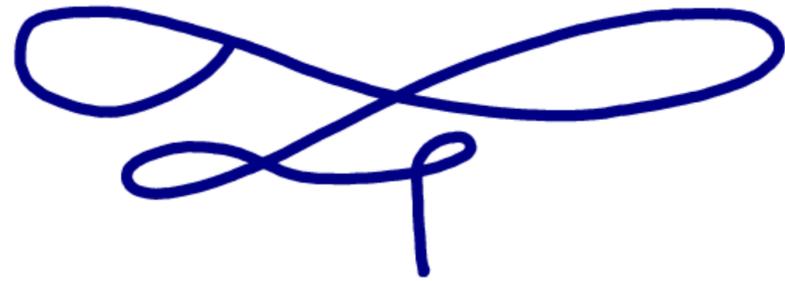


# Bluebell



An alliance of  
Relational Lifting and Independence  
for Probabilistic Reasoning



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[DRAFT ON ARXIV]

GM

✦ THE JOINT CONDITIONING  
MODALITY ✦



# GOAL

Unify and generalize Proof principles for  
Unary & Relational Probabilistic Reasoning

## Long Term:

Build an "IrisCore Logic" for  
Probabilistic Reasoning

# PROBABILISTIC PROGRAMS

We consider a simple programming language:

- Sequential & First Order
- Imperative with mutable variable store (no heap)
- Bounded Loops: everything terminates
- Normal assignments  $x := e$

Sampling assignments  $x \approx \mu$

$\mathbb{D}(\text{Val}) =$  Probability distribution over values

## BIG STEP SEMANTICS

$$\llbracket t \rrbracket : \mathbb{D}(\text{Store}) \rightarrow \mathbb{D}(\text{Store})$$

↑  
Program term

# PROBABILISTIC PROGRAMS

We consider a simple programming language:

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- Normal assignments  $x := e$

Sampling assignments  $x \approx \mu$

$\mathbb{D}(\text{Val}) =$  Probability distribution over values

Simple? Yes, but already hard enough to keep us busy for a while!

# REASONING STYLES

## UNARY

- Goal involves one program  $t$
- Example properties:
  - Output distribution of  $x$  is  $\mu$
  - Probability of  $x \geq 10$  is  $1/2$
  - Expected value of  $x$  is  $1/3$
  - By the end,  $m$  and  $c$  are probabilistically independent
    - $m$  could be a plaintext message
    - $c$  its cyphertext

## RELATIONAL

- Goal involves two programs  $[1:t_1, 2:t_2]$
- Example properties:
  - $t_1$  and  $t_2$  induce the same distribution on  $x$ 
    - $\hookrightarrow t_2$  could be an optimization of  $t_1$
    - $\hookrightarrow t_1$  could be a cryptographic protocol and  $t_2$  its idealized perfect version
  - Starting from similar input,  $t_1$  and  $t_2$  will produce "similar" distributions
    - $\hookrightarrow$  differential privacy

# UNARY EXAMPLE

// Encryption of 1 bit

$k \approx \text{Ber}(1/2)$  // New random key (1 bit)

$m \approx \text{Ber}(p)$  // Message to encrypt (arbitrary bias  $p$ )

$c := m \text{ XOR } k$  // Compute cyphertext

# UNARY EXAMPLE

// Encryption of 1 bit

$$k \approx \text{Ber}(1/2)$$

$$m \approx \text{Ber}(p)$$

$$c := m \text{ XOR } k$$

$$\{c \sim \text{Ber}(1/2)\}$$

Reasoning (informally)

①  $k$  and  $m$  are independent:

$$P(k=v, m=w) = P(k=v) \cdot P(m=w)$$

② Conditioning on  $m$ :

• if  $m=0$  then  $c=k$  so  $c \sim \text{Ber}(1/2)$

• if  $m=1$  then  $c=\neg k$  so  $c \sim \text{Ber}(1/2)$

$$\begin{aligned} \Rightarrow c &\sim p \cdot \text{Ber}(1/2) + (1-p) \text{Ber}(1/2) \\ &= \text{Ber}(1/2) \end{aligned}$$

# UNARY EXAMPLE

// Encryption of 1 bit

$$k \approx \text{Ber}(1/2)$$

$$m \approx \text{Ber}(p)$$

$$c := m \text{ XOR } k$$

$$\{c \sim \text{Ber}(1/2)\}$$

^  $c$  and  $m$  are independent!

Reasoning (informally)

①  $k$  and  $m$  are independent:

$$P(k=v, m=w) = P(k=v) \cdot P(m=w)$$

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$$\begin{aligned} \Rightarrow c &\sim p \cdot \text{Ber}(1/2) + (1-p) \text{Ber}(1/2) \\ &= \text{Ber}(1/2) \end{aligned}$$

# UNARY EXAMPLE

// Encryption of 1 bit

$$K := \text{Ber}(1/2)$$

$$\{K \sim \text{Ber}(1/2)\}$$

$$m := \text{Ber}(p)$$

$$\{K \sim \text{Ber}(1/2) * m \sim \text{Ber}(p)\}$$

$$C := m \text{ XOR } K$$

$$\{C \sim \text{Ber}(1/2) * m \sim \text{Ber}(p)\}$$

IDEA ① : Separation = Independence [PSL] [LILAC]

Reasoning (informally)

①  $K$  and  $m$  are independent:

$$P(K=v, m=w) = P(K=v) \cdot P(m=w)$$

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# UNARY EXAMPLE

// Encryption of 1 bit

$K \approx \text{Ber}(1/2)$

$\{K \sim \text{Ber}(1/2)\}$

$m \approx \text{Ber}(p)$

$\{K \sim \text{Ber}(1/2) * m \sim \text{Ber}(p)\}$

$C := m \text{ XOR } K$

$\{C \sim \text{Ber}(1/2) * m \sim \text{Ber}(p)\}$

Reasoning (informally)

② Conditioning on  $m$ :

$\mathbb{P}_{m \rightarrow v} (K \sim \text{Ber}(1/2)) * \begin{cases} \{C = K\} & \text{if } v=0 \\ \{C = \neg K\} & \text{if } v=1 \end{cases}$

↑ Deterministic value

↙ case analysis

└ Predicate over stores holds with probability 1

IDEA ① : Separation = Independence [PSL] [LILAC]

IDEA ② : Conditioning via 2 modality [LILAC]

# REASONING TOOLS

- UNARY TRIPLES:  $\{P\} \vdash \{Q\}$  Assertions over  $\mathbb{D}(\text{Store})$
- PROBABILISTIC INDEPENDENCE: Separation  $*$
- CONDITIONING: via a modality  $\mathbb{C}_{x \rightarrow v}$

# RELATIONAL REASONING

$$1: x \approx \mu$$

$$d \approx \text{unif}(-1, 1)$$

$$y := x - d$$

$$2: x \approx \mu$$

$$d \approx \text{unif}(-1, 1)$$

$$y := x + d$$

GOAL:  $y_{\langle 1 \rangle}$  is distributed like  $y_{\langle 2 \rangle}$

UNARY PROOF STRATEGY: Characterize the exact distribution of  $y$  in the two programs, then compare.

↳ Can be prohibitively hard to do!

RELATIONAL STRATEGY: Execute programs in lockstep showing that whatever the steps might be computing, the two sides remain the same

# RELATIONAL REASONING

1:  $x \approx \mu$

$$d \approx \text{unif}(-1, 1)$$

$$y := x - d$$



A world of pure imagination

2:  $x \approx \mu$

$$d \approx \text{unif}(-1, 1)$$

$$y := x + d$$

GOAL:  $y_{\langle 1 \rangle}$  is distributed like  $y_{\langle 2 \rangle}$

# RELATIONAL REASONING

$$1: x := a$$

$$d \approx \text{unif}(-1, 1)$$

$$y := x - d$$

$$a \sim \mu$$

"coupling"

$$2: x := a$$

$$d \approx \text{unif}(-1, 1)$$

$$y := x + d$$

GOAL:  $y \langle 1 \rangle$  is distributed like  $y \langle 2 \rangle$

# RELATIONAL REASONING

$$1: x := a$$

$$d := b$$

$$y := x - d$$

$$a \sim \mu$$

$$b \sim \text{unif}(-1, 1)$$

$$2: x := a$$

$$d := -b$$

$$y := x + d$$

GOAL:  $y \langle 1 \rangle$  is distributed like  $y \langle 2 \rangle$

# RELATIONAL REASONING

$$1: \quad x \approx \mu$$

$$d \approx \text{unif}(-1, 1)$$

$$y := x - d$$

$$\left[ x \langle 1 \rangle = x \langle 2 \rangle \right]$$

$$\left[ \begin{array}{l} x \langle 1 \rangle = x \langle 2 \rangle \\ d \langle 1 \rangle = -d \langle 2 \rangle \end{array} \right]$$

$$\left[ y \langle 1 \rangle = y \langle 2 \rangle \right]$$

$$2: \quad x \approx \mu$$

$$d \approx \text{unif}(-1, 1)$$

$$y := x + d$$

[pRHL]

↑  
Relation over  $\text{Store} \times \text{Store}$   
Holding with probability 1  
in some "fictional" joint  
distribution

# RELATIONAL REASONING

$$1: \quad x \approx \mu$$

$$d \approx \text{unif}(-1, 1)$$

$$y := x - d$$

$$\boxed{x \langle 1 \rangle = x \langle 2 \rangle}$$

$$\boxed{\begin{array}{l} x \langle 1 \rangle = x \langle 2 \rangle \\ d \langle 1 \rangle = -d \langle 2 \rangle \end{array}}$$

$$\boxed{y \langle 1 \rangle = y \langle 2 \rangle}$$

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[pRHL]

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Relation over  $\text{Store} \times \text{Store}$   
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= Relational  
lifting [R]

# RELATIONAL REASONING

1:  $x \approx \mu$

$d \approx \text{unif}(-1, 1)$

$y := x - d$

$[x\langle 1 \rangle = x\langle 2 \rangle]$

$[x\langle 1 \rangle = x\langle 2 \rangle$   
 $d\langle 1 \rangle = -d\langle 2 \rangle]$

$[y\langle 1 \rangle = y\langle 2 \rangle]$

2:  $x \approx \mu$

$d \approx \text{unif}(-1, 1)$

$y := x + d$

[pRHL]

↑  
Relation over  $\text{Store} \times \text{Store}$   
Holding with probability 1  
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= Relational  
lifting [R]

FUNDAMENTAL THEOREM OF RELATIONAL LIFTING: (Meta)

If  $[y\langle 1 \rangle = y\langle 2 \rangle]$  then  $y\langle 1 \rangle$  is distributed like  $y\langle 2 \rangle$

# RELATIONAL REASONING (LIMITATIONS)

$$\begin{array}{ccc} 1: & \frac{x \approx \mu}{d \approx \text{unif}(-1,1)} & \left[ \begin{array}{c} \text{????} \\ \text{????} \end{array} \right] & \frac{2: d \approx \text{unif}(-1,1)}{x \approx \mu} \\ & & & y := x - d & & y := x + d \end{array}$$

Only asserting via Relational lifting  
is too limiting!

GOAL: Improve expressivity while  
retaining the relational "spirit"

# REASONING TOOLS

- UNARY TRIPLES:  $\{P\} \vdash \{Q\}$  Assertions over  $\mathbb{D}(\text{Store})$   

- PROBABILISTIC INDEPENDENCE: Separation  $*$
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• RELATIONAL TRIPLES:  $\lfloor R_1 \rfloor [1:t_1, 2:t_2] \lfloor R_2 \rfloor$  Relations over Store  
 $R_1, R_2 \subseteq \text{Store} \times \text{Store}$

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• RELATIONAL LIFTING:  $\lfloor R \rfloor$

# REASONING TOOLS

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 $R_1, R_2 \subseteq \text{Store} \times \text{Store}$
- RELATIONAL LIFTING:  $\lfloor R \rfloor$

Can we unify and generalize?

(spoiler: YES)

# BLUEBELL

First observation We can harmonize all these features by:

- Using  $\text{Assrt} := \mathbb{D}(\text{Store}) \times \mathbb{D}(\text{Store}) \rightarrow \text{Prop}$ 
  - Unary assertions just ignore one of the two distributions  $x \langle 1 \rangle \sim \text{Ber}(1/2)$
  - Relational lifting as a construct

$$R \subseteq \text{Store} \times \text{Store} \Rightarrow \llbracket R \rrbracket : \mathbb{D}(\text{Store}) \times \mathbb{D}(\text{Store}) \rightarrow \text{Prop}$$

- Multi-ary wp from [LHC]:  $\text{wp } t \{Q\}$  *partial map Indices  $\rightarrow$  Terms*

$$\text{wp } [1:t_1, 2:t_2] \{Q\} \equiv \text{wp } [1:t_1] \{ \text{wp } [2:t_2] \{Q\} \}$$

Can have unary triples, binary triples, switch back & forth.

# SMALL EXAMPLE

1:  $x \approx \mu$

$d \approx \text{unif}(-1, 1)$

$y := x - d$

2:  $d \approx \text{unif}(-1, 1)$

$x \approx \mu$

$y := x + d$

# SMALL EXAMPLE

$$1: x \approx \mu$$

$$d \approx \text{unif}(-1, 1)$$

$$2: d \approx \text{unif}(-1, 1)$$

$$x \approx \mu$$

$$\{ x \langle 1 \rangle \approx \mu * x \langle 2 \rangle \approx \mu * d \langle 1 \rangle \approx \text{unif}(-1, 1) * d \langle 2 \rangle \approx \text{unif}(-1, 1) \}$$

$$\{ \lfloor x \langle 1 \rangle = x \langle 2 \rangle \wedge d \langle 1 \rangle = -d \langle 2 \rangle \rfloor \} \otimes$$

$$y := x - d$$

$$y := x + d$$

$$\{ \lfloor y \langle 1 \rangle = y \langle 2 \rangle \rfloor \}$$

## QUESTIONS:

1) Can entailment  $\otimes$  be proven in the logic?

2) Are there useful interactions between  $*$ ,  $\llbracket$  and  $\lfloor R \rfloor$ ?

# BLUEBELL'S KEY INSIGHT

## QUESTIONS:

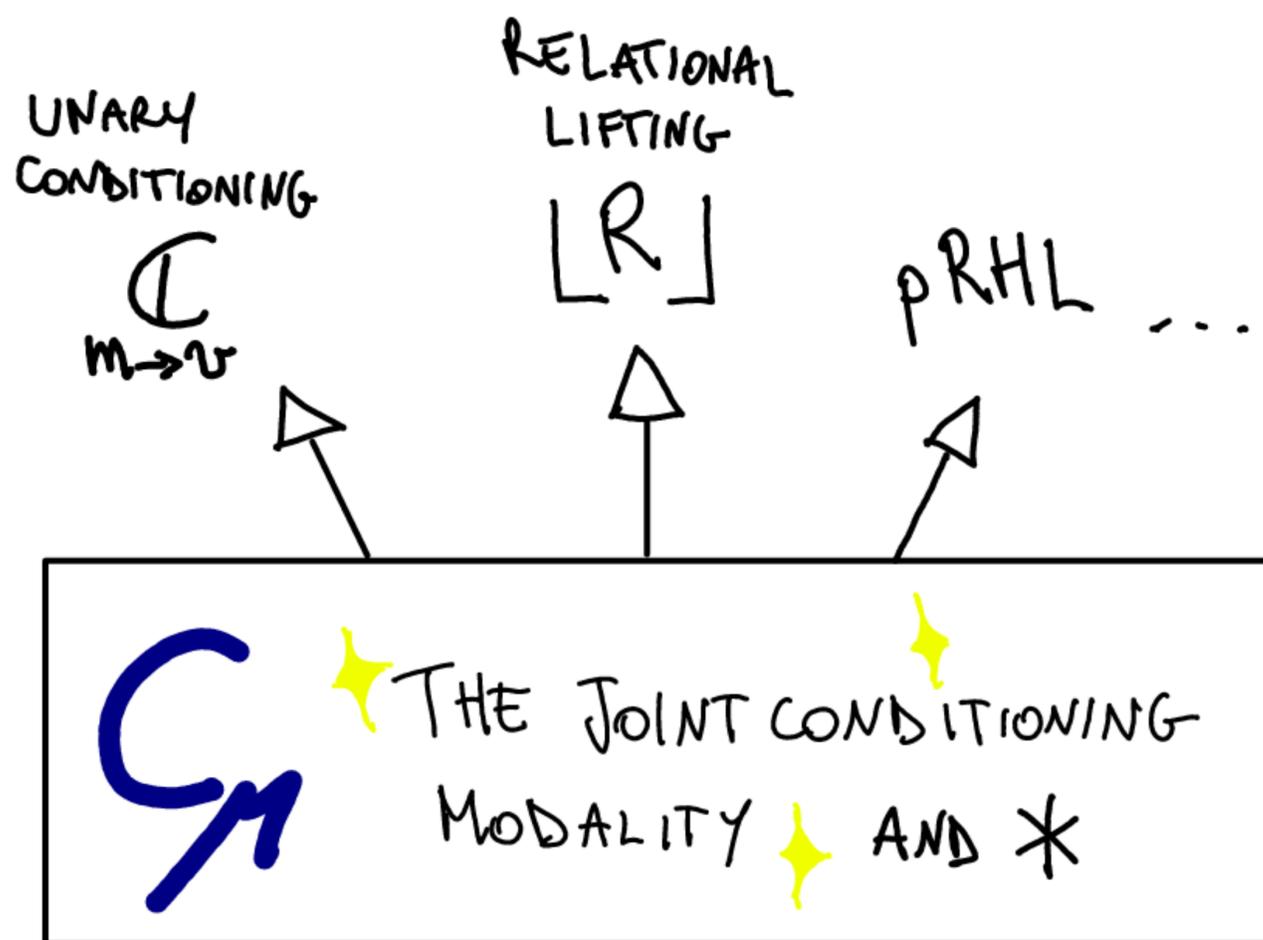
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# BLUEBELL'S KEY INSIGHT

## QUESTIONS :

- 1) Can entailment  $\otimes$  be proven in the logic?
- 2) Are there useful interactions between  $*$ ,  $\mathbb{C}$  and  $\lfloor R \rfloor$ ?

Bluebell says YES!



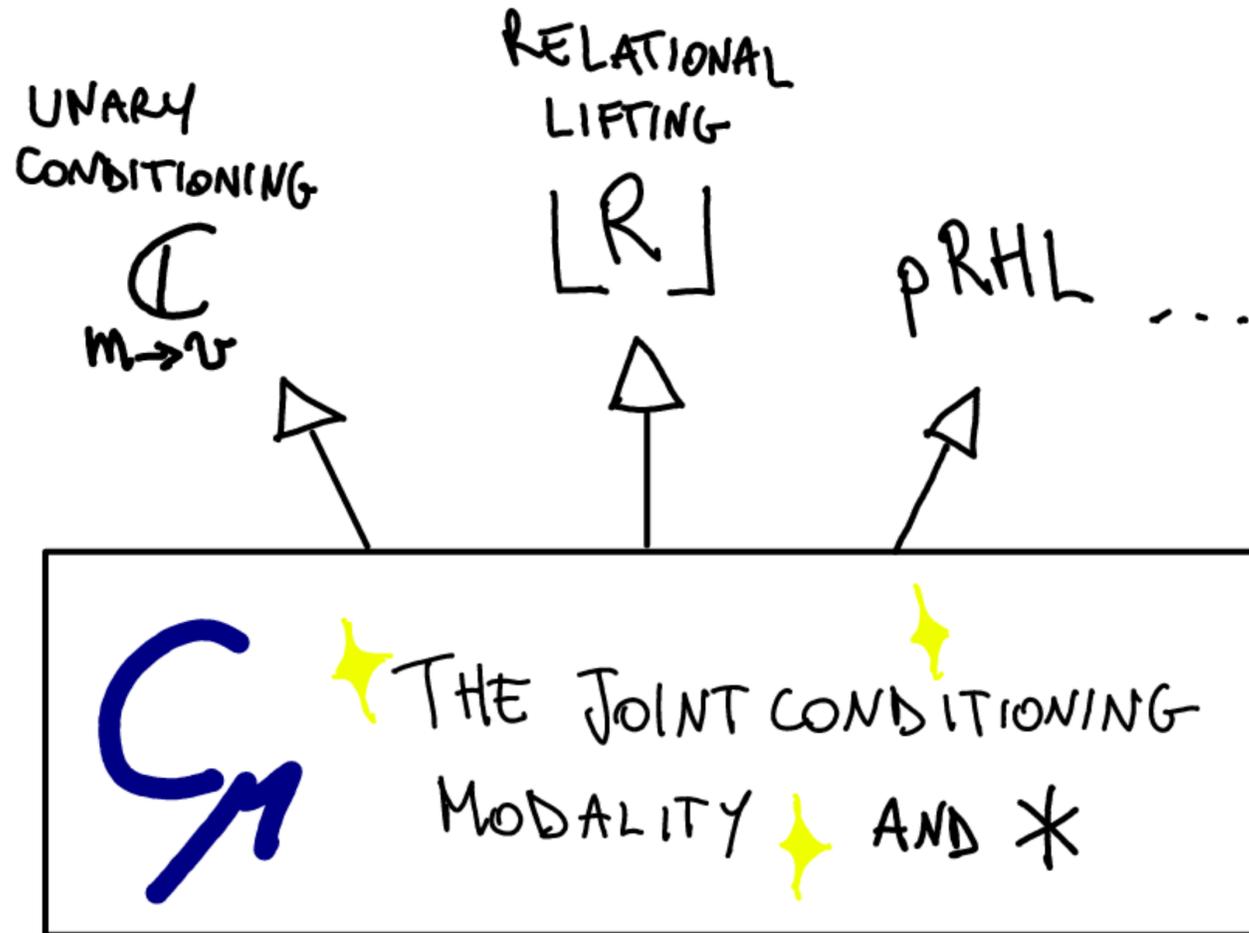
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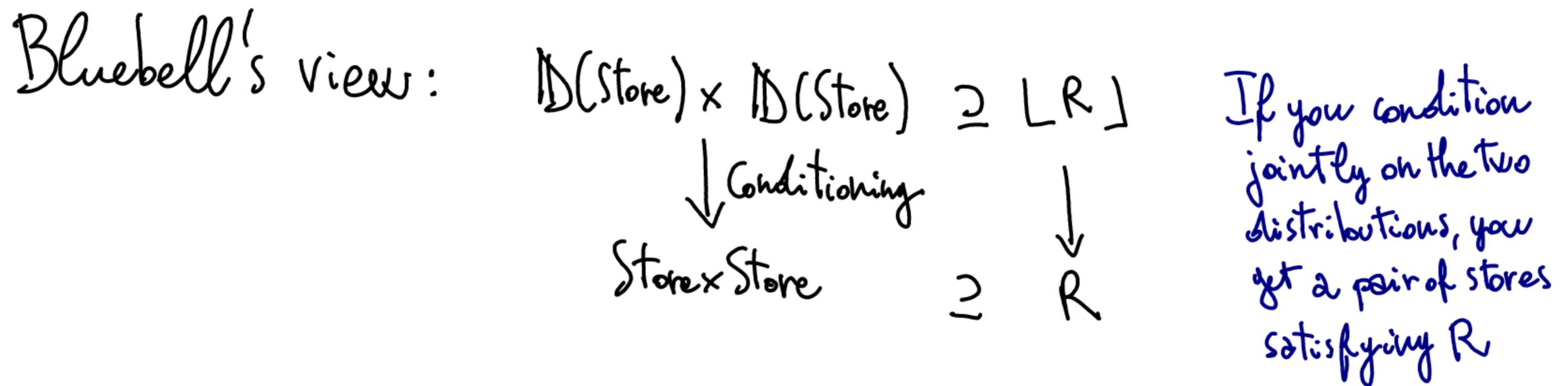
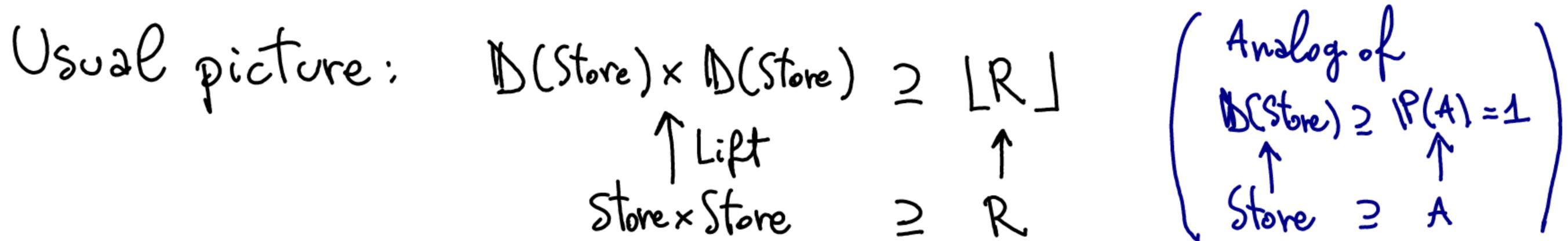
Bluebell says YES!

Their definitions  
and laws can be  
derived



Rich set of  
core laws

# RELATIONAL LIFTING AS CONDITIONING



So, what is "joint conditioning"?

# JOINT CONDITIONING

Def Given  $\mu: \mathbb{D}(A)$  and  $\kappa: A \rightarrow \mathbb{D}(\text{Store})$  define

$$\text{bind}(\mu, \kappa) := \lambda s. \sum_{a \in A} \mu(a) \kappa(a)(s)$$

Example  $A = \{0, 1\}$   $\mu = \text{Ber}(1/3)$

$$\text{bind}(\mu, \kappa) = \frac{1}{3} \kappa(0) + \frac{2}{3} \kappa(1)$$

[This is actually the bind of  
the monad  $\mathbb{D}(\cdot)$ !]

# JOINT CONDITIONING

Def Given  $\mu: \mathbb{D}(A)$  and  $P: A \rightarrow \text{Assrt}$

define  $\mathcal{C}_\mu v. P(v): \text{Assrt}$  by

$(\mu_1, \mu_2) \models \mathcal{C}_\mu v. P(v)$  iff

$$\left[ \begin{array}{l} \exists k_1, k_2: A \rightarrow \mathbb{D}(\text{store}). \\ \mu_1 = \text{bind}(\mu, k_1) \wedge \\ \mu_2 = \text{bind}(\mu, k_2) \wedge \\ \forall a \in \text{supp}(\mu). \\ (k_1(a), k_2(a)) \models P(a) \end{array} \right]$$

# JOINT CONDITIONING

$$(\mu_1, \mu_2) \models \bigcap_{\mu} v. P(v) \quad \text{iff}$$

$$\left( \begin{array}{l} \exists k_1, k_2: A \rightarrow \mathbb{D}(\text{store}). \\ \mu_1 = \text{bind}(\mu, k_1) \wedge \\ \mu_2 = \text{bind}(\mu, k_2) \wedge \\ \forall a \in \text{supp}(\mu). \\ (k_1(a), k_2(a)) \models P(a) \end{array} \right)$$

# JOINT CONDITIONING

$$(\mu_1, \mu_2) \models \bigcup_{\mu} v. P(v) \quad \text{iff}$$

$$\left( \begin{array}{l} \exists k_1, k_2: A \rightarrow \mathbb{D}(\text{store}). \\ \mu_1 = \text{bind}(\mu, k_1) \wedge \\ \mu_2 = \text{bind}(\mu, k_2) \wedge \\ \forall a \in \text{supp}(\mu). \\ (k_1(a), k_2(a)) \models P(a) \end{array} \right)$$

Example:  $A = \{0, 1\}$   $\mu = \text{Ber}(1/3)$

$$\mu_1 = \frac{1}{3} k_1(0) + \frac{2}{3} k_1(1)$$

$$\mu_2 = \frac{1}{3} k_2(0) + \frac{2}{3} k_2(1)$$

$P(0)$

$P(1)$

$X \langle 1 \rangle \sim \text{Ber}(1/3)$

$\Gamma X \langle 1 \rangle = 0 \Gamma$

$\Gamma X \langle 1 \rangle = 1 \Gamma$

$$\bigcup_{\mu} v. (\Gamma X \langle 1 \rangle = v \Gamma \neq P(v))$$

# JOINT CONDITIONING

$$(\mu_1, \mu_2) \models \sum_{\mu} v. P(v) \quad \text{iff}$$

$$\left( \begin{array}{l} \exists k_1, k_2: A \rightarrow \mathbb{D}(\text{Store}). \\ \mu_1 = \text{bind}(\mu, k_1) \wedge \\ \mu_2 = \text{bind}(\mu, k_2) \wedge \\ \forall a \in \text{supp}(\mu). \\ (k_1(a), k_2(a)) \models P(a) \end{array} \right)$$

Example:  $A = \{0, 1\}$   $\mu = \text{Ber}(1/3)$

$$\mu_1 = \frac{1}{3} k_1(0) + \frac{2}{3} k_1(1)$$

$$\mu_2 = \frac{1}{3} k_2(0) + \frac{2}{3} k_2(1)$$

$P(0)$

$P(1)$

$X \langle 1 \rangle \sim \text{Ber}(1/3)$

$\Gamma X \langle 1 \rangle = 0 \Gamma$

$\Gamma X \langle 1 \rangle = 1 \Gamma$

$$\sum_{\mu} v. (\Gamma X \langle 1 \rangle = v \Gamma) \neq P(v)$$

[C-UNIT-R]

$$X \langle 1 \rangle \sim \mu \not\models \sum_{\mu} v. \Gamma X \langle 1 \rangle = v \Gamma$$

[This reflects the right unit law of  
the underlying monad!]

# ENCODING LIFTING AS CONDITIONING

Unary Conditioning:  $C_{\mu}^v. ([x=v] * P(v))$

Relational Lifting:

$\llbracket R(x\langle 1 \rangle, x\langle 2 \rangle) \rrbracket :=$

$\exists \mu: \mathbb{D}(\text{Val} \times \text{Val}). C_{\mu}(v_1, v_2). ([x\langle 1 \rangle = v_1] * [x\langle 2 \rangle = v_2] * \overset{\text{pure}}{\downarrow} R(v_1, v_2))$

# JOINT COND. RULES

[C-UNIT-R]

$$x \langle i \rangle \sim \mu \vdash \mathcal{C}_{\mu} v. [x \langle i \rangle = v]$$

[C-FRAME]

$$P * \mathcal{C}_{\mu} v. Q(v) \vdash \mathcal{C}_{\mu} v. (P * Q(v))$$

[C-CONS]

$$\frac{\forall v \in \text{supp}(\mu). P(v) \vdash P'(v)}{\mathcal{C}_{\mu} v. P(v) \vdash \mathcal{C}_{\mu} v. P'(v)}$$

$$\mathcal{C}_{\mu} v. P(v) \vdash \mathcal{C}_{\mu} v. P'(v)$$

$$x \langle 1 \rangle \sim \mu * y \langle 1 \rangle \sim \mu' * [z = x + y]$$

$$\vdash (\mathcal{C}_{\mu} v. [x \langle 1 \rangle = v]) * y \langle 1 \rangle \sim \mu' * [z = x + y]$$

$$\vdash \mathcal{C}_{\mu} v. ([x \langle 1 \rangle = v] * y \langle 1 \rangle \sim \mu' * [z = x + y])$$

$$\vdash \mathcal{C}_{\mu} v. (\mathcal{C}_{\mu'} v'. ([x \langle 1 \rangle = v] * [y \langle 1 \rangle = v'] * [z = x + y]))$$

$$\vdash \mathcal{C}_{\mu} v. \mathcal{C}_{\mu'} v'. [x \langle 1 \rangle = v \wedge y \langle 1 \rangle = v' \wedge z = x + y]$$

[c-ASSOC]

$$\mathcal{C}_{\mu} v. \mathcal{C}_{K(v)} v'. P(v, v') \vdash \mathcal{C}_{\text{bind}'(\mu, K)} . P(v, v')$$

$\text{bind}'(\mu, K) = \text{do } v \leftarrow \mu; v' \leftarrow K(v); \text{return } (v, v')$

[c-UNASSOC]

$$\mathcal{C}_{\text{bind}(\mu, K)} v'. P(v') \vdash \mathcal{C}_{\mu} v. \mathcal{C}_{K(v)} v'. P(v')$$

# SOME DERIVABLE RULES

$$C_{\exists} \text{ v. } \lfloor R \rfloor \vdash \lfloor R \rfloor \quad (\text{Convexity of Rel Liftings})$$

$$\lfloor R_1 \rfloor * \lfloor R_2 \rfloor \vdash \lfloor R_1 \wedge R_2 \rfloor$$

NOTE

$$\lfloor R_1 \rfloor \wedge \lfloor R_2 \rfloor \not\vdash \lfloor R_1 \wedge R_2 \rfloor$$

# CHALLENGES

- Generalization to Iris-style user-defined ghost resources
- [C-WP-SWAP]

$$\text{ownVars } \wedge \text{C}_{\mu}^v. \text{wp } \vdash \{Q(v)\} \vdash \text{wp } \vdash \{ \text{C}_{\mu}^v. Q(v) \}$$

↑ Bluebell needs this for soundness

OPEN QUESTION: Can we find a model that validates the rule without ownVars?

Thanks

*L*