local4651

November 30, 2024

[3]:
```
import os
import numpy as np
import pandas as pd

import seaborn as sns
import matplotlib.pyplot as plt

import sklearn
from sklearn.impute import KNNImputer

from pyspark.sql import SparkSession
from pyspark.ml  import Pipeline
from pyspark import SparkContext, SparkConf
from pyspark.sql import SQLContext
from pyspark.sql import functions as F
from pyspark.sql import Row
from pyspark.sql.window import Window
from pyspark.sql.functions import mean, col, split, regexp_extract, when, lit,␣
 ↪input_file_name, desc
from pyspark.sql.types import StructType, StructField, IntegerType, FloatType,␣
 ↪DoubleType
from pyspark.ml.feature import StringIndexer, VectorAssembler, StandardScaler,␣
 ↪QuantileDiscretizer, VectorIndexer, Imputer
from pyspark.ml.evaluation import MulticlassClassificationEvaluator
from pyspark.ml.linalg import Vectors
from pyspark.ml.stat import Summarizer


import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset

from tqdm import tqdm
```

[ ]:
```
#from google.colab import drive
#drive.mount('/content/drive')
```

[ ]:
```python
# Create SparkSession
# alter the configue to consume more resources

spark = (SparkSession.builder.appName('child_mind_institute_data').
↪getOrCreate())
spark.sparkContext._conf.getAll()

conf = spark.sparkContext._conf.setAll([('spark.executor.memory', '4g'),␣
↪('spark.app.name', 'Spark Updated Conf'), ('spark.executor.cores', '4'),␣
↪('spark.cores.max', '4'), ('spark.driver.memory','4g')])
```

[5]:
```python
data_path = '.'
```

[ ]:
```python
train = spark.read.csv(f'{data_path}/train.csv', inferSchema=True, header=True)
test = spark.read.csv(f'{data_path}/test.csv', inferSchema=True, header=True)
```

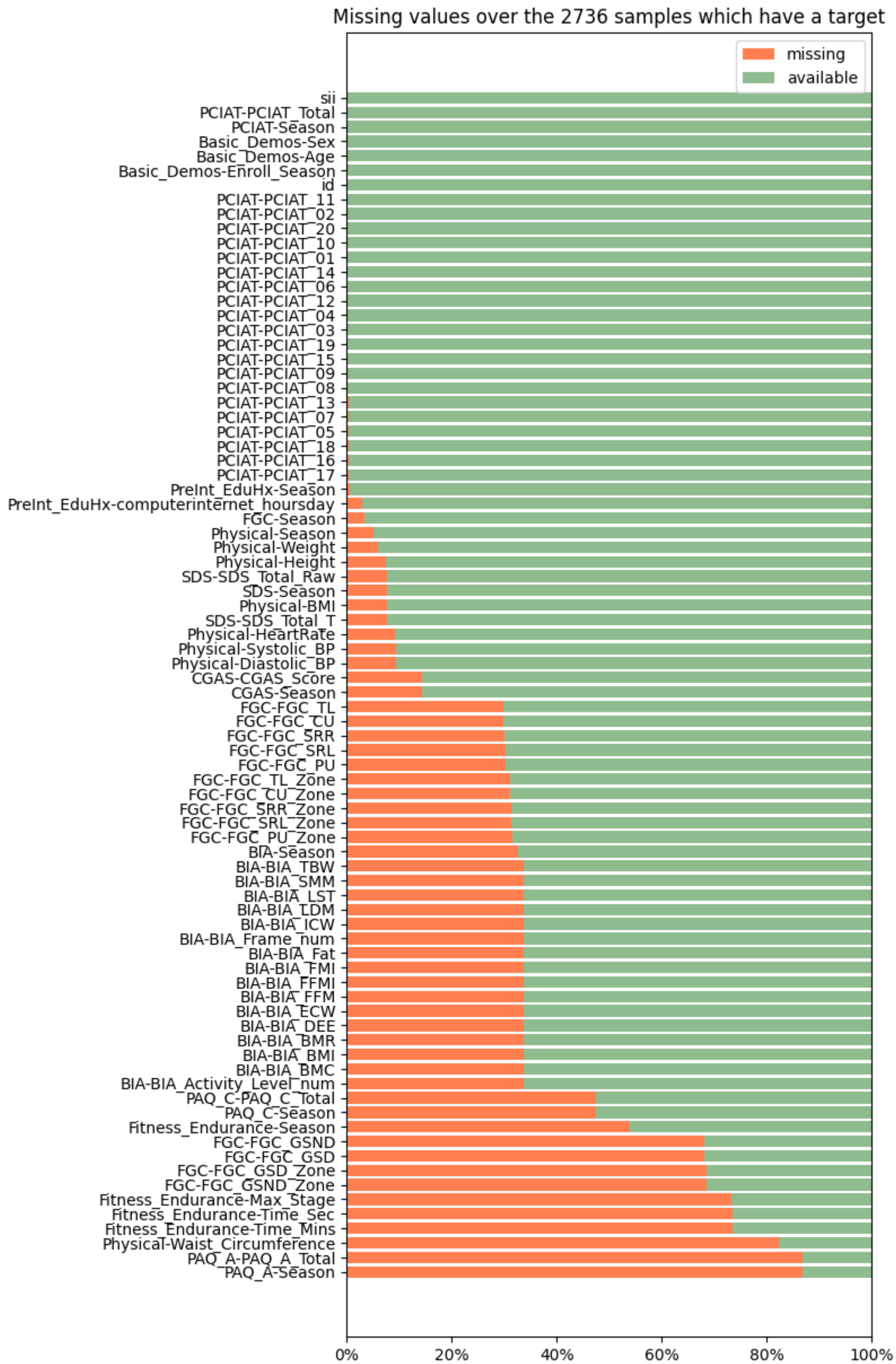
1 Data Overview

1.1 HBN Instruments

[ ]:
```python
# See which features have missing values and how many missing values
# after removing the missing values of target label 'sii'

supervised_usable = train.filter(train['sii'].isNotNull())

missing_count = []
for col_name in supervised_usable.columns:
    null_count = supervised_usable.filter(supervised_usable[col_name].isNull()).
↪count()

    null_ratio = null_count / supervised_usable.count() if supervised_usable.
↪count() > 0 else 0
    missing_count.append((col_name, null_count, null_ratio))

missing_count_df = spark.createDataFrame(missing_count, ['feature',␣
↪'null_count', 'null_ratio'])

missing_count_df = missing_count_df.orderBy(F.col('null_count').desc())

# null ratio table
# missing_count_df.show()
```

[7]:
```python
# Visualize the missing_count

import matplotlib.pyplot as plt
import numpy as np
from matplotlib.ticker import PercentFormatter
```

```
missing_count_pandas = missing_count_df.toPandas()

plt.figure(figsize=(6, 15))
plt.title(f'Missing values over the {supervised_usable.count()} samples which␣
↪have a target')

plt.barh(np.arange(len(missing_count_pandas)),␣
↪missing_count_pandas['null_ratio'], color='coral', label='missing')

plt.barh(np.arange(len(missing_count_pandas)),
         1 - missing_count_pandas['null_ratio'],
         left = missing_count_pandas['null_ratio'],
         color='darkseagreen', label='available')

plt.yticks(np.arange(len(missing_count_pandas)),␣
↪missing_count_pandas['feature'])
plt.gca().xaxis.set_major_formatter(PercentFormatter(xmax=1, decimals=0))
plt.xlim(0, 1)
plt.legend()
plt.show()
```


Missing values over the 2736 samples which have a target
missing
available
sii
PCIAT-PCIAT_Total
PCIAT-Season
Basic_Demos-Sex
Basic_Demos-Age
Basic_Demos-Enroll_Season
id
PCIAT-PCIAT_11
PCIAT-PCIAT_02
PCIAT-PCIAT_20
PCIAT-PCIAT_10
PCIAT-PCIAT_01
PCIAT-PCIAT_14
PCIAT-PCIAT_06
PCIAT-PCIAT_12
PCIAT-PCIAT_04
PCIAT-PCIAT_03
PCIAT-PCIAT_19
PCIAT-PCIAT_15
PCIAT-PCIAT_09
PCIAT-PCIAT_08
PCIAT-PCIAT_13
PCIAT-PCIAT_07
PCIAT-PCIAT_05
PCIAT-PCIAT_18
PCIAT-PCIAT_16
PCIAT-PCIAT_17
PreInt_EduHx-Season
PreInt_EduHx-computerinternet_hoursday
FGC-Season
Physical-Season
Physical-Weight
Physical-Height
SDS-SDS_Total_Raw
SDS-Season
Physical-BMI
SDS-SDS_Total_T
Physical-HeartRate
Physical-Systolic_BP
Physical-Diastolic_BP
CGAS-CGAS_Score
CGAS-Season
FGC-FGC_TL
FGC-FGC_CU
FGC-FGC_SRR
FGC-FGC_SRL
FGC-FGC_PU
FGC-FGC_TL_Zone
FGC-FGC_CU_Zone
FGC-FGC_SRR_Zone
FGC-FGC_SRL_Zone
FGC-FGC_PU_Zone
BIA-Season
BIA-BIA_TBW
BIA-BIA_SMM
BIA-BIA_LST
BIA-BIA_LDM
BIA-BIA_ICW
BIA-BIA_Frame_num
BIA-BIA_Fat
BIA-BIA_FMI
BIA-BIA_FFMI
BIA-BIA_FFM
BIA-BIA_ECW
BIA-BIA_DEE
BIA-BIA_BMR
BIA-BIA_BMI
BIA-BIA_BMC
BIA-BIA_Activity_Level_num
PAQ_C-PAQ_C_Total
PAQ_C-Season
Fitness_Endurance-Season
FGC-FGC_GSND
FGC-FGC_GSD
FGC-FGC_GSD_Zone
FGC-FGC_GSND_Zone
Fitness_Endurance-Max_Stage
Fitness_Endurance-Time_Sec
Fitness_Endurance-Time_Mins
Physical-Waist_Circumference
PAQ_A-PAQ_A_Total
PAQ_A-Season
0%
20%
40%
60%
80%
100%

[8]:
```
# There is a direct correlation between 'PCIAT-PCIAT_Total' and 'sii'
# They either have missing values or none at the same row

null_check = train.withColumn('null_match', (col('PCIAT-PCIAT_Total').isNull()␣
    ↪== col('sii').isNull()).cast('int'))
matching_ratio = null_check.agg({'null_match': 'mean'}).collect()[0][0]
print(matching_ratio)
```

```
1.0
```

[9]:
```
# 'PCIAT-PCIAT_Total': [0, 30] → 'sii': 0
# 'PCIAT-PCIAT_Total': [31, 49] → 'sii': 1
# 'PCIAT-PCIAT_Total': [50, 79] → 'sii': 2
# 'PCIAT-PCIAT_Total': [80, 100] → 'sii': 3

# Conclusion:
# 'PCIAT-PCIAT_Total' is a continuous label
# 'sii' is a discrete label

pciat_stats = train.groupBy('sii').agg(
    F.min('PCIAT-PCIAT_Total').alias('min'),
    F.max('PCIAT-PCIAT_Total').alias('max'),
    F.count('PCIAT-PCIAT_Total').alias('count'),
)
pciat_stats = pciat_stats.orderBy('sii')

pciat_stats.show()
```

```
+----+----+----+-----+
| sii| min| max|count|
+----+----+----+-----+
|NULL|NULL|NULL|    0|
|   0|   0|  30| 1594|
|   1|  31|  49|  730|
|   2|  50|  79|  378|
|   3|  80|  93|   34|
+----+----+----+-----+
```

[10]:
```
# See which feature is in trainset but not in testset
# We cannot use these features while training
# It turns out that all the "PCIAT"-related features and the label in trainset␣
    ↪are not in testset

train_columns = set(train.columns)
```

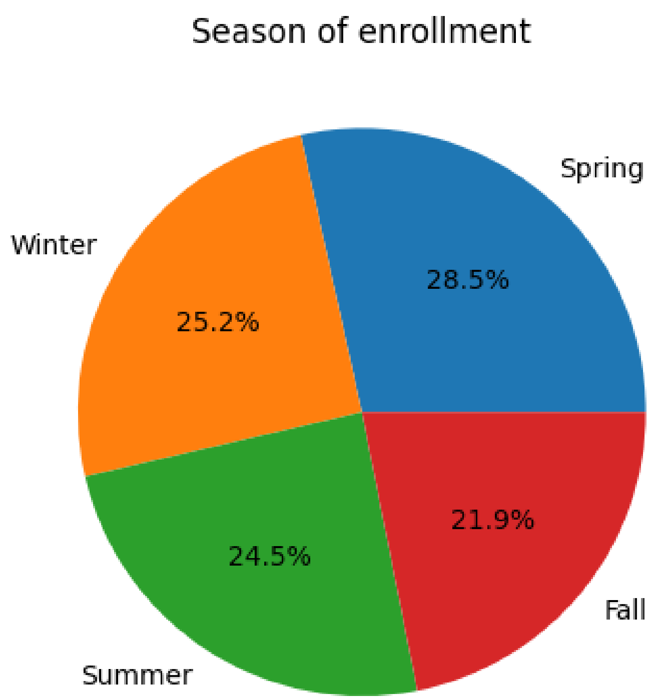
```
test_columns = set(test.columns)

missing_columns = list(train_columns - test_columns)

print('Columns missing in test')
print(missing_columns)
```

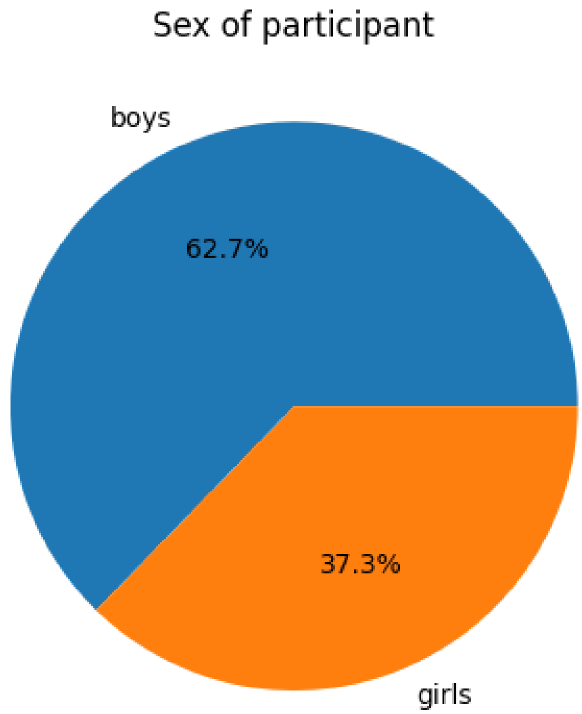
```
Columns missing in test
['PCIAT-Season', 'PCIAT-PCIAT_09', 'PCIAT-PCIAT_03', 'PCIAT-PCIAT_11', 'PCIAT-
PCIAT_07', 'PCIAT-PCIAT_20', 'PCIAT-PCIAT_17', 'PCIAT-PCIAT_04', 'PCIAT-
PCIAT_12', 'PCIAT-PCIAT_14', 'sii', 'PCIAT-PCIAT_06', 'PCIAT-PCIAT_Total',
'PCIAT-PCIAT_19', 'PCIAT-PCIAT_16', 'PCIAT-PCIAT_10', 'PCIAT-PCIAT_15', 'PCIAT-
PCIAT_08', 'PCIAT-PCIAT_18', 'PCIAT-PCIAT_01', 'PCIAT-PCIAT_02', 'PCIAT-
PCIAT_13', 'PCIAT-PCIAT_05']
```

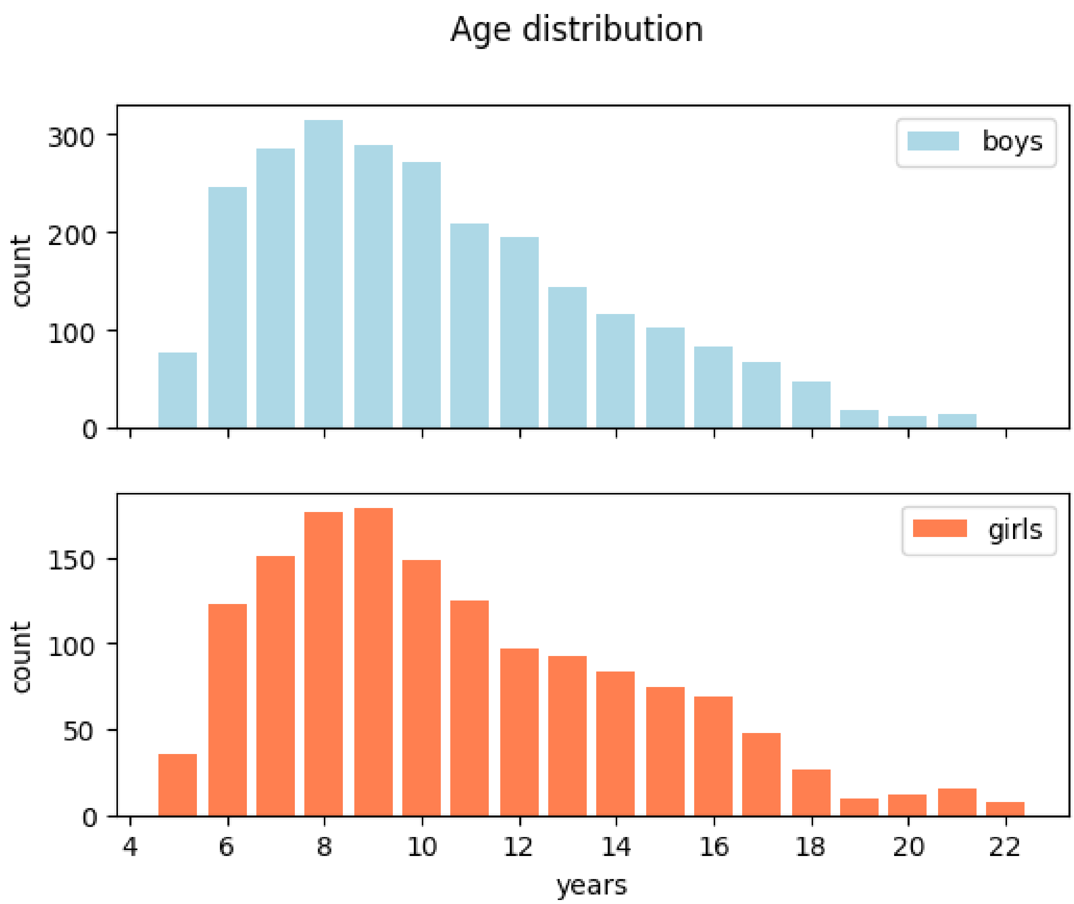
1.2 Demographic

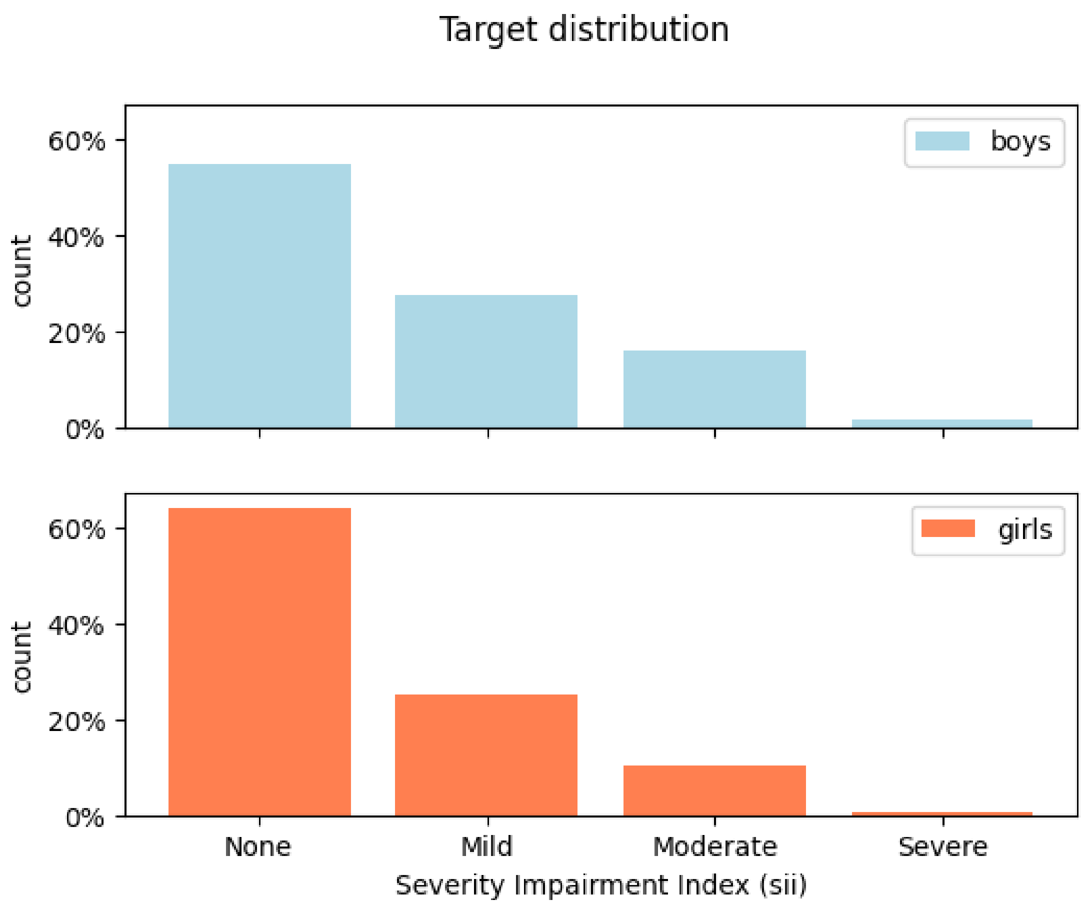
[11]:
```
# Visualize some important features' distribution

train_pd = train.toPandas()

# Enroll Seasons
vc = train_pd['Basic_Demos-Enroll_Season'].value_counts()
plt.pie(vc, labels=vc.index, autopct='%1.1f%%')
plt.title('Season of enrollment')
plt.show()

# Enroll Sex
vc = train_pd['Basic_Demos-Sex'].value_counts()
plt.pie(vc, labels=['boys', 'girls'], autopct='%1.1f%%')
plt.title('Sex of participant')
plt.show()

# Age distribution
_, axs = plt.subplots(2, 1, sharex=True)
for sex in range(2):
    ax = axs.ravel()[sex]
    sex_data = train_pd[train_pd['Basic_Demos-Sex'] == sex]
    vc = sex_data['Basic_Demos-Age'].value_counts()
    ax.bar(vc.index, vc.values, color=['lightblue', 'coral'][sex],␣
 ↪label=['boys', 'girls'][sex])
    ax.set_ylabel('count')
    ax.xaxis.set_major_locator(plt.MaxNLocator(integer=True))
    ax.legend()
plt.suptitle('Age distribution')
axs.ravel()[1].set_xlabel('years')
plt.show()
```

```
# Target distribution
_, axs = plt.subplots(2, 1, sharex=True, sharey=True)
target_labels = ['None', 'Mild', 'Moderate', 'Severe']
for sex in range(2):
    ax = axs.ravel()[sex]
    sex_data = train_pd[train_pd['Basic_Demos-Sex'] == sex]
    vc = sex_data['sii'].value_counts(normalize=True)
    ax.bar(vc.index, vc.values, color=['lightblue', 'coral'][sex],␣
 ↪label=['boys', 'girls'][sex])
    ax.set_xticks(np.arange(4))
    ax.set_xticklabels(target_labels)
    ax.yaxis.set_major_formatter(PercentFormatter(xmax=1, decimals=0))
    ax.set_ylabel('count')
    ax.legend()
plt.suptitle('Target distribution')
axs.ravel()[1].set_xlabel('Severity Impairment Index (sii)')
plt.show()
```




Sex of participant
boys
62.7%
37.3%
girls

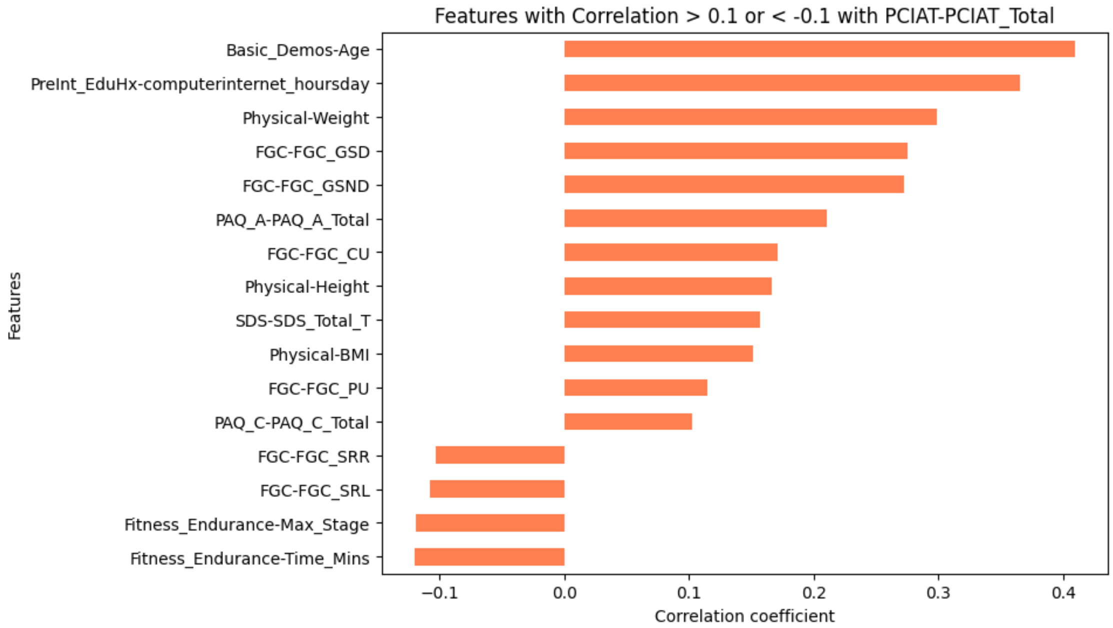

Age distribution
boys
girls
count
count
years
300
200
100
0
150
100
50
0
4
6
8
10
12
14
16
18
20
22



[12]:
```
# Select some import features, see their correlation with the continuous label␣
↪'PCIAT-PCIAT_Total'

selected_columns = [
    'PCIAT-PCIAT_Total', 'Basic_Demos-Age', 'Basic_Demos-Sex', 'Physical-BMI',
    'Physical-Height', 'Physical-Weight', 'Physical-Waist_Circumference',
    'Physical-Diastolic_BP', 'Physical-Systolic_BP', 'Physical-HeartRate',
    'PreInt_EduHx-computerinternet_hoursday', 'SDS-SDS_Total_T',␣
↪'PAQ_A-PAQ_A_Total',
    'PAQ_C-PAQ_C_Total', 'Fitness_Endurance-Max_Stage',␣
↪'Fitness_Endurance-Time_Mins', 'Fitness_Endurance-Time_Sec',
    'FGC-FGC_CU', 'FGC-FGC_GSND', 'FGC-FGC_GSD', 'FGC-FGC_PU', 'FGC-FGC_SRL',␣
↪'FGC-FGC_SRR', 'FGC-FGC_TL',
    'BIA-BIA_Activity_Level_num', 'BIA-BIA_BMC', 'BIA-BIA_BMI', 'BIA-BIA_BMR',␣
↪'BIA-BIA_DEE',
    'BIA-BIA_ECW', 'BIA-BIA_FFM', 'BIA-BIA_FFMI', 'BIA-BIA_FMI', 'BIA-BIA_Fat',␣
↪'BIA-BIA_Frame_num',
    'BIA-BIA_ICW', 'BIA-BIA_LDM', 'BIA-BIA_LST', 'BIA-BIA_SMM', 'BIA-BIA_TBW',
```

```
]

corr_dict = {}
for col in selected_columns:
    if col != 'PCIAT-PCIAT_Total':
        corr = supervised_usable.stat.corr('PCIAT-PCIAT_Total', col)
        corr_dict[col] = corr

# If the correlation > 0.1 or < -0.1, visualize it.
filtered_corr = {col: corr for col,  corr in corr_dict.items() if corr > 0.1 or␣
↪corr < -0.1}
print(filtered_corr)

filtered_corr_pd = pd.Series(filtered_corr).sort_values()
plt.figure(figsize=(8, 6))
filtered_corr_pd.plot(kind='barh', color='coral')
plt.title('Features with Correlation > 0.1 or < -0.1 with PCIAT-PCIAT_Total')
plt.xlabel('Correlation coefficient')
plt.ylabel('Features')
plt.show()
```

```
{'Basic_Demos-Age': 0.4095589300442593, 'Physical-BMI': 0.15114751746836297,
'Physical-Height': 0.1667743845043196, 'Physical-Weight': 0.29901804979726576,
'PreInt_EduHx-computerinternet_hoursday': 0.36522768449538073, 'SDS-
SDS_Total_T': 0.15712431429762028, 'PAQ_A-PAQ_A_Total': 0.210394863608451,
'PAQ_C-PAQ_C_Total': 0.10243470123646388, 'Fitness_Endurance-Max_Stage':
-0.11842935200737925, 'Fitness_Endurance-Time_Mins': -0.11958997715157199, 'FGC-
FGC_CU': 0.1715539468499386, 'FGC-FGC_GSND': 0.2725834535666146, 'FGC-FGC_GSD':
0.2755155867903572, 'FGC-FGC_PU': 0.11492578301805696, 'FGC-FGC_SRL':
-0.10784358025725917, 'FGC-FGC_SRR': -0.10301051532552276}
```



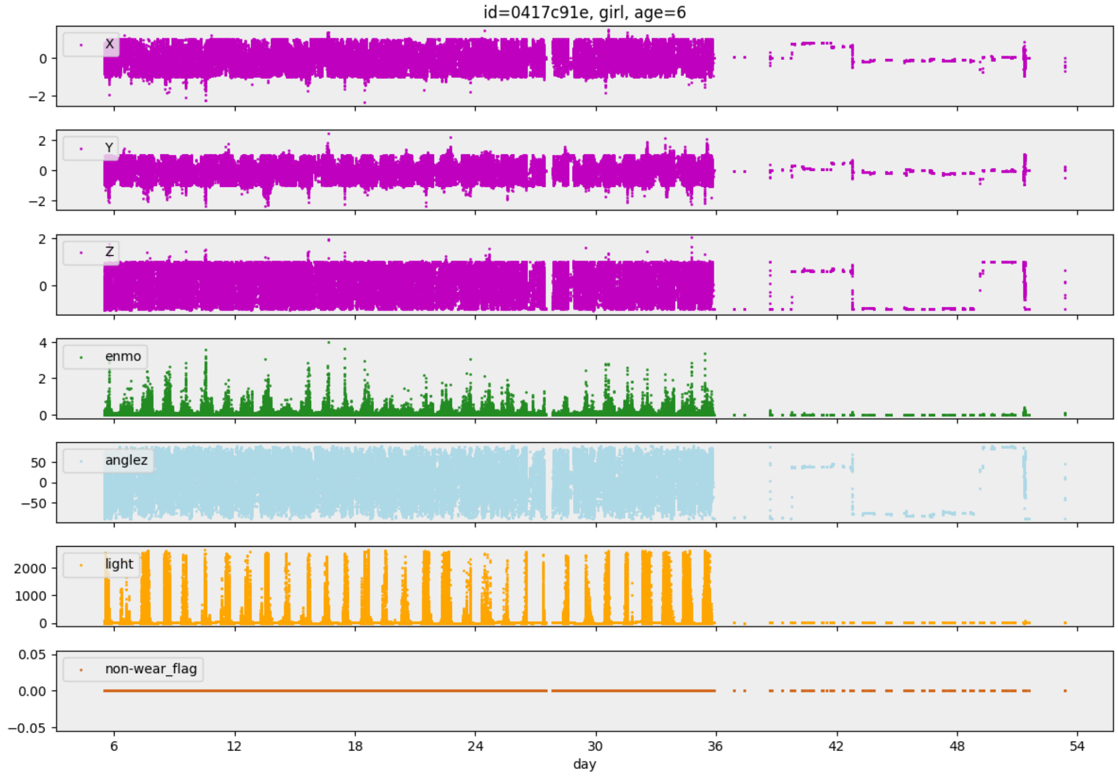
1.3 Actigraphy Files (time series)

[13]:
```
# Read only one actigraphy file and find something useful

actigraphy = spark.read.parquet(f'{data_path}/series_train.parquet/id=0417c91e/
↪part-0.parquet')
```

[5]:
```
# Visualize some features by time series

from matplotlib.ticker import MaxNLocator

def analyze_actigraphy(actigraphy, only_one_week=False, small=False):
    actigraphy = actigraphy.withColumn(
        'day', actigraphy['relative_date_PCIAT'] + actigraphy['time_of_day'] /
↪86400e9
    )

    sample = train.filter(train['id'] == '0417c91e').collect()
    age = sample[0]['Basic_Demos-Age']
    sex = ['boy', 'girl'][sample[0]['Basic_Demos-Sex']]

    window_spec = Window.orderBy('day')
    actigraphy = actigraphy.withColumn(
        'diff_seconds', (actigraphy['day'] - F.lag('day', 1).over(window_spec))
↪* 86400
    )
```

```
    actigraphy = actigraphy.withColumn(
        'norm', F.sqrt(actigraphy['X']**2 + actigraphy['Y']**2 +␣
↪actigraphy['Z']**2)
    )

    if only_one_week:
        start = np.ceil(actigraphy.agg(F.min('day')).collect()[0][0])
        mask = (start <= actigraphy['day']) & (actigraphy['day'] <= start + 7 *␣
↪3)
        mask &= ~actigraphy['non-wear_flag'].cast('boolean')
    else:
        mask = F.lit(True)

    if small:
        timelines = [('enmo', 'forestgreen'), ('light', 'orange')]
    else:
        timelines = [
            ('X', 'm'), ('Y', 'm'), ('Z', 'm'),
            ('enmo', 'forestgreen'), ('anglez', 'lightblue'),
            ('light', 'orange'), ('non-wear_flag', 'chocolate')
        ]

    actigraphy = actigraphy.filter(mask)
    actigraphy_pd = actigraphy.toPandas()

    _, axs = plt.subplots(len(timelines), 1, sharex=True, figsize=(12,␣
↪len(timelines) * 1.1 + 0.5))
    for ax, (feature, color) in zip(axs, timelines):
        ax.set_facecolor('#eeeeee')
        ax.scatter(actigraphy_pd['day'], actigraphy_pd[feature], color=color,␣
↪label=feature, s=1)
        ax.legend(loc='upper left', facecolor='#eeeeee')
        if feature == 'diff_seconds':
            ax.set_ylim(-0.5, 20.5)
    axs[-1].set_xlabel('day')
    axs[-1].xaxis.set_major_locator(MaxNLocator(integer=True))
    plt.tight_layout()
    axs[0].set_title(f'id=0417c91e, {sex}, age={age}')
    plt.show()
```

[15]:
```
analyze_actigraphy(actigraphy, only_one_week=False)
```



2 Feature Engineering

2.1 Load the file

[6]:
```
# Load the time series files (actigraphy files)

# Feature Extraction:
# Transform time series data into statistical features by calculating the␣
↪describe() of time series data for each id

from concurrent.futures import ThreadPoolExecutor

def process_file(filename, dirname):
    df = spark.read.parquet(os.path.join(dirname, filename, 'part-0.parquet'))
    df = df.drop('step') # drop useless column 'step'

    # Since we have 12 features in each actigraphy file, and Spark's describe()␣
↪has 5 statistics for each feature, we totally get 60 statistical features␣
↪for each id.
    stats = df.describe().collect()
```

```
    flattened_stats = [] # flatten the 5*12 stats into 1*60, which can be seen␣
↪as a row
    for row in stats:
        flattened_stats.extend([float(value) for value in list(row.asDict().
↪values())[1:]])

    # return the list of the 60 statistical features and the id of the␣
↪actigraphy file
    return flattened_stats, filename.split('=')[1]

def load_time_series(dirname):
    ids = os.listdir(dirname)

    results = []
    with ThreadPoolExecutor() as executor:
        results = list(tqdm(executor.map(lambda fname: process_file(fname,␣
↪dirname), ids), total=len(ids)))

    stats, indexes = zip(*results)

    stat_columns = [f"stat_{i}" for i in range(len(stats[0]))] # from stat_0 to␣
↪stat_59

    # print(stats[:1])
    # print(stat_columns)

    stats_rdd = spark.sparkContext.parallelize([(index, *stat) for index, stat␣
↪in zip(indexes, stats)])
    stats_df = spark.createDataFrame(stats_rdd, schema=['id'] + stat_columns)

    # stats_df.show(5)
    return stats_df
```

[17]:
```
train_ts = load_time_series(f'{data_path}/series_train.parquet')
test_ts = load_time_series(f'{data_path}/series_test.parquet')
```

```
100%|      | 996/996 [05:39<00:00,  2.94it/s]
100%|      | 2/2 [00:02<00:00,  1.09s/it]
```

[ ]:
```
#checkpoint of dataset of timeseries reading from parquet files
train_ts.toPandas().to_csv('tr.csv', index=False)
test_ts.toPandas().to_csv('te.csv', index=False)
```

[ ]:
```
train_df = pd.read_csv('tr.csv')
test_df = pd.read_csv('te.csv')

train_ts = spark.createDataFrame(train_df)
```

```
test_ts = spark.createDataFrame(test_df)
```

[ ]:
```
#check if is loaded
train_ts.show()
```

2.2 Dimension Reduction

[20]:
```
# We do dimension reduction because the statistical features in train_ts/
↪test_ts are too many.
# We reduct the dimension from 60 to 36 by using autoencoder.

class AutoEncoder(nn.Module):
    def __init__(self, input_dim, encoding_dim):
        super(AutoEncoder, self).__init__()
        self.encoder = nn.Sequential(
            nn.Linear(input_dim, encoding_dim*3),
            nn.ReLU(),
            nn.Linear(encoding_dim*3, encoding_dim*2),
            nn.ReLU(),
            nn.Linear(encoding_dim*2, encoding_dim),
            nn.ReLU()
        )
        self.decoder = nn.Sequential(
            nn.Linear(encoding_dim, input_dim*2),
            nn.ReLU(),
            nn.Linear(input_dim*2, input_dim*3),
            nn.ReLU(),
            nn.Linear(input_dim*3, input_dim),
            nn.Sigmoid()
        )

    def forward(self, x):
        encoded = self.encoder(x)
        decoded = self.decoder(encoded)
        return decoded
```

[35]:
```
def perform_autoencoder(df, encoding_dim=36, epochs=100, batch_size=32):
    feature_columns = df.columns
    assembler = VectorAssembler(inputCols=feature_columns, outputCol="features")
    df = assembler.transform(df)

    scaler = StandardScaler(inputCol="features", outputCol="scaled_features",␣
↪withMean=True, withStd=True)
    scaler_model = scaler.fit(df)
    df_scaled = scaler_model.transform(df)
```

```
    scaled_data = df_scaled.select("scaled_features").rdd.map(lambda row:␣
 ↪row['scaled_features'].toArray()).collect()
    data_tensor = torch.FloatTensor(scaled_data)

    dataset = TensorDataset(data_tensor)
    dataloader = DataLoader(dataset, batch_size=batch_size, shuffle=True)

    input_dim = data_tensor.shape[1]
    autoencoder = AutoEncoder(input_dim, encoding_dim)

    criterion = nn.MSELoss()
    optimizer = optim.Adam(autoencoder.parameters(), lr=0.0001)

    for epoch in range(epochs):
        for i in range(0, len(data_tensor), batch_size):
            batch = data_tensor[i : i + batch_size]
            optimizer.zero_grad()
            reconstructed = autoencoder(batch)
            loss = criterion(reconstructed, batch)
            loss.backward()
            optimizer.step()
        if (epoch + 1) % 10 == 0:
            print(f'Epoch [{epoch + 1}/{epochs}], Loss: {loss.item():.4f}]')

    with torch.no_grad():
        encoded_data = autoencoder.encoder(data_tensor)

    encoded_data = encoded_data.tolist()
    schema = StructType([StructField(f"Enc_{i}", DoubleType(), True) for i in␣
 ↪range(len(encoded_data[0]))])
    df_encoded = spark.createDataFrame([Row(*row) for row in encoded_data],␣
 ↪schema=schema)

    return df_encoded
```

[6]:
```
train_ts_noid = train_ts.drop('id')
test_ts_noid = test_ts.drop('id')
```

[37]:
```
train_ts_encoded = perform_autoencoder(train_ts_noid, encoding_dim=36,␣
 ↪epochs=100, batch_size=32)
test_ts_encoded = perform_autoencoder(test_ts_noid, encoding_dim=36,␣
 ↪epochs=100, batch_size=32)
```

```
C:\Users\akits\AppData\Local\Temp\ipykernel_7216\3626830297.py:11: UserWarning:
Creating a tensor from a list of numpy.ndarrays is extremely slow. Please
consider converting the list to a single numpy.ndarray with numpy.array() before
converting to a tensor. (Triggered internally at C:\actions-runner\_work\pytorch
```

```
\pytorch\builder\windows\pytorch\torch\csrc\utils\tensor_new.cpp:281.)
  data_tensor = torch.FloatTensor(scaled_data)
```

```
Epoch [10/100], Loss: 0.6836]
Epoch [20/100], Loss: 0.6074]
Epoch [30/100], Loss: 0.5878]
Epoch [40/100], Loss: 0.5832]
Epoch [50/100], Loss: 0.5801]
Epoch [60/100], Loss: 0.5743]
Epoch [70/100], Loss: 0.5711]
Epoch [80/100], Loss: 0.5723]
Epoch [90/100], Loss: 0.5752]
Epoch [100/100], Loss: 0.5695]
Epoch [10/100], Loss: 0.6750]
Epoch [20/100], Loss: 0.6730]
Epoch [30/100], Loss: 0.6709]
Epoch [40/100], Loss: 0.6685]
Epoch [50/100], Loss: 0.6656]
Epoch [60/100], Loss: 0.6620]
Epoch [70/100], Loss: 0.6571]
Epoch [80/100], Loss: 0.6502]
Epoch [90/100], Loss: 0.6401]
Epoch [100/100], Loss: 0.6248]
```

[ ]:
```
#time series encoding checkpoint
train_ts_encoded.toPandas().to_csv('train_ts_encoded.csv',index=False)
test_ts_encoded.toPandas().to_csv('test_ts_encoded.csv',index=False)
```

[8]:
```
train_ts_encoded = spark.createDataFrame(pd.read_csv('train_ts_encoded.csv'))
test_ts_encoded = spark.createDataFrame(pd.read_csv('test_ts_encoded.csv'))
```

[ ]:
```
#check time series encoding (should be 997 instance)
test_ts_encoded.show()
test_ts_encoded.count()
```

2.3 Merge train and train_tf

[9]:
```
# Put 'id' column back to train_ts_encoded/test_ts_encoded

train_ts_encoded_1 = train_ts_encoded.withColumn("index", F.
 ↪monotonically_increasing_id())
train_ts_1 = train_ts.withColumn("index", F.monotonically_increasing_id())
train_ts_encoded_2 = train_ts_encoded_1.join(train_ts_1.select("index", "id"),␣
 ↪on="index", how="inner").drop("index")

test_ts_encoded_1 = test_ts_encoded.withColumn("index", F.
 ↪monotonically_increasing_id())
test_ts_1 = test_ts.withColumn("index", F.monotonically_increasing_id())
```

```
test_ts_encoded_2 = test_ts_encoded_1.join(test_ts_1.select("index", "id"),␣
↪on="index", how="inner").drop("index")
```

[10]:
```
train_ts_encoded = train_ts_encoded_2
test_ts_encoded = test_ts_encoded_2
```

Merge based on 'id' col

[11]:
```
train = train.join(train_ts_encoded, on="id", how="left")
test = test.join(test_ts_encoded, on="id", how="left")
```

[ ]:
```
#check if is correctly concated
train.show()
print(train.count())
```

[ ]:
```
#checkpoint
train.toPandas().to_csv('i.csv',index=False)
```

[ ]:
```
train = spark.createDataFrame(pd.read_csv('i.csv'))
```

2.4 Fill the missing values

[ ]:
```
numeric_cols = [col for col, dtype in train.dtypes if dtype in ('int',␣
↪'double')]

# temporarily transform to pandas because spark cannot fit KNNImputer
train_numeric = train.select(numeric_cols).toPandas()

imputer = KNNImputer(n_neighbors=5) # fill by KNNImputer
imputed_data = imputer.fit_transform(train_numeric)

# transform back to spark
train_imputed_numeric = spark.createDataFrame(pd.DataFrame(imputed_data,␣
↪columns=numeric_cols))

train_imputed_numeric = train_imputed_numeric.withColumn('sii', F.round(F.
↪col('sii')).cast(IntegerType()))

# merge numerical columns with non-numerical columns
train_numeric_indexed = train_imputed_numeric.withColumn("index", F.
↪monotonically_increasing_id())
train_indexed = train.withColumn("index", F.monotonically_increasing_id())
train_imputed = train_numeric_indexed.join(train_indexed.select("index", *[col␣
↪for col in train.columns if col not in numeric_cols]), on="index",␣
↪how="inner").drop("index")

train = train_imputed
```

[ ]:
```
#check dataset
train.show()
print(train.count())
```

[ ]:
```
# checkpoint
train.toPandas().to_csv('idk.csv',index=False)
```

[ ]:
```
train = spark.createDataFrame(pd.read_csv('idk.csv'))
```

2.5 Generate some new features

You can just build new feature_enginnering function

[8]:
```
def feature_engineering(df):
    season_cols = [col for col in df.columns if 'Season' in col]
    df = df.drop(*season_cols)

    df = df.withColumn('BMI_Age', F.col('Physical-BMI') * F.
 ↪col('Basic_Demos-Age'))
    df = df.withColumn('Internet_Hours_Age', F.
 ↪col('PreInt_EduHx-computerinternet_hoursday') * F.col('Basic_Demos-Age'))
    df = df.withColumn('BMI_Internet_Hours', F.col('Physical-BMI') * F.
 ↪col('PreInt_EduHx-computerinternet_hoursday'))
    df = df.withColumn('BFP_BMI', F.col('BIA-BIA_Fat') / F.col('BIA-BIA_BMI'))
    df = df.withColumn('FFMI_BFP', F.col('BIA-BIA_FFMI') / F.col('BIA-BIA_Fat'))
    df = df.withColumn('FMI_BFP', F.col('BIA-BIA_FMI') / F.col('BIA-BIA_Fat'))
    df = df.withColumn('LST_TBW', F.col('BIA-BIA_LST') / F.col('BIA-BIA_TBW'))
    df = df.withColumn('BFP_BMR', F.col('BIA-BIA_Fat') * F.col('BIA-BIA_BMR'))
    df = df.withColumn('BFP_DEE', F.col('BIA-BIA_Fat') * F.col('BIA-BIA_DEE'))
    df = df.withColumn('BMR_Weight', F.col('BIA-BIA_BMR') / F.
 ↪col('Physical-Weight'))
    df = df.withColumn('DEE_Weight', F.col('BIA-BIA_DEE') / F.
 ↪col('Physical-Weight'))
    df = df.withColumn('SMM_Height', F.col('BIA-BIA_SMM') / F.
 ↪col('Physical-Height'))
    df = df.withColumn('Muscle_to_Fat', F.col('BIA-BIA_SMM') / F.
 ↪col('BIA-BIA_FMI'))
    df = df.withColumn('Hydration_Status', F.col('BIA-BIA_TBW') / F.
 ↪col('Physical-Weight'))
    df = df.withColumn('ICW_TBW', F.col('BIA-BIA_ICW') / F.col('BIA-BIA_TBW'))

    return df
```

[ ]:
```
train = feature_engineering(train)
train = train.dropna(thresh=10)
test = feature_engineering(test)
```

[ ]:
```
#checkpoint of final trainable result
train.toPandas().to_csv('train_final.csv',index=False)
test.toPandas().to_csv('test_final.csv',index=False)
```

[5]:
```
train = spark.createDataFrame(pd.read_csv('train_final.csv'))
test = spark.createDataFrame(pd.read_csv('test_final.csv'))
```

[ ]:
```
# check dataset
train.show()
test.show()
```

2.6 Try Training

[14]:
```
from sklearn.metrics import cohen_kappa_score
from xgboost.spark import SparkXGBRegressor
from pyspark.ml.classification import LogisticRegression
from scipy.optimize import minimize

from pyspark.ml.evaluation import MulticlassClassificationEvaluator
from pyspark.ml.tuning import CrossValidator, ParamGridBuilder,␣
↪TrainValidationSplit
```

[ ]:
```
# Get the list of columns that contain 'PCIAT' as no 'PCIAT' in test_df
pciat_cols = [col for col in train.columns if 'PCIAT' in col]

# Drop the PCIAT columns from the DataFrame
train = train.drop(*pciat_cols)

train_noid = train.drop('id')
```

[12]:
```
# evaluation score
def quadratic_weighted_kappa(y_true, y_pred):
    return cohen_kappa_score(y_true, y_pred, weights='quadratic')
```

[10]:
```
feature_cols = [col for col in train_noid.columns if col != 'sii']
assembler = VectorAssembler(inputCols=feature_cols, outputCol='features',␣
↪handleInvalid='skip')
```

[11]:
```
log_reg = LogisticRegression(featuresCol='features', labelCol='sii')

# Creating the pipeline
pipeline = Pipeline(stages=[assembler, log_reg])
```

[12]:
```
train_try, val_try = train_noid.randomSplit([0.8,0.2])
```

[13]:
```
# Fitting the model on training data
fit_model = pipeline.fit(train_try)
```

[ ]:
```python
# Storing the results on test data
results = fit_model.transform(val_try)

# Showing the results
results.show()
print(results.count())
```

[16]:
```python
results.toPandas().to_csv('result.csv',index=False)
```

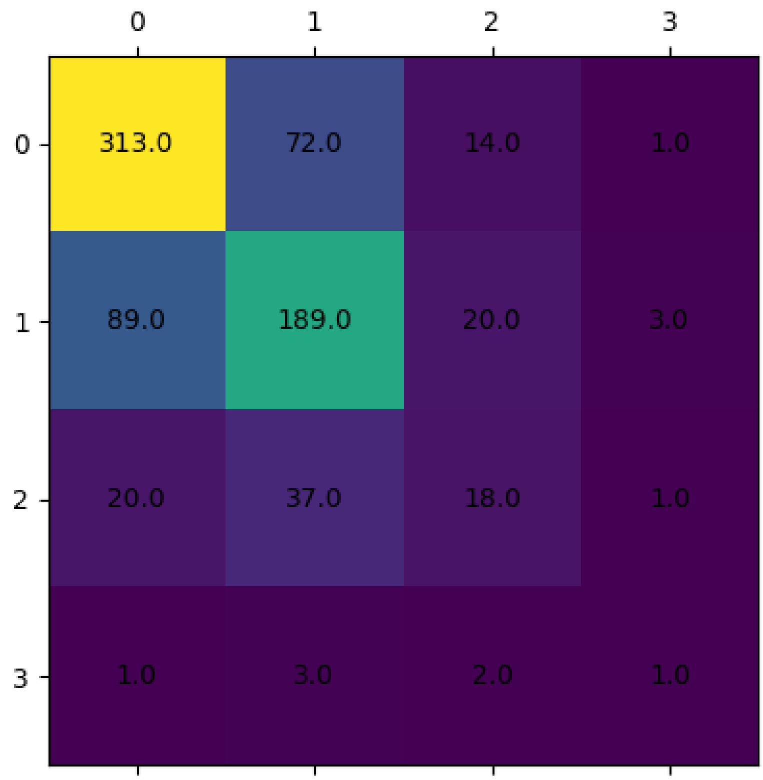
[6]:
```python
results = spark.createDataFrame(pd.read_csv('result.csv'))
```

[7]:
```python
y_true = results.select("sii").rdd.flatMap(lambda x: x).collect()
y_pred = results.select("prediction").rdd.flatMap(lambda x: x).collect()
```

[8]:
```python
print(len(y_true))
```

784

[9]:
```python
from sklearn import metrics
cn_matrix = metrics.confusion_matrix(y_true,y_pred)

fig, ax = plt.subplots()
ax.matshow(cn_matrix,label=True)


for (i, j), z in np.ndenumerate(cn_matrix):
    ax.text(j, i, '{:0.1f}'.format(z), ha='center', va='center')
```



[15]:
```
qwk_score = quadratic_weighted_kappa(y_true, y_pred)
print("Quadratic Weighted Kappa:", qwk_score)
```

```
Quadratic Weighted Kappa: 0.44788732394366193
```