FeaturesExtr

January 22, 2024

[210]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
import pandas as pd
import matplotlib.pyplot as plt
from latex import latexify, format_axes
import numpy as np
import tsfel
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import export_graphviz
from sklearn import tree
import graphviz
from sklearn.metrics import classification_report, confusion_matrix,␣
 ↪accuracy_score
import seaborn as sns
from MakeDataset import *
%matplotlib inline
# Retina
%config InlineBackend.figure_format = 'retina'
```

0.0.1 Template for PCA Plotting

[211]:
```
def PCA_Plot(dataFrame):
    latexify(fig_width = 6, columns = 2)
    for label, color in zip((classes), ("b", "g", "r", "cyan", "magenta",␣
 ↪"yellow")):
        plt.scatter(dataFrame[dataFrame["Labels"] == classes[label]].iloc[:,␣
 ↪0], dataFrame[dataFrame["Labels"] == classes[label]].iloc[:, 1], c = color,␣
 ↪s = 10, label = label)
    plt.title("108 Subject Samples in 2D for 6 activity classes")
    plt.grid()
    plt.legend(fontsize = 7)
    format_axes(plt.gca())
    plt.show()
```

0.0.2 (a_x, a_y, a_z)

[212]:
```
aXYZ_Xtrain = X_train[:, :, 0], X_train[:, :, 1], X_train[:, :, 2]
```

0.0.3 $(a_x^2 + a_y^2 + a_z^2)$

[213]:
```
X_train_TS = np.sum(np.square(X_train), axis = -1)
X_test_TS = np.sum(np.square(X_test), axis = -1)
X_val_TS = np.sum(np.square(X_val), axis = -1)
print(X_train_TS.shape, X_test_TS.shape, X_val_TS.shape)
```

```
(108, 500) (36, 500) (36, 500)
```

0.0.4 DataFrame for $(a_x^2 + a_y^2 + a_z^2)$ 108 timeseries

[229]:
```
df = pd.DataFrame(X_train_TS)
df
```

[229]:
```
            0         1         2         3         4         5         6  \
0    1.056837  1.055002  1.055806  1.056825  1.056743  1.058030  1.059746
1    1.083240  1.076504  1.071849  1.070542  1.073735  1.069331  1.065576
2    1.138189  1.118926  1.010193  0.908460  0.877500  0.799665  0.755336
3    1.181108  1.152283  1.143152  1.270364  1.238777  1.149924  1.015107
4    1.011227  1.017584  1.013233  1.011926  1.009752  1.005219  1.001461
..        …         …         …         …         …         …         …
103  2.865182  4.214804  3.753230  3.061401  2.623248  2.179369  1.739349
104  1.481487  1.741766  1.863997  2.701391  3.711884  2.941636  1.958033
105  1.059227  1.066083  1.065851  1.062518  1.058762  1.059328  1.061447
106  0.822379  0.796867  0.860853  0.768546  0.678476  0.590875  0.531713
107  1.059330  1.024984  0.890988  1.011086  0.924324  0.873101  0.833131

            7         8         9  …       490       491       492  \
0    1.056402  1.051561  1.051040  …  1.059888  1.052544  1.056687
1    1.070615  1.073486  1.074425  …  1.076160  1.072783  1.070026
2    0.604213  0.398809  0.387867  …  1.131734  1.211883  1.395558
3    0.984543  1.273980  1.684522  …  0.621903  1.029622  1.784374
4    1.005883  1.007562  1.007073  …  1.009191  1.006528  1.004264
..        …         …         …  …       …         …         …
103  1.163332  0.690809  0.565457  …  0.356185  0.427389  0.798711
104  1.226824  0.424725  0.531432  …  0.933847  1.111377  1.231115
105  1.058565  1.055911  1.054685  …  1.059269  1.056765  1.065482
106  0.612083  0.699120  0.818263  …  0.773623  0.715825  0.680630
107  0.642193  0.606104  0.555885  …  0.616638  0.569460  0.593311

          493       494       495       496       497       498       499
0    1.060374  1.060270  1.057576  1.050376  1.052854  1.056003  1.050580
1    1.066329  1.064303  1.069655  1.073976  1.075890  1.078382  1.072455
```

```
2    1.574451  1.786266  2.000218  2.163595  2.539505  2.744447  2.195609
3    2.366215  2.621218  2.250886  1.741832  1.685947  1.807674  1.804153
4    1.003962  1.007311  1.005560  0.999966  0.998143  1.002371  1.010588
..        …         …         …         …         …         …         …
103  1.197703  1.243965  0.946267  0.564336  0.293897  0.148865  0.159150
104  0.981100  0.879569  0.951810  1.042146  1.437269  1.472829  1.380977
105  1.075214  1.068180  1.058619  1.062407  1.066245  1.065190  1.068413
106  0.717506  0.754631  0.822995  0.853608  0.882437  0.884731  0.870595
107  0.642203  0.737246  0.780754  0.758168  0.791968  0.890852  1.053665

[108 rows x 500 columns]
```

0.0.5 Defining Named CLasses

[230]:
```python
classesN = {1 : 'WALKING', 2 : 'WALKING_UPSTAIRS', 3 : 'WALKING_DOWNSTAIRS', 4 :
 ↪'SITTING', 5 : 'STANDING', 6 : 'LAYING'}
namedLabel = [classesN[i] for i in y_train]
classesN
```

[230]:
```
{1: 'WALKING',
 2: 'WALKING_UPSTAIRS',
 3: 'WALKING_DOWNSTAIRS',
 4: 'SITTING',
 5: 'STANDING',
 6: 'LAYING'}
```

0.0.6 Feature Extraction on the timeseries using TSFEL

[ ]:
```python
cfg = tsfel.get_features_by_domain()
dataFrames = []
for i in df.index:
    dataFrames.append(tsfel.time_series_features_extractor(cfg, df.iloc[i, :
 ↪-1], fs = 50))
dfN = pd.concat(dataFrames, axis = 0)
```

[232]:
```python
dfN["Labels"] = y_train
dfN["Subject"] = range(1, 109)
dfN["Named_Subject"] = namedLabel
dfN.to_csv("FeaturesTimeSeries.csv")
```

0.0.7 Featurized Time Series with 383 features

[247]:
```python
dfN
```

[247]:
```
    0_Absolute energy  0_Area under the curve  0_Autocorrelation
0          558.990647               10.539676         558.990647  \
0          574.390274               10.683732         574.390274
```

```
0       786.923541              11.328686        786.923541
0       929.960228              11.865417        929.960228
0       504.910523              10.018665        504.910523
..            …                      …                …
0      1568.256890              13.254750       1568.256890
0       922.269555              11.826549        922.269555
0       567.123251              10.618080        567.123251
0       745.722170              11.132367        745.722170
0       749.384758              11.142791        749.384758

    0_Average power  0_Centroid  0_ECDF Percentile Count_0
0         56.123559    4.988923                       99.0  \
0         57.669706    4.977065                       99.0
0         79.008388    5.026153                       99.0
0         93.369501    5.165735                       99.0
0         50.693828    4.978145                       99.0
..              …           …                    …
0        157.455511    5.313609                       99.0
0         92.597345    4.866526                       99.0
0         56.940085    4.977900                       99.0
0         74.871704    4.944697                       99.0
0         75.239434    4.964639                       99.0

    0_ECDF Percentile Count_1  0_ECDF Percentile_0  0_ECDF Percentile_1
0                       399.0             1.052052             1.064478  \
0                       399.0             1.064356             1.081232
0                       399.0             0.726070             1.395558
0                       399.0             0.640615             1.741832
0                       399.0             1.001615             1.009949
..                        …                  …                    …
0                       399.0             0.401499             2.623248
0                       399.0             0.640476             1.665380
0                       399.0             1.061659             1.070245
0                       399.0             0.707780             1.428686
0                       399.0             0.750677             1.430162

    0_ECDF_0  …  0_Wavelet variance_3  0_Wavelet variance_4
0   0.002004  …              0.025006              0.037278  \
0   0.002004  …              0.025755              0.038662
0   0.002004  …              0.999999              1.591255
0   0.002004  …              1.909505              2.832818
0   0.002004  …              0.021207              0.032697
..       …  …                   …                    …
0   0.002004  …              8.614639             12.291892
0   0.002004  …              2.112537              2.891478
0   0.002004  …              0.023392              0.035887
0   0.002004  …              0.934469              1.540069
```

```
0    0.002004  …              1.027339              1.560717

    0_Wavelet variance_5  0_Wavelet variance_6  0_Wavelet variance_7  \
0               0.052396              0.070251              0.090653
0               0.053818              0.071138              0.090822
0               2.322541              3.066285              3.664628
0               3.808026              4.598930              4.948531
0               0.046494              0.062523              0.080705
..                   …                     …                     …
0              14.178359             13.191980             10.140035
0               3.289327              3.139391              2.545833
0               0.051075              0.068907              0.089307
0               2.286965              3.033829              3.571527
0               2.175698              2.781563              3.202756

    0_Wavelet variance_8  0_Zero crossing rate  Labels  Subject  \
0               0.113484                   0.0       5        1
0               0.113121                   0.0       5        2
0               3.988167                   0.0       2        3
0               4.748614                   0.0       3        4
0               0.100957                   0.0       6        5
..                   …                     …     …       …
0               6.664172                   0.0       3      104
0               1.786699                   0.0       1      105
0               0.112172                   0.0       5      106
0               3.743132                   0.0       2      107
0               3.294759                   0.0       2      108

         Named_Subject
0             STANDING
0             STANDING
0     WALKING_UPSTAIRS
0   WALKING_DOWNSTAIRS
0               LAYING
..                 …
0   WALKING_DOWNSTAIRS
0              WALKING
0             STANDING
0     WALKING_UPSTAIRS
0     WALKING_UPSTAIRS

[108 rows x 386 columns]
```

[235]:
```python
for i, feature in enumerate(dfN.columns[:-3]):
    print(f"{i} -> {feature}")
```

```
0 -> 0_Absolute energy
1 -> 0_Area under the curve
```

2 -> 0_Autocorrelation
3 -> 0_Average power
4 -> 0_Centroid
5 -> 0_ECDF Percentile Count_0
6 -> 0_ECDF Percentile Count_1
7 -> 0_ECDF Percentile_0
8 -> 0_ECDF Percentile_1
9 -> 0_ECDF_0
10 -> 0_ECDF_1
11 -> 0_ECDF_2
12 -> 0_ECDF_3
13 -> 0_ECDF_4
14 -> 0_ECDF_5
15 -> 0_ECDF_6
16 -> 0_ECDF_7
17 -> 0_ECDF_8
18 -> 0_ECDF_9
19 -> 0_Entropy
20 -> 0_FFT mean coefficient_0
21 -> 0_FFT mean coefficient_1
22 -> 0_FFT mean coefficient_10
23 -> 0_FFT mean coefficient_100
24 -> 0_FFT mean coefficient_101
25 -> 0_FFT mean coefficient_102
26 -> 0_FFT mean coefficient_103
27 -> 0_FFT mean coefficient_104
28 -> 0_FFT mean coefficient_105
29 -> 0_FFT mean coefficient_106
30 -> 0_FFT mean coefficient_107
31 -> 0_FFT mean coefficient_108
32 -> 0_FFT mean coefficient_109
33 -> 0_FFT mean coefficient_11
34 -> 0_FFT mean coefficient_110
35 -> 0_FFT mean coefficient_111
36 -> 0_FFT mean coefficient_112
37 -> 0_FFT mean coefficient_113
38 -> 0_FFT mean coefficient_114
39 -> 0_FFT mean coefficient_115
40 -> 0_FFT mean coefficient_116
41 -> 0_FFT mean coefficient_117
42 -> 0_FFT mean coefficient_118
43 -> 0_FFT mean coefficient_119
44 -> 0_FFT mean coefficient_12
45 -> 0_FFT mean coefficient_120
46 -> 0_FFT mean coefficient_121
47 -> 0_FFT mean coefficient_122
48 -> 0_FFT mean coefficient_123
49 -> 0_FFT mean coefficient_124

50 -> 0_FFT mean coefficient_125
51 -> 0_FFT mean coefficient_126
52 -> 0_FFT mean coefficient_127
53 -> 0_FFT mean coefficient_128
54 -> 0_FFT mean coefficient_129
55 -> 0_FFT mean coefficient_13
56 -> 0_FFT mean coefficient_130
57 -> 0_FFT mean coefficient_131
58 -> 0_FFT mean coefficient_132
59 -> 0_FFT mean coefficient_133
60 -> 0_FFT mean coefficient_134
61 -> 0_FFT mean coefficient_135
62 -> 0_FFT mean coefficient_136
63 -> 0_FFT mean coefficient_137
64 -> 0_FFT mean coefficient_138
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78 -> 0_FFT mean coefficient_150
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88 -> 0_FFT mean coefficient_16
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91 -> 0_FFT mean coefficient_162
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94 -> 0_FFT mean coefficient_165
95 -> 0_FFT mean coefficient_166
96 -> 0_FFT mean coefficient_167
97 -> 0_FFT mean coefficient_168

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98 -> 0_FFT mean coefficient_169
99 -> 0_FFT mean coefficient_17
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130 -> 0_FFT mean coefficient_198
131 -> 0_FFT mean coefficient_199
132 -> 0_FFT mean coefficient_2
133 -> 0_FFT mean coefficient_20
134 -> 0_FFT mean coefficient_200
135 -> 0_FFT mean coefficient_201
136 -> 0_FFT mean coefficient_202
137 -> 0_FFT mean coefficient_203
138 -> 0_FFT mean coefficient_204
139 -> 0_FFT mean coefficient_205
140 -> 0_FFT mean coefficient_206
141 -> 0_FFT mean coefficient_207
142 -> 0_FFT mean coefficient_208
143 -> 0_FFT mean coefficient_209
144 -> 0_FFT mean coefficient_21
145 -> 0_FFT mean coefficient_210
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146 -> 0_FFT mean coefficient_211
147 -> 0_FFT mean coefficient_212
148 -> 0_FFT mean coefficient_213
149 -> 0_FFT mean coefficient_214
150 -> 0_FFT mean coefficient_215
151 -> 0_FFT mean coefficient_216
152 -> 0_FFT mean coefficient_217
153 -> 0_FFT mean coefficient_218
154 -> 0_FFT mean coefficient_219
155 -> 0_FFT mean coefficient_22
156 -> 0_FFT mean coefficient_220
157 -> 0_FFT mean coefficient_221
158 -> 0_FFT mean coefficient_222
159 -> 0_FFT mean coefficient_223
160 -> 0_FFT mean coefficient_224
161 -> 0_FFT mean coefficient_225
162 -> 0_FFT mean coefficient_226
163 -> 0_FFT mean coefficient_227
164 -> 0_FFT mean coefficient_228
165 -> 0_FFT mean coefficient_229
166 -> 0_FFT mean coefficient_23
167 -> 0_FFT mean coefficient_230
168 -> 0_FFT mean coefficient_231
169 -> 0_FFT mean coefficient_232
170 -> 0_FFT mean coefficient_233
171 -> 0_FFT mean coefficient_234
172 -> 0_FFT mean coefficient_235
173 -> 0_FFT mean coefficient_236
174 -> 0_FFT mean coefficient_237
175 -> 0_FFT mean coefficient_238
176 -> 0_FFT mean coefficient_239
177 -> 0_FFT mean coefficient_24
178 -> 0_FFT mean coefficient_240
179 -> 0_FFT mean coefficient_241
180 -> 0_FFT mean coefficient_242
181 -> 0_FFT mean coefficient_243
182 -> 0_FFT mean coefficient_244
183 -> 0_FFT mean coefficient_245
184 -> 0_FFT mean coefficient_246
185 -> 0_FFT mean coefficient_247
186 -> 0_FFT mean coefficient_248
187 -> 0_FFT mean coefficient_249
188 -> 0_FFT mean coefficient_25
189 -> 0_FFT mean coefficient_26
190 -> 0_FFT mean coefficient_27
191 -> 0_FFT mean coefficient_28
192 -> 0_FFT mean coefficient_29
193 -> 0_FFT mean coefficient_3

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194 -> 0_FFT mean coefficient_30
195 -> 0_FFT mean coefficient_31
196 -> 0_FFT mean coefficient_32
197 -> 0_FFT mean coefficient_33
198 -> 0_FFT mean coefficient_34
199 -> 0_FFT mean coefficient_35
200 -> 0_FFT mean coefficient_36
201 -> 0_FFT mean coefficient_37
202 -> 0_FFT mean coefficient_38
203 -> 0_FFT mean coefficient_39
204 -> 0_FFT mean coefficient_4
205 -> 0_FFT mean coefficient_40
206 -> 0_FFT mean coefficient_41
207 -> 0_FFT mean coefficient_42
208 -> 0_FFT mean coefficient_43
209 -> 0_FFT mean coefficient_44
210 -> 0_FFT mean coefficient_45
211 -> 0_FFT mean coefficient_46
212 -> 0_FFT mean coefficient_47
213 -> 0_FFT mean coefficient_48
214 -> 0_FFT mean coefficient_49
215 -> 0_FFT mean coefficient_5
216 -> 0_FFT mean coefficient_50
217 -> 0_FFT mean coefficient_51
218 -> 0_FFT mean coefficient_52
219 -> 0_FFT mean coefficient_53
220 -> 0_FFT mean coefficient_54
221 -> 0_FFT mean coefficient_55
222 -> 0_FFT mean coefficient_56
223 -> 0_FFT mean coefficient_57
224 -> 0_FFT mean coefficient_58
225 -> 0_FFT mean coefficient_59
226 -> 0_FFT mean coefficient_6
227 -> 0_FFT mean coefficient_60
228 -> 0_FFT mean coefficient_61
229 -> 0_FFT mean coefficient_62
230 -> 0_FFT mean coefficient_63
231 -> 0_FFT mean coefficient_64
232 -> 0_FFT mean coefficient_65
233 -> 0_FFT mean coefficient_66
234 -> 0_FFT mean coefficient_67
235 -> 0_FFT mean coefficient_68
236 -> 0_FFT mean coefficient_69
237 -> 0_FFT mean coefficient_7
238 -> 0_FFT mean coefficient_70
239 -> 0_FFT mean coefficient_71
240 -> 0_FFT mean coefficient_72
241 -> 0_FFT mean coefficient_73
```

242 -> 0_FFT mean coefficient_74
243 -> 0_FFT mean coefficient_75
244 -> 0_FFT mean coefficient_76
245 -> 0_FFT mean coefficient_77
246 -> 0_FFT mean coefficient_78
247 -> 0_FFT mean coefficient_79
248 -> 0_FFT mean coefficient_8
249 -> 0_FFT mean coefficient_80
250 -> 0_FFT mean coefficient_81
251 -> 0_FFT mean coefficient_82
252 -> 0_FFT mean coefficient_83
253 -> 0_FFT mean coefficient_84
254 -> 0_FFT mean coefficient_85
255 -> 0_FFT mean coefficient_86
256 -> 0_FFT mean coefficient_87
257 -> 0_FFT mean coefficient_88
258 -> 0_FFT mean coefficient_89
259 -> 0_FFT mean coefficient_9
260 -> 0_FFT mean coefficient_90
261 -> 0_FFT mean coefficient_91
262 -> 0_FFT mean coefficient_92
263 -> 0_FFT mean coefficient_93
264 -> 0_FFT mean coefficient_94
265 -> 0_FFT mean coefficient_95
266 -> 0_FFT mean coefficient_96
267 -> 0_FFT mean coefficient_97
268 -> 0_FFT mean coefficient_98
269 -> 0_FFT mean coefficient_99
270 -> 0_Fundamental frequency
271 -> 0_Histogram_0
272 -> 0_Histogram_1
273 -> 0_Histogram_2
274 -> 0_Histogram_3
275 -> 0_Histogram_4
276 -> 0_Histogram_5
277 -> 0_Histogram_6
278 -> 0_Histogram_7
279 -> 0_Histogram_8
280 -> 0_Histogram_9
281 -> 0_Human range energy
282 -> 0_Interquartile range
283 -> 0_Kurtosis
284 -> 0_LPCC_0
285 -> 0_LPCC_1
286 -> 0_LPCC_10
287 -> 0_LPCC_11
288 -> 0_LPCC_2
289 -> 0_LPCC_3

290 -> 0_LPCC_4
291 -> 0_LPCC_5
292 -> 0_LPCC_6
293 -> 0_LPCC_7
294 -> 0_LPCC_8
295 -> 0_LPCC_9
296 -> 0_MFCC_0
297 -> 0_MFCC_1
298 -> 0_MFCC_10
299 -> 0_MFCC_11
300 -> 0_MFCC_2
301 -> 0_MFCC_3
302 -> 0_MFCC_4
303 -> 0_MFCC_5
304 -> 0_MFCC_6
305 -> 0_MFCC_7
306 -> 0_MFCC_8
307 -> 0_MFCC_9
308 -> 0_Max
309 -> 0_Max power spectrum
310 -> 0_Maximum frequency
311 -> 0_Mean
312 -> 0_Mean absolute deviation
313 -> 0_Mean absolute diff
314 -> 0_Mean diff
315 -> 0_Median
316 -> 0_Median absolute deviation
317 -> 0_Median absolute diff
318 -> 0_Median diff
319 -> 0_Median frequency
320 -> 0_Min
321 -> 0_Negative turning points
322 -> 0_Neighbourhood peaks
323 -> 0_Peak to peak distance
324 -> 0_Positive turning points
325 -> 0_Power bandwidth
326 -> 0_Root mean square
327 -> 0_Signal distance
328 -> 0_Skewness
329 -> 0_Slope
330 -> 0_Spectral centroid
331 -> 0_Spectral decrease
332 -> 0_Spectral distance
333 -> 0_Spectral entropy
334 -> 0_Spectral kurtosis
335 -> 0_Spectral positive turning points
336 -> 0_Spectral roll-off
337 -> 0_Spectral roll-on

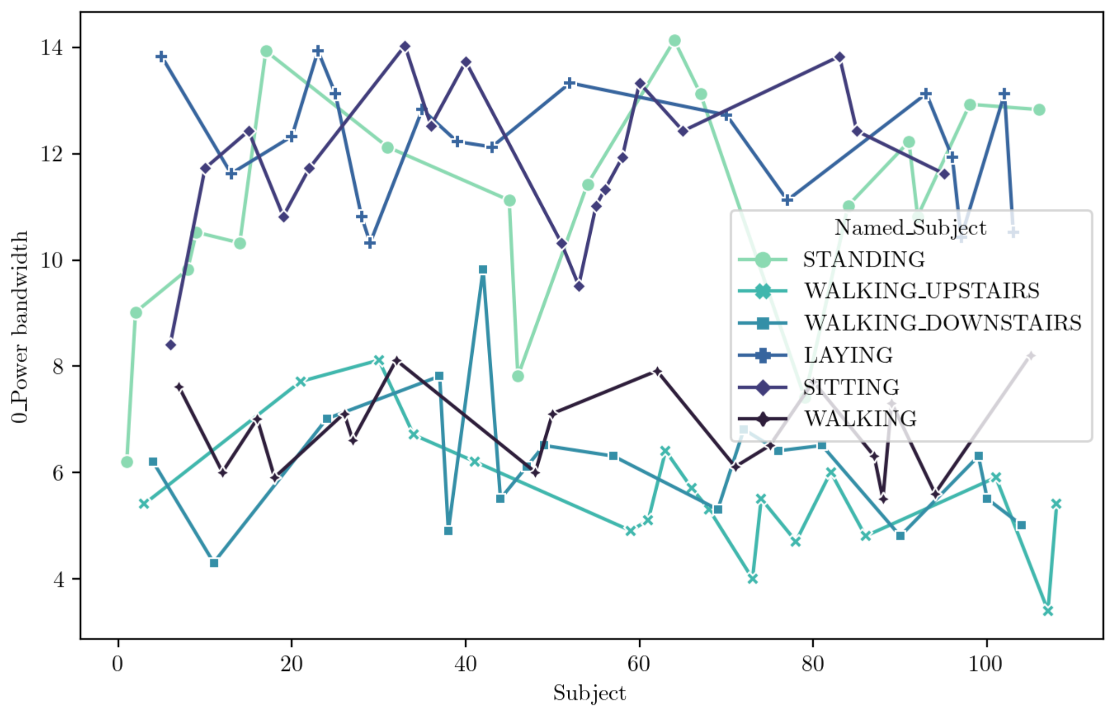
```
338 -> 0_Spectral skewness
339 -> 0_Spectral slope
340 -> 0_Spectral spread
341 -> 0_Spectral variation
342 -> 0_Standard deviation
343 -> 0_Sum absolute diff
344 -> 0_Variance
345 -> 0_Wavelet absolute mean_0
346 -> 0_Wavelet absolute mean_1
347 -> 0_Wavelet absolute mean_2
348 -> 0_Wavelet absolute mean_3
349 -> 0_Wavelet absolute mean_4
350 -> 0_Wavelet absolute mean_5
351 -> 0_Wavelet absolute mean_6
352 -> 0_Wavelet absolute mean_7
353 -> 0_Wavelet absolute mean_8
354 -> 0_Wavelet energy_0
355 -> 0_Wavelet energy_1
356 -> 0_Wavelet energy_2
357 -> 0_Wavelet energy_3
358 -> 0_Wavelet energy_4
359 -> 0_Wavelet energy_5
360 -> 0_Wavelet energy_6
361 -> 0_Wavelet energy_7
362 -> 0_Wavelet energy_8
363 -> 0_Wavelet entropy
364 -> 0_Wavelet standard deviation_0
365 -> 0_Wavelet standard deviation_1
366 -> 0_Wavelet standard deviation_2
367 -> 0_Wavelet standard deviation_3
368 -> 0_Wavelet standard deviation_4
369 -> 0_Wavelet standard deviation_5
370 -> 0_Wavelet standard deviation_6
371 -> 0_Wavelet standard deviation_7
372 -> 0_Wavelet standard deviation_8
373 -> 0_Wavelet variance_0
374 -> 0_Wavelet variance_1
375 -> 0_Wavelet variance_2
376 -> 0_Wavelet variance_3
377 -> 0_Wavelet variance_4
378 -> 0_Wavelet variance_5
379 -> 0_Wavelet variance_6
380 -> 0_Wavelet variance_7
381 -> 0_Wavelet variance_8
382 -> 0_Zero crossing rate
```

[295]:
```
palette = sns.color_palette("mako_r", 6)
def FeaturePlot(dataFrame, feature = None, idx =  None):
    latexify(columns = 2, fig_width = 8)
    if idx is None:
        sns.lineplot(data = dataFrame, x = "Subject", y = feature, hue =␣
 ↪"Named_Subject", style = "Named_Subject", markers = True, dashes = False,␣
 ↪palette = palette)
    else:
        sns.lineplot(data = dataFrame, x ="Subject", y = dataFrame.
 ↪columns[idx], hue = "Named_Subject", style = "Named_Subject", markers =␣
 ↪True, dashes = False, palette = palette)
    plt.show()
```

[324]:
```
features_sel = ["0_Area under the curve", "0_Mean", "0_Variance", "0_Peak to␣
 ↪peak distance", "0_Mean absolute deviation", "Labels", "Subject",␣
 ↪"Named_Subject"]
```

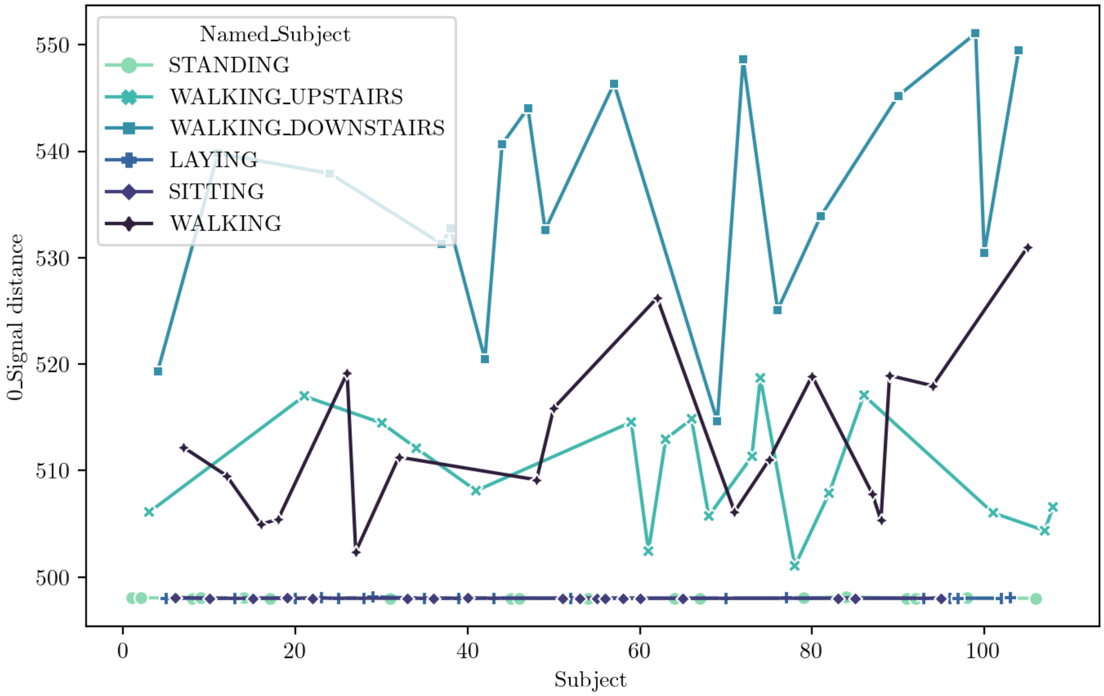
0.1 Power Bandwidth

[344]:
```
FeaturePlot(dfN, idx = 325)
```



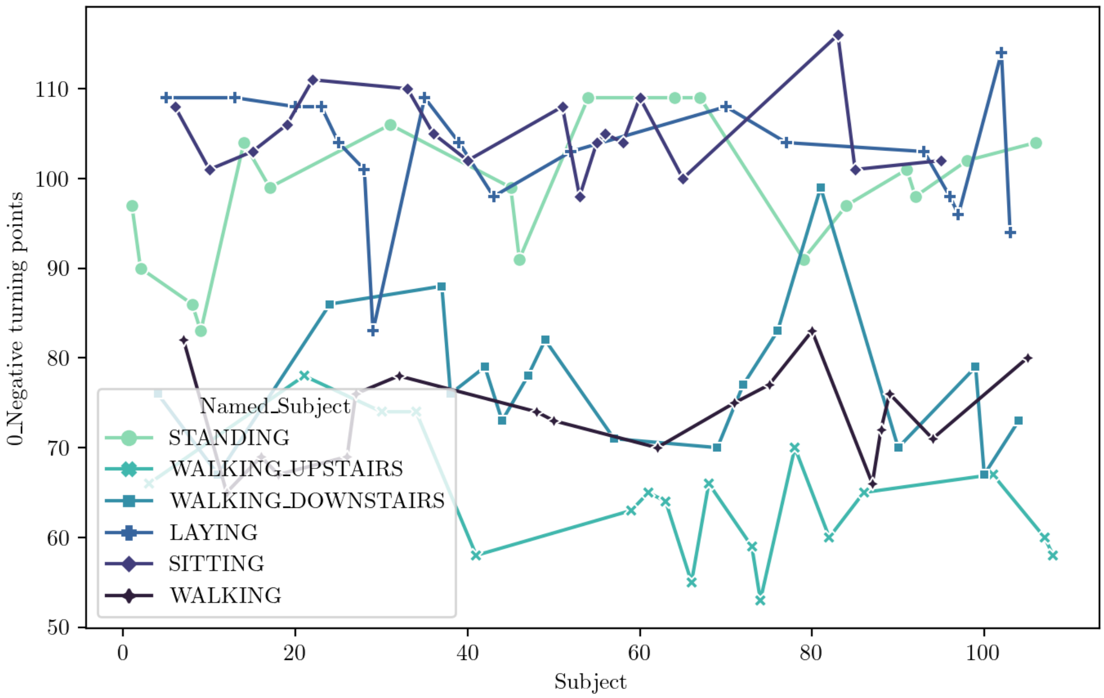
0.2 Signal Distance

[312]:
```
FeaturePlot(dfN, idx = 327)
```



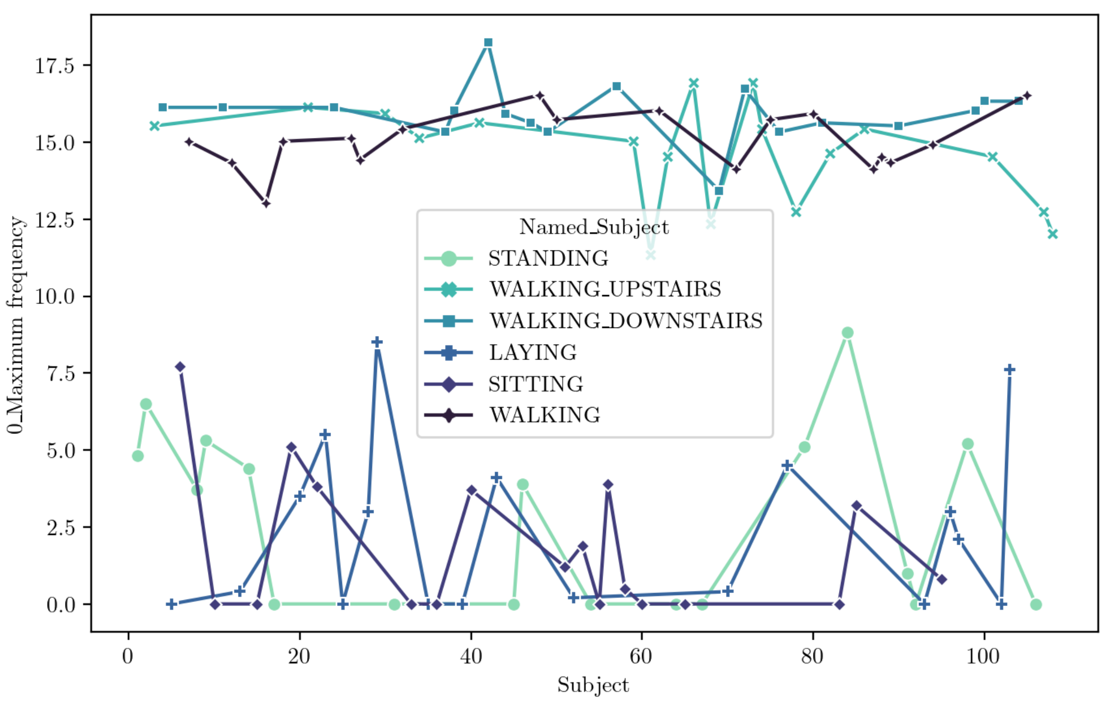
0.3 Negative Turning Point

[310]:
```
FeaturePlot(dfN, idx = 321)
```



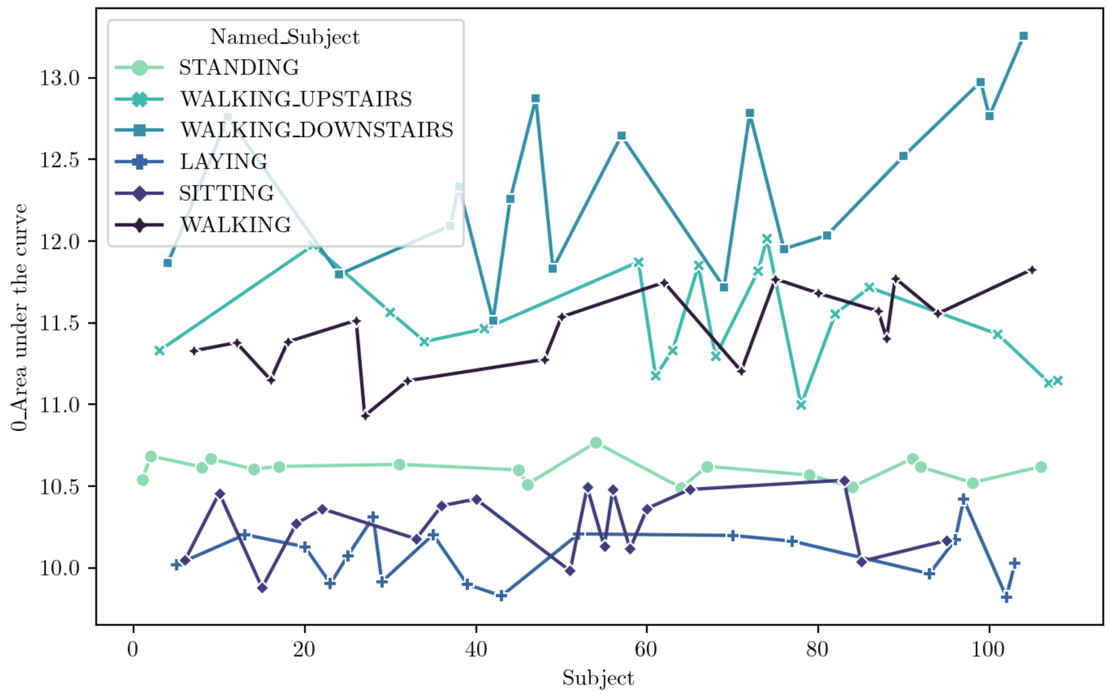
0.4 Maximum Frequency

[309]:
```
FeaturePlot(dfN, idx = 310)
```



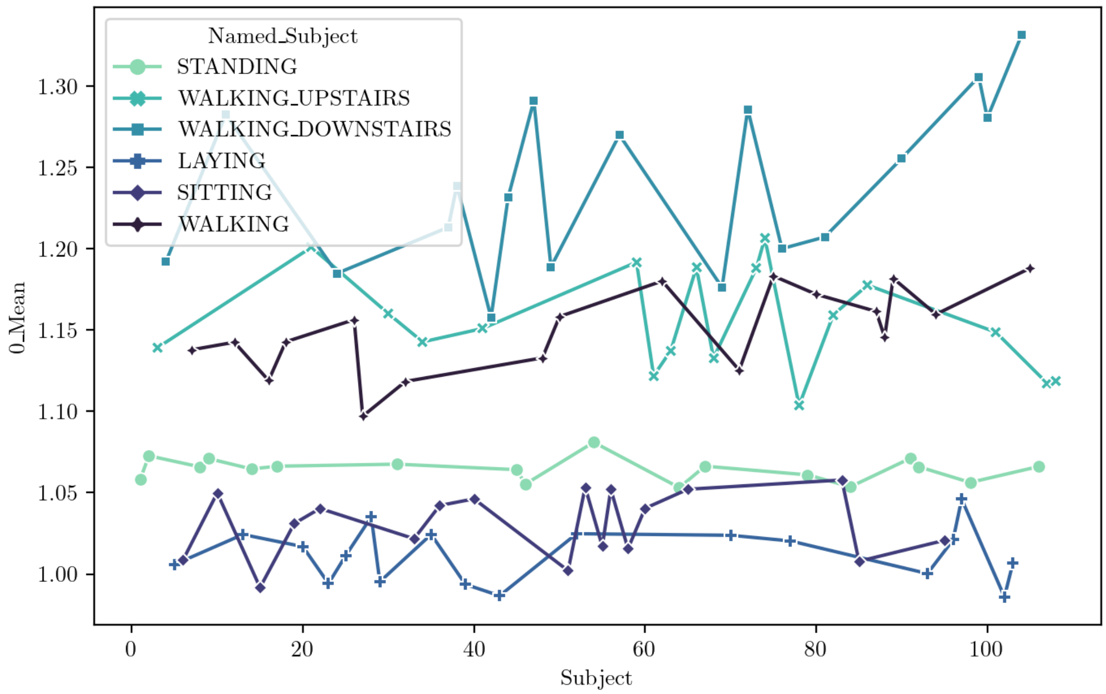
0.5 Area under Curve

[240]:
```
FeaturePlot(dfN, feature = features_sel[0])
```



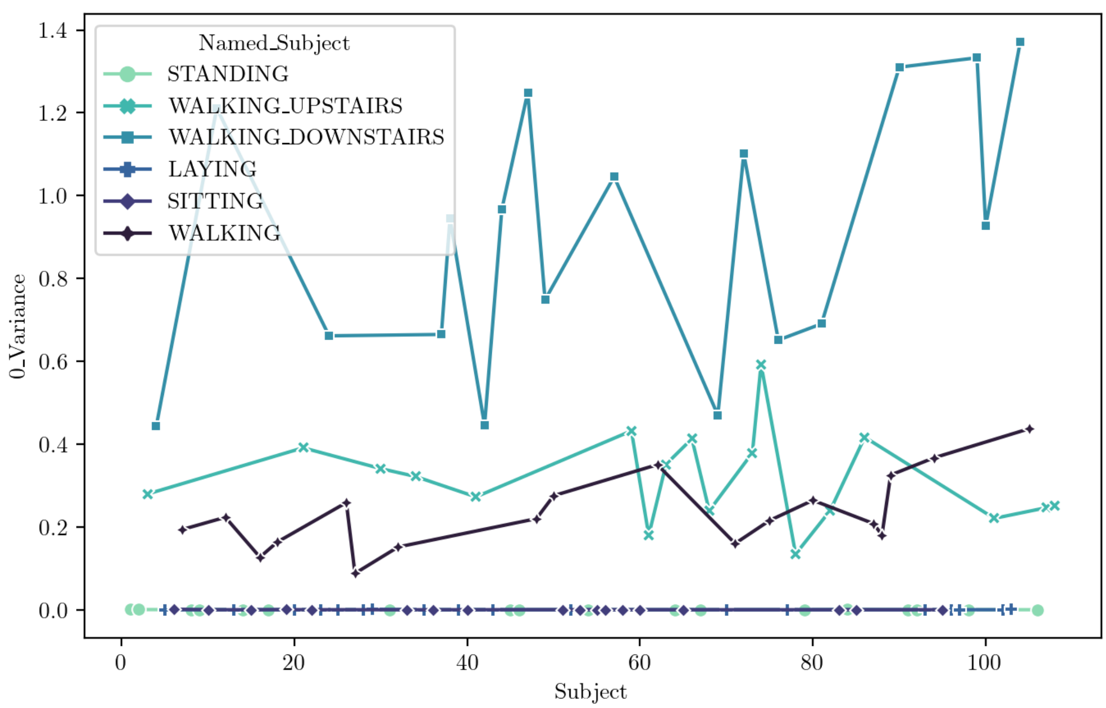
0.6 Mean

[241]:
```
FeaturePlot(dfN, feature = features_sel[1])
```



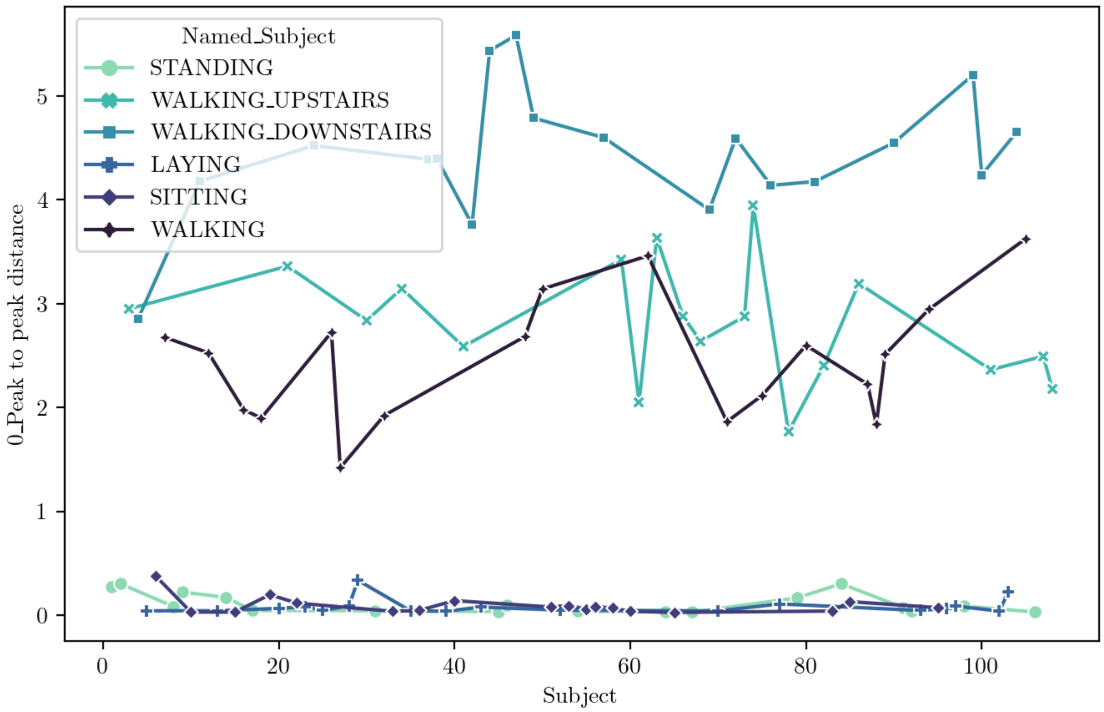
0.7 Variance

[242]:
```
FeaturePlot(dfN, feature = features_sel[2])
```



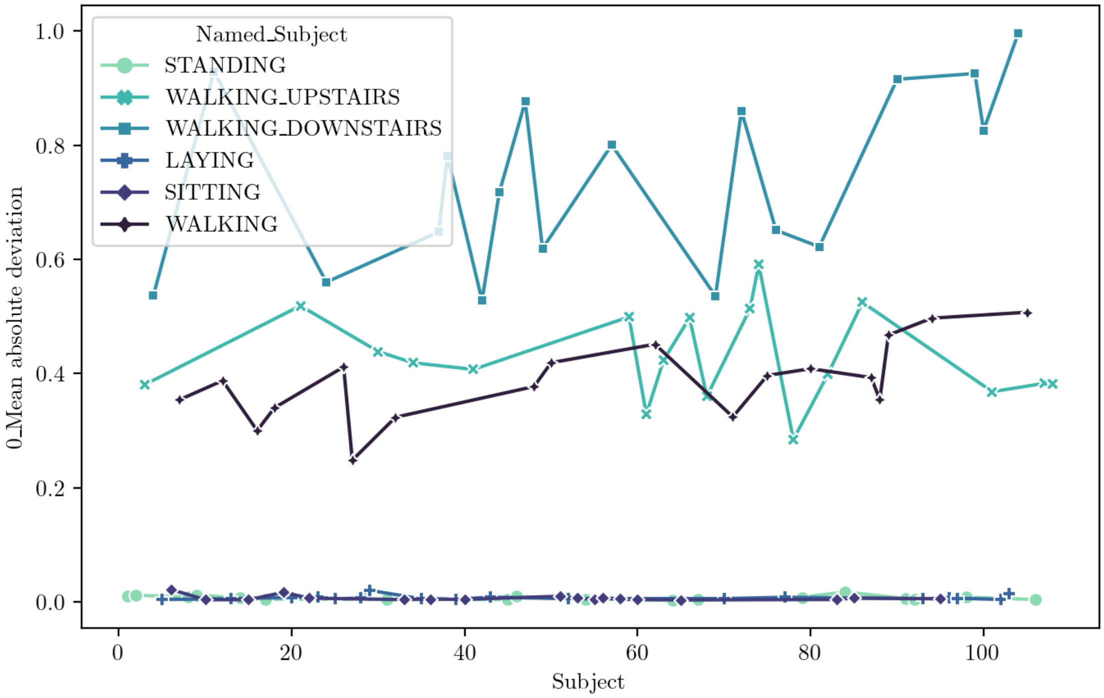
0.8 TIME SERIES PEAK-TO-PEAK DISTANCE

[243]:
```
FeaturePlot(dfN, feature = features_sel[3])
```



0.9 Mean Absolute Deviation

[244]:
```
FeaturePlot(dfN, feature = features_sel[4])
```



0.9.1 Our Selected Features

- Mean
- Area under Curve
- Peak-to-Peak Distance
- Variance
- Mean Absolute Deviation
- Maximum Frequency > Newly Added
- 0_Power bandwidth
- 0_Spectral centroid
- 0_Spectral decrease
- 0_Spectral distance
- 0_Spectral entropy
- 0_Spectral kurtosis
- 0_Spectral positive turning points
- 0_Spectral roll-off
- 0_Spectral roll-on
- 0_Spectral skewness
- 0_Spectral slope
- 0_Spectral spread
- 0_Spectral variation

0.9.2 Let's add some spectral features too to the 5 already selected -> 18 Featured Data

[345]:
```
f_sel = ["0_Area under the curve", "0_Mean", "0_Variance", "0_Peak to peak␣
↪distance", "0_Mean absolute deviation", "0_Power bandwidth", "0_Spectral␣
↪centroid", "0_Spectral decrease", "0_Spectral distance", "0_Spectral␣
↪entropy", "0_Spectral kurtosis", "0_Spectral positive turning points",␣
↪"0_Spectral roll-off", "0_Spectral roll-on", "0_Spectral skewness",␣
↪"0_Spectral slope", "0_Spectral spread", "0_Spectral variation", "Labels",␣
↪"Subject", "Named_Subject"]
dfFeat = dfN[f_sel]
dfFeat
```

[345]:
```
   0_Area under the curve    0_Mean  0_Variance  0_Peak to peak distance
0               10.539676  1.058197    0.000441                 0.276308  \
0               10.683732  1.072680    0.000440                 0.302652
0               11.328686  1.139029    0.279613                 2.951101
0               11.865417  1.191914    0.442988                 2.853736
0               10.018665  1.005892    0.000026                 0.042222
..                    …         …          …                       …
0               13.254750  1.331151    1.370835                 4.655614
0               11.826549  1.187985    0.436927                 3.625210
0               10.618080  1.066065    0.000026                 0.031092
0               11.132367  1.117178    0.246346                 2.492894
0               11.142791  1.118466    0.250806                 2.180257

   0_Mean absolute deviation  0_Power bandwidth  0_Spectral centroid
0                   0.010246           6.212425             0.639077  \
0                   0.011577           9.018036             0.850078
0                   0.380676           5.410822             3.887285
0                   0.537075           6.212425             4.521254
0                   0.004001          13.827655             0.281477
..                       …                 …                    …
0                   0.995919           5.010020             4.916563
0                   0.507468           8.216433             5.361472
0                   0.004030          12.825651             0.275996
0                   0.382848           3.406814             3.119947
0                   0.382529           5.410822             3.392079

   0_Spectral decrease  0_Spectral distance  0_Spectral entropy  …
0           -46.590172        -70826.079944            0.727967  …  \
0           -41.721346        -71473.612034            0.781145  …
0            -2.433189       -169599.425066            0.547602  …
0            -1.803868       -204731.964203            0.592184  …
0          -151.116426        -63806.084893            0.806408  …
..                 …                    …                 …  …
0            -1.218502       -294434.103156            0.565975  …
```

```
0           -2.037178      -167545.154695           0.492424  …
0         -158.072078       -67537.987024           0.818778  …
0           -2.902698      -160379.192325           0.469127  …
0           -2.718273      -163036.885100           0.501480  …

    0_Spectral positive turning points  0_Spectral roll-off
0                                 73.0             4.809619  \
0                                 72.0             6.513026
0                                 78.0            15.531062
0                                 80.0            16.132265
0                                 79.0             0.000000
..                                 …                  …
0                                 78.0            16.332665
0                                 81.0            16.533066
0                                 87.0             0.000000
0                                 81.0            12.725451
0                                 74.0            12.024048

    0_Spectral roll-on  0_Spectral skewness  0_Spectral slope
0                  0.0             4.906914         -0.000905  \
0                  0.0             4.151249         -0.000889
0                  0.0             1.869257         -0.000657
0                  0.0             1.632312         -0.000608
0                  0.0             7.583021         -0.000933
..                 …                  …                 …
0                  0.0             1.444425         -0.000578
0                  0.0             1.054264         -0.000544
0                  0.0             7.708759         -0.000933
0                  0.0             1.982978         -0.000716
0                  0.0             1.739971         -0.000695

    0_Spectral spread  0_Spectral variation  Labels  Subject
0            2.304270              0.903439       5        1  \
0            2.828170              0.951706       5        2
0            5.062929              0.735493       2        3
0            5.077597              0.698450       3        4
0            1.753868              0.851520       6        5
..                …                    …      …       …
0            5.130396              0.469507       3      104
0            5.306712              0.819865       1      105
0            1.746586              0.950194       5      106
0            4.165671              0.738380       2      107
0            4.187673              0.750399       2      108

         Named_Subject
0             STANDING
0             STANDING
```

```
0     WALKING_UPSTAIRS
0   WALKING_DOWNSTAIRS
0               LAYING
..                 …
0   WALKING_DOWNSTAIRS
0              WALKING
0             STANDING
0     WALKING_UPSTAIRS
0     WALKING_UPSTAIRS

[108 rows x 21 columns]
```

0.9.3 PCA on 18 Featured Data

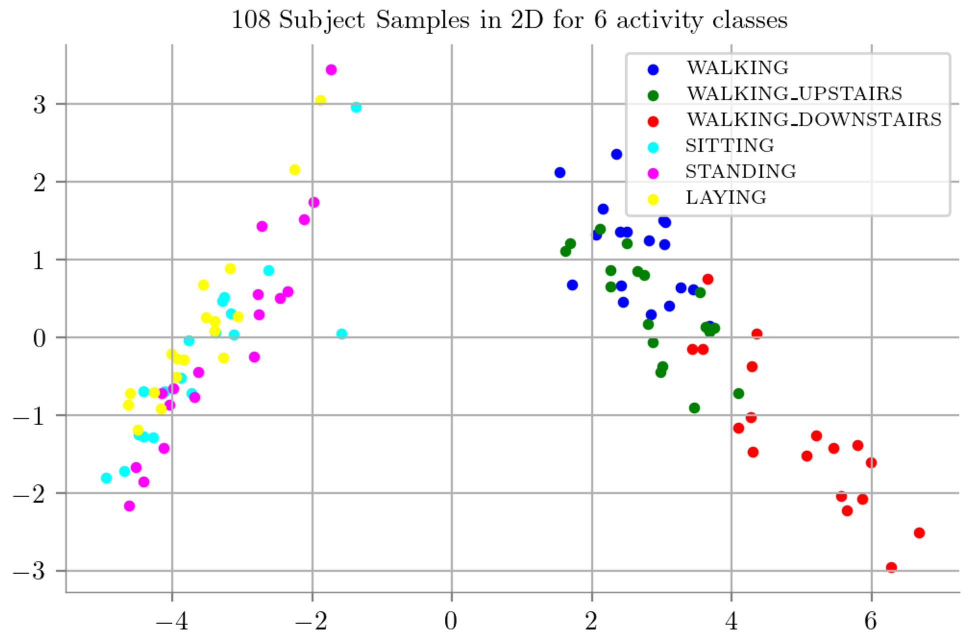
[347]:
```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(dfFeat.iloc[:, :-3])
model = PCA(n_components = 2)
X_trainFeat_2D = model.fit_transform(X_scaled)
dfPCAFeat = pd.DataFrame(X_trainFeat_2D)
dfPCAFeat["Labels"] = y_train
dfPCAFeat
```

[347]:
```
            0         1  Labels
0   -2.119269  1.516116       5
1   -1.979877  1.739336       5
2    2.746499  0.798706       2
3    3.579078 -0.146838       3
4   -4.607082 -0.719782       6
..        …         …     …
103  6.670144 -2.509504       3
104  3.678577  0.154650       1
105 -4.411194 -1.856612       5
106  2.263685  0.657534       2
107  2.115628  1.393518       2

[108 rows x 3 columns]
```

0.10 18 Featured Data PCA to 2D

[348]:
```
PCA_Plot(dfPCAFeat)
```



0.10.1 Extracting DataFrame for our 5 featurized Data

0.10.2 Featurized DataFrame

[263]:
```
dfNewFeaturized = dfN[features_sel]
dfNewFeaturized
```

[263]:
```
   0_Area under the curve    0_Mean  0_Variance  0_Peak to peak distance  \
0               10.539676  1.058197    0.000441                 0.276308
0               10.683732  1.072680    0.000440                 0.302652
0               11.328686  1.139029    0.279613                 2.951101
0               11.865417  1.191914    0.442988                 2.853736
0               10.018665  1.005892    0.000026                 0.042222
..                    …         …          …                        …
0               13.254750  1.331151    1.370835                 4.655614
0               11.826549  1.187985    0.436927                 3.625210
0               10.618080  1.066065    0.000026                 0.031092
0               11.132367  1.117178    0.246346                 2.492894
0               11.142791  1.118466    0.250806                 2.180257

   0_Mean absolute deviation  Labels  Subject        Named_Subject
0                   0.010246       5        1             STANDING
0                   0.011577       5        2             STANDING
0                   0.380676       2        3     WALKING_UPSTAIRS
0                   0.537075       3        4   WALKING_DOWNSTAIRS
0                   0.004001       6        5               LAYING
```

```
..                         …      …      …                 …
0                   0.995919      3    104  WALKING_DOWNSTAIRS
0                   0.507468      1    105             WALKING
0                   0.004030      5    106            STANDING
0                   0.382848      2    107    WALKING_UPSTAIRS
0                   0.382529      2    108    WALKING_UPSTAIRS

[108 rows x 8 columns]
```

0.10.3 PCA on our chosen 5 Featurized Data

[330]:
```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(dfNewFeaturized.iloc[:, :-3])
model = PCA(n_components = 2)
X_trainOurF_2D = model.fit_transform(X_scaled)
dfPCAFeat = pd.DataFrame(X_trainFeat_2D)
dfPCAFeat["Labels"] = y_train
dfPCAFeat
```

[330]:
```
            0         1  Labels
0   -2.408634  1.329825       5
1   -2.039138  1.697191       5
2    2.543982  0.746600       2
3    3.471005 -0.131893       3
4   -4.349947 -0.661725       6
..        …         …       …
103  6.572669 -2.406062       3
104  3.731875  0.248615       1
105 -4.227187 -1.883089       5
106  1.883058  0.470228       2
107  1.891408  1.328787       2

[108 rows x 3 columns]
```

[252]:
```
dfPCAOurF = pd.DataFrame(X_trainOurF_2D)
dfPCAOurF["Labels"] = y_train
dfPCAOurF
```

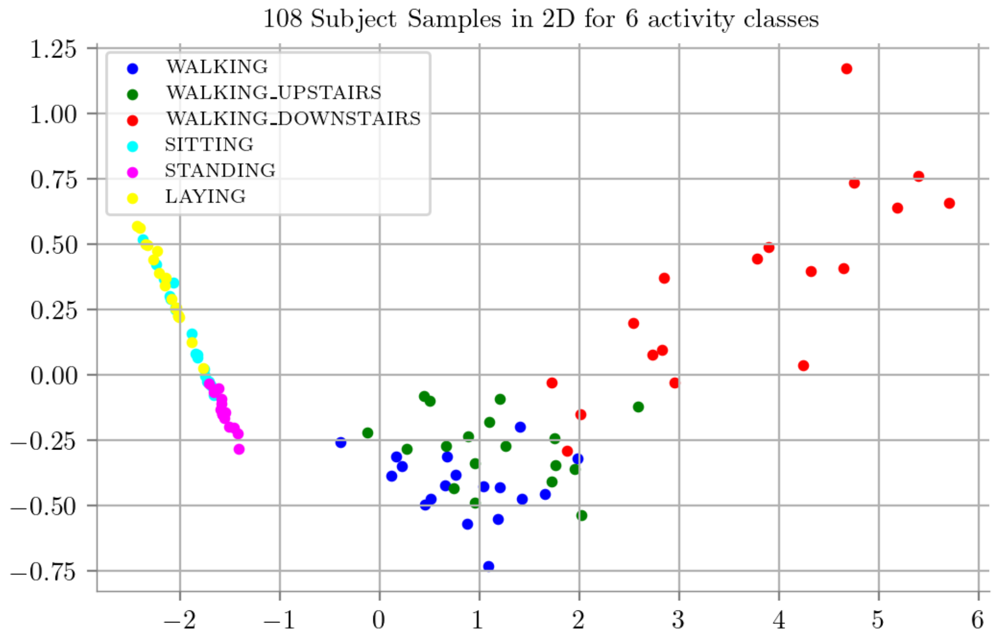
[252]:
```
            0         1  Labels
0   -1.591114 -0.091353       5
1   -1.427712 -0.222992       5
2    0.880008 -0.234883       2
3    1.874859 -0.287865       3
4   -2.220049  0.391626       6
..        …         …       …
103  5.704453  0.657241       3
104  1.976794 -0.320237       1
```

```
105 -1.580248 -0.149378       5
106  0.502482 -0.098926       2
107  0.439838 -0.079656       2

[108 rows x 3 columns]
```

0.11 5 Featurized PCA datapoints

[254]:
```python
PCA_Plot(dfPCAOurF)
```



0.11.1 PCA on our raw timeseries data

[251]:
```python
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X_train_TS)
model = PCA(n_components = 2)
X_train_2D = model.fit_transform(X_scaled)
```

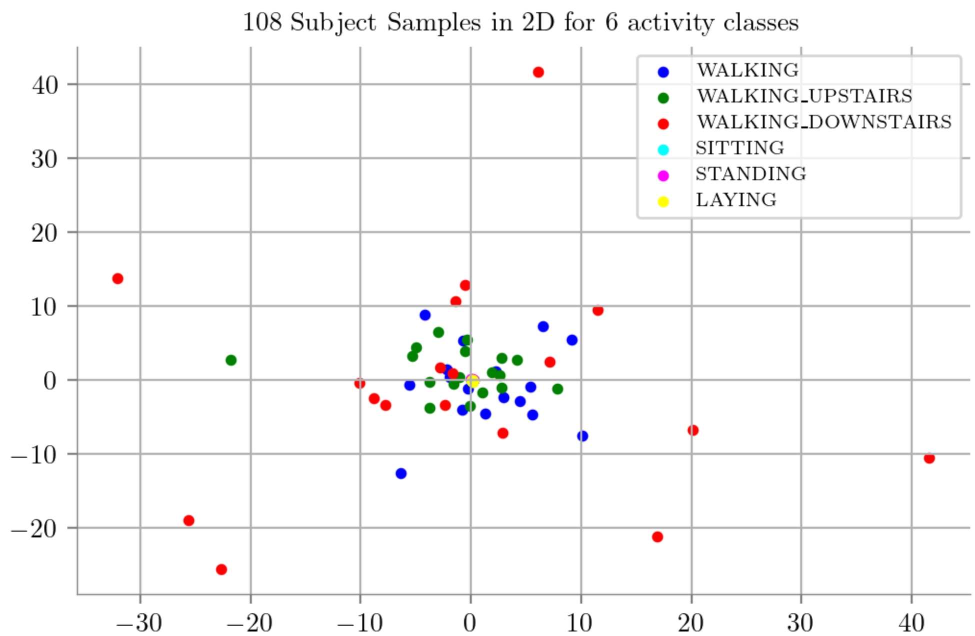
[255]:
```python
dfPCA = pd.DataFrame(X_train_2D)
dfPCA["Labels"] = y_train
dfPCA
```

[255]:
```
          0         1  Labels
0  0.171000 -0.058009       5
1 -0.008648  0.128133       5
2  2.803362  2.955462       2
```

```
3     2.856289   -7.198528        3
4     0.192954   -0.168915        6
..         …          …       …
103   6.098028   41.782163        3
104  -4.212006    8.896049        1
105   0.105575    0.038338        5
106   2.634434    0.671926        2
107   4.157850    2.671812        2

[108 rows x 3 columns]
```

0.12 Raw Timeseries PCA datapoints

[256]:
```
PCA_Plot(dfPCA)
```



0.12.1 PCA on entire 383 Featurized Data

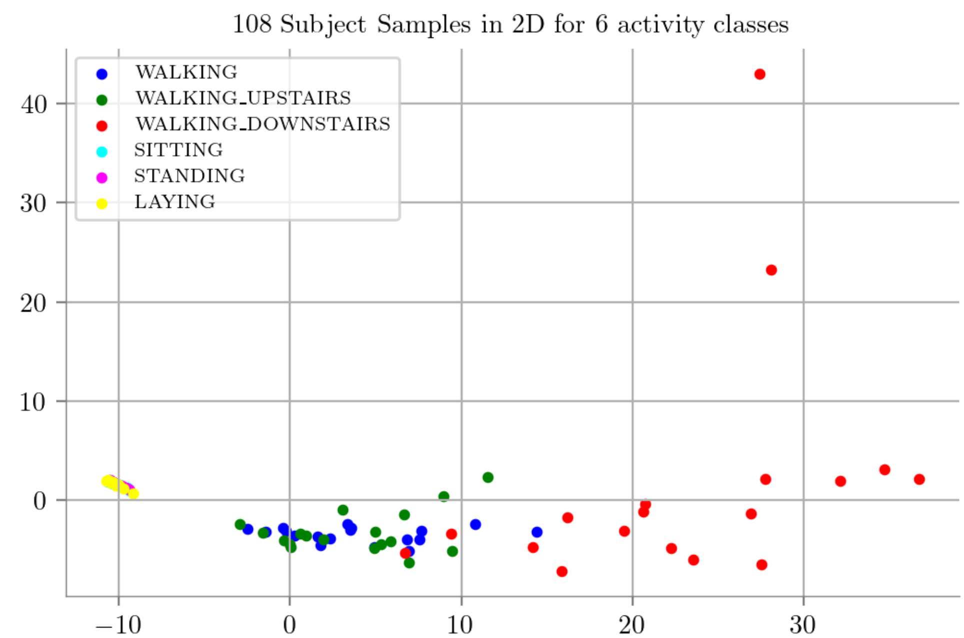
[257]:
```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(dfN.iloc[:, :-3])
model = PCA(n_components = 2)
X_trainF_2D = model.fit_transform(X_scaled)
```

[258]:
```
dfPCAF = pd.DataFrame(X_trainF_2D)
dfPCAF["Labels"] = y_train
dfPCAF
```

```
[258]:               0         1  Labels
0    -9.656330  1.259515       5
1    -9.507877  1.189473       5
2     0.904597 -3.530496       2
3     9.379393 -3.324217       3
4   -10.632995  2.040261       6
..         ...       ...     ...
103  34.743740  3.095295       3
104  14.424106 -3.185719       1
105 -10.430969  1.901364       5
106  -0.354879 -4.074157       2
107  -0.018798 -4.441626       2

[108 rows x 3 columns]
```

0.13 383 Featurized PCA Datapoints

```
[259]: PCA_Plot(dfPCAF)
```



1 TESTING PART

1.1 dfNewFeaturized has 5 selected features and dfFeat has 18 selected features

1.2 Template Funtion to Featurize a Dataset

[260]:
```
def Featuriser(XTimeSeries, YTimeSeries, features):
    cfg = tsfel.get_features_by_domain()
    df = pd.DataFrame(XTimeSeries)
    dataFrames = []
    for i in df.index:
        dataFrames.append(tsfel.time_series_features_extractor(cfg, df.iloc[i,:
 ↪], fs = 50))
    dfN = pd.concat(dataFrames, axis = 0)
    dfN["Labels"] = YTimeSeries
    namedLabel = [classesN[i] for i in YTimeSeries]
    dfN["Named_Subject"] = namedLabel
    dfN["Subject"] = range(1, len(XTimeSeries) + 1)
    dfNFeaturized = dfN[features]
    return dfNFeaturized
```

1.2.1 The features we wish to select for our dataframe

[350]:
```
# 5 Features
features_sel = ["0_Area under the curve", "0_Mean", "0_Variance", "0_Peak to␣
 ↪peak distance", "0_Mean absolute deviation", "Labels", "Subject",␣
 ↪"Named_Subject"]

# 18 Features
f_sel = ["0_Area under the curve", "0_Mean", "0_Variance", "0_Peak to peak␣
 ↪distance", "0_Mean absolute deviation", "0_Power bandwidth", "0_Spectral␣
 ↪centroid", "0_Spectral decrease", "0_Spectral distance", "0_Spectral␣
 ↪entropy", "0_Spectral kurtosis", "0_Spectral positive turning points",␣
 ↪"0_Spectral roll-off", "0_Spectral roll-on", "0_Spectral skewness",␣
 ↪"0_Spectral slope", "0_Spectral spread", "0_Spectral variation", "Labels",␣
 ↪"Subject", "Named_Subject"]
```

1.2.2 Featurizing the TEST dataset for our chosen 5 features

[ ]:
```
dfNF_test = Featuriser(X_test_TS, y_test, features_sel)
```

1.3 Decision Tree Classifier on our 5 Featurized Data

1.4 Classifier for 5 Featured dfNewFeaturized

[264]:
```
model = DecisionTreeClassifier()
clfg = model.fit(dfNewFeaturized.iloc[:, :-3], dfNewFeaturized.iloc[:, 5])
y_pred = clfg.predict(dfNF_test.iloc[:, :-3])
```

```
y_pred
```

[264]:
```
array([3, 3, 6, 2, 6, 5, 6, 1, 2, 3, 5, 6, 2, 5, 2, 4, 5, 5, 1, 6, 5, 1,
       2, 5, 2, 1, 2, 4, 3, 6, 4, 6, 4, 2, 3, 1])
```

[265]:
```
y_test
```

[265]:
```
array([3, 3, 6, 2, 6, 5, 6, 1, 1, 3, 5, 6, 1, 5, 3, 4, 5, 5, 1, 6, 4, 1,
       2, 5, 2, 1, 3, 6, 3, 4, 4, 4, 4, 2, 2, 2])
```

1.4.1 Accuracy Score for decision tree classifier on TEST data trained on our 5 featurized dataset

[266]:
```
accuracy_score(y_test, y_pred)
```

[266]: 0.7222222222222222

1.4.2 Classification Report for decision tree classifier on TEST data trained on our 5 featurized dataset

[267]:
```
print(classification_report(y_test, y_pred, labels = np.unique(y_pred)))
```

```
              precision    recall  f1-score   support

           1       0.80      0.67      0.73         6
           2       0.50      0.67      0.57         6
           3       0.80      0.67      0.73         6
           4       0.75      0.50      0.60         6
           5       0.86      1.00      0.92         6
           6       0.71      0.83      0.77         6

    accuracy                           0.72        36
   macro avg       0.74      0.72      0.72        36
weighted avg       0.74      0.72      0.72        36
```

1.4.3 Confusion Matrix for the above prediction

[270]:
```
cm = confusion_matrix(y_test, y_pred)
df_cm = pd.DataFrame(cm, index = [classT for classT in classes], columns =
 ↪[classT for classT in classes])
df_cm
```

[270]:
```
                    WALKING  WALKING_UPSTAIRS  WALKING_DOWNSTAIRS  SITTING
WALKING                   4                 2                   0        0  \
WALKING_UPSTAIRS          1                 4                   1        0
WALKING_DOWNSTAIRS        0                 2                   4        0
SITTING                   0                 0                   0        3
```

```
STANDING                  0                  0                    0         0
LAYING                    0                  0                    0         1

                    STANDING  LAYING
WALKING                    0       0
WALKING_UPSTAIRS           0       0
WALKING_DOWNSTAIRS         0       0
SITTING                    1       2
STANDING                   6       0
LAYING                     0       5
```

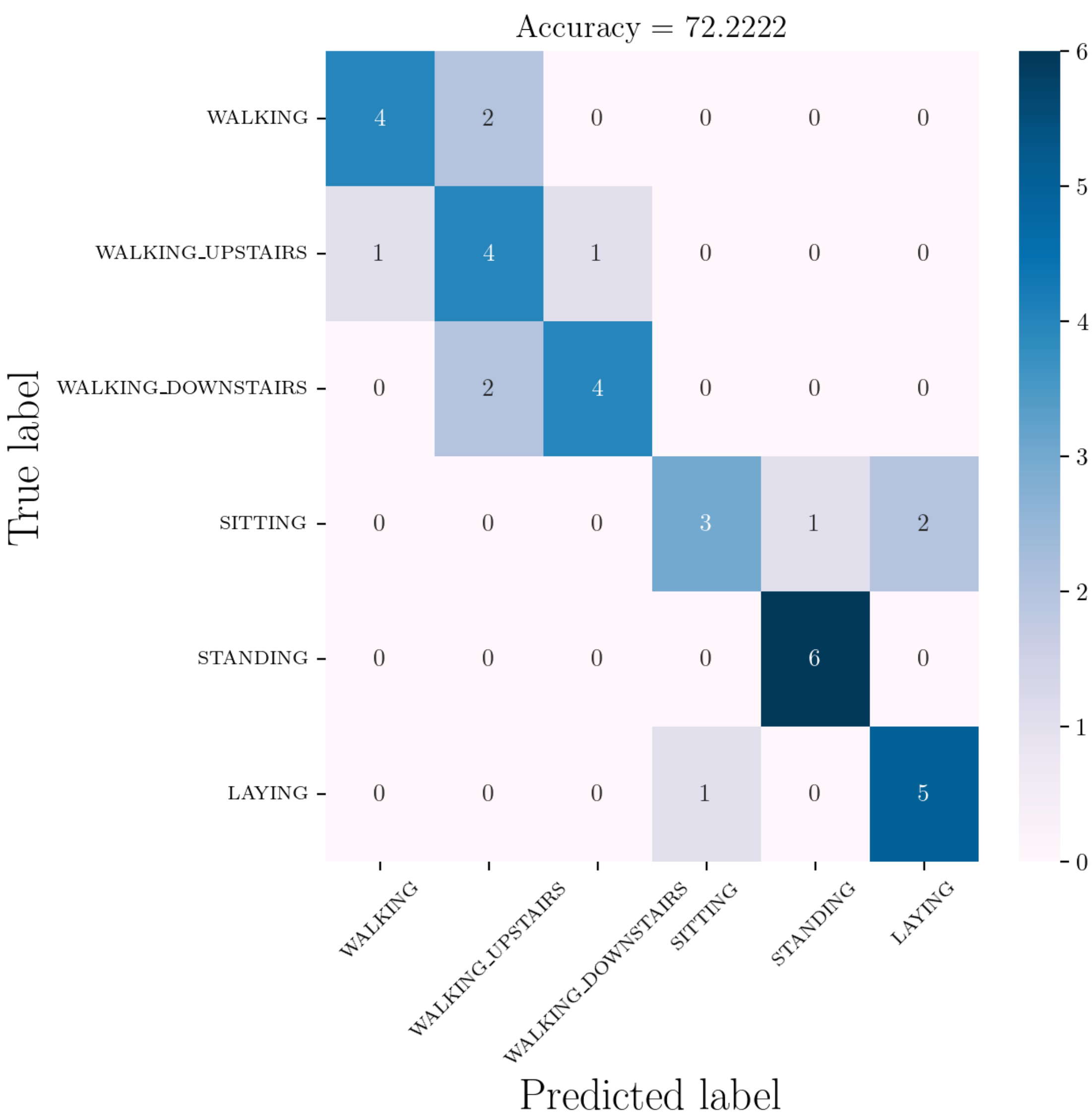
1.5 Template Code for Displaying Confusion Matrix

[271]:

```python
## flag = 1 for a single plot and 0 for subplots for 2 - 8 depths
def confMatrix(dataFrame, flag = 1, accuracies = None):
    if flag:
        plt.figure(figsize = (6, 6))
        ax = sns.heatmap(dataFrame, annot = True, cmap = "PuBu")
        plt.setp(ax.get_xticklabels(), rotation = 45, fontsize = 8)
        plt.setp(ax.get_yticklabels(), fontsize = 8)
        plt.ylabel("True label", fontsize = 18)
        plt.xlabel("Predicted label", fontsize = 18)
        plt.title(f"Accuracy = {accuracy_score(y_test, y_pred)*100: .4f}%",␣
↪fontweight = "bold", fontsize = 13)
        plt.show()
    else:
        fig, axes = plt.subplots(3, 3, figsize = (25, 25))
        axes = axes.flatten()

        for i, df in enumerate(dataFrame):
            ax = sns.heatmap(df, annot = True, ax = axes[i], cbar = False, cmap␣
↪= "PuBu")

            plt.setp(ax.get_xticklabels(), rotation = 45, fontsize = 6)
            plt.setp(ax.get_yticklabels(), fontsize = 8)
            ax.set_title(f"Depth = {i + 2}\nAccuracy = {accuracies[i] * 100: .
↪4f}%", fontsize = 10)
            ax.set_ylabel("True label", fontsize = 12)
            ax.set_xlabel("Predicted label", fontsize = 12)

        plt.delaxes(axes[7])
        plt.delaxes(axes[8])
        plt.tight_layout()
        plt.subplots_adjust(wspace = 1.1, hspace = 1.1)
        plt.show()
```

1.5.1 Confusion Matrix for the model trained on our 5-featured Dataset

[272]:
```
confMatrix(df_cm, flag = 1)
```



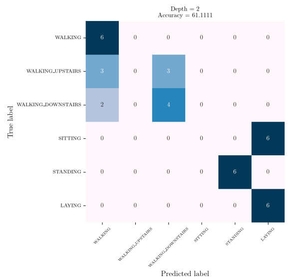
1.5.2 Fetching the Connfusion Matrices, Class Reports, Accuracies for Depth $(2-8)$ Tree on 5-Featurized Data

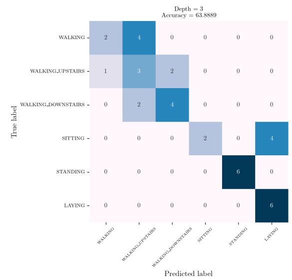
[273]:
```
confusion_matrices, class_reports, class_reports_dict, accuracies = [], [], [],␣
↪[]
for i in range(2, 9):
    model = DecisionTreeClassifier(max_depth = i, random_state = 42)
    clfg = model.fit(dfNewFeaturized.iloc[:, :-3], dfNewFeaturized.iloc[:, 5])
```

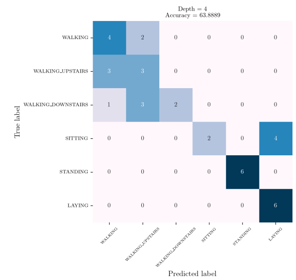
```
    y_pred = clfg.predict(dfNF_test.iloc[:, :-3])

    pred, actual = y_pred, y_test

    cm = confusion_matrix(actual, pred)

    confusion_matrices.append(pd.DataFrame(cm, index = [classT for classT in␣
↪classes], columns = [classT for classT in classes]))
    class_reports.append(classification_report(actual, pred, labels = np.
↪unique(pred)))
    class_reports_dict.append(classification_report(actual, pred, labels = np.
↪unique(pred), output_dict = True))
    accuracies.append(accuracy_score(actual, pred))
```

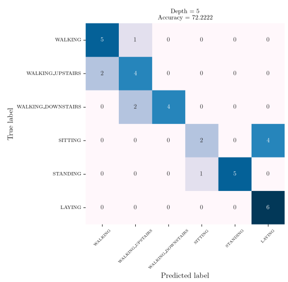
1.5.3 7 Confusion Matrices for 5-Featurized Data

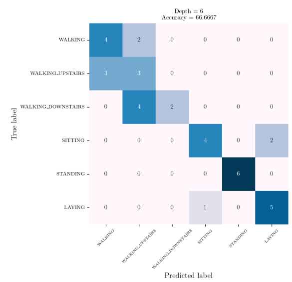
[274]:
```
confMatrix(confusion_matrices, flag = 0, accuracies = accuracies)
```

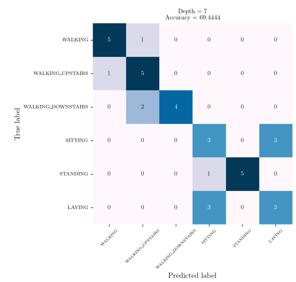


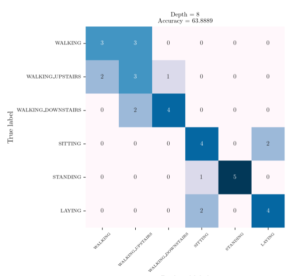












1.6 Decision Tree Classifier on RAW TimeSeries Data `X_train_TS`

[285]:
```
model = DecisionTreeClassifier()
clfg = model.fit(X_train_TS, y_train)
y_pred1 = clfg.predict(X_test_TS)
cm1 = confusion_matrix(y_test, y_pred1)
df_cm1 = pd.DataFrame(cm1, index = [classT for classT in classes], columns =␣
 ↪[classT for classT in classes])
df_cm1
```

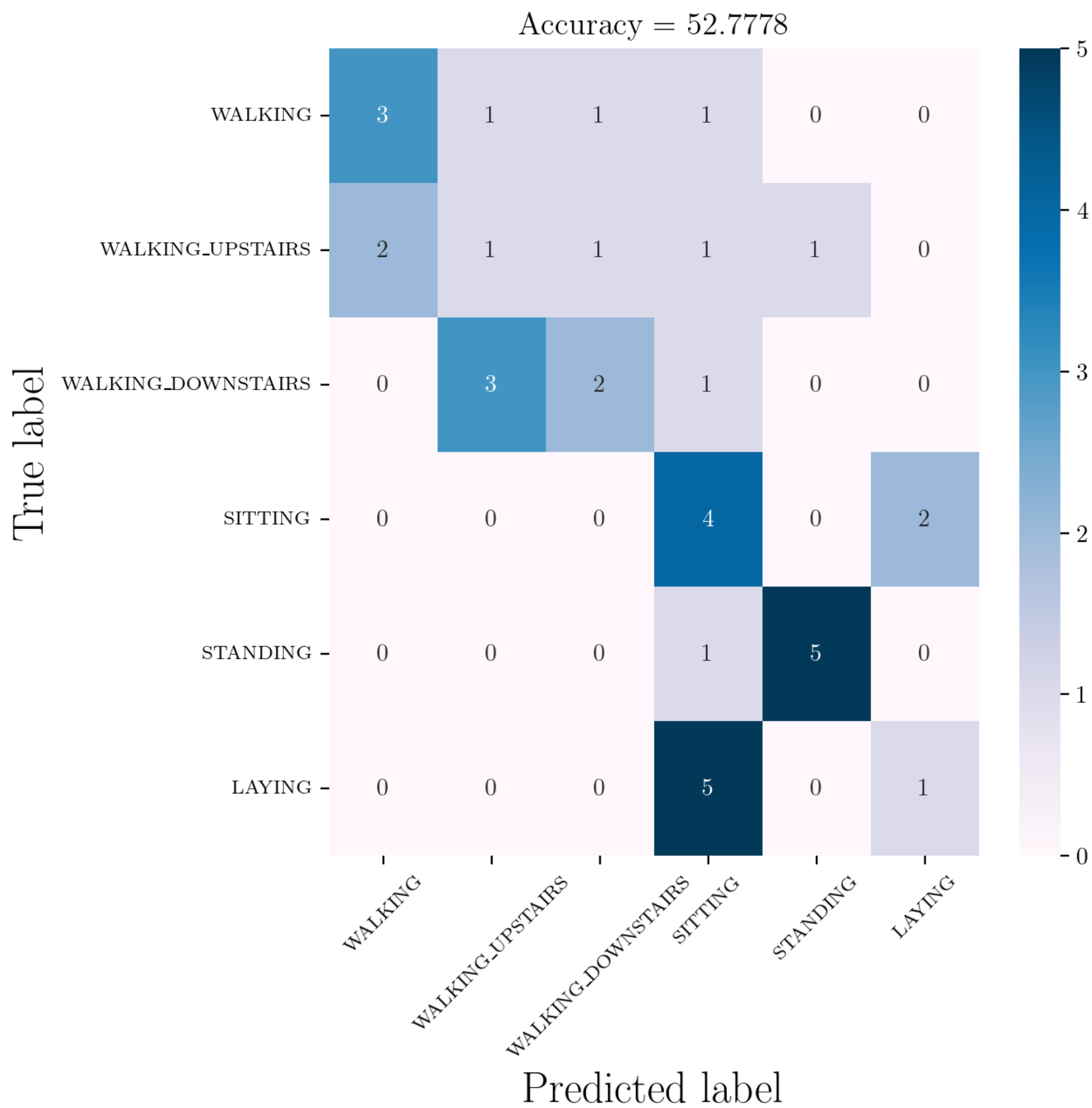
[285]:
```
                          WALKING  WALKING_UPSTAIRS  WALKING_DOWNSTAIRS  SITTING
WALKING                         3                 1                   1        1  \
```

```
WALKING_UPSTAIRS          2                  1                   1         1
WALKING_DOWNSTAIRS        0                  3                   2         1
SITTING                   0                  0                   0         4
STANDING                  0                  0                   0         1
LAYING                    0                  0                   0         5

                    STANDING  LAYING
WALKING                    0       0
WALKING_UPSTAIRS           1       0
WALKING_DOWNSTAIRS         0       0
SITTING                    0       2
STANDING                   5       0
LAYING                     0       1
```

1.6.1 Confusion Matrix for the model trained on RAW TimeSeries Data

[286]:

```
confMatrix(df_cm1, flag = 1)
```



1.6.2 Fetching the Connfusion Matrices, Class Reports, Accuracies for Depth $(2-8)$ Tree on Raw Time Series Data

[280]:

```
confusion_matrices1, class_reports1, class_reports_dict1, accuracies1 = [], [],␣
↪[], []
for i in range(2, 9):
    model = DecisionTreeClassifier(max_depth = i,random_state=42)
    clfg = model.fit(X_train_TS, y_train)
    y_pred = clfg.predict(X_test_TS)

    pred, actual = y_pred, y_test
```

```
    cm = confusion_matrix(actual, pred)

    confusion_matrices1.append(pd.DataFrame(cm, index = [classT for classT in classes], columns = [classT for classT in classes]))
    class_reports1.append(classification_report(actual, pred, labels = np.unique(pred)))
    class_reports_dict1.append(classification_report(actual, pred, labels = np.unique(pred), output_dict = True))
    accuracies1.append(accuracy_score(actual, pred))
```

1.6.3 7 Confusion Matrices for Raw Time Series Data

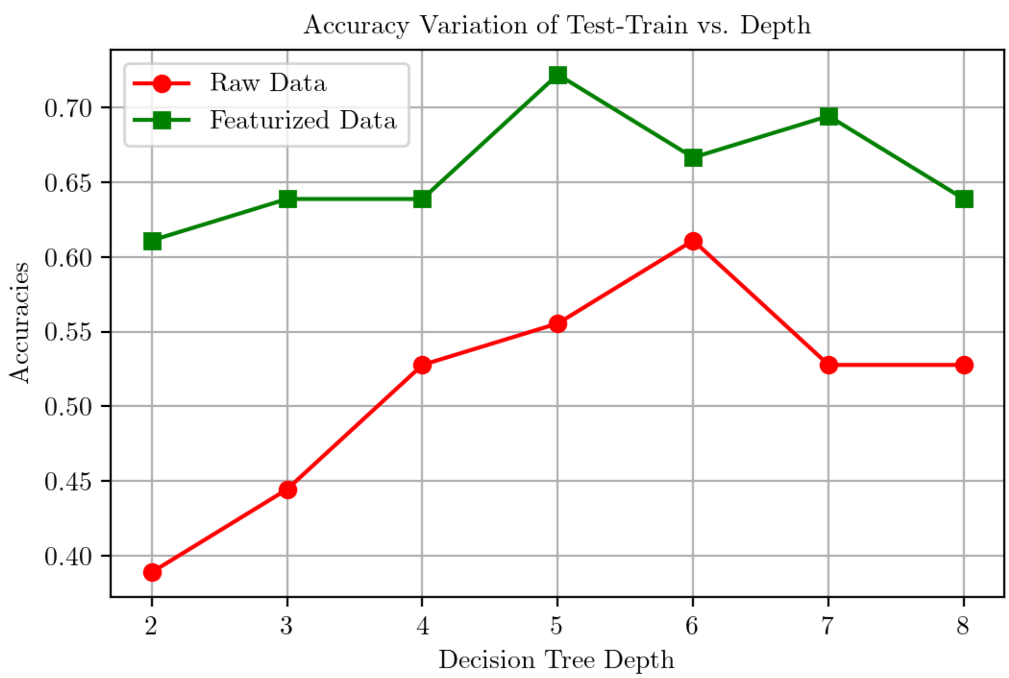
[281]:
```
confMatrix(confusion_matrices1, flag = 0, accuracies = accuracies1)
```

1.7 Accuracy Comparison for both RAW TimeSeries and 5-Featurized Data

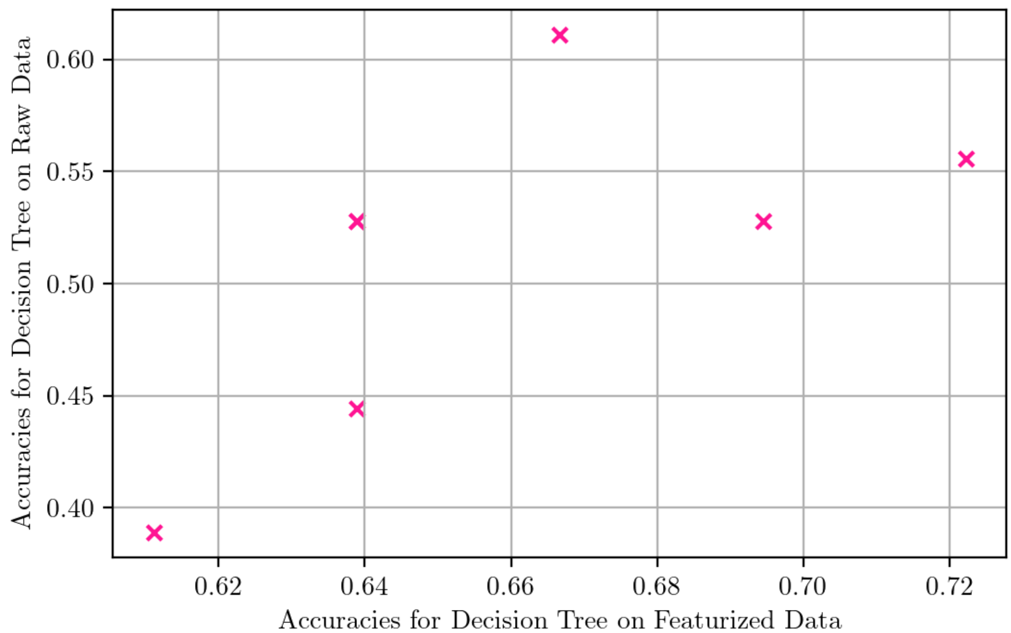
[282]:
```
print(accuracies)
print(accuracies1)
```

```
[0.6111111111111112, 0.6388888888888888, 0.6388888888888888, 0.7222222222222222,
0.6666666666666666, 0.6944444444444444, 0.6388888888888888]
[0.3888888888888889, 0.4444444444444444, 0.5277777777777778, 0.5555555555555556,
0.6111111111111112, 0.5277777777777778, 0.5277777777777778]
```

[294]:
```
plt.plot(range(2, 9), accuracies1, color = "r", marker = "o")
plt.plot(range(2, 9), accuracies, color = "g", marker = "s")
plt.xlabel("Decision Tree Depth")
plt.ylabel("Accuracies")
plt.title("Accuracy Variation of Test-Train vs. Depth")
plt.legend(["Raw Data", "Featurized Data"])
plt.grid()
```



[291]:
```
plt.scatter(accuracies, accuracies1, marker = "x", color = "deeppink", s = 30)
plt.xlabel("Accuracies for Decision Tree on Featurized Data")
plt.ylabel("Accuracies for Decision Tree on Raw Data")
plt.grid()
```



1.8 Now same for 18 Featured dfFeat

1.8.1 Firstly Featurize the Test Dataset according to the 18 features

[ ]:
```
dfNF_test = Featuriser(X_test_TS, y_test, f_sel)
```

[354]:
```
model = DecisionTreeClassifier()
clfg = model.fit(dfFeat.iloc[:, :-3], dfFeat.iloc[:, 18])
y_pred = clfg.predict(dfNF_test.iloc[:, :-3])
y_pred
```

[354]:
```
array([3, 3, 6, 2, 6, 4, 6, 1, 1, 2, 4, 6, 2, 5, 2, 4, 5, 5, 2, 6, 4, 1,
       2, 5, 3, 2, 2, 4, 3, 4, 6, 6, 4, 3, 3, 1])
```

[355]:
```
y_test
```

[355]:
```
array([3, 3, 6, 2, 6, 5, 6, 1, 1, 3, 5, 6, 1, 5, 3, 4, 5, 5, 1, 6, 4, 1,
       2, 5, 2, 1, 3, 6, 3, 4, 4, 4, 4, 2, 2, 2])
```

1.8.2 Accuracy Score for decision tree classifier on TEST data trained on our 18 featurized dataset

[356]:
```
accuracy_score(y_test, y_pred)
```

[356]:
```
0.5833333333333334
```

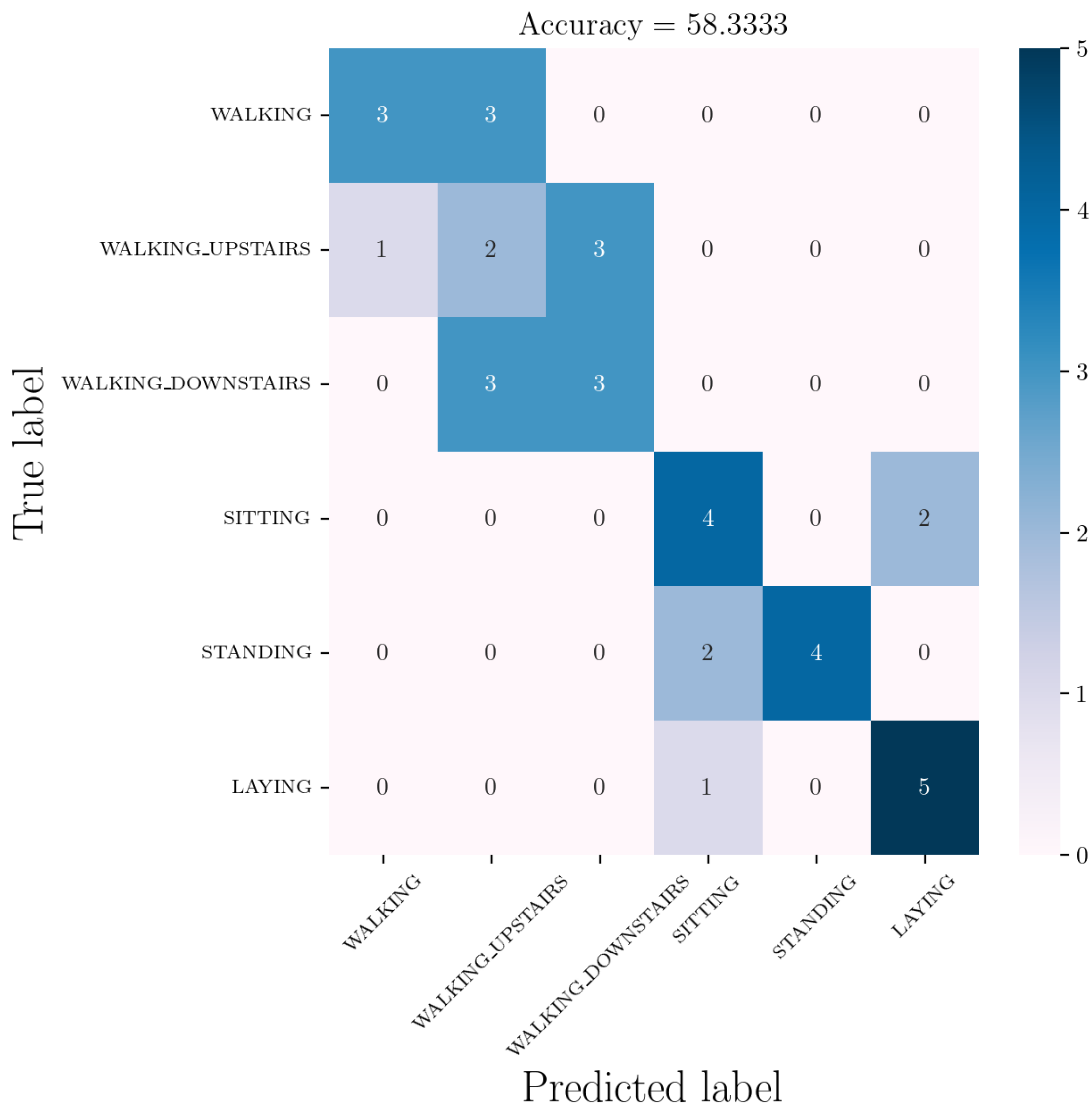
1.8.3 Classification Report for decision tree classifier on TEST data trained on our 18 featurized dataset

[357]:
```
print(classification_report(y_test, y_pred, labels = np.unique(y_pred)))
```

```
              precision    recall  f1-score   support

           1       0.75      0.50      0.60         6
           2       0.25      0.33      0.29         6
           3       0.50      0.50      0.50         6
           4       0.57      0.67      0.62         6
           5       1.00      0.67      0.80         6
           6       0.71      0.83      0.77         6

    accuracy                           0.58        36
   macro avg       0.63      0.58      0.60        36
weighted avg       0.63      0.58      0.60        36
```

[358]:
```
cm = confusion_matrix(y_test, y_pred)
df_cm = pd.DataFrame(cm, index = [classT for classT in classes], columns =␣
 ↪[classT for classT in classes])
```

[359]:
```
confMatrix(df_cm, flag = 1)
```



1.8.4 Fetching the Connfusion Matrices, Class Reports, Accuracies for Depth $(2-8)$ Tree on 18-Featurized Data

[360]:
```
confusion_matrices, class_reports, class_reports_dict, accuracies = [], [], [],␣
↪[]
for i in range(2, 9):
    model = DecisionTreeClassifier(max_depth = i, random_state = 42)
    clfg = model.fit(dfFeat.iloc[:, :-3], dfFeat.iloc[:, 18])
    y_pred = clfg.predict(dfNF_test.iloc[:, :-3])

    pred, actual = y_pred, y_test
```

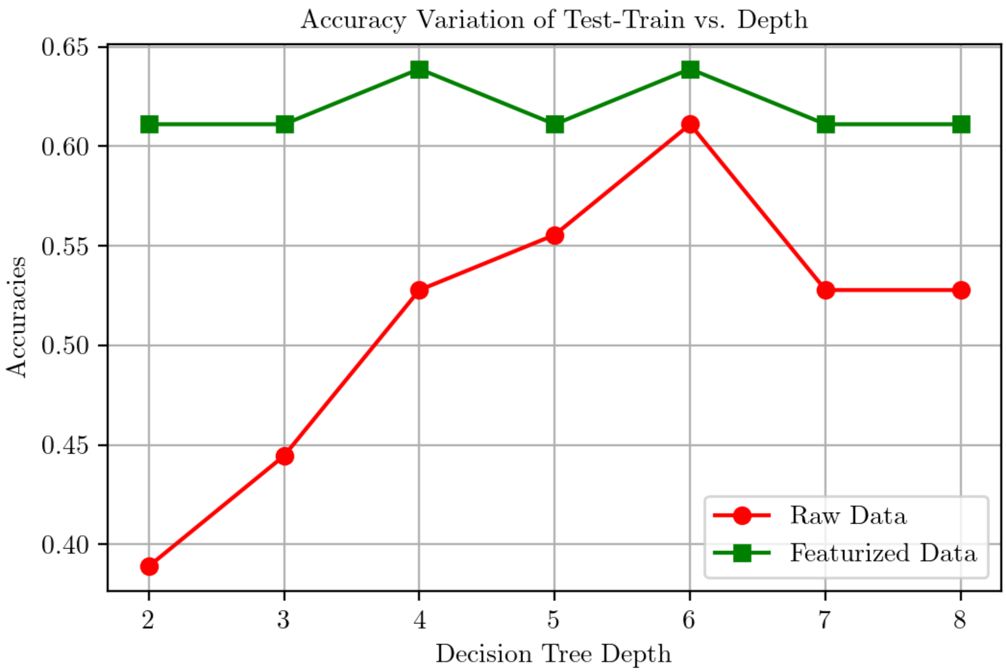
```
    cm = confusion_matrix(actual, pred)

    confusion_matrices.append(pd.DataFrame(cm, index = [classT for classT in classes], columns = [classT for classT in classes]))
    class_reports.append(classification_report(actual, pred, labels = np.unique(pred)))
    class_reports_dict.append(classification_report(actual, pred, labels = np.unique(pred), output_dict = True))
    accuracies.append(accuracy_score(actual, pred))
```

1.8.5 7 Confusion Matrices for 18-Featurized Data

[361]:
```
confMatrix(confusion_matrices, flag = 0, accuracies = accuracies)
```

1.9 Accuracy Comparison for both RAW TimeSeries and 18-Featurized Data

[362]:
```
plt.plot(range(2, 9), accuracies1, color = "r", marker = "o")
plt.plot(range(2, 9), accuracies, color = "g", marker = "s")
plt.xlabel("Decision Tree Depth")
plt.ylabel("Accuracies")
plt.title("Accuracy Variation of Test-Train vs. Depth")
plt.legend(["Raw Data", "Featurized Data"])
plt.grid()
```



1.10 The 5 - Featured `dfNewFeaturized` is better than the 18 - Featured `dfFeat` that had spectral features included too