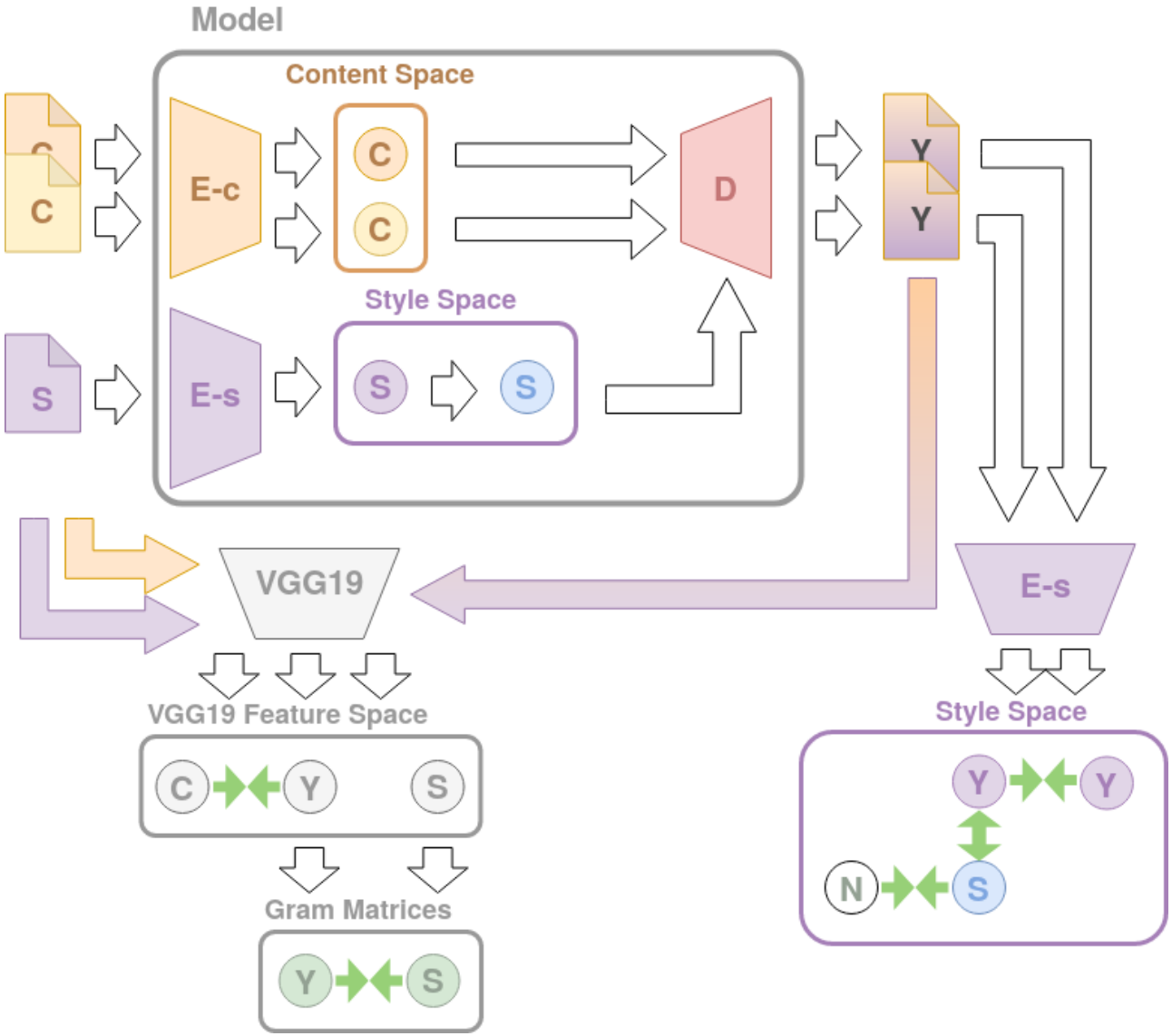

- **Style Loss**: Gram matrices of feature activations

# Our Approach - Disentanglement Loss



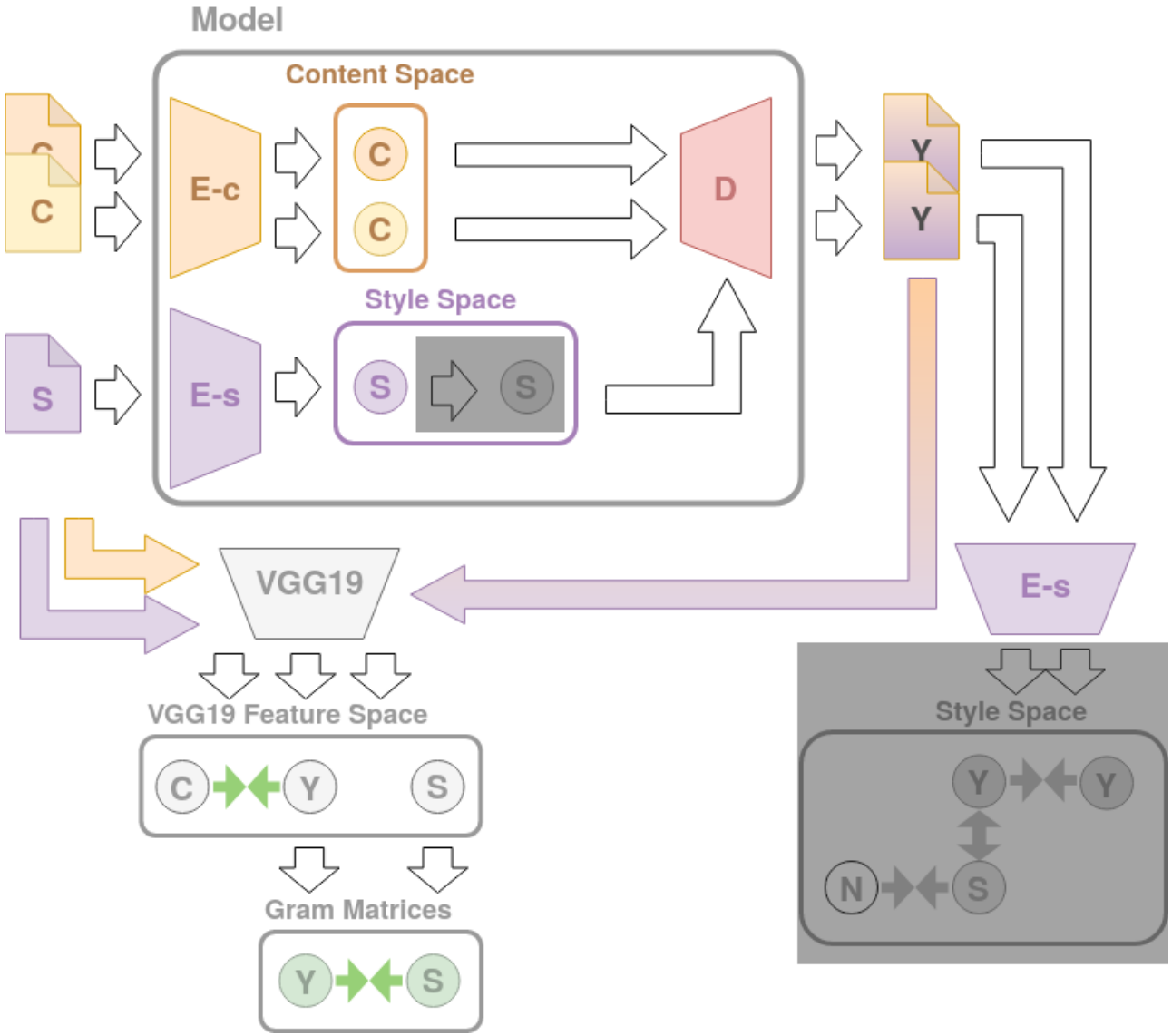

- **Disentanglement Loss**: Disentangles content and style

# Our Approach - Regularization Loss




- **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.

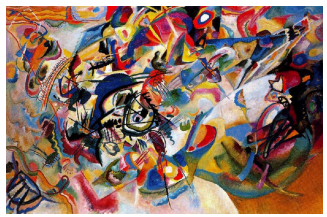
[1] `https://pytorch.org/docs/stable/torchvision/models.html`
[2] https://github.com/naoto0804/pytorch-AdaIN
[3] `https://github.com/leongatys/PytorchNeuralStyleTransfer`

# 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 $\Phi$

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

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**:

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

# Adaptive Instance Normalization

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

[2] showed that $\mu$ and $\sigma$ **encapsulate style information**: $\rightarrow$

**Adaptive Instance Normalization**:

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

**transfers instance-wise statistics** from $y$ to $x$

**No learnable parameters!**

# Variational Autoencoders I

**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

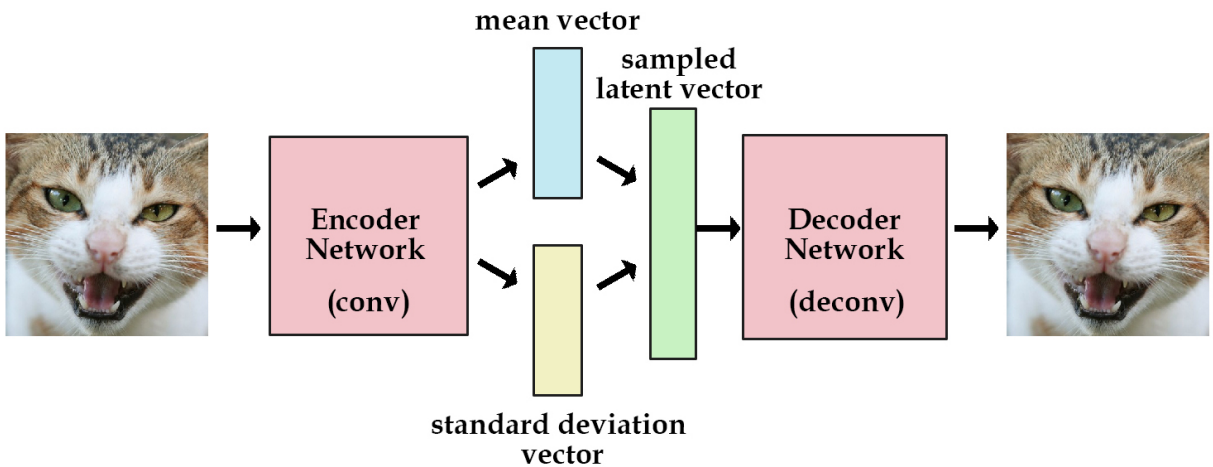



Figure: taken from
`http://kvfrans.com/variational-autoencoders-explained/`

# 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**.