

# A Greedy Algorithm for Budgeted Multiple-Product Profit Maximization in Social Network

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# Outline

Introduction

Related Works

Problem Formulation

Proposed Method

Experiments

Conclusions and Future Works

# Introduction

## Profit Maximization (PM) Problem

- Information can be **disseminated widely and quickly** through social networks
  - **Viral marketing** takes advantage of the **word-of-mouth effects** on social networks
- Profit Maximization (PM) problem
  - The goal is to **maximize profits from viral marketing**
  - The company needs to select potential influencers to propagate the product information
  - To maximize the profit for the company, the **effectiveness of influence propagation** and the **cost of the influencers** are both required to be considered

# Introduction

## PM Problem on Single / Multiple Products

- Most studies focus on the diffusion process for a **single product**
  - But **in fact** most companies **provide several kinds of products** for various demands
  - **Not suitable** to the business model in reality
- Therefore, we study the problem for **multiple products**
  - Moreover, the **purchasing ability of a user** should be different for different products

# Introduction

## Budgeted Multiple-Product Profit Maximization (BMPPM) Problem

- Budgeted Profit Maximization (BPM) Problem (proposed by Zhang et al.)
  - Aimed at maximizing the overall profit of multiple products by selecting seeds with budget constraints
  - BPM problem has no limitation on the purchasing ability
- We propose the Budgeted Multiple-Product Profit Maximization (BMPPM) Problem
  - Consider the consumers' purchasing ability among multiple products

# Introduction

## BG (BMPPM Greedy)

- A **greedy algorithm named BG** is proposed to solve the BMPPM problem
  - The **purchasing ability distribution** is taken consideration
    - Estimate the purchasing ability of users
    - Emphasize the importance of different products
- The **graph structure PW DAG** (Product Weighted Directed Acyclic Graph) is designed
  - Approximate the influence propagation

# Related Works

## Influence Maximization (IM) Problem

- Select the seeds to maximize the **influence**
- Hill-climbing algorithms
  - Naïve Greedy
  - **CELF**
- Pros: high quality
- Cons: high time cost
- Heuristic algorithms
  - **PMIA**
  - **DAGs**
- Pros: less time cost
- Cons: unstable quality

# Related Works

## Profit Maximization (PM) Problem

- Select the seeds to maximize the [profit](#)
- Single Product
  - Without Budget Limitation
    - DGIP
  - [With Budget Limitation](#)
    - [INFOCOM'18](#)
- Multiple Products
  - Without Budget Limitation
    - RevMax-Separate
  - [With Budget Limitation](#)
    - [PMIS](#)



# Problem Formulation

## Expected Profit

- Given a social network graph  $G = (V, E)$ , a product set  $P$ , and a seed set  $S$  where each seed  $s \in S$  is a pair consisting of a product  $p \in P$  and a node  $v \in V$

expect profit of seed set

profit of product  $p$

$$\rho(S) = \sum_{p \in P} \sum_{v \in V} ap(S, p, v) \times profit(p)$$

activated probability that a node  $v$  will adopt a product  $p$   
because of the influence from seed set  $S$

# Problem Formulation

## BMPM Problem

- For a given multiple-product diffusion model, such as MPIC, the goal of BMPM problem is **finding a seed set for multiple products to maximize the overall profit**
- Given a social network graph  $G = (V, E)$ , a product set  $P$ , and the seed budget limitation  $B$ , the BMPM problem aims to **find the optimal seed** set such that is maximized

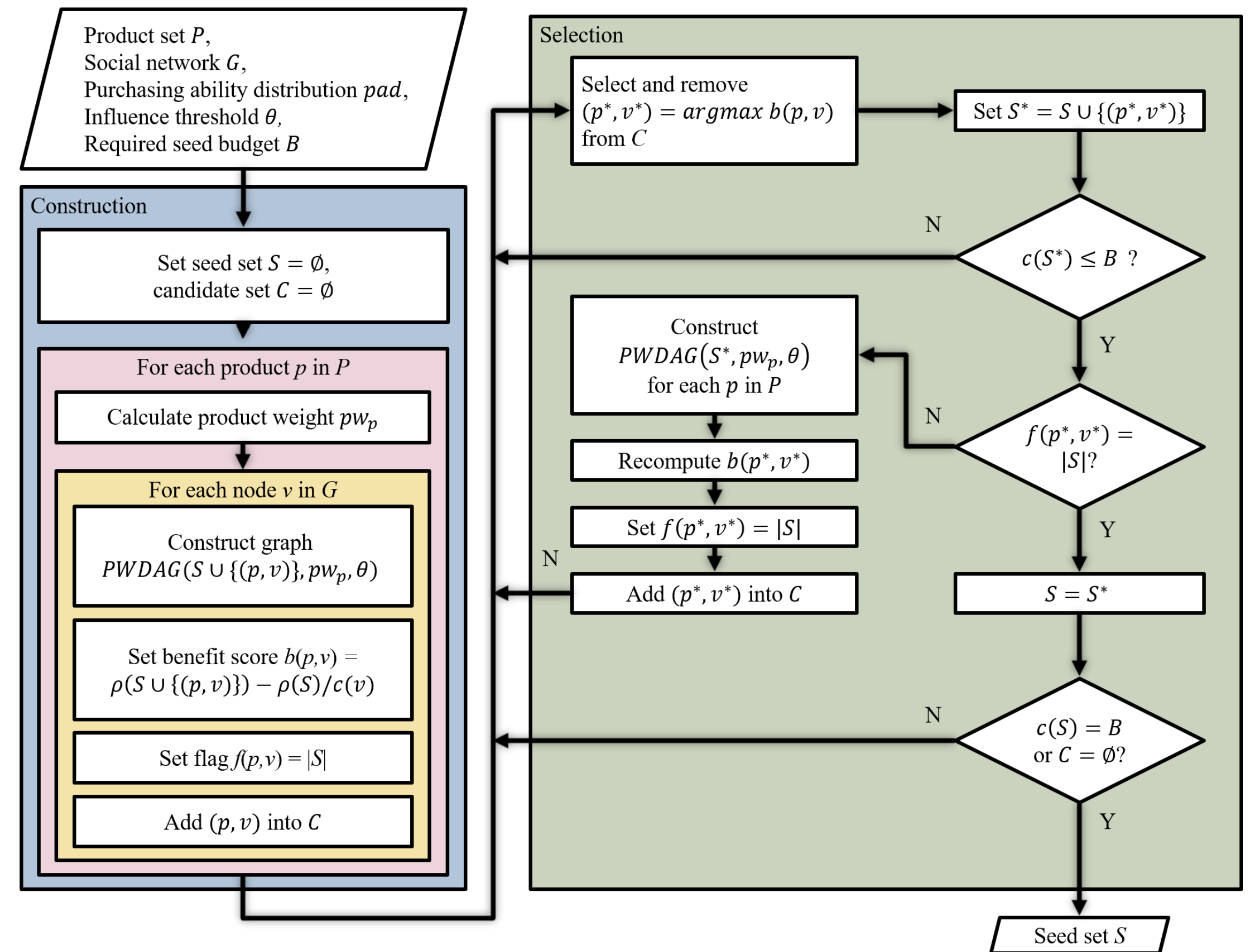
$$S^* = \arg \max_{S \subset V} \rho(S) \text{ s.t. } c(S) \leq B$$

optimal seed set      expect profit      total cost of seeds in  $S$       seed budget limitation

# Proposed Method

## BG (BMPPM Greedy)

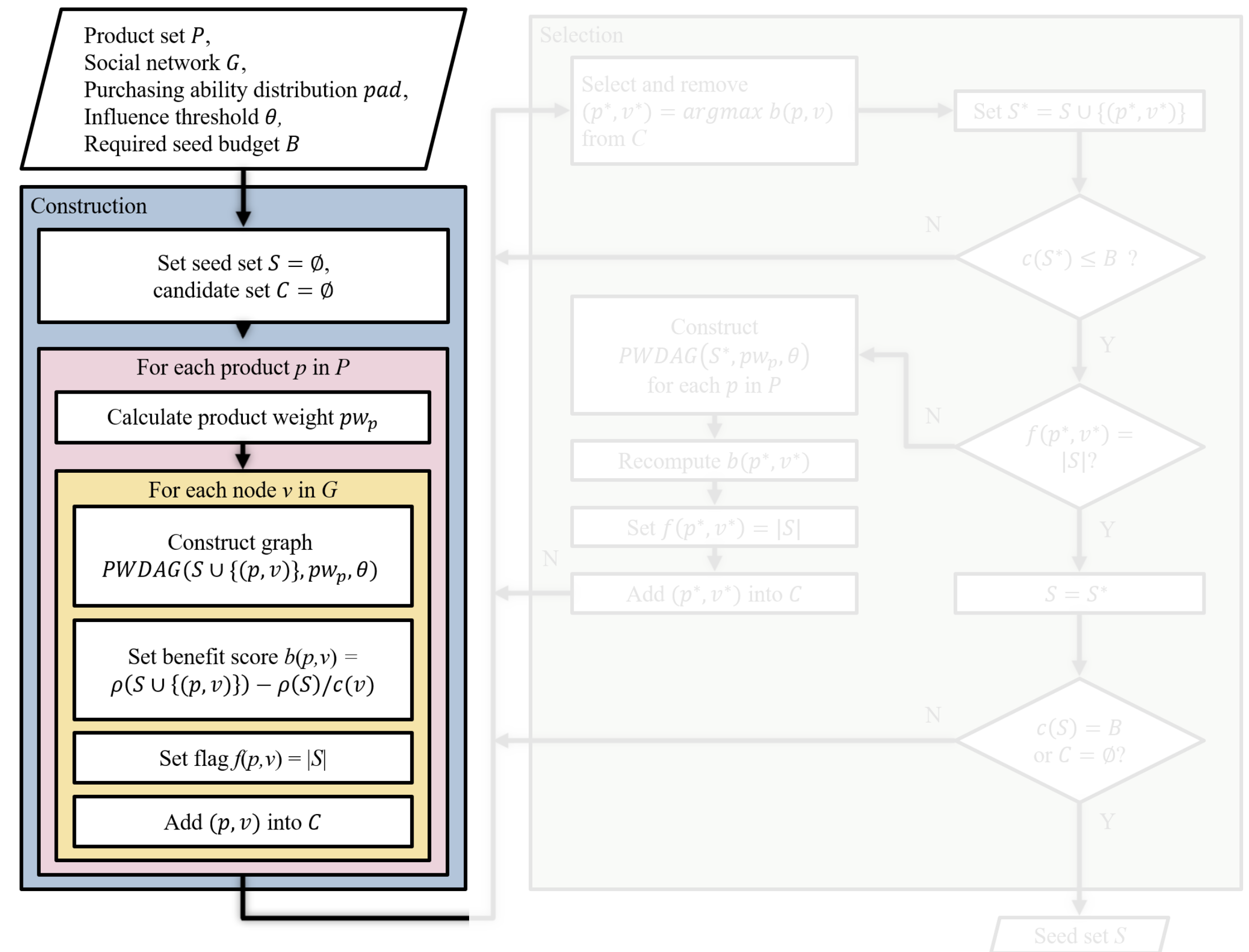
- Construction Phase
  - Calculate Product Weights
  - Construction of Influence Approximation Graphs
- Selection Phase
  - Benefit Score
  - Limitation of Selecting the Seed



# Proposed Method

## BG (BMPPM Greedy)

- Construction Phase
  - Calculate Product Weights
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# Proposed Method

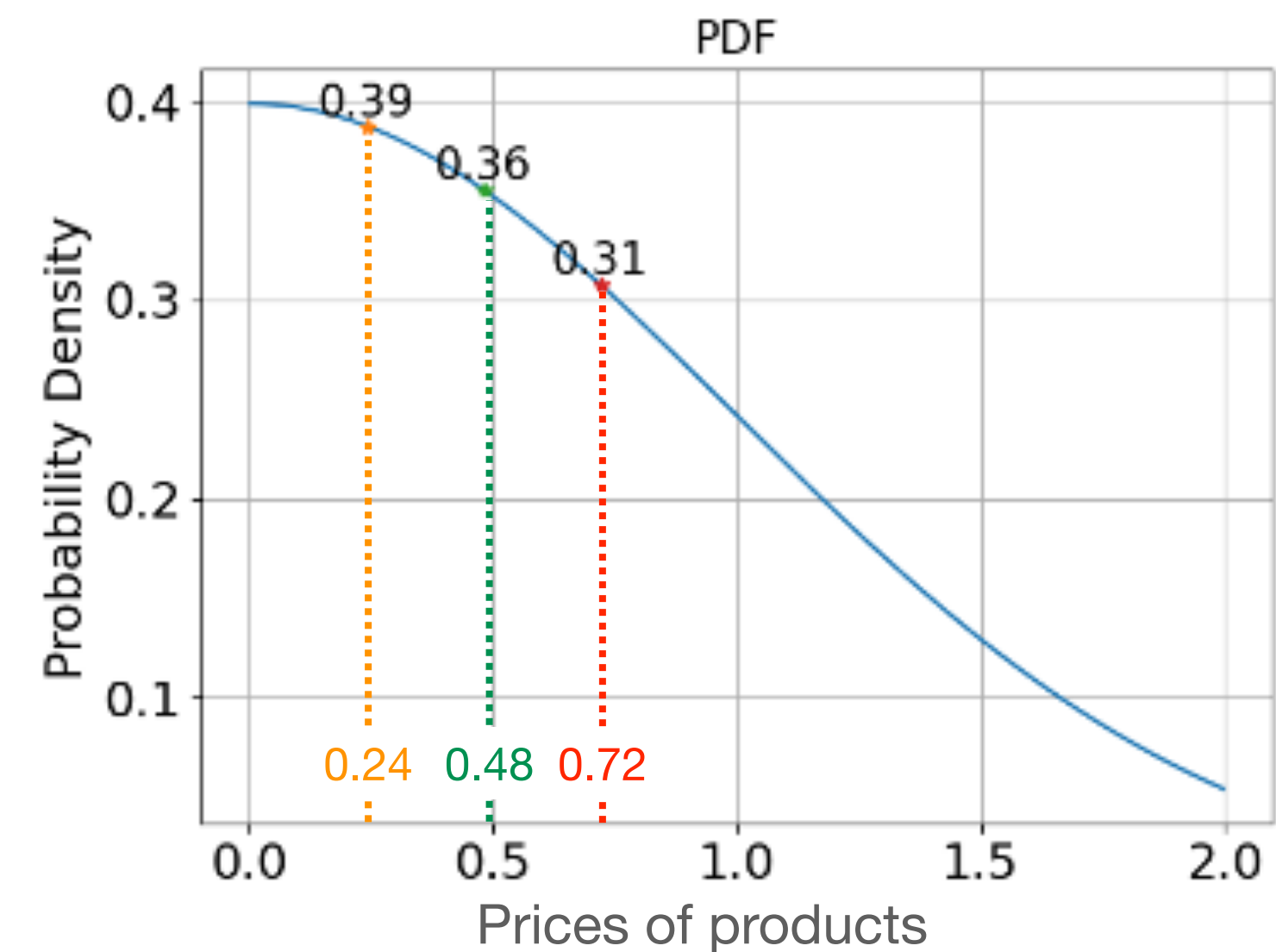
## Product Weights

- **Emphasize the importance** of different products in diffusion process
- Considered as probability of node purchasing product immediately, and propagating product information to its out-neighbors
- If price of product is higher, product weights will be lower, and vice versa

# Proposed Method

## Purchasing Ability

- We cannot actually know the **purchasing ability of users**
  - The **purchasing ability distribution** *pad* is considered as a probability density function (PDF)
  - To estimate the probabilities of users in the market to purchase given product
  - Assume *pad* can anticipate purchasing ability of users
- Example: product weight calculation
  - Product prices: **0.24**, **0.48**, **0.72**
  - Purchasing ability of user: **0.39**, **0.36**, **0.31** (Percentage of users who can afford the price)





# Proposed Method

## Purchasing Ability

- Obtain CDF by integrating PDF, then calculate complementary cumulative distribution function (CCDF)

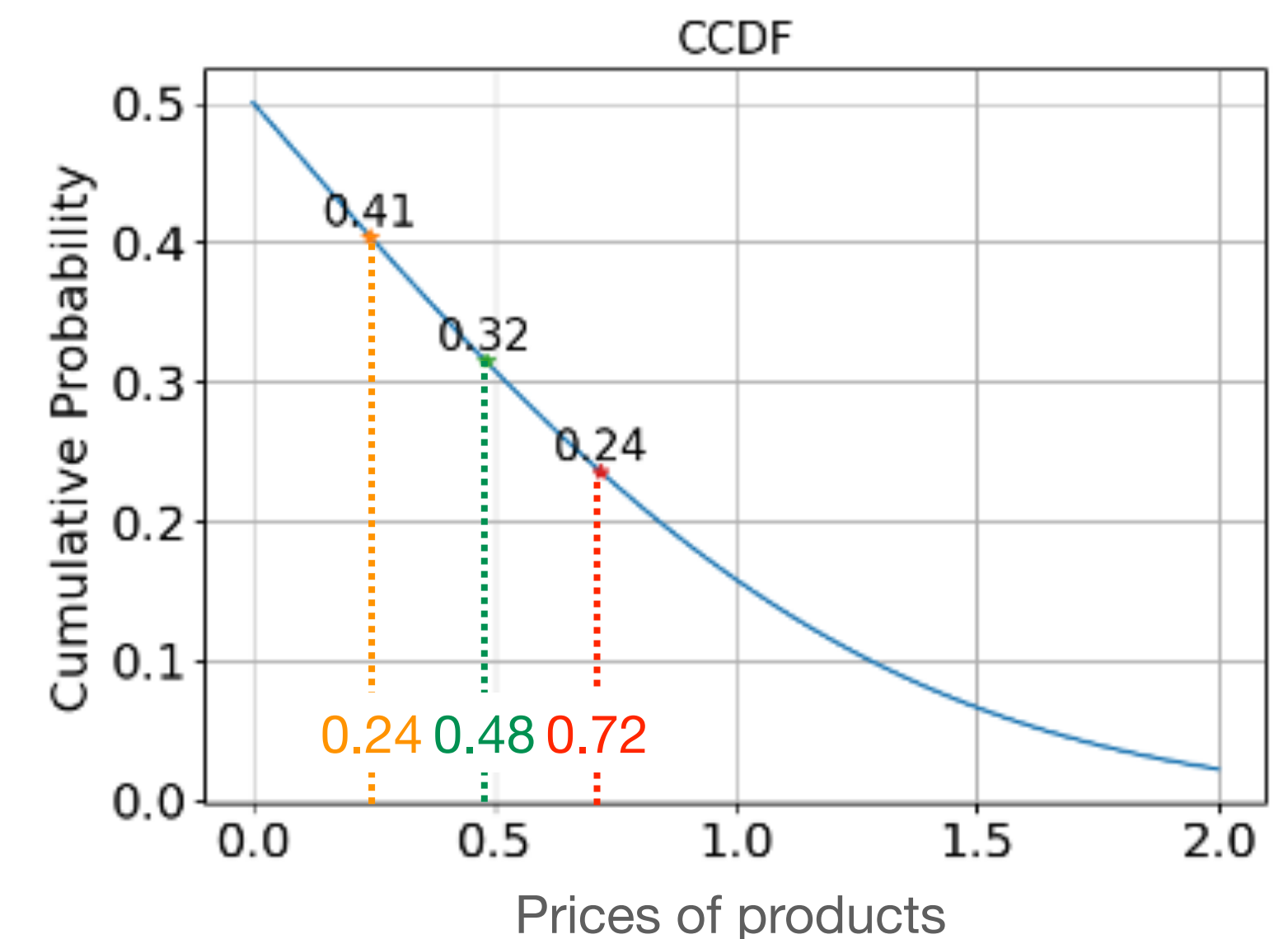
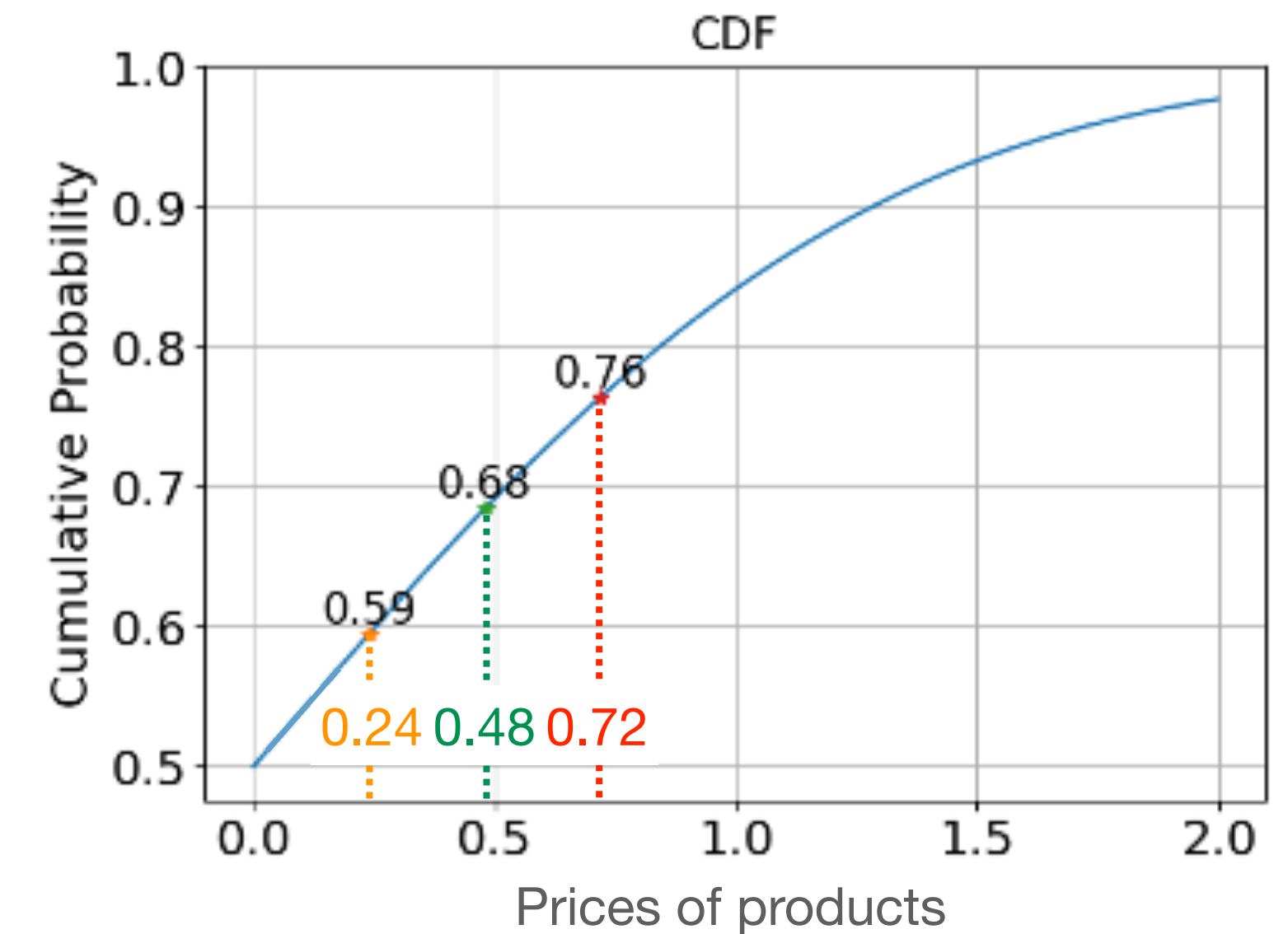
$$\bar{F}_X(x) = P(X > x)$$

probability that the user  
can afford the product at price  $x$

random variable      price

$$F_X(x) = P(X \leq x)$$

$$\bar{F}_X(x) = P(X > x)$$



# Proposed Method

## Construction of Influence Approximation Graphs

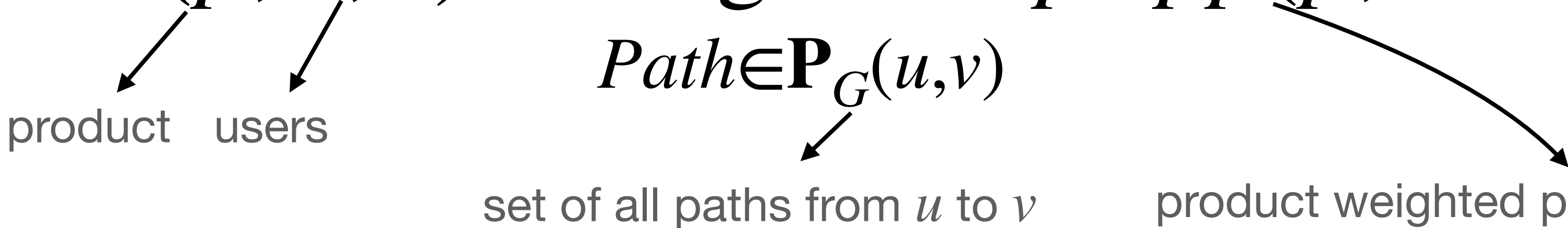
- **Product Weighted Directed Acyclic Graph (PWDAG)**
  - Extension of DAG structures
    - **Reduce the computing time** for estimating the influence propagation
  - To approximate the influence propagation for different products
    - Small region of influence for high-priced products and vice versa



# Proposed Method

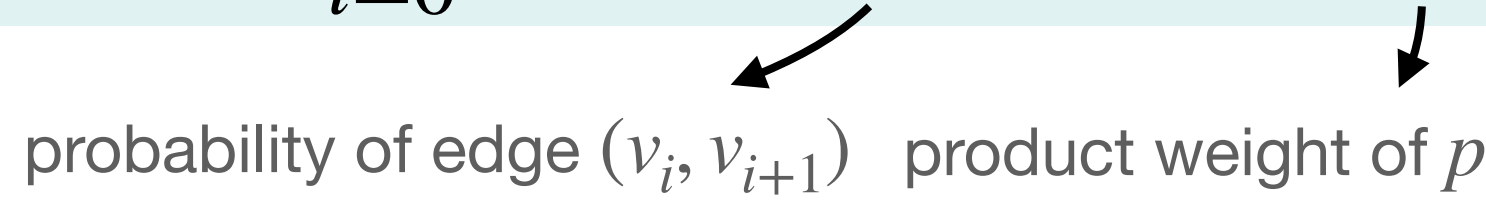
## Product Weighted Maximum Influence Path (PWMIP)

- Path from  $u \rightarrow v$  with the maximum product weighted propagation probability
- Consider  $pw_p$  as purchasing probability of product  $p$

$$PWMIP(p, u, v) = \arg \max_{Path \in \mathbf{P}_G(u, v)} pwpp(p, Path)$$


set of all paths from  $u$  to  $v$

product weighted propagation probability

$$pwpp(p, Path) = \prod_{i=0}^{|Path|-1} pp(v_i, v_{i+1}) \times pw_p$$


probability of edge  $(v_i, v_{i+1})$  product weight of  $p$

# Proposed Method

## Product Weighted Maximum Influence Out-Arborescence (*PWMIOA*)

- Product weighted **influence region** of  $u$

$$PWMIOA(p, u, \theta) = \bigcup_{pwpp(p, PWMIP(p, u, v)) \geq \theta} PWMIP(p, u, v)$$

Diagram illustrating the definition of  $PWMIOA(p, u, \theta)$ :

- $p$ : product
- $u$ : user
- $\theta$ : influence threshold
- The union is over all  $v$  such that  $pwpp(p, PWMIP(p, u, v)) \geq \theta$ .
- $PWMIP(p, u, v)$  is the Product Weighted Maximum Influence Path from  $u$  to  $v$ .
- user:  $\forall v \in V/u$

# Proposed Method

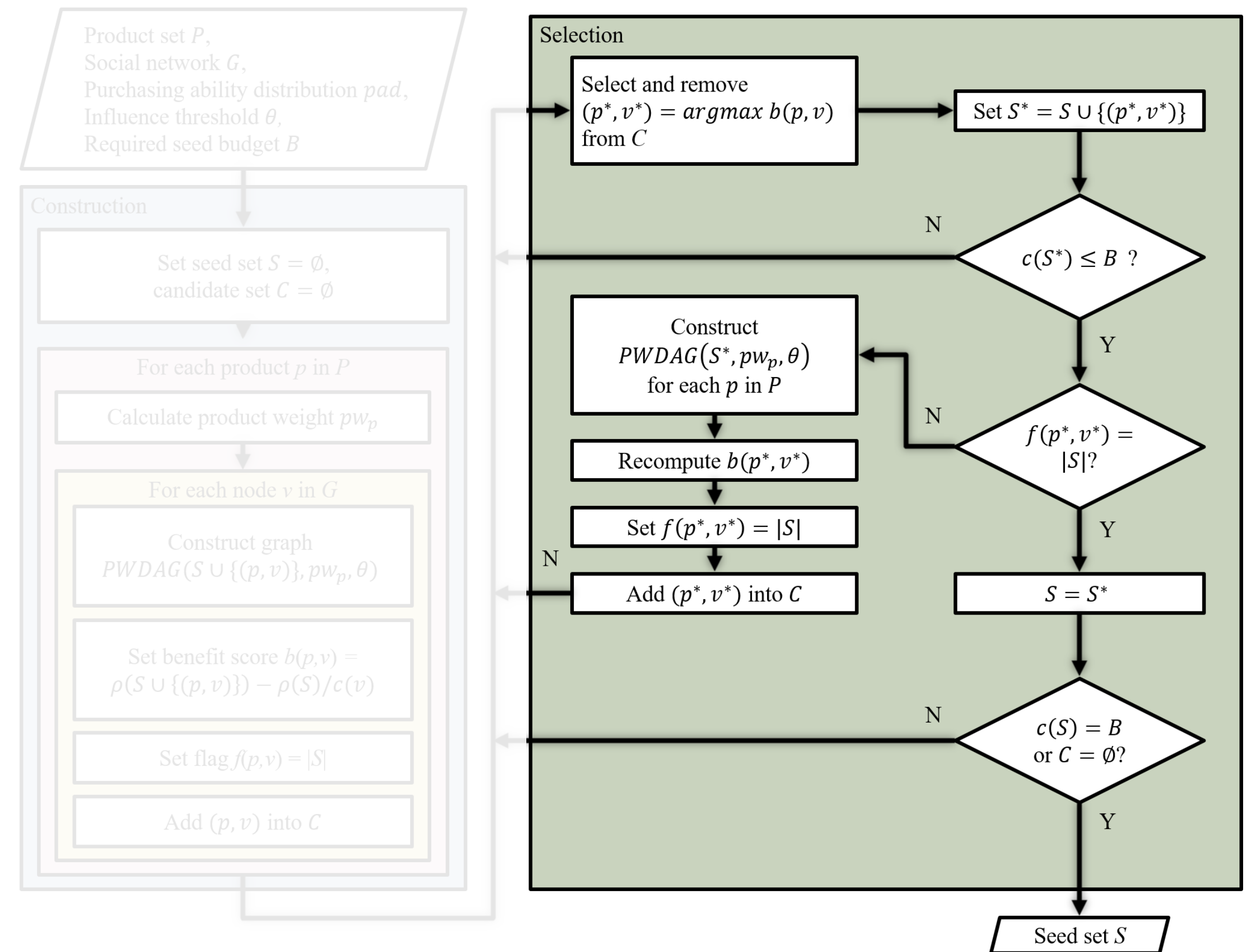
## Steps of constructing the PWDAG

- PWDAG<sub>1</sub>
- Regarding **all seeds as a whole** to calculate PWMIOA for estimating the influence propagation region of the seed set
  - Build a super root  $R$  connecting all seeds with probability 1
  - Construct **PWMIOA** of  $R$
  - Remove  $R$
  - Include some edges ending in PWDAG<sub>1</sub>
- PWDAG<sub>2</sub>
- Considers regions of propagation influence of **different seeds** and adopts their calculated propagation influence regions
  - Union **PWMIOAs** of seeds
  - Remove some edges

# Proposed Method

## BG (BMPPM Greedy)

- Construction Phase
  - Calculate Product Weights
  - Construction of Influence Approximation Graphs
- Selection Phase
  - Benefit Score
  - Limitation of Selecting the Seed



# Proposed Method

## Benefit Score

- Select the **cost-effective seeds**
  - High profit seeds have high cost
    - A small amount of seeds under budget limitations, not suitable to BMPM problem

$$b(p, v) = \frac{\rho(S \cup \{(p, v)\}) - \rho(S)}{c(v)}, \forall v \in V \setminus S, p \in P$$

$\downarrow$   
product

$\swarrow$   
 $\rho(\cdot)$ : profit

$\swarrow$   
 $c(\cdot)$ : cost

# Proposed Method

## Limiting on Selecting the Seed

- Use **Flag** to **record the validity** of  $b(p, v)$ . (KDD'07)
- Record size of seed set at that time when calculating  $b(p, v)$ 
  - $f(p, v) = |S|$ 
    - $b(p, v)$  **is calculated** with the current seed set
  - $f(p, v) < |S|$ 
    - $b(p, v)$  **is not calculated** with the current seed set

# Experiments

## Social Network Datasets

	Email	NetPHY
Direction	Undirected	Undirected
# of Node	1.1K	37.2K
# of Edge	5.5K	23.2K
Max Degree	105	218
Description	Node: an email address	Node: an author
	Edge: two people have communicate by email	Edge: two authors have a collaborative relationship



# Experiments

## Baselines

- **DAG<sub>1</sub>-LBP & DAG<sub>2</sub>-SPBP**: the best-performed algorithm on static networks and the fastest algorithm on rapidly changing communities respectively
- **CELF**: a greedy algorithm based on a lazy-forward optimization in selecting seeds and uses 1000 times of Monte Carlo simulation to estimate the influence
- **CPHU**: designed for the BPM problem that implements the cost performance update heuristics. It picks up the seed with the maximum expected number of cost performance and then updates other seeds until no more candidate seeds
- **High Degree (HD)**: selects the nodes with the highest degree as seeds unless the seed budget limitation is exceeded
- **Random**: selects seeds randomly unless the seed budget limitation is exceeded.



# Experiments

## Proposed Methods

- $BG_1$ 
  - Use  $PWDAG_1$
- $BG_2$ 
  - Use  $PWDAG_2$

# Experiments

## Settings

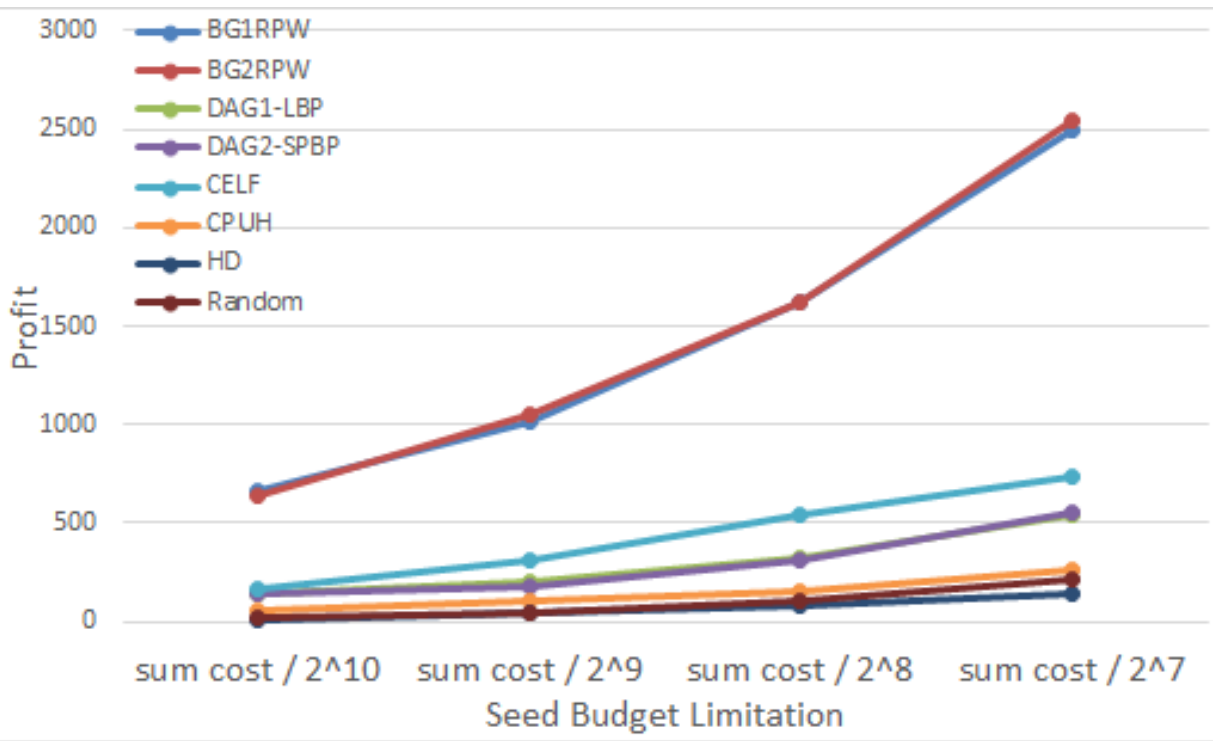
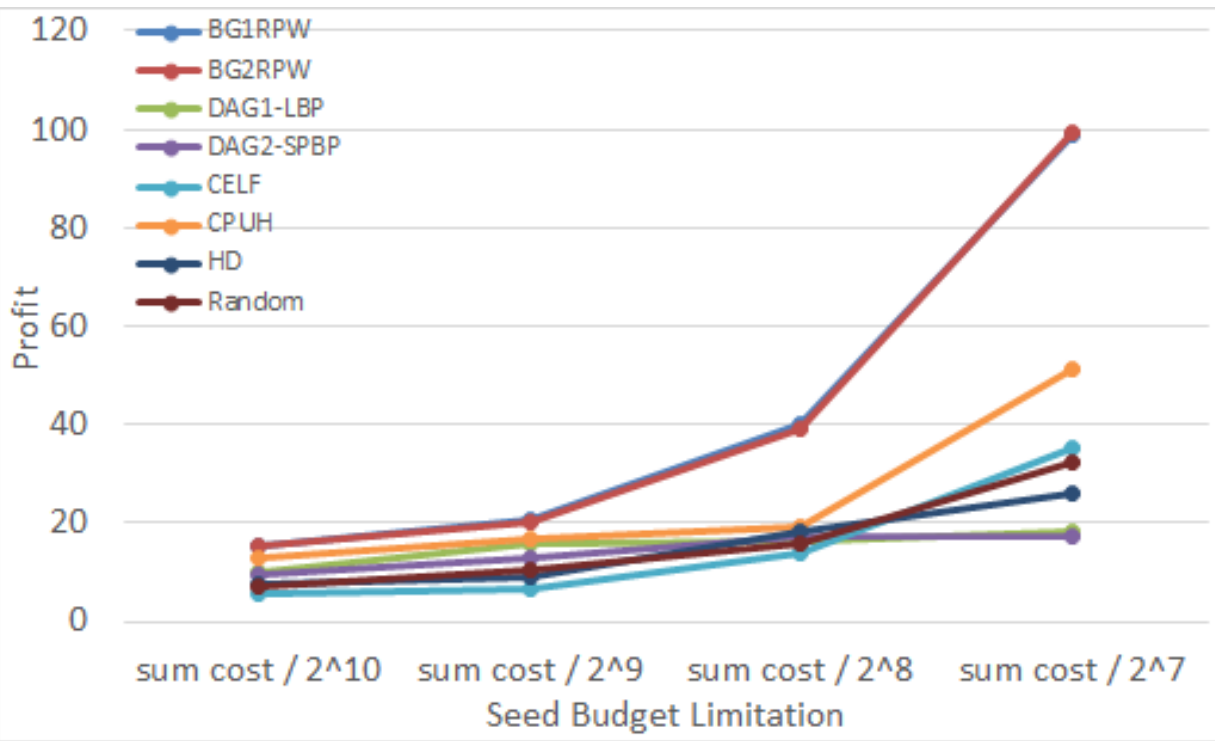
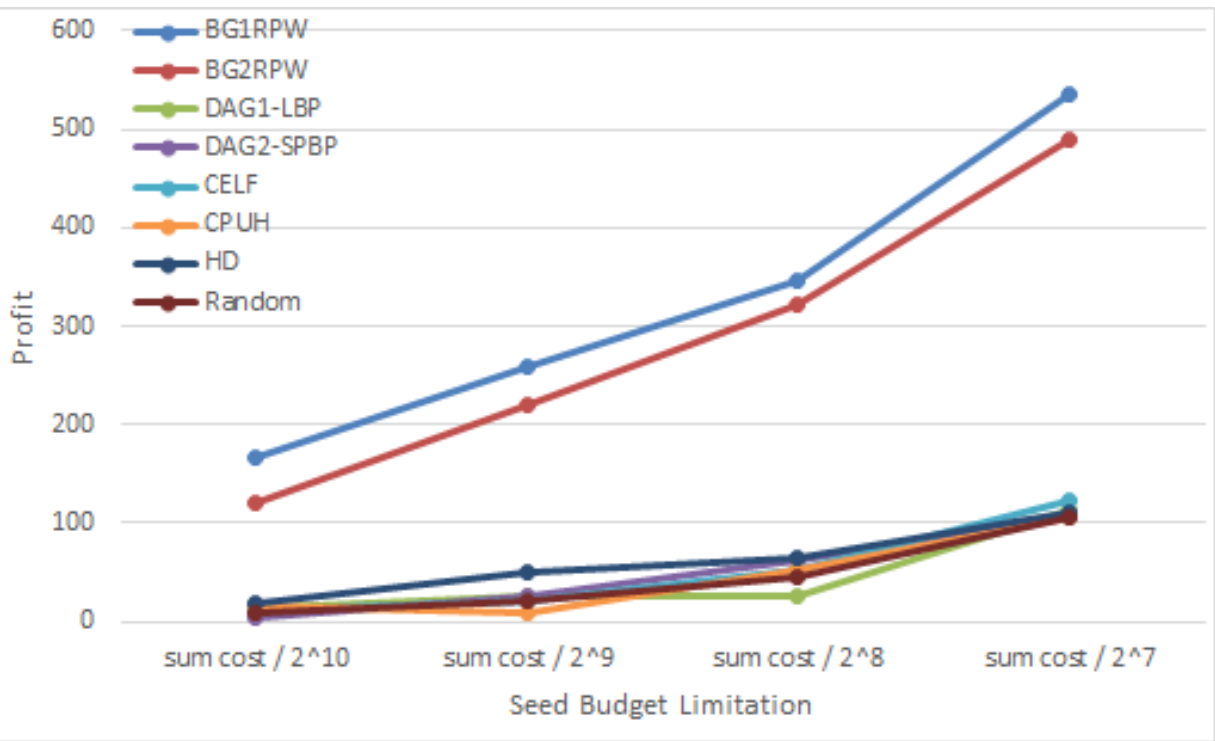
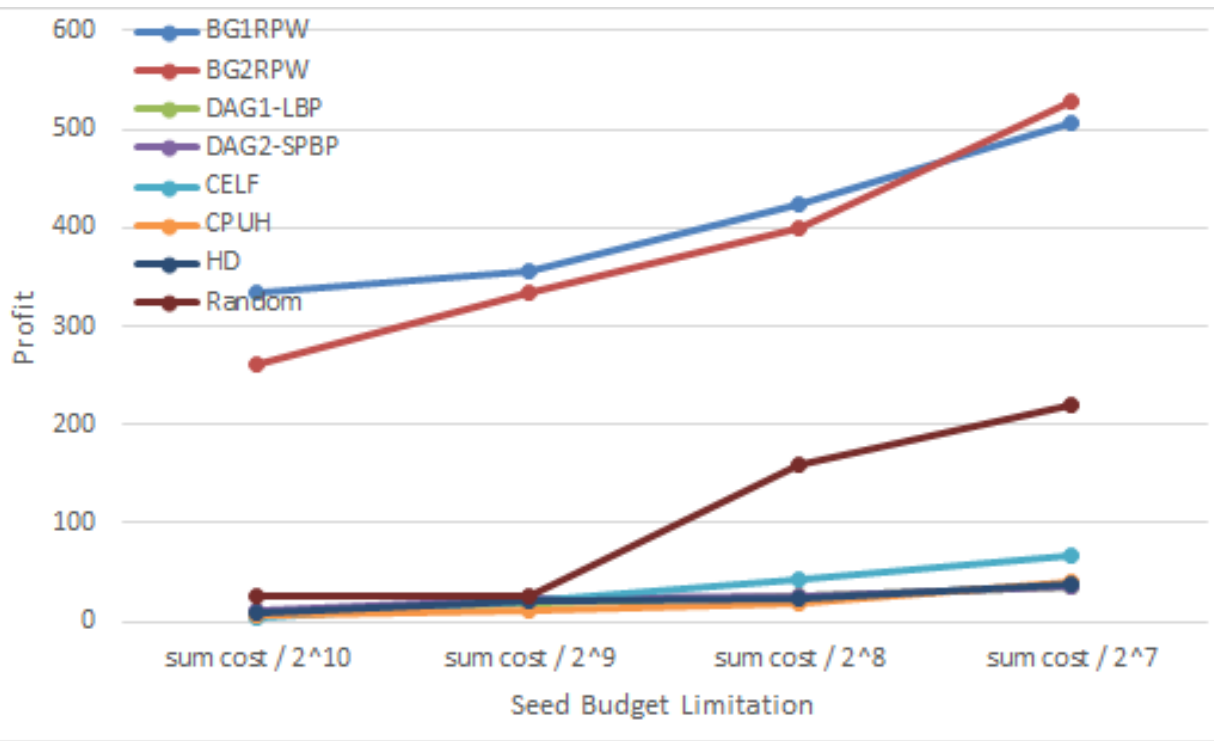
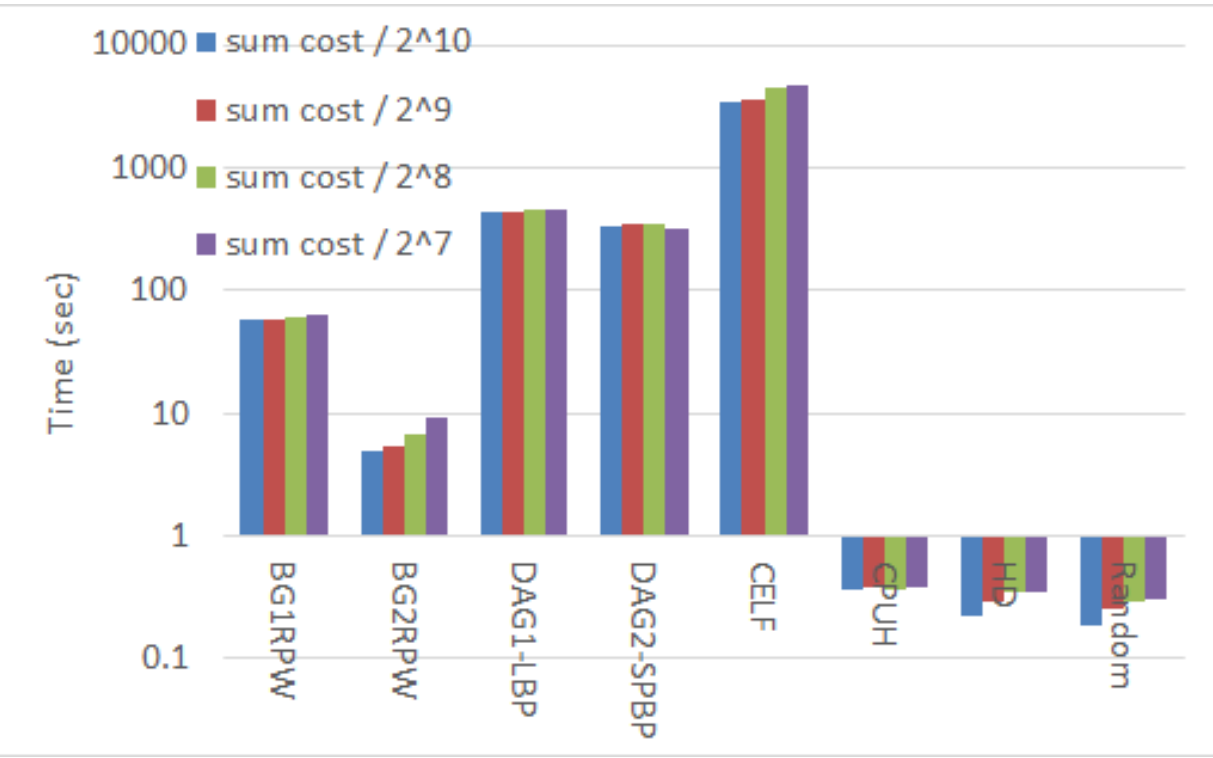
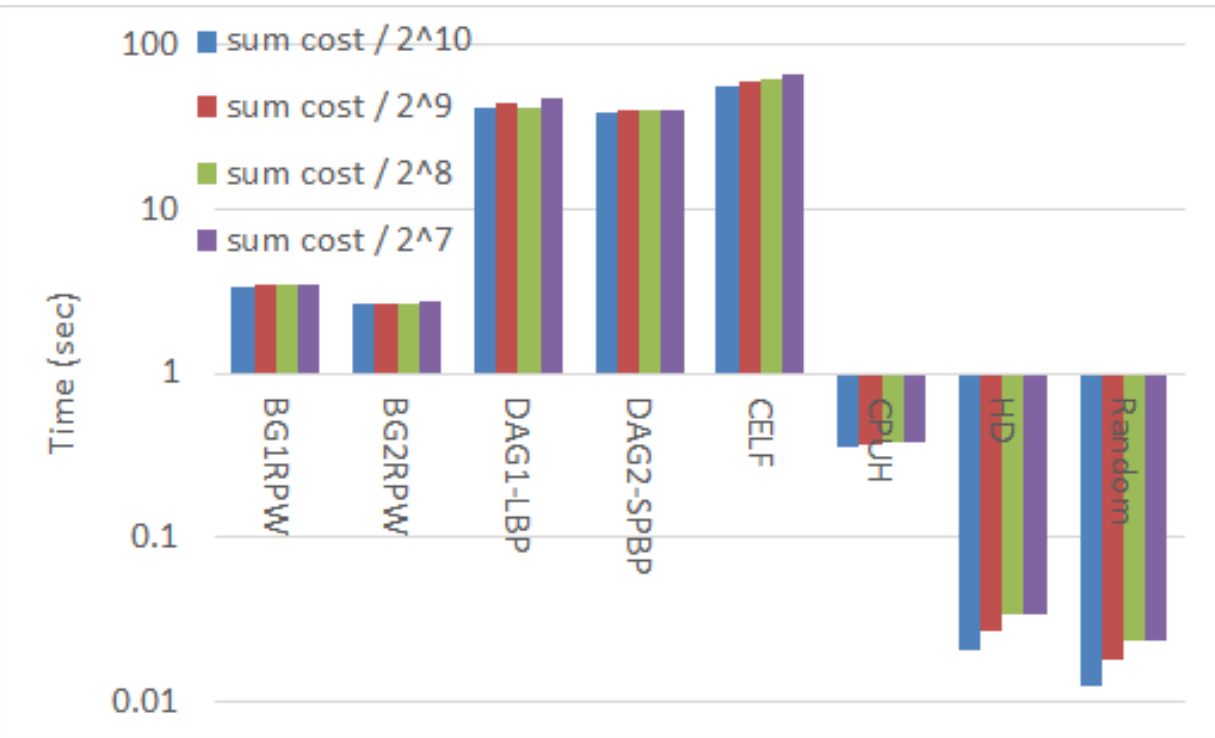
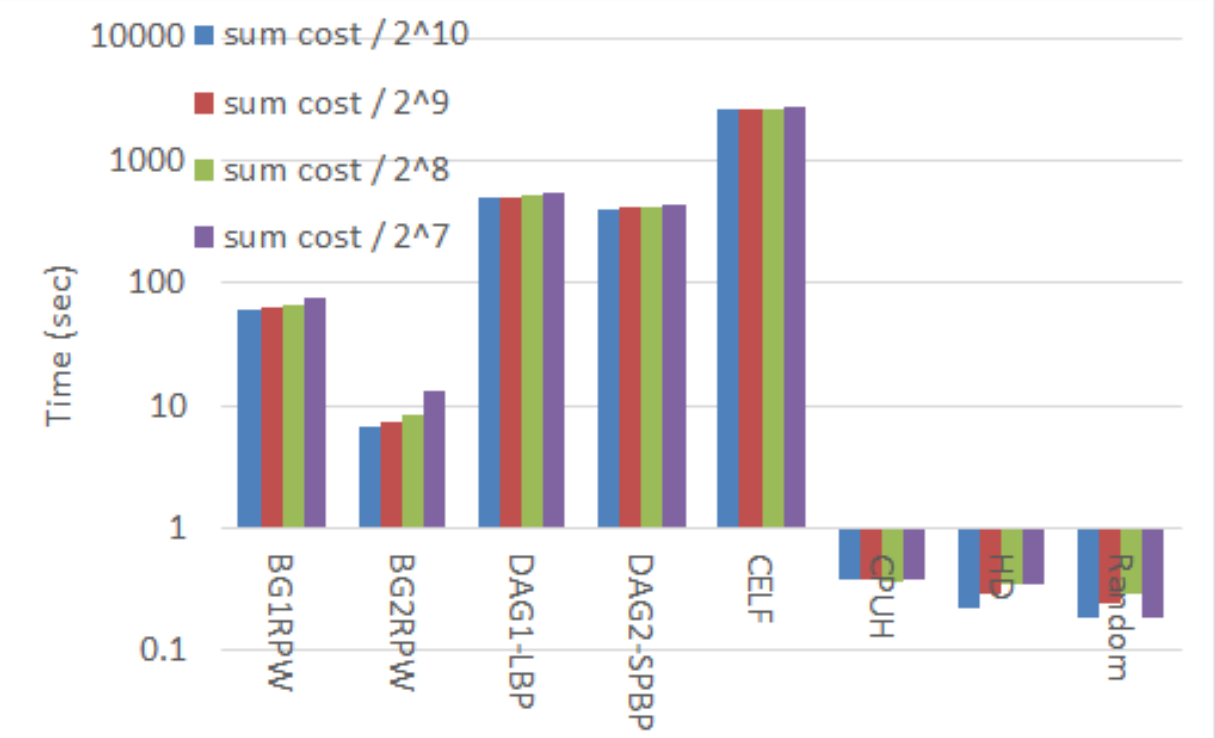
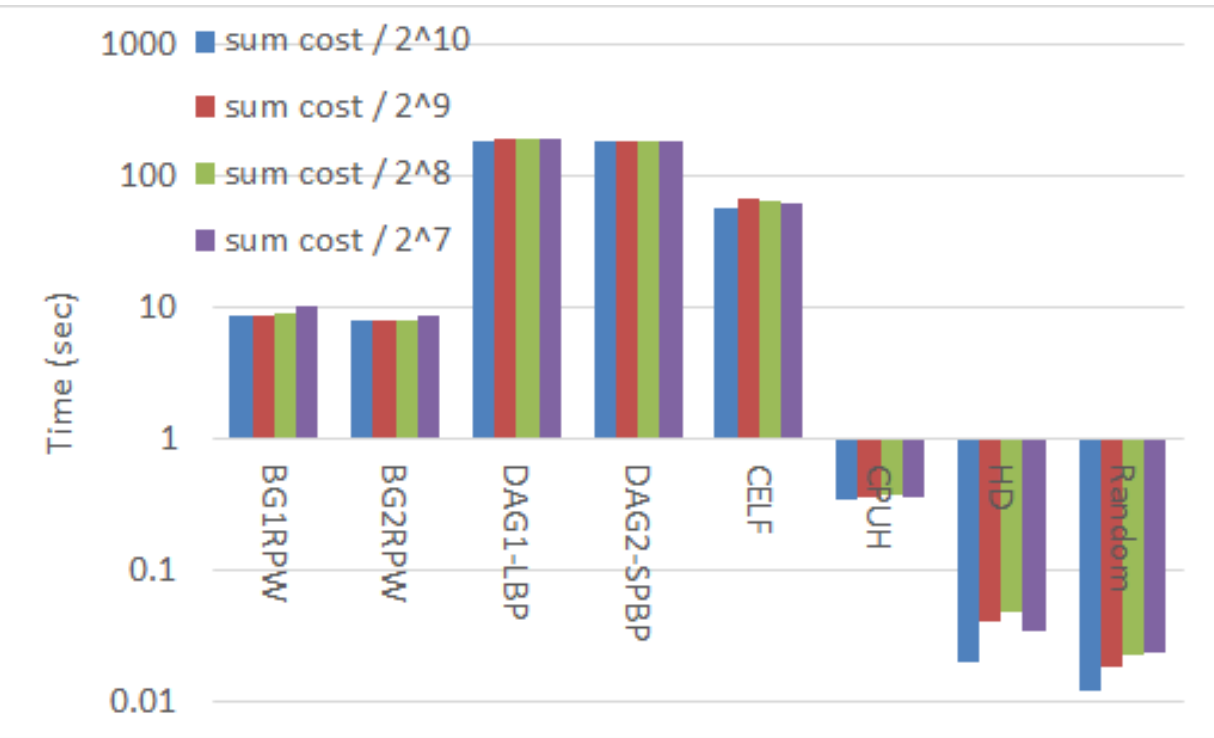
- Budget of the seed set
  - 1/1024, 1/512, 1/256, 1/128 of total cost of all nodes selected as seeds
- Use the IC & WC model to generate the probability of each edge
  - IC model:  $pp(u, v) = 0.1$
  - WC model:  $pp(u, v) = 1/(|N_v^+|)$
- Monte Carlo simulations: 1000 times
- Influence threshold:  $\theta = 0.001$

# Experiments

## Results

- BG<sub>1</sub>
- BG<sub>2</sub>
- DAG<sub>1</sub>-LBP
- DAG<sub>2</sub>-SPBP
- CELF
- CPUH
- HD
- Random

IC model propagation



Email

NetPHY

Email

NetPHY

# Conclusions and Future Works

## of BG (BMPPM Greedy)

- We proposed the **greedy algorithm named BG** to solve BMPPM problem
  - Concept of **purchasing ability distribution** is applied to **produce product weight**
    - To emphasize the importance of different product
  - Graph structure using product weights **reduce the time cost**
    - Suitable to approximate the influence propagation for multiple products
- We will explore the **relationship between products** in the future work

# Thanks for listening!

## **A Greedy Algorithm for Budgeted Multiple-Product Profit Maximization in Social Network**

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# Experiments

## Product set & Purchasing Ability Distribution

	P
Profit	2.7, 4.2, 9
Cost	1.8, 2.8, 6
Price	4.5, 7, 15
Description	<p>Profit is higher than cost.</p> <p>The products are the more profitable products in reality.</p>

3 products from the book category in the Amazon dataset

