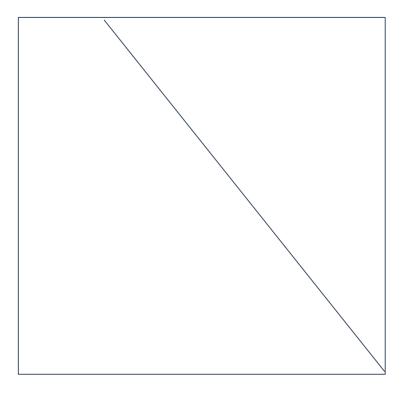


Reminder Dimensionality Reduction

Picture of a Line (500x500 pixels=250,000 Numbers)



Equation: y=m*x+b (2 numbers)

Both have the same information in different formats

It's often a lot easier to analyze 2 number than 250,000

A Reminder

• PCA

- Linear algorithm that finds the directions with the largest variance
- You can trust inter and intra cluster distances
- You may have more important PCA components than you want to plot
- Lossless until you discard higher PC dimensions

TSNE/UMAP

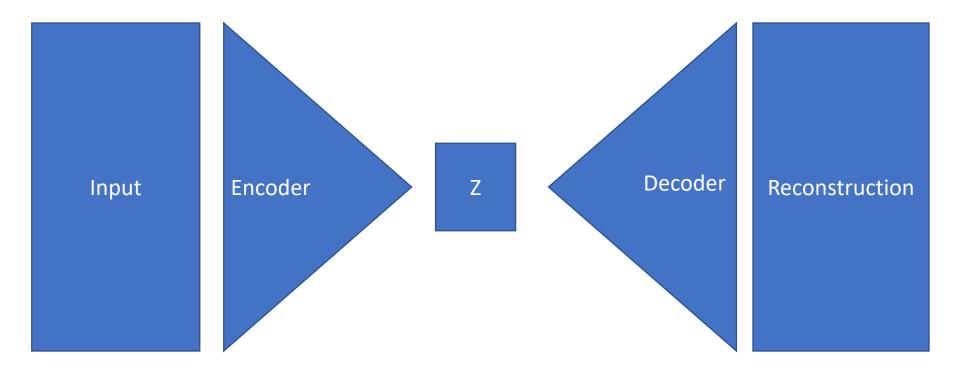
- Relies on nearest-neighbors information
- You can **not** trust inter and intra cluster distances
- You can pick the dimension size you want to reduce to use
- What if you want to get the best of both worlds
- What if you want to use un-structured data

Deep Unsupervised Learning Vocab

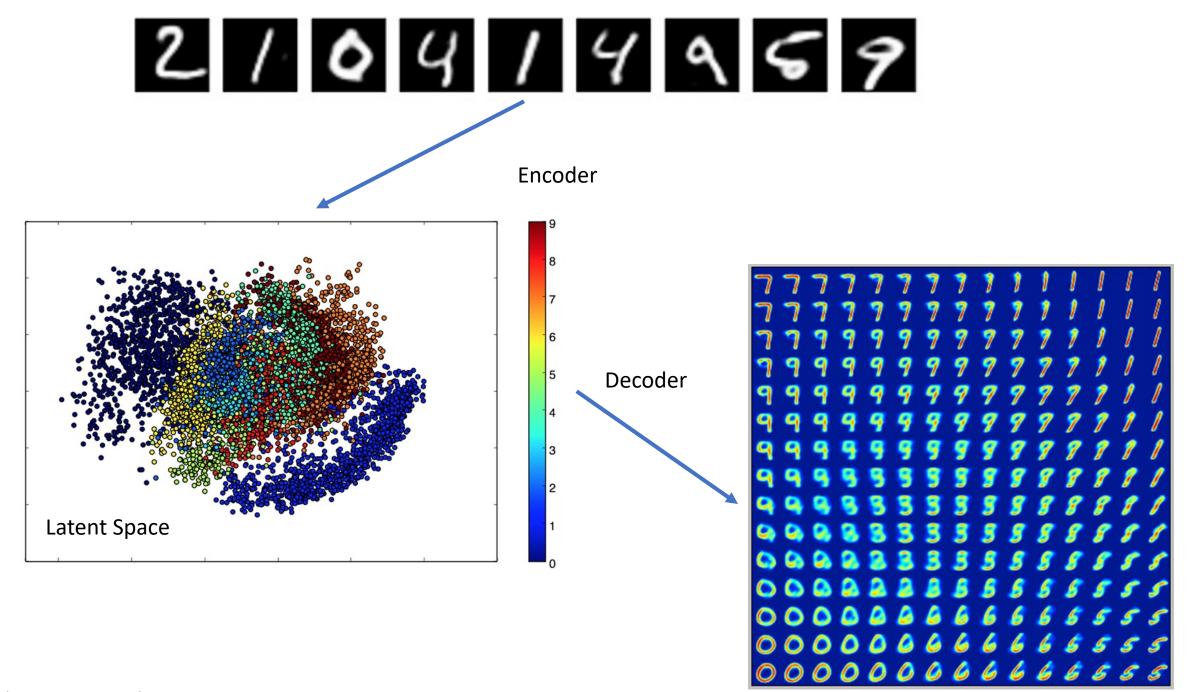
- Deep learning uses stack of layers to approximate a function. In unsupervised learning that function is a mapping from your input data to a latent space
- Latent space often denoted z (like x denotes inputs), think of this like your principal components or outputs of UMAP it's then transformed space that normally has a lower dimension than the original.
- Encoder A function that maps x -> z it 'encodes' your input data
- Decoder A function that maps z -> x it 'decodes' your input data
- Algorithms may use some variations one or all of these

Autoencoder

A common deep learning model for dimensionality reduction

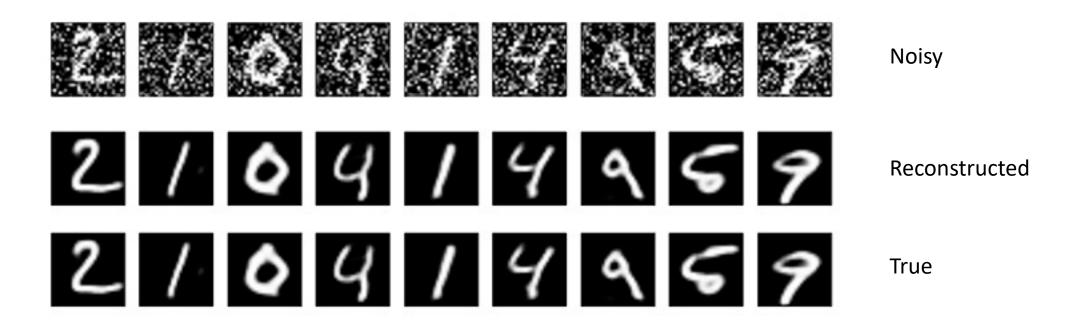


- Trained to find the best way to 'compress' all the information into z possible to recreate the original data
- The encoder preforms some dimensionality reduction, and the decoder tries to reverse this process



Denoising

Another handy feature of Autoencoders is their ability to denoise

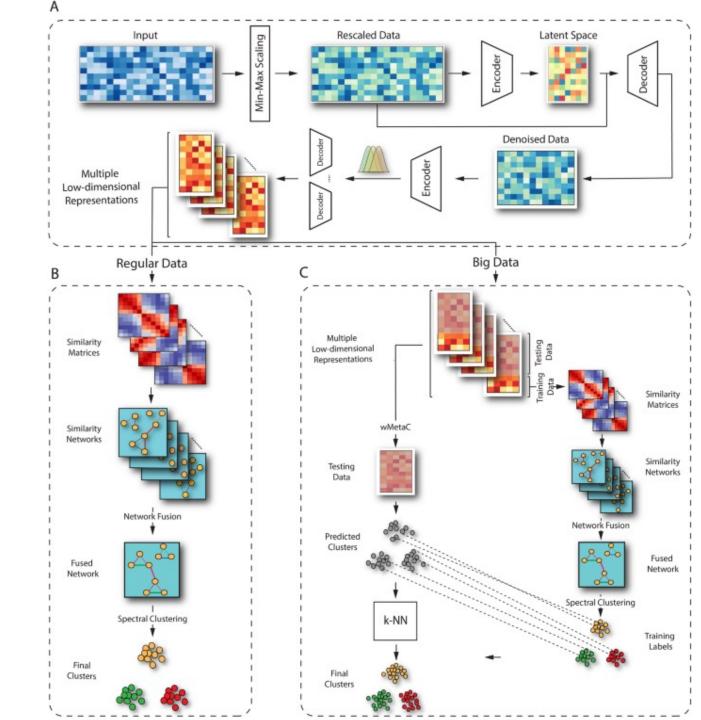


Becoming Available as Tools in Genomics

https://www.nature.com/articles/s41598-022-14218-6

scCAN: single-cell clustering using autoencoder and network fusion

Lots of exploration in this space, so there are lots of new algorithms to try, this one has a convenient R package

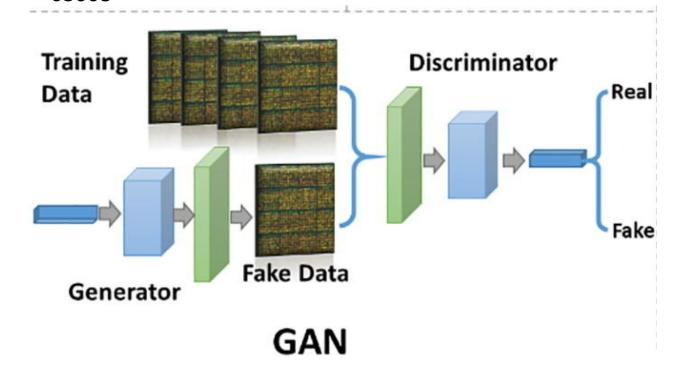


Generative Adversarial Learning (GANS)

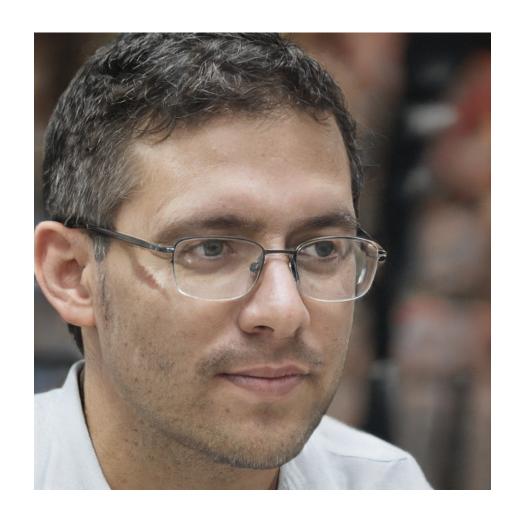
- A different model with only a generator, its goal is to generate new examples that have the same properties as your data.
- Usually Better reconstructions that auto-encoders
- Usually worse latent spaces
- Application lean toward generating new examples
 - Therapeutic Proteins
 - Genomes
 - Etc.

Example https://thisstartupdoesnotexist.com/

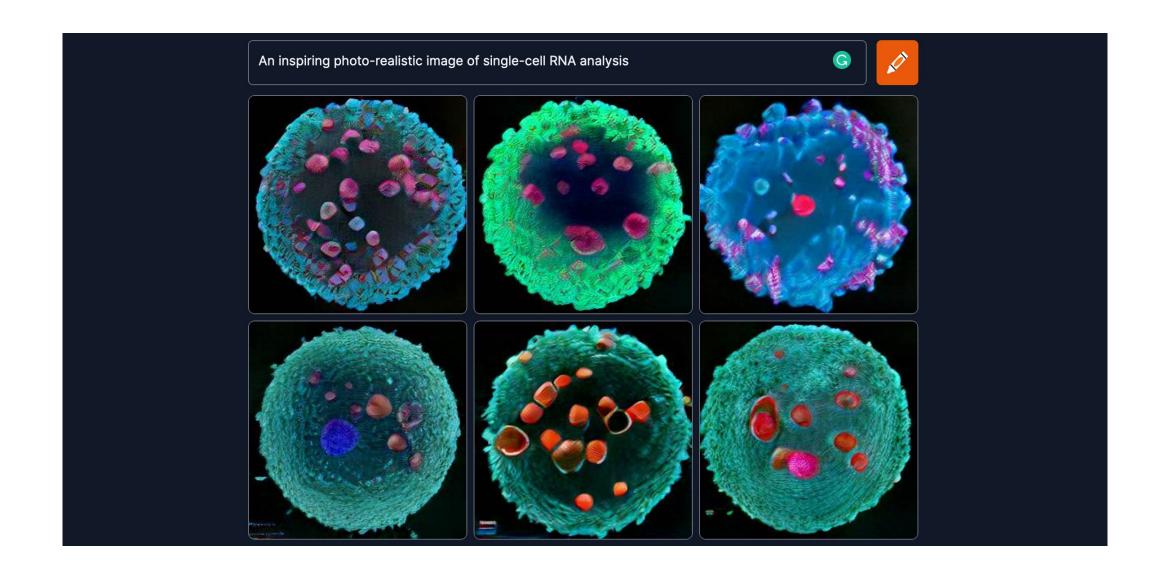
https://www.sciencedirect.com/science/article/pii/S20010370203 03068



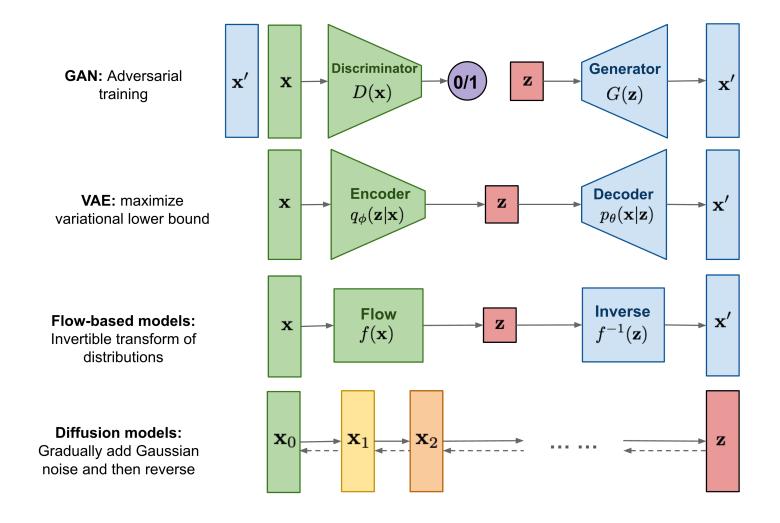
These Networks have produced incredible results for images



https://thispersondoesnotexist.com/



Other Models



https://lilianweng.github.io/posts/2021-07-11-diffusion-models/

Conclusions

- Lots of interesting capabilities coming out of deep learning
- Exactly how this will impact genomics is being figured out as we speak
- Keep an eye out and try new methods as they come out