

Neural Computation Revision

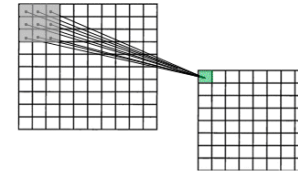
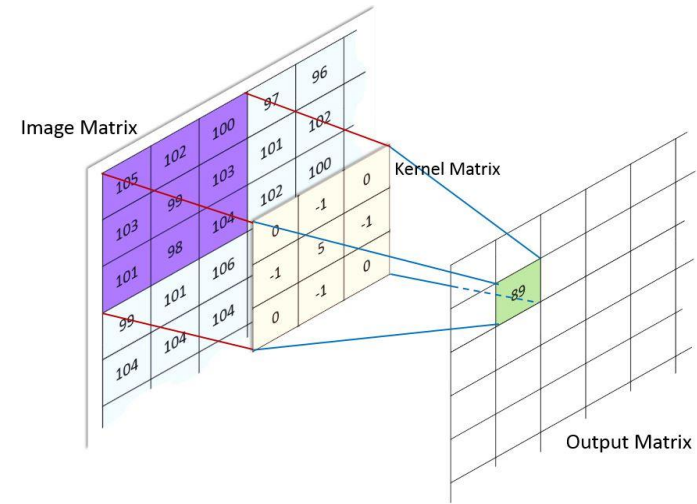
Part 2

Jinming Duan

Convolutional Networks

Convolutional Networks

- Convolutional Neural Networks
 - Popular for image recognition and computer vision, etc.
 - How to train a network
 - Convolution operation
 - Convolutional layers
- Pooling stage (e.g. max-pooling, downsampling, upsampling, transpose convolution, etc.)
- Non-linearity (e.g. Relu, leaky Relu, Tanh, etc.)
- Number of parameters and size of feature maps
- Backpropagation (gradients)
- Data processing (min-max, z-score, Tanh, etc)



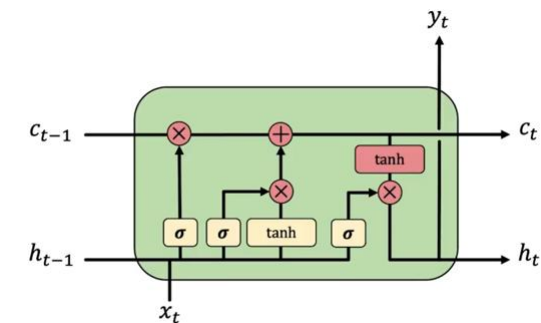
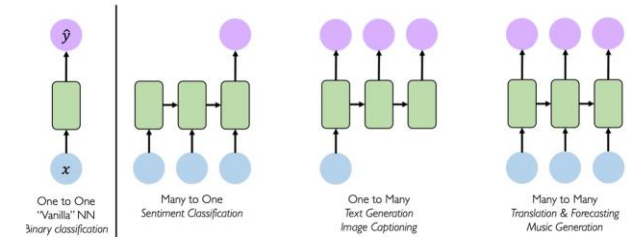
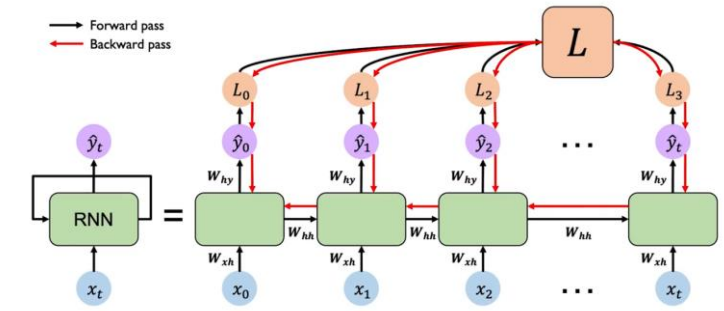
Example Questions

- Compute the convolution between an input and a kernel
- State some important properties of CNNs relative to fully connected NNs
- Compute number of parameters or size of outputs
- What are typical applications of CNNs?

Recurrent Networks

Recurrent Networks

- Recurrent Neural Networks
 - Popular for modeling sequence data, etc.
 - Vanilla RNN
 - Sequence modeling applications (one to one, many to one, etc)
- Neurons with recurrence (unfold RNNs, shared weights, computational graph)
- Design criteria (variable length inputs, long term dependencies, maintain information about order, shared parameters across the sequence)
- BPTT (exploding/vanishing gradients, solutions)
- LSTMs (forget, store, update, output)



Example Questions

- How is an RNN handling variable length inputs
- How is hidden state updated at each time step
- Whats an RNN's application in terms of inputs and outputs
- Methods to tackle long term dependencies issues
- Compute the outputs of an RNN, given some inputs
- How do LSTMs work? Why is it better?

Compulsory Material

- All material not marked optional on the “Modules” page on Canvas is compulsory reading, e.g.,
 - Lecture notes
 - Reading lists (only contents covered in lectures)
 - Videos
 - Exercises, lab sheets
- Exam can cover anything covered by compulsory material

AutoEncoders

Unsupervised Learning

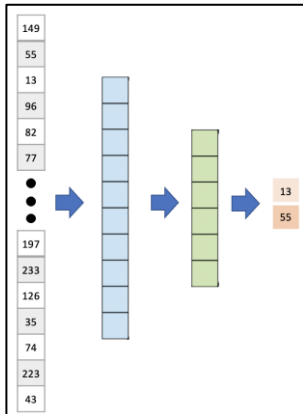
Available data: $x_1, \dots, x_N \sim p_{data}(x)$

Goal: Learn “**useful features**” of the data / Learn “**the structure**” of the data.

Useful for:

- Dimensionality Reduction (compression)
- Clustering
- Generation / Synthesis
- Learn from loads unlabeled data, when labeled data are limited
- Probability Density Estimation
- ...

Dimensionality Reduction



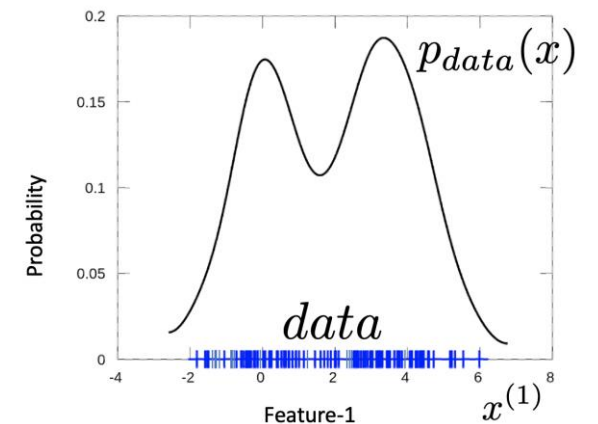
Clustering



Generation / Synthesis

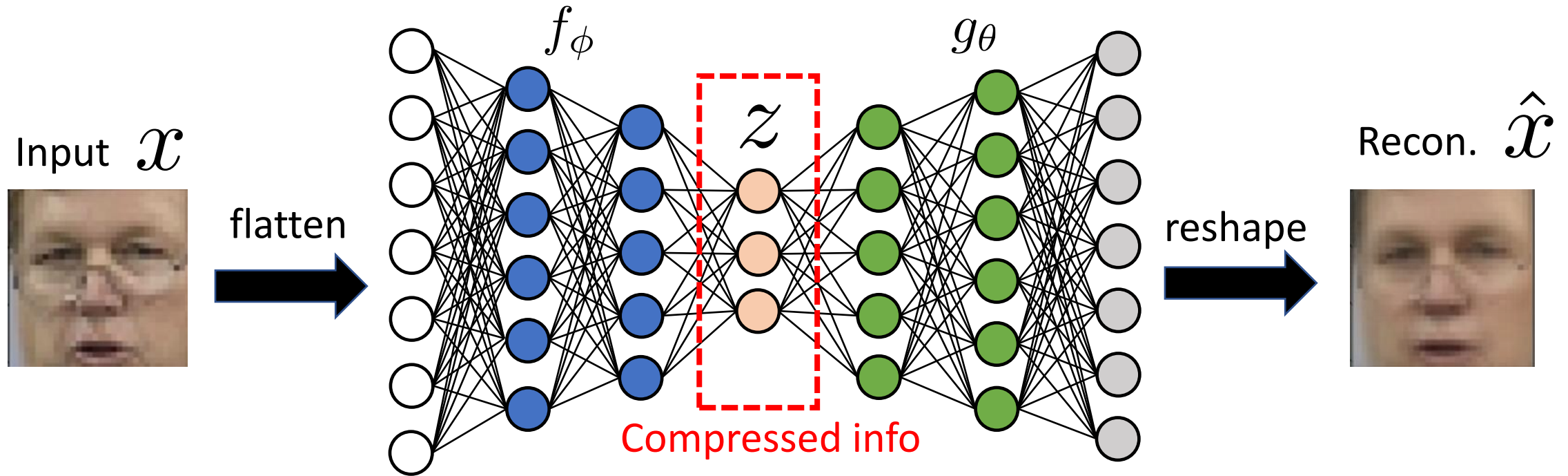


Probability Density Estimation



Auto-Encoders with bottleneck

$$f_{\phi} : \mathcal{X} \in \mathbb{R}^d \rightarrow \mathcal{Z} \in \mathbb{R}^v, \text{ where } v < d$$



What we learned about Auto-Encoders:

Part 1:

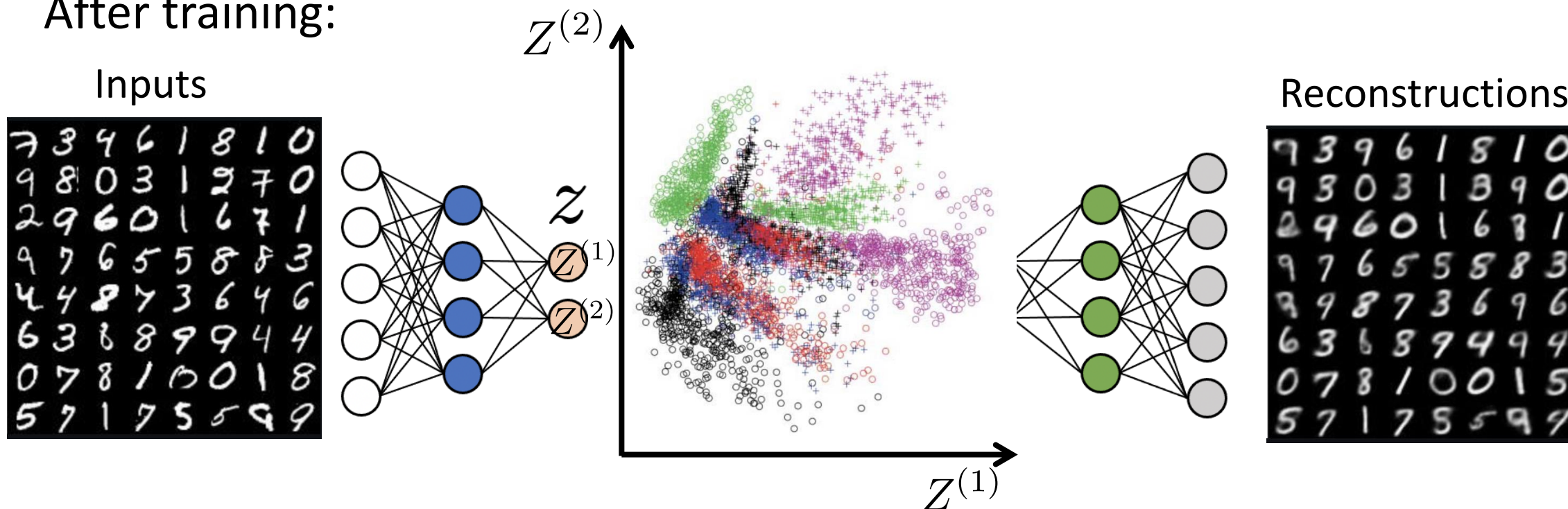
- What is the basic auto-encoder
- How to train auto-encoders
- What is an AE with a bottleneck layer and why to use it
- What feature representations do they learn

Part 2:

- What can they be used for (dimensionality reduction, clustering, pretraining,...)
- What AEs are not good at and why

AEs for learning clusters of data

After training:



From: Hinton and Salakhutdinov, Reducing the Dimensionality of Data with Neural Networks, Science, 2006

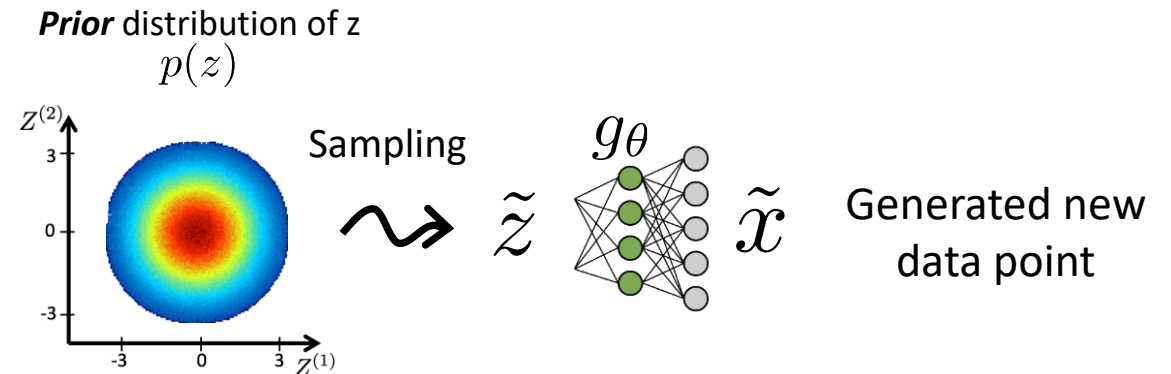
Variational AutoEncoders

What is a Generative Model?

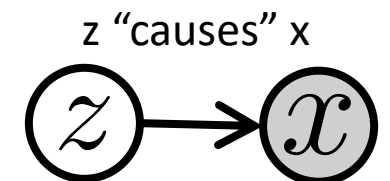
“A generative model describes **how a dataset is generated**, in terms of a **probabilistic model**.
By sampling from this model, we are able to generate new data.”

Generative Deep Learning, by David Foster

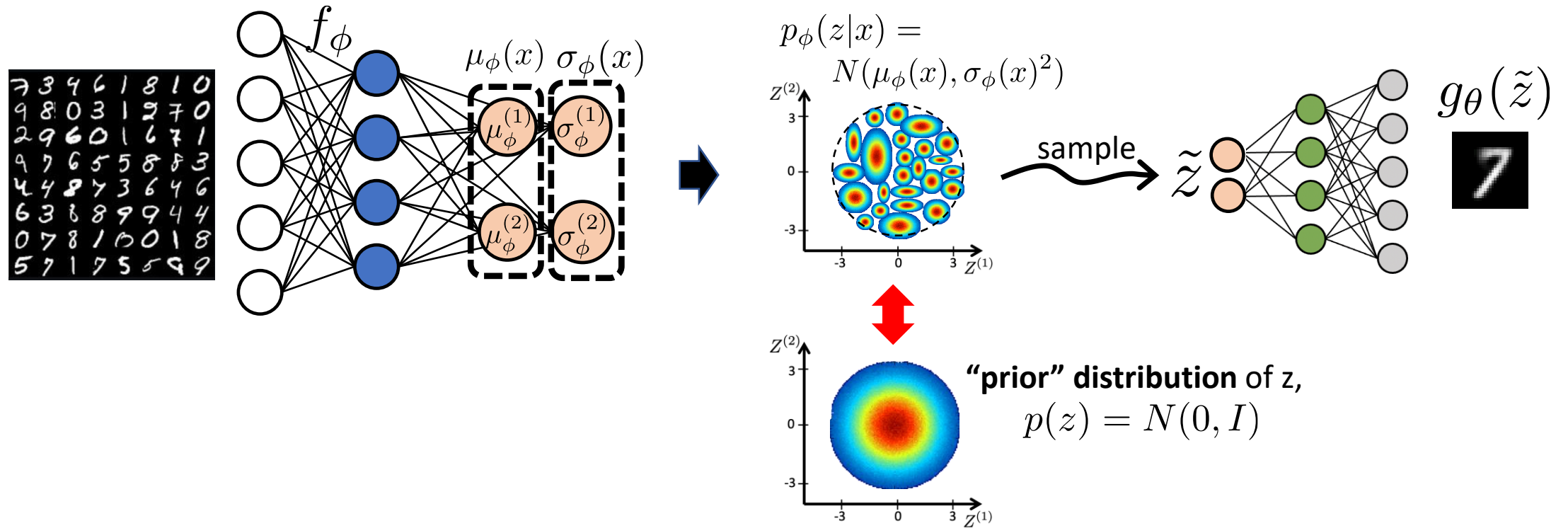
Generative models: $g : \mathcal{Z} \rightarrow X$
We assume: z “causes” x



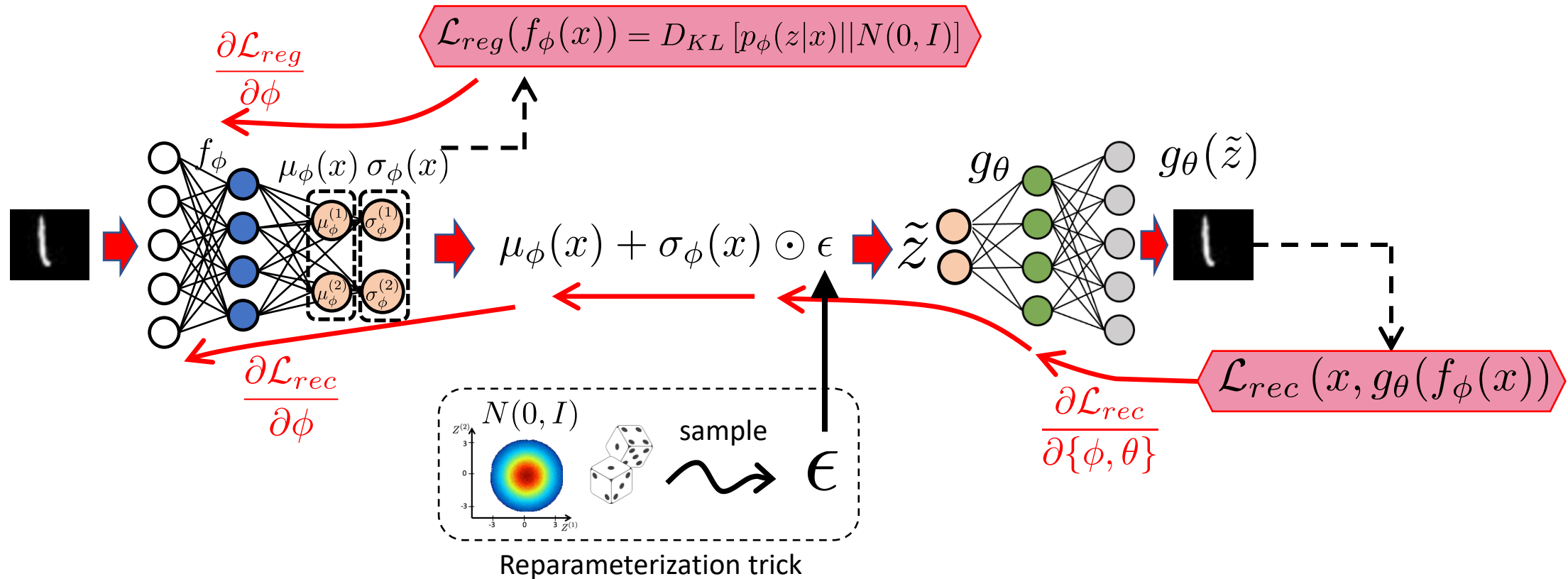
z : content, lighting, zoom ...
 x : the photo



Variational Auto-Encoder



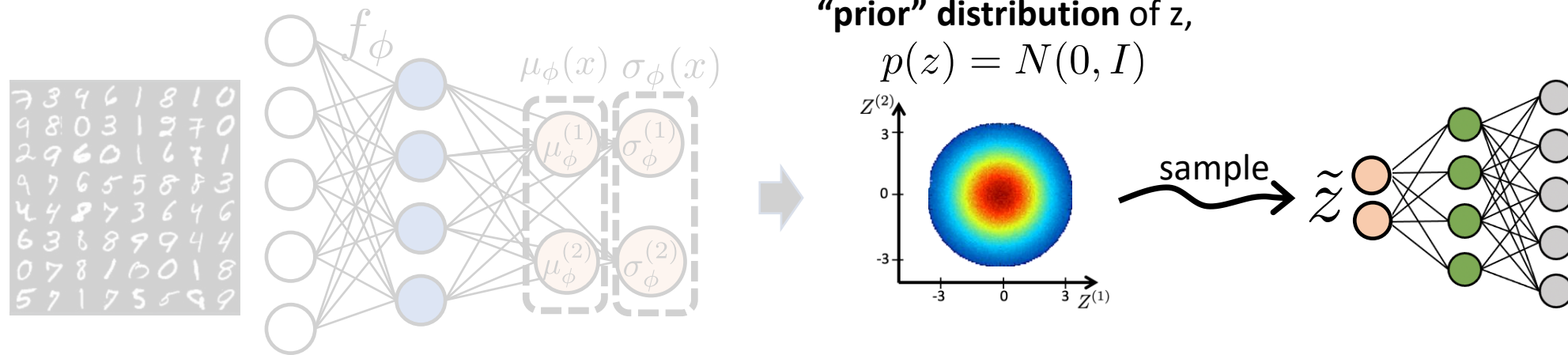
Variational Auto-Encoders and Re-parameterization trick



Kingma & Welling, Auto-encoding variational bayes, ICLR 2014

Rezende et al, Stochastic Backpropagation and Approximate Inference in Deep Generative Models, ICML 2014

VAE: Generating new data by sampling from prior



What we learned about VAEs:

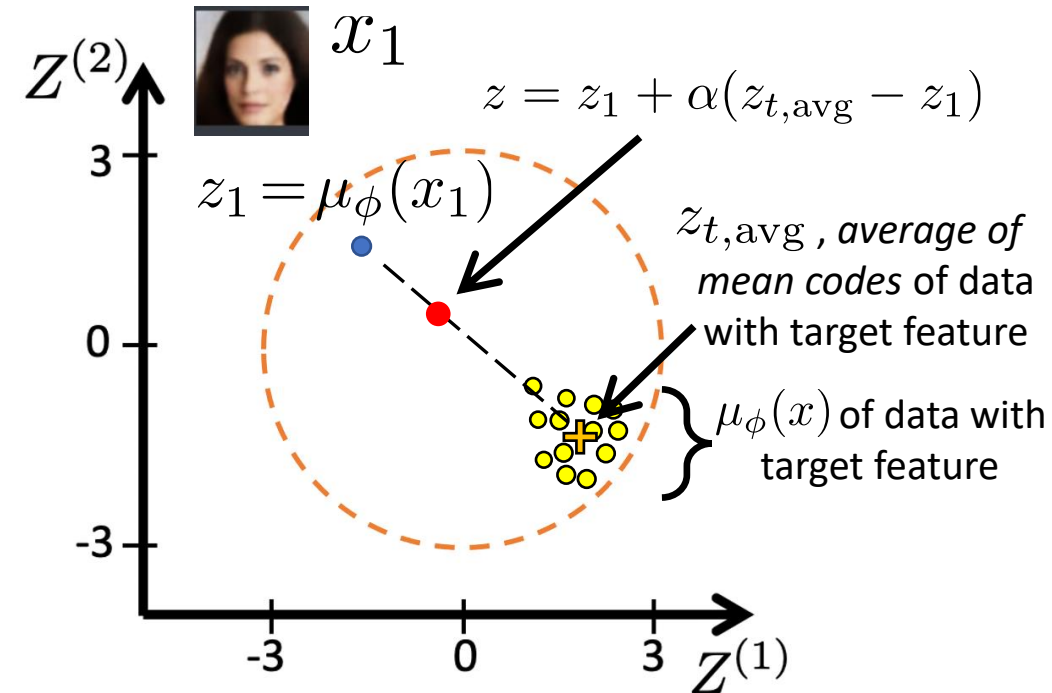
Part 1: The “simple” explanation of a VAE, as a regularized AE

- What is a VAE
- How to train VAEs
- How do different terms of training loss influence what VAE learns
- How does a VAE relate to the basic AE

Part 2: Applications of VAE for...

- Generation of new data points
- Modifying data via interpolating between 2 inputs
- Modifying specific feature of an input
- Compression => Reconstruction

Altering specific features of data with VAE



Algorithm:

1. **Encode** original input x and use predicted $\mu_\phi(x)$ as its code:
E.g. $z_1 = \mu_\phi(x_1)$
2. Identify all training samples that have the desired “target” characteristic. E.g. blondes. Assume these are $x_{t,1}, x_{t,2}, \dots$
3. **Encode** all training samples with the target characteristic. Use mean of the Gaussian predicted by encoder as the code.
E.g. $z_{t,1} = \mu_\phi(x_{t,1}), z_{t,2} = \mu_\phi(x_{t,2}), \dots$
4. Compute **average** value of codes of all samples with target characteristic: $z_{t,\text{avg}} = \text{average}(z_{t,1}, z_{t,2}, \dots)$
5. Create **new z** code by **interpolation**
E.g. $z = z_1 + \alpha(z_{t,\text{avg}} - z_1)$
6. **Decode** z with decoder.

Possible with more than 1 target features, similarly to algo on Slide 7.

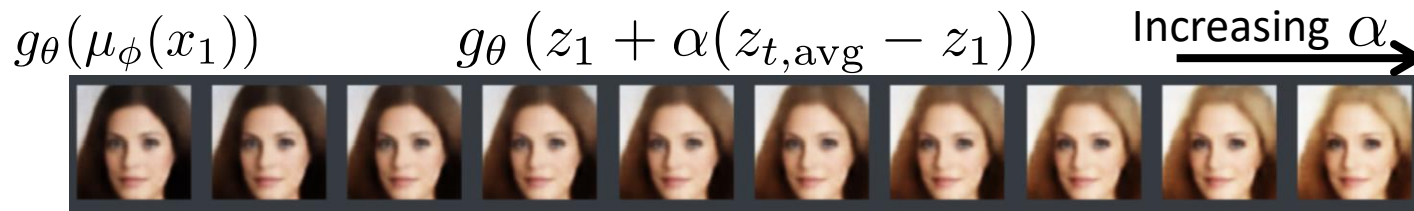
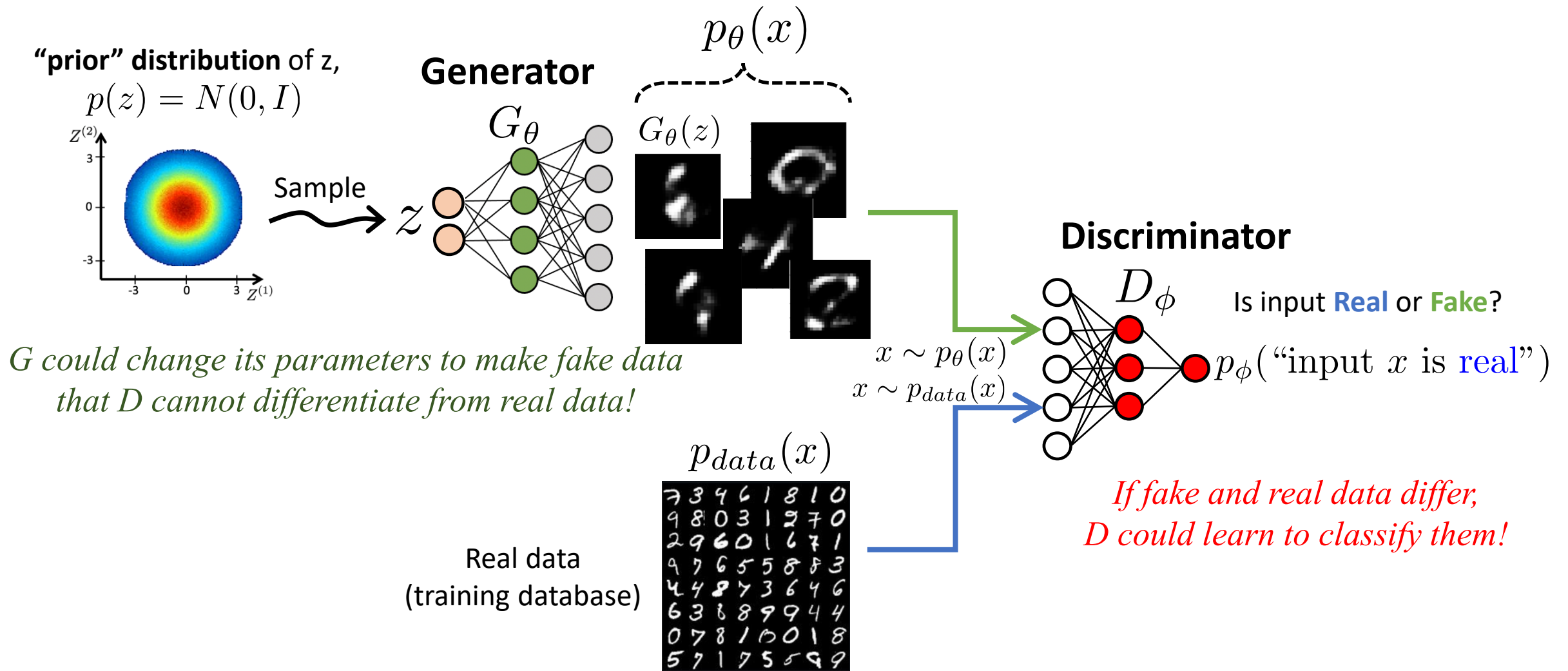


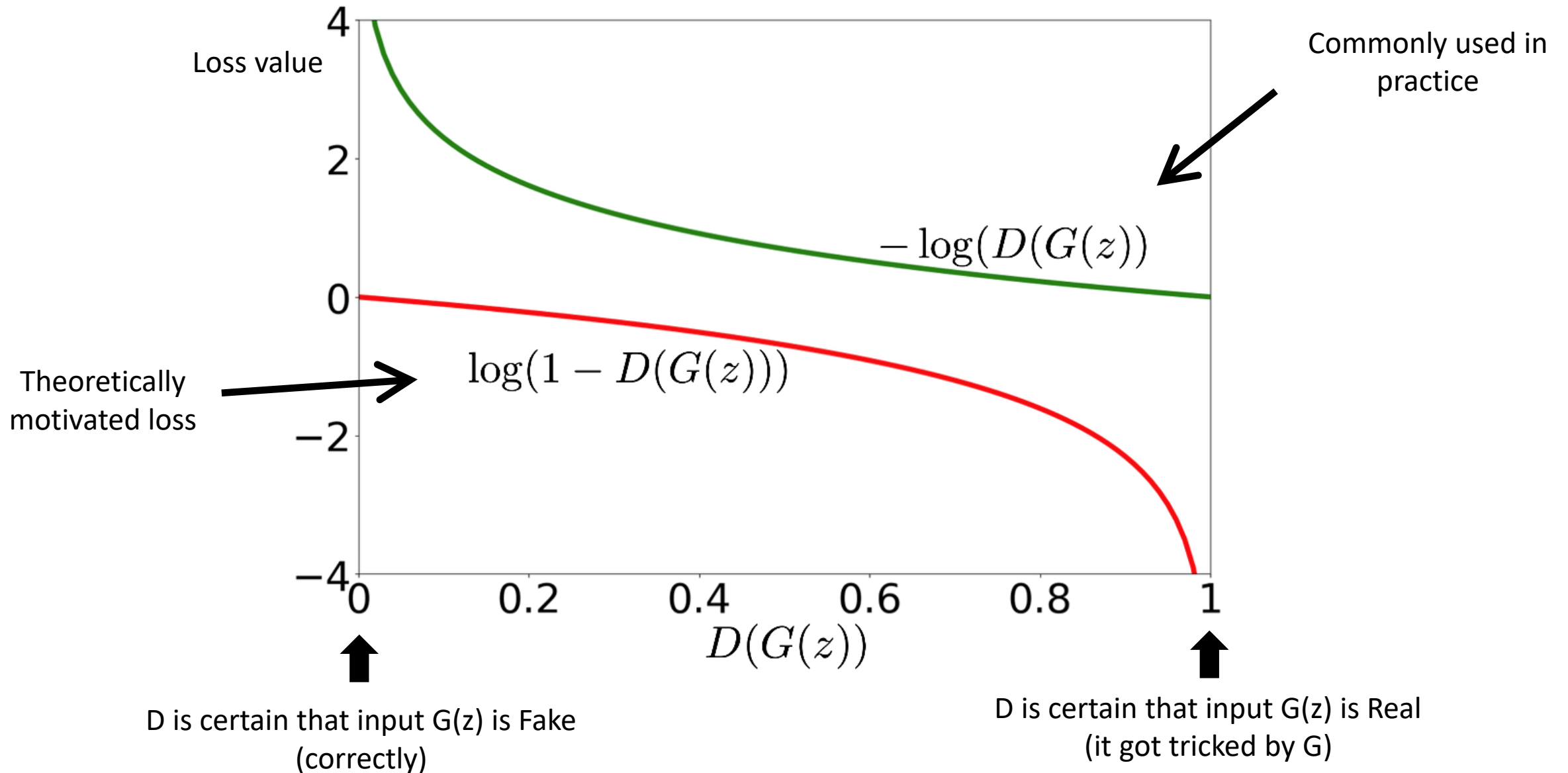
Image from: Steven Flores ([link](#))

Generative Adversarial Networks

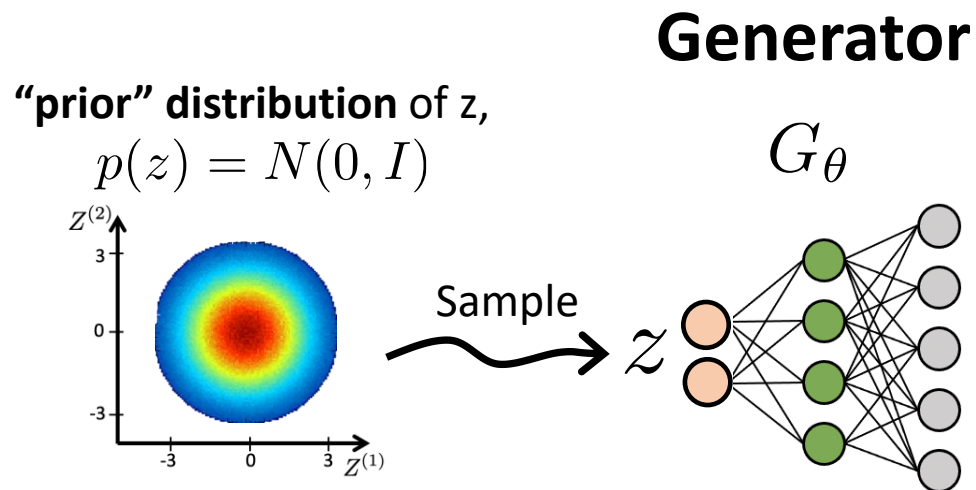
Generative Adversarial Networks



Losses for training the Generator G



Generating new data points with trained GAN



To generate new data from a GAN:

Step 1. sample z from prior $N(0, I)$

Step 2. “Decode” using G , obtaining $G(z)$, the generated sample.

What we learned about GANs:

- What is the GAN (architecture)
- The min-max GAN objective
- How to train a GAN
- Two loss functions for training the Generator (theoretical/practical)
- Use of GANs for Generation of new datapoints

OPTIONAL – NON ASSESSED:

- *Issues of GANs*
- *Extensions / more advanced models*

Assessed material:

Anything written or discussed in:

- Slide decks
- Pre-recorded videos
- Lectures
- Tutorials (not code / implementation, but understanding of models & behaviour)

NOT assessed:

- Material in “further reading” that is not already part of the above assessed material.
- “Optional” material on VAEs (probabilistic derivation) and GANs (issues and advanced models).

Thank you!