A one–minute introduction to the gRain package

Søren Højsgaard
Aarhus University, Denmark

June 12, 2008

Contents

1 Introduction

The gRain package is accompanied by a larger manual which is also available from http://gbi.agrsci.dk/~shd/public/gRainweb/. This vignette is just an excerpt from this manual.

2 A worked example: chest clinic

This section reviews the chest clinic example of Lauritzen and Spiegelhalter (1988) (illustrated in Figure 1) and shows one way of specifying the model in gRain. Lauritzen and Spiegelhalter (1988) motivate the chest clinic example as follows:

> "Shortness–of–breath (dyspnoea) may be due to tuberculosis, lung cancer or bronchitis, or none of them, or more than one of them. A recent visit to Asia increases the chances of tuberculosis, while smoking is known to be a risk factor for both lung cancer and bronchitis. The results of a single chest X–ray do not discriminate between lung cancer and tuberculosis, as neither does the presence or absence of dyspnoea."

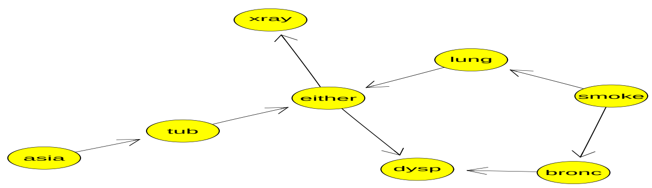

Figure 1: Chest clinic example from LS.

2.1 Building a `iNet`

A Bayesian network is a special case of graphical independence networks. In this section we outline how to build a Bayesian network. The starting point is a probability distribution factorising accoring to a DAG with nodes V. Each node $v \in V$ has a set $pa(v)$ of parents and each node $v \in V$ has a finite set of states. A joint distribution over the variables V can be given as

$$p(V) = \prod_{v \in V} p(v|pa(v)) \tag{1}$$

where $p(v|pa(v))$ is a function defined on $(v, pa(v))$. This function satisfies that $\sum_{v^*} p(v = v^*|pa(v)) = 1$, i.e. that for each configuration of the parents $pa(v)$, the sum over the levels of v equals one. Hence $p(v|pa(v))$ becomes the conditional distribution of v given $pa(v)$. In practice $p(v|pa(v))$ is specified as a table called a conditional probability table or a CPT for short. Thus, a Bayesian network can be regarded as a complex stochastic model built up by putting together simple components (conditional probability distributions).

Thus the DAG in Figure 1 dictates a factorization of the joint probability function as

$$p(V) = p(\alpha)p(\sigma)p(\tau|\alpha)p(\lambda|\sigma)p(\beta|\sigma)p(\epsilon|\tau, \lambda)p(\delta|\epsilon, \beta)p(\xi|\epsilon). \tag{2}$$

In (2) we have α = asia, σ = smoker, τ = tuberculosis, λ = lung cancer, β = bronchitis, ϵ = either tuberculosis or lung cancer, δ = dyspnoea and ξ = xray. Note that ϵ is a logical variable which is true if either τ or λ are true and false otherwise.

2.2 Queries to `iNets`

Suppose we are given evidence that a set of variables $E \subset V$ have a specific value e^*. For example that a person has recently visited Asia and suffers from dyspnoea, i.e. α = yes and δ = yes.

With this evidence, we are often interested in the conditional distribution $p(v|E = e^*)$ for some of the variables $v \in V \setminus E$ or in $p(U|E = e^*)$ for a set $U \subset V \setminus E$.

In the chest clinic example, interest might be in $p(\lambda|e^*)$, $p(\tau|e^*)$ and $p(\beta|e^*)$, or possibly in the joint (conditional) distribution $p(\lambda, \tau, \beta|e^*)$.

Interest might also be in calculating the probability of a specific event, e.g. the probability of seeing a specific evidence, i.e. $p(E = e^*)$.

2.3 A one–minute version of `gRain`

A simple way of specifying the model for the chest clinic example is as follows.

1. Specify conditional probability tables (with values as given in Lauritzen and Spiegelhalter (1988)):

```
> yn <- c("yes", "no")
> a <- cpt(~asia, values = c(1, 99), levels = yn)
> t.a <- cpt(~tub + asia, values = c(5, 95, 1, 99), levels = yn)
> s <- cpt(~smoke, values = c(5, 5), levels = yn)
> l.s <- cpt(~lung + smoke, values = c(1, 9, 1, 99), levels = yn)
> b.s <- cpt(~bronc + smoke, values = c(6, 4, 3, 7), levels = yn)
> e.lt <- cpt(~either + lung + tub, values = c(1, 0, 1, 0, 1, 0, 0,
+     1), levels = yn)
> x.e <- cpt(~xray + either, values = c(98, 2, 5, 95), levels = yn)
> d.be <- cpt(~dysp + bronc + either, values = c(9, 1, 7, 3, 8, 2,
+     1, 9), levels = yn)
```

2. Create the `iNet` from the conditional probability tables:

```
> plist <- cptspec(list(a, t.a, s, l.s, b.s, e.lt, x.e, d.be))
> in1 <- newgmInstance(plist)
> in1

Independence network: Compiled: FALSE Propagated: FALSE
```

3. The `iNet` can be queried to give marginal probabilities:

```
> querygm(in1, nodes = c("lung", "bronc"), type = "marginal")

$lung
lung
  yes    no
0.055 0.945

$bronc
bronc
 yes   no
0.45 0.55
```

Likewise, a joint distribution can be obtained.

```
> querygm(in1, nodes = c("lung", "bronc"), type = "joint")

     bronc
lung     yes     no
  yes 0.0315 0.0235
  no  0.4185 0.5265
```

4. Evidence can be entered as:

```
> in12 <- enterEvidence(in1, nodes = c("asia", "dysp"), states = c("yes",
+     "yes"))
```

5. The `iNet` can be queried again:

```
> querygm(in12, nodes = c("lung", "bronc"))

$lung
lung
       yes         no
0.09952515 0.90047485

$bronc
bronc
      yes        no
0.8114021 0.1885979

> querygm(in12, nodes = c("lung", "bronc"), type = "joint")

     bronc
lung         yes         no
  yes 0.06298076 0.03654439
  no  0.74842132 0.15205354
```

References

Steffen Lilholt Lauritzen and David Spiegelhalter. Local computations with probabilities on graphical structures and their application to expert systems. *J. Roy. Stat. Soc. Ser. B*, 50(2):157–224, 1988.