

On Pólya Urn Scheme with Infinitely Many Colors

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Generalization of the Polya Urn scheme to infinitely many colors

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- The initial configuration of the urn U_0 is taken to be a probability vector and can be thought to be the proportion of balls of each color/type we start with. Then
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$$U_{n+1} = U_n + I_{n+1}R \tag{1}$$

where $I_n = (\dots, I_{n,-1}, I_{n,0}, I_{n,1} \dots)$ where $I_{n,i} = 1$ for $i = j$ and 0 elsewhere.

We study this process for the replacement matrices R which arise out of the Random Walks on \mathbb{Z} .

We can generalize this process to general graphs on \mathbb{R}^d , $d \geq 1$. Let $G = (V, E)$ be a connected graph on \mathbb{R}^d with vertex set V which is countably infinite. The edges are taken to be bi-directional and there exists $m \in \mathbb{N}$ such that $d(v) = m$ for every $v \in V$. Let the distribution of X_1 be given by

$$\mathbb{P}(X_1 = \mathbf{v}) = p(\mathbf{v}) \text{ for } \mathbf{v} \in B \text{ where } |B| < \infty. \quad (2)$$

where $\sum_{\mathbf{v} \in B} p(\mathbf{v}) = 1$. Let $S_n = \sum_{i=1}^n X_i$.

Let R be the matrix/operator corresponding to the random walk S_n and the urn process evolve according to R . In this case, the configuration U_n of the process is a row vector with co-ordinates indexed by V . The dynamics is similar to that in one-dimension, that is an element is drawn at random, its type noted and returned to the urn. If the \mathbf{v}^{th} type is selected at the $n + 1^{\text{st}}$ trial, then

$$U_{n+1} = U_n + e_{\mathbf{v}}R \quad (3)$$

where $e_{\mathbf{v}}$ is a row vector with 1 at the \mathbf{v}^{th} co-ordinate and zero elsewhere.

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- Hence $\frac{U_n}{n+1}$ is a **random** probability vector. For every $\omega \in \Omega$, we can define a random d -dimensional vector $T_n(\omega)$ with law $\frac{U_n(\omega)}{n+1}$.
- Also $\frac{(\mathbb{E}[U_{n,\mathbf{v}}])_{\mathbf{v} \in V}}{n+1}$ is a probability vector. Therefore we can define a random vector Z_n with law $\frac{(\mathbb{E}[U_{n,\mathbf{v}}])_{\mathbf{v} \in V}}{n+1}$.

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Theorem

Let the process evolve according to a random walk on \mathbb{R}^d with bounded increments. Let the process begin with a single ball of type $\mathbf{0}$. For $X_1 = (X_1^{(1)}, X_1^{(2)} \dots X_1^{(d)})$, let $\mu = (\mathbb{E}[X_1^{(1)}], \mathbb{E}[X_1^{(2)}], \dots, \mathbb{E}[X_1^{(d)}])$ and $\Sigma = [\sigma_{ij}]_{d \times d}$ where $\sigma_{i,j} = \mathbb{E}[X_1^{(i)} X_1^{(j)}]$. Let B be such that Σ is positive definite. Then

$$\frac{Z_n - \mu \log n}{\sqrt{\log n}} \xrightarrow{d} N(\mathbf{0}, \Sigma) \text{ as } n \rightarrow \infty \quad (4)$$

where $N(\mathbf{0}, \Sigma)$ denotes the d -dimensional Gaussian with mean vector $\mathbf{0}$ and variance-covariance matrix Σ . Furthermore there exists a subsequence $\{n_k\}$ such that as $k \rightarrow \infty$ almost surely

$$\frac{T_{n_k} - \mu \log n}{\sqrt{\log n}} \xrightarrow{d} N(\mathbf{0}, \Sigma) \quad (5)$$

Corollary

Let $d \geq 1$ and we consider the SSRW. Let the process begin with a single ball of type $\mathbf{0}$. If Z_n be the random d -dimensional vector corresponding to the probability distribution $\frac{(\mathbb{E}[U_{n,v}])_{v \in \mathbb{Z}^d}}{n+1}$, then

$$\frac{Z_n}{\sqrt{\log n}} \xrightarrow{d} N(\mathbf{0}, d^{-1} \mathbb{I}_d) \text{ as } n \rightarrow \infty \quad (6)$$

where \mathbb{I}_d is the d -dimensional identity matrix. Furthermore, there exists a subsequence $\{n_k\}$ such that almost surely as $k \rightarrow \infty$

$$\frac{T_{n_k}}{\sqrt{n_k}} \xrightarrow{d} N(\mathbf{0}, d^{-1} \mathbb{I}_d). \quad (7)$$

Corollary

Let $d = 1$ and $\mathbb{P}(X_1 = 1) = 1$. Let $U_0 = 1_{\{0\}}$. If Z_n be the random variable corresponding to the probability mass function $\frac{(\mathbb{E}[U_{n,k}])_{k \in \mathbb{Z}}}{n+1}$, then

$$\frac{Z_n - \log n}{\sqrt{\log n}} \xrightarrow{d} N(0, 1) \text{ as } n \rightarrow \infty. \quad (8)$$

Also there exists a subsequence n_k such that almost surely as $k \rightarrow \infty$

$$\frac{T_{n_k} - \log n_k}{\sqrt{n_k}} \xrightarrow{d} N(0, 1). \quad (9)$$

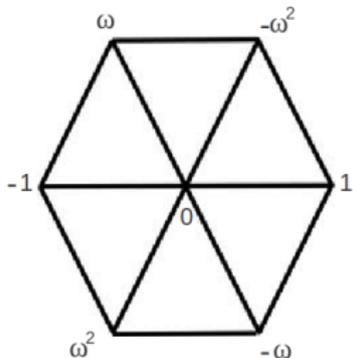


Figure: Triangular Lattice

Corollary

Let the urn model evolve according to the random walk on triangular lattice on \mathbb{R}^2 and the process begin with a single particle of type 0, then as $n \rightarrow \infty$

$$\frac{Z_n}{\sqrt{\log n}} \xrightarrow{d} N\left(\mathbf{0}, \frac{1}{2}\mathbb{I}_2\right). \quad (10)$$

Corollary (continued)

Furthermore, there exists a subsequence $\{n_k\}$ such that as $k \rightarrow \infty$,

$$\frac{T_{n_k}}{\sqrt{\log n_k}} \xrightarrow{d} N\left(0, \frac{1}{2}\mathbb{I}_2\right) \quad (11)$$

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- In both cases, with a scaling of $\sqrt{\log n}$ the asymptotic behavior of the models are similar.
- On \mathbb{Z} , the random walks are recurrent or transient depending on $\mathbb{E}[X_1] = 0$ or not. Asymptotically both behave similarly upto centering and scaling.
- We conjecture that in the infinite type/ color case, the asymptotic behavior of the process is not determined completely by the underlying Markov Chain of the operator, but by the qualitative properties of the underlying graph.

- We present the proof for SSRW on $d = 2$ for notational simplicity. We use the martingale methods for the proof.

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- For every $\mathbf{t} = (t_1, t_2) \in \mathbb{R}^2$, $e(\mathbf{t}) = \frac{1}{4} \sum_{\mathbf{u} \in N(\mathbf{0})} e^{\langle \mathbf{u}, \mathbf{t} \rangle}$ is an eigen value for the operator R where $\mathbf{0}$ stands for the origin in \mathbb{Z}^2 and $\langle \cdot, \cdot \rangle$ stands for the inner product.

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- The corresponding right eigen vectors are $\underline{x}(\mathbf{t}) = (x_{\mathbf{t}}(\mathbf{v}))_{\mathbf{v} \in \mathbb{Z}^2}$ where $x_{\mathbf{t}}(\mathbf{v}) = e^{\langle \mathbf{t}, \mathbf{v} \rangle}$.

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- We have noted earlier that $\frac{U_n}{n+1}$ is a **random** probability vector.
- The moment generating function for this vector is given by $\frac{U_n \cdot \underline{x}(\mathbf{t})}{n+1}$ for every $\mathbf{t} \in \mathbb{R}^2$.

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- The moment generating function for this vector is given by $\frac{U_n \cdot \underline{x}(\mathbf{t})}{n+1}$ for every $\mathbf{t} \in \mathbb{R}^2$.
- Using (1), it can be shown that $\overline{M}_n(\mathbf{t}) = \frac{U_n \cdot \underline{x}(\mathbf{t})}{\Pi_n(e^{\langle \cdot, \mathbf{t} \rangle})}$ is a non-negative martingale, where $\Pi_n(\beta) = \prod_{j=1}^n (1 + \frac{\beta}{j})$.

- Since we begin with one element of type $\mathbf{0}$,

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- We will show that for a suitable $\delta > 0$ and for all $\mathbf{t} \in [-\delta, \delta]^2$

$$\frac{E_n \cdot \underline{x}\left(\frac{\mathbf{t}}{\sqrt{\log n}}\right)}{n+1} \longrightarrow e^{\frac{\|\mathbf{t}\|_2^2}{4}} \quad (13)$$

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- We know that

$$E_n \cdot \underline{x}(\mathbf{t}_n) = \Pi_n (e(\mathbf{t}_n)) \quad (14)$$

where $\mathbf{t}_n = \frac{\mathbf{t}}{\sqrt{\log n}}$.

- We use the following fact due to Euler,

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- It is easy known that this convergence is uniform for all $\beta \in [1 - \eta, 1 + \eta]$ for a suitable choice of η .
- Due to the uniform convergence, it follows immediately that $\forall \mathbf{t} \in [-\delta, \delta]^2$

$$\lim_{n \rightarrow \infty} \frac{\Pi_n(e(\mathbf{t}_n))}{n^{e(\mathbf{t}_n)} / \Gamma(e(\mathbf{t}_n) + 1)} = 1. \quad (15)$$

- Simplifying the left hand side of [13] we get

$$\frac{\Pi_n(e(\mathbf{t}_n))}{n+1} \quad (16)$$

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$$\begin{aligned} \lim_{n \rightarrow \infty} -\log(n+1) + e(\mathbf{t}_n) \log n - \log(\Gamma(e(\mathbf{t}_n) + 1)) \\ = \frac{\|\mathbf{t}\|_2^2}{4}. \end{aligned} \quad (17)$$

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- Expanding $e(\mathbf{t}_n)$ into power series and noting that $\Gamma(x)$ is continuous as a function of x we can prove (17).

Thank You!