

# Notes for CS 485

## 2/1/06, Thomas Womack

### Contents:

Proof that isolated verticies disappear at  $p = \frac{\ln n}{n}$

Proof of Markov and Chebyshov's Inequalities

Demonstration of Second Moment Method on Isolated Verticies,

#### 1. Isolated verticies disappear at $p = \frac{\ln n}{n}$

Let the random variable  $X$  be the number of isolated verticies.

From before, we know that if

$p = \frac{c \ln n}{n}$  where  $c$  is a constant, then

$$E(X) = n^{1-c}$$

$$\lim_{n \rightarrow \infty} E(X) = \lim_{n \rightarrow \infty} n^{1-c} = \begin{cases} 0 & c > 1, \text{ which implies } \text{Prob}(X=0) = 1 \\ \infty & c < 1, \text{ which might imply } \text{Prob}(X=0) < 1 \end{cases}$$

For  $E(X) \rightarrow \infty$ ,  $\text{Prob}(X=0)$  could still approach 1, if all of the isolated verticies are confined to only a few graphs in the ensemble of possible graphs:

graph:  $G_0 G_1 G_2 G_3 \dots$

$X : \infty 0 0 0 \dots$

[Table shows all graphs, and # isolated verticies for each graph]

To rule this possibility out, we use the 2nd moment method to show that  $\text{Var}(X)$  is much smaller than  $E(X)$  as  $n \rightarrow \infty$

#### 2. Proof of Markov and Chebyshov Inequalities.

Let  $X$  be a random variable s.t.  $X \geq 0$ .

The Markov inequality states that for all  $a > 0$

$\text{Prob}(X \geq a) \leq \frac{E(X)}{a}$  or by setting  $b = \frac{a}{E(X)}$ ,  $\text{Prob}(X \geq bE(X)) \leq \frac{1}{b}$

Proof: Let  $p(x)$  be probability distribution on  $X$ . Then

$$E(X) = \int_0^\infty x p(x) dx = \int_0^a x p(x) dx + \int_a^\infty x p(x) dx \geq 0 + \int_a^\infty x p(x) dx \geq \int_a^\infty a p(x) dx$$

$$E(X) \geq a \int_a^\infty p(x) dx = a [\text{Prob}(X \geq a)] \geq 0, \text{ and finally}$$

$$\text{Prob}(X \geq a) \leq \frac{E(X)}{a}$$

2. Continued:

The Chebychev Inequality states that for any distribution over the random variable  $X$ , with mean  $E(x)$  and variance  $\sigma^2$ , and any  $t \geq 0$ ,  $\text{Prob}(|X - E(x)| \geq \sigma t) \leq \frac{1}{t^2}$

Proof: Square both sides in probability and let  $X' = (X - E(x))^2$ ,  $a' = \sigma^2 t^2$   
 $\text{Prob}(|X - E(x)| \geq \sigma t) = \text{Prob}((X - E(x))^2 \geq \sigma^2 t^2) = \text{Prob}(X' \geq a')$

$X' \geq 0$  so we can use Markov's inequality

$$\text{Prob}(X' \geq a') \leq \frac{E(X')}{a'} = \frac{E((X - E(x))^2)}{\sigma^2 t^2} = \frac{\sigma^2}{\sigma^2 t^2} \text{ by the definition of variance}$$

$$\text{Prob}(|X - E(x)| \geq \sigma t) \leq \frac{\sigma^2}{\sigma^2 t^2} = \frac{1}{t^2}$$

3. The Second Moment Method.

Consider a random variable  $X$  s.t.  $X \geq 0$  and the mean  $E(x)$  and the deviation  $\sigma$  are known

$$\text{Prob}(X=0) = \text{Prob}(E(x) - X = E(x)) \leq \text{Prob}(|X - E(x)| \geq E(x))$$

Let  $E(x) = t\sigma$ , then

$$\text{Prob}(X=0) \leq \text{Prob}(|X - E(x)| \geq t\sigma) \leq \frac{1}{t^2} = \frac{\sigma^2}{E^2(x)}$$

$$\begin{aligned}\sigma^2 &= E((X - E(x))^2) = E(X^2 - 2XE(x) + E^2(x)) = E(X^2) - 2E(x)E(x) + E^2(x) \\ &= E(X^2) - E^2(x) \quad \text{so that}\end{aligned}$$

$$\text{Prob}(X=0) \leq \frac{E(X^2) - E^2(x)}{E^2(x)} = \frac{E(X^2)}{E^2(x)} - 1$$

Suppose that the distribution on  $X$ , depends on a variable  $n$ .

i.e., If  $\lim_{n \rightarrow \infty} \frac{E(X^2)}{E^2(x)} = 1$ , then  $\lim_{n \rightarrow \infty} \text{Prob}(X=0) = 0$

### 3. Continued

The 2nd moment method applied to isolated vertices

Let  $X = \# \text{ isolated vertices}$ .  
 $X = \sum_{i=1}^n X_i$  where  $X_i = \begin{cases} 1 & \text{if } i\text{th vertex is isolated} \\ 0 & \text{otherwise} \end{cases}$

$$X^2 = \sum_{i,j} X_i X_j = \sum_i X_i^2 + \sum_{i \neq j} X_i X_j = \sum_i X_i + \sum_{i \neq j} X_i$$

$$\sum_{i=1}^n X_i^2 = \sum_{i=1}^n X_i = X \quad \text{since } X_i^2 = X_i$$

$$\begin{aligned} E(X^2) &= E\left(\sum_{i=1}^n X_i^2\right) + E\left(\sum_{i \neq j} X_i X_j\right) = E(X) + \sum_{i \neq j} E(X_i X_j) \\ &= E(X) + n(n-1)E(X_1 X_2) \quad \text{since } E(X_i X_j) \text{ is the same for all } i, j, i \neq j \end{aligned}$$

$$E(X_1 X_2) = \text{Prob}(X_1 X_2 = 1) = \text{Prob}(X_1 = 1) \text{Prob}(X_2 = 1 | X_1 = 1)$$

$\text{Prob}(X_1 = 1) = (1-p)^{n-1}$  since there can be no edges to the other  $n-1$  vertices

$\text{Prob}(X_2 = 1 | X_1 = 1) = (1-p)^{n-2}$  since we need not consider vertex 1.

$$E(X) = n(1-p)^{n-1} \quad \text{and} \quad E(X_1 X_2) = (1-p)^{2n-3}$$

$$E(X^2) = E(X) + n(n-1)E(X_1 X_2) = n(1-p)^{n-1} + n(n-1)(1-p)^{2n-3}$$

$$\frac{E(X^2)}{E^2(X)} = \frac{1}{n(1-p)^{n-1}} + \frac{n(n-1)(1-p)^{2n-3}}{n^2(1-p)^{2n-2}} = \frac{1}{n(1-p)^{n-1}} + \frac{n-1}{n} \frac{1}{1-p}$$

For  $p = \frac{c \ln n}{n}$ ,  $n \rightarrow \infty$  and  $c < 1$

$$\frac{E(X^2)}{E^2(X)} = \frac{1}{n^{1/2}} + \frac{1}{1 - \frac{c \ln n}{n}} = 0 + \frac{1}{1-0} = 1$$

Therefore, for  $c < 1$ ,  $\lim_{n \rightarrow \infty} \text{Prob}(X=0) = 0$

so that for  $p < \frac{\ln n}{n}$ , there will almost certainly be an isolated vertex.