Part a

1. My standard model with randomly initialized conditional probabilities

Class priors: [0.18936185 0.21768785 0.13887754 0.45407276]

Final Q value: -1641.9693155148273

2. Explore how results will change by changing initialization

1) uniform conditional probability (0.2)

The class priors don’t change throughout the iterations, and the conditional probabilities are also uniform across the classes, i.e., no matter what class it is, the conditional probabilities are the same given the attribute and the value it takes.

2) change to different seed values (seed(4))

Class priors: [0.45077768 0.14082959 0.22223622 0.18615651]

Final Q value: -1642.5360304373626

Compared to my standard model, the final Q value is similar, but the class priors “flip” between the classes: classes 1,4 roughly exchange probabilities and same for classes 2,3.

Part b

confusion matrix for test data:

```
[[[49  9]
  [12  5]]

 [[37 19]
  [ 7 12]]

 [[42 12]
  [ 9 12]]

 [[55  2]
  [14  4]]]
```

label	misclassification error
1	0.28
2	0.3466666666666667
3	0.28
4	0.21333333333333335

mean classification error = 0.28

Part c

Pick uniform value at random for x6 predictions, we can choose 1,2,3,or 4. In the worst case, for all labels, their misclassification errors will be around 0.5, resulting in the worst mean misclassification error being 0.5.

Compared with the mean misclassification error obtained from the NB model, this expected misclassification error is much worse, almost twice as the NB model one.

Extra Credit

null hypothesis: $\mu_{NB} = \mu_{random}$

p value is: $2.7008010182740486e\text{-}26 < 0.05$

There is less than 5% probability that the null hypothesis is correct. Thus, it indicates strong evidence to reject the null hypothesis, meaning that the two results are significantly different.