A Qualitative Study on

# Online Platform Product Ranking

Mahsa Derakhshan., Negin Golrezaei,. Vahideh Manshadi., & Vahab Mirrokni

T. Vijaya Kumar , MTech-AI, IISC

vijayakumart@iisc.ac.in (18191)

# Introduction

Online platform opening best opportunities for consumers as well as sellers so that they could virtually be at one place and buy products according to their taste.

## How well this online platforms satisfying buyers and sellers ?

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# Objective

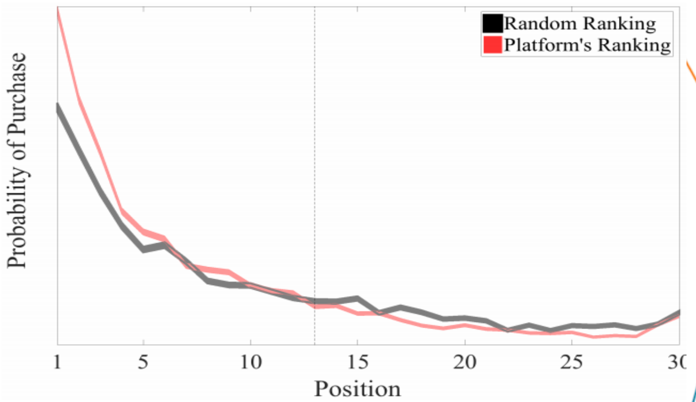
## Consumer Problem

- Buyer want good product(Quality)
- Buyer need to get above good product without spending a lot of time in online platform(Fast)
- Buyer need to get it with maximum utility(Cheap)


Online platform make sures providers are providing quality product in order to sustain business – Quality ✓

Due to huge number of providers in market there is availability of same product with different costs – Cheap ✓

Do they able to extract above product searching all product in online platform ? NO –Fast ✗




Probability of purchasing low ranked products by consumer decreases as he has limited time or patience level. This behavior can be captured by imposing **Search Cost** to his utility

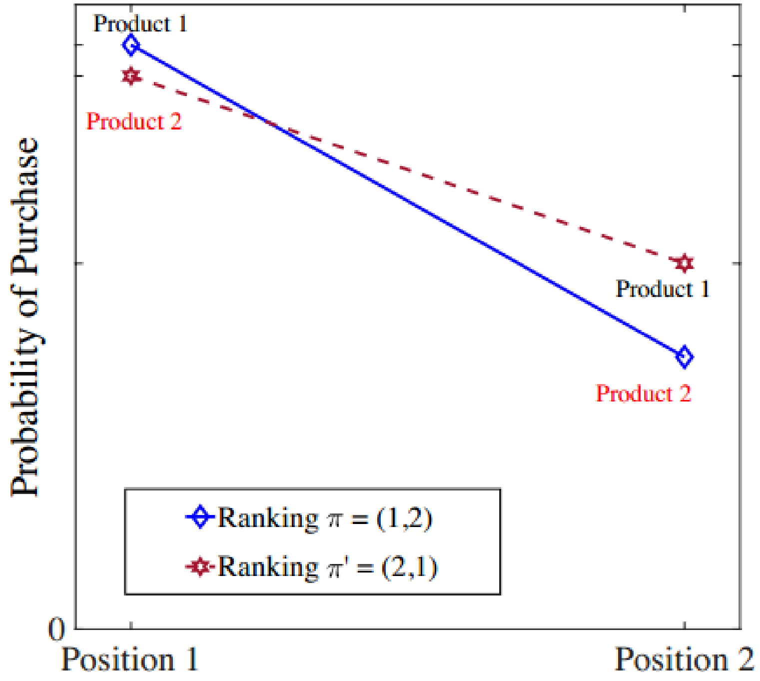
# Objective

## Consumer Problem

- Say two products Product 1, Product 2.
- Product 1 is more popular than product 2

If you put Product1 at higher position probability of purchasing Product2 decreases 51%

If Product2 positioned in top purchase probability for Product1 will drop to 35%




This puts the first objective that How to can we maximize consumer welfare ?

# Objective

## Market share problem

- All Providers need good market share.
- As we discussed above ranking effects the probability of purchase which implies low rank positioned product providers not getting market share well

This puts the second objective that How to can we maximize Market share?

## Objectives

- Maximizing market share
- Maximize consumer welfare

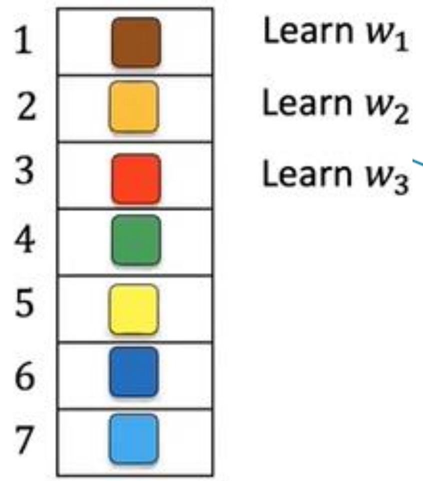
## Approach

- This paper proposes optimal search model which is mentioned as **Index-based search policy**.
- Proposed an optimal **product ranking algorithm (PTAS)** to above search model separately discussing two objectives.

# Preliminaries

## Basic Notation

- Consider N={1,2,…n} products and N={1,2,..n} positions.
- Position with lower index has higher visibility (Assumption)
- Each product has **preference weights** according to past knowledge.
- Each consumer has different taste, this can be defined on **Type** distribution θ defined with $k$.
- Consumer utility defined as two type i) **Intrinsic Utility** ii) **Idiosyncratic Utility**
- Intrinsic utility captures the screening behaviour according to preference weights by imposing **search cost** to screening process.
- Idiosyncratic utility captures the Type of consumer behaviour.

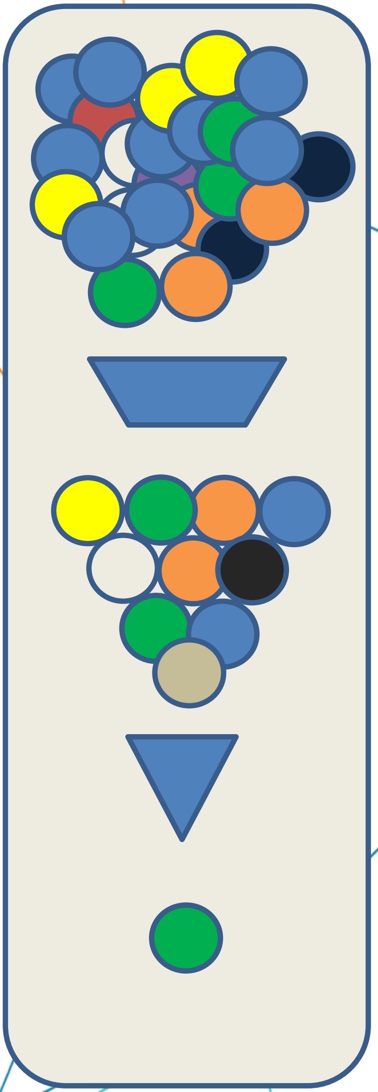



- Products denoted as $i \in [n] = \{1, 2, 3, ..., n\}$ positions $j \in [n]$
- Each product placements can be modelled with **permutation** $\pi : [n] \longrightarrow [n]$
- Search cost of type k consumer denoted with $\{s_1^k, s_2^k, .., s_n^k\}$ which is penalty to his utility when he screens a product. More he screens most search cost he is imposing
- Intrinsic Utility can defined as logarithm of preference weighs $W_i = e^{u_i}$.
- Assume search cost increases as position index increases $\{s_{j+1}^k \geq s_j^k\}$, this directly resembles the behaviour of consumer that as he screens deeper he get impatient and stop somewhere.
- Assume Consumer doesn't know these preference weights.

# Contribution

## Consumer Optimal Search Policy

- This search policy defined as two stages
- **First Stage:** Consumer builds a **Consideration** set 'C' by screening products sequentially and observe preference weights.
- **Second Stage:** Consumer again screens a product on his/her taste from consideration set C.
- Intuitively it resembles how a real person screens a product. *An actual person in online first he will add all reliable products into one list and then he choose best suitable one among all.*



- Total consumer welfare is maximizing expected utility. Following equation gives us expected welfare of consumer with search costs as penalty

$$Wel_{\pi}^{k}(C,W) = \mathbb{E}\left[\max_{i \in C \cup \{\phi\}} \{\log(w_i) + Z_i\}\right] - \sum_{i \in C} s_{\pi^{-1}(i)}^{k}$$

- As screening progresses if product '$i$' is screened weight $w_i$ is added to C, if not screened not added. This process can be explained as recursive equation as follows.

$$V(C,W)_{\pi}^{k} = max\left\{Wel_{\pi}^{k}(C,W), \max_{j \in [n] \setminus \pi^{-1}(C)} \mathbb{E}\left[V(C \cup \{\pi(j)\}), W \cup \{W_{\pi(j)}\}\right]\right\}$$

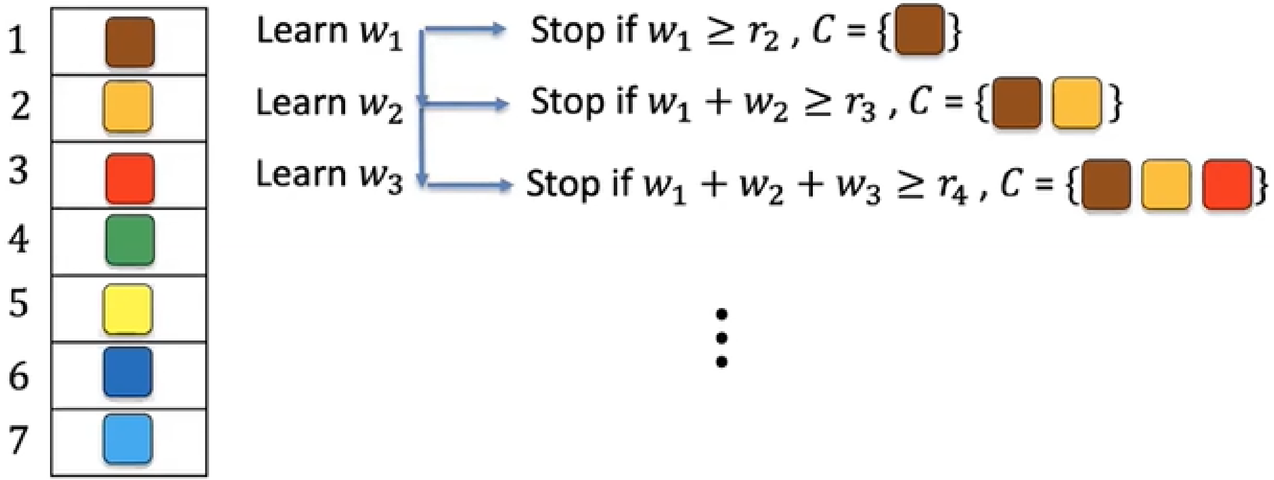
# Contribution

## Consumer Optimal Search Policy

When to stop his search ? How he deicides to select product ?

Consumer can not randomly go through products and evaluates its for weights, instead from a key result he calculates another measurement $r_j^k$ :Reservation price of product positioned at j when type k consumer screening. Use this as stopping criteria threshold of screening.

**First Stage:** consumer screens product and summation of consideration set weights not crossed reservation price he screens it.




**Algorithm**

**initialise** $C_\pi^k = \phi; j = 1$

**while** $\left( \sum_{j' \in |j|} w_{\pi(j')} \leq r_{j+1}^k \right)$

**Add product** $\pi(j+1)$ **into** $W$;

**j** $\leftarrow$ **j+1;**

**Stop**

**Second Stage:** consumer Learns Idiosyncratic part of product by analyzing only the products which are in consideration set and finalize one product..

# Contribution

## Consumer Optimal Search Policy

Okay we have stopping criteria based on reservation price, how did we get $r_j^k$ ?

Expected utility can be written as

$$\mathbb{E}\left[\max_{i \in C \cup \{0\}} \{\log(w_i) + Z_i\}\right] = log(1 + w(C)) + \gamma \qquad (1)$$

$$where\ w(C) = \sum_{i \in C} w_i\ and\ \gamma\ is\ Eular\text{-}Mascheroni\ constant$$

From above now our reservation price $r_j^k$ satisfies following equation

$$\mathbb{E}\left[\log(1 + r_j^k + W)\right] - log(1 + r_j^k) = s_j^k \qquad (2)$$

If consumer screens product welfare would be $-s_{j+1}^k + \mathbb{E}\left[\log(1 + w_j + W)\right] + \gamma$ if he don't $log(1+w_j)+\gamma$ by taking above solving for $r_j^k$ we get

Screen the product if $\boxed{\sum_{j' \in |j|} w_{\pi(j')} \geq r_{j+1}^k}$

# Contribution

## Product Ranking

Above search model is done sequentially which implies there is still affect of product ranking in consumer, market welfares. We needed optimal ranking(permutation) $\pi$ which gives maximum welfares.

Market share problem

- Consider probability of purchase when followed $\pi$ permutation as

$$P_{buying}\left[i \in C_\pi^k\right] = \frac{\sum_{i\in C_\pi^k} w_i}{1+\sum_{i\in C_\pi^k} w_i} = \frac{w(C_\pi^k)}{1+w(C_\pi^k)}$$

- Finding optimal $\pi$ is NP-Complete problem. Essentially, we needed to solve following Market share maximization problem

$$M_s = \max_{\pi\in\Pi} \sum_{k\in[K]} \theta^k \frac{w(C_\pi^k)}{1+w(C_\pi^k)}$$

- This NP-Complete problem solved by approximation algorithms and using approximation factors we decide on efficiency.

# Contribution

## Product Ranking

### W-ordered algorithm

- As there are a lot of algorithms already well knows simple algorithm is W-ordered algorithm. this algorithm put all products in the order of their preference weights. No need of any knowledge on consumer type or search strategies.

| Market share Maximization | Consumer Welfare Maximization |
|---|---|
| W-ordered algorithm has multiplicative approximation factor as ½ and additive approximation factor -0.1716 | W-ordered algorithm has multiplicative approximation factor as 1 and additive approximation factor 0.6931 |

- W-ordered algorithm decreases consideration set very small due to high weights products. This causes consumer not to have huge consideration set.

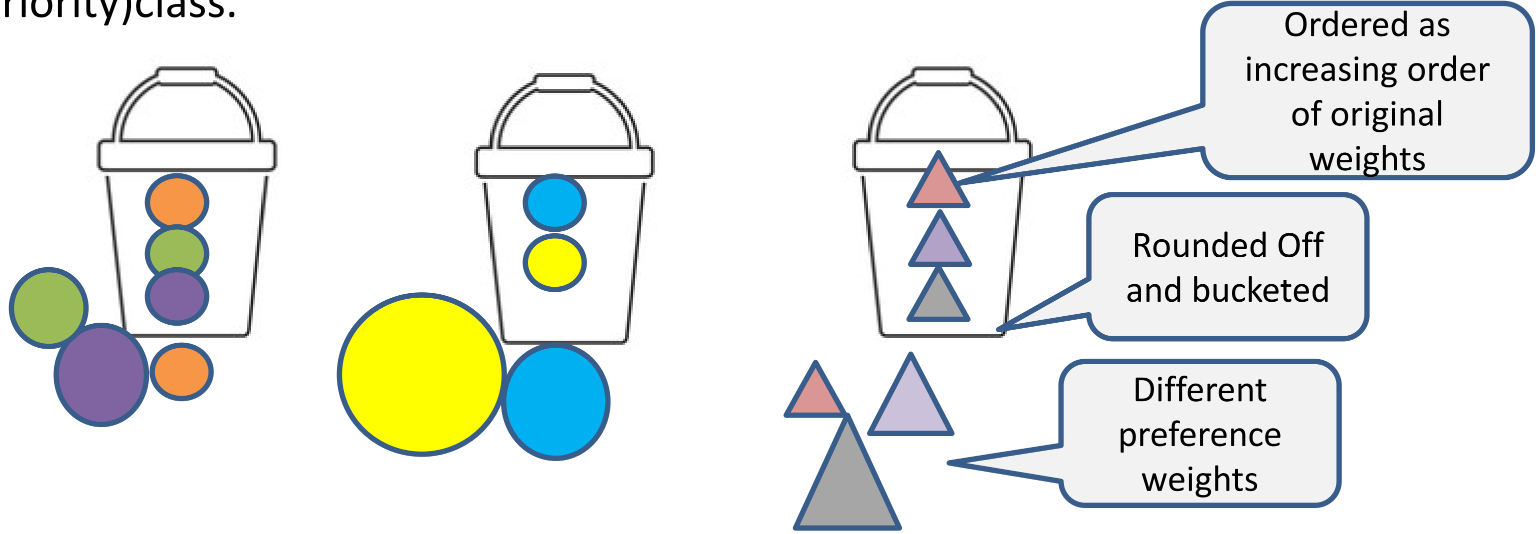
- But If any product preference weight is too much high consideration set is compact which results not good welfare.

# Contribution

## Product Ranking

### PTAS Algorithm

- We needed to put some medium weight product along with high weight products to balance the welfare. PTAS (Polynomial Time Approximation Scheme) algorithm ensures this by two stages.
- **Stage 1 –Rounding Weights:** we take all preference weights and round them to some predefined values called Buckets.
- **Stage 2 – DP based Algorithm** : Now different weights are accumulated to bucket, In that bucket if you selecting a product its original weight should be low as compared to all other product original weights in same buckets. This type of ordering called LWS (Low-weight-priority)class.



# Contribution

## Product Ranking

PTAS Algorithm : **Market Share Maximization**

- Consumer type distribution we will assume search costs $s_j^k \geq s_j^{k+1}$ , this will essentially lead us to if consumer of type $k$ not stops screening consumer of type $k' > k$ will not stop screening.
- We will award consumers who stops at position j and purchase product with reward $Rw$ then Profit that market make .

$$\frac{Rw_{\mathbb{B}}+Rw_b}{1+Rw_{\mathbb{B}}+Rw_b}\sum_{\tilde{k}=k}^{k'-1}\theta^{\tilde{k}} \qquad k' = min\left\{k \in [k, K] : w_{b(min)} + \sum_{l=1}^{j-1} w_l \leq r_{j+1}^k\right\}$$

- We can write market welfare as recursive equation as

$$W_j(S) = \max_{b\in[B]}\left\{W_{j+1}(S') + \frac{Rw_{\mathbb{B}}+Rw_b}{1+Rw_{\mathbb{B}}+Rw_b}\sum_{\tilde{k}=k}^{k'-1}\theta^{\tilde{k}}\right\}$$

- We can now pick bucket which maximizes the above share for each position, that permutation eventually leads us to Market share maximization.

$$b^* = arg\max_{b\in[B]}\left\{W_{j+1}(S') + \frac{Rw_{\mathbb{B}}+Rw_b}{1+Rw_{\mathbb{B}}+Rw_b}\sum_{\tilde{k}=k}^{k'-1}\theta^{\tilde{k}}\right\}$$

# Contribution

## Product Ranking

### PTAS Algorithm : Consumer Welfare Maximization

- This maximization simply done by algorithm considers first M products according to consumer then Applies same PTAS algorithm explained above to M products. Remaining products are ordered with decreasing weights order.
- This essentially preserve consideration set is balanced as possible.

| Market share Maximization | Consumer Welfare Maximization |
|---|---|
| **Algorithm**<br>**initialise** Buckets, Round products weights and put sorted weights (LWS) order in buckets<br>**while** $j$ not equals $n$<br>**Find** $b^* = arg \max_{b \in [B]} \left\{ W_{j+1}(S') + \frac{Rw_{\mathbb{B}} + Rw_b}{1 + Rw_{\mathbb{B}} + Rw_b} \sum_{\bar{k}=k}^{k'-1} \theta^{\bar{k}} \right\}$<br>**Fill position** $j$ **with** $\min\{w_i \in b^*\}$ **product**<br>**k** $\leftarrow$ **k';**<br>**Update** $Rw_{\mathbb{B}}, Rw_b$;<br>**j** $\leftarrow$ **j+1;**<br>**Stop** | **Algorithm**<br>**initialise** $M = \frac{\rho}{\epsilon}$ $\rho = \frac{w_{max}}{w_{min}}$ $j = 0$<br>**while** $j \leq M$<br>**obtain Ordered set** $S$ **and places** $i^{th}$ **element of ordered set in** $i^{th}$ **position.**<br>**j** $\leftarrow$ **j+1;**<br>**Stop**<br>**while** $M < j \leq n$<br>**put** $i^{th}$ **highest weight product in** $n - M$ **product in** $i^{th}$ **position.**<br>**j** $\leftarrow$ **j+1;**<br>**Stop** |

# Conclusion

## Conclusion

- This above procedure to solve our two specified objectives indeed, effectively and PTAS has given results as Very good approximation algorithms to proposed Consumer Optimal index-based search policy.
- The team has done practical implementation of this algorithm to bench mark this algorithm with existing algorithm and showed 5% increase comparably with existing ones.

## Extension Work Tried

Upon Extensive Literature survey I am mentioning two ideas which I think of good.

1. One particular Paper by Negin Golrezei Robust Algorithm to fake users[2]. This idea of making model robust to fake users made me think of Making our model to robust to preference weights. Because preference weights are more fluctuating numbers in any online platform. Above idea makes if preference weights are fake model still robust to this algorithm and maximize market, Consumer share.
2. Another idea I have got is to what if consumer searching for multiple products how we can extend this to multiple products.

# References

[1] Mahsa Derakhshan., Negin Golrezaei,. Vahideh Manshadi., & Vahab Mirrokni Product ranking on online platforms,SSRN 3130378. pp. 609–616. Cambridge, MA: MIT Press

[2]Negin Golrezaei, Vahideh Manshadi, Jon Schneider, Shreyas Sekar Learning Product Rankings Robust to Fake Users arXiv:2009.05138 (2020)