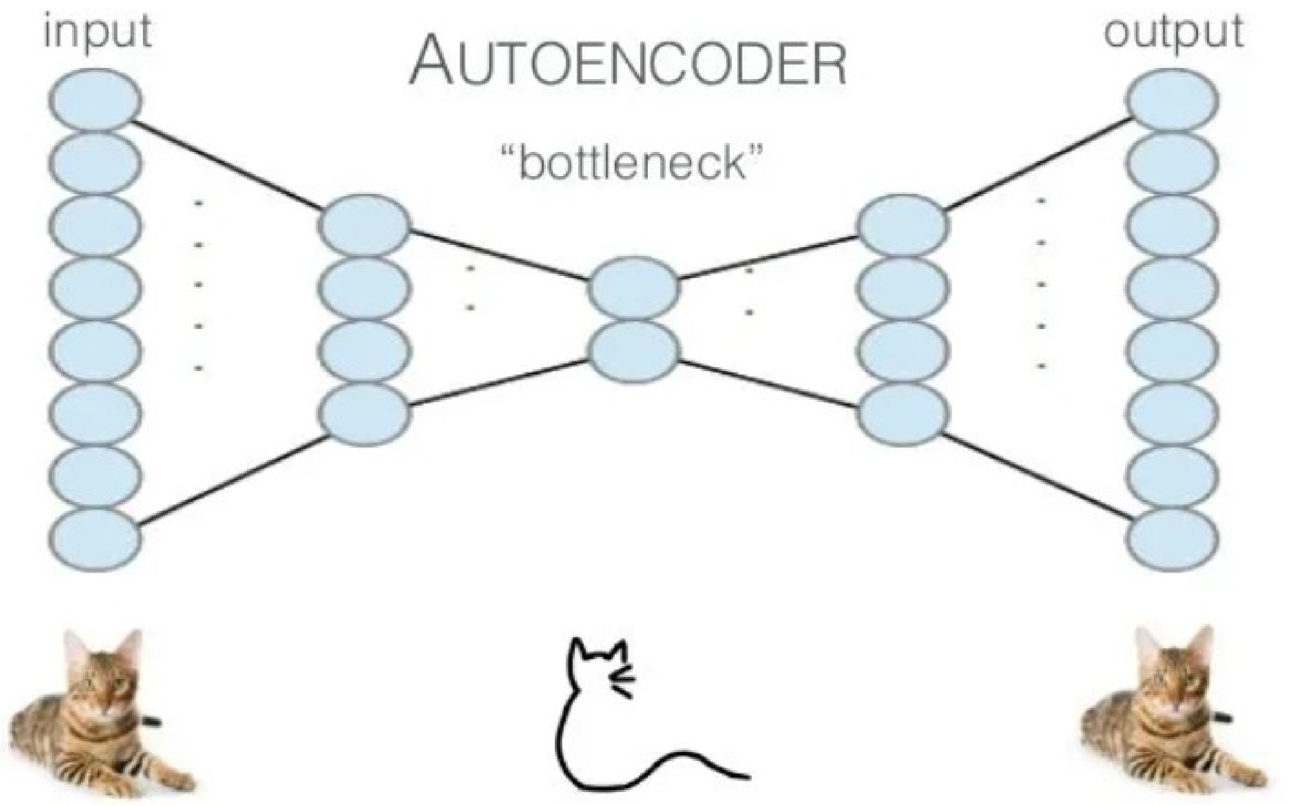
Autoencoder

Autoencoder

- Autoencoder (AE) ☾ It is an unsupervised learning algorithm.



https://sefiks.com/2018/03/21/autoencoder-neural-networks-for-unsupervised-learning/

Autoencoder

- Autoencoders are helpful when working with high-dimensional data such as images, music, or text.

- They can minimize the dimensionality of the data while keeping its vital qualities by learning a compressed version of it.

- Anomaly detection is another prominent application for autoencoders.

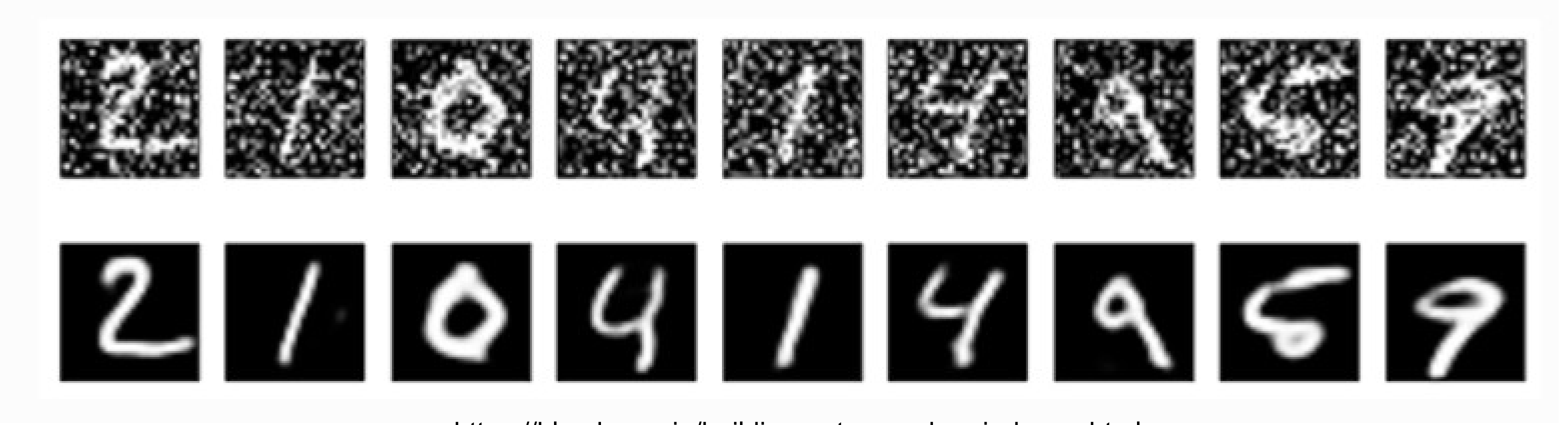
Autoencoder

- Autoencoder (AE) ☾ They can be used for:

Image denoising

Convolutional autoencoder

Dimensionality Reduction

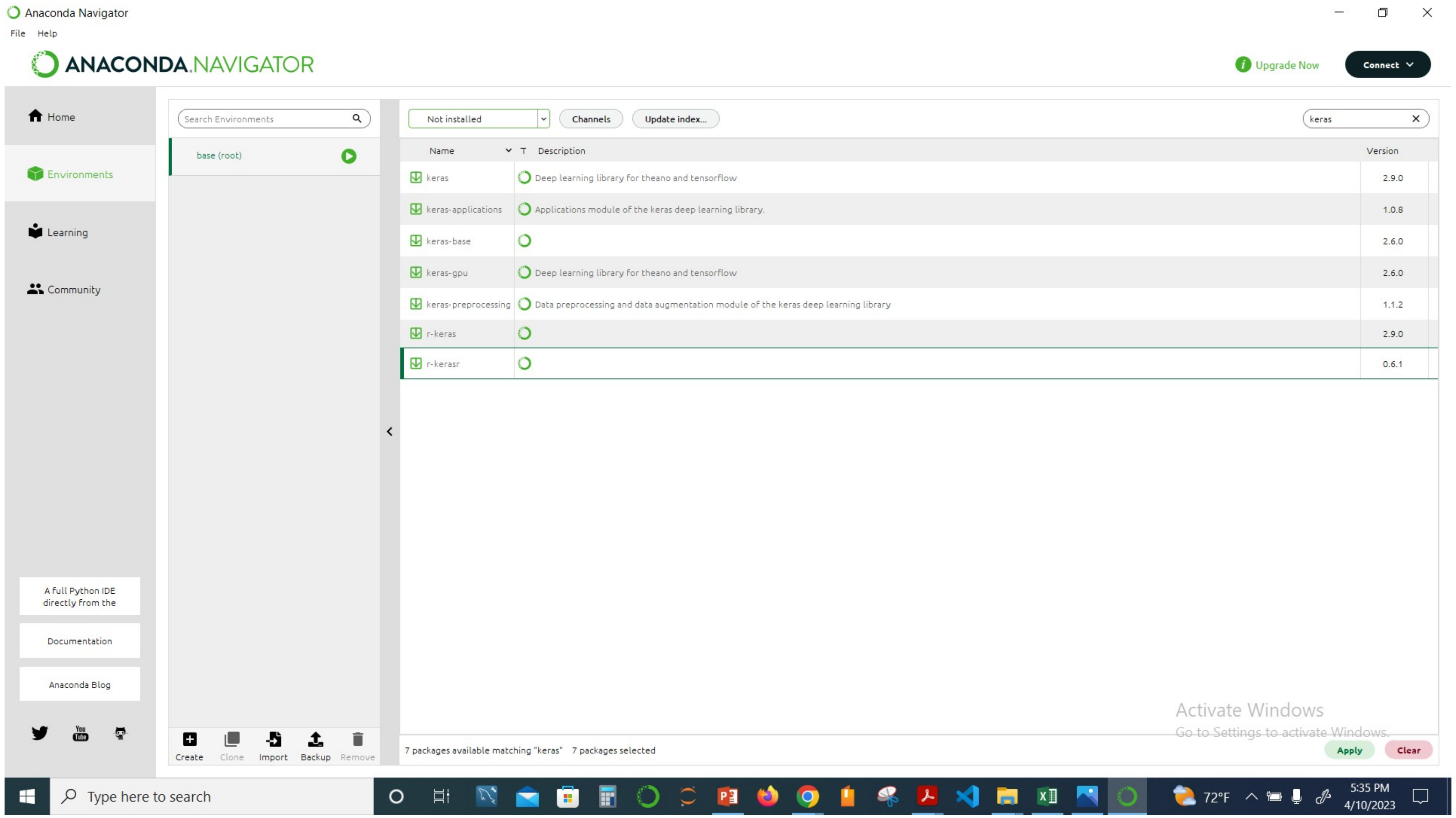


Top, the noisy digits fed to the network, and bottom, the digits are reconstructed by the network.

https://blog.keras.io/building-autoencoders-in-keras.html

Anaconda – Keras & Tensorflow libraries

- In order to use Keras & Tensorflow libraries, we need to install necessary packages on Anaconda/Environments.



Autoencoder (sample code)

Example: Design an autoencoder (AE) for the MNIST data set using Keras framework.

```
import keras
from keras import layers

# This is the size of our encoded representations
encoding_dim = 32  # 32 floats -> compression of factor 24.5, assuming the input is 784 floats

# This is our input image
input_img = keras.Input(shape=(784,))

# "encoded" is the encoded representation of the input
encoded = layers.Dense(encoding_dim, activation='relu')(input_img)

# "decoded" is the lossy reconstruction of the input
decoded = layers.Dense(784, activation='sigmoid')(encoded)

# This model maps an input to its reconstruction
autoencoder = keras.Model(input_img, decoded)
```

Autoencoder (sample code)

```
# Let's also create a separate encoder model:

# This model maps an input to its encoded representation
encoder = keras.Model(input_img, encoded)

# As well as the decoder model:

# This is our encoded (32-dimensional) input
encoded_input = keras.Input(shape=(encoding_dim,))

# Retrieve the last layer of the autoencoder model
decoder_layer = autoencoder.layers[-1]

# Create the decoder model
decoder = keras.Model(encoded_input, decoder_layer(encoded_input))
```

Autoencoder (Sample code)

```
# Now let's train our autoencoder to reconstruct MNIST digits.

# First, we'll configure our model to use a per-pixel binary crossentropy loss,
# and the Adam optimizer:

autoencoder.compile(optimizer='adam', loss='binary_crossentropy')

# Let's prepare our input data. We're using MNIST digits, and we're discarding
# the labels (since we're only interested in encoding/decoding the input
images).

from keras.datasets import mnist
import numpy as np
(x_train, _), (x_test, _) = mnist.load_data()
```

Autoencoder (Sample code)

```
# We will normalize all values between 0 and 1 and we will flatten the 28x28
# images into vectors of size 784.

x_train = x_train.astype('float32') / 255.
x_test = x_test.astype('float32') / 255.
x_train = x_train.reshape((len(x_train), np.prod(x_train.shape[1:])))
x_test = x_test.reshape((len(x_test), np.prod(x_test.shape[1:])))
print(x_train.shape)
print(x_test.shape)
```

Autoencoder (Sample code)

```
# Now let's train our autoencoder for 50 epochs:

autoencoder.fit(x_train, x_train,
                epochs=50,
                batch_size=256,
                shuffle=True,
                validation_data=(x_test, x_test))

# After 50 epochs, the autoencoder seems to reach a stable train/validation loss
# value of about 0.09. We can try to visualize the reconstructed inputs and the
# encoded representations. We will use Matplotlib.

# Encode and decode some digits
# Note that we take them from the *test* set
encoded_imgs = encoder.predict(x_test)
decoded_imgs = decoder.predict(encoded_imgs)
```

Autoencoder (Sample code)

```
# We can use Matplotlib
import matplotlib.pyplot as plt

n = 10  # How many digits we will display
plt.figure(figsize=(20, 4))
for i in range(n):
    # Display original
    ax = plt.subplot(2, n, i + 1)
    plt.imshow(x_test[i].reshape(28, 28))
    plt.gray()
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)

    # Display reconstruction
    ax = plt.subplot(2, n, i + 1 + n)
    plt.imshow(decoded_imgs[i].reshape(28, 28))
    plt.gray()
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)
plt.show()
```

Autoencoder (Sample code)

Here's what we get. The top row is the original digits, and the bottom row is the reconstructed digits. We are losing quite a bit of detail with this basic approach.

Original digits

Reconstructed digits