

# ProbProg6

Jan Boerman, Jasper van Rooijen

April 5, 2019

## 1 Bayesian Networks

### A

$$\begin{aligned} Pr(R = 0 | G = 0, S = 0) \\ &= Pr(R = 0, G = 0, S = 0) / Pr(S = 0, G = 0) \\ &= 0.8 * 0.6 * 1 / ((0.2 * 0.99 + 0.8 * 0.6) * (0.2 * 0.2 + 0.8 * 1)) = 0.8428 \end{aligned}$$

### B

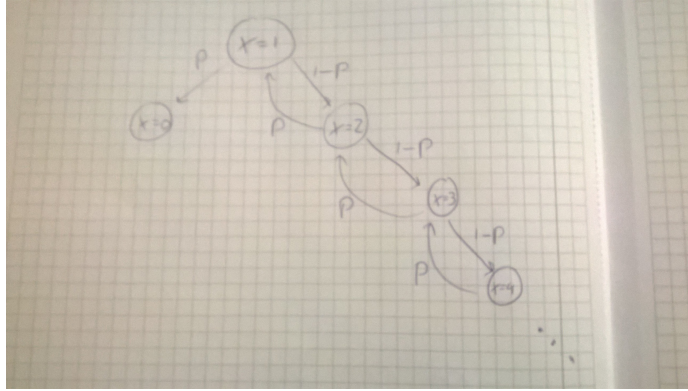
```
sR, sS, sG = R, S, G; flag = True;
while(flag) {
    R, S, G = sR, sS, sG; flag = False;
    R = 1 [0.2] R = 0;
    if (R==0) {
        S = 1 [0.4] S = 0;
    } else {
        S = 1 [0.01] S = 0;
    }
    if (R==0 && S==0) {
        G = 0;
    } else if (R==1 && S==0) {
        G = 1 [0.8] G = 0;
    } else if (R==0 && S==1) {
        G = 1 [0.9] G = 0;
    } else if (R==1 && S==1) {
        G = 1 [0.99] G = 0;
    }
    flag = (G+S==0);
}
```

## 2 Random walks

We've got the following program that models the situation:

```
x := 1;
while (x > 0) \{
  x  $\xrightarrow{[p]}$  x++
\}
```

which expands to the following markov chain:



If  $p$  is strictly larger than  $1 - p$ , then over time eventually the execution will of the program will reach the left-most state, where  $x$  equals 0. This happens because the markov property, the memorylessness ensures that every step deeper into the chain, the probabilities remain  $p$  and  $1 - p$ .

## 3 Computing the expected runtime

$P =$

```
1.      {b := true} [1/2] {b := false};
2.      if (b) {
3.          s := true;
4.      } else {
5.          {b := true} [1/2] {b := false};
6.          if (b) {
7.              s := true;
8.          } else {
9.              s := false;
10.         }
11.     }
```

$ert(P, 0) = ert(line1, ert(line2 - 11, 0))$

$ert(line2 - 11, 0) = 1 + [b] * ert(s := true, 0) + [\neg b] * ert(line5 - 10, 0)$

$ert(line5 - 10, 0) = ert(line5; line6 - 10, 0)$

$ert(line5 - 10, 0) = ert(\{b := true\}[1/2]\{b := false\}, ert(line6 - 10, 0))$

$ert(line6 - 10, 0) = 1 + [b] * ert(\{s := true\}, 0) + [\neg b] * ert(\{s := false\}, 0)$   
 $ert(P, 0) = 2 + 1 + 0.5 * 1 + 0.5 * (2 + 1 + 0.5 * 1 + 0.5 * 1)$   
 $ert(P, 0) = 5.5$

## 4 From pGCL programs to Bayesian networks

### A

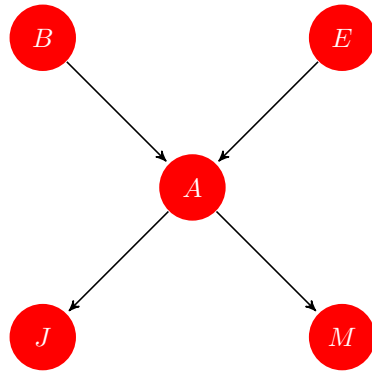
B=True	B=False
0.001	0.999

E=True	E=False
0.002	0.998

	A=True	A=False
B=True,E=True	0.95	0.05
B=True,E=False	0.94	0.06
B=False,E=True	0.29	0.71
B=False,E=False	0.01	0.99

	J=True	J=False
A=True	0.90	0.10
A=False	0.05	0.95

	M=True	M=False
A=True	0.70	0.30
A=False	0.01	0.99



## B

$$\begin{aligned} &Pr(\neg B|\neg E, A) \\ &= \frac{Pr(\neg B, \neg E, A)}{Pr(\neg E, A)} \\ &= \frac{0.999*0.998*0.01}{0.998*(0.001*0.94+0.999*0.01)} \\ &= 0.914 \end{aligned}$$