

# Verifying Probabilistic Properties with Probabilistic Couplings

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# Work with brilliant collaborators



# What Are Probabilistic “Relational Properties”?

# Today's target properties

## Probabilistic

- ▶ Programs can take random samples (flip coins)
- ▶ Map (single) input value to a distribution over outputs

## Relational

- ▶ Compare **two** executions of a program (or: two programs)
- ▶ Describe outputs (**distributions**) from two related inputs
- ▶ Also known as **2-properties**, or **hyperproperties**

# Examples throughout computer science...

## Security and privacy

- ▶ Indistinguishability
- ▶ Differential privacy

## Machine learning

- ▶ Uniform stability

## ... and beyond

- ▶ Incentive properties (game theory/mechanism design)
- ▶ Convergence and mixing (probability theory)

# Challenges for formal verification

## Reason about two sources of randomness

- ▶ Two executions may behave very differently
- ▶ Completely different control flow (even for same program!)

## Quantitative reasoning

- ▶ Target properties describe distributions
- ▶ Probabilities, expected values, etc.
- ▶ Very messy for formal reasoning

Today: Combine two ingredients

Probabilistic Couplings

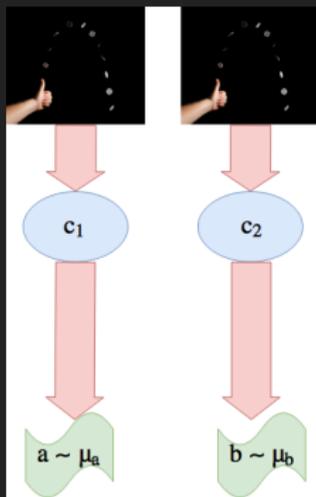
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Relational Program Logics

# Probabilistic Couplings and “Proof by Coupling”

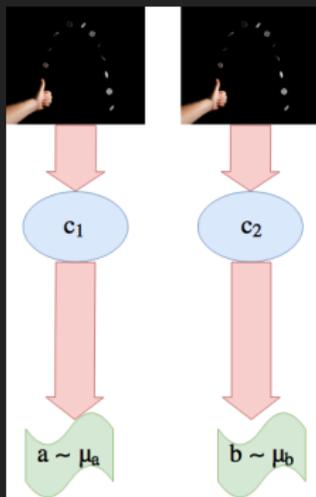
Given: programs  $c_1$  and  $c_2$ , each taking 10 coin flips

## Experiment #1

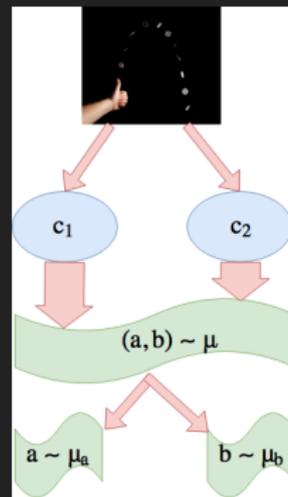


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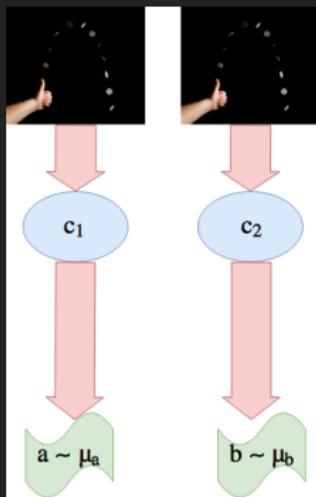


### Experiment #2

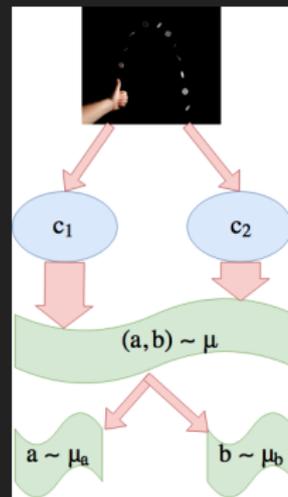


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### Experiment #2



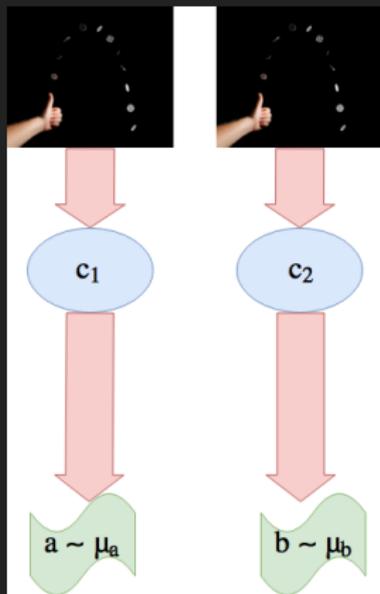
Distributions equal in Experiment #1



Distributions equal in Experiment #2

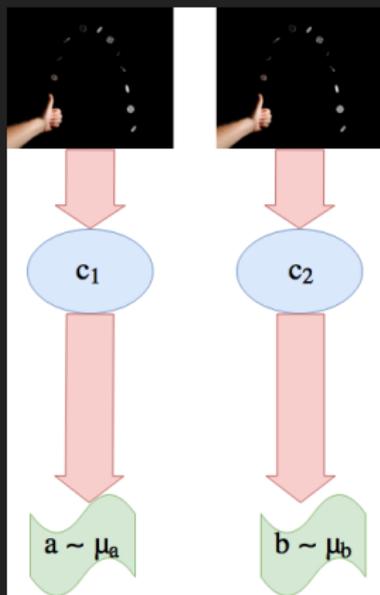
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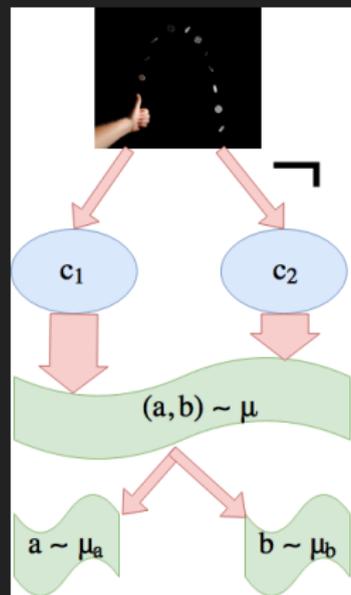


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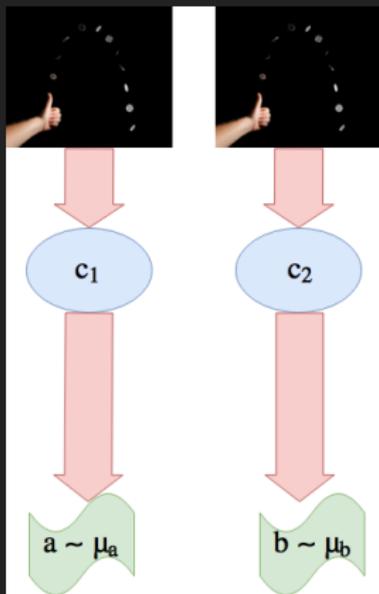


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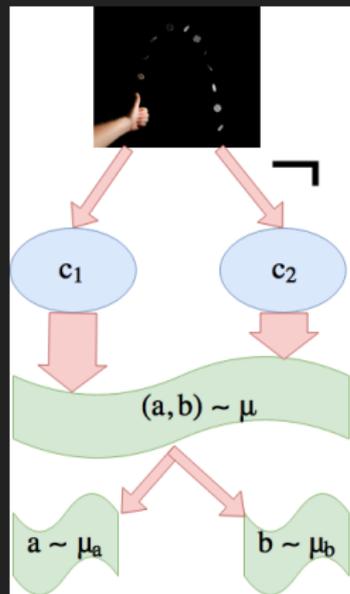


Given: programs  $c_1$  and  $c_2$ , each taking 10 coin flips

Experiment #1



Experiment #2



Distributions equal in Experiment #1



Distributions equal in Experiment #2

# Why “pretend” two executions share randomness?

## Easier to reason about one source of randomness

- ▶ Fewer possible executions
- ▶ Pairs of coordinated executions follow similar control flow

## Reduce quantitative reasoning

- ▶ Reason on (non-probabilistic) relations between samples
- ▶ Don't need to work with raw probabilities (messy)

A bit more precisely...

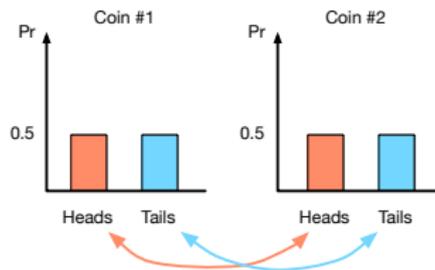
A **coupling** of two distributions  $\mu_1, \mu_2 \in \text{Distr}(A)$  is a joint distribution  $\mu \in \text{Distr}(A \times A)$  with  $\pi_1(\mu) = \mu_1$  and  $\pi_2(\mu) = \mu_2$ .

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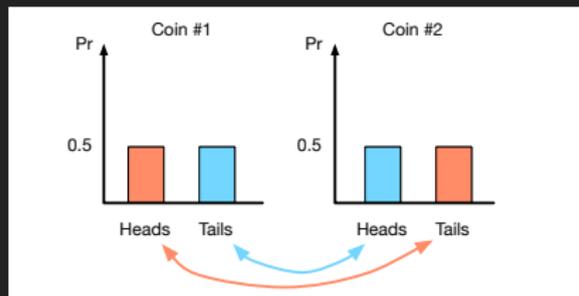
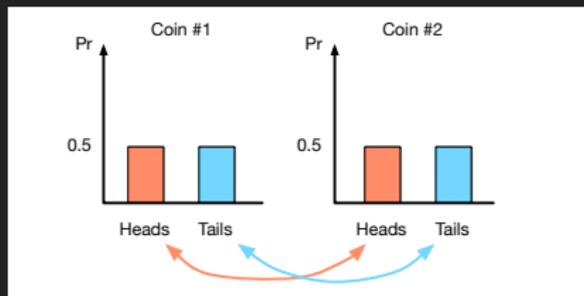
A coupling models **two** distributions sharing **one** source of randomness

# For example



		Coin #2	
		Heads	Tails
Coin #1	Heads	0.5	0
	Tails	0	0.5

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	Tails	0.5	0

Why are couplings interesting for verification?

Existence of a coupling\* can imply  
a property of two distributions

If there exists a coupling  
of  $(\mu_1, \mu_2)$  where:

then:

---

Two coupled samples differ  
with small probability

$\mu_1$  is “close” to  $\mu_2$

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First coupled sample is always  
larger than second sample

$\mu_1$  “dominates”  $\mu_2$

# Our plan to verify these properties

## Three easy steps

1. Start from two given programs
2. Show that for two related inputs, there exists a coupling of the output distributions with certain properties
3. Conclude relational property of program(s)

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### How to Draw an Owl

*A fun and creative guide for beginners*

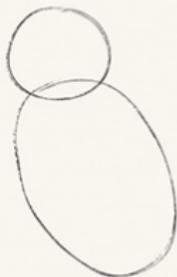


Fig 1. Draw two circles



Fig 2. Draw the rest of the damn owl

Show existence of a coupling by constructing it

A **coupling proof** is a recipe  
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## Show existence of a coupling by constructing it

A **coupling proof** is a recipe for constructing a coupling

1. **Specify**: How to couple pairs of intermediate samples
2. **Deduce**: Relation between final coupled samples
3. **Conclude**: Property about two original distributions

# Probabilistic Relational Program Logics

# Make statements about imperative programs

## Imperative language WHILE

$c ::= \text{skip} \mid x \leftarrow e \mid \text{if } b \text{ then } c \text{ else } c' \mid c; c' \mid \text{while } b \text{ do } c$

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## Imperative language WHILE

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## Semantics: WHILE programs transform memories

- ▶ **Variables:** Fixed set  $\mathcal{X}$  of program variable names
- ▶ **Memories**  $\mathcal{M}$ : functions from  $\mathcal{X}$  to values  $\mathcal{V}$  (e.g., 42)
- ▶ Interpret each command  $c$  as a **memory transformer**:

$$\llbracket c \rrbracket : \mathcal{M} \rightarrow \mathcal{M}$$

# Program logics (Floyd-Hoare logics)

Logical judgments look like this

$$\{P\} \ c \ \{Q\}$$

## Interpretation

- ▶ **Program**  $c$ , WHILE program (e.g.,  $x \leftarrow y; y \leftarrow y + 1$ )
- ▶ **Precondition**  $P$ , formula over  $\mathcal{X}$  (e.g.,  $y \geq 0$ )
- ▶ **Postcondition**  $Q$ , formula over  $\mathcal{X}$  (e.g.,  $x \geq 0 \wedge y \geq 0$ )

If  $P$  holds before running  $c$ , then  $Q$  holds after running  $c$

# Probabilistic Relational Hoare Logic (pRHL) [BGZ-B]

## Previously

- ▶ Inspired by Benton's Relational Hoare Logic
- ▶ Foundation of the EasyCrypt system
- ▶ Verified security of many cryptographic schemes

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## Previously

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## New interpretation

pRHL is a logic for formal  
proofs by coupling

# Language and judgments

## The PWHILE imperative language

$c ::= \text{skip} \mid x \leftarrow e \mid x \overset{\$}{\leftarrow} d \mid \text{if } e \text{ then } c \text{ else } c \mid c; c \mid \text{while } e \text{ do } c$

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## Semantics of PWHILE programs

- ▶ Input: a single memory (assignment to variables)
- ▶ Output: a **distribution** over memories
- ▶ Interpret each command  $c$  as:

$$\llbracket c \rrbracket : \mathcal{M} \rightarrow \text{Distr}(\mathcal{M})$$

# Basic PRHL judgments

$$\{P\} c_1 \sim c_2 \{Q\}$$

- ▶  $P$  and  $Q$  are formulas over program variables
- ▶ Labeled program variables:  $x_1, x_2$
- ▶  $P$  is precondition,  $Q$  is postcondition

# Interpreting the judgment

Logical judgments in pRHL look like this

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- ▶ As usual,  $P$  is a relation on two memories
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**Definition (Valid pRHL judgment)**

For any **pair of related inputs**  $(m_1, m_2) \in \llbracket P \rrbracket$ , **there exists a coupling**  $\mu \in \text{Distr}(\mathcal{M} \times \mathcal{M})$  of the output distributions  $(\llbracket c_1 \rrbracket m_1, \llbracket c_2 \rrbracket m_2)$  such that  $\text{supp}(\mu) \subseteq \llbracket Q \rrbracket$ .

## Encoding couplings with PRHL theorems

$$\{P\} \quad c_1 \sim c_2 \quad \{o_1 = o_2\}$$

### Interpretation

If two inputs satisfy  $P$ , there exists a coupling of the output distributions where the coupled samples have equal  $o$

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### Interpretation

If two inputs satisfy  $P$ , there exists a coupling of the output distributions where the coupled samples have equal  $o$

### This implies:

If two inputs satisfy  $P$ , the distributions of  $o$  are equal

## Encoding couplings with PRHL theorems

$$\{P\} \quad c_1 \sim c_2 \quad \{o_1 \geq o_2\}$$

This implies:

If two inputs satisfy  $P$ , then the first distribution of  $o$  stochastically dominates the second distribution of  $o$

# Proving Judgments: The Proof System of pRHL

# More convenient way to prove judgments

## Inference rules describe:

- ▶ Judgments that are always true (axioms)
- ▶ How to prove judgment for a program by combining judgments for components

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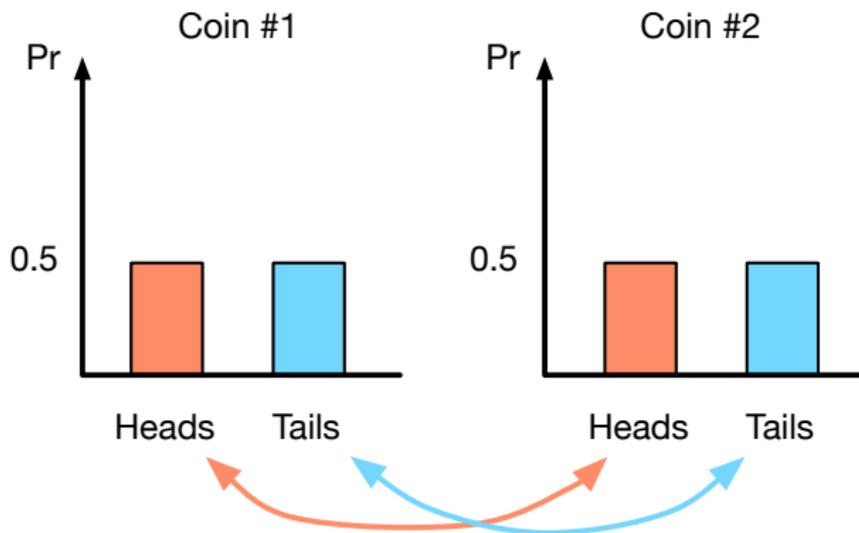
Conclude:  $\{P\} c_1 ; c_2 \{R\}$

## Reading the rules: introduce couplings

$$\frac{}{\vdash \{ \} \ x_1 \overset{\$}{\leftarrow} \textit{flip} \sim x_2 \overset{\$}{\leftarrow} \textit{flip} \ \{x_1 = x_2\}}$$

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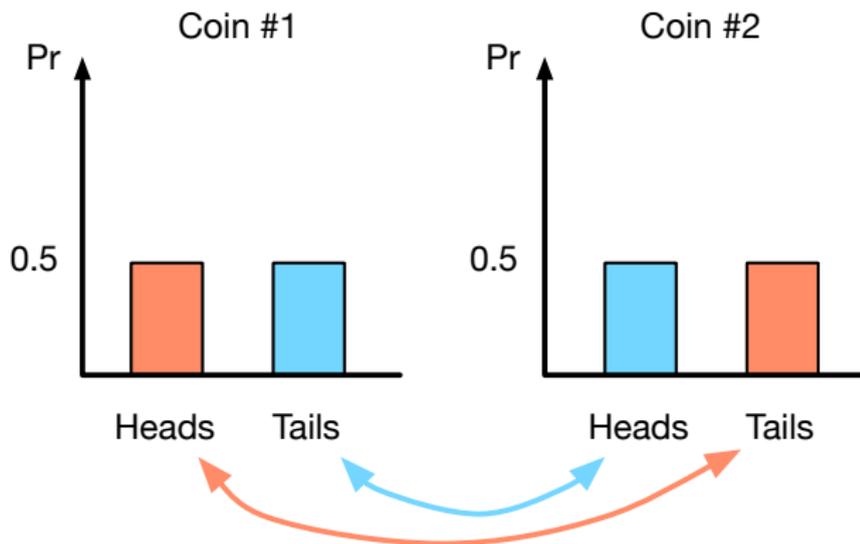


## Reading the rules: introduce couplings

$$\frac{}{\vdash \{ \} \quad x_1 \overset{\$}{\leftarrow} \text{flip} \sim x_2 \overset{\$}{\leftarrow} \text{flip} \quad \{x_1 \neq x_2\}}$$

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$$\vdash \{ \} \quad x_1 \stackrel{\$}{\leftarrow} \text{flip} \sim x_2 \stackrel{\$}{\leftarrow} \text{flip} \quad \{x_1 \neq x_2\}$$



## Reading the rules: combine couplings

$$\frac{\begin{array}{l} \vdash \{P\} \quad c_1 \sim c_2 \quad \{Q\} \\ \vdash \{Q\} \quad c'_1 \sim c'_2 \quad \{R\} \end{array}}{\vdash \{P\} \quad c_1; c'_1 \sim c_2; c'_2 \quad \{R\}}$$

## Reading the rules: combine couplings

$$\vdash \{P\} \quad c_1 \sim c_2 \quad \{Q\}$$

$$\vdash \{Q\} \quad c'_1 \sim c'_2 \quad \{R\}$$

---

$$\vdash \{P\} \quad c_1; c'_1 \sim c_2; c'_2 \quad \{R\}$$

Sequence couplings

## Reading the rules: combine couplings

$$\frac{\begin{array}{l} \vdash \{P \wedge S\} \quad c_1 \sim c_2 \quad \{Q\} \\ \vdash \{P \wedge \neg S\} \quad c_1 \sim c_2 \quad \{Q\} \end{array}}{\vdash \{P\} \quad c_1 \sim c_2 \quad \{Q\}}$$

## Reading the rules: combine couplings

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Select couplings

## Reading the rules: combine couplings

$$\frac{\vdash \{P \wedge e_1 \wedge e_2\} \quad c_1 \sim c_2 \quad \{P\} \quad \models P \rightarrow e_1 = e_2}{\vdash \{P\} \quad \text{while } e_1 \text{ do } c_1 \sim \text{while } e_2 \text{ do } c_2 \quad \{P \wedge (\neg e_1 \wedge \neg e_2)\}}$$

## Reading the rules: combine couplings

$$\frac{\vdash \{P \wedge e_1 \wedge e_2\} \quad c_1 \sim c_2 \quad \{P\} \quad \models P \rightarrow e_1 = e_2}{\vdash \{P\} \quad \text{while } e_1 \text{ do } c_1 \sim \text{while } e_2 \text{ do } c_2 \quad \{P \wedge (\neg e_1 \wedge \neg e_2)\}}$$

Repeat couplings

## Reading the rules: combine couplings

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Repeat couplings

## Not a rule: conjunction

$$\vdash \{P\} \quad c_1 \sim c_2 \quad \{Q\}$$

$$\vdash \{P\} \quad c_1 \sim c_2 \quad \{R\}$$

---

$$\vdash \{P\} \quad c_1 \sim c_2 \quad \{Q \wedge R\}$$

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$$\vdash \{P\} \quad c_1 \sim c_2 \quad \{Q\}$$

$$\vdash \{P\} \quad c_1 \sim c_2 \quad \{R\}$$

---

$$\vdash \{P\} \quad c_1 \sim c_2 \quad \{Q \wedge R\}$$

Can't compose this way

# Is this just bisimulation?

## More general property

- ▶ Relation need not be equivalence (bisimulation)
- ▶ Relation need not be preorder (simulation)

## More general model of computation

- ▶ Probabilistic imperative programs
- ▶ State space can be infinite/parametrized

## More flexible construction

- ▶ No fixed notion of a transition
- ▶ Coupling can be constructed “asynchronously”

# Formal Proofs by Coupling

## Ex. 1: Equivalence

## Target property: equivalence

*P*'s output distribution is the same for any two inputs

- ▶ Shows: output distribution is the same for **any** input
- ▶ Security: input is secret, output is encrypted

# Warmup example: secrecy of one-time-pad (OTP)

## The program

- ▶ Program input: a secret boolean  $sec$
- ▶ Program output: an encrypted version of the secret

```
key  $\xleftarrow{\$}$  flip;           // draw random key
enc  $\leftarrow sec \oplus key$ ; // exclusive or
return(enc)              // return encrypted
```

## Proof by coupling

- ▶ Either  $sec_1, sec_2$  are equal, or unequal
  1. If equal: couple sampling for  $key$  to be equal in both runs
  2. If unequal: couple sampling for  $key$  to be unequal in both runs
- ▶ Coupling ensures  $enc_1 = enc_2$ , hence distributions equal

# Formalizing the proof in PRHL

Case 1:  $sec_1 = sec_2$

- ▶ By applying identity coupling rule (general version):

$$\begin{aligned} & \{sec_1 = sec_2\} \\ & key \stackrel{\$}{\leftarrow} flip; \\ & \{key_1 = key_2\} \\ & enc \leftarrow sec \oplus key \\ & \{enc_1 = enc_2\} \end{aligned}$$

- ▶ Hence:

$$\{sec_1 = sec_2\} \quad otp \sim otp \quad \{enc_1 = enc_2\}$$

# Formalizing the proof in pRHL

Case 2:  $sec_1 \neq sec_2$

- ▶ By applying negation coupling rule (general version):

$$\begin{aligned} & \{sec_1 \neq sec_2\} \\ & key \xleftarrow{\$} flip; \\ & \{key_1 \neq key_2\} \\ & enc \leftarrow sec \oplus key \\ & \{enc_1 = enc_2\} \end{aligned}$$

- ▶ Hence:

$$\{sec_1 \neq sec_2\} \text{ otp} \sim \text{otp} \{enc_1 = enc_2\}$$

# Formalizing the proof in PRHL

Combining the cases:

$$\frac{\begin{array}{l} \{sec_1 = sec_2\} \quad otp \sim otp \quad \{enc_1 = enc_2\} \\ \{sec_1 \neq sec_2\} \quad otp \sim otp \quad \{enc_1 = enc_2\} \end{array}}{\{\top\} \quad otp \sim otp \quad \{enc_1 = enc_2\}}$$

and we are done!

# Formal Proofs by Coupling

## Ex. 2: Stochastic Domination

# Target property: stochastic domination

## Order relation on distributions

- ▶ Given: ordered set  $(A, \leq_A)$
- ▶ Lift to ordering on distributions  $(\text{Distr}(A), \leq_{sd})$

## For naturals $(\mathbb{N}, \leq)$ ...

Two distributions  $\mu_1, \mu_2 \in \text{Distr}(\mathbb{N})$  satisfy  $\mu_1 \leq_{sd} \mu_2$  if

$$\text{for all } k \in \mathbb{N}, \mu_1(\{n \mid k \leq n\}) \leq \mu_2(\{n \mid k \leq n\})$$

# Proof by coupling

```
ct ← 0;
for i= 1, ..., T1 do
  r  $\stackrel{\$}{\leftarrow}$  flip;
  if r = heads then
    ct ← ct + 1;
return(ct)
```

```
ct ← 0;
for i= 1, ..., T2 do
  r  $\stackrel{\$}{\leftarrow}$  flip;
  if r = heads then
    ct ← ct + 1;
return(ct)
```

# Proof by coupling

```
ct ← 0;  
for i= 1, ..., T1 do  
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ct ← 0;  
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Suppose  $T_1 \geq T_2$ : first loop runs more

- ▶ Want to prove  $\mu_1 \geq_{sd} \mu_2$

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Suppose  $T_1 \geq T_2$ : first loop runs more

- ▶ Want to prove  $\mu_1 \geq_{sd} \mu_2$

Suffices to construct a coupling where  $ct_1 \geq ct_2$

- ▶ Couple the first  $T_2$  samples to be equal across both runs; establishes  $ct_1 = ct_2$
- ▶ Take the remaining  $T_1 - T_2$  samples (in the first run) to be arbitrary; preserves  $ct_1 \geq ct_2$

# Formalizing the proof in pRHL

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ct ← 0;  
for i = 1, ..., T2 do  
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return(ct)
```

Goal: prove

$$\vdash \{T_1 \geq T_2\} \ c_1 \sim c_2 \ \{ct_1 \geq ct_2\}$$

# Proof sketch

## Step 1: Rewrite

```
 $ct \leftarrow 0;$   
for  $i = 1, \dots, T_2$  do  
   $r \stackrel{\$}{\leftarrow} \text{flip};$   
  if  $r = \text{heads}$  then  
     $ct \leftarrow ct + 1;$   
for  $i = T_2 + 1, \dots, T_1$  do  
   $r \stackrel{\$}{\leftarrow} \text{flip};$   
  if  $r = \text{heads}$  then  
     $ct \leftarrow ct + 1;$   
return( $ct$ )
```

```
 $ct \leftarrow 0;$   
for  $i = 1, \dots, T_2$  do  
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  r  $\stackrel{\$}{\leftarrow}$  flip;
  if r = heads then
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- ▶ Use sampling rule with identity coupling:  $r_1 = r_2$

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```

## Step 2: First loop

- ▶ Use sampling rule with identity coupling:  $r_1 = r_2$
- ▶ Establish loop invariant  $ct_1 = ct_2$

# Proof sketch

```
for  $i = T_2 + 1, \dots, T_1$  do  
   $r \stackrel{\$}{\leftarrow} \text{flip}$ ;  
  if  $r = \text{heads}$  then  
     $ct \leftarrow ct + 1$ ;  
return( $ct$ )
```

```
return( $ct$ )
```

## Step 3: Second loop

- ▶ Use “one-sided” sampling rule
- ▶ Apply “one-sided” loop rule to show invariant  $ct_1 \geq ct_2$

# Formal Proofs by Coupling

## Ex. 3: Uniformity

# Simulating a fair coin flip from a biased coin

## Problem setting

- ▶ Given: ability to draw **biased** coin flips  $flip(p)$ ,  $p \neq 1/2$
- ▶ Goal: simulate a **fair** coin flip  $flip(1/2)$

# Simulating a fair coin flip from a biased coin

## Problem setting

- ▶ Given: ability to draw **biased** coin flips  $flip(p)$ ,  $p \neq 1/2$
- ▶ Goal: simulate a **fair** coin flip  $flip(1/2)$

## Algorithm (“von Neumann’s trick”)

```
 $x \leftarrow true; y \leftarrow true;$  // initialize  $x = y$   
while  $x = y$  do // if equal, repeat  
     $x \xrightarrow{\$} flip(p);$  // flip biased coin  
     $y \xrightarrow{\$} flip(p);$  // flip biased coin  
return( $x$ ) // if not equal, return  $x$ 
```

# Simulating a fair coin flip from a biased coin

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- ▶ Given: ability to draw **biased** coin flips  $flip(p)$ ,  $p \neq 1/2$
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 $x \leftarrow true; y \leftarrow true;$            // initialize  $x = y$   
while  $x = y$  do                             // if equal, repeat  
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     $y \xrightarrow{\$} flip(p);$                      // flip biased coin  
return( $x$ )                                   // if not equal, return  $x$ 
```

How to prove that the result  $x$  is **unbiased** (uniform)?

## From existence of coupling, to uniformity

Suppose that we know there exist two couplings:

1. Under first coupling,  $x_1 = \text{true}$  implies  $x_2 = \text{false}$
2. Under second coupling,  $x_1 = \text{false}$  implies  $x_2 = \text{true}$

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As a consequence:

- ▶ By (1),  $\Pr[x_1 = \text{true}] \leq \Pr[x_2 = \text{false}]$
- ▶ By (2),  $\Pr[x_1 = \text{false}] \leq \Pr[x_2 = \text{true}]$

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But  $x_1$  and  $x_2$  have same distribution

- ▶ By (1),  $\Pr[x_1 = \text{true}] \leq \Pr[x_1 = \text{false}]$
- ▶ By (2),  $\Pr[x_1 = \text{false}] \leq \Pr[x_1 = \text{true}]$
- ▶ Hence **uniform**:  $\Pr[x_1 = \text{true}] = \Pr[x_1 = \text{false}]$

# Proof by coupling

## Algorithm (“von Neumann’s trick”)

```
 $x \leftarrow true; y \leftarrow true;$  // initialize  $x = y$   
while  $x = y$  do // if equal, repeat  
     $x \stackrel{\$}{\leftarrow} flip(p);$  // flip biased coin  
     $y \stackrel{\$}{\leftarrow} flip(p);$  // flip biased coin  
return( $x$ ) // if not equal, return  $x$ 
```

## Construct couplings such that:

1. Under first coupling,  $x_1 = true$  implies  $x_2 = false$
2. Under second coupling,  $x_1 = false$  implies  $x_2 = true$

## Consider the following coupling:

- ▶ Couple sampling of  $x_1$  to be equal to sampling of  $y_2$
- ▶ Couple sampling of  $x_2$  to be equal to sampling of  $y_1$
- ▶ Resulting coupling satisfies **both** (1) and (2)!

# Formalizing the proof in pRHL

Relate two (equivalent) versions of the program:

```
 $x \leftarrow true; y \leftarrow true;$   
while  $x = y$  do  
   $x \stackrel{\$}{\leftarrow} flip(p);$   
   $y \stackrel{\$}{\leftarrow} flip(p);$   
return( $x$ )
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Build coupling for loop bodies, then loops

- ▶ Use sampling rule with identity coupling:  $x_1 = y_2$

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Build coupling for loop bodies, then loops

- ▶ Use sampling rule with identity coupling:  $x_1 = y_2$
- ▶ Use sampling rule with identity coupling:  $y_1 = x_2$
- ▶ Use loop rule with invariant:

$$(x_1 = y_1 \rightarrow x_1 = y_2) \wedge (x_1 \neq y_1 \rightarrow x_1 \neq x_2)$$

# Formalizing the proof in pRHL

Relate two (equivalent) versions of the program:

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x ← true; y ← true;  
while x = y do  
  x  $\stackrel{\$}{\leftarrow}$  flip(p);  
  y  $\stackrel{\$}{\leftarrow}$  flip(p);  
return(x)
```

```
x ← true; y ← true;  
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  y  $\stackrel{\$}{\leftarrow}$  flip(p);  
  x  $\stackrel{\$}{\leftarrow}$  flip(p);  
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# Wrapping Up

# Variations and extensions

## Approximate couplings

- ▶ Prove differential privacy as approximate equivalence
- ▶ Coming up next in Marco's tutorial!

## Expectation couplings

- ▶ Prove quantitative bounds on distance b/t distributions
- ▶ MC convergence, stability of ML, path coupling, ...
- ▶ Program logic: <https://arxiv.org/abs/1708.02537>
- ▶ Pre-expectation calculus: <https://arxiv.org/abs/1901.06540>

## Automation

- ▶ Encode search for coupling proofs as a synthesis problem
- ▶ Coupling proofs: <https://arxiv.org/abs/1804.04052>
- ▶ Approximate couplings: <https://arxiv.org/abs/1709.05361>

# References

## Relational reasoning via probabilistic coupling

- ▶ Initial connection between couplings and pRHL (LPAR 2015)
- ▶ arXiv: <https://arxiv.org/abs/1509.03476>

## Coupling proofs are probabilistic product programs

- ▶ Extract product programs from pRHL proofs (POPL 2016)
- ▶ arXiv: <https://arxiv.org/abs/1607.03455>

## Proving uniformity and independence by self-composition and coupling

- ▶ Coupling proofs for non-relational properties (LPAR 2017)
- ▶ arXiv: <https://arxiv.org/abs/1701.06477>

# Verifying Probabilistic Properties with Probabilistic Couplings

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