

# The differential equation method

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## Describing elements of a random graph

Consider a graph  $G$  on  $n$  vertices where edges are present independently at random

Vertex set  $[n] = \{1, 2, \dots, n\}$

Edges r.v.'s  $X_{ij} = \mathbb{I}_{\{i \leftrightarrow j\}}$ , independent

Some interesting statistics:

- number of edges
- isolated vertices
- number of components (of given size)
- degree sequence
- chromatic number
- independence number

Intuitively changing one variable in  $\{X_{ij}\}$  won't change statistics by much.

This course: conditions to 'see' trends ... in a (graph) discrete process

## Chernoff bounds $t > 0$

$$\Pr(X \geq a) = \Pr(e^{tX} \geq e^{ta}) \leq \frac{\mathbb{E}[e^{tX}]}{e^{ta}}$$
$$t = 4a / \sum(b_i - a_i)^2 \quad \text{optimize } t$$

If  $S_n = \sum_{i=1}^n X_i$ ; independent  $X_i$ :

$$\Pr(S_n \geq \mathbb{E}[S_n] + \varepsilon) \leq e^{-t\varepsilon} \prod_{i=1}^n \mathbb{E}[e^{t(X_i - \mathbb{E}[X_i])}]$$

+ bounded  $X_i$  so that  $a_i \leq X_i \leq b_i$

$$\Pr(S_n \geq \mathbb{E}[S_n] + \varepsilon) \leq e^{-2\varepsilon^2 / \sum(b_i - a_i)^2}$$

This gives quantitative bounds for LLN  $\Pr(X_i \in [0, 1])$

$$\sum_{n \geq 1} \Pr\left(\left|\frac{S_n - \mathbb{E}[S_n]}{n}\right| > u\right) \leq \sum_{n \geq 1} 2e^{-nu^2/2} < \infty$$

$$\Rightarrow \Pr\left(\left|\frac{S_n - \mathbb{E}[S_n]}{n}\right| > u \text{ infinitely often}\right) = 0$$

$$\frac{S_n - \mathbb{E}[S_n]}{n} \xrightarrow{\text{a.s.}} 0$$

# Two generalization

① If  $\{Z_i\}_{i \geq 0}$  martingale,  $Z_0 = 0$

$$|Z_{i+1} - Z_i| < c_i$$

$$\mathbb{P}(Z_n \geq \mathbb{E}[Z_n] + \varepsilon) \leq e^{-2\varepsilon^2/\sum c_i^2}$$

Proof Sketch:  $\mathcal{F}_i = \sigma\text{-algebra } (Z_1, \dots, Z_i)$   
 $Z_n = \sum_{i=1}^n Z_i - Z_{i-1} = \sum_{i=1}^n V_i$

$$\mathbb{E}[e^{tZ_n}] = \mathbb{E}\left[\prod_{i=1}^n e^{tV_i}\right]$$

$$= \mathbb{E}\left[\prod_{i=1}^n e^{tV_i} \mathbb{E}[e^{tV_n} | \mathcal{F}_{n-1}]\right]$$

Now  $V_n$  satisfies conditions of Hoeffding's lemma.

② Let  $\{X_i\}$  independent  $X_i \in \mathcal{X}$

$$f: \mathcal{X}^n \rightarrow \mathbb{R}$$

Conditions

$$|\mathbb{f}(x_1, x_2, \dots, x_n) - \mathbb{f}(y_1, \dots, y_n)| \leq \sum c_i \mathbb{1}_{\{x_i \neq y_i\}}$$

$$\mathbb{P}(f(X) \geq \mathbb{E}[f] + \varepsilon) \leq e^{-2\varepsilon^2/\sum c_i^2}$$

$$V_i = \mathbb{E}[f | \mathcal{F}_i] - \mathbb{E}[f | \mathcal{F}_{i-1}]$$

$$\mathcal{F}_i = \sigma\text{-alge} (X_1, \dots, X_i)$$

3 r.v.'s  $L_i, U_i$  measurable wrt  $\mathcal{F}_{i-1}$

$$L_i \leq V_i \leq U_i \quad U_i - L_i \leq c_i$$

so can apply Hoeffding's lemma

Extension in Hamming distance

$$\underline{x} = (x_1, \dots, x_n) \in S^n \quad A \subset S^n$$

$$\text{Hamming dist } d_H(\underline{x}, \underline{y}) = \sum \mathbb{1}_{\{x_i \neq y_i\}}$$

$$d_H(\underline{x}, A) = \inf_{y \in A} d_H(\underline{x}, y)$$

$$[A]_{\epsilon} = \{\underline{x} \in S^n : d_H(\underline{x}, A) \leq \epsilon\}$$

How big becomes  $[A]_{\epsilon_n}$

$$\begin{aligned} \Pr(\underline{x} \in [A]_{\epsilon_n}) &= \Pr(d(\underline{x}, A) \leq \epsilon_n) \\ &= 1 - \Pr(d(\underline{x}, A) > \epsilon_n) \end{aligned}$$

$$* \epsilon_n > \mathbb{E}[d(\underline{x}, A)] \quad u = \epsilon_n - \mathbb{E}[d(\underline{x}, A)]$$

$$\Pr(d(\underline{x}, A) > \epsilon_n) = \Pr(d(\underline{x}, A) > \mathbb{E}[-] + u) \leq e^{-2nu^2}$$

Problem:  $\mathbb{E}[d(\underline{x}, A)]$  unknown

$$\epsilon_n \geq B \geq \mathbb{E}[d(\underline{x}, A)]$$

$$\Pr(d(\underline{x}, A) \geq \epsilon_n) \leq \Pr(d(\underline{x}, A) \geq \mathbb{E}[\cdot] + u)$$

$$u = \epsilon_n - B$$

Trick: from Hoeffding lemma ' proof

$$\mathbb{E}[e^{t(f - \mathbb{E}[f])}] \leq e^{nt^2/8}$$

$$f = -d(\underline{x}, A) \quad \mathbb{E}[e^{-t\mathbb{E}[f]}] = e^{-t\mathbb{E}[f]}$$

$$\Pr(A) = \mathbb{E}[\mathbb{1}_{A|} e^{t f}] \leq \mathbb{E}[e^{tf}] = \mathbb{E}[e^{-t d(\underline{x}, A)}]$$

$$\Pr(A) e^{-t\mathbb{E}[d(\underline{x}, A)]} \leq e^{nt^2/8}$$

Take logarithm + optimize t

$$\mathbb{E}[d(\underline{x}, A)] \leq \sqrt{\frac{-n \log \Pr(A)}{2}} = B$$

# Examples of analysis of algorithms

## ① Matchings in $G_{n,c_n}$ (Erdős-Rényi)

Graph on  $n$  vertices edges independently present w.p.  $\frac{c}{n}$

Matching : set of edges that do not share common vertices

Algorithm:

- ① Delete isolated vertices
- ② Select a uniformly random vertex of min-degree  $v$
- ③ Include in matching one of its edges
- ④ Delete  $v$  and all other incident edges.

Thm:  $c > 0$ . The algorithm obtains a maximum matching a.a.s.

$(\text{IP}(\leftrightarrow) \rightarrow 1 \text{ } n \rightarrow \infty)$

## ② 3-coloring regular $G_{n,d}$

uniformly chosen graph on those with  $n$  vertices and  $\deg(v)=d$  all  $v$ .

Proper coloring: assign colors to vertices so that no two adjacent vertices have same color

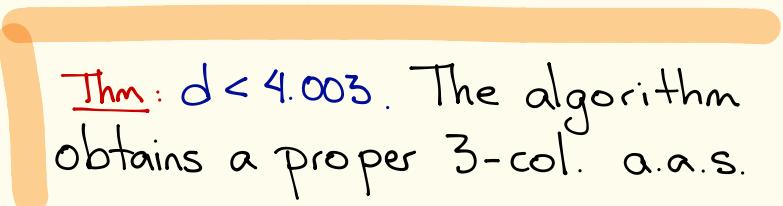
Algorithm: Classify uncolored vertices according to #available color

$$S_i(t) = \{v : i \text{ possible colors for } v\}$$

while  $S_0(t) = 0$

- ① Select minimum  $i$  with  $S_i(t) > 0$
- ② select uniform vertex in  $S_i(t)$
- ③ Color  $v$  randomly, update  $S_i(t+1)$ .

Failure if  $S_0(t) > 0$

Thm:  $d < 4.003$ . The algorithm obtains a proper 3-col. a.a.s.

### ③ 3-SAT formulae

$$(\bar{x}_1 \vee x_1 \vee x_2) \wedge (\bar{x}_2 \vee \bar{x}_1 \vee x_3)$$

clause

← literal: + or -  
variable

$$0 \vee 1 = 1$$

$$0 \wedge 1 = 0$$

Assign values to variables, to satisfy formula

Pure literal: when formula only contains literals  $x_i$  (or only  $\bar{x}_i$ )

Algorithm: while  $\exists$  pure literal available

- ① choose one at random  $x_i$  (or  $\bar{x}_i$ )
- ② assign 'positive' value  $x_i=1$  (or  $x_i=0$ )
- ③ remove all clauses containing  $x_i$

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3 literals per clause

m clause

n variables

density  $\frac{m}{n}$

Thm:  $\exists d_c > 0$ . Construct a random 3-SAT where (# literals =  $x_i$ )  $\approx \text{Poi}(\lambda_i)$  and density is  $d$ :

$d < d_c$  formula is satisf. a.a.s.

$d > d_c$  formula is not satisf. a.a.s.

## An introductory example

There are  $n$  bins and  $m = cn$  balls, sequentially place balls independent into bins  
How many empty bins there are left?

$$B = \sum_{j=1}^n B_j \quad B_j = \mathbb{I}_{\{\text{j-th bin is empty}\}} \quad P(B_j = 1) = (1 - \frac{1}{n})^{cn} \Rightarrow E[B] = n e^{-c(1/\ln(1))}$$

Let  $\{X_i\}$  iid.  $X_i \sim \text{Unif}[n] \rightarrow X_i = j \text{ if } i\text{-th ball goes to } j\text{-th bin}$

Now  $B$  satisfies the bounded differences condition

$$P(|B - E[B]| \geq \varepsilon n) \leq 2 e^{-\frac{2\varepsilon^2 n^2}{\sum_{i=1}^n 1^2}} = 2 e^{-2n\varepsilon^2/c}$$

If need to estimate  $E[B]$

$Y_i = \#\text{empty bins when } i \text{ balls have been located}$

$$|Y_{i+1} - Y_i| \leq 1$$

If need to estimate  $\mathbb{E}[B]$

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Local changes, given current information  $\mathcal{F}_i$  = generated by "info" at time  $i$

$$\mathbb{E}[Y_{i+1} - Y_i | \mathcal{F}_i] = -1 \cdot P(\text{ball into empty bin}) = -\frac{Y_i}{n}$$

Idealized ODE:

$$\frac{Y(t_n)}{n} \approx y(t) \quad \frac{Y(0)}{n} = y(0) = 1 \quad \Delta Y_i = Y_{i+1} - Y_i$$

$$\frac{\mathbb{E}\left[\frac{\Delta Y(t_n)}{n} | \mathcal{F}_{t_n}\right]}{1/n} \cong y'(t) = -y(t)$$

Solution  $y(t) = e^{-t}$        $\frac{\mathbb{E}[B]}{n} = \mathbb{E}\left[\frac{Y_{cn}}{n}\right] \approx e^{-c}$

# A toy deterministic question

How much can two collections of functions can differ if they have similar derivatives and initial values?

$\exists \lambda, \delta > 0$  small perturbations such that

$$\begin{aligned} y_k(0) &= \hat{y}_k \text{ cte} & y'_k(t) &= F_k(t, \underline{y}(t)) \\ |z_k(0) - y_k(0)| &\leq \lambda & |z'_k(t) - F_k(t, \underline{z}(t))| &\leq \delta \end{aligned}$$

Condition:  $F$  is  $L$ -Lipschitz cont. in norm  $\|\cdot\|_\infty$

in particular  $|F_k(t, y(t)) - F_k(t, z(t))| \leq L \max_{k \in I} |y_k(t) - z_k(t)|$

$$\Rightarrow \max_{k \in I} |y_k(t) - z_k(t)| \leq (\lambda + \delta T) e^{Lt} \quad \forall t \leq T$$

$$\begin{aligned}
 |y'(s) - z'(s)| &< |y'(s) - F(s, z(s))| + |\underbrace{F(s, z(s)) - z'(s)}_{\delta}| \\
 &< |F(s, y(s)) - F(s, z(s))| + \delta \\
 &\leq L \cdot |y(s) - z(s)| + \delta
 \end{aligned}$$

$$\begin{aligned}
 \underbrace{|y(t) - z(t)|}_{x(t)} &\leq |y(0) - z(0)| + \int_0^t |y'(s) - z'(s)| ds \\
 &\leq (\lambda + \delta T) + \int_0^t L x(s) ds
 \end{aligned}$$

By Grönwall's ineq.  $\Rightarrow x(t) \leq (\lambda + \delta T) e^{Lt}$