

# Decision Boundary Homework

```
In [24]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import accuracy_score, confusion_matrix
```

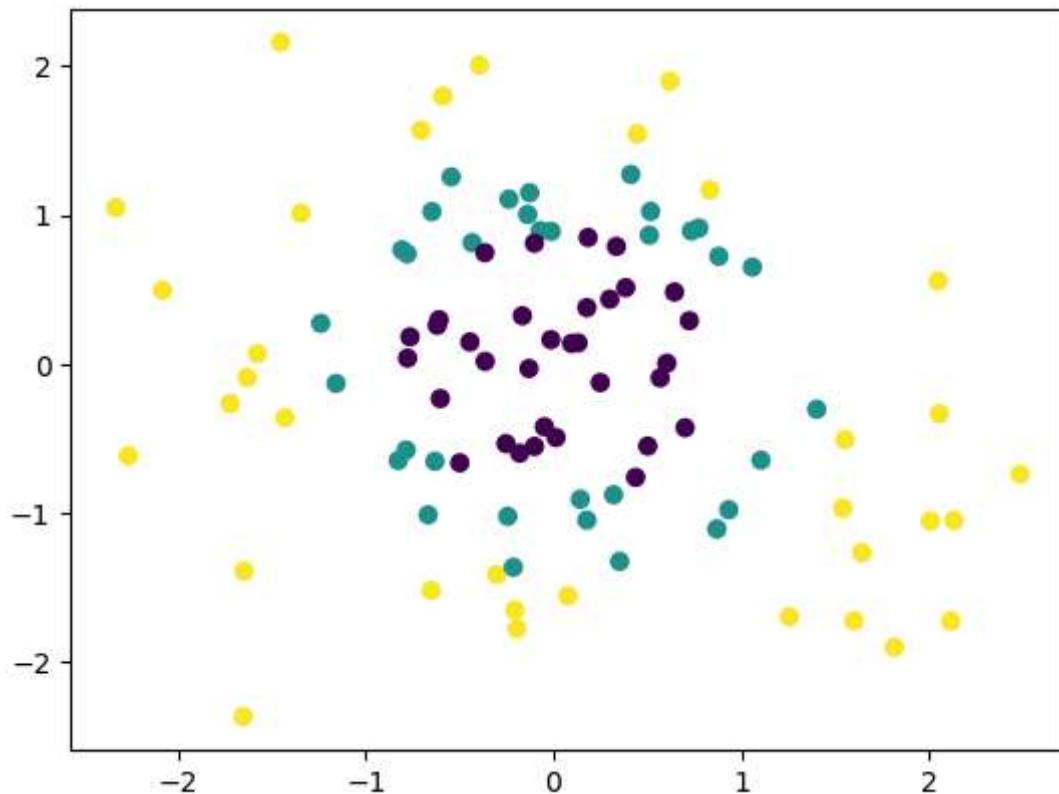
Sklearn has a couple of "standard" example data generators for use in working with classification models, these are some models used to synthesize data for practice purposes. Below are a couple of examples.

These are both pretty simple, they are using just two variables

```
In [ ]: from sklearn.datasets import make_gaussian_quantiles, make_classification

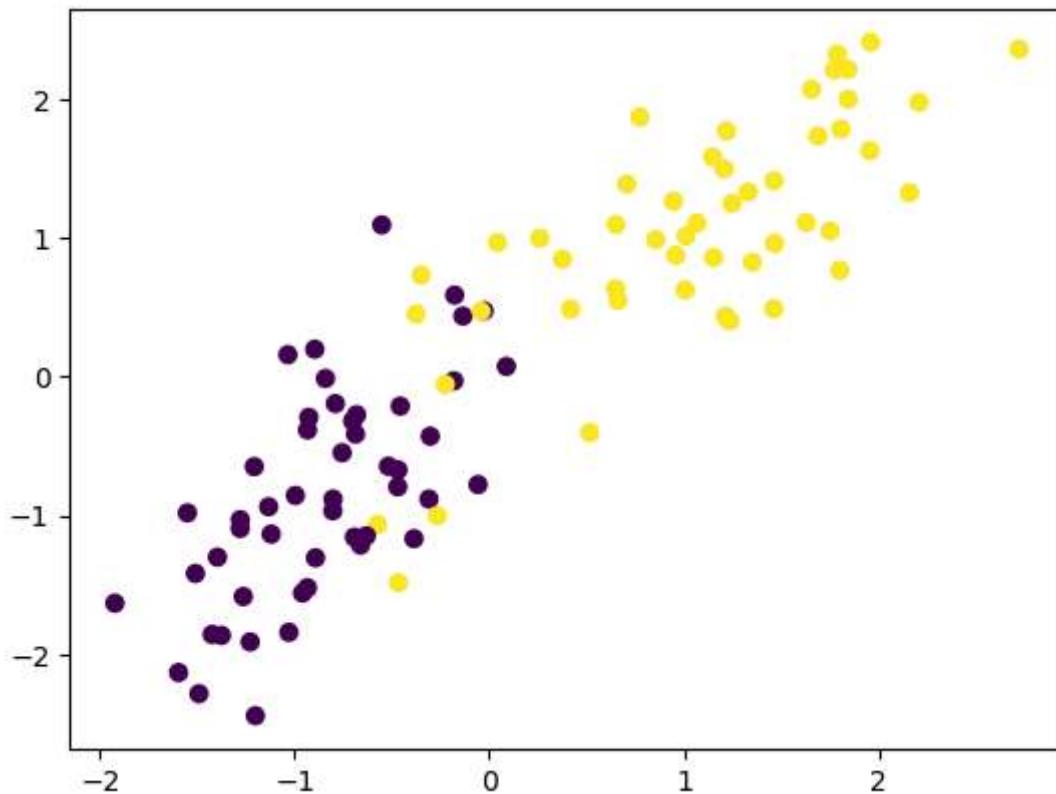
X,y=make_gaussian_quantiles(n_features=2, n_classes=3)
plt.scatter(X[:,0],X[:,1], c=y)

Out[ ]: <matplotlib.collections.PathCollection at 0x7b47c3fd4940>
```



```
In [ ]: X1, y1 = make_classification(
    n_features=2, n_redundant=0, n_informative=2, n_clusters_per_class=1
)
plt.scatter(X1[:,0],X1[:,1], c=y1)
```

Out[ ]: &lt;matplotlib.collections.PathCollection at 0x7b47c1eccd60&gt;



## Question/Action

- For each of these data sets,  $(X, y)$  and  $(X_1, y_1)$

a.) Generate two test sets  $(X_{\text{test}}, y_{\text{test}}), (X_1_{\text{test}}, y_1_{\text{test}})$ , by running the generators again, with the same parameters. This will generate test sets with the same distributions but different values.

b.) Build some a number of classifiers for each set -logistic -the logistic again, but add columns for  $X_1^2$  and  $X_2^2$  as predictors -neural net -random forest -two different boosted methods

Do some basic hyperparameter searches on each model (except the logistic)

c.) Write a function that will allow you to pass in the model and the  $X, y$  set and then generate from that a plot of the decision boundary for the example

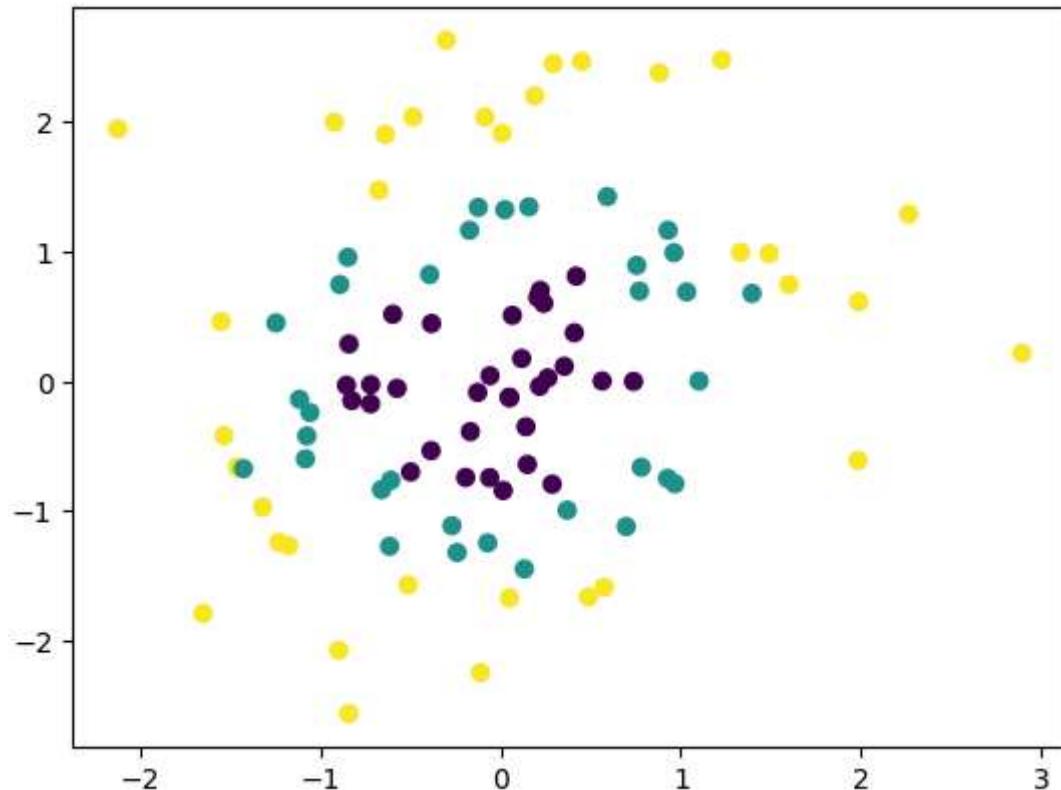
d.) Use your function to plot out the decision boundaries for each of your models and for the two data sets

e.) Based on your examination of the two data sets and the resulting plots, what can you say about the nature of the models? -which of them can generate curved boundaries? Which are all straight line boundaries? -which looks most severely overfit?

a.) Generate two test sets ( $X\_test$ ,  $y\_test$ ), ( $X1\_test$ ,  $y1\_test$ ), by running the generators again, with the same parameters. This will generate test sets with the same distributions but different values.

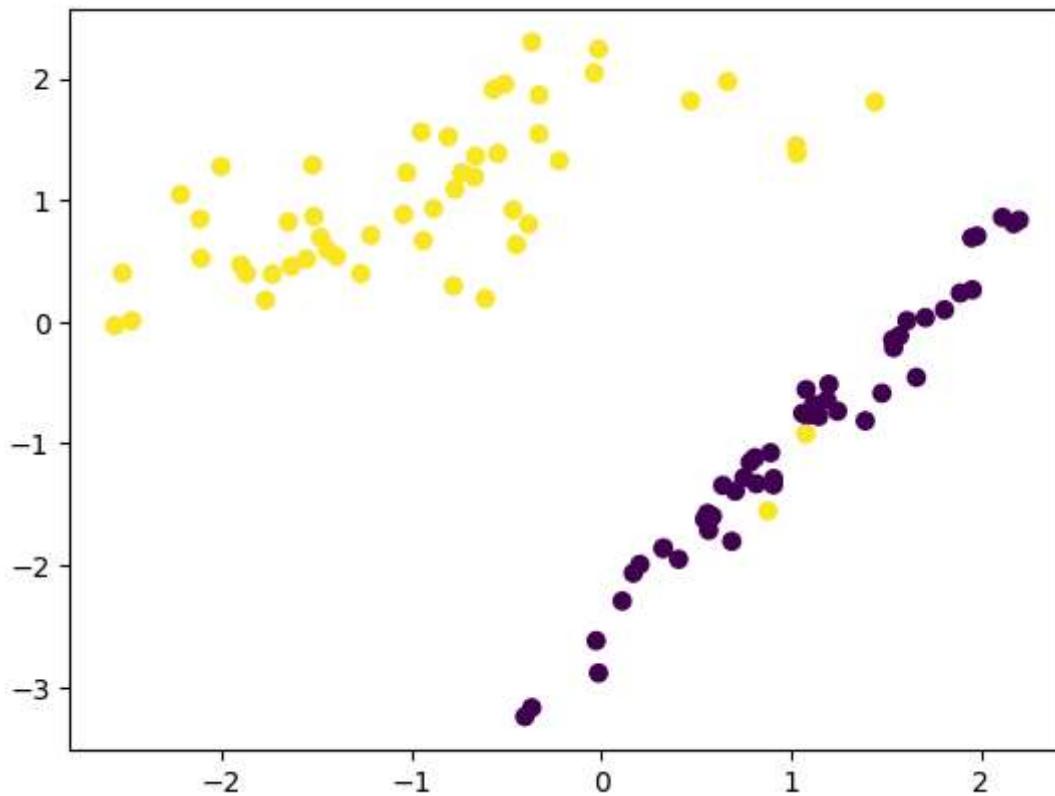
```
In [ ]: X_test,y_test=make_gaussian_quantiles(n_features=2, n_classes=3)
plt.scatter(X_test[:,0],X_test[:,1], c=y_test)
```

```
Out[ ]: <matplotlib.collections.PathCollection at 0x7b47c1d70e50>
```



```
In [ ]: X1_test, y1_test = make_classification(
    n_features=2, n_redundant=0, n_informative=2, n_clusters_per_class=1
)
plt.scatter(X1_test[:,0],X1_test[:,1], c=y1_test)
```

```
Out[ ]: <matplotlib.collections.PathCollection at 0x7b47c1de5630>
```



b.) Build some a number of classifiers for each set -logistic -the logistic again, but add columns for  $X_1^2$  and  $X_2^2$  as predictors -neural net -random forest -two different boosted methods

```
In [31]: from sklearn.linear_model import LogisticRegression

modelLogistic1 = LogisticRegression()
# fit the model
modelLogistic1.fit(X, y)

modelLogistic1_pred = modelLogistic1.predict(X_test)
print (accuracy_score(y_test,modelLogistic1_pred))

modelLogistic2 = LogisticRegression()
# fit the model
modelLogistic2.fit(X1, y1)

modelLogistic2_pred = modelLogistic2.predict(X1_test)
print (accuracy_score(y1_test,modelLogistic2_pred))

#modelLogistic1 = LogisticRegression()
# fit the model
#modelLogistic1.fit(X_test, y_test)

#modelLogistic1 = LogisticRegression()
# fit the model
#modelLogistic1.fit(X1_test, y1_test)

0.33
0.25
```

```
In [78]: modelLogisticV1 = LogisticRegression()
# fit the model
#modelLogisticV1.fit(np.concatenate((X,X**2),axis=1), y)
modelLogisticV1.fit(X**2, y)
modelLogisticV1_pred = modelLogisticV1.predict(X_test**2)

modelLogisticV2 = LogisticRegression()
# fit the model
#modelLogisticV2.fit(np.concatenate((X1,X1**2),axis=1), y1)
modelLogisticV2.fit(X1**2, y1)

modelLogisticV2_pred = modelLogisticV2.predict(X1_test**2)

print (accuracy_score(y_test,modelLogisticV1_pred))
print (accuracy_score(y1_test,modelLogisticV2_pred))

#modelLogisticV3 = LogisticRegression()
# fit the model
#modelLogisticV3.fit(np.concatenate((X_test,X_test**2),axis=1), y_test)

#modelLogisticV4 = LogisticRegression()
# fit the model
#modelLogisticV4.fit(np.concatenate((X1_test,X1_test**2),axis=1), y1_test)
```

0.95  
0.47

```
In [26]: # Nural Net

from sklearn.neural_network import MLPClassifier
clf = MLPClassifier(solver='adam', alpha=1e-5, random_state=1, batch_size=int(min(200,
clf.fit(X, y)

clf_pred = clf.predict(X_test)

clf1 = MLPClassifier(solver='adam', alpha=1e-5, random_state=1, batch_size=int(min(200
clf1.fit(X1, y1)

#clf2 = MLPClassifier(solver='adam', alpha=1e-5, random_state=1, batch_size=int(min(200
#clf2.fit(X1_test, y1_test)

#clf3 = MLPClassifier(solver='adam', alpha=1e-5, random_state=1, batch_size=int(min(200
#clf3.fit(X_test, y_test)
clf1_pred = clf1.predict(X1_test)

print (accuracy_score(y_test,clf_pred))
print (accuracy_score(y1_test,clf1_pred))
```

```
Iteration 1, loss = 1.25246050
Iteration 2, loss = 1.24335680
Iteration 3, loss = 1.23481095
Iteration 4, loss = 1.22736959
Iteration 5, loss = 1.21855166
Iteration 6, loss = 1.21241563
Iteration 7, loss = 1.20435838
Iteration 8, loss = 1.19792055
Iteration 9, loss = 1.19154283
Iteration 10, loss = 1.18510584
Iteration 11, loss = 1.17988901
Iteration 12, loss = 1.17455877
Iteration 13, loss = 1.16931349
Iteration 14, loss = 1.16389207
Iteration 15, loss = 1.15928525
Iteration 16, loss = 1.15448941
Iteration 17, loss = 1.15027063
Iteration 18, loss = 1.14645438
Iteration 19, loss = 1.14242135
Iteration 20, loss = 1.13865470
Iteration 21, loss = 1.13492207
Iteration 22, loss = 1.13115301
Iteration 23, loss = 1.12851923
Iteration 24, loss = 1.12577570
Iteration 25, loss = 1.12283303
Iteration 26, loss = 1.12006514
Iteration 27, loss = 1.11770219
Iteration 28, loss = 1.11504854
Iteration 29, loss = 1.11321852
Iteration 30, loss = 1.11116315
Iteration 31, loss = 1.10886888
Iteration 32, loss = 1.10662199
Iteration 33, loss = 1.10461667
Iteration 34, loss = 1.10267922
Iteration 35, loss = 1.10051415
Iteration 36, loss = 1.09915126
Iteration 37, loss = 1.09692967
Iteration 38, loss = 1.09515320
Iteration 39, loss = 1.09367074
Iteration 40, loss = 1.09208283
Iteration 41, loss = 1.09018441
Iteration 42, loss = 1.08870233
Iteration 43, loss = 1.08710978
Iteration 44, loss = 1.08564877
Iteration 45, loss = 1.08403840
Iteration 46, loss = 1.08242289
Iteration 47, loss = 1.08125746
Iteration 48, loss = 1.07965247
Iteration 49, loss = 1.07836416
Iteration 50, loss = 1.07683799
Iteration 51, loss = 1.07558825
Iteration 52, loss = 1.07425664
Iteration 53, loss = 1.07296738
Iteration 54, loss = 1.07180178
Iteration 55, loss = 1.07057006
Iteration 56, loss = 1.06926535
Iteration 57, loss = 1.06804552
Iteration 58, loss = 1.06703266
Iteration 59, loss = 1.06574486
Iteration 60, loss = 1.06464938
```

Iteration 61, loss = 1.06376947  
Iteration 62, loss = 1.06257155  
Iteration 63, loss = 1.06150681  
Iteration 64, loss = 1.06042712  
Iteration 65, loss = 1.05951102  
Iteration 66, loss = 1.05869288  
Iteration 67, loss = 1.05767156  
Iteration 68, loss = 1.05675483  
Iteration 69, loss = 1.05601314  
Iteration 70, loss = 1.05500674  
Iteration 71, loss = 1.05418258  
Iteration 72, loss = 1.05339048  
Iteration 73, loss = 1.05257425  
Iteration 74, loss = 1.05161894  
Iteration 75, loss = 1.05078457  
Iteration 76, loss = 1.04998513  
Iteration 77, loss = 1.04906744  
Iteration 78, loss = 1.04831507  
Iteration 79, loss = 1.04757111  
Iteration 80, loss = 1.04681259  
Iteration 81, loss = 1.04602185  
Iteration 82, loss = 1.04536258  
Iteration 83, loss = 1.04456407  
Iteration 84, loss = 1.04386307  
Iteration 85, loss = 1.04309754  
Iteration 86, loss = 1.04231076  
Iteration 87, loss = 1.04147983  
Iteration 88, loss = 1.04072762  
Iteration 89, loss = 1.03990747  
Iteration 90, loss = 1.03918973  
Iteration 91, loss = 1.03829139  
Iteration 92, loss = 1.03743520  
Iteration 93, loss = 1.03661249  
Iteration 94, loss = 1.03571958  
Iteration 95, loss = 1.03480495  
Iteration 96, loss = 1.03351158  
Iteration 97, loss = 1.03256882  
Iteration 98, loss = 1.03162066  
Iteration 99, loss = 1.03059322  
Iteration 100, loss = 1.02969212  
Iteration 101, loss = 1.02880152  
Iteration 102, loss = 1.02793867  
Iteration 103, loss = 1.02682509  
Iteration 104, loss = 1.02585497  
Iteration 105, loss = 1.02498605  
Iteration 106, loss = 1.02416248  
Iteration 107, loss = 1.02318925  
Iteration 108, loss = 1.02239779  
Iteration 109, loss = 1.02146280  
Iteration 110, loss = 1.02059435  
Iteration 111, loss = 1.01970278  
Iteration 112, loss = 1.01885905  
Iteration 113, loss = 1.01783398  
Iteration 114, loss = 1.01684218  
Iteration 115, loss = 1.01601598  
Iteration 116, loss = 1.01533525  
Iteration 117, loss = 1.01429876  
Iteration 118, loss = 1.01352410  
Iteration 119, loss = 1.01257397  
Iteration 120, loss = 1.01176006

```
Iteration 121, loss = 1.01088186
Iteration 122, loss = 1.01007506
Iteration 123, loss = 1.00923703
Iteration 124, loss = 1.00848318
Iteration 125, loss = 1.00756067
Iteration 126, loss = 1.00667551
Iteration 127, loss = 1.00578605
Iteration 128, loss = 1.00480749
Iteration 129, loss = 1.00397244
Iteration 130, loss = 1.00296579
Iteration 131, loss = 1.00196110
Iteration 132, loss = 1.00100565
Iteration 133, loss = 1.00005463
Iteration 134, loss = 0.99921592
Iteration 135, loss = 0.99828906
Iteration 136, loss = 0.99729729
Iteration 137, loss = 0.99677067
Iteration 138, loss = 0.99566829
Iteration 139, loss = 0.99491031
Iteration 140, loss = 0.99402097
Iteration 141, loss = 0.99317278
Iteration 142, loss = 0.99237789
Iteration 143, loss = 0.99151866
Iteration 144, loss = 0.99067202
Iteration 145, loss = 0.98991002
Iteration 146, loss = 0.98911860
Iteration 147, loss = 0.98830747
Iteration 148, loss = 0.98745816
Iteration 149, loss = 0.98670773
Iteration 150, loss = 0.98579522
Iteration 151, loss = 0.98498269
Iteration 152, loss = 0.98418566
Iteration 153, loss = 0.98327374
Iteration 154, loss = 0.98251496
Iteration 155, loss = 0.98169703
Iteration 156, loss = 0.98093177
Iteration 157, loss = 0.98007327
Iteration 158, loss = 0.97921338
Iteration 159, loss = 0.97841163
Iteration 160, loss = 0.97758993
Iteration 161, loss = 0.97680118
Iteration 162, loss = 0.97594386
Iteration 163, loss = 0.97513875
Iteration 164, loss = 0.97429237
Iteration 165, loss = 0.97347340
Iteration 166, loss = 0.97265610
Iteration 167, loss = 0.97180321
Iteration 168, loss = 0.97095423
Iteration 169, loss = 0.97017728
Iteration 170, loss = 0.96929144
Iteration 171, loss = 0.96845797
Iteration 172, loss = 0.96753693
Iteration 173, loss = 0.96666025
Iteration 174, loss = 0.96562113
Iteration 175, loss = 0.96444573
Iteration 176, loss = 0.96348866
Iteration 177, loss = 0.96236400
Iteration 178, loss = 0.96133665
Iteration 179, loss = 0.96023444
Iteration 180, loss = 0.95915140
```

```
Iteration 181, loss = 0.95798452
Iteration 182, loss = 0.95681134
Iteration 183, loss = 0.95564288
Iteration 184, loss = 0.95440442
Iteration 185, loss = 0.95311635
Iteration 186, loss = 0.95199793
Iteration 187, loss = 0.95053759
Iteration 188, loss = 0.94895601
Iteration 189, loss = 0.94753428
Iteration 190, loss = 0.94583320
Iteration 191, loss = 0.94411383
Iteration 192, loss = 0.94234441
Iteration 193, loss = 0.94052141
Iteration 194, loss = 0.93879862
Iteration 195, loss = 0.93706875
Iteration 196, loss = 0.93524029
Iteration 197, loss = 0.93353201
Iteration 198, loss = 0.93166349
Iteration 199, loss = 0.93009383
Iteration 200, loss = 0.92829636
Iteration 201, loss = 0.92665490
Iteration 202, loss = 0.92472779
Iteration 203, loss = 0.92270620
Iteration 204, loss = 0.92075839
Iteration 205, loss = 0.91866656
Iteration 206, loss = 0.91669029
Iteration 207, loss = 0.91445150
Iteration 208, loss = 0.91242131
Iteration 209, loss = 0.91031958
Iteration 210, loss = 0.90801145
Iteration 211, loss = 0.90578181
Iteration 212, loss = 0.90352713
Iteration 213, loss = 0.90113874
Iteration 214, loss = 0.89856030
Iteration 215, loss = 0.89621610
Iteration 216, loss = 0.89387471
Iteration 217, loss = 0.89131965
Iteration 218, loss = 0.88836256
Iteration 219, loss = 0.88567837
Iteration 220, loss = 0.88299085
Iteration 221, loss = 0.87978871
Iteration 222, loss = 0.87681879
Iteration 223, loss = 0.87353602
Iteration 224, loss = 0.87033993
Iteration 225, loss = 0.86720398
Iteration 226, loss = 0.86401343
Iteration 227, loss = 0.86076694
Iteration 228, loss = 0.85766401
Iteration 229, loss = 0.85417162
Iteration 230, loss = 0.85090657
Iteration 231, loss = 0.84759383
Iteration 232, loss = 0.84409597
Iteration 233, loss = 0.84081841
Iteration 234, loss = 0.83745643
Iteration 235, loss = 0.83403210
Iteration 236, loss = 0.83051337
Iteration 237, loss = 0.82714128
Iteration 238, loss = 0.82363183
Iteration 239, loss = 0.81985192
Iteration 240, loss = 0.81632429
```

Iteration 241, loss = 0.81269212  
Iteration 242, loss = 0.80940063  
Iteration 243, loss = 0.80602842  
Iteration 244, loss = 0.80256420  
Iteration 245, loss = 0.79871070  
Iteration 246, loss = 0.79470746  
Iteration 247, loss = 0.79100777  
Iteration 248, loss = 0.78732578  
Iteration 249, loss = 0.78371320  
Iteration 250, loss = 0.78010234  
Iteration 251, loss = 0.77650641  
Iteration 252, loss = 0.77266750  
Iteration 253, loss = 0.76909454  
Iteration 254, loss = 0.76510827  
Iteration 255, loss = 0.76135255  
Iteration 256, loss = 0.75744585  
Iteration 257, loss = 0.75345202  
Iteration 258, loss = 0.74925371  
Iteration 259, loss = 0.74526405  
Iteration 260, loss = 0.74130410  
Iteration 261, loss = 0.73780142  
Iteration 262, loss = 0.73381490  
Iteration 263, loss = 0.73021481  
Iteration 264, loss = 0.72640027  
Iteration 265, loss = 0.72313227  
Iteration 266, loss = 0.71961550  
Iteration 267, loss = 0.71618800  
Iteration 268, loss = 0.71262931  
Iteration 269, loss = 0.70935219  
Iteration 270, loss = 0.70592696  
Iteration 271, loss = 0.70261301  
Iteration 272, loss = 0.69936915  
Iteration 273, loss = 0.69633008  
Iteration 274, loss = 0.69313327  
Iteration 275, loss = 0.69006159  
Iteration 276, loss = 0.68720482  
Iteration 277, loss = 0.68399689  
Iteration 278, loss = 0.68107464  
Iteration 279, loss = 0.67812959  
Iteration 280, loss = 0.67536888  
Iteration 281, loss = 0.67243898  
Iteration 282, loss = 0.66955460  
Iteration 283, loss = 0.66676219  
Iteration 284, loss = 0.66404036  
Iteration 285, loss = 0.66125898  
Iteration 286, loss = 0.65853502  
Iteration 287, loss = 0.65581331  
Iteration 288, loss = 0.65318538  
Iteration 289, loss = 0.65044249  
Iteration 290, loss = 0.64788670  
Iteration 291, loss = 0.64507930  
Iteration 292, loss = 0.64237889  
Iteration 293, loss = 0.63946372  
Iteration 294, loss = 0.63675170  
Iteration 295, loss = 0.63396915  
Iteration 296, loss = 0.63121466  
Iteration 297, loss = 0.62857609  
Iteration 298, loss = 0.62598885  
Iteration 299, loss = 0.62327866  
Iteration 300, loss = 0.62063084

```
Iteration 301, loss = 0.61795710
Iteration 302, loss = 0.61524251
Iteration 303, loss = 0.61225498
Iteration 304, loss = 0.60948855
Iteration 305, loss = 0.60670045
Iteration 306, loss = 0.60334705
Iteration 307, loss = 0.60022078
Iteration 308, loss = 0.59732327
Iteration 309, loss = 0.59420109
Iteration 310, loss = 0.59094983
Iteration 311, loss = 0.58736637
Iteration 312, loss = 0.58393715
Iteration 313, loss = 0.58030949
Iteration 314, loss = 0.57654245
Iteration 315, loss = 0.57303644
Iteration 316, loss = 0.56968333
Iteration 317, loss = 0.56562160
Iteration 318, loss = 0.56211716
Iteration 319, loss = 0.55835544
Iteration 320, loss = 0.55473341
Iteration 321, loss = 0.55121182
Iteration 322, loss = 0.54749239
Iteration 323, loss = 0.54374510
Iteration 324, loss = 0.54040433
Iteration 325, loss = 0.53716188
Iteration 326, loss = 0.53413763
Iteration 327, loss = 0.53088312
Iteration 328, loss = 0.52798599
Iteration 329, loss = 0.52499483
Iteration 330, loss = 0.52180490
Iteration 331, loss = 0.51883649
Iteration 332, loss = 0.51605874
Iteration 333, loss = 0.51337016
Iteration 334, loss = 0.51042294
Iteration 335, loss = 0.50783346
Iteration 336, loss = 0.50515479
Iteration 337, loss = 0.50240644
Iteration 338, loss = 0.50003404
Iteration 339, loss = 0.49760135
Iteration 340, loss = 0.49533649
Iteration 341, loss = 0.49292186
Iteration 342, loss = 0.49064372
Iteration 343, loss = 0.48842480
Iteration 344, loss = 0.48610183
Iteration 345, loss = 0.48388228
Iteration 346, loss = 0.48163669
Iteration 347, loss = 0.47954123
Iteration 348, loss = 0.47731664
Iteration 349, loss = 0.47519864
Iteration 350, loss = 0.47306697
Iteration 351, loss = 0.47109854
Iteration 352, loss = 0.46900936
Iteration 353, loss = 0.46698574
Iteration 354, loss = 0.46487589
Iteration 355, loss = 0.46289387
Iteration 356, loss = 0.46088857
Iteration 357, loss = 0.45893318
Iteration 358, loss = 0.45705027
Iteration 359, loss = 0.45503446
Iteration 360, loss = 0.45311274
```

```
Iteration 361, loss = 0.45134791
Iteration 362, loss = 0.44933122
Iteration 363, loss = 0.44755648
Iteration 364, loss = 0.44568349
Iteration 365, loss = 0.44390129
Iteration 366, loss = 0.44211344
Iteration 367, loss = 0.44029503
Iteration 368, loss = 0.43857693
Iteration 369, loss = 0.43687823
Iteration 370, loss = 0.43511531
Iteration 371, loss = 0.43344582
Iteration 372, loss = 0.43174686
Iteration 373, loss = 0.42999202
Iteration 374, loss = 0.42836459
Iteration 375, loss = 0.42677147
Iteration 376, loss = 0.42505300
Iteration 377, loss = 0.42341419
Iteration 378, loss = 0.42175519
Iteration 379, loss = 0.42024941
Iteration 380, loss = 0.41850656
Iteration 381, loss = 0.41703030
Iteration 382, loss = 0.41553837
Iteration 383, loss = 0.41377140
Iteration 384, loss = 0.41232192
Iteration 385, loss = 0.41073255
Iteration 386, loss = 0.40920350
Iteration 387, loss = 0.40765060
Iteration 388, loss = 0.40621153
Iteration 389, loss = 0.40469259
Iteration 390, loss = 0.40319351
Iteration 391, loss = 0.40171260
Iteration 392, loss = 0.40023442
Iteration 393, loss = 0.39883728
Iteration 394, loss = 0.39743231
Iteration 395, loss = 0.39589152
Iteration 396, loss = 0.39457322
Iteration 397, loss = 0.39294224
Iteration 398, loss = 0.39176063
Iteration 399, loss = 0.39007823
Iteration 400, loss = 0.38872427
Iteration 401, loss = 0.38728616
Iteration 402, loss = 0.38589506
Iteration 403, loss = 0.38450966
Iteration 404, loss = 0.38320726
Iteration 405, loss = 0.38166324
Iteration 406, loss = 0.38042261
Iteration 407, loss = 0.37893247
Iteration 408, loss = 0.37756568
Iteration 409, loss = 0.37641409
Iteration 410, loss = 0.37478365
Iteration 411, loss = 0.37347335
Iteration 412, loss = 0.37214663
Iteration 413, loss = 0.37086523
Iteration 414, loss = 0.36959203
Iteration 415, loss = 0.36815889
Iteration 416, loss = 0.36676315
Iteration 417, loss = 0.36562464
Iteration 418, loss = 0.36423473
Iteration 419, loss = 0.36296037
Iteration 420, loss = 0.36158967
```

Iteration 421, loss = 0.36043251  
Iteration 422, loss = 0.35911027  
Iteration 423, loss = 0.35780567  
Iteration 424, loss = 0.35650193  
Iteration 425, loss = 0.35529227  
Iteration 426, loss = 0.35406156  
Iteration 427, loss = 0.35274048  
Iteration 428, loss = 0.35170572  
Iteration 429, loss = 0.35040617  
Iteration 430, loss = 0.34935085  
Iteration 431, loss = 0.34793200  
Iteration 432, loss = 0.34673417  
Iteration 433, loss = 0.34545587  
Iteration 434, loss = 0.34434271  
Iteration 435, loss = 0.34307177  
Iteration 436, loss = 0.34184552  
Iteration 437, loss = 0.34057656  
Iteration 438, loss = 0.33946354  
Iteration 439, loss = 0.33817137  
Iteration 440, loss = 0.33698193  
Iteration 441, loss = 0.33588223  
Iteration 442, loss = 0.33456061  
Iteration 443, loss = 0.33347324  
Iteration 444, loss = 0.33224789  
Iteration 445, loss = 0.33104476  
Iteration 446, loss = 0.32999480  
Iteration 447, loss = 0.32870302  
Iteration 448, loss = 0.32763010  
Iteration 449, loss = 0.32644933  
Iteration 450, loss = 0.32529945  
Iteration 451, loss = 0.32415104  
Iteration 452, loss = 0.32304815  
Iteration 453, loss = 0.32186662  
Iteration 454, loss = 0.32083992  
Iteration 455, loss = 0.31991740  
Iteration 456, loss = 0.31866522  
Iteration 457, loss = 0.31765736  
Iteration 458, loss = 0.31642076  
Iteration 459, loss = 0.31537140  
Iteration 460, loss = 0.31434536  
Iteration 461, loss = 0.31325710  
Iteration 462, loss = 0.31221688  
Iteration 463, loss = 0.31131310  
Iteration 464, loss = 0.30995750  
Iteration 465, loss = 0.30893565  
Iteration 466, loss = 0.30805711  
Iteration 467, loss = 0.30687594  
Iteration 468, loss = 0.30589578  
Iteration 469, loss = 0.30488244  
Iteration 470, loss = 0.30377849  
Iteration 471, loss = 0.30280530  
Iteration 472, loss = 0.30182144  
Iteration 473, loss = 0.30089741  
Iteration 474, loss = 0.29978604  
Iteration 475, loss = 0.29885540  
Iteration 476, loss = 0.29770771  
Iteration 477, loss = 0.29688882  
Iteration 478, loss = 0.29578367  
Iteration 479, loss = 0.29492760  
Iteration 480, loss = 0.29380054

```
Iteration 481, loss = 0.29303221
Iteration 482, loss = 0.29184185
Iteration 483, loss = 0.29094937
Iteration 484, loss = 0.29001010
Iteration 485, loss = 0.28897376
Iteration 486, loss = 0.28806235
Iteration 487, loss = 0.28752441
Iteration 488, loss = 0.28622409
Iteration 489, loss = 0.28543858
Iteration 490, loss = 0.28440109
Iteration 491, loss = 0.28348468
Iteration 492, loss = 0.28254008
Iteration 493, loss = 0.28166008
Iteration 494, loss = 0.28072589
Iteration 495, loss = 0.27988676
Iteration 496, loss = 0.27895817
Iteration 497, loss = 0.27803368
Iteration 498, loss = 0.27718542
Iteration 499, loss = 0.27639075
Iteration 500, loss = 0.27541074
Iteration 1, loss = 0.90172150
Iteration 2, loss = 0.89022423
Iteration 3, loss = 0.87837307
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (500) reached and the optimization hasn't converged yet.
```

```
warnings.warn(
```

```
Iteration 4, loss = 0.86787407
Iteration 5, loss = 0.85597044
Iteration 6, loss = 0.84550253
Iteration 7, loss = 0.83392755
Iteration 8, loss = 0.82307967
Iteration 9, loss = 0.81202447
Iteration 10, loss = 0.80132376
Iteration 11, loss = 0.79016590
Iteration 12, loss = 0.77962600
Iteration 13, loss = 0.76890119
Iteration 14, loss = 0.75822536
Iteration 15, loss = 0.74738611
Iteration 16, loss = 0.73733969
Iteration 17, loss = 0.72669745
Iteration 18, loss = 0.71637174
Iteration 19, loss = 0.70604750
Iteration 20, loss = 0.69583577
Iteration 21, loss = 0.68574226
Iteration 22, loss = 0.67631065
Iteration 23, loss = 0.66651566
Iteration 24, loss = 0.65715326
Iteration 25, loss = 0.64756990
Iteration 26, loss = 0.63782130
Iteration 27, loss = 0.62857612
Iteration 28, loss = 0.61919359
Iteration 29, loss = 0.61004063
Iteration 30, loss = 0.60090847
Iteration 31, loss = 0.59212838
Iteration 32, loss = 0.58299690
Iteration 33, loss = 0.57400075
Iteration 34, loss = 0.56544869
Iteration 35, loss = 0.55699335
Iteration 36, loss = 0.54837480
Iteration 37, loss = 0.54044959
Iteration 38, loss = 0.53188619
Iteration 39, loss = 0.52398105
Iteration 40, loss = 0.51598926
Iteration 41, loss = 0.50809546
Iteration 42, loss = 0.50047571
Iteration 43, loss = 0.49310287
Iteration 44, loss = 0.48583752
Iteration 45, loss = 0.47849239
Iteration 46, loss = 0.47098148
Iteration 47, loss = 0.46388068
Iteration 48, loss = 0.45709826
Iteration 49, loss = 0.45042680
Iteration 50, loss = 0.44345459
Iteration 51, loss = 0.43704702
Iteration 52, loss = 0.43063059
Iteration 53, loss = 0.42448115
Iteration 54, loss = 0.41794371
Iteration 55, loss = 0.41196418
Iteration 56, loss = 0.40587786
Iteration 57, loss = 0.40006769
Iteration 58, loss = 0.39453266
Iteration 59, loss = 0.38894264
Iteration 60, loss = 0.38331233
Iteration 61, loss = 0.37806819
Iteration 62, loss = 0.37309259
Iteration 63, loss = 0.36819002
```

Iteration 64, loss = 0.36308601  
Iteration 65, loss = 0.35843562  
Iteration 66, loss = 0.35391359  
Iteration 67, loss = 0.34925153  
Iteration 68, loss = 0.34512466  
Iteration 69, loss = 0.34099783  
Iteration 70, loss = 0.33682958  
Iteration 71, loss = 0.33296512  
Iteration 72, loss = 0.32902943  
Iteration 73, loss = 0.32538156  
Iteration 74, loss = 0.32167931  
Iteration 75, loss = 0.31818290  
Iteration 76, loss = 0.31465003  
Iteration 77, loss = 0.31143623  
Iteration 78, loss = 0.30814236  
Iteration 79, loss = 0.30483761  
Iteration 80, loss = 0.30173857  
Iteration 81, loss = 0.29863597  
Iteration 82, loss = 0.29570611  
Iteration 83, loss = 0.29310765  
Iteration 84, loss = 0.29025009  
Iteration 85, loss = 0.28769216  
Iteration 86, loss = 0.28513593  
Iteration 87, loss = 0.28252883  
Iteration 88, loss = 0.28017429  
Iteration 89, loss = 0.27770780  
Iteration 90, loss = 0.27552167  
Iteration 91, loss = 0.27343011  
Iteration 92, loss = 0.27122989  
Iteration 93, loss = 0.26927613  
Iteration 94, loss = 0.26721234  
Iteration 95, loss = 0.26537001  
Iteration 96, loss = 0.26342485  
Iteration 97, loss = 0.26171434  
Iteration 98, loss = 0.25988487  
Iteration 99, loss = 0.25815412  
Iteration 100, loss = 0.25657959  
Iteration 101, loss = 0.25497198  
Iteration 102, loss = 0.25345878  
Iteration 103, loss = 0.25198095  
Iteration 104, loss = 0.25048446  
Iteration 105, loss = 0.24907055  
Iteration 106, loss = 0.24765870  
Iteration 107, loss = 0.24638124  
Iteration 108, loss = 0.24502921  
Iteration 109, loss = 0.24381655  
Iteration 110, loss = 0.24270990  
Iteration 111, loss = 0.24147300  
Iteration 112, loss = 0.24045012  
Iteration 113, loss = 0.23922968  
Iteration 114, loss = 0.23821360  
Iteration 115, loss = 0.23712818  
Iteration 116, loss = 0.23612694  
Iteration 117, loss = 0.23515279  
Iteration 118, loss = 0.23420417  
Iteration 119, loss = 0.23314215  
Iteration 120, loss = 0.23235412  
Iteration 121, loss = 0.23145059  
Iteration 122, loss = 0.23055873  
Iteration 123, loss = 0.22971299

Iteration 124, loss = 0.22899793  
Iteration 125, loss = 0.22805565  
Iteration 126, loss = 0.22734196  
Iteration 127, loss = 0.22658892  
Iteration 128, loss = 0.22583340  
Iteration 129, loss = 0.22510805  
Iteration 130, loss = 0.22440910  
Iteration 131, loss = 0.22372110  
Iteration 132, loss = 0.22301739  
Iteration 133, loss = 0.22235932  
Iteration 134, loss = 0.22167840  
Iteration 135, loss = 0.22104988  
Iteration 136, loss = 0.22043098  
Iteration 137, loss = 0.21984548  
Iteration 138, loss = 0.21919507  
Iteration 139, loss = 0.21860652  
Iteration 140, loss = 0.21813690  
Iteration 141, loss = 0.21754047  
Iteration 142, loss = 0.21698099  
Iteration 143, loss = 0.21644561  
Iteration 144, loss = 0.21590977  
Iteration 145, loss = 0.21538919  
Iteration 146, loss = 0.21486248  
Iteration 147, loss = 0.21443452  
Iteration 148, loss = 0.21391915  
Iteration 149, loss = 0.21341183  
Iteration 150, loss = 0.21293316  
Iteration 151, loss = 0.21249172  
Iteration 152, loss = 0.21208916  
Iteration 153, loss = 0.21157849  
Iteration 154, loss = 0.21115764  
Iteration 155, loss = 0.21072836  
Iteration 156, loss = 0.21032432  
Iteration 157, loss = 0.20986477  
Iteration 158, loss = 0.20942901  
Iteration 159, loss = 0.20904668  
Iteration 160, loss = 0.20863650  
Iteration 161, loss = 0.20820638  
Iteration 162, loss = 0.20778327  
Iteration 163, loss = 0.20743898  
Iteration 164, loss = 0.20699071  
Iteration 165, loss = 0.20660722  
Iteration 166, loss = 0.20622015  
Iteration 167, loss = 0.20584862  
Iteration 168, loss = 0.20545800  
Iteration 169, loss = 0.20505275  
Iteration 170, loss = 0.20465400  
Iteration 171, loss = 0.20426338  
Iteration 172, loss = 0.20388146  
Iteration 173, loss = 0.20346449  
Iteration 174, loss = 0.20310845  
Iteration 175, loss = 0.20271947  
Iteration 176, loss = 0.20233295  
Iteration 177, loss = 0.20197111  
Iteration 178, loss = 0.20160998  
Iteration 179, loss = 0.20124394  
Iteration 180, loss = 0.20096854  
Iteration 181, loss = 0.20059708  
Iteration 182, loss = 0.20029779  
Iteration 183, loss = 0.19995601

```
Iteration 184, loss = 0.19966196
Iteration 185, loss = 0.19936112
Iteration 186, loss = 0.19907626
Iteration 187, loss = 0.19875019
Iteration 188, loss = 0.19848010
Iteration 189, loss = 0.19822437
Iteration 190, loss = 0.19798778
Iteration 191, loss = 0.19764600
Iteration 192, loss = 0.19738560
Iteration 193, loss = 0.19715135
Iteration 194, loss = 0.19685127
Iteration 195, loss = 0.19662033
Iteration 196, loss = 0.19637319
Iteration 197, loss = 0.19608474
Iteration 198, loss = 0.19585817
Iteration 199, loss = 0.19560036
Iteration 200, loss = 0.19536424
Iteration 201, loss = 0.19506658
Iteration 202, loss = 0.19483513
Iteration 203, loss = 0.19465730
Iteration 204, loss = 0.19442696
Iteration 205, loss = 0.19414657
Iteration 206, loss = 0.19394085
Iteration 207, loss = 0.19369135
Iteration 208, loss = 0.19347540
Iteration 209, loss = 0.19324261
Iteration 210, loss = 0.19302435
Iteration 211, loss = 0.19279108
Iteration 212, loss = 0.19262603
Iteration 213, loss = 0.19236214
Iteration 214, loss = 0.19218930
Iteration 215, loss = 0.19193753
Iteration 216, loss = 0.19171067
Iteration 217, loss = 0.19149766
Iteration 218, loss = 0.19130936
Iteration 219, loss = 0.19115226
Iteration 220, loss = 0.19089827
Iteration 221, loss = 0.19073447
Iteration 222, loss = 0.19048503
Iteration 223, loss = 0.19030497
Iteration 224, loss = 0.19011103
Iteration 225, loss = 0.18989381
Iteration 226, loss = 0.18969044
Iteration 227, loss = 0.18952567
Iteration 228, loss = 0.18931603
Iteration 229, loss = 0.18912446
Iteration 230, loss = 0.18895619
Iteration 231, loss = 0.18876078
Iteration 232, loss = 0.18858598
Iteration 233, loss = 0.18841593
Iteration 234, loss = 0.18819411
Iteration 235, loss = 0.18803231
Iteration 236, loss = 0.18790028
Iteration 237, loss = 0.18765407
Iteration 238, loss = 0.18749095
Iteration 239, loss = 0.18730659
Iteration 240, loss = 0.18714834
Iteration 241, loss = 0.18696131
Iteration 242, loss = 0.18676275
Iteration 243, loss = 0.18659962
```

Iteration 244, loss = 0.18644957  
Iteration 245, loss = 0.18628634  
Iteration 246, loss = 0.18613208  
Iteration 247, loss = 0.18596496  
Iteration 248, loss = 0.18579790  
Iteration 249, loss = 0.18565722  
Iteration 250, loss = 0.18550551  
Iteration 251, loss = 0.18536298  
Iteration 252, loss = 0.18521539  
Iteration 253, loss = 0.18506336  
Iteration 254, loss = 0.18495400  
Iteration 255, loss = 0.18484377  
Iteration 256, loss = 0.18462232  
Iteration 257, loss = 0.18448791  
Iteration 258, loss = 0.18436258  
Iteration 259, loss = 0.18421035  
Iteration 260, loss = 0.18410745  
Iteration 261, loss = 0.18392722  
Iteration 262, loss = 0.18381806  
Iteration 263, loss = 0.18367992  
Iteration 264, loss = 0.18355847  
Iteration 265, loss = 0.18339955  
Iteration 266, loss = 0.18332897  
Iteration 267, loss = 0.18311966  
Iteration 268, loss = 0.18300150  
Iteration 269, loss = 0.18290972  
Iteration 270, loss = 0.18278862  
Iteration 271, loss = 0.18261040  
Iteration 272, loss = 0.18247634  
Iteration 273, loss = 0.18239460  
Iteration 274, loss = 0.18227639  
Iteration 275, loss = 0.18211863  
Iteration 276, loss = 0.18199094  
Iteration 277, loss = 0.18184804  
Iteration 278, loss = 0.18173616  
Iteration 279, loss = 0.18159880  
Iteration 280, loss = 0.18144893  
Iteration 281, loss = 0.18136770  
Iteration 282, loss = 0.18118460  
Iteration 283, loss = 0.18108293  
Iteration 284, loss = 0.18098576  
Iteration 285, loss = 0.18079904  
Iteration 286, loss = 0.18068134  
Iteration 287, loss = 0.18061105  
Iteration 288, loss = 0.18045736  
Iteration 289, loss = 0.18031751  
Iteration 290, loss = 0.18021483  
Iteration 291, loss = 0.18015679  
Iteration 292, loss = 0.18000878  
Iteration 293, loss = 0.17986524  
Iteration 294, loss = 0.17978824  
Iteration 295, loss = 0.17965517  
Iteration 296, loss = 0.17951351  
Iteration 297, loss = 0.17943511  
Iteration 298, loss = 0.17928565  
Iteration 299, loss = 0.17918786  
Iteration 300, loss = 0.17906745  
Iteration 301, loss = 0.17896505  
Iteration 302, loss = 0.17891453  
Iteration 303, loss = 0.17872975

```
Iteration 304, loss = 0.17862732
Iteration 305, loss = 0.17851900
Iteration 306, loss = 0.17842198
Iteration 307, loss = 0.17832292
Iteration 308, loss = 0.17824067
Iteration 309, loss = 0.17815589
Iteration 310, loss = 0.17811244
Iteration 311, loss = 0.17792543
Iteration 312, loss = 0.17781699
Iteration 313, loss = 0.17770112
Iteration 314, loss = 0.17760548
Iteration 315, loss = 0.17751990
Iteration 316, loss = 0.17741562
Iteration 317, loss = 0.17733624
Iteration 318, loss = 0.17723507
Iteration 319, loss = 0.17715045
Iteration 320, loss = 0.17703931
Iteration 321, loss = 0.17693450
Iteration 322, loss = 0.17683024
Iteration 323, loss = 0.17673687
Iteration 324, loss = 0.17660708
Iteration 325, loss = 0.17651185
Iteration 326, loss = 0.17642083
Iteration 327, loss = 0.17634481
Iteration 328, loss = 0.17623692
Iteration 329, loss = 0.17614825
Iteration 330, loss = 0.17605916
Iteration 331, loss = 0.17593283
Iteration 332, loss = 0.17586546
Iteration 333, loss = 0.17575322
Iteration 334, loss = 0.17564652
Iteration 335, loss = 0.17557936
Iteration 336, loss = 0.17546367
Iteration 337, loss = 0.17537302
Iteration 338, loss = 0.17528205
Iteration 339, loss = 0.17520446
Iteration 340, loss = 0.17509713
Iteration 341, loss = 0.17501915
Iteration 342, loss = 0.17491669
Iteration 343, loss = 0.17483368
Iteration 344, loss = 0.17471180
Iteration 345, loss = 0.17464744
Iteration 346, loss = 0.17453564
Iteration 347, loss = 0.17443074
Iteration 348, loss = 0.17435032
Iteration 349, loss = 0.17428403
Iteration 350, loss = 0.17417594
Iteration 351, loss = 0.17408033
Iteration 352, loss = 0.17414560
Iteration 353, loss = 0.17396530
Iteration 354, loss = 0.17383976
Iteration 355, loss = 0.17370746
Iteration 356, loss = 0.17368203
Iteration 357, loss = 0.17353041
Iteration 358, loss = 0.17344188
Iteration 359, loss = 0.17336586
Iteration 360, loss = 0.17326491
Iteration 361, loss = 0.17316592
Iteration 362, loss = 0.17307031
Iteration 363, loss = 0.17299617
```

```
Iteration 364, loss = 0.17293813
Iteration 365, loss = 0.17281136
Iteration 366, loss = 0.17272162
Iteration 367, loss = 0.17263215
Iteration 368, loss = 0.17253899
Iteration 369, loss = 0.17245925
Iteration 370, loss = 0.17235941
Iteration 371, loss = 0.17231334
Iteration 372, loss = 0.17220007
Iteration 373, loss = 0.17208679
Iteration 374, loss = 0.17201301
Iteration 375, loss = 0.17191421
Iteration 376, loss = 0.17187719
Iteration 377, loss = 0.17174427
Iteration 378, loss = 0.17168585
Iteration 379, loss = 0.17155223
Iteration 380, loss = 0.17154276
Iteration 381, loss = 0.17138146
Iteration 382, loss = 0.17129246
Iteration 383, loss = 0.17120438
Iteration 384, loss = 0.17114636
Iteration 385, loss = 0.17103029
Iteration 386, loss = 0.17094099
Iteration 387, loss = 0.17089329
Iteration 388, loss = 0.17076650
Iteration 389, loss = 0.17066130
Iteration 390, loss = 0.17060802
Iteration 391, loss = 0.17049104
Iteration 392, loss = 0.17042682
Iteration 393, loss = 0.17031588
Iteration 394, loss = 0.17022187
Iteration 395, loss = 0.17013178
Iteration 396, loss = 0.17004526
Iteration 397, loss = 0.16996494
Iteration 398, loss = 0.16990118
Iteration 399, loss = 0.16974774
Iteration 400, loss = 0.16968204
Iteration 401, loss = 0.16956225
Iteration 402, loss = 0.16950047
Iteration 403, loss = 0.16939219
Iteration 404, loss = 0.16929554
Iteration 405, loss = 0.16920859
Iteration 406, loss = 0.16910722
Iteration 407, loss = 0.16903283
Iteration 408, loss = 0.16893831
Iteration 409, loss = 0.16885312
Iteration 410, loss = 0.16876734
Iteration 411, loss = 0.16864815
Iteration 412, loss = 0.16855915
Iteration 413, loss = 0.16845375
Iteration 414, loss = 0.16838974
Iteration 415, loss = 0.16828123
Iteration 416, loss = 0.16821643
Iteration 417, loss = 0.16809555
Iteration 418, loss = 0.16800059
Iteration 419, loss = 0.16791657
Iteration 420, loss = 0.16782404
Iteration 421, loss = 0.16781243
Iteration 422, loss = 0.16771251
Iteration 423, loss = 0.16755036
```

Iteration 424, loss = 0.16746489  
Iteration 425, loss = 0.16736350  
Iteration 426, loss = 0.16730376  
Iteration 427, loss = 0.16717460  
Iteration 428, loss = 0.16709183  
Iteration 429, loss = 0.16700363  
Iteration 430, loss = 0.16695806  
Iteration 431, loss = 0.16682427  
Iteration 432, loss = 0.16673714  
Iteration 433, loss = 0.16663189  
Iteration 434, loss = 0.16655727  
Iteration 435, loss = 0.16647746  
Iteration 436, loss = 0.16638905  
Iteration 437, loss = 0.16632380  
Iteration 438, loss = 0.16618744  
Iteration 439, loss = 0.16614146  
Iteration 440, loss = 0.16602025  
Iteration 441, loss = 0.16596043  
Iteration 442, loss = 0.16582270  
Iteration 443, loss = 0.16577367  
Iteration 444, loss = 0.16566223  
Iteration 445, loss = 0.16556865  
Iteration 446, loss = 0.16548176  
Iteration 447, loss = 0.16542248  
Iteration 448, loss = 0.16531945  
Iteration 449, loss = 0.16520770  
Iteration 450, loss = 0.16512702  
Iteration 451, loss = 0.16508345  
Iteration 452, loss = 0.16497028  
Iteration 453, loss = 0.16494078  
Iteration 454, loss = 0.16478455  
Iteration 455, loss = 0.16468803  
Iteration 456, loss = 0.16462460  
Iteration 457, loss = 0.16452188  
Iteration 458, loss = 0.16443972  
Iteration 459, loss = 0.16437994  
Iteration 460, loss = 0.16424791  
Iteration 461, loss = 0.16416216  
Iteration 462, loss = 0.16404108  
Iteration 463, loss = 0.16394059  
Iteration 464, loss = 0.16385305  
Iteration 465, loss = 0.16378331  
Iteration 466, loss = 0.16366400  
Iteration 467, loss = 0.16356027  
Iteration 468, loss = 0.16347727  
Iteration 469, loss = 0.16340180  
Iteration 470, loss = 0.16327755  
Iteration 471, loss = 0.16321367  
Iteration 472, loss = 0.16308082  
Iteration 473, loss = 0.16297716  
Iteration 474, loss = 0.16285192  
Iteration 475, loss = 0.16276242  
Iteration 476, loss = 0.16268870  
Iteration 477, loss = 0.16255953  
Iteration 478, loss = 0.16244625  
Iteration 479, loss = 0.16238222  
Iteration 480, loss = 0.16225985  
Iteration 481, loss = 0.16219688  
Iteration 482, loss = 0.16207948  
Iteration 483, loss = 0.16204515

```

Iteration 484, loss = 0.16194338
Iteration 485, loss = 0.16180692
Iteration 486, loss = 0.16173883
Iteration 487, loss = 0.16163632
Iteration 488, loss = 0.16160413
Iteration 489, loss = 0.16151269
Iteration 490, loss = 0.16138770
Iteration 491, loss = 0.16134984
Iteration 492, loss = 0.16122830
Iteration 493, loss = 0.16124558
Iteration 494, loss = 0.16104789
Iteration 495, loss = 0.16094218
Iteration 496, loss = 0.16092323
Iteration 497, loss = 0.16076925
Iteration 498, loss = 0.16067836
Iteration 499, loss = 0.16060737
Iteration 500, loss = 0.16054915
0.93
0.34
/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (500) reached and the optimization hasn't converged yet.
    warnings.warn(

```

In [60]: *#-random forest*

```

from sklearn.ensemble import RandomForestClassifier

rnd_clf = RandomForestClassifier(n_estimators=500, max_leaf_nodes=50, n_jobs=-1)
rnd_clf.fit(X, y)

y_pred_rf = rnd_clf.predict(X_test)

print (sum(y_pred_rf==y_test)/y_test.size)

```

0.88

In [61]: *rnd\_clf2 = RandomForestClassifier(n\_estimators=500, max\_leaf\_nodes=8, n\_jobs=-1)*  
*rnd\_clf2.fit(X1, y1)*

```

y_pred_rf = rnd_clf.predict(X1_test)

print (sum(y_pred_rf==y1_test)/y1_test.size)

```

0.14

In [52]: *# Gradient Boosting*

```

from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import accuracy_score, confusion_matrix
gb_clf=GradientBoostingClassifier(learning_rate=0.1, n_estimators=100, subsample=1, ma

gb_clf.fit(X, y)

y_pred_gb = rnd_clf.predict(X_test)
print (accuracy_score(y_test,y_pred_gb))

```

0.42

```
In [53]: # Gradient Boosting2
```

```
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import accuracy_score, confusion_matrix
gb_clf2=GradientBoostingClassifier(learning_rate=0.1, n_estimators=100, subsample=1, n_iter_no_change=10)
gb_clf2.fit(X1, y1)

y2_pred_gb = rnd_clf.predict(X1_test)
print (accuracy_score(y1_test,y2_pred_gb))
```

0.21

```
In [46]: import xgboost
```

```
xgb_reg = xgboost.XGBClassifier()  
xgb_reg.fit(X,y)  
y_pred_XG = xgb_reg.predict(X_test)  
  
print (accuracy_score(y_test,y_pred))
```

0.85

In [47]: `import xgboost`

```
xgb_reg2 = xgboost.XGBClassifier()  
xgb_reg2.fit(X1,y1)  
y1_pred = xgb_reg2.predict(X1_test)  
  
print(accuracy_score(y1_test,y1_pred))
```

0.15

c.) Write a function that will allow you to pass in the model and the X, y set and then generate from that a plot of the decision boundary for the example

In [33]:

```
In [81]: def decisionBoundary(model, X,y,special):
    # define bounds of the domain
    min1, max1 = X[:, 0].min()-1, X[:, 0].max()+1
    min2, max2 = X[:, 1].min()-1, X[:, 1].max()+1
    # define the x and y scale
    x1grid = np.arange(min1, max1, 0.1)
    x2grid = np.arange(min2, max2, 0.1)
    # create all of the lines and rows of the grid
    xx, yy = np.meshgrid(x1grid, x2grid)
    # flatten each grid to a vector
    r1, r2 = xx.flatten(), yy.flatten()
    r1, r2 = r1.reshape((len(r1), 1)), r2.reshape(
```

```
# horizontal stack vectors to create x1,x2 input for the model
grid = np.hstack((r1,r2))

if special == False:
    y_pred_grid = model.predict(grid)
else:
    y_pred_grid = model.predict(grid**2)
zz = y_pred_grid.reshape(xx.shape)
plt.contourf(xx, yy, zz, cmap='Paired')

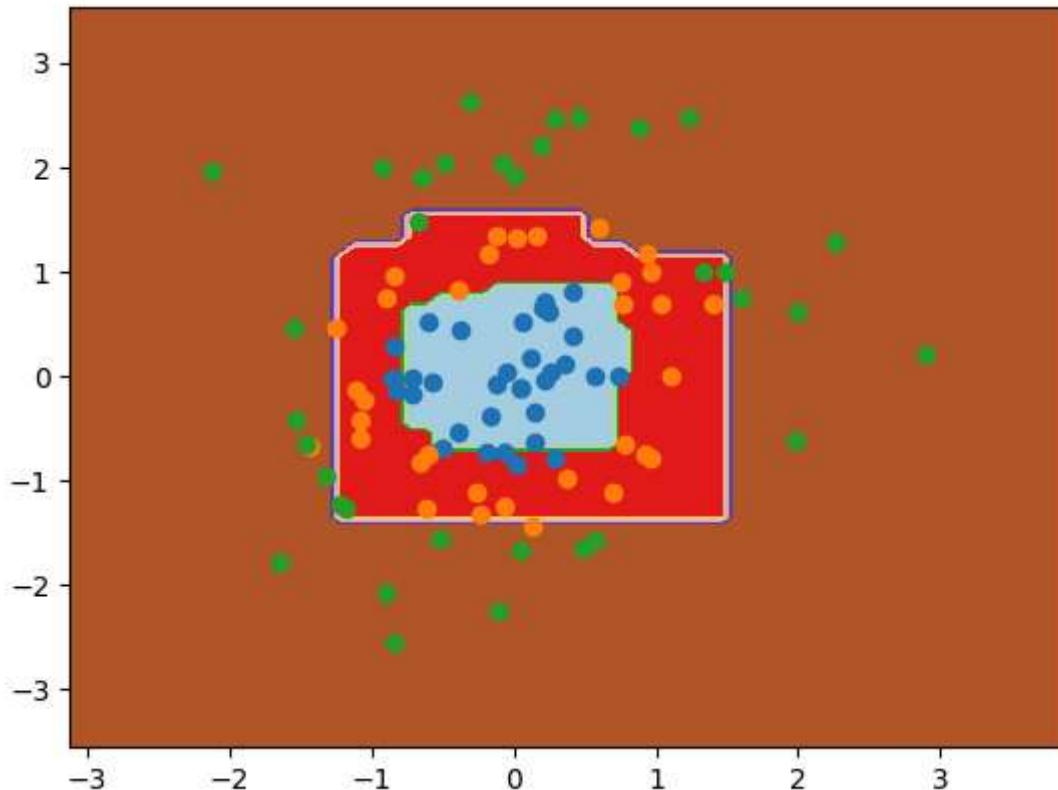
for class_value in range(len(np.unique(y))):
    # get row indexes for samples with this class
    row_ix = np.where(y == class_value)
    # create scatter of these samples
    plt.scatter(X[row_ix, 0], X[row_ix, 1], cmap='Paired')
```

d.) Use your function to plot out the decision boundaries for each of your models and for the two data sets

XGboost

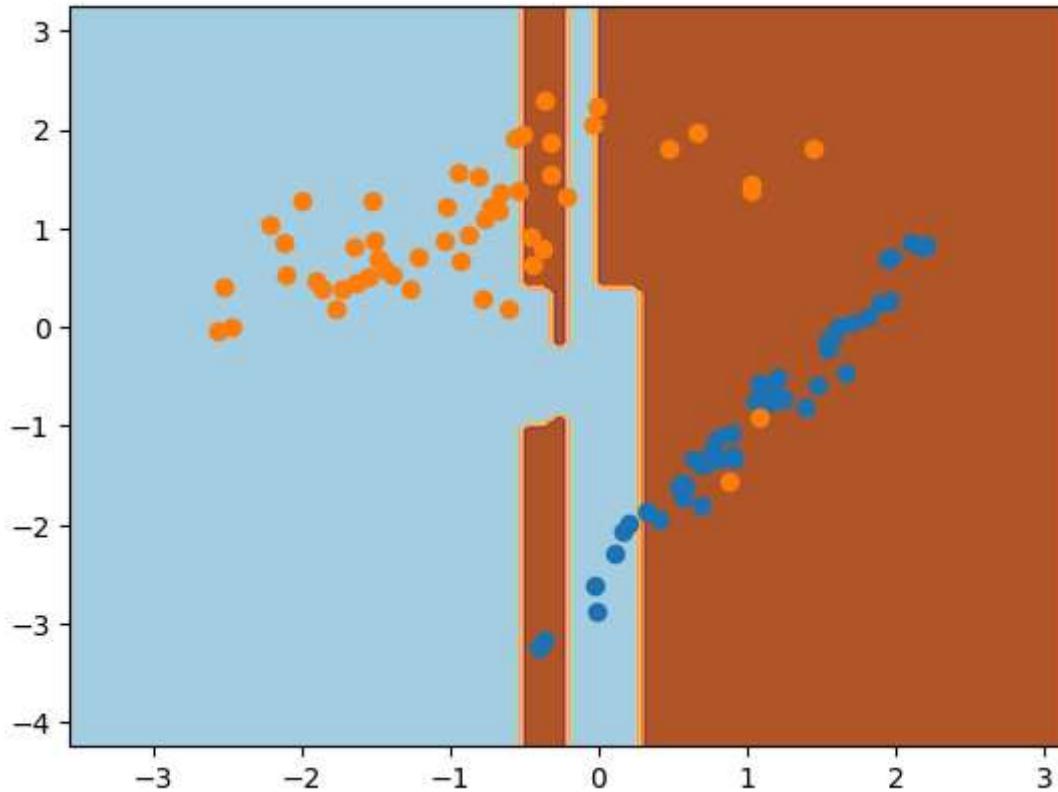
```
In [96]: #XHboost
decisionBoundary(xgb_reg,X_test,y_test,False)
```

```
<ipython-input-81-125e0d01568d>:27: UserWarning: No data for colormapping provided via 'c'. Parameters 'cmap' will be ignored
plt.scatter(X[row_ix, 0], X[row_ix, 1], cmap='Paired')
```



```
In [95]: decisionBoundary(xgb_reg2,X1_test,y1_test,False)
```

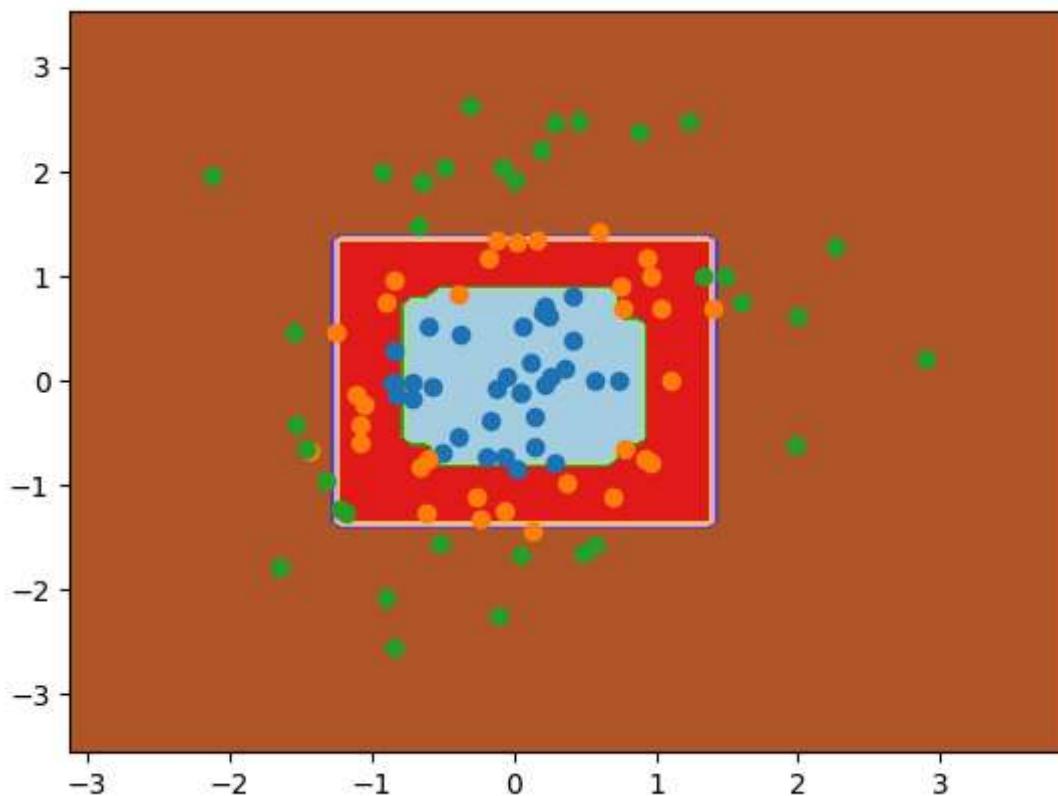
```
<ipython-input-81-125e0d01568d>:27: UserWarning: No data for colormapping provided via 'c'. Parameters 'cmap' will be ignored
plt.scatter(X[row_ix, 0], X[row_ix, 1], cmap='Paired')
```



In [94]: #Gradient Boost

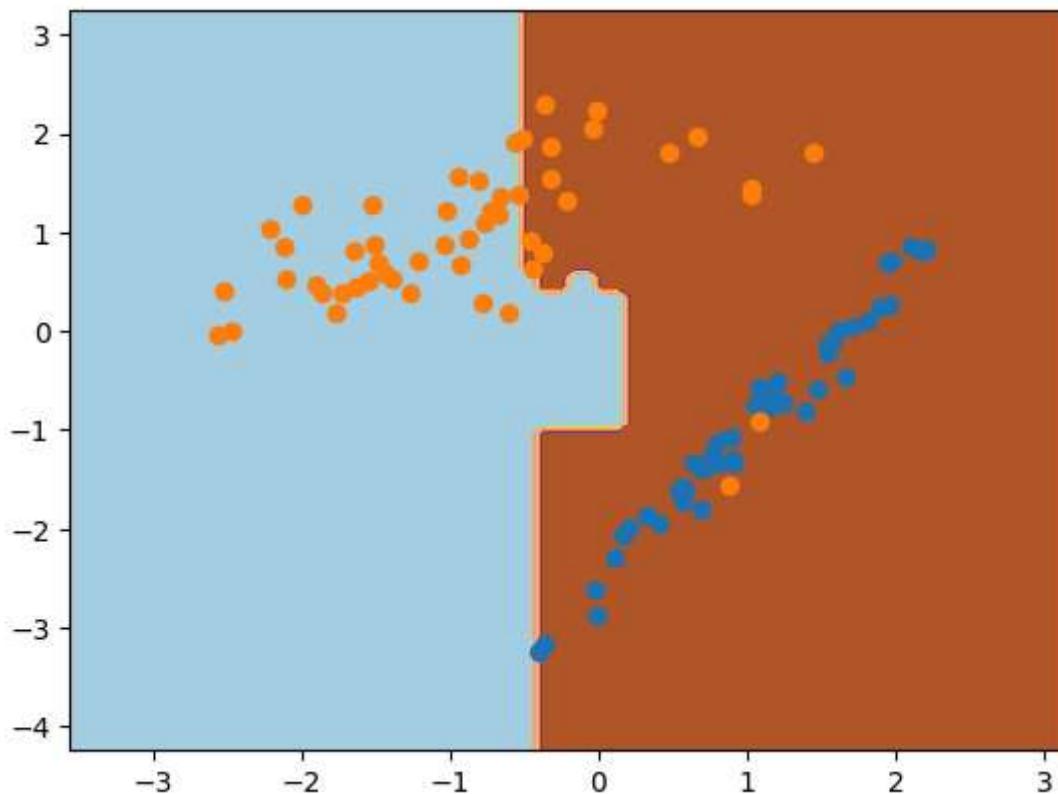
```
decisionBoundary(gb_clf,X_test,y_test, False)
```

```
<ipython-input-81-125e0d01568d>:27: UserWarning: No data for colormapping provided via 'c'. Parameters 'cmap' will be ignored
plt.scatter(X[row_ix, 0], X[row_ix, 1], cmap='Paired')
```



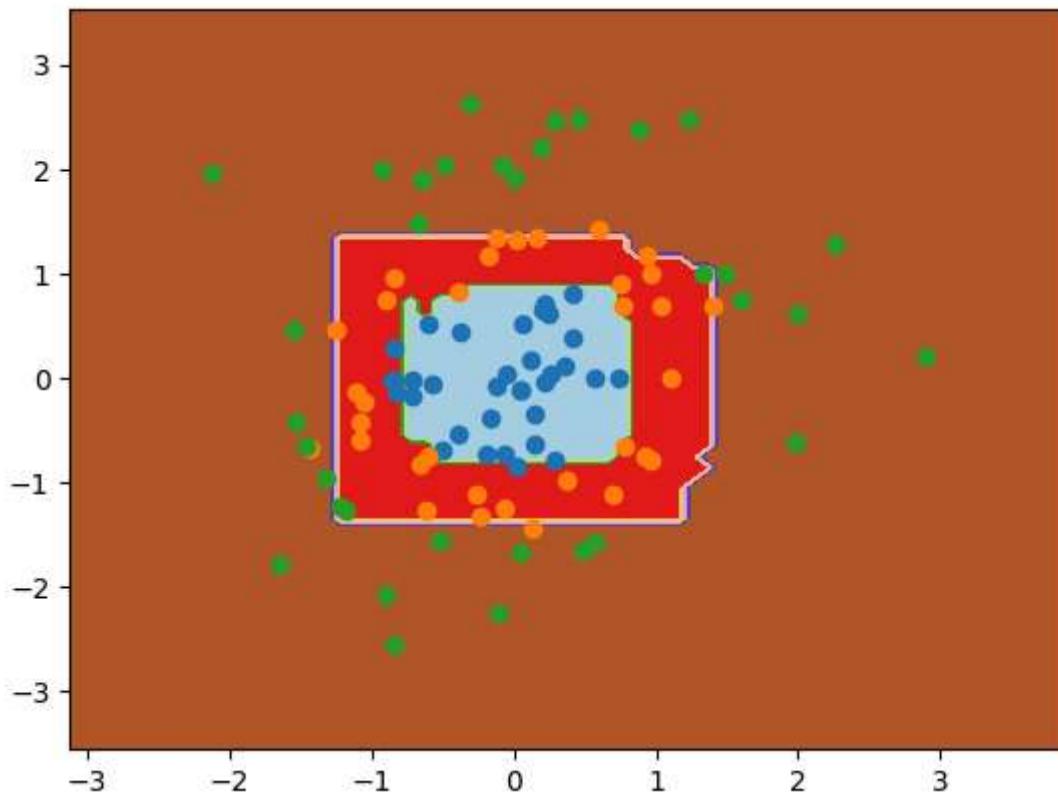
```
In [93]: decisionBoundary(gb_clf2,X1_test,y1_test, False)
```

```
<ipython-input-81-125e0d01568d>:27: UserWarning: No data for colormapping provided via 'c'. Parameters 'cmap' will be ignored  
plt.scatter(X[row_ix, 0], X[row_ix, 1], cmap='Paired')
```



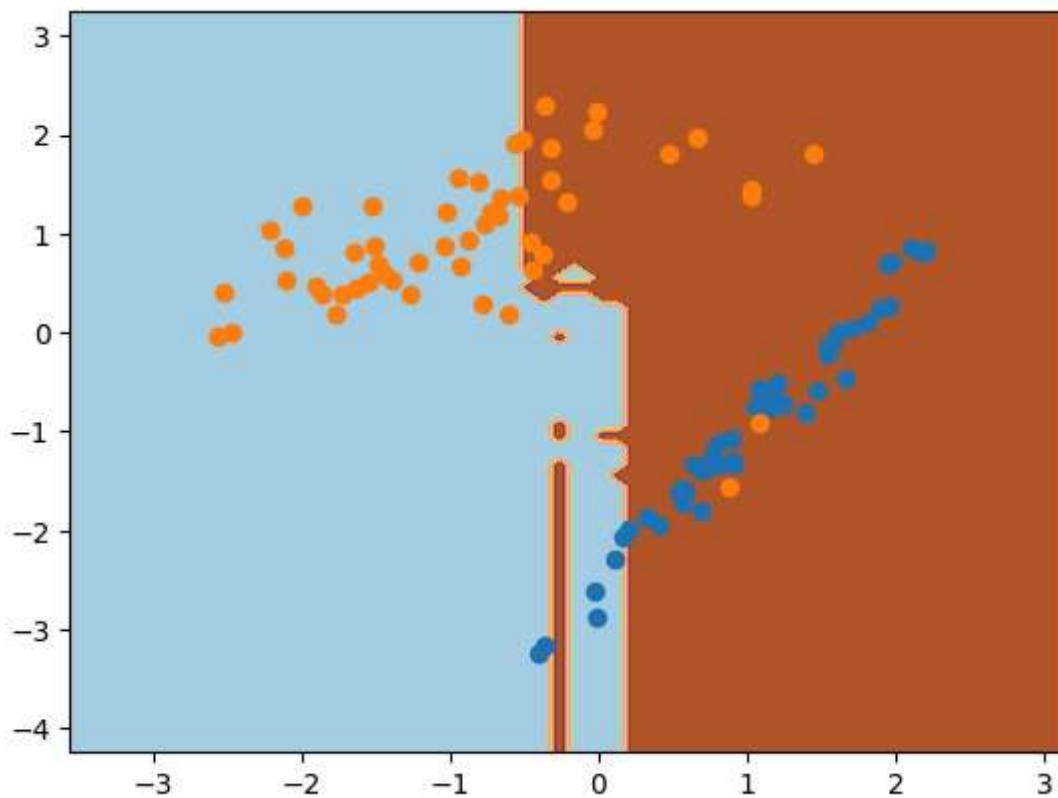
```
In [92]: # Random Forest  
decisionBoundary(rnd_clf,X_test,y_test, False)
```

```
<ipython-input-81-125e0d01568d>:27: UserWarning: No data for colormapping provided via 'c'. Parameters 'cmap' will be ignored  
plt.scatter(X[row_ix, 0], X[row_ix, 1], cmap='Paired')
```



```
In [91]: decisionBoundary(rnd_clf2,X1_test,y1_test, False)
```

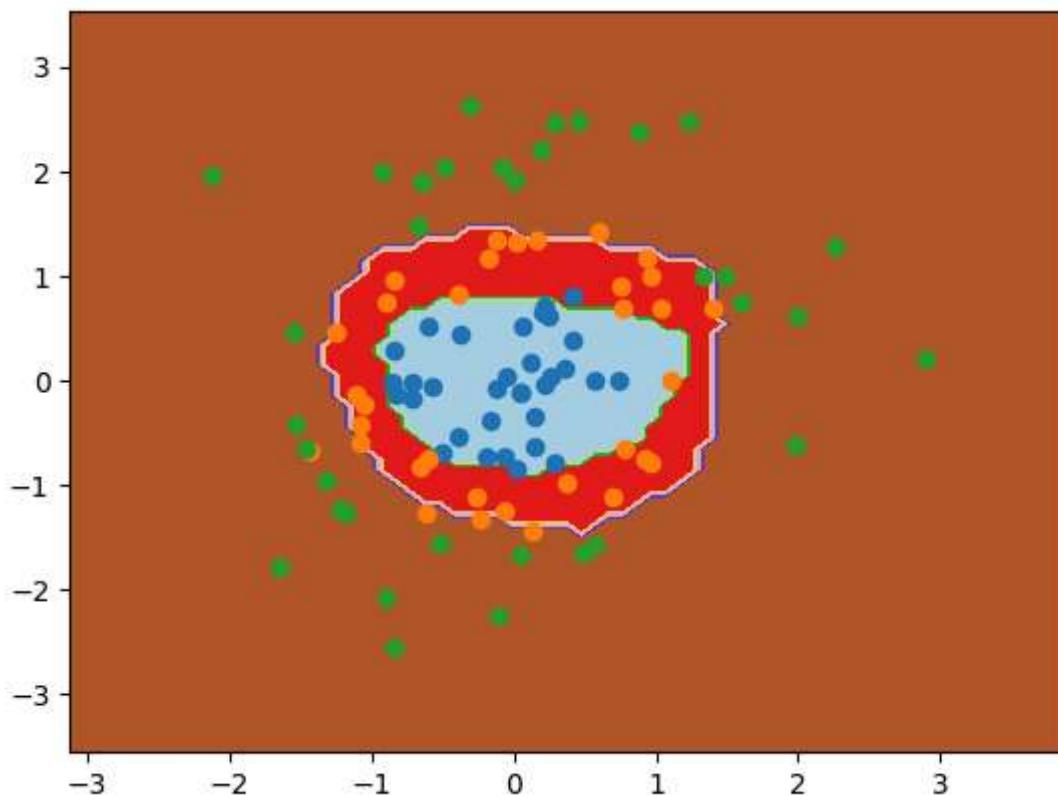
```
<ipython-input-81-125e0d01568d>:27: UserWarning: No data for colormapping provided via 'c'. Parameters 'cmap' will be ignored  
plt.scatter(X[row_ix, 0], X[row_ix, 1], cmap='Paired')
```



```
In [90]: # Nural net
```

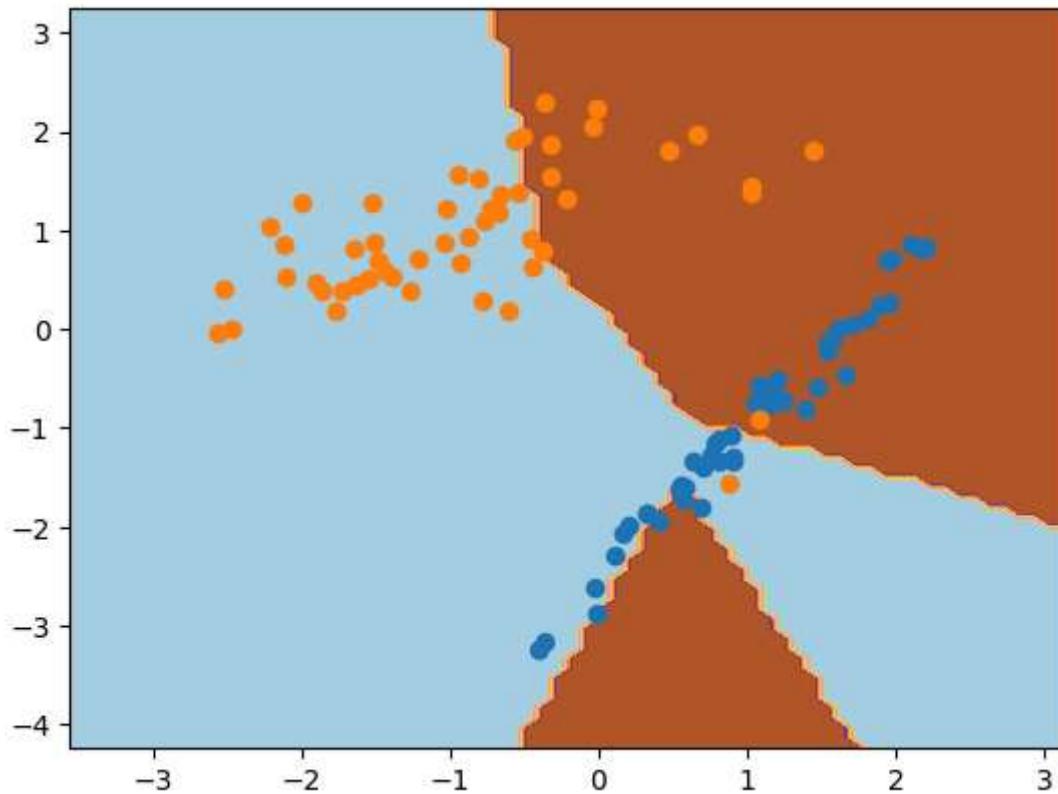
```
decisionBoundary(clf,X_test,y_test, False)
```

```
<ipython-input-81-125e0d01568d>:27: UserWarning: No data for colormapping provided via 'c'. Parameters 'cmap' will be ignored  
plt.scatter(X[row_ix, 0], X[row_ix, 1], cmap='Paired')
```



```
In [89]: decisionBoundary(clf1,X1_test,y1_test, False)
```

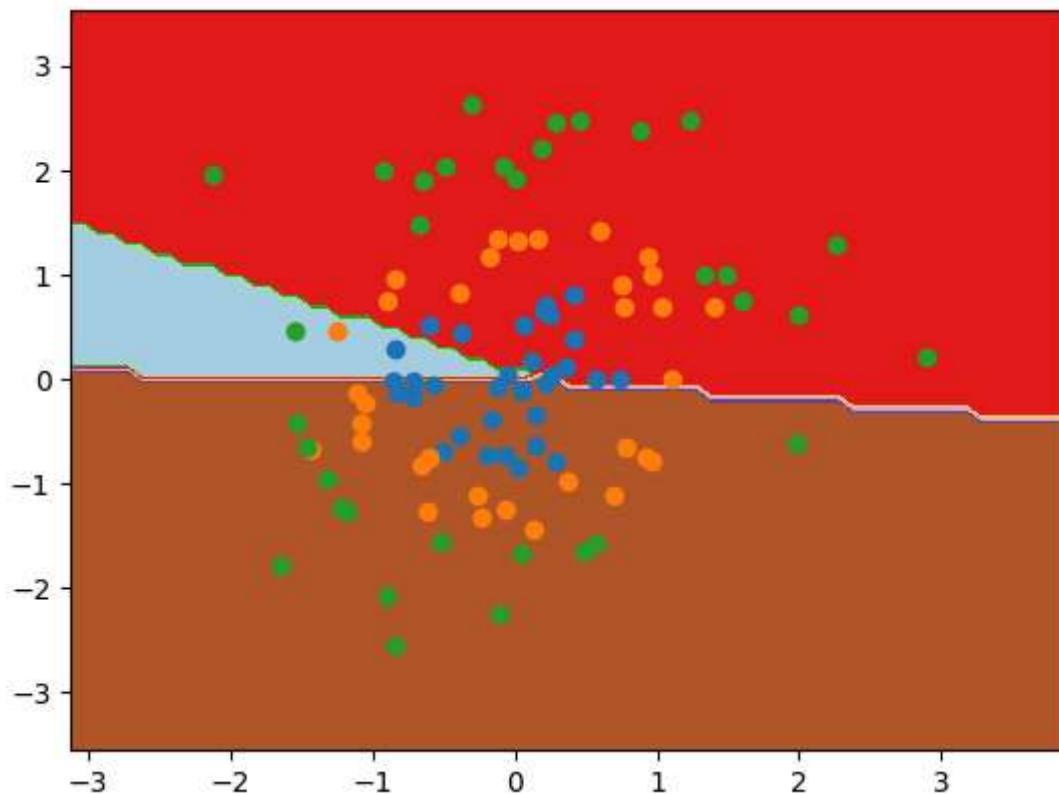
```
<ipython-input-81-125e0d01568d>:27: UserWarning: No data for colormapping provided via 'c'. Parameters 'cmap' will be ignored  
plt.scatter(X[row_ix, 0], X[row_ix, 1], cmap='Paired')
```



```
In [88]: #Logistic Regular
```

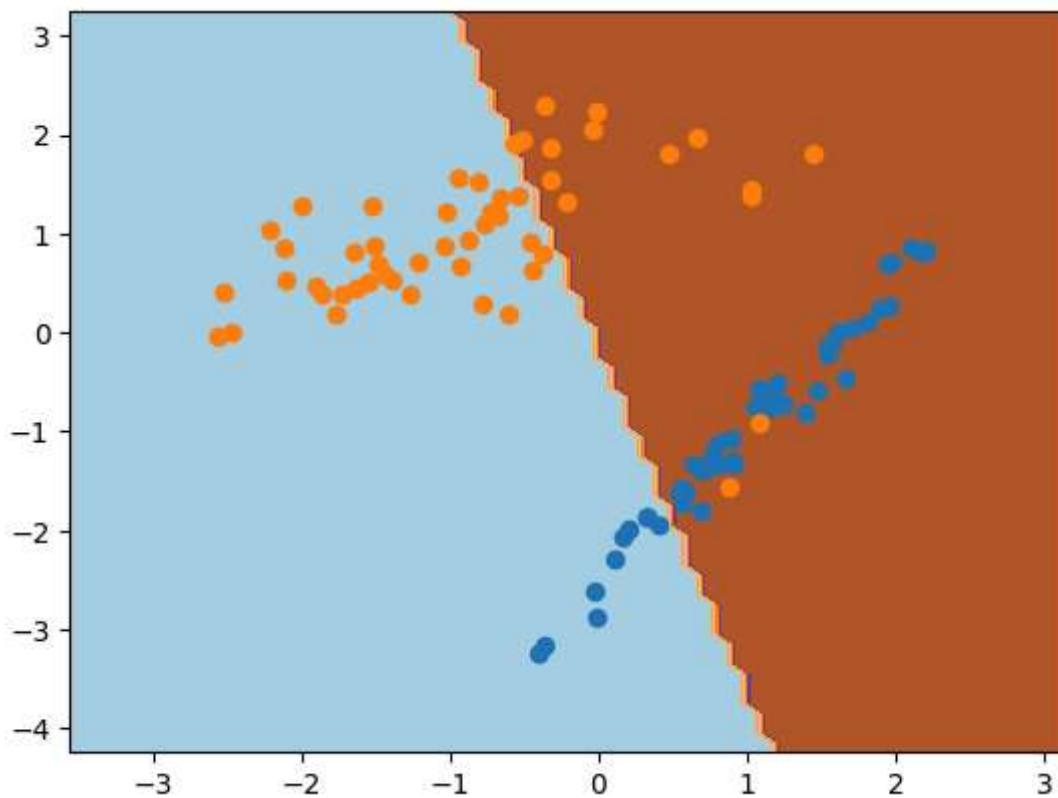
```
decisionBoundary(modelLogistic1,X_test,y_test, False)
```

```
<ipython-input-81-125e0d01568d>:27: UserWarning: No data for colormapping provided via 'c'. Parameters 'cmap' will be ignored  
plt.scatter(X[row_ix, 0], X[row_ix, 1], cmap='Paired')
```



```
In [87]: decisionBoundary(modelLogistic2,X1_test,y1_test, False)
```

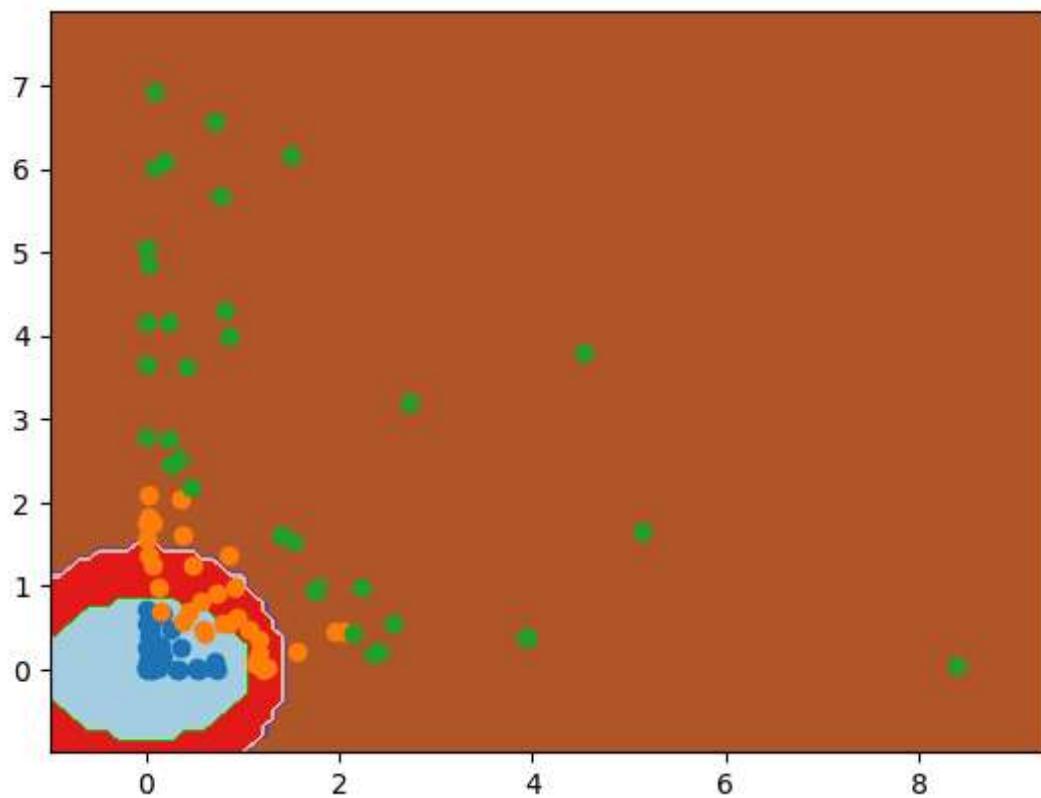
```
<ipython-input-81-125e0d01568d>:27: UserWarning: No data for colormapping provided via 'c'. Parameters 'cmap' will be ignored  
plt.scatter(X[row_ix, 0], X[row_ix, 1], cmap='Paired')
```



```
In [97]: #LogisticX^2 and X1^2
```

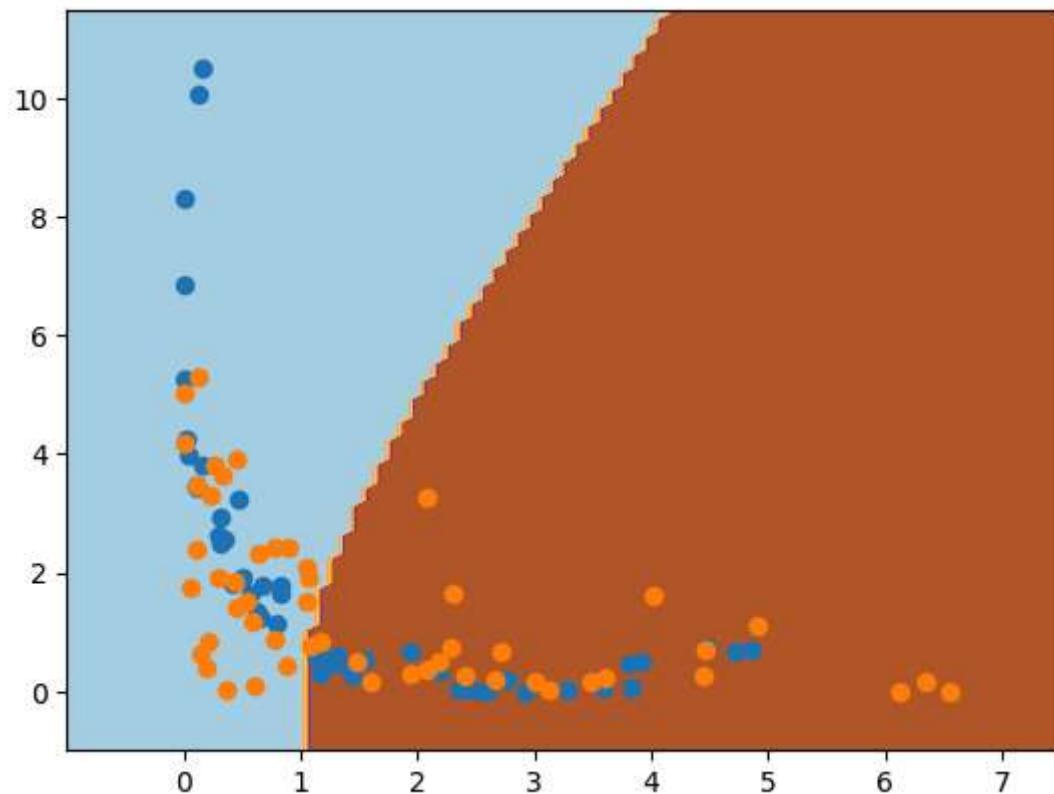
```
decisionBoundary(modelLogisticV1,X_test**2,y_test,True)
```

```
<ipython-input-81-125e0d01568d>:27: UserWarning: No data for colormapping provided via 'c'. Parameters 'cmap' will be ignored
    plt.scatter(X[row_ix, 0], X[row_ix, 1], cmap='Paired')
```



```
In [86]: decisionBoundary(modelLogisticV2,X1_test**2,y1_test,True)
```

```
<ipython-input-81-125e0d01568d>:27: UserWarning: No data for colormapping provided via 'c'. Parameters 'cmap' will be ignored  
plt.scatter(X[row_ix, 0], X[row_ix, 1], cmap='Paired')
```



e.) Based on your examination of the two data sets and the resulting plots, what can you say about the nature of the models? -which of them can generate curved boundaries? Which are all straight line boundaries?

Curved : LogisticX^2 and X1^2, Nural net Straight: XGboost, Gradient boost, random forest , regualr logistic -which looks most severely overfit? modelLogisticV1 lossts most severely overfit.

In [ ]: