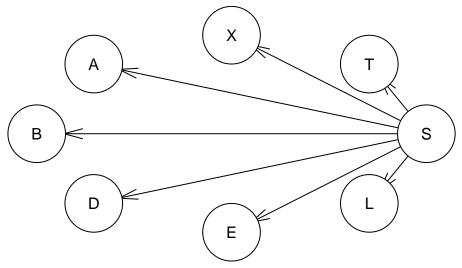
exam-2018-with-solutions

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Graphical Models

```
set.seed(567)
data("asia")
ind <- sample(1:5000, 4000)</pre>
train <- asia[ind,]</pre>
test <- asia[-ind,]</pre>
train_10 = train[1:10,]
train_20 = train[1:20,]
train_50 = train[1:50,]
train_100 = train[1:100,]
train_1000 = train[1:1000,]
train_2000 = train[1:2000,]
test_1000 = test[1:1000,]
## Training the network
train_bayesian_network = function(structure = NULL,
                                   data,
                                   learning_algorithm = iamb,
                                   ...) {
  # Network
  if (is.null(structure)) {
    bayesian_network = learning_algorithm(data, ...)
  }
  else {
    bayesian_network = structure
  }
  # Parameters
  bayesian_network_fit = bn.fit(bayesian_network, data, method="bayes")
  bayesian_network_grain = compile(as.grain(bayesian_network_fit))
  return(list(bn_grain=bayesian_network_grain,
              bn_fit=bayesian_network_fit,
              bn_structure=bayesian_network))
}
# Structure
bn_naive_bayes = model2network("[S][A|S][T|S][L|S][B|S][E|S][X|S][D|S]")
plot(bn_naive_bayes)
```



```
## Warning in check.data(data, allow.missing = TRUE): variable A has levels
## that are not observed in the data.
```

Warning in check.data(data, allow.missing = TRUE): variable T has levels
that are not observed in the data.

Warning in check.data(data, allow.missing = TRUE): variable A has levels
that are not observed in the data.

Warning in check.data(data, allow.missing = TRUE): variable T has levels
that are not observed in the data.

Warning in check.data(data, allow.missing = TRUE): variable T has levels
that are not observed in the data.

Warning in check.data(data, allow.missing = TRUE): variable T has levels
that are not observed in the data.

```
## Predicting with the network
predict_bayesian_network = function(bayesian_network,
                                    testX_ = testX,
                                    testY = testY) {
  res = apply(testX_, 1, FUN = function(x) {
   return(querygrain(setEvidence(bayesian_network$bn_grain, names(x), x))$S)
  })
  # Classify
  pred = apply(res, 2, FUN = function(x) {
   if (x[2] > 0.5) return("yes")
   return("no")
  })
  # Factorise
  testY_factor = testY_
  pred_factor = factor(pred)
  # Call to a library to calculate interesting metrics
  confusion_matrix = table(pred_factor, testY_factor)
 return(list(res=res, pred=pred, cf=confusion_matrix))
}
myResConf10 = predict_bayesian_network(bn_naive_bayes10, test_1000[,-2], test_1000$$)$cf
myResConf20 = predict_bayesian_network(bn_naive_bayes20, test_1000[,-2], test_1000$$)$cf
myResConf50 = predict_bayesian_network(bn_naive_bayes50, test_1000[,-2], test_1000$$)$cf
myResConf100 = predict_bayesian_network(bn_naive_bayes100, test_1000[,-2], test_1000$$)$cf
myResConf1000 = predict_bayesian_network(bn_naive_bayes1000, test_1000[,-2], test_1000$$)$cf
myResConf2000 = predict_bayesian_network(bn_naive_bayes2000, test_1000[,-2], test_1000$$)$cf
acc10 = sum(diag(myResConf10))/sum(myResConf10)
acc20 = sum(diag(myResConf20))/sum(myResConf20)
acc50 = sum(diag(myResConf50))/sum(myResConf50)
acc100 = sum(diag(myResConf100))/sum(myResConf100)
acc1000 = sum(diag(myResConf1000))/sum(myResConf1000)
acc2000 = sum(diag(myResConf2000))/sum(myResConf2000)
print(c(acc10, acc20, acc50, acc100, acc1000, acc2000))
```

[1] 0.672 0.672 0.665 0.665 0.665