

# Chapter 9 : Influence maximization

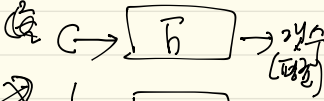
→ **IF-MAX is NP-hard**

→ approximation algorithms? ( - polynomial time  
 - solution quality ) ~~vs~~ original solution (not)

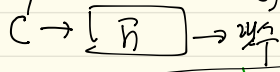
→ approximation ratio lesson set approximation ratio



$f(C)$



**CCC'**



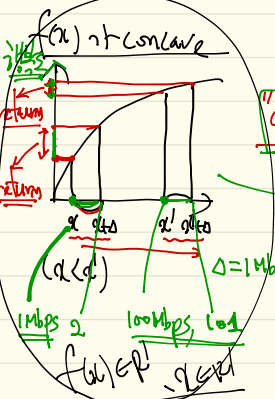
$f(C') \geq f(C)$  (proof)

• diminishing return

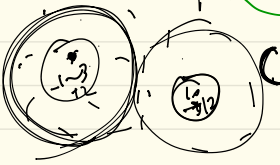
$C+A$        $C'+A$        $(C' \cup C)$

$f(C+A) - f(C) \geq f(C'+A) - f(C')$

is it a set function? diminishing return



"diminishing return"



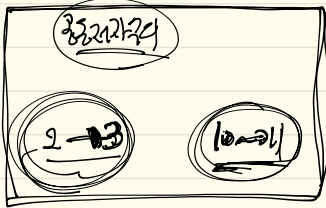
Approximation

(increasing diminishing returns  $\rightarrow$  set function  $\rightarrow$  max)

greedy algorithm of approximation

set

**Submodular function**



(Homework) Submodular set function의 2nd part 풀기

3/23/21

2/11 page, 9.1

(Homework)  $F(C)$ 가 submodular 이다 증명

$F(C) = E(|V(C)|)$   $\Rightarrow$   $\sum_{C \subseteq V} |V(C)| = \sum_{v \in V} \sum_{C \subseteq V, v \in C} 1$

$F(C) = E(|V(C)|)$  : random variable

Greedy algorithm

- Choose nodes,  $v_1, \dots, v_k \in V$  recursively as follows:  
in the  $i$ -th step,

$v_i \in \arg \max_{v \in V \setminus C_{i-1}} (F(C_{i-1} \cup \{v\}) - F(C_{i-1}))$   $i=1, \dots, k$

where  $C_0 = \emptyset$  and  $C_j = \{v_1, \dots, v_j\}$ ,  $j=1, \dots, k-1$ .

- then  $C = C_k$

이항 노드 선택

이것이 generalization? Define a relaxed, generalized version of

the greedy algorithm, which we call  $(\epsilon, \delta)$ -greedy algorithm, as follows: "a class of greedy algorithm"

$\epsilon \in [0, 1]$   
 $\delta \geq 0$

We say that the sequence  $(v_1, v_2, \dots, v_k)$  is  $(\epsilon, \delta)$ -greedy if the following is satisfied: at each step  $i$

$$F(C_{i-1} \cup \{v_i\}) - F(C_{i-1}) \geq \epsilon \max_{v \in V \setminus C_{i-1}} (F(C_{i-1} \cup \{v\}) - F(C_{i-1}))$$

$\epsilon, \delta$   $\downarrow$  multiplicative suboptimality factor  
 $\delta$   $\downarrow$  additive factor

$(1, 0)$ -greedy  $\rightarrow$  original greedy

(Question)

Q1: Greedy algorithm  $\rightarrow$   $\epsilon, \delta$ ?

Q2:  $(\epsilon, \delta)$ -greedy  $\subset$   $\{ \epsilon, \delta \}$

$\epsilon^*$

$\epsilon^* - \delta$

$\max F(C)$

optimal solution produce  $\epsilon, \delta$ ?

Thm 9.2

Consider a submodular function  $f: 2^V \rightarrow \mathbb{R}$  that takes non-negative values and is non-decreasing. Let  $(v_1, \dots, v_k)$  be an  $(\epsilon, \delta)$ -greedy sequence. Then

$$f(C_k) \geq (1 - e^{-\epsilon}) \frac{\max_{C \subset V, |C|=k} f(C)}{\epsilon} - \delta$$

이론상 최적 해를 찾는 것

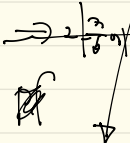
(Pf)

Let us consider a subset  $C = \{w_1, \dots, w_k\}$  which is fixed.

(Lemma 1) For any index  $i \in \{2, \dots, k-1\}$  we have:

$$f(C_i) - f(C_{i-1}) \leq \left(1 - \frac{\epsilon}{k}\right) (f(C_i) - f(C_{i-1})) + \delta$$

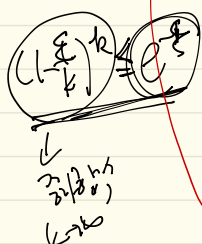
where  $C_i$  is the set  $\{v_1, \dots, v_k\}$  of the  $i$ -first element in an arbitrary  $(\epsilon, \delta)$ -greedy sequence.



~~이항~~ 등차수열의 성질

$$a_{n+1} \leq a_n + \delta$$

$$\begin{aligned} f(C_i) - f(C_{i-1}) &\leq \left(1 - \frac{\epsilon}{k}\right) (f(C_i) - f(C_{i-1})) + \delta \\ &\leq \left(1 - \frac{\epsilon}{k}\right) \left( \left(1 - \frac{\epsilon}{k}\right) (f(C_i) - f(C_{i-2})) + \delta \right) + \delta \\ &\vdots \\ &\leq \left(1 - \frac{\epsilon}{k}\right)^k (f(C_i) - f(C_0)) + \delta \sum_{l=0}^{k-1} \left(1 - \frac{\epsilon}{k}\right)^l \\ &\leq \left(1 - \frac{\epsilon}{k}\right)^k f(C_i) + \delta \cdot \frac{1}{1 - \frac{\epsilon}{k}} \rightarrow \frac{\delta k}{\epsilon} \\ &\leq e^{-\epsilon} f(C_i) + \frac{\delta k}{\epsilon} \end{aligned}$$



$$f(C_k) \geq \max_C (1 - e^{-\epsilon}) f(C) - \frac{\delta k}{\epsilon}$$

↑  
arbitrary



(Proof of Lemma)  $f(C_i) - f(C_{i-1}) \leq \left(1 - \frac{\epsilon}{k}\right) (f(C_i) - f(C_{i-1})) + \delta$

$$f(C_{i-1}) - f(C_0) \geq \left[ \frac{\epsilon}{k} (f(C_i) - f(C_{i-1})) - \delta \right] \leq \frac{\delta k}{\epsilon}$$



$\sum_{i=1}^k |a_i| \leq \sum_{i=1}^k |b_i|$  (i)  $F$  is monotone, submodular  
 (ii)  $C_i \rightarrow (k, \delta)$ -greedy sequence  $\exists \frac{1}{k} \frac{b}{a}$

~~Since~~ ~~Since~~

$$F(C_{opt}) - F(C_i) \geq \epsilon \cdot (F(C_i \cup \text{some nodes}) - F(C_i)) - \delta \quad (1)$$

From given  $C_i \cup U_{opt}$

Define  $\left\{ \begin{aligned} D_j &= C_i \cup \{w_1, \dots, w_j\} \\ D_0 &= C_i \\ D_k &= C_i \cup C \end{aligned} \right.$

$$\begin{aligned}
 (ii) \sum_{j=1}^k (F(D_j) - F(D_{j-1})) &= F(D_k) - F(D_0) = F(C_i \cup C) - F(C_i) \\
 &\geq F(C) - F(C_i)
 \end{aligned}$$

monotone

$\downarrow$   
 $\downarrow$   
 $(k) = \frac{1}{k} \frac{b}{a}$

$$\exists j^*, \text{ s.t. } F(D_{j^*}) - F(D_{j^*-1}) \geq \frac{1}{k} (F(C) - F(C_i))$$

for notational simplicity

$$\exists j, \text{ s.t. } F(D_j) - F(D_{j-1}) \geq \frac{1}{k} (F(C) - F(C_i)) \quad (2)$$

$$\begin{aligned}
 \sum_{j=1}^k a_j &\geq b \\
 \exists j^*, \text{ s.t. } a_{j^*} &\geq \frac{b}{k}
 \end{aligned}$$

$$F(C_i \cup \{w_j\}) - F(C_i) \geq \frac{1}{k} (F(C) - F(C_i)) - \delta$$

diminishing returns

$$F(D_j) - F(D_{j-1}) \geq \frac{1}{k} (F(C) - F(C_i)) - \delta \quad (3)$$

$$D_{j-1} \cup \{w_j\}$$

$$C_i \cup C \supseteq D_{j-1}$$

$$F(C_{opt}) - F(C_i) \geq \sum_{i=1}^k (F(C) - F(C_i)) - \delta$$

$$\sum_{i=1}^k |a_i| \geq \sum_{i=1}^k |b_i|$$

???



$$F(C) = E(|V(C)|)$$

set  $C \subseteq \mathbb{Z}^2$  initial seed set  $\rightarrow$  가중치 설정, 가중치

점:  $\mathbb{Z}^2 \leftarrow$  random

for a given set  $C$ ,  
 $F(C)$ 의 값은? 가중치?

$$f(x) = x^2 - 2x + 3$$

$f(1)$ ?  $\rightarrow$  값이다.

greedy,  $(\epsilon, \delta)$ -greedy  
 (Computational cost)  $\rightarrow$  가중치  
 $\rightarrow$  가중치  $(x)$

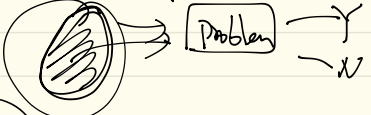
Computation theory

Optimization

Problem:  $\mathbb{Z}^2$  값 / 가중치

Yes / No

• certificate: decision problem (decision)  $\rightarrow$  Yes  $\mathbb{Z}^2$  produce 하는 입력



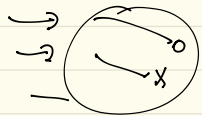
NP class: difficulty of finding certificates 복잡도가 크다.  
 (  $\mathbb{Z}^2$ ,  $\mathbb{Z}^2$ 인 input 이 certificate 이  $\mathbb{Z}^2$  이 값 이 가중치 이 가중치 이 가중치 )

a class of problem

#P class: Counting problem의 difficulty

(Sharp P)  $\mathbb{Z}^2$ , certificate 이  $\mathbb{Z}^2$  이 가중치 이 가중치 이 가중치 이 가중치 이 가중치

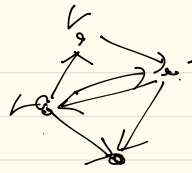
~~BP class~~



$\rightarrow$  exponential time

Example (Graph Reliability Problem)

- Directed graph over  $n$  nodes



- Each node can fail w.p.  $\frac{1}{2}$

Q Probability that node 1 has a path to ~~n nodes~~ <sup>node</sup> n

Under this simple failure model, the surviving graph is uniformly chosen at random from all ~~subgraphs~~ <sup>subgraphs</sup> of the original graph

= # of subgraphs in which node 1 has a path to n

counting

$2^n$

→ 이항분포

⇒ # of class

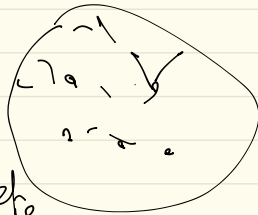
이항분포 → counting  $2^n$

$F(c) = E(|V(c)|)$

$|V(c)| = 100 \cdot \frac{1}{2} \cdot \frac{1}{2}$

# of class

→  $F(c)$ 의 값 이항분포



← 이항분포 → (sampling simulation)  $\hat{=}$  이항분포

X  $E(X)$ ? @  $P(X=1)$ ?

→ 이항분포

ML 방법

M ↑

이항분포

Chernoff bound

F

$f(x)$ 의 sampling:  $M$  i.i.d sample

$$\hat{f}(x) = \frac{U_1(x) + U_2(x) + U_3(x) + \dots + U_M(x)}{M}$$

$\uparrow \quad \uparrow \quad \uparrow \quad \dots \quad \uparrow$

$M$

$\epsilon, \gamma, \tau$

Q1)  $f(x)$ 와  $\hat{f}(x)$ 의 차이?

Lemma (Chebyshev bound)

$$\Pr(|\hat{f}(x) - f(x)| \geq \gamma f(x)) \leq 2 \cdot e^{-M h(\gamma/m)} \quad \mu \rightarrow \Delta$$

$\rightarrow 0$

$U_i(x)$ :  $\{0, \dots, m\}$  valued RV

$\{0, 1\}$ -valued RV

where  $h(x) = (1+x) \log(1+x) - x$ .

Algorithm P

~~Algorithm P~~ Greedy algorithm은 적용가능한  $f(x)$ 가

가능한  $M$ 개의 i.i.d sample를 받아서  $\hat{f}(x)$ 를 가지고 greedy suboptimality (optimal algorithm이 아님) scheme을 적용한다

- ①  $f(x)$ 는 적용가능 compute 할 수 있는 값을 가진 greedy
- ②  $f(x)$ 는 적용가능 compute 할 수 있는 (어떤) sampling

Q2) P가 왜?

(optimal algorithm이 적용가능)

→  $f(x)$ 는 어떤 것이 선택될 수 있는가?

$M = n^4 \log n$



**Prop 9.3** Let  $r > 0$  be fixed. (with  $\frac{1}{m}$  as a parameter)  
 Assume that  $M$  random graphs are generated whenever  $f(C)$  needs to be computed. Assume that we use "pure greedy" with estimated  $f(C)$  ( $\hat{f}(C)$ ).

Then, with probability at least  $1 - 2nrk e^{-M h(r/m^2)}$

$$f(C_{gr}) \geq \left(1 - \frac{1}{e} - 4r - O\left(\frac{1}{m}\right)\right) \left(\sup_{C \in \mathcal{C}} f(C)\right)$$

(algorithm)  $\nearrow$   $\left(1 - \frac{1}{e} - 4r - O\left(\frac{1}{m}\right)\right)$   $\left(\sup_{C \in \mathcal{C}} f(C)\right)$   $\longleftarrow$  (optimal solution)

$(r \uparrow \rightarrow \text{suboptimality gap} \uparrow)$   
 $(r \uparrow \rightarrow \text{probability of failure} \uparrow)$

**Lemma 9** Sampling  $\hat{f}(C)$  is  $\frac{1}{m}$  error

$$\left| \hat{f}(C) - f(C) \right| \leq r f(C)$$

$\frac{1-r}{1+r} \frac{4r}{1+r}$  - greedy  
 $\frac{1}{2} \frac{1}{2}$  - sequence

algorithm  $\rightarrow$  greedy algorithm  $\rightarrow$   $f(C)$

$\Rightarrow$  prob:  $p_{1/3}$  error  $\sim$   $p_{1/4}$  error

**Proof 9.3**  
 Choose  $r$ , such that  $r = \frac{1}{m}$ . (choose  $r$  such that  $\frac{1}{m}$  is small)

Then, with at least w.p.  $1 - 2 \frac{nr}{k} e^{-Mh(kr/n^2)}$   $\leftarrow$

$F(c_k) \geq (1 - e^{-\epsilon}) \max_{CCV, k \leq k} F(c) - \frac{kd}{\epsilon}$  where

Why?  $\epsilon = \frac{1-r}{1+r}, \delta = \frac{4rm}{1+r}, r = \frac{r}{m}$

$1 - 2 \frac{nr}{k} e^{-Mh(kr/n^2)}$   $\epsilon, \delta$  greedy  $\approx$   $\frac{1-r}{1+r}$

~~Better~~ seed selection  
 at maximum  $\hat{F}(c) \approx \text{argmax}$

Note that for all  $c$  such that  $|c| \geq k \Rightarrow F(c) \geq k$

$\Rightarrow (1 - e^{-\epsilon}) \max F(c) - \frac{F(c) \cdot \delta}{r}$   $r = \frac{r}{m}$

$F(c_k) \geq (1 - e^{-\frac{\epsilon}{2}} - \frac{\delta}{\epsilon}) \max F(c)$

$\epsilon = \frac{1-r}{1+r}, \delta = \frac{4rm}{1+r}$

We choose  $\epsilon = 1 - O(\frac{1}{m})$ ,  $\frac{\delta}{\epsilon} = 4r - O(\frac{1}{m})$ .

$1 - e^{-1} - 4r - O(\frac{1}{m})$

$\epsilon = \frac{1 - \frac{1}{m}}{1 + \frac{1}{m}} = \frac{m-1}{m+1} = \frac{m+r-2r}{m+r} = 1 - \frac{2r}{m+r}$

$\frac{\delta}{\epsilon} = \frac{\frac{4rm}{1+r}}{\frac{1-r}{1+r}} = \frac{4rm}{1-r} = \frac{4rm}{1-\frac{r}{m}} = \frac{4rm}{1-\frac{r}{m}} = 4r + O(\frac{1}{m})$

(Last Question):  $M \approx \frac{1}{2} \log \frac{1}{\epsilon}$  with high probability  $\frac{1}{2}$   
~~state or case~~ approximations  $\frac{1}{2} \log \frac{1}{\epsilon}$   $\frac{1}{2}$   $\frac{1}{2}$ ?

Sampling complexity

$$h(x) = 0$$

$$h(r/\eta^2) = \Theta\left(\frac{r^2}{\eta^4}\right)$$

$$1 - 2^{-M} \approx e^{-M \log 2}$$

$$e^{-M \frac{r^2}{\eta^4}}$$

$$M = \eta^4 \log \frac{1}{\epsilon}$$

if  $\frac{r^2}{\eta^4}$  is order

$$\eta \cdot e^{-\log \frac{1}{\epsilon} r^2}$$

$$= \eta \cdot \frac{1}{\epsilon^{r^2}} = \underline{\underline{o(1)}}$$

$r^2 > 1$