Documentation Part2 - Πρόβλεψη, Ταξινόμηση, Ομαδοποίηση σε Καρδιοτοκογραφικά Δεδομένα

<u>Σημείωση:</u>

- Ο κώδικας που θα ακολουθήσει βρίσκεται στο φάκελο:
  Code/Part2.ipynb
- Τα δεδομένα(data) βρίσκονται στο φάκελο:
  Data/data2.csv
- *Τα δεδομένα έχουν τροποποιηθεί στο αρχείο csv. Αρχικά έχουν διαγραφεί οι επικεφαλίδες έτσι ώστε να έχουμε το πρόβλημα supervised.*

Επεξήγηση Κώδικα

Ερώτημα 1 (Data Cleaning):

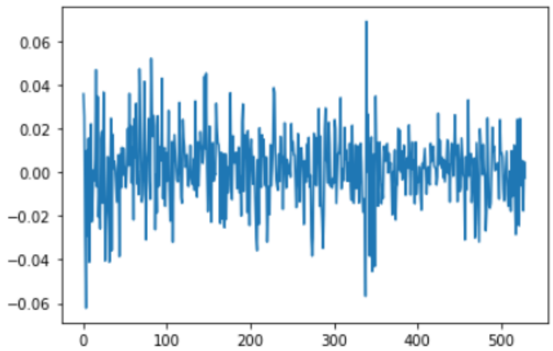
```
data = pd.read_csv("../Data/data 2.csv", header = None, sep=',')
```

```
# Data Cleaning

data = data[data.columns[1:]]
data.dropna(inplace=True)
data.reset_index(inplace=True)
data = data.iloc[:530]

data.info()
print("\n")
plt.plot(data[1])
plt.show()
print("\n")
data.head()
```

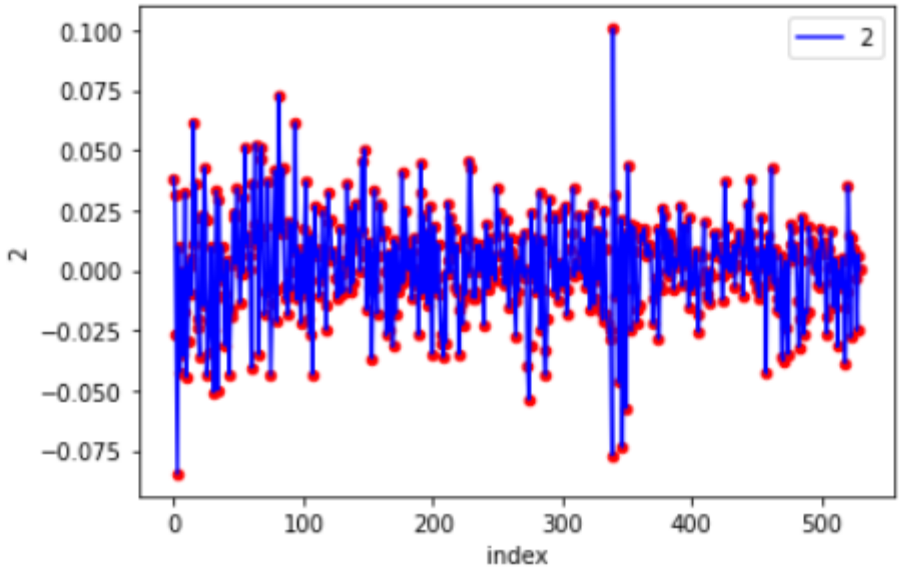
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 530 entries, 0 to 529
Data columns (total 10 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   index   530 non-null    int64
 1   1       530 non-null    float64
 2   2       530 non-null    float64
 3   3       530 non-null    float64
 4   4       530 non-null    float64
 5   5       530 non-null    float64
 6   6       530 non-null    float64
 7   7       530 non-null    float64
 8   8       530 non-null    float64
 9   9       530 non-null    float64
dtypes: float64(9), int64(1)
memory usage: 41.5 KB
```



	index	1	2	3	4	5	6	7	8	9
0	0	0.035754	0.038376	-0.004679	0.002193	0.003894	0.000000	0.031190	0.012698	0.028524
1	1	0.025426	0.031813	0.007787	0.008455	0.012866	0.004162	0.018920	0.011341	0.008773
2	2	-0.028862	-0.026353	-0.030469	-0.017833	-0.028735	0.017293	-0.035899	-0.017073	-0.020015
3	3	-0.062208	-0.084716	0.003391	-0.011726	-0.000466	-0.040061	0.028283	-0.005561	-0.019424
4	4	0.009860	0.009658	-0.021533	-0.019873	-0.012710	-0.004474	-0.009764	-0.010989	-0.007802

Δημιουργία Scatter Plot για την καλύτερη αντίληψη του γραφήματος:

```
# a scatter plot comparing num_children and num_pets
ax = plt.gca()
data.plot(kind='line', x='index',y=2, color='blue', ax=ax)
data.plot(kind='scatter', x='index',y=2, color='red', ax=ax)
plt.show()
```



Καθορίζουμε το input ως προετοιμασία για την υλοποίηση τουπροβλήματος supervised:

```
#Convert data to input-output
df = data[1].to_frame(name='ISE_TL')

df.head()
```

	ISE_TL
0	0.035754
1	0.025426
2	-0.028862
3	-0.062208
4	0.009860

Κανονικοποίηση Δεδομένων:

```
# normalize the dataset
df0 = df.copy()
scaler = MinMaxScaler(feature_range=(0, 1))
df = scaler.fit_transform(np.reshape(df['ISE_TL'].values, (df.shape[0], 1)))
df = pd.DataFrame(data=df, columns=['ISE_TL'])

df.head()
```

	ISE_TL
0	0.746889
1	0.668147
2	0.254242
3	0.000000
4	0.549467

Εκτελούμε τη συνάρτηση 'timeseries_to_supervised', η οποία λύνει το πρόβλημα του supervised:

```
n_in = 6
n_out = 1
sdf = timeseries_to_supervised(df, n_in, n_out)

sdf.head()
```

	ISE_TL(t-6)	ISE_TL(t-5)	ISE_TL(t-4)	ISE_TL(t-3)	ISE_TL(t-2)	ISE_TL(t-1)	ISE_TL(t)
6	0.746889	0.668147	0.254242	0.000000	0.549467	0.251732	0.592052
7	0.668147	0.254242	0.000000	0.549467	0.251732	0.592052	0.160419
8	0.254242	0.000000	0.549467	0.251732	0.592052	0.160419	0.479339
9	0.000000	0.549467	0.251732	0.592052	0.160419	0.479339	0.642311
10	0.549467	0.251732	0.592052	0.160419	0.479339	0.642311	0.301278

timeseries_to_supervised:

```
def timeseries_to_supervised(df, n_in, n_out):
   agg = pd.DataFrame()

   for i in range(n_in, 0, -1):
      df_shifted = df.shift(i).copy()
      df_shifted.rename(columns=lambda x: ('%s(t-%d)' % (x, i)), inplace=True)
      agg = pd.concat([agg, df_shifted], axis=1)

   for i in range(0, n_out):
      df_shifted = df.shift(-i).copy()
      if i == 0:
         df_shifted.rename(columns=lambda x: ('%s(t)' % (x)), inplace=True)
      else:
         df_shifted.rename(columns=lambda x: ('%s(t+%d)' % (x, i)), inplace=True)
      agg = pd.concat([agg, df_shifted], axis=1)
   agg.dropna(inplace=True)
   return agg
```

Προετοιμασία για την εκπαίδευση:

```
X, y = sdf[[('ISE_TL(t-%d)' % i) for i in range(6, 0, -1)]].values, sdf['ISE_TL(t)'].values
print(X.shape, y.shape)
```

```
(524, 6) (524,)
```

```
# Preparation for Training

# Split data into train and test
len_data = X.shape[0]
train_size = int(len_data * .5)
print ("Train size: %d" % train_size)
print ("Test size: %d" % (len_data - train_size))

xtr, ytr = X[:train_size, :], y[:train_size]
xte, yte = X[train_size:, :], y[train_size:]
print(xtr.shape, ytr.shape)
print(xte.shape, yte.shape)
```

```
Train size: 262
Test size: 262
(262, 6) (262,)
(262, 6) (262,)
```

Ερώτημα 2α (υλοποίηση MPL):

```
#------------------------------------------------- MLP & RNN ------------------------------
batch_size = 1 #1
model = Sequential()

# MLP
xtr, ytr = X[:train_size, :], y[:train_size]
xte, yte = X[train_size:, :], y[train_size:]

model.add(Dense(units=100, input_dim=xtr.shape[1], activation="relu"))
model.add(Dense(50, activation="relu"))
model.add(Dense(1))
model.compile(loss='mean_squared_error', optimizer='adam')
model.summary()

# # RNN
# model.add(SimpleRNN(units=100, batch_input_shape=(batch_size, xtr.shape[1],
#                                                  xtr.shape[2]), activation="relu",
#                                                  return_sequences=True))
# model.add(Dense(50, activation="relu"))
# model.add(Dense(1))
# model.compile(loss='mean_squared_error', optimizer='adam')
# model.summary()


model.fit(xtr,ytr, epochs=10, batch_size=batch_size, verbose=0)
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 100)               700
_________________________________________________________________
dense_1 (Dense)              (None, 50)                5050
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 51
=================================================================
Total params: 5,801
Trainable params: 5,801
Non-trainable params: 0
_________________________________________________________________
<keras.callbacks.History at 0x206cee64700>
```

Τελικό Αποτέλεσμα (MLP):

```
# Predicting and plotting the result
trainPredict = model.predict(xtr, batch_size=batch_size)
testPredict = model.predict(xte, batch_size=batch_size)
```

```
# invert predictions
trainPredict = np.reshape(trainPredict, (samples*steps, features_out))
ytr2d = np.reshape(ytr, (samples*steps, features_out))
testPredict = np.reshape(testPredict, (samples*steps, features_out))
yte2d = np.reshape(yte, (samples*steps, features_out))
```

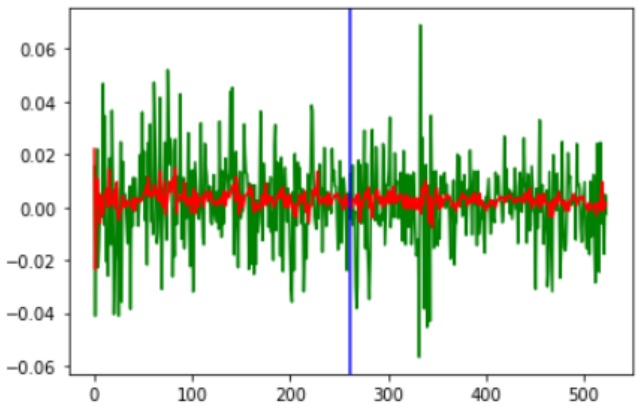
```
trainPredict = scaler.inverse_transform(trainPredict)
trainY = scaler.inverse_transform(ytr2d)
testPredict = scaler.inverse_transform(testPredict)
testY = scaler.inverse_transform(yte2d)
```

```
# Calculate error
print("Test MSE: ", mean_squared_error(testY, testPredict))
print("Test MSE: ", sum(np.square(testY-testPredict))/testY.shape[0])
print("Test MAE: ", sum(abs(testY-testPredict))/testY.shape[0])
print("Test R2: ", r2_score(testY, testPredict))
print("Test R2: ", 1-(sum(np.square(testY-testPredict))/sum(np.square(testY-testY.mean()))))
```

```
Test MSE:  0.00022988309861643038
Test MSE:  [0.00022988]
Test MAE:  [0.01114386]
Test R2:  -0.05759813323646745
Test R2:  [-0.05759813]
```

```
# Finally, we check the result in a plot.
# A vertical line in a plot identifies a splitting point between
# the training and the test part.
predicted = np.concatenate((trainPredict,testPredict),axis=0)

original = np.concatenate((trainY,testY),axis=0)
predicted = np.concatenate((trainPredict,testPredict),axis=0)
index = range(0, original.shape[0])
plt.plot(index,original, 'g')
plt.plot(index,predicted, 'r')
plt.axvline(df.index[train_size], c="b")
plt.show()
```



Ερώτημα 2β (RNN):

Προετοιμασία για την υλοποίηση του νευρωνικού δικτύου RNN :

```
# Initialization of [samples, steps, features]

samples = train_size
steps = 1
features_in = n_in
features_out = n_out
```

```
xtr = np.reshape(xtr, (samples, steps, features_in))
ytr = np.reshape(ytr, (samples, steps, features_out))
print(xtr.shape, ytr.shape)
xte = np.reshape(xte, (samples, steps, features_in))
yte = np.reshape(yte, (samples, steps, features_out))
print(xte.shape, yte.shape)
```

```
(262, 1, 6) (262, 1, 1)
(262, 1, 6) (262, 1, 1)
```

Υλοποίηση RNN:

```
#---------------------------------------------------- MLP & RNN ------------------
batch_size = 1 #1
model = Sequential()

# MLP
# xtr, ytr = X[:train_size, :], y[:train_size]
# xte, yte = X[train_size:, :], y[train_size:]

# model.add(Dense(units=100, input_dim=xtr.shape[1], activation="relu"))
# model.add(Dense(50, activation="relu"))
# model.add(Dense(1))
# model.compile(loss='mean_squared_error', optimizer='adam')
# model.summary()

# RNN
model.add(SimpleRNN(units=100, batch_input_shape=(batch_size, xtr.shape[1],
                                                  xtr.shape[2]), activation="relu",
                                                  return_sequences=True))
model.add(Dense(50, activation="relu"))
model.add(Dense(1))
model.compile(loss='mean_squared_error', optimizer='adam')
model.summary()


model.fit(xtr,ytr, epochs=10, batch_size=batch_size, verbose=0)
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
simple_rnn (SimpleRNN)       (1, 1, 100)               10700
_________________________________________________________________
dense (Dense)                (1, 1, 50)                5050
_________________________________________________________________
dense_1 (Dense)              (1, 1, 1)                 51
=================================================================
Total params: 15,801
Trainable params: 15,801
Non-trainable params: 0
_________________________________________________________________
<keras.callbacks.History at 0x18e2d89a1f0>
```

Έξοδος RNN:

```
# Predicting and plotting the result
trainPredict = model.predict(xtr, batch_size=batch_size)
testPredict = model.predict(xte, batch_size=batch_size)
```

```
# invert predictions
trainPredict = np.reshape(trainPredict, (samples*steps, features_out))
ytr2d = np.reshape(ytr, (samples*steps, features_out))
testPredict = np.reshape(testPredict, (samples*steps, features_out))
yte2d = np.reshape(yte, (samples*steps, features_out))
```

```
trainPredict = scaler.inverse_transform(trainPredict)
trainY = scaler.inverse_transform(ytr2d)
testPredict = scaler.inverse_transform(testPredict)
testY = scaler.inverse_transform(yte2d)
```

```
# Calculate error
print("Test MSE: ", mean_squared_error(testY, testPredict))
print("Test MSE: ", sum(np.square(testY-testPredict))/testY.shape[0])
print("Test MAE: ", sum(abs(testY-testPredict))/testY.shape[0])
print("Test R2: ", r2_score(testY, testPredict))
print("Test R2: ", 1-(sum(np.square(testY-testPredict))/sum(np.square(testY-testY.mean()))))
```

```
Test MSE:  0.00023423351002383 98
Test MSE:  [0.00023423]
Test MAE:  [0.01133209]
Test R2:  -0.07761259715738311
Test R2:  [-0.0776126]
```

```
# Finally, we check the result in a plot.
# A vertical line in a plot identifies a splitting point between
# the training and the test part.
predicted = np.concatenate((trainPredict,testPredict),axis=0)

original = np.concatenate((trainY,testY),axis=0)
predicted = np.concatenate((trainPredict,testPredict),axis=0)
index = range(0, original.shape[0])
plt.plot(index,original, 'g')
plt.plot(index,predicted, 'r')
plt.axvline(df.index[train_size], c="b")
plt.show()
```