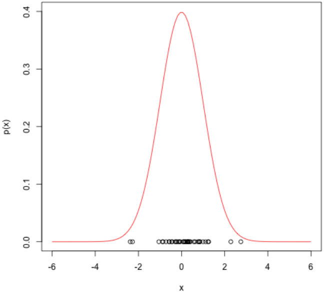
Deep Learning

Introduction to Generative Models



Learning goals

- learning a generative model
- examples of generative models

WHICH FACE IS FAKE?

Fake faces generated by ThisPersonDoesNotExist.com. | Image: The Verge

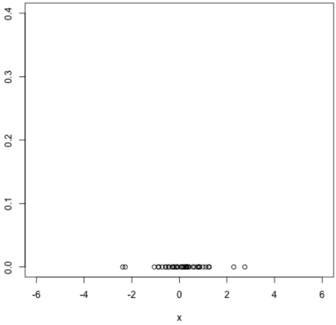
DEEP UNSUPERVISED LEARNING

There are two main goals of **deep unsupervised learning**:

- **Representation Learning**
  - Examples are: manifold learning, feature learning, etc.
  - Can be done by an autoencoder
  - Examples of applications:
    - dimensionality reduction / data compression
    - transfer learning / semi-supervised learning
- **Generative Models**
  - Given a training set $\mathcal{D} = \left(\mathbf{x}^{(1)}, \dots, \mathbf{x}^{(n)}\right)$ where each $\mathbf{x}^{(i)} \sim \mathbb{P}_x$, the goal is to estimate $\mathbb{P}_x$.
  - **Goal:** Take as input training samples from some distribution and learn a model that represents that distribution!
  - Examples of applications:
    - generating music, videos, volumetric models for 3D printing, synthetic data for learning algorithms, outlier identification, images denoising, inpainting, etc.

DENSITY FITTING / LEARNING A GENERATIVE MODEL

Given $\mathcal{D} = \left(\mathbf{x}^{(1)}, \mathbf{x}^{(2)}, \ldots, \mathbf{x}^{(n)}\right) \sim \mathbb{P}_x$ learn a model of $\mathbb{P}_x$ (for example, fitting a Gaussian distribution via Maximum Likelihood Estimation).



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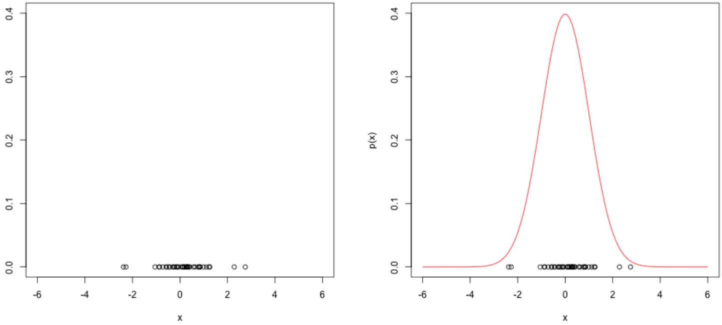

WHY GENERATIVE MODELS?

Generative model are capable of uncovering underlying latent variables in a dataset and can be used for

- sampling / data generation
- outlier detection
- missing feature extraction
- image denoising / reconstruction
- representation learning
- planning in reinforcement learning
- ...

APPLICATION EXAMPLE: IMAGE GENERATION

Source: Karras et al. (2018)

Figure: Synthetic faces generated by a Generative Adversarial Network (more on this later).

APPLICATION EXAMPLE: NEURAL STYLE TRANSFER

A photograph is “redrawn” in the style of another image! (Gatys et al., 2015)

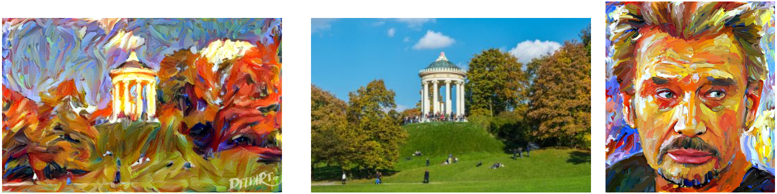

Figure: Examples generated on https://deepart.io/. The image on the left has been generated by translating the original image (middle) to the style of the image on the right.

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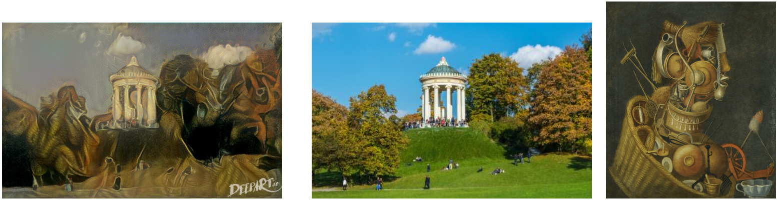

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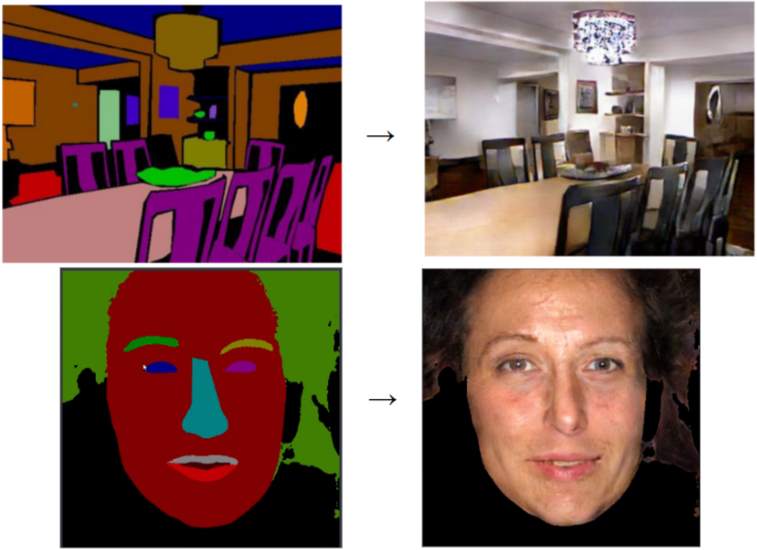
APPLICATION EXAMPLE: IMAGE INPAINTING

Source: Demir et al (2018)

Figure: A generative model fills in the missing portion of the image based on the surrounding context.

APPLICATION EXAMPLE: SEMANTIC LABELS –> IMAGES



Source: Wang et al (2017)

APPLICATION EXAMPLE: GENERATING IMAGES FROM TEXT

Source: Zhang et al (2017)

REFERENCES

Ugur Demir, Gozde Unal (2018)
Patch-Based Image Inpainting with Generative Adversarial Networks
https://arxiv.org/abs/1803.07422

Tero Karras, Timo Aila, Samuli Laine, Jaakko Lehtinen (2018)
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https://arxiv.org/abs/1710.10196

Leon A. Gatys et al. (2015)
Neural Algorithm of Artistic Style
https://arxiv.org/abs/1508.06576