

For the upper bound, as previously,

$$\begin{aligned} P(|C(1)| \geq k_n) &\stackrel{(3.8)}{\leq} P_{n,p}^{\text{BP}}(T \geq k_n) \stackrel{(2.47)}{\leq} P_{\lambda}^{\text{BP}}(T \geq k_n) + \frac{k_n \lambda^2}{n} = \\ &= P_{\lambda}^{\text{BP}}(T = \infty) + P_{\lambda}^{\text{BP}}(k_n \leq T < \infty) + O\left(\frac{k_n}{n}\right) \\ &\stackrel{(3.29) \text{ (2.26)}}{\leq} \xi_{\lambda} + c_{\lambda} e^{-I_{\lambda} k_n} + O(k_n/n) \leq \xi_{\lambda} + O(n^{-1}) + O\left(\frac{k_n}{n}\right). \end{aligned}$$

where we used $I_{\lambda} = \sup (+\log E[e^{+P_{\text{ois}}(\lambda)}])$, recall (3.12), and $k_n \geq a \log n$, $a > \frac{1}{I_{\lambda}}$.

For the lower bound, setting $\lambda_n = \frac{n-k_n}{n} \cdot \lambda = \lambda(1 - \frac{k_n}{n})$

$$P(|C(1)| \geq k_n) \geq P_{n-k_n, p}^{\text{BP}}(T \geq k_n) \geq P_{\lambda_n}^{\text{BP}}(T \geq k_n) + O\left(\frac{k_n}{n}\right).$$

By (2.26) again

$$P_{\lambda_n}^{\text{BP}}(T \geq k_n) = \xi_{\lambda_n} + O(e^{-k_n I_{\lambda_n}}) = \xi_{\lambda_n} + O\left(\frac{1}{n}\right), \text{ as } a > \frac{1}{I_{\lambda}}$$

Finally, we need to show that $|\xi_{\lambda_n} - \xi_{\lambda}| \leq \frac{k_n}{n}$. This follows from the

(3.34) Exercise: Show that $\lambda \mapsto \xi_{\lambda}$ is differentiable on $\lambda \in (1, \infty)$ with $\frac{d}{d\lambda} \xi_{\lambda} \big|_{\lambda=1} = 2$. (Hint: recall (2.4), (2.10))

Step 2: We now show that the number of vertices in "large" clusters concentrates. We will need another estimate on the variance of Z_k , cf. (3.24)

(3.35) Lemma: For every $n \geq 1$ and $k \in [n]$

$$\text{Var}_{n, \frac{\lambda}{n}}^{\text{ER}}(Z_k) \leq (\lambda k + 1) n \cdot E_{n, \frac{\lambda}{n}}^{\text{ER}}[|C(1)| \mathbb{1}_{|C(1)| < k}]$$

(3.36) Remark: In the case when one expects that $C(1) \sim n$ with positive probability this is much better than (3.24), which would give $\text{Var}(Z_n) \sim n^2$, which is essentially trivial.

Proof of (3.35): We set $Y_k = n - Z_k = \#\{x \in [n] : |C(x)| < k\}$

As $\text{Var}(Y_k) = \text{Var}(Z_k)$, it suffices to show (3.35) for Y_k .

Similarly as in (3.24),

$$(3.37) \quad \text{Var}(Y_k) = \sum_{x, y \in [n]} (P(|\mathcal{C}(x)| < k, |\mathcal{C}(y)| < k) - P(|\mathcal{C}(x)| < k)^2)$$

We split the sum according to $x \leftrightarrow y$ again.

$$(3.38) \quad \begin{aligned} \sum_{x, y} P(|\mathcal{C}(x)| < k, |\mathcal{C}(y)| < k, x \leftrightarrow y) &= \quad (\text{if } x \leftrightarrow y, \text{ then } \mathcal{C}(x) = \mathcal{C}(y)) \\ &= \sum_{x, y} P(|\mathcal{C}(x)| < k, x \leftrightarrow y) \\ &= \frac{1}{n} E \left[\sum_y \mathbb{1}_{|\mathcal{C}(1)| < k} \sum_y y \leftrightarrow 1 \right] = n \cdot E \left[|\mathcal{C}(1)| \mathbb{1}_{|\mathcal{C}(1)| < k} \right]. \end{aligned}$$

On the other hand, for $l < k$,

$$(3.39) \quad \begin{aligned} P(|\mathcal{C}(x)| = l, |\mathcal{C}(y)| < k, x \leftrightarrow y) &= P(|\mathcal{C}(x)| = l) \cdot P(x \leftrightarrow y \mid |\mathcal{C}(x)| = l) \cdot P(|\mathcal{C}(y)| < k \mid |\mathcal{C}(x)| = l, x \leftrightarrow y) \\ &\leq 1. \end{aligned}$$

On $\{|\mathcal{C}(x)| = l, x \leftrightarrow y\}$, law of $|\mathcal{C}(y)|$ coincides with the law of $|\mathcal{C}(1)|$ in $ER(n-l, p)$. Thinking $ER(n-l, p)$ as a subset of $ER(n, p)$, $P_{n-l, p}(|\mathcal{C}(1)| < k) - P(|\mathcal{C}(1)| < k) = P_{n, p}(|\tilde{\mathcal{C}}(1)| < k, |\mathcal{C}(1)| \geq k)$, where $\tilde{\mathcal{C}}(1) = \{y \in [n-l], 1 \leftrightarrow y\}$. The last event can occur only if there is at least one edge connecting $\tilde{\mathcal{C}}(1)$ with $[n] \setminus [n-l]$, but this has probability $\leq p \cdot k \cdot l = \frac{1}{n} k l$.

Hence, coming back to (3.39),

$$P(|\mathcal{C}(y)| < k \mid |\mathcal{C}(x)| = l, x \leftrightarrow y) - P(|\mathcal{C}(y)| < k) \leq \frac{1}{n} k l$$

Inserting this into (3.39) and using this in (3.37),

$$(3.40) \quad \begin{aligned} \sum_{x, y} \{P(|\mathcal{C}(x)| < k, |\mathcal{C}(y)| < k, x \leftrightarrow y) - P(|\mathcal{C}(x)| < k)^2\} &\leq \\ &\leq \sum_{l=1}^{k-1} \sum_{x, y \in [n]} \frac{1}{n} k l P(|\mathcal{C}(x)| = l) = \frac{1}{n} k^2 E[|\mathcal{C}(1)| \mathbb{1}_{|\mathcal{C}(1)| < k}] \end{aligned}$$

Combining (3.37), (3.38), (3.40) finishes the proof $\square$.

Step 3: We now show that it is extremely unlikely, that there are "middle ground" clusters of size between k_n and αn .

We start with an auxiliary claim.

(3.41) Lemma: Let S_n be as in (3.4), (3.6) that is $S_0 = 1$, $S_k = S_{k-1} + X_k - 1$, $k \geq 1$, with $X_k \sim \text{Bin}(n - (k-1) - S_{k-1}, p)$ (this defines S_k beyond H_0), and set $N_k = n - k - S_k$. Then

$$N_k \sim \text{Bin}(n-1, (1-p)^k) \text{ and thus } S_k \sim \text{Bin}(n-1, 1 - (1-p)^k) - (k-1)$$

Proof: By the above recursion,

$$N_k = n - k - S_k = n - k - S_{k-1} - X_k + 1 = N_{k-1} - X_k \sim \text{Bin}(N_{k-1}, 1-p)$$

Using induction in k we then obtain $N_k \sim \text{Bin}(n-1, (1-p)^k)$, since $N_0 = n-1$. The second claim then follows since $n-1 - N_k \sim \text{Bin}(n-1, 1 - (1-p)^k)$, by usual properties of binomial distribution. $\square$

(3.42) Lemma: Let $k_n = a \log n$ with $a > \frac{1}{1-\lambda}$ and $\alpha < \frac{1}{\lambda}$. Then there is $\delta(a, \alpha) > 0$ such that, for n large,

$$P(k_n \leq |C(1)| \leq \alpha n) \leq e^{-k_n \delta}$$

Proof: $P(k_n \leq |C(1)| \leq \alpha n) = \sum_{l=k_n}^{\alpha n} P(|C(1)| = l)$
 $\stackrel{(3.3)}{\leq} \sum_{l=k_n}^{\alpha n} P(S_l = 0) \stackrel{(3.41)}{\leq} \sum_{l=k_n}^{\alpha n} P[\text{Bin}(n-1, 1-(1-p)^l) = l-1]$
 $\leq \sum_{l=k_n}^{\alpha n} P(\text{Bin}(n-1, 1-(1-p)^l) \leq l-1) \quad (1-p \leq e^{-p})$
 $\leq \sum_{l=k_n}^{\alpha n} P(\text{Bin}(n, 1-e^{-pl}) \leq l) \quad (\text{Hoeffding, } S \geq 0)$
 $\leq \sum_{l=k_n}^{\alpha n} l E[e^{-S \text{Bin}(n, 1-e^{-pl})}]$
 $= \sum_{l=k_n}^{\alpha n} l ((1-e^{-pl})e^{-S} + e^{-pl})^n$
 $= \sum_{l=k_n}^{\alpha n} l (1 - (1-e^{-pl})(1-e^{-S}))^n \quad (1-x) \leq e^{-x}$

$$\leq \sum_{\ell} \sup \left\{ s\ell - n(1 - e^{-\frac{\ell}{n}})(1 - e^{-s}) \right\}$$

Optimizing over s , i.e. taking $s = s^* = \log \left(\frac{n}{\ell} (1 - e^{-\frac{\ell}{n}}) \right)$

and writing $g(\beta, \lambda) = \frac{1}{\beta} (1 - e^{-\lambda\beta})$ we obtain

$$(3.43) \quad P(k_n \leq |C(\lambda)| \leq \alpha n) \leq \sum_{\ell=k_n}^{\alpha n} \sup \left\{ +\ell (\log g(\frac{\ell}{n}, \lambda) - g(\frac{\ell}{n}, \lambda) + 1) \right\}$$

Observe now that

$$\lim_{\beta \downarrow 0} g(\beta, \lambda) = \lambda > 1$$

$$(3.44) \quad \frac{\partial}{\partial \beta} g(\beta, \lambda) = e^{-\lambda\beta} \frac{\lambda\beta - (e^{\lambda\beta} - 1)}{\beta^2} < 0$$

$$g(\xi_\lambda, \lambda) = \frac{1}{\xi_\lambda} (1 - e^{-\lambda\xi_\lambda}) \stackrel{(2.40)}{\stackrel{(3.29)}}{=} \frac{(1 - \eta_\lambda)}{1 - \eta_\lambda} = 1.$$

Hence $s^* \geq 0$ only if $\frac{\ell}{n} \leq \xi_\lambda$ which is the case since $\alpha < \xi_\lambda$, that is (3.43) indeed holds.

Coming back to (3.43), since $x \mapsto \log x - x + 1$ is strictly decreasing on $x \geq 1$ and $g(\frac{\ell}{n}, \lambda) > 1$ for all considered ℓ 's,

$$(3.45) \quad P(k_n \leq |C(\lambda)| \leq \alpha n) \leq \sum_{\ell=k_n}^{\alpha n} \sup \left\{ +\ell (\log g(\alpha, \lambda) - g(\alpha, \lambda) + 1) \right\} \\ \leq e^{-k_n \cdot \delta(\alpha, \lambda)}$$

where in the last inequality we used that

$$\log(g(\xi_\lambda, \lambda)) - g(\xi_\lambda, \lambda) + 1 = 0 \quad \text{and thus}$$

$$\log(g(\alpha, \lambda)) - g(\alpha, \lambda) + 1 < 0 \quad \square$$

Step 4: Conclusion.

$$(3.46) \quad \text{Let } k_n = k \log n \text{ with } k \text{ large, } \alpha \in (3\xi_\lambda/4, \xi_\lambda), \varepsilon \in (0, \frac{\xi_\lambda}{4}). \text{ Set} \\ \mathcal{E}_n = \{ |Z_{k_n} - n\xi_\lambda| \leq \varepsilon n \} \cap \{ \nexists x \in [n] : k_n \leq |C(x)| \leq \alpha n \}.$$

By Lemmas (3.32), (3.35) and Chebyshev inequality

$$(3.47) \quad P[|Z_{k_n} - n\xi_\lambda| \geq \varepsilon n] \leq \frac{1}{\varepsilon^2 n^2} n k_n^2 \xrightarrow{n \rightarrow \infty} 0$$

and by Lemma (3.42), $P[\exists x : k_n \leq |C(x)| \leq \alpha n] \leq n e^{-k_n \delta} \xrightarrow{n \rightarrow \infty} 0$,
for k sufficiently large.

Hence $\mathbb{P}_{\text{np}}^{\text{ER}}[\Sigma_n] \xrightarrow{n \rightarrow \infty} 1$.

To conclude, we claim

(3.48) $\text{On } \Sigma_n, |C_{\max}| = Z_{k_n}.$

Indeed, from the definition of $Z_{k_n} = \#\{x \in [n], |C(x)| \geq k_n\}$ it follows easily that $|C_{\max}| \leq Z_{k_n}$, since $|C(x)| = |C_{\max}|$ for all $x \in C_{\max}$. On the other hand, $|C_{\max}| < Z_{k_n}$ implies that there are at least two connected components of size at least k_n . Also, on Σ_n , there are no connected components of size between k_n and αn . Therefore, there must be two connected components of size at least αn , which implies $Z_{k_n} \geq 2\alpha n \geq \frac{3}{2}\epsilon_1 n$, which contradicts $|Z_{k_n} - n| \leq \epsilon n$, since $\epsilon < \frac{1}{4}$. Hence, we conclude that (3.48) holds $\square$.

IV CRITICAL ER GRAPH.

In previous chapter we proved that the Erdős-Rényi graph with $p = \frac{\lambda}{n}$ is "subcritical" for $\lambda < 1$ and "supercritical" for $\lambda > 1$. We now consider the case when p equals or is close to $\frac{1}{n}$. It turns out that in this regime $C_{\max}$ has nontrivial behavior that we try understand in detail.

We study the size of $C_{\max}$ first.

(4.1) Theorem: Let $p = \frac{\lambda}{n}$ with $\lambda = 1 + \Theta n^{-\frac{1}{3}}$, then is

(4.2)
$$p = \frac{1}{n} + \frac{\theta}{n^{4/3}}, \quad \theta \in \mathbb{R}.$$

Then, there exists $b = b(\theta) > 0$ such that for all $A > 1$

(4.3)
$$\mathbb{P}_{n,p}^{\text{ER}} \left(A^{-1} n^{2/3} \leq |C_{\max}| \leq A n^{2/3} \right) \geq 1 - \frac{b}{A}.$$

In particular the sequence $\left(\frac{|C_{\max}(n)|}{n^{2/3}} \right)_{n \geq 1}$ is tight.

Proof: The proof follows similar strategy as in Chapter III, so we will skip some parts of the argument and concentrate on key steps that explain the $n^{2/3}$ -scaling. We need two lemmas

(4.4) Lemma: (Critical cluster tails, $\lambda = 1 + \frac{\theta}{n^{1/3}}$, $\theta \in \mathbb{R}$)

Let $k > 0$ and $k \leq n^{2/3}$. Then there are $0 < c_1 < c_2 < \infty$ with $c_1 = c_1(n, \theta)$ s.t. for n large

$$\frac{c_1}{\sqrt{k}} \leq \mathbb{P}_{n,p}^{\text{ER}} (|C(i)| \geq k) \leq c_2 \left((\theta \vee 0) n^{-1/3} + \frac{1}{\sqrt{k}} \right).$$

(4.5) Lemma (Expected critical cluster size, $\lambda = 1 + \frac{\theta}{n^{1/3}}$, $\theta < 0$)

For every $n \geq 1$, $\mathbb{E}_{n,p}^{\text{ER}} |C(i)| \leq n^{1/3} / |\theta|.$

(4.6) Remarks:

(a) Lemma (4.4) should be compared with (2.46) where we showed that for Poisson(1)-branching process

$$P_1^{\text{BP}}(T=k) = ck^{-\frac{3}{2}}(1+o(1)), \text{ that is } P^{\text{BP}}(T \geq k) = ck^{-1/2}(1+o(1)).$$

Of course, one cannot expect this bound to be true for all k , but (4.4) implies that it holds for $k \leq cn^{2/3}$.

(b) (4.5) is "intuitively" consistent with (4.1). If one believes/ expects that $E|C(i)|$ is dominated by the contribution of the case when $i \in C_{\max}$, we have

$$(4.7) \quad \begin{aligned} E[|C(i)|] &\approx E[|C(i)| \mathbb{1}_{i \in C_{\max}}] = E[|C_{\max}| \mathbb{1}_{i \in C_{\max}}] \\ &= \frac{1}{n} E[|C_{\max}|^2] \end{aligned}$$

(Here, " $\approx$ " is uncontrolled, but can be justified by (4.4)).

When $|C_{\max}|$ is typically $\sim n^{2/3}$, then $E(|C_{\max}|^2) \sim n^{4/3}$, i.e., by (4.7), $E(|C(i)|) \sim n^{1/3}$ as in (4.5).

Proof of (4.1) using (4.4) & (4.5).

By taking δ large we may assume that A is large, or else otherwise the RHS of (4.3) is negative. We also w.l.o.g. assume that n is large.

Upper bound: We recall $Z_k = \#\{x \in [n] : |C(x)| \geq k\}$ and thus $\{|C_{\max}| \geq k\} = \{Z_k \geq k\}$. (cf. under (3.19)).

Therefore,

$$(4.8) \quad \begin{aligned} P(|C(i)| \geq A n^{2/3}) &= P(Z_{A n^{2/3}} \geq A n^{2/3}) \leq A^{-1} n^{-2/3} E[Z_{A n^{2/3}}] \\ &= A^{-1} n^{-2/3} \cdot P(|C(i)| \geq A n^{2/3}) \stackrel{(4.4)}{\leq} A^{-1} n^{\frac{1}{3}} \cdot c_2 (\Theta v_0) n^{-\frac{1}{3}} + \frac{1}{A n^{1/3}} \\ &= \frac{c_2}{A} (\Theta v_0 + \frac{1}{A}) \leq \frac{1}{A} \cdot (c_2 (\Theta v_0) + 1). \end{aligned}$$

Lower bound: Since, $|C_{\max}|$ is "increasing in λ ", it is sufficient to establish the LB for $\theta \leq -1$.

Using $\{|C_{\max}| \leq k\} = \{Z_k = 0\}$ and Chebyshev

$$(4.9) \quad \begin{aligned} P(|C_{\max}| \leq A^{-1} n^{2/3}) &= P(Z_{A^{-1} n^{2/3}} = 0) \\ &\leq \frac{\text{Var}(Z_{A^{-1} n^{2/3}})}{E[Z_{A^{-1} n^{2/3}}]^2} \end{aligned}$$

By (4.5), as in (4.8),

$$(4.10) \quad E[Z_{A^{-1} n^{2/3}}] = n \cdot P[|C(1)| \geq A^{-1} n^{2/3}] \geq c_1 \sqrt{A} n^{2/3}.$$

By Lemma (3.24), (4.5), $\theta \leq -1$,

$$(4.11) \quad \text{Var}(Z_{A^{-1} n^{2/3}}) \leq n \cdot E[|C(1)|] \stackrel{(4.5)}{\leq} n^{4/3}.$$

Combining (4.9)-(4.11) yields the lower bound $\square$.

Proof of (4.5). By the comparison with binomial BP, (3.8)

$$E_{n,p}(|C(1)|) \leq E_{n,p}^{\text{BP}}[T] = \sum_{k \geq 0} E_{n,p}^{\text{BP}}(Z_k)$$

where Z_k denotes the size of k -th generation, c.f. (2.2)

By (2.17), since $\theta < 0$,

$$\begin{aligned} &= \sum_{k \geq 0} (n \cdot p)^k = \frac{1}{1 - np} = \frac{1}{1 - n(\frac{1}{n} + \frac{\theta}{n^{4/3}})} = \frac{n^{1/3}}{|\theta|}. \quad \square \end{aligned}$$

Proof of (4.4): Is long and uses the same strategy as before, based on comparison lemmas (3.8), (3.10) and properties of Binomial / Poisson BP. For details see [vdH], pages 154-155. As we will prove better results soon, we omit it here. $\square$