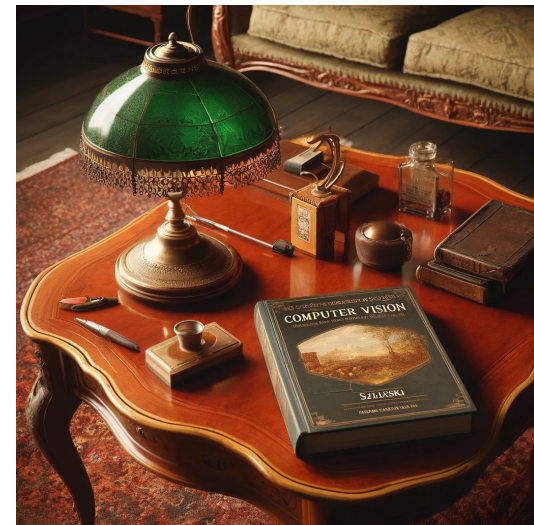


# **Quiz 10 (on Canvas)**

**Ends at 1:06pm**

# CS5670: Computer Vision

## Diffusion models



“A copy of a computer vision textbook entitled ‘Szeliski 2nd Edition’ sitting on a beautiful coffee table”  
(according to ChatGPT 4)

# Announcements

- In class final this coming Tuesday, May 7
  - 2 sheets of notes (front and back) allowed
  - Final is comprehensive (covers entire course)
- Course evaluations are open
  - We would love your feedback!
  - Small amount of extra credit for filling out
    - What you write is still anonymous; instructors only see if students filled it out
  - <https://apps.engineering.cornell.edu/CourseEval/>

# Readings

- 5-Minute Graphics from Steve Seitz:
  - [Large Language Models from scratch](#)
  - [Large Language Models: Part 2](#)
  - [Text to Image in 5 minutes: Parti, Dall-E 2, Imagen](#)
  - [Text to Image: Part 2 -- how image diffusion works in 5 minutes](#)

# Recall: The Space of All Images

- Lets consider the space of all 100x100 images
- Now lets randomly sample that space...
- Conclusion: Most images are noise



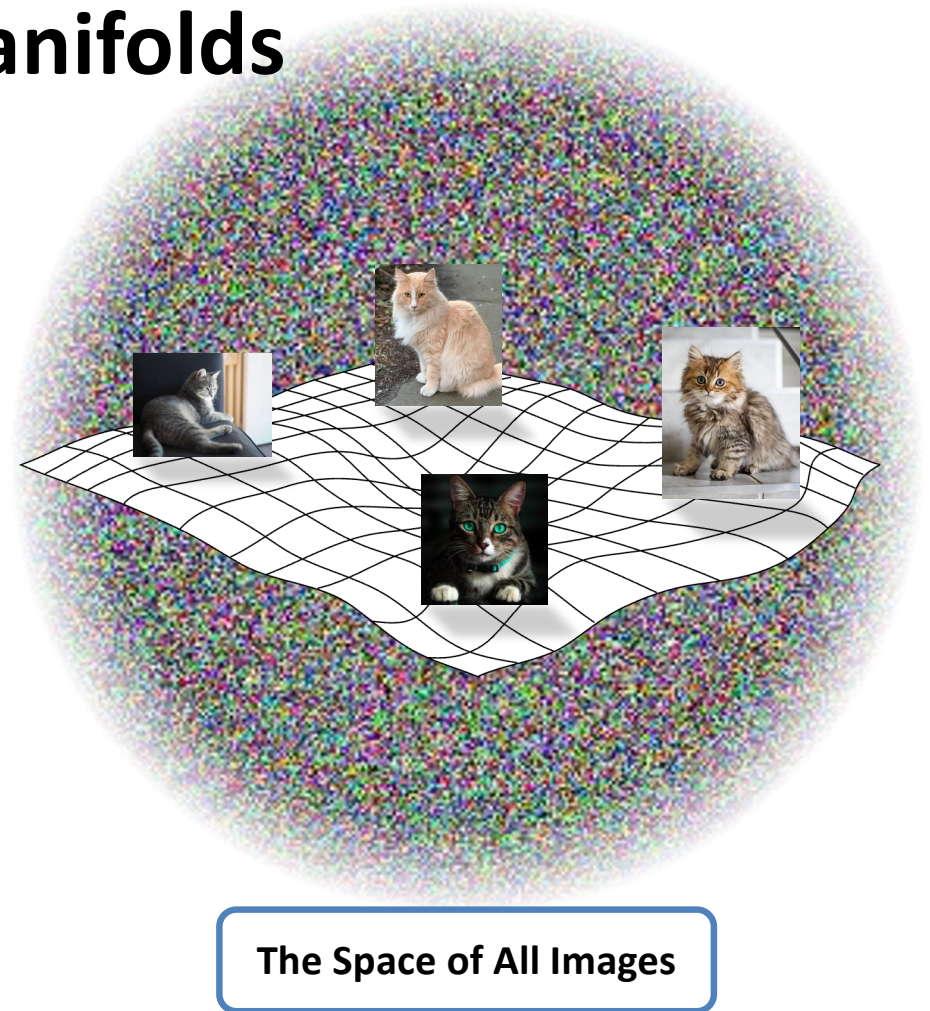
## Question:

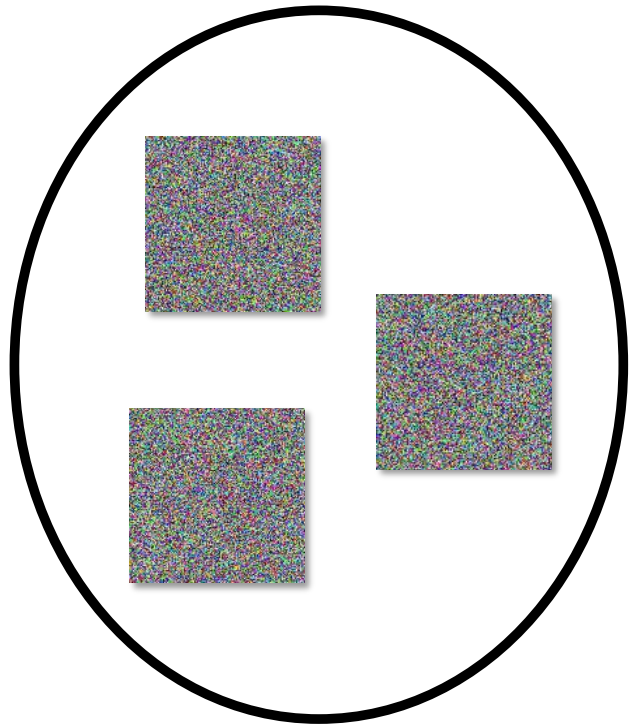
What do we expect a random uniform sample of all images to look like?

```
pixels = np.random.rand(100, 100, 3)
```

# Recall: Natural Image Manifolds

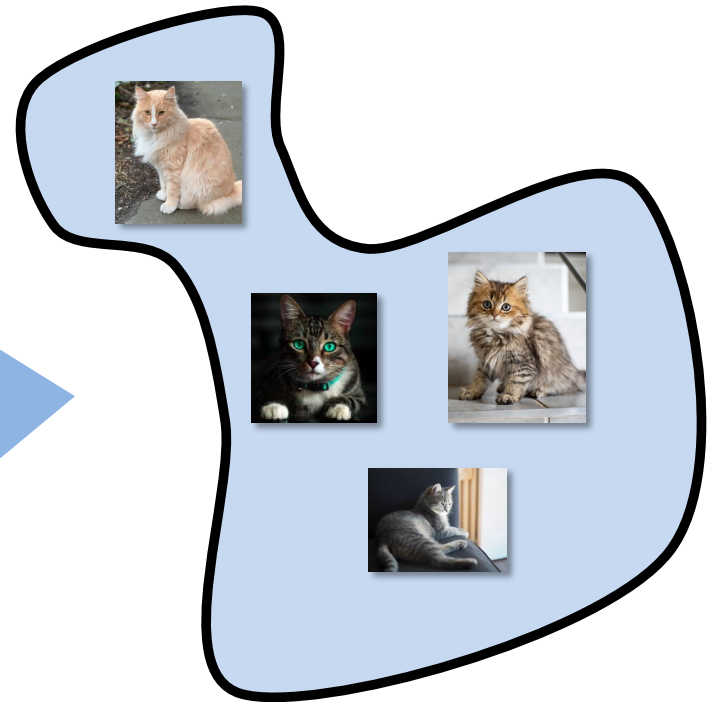
- Most images are “noise”
- “Meaningful” images tend to form some manifold within the space of all images
- Images of a particular class fall on manifolds within that manifold...





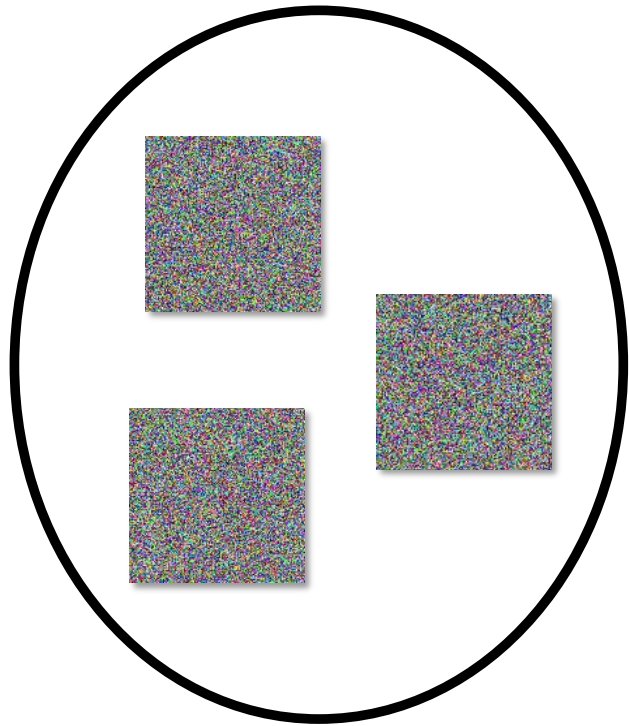
Random images

**Diffusion**



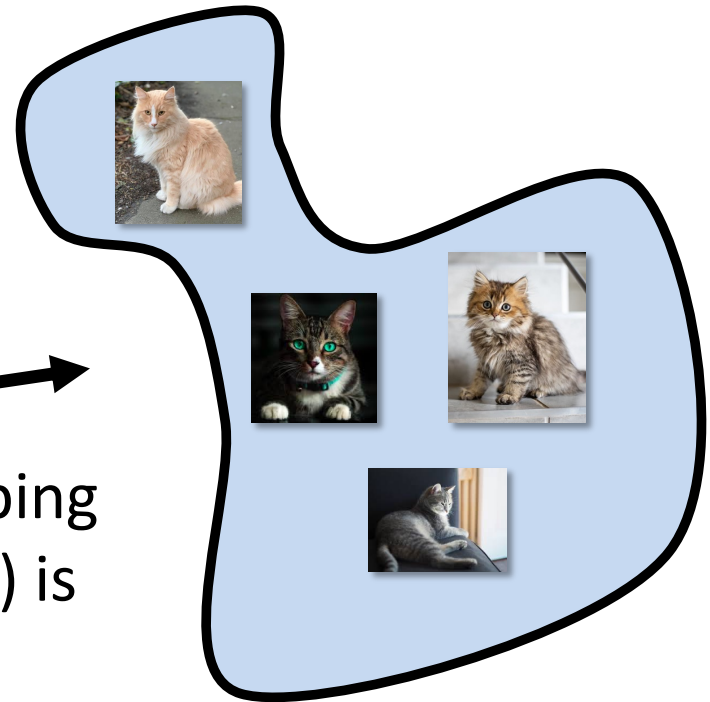
Manifold of cat images





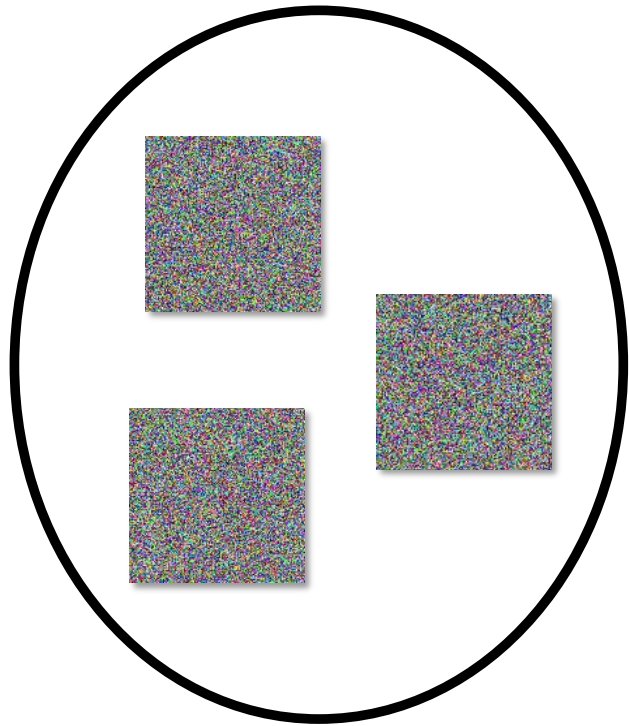
Random images

Forward mapping  
(noise to cats) is  
hard



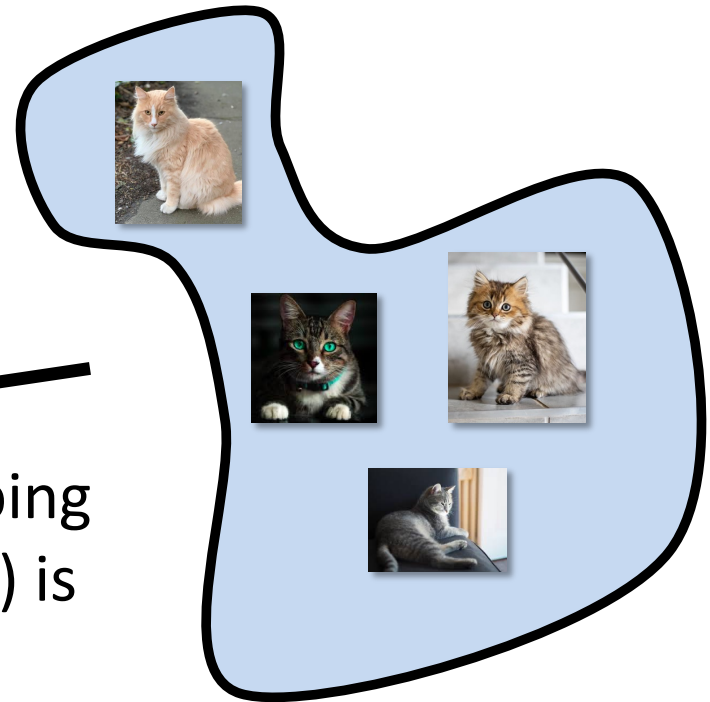
Manifold of cat images



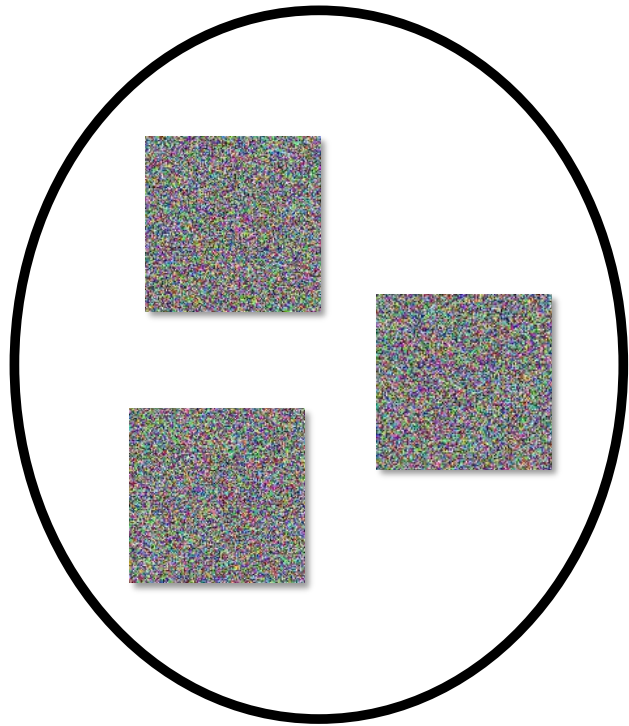


Random images

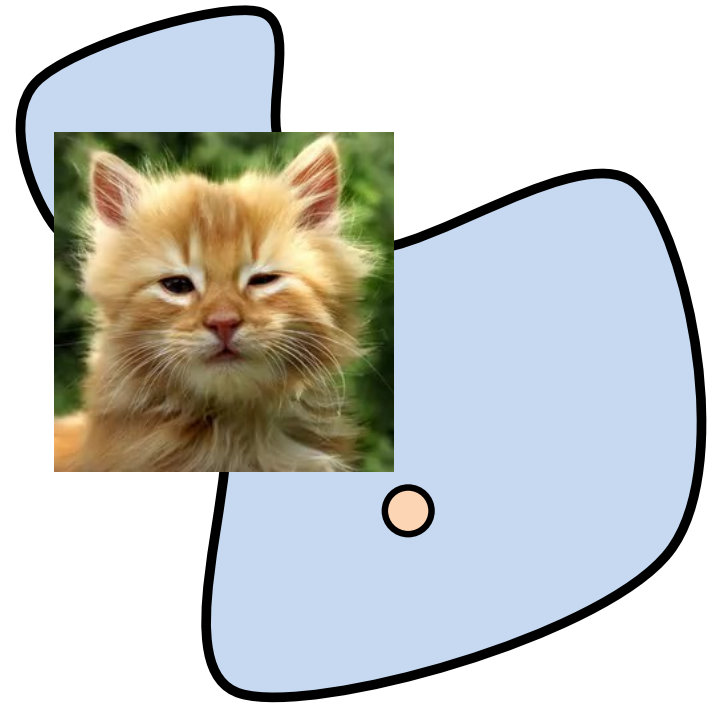
Reverse mapping  
(cats to noise) is  
easy



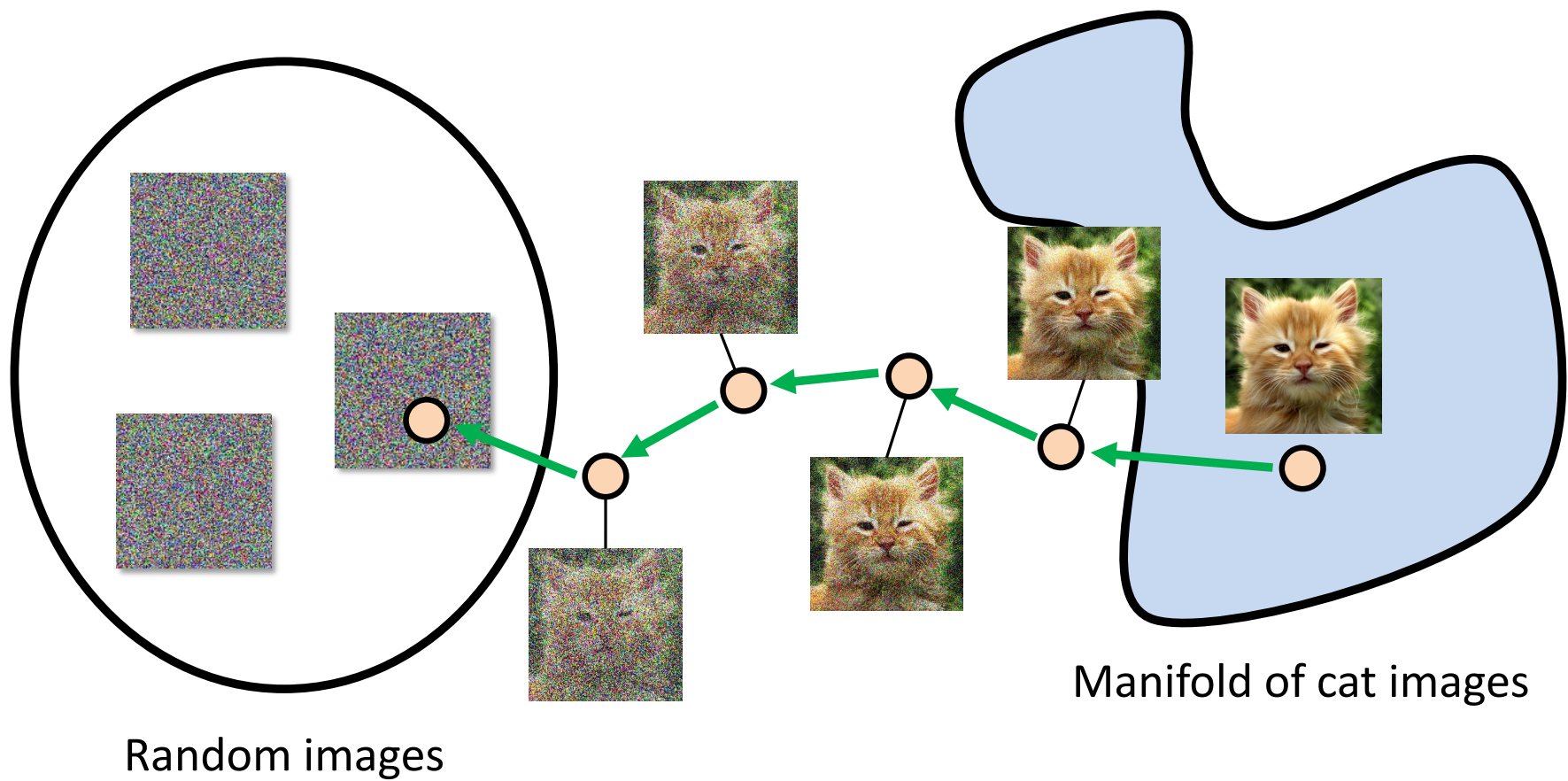
Manifold of cat images

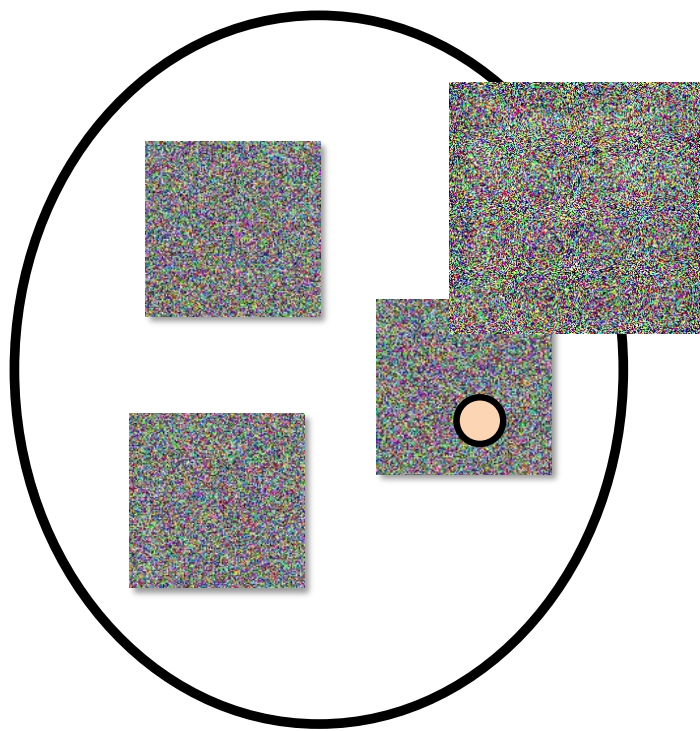


Random images

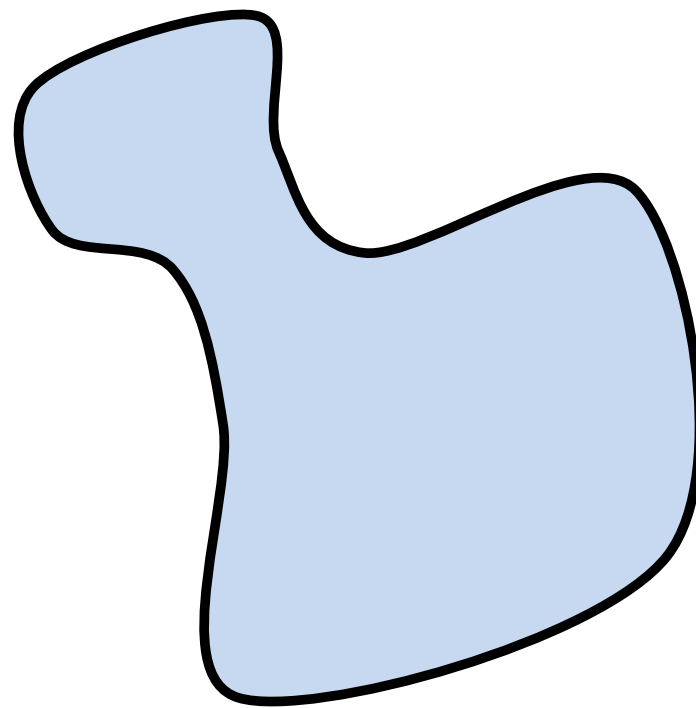


Manifold of cat images

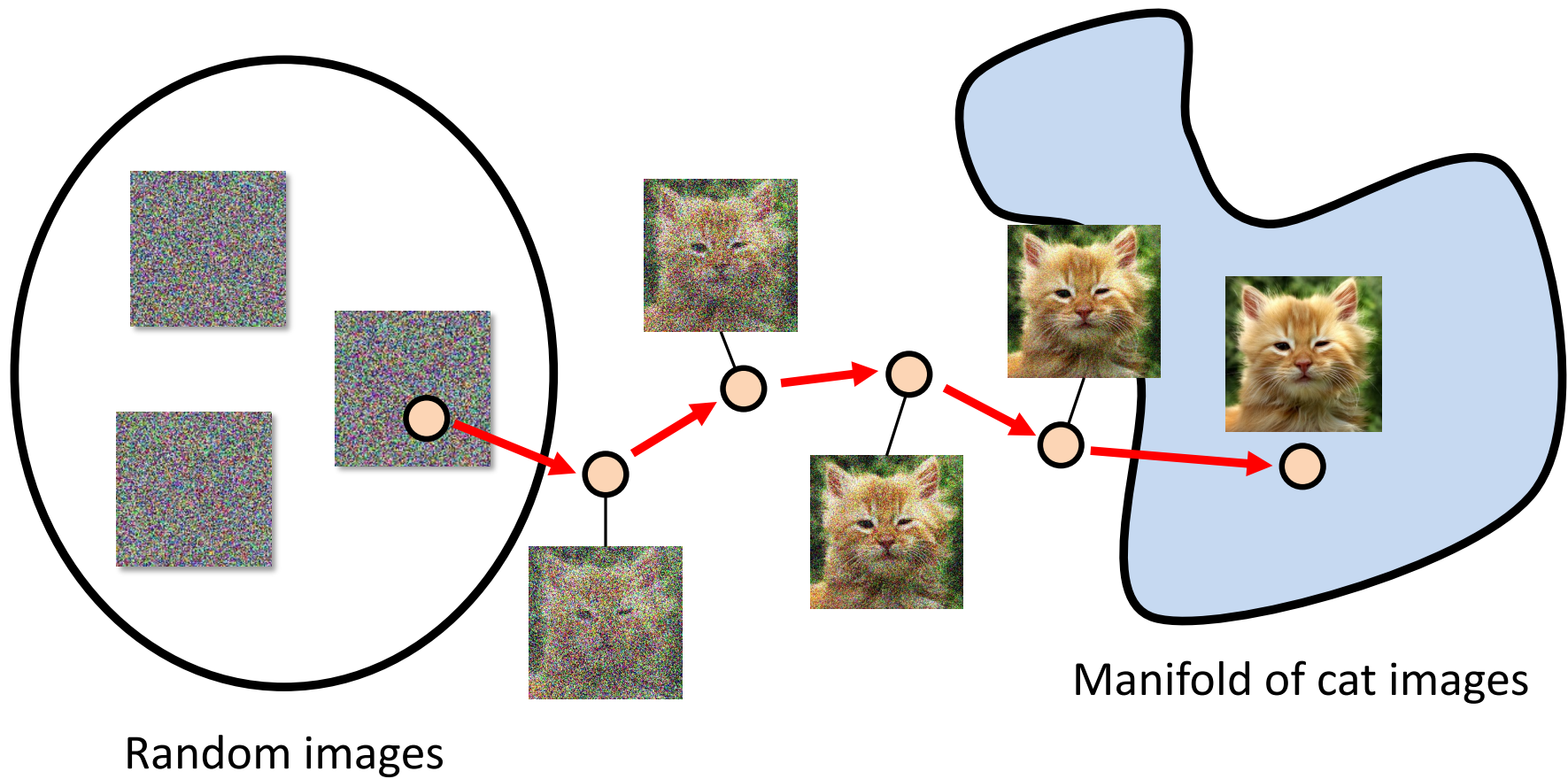


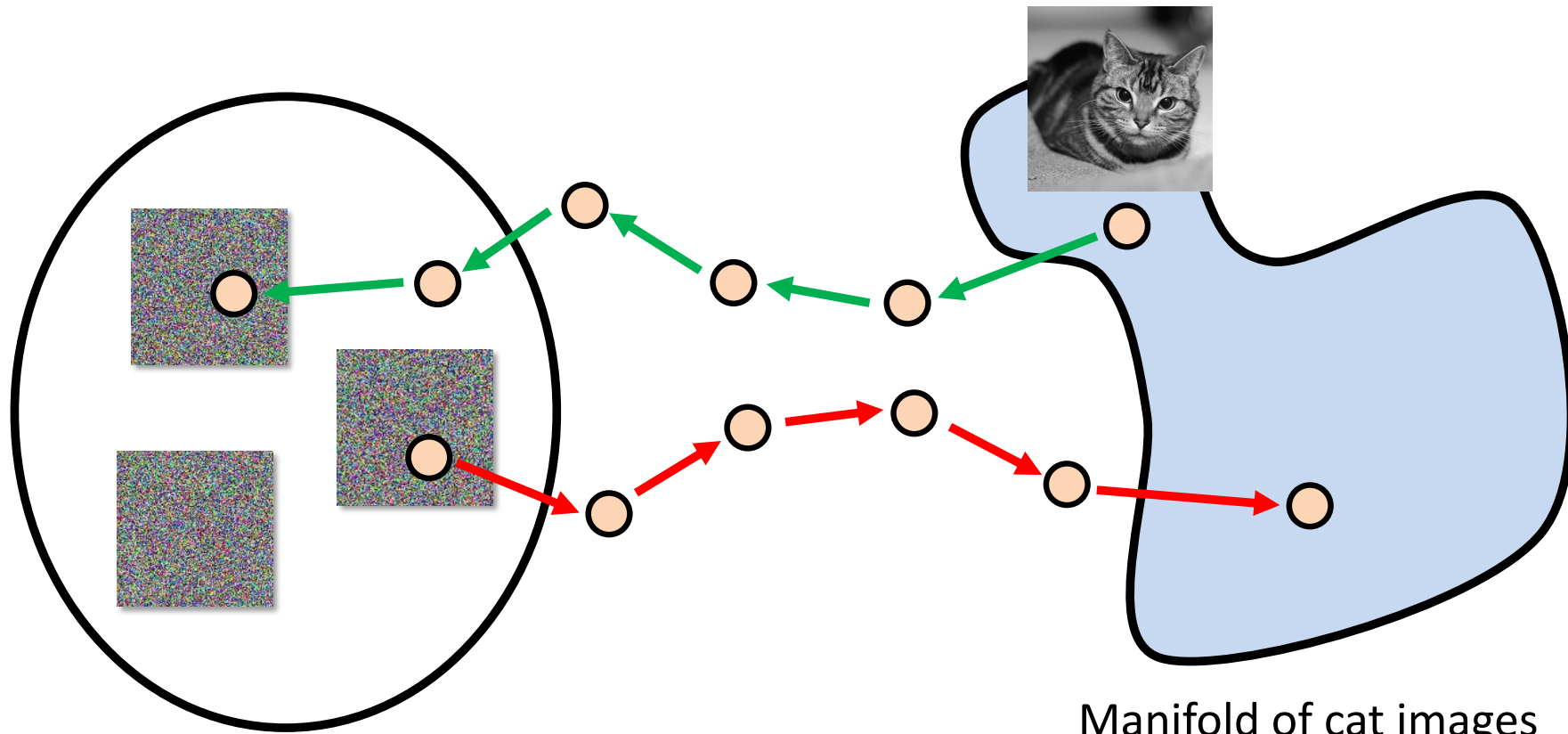


Random images



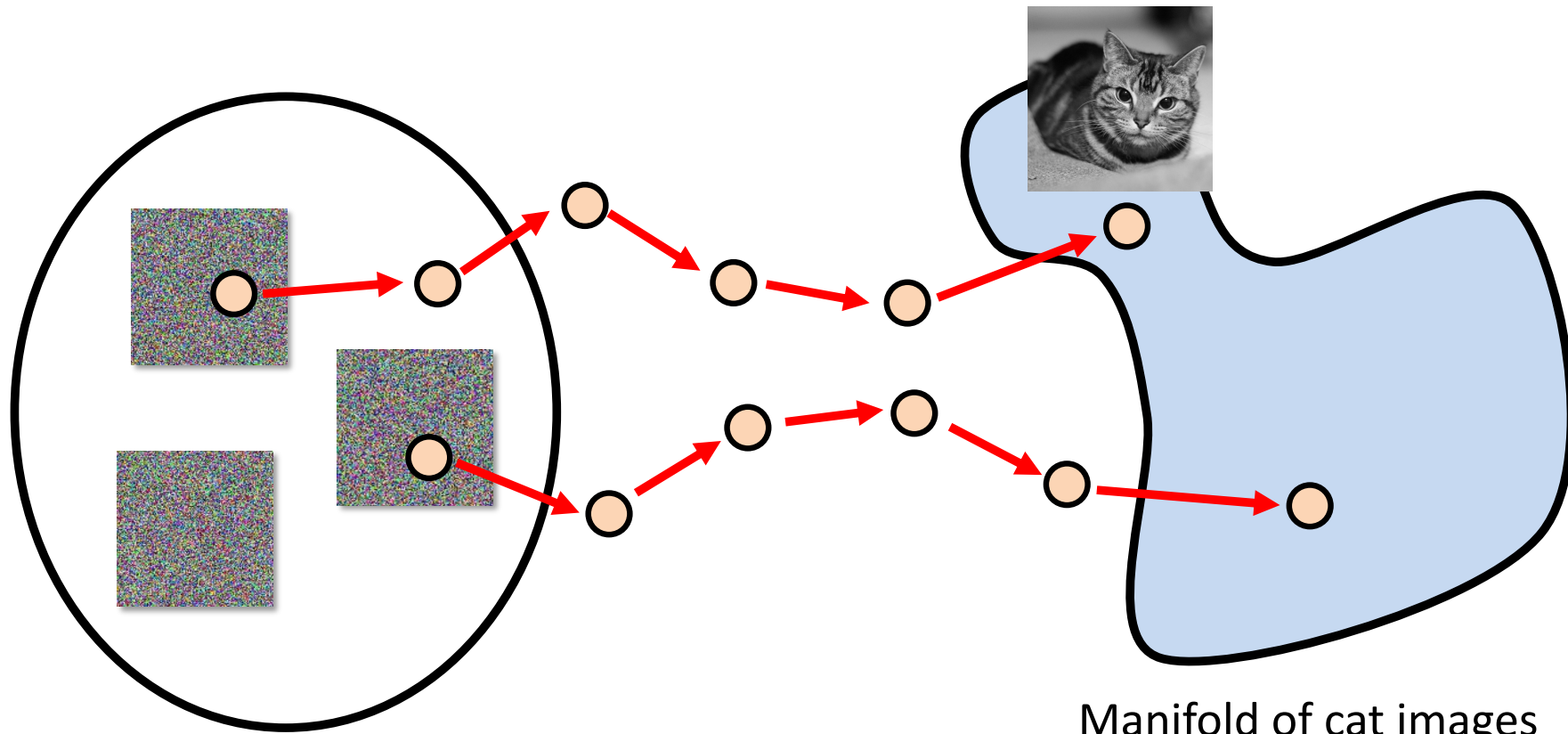
Manifold of cat images





Random images

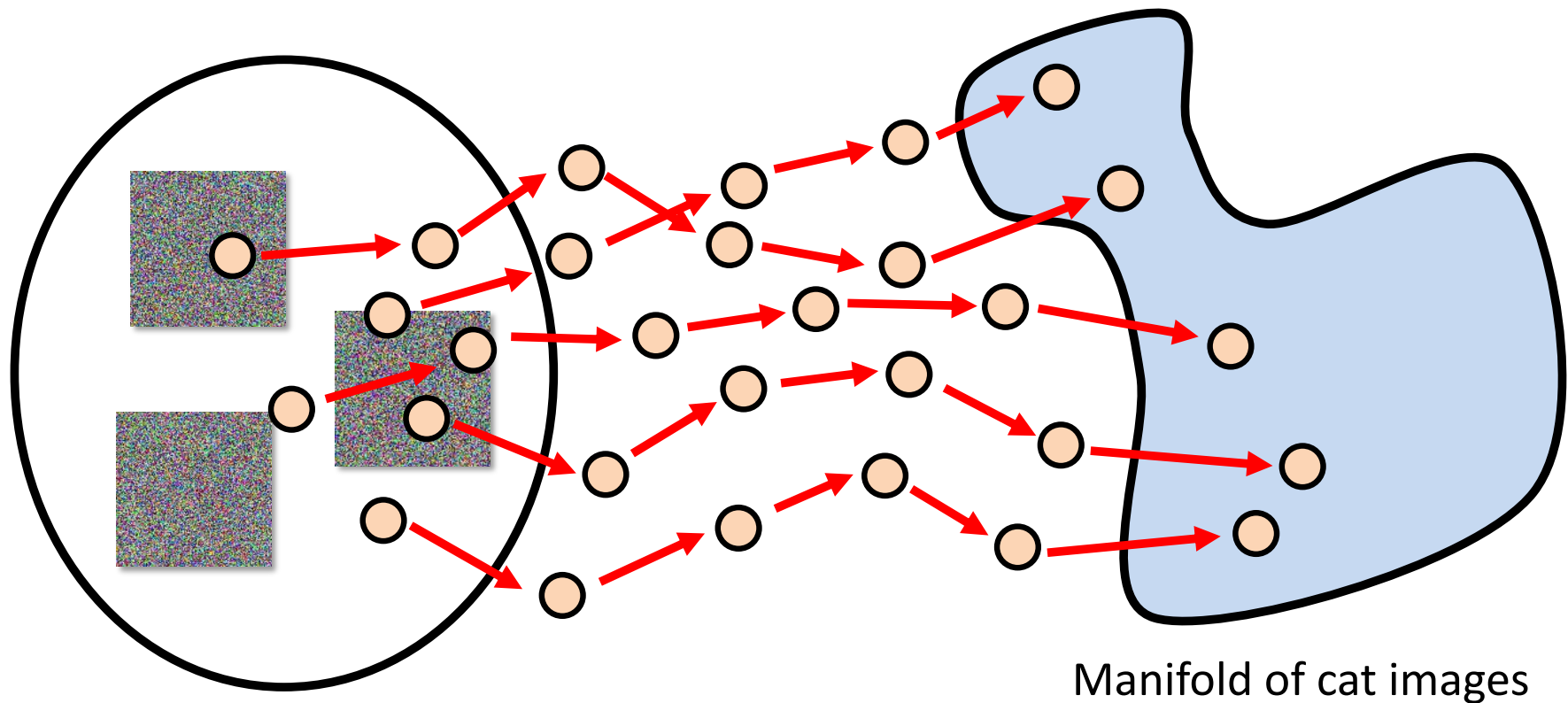
Manifold of cat images



Random images

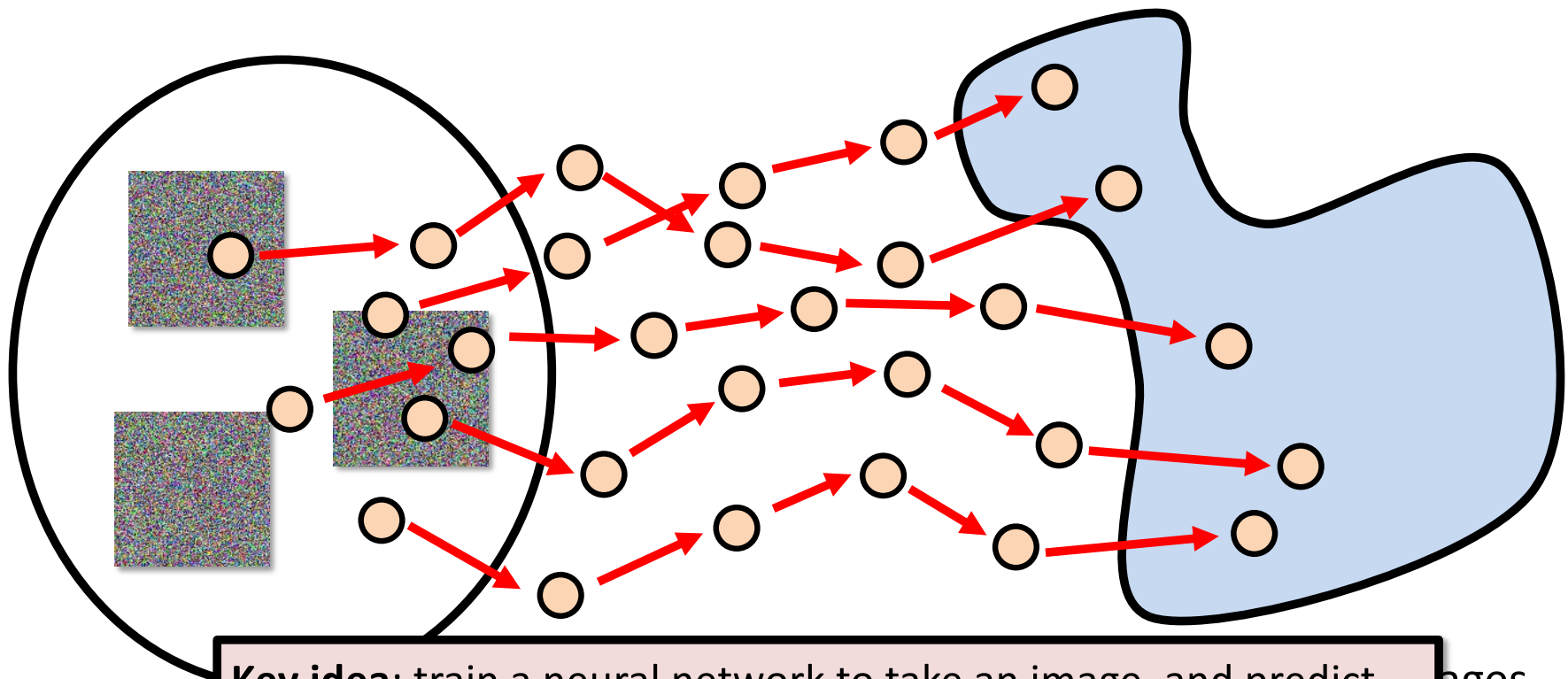
Manifold of cat images





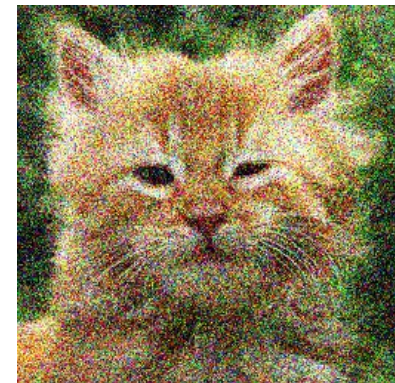
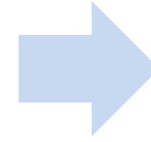
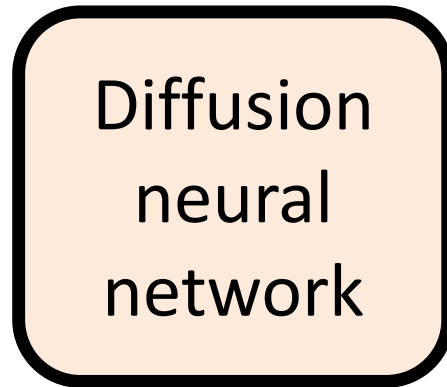
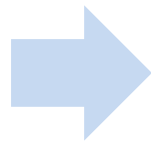
Random images

Manifold of cat images



**Key idea:** train a neural network to take an image, and predict the corresponding arrow above; that is, predict to convert a noisy image to a slightly less noisy image that is closer to the desired image manifold, using the examples above to train.

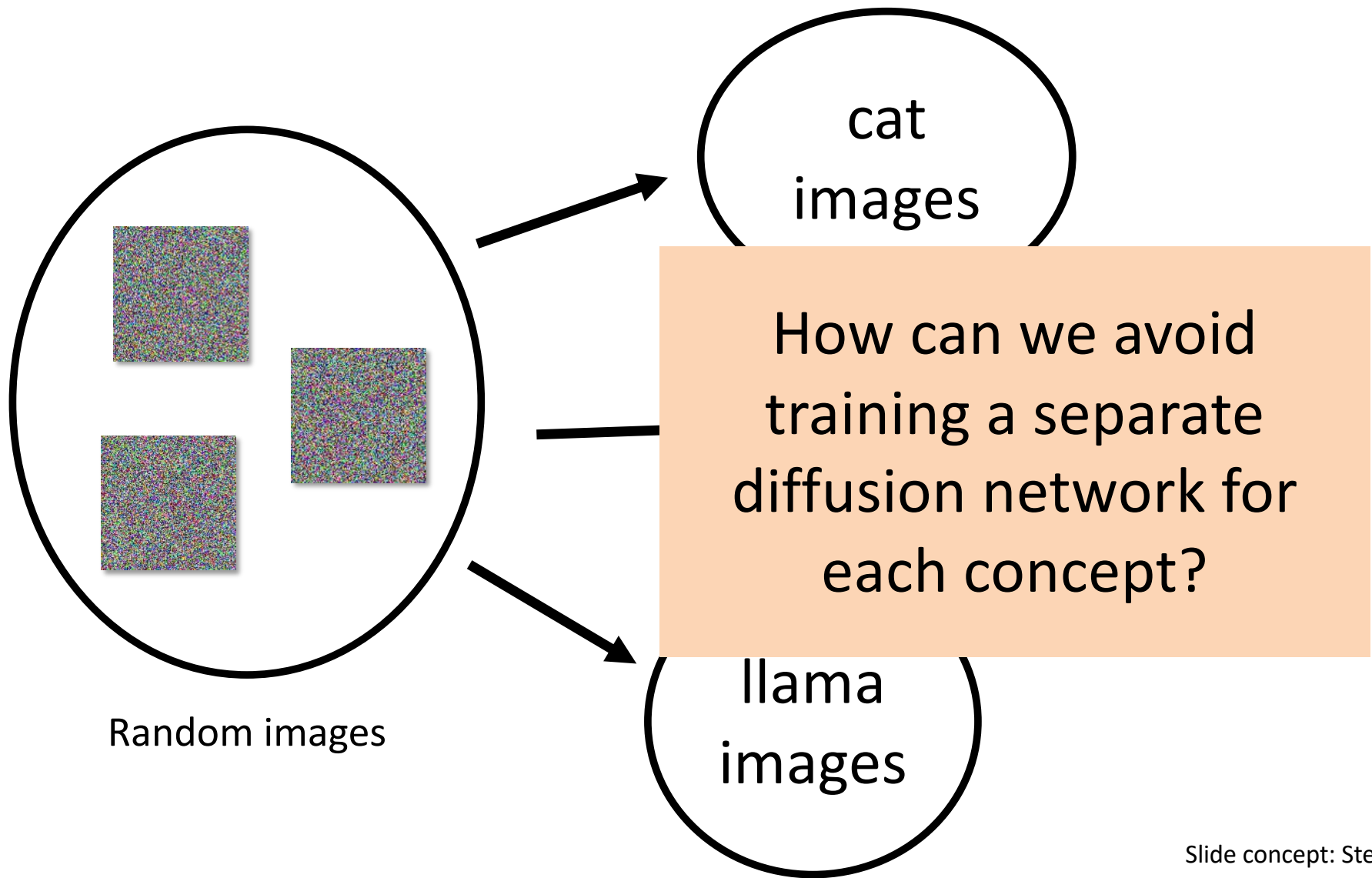
# Denoising diffusion neural network



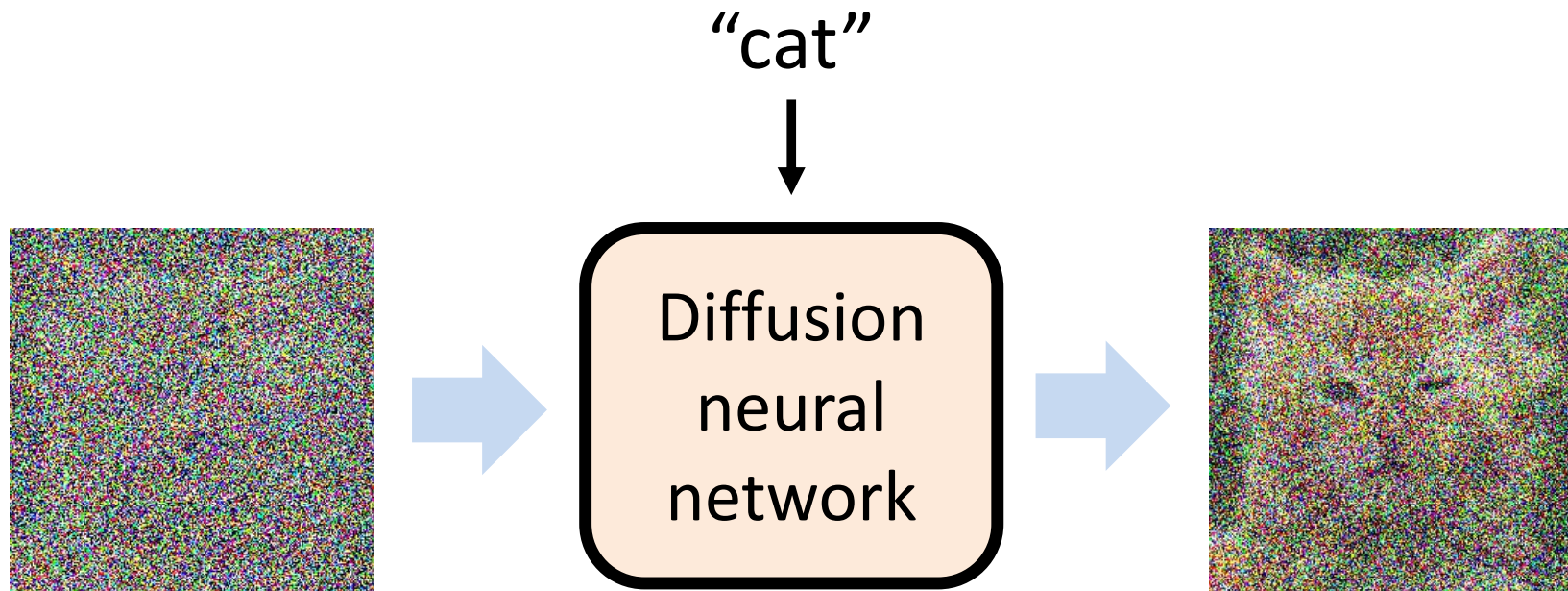
This network can be a U-Net or other suitable image-to-image network

# Generating new images

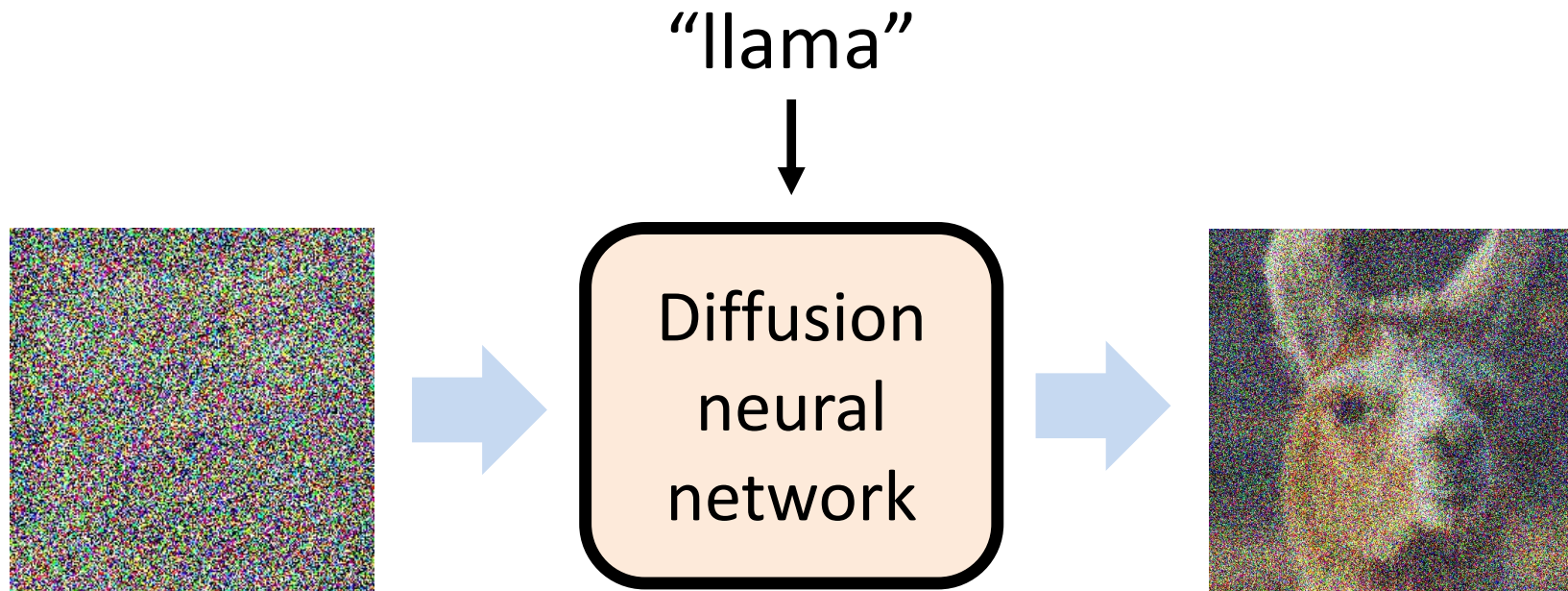
- Once diffusion network has been trained, generate new images by starting with a random noise image, and iteratively applying the network to slowly remove noise, for some number of steps (e.g., 1,000 for DALL-E 2)
- “Walking from random images towards the manifold of natural images”



# Idea 1: add a text label as conditioning

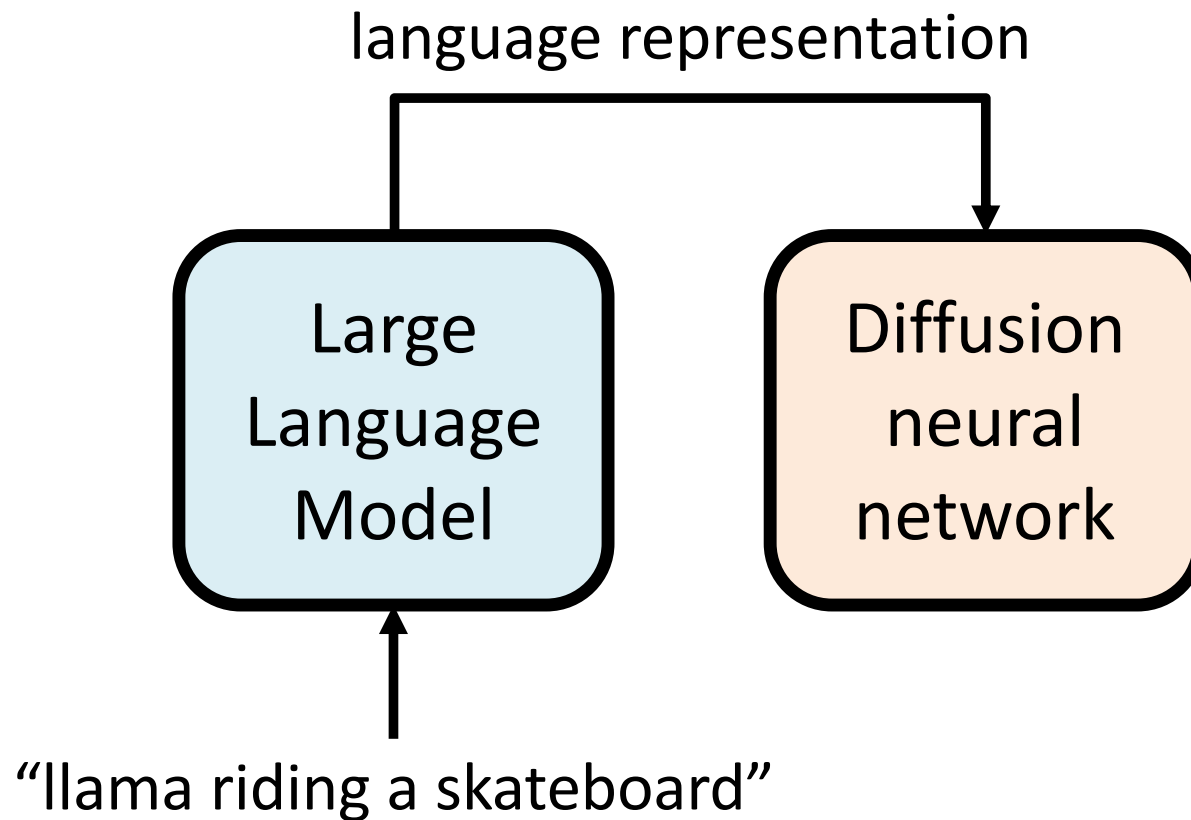


# Idea 1: add a text label as conditioning






## Idea 2: condition using large language model



# Training on images + captions



A pack llama in the Rocky Mountain National Park 

<https://en.wikipedia.org/wiki/Llama>

# DALL-E 2



“A llama riding a skateboard”



“A llama riding a skateboard captured with a DSLR”

# Imagen



“Sprouts in the shape of text 'Imagen' coming out of a fairytale book.”



“A dragon fruit wearing karate belt in the snow.”



# Other applications of diffusion models

- Uncropping



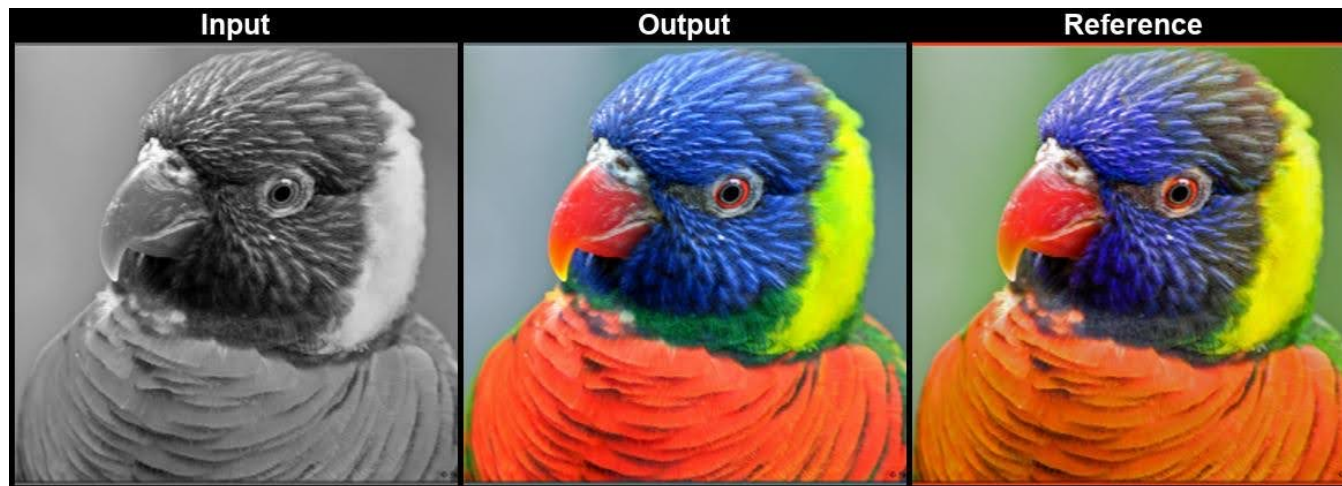
Progressively zooming out. The most zoomed-in image is the input

[Palette: Image-to-Image Diffusion Models](#)

Saharia et al. arXiv 2022.

# Other applications of diffusion models

- Colorization

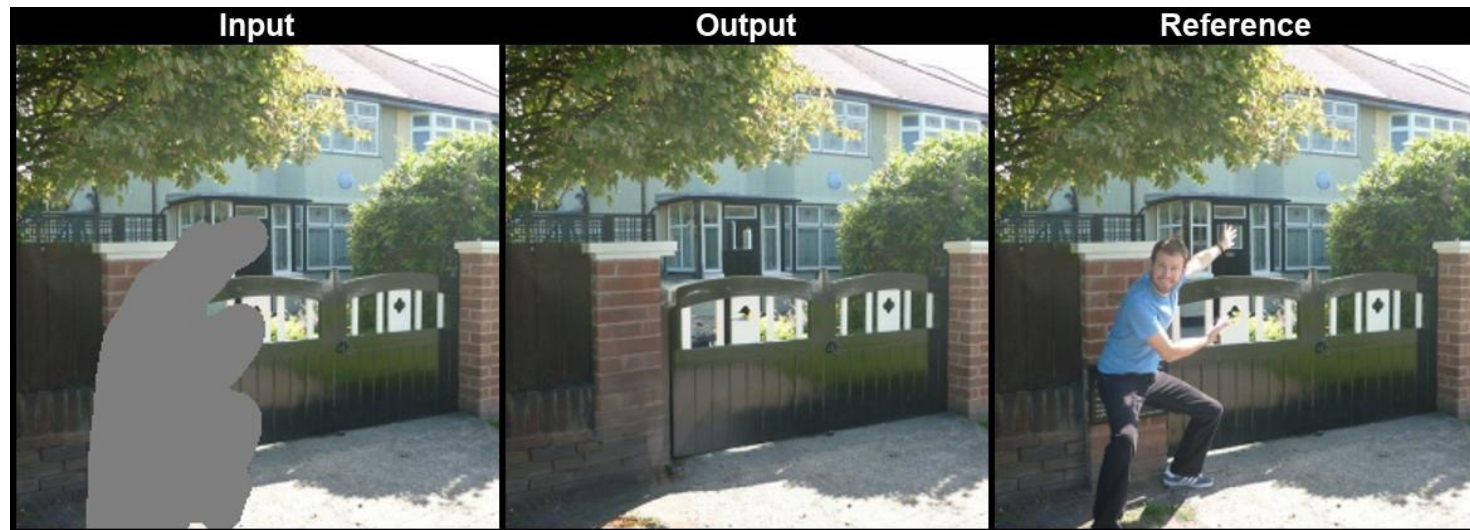


[Palette: Image-to-Image Diffusion Models](#)

Saharia et al. arXiv 2022.

# Other applications of diffusion models

- Inpainting



[Palette: Image-to-Image Diffusion Models](#)

Saharia et al. arXiv 2022.



# DreamFusion: Text-to-3D using 2D Diffusion



“a DSLR photo of a squirrel”

<https://dreamfusion3d.github.io/>

# DreamBooth: Fine Tuning Text-to-Image Diffusion Models for Subject-Driven Generation

[Nataniel Ruiz](#) [Yuanzhen Li](#) [Varun Jampani](#) [Yael Pritch](#) [Michael Rubinstein](#) [Kfir Aberman](#)

Google Research



Input images



in the Acropolis

swimming

sleeping

in a doghouse

in a bucket

getting a haircut

*It's like a photo booth, but once the subject is captured, it can be synthesized wherever your dreams take you...*

[\[Paper\]](#) (new!) [\[Dataset\]](#) [\[BibTeX\]](#)

# Comparison with GANs

- Diffusion models tend to be easier to train and more scalable
- Diffusion models tend to be slower – often many iterations of denoising are required
- However, recent work is mitigating some of these issues (with both GANs and diffusion models)

# Text-to-image model zoo

- Diffusion models
  - DALL-E 2/3, Imagen, Stable Diffusion
- Transformer-based models
  - DALL-E, Parti, MUSE

**Questions?**