# Expanders in Power Law Graphs 

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## Approval

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## Abstract

Random power-law graphs on $n$ vertices can be defined in different ways. One model we study describes graphs where the expected number of vertices of degree $x$ is proportional to a power law $1 / x^{\beta}$, for constant $\beta>0$. In another model, the exact degree sequence follows the power-law distribution and each vertex $i$ has degree $p n / i^{\beta}$, for $0<p \leq 1$ and $\beta \geq 0$.

We show that for these models, power-law graphs contain "large" edge and vertex expanders. Those are graphs in which all subsets of vertices up to a certain size have, respectively, many outgoing edges or large vertex boundary. We also explore the trade-offs between expansion of the subsets and their maximum size.

Our findings agree with and complement known results about the presence of linear size expanders in Erdős-Rényi graphs and about the connected components of power-law graphs.

Keywords: random power-law graphs; expanders; expansion property; diameter

## Dedication

This work is wholeheartedly dedicated to my dear parents and family.
They always provide me with unconditional love and lift my spirits.

## Acknowledgements

First and foremost, I would like to express the deepest gratitude to my senior supervisor Valentine Kabanets. I recognize that this work would be impossible without him giving me this opportunity and providing invaluable guidance along the way. Valentine also introduced me to complexity theory beyond the P versus NP problem and helped in exploring its deep connections to many other fields. Now I have a feeling of great respect for this area and people who work in it.

I am thankful to my supervisor Andrei Bulatov for his support and helpful advices on how to refine this thesis. In addition, I would like to thank Bojan Mohar for agreeing to examine this thesis, as well as Binay Bhattacharya for being the defence chair.

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## Chapter 1

## Introduction

A power-law distribution is widespread and has been studied for almost a century [Lot26]. Its natural examples range from Pareto principle [Par97] to the distribution of species within genera of plants [Yul25], population of cities [Zip49], and magnitude of earthquakes [GR54]. As for computing science, many industrial SAT (boolean satisfiability) instances that reflect real-world problems were found to follow a power law [ABL09a]. Another notable example is Barabási-Albert model [BA99]: it describes preferential attachment processes known as "the rich get richer", and implicitly develops a power-law distribution with the exponent 3 .

Generally, a power law is a relation $f(x)=a x^{b}$. A few examples are shown in Figure 1.1. One of its important characteristics is that it is scale-free: $f\left(c_{1} x\right)=\left(a c_{1}^{b}\right) x^{b}=c_{2} f(x)$. For instance, scale-free networks like the Internet topology and social networks are of a special interest: they preserve the overall properties at any scale, resulting in their high resistance to accidental failures [BB03, FFF99].

Power-law graphs are those with either degrees or degree frequencies being proportional to a power law $x^{-\beta}$, where $\beta \geq 0$ is a constant. Figure 1.2 illustrates a power-law graph with $n=200$ vertices, each vertex $i$ having degree $n^{0.6} / i^{0.4}$.

Graph expansion is another basic concept of this work. It was introduced in 1960s [KB67], but expanders, graphs having a high expansion, were later rediscovered and received their name in 1973 [Pin73]. One example of such a sparse yet well-connected graph would be a Paley graph shown in Figure 1.3.

Expanders were proven to be beneficial for solving routing problems. Discovered routing schemes have robustness and path diversity close to those of the underlying graph [FGRV14], and achieve an optimal congestion in case of power-law graphs [GMS03], all this while using only linear number of edges. Decomposing a graph of arbitrary density into a collection of edge expanders is a base of some divide-and-conquer algorithms [MS17]. Fast convergence of random walks on expanders [Mih89] helps with graph exploration. In addition, expanders often arise when justifying the results like SAT lower bounds [AHI05, $\mathrm{ABBO}^{+} 05$, PRST16], the hardness of pseudorandom generators [ABSRW04] for various proof systems, and even PCP theorem [Din07].


Figure 1.1: Power-law functions


Figure 1.2: Example of a power-law graph and its degree distribution

The original motivation for this research was trying to learn about SAT formulas with power-law structure. Intuitively, such an additional information may lead to faster algorithms for some restricted families of formulas.

Another intriguing idea was about the presence of expanders in the variable incidence graphs (VIG) of SAT formulas. Expanders would represent tight and relatively short connections between the variables. Thus one would typically assume that if there are no large expanders in VIG, it might indicate that satisfiability of the formula could be efficiently decided, e.g., via decomposition.

In this thesis, we work with several models of random power-law graphs, study their properties and trade-offs between the parameters, and show existence of expanding subgraphs for different ranges of the exponent $\beta$.

### 1.1 Related Work

The following results inspired us to look for expanders inside power-law graphs.
Aiello, Chung, and Lu [ACL01] introduced a random graph model for power-law graphs and described different properties, including connectivity and emergence of giant connected


Figure 1.3: 13-Paley graph is an example of an expander
components. This model is asymptotically equivalent to our coin toss model from Section 3.2. The difference is that our model defines the expected degree sequence rather than the exact one, and that is crucial for our proof.

Chung and Lu [CL04] found the average distance in random graphs with given expected degree sequences, both general and power-law with $2<\beta<3$. The latter produces the "octopus" graphs described in Section 3.5.

Ansotegui, Bonet, and Levy [ABL09b] presented a power-law model which was shown to fit well industrial SAT instances used in recent international competitions for SAT solvers. They also focused on fitting the SAT instances, i.e., estimating the appropriate distributions that would produce analogous degree sequences. We talk about this model in Section 3.4.

Krivelevich [Kri18] looked for a linearly sized expanders inside graphs that are "locally sparse", as well as inside random $G(n, p)$ graphs. The paper also contained the algorithm for actually finding the expanding subgraphs.

Finally, Mihail, Saberi, and Tetali [MST06] capitalized on the structure of power-law graphs by displaying that one can discover the nodes via a random walk with lookahead in sublinear time. Considering another work by Mihail [Mih89], this result also hints on possible expansion properties of graphs with paths of constant length replaced by new edges.

As can be seen, there is a substantial amount of research done concerning separately power-law models and expander graphs due to their wide popularity and usefulness. Gkantsidis, Mihail, and Saberi [GMS03] made significant steps in the direction of combining these two topics. They considered random power-law graphs with the exponent $2<\beta<3$, degrees of vertices between 3 and $O(\sqrt{n})$, and volume $O(n)$. They also had to slightly modify graph construction used by Aiello et al. [ACL01] in order to ensure certain connectivity properties. These graphs were shown to have conductance $\Theta(1)$, which generalizes the notion of $(n / 2, \Theta(1))$ edge expansion.

Table 1.1: Comparison of power-law graph models

| Model | Object |  | Definition |
| :---: | :---: | :---: | :---: |
| Permutation model | exact | degrees | $\operatorname{deg}(i)=\frac{p n}{i^{\beta}}$ |
| Model 3 [ACL01] |  | frequencies of degrees | $\|\{i \in V \mid \operatorname{deg}(i)=x\}\|=\frac{e^{\alpha}}{x^{\beta}}$ |
| Coin toss model | expected |  | $\underset{G}{\mathbb{E}}[\|\{i \in V \mid \operatorname{deg}(i)=x\}\|]=\frac{e^{\alpha}}{x^{\beta}}$ |
| Model 4 [CL04] |  | degrees | $\underset{G}{\mathbb{E}}[\operatorname{deg}(i)]=w_{i}=c i^{-1 /(\beta-1)}, \beta>2$ |

### 1.2 Contribution of the Thesis

We defined the models of power-law graphs, which would complement the ones studied earlier. Table 1.1 presents their comparison. The permutation model was chosen so as to fit the uniformly random case when the exponent $\beta=0$.

The main result is that, under these models, the subgraphs containing the vertices of sufficiently large degrees are edge or vertex expanders w.h.p.

More precisely, in the coin toss model, if $\beta<1$, actually the whole graph is an edge expander. For $1 \leq \beta \leq 1.6$ we have a linear size expanding subgraph, and for $\beta>1.6$ the size of the expander is only $\Theta\left(n^{1 / \beta}\right)$. In all the cases edge expansion is close to one half of the expected average degree $d$, which is linear in the size of the subgraph.

In the permutation model, the case $\beta=0$ matches the previously known fact that the whole graph has edge and vertex expansion almost $d-2$. When $\beta>0$, we generalize the argument to show existence of the edge expanders of size $n / 2$ with expansion $d / 2$, but the average degree $d$ deteriorates for larger $\beta$. Also, if $\beta>1$, there is an additional constraint $p \zeta(\beta)>2$ which essentially limits $\beta \leq 1.72$. Meanwhile, vertex expansion of the subgraph with vertices of degree at least $d_{0}$ is almost $d_{0} / 2-2$ whenever $\beta>0$.

Obtained results about linear size expanders inside power-law graphs resemble existing result of the same nature for Erdős-Rényi graphs [Kri18]. The size of our expanders is also comparable to the sizes of the largest connected components in power-law graphs [ACL01], i.e., we say that the largest components are not just connected, but "highly connected". Table 1.2 summarizes these details.

We proceed by showing that the core of the "octopus" graph with the vertices of degree at least $n^{1 / \log \log n}$ is an edge expander w.h.p. and it contains a large vertex expander.

As a side result, we prove the logarithmic diameter of vertex expanders with only small expanding subsets of size at most $\epsilon n$, for some constant $\epsilon>0$, as opposed to $\epsilon=1 / 2$ in the canonical result.

Table 1.2: Consistency of sizes between our results and the other papers

|  | $(0 ; 1.6]$ | $(1.6 ; 1.72]$ | $(1.72 ; 3.48)$ | $(3.48 ; \infty)$ |
| :--- | :---: | :---: | :---: | :---: |
| The largest components <br> in power-law graphs [ACL01] | the giant component, $\Theta(n)$ |  | $O\left(n^{2 / \beta} \log n\right)$ |  |
| Our edge expanders <br> in coin toss model | $\Theta(n)$ | $\Theta\left(n^{1 / \beta}\right)$ |  |  |
| Vertex/edge expanders <br> in $G(n, p)$ [Kri18] | $\Theta(n)$ |  |  | - |
| Our edge expanders <br> in permutation model | $\Theta(n)$ |  |  |  |

To sum up, our findings provide better understanding of the structure of power-law graphs from some general families for a wide range of parameters. This knowledge can be further used to employ any techniques applicable to expanders on these power-law graphs.

### 1.3 Our Methods

For the coin toss model, we first obtain the necessary lower bounds on the expected average degree. This is done by approximating the expected size of an arbitrary cut, applying Chernoff concentration bounds, and following the common argument for edge expansion. Then we decide the size of an expanding subgraph and try to keep it linear in the size of the whole graph by choosing an appropriate minimum degree of vertices to be included in this subgraph.

While working with the permutation model, we adopt and generalize the existing approaches from Section 2.5.2 and 2.5.3 for edge and vertex expansion of regular graphs.

Throughout this work, we deal with varying approximations of harmonic numbers, so we have to treat different ranges of the exponent $\beta$ separately. Lastly, our proof of small diameter of vertex expanders resembles a common technique for graph decomposition.

### 1.4 Thesis Structure

In Chapter 2 we present all the necessary definitions, approximations, and known results about expanders, on which this research is based. Chapter 3 contains the detailed description of the main models of power-law graphs used in this work. In Chapter 4 we show the existence of expanding subgraphs for the coin toss and permutation models, and analyze the diameter of graphs with vertex expansion of small sets. Finally, we compare the behavior of the random graphs under different models in Chapter 5, including their diameters and sizes of expanders and connected components.

## Chapter 2

## Preliminaries

Here we explain the basic definitions as well as the notation used in the following chapters.

### 2.1 Probability Theory and Inequalities

We say an event $E(n)$ over a sample space $\Omega$ happens with high probability (w.h.p.) when

$$
\begin{equation*}
\lim _{n \rightarrow \infty} \operatorname{Pr}_{\Omega}[E(n)]=1 \tag{2.1}
\end{equation*}
$$

### 2.1.1 Union Bound

If $\Omega$ is a sample space and $E_{1}, \ldots, E_{n}$ are events over $\Omega$, then

$$
\begin{equation*}
\operatorname{Pr}_{\Omega}\left[\bigcup_{i=1}^{n} E_{i}\right] \leq \sum_{i=1}^{m} \operatorname{Pr}_{\Omega}\left[E_{i}\right] \tag{2.2}
\end{equation*}
$$

### 2.1.2 Chernoff Bounds

Let $X_{1}, \ldots, X_{n} \in\{0,1\}$ be independent random variables, and $X=\sum_{i=1}^{n} X_{i}$ with expected value $\mu=\mathbb{E}[X]=\sum_{i=1}^{n} \operatorname{Pr}\left[X_{i}=1\right]$.

$$
\begin{align*}
& \operatorname{Pr}[X \geq(1+\delta) \mu] \leq \begin{cases}\exp \left(-\delta^{2} \mu /(2+\delta)\right) & \text { if } \delta>1, \\
\exp \left(-\delta^{2} \mu / 3\right) & \text { if } 0<\delta \leq 1 .\end{cases}  \tag{2.3}\\
& \operatorname{Pr}[X \leq(1-\delta) \mu] \leq \exp \left(-\delta^{2} \mu / 2\right), \text { for } 0<\delta<1 \tag{2.4}
\end{align*}
$$

We can combine these two:

$$
\begin{equation*}
\operatorname{Pr}[|X-\mu| \geq \delta \mu] \leq 2 \exp \left(-\delta^{2} \mu / 3\right), \text { for } 0<\delta<1 \tag{2.5}
\end{equation*}
$$

### 2.1.3 Combinations

$$
\begin{equation*}
\left(\frac{n}{k}\right)^{k} \leq\binom{ n}{k}=\frac{n!}{k!(n-k)!} \leq\left(\frac{e n}{k}\right)^{k} \tag{2.6}
\end{equation*}
$$

It is easy to show:
$\frac{n}{k} \leq \frac{n-m}{k-m}$, for $0 \leq m<k \leq n$, so $\left(\frac{n}{k}\right)^{k}=\frac{n}{k} \cdots \frac{n}{k} \leq \frac{n}{k} \frac{n-1}{k-1} \ldots \frac{n-k+1}{1}=\binom{n}{k}$
$\binom{n}{k}=\frac{n}{k} \frac{n-1}{k-1} \ldots \frac{n-k+1}{1} \leq \frac{n^{k}}{k!}=\frac{k^{k}}{k!}\left(\frac{n}{k}\right)^{k} \leq\left(\frac{e n}{k}\right)^{k}$
The last step uses the Maclaurin series of the exponential function:

$$
\begin{equation*}
e^{k}=\sum_{n=0}^{\infty} \frac{k^{n}}{n!} \geq \frac{k^{k}}{k!} \tag{2.7}
\end{equation*}
$$

### 2.1.4 Stirling's Approximation and the Number of Perfect Matchings

Let $M(m)$ denote the number of perfect matchings on the set of even size $m$ :

$$
\begin{equation*}
M(m)=(m-1)!!=(m-1)(m-3) \ldots(3)(1)=\frac{m!}{2^{m / 2}(m / 2)!} \tag{2.8}
\end{equation*}
$$

We can use Stirling's approximation:

$$
\begin{gather*}
m!=(1+o(1)) \sqrt{2 \pi m}(m / e)^{m}  \tag{2.9}\\
M(m)=(1+o(1)) \frac{\sqrt{2 \pi m}(m / e)^{m}}{2^{m / 2} \sqrt{\pi m}(m / 2 e)^{m / 2}}=(1+o(1)) \sqrt{2}(m / e)^{m / 2} \tag{2.10}
\end{gather*}
$$

### 2.1.5 The Upper Bounds for the Sum of a Special Series

The following sum $S_{n}$ occurs in several proofs. We will need to upper bound it for $n \rightarrow \infty$ and some constants $0<\alpha \leq 1 / 2, c_{1}>0$, and $c_{2}>0$ :

$$
\begin{equation*}
S_{n}=\sum_{s=1}^{\alpha n}\left(c_{1}(s / n)^{c_{2}}\right)^{s} \tag{2.11}
\end{equation*}
$$

Each subsequent bound will require more rigorous analysis.
Proposition 2.1. $S_{n}<1$, when $c_{2} \geq 1+\log c_{1}$.
Proof. $S_{n}=\sum_{s=1}^{\alpha n}\left(c_{1}(s / n)^{c_{2}}\right)^{s} \leq \sum_{s=1}^{\alpha n}\left(c_{1} \alpha^{c_{2}}\right)^{s} \leq \sum_{s=1}^{\infty} 2^{-c_{3} s} \leq \sum_{s=1}^{\infty} 2^{-s}<1$, where $c_{3}=c_{2}-\log c_{1}$ is a constant greater or equal 1 :

$$
\begin{gather*}
c_{3} \geq 1 \Longleftrightarrow c_{2} \geq 1+\log c_{1}  \tag{2.12}\\
c_{1} \alpha^{c_{2}} \leq c_{1} 2^{-c_{2}}=2^{-c_{3}} \leq 2^{-1} \tag{2.13}
\end{gather*}
$$

Proposition 2.2. $S_{n} \leq o(1)$ for some sufficiently small $\alpha$.
Proof. First, we pick $\alpha$ so that $\left(c_{1} \alpha^{c_{2}}\right)<1 / 10$, using some constant $c_{3}>10$ :

$$
\begin{equation*}
\alpha=\left(c_{1} c_{3}\right)^{-1 / c_{2}} \tag{2.14}
\end{equation*}
$$

Then we consider small and large values of $s$ separately. Define $0<\epsilon<1$ such that

$$
\begin{gather*}
\epsilon<(1-\epsilon) c_{2} \Longleftrightarrow \epsilon<\frac{c_{2}}{1+c_{2}}  \tag{2.15}\\
S^{\prime}=\sum_{s=1}^{n^{\epsilon}}\left(c_{1}(s / n)^{c_{2}}\right)^{s} \leq \sum_{s=1}^{n^{\epsilon}}\left(\frac{c_{1}}{n^{(1-\epsilon) c_{2}}}\right)^{s} \leq n^{\epsilon} \frac{c_{1}}{n^{(1-\epsilon) c_{2}}}=o(1)  \tag{2.16}\\
S^{\prime \prime}=\sum_{s=n^{\epsilon}+1}^{\alpha n}\left(c_{1}(s / n)^{c_{2}}\right)^{s}<\sum_{s=n^{\epsilon}+1}^{\alpha n} 10^{-s} \leq \frac{\alpha n}{10^{n^{\epsilon}}}=o(1) \tag{2.17}
\end{gather*}
$$

$$
S_{n}=S^{\prime}+S^{\prime \prime} \leq o(1)
$$

Proposition 2.3. $S_{n} \leq o(1)$ for any $\alpha \leq 1 / 2$ and $c_{2}>\max \left\{1, \log c_{1}\right\}$.
Moreover, $c_{1}$ and $c_{2}$ can be superconstants in terms of $n$, as long as $c_{1}=o\left(n^{c_{2}-1}\right)$.
Proof. The argument is identical to the known one [GMS03].
For $s \geq 1$, let's define $f(s)=\left(c_{1}(s / n)^{c_{2}}\right)^{s}$, then $S_{n}=\sum_{s=1}^{\alpha n} f(s)$. The first two derivatives will help us understand the behavior of $f(s)$.

First, the simple case is when $c_{1}=c_{2}=1$ :

$$
\begin{gathered}
\frac{d}{d s}\left(\frac{s}{n}\right)^{s}=\frac{d}{d s} \exp \left(s \ln \frac{s}{n}\right)=\left(\frac{s}{n}\right)^{s}\left(\ln \frac{s}{n}+s \frac{1 / n}{s / n}\right)=\left(\frac{s}{n}\right)^{s}\left(\ln \frac{s}{n}+1\right) \\
\frac{d^{2}}{d s^{2}}\left(\frac{s}{n}\right)^{s}=\left(\frac{s}{n}\right)^{s}\left(\frac{1}{s}+\left(1+\ln \frac{s}{n}\right)^{2}\right)>0
\end{gathered}
$$

We can see that $\left(\frac{s}{n}\right)^{s}$ is concave up for any $s \geq 1$ and attains its minimum at $s=n / e$.

Then we perform similar steps for $f(s)$ :

$$
\begin{align*}
f^{\prime}(s) & =\frac{d}{d s}\left(c_{1}\left(\frac{s}{n}\right)^{c_{2}}\right)^{s}=\frac{d}{d s} \exp \left(s \ln \left(c_{1}\left(\frac{s}{n}\right)^{c_{2}}\right)\right)= \\
& =f(s)\left(\ln \left(c_{1}\left(\frac{s}{n}\right)^{c_{2}}\right)+s \frac{c_{1} c_{2}(s / n)^{c_{2}-1}(1 / n)}{c_{1}(s / n)^{c_{2}}}\right)= \\
& =f(s)\left(\ln \left(c_{1}\left(\frac{s}{n}\right)^{c_{2}}\right)+c_{2}\right)=  \tag{2.18}\\
& =f(s) c_{2}\left(\ln \frac{c_{1}^{1 / c_{2}} s}{n}+1\right)= \\
& =f(s) c_{2}\left(\ln \frac{s}{n}+\frac{\ln c_{1}}{c_{2}}+1\right) \\
f^{\prime \prime}(s) & =\frac{d^{2}}{d s^{2}}\left(\frac{s}{n}\right)^{s}=\left(\frac{s}{n}\right)^{s}\left(\frac{1}{s}+\left(1+\ln \frac{s}{n}\right)^{2}\right)= \\
& =\frac{c_{2}}{s} f(s)+c_{2}\left(\ln \frac{s}{n}+1\right) f^{\prime}(s)+\left(\ln c_{1}\right) f^{\prime}(s)=  \tag{2.19}\\
& =\frac{c_{2}}{s} f(s)+c_{2}\left(\ln \frac{s}{n}+\frac{\ln c_{1}}{c_{2}}+1\right) f^{\prime}(s)= \\
& =\frac{c_{2}}{s} f(s)+\frac{\left(f^{\prime}(s)\right)^{2}}{f(s)}
\end{align*}
$$

Define $s_{0}$ to be an extreme point of $f(s)$ :

$$
\begin{gather*}
f^{\prime}\left(s_{0}\right)=0  \tag{2.20}\\
\ln \frac{c_{1}^{1 / c_{2}} s}{n}=-1  \tag{2.21}\\
s_{0}=\frac{n}{e c_{1}^{1 / c_{2}}} \tag{2.22}
\end{gather*}
$$

And verify that $f^{\prime \prime}(s)>0$ for any $s \geq 1$ :

$$
\begin{gather*}
\frac{c_{2}}{s} f(s)+\frac{\left(f^{\prime}(s)\right)^{2}}{f(s)}>0  \tag{2.23}\\
\frac{c_{2}}{s}+\left(\frac{f^{\prime}(s)}{f(s)}\right)^{2}>0 \tag{2.24}
\end{gather*}
$$

Therefore, $f(s)$ is concave up on the whole interval $[1 ; \alpha n]$ with these endpoints:

$$
\begin{gather*}
f(1)=\frac{c_{1}}{n^{c_{2}}}  \tag{2.27}\\
f(\alpha n)=\left(c_{1} \alpha^{c_{2}}\right)^{\alpha n} \leq\left(c_{1} 2^{-c_{2}}\right)^{\alpha n} \tag{2.28}
\end{gather*}
$$

$f(1)=o(1 / n)$ when $c_{2}>1$, and $f(\alpha n)=o(1 / n)$ when $c_{1} 2^{-c_{2}}<1 \Longleftrightarrow c_{2}>\log c_{1}$.
Additionally, both $c_{1}$ and $c_{2}$ might be superconstants in terms of $n$, if this holds:

$$
\begin{equation*}
c_{1}=o\left(n^{c_{2}-1}\right) \tag{2.29}
\end{equation*}
$$

To sum up, given $c_{2}>\max \left\{1, \log c_{1}\right\}$,

$$
S_{n}=\sum_{s=1}^{\alpha n} f(s) \leq \sum_{s=1}^{\alpha n} \max \{f(1), f(\alpha n)\}=o\left(\frac{\alpha n}{n}\right)=o(1) .
$$

Note that if $c_{2}$ in Proposition 2.3 is not large enough, there is no advantage in terms of the size of expanding sets compared to Proposition 2.2:

$$
\begin{equation*}
c_{1} \alpha^{c_{2}}<1 \Longleftrightarrow \alpha<c_{1}^{-1 / c_{2}} \tag{2.30}
\end{equation*}
$$

### 2.2 Generalized Harmonic Numbers and Riemann Zeta Function

Generalized harmonic numbers are defined as

$$
\begin{equation*}
H_{n, m}=\sum_{k=1}^{n} \frac{1}{k^{m}} \tag{2.31}
\end{equation*}
$$

We will extensively use these approximations for large $n$ :

$$
H_{n, \beta} \approx \begin{cases}\frac{n^{1-\beta}}{1-\beta} & \text { if } \beta<1  \tag{2.32}\\ \ln n & \text { if } \beta=1 \\ \zeta(\beta) & \text { if } \beta>1\end{cases}
$$

The zeta function was introduced in 1737 by Euler, later Riemann allowed its argument to be a complex number. Riemann zeta function is defined for all $s \in \mathbb{C}$ with $\Re(s)>1$, see Figure 2.1:

$$
\begin{equation*}
\zeta(s)=\sum_{n=1}^{\infty} \frac{1}{n^{s}} \tag{2.33}
\end{equation*}
$$

For $x \in \mathbb{R}$, we know that $\zeta(x) \approx 1+2^{-x}$ when $x \gg 1$, and $\lim _{x \rightarrow \infty} \zeta(x)=1$.


Figure 2.1: Riemann zeta function for $s \in \mathbb{C}$ with $\Re(s)>1$ and $\Im(s)=0$

For $m>1$ as $n \rightarrow \infty$, applying the Euler-Maclaurin formula (A.1) to the remainders $\sum_{n>N} n^{-s}$ of the sum (2.33) provides the following connection:

$$
\begin{array}{r}
\zeta(s)=H_{N, s}+\frac{1}{(s-1) N^{s-1}}+\frac{1}{2 N^{s}}+O\left(\frac{1}{N^{s+1}}\right), \quad \text { for some } N \gg 1 \\
H_{n, m}=\zeta(m)-\frac{1}{(m-1) n^{m-1}}-\frac{1}{2 n^{m}}-O\left(\frac{1}{n^{m+1}}\right)=\zeta(m)-o(1) \tag{2.35}
\end{array}
$$

### 2.3 Gilbert and Erdős-Rényi Random Graphs

The most commonly used models of uniform random graphs are $G(n, p)$ and $G(n, m)$ introduced by Gilbert [Gil59] and by Erdős and Rényi [ER59].
$G(n, p)$ contains all graphs where each pair of vertices is connected by an edge with probability $p$. We denote the maximum number of edges $N=\binom{n}{2}$, then the expected number of edges in such graphs is $p N$.

$$
\begin{gather*}
\operatorname{Pr}_{G \sim G(n, p)}[G \text { has } m \text { edges }]=\binom{N}{m} p^{m}(1-p)^{N-m}  \tag{2.36}\\
\operatorname{Pr}_{G \sim G(n, p)}[\operatorname{deg}(v)=k]=\binom{n-1}{k} p^{k}(1-p)^{n-k-1}, \text { for } v \in V(G) \tag{2.37}
\end{gather*}
$$

On the other hand, $G(n, m)$ describes the graphs with $n$ vertices and exactly $m$ edges. They may be generated by successively selecting $m$ pairs of not yet connected vertices, so that each of $\binom{N}{m}$ possible graphs is chosen uniformly at random.

Erdős and Rényi [ER60] depict the following structural properties of $G(n, p)$ graphs. When $p=o(1 / n)$, the graph is simply a disjoint union of trees. Then consider the case $p=c / n$, where $c$ is some constant. If $c<1$, the size of the largest component is just $O(\log n)$,
at the critical point $c=1$ its size is $\Theta\left(n^{2 / 3}\right)$, and a unique giant component of size $\Theta(n)$ emerges when $c>1$. Finally, the graphs are disconnected w.h.p. when $p<(1-\epsilon) \log n / n$ and become connected w.h.p. when $p>(1+\epsilon) \log n / n$, for any $\epsilon>0$ [ER59].

As per Chung and Lu [CL01, CL04], the diameter of $G(n, p)$ is $\Theta(\log n)$ when $p=c / n$, for some constant $c>1$, and $(1+o(1)) \frac{\log n}{\log n p}$ if $p=\omega(1 / n)$. The diameter of a disconnected graph is assumed to be the maximum diameter of its connected components.

If we choose $m=p N, G(n, p)$ and $G(n, m)$ models are almost identical for large $n$ and $p>\log n / n$, but some important properties might be different for smaller $p$. For example, let $p=3 / n$ and so $m=\frac{3}{2}(n-1)$. In this case $G(n, p)$ is disconnected w.h.p., while $G(n, m)$ yields a connected graph with high expansion [Mah09] as almost 3-regular.

Independence of edges of $G(n, p)$ makes it similar to our coin toss model for power-law graphs, and $G(n, m)$ corresponds more to $m$ edges model and permutation model, which will be defined in Chapter 3.

### 2.4 Expander Graphs

### 2.4.1 Combinatorial Expansion

First, we look at the combinatorial notions of expansion.
Definition 2.4. A graph $G$ is called $(\alpha n, \gamma)$ edge expander if for some $\gamma>0$

$$
\begin{equation*}
\min _{\substack{S \subset V \\ 0<|S| \leq \alpha n}} \frac{|\partial S|}{|S|} \geq \gamma \tag{2.38}
\end{equation*}
$$

where the left-hand side expression with $\alpha=1 / 2$ is the Cheeger constant $h(G)$, and

$$
\begin{equation*}
\partial S=e(S, V \backslash S)=\{(u, v) \in E \mid u \in S, v \in V \backslash S\} \tag{2.39}
\end{equation*}
$$

Definition 2.5. Analogously, $(\alpha n, \gamma)$ vertex expander satisfies the following condition:

$$
\begin{equation*}
\min _{\substack{S \subset V \\ 0<|S| \leq \alpha n}} \frac{\left|N_{G}(S)\right|}{|S|} \geq \gamma \tag{2.40}
\end{equation*}
$$

where $N_{G}(S)$ is the external neighborhood of $S$ in $G$, i.e.,

$$
\begin{equation*}
N_{G}(S)=\{v \in V \backslash S \mid \exists u \in S,(u, v) \in E\} \tag{2.41}
\end{equation*}
$$

Definition 2.6. ( $\alpha n, \gamma$ ) unique-neighbor expander is a graph satisfying

$$
\begin{equation*}
\min _{\substack{S \subset V \\ 0<|S| \leq \alpha n}} \frac{\mid\{v \in V \backslash S \mid v \text { is adjacent to exactly one } u \in S\} \mid}{|S|} \geq \gamma \tag{2.42}
\end{equation*}
$$

### 2.4.2 Spectral Expansion

Let the vertex $v$ have $\operatorname{deg}(v)$ and define $T=\operatorname{diag}(\operatorname{deg}(v))$. The Laplacian of $G$ without loops or multiple edges is $\mathcal{L}=T^{-\frac{1}{2}} L T^{-\frac{1}{2}}$. If $G$ is $d$-regular, then $\mathcal{L}=I-A / d$ [Chu97].

$$
\begin{align*}
& L_{u, v}= \begin{cases}\operatorname{deg}(v) & \text { if } u=v, \\
-1 & \text { if }(u, v) \in E(G), \\
0 & \text { otherwise. }\end{cases}  \tag{2.43}\\
& \mathcal{L}_{u, v}= \begin{cases}1 & \text { if } u=v \text { and } \operatorname{deg}(v) \neq 0 \\
-\frac{1}{\sqrt{\operatorname{deg}(u) \operatorname{deg}(v)}} & \text { if }(u, v) \in E(G), \\
0 & \text { otherwise. }\end{cases} \tag{2.44}
\end{align*}
$$

The spectrum of $G$ are the eigenvalues of $\mathcal{L}\left\{\lambda_{1}, \ldots, \lambda_{n}\right\}, 0=\lambda_{1} \leq \lambda_{2} \leq \cdots \leq \lambda_{n}$. Eigenvalue 0 has eigenvector $T^{1 / 2} \mathbf{1}$.

Let $g: V \rightarrow \mathbb{R}$ be an arbitrary function, $g=T^{1 / 2} f$ for some $f$, and both $g$ and $f$ are viewed as column vectors. The Rayleigh quotient is

$$
\begin{equation*}
\frac{\langle g, \mathcal{L} g\rangle}{\langle g, g\rangle}=\frac{\sum_{u \sim v}(f(u)-f(v))^{2}}{\sum_{v} f(v)^{2} \operatorname{deg}(v)} \tag{2.45}
\end{equation*}
$$

and it is related to the spectral expansion of $G$, also known as the spectral gap,

$$
\begin{equation*}
\lambda_{G}=\lambda_{2}=\inf _{f \perp T^{\frac{1}{2}} 1} \frac{\sum_{u \sim v}(f(u)-f(v))^{2}}{\sum_{v} f(v)^{2} \operatorname{deg}(v)} \tag{2.46}
\end{equation*}
$$

### 2.4.3 Connections Between Different Types of Expansion

Trivially, vertex expansion $\gamma_{1}$ implies edge expansion $\gamma_{1}$. For $d$-regular graphs, edge expansion $\gamma_{2}$ implies vertex expansion $\gamma_{2} / d$.

The Cheeger inequalities [Che69, HLW06, Chu07] provide the link between combinatorial and spectral expansion:

$$
\begin{gather*}
\frac{h^{2}(G)}{2} \stackrel{(1)}{\leq} \lambda_{G} \stackrel{(2)}{\leq} 2 h(G),  \tag{2.47}\\
\text { or equivalently } \frac{\lambda_{G}}{2} \leq h(G) \leq \sqrt{2 \lambda_{G}} \tag{2.48}
\end{gather*}
$$

### 2.4.4 Construction of Expanders

There are many ways to generate expander graphs: algebraic constructions and zig-zag product [HLW06, Vad12], lifts [AL06], splicers and selectors [FGRV14], local edge flips [ABL ${ }^{+}$16], random coverings of a fixed good expander [Pud15], and so on.

In Chapter 4 we show yet another way - random power-law graphs contain expanding induced subgraphs with vertices of large degrees.

### 2.5 Expansion of Random Regular Graphs

Theorem 2.7 (Theorem 4.16 [HLW06]). $\forall d \geq 3 \forall \delta>0 \exists \gamma, \alpha>0$ such that a random $d$-regular graph on $n$ vertices is $(\alpha n, \gamma)$ edge expander and $(\alpha n, \gamma)$ vertex expander w.h.p., $\gamma=d-2-\delta$.

### 2.5.1 Vertex Expansion of Leftregular Bipartite Graphs

Here $G$ is assumed to be a bipartite multigraph with $n$ vertices on each side.
Definition 2.8. A graph $G$ is called $d$-leftregular if each left-vertex is connected to exactly $d$ vertices from the right. In this case expansion is checked for all subsets $S$ of left-vertices.

Theorem 2.9 ([Vad12]). $\forall d \geq 2 \exists \alpha>0 \forall n:$ a uniformly random d-leftregular $G$ is $(\alpha n, d-2)$ vertex expander w.h.p.

Proof. For a subset $S$ of a fixed size $s \leq \alpha n$ from the left side, $N_{G}(S)$ is a set of at most $s d$ vertices from the right labeled $v_{1}, v_{2}, \ldots, v_{s d}$. For each successively chosen $v_{i}$ from $N_{G}(S)$,

$$
\begin{aligned}
& \operatorname{Pr}_{G, S}\left[v_{i} \in\left\{v_{1}, \ldots, v_{i-1}\right\}\right]=\frac{\left|\left\{v_{1}, \ldots, v_{i-1}\right\}\right|}{n} \leq \frac{i-1}{n} \leq \frac{s d}{n} \\
& \underset{G, S}{\operatorname{Pr}}\left[\left|N_{G}(S)\right| \leq(d-2) s\right] \leq \operatorname{Pr}_{G, S}\left[\text { at least } 2 s \text { repeats in } N_{G}(S)\right] \leq\binom{ s d}{2 s}\left(\frac{s d}{n}\right)^{2 s} \\
& \underset{G}{\operatorname{Pr}}[\exists \text { non-expanding } S] \leq\binom{ n}{s}\binom{s d}{2 s}\left(\frac{s d}{n}\right)^{2 s} \leq\left(\frac{e n}{s}\right)^{s}\left(\frac{e s d}{2 s}\right)^{2 s}\left(\frac{s d}{n}\right)^{2 s}=\left(\frac{e^{3} d^{4} s}{4 n}\right)^{s} \\
& \text { Denote } c=\left(e^{3} d^{4}\right) / 4 \text { and choose } \alpha=e^{-3} d^{-4}, \text { so that } c \alpha=1 / 4 .
\end{aligned}
$$

$$
\operatorname{Pr}_{G}[G \text { is not }(\alpha n, d-2) \text { vertex expander }] \leq \sum_{s=1}^{\alpha n}\left(c \frac{s}{n}\right)^{s}=o(1)
$$

### 2.5.2 Edge Expansion of Regular Graphs

Theorem 2.10 ([Mag06]). $\forall d \geq 3 \forall \delta>0 \exists \gamma, \alpha>0 \forall$ even $n$ : a random d-regular graph $G=\left(V_{G}, E_{G}\right)$ is $(\alpha n, \gamma)$ edge expander w.h.p., $\gamma=d-2-\delta$.

Proof. Consider a new graph $H=\left(V_{H}, E_{H}\right)$ with $d n$ vertices and $E_{H}$ being a uniformly random perfect matching. Partition $V_{H}$ into sets $S_{1}, \ldots, S_{n}$ of size $d$, and identify the vertices from each $S_{i}$ with a single vertex $i$ in $G$.

Let $S \subseteq V_{G}=\{1, \ldots, n\}$ be such that $|S|=s \leq \alpha n$. We can assume $S=\{1, \ldots, s\}$ and it is identified with $S_{1} \cup \ldots \cup S_{s}$. Then to pick $S$ we simply choose $d s$ vertices from $H$.

To upper bound $|\partial(S)|$ we can lower bound the number of edges inside $S$.

$$
\operatorname{Pr}_{G, S}\left[\left|e\left(S, V_{G} \backslash S\right)\right|<\gamma s\right]=\operatorname{Pr}_{G, S}\left[|e(S, S)| \geq \frac{(d-\gamma) s}{2}\right] \leq \frac{\binom{d n / 2}{(d-\gamma) s / 2}\binom{d n-(d-\gamma) s}{\gamma s}}{\binom{d n}{d s}}
$$

$$
\begin{aligned}
\operatorname{Pr}_{G}
\end{aligned} \quad \begin{aligned}
& G \text { is not }(\alpha n, \gamma) \text { edge expander }] \leq \sum_{s=1}^{\alpha n}\binom{n}{s} \frac{\left(e \frac{d n}{(d-\gamma) s}\right)^{(d-\gamma) s / 2}\left(e \frac{d n-(d-\gamma) s}{\gamma s}\right)^{\gamma s}}{\left(\frac{n}{s}\right)^{d s}}= \\
& \\
& \quad=\sum_{s=1}^{\alpha n}\binom{n}{s} \frac{(e d n)^{(d-\gamma) s / 2} e^{\gamma s}(d n-(d-\gamma) s)^{\gamma s} s^{d s}}{((d-\gamma) s)^{(d-\gamma) s / 2}(\gamma s)^{\gamma s} n^{d s}} \leq \\
& \\
& \quad \leq \sum_{s=1}^{\alpha n}\binom{n}{s} \frac{(e d)^{d s / 2}(e d n)^{\gamma s} s^{d s}}{(d-\gamma)^{(d-\gamma) s / 2}(\gamma s)^{\gamma s} n^{d s}}\left(\frac{n}{s}\right)^{(d-\gamma) s / 2}= \\
& \\
& =\sum_{s=1}^{\alpha n}\binom{n}{s} \frac{(e d)^{d s / 2+\gamma s}}{(d-\gamma)^{(d-\gamma) s / 2} \gamma^{\gamma s}}\left(\frac{s}{n}\right)^{(d-\gamma) s / 2} \leq \\
& \\
& \quad \leq \sum_{s=1}^{\alpha n} \frac{(e d)^{d s / 2+\gamma s}}{(d-\gamma)^{(d-\gamma) s / 2}}\left(\frac{e}{\gamma^{\gamma}}\right)^{s}\left(\frac{s}{n}\right)^{\left(\frac{d-\gamma}{2}-1\right) s}= \\
& \\
& =\sum_{s=1}^{\alpha n}\left(c_{1}(s / n)^{c_{2}}\right)^{s},
\end{aligned}
$$

where $c_{1}=\frac{e(e d)^{d / 2+\gamma}}{\gamma^{\gamma}(d-\gamma)^{(d-\gamma) / 2}} \geq 0$ and $c_{2}=\frac{d-\gamma}{2}-1$.
We need $c_{2}>0$, which requires

$$
\begin{equation*}
\gamma<d-2, \tag{2.49}
\end{equation*}
$$

then by Proposition 2.2,
$\underset{G}{\operatorname{Pr}}[G$ is not $(\alpha n, \gamma)$ edge expander $]=o(1)$.
We will prove one of our results, Theorem 4.5, in a similar fashion.
Theorem 2.11 ([Bol88]). Let $d \geq 3$ and $0<\epsilon<1$ be such that

$$
\begin{equation*}
(1-\epsilon) \log (1-\epsilon)+(1+\epsilon) \log (1+\epsilon)>4 / d \tag{2.50}
\end{equation*}
$$

Then any random d-regular graph $G$ has $h(G) \geq(1-\epsilon) d / 2$ w.h.p.
The proof of this result uses the number of matchings between endpoints of edges not crossing the cut ( $S, V \backslash S$ ).

Note that these two theorems sacrifice different parameters. While Theorem 2.10 shows how to achieve almost optimal expansion close to $d-2$, only sufficiently small subsets are expanding. On the contrary, Theorem 2.11 talks about the Cheeger constant $h(G)$, so the subsets may be as large as $n / 2$, but the expansion might be as small as $d / 2$.

### 2.5.3 Vertex Expansion of Regular Graphs

Theorem 2.12 ([Rao12]). $\forall d \geq 3 \forall \delta>0 \exists \gamma, \alpha>0 \forall$ even $n$ : a random d-regular graph $G=(V, E)$ is $(\alpha n, \gamma)$ vertex expander w.h.p., $\gamma=d / 2-2-\delta$.

Proof. Let $E$ be the union of $d$ uniformly random perfect matchings.
For any subset $S$ of size $|S|=s \leq \alpha n$, and any subset $T$ of $(1+\gamma) s$ vertices we will bound the probability that $N_{G}(S) \subseteq T$ under one of the perfect matchings.

Any fixed perfect matching $E^{\prime} \subset E$ might be viewed as connecting one pair of unmatched vertices sequentially, until every vertex has a match. Let $E_{i}$ denote the event that $i$ 'th vertex in $S$ is matched to some vertex in $T$ under $E^{\prime}$. Of course, $E_{i}$ is well defined only for $i \leq\left\lceil\frac{s}{2}\right\rceil$. For the sake of simplicity, lets assume $s$ is even.

$$
\begin{aligned}
& \operatorname{Pr}_{G, S, T, E^{\prime}}^{\operatorname{Pr}}\left[\bigwedge_{i=1}^{s / 2} E_{i}\right]=\prod_{i=1}^{s / 2} \operatorname{Pr}_{G, S, T, E^{\prime}}\left[E_{i} \bigwedge_{k=1}^{i-1} E_{k}\right] \leq \prod_{i=1}^{s / 2} \operatorname{Pr}_{G, S, T, E^{\prime}}\left[E_{i}\right] \leq\left(\frac{(1+\gamma) s}{n}\right)^{s / 2} \\
& \left.\begin{array}{c}
\operatorname{Pr}_{G, S, T}[
\end{array} N_{G}(S) \subseteq T\right] \leq\left(\frac{(1+\gamma) s}{n}\right)^{s d / 2} \\
& \operatorname{Pr}_{G}^{\operatorname{Pr}}[\exists \text { non-expading } S \text { of size } s] \leq\binom{ n}{s}\binom{n}{(1+\gamma) s}\left(\frac{(1+\gamma) s}{n}\right)^{s d / 2} \leq \\
& \quad \leq\left(\frac{e n}{s}\right)^{s}\left(\frac{e n}{(1+\gamma) s}\right)^{(1+\gamma) s}\left(\frac{(1+\gamma) s}{n}\right)^{s d / 2}=\left(\frac{(e n)^{2+\gamma}((1+\gamma) s)^{d / 2}}{n^{d / 2}(1+\gamma)^{1+\gamma} s^{2+\gamma}}\right)^{s}= \\
& \quad=\left(e^{2+\gamma}(1+\gamma)^{d / 2-1-\gamma}\left(\frac{s}{n}\right)^{d / 2-2-\gamma}\right)^{s}= \\
& \quad=\left(c_{1}(s / n)^{c_{2}}\right)^{s} .
\end{aligned}
$$

We need $c_{2}>0$, which requires $\gamma<d / 2-2$. For sufficiently small $\alpha$,
$\operatorname{Pr}_{G}[G$ is not $(\alpha n, \gamma)$ vertex expander $] \leq \sum_{s=1}^{\alpha n}\left(c_{1}(s / n)^{c_{2}}\right)^{s}=o(1)$.

### 2.6 Edge Expansion of Random Graphs With Given Degrees

Gkantsidis et al. [GMS03] deal with the power-law graphs and their model is based on the one from Aiello et al. [ACL01]. However, this following result holds for random graphs with general degree sequences.

Theorem 2.13 (Lemma 3.2 [GMS03]). Let $\left(w_{1}, \ldots, w_{n}\right)$ be a sequence of integers and

$$
\begin{gather*}
w_{1} \geq w_{2} \geq \ldots \geq w_{n} \geq d_{\text {min }}=3  \tag{2.51}\\
D=\sum_{i=1}^{n} w_{i} \tag{2.52}
\end{gather*}
$$

Let $G=(V, E)$ be a random graph with a degree sequence $\left(w_{1}, \ldots, w_{n}\right)$ generated according to the permutation model from Section 3.1.3. Then there is a constant $\gamma>0$ satisfying

$$
\left\{\begin{array}{l}
\gamma<1-2 / d_{\min }  \tag{2.53}\\
\gamma \leq 1-8 /\left(3 d_{\min }\right) \\
\gamma \leq 0.0175
\end{array}\right.
$$

and w.h.p. the conductance of $G$ is $\min _{\substack{S \subset V \\ 0<\operatorname{vol}(S) \leq D / 2}} \frac{|e(S, V \backslash S)|}{\operatorname{vol}(S)} \geq \gamma$, where $\operatorname{vol}(S)=\sum_{i \in S} w_{i}$.

Proof. For a constant $\gamma>0$ a set $S$ with $\operatorname{vol}(S) \leq D / 2$ is called " $\operatorname{bad}$ " if $\frac{|e(S, V \backslash S)|}{\operatorname{vol}(S)}<\gamma$.
We will show that for some $\gamma, \operatorname{Pr}_{G}[\exists \operatorname{bad} S] \leq o(1)$.

$$
\begin{aligned}
& \operatorname{Pr}_{G}[\exists \operatorname{bad} S]=\sum_{k=d_{\text {min }}}^{D / 2} \operatorname{Pr}_{G}[\exists \operatorname{bad} S, \operatorname{vol}(S)=k] \leq \\
& \quad \leq \sum_{k=d_{\text {min }}}^{D / 2}\binom{D / d_{\text {min }}}{k / d_{\min }} \underset{G}{\operatorname{Pr}}[\text { a fixed } S, \operatorname{vol}(S)=k, \text { is bad }] .
\end{aligned}
$$

Let $A$ denote a set of $k$ mini-vertices corresponding to $S$, and $\bar{A}$ to be ( $D-k$ ) minivertices that correspond to $V \backslash S$. Let $B_{A} \subset A$ be a set of mini-vertices matched to the ones from $\bar{A}$, and similarly $B_{\bar{A}} \subset \bar{A}$ is matched to some mini-vertices from $A$. $S$ is "bad" when $\left|B_{A}\right|=\left|B_{\bar{A}}\right|<\gamma k$. For each cardinality from 0 to $\gamma k$, there are at most $\binom{k}{\gamma k}$ and $\binom{D-k}{\gamma k}$ ways to choose $B_{A}$ and $B_{\bar{A}}$ respectively. Then we consider a random perfect matchings with all mini-vertices from $A \backslash B_{A}$ matched inside $A \backslash B_{A}$, and the same for $\bar{A} \backslash B_{\bar{A}}$ and $B_{A} \cup B_{\bar{A}}$.

$$
\underset{G}{\operatorname{Pr}}[\exists \operatorname{bad} S] \leq \sum_{k=d_{\min }}^{D / 2}\binom{D / d_{\min }}{k / d_{\min }} \gamma k\binom{k}{\gamma k}\binom{D-k}{\gamma k} \frac{M(2 \gamma k) M(k-\gamma k) M(D-k-\gamma k)}{M(D)}
$$

We will use the approximation (2.10) for the number of perfect matchings on $m$ vertices, where $c_{1}$ and $c_{2}$ are some positive constants:

$$
\begin{aligned}
& c_{1}(m / e)^{m / 2}<M(m)<c_{2}(m / e)^{m / 2} \\
& \gamma k \frac{M(2 \gamma k) M(k-\gamma k) M(D-k-\gamma k)}{M(D)}< \\
& <c_{4} \gamma k\left(\frac{2 \gamma k}{e}\right)^{\gamma k}\left(\frac{k-\gamma k}{e}\right)^{(k-\gamma k) / 2}\left(\frac{D-k-\gamma k}{e}\right)^{(D-k-\gamma k) / 2}\left(\frac{e}{D}\right)^{D / 2}= \\
& =c_{4} \gamma k \frac{(2 \gamma k)^{\gamma k}(k-\gamma k)^{(k-\gamma k) / 2}(D-k-\gamma k)^{(D-k-\gamma k) / 2}}{D^{D / 2}}< \\
& <c_{4} \gamma k(2 \gamma)^{\gamma k} \frac{k^{(k+\gamma k) / 2}(D-k)^{(D-k-\gamma k) / 2}}{D^{D / 2}}
\end{aligned}
$$

We apply Stirling's approximation (2.9), for some constant $c_{3}>0$.

$$
\begin{aligned}
& \binom{D / d_{\min }}{k / d_{\min }}=\frac{\left(D / d_{\min }\right)!}{\left(k / d_{\min }\right)!\left((D-k) / d_{\min }\right)!}< \\
& \quad<\Theta(1)\left(\frac{D}{d_{\min }}\right)^{D / d_{\min }+1 / 2}\left(\frac{d_{\min }}{k}\right)^{k / d_{\min }+1 / 2}\left(\frac{d_{\min }}{D-k}\right)^{(D-k) / d_{\min }+1 / 2} \leq \\
& \quad \leq c_{3}\left(\frac{D^{D}}{k^{k}(D-k)^{D-k}}\right)^{1 / d_{\min }}
\end{aligned}
$$

Finally, we use $\binom{n}{m} \leq(e n / m)^{m}$.

$$
\binom{k}{\gamma k}\binom{D-k}{\gamma k} \leq\left(\frac{e}{\gamma}\right)^{2 \gamma k}\left(\frac{D-k}{k}\right)^{\gamma k}
$$

Let's combine all of the above.
$\operatorname{Pr}_{G}[\exists \operatorname{bad} S]<\sum_{k=d_{\text {min }}}^{D / 2} c_{5} \gamma k \frac{2^{\gamma k} e^{2 \gamma k}}{\gamma^{\gamma k}}\left(\frac{k}{D}\right)^{k\left((1-\gamma) / 2-1 / d_{\text {min }}\right)}$
Define $\alpha=\frac{2 e^{2}}{\gamma}, \beta=\frac{1-\gamma}{2}-\frac{1}{d_{\text {min }}}$, and

$$
\begin{equation*}
G(k)=c_{5} \gamma k \alpha^{\gamma k}\left(\frac{k}{D}\right)^{\beta k} \tag{2.55}
\end{equation*}
$$

We require $\beta>0$, which means $d_{\min }>\frac{2}{1-\gamma}$, so $d_{\min } \geq 3$. Also $\gamma<1-2 / d_{\text {min }}$.

$$
\begin{align*}
\frac{d G(k)}{d k} & =\left(\frac{1}{k}+\gamma \ln \alpha+\beta \ln \frac{k}{D}+\beta\right) G(k)  \tag{2.56}\\
\frac{d^{2} G(k)}{d k^{2}} & =\left(-\frac{1}{k^{2}}+\frac{\beta}{k}+\left(\frac{d G(k)}{d k}\right)^{2}\right) G(k) \tag{2.57}
\end{align*}
$$

$d G(k) / d k<0$ for $k=3 d_{\text {min }}$ when $D$ is large.
$d^{2} G(k) / d k^{2}>0$ for $k \geq 3 d_{\text {min }}$ and $\gamma \leq 1-8 /\left(3 d_{\text {min }}\right)$.
Clearly, $\sum_{k=d_{\text {min }}}^{3 d_{\text {min }}} G(k)=o(1)$.
To upper bound the sum for $3 d_{\min } \leq k \leq D / 2$, we can use $\max \left\{G\left(3 d_{\min }\right), G(D / 2)\right\}$.

$$
\begin{align*}
& G\left(3 d_{\min }\right)=c_{6} D^{-3 d_{\min } \beta}=o\left(\frac{1}{D}\right)  \tag{2.58}\\
& G(D / 2)=c_{7} D\left(\frac{\alpha^{\gamma}}{2^{\beta}}\right)^{D / 2}=o\left(\frac{1}{D}\right) \tag{2.59}
\end{align*}
$$

for constants $c_{6}, c_{7}$, and

$$
\left\{\begin{array} { l } 
{ 3 d _ { \operatorname { m i n } } \beta > 1 }  \tag{2.60}\\
{ \alpha ^ { \gamma } < 2 ^ { \beta } }
\end{array} \Longrightarrow \left\{\begin{array}{l}
\gamma \leq 1-8 /\left(3 d_{\min }\right) \\
\gamma\left(\frac{1}{2}+2 \log _{2} e-\log _{2} \gamma\right)<\frac{1}{2}-\frac{1}{d_{\min }}
\end{array}\right.\right.
$$

If $d_{\min }=3$, the last inequality holds whenever $\gamma \leq 0.0175$.

$$
\underset{G}{\operatorname{Pr}}[\exists \operatorname{bad} S]<\sum_{k=d_{m i n}}^{3 d_{m i n}} G(k)+\sum_{k=3 d_{m i n}}^{D / 2} G(k) \leq o(1)
$$

### 2.7 Vertex Expanders in Locally Sparse Graphs and $G(n, p)$

For a graph $G=(V, E)$ on $n$ vertices and a subset $W \subseteq V$ set $\operatorname{vol}(W)=\sum_{v \in W} \operatorname{deg}(v)$.
We say that the set $S \subseteq V$ touches an edge, if it contains at least one of its endpoinds, and $S$ spans an edge, if it contains both endpoints.

Theorem 2.14 ([Kri18]). Let $c_{1}>c_{2}>0,0<\alpha<1, \Delta>0$, and $G=(V, E), \Delta(G) \leq$ $\Delta, \frac{|E|}{|V|} \geq c_{1}$. Then there exist a constant $\gamma=\gamma\left(c_{1}, c_{2}, \alpha, \Delta\right)>0$ and poly $(n)$-time algorithm that finds either $W \subset V$ of size $|W| \leq \alpha n$ spanning at least $c_{2}|W|$ edges, or an induced ( $|W| / 2, \gamma$ ) vertex expander on $|W| \geq \alpha n$ vertices.

Proof outline. The idea is to begin with $G$ and iteratively decrease the number of vertices, while maintaining the density. See Algorithm 1 for details.
Proposition 2.15 ([Kri18]). Let $c_{1}>c_{2}>1$ be reals. Define $\alpha=\left(\frac{c_{2}}{5 c_{1}}\right)^{c_{2} /\left(c_{2}-1\right)}$. Let $G$ be a random graph drawn from the probability distribution $G\left(n, \frac{c_{1}}{n}\right)$. Then w.h.p. every set of $k \leq \alpha n$ vertices of $G$ spans fewer than $c_{2} k$ edges.

Proposition 2.16 ([Kri18]). For every $c>0$ and all sufficiently small $\delta>0$ the following holds. Let $G$ be a random graph drawn from the probability distribution $G\left(n, \frac{c}{n}\right)$. Then w.h.p. every set of $\frac{\delta}{\ln 1 / \delta} n$ vertices of $G$ touches fewer than $\delta n$ edges.

Theorem 2.17 (Linear size expanders in $G(n, p)$ graphs [Kri18]). $\forall \epsilon>0 \exists \gamma>0$ : $a$ random graph $G \sim G\left(n, \frac{1+\epsilon}{n}\right)$ contains w.h.p. an induced bounded degree $\left(n^{\prime} / 2, \gamma\right)$ vertex expander on $n^{\prime} \geq \gamma n$ vertices.

Proof outline. A known fact about $G\left(n, \frac{1+\epsilon}{n}\right)$ is the existence of a giant connected component with "enough" edges. Removing a constant fraction of vertices having the highest degree, we get the bounded maximum degree by Proposition 2.16. Then Proposition 2.15 guarantees the local sparsity, and we apply Theorem 2.14.

## Chapter 3

## Random Power-Law Graphs

### 3.1 Models of Graphs

We will work with models of graphs that define either degree sequences or frequencies of degrees. In the latter case one can easily obtain the degree sequence as well, e.g., the frequencies $\left(x_{1}, x_{2}, x_{3}\right)=(2,1,4)$ would be transformed into the degrees $(1,1,2,3,3,3,3)$.

Given a degree sequence $\left(w_{1}, \ldots, w_{n}\right)$, there are several ways to generate corresponding random graphs $G=(V, E)$ [Hop08]. Depending on the particular model, this will be either exact (fixed) or expected degree sequence.

All subsequent models possibly result in pseudographs - multigraphs with self-loops. Therefore, the degree sequences are only required to be pseudographic: degrees must be non-negative, and in case of exact degrees, they should add up to an even number [Hak62].

### 3.1.1 Coin Toss Model

For each pair of vertices $i$ and $j$, we include the edge $(i, j)$ in the graph with probability

$$
p_{i j}=\operatorname{Pr}_{G}[(i, j) \in E]= \begin{cases}\frac{w_{i} w_{j}}{\sum_{k \in V} w_{k}} & \text { if } i \neq j,  \tag{3.1}\\ \frac{w_{i}^{2}}{2 \sum_{k \in V} w_{k}} & \text { otherwise } .\end{cases}
$$

Given expression is a valid probability, if we have

$$
\begin{equation*}
\max _{k} w_{k}^{2}<\sum_{k \in V} w_{k} \tag{3.2}
\end{equation*}
$$

This assumption also implies that the sequence is graphic, i.e., realizable by some graph.
The standard convention is that self-loop edges contribute 2 to the degrees of the nodes. Considering this, we show that the model is well-defined:

$$
\begin{equation*}
\underset{G}{\mathbb{E}}[\operatorname{deg}(i)]=\sum_{j \neq i} p_{i j}+2 p_{i i}=\frac{\sum_{j \neq i} w_{i} w_{j}+w_{i}^{2}}{\sum_{j \in V} w_{j}}=w_{i} \tag{3.3}
\end{equation*}
$$

Alternatively, one can generate a graph by including some number of edges between $i$ and $j$ according to a Poisson process with mean $\lambda=\frac{w_{i} w_{j}}{\sum_{k \in V} w_{k}}$. High degree vertices would then form a clique.

In this model all edges are independent, and $\left(w_{1}, \ldots, w_{n}\right)$ are the expected degrees.

### 3.1.2 $m$ Edges Model

We generate $m=\frac{1}{2} \sum_{k \in V} w_{k}$ edges uniformly at random by successively selecting pairs of vertices with probability proportional to their degrees. In this case $w_{i}$ 's are also expected degrees, however, we get the exact number of edges, which are no longer independent.

### 3.1.3 Permutation Model

We create a sequence with $w_{i}$ mini-vertices for each vertex $i$, randomly permute it, and connect each consecutive non-intersecting pair of mini-vertices with an edge. Equivalently, one can choose a uniformly random perfect matching on this sequence. Then we put an edge between vertices $i$ and $j$ if at least one pair of mini-vertices corresponding to both of them is adjacent.

This model guarantees the exact number of edges and they are not independent, but the degree sequence is now exact.

### 3.1.4 Full Graph Selection Model

We randomly pick a graph $G$ from a family of all graphs with given exact degree sequence, but it is usually not practical.

In this chapter we will examine the properties of power-law graphs under different models.

### 3.2 Coin Toss Power-Law Model

We are given the expected degree sequence $\left(w_{1}, \ldots, w_{n}\right)$, where $w_{v}=\mathbb{E}[\operatorname{deg}(v)]$.

$$
\begin{gather*}
\operatorname{Pr}_{G}[(u, v) \in E]=\frac{w_{u} w_{v}}{\operatorname{Vol}(G)}, \quad \text { assuming } \max _{v} w_{v}^{2}<\operatorname{Vol}(G)  \tag{3.4}\\
\operatorname{Vol}(G)=\underset{G}{\mathbb{E}}[\operatorname{Vol}(G)]=\underset{G}{\mathbb{E}}\left[\sum_{v \in V} \operatorname{deg}(v)\right]=\sum_{v \in V} w_{v} \tag{3.5}
\end{gather*}
$$

Let the expected number of vertices with degree $x$ be equal to $y$, which follows the power-law distribution for some $\alpha=\alpha(n)>0$ and constant $\beta>0$. Note that $\alpha$ and $\beta$ are the only open parameters is this model.

$$
\begin{equation*}
\underset{G}{\mathbb{E}}[|\{v \in V \mid \operatorname{deg}(v)=x\}|]=y=\frac{e^{\alpha}}{x^{\beta}}, \quad \text { where } x \in\left\{1, \ldots, d_{\max }\right\} . \tag{3.6}
\end{equation*}
$$

Table 3.1: Properties of power-law graphs [ACL01], $\beta_{0} \approx 3.4785$

|  | $(0 ; 1)$ | 1 | $(1 ; 2)$ | 2 | $\left(2 ; \beta_{0}\right)$ | $\left(\beta_{0} ; \infty\right)$ |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| the largest <br> component | $n$ | the giant component, $\Theta(n)$ |  |  |  | $O\left(n^{2 / \beta} \log n\right)$ |
| the 2nd largest <br> component | - | $O(1)$ |  | $O\left(\frac{\log n}{\log \log n}\right)$ | $O(\log n)$ |  |
| $\|V\|=n$ | $\frac{e^{\alpha / \beta}}{1-\beta}$ | $\alpha e^{\alpha}$ | $\zeta(\beta) e^{\alpha}$ |  |  |  |
| $\|E\|$ | $\frac{1}{2} \frac{e^{2 \alpha / \beta}}{2-\beta}$ |  |  |  |  | $\frac{1}{4} \alpha e^{\alpha}$ |

Our model is asymptotically identical to Aiello et al. [ACL01], whose properties are summarized in Table 3.1. The only distinction is in defining the expected frequencies instead of the exact ones.

### 3.2.1 Maximum Degree, Expected Size, and the Number of Edges

Like Aiello et al. [ACL01], we ignore isolated vertices, $y \geq 1$ and $0 \leq \ln y=\alpha-\beta \ln x$, consequently, we may deduce

$$
\begin{equation*}
d_{\max }=e^{\alpha / \beta} \tag{3.7}
\end{equation*}
$$

The size of the graph and the expected number of edges are

$$
\begin{equation*}
n=\sum_{x=1}^{e^{\alpha / \beta}} \frac{e^{\alpha}}{x^{\beta}} \quad \underset{G}{\mathbb{E}}[|E|]=\frac{\operatorname{Vol}(G)}{2}=\frac{1}{2} \sum_{x=1}^{e^{\alpha / \beta}} x \frac{e^{\alpha}}{x^{\beta}} \tag{3.8}
\end{equation*}
$$

To get some intuition about the density of $G$, we consider the special case when $d_{\max }=n$.

$$
\begin{gather*}
n=\sum_{x=1}^{n} \frac{e^{\alpha}}{x^{\beta}}=e^{\alpha} H_{n, \beta} \quad e^{\alpha}=\frac{n}{H_{n, \beta}}  \tag{3.9}\\
\underset{G}{\mathbb{E}}[m]=\frac{1}{2} \underset{G}{\mathbb{E}}\left[\sum_{v \in V} \operatorname{deg}(v)\right]=\frac{1}{2} \sum_{x=1}^{n} x \frac{e^{\alpha}}{x^{\beta}}=\frac{e^{\alpha}}{2} \sum_{x=1}^{n} x^{1-\beta}=\frac{e^{\alpha}}{2} H_{n, \beta-1}=\frac{n}{2} \frac{H_{n, \beta-1}}{H_{n, \beta}}  \tag{3.10}\\
H_{n,-1}=\frac{n(n+1)}{2}, \quad H_{n, 0}=n, \quad H_{n, 1}=\log n+O(1), \quad H_{n, \beta}=O(1), \text { if } \beta>1 . \\
\underset{G}{\mathbb{E}}[m]= \begin{cases}\Theta\left(n^{2}\right) & \text { if } \beta=0, \\
\Theta\left(n^{2} / \log n\right) & \text { if } \beta=1, \\
\Theta(n \log n) & \text { if } \beta=2, \\
\Theta(n) & \text { if } \beta>2 .\end{cases} \tag{3.11}
\end{gather*}
$$

### 3.2.2 Expected Volume and Average Degree

When $n \rightarrow \infty$, the expected volume $\operatorname{Vol}(G)$ is well-defined only for $\beta>2$.

$$
\begin{equation*}
\operatorname{Vol}(G) \approx \int_{1}^{\infty} x \frac{e^{\alpha}}{x^{\beta}} d x=\frac{e^{\alpha}}{2-\beta}\left[x^{-\beta+2}\right]_{1}^{\infty}=\frac{e^{\alpha}}{\beta-2} \tag{3.12}
\end{equation*}
$$

On the other hand, considering $d_{\max }=e^{\alpha / \beta}$ we get

$$
\begin{equation*}
\operatorname{Vol}(G) \approx \frac{e^{\alpha}}{2-\beta}\left(\left(e^{\alpha / \beta}\right)^{-\beta+2}-1\right)=\frac{1}{2-\beta}\left(e^{2 \alpha / \beta}-e^{\alpha}\right) \tag{3.13}
\end{equation*}
$$

The expected average degree is

$$
\begin{equation*}
d=\frac{\operatorname{Vol}(G)}{n} \tag{3.14}
\end{equation*}
$$

The second-order average degree is

$$
\tilde{d}=\frac{\sum_{v \in V} w_{v}^{2}}{\operatorname{Vol}(G)} \approx \begin{cases}d \frac{(\beta-2)^{2}}{(\beta-1)(\beta-3)} & \text { if } \beta>3  \tag{3.15}\\ \frac{1}{2} d \ln \frac{2 d_{\text {max }}}{d} & \text { if } \beta=3 \\ d^{\beta-2} \frac{(\beta-2)^{\beta-1} d_{\max }^{3-\beta}}{(\beta-1)^{\beta-2}(3-\beta)} & \text { if } 2<\beta<3\end{cases}
$$

### 3.3 Permutation Power-Law Model

In the permutation model each vertex $v \in\{1, \ldots, n\}$ has exactly $w_{v}$ neighbors chosen with probability proportional to their degrees,

$$
\begin{equation*}
\operatorname{deg}(v)=w_{v}=\frac{p n}{v^{\beta}}, \quad 0<p \leq 1 . \tag{3.16}
\end{equation*}
$$

If $\beta=0$, the coin toss model with expected degree sequence $\left(w_{1}, \ldots, w_{n}\right)$ would be identical to $G(n, p)$ with self-loops:

$$
\begin{gathered}
w_{v}=p n \quad \operatorname{vol}(G)=p n^{2} \quad|E|=\frac{p n^{2}}{2} \\
\operatorname{Pr}_{G}[(u, v) \in E]=\frac{w_{u} w_{v}}{\sum_{i} w_{i}}=\frac{(p n)^{2}}{p n^{2}}=p
\end{gathered}
$$

Note that the degrees $w_{i}$ should be integers so we have to round down (3.16). The issue of emerging error is addressed in Section 4.2.1.

## 3.4 k-CNF Power-Law Model

Generation of CNF $f$ having $m$ clauses with $k$ literals each is done by adding variable $i \in\{1, \ldots, n\}$ with a random sign to the current clause $C \in\left\{C_{1}, \ldots, C_{m}\right\}$ at a position $t$, $1 \leq t \leq k$, with probability $p_{i}=\frac{w_{i}}{\sum_{j=1}^{n} w_{j}}$, where $w_{i}=i^{-\beta}$ [ABL09b].

If any resulting clause is a tautology (it contains both some variable and its negation) or simplifiable (there is the same literal at multiple positions), then it is discarded and regenerated from scratch. Essentially it means that we are choosing variables for each clause without replacement.

The variable incidence graph (VIG) $G(f)=(V, E)$ is defined on $V=\{1, \ldots, n\}$, and edge $(i, j)$ is added to $E$ whenever both $i$ and $j$ appear in the same clause. The signs of the literals are ignored in VIG, so we will ignore them as well, writing " $i \in C$ " instead of " $i \in C \vee-i \in C$ ".

$$
\begin{equation*}
\underset{G(f)}{\operatorname{Pr}}[(i, j) \in E]=1-\prod_{C}(1-\operatorname{Pr}[i \in C \wedge j \in C]) \text {, for } i \neq j \tag{3.17}
\end{equation*}
$$

For simplicity, let's assume $k=3$.

$$
\begin{aligned}
& \operatorname{Pr}[i \in C \wedge j \in C]=\sum_{\substack{1 \leq x \leq n \\
x \notin\{i, j\}}}(\operatorname{Pr}[C=(i, j, x)]+\operatorname{Pr}[C=(j, i, x)]+\ldots+\operatorname{Pr}[C=(x, j, i)]) \\
& p_{x} \leq 1-p_{i}-p_{j} \\
& \operatorname{Pr}[C=(i, j, x)]=p_{i} \frac{p_{j}}{1-p_{i}} \frac{p_{x}}{1-p_{i}-p_{j}} \\
& \operatorname{Pr}[C=(i, x, j)]=p_{i} \frac{p_{x}}{1-p_{i}} \frac{p_{j}}{1-p_{i}-p_{x}}, \text { and so on. }
\end{aligned}
$$

### 3.4.1 Noncentral Hypergeometric Distribution

Sampling of elements from different classes with weights without replacement is captured by Wallenius' noncentral hypergeometric distribution.

We have $\sum_{i=1}^{c} m_{i}$ objects total from $c$ classes, $m_{i}$ is the number of objects of class $i . n$ objects are sampled without replacement. The probability that an object from class $i$ is sampled is proportional to $w_{i}$.

If at step $t$ we have sampled $\left(x_{1, t}, \ldots, x_{c, t}\right)$ objects, i.e., exactly $x_{i, t}$ objects from class $i$, then the probability that the next draw gives an object from class $i$ is

$$
\begin{equation*}
\frac{\left(m_{i}-x_{i, t}\right) w_{i}}{\sum_{j=1}^{c}\left(m_{j}-x_{j, t}\right) w_{j}} \tag{3.18}
\end{equation*}
$$

The multivariate case:

$$
\begin{gather*}
\operatorname{mwnchypg}(\mathbf{x} ; n, \mathbf{m}, \mathbf{w})=\left(\prod_{i=1}^{c}\binom{m_{i}}{x_{i}}\right)\left(\int_{0}^{1} \prod_{i=1}^{c}\left(1-t^{w_{i} / d}\right)^{x_{i}} d t\right)  \tag{3.19}\\
d=\mathbf{w}(\mathbf{m}-\mathbf{x})=\sum_{i=1}^{c} w_{i}\left(m_{i}-x_{i}\right) \tag{3.20}
\end{gather*}
$$

The probability function can be calculated using a variety of methods: recursive calculation, binomial expansion methods, Taylor expansion methods, continued fraction expansion, and numerical integration [Fog08]. At the same time direct formal analysis does not look promising. Instead, we can use the fact that the sequence of expected degrees in VIG $G(f)$ also follows power-law distribution.

Theorem 3.1 (Theorem 1 [ABL09b]). In the $k$-CNF power-law model with continuous probability distribution $\phi(x, \beta)=(1-\beta) x^{-\beta}$, when $n \rightarrow \infty$,

$$
\begin{equation*}
\underset{f}{\operatorname{Pr}}[\text { variable } i \text { has } k \text { occurrences }] \propto k^{-\alpha}, \quad \text { where } \alpha=1 / \beta+1 . \tag{3.21}
\end{equation*}
$$

Let $x_{i}$ be the number of occurrences/clauses with variable $i$.

$$
\begin{equation*}
\operatorname{Pr}\left[x_{i}=k\right]=c k^{-\alpha} \tag{3.22}
\end{equation*}
$$

Events "occurrence of $i$ in clause $C$ " are independent for all clauses, so the actual number of occurrences will be close to its expectation.

$$
\mathbb{E}\left[x_{i}\right]=\sum_{k=1}^{m} k \operatorname{Pr}\left[x_{i}=k\right]=\sum_{k=1}^{m} c k^{1-\alpha}=c H_{m, \alpha-1}
$$

For any pair $(i, j)$, if $x_{i}+x_{j} \geq m$, then $\operatorname{Pr}[(i, j) \in E]=1$ by the pigeonhole principle. Otherwise $x_{i}+x_{j}<m$ and

$$
\begin{aligned}
\operatorname{Pr}_{G(f)} & {[(i, j) \in E]=\operatorname{Pr}[\exists C: i \in C \wedge j \in C]=1-\frac{\binom{m-x_{i}}{x_{j}}}{\binom{m}{x_{j}}}=} \\
& =1-\frac{\left(m-x_{i}\right)!}{\left(m-x_{i}-x_{j}\right)!} \frac{\left(m-x_{j}\right)!}{m!}= \\
& =1-\prod_{k=0}^{x_{j}-1} \frac{m-x_{i}-k}{m-k} .
\end{aligned}
$$

Table 3.2: Properties of the "octopus" graphs [CL04], $\beta^{\prime}$ is the actual exponent

| $\beta$ | $(2 ; 3)$ | 3 | $(3 ; \infty)$ |
| ---: | :---: | :---: | :---: |
| $\beta^{\prime}=1 /(\beta-1)$ | $(1 / 2 ; 1)$ | $1 / 2$ | $(0 ; 1 / 2)$ |
| average distance | $O(\log \log n)$ | $\Theta(\log n / \log \log n)$ | $\Theta(\log n / \log \tilde{d})$ |
| diameter | $\Theta(\log n)$ |  |  |

## 3.5 "Octopus" Power-Law Graph Model

The "octopus" graph model was defined by Chung and Lu [CL04]:

$$
\begin{gather*}
\underset{G}{\mathbb{E}}[\operatorname{deg}(i)]=w_{i}=c i^{-1 /(\beta-1)}  \tag{3.23}\\
i_{0} \leq i<n+i_{0}  \tag{3.24}\\
c=\frac{\beta-2}{\beta-1} d n^{\frac{1}{\beta-1}}  \tag{3.25}\\
i_{0}=n\left(\frac{d(\beta-2)}{d_{\max }(\beta-1)}\right)^{\beta-1} \tag{3.26}
\end{gather*}
$$

The known results about the average distance and the diameter of resulting graphs are collected in Table 3.2. The generation process is the same as in Section 3.1.1.

We consider the same specific family of such graphs, as Chung and Lu [CL04]:

$$
\begin{gather*}
2<\beta<3 \Longrightarrow \frac{1}{2} \leq \frac{1}{\beta-1} \leq 1  \tag{3.27}\\
d>1  \tag{3.28}\\
d_{\max } \gg d  \tag{3.29}\\
\log d_{\max } \gg \log n / \log \log n \tag{3.30}
\end{gather*}
$$

The graphs are generated like in the coin toss model and (3.2) is assumed to be true.
Note that $d_{\max }$ and $d$ are simply parameters of this model.
The maximum degree $w_{i_{0}}=\frac{\beta-2}{\beta-1} d n^{\frac{1}{\beta-1}} i_{0}^{-1 /(\beta-1)}=d_{\text {max }}$.
And the average degree is $\frac{1}{n} \sum_{k=i_{0}}^{n+i_{0}} w_{i} \approx \frac{1}{n} \sum_{k=1}^{n} w_{i}=\frac{1}{n} \sum_{k=1}^{n} \frac{\beta-2}{\beta-1} d n^{\frac{1}{\beta-1}} k^{-1 /(\beta-1)}=$

$$
\begin{aligned}
& =\frac{\beta-2}{\beta-1} \frac{d}{n^{(\beta-2) /(\beta-1)}} \sum_{k=1}^{n} k^{-1 /(\beta-1)} \approx \\
& \approx \frac{\beta-2}{\beta-1} \frac{d}{n^{(\beta-2) /(\beta-1)}} \frac{n^{1-1 /(\beta-1)}}{1-1 /(\beta-1)}=d .
\end{aligned}
$$

### 3.5.1 The Second-Order Average Degree of "Octopus" Graphs

Chung and Lu [CL04] only state the final results, so we provide the derivations here for completeness.

$$
\begin{aligned}
\tilde{d} & =\frac{1}{d n} \sum_{k=1}^{n} w_{i}^{2}=\frac{1}{d n} \sum_{k=1}^{n}\left(\frac{\beta-2}{\beta-1}\right)^{2} d^{2} n^{\frac{2}{\beta-1}} k^{-2 /(\beta-1)}= \\
& =\left(\frac{\beta-2}{\beta-1}\right)^{2} \frac{d}{n^{1-2 /(\beta-1)}} \sum_{k=1}^{n} k^{-2 /(\beta-1)}
\end{aligned}
$$

Case $\beta>3$ :

$$
\tilde{d} \approx\left(\frac{\beta-2}{\beta-1}\right)^{2} \frac{d}{n^{1-2 /(\beta-1)}} \frac{n^{(\beta-3) /(\beta-1)}}{(\beta-3) /(\beta-1)}=\frac{(\beta-2)^{2}}{(\beta-1)(\beta-3)} d
$$

Case $\beta=3$ :

$$
\begin{aligned}
& i_{0}=n\left(\frac{d}{2 d_{\max }}\right)^{2} \\
& \tilde{d} \approx \frac{d}{4} \sum_{k=i_{0}}^{n} k^{-1} \approx \frac{d}{4}\left(\ln n-\ln i_{0}\right)=\frac{d}{4}\left(\ln n-\ln n-2 \ln \frac{d}{2 d_{\max }}\right)=\frac{d}{2} \ln \frac{2 d_{\max }}{d}
\end{aligned}
$$

Case $2<\beta<3$ :

$$
\begin{aligned}
\tilde{d} & \approx\left(\frac{\beta-2}{\beta-1}\right)^{2} \frac{d}{n^{(\beta-3) /(\beta-1)}} \sum_{k=i_{0}}^{n} k^{-2 /(\beta-1)} \approx \\
& \approx\left(\frac{\beta-2}{\beta-1}\right)^{2} \frac{d}{n^{(\beta-3) /(\beta-1)}}\left(\frac{n^{(\beta-3) /(\beta-1)}}{(\beta-3) /(\beta-1)}-\frac{i_{0}^{(\beta-3) /(\beta-1)}}{(\beta-3) /(\beta-1)}\right) \approx \\
& \approx-\frac{(\beta-2)^{2}}{(\beta-1)(\beta-3)} d\left(\frac{d(\beta-2)}{d_{\max }(\beta-1)}\right)^{\beta-3}=\frac{(\beta-2)^{\beta-1}}{(\beta-1)^{\beta-2}(3-\beta)} d^{\beta-2} d_{\max }^{3-\beta} .
\end{aligned}
$$

### 3.5.2 Diameter of "Octopus" Graphs

Theorem 3.2 (Theorem 2.6 [CL04]). Suppose a power-law random graph with exponent $\beta$ has average degree $d>1$ and maximum degree $d_{\max } \gg n^{1 / \log \log n}$. If $2<\beta<3$, its diameter is $\Theta(\log n)$ w.h.p.

Proof outline. The core of the "octopus" graph is defined to contain all vertices of degree at least $n^{1 / \log \log n}$. Combining the following claims gives $O(\log n)$ diameter of the graph w.h.p.

Claim 1: The diameter of the core is $O(\log \log n)$ w.h.p.
Claim 2: Almost all vertices with degree at least $\log n$ are within distance $O(\log \log n)$ from the core.

Claim 3: Each vertex in the giant connected component is within distance $O(\log n)$ from a vertex of degree at least $O(\log n)$.

Such a specific structure explains the name of these graphs.

## Chapter 4

## Expanders in Power-Law Graphs

From now on, we will work with an induced subgraph $H=\left(V_{H}, E_{H}\right)$ of $G$, obtained by retaining only vertices of degree at least $d_{0}$. This definition is both intuitive and easy to work with. We denote the size $\left|V_{H}\right|=n^{\prime}$.

If $H$ is an expander, then outputting $H$ is as simple as checking the degree of each vertex during the process of generation of the graph $G$. Connecting large spectral gap with high combinatorial expansion would allow one to eliminate error of outputting non-expander, but it is still an open problem for our models.

### 4.1 Coin Toss Model

Theorem 4.1 (Existence of an edge expander). $\exists d_{0} \forall c<1 / 3 \forall \delta>0 \exists \gamma, c_{1}=c_{1}(\beta, c)>0$ : let $G=(V, E)$ be a random power-law graph and $H=\left(V_{H}, E_{H}\right)$ be its induced subgraph on $\left|V_{H}\right|=n^{\prime}$ vertices, such that $V_{H}=\left\{v \in V \mid \operatorname{deg}(v) \geq d_{0}\right\}$.

Then if $0<\beta<1$, the whole graph $G$ is $(n / 2, \gamma)$ edge expander w.h.p.
Otherwise, the subgraph $H$ is $\left(n^{\prime} / 2, \gamma\right)$ edge expander w.h.p.

$$
\begin{gather*}
d_{\max }=\max _{v \in V} \operatorname{deg}(v)  \tag{4.1}\\
d_{0}= \begin{cases}1 & \text { if } 0<\beta<1, \\
d_{\max } / \sqrt{n} & \text { if } \beta=1, \\
\frac{d_{\max }}{n^{1 / \beta}} & \text { if } 1<\beta \leq 1.6, \\
c d_{\max } & \text { if } \beta>1.6 .\end{cases} \tag{4.2}
\end{gather*}
$$

$$
\begin{align*}
& n^{\prime}= \begin{cases}n & \text { if } 0<\beta<1, \\
n / 2 \quad & \text { if } \beta=1, \\
\frac{n}{(\beta-1) \zeta(\beta)^{1 / \beta}} & \text { if } 1<\beta \leq 1.6, \\
\frac{c^{-\beta+1}-1}{\beta-1}(n / \zeta(\beta))^{1 / \beta}=\Theta\left(n^{1 / \beta}\right) & \text { if } \beta>1.6 .\end{cases}  \tag{4.3}\\
& c_{1}= \begin{cases}\frac{(1-\beta)^{2}}{2-\beta} & \text { if } 0<\beta<1, \\
\frac{1-c}{(\ln 1 / c)^{2}} & \text { if } \beta=1, \\
\frac{(\beta-1)^{2}}{2-\beta} \frac{1-c^{2-\beta}}{\left(c^{-\beta+1}-1\right)^{2}} & \text { if } 1<\beta<2 \text { or } \beta>2, \\
\frac{\ln 1 / c}{(1 / c-1)^{2}} & \text { if } \beta=2 .\end{cases} \tag{4.4}
\end{align*}
$$

In all cases the average degree $d$ and the expansion $\gamma$ are as follows:

$$
\begin{gather*}
d=c_{1} n^{\prime}  \tag{4.5}\\
\gamma=\frac{d}{2}-\delta \tag{4.6}
\end{gather*}
$$

The proof of the theorem is on page 36 .
Lemma 4.2. $\forall \delta>0 \exists \gamma$ : If the expected average degree of a graph $H$ on $n^{\prime}$ vertices is $d>10 \ln n^{\prime}$, then $H$ is $\left(n^{\prime} / 2, \gamma\right)$ edge expander w.h.p., $\gamma=d / 2-\delta$.

Proof. Given an arbitrary cut $(S, T): e(S, T)=\left\{(u, v) \in E_{H} \mid u \in S, v \in T\right\}$. Using (3.4),

$$
\begin{equation*}
\underset{G}{\mathbb{E}}[|e(S, T)|]=\frac{\operatorname{Vol}(S) \operatorname{Vol}(T)}{\operatorname{Vol}(H)} \tag{4.7}
\end{equation*}
$$

The volume of an arbitrary subset $S \subset V_{H}$ of a fixed size $|S|=s \leq n^{\prime} / 2$ is $\operatorname{Vol}(S)=s d$, where $d=\operatorname{Vol}(H) / n^{\prime}$ is the expected average degree of $H$.

Define a random variable $X_{S}$ to be the size of a cut ( $S, V_{H} \backslash S$ ) with expected value $\mu$.

$$
\begin{gather*}
X_{S}=\left|e\left(S, V_{H} \backslash S\right)\right|  \tag{4.8}\\
\mu=\underset{G}{\mathbb{E}}\left[X_{S}\right]=\frac{\operatorname{Vol}(S) \operatorname{Vol}\left(V_{H} \backslash S\right)}{\operatorname{Vol}(H)}=\operatorname{Vol}(S)\left(1-\frac{s}{n^{\prime}}\right)  \tag{4.9}\\
\frac{\mu}{s}=d\left(1-\frac{s}{n^{\prime}}\right)  \tag{4.10}\\
\frac{d}{2} \leq \frac{\mu}{s} \leq d \tag{4.11}
\end{gather*}
$$

We will use the Chernoff bound for the lower tail (2.4) for some $0<\lambda<1$.

$$
\begin{gather*}
\gamma s=(1-\lambda) \mu \\
0<\lambda=1-\gamma s / \mu \\
\gamma<\mu / s \tag{4.12}
\end{gather*}
$$

Therefore, the only requirement is $\gamma<d / 2$. Now, as for the expansion of $H$,
$\operatorname{Pr}_{G, S}[S$ is non-expanding $]=\operatorname{Pr}_{G, S}\left[X_{S} \leq \gamma s\right] \leq \exp \left(-\lambda^{2} \mu / 2\right)=\exp \left(-(\mu-\gamma s)^{2} / 2 \mu\right)=$

$$
=\exp \left(-\mu / 2+\gamma s-\gamma^{2} s^{2} / 2 \mu\right) \leq \exp (\gamma s-\mu / 2)
$$

$\operatorname{Pr}_{G}^{\operatorname{Pr}}\left[H\right.$ is not $\left(n^{\prime} / 2, \gamma\right)$ edge expander $] \leq \sum_{s=1}^{n^{\prime} / 2}\binom{n^{\prime}}{s} \underset{G, S}{\operatorname{Pr}}[S$ is non-expanding $] \leq$

$$
\leq \sum_{s=1}^{n^{\prime} / 2}\left(\frac{e n^{\prime}}{s} \exp \left(-\frac{(\mu / s-\gamma)^{2}}{2 \mu / s}\right)\right)^{s}=\sum_{s=1}^{n^{\prime} / 2} \exp \left(\left(1+\ln \frac{n^{\prime}}{s}-\frac{(\mu / s-\gamma)^{2}}{2 \mu / s}\right) s\right) \leq
$$

$$
\leq \sum_{s=1}^{n^{\prime} / 2} \exp \left(\left(1-\ln \frac{s}{n^{\prime}}-\frac{d}{2}\left(1-s / n^{\prime}\right)+\gamma-\frac{\gamma^{2}}{2 d\left(1-s / n^{\prime}\right)}\right) s\right) \leq
$$

$$
\leq \sum_{s=1}^{n^{\prime} / 2} \exp \left(\left(1+\ln n^{\prime}-\frac{d}{4}+\gamma\right) s\right) \leq
$$

$$
\leq \sum_{s=1}^{n^{\prime} / 2}\left(\frac{1}{n^{\prime(1+\sigma)}}\right)^{s} \leq \frac{n^{\prime} / 2}{n^{\prime(1+\sigma)}}=o(1)
$$

The last line is obtained if we satisfy this inequality for some small constant $\sigma>0$ :

$$
\begin{gathered}
1+\ln n^{\prime}-\frac{d}{4}+\gamma \leq-(1+\sigma) \ln n^{\prime} \\
0<\gamma \leq \frac{d}{4}-(2+\sigma) \ln n^{\prime}-1 \\
d>4\left((2+\sigma) \ln n^{\prime}+1\right) \\
d>10 \ln n^{\prime}
\end{gathered}
$$

Lemma 4.3 (Size and volume of the subgraph H). If $d_{0}=c d_{\text {max }}$ for $0<c<1$, then

$$
\begin{gather*}
n^{\prime}= \begin{cases}\left(1-c^{1-\beta}\right) n & \text { if } \beta<1, \\
\frac{\ln 1 / c}{\alpha} n \approx(\ln 1 / c) \frac{n}{\ln n} & \text { if } \beta=1, \\
\frac{c^{-\beta+1}-1}{\beta-1}(n / \zeta(\beta))^{1 / \beta} & \text { if } \beta>1 .\end{cases}  \tag{4.13}\\
\operatorname{Vol}(H)= \begin{cases}\frac{1-c^{2-\beta}}{2-\beta} e^{2 \alpha / \beta} & \text { if } \beta<2, \\
(\ln 1 / c) e^{\alpha} & \text { if } \beta=2, \\
\frac{c^{-\beta+2}-1}{\beta-2} e^{2 \alpha / \beta}+\frac{c^{-\beta+1}-1}{2} e^{\alpha / \beta} & \text { if } \beta>2 . \\
d=\frac{\operatorname{Vol}(H)}{n^{\prime}}=\Theta\left(n^{\prime}\right)\end{cases} \tag{4.14}
\end{gather*}
$$

Proof. Consider (3.8) and $n^{\prime}=\sum_{x=d_{0}}^{d_{\text {max }}} \frac{e^{\alpha}}{x^{\beta}}, \operatorname{Vol}(H)=\sum_{x=d_{0}}^{d_{\text {max }}} x \frac{e^{\alpha}}{x^{\beta}}$.
Case $\beta<1$ : similarly to (3.13),

$$
n=\frac{e^{\alpha / \beta}}{1-\beta} \quad n^{\prime}=\frac{e^{\alpha}}{1-\beta}\left(d_{\max }^{1-\beta}-d_{0}^{1-\beta}\right)=\frac{1-c^{1-\beta}}{1-\beta} e^{\alpha / \beta}
$$

Case $\beta=1$ : $d_{\text {max }}=e^{\alpha}$.

$$
n=\left(\ln d_{\max }\right) e^{\alpha}=\alpha e^{\alpha} \quad n^{\prime}=\left(\ln d_{\max }-\ln d_{0}\right) e^{\alpha}=(\ln 1 / c) e^{\alpha}
$$

Case $\beta>1$ :

$$
\begin{aligned}
n= & e^{\alpha} H_{d_{\text {max }}, \beta} \\
n^{\prime}= & e^{\alpha}\left(H_{d_{\text {max }}, \beta}-H_{c d_{\text {max }}, \beta}\right)=\left(1-\frac{H_{c d_{\text {max }}, \beta}}{H_{d_{\max }, \beta}}\right) n= \\
& =\left(1-\frac{\zeta(\beta)-\frac{1}{(\beta-1)\left(c d_{\max }\right)^{\beta-1}}-\frac{1}{2\left(c d_{\text {max }}\right)^{\beta}}-O\left(\frac{1}{\left(c d_{\text {max }}\right)^{\beta+1}}\right)}{\zeta(\beta)-\frac{1}{(\beta-1) d_{\text {max }}^{\beta-1}}-\frac{1}{2 d_{\text {max }}^{\beta}}-O\left(\frac{1}{d_{\text {max }}^{\beta+1}}\right)}\right) n= \\
& =\left(\frac{\frac{c^{-\beta+1}-1}{(\beta-1) d_{\text {max }}^{\beta-1}}+\frac{c^{-\beta}-1}{2 d_{\text {max }}^{\beta}}+O\left(\frac{1}{d_{\text {max }}^{\beta+1}}\right)}{\zeta(\beta)-\frac{1}{(\beta-1) d_{\text {max }}^{\beta-1}}-\frac{1}{2 d_{\text {max }}^{\beta}}-O\left(\frac{1}{d_{\text {max }}^{\beta+1}}\right)}\right) n= \\
& =\left(\frac{c^{-\beta+1}-1}{(\beta-1) d_{\text {max }}^{\beta-1}}+\frac{c^{-\beta}-1}{2 d_{\text {max }}^{\beta}}+O\left(\frac{1}{d_{\text {max }}^{\beta+1}}\right)\right) e^{\alpha}= \\
& =\frac{c^{-\beta+1}-1}{\beta-1} d_{\text {max }}+\frac{c^{-\beta}-1}{2}+O\left(\frac{1}{d_{\text {max }}}\right) \approx \\
& \approx \frac{c^{-\beta+1}-1}{\beta-1} e^{\alpha / \beta} \approx \frac{c^{-\beta+1}-1}{\beta-1}\left(\frac{n}{\zeta(\beta)}\right)^{1 / \beta} .
\end{aligned}
$$

Now for the expected volume, case $\beta<2$ :

$$
\operatorname{Vol}(H)=\frac{e^{\alpha}}{2-\beta}\left(d_{\max }^{2-\beta}-d_{0}^{2-\beta}\right)=\frac{1-c^{2-\beta}}{2-\beta} e^{2 \alpha / \beta}
$$

Case $\beta=2: d_{\max }=e^{\alpha / 2}$.

$$
\operatorname{Vol}(H)=\left(\ln d_{\max }-\ln d_{0}\right) e^{\alpha}=(\ln 1 / c) e^{\alpha}
$$

Case $\beta>2$ :

$$
\begin{gathered}
\operatorname{Vol}(H)=e^{\alpha}\left(H_{d_{\max }, \beta-1}-H_{c d_{\max }, \beta-1}\right)= \\
=\left(-\frac{1}{(\beta-2) d_{\max }^{\beta-2}}-\frac{1}{2 d_{\max }^{\beta-1}}+\frac{1}{(\beta-2)\left(c d_{\max }\right)^{\beta-2}}+\frac{1}{2\left(c d_{\max }\right)^{\beta-1}}+O\left(\frac{1}{d_{\max }^{\beta}}\right)\right) e^{\alpha}= \\
=\left(\frac{c^{-\beta+2}-1}{(\beta-2) d_{\max }^{\beta-2}}+\frac{c^{-\beta+1}-1}{2 d_{\max }^{\beta-1}}+O\left(\frac{1}{d_{\max }^{\beta}}\right)\right) e^{\alpha}= \\
=\frac{c^{-\beta+2}-1}{\beta-2} d_{\max }^{2}+\frac{c^{-\beta+1}-1}{2} d_{\max }+O(1) \approx \\
\approx \frac{c^{-\beta+2}-1}{\beta-2} e^{2 \alpha / \beta}+\frac{c^{-\beta+1}-1}{2} e^{\alpha / \beta}
\end{gathered}
$$

Finally, the average degree is always $\Theta\left(n^{\prime}\right)$.

$$
d=\frac{\operatorname{Vol}(H)}{n^{\prime}}= \begin{cases}\frac{1-\beta}{2-\beta} \frac{1-c^{2-\beta}}{1-c^{1-\beta}} e^{\alpha / \beta} & \text { if } \beta<1, \\ \frac{1-c}{\ln 1 / c} e^{\alpha} & \text { if } \beta=1, \\ \frac{\beta-1}{2-\beta} \frac{1-c^{2-\beta}}{c^{-\beta+1}-1} e^{\alpha / \beta} & \text { if } 1<\beta<2, \\ \frac{\ln 1 / c}{1 / c-1} e^{\alpha / 2} & \text { if } \beta=2, \\ \frac{\beta-1}{\beta-2} \frac{c^{-\beta+2}-1}{c^{-\beta+1}-1} e^{\alpha / \beta}+O(1) & \text { if } \beta>2 .\end{cases}
$$

Considering $H$ independently from $G \backslash H$, we need to account for $e(H, G \backslash H)$.

$$
\begin{gather*}
\operatorname{Vol}(G)= \begin{cases}\Theta\left(n^{2}\right) & \text { if } \beta<1, \\
\Theta\left(\left(\frac{n}{\log n}\right)^{2}\right) & \text { if } \beta=1, \\
\Theta\left(n^{2 / \beta}\right) & \text { if } 1<\beta<2, \\
\Theta(n \log n) & \text { if } \beta=2, \\
\Theta(n) & \text { if } \beta>2 .\end{cases}  \tag{4.16}\\
\operatorname{Vol}(H)=\sum_{v \in H} w_{v}=\Theta\left(n^{\prime 2}\right)= \begin{cases}\Theta\left(n^{2}\right) & \text { if } \beta<1, \\
\Theta\left(\begin{array}{l}
\left.\left(\frac{n}{\log n}\right)^{2}\right)
\end{array}\right. & \text { if } \beta=1, \\
\Theta\left(n^{2 / \beta}\right)\end{cases}  \tag{4.17}\\
2|e(H)|=\operatorname{Vol}(H)-|e(H, G \backslash H)|  \tag{4.18}\\
|e(H, G \backslash H)|=\frac{\operatorname{Vol}(H) \operatorname{Vol}(G \backslash H)}{\operatorname{Vol}(G)}  \tag{4.19}\\
|e(G)|=\frac{\operatorname{Vol}(H)^{2}}{2 \operatorname{Vol}(G)}=|e(H)|+|e(H, G \backslash H)|+|e(G \backslash H)|=
\end{gather*}, \begin{aligned}
& \operatorname{Vol}(H)^{2} / 2+\operatorname{Vol}(H) \operatorname{Vol}(G \backslash H)+\operatorname{Vol}(G \backslash H)^{2} / 2  \tag{4.20}\\
& =
\end{aligned}
$$

How much smaller would $2 e(H)$ be than $\operatorname{Vol}(H)$ that we use?

$$
\begin{gather*}
2 e(H)=\frac{\operatorname{Vol}(H)^{2}}{\operatorname{Vol}(G)}=\operatorname{Vol}(H) x  \tag{4.22}\\
x=\frac{\operatorname{Vol}(H)}{\operatorname{Vol}(G)}= \begin{cases}\Theta(1) & \text { if } \beta<2, \\
\frac{1}{\log _{1}} & \text { if } \beta=2, \\
n^{1-2 / \beta} & \text { if } \beta>2 .\end{cases} \tag{4.23}
\end{gather*}
$$

It means the larger $\beta$, the fewer edges are between high-degree vertices in $H$ than edges from $H$ to low-degree vertices in $G \backslash H$.

In order to get larger subgraph $H$ for $\beta \geq 1$, we need to include more vertices in $H$.
Lemma 4.4 (Linear size subgraph H ). When $\beta=1$, leaving the vertices of degree at least $d_{0}=d_{\max } / \sqrt{n}$ results in the subgraph $H$ of size $n^{\prime}=n / 2$. And when $1<\beta \leq 1.6$, we pick $d_{0}=\frac{d_{\max }}{n^{1 / \beta}}$ to get $H$ of size $n^{\prime}=\Theta(n)$.

Proof. Case $\beta=1: d_{\max }=e^{\alpha}$. In this case $n=\alpha e^{\alpha}$ and $\alpha \approx \ln n$ by (A.4).

$$
\begin{gathered}
d_{0}=d_{\max } e^{-x} \\
\ln d_{0}=\ln d_{\max }-x \\
n^{\prime}=\left(\ln d_{\max }-\ln d_{0}\right) \frac{n}{\alpha}=\frac{x n}{\alpha} \\
x=\frac{\ln n}{2}: \quad d_{0}=\frac{d_{\max }}{\sqrt{n}}, \quad n^{\prime} \approx \frac{n}{2} \\
x=c \ln n: \quad d_{0}=\frac{d_{\max }}{n^{c}}, \quad n^{\prime} \approx c n
\end{gathered}
$$

$$
\begin{gathered}
\operatorname{Vol}(H)=e^{\alpha}\left(d_{\text {max }}-d_{\text {max }} n^{-c}\right)=e^{2 \alpha}\left(1-n^{-c}\right) \\
d=\frac{\operatorname{Vol}(H)}{n^{\prime}}=\frac{e^{\alpha}}{c \alpha}\left(1-n^{-c}\right)=\frac{n^{\prime}}{c^{2} \alpha^{2}}\left(1-\left(n^{\prime} / c\right)^{-c}\right) \approx \frac{1}{c^{2}}\left(1-\left(n^{\prime} / c\right)^{-} c\right) \frac{n^{\prime}}{\left(\ln \left(n^{\prime} / c\right)\right)^{2}}
\end{gathered}
$$

If $c=1 / 2, \quad d \approx 4\left(1-\frac{1}{\sqrt{2 n^{\prime}}}\right) \frac{n^{\prime}}{\left(\ln \left(2 n^{\prime}\right)\right)^{2}}=\omega\left(\ln n^{\prime}\right)$.
Case $\beta>1$ :

$$
\begin{gathered}
n^{\prime}=\left(1-\frac{H_{x, \beta}}{H_{d_{\max }, \beta}}\right) n \\
1-\frac{H_{x, \beta}}{H_{d_{\max }, \beta}}=c \\
(1-c) H_{d_{\max }, \beta}=H_{x, \beta} \\
(1-c) \sum_{k=1}^{d_{\max }} \frac{1}{k^{\beta}}=\sum_{k=1}^{x} \frac{1}{k^{\beta}} \quad(1-c) \sum_{k=x+1}^{d_{\max }} \frac{1}{k^{\beta}}=c \sum_{k=1}^{x} \frac{1}{k^{\beta}}
\end{gathered}
$$

Known special case: $H_{2 x, 2}=\frac{1}{2}\left(\zeta(2)+\frac{1}{2}\left(H_{x, 2}+H_{x-\frac{1}{2}, 2}\right)\right)$

$$
\begin{gathered}
(1-c)\left(\zeta(\beta)-\frac{1}{(\beta-1) d_{\max }^{\beta-1}}-\frac{1}{2 d_{\text {max }}^{\beta}}-O\left(\frac{1}{d_{\text {max }}^{\beta+1}}\right)\right)= \\
=\zeta(\beta)-\frac{1}{(\beta-1) x^{\beta-1}}-\frac{1}{2 x^{\beta}}-O\left(\frac{1}{x^{\beta+1}}\right) \\
\frac{1}{(\beta-1) x^{\beta-1}}+\frac{1}{2 x^{\beta}}-\frac{1-c}{(\beta-1) d_{\max }^{\beta-1}}-\frac{1-c}{2 d_{\text {max }}^{\beta}}+O\left(\frac{1}{x^{\beta+1}}\right)=c \zeta(\beta)
\end{gathered}
$$

$$
\begin{gathered}
(1-c) H_{d_{\max }, \beta}=H_{x, \beta} \\
(1-c) \sum_{k=1}^{d_{\max }} \frac{1}{k^{\beta}}=\sum_{k=1}^{x} \frac{1}{k^{\beta}} \\
\zeta(\beta)-H_{a, \beta}=\int_{a}^{\infty} \frac{1}{t^{\beta}} d t+\frac{1}{2 a^{\beta}}-\sum_{i=2}^{k} \frac{b_{i}}{i!} f^{(i-1)}(a)-\int_{a}^{\infty} \frac{B_{k}(\{1-t\})}{k!} f^{(k)}(t) d t= \\
=\frac{1}{(\beta-1) a^{\beta-1}}+\frac{1}{2 a^{\beta}}-\frac{-\beta}{12 a^{\beta+1}}-O\left(\frac{1}{a^{\beta+1}}\right) \\
(1-c) H_{d_{\text {max }}, \beta}=(1-c)\left(\zeta(\beta)-\frac{1}{(\beta-1) d_{\max }^{\beta-1}}-\frac{1}{2 d_{\max }^{\beta}}+O\left(\frac{1}{d_{\max }^{\beta+1}}\right)\right) \\
H_{d_{0}, \beta}=\zeta(\beta)-\frac{1}{(\beta-1) d_{0}^{\beta-1}}-\frac{1}{2 d_{0}^{\beta}}+O\left(\frac{1}{d_{0}^{\beta+1}}\right)
\end{gathered}
$$

If $d_{0}=x d_{\text {max }}$,

$$
\begin{gathered}
d_{\max }=e^{\alpha / \beta} \\
n=e^{\alpha} H_{d_{\max , \beta}, \beta} \approx e^{\alpha} \zeta(\beta)=d_{\max }^{\beta} \zeta(\beta) \\
n^{\prime}=e^{\alpha}\left(H_{d_{\max }, \beta}-H_{x d_{\max }, \beta}\right)= \\
=e^{\alpha}\left(\frac{x^{-\beta+1}-1}{(\beta-1) d_{\max }^{\beta-1}}+\frac{x^{-\beta}-1}{2 d_{\max }^{\beta}}+O\left(\frac{1}{d_{\max }^{\beta+1}}\right)\right)= \\
=\frac{x^{-\beta+1}-1}{(\beta-1)} d_{\max }+\frac{x^{-\beta}-1}{2}+O\left(\frac{1}{d_{\max }}\right) \approx \frac{x^{-\beta+1}-1}{(\beta-1)}\left(\frac{n}{\zeta(\beta)}\right)^{1 / \beta}
\end{gathered}
$$

We now choose $x=n^{y}$.

$$
\begin{aligned}
& n^{\prime} \approx \frac{n^{1 / \beta-y(\beta-1)}}{(\beta-1) \zeta(\beta)^{1 / \beta}} \\
& 1 / \beta-y(\beta-1)=1 \\
& y=\frac{1 / \beta-1}{\beta-1}=-1 / \beta
\end{aligned}
$$

$$
d_{0}=\frac{d_{\max }}{n^{1 / \beta}} \Longrightarrow n^{\prime} \approx \frac{n}{(\beta-1) \zeta(\beta)^{1 / \beta}}=\Theta(n)
$$

We note that $(\beta-1) \zeta(\beta)^{1 / \beta}>1$ requires $\beta \leq 1.6$.

Finally, we get the expected average degree $d$ for different ranges of $\beta$ :

$$
\begin{aligned}
& d=\frac{\operatorname{Vol}(H)}{n^{\prime}}=\frac{H_{d_{\max }, \beta-1}-H_{d_{0}, \beta-1}}{H_{d_{\max }, \beta}-H_{d_{0}, \beta}} \\
& 1<\beta<2: d=\frac{d_{\max }^{2-\beta}-d_{0}^{2-\beta}}{(2-\beta) \Theta(1)}=\frac{1-n^{-(2-\beta) / \beta}}{(2-\beta) \Theta(1)} d_{\max }^{2-\beta}=\Theta\left(d_{\max }^{2-\beta}\right)=\Theta\left(n^{\prime(2-\beta) / \beta}\right) \\
& \beta=2: d=\frac{\ln d_{\max }-\ln d_{0}}{\Theta(1)}=\frac{\frac{1}{\beta} \ln n}{\Theta(1)}=\Theta\left(\ln n^{\prime}\right) \\
& \beta>2: d=\Theta(1)
\end{aligned}
$$

We can see that Lemma 4.2 is applicable for $1 \leq \beta \leq 1.6$ because $d=\omega\left(\ln n^{\prime}\right)$.
Proof of Theorem 4.1. For $1 \leq \beta \leq 1.6$ we use Lemma 4.4 and Lemma 4.2 and we are done.
Otherwise, we get $n^{\prime}$ and $\operatorname{Vol}(H)$ from Lemma 4.3, which covers all possible values of $\beta$.
Case $0<\beta<1$ :

$$
\operatorname{Vol}(S)=s \frac{1-\beta}{2-\beta} \frac{1-c^{2-\beta}}{1-c^{1-\beta}} e^{\alpha / \beta}=\frac{(1-\beta)^{2}}{2-\beta} \frac{1-c^{2-\beta}}{\left(1-c^{1-\beta}\right)^{2}} s n^{\prime}
$$

Let $c_{1}=\frac{(1-\beta)^{2}}{2-\beta} \frac{1-c^{2-\beta}}{\left(1-c^{1-\beta}\right)^{2}}>0$, then $\operatorname{Vol}(S)=c_{1} s n^{\prime}$.
${\underset{G}{\mathrm{Pr}}, S}[S$ is non-expanding $] \leq \exp (\gamma s-\mu / 2)=\exp \left(\left(\gamma-c_{1}\left(n^{\prime}-s\right) / 2\right) s\right)$.
$\underset{G}{\operatorname{Pr}}\left[H\right.$ is not $\left(\epsilon n^{\prime}, \gamma\right)$ edge expander $] \leq \sum_{s=1}^{\epsilon n^{\prime}}\binom{n^{\prime}}{s} \underset{G, S}{\operatorname{Pr}}[S$ is non-expanding $] \leq$

$$
\leq \sum_{s=1}^{\epsilon n^{\prime}}\left(e^{\gamma+1} \frac{n^{\prime}}{s} e^{-c_{1}\left(n^{\prime}-s\right) / 2}\right)^{s}=o(1) .
$$

When $1 \leq s \leq \epsilon n^{\prime}$, the last equality holds for any $\epsilon>0$ satisfying the following condition:

$$
\begin{gathered}
e^{\gamma+1} \frac{n^{\prime}}{s} e^{-c_{1}\left(n^{\prime}-s\right) / 2}<\frac{1}{10} \\
e^{\gamma+1} n^{\prime} e^{-c_{1} n^{\prime}(1-\epsilon) / 2}<\frac{1}{10} \\
c_{1} n^{\prime}(1-\epsilon) / 2>\ln \left(10 e^{\gamma+1} n^{\prime}\right) \\
\epsilon<1-\frac{2}{c_{1} n^{\prime}} \ln \left(10 e^{\gamma+1} n^{\prime}\right)=1-\frac{\ln \left(c_{2} n^{\prime}\right)}{c_{3} n^{\prime}}=1-o(1)
\end{gathered}
$$

We choose $\epsilon=1 / 2$.
To satisfy the requirement (4.12) when $1 \leq s \leq n^{\prime} / 2$,

$$
\begin{gathered}
\gamma<\mu / s=c_{1}\left(1-\frac{s}{n^{\prime}}\right) n^{\prime} \\
\gamma=\frac{c_{1}}{2} n^{\prime}-\delta, \text { for any } \delta \geq 0
\end{gathered}
$$

Finally, we restrict $c<1 / 3$ to have $c_{1} \leq 1$ and $\operatorname{Vol}(S) \leq s n^{\prime}$.

Note that if $0<\beta<1$ and $d_{0}=1$, then $n^{\prime}=n$ and $\operatorname{Vol}(H)=\operatorname{Vol}(G)$ but the argument still holds, i.e., the whole graph $G$ is an edge expander w.h.p.

Case $\beta=1$ :

$$
\operatorname{Vol}(S)=s \frac{1-c}{\ln 1 / c} e^{\alpha}=\frac{1-c}{(\ln 1 / c)^{2}} s n^{\prime}
$$

Let $c_{1}=\frac{1-c}{(\ln 1 / c)^{2}}>0$, then $\operatorname{Vol}(S)=c_{1} s n^{\prime}$.
The rest of the proof is identical to the previous case, but necessarily $c>0$.
Case $1<\beta<2$ :

$$
\operatorname{Vol}(S)=s \frac{\beta-1}{2-\beta} \frac{1-c^{2-\beta}}{c^{-\beta+1}-1} e^{\alpha / \beta}=\frac{(\beta-1)^{2}}{2-\beta} \frac{1-c^{2-\beta}}{\left(c^{-\beta+1}-1\right)^{2}} s n^{\prime}
$$

Let $c_{1}=\frac{(\beta-1)^{2}}{2-\beta} \frac{1-c^{2-\beta}}{\left(c^{-\beta+1}-1\right)^{2}}>0$, then $\operatorname{Vol}(S)=c_{1} s n^{\prime}$.
The case is identical to $\beta=1$.
Case $\beta=2$ :

$$
\operatorname{Vol}(S)=s \frac{\ln 1 / c}{1 / c-1} e^{\alpha / 2}=\frac{\ln 1 / c}{(1 / c-1)^{2}} s n^{\prime}
$$

Analogously, $c_{1}=\frac{\ln 1 / c}{(1 / c-1)^{2}}>0$ and again $\operatorname{Vol}(S)=c_{1} s n^{\prime}$.
Case $\beta>2$ : similarly to the case $1<\beta<2$,

$$
\operatorname{Vol}(S)=s\left(\frac{\beta-1}{\beta-2} \frac{c^{-\beta+2}-1}{c^{-\beta+1}-1} e^{\alpha / \beta}+O(1)\right) \approx \frac{(\beta-1)^{2}}{\beta-2} \frac{c^{-\beta+2}-1}{\left(c^{-\beta+1}-1\right)^{2}} s n^{\prime}
$$

### 4.2 Permutation Model

According to our choice of $H, n^{\prime}=\left|V_{H}\right|$ is the largest number from $\{1, \ldots, n\}$ such that

$$
\begin{gather*}
\operatorname{deg}\left(n^{\prime}\right)=\frac{p n}{n^{\prime \beta}} \geq d_{0}  \tag{4.24}\\
n^{\prime} \approx\left(p n / d_{0}\right)^{1 / \beta}  \tag{4.25}\\
\operatorname{vol}(H)=\sum_{v=1}^{n^{\prime}} \frac{p n}{v^{\beta}}=p n H_{n^{\prime}, \beta}=d_{0} n^{\prime \beta} H_{n^{\prime}, \beta}  \tag{4.26}\\
\operatorname{vol}(S)=s \frac{\operatorname{vol}(H)}{n^{\prime}} \tag{4.27}
\end{gather*}
$$

We can apply Theorem 2.13 to show small constant conductance of $H$, as long as $d_{0} \geq 3$. For edge and vertex expansion we have the following theorems.

Theorem 4.5 (Existence of an edge expander). $\forall 0<p \leq 1 \exists d_{0}=d_{0}(p, n, \beta) \forall \delta>0 \exists \gamma, \epsilon>$ 0 : let $G$ be a random power-law graph where each vertex $v$ has $\operatorname{deg}(v)=p n v^{-\beta}$, and $H$ is its induced subgraph of size $n^{\prime}$ obtained by retaining vertices of degree at least $d_{0}$.

Then if $\beta=0$, the whole graph $G$ is $(\epsilon n, \gamma)$ edge expander w.h.p.
Otherwise, $H$ is $\left(\epsilon n^{\prime}, \gamma\right)$ edge expander w.h.p.
When $\beta>1$, the additional requirement is $p \zeta(\beta)>2$. More roughly, $\zeta(\beta)>2$ or $\beta \leq 1.72$, and the smaller $p$, the smaller $\beta$ for which subsets still expand.

$$
\begin{gather*}
n^{\prime}= \begin{cases}n & \text { if } \beta=0, \\
n / 2 & \text { if } \beta>0\end{cases}  \tag{4.28}\\
d_{0}= \begin{cases}p n & \text { if } \beta=0, \\
2^{\beta} p n^{1-\beta} & \text { if } \beta>0 .\end{cases}  \tag{4.29}\\
d=\left\{\begin{array}{ll}
d_{0} \\
d_{0} /(1-\beta) \\
d_{0} \ln n^{\prime} \\
d_{0} \zeta(\beta) n^{\prime \beta-1}
\end{array}= \begin{cases}p n & \text { if } \beta=0, \\
\frac{2^{\beta} p}{1-\beta} n^{1-\beta} & \text { if } 0<\beta<1 \\
2 p \ln (n / 2) & \text { if } \beta=1\end{cases} \right.  \tag{4.30}\\
\gamma= \begin{cases}d-2-\delta & \text { if } \beta=0, \\
d / 2 & \text { if } \beta>0\end{cases} \tag{4.31}
\end{gather*}
$$

Theorem 4.6 (Existence of a vertex expander). $\forall 0<p \leq 1 \exists d_{0}=d_{0}(p, n, \beta) \forall \delta>$ $0 \exists \gamma, \epsilon>0$ : let $G$ be a random power-law graph where each vertex $v$ has $\operatorname{deg}(v)=p n v^{-\beta}$, and $H$ is its induced subgraph of size $n^{\prime}$ obtained by retaining vertices of degree at least $d_{0}$.

Then if $\beta=0$, the whole graph $G$ is $(\epsilon n, \gamma)$ vertex expander w.h.p.
Otherwise, if $0<\beta<1, H$ is $\left(\epsilon n^{\prime}, \gamma\right)$ vertex expander w.h.p. At the same time, either $\epsilon=1 / 2$ and $\gamma=1-\delta$, or $\epsilon$ is sufficiently small and

$$
\gamma= \begin{cases}d / 2-2-\delta & \text { if } \beta=0  \tag{4.32}\\ d_{0} / 2-2-\delta & \text { if } 0<\beta<1\end{cases}
$$

The proof of this theorem can be found on page 41.
Proof of Theorem 4.5. Case $\beta=0: \operatorname{deg}(v)=p n$ for each $v \in V$, so we choose $d_{0}=p n$, then trivially $H=G$ and $n^{\prime}=n$. This reduces the proof to known case for regular graphs described in Section 2.5.2.

As for the other cases when $\beta>0$, we want our subgraph $H$ to have linear size, so we need to choose appropriate $d_{0}$.

$$
\begin{aligned}
& n^{\prime}=\left(p n / d_{0}\right)^{1 / \beta}=c n \\
& d_{0}=\frac{p n}{(c n)^{\beta}}=\frac{p}{c^{\beta}} n^{1-\beta}
\end{aligned}
$$

Fixing $c=1 / 2$ gives us

$$
\begin{aligned}
& n^{\prime}=n / 2 \\
& d_{0}=2^{\beta} p n^{1-\beta}=2 p n^{1-\beta} \\
& \underset{G}{\operatorname{Pr}}\left[H \text { is not }\left(\epsilon n^{\prime}, \gamma\right) \text { edge expander }\right]=\sum_{s=1}^{\epsilon n^{\prime}}\binom{n^{\prime}}{s} \underset{G, S}{\operatorname{Pr}}\left[\left|e\left(S, V_{H} \backslash S\right)\right|<\gamma s\right]= \\
& =\sum_{s=1}^{\epsilon n^{\prime}}\binom{n^{\prime}}{s} \underset{G, S}{\operatorname{Pr}}\left[|e(S, S)| \geq \frac{\operatorname{vol}(S)-\gamma s}{2}\right] \leq \\
& \leq \sum_{s=1}^{\epsilon n^{\prime}}\binom{n^{\prime}}{s} \frac{\binom{\operatorname{vol}(H) / 2}{(\operatorname{vol}(S)-\gamma s) / 2}\binom{\operatorname{vol}(H)-(\operatorname{vol}(S)-\gamma s)}{\gamma s}}{\binom{\operatorname{vol}(H)}{\operatorname{vol}(S)}} \leq \\
& \leq \sum_{s=1}^{\epsilon n^{\prime}}\left(\frac{e n^{\prime}}{s}\right)^{s} \frac{\left(e \frac{\operatorname{vol}(H)}{\operatorname{vol}(S)-\gamma s}\right)^{(\operatorname{vol}(S)-\gamma s) / 2}\left(e^{\left.\frac{\operatorname{vol}(H)-(\operatorname{vol}(S)-\gamma s)}{\gamma s}\right)^{\gamma s}}\right.}{\left(\frac{\operatorname{vol}(H)}{\operatorname{vol}(S)}\right)^{\operatorname{vol}(S)}} \leq \\
& \leq \sum_{s=1}^{\epsilon n^{\prime}}\left(\frac{e n^{\prime}}{s} \frac{\left(\frac{e \operatorname{vol}(H)}{\left(\operatorname{lvol}(H) / n^{\prime}-\gamma\right) s}\right)^{\left(\operatorname{vol}(H) / n^{\prime}-\gamma\right) / 2}\left(\frac{e \operatorname{vol}(H)}{\gamma s}\right)^{\gamma}}{\left(\frac{n^{\prime}}{s}\right)^{\operatorname{vol}(H) / n^{\prime}}}\right)^{s}= \\
& =\sum_{s=1}^{\epsilon n^{\prime}}\left(\frac{e^{1+\gamma / 2}}{\gamma^{\gamma}} e^{d / 2}\left(\frac{1}{d-\gamma}\right)^{(d-\gamma) / 2}\left(\frac{\operatorname{vol}(H)}{s}\right)^{(d+\gamma) / 2}\left(\frac{s}{n^{\prime}}\right)^{d-1}\right)^{s}= \\
& =\sum_{s=1}^{\epsilon n^{\prime}}\left(\frac{e^{1+\gamma / 2}}{\gamma^{\gamma}} e^{d / 2} \frac{d^{(d+\gamma) / 2}}{(d-\gamma)^{(d-\gamma) / 2}}\left(\frac{s}{n^{\prime}}\right)^{d / 2-\gamma / 2-1}\right)^{s},
\end{aligned}
$$

where $d=\operatorname{vol}(H) / n^{\prime}$ is the average degree of $H$.
In order to upper bound the probability of $H$ not being an edge expander we need

$$
\begin{equation*}
d-\gamma-2>0 \tag{4.33}
\end{equation*}
$$

Let $\gamma=d / 2$ so we can simplify further. Note that (4.33) becomes $d>4$.
$\underset{G}{\operatorname{Pr}}\left[H\right.$ is not $\left(\epsilon n^{\prime}, \gamma\right)$ edge expander $] \leq \sum_{s=1}^{\epsilon n^{\prime}}\left(\frac{e^{1+d / 4}}{(d / 2)^{d / 2}} e^{d / 2} \frac{d^{3 d / 4}}{(d / 2)^{d / 4}}\left(\frac{s}{n^{\prime}}\right)^{d / 4-1}\right)^{s}=$

$$
=\sum_{s=1}^{\epsilon n^{\prime}}\left(e(2 e)^{3 d / 4}\left(\frac{s}{n^{\prime}}\right)^{d / 4-1}\right)^{s} .
$$

Unfortunately, we cannot use Proposition 2.3 with $c_{1}=e(2 e)^{3 d / 4}, c_{2}=d / 4-1$ because $c_{2}<\log c_{1}$, even though the condition $c_{1}=o\left(n^{c_{2}-1}\right)$ is met.

What's left to argue is that in all cases this expression may be upper bounded by $o(1)$, while also maintaining $d>4$.

Case $0<\beta<1$ :

$$
\begin{gathered}
\operatorname{vol}(H)=\frac{d_{0}}{1-\beta} n^{\prime} \\
d=\frac{d_{0}}{1-\beta}=\frac{2 p}{1-\beta} n^{\prime 1-\beta}=\Theta\left(n^{\prime 1-\beta}\right)
\end{gathered}
$$

Clearly, our choice of $d_{0}$ satisfies (4.33).
As for the summation, we consider small and large values of $s$ separately.

- $s \leq \sqrt{n^{\prime}}: \sum_{s=1}^{\sqrt{n^{\prime}}}\left(e(2 e)^{3 d / 4}\left(\frac{s}{n^{\prime}}\right)^{d / 4-1}\right)^{s} \leq e^{\sqrt{n^{\prime}}}(2 e)^{\sqrt{n^{\prime}} 3 d / 4} \sum_{s=1}^{\sqrt{n^{\prime}}}\left(\frac{s}{n^{\prime}}\right)^{(d / 4-1) s}$

$$
\begin{aligned}
& \leq e^{\sqrt{n^{\prime}}}(2 e)^{\sqrt{n^{\prime}} 3 d / 4} \sum_{s=1}^{\sqrt{n^{\prime}}}\left(\frac{1}{\sqrt{n^{\prime}}}\right)^{d / 4-1} \\
& \leq e^{\sqrt{n^{\prime}}}(2 e)^{\sqrt{n^{\prime}} 3 d / 4} \frac{\sqrt{n^{\prime}}}{n^{d / 4-1}} \\
& =e^{n^{\prime 1 / 2}}(2 e)^{\frac{3}{4} \Theta\left(n^{\prime 3 / 2-\beta}\right)} \frac{1}{n^{\prime \Theta\left(n^{\prime 1-\beta}\right) / 4-3 / 2}}=o(1)
\end{aligned}
$$

- otherwise: $\sum_{s=\sqrt{n^{\prime}}+1}^{\epsilon n^{\prime}}\left(e(2 e)^{3 d / 4}\left(\frac{s}{n^{\prime}}\right)^{d / 4-1}\right)^{s}<\sum_{s=\sqrt{n^{\prime}}+1}^{\epsilon n^{\prime}} 10^{-s} \leq \frac{\epsilon n^{\prime}}{10^{\sqrt{n^{\prime}}}}=o(1)$

For this we need: $e(2 e)^{3 d / 4} \epsilon^{d / 4-1}<\frac{1}{10}$, or $\frac{\left((2 e)^{3} \epsilon\right)^{d / 4}}{\epsilon}<\frac{1}{10 e}$.
We can choose $\epsilon=\frac{1}{10(2 e)^{3}}$, and we are done because $d=\Theta\left(n^{11-\beta}\right)$.
$\underset{G}{\operatorname{Pr}}\left[H\right.$ is not $\left(\epsilon n^{\prime}, \gamma\right)$ edge expander $] \leq o(1)$.
$\stackrel{G}{\text { Case }} \beta=1$ :

$$
\begin{gathered}
n^{\prime}=p n / d_{0} \\
\operatorname{vol}(H)=d_{0} n^{\prime} \ln n^{\prime} \\
d=\frac{\operatorname{vol}(H)}{n^{\prime}}=d_{0} \ln n^{\prime}=\Theta\left(n^{\prime 1-\beta} \ln n^{\prime}\right)
\end{gathered}
$$

This is identical to the previous case $0<\beta<1$.
Case $\beta>1$ :

$$
\begin{gathered}
\operatorname{vol}(H)=\zeta(\beta) d_{0} n^{\prime \beta} \\
d_{0}=2 p n^{\prime 1-\beta} \\
d=\zeta(\beta) d_{0} n^{\prime \beta-1}=2 p \zeta(\beta)=O(1)
\end{gathered}
$$

Here we get an additional requirement $p \zeta(\beta)>2$, because we need $d>4$. As $0<p \leq 1$ and $\zeta(\beta)$ is monotonically decreasing, it serves as an upper bound for $\beta$.

Finally, let $c_{1}=e(2 e)^{3 d / 4}, c_{2}=d / 4-1$ be some positive constants, then for sufficiently small $\epsilon$ :

$$
\underset{G}{\operatorname{Pr}_{G}}\left[H \text { is not }\left(\epsilon n^{\prime}, \gamma\right) \text { edge expander }\right] \leq \sum_{s=1}^{\epsilon n^{\prime}}\left(c_{1}\left(\frac{s}{n^{\prime}}\right)^{c_{2}}\right)^{s}=o(1) .
$$

More precisely, $c_{1} \epsilon^{c_{2}}<1 / 10$, or $\epsilon=\left(c_{1} c_{3}\right)^{-1 / c_{2}}$ for some $c_{3}>10$.
Proof of Theorem 4.6. The approach is identical to Theorem 2.12, but $d$ perfect matchings on $n$ vertices are replaced by a single perfect matching on $\operatorname{vol}(H)$ mini-vertices, which correspond to $n^{\prime}$ vertices of $H$.

When $\beta=0, G$ is $p n$-regular graph, so the original proof with Proposition 2.2 or Proposition 2.3 suffice.

Otherwise, $\beta>0$. For any $S \subset V_{H}$ of size $|S|=s \leq \epsilon n^{\prime}$ and $T \subset V_{H}$ of size $(1+\gamma) s$,

$$
\begin{gather*}
d=\frac{\operatorname{vol}(H)}{n^{\prime}}  \tag{4.34}\\
\operatorname{vol}(S)=s d  \tag{4.35}\\
\operatorname{vol}(T)=(1+\gamma) s d \tag{4.36}
\end{gather*}
$$

All mini-vertices from $S$ are matched to mini-vertices in $T$ with probability
$\operatorname{Pr}_{G, S, T}\left[N_{H}(S) \subseteq T\right] \leq\left(\frac{\operatorname{vol}(T)}{\operatorname{vol}(H)}\right)^{\operatorname{vol}(S) / 2}$
As for the number of sets $S$ of a given size (the same goes for $T$ ), $\binom{n^{\prime}}{s}$ would only work for regular graphs, while $\binom{\operatorname{vol}(H)}{\operatorname{vol}(S)}$ would overcount because mini-vertices corresponding to the same vertex in $H$ are indistinguishable. Instead we use the trick as Gkantsidis et al. [GMS03] by taking the minimum degree $d_{0}$ into account.

$$
\begin{aligned}
\operatorname{Pr}_{G} & \exists \exists \text { non-expading } S \text { of size } s] \leq\binom{\operatorname{vol}(H) / d_{0}}{\operatorname{vol}(S) / d_{0}}\binom{\operatorname{vol}(H) / d_{0}}{\operatorname{vol}(T) / d_{0}}\left(\frac{\operatorname{vol}(T)}{\operatorname{vol}(H)}\right)^{\operatorname{vol}(S) / 2} \leq \\
& \leq\left(\frac{e n^{\prime}}{s}\right)^{s d / d_{0}}\left(\frac{e n^{\prime}}{(1+\gamma) s}\right)^{(1+\gamma) s d / d_{0}}\left(\frac{(1+\gamma) s}{n^{\prime}}\right)^{s d / 2}= \\
& =\left(\left(\frac{e n^{\prime}}{s}\right)^{(2+\gamma) d / d_{0}}\left(\frac{1}{1+\gamma}\right)^{(1+\gamma) d / d_{0}}\left(\frac{(1+\gamma) s}{n^{\prime}}\right)^{d / 2}\right)^{s}= \\
& =\left(e^{(2+\gamma) d / d_{0}}(1+\gamma)^{d\left(1 / 2-(1+\gamma) / d_{0}\right)}\left(\frac{s}{n^{\prime}}\right)^{d\left(1 / 2-(2+\gamma) / d_{0}\right)}\right)^{s}
\end{aligned}
$$

In order to proceed we need this exponent to be positive:

$$
\begin{gather*}
d\left(1 / 2-(2+\gamma) / d_{0}\right)>0  \tag{4.37}\\
0 \leq \gamma<d_{0} / 2-2 \tag{4.38}
\end{gather*}
$$

Note that this requires $d_{0}>4$, while similar theorems 2.12 and 2.13 ask for $d_{0} \geq 3$.
When $\beta>0$, it translates into

$$
\begin{gather*}
d_{0}=2^{\beta} p n^{1-\beta}>4  \tag{4.39}\\
n^{1-\beta}>2^{2-\beta}  \tag{4.40}\\
\beta<1 \tag{4.41}
\end{gather*}
$$

$\underset{G}{\operatorname{Pr}}\left[H\right.$ is not $\left(\epsilon n^{\prime}, \gamma\right)$ vertex expander $] \leq \sum_{s=1}^{\epsilon n^{\prime}} \underset{G}{\operatorname{Pr}}[\exists$ non-expading $S$ of size $s]=o(1)$.
This final step may be achieved in two ways. First, we may apply Proposition 2.2, then $\epsilon$ must be some small constant. Secondly, it also follows from Proposition 2.3, but we need to verify $c_{1}=o\left(n^{c_{2}-1}\right)$ and $c_{2}>\max \left\{1, \log c_{1}\right\}$.

$$
\begin{gathered}
c_{1}=e^{(2+\gamma) d / d_{0}}(1+\gamma)^{d\left(1 / 2-(1+\gamma) / d_{0}\right)} \\
\log c_{1}=(\log e)(2+\gamma) d / d_{0}+(\log (1+\gamma))\left(d / 2-(1+\gamma) d / d_{0}\right) \\
c_{2}=d / 2-(2+\gamma) d / d_{0} \\
c_{2}-\log c_{1}=d / 2-(2+\gamma) d / d_{0}-(\log e)(2+\gamma) d / d_{0}-(\log (1+\gamma))\left(d / 2-(1+\gamma) d / d_{0}\right) \\
c_{2}-\log c_{1}>0, \text { for any } \gamma<1,
\end{gathered}
$$

In this case we get $\epsilon=1 / 2$, but both conditions are satisfied only when $\gamma<1$.

### 4.2.1 Error from Rounding Degrees

To get the exact degree sequence, one needs to round down the expression (3.16) for $\operatorname{deg}(v)$. In this case the error of $\operatorname{vol}(G)$ is at most $n$. For our choice of $d_{0}$ this error is negligible compared to $\operatorname{vol}(H)$ when $0 \leq \beta \leq 1$, but it might be significant otherwise.

$$
\operatorname{vol}(H)= \begin{cases}\Theta\left(n^{2}\right) & \text { if } \beta=0  \tag{4.42}\\ \Theta\left(n^{2-\beta}\right) & \text { if } 0<\beta<1 \\ \Theta(n \log n) & \text { if } \beta=1 \\ \Theta(n) & \text { if } \beta>1\end{cases}
$$

## 4.3 "Octopus" Graphs

The core of the "octopus" graph is defined as an induced subgraph with all the vertices of degree at least $d_{0}=n^{1 / \log \log n}$.

The number of vertices of degree more than $d$ is about $\left(\frac{\beta-2}{\beta-1}\right)^{\beta-1} n$.

$$
\begin{aligned}
w_{x}= & \frac{\beta-2}{\beta-1} d n^{\frac{1}{\beta-1}} x^{-1 /(\beta-1)}>d \\
& \frac{\beta-2}{\beta-1} n^{\frac{1}{\beta-1}}>x^{1 /(\beta-1)} \\
& x<\left(\frac{\beta-2}{\beta-1}\right)^{\beta-1} n
\end{aligned}
$$

Analogously, $i_{1}$ is the index of the last vertex included in the core:

$$
\begin{gathered}
w_{x}=\frac{\beta-2}{\beta-1} d n^{\frac{1}{\beta-1}} x^{-1 /(\beta-1)} \geq n^{1 / \log \log n}=d_{0} \\
\frac{\beta-2}{\beta-1} d n^{\frac{1}{\beta-1}-1 / \log \log n} \geq x^{1 /(\beta-1)} \\
x \leq\left(\frac{\beta-2}{\beta-1} d\right)^{\beta-1} n^{1-\frac{\beta-1}{\log \log n}}=\left(\frac{c}{d_{0}}\right)^{\beta-1}=i_{1}
\end{gathered}
$$

$i_{1} \leq n$ implies a restriction on the average degree:

$$
\begin{equation*}
d \leq \frac{\beta-1}{\beta-2} n^{1 / \log \log n} \tag{4.43}
\end{equation*}
$$

By our assumptions, $i_{1}=i_{0}\left(\frac{d_{\max }}{n^{1 / \log \log n}}\right)^{\beta-1} \gg i_{0}$.
Let $n^{\prime}$ denote the size of the core.

$$
\begin{gather*}
n^{\prime}=i_{1}-i_{0}  \tag{4.44}\\
\log n^{\prime} \approx \log i_{1} \approx \log n\left(1-\frac{\beta-1}{\log \log n}\right) \tag{4.45}
\end{gather*}
$$

The average degree of the core is

$$
\begin{aligned}
& \frac{\sum_{k=i_{0}}^{i_{1}} w_{i}}{i_{1}-i_{0}} \approx \frac{\beta-2}{\beta-1} d n^{\frac{1}{\beta-1}} \frac{1}{i_{1}} \sum_{k=1}^{i_{1}} k^{-1 /(\beta-1)} \approx \frac{\beta-2}{\beta-1} d n^{\frac{1}{\beta-1}} \frac{1}{i_{1}} \frac{i_{1}^{1-1 /(\beta-1)}}{(\beta-2) /(\beta-1)}= \\
& \quad=d\left(\frac{n}{i_{1}}\right)^{\frac{1}{\beta-1}}=d\left(\left(\frac{\beta-2}{\beta-1} d\right)^{\beta-1} n^{-\frac{\beta-1}{\log \log n}}\right)^{-\frac{1}{\beta-1}}=d\left(\frac{\beta-2}{\beta-1} d\right)^{-1} n^{1 / \log \log n}= \\
& \quad=\frac{\beta-1}{\beta-2} n^{1 / \log \log n}=\omega\left(\log n^{\prime}\right)
\end{aligned}
$$

As a result, the core is edge expander w.h.p. by Lemma 4.2.
Moreover, this core contains $G\left(n^{\prime}, p\right)$ with $p=d_{0}^{2} / d n$ [CL04], and if $d=\Theta(1)$, then its expected degrees are
$n^{\prime} p=\left(\frac{c}{d_{0}}\right)^{\beta-1} \frac{d_{0}^{2}}{d n}=\Theta\left(d^{\beta-2} d_{0}^{3-\beta}\right)=\Theta\left(d^{\beta-2} n^{(3-\beta) / \log \log n}\right)=\omega(\log n)$
Chung and $\mathrm{Lu}[\mathrm{CL} 04]$ use this fact to prove $O(\log \log n)$ diameter of the core.

We can apply Theorem 2.17 on this $G\left(n^{\prime}, p\right)$ to get linear size vertex expander of diameter $O(\log n)$ inside of the core. If we could also say that other vertices are not "too far" from this expander, it could serve as an alternative step for the proof of $O(\log n)$ diameter of the whole "octopus" graph.

### 4.4 Diameter of Vertex Expanders

In this section we focus on $(\epsilon n, \gamma)$ vertex expanders, especially on the case $\epsilon<1 / 2$, and the results apply to all graph models.

First, consider an example: a graph $G$ that consists of two disconnected $(n / 4, \gamma)$ vertex expanders of size $n / 2$ each. Any subset of $G$ of size up to $n / 4$ is the union of subsets of these two parts, and it expands proportionally. Therefore, $G$ is $(n / 4, \gamma)$ vertex expander as well, and yet it is not connected.

In general, when $\epsilon \leq 1 / 4$, the connectivity of $(\epsilon n, \gamma)$ vertex expander is not guaranteed.
A well known fact about $(n / 2, \gamma)$ vertex expanders is that they have diameter $O(\log n)$ [Rao12, HLW06]. We extend on this by demonstrating that the diameter is still $O(\log n)$ even for small constant $\epsilon<1 / 2$, assuming the graph is connected.

Theorem 4.7. Let $G=(V, E)$ be a connected $(s(n), \gamma)$ vertex expander of size $n$, where $s(n) \leq n / 2$ and $\gamma=\Omega(1)$. Then the diameter of $G$ is $O\left(\frac{n}{s(n)} \log s(n)\right)$.

Corollary 4.7.1. The diameter of a connected $(\epsilon n, \gamma)$ vertex expander of size $n$, where $\epsilon \leq 1 / 2$ and $\gamma$ are some positive constants, is $O(\log n)$.

Similarly, $s(n)=\Theta\left(\frac{n}{\log n}\right)$ gives us diameter $O\left(\log ^{2} n\right)$, and $s(n)=\Theta(\sqrt{n})$ gives $O(\sqrt{n} \log n)$. We now prove an intermediate result needed for the theorem.

Lemma 4.8. If $G=(V, E)$ is a connected $(s(n), \gamma)$ vertex expander, then there exists a partitioning $\left\{S_{1}, \ldots, S_{k}\right\}$ of $V$, such that $k=O(n / s(n))$ and each $S_{i}$ has diameter $O(\log s(n))$.

Proof. Let $B(v, r)=\{u \in V \mid \operatorname{dist}(v, u) \leq r\}$ denote a ball of radius $r \geq 0$ around vertex $v$.
For any $v \in V$ and $r \geq 1$, if $|B(v, r-1)| \leq s(n)$, then $|B(v, r)| \geq \min \left\{s(n),(1+\gamma)^{r}\right\}$ by the expansion property of $G$. As all subsets of size up to $s(n)$ are expanding, there exists

$$
\begin{equation*}
r_{0}=\left\lceil\log _{1+\gamma} s(n)\right\rceil=\Theta(\log s(n)) \tag{4.46}
\end{equation*}
$$

such that $\left|B\left(v, r_{0}\right)\right| \geq s(n)$. The diameter of $B\left(v, r_{0}\right)$ is $O\left(r_{0}\right)$.
We maintain an invariant that all $S_{i}$ are disjoint and have diameter $O\left(r_{0}\right)$ throughout the following partitioning process.

Begin with arbitrary $v_{1} \in V$ and select $S_{1}=B\left(v_{1}, r_{0}\right)$. As long as there is some other vertex $v$ whose $B\left(v, r_{0}\right)$ contains at least $s(n) / 2$ of not yet selected vertices, add these new
vertices to the next set $S_{i}$. We will stop after $k \leq 2 n / s(n)$ steps. Every remaining vertex $u$ must be within distance $r_{0}$ from some $S_{j}$, so we add each such $u$ to the corresponding $S_{j}$.

Proof of Theorem 4.7. Lemma 4.8 gives us the partitioning $\left\{S_{1}, \ldots, S_{k}\right\}$ of $V$. We create a graph $G^{\prime}$ of size $k$ from $G$ by contracting each $S_{i}$ into a single vertex and merging multiple edges. Note that $G^{\prime}$ is connected by construction.

Now consider arbitrary $u, v$ from $G$. Clearly, the distance between their corresponding vertices in $G^{\prime}$ is at most $k$. Let $D$ be the maximum diameter of any $S_{i}$. Then $\operatorname{dist}(u, v)$ in $G$ is at most $k(2 D+1)$ which is exactly $O\left(\frac{n}{s(n)} \log s(n)\right)$.

## Chapter 5

## Comparison of the Graph Models

We have briefly compared our findings to some previous papers in Chapter 1. Now we would like to address more correspondences, both quantitative and qualitative.

### 5.1 Overview of the Expansion Properties

As usual, we denote the size of the subgraphs $n^{\prime}$, the minimum degree $d_{0}$ and the average degree $d$, the expansion $\gamma$, and $\epsilon, \delta>0$ are some arbitrary small constants.

### 5.1.1 Previously Known Results

We saw in Chapter 2 that random $d$-regular graphs are themselves $(\epsilon n, d-2-\delta)$ vertex and edge expanders.

The model from Gkantsidis et al. [GMS03] is similar to our coin toss model and it describes the graphs with a small constant conductance 0.0175 , which is a generalization of $(n / 2, \gamma)$ edge expansion.

Lastly, $G(n, p)$ graphs contain $\left(n^{\prime} / 2, \Theta(1)\right)$ vertex expanders of linear size [Kri18].

### 5.1.2 Our Results

Graphs in the coin toss model contain $\left(n^{\prime} / 2, d / 2-\delta\right)$ edge expanders. The size of these subgraphs is $n^{\prime}=\Theta(n)$ when $\beta \leq 1.6$, but only $n^{\prime}=\Theta\left(n^{1 / \beta}\right)$ for larger $\beta$.

In the permutation model, on the other hand, we were able to prove the existence of $\left(n^{\prime} / 2, d / 2\right)$ edge expanders if $\beta \leq 1.72$, and also both $\left(n^{\prime} / 2,1-\delta\right)$ and $\left(\epsilon n^{\prime}, d_{0} / 2-2-\delta\right)$ vertex expanders for $0<\beta<1$. The trade-off between the maximum size of expanding subsets and the expansion rate is the most apparent in this model. And as we know, any vertex expansion would imply the same edge expansion, but unluckily, we couldn't secure even weak vertex expansion for $\beta>1.72$.

### 5.2 Uniform Random Graphs

Although power-law graphs have less uniform structure than $G(n, p)$, we produced evidence that they are still random enough because of the large expanding subgraphs.
$G(n, p)$ graphs have a sharp threshold for connectivity [ER59] and become connected w.h.p. when $p=(1+\epsilon) \log n / n$, for $\epsilon>0$, that is, when the expected degrees are $d \approx p n>$ $\log n$. It harmonizes with our Lemma 4.2, which explains that graphs with the expected average degree $d>10 \log n$ are $(n / 2, d / 2-\delta)$ edge expanders, for any small constant $\delta>0$.

Theorem 2.17 adds to this by saying that $G(n, p)$ graph in supercritical regime with $p=(1+\epsilon) / n$ w.h.p. contains $\left(n^{\prime} / 2, \gamma\right)$ vertex expander on $n^{\prime}=\Theta(n)$ vertices [Kri18].

The parameters are $c_{1}=1+\epsilon, c_{2}=1+\epsilon^{2} / 10, \alpha=\left(\frac{c_{2}}{5 c_{1}}\right)^{c_{2} /\left(c_{2}-1\right)}$, and $\Delta=4 \ln \frac{1}{\epsilon}$.
In this case it guarantees the vertex expansion

$$
\begin{equation*}
\gamma=\frac{c_{1}-c_{2}}{\Delta \log _{2} \frac{1}{\alpha}}=\frac{\epsilon-\epsilon^{2} / 10}{\left(4 \ln \frac{1}{\epsilon}\right) \frac{c_{2}}{c_{2}-1} \log _{2} \frac{5 c_{1}}{c_{2}}}=\frac{\epsilon-\epsilon^{2} / 10}{\left(4 \ln \frac{1}{\epsilon}\right) \frac{1+\epsilon^{2} / 10}{\epsilon^{2} / 10} \log _{2} \frac{5 c_{1}}{c_{2}}}<\frac{\epsilon}{8 \ln (1 / \epsilon)} \tag{5.1}
\end{equation*}
$$

which is less than 1 for $\epsilon<0.89$, so it is also similar to our $\left(n^{\prime \prime} / 2,1-\delta\right)$ vertex expander for the permutation model with $0<\beta<1, n^{\prime \prime}=n / 2$, and arbitrary small constant $\delta>0$.

### 5.3 Connected Components and the Coin Toss Model

Table 1.1 highlights similarities between the sizes of our expanding subgraphs in the coin toss model from Section 3.2 and the largest connected components of power-law graphs from Aiello et al. [ACL01], although there are still some gaps.

For example, we know that the giant component exists for $\beta \in(0 ; 3.48)$ [ACL01, CL06]. For $3.48<\beta<4$, the size of each connected component is at most $\Theta\left(n^{2 / \beta} \log n\right)$, and for $\beta>4$ it is $\Theta\left(n^{2 /(\beta+2)} \log n\right)$.

Our proof provides a linear size edge expander only for $\beta$ up to 1.6 , and then we have a single jump to $\Theta\left(n^{1 / \beta}\right)$, which is close to a square root of the size of the corresponding largest component. The conclusion here is that the largest connected components of powerlaw graphs have strong expansion properties, even though their average degree $d=\omega(1)$, so they are not sparse.

### 5.4 Coin Toss and Permutation Models

If we consider the graphs from permutation model when $p=1$, we notice that we get the same $\left(n^{\prime} / 2, d / 2-\delta\right)$ edge expander as in the coin toss model for any $0<\beta \leq 1.6$. It demonstrates that power-law graphs with small $\beta$ possess a similar structure regardless of whether we define degrees or frequencies of degrees to follow a power law.

## Chapter 6

## Conclusions

In this work we established existence of expanders in power-law graphs under several models and studied their behavior for various ranges of the exponent $\beta$. We also made an overview of the structure of random graphs, comparing them side by side with our findings to contrast some correspondences and differences. In particular, we showed that power-law graphs with small $\beta$ have similar to $G(n, p)$ expansion properties, just as one would expect. Also the largest components of power-law graphs and our edge expanders have comparable sizes, so these components are presumably well-connected.

One possible direction for future research is the improvement of the current results. This includes tightening gaps between sizes of connected components and expanding subgraphs, increasing the quality of expansion, and weakening the conditions for having large expanding sets of size up to $n / 2$. It would be useful to connect spectral and combinatorial expansion of power-law graphs. By analogy with connectivity in percolation theory, interesting open problem is to decide the expansion of sparse graphs obtained by randomly removing each edge with probability proportional to the degrees of its endpoints.

Another promising direction is the development of enhanced SAT algorithms for powerlaw formulas, facilitated by the available structural information. Self-similarity of a power law might be exploited to design recursive SAT algorithms. Finally, the results about random walks with lookahead suggest studying the expansion of $k$-th power of power-law graphs, for some small constant $k$.

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## Appendix A

## Miscellaneous

## A. 1 Approximations

## A.1.1 Euler-Maclaurin Formula

Euler-Maclaurin summation formula provides an approximation of the sum $\sum_{i=0}^{n} f(i)$ via the integral $\int_{0}^{n} f(x) d x$, and the error term is an integral with Bernoulli numbers.

$$
\begin{align*}
\sum_{n=a}^{b} f(n) & =\int_{a}^{b} f(t) d t+\frac{1}{2}(f(b)+f(a))+ \\
& +\sum_{i=2}^{k} \frac{b_{i}}{i!}\left(f^{(i-1)}(b)-f^{(i-1)}(a)\right)-  \tag{A.1}\\
& -\int_{a}^{b} \frac{B_{k}(\{1-t\})}{k!} f^{(k)}(t) d t
\end{align*}
$$

where $\{x\}$ denotes the fractional part of $x$. One of its interesting applications is the Stirling's approximation formula.

If $f(x)$ and all its derivatives tend to 0 as $x \rightarrow \infty$, the formula can be simplified.

$$
\begin{equation*}
\sum_{n=a}^{\infty} f(n)=\int_{a}^{\infty} f(t) d t+\frac{1}{2} f(a)-\sum_{i=2}^{k} \frac{b_{i}}{i!} f^{(i-1)}(a)-\int_{a}^{\infty} \frac{B_{k}(\{1-t\})}{k!} f^{(k)}(t) d t \tag{A.2}
\end{equation*}
$$

For $k \geq 2: \quad\left|B_{k}(\{x\})\right| \leq \frac{\pi^{2}}{3} \frac{k!}{(2 \pi)^{k}}<4 \frac{k!}{(2 \pi)^{k}}$.

## A.1.2 Lambert Function

Lambert function $W(x)$ is defined by the relation

$$
\begin{equation*}
z=W\left(z e^{z}\right) \tag{A.3}
\end{equation*}
$$

When $x>0, W(x)=\ln x-\ln W(x)$, and $\lim _{x \rightarrow \infty} \frac{W(x)}{\ln x}=1$. Thus, we can approximate it as

$$
\begin{equation*}
W(x) \approx \ln x \tag{A.4}
\end{equation*}
$$

## A. 2 Finding Expanding Subsets In Locally Sparse Graphs

```
Algorithm 1 Algorithmic proof of Theorem 2.14 ([Kri18])
    procedure FindExpander \((G, \alpha)\)
        \(V_{1} \leftarrow V\)
        for \(i \leftarrow 1, i_{\text {max }}\) do
            \(d_{i}=\frac{\left|E_{i}\right|}{\left|V_{i}\right|} \geq c_{2}\)
            \(\delta=\) edge boundary of the sparsest cut \(\left(W_{i}, V_{i} \backslash W_{i}\right)\)
            if \(\left|V_{i}\right| \leq \alpha n\) then \(\quad \triangleright G_{i}\) is small and dense
                break
            else if there are isolated vertices then
                remove isolated vertices \(\triangleright\) density increases
                continue
            else if \(\lambda_{G_{i}}>\frac{\delta^{2}}{2 \Delta^{2}}\) then
                \(G_{i}\) is edge-expander by (2.47)(2)
                and \(\Delta\left(G_{i}\right) \leq \Delta \quad \triangleright G_{i}\) is a vertex-expander
                break
            else
                find \(W_{i} \subset V_{i}\) using the proof of (2.47)(1)
                s.t. \(\operatorname{vol}\left(W_{i}\right) \leq \operatorname{vol}\left(V_{i}\right) / 2\)
                and \(e_{G_{i}}\left(W_{i}, V_{i} \backslash W_{i}\right) \leq \delta\left|W_{i}\right|\)
                if \(W_{i}\) touches at most \(d_{i}\left|W_{i}\right|\) edges then
                remove \(W_{i} \quad \triangleright\) density doesn’t decrease
                else \(\quad \triangleright W_{i}\) spans less than \(\left(d_{i}-\delta\right)\left|W_{i}\right|\) edges
                remove \(V_{i} \backslash W_{i}\)
                \(d_{i+1} \geq d_{i}-\delta\)
                end if
            end if
        end for
    end procedure
```

