### Introduction to diffusion models

Accelerate Programme for Scientific Discovery







### Welcome!

#### About the course

- The history of generative Al
- Inspiration from physics
- Building blocks of diffusion
- Where can you get them from
- Code!

Code and slides available on:

Accelerate Science GitHub repo





# **Today's Schedule**

- Introduction to the Accelerate Science Programme
- History of Generative Al
- Inspiration from Physics
- BREAK
- Building blocks
  - VAEs
  - U-Net
  - CLIP
- 。 LUNCH
- DDPM Algorithm
- Applications
- Data Ethics
- BREAK
- Evaluation
- What's out there?
- No code





## **Accelerate Science Programme**

"Accelerate Science pursues research at the interface of AI and the sciences, generating new scientific insights and developing AI methods that can be deployed to advance scientific knowledge."





## **Accelerate Science Programme**

### Diffusion Workshop Goals

#### We want to:

- Support researchers across the university to use AI that's diffusion models in this group.
- Better understand the challenges that researchers face.
- Identify what training courses or software resources we might want the Accelerate Science Programme to create.
  - Including shared code
- Start to build a community of like-minded researchers across the university.





# What do you know...?

What do you know about Diffusion Models...?



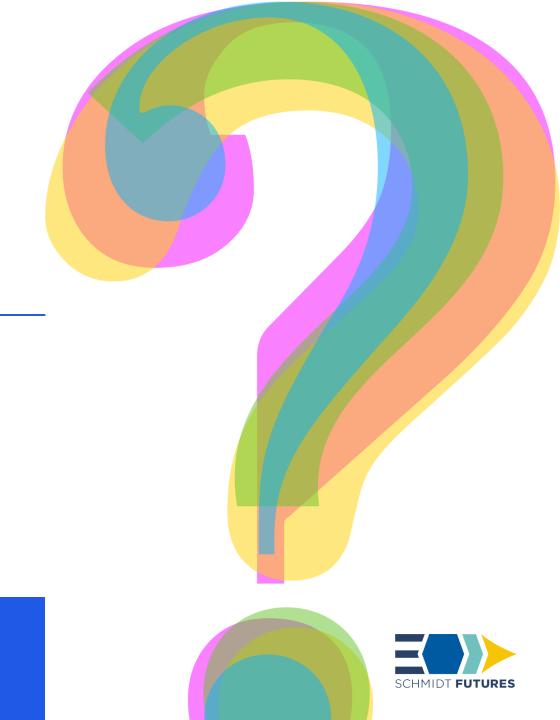


# What do you know...?

- ...about diffusion models?
- o How do they work?
- Can you name any?
- What can you use them for?
- What are potential problems?
- What do YOU intend to use them for?









### GenAl as we know it today really began in the mid 2000s

- "A fast learning algorithm for deep belief nets", 2006, Hinton et al ~ 21k citations
- Restricted Boltzmann machines

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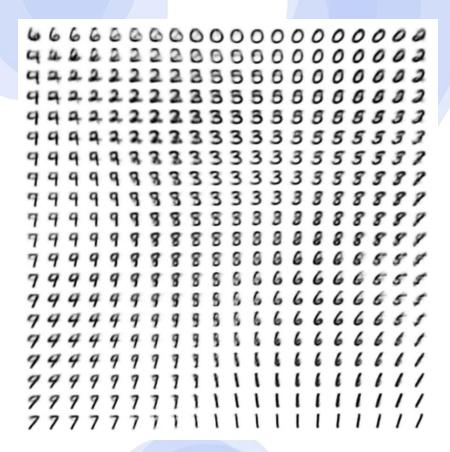


#### Variational Autoencoders

- "Auto-Encoding Variational Bayes" Kingma & Weilling, 2013,
  ~ 36k citations
- Connect an encoder and decoder via a probabilistic latent space
- We will talk more about this later...

Kingma, Diederik P., and Max Welling. "Auto-encoding variational bayes." arXiv preprint arXiv:1312.6114 (2013).







### Generative Adversarial Networks (GANs)

Generative Adversarial Networks, 2014, Goodfellow et al, ~67k citations



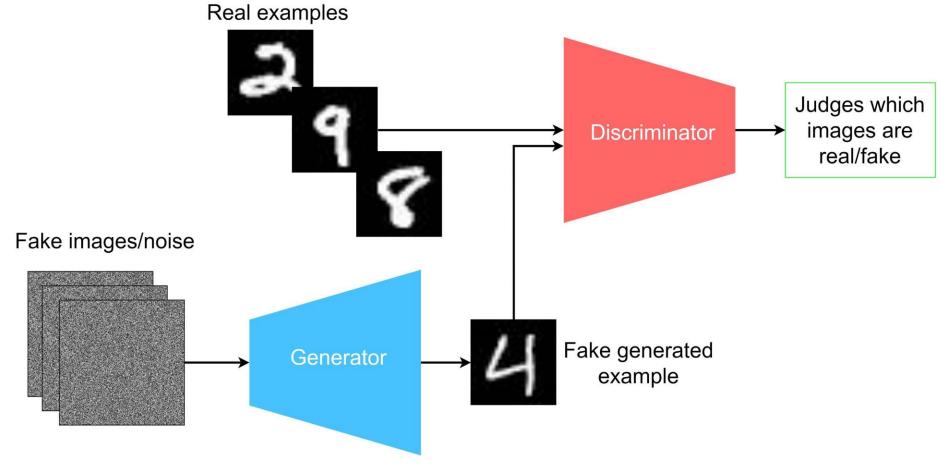


Goodfellow, Ian, et al. "Generative adversarial nets." Advances in neural information processing systems 27 (2014).





### **GANs**





SCHMIDT FUTURES

### **GANs**

They quickly advanced...

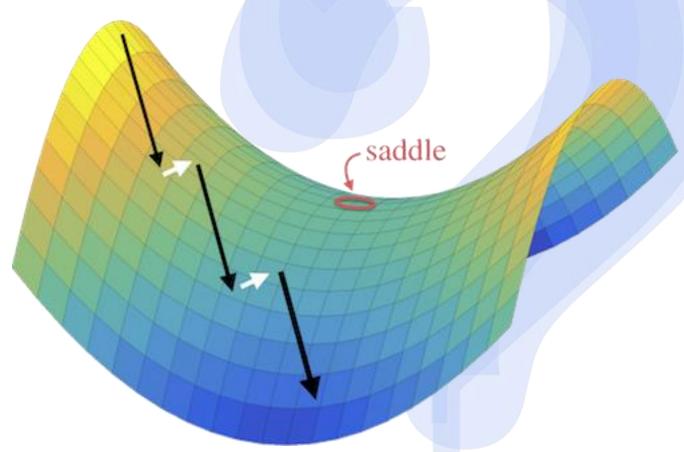






#### **GANs**

- Training GANs is hard
- We want to find a point on a saddle that is a minimum about the generator, and a maximum about the discriminator.
- We can inject noise into the discriminator using a noise schedule determined by a diffusion model.
- Subject to mode collapse



Min, Zhiyu. "Generative adversarial networks, Wasserstein distance and adversarial loss." Alibaba AliMe X-Lab





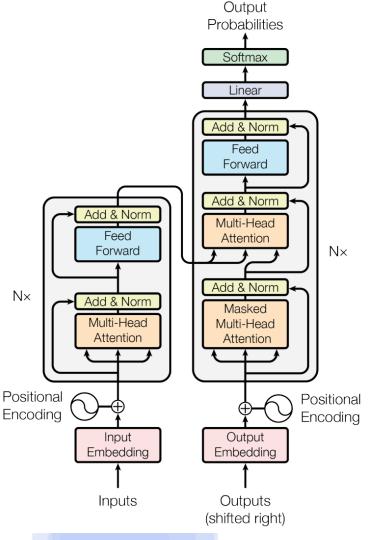
### We know what has been dominating this space...

- "Attention is all you need", Vaswani et al, 2017, ~ 125k citations
- Introduced scaled dot-produce attention and the transformer architecture











#### Diffusion

- Deep unsupervised learning using nonequilibrium thermodynamics, Sohl-Dickstein et al, 2015, ~ 5k citations
- Denoising diffusion probabilistic models (DDPM), Ho et al, 2020 ~ 10k citations
- High-resolution image synthesis with latent diffusion models, Rombach et al 2022, ~ 8k citations

