Generative Models

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Organizational matters

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Presence is mandatory. 4 absences are allowed.

You will work in pairs both on presentation and code. Main goal will be to reproduce model from the chosen paper.

What will you learn?

- Read and understand scientific publications
- Ability to transfer theoretical idea into code
- PyTorch
- Public presentation of your results

Generative models - what are they?

There are two main types of models in Machine Learning:

- **discriminative -** model of the conditional probability of the target Y, given an observation x - $\mathbb{P}(Y|X = x)$
- **generative -** model of the conditional probability of the observable X, given a target y - $\mathbb{P}(X|Y = y)$

Cat

Not cat

Generative models - why do we need them?

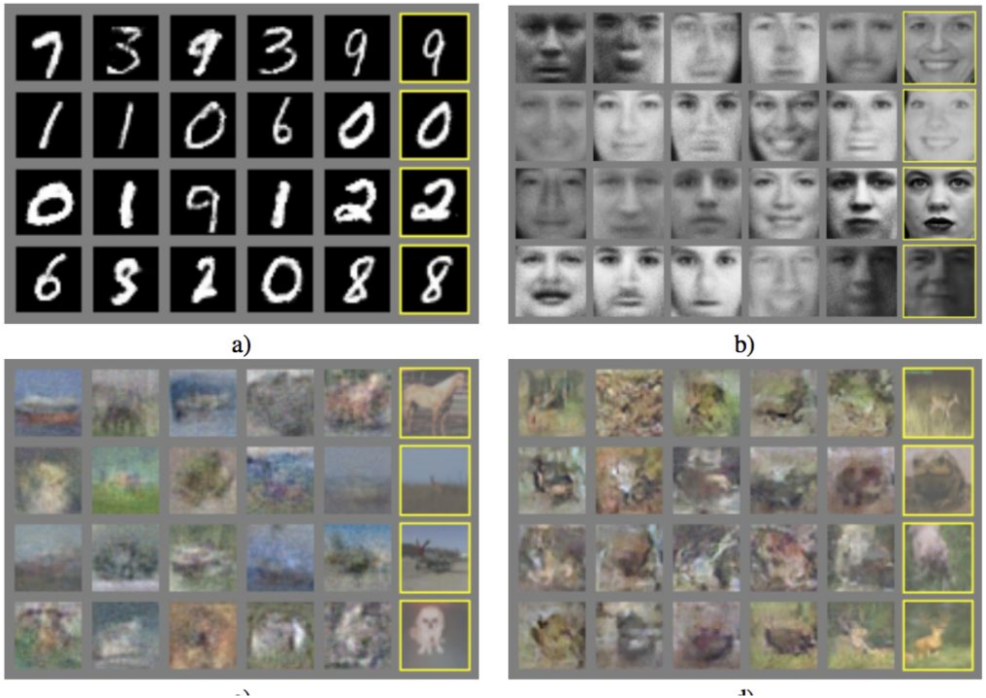
Generative models - why do we need them?

What I cannot create, I do not understand.

- Richard Feynman

… and they are fun :)

Generating new images

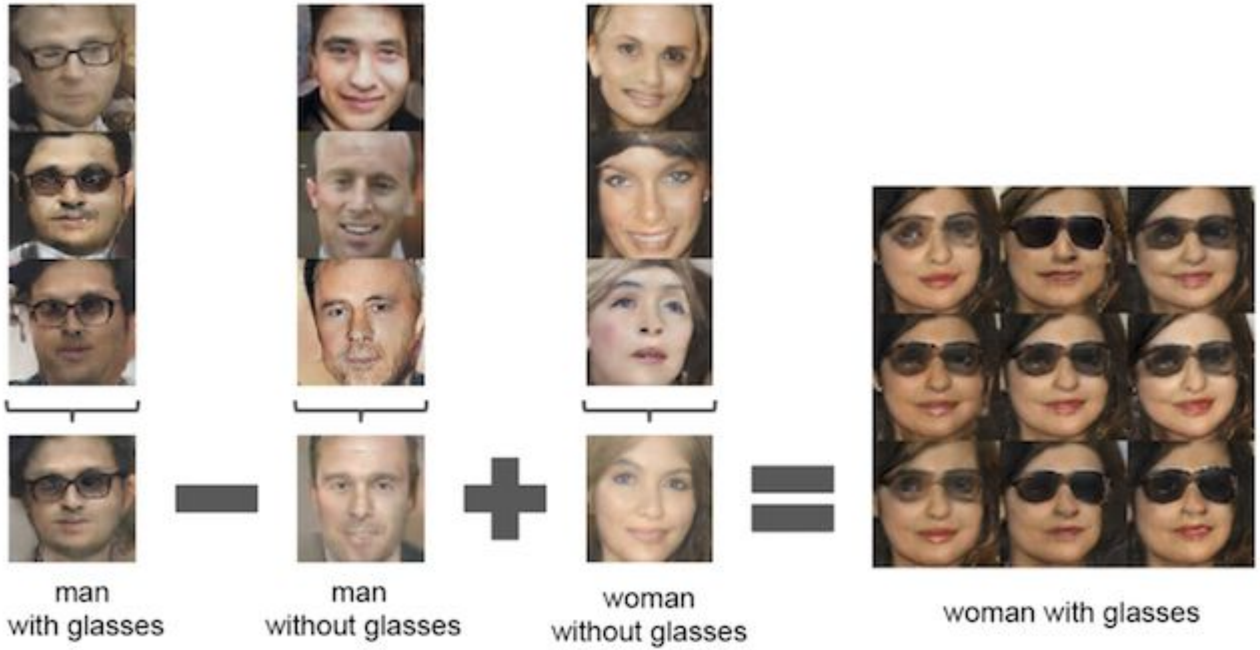


Goodfellow I. et al., *Generative Adversarial Networks*, https://arxiv.org/abs/1406.2661

Generating new images

Radford A., Metz L. et al., *Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks*, https://arxiv.org/abs/1511.06434

Vector arithmetic for generated samples

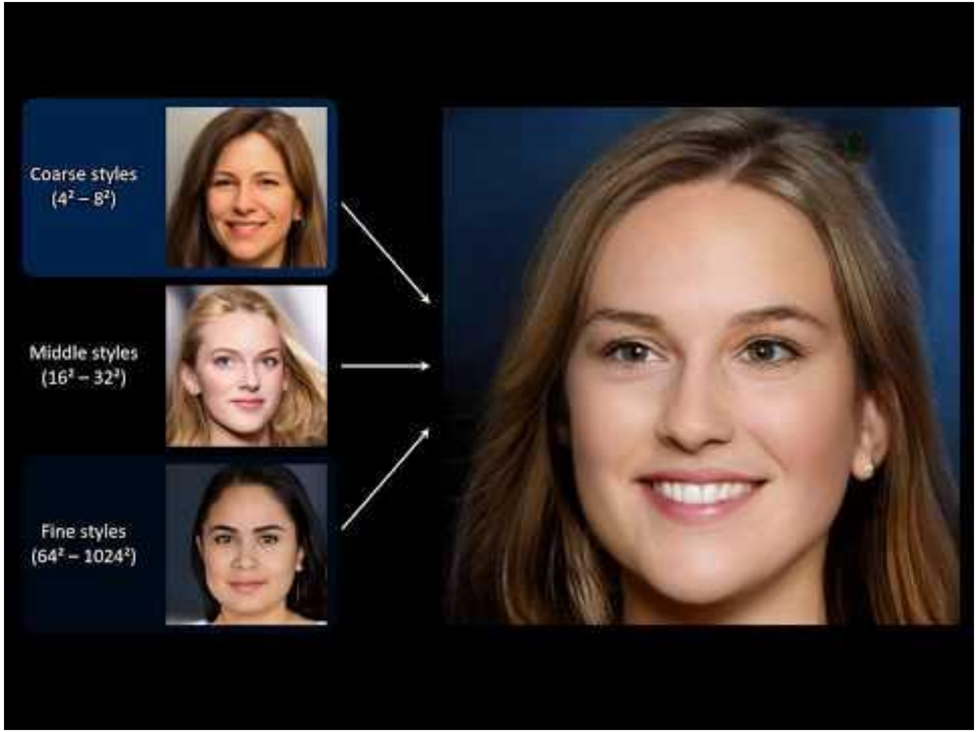


Radford A., Metz L. et al., *Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks*, https://arxiv.org/abs/1511.06434

High resolution samples

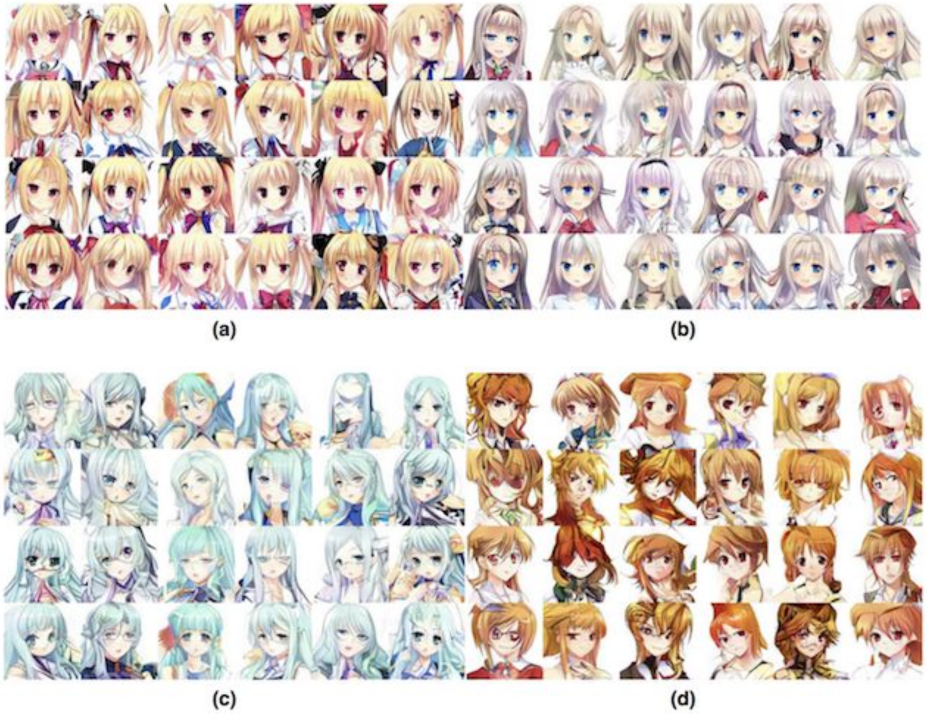
Karras T. et al., *Progressive Growing of GANs for Improved Quality, Stability, and Variation*, https://arxiv.org/abs/1710.10196

High resolution samples



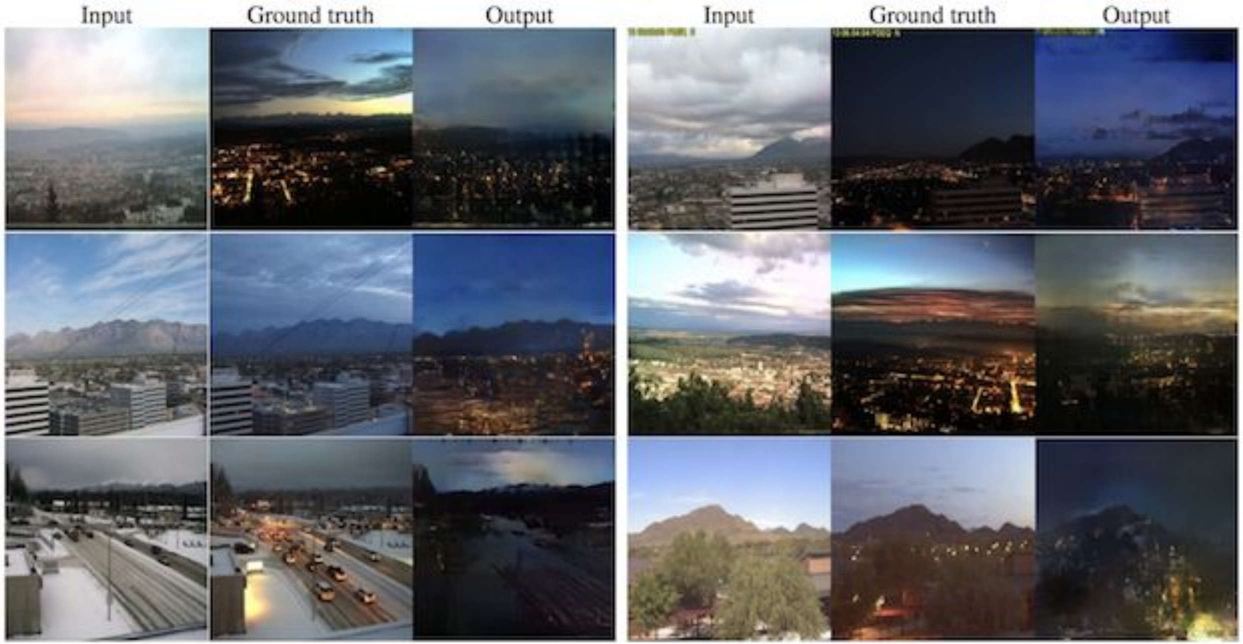
Karras T. et al., *A Style-Based Generator Architecture for Generative Adversarial Networks*, https://arxiv.org/abs/1812.04948

Cartoon Characters



Jin Y. et al., *Towards the Automatic Anime Characters Creation with Generative Adversarial Networks*, https://arxiv.org/abs/1708.05509

Change of daytime

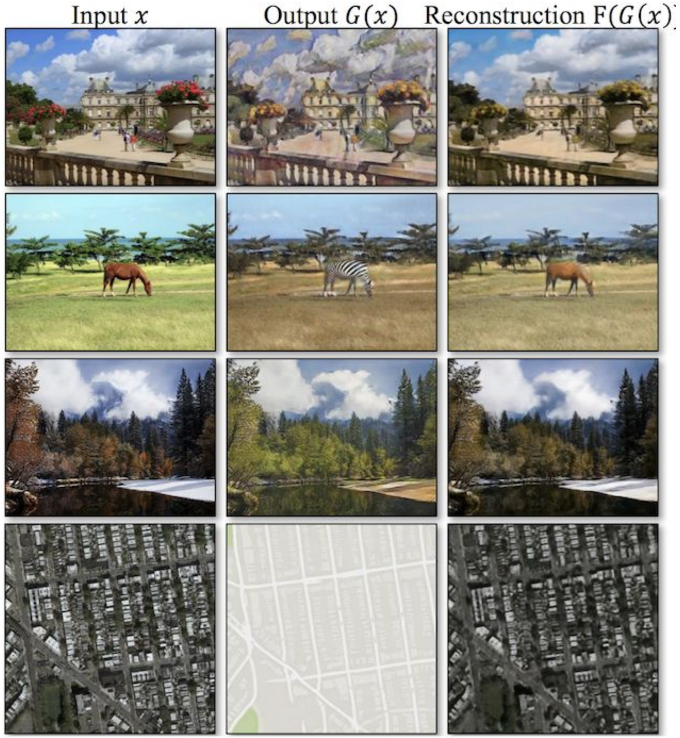


Isola P. et al., *Image-to-Image Translation with Conditional Adversarial Networks*, https://arxiv.org/abs/1611.07004

Sketches to photographs

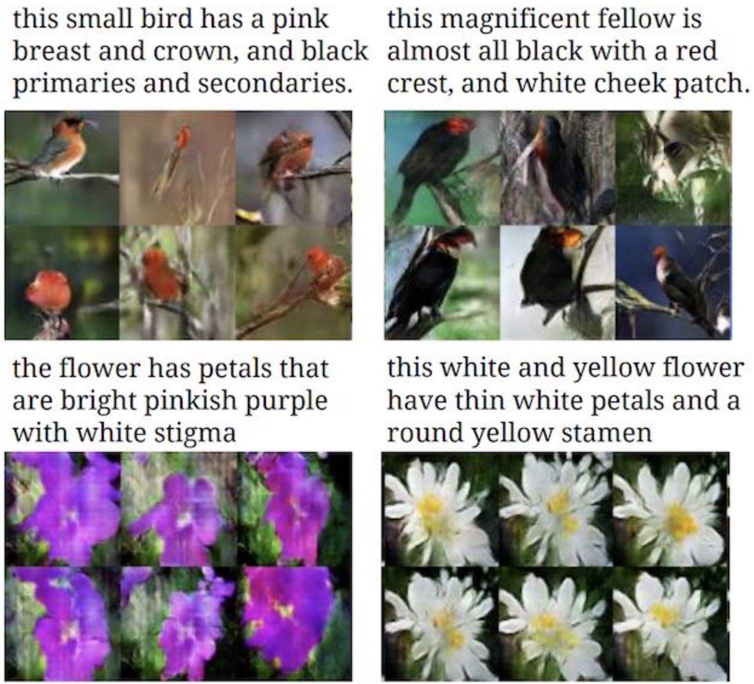
Isola P. et al., *Image-to-Image Translation with Conditional Adversarial Networks*, https://arxiv.org/abs/1611.07004

Pictures translation



Zhu J., Park T. et al. *Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks*, https://arxiv.org/abs/1703.10593

Text to image synthesis

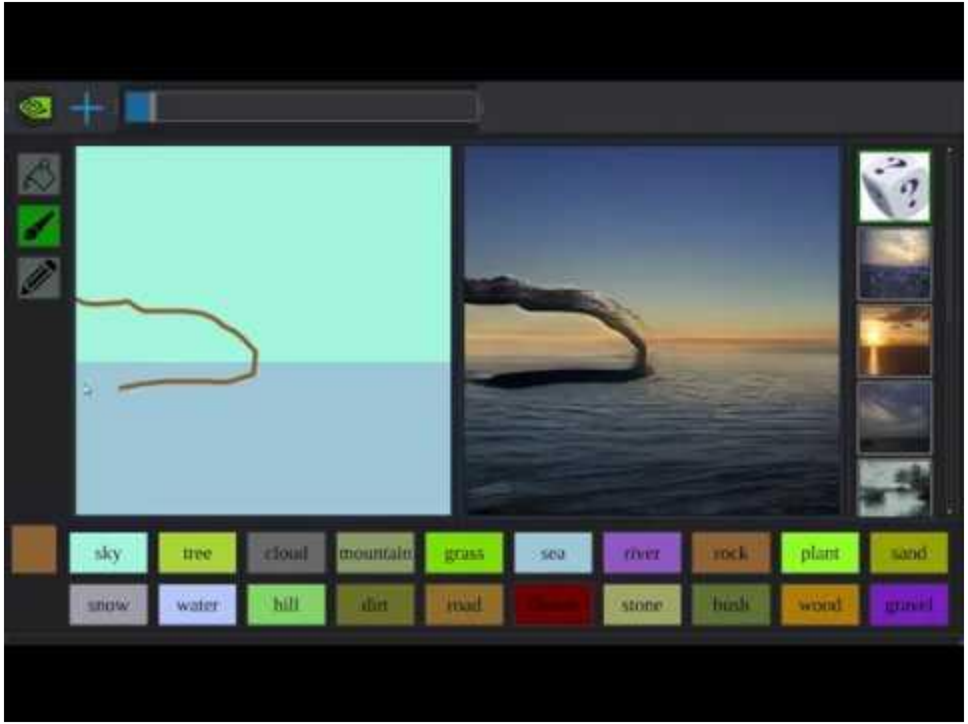


Reed S. et al. *Generative Adversarial Text to Image Synthesis*, https://arxiv.org/abs/1605.05396

High-resolution Image Synthesis

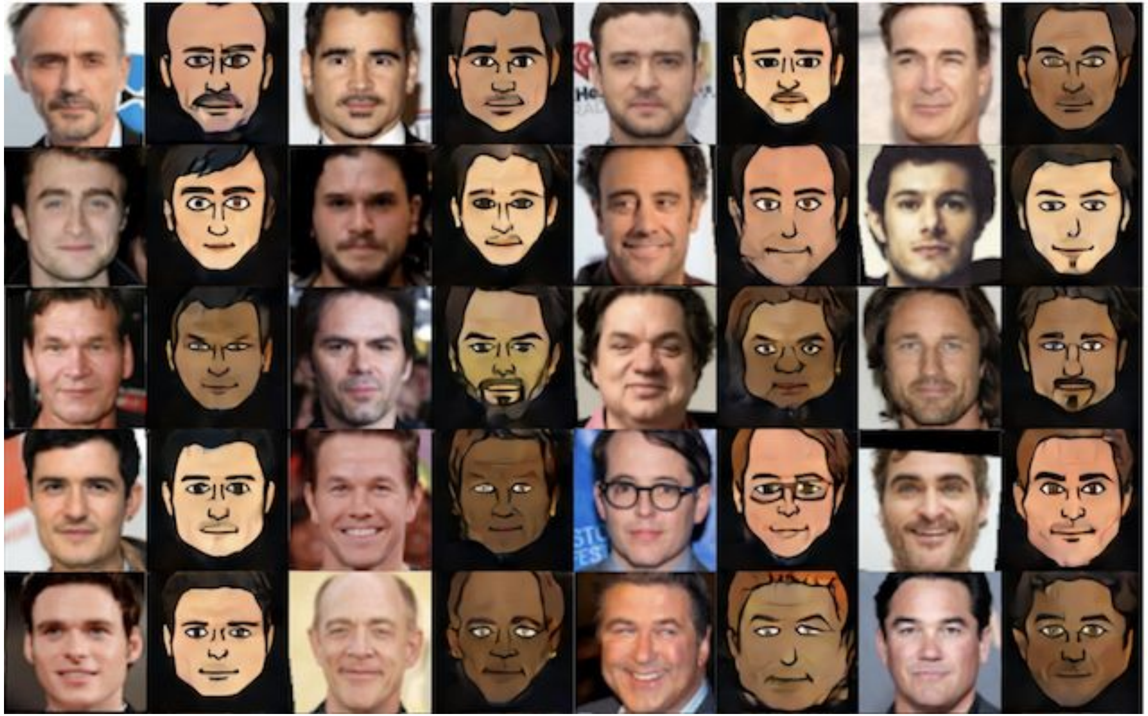
Wang T. et al. *High-Resolution Image Synthesis and Semantic Manipulation with Conditional GANs*, https://arxiv.org/abs/1711.11585

GauGAN



Park T. et al. *Semantic Image Synthesis with Spatially-Adaptive Normalization*, https://arxiv.org/abs/1903.07291

Photos to Emojis

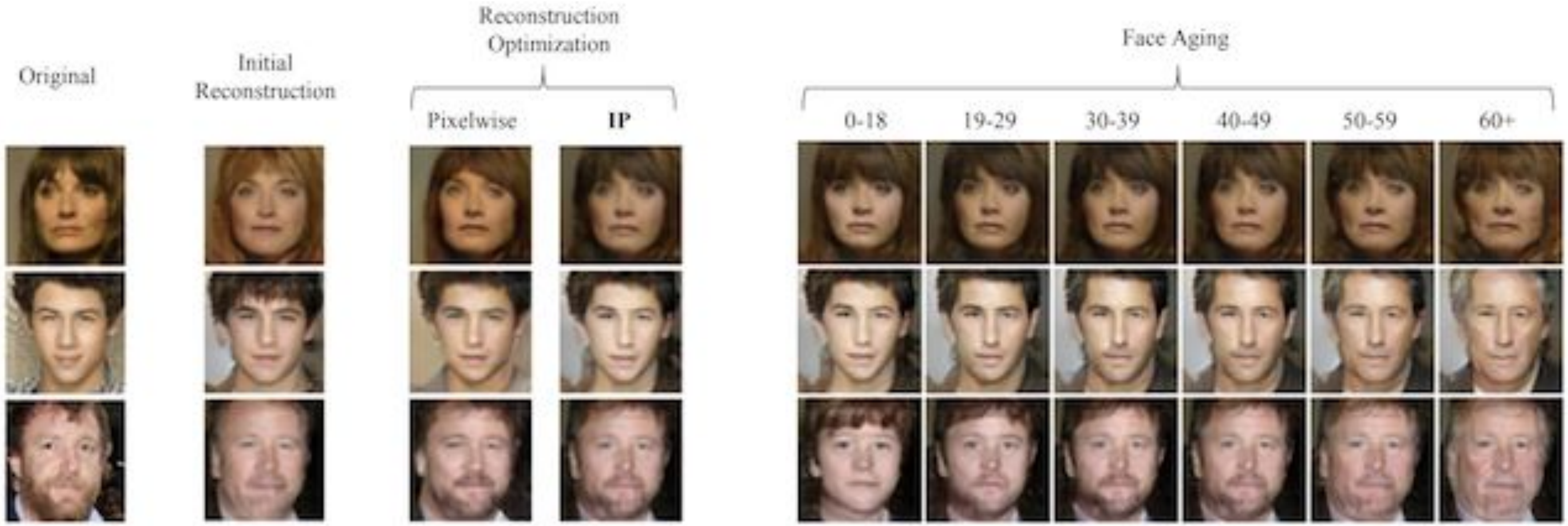


Taigman Y. et al. *Unsupervised Cross-Domain Image Generation*, https://arxiv.org/abs/1611.02200

Photo de-raining

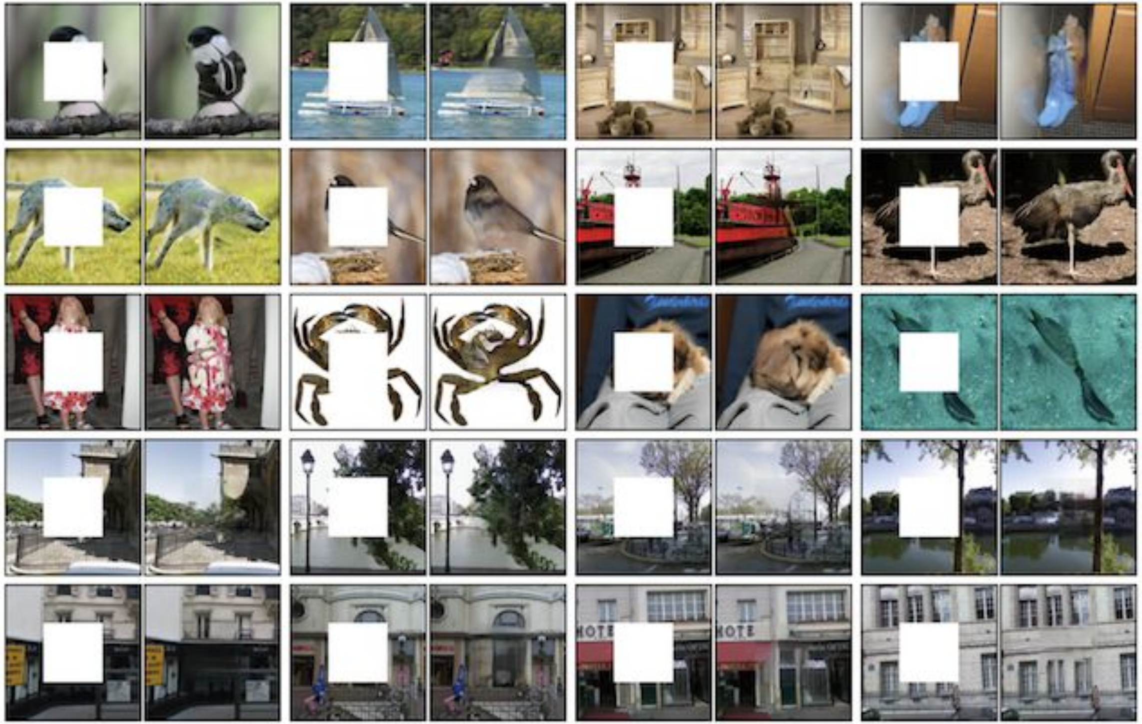
Zhang H. et al. *Image De-raining Using a Conditional Generative Adversarial Network*, https://arxiv.org/abs/1701.05957

Face aging



Antipov G. et al. *Face aging with conditional generative adversarial networks*, https://ieeexplore.ieee.org/document/8296650

Image inpainting



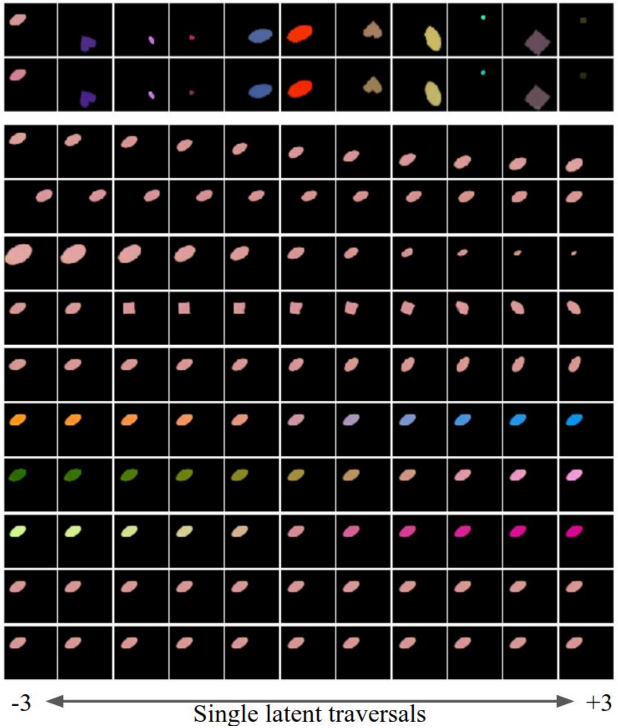
Pathak D. et al. *Context Encoders: Feature Learning by Inpainting*, https://arxiv.org/abs/1604.07379

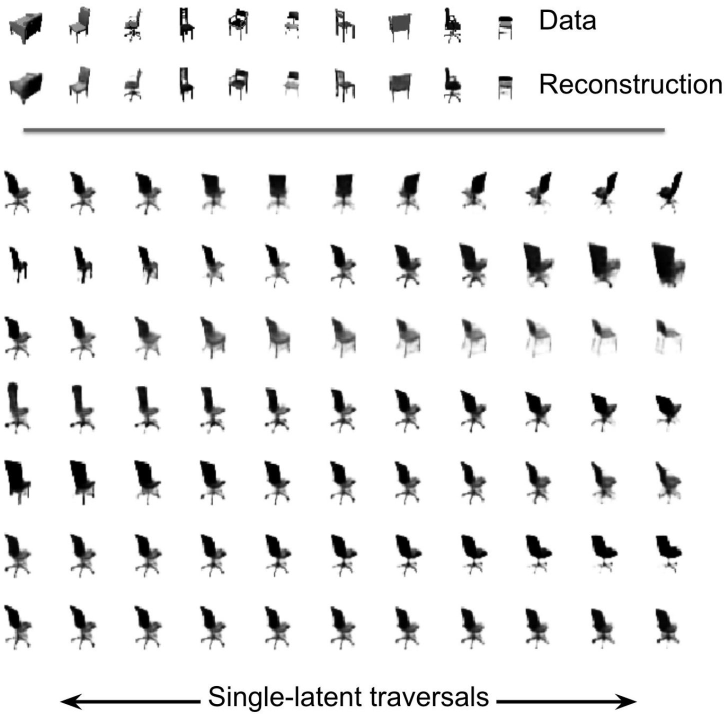
Speech synthesis

https://nv-adlr.github.io/WaveGlow

Karras T. et al. *Progressive Growing of GANs for Improved Quality, Stability, and Variation*, https://arxiv.org/abs/1710.10196

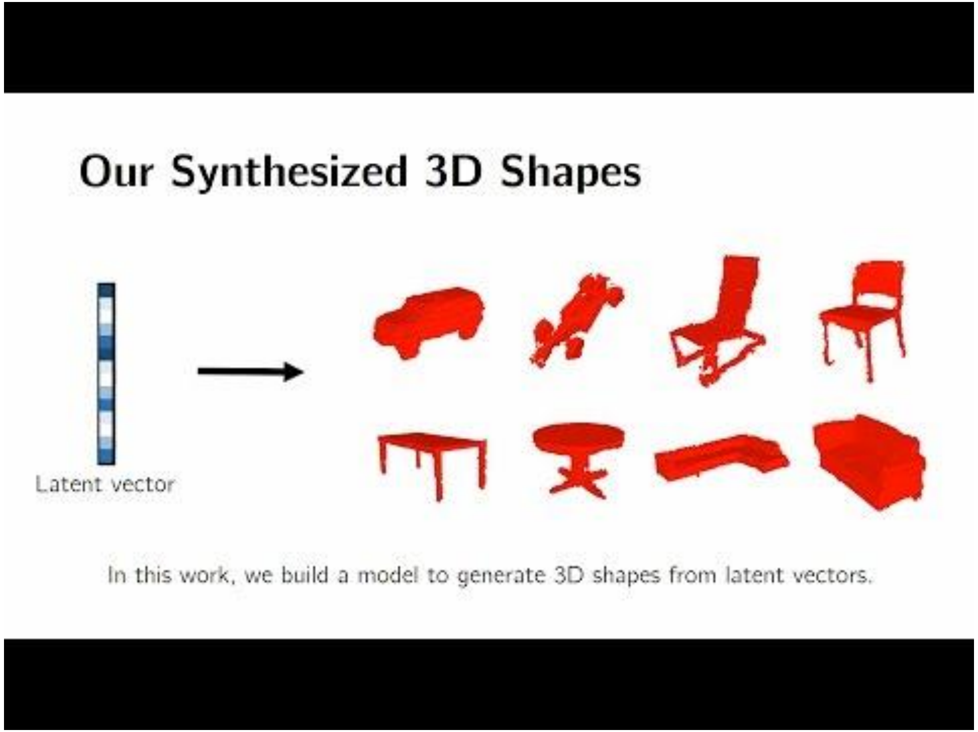
Features disentanglement





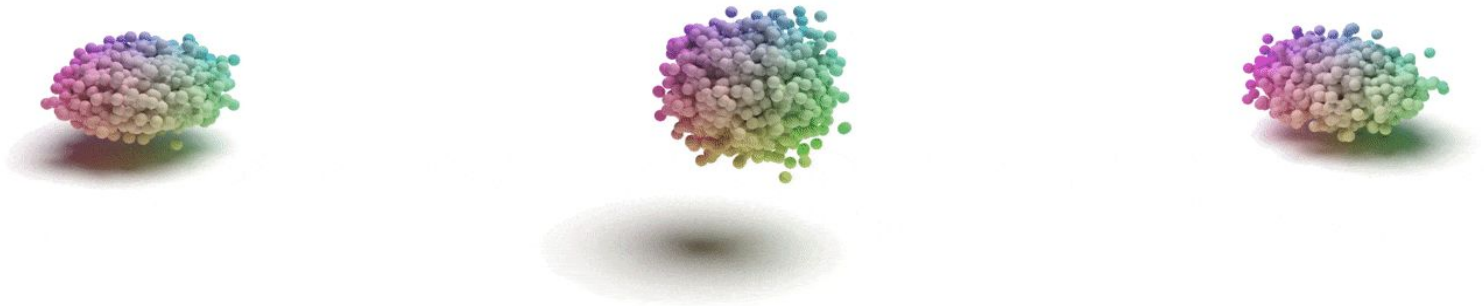
Burgess C. et al. *Understanding disentangling inβ-VAE,* https://arxiv.org/abs/1804.03599

Point clouds generation



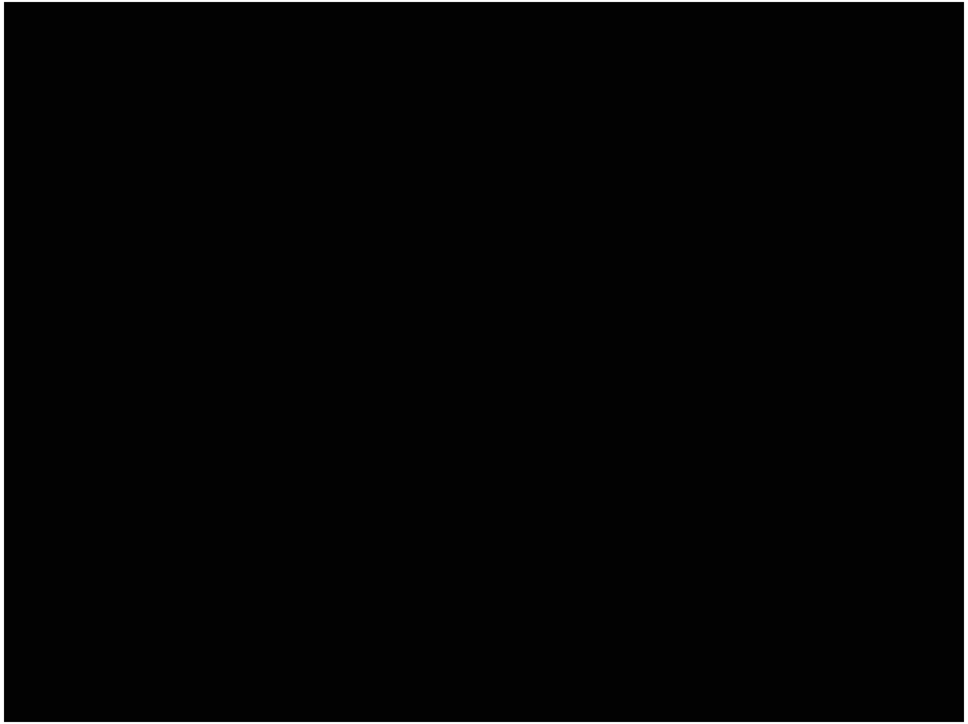
Wu J., Zhang C. et al. *Learning a Probabilistic Latent Space of Object Shapes via 3D Generative-Adversarial Modeling*, https://arxiv.org/abs/1610.07584

Flows for point cloud generation



Yang G., Huang X. et al., *PointFlow: 3D Point Cloud Generation with Continuous Normalizing Flows*, https://arxiv.org/abs/1906.12320

Interpolation between objects



Types of generative models

1. Classic
    - Gaussian mixture model
    - Hidden Markov model
    - Naive Bayes
2. Deep
    - Boltzmann machine
    - Autoregressive models (Pixel CNN/RNN)
    - Variational autoencoders (VAEs)
    - Generative adversarial networks (GANs)
    - Flow-based models

Naive Generation

Simplest generative model for ham or spam messages.

Given the dataset containing *ham* or *spam* SMS we are able to learn conditional distributions $\mathbb{P}(word|target)$ by counting occurrences of *word* in *target*-type SMS.

We can generate new text given desired target.

What is wrong with this approach?

References

https://en.wikipedia.org/wiki/Generative_model

https://openai.com/blog/generative-models/

What’s next?

Date	Topic
08.10.2019	Intro
15.10.2019	Logistic Regression + NN
22.10.2019	PyTorch

Bring your laptops on 22.10.2019 (I’ll let you know earlier if there is any computer room available).

Students’ first presentation is planned on 05.11.2019.