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Limit theorems for some statistics of a generalized threshold network model

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Abstract

In this report, we state limit theorems for the number of edges, the number of triangles and the clustering coefficients of a generalized threshold network model. We also give examples of these limit theorems.

1 Introduction

The threshold network model is a type of finite random graphs that is generated on n vertices labeled $1, \dots, n$ with independent and identically distributed (i.i.d.) random variables $X_1, \dots, X_n$. We connect a pair of vertices i and j with $i \neq j$ by an edge when $X_i + X_j > \theta$ for a given threshold θ. The threshold network model is a subclass of so called hidden variable models, and its mean behavior [1, 2, 5, 7, 8] and limit theorems [4, 6] have been analyzed. Recently, a generalization of the threshold network model was formulated and several limit theorems were studied [3]. Here we review the generalized model. Let $\mathbb{R}^d$ be the d-dimensional Euclidean space. We prepare an i.i.d. sequence of $\mathbb{R}^d$-valued random variables $X_1, \dots, X_n$ and associate the random variable X_i with vertex i. Let $\mathcal{B}(\mathbb{R})$ be the Borel σ-field of $\mathbb{R}$. Now we introduce Borel measurable functions $f_c^m : (\mathbb{R}^d)^2 \to \mathbb{R}$ with $f_c^m(x, y) = f_c^m(y, x)$ for all $m \in \{1, \dots, l\}$. For a given finite collection of Borel measurable sets $\mathcal{C} = \{B_1, \dots, B_l\}$ with $B_m \in \mathcal{B}(\mathbb{R})$ for all $m \in \{1, \dots, l\}$, we connect vertices i and j $(i \neq j)$ if $f_c^m(X_i, X_j) \in B_m$ for all $m \in \{1, \dots, l\}$. In other words, we form an edge $\langle i, j \rangle$ if $\prod_{m=1}^{l} I_{B_m}(f_c^m(X_i, X_j)) = 1$ for $i \neq j$, where $I_A(x)$ denotes the indicator function, i.e., $I_A(x) = 1$ for $x \in A$ and $I_A(x) = 0$ otherwise. Thus we obtain a random graph $G_{\mathcal{C}}(X_1, \dots, X_n)$. References and more details are found in [3].

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2 Limit Theorems

In this section, we state the limit theorems that are suitable modifications of the theorems proved in [3]. Hereafter, we only consider the one-dimensional ($d = 1$) and $l = 1$ case. Extensions of the following results to general d and l are straightforward. For simplicity, we may write $f_c \equiv f_c^1$ and $B \equiv \mathcal{C} = \{B_1\}$.

2.1 Edges and Triangles

When we choose $h_D(x, y) = I_B(f_c(x, y))$, as the kernel function, we define the following two statistics:

$$D_n = \sum_{1 \leq i < j \leq n} h_D(X_i, X_j), \quad \text{and} \quad D_n(i) = \sum_{\substack{1 \leq j \leq n \\ j \neq i}} h_D(X_i, X_j).$$

Here D_n is the number of edges in the random graph $G_B(X_1, \ldots, X_n)$ and $D_n(i)$ is the number of edges connected to vertex i, i.e., the degree of vertex i. Using another kernel function $h_T(x, y, z) = I_B(f_c(x, y)) \cdot I_B(f_c(y, z)) \cdot I_B(f_c(z, x))$, we define the following statistics for the number of triangles:

$$T_n = \sum_{1 \leq i < j < k \leq n} h_T(X_i, X_j, X_k), \quad \text{and} \quad T_n(i) = \sum_{\substack{1 \leq j < k \leq n \\ j,k \neq i}} h_T(X_i, X_j, X_k).$$

Here T_n denotes the number of triangles in the random graph and $T_n(i)$ is the number of triangles including vertex i. Limit theorems for the statistics are the following:

Theorem 1. *As* $n \to \infty$,

(i) for any $x \in \mathbb{R}$, $\dfrac{D_n(1; x)}{n - 1} \to D(1; x) \equiv \mathbb{P}(h_D(x, X_2) = 1)$ *almost surely,*

(ii) $\dfrac{D_n}{\binom{n}{2}} \to D \equiv \mathbb{E}[D(1; X_1)] = \mathbb{P}(h_D(X_1, X_2) = 1)$ *almost surely,*

(iii) for any $x \in \mathbb{R}$, $\dfrac{T_n(1; x)}{\binom{n-1}{2}} \to T(1; x) \equiv \mathbb{P}(h_T(x, X_2, X_3) = 1)$ *almost surely,*

(iv) $\dfrac{T_n}{\binom{n}{3}} \to T \equiv \mathbb{E}[T(1; X_1)] = \mathbb{P}(h_T(X_1, X_2, X_3) = 1)$ *almost surely,*

where

$$D_n(i; x) = \sum_{\substack{1 \leq j \leq n \\ j \neq i}} h_D(x, X_j), \quad \textit{and} \quad T_n(i; x) = \sum_{\substack{1 \leq j < k \leq n \\ j,k \neq i}} h_T(x, X_j, X_k).$$

2.2 Clustering Coefficients

The local clustering coefficient $C_n(i)$ of vertex i is defined by

$$C_n(i) = \frac{T_n(i)}{\binom{D_n(i)}{2}} \cdot I_{\{D_n(i) \geq 2\}} + w \cdot I_{\{D_n(i) = 0, 1\}},$$

for an indeterminate w. The global clustering coefficient C_n is defined by

$$C_n = \frac{1}{n}\sum_{i=1}^{n} C_n(i).$$

The following limit theorems for the local and global clustering coefficients were proved:

Theorem 2. *As $n \to \infty$,*
(i) for any $x \in \mathbb{R}$, $C_n(1;x) \to C(1;x) \equiv \frac{T(i;x)}{D(i;x)^2}\cdot I_{\{D(i;x)>0\}} + w\cdot I_{\{D(i;x)=0\}}$ *almost surely,*
(ii) $C_n \to C \equiv \mathbb{E}[C(1;X_1)]$ *almost surely,*

where

$$C_n(i;x) = \frac{T_n(i;x)}{\binom{D_n(i;x)}{2}} \cdot I_{\{D_n(i;x)\geq 2\}} + w \cdot I_{\{D_n(i;x)=0,1\}}.$$

3 Examples

In this section, we give several examples for $D(1;x)$, $T(1;x)$, $C(1;x)$, D, T, C and the distribution of $D(1) \equiv D(1;X_1)$. Let f and $f_{D(1)}$ denote the distributions of X_1 and $D(1)$, respectively. Note that domain of $f_{D(1)}(k)$ is always $0 \leq k \leq 1$.

Case 1 : When we choose $f_c(x,y) = x + y$ and $B = (\theta, \infty)$ for $\theta \in \mathbb{R}$, the random graph becomes the original threshold network model. First, we give a table of examples for the Bernoulli distribution. For simplicity, we omit trivial cases ($\theta < 0, 2 \leq \theta$).

distribution	Bernoulli
$f(x)$	$p\cdot\delta_1(x) + (1-p)\cdot\delta_0(x)\ :\ p \in (0,1)$
$f_{D(1)}(k)$	$\begin{cases} p\cdot\delta_1(k) + (1-p)\cdot\delta_p(k) & \text{if } 0 \leq \theta < 1, \\ p\cdot\delta_p(k) + (1-p)\cdot\delta_0(k) & \text{if } 1 \leq \theta < 2. \end{cases}$
$D(1;x)$	$\begin{cases} D(1;1) = 1,\ D(1;0) = p & \text{if } 0 \leq \theta < 1, \\ D(1;1) = p,\ D(1;0) = 0 & \text{if } 1 \leq \theta < 2. \end{cases}$
$T(1;x)$	$\begin{cases} T(1;1) = p(2-p),\ T(1;0) = p^2 & \text{if } 0 \leq \theta < 1, \\ T(1;1) = p^2,\ T(1;0) = 0 & \text{if } 1 \leq \theta < 2. \end{cases}$
$C(1;x)$	$\begin{cases} C(1;1) = p(2-p),\ C(1;0) = 1 & \text{if } 0 \leq \theta < 1, \\ C(1;1) = 1,\ C(1;0) = w & \text{if } 1 \leq \theta < 2. \end{cases}$
$D,\ T,\ C$	$\begin{cases} D = p(2-p),\ T = p^2(3-2p),\ C = 1 - p(1-p)^2 & \text{if } 0 \leq \theta < 1, \\ D = p^2,\ T = p^3,\ C = p + (1-p)\cdot w & \text{if } 1 \leq \theta < 2. \end{cases}$

Next, we give a table for the exponential distribution [5].

distribution	exponential
$f(x)$	$\lambda e^{-\lambda x},\ x \in (0,\infty)\ :\ \lambda > 0$
$f_{D(1)}(k)$	$\begin{cases} \delta_1(k) & \text{if } \theta \le 0, \\ I_{(e^{-\lambda\theta},1)}(k)\cdot \frac{e^{-\lambda\theta}}{k^2} + e^{-\lambda\theta}\cdot\delta_1(k) & \text{if } \theta > 0. \end{cases}$
$D(1;x)$	$\begin{cases} I_{(0,\infty)}(x) & \text{if } \theta \le 0, \\ I_{(0,\theta)}(x)\cdot e^{-\lambda(\theta-x)} + I_{(\theta,\infty)}(x) & \text{if } \theta > 0. \end{cases}$
$T(1;x)$	$\begin{cases} I_{(0,\infty)}(x) & \text{if } \theta \le 0, \\ I_{(0,\theta/2]}(x)\cdot e^{-2\lambda(\theta-x)} + I_{(\theta/2,\theta]}(x)\cdot[\lambda(2x-\theta)+1]e^{-\lambda\theta} & \\ +I_{(\theta,\infty)}(x)\cdot(\lambda\theta+1)e^{-\lambda\theta} & \text{if } \theta > 0. \end{cases}$
$C(1;x)$	$\begin{cases} I_{(0,\infty)}(x) & \text{if } \theta \le 0, \\ I_{(0,\theta/2]}(x) + I_{(\theta/2,\theta]}(x)\cdot[\lambda(2x-\theta)+1]e^{-\lambda(2x-\theta)} & \\ +I_{(\theta,\infty)}(x)\cdot(\lambda\theta+1)e^{-\lambda\theta} & \text{if } \theta > 0. \end{cases}$
$D,\ T,\ C$	$\begin{cases} D=1,\ T=1,\ C=1 & \text{if } \theta \le 0, \\ D=(\lambda\theta+1)e^{-\lambda\theta},\ T=4e^{-3\lambda\theta/2}-3e^{-2\lambda\theta}, & \\ C=1-\frac{4}{9}e^{-\lambda\theta/2}+\frac{1}{2}(3\lambda\theta+2)e^{-2\lambda\theta} & \text{if } \theta > 0. \end{cases}$

A remarkable feature of $f_{D(1)}$ is existence of the power law k^{-2} which is referred to as the scale-free property. Remark that existence of the delta measure δ_1 is always proved for distributions that are absolutely continuous and have a lower cutoff, i.e., $\operatorname{supp} f = [a,\infty)$, where $a \in \mathbb{R}$ and $\operatorname{supp} f = \overline{\{x \in \mathbb{R} : f(x) \neq 0\}}$ is the support of f.

Finally, we consider the bilateral exponential distribution. For simplicity, we only show $D(1;x)$ and the distribution of $D(1)$.

distribution	bilateral exponential
$f(x)$	$\frac{1}{2}e^{-\lambda\lvert x\rvert}\ :\ \lambda > 0$
$f_{D(1)}(k)$	$\begin{cases} e^{\lambda\theta}\cdot I_{(0,\frac{1}{2})}(k) + I_{(\frac{1}{2},1-\frac{1}{2}e^{\lambda\theta})}(k)\cdot\frac{e^{-\lambda\theta}}{4(1-k)^2} + e^{-\lambda\theta}\cdot I_{(1-\frac{1}{2}e^{\lambda\theta},1)}(k) & \text{if } \theta < 0, \\ I_{(0,1)}(k) & \text{if } \theta = 0, \\ e^{\lambda\theta}\cdot I_{(0,\frac{1}{2}e^{-\lambda\theta})}(k) + I_{(\frac{1}{2}e^{-\lambda\theta},\frac{1}{2})}(k)\cdot\frac{e^{-\lambda\theta}}{4k^2} + e^{-\lambda\theta}\cdot I_{(\frac{1}{2},1)}(k) & \text{if } \theta > 0. \end{cases}$
$D(1;x)$	$I_{(-\infty,\theta)}(x)\cdot\frac{1}{2}e^{-\lambda(\theta-x)} + I_{(\theta,\infty)}(x)\cdot\left(1-\frac{1}{2}e^{\lambda(\theta-x)}\right)$

In this case, $f_{D(1)}$ is mixture of the uniform distribution and the power law (k^{-2} or $(1-k)^{-2}$). Particularly, when $\theta = 0$, the distribution of $D(1)$ becomes the uniform distribution on $(0,1)$. Note that when $\theta = 0$, the same result also holds for distributions that are absolutely continuous, symmetric, i.e., $f(x) = f(-x)$, and of infinite support, i.e., $\operatorname{supp} f = (-\infty,\infty)$.

Case 2 : Next we consider the case $f_c(x,y) = x + y$, $B = \bigcup_{j=1}^{N}(a_j,b_j]$ for a finite $N \in \{1,2,\ldots\}$, where $0 \le a_1 \le b_1 \le \ldots \le a_j \le b_j \le a_{j+1} \le \ldots \le a_N \le b_N$. We derive the following distribution of $D(1)$ for the exponential distribution with parameter λ:

$$f_{D(1)}(k) = \sum_{j=0}^{N} I_{(e^{\lambda b_j} S_{j+1}, e^{\lambda a_{j+1}} S_{j+1})} \cdot \frac{S_{j+1}}{k^2} + \sum_{j=1}^{N} I_{(e^{\lambda b_j} S_{j+1}, e^{\lambda a_j} S_j)} \cdot \frac{e^{-\lambda b_j} - S_{j+1}}{(1-k)^2},$$

where $b_0 = 0$ and $S_j = \sum_{i=j}^{N} \left(e^{-\lambda a_i} - e^{-\lambda b_i}\right) = \mathbb{P}(X_1 \in \bigcup_{i=j}^{N}(a_i, b_i]) \in [0,1]$ for $j \in \{1, \ldots, N\}$. The original threshold network model is the case $N = 1$ with $a_1 = \theta$ and $b_1 = \infty$, where we set $e^{-\lambda\infty} \equiv 0$. For $B = \bigcup_{j=1}^{\infty}(a_j, b_j]$, we can obtain $f_{D(1)}$ by replacing N with ∞.

Case 3: Let us consider the case in which $f_c(x,y) = x + y$, $B = \bigcup_{j=1}^{N}(a_j, b_j]$ for a finite $N \in \{1, 2, \ldots\}$, where $0 \le a_1 \le b_1 \le \ldots \le a_j \le b_j \le a_{j+1} \le \ldots \le a_N \le b_N \le 1$, and the distribution of X_1 is the uniform distribution on $(0,1)$. We derive the following distribution of $D(1)$:

$$f_{D(1)}(k) = I_{(0,S_1)}(k) + (1 - b_N) \cdot \delta_0(k) + \sum_{i=1}^{N} (a_i - b_{i-1}) \cdot \delta_{S_i}(k),$$

where $b_0 = 0$ and $S_j = \sum_{i=j}^{N}(b_i - a_i) = \mathbb{P}(X_1 \in \bigcup_{i=j}^{N}(a_i, b_i])$. The uniform distribution $I_{(0,S_1)}(k)$ corresponds to intervals included in B, and the delta measures correspond to gaps, i.e., sets included in $[0,1] \setminus B$. As an example, let us consider the case

$$B = K_n \equiv \bigcup_{\substack{a_m = 0,2 \\ 1 \le m \le n}} \left[\sum_{m=1}^{n} \frac{a_m}{3^m}, \sum_{m=1}^{n} \frac{a_m}{3^m} + \frac{1}{3^n} \right].$$

For example, $K_2 = [0, 1/3^2] \cup [2/3^2, 3/3^2] \cup [6/3^2, 7/3^2] \cup [8/3^2, 1]$. We obtain

$$f_{D(1)}(k) = I_{(0,2^n/3^n)}(k) + \frac{1}{3^n} \cdot \sum_{i=1}^{2^n - 1} \delta_{\frac{2i-1}{3^n}}(k) + \sum_{i=1}^{2^{n-1}-1} \frac{1}{3 \cdot 3^{|n-1-i|}} \cdot \delta_{\frac{2i}{3^n}}(k).$$

The limit set $K = \bigcap_{n=1}^{\infty} K_n$ is the Cantor set. Because the Lebesgue measure of K equals zero, it is trivial that $f_{D(1)}(k) = \delta_0(k)$ for absolutely continuous distributions.

Case 4 : We study the case $f_c(x,y) = xy$, $B = (\theta, \infty)$, $\theta > 0$ as an example of f_c that is different from addition. The distribution of $D(1)$ for the exponential distribution with parameter λ is the following:

$$f_{D(1)}(k) = I_{(0,1)}(k) \cdot \frac{\lambda^2 \theta \cdot e^{\lambda^2 \theta / \log k}}{k (\log k)^2}.$$

In this case, the distribution deviates from the power law.

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