

# Junior Seminar Notes

Alan Yan

Project Advisor: Professor Allan Sly

February 16, 2022

## Contents

1	The Initial Conditions	2
---	------------------------	---

# 1 The Initial Conditions

We first describe the initial markov chain.

**Definition 1** (Markov Chain I). *We have a Markov chain  $x_0, x_1, \dots$  where  $x_0$  is some initial vector in  $\mathbb{R}^n$ . Notation-wise, let  $x_k = (x_{k,1}, \dots, x_{k,n})$ . The Markov chain progresses as follows: given  $x_k$  pick two distinct coordinates  $I$  and  $J$  uniformly at random, and replace  $x_{k,I}$  and  $x_{k,J}$  by their average  $\frac{x_{k,I} + x_{k,J}}{2}$ .*

We have a Markov chain  $x_0, x_1, \dots$  where  $x_0$  is some initial vector in  $\mathbb{R}^n$ . Notation-wise, let  $x_k = (x_{k,1}, \dots, x_{k,n})$ . The Markov chain progresses as follows: given  $x_k$  pick two distinct coordinates  $I$  and  $J$  uniformly at random, and replace  $x_{k,I}$  and  $x_{k,J}$  by their average  $\frac{x_{k,I} + x_{k,J}}{2}$ . We want to study the rate of convergence of this Markov chain to its average  $(\bar{x}_0, \dots, \bar{x}_0)$  where

$$\bar{x}_0 = \frac{x_{0,1} + \dots + x_{0,n}}{n}.$$

We have two ways to measure the distance from the average:

$$T(k) = \sum_{i=1}^n |x_{k,i} - \bar{x}_0|$$

$$S(k) = \sum_{i=1}^n |x_{k,i} - \bar{x}_0|^2.$$

We have an exact formula for the expected  $L^2$  norm. Without loss of generality, we can assume  $\bar{x}_0 = 0$ .

**Proposition 1** (Proposition 2.1 in the paper). *For any  $k \geq 0$ , we have*

$$\mathbb{E}(S(k+1)|\mathcal{F}_k) = \left(1 - \frac{1}{n-1}\right) S(k).$$

*Proof.* The calculation is done in the paper. □

To avoid issues of dependence in the discrete time setting, we approximate Markov chain I with the following continuous time Markov chain.

**Definition 2** (Markov Chain II). *We have a Markov chain  $\{x_t\}_{t \geq 0}$ . Give each pair of coordinates an independent Poisson clock with rate  $\binom{n}{2}^{-1}$ . When a clock rings, replace the corresponding pair of coordinates with their average.*

With this new Markov chain, we introduce the same measurements from the average.

$$T'(k) := \sum_{i=1}^n |x_{t,i} - \bar{x}_0|$$

$$S'(k) := \sum_{i=1}^n |x_{t,i} - \bar{x}_0|^2.$$

We get a similar formula for the expected  $L^2$  distance.

**Proposition 2.** *For any  $t \geq s \geq 0$ , we have that*

$$\mathbb{E}[S'(t)|\mathcal{F}_s] = \exp\left(-\frac{t-s}{n-1}\right) S'(s).$$

*Proof.* Let  $E_k$  be the event that there are  $k$  rings between times  $s$  and  $t$ . Then

$$\begin{aligned} \mathbb{E}[S'(t)|\mathcal{F}_s] &= \sum_{k=0}^{\infty} \mathbb{E}[S'(t)|\mathcal{F}_s \text{ and } k \text{ rings}] \cdot \Pr[E_k] \\ &= \sum_{k=0}^{\infty} \left(1 - \frac{1}{n-1}\right)^k S'(s) \cdot e^{-(t-s)} \cdot \frac{(t-s)^k}{k!} \\ &= \exp\left((t-s) \left(1 - \frac{1}{n-1}\right)\right) \cdot e^{-(t-s)} S'(s) \\ &= \exp\left(-\frac{t-s}{n-1}\right) \cdot S'(s). \end{aligned}$$

This suffices for the proof. □

From here on out, we study the process starting from  $x_0 = (1 - 1/n, -1/n, \dots, -1/n)$ . The main theorem that the paper proves is the following.

**Theorem 1** (Theorem 2.3 in the paper). *Take  $\Phi : \mathbb{R} \rightarrow [0, 1]$  as the cdf of the standard normal distribution. For any  $a \in \mathbb{R}$ , we have  $T'(n(\log_2(n) + a\sqrt{\log_2(n)})/2) \xrightarrow{\mathbb{P}} 2\Phi(-a)$  in probability as  $n \rightarrow \infty$ .*

In the discrete case, we have the following theorem.

**Theorem 2** (Theorem 1.2 in the paper). *For any  $a \in \mathbb{R}$ , we have that*

$$T(\lfloor n(\log_2(n) + a\sqrt{\log_2(n)})/2 \rfloor) \xrightarrow{\mathbb{P}} 2\Phi(-a).$$

**Proposition 3.** *Theorem 1 and Theorem 2 are equivalent.*

*Proof.* TODO □