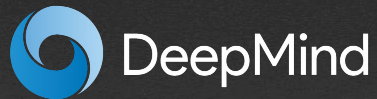
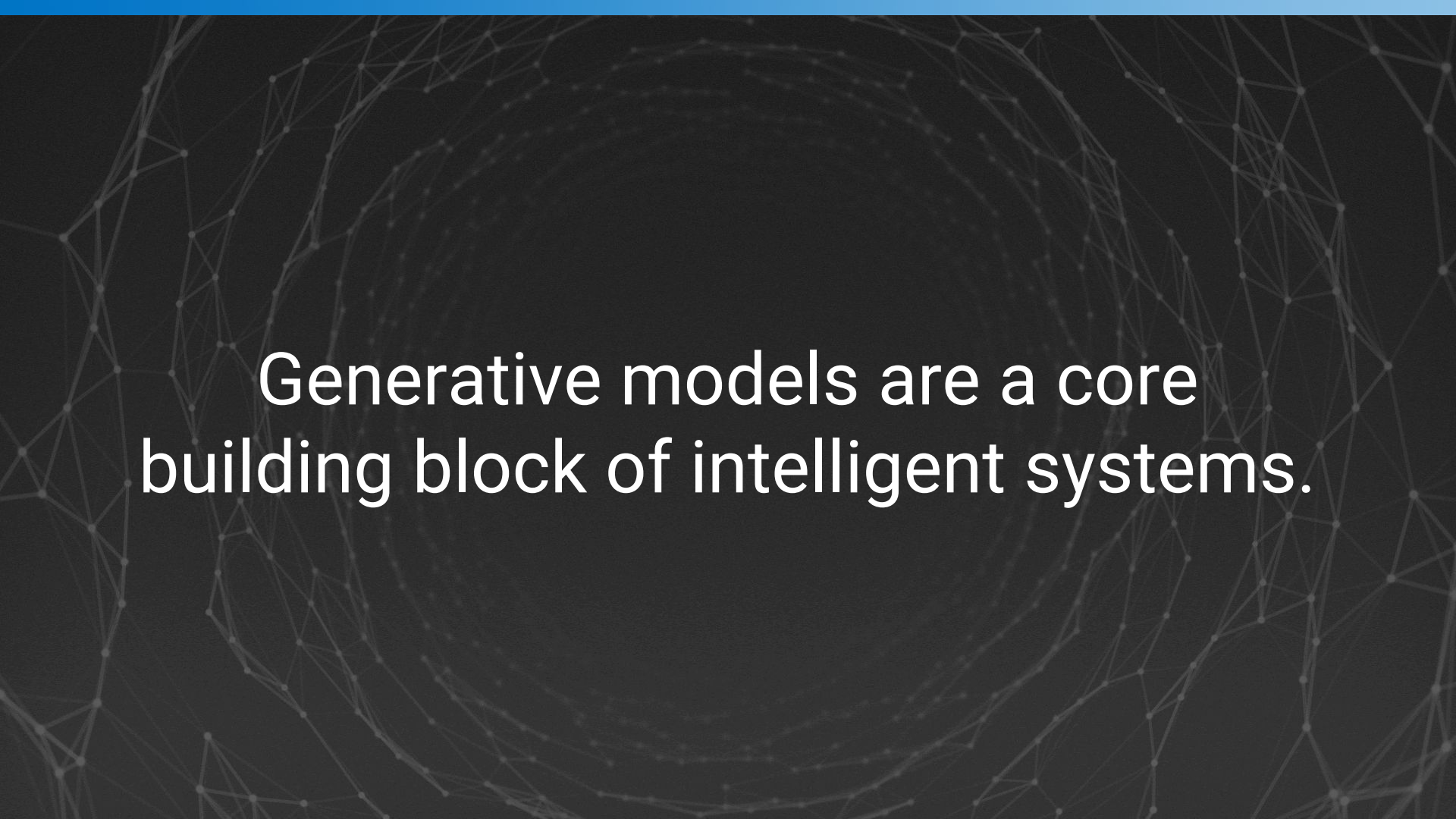


# Introduction to generative models

Mihaela Rosca  
@elaClaudia





Generative models are a core  
building block of intelligent systems.

# What do intelligent systems need?

- Generate new data
- Imagine possible futures & have a model of the world
- Translate between data modalities
- Learn useful representations
- Completing missing data

# Generate new data

What do intelligent systems need?

Royour was I did too jest of this forget  
That I must I should be report of tale  
Decost we are bewarved:'d: yet my fearful scope  
From whence the duty I may need their course,  
Which thou wert sorry for my party was to show  
Forthwith Edward for what stout King Richard death!  
The queen hath cast froths me to said,  
Is, and not to be framed, and let's with him.



<https://arxiv.org/abs/1710.10196>  
<https://arxiv.org/pdf/1609.03499.pdf>  
<https://arxiv.org/abs/1308.0850>



# Complete missing data

What do intelligent systems need?



<http://math.univ-lyon1.fr/homes-www/masnou/fichiers/publications/survey.pdf>

<http://www.dtic.upf.edu/~mbertalmio/bertalmi.pdf>

Introduction to generative models— Mihaela Rosca

# Translate between data modalities

What do intelligent systems need?

Monet ↔ Photos



Monet → photo

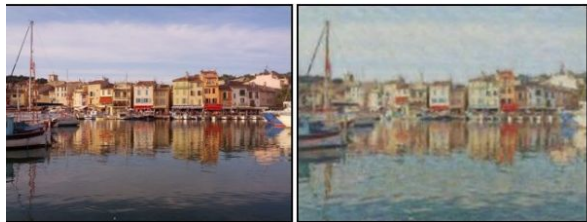


photo → Monet

Zebras ↔ Horses



zebra → horse

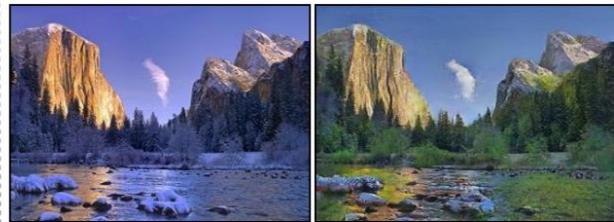


horse → zebra

Summer ↔ Winter



summer → winter

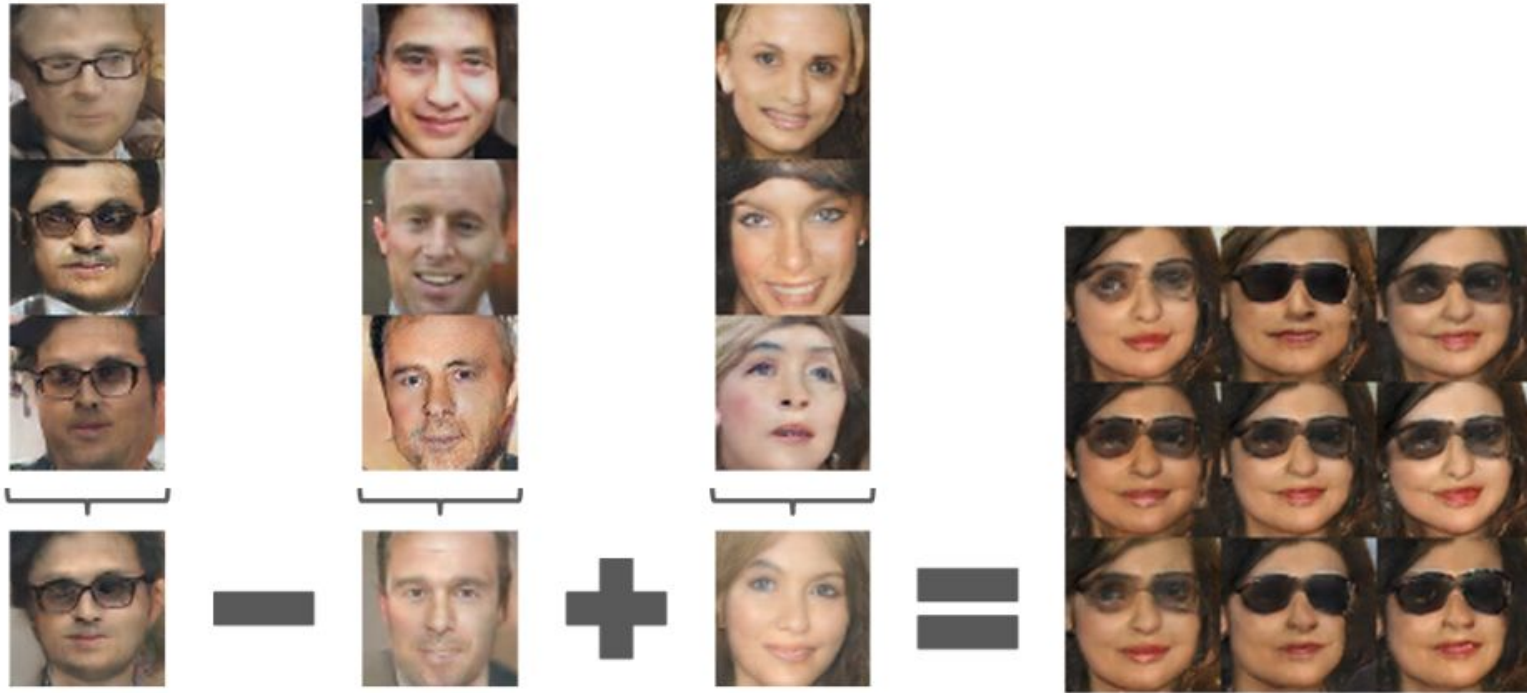


winter → summer

CycleGAN: <https://arxiv.org/abs/1703.10593>

# Learn useful representations

What do intelligent systems need?



man  
with glasses

man  
without glasses

woman  
without glasses

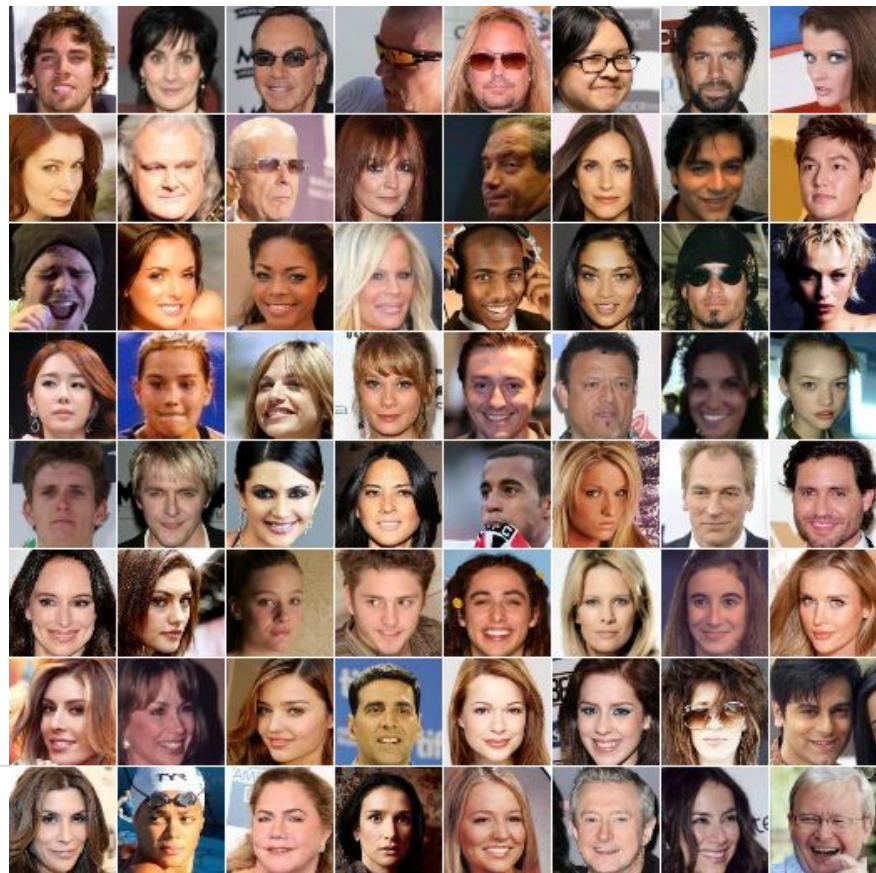
woman with glasses  
<https://arxiv.org/pdf/1511.06434.pdf>



# Learn useful representations

What do intelligent systems need?

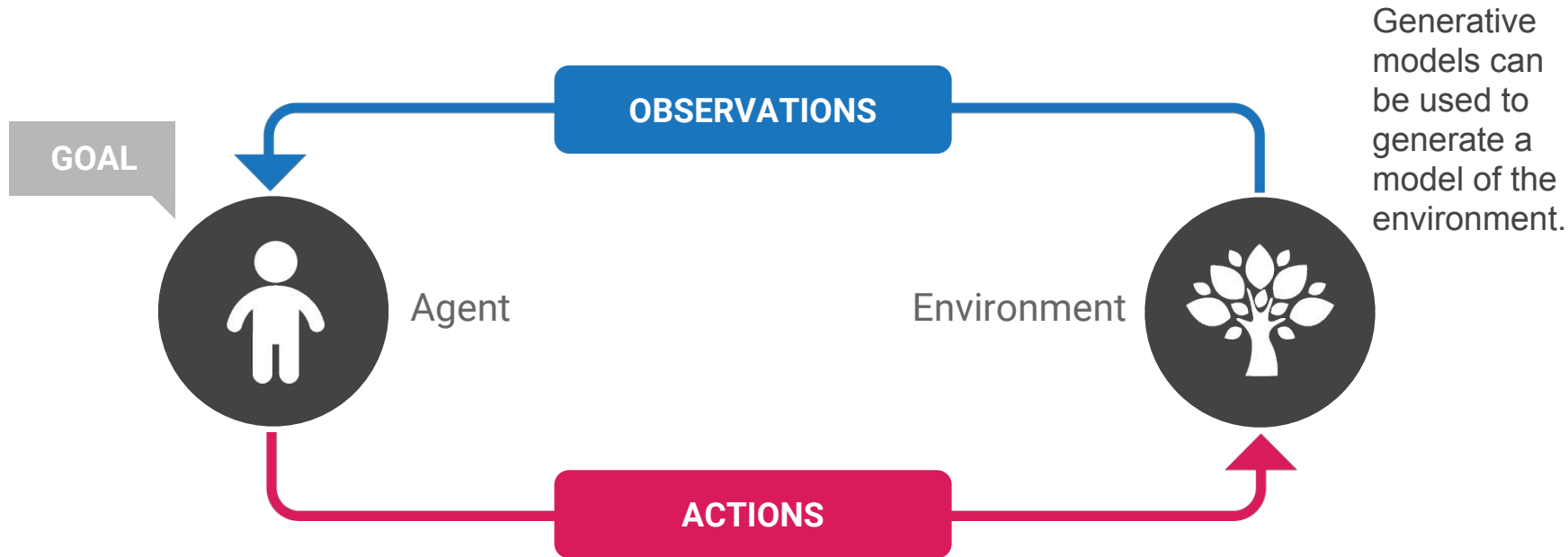
Leverage learned structure for better classification performance on labelled data.





# Have a model of the world

What do intelligent systems need?





How do generative models allow us  
to build intelligent systems?

# The goal of generative models

Learn a model of the true underlying data distribution  
 $p^*(x)$  from samples

$$x_1, x_2 \dots x_n$$

# Generative models learning principles

The goal of generative models

Find  $p_{\theta}$  to minimize the distance between  $p_{\theta}$  and  $p^*$



# Finding $p_\theta$

## Choices in generative models

- Model of  $p_\theta$ 
  - you can leverage prior knowledge of the problem
    - what kind of data do you have?
    - what kind of process generated the data?
- The learning principle used to minimize the distance between  $p_\theta$  and  $p^*$

Generative model algorithm = learning principle + model

## Learning principle

Model of  $p_\theta$

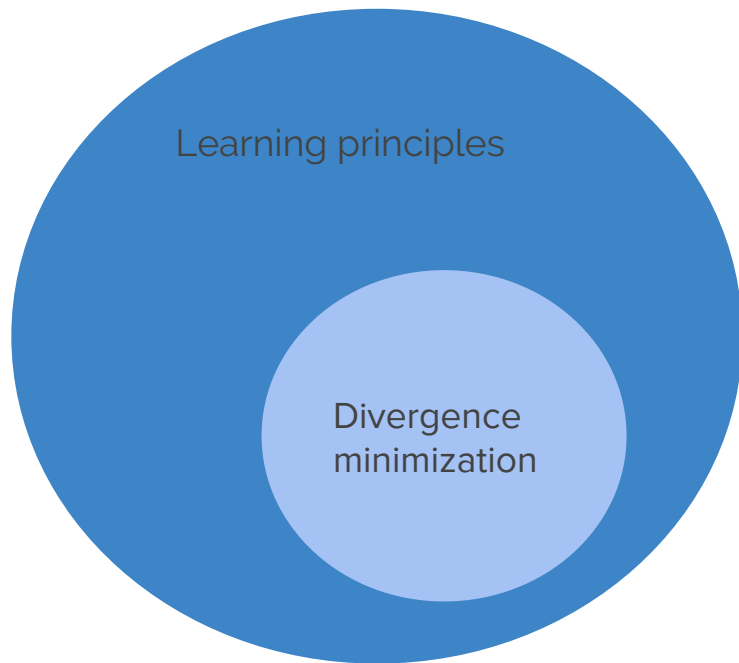
	Moment matching	Maximum likelihood	...	Optimal transport
Autoregressive				
Implicit		Algorithm		
...				
Encoder-decoder				



# Learning principles



# Divergence minimization as a learning principle



Other learning principles:  
moment matching  
optimal transport

# Divergences minimized

Divergence minimization for generative model learning

Aim: Minimize a divergence between  $p_\theta$  and  $p^*$

# Divergences minimized

Common divergence choices

- KL divergence (most common)
  - results in *maximum likelihood* learning
- Reverse KL divergence
- Jensen Shannon

# KL divergence

Maximum likelihood

Minimizing the KL divergence between  $p_\theta$  and  $p^* \Rightarrow$  maximum likelihood learning:

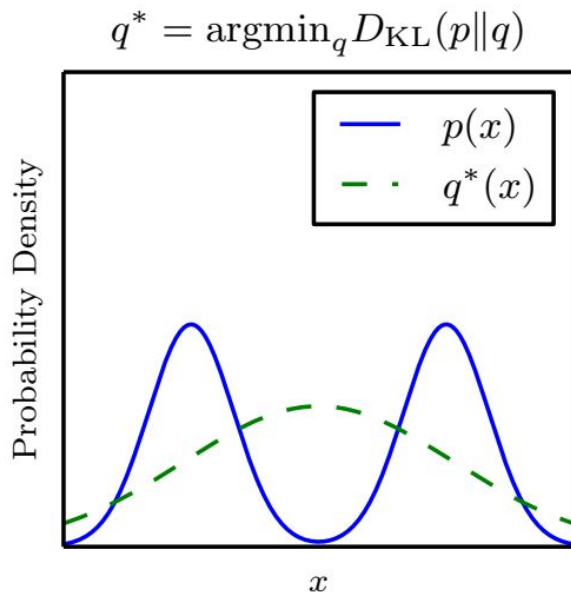
$$\operatorname{argmax}_\theta \mathbb{E}_{x \sim p^*} \log p_\theta(x)$$

**Intuition:** find the model which gives highest likelihood to the data.

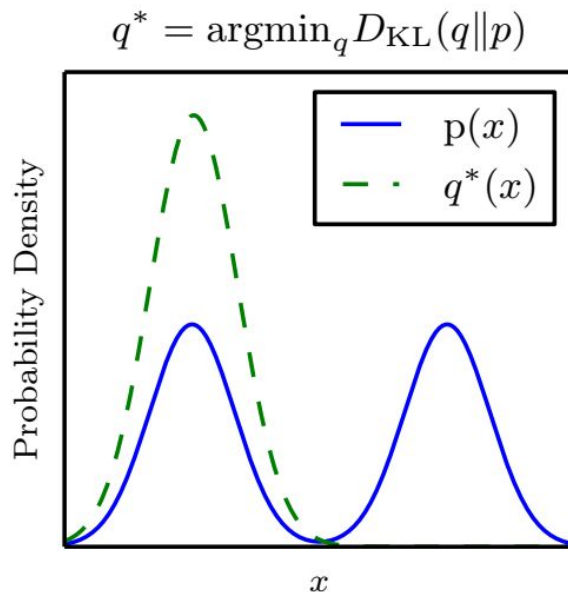


# Trade-offs for a fixed model choice

KL vs Reverse KL model fit



Maximum likelihood



Reverse KL

<https://arxiv.org/pdf/1701.00160.pdf>



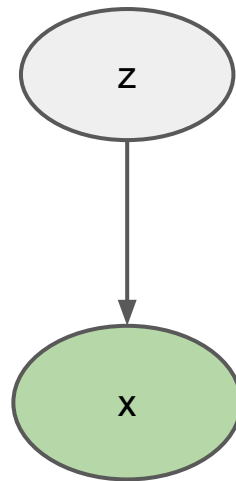
# Model choices

# Model choices

Graphical structure

Directly model  $p_{\theta}(x)$

Leverage underlying data structure  
in generative process.



$z$  = latents  
 $x$  = observed

# Model choices

Embedding priors in your model

Leverage data knowledge:

- convolutional models for images
- recurrent models for text and sound
- appropriate priors for latent variables



# Algorithms

# PixelCNN, PixelRNN, WaveNet

Autoregressive maximum likelihood models

**Principle:** maximum likelihood

**Model:** Autoregressive model with no latent variables

$$p_{\theta}(x) = \prod_i p_{\theta}(x_i | x_1, x_2, \dots, x_{i-1})$$

Model  $p_{\theta}(x_i | x_1, x_2, \dots, x_{i-1})$  using a recurrent neural network or convolutional masking.

WaveNet: A Generative Model for Raw Audio

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

<https://arxiv.org/abs/1606.05328>

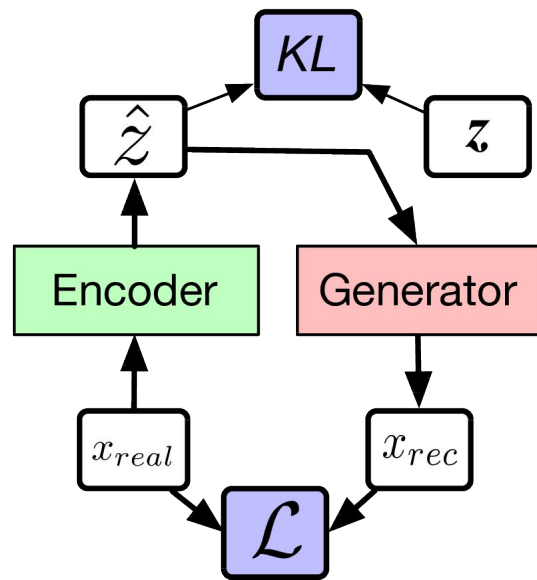
<https://deepmind.com/blog/wavenet-generative-model-raw-audio/>

# Variational autoencoders

Latent approximate maximum likelihood models

**Principle:** (approximate) maximum likelihood

**Model:** Encoder-decoder model with latent variables



$$\log p_{\theta}(\mathbf{x}) = \log \int p_{\theta}(\mathbf{x}|\mathbf{z})p(\mathbf{z})d\mathbf{z} \geq \mathbb{E}_{q_{\eta}(\mathbf{z}|\mathbf{x})}[\log p_{\theta}(\mathbf{x}|\mathbf{z})] - \text{KL}[q_{\eta}(\mathbf{z}|\mathbf{x})||p(\mathbf{z})]$$

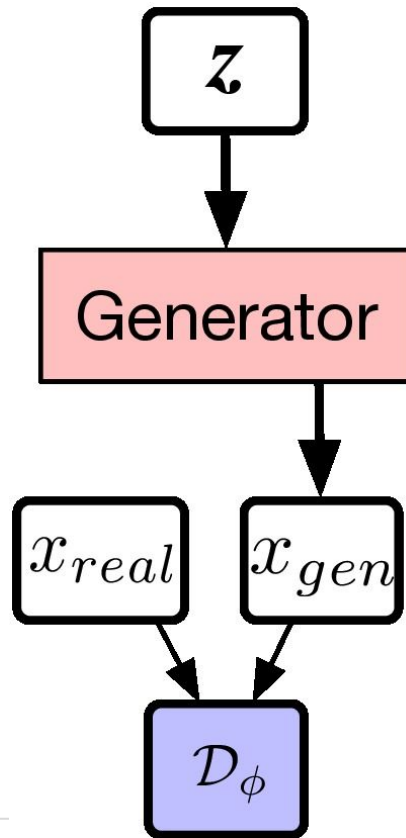
<https://arxiv.org/abs/1312.6114>



# Generative adversarial networks

Latent variable models without maximum likelihood

- Minimize distance between  $p_\theta$  and  $p^*$ 
  - Jensen Shannon
  - Earth movers
- How they model  $p_\theta$ 
  - Implicitly: you do not have access to  $p_\theta$ , but you can sample from it
  - Latent models



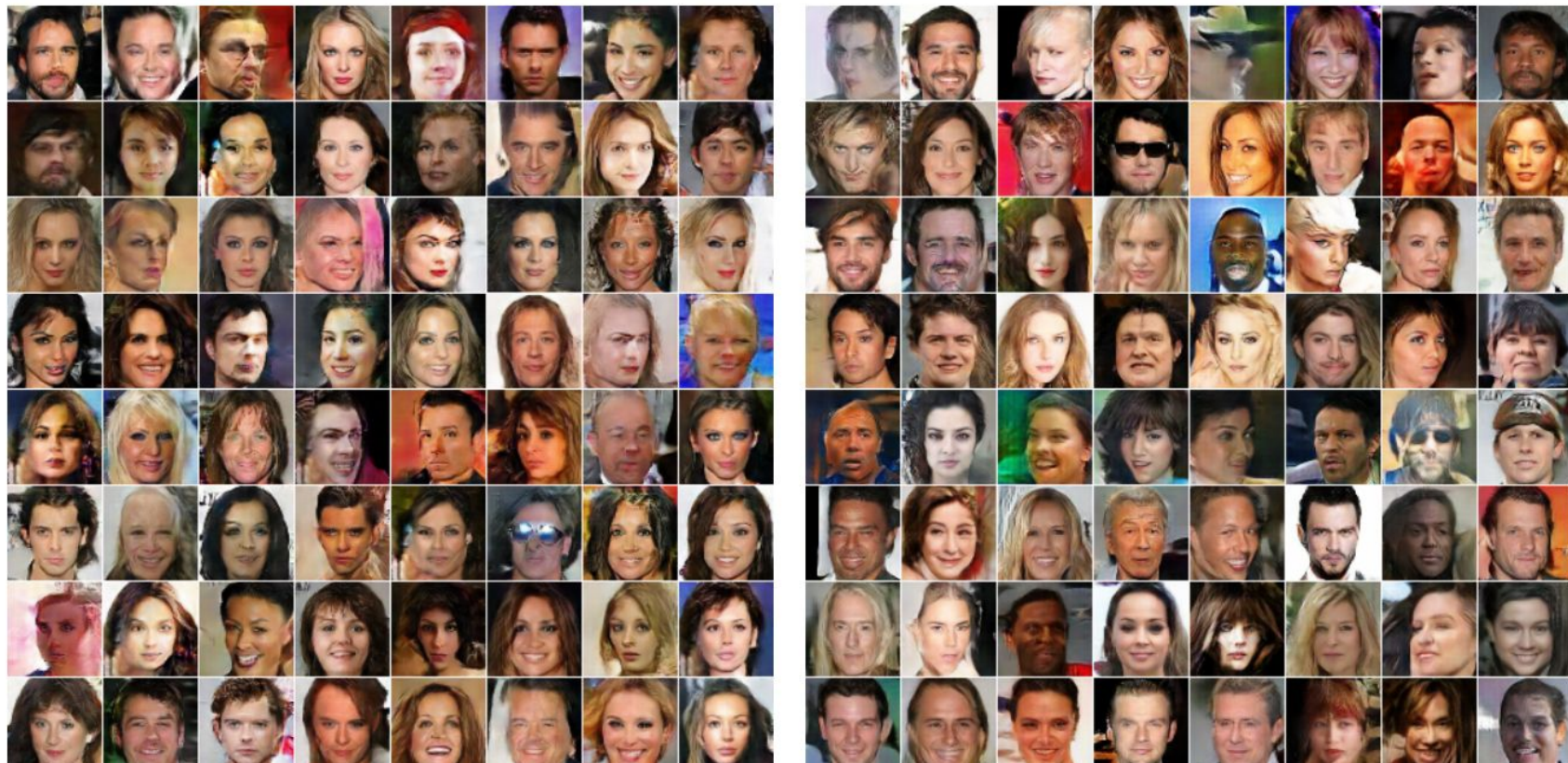
<https://papers.nips.cc/paper/5423-generative-adversarial-nets.pdf>



# Evaluating generative models

# Evaluation of generative models

How can we compare generative models?



# Evaluation of generative models

Use application specific metrics

**No evaluation metric is able to capture all desired properties.**

Evaluate performance based on the end goal:

- semi supervised learning: classification accuracy
- reinforcement learning: total agent reward
- data generation (eg: text to speech): human (user) evaluation via beta testing





# When to think about generative models

# Using generative models

Use them when...

- learning with scarce labelled data
- estimating uncertainty
- eliminating outliers
- completing missing data
- generating data
- building useful (disentangled) representations

# Using generative models

What model to use?

- need to learn underlying structure?
  - ⇒ use an inference model
- need only samples?
  - ⇒ consider GANs
- need a likelihood  $p(x)$ 
  - ⇒ use maximum likelihood models
  - ⇒ use autoregressive models if sampling cost is not an issue





# ***THANK YOU***

## **Credits**

Shakir Mohamed, Balaji Lakshminarayanan

**Additional Credits**