Making Hard Decisions: Which Stores To Close?

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***Abstract*—Many studies propose methods for finding the best location for new stores and facilities, but few studies address the store closing problem. As a result of the recent COVID-19 pandemic, many companies have been facing financial issues. In this situation, one of the most common solutions to prevent loss is to downsize by closing one or more chain stores. Such decisions are usually made based on single-store performance; therefore, the under-performing stores are subject to closures. In this study, we first propose a multiplicative variation of the well-known Huff gravity model and introduce a new attractiveness factor to the model. Then we use a forward-backward approach to train and predict customer behavior and revenue loss after the hypothetical closure of a particular store from a chain. We study the case of department stores in New York City using large-scale spatial, mobility, and spending datasets. The case study results suggest that the stores recommended being closed under our proposed model may not always match the single store performance, and emphasizes the fact that performance of a chain is a result of interaction among the stores rather than a simple sum of their performance considered as isolated and independent units. Our proposed approach provides decision-makers with new insights into store closing decisions and will likely reduce revenue loss due to store closures.**

***Index Terms*—Store closing, closure decision, economic and financial crisis, Huff gravity model, downsizing, mobility, COVID-19 pandemic**

I. Introduction

COVID-19 has brought an unprecedented crisis to human society and the world economy, where many commercial brands have faced severe challenges in survival. All over the world, the continuous lockdown policies and people's concerns about their health have significantly reduced the number of visitors in physical stores [1], [2]. Out of the reliance on cooperation with other social institutions, small and medium-sized enterprises (SMEs) are doomed to suffer during this turbulent business cycle [3]. Recent research reports that SMEs witnessed a higher prevalence of business failure and unemployment during the pandemic [2]–[5]. Simultaneously, the spread of COVID-19 has pressed many large enterprises, such as Sears and J. Crew, to reduce their production and sales scale, while facing the threat of bankruptcy [1], [6]. This status quo drives many companies to choose to close some physical stores to ensure the continuity of their regular operations [1], [2].

A recent report [7] pointed out that in the United States, 17.7% of retail and food stores disappeared from April 2020 to May 2020, and the total estimated closed stores for the retail industry is between 20,000 to 25,000 nationwide. The report states that department stores such as J.C. Penney are particularly vulnerable due to the pandemic. This phenomenon has prompted us to study how to help companies better choose stores that need to be closed to better weather the crisis.

A critical factor in determining store closure decisions is brand loyalty. Store brands can have a positive effect on the attractiveness of a chain to its customers [8]. For example, if a company such as Target wants to close a store, decision-makers must consider customers' loyalty to company brands such as Archer Farms for food items and Art Class for clothing. Brand loyalty causes customers to pass other stores that may have slightly similar products but not necessarily the preferred brands. Therefore, store location should only be one part of the final decision in store closings. Furthermore, we believe that there are additional factors such as ambiance or marketing that contribute to customers' preference of one chain over another. We suggest that this overarching chain loyalty factor will be an important component of our model.

Donald Cavan [9] listed four possibilities of store closure reasons including poor performance, exchange zone arrangement, bankruptcy, and resource reallocation. Specific information regarding closed stores comes from companies' announcements through the media. From 2008 to 2016, around 490 million square feet of retail stores closed [9]. Such large scale closures are an important issue faced by retailers and many studies discuss how retail chains should select locations for new stores (see, e.g., [10], [11]), but so far, only a few studies discuss how commercial chains should make decisions about closing a store. This study aims to leverage customer patronization models to analyze how the number of visits to remaining stores of a chain and its competitors' stores will be affected after closing a store. We use various large-scale datasets for this aim, including spatial, mobility, spending, and open census datasets.

We aim to model and predict the customer response to closing a single store. The main contribution of our work is twofold. First, we propose a variation of the Huff gravity model, adding a new attractiveness factor that measures the demographic similarity of customers' home neighborhoods and neighborhoods where stores are located, contributing to the model performance. Then we use the proposed model - which is originally designed to estimate the market share to help with *opening a store* - in a reverse direction to estimate the market share of a chain after *closing a store*. Our study attempts to understand how visits to different chains would change in case of a closure, which could serve as a reference in store closing decisions.

II. Literature Review

A. Foregoing Store Closure Studies

Store closing is one of the most critical issues of the retailer decision-making process [12]. Researchers have proposed various methods to study how to make wiser decisions on which store(s) to close. The theory of dynamic decision modeling (DDM) which was proposed as early as 1962 connects recent decisions with ever-changing environments and previous choices [13]. Therefore, it is essential to acquire previous store-closing data and use it in DDM as a reference to deal with future challenges [14]. With the development of computational methods, computer simulations were introduced to draw pictures of human behavior as part of applying this theory that treats the decision-making process as a complex system [15]. Recent research also pioneered in using DDM to analyze the performance of retail stores that can be used to decide which stores to close [12].

Until now, DDM has been applied generally using two approaches, namely: Instance Based Learning Theory (IBLT) and Reinforcement Learning (RL) [14]. IBLT takes the sequential impact of previous decisions into account and allows multiple units to exist in the environment. However, this theory did not give a direct answer to store closure issues, which drives us to embrace the Huff Gravity model [16]. As for RL, although a small data size is enough to do the computations, these models aim to establish the relationship between the outcome in the real world and previous decisions or environmental changes [14]. In other words, past decisions are required to tune the hyperparameters, and these models serve as a reference for making plans. Decision-makers can set a future goal to replace the obtained outcome to test possible decisions and at the same time testify that the future goal is achievable [14].

Previous studies took spatial factors into account for store-closing decisions using Geographical Information Systems (GIS) to perform integrated location analysis and one case study explored these methods with K-mart stores [17]. We traced this theoretical framework back to 1931 when Reilly [18] proposed the law of retail gravitation. According to this theory, the larger the retail stores, the more likely it is for consumers to come from longer distances. The attention to the store area and the distance between a store and visitors inspired our model. In addition, Shields and Kures [17] took each store's location into account to achieve the highest estimated profits. To predict the number of closed stores, they used a logit model with independent variables including the area of the store, the proportion of households within 15 minutes to each store whose yearly income fell between \$20K and \$50K, the Euclidean distances from a K-mart store to the closest three stores of two competitive chains and K-mart itself, transportation costs, and demographic information related to children and poverty. This study sheds light on our research in selecting factors that influence decision-making processes for closing a store.

Mayadunne, Johar, and Saydam [19] studied the store-closing issue faced with the sluggish economy in the late 2000s. Their study is based on the principle that store locations are tied to customer demand and their competitors' fixed locations. This principle indicates that a store should seek its place where nearby customers have a stronger preference for their company, and its competitors will share the purchases in the store if this store is closed. This perspective is reflected in our study as well. To be specific, the constructed a model to maximize the company's total profits in various stages. In one step, they allocate the total demand in a region across different stores belonging to various companies according to demand functions and the distance between a store and each customer and set a distance threshold for each store to control the demand share. Furthermore, they applied a multi-period heuristic using mixed-integer programming to determine the equilibrium status of store-closing decisions of two competing companies over different periods. This study pioneers in analyzing the dynamics between two companies in the same region on closing stores. However, one weakness is that the independent variables in the model demonstrating competition between the stores of the two companies are fixed, which is hard to achieve in the real world since consumer behavior varies from one region to another.

In contrast, our study tested the significance of independent variables that worked as a reference for us to choose features and adjust our proposed gravity model. In addition, distance threshold can be a decisive factor that drives consumers to one store, but not always. When the distances between a consumer and various stores are not significantly different, other factors, including chain and brand loyalty, are expected to be a determinant. Therefore, merely using distance as a rule to reallocating consumption when one store is closed lacks persuasiveness, while it is still an independent variable in our model. Furthermore, their model can only be used to analyze the dynamics between two companies [20] while our model allows multiple ones. In addition, we studied companies that focus on products regarded as essentials in daily life, for which demands are rigid.

Haans and Gijsbrechts [21] studied the effect of store closures on the performance of other stores using classical discrete choice specification and a three-level nested multinomial logit model to obtain unconditional choice probabilities describing consumers selections [21]–[23]. They also adopted Tobit models to imitate consumption of different categories of products [21], [24]. This research inspired us to consider the changes made by consumers regarding product choices after one store is closed, and this will be reflected in our calculation of chain and brand loyalty for this topic.

B. *Huff Gravity Model*

As discussed above, store location selection is never an outdated topic for retailers. Apart from empirical studies, theories and models have been gradually developed to quantify the commercial environment and consumer preferences [25] that cover techniques involving market share [26]. Huff gravity model [16], together with proximity [27], deterministic utility models [28], random utility [29], [30] and cover-based [31] models are the most commonly used ones among them.

In the proximity model, Hotelling proposed that the gravitation of a consumer towards a store will push the consumer to visit the store, where the gravitation is only computed using distance [32]. When consumers can choose more efficient means of transportation or there is no significant difference in the distances between consumers and two stores, it is unrealistic to judge the attractiveness of different stores by considering the distance alone. Deterministic utility models are aggregated models assuming the consumer patronizes the store with the highest weighted utility [25], [28], [33]. According to the random utility model, consumers preferences towards various brands will impact store selections, as they tend to patronize specific chains to which that are loyal.

In addition, the utilities of stores to consumers have a multivariate normal distribution [29], [30]. In the cover-based models, each store is expected to exert a sphere of influence on consumers, and a consumers buying power is equally distributed to stores whose sphere of influence includes the consumer [31]. When considering stores of the same company or companies with products that are highly homogeneous, equal shares of buying power can be expected. Our research seeks to quantify competitiveness among stores affiliated with different brands where consumer preferences cannot be ignored.

The Huff gravity model proposed in 1964 [16] works under the assumption that the probability for a customer to patronize a store depends on its proportion of the sum of utilities of all potential stores by the following equation:

$$P_{ij} = \frac{U_{ij}}{\sum_{k=1}^{n} U_{ik}} \tag{1}$$

where U_{ij} is the utility for customer i from visiting store j, P_{ij} is the probability that customer i patronizes the store j, and n corresponds to the number of stores.

$$U_{ij} = \frac{A_j^{\alpha}}{D_{ij}^{\beta}} \tag{2}$$

Equation 2 defines the utility of store j for customer i, where A_j refers to the attractiveness of the store j and D_{ij} refers to the distance between the customer i and the store j. Parameters α and β are used to adjust the model's sensitivity to the two factors of attractiveness and distance. The original Huff model uses store area as the measure of attractiveness and assumes α is equal to 1. With studies leveraging the Huff gravity model with new data resources, the attractiveness of stores started to be defined by extra factors besides their areas. Nakanishi and Cooper [34] proposed a multiplicative competitive interaction (MCI) model that brings into account multiple dimensions of attractiveness. The MCI replaces the floor area with a product of attractiveness factors, where a parameter adjusts each factor in the product. Equation 3 shows the MCI model when multiple factors are included in attractiveness.

$$P_{ij} = \frac{\frac{\prod_{h=1}^{H} A_{hj}^{\alpha_m}}{D_{ij}^{\beta}}}{\sum_{k=1}^{n} \frac{\prod_{h=1}^{H} A_{hk}^{\alpha_m}}{D_{ik}^{\beta}}} \tag{3}$$

Many extensions of the Huff model were proposed by researchers using different attractiveness measures and distance decay functions. Chain and brand loyalty, diversity and number of amenities in store's vicinity, product price level, availability of parking area, and customer demographic and socio-economic information were used to shape a store's attractiveness [8], [35]–[40].

The set of parameters α and β can be tuned and one can apply the Huff gravity model to target different consumer populations and across regions. Therefore, parameter calibration plays an essential role in improving the accuracy of Huff gravity model applications. The ordinary least squares technique (OLS), geographically weighted regression (GWR), and particle swarm optimization (PSO) are the main approaches used in the literature so far [25], [34], [41]–[44]. OLS is sensitive to outliers and GWR disregards consumer preferences by focusing on location. Moreover, in the current urban setting, especially in metropolitan areas like NYC, stores may be located very close to customers' home. This leads people to ignore the minimal differences in distances to locations.

PSO is a continuous nonlinear optimization technique modeled after bird flocks. Theses particles which represent humans only use velocity and position to simulate behavior [44]. Each particle moves to seek the optimal local location until the model converges or a maximum threshold, such as movement time, is reached [45]. By comparison to OLS and GWR, PSO uses few assumptions [41], and gives more freedom to design models.

III. Data

This study utilizes various large-scale datasets from different sources, including the open U.S. census dataset, spending, and mobility datasets available for academic research purposes.

A. Mobility data

This dataset is provided by SafeGraph[1], a location intelligence company that collects location information from about 50 million smartphone devices in the United States. The data covers visits to more than 6.5 million points of interest (POIs) from January 2018 to December 2020. The mobility patterns data comes in different time and geographic aggregations to preserve users' privacy. The users' visit patterns are aggregated at the census block group (CBG) level. These patterns are available at weekly and monthly aggregations. Thus, no information could potentially be used to track or identify individual users. The POI dataset includes information about each POI's name, brand name if applicable, address and contact information, business category, North American Industry Classification System (NAICS) code, and area in square feet. The datasets are made available by the Safegraph data consortium for researchers as a part of the Data For Good program in order to help provide insights about the effects of the COVID-19 pandemic on human life.

B. Transaction Data

The customer spending data for this research is provided by Facteus[2]. The dataset includes daily spending of a sample from general-purpose debit cards, payroll cards, and government cards in the United States. The user spending is aggregated by users' home ZIP code, and merchants are specified only with their brands. This dataset has a reasonable coverage on the mentioned types of cards. For example, it captures 2.76% of payroll cards, 3.94% of debit cards, 3.00% of general-purpose debit cards, and 0.81% of government cards in Pennsylvania. This dataset is also a part of the Safegraph data consortium and Data For Good program and spans from January 2017 to May 2020.

C. Open Census Data

This dataset is publicly available and provided by the United States Census Bureau[3]. We collected the demographics and socio-economic information of every census block group in the country. This dataset contains numerous variables from which we extracted population, median income, median age, racial composition, and education level of each CBG's residents.

IV. Methodologies

A. Model Construction

We use an MCI variation of the Huff gravity model using various attractiveness measures from the literature and introduce a new attractiveness measure. The factors we use from the literature are (1) the area of store, (2) availability of parking space for store customers, (3) loyalty of customers to store brand, (4) number of POIs, and (5) diversity [46] of POIs in the vicinity of a store. Inspired by the vast array of network studies that show the association of homophily with human decision-making [47]–[49] we introduce a new attractiveness factor to include the socio-demographic similarity of the customers with the residents of the neighborhood where the store is located. This new factor indicates that considering other attractiveness and accessibility factors the same, a customer is more likely to choose the store within the neighborhood with similar socio-demographic features to theirs over other alternatives. We measure this by computing cosine similarity between customers' and neighborhoods' demographic vectors. The vectors include elements of education level, income level, age, and racial composition of residents. The output of the cosine similarity is a real number between -1 and 1, where 1 shows a perfect similarity between socio-demographic features of a customer's home neighborhood and that of a neighborhood where the store is located, and -1 indicates a perfect dissimilarity. Details about the attractiveness measures we use in our model are provided in Table I.

TABLE I

Variables in our proposed variation of the Huff Gravity Model indices i and j correspond to customer and store respectively

Variable	Information
$Area_j$	The area of store j in squared meters
Prk_j	The dummy variable (binary) showing whether store j provides parking space for its customers
$NPOI_j$	The number of POIs in the vicinity of store j
$DPOI_j$	The diversity of POIs in the vicinity of store j based on their business type using Shannon entropy using the formula below: $$DPOI_j = \sum_c -P_c^{(j)} \log(P_c^{(j)}) \quad (4)$$ where $P_c^{(j)}$ denotes the fraction of POIs from category type c in the vicinity of store j.
ChL_{ij}	The fraction of total spending by residents of neighborhood i in all stores of the chain that owns stores j over total spending in the same business category as store j.
Sim_{ij}	The cosine similarity of socio-demographic features of neighborhood i where the customers come form, and the neighborhood store j is located. The socio-demographic information used are education level, income level, age, and racial composition of residents. This measure is computed using the following formula: $$Sim_{ij} = \frac{V_i.V_j}{\lvert\lvert V_i \rvert\rvert \times \lvert\lvert V_j \rvert\rvert} \quad (5)$$ where V_i and V_j are the demographic feature vectors for the customer and store neighborhoods.
D_{ij}	The Haversine distance between the store j coordinates (X_j, Y_j) and the neighborhood i polygon centroid (X_i, Y_i). This is the great-circle distance between two points on a sphere and is computed using the formula below: $$D_{ij} = 2r sin^{-1}(h) \quad (6)$$ $$h = \sqrt{sin^2(\frac{Y_i - Y_j}{2}) + sin^2(\frac{X_i - X_j}{2}) cos(Y_i) cos(Y_j)} \quad (7)$$ where r is the radius of the planet earth.

[1]https://www.safegraph.com/academics

[2]https://www.facteus.com/

[3]https://www.census.gov/

Since the attractiveness metrics are in different magnitudes and units, using the min-max normalization, we normalize all of them (other than parking space availability which is a binary variable) to range between 1 and 10. This approach will help us avoid very large or minimal model parameters after tuning, making them comparable.

Additionally, for the case of parking space availability which is a binary variable, raising the binary variable to a power as a parameter is meaningless. Instead, we use expression (8) where ϵ is the parameter and the binary variable Prk_j is in power. If $Prk_j = 0$, then the expression is equal to 1 and has no effects on the store's attractiveness, else if $Prk_j = 1$, then ϵ will affect the attractiveness of the store.

$$(1+\epsilon)^{Prk_j} \qquad , \epsilon > 0 \tag{8}$$

Equations (9)-(11) show the final structure of our model. f in equation (11) corresponds to the fraction of visits from neighborhood i to store j and J is the set of all stores from the same business category.

$$U_{ij} = \frac{A_{ij}^{\alpha}}{D_{ij}^{\beta}} \tag{9}$$

$$\begin{aligned} A_{ij}^{\alpha} = Area_j^{\gamma} \times (1+\epsilon)^{Prk_j} \times ChL_{ij}^{\delta} \\ \times NPOI_j^{\theta} \times DPOI_j^{\mu} \times Sim_{ij}^{\psi} \end{aligned} \tag{10}$$

$$f_{ij} = \frac{U_{ij}}{\sum_{j' \in J} U_{ij'}} \tag{11}$$

B. Parameter Estimation

For estimating the model parameters, we use PSO to calibrate β, γ, ϵ, δ, θ, μ, ψ for each neighborhood i. We test various combinations to find the best parameter ranges. Our objective function is to maximize the value of Pearson correlation between the estimated fraction ($\hat{f}_{ij}$) and the actual fraction (f_{ij}) of the visits of consumers from neighborhood i to the store j.

C. Simulating store closure

After calibrating the parameters with actual data, one can use the proposed variation of the Huff model in a reverse direction to estimate the market share of remaining stores after closing a particular store. The Huff model has primarily been used to estimate the stores' market share after a new store is opened, but in this case, we are removing one of the stores from the set of all stores within the same category. Assuming the total demand is fixed, we can estimate the fractions ($\hat{f}_{ij}$) for the new set of stores after closing store j^* using equation 12.

$$\hat{f}_{ij} = \frac{U_{ij}}{\sum_{j' \in (J - j^*)} U_{ij'}} \tag{12}$$

After computing the estimated fractions, it is straightforward to compute the estimated visit count from each neighborhood i to each store j^* by simply multiplying the fractions with total demand that was assumed fixed. The outcome is the predicted visits from each neighborhood to each store. Subtracting the predicted number of visits after closing a store from the actual visits when the store was operating will indicate the predicted customer visit gain or loss for each remaining store. It is important to note that, for the chain stores, the gain or loss is computed as the sum of all predicted visits after closure minus the actual total visits before closure. Multiplying the predicted visit counts by average spending of that neighborhood in a particular brand can give the estimated revenue of the store. We perform this multiplication because there might be differences between the spending amounts of two customers from different neighborhoods in the same store, and examining only the number of visits does not consider such differences in spending.

D. Which store to close?

The question of which store to close leads us to choose the store whose closure results in the minimum loss of estimated revenue for all the stores of the given brand combined. Therefore, we use the following algorithm to determine the magnitude of total loss after closing each chain store.

Algorithm

1) *Use actual visit fractions $f_{ij}^{(t)}$ from historical data in time period t to calibrate the model parameters for each neighborhood using the PSO method.*
2) *Predict the total demand (visits) using historical data for time period $t+1$.*
3) *Disaggregate the total predicted demand among the stores into $\hat{f}_{ij}^{(t+1)}$ using the calibrated model.*
4) *Estimate the total revenue of a chain $\hat{R}_{cJ}^{(t+1)}$ by summation over multiplication of total predicted visits from each neighborhood to the chain by their average spending in the same category from historical data.*
5) *Using parameters from Step 1 and total predicted visits from Step 2, perform Step 3 after removing stores of a chain one at a time from the set of stores.*
6) *Repeat Step 4 using the total predicted visits from Step 5 to compute the estimated revenue after closing each store $\hat{R}_{c(J-j^*)}^{(t+1)}$*
7) *Compute the estimated profit/loss from closing store j^* by subtracting estimated revenues from Steps 4 and 6.*
$$\Delta \hat{R}_{c(J-j^*)}^{(t+1)} = \hat{R}_{cJ}^{(t+1)} - \hat{R}_{c(J-j^*)}^{(t+1)} \tag{13}$$
8) *Rank the stores based on the predicted revenue loss and choose the one with minimum revenue loss.*

V. Case Study and Results

A. Experimental Setting

In this research, we study the case of department stores and, in particular, Target Corporation stores in New York City (NYC) for years 2018 and 2019. Therefore, we filtered the datasets based on the NYC administrative boundaries.

Census block groups (CBG) are the smallest geographical unit used by the United States Census Bureau and have the highest spatial resolution with socio-demographic information publicly available. Therefore, we consider each CBG as a demand or customer center. There are 6493 CBGs inside NYC boundaries. From the POIs falling inside the CBG polygons, and using the business category of department store, 24 chains are chosen to be included in our case study, which consist of 282 stores in total (20 Target Corporation stores and 262 stores of competitor chains). The competitor chains include Family Dollar Stores, Dollar General, Dollar Tree, Saks Off Fifth, Macy's, BJ's Wholesale Club, Sears Home Services, Five Below, JCPenney, T.J. Maxx, Kmart, Barneys New York, Kohl's, Bloomingdale's, Neiman Marcus, Amazon 4-Star, Herms, Walmart, Costco Wholesale Corp., DAISO, Lou & Grey, Sears, Bottega Veneta, and Saks Fifth Avenue. Figure 1 shows the spatial distribution of Target Corporation stores and CBG polygons in New York City. In order to make a referral to stores more accessible, we assign an id to each of 20 stores starting by letter 'T' followed by two digits from '01' to '20'. Figure 2 shows the locations for all 282 department stores of our case study in New York City.

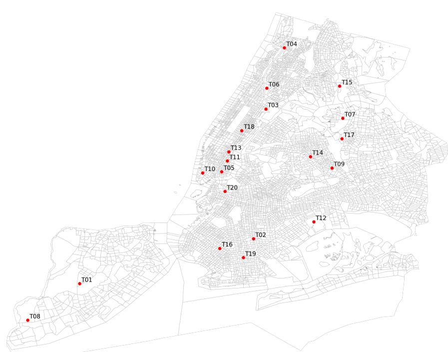

Fig. 1. Target Corporation stores in New York City

For each store, we have its category, latitude and longitude coordinates, CBG id, brand name, area, and whether it provides parking for customers or not. We use the number and category of POIs falling inside each CBG polygon to compute the number and diversity of POIs in the CBG as attractiveness factors ($NPOI_j$ and $DPOI_j$) for the store. We consider each CBG polygon centroid as a customer location and compute the haversine distance D_{ij} between the customer CBG centroid i and store location j.

For chain loyalty (ChL_{ij}), we used a spending dataset, which provides customer spending, aggregated customers by ZIP code of their home location and stores by their brands. Since there is no complete coverage and one to one mapping between ZIP codes and CBGs, we infer the spending of CBGs by taking a weighted average using the ratio of the population of a CBG in ZIP codes that cover the CBG partially by

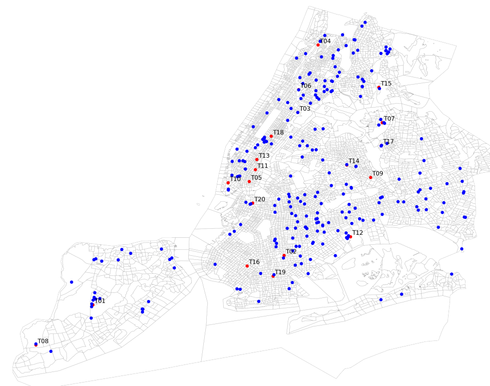

Fig. 2. All Department Stores in New York City. Target Corporation stores are shown in red and its competitors in blue

equations 14 and 15 where Z is the set of all ZIP codes that cover CBG_i.

$$w_{iz} = \frac{population\ \ of\ \ CBG_i\ \ in\ \ Zipcode_z}{population\ \ of\ \ Zipcode_z} \tag{14}$$

$$Spending\ by\ CBG_i = \sum_{z \in Z} (w_{iz} \times Spending\ by\ Zipcode_z) \tag{15}$$

Then we aggregated the total spending by each CBG in a category (i.e. department stores) and computed the fraction of it spent in each chain [8]. Additionally, we computed the average spending by each CBG's residents in each category used to estimate the revenue of store per visit from the CBG. Since our datasets have complete intersections in 2018 and 2019, we limited our study to those two years. For the case of similarity, we used the cosine similarity between the demographic features of customer CBG and store CBG. Demographic features were extracted at the CBG level from the U.S. census API.

B. Proposed Model Performance Evaluation

As our first experiment, we tried to evaluate the performance of the proposed model in equations (9)-(11). We trained our model by data from 2018 and calibrated parameters to predict the visits to stores in 2019 for each CBG-store pair in NYC. Only 6298 out of the total 6493 CBGs are recognized to have visits to different stores. Consequently, our computation, prediction, and performance analysis are based on the results from the *live* CBGs in 2018. In other words, for the CBGs that we do not see visits in 2018, we assume the actual and predicted visits in these regions to be 0. Thus, we exclude them from measuring the performance of our model. Using information for 6298 CBGs and 282 stores, we predict more than **1.77 million** data points of store-CBG pair visits. We evaluate the model performance by measuring the Pearson correlation between actual and predicted visits in 2019.

Figure 3 displays the box plot of Pearson correlation distribution of the predicted and actual visits of each CBG in NYC. To elucidate, the box plot shows the distribution of 6298 correlations, each corresponding to correlation between a CBG's actual versus predicted visits to the 282 stores of study. The general Pearson correlation between actual and predicted visits for all **1,776,036** CBG-store pairs (6298 $\times$ 282) is **0.6535** with a p-value almost 0 in terms of each store-CBG pair. We also compared the actual visits and predicted visits to each brand (282 data points), and we got a significant Pearson correlation coefficient of **0.77384** with a very small p-value ($1.796\mathrm{e}{-57}$). The results indicate that our proposed variation of the Huff model performs well in terms of Pearson correlation and the large data size.

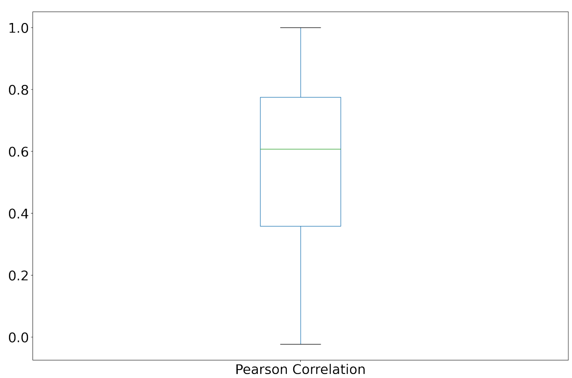

Fig. 3. Pearson correlation of the predicted and actual visits per CBG-store pair in NYC

Figures 4 and 5 show the actual and predicted visits to Target Corporation stores in 2019 from the 6298 *live* CBGs located in NYC, respectively.

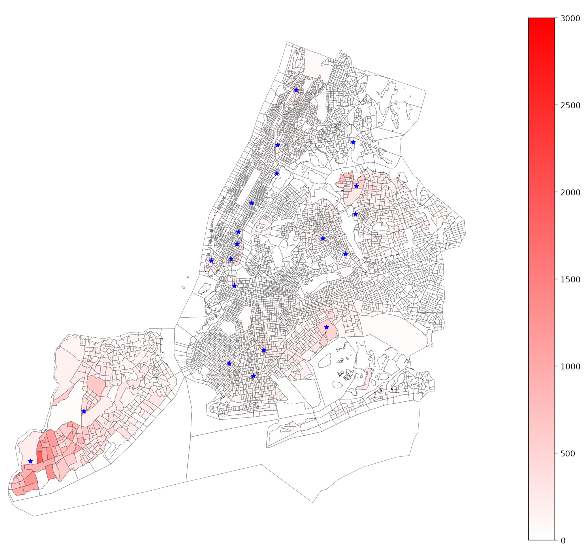

Fig. 4. Actual visits by each CBG to Target Corporation stores in 2019

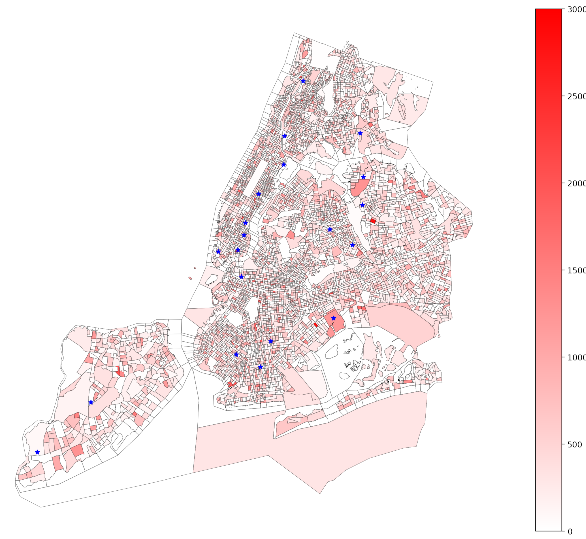

Fig. 5. Predicted visits by each CBG to Target Corporation stores in 2019

C. Baseline

It is not uncommon that the stakeholders make closure decisions based on single store performance, choosing the store with the poorest performance (e.g., profitability, visitor count, total revenue) to close. We use the single store performance as a baseline method to compare against the results our model produces. As a performance measure, we use the estimated revenue (visit count multiplied by average customer spending), meaning that the store with the lowest estimated revenue should be closed. Based on this criterion, store T09 with the lowest foot traffic and the estimated revenue is ranked first for closing. Figure 6 shows store T09 and the spatial distribution of its customers.

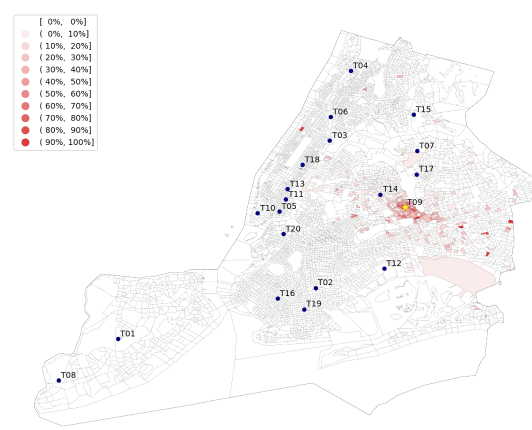

Fig. 6. Target Corporation store T09 customer distribution. Colors indicate the percentage of spending by each CBG covered by store T09

D. Store Closing Simulation

Using the algorithm proposed in section IV-D we study the case of closure of Target Corporation stores in NYC. We use the dataset from the year 2018 to compute the actual CBG-store visits and CBG-brand spending for all 6298 CBGs and 282 stores. Then considering fixed demand (visits) for 2019, we hypothetically consider each store closed and compute the estimated total revenue loss for the chain. Table II compares the result of our proposed model for closing recommendation versus the baseline using single store historical performance based on their estimated revenue (summed multiplication of average spending of CBGs in the category by total visit count). We used a color pallet to make the visual comparison easy among the two columns. The color range in the second column indicates the predicted loss ordering (closure rank), and in the third column, we used the same color for each store as in the second column.

TABLE II
RESULTS FOR STORE CLOSURE RANKING BY OUR PROPOSED MODEL VS THE SINGLE STORE PERFORMANCE BASELINE.

Closure Priority	Proposed Method	Baseline Method
1	T14	T09
2	T09	T13
3	T15	T15
4	T13	T03
5	T10	T18
6	T20	T05
7	T11	T19
8	T05	T11
9	T18	T16
10	T03	T14
11	T06	T06
12	T19	T10
13	T07	T20
14	T16	T17
15	T02	T08
16	T01	T04
17	T08	T02
18	T04	T01
19	T17	T07
20	T12	T12

Our proposed method is built based on the idea that closing a store from a chain does not necessarily result in losing all the customers of that particular store, yet a fraction of those customers will be retained by the remaining stores of the same chain. As reported in Table II, while the single store performance idea recommends store T09 to be closed, our proposed method suggested store T14 as the first option, which is ranked 10th to be closed by the baseline method. The difference in the store choice between the two methods indicates that our proposed model predicts that in the case of closing store T14, the set of remaining operating stores are more capable of capturing the former customers of T14, rather than the case of closing store T09. Figure 7 shows store T14 and spatial distribution of its customers.

The results of this case study suggest that the stores recommended being closed under our proposed model may not always match the single store performance, emphasizing that the performance of a chain as a whole is not simply the outcome of operating stores as isolated units but a network of stores interacting with each other.

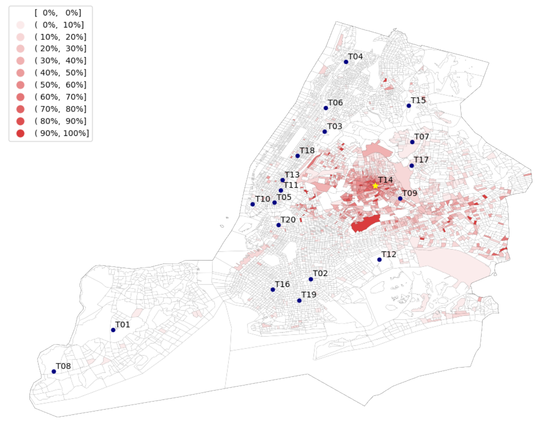

Fig. 7. Target Corporation store T14 customer distribution. Colors indicate the percentage of spending by each CBG covered by store T09

VI. Discussion & Conclusion

Modeling store closure is difficult due to the complexity of real-world data. Making a more insightful decision on this issue appears to be increasingly challenging and vital. Our proposed variation of the Huff Gravity Model leverages precedent theories and empirical studies to consider seven variables. The set of variables we use includes six variables from the literature, and a new variable that we propose in this study, which inspired by the idea of homophily, brings into account the demographic similarity between the customer and store neighborhoods and was able to help improve the model performance. The variables we use in our proposed model are:

- the area of a store
- the parking lot ownership of a store
- chain loyalty of visitors
- the number of POIs in a particular region
- the diversity of POIs in a particular region
- the distance between a visitor's home and store location
- the demographic similarity between the customer and store neighborhoods

In particular, we study the case of department stores in New York City, which is considered as an impressive **micro world** [15] for our case study, since it is a highly-developed modern city where a variety of commercial brands settle in and compete for the attraction of many residents. Our model performs reasonably well in terms of Pearson correlation and the large data size. In our case study, the model predicted the visit distribution among department stores in New York City with a high Pearson correlation coefficient of **0.77384** at the store level and **0.6535** predicting more than **1.77 million** data points for store-CBG pair visits. Finally, we designed an algorithm that uses the proposed model in the reverse direction to simulate the customer visit distribution after hypothetically closing a store from a chain utilizing behavioral analytics extracted from the historical mobility data.

This study has limitations mainly arising from restricted access to and availability of detailed data. Since we do not have access to stores' internal data, we need to replace the profit with estimated revenue based on the mobility data that does not capture all the stores' customers and has limited coverage in some areas. The same argument is valid for the spending data. Our dataset does not provide a visit history for the stores that were permanently closed. Therefore, we merely redistributed the visits based on the calibrated parameters instead of modeling human behavior, assuming that any store in our list is closed.

Although we do not see the customer response to closing a store using our model yet, it is believed to portray a good picture for store visit prediction with a substantial theoretic and empirical foundation. The case study and simulation results suggest that the stores recommended being closed under our proposed model may not always match the single store performance, which highlights the fact that the performance of a chain is a result of interaction among the stores rather than a simple sum of their performance considered as isolated units. Our proposed approach provides decision-makers with new insights into store closing decisions and will likely reduce store closure's consequences on revenue loss. Our proposed approach can also be potentially used by competitors when they see a particular chain store closed. They can use the model to predict the probability of new customers from different neighborhoods and start or adjust their marketing strategies based on the socio-demographic information and taste of the potential customers.

Availability of Code and Data

The code and more detailed visualizations are available on the GitHub page of this research project at https://github.com/Yilun0221/Making-Hard-Decisions-Which-Stores-To-Close- The mobility data from Safegraph is available for academic research purposes as a part of Safegraph data for a good program. The spending data was available as a part of Safegraph data for good COVID-19 consortium, which is currently unavailable. Aggregated used data for the case study are available on the research GitHub page.

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Abbreviations Used

CBG: Census Block Group
DDM: Dynamic Decision Modeling
GIS: Geographical Information Systems
GWR: Geographically Weighted Regression
IBLT: Instance Based Learning Theory
MCI: Multiplicative Competitive Interaction
NAICS: North American Industry Classification System
NYC: New York City
OLS: Ordinary Least Squares
PSO: Particle Swarm Optimization
RL: Reinforcement Learning
SME: Small and Medium sized Enterprise

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Authors' Contributions

Y.X. and M.B. and M.T. were involved in idea generation, design and implementation of experiments, drafting the article, writing, and developing the online interactive dashboard. Whereas B.B. and A.P. were involved in idea generation, results, discussion, feedback, and final revision and drafting of the article.

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