



# AutoEncoders

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# Exercise

Draw an image of a 100-peso bill

Draw from what you can remember only

Do not look and copy a 100-peso bill



# AutoEncoder

A self-supervised/unsupervised network

Supply it with data, it will figure out the mapping from input to output

A neural network that attempts to copy its input to its output

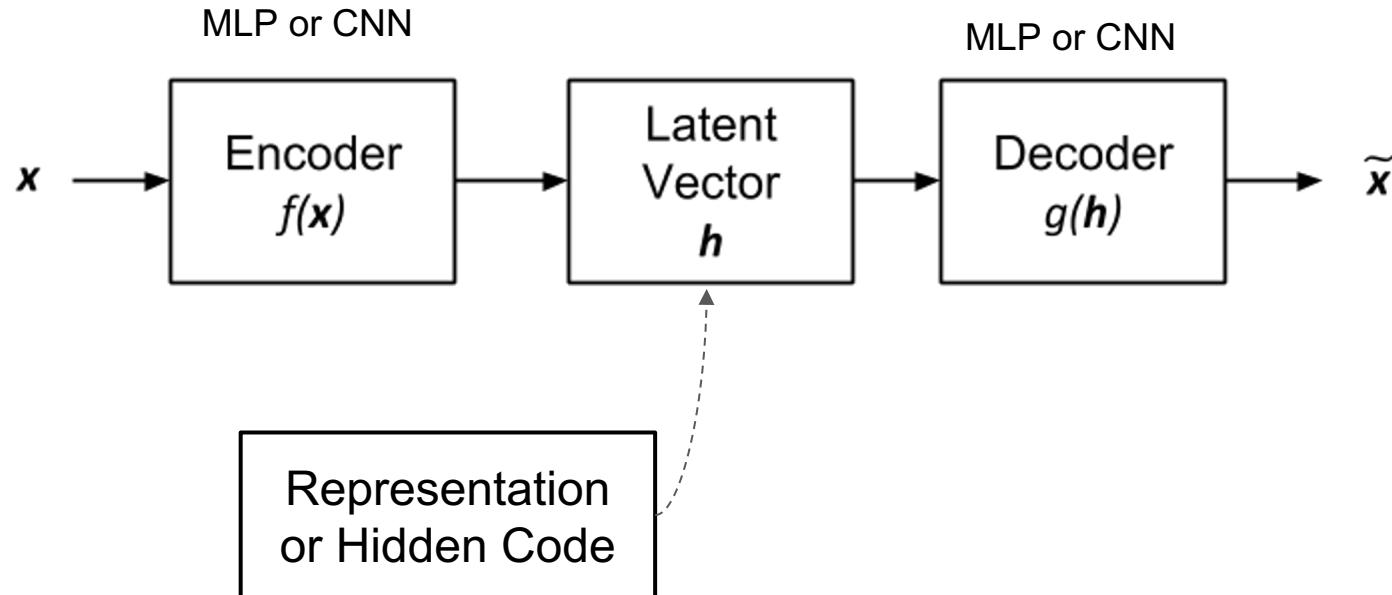
In doing so, it learns a hidden code,  $h$ , that represents its input

The network has 2 parts

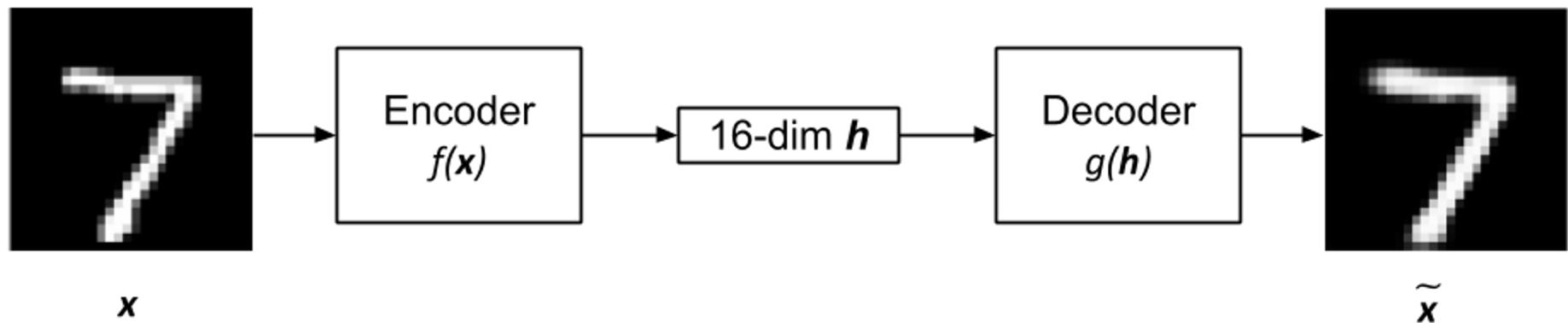
An encoder:  $h = f(x)$

A decoder:  $r = g(h)$

# AutoEncoder



# AutoEncoder



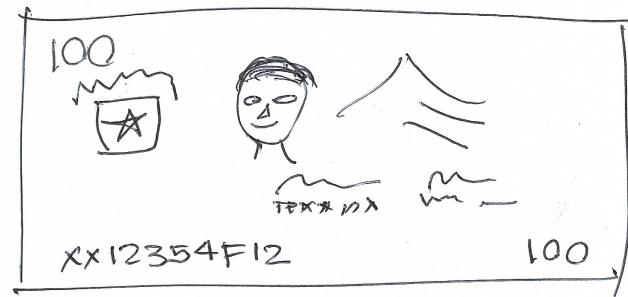
# AutoEncoder

Autoencoder must not learn:  $g(\mathbf{h}) = g(f(\mathbf{x})) = \mathbf{x}$

Instead it must learn to approximate  $\mathbf{x}$  only;

In doing so, it learns special properties of  $\mathbf{x}$

Roughly, our brain compresses (lossy) information about what it senses



# AutoEncoder

For example in MNIST, properties could be writing style, tilt, thickness, roundness of stroke, etc.

All properties needed to represent digits 0 to 9.

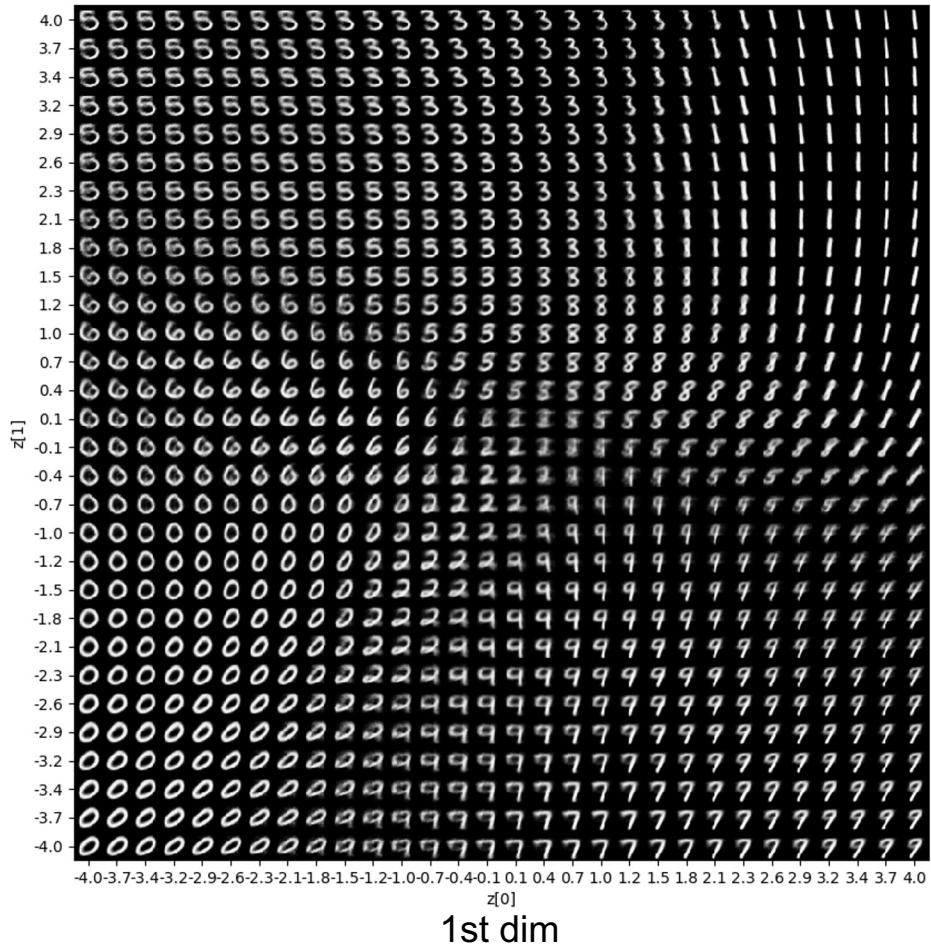
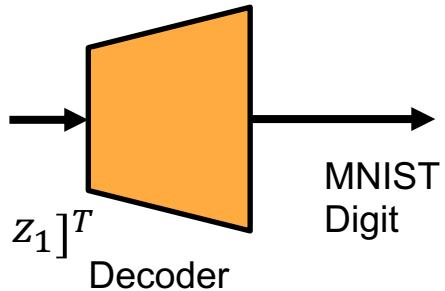
Autoencoder is not an identity function

Applications

# AutoEncoder Decoder as a Generative Model

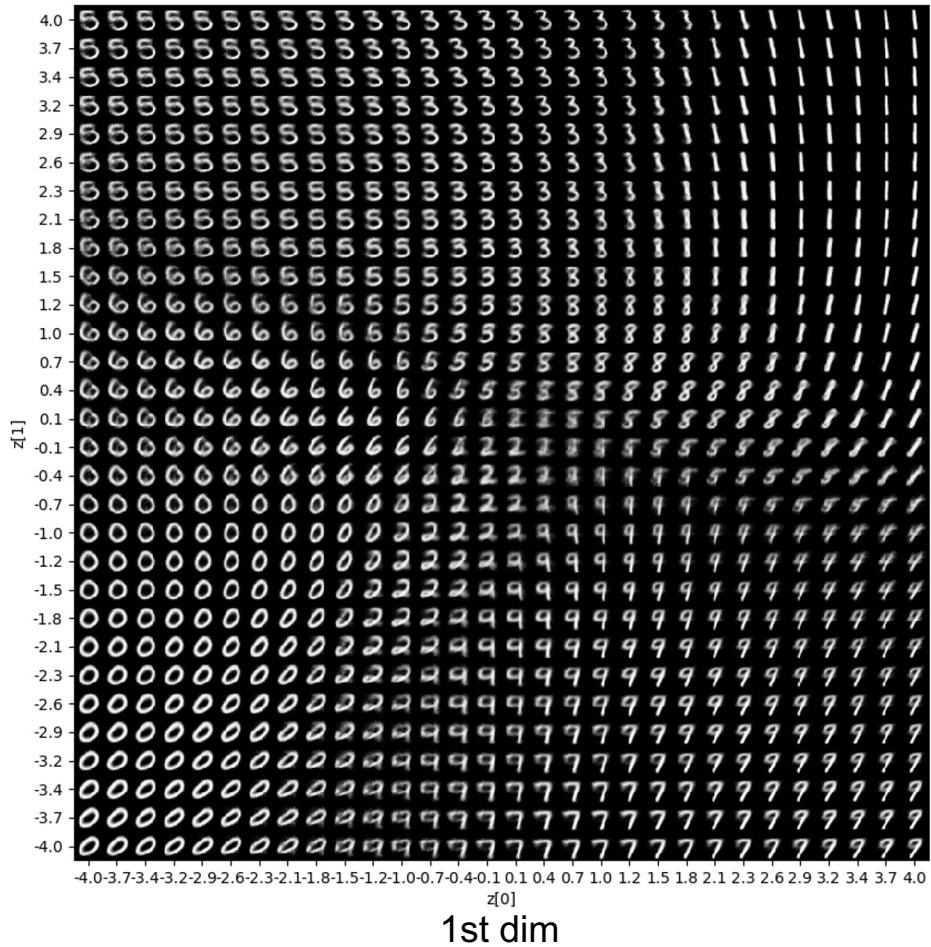
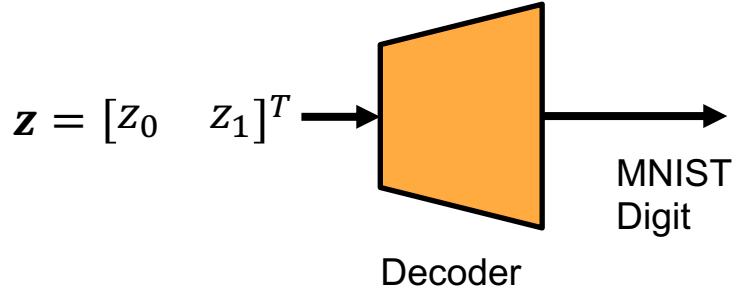
# Digits over latent code (2-dim)

Anywhere we navigate the latent space, there is a corresponding decodable MNIST digit-like image.



# Application

The decoder is a generative model

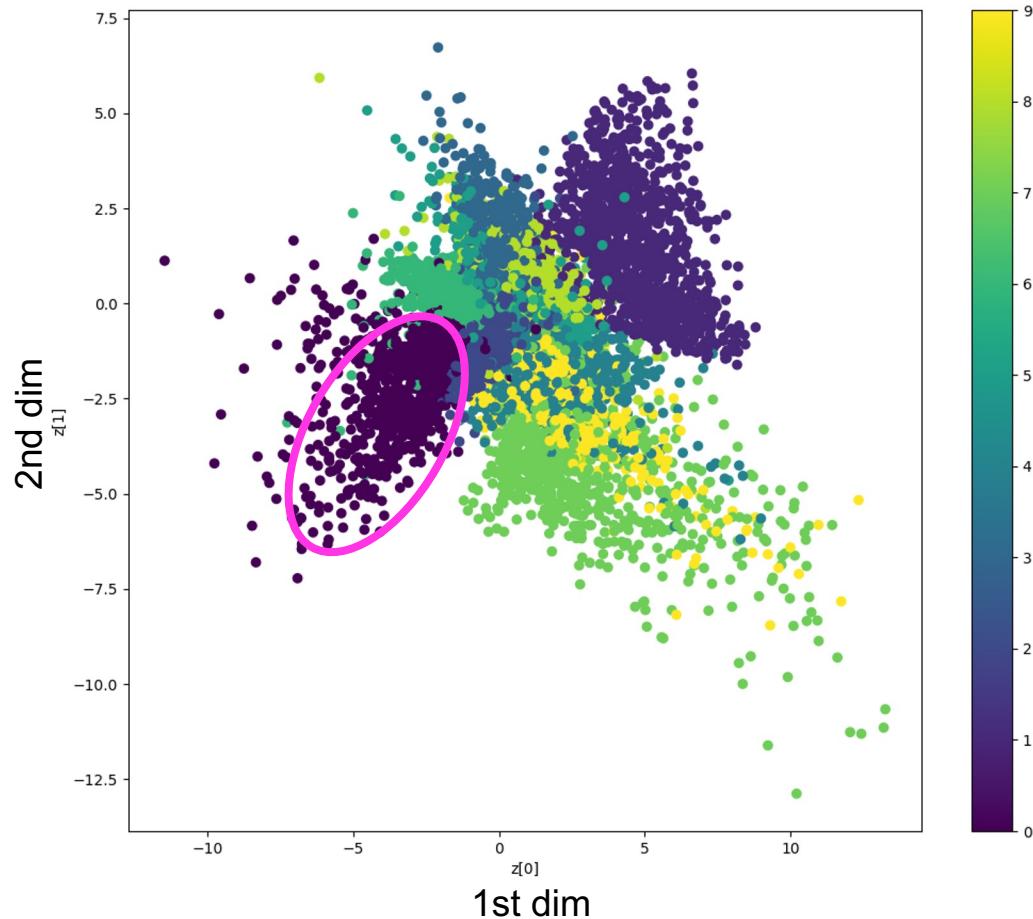


## Applications

AutoEncoder Encoder as a  
Clustering Network

# Digits over latent code (2-dim)

Similar digits appear to cluster in one region.

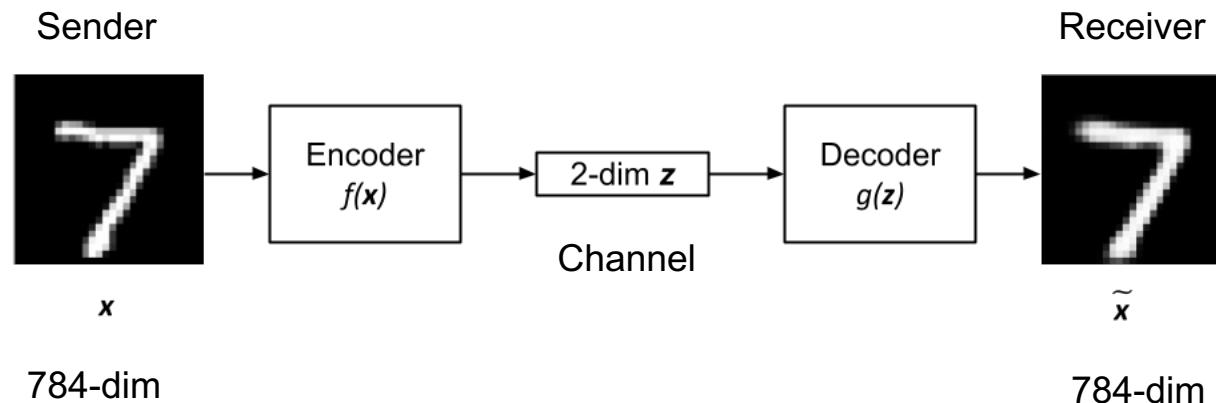


# Other Applications

Dimensionality reduction (compression)

Feature learning

Many more...



# The hidden code, $h$

Dimensionality is much less than  $x$

For example, MNIST  $x$  could be  $28 \times 28 = 784$  but  $h$  could be 2 or 4

The small dimension of  $h$  forces the neural network to learn only the most important features of  $x$

# How to train an autoencoder

The learning process is described by minimizing a loss function

$$L(x, g(f(x)))$$

$L$  penalizes  $g$  as being dissimilar from  $x$

Such as mean squared error (MSE)

# AutoEncoder vs PCA

Principal Component Analysis (PCA) or SVD can only learn linear feature representation

Autoencoder can learn both linear and non-linear feature representations

# Stochastic Encoder and Decoder

In AutoEncoder, the input is also the output

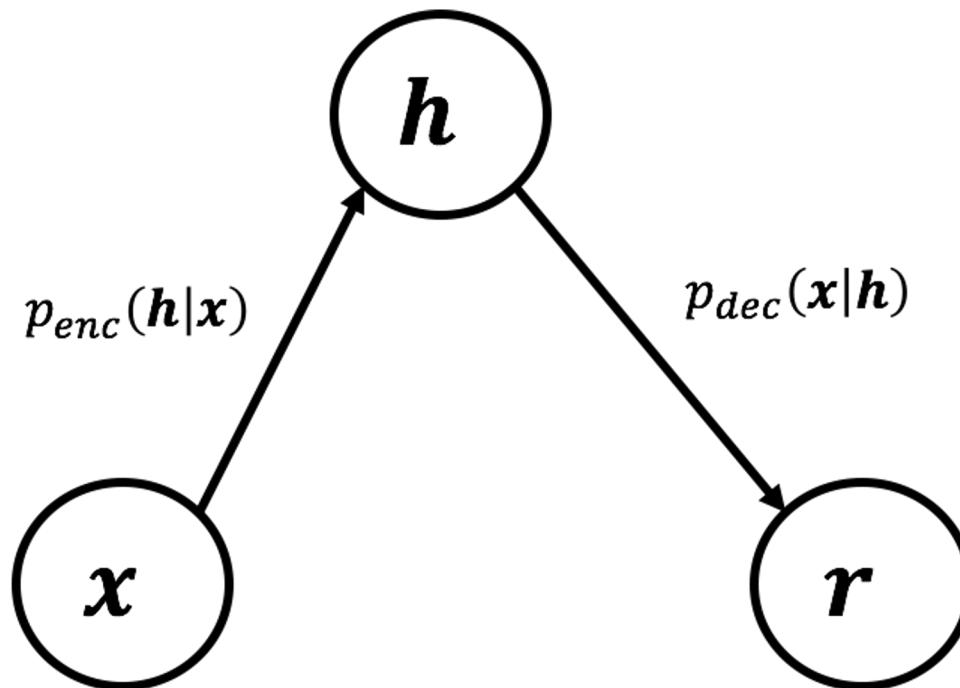
Encoder:  $p_{enc}(\mathbf{h} | \mathbf{x})$

Decoder:  $p_{dec}(\mathbf{x} | \mathbf{h})$

Similar to other networks, the goal of stochastic autoencoder is to minimize

$$-\log p_{dec}(\mathbf{x} | \mathbf{h})$$

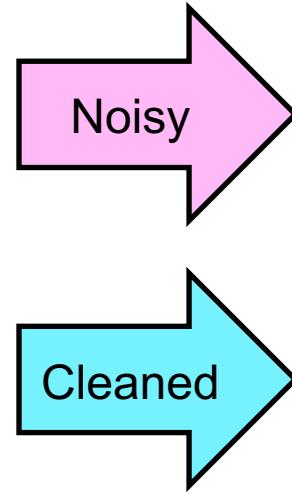
# Encoding/Decoding Distribution Graphical Model



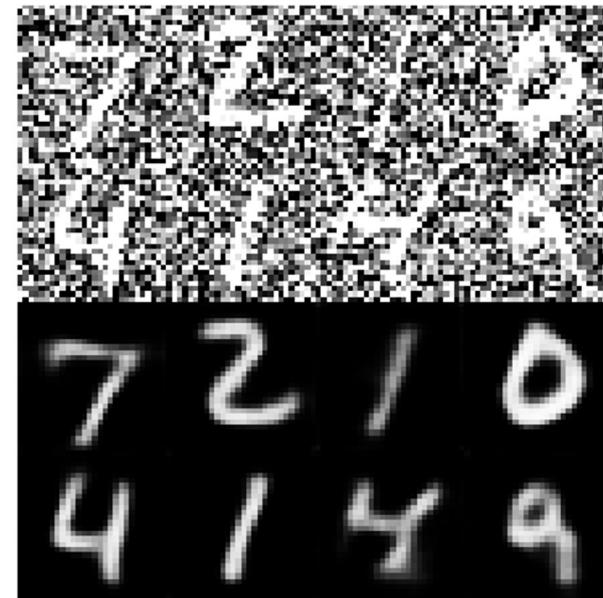
# Applications

# Denoising AutoEncoder

Can we recover clean data  
given noised data?



Corrupted Input: 1st 2 rows, Denoised Output: last 2 rows



# Denoising AutoEncoder

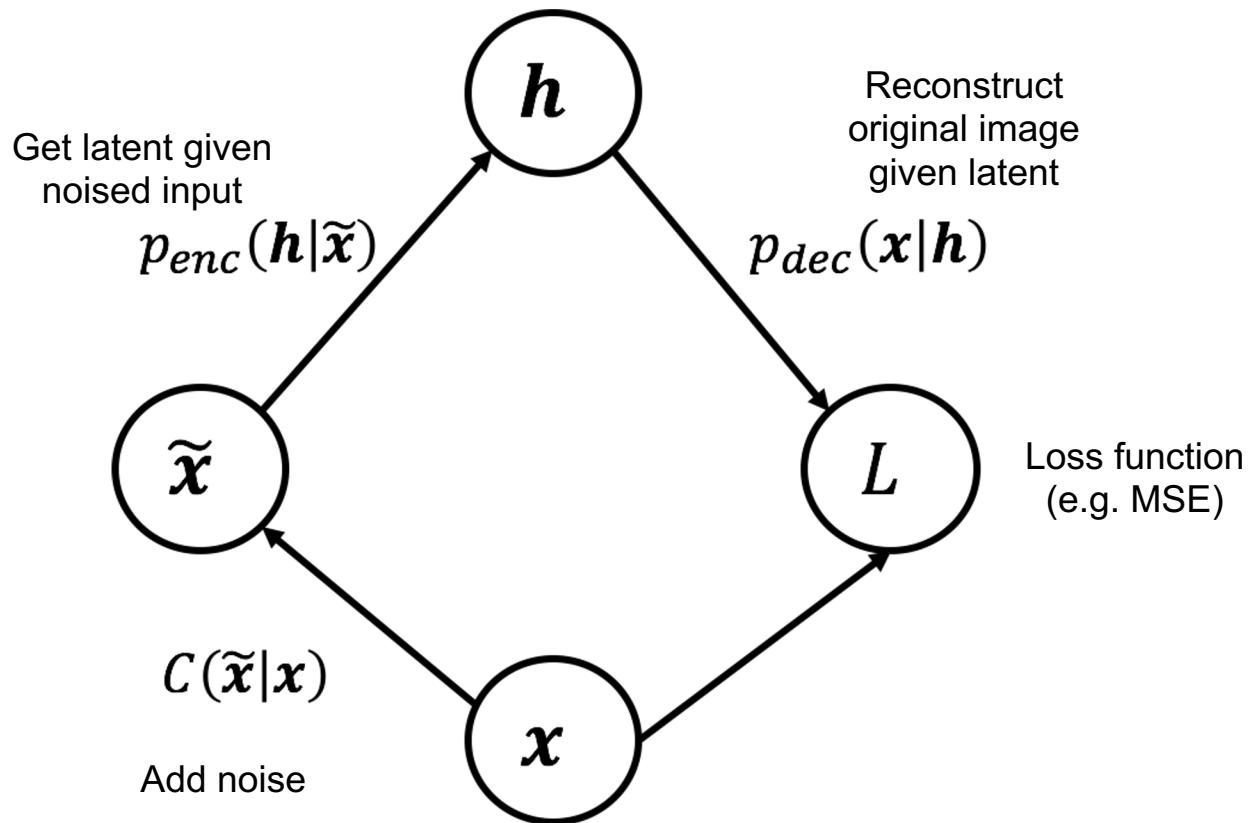
The idea is to recover the true distribution from a corrupted input:

$$L(x, g(f(\tilde{x})))$$

$\tilde{x}$  is the corrupted version of  $x$

The network receives a corrupted input and generates a clean output (clean or uncorrupted version of input)

# Denoising AutoEncoder Graphical Model



# Denoising AutoEncoder

Sample a training example  $x$  from training data

Sample a corrupted version of  $x$  using corruption process

$$C(\tilde{x}|x)$$

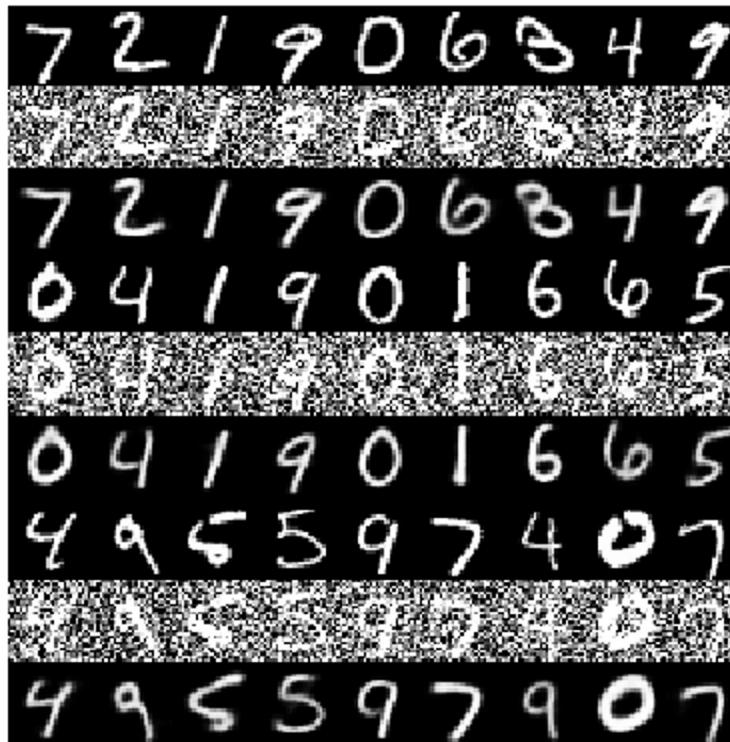
Use data points  $(\tilde{x}, x)$  to train the network to estimate autoencoder reconstruction distribution

$$p_{recon}(x|\tilde{x}) = p_{dec}(x|h)$$

where  $h$  is the output of the encoder  $h = f(\tilde{x})$

# Denoising AutoEncoder on MNIST

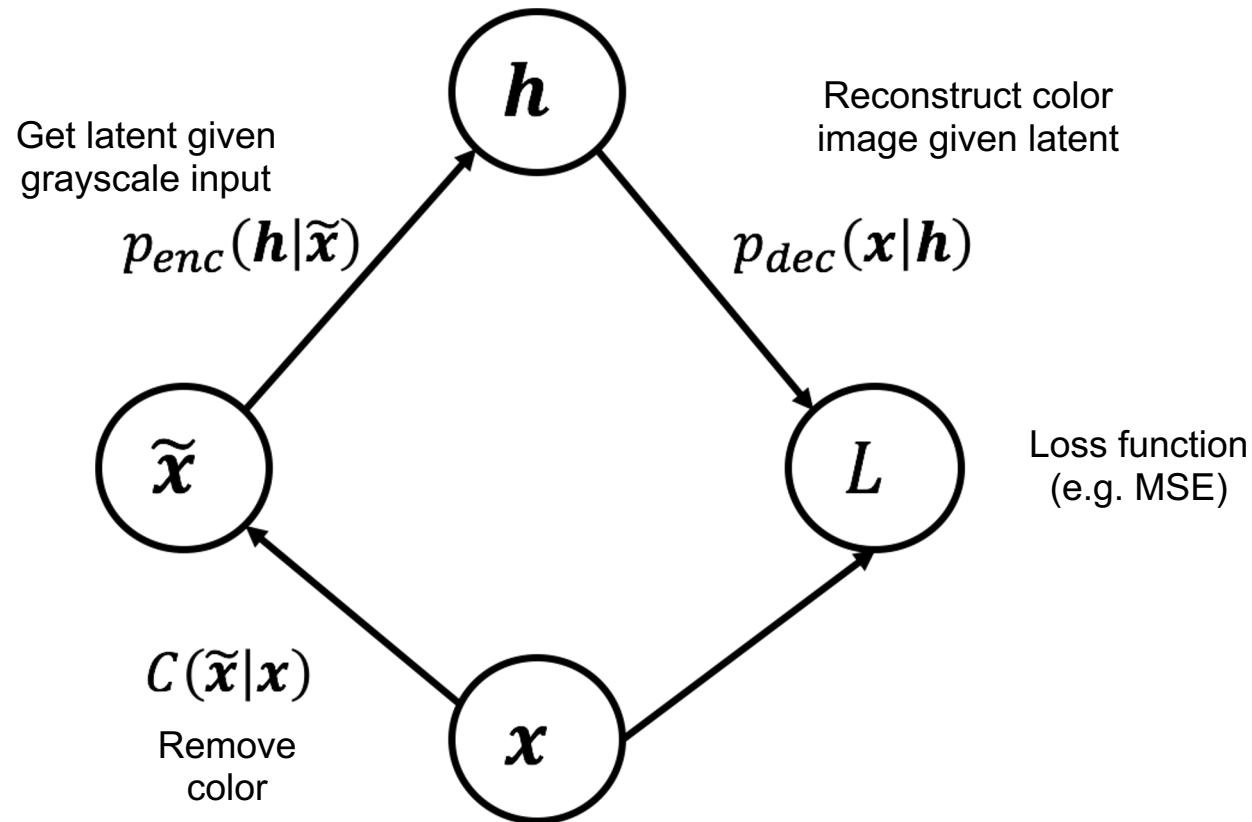
Original images: top rows, Corrupted Input: middle rows, Denoised Input: third rows



# Colorization

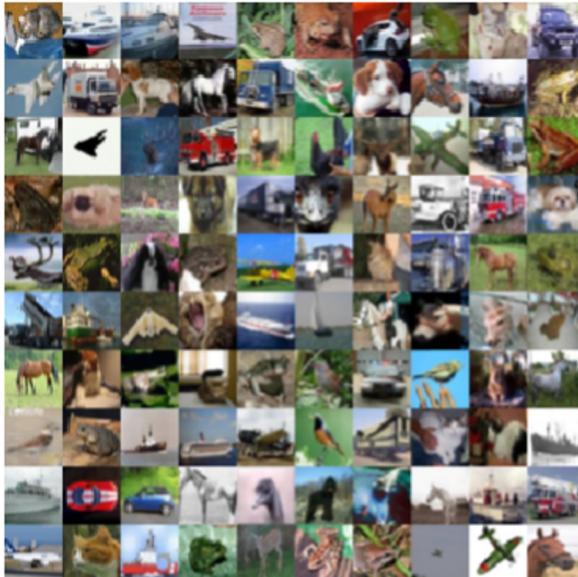


# Colorization AutoEncoder



# Colorization AutoEncoder on CIFAR10

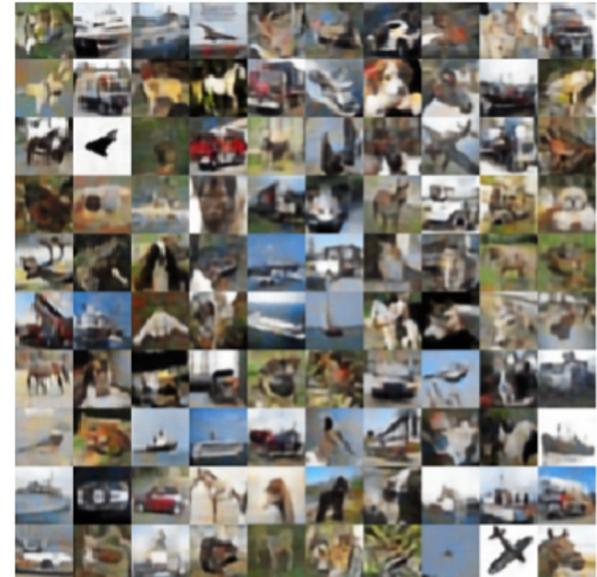
Test color images (Ground Truth)



Test gray images (Input)



Colorized test images (Predicted)



Code demo is next