118430Q5_1

July 7, 2020

IA353 - Redes Neurais

EFC3 - Questão 5

Autoencoder training and manifold visualization

Partially based on https://www.kaggle.com/apapiu/manifold-learning-and-autoencoders

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5.1. Imports

[1]:
```
import tensorflow as tf
import os
from multiprocessing import cpu_count

import warnings
warnings.filterwarnings('ignore')

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

from sklearn import metrics
from sklearn.neighbors import NearestNeighbors

from keras.models import Sequential, Model
from keras.layers import Dense, Dropout, Convolution2D, MaxPooling2D, Flatten, Input,␣
↪Conv2D, UpSampling2D, Reshape, Deconvolution2D, Conv2DTranspose, BatchNormalization
from keras.optimizers import adam
from keras.utils.np_utils import to_categorical
```

```
Using TensorFlow backend.
```

[2]:
```
# version
tf.__version__
```

[2]:
```
'2.2.0'
```

[3]:
```
#-------------------------------------------------
# additional config
#-------------------
```

```
# random seed generator
os.environ['PYTHONHASHSEED']=str(42)
np.random.seed(42)
tf.random.set_seed(42)
os.environ['TF_DETERMINISTIC_OPS'] = '1'
```

[ ]:
```
# choose between CPU and GPU
device = tf.device('/cpu:0')
if tf.config.list_physical_devices('GPU'):
    device = tf.device('/device:GPU:0')
#    device_model = torch.cuda.get_device_name(0)
#    device_memory = torch.cuda.get_device_properties(device).total_memory / 1e9
    device_number = len(tf.config.experimental.list_physical_devices('GPU'))
    #----------------------------
    #from tensorflow.python.client import device_lib
    #print(device_lib.list_local_devices())
    #----------------------------
    print('Device: gpu')
    #print('GPU model:', device_model)
    #print('GPU memory: {0:.2f} GB'.format(device_memory))
    print("GPUs available: ", device_number)
    print('#-------------------')
print('CPU cores:', cpu_count())
```

5.2. Reading the data

[5]:
```
mnist = tf.keras.datasets.mnist
(x_train, y_train),(x_test, y_test) = mnist.load_data()
```

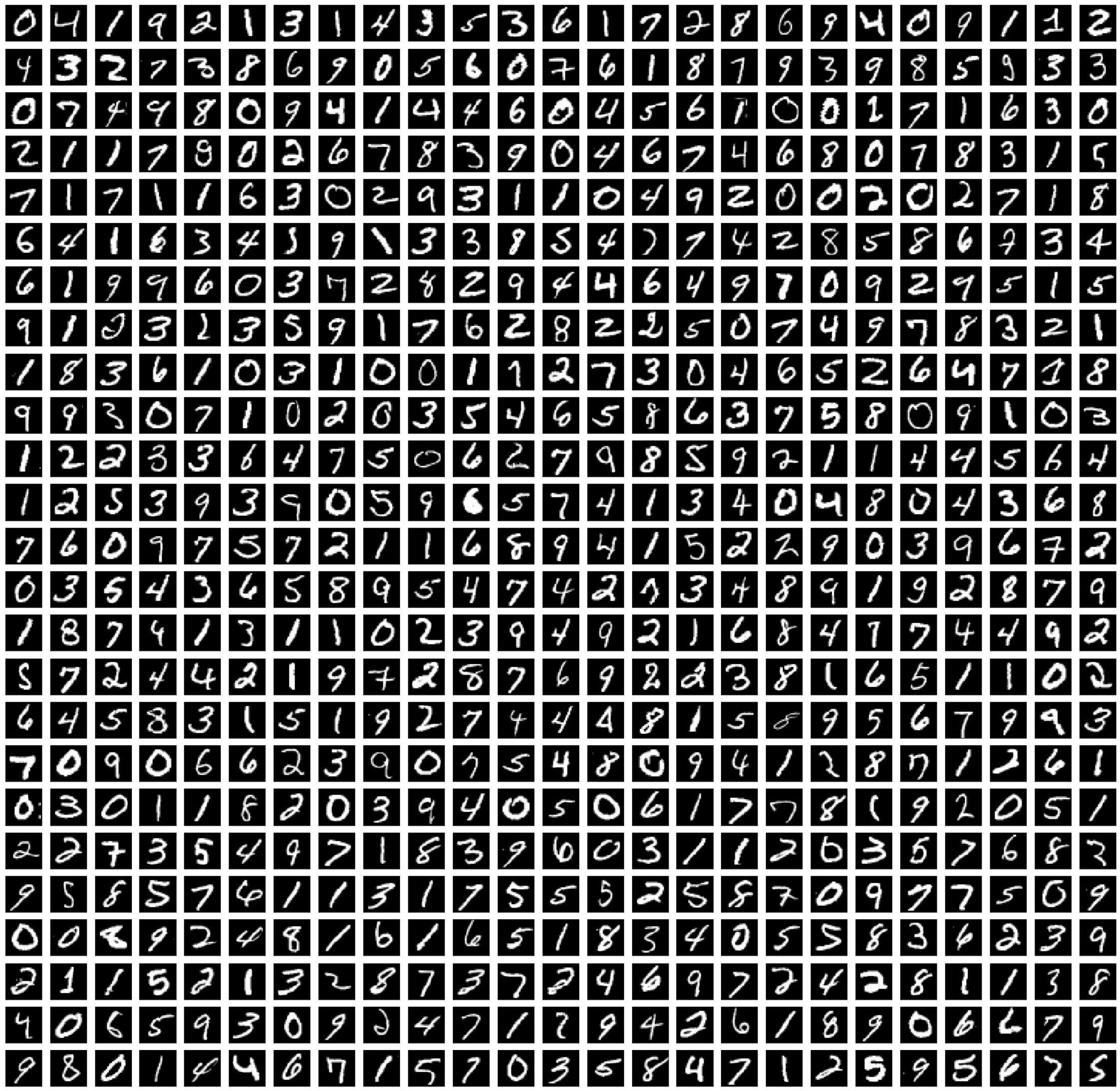
```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-
datasets/mnist.npz
11493376/11490434 [==============================] - 0s 0us/step
```

[6]:
```
x_train, x_test = x_train / 255.0, x_test / 255.0
```

[7]:
```
x_images = x_train.reshape(x_train.shape[0], 28, 28)
```

[8]:
```
# Definition of a function to visualize some digits
def show(img):
    plt.imshow(img, cmap = "gray", interpolation = "none")
```

[9]:
```
# Visualization of 25 x 25 original images of digits
fig = plt.figure(figsize=(28,28))
ind = 1
for i in range(1, 26, 1):
    for j in range(1, 26, 1):
        fig.add_subplot(25,25,ind)
        show(x_images[ind])
        plt.xticks([])
        plt.yticks([])
        ind+=1
```



5.3 Proposal for the autoencoder architecture

[10]:
```python
input_img = Input(shape=(784,))
#==========================================================
reshape = Reshape((28,28,1))(input_img)
encoded = Conv2D(32, (3, 3), activation='relu', strides=2, padding='same')(reshape)            # (60000,14,14,32)
encoded = Conv2D(64, (3, 3), activation='relu', strides=2, padding='same')(encoded)            # (60000,7,7,64)
encoded = Conv2D(128, (3, 3), activation='relu', strides=2, padding='valid')(encoded)            # (60000,3,3,128)
#----------------------------
encoded = Flatten()(encoded)                            # (60000,1152)
encoded = Dense(128, activation='tanh')(encoded)        # (60000,128)
encoded = Dense(16, activation='tanh')(encoded)         # (60000,16)
```

```
#==========================================================
encoded = Dense(2, activation=None)(encoded)                # (60000,2) --> bottleneck
#==========================================================
decoded = Dense(16, activation='tanh')(encoded)             # (60000,16)
decoded = Dense(128, activation='tanh')(decoded)            # (60000,128)
decoded = Dense(1152, activation='tanh')(decoded)           # (60000,1152)
decoded = Reshape((3, 3, 128))(decoded)                                                  ␣
 ↪          # (60000,3,3,128)
#----------------------------
decoded = Conv2DTranspose(64, (3,3), strides=2, activation='relu',␣
 ↪padding='valid')(decoded)    # (60000,7,7,64)
decoded = BatchNormalization()(decoded)
#----------------------------
decoded = Conv2DTranspose(32, (3,3), strides=2, activation='relu',␣
 ↪padding='same')(decoded)     # (60000,14,14,32)
decoded = BatchNormalization()(decoded)
#----------------------------
decoded = Conv2DTranspose(1, (3,3), strides=2, activation='sigmoid',␣
 ↪padding='same')(decoded)   # (60000,28,28,1)
decoded = Reshape((784,))(decoded)
#==========================================================
autoencoder = Model(input=input_img, output=decoded)
```

[12]:

```
autoencoder.summary()
```

```
Model: "model_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         (None, 784)               0
_________________________________________________________________
reshape_1 (Reshape)          (None, 28, 28, 1)         0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 14, 14, 32)        320
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 7, 7, 64)          18496
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 3, 3, 128)         73856
_________________________________________________________________
flatten_1 (Flatten)          (None, 1152)              0
_________________________________________________________________
dense_1 (Dense)              (None, 128)               147584
_________________________________________________________________
dense_2 (Dense)              (None, 16)                2064
_________________________________________________________________
dense_3 (Dense)              (None, 2)                 34
_________________________________________________________________
dense_4 (Dense)              (None, 16)                48
_________________________________________________________________
dense_5 (Dense)              (None, 128)               2176
_________________________________________________________________
dense_6 (Dense)              (None, 1152)              148608
_________________________________________________________________
```

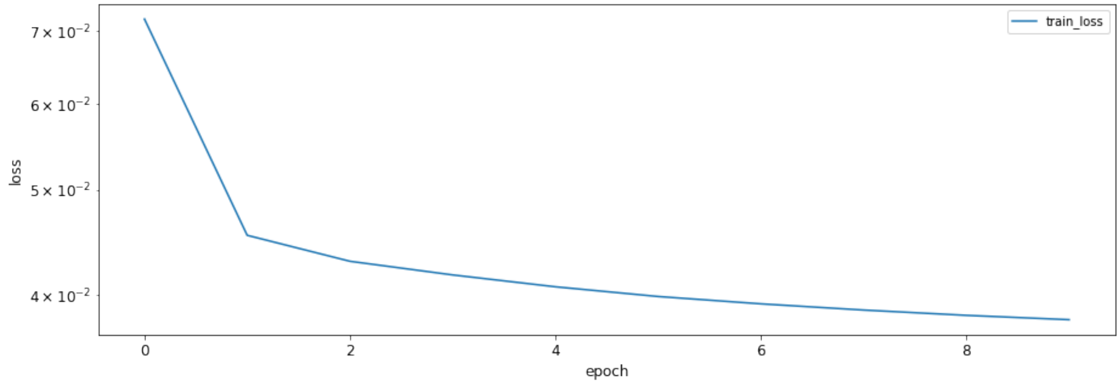
```
reshape_2 (Reshape)          (None, 3, 3, 128)         0
_________________________________________________________________
conv2d_transpose_1 (Conv2DTr (None, 7, 7, 64)          73792
_________________________________________________________________
batch_normalization_1 (Batch (None, 7, 7, 64)          256
_________________________________________________________________
conv2d_transpose_2 (Conv2DTr (None, 14, 14, 32)        18464
_________________________________________________________________
batch_normalization_2 (Batch (None, 14, 14, 32)        128
_________________________________________________________________
conv2d_transpose_3 (Conv2DTr (None, 28, 28, 1)         289
_________________________________________________________________
reshape_3 (Reshape)          (None, 784)               0
=================================================================
Total params: 486,115
Trainable params: 485,923
Non-trainable params: 192
_________________________________________________________________
```

[14]:
```
with device:
    autoencoder.compile(optimizer='adam', loss = "mse")
    X = x_train.reshape(x_train.shape[0], 784)
    history = autoencoder.fit(
        X,
        X,
        batch_size = 128,
        nb_epoch = 10,
        verbose = 1,
    )
```

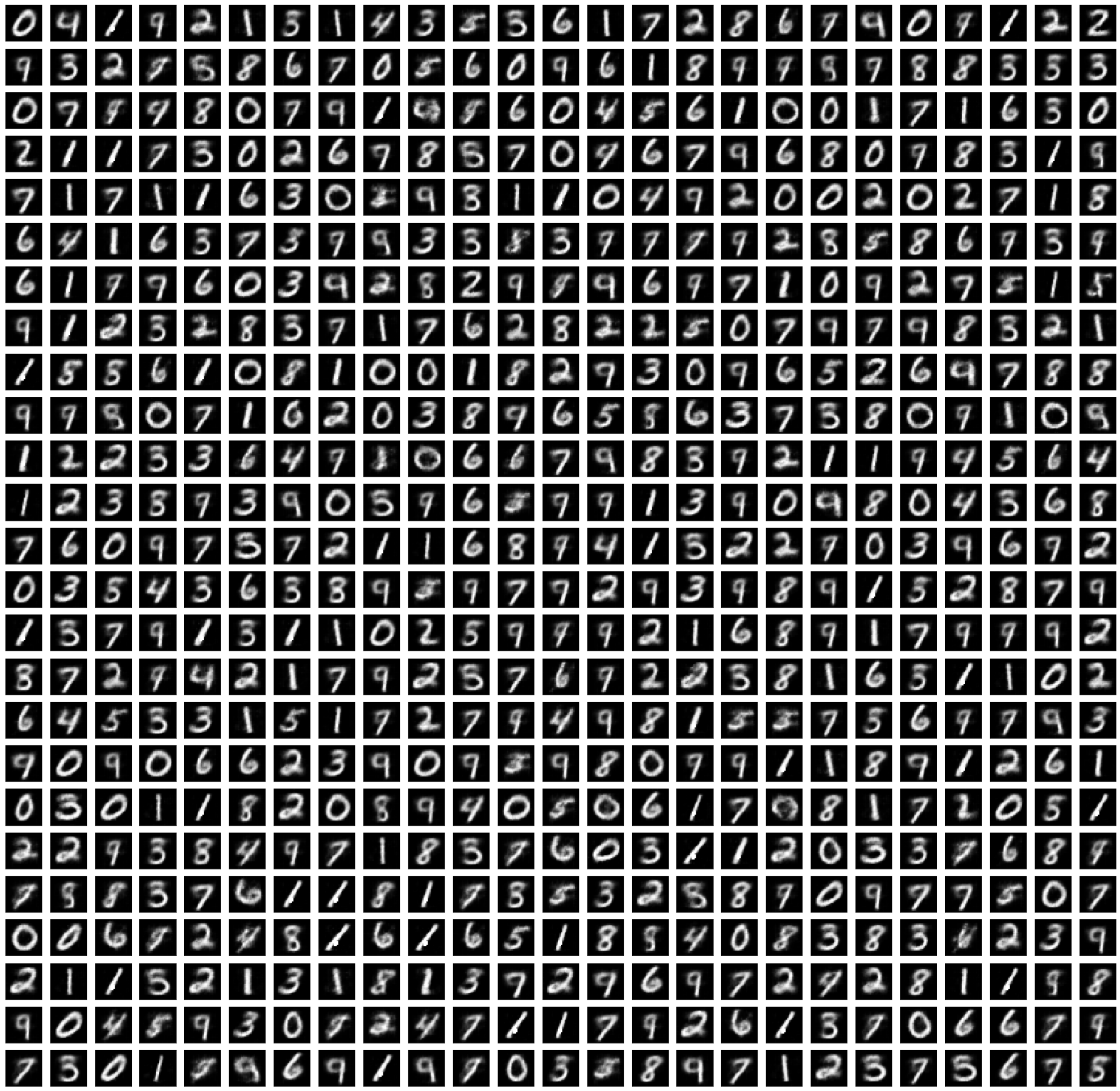
```
Epoch 1/10
60000/60000 [==============================] - 13s 222us/step - loss: 0.0718
Epoch 2/10
60000/60000 [==============================] - 6s 105us/step - loss: 0.0454
Epoch 3/10
60000/60000 [==============================] - 6s 103us/step - loss: 0.0430
Epoch 4/10
60000/60000 [==============================] - 6s 102us/step - loss: 0.0417
Epoch 5/10
60000/60000 [==============================] - 6s 104us/step - loss: 0.0407
Epoch 6/10
60000/60000 [==============================] - 6s 103us/step - loss: 0.0399
Epoch 7/10
60000/60000 [==============================] - 6s 104us/step - loss: 0.0393
Epoch 8/10
60000/60000 [==============================] - 6s 103us/step - loss: 0.0388
Epoch 9/10
60000/60000 [==============================] - 6s 102us/step - loss: 0.0383
Epoch 10/10
60000/60000 [==============================] - 6s 102us/step - loss: 0.0380
```

[15]:
```
plot_df = pd.DataFrame.from_dict({'train_loss':history.history['loss']})
plot_df.plot(logy=True, figsize=(15,5), fontsize=12)
plt.xlabel('epoch', fontsize=12)
```

```
plt.ylabel('loss', fontsize=12)
plt.show()
```



[16]:
```
# Visualization of 25 x 25 reconstructed images of digits
fig = plt.figure(figsize=(28,28))
ind = 1
for i in range(1, 26, 1):
    for j in range(1, 26, 1):
        fig.add_subplot(25,25,ind)
        show(autoencoder.predict(np.expand_dims(x_images[ind].flatten(), 0)).
 ↪reshape(28, 28))
        plt.xticks([])
        plt.yticks([])
        ind+=1
```



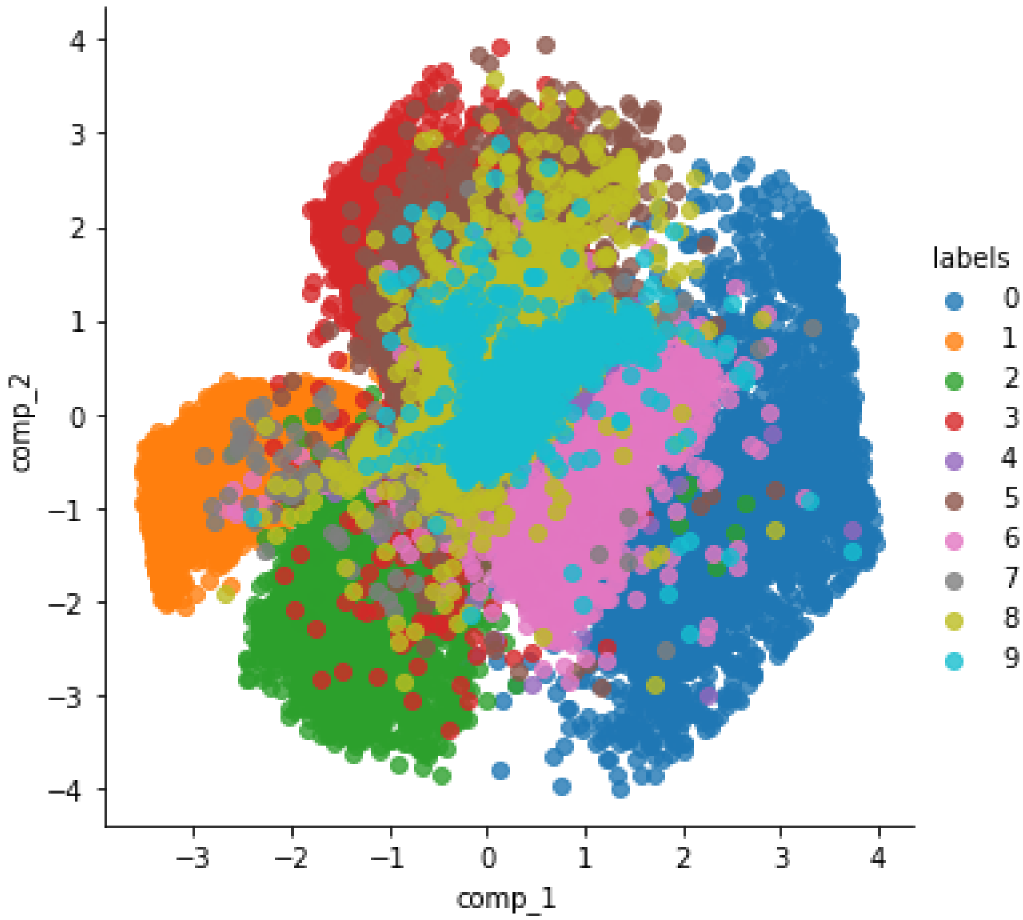
[18]:
```
encoder = Model(input = input_img, output = encoded)

# Building the decoder
encoded_input = Input(shape=(2,))
encoded_layer_1 = autoencoder.layers[-10]
encoded_layer_2 = autoencoder.layers[-9]
encoded_layer_3 = autoencoder.layers[-8]
encoded_layer_4 = autoencoder.layers[-7]
encoded_layer_5 = autoencoder.layers[-6]
encoded_layer_6 = autoencoder.layers[-5]
encoded_layer_7 = autoencoder.layers[-4]
encoded_layer_8 = autoencoder.layers[-3]
encoded_layer_9 = autoencoder.layers[-2]
encoded_layer_10 = autoencoder.layers[-1]

decoder = encoded_layer_1(encoded_input)
```

```
decoder = encoded_layer_2(decoder)
decoder = encoded_layer_3(decoder)
decoder = encoded_layer_4(decoder)
decoder = encoded_layer_5(decoder)
decoder = encoded_layer_6(decoder)
decoder = encoded_layer_7(decoder)
decoder = encoded_layer_8(decoder)
decoder = encoded_layer_9(decoder)
decoder = encoded_layer_10(decoder)
decoder = Model(input=encoded_input, output=decoder)
```

5.4 Visualizing the mapping of the labeled images in the manifold

[19]:
```
import seaborn as sns

x_flat = x_train.reshape(x_train.shape[0], x_train.shape[1] * x_train.shape[2])

x_proj = encoder.predict(x_flat[:60000])
x_proj.shape

proj = pd.DataFrame(x_proj)
proj.columns = ["comp_1", "comp_2"]
proj["labels"] = y_train[:60000]
sns.lmplot("comp_1", "comp_2", hue="labels", data=proj, fit_reg=False)
```

[19]:
```
<seaborn.axisgrid.FacetGrid at 0x7fb9da4d3ba8>
```

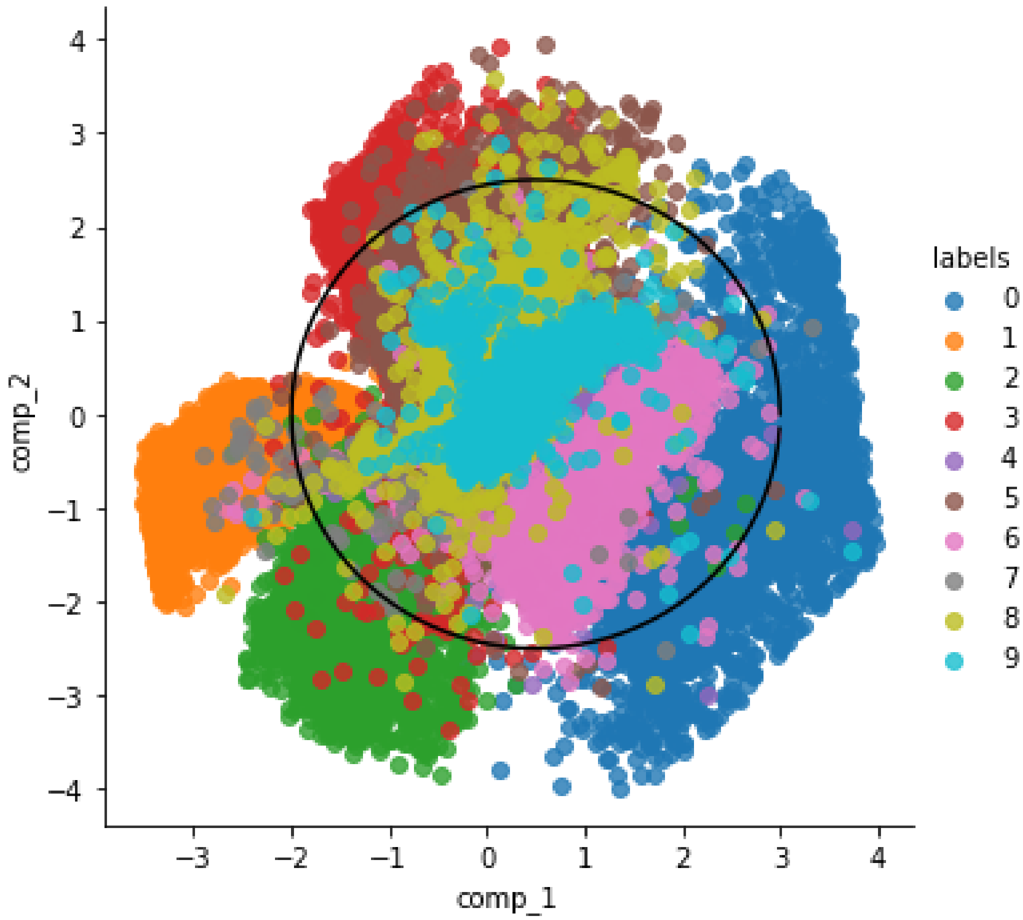


5.5. Generating new digits by moving along the manifold (latent 2D space)

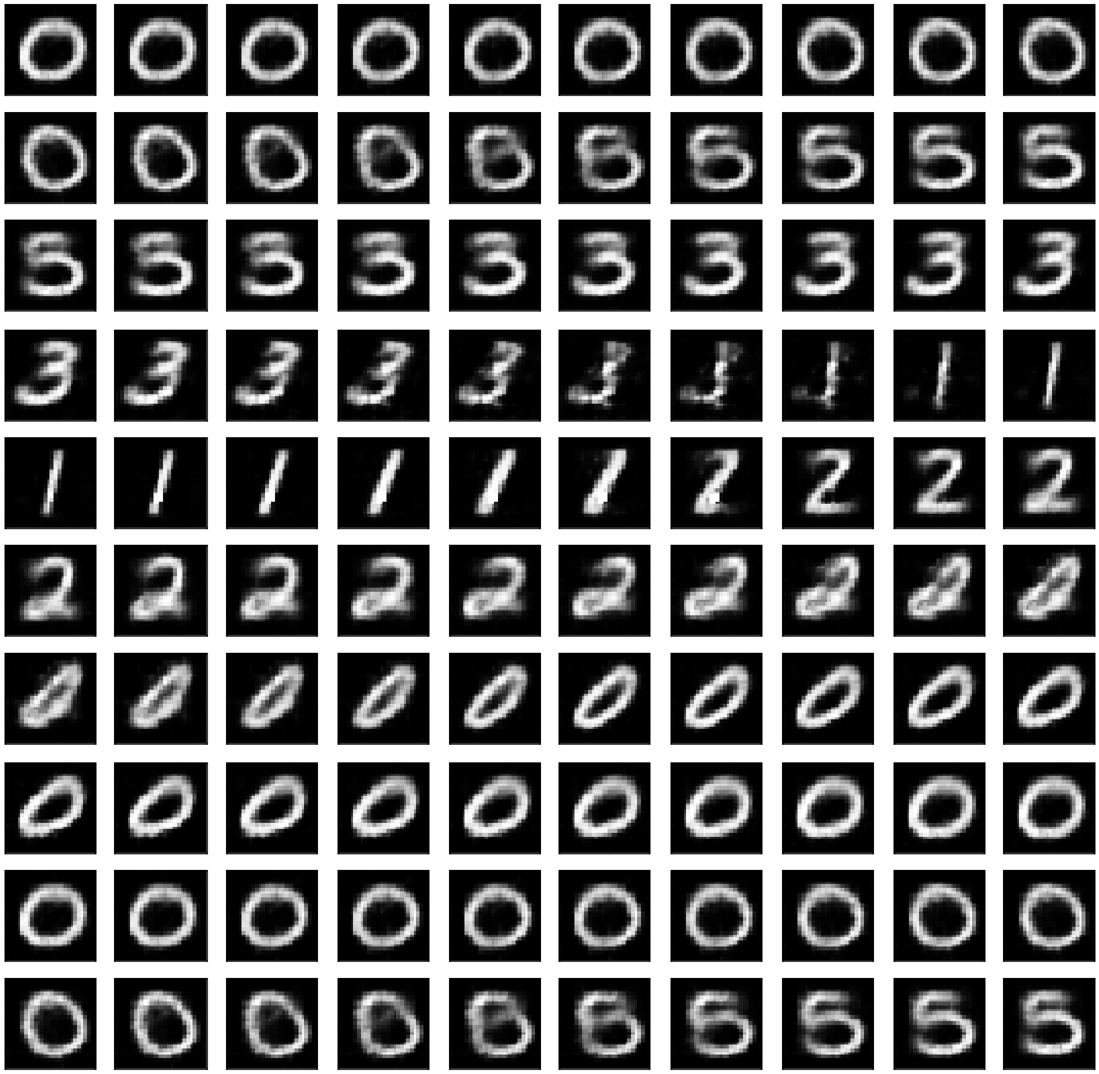
Please, adjust the scale whenever necessary.

5.5.1 Moving along a circle

[38]:
```
_ = sns.lmplot("comp_1", "comp_2", hue="labels", data=proj, fit_reg=False)
all_x = [2.5 * np.cos(2 * np.pi / 100 * i) + 0.5 for i in range(100)]
all_y = [2.5 * np.sin(2 * np.pi / 100 * i) + 0 for i in range(100)]
_ = plt.plot(all_x, all_y, 'black')
```

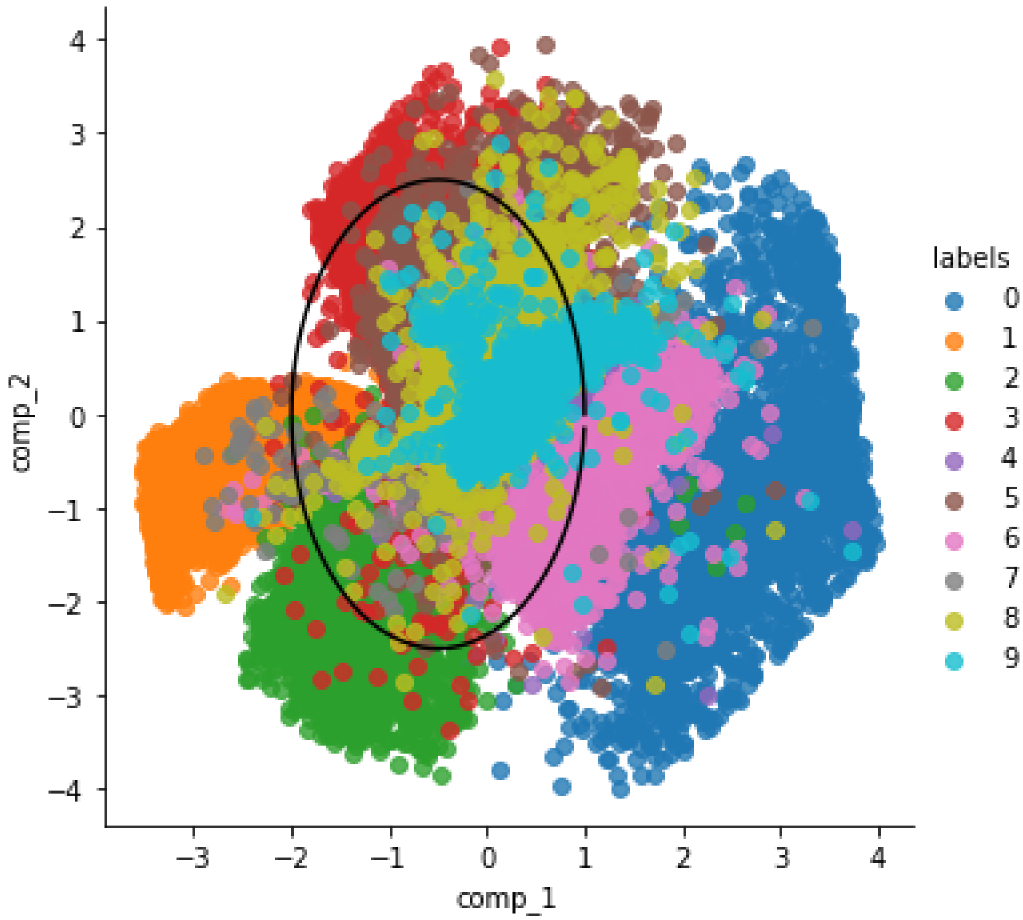


[39]:
```
# moving along a circle:
_ = plt.figure(figsize=(10, 10))

for i in range(100):
    _ = plt.subplot(10, 10, i+1)

    x = 3 * np.cos(2.5 * np.pi / 100 * i) + 0.5
    y = 3 * np.sin(2.5 * np.pi / 100 * i) + 0

    pt = np.array([[x, y]])
    _ = show(decoder.predict(pt).reshape((28, 28)))
    _ = plt.xticks([])
    _ = plt.yticks([])
```

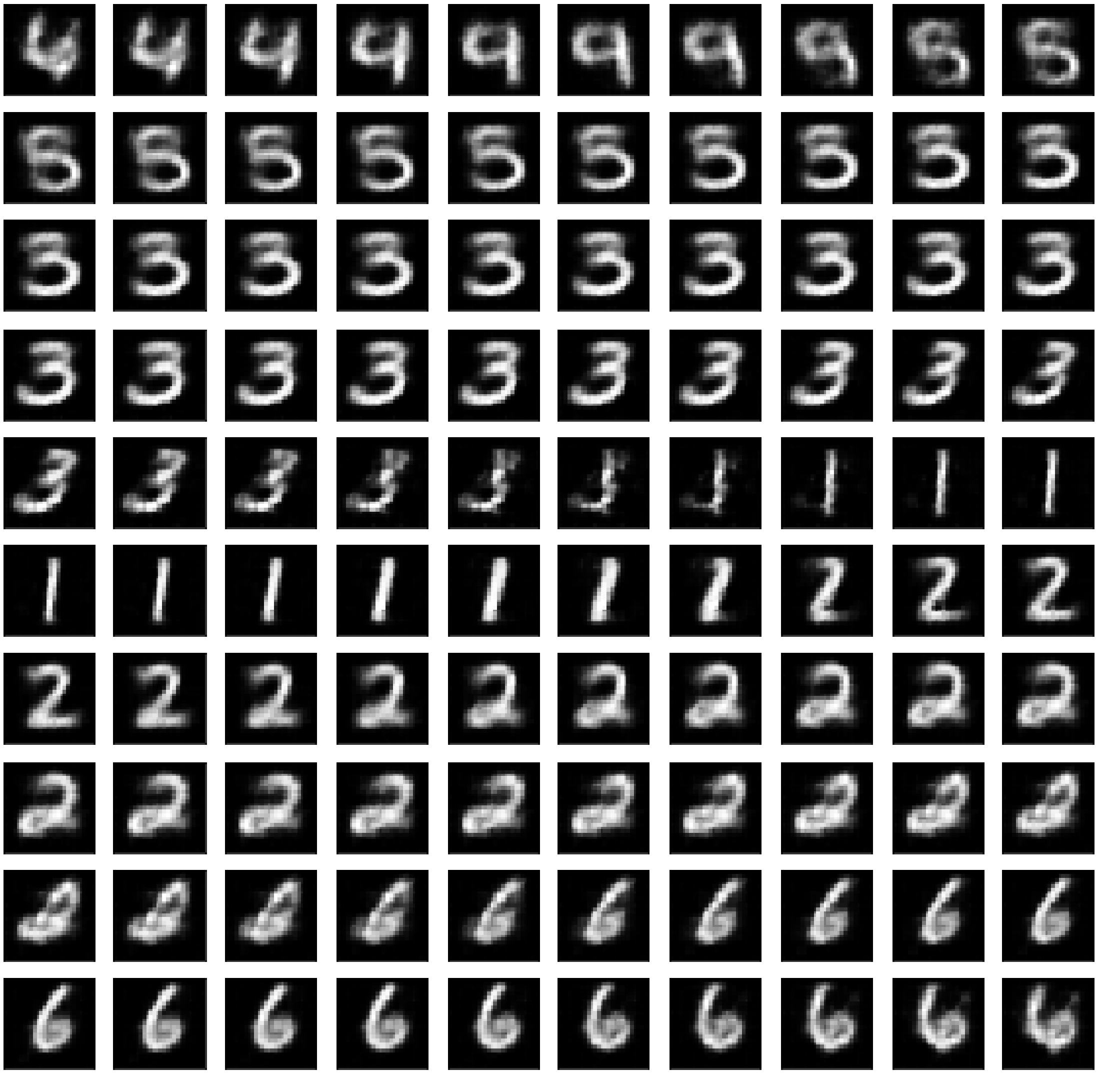


5.5.2 Moving along an ellipse

[42]:
```
_ = sns.lmplot("comp_1", "comp_2", hue="labels", data=proj, fit_reg=False)
all_x = [1.5 * np.cos(2 * np.pi / 100 * i) - 0.5 for i in range(100)]
all_y = [2.5 * np.sin(2 * np.pi / 100 * i) - 0 for i in range(100)]
_ = plt.plot(all_x, all_y, 'black')
```



[43]:
```
# moving along a elipse:
_ = plt.figure(figsize=(10, 10))

for i in range(100):
    _ = plt.subplot(10, 10, i+1)

    x = 1.5 * np.cos(2 * np.pi / 100 * i) - 0.5
    y = 2.5 * np.sin(2 * np.pi / 100 * i) - 0

    pt = np.array([[x, y]])
    _ = show(decoder.predict(pt).reshape((28, 28)))
    _ = plt.xticks([])
    _ = plt.yticks([])
```



5.5.3 Moving along a grid

[45]:
```
# moving along a elipse:
_ = plt.figure(figsize=(12, 12))

for i in range(20):
    for j in range(20):

        _ = plt.subplot(20, 20, i * 20 + j + 1)
        # range adapted to go from -2 to +2 in both X and Y axis
        pt = np.array([[ -2 + 4 * i/19, -2 + 4 * j/19]])
        _ = show(decoder.predict(pt).reshape((28, 28)))
        _ = plt.xticks([])
        _ = plt.yticks([])
```