



Food Discovery with Uber Eats:

Holistic Multi-Objective Optimization for the Marketplace



Yuyan Wang, 08/26/2019



Uber Mission:

**Transportation as
reliable as running
water, everywhere for
everyone.**

Uber Eats Mission:

**Make eating well
effortless at any time,
for anyone.**

Number of decisions a person makes in an average day:

35,000

Where to eat?



Ranking and recommendation: We are not alone

Recommending a job

Recommending a video / song

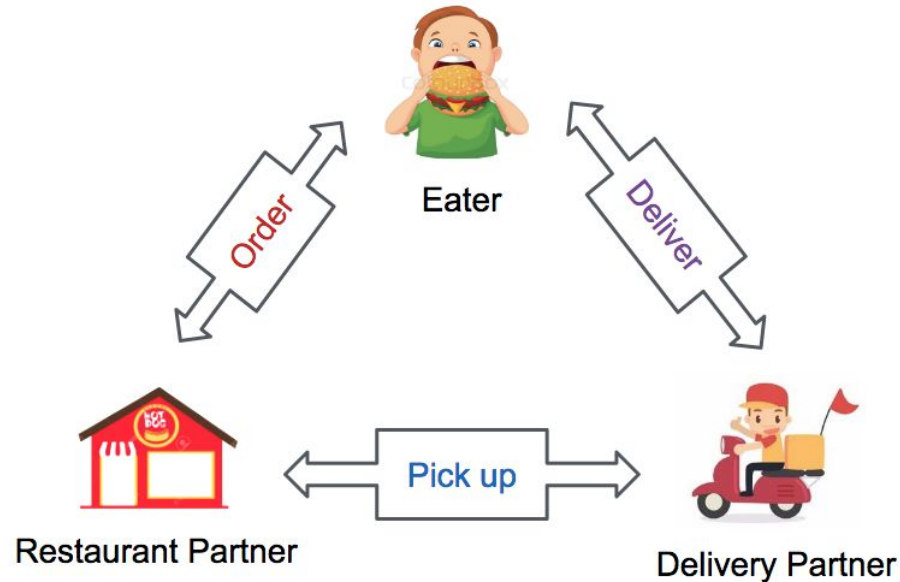
Recommending a product

Recommending news / tweet

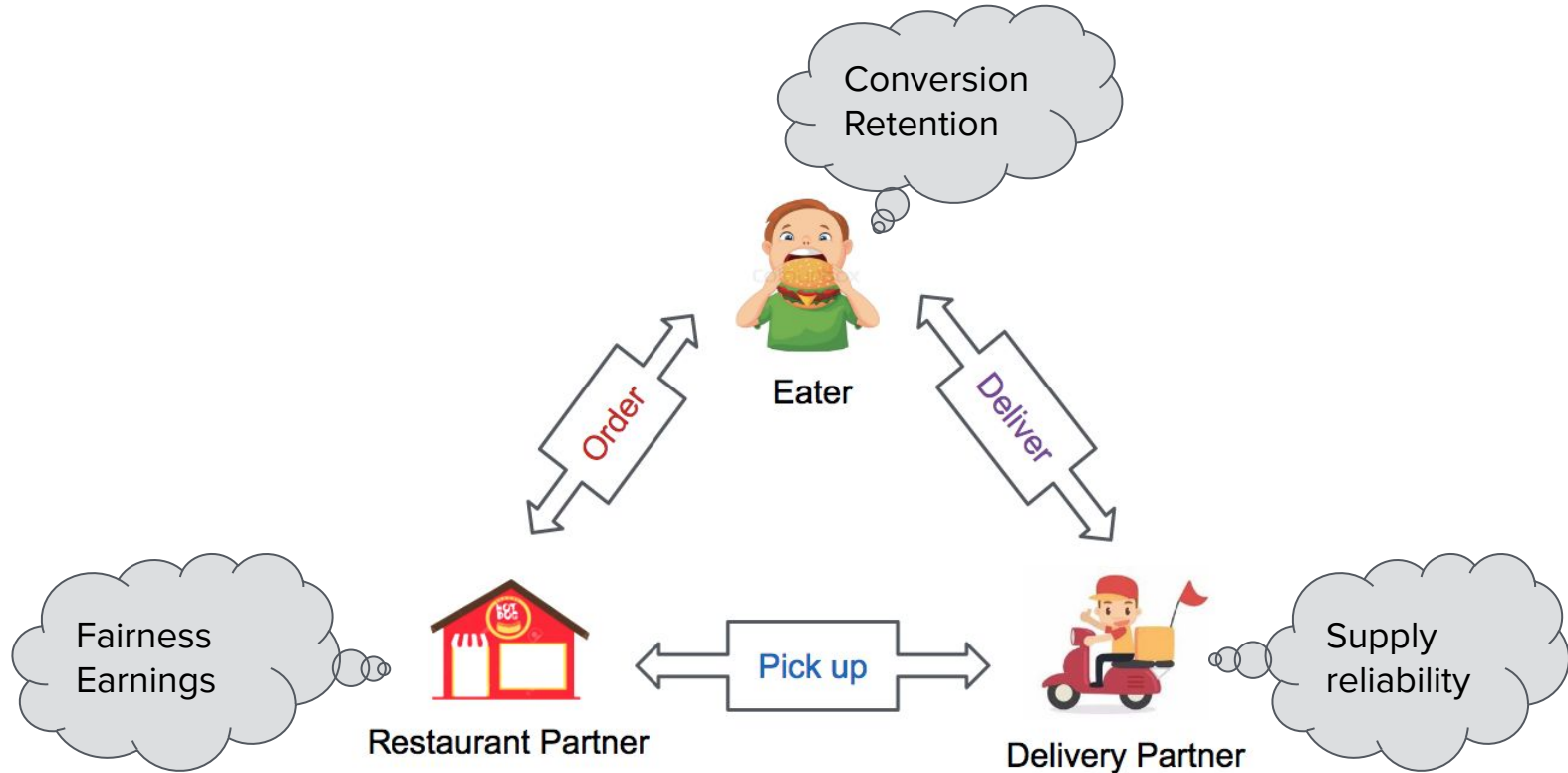
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Ranking and recommendation: We are unique

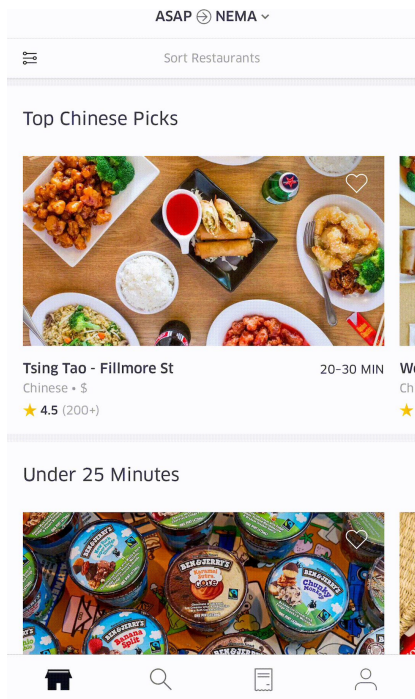
3-sided marketplace



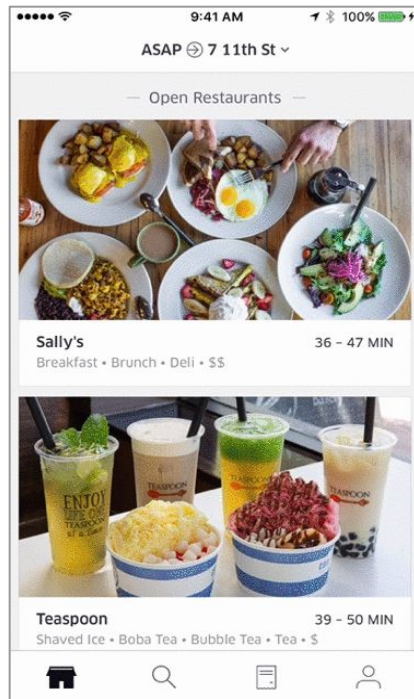
Ranking and recommendation: We are unique



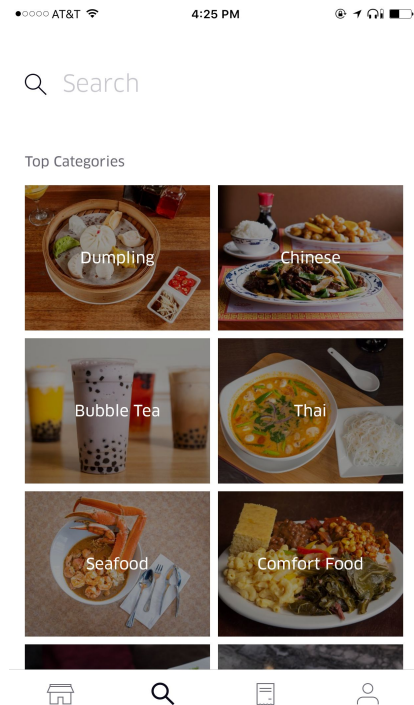
Another challenge: Heterogeneous & hierarchical content



Row Ranking



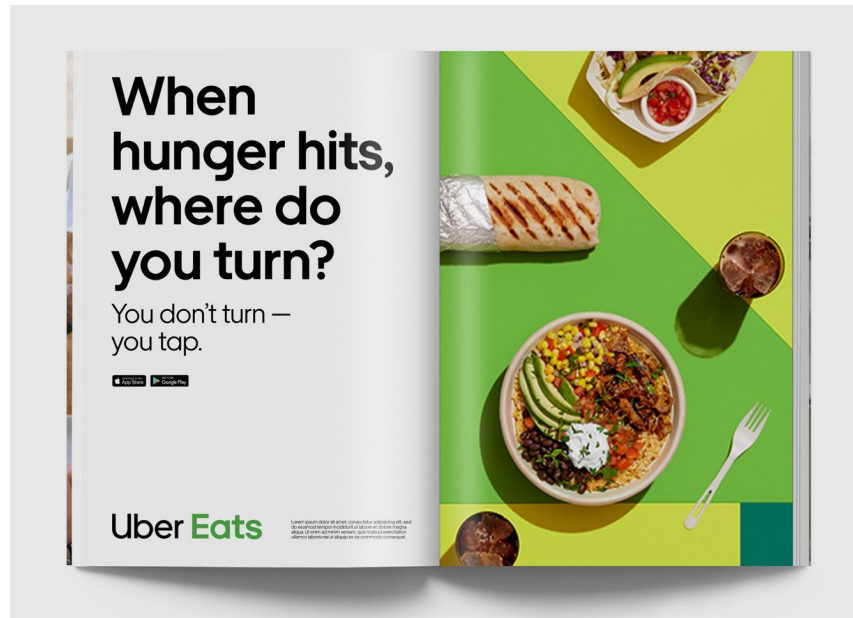
Vertical Ranking



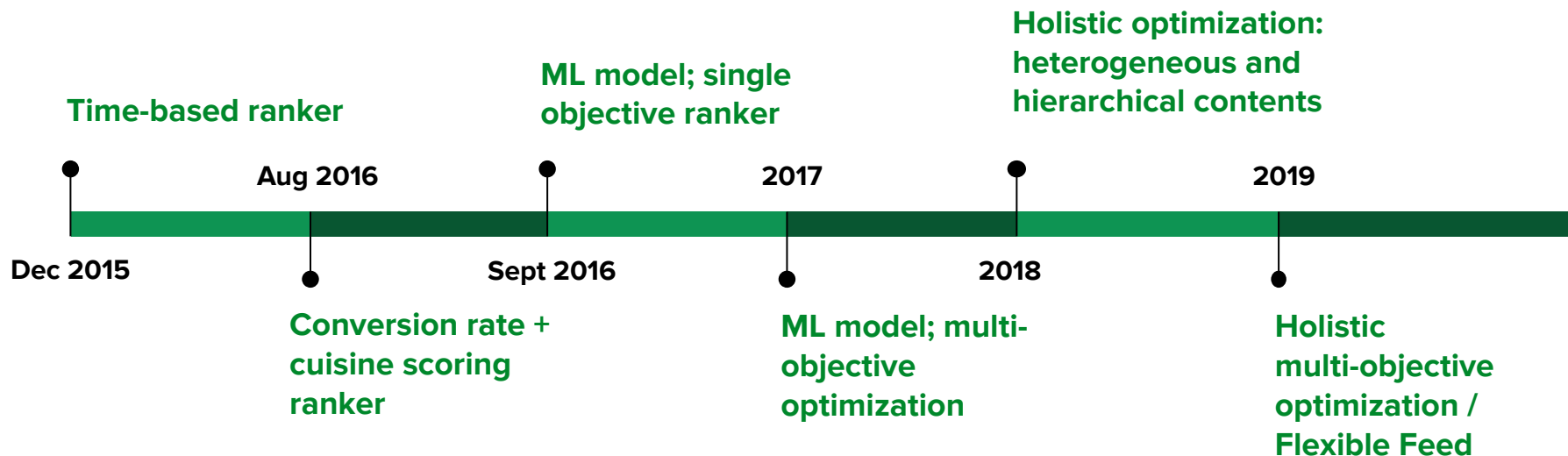
Search

Outline

- The Journey of Ranking
- Multi-Objective Optimization (MOO)
- Holistic optimization: Heterogeneous and hierarchical Content
- Ongoing efforts



The Journey of Ranking



Single Objective Ranking

- **Real-time**
 - For every *(eater, store)* pair
- **ML-based Prediction**
 - Impression level conversion rate
- **Personalized**
 - Important features: Collaborative filtering
- **ML model**
 - GBDT, XGBoost

Multi-objective Optimization (MOO)



Single objective:

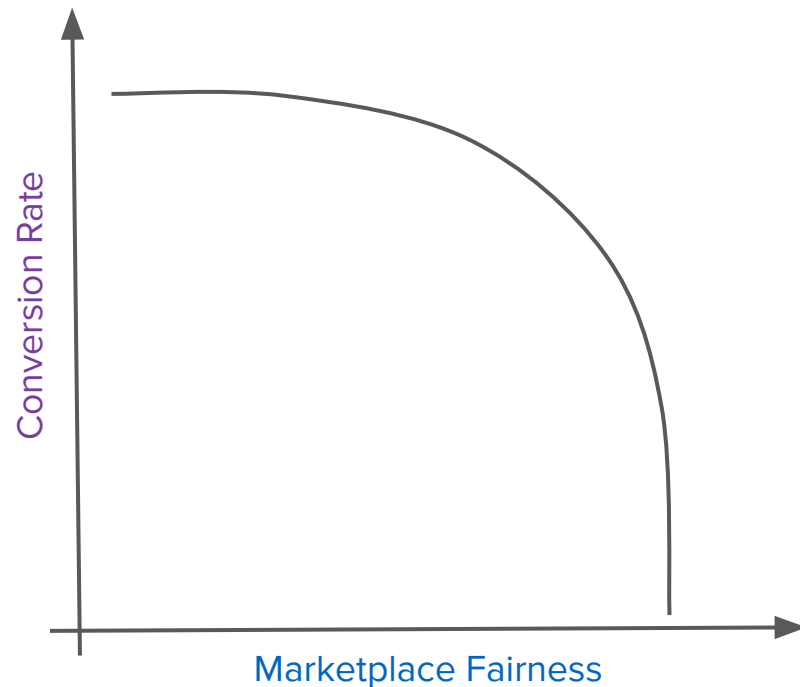
- Eater conversion

Multiple objectives:

- Eater conversion
- Restaurant earnings
- Delivery partner supply reliability
- ...

MOO: Ranking to Serve the Marketplace

- Conventional ML model
 - Single objective: eater
 - GBDT, XGBoost
- **Multi-objective Optimization:**
 - Multiple objectives:
eater / restaurant / delivery partner
 - Tradeoff
 - Linear / Quadratic programming



MOO: Building a Fair Marketplace

MOO: Building a Fair Marketplace



vs.



Well-established Restaurants

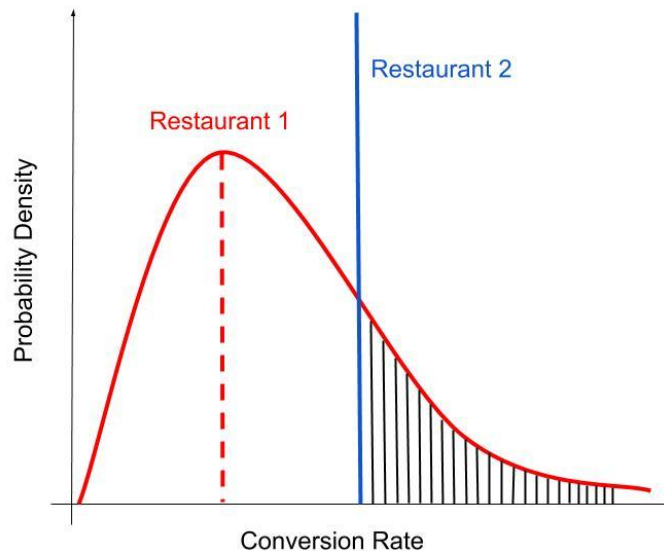
New/Low-volume Restaurants

Explore-Exploit with Multi-Armed Bandit

- Explore/exploit **tradeoff**
 - Exploit: restaurants with high predicted conv
 - Explore: new / low-volume restaurants

Explore-Exploit with Multi-Armed Bandit

- Explore/exploit **tradeoff**
 - Exploit: restaurants with high predicted conv
 - Explore: new / low-volume restaurants
- Bayesian modeling for posterior variance
 - New / low volume restaurant - High var
 - Well-established restaurant - Low var
 - Beta-binomial distribution
- Multi-armed bandit
 - ML model to estimate the mode of conversion
 - Bandit algorithm for explore-exploit (UCB/Thompson sampling)



Relevance vs. Diversity

- What's wrong with ranking wrt relevance?
 - Overwhelming restaurants that are too similar to each other in a consecutive order
 - Recommendations should be both **accurate** and **diverse**

Ken Ken Ramen	20-30 MIN
Ramen · Japanese · \$\$	

Genki Ramen	25-35 MIN
Seafood · Japanese · \$\$	

Jika Ramen & Sushi	30-40 MIN
Sushi · Japanese · \$	

The Ramen Bar	35-45 MIN
Ramen · Japanese · Noodles · \$\$	

Uchiwa Ramen	40-50 MIN
Ramen · Japanese · \$\$	

Ramen Izakaya	35-45 MIN
Sushi · Japanese · \$\$	

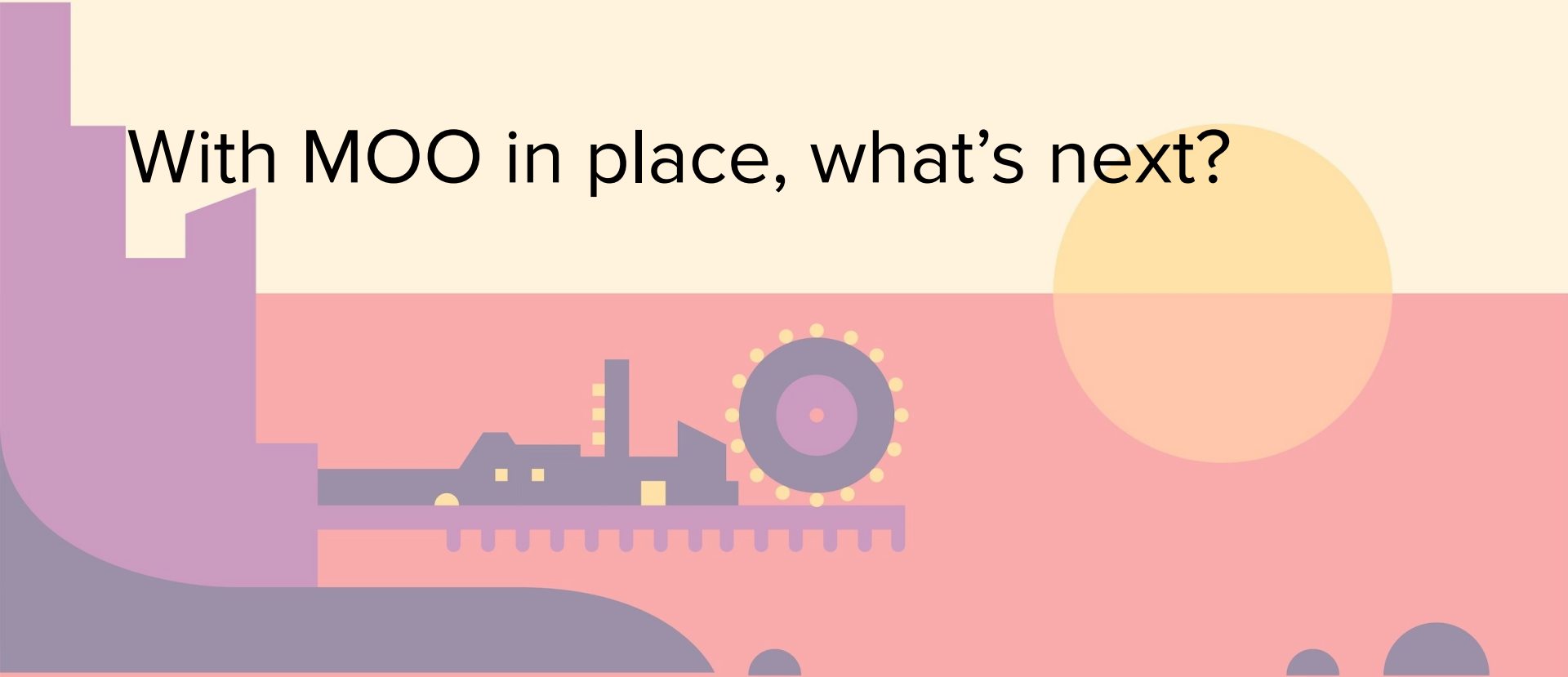
Ramen Doraku	30-40 MIN
Japanese · Ramen · \$\$	

Relevance vs. Diversity

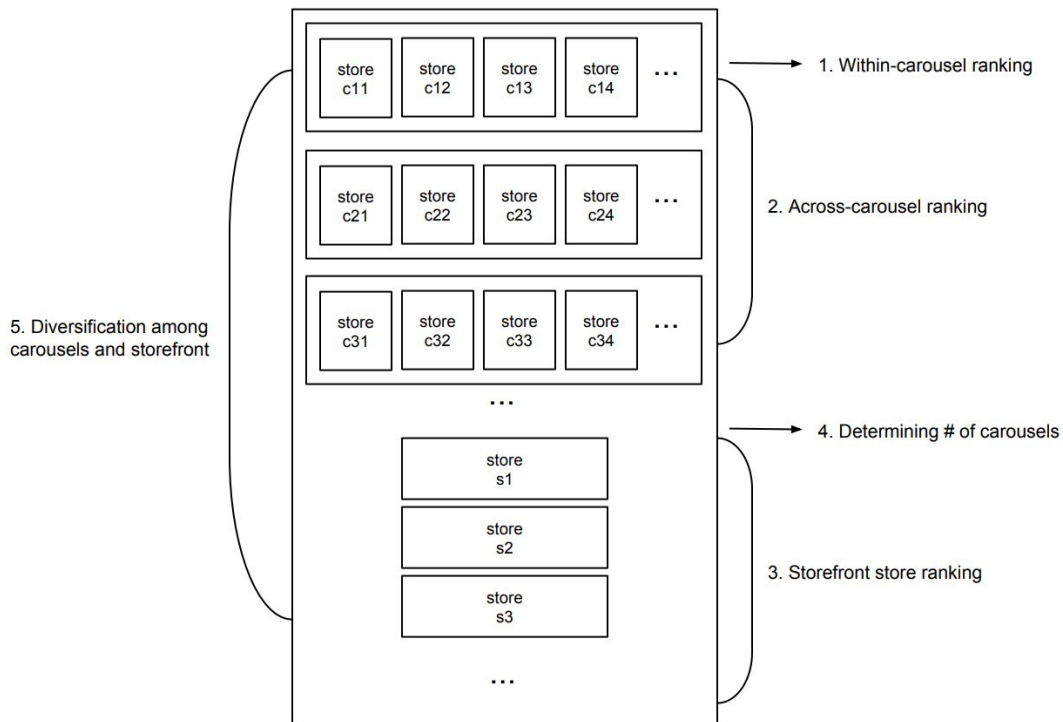
- What's wrong with ranking wrt relevance?
 - Overwhelming restaurants that are too similar to each other in a consecutive order
 - Recommendations should be both **accurate** and **diverse**
- **Personalized** diversification algorithm
 - Eater representation (taste profile)
 - Restaurant representation (cuisine profile)
 - Sequential/greedy optimization

Ken Ken Ramen	20-30 MIN
Ramen · Japanese · \$\$	
Genki Ramen	25-35 MIN
Seafood · Japanese · \$\$	
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Japanese · Ramen · \$\$	

With MOO in place, what's next?



HRank: Holistic optimization of heterogeneous and hierarchical contents



HRank: Methodology

- A personalized, holistic approach for optimal home feed layout
- Key model components / assumptions
 - Triplet model: (*eater*, *store*, *source*)
 - Scrolling discounting factor
 - User has limited patience
 - Within-row
 - Across-row

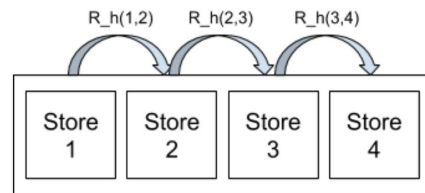


Figure 4: Horizontal impression discounting factor.

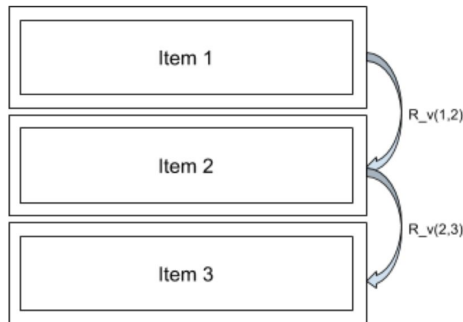


Figure 5: Vertical impression discounting factor.

HRank: Methodology

- A personalized, holistic approach for optimal home feed layout
- Key model components / assumptions
 - Triplet model: (*eater*, *store*, *source*)
 - Scrolling discounting factor
 - User has limited patience
 - Within-row
 - Across-row
 - **Law of total probability:**
Holistically optimize for **session-level** conversion
(as opposed to **impression-level** conversion)

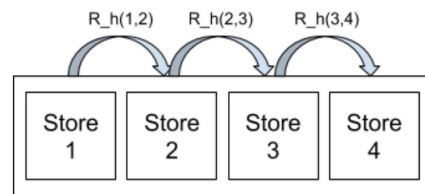


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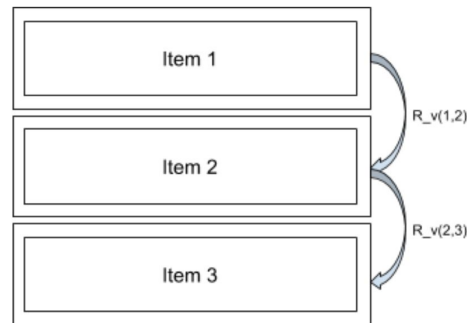


Figure 5: Vertical impression discounting factor.

$$P(O_{ic} = 1) = p_1 + (1 - p_1) \underline{R_h(1,2)} p_2 + (1 - p_1)(1 - p_2) \underline{R_h(1,3)} p_3 + \dots + (1 - p_1) \cdots (1 - p_{N-1}) \underline{R_h(1,N)} p_N.$$

Ongoing efforts: Holistic Multi-Objective Optimization

- Challenge 1: Heterogeneous & Hierarchical Contents

=> Need a holistic optimization and recommendation framework



HRank



- Challenge 2: Three-sided marketplace
=> Trade-off among different objectives

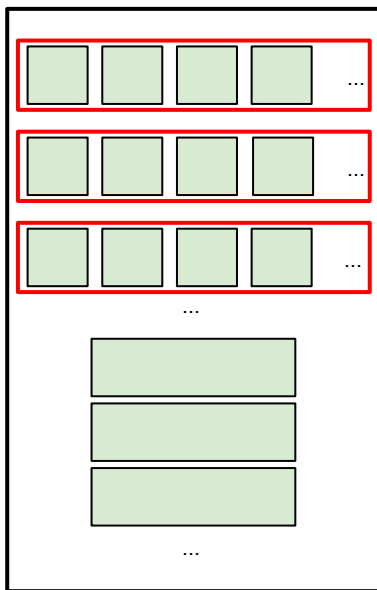


MOO



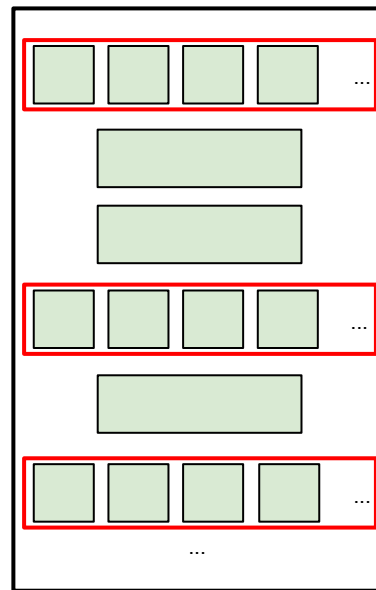
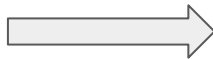
HMOO

Flexible Feed: Unlocking more potential for HMOO



Constrained
Optimization

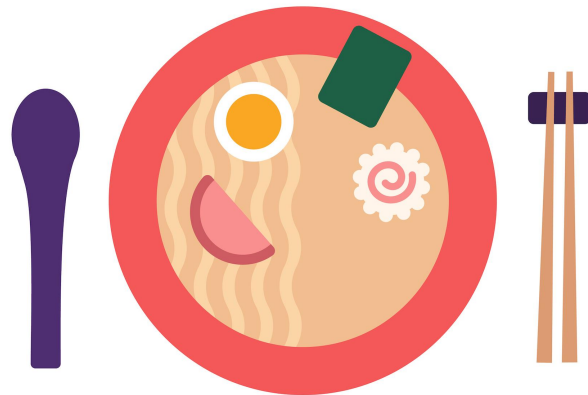
HMOO
+
Flexible
Feed



Unconstrained
Optimization

Summary

- The Journey of Ranking
- Multi-Objective Optimization (MOO)
 - Building a Fair Marketplace
 - Relevance vs. Diversity
- Holistic Optimization
- Riders-to-Eaters
 - Using rider history to solve cold start problem for new eaters
- Dish recommendation



Thank you.

Uber **Eats**

Appendix

MOO: Multi-Objective Optimization

- Formulation

- Expected total # of orders:

$$T(X) = \sum_i \sum_j x_{ij} p_{ij}$$

- Expected total gross booking fee:

$$G(X) = \sum_i \sum_j x_{ij} p_{ij} g_j$$

- Linear programming (LP):

$$\begin{aligned} & \max_X G(X) \\ & s.t. \ T(X) \geq \alpha \cdot T(X^*) \\ & \quad x_{ij} \geq 0, \forall i, j \\ & \quad \sum_j x_{ij} = 1, \forall i \end{aligned}$$

Notation	Meaning
i	Indexes users
j	Indexes stores (restaurants)
$X = \{x_{ij}\}$	Serving plan (variable to be optimized)
x_{ij}	Probability that the serving scheme will recommend j th store to user i
$Q = \{q_{ij}\}$	Uniform serving plan with $q_{ij} = \frac{1}{J}$, where J is the total number of open stores.
p_{ij}	Estimated conversion rate of user i on store j
g_j	Estimated gross booking fee for store j (can be personalized as g_{ij})

A **huge** linear programming problem
-> scalability issue!

MOO: Multi-Objective Optimization

- LP \Rightarrow QP (quadratic programming):

$$\begin{aligned} \max_X & G(X) \\ \text{s.t. } & T(X) \geq \alpha \cdot T(X^*) \\ & x_{ij} \geq 0, \forall i, j \\ & \sum_j x_{ij} = 1, \forall i \end{aligned}$$



$$\begin{aligned} \max_X & G(X) - \frac{1}{2}\gamma \|X - Q\|^2 \\ \text{s.t. } & T(X) \geq \alpha \cdot T(X^*) \\ & x_{ij} \geq 0, \forall i, j \\ & \sum_j x_{ij} = 1, \forall i \end{aligned}$$

Lagrangian Multiplier
 \Rightarrow
KKT condition

$$x_{ij} = \text{const} + \frac{1}{c \cdot \gamma} \cdot p_{ij} \cdot (1 + \lambda_g \cdot g_j), \text{ if } x_{ij} > 0$$

Notation	Meaning
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Personalized Diversification

- Captures individual's cuisine and diversity preference.

Algorithm 1 IA-SELECT

Input $k, q, C(q), R(q), C(d), P(c|q), V(d|q, c)$

Output set of documents S

```
1:  $S = \emptyset$ 
2:  $\forall c, U(c|q, S) = P(c|q)$ 
3: while  $|S| < k$  do
4:   for  $d \in R(q)$  do
5:      $g(d|q, c, S) \leftarrow \sum_{c \in C(d)} U(c|q, S) V(d|q, c)$ 
6:   end for
7:    $d^* \leftarrow \operatorname{argmax} g(d|q, c, S)$  [ties broken arbitrarily]
8:    $S \leftarrow S \cup \{d^*\}$ 
9:    $\forall c \in C(d^*), U(c|q, S) = (1 - V(d^*|q, c)) U(c|q, S \setminus \{d^*\})$ 
10:   $R(q) \leftarrow R(q) \setminus \{d^*\}$ 
11: end while
12: return  $S$ 
```

Prob(user will order from store |
user will not order from all
previous recommended stores)

Prob(user will order from cuisine |
user will not order from all
previous recommended stores)

HRank: Methodology

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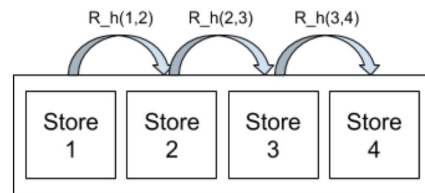


Figure 4: Horizontal impression discounting factor.

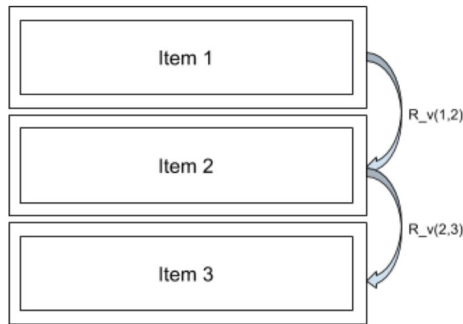


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HMOO: Overview

- Challenges
 - MOO only applies to 1-dim world
 - Current world is **2-dim** with heterogeneous & hierarchical contents
- Soln: 2-step procedure
 - 2-dim => 1-dim
 - Define MOO objective on item (restaurant/carousel) level
 - Apply 1-dim MOO
- Goal
 - A personalized, *holistic* home feed that is optimized for all sides of the marketplace
 - HRank: holistic optimization of eater conversion
 - HMOO: holistic optimization of marketplace objectives (e.g. gross bookings)

HMOO: Methodology

- Expanding the HRank framework
 - Law of total probability => HRank
 - Law of total expectation => HMOO

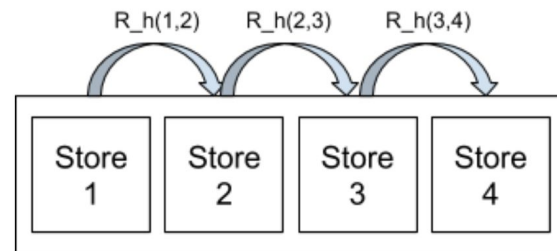


Figure 4: Horizontal impression discounting factor.

$$E[B_{ic}] = E[B_{ic} \mid O_{ic} = 1]P(O_{ic} = 1) + E[B_{ic} \mid O_{ic} = 0]P(O_{ic} = 0).$$

↑
Expected \$ from a
carousel

↑
Conversion rate of
the carousel

HMOO: Methodology

- Expanding the HRank framework
 - Law of total probability => HRank
 - Law of total expectation => HMOO

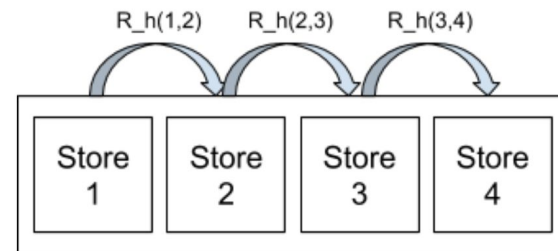


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$$E[B_{ic}] = E[B_{ic} | O_{ic} = 1]P(O_{ic} = 1) + E[B_{ic} | O_{ic} = 0]P(O_{ic} = 0).$$

Diagram illustrating the components of the equation:

- $E[B_{ic}]$: Expected \$ from a carousel (By Law of total expectation)
- $E[B_{ic} | O_{ic} = 1]$: HMOO score of the carousel (indicated by a blue box and arrow)
- $P(O_{ic} = 1)$: Conversion rate of the carousel (HRank)

A blue diagonal line is drawn across the equation.

- Readily applies to **other objectives / multiple objectives**

Basket size objective for carousels

- Law of total expectation:

$$E[B_{ic}] = E[B_{ic} \mid O_{ic} = 1]P(O_{ic} = 1) + E[B_{ic} \mid O_{ic} = 0]P(O_{ic} = 0).$$

$$E[B_{ic}] = p_1 b_1 + (1 - p_1)R_h(1,2)p_2 b_2 + (1 - p_1)(1 - p_2)R_h(1,3)p_3 b_3 + \dots + (1 - p_1) \dots (1 - p_{N-1})R_h(1,N)p_N b_N.$$

$$P(O_{ic} = 1) = p_1 + (1 - p_1)R_h(1,2)p_2 + (1 - p_1)(1 - p_2)R_h(1,3)p_3 + \dots + (1 - p_1) \dots (1 - p_{N-1})R_h(1,N)p_N.$$

- Putting everything together

$$E[B_{ic} \mid O_{ic} = 1] = \frac{p_1 b_1 + (1 - p_1)R_h(1,2)p_2 b_2 + (1 - p_1)(1 - p_2)R_h(1,3)p_3 b_3 + \dots + (1 - p_1) \dots (1 - p_{N-1})R_h(1,N)p_N b_N}{p_1 + (1 - p_1)R_h(1,2)p_2 + (1 - p_1)(1 - p_2)R_h(1,3)p_3 + \dots + (1 - p_1) \dots (1 - p_{N-1})R_h(1,N)p_N}$$

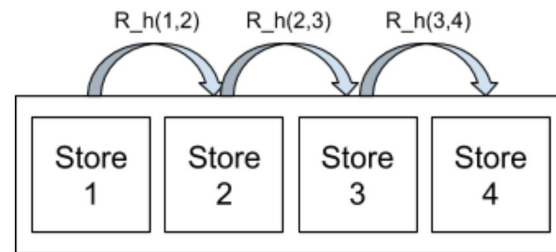


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