Food Discovery with Uber Eats:

Holistic Multi-Objective Optimization for the Marketplace

Uber | Yuyan Wang, 06/24/2019

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?


Jersey Mike's Subs
Yalla Mediterranean
Quickly
Kasa Indian Eatery - Castro
Pizzelle di North Beach
Saffron 685
Alec's Pizza
Varun
Mealmade
Masala Dosa
Pista House
Spicy Bite
Octavia
DNA Pizza
Bistro SF Grill
Chaat Bhavan
Srasa Kitchen
Jiffy Dog
New York Pizza
Premier Pizza
Maykadeh
NEWA
Tacolicious
Sprig
Elmira
Oz Pizza
Pete's
Fritz
La Salsa
aa
Jane
ZeroCater
Melody Cafe
AG Ferrari
Kisu
DOSA
Futo
CAN CAN Cleanse
El Gran Taco Loco
Baiano Pizzeria
Tambo
Leo's Oyster Bar
Katani Pizza
New Emmy's Restaurant
Krispy Kreme (Pacific Commons
Nan Cafe
Cafe 15
Chatime
Sweet Woodruff
DUPE-Natty Cakes
Fat Angel
Grab 'N Go
Patxi's Hayes
Blue Iguana
MM:10
EVault
Hey Day
Lobster Me
Green Pea Cookie
Mom's Pozole
Sushinista
Chouquet's
The Grubbies
Nguyen Nguyen
Taqueria Vallarta - 24th Stree
Blessed Garden
77 Chinese Cuisine
El Sur
Athena Grill
JZ Inc
Orchids Thai
LeTea
Little Szechuan
Slava
Mohit
blah blah
Firenza Pizza
Redford
Bodega
JotMahal
karen's noodle
03 Bistro & Lounge
Bonchon - San Jose
INTELLIZ LLC
T4
On a Roll
Arroz Rojo
Sour Flour
Clover
Rita's of Pleasanton
abc xyz
Chim
Mi Casa
res175
Cheng's Restaurant
iSlice
Opa Cafe
Bubblecup
Green Straw
RIYA ENTERPRISES
Messob
Kyowa
hottei
Yogurtland
MM:6
Palmyra
Park Gyros Express
Dong Lai Shun
HIT
Shido
Raavi
Dim Sum King
Bona Pizza
Kyoto
Sheba Dining
Oro
Vitality Bowls - Dublin
BoDillaz Togo
Mangia Tutti
Kusina Ni Tess
Palo Alto Pizza Co.
Duy Le
Cologne
The Sycamore
Raw Sugar Factory
Tammy Thai
Toasty
Curry Boyzz
Starbird
Plaza Garibaldi
Frightcord
Slice Poke Bar
Bite
Matador
Varun's
Centonove
Le Petit Cochon
Varun' Kitchen
Pizza California
The Cavalier
Bravo House of Enchiladas
Pallo D'Asti
Xolo Taqueria
Tran Diner SF 1
Gonutz
Teaster
Samiia Thai Restaurant
TeaOne Berkeley
California Mochi
Julie's Cafe
Allan Food
Crepe La Vie
Panda Express (1050 El Camino
Bubble Bay Tea
Manila Bowl
Extreme Pizza - San Rafael
Mission Heirloom Cafe
Yanagi Sushi & Grill
Sunrise Deli
Shihlin 313 Orchard
Nick the Greek - Almaden
Swamp
Salsa Mexican Grill
McDonald's® (6623 San Pablo Av
Eddie Papa's American Hangout

Ranking and recommendation: We are not alone

Recommending a job

Recommending a video / song

Recommending a product

Recommending news / tweet

...

Ranking and recommendation: We are unique

3-sided marketplace

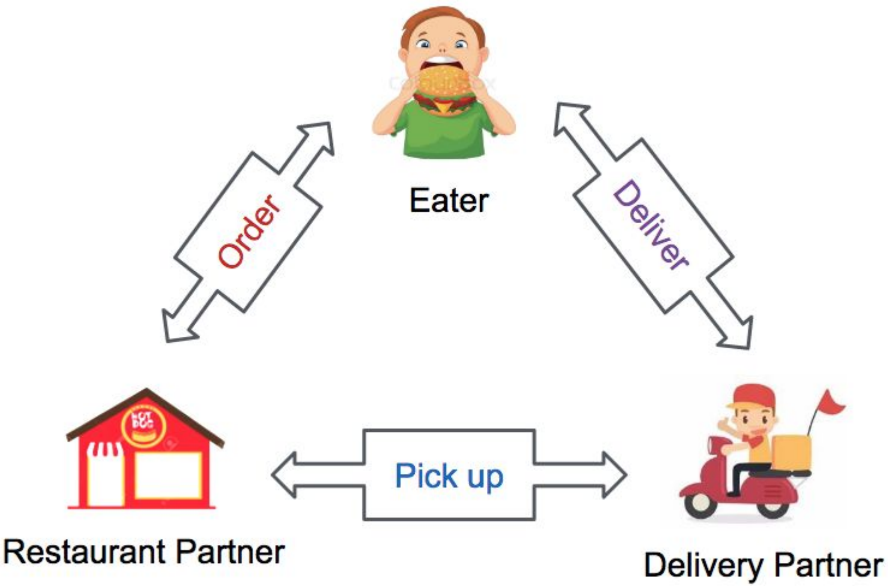
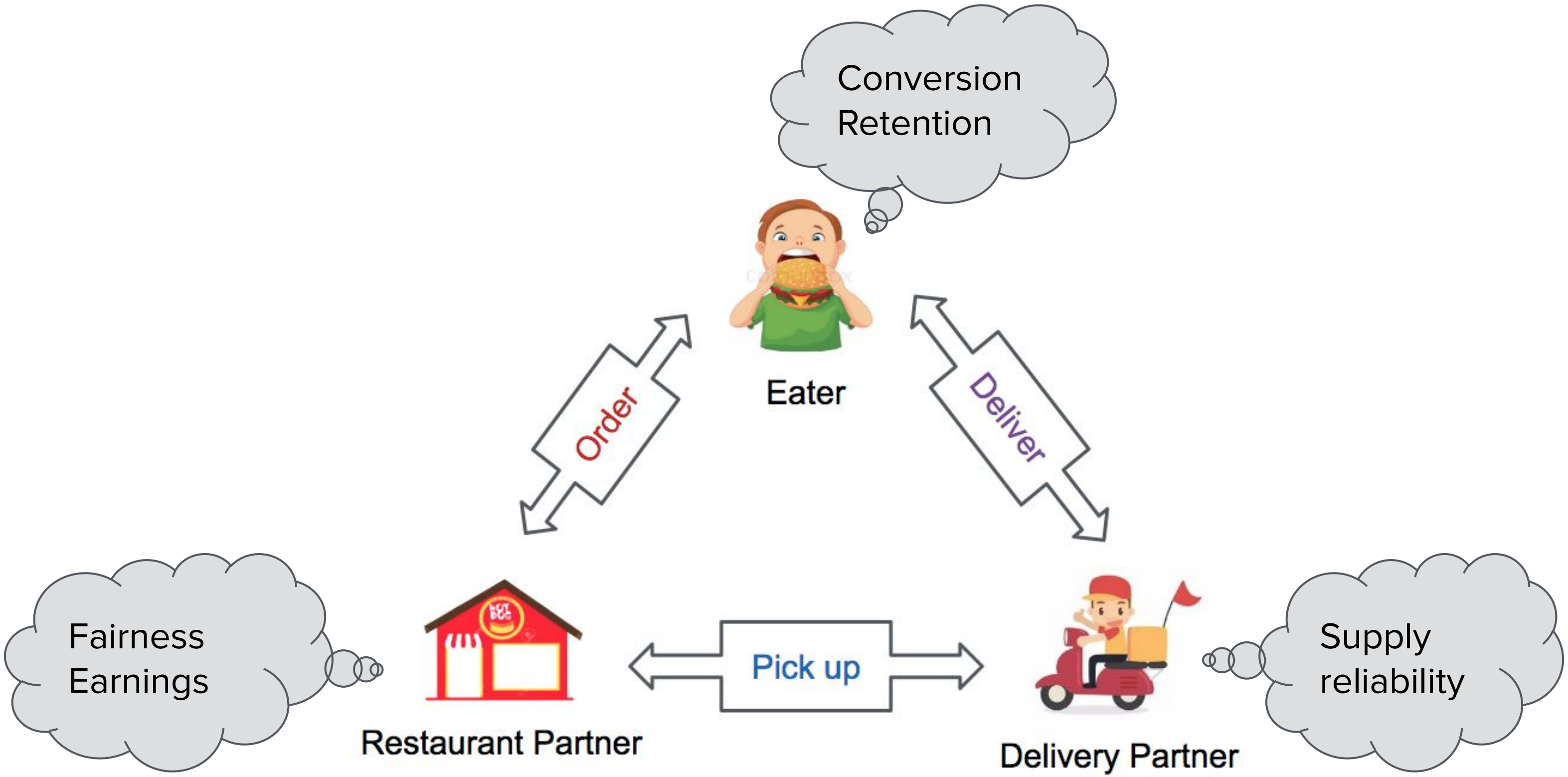


Image Source: https://www.shutterstock.com

Ranking and recommendation: We are unique



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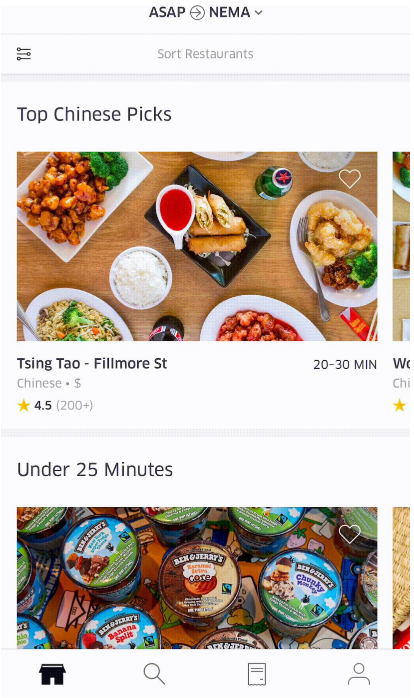
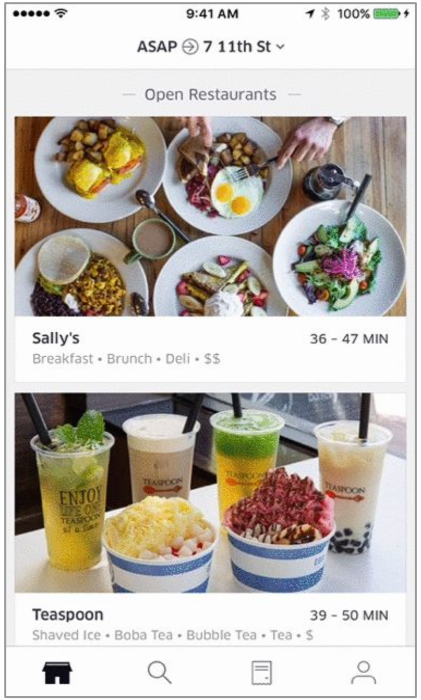
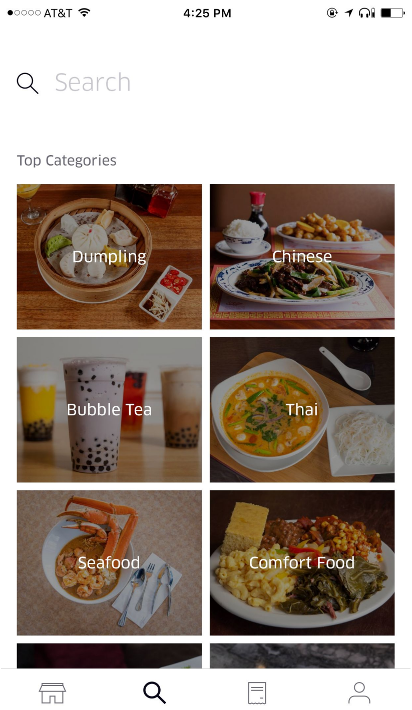
Another challenge: Heterogeneous & hierarchical content



Row Ranking



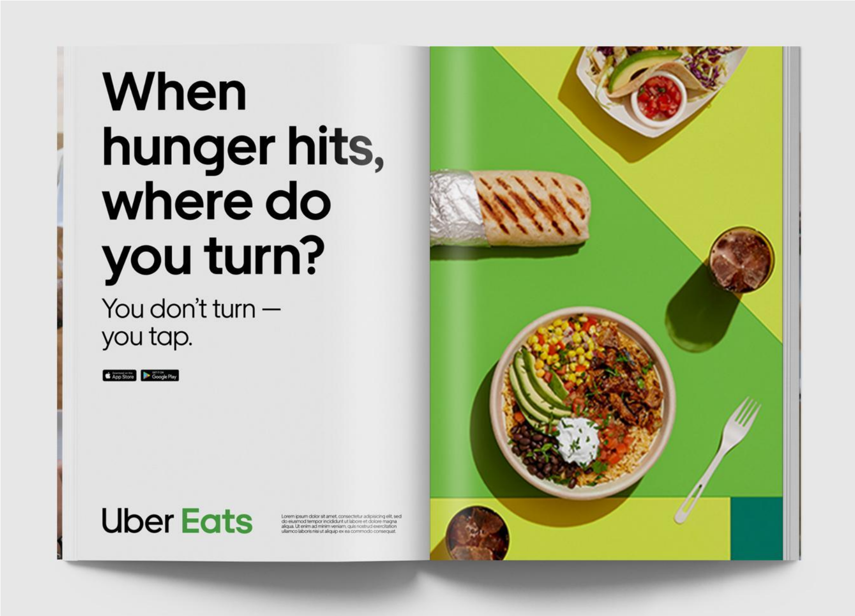
Vertical Ranking



Search

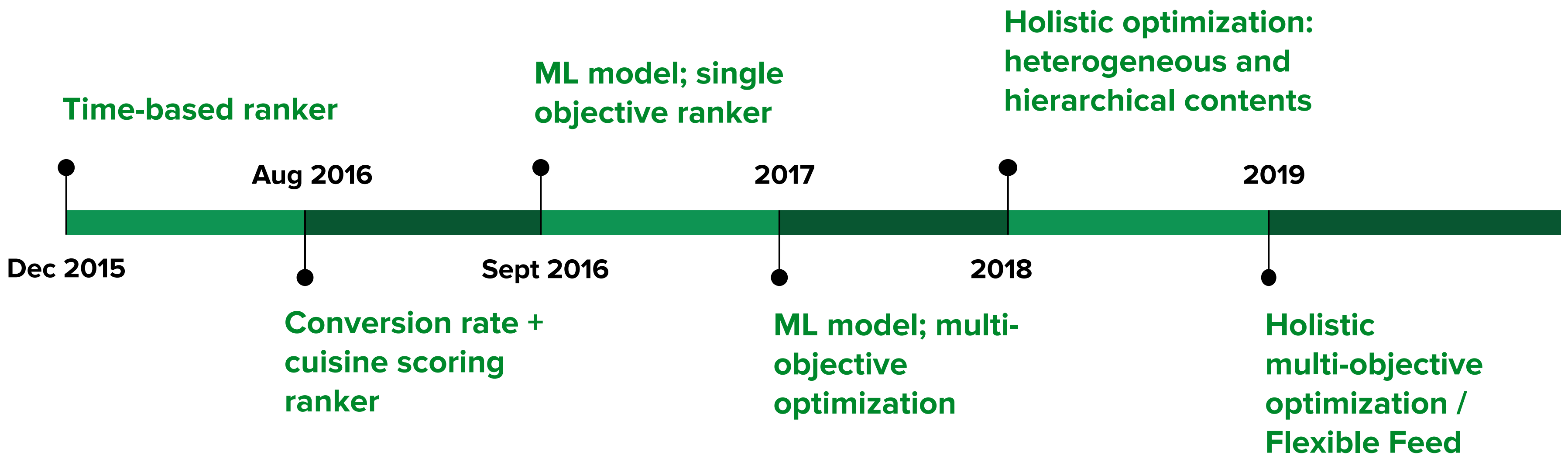
Outline

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



Uber Eats 优食 Uber Eats 優食 أوبر إيتس Uber Eats

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:

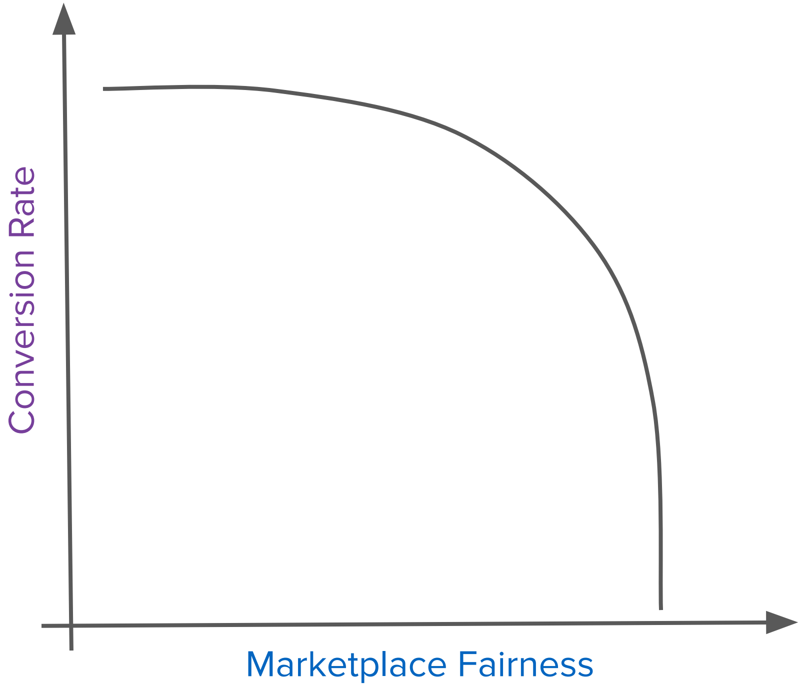
- Eater conversion
- Restaurant earnings
- Delivery partner supply reliability
- ...

Image Source: https://www.shutterstock.com

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

Image Source: https://thehalalguys.com/, http://www.istockphoto.com/

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

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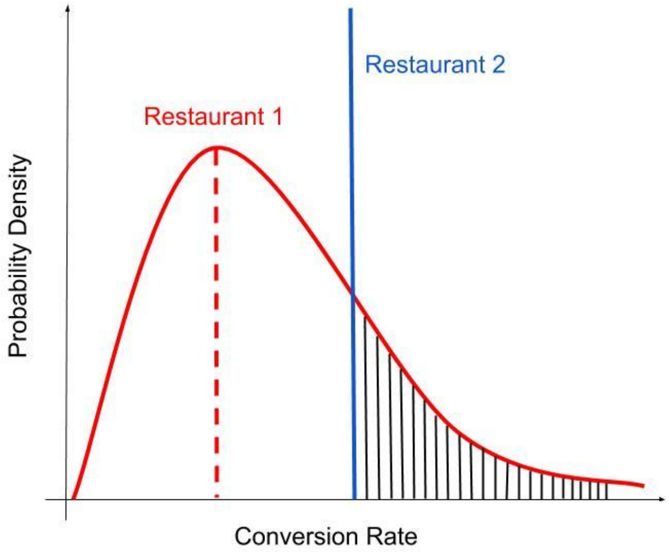
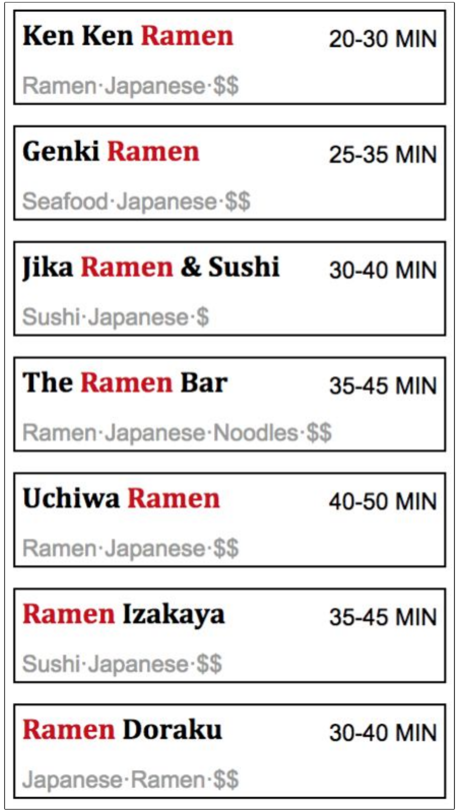
- Bayesian modeling for posterior variance
  - New / low volume restaurant - High var
  - Well-established restaurant - Low var
  - Beta-binomial distribution

- Multi-armed bandit
  - ML model to estimate the mode of conversion
  - Bandit algorithm for explore-exploit (UCB/Thompson sampling)



Relevance vs. Diversity

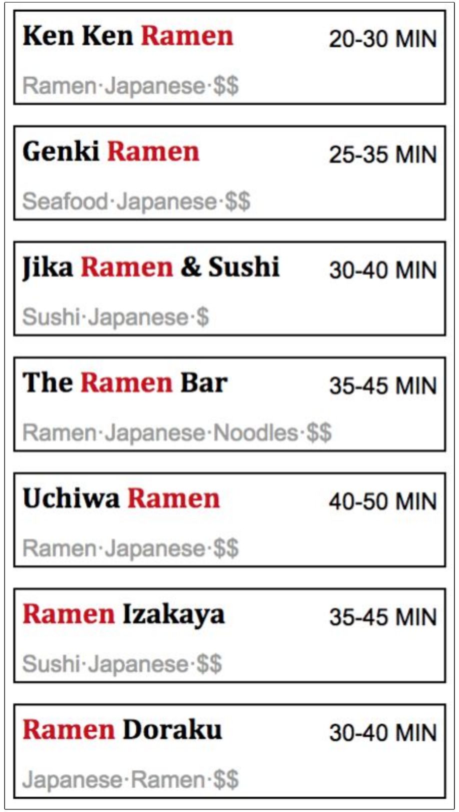
- What's wrong with ranking wrt relevance?
  - Overwhelming restaurants that are too similar to each other in a consecutive order
  - Recommendations should be both **accurate** and **diverse**



Relevance vs. Diversity

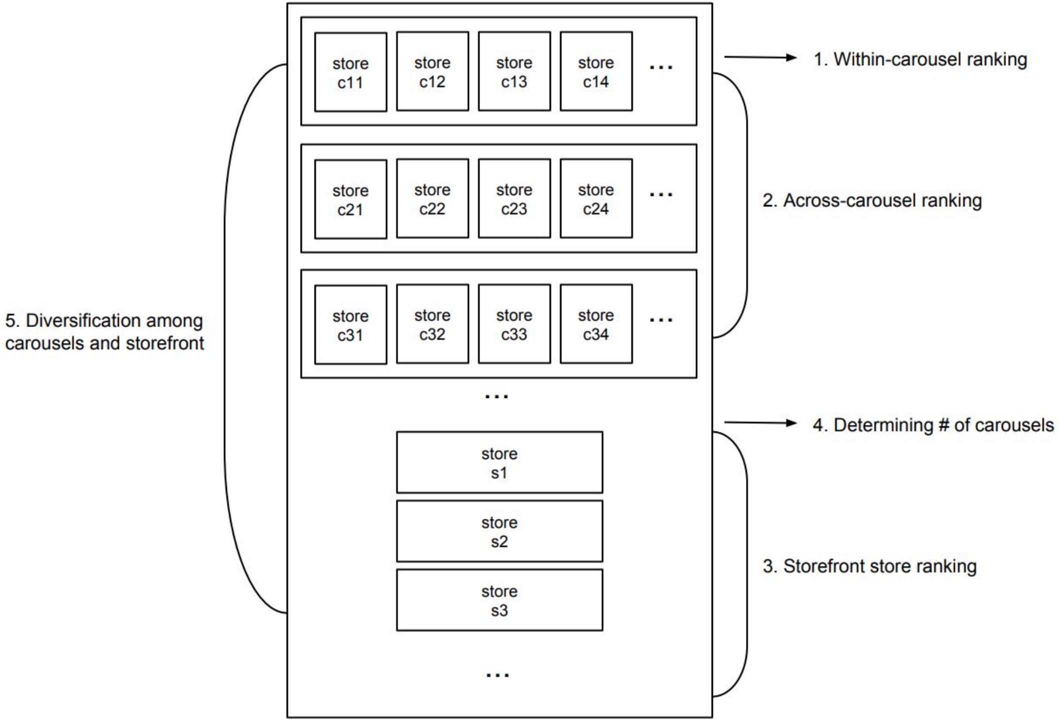
- What's wrong with ranking wrt relevance?
  - Overwhelming restaurants that are too similar to each other in a consecutive order
  - Recommendations should be both **accurate** and **diverse**

- Personalized diversification algorithm
  - Eater representation (taste profile)
  - Restaurant representation (cuisine profile)
  - Sequential/greedy optimization



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

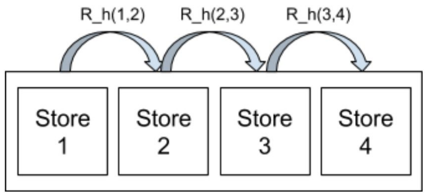


Figure 4: Horizontal impression discounting factor.

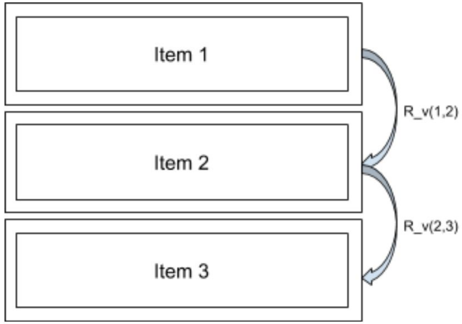


Figure 5: Vertical impression discounting factor.

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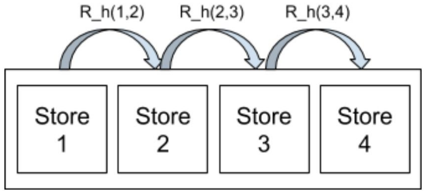
  - **Law of total probability**:
    Holistically optimize for **session-level** conversion
    (as opposed to **impression-level** conversion)



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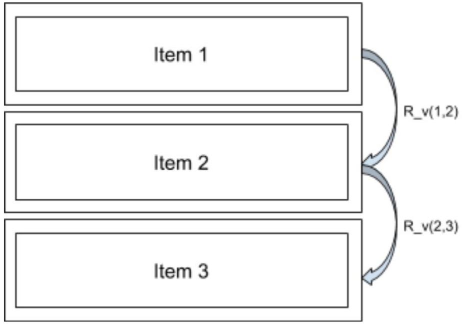


Figure 5: Vertical impression discounting factor.

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

Ongoing efforts: Holistic Multi-Objective Optimization

- Challenge 1: Heterogeneous & Hierarchical Contents

  => Need a holistic optimization and recommendation framework

- Challenge 2: Three-sided marketplace

  => Trade-off among different objectives

HRank

MOO

HMOO

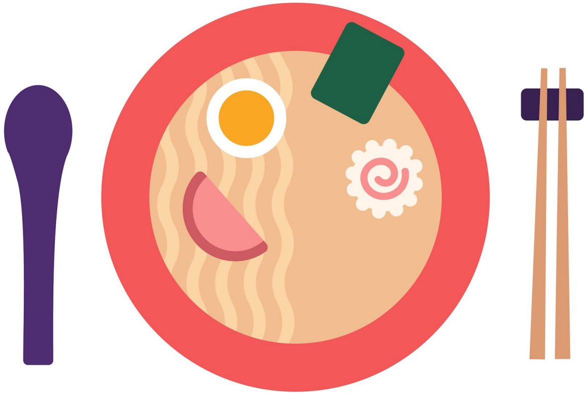
Flexible Feed: Unlocking more potential for HMOO

Constrained Optimization

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



Uber Eats 优食　Uber Eats 優食　أوبر إيتس Uber Eats

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):

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

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 => QP (quadratic programming):

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

$$\Downarrow$$

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

$$\xrightarrow[\text{KKT condition}]{\text{Lagrangian Multiplier}}$$

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

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Personalized Diversification

- Captures individual's cuisine and diversity preference.

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)

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

$S = \emptyset$
$\forall c, U(c|q,S) = P(c|q)$
while $|\mathrm{S}| < \mathrm{k}$ **do**
  for $d \in R(q)$ **do**
    $g(d|q,c,S) \leftarrow \sum_{c \in C(d)} U(c|q,S)V(d|q,c)$
  end for
  $d^* \leftarrow argmax\ g(d|q,c,S)$ [ties broken arbitrarily]
  $S \leftarrow S \cup \{d^*\}$
  $\forall c \in C(d^*), U(c|q,S) = (1 - V(d^*|q,c))U(c|q,S \setminus \{d^*\})$
  $R(q) \leftarrow R(q) \setminus \{d^*\}$
end while
return S

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  - Triplet model: ***(eater, store, source)***
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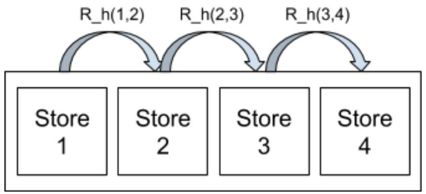
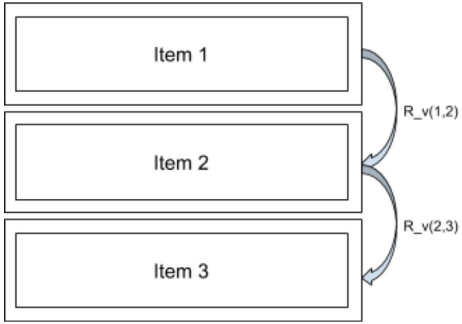


Figure 4: Horizontal impression discounting factor.



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

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

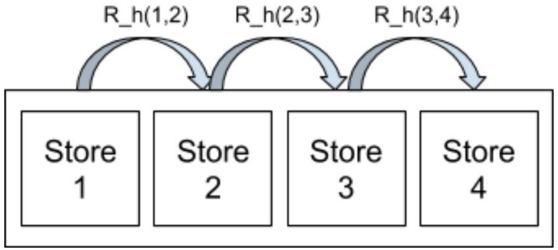


Figure 4: Horizontal impression discounting factor.

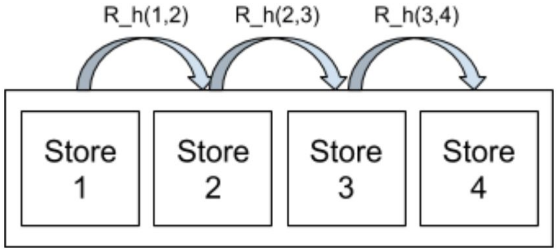
- Expanding the HRank framework
  - Law of total probability => HRank
  - Law of total expectation => HMOO

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

Expected $ from a carousel

Conversion rate of the carousel

HMOO: Methodology



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

$$E[B_{ic}] = \underbrace{E[B_{ic} \mid O_{ic} = 1]}_{\boxed{\text{HMOO score of the carousel}}} P(O_{ic} = 1) + \cancel{E[B_{ic} \mid O_{ic} = 0]P(O_{ic} = 0)}.$$

Expected $ from a carousel

By Law of total expectation

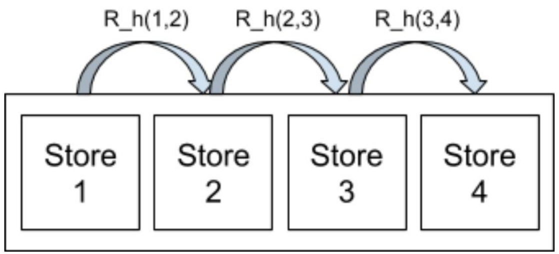
Conversion rate of the carousel

HRank

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

HMOO

Basket size objective for carousels



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- Law of total expectation:

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

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

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

- Putting everything together

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