

# Agenda

9.1 Data Preparation

9.2 NN Model Training and Testing

9.3 CNN Model Training and Testing



# 9.1 Data Preparation

Data Exploration and Cleaning / Transform / Feature Selection /Train-Test-Split

#### **LIBRARIES**

|   | import numpy as np   |
|---|--|
| 2 | • import pandas as pd  |
| 3 | import matplotlib.pyplot as plt  |
| 4 | from sklearn.preprocessing import StandardScaler                                       |
| 3 | from sklearn.model_selection import train_test_split, cross_val_score, StratifiedKFold |
| E | from sklearn.svm import SVC  |
| 7 | from sklearn import metrics  |
| 8 | from sklearn.model_selection import GridSearchCV, RandomizedSearchCV                   |
| 9 | • from sklearn.metrics import accuracy_score, classification_report, confusion_matrix  |
| I | • import glob  |
| 1 | from scipy import stats  |
|   | import datetime as dt  |
|   |  |

## 9.1.1 -> 8.1 (a) Load and Prepare Data

- # Load data from csv 3 files
- # acceleration.txt, heartrate.txt, labeled\_sleep.txt
  - ACC = read\_csv(acceleration.txt, sep = ' ',names=['timedelta', 'accX', 'accY', 'accZ'])
  - **HeartR = read\_csv(**heartrate.txt, sep = ',',names=['timedelta', 'heartrate'])
  - SleepL = read csv(labeled sleep.txt, sep = '',names=['timedelta', 'sleep'])
- # Check 'timedelta' max(), min() of ACC, HeartR, SleepL (ช่วงเวลาที่มีข้อมูลใกล้กัน)
  - Ex
    - ACC\_max\_date = ACC['timedelta'].max()
    - ACC\_min\_date = ACC['timedelta'].min()
    - หา start\_timedelta, end\_timedelta

ACC start: -124489.16105 ACC end: 17643.046417
HeartR start: -355241.73971 HeartR end: 34491.1535499

SleepL start: 0 SleepL end: 28530

- # select only intersected timedelta (ACC, HeartR, SleepL) (ช่วงเวลาที่มีข้อมูลใกล้กัน)
- Ex
  - ACC\_new = ACC[(ACC['timedelta'] > start\_timedelta) &(df\_acc['timedelta'] < end\_timedelta) ]

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### 9.1.1 -> 8.1 (b) Load and Prepare Data (ACC)

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- # ----- Rounding ACC (Rounding to 1 sec) -----
  - # Convert to datetime and round to second,
    - ACC\_new['timedelta'] = pd.DataFrame(pd.to\_timedelta(ACC\_new['timedelta'], timedelta\_unit).round('1s'))

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- # Average rounding duplicated time
- # df\_acc\_X = ACC\_new.groupby('timedelta')['accX'].mean().reset\_index()
- df\_acc\_Y = ACC\_new.groupby('timedelta')['accY'].mean().reset\_index()
- df\_acc\_Z = ACC\_new.groupby('timedelta')['accZ'].mean().reset\_index()

• # acc\_X, acc\_Y, acc\_Z

- Ex
  - pd.concat([df\_acc\_X, df\_acc\_Y, df\_acc\_Z], axis=1)

# Before / After convert datetime and round and average to 1s

```
Before convert datetime and round and average to 1s ------
      timedelta
                     accX
                               accY
                                         accZ
0 -124489.161050 0.017487 -0.586700 -0.805771
1 -124489.116395 0.018982 -0.589676 -0.809158
2 -124489.115548 0.020966 -0.580887 -0.815048
3 -124489.114691 0.019485 -0.580872 -0.813583
4 -124489.097700 0.016998 -0.587204 -0.806259
----- After convert datetime and round and average to 1s -------
       timedelta
                      accX
                                accY
                                         accZ
0 0 days 00:00:00 -0.243203 0.895372 0.367591
1 0 days 00:00:01 -0.240757 0.873826 0.415446
2 0 days 00:00:02 -0.244620 0.883943 0.387026
3 0 days 00:00:03 -0.248036 0.902427 0.347812
4 0 days 00:00:04 -0.241778 0.912946 0.321502
```

## 9.1.1 ->8.1 (c) Load and Prepare Data (Heart rate)



- # ----- Rounding Heart Rate (Rounding to 1 sec) ------
- HeartR\_new['timedelta'] = pd.DataFrame(pd.to\_timedelta(HeartR\_new['timedelta'], timedelta\_unit).round('1s'))

- # Resampling every 1s with median with ffill
- resample rule = '1s'
- HeartR\_new2 = HeartR\_new.set\_index('timedelta').resample(resample\_rule,).median().ffill()

#### 9.1.1 -> 8.1 (d) Load and Prepare Data (Sleep Label)



- # ----- Rounding Sleep Label (Rounding to 1 sec) ------
- SleepL\_new['timedelta'] = pd.DataFrame(pd.to\_timedelta(SleepL\_new['timedelta'], timedelta\_unit).round('1s'))

- # Resampling every 1s with median with ffill
- resample\_rule = '1s'
- Sleepl\_new2 = Sleepl\_new.set\_index('timedelta').resample(resample\_rule,).median().ffill()

#### 9.1.1 -> 8.1 (e) Merge Data and Standardized data

• # ------Merge All Data -----

- df = []
- df = pd.merge\_asof(ACC\_new2, HeartR\_new2, on='timedelta')
- df = pd.merge\_asof(df, df\_SleepL\_new2, on = 'timedelta')
- # Fill NA
- # Heart rate
  - Fillna() # using median()
- # Sleep Label
  - Fillna() # with 0
- # Drop column
- drop('timedelta')
- # Standardized data
- feature columns = ['accX', 'accY', 'accZ', 'heartrate']
- label\_columns = ['sleep']
- df\_feature = df[feature\_columns] <= standardized data of df\_feature
- df\_label = df[label\_columns]
- # Visualize signals
  - df\_feature.plot(), df\_label.plot()

## 9.2.1 Create 3d input

- # ----- 1D to 3D feature-----
- # set sliding window parameter
- slidingW = 100
- Stride\_step = 5
- For t in range( 0 , len(df\_feature), stride\_step )
- F3d= df\_feature( t : t + slidingW))
- df\_feature3D.append(F3d)
- df\_feature3D.reshape(slidingW, n\_feature, 1)
- Labels = stats.mode( df\_label ( t : t+slidingW ) )
- df\_label\_new.append(Labels)

|       | 1  | 1  | 1  | 1  |                  |
|-------|----|----|----|----|------------------|
|       |    | -  |    |    |                  |
|       | 2  | 2  | 2  | 2  |                  |
|       | 3  | 3  | 3  | 3  |                  |
|       | 4  | 4  | 4  | 4  |                  |
| set#1 | 5  | 5  | 5  | 5  | L1               |
|       | 6  | 6  | 6  | 6  | majority(L1:10)  |
|       | 7  | 7  | 7  | 7  |                  |
|       | 8  | 8  | 8  | 8  |                  |
|       | 9  | 9  | 9  | 9  |                  |
|       | 10 | 10 | 10 | 10 |                  |
|       | 5  | 5  | 5  | 5  |                  |
|       | 6  | 6  | 6  | 6  |                  |
|       | 7  | 7  | 7  | 7  |                  |
|       | 8  | 8  | 8  | 8  |                  |
| set#2 | 9  | 9  | 9  | 9  | L2               |
|       | 10 | 10 | 10 | 10 | majority(L5:14)  |
|       | 11 | 11 | 11 | 11 |                  |
|       | 12 | 12 | 12 | 12 |                  |
|       | 13 | 13 | 13 | 13 |                  |
|       | 14 | 14 | 14 | 14 |                  |
|       | 10 | 10 | 10 | 10 |                  |
|       | 11 | 11 | 11 | 11 |                  |
|       | 12 | 12 | 12 | 12 |                  |
|       | 13 | 13 | 13 | 13 |                  |
| set#3 | 14 | 14 | 14 | 14 | L3               |
|       | 15 | 15 | 15 | 15 | majority(L10:19) |
|       | 16 | 16 | 16 | 16 |                  |
|       | 17 | 17 | 17 | 17 |                  |
|       | 18 | 18 | 18 | 18 |                  |
|       | 19 | 19 | 19 | 19 |                  |

ACC X ACC Y ACC Z HeartR

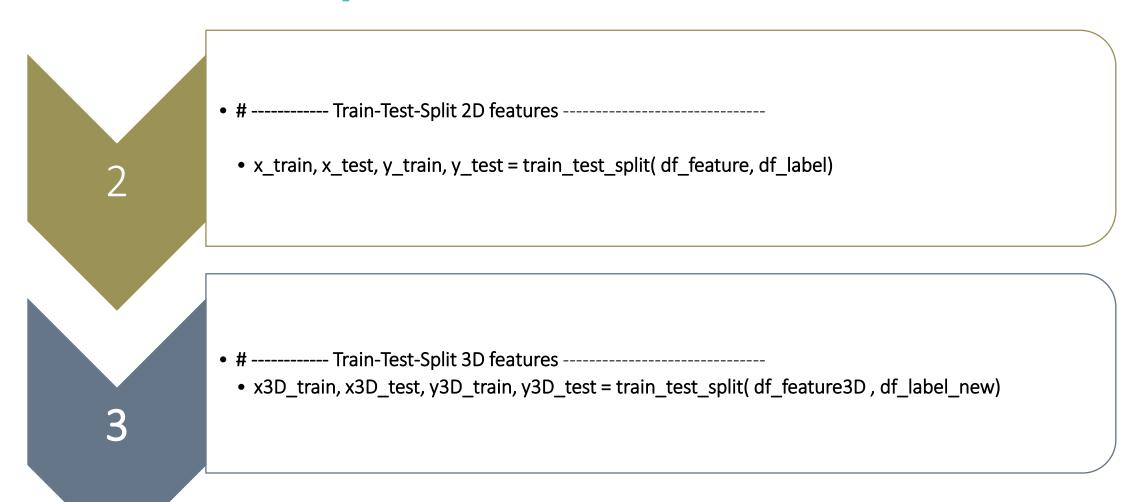
label

i/p shape: (timestamp\_size, features) (Nrows, 4)



o/p shape: (Nsets, slidingW, n\_feature, 1) (Nsets, 100, 4, 1)

#### 9.1.2 Train Test Split





# 9.2 NN Model Train and Test

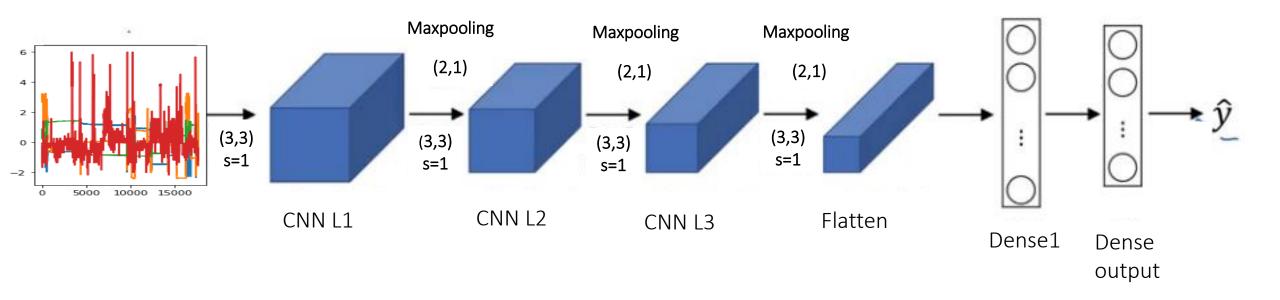
#### 9.2.1 NN Model Train Test

• # ----- NN Architecture parameter -----• Hidden\_Layer\_param = (30, 30, 30) mlp = MLPClassifier(hidden\_layer\_sizes = Hidden\_Layer\_param) • # View NN model parameters • # ----- Training NN using 1D features ----mlp.fit(X\_train,y\_train) mlp\_pred = mlp.predict(X\_test) • View Confusion Matrix and Classification Report

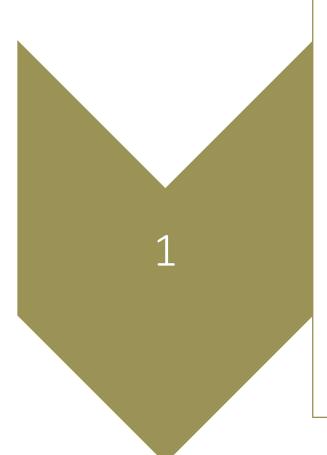


# 9.3 CNN Model Train and Test

## **CNN Model Architecture**

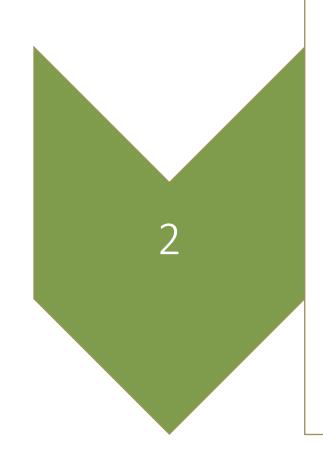


#### 9.3.1 CNN Model Train Test



- # ----- CNN Architecture parameter -----
- # Nlayer (CNN, dense), Nnode, Activation
  - CNN\_L1 = 16, CNN\_L2 = 64, CNN\_L3 = 128
  - D\_L1 = 512, D\_out = 6
  - Activation = "Relu"
  - Ker\_size = (3,3)
  - Pooling\_size = (2,1)
  - Input\_shape = (slidingW, n\_feature, 1)

#### 9.3.1 CNN Model Train Test



- # ----- Create CNN Model -----
- model.add(Conv2D(CNN\_L1, kernel\_size=Ker\_size, activation=Act\_func, input\_shape=Input\_shape,padding='same'))
- model.add(MaxPooling2D(pool\_size=Pooling\_size))
- model.add(Dropout(0.4))
- model.add(Conv2D(CNN\_L2, kernel\_size=Ker\_size, activation= Act\_func, padding='same'))
- model.add(MaxPooling2D(pool\_size= Pooling\_size))
- model.add(Dropout(0.4))
- model.add(Conv2D(CNN\_L3, kernel\_size=Ker\_size, activation= Act\_func,
- padding='same'))
- model.add(MaxPooling2D(pool\_size= Pooling\_size))
- model.add(Dropout(0.4))
- model.add(Flatten())
- model.add(Dense(D\_L1\_size, activation= Act\_func))
- model.add(Dense(D\_out, activation='sigmoid'))
- model.compile(optimizer='adam', metrics=['accuracy'])
- model.summary()

#### 9.3.1 CNN Model Train Test

• # ----- Create Optimizer -----• model.compile(optimizer='adam', • loss=tf.keras.losses.SparseCategoricalCrossentropy(from\_logits=True), metrics=["acc"]) • # ----- Train CNN using 3D feature----• history = model.fit(X3D\_train, y3D\_train, epochs=50, batch\_size=64, validation\_data=(X3D\_test, y3D\_test)) • # ----- Test CNN -----• CNN\_pred = model.predict(X3D\_test)

#### 9.3.2 Performnace of CNN Model

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• # ------ View Confusion Matrix, Classification Report -----



- # View Accuracy Graph
- # summarize history for accuracy
- plt.plot(history.history['acc'])
- plt.plot(history.history['val\_acc'])
- plt.show()
- # View Loss Graph
- # summarize history for loss
- plt.plot(history.history['loss'])
- plt.plot(history.history['val\_loss'])
- plt.show()

# History Graph (Accuracy, Loss)

