AUTOENCODERS

Lecture 4

MAL2, Spring 2025

AUTOENCODERS

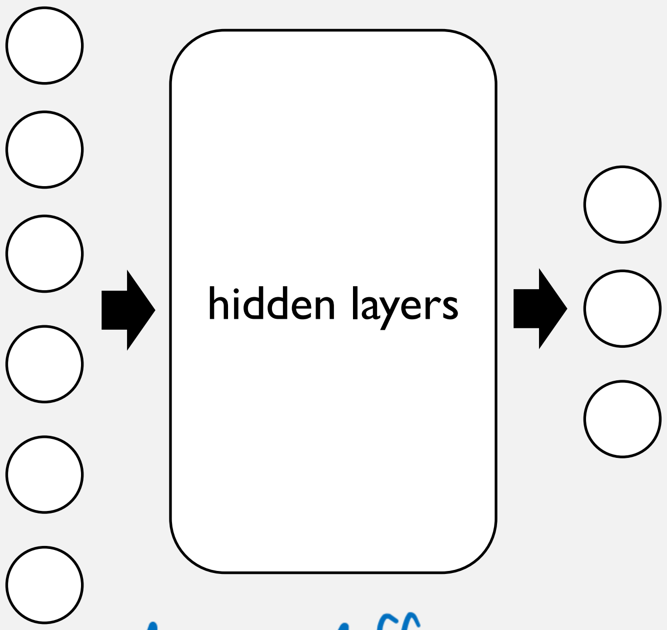
- What if Y was X?
- Dimensionality reduction
- Unsupervised pretraining
- Denoising images
- Colorization

WHAT IF Y WAS X?

Every neural network we have seen so far has looked like this:

input layer

#neurons= #features



output layer

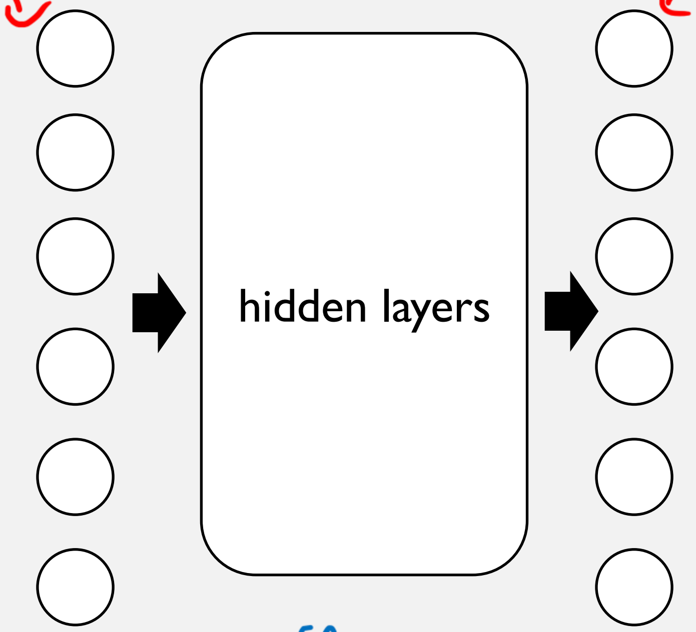
#neurons= #classes

loss = difference between X & y

What if we were crazy enough to make it look like this?

reconstruction

X

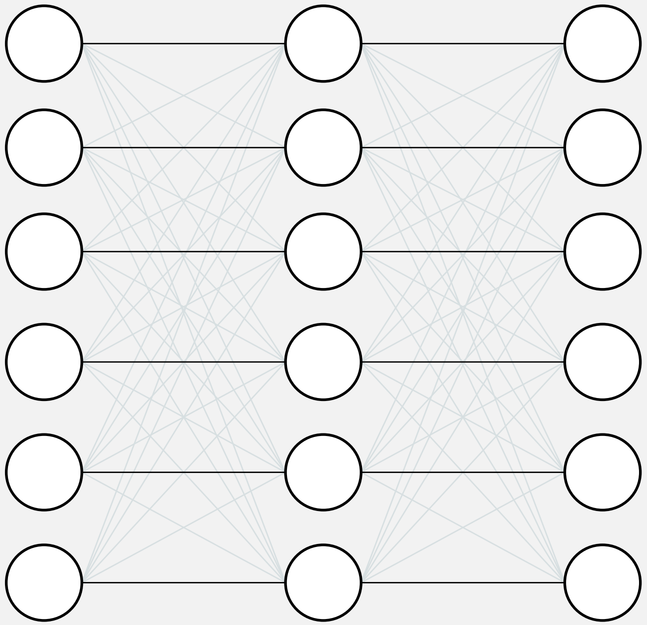


X again

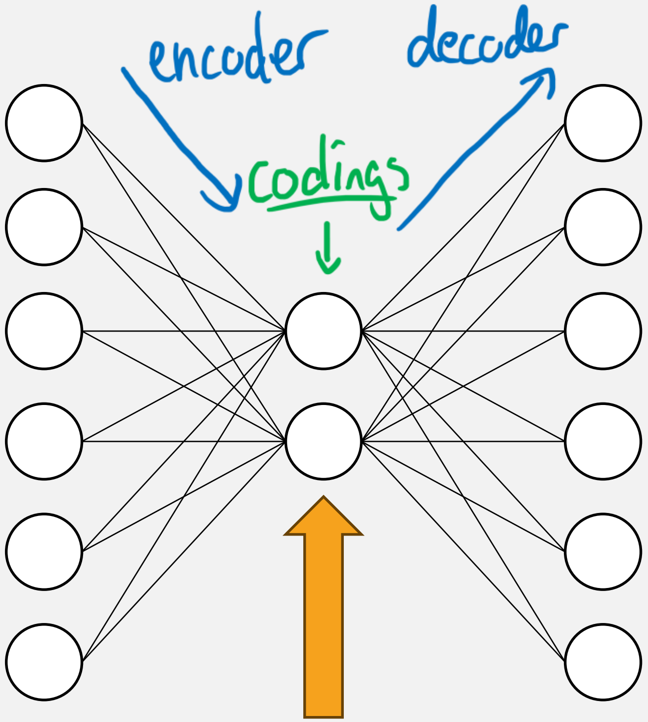
"reconstruction" loss=difference between X & X

BUT ISN'T THAT EASY?

Yes, but not if we constrain it!



AN UNDERCOMPLETE AUTOENCODER



To reconstruct X, we need to express as much information as possible in these two neurons

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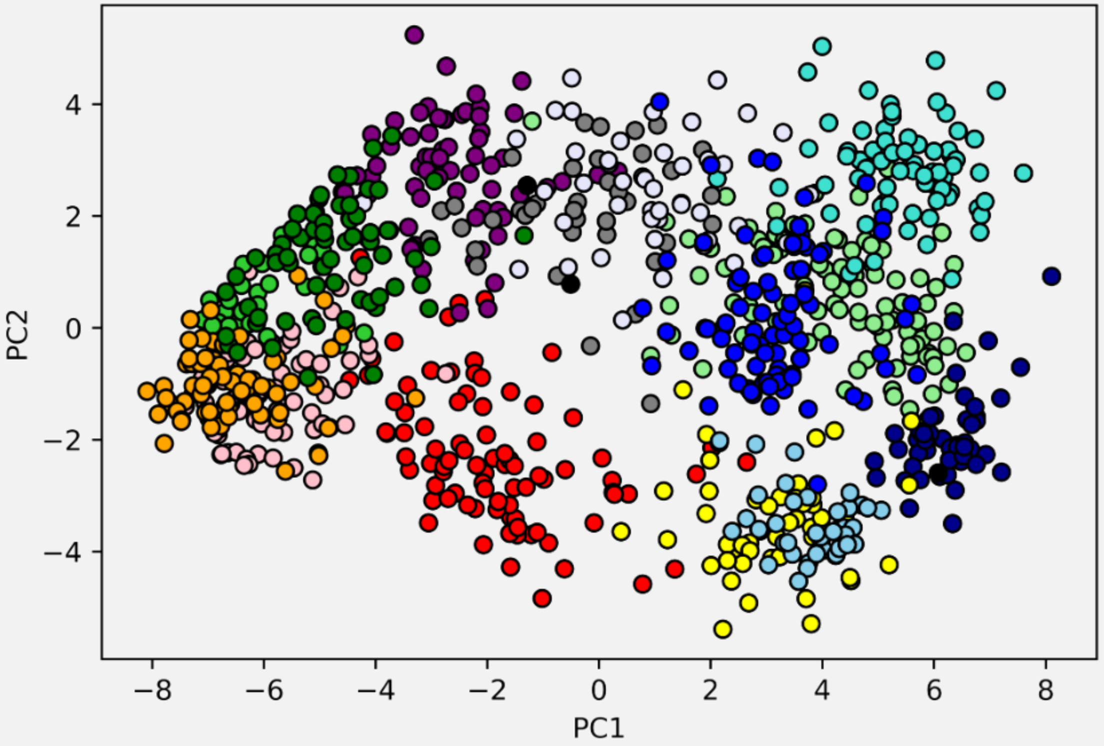
REMEMBER THIS?



PERFORMING PCA WITH AN AUTOENCODER

like PCA

linear

```
encoder = Sequential([Dense(2)])
```

encoder w/ 2 neurons, no activation

```
decoder = Sequential([Dense(49)])
```

#questions

```
autoencoder = Sequential([encoder, decoder])
```

construct full NN

```
optimizer = SGD(learning_rate=0.5)
```

it will be fast, so GD ok

```
autoencoder.compile(loss="mse", optimizer=optimizer)
```

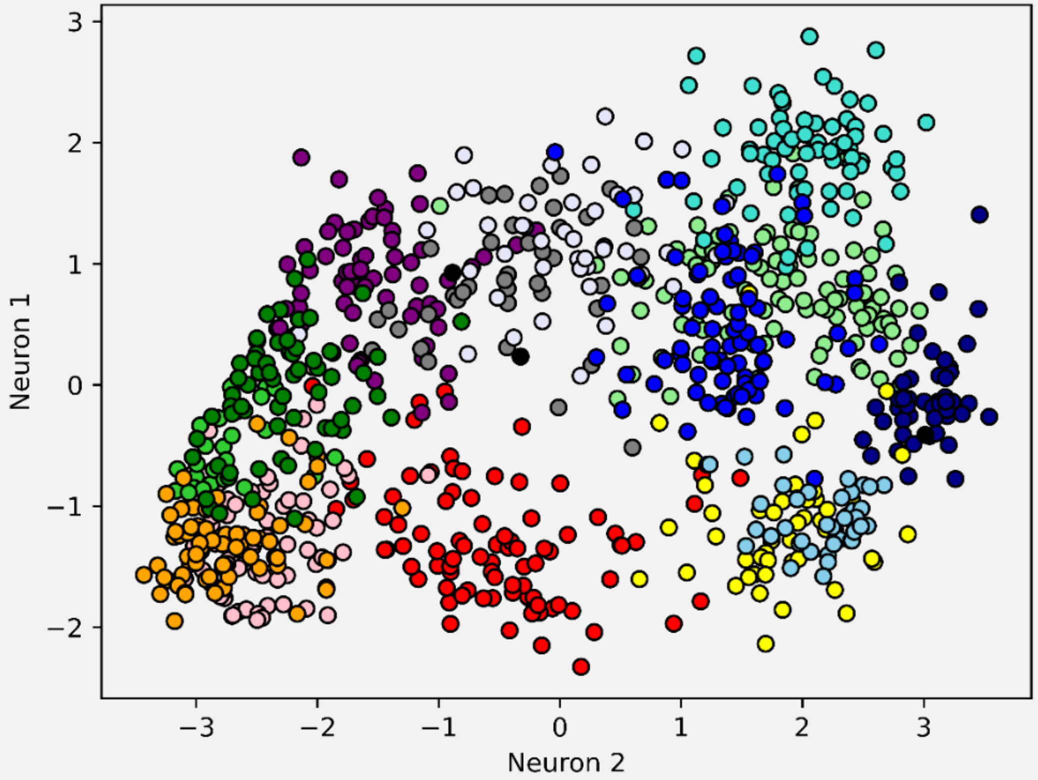
reconstruction loss $(X-\hat{X})^2$

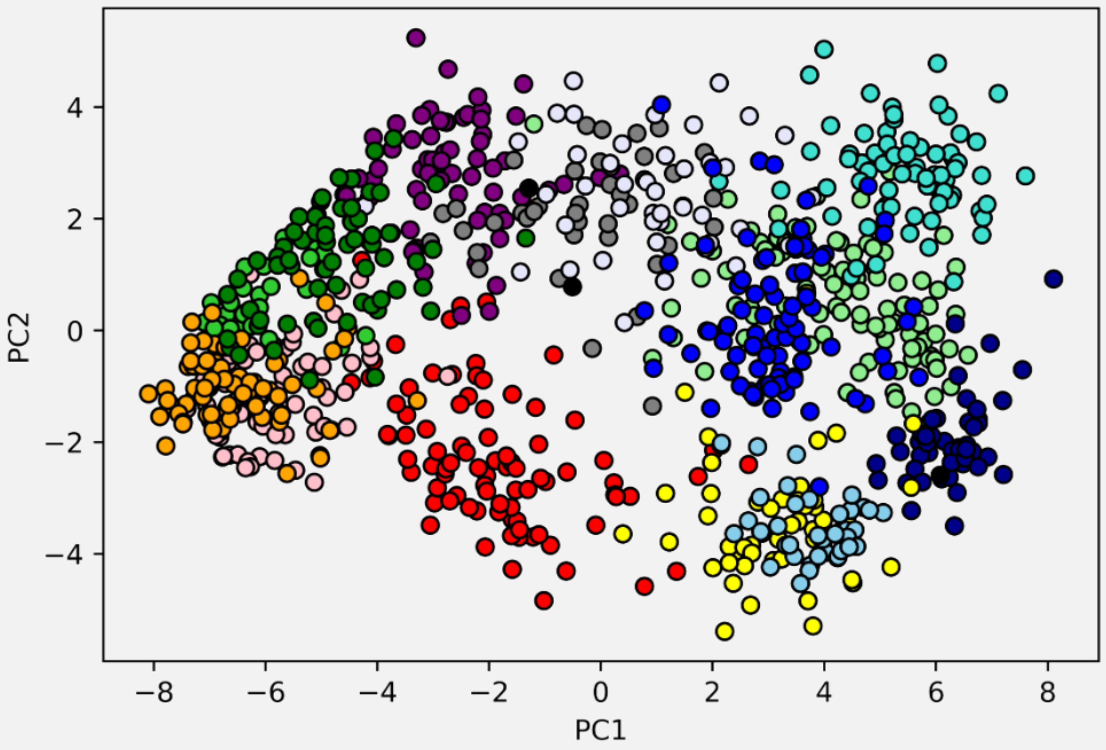
long time

```
history = autoencoder.fit(X, X, epochs=500, verbose = False)
```

```
codings = encoder.predict(X)
```

AUTOENCODERS VS PCA

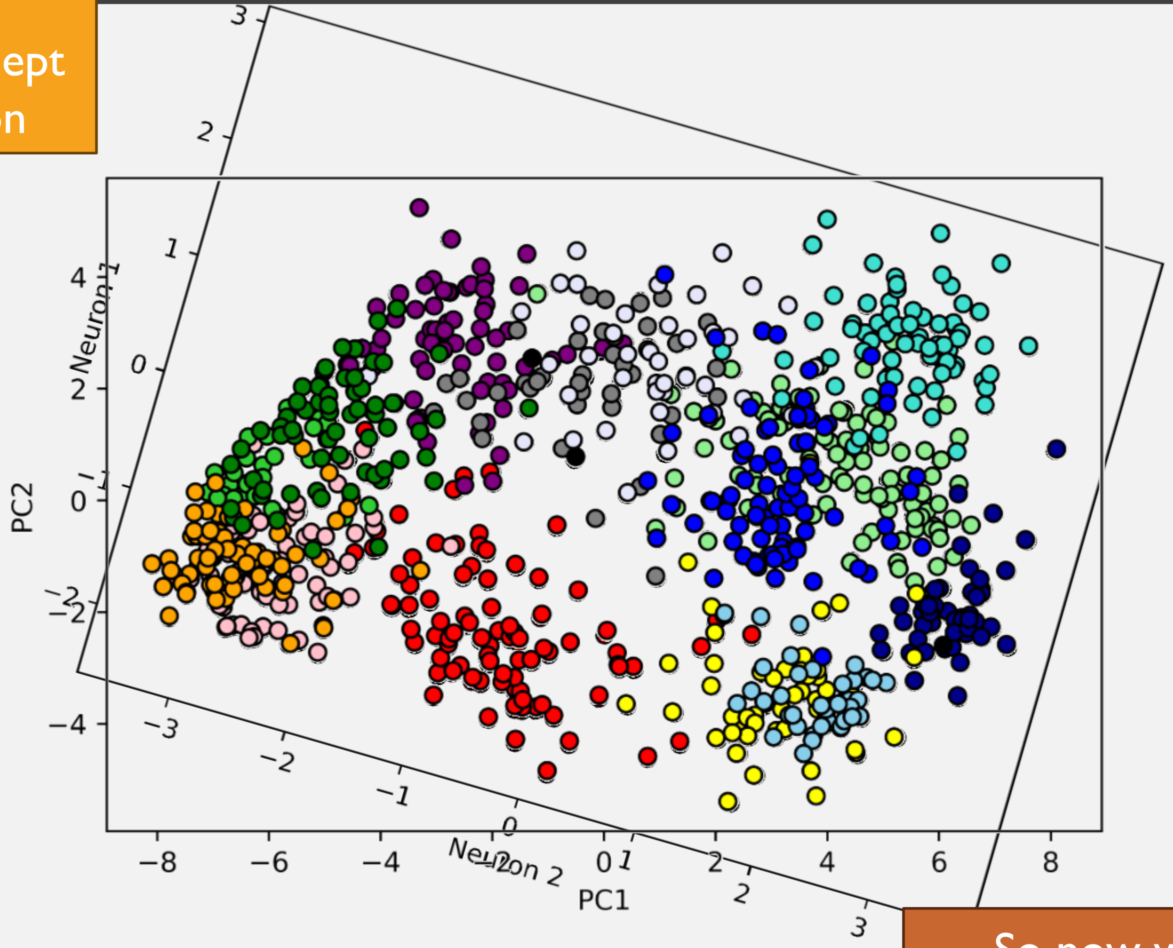




AUTOENCODERS VS PCA

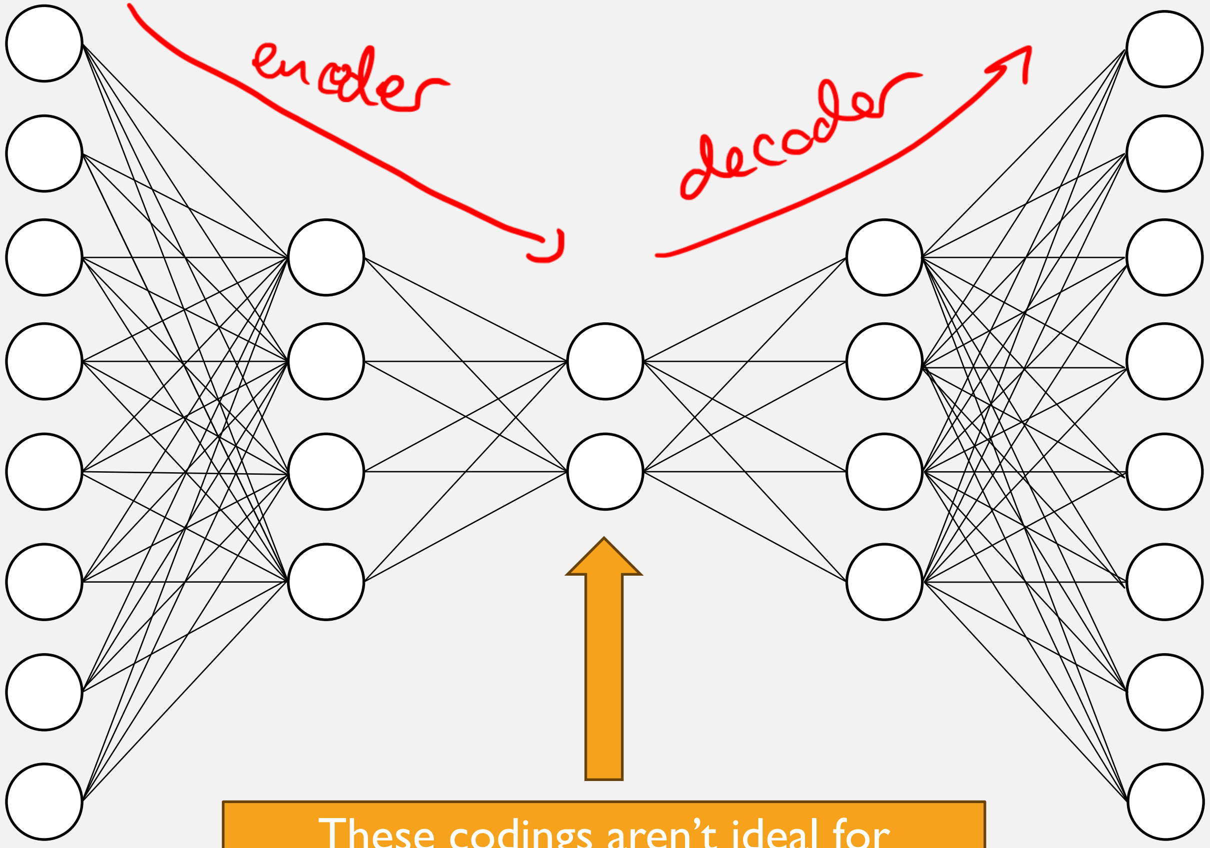
An autoencoder with linear activation is essentially PCA except for a scale factor and a rotation

linear algebra:
they span
the same
subspace



So now we can do PCA in an overcomplicated way … why care?

DEEP AUTOENCODERS



These codings aren't ideal for visualization as the transformation to the reconstructions is complex

symmetrical
non-linear
NN's capable
of learning
complex
codings

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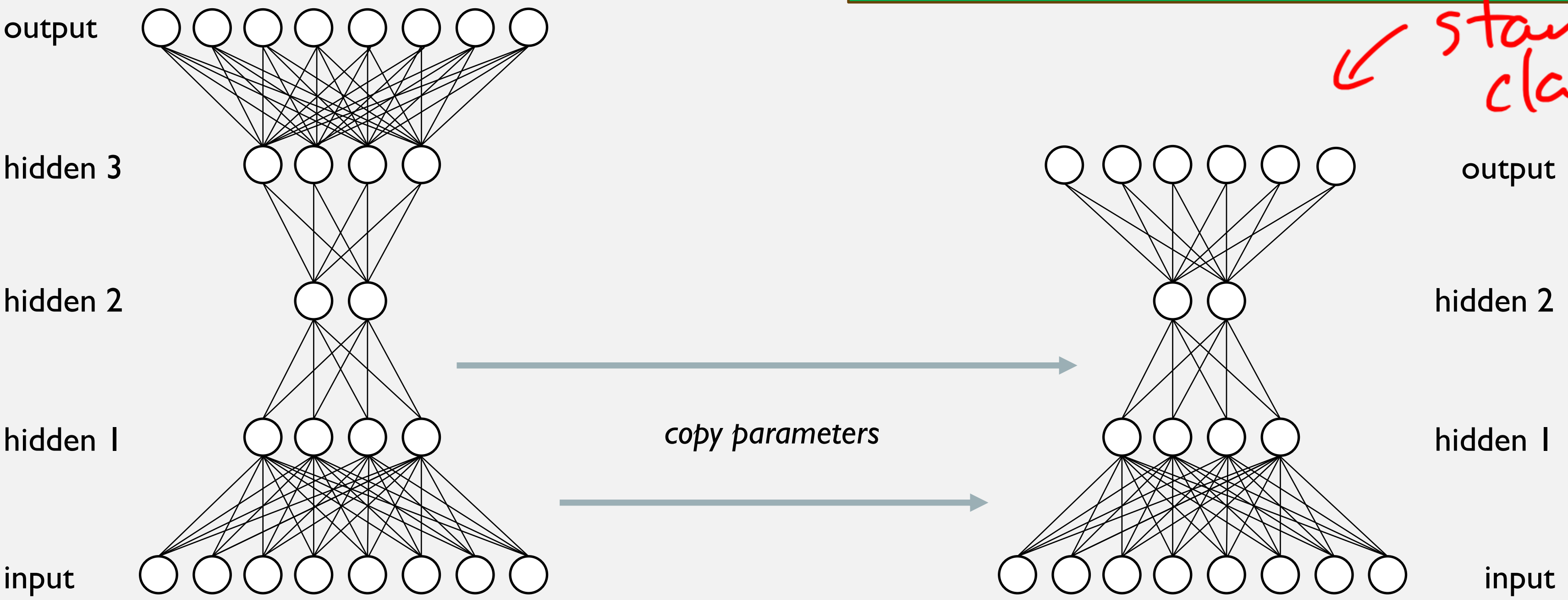
UNSUPERVISED PRETRAINING

Sometimes, you have a lot of data, but only a fraction of it is labeled

It works because the classifier won't have to learn all the low-level features

standard classifier



① Train AE on all the data

② Train classifier on the labeled data

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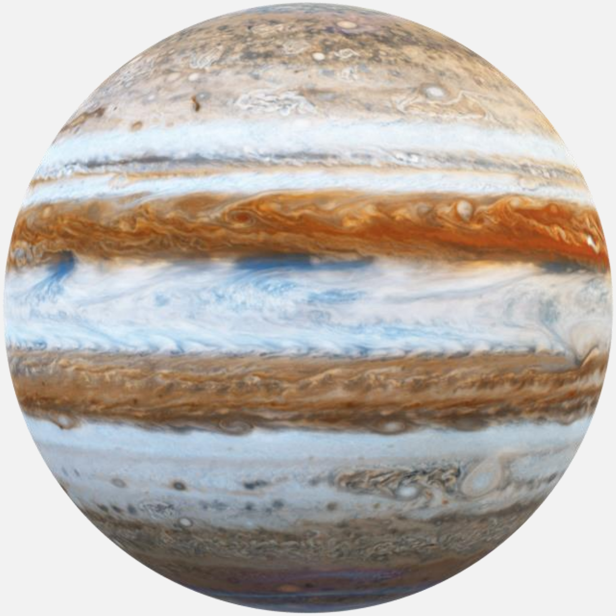
DENOISING

Add noise to the input and try to reconstruct the noise-free image



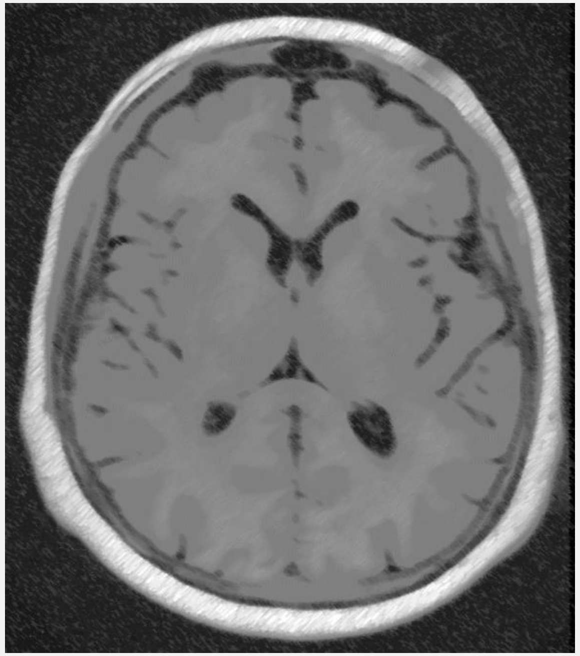
DENOISING

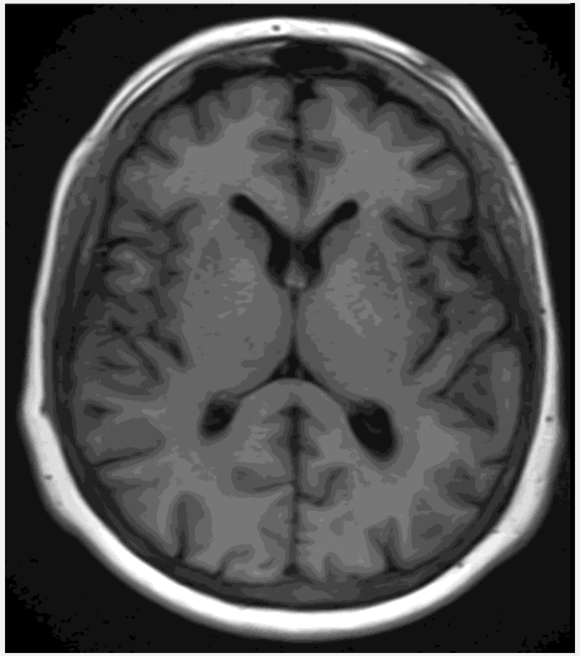
Take the autoencoder we just made

and experiment with the constraint

You have 15 minutes

AN INTERESTING APPLICATION





train AE to turn low-res into high-res
⇒ high-res w/ low rad. dose

low-radiation dose image of brain

high-radiation image

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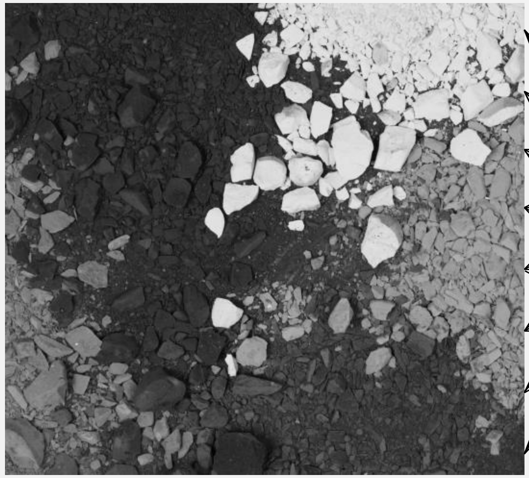
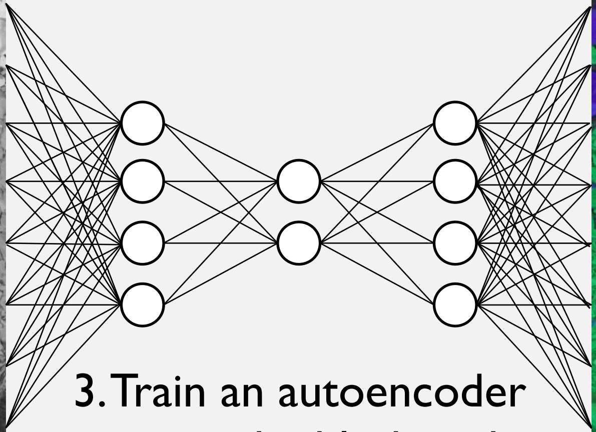
Great idea for a final project!

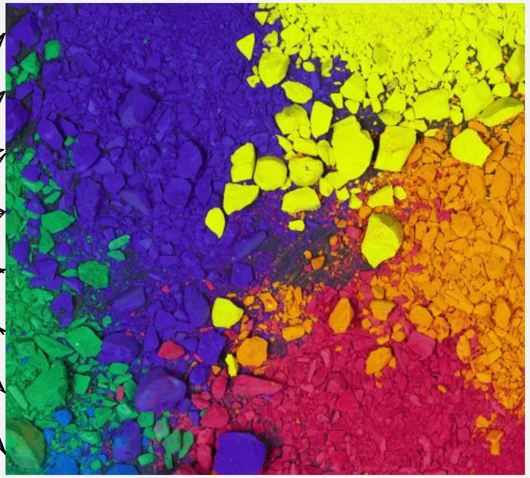
COLORIZATION

2. Make a copy of the dataset and turn each picture black-and-white.

1. Get a dataset of color pictures.







3. Train an autoencoder to turn the black-and-white pictures into the colored ones.

```
conv_encoder = Sequential([
    Conv2D(…),
    MaxPool2D(…),
    …
])
```

```
conv_decoder = Sequential([
    Conv2D(…),
    UpSamling2D(…),
    …
])
```

Conv2DTranspose

YOUR TICKET OUT THE DOOR

Scan this QR code

and tell me about something
you are still unsure about