labassignment5.R

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2023-02-06

```
# Installs pacman ("package manager") if needed
if (!require("pacman")) install.packages("pacman")
```

```
## Loading required package: pacman
```

```
# Use pacman to load add-on packages as desired
pacman::p_load(pacman, bnlearn, bnclassify)

# Read the data file using read.table function
data <- read.table("https://raw.githubusercontent.com/pratikiiitv/graphicalmodels/main/2020_bn_nb_data.t

# Convert character variables to factor variables
data[sapply(data, is.character)] <- lapply(data[sapply(data, is.character)], as.factor)

# Convert the data frame into a Bayesian network object
bn<- hc(data[,-9],score = 'k2')

# Inspect the learned Bayesian network structure
plot(bn)
bn
```

```
##
##   Bayesian network learned via Score-based methods
##
##   model:
##    [IT161][IT101|IT161][MA101|IT101][HS101|IT101][EC100|MA101][PH160|HS101]
##    [EC160|EC100][PH100|EC100]
##   nodes:                                 8
##   arcs:                                  7
##     undirected arcs:                     0
##     directed arcs:                       7
##   average markov blanket size:           1.75
##   average neighbourhood size:            1.75
##   average branching factor:              0.88
##
##   learning algorithm:                    Hill-Climbing
##   score:                                 Cooper & Herskovits' K2
##   tests used in the learning procedure:  105
##   optimized:                             TRUE
```

```r
# fit the Bayesian network to the data
fitted_bn <- bn.fit(bn, data[,-9])
fitted_bn$EC100
```

```
##
##   Parameters of node EC100 (multinomial distribution)
##
## Conditional probability table:
##
##      MA101
## EC100         AA         AB         BB         BC         CC         CD
##    AA 0.75000000 0.07692308 0.03846154 0.01851852 0.00000000 0.00000000
##    AB 0.00000000 0.46153846 0.25000000 0.05555556 0.00000000 0.00000000
##    BB 0.25000000 0.23076923 0.32692308 0.22222222 0.04081633 0.00000000
##    BC 0.00000000 0.15384615 0.28846154 0.27777778 0.32653061 0.00000000
##    CC 0.00000000 0.07692308 0.09615385 0.24074074 0.32653061 0.04166667
##    CD 0.00000000 0.00000000 0.00000000 0.12962963 0.26530612 0.33333333
##    DD 0.00000000 0.00000000 0.00000000 0.03703704 0.04081633 0.50000000
##    F  0.00000000 0.00000000 0.00000000 0.01851852 0.00000000 0.12500000
##      MA101
## EC100         DD          F
##    AA 0.00000000 0.00000000
##    AB 0.00000000 0.00000000
##    BB 0.00000000 0.00000000
##    BC 0.00000000 0.00000000
##    CC 0.00000000 0.00000000
##    CD 0.04761905 0.00000000
##    DD 0.19047619 0.00000000
##    F  0.76190476 1.00000000
```

```r
fitted_bn$EC160
```

```
##
##   Parameters of node EC160 (multinomial distribution)
##
## Conditional probability table:
##
##      EC100
## EC160         AA         AB         BB         BC         CC         CD
##    AA 0.42857143 0.22727273 0.05714286 0.04166667 0.00000000 0.00000000
##    AB 0.42857143 0.22727273 0.08571429 0.04166667 0.08333333 0.00000000
##    BB 0.14285714 0.31818182 0.20000000 0.22916667 0.08333333 0.03448276
##    BC 0.00000000 0.22727273 0.42857143 0.43750000 0.36111111 0.17241379
##    CC 0.00000000 0.00000000 0.22857143 0.25000000 0.30555556 0.34482759
##    CD 0.00000000 0.00000000 0.00000000 0.00000000 0.11111111 0.27586207
##    DD 0.00000000 0.00000000 0.00000000 0.00000000 0.05555556 0.17241379
##    F  0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000
##      EC100
## EC160         DD          F
##    AA 0.00000000 0.00000000
##    AB 0.00000000 0.00000000
##    BB 0.05000000 0.00000000
##    BC 0.00000000 0.00000000
```

```
##    CC 0.25000000 0.02857143
##    CD 0.55000000 0.40000000
##    DD 0.15000000 0.34285714
##    F  0.00000000 0.22857143
```

```
fitted_bn$IT101
```

```
##
##   Parameters of node IT101 (multinomial distribution)
##
## Conditional probability table:
##
##      IT161
## IT101         AA          AB          BB          BC          CC          CD
##    AA 0.35000000 0.08000000 0.05714286 0.02040816 0.00000000 0.00000000
##    AB 0.30000000 0.40000000 0.17142857 0.02040816 0.02380952 0.02857143
##    BB 0.25000000 0.40000000 0.31428571 0.14285714 0.00000000 0.02857143
##    BC 0.10000000 0.04000000 0.28571429 0.36734694 0.28571429 0.14285714
##    CC 0.00000000 0.08000000 0.14285714 0.32653061 0.33333333 0.11428571
##    CD 0.00000000 0.00000000 0.02857143 0.12244898 0.26190476 0.31428571
##    DD 0.00000000 0.00000000 0.00000000 0.00000000 0.04761905 0.34285714
##    F  0.00000000 0.00000000 0.00000000 0.00000000 0.04761905 0.02857143
##      IT161
## IT101         DD          F
##    AA 0.00000000 0.00000000
##    AB 0.00000000 0.00000000
##    BB 0.00000000 0.00000000
##    BC 0.04347826 0.00000000
##    CC 0.04347826 0.00000000
##    CD 0.21739130 0.33333333
##    DD 0.39130435 0.00000000
##    F  0.30434783 0.66666667
```

```
fitted_bn$IT161
```

```
##
##   Parameters of node IT161 (multinomial distribution)
##
## Conditional probability table:
##          AA          AB          BB          BC          CC          CD          DD
## 0.08620690 0.10775862 0.15086207 0.21120690 0.18103448 0.15086207 0.09913793
##          F
## 0.01293103
```

```
fitted_bn$MA101
```

```
##
##   Parameters of node MA101 (multinomial distribution)
##
## Conditional probability table:
##
##      IT101
```

```
## MA101         AA          AB          BB          BC          CC          CD
##    AA 0.16666667 0.04000000 0.00000000 0.00000000 0.02380952 0.00000000
##    AB 0.25000000 0.20000000 0.02941176 0.08163265 0.00000000 0.00000000
##    BB 0.33333333 0.56000000 0.38235294 0.22448980 0.19047619 0.05714286
##    BC 0.16666667 0.16000000 0.29411765 0.36734694 0.23809524 0.22857143
##    CC 0.08333333 0.00000000 0.20588235 0.28571429 0.35714286 0.31428571
##    CD 0.00000000 0.04000000 0.08823529 0.02040816 0.16666667 0.11428571
##    DD 0.00000000 0.00000000 0.00000000 0.02040816 0.02380952 0.22857143
##    F  0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.05714286
##      IT101
## MA101         DD          F
##    AA 0.00000000 0.00000000
##    AB 0.00000000 0.00000000
##    BB 0.00000000 0.00000000
##    BC 0.08695652 0.00000000
##    CC 0.04347826 0.00000000
##    CD 0.30434783 0.08333333
##    DD 0.39130435 0.16666667
##    F  0.17391304 0.75000000
```

```
fitted_bn$PH100
```

```
##
##   Parameters of node PH100 (multinomial distribution)
##
## Conditional probability table:
##
##      EC100
## PH100         AA          AB          BB          BC          CC          CD
##    AA 0.71428571 0.40909091 0.22857143 0.08333333 0.00000000 0.00000000
##    AB 0.14285714 0.31818182 0.20000000 0.18750000 0.05555556 0.00000000
##    BB 0.00000000 0.18181818 0.31428571 0.29166667 0.13888889 0.03448276
##    BC 0.14285714 0.04545455 0.14285714 0.22916667 0.33333333 0.13793103
##    CC 0.00000000 0.04545455 0.11428571 0.18750000 0.25000000 0.41379310
##    CD 0.00000000 0.00000000 0.00000000 0.02083333 0.19444444 0.31034483
##    DD 0.00000000 0.00000000 0.00000000 0.00000000 0.02777778 0.10344828
##    F  0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000
##      EC100
## PH100         DD          F
##    AA 0.00000000 0.00000000
##    AB 0.00000000 0.00000000
##    BB 0.05000000 0.00000000
##    BC 0.00000000 0.00000000
##    CC 0.20000000 0.02857143
##    CD 0.45000000 0.11428571
##    DD 0.20000000 0.45714286
##    F  0.10000000 0.40000000
```

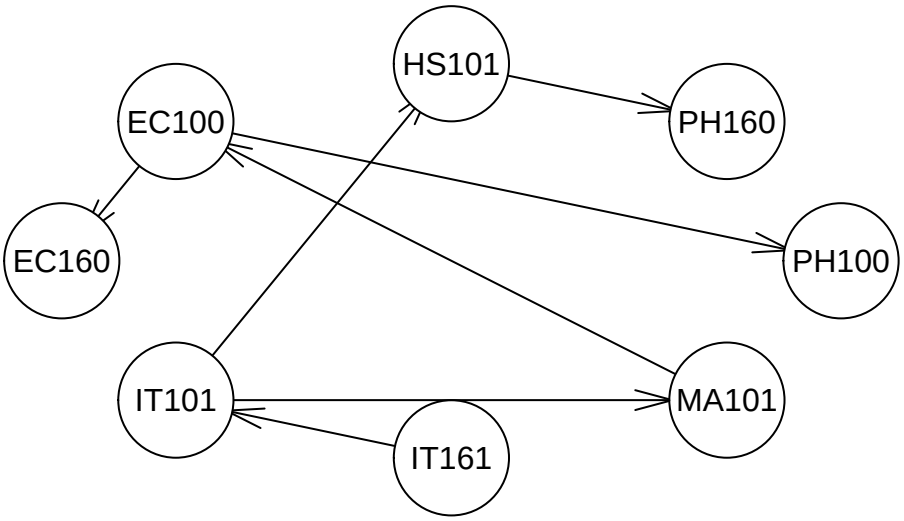
```
fitted_bn$HS101
```

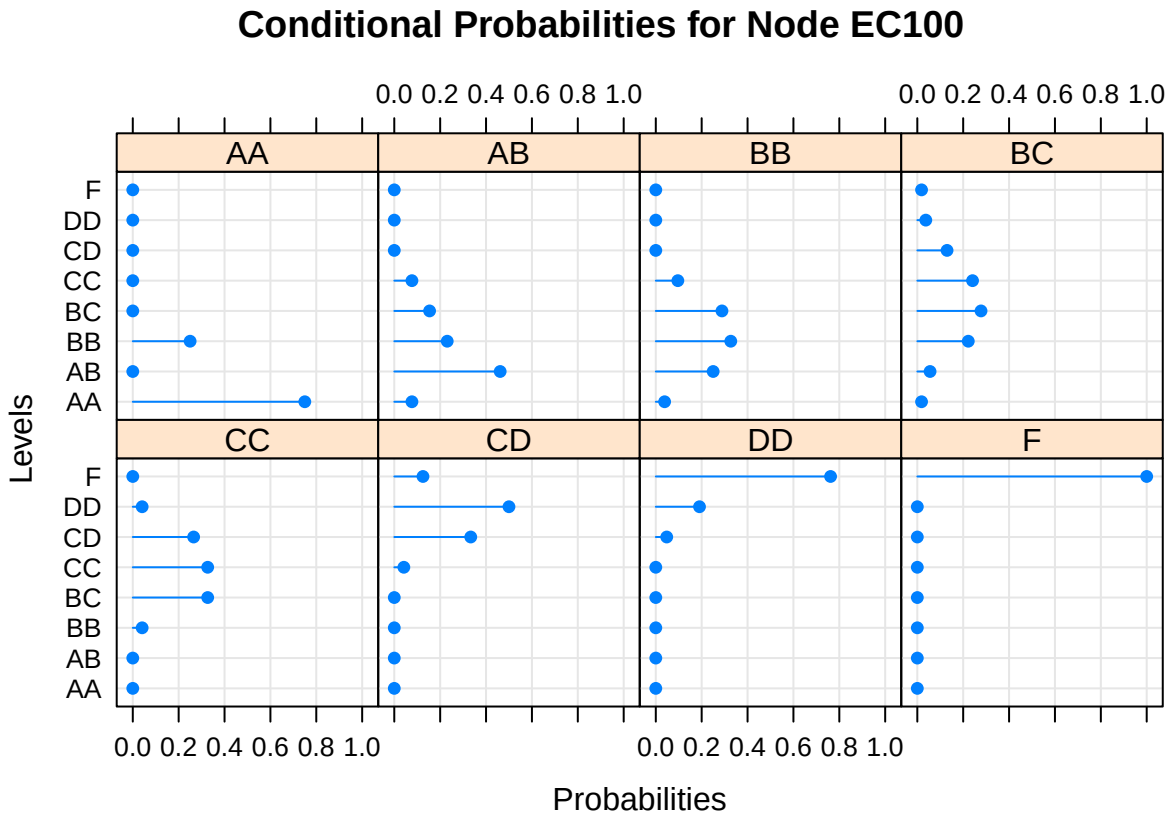
```
##
##   Parameters of node HS101 (multinomial distribution)
##
```

```
## Conditional probability table:
##
##      IT101
## HS101         AA         AB         BB         BC         CC         CD
##    AA 0.58333333 0.56000000 0.32352941 0.10204082 0.07142857 0.05714286
##    AB 0.33333333 0.24000000 0.11764706 0.22448980 0.14285714 0.08571429
##    BB 0.00000000 0.12000000 0.26470588 0.26530612 0.26190476 0.11428571
##    BC 0.08333333 0.08000000 0.08823529 0.24489796 0.23809524 0.20000000
##    CC 0.00000000 0.00000000 0.11764706 0.12244898 0.14285714 0.11428571
##    CD 0.00000000 0.00000000 0.05882353 0.02040816 0.14285714 0.20000000
##    DD 0.00000000 0.00000000 0.02941176 0.02040816 0.00000000 0.22857143
##    F  0.00000000 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000
##      IT101
## HS101         DD          F
##    AA 0.00000000 0.00000000
##    AB 0.00000000 0.00000000
##    BB 0.00000000 0.00000000
##    BC 0.04347826 0.00000000
##    CC 0.26086957 0.00000000
##    CD 0.13043478 0.08333333
##    DD 0.52173913 0.58333333
##    F  0.04347826 0.33333333
```

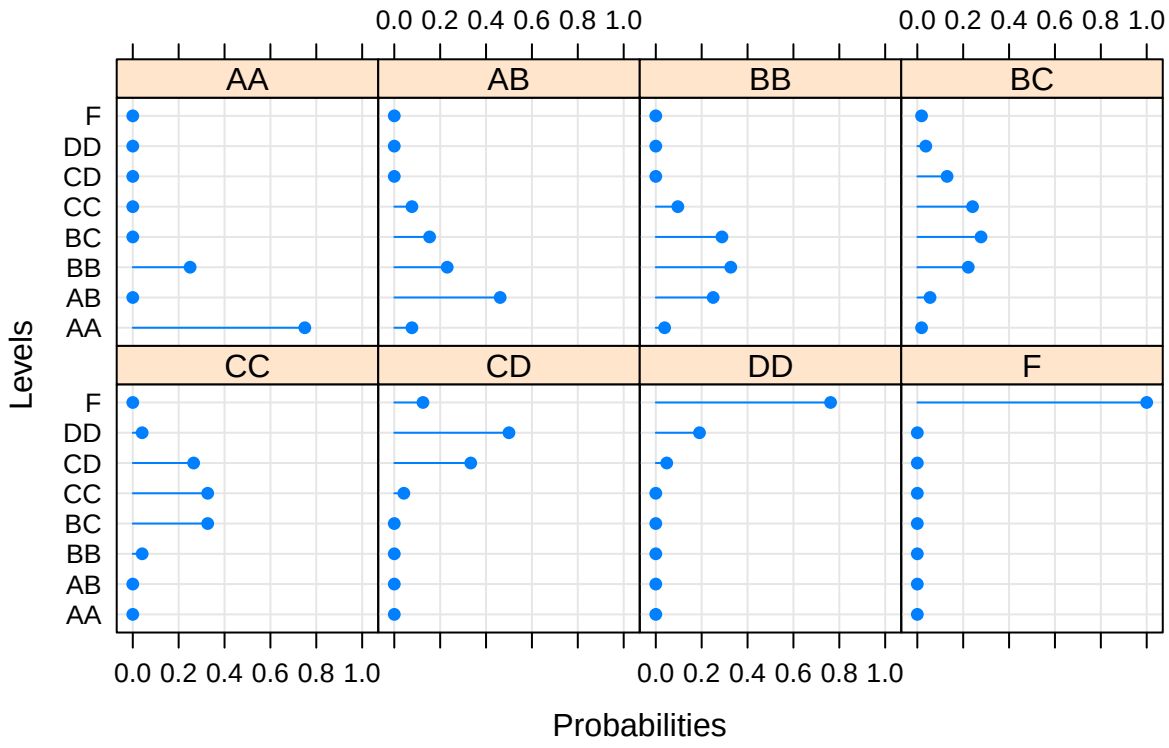
```
# Plot the CPTs of each node as a dot plot (similar to bar chart) using bn.fit.dotplot
bn.fit.dotplot(fitted_bn$EC100)
```

```
## Loading required namespace: lattice
```

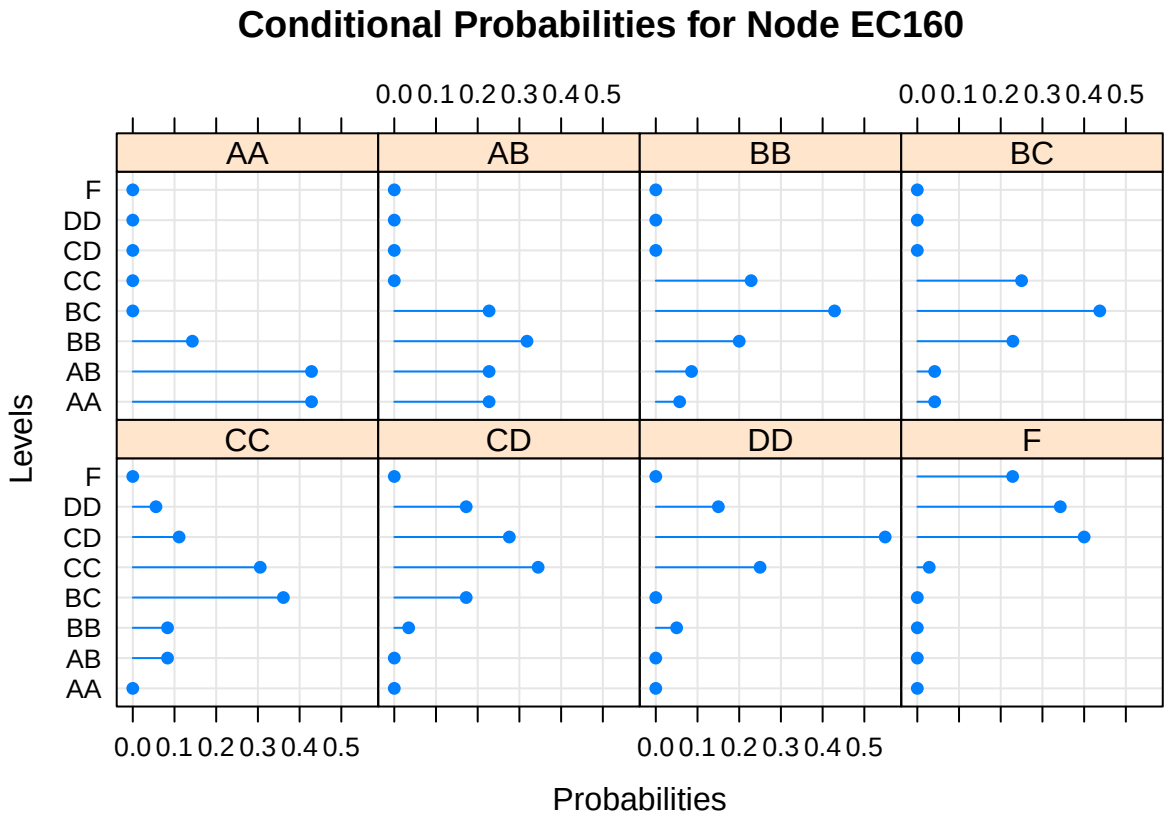

HS101
EC100
PH160
EC160
PH100
IT101
MA101
IT161



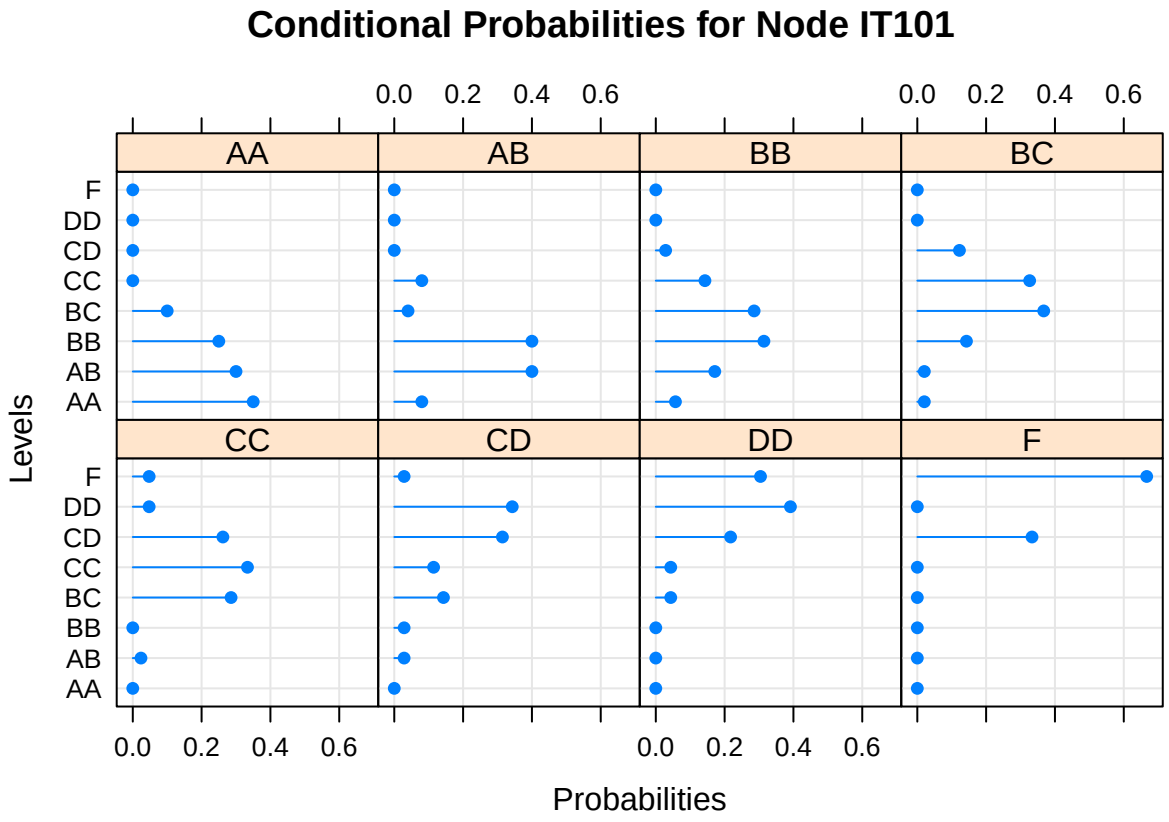

```
bn.fit.dotplot(fitted_bn$EC100)
```



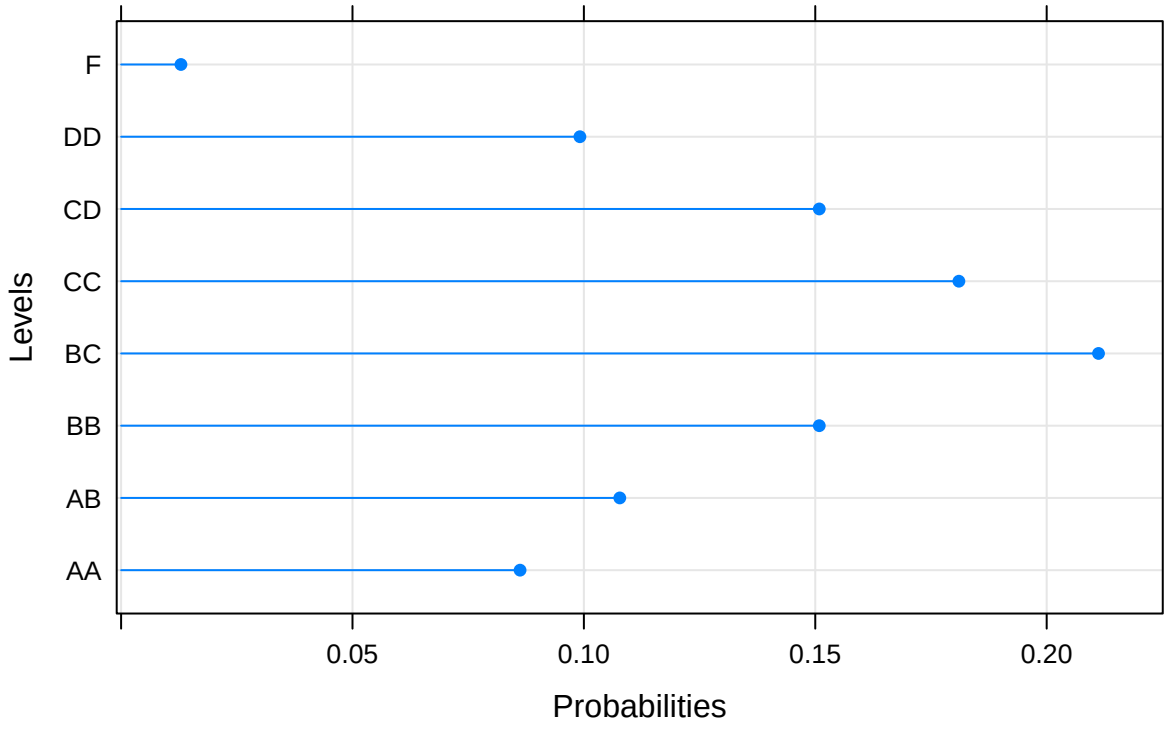

```
bn.fit.dotplot(fitted_bn$EC160)
```



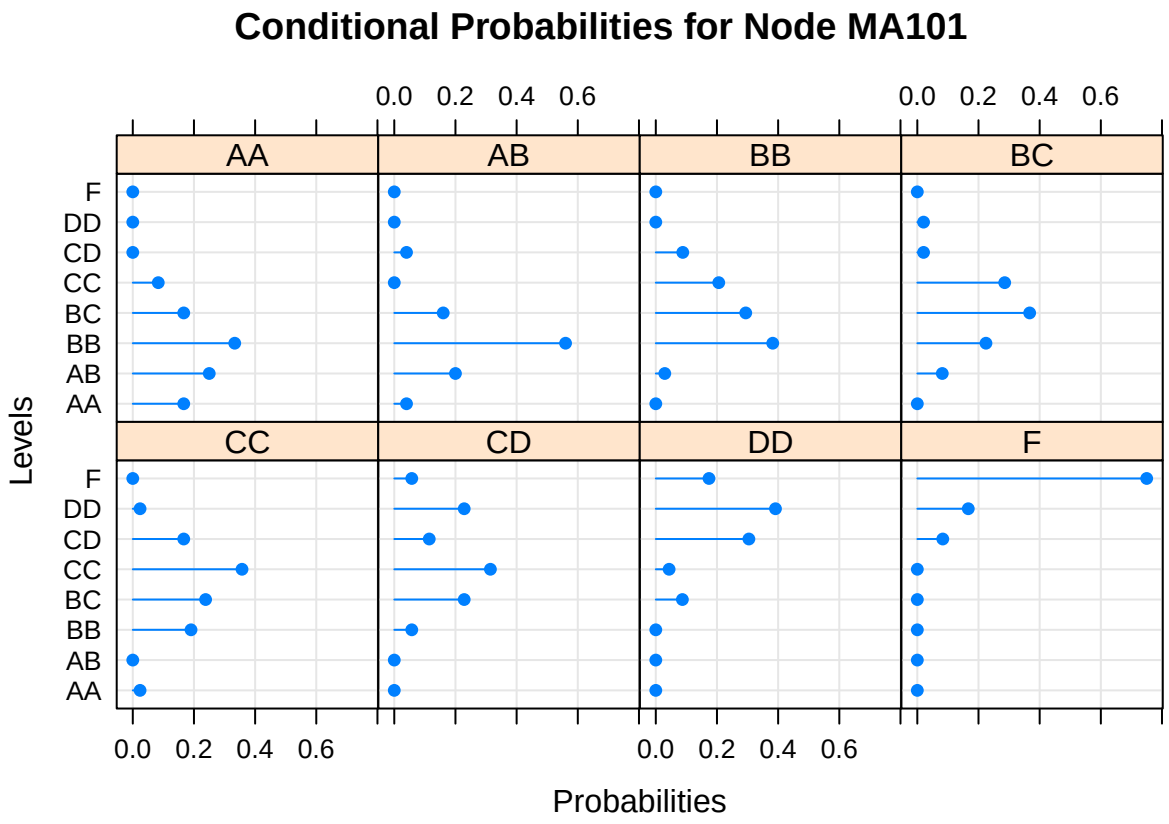

```
bn.fit.dotplot(fitted_bn$IT101)
```



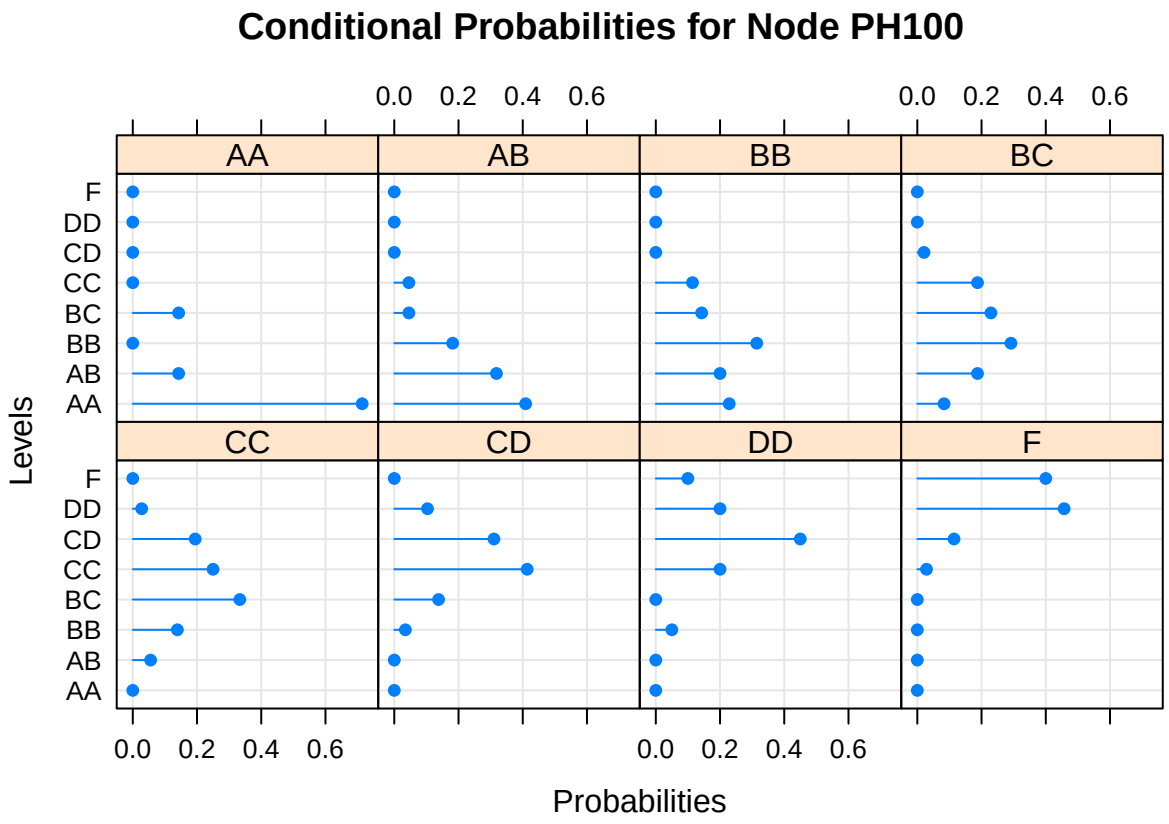

```
bn.fit.dotplot(fitted_bn$IT161)
```



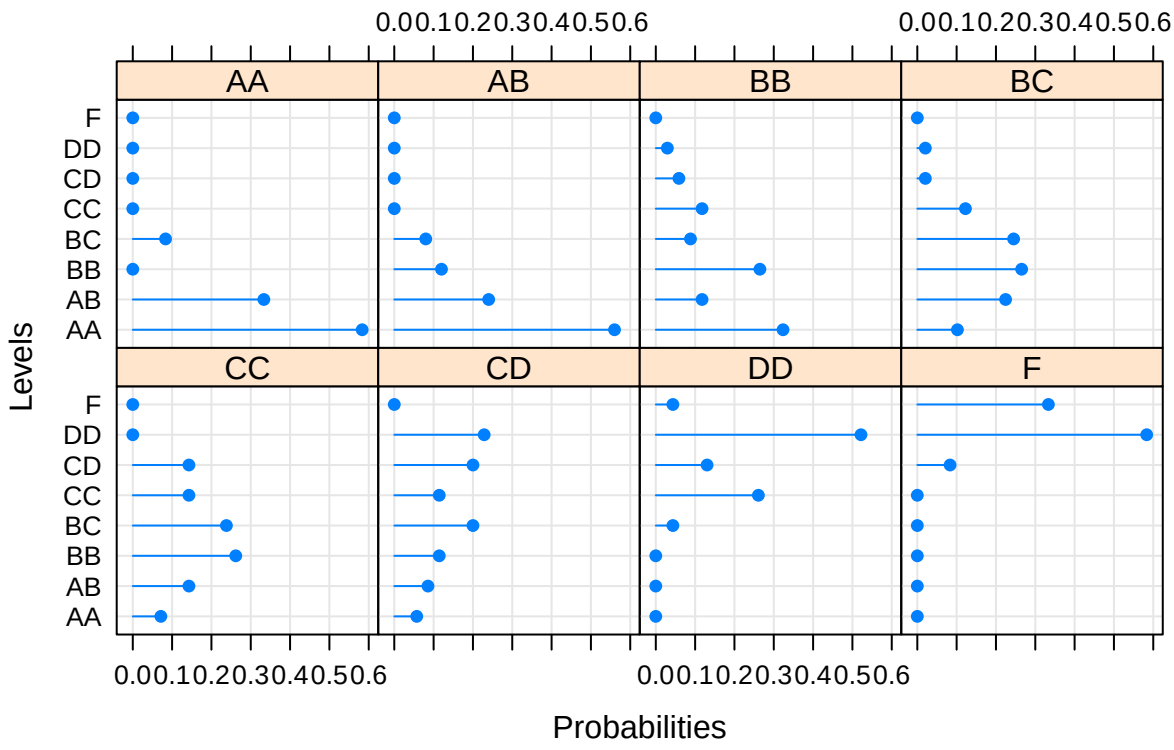

```
bn.fit.dotplot(fitted_bn$MA101)
```




```
bn.fit.dotplot(fitted_bn$PH100)
```



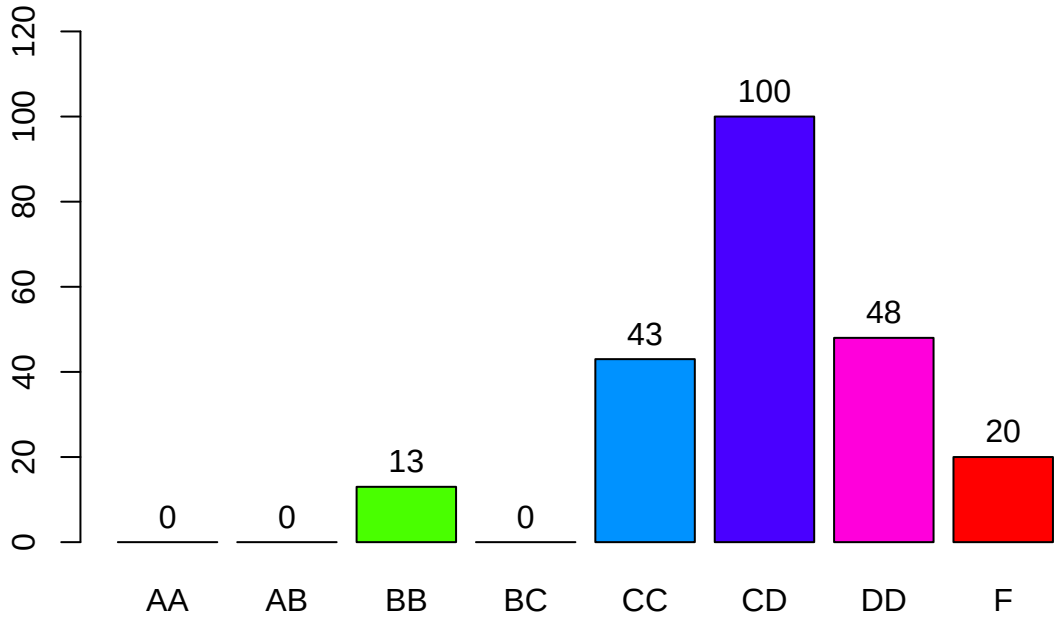

```
bn.fit.dotplot(fitted_bn$HS101)
```




```
# What grade will a student get in PH100 if he earns DD in EC100, CC in IT101 and CD in MA101:

# Predict the grade in PH100 based on evidence provided
prediction.PH100 <- data.frame(cpdist(fitted_bn, nodes = c("PH100"), evidence = (EC100 == "DD" & IT101 =

# plot(prediction.PH100)
my_table <- table(prediction.PH100)
my_table
```

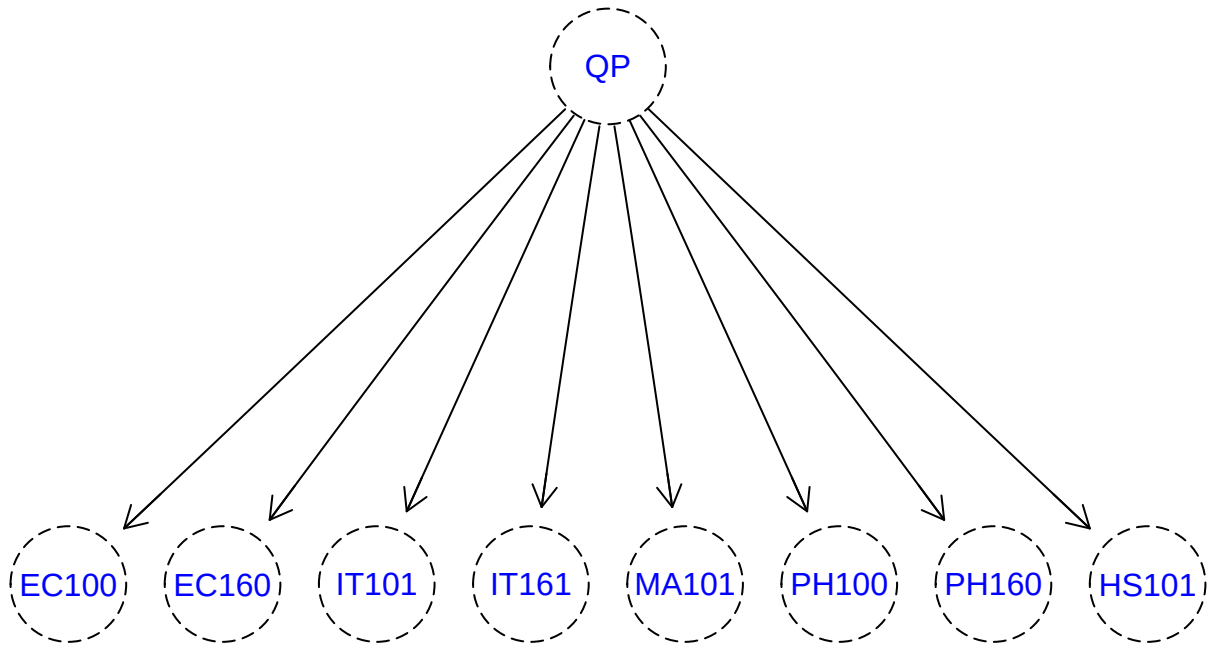
```
## PH100
##  AA  AB  BB  BC  CC  CD  DD   F
##   0   0  13   0  43 100  48  20
```

```
barp <- barplot(my_table, col = hsv(seq(0, 1, length.out = 8), 1, 1), ylim = c(0, 120))
text(barp, my_table + 6, labels = my_table)
```




```
# Set the seed for reproducibility
set.seed(101)

# Initialize an empty vector to store accuracy results
accuracy_results <- c()

# Loop 20 times
for (i in 1:20) {

# Split the data into training and testing sets using the sample function
sample <- sample.int(n = nrow(data), size = floor(.7*nrow(data)), replace = F)
data.train <-data[sample,]
data.test<- data[-sample,]

# Build the naive Bayes classifier on the training data using the nb function from the bnlearn package.
nb.grades <- nb(class = "QP",dataset= data.train)

#Fit the naive Bayes classifier to the training data using the lp function
nb.grades<-lp(nb.grades, data.train, smooth=0)
#nb.grades$.params

#Use the predict function to predict the grades of the test data
p<-predict(nb.grades, data.test)
#Compute the confusion matrix using the table function
cm<-table(predicted=p, true=data.test$QP)
cm
```

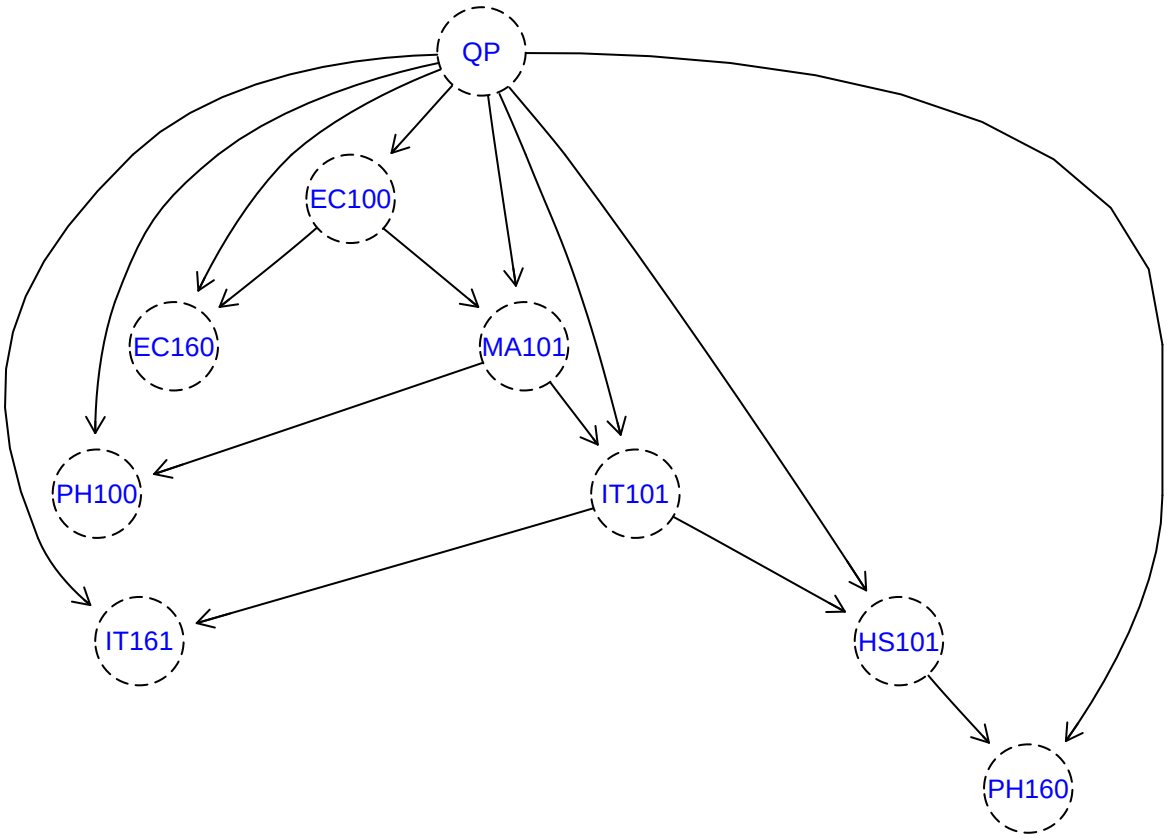
```
#Compute the accuracy of the prediction using the accuracy function from the bnclassify package
accuracy <- bnclassify:::accuracy(p, data.test$QP)

# Store the accuracy in the vector
accuracy_results <- c(accuracy_results, accuracy)

}

plot(nb.grades)
```




```
# Report the mean accuracy of the classifier
mean(accuracy_results)
```

```
## [1] 0.9528571
```

```
#Build the TAN classifier on the training data using the tan_cl function from the bnlearn package.
tn <- tan_cl("QP", data.train)
#Fit the TAN classifier to the training data using the lp function
tn <- lp(tn, data.train, smooth = 1)
plot(tn)
```




```
#Use the predict function to predict the grades of the test data.
p <- predict(tn, data.test)
#Compute the confusion matrix using the table function
cm1<-table(predicted=p, true=data.test$QP)
cm1
```

```
##           true
## predicted  n  y
##         n 21  1
##         y  3 45
```

```
#Compute the accuracy of the prediction using the accuracy function from the bnclassify package
bnclassify:::accuracy(p, data.test$QP)
```

```
## [1] 0.9428571
```

```
#Clear Console
cat("\014")
```

```r
#Clear all plots
dev.off()
```

```
## null device
##           1
```