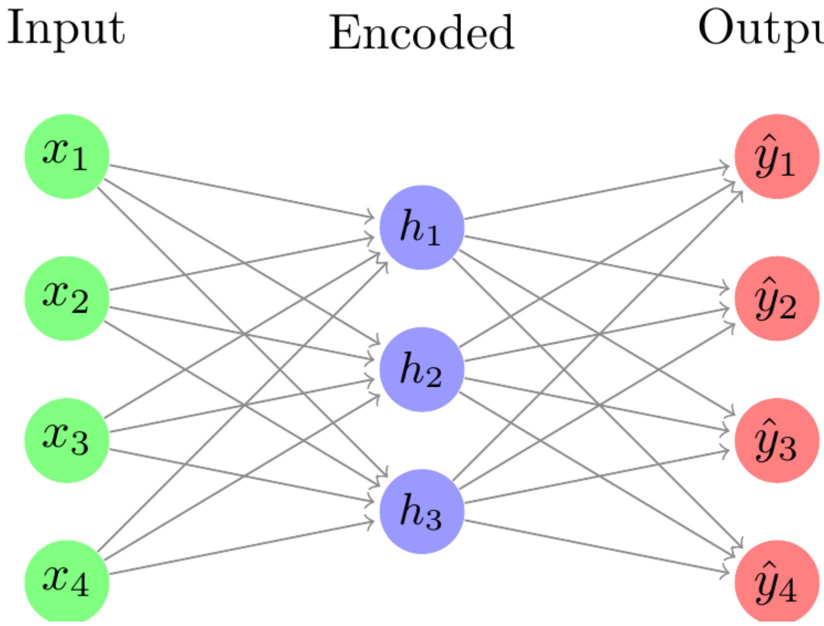
Análisis de Datos y Aprendizaje Máquina con Tensorflow 2.0: Redes neuronales convolucionales

2019/09/30

1 Autoencoders

- Objetivo: comprender el funcionamiento de los autoencoders en el procesamiento de imágenes y aplicarlos para reconstruir imágenes
- Referencia: https://blog.keras.io/building-autoencoders-in-keras.html

Modelo que transforma una dimensión a una dimensión codificada para después reconstruir los datos. Usado para eliminar ruido y principio de los modelos ent-to-end ó Seq-to-seq



Un autoencoder consiste en un 'encoder' que codifica la entrada a una dimensión indicada y un 'decoder' el cual genera la entrada a partir de la codificación del encoder.

- Tipos de datos a los que se aplican autoencoders:
  - Imagenes
  - Audio
  - Video

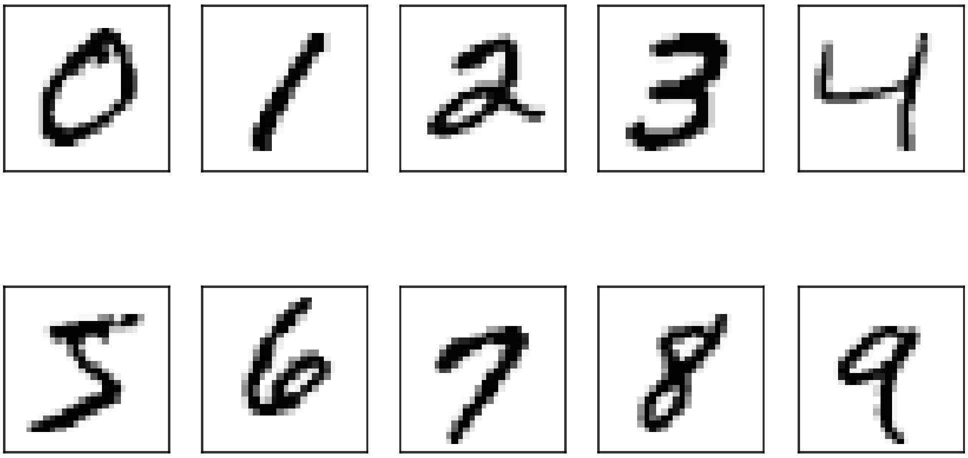
Un autoencoder aprende una distribución de los datos para despúes generarlos.

In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow import keras

from tensorflow.keras.layers import Dense, Input
from tensorflow.keras.models import Model

mnist = keras.datasets.mnist
```

In [2]:
```
(x_train, y_train), (x_test, y_test) = mnist.load_data()
```

In [3]:
```
x_train = x_train.astype('float32') / 255
x_test = x_test.astype('float32') / 255
```

In [4]:
```
fig, ax = plt.subplots(nrows=2, ncols=5, sharex=True, sharey=True,)
ax = ax.flatten()
for i in range(10):
    img = x_train[y_train == i][0].reshape(28, 28)
    ax[i].imshow(img, cmap='Greys', interpolation='nearest')

ax[0].set_xticks([])
ax[0].set_yticks([])
plt.tight_layout()
plt.show()
```



1.1 Modelo de autoencoder

- Autoencoder con una sola capa oculta

- Se define la dimensión a codificar, en este caso d=10

In [5]:
```
epoch = 5
verbose = 1
batch = 50
```

- Indicar dimensión de codificación

In [6]:
```
d = 10
```

In [7]:
```
encoder = keras.models.Sequential([
    keras.layers.Flatten(input_shape=(28, 28)),
    keras.layers.Dense(d, activation="relu"),
])

decoder = keras.models.Sequential([
    keras.layers.Dense(28 * 28, activation="sigmoid", input_shape=[d]),

    keras.layers.Reshape((28, 28))
])

model = keras.models.Sequential([encoder, decoder])
```

In [8]:
```
model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
sequential (Sequential)      (None, 10)                7850
_________________________________________________________________
sequential_1 (Sequential)    (None, 28, 28)            8624
=================================================================
Total params: 16,474
Trainable params: 16,474
Non-trainable params: 0
_________________________________________________________________
```

In [9]:
```
model.compile(loss="binary_crossentropy", optimizer='adam', metrics=['accuracy'])

model.fit(x_train, x_train, epochs=epoch)
```

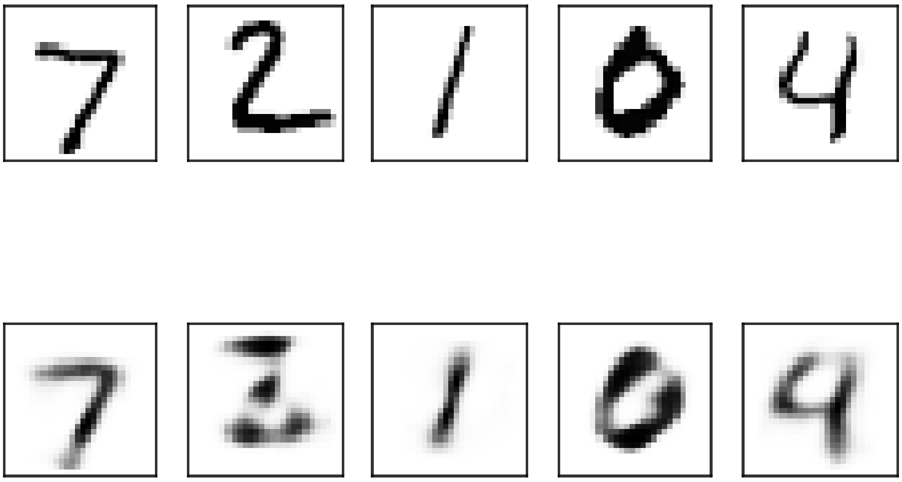
```
Train on 60000 samples
Epoch 1/5
60000/60000 [==============================] - 4s 72us/sample - loss: 0.2082 - accuracy: 0.7959
Epoch 2/5
60000/60000 [==============================] - 4s 62us/sample - loss: 0.1646 - accuracy: 0.8029
Epoch 3/5
60000/60000 [==============================] - 4s 63us/sample - loss: 0.1596 - accuracy: 0.8042
Epoch 4/5
```

```
60000/60000 [==============================] - 4s 61us/sample - loss: 0.1572 - accuracy: 0.8048
Epoch 5/5
60000/60000 [==============================] - 4s 61us/sample - loss: 0.1560 - accuracy: 0.8051
```

```
Out[9]: <tensorflow.python.keras.callbacks.History at 0x7fe9a7796310>
```

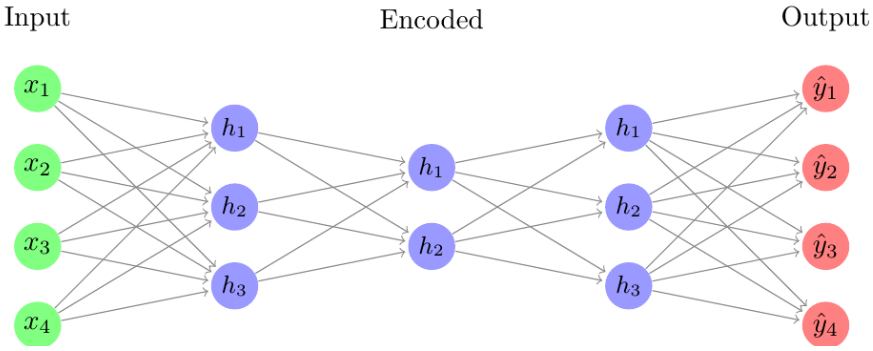
```
In [10]: decoded_imgs = model.predict(x_test[:5])
```

```
In [11]: n = 5
         for i in range(n):
             # instancias de prueba
             ax = plt.subplot(2, n, i+1)
             plt.imshow(x_test[i].reshape(28,28), cmap='Greys', interpolation='nearest')


             ax.get_xaxis().set_visible(False)
             ax.get_yaxis().set_visible(False)

             # reconstrucción
             ax = plt.subplot(2, n, i+n+1)
             plt.imshow(decoded_imgs[i].reshape(28,28),cmap='Greys', )

             ax.get_xaxis().set_visible(False)
             ax.get_yaxis().set_visible(False)
         plt.show()
```



1.2 Deep Autoencoder

- Los Autoencoders generalmente son profundos y pueden estar conformados por diferentes tipos de capas



Deep Autoencoder

In [12]:
```
encoder = keras.models.Sequential([
    keras.layers.Flatten(input_shape=(28, 28)),
    keras.layers.Dense(50, activation="relu"),
    keras.layers.Dense(d, activation="relu"),
])

decoder = keras.models.Sequential([
    keras.layers.Dense(50, activation="relu", input_shape=[d]),
    keras.layers.Dense(28 * 28, activation="sigmoid"),
    keras.layers.Reshape((28, 28))
])

model = keras.models.Sequential([encoder, decoder])
```

In [13]:
```
model.summary()
```

```
Model: "sequential_5"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
sequential_3 (Sequential)    (None, 10)                39760
_________________________________________________________________
sequential_4 (Sequential)    (None, 28, 28)            40534
=================================================================
Total params: 80,294
Trainable params: 80,294
Non-trainable params: 0
_________________________________________________________________
```

In [14]:
```
model.compile(loss="binary_crossentropy", optimizer='adam', metrics=['accuracy'])

model.fit(x_train, x_train, epochs=epoch)
```

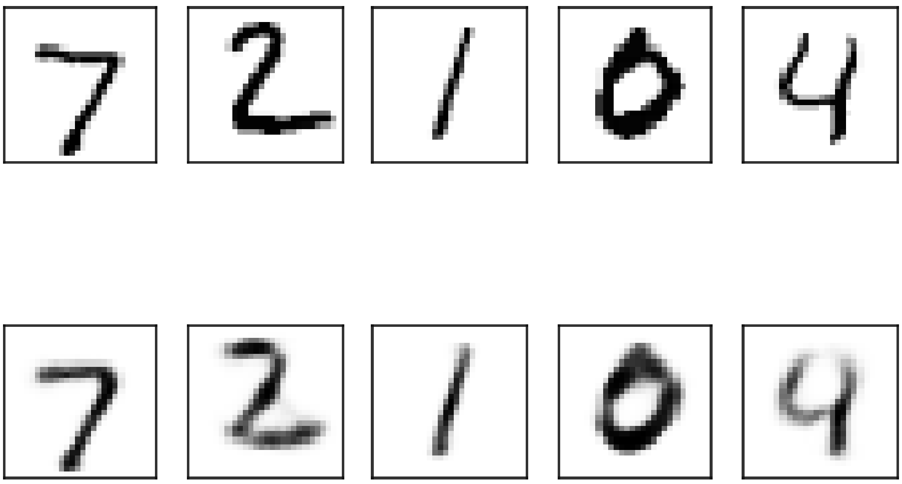
```
Train on 60000 samples
Epoch 1/5
```

```
60000/60000 [==============================] - 4s 72us/sample - loss: 0.1864 - accuracy: 0.7977
Epoch 2/5
60000/60000 [==============================] - 4s 68us/sample - loss: 0.1445 - accuracy: 0.8057
Epoch 3/5
60000/60000 [==============================] - 4s 70us/sample - loss: 0.1368 - accuracy: 0.8071
Epoch 4/5
60000/60000 [==============================] - 4s 66us/sample - loss: 0.1338 - accuracy: 0.8076
Epoch 5/5
60000/60000 [==============================] - 4s 66us/sample - loss: 0.1318 - accuracy: 0.8080
```

Out[14]: <tensorflow.python.keras.callbacks.History at 0x7fe94c113850>

In [15]:
```
decoded_imgs = model.predict(x_test[:5])
```

In [16]:
```
n = 5
for i in range(n):
    # instancias de prueba
    ax = plt.subplot(2, n, i+1)
    plt.imshow(x_test[i].reshape(28,28), cmap='Greys', interpolation='nearest')


    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)

    # reconstrucción
    ax = plt.subplot(2, n, i+n+1)
    plt.imshow(decoded_imgs[i].reshape(28,28),cmap='Greys', interpolation='nearest')

    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)
plt.show()
```



1.3 Autoencoder Convolucional

- Los Autoencoders Convolucionales trabajan con capas convolucionales y pooling. Para el decoder se puede usar 'Conv2DTranspose'
- Los autoencoders variacionales generan nuevos datos. Los modelos generativos pueden tener muchas aplicaciones

In [17]:
```
from tensorflow.keras.layers import Input, LeakyReLU, Reshape, Dense, Conv2D, MaxPooling
from tensorflow.keras.models import Model,Sequential
import tensorflow as tf
```

In [18]:
```
(x_train, y_train), (x_test, y_test) = mnist.load_data()


x_train = x_train.reshape(x_train.shape[0], 28, 28, 1).astype('float32') / 255
x_test = x_test.reshape(x_test.shape[0], 28, 28, 1).astype('float32') / 255
```

In [19]:
```
print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(60000, 28, 28, 1)
(10000, 28, 28, 1)
(60000,)
(10000,)
```

In [20]:
```
def conv_ae():
    # encoder
    inputs = Input(shape=(28, 28, 1))
    x = Conv2D(16, 3, activation='relu', padding='same')(inputs)

    x = Conv2D(32, 3, activation='relu', padding='same')(x)

    x = Conv2D(64, 3, activation='relu', padding='same')(x)
    x = MaxPooling2D(padding='same')(x)

    x = Conv2D(128, 3, activation='relu', padding='same')(x)
    x = MaxPooling2D(padding='same')(x)

    encoded = Conv2D(256, 3, activation='relu', padding='same')(x)


    # decoder
    x = Conv2DTranspose(256, 3, strides=(2, 2), activation='relu', padding='same')(encod
    x = Conv2DTranspose(128, 3, strides=(2, 2), activation='relu', padding='same')(x)
```

```
    x = Conv2DTranspose(64, 3, strides=(1, 1), activation='relu', padding='same')(x)
    x = Conv2DTranspose(32, 3, strides=(1, 1), activation='relu', padding='same')(x)
    x = Conv2DTranspose(16, 3, strides=(1, 1), activation='relu', padding='same')(x)
    decoded = Conv2DTranspose(1, 3, activation='sigmoid', padding='same')(x)


    autoencoder = Model(inputs, decoded)
    autoencoder.compile(optimizer='adam',
                        loss='binary_crossentropy')
    return autoencoder


autoencoder = conv_ae()
```

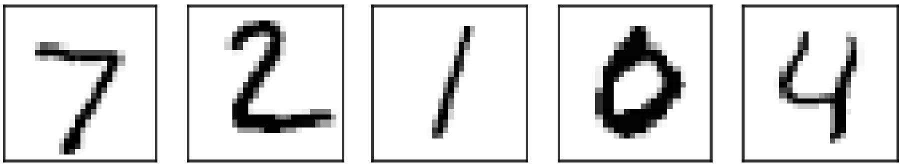
In [21]:
```
autoencoder.fit(x_train, x_train, epochs=1)
```

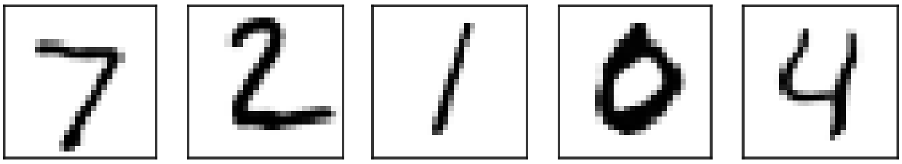
```
Train on 60000 samples
60000/60000 [==============================] - 76s 1ms/sample - loss: 0.0734
```

Out[21]: <tensorflow.python.keras.callbacks.History at 0x7fe9243428d0>

In [22]:
```
decoded_imgs = autoencoder.predict(x_test[:5])
```

In [23]:
```
n = 5
for i in range(n):
    # instancias de prueba
    ax = plt.subplot(2, n, i+1)
    plt.imshow(x_test[i].reshape(28,28), cmap='Greys', interpolation='nearest')


    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)

    # reconstrucción
    ax = plt.subplot(2, n, i+n+1)
    plt.imshow(decoded_imgs[i].reshape(28,28),cmap='Greys', interpolation='nearest')

    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)
plt.show()
```





- La reconstrucción de los datos es mucho mas potente con capas de convoluciones.
- Probar con diferente número de capas, neuronas y funciones de costo, argumentar los resultados de la reconstrucción
- Experimentar con otro dataset