

# Data Science and Deep Learning (2024)

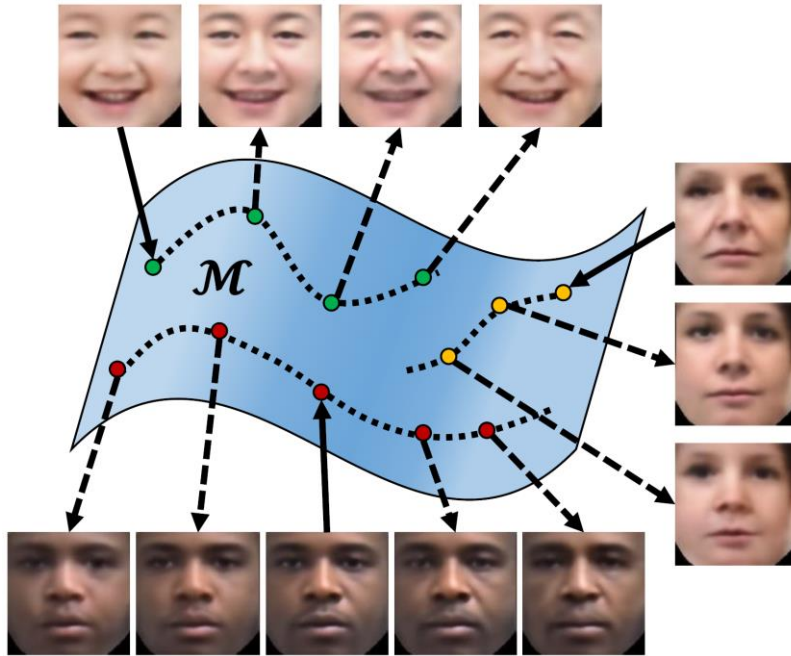
## Lecture 3

# Representation Learning

Stan Z. Li



# Encoding and Decoding

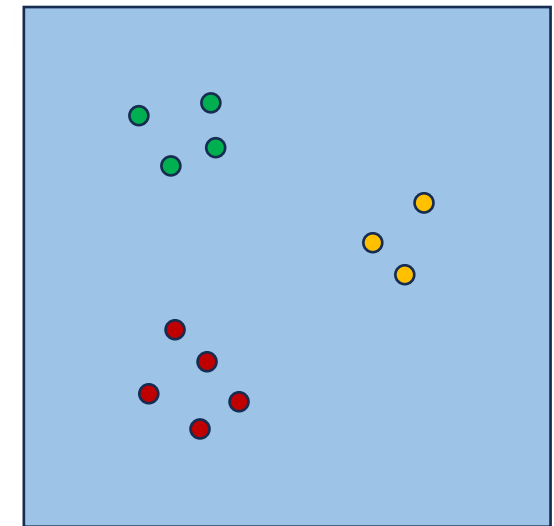


Samples on low-dim but complex manifold in high-dim data space

**Feature Extraction  
By Encoder  
Neural Network**



**Data Generation  
by Decoder  
Neural Network**



Features in lower-dim Euclidean embedding space

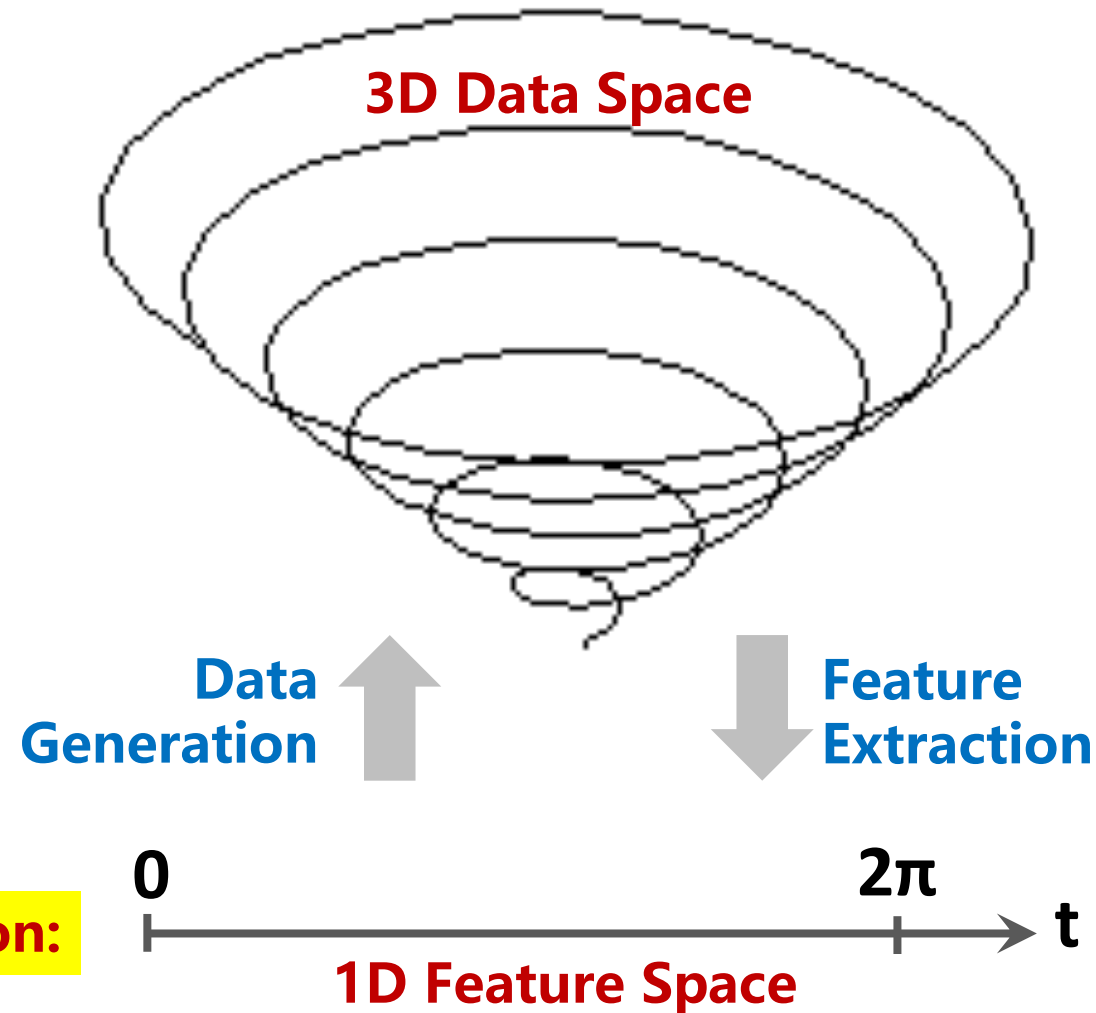
# Key Problems in Representation Learning

- Q1(a). Representation Learning: How to **encode** observable data into a latent space (embedding)
- Q1(b). Generative Learning: How to **decode** a latent code into observable data
- Q2. Neural Networks: How to design a (parametric) neural network **architecture** to perform the desired (nonlinear) transformation
- Q3. Optimization: How to learn (find) **optimal parameters** for the neural network

# Purposes of Representation Learning

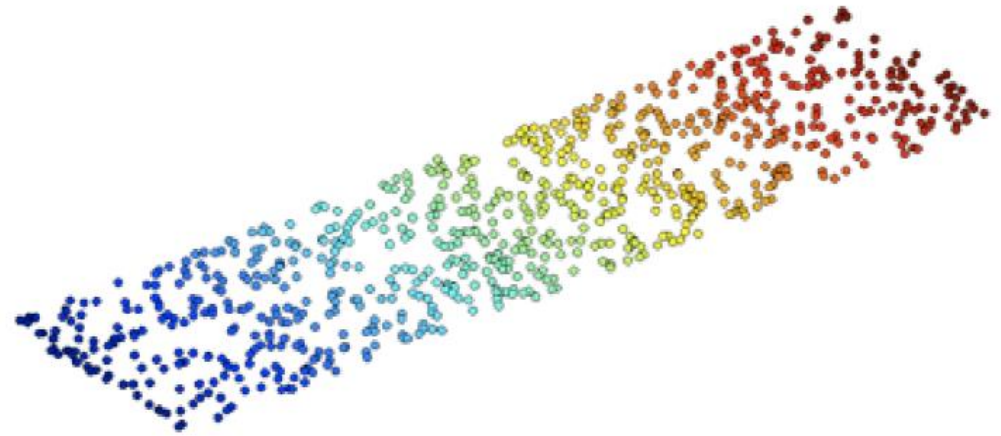
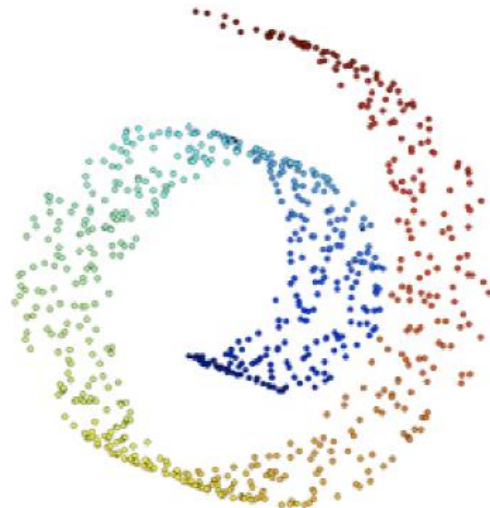
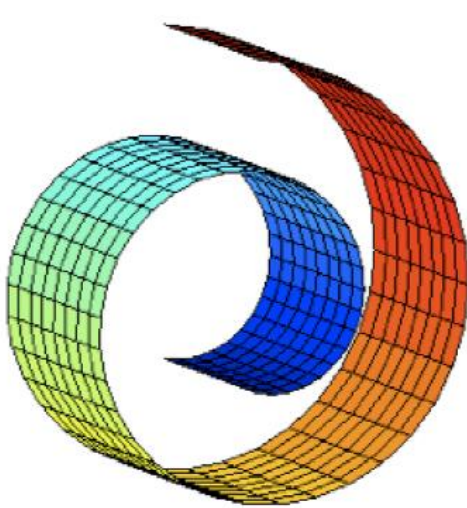
- 1.Feature Learning:** To automatically discover the representations or features from raw data that are most useful for classification or other tasks.
- 2.Dimensionality Reduction:** To reduce the dimensionality of the data to improve computational efficiency, reduce noise, and facilitate data visualization.
- 3.....**

# 1D Manifold in 3D Space



# 2D Manifold in 3D Space

**The Best Representation:**



**Swiss Roll:**

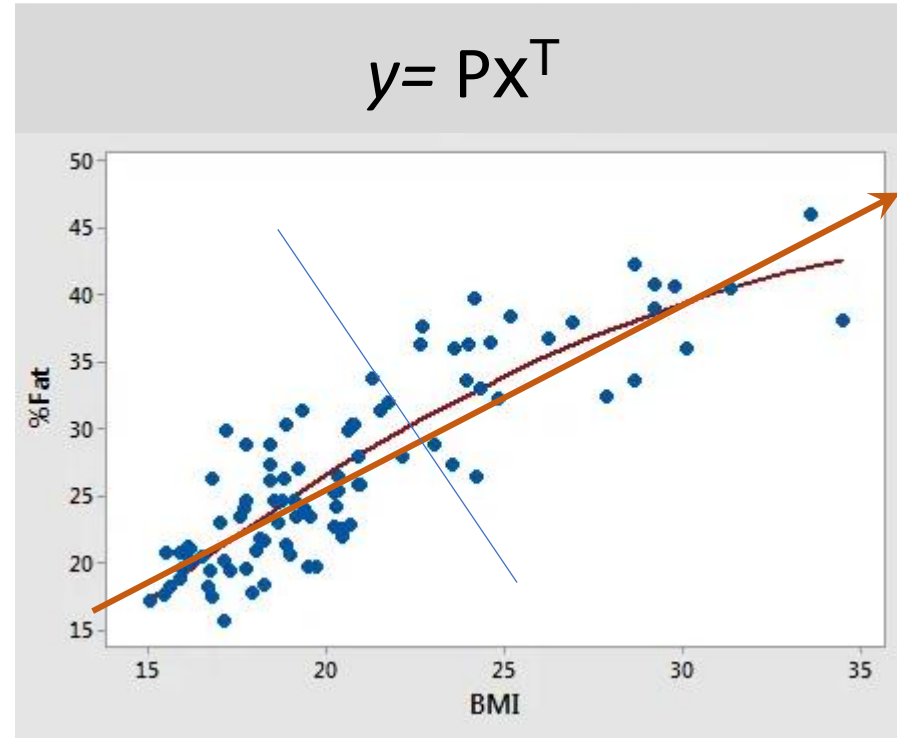
$$x = \varphi \cos(\varphi), y = \varphi \sin(\varphi), z = \psi$$
$$1.5\pi \leq \varphi \leq 4.5\pi, 0 \leq \psi \leq 10$$

**Manifold: 2D rectangle**  
generated by two latent  
variables  $\varphi, \psi$

# Linear Projection

- $x$  --- high dimensional data ( $N \times 1$  vector)
- $y$  --- low dimensional feature ( $n \times 1$  vector)
- $P$  --- projection matrix ( $n \times N$  matrix)
- $y = Px^T$
- $P$  can be learned from training data,  
e.g. Principal Component Analysis (PCA)

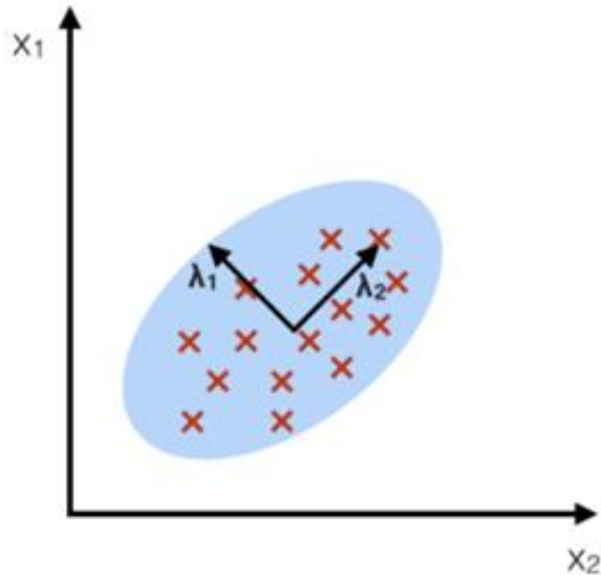
# Linear Regression Fitting





# Principal Component Analysis (PCA)

component axes that  
maximize the variance



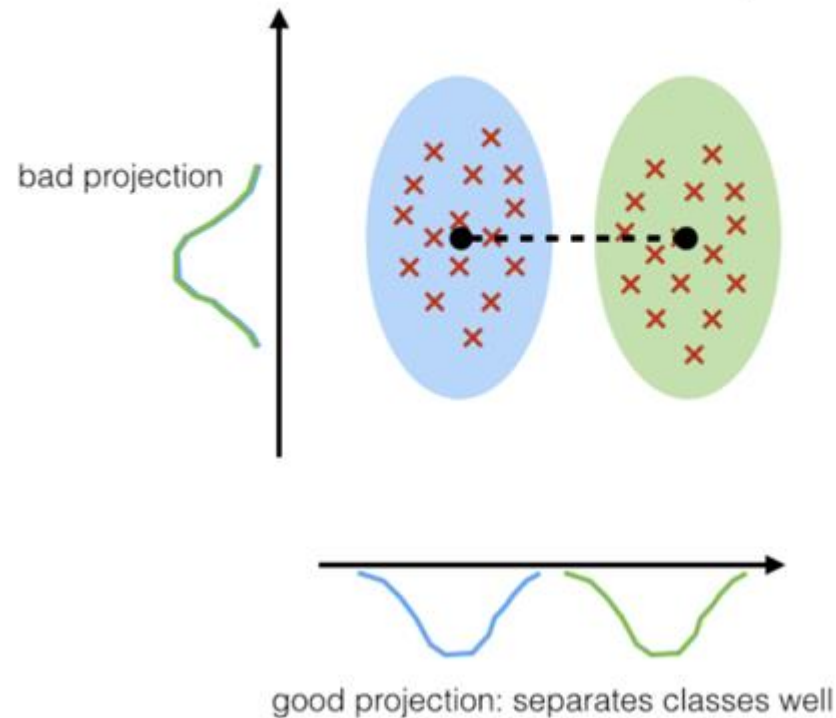
**Step 1:  $\mathbf{x} - \bar{\mathbf{x}} \rightarrow \mathbf{x}$**

**Step 2:  $\mathbf{y} = \mathbf{P}\mathbf{x}^T = f(\mathbf{x})$**

**Reconstruction by  $\mathbf{x}^T = \mathbf{P}^{-1} \mathbf{y}$  ?**

# Linear Discriminant Analysis (LDA)

maximizing the component  
axes for class-separation



# Thanks

