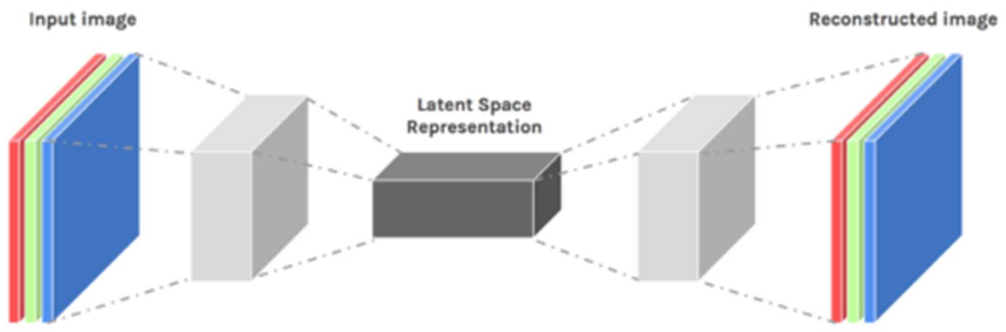
Autoencoders Tutorial : A Beginner's Guide to Autoencoders

What are Autoencoders?

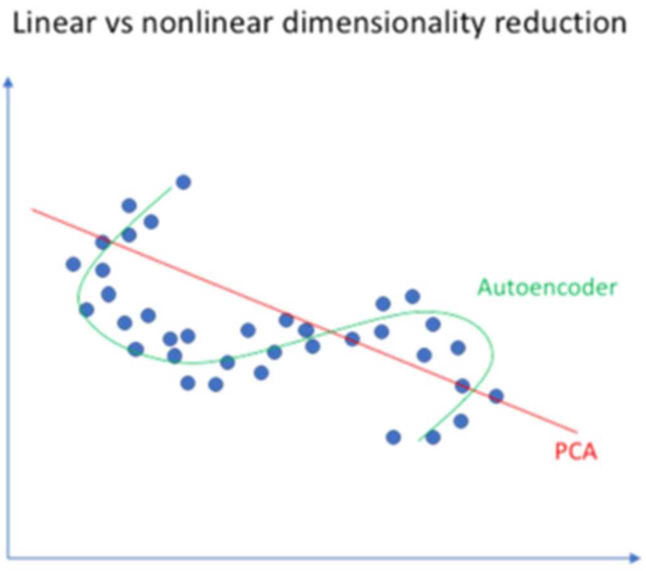
An autoencoder **neural network** is an **Unsupervised Machine learning** algorithm that applies backpropagation, setting the target values to be equal to the inputs. Autoencoders are used to reduce the size of our inputs into a smaller representation. If anyone needs the original data, they can reconstruct it from the compressed data.



We have a similar machine learning algorithm ie. PCA which does the same task. So you might be thinking why do we need Autoencoders then? Let's continue this Autoencoders Tutorial and find out the reason behind using Autoencoders.

Autoencoders Tutorial: Its Emergence

Autoencoders are preferred over PCA because:



- An autoencoder can learn **non-linear transformations** with a **non-linear activation function** and multiple layers.
- It doesn't have to learn dense layers. It can use **convolutional layers** to learn which is better for video, image and series data.
- It is more efficient to learn several layers with an autoencoder rather than learn one huge transformation with PCA.
- An autoencoder provides a representation of each layer as the output.
- It can make use of **pre-trained layers** from another model to apply transfer learning to enhance the encoder/decoder.

Now let's have a look at a few Industrial Applications of Autoencoders.

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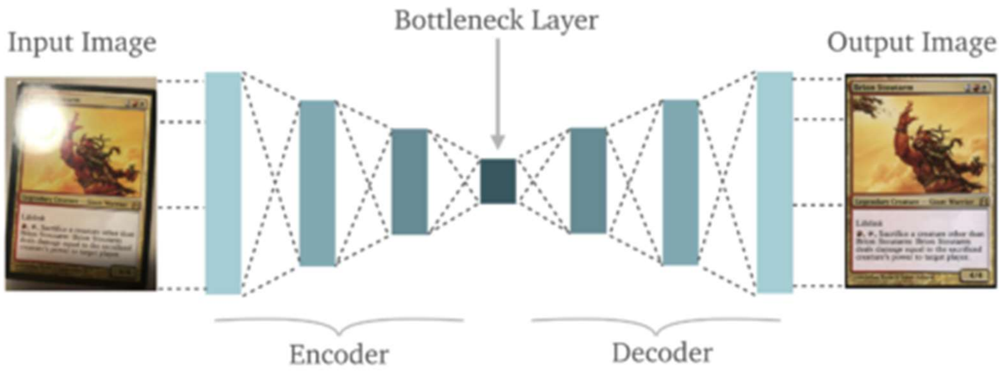
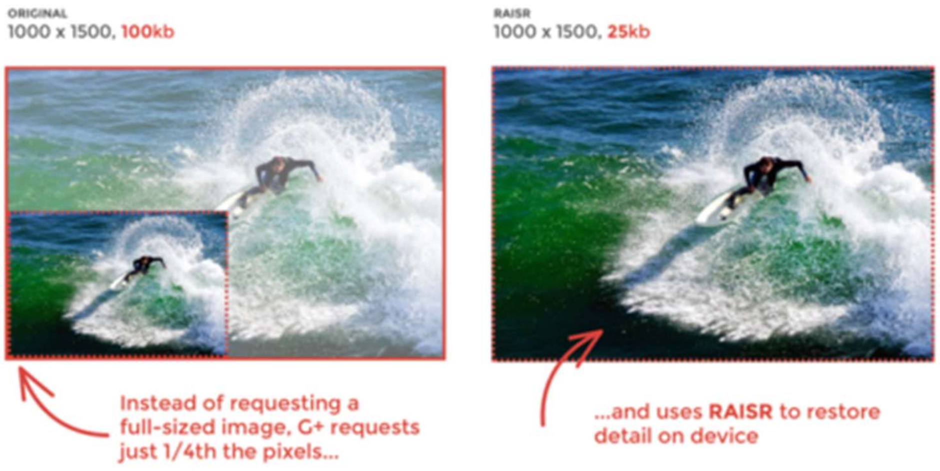
Applications of Autoencoders

Image Coloring

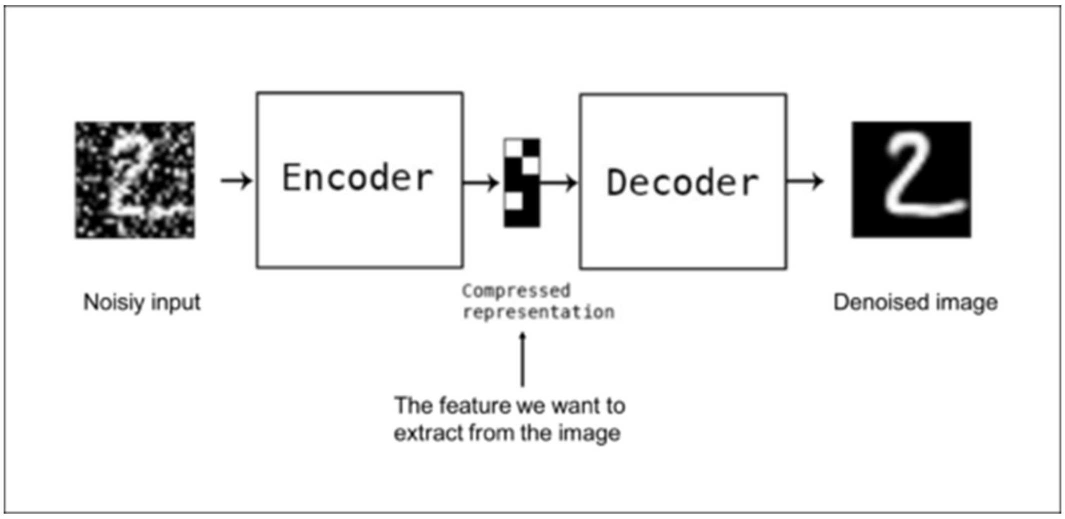
Autoencoders are used for converting any black and white picture into a colored image. Depending on what is in the picture, it is possible to tell what the color should be.



Feature variation
It extracts only the required features of an image and generates the output by removing any noise or unnecessary interruption.


ORIGINAL
1000 x 1500, 100kb
RAISR
1000 x 1500, 25kb
Instead of requesting a full-sized image, G+ requests just 1/4th the pixels...
...and uses RAISR to restore detail on device

Dimensionality Reduction
The reconstructed image is the same as our input but with reduced dimensions. It helps in providing the similar image with a reduced pixel value.


Encoder
Decoder
Noisiy input
Compressed representation
Denoised image
The feature we want to extract from the image

Denoising Image
The input seen by the autoencoder is not the raw input but a stochastically corrupted version. A denoising autoencoder is thus trained to reconstruct the original input from the noisy version.

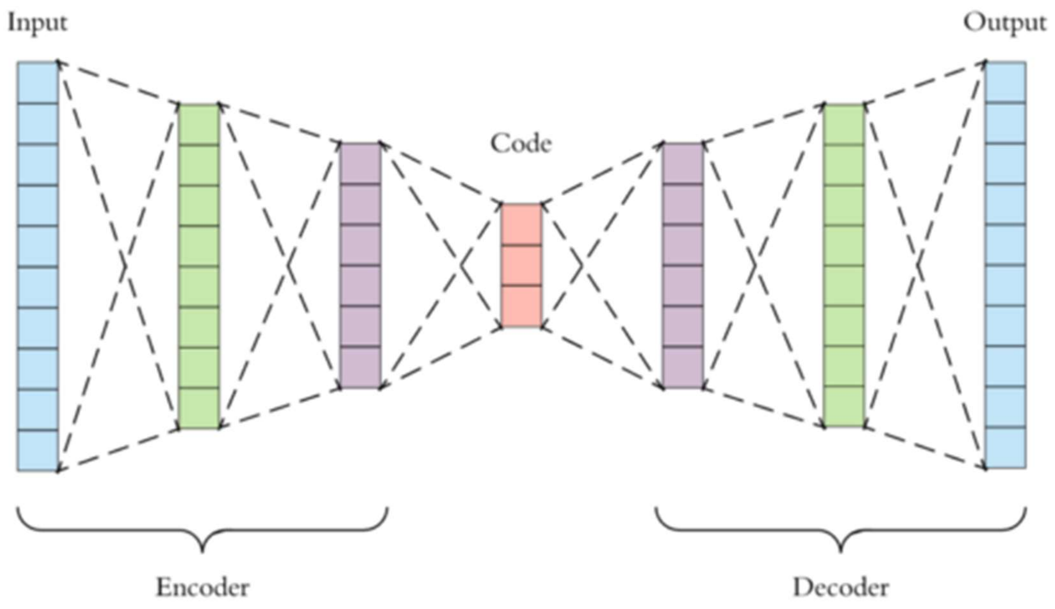
Watermark Removal
It is also used for removing watermarks from images or to remove any object while filming a video or a movie.

Now that you have an idea of the different industrial applications of Autoencoders, let’s continue our Autoencoders Tutorial Blog and understand the complex architecture of Autoencoders.

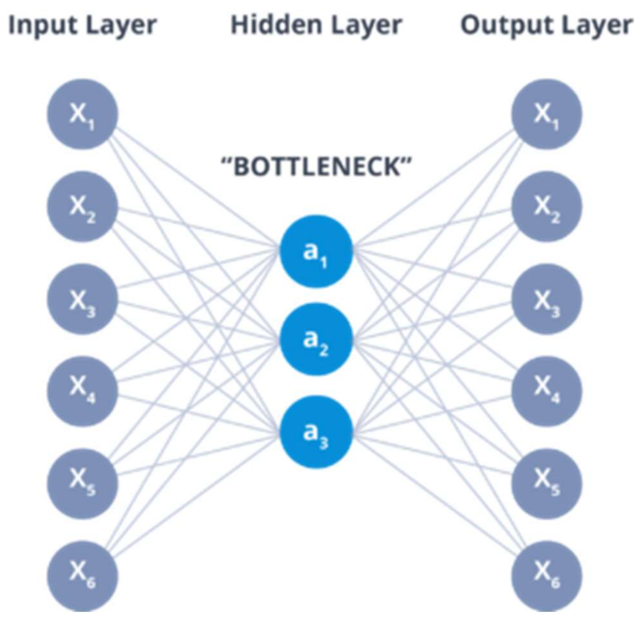
Architecture of Autoencoders

An Autoencoder consist of three layers:

1. **Encoder**
2. **Code**
3. **Decoder**



- **Encoder:** This part of the network compresses the input into a **latent space representation**. The encoder layer **encodes** the input image as a compressed representation in a reduced dimension. The compressed image is the distorted version of the original image.
- **Code:** This part of the network represents the compressed input which is fed to the decoder.
- **Decoder:** This layer **decodes** the encoded image back to the original dimension. The decoded image is a lossy reconstruction of the original image and it is reconstructed from the latent space representation.



The layer between the encoder and decoder, ie. the code is also known as **Bottleneck**. This is a well-designed approach to decide which aspects of observed data are relevant information and what aspects can be discarded. It does this by balancing two criteria :

- Compactness of representation, measured as the compressibility.
- It retains some behaviourally relevant variables from the input.

Now that you have an idea of the architecture of an Autoencoder. Let's continue our Autoencoders Tutorial and understand the different properties and the Hyperparameters involved while training Autoencoders.

Properties and Hyperparameters

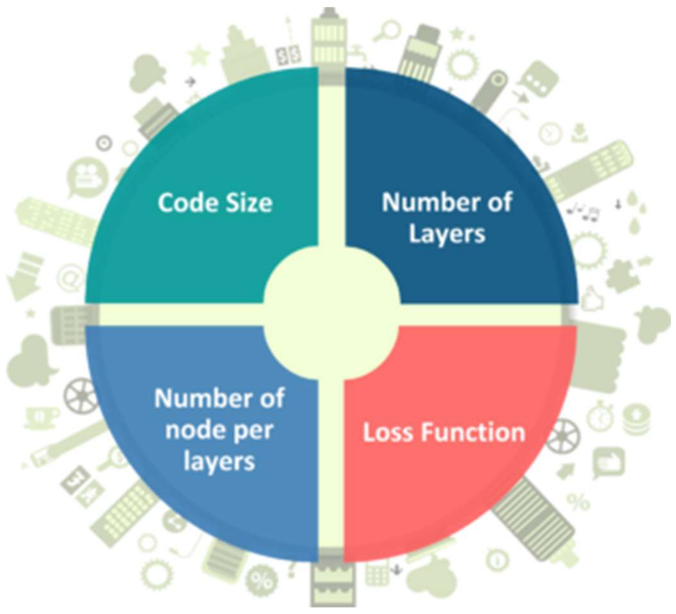
Properties of Autoencoders:

- **Data-specific**: Autoencoders are only able to compress data similar to what they have been trained on.

- **Lossy:** The decompressed outputs will be degraded compared to the original inputs.

- **Learned automatically from examples:** It is easy to train specialized instances of the algorithm that will perform well on a specific type of input.

Hyperparameters of Autoencoders:



There are **4** hyperparameters that we need to set before training an autoencoder:

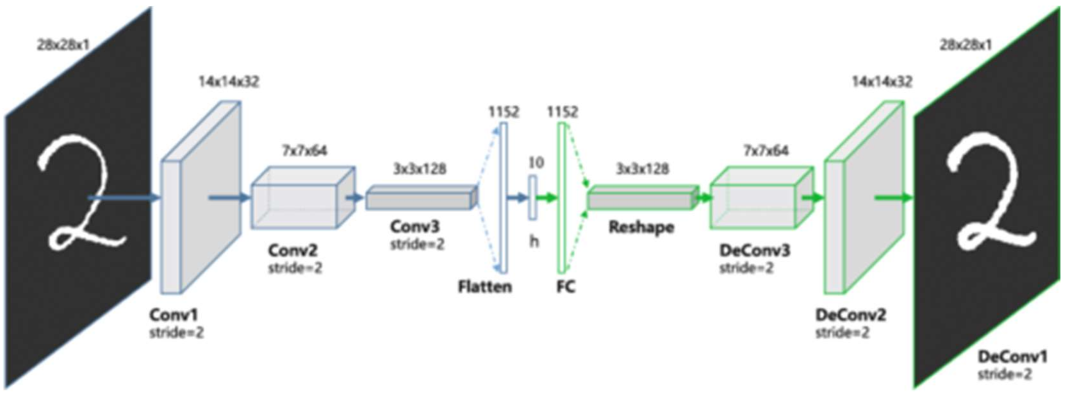
- **Code size**: It represents the number of nodes in the middle layer. Smaller size results in more compression.
- **Number of layers**: The autoencoder can consist of as many layers as we want.
- **Number of nodes per layer**: The number of nodes per layer decreases with each subsequent layer of the encoder, and increases back in the decoder. The decoder is symmetric to the encoder in terms of the layer structure.
- **Loss function:** We either use mean squared error or binary cross-entropy. If the input values are in the range [0, 1] then we typically use cross-entropy, otherwise, we use the mean squared error.

Now that you know the properties and hyperparameters involved in the training of Autoencoders. Let's move forward with our Autoencoders Tutorial and understand the different types of autoencoders and how they differ from each other.

Types of Autoencoders

Convolution Autoencoders

Autoencoders in their traditional formulation does not take into account the fact that a signal can be seen as a sum of other signals. Convolutional Autoencoders use the convolution operator to exploit this observation. They learn to encode the input in a set of simple signals and then try to reconstruct the input from them, modify the geometry or the reflectance of the image.

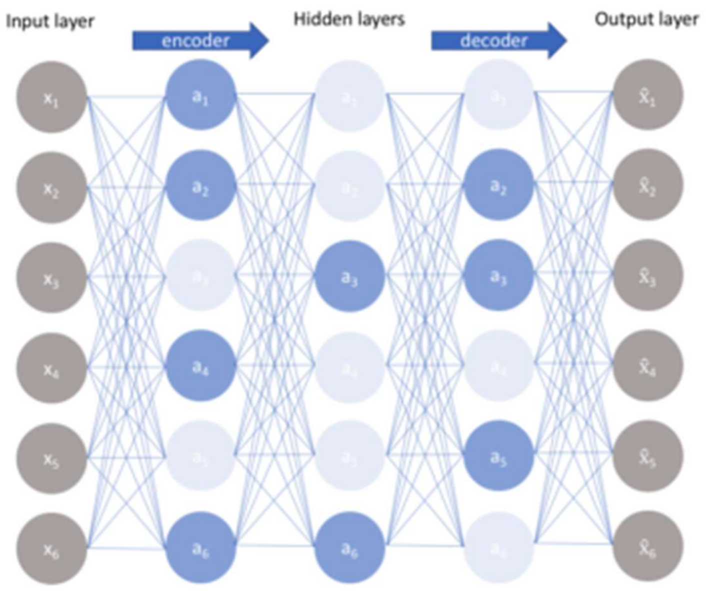


Use cases of CAE:

- Image Reconstruction
- Image Colorization
- latent space clustering
- generating higher resolution images

Sparse Autoencoders

Sparse autoencoders offer us an alternative method for introducing an information bottleneck **without requiring a reduction in the number of nodes** at our hidden layers. Instead, we'll construct our loss function such that we penalize activations within a layer.

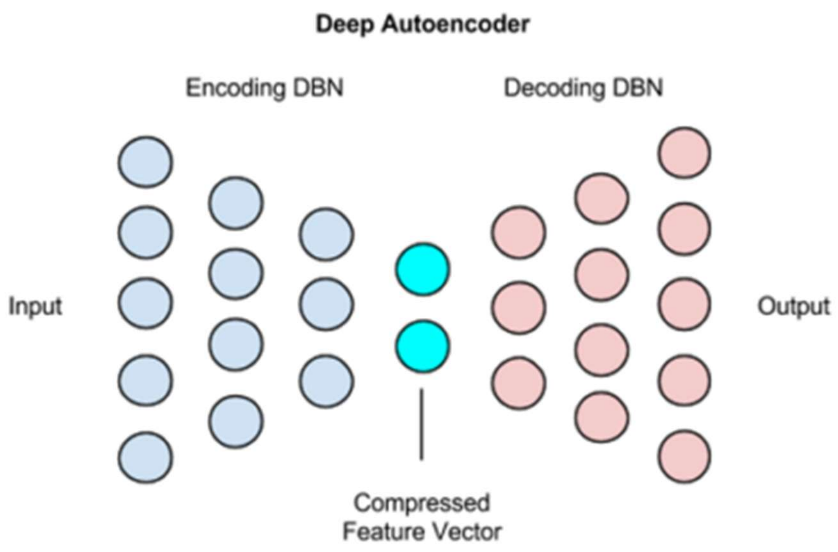


Deep Autoencoders

The extension of the simple Autoencoder is the **Deep Autoencoder**. The first layer of the Deep Autoencoder is used for first-order features in the **raw input**. The second layer is used for second-order features corresponding to **patterns** in the appearance of first-order features. Deeper layers of the Deep Autoencoder tend to learn even higher-order features.

A **deep autoencoder** is composed of two, symmetrical deep-belief networks-

1. First four or five shallow layers representing the encoding half of the net.
2. The second set of four or five layers that make up the decoding half.



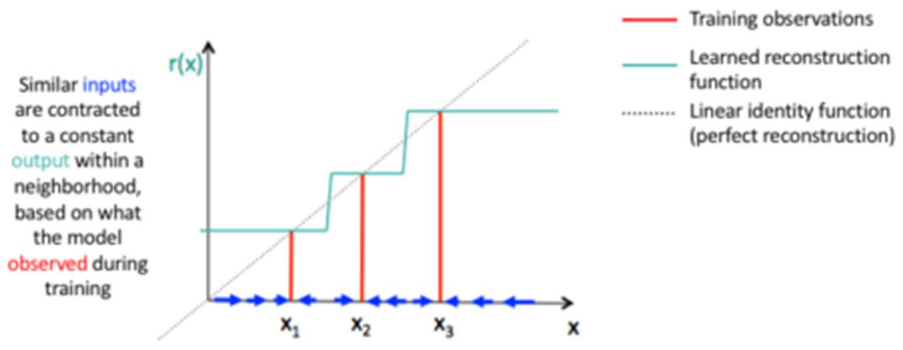
Use cases of Deep Autoencoders

- Image Search
- Data Compression
- Topic Modeling & Information Retrieval (IR)

Contractive Autoencoders

A **contractive autoencoder** is an unsupervised deep learning technique that helps a neural network encode unlabeled training data. This is accomplished by constructing a **loss term** which penalizes large derivatives of our hidden layer activations with respect to the input training examples, **essentially**

penalizing instances where a small change in the input leads to a large change in the encoding space.


Similar inputs are contracted to a constant output within a neighborhood, based on what the model observed during training
r(x)
x
x_1
x_2
x_3
Training observations
Learned reconstruction function
Linear identity function (perfect reconstruction)

Now that you have an idea of what Autoencoders is, it's different types and it's properties. Let's move ahead with our Autoencoders Tutorial and understand a simple implementation of it using TensorFlow in Python.