# Pricing on Social Networks with Partial Information

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 Many modern companies make use of discounts and specials in an attempt to optimize profits



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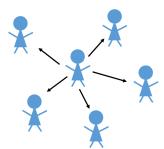


 The goal is influential people are offered discounts to buy more and their use of the product incentives others to buy.

# Introducing the Model

#### Consider a network G with:

- N individuals as nodes
- $G_{ij} \geq 0$  is the influence j has on i
- Each Person chooses an amount of a divisible good to buy that maximizes their utility
- This depends (positively) on how much the people around them consume.



# Utility

We model utility of the ith person as

$$u_i = a * x_i - p_i x_i - x_i^2 + 4\rho x_i \sum_{i \neq j} \frac{G_{ij}}{\|G + G^T\|} x_j$$

#### Where:

- u<sub>i</sub> is utility
- x<sub>i</sub> amount purchased
- p<sub>i</sub> price charged
- $a > 0, 0 < \rho < 1$  constants.

Note that aside from position in the network, everyone has the same utility function. This model of utility has been previously studied. [HMW22], [CBO12] [FG16] [BQ13]



# Consumption

Each individual will consume an amount that maximizes their utility Unique Equilibrium Consumption  $x(\mathbf{p})$  is

$$x(\mathbf{p}) = \frac{1}{2} \left( I - 2 \frac{\rho}{\|G + G^T\|} G \right)^{-1} * (a * \mathbf{1} - \mathbf{p})$$

[CBO12]

### **Profits**

The goal of the firm is to charge each consumer a different amount to maximize profit based on the network

$$max_p(p-c\mathbf{1})^T\mathbf{x}(p)$$

Where a > c > 0 is the unit cost to produce one unit of the good.

# **Optimal Prices**

The firm will attempt to maximize profits by strategically choosing prices. If they are unrestricted then the optimal price vector is

$$\begin{split} \rho^* &= \frac{a+c}{2} \mathbf{1} \\ &+ \frac{a-c}{2} \frac{\rho}{\|G+G^T\|} G * \mathcal{K}(G+G^T, \frac{\rho}{\|G+G^T\|}) \mathbf{1} \\ &- \frac{a-c}{2} \frac{\rho}{\|G+G^T\|} G^T * \mathcal{K}(G+G^T, \frac{\rho}{\|G+G^T\|}) \mathbf{1} \end{split} \tag{Markup}$$

[CBO12]

Where  $K(G, \alpha) = (I - \alpha G)^{-1} = \sum_{i=0}^{\infty} (\alpha G)^i$  is the Bonacich centrality vector

and profit

$$\pi^* = \frac{1}{8}(a-c)^2 \mathbf{1}^T (I - \frac{\rho}{\|G + G^T\|} (G + G^T))^{-1} \mathbf{1}[HMW22]$$



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New viewpoint: Under optimal pricing the consumption is proportional to  $\mathcal{K}(G+G^T,\frac{\rho}{\|G+G^T\|})$ 

#### Uniform Price

If we require that we charge one price instead then

- **1** the optimal uniform price  $\mathbf{p}_0$  is  $\mathbf{p}_0 = \frac{a+c}{2}\mathbf{1}$
- **3** the profit  $\pi_0$  is  $\pi_0 = \frac{1}{8}(a-c)^2 \mathbf{1}(I \frac{2\rho}{\|G + G^T\|}G)^{-1} \mathbf{1}$

# Regret for Random Graphs

Over Erdos-Renyi Graphs and Power-law graphs with lpha > 2 with n nodes.

#### Theorem

(Uniform Regret) 
$$\lim_{n \to \infty} E[1 - \frac{\pi_0}{\pi^*}] = 0$$

[HMW22]

# Regret for Random Graphs

Over Erdos-Renyi Graphs and Power-law graphs with lpha > 2 with n nodes.

#### **Theorem**

(Uniform Regret)  $\lim_{n \to \infty} E[1 - \frac{\pi_0}{\pi^*}] = 0$ 

[HMW22] This means for large Erdos-Renyi and powerlaw Graphs there is no benefit using optimal prices instead of uniform prices.

Is there is a class of random graphs with an asymptotically positive value of regret?

- Take an  $m \times m$  matrix with  $P_{ij}$  being the probability of an edge from a Community i node to a community j node.
- Pick n to be the size of each community. We can build an  $(nm) \times (nm)$  network in two ways.

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- 1) Build a truly random A from sampling each edge independently according to  ${\cal P}$
- 2) Build a matrix that reflects the average density i.e.  $\bar{A}_{ij} = P_{C(i),C(j)}$  where C(i) is the index for the community that i is a part of

# Example

If 
$$P = \begin{bmatrix} 0.25 & 0.5 \\ 1 & 0.75 \end{bmatrix}$$
 If there are 2 individuals in each community then  $\bar{A} = \begin{bmatrix} 0.25 & 0.25 & 0.5 & 0.5 \\ 0.25 & 0.25 & 0.5 & 0.5 \\ 1 & 1 & 0.75 & 0.75 \\ 1 & 1 & 0.75 & 0.75 \end{bmatrix}$ 

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And a sample A could look like 
$$A = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 0 & 1 \end{bmatrix}$$



#### Performance

In practice we find that only knowing the community level information is sufficient

Specifically let  $\textit{Regret}(\textit{v}) = 1 - \frac{\mathsf{Profit}(\textit{v})}{\pi*}$  where

- ullet v is the price vector we derive from  $ar{A}$
- $\pi*$  optimal profit of A

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- $| \lim_{n \to \infty} E[Regret(Uniform)] > 0$

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The first part says the limited information is sufficient to get good performance and the second says there is a loss if you don't use graph information.



# Blocking

One way to use this idea is given a partition of the network ask that everyone in each block of the partition is charged the same price. How do we do we determine prices?



Figure: Neighborhoods of Los Angeles. Instead of being able to charge individuals prices a realistic constraint is that we set the price in each neighborhood.

# **Partitioning**

- Letting  $B = \frac{1}{2}(I 2\rho G)^{-1}$  one can express the prices p to charge is  $(B + B^T)v = (aB\mathbf{1} + c * B^T\mathbf{1})$
- We adapt this to a given partition with q blocks.

Let 
$$\mathcal{P}$$
 be a  $q \times \underbrace{mn}_{\mathsf{Size of network}}$  matrix where  $\mathcal{P}_{ij} = \begin{cases} 1 & \mathsf{lf j} \in \mathsf{Block} \ i \\ 0 & \mathsf{Else} \end{cases}$ 

- Then the optimal prices to charge in each block are  $\mathcal{P}(B+B^T)\mathcal{P}^T v = a * \mathcal{P}B\mathbf{1} + c * \mathcal{P}B^T\mathbf{1}$
- Denote by q the price vector from such a partitioning scheme.

#### Losses

- Let  $p^*$  optimal price vector, q prices calculated from partition
- We conjecture based on experiment that the loss of using q instead of p\* is

$$Profit(p^*) - Profit(q) = (p^*)^T B p^* - q^T B q$$



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- This is not true for general prices.
- The set of prices that satisfy this is not linear subspace.



# Examples

With 
$$a = 6, c = 4, \rho = 0.9$$

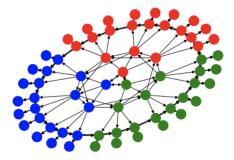


Figure: Bad Partition of 3 blocks. The three colors blocks are identical. Under this restriction of prices the graph acts like a symmetric graph which has no benefit to price discrimination. The optimal price here is the uniform price  $\frac{a+c}{2}=5$  and the profit is 166.73

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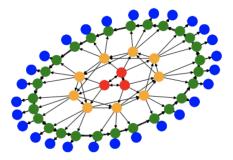


Figure: A good Partition using 4 blocks. Under this restriction of prices the graph acts like a directed line graph which does benefit to price discrimination. The profit is 295.14 and is the true optimal. This is 77% increase in profit over the previous partition.

# Thank you

# Questions?

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- [HMW22] Jiali Huang, Ankur Mani, and Zizhuo Wang. "The value of price discrimination in large social networks". In: <u>Management Science</u> 68.6 (2022), pp. 4454–4477.