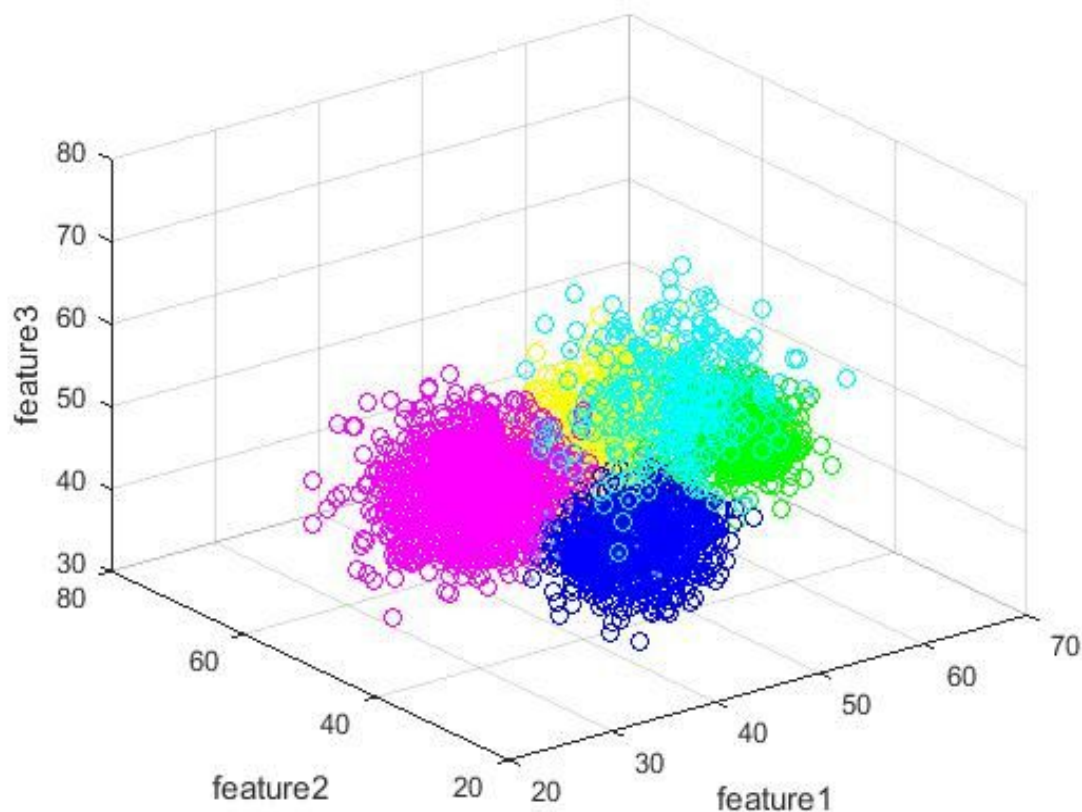


For Part A , I divide input to 5 class and I calculate $g(x)$ values for every class.After that, I assign a point to the class with respect to $g(x)$ values. I use `fscanf()` function for reading input and `scatter3()` function for plot figure.



I find points like in figure in Part A.For seperation of classes,I use different colors or circles and to show incorrect guesses,I use red dots.

Accuracy=0,9425

Incorrect guesses=232

Class 1 members=602(green)

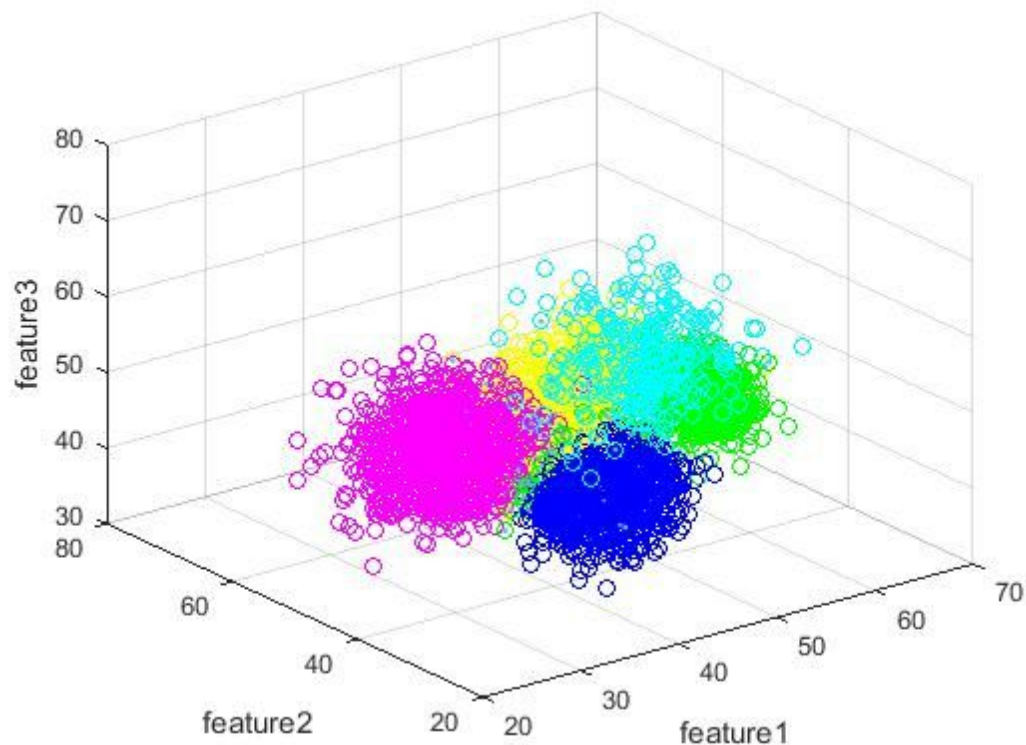
Class 2 members=1029(blue)

Class 3 members=984(yellow)

Class 4 members=317(cyan)

Class 5 members=1104(magenta)

For Part B, I did every steps same with partA except calculating $h(x)$ values. In partB I use risk matrice to form decision rule.



Accurancy=0,9078

Incorrect guesses=372

Class 1 members=606(green)

Class 2 members=1012(blue)

Class 3 members=1198(yellow)

Class 4 members=292(cyan)

Class 5 members=928(magenta)

For Part B , i use my risk matrice as $R = \begin{bmatrix} 0 & 1 & 100 & 1 & 2 \\ 2 & 0 & 100 & 3 & 5 \\ 1 & 2 & 0 & 2 & 4 \\ 1 & 1 & 100 & 0 & 3 \\ 2 & 4 & 100 & 1 & 0 \end{bmatrix}$

Purposely, I pick big numbers to 3.colomn than other colors. It means , if a point's nature is Class3 and some other class is picked for this point,it has big penalty.By doing that,I aim to observe Class3 has bigger area. So,you can observe this by looking graphs that yellow area is increased. Moreover,if you check count of class members,while count of Class3 is increase,(from 984 to 1198),all other classes counts are decreased.

To sum up, if all of the classes are same sensitivity for user, using zero-one loss scheme gives optimal solution. On contrary, if one or more classes' true discrimination is more important than other classes, you should introduce risk matrices.