Learning Material Manifold for Efficient Space Exploration

CS 482 mid-term project presentation

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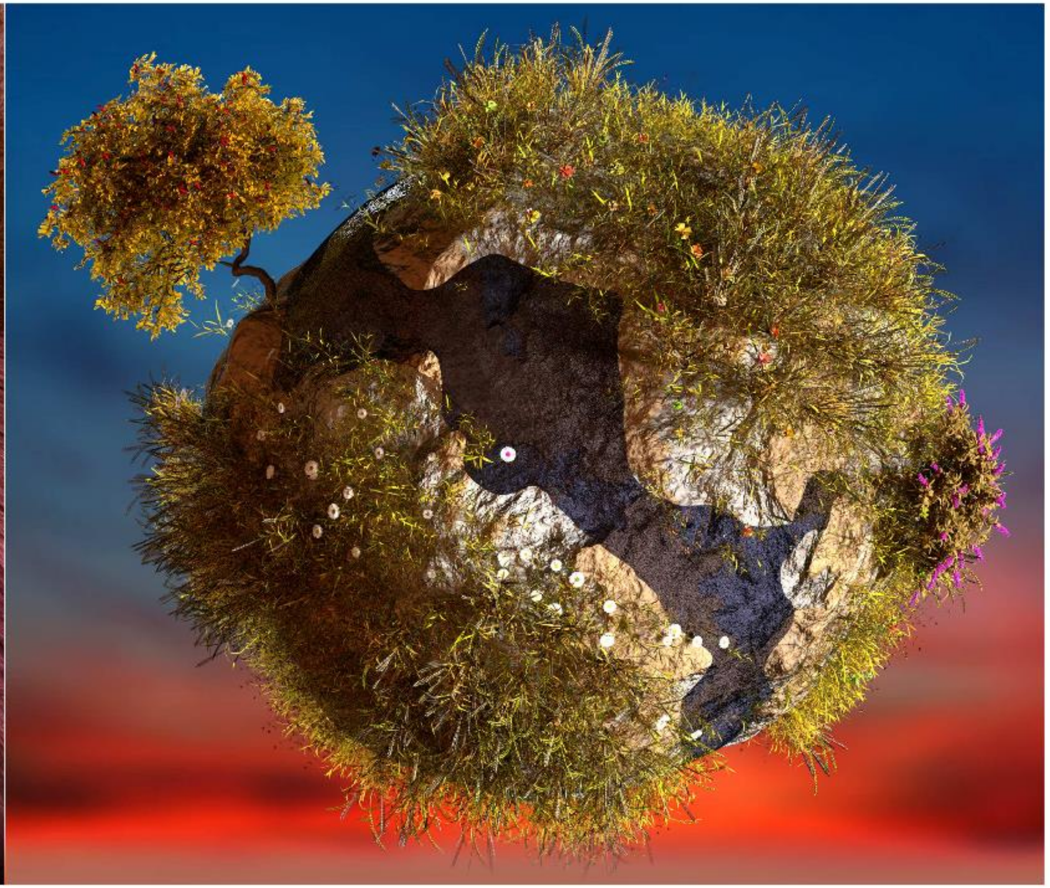
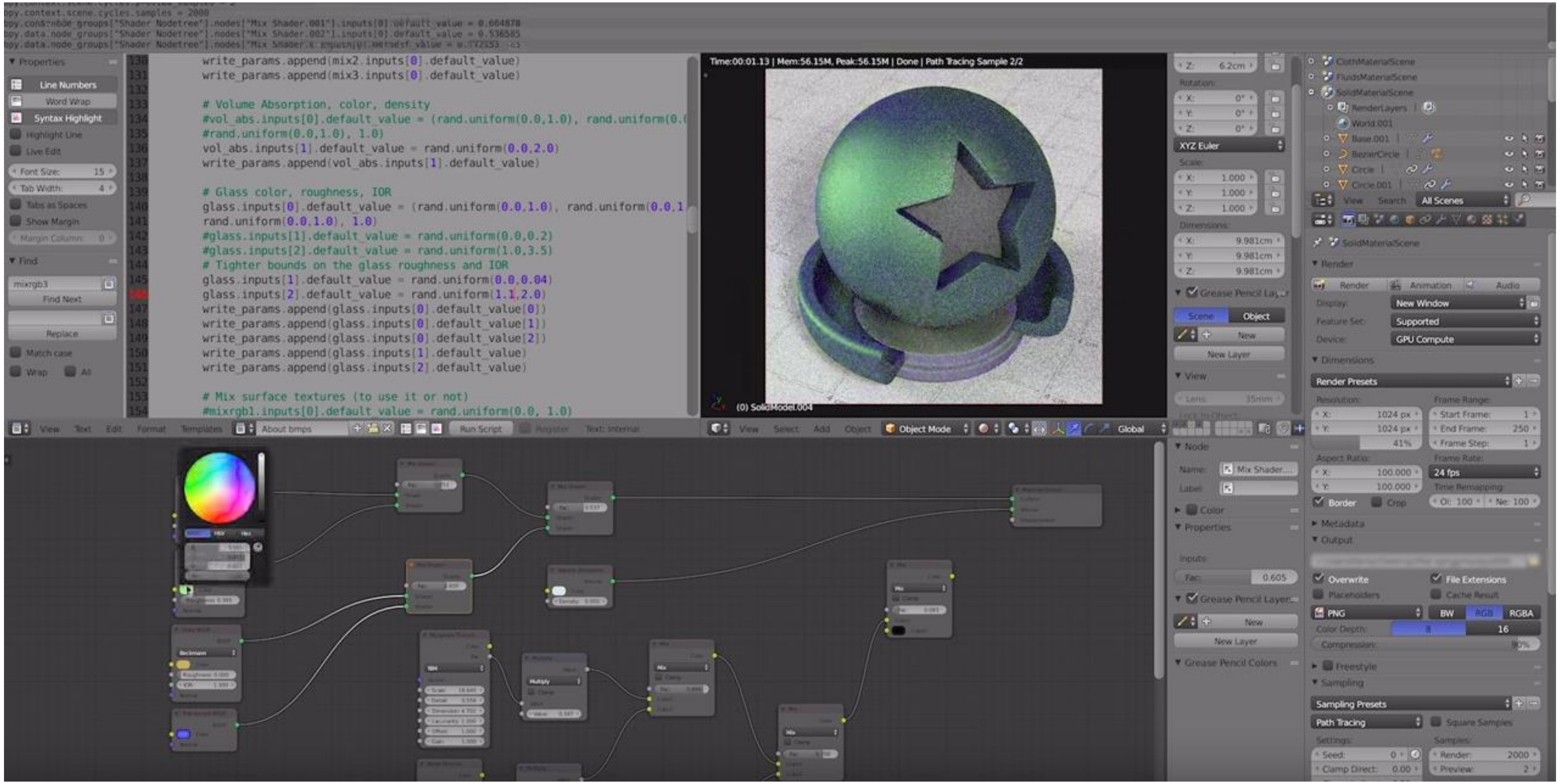
Material Synthesis

a scene with metals and minerals, translucent, glittery and glassy materials



more than a hundred synthesized materials and objects for the vegetation of the planet

Manual Material Synthesis is **Labor-intensive**



```
bpy.context.scene.cycles.samples = 2000
bpy.data.node_groups["Shader Nodetree"].nodes["Mix Shader.001"].inputs[0].default_value = 0.664878
bpy.data.node_groups["Shader Nodetree"].nodes["Mix Shader.002"].inputs[0].default_value = 0.536585
```

```
        write_params.append(mix2.inputs[0].default_value)
        write_params.append(mix3.inputs[0].default_value)

        # Volume Absorption, color, density
        #vol_abs.inputs[0].default_value = (rand.uniform(0.0,1.0), rand.uniform(0.(
        #rand.uniform(0.0,1.0), 1.0)
        vol_abs.inputs[1].default_value = rand.uniform(0.0,2.0)
        write_params.append(vol_abs.inputs[1].default_value)

        # Glass color, roughness, IOR
        glass.inputs[0].default_value = (rand.uniform(0.0,1.0), rand.uniform(0.0,1
        rand.uniform(0.0,1.0), 1.0)
        #glass.inputs[1].default_value = rand.uniform(0.0,0.2)
        #glass.inputs[2].default_value = rand.uniform(1.0,3.5)
        # Tighter bounds on the glass roughness and IOR
        glass.inputs[1].default_value = rand.uniform(0.0,0.04)
        glass.inputs[2].default_value = rand.uniform(1.1,2.0)
        write_params.append(glass.inputs[0].default_value[0])
        write_params.append(glass.inputs[0].default_value[1])
        write_params.append(glass.inputs[0].default_value[2])
        write_params.append(glass.inputs[1].default_value)
        write_params.append(glass.inputs[2].default_value)

        # Mix surface textures (to use it or not)
        #mixrgb1.inputs[0].default_value = rand.uniform(0.0, 1.0)
```

It might be a well fit for an expert, but ...

$\mathbf{x}_i \in \mathbb{R}^m$

Many parameters to tune.

From Authors Video: https://www.youtube.com/watch?v=6FzVhIV_t3s

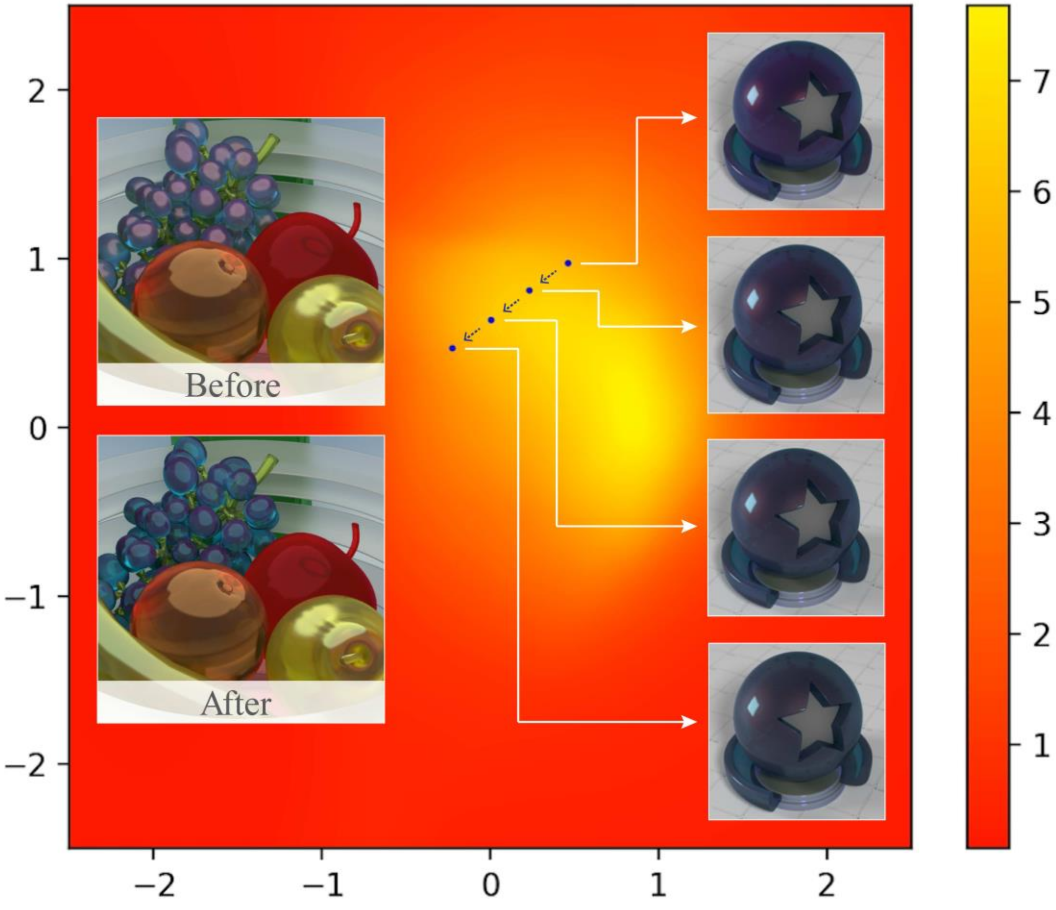
Stage 1: A User Scores a Gallery

From Authors Video: https://www.youtube.com/watch?v=6FzVhIV_t3s

Cons: It is hard for a user to assign dense scores to every candidates with high accuracy
Improvement: Let the user just perform binary selections (select or not)

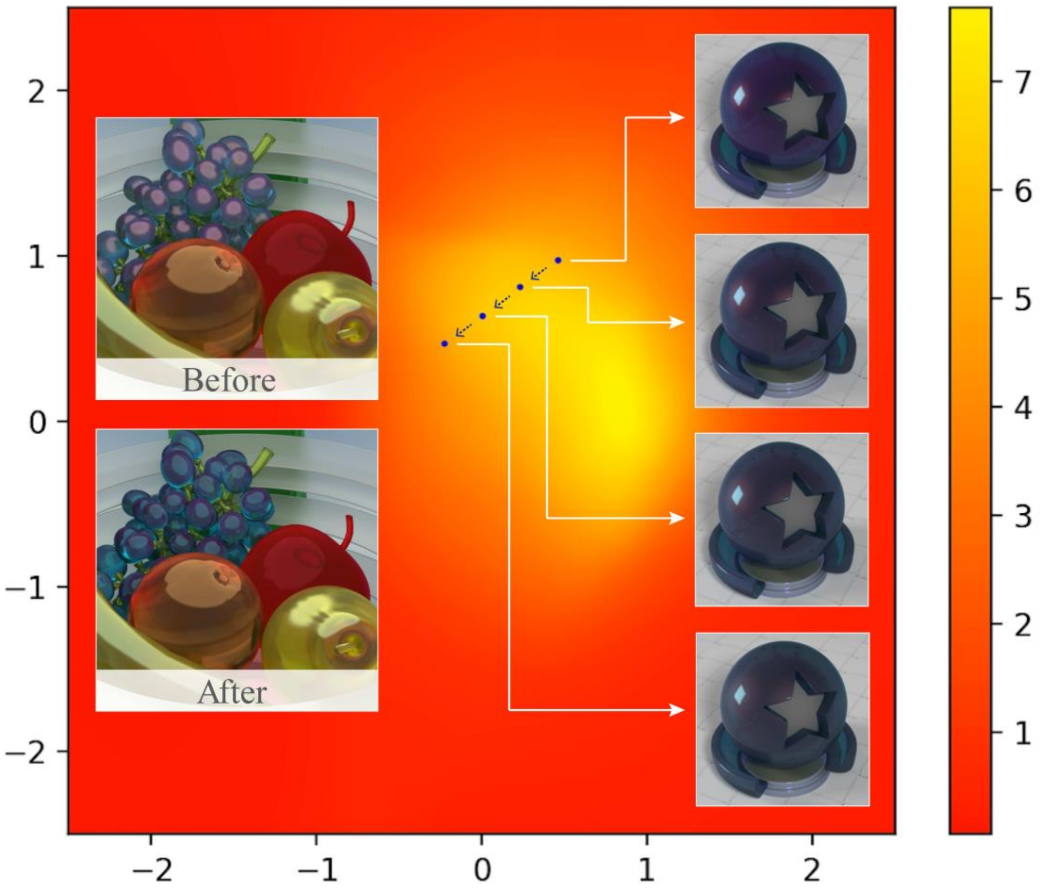
Stage 2: Recommendations are Generated

Stage 3: Fine-searching in Latent Space



Cons: While GP-based methods are good in sample efficiency, the time complexity is high
Improvement: Adopt recent manifold learning (dimensionality reduction) techniques (e.g., GAN)

Latent Space Exploration



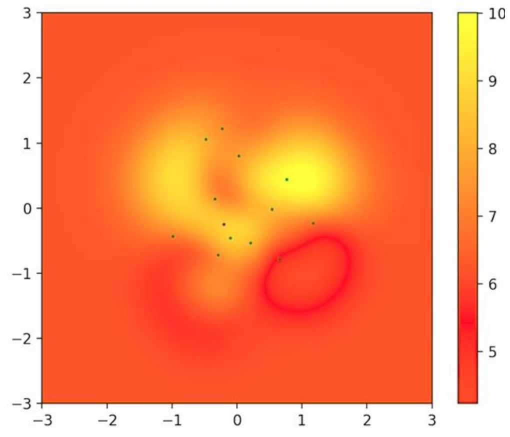
Low-dimensional latent space (m=2), with color representing score. GPLVM (Gaussian Process Latent Variable Model)

A few tens of high-scoring materials from the gallery are embedded into the low-dimensional latent space.

$$\mathbf{X} = \left[\cdots \mathbf{x}_i \cdots\right]^T \text{ with } \mathbf{x}_i \in \mathbb{R}^m$$

$$\mathbf{L} = \left[\cdots \mathbf{l}_i \cdots\right]^T \text{ with } \mathbf{l}_i \in \mathbb{R}^l$$

$$m \gg l$$



GPR family requires kernel, and it is expensive

$$k(\mathbf{x}, \mathbf{x}') = \sigma_f^2 \exp\left[-\frac{(\mathbf{x}-\mathbf{x}')^2}{2l^2}\right] + \beta^{-1}\delta_{xx'}$$

$$\mathbf{K} = \begin{bmatrix} k(\mathbf{x}_1, \mathbf{x}_1) & k(\mathbf{x}_1, \mathbf{x}_2) & \dots & k(\mathbf{x}_1, \mathbf{x}_n) \\ k(\mathbf{x}_2, \mathbf{x}_1) & k(\mathbf{x}_2, \mathbf{x}_2) & \dots & k(\mathbf{x}_2, \mathbf{x}_n) \\ \vdots & \vdots & \ddots & \vdots \\ k(\mathbf{x}_n, \mathbf{x}_1) & k(\mathbf{x}_n, \mathbf{x}_2) & \dots & k(\mathbf{x}_n, \mathbf{x}_n) \end{bmatrix}$$

$$\mathbf{k}_* = \left[k(\mathbf{x}^*, x_1), k(\mathbf{x}^*, x_2), \dots, k(\mathbf{x}^*, x_n)\right]^T$$

Kernel function,
Kernel matrix

Joint distribution over scores

$$\begin{bmatrix} \mathbf{U} \\ u(\mathbf{x}^*) \end{bmatrix} \sim \mathcal{N}\left(0, \begin{bmatrix} \mathbf{K} & \mathbf{k}_*^T \\ \mathbf{k}_* & k_{**} \end{bmatrix}\right)$$

Conditional distribution over scores given **observations**

$$P(u(\mathbf{x}^*) \mid \mathbf{U})$$

test input

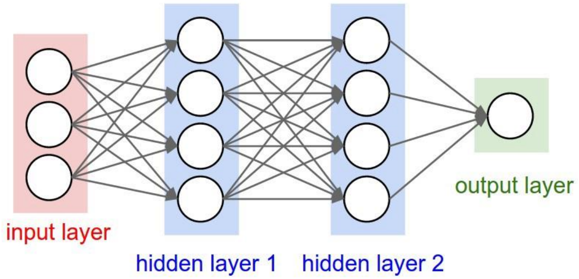
observations

$$u(\mathbf{x}^*) = \mathbf{k}_*^T \mathbf{K}^{-1} \mathbf{U},$$
$$\sigma(u(\mathbf{x}^*)) = k_{**} - \mathbf{k}_* \mathbf{K}^{-1} \mathbf{k}_*^T$$

Parametric vs. Non-parametric

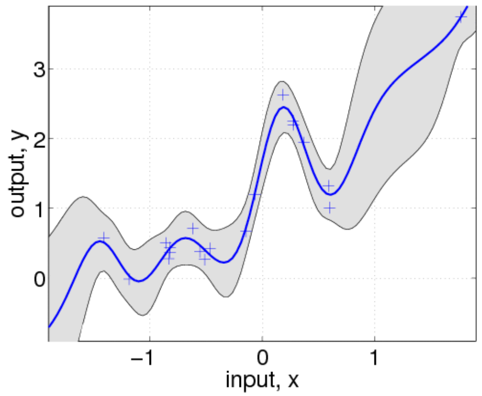
observations is quite small (= # material-score pairs labeled by the user), which is in the order of a few of tens.

Parametric Model



Data is absobed into the weights: new prediction is affected by the estimated parameter. It requires **many samples for an accurate parameter estimation**

Non-parametric Model



'**Let the data speaks**'
: new prediction is highly affected by the past observations

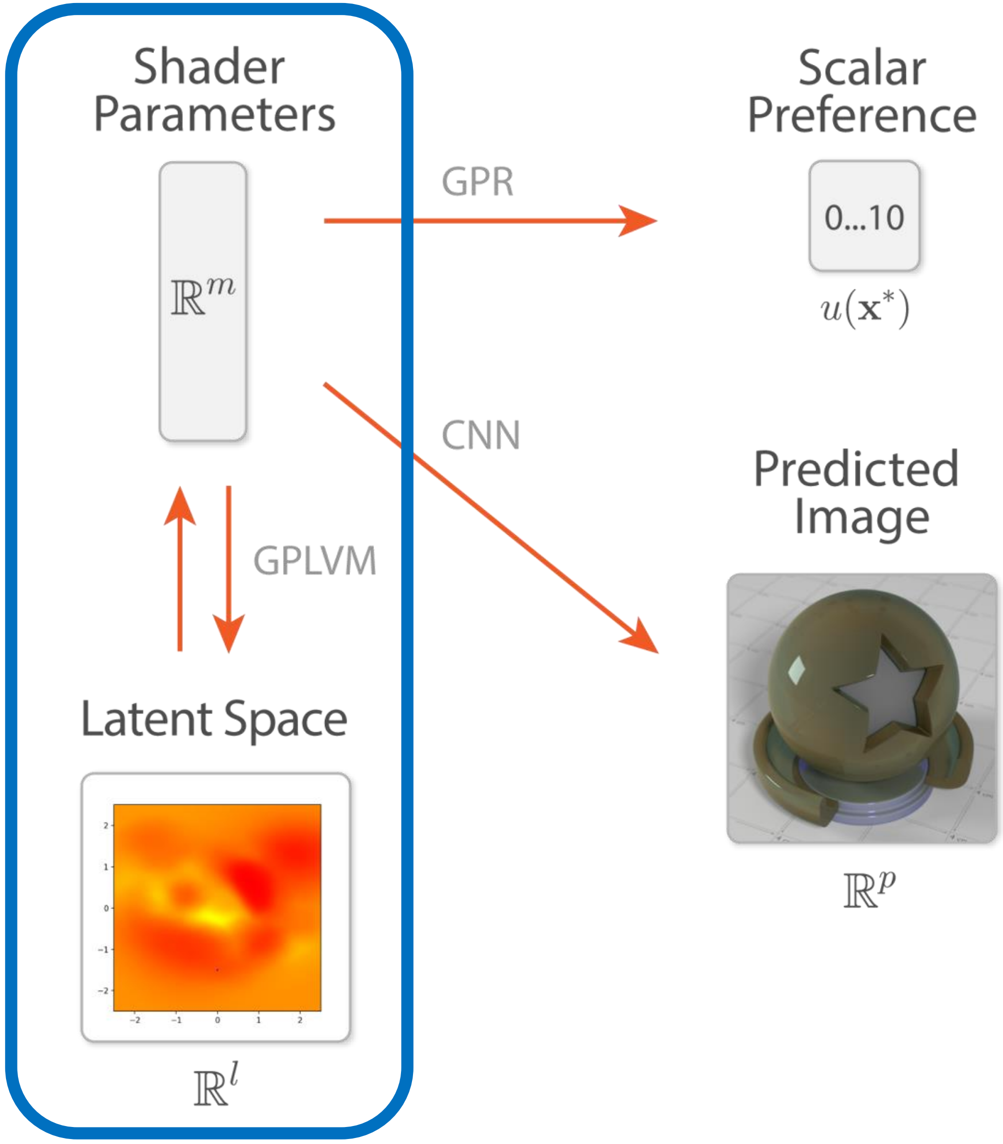
$$\mathbf{K} = \begin{bmatrix} k(\mathbf{x}_1,\mathbf{x}_1) & k(\mathbf{x}_1,\mathbf{x}_2) & \dots & k(\mathbf{x}_1,\mathbf{x}_n) \\ k(\mathbf{x}_2,\mathbf{x}_1) & k(\mathbf{x}_2,\mathbf{x}_2) & \dots & k(\mathbf{x}_2,\mathbf{x}_n) \\ \vdots & \vdots & \ddots & \vdots \\ k(\mathbf{x}_n,\mathbf{x}_1) & k(\mathbf{x}_n,\mathbf{x}_2) & \dots & k(\mathbf{x}_n,\mathbf{x}_n) \end{bmatrix}$$

$$\mathbf{k}_* = \left[k(\mathbf{x}^*,x_1), k(\mathbf{x}^*,x_2), \dots, k(\mathbf{x}^*,x_n)\right]^T$$

$$u(\mathbf{x}^*) = \mathbf{k}_*^T \mathbf{K}^{-1}\mathbf{U},$$

$$\sigma(u(\mathbf{x}^*)) = k_{**} - \mathbf{k}_*\mathbf{K}^{-1}\mathbf{k}_*^T$$

The Component of **Interest**

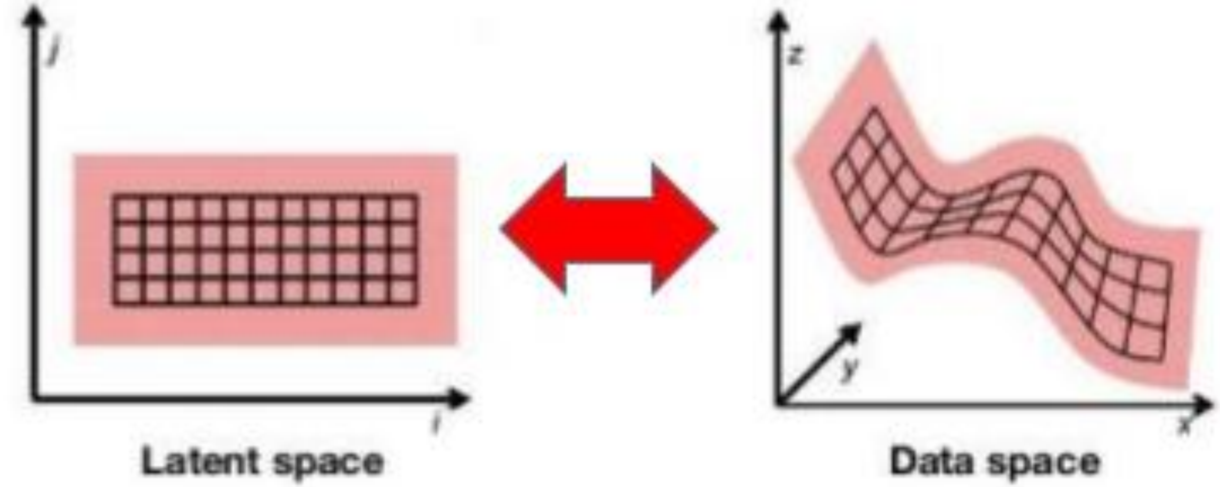


1. **GPR** is used to learn the user-specified material preferences
2. The system **recommends** new **materials** with **visualization**

3. Optionally, GPLVM can be used to provide an intuitive 2D space for variant generation.

Manifold Assumption

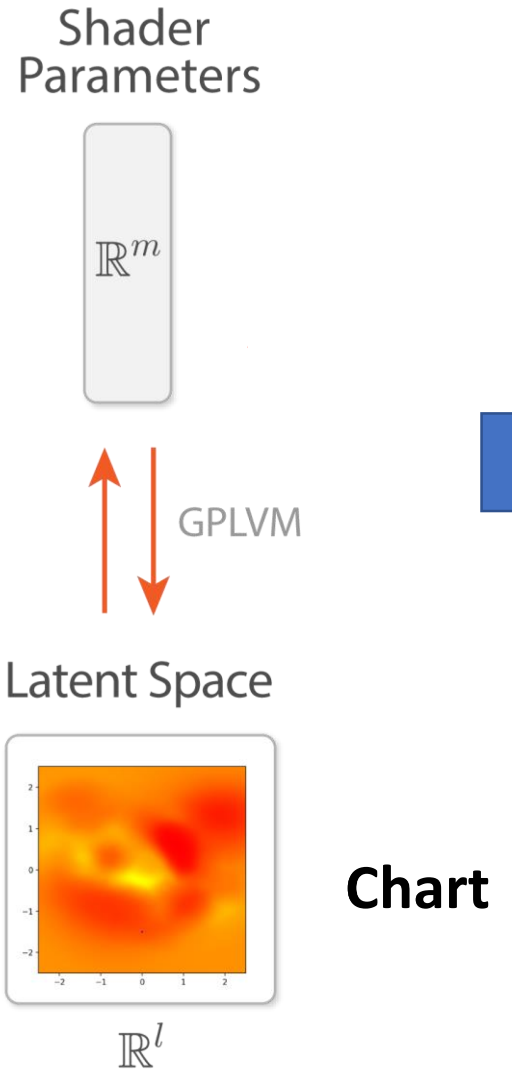
- Data lie approximately on a manifold of much lower dimension than the input space
- Mapping between two space is unique & reversible

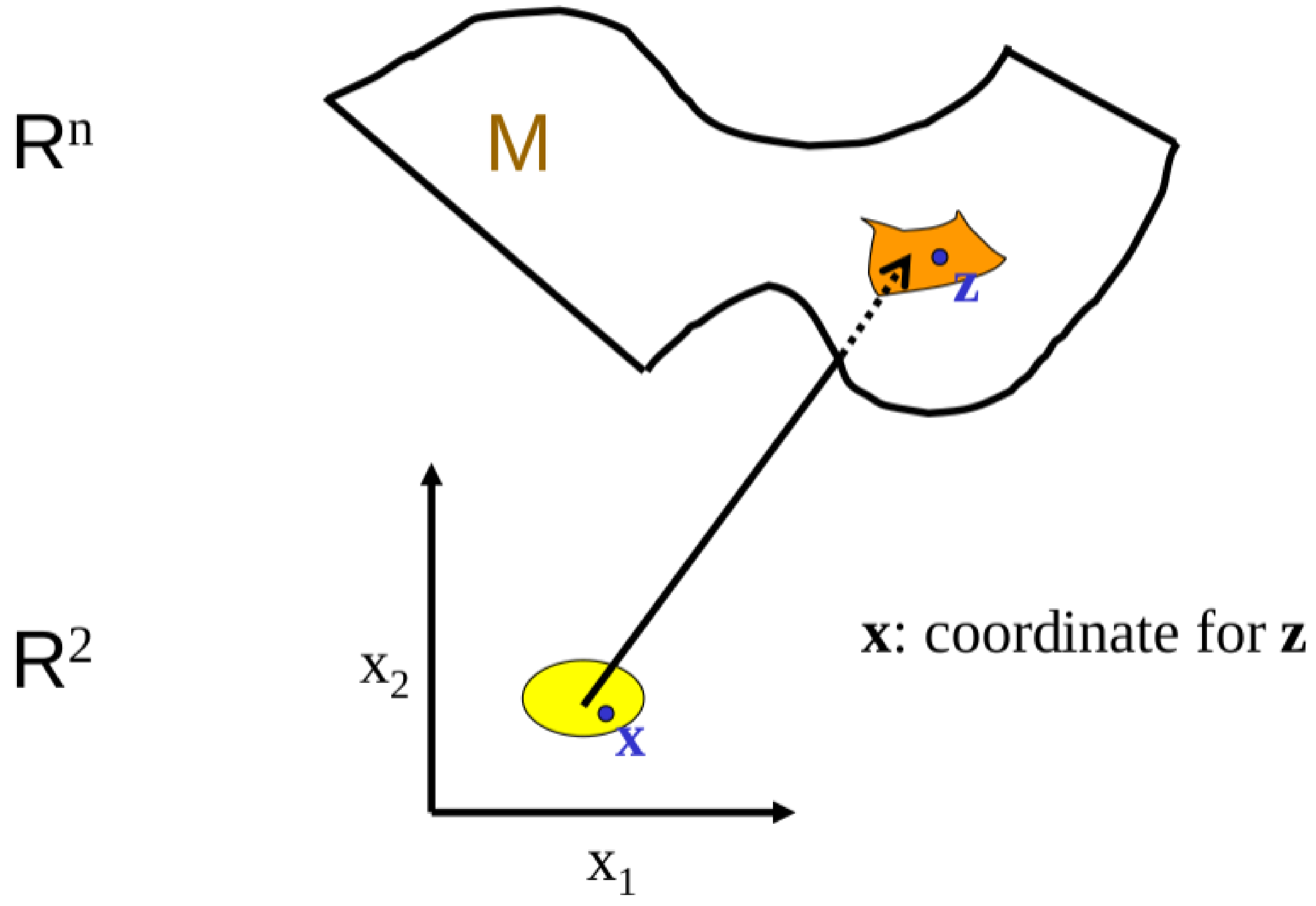


https://www.slideshare.net/ssuser06e0c5/anomaly-detection-with-gans

Goal of the Project

1. Find (learn) a meaningful **manifold**
2. FInd (learn) a **mapping** between the lowdimensional chart and the manifold





Manifold Learning

Why Dimensionality Reduction?

- Most machine learning and data mining techniques may not be effective for high-dimensional data
  - Curse of Dimensionality
  - Query accuracy and efficiency degrade rapidly as the dimension increases.
- The intrinsic dimension may be small.
  - For example, the number of genes responsible for a certain type of disease may be small.

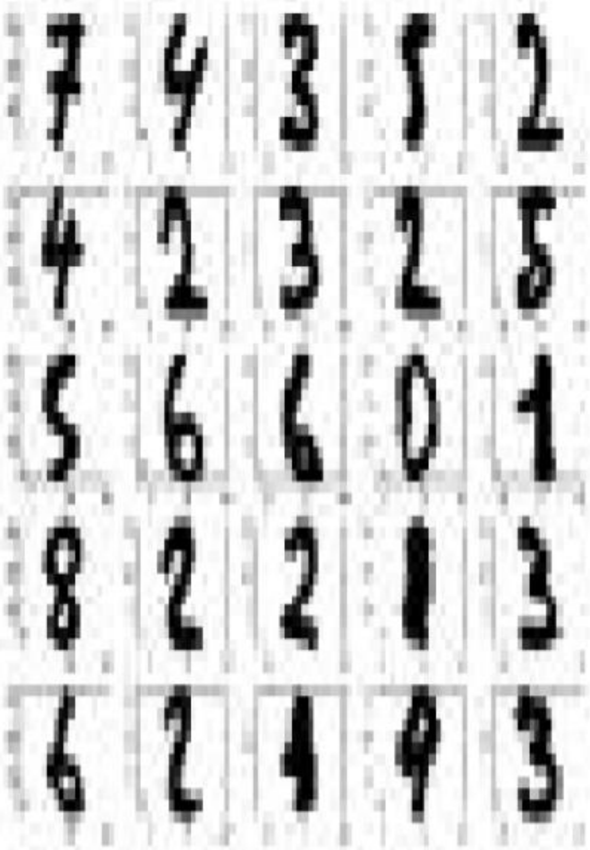
Slides from Lei Yu, Binghamton University
http://www.cs.binghamton.edu/~lyu/SDM07/DR-SDM07.pdf

Why Dimensionality Reduction?

- Visualization: projection of high-dimensional data onto 2D or 3D.
- Data compression: efficient storage and retrieval.
- Noise removal: positive effect on query accuracy.

Other Types of High-Dimensional Data

Face images

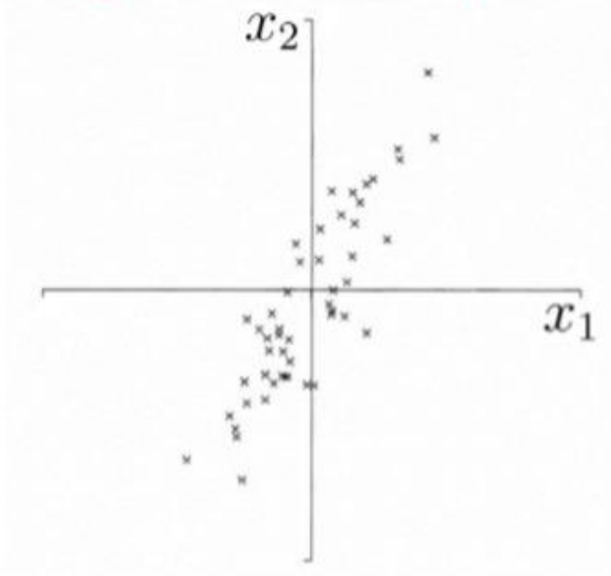


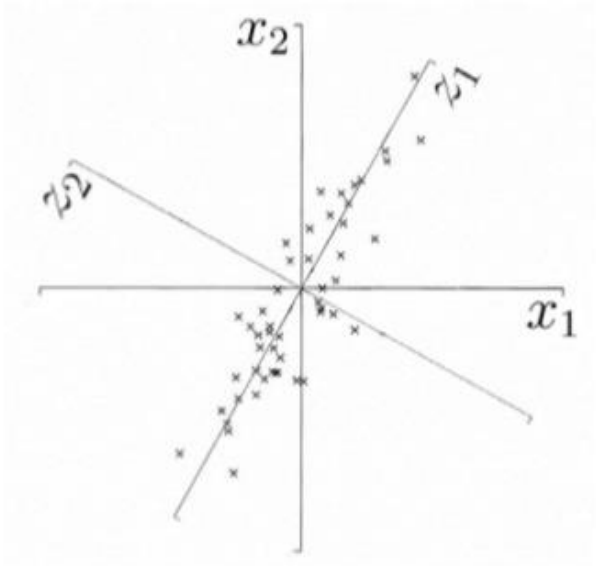
Handwritten digits

Feature Reduction Algorithms

- Linear
  - Latent Semantic Indexing (LSI): truncated SVD
  - Principal Component Analysis (PCA)
  - Linear Discriminant Analysis (LDA)
  - Canonical Correlation Analysis (CCA)
  - Partial Least Squares (PLS)
- Nonlinear
  - Nonlinear feature reduction using kernels
  - Manifold learning

Geometric Picture of Principal Components (PCs)



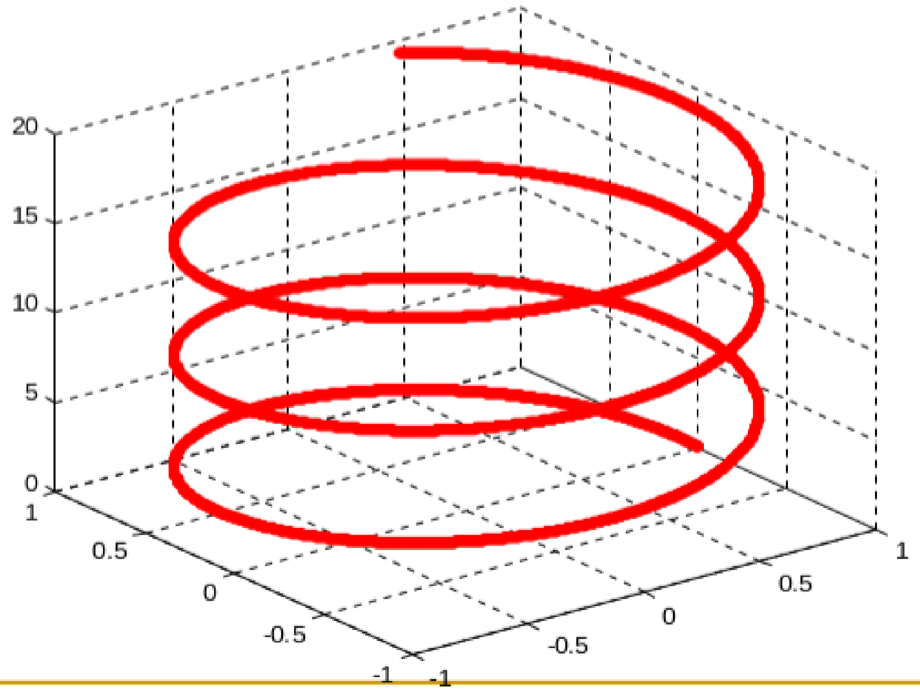


- the 1st PC z_1 is a minimum distance fit to a line in X space
- the 2nd PC z_2 is a minimum distance fit to a line in the plane perpendicular to the 1st PC

PCs are a series of linear least squares fits to a sample, each orthogonal to all the previous.

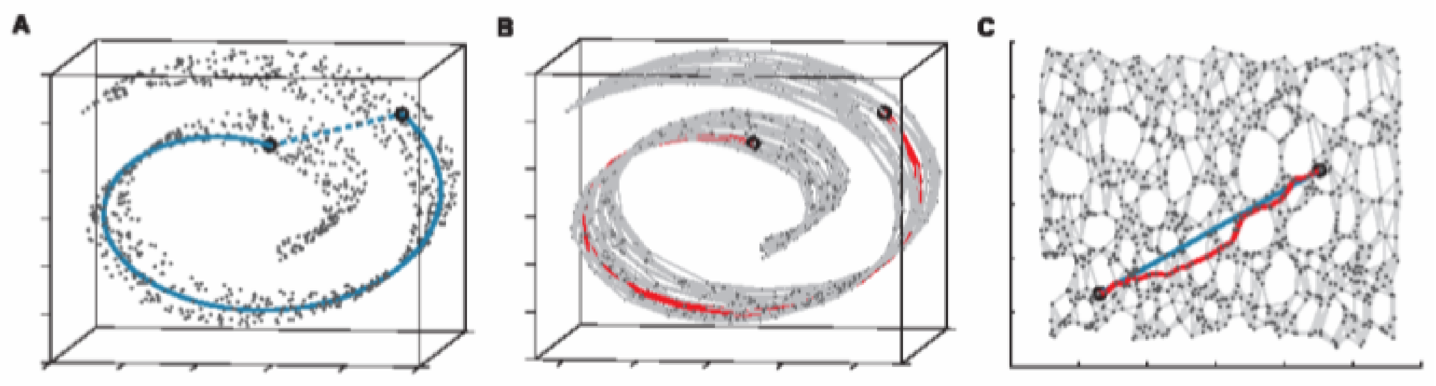
Deficiencies of Linear Methods

- Data may not be best summarized by linear combination of features
  - Example: PCA cannot discover 1D structure of a helix



Nonlinear Approaches- Isomap

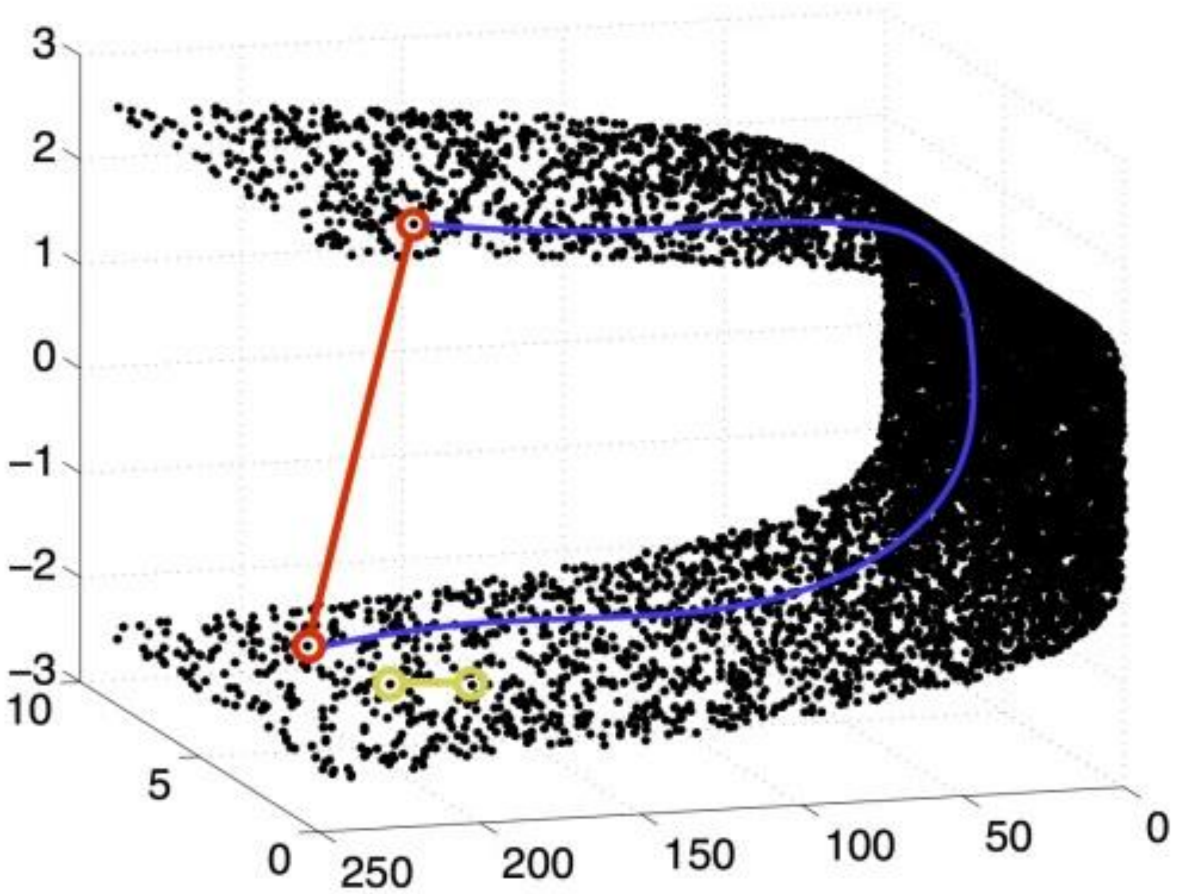
Josh. Tenenbaum, Vin de Silva, John langford 2000



- Constructing neighbourhood graph G
- For each pair of points in G, Computing shortest path distances ---- geodesic distances.
- Use Classical MDS with geodesic distances.

Euclidean distance→ Geodesic distance

Intrinsic Geometrical Property

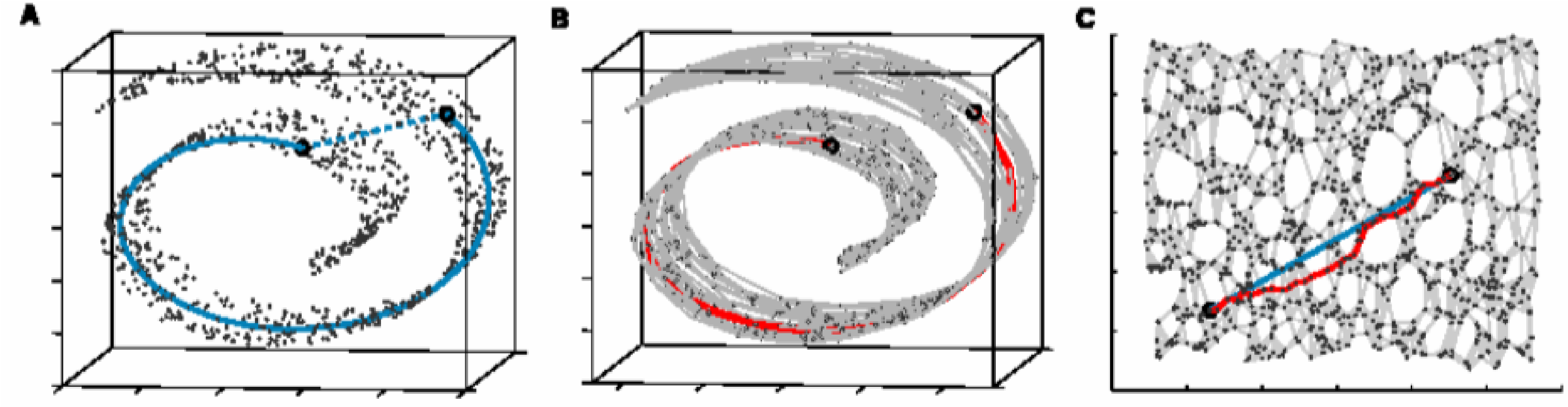


https://ralfbanisch.wordpress.com/2016/03/22/research-perspectives/

Construct Neighborhood Graph G

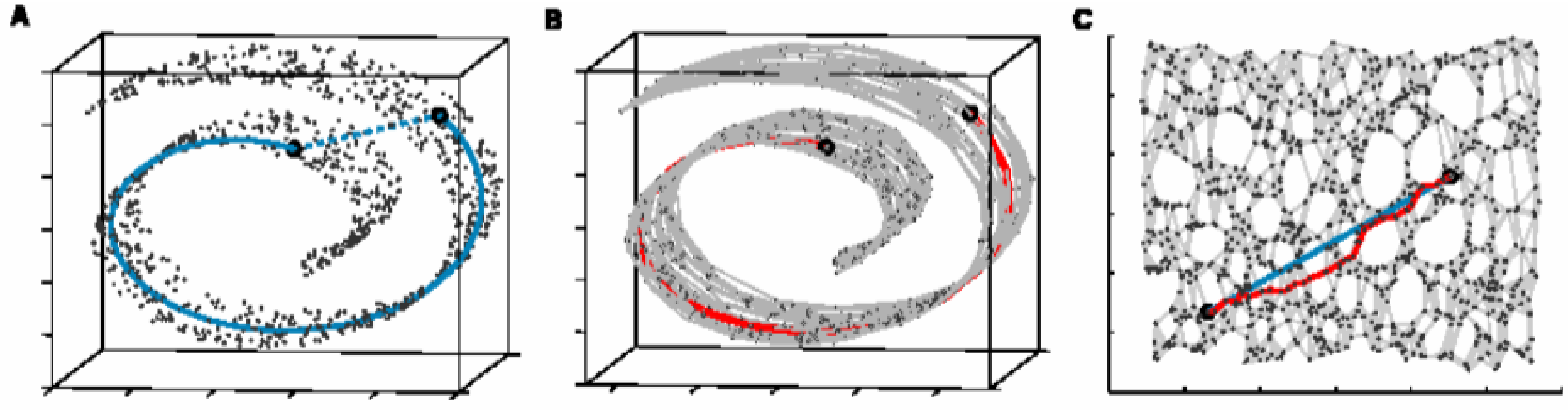
K- nearest neighborhood (K=7)

D_G is 1000 by 1000 (Euclidean) distance matrix of two neighbors (figure A)



Compute All-Points Shortest Path in G

Now D_G is 1000 by 1000 geodesic distance matrix of two arbitrary points along the manifold (figure B)



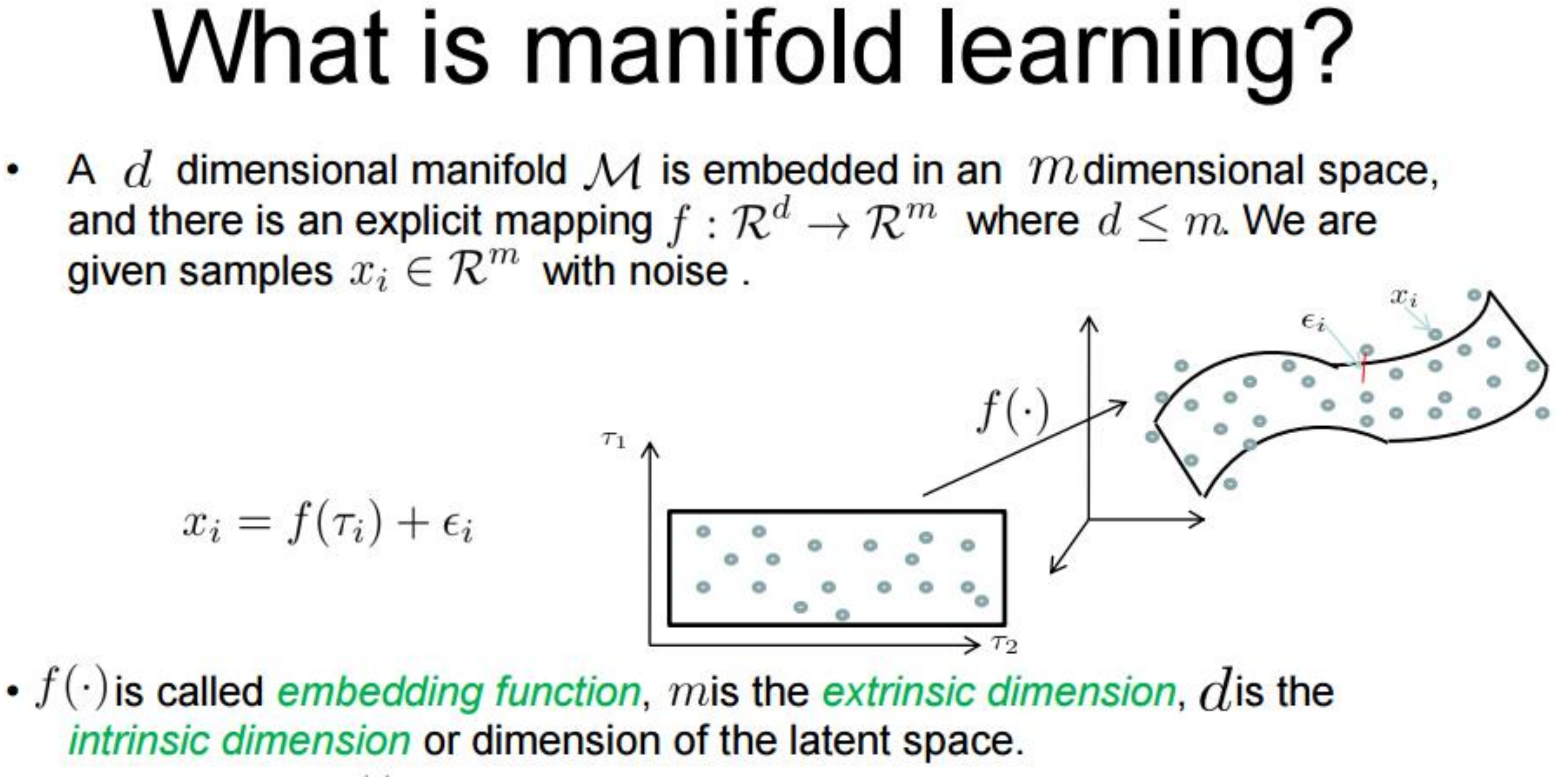
Isomap: Advantages

- Nonlinear
- Globally optimal
    - Still produces globally optimal low-dimensional Euclidean representation even though input space is highly folded, twisted, or curved.
- Guarantee asymptotically to recover the true dimensionality.

Isomap: Disadvantages

- May not be stable, dependent on topology of data
- Guaranteed asymptotically to recover geometric structure of nonlinear manifolds
  - As N increases, pairwise distances provide better approximations to geodesics, but cost more computation
  - If N is small, geodesic distances will be very inaccurate.

More formally,



What is manifold learning?

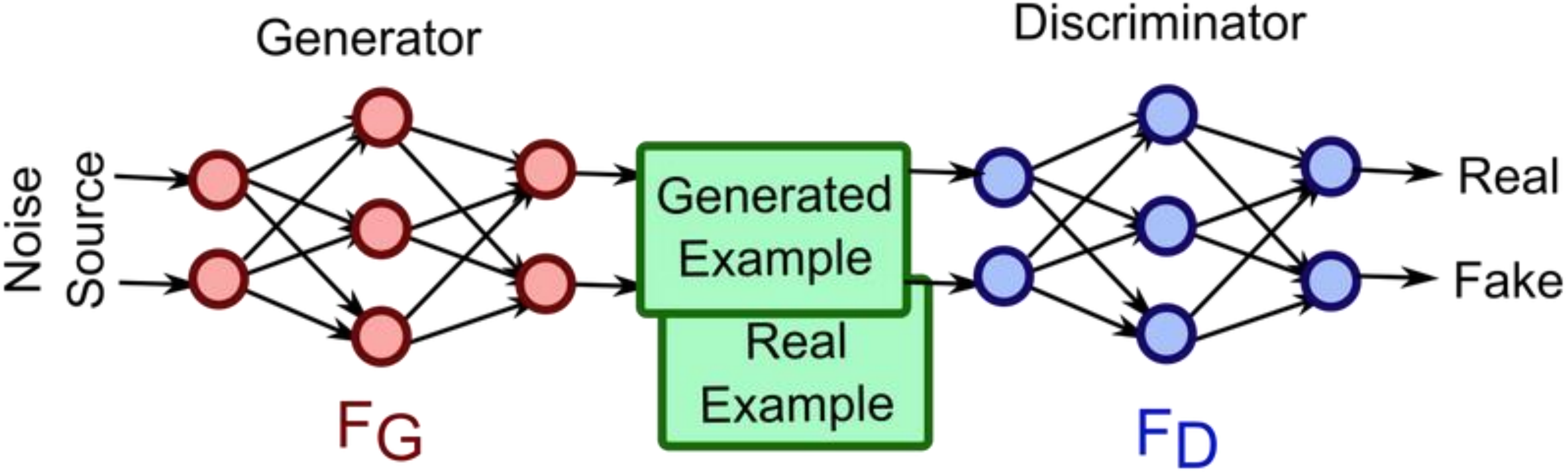
- A d dimensional manifold $\mathcal{M}$ is embedded in an m dimensional space, and there is an explicit mapping $f : \mathcal{R}^d \rightarrow \mathcal{R}^m$ where $d \leq m$. We are given samples $x_i \in \mathcal{R}^m$ with noise .

$$x_i = f(\tau_i) + \epsilon_i$$

- $f(\cdot)$ is called *embedding function*, m is the *extrinsic dimension*, d is the *intrinsic dimension* or dimension of the latent space.

https://math.stackexchange.com/questions/1203714/manifold-learning-how-should-this-method-be-interpreted

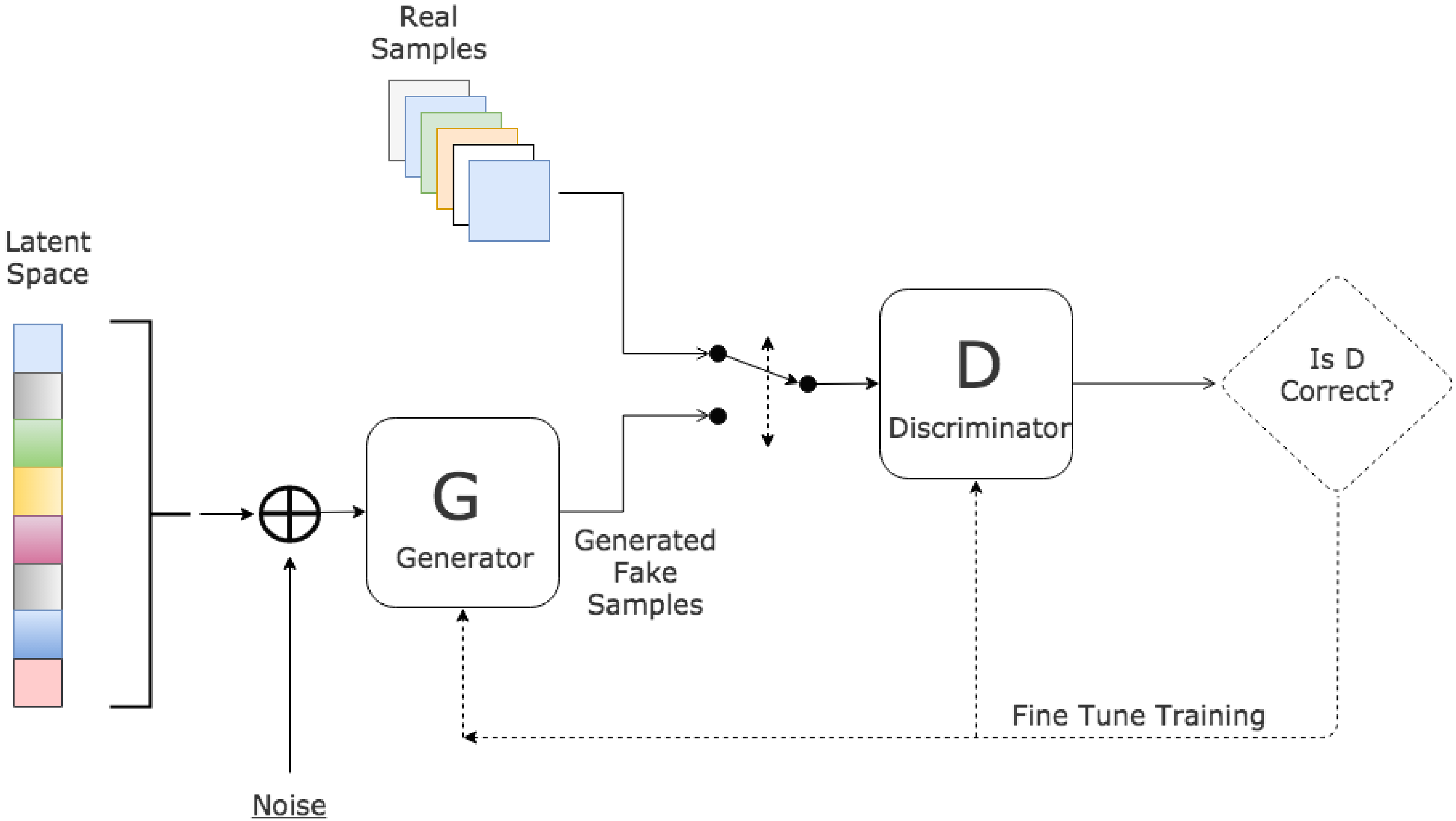
Generative Adversarial Networks



https://akshaynathr.wordpress.com/2018/01/02/gan-generative-adversarial-network/

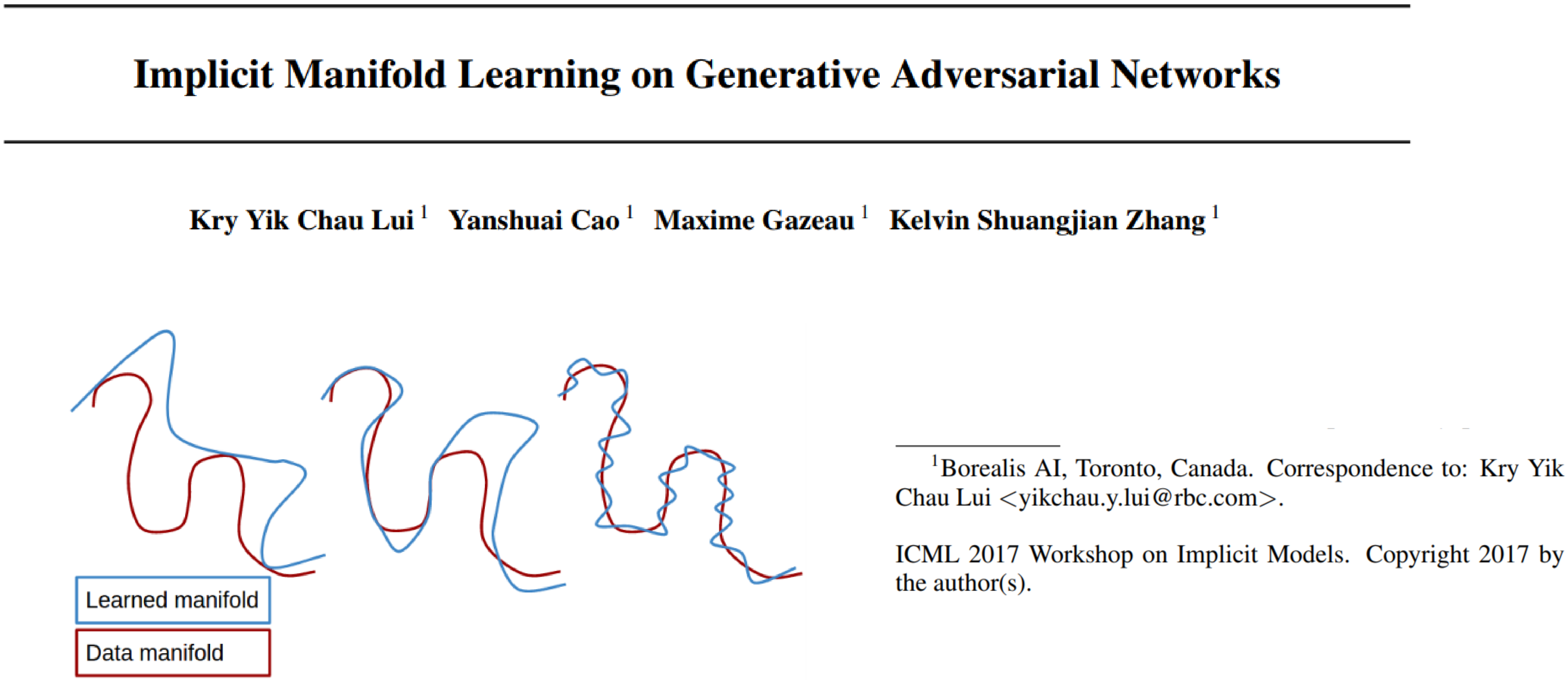
Goodfellow, Ian; Pouget-Abadie, Jean; Mirza, Mehdi; Xu, Bing; Warde-Farley, David; Ozair, Sherjil; Courville, Aaron; Bengio, Yoshua (2014). "Generative Adversarial Networks".

Generative Adversarial Network



https://stats.stackexchange.com/questions/277756/some-general-questions-on-generative-adversarial-networks

Manifold Learning through GAN ?



Implicit Manifold Learning on Generative Adversarial Networks

Kry Yik Chau Lui [1] Yanshuai Cao [1] Maxime Gazeau [1] Kelvin Shuangjian Zhang [1]

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[1] Borealis AI, Toronto, Canada. Correspondence to: Kry Yik Chau Lui <yikchau.y.lui@rbc.com>.

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