

M. Jerrum, "Mathematical foundations of the Markov chain Monte Carlo method." In: M. Habib et al (eds.), *Probabilistic Methods for Algebraic Discrete Mathematics*. Springer-Verlag, Berlin, 1998.

A seminar talk based on

teeemu.hirsimaki@hut.fi

Teemu Hirsimäki

## Coupling methods

chain.

- The **Coupling Lemma** gives the mixing time for the original chain.
- Show that the chains **coalesce** with some probability.
- Run two copies of the chain **coupled** together.
- To estimate how long is enough:
  - Create a clever Markov chain and run it long enough.
  - A random colouring of a graph
  - A random sample from a complex distribution is needed (e.g.
  - The basic idea:

## What is coupling used for?

$$(2) \quad P(y|x, y) = P^M(y|x)$$

$$(1) \quad P(x|x, y) = P^M(x|y)$$

following equations:

- Coupling  $((X_t, Y_t) : t \in \mathbb{N})$  is a Markov chain satisfying the

transition probabilities  $P^M(\cdot | \cdot)$ .

- Suppose  $M$  is a countable and ergodic Markov chain with

What is coupling?

- Walking randomly among 2-colourings of two vertices by selecting a random vertex and a random color.
- Running the chains separately satisfies Equations 1 and 2, but instead, make the same change in both chains. The equations does not help much.
- Equations 1 and 2 allow that  $P(x, y|x, y) \neq P(x|x)P(y|y)$ .
- This important property makes it possible to create clever couplings, so that  $(X^t)$  and  $(Y^t)$  are forced to coalesce!

## Examples of coupled chains

- The idea: If  $P(X_t \neq Y_t)$  gets small fast enough when  $t$  grows, we get also a bound for the mixing time of the original chain.
- Formally: Suppose that  $M$  is a countable, ergodic Markov chain coupling, i.e. a Markov process satisfying (1) and (2). Suppose further that  $t : (0, 1] \rightarrow \mathbb{N}$  is a function such that  $P(X^{t(\epsilon)} \neq Y^{t(\epsilon)}) \leq \epsilon$  for all  $\epsilon \in (0, 1]$ , uniformly over the choice of initial state  $(X^0, Y^0)$ . Then the mixing time  $\tau(\epsilon)$  of  $M$  is bounded above by  $t(\epsilon)$ .

## The Coupling Lemma

$$\tau(\epsilon) = \min\{t : \varphi^x(t) < \epsilon \text{ for all } t \geq t\}$$

- The mixing time of the chain:

$$\varphi^x(t) := D_{t\alpha}(\cdot, x)$$

- The distance to the stationarity distribution:

$$D_{t\alpha}(x, \pi) := \max_{A \in \Sigma} |\pi(A) - \varphi^x(A)| = \frac{1}{2} \sum_{x \in \Sigma} |\pi(x) - \varphi^x(x)|$$

two distributions:

- Total variation distance is used to measure the distance between

## The mixing time

- Colouring an empty graph  $G = (V, \emptyset)$  with colours from  $\mathcal{Q}$ .
- Each state of the Markov process is a valid colouring.
- The transition  $(X^t, Y^t) \rightarrow (X^{t+1}, Y^{t+1})$  in the coupling:

  1. Select a vertex  $v \in V$ , uniformly at random (u.a.r.)
  2. Select a colour  $c \in \mathcal{Q}$ , u.a.r.
  3. Recolour vertex  $v$  in  $X^t$  and  $Y^t$  with  $c$  to get  $X^{t+1}$  and  $Y^{t+1}$ .

## Toy example: An empty graph

$$(0 < |{}^t D|) \equiv P({}^t X \neq {}^t Y)$$

- Now  $|{}^t D| < 0 \Leftrightarrow {}^t X \neq {}^t Y$ , i.e.

$$\{(\alpha){}^t X \neq (\alpha){}^t Y : \Lambda \ni \alpha\} = {}^t D$$

- Let  $D^t$  the set of vertices on which  $X^t$  and  $Y^t$  differ:
- $P(X^t \neq Y^t) > \epsilon$ .
- To utilise the Coupling Lemma, we need  $t(\epsilon)$  for each  $\epsilon$  to force

Toy example: Deriving the bound

$$|{}^0D| \left( \frac{u}{1} - 1 \right) = ({}^0D | | {}^t D |) E$$

$$| {}^t D | \left( \frac{u}{1} - 1 \right) = ({}^t D | | {}^{t+1} D |) E$$

selected u.a.r.

- To bound  $P(|D^t| < 0)$ , we can use the expected value. Since  $u$  is selected u.a.r.
  - $D^{t+1} = D^t$ , otherwise.
  - $D^{t+1} = D^t \setminus u$ , if the selected  $u$  is in  $D^t$ .
- How does  $D^t$  change in transitions?

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**Toy example: Deriving the bound**

- $T^x(\epsilon) \leq n(\ln n + \ln \epsilon^{-1})$ , independent of the starting state  $x$ .
- Lemma says, that the mixing time of the Markov process
- Now, if  $t \geq n \ln n \epsilon^{-1}$ , we have  $P(X^t \neq Y^t) < \epsilon$ , and the Coupling

$$\begin{aligned} u/t - \epsilon u &> \\ \left( \frac{u}{t} - 1 \right) u &\leq \\ P(D^t < 0 | D^0) &\leq \end{aligned}$$

- Inequality tells us that
- Since  $|D^t|$  is a non-negative integer random variable, Markov's

Toy example: The bound

- What goes wrong if couple the chains more strongly than allowed by (1) and (2)?
- What if want colourings from a distribution which is not uniform?
- What if want colourings from a distribution which is not uniform?
- Questions so far?

## Discussion

$c_Y$  are selected from a clever joint distribution.

- After selecting a common vertex  $v$  randomly, the colours  $c_X$  and  $c_Y$  are selected from a clever joint distribution.
  - But still,  $X_{t+1}$  must depend only on  $X_t$ .
  - valid colourings.
- More constraints are needed, because we want to walk among valid colourings.
- The transitions must be chosen more carefully.

$$q \geq 2\Delta + 1 \text{ colours.}$$

- Colouring a low-degree graph of maximum degree  $\Delta$  with

## Real example: Colouring a graph

$$(3) \quad \frac{\{xy, xb\}}{bxy} = \max_{cy} P(cy = cx)$$

- and the joint sample space satisfies
  - $cy$  is selected u.a.r. from the set  $\mathcal{O} \setminus Y^t(\mathcal{L}(v))$
  - $cx$  is selected u.a.r. from the set  $\mathcal{O} \setminus X^t(\mathcal{L}(v))$
- jointly so that the following conditions are met:
- Select a vertex  $v \in V$  u.a.r., and choose colours  $cx$  and  $cy$
  - $bxy = |((v)\mathcal{L}^t \cap ((v)\mathcal{L}^t \setminus \mathcal{O})|$
  - $bx = |\mathcal{O} \setminus X^t(\mathcal{L}(v))|, by = |\mathcal{O} \setminus Y^t(\mathcal{L}(v))|$ , and
  - neighbours of  $v$  in the graph  $G$ . Let  $X^t(U) = \{n : n \in U\}$
  - Let  $\mathcal{O}$  be the set of colours, and denote by  $\mathcal{L}(v) \subseteq V$  the set of all

## Real example: Selecting colours

where  $q$  is the number of colours.

$$(9) \quad (a) p - \nabla - b \geq qxy$$

$$(5) \quad (a) p \geq qxy - qb$$

$$(4) \quad (a) p \geq qxy - xb$$

- Let's consider first the probability that  $|D^{t+1}| = |D^t| + 1$ . We know that  $v$  is in  $A^t$ , and the colours are not equal. Denote by  $d(v)$  the number of edges between  $A$  and  $D$ . Then we have

- Let's consider first the probability that  $|D^{t+1}| = |D^t| + 1$ . We know that  $|D^{t+1}| - |D^t| \in \{-1, 0, 1\}$ , and want to show that  $1$  is more probable than  $-1$ .
- We know that  $|D^{t+1}| - |D^t| \in \{-1, 0, 1\}$ , and the set on which the colourings disagree.
- Let  $A^t$  be the set of vertices on which the colourings agree, and

## Real example: Deriving the bound

and  $D$ .

where  $m' = \sum_{v \in A} d'_v(v)$ , i.e. the edges between  $A$

$$\begin{aligned} (\mathcal{L}) \quad & \frac{u(\nabla - b)}{m'} = \\ & \frac{\nabla - b}{(a)p} \sum_{v \in A} \frac{u}{1} \geq (1 + |D'|)P(D') \end{aligned}$$

$$\begin{aligned} & \frac{\nabla - b}{(a)p} - 1 \leq \\ & \frac{\lambda X b + (a)p}{\lambda X b} \leq \\ & \frac{\max\{\lambda b, \lambda p\}}{\lambda X b} = (\lambda c_x - c_y)P(D) \end{aligned}$$

Starting from (3) and using (4-6) we get

$$\begin{aligned}
 & \frac{\nabla - b}{(\alpha)p} + \frac{\nabla - b}{2\Delta - b} \leq \\
 & \frac{\lambda X b + (\alpha)p - \nabla}{\lambda X b} \leq \\
 & \frac{\max\{\lambda b, \alpha b\}}{\lambda X b} = P(c_x = c_y)
 \end{aligned}$$

and we get

$$\begin{aligned}
 & (\alpha)p + \nabla - b \leq \lambda X b \\
 & (\alpha)p - \nabla \geq \lambda X b - \lambda b \\
 & (\alpha)p - \nabla \geq \lambda X b - X b
 \end{aligned}$$

the following inequalities:

in  $D$  and the selected colours must be equal. In this case we have

- Similarly, for the case  $|D^{t+1}| = |D^t| - 1$  we know that  $\alpha$  must be

and we know that  $a < 0$  since we assumed  $y \geq 2\Delta + 1$ .

$$q + |D^{t+1}| = |D^t| - 1 \geq a|D^t|$$

$$P(|D^{t+1}| = |D^t| + 1) \leq q$$

we can see that the size of the set  $D^t$  tends to decrease, because

$$\frac{u(\nabla - b)}{u} = (\mu)q = q \quad \frac{u(\nabla - b)}{\nabla - 2\Delta} = a$$

- If we define

$$(8) \quad \frac{u(\nabla - b)}{u} + |D| \frac{u(\nabla - b)}{\nabla - 2\Delta} = \\ \left( \frac{\nabla - b}{(\mu)p} + \frac{\nabla - b}{\nabla - 2\Delta} \right) \sum_{l=1}^{|D|} \frac{u}{l} \leq (1 - |D|) = |D^{t+1}| = P(|D^{t+1}| = |D^t| + 1)$$

Then we get the probability that  $|D^t|$  decreases

$$t \geq a^{-1} \ln(n_{\epsilon})$$

$P(|D^t| \neq 0) > n(1 - a)^t \geq n e^{-at}$ . So,  $P(|D^t| \neq 0) > \epsilon$ , provided

- Now because  $|D^t|$  is a non-negative integer random variable,

$$\cdot (1 - a)^t |D^t| \geq n(1 - a)^t \geq |D^t| E(|D^t|)$$

and

$$(1 - a)^t |D^t| =$$

$$+ (1 - a)^t |D^t| - 2a |D^t|$$

$$(1 - a)^t |D^t| + q(|D^t| + 1) + (1 - a)^t |D^t| - 1 \geq |D^{t+1}| E(|D^{t+1}|) + q(|D^t| + 1)$$

- Finally, using (7) and (8) we get

## Real example: The bound

- The book presents two newer techniques
  - The hardest thing is to design the coupling.
  - Estimating the volume of a convex body.
- Counting independent sets in a low-degree graph.
- Estimating the volume of a convex body.
- Path Coupling: coupling is defined only on pairs of adjacent states.
- Exact sampling can be done with Coupling From the Past (CFTP).

## About coupling methods

- What happens if we do not avoid invalid colourings?
- Proof of the Coupling Lemma?
- Questions?

## Discussion