Recommending for a Three-Sided Food Delivery Marketplace: A Multi-Objective Hierarchical Approach

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* Work done at Uber.

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Motivation

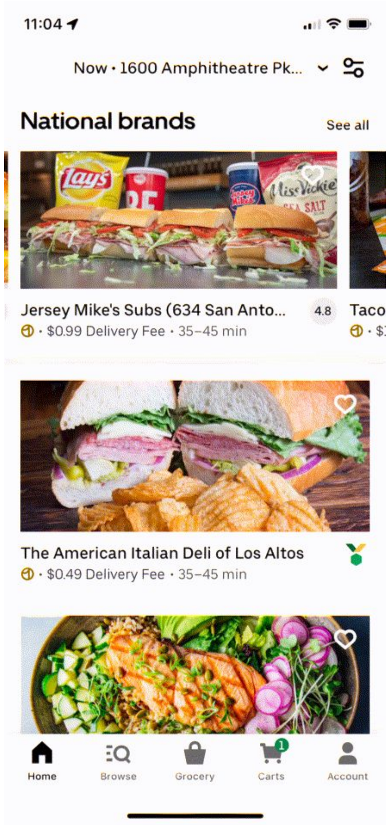
Recommending for a food-delivery marketplace

Recommender Systems

- Number of decisions an average person makes in average day: 35,000
- Recommender Systems (Recsys):
  - Facilitates information acquisition for the **users**
  - Helps user targeting for the **content providers**

... ...

Food Recommender Systems



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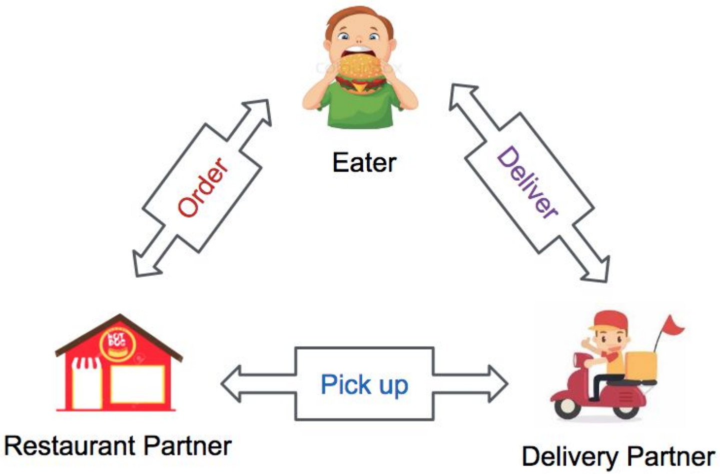
Challenge 1: Multi-sided trade-off

Three-sided marketplace...



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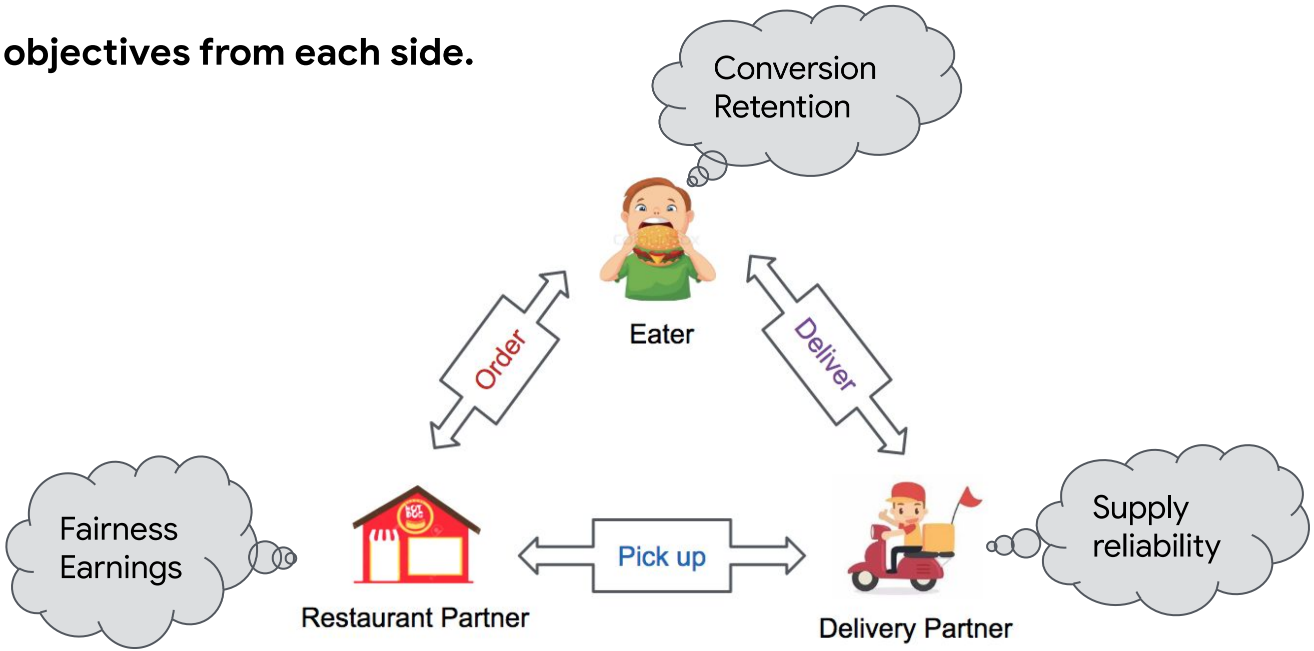
Challenge 1: Multi-sided trade-off

Three-sided marketplace...

...with **different objectives from each side.**



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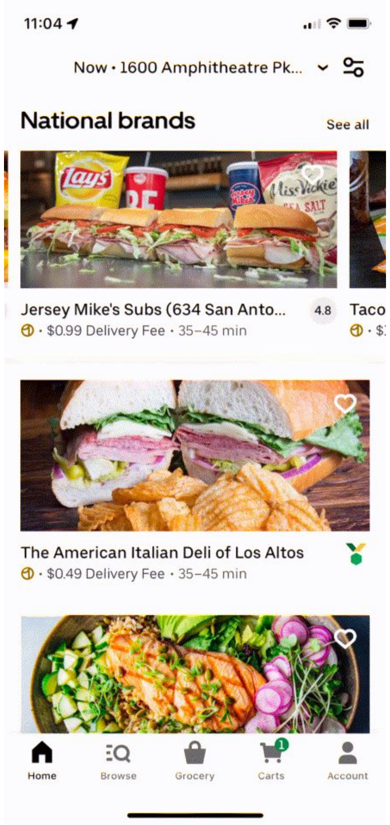
Challenge 2: Heterogeneous and hierarchical items



A **recommendation item** can be:

A single restaurant: a restaurant presented as a row;

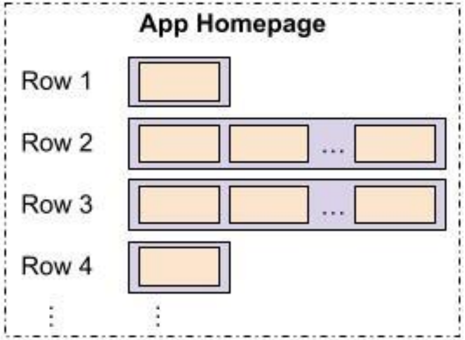
A carousel: a collection of restaurants belonging to a theme (e.g. Fast delivery, same cuisine) presented as a row.

⇩

The Homepage is a two-dimensional grid consisting of ***heterogeneous*** and ***hierarchical*** contents.

⇩

Off-the-shelf recommender systems are **NOT** directly applicable as they focus on ranking items of the same type in a one-dimensional list.



Research Objective

Can we build a recommender system for a food-delivery platform that simultaneously tackles these two challenges?

In particular, it should be able to:

- *Address the **multi-sided trade-off** in a principled way*
- *Handle **heterogeneous and hierarchical recommendation items** in a holistic framework*

Method

MOHR: Multi-Objective Hierarchical Recommender

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MOHR: Multi-objective hierarchical recommender

MO-step	**Machine learning** models for multiple objectives
H-step	A probabilistic **hierarchical model** for hierarchical recommendation
R-step	Scalable **constrained optimization** for multi-sided ranking

MO-step: Multi-objective prediction

We build ML models for four objectives for the three-sided food delivery marketplace:

- **User conversion**: whether the user places an order
- **User retention**: whether the user returns to the platform and orders **again** within the next X days
- **Basket value**: dollar amount of the order
- **Marketplace fairness**: exposure that the new restaurants receive on the platform

For every ***(user, restaurant, source)*** triplet, where ***source*** is the hierarchy information of the restaurant (e.g. belongs to “Italian food” carousel)

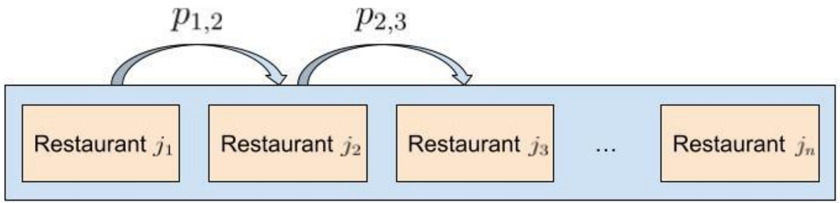
-> Different from the usual recsys setting where prediction is done on (user, restaurant) pairs.

H-step: Hierarchical recommendation

Users have **limited patience**, at each position inside a carousel, she:

- orders from the current restaurant,
- continues browsing the next restaurant inside the carousel, or
- abandon the whole carousel.

We define a **user browsing model** for this:



$$p_{l,l+1} = \mathbf{P}(\text{the user scrolls to position } l+1 \mid \text{currently at position } l).$$

H-step: Hierarchical recommendation

Therefore, carousel-level objectives can be expressed as

Carousel-level objective

$$
\begin{aligned}
c(i,k) = \sum_{l=1}^{n} \Big[& \mathbf{P}(\text{user } i \text{ orders from restaurant } j_l \text{ at position } l \mid \text{user } i \text{ scrolls to position } l) \\
& \times \mathbf{P}(\text{user } i \text{ scrolls to position } l) \Big] \\
= \sum_{l=1}^{n} \Big[& c(i, j_l, k) \prod_{l'=1}^{l} \mathbf{P}(\text{user } i \text{ did not order at position } l'-1, \text{ and scrolls to position } l') \Big] \\
= \sum_{l=1}^{n} \Big[& c(i, j_l, k) \prod_{l'=1}^{l} (1 - c(i, j_{l'-1}, k)) \cdot p_{l'-1, l'} \Big],
\end{aligned}
$$

An interpretable aggregation of restaurant-level objectives

R-step: Multi-objective optimization for ranking

Maximize one of the objectives while constraining on the amount of **tolerable sacrifice** on other objectives:

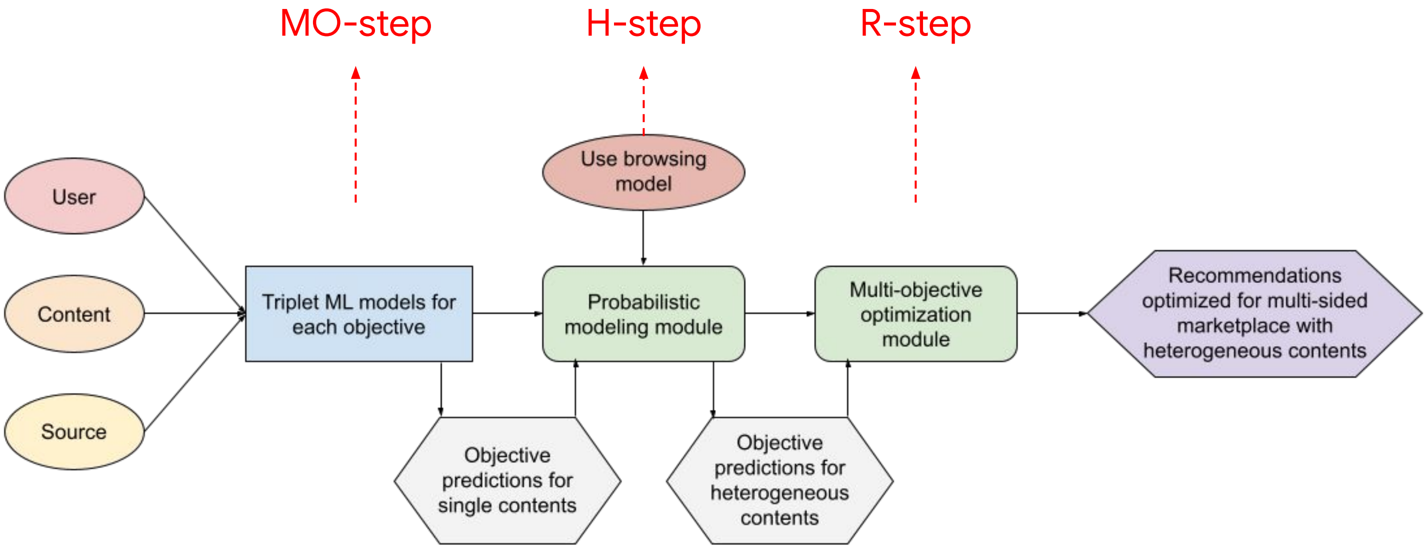
$$\text{Maximize } \; Objective_1$$

$$\text{s.t. } \; Objective_2 \geq (1 - \alpha_2) \cdot objective_2^{opt}$$

$$Objective_3 \geq (1 - \alpha_3) \cdot objective_3^{opt}$$

$$Objective_4 \geq (1 - \alpha_4) \cdot objective_4^{opt}$$

MOHR: Putting everything together



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Results

Offline and live experiments at Uber Eats

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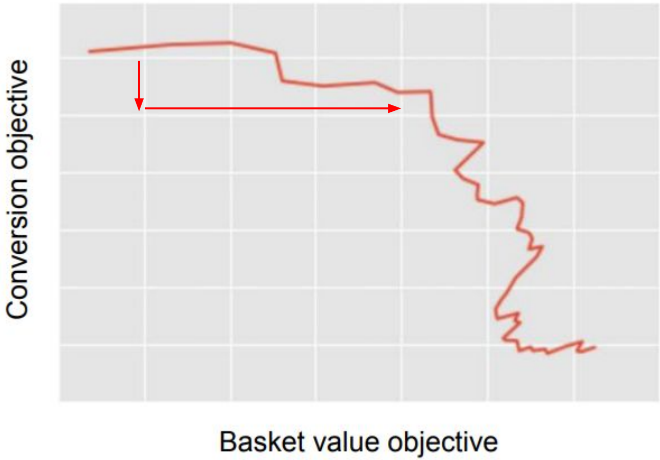
Offline: counterfactual Pareto frontiers

Generated by the offline replay method [1], using **random ranking data** where restaurants are randomly shuffled and presented to the users.



(Top and right is better)

[1] Li L, Chu W, Langford J, Wang X. Unbiased offline evaluation of contextual-bandit-based news article recommendation algorithms. WSDM 2011.

Live experiment at Uber Eats

To understand the contribution of each part separately, we experimented with

- **Multi-objective recommender ("MOR")**: only MO-step + R-step
- **Hierarchical single-objective recommender ("H")**: only H-step with conversion as single-objective.
- **Multi-objective hierarchical recommender ("MOHR")**: the full MOHR framework.

Data and Experiment setup:

- Online controlled experiment (a.k.a "A/B testing")
- 2% of Uber Eats' global user traffic from 06/01/2019 - 06/28/2019

Results on MOR

	Basket value	User retention	Marketplace fairness	Combined
Conversion rate	-	-	-	-
Basket value per order	+0.5%	-	-	+0.5%
Retention rate	-	+0.7%	-	+0.7%
Orders per user	-	+0.8%	-	+0.8%
New restaurants impression ratio	-	-	+150%	+150%
New restaurants order ratio	-	-	+108%	+108%

Table 4 Results on multi-objective recommendation ("MOR"). Metric differences that are statistically significant at 95% confidence interval are reported, in the form of relative changes over the control group.

MOR is able to achieve **Pareto improvements** on the individual objectives.

Results on H

Metric	Conversion rate	Average vertical order position	Search rate
Relative change over control	+1.5%**	-5.7%***	-0.9%***

Table 5 **Results on hierarchical single-objective recommendation ("H"). Metric are reported as relative changes over the control group.** $^{***}p < 0.01$, $^{**}p < 0.05$.

The hierarchical modeling component not only improves user conversion, but also **reduces the search effort** from the users.

Results on the full MOHR

Metric	Conversion rate	Basket value per order	Retention rate
Relative change	+0.5%**	+0.5%***	+0.7%***
Metric	Orders per user	New restaurants impression ratio	New restaurants order ratio
Relative change	0.9%***	+150%***	+108%***
Metric	Average vertical order position	Search rate	
Relative change	-3.2%***	-0.8%**	

Table 6 Results on the full multi-objective hierarchical recommender ("MOHR"). Metric are reported as relative changes over the control group. ***$p < 0.01$, **$p < 0.05$.

MOHR effectively pushes forward the Pareto frontier for the three-sided marketplace.

MOHR has been deployed globally as the recsys for Uber Eats' homepage.

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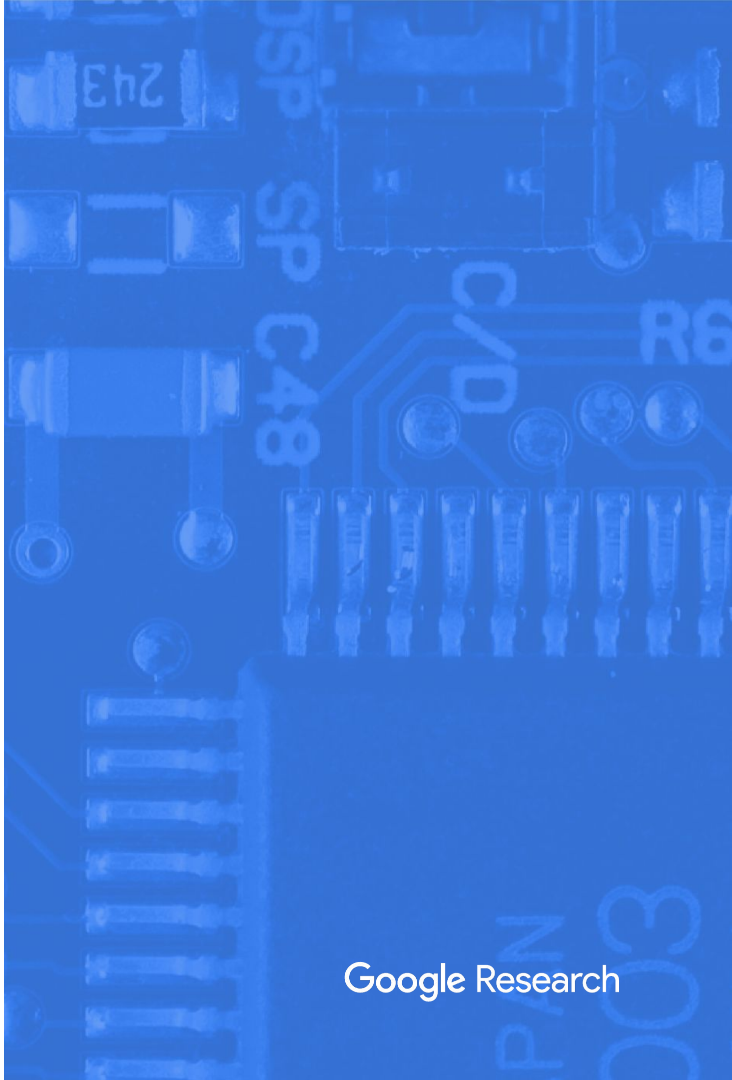
Key Takeaways

- ➢ Recommending for a three-sided food-delivery marketplace faces two prominent challenges: **multi-objective trade-off** and **heterogeneity of recommendation items**.

- ➢ We propose **MOHR**, a model-based three-step recommendation framework combining **machine learning**, **structural modeling** and **multi-objective optimization** for recommending restaurants and aggregation of restaurants on food-delivery platforms.

- ➢ Live experiment results demonstrate that MOHR effectively **pushes forward the Pareto frontier** for the three-sided marketplace.



Thank You

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