## Week 5: 8-12 February, 2021

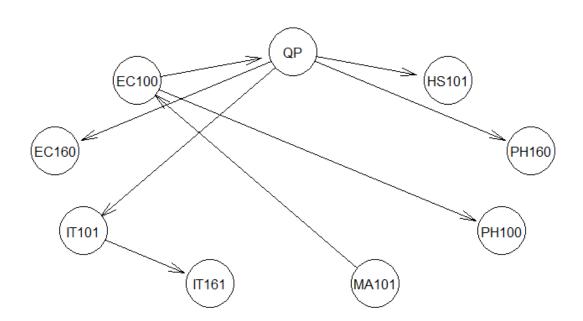
Lab Assignment 5

**Problem Statement:** 

A table containing grades earned by students in respective courses is made available to you in (codes folder) 2020\_bn\_nb\_data.txt.

## 1. Consider grades earned in each of the courses as random variables and learn the dependencies between courses.

```
> library(bnlearn)
> library(caret)
> library(e1071)
> mydata <- read.table("C:/Users/ADMIN/Desktop/AI Codes/Week_5/2020_bn_nb_data.txt", header=TRUE)
> mydata.net<-hc(mydata,score="k2",start=NULL)</pre>
 print(mydata.net)
 Bayesian network learned via Score-based methods
   arcs:
                                       8
   undirected arcs:
                                       0
   directed arcs:
                                       8
  average markov blanket size:
                                       1.78
  average neighbourhood size:
  average branching factor:
  learning algorithm:
                                       Hill-Climbing
                                       Cooper & Herskovits' K2
  tests used in the learning procedure:
  optimized:
```



## 2. Using the data, learn the CPTs for each course node.

```
> library(bnlearn)
> library(caret)
> library(e1071)
> mydata <- read.table("C:/Users/ADMIN/Desktop/AI Codes/Week_5/2020_bn_nb_data.txt", header=TRUE)
> mydata.net<-hc(mydata,score="k2",start=NULL)</pre>
> mydata.net.fit<-bn.fit(mydata.net, mydata)
> print(mydata.net.fit)
  Bayesian network parameters
  Parameters of node EC100 (multinomial distribution)
Conditional probability table:
    MA101
EC100
                                           BC
                                                     CC
  BB 0.25000000 0.23076923 0.32692308 0.22222222 0.04081633 0.00000000 0.00000000 0.00000000
  BC 0.00000000 0.15384615 0.28846154 0.27777778 0.32653061 0.00000000 0.00000000 0.00000000
  CC 0.00000000 0.07692308 0.09615385 0.24074074 0.32653061 0.04166667 0.00000000 0.00000000
  CD 0.00000000 0.00000000 0.00000000 0.12962963 0.26530612 0.33333333 0.04761905 0.00000000
  DD 0.00000000 0.00000000 0.00000000 0.03703704 0.04081633 0.50000000 0.19047619 0.00000000
  F 0.00000000 0.00000000 0.00000000 0.01851852 0.00000000 0.12500000 0.76190476 1.00000000
  Parameters of node EC160 (multinomial distribution)
Conditional probability table:
    QΡ
EC160
             n
  AA 0.00000000 0.07500000
  AB 0.00000000 0.10000000
  BB 0.01388889 0.18750000
  BC 0.01388889 0.36250000
  CC 0.15277778 0.22500000
  CD 0.44444444 0.03125000
  DD 0.26388889 0.01875000
  F 0.11111111 0.00000000
 Parameters of node IT101 (multinomial distribution)
```

```
Conditional probability table:
   QP
IT101
  AA 0.00000000 0.07500000
  AB 0.00000000 0.15625000
BB 0.04166667 0.19375000
BC 0.02777778 0.29375000
  CC 0.13888889 0.20000000
  CD 0.30555556 0.08125000
  DD 0.31944444 0.00000000 F 0.16666667 0.00000000
 Parameters of node IT161 (multinomial distribution)
Conditional probability table:
   IT101
  IT161
 Parameters of node MA101 (multinomial distribution)
Conditional probability table:

AA AB BB BC CC CD
0.01724138 0.05603448 0.22413793 0.23275862 0.21120690 0.10344828 0.09051724 0.06465517
 Parameters of node PH100 (multinomial distribution)
Conditional probability table:
   EC100
```

Parameters of node PH160 (multinomial distribution)

```
Conditional probability table:
QP
PH160
    AA 0.055555556 0.14375000
AB 0.09722222 0.15625000
    BB 0.02777778 0.17500000
   BC 0.18055556 0.34375000
CC 0.29166667 0.13750000
CD 0.19444444 0.04375000
    DD 0.12500000 0.00000000
    F 0.02777778 0.00000000
  Parameters of node HS101 (multinomial distribution)
Conditional probability table:
HS101
    AA 0.00000000 0.26250000
    AB 0.00000000 0.21250000
BB 0.05555556 0.22500000
BC 0.12500000 0.16875000
    CC 0.18055556 0.08125000
    CD 0.19444444 0.03750000
   DD 0.37500000 0.01250000
F 0.06944444 0.00000000
  Parameters of node QP (multinomial distribution)
Conditional probability table:
  P AA AB BB BC CC CD DD F n 0.0000000 0.0000000 0.0000000 0.1388889 0.4482759 0.9500000 1.0000000 y 1.0000000 1.0000000 1.0000000 0.8611111 0.5517241 0.0500000 0.0000000
QP
```

3. What grade will a student get in PH100 if he earns DD in EC100, CC in IT101 and CD in MA101.

```
> cpquery(mydata.net.fit, event = ( PH100 == "CD" ), evidence = ( EC100 == "DD" & IT101 == "CC" & MA101 == "CD" ))
[1] 0.45
> |
```

4. The last column in the data file indicates whether a student qualifies for an internship program or not. From the given data, take 70 percent data for training and build a naive Bayes classifier (considering that the grades earned in different courses are independent of each other) which takes in the student's performance and returns the qualification status with a probability. Test your classifier on the remaining 30 percent data. Repeat this experiment for 20 random selection of training and testing data. Report results about the accuracy of your classifier.

```
> data_train <- data1[random == 1, ]</pre>
> data_test <- data[random == 2, ]
> data_nb <- naiveBayes(QP ~ . , data = data_train)
> print(data_nb)
Naive Bayes Classifier for Discrete Predictors
naiveBayes.default(x = X, y = Y, laplace = laplace)
A-priori probabilities:
0.2830189 0.7169811
Conditional probabilities:
                                  ВВ
                                             BC
                                                        CC
 ВВ
                                             BC
                       AB
 y 0.09649123 0.10526316 0.18421053 0.32456140 0.22807018 0.03508772 0.02631579 0.00000000
 AA AB BB BC CC CD DD F
n 0.00000000 0.00000000 0.06666667 0.02222222 0.13333333 0.28888889 0.3111111 0.17777778
y 0.08771930 0.16666667 0.19298246 0.27192982 0.20175439 0.07894737 0.00000000 0.00000000
 AA AB BB BC CC CD DD F
n 0.00000000 0.02222222 0.02222222 0.04444444 0.22222222 0.28888889 0.37777778 0.02222222
y 0.10526316 0.17543860 0.18421053 0.30701754 0.16666667 0.05263158 0.00877193 0.00000000
 AA AB BB BC CC CD DD F n 0.000000000 0.000000000 0.08888889 0.13333333 0.24444444 0.35555556 0.17777778
 y 0.03508772 0.10526316 0.35087719 0.26315789 0.22807018 0.01754386 0.00000000 0.00000000
                                             BC
 PH160
                                 ВВ
                                             BC
                                                        CC
                                                                   CD
 n 0.06666667 0.15555556 0.00000000 0.13333333 0.28888889 0.177777778 0.13333333 0.04444444
 y 0.14912281 0.14912281 0.14912281 0.35964912 0.15789474 0.03508772 0.00000000 0.00000000
                                                        CC
  n 0.00000000 0.00000000 0.02222222 0.13333333 0.20000000 0.15555556 0.40000000 0.08888889
  y 0.28070175 0.22807018 0.21929825 0.13157895 0.07894737 0.04385965 0.01754386 0.00000000
```

```
> pred_nb <- predict(data_nb, data_test)</pre>
 confusionMatrix(table(pred_nb, data_test$QP))
Confusion Matrix and Statistics
pred_nb n y
n 24 0
      y 3 46
                 Accuracy : 0.9589
95% CI : (0.8846, 0.9914)
     No Information Rate : 0.6301
    P-Value [Acc > NIR] : 3.09e-11
                    Kappa : 0.9098
 Mcnemar's Test P-Value: 0.2482
              Sensitivity: 0.8889
             Specificity: 1.0000
          Pos Pred Value : 1.0000
Neg Pred Value : 0.9388
Prevalence : 0.3699
          Detection Rate: 0.3288
   Detection Prevalence : 0.3288
       Balanced Accuracy: 0.9444
        'Positive' Class : n
> |
```

5. Repeat 4, considering that the grades earned in different courses may be dependent.

```
> data_train <- data1[random == 1, ]</pre>
> data_test <- data1[random == 2, ]</pre>
> tn <- tan_cl('QP', data_train)</pre>
> tn<- lp(tn,data_train, smooth =1)</pre>
> pred_nb_2 <- predict(tn, data_test)
 accuracy(pred_nb_2 , data_test $QP)
> confusionMatrix(table(pred_nb_2, data_test $QP))
Confusion Matrix and Statistics
pred_nb_2 n y
        n 20 1
        y 7 45
                Accuracy: 0.8904
    95% CÍ : (0.7954, 0.9515)
No Information Rate : 0.6301
    P-Value [Acc > NIR] : 5.405e-07
                   карра: 0.7536
 Mcnemar's Test P-Value: 0.0771
             Sensitivity: 0.7407
         Specificity : 0.9783
Pos Pred Value : 0.9524
         Neg Pred Value: 0.8654
              Prevalence: 0.3699
         Detection Rate: 0.2740
   Detection Prevalence: 0.2877
      Balanced Accuracy: 0.8595
       'Positive' Class : n
```