

# Structural Learning in BN

27<sup>th</sup> March, 2020

# Revision

For coins with Beta priors:

- **Prior:**  $P(X = 1) = E(F) = \alpha / (\alpha + \beta)$
- **Posterior:**  $P(X = 1|d) = E(F|d) = (\alpha + s) / (\alpha + \beta + s + t)$
- **Likelihood:**  $P(d) = \frac{B(\alpha + s, \beta + s)}{B(\alpha, \beta)}$  ; where  $B(x, y) = \frac{\Gamma(x)\Gamma(y)}{\Gamma(x + y)}$
- **Generalised Formula:**

$$P(d) = \prod_{i=1}^n \prod_{j=1}^{n_i} \frac{B(\alpha_{ij} + s_{ij}, \beta_{ij} + t_{ij})}{B(\alpha_{ij}, \beta_{ij})}$$

- **Previous Assumption:** The graph structure (DAG - Directed Acyclic Graph) was known to us.
- Hence  $P(d)$  was  $P(d|G)$  actually.
- For multiple graphs  $\{G_1, G_2, \dots, G_n\}$ ,  $P(d)$  can be calculated as:

$$P(d) = P(d|G_1)*P(G_1) + P(d|G_2)*P(G_2) + \dots + P(d|G_n)*P(G_n)$$

If we have several potential DAG structures  $G_1, G_2, \dots, G_n$  we can use Bayes' theorem to calculate:

$$P(G_i | D) = \alpha P(D|G_i)P(G_i)$$

And then choose the Graph which has maximum probability given the data  $D$ .

**Ex1:** Suppose we are doing a study concerning individuals who were married by age 30, and we want to see if there is a correlation between graduating college and getting divorced.

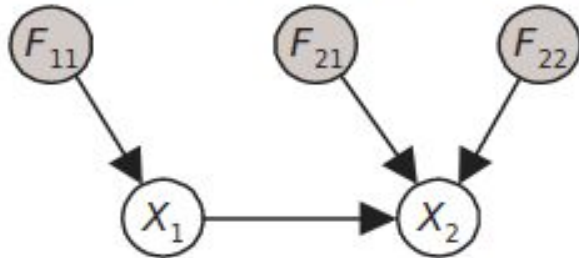
Variable	Value	When the Variable Takes this Value
$X_1$	1	<i>Individual graduated college</i>
	2	<i>Individual did not graduate college</i>
$X_2$	1	<i>Individual was divorced by age 50</i>
	2	<i>Individual was not divorced by age 50</i>

Next, we observe following data:

Case	$X_1$	$X_2$
1	1	1
2	1	2
3	1	1
4	2	2
5	1	1
6	2	1
7	1	1
8	2	2

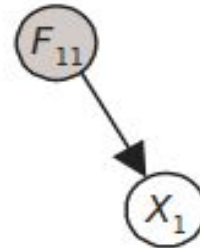
Now, given two potential graphs, find out which graph is more probable.

$\beta(f_{11}; 2,2)$        $\beta(f_{21}; 1,1)$        $\beta(f_{22}; 1,1)$



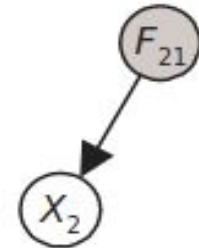
$gp_1$

$\beta(f_{11}; 2,2)$



$gp_2$

$\beta(f_{21}; 2,2)$



**Ans.**

**Step1:** Calculate  $P(d|G_i)$ ; here  $i \in \{1,2\}$ .

$$\begin{aligned} P(d|gp_1) &= \left( \frac{\Gamma(4)}{\Gamma(4+8)} \frac{\Gamma(2+5)\Gamma(2+3)}{\Gamma(2)\Gamma(2)} \right) \left( \frac{\Gamma(2)}{\Gamma(2+5)} \frac{\Gamma(1+4)\Gamma(1+1)}{\Gamma(1)\Gamma(1)} \right) \left( \frac{\Gamma(2)}{\Gamma(2+3)} \frac{\Gamma(1+1)\Gamma(1+2)}{\Gamma(1)\Gamma(1)} \right) \\ &= 7.2150 \times 10^{-6} \end{aligned}$$

$$\begin{aligned} P(d|gp_2) &= \left( \frac{\Gamma(4)}{\Gamma(4+8)} \frac{\Gamma(2+5)\Gamma(2+3)}{\Gamma(2)\Gamma(2)} \right) \left( \frac{\Gamma(4)}{\Gamma(4+8)} \frac{\Gamma(2+5)\Gamma(2+3)}{\Gamma(2)\Gamma(2)} \right) \\ &= 6.7465 \times 10^{-6} \end{aligned}$$

## Step2:

Assume that our prior belief is that neither model ( $gp_1$ ,  $gp_2$ ) is more probable than the other, hence we say that each model is equally likely.

$$P(gp_1) = P(gp_2) = 0.5$$

**Step3:** Using Bayes' theorem:

$$\begin{aligned} P(gp_1|d) &= \frac{P(d|gp_1)P(gp_1)}{P(d)} \\ &= ( 7.2150 \times 10^{-6} * (0.5) ) / P(d) \\ &= \alpha(3.6075 \times 10^{-6}) \qquad \text{Here } \alpha = 1/P(d) \end{aligned}$$

Similarly,

$$\begin{aligned}P(gp_2|d) &= \frac{P(d|gp_1)P(gp_1)}{P(d)} \\&= ( 6.746 5 \times 10^{-6} (.5) ) / P(d) \\&= \alpha(3.373 25 \times 10^{-6})\end{aligned}$$

Eliminating  $\alpha$  we get,

$$P(gp_1|d) = 0.51678$$

$$P(gp_2|d) = 0.48322$$

Hence, we conclude it is more probable that college attendance and divorce are correlated.



**Q1.** Suppose for the same potential graph models  $gp_1$  and  $gp_2$  as given in the previous example the observed data is the following:

<i>Case</i>	$X_1$	$X_2$
1	1	1
2	1	1
3	1	1
4	1	1
5	2	2
6	2	2
7	2	2
8	2	2

Find the probabilities of these DAG's occurring given the above mentioned data. Also, prior beliefs for both of these graphs are equal.

**Ans.**

$$P(d|gp_1) = \left( \frac{\Gamma(4)}{\Gamma(4+8)} \frac{\Gamma(2+4)\Gamma(2+4)}{\Gamma(2)\Gamma(2)} \right) \left( \frac{\Gamma(2)}{\Gamma(2+4)} \frac{\Gamma(1+4)\Gamma(1+0)}{\Gamma(1)\Gamma(1)} \right) \left( \frac{\Gamma(2)}{\Gamma(2+4)} \frac{\Gamma(1+0)\Gamma(1+4)}{\Gamma(1)\Gamma(1)} \right)$$
$$= \alpha(8.6580 \times 10^{-5})$$

$$P(d|gp_2) = \left( \frac{\Gamma(4)}{\Gamma(4+8)} \frac{\Gamma(2+4)\Gamma(2+4)}{\Gamma(2)\Gamma(2)} \right) \left( \frac{\Gamma(4)}{\Gamma(4+8)} \frac{\Gamma(2+4)\Gamma(2+4)}{\Gamma(2)\Gamma(2)} \right)$$
$$= \alpha(4.6851 \times 10^{-6})$$

**Using Bayes' theorem,**

$$P(gp_1|d) = 0.94866$$

$$P(gp_2|d) = 0.05134$$

Hence  $gp_1$  is more probable.

**Q2.** Suppose for the same potential graph models  $gp_1$  and  $gp_2$  as given in the previous example the observed data is the following:

<i>Case</i>	$X_1$	$X_2$
1	1	1
2	1	1
3	1	2
4	1	2
5	2	1
6	2	1
7	2	2
8	2	2

Find the probabilities of these DAG's occurring given the above mentioned data. Also, prior beliefs for both of these graphs are equal.

**Ans.**

$$P(d|gp_1) = \left( \frac{\Gamma(4)}{\Gamma(4+8)} \frac{\Gamma(2+4)\Gamma(2+4)}{\Gamma(2)\Gamma(2)} \right) \left( \frac{\Gamma(2)}{\Gamma(2+4)} \frac{\Gamma(1+2)\Gamma(1+2)}{\Gamma(1)\Gamma(1)} \right) \left( \frac{\Gamma(2)}{\Gamma(2+4)} \frac{\Gamma(1+2)\Gamma(1+2)}{\Gamma(1)\Gamma(1)} \right)$$
$$= \alpha(2.4050 \times 10^{-6})$$

$$P(d|gp_2) = \left( \frac{\Gamma(4)}{\Gamma(4+8)} \frac{\Gamma(2+4)\Gamma(2+4)}{\Gamma(2)\Gamma(2)} \right) \left( \frac{\Gamma(4)}{\Gamma(4+8)} \frac{\Gamma(2+4)\Gamma(2+4)}{\Gamma(2)\Gamma(2)} \right)$$
$$= \alpha(4.6851 \times 10^{-6})$$

**Using Bayes' theorem,**

$$P(gp_1|d) = 0.33921$$

$$P(gp_2|d) = 0.66079$$

Hence  $gp_2$  is more probable.

THANK YOU!