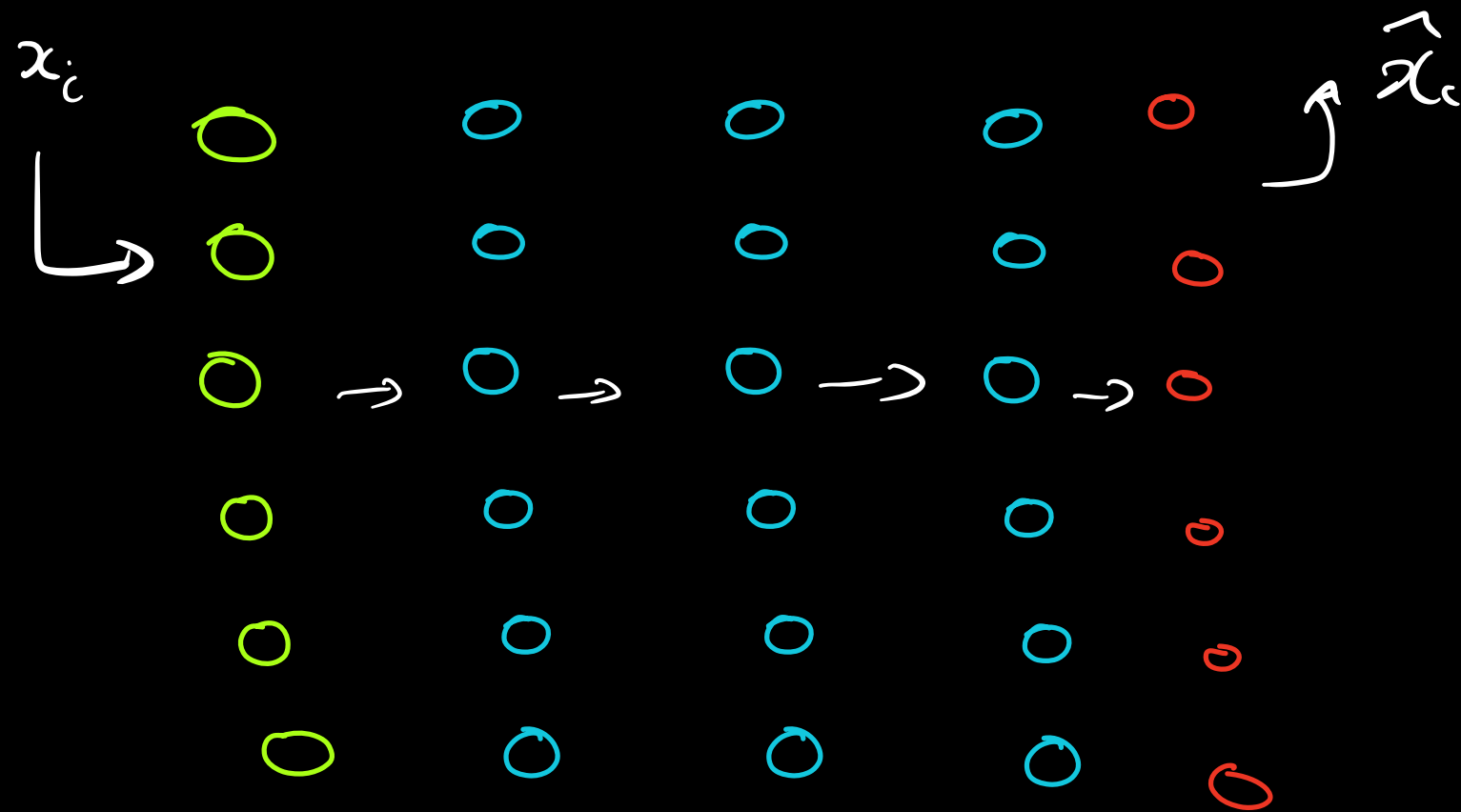


# Auto Encoders

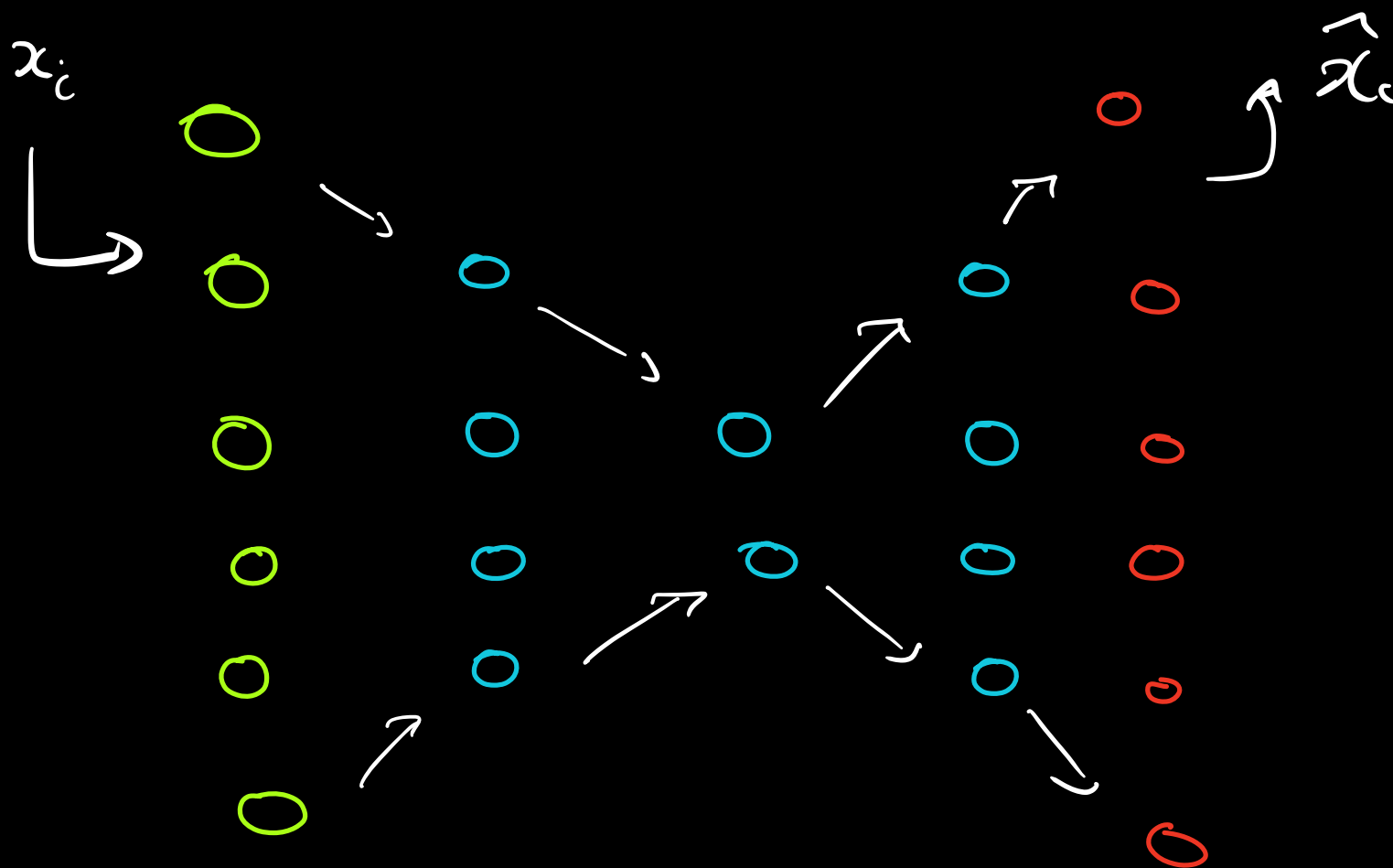
[NN]

Consider this network



I want to put  $x_i$  in and get  $x_i$  out. Do you think this is possible?

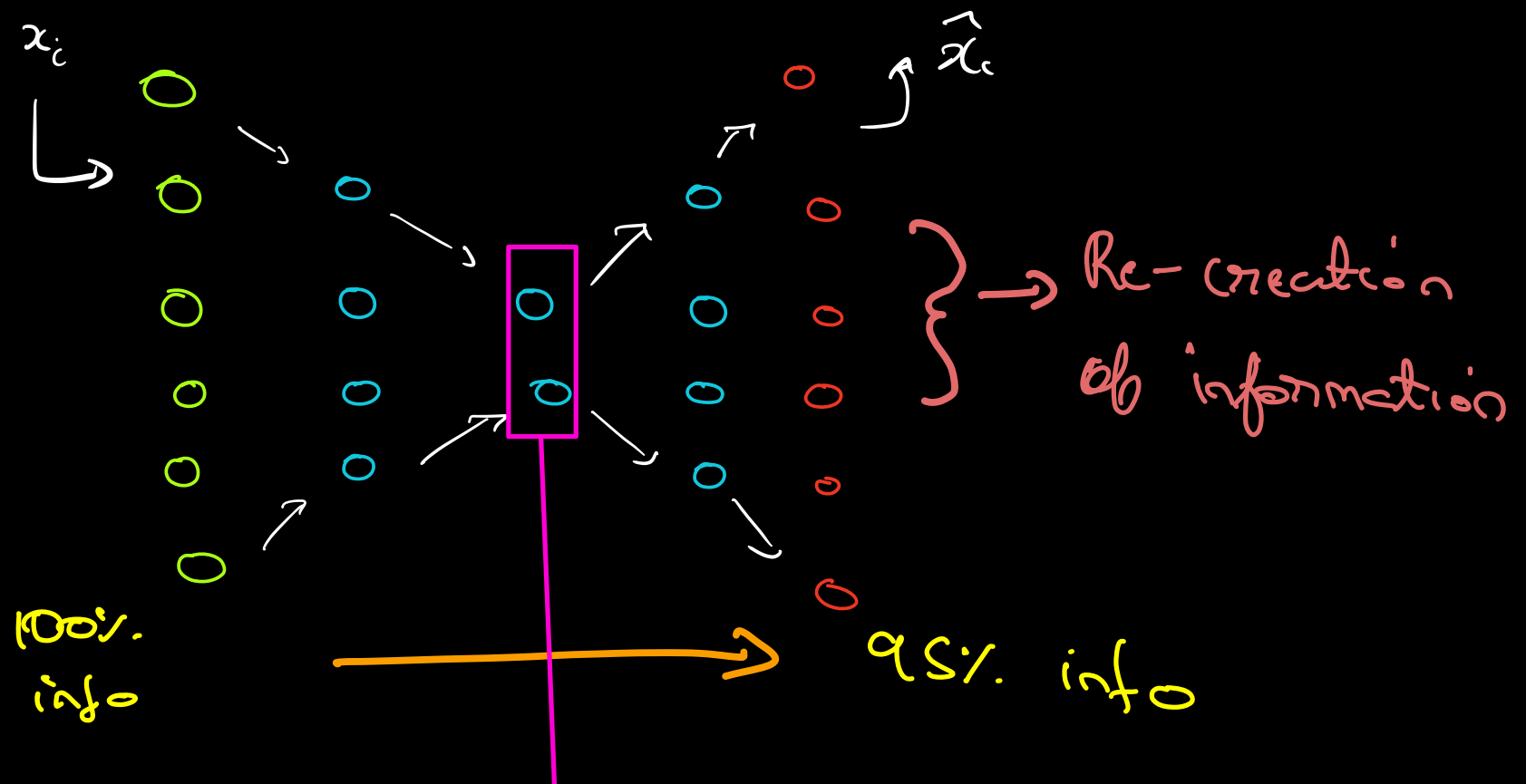
Now let's make a small edit:



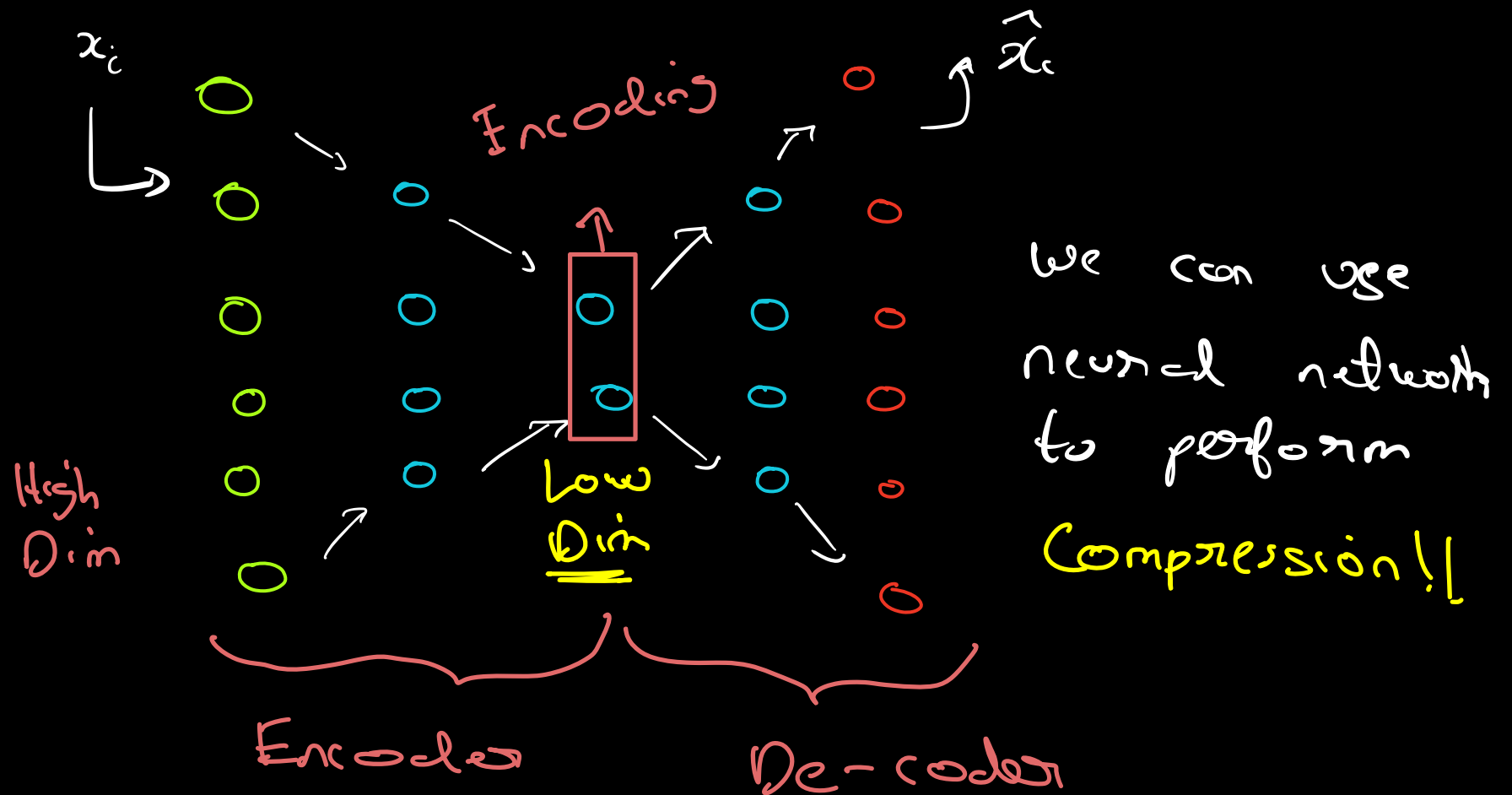
Do you think it's possible now?  
To do  $\rightarrow$  what activation?

Let's say we train this model. We will  
get a predicted  $\hat{x}_i \sim x_i \forall i$ .

But why did we do this?



↓  
Does this mean that this layer had ~75%  
of all the information? → Yes!



Encoding  $\sim$  Embedding  $\sim$  Latent Features

## Applications of AE

→ Compression / Dim reduction

→ Visualisation

→ De-noising

→ Embeddings [Feature Eng (Automatic)]

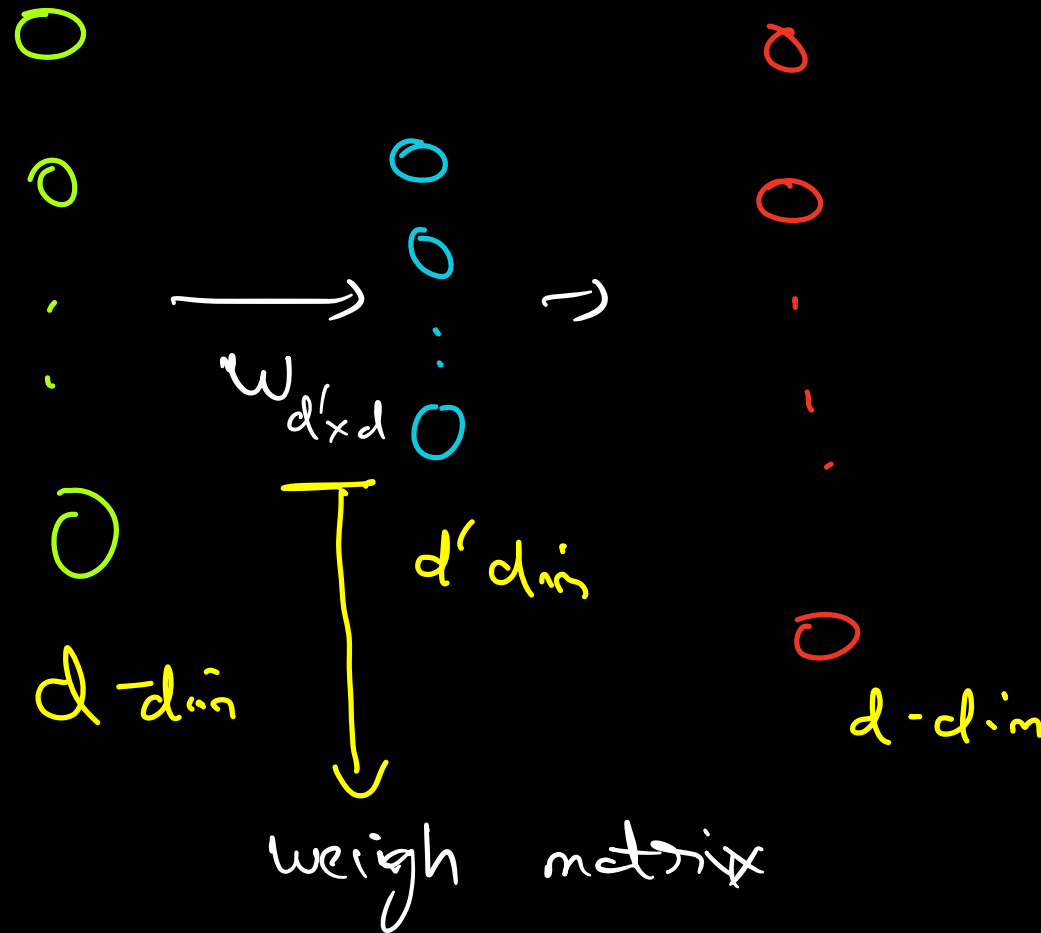
→ Recommender Systems

→ Clustering

→ Search, etc.

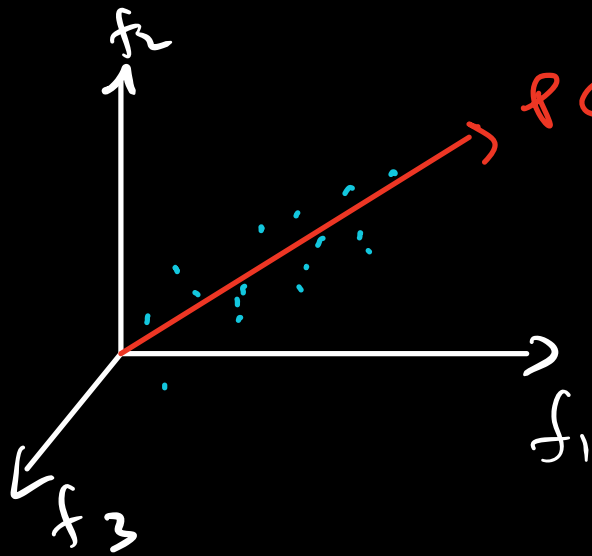
→ code  
Dim / Red

Can we create a PCA equivalent network?



Note that a principal component is

a linear combination of input axes!



$$PC = \alpha f_1 + \beta f_2 + \gamma f_3$$

↓  
linear combination

Hence, if we use a linear activation function and make biases = 0.

[loosely speaking]

So a single layer Linear auto encoder can simulate PCA.

Also, we may add constraints to make weight matrix columns  $\perp$  (e.vectors).

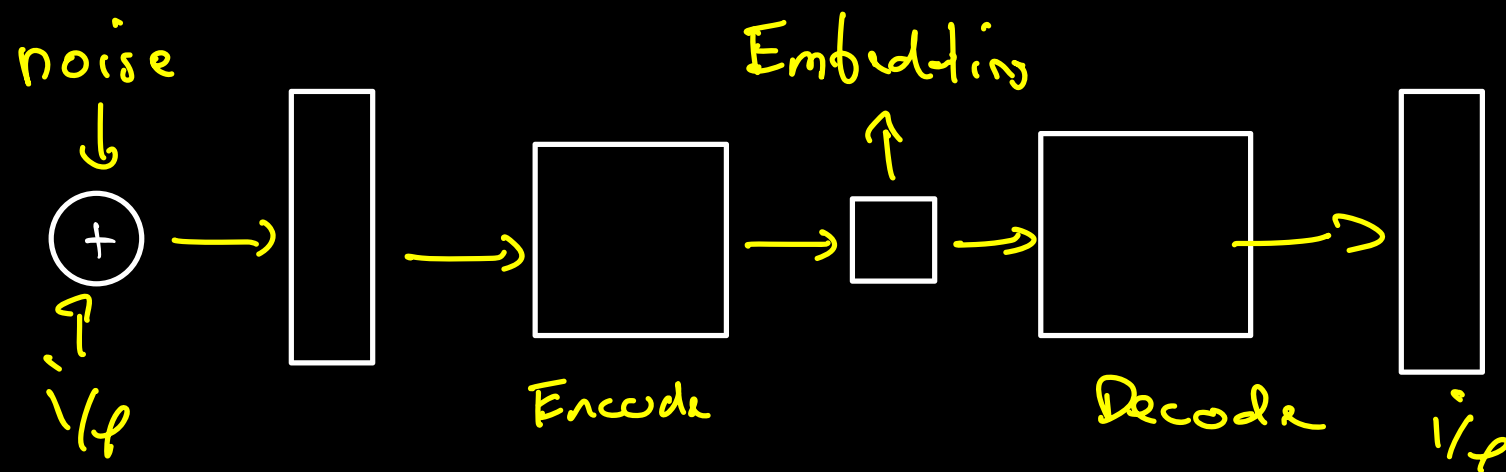


→ There is no need for encoder and decoder to be symmetric. But it is common.

## Denosing Auto Encoder (DAE)

→ Sometimes auto encoders can overfit and learn something called an "Identity fn"

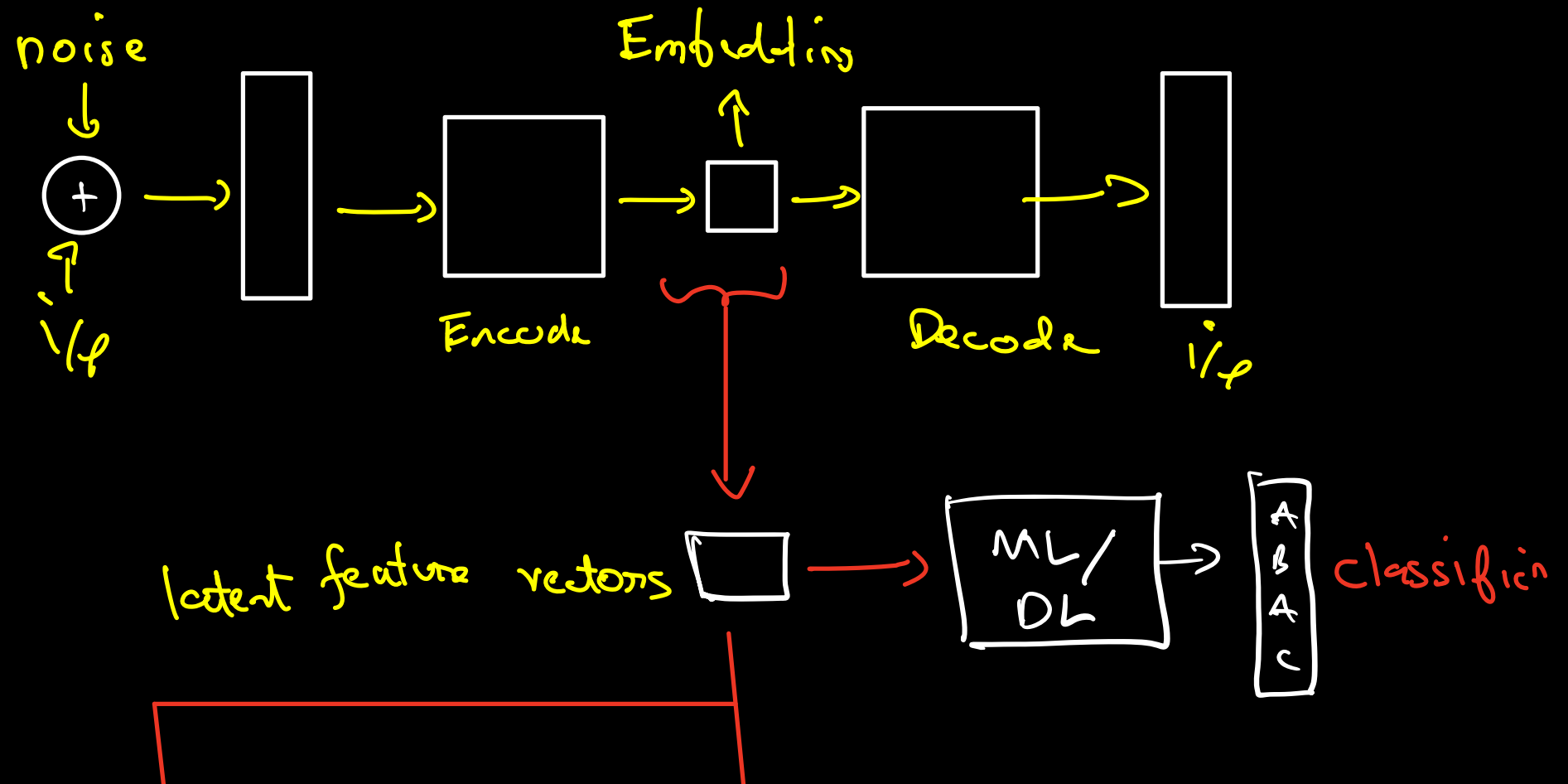
This means that  $\text{output} = \text{input}$   
↳ useless.

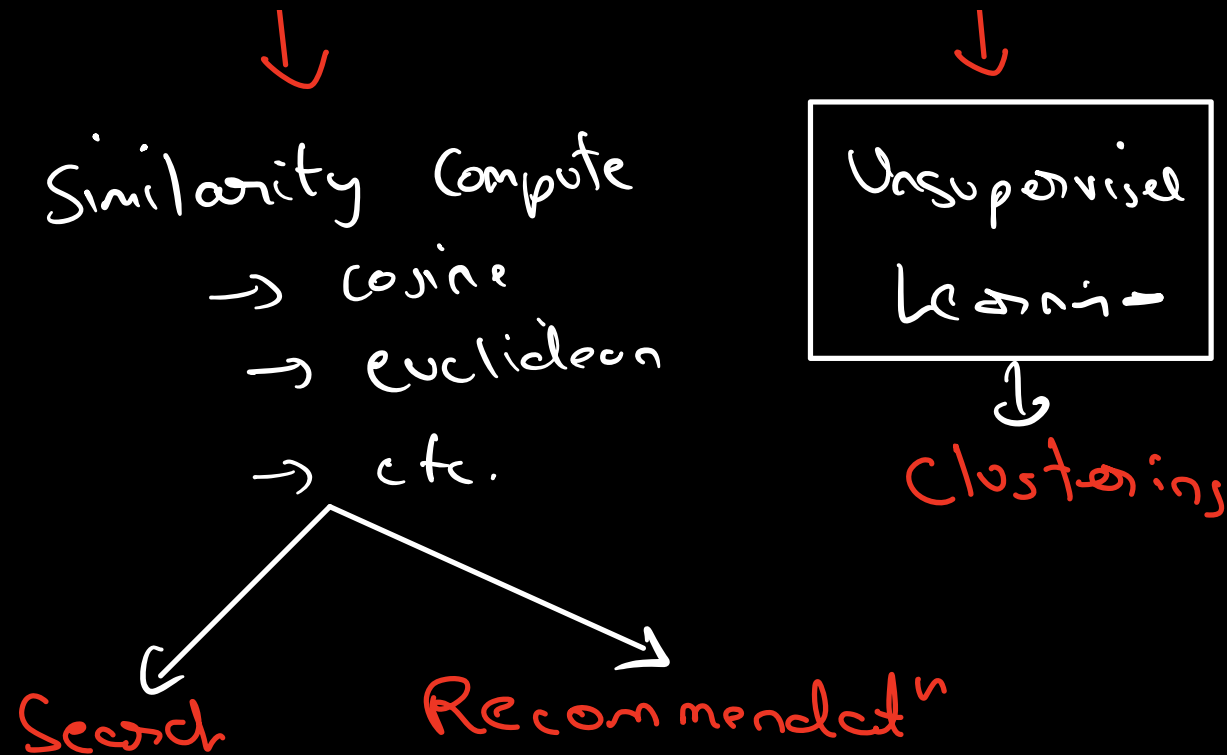


This reduces overfitting and ensures that the "encoding" is useful.

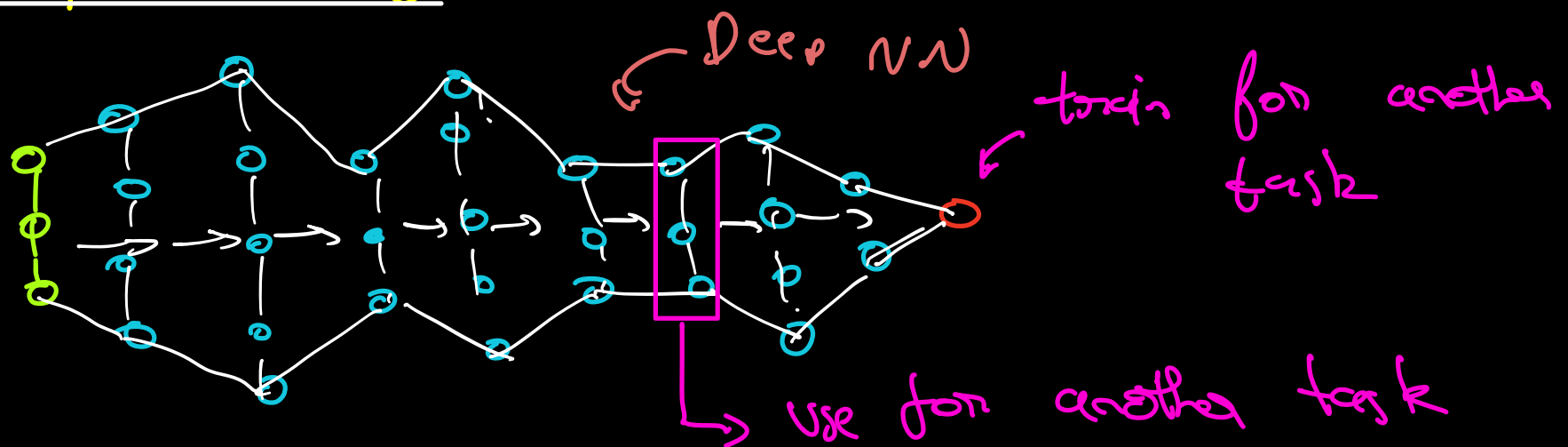
→ Further → this model is useful in the real world because in reality most images are noisy.

# Feature Extraction and Intro to Transfer Learning

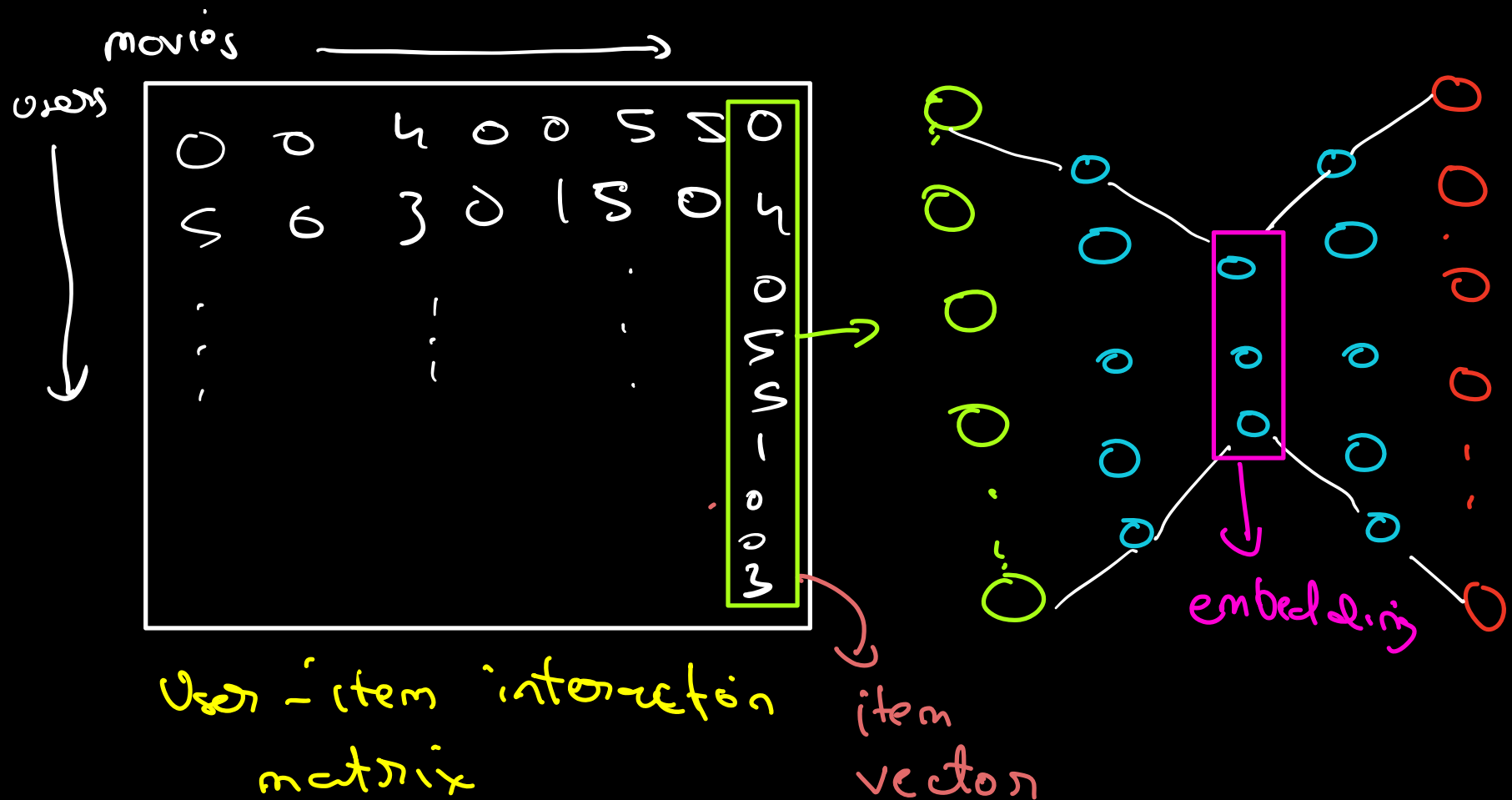




## Transfer learning



# Collaborative Filtering with AE



→ It is advised to only compare the non-zero values in the loss.