

Deep Generative Models

Lecture 1

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Ozon Masters

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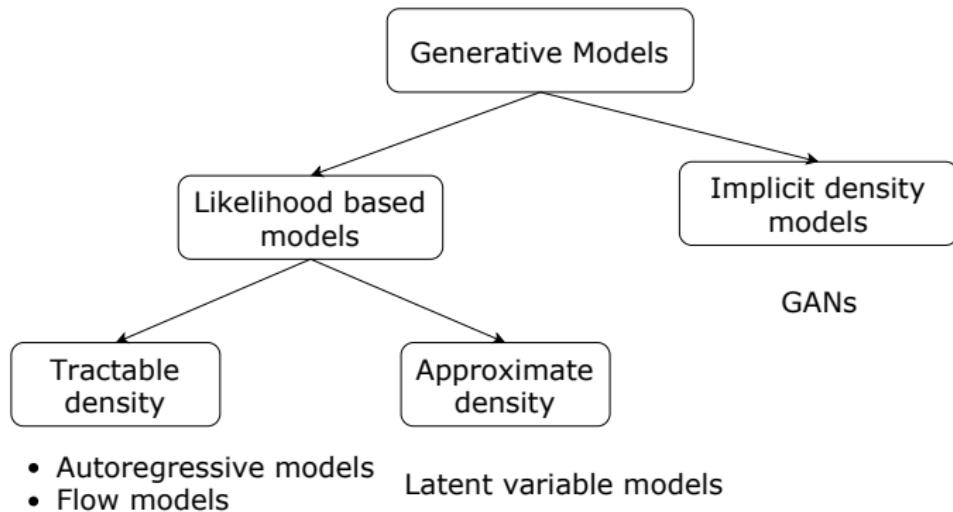
Logistics

- ▶ homeworks: 30 points
 - ▶ hw1: autoregressive models
 - ▶ hw2: latent variable models
 - ▶ hw3: flow models
 - ▶ hw4: adversarial models
- ▶ exam: 30 points
- ▶ final project: 40 points

Last year course page: [link](#)

Admission: [link](#)

Generative models zoo



Motivation

■ "Pure" Reinforcement Learning (cherry)

- ▶ The machine predicts a scalar reward given once in a while.
- ▶ **A few bits for some samples**

■ Supervised Learning (icing)

- ▶ The machine predicts a category or a few numbers for each input
- ▶ Predicting human-supplied data
- ▶ **10→10,000 bits per sample**

■ Unsupervised/Predictive Learning (cake)

- ▶ The machine predicts any part of its input for any observed part.
- ▶ Predicts future frames in videos
- ▶ **Millions of bits per sample**



Applications: Image generation (VAE)



Kingma D. P., Welling M. Auto-encoding variational bayes

<https://arxiv.org/pdf/1312.6114.pdf>

Applications: Image generation (DCGAN)



Radford A., Metz L., Chintala S. Unsupervised representation learning with deep convolutional generative adversarial networks <https://arxiv.org/abs/1511.06434>

Applications: SuperResolution (SRGAN)



Ledig C. et al. Photo-realistic single image super-resolution using a generative adversarial network <https://arxiv.org/abs/1609.04802>

Applications: Domain translation (CycleGAN)



Zhu J. Y. et al. Unpaired image-to-image translation using cycle-consistent adversarial networks <https://arxiv.org/abs/1703.10593>

Applications: Face generation (StyleGAN)



Karras T., Laine S., Aila T. A style-based generator architecture for generative adversarial networks <https://arxiv.org/abs/1812.04948>

Applications: Face generation (VQ-VAE-2)



Razavi A., Oord A., Vinyals O. Generating Diverse High-Fidelity Images with
VQ-VAE-2 <https://arxiv.org/abs/1906.00446>

Applications

- ▶ Audio Generation (WaveNet, ...)
- ▶ Video Generation (DVD-GAN)
- ▶ NLP (Transformer, BERT, GPT-3, ...)
- ▶ Compression

Problem Statement

We are given samples $\{\mathbf{x}_i\}_{i=1}^n \in X$ from unknown distribution $\pi(\mathbf{x})$.

Goal

We would like to learn a distribution $\pi(\mathbf{x})$ for

- ▶ evaluating $\pi(\mathbf{x})$ for new samples;
- ▶ sampling from $\pi(\mathbf{x})$.

Challenge

Data is complex and high-dimensional (curse of dimensionality).

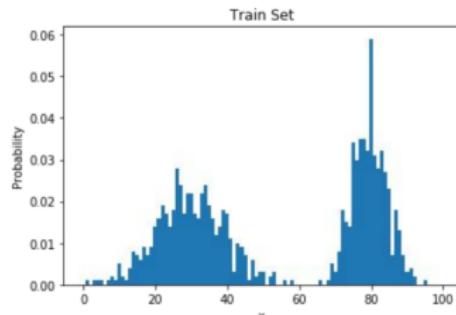
Histogram as a generative model

The histogram is totally defined by

$$p_k = p(x = k) = \frac{\sum_{i=1}^k [x_i = k]}{n}.$$

Problem: curse of dimensionality.

MNIST: 28x28 gray-scaled images
 $2^{28 \times 28} - 1$ parameters to specify $p(\mathbf{x})$



$$p(\mathbf{x}) = p(x_1) \cdot p(x_2|x_1) \cdot \dots \cdot p(x_m|x_{m-1}, \dots, x_1).$$

Question: How many parameters do we need in these cases?

$$p(\mathbf{x}) = p(x_1) \cdot p(x_2) \cdot \dots \cdot p(x_m).$$

$$p(\mathbf{x}) = p(x_1) \cdot p(x_2|x_1) \cdot \dots \cdot p(x_m|x_{m-1}).$$

Maximum likelihood

Fix probabilistic model $p(\mathbf{x}|\theta)$ – the set of parameterized distributions .

Instead of searching true $\pi(\mathbf{x})$ over all probability distributions, learn function approximation $p(\mathbf{x}|\theta) \approx \pi(\mathbf{x})$.

MLE problem

$$\boldsymbol{\theta}^* = \arg \max_{\theta} p(\mathbf{X}|\theta) = \arg \max_{\theta} \prod_{i=1}^n p(\mathbf{x}_i|\theta) = \arg \max_{\theta} \sum_{i=1}^n \log p(\mathbf{x}_i|\theta).$$

The problem is solved with SGD.

Requirements

- ▶ efficiently compute $\log p(\mathbf{x}|\theta)$;
- ▶ efficiently compute gradient of $\log p(\mathbf{x}|\theta)$.

Autoregressive model

MLE problem

$$\theta^* = \arg \max_{\theta} p(\mathbf{X}|\theta) = \arg \max_{\theta} \prod_{i=1}^n p(\mathbf{x}_i|\theta) = \arg \max_{\theta} \sum_{i=1}^n \log p(\mathbf{x}_i|\theta).$$

Challenge

$p(\mathbf{x}|\theta)$ could be intractable.

Likelihood as product of conditionals

Let $\mathbf{x} = (x_1, \dots, x_m)$, $\mathbf{x}_{1:i} = (x_1, \dots, x_i)$. Then

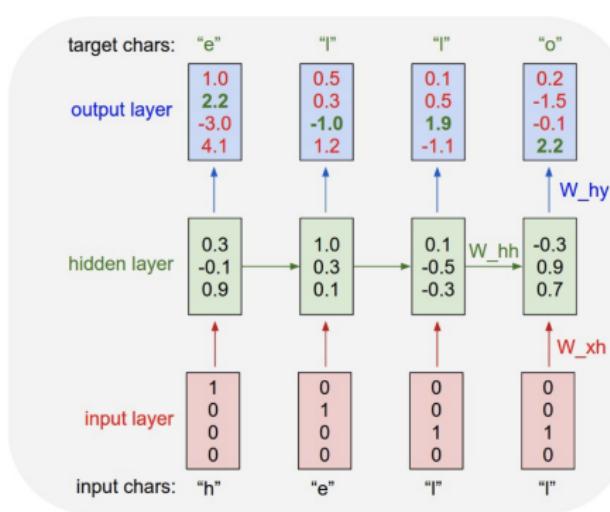
$$p(\mathbf{x}|\theta) = \prod_{i=1}^m p(x_i|\mathbf{x}_{1:i-1}, \theta); \quad \log p(\mathbf{x}|\theta) = \sum_{i=1}^m \log p(x_i|\mathbf{x}_{1:i-1}, \theta).$$

Autoregressive models

$$\log p(\mathbf{x}|\boldsymbol{\theta}) = \sum_{i=1}^m \log p(x_i|\mathbf{x}_{1:i-1}, \boldsymbol{\theta})$$

- ▶ Each conditional could be modelled by neural network.
- ▶ To extend to high dimensions share parameters across conditionals.
- ▶ Sampling is sequential.

Char RNN (2015)



PANDARUS:

Alas, I think he shall be come approached and the day
When little strain would be attain'd into being never fed,
And who is but a chain and subjects of his death,
I should not sleep.

Second Senator:

They are away this miseries, produced upon my soul,
Breaking and strongly should be buried, when I perish
The earth and thoughts of many states.

DUKE VINCENTIO:

Well, your wit is in the care of side and that.

Second Lord:

They would be ruled after this chamber, and
my fair nues begun out of the fact, to be conveyed,
Whose noble souls I'll have the heart of the wars.

Clown:

Come, sir, I will make did behold your worship.

VIOLA:

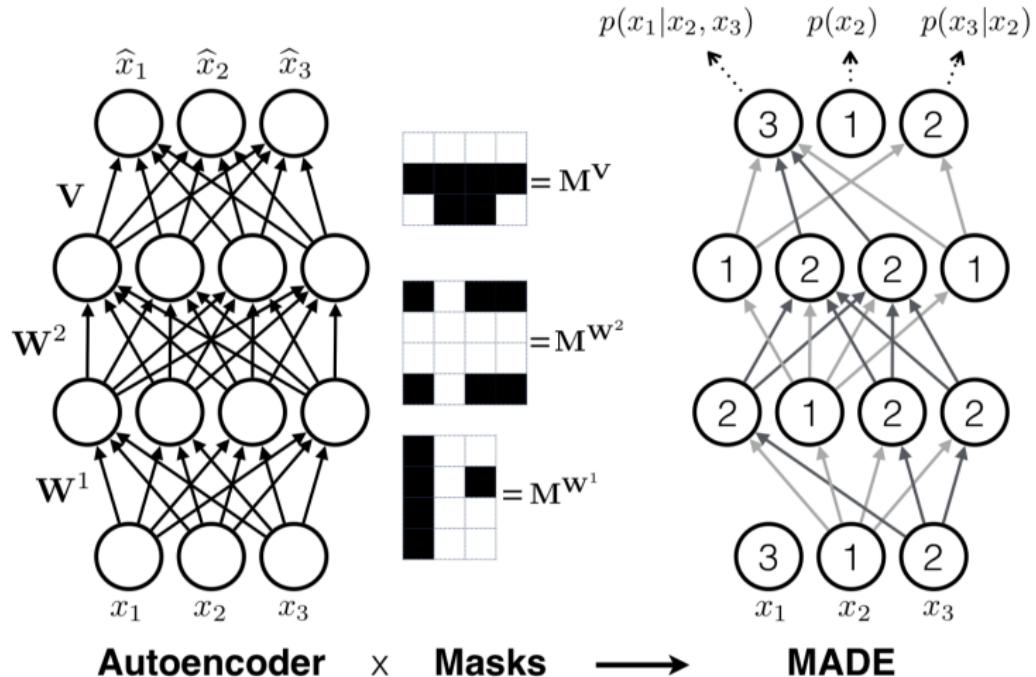
I'll drink it.

Drawback

Sequential computation of all conditionals $p(x_i | \mathbf{x}_{1:i-1}, \theta)$.

<http://karpathy.github.io/2015/05/21/rnn-effectiveness/>

MADE (2015)



Germain M. et al. Made: Masked autoencoder for distribution estimation

<https://arxiv.org/pdf/1502.03509.pdf>

WaveNet (2016)

Goal

Efficient generation of raw audio waveforms with natural sounds.

Solution

Autoregressive model

$$p(\mathbf{x}|\theta) = \prod_{t=1}^T p(x_t|\mathbf{x}_{1:t-1}, \theta).$$

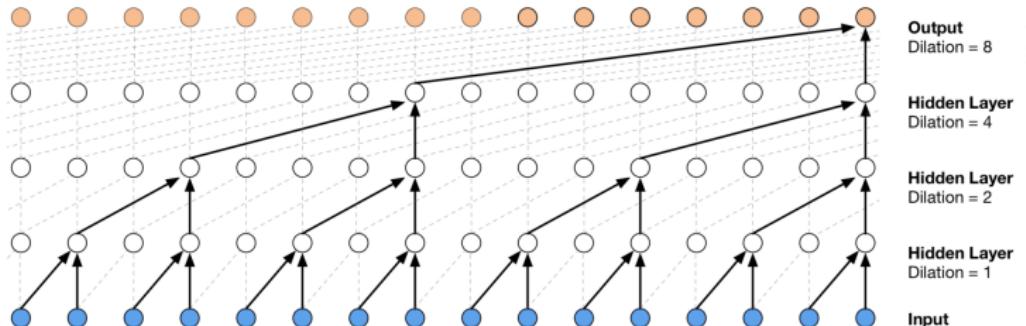
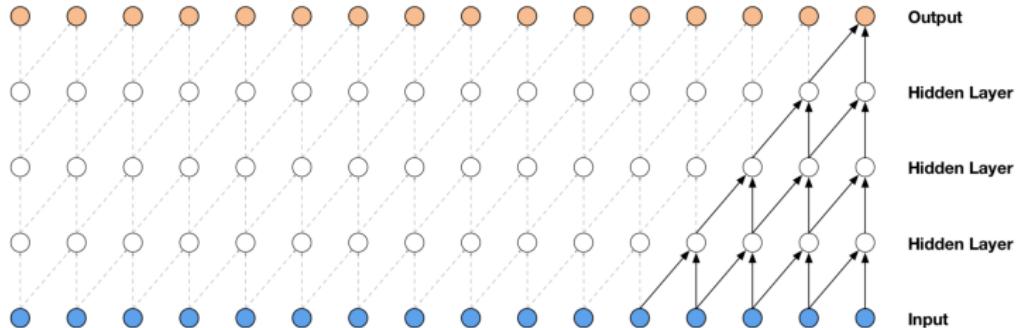
The model uses causal dilated convolutions.



Oord A. et al. Wavenet: A generative model for raw audio

<https://arxiv.org/pdf/1609.03499.pdf>

WaveNet (2016)



Oord A. et al. Wavenet: A generative model for raw audio

<https://arxiv.org/pdf/1609.03499.pdf>

PixelCNN (2016)

Goal

Model a distribution of natural images.

Solution

Autoregressive model

$$p(\mathbf{x}|\boldsymbol{\theta}) = \prod_{i=1}^{n^2} p(x_i|\mathbf{x}_{1:i-1}, \boldsymbol{\theta}).$$

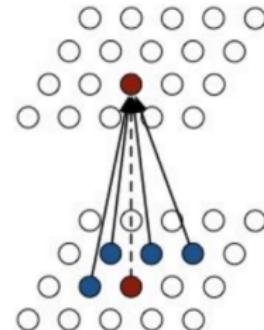
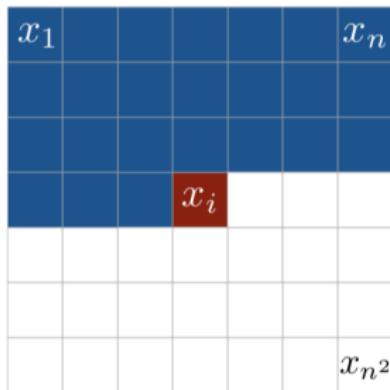
- ▶ masked convolutions;
- ▶ dependencies over RGB channels.

Oord A., Kalchbrenner N., Kavukcuoglu K. Pixel recurrent neural networks

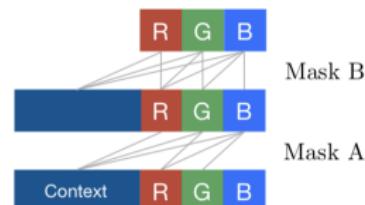
<https://arxiv.org/pdf/1601.06759.pdf>

PixelCNN (2016)

1	1	1
1	0	0
0	0	0



PixelCNN



Oord A., Kalchbrenner N., Kavukcuoglu K. Pixel recurrent neural networks
<https://arxiv.org/pdf/1601.06759.pdf>

Summary

- ▶ Sampling from autoregressive models is trivial, but sequential
 - ▶ sample $x_0 \sim p(x_0)$;
 - ▶ sample $x_1 \sim p(x_1|x_0)$;
 - ▶
- ▶ Estimating probability:

$$p(\mathbf{x}) = \prod_{i=1}^m p(x_i|\mathbf{x}_{1:i-1}).$$

- ▶ Work on both continuous and discrete data.
- ▶ There is no natural way to do unsupervised learning.

References

- ▶ **MADE: Masked Autoencoder for Distribution Estimation**
<https://arxiv.org/pdf/1502.03509.pdf>
Summary: Create masked autoencoder that models autoregression (autoregression allows to make the distribution properly normalized). Sampling is performed iteratively (to generate MNIST image 784 forward passes are needed). Discrete data.
- ▶ **PixelRNN + PixelCNN: Pixel recurrent neural networks**
<https://arxiv.org/abs/1601.06759>
Summary: 2 models are proposed: PixelRNN, PixelCNN. The models are autoregression and sampling is sequential. For RNN two types of LSTM blocks are used: Row LSTM and DiagonalBiLSTM. CNN uses Masked convolutions. RNN outperforms, but is slower.
- ▶ **GatedPixelCNN: Conditional Image Generation with PixelCNN Decoders**
<https://arxiv.org/pdf/1606.05328.pdf>
Summary: Improvements for PixelCNN: gated units (like in lstm), horizontal+vertical stacks (remove blind spots). The result is now similar to PixelRNN.
- ▶ **WaveNet: a Generative Model for Raw Audio**
<https://arxiv.org/pdf/1609.03499.pdf>
Summary: Model for autoregressive audio generation, inspired by PixelCNN. Use causal convolutions for the right conditioning, and dilated atrous convolution to extend receptive field.
- ▶ **PixelCNN++: Improving the PixelCNN with Discretized Logistic Mixture Likelihood and Other Modifications**
<https://arxiv.org/pdf/1701.05517.pdf>
Summary: Improved version of PixelCNN. Models mixture of logistic mixture distribution instead of softmax. Architectural modifications: skip connections, up/down sampling, dropout. Experiment with dequantization: discretization works better.
- ▶ **PixelSNAIL: An Improved Autoregressive Generative Model**
<https://arxiv.org/pdf/1712.09763.pdf>
Summary: Autoregressive model. Uses masked causal convolutions. Adjust self-attention to PixelCNN.