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[K. Han et al. Neurips 2020]

# Deterministic Approximation for Submodular Maximization over a Matroid in Nearly Linear Time

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# Introduction

# Definitions

- For a ground set  $\mathcal{N}$ ,  $f : 2^{\mathcal{N}} \rightarrow \mathbb{R}$  is
  - submodular if  $\forall X, Y \in \mathcal{N}, f(X) + f(Y) \geq f(X \cup Y) + f(X \cap Y)$
  - non-negative if  $\forall X \subseteq N, f(X) \geq 0$
  - non-monotone if  $\exists X \subset Y, f(X) > f(Y)$
- For sake of convenience, let
  - $f(X \mid Y) = f(X \cup Y) - f(Y)$ , called *marginal gain* of  $X$  w.r.t.  $Y$
  - $f(x \mid Y) = f(\{x\} \mid Y)$

# Definitions

- For a ground set  $\mathcal{N}$  and  $\mathcal{I} \subseteq 2^{\mathcal{N}}$ ,  $(\mathcal{N}, \mathcal{I})$  is an independence system if i, ii holds. An independence system is a matroid if iii holds.
  - i.  $\emptyset \in \mathcal{I}$
  - ii.  $A \subseteq B, B \in \mathcal{I} \implies A \in \mathcal{I}$  (hereditary property)
  - iii.  $A, B \in \mathcal{I}, |A| < |B| \implies \exists x \in B - A, A \cup \{x\} \in \mathcal{I}$  (exchange property)
- For an independence system  $(\mathcal{N}, \mathcal{I})$  and  $X \subseteq \mathcal{N}$ , a subset  $Y \subseteq X$  is called *base* if  $Y$  is a maximally independent subset of  $X$ .

## Some Properties

- For  $X \subseteq Y \subseteq \mathcal{N}$  and  $Z \subset \mathcal{N} - Y$ ,  $f(Z \mid Y) \leq f(Z \mid X)$ .
- For  $X \subseteq Y \subseteq \mathcal{N}$ , and a partition  $Z_1, Z_2, \dots, Z_t$  of  $Y - X$ ,

$$f(Y \mid X) = \sum_{j=1}^t f(Z_j \mid Z_1 \cup \dots \cup Z_{j-1} \cup X) \leq \sum_{j=1}^t f(Z_j \mid X).$$

## Notations

- $f$  represents a (non-monotone,) non-negative submodular functions
- $[n] = \{1, 2, \dots, n\}$
- $r = \max\{|S| : S \in \mathcal{I}\}$  (i.e. rank)
- $O$ : optimal solution to the problem (which will be presented in the next section)

## Main Goal

**Problem.** Given a (non-monotone) submodular function  $f$  and a matroid  $(\mathcal{N}, \mathcal{I})$ , compute  $\max\{f(S) : S \in \mathcal{I}\}$ .

## Compared to Previous Works:

Table 1: Approximation for Non-monotone Submodular Maximization over a Matroid

Algorithms	Ratio	Time Complexity	Type
Lee et al. [38]	$1/4 - \epsilon$	$\mathcal{O}((n^4 \log n)/\epsilon)$	Deterministic
Mirzasoleiman et al. [44]	$1/6 - \epsilon$	$\mathcal{O}(nr + r/\epsilon)$	Deterministic
Feldman et al. [25]	$1/4$	$\mathcal{O}(nr)$	Randomized
Buchbinder and Feldman [10]	0.385	$\text{poly}(n)$	Randomized
TwinGreedy (Alg. 1)	$1/4$	$\mathcal{O}(nr)$	Deterministic
TwinGreedyFast (Alg. 2)	$1/4 - \epsilon$	$\mathcal{O}((n/\epsilon) \log(r/\epsilon))$	Deterministic



# TwinGreedy Algorithm

# TwinGreedy Algorithm

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**Algorithm 1:** TwinGreedy( $\mathcal{N}, \mathcal{I}, f(\cdot)$ )

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```
1  $S_1 \leftarrow \emptyset; S_2 \leftarrow \emptyset;$ 
2 repeat
3    $\mathcal{M}_1 \leftarrow \{e \in \mathcal{N} \setminus (S_1 \cup S_2) : S_1 \cup \{e\} \in \mathcal{I}\}$ 
4    $\mathcal{M}_2 \leftarrow \{e \in \mathcal{N} \setminus (S_1 \cup S_2) : S_2 \cup \{e\} \in \mathcal{I}\}$ 
5    $C \leftarrow \{j \mid j \in \{1, 2\} \wedge \mathcal{M}_j \neq \emptyset\}$ 
6   if  $C \neq \emptyset$  then
7      $(i, e) \leftarrow \arg \max_{j \in C, u \in \mathcal{M}_j} f(u \mid S_j);$  (ties broken arbitrarily)
8     if  $f(e \mid S_i) \leq 0$  then Break;
9      $S_i \leftarrow S_i \cup \{e\};$ 
10 until  $\mathcal{M}_1 \cup \mathcal{M}_2 = \emptyset;$ 
11  $S^* \leftarrow \arg \max_{X \in \{S_1, S_2\}} f(X)$ 
12 return  $S^*$ 
```

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# TwinGreedy Algorithm - Proof

**Definition 1** Consider the two solution sets  $S_1$  and  $S_2$  when TwinGreedy returns. We can write  $S_1 \cup S_2$  as  $\{v_1, v_2, \dots, v_k\}$  where  $k = |S_1 \cup S_2|$ , such that  $v_t$  is added into  $S_1 \cup S_2$  by the algorithm before  $v_s$  for any  $1 \leq t < s \leq k$ . With this ordered list, given any  $e = v_j \in S_1 \cup S_2$ , we define

$$\text{Pre}(e, S_1) = \{v_1, \dots, v_{j-1}\} \cap S_1; \quad \text{Pre}(e, S_2) = \{v_1, \dots, v_{j-1}\} \cap S_2; \quad (2)$$

That is,  $\text{Pre}(e, S_i)$  denotes the set of elements in  $S_i$  ( $i \in \{1, 2\}$ ) that are added by the TwinGreedy algorithm before adding  $e$ . Furthermore, we define

$$\begin{aligned} O_1^+ &= \{e \in O \cap S_1 : \text{Pre}(e, S_2) \cup \{e\} \in \mathcal{I}\}; & O_1^- &= \{e \in O \cap S_1 : \text{Pre}(e, S_2) \cup \{e\} \notin \mathcal{I}\} \\ O_2^+ &= \{e \in O \cap S_2 : \text{Pre}(e, S_1) \cup \{e\} \in \mathcal{I}\}; & O_2^- &= \{e \in O \cap S_2 : \text{Pre}(e, S_1) \cup \{e\} \notin \mathcal{I}\} \\ O_3 &= \{e \in O \setminus (S_1 \cup S_2) : S_1 \cup \{e\} \notin \mathcal{I}\}; & O_4 &= \{e \in O \setminus (S_1 \cup S_2) : S_2 \cup \{e\} \notin \mathcal{I}\} \end{aligned}$$

We also define the marginal gain of any  $e \in S_1 \cup S_2$  as  $\delta(e) = f(e \mid \text{Pre}(e, S_1)) \cdot \mathbf{1}_{S_1}(e) + f(e \mid \text{Pre}(e, S_2)) \cdot \mathbf{1}_{S_2}(e)$ , where  $\mathbf{1}_{S_i}(e) = 1$  if  $e \in S_i$  and  $\mathbf{1}_{S_i}(e) = 0$  otherwise ( $\forall i \in \{1, 2\}$ ).

## TwinGreedy Algorithm - Proof

**Lemma 1.** There's an injective function  $\pi_1 : O_1^+ \cup O_1^- \cup O_2^- \cup O_3 \mapsto S_1$  such that

1. For any  $e \in O_1^+ \cup O_1^- \cup O_2^- \cup O_3$ ,  $Pre(\pi_1(e), S_1) \cup \{e\} \in \mathcal{I}$
2. For each  $e \in O_1^+ \cup O_1^-$ ,  $\pi_1(e) = e$

Similarly there's  $\pi_2 : O_1^- \cup O_2^+ \cup O_2^- \cup O_4 \mapsto S_2$  s.t.  $Pre(\pi_2(e), S_2) \cup \{e\} \in \mathcal{I}$  for each  $e \in O_1^- \cup O_2^+ \cup O_2^- \cup O_4$  and  $\pi_2(e) = e$  for each  $e \in O_2^+ \cup O_2^-$ .

Instead of giving whole proof to this lemma, we will just show some sketch including constructing  $\pi_1$ .

## TwinGreedy Algorithm - Proof

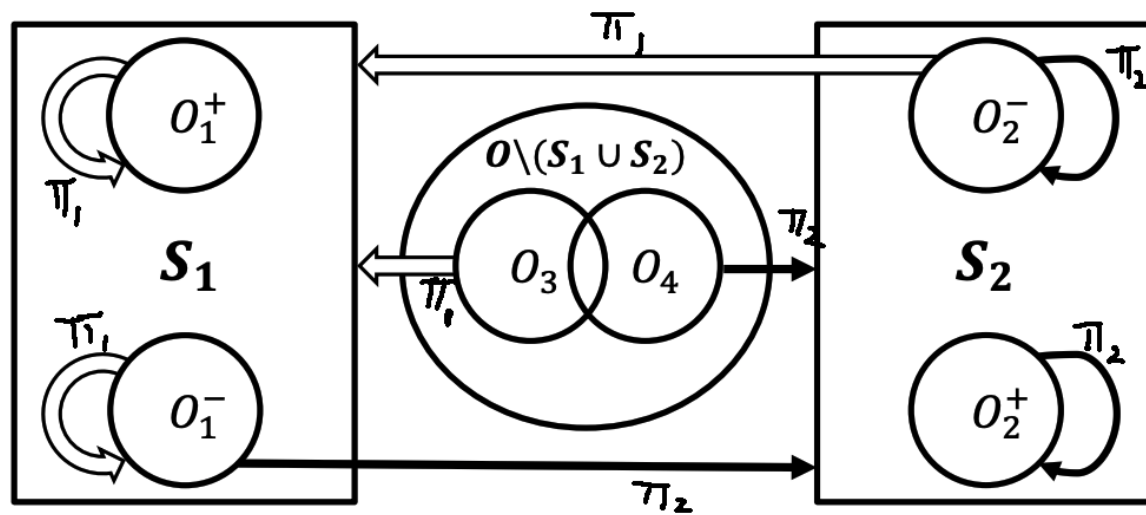
Let  $S_1 = \{u_1, \dots, u_s\}$  where  $u_i$  is added prior to  $u_j$  when  $i < j$ . Define  $L_s = O_1^+ \cup O_1^- \cup O_2^- \cup O_3$ . Run following algorithm.

for  $j := s$  to 1

- $A_j := \{x \in L_j - \{u_1, \dots, u_{j-1}\} \mid \{u_1, \dots, u_{j-1}, x\} \in \mathcal{I}\}$
- if  $A_j = \emptyset$ : continue
- if  $u_j \in O_1^+ \cup O_1^-$  // (Note that  $u_j \in A_j$ )
  - $\pi_1(u_j) = u_j, L_{j-1} = L_j - \{u_j\}$
- else
  - $e :=$  arbitrary element of  $A_j$
  - $\pi_1(e) = u_j, L_{j-1} = L_j - \{e\}$

# TwinGreedy Algorithm - Proof

Visualization of sets and mappings:



## TwinGreedy Algorithm - Proof

Lemma 2.

- $f(O_1^+ \mid S_2) \leq \sum_{e \in O_1^+} \delta(\pi_1(e)); \quad f(O_2^+ \mid S_1) \leq \sum_{e \in O_2^+} \delta(\pi_2(e))$
- $f(O_1^- \mid S_2) \leq \sum_{e \in O_1^-} \delta(\pi_2(e)); \quad f(O_2^- \mid S_1) \leq \sum_{e \in O_2^-} \delta(\pi_1(e))$
- $f(O_4 \mid S_2) \leq \sum_{e \in O_4} \delta(\pi_2(e)); \quad f(O_3 \mid S_1) \leq \sum_{e \in O_3} \delta(\pi_1(e))$

## TwinGreedy Algorithm - Proof

The authors decomposed Lemma 2 into 3 lemmas. Since I tried to follow the authors' numbering, I also decomposed it into 3 lemmas.

**Lemma 4.**  $f(O_1^+ \mid S_2) \leq \sum_{e \in O_1^+} \delta(\pi_1(e)); \quad f(O_2^+ \mid S_1) \leq \sum_{e \in O_2^+} \delta(\pi_2(e))$

**Lemma 5.**  $f(O_1^- \mid S_2) \leq \sum_{e \in O_1^-} \delta(\pi_2(e)); \quad f(O_2^- \mid S_1) \leq \sum_{e \in O_2^-} \delta(\pi_1(e))$

**Lemma 6.**  $f(O_4 \mid S_2) \leq \sum_{e \in O_4} \delta(\pi_2(e)); \quad f(O_3 \mid S_1) \leq \sum_{e \in O_3} \delta(\pi_1(e))$



## TwinGreedy Algorithm - Proof

**Lemma 4.**  $f(O_1^+ \mid S_2) \leq \sum_{e \in O_1^+} \delta(\pi_1(e)); \quad f(O_2^+ \mid S_1) \leq \sum_{e \in O_2^+} \delta(\pi_2(e))$

At the exact moment  $e \in O_1^+$  is added to  $S_1$ , one can also add  $e$  into  $S_2$ . So from greedy choice of the algorithm, we have  $f(e \mid Pre(e, S_2)) \leq \delta(e)$ .

From submodularity, we get:

$$\begin{aligned} f(e \mid S_2) &\leq f(e \mid Pre(e, S_2)) \leq \delta(e) = \delta(\pi_1(e)), \\ \sum_{e \in O_1^+} f(O_1^+ \mid S_2) &\leq \sum_{e \in O_1^+} f(e \mid S_2) \leq \sum_{e \in O_1^+} \delta(\pi_1(e)). \quad \square \end{aligned}$$

## TwinGreedy Algorithm - Proof

**Lemma 5.**  $f(O_1^- \mid S_2) \leq \sum_{e \in O_1^-} \delta(\pi_2(e)); \quad f(O_2^- \mid S_1) \leq \sum_{e \in O_2^-} \delta(\pi_1(e))$

Consider the exact moment  $\pi_2(e)$  is added to  $S_2$  (where  $e \in O_1^-$ ):

- one can add  $e$  to  $S_2$ .
- $e$  has not been inserted to  $S_1$  yet.

## TwinGreedy Algorithm - Proof

**Lemma 5.**  $f(O_1^- \mid S_2) \leq \sum_{e \in O_1^-} \delta(\pi_2(e)); \quad f(O_2^- \mid S_1) \leq \sum_{e \in O_2^-} \delta(\pi_1(e))$

Consider the exact moment  $\pi_2(e)$  is added to  $S_2$  (where  $e \in O_1^-$ ):

- one can add  $e$  to  $S_2$ .
- $e$  has not been inserted to  $S_1$  yet.

So, since  $\pi_2(e)$  has been added to  $S_2$  (*instead of*  $e$ ) by the algorithm, from greedy-choice property, we have  $f(e \mid Pre(\pi_2(e), S_2)) \leq \delta(\pi_2(e))$ .

Since  $Pre(\pi_2(e), S_2) \subseteq S_2$ , we also have  $f(e \mid S_2) \leq f(e \mid Pre(\pi_2(e), S_2))$ .

## TwinGreedy Algorithm - Proof

**Lemma 5.**  $f(O_1^- \mid S_2) \leq \sum_{e \in O_1^-} \delta(\pi_2(e)); \quad f(O_2^- \mid S_1) \leq \sum_{e \in O_2^-} \delta(\pi_1(e))$

So, since  $\pi_2(e)$  has been added to  $S_2$  (*instead of*  $e$ ) by the algorithm, from greedy-choice property, we have  $f(e \mid Pre(\pi_2(e), S_2)) \leq \delta(\pi_2(e))$ .

Since  $Pre(\pi_2(e), S_2) \subseteq S_2$ , we also have  $f(e \mid S_2) \leq f(e \mid Pre(\pi_2(e), S_2))$ .

Therefore,

$$f(O_1^- \mid S_2) \leq \sum_{e \in O_1^-} f(e \mid S_2) \leq \sum_{e \in O_1^-} f(e \mid Pre(\pi_2(e), S_2)) \leq \sum_{e \in O_1^-} \delta(\pi_2(e)). \square$$

## TwinGreedy Algorithm - Proof

**Lemma 6.**  $f(O_4 \mid S_2) \leq \sum_{e \in O_4} \delta(\pi_2(e)); \quad f(O_3 \mid S_1) \leq \sum_{e \in O_3} \delta(\pi_1(e))$

At the moment  $\pi_1(e)$  is added to  $S_1$  (for  $e \in O_3$ ), one can add  $e$  to  $S_1$ .

From the property of greedy choice, we have  $f(e \mid Pre(\pi_1(e), S_1)) \leq \delta(\pi_1(e))$ . (If not,  $e$  should be added to  $S_1$  instead of  $\pi_1(e)$ .)

Therefore,

$$f(O_3 \mid S_1) \leq \sum_{e \in O_3} f(e \mid S_1) \leq \sum_{e \in O_3} f(e \mid Pre(\pi_1(e), S_1)) \leq \sum_{e \in O_3} \delta(\pi_1(e)). \square$$

## TwinGreedy Algorithm - Proof

**Theorem 1.** When  $(\mathcal{N}, \mathcal{I})$  is a matroid, the algorithm returns a solution  $S^*$  with  $\frac{1}{4}$  approximation ratio, under time complexity  $\mathcal{O}(nr)$ .

# TwinGreedy Algorithm - Proof

**Theorem 1.** When  $(\mathcal{N}, \mathcal{I})$  is a matroid, the algorithm returns a solution  $S^*$  with  $\frac{1}{4}$  approximation ratio, under time complexity  $\mathcal{O}(nr)$ .

1. When  $S_1 = \emptyset$  or  $S_2 = \emptyset$ , we get an optimal solution, so assume  $S_1, S_2 \neq \emptyset$ .

- WLOG, suppose  $S_2$  is empty.

- From greedy choice,

$$f(O \cap S_1 \mid \emptyset) \leq \sum_{e \in O \cap S_1} f(e \mid \emptyset) \leq \sum_{O \cap S_1} \delta(e) \leq \sum_{e \in S_1} \delta(e) = f(S_1 \mid \emptyset)$$

- and  $f(O - S_1 \mid \emptyset) \leq \sum_{e \in O - S_1} f(e \mid \emptyset) \leq 0$ . (If not, they would have been added to  $S_2$ .)

- From  $f(O - S_1) + f(O \cap S_1) \geq f(O) + f(\emptyset)$ ,  $f(S_1) \geq f(O)$ .  $\square$

## TwinGreedy Algorithm - Proof

**Theorem 1.** When  $(\mathcal{N}, \mathcal{I})$  is a matroid, the algorithm returns a solution  $S^*$  with  $\frac{1}{4}$  approximation ratio, under time complexity  $\mathcal{O}(nr)$ .

2. Define  $O_5 := O - (S_1 \cup S_2 \cup O_3)$ ,  $O_6 := O - (S_1 \cup S_w \cup O_4)$ .
- $f(O \cup S_1) - f(S_1) \leq f(O_2^+ \mid S_1) + f(O_2^- \mid S_1) + f(O_3 \mid S_1) + f(O_5 \mid S_1)$  and its variant for  $f(O \cup S_2) - f(S_2)$ .

Because

- For  $X \subseteq Y \subseteq \mathcal{N}$ , and a partition  $Z_1, Z_2, \dots, Z_t$  of  $Y - X$ ,

$$f(Y \mid X) = \sum_{j=1}^t f(Z_j \mid Z_1 \cup \dots \cup Z_{j-1} \cup X) \leq \sum_{j=1}^t f(Z_j \mid X).$$



## TwinGreedy Algorithm - Proof

**Theorem 1.** When  $(\mathcal{N}, \mathcal{I})$  is a matroid, the algorithm returns a solution  $S^*$  with  $\frac{1}{4}$  approximation ratio, under time complexity  $\mathcal{O}(nr)$ .

2. Define  $O_5 := O - (S_1 \cup S_2 \cup O_3)$ ,  $O_6 := O - (S_1 \cup S_w \cup O_4)$ .
  - $f(O \cup S_1) - f(S_1) \leq f(O_2^+ | S_1) + f(O_2^- | S_1) + f(O_3 | S_1) + f(O_5 | S_1)$  and its variant for  $f(O \cup S_2) - f(S_2)$ .
  - $f(O_2^+ | S_1) + f(O_2^- | S_1) + f(O_3 | S_1) + f(O_1^+ | S_2) + f(O_1^- | S_2) + f(O_4 | S_2) \leq f(S_1) + f(S_2)$ .

## TwinGreedy Algorithm - Proof

**Theorem 1.** When  $(\mathcal{N}, \mathcal{I})$  is a matroid, the algorithm returns a solution  $S^*$  with  $\frac{1}{4}$  approximation ratio, under time complexity  $\mathcal{O}(nr)$ .

Some computations...

$$\begin{aligned} f(O_2^+ \mid S_1) + f(O_2^- \mid S_1) + f(O_3 \mid S_1) + f(O_1^+ \mid S_2) + f(O_1^- \mid S_2) + f(O_4 \mid S_2) \\ \leq \sum_{e \in O_1^+ \cup O_2^- \cup O_3} \delta(\pi_1(e)) + \sum_{e \in O_1^- \cup O_2^+ \cup O_4} \delta(\pi_2(e)) \\ \leq \sum_{e \in S_1} \delta(e) + \sum_{e \in S_2} \delta(e) \\ \leq f(S_1) + f(S_2) \end{aligned}$$

## TwinGreedy Algorithm - Proof

**Theorem 1.** When  $(\mathcal{N}, \mathcal{I})$  is a matroid, the algorithm returns a solution  $S^*$  with  $\frac{1}{4}$  approximation ratio, under time complexity  $\mathcal{O}(nr)$ .

2. Define  $O_5 := O - (S_1 \cup S_2 \cup O_3)$ ,  $O_6 := O - (S_1 \cup S_w \cup O_4)$ .
- $f(O \cup S_1) - f(S_1) \leq f(O_2^+ | S_1) + f(O_2^- | S_1) + f(O_3 | S_1) + f(O_5 | S_1)$  and its variant for  $f(O \cup S_2) - f(S_2)$ .
  - $f(O_2^+ | S_1) + f(O_2^- | S_1) + f(O_3 | S_1) + f(O_1^+ | S_2) + f(O_1^- | S_2) + f(O_4 | S_2) \leq f(S_1) + f(S_2)$ .
  - $f(O_5 | S_1) \leq \sum_{e \in O_5} f(e | S_1) \leq 0$ ,  $f(O_6 | S_2) \leq \sum_{e \in O_6} f(e | S_2) \leq 0$ .

## TwinGreedy Algorithm - Proof

**Theorem 1.** When  $(\mathcal{N}, \mathcal{I})$  is a matroid, the algorithm returns a solution  $S^*$  with  $\frac{1}{4}$  approximation ratio, under time complexity  $\mathcal{O}(nr)$ .

2. Define  $O_5 := O - (S_1 \cup S_2 \cup O_3)$ ,  $O_6 := O - (S_1 \cup S_w \cup O_4)$ .
- $f(O \cup S_1) - f(S_1) \leq f(O_2^+ | S_1) + f(O_2^- | S_1) + f(O_3 | S_1) + f(O_5 | S_1)$  and its variant for  $f(O \cup S_2) - f(S_2)$ .
  - $f(O_2^+ | S_1) + f(O_2^- | S_1) + f(O_3 | S_1) + f(O_1^+ | S_2) + f(O_1^- | S_2) + f(O_4 | S_2) \leq f(S_1) + f(S_2)$ .
  - $f(O_5 | S_1) \leq \sum_{e \in O_5} f(e | S_1) \leq 0$ ,  $f(O_6 | S_2) \leq \sum_{e \in O_6} f(e | S_2) \leq 0$ .
  - $f(O) \leq f(O) + f(O \cup S_1 \cup S_2) \leq f(O \cup S_1) + f(O \cup S_2)$   
(from submodularity and  $S_1 \cap S_2 = \emptyset$ )

## TwinGreedy Algorithm - Proof

**Theorem 1.** When  $(\mathcal{N}, \mathcal{I})$  is a matroid, the algorithm returns a solution  $S^*$  with  $\frac{1}{4}$  approximation ratio, under time complexity  $\mathcal{O}(nr)$ .

- $f(O \cup S_1) - f(S_1) \leq f(O_2^+ \mid S_1) + f(O_2^- \mid S_1) + f(O_3 \mid S_1) + f(O_5 \mid S_1)$  and its variant for  $f(O \cup S_2) - f(S_2)$ .
- $f(O_2^+ \mid S_1) + f(O_2^- \mid S_1) + f(O_3 \mid S_1) + f(O_1^+ \mid S_2) + f(O_1^- \mid S_2) + f(O_4 \mid S_2) \leq f(S_1) + f(S_2)$ .
- $f(O_5 \mid S_1) \leq \sum_{e \in O_5} f(e \mid S_1) \leq 0, f(O_6 \mid S_2) \leq \sum_{e \in O_6} f(e \mid S_2) \leq 0$ .
- $f(O) \leq f(O) + f(O \cup S_1 \cup S_2) \leq f(O \cup S_1) + f(O \cup S_2)$

Now let's put them all together!

# TwinGreedy Algorithm - Proof

**Theorem 1.** When  $(\mathcal{N}, \mathcal{I})$  is a matroid, the algorithm returns a solution  $S^*$  with  $\frac{1}{4}$  approximation ratio, under time complexity  $\mathcal{O}(nr)$ .

- $f(O \cup S_1) - f(S_1) \leq f(O_2^+ | S_1) + f(O_2^- | S_1) + f(O_3 | S_1) + f(O_5 | S_1)$  and its variant for  $f(O \cup S_2) - f(S_2)$ .
- $f(O_2^+ | S_1) + f(O_2^- | S_1) + f(O_3 | S_1) + f(O_1^+ | S_2) + f(O_1^- | S_2) + f(O_4 | S_2) \leq f(S_1) + f(S_2)$ .
- $f(O_5 | S_1) \leq \sum_{e \in O_5} f(e | S_1) \leq 0, f(O_6 | S_2) \leq \sum_{e \in O_6} f(e | S_2) \leq 0$ .
- $f(O) \leq f(O) + f(O \cup S_1 \cup S_2) \leq f(O \cup S_1) + f(O \cup S_2)$

Now let's put them all together!

$$f(O) \leq 2f(S_1) + 2f(S_2) \leq 4 \cdot \max(f(S_1), f(S_2)) \square$$

## TwinGreedy Algorithm - Proof

**Theorem 1.** When  $(\mathcal{N}, \mathcal{I})$  is a matroid, the algorithm returns a solution  $S^*$  with  $\frac{1}{4}$  approximation ratio, under time complexity  $\mathcal{O}(nr)$ .

**Remark.** If monotone condition of  $f$  is given, the algorithm guarantees  $1/2$  approximation ratio.

# **TwinGreedyFast Algorithm**



# TwinGreedyFast Algorithm

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**Algorithm 2:** TwinGreedyFast( $\mathcal{N}, \mathcal{I}, f(\cdot), \epsilon$ )

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```
1  $\tau_{max} \leftarrow \max\{f(e) : e \in \mathcal{N} \wedge \{e\} \in \mathcal{I}\};$ 
2  $S_1 \leftarrow \emptyset; S_2 \leftarrow \emptyset;$ 
3 for ( $\tau \leftarrow \tau_{max}; \tau > \epsilon\tau_{max}/[r(1 + \epsilon)]; \tau \leftarrow \tau/(1 + \epsilon)$ ) do
4   foreach  $e \in \mathcal{N} \setminus (S_1 \cup S_2)$  do
5      $\Delta_1 \leftarrow -\infty; \Delta_2 \leftarrow -\infty$  /*two signals*/
6     if  $S_1 \cup \{e\} \in \mathcal{I}$  then  $\Delta_1 \leftarrow f(e \mid S_1);$ 
7     if  $S_2 \cup \{e\} \in \mathcal{I}$  then  $\Delta_2 \leftarrow f(e \mid S_2);$ 
8      $i \leftarrow \arg \max_{j \in \{1,2\}} \Delta_j;$  (ties broken arbitrarily)
9     if  $\Delta_i \geq \tau$  then  $S_i \leftarrow S_i \cup \{e\};$ 
10  $S^* \leftarrow \arg \max_{X \in \{S_1, S_2\}} f(X)$ 
11 return  $S^*$ 
```

---

# TwinGreedyFast Algorithm - Proof

This algorithm has similar properties compared to TwinGreedy but proofs are somewhat more time-consuming, so I will omit the proof.

---

**Algorithm 2:** TwinGreedyFast( $\mathcal{N}, \mathcal{I}, f(\cdot), \epsilon$ )

---

```
1  $\tau_{max} \leftarrow \max\{f(e) : e \in \mathcal{N} \wedge \{e\} \in \mathcal{I}\};$ 
2  $S_1 \leftarrow \emptyset; S_2 \leftarrow \emptyset;$ 
3 for ( $\tau \leftarrow \tau_{max}; \tau > \epsilon\tau_{max}/[r(1 + \epsilon)]; \tau \leftarrow \tau/(1 + \epsilon)$ ) do
4   foreach  $e \in \mathcal{N} \setminus (S_1 \cup S_2)$  do
5      $\Delta_1 \leftarrow -\infty; \Delta_2 \leftarrow -\infty$  /*two signals*/
6     if  $S_1 \cup \{e\} \in \mathcal{I}$  then  $\Delta_1 \leftarrow f(e \mid S_1);$ 
7     if  $S_2 \cup \{e\} \in \mathcal{I}$  then  $\Delta_2 \leftarrow f(e \mid S_2);$ 
8      $i \leftarrow \arg \max_{j \in \{1,2\}} \Delta_j;$  (ties broken arbitrarily)
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```

---

## TwinGreedyFast Algorithm - Proof

**Lemma 3.** The algorithm satisfies:

- $f(O_1^+ \mid S_2) \leq \sum_{e \in O_1^+} \delta(\pi_1(e)),$   
 $f(O_2^+ \mid S_1) \leq \sum_{e \in O_2^+} \delta(\pi_2(e))$
- $f(O_1^- \mid S_2) \leq (1 + \epsilon) \sum_{e \in O_1^-} \delta(\pi_2(e)),$   
 $f(O_2^- \mid S_1) \leq (1 + \epsilon) \sum_{e \in O_2^-} \delta(\pi_1(e))$
- $f(O_4 \mid S_2) \leq (1 + \epsilon) \sum_{e \in O_4} \delta(\pi_2(e)),$   
 $f(O_3 \mid S_1) \leq (1 + \epsilon) \sum_{e \in O_3} \delta(\pi_1(e))$

## TwinGreedyFast Algorithm - Proof

**Theorem 2.** When  $(\mathcal{N}, \mathcal{I})$  is a matroid, the algorithm returns a solution with  $1/4 - \epsilon$  approximation ratio, with time complexity of  $\mathcal{O}\left(\frac{n}{\epsilon} \log \frac{r}{\epsilon}\right)$ .

# Extensions

## Extensions

For a ground set  $\mathcal{N}$  and  $\mathcal{I} \subseteq 2^{\mathcal{N}}$ ,  $(\mathcal{N}, \mathcal{I})$  is an independence system if 1, 2 holds. An independence system is a  $p$ -set system if 3 holds.

1.  $\emptyset \in \mathcal{I}$
2.  $A \subseteq B, B \in \mathcal{I} \implies A \in \mathcal{I}$  (hereditary property)
3. For every  $Y \subseteq N$  and two base  $X_1, X_2$  of  $Y$ ,  $|X_1| \leq p|X_2|$  where  $p \geq 1$ .

## Extensions

**Theorem 3.** TwinGreedyFast algorithm can be used to handle the problem of submodular maximization over a  $p$ -set system. It returns a solution with  $\frac{1}{2^{p+2}} - \epsilon$  approximation ratio, with time complexity of  $\mathcal{O}\left(\frac{n}{\epsilon} \log \frac{r}{\epsilon}\right)$ .

# Applications



## Applications - Social Network Monitoring

**Problem.** Suppose given a graph  $G = (V, E, w)$ . Let  $\{V_1, V_2, \dots, V_h\}$  be the partition of  $V$ . We want to select  $S \subseteq V$  to maximize total amount of monitored content:

$$f(S) = \sum_{(u,v) \in E, u \in S, v \notin S} w(u, v). \text{ We also want } |S \cap V_i| \leq k \text{ for every } i, \text{ where } k \text{ is}$$

some constant.

## Applications - Multi-Product Viral Marketing

**Problem.** Suppose given a graph  $G = (V, E, c)$  where  $c(u)$  represents some cost for node  $u$  and non-negative submodular functions  $f_1, f_2, \dots, f_m$  with domain  $2^V$ . We have two constants  $B, k$  and want to maximize  $\sum_{i \in [m]} f_i(S_i) + (B - \sum_{i \in [m]} \sum_{v \in S_i} c(v))$ .

No two of  $S_i$  share elements.

# Applications - Multi-Product Viral Marketing

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No two of  $S_i$  share elements.

**Lemma.** Define the ground set  $\mathcal{N} = V \times [m]$  and  $\mathcal{I} = \{X \subseteq \mathcal{N} : |X| \leq k \wedge \forall u \in V, |X \cap N_u| \leq 1\}$ , where  $N_u = \{(u, i) : i \in [m]\}$ . Then,  $(\mathcal{N}, \mathcal{I})$  is a matroid.

**Lemma.** For any  $S \subseteq \mathcal{N}$  and  $S \neq \emptyset$ , define  $f(S) = \sum_{i \in [m]} f_i(S_i) + (B - \sum_{i \in [m]} \sum_{v \in S_i} c(v))$ , where  $S_i := \{u : (u, i) \in S\}$  and  $f_i$  is a non-negative submodular with domain  $2^V$ . Define  $f(\emptyset) = 0$ . Then,  $f$  is a submodular function defined on  $2^{\mathcal{N}}$ .

# Conclusion

## Conclusion

- We have discovered two simple deterministic greedy algorithms maximizing (non-monotone) non-negative submodular function over a matroid with  $1/4(-\epsilon)$  approximation ratio.
- TwinGreedy algorithm achieves  $1/2$  approximation ratio with monotone constraint.
- TwinGreedyFast algorithm can also be directly used to handle more general  $p$ -set system constraint.
- We have discovered two real-world problems that the paper's algorithms can be used.