

The number of vertices of fixed degree in the preferential attachment model with choice

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Abstract. The preferential attachment models are widely used to describe different web and social network (random) graphs. We concentrate on some generalizations of these models. Namely, a random tree under consideration is constructed in the following way. Let $d(1), d(2), \dots$ be i.i.d. integer-valued random variables. At each step n a new vertex is introduced. Then we select $d(n)$ vertices, chosen from the old vertices with probabilities proportional to their degrees and conditionally independent given $d(n)$, and connect new vertex to the vertex from the sample with largest degree. In preferential attachment without choice $d(n) = 1$ for all n . We establish the upper class law of the iterated logarithm for the number of vertices of degree k at step n . The proof employs results of stochastic approximation theory along with analysis of specified martingales and system of the equations describing an evolution of the model.

Keywords: random trees, stochastic approximation, preferential attachment.

1. Introduction

In the present work, we study how the addition of choice affects the Mori's preferential attachment model. Let describe the max-choice Mori's preferential attachment tree model. This model is a time-indexed inductively constructed sequence of trees, built in the following way. First, fix number $\beta > -1$ and distribution of a random variable d with values in \mathbb{N} . These are the parameters of our model. Consider set of vertices $V = \{v_i\}_{i=1}^{\infty}$. Define a sequence of random trees $\{T_n\}$, $n \in \mathbb{N}$, by the following inductive rule. Let T_1 be the one-edge tree which consists of vertices v_1 and v_2 and an edge between them. Given T_n , we construct T_{n+1} by adding one vertex and drawing one edge in the following way. First, we add a vertex v_{n+2} to T_n . So, for the set $V(T_{n+1})$ of vertices of T_{n+1} we get $V(T_{n+1}) = \{v_i, i = 1, \dots, n+2\}$. Note that $\sum_{v_i \in V(T_n)} \deg_{T_n} v_i = 2n$, where $\deg_{T_n} v_i$ is the degree of v_i in T_n . Second, we draw an edge between v_{n+2} and $Y_n \in V(T_n)$, which we choose by the rule describe below. So, for the set $E(T_{n+1})$ of edges of T_{n+1} we get $E(T_{n+1}) = E(T_n) \cup \{v_{n+2}, Y_n\}$. The randomness of T_{n+1} given T_n is due to randomness of Y_n . Order the set $V(T_n)$ by the vertices degrees in T_n . In other words, $V(T_n) = \{v_{(1)}^n, \dots, v_{(n+1)}^n\}$, $\deg_{T_n} v_{(i)}^n \leq \deg_{T_n} v_{(i+1)}^n$. Let

$\vartheta_j(n)$ denote the position of vertex v_j in ordered set $\{v_{(1)}^n, \dots, v_{(n+1)}^n\}$, i.e. $v_j = v_{(\vartheta_j(n))}^n$ and if $\deg_{T_n} v_i = \deg_{T_n} v_j$ and $i < j$, then $\vartheta_i(n) < \vartheta_j(n)$. Consider i.i.d. random variables $\{U_n^i\}_{n \in \mathbb{N}, i \in \mathbb{N}}$, distributed uniformly on $[0, 1]$. Define random variables $X_n^i, i \in \mathbb{N}$ with values in $V(T_n)$ as follow. Let $X_n^i = v_{(1)}^n$ if $U_n^i \leq \frac{\deg_{T_n} v_{(1)}^n + \beta}{(2+\beta)n + \beta}$ and $X_n^i = v_{(j)}$, $1 < j \leq n + 1$, if $\sum_{l=1}^{j-1} \frac{\deg_{T_n} v_{(l)}^n + \beta}{(2+\beta)n + \beta} < U_n^i \leq \sum_{l=1}^j \frac{\deg_{T_n} v_{(l)}^n + \beta}{(2+\beta)n + \beta}$. Let d_1, d_2, \dots be i.i.d. random variable distributed as d . Finally, we take Y_n as the vertex among $X_n^1, \dots, X_n^{d_n}$ with the largest degree. In the case of a tie, choose the vertex with the largest index.

Remark 1 Since T_{n+1} is well defined by Y_1, \dots, Y_n , all its parameters are \mathcal{F}_{n+1} measurable.

Remark 2 Prove of the main result would require analysis of event $A_n = \{(U_1^n, \dots, U_{d_n}^n) \in D_n\}$ for random sets $D_i \in \mathbb{R}^i$, $i \in \mathbb{N}$. Note that if $|D_i|$ (here $|B|$ stands for the Lebesgue measure of B) does not depend on \mathcal{F}_n , then A_n does not depend on \mathcal{F}_n .

Let formulate our theorem. Let $N_k(n)$ be the number of vertices of degree k in tree T_n , $Z_k(n) = \frac{N_k(n)}{n}$ and $W_k(n) = (Z_1(n), \dots, Z_k(n))$. Theorem 5.1 of [1] states that there is a point $\rho_k^* = (x_1^*, \dots, x_k^*)$ and a positively defined symmetric matrix $B_k = (b_{i,j})_{1 \leq i, j \leq k}$ (both depends on β and distribution of d) such that $n^{1/2}(W_k(n) - \rho_k^*)$ converge in distribution to normal distribution $N(0, B)$ as $n \rightarrow \infty$. We will prove an upper class law of the iterated logarithm for variables $N_k(n)$.

Theorem 3 Let $\mathbb{E}d^2 < \infty$. Then, for any $k \in \mathbb{N}$ one has

$$\limsup_{n \rightarrow \infty} \left| \frac{N_k(n) - nx_k^*}{\sqrt{2b_{k,k}n \ln \ln n}} \right| \leq 1 \quad a.s.$$

2. Proof of the main result

For $x_1, \dots, x_k \in \mathbb{R}_+$, $k \in \mathbb{N}$, define functions

$$\begin{aligned} h_0 &= 1, \quad h_1(x_1) = \sum_{m=1}^{\infty} \mathbb{P}(d = m) \left(x_1 \frac{1 + \beta}{2 + \beta} \right)^m, \quad h_k(x_1, \dots, x_k) = \\ &= \sum_{m=1}^{\infty} \mathbb{P}(d = m) \left(\left(\sum_{j=1}^k x_j \frac{(j + \beta)}{2 + \beta} \right)^m - \left(\sum_{j=1}^{k-1} x_j \frac{(j + \beta)}{2 + \beta} \right)^m \right), \end{aligned}$$

$$f_k(x_1, \dots, x_k) = h_{k-1}(x_1, \dots, x_{k-1}) - h_k(x_1, \dots, x_k),$$

$$g_k(x_1, \dots, x_k) = f(x_1, \dots, x_k) - x_k.$$

As it is shown in [1],

$$b_{1,1} = 1 - \sum_{m=1}^{\infty} \mathbb{P}(d = m) \left(x_1^* \frac{1 + \beta}{2 + \beta} \right)^m,$$

$$\mathbb{P}(N_1(n+1) - N_1(n) = 1 | \mathcal{F}_n) = \sum_{m=1}^{\infty} \mathbb{P}(d = m) \left(1 - \left(\frac{N_1(n)(1 + \beta)}{(2 + \beta)n + \beta} \right)^m \right)$$

and

$$\begin{aligned} b_{k,k} &= h_k(x_1^*, \dots, x_k^*) + h_{k-1}(x_1^*, \dots, x_{k-1}^*), \\ g_k(x_1^*, \dots, x_k^*) &= 0, \end{aligned} \quad (1)$$

$$\mathbb{P}(N_k(n+1) - N_k(n) = 1 | \mathcal{F}_n) = h_{k-1}(\tilde{Z}_1(n), \dots, \tilde{Z}_k(n)), \quad (2)$$

$$\mathbb{P}(N_k(n+1) - N_k(n) = -1 | \mathcal{F}_n) = h_k(\tilde{Z}_1(n), \dots, \tilde{Z}_k(n)) \quad (3)$$

for $k > 1$, where

$$\tilde{Z}_i(n) = \frac{N_i(n)}{n + \frac{\beta}{2+\beta}} = Z_i(n) \frac{1}{1 + \frac{\beta}{n(2+\beta)}}, \quad i = 1, \dots, k.$$

Also there are random \mathcal{F}_n -measurable sets $D_n^+(k, m), D_n^-(k, m) \subset [0, 1]^m$, $m, k, n \in \mathbb{N}$, such that

$$\{N_k(n+1) - N_k(n) = 1\} = \{(U_n^1, \dots, U_n^{d_n}) \in D_n^+(k, d_n)\},$$

$$\{N_k(n+1) - N_k(n) = -1\} = \{(U_n^1, \dots, U_n^{d_n}) \in D_n^-(k, d_n)\}.$$

Therefore,

$$\begin{aligned} N_k(n+1) - N_k(n) &= \mathbf{1}\{(U_n^1, \dots, U_n^{d_n}) \in D_n^+(k, d_n)\} \\ &\quad - \mathbf{1}\{(U_n^1, \dots, U_n^{d_n}) \in D_n^-(k, d_n)\}. \end{aligned}$$

Hence, from (2), (3) and definition of h_k , we have for $k > 1$

$$|D_n^-(k, m)| = \left(\left(\sum_{j=1}^k \tilde{Z}_j(n) \frac{(j + \beta)}{2 + \beta} \right)^m - \left(\sum_{j=1}^{k-1} \tilde{Z}_j(n) \frac{(j + \beta)}{2 + \beta} \right)^m \right),$$

$$|D_n^+(k, m)| = \left(\left(\sum_{j=1}^{k-1} \tilde{Z}_j(n) \frac{(j + \beta)}{2 + \beta} \right)^m - \left(\sum_{j=1}^{k-2} \tilde{Z}_j(n) \frac{(j + \beta)}{2 + \beta} \right)^m \right)$$

and for $k = 1$ we get $|D_n^-(1, m)| = 0$, $|D_n^+(1, m)| = 1 - \left(\frac{N_1(n)(1+\beta)}{(2+\beta)n+\beta}\right)^m$.
Let $\alpha_{1,m}^- = 0$, $\alpha_{1,m}^+ = \left(1 - \left(x_1^* \frac{(1+\beta)}{2+\beta}\right)^m\right)$ and for $k > 1$

$$\alpha_{k,m}^- = \left(\left(\sum_{j=1}^k x_j^* \frac{(j+\beta)}{2+\beta} \right)^m - \left(\sum_{j=1}^{k-1} x_j^* \frac{(j+\beta)}{2+\beta} \right)^m \right),$$

$$\alpha_{k,m}^+ = \left(\left(\sum_{j=1}^{k-1} x_j^* \frac{(j+\beta)}{2+\beta} \right)^m - \left(\sum_{j=1}^{k-2} x_j^* \frac{(j+\beta)}{2+\beta} \right)^m \right).$$

Introduce random \mathcal{F}_n -measurable sets $D_*^+(k, m, n)$ and $D_*^-(k, m, n)$ such that $|D_*^+(k, m, n)| = \alpha_{k,m}^+$, $|D_*^-(k, m, n)| = \alpha_{k,m}^-$. Moreover if $|D_n^+(k, m)| > \alpha_{k,m}^+$ then $D_*^+(k, m, n) \subset D_n^+(k, m)$, if $|D_n^+(k, m)| \leq \alpha_{k,m}^+$, then $D_n^+(k, m) \subset D_*^+(k, m, n)$, if $|D_n^-(k, m)| > \alpha_{k,m}^-$, then $D_*^-(k, m, n) \subset D_n^-(k, m)$ and if $|D_n^-(k, m)| \leq \alpha_{k,m}^-$, then $D_n^-(k, m) \subset D_*^-(k, m, n)$. Let

$$X_k(n) = \mathbf{1}\{(U_n^1, \dots, U_n^{d_n}) \in D_*^+(k, d_n, n)\} \\ - \mathbf{1}\{(U_n^1, \dots, U_n^{d_n}) \in D_*^-(k, d_n, n)\} - x_k^*.$$

Note that due to Remark 2 and formula (1) we have that $X_k(n)$, $n \in \mathbb{N}$ are i.i.d. random variables and

$$\mathbb{E}X_k(n) = g_k(x_1^*, \dots, x_k^*) = 0.$$

Also $\mathbb{E}X_k(n)^2 = b_{k,k}$. Hence, by the law of the iterated logarithm for i.i.d. random variables

$$\limsup_{n \rightarrow \infty} \left| \frac{\sum_{i=1}^n X_k(i)}{\sqrt{2b_{k,k}n \ln \ln n}} \right| = 1 \quad a.s.$$

Introduce random variables

$$\epsilon_k(n) = \mathbf{1}\{(U_n^1, \dots, U_n^{d_n}) \in D_n^+(k, d_n) \setminus D_*^+(k, d_n, n)\} \\ - \mathbf{1}\{(U_n^1, \dots, U_n^{d_n}) \in D_*^+(k, d_n, n) \setminus D_n^+(k, d_n)\} \\ - \mathbf{1}\{(U_n^1, \dots, U_n^{d_n}) \in D_n^-(k, d_n) \setminus D_*^-(k, d_n, n)\} \\ + \mathbf{1}\{(U_n^1, \dots, U_n^{d_n}) \in D_*^-(k, d_n, n) \setminus D_n^-(k, d_n)\}.$$

Therefore,

$$N_k(n+1) - N_k(n) - x_k^* = X_k(n) + \epsilon_k(n).$$

To complete the proof we need to estimate $\sum_{i=1}^n \epsilon_k(i)$. We give the sketch of the proof. Define

$$\begin{aligned} S_i(n) &= N_i(n+1) - N_i(n) - x_i^*, \quad Y_k(n) = (S_1(n), \dots, S_k(n)), \\ F_k(x_1, \dots, x_k) &= (f_1(x_1), \dots, f_k(x_1, \dots, x_k)), \\ A_k(n) &= (\epsilon_1(n), \dots, \epsilon_k(n)), \quad \widetilde{W}_k(n) = (\widetilde{Z}_1(n), \dots, \widetilde{Z}_k(n)). \end{aligned}$$

We get

$$\mathbb{E}(Y_k(n)|\mathcal{F}_n) = F_k(\widetilde{Z}_1(n), \dots, \widetilde{Z}_k(n)) - F_k(x_1^*, \dots, x_k^*).$$

Consequently,

$$\begin{aligned} \mathbb{E}(A_k(n)|\mathcal{F}_n) &= \mathbb{E}(Y_k(n)|\mathcal{F}_n) = \nabla F_k \left(\widetilde{W}_k(n) - \rho_k^* \right) + O(\|\widetilde{W}_k(n) - \rho_k^*\|^2) \\ &= \nabla F_k \left(\frac{1}{n} \left((N_1(0), \dots, N_k(0)) + \sum_{i=1}^n Y_k(i) \right) \right) + O(\|\widetilde{W}_k(n) - \rho_k^*\|^2). \end{aligned}$$

Since all eigenvalues of ∇F_k are negative, $A_k(n)$ could be decomposed as $A_k(n) = A_k^1(n) + A_k^2(n)$ (with $\epsilon_i(n) = \epsilon_i^1(n) + \epsilon_i^2(n)$, $i = 1, \dots, k$) where a.s. $A_k^1(n)$ is of opposite sign to $\sum_{i=1}^n Y_k(i)$ and $\mathbb{E}(A_k^2(n)|\mathcal{F}_n) = 0$. Therefore, by the law of the iterated logarithm for martingales (see, e.g., [2]) $\sum_{i=1}^n A_k^2(i)$ is of order $(n^{1/2} \ln \ln n)^{1/2}$. Thus,

$$\begin{aligned} \left| \sum_{i=1}^n S_k(i) \right| &= \left| \sum_{i=1}^n S_k(i) + \epsilon_k^1(n) + \epsilon_k^2(n) + X_k(n) \right| \\ &\leq \left| \sum_{i=1}^n S_k(i) + \epsilon_k^1(n) \right| + |\epsilon_k^2(n)| + |X_k(n)| \leq \left| \sum_{i=1}^n S_k(i) \right| + |\epsilon_k^2(n)| + |X_k(n)| \\ &\leq \dots \leq \left| \sum_{i=1}^n \epsilon_k^2(i) \right| + \left| \sum_{i=1}^n X_k(i) \right|. \end{aligned}$$

We come to the desire statement.

References

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