

Outline

- Generative Models Basics
- **Autoregressive Models**
- Autoencoder and Variational Autoencoder
- Generative Adversarial Network
- Diffusion Models

Fully visible belief network

Explicit density model

Use chain rule to decompose likelihood of an image x into product of 1-d distributions:

$$p(x) = \prod_{i=1}^n p(x_i | x_1, \dots, x_{i-1})$$

Likelihood of image x

Probability of i 'th pixel value given all previous pixels

Then maximize likelihood of training data

Fully visible belief network

Explicit density model

Use chain rule to decompose likelihood of an image x into product of 1-d distributions:

$$p(x) = \prod_{i=1}^n p(x_i | x_1, \dots, x_{i-1})$$

Likelihood of
image x

Probability of i 'th pixel value
given all previous pixels

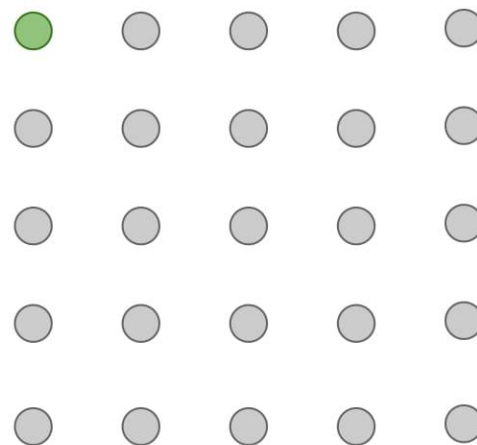
Complex distribution over pixel values => Express using a neural network!

Then maximize likelihood of training data

PixelRNN *[van der Oord et al. 2016]*

Generate image pixels starting from corner

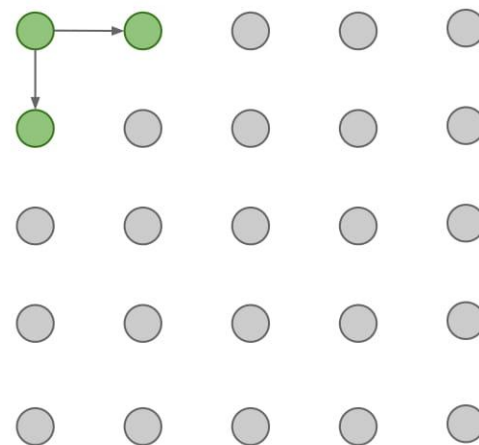
Dependency on previous pixels modeled
using an RNN (LSTM)



PixelRNN *[van der Oord et al. 2016]*

Generate image pixels starting from corner

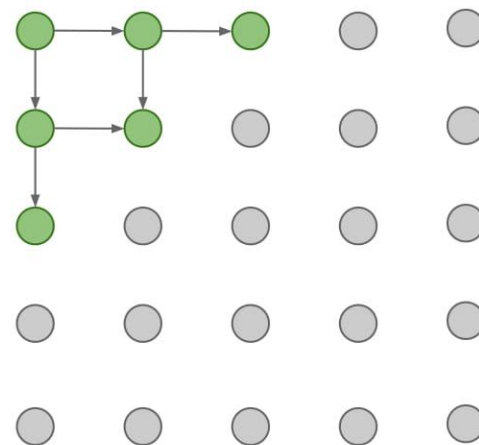
Dependency on previous pixels modeled
using an RNN (LSTM)



PixelRNN *[van der Oord et al. 2016]*

Generate image pixels starting from corner

Dependency on previous pixels modeled
using an RNN (LSTM)

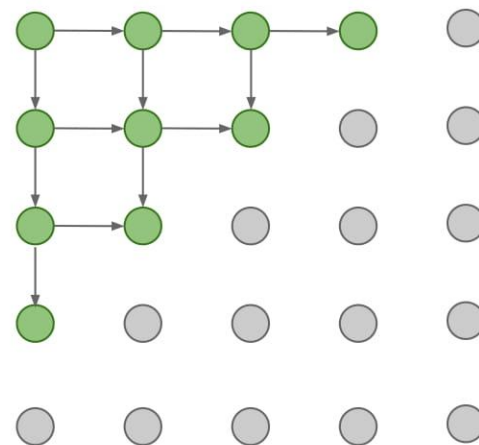


PixelRNN *[van der Oord et al. 2016]*

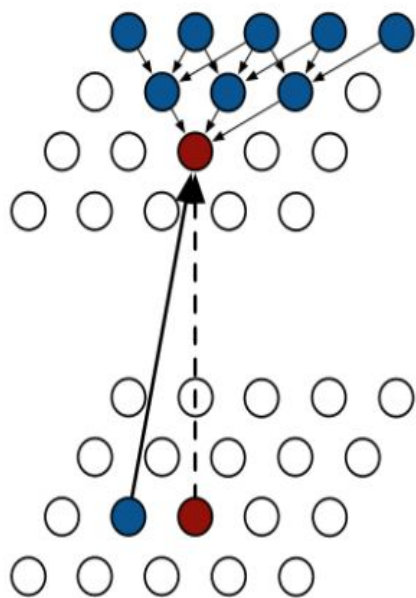
Generate image pixels starting from corner

Dependency on previous pixels modeled using an RNN (LSTM)

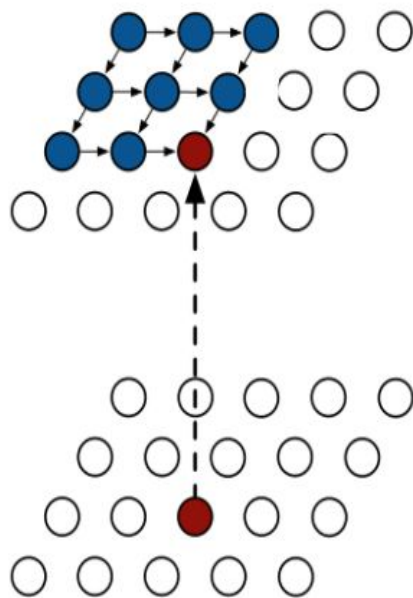
Drawback: sequential generation is slow!



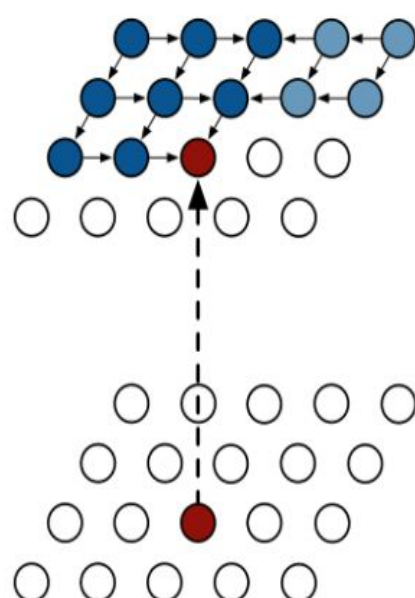
Variants of Pixel RNN (LSTM)



Row LSTM



Diagonal LSTM



Diagonal BiLSTM

PixelCNN *[van der Oord et al. 2016]*

Still generate image pixels starting from corner

Dependency on previous pixels now modeled using a CNN over context region

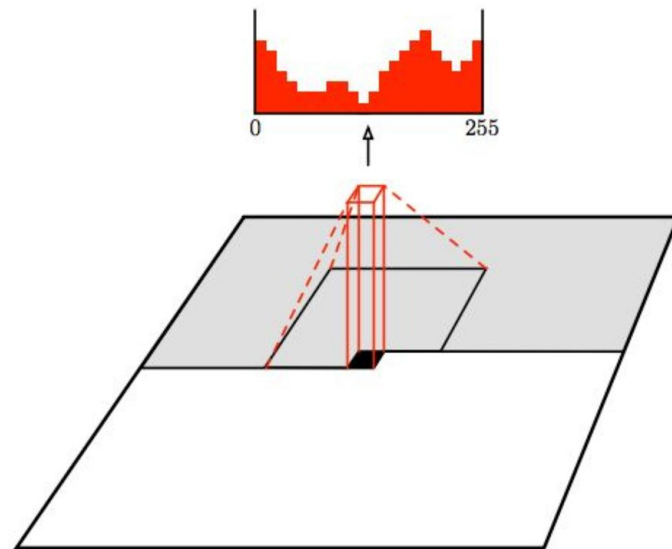


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PixelCNN *[van der Oord et al. 2016]*

Still generate image pixels starting from corner

Dependency on previous pixels now modeled using a CNN over context region

Training: maximize likelihood of training images

$$p(x) = \prod_{i=1}^n p(x_i | x_1, \dots, x_{i-1})$$

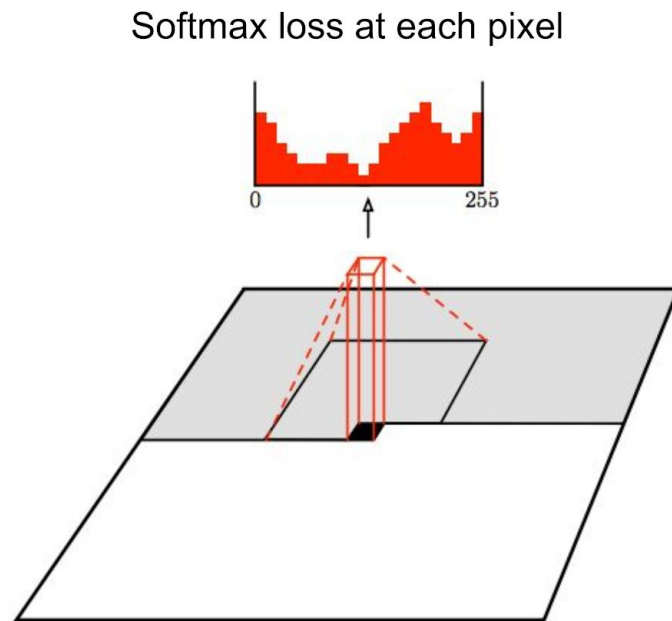


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PixelCNN *[van der Oord et al. 2016]*

Still generate image pixels starting from corner

Dependency on previous pixels now modeled using a CNN over context region

Training is faster than PixelRNN
(can parallelize convolutions since context region values known from training images)

Generation must still proceed sequentially
=> still slow

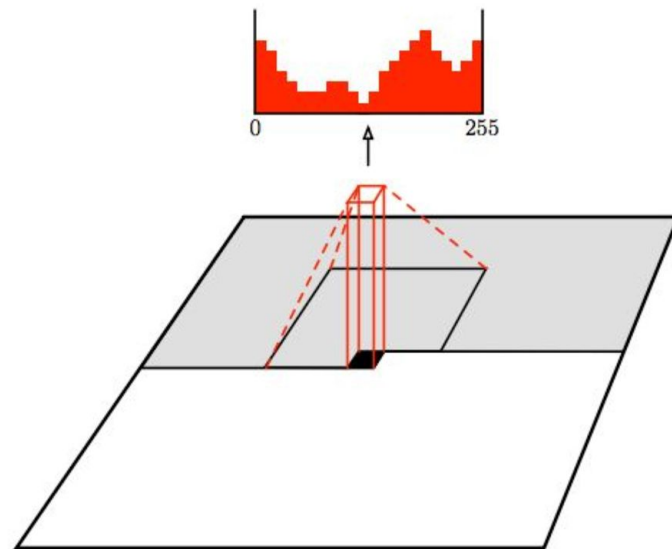
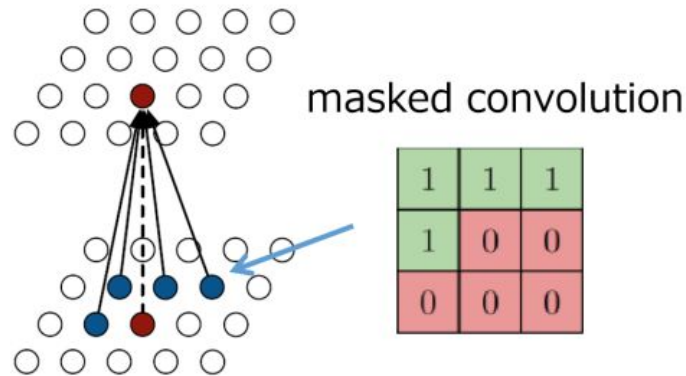


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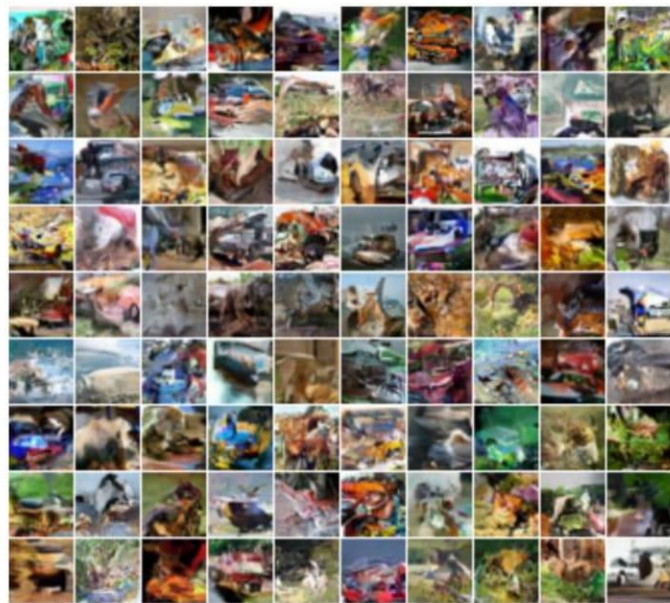
PixelCNN

- 2D convolution on previous layer
- Apply masks so a pixel does not see future pixels (in sequential order)

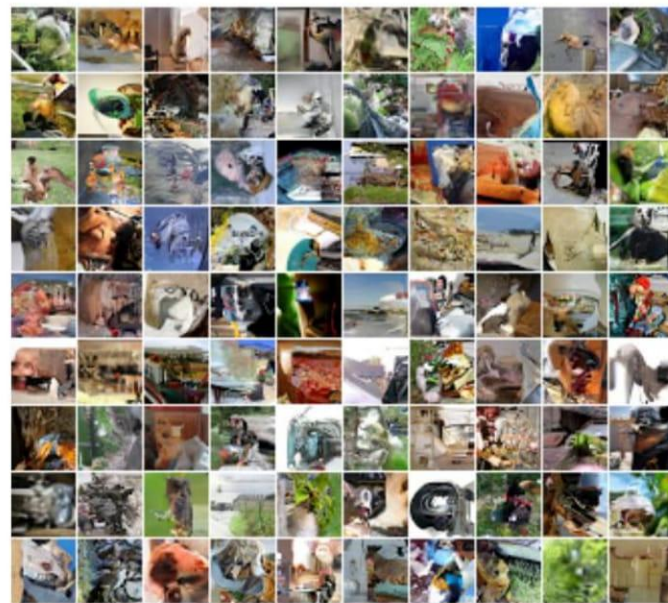


[Pixel recurrent neural networks](#), ICML 2016

Generation Samples



32x32 CIFAR-10



32x32 ImageNet

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PixelRNN and PixelCNN

Pros:

- Can explicitly compute likelihood $p(x)$
- Explicit likelihood of training data gives good evaluation metric
- Good samples

Con:

- Sequential generation => slow

Improving PixelCNN performance

- Gated convolutional layers
- Short-cut connections
- Discretized logistic loss
- Multi-scale
- Training tricks
- Etc...

See

- Van der Oord et al. NIPS 2016
- Salimans et al. 2017 (PixelCNN++)