

# Random Forest Algorithm

Prajwal Vijaywargya - 2017B3A70954H  
Siddhi Mahesh Burse - 2017B3A70972H  
Parth Krishna Sharma - 2017B3A70907H

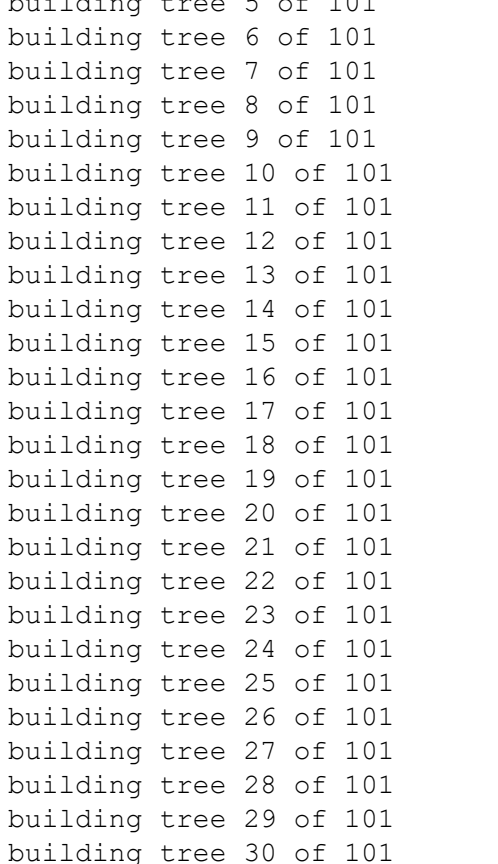
```
In [1]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn.metrics
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

In [2]: train_file = pd.read_csv('D:/BITS/DL/Assignments/Assignment1/mnist_train.csv')
test_file = pd.read_csv('D:/BITS/DL/Assignments/Assignment1/mnist_test.csv')

In [3]: X_train,y_train = train_file.iloc[:,1:].values, train_file.iloc[:,0].values
X_test,y_test = test_file.iloc[:,1:].values,test_file.iloc[:,0].values

In [4]: index = 3
print("Label: " + str(y_train[index]))
plt.imshow(X_train[index].reshape((28,28)), cmap='gray')
plt.show()

Label: 1
```



```
In [5]: clf = RandomForestClassifier(n_estimators=101,criterion='entropy',max_features = 'sqrt',verbose=2)
clf.fit(X_train,y_train)

building tree 1 of 101

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 1 out of 1 | elapsed: 1.0s remaining: 0.0s

building tree 2 of 101
building tree 3 of 101
building tree 4 of 101
building tree 5 of 101
building tree 6 of 101
building tree 7 of 101
building tree 8 of 101
building tree 9 of 101
building tree 10 of 101
building tree 11 of 101
building tree 12 of 101
building tree 13 of 101
building tree 14 of 101
building tree 15 of 101
building tree 16 of 101
building tree 17 of 101
building tree 18 of 101
building tree 19 of 101
building tree 20 of 101
building tree 21 of 101
building tree 22 of 101
building tree 23 of 101
building tree 24 of 101
building tree 25 of 101
building tree 26 of 101
building tree 27 of 101
building tree 28 of 101
building tree 29 of 101
building tree 30 of 101
building tree 31 of 101
building tree 32 of 101
building tree 33 of 101
building tree 34 of 101
building tree 35 of 101
building tree 36 of 101
building tree 37 of 101
building tree 38 of 101
building tree 39 of 101
building tree 40 of 101
building tree 41 of 101
building tree 42 of 101
building tree 43 of 101
building tree 44 of 101
building tree 45 of 101
building tree 46 of 101
building tree 47 of 101
building tree 48 of 101
building tree 49 of 101
building tree 50 of 101
building tree 51 of 101
building tree 52 of 101
building tree 53 of 101
building tree 54 of 101
building tree 55 of 101
building tree 56 of 101
building tree 57 of 101
building tree 58 of 101
building tree 59 of 101
building tree 60 of 101
building tree 61 of 101
building tree 62 of 101
building tree 63 of 101
building tree 64 of 101
building tree 65 of 101
building tree 66 of 101
building tree 67 of 101
building tree 68 of 101
building tree 69 of 101
building tree 70 of 101
building tree 71 of 101
building tree 72 of 101
building tree 73 of 101
building tree 74 of 101
building tree 75 of 101
building tree 76 of 101
building tree 77 of 101
building tree 78 of 101
building tree 79 of 101
building tree 80 of 101
building tree 81 of 101
building tree 82 of 101
building tree 83 of 101
building tree 84 of 101
building tree 85 of 101
building tree 86 of 101
building tree 87 of 101
building tree 88 of 101
building tree 89 of 101
building tree 90 of 101
building tree 91 of 101
building tree 92 of 101
building tree 93 of 101
building tree 94 of 101
building tree 95 of 101
building tree 96 of 101
building tree 97 of 101
building tree 98 of 101
building tree 99 of 101
building tree 100 of 101
building tree 101 of 101

[Parallel(n_jobs=1)]: Done 101 out of 101 | elapsed: 1.8min finished

Out [5]: RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
criterion='entropy', max_depth=None, max_features='sqrt',
max_leaf_nodes=None, max_samples=None,
min_impurity_decrease=0.0, min_impurity_split=None,
min_samples_leaf=1, min_samples_split=2,
min_weight_fraction_leaf=0.0, n_estimators=101,
n_jobs=None, oob_score=False, random_state=None,
verbose=2, warm_start=False)
```

```
In [6]: prediction_test = clf.predict(X_test)

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 1 out of 1 | elapsed: 0.0s remaining: 0.0s
[Parallel(n_jobs=1)]: Done 101 out of 101 | elapsed: 0.5s finished
```

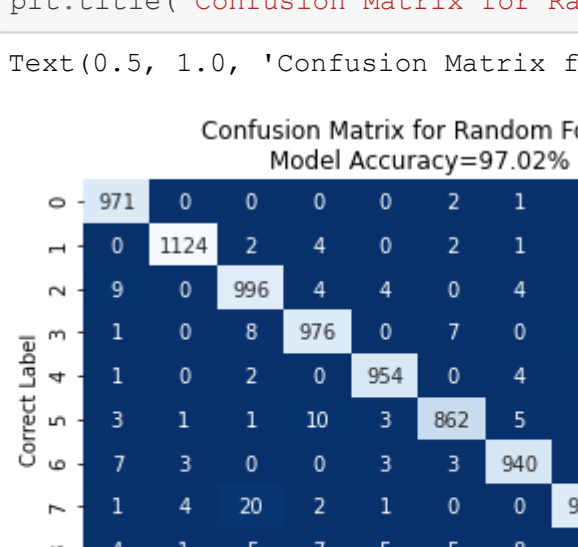
```
In [7]: acc = accuracy_score(y_test,prediction_test)
acc

Out [7]: 0.9702
```

```
In [15]: n_est=101

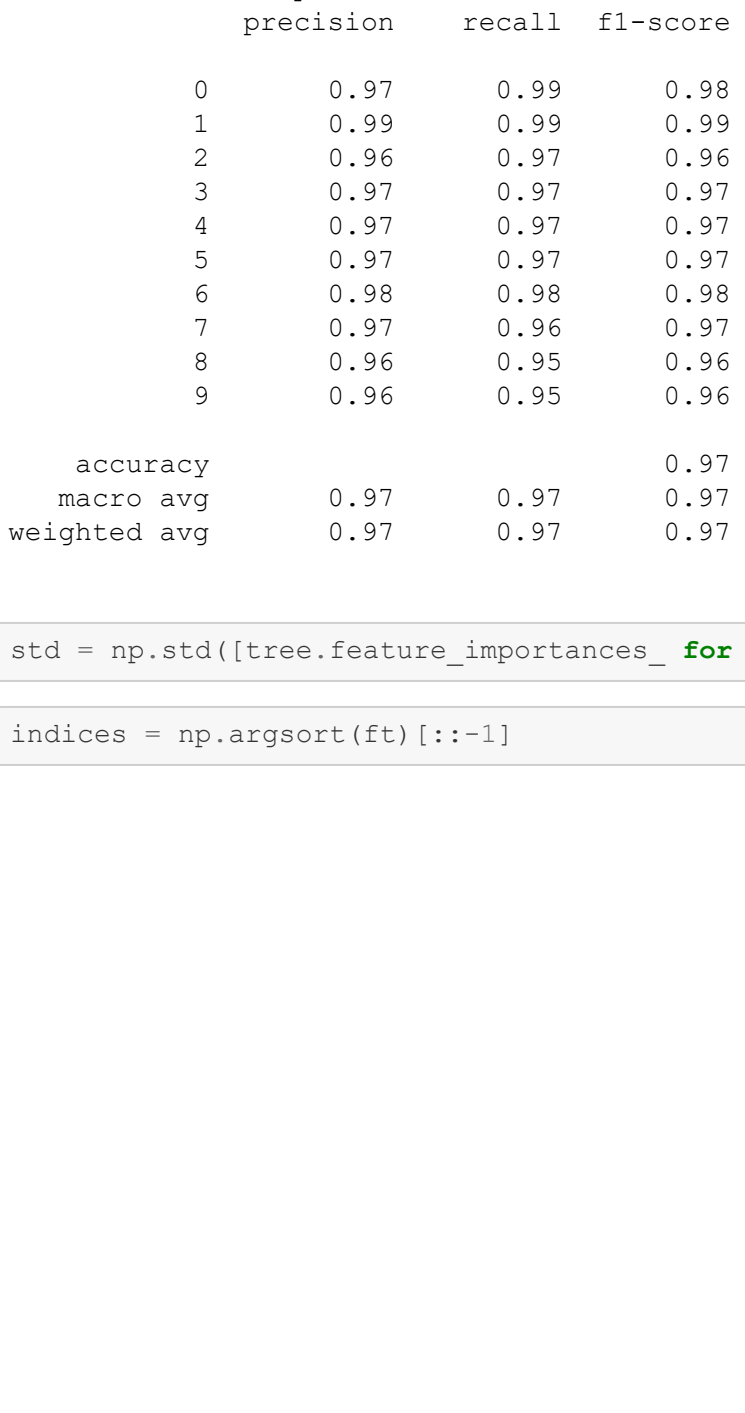
In [16]: ft = clf.feature_importances_
ft = ft*1500
plt.imshow(ft.reshape((28,28)))
plt.title("Feature Importances learnt via Random Forest Classifier\nCriterion: Entropy, n_estimators={}\nTest Accuracy={}%".format(n_est,acc*100))

Out [16]: Text(0.5, 1.0, 'Feature Importances learnt via Random Forest Classifier\nCriterion: Entropy, n_estimators=101\nTest Accuracy=97.02%')
```



```
In [17]: sns.heatmap(confusion_matrix(y_test,prediction_test),cmap='Blues_r',fmt='',annot=True, char=False)
plt.ylabel("Correct Label")
plt.xlabel("Predicted Label")
plt.title("Confusion Matrix for Random Forest\nModel Accuracy={}%".format(acc*100))

Out [17]: Text(0.5, 1.0, 'Confusion Matrix for Random Forest\nModel Accuracy=97.02%')
```



```
In [18]: print("Classification Report for Random Forest:\n").format(classification_report(y_test,prediction_test))

Classification Report for Random Forest:
              precision    recall  f1-score   support

0               0.97         0.99         0.98         980
1               0.99         0.99         0.99         1195
2               0.96         0.97         0.96         1032
3               0.97         0.97         0.97         1010
4               0.97         0.97         0.97          902
5               0.97         0.97         0.97          892
6               0.98         0.98         0.98          958
7               0.97         0.96         0.97         1028
8               0.96         0.95         0.96          974
9               0.96         0.95         0.96         1009

accuracy               0.97
macro avg              0.97
weighted avg           0.97
```

```
In [19]: std = np.std((tree.feature_importances_ for tree in clf.estimators_),axis=0)

In [20]: indices = np.argsort(ft)[::-1]
```



```
def train(train_data, test_data):  
    for f in range(X_train.shape[1]):  
        print("f: {} Feature (f) = {}".format(f+1, indices[f], ft(indices[f])))
```

```
Feature Ranking:  
1 Feature 405: 0.3003702484978864  
2 Feature 378: 0.26637576752742723  
3 Feature 350: 0.26637576752742723  
4 Feature 462: 0.2654963276835312  
5 Feature 433: 0.2654963276835312  
6 Feature 377: 0.245506713075428  
7 Feature 155: 0.23629958758568666  
8 Feature 499: 0.2334839581534282  
9 Feature 381: 0.2299168209319677  
10 Feature 346: 0.22574776694027231  
11 Feature 541: 0.213921406676512  
12 Feature 402: 0.213921406676512  
13 Feature 570: 0.20800121517259066  
14 Feature 347: 0.2058653224851144  
15 Feature 432: 0.2046318256240538  
16 Feature 437: 0.19476621327790932  
17 Feature 406: 0.1927661987020204  
18 Feature 154: 0.1914597013851408  
19 Feature 569: 0.18940400531951122  
20 Feature 567: 0.18940400531951122  
21 Feature 153: 0.188017059093061  
22 Feature 461: 0.18799057107125393  
23 Feature 461: 0.182249592183716093  
24 Feature 568: 0.18138964749316713  
25 Feature 188: 0.1774923541384648  
26 Feature 381: 0.1749349253196677  
27 Feature 434: 0.17315112680460388  
28 Feature 187: 0.1684306293268587  
29 Feature 434: 0.1677948162793042  
30 Feature 624: 0.156124948748528508  
31 Feature 515: 0.15480135113966544  
32 Feature 517: 0.15280218911273136  
33 Feature 319: 0.15228028693401657  
34 Feature 374: 0.15122351808635446  
35 Feature 118: 0.149359355484862  
36 Feature 114: 0.149359355484862  
37 Feature 429: 0.14786659033740037  
38 Feature 303: 0.14517531543192925  
39 Feature 402: 0.14517531543192925  
40 Feature 373: 0.14368937050000018  
41 Feature 486: 0.14200054820564532  
42 Feature 189: 0.14192327650271914  
43 Feature 490: 0.137760940656571  
44 Feature 409: 0.1344963286351538  
45 Feature 128: 0.1342920184639548  
46 Feature 429: 0.1342920184639548  
47 Feature 437: 0.1330542264081947  
48 Feature 116: 0.13248287516774273  
49 Feature 402: 0.13248287516774273  
50 Feature 379: 0.13099103806891  
51 Feature 657: 0.1294575185766185  
52 Feature 730: 0.12735485117225438  
53 Feature 298: 0.127333982668682  
54 Feature 187: 0.12671017779624573  
55 Feature 501: 0.125407356742075  
56 Feature 498: 0.125407356742075  
57 Feature 317: 0.1245740948962202  
58 Feature 656: 0.124216820041928  
59 Feature 547: 0.1240218911273136  
60 Feature 655: 0.1227703414064668  
61 Feature 400: 0.12092787629187818  
62 Feature 189: 0.1207948625120223  
63 Feature 429: 0.1207948625120223  
64 Feature 404: 0.1207424925074551  
65 Feature 112: 0.11595769140463288  
66 Feature 189: 0.11595769140463288  
67 Feature 289: 0.1149024971482189  
68 Feature 349: 0.1143868249115504  
69 Feature 188: 0.11437721650221279  
70 Feature 376: 0.1137255595025784  
71 Feature 625: 0.11206270328073  
72 Feature 511: 0.1103462501874842  
73 Feature 137: 0.109568132161373  
74 Feature 323: 0.108436990944318  
75 Feature 571: 0.10842692915379232  
76 Feature 590: 0.10842692915379232  
77 Feature 380: 0.1072088483408064  
78 Feature 485: 0.10714654058929403  
79 Feature 193: 0.10573493261326213  
80 Feature 298: 0.10573493261326213  
81 Feature 654: 0.10544299885742404  
82 Feature 137: 0.10544299885742404  
83 Feature 351: 0.1036697059083013  
84 Feature 210: 0.10237588163773504  
85 Feature 591: 0.10237588163773504  
86 Feature 626: 0.10078059400700239  
87 Feature 544: 0.1005759876679948  
88 Feature 117: 0.1003399104638784  
89 Feature 128: 0.1003399104638784  
90 Feature 463: 0.99967291609767  
91 Feature 182: 0.99327533474541  
92 Feature 561: 0.984291864782593  
93 Feature 438: 0.9823579831413356  
94 Feature 382: 0.9556792515822713  
95 Feature 378: 0.9523762154265438  
96 Feature 298: 0.9518247653578  
97 Feature 348: 0.9438247653578  
98 Feature 322: 0.932300013679023  
99 Feature 407: 0.914929391147393  
100 Feature 345: 0.91010136292133  
101 Feature 407: 0.91010136292133  
102 Feature 345: 0.91010136292133  
103 Feature 517: 0.889261464795282  
104 Feature 513: 0.889261464795282  
105 Feature 183: 0.8734992578786361  
106 Feature 265: 0.864400162801524  
107 Feature 298: 0.8574700608998191  
108 Feature 658: 0.8569135074657655  
109 Feature 275: 0.848386915984733  
110 Feature 275: 0.848386915984733  
111 Feature 436: 0.846275966713326  
112 Feature 320: 0.846064918021298  
113 Feature 591: 0.8459139244031936  
114 Feature 483: 0.8389666641925545  
115 Feature 295: 0.8319341692021412  
116 Feature 205: 0.8243930519310739  
117 Feature 429: 0.8243930519310739  
118 Feature 266: 0.8210485050187313  
119 Feature 468: 0.81835967446609  
120 Feature 321: 0.8127744820547344  
121 Feature 325: 0.808494202385217  
122 Feature 236: 0.805483858471407  
123 Feature 523: 0.8026505316253154  
124 Feature 264: 0.8016946459597  
125 Feature 234: 0.798028112880713  
126 Feature 659: 0.797925871661928  
127 Feature 187: 0.7950139244031936  
128 Feature 242: 0.791088077614804  
129 Feature 184: 0.79089667526791  
130 Feature 187: 0.79089667526791  
131 Feature 292: 0.765331136576724  
132 Feature 180: 0.760159966358769  
133 Feature 595: 0.7571457836256213  
134 Feature 298: 0.7545914587386887  
135 Feature 321: 0.7276065439770703  
136 Feature 265: 0.726420573478201  
137 Feature 591: 0.726420573478201  
138 Feature 455: 0.7141068703700081  
139 Feature 181: 0.706851863018542  
140 Feature 572: 0.70644609718935  
141 Feature 262: 0.695862878240195  
142 Feature 373: 0.695862878240195  
143 Feature 591: 0.695862878240195  
144 Feature 272: 0.6846581921191762  
145 Feature 178: 0.681474303739387  
146 Feature 241: 0.681474303739387  
147 Feature 241: 0.670413670560174  
148 Feature 491: 0.664996741423467  
149 Feature 349: 0.6573749231625438  
150 Feature 593: 0.6573749231625438  
151 Feature 213: 0.6456601922940932  
152 Feature 545: 0.6412026193205847  
153 Feature 657: 0.6408264886105395  
154 Feature 627: 0.6381720630946188  
155 Feature 627: 0.6329703220771782  
156 Feature 591: 0.6329703220771782  
157 Feature 327: 0.6169092400557707  
158 Feature 293: 0.61558770503010095  
159 Feature 235: 0.59339625789864  
160 Feature 429: 0.59339625789864  
161 Feature 577: 0.584089541370546  
162 Feature 207: 0.584089541370546  
163 Feature 185: 0.57506130512903226  
164 Feature 518: 0.5735499320950978  
165 Feature 559: 0.5702063216305375  
166 Feature 399: 0.565845337324676  
167 Feature 427: 0.564498043886769  
168 Feature 566: 0.5634923934930596  
169 Feature 590: 0.56771314620386276  
170 Feature 467: 0.5648965986473  
171 Feature 214: 0.5573060491934551  
172 Feature 657: 0.5569454175024963  
173 Feature 300: 0.5438103528925813  
174 Feature 151: 0.543304011251244  
175 Feature 208: 0.54236231606162  
176 Feature 208: 0.54236231606162  
177 Feature 410: 0.52854672246208885  
178 Feature 523: 0.524702870297584  
179 Feature 590: 0.524702870297584  
180 Feature 344: 0.5132809754411673  
181 Feature 288: 0.501635148231453  
182 Feature 494: 0.501635148231453  
183 Feature 494: 0.501635148231453  
184 Feature 576: 0.497457565189375  
185 Feature 576: 0.497457565189375  
186 Feature 576: 0.497457565189375  
187 Feature 625: 0.493621293988325  
188 Feature 323: 0.49114154586535236  
189 Feature 261: 0.49039158674602875  
190 Feature 87: 0.49039158674602875  
191 Feature 127: 0.485044934266234  
192 Feature 329: 0.481806770171179  
193 Feature 593: 0.481806770171179  
194 Feature 359: 0.47237529530982  
195 Feature 205: 0.4699512441789868  
196 Feature 328: 0.4673528703619233  
197 Feature 180: 0.4673528703619233  
198 Feature 519: 0.4524064659504876  
199 Feature 178: 0.4538859765384048  
200 Feature 81: 0.4538859765384048  
201 Feature 573: 0.4492459317183974  
202 Feature 600: 0.4390870154673696  
203 Feature 412: 0.43742321606162  
204 Feature 442: 0.43742321606162  
205 Feature 628: 0.4335464276545512  
206 Feature 603: 0.431347108721687  
207 Feature 749: 0.431347108721687  
208 Feature 492: 0.425501314088315  
209 Feature 186: 0.4155268893529496  
210 Feature 591: 0.4155268893529496  
211 Feature 684: 0.40770110248491625  
212 Feature 356: 0.397837100927616  
213 Feature 383: 0.395752362520246  
214 Feature 612: 0.395752362520246  
215 Feature 469: 0.395752362520246  
216 Feature 469: 0.395752362520246  
217 Feature 575: 0.3871158092112024  
218 Feature 87: 0.3871158092112024  
219 Feature 493: 0.375222157516047  
220 Feature 331: 0.3748943509939374  
221 Feature 501: 0.3730762154265438  
222 Feature 660: 0.3622818263406844  
223 Feature 631: 0.3622818263406844  
224 Feature 187: 0.357073366387466  
225 Feature 685: 0.357073366387466  
226 Feature 385: 0.3494501449409353  
227 Feature 357: 0.3494501449409353  
228 Feature 150: 0.3489321935819596  
229 Feature 622: 0.3489321935819596  
230 Feature 244: 0.3464792551022  
231 Feature 159: 0.3464792551022  
232 Feature 605: 0.34479848483954  
233 Feature 520: 0.3322290432013327  
234 Feature 547: 0.3322290432013327  
235 Feature 629: 0.3322290432013327  
236 Feature 468: 0.326841723482846  
237 Feature 468: 0.326841723482846  
238 Feature 403: 0.326841723482846  
239 Feature 403: 0.326841723482846  
240 Feature 403: 0.326841723482846  
241 Feature 403: 0.326841723482846  
242 Feature 403: 0.326841723482846  
243 Feature 384: 0.31807671143266177  
244 Feature 181: 0.31807671143266177  
245 Feature 357: 0.3170721460912026  
246 Feature 495: 0.3133673490238127  
247 Feature 187: 0.3133673490238127  
248 Feature 622: 0.3133673490238127  
249 Feature 603: 0.3133673490238127  
250 Feature 683: 0.298474829469879  
251 Feature 548: 0.298474829469879  
252 Feature 622: 0.298474829469879  
253 Feature 273: 0.298474829469879  
254 Feature 552: 0.298474829469879  
255 Feature 177: 0.288772646689713  
256 Feature 125: 0.28639795153589  
257 Feature 594: 0.28639795153589  
258 Feature 622: 0.28639795153589  
259 Feature 622: 0.28639795153589  
260 Feature 99: 0.2713361705592605  
261 Feature 709: 0.2713361705592605  
262 Feature 217: 0.2696805172001703  
263 Feature 287: 0.268337525483323  
264 Feature 627: 0.268337525483323  
265 Feature 412: 0.263458823141766  
266 Feature 124: 0.2629937058432042  
267 Feature 607: 0.261167651947453  
268 Feature 607: 0.261167651947453  
269 Feature 440: 0.2546821450478846  
270 Feature 218: 0.2546821450478846  
271 Feature 643: 0.2546821450478846  
272 Feature 632: 0.2546821450478846  
273 Feature 710: 0.243813907247976  
274 Feature 189: 0.243813907247976  
275 Feature 623: 0.243813907247976  
276 Feature 524: 0.243813907247976  
277 Feature 524: 0.243813907247976  
278 Feature 663: 0.243813907247976  
279 Feature 781: 0.243813907247976  
280 Feature 622: 0.243813907247976  
281 Feature 315: 0.243813907247976  
282 Feature 246: 0.2233413058954663  
283 Feature 274: 0.2233413058954663  
284 Feature 213: 0.2233413058954663  
285 Feature 101: 0.2210451853384302  
286 Feature 370: 0.2210451853384302  
287 Feature 757: 0.2210451853384302  
288 Feature 370: 0.2210451853384302  
289 Feature 757: 0.2210451853384302  
290 Feature 651: 0.218579556611927  
291 Feature 688: 0.218579556611927  
292 Feature 176: 0.218579556611927  
293 Feature 232: 0.2132788258278843  
294 Feature 388: 0.2129432768139482  
295 Feature 615: 0.2129432768139482  
296 Feature 149: 0.2129432768139482  
297 Feature 247: 0.2129432768139482  
298 Feature 247: 0.2129432768139482  
299 Feature 247: 0.2129432768139482  
300 Feature 682: 0.2122064805940816  
301 Feature 190: 0.2122064805940816  
302 Feature 189: 0.2122064805940816  
303 Feature 442: 0.2122064805940816  
304 Feature 553: 0.2122064805940816  
305 Feature 608: 0.2122064805940816  
306 Feature 167: 0.2122064805940816  
307 Feature 525: 0.2122064805940816  
308 Feature 470: 0.2122064805940816  
309 Feature 149: 0.2122064805940816  
310 Feature 581: 0.2122064805940816  
311 Feature 102: 0.2122064805940816  
312 Feature 166: 0.2122064805940816  
313 Feature 340: 0.2122064805940816  
314 Feature 414: 0.2122064805940816  
315 Feature 757: 0.2122064805940816  
316 Feature 130: 0.2122064805940816  
317 Feature 711: 0.2122064805940816  
318 Feature 130: 0.2122064805940816  
319 Feature 593: 0.2122064805940816  
320 Feature 509: 0.2122064805940816  
321 Feature 709: 0.2122064805940816  
322 Feature 122: 0.2122064805940816  
323 Feature 643: 0.2122064805940816  
324 Feature 275: 0.2122064805940816  
325 Feature 680: 0.2122064805940816  
326 Feature 470: 0.2122064805940816  
327 Feature 231: 0.2122064805940816  
328 Feature 314: 0.2122064805940816  
329 Feature 623: 0.2122064805940816  
330 Feature 524: 0.2122064805940816  
331 Feature 103: 0.2122064805940816  
332 Feature 123: 0.2122064805940816  
333 Feature 660: 0.2122064805940816  
334 Feature 101: 0.2122064805940816  
335 Feature 370: 0.2122064805940816  
336 Feature 757: 0.2122064805940816  
337 Feature 651: 0.2122064805940816  
338 Feature 130: 0.2122064805940816  
339 Feature 130: 0.2122064805940816  
340 Feature 509: 0.2122064805940816  
341 Feature 709: 0.2122064805940816  
342 Feature 122: 0.2122064805940816  
343 Feature 643: 0.2122064805940816  
344 Feature 275: 0.2122064805940816  
345 Feature 680: 0.2122064805940816  
346 Feature 470: 0.2122064805940816  
347 Feature 231: 0.2122064805940816  
348 Feature 314: 0.2122064805940816  
349 Feature 623: 0.2122064805940816  
350 Feature 524: 0.2122064805940816  
351 Feature 103: 0.2122064805940816  
352 Feature 123: 0.2122064805940816  
353 Feature 660: 0.2122064805940816  
354 Feature 101: 0.2122064805940816  
355 Feature 370: 0.2122064805940816  
356 Feature 757: 0.2122064805940816  
357 Feature 651: 0.2122064805940816  
358 Feature 130: 0.2122064805940816  
359 Feature 130: 0.2122064805940816  
360 Feature 509: 0.2122064805940816  
361 Feature 709: 0.2122064805940816  
362 Feature 122: 0.2122064805940816  
363 Feature 643: 0.2122064805940816  
364 Feature 275: 0.2122064805940816  
365 Feature 680: 0.2122064805940816  
366 Feature 470: 0.2122064805940816  
367 Feature 231: 0.2122064805940816  
368 Feature 314: 0.2122064805940816  
369 Feature 623: 0.2122064805940816  
370 Feature 524: 0.2122064805940816  
371 Feature 103: 0.2122064805940816  
372 Feature 123: 0.2122064805940816  
373 Feature 660: 0.2122064805940816  
374 Feature 101: 0.2122064805940816  
375 Feature 370: 0.2122064805940816  
376 Feature 757: 0.2122064805940816  
377 Feature 651: 0.2122064805940816  
378 Feature 130: 0.2122064805940816  
379 Feature 130: 0.2122064805940816  
380 Feature 509: 0.2122064805940816  
381 Feature 709: 0.2122064805940816  
382 Feature 122: 0.2122064805940816  
383 Feature 643: 0.2122064805940816  
384 Feature 275: 0.2122064805940816  
385 Feature 680: 0.2122064805940816  
386 Feature 470: 0.2122064805940816  
387 Feature 231: 0.2122064805940816  
388 Feature 314: 0.2122064805940816  
389 Feature 623: 0.2122064805940816  
390 Feature 524: 0.2122064805940816  
391 Feature 103: 0.2122064805940816  
392 Feature 123: 0.2122064805940816  
393 Feature 660: 0.2122064805940816  
394 Feature 101: 0.2122064805940816  
395 Feature 370: 0.2122064805940816  
396 Feature 757: 0.2122064805940816  
397 Feature 651: 0.2122064805940816  
398 Feature 130: 0.2122064805940816  
399 Feature 130: 0.2122064805940816  
400 Feature 509: 0.2122064805940816  
401 Feature 709: 0.2122064805940816  
402 Feature 122: 0.2122064805940816  
403 Feature 643: 0.2122064805940816  
404 Feature 275: 0.2122064805940816  
405 Feature 680: 0.2122064805940816  
406 Feature 470: 0.2122064805940816  
407 Feature 231: 0.2122064805940816  
408 Feature 314: 0.2122064805940816  
409 Feature 623: 0.2122064805940816  
410 Feature 524: 0.2122064805940816  
411 Feature 103: 0.2122064805940816  
412 Feature 123: 0.2122064805940816  
413 Feature 660: 0.2122064805940816  
414 Feature 101: 0.2122064805940816  
415 Feature 370: 0.2122064805940816  
416 Feature 757: 0.21220648
```