

# A one-minute introduction to the **gRain** package

Søren Højsgaard  
Aarhus University, Denmark

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## 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.”

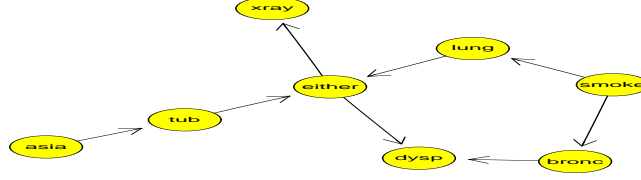


Figure 1: Chest clinic example from LS.

## 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 according 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

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

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

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

In (2) we have  $\alpha = \text{asia}$ ,  $\sigma = \text{smoker}$ ,  $\tau = \text{tuberculosis}$ ,  $\lambda = \text{lung cancer}$ ,  $\beta = \text{bronchitis}$ ,  $\epsilon = \text{either tuberculosis or lung cancer}$ ,  $\delta = \text{dyspnoea}$  and  $\xi = \text{xray}$ . Note that  $\epsilon$  is a logical variable which is true if either  $\tau$  or  $\lambda$  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.  $\alpha = \text{yes}$  and  $\delta = \text{yes}$ .

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 <- cptable(~asia, values = c(1, 99), levels = yn)
> t.a <- cptable(~tub + asia, values = c(5, 95, 1, 99), levels = yn)
> s <- cptable(~smoke, values = c(5, 5), levels = yn)
> l.s <- cptable(~lung + smoke, values = c(1, 9, 1, 99), levels = yn)
> b.s <- cptable(~bronc + smoke, values = c(6, 4, 3, 7), levels = yn)
> e.lt <- cptable(~either + lung + tub, values = c(1, 0, 1, 0, 1,
+      0, 0, 1), levels = yn)
> x.e <- cptable(~xray + either, values = c(98, 2, 5, 95), levels = yn)
> d.be <- cptable(~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 <- grain(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 <- setFinding(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 Liholt 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.