Q2_Nonlinear_Autoencoder

March 23, 2022

1 Allowing Import from Parent Directory

2 Importing Packages

```
[2]: import glob
     import numpy as np
     import pandas as pd
     import matplotlib.pyplot as plt
     import time
     import tools.loaddata as loaddata
     import tools.dataassimilation as da
     import tools.visualisation as visual
     import sklearn
     assert sklearn.__version__ >= "0.20"
     from sklearn.metrics import mean_squared_error
     from sklearn.decomposition import PCA
     # TensorFlow 2.0 is required
     import tensorflow as tf
     from tensorflow import keras
     assert tf.__version__ >= "2.0"
```

3 Loading and Reshaping Data

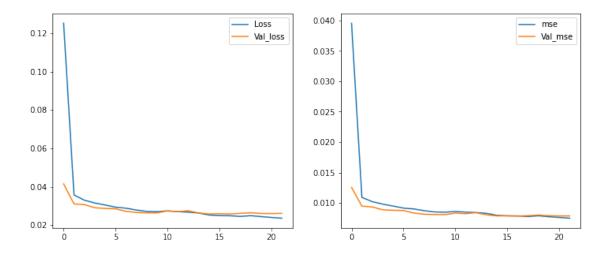
```
[ ]: path_train = "../data/train/"
     path_test = "../data/test/"
     path_back = "../data/background/"
     path_obs = "../data/satellite/"
[4]: train_full, test, model_data, satellite_data = loaddata.
      →load_all_data(path_train, path_test, path_back, path_obs)
[5]: train = train_full[0:1200]
[6]: print(f"Train data before reshaping: {np.shape(train)}")
     print(f"Test data before reshaping: {np.shape(test)}")
     print(f"background data before reshaping: {np.shape(model data)}")
     print(f"observational data before reshaping: {np.shape(satellite_data)}")
    Train data before reshaping: (1200, 871, 913)
    Test data before reshaping: (300, 871, 913)
    background data before reshaping: (5, 871, 913)
    observational data before reshaping: (5, 871, 913)
[7]: train_1D, test_1D, model_data_1D, satellite_data_1D = loaddata.
     →reshape_all_datasets(train, test, model_data, satellite_data)
[8]: print(f"Train data after reshaping: {train_1D.shape}")
     print(f"Test data after reshaping: {test 1D.shape}")
     print(f"Model data after reshaping: {model_data_1D.shape}")
     print(f"Observational data after reshaping: {satellite_data_1D.shape}")
    Train data after reshaping: (1200, 795223)
    Test data after reshaping: (300, 795223)
    Model data after reshaping: (5, 795223)
    Observational data after reshaping: (5, 795223)
```

4 Non-linear Autoencoder

```
keras.layers.Dense(795223, __
 →activation='sigmoid')])
autoencoder = keras.models.Sequential([encoder, decoder])
autoencoder.compile(loss='binary_crossentropy',
              optimizer=keras.optimizers.Adam(),
              metrics=['mse'])
print('Encoder:')
encoder.summary()
print('\nDencoder:')
decoder.summary()
print('\nAutoencoder:')
autoencoder.summary()
Encoder:
Model: "sequential"
                   Output Shape
Layer (type)
_____
dense (Dense)
                    (None, 128)
                                       101788672
dense_1 (Dense)
                   (None, 64)
                                       8256
Total params: 101,796,928
Trainable params: 101,796,928
Non-trainable params: 0
_____
Dencoder:
Model: "sequential_1"
Layer (type) Output Shape
______
dense_2 (Dense)
                    (None, 128)
                                       8320
dense_3 (Dense)
                   (None, 795223)
                                      102583767
_____
Total params: 102,592,087
Trainable params: 102,592,087
Non-trainable params: 0
_____
Autoencoder:
Model: "sequential_2"
```

```
Layer (type)
                                 Output Shape
                                                           Param #
     ______
      sequential (Sequential)
                                                           101796928
                                  (None, 64)
      sequential 1 (Sequential)
                                  (None, 795223)
                                                          102592087
     Total params: 204,389,015
     Trainable params: 204,389,015
     Non-trainable params: 0
[10]: # Callback to prevent overfitting
     from keras import callbacks
     earlystopping = callbacks.EarlyStopping(monitor ="val_loss",
                                             mode ="min", patience = 5,
                                             restore_best_weights = True)
 []: start = time.time()
     history = autoencoder.fit(train_1D,
                               train_1D,
                               epochs=50,
                               batch_size=32,
                               verbose=2,
                               validation_data = (test_1D, test_1D),
                               shuffle = True, callbacks = [earlystopping])
     time_ae = time.time() - start
     print('Execution time: ', time_ae)
[13]: # The validation loss began to increase when the number of epochs
      # was at 38. This means that the model begins to overfit the data after 38_{\sqcup}
      \rightarrow epochs.
      # The optimum combination of epoch size and batch size we found is 38 and 32_{f \sqcup}
      →respectively, with 64 hidden layers.
[14]: fig, axes = plt.subplots(1,2, figsize=(12,5))
     axes[0].plot(history.history['loss'])
     axes[0].plot(history.history['val_loss'])
     axes[0].legend(['Loss', 'Val_loss'])
     axes[1].plot(history.history['mse'])
     axes[1].plot(history.history['val mse'])
     axes[1].legend(['mse', 'Val_mse'])
```

[14]: <matplotlib.legend.Legend at 0x7fb6d6da4f10>



```
[15]: test_recovered = autoencoder.predict(test_1D)
mse_test = da.mse(test_1D, test_recovered)
print('mse: ', mse_test)
```

mse: 0.007834356550550689

5 Data Assimilation - Kalman Filter (BLUE)

By adjusting the error covariance matrices R and B, we found that the following forms of matrices give us the lowest mse result after data assimilation.

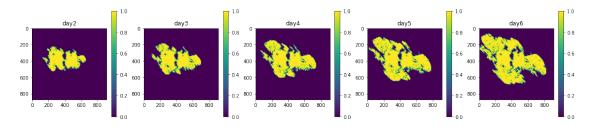
```
print('MSE after assimilation in latent space: ', mse_after_DA)

## Printing MSE in Physical space space
updated_data_recon = decoder.predict(updated_data_array)
mse_before_DA_physical = da.mse(satellite_data_1D, model_data_1D)
mse_after_DA_physical = da.mse(satellite_data_1D, updated_data_recon)

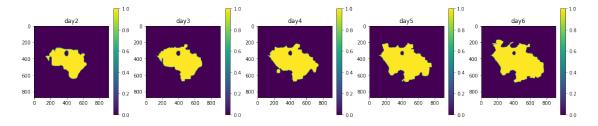
print('MSE before assimilation in physical space: ', mse_before_DA_physical)
print('MSE after assimilation in physical space: ', mse_after_DA_physical)
```

MSE before assimilation in latent space: 4188.5737
MSE after assimilation in latent space: 715.8404601641759
MSE before assimilation in physical space: 0.1191695914227833
MSE after assimilation in physical space: 0.08701994260920441

[18]: # Plot model data visual.plot_data(model_data)



[19]: # Plot satellite data visual.plot_data(satellite_data)



[20]: # Plot reconstructed model updated_data_recon = np.reshape(updated_data_recon, (5, 871, 913)) visual.plot_data(updated_data_recon)

```
[]: !wget -nc https://raw.githubusercontent.com/brpy/colab-pdf/master/colab_pdf.py
from colab_pdf import colab_pdf
colab_pdf('Q2_Nonlinear_Autoencoder.ipynb')
```

--2022-03-23 23:29:15-- https://raw.githubusercontent.com/brpy/colab-pdf/master/colab_pdf.py
Resolving raw.githubusercontent.com (raw.githubusercontent.com)...
185.199.108.133, 185.199.109.133, 185.199.110.133, ...
Connecting to raw.githubusercontent.com
(raw.githubusercontent.com)|185.199.108.133|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 1864 (1.8K) [text/plain]
Saving to: 'colab_pdf.py'

colab_pdf.py 100%[===========] 1.82K --.-KB/s in 0s

2022-03-23 23:29:15 (46.0 MB/s) - 'colab_pdf.py' saved [1864/1864]

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