DTU Course 02456 Deep learning
5 Un- and semi-supervised learning
2017 Updates

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Objectives of lectures week 5

- Pro and cons of variational auto-encoders (VAE).
- Generative adversarial networks (GAN)
- Some extensions of VAE and GAN.

VAE pro and con

- Pro: variational auto-encoder computes a lower bound on the log likelihood

$$\log p(x) \geq \int q(z|x) \log \frac{p(x|z)p(z)}{q(z|x)}$$

- Quantitative model comparison for test data x_{test}.: $\log p(x_{\text{test}})$.
- Pro: It is a generative model - we can synthesise new data

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- Con: Too restricted choice of variational distribution $\rightarrow$ $q(z|x)$ is far from

$$p(z|x) = \frac{p(x|z)p(z)}{p(x)}$$

and the generative model we learn will be poor.
- Con: If our likelihood function $p(x|z)$ is a poor fit to reality

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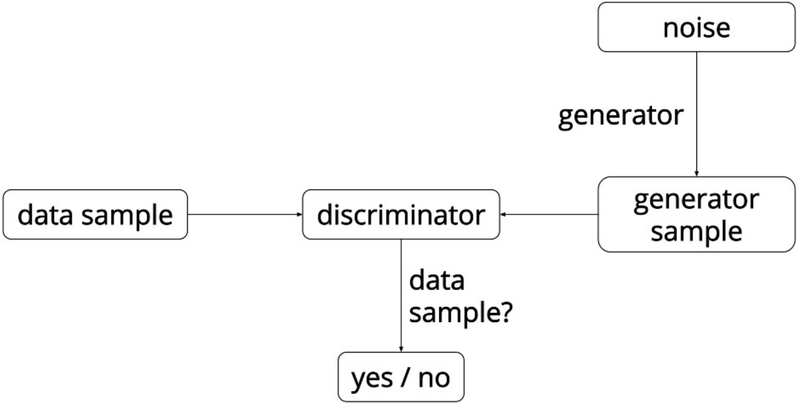

GAN

- GAN has two components:
  - Non-probabilistic generative model $G(z)$:

    $$z \sim p(z)$$
    $$x = G(z)$$

    should be able generate realistic data.
  - Binary true/generated data discriminator $D(x)$ should be able distinguish real and fake data.

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- Objective:
  - Generated data - $z \sim p(z)$, $x = G(z)$:

$$\max_D \min_G \log(1 - D(G(z)))$$

  - True data x:

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- In practice hard to solve this min max objective.
- Generates very nice images.

Generating faces with GAN

http://torch.ch/blog/2015/11/13/gan.html

Cycle GAN

- GAN very popular - really nice images.
- Many variants - here example on style transfer.
- Make two generators F and G - for example:
  - F: Van Gogh $\rightarrow$ Cezanne style
  - G: Cezanne $\rightarrow$ Van Gogh style

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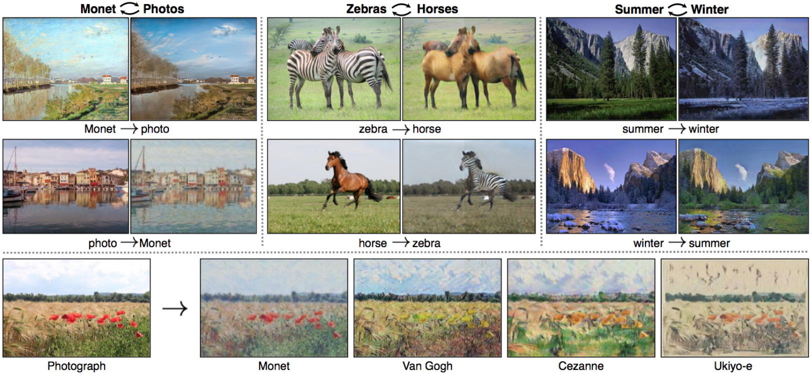
- Make two generators F and G - for example:
  - F: Van Gogh $\rightarrow$ Cezanne style
  - G: Cezanne $\rightarrow$ Van Gogh style
- Objective: normal GAN +
  - Van Gogh image x: $x \approx G(F(x))$
  - Cezanne image y: $y \approx F(G(y))$.



Grammar VAE

- When data has certain structure then the generative model becomes better if we can build that into the model $\rightarrow$
- It will always generate data obeying the structure.
- Example - context-free grammar:

```
S → S '+' T | S '*' T | S '/' T | T
T → '(' S ')' | 'sin(' S ')' | 'exp(' S ')'
T → 'x' | '1' | '2' | '3'
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\begin{aligned}
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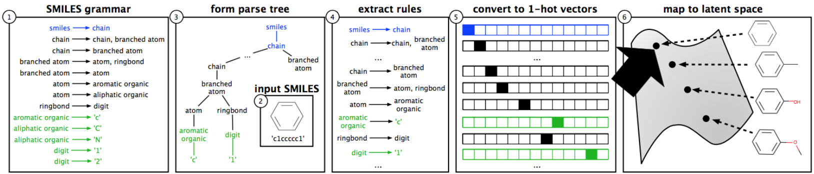
T &\rightarrow \text{`(' } S \text{ `)'} \mid \text{`sin(' } S \text{ `)'} \mid \text{`exp(' } S \text{ `)'} \\
T &\rightarrow \text{`x'} \mid \text{`1'} \mid \text{`2'} \mid \text{`3'}
\end{aligned}
$$

- Encoder model for SMILES representation of molecules:



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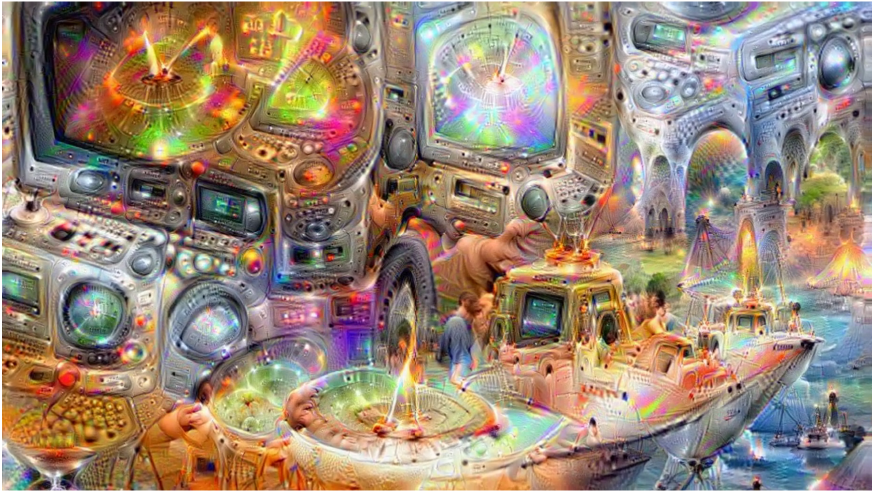

Thanks!
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