

Interactive Bayesian Probabilistic Programming and Debugging

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Javier Burroni, Arjun Guha, David Jensen

Definition of (Bayesian) Probabilistic Programming Languages

Regular PL with two special constructs:

- sample
- observe

Gordon, A. D., Henzinger, T. A., Nori, A. V. & Rajamani, S. K. Probabilistic programming. in Proceedings of the on Future of Software Engineering 167–181 (ACM, 2014).

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And a way to access results:

- `query`

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And a way to access results:

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```
random Real Mu() ~ Gaussian(100.0, 10.0);
random Real X() ~ Gaussian(Mu(), 15.0);

obs X() > 120;
query Mu() > 100;
```

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Example of PPL

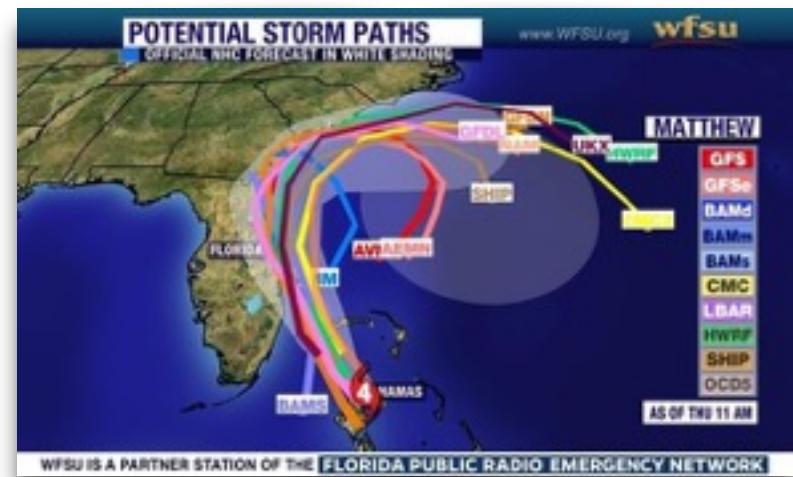
```
0: type City;
1: type PrepLevel;
2: type DamageLevel;

3: random City First ~ UniformChoice({c for City c});
4: random City NotFirst ~ UniformChoice({c for City c: c != First});
5: random PrepLevel Prep(City c) ~
6:   if (First == c) then Categorical({High -> 0.5, Low -> 0.5})
7:   else case Damage(First) in
8:     {Severe -> Categorical({High -> 0.9, Low -> 0.1}),
9:      Mild -> Categorical({High -> 0.1, Low -> 0.9})};
10: random DamageLevel Damage(City c) ~
11:   case Prep(c) in {High -> Categorical({Severe -> 0.2, Mild -> 0.8}),
12:                     Low -> Categorical({Severe -> 0.8, Mild -> 0.2})};

13: distinct City A, B;
14: distinct PrepLevel Low, High;
15: distinct DamageLevel Severe, Mild;

16: obs Damage(First) = Severe;

17: query Damage(NotFirst);
```



Milch, B. et al. BLOG: Probabilistic models with unknown objects. in (2005).

Example of PPL

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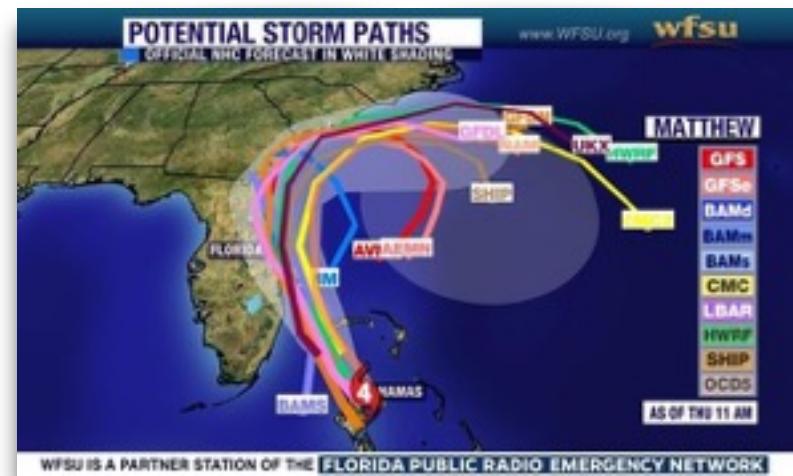
13: distinct City A, B;
14: distinct PrepLevel Low, High;
15: distinct DamageLevel Severe, Mild;
```

```
16: obs Damage(First) = Severe;
```

```
17: query Damage(NotFirst);
```

```
query Damage(NotFirst)
```

```
Mild      0.733241
Severe    0.266759
dtype: float64
```



Milch, B. et al. BLOG: Probabilistic models with unknown objects. in (2005).

Interactive limitations

- New queries require re-execution of the entire program
 - ◆ Not efficient as neither data nor generative model were changed

Our approach

- Perform backward inference only once
- The result of inference is a posterior distribution over **traces** — FOL structures.
- New keyword: `inspect(expr) -> value`.
Evaluate the expression in a trace
- `query(expr)` implemented as application of `inspect` over a sample of the posterior distribution of **traces**.

Advantages

- No need to know the queries before running inference
 - ◆ Allows interactively querying of the posterior distribution

Dynamically querying

```
0: type City;
1: type PrepLevel;
2: type DamageLevel;

3: random City First ~ UniformChoice({c for City c});
4: random City NotFirst ~ UniformChoice({c for City c: c != First});
5: random PrepLevel Prep(City c) ~
6:   if (First == c) then Categorical({High -> 0.5, Low -> 0.5})
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10: random DamageLevel Damage(City c) ~
11:   case Prep(c) in {High -> Categorical({Severe -> 0.2, Mild -> 0.8}),
12:                      Low -> Categorical({Severe -> 0.8, Mild -> 0.2})};

13: distinct City A, B;
14: distinct PrepLevel Low, High;
15: distinct DamageLevel Severe, Mild;

16: obs Damage(First) = Severe;
17: query Damage(NotFirst);
```

```
query Damage(A)
```

Severe	0.641092
Mild	0.358908

```
query if Damage(A) == Severe then Prep(A) else Prep(B);
```

Low	0.741546
High	0.258454

Advantages

- No need to know the queries before running inference
 - ◆ Allows interactively querying of the posterior distribution
- `inspect(expr)` accepts any valid BLOG expression

Inspect one world

```
0: type City;
1: type PrepLevel;
2: type DamageLevel;

3: random City First ~ UniformChoice({c for City c});
4: random City NotFirst ~ UniformChoice({c for City c: c != First});
5: random PrepLevel Prep(City c) ~
6:   if (First == c) then Categorical({High -> 0.5, Low -> 0.5})
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13: distinct City A, B;
14: distinct PrepLevel Low, High;
15: distinct DamageLevel Severe, Mild;

16: obs Damage(First) = Severe;
17: query Damage(NotFirst);
```

```
inspect if Damage(A) == Severe then Prep(A) else Prep(B)
```

```
value: Low
```

Advantages

- No need to know the queries before running inference
 - ◆ Allows interactively querying of the posterior distribution
- `inspect(expr)` accepts any valid BLOG expression
 - ◆ The generative model is made of BLOG expressions
 - ◆ step-by-step debugging can be implemented by recursively inspecting the generative process

Step debugging

```
0: type City;
1: type PrepLevel;
2: type DamageLevel;

3: random City First ~ UniformChoice({c for City c});
4: random City NotFirst ~ UniformChoice({c for City c: c != First});
5: random PrepLevel Prep(City c) ~
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13: distinct City A, B;
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15: distinct DamageLevel Severe, Mild;

16: obs Damage(First) = Severe;
17: query Damage(NotFirst);
```

Step debugging

```
debugger.step()  
Entering: obs Damage(First) = Severe
```

```
0: type City;  
1: type PrepLevel;  
2: type DamageLevel;  
  
3: random City First ~ UniformChoice({c for City c});  
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13: distinct City A, B;  
14: distinct PrepLevel Low, High;  
15: distinct DamageLevel Severe, Mild;  
  
→ 16: obs Damage(First) = Severe;  
17: query Damage(NotFirst);
```

Step debugging

```
debugger.step()  
Entering: obs Damage(First) = Severe  
  
debugger.step()  
Entering: Damage(First)
```

```
0: type City;  
1: type PrepLevel;  
2: type DamageLevel;  
  
3: random City First ~ UniformChoice({c for City c});  
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13: distinct City A, B;  
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15: distinct DamageLevel Severe, Mild;  
  
16: obs Damage(First) = Severe;  
17: query Damage(NotFirst);
```



Step debugging

```
debugger.step()
Entering: obs Damage(First) = Severe

debugger.step()
Entering: Damage(First)

debugger.step()
Entering: First
```



```
0: type City;
1: type PrepLevel;
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Step debugging

```
debugger.step()
Entering: obs Damage(First) = Severe

debugger.step()
Entering: Damage(First)

debugger.step()
Entering: First

debugger.step()
Entering: UniformChoice({c for City c})
```



```
0: type City;
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3: random City First ~ UniformChoice({c for City c});
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16: obs Damage(First) = Severe;
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```

Step debugging

```
debugger.step()
Entering: obs Damage(First) = Severe

debugger.step()
Entering: Damage(First)

debugger.step()
Entering: First

debugger.step()
Entering: UniformChoice({c for City c})

debugger.runToLine(11)
Entering: case Prep(c) in
{
    High -> Categorical({
        Severe -> 0.2,
        Mild -> 0.8}),
    Low -> Categorical({
        Severe -> 0.8,
        Mild -> 0.2})}
```



```
0: type City;
1: type PrepLevel;
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13: distinct City A, B;
14: distinct PrepLevel Low, High;
15: distinct DamageLevel Severe, Mild;

16: obs Damage(First) = Severe;
17: query Damage(NotFirst);
```

Inspect local variables

```
debugger.inspect('c');
Inspect: c
value: B
```

```
0: type City;
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Inspect local variables

```
debugger.inspect('c');
Inspect: c
value: B

debugger.inspect('Prep(c)');
Inspect: Prep(c)
value: Low
```

```
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```



Inspect local variables

```
debugger.inspect('c');
Inspect: c
value: B

debugger.inspect('Prep(c)');
Inspect: Prep(c)
value: Low

debugger.switchTo('Prep(B) == High')
switching to trace compatible: #175
Entering: obs Damage(First) = Severe
```

```
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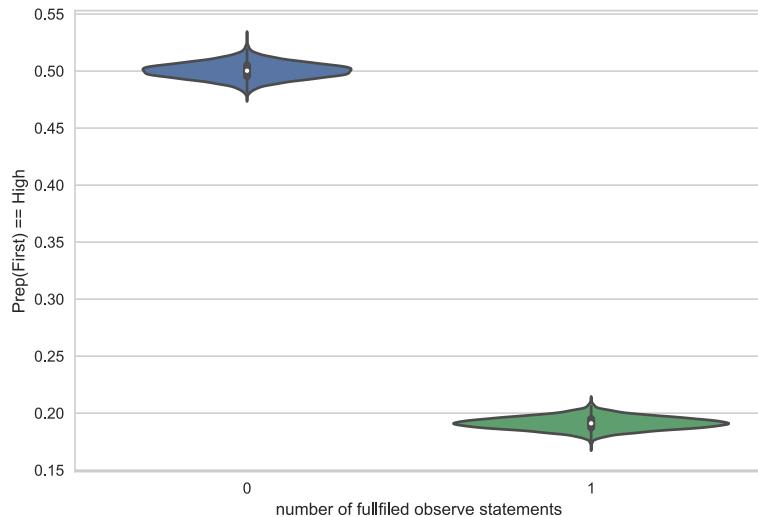

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```

Advantages

- No need to know the queries before running inference
 - ◆ Allows interactively querying of the posterior distribution
- `inspect(expr)` accepts any valid BLOG expression
 - ◆ The generative model is made of BLOG expressions
 - ◆ step-by-step debugging can be implemented by recursively inspecting the generative process
- Evaluate impact of information for any query
 - ◆ Compute the posterior with different subsets of observations, and evaluate the expression in each sample of the posterior.

Impact of data



```
0: type City;
1: type PrepLevel;
2: type DamageLevel;

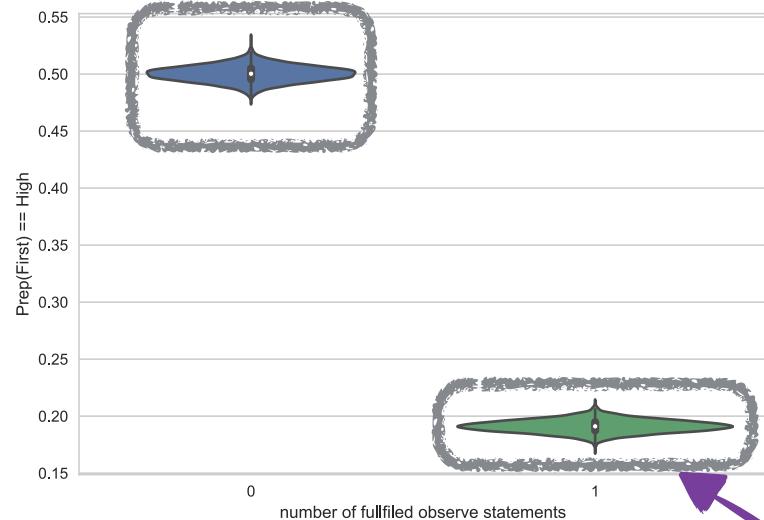
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13: distinct City A, B;
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15: distinct DamageLevel Severe, Mild;

16: obs Damage(First) = Severe;
17: query Damage(NotFirst);
```

```
debugger.plot_query('Prep(First) == High')
```

Prior



Impact of data

```
0: type City;
1: type PrepLevel;
2: type DamageLevel;

3: random City First ~ UniformChoice({c for City c});
4: random City NotFirst ~ UniformChoice({c for City c: c != First});
5: random PrepLevel Prep(City c) ~
6:   if (First == c) then Categorical({High -> 0.5, Low -> 0.5})
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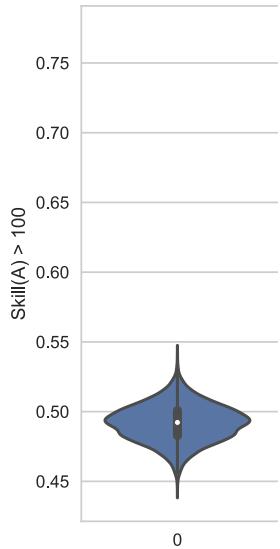
13: distinct City A, B;
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15: distinct DamageLevel Severe, Mild;

16: obs Damage(First) = Severe;
17: query Damage(NotFirst);
```

Posterior

```
debugger.plot_query('Prep(First) == High')
```

Impact of data

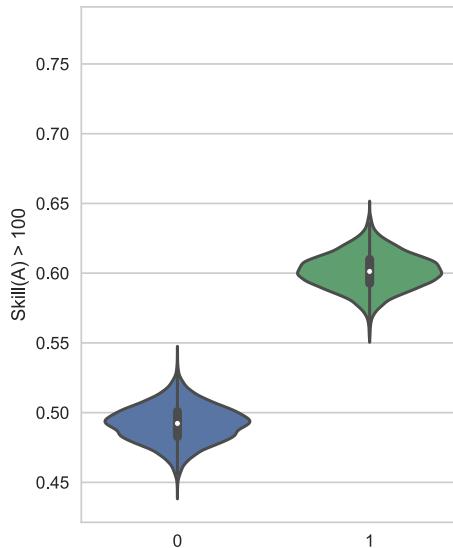


Bayesian Skill rating

```
debugger.plot_query('Skill(A) > 100')
```

Gordon, A. D., Henzinger, T. A., Nori, A. V. & Rajamani, S. K. Probabilistic programming. in Proceedings of the on Future of Software Engineering 167–181 (ACM, 2014).

Impact of data



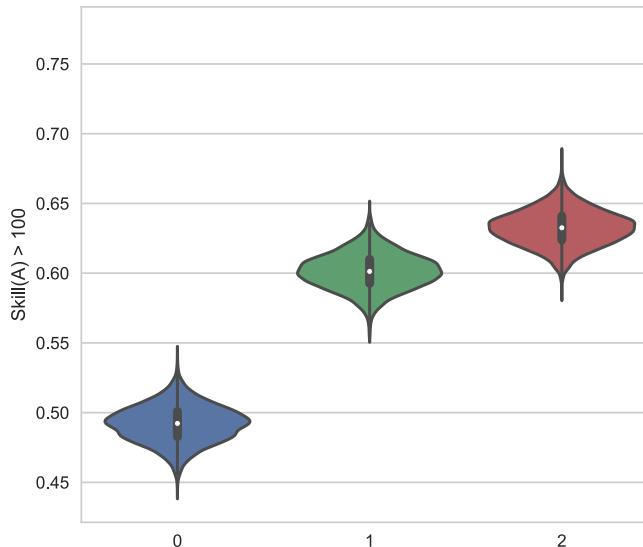
```
obs Winner(G1, A, B) = A;
```

Bayesian Skill rating

```
debugger.plot_query('Skill(A) > 100')
```

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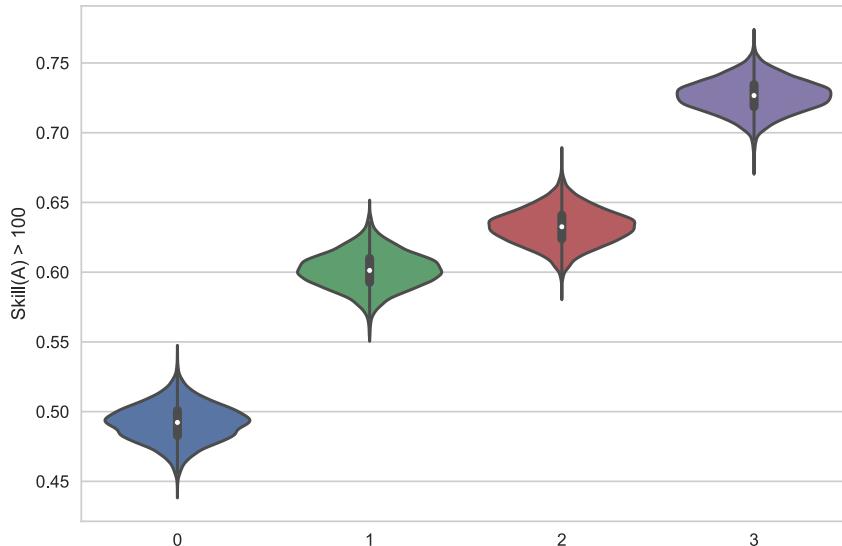
```
obs Winner(G1, A, B) = A;  
obs Winner(G2, B, C) = B;
```

Bayesian Skill rating

```
debugger.plot_query('Skill(A) > 100')
```

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Impact of data



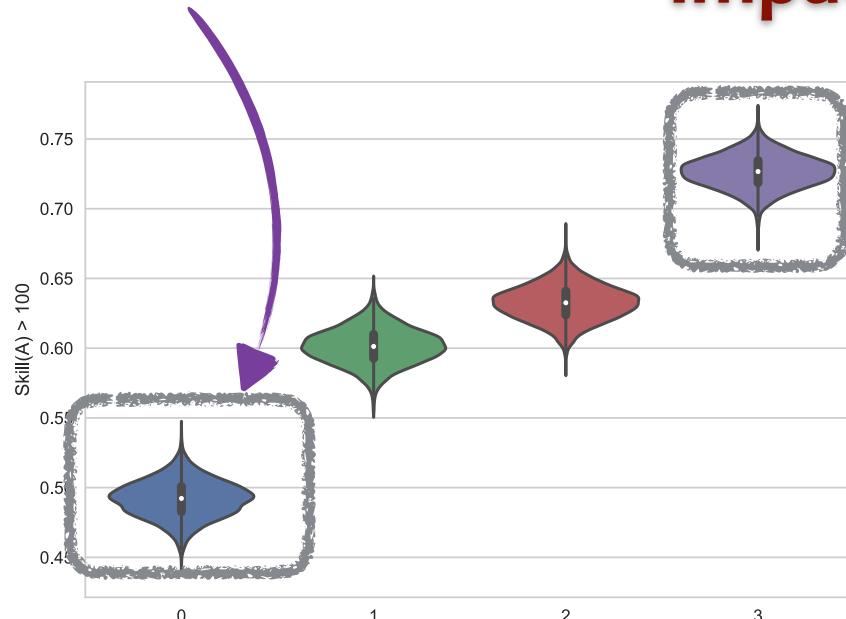
```
obs Winner(G1, A, B) = A;  
obs Winner(G2, B, C) = B;  
obs Winner(G3, A, C) = A;
```

Bayesian Skill rating

```
debugger.plot_query('Skill(A) > 100')
```

Gordon, A. D., Henzinger, T. A., Nori, A. V. & Rajamani, S. K. Probabilistic programming. in Proceedings of the on Future of Software Engineering 167–181 (ACM, 2014).

Prior



Impact of data

```
obs Winner(G1, A, B) = A;  
obs Winner(G2, B, C) = B;  
obs Winner(G3, A, C) = A;
```

Posterior

Bayesian Skill rating

```
debugger.plot_query('Skill(A) > 100')
```

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Final remarks

- This debugger is not meant to find bugs, but as a tool for understanding the program —the probabilistic model.
- It uses information that Bayesian PPL (e.g. anglican) uses:
 - ◆ Information regarding `sample` and `observe` are stored in *addresses*
 - ◆ Taking subsets of observations is a fundamental step for Sequential Monte Carlo sampling
- So it can be implemented in other languages.

query Questions?

Appendix A: Bayesian Skill rating model

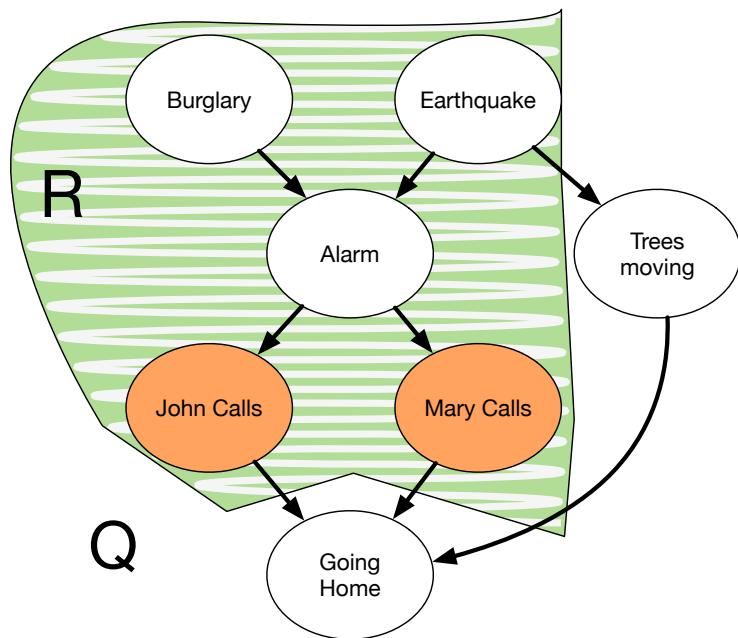
```
type Player;
type Game;
distinct Player A, B, C;
distinct Game G1, G2, G3;

random Real Skill(Player p) ~ Gaussian(100.0, 10.0);
random Real Performance(Player p, Game g) ~ Gaussian(Skill(p), 15.0);
random Player Winner(Game g, Player p1, Player p2) ~
    if (Performance(p1, g) > Performance(p2, g))
        then p1
    else p2;

obs Winner(G1, A, B) = A;
obs Winner(G2, B, C) = B;
obs Winner(G3, A, C) = A;
```

Gordon, A. D., Henzinger, T. A., Nori, A. V. & Rajamani, S. K. Probabilistic programming. in Proceedings of the on Future of Software Engineering 167–181 (ACM, 2014).

Appendix B: backward and forward inference



- Region R is learned using backward inference
- Region Q is learned lazily using forward inference