

# Auto-encoders

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## Dimension reduction by linear transformation

PCA is linear dimension reduction technique.

It seeks a parsimonious representation for data in a large ( $p$ ) dimensional space.

So the goal is to map  $p$ -dimensional vectors  $x_i$ , for  $i = 1, \dots, n$

- ▶ assembled in an  $n \times p$  design matrix  $X$

onto an  $m \ll p$  dimensional space, wherein they take on the representation  $z_i$ , for  $i = 1, \dots, n$

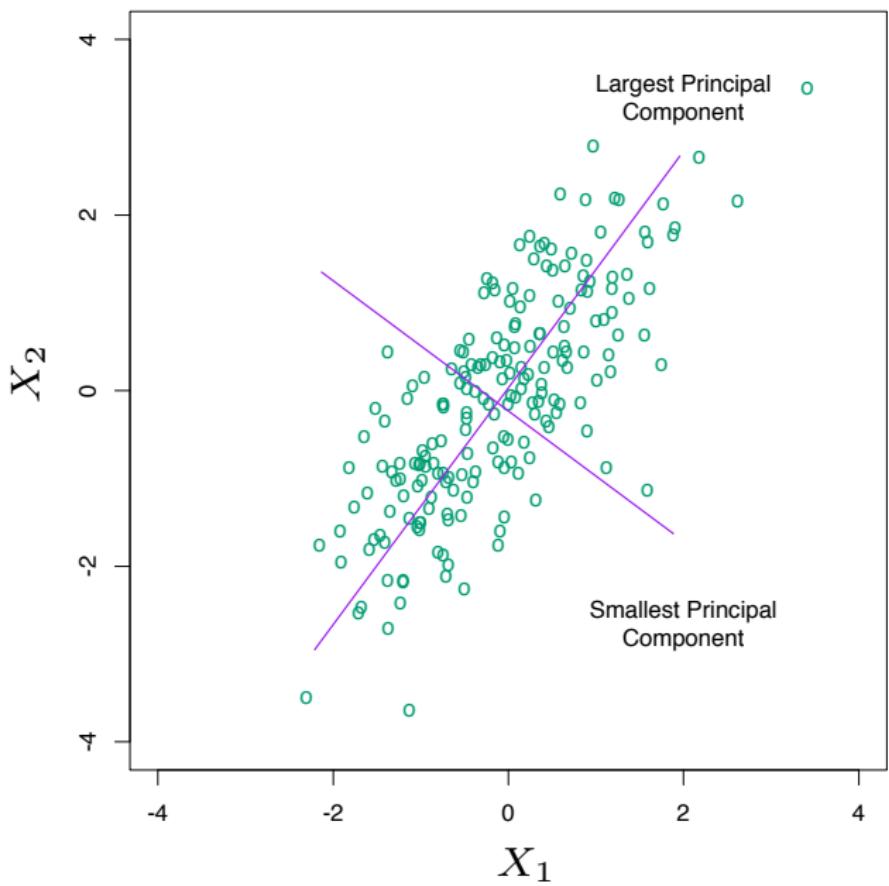
- ▶ assembled into the  $n \times m$  design matrix  $Z$ .

Once in the lower ( $m$ ) dimensional space

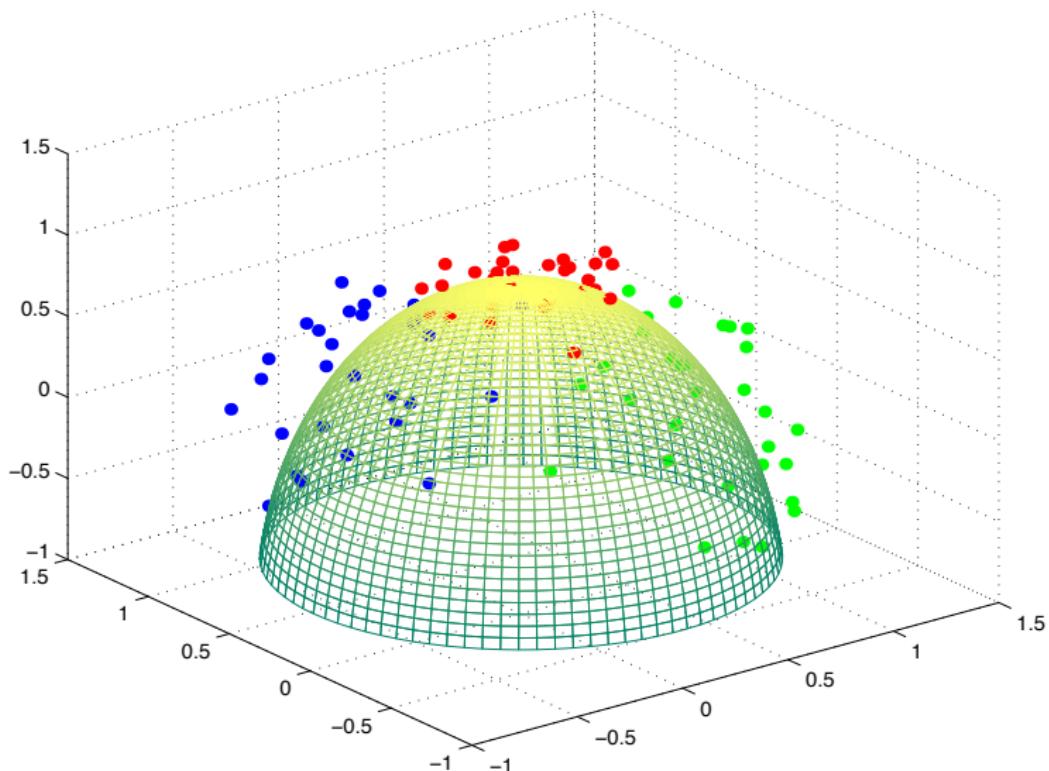
- ▶ regressions are easier,
- ▶ predictions are more stable,
- ▶ and interpretation is parsimonious.

In the (linear) regression context, which is the biggest consumer of dimension reduction techniques, the fact that the procedure operates only on the  $x$ 's

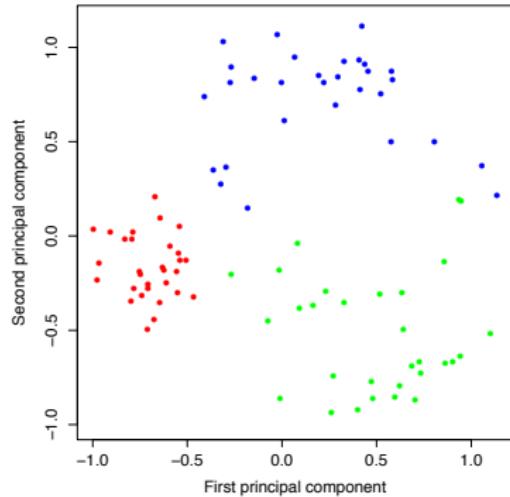
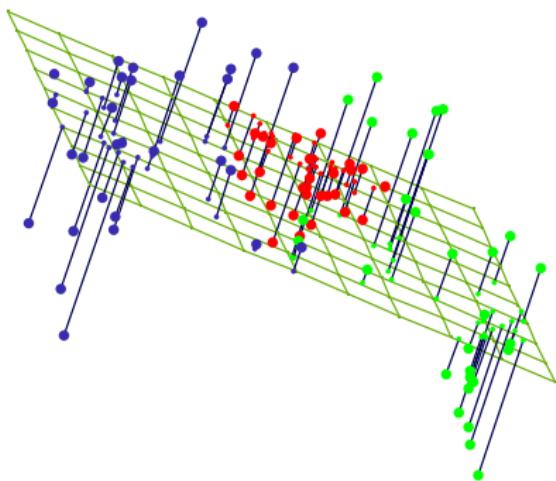
- ▶ ignoring the response (variable of interest),  $y$  classifies PCA as form of **unsupervised** learning.



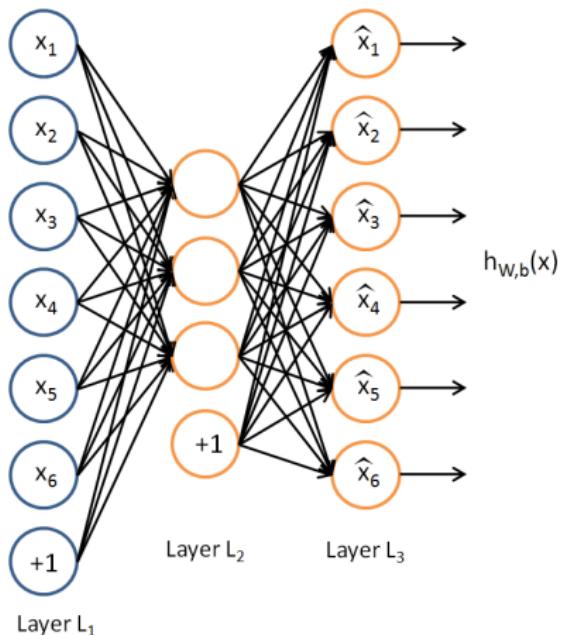
Half-sphere data:



Projecting down onto the right linear subspace helps separate the colors.



# Autoencoder



Network trained to reproduce its input at the output layer.  
Usually tie the weights that go into and out of the hidden layer.

# Autoencoder

## Loss function

- ▶ For real valued inputs, try to find weights such that

$$\frac{1}{2} \sum_k (x_k - \hat{x}_k)^2$$

is minimized

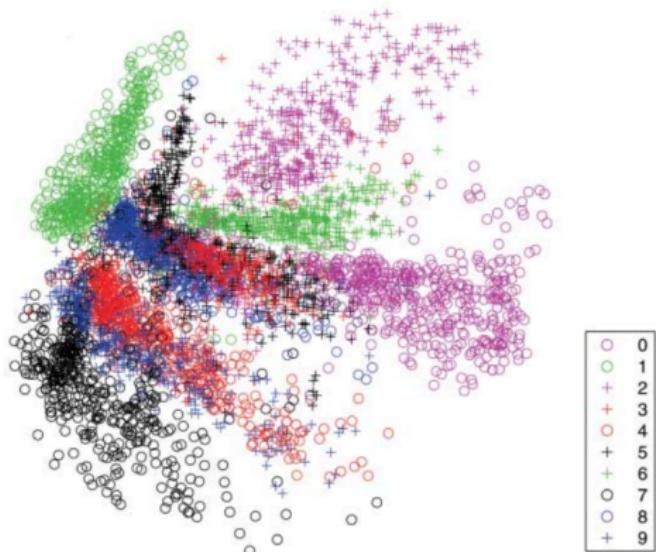
- ▶ For binary input cross entropy is used, which is similar to deviance

## Fitting autoencoder

- ▶ Same tricks as before
- ▶ Greedy learning of stacked autoencoders
- ▶ <https://www.cs.toronto.edu/~hinton/science.pdf>

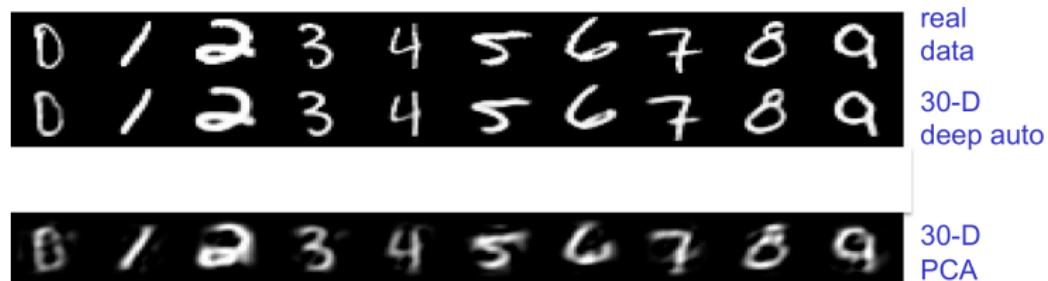
# Autoencoder: Why are they useful?

Learning compressed representation of the input distribution  
(dimensionality reduction)



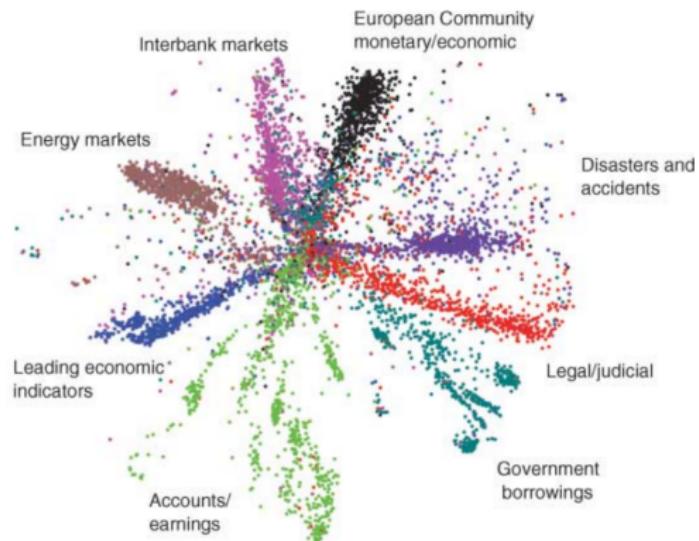
Autoencoder structure: 784 — 1000 — 500 — 250 — 2  
<https://www.cs.toronto.edu/~hinton/science.pdf>

A comparison of methods for compressing digit images to 30 real numbers



# Autoencoder: Why are they useful?

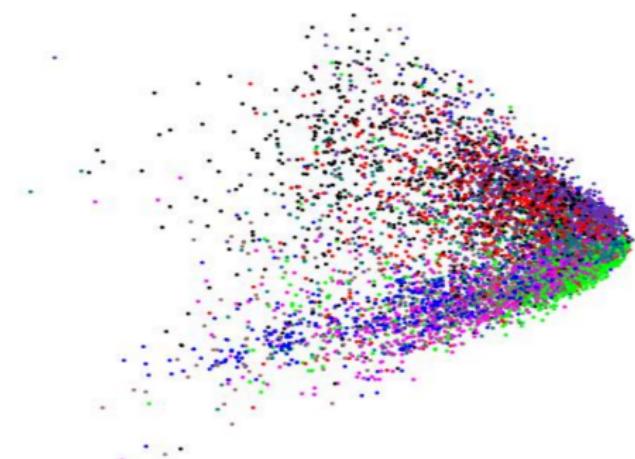
Information retrieval: 804,414 newswire stories



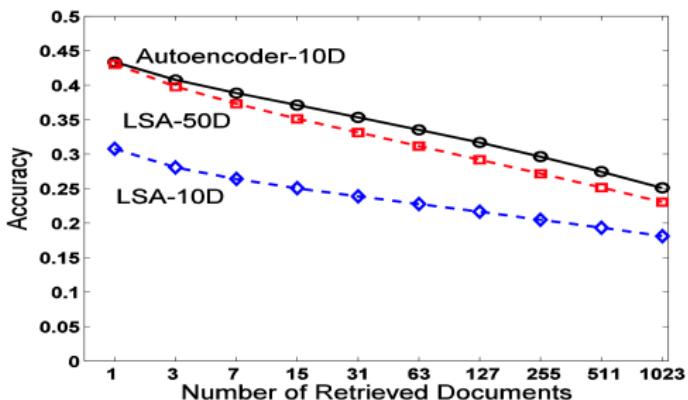
Autoencoder structure: 2000 — 500 — 250 — 125 — 2

<https://www.cs.toronto.edu/~hinton/science.pdf>

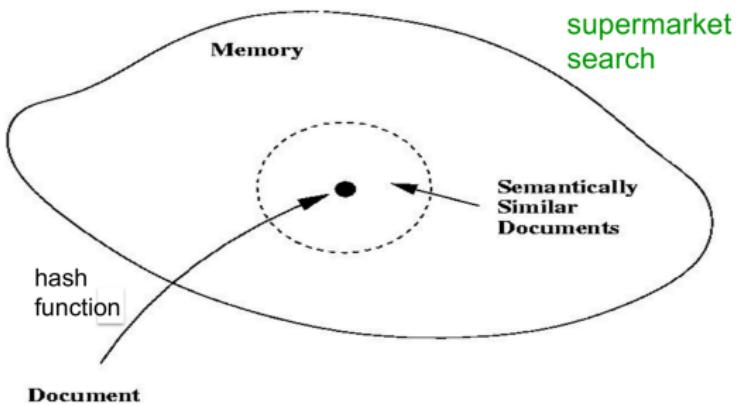
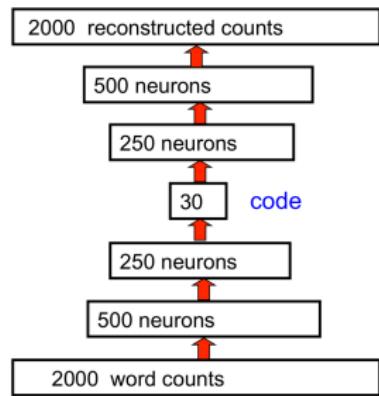
## Comparison with PCA



# Retrieval performance on 400,000 Reuters business news stories

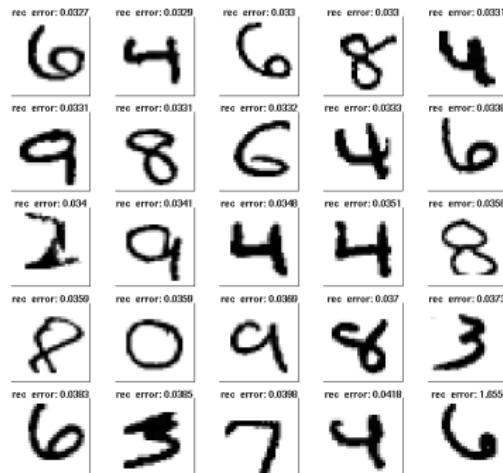


# Finding binary codes for documents



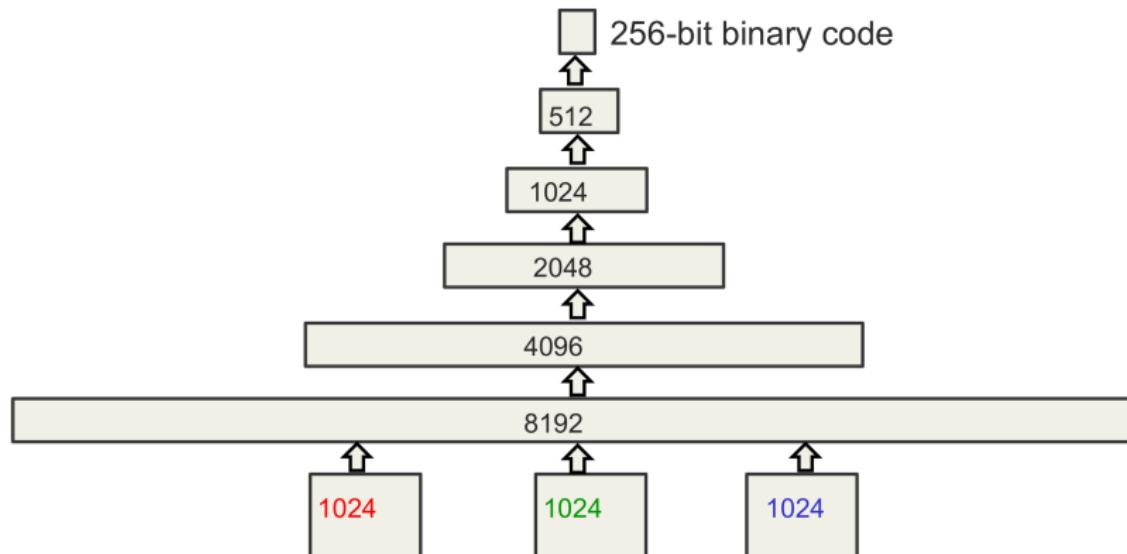
# Autoencoder: Why are they useful?

- ▶ unsupervised pretraining of weights (many unlabeled images, but only few labeled)
- ▶ anomaly detection

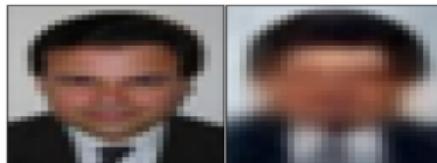


# Autoencoder: Why are they useful?

Image retrieval



## Reconstructions of 32x32 color images from 256-bit codes



retrieved using 256 bit codes



retrieved using Euclidean distance in pixel intensity space

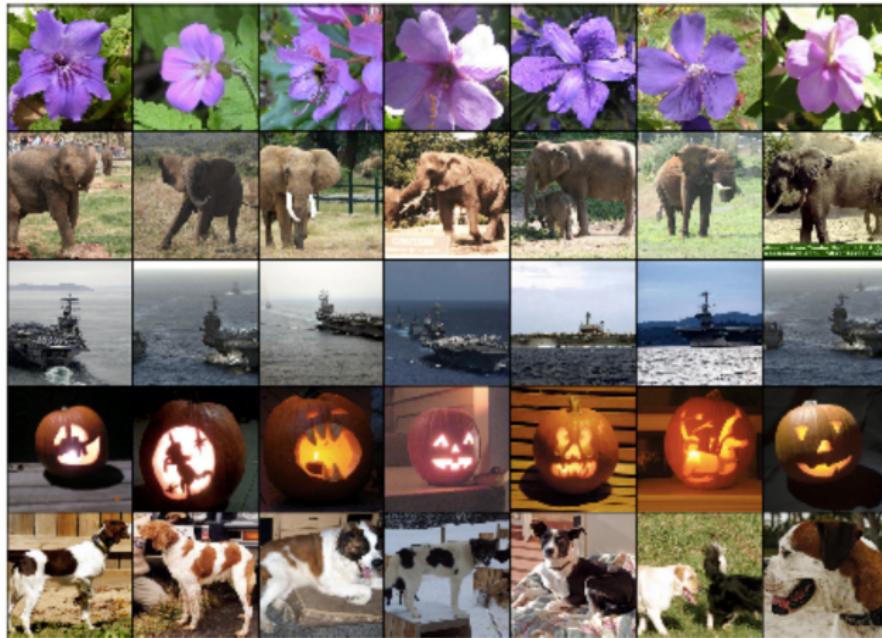


retrieved using 256 bit codes



retrieved using Euclidean distance in pixel intensity space





Leftmost column  
is the search  
image.

Other columns  
are the images  
that have the  
most similar  
feature activities  
in the last hidden  
layer.