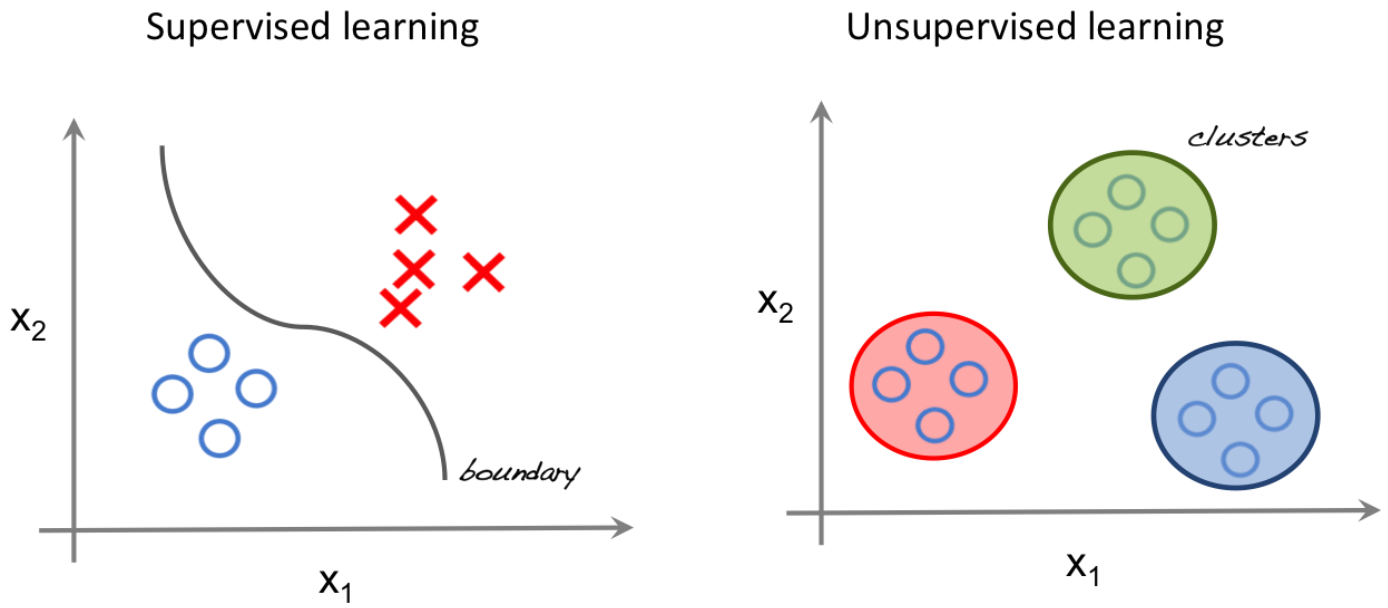
Unsupervised Deep Learning

Session Coverage

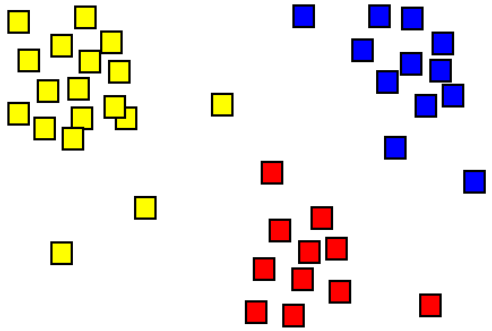
- Unsupervised Learning
- Sparse Coding
- Restricted Boltzmann Machines
- Deep Belief Network
- Autoencoder
- Variants of Autoencoders
- Deep Autoencoder
- Discriminative vs Generative Learning
- Variational Autoencoder
- Generative Adversarial Networks

Unsupervised Learning

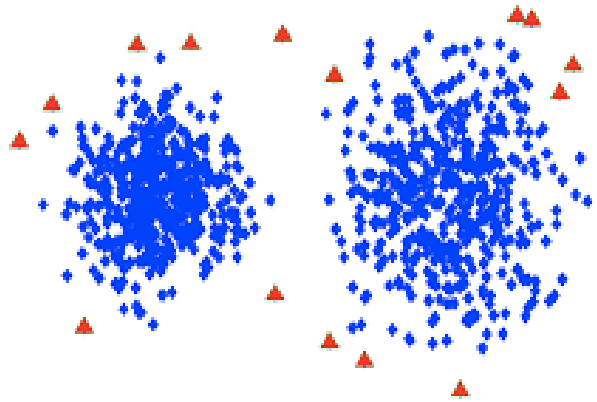
- Used when there is input data (X) and **no** corresponding output label (Y)
- Objective is to explore the data and find some pattern within
- Very useful when there is lot of data but few labels
- Example tasks such as association rule, clustering, compression, dimensionality reduction, data generation



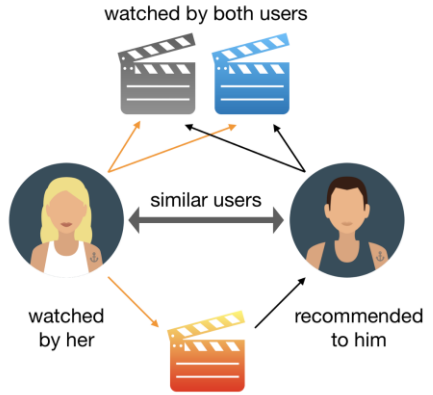
Applications of Unsupervised Learning



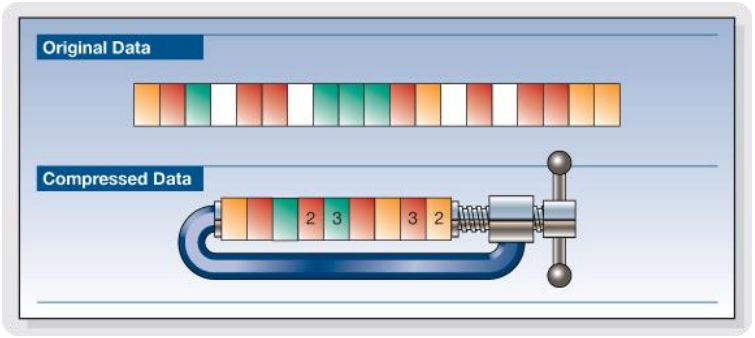
Clustering



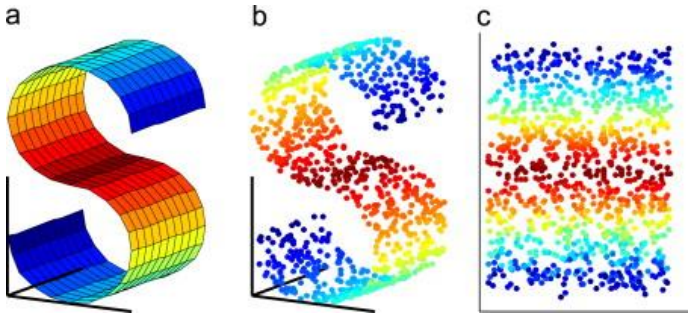
Anomaly Detection



Recommender System



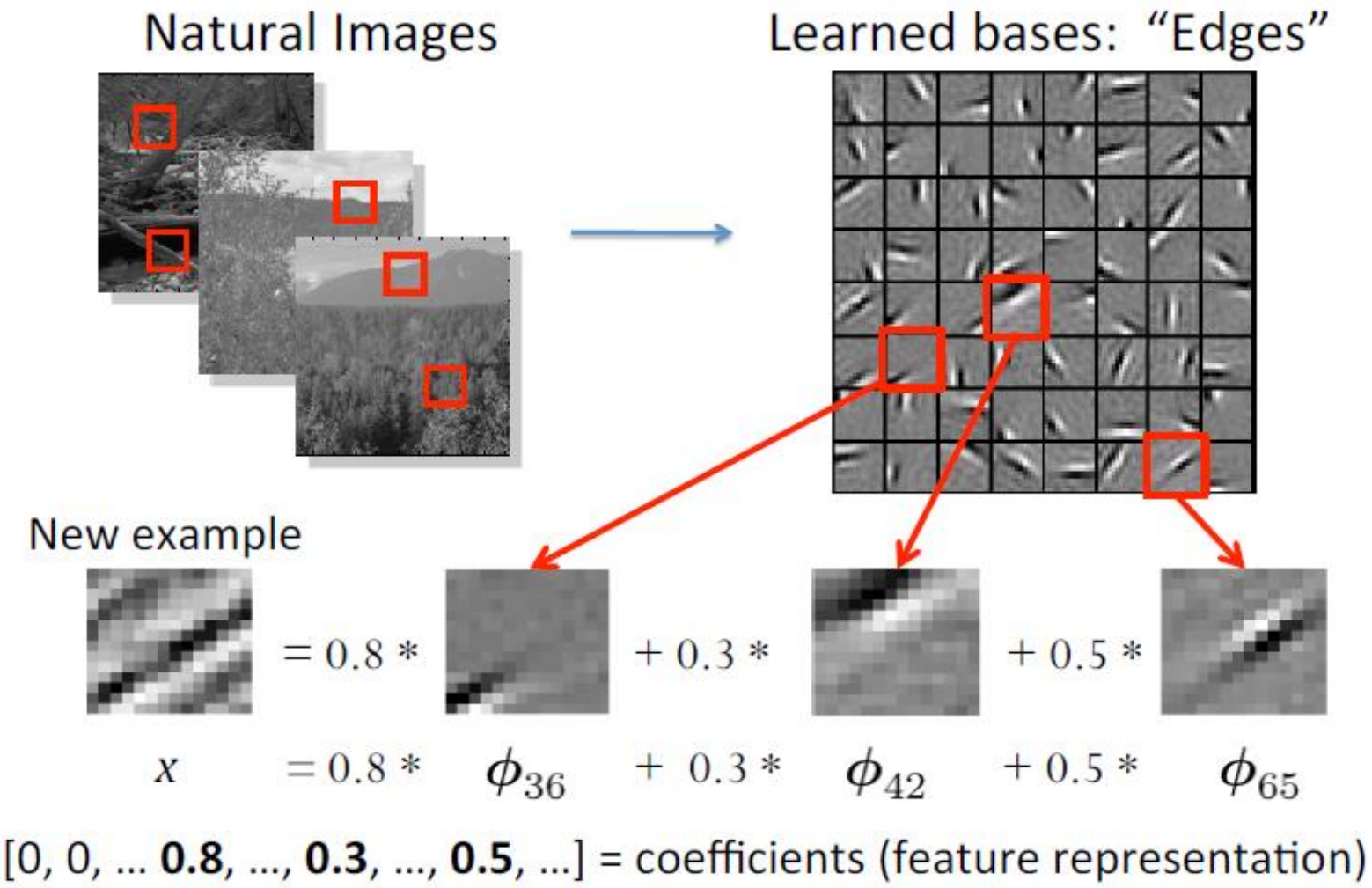
Data Compression



Dimensionality Reduction

Data Generation

Sparse Coding



Sparse Coding

- Sparse coding (Olshausen & Field, 1996). Originally developed to explain early visual processing in the brain (edge detection).

- Objective: Given a set of input data vectors $\{\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_N\}$, learn a dictionary of bases $\{\boldsymbol{\phi}_1, \boldsymbol{\phi}_2, ..., \boldsymbol{\phi}_K\}$, such that:

$$\mathbf{x}_n = \sum_{k=1}^{K} a_{nk} \boldsymbol{\phi}_k,$$

Sparse: mostly zeros

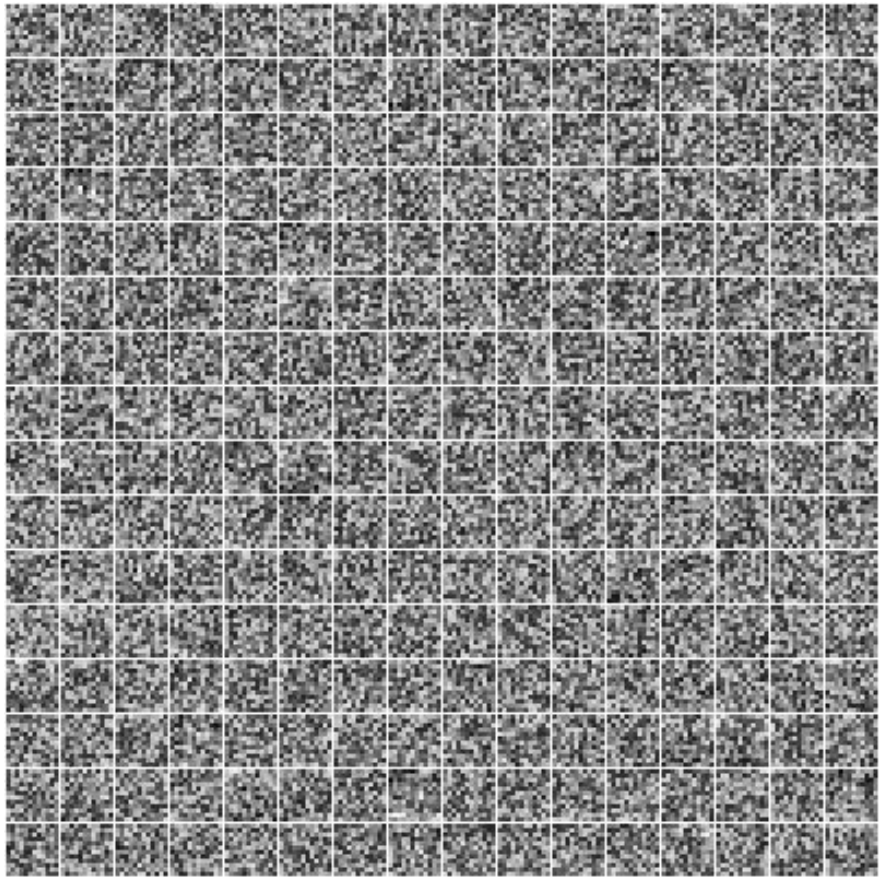
- Each data vector is represented as a sparse linear combination of bases.

Sparse Coding Training

- Input image patches: $\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_N \in \mathbb{R}^D$
- Learn dictionary of bases: $\boldsymbol{\phi}_1, \boldsymbol{\phi}_2, ..., \boldsymbol{\phi}_K \in \mathbb{R}^D$

$$\min_{\mathbf{a},\boldsymbol{\phi}} \sum_{n=1}^{N} \left\| \mathbf{x}_n - \sum_{k=1}^{K} a_{nk}\boldsymbol{\phi}_k \right\|_2^2 + \lambda \sum_{n=1}^{N}\sum_{k=1}^{K} |a_{nk}|$$

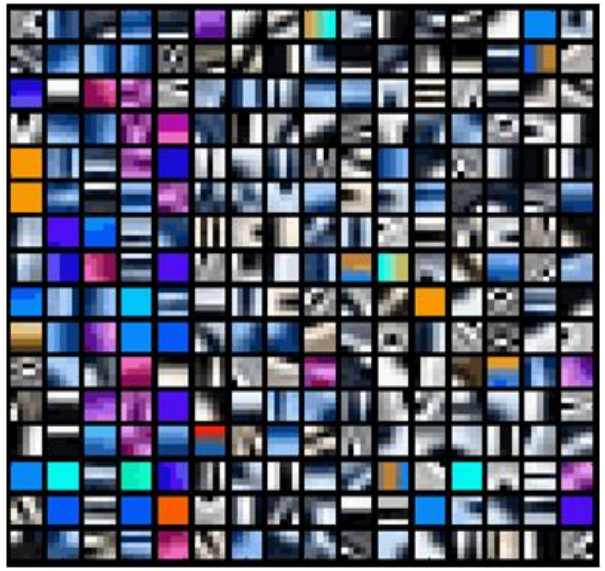
Reconstruction error Sparsity penalty



- Alternating Optimization:
  1. Fix dictionary of bases $\boldsymbol{\phi}_1, \boldsymbol{\phi}_2, ..., \boldsymbol{\phi}_K$ and solve for activations **a** (a standard Lasso problem).
  2. Fix activations **a**, optimize the dictionary of bases (convex QP problem).

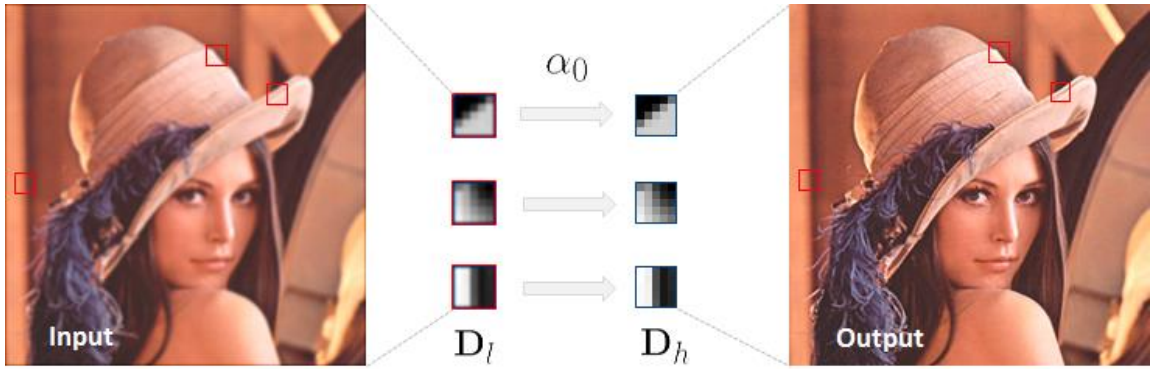
SC for Image Quality Enhancement

- **Input:** Corrupted image patch
- **Output:** HQ Reconstructed image patch



Dictionary Learned

Inpainting

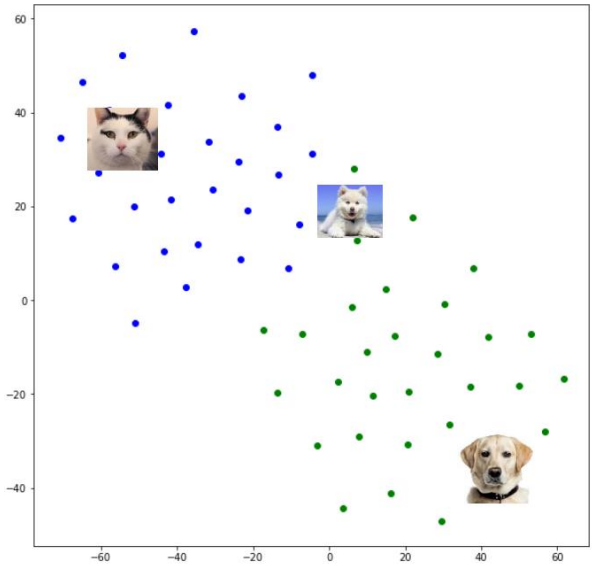


Super-Resolution

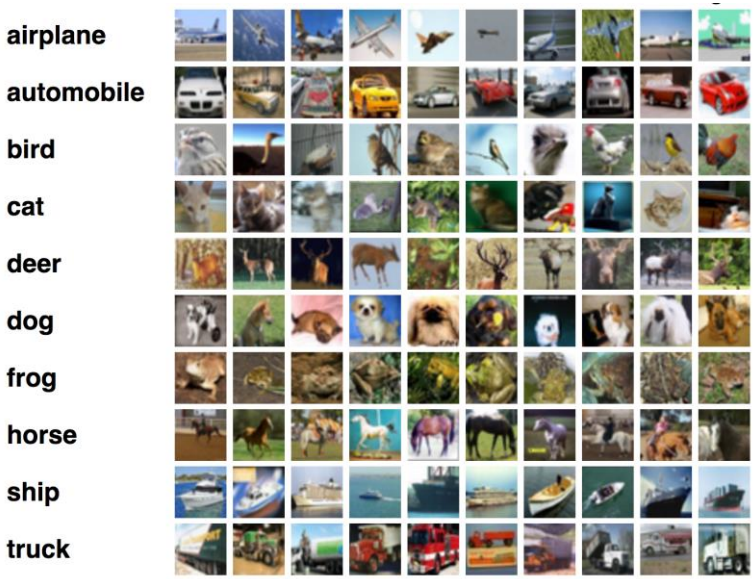
Deblurring

SC as Feature Descriptor

- Images can be represented in terms of **sparse coefficients**
- Any DL/ML model can be trained based on those sparse features as features



Clustering



Object Recognition

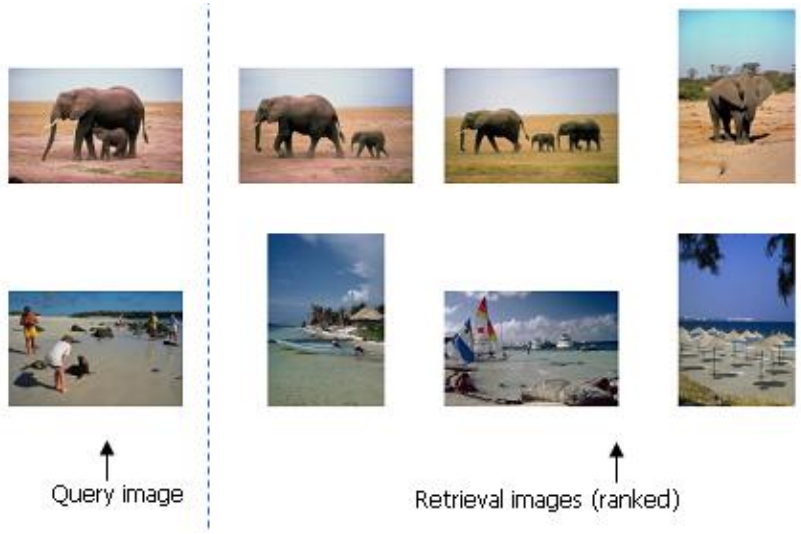
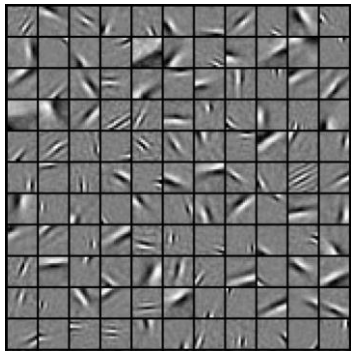


Image Retrieval

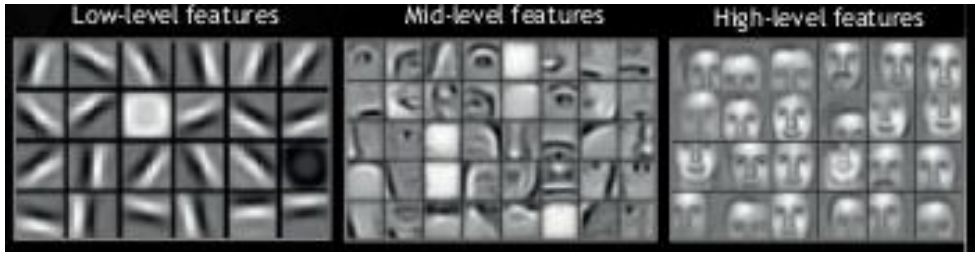
Analysis of Sparse Coding

- **Pros**
- Faster and works well for small image patches
- Similar as how visual cortex works i.e. biologically plausible

- **Cons**
- Does not scale well for bigger patches/images
- Sparse codes are only single level of image representation, not hierarchical as neural networks



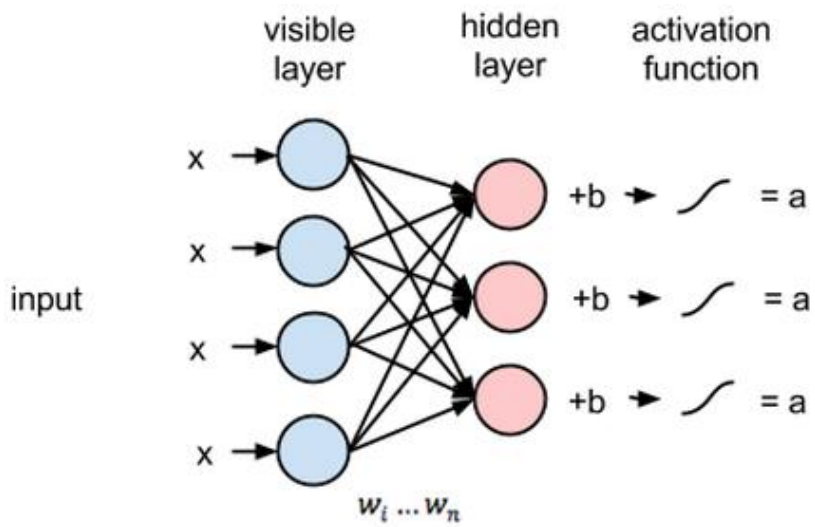
vs



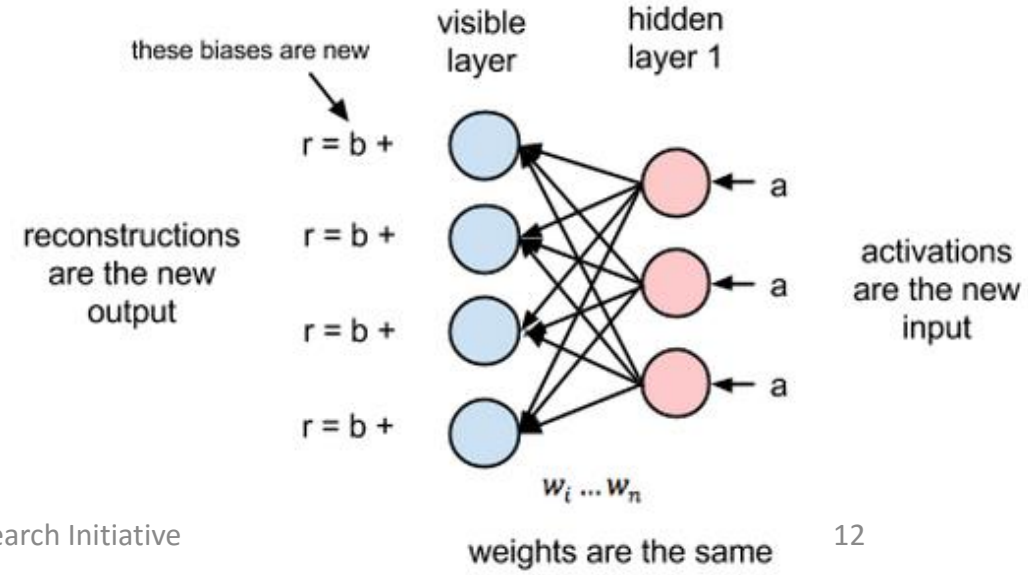
Restricted Boltzmann Machine

- **RBM** is a symmetrical, bipartite and bidirectional graph
- **Bipartite**: No connection b/w nodes of same layer
- **Symmetrical**: It uses shared weights for both activation and reconstruction
- **Bidirectional**: Connection is common for both activation and reconstruction
- RBM gets an input, generate some activation based weights. Then the activation is given as input from the hidden layer to reconstruct the input again using same weights.

Stage 1: Activation

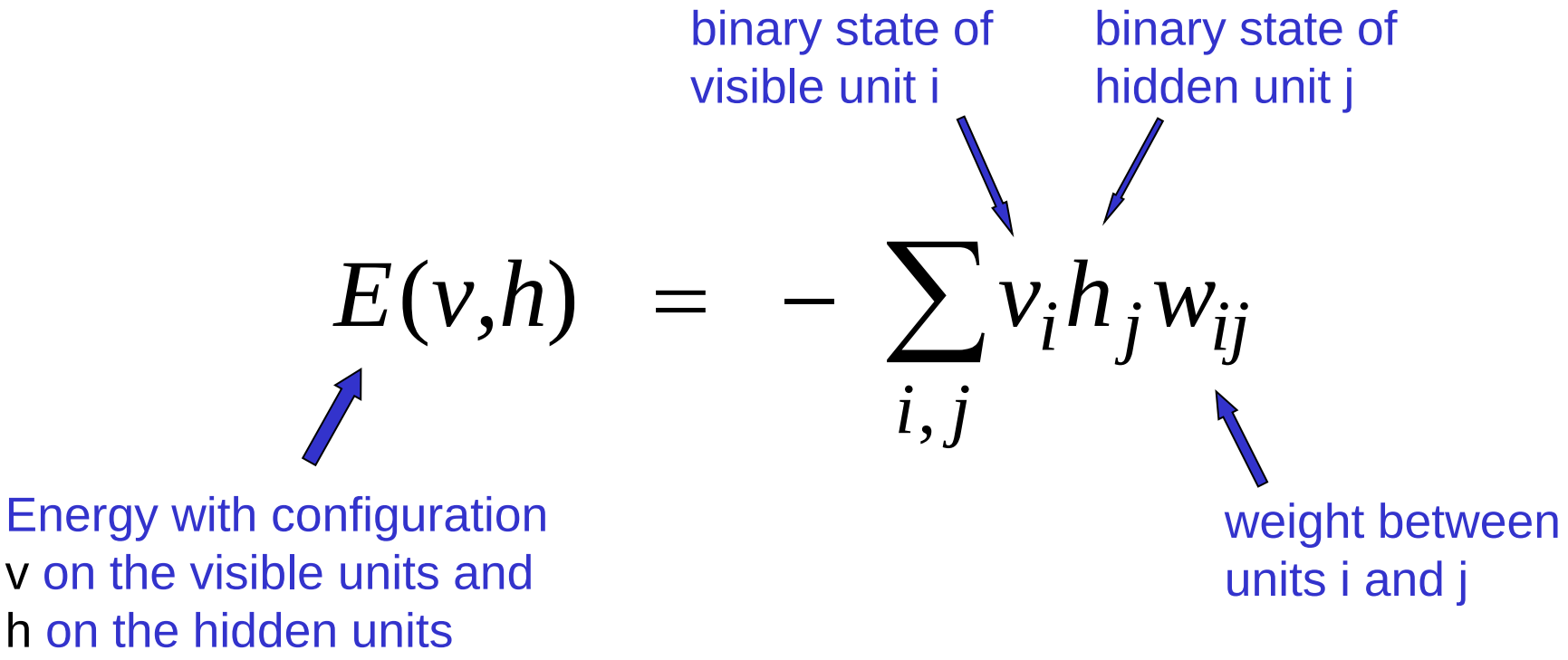


Stage 2: Reconstruction



The Energy of a joint configuration

(ignoring terms to do with biases)



$$-\frac{\partial E(v,h)}{\partial w_{ij}} = v_i h_j$$

Weights → Energies → Probabilities

- Each possible joint configuration of the visible and hidden units has an energy
  - The energy is determined by the weights and biases (as in a Hopfield net).
- The energy of a joint configuration of the visible and hidden units determines its probability:

$$p(v,h) \propto e^{-E(v,h)}$$

- The probability of a configuration over the visible units is found by summing the probabilities of all the joint configurations that contain it.

Using energies to define probabilities

- The probability of a joint configuration over both visible and hidden units depends on the energy of that joint configuration compared with the energy of all other joint configurations.

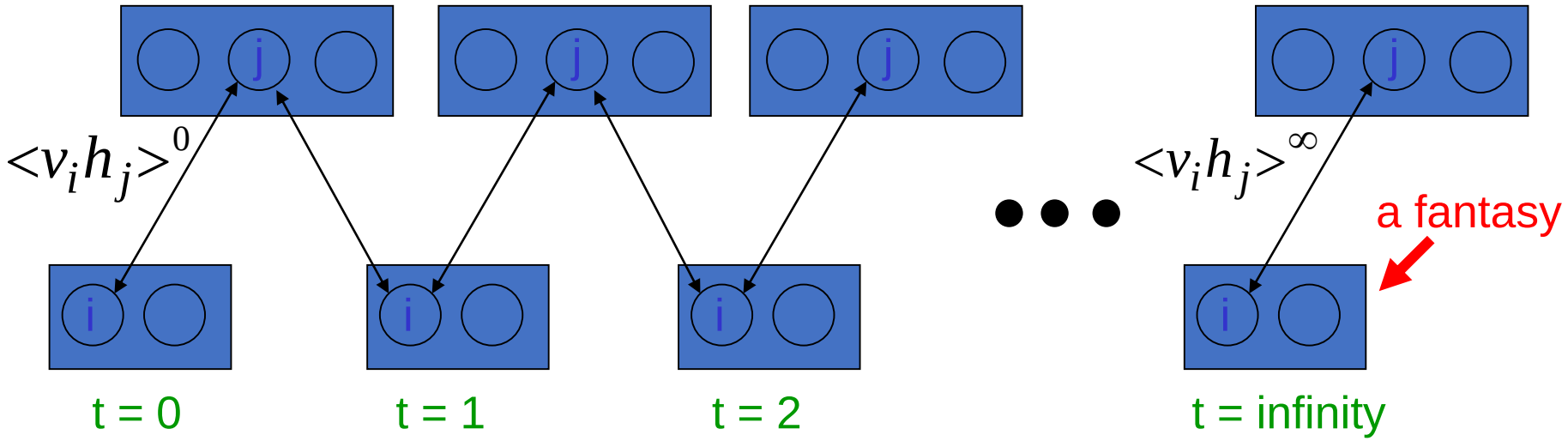
$$p(v,h) = \frac{e^{-E(v,h)}}{\sum_{u,g} e^{-E(u,g)}}$$

partition function

- The probability of a configuration of the visible units is the sum of the probabilities of all the joint configurations that contain it.

$$p(v) = \frac{\sum_{h} e^{-E(v,h)}}{\sum_{u,g} e^{-E(u,g)}}$$

A picture of the maximum likelihood learning algorithm for an RBM



Start with a training vector on the visible units.

Then alternate between updating all the hidden units in parallel and updating all the visible units in parallel.

$$\frac{\partial \log p(v)}{\partial w_{ij}} = <v_i h_j>^0 - <v_i h_j>^\infty$$

RBM Training

- Energy function of RBM

$$E(\mathbf{v}, \mathbf{h}) = -\sum_i a_i v_i - \sum_j b_j h_j - \sum_{i,j} v_i h_j w_{ij}$$

- Joint Distribution for **v** and **h**

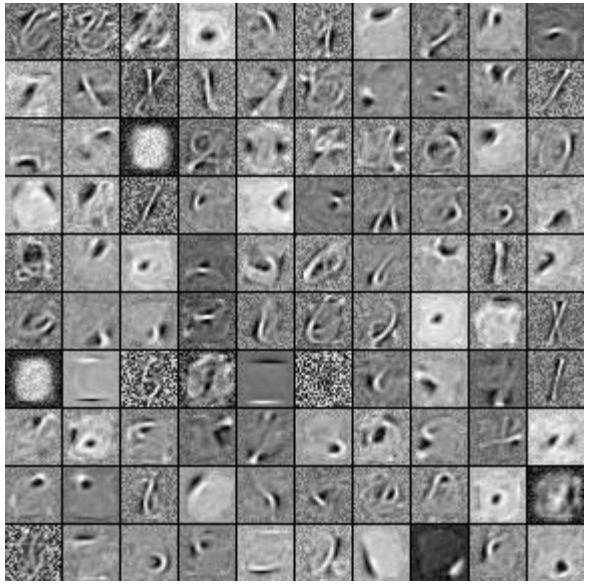
$$p(\mathbf{v}, \mathbf{h}) = \frac{1}{Z} e^{-E(\mathbf{v}, \mathbf{h})}$$

$$Z = \sum_{\mathbf{v}, \mathbf{h}} e^{-E(\mathbf{v}, \mathbf{h})}$$

- Conditional probabilities for h and v

$$p(h_j = 1 | \mathbf{v}) = \frac{1}{1 + e^{(-(b_j + W_j v_i))}} = \sigma(b_j + \sum_i v_i w_{ij})$$

$$p(v_i = 1 | \mathbf{h}) = \frac{1}{1 + e^{(-(a_i + W_i h_j))}} = \sigma(a_i + \sum_j h_j w_{ij})$$



Learned RBM filters for MNIST

Samples from RBM

Example: Movie Recommendations

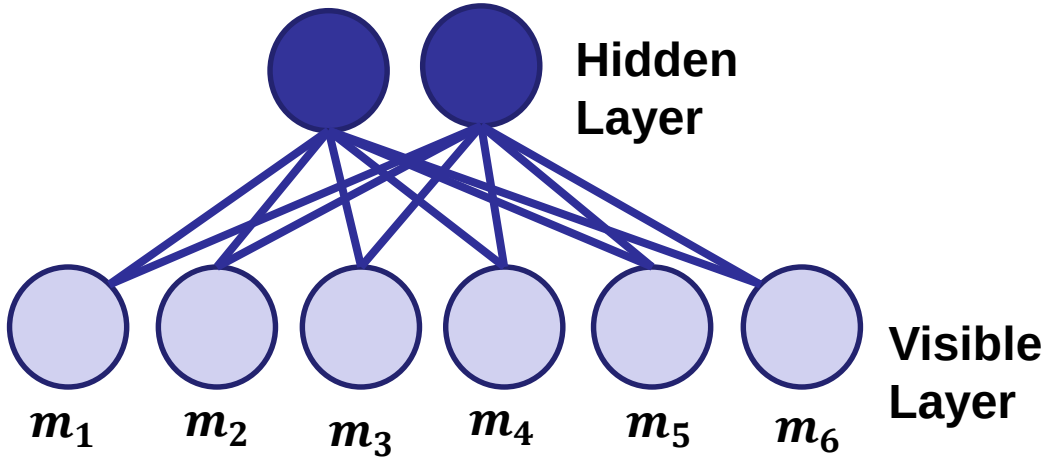
- In this example, a simple RBM will be constructed and utilized for movie recommendations
- In 2007, Hinton proposed the utilization of RBMs in order to produce more accurate movie recommendations with Netflix data
- Essentially, the input data is comprised of the movies that users liked. The output is a set of weights that activate (or not) the hidden units that, in this case will represent movie genre.
- As it was shown in the RBM training section, the input will be passed to the hidden layer, where the activation energy is calculated and the weights and biases are updated
- The input is then attempted to be reconstructed in a similar manner and the hidden units are updated accordingly
- In this example the visible units will represent a movie and the input will be 1 if the user liked it, and 0 if the user did not like it
- For a new user, the activation (or not activation) of the hidden units, indicates whether or not the use should be recommended to a set of movies
- Note that this is a simple example to illustrate one application of RBMs

Example: Movie Recommendations

- The RBM used in this examples is constructed to have 6 visible units and 2 hidden units

m_1: *Harry Potter*
m_2: *Avatar*
m_3: *Lord of the Rings 3*

m_4: *Gladiator*
m_5: *Titanic*
m_6: *Glitter*



Input for Training

User#: $[m_1\ m_2\ m_3\ m_4\ m_5\ m_6]$

User1: [1 1 1 0 0 0]
User2: [1 0 1 0 0 0]
User3: [1 1 1 0 0 0]
User4: [0 0 1 1 1 0]
User5: [0 0 1 1 0 1]
User6: [0 0 1 1 1 0]

1: User liked the movie
0: User did not like the movie

In this case, the hidden units will learn two latent variables underlying the movie preferences.

For example: It could learn to identify the Sci-Fi/Fantasy movies from the Oscar winning movies

Example: Movie Recommendations

- Running the code for the specified RBM and the provided examples produces the following weights:

	Bias	Hidden 1	Hidden 2
Bias	0.456435	1.996482	-0.167825
Harry Potter	-0.060682	4.423909	-7.798776
Avatar	-1.355282	1.975963	-5.380187
LOTR 3	4.019619	4.328605	2.528894
Gladiator	-0.602309	-3.658956	7.534837
Titanic	-0.008771	-6.998655	3.544674
Glitter	-4.027742	-3.010979	-2.887497

The probability of activation is the sigmoid of the activation energy, negative values will correspond to low probability of activation.

- It can be seen that the first hidden layer activates for Sci-Fi/Fantasy movies, while the second hidden layer corresponds to Oscar Winners.

When entering the information of a new user that likes Titanic and Gladiator, we get this result:

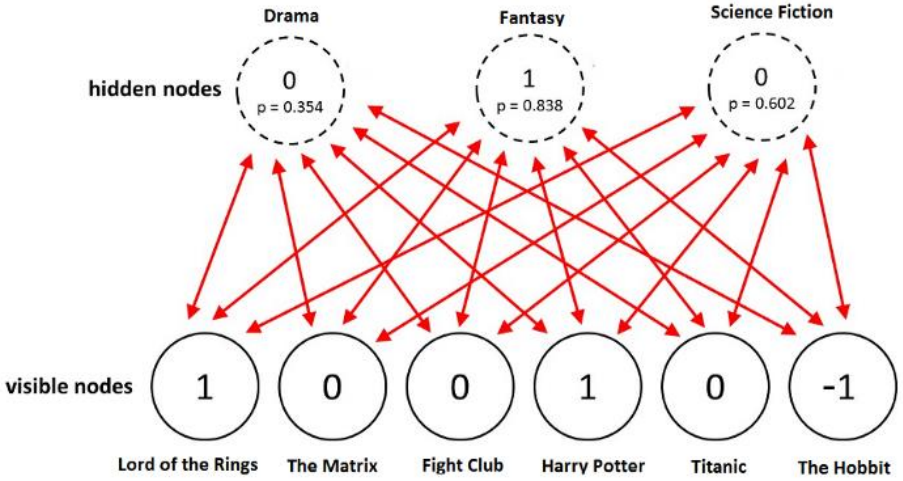
```
ACTIVATED UNIT
          Hidden1  Hidden2
weights       0.0      1.0
```

In this sense, the system is more likely to recommend Oscar Winning Movies to the new user.

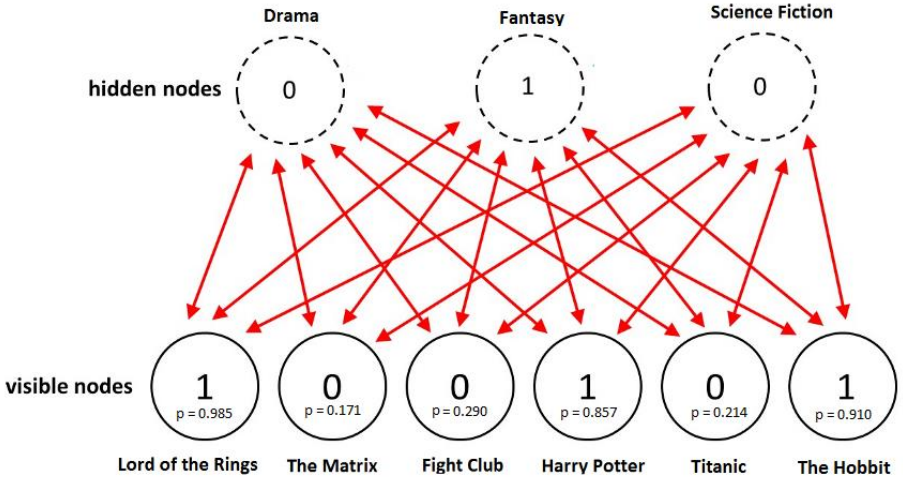
RBM for Collaborative Filtering

Steps in RBM

1. Train the network on the data of all users
2. During inference time take the training data of a specific user
3. Use this data to obtain the activations of hidden neurons
4. Use the hidden neuron values to get the activations of input neurons
5. The new values of input neurons show the rating the user would give yet unseen movies



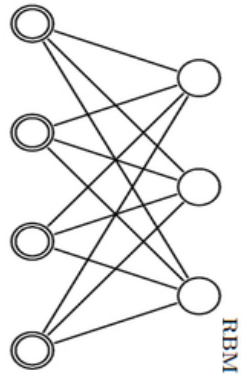
New user input to find latent factor



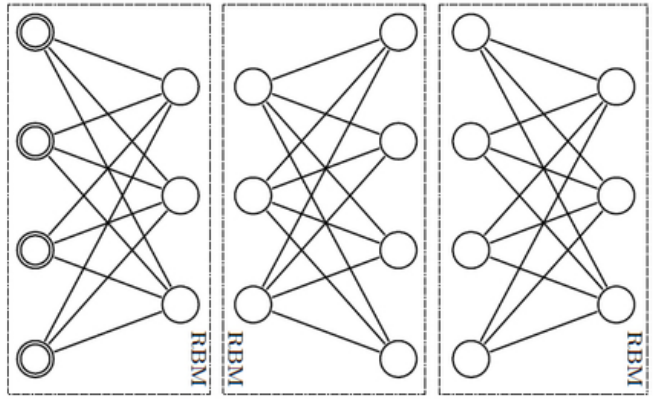
Reconstruction to predict rating

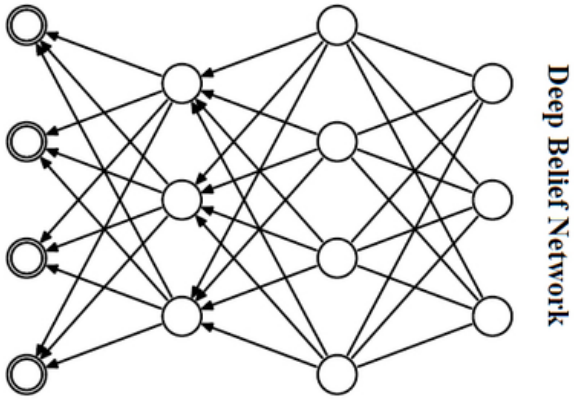
Deep-Belief Network

- Deep-Belief network can be defined as a stack of restricted Boltzmann machines
- Each RBM layer communicates with both the previous and subsequent layers
- Stack of RBMs might end with a a Softmax layer to create a classifier, or it may simply help cluster unlabeled data in an unsupervised learning scenario
- Often used for **unsupervised pretraining**
- **Applications:** Deep-belief networks are used to recognize, cluster and generate images, video sequences and motion-capture data
- **Note**: Rarely used these days… **but why?**



RBM





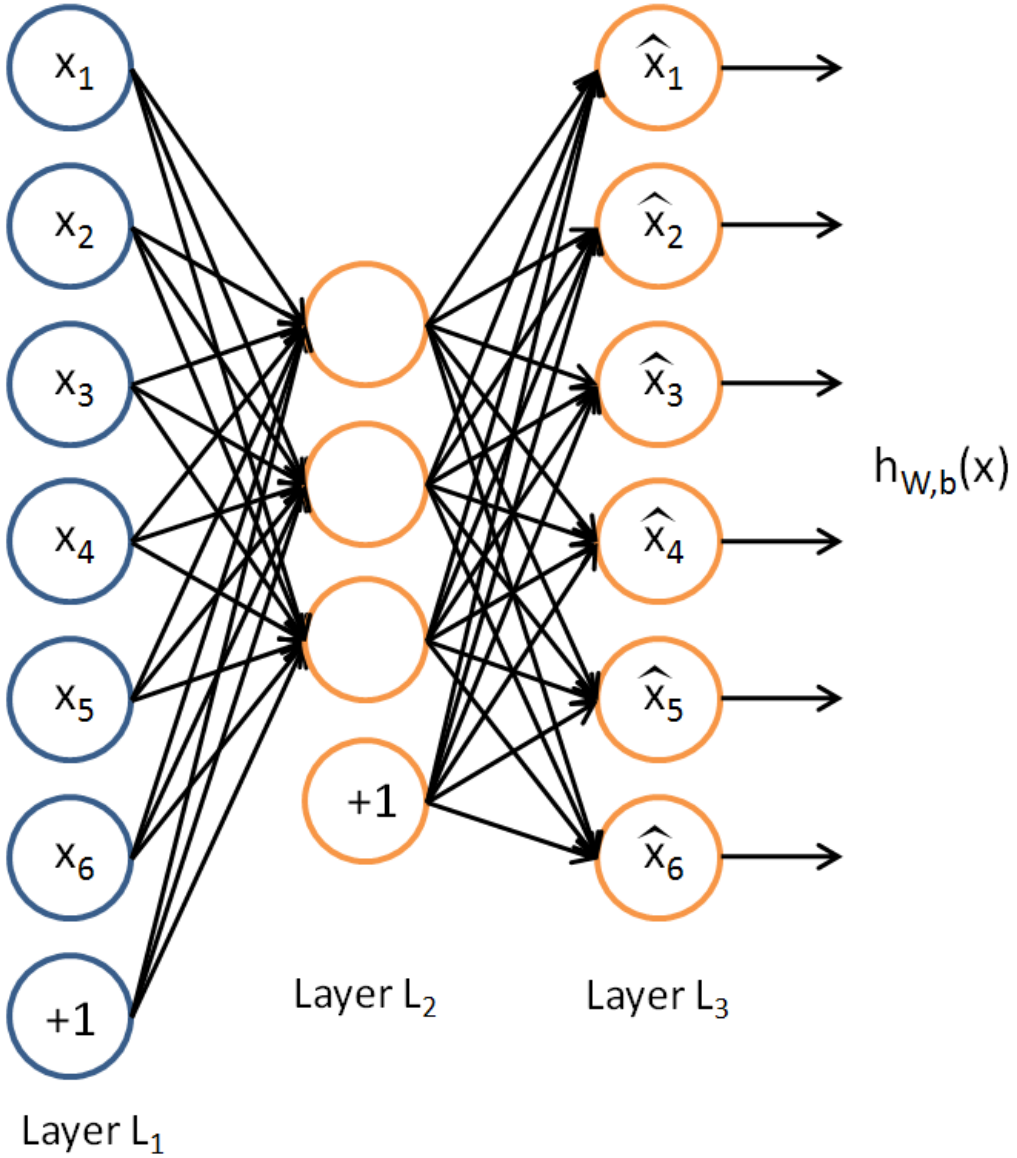
Deep Belief Network

Autoencoder

An Autoencoder is a feedforward neural network that learns to predict the input itself in the output.

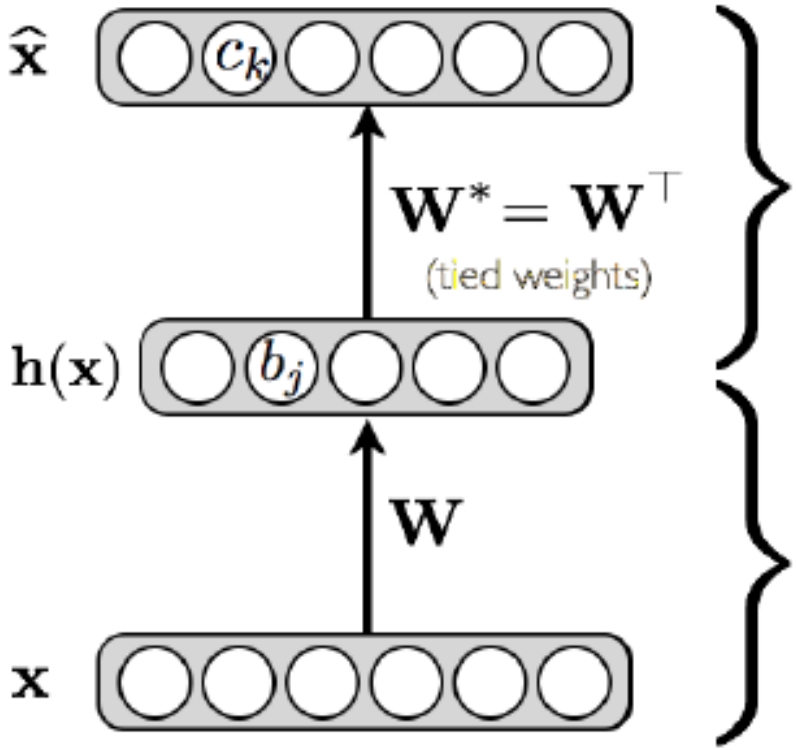
$$y^{(i)} = x^{(i)}$$

- The input-to-hidden part corresponds to an **encoder**
- The hidden-to-output part corresponds to a **decoder**
- Different from RBM which is not a feedforward network but a probabilistic model
- Many cool applications are based on encoder-decoder frameworks



Autoencoder

- Feed-forward neural network trained to reproduce its input at the output layer



Decoder

$$\begin{aligned}\hat{\mathbf{x}} &= o(\hat{\mathbf{a}}(\mathbf{x})) \\ &= \underbrace{\mathrm{sigm}(\mathbf{c} + \mathbf{W}^*\mathbf{h}(\mathbf{x}))}_{\text{For binary units}}\end{aligned}$$

Encoder

$$\begin{aligned}\mathbf{h}(\mathbf{x}) &= g(\mathbf{a}(\mathbf{x})) \\ &= \mathrm{sigm}(\mathbf{b} + \mathbf{W}\mathbf{x})\end{aligned}$$

Loss Function

- Loss function for binary inputs

$$l(f(\mathbf{x})) = -\sum_k \left(x_k \log(\widehat{x}_k) + (1 - x_k) \log(1 - \widehat{x}_k)\right)$$

  - Cross-entropy error function (reconstruction loss) $f(\mathbf{x}) \equiv \widehat{\mathbf{x}}$

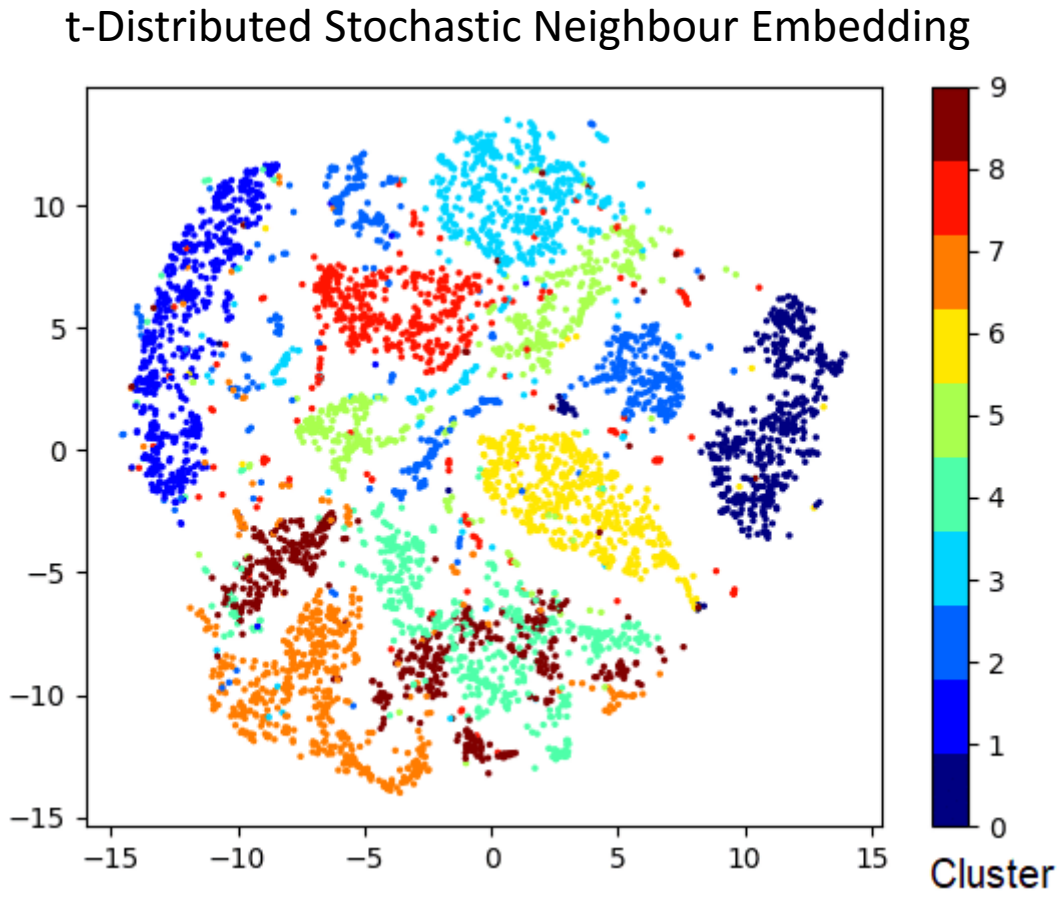
- Loss function for real-valued inputs

$$l(f(\mathbf{x})) = \frac{1}{2} \sum_k (\widehat{x}_k - x_k)^2$$

  - sum of squared differences (reconstruction loss)
  - we use a linear activation function at the output

AE for Dimensionality Reduction

- **Visualizing high-dimensional data** is challenging.
- **t-SNE** is the most commonly used method but struggles with large number of dimensions (typically above 32).
- Autoencoders are used as a pre-processing step to reduce the dimensionality, and this compressed representation is used by t-SNE to visualize the data in 2D space.

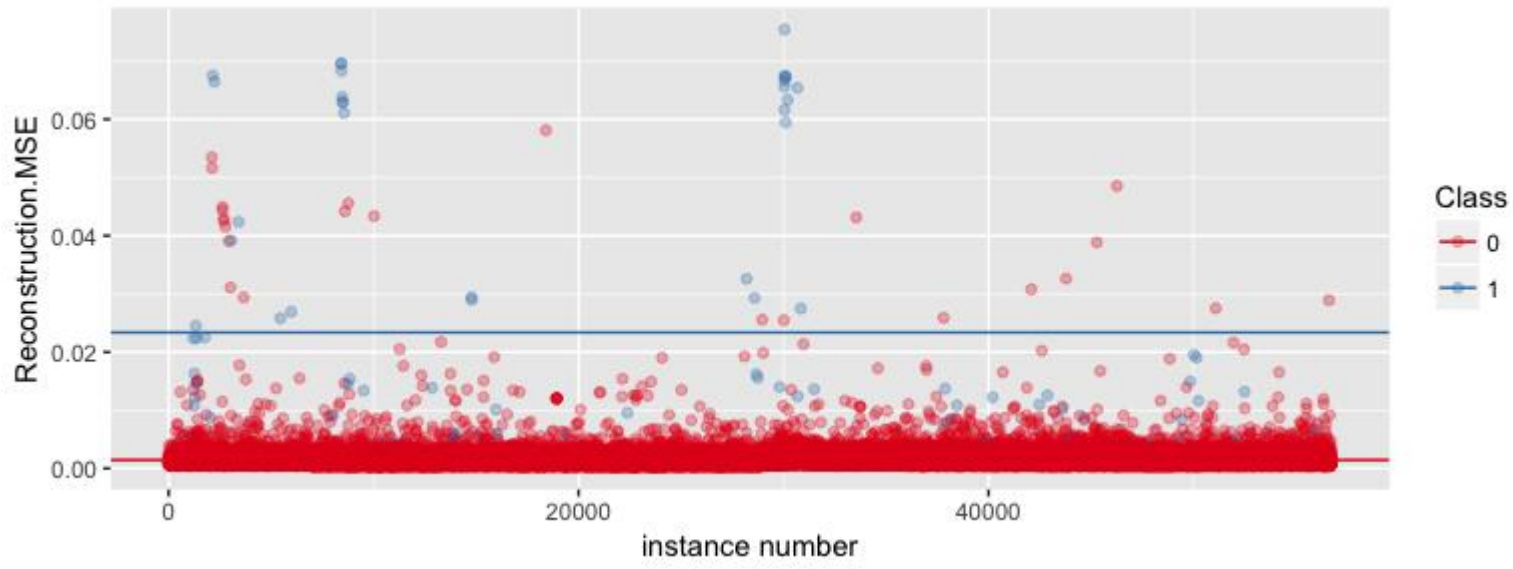


t-SNE visualizations for clustering on MNIST dataset

AE for Anomaly Detection

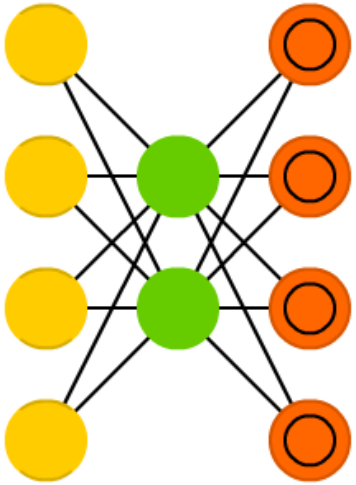
- AE can be used for anomaly detection such as Credit Card Frauds
- **Features:** such as time, amount, etc can be learned using an AE
- **Training**: AE will aim to minimize the reconstruction error of training data
- **Testing:** Transactions with **higher reconstruction er**ror will be labelled as Credit Card Frauds based on some threshold

Note: there is no perfect classification into fraud and non-fraud cases but the mean MSE is definitely higher for fraudulent transactions than for regular ones



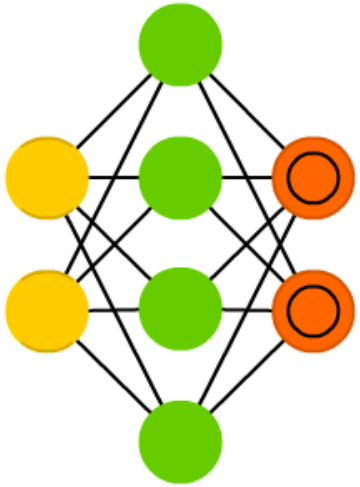
Reconstruction error rate is high for anomalous transactions

Autoencoder: Undercomplete vs Overcomplete



Undercomplete Autoencoder

- Used for compressing data into low dimension
- Objective is to minimize the reconstruction error

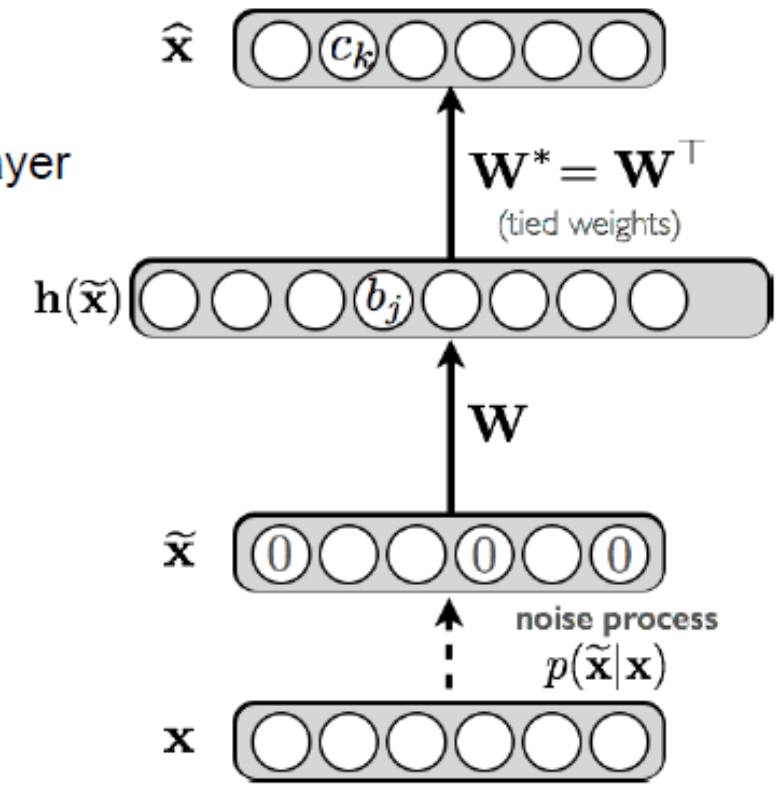


Overcomplete Autoencoder

- Used for representing data with more features via high dimension (useful for supervised learning tasks)
- Caution: Sometimes memorizes data since reconstruction error is low… **Solution: Add noise**

Denoising Autoencoder

- Idea: representation should be robust to introduction of noise:
  - random assignment of subset of inputs to 0, with probability ν
  - Similar to dropouts on the input layer
  - Gaussian additive noise

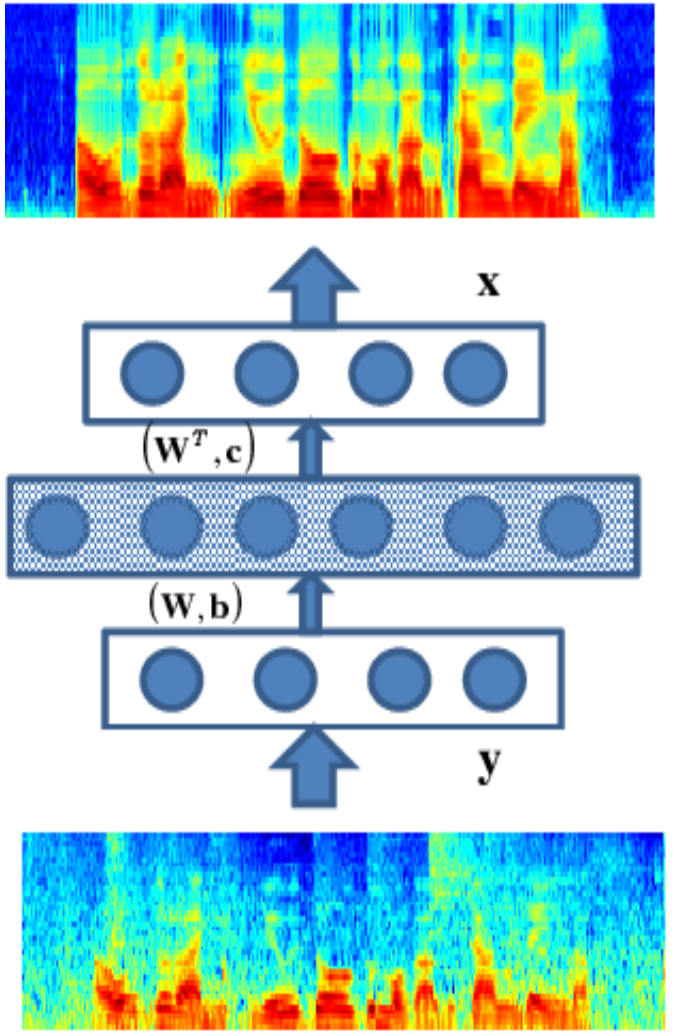


- Reconstruction $\hat{\mathbf{X}}$ computed from the corrupted input $\tilde{\mathbf{X}}$

- Loss function compares $\hat{\mathbf{X}}$ reconstruction with the noiseless input $\mathbf{X}$

DAE for Speech Enhancement

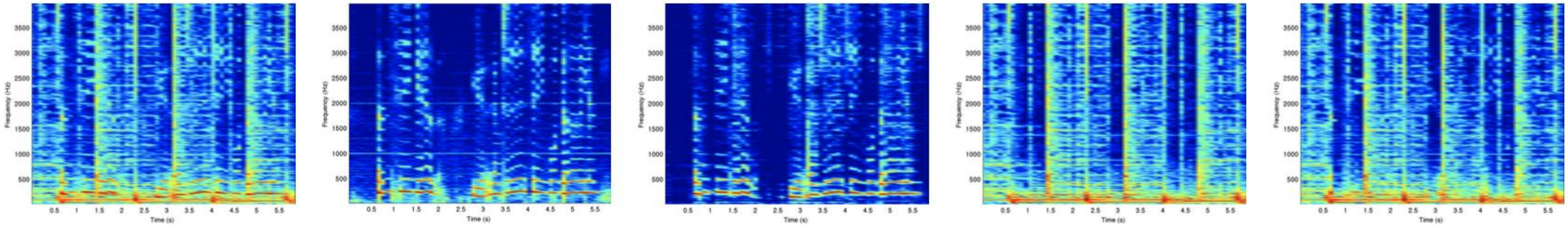
- **Features:** Raw audio or frequency features such as STFT, MFCC, etc.
- **Training:** DAE will get noisy audio as input and aim to construct noiseless audio as output
- **Testing:** Noisy audio input will be processed where DAE will loose the noises in the latent representation and clean audio will come as output in decoder.
- **Data:** Noisy and noiseless versions of same audio
- What if you have only noiseless audio?
  - Solution: Add some noise through augmentation and generate
- What if you have only noisy audio?
  - Solution: Manual/semi automated cleaning of audio



DAE based Speech Enhancer

DAE for Music Voice Separation

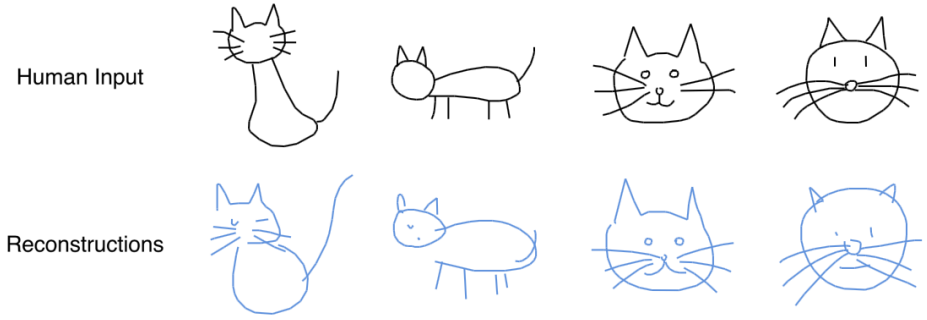
- Music can be model as noise where voice can be modelled as target
- Or voice can be modelled as noise where music can be predicted as target
- Recent Example: MaD TwinNet for music voice separation



(a) Mixutre (b) Clean vocal (c) Recovered vocal (d) Clean music (e) Recovered music

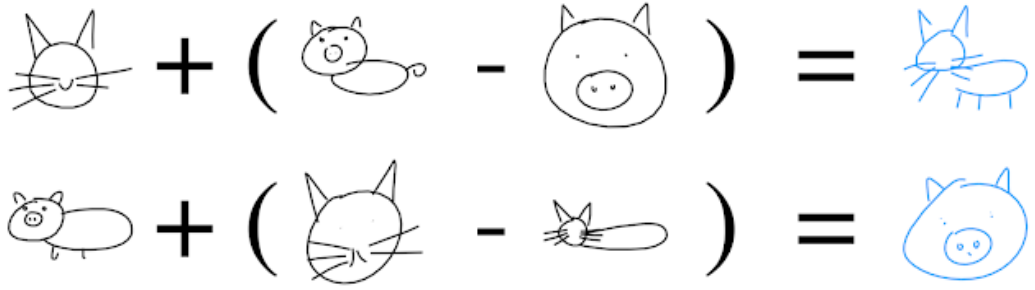
Output of DAE that separates voice from music

Sequence-to-sequence (seq2seq) Autoencoder



Training of seq2seq model

Latent Space Interpolations

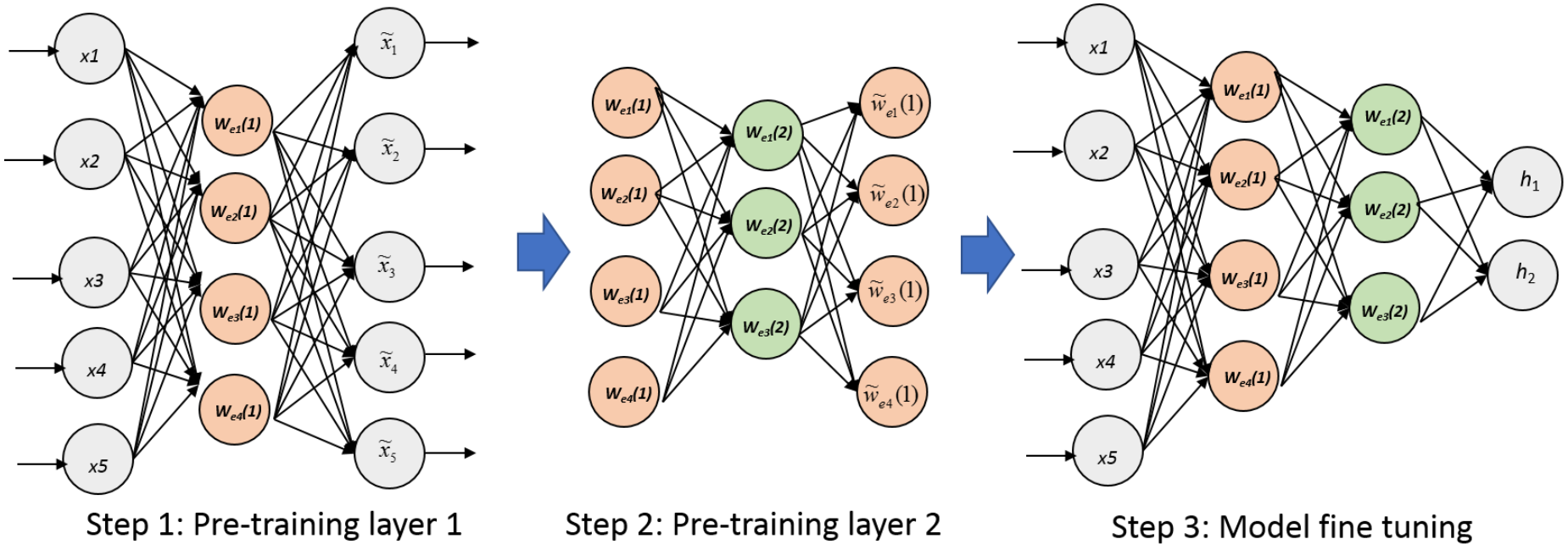


Latent Space Arithmetic

Magenta Project https://magenta.tensorflow.org/

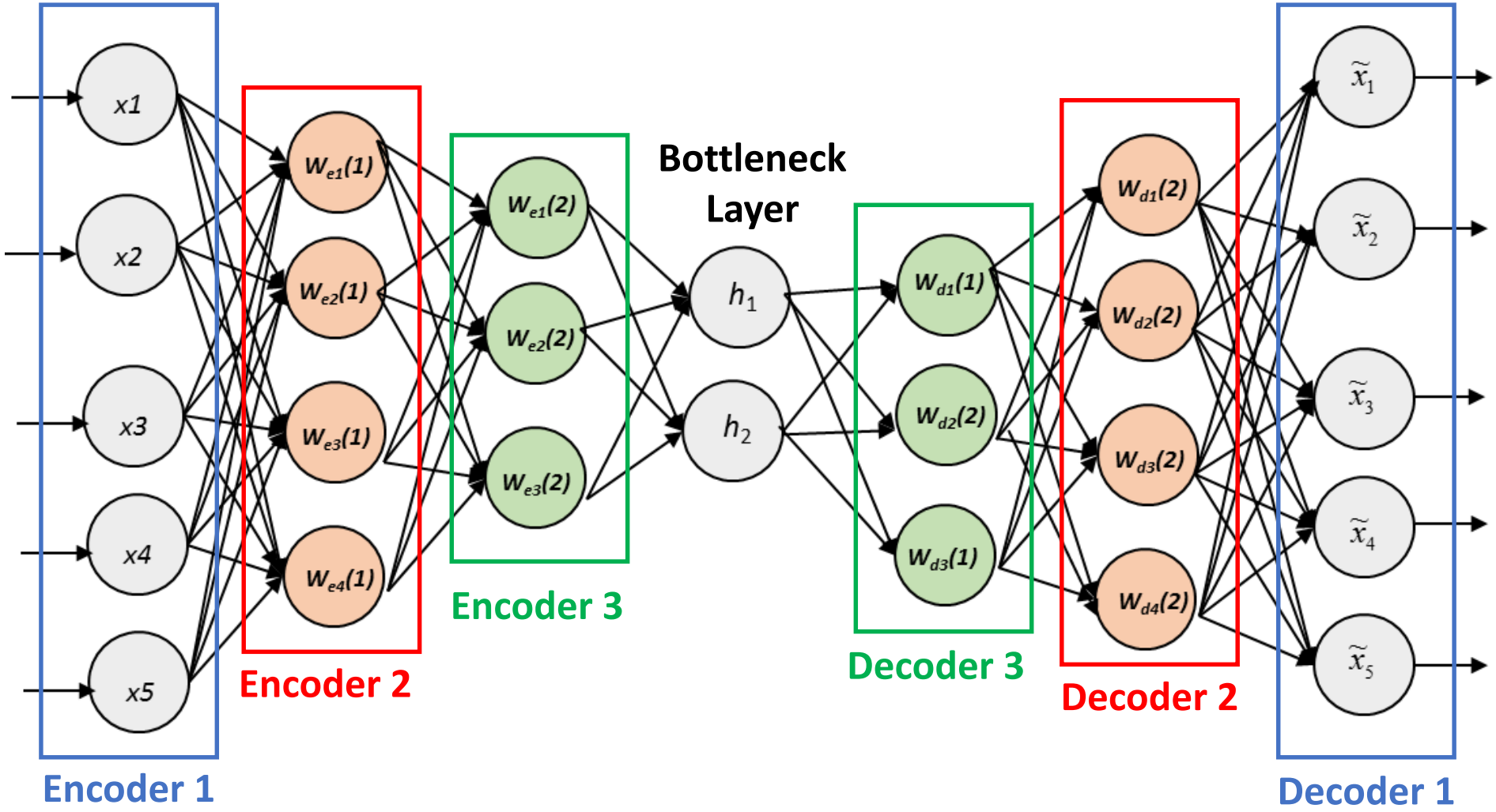
Stacked Autoencoders

- Autoencoders can be trained layer-wise and further concatenated to create stack of autoencoders
- Each hidden layer will be treated as input layer to further compress it



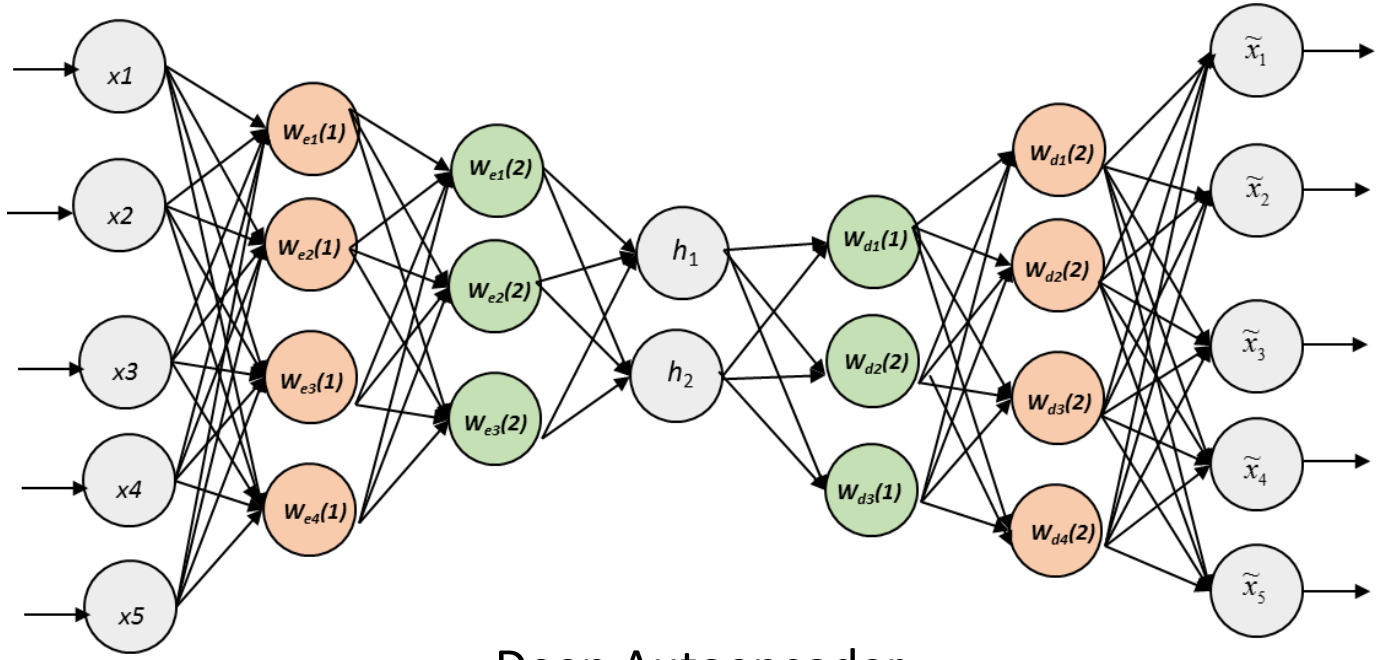
Step 1: Pre-training layer 1 Step 2: Pre-training layer 2 Step 3: Model fine tuning

Stacked Autoencoders



Deep Autoencoder

- Deep Neural Network with multilayer encoder and decoder can be trained
- Any number of layers and their nodes can be chosen but usually symmetry is preferred
- Output activation depends upon input values X



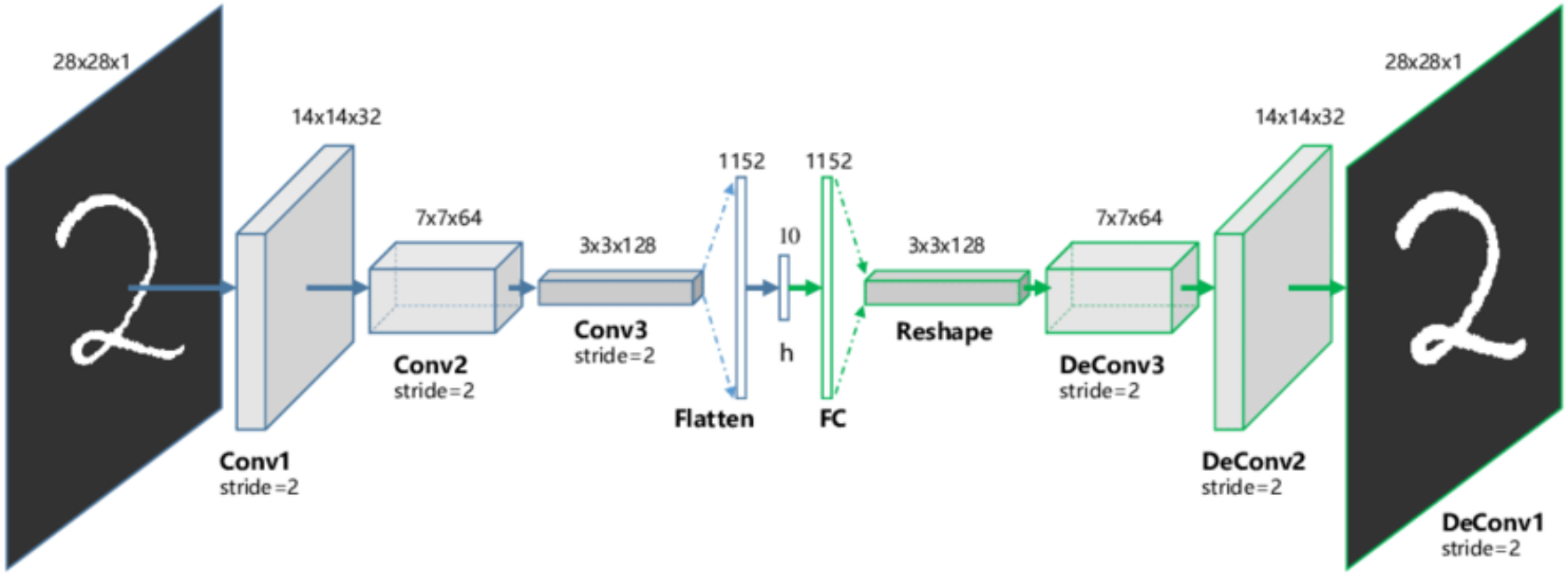
Deep Autoencoder

Stacked vs Deep Autoencoder

- Stacked autoencoders
  - We can continuously monitor how each layer is learning
  - Error during training of each layer is added further and become overall error of model
- Deep autoencoders
  - Training is easy where error reaches minimum as there is no intervention from us
- Stacked autoencoders are preferred less as layer-wise pretraining is hectic.
- End-to-end training of deep autoencoder is preferred in most cases
- **Naming convention:** people often prefer the term **autoencoder** to mean any autoencoder in general, irrespective of whether they are denoising, stacked, deep, convolutional, recurrent etc.

Convolutional Autoencoder

- ConvAE comprises encoder with convolution pooling and decoder with deconvolution and up sampling.
- Referred as Hourglass Model ⌛



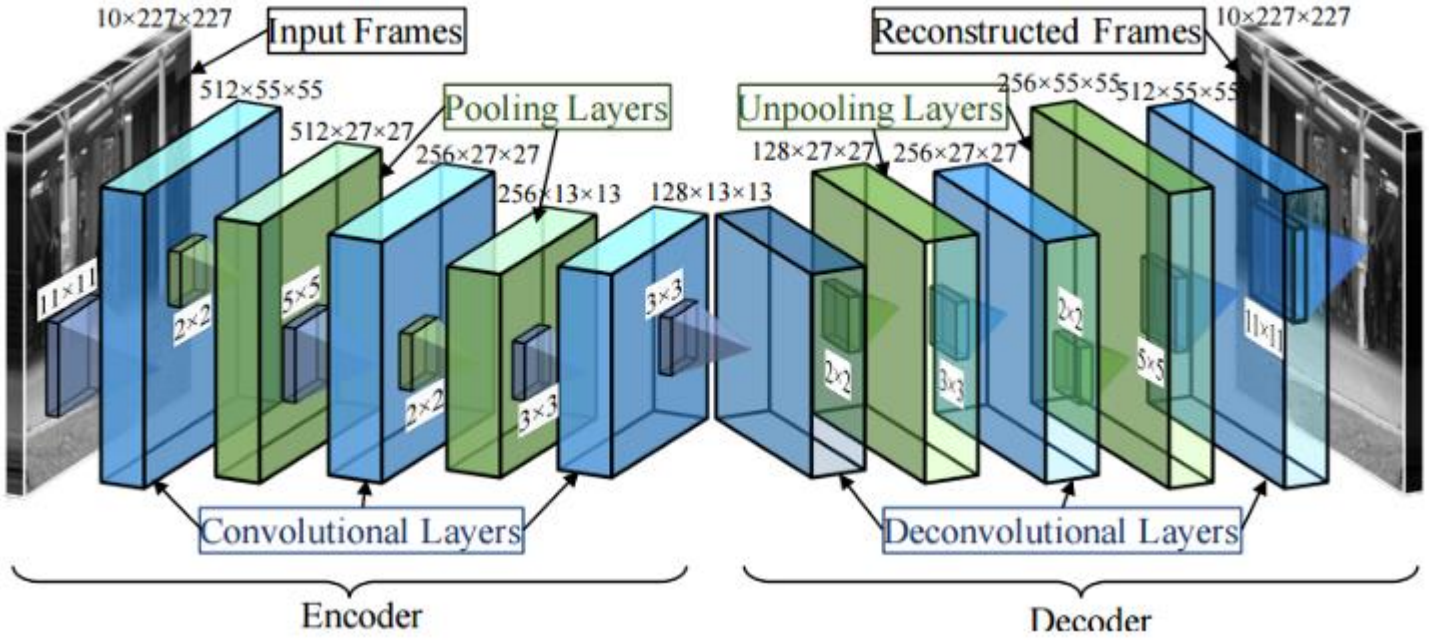
Convolutional Autoencoder

ConvAE for Content Based Image Retrieval

- Hidden activation of ConvAE can be exploited as feature vector which is further used for task such as retrieval or supervised image classification etc.

Conv AE for Anomaly Detection

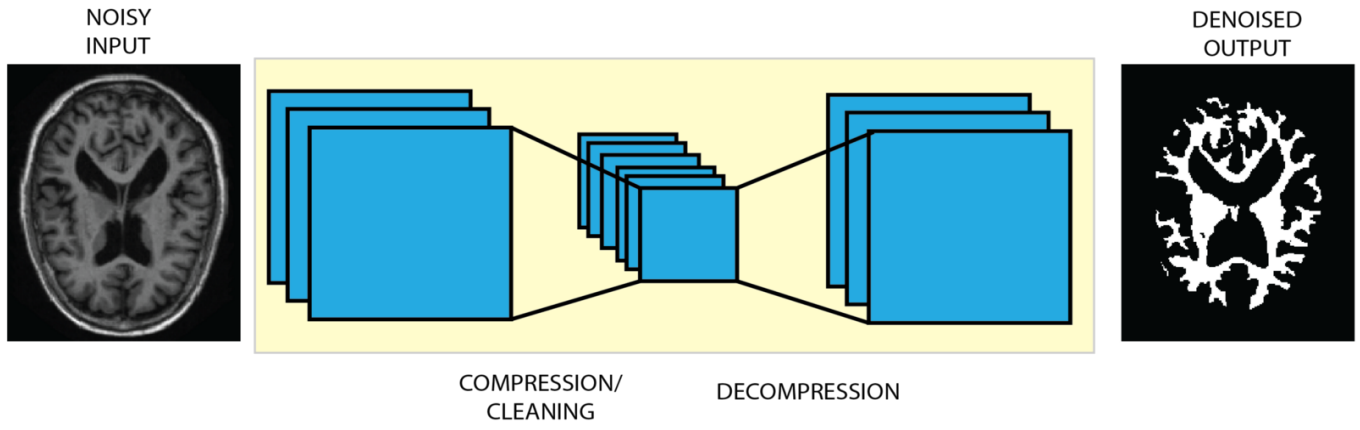
- **Training**: Video frames can be compressed and decompressed using ConvAE
- **Testing**: Frames with higher reconstruction error are labelled as anomalous frames

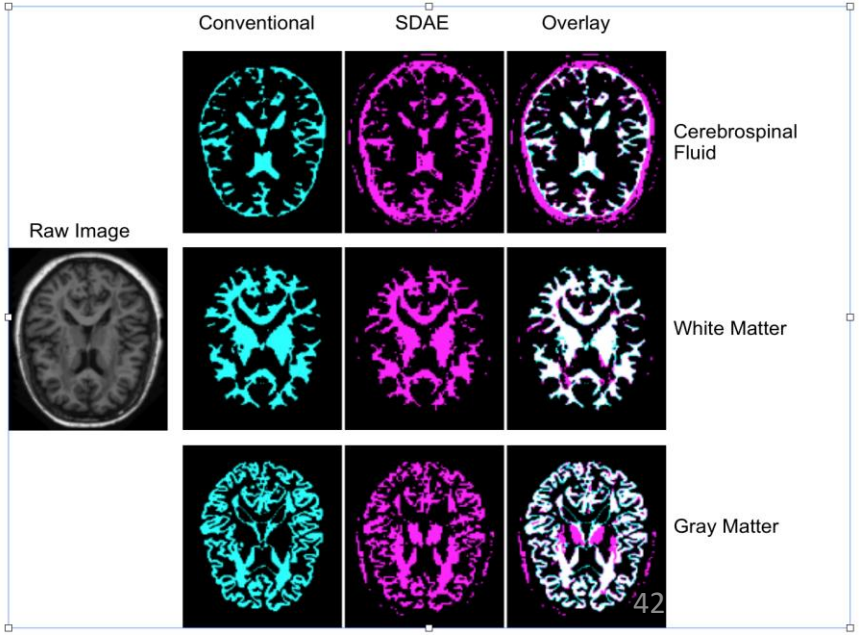


Video Frames are encoded and decoded

AE for Image Denoising

- The ‘Noisy Input’ images is first encoded into the latent space, which has lower dimensionality.
- This is similar to compression that leads to loss of information (in this case we should lose information about the noise).
- The latent space representation is then decoded (the decompression part), which gives us the ‘Denoised’ reconstructed image.



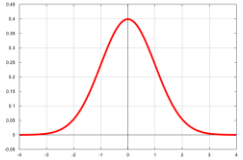


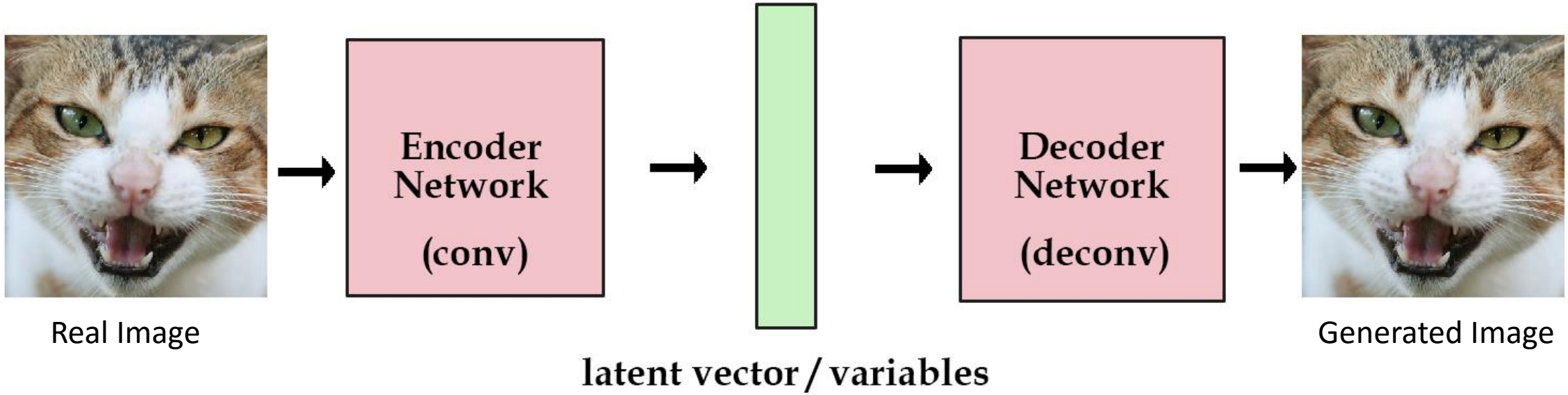
From Autoencoder to Variational Autoencoder

- Autoencoders learn a “compressed representation” of input automatically by first compressing the input and decompressing it back
- AE has no control over the Latent activations of the network hence data generation becomes difficult
- Instead of learning a mapping function, Variational Auto Encoder learns the parameters of the probability distribution representing the data
- In VAE, we have the control over hidden activations because we keep in near the Unit Gaussian
- Add a Constraint in encoding network, that forces it to generate latent vector, that roughly follow the unit Gaussian distribution.
- For generation , it is easy now, sample a latent vector from unit Gaussian distribution, and pass it to the decoder. Decoder will generate the image for that latent vector.

Loss Function

Unit Gaussian Distribution

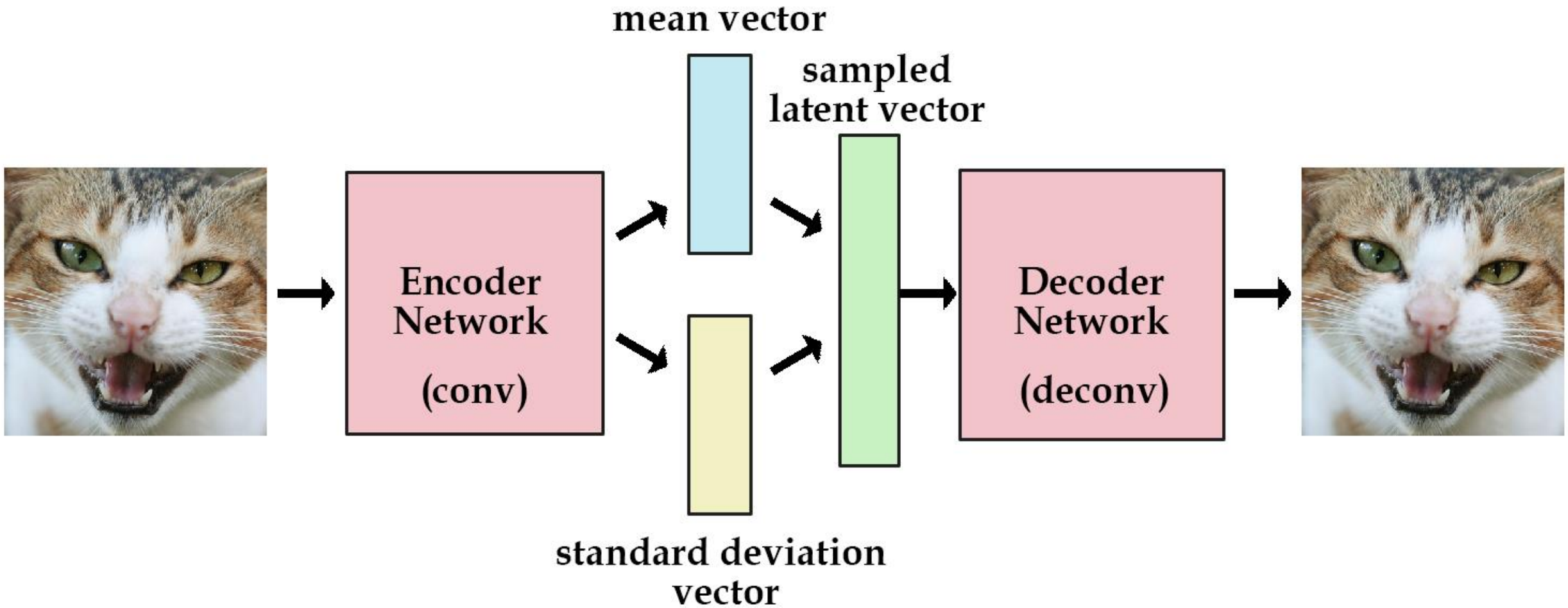




Generation Loss = Mean(Square(Generated Image – Real Image))

Latent Loss = KL-Divergence(Latent Variable, Unit Gaussian)

Loss = Generation Loss + Latent Loss


mean vector
sampled
latent vector
Encoder
Network
(conv)
Decoder
Network
(deconv)
standard deviation
vector

Optimization problem

Objective function

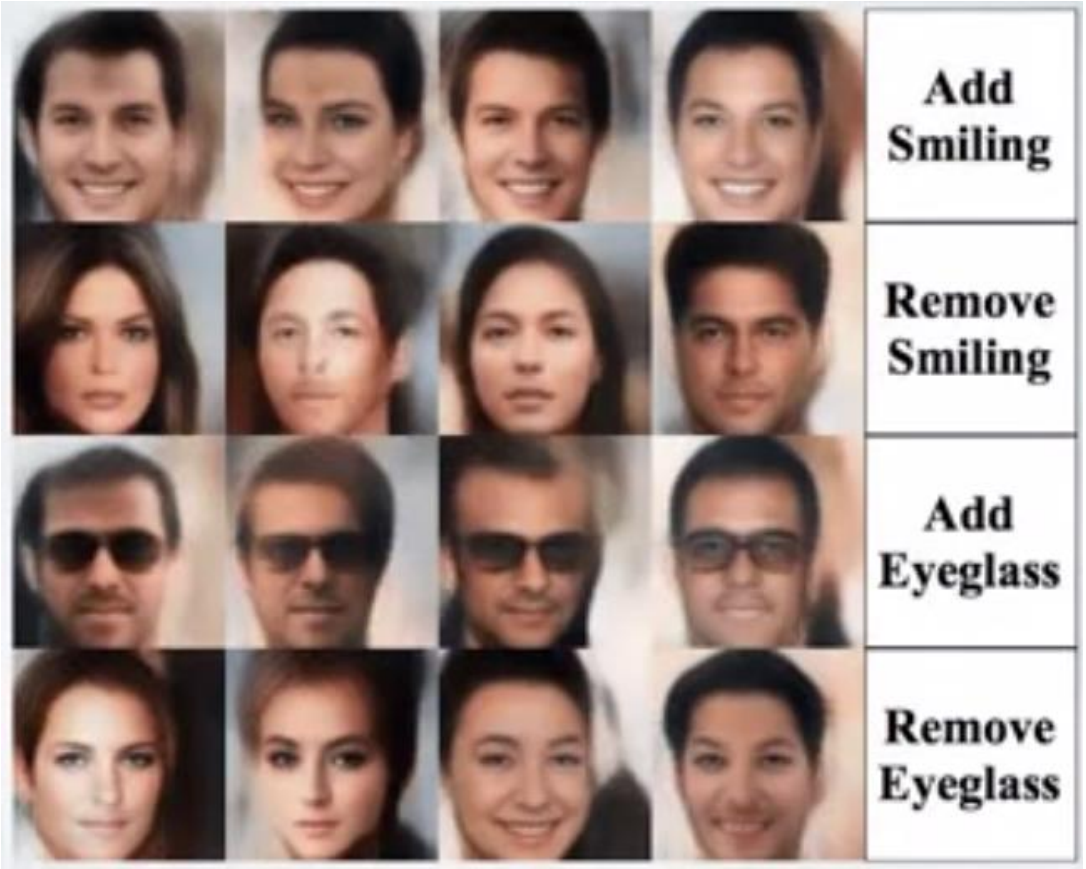
- $L_{\phi,\theta} = E_{z\sim q_\phi} \log p_\theta(x|z) - D_{KL}\left(q_\phi(z|x)\|p(z)\right)$

This is a variational lower bound

- $L_{\phi,\theta} \leq \log p_\theta(x)$
- Specifically: $L_{\phi,\theta} = \log p_\theta(x) - D_{KL}\left(q_\phi(z|x)|p_\theta(z|x)\right)$
- maximizing $L_{\phi,\theta}$ is a proxy to making $q_\phi(z|x)$ match $p_\theta(z|x)$

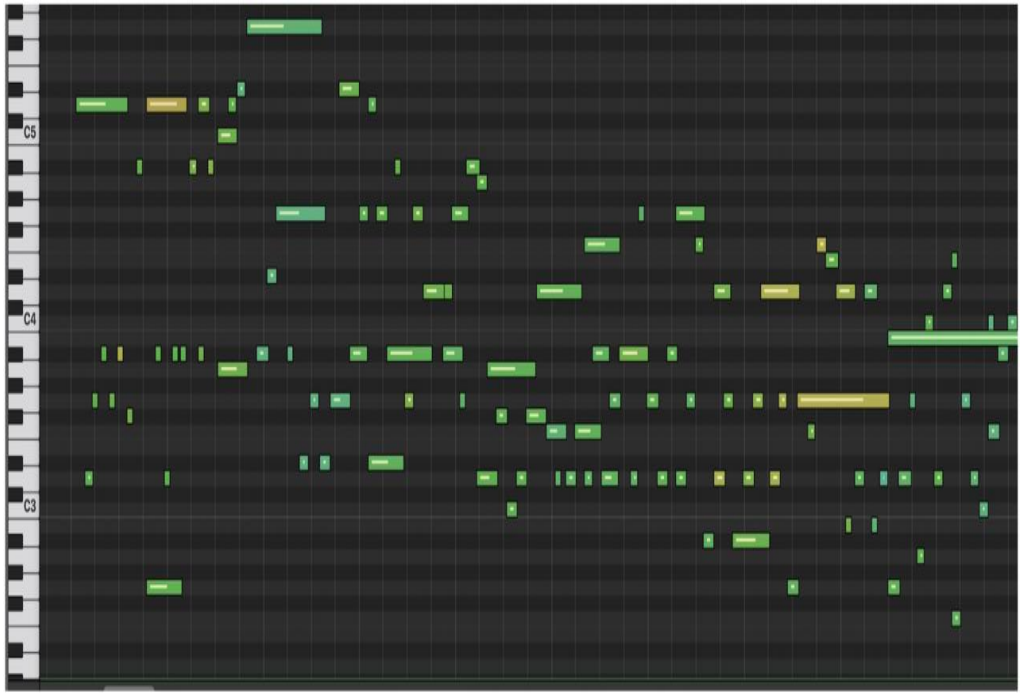
VAE for Image Editing

- VAE can generate a latent vector that contains activations for specific features such smile, eye glass, beard etc. like [1,1,1]
- We can turn a specific feature on/off in the latent vector during new image generation.
- For example, smiley face with beard can be generated using [1,0,1]



VAE for Music

- Google use's Autoencoders for creating new music and sounds



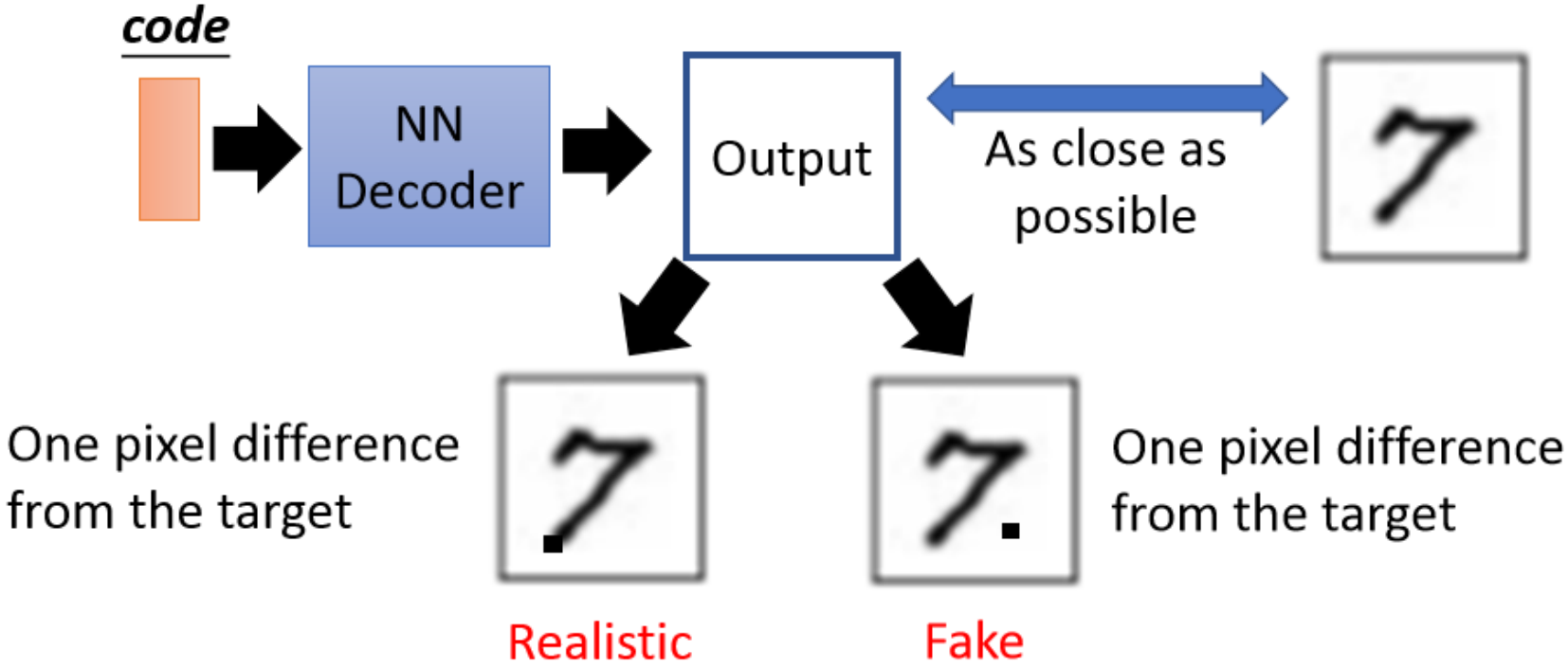
MusicVAE

NSynth Super

Magenta Project https://magenta.tensorflow.org/

Problem of VAE

- VAE does not simulate realistic images since the original objective of Autoencoders is to compress and decompress specific parts of images



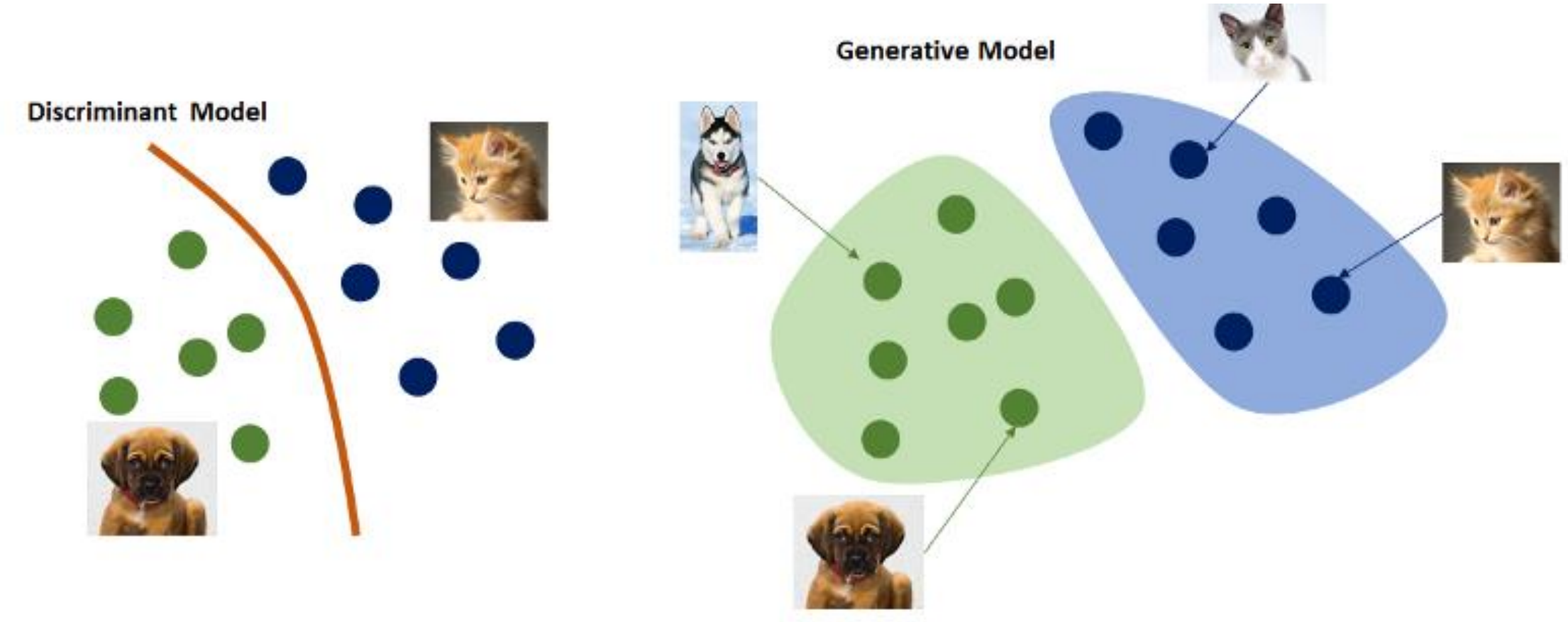
VAE Images

Discriminative Vs Generative Learning

- **Discriminative models**
- A discriminative model **does not** care how the data is generated. Here we just care about P(y|x).
- **Example**: Classifying whether image contains cat or not?

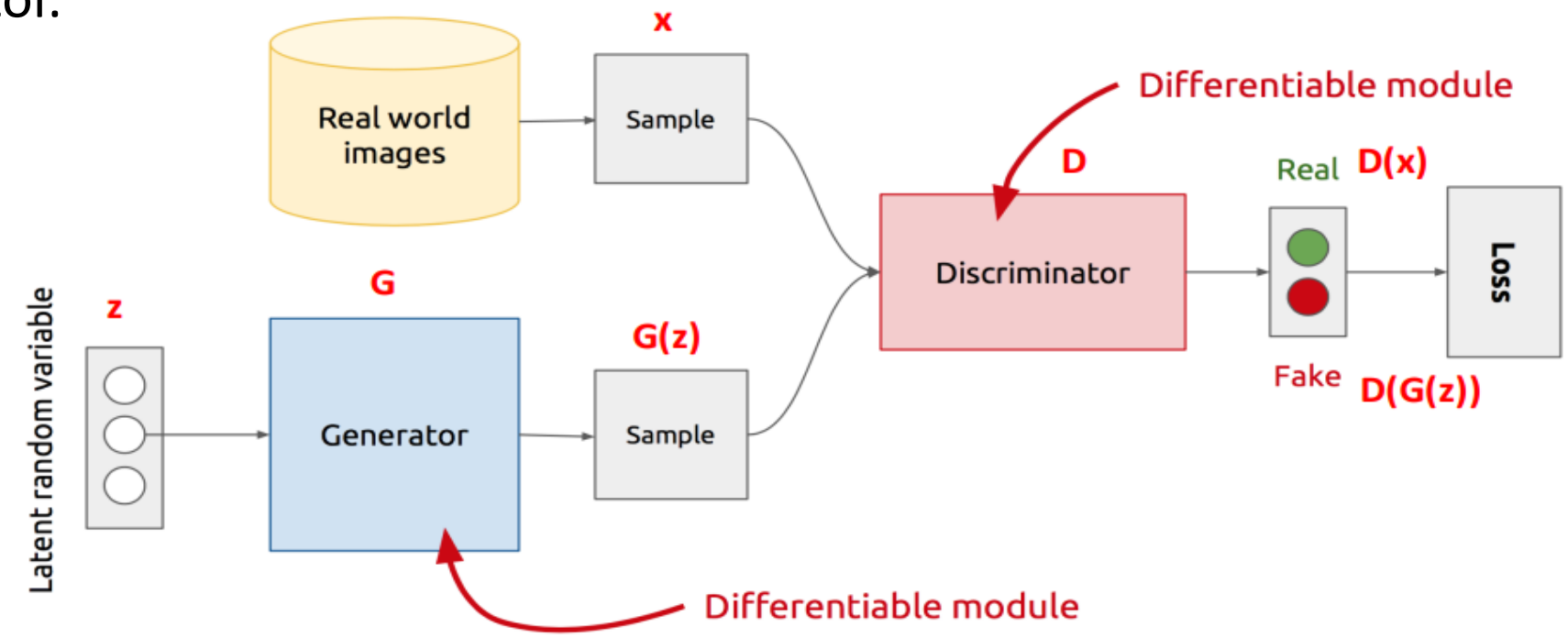
- **Generative models**
- Generative models describe **how data is generated** using probabilistic models. They predict P(y|x), the probability of y given x, calculating the P(x,y), the probability of x and y.
- **Example:** Generating a new cat image

Discriminative Vs Generative Models



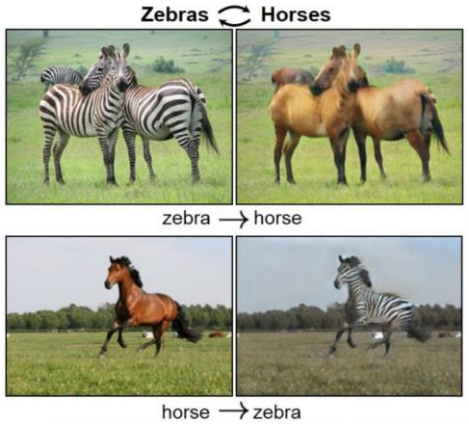
Generative Adversarial Network

- A **Generator Model** G learns to capture the data distribution
- A **Discriminator Model** D estimates the probability that a sample came from the data distribution rather than model distribution.
- This can be think of the minimax game between two networks Discriminator and Generator.



Recent GAN Applications

Anime Characters



CycleGAN

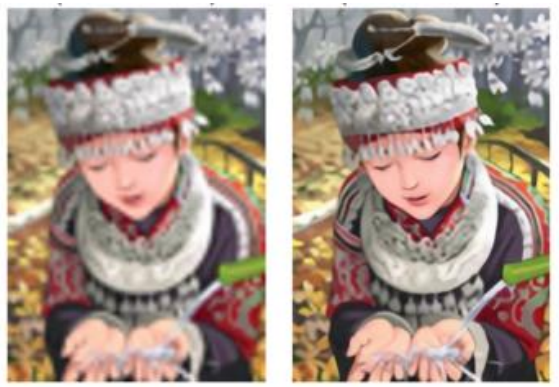


Image Super Resoultion

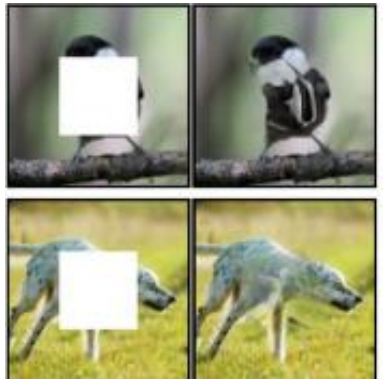


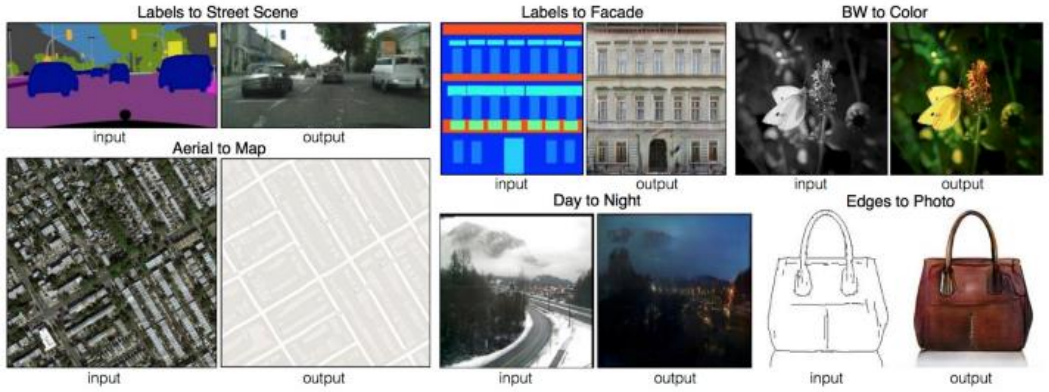
Image Inpainting

Pose Guided Person Image Generation

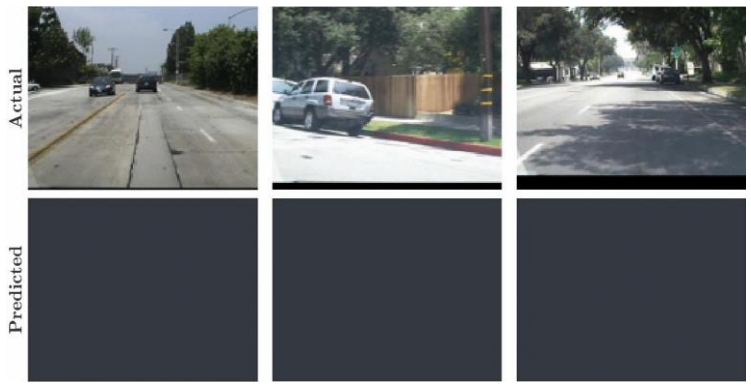
Recent GAN Applications

Fake Celebrities

Text to Image



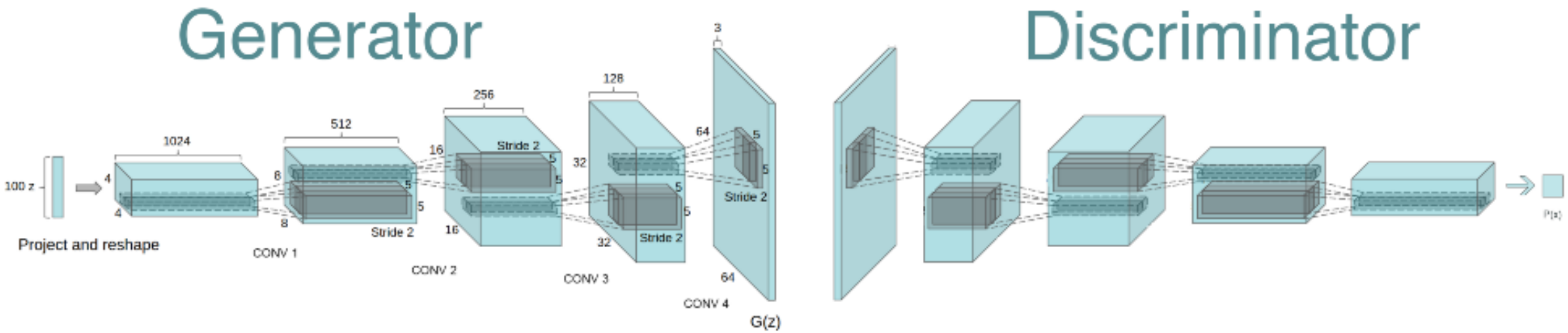
Pix2Pix



Next Frame Prediction

Emoji Generator

Generator vs Discriminator

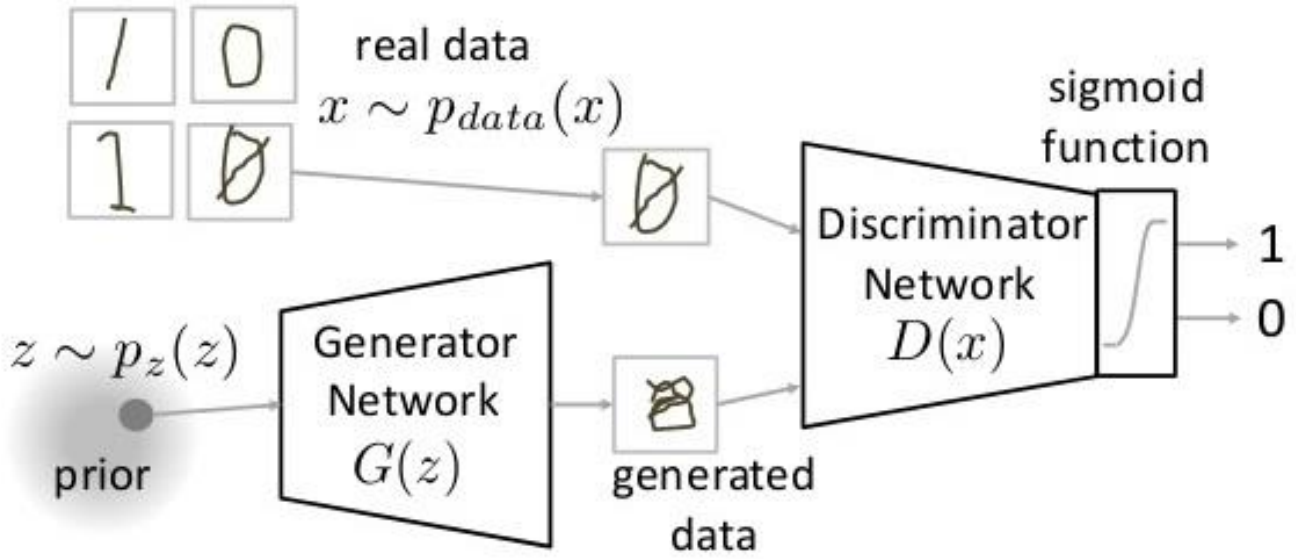


Objective of the **Generator** is to **cheat** the **Discriminator** by simulating **Realistic** images

Objective of the **Discriminator** is to find out whether image is **Real** or **Fake**

Training a GAN

Pdata(x) - Distribution of real data
X - sample from pdata(x)
P(z) - distribution of generator
Z - sample from p(z)
G(z) - Generator Network
D(x) - Discriminator Network



GANs objective is to solving a minimax problem

$$\min_G \max_D V(D,G)$$

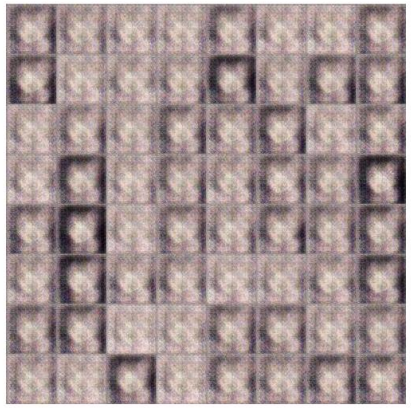
$$V(D,G) = \mathbb{E}_{x \sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z \sim p_z(z)}[\log(1 - D(G(z))]$$

Training a GAN

- In Function V(D, G), the first term is entropy that the data from real distribution (pdata(x)) passes through the discriminator (aka best case scenario). The discriminator tries to maximize this to 1.
- The second term is entropy that the data from random input (p(z)) passes through the generator, which then generates a fake sample which is then passed through the discriminator to identify the fakeness (aka worst case scenario). In this term, discriminator tries to maximize it to 0 (i.e. the log probability that the data from generated is fake is equal to 0).
- **So overall, the discriminator is trying to maximize the function V**. On the other hand, **the task of generator is exactly opposite, i.e. it tries to minimize the function V** so that the differentiation between real and fake data is bare minimum.
- This, in other words is a cat and mouse game between generator and discriminator!

GAN Training Example

100 rounds



1000 rounds

2000 rounds

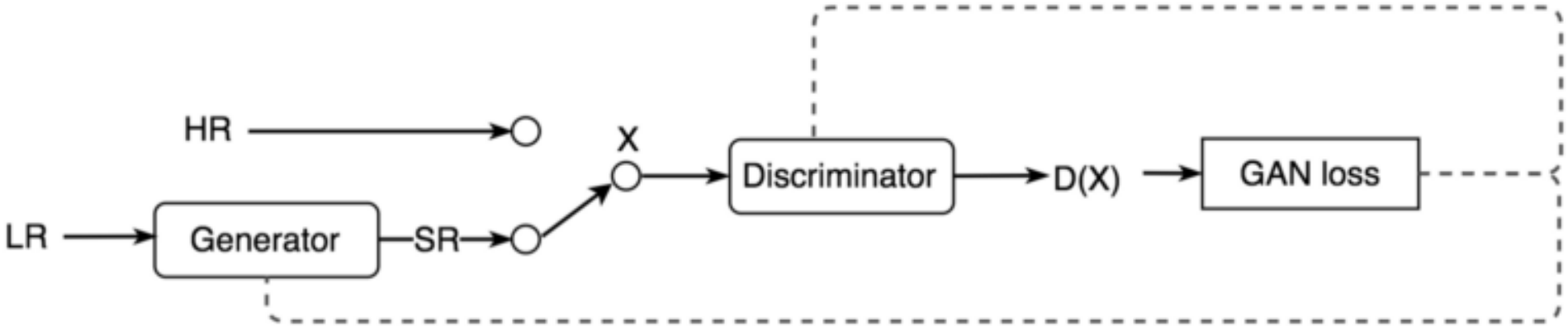
5000 rounds

10,000 rounds

50,000 rounds

GANs for Image Super-resolution: SRGAN

- Generator: gets low-resolution image as input and super-resolution image as output
- Discriminator: aims to differentiate between high-resolution image vs super-resolution image



Architecture of SRGAN

Lab

http://tinyurl.com/lab-bu-ae

http://tinyurl.com/lab-bu-gans

Questions ?

Thanks