

# Breaking the Ice: Solving the Item Cold Start Problem in E-commerce Search

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MICES EU 2023



## Data Scientist with 4 years of experience:

- **Startup**
  - Fashion AI
- **University thesis on ML in medicine**
  - DSS for diabetes management
- **Banking industry**
  - NLP
  - AutoML tools
- **Currently at Delivery Hero**
  - Search Ranking





- Food ordering & delivery
- Restaurants & Quick commerce
- 70+ countries

## Brands:



**2.8 billion orders**

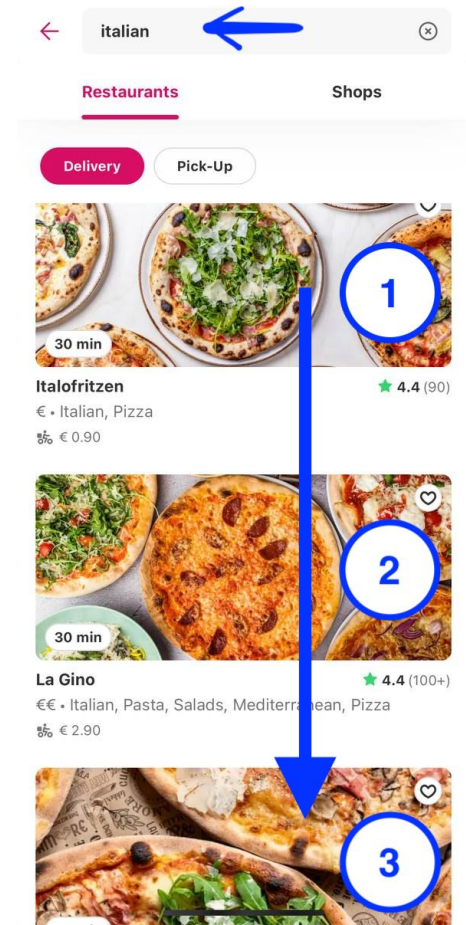
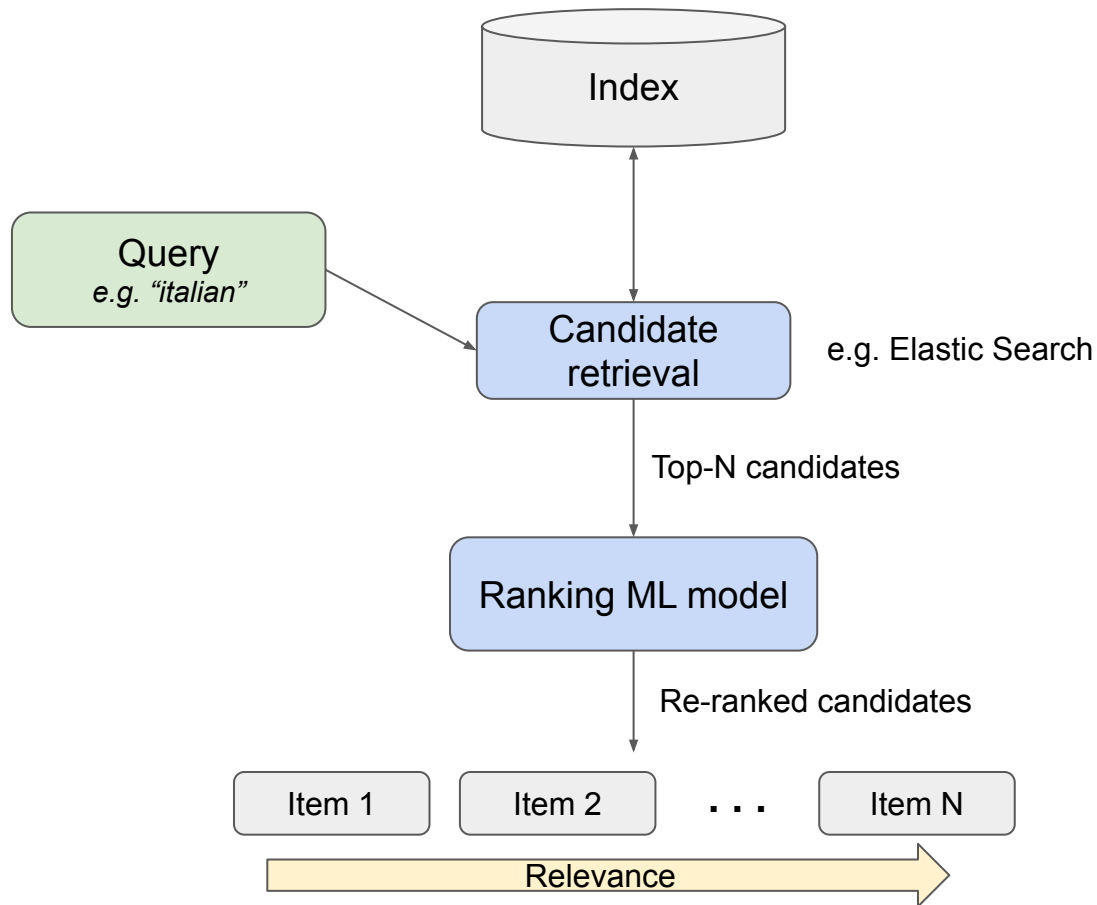
\*2021 public data

**500 000 restaurants**

\*2020 public data

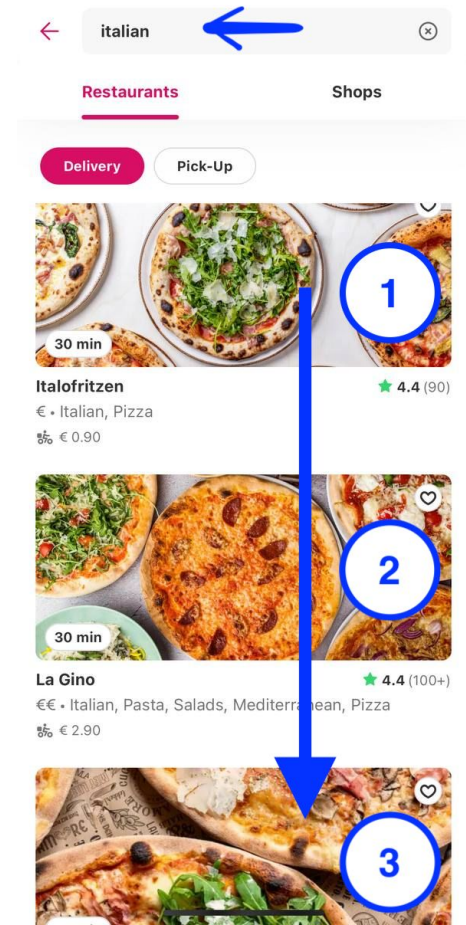
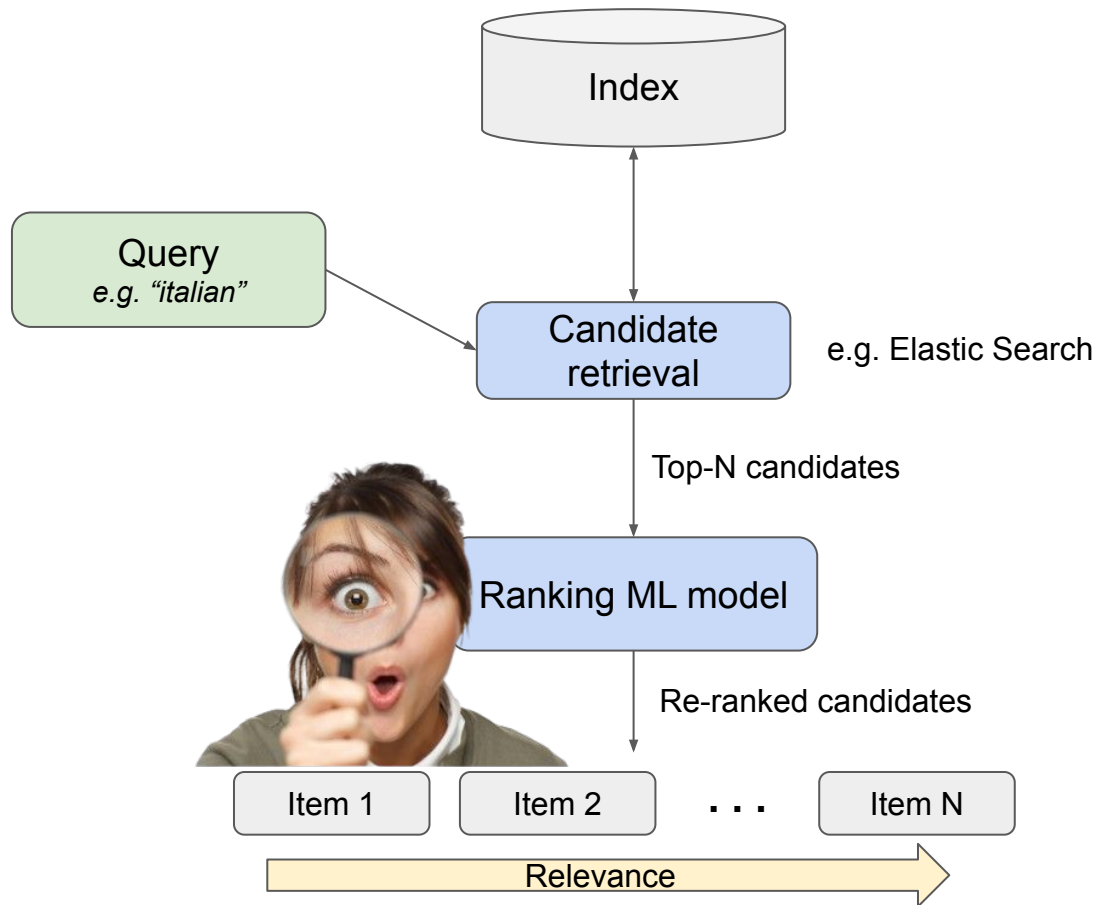
# E-commerce Search Ranking

DeliveryTech

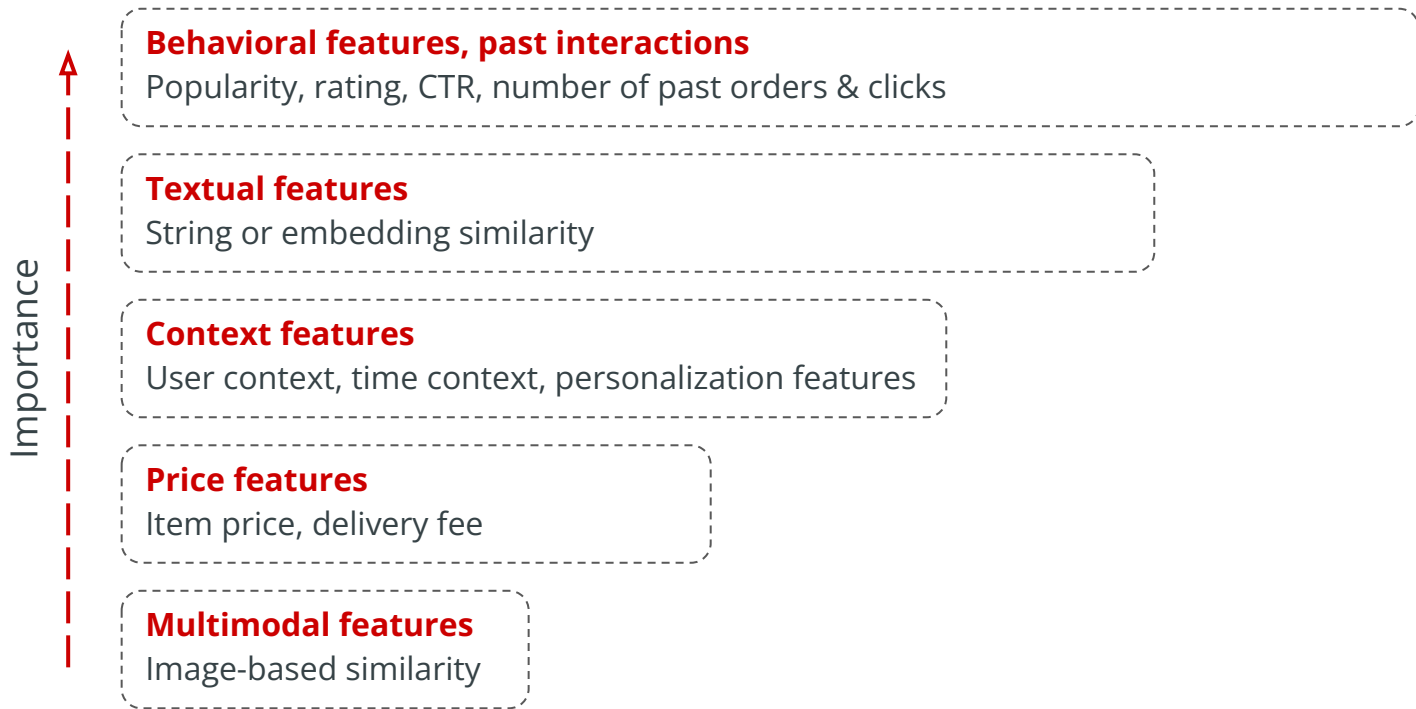


# E-commerce Search Ranking

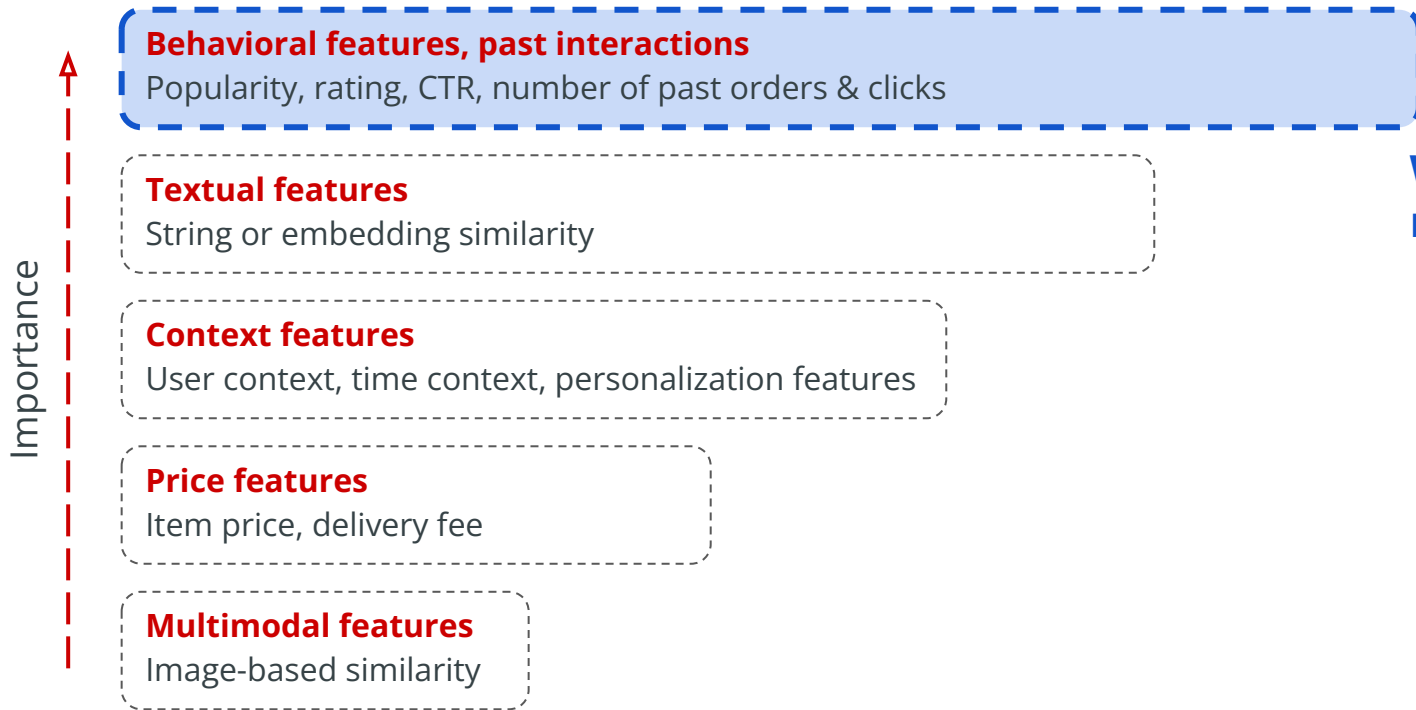
DeliveryTech



## Features:



## Features:



What about new restaurants?

New restaurant signing up on Delivery Hero platform:





New restaurant signing up on Delivery Hero platform:

0 past orders



# New restaurant challenges

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***Delivery***Tech

New restaurant signing up on Delivery Hero platform:

0 past orders

No trackable CVR

0 past clicks



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*Delivery*Tech

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Position in search results: 47

# New restaurant challenges

*Delivery*Tech

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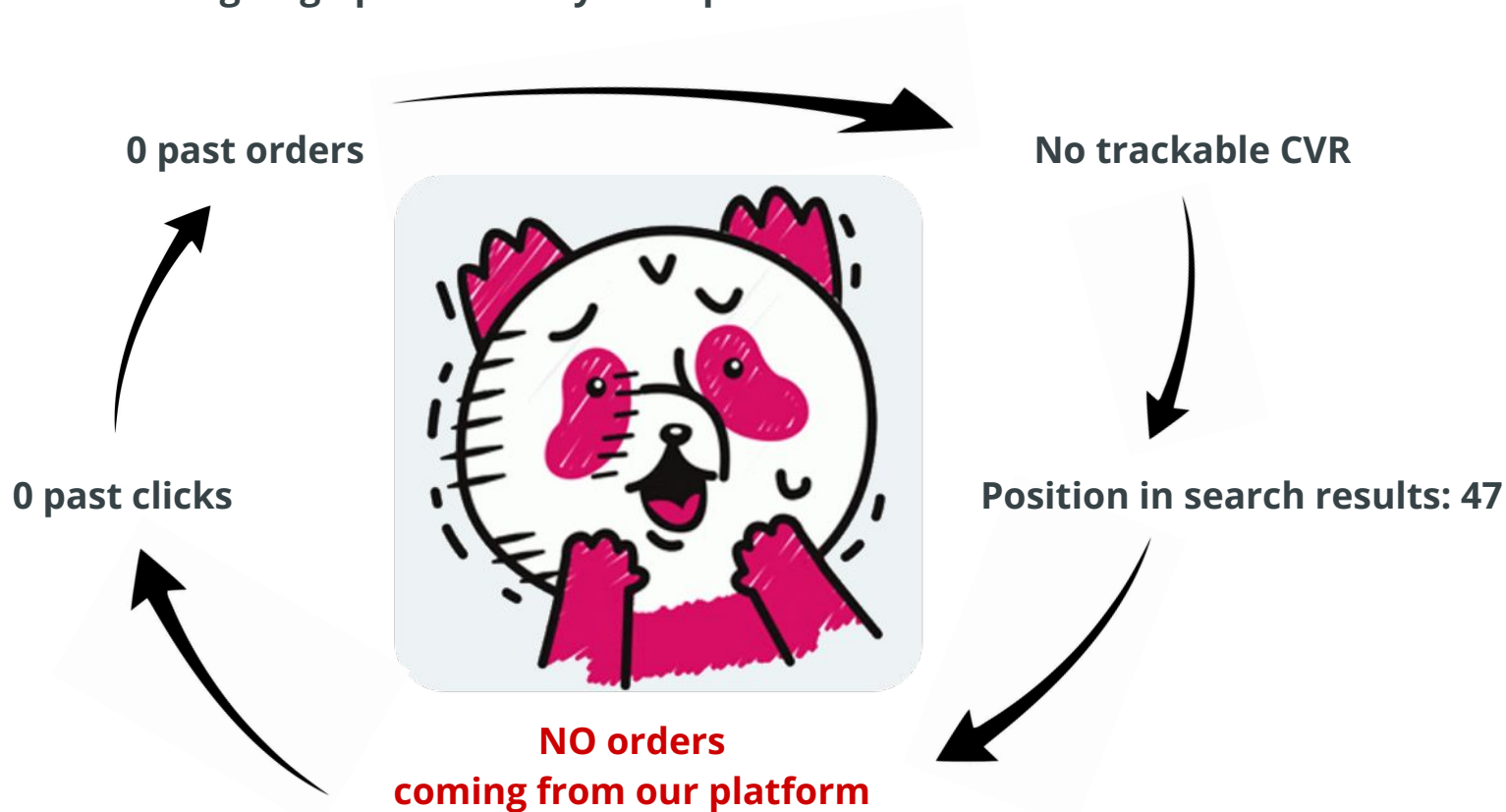
Position in search results: 47

**NO orders  
coming from our platform**

# New restaurant challenges

*Delivery*Tech

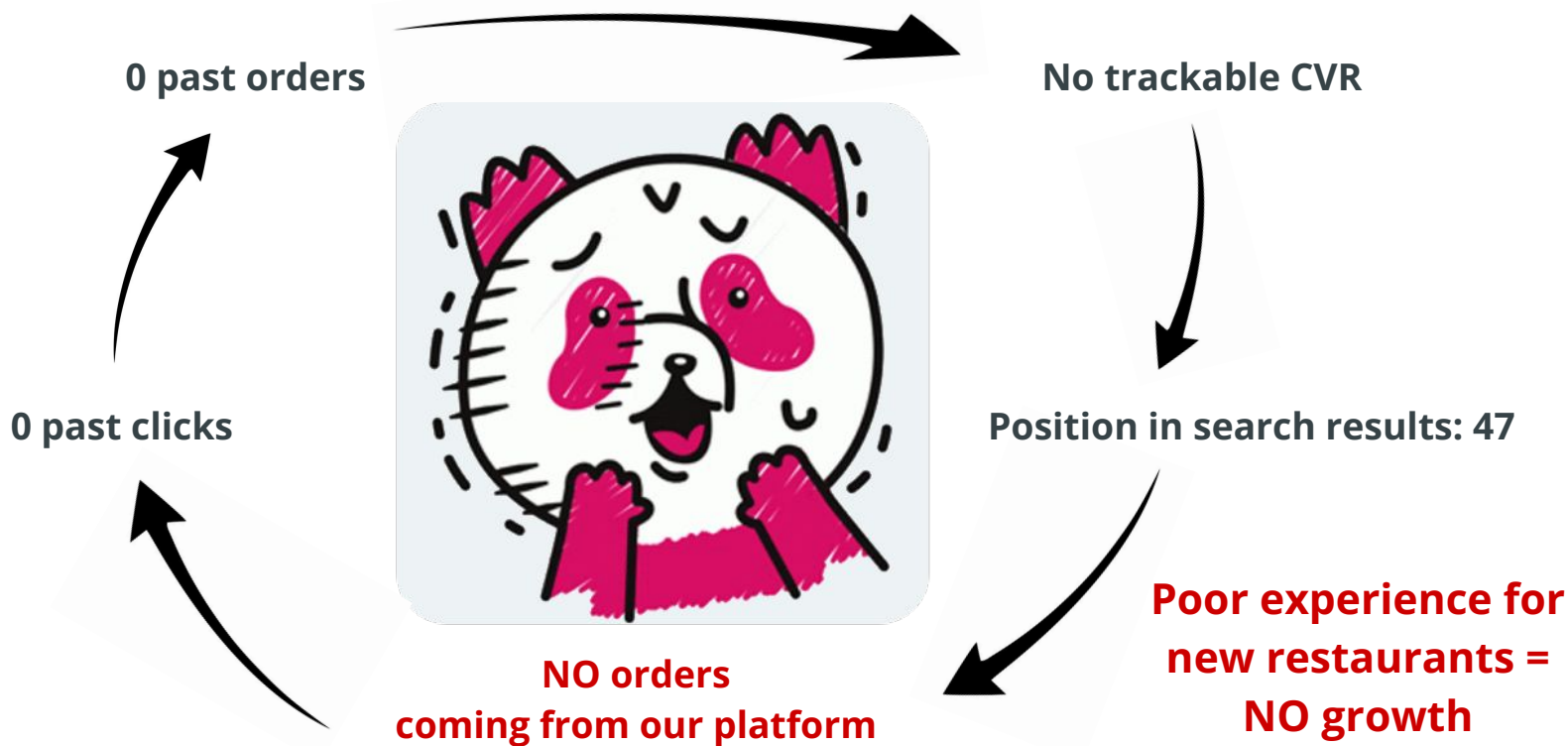
New restaurant signing up on Delivery Hero platform:



# New restaurant challenges

*DeliveryTech*

New restaurant signing up on Delivery Hero platform:

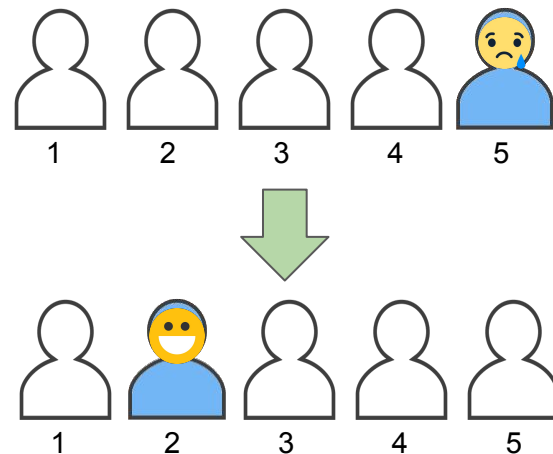


## Context:

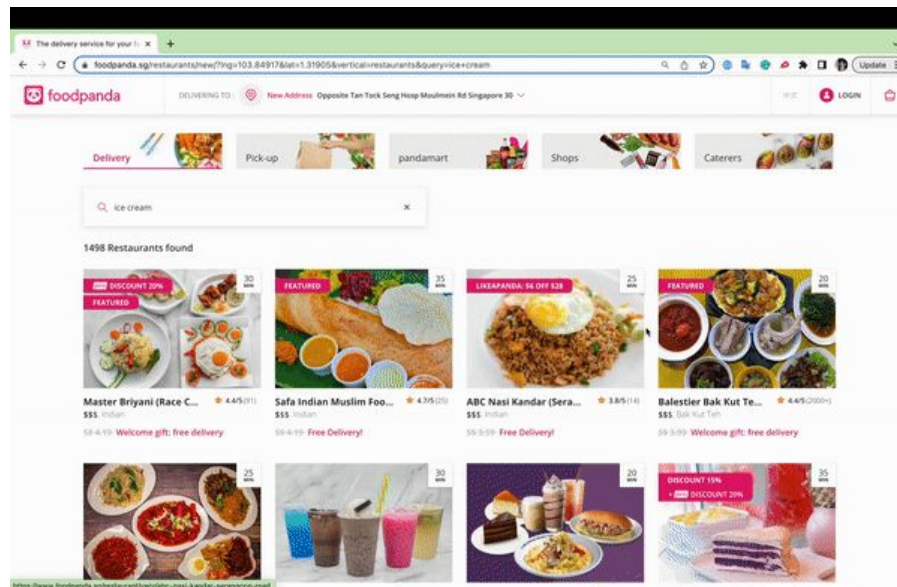
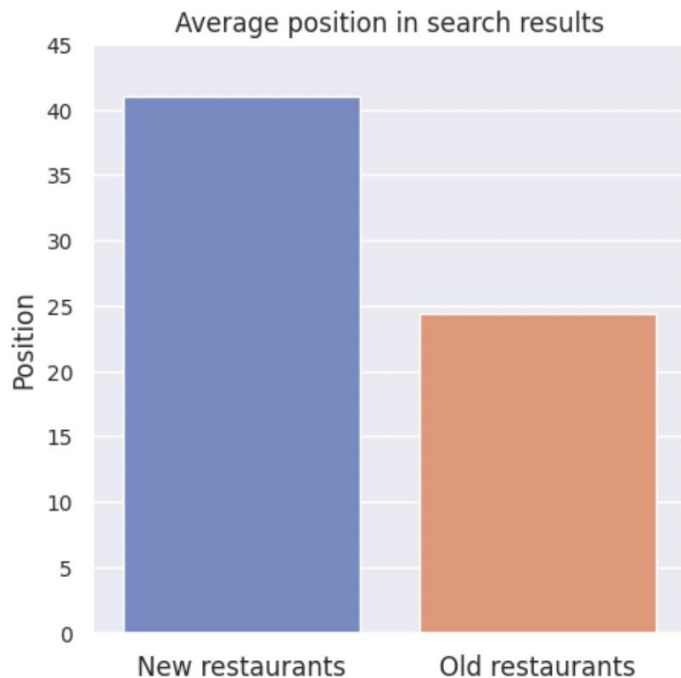
- Ranking ML model relies on past interactions
- New items do not have any past interactions
- New items are displayed on lower positions and receive few clicks and orders

## Goal:

- Increase visibility & traffic for new items without quality loss for others



## Cold start problem at Delivery Hero:

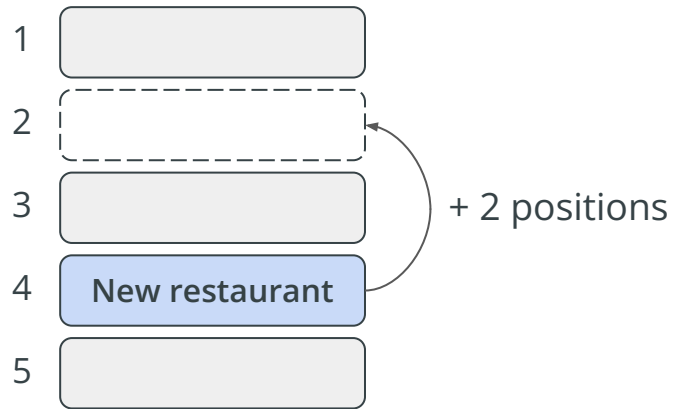




# Approach 1: Artificial Boosting

## Boost cold start restaurants

Artificially move new restaurants N positions higher  
or use a multiplier for their score



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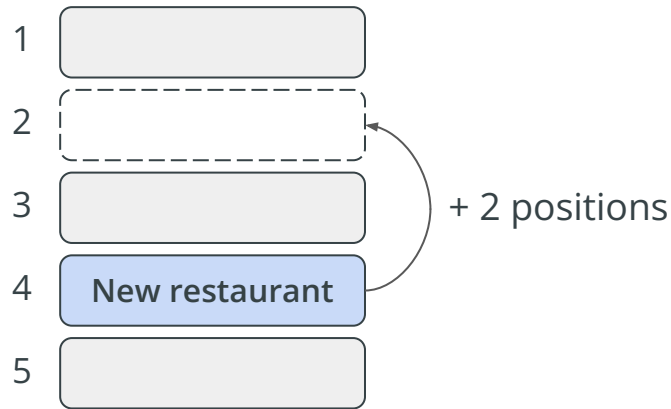
## Boost cold start restaurants

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**Result:**



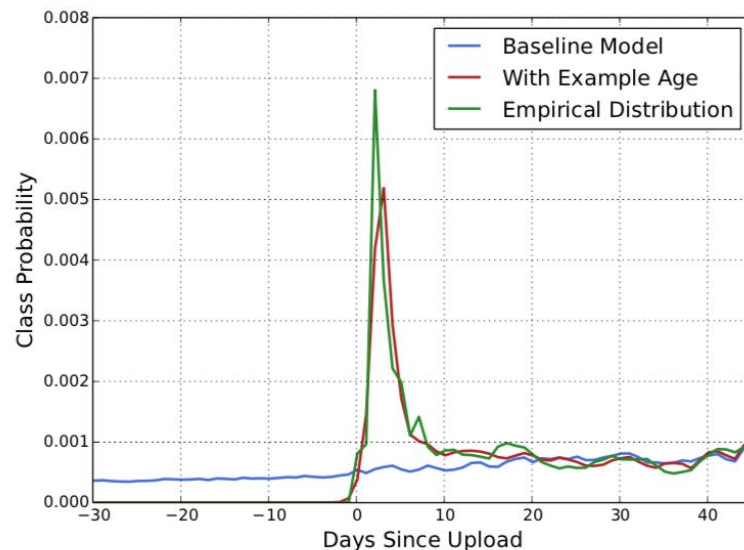
Neutral A/B test



# Approach 2: Cold Start Features

## Use cold start as a feature

Use “restaurant age” / “item age” / “days since upload”  
as a feature for ML model



Deep Neural Networks for YouTube Recommendations

<https://research.google/pubs/pub45530/>

# Approach 2: Cold Start Features

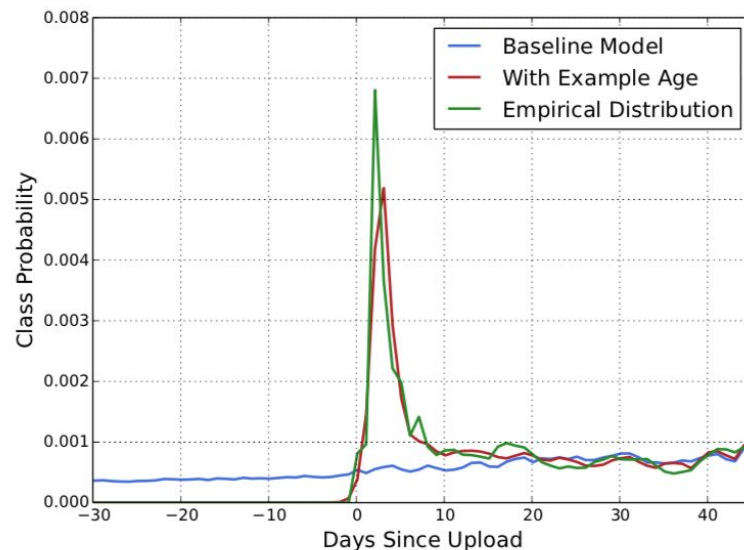
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Use “restaurant age” / “item age” / “days since upload”  
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**Result:**



No improvement in offline metrics



Deep Neural Networks for YouTube Recommendations

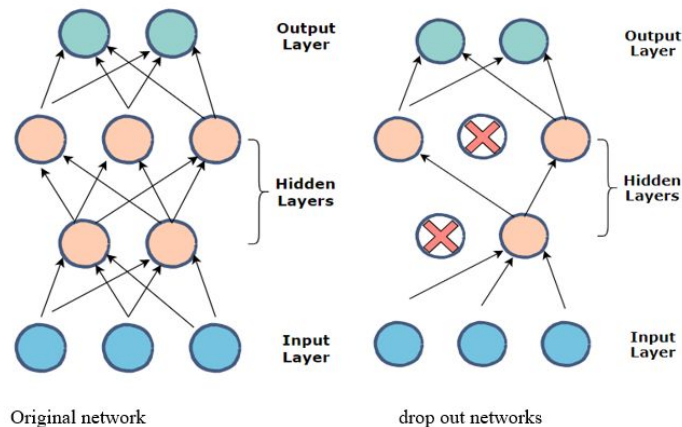
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## DropoutNet

Inspired by neural networks dropout

During the training, randomly apply *input dropout* to past interaction features: set them to 0 for some fraction of restaurants

This way model does not rely on past interactions too much and learns to generalize to cold start while preserving warm start accuracy



DropoutNet: Addressing Cold Start in Recommender Systems

[https://www.cs.toronto.edu/~mvolkovs/nips2017\\_deepcf.pdf](https://www.cs.toronto.edu/~mvolkovs/nips2017_deepcf.pdf)

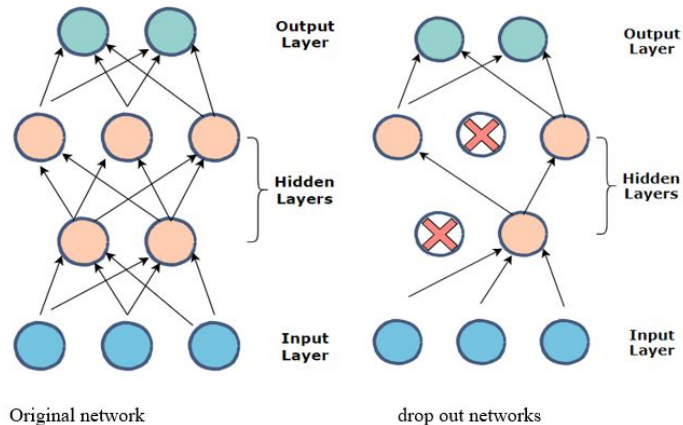
# Approach 3: DropoutNet

## DropoutNet

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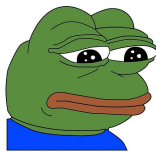
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**Result:**



No improvement in offline metrics  
again

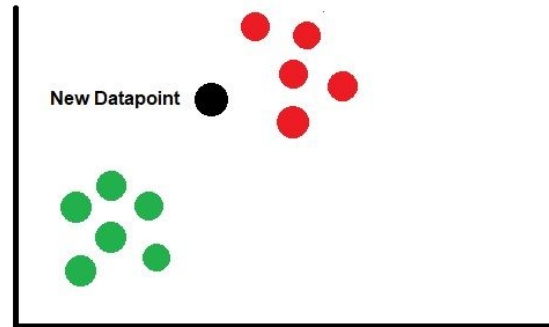


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[https://www.cs.toronto.edu/~mvolkovs/nips2017\\_deepcf.pdf](https://www.cs.toronto.edu/~mvolkovs/nips2017_deepcf.pdf)

## Fill missing past interaction features

- **Representative based**

- Assumption: new restaurant's interaction counts would be close to similar "old" restaurants.
- Thus we can approximate its interaction feature values with average of those of similar restaurants.



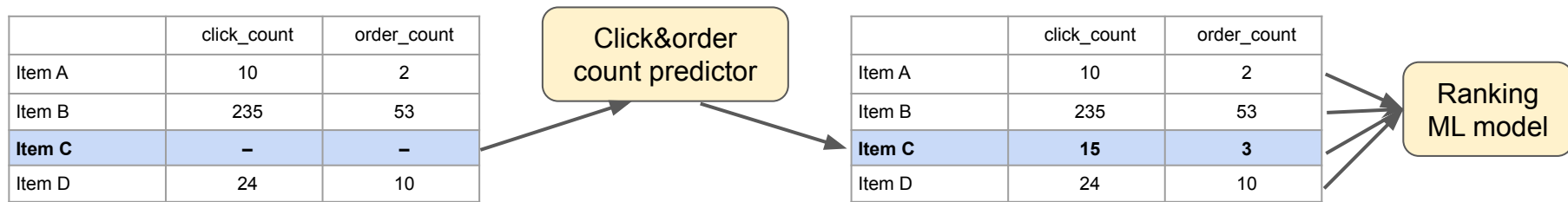
- **Predicting priors**

Create a separate model to predict interaction features for new cold start restaurants.  
(This model should be trained on "old" restaurants)

# Approach 4: Fill Missing Interactions

## Steps to predict interaction features:

1. Create a separate model to predict order & click counts based on some query and item features
2. Use this model to fill missing interaction features for cold start items
3. Apply the normal ranking ML model










## Hybrid ranking

- Have a separate ranking algorithm that would not not rely on past interaction features (e.g. model trained on content features only)
- Fall back for that algorithm for cold start restaurants



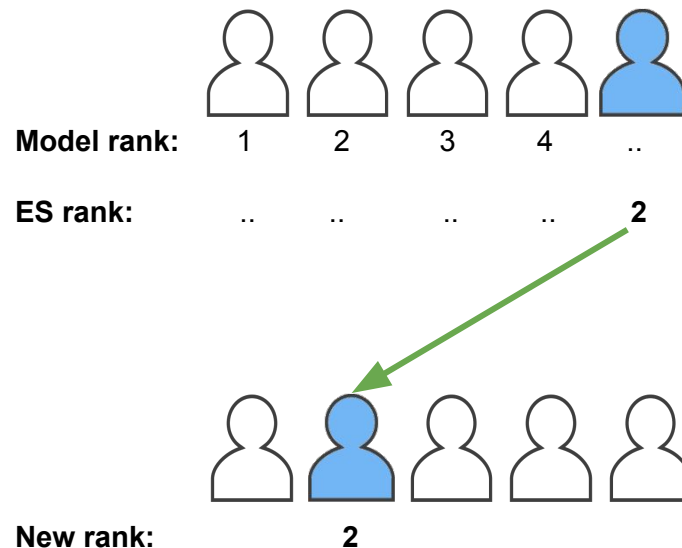
## Elastic Search rank “hack”

1. Keep ES rank for cold start restaurants
2. The rest of the restaurants are ranked and ordered with the normal ranking model

					
<b>Model rank:</b>	1	2	3	4	..
<b>ES rank:</b>	..	..	..	..	2

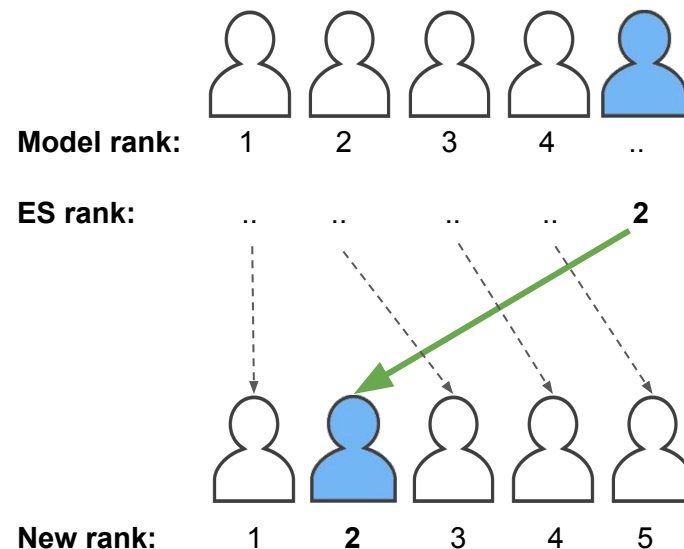
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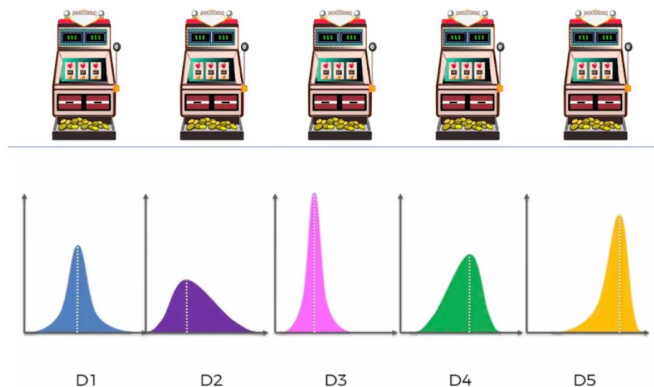
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## Multi-Armed Bandits

- Balance between exploration and exploitation
- Preferring old vendors - exploitation
- Preferring new vendors - exploration



- **Scenario:** Pull machine  $k \rightarrow$  sample from **unknown** reward distribution  $D_k \rightarrow$  observe reward.
- **Problem:** Given a finite number of pulls  $T$ , how can I optimize my winnings?
- How much should I **explore**? How much should I **exploit**?



## Overall nDCG

- Non-significant difference ( $<0.1\%$ )

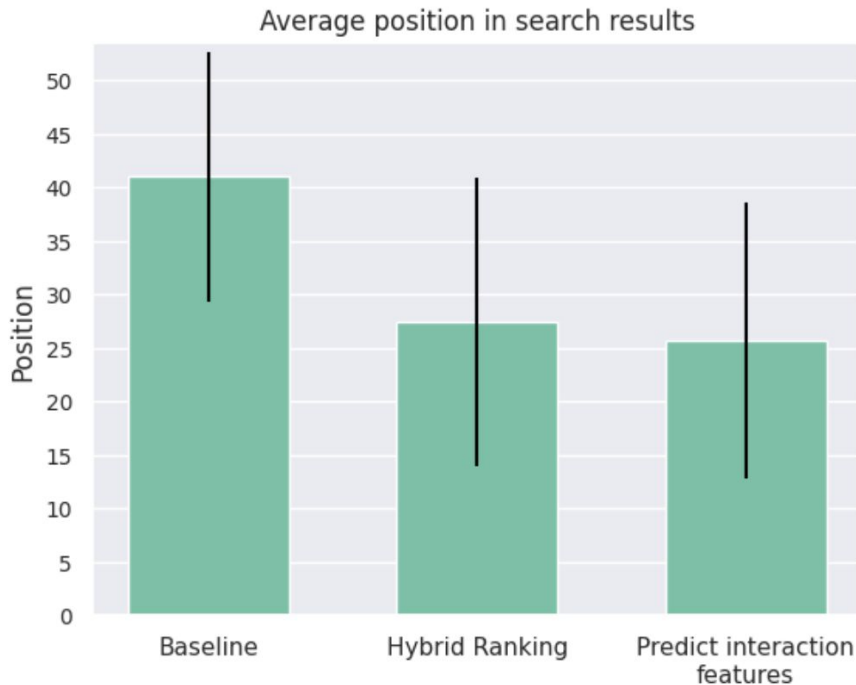
## Cold start sessions nDCG

- Hybrid Ranking: **+39.9%**
- Predict interaction features: **+52.1%**

## Average position of new restaurants

- Hybrid Ranking: **27**
- Predict interaction features: **26**
- Baseline: **41**

**A/B test is ongoing**





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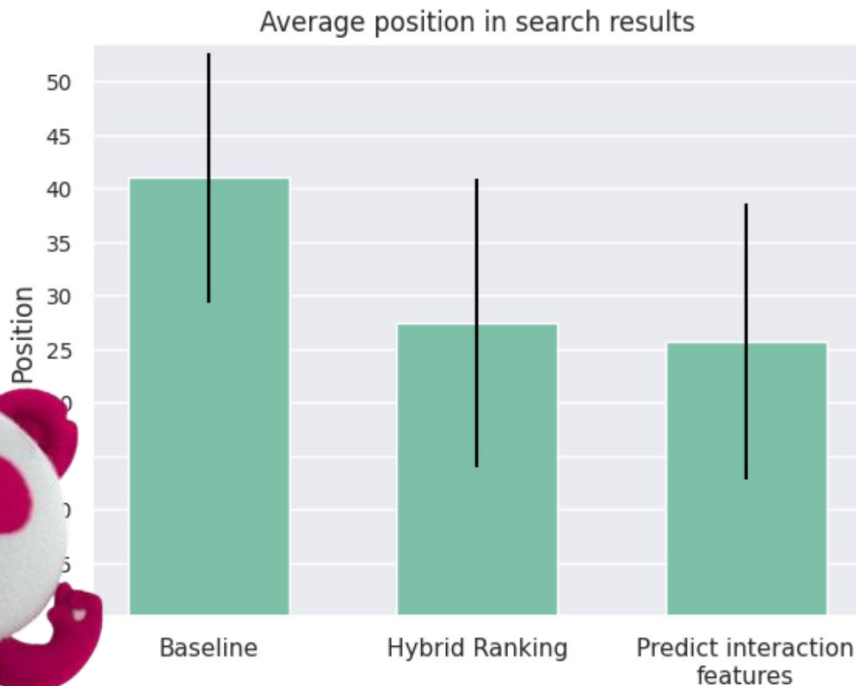
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# Thank you!



Delivery Hero Tech Blog: [tech.deliveryhero.com](https://tech.deliveryhero.com)

Me: [linkedin.com/in/evgeniia-trufanova](https://linkedin.com/in/evgeniia-trufanova)