Different approaches to random graphs: Erdös-Rényi and Branching Processes

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Contents

Chapter 1

An introduction to random graphs

1.1 Notes for the reader

This report has been written as a survey on random graphs and the different ways to approach them. This section gives an overview of the structure of the report and different notations that are used in this report, all of the vocabulary introduced here will be properly defined is the following of this report.

Structure of the report It is structured in three different chapters, the first one is mostly an introduction to the language of graph theory followed by a very short introduction to what is a random graph. The last part of the introduction is a proof of Cayley's formula, formula which is central in many enumerative proofs on random graphs.
The second chapter gives a description of the Erdös-Rényi model. Different techniques to solve graph problems are used, the theorem on connectivity and the stability number use enumerative techniques. The section on the diameter contains a long proof which is applied in the end using the probabilistic method which exhibits the existence of graphs satisfying certain properties. The second chapter also contains a formal characterisation of properties and a theorem on the existence of thresholds.
The third chapter is focused on the phase transition of random graphs and it uses many different exploration techniques. The first part is on a formal definition of a Galton-Watson process and the probability of survival of such a process using martingales. It also contains important results on the links between different kinds of Galton-Watson process and random graphs. Then a study is done on the subcritical case using the Breadth-First search algorithm and a study of the supercritical case is done using the recent approach which uses the Depth-First search algorithm.
The last chapter is quite different, first of all a generalised model of Erdös-Rényi

is introduced and a simple result is proved which gives a result on the classical Erdös-Rényi model and on Bipartite random graphs. The last section is an overview of an approach of random graphs defined by their degree sequence using generating functions, several results on the phase transition are found and they are applied to the Erdös-Rényi model and results from chapter 3 are obtained again.
This report also contains an Appendix in which several results used in the report are detailed and most of them are proved.
In this report most of the results are proved and it is nearly self-contained. However some results are admitted otherwise the report would have vastly exceeded the expected length.

Notations The author has tried to be as close as possible from standard notations. Here some notations are presented, $\mathbb{P}, \mathbb{E}, \mathbb{V}$ respectively define a probability measure, the expectation and the variance. $\mathcal{G}_n$ will denote a probability space of random graphs on n vertices and $\mathbb{G}_n$ will be a random (graph) variable in a specified space of random graphs. The distinction between $\mathcal{G}$ and $\mathbb{G}$ is not necessarily done. We will say that a property is satisfied with high probability if its probability is tending to one as n goes to infinity.

1.2 Graph theory

[1] Formally a *graph* G is defined as $G = (V(G), E(G))$, with $V(G)$ denoting the vertex set (the points or nodes) of G and $E(G)$ as $E(G) \subseteq \{\{x, y\}, x, y, \in V(G), x \neq y\}$, the set of edges (the lines) of G.
This is the simplest way to define a graph, hence this kind of graph is usually called a *simple graph*. More general graphs can be defined, for instance the loopy graphs, multigraphs, directed graphs or hypergraphs. They are not of major importance in this report so they won't be detailed here, their formal definition can be found in almost any book on graph theory (see for instance [BM08]).
We will call two vertices $u, v \in V(G)$ as *adjacent* if $\{u, v\} \in E(G)$ and we will write it as $u \leftrightarrow v$. We may also refer to edges being adjacent if they share a vertex.
As an example of a graph we can consider the following graph with $V(G) = \{a, b, c, d, e\}, E(G) = \{e_1, e_2, e_3, e_4, e_5, e_6, e_7\}$ for:

$$e_1 = \{a, b\} \quad e_2 = \{a, c\} \quad e_3 = \{b, c\} \quad e_4 = \{a, d\}$$
$$e_5 = \{c, d\} \quad e_6 = \{a, e\} \quad e_7 = \{c, e\}$$

The *adjacency matrix* of a graph G is the $n \times n$ matrix defined as $A_G = (a_{u,v})$

[1] For a very simple introduction to graph theory, see [Tru93], for an advanced review of graph theory, see [BM08]

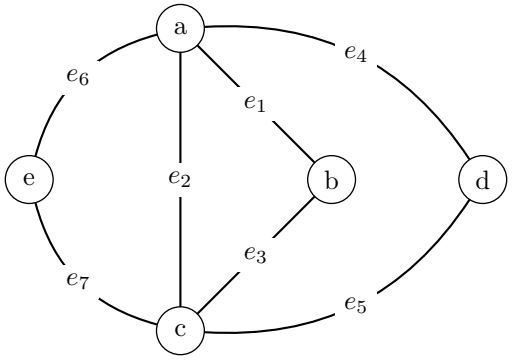

Figure 1.1: A graphical representation of G

with $a_{u,v} = \mathbb{1}_{E(G)}(\{u, v\})$

$$A_G = \begin{array}{c} \\ a \\ b \\ c \\ d \\ e \end{array} \begin{array}{c} \begin{array}{ccccc} a & b & c & d & e \end{array} \\ \begin{bmatrix} 0 & 1 & 1 & 1 & 1 \\ 1 & 0 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 \end{bmatrix} \end{array} \tag{1.1}$$

It is interesting to note that an adjacency matrix is real and Hermitian, thus all of its eigenvalues are real and the study of their distribution is a classical topic in graph theory.
An important property of graphs is the *degree* of the vertices, so we will denote by $d_G(v)$ the number of edges incident with $v \in V(G)$. Observing that each edge has two ends and that the degree of a vertex is the number of edges having this vertex as an end. We obtain :

$$\sum_{v \in V(G)} d_G(v) = 2|E(G)| \tag{1.2}$$

We also call the degree sequence the non-increasing sequence of its vertex degrees. And we can also define the two following notations that will be useful in the following of this report, $\delta(G)$ as the minimal degree of G and $\Delta(G)$ as the maximal degree of G.
We define a *path* on a graph as a sequence of edges being two by two adjacent. One of the most fundamental properties of graphs is the connectivity. We will say that a graph is *connected*, if there is a path connecting any two edges. In fact we will consider simple[2] paths because we are studying simple graphs. It is clear that if a path exists it is always possible to extract a simple path from it. There are two famous kinds of path, the *Hamiltonian path*, it is a path that

[2] More generally, the use of the adjective *simple* denotes that we study something without loop or multi-edge

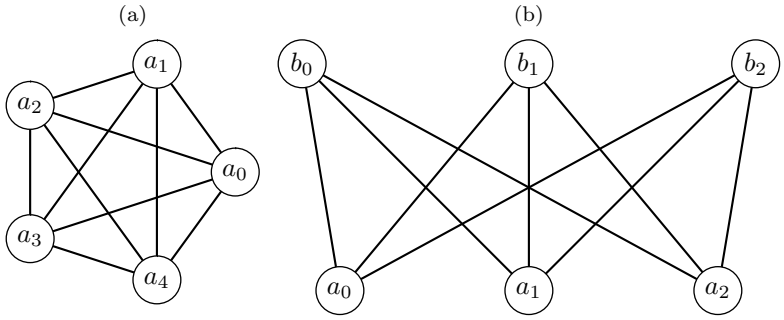

Figure 1.2: (a) The complete graph K_5 and (b) the complete bipartite graph $K_{3,3}$.

includes all vertices of G. Analogously, an *Eulerian path* is a path in which all edges are used exactly once.
If v is a vertex, we will write $N(v)$ the set of vertices adjacent to v which are called the *neighbours* of v. From this definition we may observe that $d_G(v) = |N(v)|$ if G is a graph without loops. And we will call a (connected) *component* of a vertex the set of vertices that can be reached from this vertex. Then a connected graph is a graph with only one component.
Some interesting graphs to which we will often refer are the complete graph on n vertices, denoted by K_n, and the complete bipartite graph $K_{n,m}$. A *complete graph* is a graph in which for any vertex, the set of neighbours is the rest of the graph. A graph is *bipartite* if its set of vertices can be partitioned in two subsets X and Y such that every edge has one end in X and one in Y. The *complete bipartite graph* is a bipartite graph such that for all $x \in X$ we have $N(x) = Y$. This implies the same condition on the vertices in Y. We will also call a *cycle*, of size $n \geq 3$, denoted C_n a graph whose vertices can be arranged in a cyclic sequence in such a way that two vertices are adjacent if and only if they are consecutive in the sequence.

As there is usually no confusion possible we will denote $V = V(G)$ and $E = E(G)$.

1.3 Random graphs

The study of random graphs is a flourishing area of mathematics since its founding papers have been published by Erdős and Renyi between 1959 and 1963 [ER59] [ER60] [ER61b] [ER61a] [ER63]). Since then a lot of work has been done on random graphs, most of the questions on the Erdős-Renyi model have found satisfying answers, and the model being simplistic, many new models have been developed. So we will use the very vague definition by Janson [Sva14].

Definition 1.3.1. A *random graph* is a graph where nodes, or edges, or both are selected by a random procedure.

More formally, a random graph is a random variable on a space of graphs. This means that when studying random graphs, we can not only change the distribution but also the space in which we sample.
Usually we make the choice of sampling on a space of graphs containing any graph with a specified number of vertices. [3] Some restrictions on this space might be done, for instance by selecting graphs with each vertex of the same degree (r-regular random graphs), or with the degree sequence following a specific distribution (like the Newman-Strogatz-Watts model [NSW01], [NWS02]). Sometimes random graphs are developped in order to produce a sampling space matching some particular phenomenom observed in real-world networks.

For instance in social networks, two persons having a friend in common are likely to be friends which in the vocabulary of graph theory indicates the presence of a triangle. For this purpose was developped the Watts-Strogatz small world model [WS98] which has a large enough number of triangle. [4] It also features a "small world" characteristic meaning that for most of the vertices there exists a path linking them which is small enough.

1.4 Cayley's formula

In this section we will prove an important result that will be used several times in crucial demonstrations in this report. Indeed it will give an exact result on the number of spanning trees, which are the building blocks of connected graphs. A *tree* is a special case of graph structure that can be defined in several equivalent ways. For instance, a tree is a connected graph such that upon removal of any of its edges, it becomes disconnected, equivalently it is a connected and acyclic graph [5]. We say of a tree that it is *spanning* on its vertex set.

Theorem 1.4.1 (Cayley's formula)**.** We have

$$t_n = n^{n-2} \tag{1.3}$$

with t_n the number of spanning trees of a given set of n vertices.

The proof will need to make use of directed trees. More generally, we define *directed graphs* as graphs [6] in which the adjacency relation is not assumed to be symmetric [7]. We also define doubly rooted trees as trees with two special labels "Start" and "End" that can be attached to any vertices. In such a tree, for any vertex, there exists a path to the vertex labelled "End" [8]. We will call

[3] This choices differs from what usually appear in the real-world where networks are grown through time, see [Cal+01] for a discussion on fundamental differences between grown random graphs and the static random graphs.

[4] More formally, a positive density of triangles

[5] An acyclic graph is a graph that doesn't contain any cycle.

[6] Often simply called digraphs (or ditrees).

[7] In a directed graph an edge can only be followed in one direction.

[8] A tree with only the label "End" is called a *rooted* tree, we observe that the corresponding directed tree is unique.

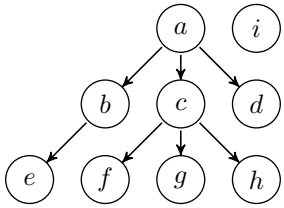

Figure 1.3: An example of a directed tree spanning on the vertex set $\{a, b, c, d, e, f, g, h\}$ but not spanning on the whole set (which includes i).

"SEL" the vertices that are in the path from "Start" to "End". We also denote by DRT_n the set of doubly rooted trees on n vertices.
As a consequence of this definition we have $|DRT_n| = n^2 t_n$, with $|\ |$ denoting the cardinal. To prove the theorem it is then sufficient to prove that the number of elements in DRT_n is equal to n^n. We will base our approach on Joyal's proof [Joy81] and show a bijection between the set of doubly rooted trees on n vertices and the set of functions from $\{1, 2, \ldots, n\}$ to $\{1, 2, \ldots, n\}$. The presentation of the proof we use comes from [LZ12]. We recommend the reader to follow the proof using a given function as an example, see for instance Figure **??** which is the corresponding doubly rooted tree of the function defined in (1.5).

Proof. We will use the notation $[n] = \{1, 2, ..., n\}$ and $V = [n]$. Let's take $f : V \longrightarrow V$, and let's consider the directed graph of f. That is, $\forall v_1, v_2 \in V$ we have $v_1 \to v_2$ if and only if $f(v_1) = v_2$. Drawing such a graph for any function, and it will appear two different kind of structures: directed lines leading to cycles, and cycles. And the whole graph will be a disjoint union of such components. It can be interesting to observe the case in which f is a permutation and then observe that the graph of f is a union of disjoint cycles as expected from the common group theory result.
We now take $C \subseteq V$ the set of vertices that are part of a cycle under the action of f. Equivalently,

$$C = \{x : \exists i \geq 1 s.t. f^i(x) = x\}$$

Let $k = |C|$ and write $C_<$ as $C_< = (c_1 < c_2 < ... < c_k)$ the ordered set [9] and now we will construct a graph with the vertex set $C = f(C)$, and the edge set $E = \bigcup_{i=1}^{k-1} f(c_i)f(c_{i+1})$. We now have $G = (C, E)$ as a line of k vertices, and we will call $f(c_1)$ the "Start" and $f(c_k)$ the "End" which is an oriented graph. Now we will just append to this line the set of vertices that are not in G. So we construct $\tilde{E} = \bigcup_{x \in V \setminus C} xf(x)$ and $\tilde{G} = (V, E \cup \tilde{E})$ is a (directed doubly rooted) tree as it doesn't contain any cycle by construction and is clearly connected. It's obviously directed and doubly rooted. We have now done the biggest part of the proof, that is, going from a function to a doubly rooted tree.
We will now take a doubly rooted tree and transform it in a function. From the

[9] The c_i being integers we simply order them in increasing order.

definition of trees there is a unique "Start" to "End" (SEL) path.
For vertices not on the SEL, for instance some vertex j, we define $f(j)$ as the first neighbour on the j to end line.
For vertices on the SEL,

$$SEL = (x_1, x_2, ..., x_k), \text{ and } SEL_< = (x_{\sigma_1}, x_{\sigma_2}, ..., x_{\sigma_k}) \tag{1.4}$$

we define $f(x_{\sigma_i}) = x_i, \forall i \in [k]$.
Thus, we have two injective constructions, if composed give the identity, hence we have a bijection between the set of endomorphism of $[n]$ and the space of doubly rooted trees on n vertices. So the proof is complete. □

An example We will here illustrate the proof using an example of a transformation from a function to a doubly rooted tree using the following function:

$$\begin{pmatrix} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 \\ 3 & 1 & 1 & 6 & 7 & 5 & 4 & 4 \end{pmatrix}. \tag{1.5}$$

The corresponding doubly rooted tree is then:

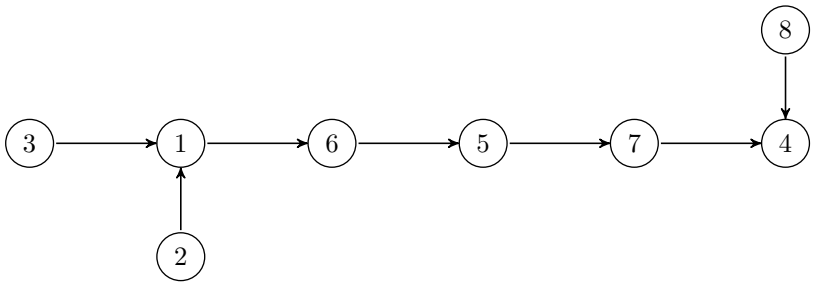

Figure 1.4: The corresponding doubly-rooted tree of (1.5), the "Start" root is vertex 3, the "End" root is vertex 4.

Chapter 2

The Erdos-Renyi Model

2.1 Different approaches of the same space

As said in the title of the section there are different ways to approach the Erdős-Renyi model that we may call paradigms as they will give us the same kind of results but depending on the context, one might be much more convenient to use than the others.
The first paper published on random graphs that gained notoriety was from Erdős and Renyi in 1959 [ER59], in which they give the following construction:

Definition 2.1.1. We define by $\mathcal{G}_{n,M}$ the space of uniformly distributed graph among the graphs with n given vertices and exactly M edges.

One may observe that changes in notations are made compared to the articles from Erdös and Rényi in order to be more adapted with the modern study of random graphs. We will also adopt for the following $N = \binom{n}{2}$ to denote the total number of possible edges on n labelled vertices. From the previous definition, the probability of obtaining a chosen graph in with n vertices and M edges in $\mathcal{G}_{n,M}$ is $1/\binom{N}{M}$. The associated probability measure is denoted by $\mathbb{P}_M$.
We then arrive at our main model that has been the most extensively studied in the literature of random graphs, that is $\mathcal{G}_{n,p}$ on which each of the N possible edges is taken with probability $p \in [0,1]$, independently of the others. This model was first introduced by Gilbert in 1959, see [Gil59][1]. Now if we denote by e_G the number of edges of a graph G on the vertex set $[n]$, we have :

$$\mathbb{P}_p(G) = p^{e_G}(1-p)^{N-e_G} \tag{2.1}$$

This model is called the *binomial model*. When there is no confusion possible, in order to shorten the writings we consider $\mathbb{P} = \mathbb{P}_p$. It is expected that this model is close to the first one if Np is close to M.
The third model that we will investigate is on the form of a Markov process, see

[1] It is interesting to note that Gilbert's paper who was at the time working at Bell's laboratories formulated the question of connectivity based on real life phone networks.

in Appendix for a discussion on properties used here from Markov chains. At time 0 there is no edge in the graph and an edge is selected at random among all of the possible edges. At time t, an edge is chosen among all the edges not already present in the graph. We denote this process by $\{\mathcal{G}_{n,t}\}_t$, with t the number of edges added. It is clear that this model is perfectly equivalent to the first model presented if we fix $t = M$. This model was also introduced in 1959 by Erdős and Renyi and is usually referred to as the *random graph process*. The advantage of this model is that it allows one to study properties on the verge of their realisations. For instance, using this model Bollobás and Thomason [BT85] proved that a graph is fully connected, when the last connection made is between an isolated vertex and the giant component. Equivalently, at the first time when $\delta(G) > 1$.
The three models introduced above ($\mathcal{G}_{n,M}$, $\mathcal{G}_{n,p}$ and $\{\mathcal{G}_{n,t}\}_t$) are usually designated in the literature as Erdős-Rényi model. However, even if the first two are quite similar (static random graphs) the last one is of a different nature as it is dynamic.
In this report we will mainly focus on $\mathcal{G}_{n,p}$ which is in fact easier to study than $\mathcal{G}_{n,M}$. [2] We might also make use of the notation $\mathbb{P}_p$ (resp. $\mathbb{P}_M$) to designate the probability law associated with $\mathcal{G}_{n,p}$ (resp. $\mathcal{G}_{n,M}$). We will see in (2.3.2) that there is a strong relation between those two models.

2.2 Connectivity

One of the most fundamental structure of a graph is its number of connected components. Hence, the first question we will try to ask is with which probability a random graph following the Erdős-Renyi model is connected. It is essential to answer this question as many other questions might not make sense or have an obvious answer on a graph that is not connected (for instance the diameter, the existence of Hamiltonian paths or the stability number of the graph).
It is also an interesting first topic to have an insight of the kind of elegant results that arise from the study of random graphs. The main aim of this section will be to prove the following theorem in a detailed way as it is the first random graphs proof that we will study.

Theorem 2.2.1. Let $p = p(n) = \frac{\log(n)+c}{n}$, $c \in \mathbb{R}$ independent of n.
Then $\lim_{n \to \infty} P(G \in \mathcal{G}_{n,p}$ is connected $) = e^{-e^{-c}}$

The proof of this theorem will be in two parts, first we will show that a graph is connected with high probability if there are no isolated vertices and then we will estimate the distribution of the number of isolated vertices. We designate by giant component a component with a size larger than a constant times n.

Theorem 2.2.2. With $p = \frac{\log(n)+c}{n}$ A graph following $\mathcal{G}_{n,p}$ consists in a single giant component and isolated vertices with probability going to 1 when $n \to \infty$.

[2] There is usually no confusion possible on the model being studied.

Proof. This proof can be found in [Spe14] or [Bol01].
During this proof we will consider the random value X_k that counts the number of connected components of size k. So, let's estimate the probability $\mathbb{P}(X_2 > 0) = \mathbb{P}(X_2 \geq 1)$. In order to do so we will use the method of first moment.

$$\mathbb{P}(X_2 \geq 1) \leq \mathbb{E}(X_2) = \binom{n}{2}\mathbb{P}(\text{"drawing an isolated edge"}) \tag{2.2}$$
$$= \binom{n}{2}p((1-p)^{n-1})^2 \tag{2.3}$$
$$\leq (\frac{ne}{2})^2 p(e^{-p})^{2(n-2)} \tag{2.4}$$
$$= \mathcal{O}\left(n^2 p e^{-2pn}\right) \tag{2.5}$$
$$= \mathcal{O}(n^2 p e^{-2(\log(n)+c)}) = \mathcal{O}(p) \tag{2.6}$$

However, this is not sufficient to prove that there is no isolated component other than isolated vertices. We will observe that there can't have any component of size larger than $\lceil \frac{n}{2} \rceil$ that is not the largest component in the graph. Hence, we will study the probability that there is any component of intermediary size that is not the greatest component.

$$\mathbb{P}(X_k \geq 1) \leq \mathbb{E}(X_k) \quad , \forall k \geq 3 \tag{2.7}$$
$$\leq \binom{n}{k} k^{k-2} q_k \tag{2.8}$$
$$\leq \binom{n}{k} k^{k-2} p^{k-1} ((1-p)^{n-k})^k \tag{2.9}$$

In the above, the "n choose k" term represents the number of possible subsets for the k vertices of a connected component. The term k^{k-2} is the number of possible spanning trees for each of these subset of k vertices. The q_k is the probability that a set of k vertices is not connected to any other of the $n-k$ vertices. Hence the term p^{k-1} is the probability that the edges of the spanning tree are selected and the $((1-p)^{n-k})^k$ is the probability that every vertex of the spanning tree are not connected to any of the other $n-k$ vertices.
Now we will try to have an upper bound of the RHS such that the sum on k will converges to a $o(n^{-\delta})$ for some $\delta > 0$.

$$\mathbb{P}(X_k \geq 1) \leq k^{-2} p^{-1} (\frac{ne}{k})^k k^k p^k e^{-pk(n-k))} \tag{2.10}$$
$$\leq k^{-2} p^{-1} ((\frac{ne}{k}) kpe^{-p(n-k)})^k \tag{2.11}$$
$$\leq p^{-1} (nepe^{-p(n-k)})^k \tag{2.12}$$

If we denote the term in the parentheses by A, then, if $k \leq \frac{n}{2}$

$$A = \mathcal{O}(\log(n) n^{-\frac{1}{2}}) \tag{2.13}$$

Hence, we obtain

$$\sum_{k=2}^{\lfloor n/2 \rfloor} \mathbb{P}(X_k \geq 1) \leq o(1) + p^{-1} \sum_{k=3}^{\lfloor n/2 \rfloor} A^k = o(1) \tag{2.14}$$

Hence, the graph has, with probability tending to one, no component of size between 2 to $\lfloor \frac{n}{2} \rfloor$. Hence it has only isolated vertices and components of size at least $\lceil \frac{n}{2} \rceil$. Necessarily, there is at most one component of size at least $\lceil \frac{n}{2} \rceil$.
On the other hand, such component exists with probability going to 1. Otherwise, the graph would have only isolated vertices and then no edges, which occurs with probability $(1 - p(n))^N \longrightarrow_{n\to\infty} 0$.

This proves theorem (2.2.2). □

Theorem (2.2.1) is proved in a more general setting later in this report in 4.1.1, proofs restricted to the model $\mathcal{G}_{n,p}$ can be found in [JŁR00].

2.3 Existence of thresholds

[3] One of the most surprising features on random graphs, which seems to have motivated Erdős to publish his results from 1959, is the existence of thresholds. Indeed the property of appearance of certain graph properties will be either close to 0 or close to 1 for a great range of functions p.
For instance from the previous theorem we observe that $\forall \epsilon > 0$ if $p = (1 + \epsilon)\frac{\log(n)}{n}$ or if $p = \frac{\log(n)+\omega(n)}{n}$ with $\lim_{n\to\infty} \omega(n) = \infty$ then $\lim_{n\to\infty} \mathbb{P}(G \in \mathcal{G}_{n,p}$ is connected$) = 1$. We would say that for such p, $\mathcal{G}_{n,p}$ is connected with high probability. We also observe that if in the previous definitions of p we changed the $+$ signs into $-$ signs, we would find that $\mathcal{G}_{n,p}$ is disconnected with high probability.
Hence, the function p from (2.2.1) has some very peculiar behaviour on the property of connectivity. We will call such a function a *threshold* (here, for connectivity).
The aim of this section is to detail formally what we mean by a graph property and a threshold function. We will also show a formal relation between $\mathcal{G}_{n,p}$ and $\mathcal{G}_{n,M}$ and a proof of the existence of thresholds on a family of graph properties. It has been shown by Bollobás and Thomason [BT87] that this is in fact not exclusive to random graphs, but true for all monotone properties on random subsets.

Definition 2.3.1. We will call a *graph property* a family of graphs that is closed under isomorphism.

This means that a graph property is independent of the labelling and of the drawing of the graph. We can refine properties in the following definition.

[3] The proofs and results from this section are from [JŁR00] and [Bol01]

Definition 2.3.2. A property is *monotone* [4] *increasing* (resp. *decreasing*) if it's stable under the the addition (resp. removal) of an edge. A graph property $\mathcal{Q}$ is *convex* if when $A, C \in \mathcal{Q}$ and $A \subseteq B \subseteq C$[5] then $B \in \mathcal{Q}$.

For instance, being connected or containing a specific subgraph are monotone increasing properties whereas being planar or containing an isolated vertex are monotone decreasing. As an example of property that is neither monotone increasing or decreasing, we can think of being k-regular for some k (this means that all vertices are of degree k). Having exactly k isolated vertices is an example of a convex not monotone property.
Here is a theorem showing that monotone increasing properties make probability distributions on these properties also monotone increasing.

Theorem 2.3.1. Suppose $\mathcal{Q}$ is a monotone increasing property, $0 \leq M_1 \leq M_2 \leq N$ and $0 \leq p_1 \leq p_2 \leq 1$.
Then

$$\mathbb{P}_{M_1}(\mathcal{Q}) \leq \mathbb{P}_{M_2}(\mathcal{Q}) \text{ and } \mathbb{P}_{p_1}(\mathcal{Q}) \leq \mathbb{P}_{p_2}(\mathcal{Q}). \tag{2.15}$$

Proof. The first inequality is clear, as the only difference between the two spaces on which we evaluate the property $\mathcal{Q}$ is that on the RHS edges have been added, hence, the probability of realising a monotone increasing property has been increased.
For the second inequality, let $p = \frac{p_2 - p_1}{1 - p_1}$. Let $G_1 \in \mathcal{G}_{n,p_1}, G \in \mathcal{G}_{n,p}$ independent to each other.
So if $G_2 = G_1 \cup G$ its edges are chosen with probability $p_1 + p - p_1 p = p_2$. So G_2 follows $\mathcal{G}_{n,p_2}$ and contains G_1, the property being monotone increasing, we have $\mathbb{P}_{p_1}(\mathcal{Q}) \leq \mathbb{P}_{p_2}(\mathcal{Q})$ □

The following result follows from definition, when $\mathcal{Q}$ is any property:

$$\mathbb{P}(\mathcal{Q}) = \sum_{A \in \mathcal{Q}} p^{|A|}(1-p)^{N-|A|} \tag{2.16}$$

However this result requires to know all of the elements in $\mathcal{Q}$ and as we are often interested with properties for very large n this result won't be magical...
The following theorem shows that if we know quite accurately $\mathbb{P}_M(\mathcal{Q})$ for every M close to pN then we know $\mathbb{P}_p(\mathcal{Q})$ with a comparable accuracy. The converse being clearly false, for instance the property of containing M edges.

Theorem 2.3.2. Suppose $\mathcal{Q}$ is any property and $0 < p = M/N < 1$.
Then $\mathbb{P}_M(\mathcal{Q}) \leq 3\sqrt{M}\mathbb{P}_p(\mathcal{Q})$

Proof. Let $\mathcal{Q}$ be any property, then we will write $\mathcal{Q}$ as a disjoint union based on the number of edges in each graph contained in $\mathcal{Q}$.
So we have

$$\mathcal{Q} = \bigsqcup_{m=0}^{N} \mathcal{Q}_m \quad , \text{ with } \forall G \in \mathcal{Q}_m, e(G) = m$$

[4] A property is monotone if it is either increasing or decreasing
[5] $\subseteq$ is the inclusion of the edges on the same set of vertices

We have $\mathbb{P}_m(\mathcal{Q}) = |\mathcal{Q}_m|\binom{N}{m}^{-1}$ From this we can obtain, with $q = 1 - p$

$$\begin{aligned}
\mathbb{P}_p(\mathcal{Q}) &= \sum_{A\in\mathcal{Q}} p^{|A|}q^{N-|A|} = \sum_{m=0}^{N}\sum_{A\in\mathcal{Q}_m} p^{|A|}q^{N-|A|} \\
&= \sum_{m=0}^{N}\sum_{A\in\mathcal{Q}_m} p^m q^{N-m} = \sum_{m=0}^{N} |\mathcal{Q}_m| p^m q^{N-m} \\
&= \sum_{m=0}^{N} p^m q^{N-m}\binom{N}{m}\mathbb{P}_m(\mathcal{Q}) \geq \binom{N}{M} p^M q^{N-M}\mathbb{P}_M(\mathcal{Q}) \\
&\geq \mathbb{P}_M(\mathcal{Q})(e^{\frac{1}{6M}}\sqrt{2\pi pqN})^{-1}
\end{aligned}$$

The last inequality coming from inequality (1.5) of Chapter 1 in [Bol01]. The proof of the inequality uses the sharp estimates of Stirling's $n! \sim (\frac{n}{e})^n\sqrt{2\pi n}e^{\alpha_n}$ for some α_n such that $\frac{1}{12n+1} < \alpha_n < \frac{1}{12n}$ proved in [Rob55]. The proof being rather lengthy and out of the topic of this report we will admit it.

$$\mathbb{P}_M(\mathcal{Q}) \leq \mathbb{P}_p(\mathcal{Q})e^{\frac{1}{6M}}\sqrt{2\pi pqN} \tag{2.17}$$

Observing that $q \leq 1$ and $\sqrt{2\pi}e^{\frac{1}{6}} \approx 2.961... < 3$ the proof is complete. □

The previous section was about connectivity in $\mathcal{G}_{n,p}$, in this section we have seen that connectivity can be characterised as a monotone increasing property. Also it was observed that the function p was somehow best possible, by that we mean that modifying it slightly would imply to only have a zero-one law. We call such a function p a threshold (in that case for the connectivity).

More formally, let $\mathcal{Q}$ a monotone increasing property, in $\mathcal{G}_{n,p}$, we call $\hat{p} = \hat{p}(n)$ a threshold if

$$\mathbb{P}(\mathcal{G}_{n,p} \in \mathcal{Q}) \to \begin{cases} 0 & \text{if } p/\hat{p} \to 0, \\ 1 & \text{if } p/\hat{p} \to \infty. \end{cases} \tag{2.18}$$

Analogously, in $\mathcal{G}_{n,M}$, we call $\hat{M} = \hat{M}(n)$ a threshold if

$$\mathbb{P}(\mathcal{G}_{n,M} \in \mathcal{Q}) \to \begin{cases} 0 & \text{if } M/\hat{M} \to 0, \\ 1 & \text{if } M/\hat{M} \to \infty. \end{cases} \tag{2.19}$$

In fact, thresholds are unique with respect to the multiplication by a positive constant. So for the following, we should denote a threshold for a property as *the* threshold.
As said in the introduction of this section, the fact that thresholds could be found for many of the properties that where investigated is one of the main reason behind the study of random graphs. In fact, the following theorem

from Bollobás and Thomason in [BT87] confirms that we can always expect the existence of a threshold if the property investigated is non trivial [6].

Theorem 2.3.3. Every non-trivial monotone graph property has a threshold

Proof. We consider without loss of generality that $\mathcal{P}$ is a non-trivial monotone increasing graph property. Given $0 < \epsilon < 1$ we define $p : [0,1] \to [0,1]$ such that :

$$\mathbb{P}(\mathcal{G}_{n,p} \in \mathcal{P}) = \epsilon \tag{2.20}$$

The existence of p is guaranteed from (2.16) because it is an increasing polynomial in p, from 0 to 1. Indeed, we know that it is increasing from (2.3.1).
We will show that $p^* = p(\frac{1}{2})$ is a threshold for $\mathcal{P}$ through a coupling argument. We take $G_1, G_2, ..., G_k$ independent random variables following $\mathcal{G}_{n,p}$. Then we claim that $G_1 \cup G_2 \cup ... \cup G_k$ is distributed like $\mathcal{G}_{n,1-(1-p)^k}$. This is clear by induction on k since we observe the following equivalence for $p_1 < p$ and p_2.

$$1 - p = (1 - p_1)(1 - p_2) \iff p = p_1 + p_2 - p_1 p_2 \tag{2.21}$$

The previous equation being satisfied with $p = 1 - (1-p)^k$, $p_1 = 1 - (1-p)^{k-1}$ and $p_2 = p$.
We may now use Bernoulli's inequality (A.1.4), $1 - (1-p)^k \leq kp$ to obtain that we can couple the graphs in such a way that:

$$\mathbb{G}_{n,1-(1-p)^k} \subseteq \mathbb{G}_{n,kp} \tag{2.22}$$

and so $\mathbb{G}_{n,kp} \notin \mathcal{P}$ implies $G_1, G_2, ..., G_k \notin \mathcal{P}$. We obtain

$$\mathbb{P}(\mathbb{G}_{n,kp} \notin \mathcal{P}) \leq (\mathbb{P}(\mathbb{G}_{n,p} \notin \mathcal{P}))^k \tag{2.23}$$

Let ω be a function of n growing arbitrarily slowly such that $\lim_{n\to\infty} \omega(n) = \infty$. Suppose also $p^* = p(\frac{1}{2})$ and $k = \omega$, then

$$\mathbb{P}(\mathbb{G}_{n,\omega p^*} \notin \mathcal{P}) \leq 2^{-\omega} = o(1) \tag{2.24}$$

On the other hand,

$$\frac{1}{2} = \mathbb{P}(\mathbb{G}_{n,p^*} \notin \mathcal{P}) \leq (\mathbb{P}(\mathbb{G}_{n,\frac{p^*}{\omega}} \notin \mathcal{P}))^\omega \tag{2.25}$$

Finally,

$$\mathbb{P}(\mathbb{G}_{n,\frac{p^*}{\omega}} \notin \mathcal{P}) \geq 2^{-\frac{1}{\omega}} = 1 - o(1) \tag{2.26}$$

This proves that p^* is a threshold for $\mathcal{P}$. □

[6] A property being trivial if it is always or never satisfied, for instance, having a specified number of vertices or the empty-set propery.

2.4 The stability number

[7] Another property of graphs that one might be interested to study is the stability number. The *stability number* of a graph is the size of the largest set of vertices we can choose in a graph such that no two vertices are adjacent. One of the reasons that makes this an interesting property to study is that it is linked to one of the most fundamental property of graphs, $\chi(G)$, the *chromatic number*. Indeed, the chromatic number is the smallest number of colours[8] that makes a *proper colouring* of a graph, that means a colouring on which there are no two adjacent vertices of the same colour. If we denote by $\alpha(G)$ the stability number of a graph, it is not difficult to get [9]

$$\chi(G) \geq \frac{n}{\alpha(G)} \tag{2.27}$$

Before giving a lower bound on the stability number of a graph it might be interesting to notice that the notion of stable set is dual to the notion of clique and is analogous to the notion of perfect matching that concerns the edges. Although the following theorem will give a bound that is quite tight in $\mathcal{G}_{n,p}$ the problem of finding the actual maximum stable set of a graph is a NP-hard problem.

Theorem 2.4.1. The stability number of a graph in $\mathcal{G}_{n,p}$, is at most $\lceil 2p^{-1}\log(n)\rceil$, with probability going to 1 when $n \longrightarrow \infty$.

Proof. Let $G \in \mathcal{G}_{n,p}$ and $S \subseteq V$ such that S contains $k+1$ vertices. Then we have

$$\mathcal{P}(\text{"S is a stable set"}) = (1-p)^{\binom{k+1}{2}} \tag{2.28}$$

as none of the $\binom{k+1}{2}$ possible edges must be selected.
Let's define our random values as follows, $X_S = \mathbb{1}(\text{" } S \text{ is a stable set "})$ and

$$X_{k+1} = \sum_{\substack{S\subseteq V \\ |S|=k+1}} X_S \tag{2.29}$$

the random variable counting the number of stable sets of size $k+1$, so what we are investigating here is the smallest α such that $X_k = 0, \forall k > \alpha$. Such an

[7] This section is from [BM08]

[8] A colouring of a graph is just assigning to each edge a colour. Colours can be thought as "red, green, blue, ..." or as numbers.

[9] We use this link with the chromatic as a simple motivation for studying the stability number. It is a number which is in fact of great importance in graph theory but on matters that are out of the scope of this report. See for instance Chapter 12 in [BM08].

α would then be the stability number.

$$\mathbb{E}X_{k+1} = \sum_{\substack{S\subseteq V \\ |S|=k+1}} \mathbb{E}X_S = \sum_{\substack{S\subseteq V \\ |S|=k+1}} \mathbb{P}(X_S = 1) \tag{2.30}$$

$$= \sum_{\substack{S\subseteq V \\ |S|=k+1}} (1-p)^{\binom{k+1}{2}} = (1-p)^{\binom{k+1}{2}} \sum_{\substack{S\subseteq V \\ |S|=k+1}} 1 \tag{2.31}$$

$$= \binom{n}{k+1}(1-p)^{\binom{k+1}{2}} \tag{2.32}$$

Now we will use the inequalities $\binom{n}{k+1} \leq \frac{n^{k+1}}{(k+1)!}$ and $(1-p) \leq e^{-p}$ (see A.1.5.1). And we have

$$\mathbb{E}X_{k+1} \leq \frac{n^{k+1}}{(k+1)!}e^{-p\binom{k+1}{2}} = \frac{n^{k+1}}{(k+1)!}e^{-p\frac{k(k+1)}{2}} \tag{2.33}$$

$$\leq \frac{(ne^{-p\frac{k}{2}})^{k+1}}{(k+1)!} \tag{2.34}$$

So, if we consider $k = \lceil 2p^{-1}\log(n)\rceil \leq 2p^{-1}\log(n)$ we have that $ne^{-p\frac{k}{2}} \leq 1$. We finally obtain

$$\mathbb{E}X_{k+1} \longrightarrow_{n\to\infty} 0 \tag{2.35}$$

And then $X_{k+1} = 0$ with probability tending to 1 which proves the theorem.

□

2.5 The diameter

[10]

Definition 2.5.1. The *diameter* of a graph is the greatest distance between any pair of vertices. We denote it by $\mathrm{diam}(G)$ and say it is equal to ∞ if the graph is not connected.

It is quite easy to understand that the diameter is a value that is a great importance particularly in applied systems. For instance, the small world phenomena is quite notorious (and will be discussed later in this report) but we can also think of optimisation problems in which the fact that two points are far apart might be of great consequences. This section won't be focused on real world applications of the diameter because as we will see we are studying a model which is not realistic for that. Hence we will first discuss some graph theoretic problems and results on the diameter and after giving the main theorem on the diameter we will prove it through several technical lemmas, some of which will be admitted. Finally some corollary will be obtained from the theorem.

[10] This section uses [Bol01]

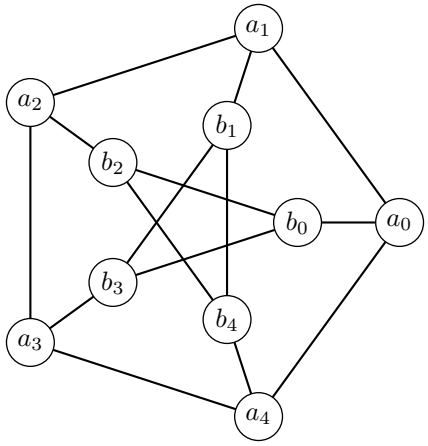

Figure 2.1: A representation of Petersen's graph, $D = 2$, $\Delta = 3$

One of the challenging questions in graph theory is estimating the following function

$$n(D, \Delta) = max\{|G|, \text{diam}(G) \leq D, \Delta(G) \leq \Delta\} \tag{2.36}$$

n is the function that for a fixed diameter D and a fixed maximal degree Δ, gives the maximal number of vertices of a graph that verifies both conditions. This is the kind of problem that is part of *extremal graph theory*.
For instance if we take $\Delta = 2$ we obtain easily by construction that a graph that maximises the number of vertices with a diameter D is a $(2D + 1)$-cycle. Hence,

$$n(D, 2) = 2D + 1, \forall D \in \mathbb{N} \tag{2.37}$$

But it is in fact very hard to obtain such a formula for other values of D or Δ. If we take a graph of max degree Δ we observe that there are at most $\Delta(\Delta-1)^{k-1}$ vertices at distance k from a chosen vertex. It is easily to be convinced of this simply by drawing such a graph. From this very simple construction we can obtain the following upper bound

$$n(D, \Delta) \leq 1 + \Delta \sum_{j=1}^{D} (\Delta - 1)^{j-1} = \frac{\Delta(\Delta - 1)^D - 2}{\Delta - 2} = n_0(D, \Delta) \tag{2.38}$$

n_0 is called the Moore bound and a graph for which the Moore bound is best possible is called a Moore graph. The *Petersen's graph* is such a graph with parameter $D = 2$ and $\Delta = 3$, see Figure 2.1. When $D = 2$ explicit constructions of Moore graphs have been found with $\Delta = 2$ (pentagon) and $\Delta = 3$ (Petersen's graph) as we have seen above. There also exists an explicit construction with $\Delta = 7$, the Hoffman-Singleton graph on 50 vertices. There might exist a graph with $\Delta = 57$ on 3250 vertices but its existence is still an open-question. However, it is proved that no other graph of diameter 2 can be a Moore graph, see [HS60].

In the end of this section we will give a quite good lower bound on n, in order to do so, we will see that we can select a probability function p such that the value of the diameter is highly concentrated.
In the following we will consider that $d = d(n) \geq 2$ is a natural number (representing the diameter) and c is a positive real number.
Now let's give some functions that will allow us to make a study of the diameter in random graphs. If we choose x a vertex in a graph, then we define $\Gamma_k(x)$ as the set of vertices at distance k from x. And from this we will define $N_k(x)$ as the set of vertices of distance less than or equal to k. Formally, we have

$$\Gamma_k(x) = \{v : d(x, v) = k\} \tag{2.39}$$

$$N_k(x) = \bigcup_{i=1}^{k} \Gamma_i(x) \tag{2.40}$$

And we can link those with the diameter using, $\text{diam}(G) \leq d$ if and only if $N_d(x) = V(G), \forall x$.
Similarly $\text{diam}(G) \geq d$ if and only if $\exists y, N_{d-1}(y) \neq V(G)$.
Now we will define the probability function that we will use in the following of this section as

$$p^d n^{d-1} = \log(\frac{n^2}{c}) \quad , \text{ for some } c > 0 \tag{2.41}$$

Moreover, we will assume

$$\frac{pn}{(\log(n))^3} \longrightarrow \infty \tag{2.42}$$

Note that this condition is automatically satisfied if $d(n)$ is uniformly bounded.
The aim of this section will be to prove the following theorem.

Theorem 2.5.1. Using all previous definitions and conditions on p, d and c, we have,

$$\mathbb{P}(\text{diam}(\mathbb{G}_{n,p}) = d) \longrightarrow e^{-\frac{c}{2}} \tag{2.43}$$

$$\mathbb{P}(\text{diam}(\mathbb{G}_{n,p}) = d + 1) \longrightarrow 1 - e^{-\frac{c}{2}} \tag{2.44}$$

This theorem states that in $\mathcal{G}_{n,p}$ with p defined as in (2.41) the diameter is spread on only two values. As a corollary we clearly have

Corollary 2.5.1.1. Using all previous definitions on p, d and c. We have,

$$\mathbb{P}(\text{diam}(\mathbb{G}_{n,p} \in \{d, d + 1\}) \longrightarrow 1 \tag{2.45}$$

In fact the number of values that the diameter can take has been fully resolved by Chung and Lu in [CL01].
Before proving such a theorem we will need some technical lemmas and assumptions. So we will give here some equations for reference later. Also from (2.42),

$$p(\frac{\log(n)}{n})^{-1} \longrightarrow_{n \to \infty} \infty. \tag{2.46}$$

The previous limit (2.46) meaning that p grows faster $\log(n)/n$ should not be too surprising as the threshold for connectivity is $\frac{\log(n)+c}{n}$ as shown before. Hence we are studying a connected graph with high probability. We may also observe, since $d(n) \geq 2$ that $p = o(n^{-\frac{1}{2}+\epsilon}), \forall \epsilon > 0$. We observe that p and d are connected as follows:

$$p = n^{\frac{1}{d}-1}(\log(\frac{n^2}{c}))^{\frac{1}{d}} \tag{2.47}$$

$$d = \frac{1}{\log(pn)}(\log(n) + \log\log(n) + \log(2) + \mathcal{O}(\frac{1}{\log(n)})) \tag{2.48}$$

$$= \mathcal{O}((1+o(1))\frac{\log(n)}{\log\log(n)}) \tag{2.49}$$

And finally

$$p(pn)^{d-2} = o(1) \tag{2.50}$$

The first lemma that we present here gives a tail inequality of $\Gamma_k(x)$ conditionally on some space that we will now define. In this section, Ω_k is $\mathcal{G}_{n,p}$ conditionned on $a = |\Gamma_{k-1}(x)|$ and $b = |N_{k-1}(x)|$ that satisfy

$$\begin{cases} \frac{1}{2}(pn)^{k-1} \leq a & \leq \frac{3}{2}(pn)^{k-1} \\ b & \leq 2(pn)^{k-1} \end{cases} \tag{2.51}$$

Lemma 2.5.2. Let x be a fixed vertex.

$$1 \leq k = k(n) \leq d-1 \tag{2.52}$$

And $K = K(n)$ that satisfy $6 \leq K \leq \frac{1}{12}\sqrt{pn\frac{1}{\log(n)}}$ We also define

$$\alpha_k = K\sqrt{\frac{\log n}{(pn)^k}}, \quad \beta_k = p(pn)^{k-1}, \quad \gamma_k = 2\frac{(pn)^{k-1}}{n} = \frac{2\beta_k}{pn} \tag{2.53}$$

Then

$$\mathbb{P}(|\Gamma_k(x)| - apn| \geq (\alpha_k + \beta_k + \gamma_k)apn \quad | \quad \Omega_k) \leq n^{-\frac{K^2}{9}} \tag{2.54}$$

Proof. Conditionally on $|\Gamma_{k-1}(x)| = a$ and $|N_{k-1}(x)| = b$, $|\Gamma_k(x)|$ follows a binomial distribution of parameters $n_k = n - b$ and

$$p_a = 1 - (1-p)^a \tag{2.55}$$

Indeed $\Gamma_k(x)$ is the set of vertices not in $N_{k-1}(x)$ and connected to at least one element of $\Gamma_{k-1}(x)$.
In the following inequalities we will assume that n is large enough, this will allow us to do certain inequalities that are only asymptotically satisfying. Also to make it more easy for the reader we consider that all of these inequalities

take place in Ω_k without writing it explicitly. Under the event we consider, we have:

$$|\Gamma_k(x)| - apn| \geq (\alpha_k + \beta_k + \gamma_k)apn \tag{2.56}$$
$$\geq (\alpha_k + \beta_k + \gamma_k)apn + ap(n - n_k) \tag{2.57}$$
$$= (\alpha_k + \beta_k + \gamma_k + 1 - \frac{n_k}{n})apn \tag{2.58}$$
$$= (\alpha_k + \beta_k + \gamma_k - \frac{b}{n})apn \tag{2.59}$$
$$\tag{2.60}$$

Using, (2.51), we obtain the following inequality:

$$\gamma_k - \frac{b}{n} = \frac{1}{n}(\frac{2\beta_k}{p} - b) = \frac{1}{n}(2(pn)^{k-1} - b) > 0 \tag{2.61}$$

From which we get:

$$(\alpha_k + \beta_k + \gamma_k - \frac{b}{n})apn \geq (\alpha_k + \beta_k)apn \geq (\alpha_k + \beta_k)apn_k \tag{2.62}$$

From this first sequence of inequalities we managed to remove γ_k and we used some n_k that is less than n. The point in evaluating these inequalities is that we now have

$$\mathbb{P}(|\Gamma_k(x)| - apn| \geq (\alpha_k + \beta_k + \gamma_k)apn \quad | \quad \Omega_k) \tag{2.63}$$
$$\leq \mathbb{P}(|\Gamma_k(x)| - apn_k| \geq (\alpha_k + \beta_k)apn_k \quad | \quad \Omega_k) \tag{2.64}$$

Now using $ap - p_a \leq \beta_k ap$ and the triangular inequality we have

$$\leq \mathbb{P}(|\Gamma_k(x)| - p_a n_k| \geq \alpha_k apn_k \quad | \quad \Omega_k) \tag{2.65}$$
$$\leq \mathbb{P}(|\Gamma_k(x)| - p_a n_k| \geq \alpha_k p_a n_k \quad | \quad \Omega_k) \tag{2.66}$$
$$\tag{2.67}$$

And using the tail inequality of Theorem 1.7 from Bollobás [Bol01] which we admit, we have,

$$\leq \frac{1}{\sqrt{\alpha_k^2 p_a n_k}} \exp(-\frac{1}{3}\alpha_k^2 p_a n_k) \tag{2.68}$$
$$\leq \exp(-\frac{1}{3}\alpha_k^2 p_a n_k) \tag{2.69}$$

And using $p_a \geq pa(1 - \frac{pa}{2})$, $a \geq \frac{1}{2}(pn)^{k-1}$ and using $n_k = n - b$ we obtain $p_a n_k > \frac{(pn)^k}{3}$ that we insert in the previous inequality that will give us the result expected.

$$\leq \exp(-\alpha_k^2 \frac{(pn)^k}{9}) = n^{-\frac{K^2}{9}} \tag{2.70}$$

□

We will now prove another lemma

Lemma 2.5.3. Let $K > 12$ a constant and $\alpha_k, \beta_k, \gamma_k, k = 1, ..., d-1$ as before. Set

$$\delta_k = \exp(2\sum_{l=1}^{k}(\alpha_l + \beta_l + \gamma_l)) - 1 \tag{2.71}$$

Then if n is sufficiently large, with probability at least $1 - n^{-K-2}$ for every vertex x and every natural number $k, 1 \leq k \leq d-1$ we have

$$||\Gamma_k(x)| - (pn)^k| \leq \delta_k (pn)^k \tag{2.72}$$

Proof. As $\delta_{d-1} \longrightarrow_{n\to\infty} 0$ we may assume that $\delta_{d-1} < \frac{1}{4}$. For a fixed vertex x, we denote by Ω_k^* the set of graph for which

$$||\Gamma_l(x)| - (pn)^l| \leq \delta_l (pn)^l \quad , 0 \leq l \leq k \tag{2.73}$$

And it is easy to verify that it is decreasing. Anf if one replaces $|\Gamma_l(x)|$ by a it is clear that we have

$$\Omega_k^* \subseteq \Omega_{k-1}^* \subseteq \Omega_k \tag{2.74}$$

We shall now prove by induction that:

$$1 - \mathbb{P}(\Omega_k^*) \leq 2kn^{-\frac{K^2}{9}} \tag{2.75}$$

Now, simply applying Bayes formula (for the complementary) we have

$$1 - \mathbb{P}(\Omega_k^*) = 1 - \mathbb{P}(\Omega_{k-1}^*) + \mathbb{P}(\Omega_{k-1}^*)\mathbb{P}(||\Gamma_k(x)| - (pn)^k| > \delta_k (pn)^k | \Omega_{k-1}^*) \tag{2.76}$$

If $G \in \Omega_{k-1}^*$ and $|a| = |\Gamma_{k-1}(x)|$, then by applying the definition of belonging to Ω_{k-1}^* and multiplying both sides by pn we have

$$|(pn)^k - apn| \leq \delta_{k-1}(pn)^k \tag{2.77}$$

And we obtain using the second triangular inequality

$$\mathbb{P}(\neg\Omega_k^* | \Omega_{k-1}^*) \leq \mathbb{P}(\Omega_{k-1}^*)^{-1}\mathbb{P}(||\Gamma_k(x)| - apn| \ \geq (\delta_k - \delta_{k-1})(pn)^k | \Omega_k) \tag{2.78}$$

$$\leq (1 - 2(k-1)n^{-\frac{K^2}{9}})^{-1}\mathbb{P}(||\Gamma_k(x)| - apn| \ \geq 2(\alpha_k + \beta_k + \gamma_k)(pn)^k | \Omega_k) \tag{2.79}$$

The last inequality being obtained from the hypothesis of induction and using $(1 + x) \leq \exp(x)$. Now using the fact that $apn \leq \frac{3}{2}(pn)^k$ we have

$$\leq 2\mathbb{P}(||\Gamma_k(x)| - apn| \ \geq (\alpha_k + \beta_k + \gamma_k) apn | \Omega_k) \tag{2.80}$$

$$\leq 2n^{-\frac{K^2}{9}} \tag{2.81}$$

which proves (2.75). If we combine the last inequality that is obtained applying the previous lemma with (2.76) then we have the result. □

Definition 2.5.2. For x and y two vertices of G, we say that x and y are remote if $y \notin N_d(x)$.

We shall now prove that with high probability, two remote pairs of vertices in $\mathcal{G}_{n,p}$ do not share a vertex. From 2.5.3 we can obtain the following equation.

$$\mathbb{P}(|N_{d-1}(x)| < \frac{5}{6}(pn)^{d-1}) < n^{-4} \tag{2.82}$$

Now we estimate the probability that a vertex y is joined to no vertex in a set W with $|W| \geq \frac{5}{6}(pn)^{d-1}$

$$(1-p)^{|W|} \leq \exp(-|W|) \leq \exp(-p|W|) = \exp(-\frac{5}{6}\log(\frac{n^2}{c})) = c^{\frac{5}{6}}n^{-\frac{5}{3}} \tag{2.83}$$

Hence, if x, y, z are distinct vertices we have

$$\begin{aligned}
&\mathbb{P}(x \text{ is remote from } y \text{ and } z\ ) && (2.84)\\
&\quad \leq \mathbb{P}(|N_{d-1}(x)| \leq \frac{5}{6}(pn)^{d-1}) && (2.85)\\
&\quad + \mathbb{P}(\{y,z\} \cap N_{d-1}(x) = \emptyset |\ |N_{d-1}(x)|\ \geq \frac{5}{6}(pn)^{d-1}) && (2.86)\\
&\quad \leq \mathbb{P}(|N_{d-1}(x)| \leq \frac{5}{6}(pn)^{d-1}) && (2.87)\\
&\quad + (\mathbb{P}(y \text{ is not joined to } W = N_{d-1}(x) | W \geq \frac{5}{6}(pn)^{d-1}))^2 && (2.88)\\
&\quad \leq n^{-4} + c^{\frac{5}{3}}n^{-\frac{10}{3}} && (2.89)\\
&\quad \leq n^{-3}n^{-\frac{1}{4}} && (2.90)
\end{aligned}$$

So, we obtain

$$\begin{aligned}
&\mathbb{P}(\mathcal{G}_{n,p} \text{ contains two remote vertices pairs sharing a vertex }) && (2.91)\\
&\quad \leq \sum_x \sum_{(y \neq z)} \mathbb{P}(\ x \text{ is remote from } y \text{ and } z\ ) && (2.92)\\
&\quad \leq \sum_x \binom{n}{2} n^{-3-\frac{1}{4}} = n\binom{n}{2} n^{-3-\frac{1}{4}} && (2.93)\\
&\quad \leq n^{-\frac{1}{4}} && (2.94)
\end{aligned}$$

The following lemma can be obtained quite easily simply by construction.

Lemma 2.5.4. From r disjoint pair of vertices, there are 2^r r-tuples of vertices meeting each pair.

As we have seen above, the number of remote pairs is within $o(1)$ the number of remote disjoint pairs, which gives the following lemma.

Lemma 2.5.5. The r-th factorial moment of X, X being the number of remote pairs of vertices, is within $o(1)$ of the expected number of ordered r-tuples of disjoint remote pairs.

If we denote by $\mathbb{F}_r$ the probability that a fixed r-tuple consists of vertices remote from other vertices. Then,

$$\mathbb{E}_r(X) = \frac{n!}{(n-r)!}2^{-r}\mathbb{F}_r(1+o(1)) + o(1) \tag{2.95}$$

In order to shorten the proof, we admit the following lemma that requires a quite long and technical proof. The proof can be found in [Bol81].

Lemma 2.5.6. Let $K = \max\{r+2, e^7\}$ and using all previous definitions on p, d and c, in particular (2.42). With probability at least $1 - n^{-K}$

$$(1-n^{-K})Q_r \leq \mathbb{F}_r \leq (1-n^{-K})Q_r + n^{-K} \tag{2.96}$$

with $Q_r = (\frac{c}{n})^r(1+o(1))$.
In particular:

$$\mathbb{F}_r = (\frac{c}{n})^r(1+o(1)) \tag{2.97}$$

and we can obtain the asymptotical estimate

$$\mathbb{E}_r(X) = n^r 2^{-r}(\frac{c}{n})^r(1+o(1)) + o(1) \tag{2.98}$$

Using the following theorem

Theorem 2.5.7. [11] Let $X_1, X_2, \ldots$ be non-negative integer valued random variables and X a random variable following a Poisson distribution of parameter λ. Suppose

$$\lim_{n\to\infty} \mathbb{E}_r(X_n) = \lambda^r, \quad r = 0, 1, \ldots \tag{2.99}$$

and

$$\lim_{r\to\infty} \frac{E_r(X)r^m}{r!} = 0, \quad m = 0, 1, \ldots \tag{2.100}$$

Then

$$X_n \longrightarrow_d X \tag{2.101}$$

Then we have that X converges in distribution to Poisson law of parameter $\frac{c}{2}$.
We can then obtain

$$\mathbb{P}(X=0) = \mathbb{P}(\mathrm{diam}(G) \leq d) \longrightarrow e^{-\frac{c}{2}} \tag{2.102}$$

that proves the first part of the theorem. For each fixed c, we have $p \geq p'$ where $(p')^{d+1}n^d = \log(\frac{n^2}{c})$, when n is large enough. Hence, by the previous estimates, with d replaced by $d+1$, we get,

$$\liminf_{n\to\infty} \mathbb{P}(\mathrm{diam}(G) \leq d+1) \geq e^{-\frac{c}{2}} \tag{2.103}$$

[11] See (A.1.3) for a proof

and since c is arbitrary

$$\mathbb{P}(\text{diam}(G) \leq d+1) \longrightarrow_{n\to\infty} 1 \tag{2.104}$$

Finally, if we combine the last result with (2.102) it is clear that the proof if complete.
To end this section we present two theorems that are much easier to prove with a similar flavor to the previous one.

Theorem 2.5.8. Suppose

$$i) \quad p^2 n - 2\log(n) \longrightarrow \infty \tag{2.105}$$

$$ii) \quad n^2(1-p) \longrightarrow \infty \tag{2.106}$$

Then almost every graph in $\mathcal{G}_{n,p}$ has diameter 2.

Proof. for two distinct vertices x and y,

$$\mathbb{P}(\text{dist}(x,y) > 2) = (1-p^2)^{n-2}(1-p) \tag{2.107}$$

as it is the probability that two vertices x and y are not connected by a path of length one or two.
Then using the the first moment method.

$$\mathbb{P}(\text{diam}(\mathbb{G}_{n,p}) > 2) \leq \mathbb{E}(\text{number of pairs of vertices with distance} > 2) \tag{2.108}$$

$$\leq \binom{n}{2}(1-p)(1-p^2)^{n-2} = \mathcal{O}(n^2 e^{-np^2}) \tag{2.109}$$

which tends to 0 by i). Hence, with high proability, the diameter of $\mathbb{G}_{n,p}$ is less than 2. In order to finish to prove the theorem we need to show that the diameter of $\mathbb{G}_{n,p}$ is not 1 with high probability. A graph of diameter 1 being a complete graph we have

$$\mathbb{P}(\text{diam}(\mathbb{G}_{n,p}) = 1) = \mathbb{P}(\mathbb{G}_{n,p} = K_n) = p^{\binom{n}{2}} \longrightarrow 0 \tag{2.110}$$

$$\text{iff } \log p^{\binom{n}{2}} \longrightarrow -\infty \tag{2.111}$$

$$\text{iff } n^2 \log p \longrightarrow -\infty \tag{2.112}$$

$$\text{iff } n^2(1-p) \longrightarrow +\infty \tag{2.113}$$

□

And simply if we remember the previous theorem (2.3.2) linking $\mathcal{G}_{n,p}$ and $\mathcal{G}_{n,M}$ we obtain the following corollary:

Corollary 2.5.8.1. If $M = M(n) < \binom{n}{2}$ satisfies

$$\frac{2M^2}{n^3} - \log(n) \longrightarrow \infty \tag{2.114}$$

Then with high probability $\mathbb{G}_{n,M}$ is of diameter 2.

Proof. The first condition makes that we are not studying a complete graph then the diameter is not 1. And we have the proof simply using (2.3.2) with $pN = M$ and combining it with the previous theorem (2.5.8) we have the result. □

Now that we know that the diameter is spread on two values we are interested in restricting it on only one value. We may observe that theorem (2.5.8) gives us enough information to do so. Indeed, we see that if we forced $c \to 0$ then the diameter would be d. This would translate in (2.41) as

$$p^d n^{d-1} - 2\log(n) \longrightarrow \infty \tag{2.115}$$

But this restriction is not sufficient because the values of the diameter might be smaller than d then we will need to make sure that the probability that the diameter is $d-1$ goes to 0 which we could do forcing $c \to \infty$. In the same fashion as previously this would translate as

$$p^{d-1} n^{d-2} - 2\log(n) \longrightarrow -\infty \tag{2.116}$$

This informal reasoning gives motivation for the following corollary of (2.5.8) that we will now formally prove. [12]

Corollary 2.5.8.2. Suppose $d = d(n) \geq 3$ and $p = p(n)$ satisfy

$$\frac{\log(n)}{d} - 3\log\log n \to \infty \tag{2.117}$$

$$p^d n^{d-1} - 2\log(n) \longrightarrow \infty \quad \text{and} \quad p^{d-1} n^{d-2} - 2\log(n) \longrightarrow -\infty \tag{2.118}$$

Then almost every $\mathbb{G}_{n,p}$ has diameter d.

Proof. Let K_1 and K_2 be positive constants and define $0 < p_1 < p_2 < 1$ by

$$p_1^d n^{d-1} = \log(\frac{n^2}{K_1}) \quad \text{and} \quad p_2^{d-1} n^{d-2} = \log(\frac{n^2}{K_2}) \tag{2.119}$$

Then

$$\limsup_{n\to\infty} \mathbb{P}(\text{diam}\mathbb{G}_{n,p} \geq d+1) \leq \limsup_{n\to\infty} \mathbb{P}(\text{diam}\mathbb{G}_{n,p_1} \geq d+1) = 1 - e^{-\frac{K_1}{2}} \tag{2.120}$$

$$\limsup_{n\to\infty} \mathbb{P}(\text{diam}\mathbb{G}_{n,p} \leq d-1) \leq \limsup_{n\to\infty} \mathbb{P}(\text{diam}\mathbb{G}_{n,p_2} \leq d-1) = e^{-\frac{K_2}{2}} \tag{2.121}$$

As we can choose an arbitrary small K_1 and an arbitrarily large K_2 the assertion follows. □

Now, going back to the degree-diameter problem defined in (2.36), which is of finding the largest graph with fixed diameter and maximal degree. As we already have the Moore upper bound, we are interested in finding a lower bound,

[12] In fact it is a immediate consequence of the last part of the proof of (2.5.8) but we will prove it only assuming the theorem itself.

and maybe hope that it would be close from Moore's bound in order to obtain precise estimate of $n(D, \Delta)$. To obtain such a bound here we will make use of the probabilistic method by sampling on an appropriate graph space (with known diameter and max degree), we will show that a specified property appears with positive probability, which ensures the existence of at least one graph satisfying the property.
We admit the following result from [Bol01].

Theorem 2.5.9. If $\frac{pn}{\log n} \to \infty$, then with high probability, $\mathbb{G}_{n,p}$ satisfies

$$\Delta(\mathbb{G}_{n,p}) = (1 + o(1))pn \tag{2.122}$$

We can obtain the following result :

Theorem 2.5.10. Suppose $0 < \epsilon < 1$ and the sequence $(D_k), (\Delta_k)$ are such that

$$D_k^4 \leq \Delta_k \quad \text{and} \quad D_k \to \infty \tag{2.123}$$

Then if k is sufficiently large,

$$n(D_k, \Delta_k) \geq \frac{((1-\epsilon)\Delta_k)^{D_k}}{2D_k \log \Delta_k} \tag{2.124}$$

Proof. We consider a random graph with $\mathcal{G}_{n_k,p_k}$, with:

$$n_k = \lceil \frac{((1-\epsilon)\Delta_k)^{D_k}}{2D_k \log \Delta_k} \rceil \tag{2.125}$$

$$p_k = n_k^{\frac{1}{D_k}-1}(2\log(n_k) + \log\log(n_k))^{1/D_k} \tag{2.126}$$

From the previous corollary (2.5.8.2), $\mathbb{G}_{n_k,p_k}$ has diameter at most D_k with probability going to 1. By Theorem (2.5.9), $\mathbb{G}_{n_k,p_k}$ has with high probability maximal degree $(1 + o(1))p_k n_k$. Which gives:

$$\begin{aligned}
\Delta(\mathbb{G}_{n_k,p_k}) &= (1 + o(1))n_k p_k && (2.127)\\
&= (1 + o(1))n_k^{1/D_k}(2\log n_k + \log\log n_k)^{1/D_k} && (2.128)\\
&= (1 + o(1))\lceil \frac{(1-\epsilon)\Delta_k}{(2D_k \log(\Delta_k))^{1/D_k}} \rceil (2\log n_k + \log\log n_k)^{1/D_k} && (2.129)\\
&\leq \frac{(1 + o(1))(1-\epsilon)\Delta_k}{(2D_k \log \Delta_k)^{1/D_k}}(2D_k \log((1-\epsilon)\Delta_k))^{1/D_k} && (2.130)\\
&\leq (1 + o(1))(1-\epsilon)\Delta_k && (2.131)\\
&< \Delta_k && (2.132)
\end{aligned}$$

This provides the existence of a graph with n_k vertices, diameter at most D_k, degree at most Δ_k. Hence,

$$n(D_k, \Delta_k) \geq n_k \geq \frac{((1-\epsilon)\Delta_k)^{D_k}}{2D_k \log \Delta_k} \tag{2.133}$$

□

As a strengthening of this result, Bollobás [Bol04] conjectured that for each $\epsilon > 0$, it should be the case that

$$n(D, \Delta) > (1 - \epsilon)\Delta^D$$

if Δ and D are sufficiently large.
A quite recent survey on the degree-diameter problem can be found in [MS13].

Chapter 3

Branching processes on random graphs

3.1 Galton-Watson trees

A branching process is the simplest model that can be used to describe the evolution of a population over time. Typically in a branching process we start with one individual, consider it will create a number of individuals through his lifetime. The distribution of this number is called the offspring distribution and we denote it by $\{p_i\}_0^\infty$ such as

$$p_i = \mathbb{P}(\text{ having i children }) \tag{3.1}$$

In order to avoid trivialities we assume in the following $p_0 > 0$. When we say that a branching process is a "something" branching process, that means that the offspring distribution follows the "something" law (typically a Poisson branching process). And we also denote by Z_n the number of individuals in the n-th generation. Then if we consider that the offspring distribution doesn't depend on the generation of the individual considered we have

$$Z_n = \sum_{i=1}^{Z_{n-1}} X_{n,i} \quad , \text{ with } X = \{X_{n,i}\}_{n,i}, \text{ i.i.d.} \tag{3.2}$$

Observing this distribution, we observe that if for some generation k_0 we have $Z_{k_0} = 0$, then $Z_{k_0+k} = 0$ for any k. We would say that that the population dies out at k_0 and one might be interested to study under which condition a population will die out. It was in fact this question that was studied by Galton and Watson in 1874 regarding the fact that aristocratic surnames seemed to disappear. We will refer to these branching processes as Galton-Watson processes or trees (GW). Branching processes have not only been applied to genealogy but also for such objects as genes, neutrons or cosmic rays, see [Har64]. We define $\mu = \mathbb{E}X_{1,1} < \infty$ which we assume to be finite and different from zero.

Lemma 3.1.1. $M_n = \frac{1}{\mu^n} Z_n$ is a martingale. [1]

Proof. Recall that a martingale satisfies for all $n \geq 0$, $\mathbb{E}(|M_n|) < \infty$ and $\mathbb{E}(M_{n+1} | \mathcal{F}_n) = M_n$. Let's first show the integrability property.

$$\mathbb{E}Z_{n+1} = \mathbb{E}(X_{n,1} + X_{n,2} + ... + X_{n,Z_n}) \tag{3.3}$$

$$= \sum_{k=0}^{\infty} \mathbb{P}(Z_n = k)\mathbb{E}(X_{n,1} + ... + X_{n,k}) \tag{3.4}$$

$$= \sum_{k=0}^{\infty} \mathbb{P}(Z_n = k)\mu k = \mu \mathbb{E}Z_n \tag{3.5}$$

$$= \mu^{n+1}\mathbb{E}Z_0 = \mu^{n+1} \tag{3.6}$$

Then we have that $\mathbb{E}M_{n+1} = 1$.
Now let's prove the property on the conditional expectation.

$$\mathbb{E}(Z_{n+1}|\mathcal{F}_n) = \mathbb{E}(X_{n,1} + X_{n,2} + ... + X_{n,Z_n}|\mathcal{F}_n) \tag{3.7}$$

$$= \mathbb{E}X_{n,1}\mathbb{E}(Z_n|\mathcal{F}_n) = \mu Z_n \tag{3.8}$$

And we obtain,

$$\mathbb{E}(M_{n+1} \mid \mathcal{F}_n) = \mathbb{E}(\frac{Z_{n+1}}{\mu^{n+1}}) = \frac{Z_n}{\mu^n} = M_n \tag{3.9}$$

□

We now define the following generating function

$$\phi(s) = \sum_{k=0}^{\infty} p_k s^k \quad , |s| < 1 \tag{3.10}$$

Then if we define the extinction probability ζ as $\zeta = \mathbb{P}(\lim_{n\to\infty} Z_n = 0)$ we have

Theorem 3.1.2. The extinction probability is a fixed point of ϕ.

Proof. For this proof we will rewrite the expression for Z_{n+1} as a sum of independent Galton-Watson process. In order to do so we simply consider that the progeny of the second generation is a sum of Z_1 GW process. For all of the $1 \leq j \leq Z_1$ children, we denote by $Z_n(j)$ as the number of descendants of n-th generation of j.

$$Z_{n+1} \ = \sum_{j=1}^{Z_1} Z_n(j) \tag{3.11}$$

Each of these $Z_n(j)$ is a GW process independent from the others and for each of them we can then construct $M_n(j)$ as in (3.1.1). As these are martingales,

[1] We take $\mathcal{F}_n = \sigma(X_{n,j}, i \in \mathbb{N})$ as the filtration adapted to M_n

using the convergence theorem of martingales [2] we have that they converge to some random values that we denote by M and $M(j)$. Now if we divide both sides in (3.11) by μ^{n+1}.

$$\frac{Z_{n+1}}{\mu^{n+1}} = M_{n+1} = \mu^{-1} \sum_{j=1}^{Z_1} M_n(j) \tag{3.12}$$

And by taking limits we have

$$M = \frac{1}{\mu} \sum_{j=1}^{Z_1} M(j) \tag{3.13}$$

which gives that μM is distributed as $\sum_{j=1}^{Z_1} M(j)$ and we can finally obtain

$$\mathbb{P}(M = 0) = \mathbb{P}(\mu M = 0) = \mathbb{P}(\sum_{j=1}^{Z_1} M_j = 0) \tag{3.14}$$

$$= \sum_{k=1}^{\infty} p_k \mathbb{P}(\sum_{j=1}^{k} M(j) = 0 | Z_1 = k) \tag{3.15}$$

$$= \sum_{k=1}^{\infty} p_k (\mathbb{P}(M = 0))^k \tag{3.16}$$

$$= \phi(\mathbb{P}(M = 0)) \tag{3.17}$$

□

Using this result we can obtain the following result

Theorem 3.1.3. The extinction probability of a Poisson branching process of parameter λ is a solution of $x = e^{-\lambda(1-x)}$.

Proof.

$$\phi(s) = \sum_{k=0}^{\infty} p_k s^k = e^{-\lambda} \sum_{k=0}^{\infty} \frac{\lambda^k}{k!} s^k \tag{3.18}$$

$$= e^{-\lambda} e^{\lambda s} = e^{-\lambda(1-s)} \tag{3.19}$$

□

We can obtain the following theorem

Theorem 3.1.4. If $\mathbb{E}X \leq 1$ then the population dies out almost surely.

Proof. If $\lambda \leq 1$

$$\phi'(s) < \phi'(1) = \lambda \leq 1 \tag{3.20}$$

The only fixed point is 1. Hence, the probability of survival is 0. □

[2] See Theorem 9.4.6 from [Chu00] for a proof.

Theorem 3.1.5. If $\mathbb{E}X > 1$ then the population survives with a non-zero probability.

Proof. First of all, let's observe that the k-th iterate of $\phi(0)$ is the probability of extinction at generation k. It is clear that the probability of extinction at the first generation is p_0 which is equal to $\phi(0)$. If the progeny goes extinct at the second generation it means that if there is only one child, it goes extinct with probability p_0, if there are two childs, with probability p_0^2, and so on. Hence the probability of extinction at the second generation is $p_1 p_0 + p_2 p_0^2 + \dots$ which is equal to $\phi(\phi(0)) = \phi^2(0)$. Applying this inductive reasonning proves that the probability of extinction at generation k is $\phi^k(0)$.
If $\mathbb{E}X > 1$ then $\phi(s) < s$ when s is slightly less than 1, but $\phi(0) \geq 0$, hence there must have a solution to $s = \phi(s)$ in $[0, 1)$. By convexity of ϕ and Rolle's theorem this solution is unique. Moreover, the iterates $\phi^k(0)$ are non decreasing, which gives that the probability of survival is $\lim_{k\to\infty} \phi^k(0)$ which is the smallest fixed point of ϕ. □

We will now define an exploration process of such a branching process. We will use the model and notations from Bollobás and Riordan [BR12], which is in fact an extension of the process introduced by Karp in [Kar90]. In this model we consider a graph with n vertices and the exploration will take n steps. For now we will consider the case where we are exploring a connected component. With this process we think of vertices in three different positions, a vertex can be active, that means the algorithm knows the existence of the vertex and is evaluating it. A vertex can be explored, in that case we can consider that the vertex has been completely evaluated and sorted, in some fashion we can forget about it. Otherwise a vertex can be unseen, meaning that we still have no idea of what it is. So in terms of set, we can consider that at time (step) t we have :

$$A_t : \text{ the set of active vertices at time } t \tag{3.21}$$
$$E_t : \text{ the set of explored vertices at time } t \tag{3.22}$$
$$U_t : \text{ the set of unseen vertices at time } t \tag{3.23}$$

The process starts as follows, at $t = 0$, we place one randomly chosen vertex v_0 in A_0, so $U_0 = V \backslash \{v_0\}$ and $A_0 = \{v_0\}, E_0 = \emptyset$.
For the following steps, at time $t \geq 1$, the process is as follows: a vertex v_t is picked at random in A_{t-1}. For convenience we will define the variable $\eta_t = |N(v_t) \cap U_{t-1}|$ the number of vertices not yet seen that are neighbours from v_t. And then $A_t = (N(v_t) \cap U_{t-1}) \cup A_{t-1} \backslash \{v_t\}$. Finally, we move v_t to E_t and the process stops when all vertices in the connected component of order n are explored $|E_t| = n$, equivalently $t = n$, equivalently $|A_t| = 0$. [3]
This process is called *Breadth First Search* and might be referred to as BFS and

[3] This process can be very easily extended to explore every vertices simply by picking a vertex not yet explored when the set of active vertices is empty

we may summarise it by the following expression:

$$A_t = (N(v_t) \cap U_{t-1}) \cup A_{t-1} \backslash \{v_t\} \tag{3.24}$$
$$U_t = U_{t-1} \backslash N(v_t) \tag{3.25}$$
$$E_t = E_{t-1} \cup \{v_t\} \tag{3.26}$$

See Figure 3.1 for a visual representation of the BFS. Notice that we have:

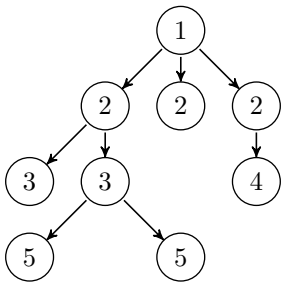

Figure 3.1: Order in which BFS explores a fixed tree.

$$\begin{cases} |A_0| & = 1 \\ |A_i| & = |A_{i-1}| + \eta_i - 1 = \eta_1 + ... + \eta_i - (i-1) \end{cases} \tag{3.27}$$

In this case (a Galton-Watson process) all the η_i are independent and identically distributed random variables. We can then define T as the instant the population dies out. Connecting this to a Galton-Watson tree, η_t is the direct progeny of v_t so η_t follows the offspring distribution defined by $X_{1,1}$ and we consider that the population dies out if and only if the algorithm finishes. We can then define T as the instant the population dies out.

$$T := \min\{t : A_t = 0\} \tag{3.28}$$

Connecting this to a Galton-Watson tree, η_t is the direct progeny of v_t so η_t follows the offspring distribution defined by $X_{1,1}$ and we consider that the population dies out if and only if the algorithm finishes. If $T = \infty$ then we say that the population survives.
We have that $\{v_t\}_t$ is a random walk on the tree under exploration and we also get the following evolution equation

$$|A_t| = |A_{t-1}| + \eta_t - 1 \tag{3.29}$$

When we are considering the Erdős Renyi model as a random graph process, we consider that in this random walk each vertex v has a probability p of turning active. Studying the random walk in that case we observe that the number of vertices to which we can connect the vertex v is

$$|U_{t-1}| = n - |E_{t-1}| - |A_{t-1}| = n - (t-1) - |A_{t-1}| \tag{3.30}$$

So we have, conditionally on $|A_{t-1}|$, [4]

$$\eta_t \sim \text{Bin}(n-(t-1)-|A_{t-1}|, p) \tag{3.31}$$

and we observe comparing it to (3.27) that our random values η_i are no longer independently distributed. However we notice that if A_{t-1} is "small enough" and n "large enough" the r.v. are "almost independently distributed". We also denote that the random walk we defined explores only a connected component so intuitively we want to say that if the connected components are small enough and sparse enough, then, they follow a Galton Watson process, hence our random graph would be made of Galton Watson trees. This will be the point of this chapter, studying links between random graphs and branching process, so we will consider that our probability p has to be small enough such that there is not a single connected component. From Theorem 2.2.2 we will consider that $p = \frac{\lambda}{n}$.
As the Poisson law is more convenient to work with than the binomial, and also being its limit in distribution, let's observe through a few theorems the connecting between Poisson and binomial branching process.

Theorem 3.1.6. For a branching process with a binomial offspring distribution with parameter n and p and a branching process with a Poisson offspring distribution with parameter $\lambda = np$

$$\mathbb{P}_{n,p}(T \geq k) = \mathbb{P}^*_\lambda(T^* \geq k) + e_k(n) \quad , \forall k \geq 1 \tag{3.32}$$

with T (resp. T^*) the total progeny of the binomial (resp. Poisson) resulting branching process, and

$$|e_k(n)| \leq \frac{2\lambda^2}{n} \sum_{s=1}^{k-1} \mathbb{P}^*_\lambda(T^* \geq s) \leq \frac{2\lambda^2 k}{n} \tag{3.33}$$

Proof. From the result of the appendix A.2.2.1, one can couple independent binomial random variables $X_i \sim \text{Bin}(n, \frac{\lambda}{n})$ and independent Poisson random variables $X_i^* \sim \text{Poi}(\lambda)$ in such a way that

$$\mathbb{P}(X_i \neq X_i^*) \leq \frac{\lambda^2}{n}. \tag{3.34}$$

Also, with T (resp. T^*) defined as in (3.28) for a binomial (resp. Poisson) branching process.

$$\mathbb{P}_{n,p}(T \leq k) = \mathbb{P}(T \geq k, T^* \geq k) + \mathbb{P}(T \geq k, T^* < k) \tag{3.35}$$
$$\mathbb{P}^*_\lambda(T^* \leq k) = \mathbb{P}(T \geq k, T^* \geq k) + \mathbb{P}(T < k, T^* \geq k) \tag{3.36}$$

which gives,

$$|\mathbb{P}_{n,p}(T \geq k) - \mathbb{P}^*_\lambda(T^* \geq k)| \tag{3.37}$$
$$\leq \mathbb{P}(T \geq k, T^* < k) + \mathbb{P}(T < k, T^* \geq k) \tag{3.38}$$

[4] This is the conditional law of the number of neighbours of a vertex knowing $|A_{t-1}|$

The following part, until the end of the proof, is valid if we exchange T by T^* and X by X^*.
By construction of T, the event $\{T \geq k\}$ is only defined by the events $X_1, ..., X_{k-1}$ Then we have $T \geq k$ and $T^* < k$ only if there exists some s such as $X_s \neq X_s^*$. Hence,

$$\mathbb{P}(T \geq k, T^* < k) \leq \sum_{s=1}^{k-1} \mathbb{P}(T \geq k, X_i \neq X_i^*, \forall i \leq s-1, X_s \neq X_s^*) \tag{3.39}$$

If we are in the event,$T \geq k, X_i \neq X_i^*, \forall i \leq s-1$ then

$$X_1^* + ... + X_i^* \geq i, \forall i \leq s-1 \tag{3.40}$$

In particular,

$$X_1^* + ... + X_s^* \geq s-1 \tag{3.41}$$

from which we have $T^* \geq s$. Moreover the event $\{T^* \geq s\}$ depends only on the $X_i^*, i \leq s-1$ thus it is independent of the event $X_s \neq X_s^*$. Combining these elements, we obtain

$$\mathbb{P}(T \geq k, T^* < k) \leq \sum_{s=1}^{k-1} \mathbb{P}(T^* \geq s, X_s \neq X_s^*) \tag{3.42}$$

$$\leq \sum_{s=1}^{k-1} \mathbb{P}(T^* \geq s)\mathbb{P}(X_s \neq X_s^*) \tag{3.43}$$

$$\leq \frac{\lambda^2}{n} \sum_{s=1}^{k-1} \mathbb{P}(T^* \geq s) \tag{3.44}$$

The last inequality being obtained by the theorem on couplings A.2.2.1. Using the remark on the fact that this portion of the proof is valid for both the binomial and the Poisson case we obtain the following inequality which finishes the proof.

$$e_k(n) = |\mathbb{P}_{n,p}(T \geq k) - \mathbb{P}_\lambda^*(T^* \geq k)| \leq \frac{2\lambda^2}{n} \sum_{s=1}^{k-1} \mathbb{P}(T^* \geq s) \tag{3.45}$$

□

The last theorem gives us some kind of "point wise" convergence between Poisson and binomial branching for trees to be larger than some fixed constant. Now we want to investigate the typical size of a connected component in $\mathcal{G}_{n,p}$. We denote the connected comported of a vertex v by $\mathcal{C}(v)$ and as a typical component we take $\mathcal{C}(1)$.

Theorem 3.1.7. For all $k \geq 1$,

$$\mathbb{P}_{n,p}(|\mathcal{C}(1)| \geq k) \leq \mathbb{P}_{n,p}(T \geq k) \tag{3.46}$$

Proof. Since conditionally on $|A_{t-1}|$, η_t is binomial with parameters $n-(t-1)-|A_{t-1}| \leq n$ and p, one can couple $(\eta_t)_{t\geq 1}$ with i.i.d. random variables $(\eta'_t)_{t\geq 1}$ such that $\eta_t \sim \mathrm{Bin}(n,p)$ and $\eta_t \leq \eta'_t$.
The size of the component of 1 is the first index i such that $\eta_1+\ldots+\eta_i-(i-1)\leq 0$, and then it is at most the first index i such that $\eta'_1+\ldots+\eta'_i-(i-1)\leq 0$. Hence, $|\mathcal{C}(1)|$ is smaller than the total progeny of a Galton-Watson tree with offspring distribution $\mathrm{Bin}(n,p)$. □

Another similar theorem is the following one that gives a lower bound on the size of a typical connected component.

Theorem 3.1.8. We have

$$\mathbb{P}_{n,p}(|\mathcal{C}(1)|\geq k)\geq \mathbb{P}_{n-k,p}(T\geq k), \tag{3.47}$$

where T is the total progeny of a binomial branching process with parameter $n-k$ and p.

Proof. In this case, we couple η_t with i.i.d. random variables η''_t which are binomial with parameters $n-k$ and p in such a way that $\eta_t \geq \eta''_t$ when $n-(t-1)-|A_{t-1}|\geq n-k$. On the event $T<k$ this condition is always satisfied since the number of unseen vertices in the graph is larger that $n-k$. Since in this event, for some $i\leq k$, we have $\eta_i+\ldots+\eta_{i-1}-(i-1)\leq 0$, the total progeny of the Galton-Watson tree is smaller than k. □

We will now admit the following theorem which gives a way to obtain the probability that the total progeny of a Galton-Watson branching process is of a specified size.

Theorem 3.1.9 (Hitting-time Theorem)**.** Let (Z_t) be a Galton-Watson branching process with total progeny T. Then,

$$\mathbb{P}(T=t)=\frac{1}{t}\mathbb{P}(X_1+X_2+\ldots+X_t=t-1), \tag{3.48}$$

for all $t\geq 1$.

The proof is admitted as it needs to make use of Spetzner's combinatorial lemma which is out of the scope of this report. A complete proof can be found in Chapter 5 of [Roc15].
However we will use the hitting-time Theorem to obtain the following corollary,

Corollary 3.1.9.1. Let (Z_t) be a Poisson branching process with offspring distribution $\mathrm{Poi}(\lambda)$,

$$\mathbb{P}_\lambda(T^*=k)=e^{-\lambda t}\frac{(\lambda t)^{t-1}}{(t-1)!}. \tag{3.49}$$

To obtain the previous corollary simply notice that a sum of t independent Poisson random variables of parameter λ is a Poisson random variable of parameter λt. Before finishing this section, here is a theorem that gives the probability law of $|A_t|$ in a random graph branching process.

Theorem 3.1.10.

$$|A_t| + (t-1) \sim \text{Bin}(n-1, 1-(1-p)^t) \tag{3.50}$$

Proof. Let's first observe by symmetry that

$$X \sim \text{Bin}(m,p) \iff Y = m - X \sim \text{Bin}(m, 1-p) \tag{3.51}$$

So to prove the theorem we will prove the equivalent statement

$$n - t - |A_t| = |U_t| \sim \text{Bin}(n-1, (1-p)^t) \tag{3.52}$$

Indeed, conditionally on $|A_{t-1}|$

$$\begin{aligned} |U_t| &= n - t - |A_t| = n - t - |A_{t-1}| - |\eta_t| + 1 && (3.53)\\ &= n - (t-1) - A_{t-1} - \eta_t && (3.54)\\ &= n - (t-1) - A_{t-1} - \text{Bin}(n-(t-1) - |A_{t-1}|, p) && (3.55)\\ &= |U_{t-1}| - \text{Bin}(|U_{t-1}|, p) = \text{Bin}(|U_{t-1}|, 1-p) && (3.56) \end{aligned}$$

Induction on the last result gives the expected result. □

3.2 The subcritical case: $\lambda < 1$

Now we will apply the results from the previous section in order to prove the following theorem, with $C_{\max}$ the size of the largest connected component of the graph $\mathcal{G}_{n,\frac{\lambda}{n}}$.

Theorem 3.2.1. If $\lambda < 1$
Then

$$\frac{C_{\max}}{\log(n)} \longrightarrow_{\mathbb{P}} I_\lambda^{-1} \tag{3.57}$$

Theorem 3.2.2. $\mathbb{P}_\lambda(|\mathcal{C}(1)| > t) \leq e^{-I_\lambda t}$

In the previous theorem, I_λ stands for the large deviation rate function corresponding to the Poisson random variables and is defined as follows.

$$I_\lambda = \lambda - 1 - \log(\lambda) \tag{3.58}$$

It is interesting to note that I_λ is positive if $\lambda \neq 0$.

Proof of Theorem 3.2.2. This proof uses the fact that $|A_t| = 0$ means that the whole connected component has been explored after t steps, so the connected component is of size less than t. Using Theorem 3.1.10 we obtain that $|A_t| \sim \text{Bin}(n-1, 1-(1-p)^t) - (t-1)$, so

$$\mathbb{P}_\lambda(|\mathcal{C}(1)| > t) \leq \mathbb{P}(|A_t| > 0) \leq \mathbb{P}(\text{Bin}(n-1, 1-(1-p)^t) \geq t) \tag{3.59}$$

Using Bernoulli's inequality (A.1.4) $1-(1-p)^t \leq tp$ and observing that for all s positive the following is true

$$\mathbb{P}(\text{Bin}(n-1, 1-(1-p)^t) \geq t) \leq \mathbb{P}(e^{s\text{Bin}(n-1,tp)} \geq e^{st}), \tag{3.60}$$

then we can apply Markov inequality which gives, $\forall s \geq 0$,

$$\mathbb{P}_\lambda(|\mathcal{C}(1)| > t) \leq e^{-st}\mathbb{E}(e^{s\text{Bin}(n,\frac{t\lambda}{n})}) \tag{3.61}$$

Replacing the moment generating function of the binomial with its value (A.1.1), we obtain

$$\mathbb{P}_\lambda(|\mathcal{C}(1)| > t) \leq e^{-st}(1-\frac{t\lambda}{n}+e^s\frac{t\lambda}{n})^n \leq e^{-t(s-\lambda e^s+\lambda)} \tag{3.62}$$

Using $s = \log(1/\lambda)$, which minimises the bound [5], we obtain

$$\mathbb{P}_\lambda(|\mathcal{C}(1)| > t) \leq e^{-I_\lambda t} \tag{3.63}$$

□

Now using this result we will obtain a logarithmic bound on the largest connected component.
For this we will use the random variable

$$Z_{\geq k} = \sum_{v\in V} \mathbb{1}_{|\mathcal{C}(v)|\geq k} \tag{3.64}$$

We observe that $Z_{\geq k}$ is equal to 0 if k is larger than $C_{\max}$, the size of the greatest connected components. Hence we have

$$C_{\max} = \max\{k : Z_{\geq k} \ \geq k\} \tag{3.65}$$

and we obtain

$$\mathbb{E}_\lambda(Z_{\geq k}) = n\mathbb{P}_\lambda(|\mathcal{C}(1)| \geq k) \tag{3.66}$$

Applying theorem 3.2.2 we immediately have the following result.

Lemma 3.2.3. For $a > I_\lambda^{-1}$, there exists $\delta > 0$ such that:

$$\mathbb{P}_\lambda(C_{\max} > a\log n) = \mathcal{O}(n^{-\delta}) \tag{3.67}$$

We will now prove the next lemma that is similar to the previous one but gives an upper bound on the greatest connected component instead (in the sub-critical regime). These two lemmas together imply Theorem 3.2.1.

Lemma 3.2.4. For $a < I_\lambda^{-1}$, there exists $\delta > 0$ such that

$$\mathbb{P}_\lambda(C_{\max} < a\log(n)) = \mathcal{O}(n^{-\delta}) \tag{3.68}$$

[5] Observe that as s must be positive, λ must be smaller than 1 for the argument to be true.

Proof. This proof will be a little bit more technical as it uses the second moment method. First of all we will need an estimate of the variance on $Z_{\geq}$, for this purpose we will use the following function

$$\chi_k(\lambda) = \mathbb{E}_\lambda(|\mathcal{C}(1)|\mathbb{1}_{\{|\mathcal{C}(1)|\geq k\}}) \tag{3.69}$$

Lemma 3.2.5. $\mathbb{V}_\lambda(Z_{\geq k}) \leq n\chi_k(\lambda)$, where $\mathbb{V}$ denotes the variance.

Proof. By definition of the variance

$$\mathbb{V}_\lambda(Z_{\geq k}) = \sum_{i,j\in V} \mathbb{P}_\lambda(|\mathcal{C}(i)| \geq k, |\mathcal{C}(j)| \geq k) - \mathbb{P}_\lambda(|\mathcal{C}(i)| \geq k)\mathbb{P}_\lambda(|\mathcal{C}(j)| \geq k) \tag{3.70}$$

And we can split those probabilities as components form an obvious partition of the vertex set as follows

$$\mathbb{P}_\lambda(|\mathcal{C}(i)| \geq k, |\mathcal{C}(j)| \geq k) = (\mathbb{P}_\lambda(|\mathcal{C}(i)| \geq k, i \leftrightarrow j) + (\mathbb{P}_\lambda(|\mathcal{C}(i)| \geq k, |\mathcal{C}(j)| \geq k, i \not\leftrightarrow j) \tag{3.71}$$

where $i \leftrightarrow j$ means that i and j are in the same connected component of the graph. Furthermore, conditionally to $\mathcal{C}(i)$, in the event $i \not\leftrightarrow j$, the order of $\mathcal{C}(j)$ is stochastically smaller than the order of $\mathcal{C}(j)$ without conditioning. Hence,

$$\mathbb{P}_\lambda(|\mathcal{C}(j)| \ \geq k|\mathcal{C}(i), i \not\leftrightarrow j) \leq \mathbb{P}_\lambda(|\mathcal{C}(j)| \geq k). \tag{3.72}$$

Multiplying both sides by $\mathbb{1}_{\mathcal{C}(i)| \geq k}$ we have

$$\begin{aligned}\mathbb{P}_\lambda(|\mathcal{C}(i)| \ \geq k, |\mathcal{C}(j)| \geq k|\mathcal{C}(i), i \not\leftrightarrow j) &\leq \mathbb{P}_\lambda(|\mathcal{C}(j)| \geq k)\mathbb{1}_{|\mathcal{C}(i)| \geq k} &(3.73)\\ &\leq \mathbb{P}_\lambda(|\mathcal{C}(j)| \geq k)\mathbb{P}_\lambda(|\mathcal{C}(i)| \geq k). &(3.74)\end{aligned}$$

We deduce:

$$\mathbb{V}(Z_{\geq k}) \leq \sum_{i,j\in V} \mathbb{P}_\lambda(|\mathcal{C}(i)| \geq k, i \leftrightarrow j) \tag{3.75}$$

and then,

$$\begin{aligned}\mathbb{V}(Z_{\geq k}) &\leq \sum_{i\in V}\sum_{j\in V} \mathbb{E}_\lambda(\mathbb{1}_{|\mathcal{C}(i)|\geq k}\mathbb{1}_{j\in\mathcal{C}(i)}) &(3.76)\\ &\leq \sum_{i\in V} \mathbb{E}_\lambda(\mathbb{1}_{|\mathcal{C}(i)|\geq k}\sum_{j\in V}\mathbb{1}_{j\in\mathcal{C}(i)}) &(3.77)\\ &\leq \sum_{i\in V} \mathbb{E}_\lambda(\mathbb{1}_{|\mathcal{C}(i)|\geq k}|\mathcal{C}(i)|) = n\chi_k(\lambda) &(3.78)\end{aligned}$$

□

As we want to prove for $k_n = \lceil a\log n\rceil$ that $\mathbb{P}_\lambda(Z_{\geq k_n} = 0)$ goes to 0 for n going to infinity using Bienaymé-Tchebychev inequality, we use the previous upper bound on the variance and a lower bound on the expectation of $Z_{\geq k_n}$. We have,

$$\chi_{k_n}(\lambda) = k_n\mathbb{P}_\lambda(|\mathcal{C}(1)| \geq k_n) + \sum_{t=k_n+1}^{n} \mathbb{P}_\lambda(|\mathcal{C}(1)| > t) \tag{3.79}$$

And using Theorem 3.2.2 we obtain

$$\chi_{k_n}(\lambda) \leq k_n e^{-I_\lambda(k_n-1)} + \sum_{t=k_n+1}^{n} e^{-I_\lambda(t-1)} \leq \frac{e^{-(k_n-1)I_\lambda}}{1-e^{-I_\lambda}} = \mathcal{O}(n^{-u}) \tag{3.80}$$

for all $u < aI_\lambda$. And now we need to find a lower bound on the expectation of $Z_{\geq k}$. In the following inequality we make use of (3.66), then lemmas 3.1.8 and 3.1.6. So we have

$$\mathbb{E}Z_{\geq k} = n\mathbb{P}_\lambda(|\mathcal{C}(1)| \geq k) \geq n\mathbb{P}_{n-k,p}(T \geq k) = n(\mathbb{P}^*_{\lambda_n}(T^* \geq k) + o(1)) \tag{3.81}$$

T and T^* being the total progeny of branching process (Binomial and Poisson), and $\lambda_n = (n-k)p = \frac{n-k}{n}p$ from (3.1.6).
And we can compute the term on the RHS using the corollary 3.1.9.1 as follows:

$$\mathbb{P}^*_{\lambda_n}(T^* \geq k) = \sum_{t=k}^{\infty} \mathbb{P}^*_{\lambda_n}(T^* = k) = \sum_{t=k}^{\infty} \frac{(\lambda_n t)^{t-1}}{t!} e^{-\lambda_n t}. \tag{3.82}$$

To simplify the writings we observe $\lambda_n = (1-o(1))\lambda$ and $I_{\lambda_n} = I_\lambda + o(1)$, then applying Stirling's formula we obtain

$$\frac{(\lambda_n t)^{t-1}}{t!} e^{-\lambda_n t} = \frac{\lambda^{t-1}(1-o(1))^{t-1}t^{t-1}}{t^t} \frac{e^t}{\sqrt{2\pi t}(1+o(1))} e^{-(1-o(1))\lambda t}. \tag{3.83}$$

Simplifying we get

$$\frac{(\lambda_n t)^{t-1}}{t!} e^{-\lambda_n t} = \frac{1}{\lambda t^{\frac{3}{2}}}(\lambda t t^{-\lambda})^t(1+o(1)) = \frac{e^{-I_\lambda t}}{\lambda t^{\frac{3}{2}}}(1+o(1)) \geq \frac{1}{\lambda} e^{-I_\lambda t}. \tag{3.84}$$

Now, as the summand is decreasing we can bound it by the integral as follows.

$$n\mathbb{P}^*_{\lambda_n}(T^* \geq k) \geq \frac{n}{\lambda} \int_k^\infty e^{-I_\lambda t} \mathrm{d}t = \frac{e^{-I_\lambda k}}{\lambda I_\lambda} \tag{3.85}$$

With $k_n = a\log(n)$ we have

$$\mathbb{E}Z_{k_n} \geq n\mathbb{P}^*_{\lambda_n}(T^* \geq k_n) \geq n^{-I_\lambda a+1} \tag{3.86}$$

and finally we have

$$\mathbb{P}(Z_{k_n} = 0) \leq \frac{\mathbb{V}Z_{k_n}}{(\mathbb{E}Z_{k_n})^2} \leq \frac{\mathcal{O}(n^{1-u})}{n^{-2I_\lambda a+2}\lambda I_\lambda} = \mathcal{O}(n^{\ -\delta}) \tag{3.87}$$

when u is close enough to aI_λ and $\delta > 0$ small enough.
So, if $a < I_\lambda^{-1}$ there is no component larger than $a\log(n)$ with probability going to one. □

Now, simply combining the previous results (3.2.3) and (3.2.4) we have our proof of our main theorem in this section (3.2.1). Hence, in $\mathcal{G}_{n,\frac{\lambda}{n}}$ with $\lambda < 1$ the largest connected components grow at a logarithmic speed. We will see in the next section that this is very different from the case where $\lambda > 1$ in which components grow linearly. This change of speed in the growth rate is called a phase transition.

3.3 The supercritical case : $\lambda > 1$

First we will show that that in the supercritical case there is a component of linear size (in n). In order to show this result we will use the fact that if there exists a path of a linear size, then it is contained in a component of linear size too. Then we will make this result a little bit better with a very similar proof. In fact there exists stronger results that use the same method but make a use of martingales in order to get a really sharp result on the asymptotic size of the greatest connected component, see Bollobás and Riordan [BR12].
Here we will consider $p = \frac{1+\epsilon}{n}$. For the beginning we will use the recent approach from Sudakov [KS13] which makes use of an algorithm of graph exploration called the *depth first search* (DFS).

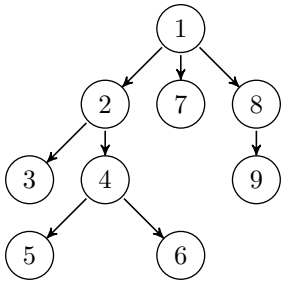

Figure 3.2: Order in which DFS explores a fixed tree.

We made use of the breadth first search (BFS) which when exploring a vertex added all the set of neighbours to its active stack. Here the approach is quite different as instead of adding all of the neighbours, we check for existence of neighbours one by one, and if one is found then the algorithms moves to this new vertex. If no adjacent vertex can be found then it goes back to the previous vertex.
More formally we will use the same partition of vertex as in the BFS, A_t the *Last-In/First-Out stack* [6] of active vertices, E_t the sorted vertices that we do not have to treat anymore and U_t the vertices that have not yet been added to A_t. The interest of using DFS here is that A_t is by construction always a path. We will describe the behaviour in the case of the exploration of a random graph so we say that we feed our DFS algorithm with $X = \{X_i\}_i^N$ a sequence of i.i.d. random values, one for each possible edge, recall that $N = \frac{n(n-1)}{2}$. So the algorithm starts at some specified vertex. From there it checks for edges using each time one of the X_i, the number of evaluations is what we refer to as time. If $X_t = 1$, then the new vertex under evaluation is moved from U_t into A_t and the same procedure repeats. In the case that all possible edges from a vertex have been tested and answered negatively, then the vertex is moved to set of explored vertices of corresponding time, so it is moved from A_t to E_t.

[6] A LIFO stack is a set in which elements are ordered according to the time they were added in the stack. Only the last element added can be extracted from a LIFO stack.

The algorithm stops when U_t is empty.
In order for the algorithm to be able to explore all components, when A_t is empty, a vertex is selected from U_t.
The proof will make an extensive use of the depth-first search algorithm, at each step of the algorithm, when it is searching for a neighbour it is simply following a Bernoulli random variable of parameter p. So we consider $X = \{X_i\}_i^N$ our sequence of i.i.d. random variables where each X_i follows a Bernoulli of parameter p in order to get an Erdös-Renyi random graph process. So we obtain the following inequality, as in the event $X_i = 1$, then a vertex is simply moved from U_i to A_i. And if there is a sequence of $X_i = 0$ then the vertices might only move from A to E.

$$|A_t \cup E_t| \geq \sum_{i=1}^{t} X_i \tag{3.88}$$

And for the set of active vertices we have

$$|A_t| \leq 1 + \sum_{i=1}^{t} X_i \tag{3.89}$$

From these two inequalities we understand that having knowledge on X will give us knowledge on the behaviour of our depth first search algorithm. And we might make use of this knowledge to obtain information on our connected component.
The following simple lemma will give us information on the behaviour of binomial random variables. It is the only probabilistic tool that we will use to show our theorem on the growth rate of the giant component.

Lemma 3.3.1. Let $p = \frac{1+\epsilon}{n}$ and $N_0 = \lceil \frac{\epsilon n^2}{2} \rceil$. Then,

$$|\sum_{i=1}^{N_0} X_i - N_0 p| \ \leq n^{\frac{2}{3}} \quad \text{with probability tending to 1 when } n \to \infty. \tag{3.90}$$

Proof. Let's observe that $\mathbb{E}X_{N_0} = N_0 p = \frac{\epsilon(1+\epsilon)}{2} n$. Simply using Chernoff inequality (A.1.7).

$$\mathbb{P}(|X_{N_0} - \mathbb{E}X_{N_0}| > n^{\frac{2}{3}}) \leq 2e^{-\frac{n^{\frac{4}{3}}}{2n}} \tag{3.91}$$

So with high probability we have

$$|X_{N_0} - \mathbb{E}X_{N_0}| \leq n^{\frac{2}{3}} \tag{3.92}$$

□

Now we can state and prove the following theorem making use of the previous lemma and of our knowledge of the depth first search algorithm.

Theorem 3.3.2. Let $p = \frac{1+\epsilon}{n}$. Then, $\mathbb{G}_{n,p}$ contains a path of length at least $\frac{\epsilon^2 n}{5}$.

Proof. The proof will be done by contradiction.
We consider X_N with parameter $p = \frac{1+\epsilon}{n}$. We claim that if $N_0 = \frac{\epsilon n^2}{2}$ then $|A_{N_0}| \geq \frac{\epsilon^2 n}{5}$.
Let's first show that $|E_{N_0}| < \frac{n}{3}$.
If it was not the case, elements flowing in E one by one, there would exist a t such that $|E_t| = \lfloor \frac{n}{3} \rfloor$. Also from (3.89) and Lemma 3.3.1 we would have with high probability for n large enough,

$$|A_t| \leq 1 + \sum_{i=1}^{t} X_i < 1 + n^{\frac{2}{3}} < \frac{n}{3}. \tag{3.93}$$

Then using the fact that the sets used in the depth first search do not intersect we have

$$|U_t| = n - |A_t| - |E_t| \geq \frac{n}{3} \tag{3.94}$$

So, we obtain that the algorithm has tested all the $|E_t||U_t| \geq \frac{n^2}{9}$ possible pairs between the set of explored vertices and not seen vertices. But $\frac{n^2}{9} > \epsilon \frac{n^2}{2} = N_0$ [7] and as we assumed that we are at a step t of the algorithm that is less than N_0 we have a contradiction.
We are then sure from the previous argument that $|E_{N_0}| < \frac{n}{3}$ and we claim $|A_{N_0}| < \frac{\epsilon^2 n}{5}$, then $U_{N_0} \neq \emptyset$. Which means that there are still elements that can be added to the connected component. We are going to use the same arguments as previously.
By lemma (3.3.1), the number of edges (or vertices) added is at least $\frac{\epsilon(1+\epsilon)n}{2} - n^{\frac{2}{3}}$. Which gives that the number of active and explored vertices is at least as follows

$$|A_{N_0} \cup E_{N_0}| \geq \frac{\epsilon(1+\epsilon)n}{2} - n^{\frac{2}{3}} \tag{3.95}$$

So $|E_{N_0}| \geq \frac{\epsilon n}{2} + \frac{3\epsilon^2 n}{10} - n^{\frac{2}{3}}$ and that would mean all of the pairs between E_{N_0} and A_{N_0} have been explored. So we obtain the following set of inequalities.

$$N_0 = \frac{\epsilon n^2}{2} \geq |E_{N_0}||A_{N_0}| \geq (\frac{\epsilon n}{2} + \frac{3\epsilon^2 n}{10} - n^{\frac{2}{3}})(n - \frac{\epsilon n}{2} - \frac{\epsilon^2 n}{2} + n^{\frac{2}{3}}) \tag{3.96}$$

$$\geq \frac{\epsilon n^2}{2} + \frac{\epsilon^2 n^2}{20} - o(\epsilon^3)n^2 \tag{3.97}$$

The last inequality being only with the dominating terms (i.e. the n^2) and for $\epsilon < 1$ it is larger than $\frac{\epsilon n^2}{2}$ Which is a contradiction. Then A_{N_0} must be larger or equal than $\frac{\epsilon^2 n}{5}$ and observing that A_{N_0} must be a path we have the result. □

In fact, we can refine this result to the size of the connected component and not simply the size of a walk with the following theorem.

Theorem 3.3.3. Let $p = \frac{1+\epsilon}{n}$ and $N_0 = \frac{\epsilon n^2}{5}$. Then, $G \sim \mathcal{G}_{n,p}$ contains a connected component of size at least $\frac{\epsilon n}{2}$

[7] ϵ is small enough

This theorem can be proved using the same method as in the previous proof. However, a much more precise result will be proved later in this report on the size of the largest component in the supercritical phase, see Theorem 4.2.1.

Some words on the critical phase We have in the two previous sections investigated the different behaviours of $\mathcal{G}_{n,\frac{\lambda}{n}}$ for fixed values of $\lambda \neq 1$. We have seen that if $\lambda < 1$ then the largest component is growing in size as a logarithm of n and the components will be trees or isolated vertices. Moreover, if $\lambda > 1$ then many components will have merged compared to $\lambda < 1$ and the largest component will be growing as a linear function of n. The transition from tree components to a giant component will be made through the creation of *complex* components [8] in the critical window $\lambda(n) = 1 + \theta n^{-\frac{1}{3}}$ for some fixed $\theta \in \mathbb{R}$. In this critical window there will be with positive probability never more than one complex component (Janson, Knuth, Luczak and Pittel [JKŁ93], proved that this probability is exactly $\frac{5\pi}{18}$), and the largest component will be of size about $n^{2/3}$. A brief introductory review on the phase transition of Erdös-Renyi random graphs and other settings in which a similar phase transition can be observed (bond percolation, d-regular random graphs, specified degree sequence, ...) can be found in [Spe09].

[8] An l-complex component is a component of k vertices with $k + l$ edges for some $l \geq 1$.

Chapter 4

Generalised models

4.1 Generalized Binomial Graph

We are now interested in a generalization of the (binomial) Erdös-Rényi model which was first considered by Kovalenko in [Kov71]. In this model, often referred to as *inhomogeneous*, the probability of appearance of the edge (i, j), that we call p_{ij}, is not necessarily the same for all pairs of vertices i, j.
From this definition it is very natural to write those edge probabilities in an $n \times n$ matrix, which we denote by

$$\mathbf{P} = [p_{ij}]_{1 \leq i,j \leq n} \tag{4.1}$$

As previously we consider graphs without loops, so $p_{ii} = 0$ for all $i \in V$, we also consider that the graph is not directed so the probability that i connects to j has to be the same as the probability that j connects to i (i.e. $p_{ij} = p_{ji}$), hence $\mathbf{P}$ is symmetric. In order to shorten the writing, we put $q_{ij} = 1 - p_{ij}$.
We denote the probability space of this generalised model as $\mathcal{G}_{n,\mathbf{P}}$ and as before we denote a random variable in this space as $\mathbb{G}_{n,\mathbf{P}}$.
We now define

$$Q_i = \prod_{j=1}^{n} q_{ij}, \quad \lambda_n = \sum_{i=1}^{n} Q_i \tag{4.2}$$

and we observe that Q_i is the probability that vertex i is isolated, hence λ_n is the expected number of isolated vertices.
We also need to define

$$R_{ik} = \min_{1 \leq j_1 < j_2 < \ldots < j_k \leq n} q_{ij_1} q_{ij_2} \cdots q_{ij_k} \tag{4.3}$$

In the following, we suppose that the edge probabilities p_{ij} are chosen in such a way that the following equations are simultaneously satisfied as $n \to \infty$.

$$\max_{1 \leq i \leq n} Q_i \to 0 \tag{4.4}$$

$$\lim_{n \to \infty} \lambda_n = \lambda = \text{constant} \tag{4.5}$$

$$\lim_{n \to \infty} \sum_{k=1}^{\lfloor n/2 \rfloor} \frac{1}{k!} (\sum_{i=1}^{n} \frac{Q_i}{R_{ik}})^k = e^{\lambda} - 1 \tag{4.6}$$

In this section we are interested in proving the following theorem.

Theorem 4.1.1. Let X_0 denote the number of isolated vertices in $\mathbb{G}_{n,\mathbf{P}}$. If (4.4), (4.5), (4.6) are satisfied, then the number of isolated vertices is asymptotically Poisson distributed with mean λ.
i.e. for $k \in \mathbb{N}$,

$$\lim_{n \to \infty} \mathbb{P}(X_0 = k) = \frac{\lambda^k}{k!} e^{-\lambda} \tag{4.7}$$

Let's first show as a corollary that this theorem allows us to conclude the proof of 2.2.1.

Corollary 4.1.1.1. If $p(n) = \frac{\log n + c}{n}$, then (4.4), (4.5), (4.6) are satisfied, and the number of isolated vertices is asymptotically Poisson distributed with mean e^{-c}.

Proof of Corollary 4.1.1.1. We observe that $\mathcal{G}_{n,p}$ and $\mathcal{G}_{n,\mathbf{P}}$ when $p_{ij} = p$ for all $i \neq j$.
We observe that $Q_i = Q = q^{n-1}$ (and (4.4) is obviously satisfied) and $R_{ik} = R_k = q^k$. From this we get

$$\lambda_n = nQ = nq^{n-1} = n(1-p)^{n-1} \tag{4.8}$$

and we have $\lim \lambda_n = e^{-c} = \lambda$, so (4.5) is also satisfied.
Let's observe that it is enough to show $\sum_{i=1}^{n} \frac{Q_i}{R_{ik}}$ converges uniformly to $\lambda = e^{-c}$ for (4.6) to be satisfied.

$$\sum_{i=1}^{n} \frac{Q_i}{R_{ik}} = \sum_{i=1}^{n} \frac{Q}{R_k} = n \frac{Q}{R_k} = nq^{n-1-k} \tag{4.9}$$

And $\lim_{n \to \infty} nq^{n-1-k} = e^{-c}$ finally proves the corollary. □

Proof of Theorem 4.1.1. Let Y_{ij} a random variable following a Bernoulli of parameter p_{ij}. [1] We denote by Y_i the indicator of the event that vertex i is isolated, i.e. $Y_i = \mathbb{1}_{\sum_{j=1}^{n} Y_{ij} = 0}$. In order to show the convergence of X_0 in distribution to the Poisson random variable we will use the method of factorial moments. So, we want to show that for any natural number k we have

$$\mathbb{E}(\sum_{1 \leq i_1 < i_2 < \ldots < i_k \leq n} X_{i_1} X_{i_2} \ldots X_{i_k}) \to_{n \to \infty} \frac{\lambda^k}{k!} \tag{4.10}$$

[1] Recall that a Bernoulli of parameter p is 1 with prob. p and 0 with prob. $1 - p$.

Let's observe that the LHS of (4.10) is the sum of $\mathbb{E}(X_{i_1}X_{i_2}\dots X_{i_k})$ over all $i_1 < i_2 < \dots i_k$.

$$\mathbb{E}(X_{i_1}X_{i_2}\dots X_{i_k}) = \prod_{r=1}^{k} \mathbb{P}(X_{i_r} = 1|\ X_{i_1} = \dots = X_{i_{r-1}} = 1) \tag{4.11}$$

$$= \prod_{r=1}^{k} \frac{\prod_{j=1}^{n} q_{i_r j}}{\prod_{s=1}^{r-1} q_{i_r i_s}} \tag{4.12}$$

From which we get,

$$Q_{i_r} \leq \mathbb{P}(X_{i_r} = 1|\ X_{i_1} = \dots = X_{i_{r-1}} = 1) \leq \frac{Q_{i_r}}{R_{i_r,r-1}} \leq \frac{Q_{i_r}}{R_{i_r k}} \tag{4.13}$$

Hence,

$$Q_{i_1}\dots Q_{i_k} \leq \mathbb{E}(X_{i_1}\dots X_{i_k}) \ \leq \frac{Q_{i_1}}{R_{i_1 k}}\dots\frac{Q_{i_k}}{R_{i_k k}} \tag{4.14}$$

$$\sum_{1\leq i_1<\dots<i_k\leq n} Q_{i_1}\dots Q_{i_k} = \frac{1}{k!}\sum_{1\leq i_1\neq\dots\neq i_r\leq n} Q_{i_1}\dots Q_{i_k} \geq \tag{4.15}$$

$$\frac{1}{k!}\sum_{1\leq i_1,\dots,i_k\leq n} Q_{i_1}\dots Q_{i_k} - \frac{k}{k!}\sum_{i=1}^{n} Q_i^2\Big(\sum_{1\leq i_1,\dots,i_{k-2}\leq n} Q_{i_1}\dots Q_{i_{k-2}}\Big) \tag{4.16}$$

$$\geq \frac{\lambda_n^k}{k!} - (\max_i Q_i)\lambda_n^{k-1} \longrightarrow \frac{\lambda^k}{k!} \tag{4.17}$$

Now, by definition of R_{ik}, we have,

$$\sum_{i=1}^{n}\frac{Q_i}{R_{ik}} \geq \sum_{i=1}^{n} Q_i = \lambda_n \tag{4.18}$$

If we suppose that $\limsup_{n\to\infty}\sum_{i=1}^{n}\frac{Q_i}{R_{ik}} > \lambda$, this would imply that

$$\limsup_{n\to\infty}\sum_{k=1}^{\frac{n}{2}\rfloor}\frac{1}{k!}\Big(\sum_{i=1}^{n}\frac{Q_i}{R_{ik}}\Big)^k > e^{\lambda} - 1 \tag{4.19}$$

which contradicts (4.6). It follows that

$$\lim_{n\to\infty}\sum_{i=1}^{n}\frac{Q_i}{R_{ik}} = \lambda \tag{4.20}$$

We obtain,

$$\sum_{1\leq i_1<\dots<i_k\leq n} Q_{i_1}\dots Q_{i_k} \leq \frac{1}{k!}\Big(\sum_{i=1}^{n}\frac{Q_i}{R_{ik}}\Big)^k \longrightarrow \frac{\lambda^k}{k!} \tag{4.21}$$

Combining (4.21) and (4.15) we have $\lim_{n\to\infty}\sum_{1\leq i_1<\dots<i_k\leq n} Q_{i_1}\dots Q_{i_k} = \frac{\lambda^k}{k!}$, which is the result we wanted to prove. □

It is interesting to note through the following theorem, which we will not prove, that under certain conditions, a similar behaviour appears between the binomial model $\mathcal{G}_{n,p}$ and the generalised binomial $\mathcal{G}_{n,\mathbf{P}}$ at the connectivity threshold.

Theorem 4.1.2. If (4.4), (4.5), (4.6) are satisfied, then,

$$\lim_{n\to\infty} \mathbb{P}(\mathbb{G}_{n,\mathbf{P}} \text{ is connected}) = e^{-\lambda} \tag{4.22}$$

Above we have seen a generalised binomial model which changed the probability distribution on the set of all edges, now we will describe models in which we change the edge set.

Bipartite random graphs Complete Bipartite graphs are formally defined as $K_{n,m} = G([n+m], E)$ with $E = \{\{x, y\} : x \in [n], y \in n + [m]\}$. In the above we have studied graphs as subgraphs of the complete graph, now we restrict ourselves to graphs which are subgraphs of the complete bipartite graph. They are an appropriate way to describe many networks, for instance if you consider a graph in which you consider a graph on the set of movie actors and you draw an edge linking two actors if they have collaborated in a movie. The resulting graph looks very convoluted, with many cliques and doesn't seem to give much information on what we might be interested for. However, if you consider that the set of vertices is the set of actors *and* the set of movies, and there is an edge only between an actor and a movie if the actor played in the movie. This graph would give much more information on the nature of this network.
Hence, an important part of research has been studying random bipartite graph and we can very naturally define $\mathcal{G}_{n,n,p}$ with the generalised binomial model. Indeed, a (n, n)-bipartite graph represented through its adjacency matrix has the following block representation:

$$\left[\begin{array}{c|c} 0 & A \\ \hline A & 0 \end{array}\right] \tag{4.23}$$

with A a n by n matrix containing only zeros and ones. Hence, if we consider 1_n the n by n matrix made only of 1, then we have $\mathcal{G}_{n,n,p} = \mathcal{G}_{2n,\mathbf{p}}$ with

$$\mathbf{p} = p\left[\begin{array}{c|c} 0 & 1_n \\ \hline 1_n & 0 \end{array}\right] \tag{4.24}$$

This raises interest in studying random bipartite graphs through the point of view of the generalised model. For instance we will prove the following theorem for connectivity in $\mathcal{G}_{n,n,p}$:

Theorem 4.1.3. Let $c \in \mathbb{R}$ and $p = \frac{\log(n)+c}{n}$, then the number of isolated vertices of $\mathcal{G}_{n,n,p}$ follows a Poisson of mean $2e^{-c}$ for n large enough.

Proof. Let $\mathbf{p}$ as in 4.24, and let's show that the conditions (4.4), (4.5), (4.6) of Theorem 4.1.1 are satisfied.

$$Q_i = Q = q^n \tag{4.25}$$

And,

$$\lambda_n = 2nq^n = 2n(1-p)^n \longrightarrow 2e^{-c}, \tag{4.26}$$

and noticing

$$R_{ik} = R_k = \begin{cases} q^k & \text{if } k \leq n, \\ q^{k-n} & \text{if } k > n. \end{cases} \tag{4.27}$$

And as the sum in (4.6) only goes to n in the sum we evaluate we have $R_k = q^k$, and as in the corollary we simply evaluate the following:

$$\sum_{i=1}^{2n} \frac{Q}{R_k} = 2nq^{n-k} \longrightarrow_{n\to\infty} 2e^{-c} = \lambda. \tag{4.28}$$

Hence as a consequence of Theorem 4.1.1, the number of isolated vertices follows a Poisson of mean $2e^{-c}$. □

As shown in Bollobas 2001 [Bol01], there is the same hitting time for connectivity and $\delta \geq 1$ with high probability, as a consequence of the previous Theorem one could prove that the probability of connectivity of $\mathcal{G}_{n,n,p}$ is $e^{-2e^{-c}}$.

4.2 An arbitrary degree sequence

As seen in the previous section, an Erdös-Rényi random graph has degrees following a Poisson distribution. However, in practice networks usually have a degree sequence following a power-law, these are usually referred to as scale free networks. Recent interest in scale free models started with [BA99] by Barabasi and Albert in which they exhibited that the world wide web and several social networks were scale free. Hence, the fraction of vertices of degree k is $p_k = Ck^{-\beta}$, with C the normalisation constant and typically most of the observed networks which can be represented by a power-law distribution have β between 2 and 3. We are here interested in constructing and investigating graphs following a specified degree distribution.
First of all, let's consider a finite case in which we have a sequence of degrees $d_1, d_2, \ldots, d_n$ such that $d_i = d(i)$. We need for this definition to be correct to make sure that the sum of the degrees is an even number. In order to build the graph, we will assign to each vertex i, d_i "half-edges", and now connecting each of these edges will give a graph with the appropriate degree sequence. The way these "half-edges" are paired is not unique and we will here consider that the pairings are made at random, hence, loops and multi-edges might appear. We will investigate in the following the proportion of these loops and multi-edges and how they affect the model. A realistic model having often no loops or multi-edge (for instance in a social network, one is not often friend with himself or friend several times with someone else). Here we are not interested in the way such graphs are constructed, see the following works cited in which there is a formal construction of the model, however it is important to note that it is

possible to prove that there is a positive probability of obtaining a simple graph using this construction. The fact that the probability is positive ensures that results which are true with high probability are also true with high probability on simple graphs which follow the specified degree sequence.
The approach from Newman, Strogatz and Watts [NSW01] makes an extensive use of generating functions defining the degree sequence, we will here only prove some simple results on the average cluster size. We may refer the reader to [Hof16] and [Dur06] for a similar approach as Newman, Watts and Strogatz or to [MR98] and[FK15] for a more probabilistic approach. In the following we will make use of generating functions in order to obtain several distributions of interest in a general setting. First of all, let's consider that p_k is the probability that a vertex is of degree k, then we naturally define the associated generating function [2] , for $|x| < 1$:

$$G_0(x) = \sum_k p_k x^k \tag{4.29}$$

We may here observe that (4.29) satisfies a condition of normalisation with $G_0(1) = 1$. As in the following we will base our approach on this generating function it is interesting to note that this normalisation condition is the only we require. Hence, it is very convenient to work with if the only knowledge we have on our random graph is the degree of each vertex, which is often the case. For instance, if we consider that we have n_k vertices of degree k, we naturally define G_0 as:

$$G_0(x) = \frac{\sum_k n_k x^k}{\sum_k n_k}, \tag{4.30}$$

which satisfies the normalisation condition. As an example, suppose that in a network of 100 nodes, you observe that there are 20 nodes of degree 0, 10 nodes of degree 1, 30 nodes of degree 3 and 40 nodes of degree 5, then the generating function is defined as:

$$G_0(x) = \frac{20 + 10x + 30x^3 + 40x^5}{100} \tag{4.31}$$

Returning to the general case, the average degree of a vertex is:

$$z = \sum_k k p_k = G_0'(1), \tag{4.32}$$

so once we can compute a generating function, we can also calculate the mean of the probability distribution it generates. It is in fact clear from the distribution that when G is a generating function of a probability distribution, then $G'(1)$ is the expectation of the probability distribution it defines. In this section we will investigate the probability distribution of the cluster (connected component) size.
Let's remark that if we take an edge chosen at random, then it arrives at a vertex with a probability that is proportional to its degree. Hence, such a vertex has a

[2] See [Wil06] for a study of generating functions and their use in discrete mathematics.

probability distribution on its degree proportional to kp_k. Which give that the normalised generating function of the degree of vertices that we arrive at by a randomly chosen edge is:

$$\frac{\sum_k kp_k x^k}{\sum_k kp_k} = x\frac{G_0'(x)}{G_0'(1)}. \tag{4.33}$$

Using the equation above, we obtain that the number of outgoing edges generated by this function has the generating function

$$G_1(x) = \frac{G_0'(x)}{G_0'(1)} = \frac{1}{z}G_0'(x) \tag{4.34}$$

which is (4.33) once we have removed a power of x, which is the edge used to reach the vertex. Here we may observe that if the degrees follow a Poisson distribution of parameter z [3], then the moment generating function of a Poisson distribution being[4]

$$G_0(x) = e^{z(x-1)}, \tag{4.35}$$

we obtain $G_0'(x) = zG_0(x)$ and

$$G_1(x) = G_0(x). \tag{4.36}$$

This means that a random graph following a Poisson distribution on its degree has the same distribution of outgoing edges at a vertex whether we arrived by a randomly chosen edge or if we picked a vertex at random. This being not true in general makes that studying an Erdös Rényi graph is much easier than most of the other models.
Let's now investigate the distribution of the number of neighbours. In order to reach neighbours, one can think that we start from a randomly chosen vertex, count the number of outgoing edges and for each vertex at the end of those edges we count the number of outgoing edges. This gives the following distribution for the number of second neighbours of a vertex:

$$\sum_k p_k(G_1(x))^k = G_0(G_1(x)). \tag{4.37}$$

And we can now compute the expected number of second neighbours as:

$$z_2 = (\frac{d}{dx}G_0(G_1(x)))_{x=1} = G_0'(1)G_1'(1). \tag{4.38}$$

As a matter of fact, the generating function for the distribution of the number of n-th neighbours can be obtained as follows

$$G_0(G_1^{n-1}(x)) \tag{4.39}$$

with G_1^{n-1} denoting the $n-1$ composed of G_1.
We now define H_1 as the generating function for the distribution of the size of the connected component reached by an edge chosen at random.

[3] This is also true for the limiting distribution in n of a binomial with parameter n and z/n
[4] It can be deduced from theorem A.1.1 in appendix

No giant component We consider for the moment that there is no giant component with the degree distribution we investigate, removing this component growing linearly in n allows us to set a normalisation condition on H_1 such that $H_1(1) = 1$. Note that the following results are also formally true if there is a giant component as long as we do not consider that H_1 is not normalised. Defining q_k as the probability that the initial site has k-edges coming out, excluding the edge from which we came along, then

$$H_1(x) = xq_0 + xq_1H_1(x) + xq_2(H_1(x))^2 + \dots \tag{4.40}$$

$$= x\sum_k q_k(H_1(x))^k = xG_1(H_1(x)). \tag{4.41}$$

And similarly we obtain that if we started at a randomly chosen vertex instead of an edge, we can define H_0 as

$$H_0(x) = xG_0(H_1(x)). \tag{4.42}$$

Denoting by s the expected cluster size, then,

$$s = H_0'(1) = \sum_k p_k H_1(1)^k + \sum_k xkp_k H_1'(1)H_1(1)^{k-1} \tag{4.43}$$

$$= G_0(H_1(1)) + H_1'(1)G_0'(1) \tag{4.44}$$

With $H_1(1) = 1$ we have

$$s = 1 + H_1'(1)G_0'(1). \tag{4.45}$$

Similarly for H_1' we can get from (4.40)

$$H_1'(1) = G_1(H_1(1)) + G_1'(1)H_1'(1) \tag{4.46}$$

which gives when $H_1(1) = 1$,

$$H_1'(1) = \frac{1}{1 - G_1'(1)}. \tag{4.47}$$

Replacing the above in (4.45) we obtain

$$s = 1 + \frac{G_0'(1)}{1 - G_1'(1)} = 1 + \frac{z_1^2}{z_1 - z_2}. \tag{4.48}$$

The above formula (4.48) gives the expected cluster size in the "subcritical" case $G_1'(1) < 1$, as we could have expected from the study we lead on the phase transition, it is finite. It is interesting to note that the expression above diverges when $G_1'(1) \geq 1$ which corresponds to the result we found investigating branching processes through other methods. We also observe the equivalent condition in the rightmost part which gives the divergence when $z_2 \geq z_1$ which translated in usual languages states that the phase transition between guaranteed extinction and possible survival happens when the expected number of neighbours at

distance 2 is larger than the expected number of neighbours at distance 1. This formulation should not be too surprising.
Now that we have defined those generating functions and variables, we main state the theorem from this section which includes the cases treated above without a giant component and the event of the existence of a giant component.

Theorem 4.2.1. 1. $G_1'(1) < 1$:

- There is with high probability no giant component.
- The average cluster size is : $H_0'(1) = 1 + \frac{G_0'(1)}{1-G_1'(1)}$

2. $G_1'(1) > 1$:

- There is with high probability a giant component.
- The fraction of vertices in the giant component is asymptotically: $1 - G_0(\rho_1)$, with ρ_1 the smallest fixed point of G_1,
- i.e. $\frac{C_{max}}{n} \longrightarrow 1 - G_0(\rho_1)$.

Above the phase transition We consider the two steps branching process starting from a half edge which has a probability distribution defined by G_1. Using Theorem 3.1.2 on general branching processes, we know that the probability of extinction starting from an edge is the smallest fixed point of G_1 which we denote by ρ_1. So the probability that k edges will be extinct if we wait long enough is ρ_1^k as each branching process is independent from the others. From which we get the following formula on the probability of survival:

$$\sum_k p_k(1 - \rho_1^k) \tag{4.49}$$

which is equal to

$$1 - G_0(\rho_1). \tag{4.50}$$

The probability of survival being asymptotically equivalent to the ratio of infinite components compared to the whole vertex set we can write

$$\frac{C_{max}}{n} \longrightarrow 1 - G_0(\rho_1). \tag{4.51}$$

Hence, C_{max} is growing linearly which means that C_{max} is a giant component as long as $G_0(\rho_1)$ is different from 1. One may observe that what we proved here doesn't depend on the value of $G_1'(1)$, however in that case we would have that $\rho_1 = 1$ and then using the fact that $G_0(1) = 1$ we have that

$$\frac{C_{max}}{n} \longrightarrow 0, \quad \text{if } G_1'(1) < 1 \tag{4.52}$$

which concludes the proof of 4.2.1.

The Poisson Case As seen above if the degree sequence follows a Poisson distribution as it is the case in the Erdös-Rényi model, as observed in (4.36) then $G_0 = G_1$, hence they have the same fixed points. From this observation and considering that $np \longrightarrow \lambda$, we can apply Theorem 4.2.1. So we obtain that the average cluster size if $\lambda = 1 - \epsilon$ for any $\epsilon > 0$ in $\mathcal{G}_{n,\frac{1-\epsilon}{n}}$ is

$$1 + \frac{\lambda}{1-\lambda} = \frac{1}{\epsilon}. \tag{4.53}$$

In the event $\lambda > 1$ and ρ_1 is the solution of the equation $x = e^{\lambda(x-1)}$ then we have

$$C_{max} \longrightarrow (1 - \rho_1)n. \tag{4.54}$$

Appendix A

Some probabilistic tools

A.1 Common inequalities and simple probabilistic results

This section presents inequalities that are used in this report and proves most of them.

Theorem A.1.1 (The moment generating function of a binomial)**.** If $X \sim \mathrm{Bin}(n, p)$, then

$$\mathbb{E}(e^{tX}) = (1 - p + e^t p)^n \tag{A.1}$$

Proof.

$$\mathbb{E}(e^{tX}) = \sum_{k=1}^{n} e^{tk} \mathbb{P}(X = k) \tag{A.2}$$

$$= \sum_{k=1}^{n} \binom{n}{k} e^{tk} p^k (1-p)^k \tag{A.3}$$

$$= \sum_{k=1}^{n} \binom{n}{k} (e^t p)^k (1-p)^k \tag{A.4}$$

$$= (1 - p + e^t p)^n \tag{A.5}$$

□

From this theorem we can obtain the moment generating function of Y following a Poisson distribution of parameter $\lambda = \lim_{n\to\infty} np$ as

$$\mathbb{E}(e^{tY}) = e^{\lambda(1-e^t)} \tag{A.6}$$

simply by taking the limit in the previous theorem.

Theorem A.1.2 (Convergence of factorial moments implies convergence in distribution)**.** Let X be a random variable with a distribution that is determined by its moments. If $X_1, X_2, ...$ are random variables with finite moments such that $\mathbb{E}_k(X_n) \longrightarrow \mathbb{E}_k(X)$ when $n \to \infty$ for every integer $k \geq 1$ then

$$X_n \longrightarrow_d X \tag{A.7}$$

See Theorem 2.3 from [Hof16] for a proof.

Theorem A.1.3 (Factorial moments of a Poisson)**.** If $X \sim \text{Poi}(\lambda)$ then

$$\mathbb{E}_r(X) = \lambda^r \tag{A.8}$$

Proof.

$$\mathbb{E}_r(X) = \mathbb{E}(X(X-1)\dots(X-r+1)) \tag{A.9}$$

$$= \sum_{k=0}^{\infty} (k)_r e^{-\lambda} \frac{\lambda^k}{k!} \tag{A.10}$$

$$\tag{A.11}$$

With $(k)_r = k(k-1)\dots(k-r+1)$ and $(k)_r = 0$ if $k < r$, then,

$$\mathbb{E}_r(X) = e^{-\lambda} \sum_{j=0}^{\infty} \lambda^r \frac{\lambda^j}{j!} = \lambda^r \tag{A.12}$$

□

Theorem A.1.4 (Bernoulli's inequality)**.**

$$1 - (1-p)^t \leq tp \tag{A.13}$$

Theorem A.1.5 (Stirling's formula)**.** We have for all integer $n \geq 1$:

$$n! \geq (\frac{n}{e})^n, \quad n! \sim (\frac{n}{e})^n \sqrt{2\pi n} \tag{A.14}$$

Corollary A.1.5.1 (n choose k approximation)**.**

$$\binom{n}{k} \leq \frac{n^k}{k!} \leq (\frac{ne}{k})^k \tag{A.15}$$

Proof.

$$\binom{n}{k} = \frac{n!}{k!(n-k)!} = \frac{n(n-1)\dots(n-k+1)}{k!} \leq \frac{n^k}{k!} \tag{A.16}$$

Using $\frac{1}{k!} \leq (\frac{e}{k})^k$ we can conclude the proof. □

Theorem A.1.6 (Markov's inequality)**.**

$$\mathbb{P}(X \geq a) \leq \frac{\mathbb{E}X}{a} \tag{A.17}$$

Proof.

$$\mathbb{E}X \geq \mathbb{E}(a\mathbb{1}_{X\geq a}) = a\mathbb{P}(X \ \geq a) \tag{A.18}$$

□

Corollary A.1.6.1 (Chebyshev's inequality)**.** For all positive random variables X, and all $a > 0$,

$$\mathbb{P}(|X - \mathbb{E}X| \geq k\mathbb{V}X) \leq \frac{1}{k^2} \tag{A.19}$$

Proof. Apply (A.1.6) using the random variable $(X - \mathbb{E}X)^2$ □

Theorem A.1.7. Let $X_1, \ldots, X_n$ be independent random variables (not necessariliy with the same distribution). Assume $0 \leq X_i \leq 1$ for each i. Let $X = X_1 + \ldots X_n$ and $\mu = \mathbb{E}(X)$, then for any $0 \leq \epsilon \leq 1$,

$$\mathbb{P}(|X - \mathbb{E}(X)| \ \geq \epsilon\mu) \leq 2\exp(-\frac{\epsilon^2}{3}\mu). \tag{A.20}$$

This inequality can be obtained in many ways, for instance it can be derived Chernoff's bound or Hoeffding-Azuma's inequality. We refer the reader to Section A.1. of [AS16] for a formal proof.

A.2 Couplings

Two random variables, for instance X and Y, are coupled if they are defined on the same probability space. If we are given two random variables X and Y and we want to couple them, we define the random pair $(\hat{X}, \hat{Y})$ with a joint probability $\mathbb{P}$ such that the marginal distribution of $\hat{X}$ (resp. $\hat{Y}$) coincides with the distribution of X (resp. Y). We consider P and Q the probability measures associated with X and Y. P and Q are defined on a σ-algebra $\mathcal{F}$ of subsets of the countable sample space Ω. We define the *total variation distance* as:

$$d_{TV} = \sup_{A\in\mathcal{F}} \ |P(A) - Q(A)| \tag{A.21}$$

First of all, let's observe that the absolute value can be removed as $P(A^c) - Q(A^c) = -(P(A) - Q(A))$ for any $A \in \mathcal{F}$. using the fact that Ω is countable we can construct the set reaching the supremum as $A = \{x \in \Omega : P((x) \geq Q(x)\}$. We have $P(A) - Q(A) = \sum_{x\in A} \ |P(x) - Q(x)|$ and we obtain the simple formula:

$$d_{TV}(P, Q) = \frac{1}{2}\sum_{x\in\Omega} |P(x) - Q(x)| \tag{A.22}$$

simply using the "complementary" remark above which makes that we need the one half factor otherwise we would obtain a value two times larger. We can now obtain the following lemma,

Lemma A.2.1 (Coupling inequality)**.** With all the definitions and notations above, we have,

$$d_{TV}(P,Q) \leq \mathbb{P}(\hat{X} \neq \hat{Y}). \tag{A.23}$$

Proof. For $A \in \mathcal{F}$,

$$\begin{aligned} P(A) - Q(A) &= \mathbb{E}(\mathbb{1}(X \in A) - \mathbb{1}(Y \in A)) && \text{(A.24)} \\ &= \mathbb{E}((\mathbb{1}(X \in A) - \mathbb{1}(Y \in A))\mathbb{1}(X \neq Y)) && \text{(A.25)} \\ &\leq \mathbb{E}(\mathbb{1}(X \neq Y)). && \text{(A.26)} \end{aligned}$$

□

Now let's prove the following Theorem from [Hof16] on couplings:

Theorem A.2.2. Let $\{I_i\}_{i=1}^n$ be independent with $I_i \sim \text{Be}(p_i)$, and let $\lambda = \sum_{i=1}^n p_i$. Let $X = \sum_{i=1}^n I_i$ and let Y be a Poisson random variable with parameter λ. Then there exists a coupling $(\hat{X}, \hat{Y})$ of (X, Y) such that

$$\mathbb{P}(\hat{X} \neq \hat{Y}) \leq \sum_{i=1}^n p_i^2. \tag{A.27}$$

Proof. Throughout this proof we will consider for $i \leq n$, $I_i \sim \text{Be}(p_i)$ are independent, and we let $J_i \sim \text{Poi}(p_i)$ also independent. We define

$$p_{i,1} = \mathbb{P}(I_i = 1) = 1 - p_{i,0}, \quad q_{i,x} = \mathbb{P}(J_i = x) = e^{-p_i}\frac{p_i^x}{x!} \tag{A.28}$$

which are the Bernoulli and Poisson probability mass function[1].
For each pair I_i, J_i, we consider the (maximal) coupling $(\hat{I}_i, \hat{J}_i)$:

$$\mathbb{P}(\hat{I}_i = \hat{J}_i = x) = \min\{p_{1,x}, q_{1,x}\} = \begin{cases} 1 - p_i & \text{for } x = 0, \\ p_i e^{-p_i} & \text{for } x = 1, \\ 0 & \text{for } x \geq 2 \end{cases} \tag{A.29}$$

Thus we have,

$$\mathbb{P}(\hat{I}_i \neq \hat{J}_i) = 1 - \mathbb{P}(\hat{I}_i = \hat{J}_i) = 1 - (1 - p_i) - p_i e^{-p_i} = p_i(1 - e^{-p_i}) \leq p_i^2. \tag{A.30}$$

Using $\hat{X} = \sum_{i=1}^n \hat{I}_i$ and $\hat{Y} = \sum_{i=1}^n \hat{J}_i$ the proof can be easily completed. □

We can obtain the following result as a corollary,

Corollary A.2.2.1. For every $\lambda > 0$ and $n \in \mathbb{N}$, there exists a coupling $(\hat{X}, \hat{Y})$ where $\hat{X} \sim \text{Bin}(n, \frac{\lambda}{n})$ and $\hat{Y} \sim \text{Poi}(\lambda)$ there exists a coupling $(\hat{X}, \hat{Y})$ such that

$$\mathbb{P}(\hat{X} \neq \hat{Y}) \leq \frac{\lambda^2}{n}, \tag{A.31}$$

which in turn implies, for every $i \in \mathbb{N}$

$$|\mathbb{P}(X = i) - \mathbb{P}(Y = i)| \leq \frac{\lambda^2}{n}. \tag{A.32}$$

[1]The probability mass function of X is the probability density function of X with respect to the counting measure.

The first claim should be clear using the previous theorem. The second claim comes from the coupling inequality A.2.1.

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