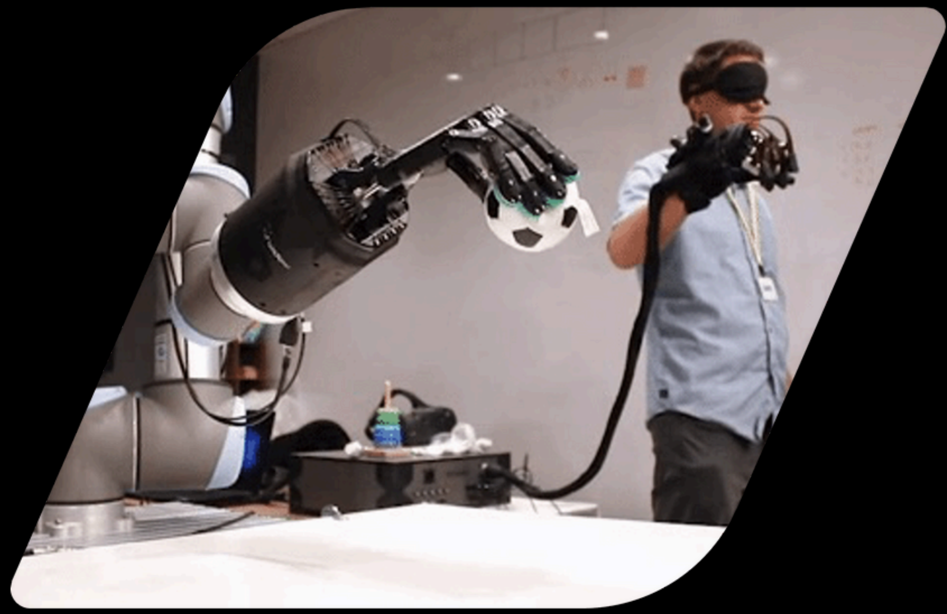
An Interactive Approach for Teaching Flow Matching

By Dylan, Hayley and Isaac

Motivation

Image Generation and Frame Prediction



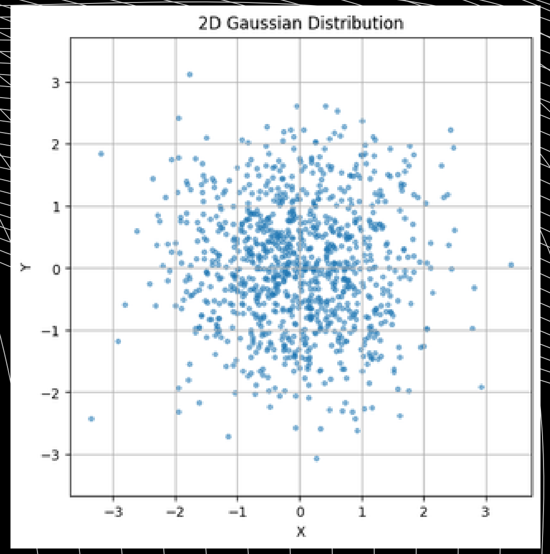
The Main Problem

Image Dataset

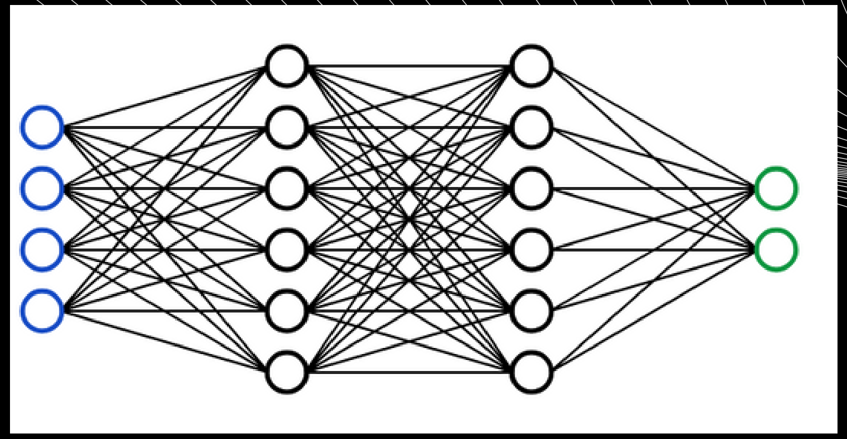
Flow Matching

A black box
(at least for now)

Input



Trained Model

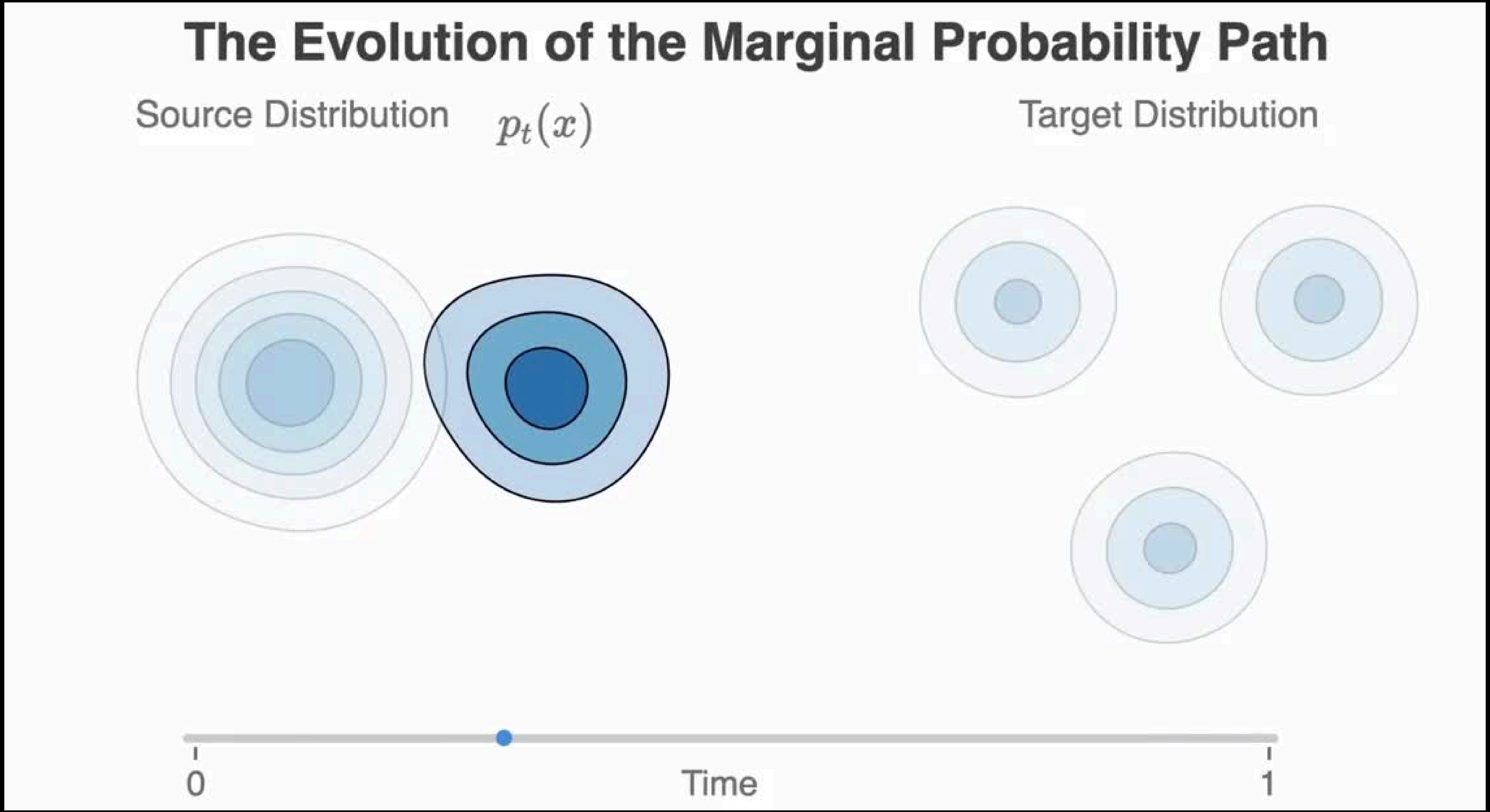


Source: Victor Zhou – Neural Networks from Scratch – victorzhou.com

Output

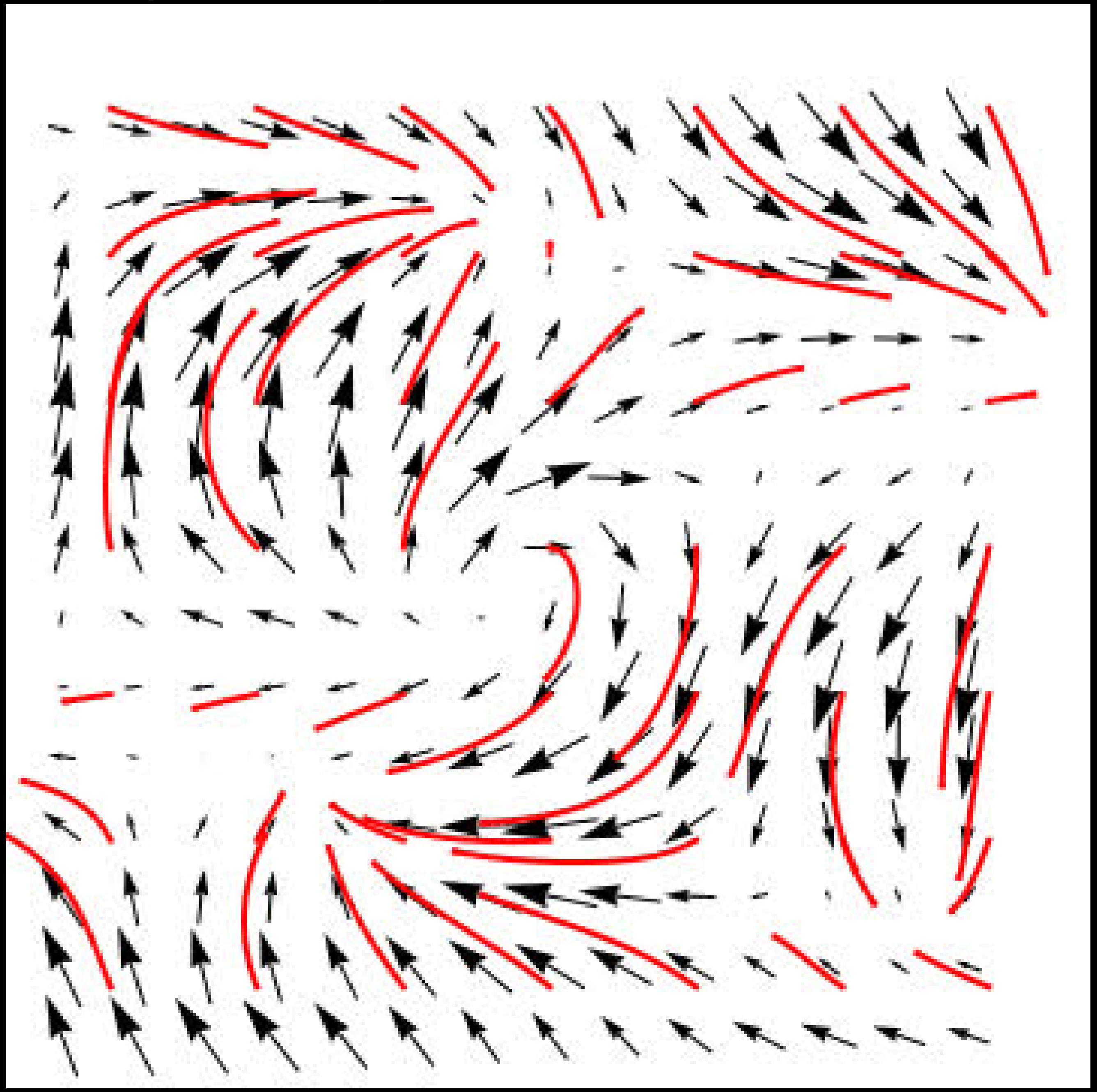
Dataset – MNIST

The numbers dataset


The Evolution of the Marginal Probability Path
Source Distribution
$p_t(x)$
Target Distribution
0
Time
1

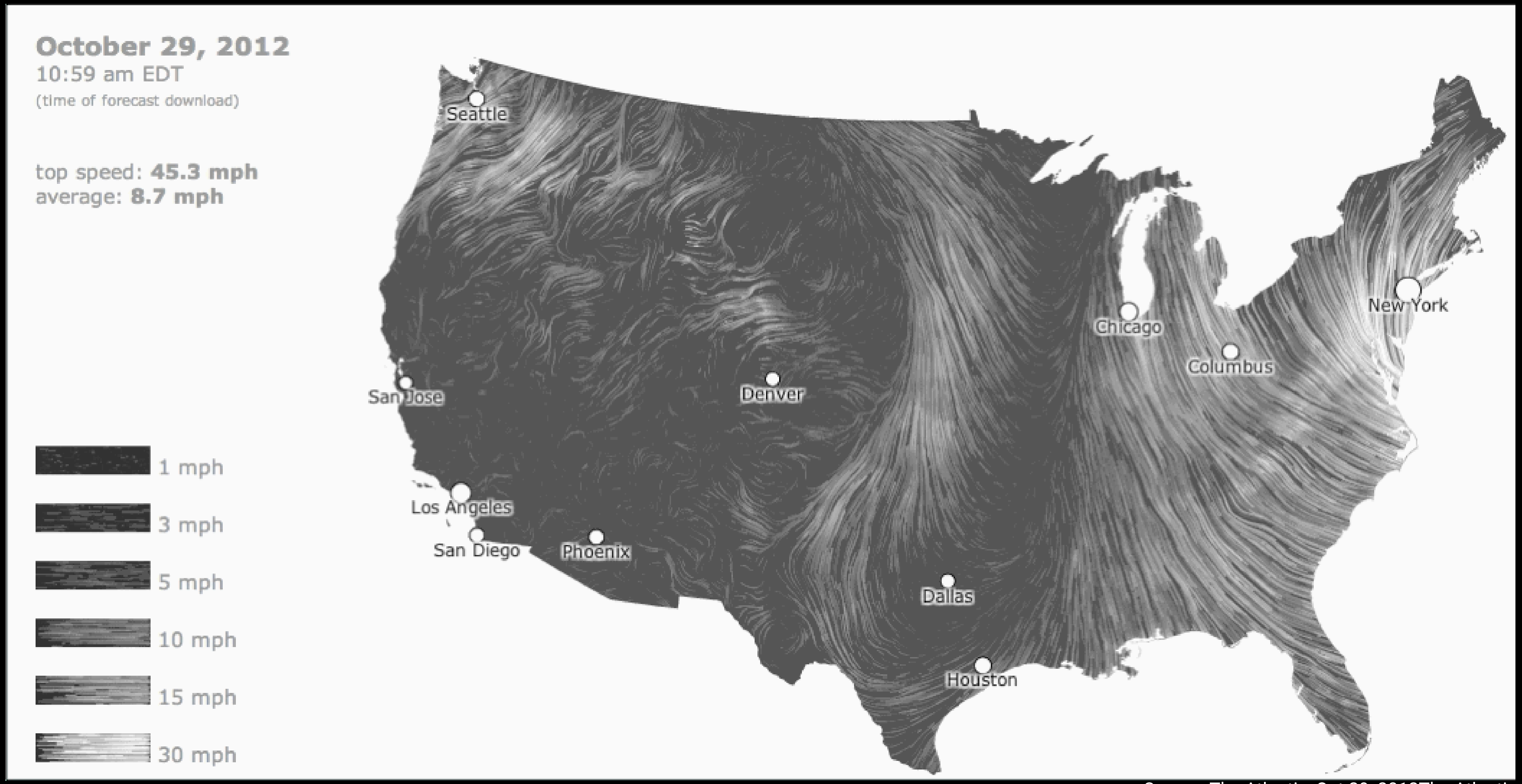
Vector Fields

A representation of vectors of each point in space

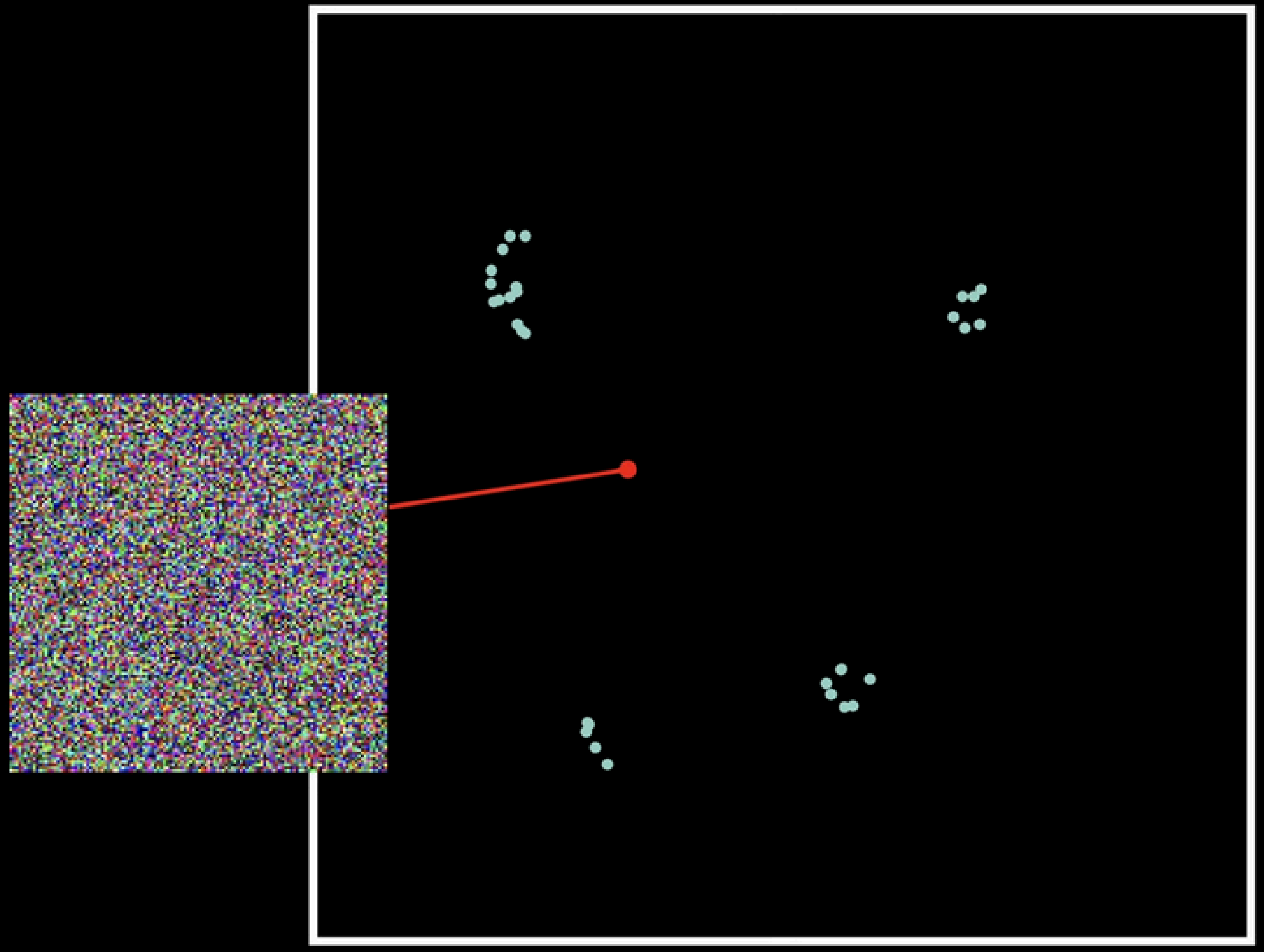


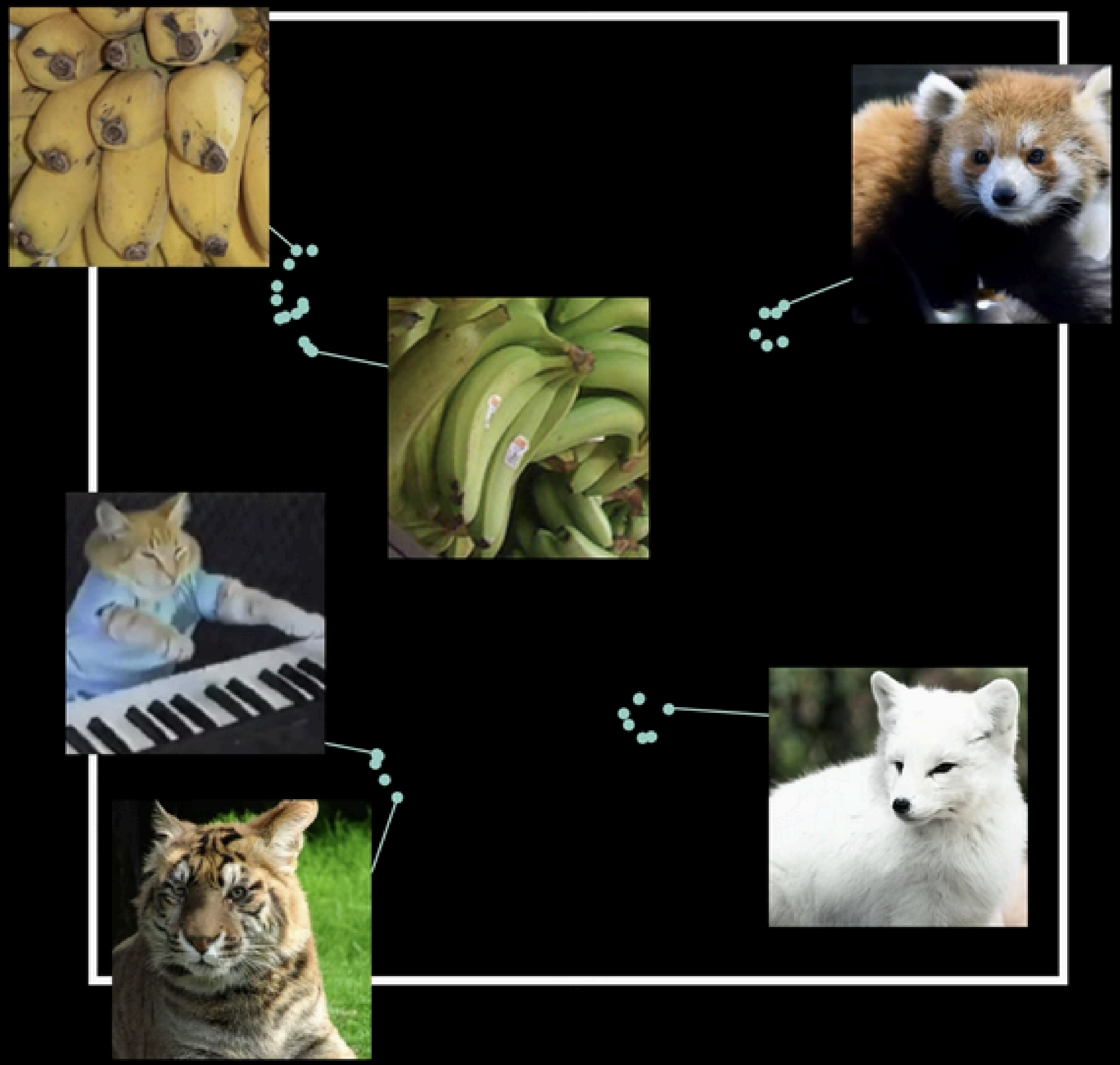
Vector Fields

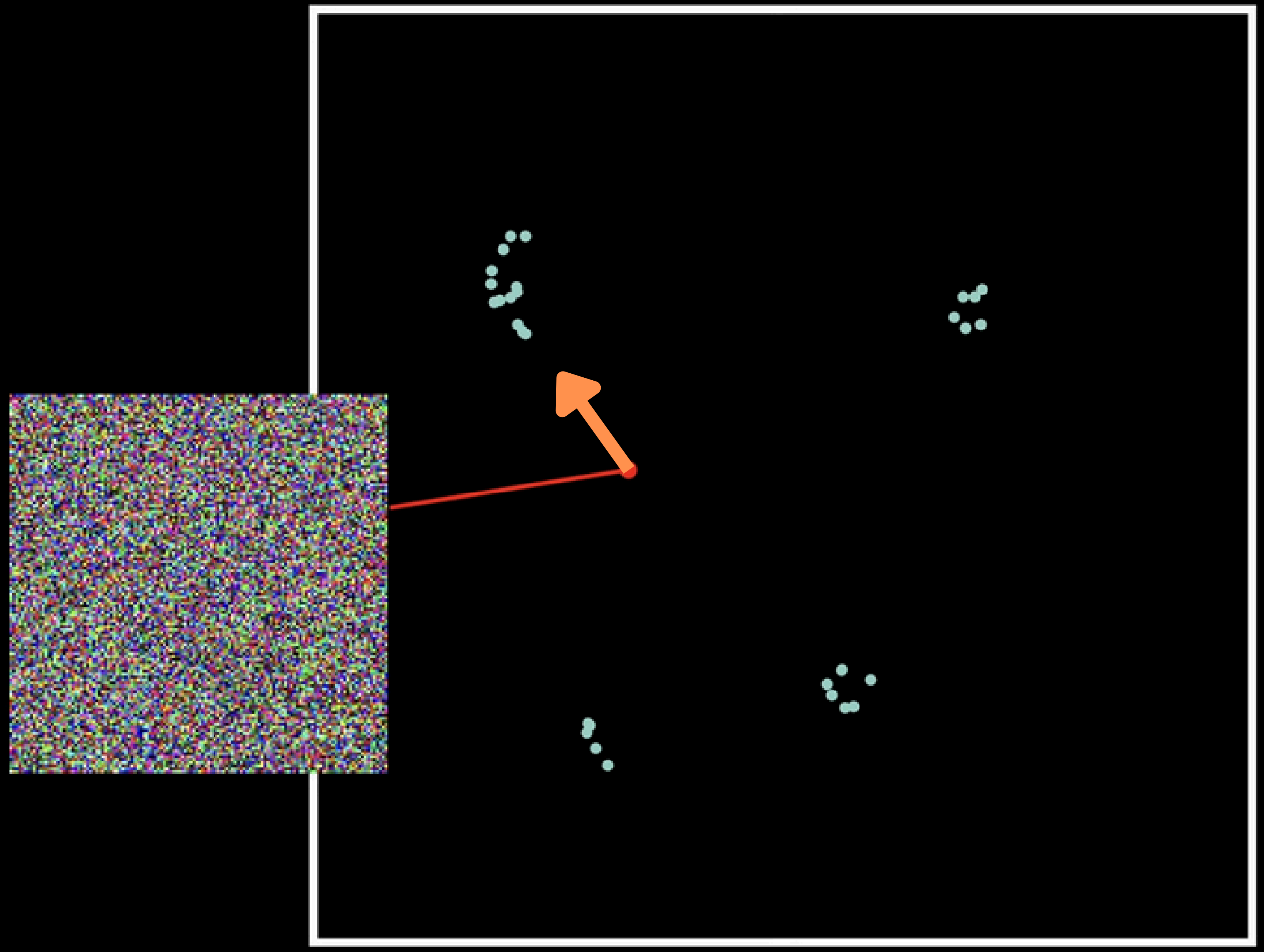
A real word representation

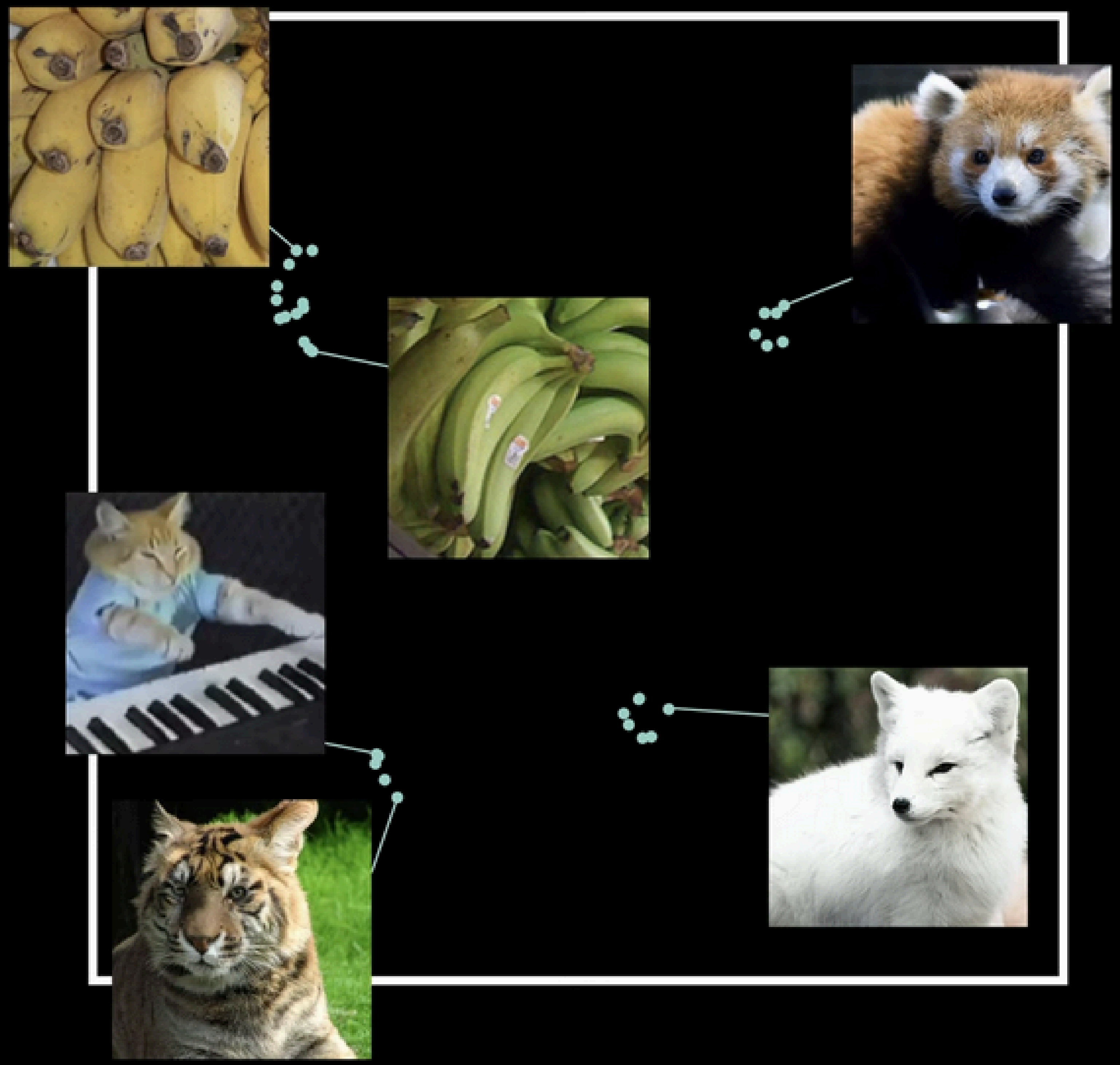


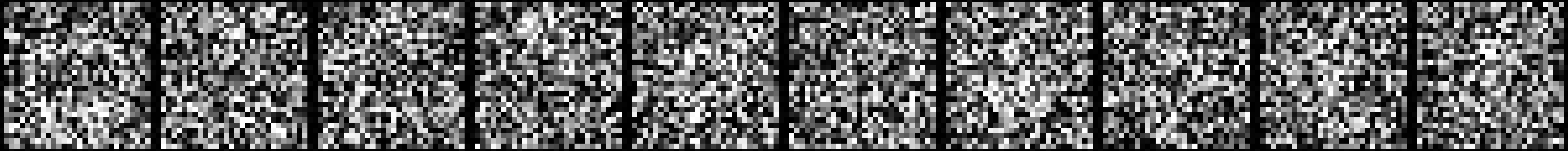
Source: The Atlantic, Oct 29, 2012The Atlantic





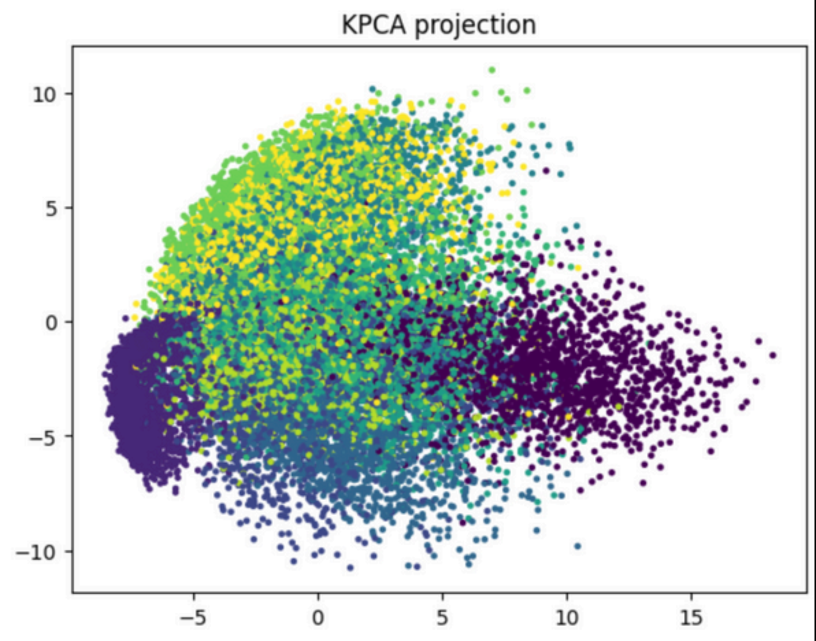


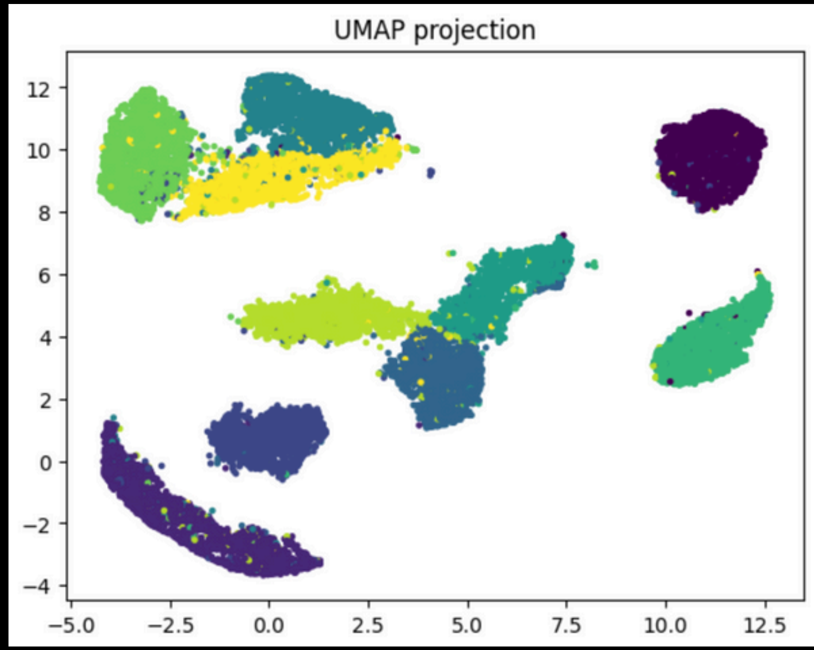


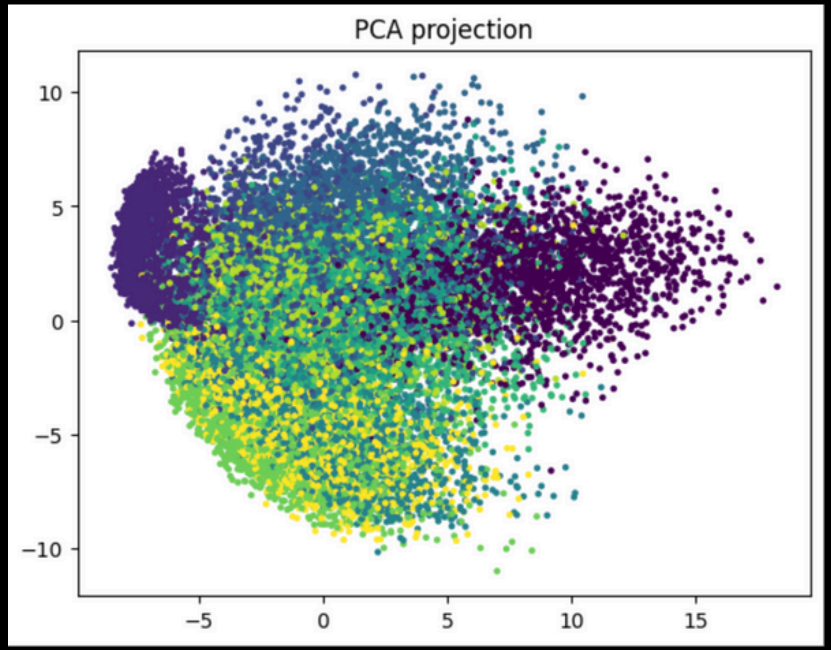


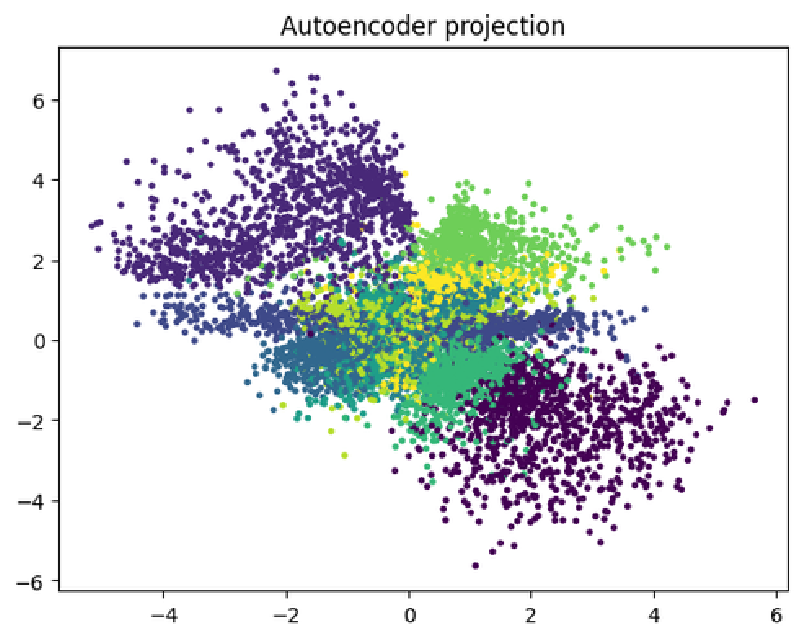
In reality…

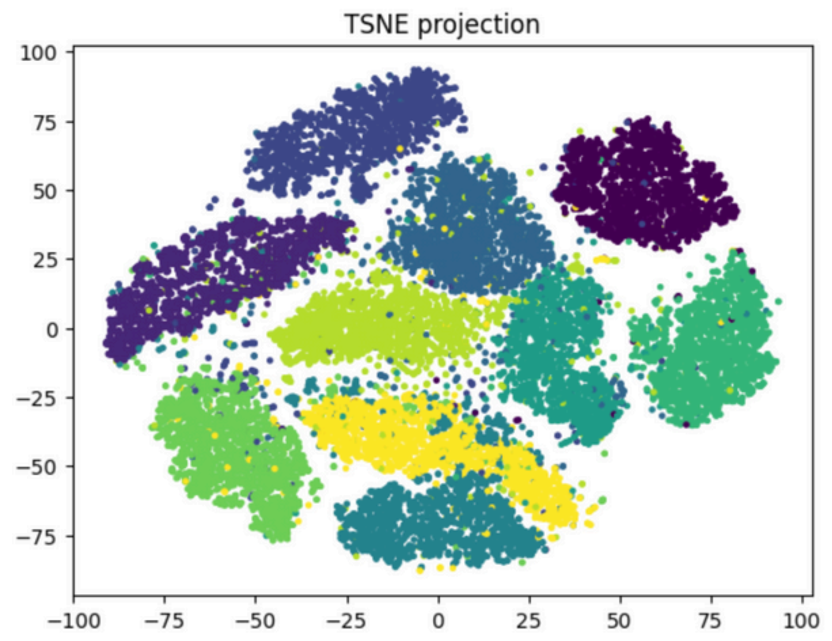
Latent Space Representations



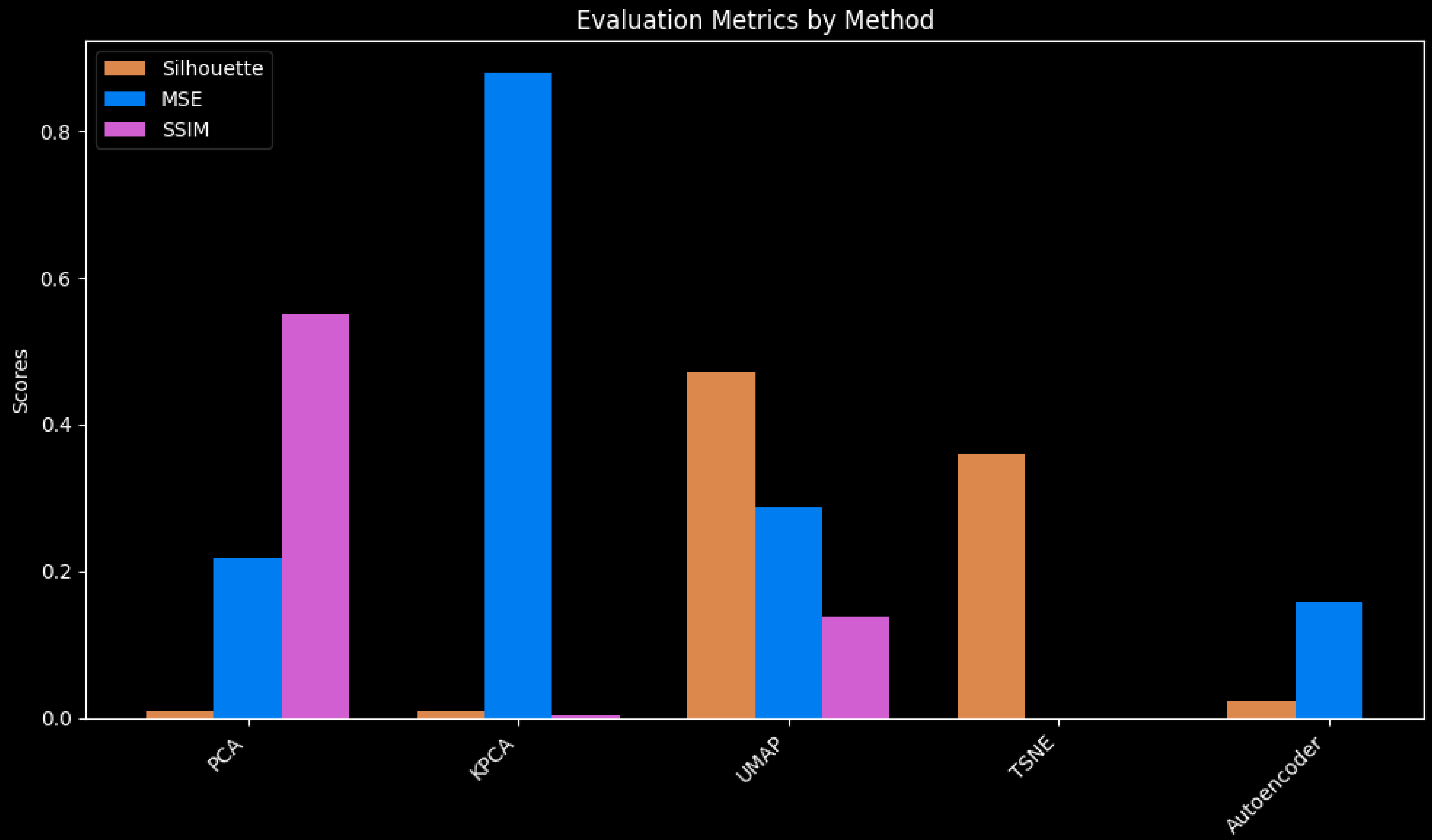




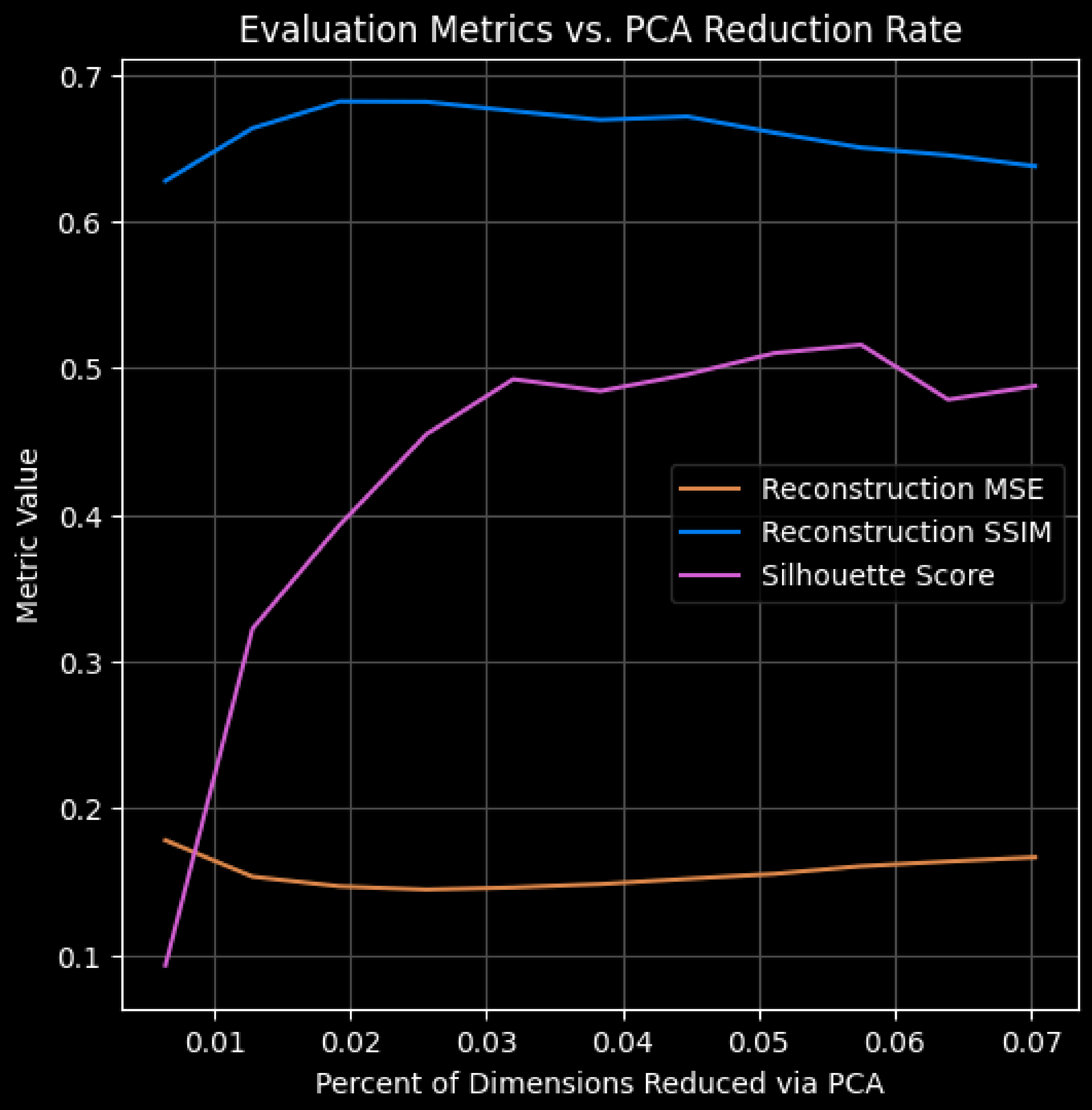


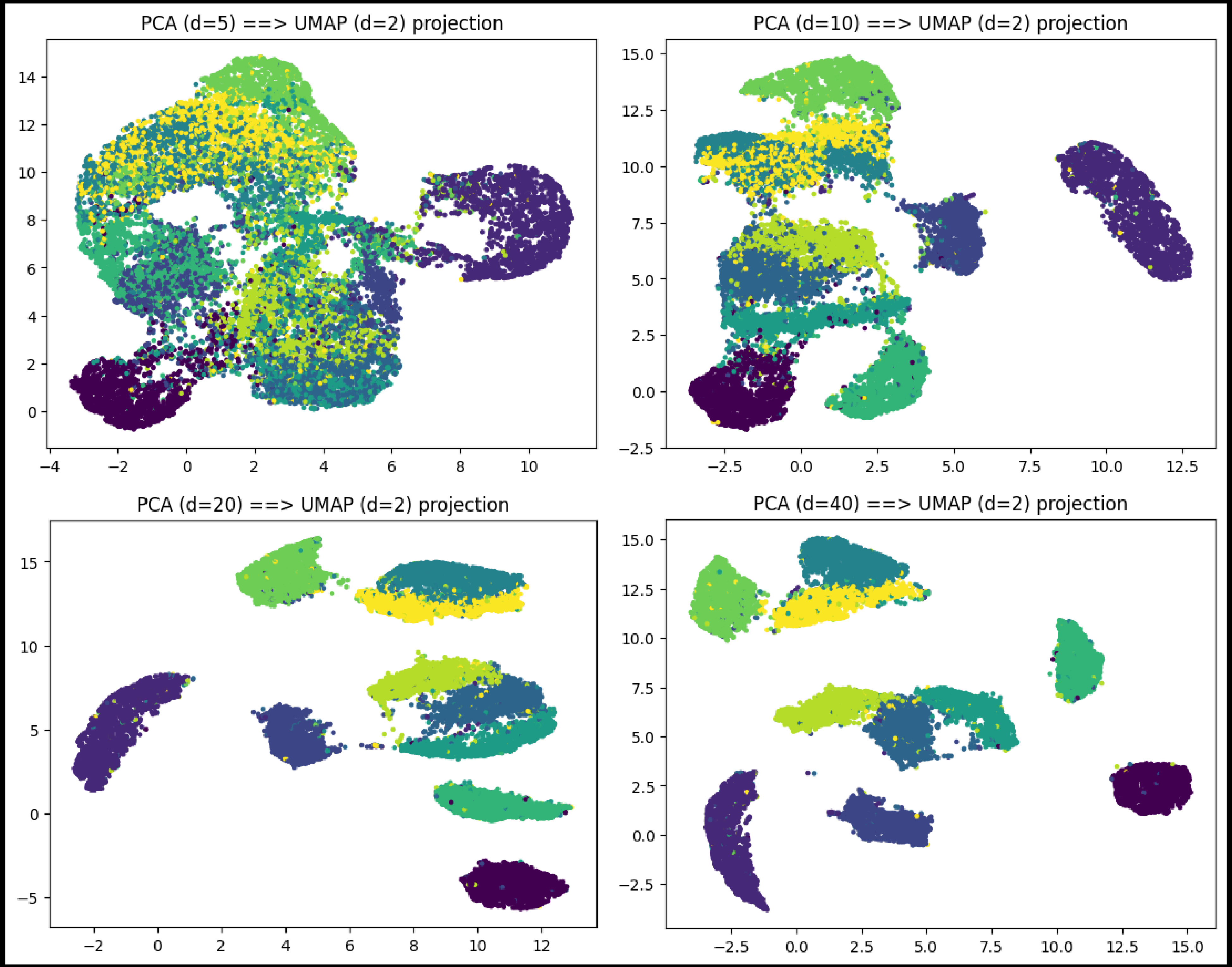


Comparing Approaches

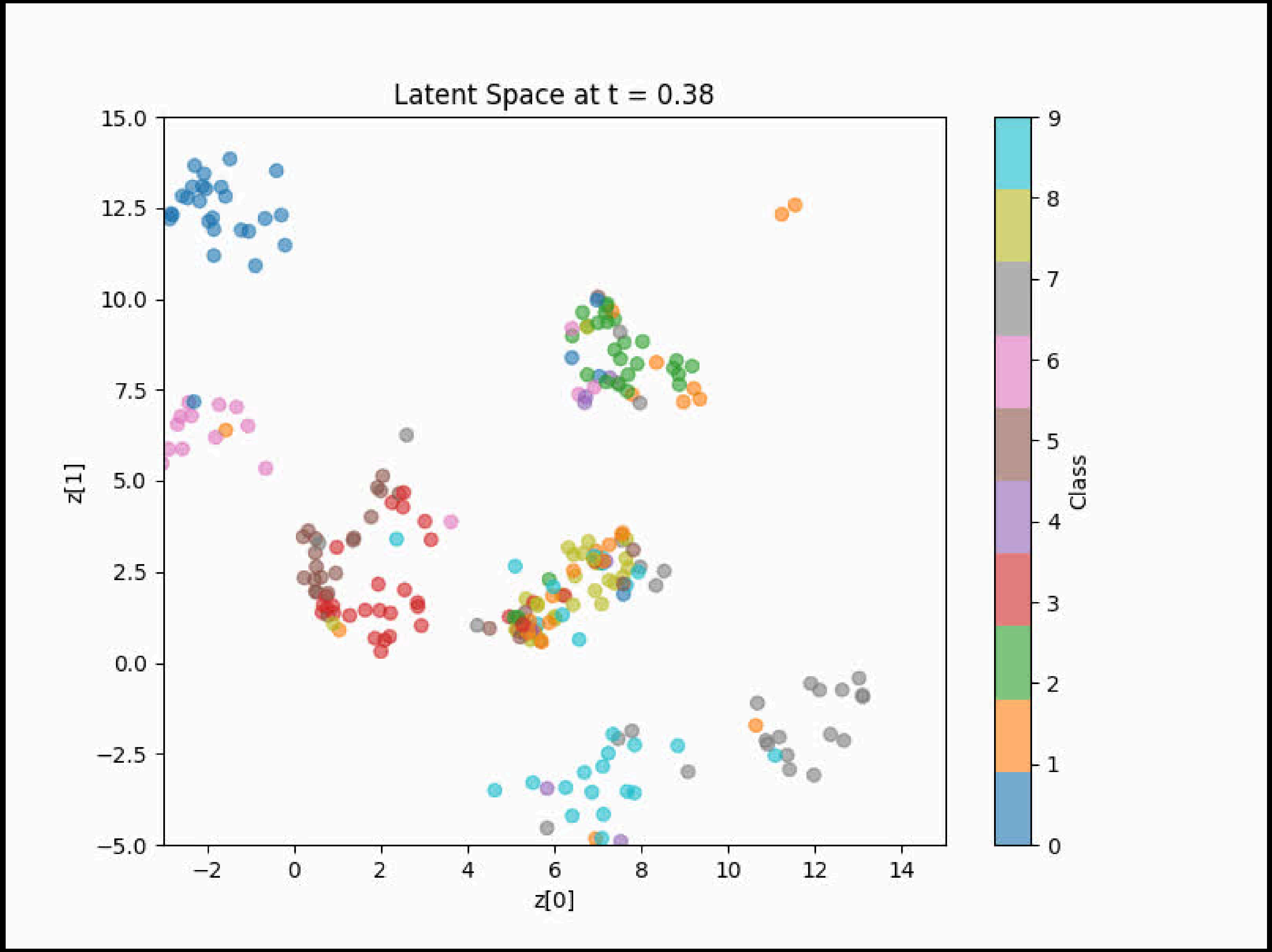


Combining PCA and UMAP

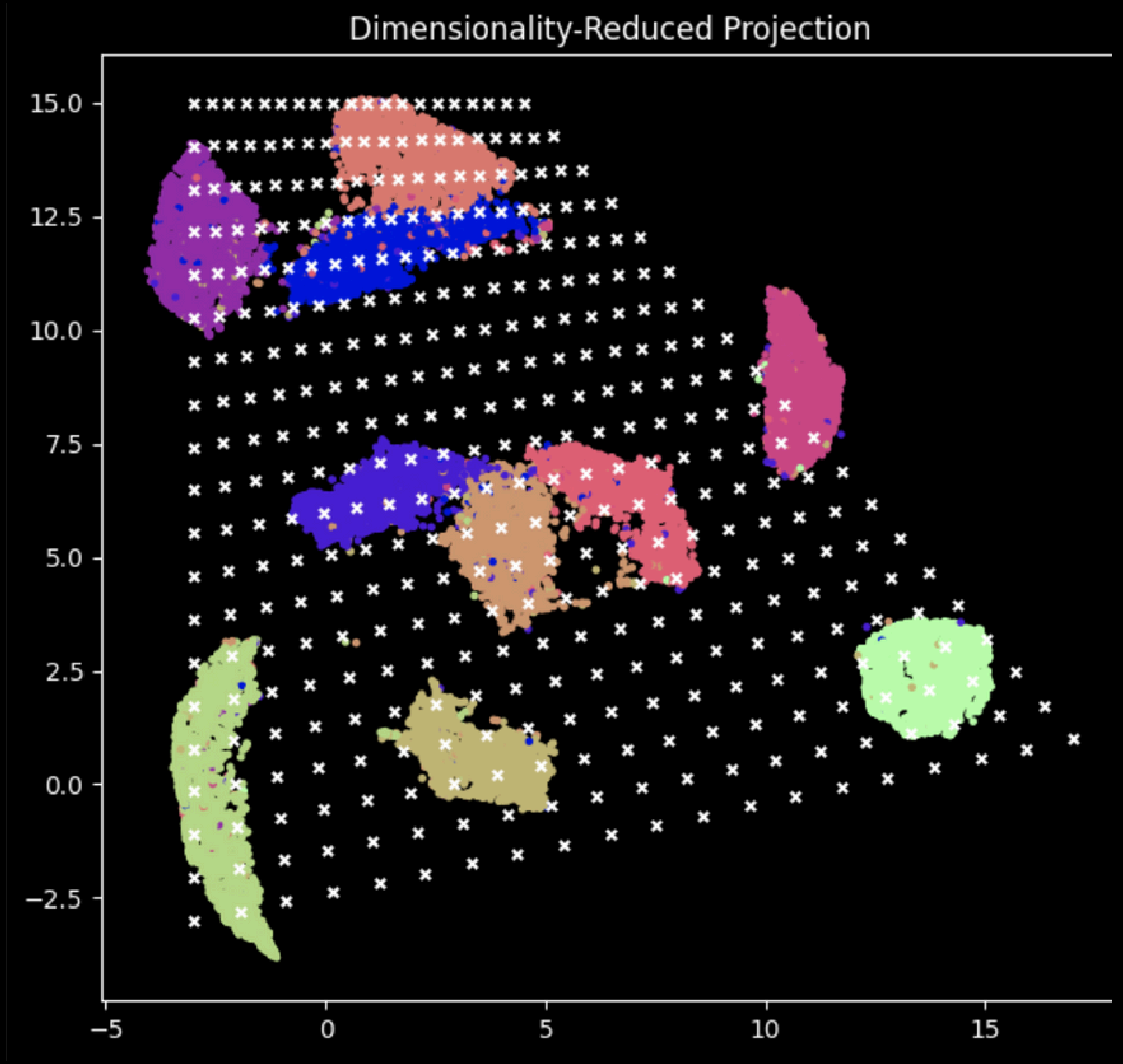


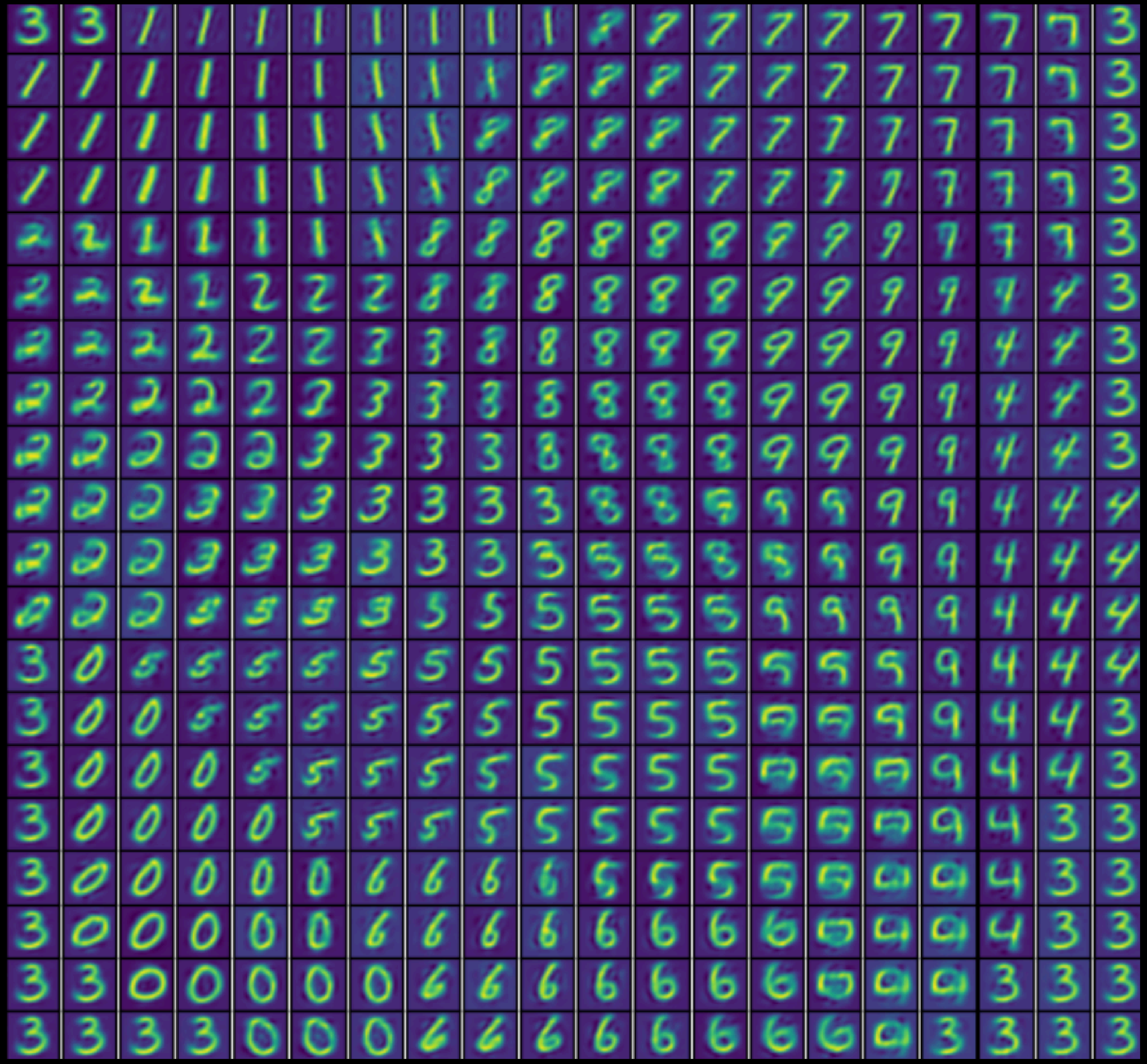


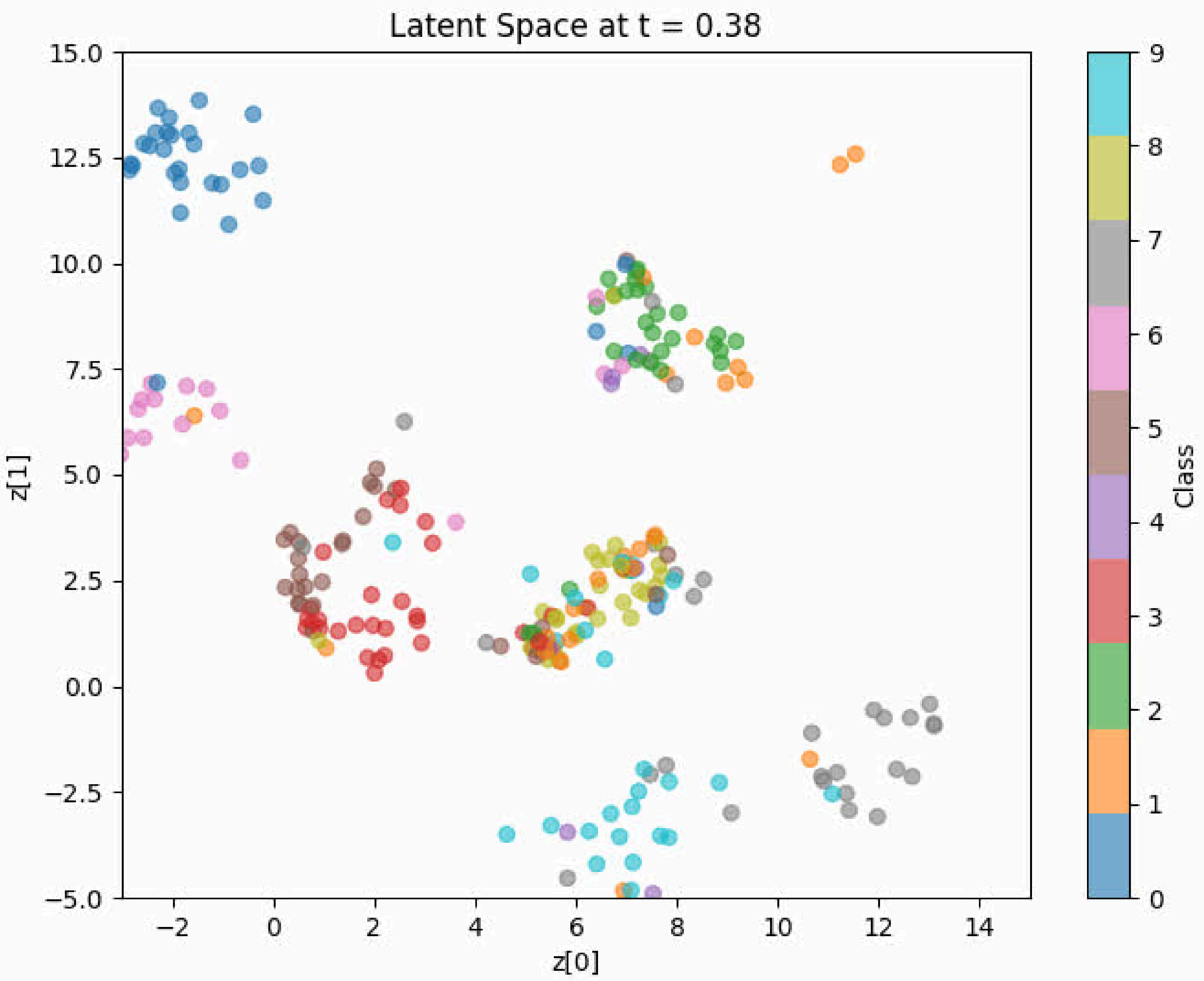
Combining PCA and UMAP



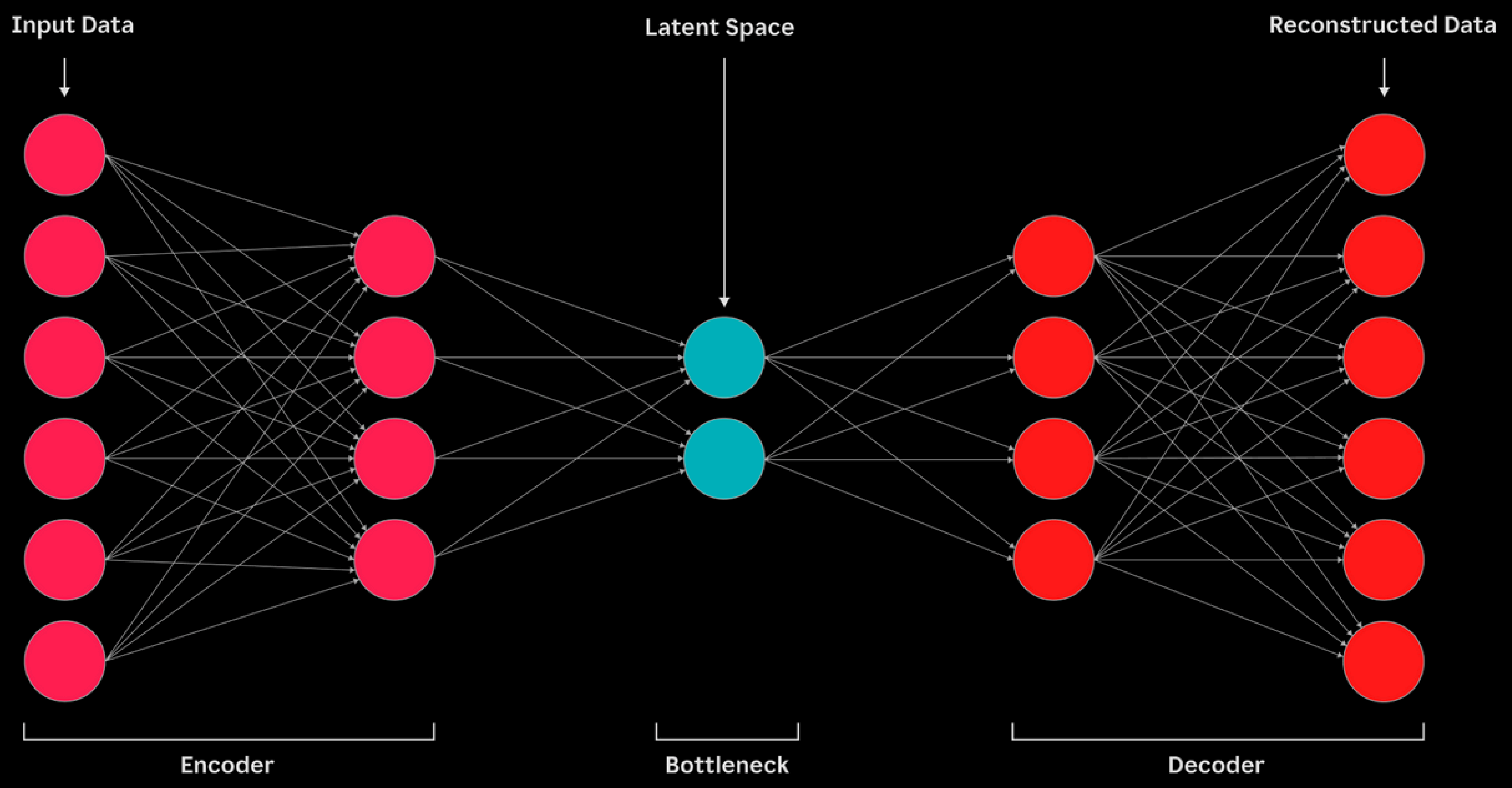
Latent Spaces



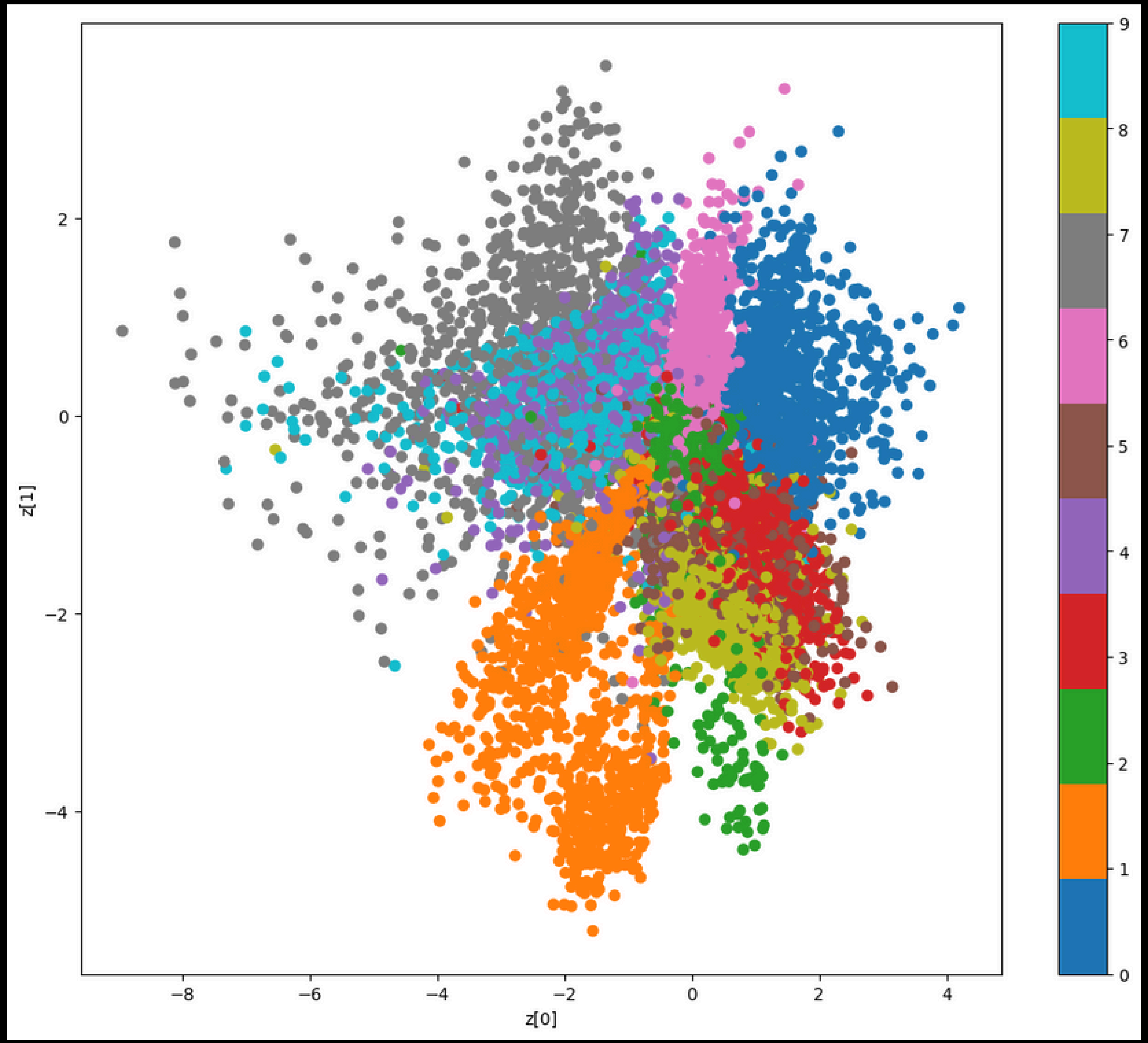


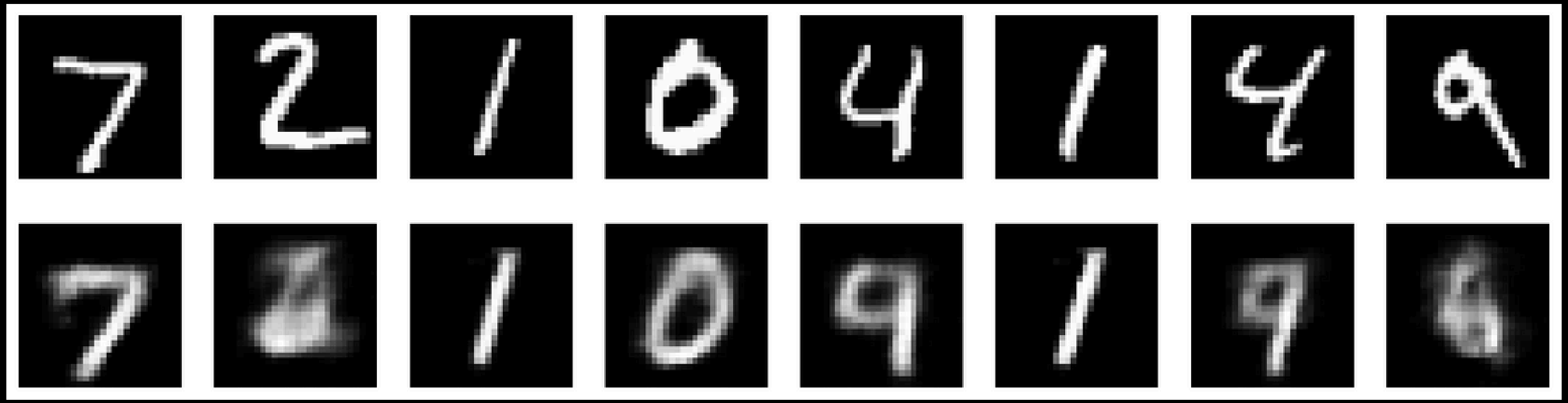

Latent Space at t = 0.38
z[0]
z[1]
Class
15.0
12.5
10.0
7.5
5.0
2.5
0.0
−2.5
−5.0
−2
0
2
4
6
8
10
12
14
0
1
2
3
4
5
6
7
8
9

Let’s try Autoencoders!

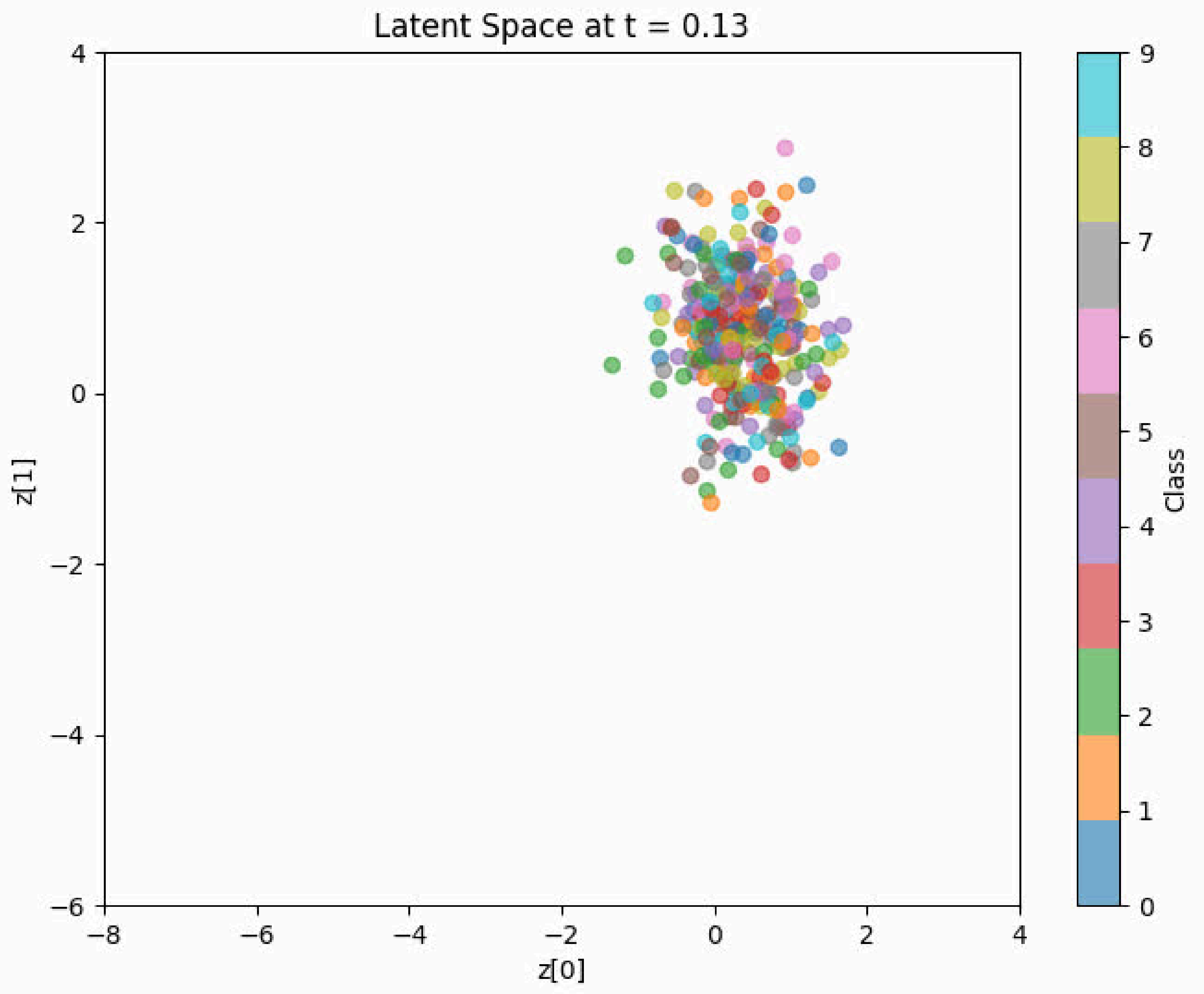


2 Dimensional Autoencoder





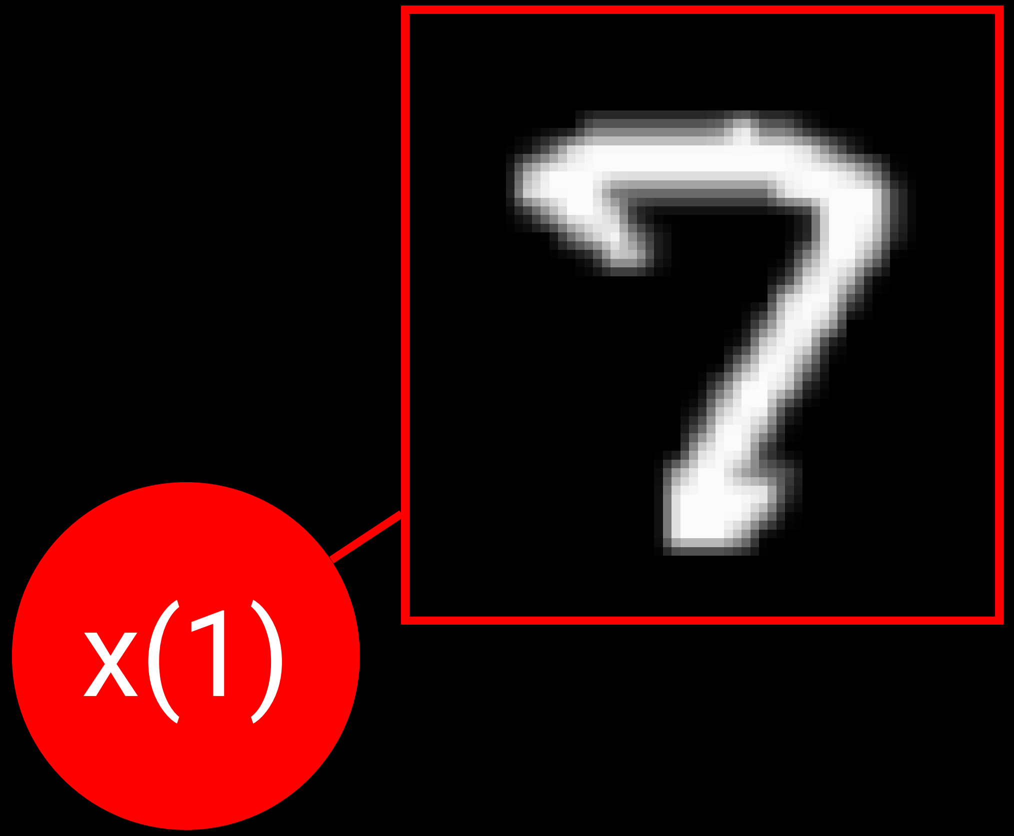
Now to Apply to FM


Latent Space at t = 0.13
z[0]
z[1]
Class
−8
−6
−4
−2
0
2
4
−6
−4
−2
0
2
4
0
1
2
3
4
5
6
7
8
9

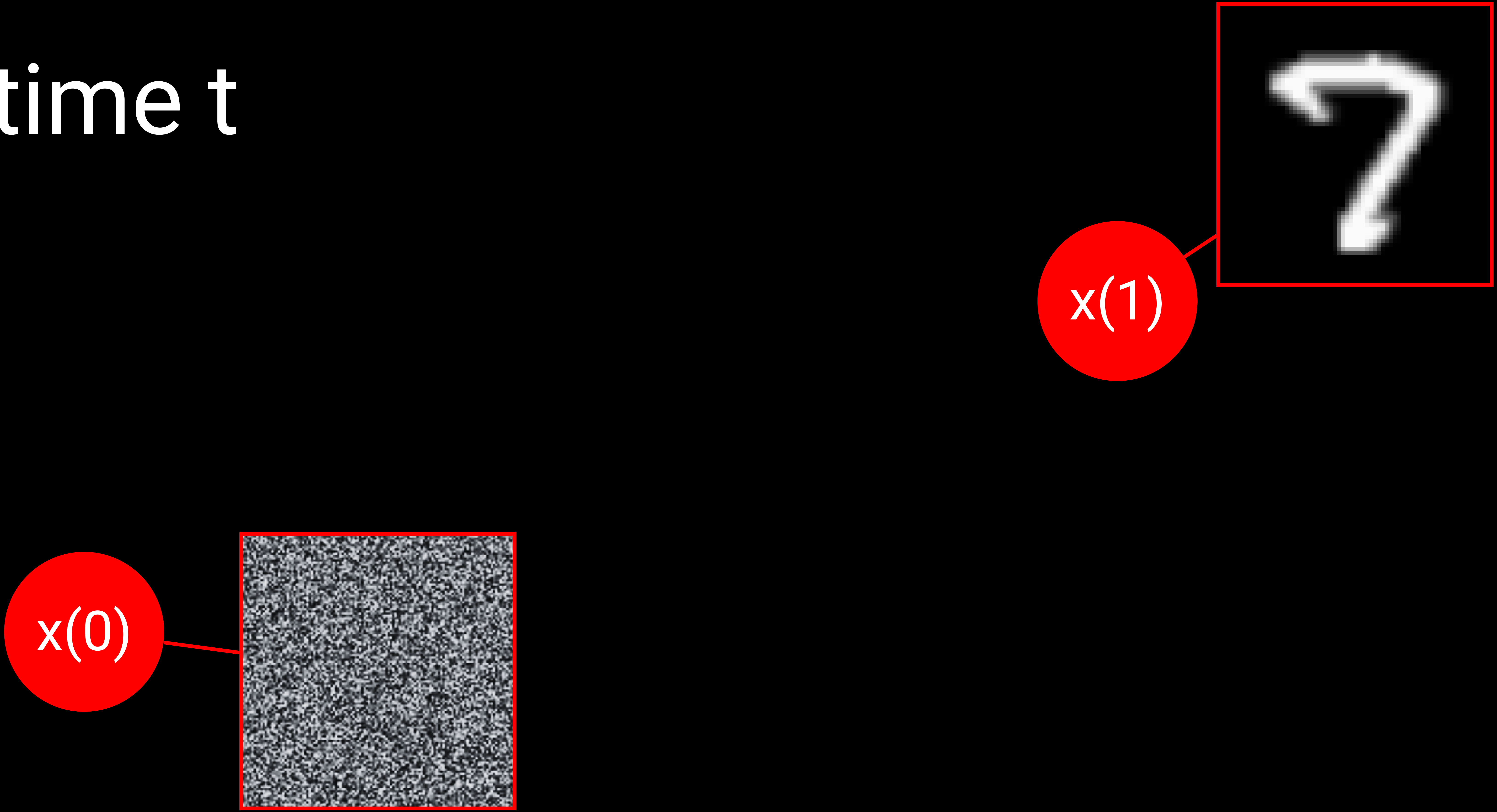
How do we train the model?

(Flow Matching Process)

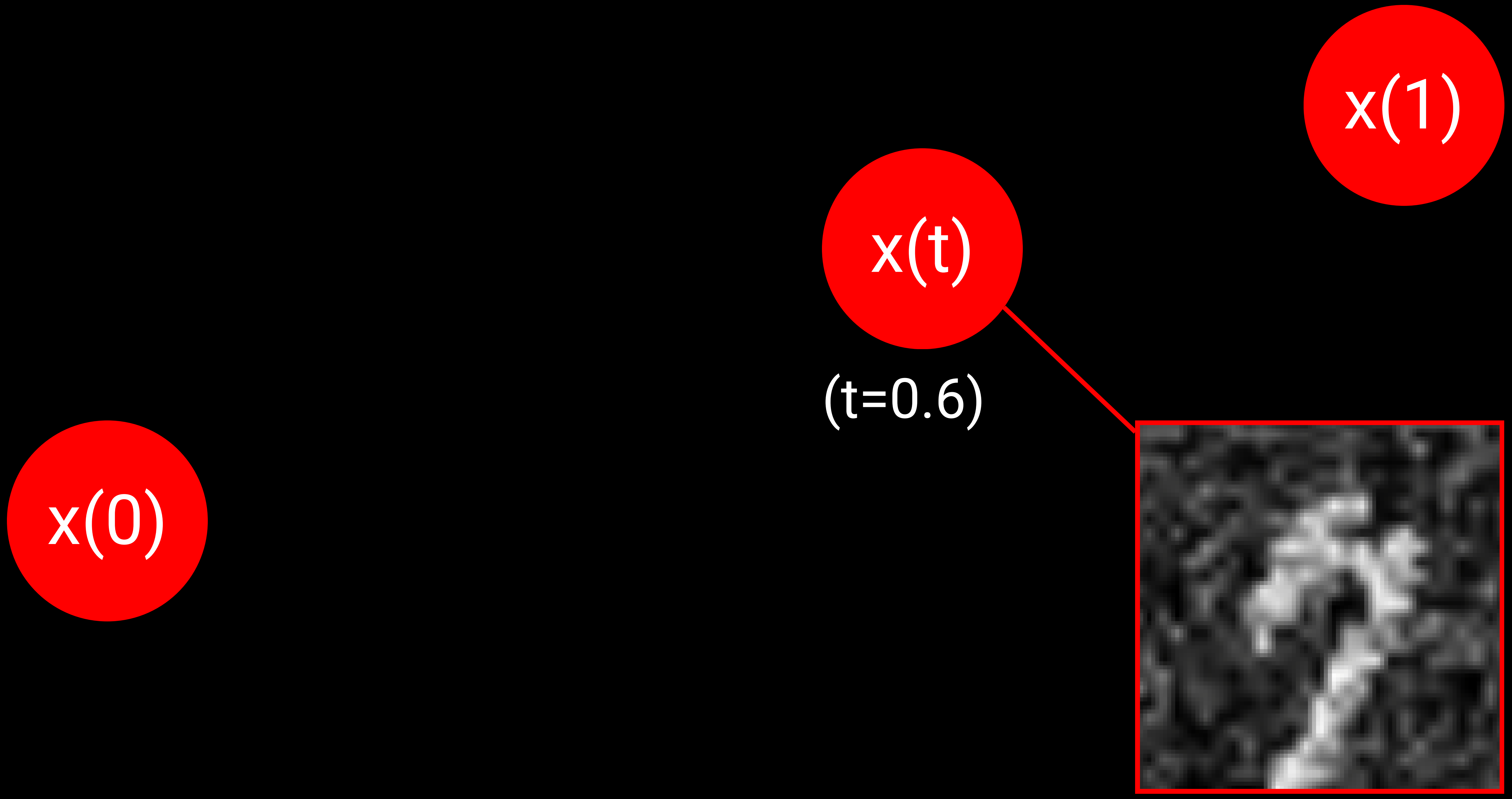
At time t



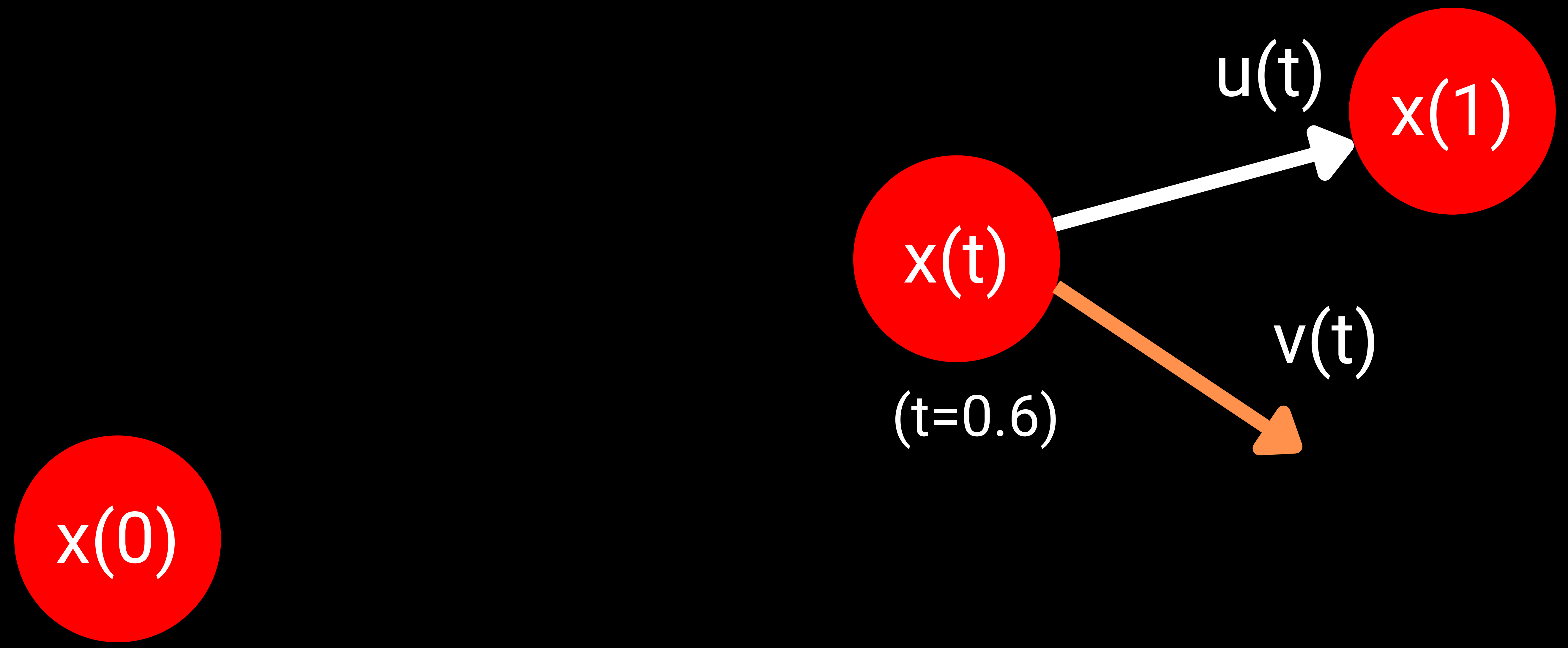
At time t



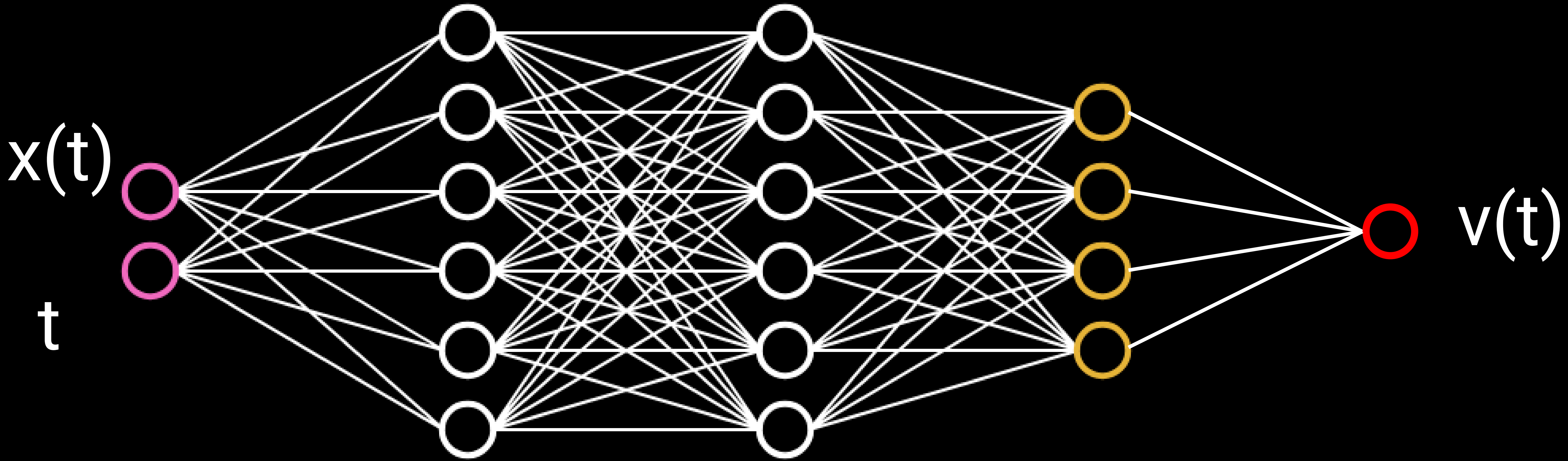
At time t



At time t



Flow Matching Model



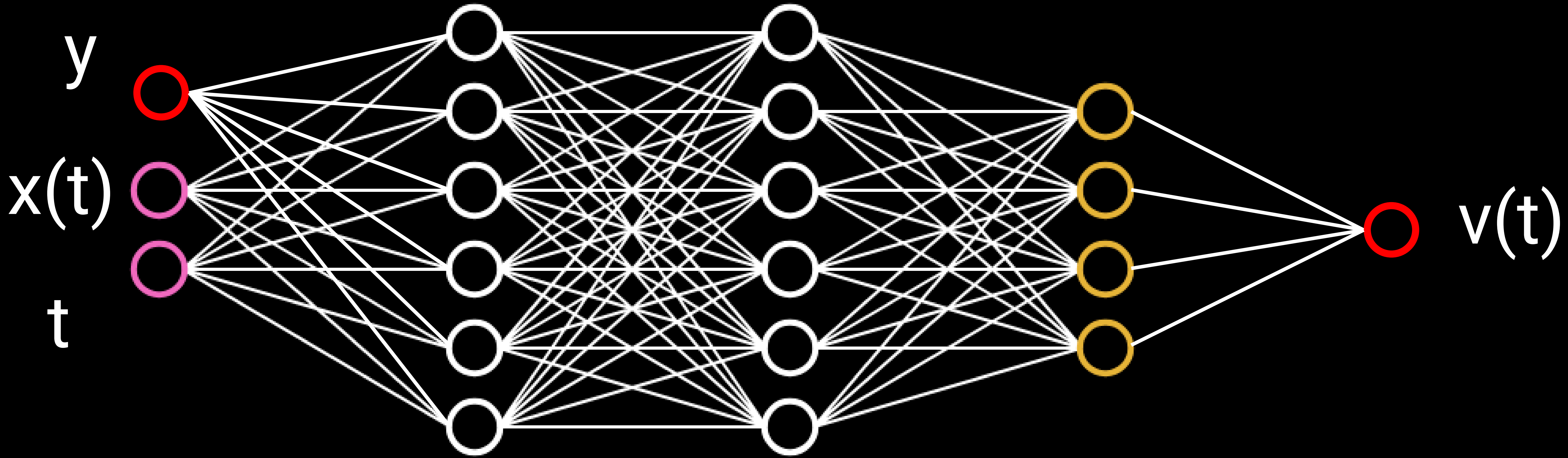
Source: Victor Zhou – Neural Networks from Scratch – victorzhou.com

Simplifications we Made

- This process is called Exact Optimal Transport FM, there are others

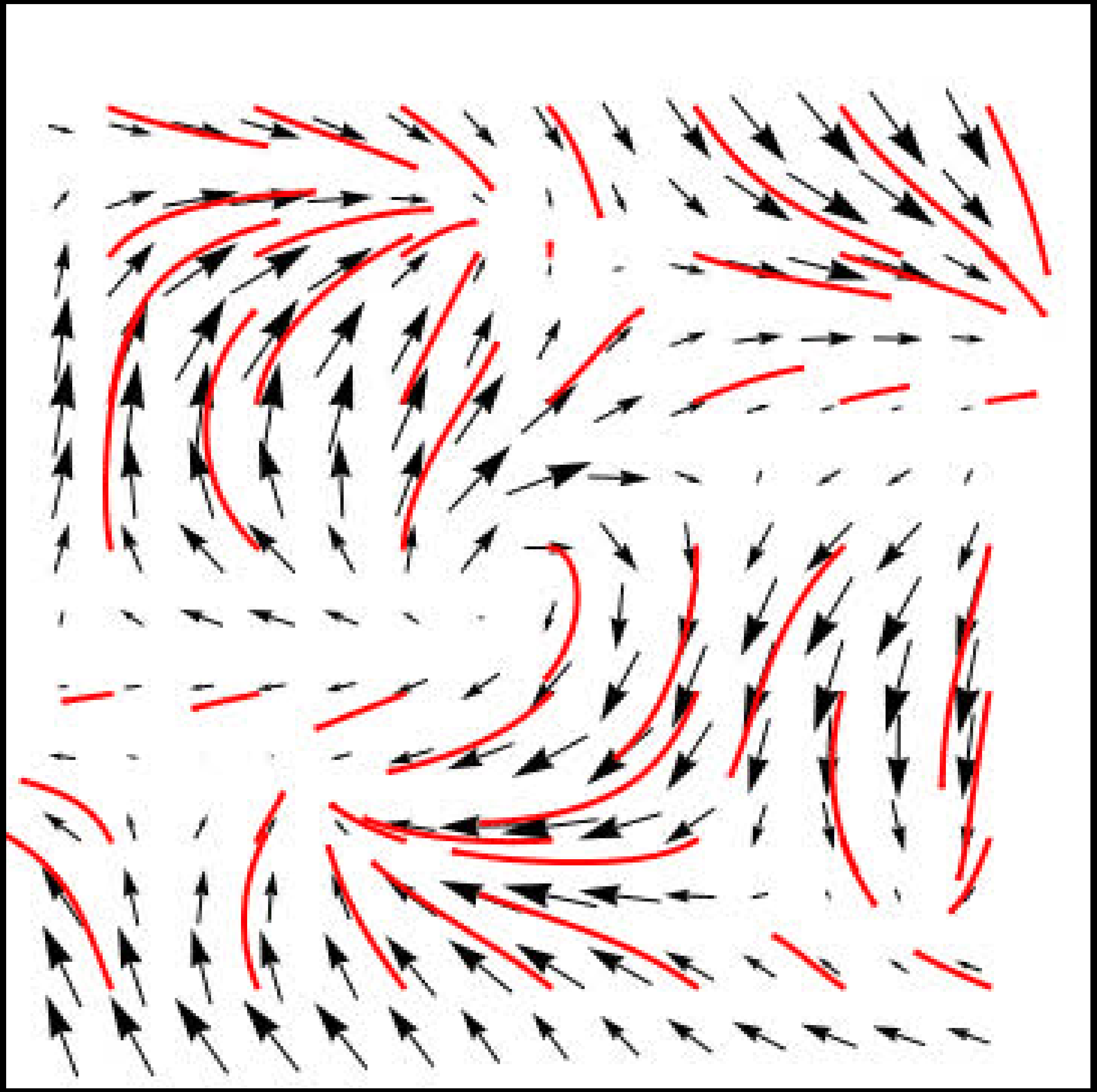
- In order to generate all MNIST numbers, we add a class conditioning input as well.

Conditional Flow Matching Model



Source: Victor Zhou – Neural Networks from Scratch – victorzhou.com

Neural ODE



Conditional vs Marginal Probability Paths

Conditional Probability Path

The transformation from a gaussian distribution to a single point
Hasfura, 2025

Marginal Probability Path

The distribution that results from first sampling a z from p_data and then sampling from the CPP p_t(x|z).
Hasfura, 2025

Flow Matching

Learn global vector field by aggregating conditional probability paths to match the evolution of the marginal probability distribution over time.

Confusing Terms

Probability Path

The entire state of the latent variables' probability distribution of changes at a point in time.
ie. probability of leaf flowing in a direction

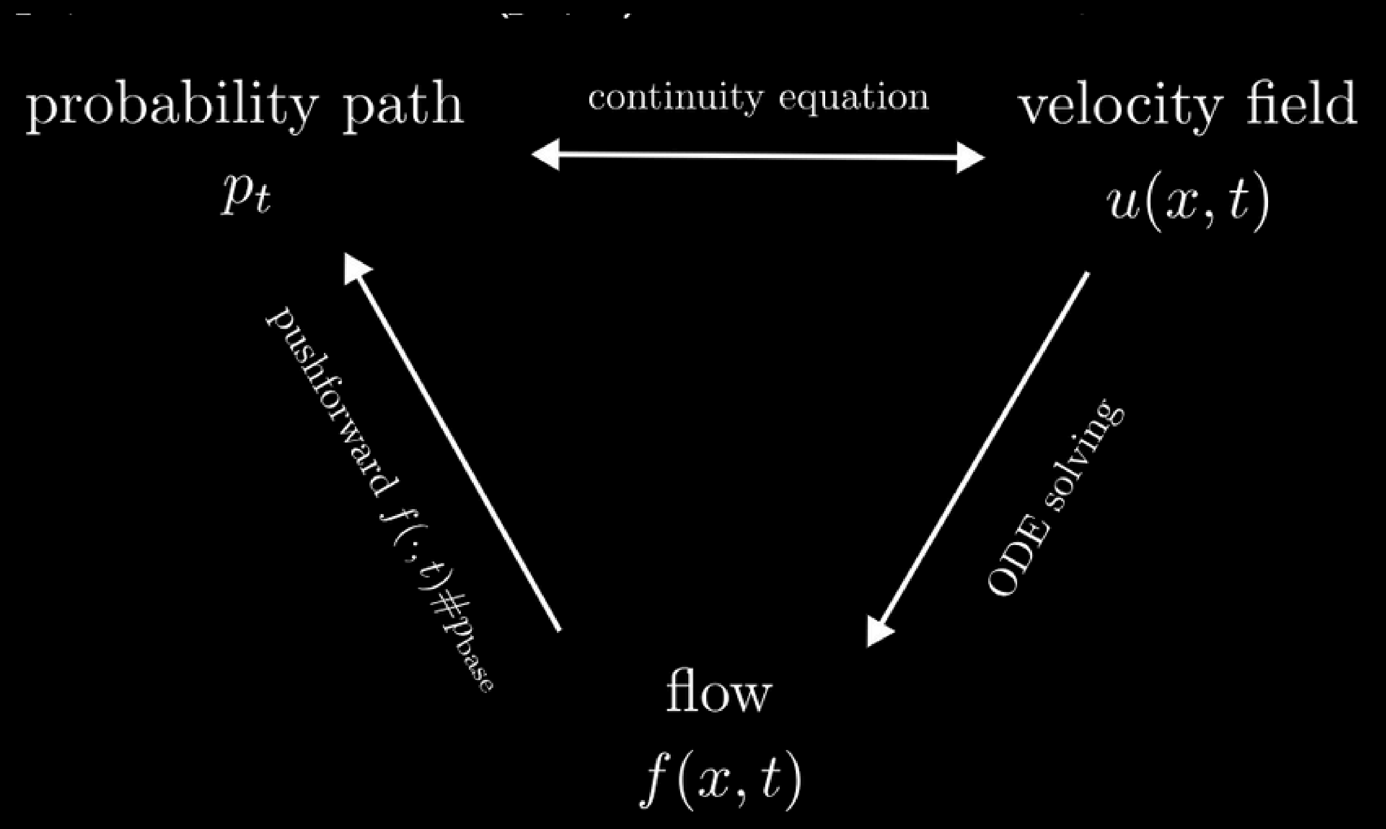


Figure 4. Link between the probability path, the velocity field and the flow.

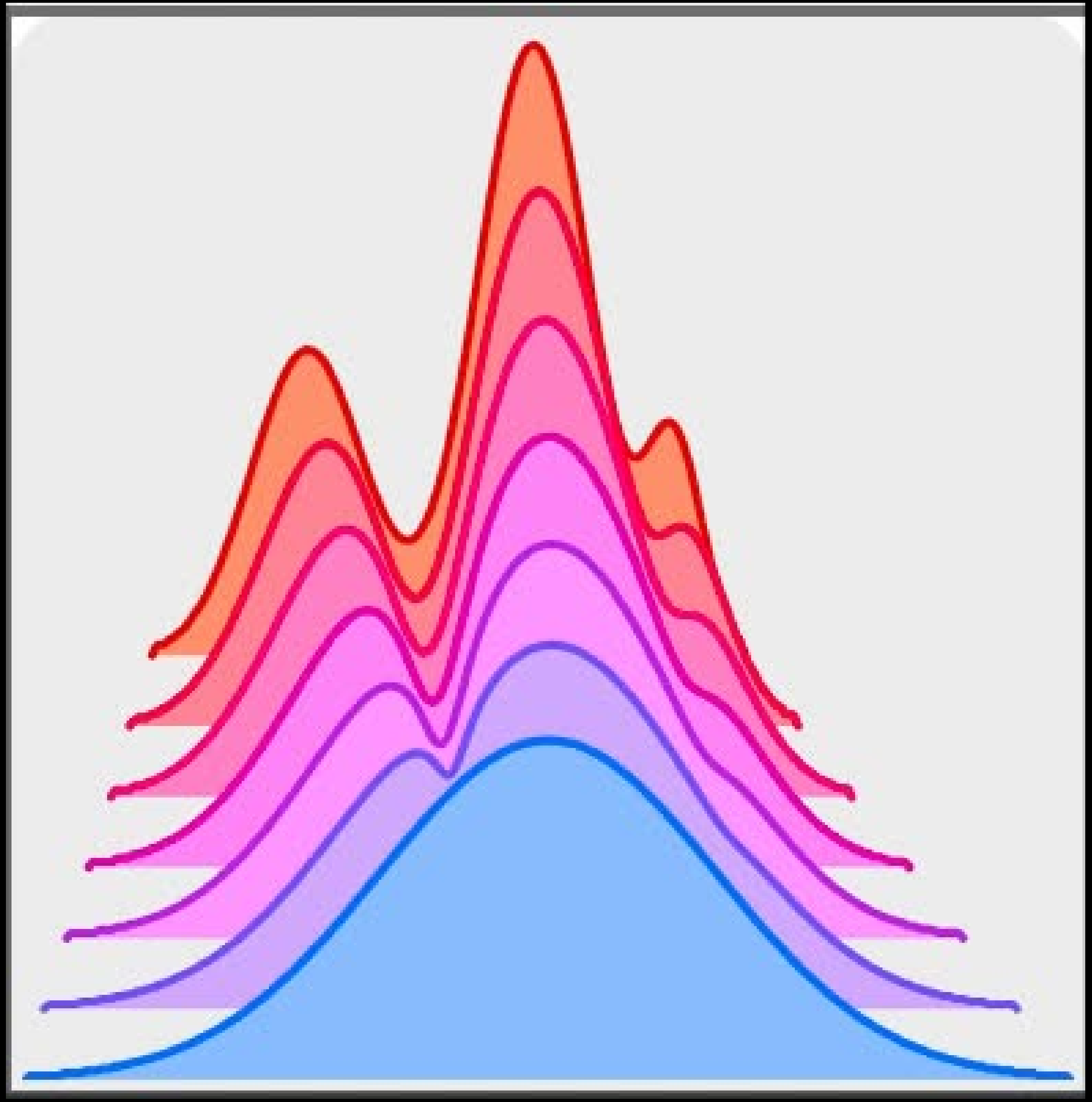
Vector/Velocity Field

At this moment in time, a particle should move this fast in a specific direction.
ie. how fast we think and what direction we think a leaf will go in a creek

Flow

The actual trajectory of x(t) over.
ie. actual path leaf flows down in creek

Related Works



Variational Inference with Normalizing Flows (snapshots over time)

Use normalizing flow to change one distribution by modeling density distribution of latent variables and tracking distribution by predicting exact log probability.

Continuous-Time Flows for Efficient Inference and Density Estimation

Replace discrete steps with continuous transformation using ordinary differential equations for more efficient probabilistic model >> exact path to get to next point

Score-Based Generative Modeling through Stochastic Differential Equations

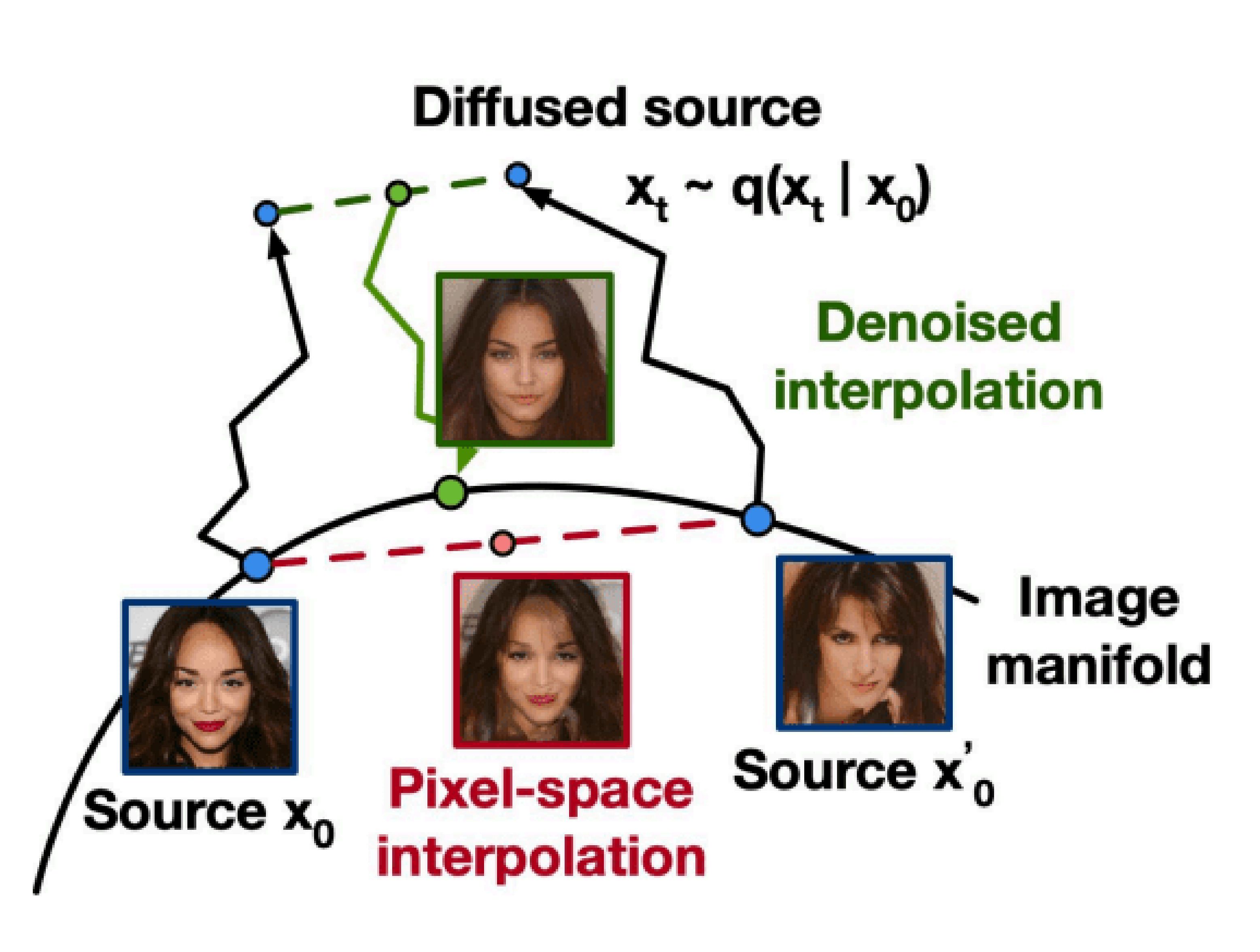
Learn direction that we should denoise with scoring guidance using score function. Think diffusion in continuous time math.

Denoising Diffusion Probabilistic Models

Gradually removing noise from image step by step

Flow Matching is now SoTA

Stable Diffusion 3.5



Flow Matching's Biggest Competitor

Diffusion vs. Flow Matching

Diffusion Models	Flow Matching
Discrete time or stochastic differential equation-based	Learn vector field through regression
Gradually remove noise step by step	Push starting x0 to goal data distribution
Slow (takes many steps, ie. 1000)	Efficient (via ordinary differential equation solver)

Key Insights & Retrospective

Unifies with Diffusion Models

Diffusion could be equivalant to flow matching in certain instances.

No Score Function Needed

Fast training and stable. Not prone to mode collapse like GANS and faster than basic diffusion.

Flexible Framework

Can encompass diffusion (learn denoising function), score-based models (diffusion model training on score function), and ODE-models

Flow Matching == Next Big Thing

Fast training and stable. Not prone to mode collapse like GANS and faster than basic diffusion.

Kahoot!

Try it yourself!

https://tinyurl.com/CSC566-FM-Notebook

https://tinyurl.com/CSC566-FM-Solution

Flow Matching Q & A

By Dylan, Hayley and Isaac