



COMPARISON BETWEEN CONFIGURATION MODEL  
WITH I.I.D.  $\text{BINOMIAL}(N, p)$  DEGREE  
DISTRIBUTION AND THE CORRESPONDING  
ERDŐS-RÉNYI BINOMIAL RANDOM GRAPH

SAPTASHWA BAISYA  
BS2226

A JOINT WORK WITH SOMARDDHA DAS

13TH MAY, 2025

# Contents

1. Definitions	2
2. Works	2
• Probability of Simplicity	2
• Thresholds of some known properties	5
– Connectivity Threshold	5
– $\triangle$ Containment Threshold	5
– $\square$ Containment Threshold	6
– $K_4$ Containment Threshold	6
• Size of the Largest Connected Component	6
– Sub-Critical Regime	6
– Super-Critical Regime	7
– CLT in Super-Critical Regime	8
3. Discussion	9
4. Concluding Remarks	10
5. References	10

This report entails the simulation studies carried out by us in order to study the (possible) differences between Configuration Model with i.i.d. Binomial( $n, p$ ) Degree Distribution and the Corresponding Erdős-Rényi Binomial Random Graph. All the guesses are simulation based and require theoretical backing either in the form of a proof or a disproof.

We recall the following definitions:

## 1 Definitions

- $G(n, p)$  : Consider a simple graph with vertex set  $V = [n]$  and edge set  $E$ . Label the  $\binom{n}{2}$  pair of vertices  $p_1, \dots, p_{\binom{n}{2}}$ . Let  $e_1, \dots, e_{\binom{n}{2}} \sim \text{Ber}(p)$ . Set  $E = \{p_i | e_i = 1\}$ .  $G = (V, E)$  is said to be an Erdős-Rényi Binomial Random Graph and it is said  $G \sim G_{n,p}$  or  $G \sim ER_{n,p}$
- $\text{Conf}(n, p)$  : Given a sequence of  $n$  non-negative integers  $d_1, \dots, d_n$  (with an even sum), one can construct a (possibly multi-) graph (which is random) on  $V = [n]$  by the method of joining half-edges such that vertex  $i$  has degree  $d_i \forall i$ . Let  $d_1, \dots, d_n \sim \text{Bin}(n-1, p)$  and if  $\sum_i d_i$  is odd, we increase  $d_1$  by 1. (To guarantee that the sum of degrees is even). Let the random graph generated by the above procedure be  $G$ , then we say that  $G \sim \text{Conf}_{n,p}$

## 2 Works

### 2.1 Probability of Simplicity:

Before getting to the comparisons, we would like to study the  $\text{Conf}(n, p)$  model. In case of the usual configuration model, we have the following result:

*Theorem 2.1.1: Let  $D_1, \dots, D_n, \dots$  be iid copies of  $D$ , where  $\mathbb{E}(D^2) < \infty$  and  $\mathbb{P}(D \geq 1) = 1$ .  $G_n$  denote the configuration model obtained by using  $D_1, \dots, D_n$  (adjusted, if required) if  $S_n, M_n$  denote the number of self loops and multiple edges in  $G_n$  then*

$$(S_n, M_n) \xrightarrow{d} (S, M)$$

where  $\nu = \frac{\mathbb{E}(D(D-1))}{\mathbb{E}(D)}$ ,  $S \sim \text{Poi}\left(\frac{\nu}{2}\right)$ ,  $M \sim \text{Poi}\left(\frac{\nu^2}{4}\right)$  and  $S, M$  are independent.

Corollary:  $\lim_{n \rightarrow \infty} \mathbb{P}(G_n \text{ is simple}) = e^{-\frac{\nu}{2} - \frac{\nu^2}{4}}$

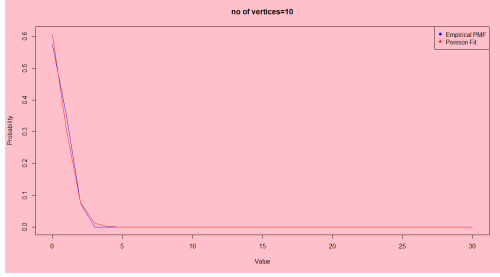
We would like to see if such a result holds incase  $G_n \sim \text{Conf}(n, \frac{\lambda}{n})$ . If  $G \sim \text{Conf}(n, \frac{\lambda}{n})$  : Then for large enough  $n$ , the degree distribution will be roughly  $\text{Poi}(\lambda)$ . Thus it seems reasonable to guess that the above theorem *might* hold true in this case, with  $D \sim \text{Poi}(\lambda)$ .

Note: In that case  $\nu = \frac{\mathbb{E}(D(D-1))}{\mathbb{E}(D)} = \lambda$ .

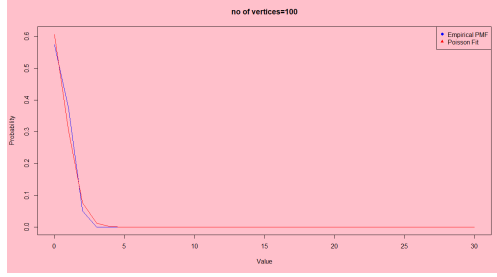
For  $G_n \sim Conf(n, \frac{\lambda}{n})$ , we define  $S_n, M_n$  similarly.

- We check if  $S_n \xrightarrow{d} Poi\left(\frac{\lambda}{2}\right)$

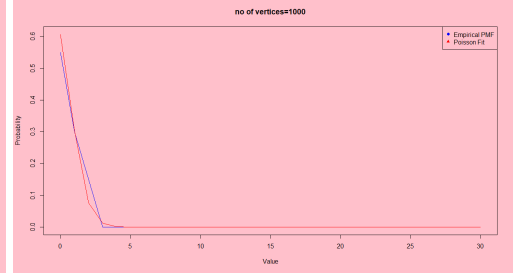
no. of vertices=10



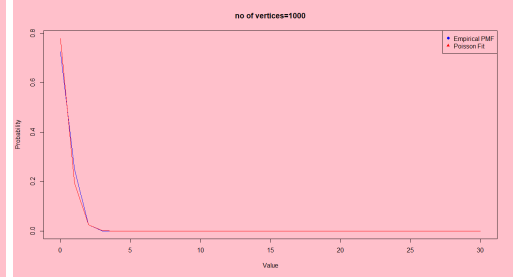
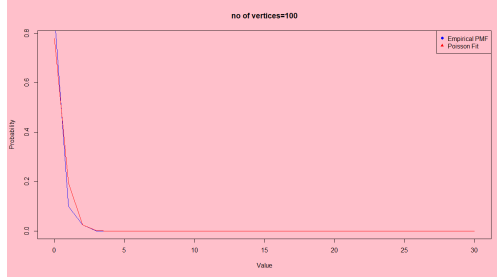
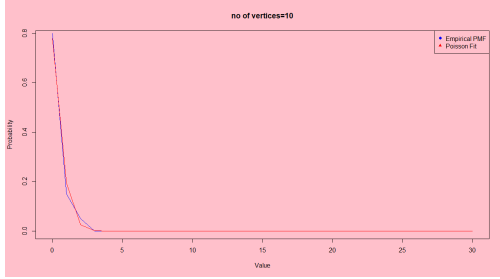
no. of vertices=100



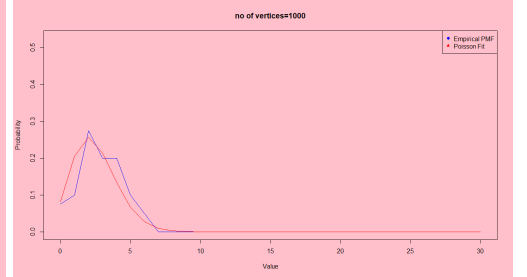
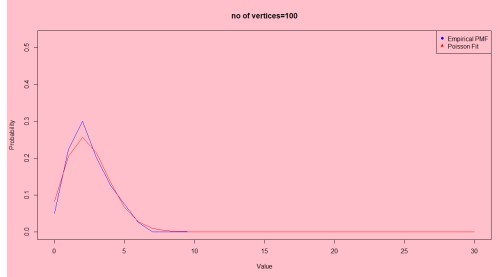
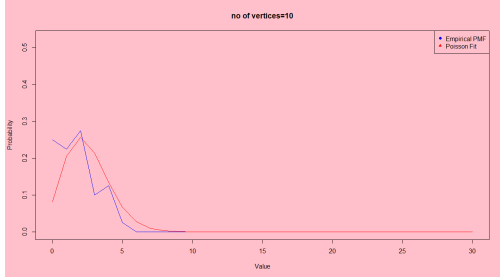
no. of vertices=1000



$\lambda = 0.5$



$\lambda = 1$



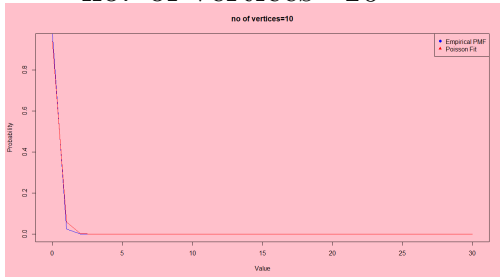
$\lambda = 5$

In each plot, the red curve is the probability mass function for  $Poi\left(\frac{\lambda}{2}\right)$ , while the blue curve is the emperical probability mass function.

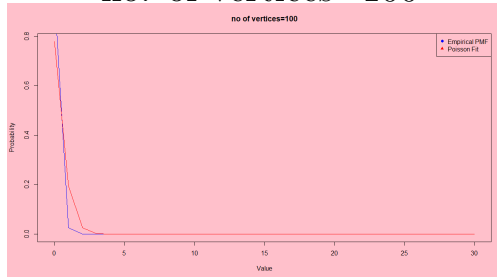
The Poisson fit, appears to be a good one, especially for large values of  $n$  (no. of vertices).

- We check if  $M_n \xrightarrow{d} Poi\left(\frac{\lambda^2}{4}\right)$

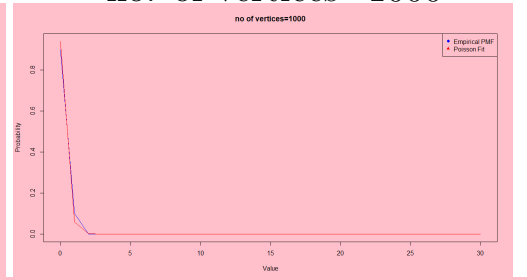
no. of vertices=10



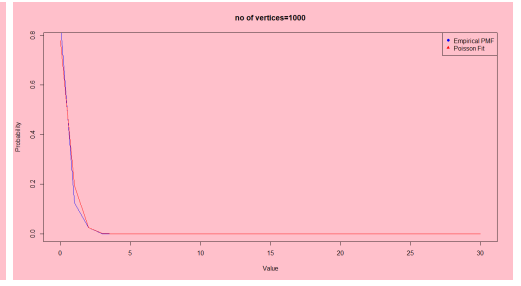
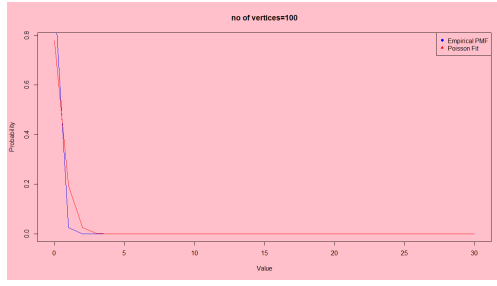
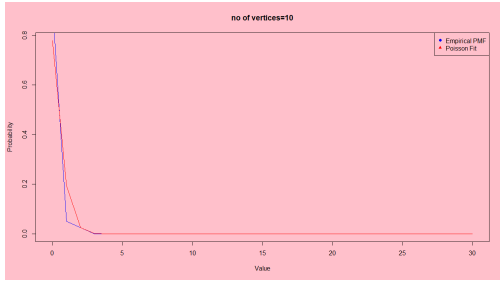
no. of vertices=100



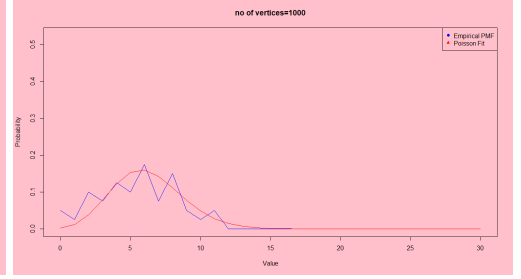
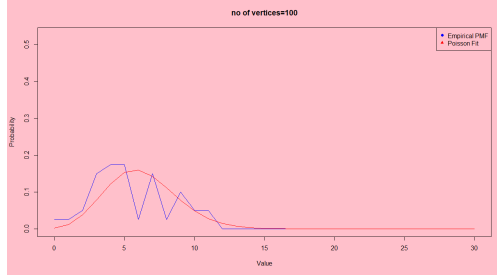
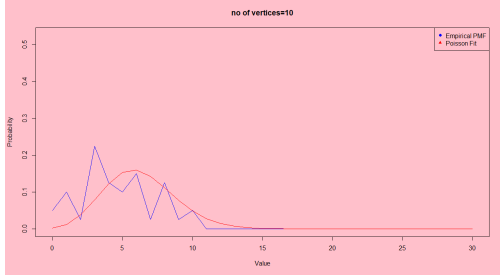
no. of vertices=1000



$\lambda = 0.5$



$\lambda = 1$



$\lambda = 5$

In each plot, the red curve is the probability mass function for  $Poi\left(\frac{\lambda^2}{4}\right)$ , while the blue curve is the empirical probability mass function.

For small values of  $\lambda$ , the fit becomes good for small values of  $n$  as the number of edges are very small. However for larger values of  $\lambda$ , the Poisson fit becomes better as  $n$  increases.

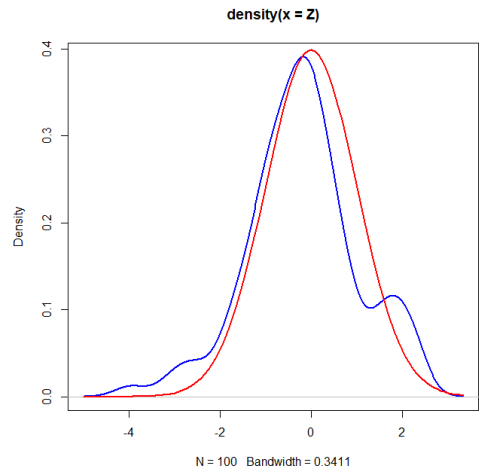
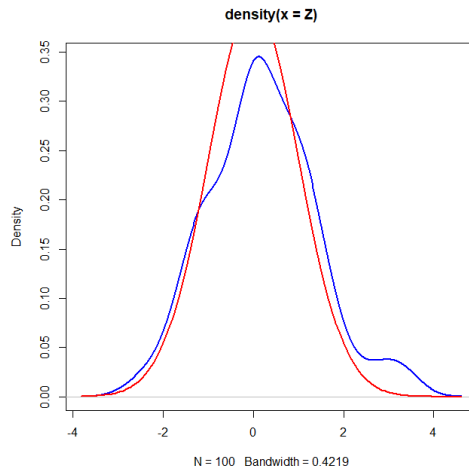
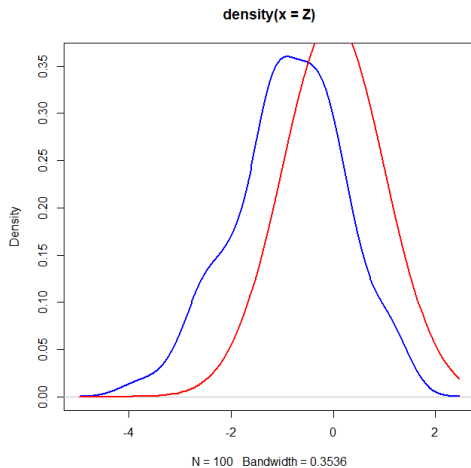
- We now finally check if asymptotically  $S_n, M_n$  are independent:

We take help of Kendall's Tau ( $\tau$ ).

Let  $\tau_m$  denote the kendalls tau calculated using the points  $(X_1, Y_1), \dots, (X_m, Y_m)$  (where all the points are iid). Then under the assumption that  $X_1, Y_1$  are independent

$$\sqrt{m}\tau_m \xrightarrow{d} N\left(0, \frac{4}{9}\right)$$

For various values of  $n$ , we plot the empirical density of a properly scaled  $\tau$  (calculated using 40 pair of values (value of  $m$  in above expression) of  $S_n, M_n$ ) and overlay the pdf of  $N(0, 1)$  over it, to see if independence might hold.



No. of vertices=10

No. of vertices=100

No. of vertices=1000

Here, the red curve is the pdf of  $N(0, 1)$ , whereas the blue curve is the estimated pmf of  $\frac{3}{2}\sqrt{n}\tau_n$ .

We observe that the 2 curves are close, especially for larger number of vertices, which indicates that independence might actually hold.

Using these observations, we state the following conjecture analogous to Theorem 2.1.1:

*Conjecture 2.1.1: Let  $G_n \sim \text{Conf}(n, \frac{\lambda}{n})$ .  $S_n, M_n$  denote the number of self-loops and multiple edges in  $G_n$ . Then*

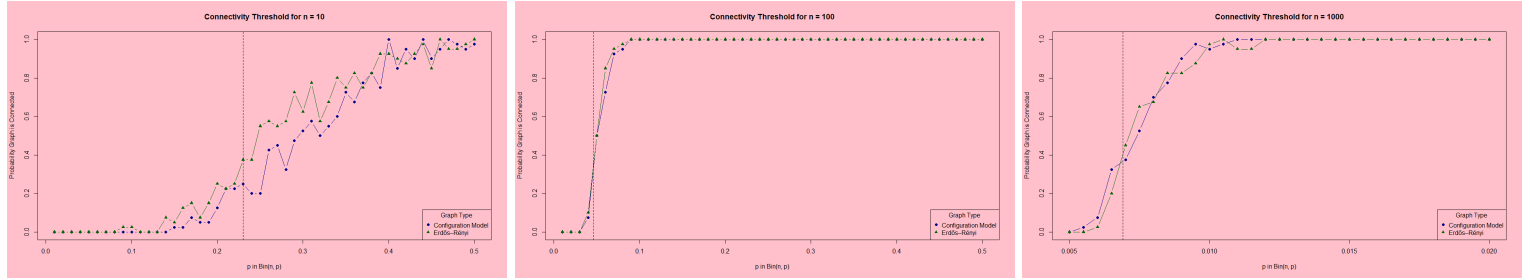
$$(S_n, M_n) \xrightarrow{d} (S, M)$$

where  $S \sim \text{Poi}\left(\frac{\lambda}{2}\right), M \sim \text{Poi}\left(\frac{\lambda^2}{4}\right)$  and  $S, M$  are independent.

## 2.2 Threshold of Some Known Properties

We now return to the comparison of  $G_{n,p}$  and  $\text{Conf}(n, p)$ . Now we look at thresholds of some known properties.

### • Connectivity Threshold:



No. of vertices=10

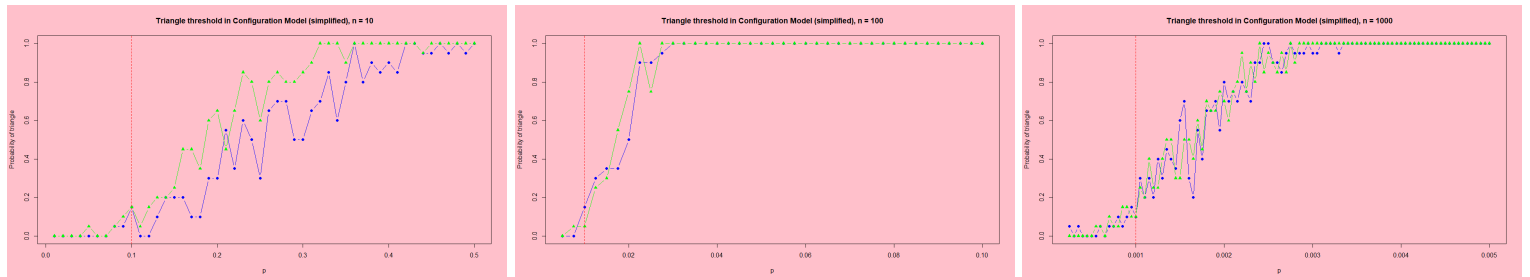
No. of vertices=100

No. of vertices=1000

We look at the plots of probability of connectivity of both  $G_{n,p}$  (green) and  $\text{Conf}(n, p)$  (blue) as a function of  $p$  after fixing  $n$ . The 2 curves appear to be very close. The vertical line  $x = \frac{\log(n)}{n}$  (connectivity threshold for  $G_{n,p}$ ) has been added to aid the visualization. This leads us to the following conjecture:

*Conjecture 2.2.1:  $\hat{p}_n = \frac{\log(n)}{n}$  is the connectivity threshold for  $\text{Conf}(n, p)$*

### • Triangle Containment Threshold



No. of vertices=10

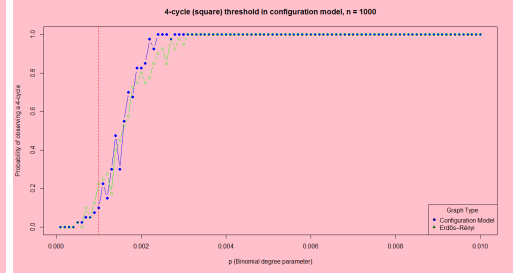
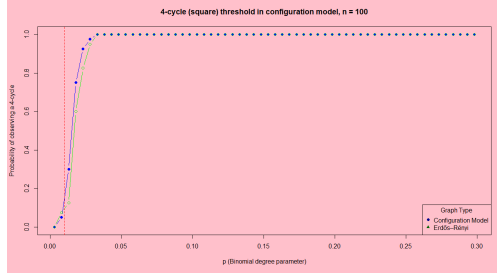
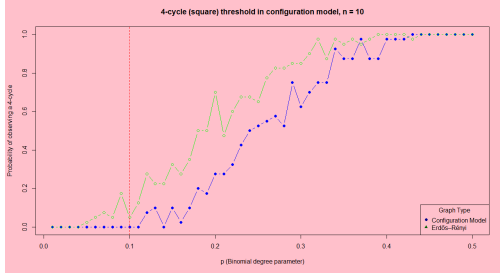
No. of vertices=100

No. of vertices=1000

We repeat the same exercise here, and we add the vertical line  $x = \frac{1}{n}$  (Triangle Containment Threshold for  $G_{n,p}$ ). This leads us to the following conjecture:

*Conjecture 2.2.2:  $\hat{p}_n = \frac{1}{n}$  is the triangle containment threshold for  $\text{Conf}(n, p)$*

### • Square Containment Threshold



No. of vertices=10

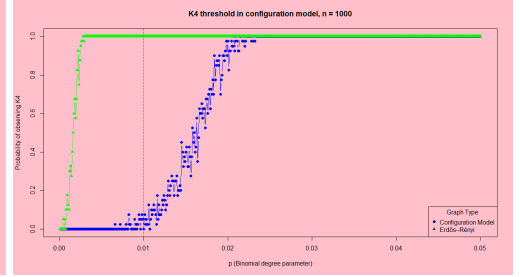
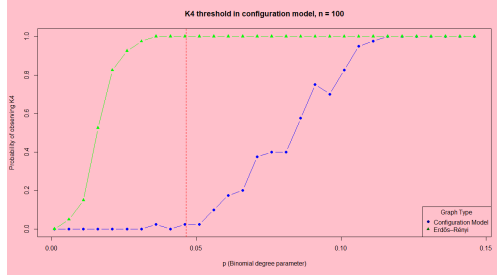
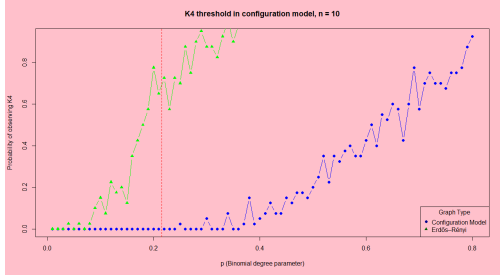
No. of vertices=100

No. of vertices=1000

We repeat the same exercise here, and we add the vertical line  $x = \frac{1}{n}$  (Square Containment Threshold for  $G_{n,p}$ ). This leads us to the following conjecture:

*Conjecture 2.2.3:  $\hat{p}_n = \frac{1}{n}$  is the square containment threshold for  $\text{Conf}(n, p)$*

### • $K_4$ Containment Threshold



No. of vertices=10

No. of vertices=100

No. of vertices=1000

We repeat the same exercise here, and we add the vertical line  $x = \frac{1}{n^3}$  ( $K_4$  Containment Threshold for  $G_{n,p}$ ). This leads us to the following conjecture:

*Conjecture 2.2.4:  $\hat{p}_n = \frac{1}{n^3}$  is the  $K_4$  containment threshold for  $\text{Conf}(n, p)$*

## 2.3 Size of the largest connected component

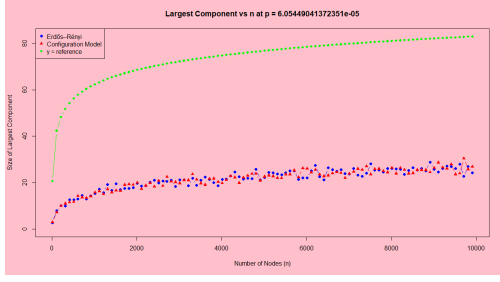
For  $\text{Conf}(n, \frac{\lambda}{n})$ , we define (analogously to  $G_{n, \frac{\lambda}{n}}$ ) the sub-critical regime to be  $\lambda < 1$  and the super-critical regime to be  $\lambda > 1$ . Now for each of the regimes, we fix a value of  $\lambda$  and we plot the size of the largest connected component as a function of  $n$  (the total number of vertices) for both  $G_{n,p}$  and  $\text{Conf}(n, p)$

### • The Sub-Critical Regime: $\lambda < 1$

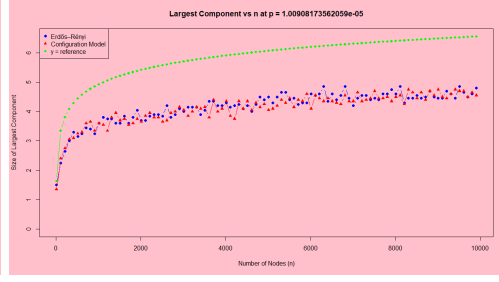
*Theorem 2.3.1: If  $G_n \sim G_{n, \frac{\lambda}{n}}$ , and  $|C_{max}|$  denote the size of the largest connected component of  $G_n$ , then*

$$\frac{|C_{max}|}{\log(n)} \xrightarrow{P} \frac{1}{I_\lambda}, \text{ where } I_\lambda = \lambda - 1 - \log(\lambda)$$

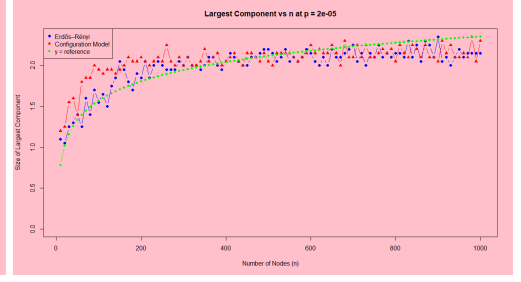
We wish to see if a similar result holds for  $Conf\left(n, \frac{\lambda}{n}\right)$ .



$$\lambda = 0.6$$



$$\lambda = 0.1$$



$$\lambda = 0.02$$

The red curve indicates the size of the largest connected component in the  $Conf(n, \frac{\lambda}{n})$ , whereas the blue curve indicates the size of the largest connected component in the  $G_{n, \frac{\lambda}{n}}$ . The green curve is the reference size  $\frac{\log(n)}{I_\lambda}$ . It appears that the 2 curves near to each other however may be very far from the reference curve. However we expect them to come close, except for the fact that it will happen after a very large  $n$ , this is because the rate of increase of  $\log(x)$  decreases as  $x$  increases.

We also observe that as  $\lambda$  moves farther from the critical value of 1, the green curve gets closer to the red and blue curves, i.e. the convergence occurs for relatively small values of  $n$ .

*Conjecture 2.3.1: If  $G_n \sim conf(n, \frac{\lambda}{n})$ , and  $|C_{max}|$  denote the size of the largest connected component of  $G_n$ , then*

$$\frac{|C_{max}|}{\log(n)} \xrightarrow{P} \frac{1}{I_\lambda}, \text{ where } I_\lambda = \lambda - 1 - \log(\lambda)$$

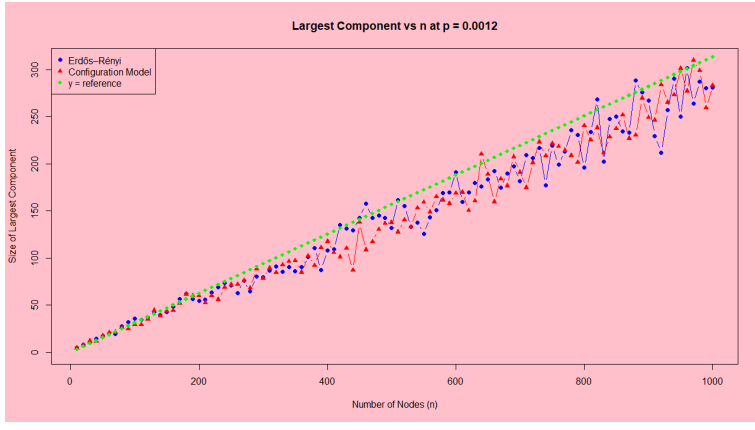
### • The Super-Critical Regime: $\lambda > 1$

*Theorem 2.3.2: If  $G_n \sim G_{n, \frac{\lambda}{n}}$ , and  $|C_{max}|$  denote the size of the largest connected component of  $G_n$ , then*

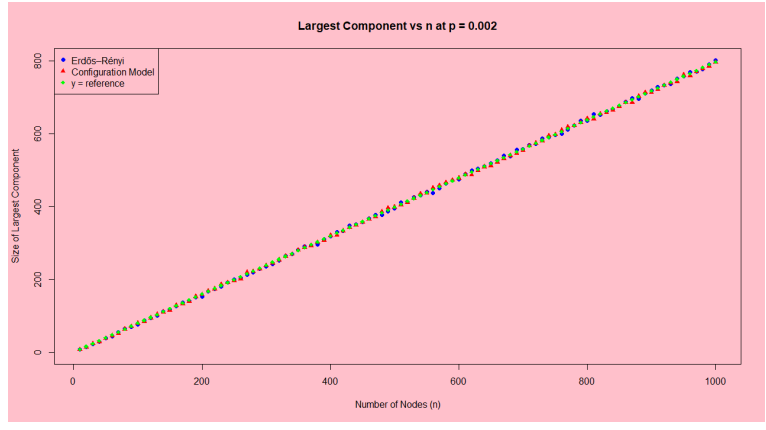
$$\frac{|C_{max}|}{n} \xrightarrow{P} \zeta_\lambda, \text{ where } \zeta_\lambda \text{ is the non zero-root of } 1 - x - e^{\lambda x}$$

We wish to see if a similar result holds for  $Conf\left(n, \frac{\lambda}{n}\right)$ .





$$\lambda = 1.2$$



$$\lambda = 2$$

The red curve indicates the size of the largest connected component in the  $Conf(n, \frac{\lambda}{n})$ , whereas the blue curve indicates the size of the largest connected component in the  $G_{n, \frac{\lambda}{n}}$ . The green curve is the reference size  $n\zeta_\lambda$ .

The 3 curves are close, but they come closer as  $\lambda$  moves farther from the critical value of  $\lambda = 1$ .

*Conjecture 2.3.2: If  $G_n \sim conf(n, \frac{\lambda}{n})$ , and  $|C_{max}|$  denote the size of the largest connected component of  $G_n$ , then*

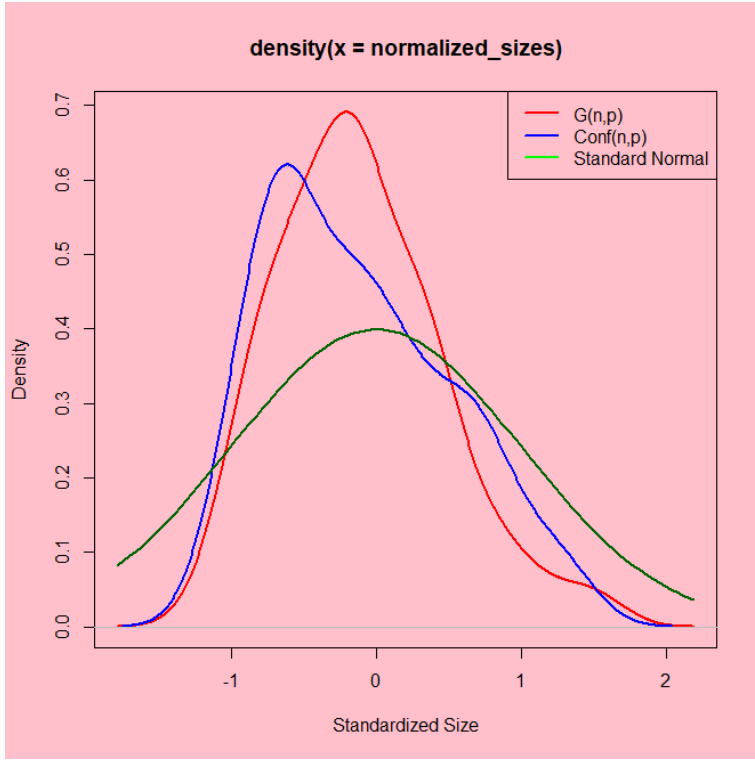
$$\frac{|C_{max}|}{n} \xrightarrow{P} \zeta_\lambda, \text{ where } \zeta_\lambda \text{ is the non zero-root of } 1 - x - e^{\lambda x}$$

### • CLT for Giant Components in Super-Critical Regime:

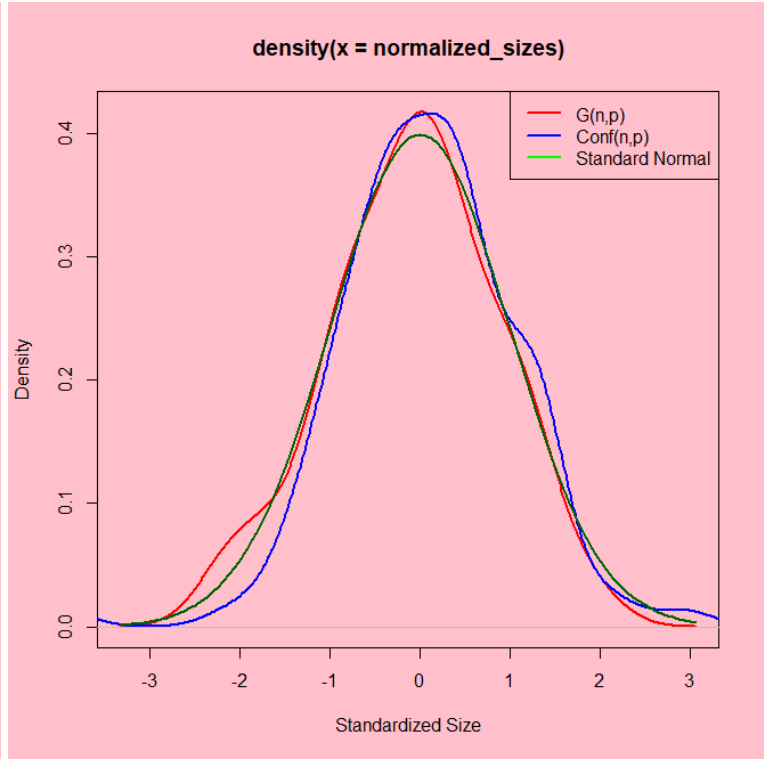
*Theorem 2.3.1: Fix  $\lambda > 1$ , if  $G_n \sim G_{n, \frac{\lambda}{n}}$ , and  $|C_{max}|$  denote the size of the largest connected component of  $G_n$ , then*

$$\frac{|C_{max}| - n\zeta_\lambda}{\sqrt{n \cdot \sigma_\lambda^2}} \xrightarrow{d} N(0, 1), \text{ where } \sigma_\lambda^2 = \frac{\zeta_\lambda(1 - \zeta_\lambda)}{(1 - \lambda + \lambda\zeta_\lambda)^2}$$

We wish to see if a similar result holds for  $Conf\left(n, \frac{\lambda}{n}\right)$ .



$\lambda = 1.2$



$\lambda = 2$

For  $n = 1000$  and the specified value of  $\lambda$ , we plot the density of  $\frac{|C_{max}| - n\zeta_\lambda}{\sqrt{n \cdot \sigma_\lambda^2}}$  for  $Conf\left(n, \frac{\lambda}{n}\right)$  (in blue)  $G_{n, \frac{\lambda}{n}}$  (in red) and overlay the  $N(0, 1)$  pdf on them. Here too, we observe that as  $\lambda$  moves away from the critical value, the 3 curves get closer, indicating that as we move away from the critical value, for smaller  $n$ , we have a better fit of the asymptotic distribution.

*Conjecture 2.3.3: Fix  $\lambda > 1$ , if  $G_n \sim Conf\left(n, \frac{\lambda}{n}\right)$ , and  $|C_{max}|$  denote the size of the largest connected component of  $G_n$ , then*

$$\frac{|C_{max}| - n\zeta_\lambda}{\sqrt{n \cdot \sigma_\lambda^2}} \xrightarrow{d} N(0, 1), \text{ where } \sigma_\lambda^2 = \frac{\zeta_\lambda(1 - \zeta_\lambda)}{(1 - \lambda + \lambda\zeta_\lambda)^2}$$

### 3 Discussion

In this report, we see that the configuration model with  $\text{Bin}(n - 1, p)$  degrees closely mimics certain  $G_{n,p}$  behavior. This might be because

- Degree distribution in  $G_{n,p}$  is  $\text{Bin}(n - 1, p)$  and for large enough  $n$ , the dependence between any 2 degrees "weakens"

However some differences crop up, especially while we look at count statistics like the total number of  $\triangle$ s,  $\square$ s in the erased model. This might be because

- While looking for thresholds, in contrast to the count statistics, we are just interested in

the **indicator** of the event. Edges contributing to self-loops and multiple edges do not affect the indicator of the event, but they do affect the count statistics.

## 4 Concluding Remarks

- There might be a result for  $Conf\left(n, \frac{\lambda}{n}\right)$  analogous to the Results of Simplicity in the usual Configuration Model with iid degree.
- Connectivity Threshold,  $\triangle$ ,  $\square$ ,  $K_4$  Containment Threshold appear to be same for both  $G_{n,p}$  and  $Conf(n, p)$ .
- Sub-critical and super-critical Law of large number behaviour seem to be matching for both  $G_{n,p}$  and  $Conf(n, p)$ .
- We also see that the CLT that we have for giant components in supercritical regime in  $G_{n,p}$  might also hold for  $Conf(n, p)$ .

## 5 References

- *Random Graphs and Complex Networks, Volume I*. Cambridge University Press, 2016.