

MLHEP 2017

day 5.1

Unsupervised learning



Yandex
Data Factory

LAMBDA 

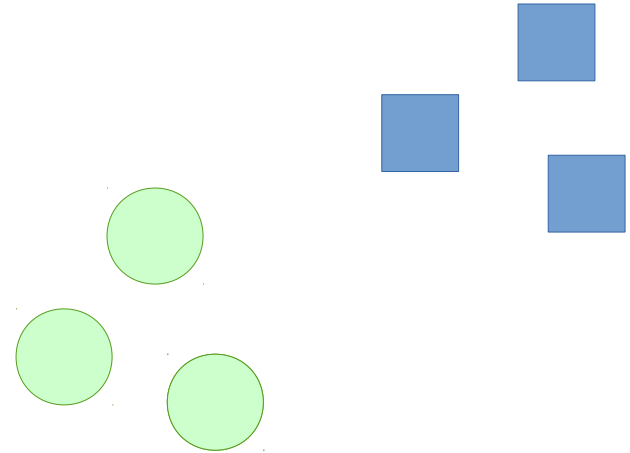


**British Hedgehog
Preservation Society**

Supervised vs Unsupervised

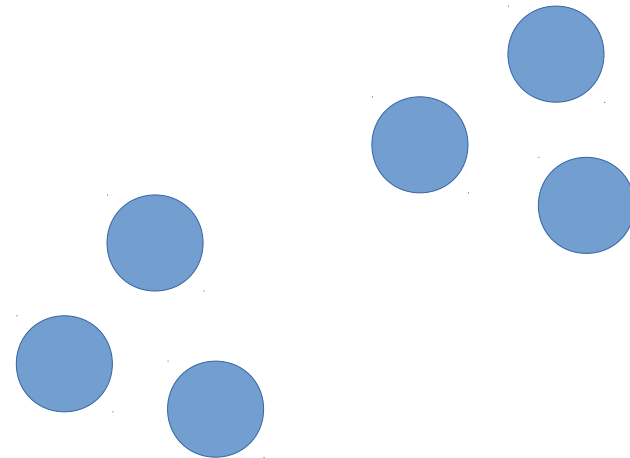
Supervised learning

- Take (x,y) pairs



Unsupervised learning

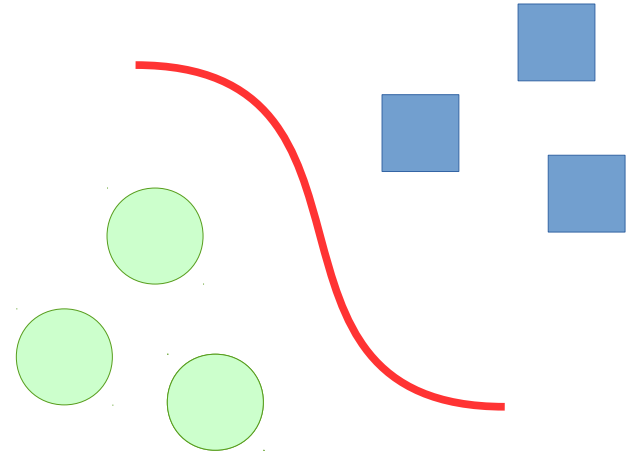
- Take x alone



Supervised vs Unsupervised

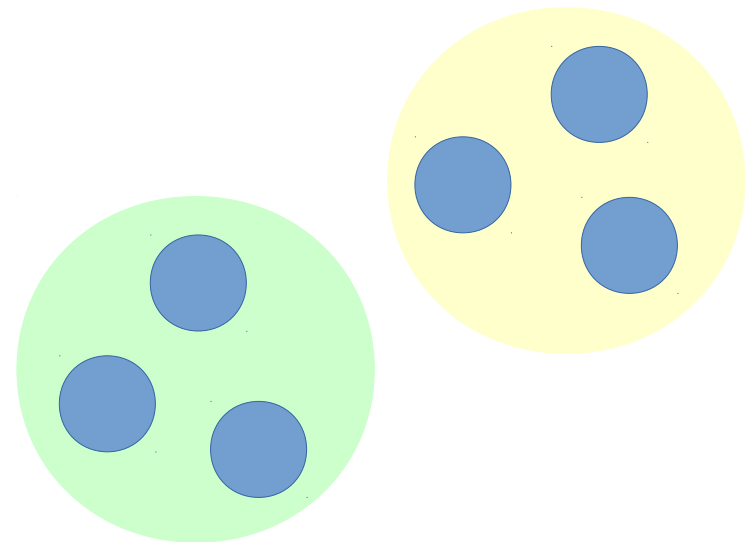
Supervised learning

- Take (x,y) pairs
- Learn mapping $x \rightarrow y$



Unsupervised learning

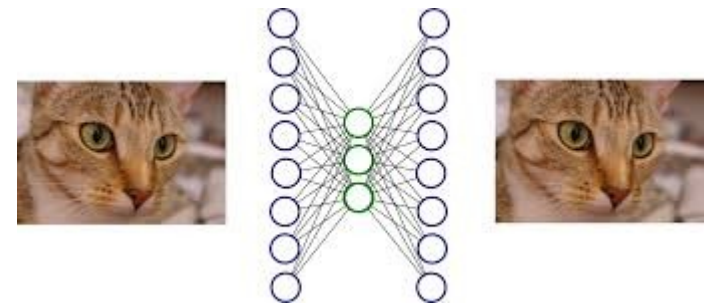
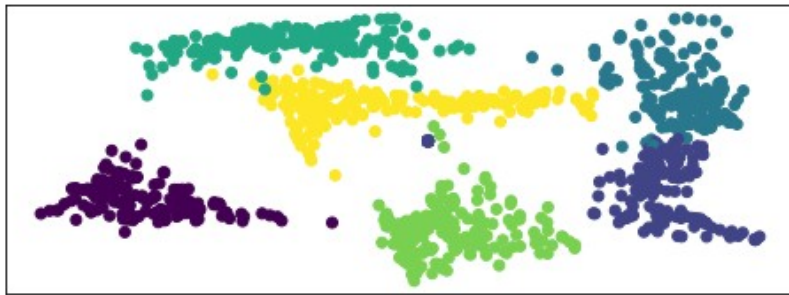
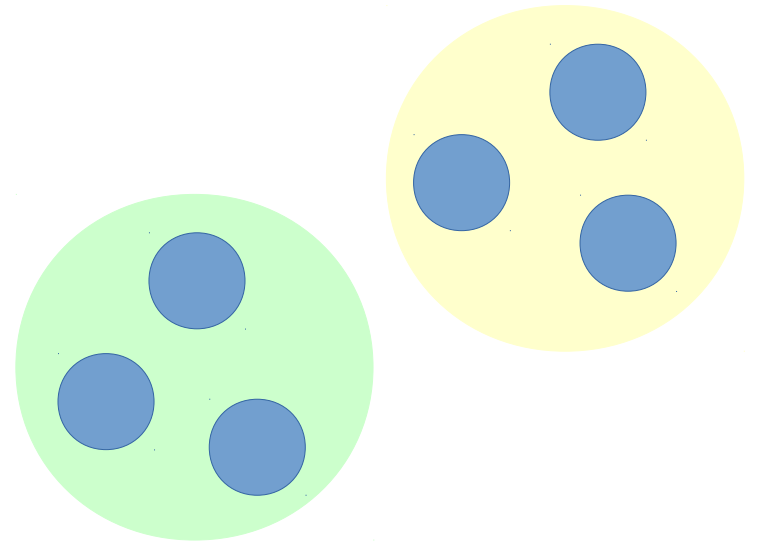
- Take unlabeled x
- Learn hidden structure behind the data



Why bother?

Unsupervised learning:

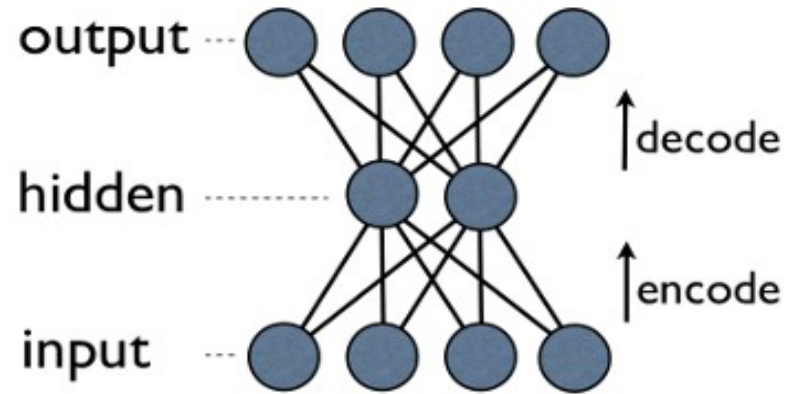
- Dimensionality reduction
- Find great features
- Explore high-dim data
- Generate new samples



Autoencoders 101

Main idea:

- Take data in some original (high-dimensional) space;
- Project data into a new space **from which it can then be accurately restored**;
- Encoder = data to hidden
- Decoder = hidden to data
- $\text{Decoder}(\text{Encoder}(x)) \sim x$



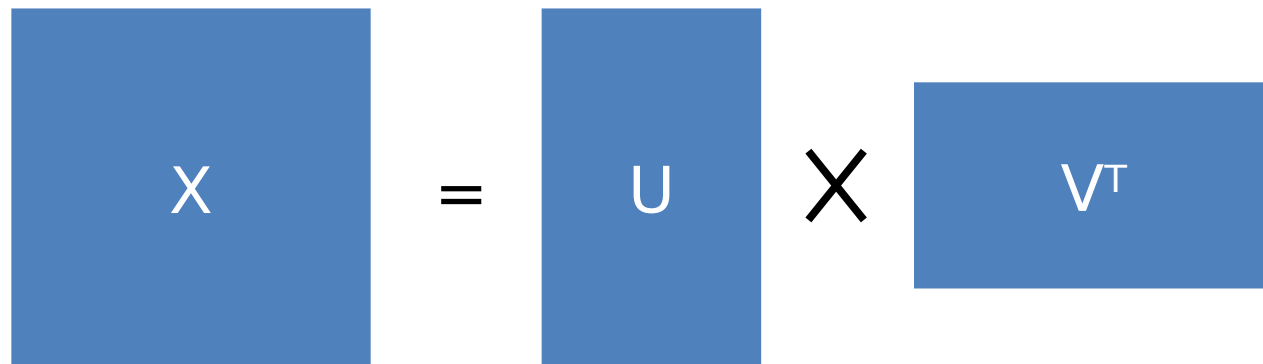
Why do we ever need that?

- Dimensionality reduction
 - $|\text{code}| \ll |\text{data}|$

<to be continued>

Matrix decompositions

Example: matrix factorization (PCA, SVD)

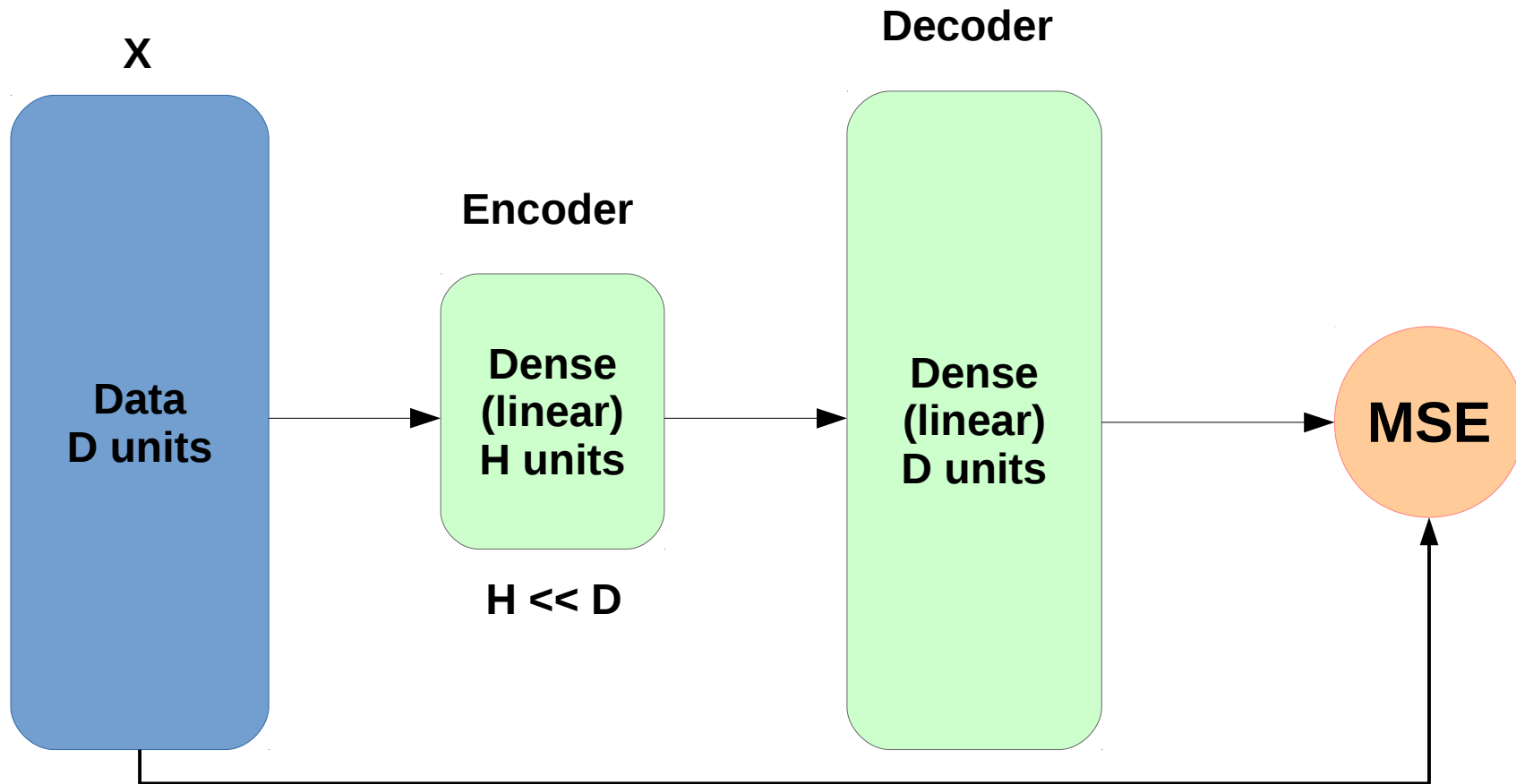

$$X = U \times V^T$$

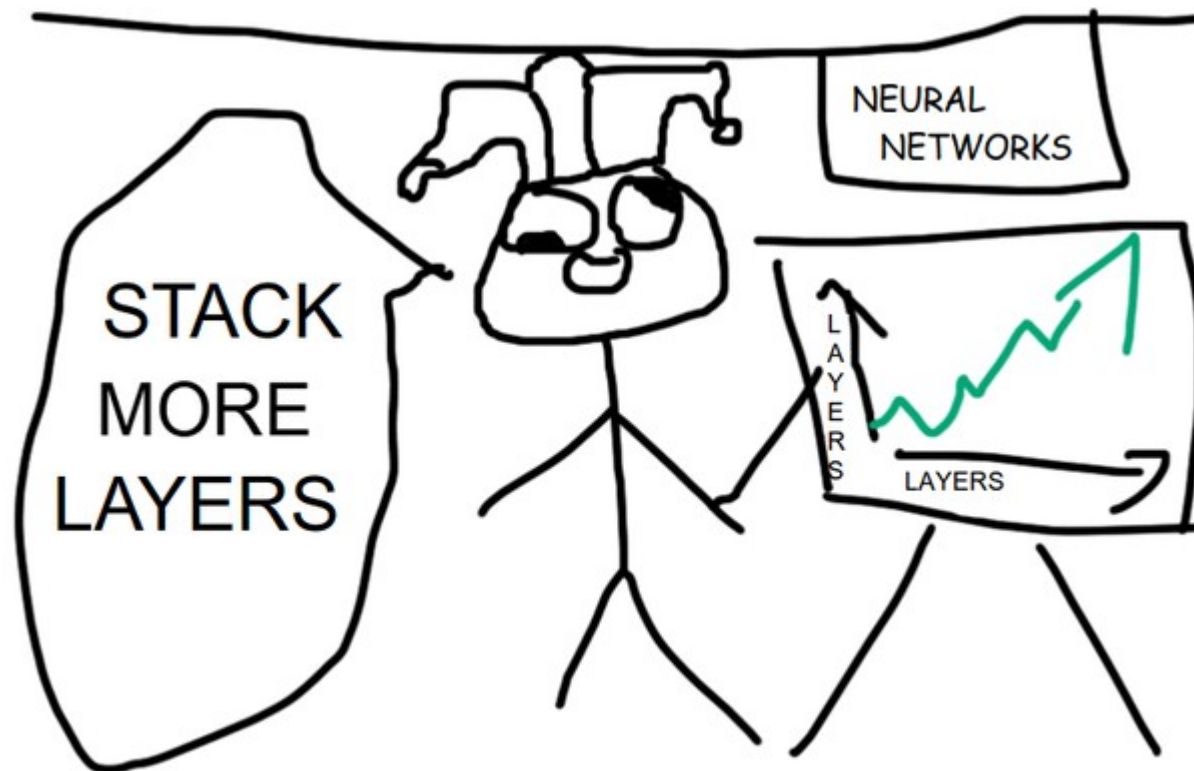
Minimizing reconstruction error

$$\|X - U \cdot V^T\| \rightarrow \min_{U, V}$$

Matrix decomposition

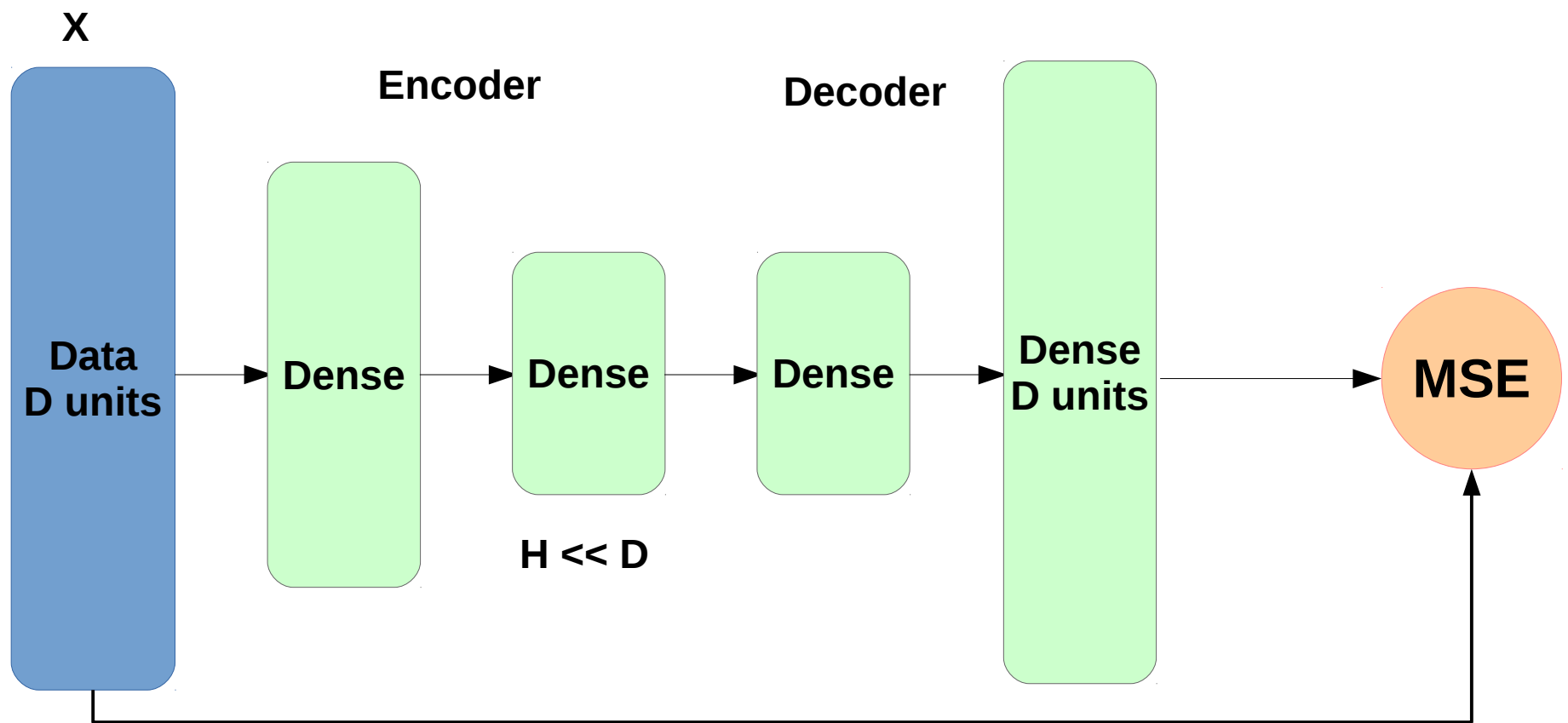
- A different perspective





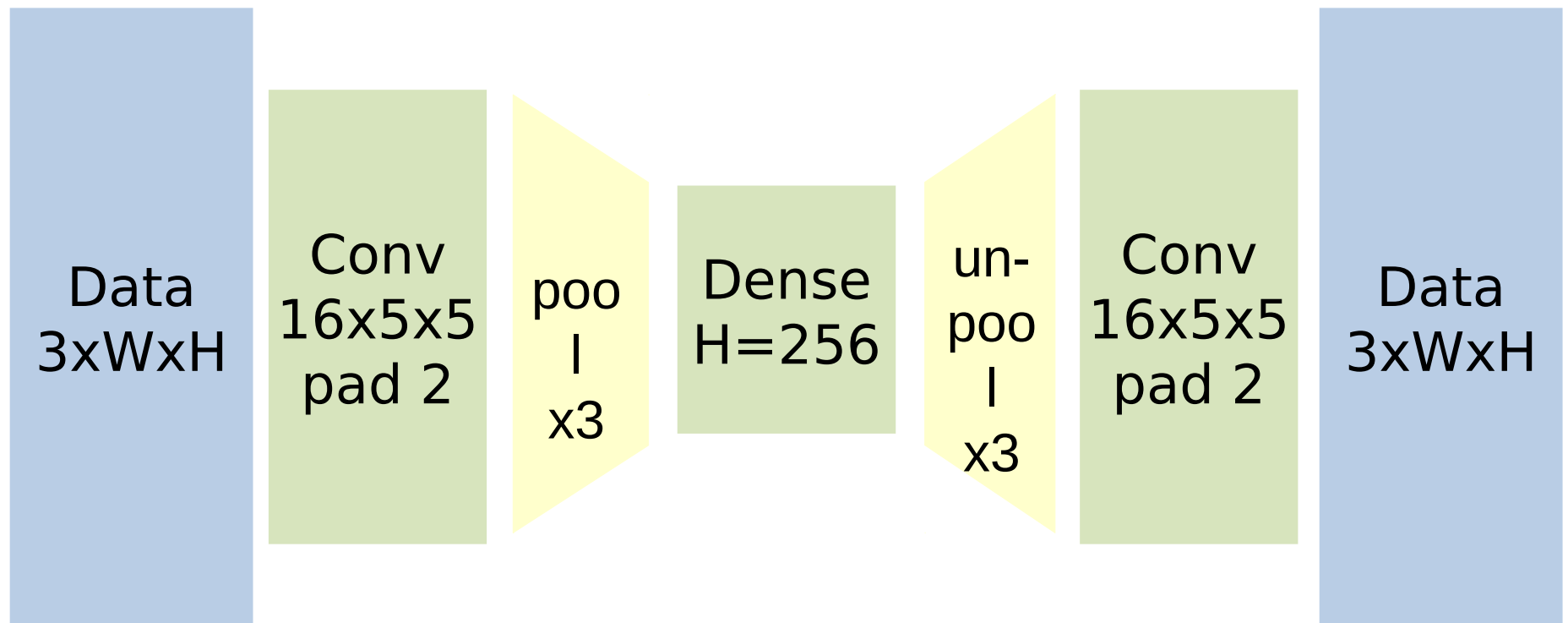
(kinda) Deep autoencoder

- Stack more layers!

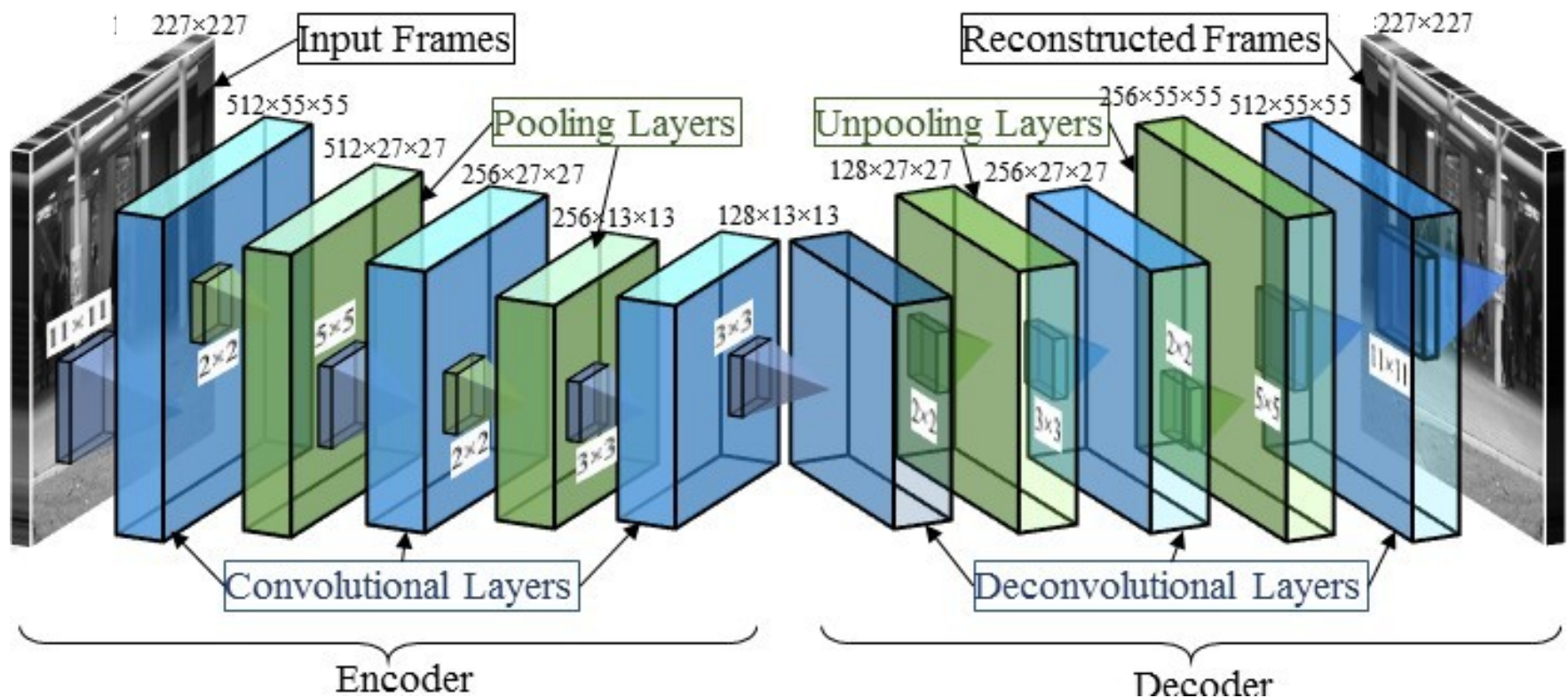


Quiz: What if data is an image?

Convolutional autoencoders



Fully-convolutional

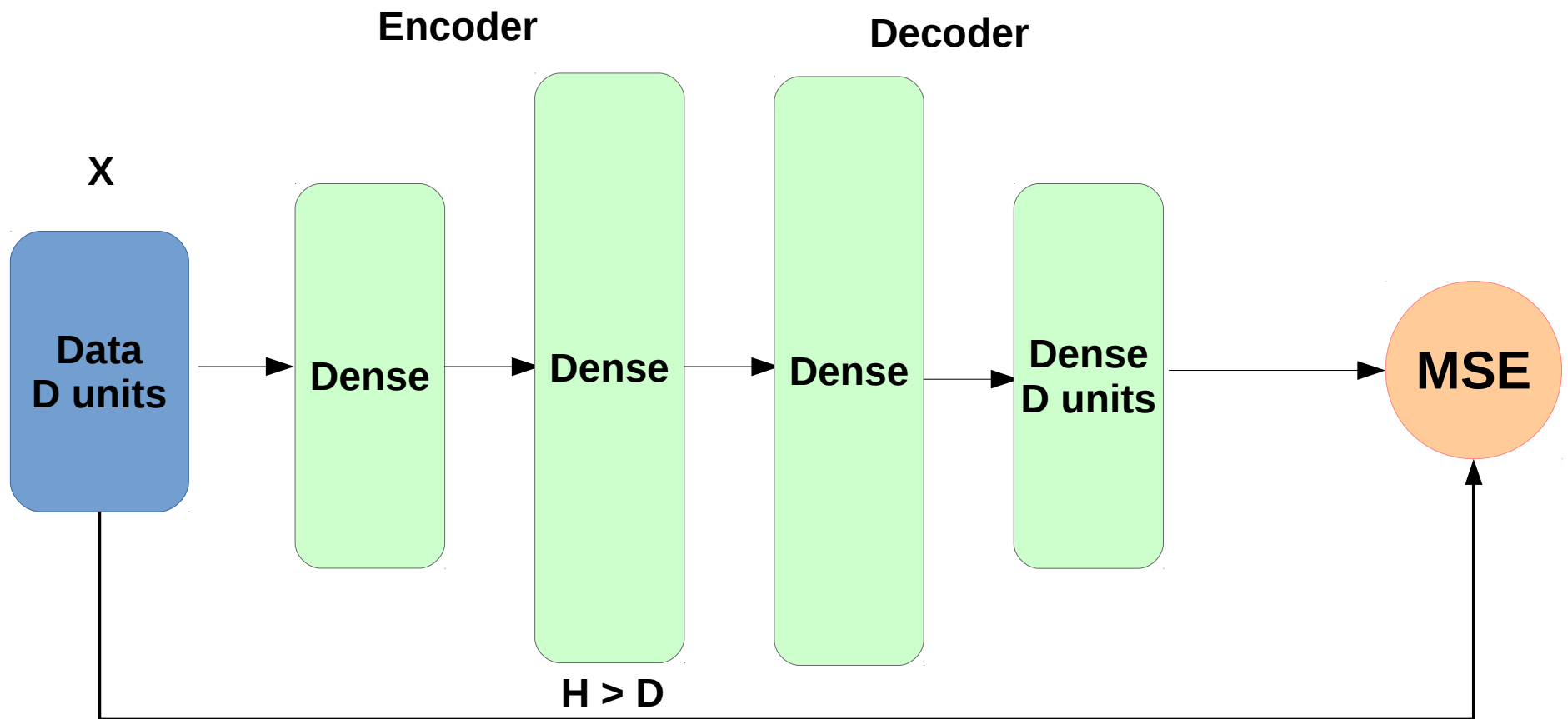


Why do we ever need that?

- Dimensionality reduction
 - $|\text{code}| \ll |\text{data}|$
- **Learn some great features!**
 - Before feeding data to your XGBoost

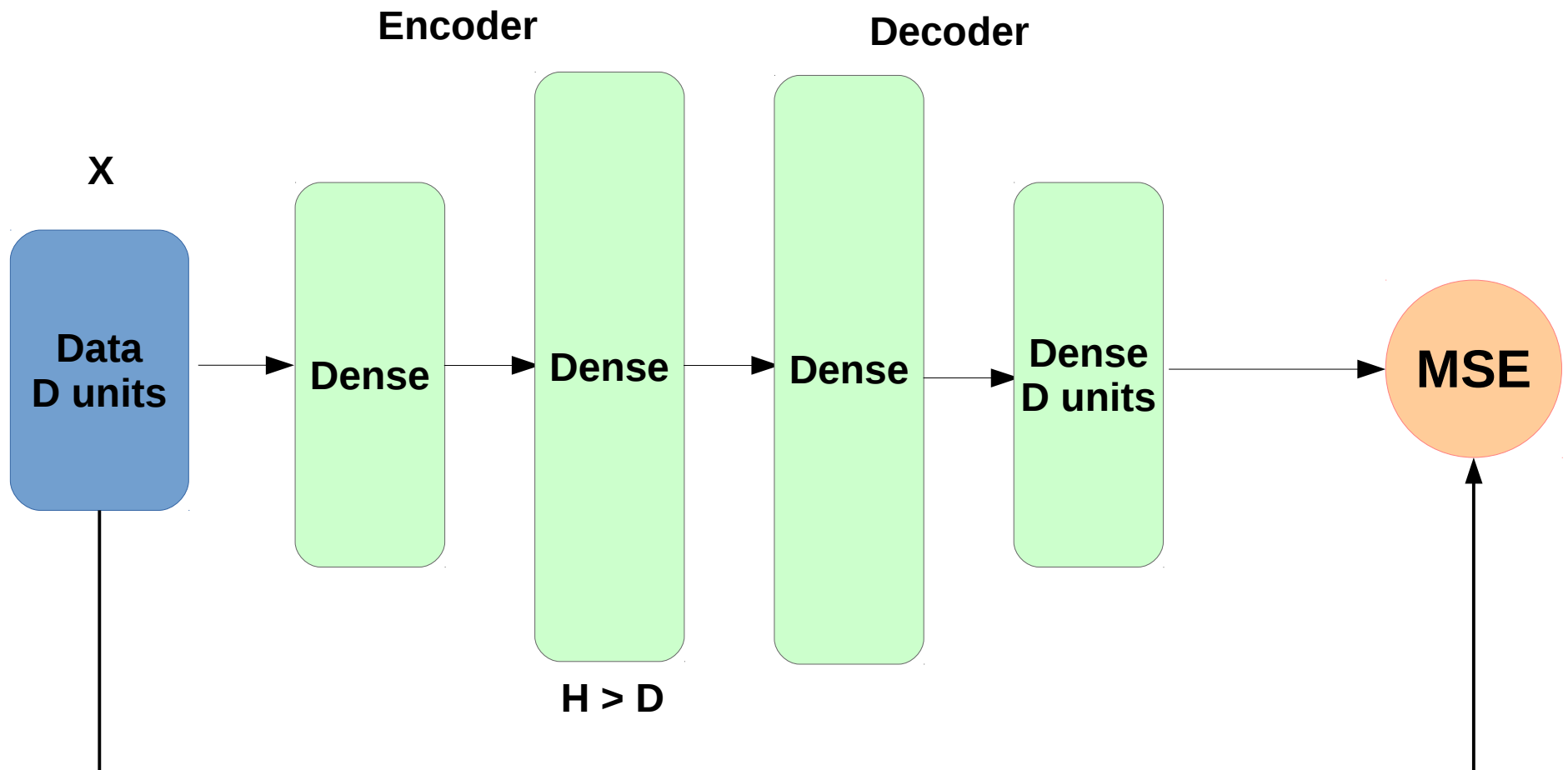
Expanding autoencoder

- Bigger/richer representation



Expanding autoencoder

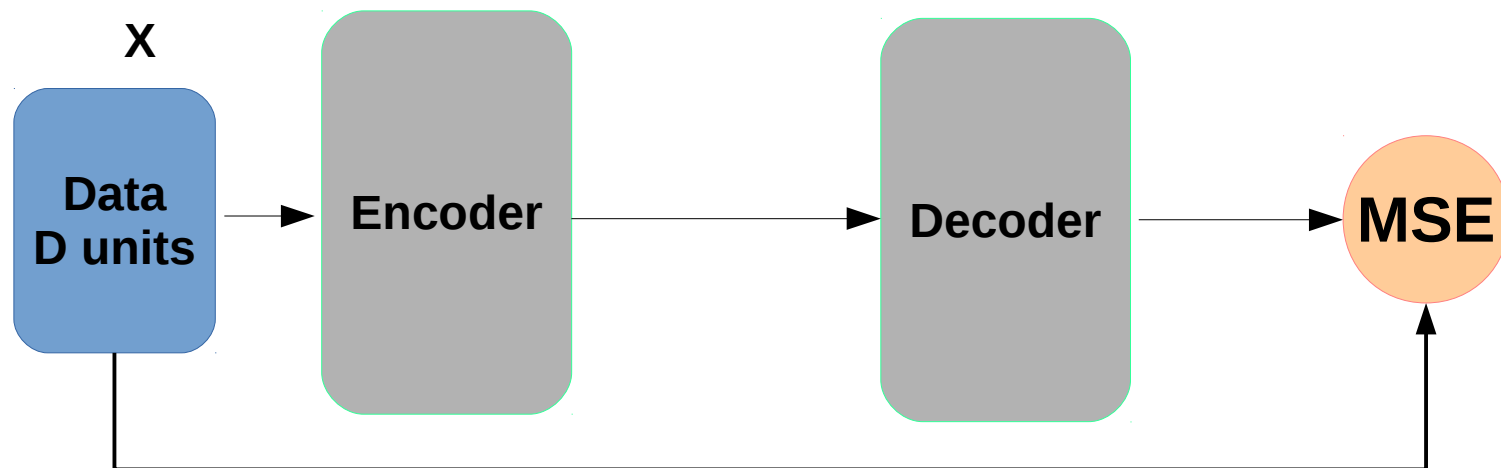
- Bigger/richer representation



Something's wrong with this guy. **Ideas?**

Expanding autoencoder

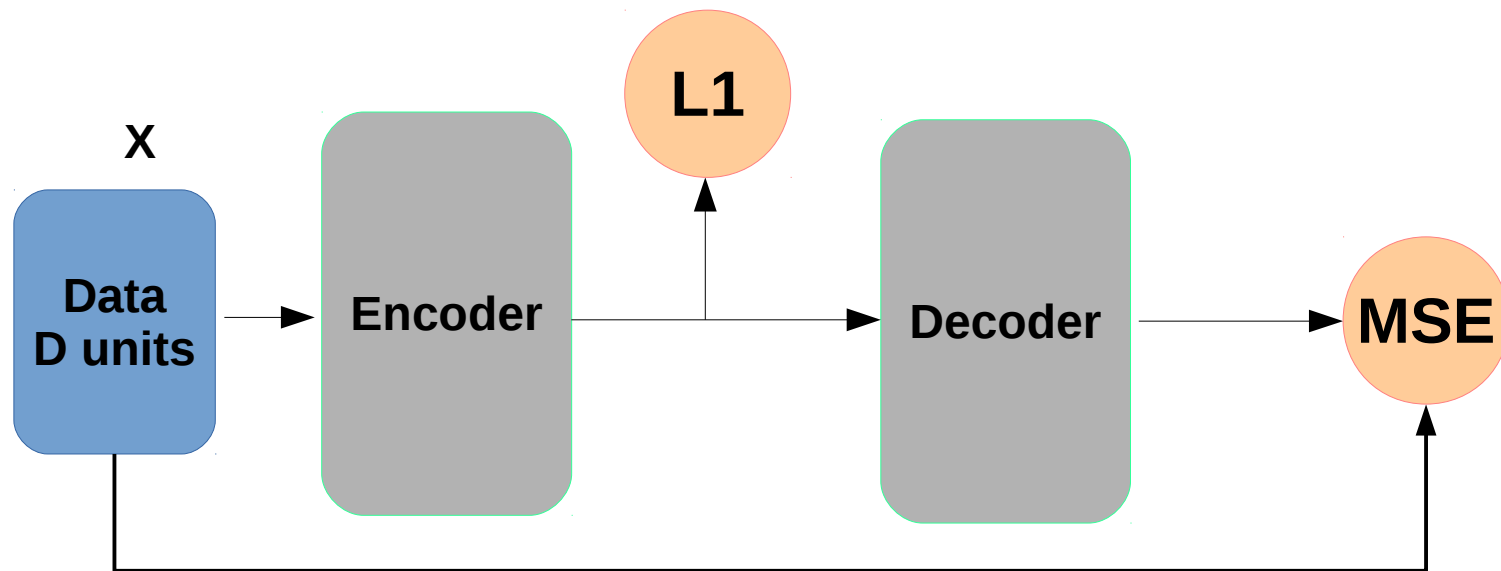
- Naive approach will learn identity function!
- Gotta regularize!



$$L = \|X - Dec(Enc(X))\|$$

Sparse autoencoder

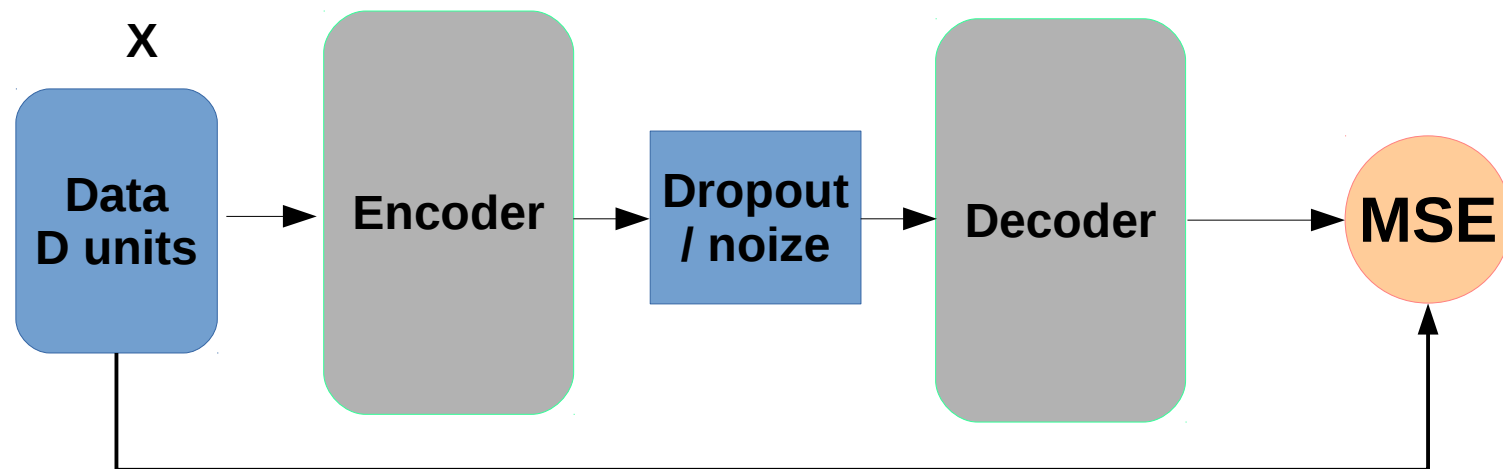
- Naive approach will learn identity function!
- Idea 1: L1 on **activations**, sparse code



$$L = ||X - Dec(Enc(X))|| + \sum_i |Enc_i(X)|$$

Redundant autoencoder

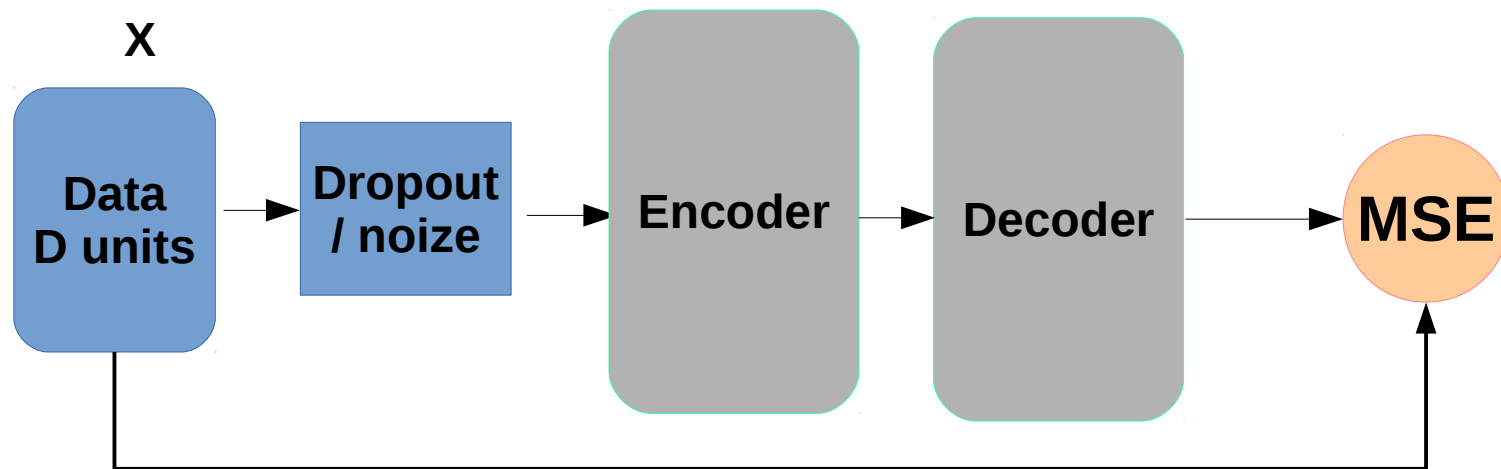
- Naive approach will learn identity function!
- Idea 2: noise/dropout, redundant code



$$L = \|X - \text{Enc}(\text{Noise}(\text{Dec}(X)))\|$$

Denoising autoencoder

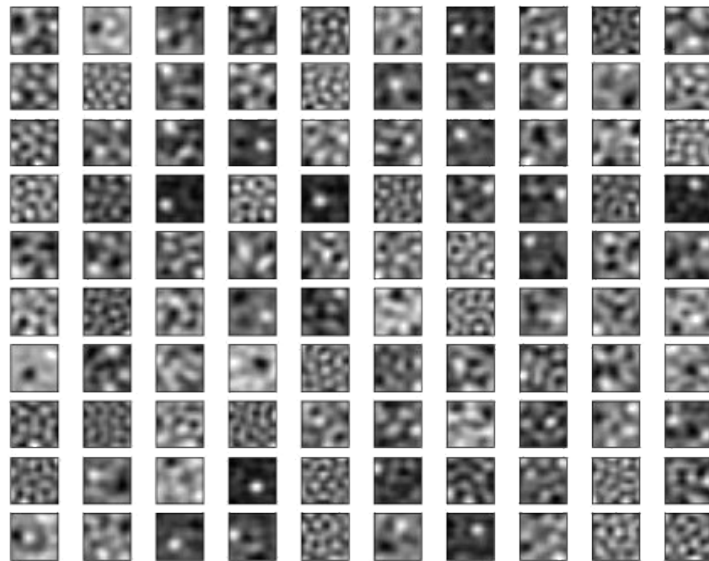
- Naive approach will learn identity function!
- Idea 3: distort input, learn to undo distortion



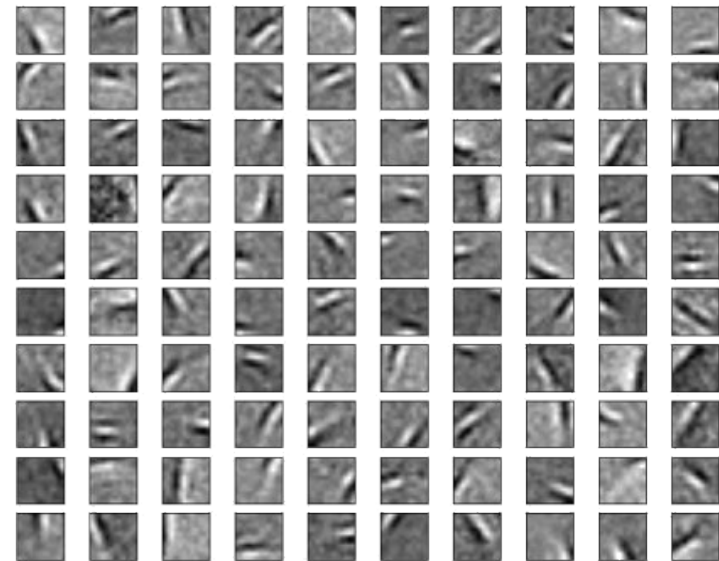
$$L = \|X - \text{Enc}(\text{Dec}(\text{Noise}(X)))\|$$

Sparse Vs Denoising

- Filter weights, 12x12 patches



Sparse AE



Denoizing AE

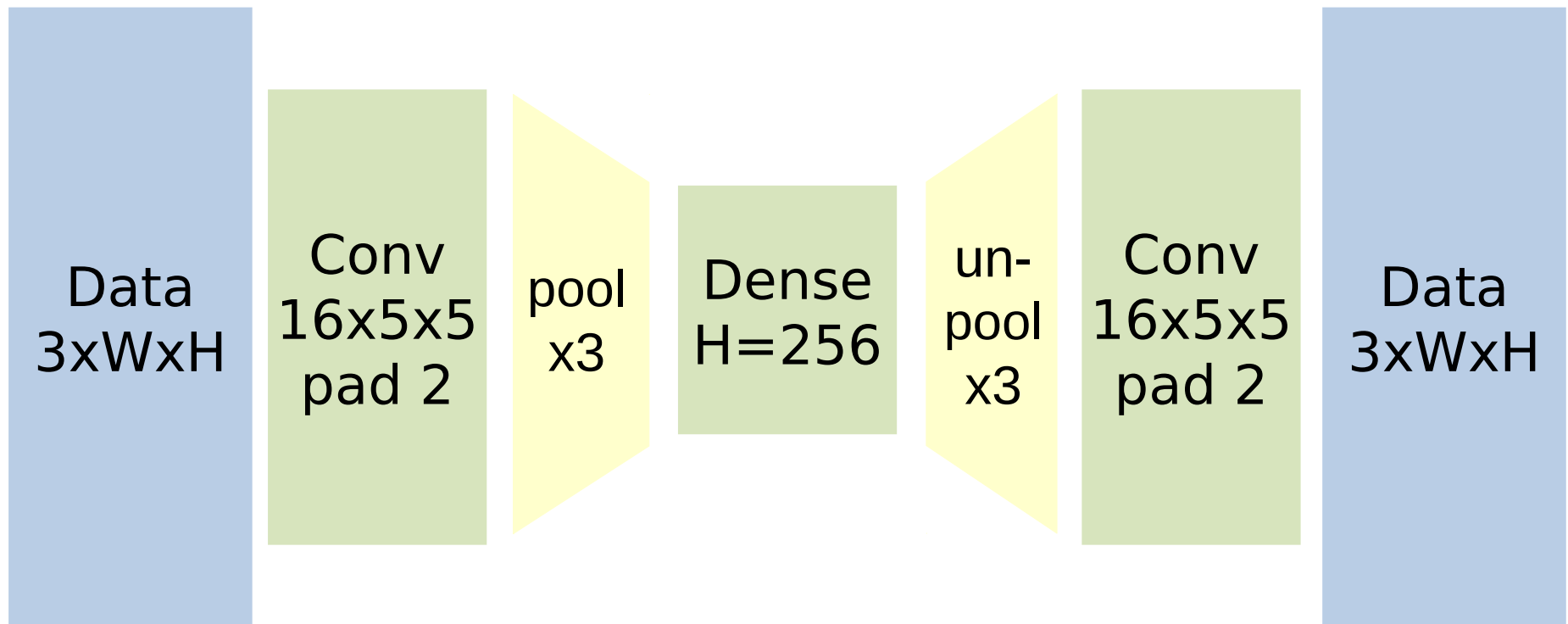
Actually meaningless :)

Why do we ever need that?

- Dimensionality reduction
 - $|\text{code}| \ll |\text{data}|$
- Learn some great features!
 - Before feeding data to your XGBoost
- **Unsupervised pretraining**
 - Exploit unlabeled data to improve classifier

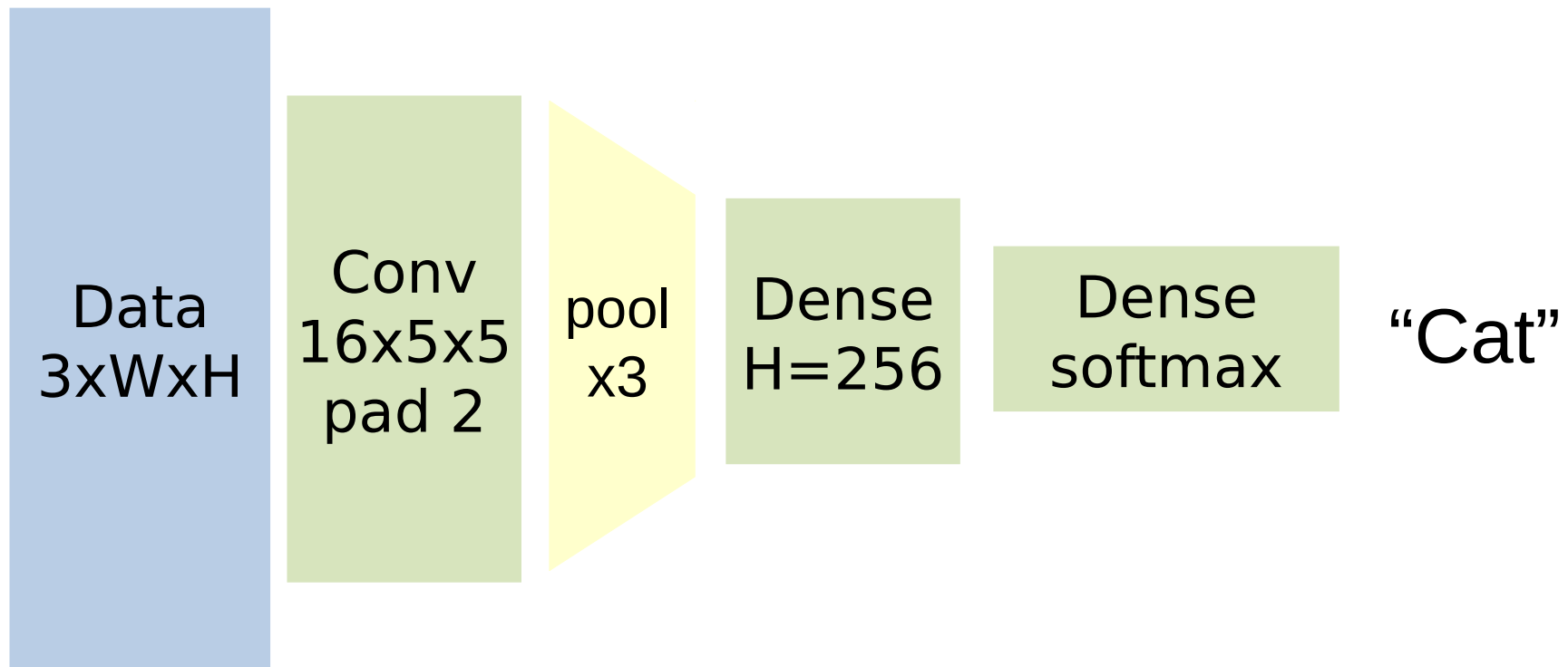
Unsupervised pre-training

Step 1: train autoencoder



Unsupervised pre-training

Use autoencoder as initialization

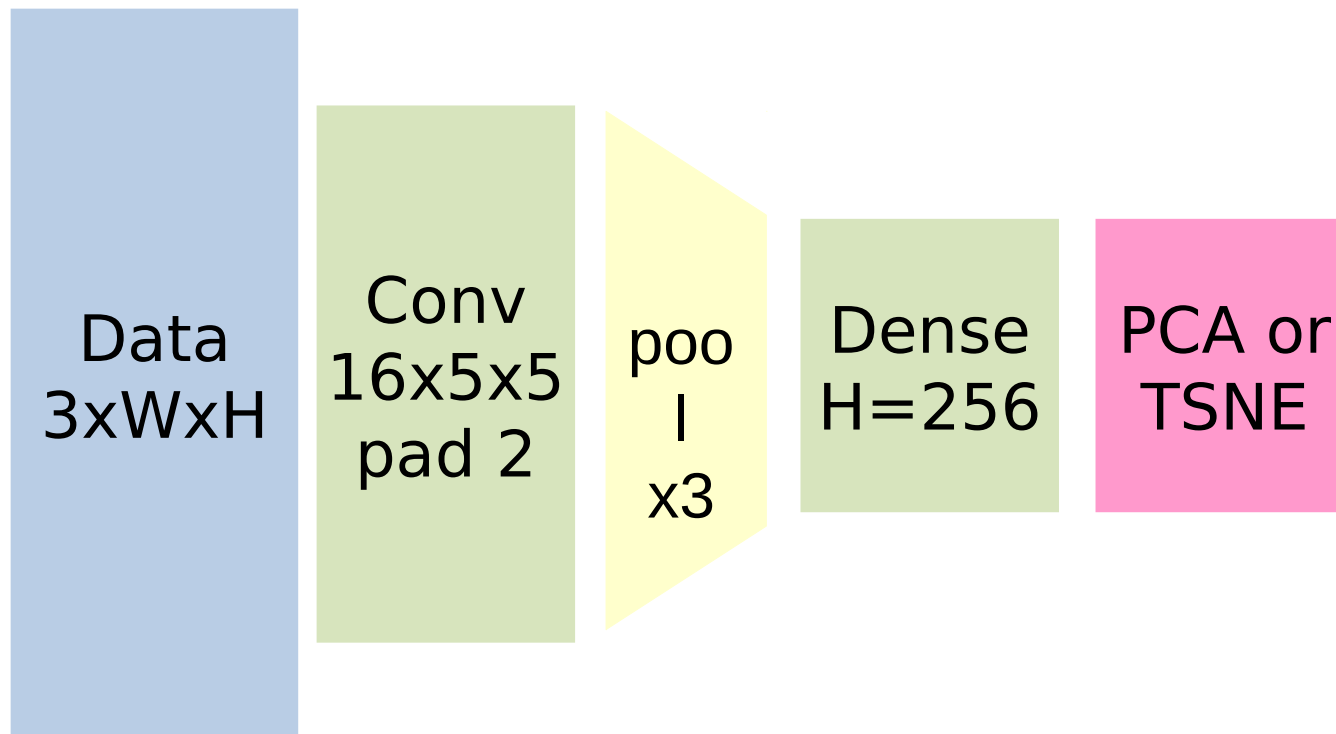


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- Dimensionality reduction
 - $|\text{code}| \ll |\text{data}|$
- Learn some great features!
 - Before feeding data to your XGBoost
- Unsupervised pretraining
 - Exploit unlabeled data to improve classifier
- Visualizing data structure

Exploratory analysis

Visualize data in hidden space



Exploratory analysis

Visualize data in hidden space



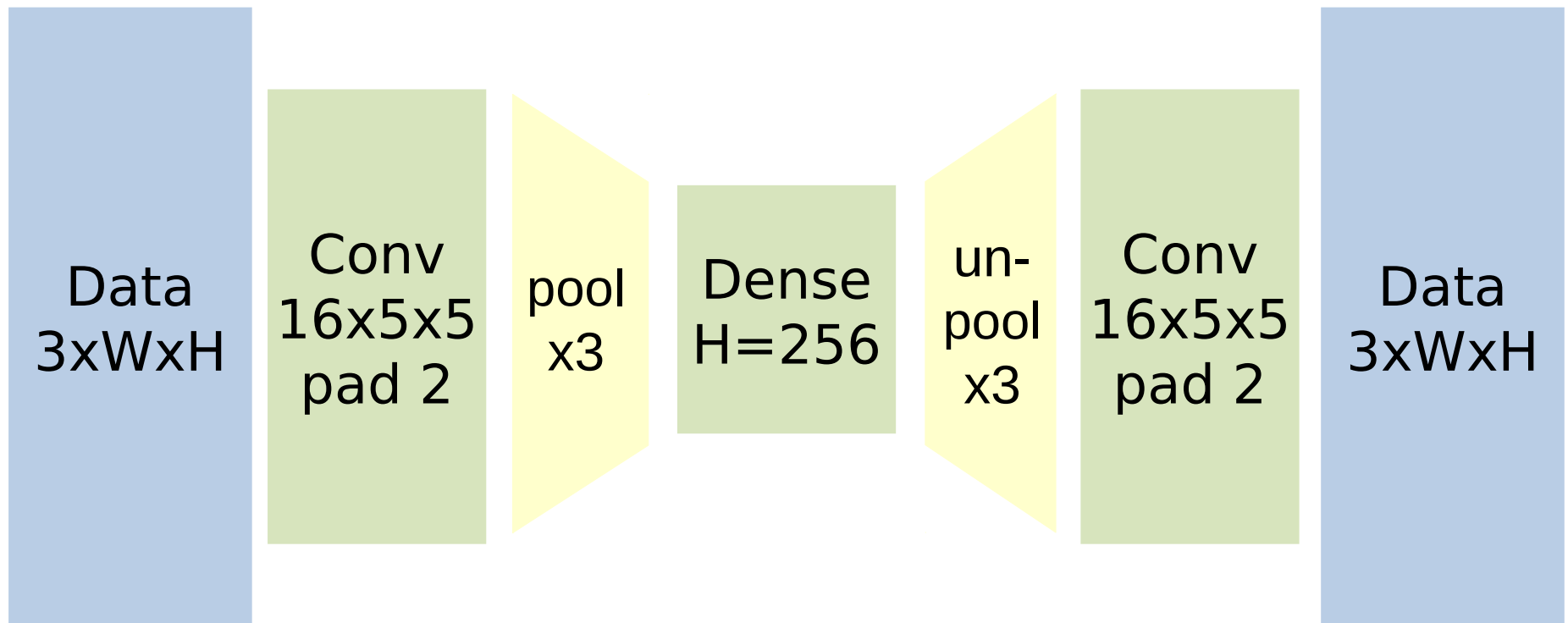
Image: <https://razi.xyz/vgg2vec/picasso>

Why do we ever need that?

- Dimensionality reduction
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- Visualizing data structure
- **Generating new data**
 - Your trainable monte-carlo

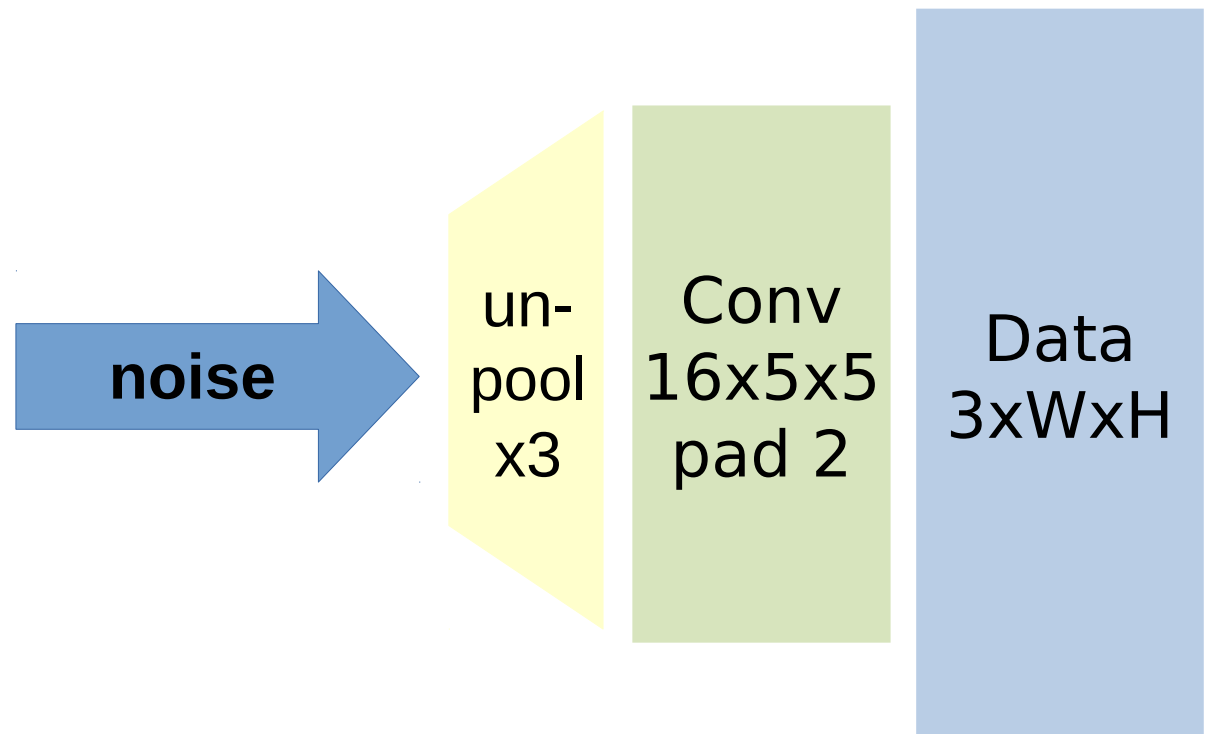
Generating images

Step 1: train autoencoder



Generating images

Step 2: use decoder to generate data



Disclaimer: this isn't the state of the art approach

Generating images

Step 2: use decoder to generate data



Img: decoded trajectories from hidden space

Image morphing with AE

Idea:

- If $\text{Enc}(\text{image1}) = c1$
 $\text{Enc}(\text{image2}) = c2$
- Than maybe $(c1+c2)/2$ is a semantic average of the two images

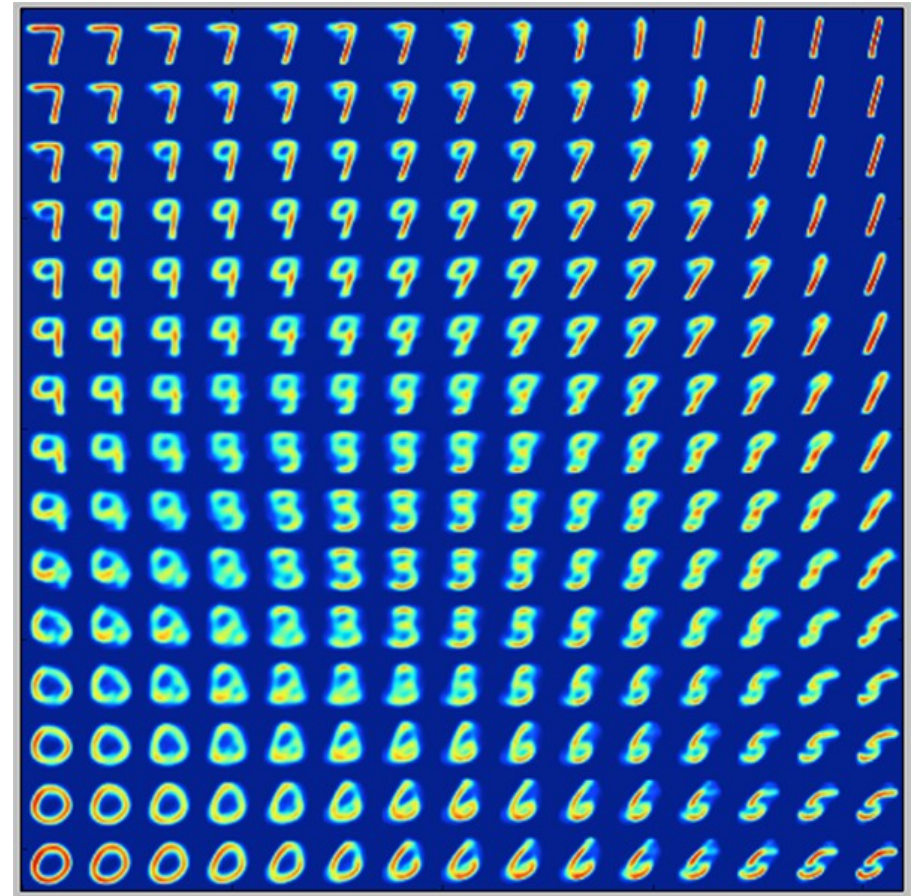


Image morphing with AE

Idea:

- Look for a common direction vector for “add mustache” or “add age” changes.
- Apply to new images



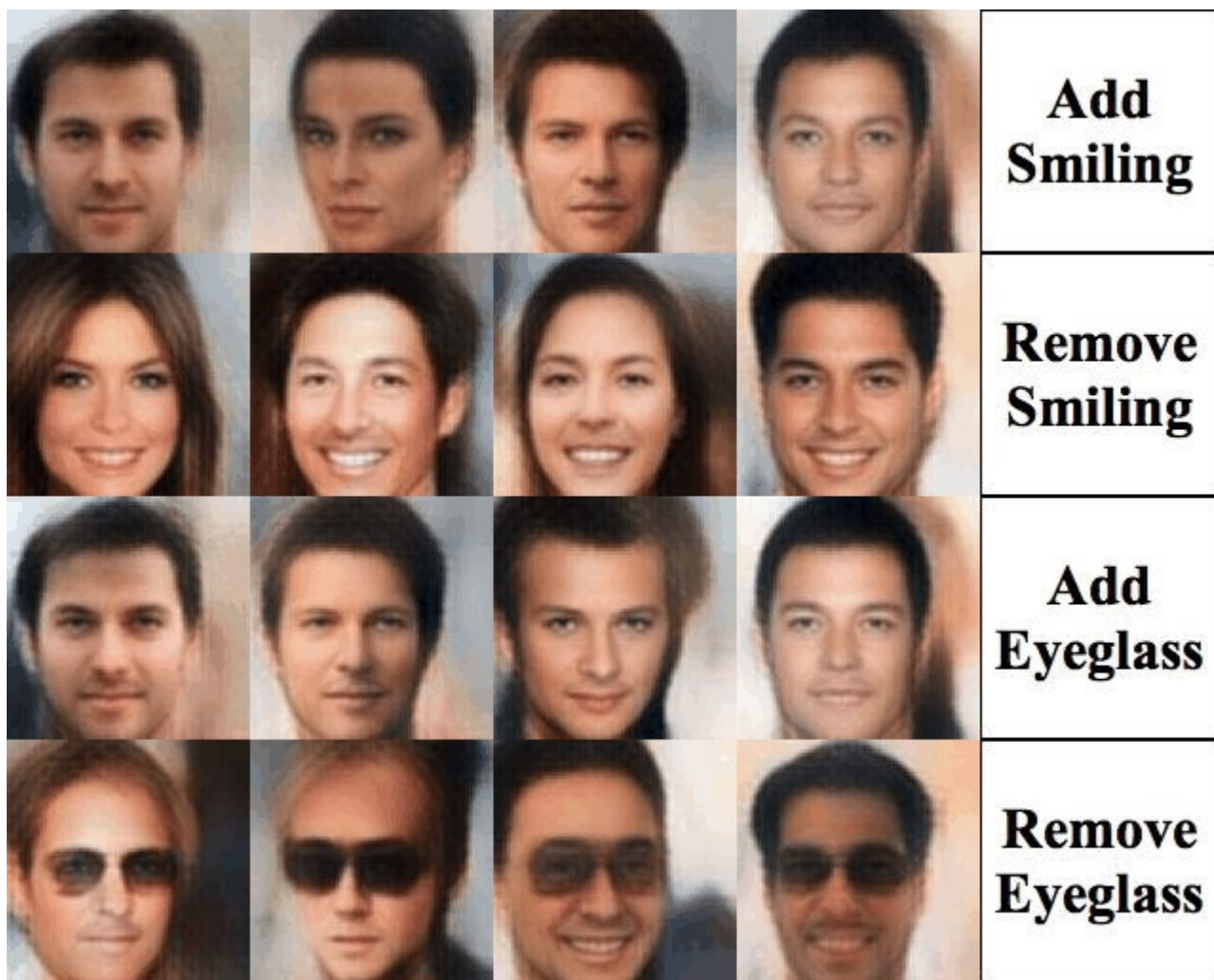
+ OLD =



- FEMALE
+ MALE =



Image morphing with AE



Brace yourselves

