

Graduation Project

Santiago Morales - 201913369

March 24, 2023

1 Introduction

2 Kahn-Kalai Conjecture

2.1 Thresholds

Let $n \in \mathbb{N}$ and $0 \leq p \leq 1$. The random graph $G(n, p)$ is a probability space over the set of graphs on n labeled vertices determined by

$$\Pr[\{i, j\} \in G] = p$$

with these events mutually independent [1]. Given a graph theoretic property A , there is a probability that $G(n, p)$ satisfies A , which we write as $\Pr[G(n, p) \models A]$.

Definition 2.1. $r(n)$ is a threshold function for a graph theoretic property A if

1. When $p(n) \in o(r(n))$, $\lim_{n \rightarrow \infty} \Pr[G(n, p(n)) \models A] = 0$,
2. When $r(n) \in o(p(n))$, $\lim_{n \rightarrow \infty} \Pr[G(n, p(n)) \models A] = 1$,

or vice versa. [1]

We give an example of a threshold function which illustrates a common method for proving that a function is a threshold.

2.1.1 Threshold function for having isolated vertices

Let G be a graph on n labeled vertices. An isolated vertex of G is a vertex which does not belong to any of the edges of G . Let A be the property that G contains an isolated vertex. We will prove that $r(n) = \frac{\ln n}{n}$ is a threshold for A .

For each vertex i in G define the variable

$$X_i = \begin{cases} 1 & \text{if } i \text{ is an isolated vertex,} \\ 0 & \text{if } i \text{ is not an isolated vertex.} \end{cases}$$

Now, the probability that a vertex i is isolated is $(1 - p)^{n-1}$ since it is the probability that none of the other $n - 1$ vertices is connected to i . Let $X = \sum_{i=1}^n X_i$, then the expected number of isolated vertices is

$$E[X] = \sum_{i=1}^n E[X_i] = \sum_{i=1}^n \Pr[X_i] = n(1 - p)^{n-1}.$$

Let $p = k \frac{\ln n}{n}$ for $k \in \mathbb{R}_{>0}$. Then

$$\begin{aligned} \lim_{n \rightarrow \infty} E[X] &= \lim_{n \rightarrow \infty} n \left(1 - k \frac{\ln n}{n} \right)^{n-1} \\ &= n e^{-k \ln n} = n^{1-k}. \end{aligned}$$

Therefore, $\lim_{n \rightarrow \infty} E[X] = 0$ if $k > 1$. Since $E[X] \geq \Pr[X > 0]$, we conclude that

$$\lim_{n \rightarrow \infty} \Pr[G(n, p) \models A] = \lim_{n \rightarrow \infty} \Pr[X > 0] = 0.$$

Now, for $k < 1$, the fact that $\lim_{n \rightarrow \infty} E[X] = \infty$ is not enough to conclude that $\lim_{n \rightarrow \infty} \Pr[G(n, p) \models A] = 1$. We have to use the second moment method.

Theorem. *If $E[X] \rightarrow \infty$ and $\text{Var}[X] = o(E[X]^2)$, then $\lim_{n \rightarrow \infty} \Pr[X > 0] = 1$. [1]*

Proof. We will prove that, in this case, $\text{Var}[X] = o(E[X]^2)$. First,

$$\begin{aligned} \sum_{i \neq j} E[X_i X_j] &= \sum_{i \neq j} \Pr[X_i = X_j = 1] \\ &= n(n-1)(1-p)^{n-1}(1-p)^{n-2} \\ &= n(n-1)(1-p)^{2n-3}, \end{aligned}$$

for if i is an isolated vertex, then there is no edge between i and j so we only have to account for the remaining $n - 2$ edges that contain j .

Thus, since $\sum_{i=1}^n E[X_i^2] = \sum_{i=1}^n E[X_i] = E[X]$ and $\lim_{n \rightarrow \infty} p = 0$,

$$\begin{aligned} \lim_{n \rightarrow \infty} \frac{\text{Var}[X]}{E[X]^2} &= \lim_{n \rightarrow \infty} \frac{E(X^2) - E[X]^2}{E[X]^2} = \lim_{n \rightarrow \infty} \frac{\sum_{i=1}^n E[X_i^2] + \sum_{i \neq j} E[X_i X_j]}{E[X]^2} - 1 \\ &= 0 + \lim_{n \rightarrow \infty} \frac{n(n-1)(1-p)^{2n-3}}{n^2(1-p)^{2n-2}} - 1 = \lim_{n \rightarrow \infty} \frac{1}{1-p} - 1 = 0. \end{aligned}$$

We conclude that $\text{Var}[X] \in o(E[X]^2)$ and so, if $k < 1$,

$$\lim_{n \rightarrow \infty} \Pr[G(n, p) \models A] = \lim_{n \rightarrow \infty} \Pr[X > 0] = 1.$$

Therefore, $r(n) = \frac{\ln n}{n}$ is a threshold function for property A .

2.2 The expectation threshold

Let X be a set and $p \in [0, 1]$. For $A \subset X$, let $P(A) = p^{|A|}(1-p)^{|X \setminus A|}$. A class \mathcal{F} of subsets of X is increasing if for $A \in \mathcal{F}$, $A \subset B$ implies $B \in \mathcal{F}$. If $\mathcal{F} \neq \emptyset$, $P(\mathcal{F}) = \sum_{A \in \mathcal{F}} P(A)$ is a strictly increasing function of p .

TODO Define increasing class and general definition of threshold [2]

TODO Define expectation threshold and show inequalities. [3]

Example 2.1. H_1 example

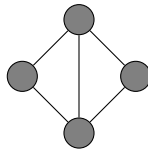


Figure 1: H_1

Example 2.2. H_2 example

Theorem 2.1 (Park Theorem [2], originally Kahn-Kalai Conjecture). **TODO**

TODO How to prove something is p-small

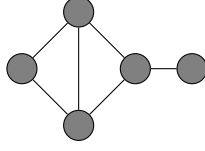


Figure 2: H_2

2.2.1 An application of the Park Theorem

TODO Prove the threshold for perfect matchings for $G(n, p)$

3 Numerical Semigroups

A *numerical semigroup* is a subset $S \subset \mathbb{N}_0$ which is closed under addition, i.e. $a, b \in S$ implies $a + b \in S$. For instance, \mathbb{N}_0 , $\mathbb{N}_0 \setminus \{0\}$, $2\mathbb{N}_0$ are all numerical semigroups, but $\mathbb{N}_0 \setminus \{2\}$ is not. Some literature requires that a semigroup has a finite complement in $\mathbb{Z}_{\geq 0}$ [4], but we prefer the more general definition.

Example 3.1. TODO McNugget Semigroup

As seen in the previous example, we can describe a numerical semigroup with a set of *generators*:

$$S = \langle a_1, \dots, a_n \rangle := \left\{ \sum_{i=1}^n k_i a_i : k_1, \dots, k_n \in \mathbb{N}_0 \right\}.$$

TODO give some examples.

The *Frobenius number* $F(S)$ of a numerical semigroup $S = \langle a_1, \dots, a_n \rangle$ is defined as the largest integer divisible by $d(S) := \gcd(a_1, \dots, a_n)$ which does not belong to S . In other terms,

$$F(S) = \max(d\mathbb{Z} \setminus S).$$

4 Probability Spaces over Numerical Semigroups

We generate a random numerical semigroup with a model similar to the Erdos-Renyi model for random graphs.

Definition 4.1. For $p \in [0, 1]$ and $M \in \mathbb{N}$, a random numerical semigroup $S(M, p)$ is a probability space over the set of semigroups $S = \langle \mathcal{A} \rangle$ with $\mathcal{A} \subset \{1, \dots, M\}$, determined by

$$\Pr[n \in \mathcal{A}] = p,$$

with these events mutually independent.

5 Expected Frobenius Number

We prove a Theorem found in [5] without the use of the simplicial complex.

Theorem 5.1. *Let $S \sim S(M, p)$, where $p = p(M)$ is a monotone decreasing function of M . If $\frac{1}{M} \ll p \ll 1$, then S is cofinite, i.e., the set of gaps is finite, a.a.s and*

$$\lim_{M \rightarrow \infty} E[e(S)] = \lim_{M \rightarrow \infty} E[g(S)] = \lim_{M \rightarrow \infty} E[F(S)] = \infty.$$

Proof. Let $X := \min(S \setminus \{0\})$ be a random variable. Then, for $0 < n \leq M$,

$$P[X = n] = p(1 - p)^{n-1},$$

and so

$$\begin{aligned} E[X] &= \sum_{n=0}^{\infty} nP[X = n] = \sum_{n=0}^M np(1 - p)^{n-1} = p \frac{d}{dp} \left[- \sum_{n=0}^M (1 - p)^n \right] \\ &= p \frac{d}{dp} \frac{(1 - p)^{M+1} - 1}{p} = p \frac{1 - (1 - p)^{M+1} - (M + 1)(1 - p)^M p}{p^2} \\ &= \frac{1 - (1 - p)^M - M(1 - p)^M p}{p} \geq \frac{1 - e^{-Mp} - Mpe^{-Mp}}{p}. \end{aligned}$$

Thus, since $\lim_{M \rightarrow \infty} Mp = \infty$, then $\lim_{M \rightarrow \infty} Mpe^{-Mp} = \lim_{M \rightarrow \infty} e^{-Mp} = 0$, which means

$$\lim_{M \rightarrow \infty} E[X] = \lim_{M \rightarrow \infty} \frac{1 - e^{-Mp} - Mpe^{-Mp}}{p} = \infty.$$

Also, note that if $p = \frac{c}{M}$, $c \in \mathbb{R}_+$ ($0 < e^{-c} + ce^{-c} < 1$),

$$\lim_{M \rightarrow \infty} E[X] = \lim_{M \rightarrow \infty} \frac{1 - e^{-c} - ce^{-c}}{p} = \infty.$$

References

- [1] N. Alon and J. H. Spencer, *The probabilistic method*. John Wiley & Sons, 2016.
- [2] J. Park and H. T. Pham, “A proof of the kahn-kalai conjecture,” *arXiv e-prints*, pp. arXiv-2203, 2022.
- [3] K. Frankston, J. Kahn, B. Narayanan, and J. Park, “Thresholds versus fractional expectation-thresholds,” *Annals of Mathematics*, vol. 194, no. 2, pp. 475–495, 2021.
- [4] S. Chapman, R. Garcia, and C. O’Neill, “Beyond coins, stamps, and chicken mc nuggets: An invitation to numerical semigroups,” *A Project-Based Guide to Undergraduate Research in Mathematics: Starting and Sustaining Accessible Undergraduate Research*, pp. 177–202, 2020.
- [5] J. De Loera, C. O’Neill, and D. Wilburne, “Random numerical semigroups and a simplicial complex of irreducible semigroups,” *arXiv preprint arXiv:1710.00979*, 2017.