Outdoor Seating versus On-Street Parking: An Agent-Based Model

Research Question

Since the COVID-19 pandemic underscored the importance of social distancing, outdoor dining has become more widespread amongst American restaurants. However, often these extra eating spaces come at the expense of on-street parking. This work inquires, how does a restaurant's choice of outdoor seating over parking change its revenue including revenue relative to other nearby, similar restaurants?

Purpose and Patterns

The purpose of this model is to test if outdoor dining affects revenues for restaurants and their neighbors within a small representation of a high street. Outdoor seating reduces parking spaces for potential driving customers, but pedestrianized streets tend to have higher customers, so these effects will be evaluated by final revenues.

Entities, State Variables, Scales

The model is a 20 x 10 grid including 1 row representing the central high street with restaurants and 1 row representing the on-street parking/outdoor eating for the central street. Other patches represent other buildings in the city. Simulations should run for 24 ticks (12 hours) to represent a typical weekend day for a popular restaurant.

The tables below detail the type of agents and their variables/states.

Variable / State	Corresponding Entity	Type	Description
pos	All agents	coordinate	Current coordinates on the grid (only changes for customers)
home	Customers	coordinate	Coordinates where customers are initialized and return to after eating out. Multiple agents can have the same home, in the same way that multiple people can live in the same apartment building.
Prob_eat	Customers	float	Probability of customer eating out
Party	Customers	integer	Number of people in the party of the customer
Tables_needed	Customers	integer	Number of tables needed based on the party size of customer (1 table sits maximum of 4 people)
Time_till_eat	Customers	float	Number of hours before customer can consider eating out again (starts at 4 hours after they eat meal and reduces by 0.5 after each tick)
Eating_duration	Customers	float	Number of hours spent eating at the restaurant (chosen randomly; choices: 0.5, 1, 1.5, 2 hours)
Rest_pick	Customers	string	The customer's choice for restaurant to dine at
Outdoor_preference	Customers	float	Ranking on how much outdoor eating matters to customer (ranges from 0 – does not matter at all to 0.9 – matters greatly); determines customer's choice
Name	Restaurant	string	Name of Restaurant
Outdoor	Restaurant	boolean	Whether the restaurant has outdoor seating or not
Tables_open	Restaurant	integer	Number of open tables at the restaurant
Revenue	Restaurant	integer	Amount of money accumulated by restaurant
Taken_parking_prob	Parking	float	Probability that a parking spot is taken at any given time
Available	Parking	boolean	Whether the parking spot is open or not

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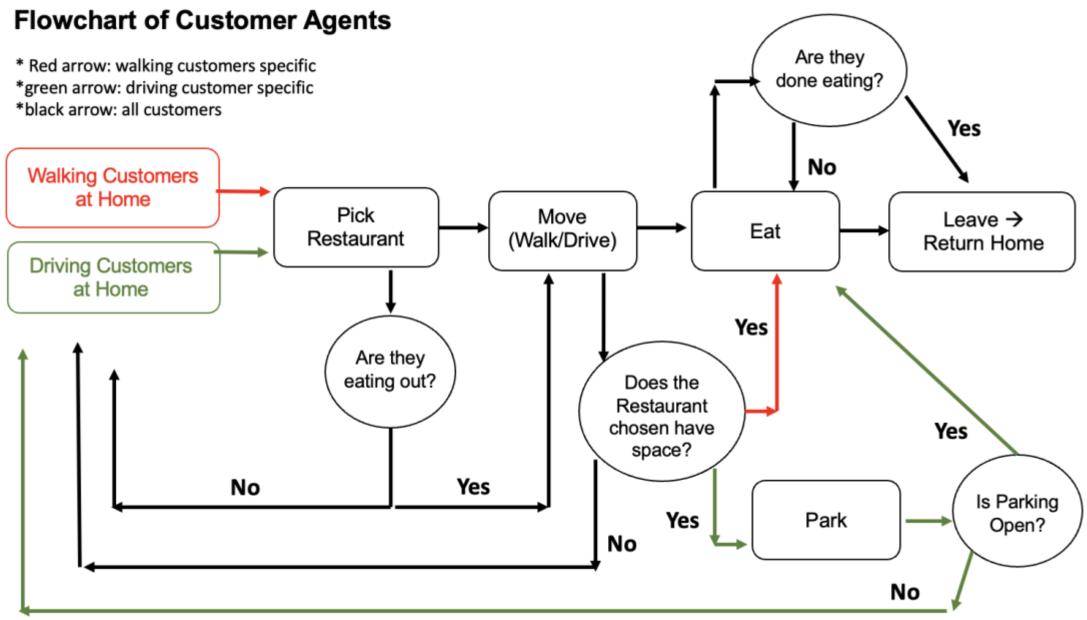
Parking_duration	Parking	float	Number of hours the parking spot is taken for (chosen randomly; choices: 0.5, 1, 1.5, 2, 2.5 hours)
Population	Model	integer	Number of potential customers in city
Walk_Ratio	Model	float	Fraction (from 0.2 to 0.8) of the population that are walking customers

Process Overview and Scheduling

The model begins by initializing the different agents and scheduling them. The random activation class in MESA randomizes the order in which the agents are activated every tick. In each tick, if a customer has not eaten within the last 4 hours, they decide if they want to eat out, and then decide a restaurant of choice. If the restaurant chosen has enough tables for the customer's party, walking customers will sit at the restaurant, but driving customers will only sit at the restaurant if there is a parking spot available. If there is no availability at the restaurant or no parking spot, the customer stays at home. Customers that get served are assigned a countdown of hours to spend eating, randomly chosen from between 0.5 to 2 hours. After the allotted hours, they leave.

Additionally, at every tick, available parking agents have a chance of being taken (not by customers). Their availability state will change accordingly, and a countdown randomly chosen between 0.5 to 2.5 hours begins. Also, restaurants accumulate revenue based on the party size of the customers sitting during that tick which is reflected in a live chart.



Design Concepts

Basic Principles
In the ABM, the parking for any of the restaurants is limited to the spots on the same street as the restaurant. This is based on the principle from various ABMs that parking behavior is based on the agent's tolerance for walking to their destination (Martens & Benenson, 2021, Waraich & Axhuasen, 2012). The ABM could be improved by adding a parameter d_{walk} as used in other ABMs (Dutta and Nicolas, 2021) that defines how far each driving customer is willing to walk to the restaurant which can add more flexibility in parking decisions of the agents.

Adaptation
Because this is a simple ABM, the adaptive measures are limited to driving agents testing out all parking spots on the street of the restaurant until they find one that is open. However, the adaptive behaviors can be expanded. For example, the submodel used to decide the restaurant could integrate adaptation based on previous experiences like in Sturley et. al's (2018) ABM of shopping customers where consumers keep a cognitive map of their past experiences at stores which is incorporated into their store choice during their next purchase.

Similarly, the restaurant agents in my model could take on adaptive behaviors by keeping track of foregone revenues from their lack of capacity as seen in ABMs modelling retail store competition (Vanhaverbeke & Macharis, 2011). Incorporating memory while allowing the stores to choose when to add or remove outdoor seating (instead of a user parameter) could give way to learning, with restaurants making future decisions of when to change capacity based on past experiences.

Initialization

The environment is created using a text file marking each cell type (restaurant, building, potential parking lot) using different numbers. The grid is colored according to the file while considering the user's parameters for what restaurants have outdoor eating. The customer population and ratio of walkers to drivers is also determined by the user. Each customer agent is randomly assigned their “home” position, a non-restaurant/non-parking patch, and in the visualization, walkers appear in the patches near to the restaurant. Other parameters set by the user at initialization are the probability of eating out and the probability that a parking spot is unavailable.

Input Data

There is no input data for this model.

Submodels

The restaurant choice is determined by the customer’s outdoor eating preference. Each customer is assigned an outdoor eating preference $Pref_C$ from 0 to 0.9 where 0 means outdoor eating has no effect on the decision and 0.9 means outdoor eating is very important to the customer.

The Weighting of the restaurant is $W_R = T_R + Pref_C$

where T_R is -1 if the restaurant does not have outdoor dining and 1 if the restaurant does.

The probability of Restaurant A, B being chosen is then:

$Probability_A = W_A / (W_A + W_B)$
$Probability_B = W_B / (W_A + W_B)$

Using these probability weights, a random choice of restaurant is made.

In this way, if a customer prefers outdoor dining, they are more likely to pick a restaurant with it over the other based on this feature’s importance to them. However, if both restaurants have outdoor eating or don’t, they have equal chance of being chosen.

Potential Exploration: Methodology

To explore the absolute change for a restaurant’s adopting outdoor eating, I would use regression analysis, creating 2 regressions, with and without outdoor dining for the same restaurant. The dependent variable would be the revenue and independent variable would be various levels of the user-settable parameters such as the ratio of drivers to walkers. I would run multiple simulations for each level and find the average. Using the regression, I not only compare revenues with versus without outdoor seating but also how these revenues differ based on the initial parameters.

To explore the change relative to neighboring restaurants, I would run multiple simulations (keeping parameters unchanged) of the model in which I make Restaurant A have outdoor seating and Restaurant B not. Then I would conduct a t-test comparing the samples of revenues from both restaurants to check if one is statistically significantly higher than the other.

Works Cited

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