Russian Academy of Sciences

Agent-based modeling of online food ordering and delivery market

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About me

- **From 2013, I have built many agent-based models (ABMs) to model various complex adaptive systems**
  - Supply chain (He et. al, 2013; He et. al, 2014)
  - Municipal solid waste treatment system (He et. al, 2017)
  - Resale housing market (He et. al, 2018)
  - Online-to-offline market (He et. al, 2016)
    - Online food ordering and delivery market (He et. al, 2019)
  - Blockchain system (Wei, Li, and He, 2020)
- **Download all papers and this slide from my website:**
  - http://AgentLab.cn/en/

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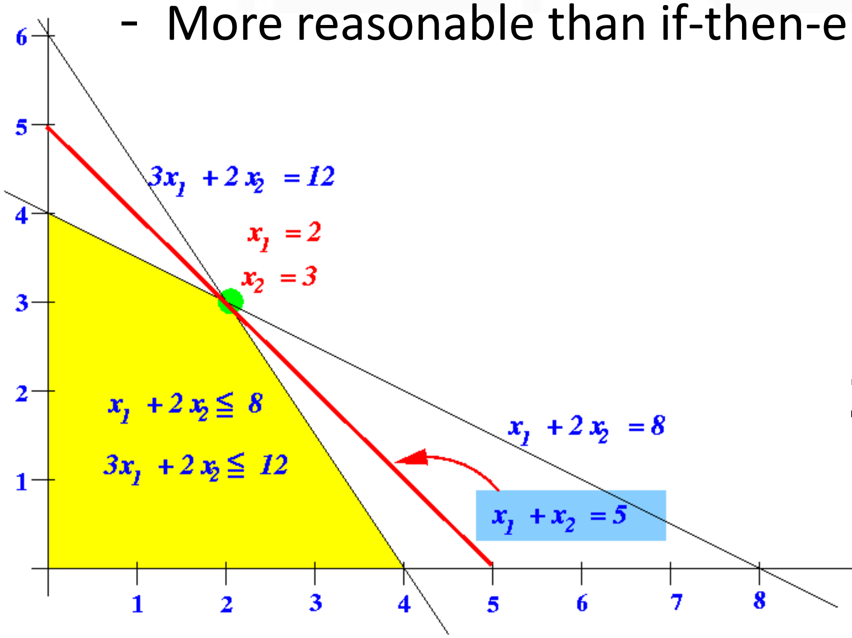
About me

Two key features of my ABMs

- **Operations research (OR) models are embedded**
  - Assume that agents are (bounded) rational, and resources are scarce
- **Algorithms for OR models are used to make decisions**
  - More reasonable than if-then-else rules



Objective function

$$Max\ Z = x_1 + x_2$$

$$x_1 + 2x_2 \leq 8$$
$$3x_1 + 2x_2 \leq 12$$
$$x_1, x_2 \geq 0$$

Constraints

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About me

Current research interests

- **ABM standardization**
  - Even under the ODD protocol, describing an ABM is still troublesome and vague.
  - How to make ABMs **comparable**? How to make ABM simulation results **replicable**? Can we develop a protocol better than ODD?
- **Agent-based operations management in digital economy**
  - New business models emerge in digital economy where individuals, organizations, technologies and data are interacting.
  - How to understand such complex systems? What are the impacts of new trends on agents? How to optimize OM for agents?

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[AD] Master/PhD/Postdoc positions in Beijing

General requirement

- Good math ability and/or coding experience
- Love building ABMs

Study as a Master student or PhD candidate?

- You can apply many scholarships: ANSO, CSC, UCAS

Work as a postdoc?

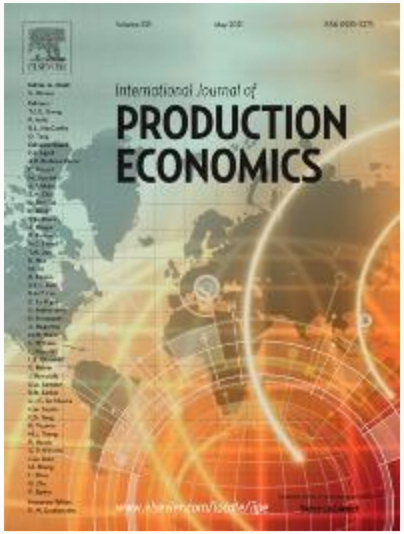
- Salary starts at approx. 60,000 USD gross per year

I will help you to apply these positions

- Email me with your CV: hezhou@ucas.ac.cn

Outline

- Motivation
- Research questions
- Assumptions
- Agents
- Results



Zhou He, Guanghua Han, T. C. E. Cheng, Bo Fan, and Jichang Dong* (2019). Evolutionary location and food quality strategies for restaurants in competitive online food ordering and delivery markets: An agent-based approach. ***International Journal of Production Economics***, 215:61-72

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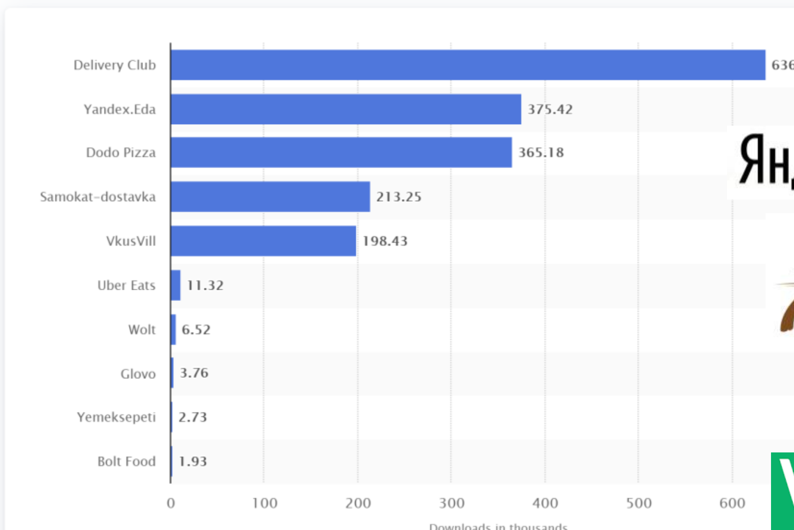
Motivation

◻ Online food ordering and delivery

- One of the most successful business models in digital economy

Leading food delivery apps in Russia in January 2021

(in 1,000s)



Partner of this study

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Motivation

◻ Identify the key factors

- According the large-scale surveys conducted in China in 2015 and 2016, diners mainly focused on two factors:

waiting time

food quality

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Motivation

◻ Agents, interactions and trends

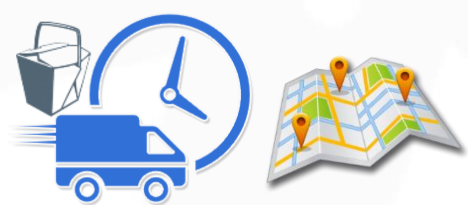
1 the increasing preference for high food quality

2 shortening food preparing time

diner

waiting time = food preparing time (food quality)

+ delivery time (distance from location to diner, delivery policy of the APP platform)



3 the increasing preference for cost saving

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Research questions

RQ1:

- What are the impacts of **three possible changes** on the **food quality and location operations of restaurants**, i.e.,
  - the increasing preference of customers for high food quality,
  - the shortening food preparing time of the restaurant, and
  - the different delivery policies of the online platform?

RQ2:

- What are the differences between the food quality and location decisions made by the **best restaurants** and those made by **others**?

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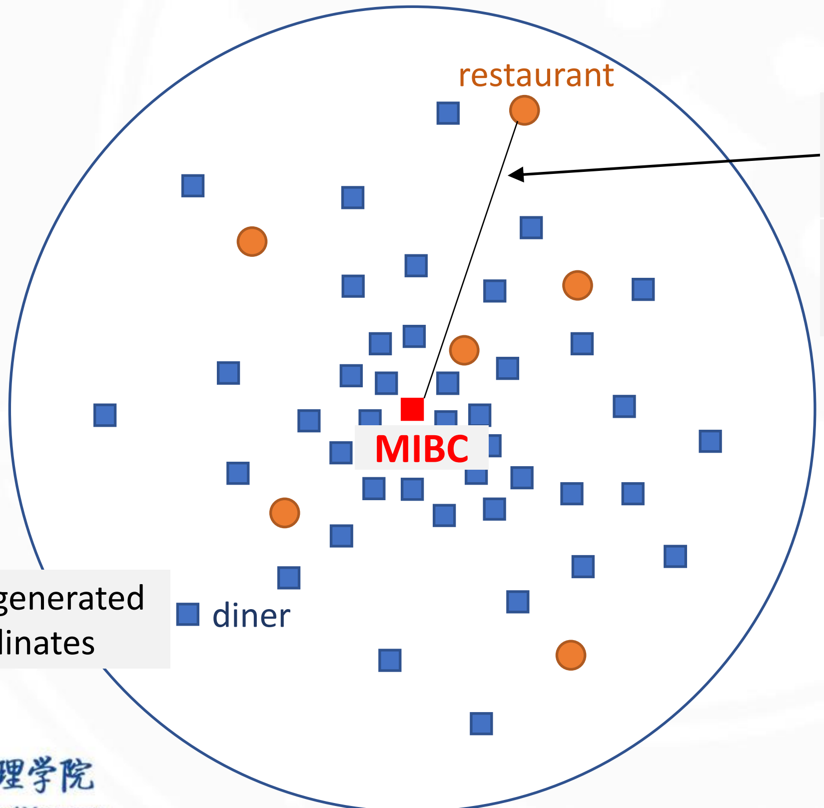
Assumptions

☐ Assumption 1:

- **Diners and restaurants are represented as discrete points and placed on a two dimensional plane with a polar coordinate system according to their polar coordinates (r, ϕ)**

Diners gather around the CBD (the pole)



Randomly generated polar coordinates

r : distance to the CBD center, **decision variable**

ϕ : randomly generated but fixed

Closer to or farther away from the CBD?

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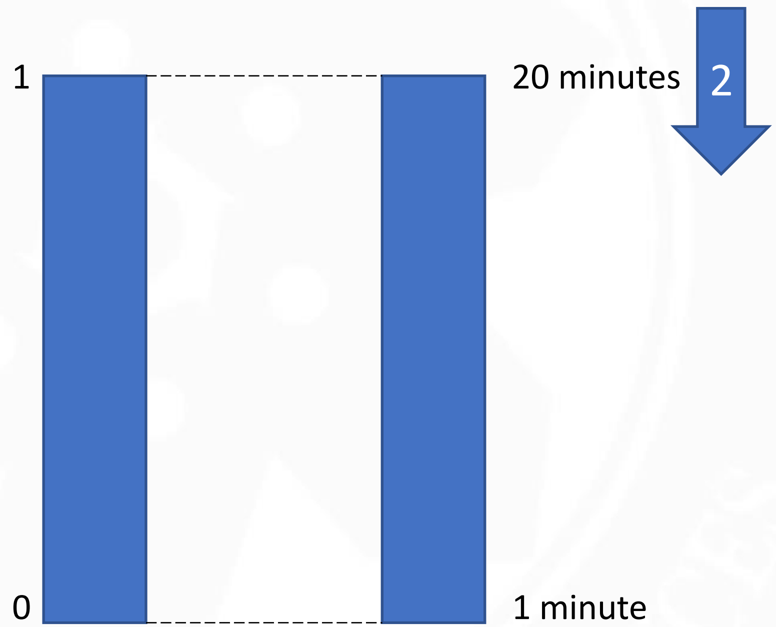
Assumptions

Assumption 2:

- **A restaurant's food preparation time has a positive and linear relationship with its quality**

Good food is worth waiting for.



Food quality, **decision variable**

Food preparation time

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Assumptions

- **Assumption 3:**
  - We exclude the other dining options like eat-in or order pick-ups at restaurants
- **Assumption 4:**
  - We do not consider restaurants that offer delivery service
- **Assumption 5:**
  - When the diner submits feedback on food quality and waiting time, we assume that submitted food quality always equals the current food quality determined by the restaurant

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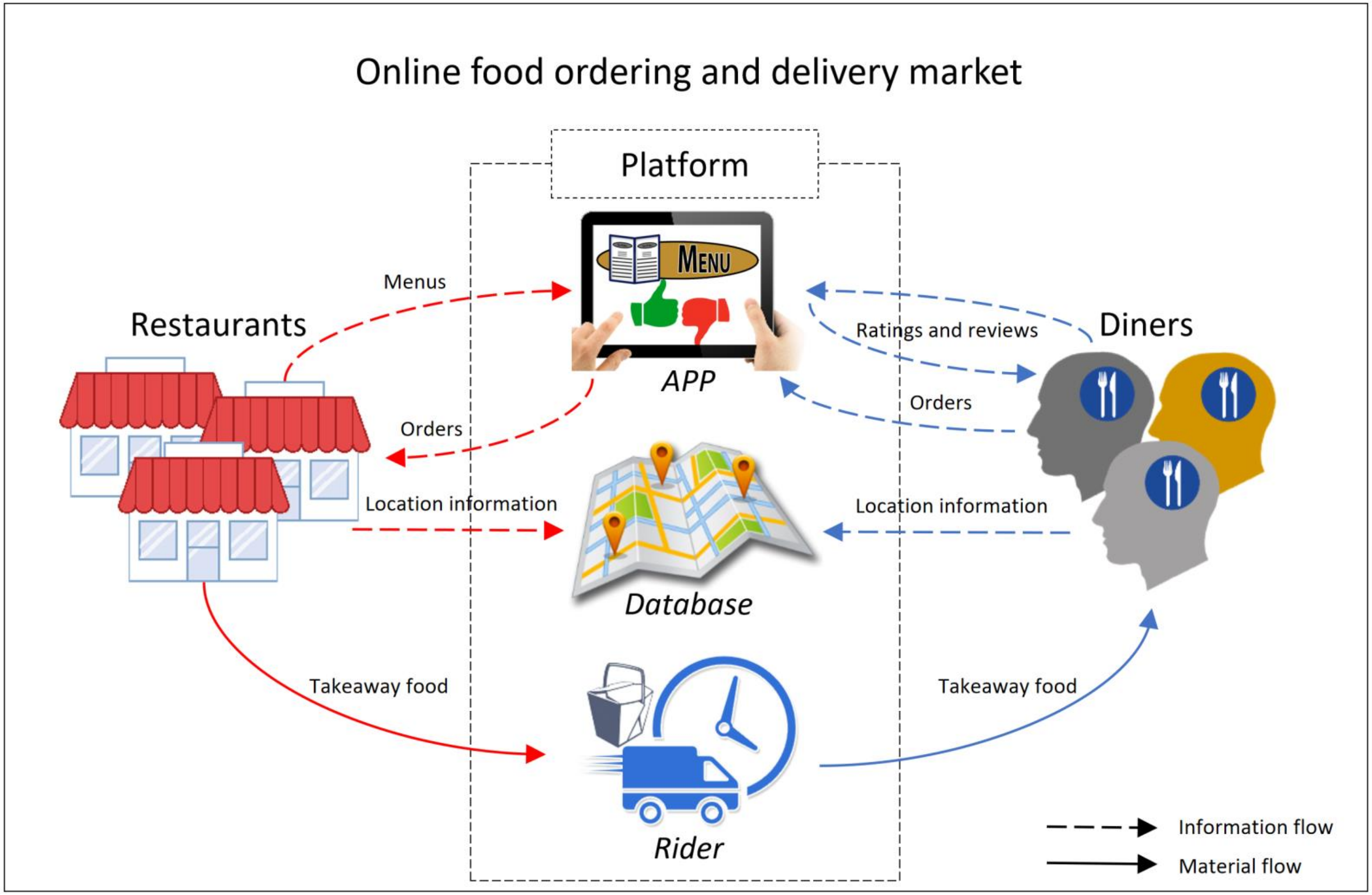
Agent type and model structure



Agents

Diner *i* at time *t*:

- **More likely to select the restaurant with higher utility**

Utility if diner *i* chooses restaurant *j*

$$U_{ij,t} = \left(\frac{W_{i,t}^{min}}{W_{ij,t}}\right)^{1-\beta} \cdot \left(\frac{Q_{j,t}}{Q_t^{max}}\right)^{\beta},$$

1

where

Waiting time from restaurant *j* to diner *i*

Fastest $W_{i,t}^{min} = \min\{W_{ij,t}\}_{j=1}^{N},$

Tastiest $Q_t^{max} = \max\{Q_{j,t}\}_{j=1}^{N}.$

Food quality of restaurant *j*

Probability for diner *i* to choose restaurant *j*

$$f_{ij,t} = \frac{e^{U_{ij,t}}}{\sum_{j=1}^{N} e^{U_{ij,t}}}$$

Logit choice model: better alternatives are chosen more often

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Platform at time *t* :

- **Deliver food by solving a complex VRPPDTW-D**
  - Dynamic vehicle routing problem with pick-ups/deliveries and time windows
  - Orders appear dynamically (no order prediction);
    pick-up time window starts only when the food is ready;
    multiple homogeneous riders are traveling with given speed and capacity;
  - Two objectives:

Minimize the maximum waiting time of all diners

Minimize the total travel distance of all the riders

$1-\alpha$: weight preference for user experience

3

α: weight preference for cost saving

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Agents

Platform at time *t*:

- **Suggested by Ele.me, we use the insertion heuristic algorithm to solve the VRPPDTW-D**
  - A rider can picks up multiple takeaway orders at different restaurants
  - A rider's route may change by the algorithm when a new order is received
  - The real-time delivery scheduling system has to continuously track the location and status of each rider and order

Collect necessary information about the dispatch job (denoted by J), e.g., distance, pick-up time window, locations of the customer and restaurant;
foreach *rider* **do**
    Update current location, capacity and status of assigned dispatch jobs;
    List all the unvisited paths, e.g., path 1, path 2, ...;
    Generate all possible new plans after inserting job J, e.g., path 1, J's pick-up path, path 2, J's deliver path, ...;
    Calculate the performance of each new plan according to the objective function of the online platform;
    Find the new plan with best performance;
end
Find the rider with best performance;
Assign J to the rider and finalize its best plan;

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Agents

Restaurant *j* at time *t* :

- **Decide food quality and location to maximize the number of received orders**
  - But the performance is affected by the interweaving decisions of both customers and rivals, as well as the delivery plans generated by the online platform
  - Hence, we incorporate the estimation-and-optimization (ESTOPT) approach proposed by He et al. (2019) to help the restaurant make the joint decision

Zhou He, Chunling Luo, Chin-Hon Tan, Hang Wu, and Bo Fan* (2019). Simulating an agent's decision-making process in black-box managerial environment: An estimation-and-optimisation approach. ***Journal of Simulation***, 13(2):111-127

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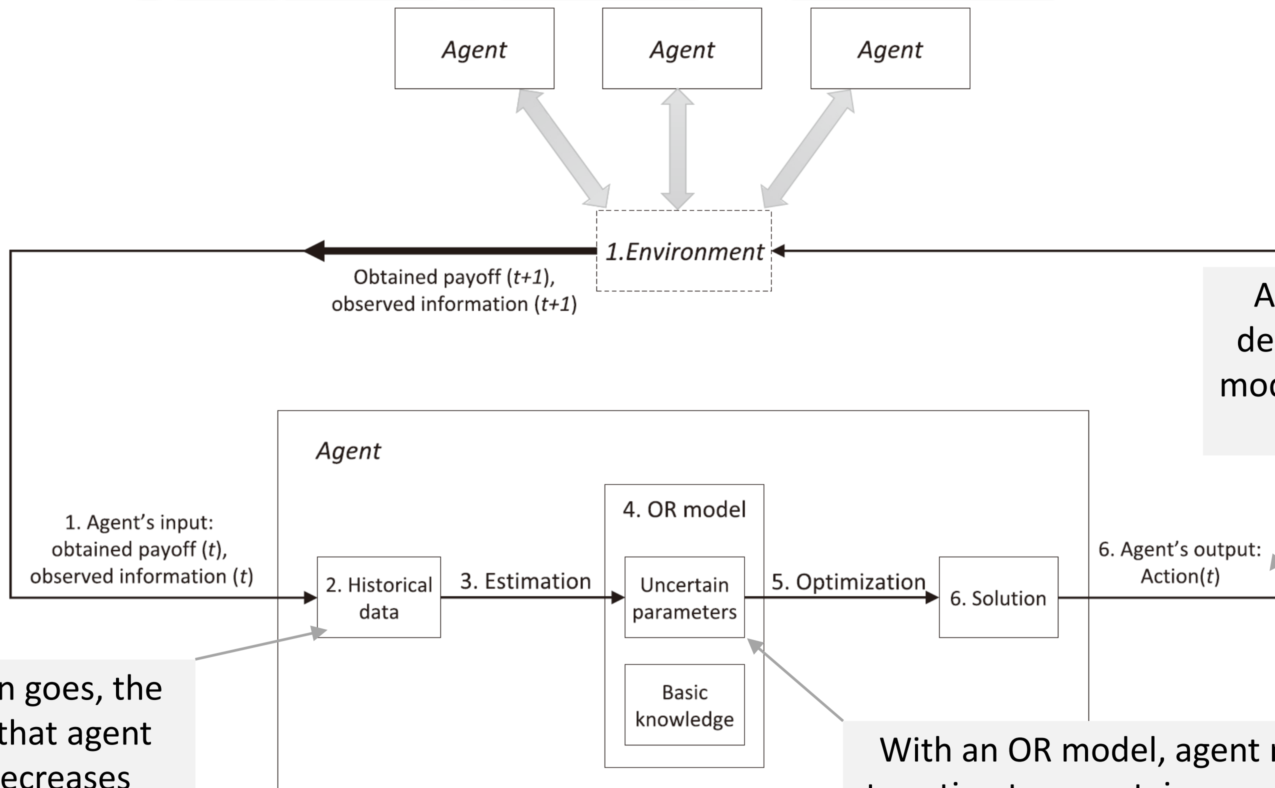
Agents

Restaurant *j* at time *t* :

- General idea of ESTOPT



Agent makes decision in two modes: randomly, optimal-ly

As simulation goes, the probability that agent explores decreases

With an OR model, agent needs to estimate uncertain parameters based on historical data

Figure 1. The architecture of the ESTOPT approach.

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Restaurant *j* at time *t* :

- **Applied ESTOPT in another paper (He et al., 2017)**
  - Agent needs to find best gate fee (price) to maximize its profit

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Agents

□ Restaurant *j* at time *t* :

- **So we need to assume a polynomial function, i.e.,**
  - number of received orders is a function of food quality and location

$$Y = z_0 X_1^2 X_2^2 + z_1 X_1^2 X_2 + z_2 X_1 X_2^2 + z_3 X_1 X_2 + z_4 X_1^2 + z_5 X_2^2 + z_6 X_1 + z_7 X_2 + z_8 .$$

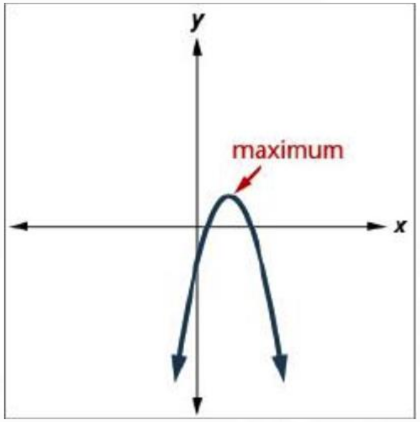
number of received orders (ϑ)

$$(X_1, X_2, Y) = \{(q_{j,\tau}, r_{j,\tau}, \theta_{j,\tau})\}_{\tau=1}^{t}$$

Food quality (q)

Location (r)

- **Why this polynomial form?**
  - Recall that restaurants face a trade-off between food quality and waiting time
  - Partial derivatives are quadratic functions opening downward and the optimal food quality could be within (0, 1)



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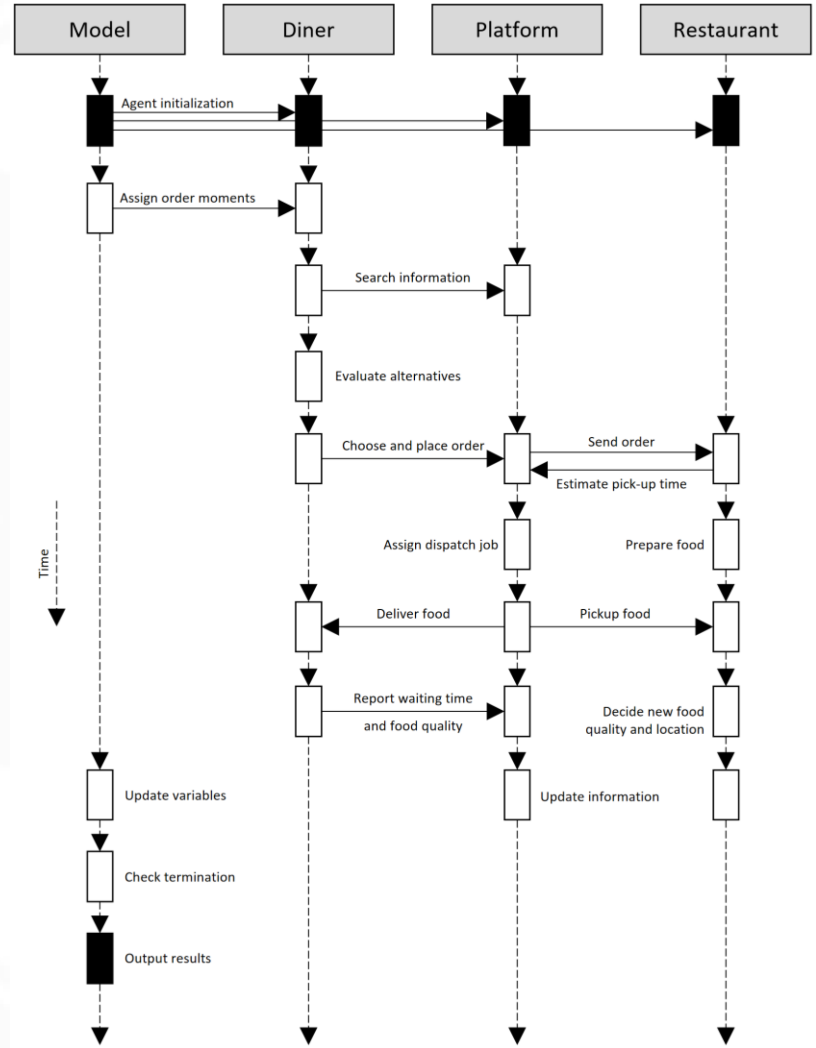
Agents

Table of agent variables

Agent[a]	Variable	Type[b]	Remark
Restaurant R_j	$q_{j,t}$	DV	Food quality, $q_{j,t} \in (0,1)$
	$r_{j,t}$	DV	The radial coordinate
	ϕ_j	XV	The angular coordinate
	$\underline{\rho}, \overline{\rho}$	XV	The minimum and maximum takeaway preparation time
	$\rho_{j,t}$	NV	Required time to preparing takeaway food
	$b_{ij,t}$	NV	The moment that the takeaway food for customer C_i is ready for collection
	$\theta_{j,t}$	NV	Current received order count
	$\Theta_{j,t}$	NV	Accumulated received order count
Customer C_i	$R^*_{j,t}$	DV	Selected restaurant
	β	XV	Preference for food quality
	(r_i, ϕ_i)	XV	The polar coordinates
	$U_{ij,t}$, $U^*_{ij,t}$	NV	Perceived and actual utility from ordering at restaurant R_j
	$a_{ij,t}$	NV	The moment C_i places order at restaurant R_j
	$d_{ij,t}$	NV	The moment C_i receives takeaway food packaged by restaurant R_j
	$w_{ij,t}$	NV	The actual waiting duration, i.e., $d_{ij,t} - a_{ij,t}$
	$f_{ij,t}$	NV	Probability that C_i selects the takeaway food of R_j
Online platform P	α	XV	Preference for cost-saving in route planning
	V	XV	Number of riders
	s, h	XV	Rider's speed and capacity
	p	XV	Number of recent time steps to update restaurant's information
	$c_{ij,t}$	NV	The moment a dispatch rider pick-ups the takeaway food
	$l_{ij,t}$	NV	The distance between customer C_i and restaurant R_j
	$W_{ij,t}$	NV	Average waiting duration of restaurant R_j rated by customers like C_i
	$Q_{ij,t}$	NV	Average food quality of restaurant R_j
Model M	N_d, N_r	XV	Number of customers and restaurants
	Γ	XV	The duration of online ordering
	$\bar{r}$	XV	The maximum radius of the local spatial market

Sequential diagram of ABM



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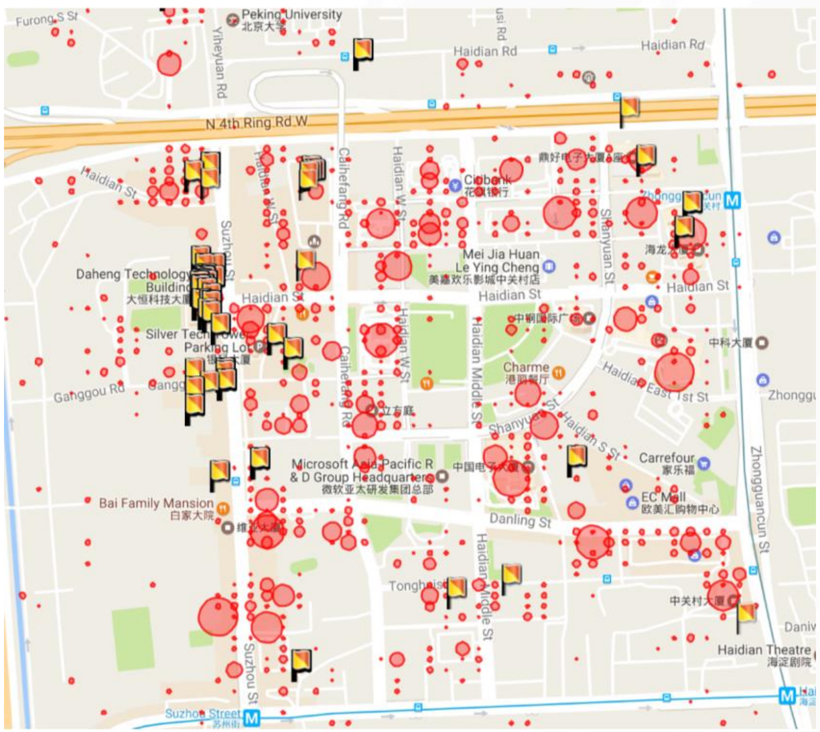
Model validation

- Based on real data from ele.me, we simulate a CBD in Beijing
- Simulation results are close to real data



A table of validation results can be found in the paper

Model indicators we are observing

1. Average waiting time reported by customers: w_{avg}.
2. Average radius: r_{avg}.
3. Average food quality: q_{avg}.
4. Average food preparation time: ρ_{avg}.
5. Average residual sum of squares: e_{avg}.
6. Average accumulated order count: Θ_{avg}.

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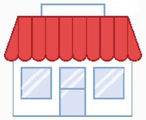
Three scenarios, to answer three research questions

1 the increasing preference for high food quality

2 shortening food preparing time



3 the increasing preference for cost saving

Table 2
Values of exogenous parameters in the simulation experiments.

Parameter	Value	Unit	Source	Remark	Changed values under scenarios
N_d	298	–	Ele.me	Number of customers	Unchanged
N_r	7	–	Ele.me	Number of restaurants	Unchanged
Γ	150	minute	Ele.me	The online ordering duration	Unchanged
$\bar{r}$	800	meter	Ele.me	The maximum radius of the spatial market	Unchanged
β	0.47	–	iResearch (2015a)	Customers' preference for food quality	$\{0.1, 0.3, \ldots, 0.9\}$ under Scenario A
$\underline{\rho}$	1	minute	Ele.me	The minimum takeaway preparation time	Unchanged
$\bar{\rho}$	20	minute	Ele.me	The maximum takeaway preparation time	$\{10, 15, \ldots, 30\}$ under Scenario B
$r_i, r_{j,0}$	$\lvert N(0, (\bar{r}/3)^2) \rvert$	meter	–	Agents' initial radial coordinates	Unchanged
ϕ_i, ϕ_j	$U(0, 360)$	degree	–	Agents' initial angular coordinates	Unchanged
p	30	–	Ele.me	Number of recent time steps to update restaurant's information	Unchanged
V	5	–	Ele.me	Number of riders	Unchanged
s	500	meter/minute	Ele.me	Rider speed	Unchanged
h	7	–	Ele.me	Rider capacity	Unchanged
α	0.5	–	Ele.me	Preference for cost-saving in route planning	$\{0.1, 0.3, \ldots, 0.9\}$ under Scenario C

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Results

◻ Three scenarios, to answer three research questions

- **Scenario A, higher food quality preference**
  - All restaurants increase food quality; location decisions not affected
  - Best restaurants make changes more markedly

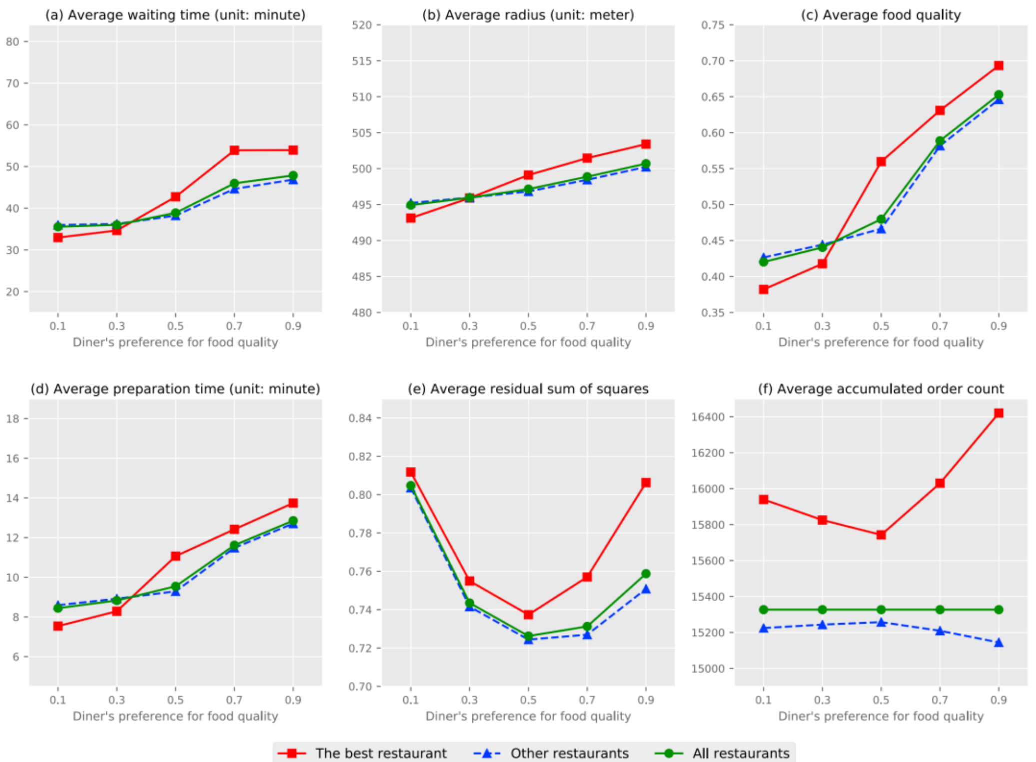

Fig. 2. Experimental results under Scenarios A.

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Results

Three scenarios, to answer three research questions

- **Scenario B, longer food preparation time**
  - Both decisions are less affected, as the diners are bearing the time cost
  - Best ones have higher food quality, greater uncertainty in decision-making, and closer to the CBD center

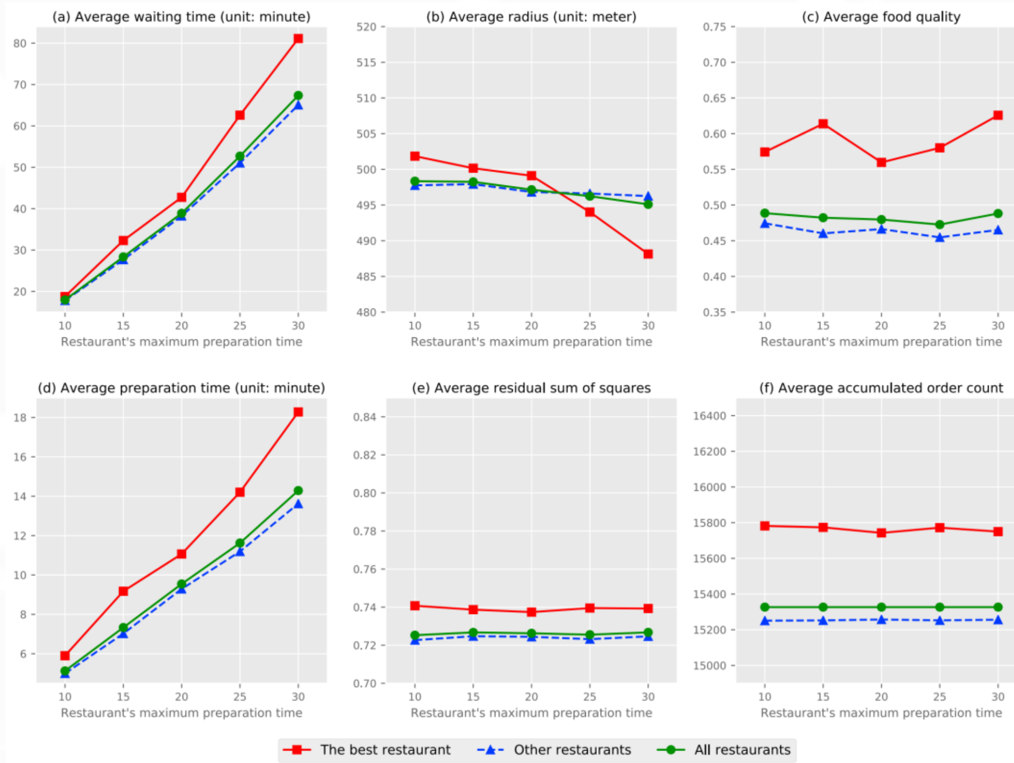

Fig. 3. Experimental results under Scenarios B.

Results

☐ Three scenarios, to answer three research questions

- **Scenario C, platform tends to save more cost**
  - Location decisions are changed more than food quality decisions
  - Best ones have much higher food quality and closer to the CBD center

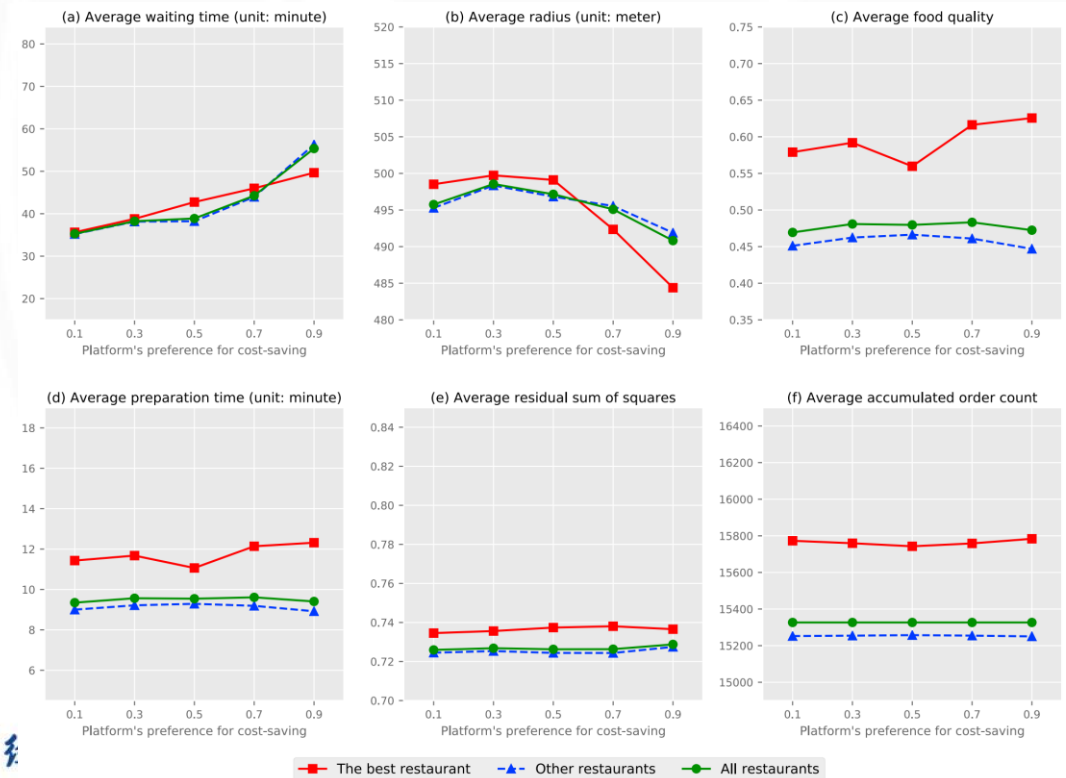

Fig. 4. Experimental results under Scenarios C.

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Take-Home Messages

- **Find ABM research opportunities in digital economy**
  - Identify the interactions of agents in new business models
- **Focus on your research problems**
  - Many elements like pricing are omitted in this study
  - Think globally, but stand with one agent type (restaurant)
- **Beyond over-simplified decision rules**
  - OR models and algorithms are seemingly more reasonable
  - Learning methods like ESTOPT can also be used

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Thanks! Q & A

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