Geographical Factors Affecting Grubhub's Business amid COVID-19 Pandemic

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Abstract. During the COVID-19 outbreak, the food delivery market in the United States began to thrive. However, Grubhub, one of the largest food delivery platforms, did not capitalize on this opportunity and experienced severe net losses and a significant decline in market share. Despite the popularity of research on the demographic factors affecting the food delivery market, geographic factors were poorly concerned. In this paper, more attention was paid to reveal the geographical factors that led to the recession of Grubhub under the pandemic. Four machine learning models, namely Linear Regression, Support Vector Regression, Bayesian Ridge Regression, and Elastic Net, were applied to identify the unusual decrease in the net income of Grubhub using Python. This paper then explore the geographical factors by visualizing the business and demographic data. The predicted results show that Grubhub's performance was far below its average over the past two years. Furthermore, by data visualization, it is found that a major geographical factor preventing Grubhub from capturing opportunities is its lack of business expansion into suburban and rural areas.

Keywords: Grubhub, Food Delivery Service, COVID-19, Geographical Factors.

1. Introduction

The United States has one of the most competitive online food delivery markets around the world, with DoorDash, Uber Eats and Grubhub vying for the leading position. Grubhub was founded in Chicago in 2004 and merged with Seamless in 2013 to become an online food delivery aggregator. Grubhub remained the largest food delivery platform in the U.S. until being surpassed by DoorDash in 2019 [1]. In 2020, as the COVID-19 pandemic stoke, the online food delivery industry in the U.S. began to thrive. However, unlike the other platforms such as DoorDash which witnessed sales growth [2], Grubhub experienced a severe net loss and a significant drop in its market share.

Previous studies on the COVID-19 pandemic affecting the online food delivery market have mostly focused on demographic factors. For instance, Poon and Tung analyzed the factors that influence users to place orders. They found that attitudes, subjective norms, positive expected emotions and negative expected emotions, and perceived behavioral control all have significant effects [3]. In a case study of Grubhub [4], Ar identified three key factors for successfully managing an online food delivery business during the pandemic: timely and innovative solutions to meet social needs during a crisis, addressing stakeholder concerns through the implementation of various policies, and supporting employees.

However, only a few researchers have paid attention to geographic factors that influence the food delivery market. According to McKinsey, geographic competition between take-out platforms may be one of the most important battlegrounds in the coming years [5]. DoorDash set up its stronghold in the suburbs in early 2013 to avoid confrontation with Grubhub, which has already dominated the food delivery business in major U.S. cities. With the onset of the pandemic, this strategy surprisingly enabled DoorDash to earn $2.88 billion, 1.5 times more than Grubhub [6]. Hence, it is reasonable to speculate whether Grubhub suffered during the COVID because of some geographic factors.

As for research methods, linear regression models have been commonly used in early studies to predict the performance of the ordering market. For example, in [7], the authors constructed an autoregressive-moving-average (ARMA) regression model to predict food ordering demand and a

Susceptible-Infected-Recovered (SIR) model to forecast future infected in the given region. A regression model was also a popular choice in the study of consumer behavior in the market. In [8], multiple regression analysis was utilized to discover predictors of customers' continuance usage intention of food delivery apps during the COVID-19 quarantine in Mexico. In [9], the authors analyze customers' responses to online food delivery services during the COVID-19 pandemic using a binary logistic regression model. While in our settings, this paper wants to predict the net income of Grubhub in 2019 and 2020 and compare the predicted figures with the true financial data collected to verify whether Grubhub faced a recession under the COVID-19 pandemic. The linear regression model may be a choice, but it is limited and a bit out of date. As a result, machine learning based linear regression model was used. In addition to this, to achieve a more accurate result, other machine learning methods such as the Support Vector Regression model, Bayesian Ridge Regression model and Elastic Net model are also adopted in this paper to predict the performance of Grubhub in 2020.

This study aims to identify the geographic factor that contributed to Grubhub's recent recession. Four machine learning models are employed to confirm the downturn Grubhub faced under the COVID-19 pandemic in the U.S.

2. Methods

2.1 Data description

In this study, financial data of Grubhub, data of the U.S. food delivery industry, and data on the impact of COVID on the U.S. were collected and used to analyze the factors for Grubhub's declining trend during the COVID-19 pandemic. Descriptions and details about the data can be seen in Table 1.

Table 1: Information on the dataset used.

Name of Dataset	Data Description	Number of Data	Statistical Information	Source
Net income of Grubhub	Annual net income of Grubhub worldwide in million U.S. dollars from 2011 to 2020	10 years	Min data: -155.86 (2020) Max data: 98.98 (2017) Average: 14.48	Statista [10]
Orders per day of Grubhub	Annual average number of Grubhub orders per day worldwide from 2011 to 2020	10 years	Min data: 45700 (2011) Max data: 622700 (2020) Average: 278520	Statista [11]
Active users of Grubhub	Annual average number of active Grubhub diners worldwide in millions from 2011 to 2020	10 years	Min data: 0.69 (2011) Max data: 31.42 (2020) Average: 11.12	Statista [12]
Revenue of Grubhub	Annual revenue of Grubhub worldwide in million U.S. dollars from 2011 to 2020	10 years	Min data: 60.61 (2011) Max data: 1819.98 (2020) Average: 621.15	Statista [13]

Market share of Grubhub and DoorDash in the U.S.	Monthly market Share of Grubhub, DoorDash and other food delivery platforms in percentage in the U.S. from Jan 2018 to June 2021	2 platforms 42 months	Range for Grubhub: 16% (202106) to 49% (201801) Range for DoorDash: 17% (201801) to 56% (202106)	Bloomberg Second Measure [14]
Market shares of Grubhub and DoorDash in different regions in the U.S. in 2020	Market shares of Grubhub, DoorDash and other food delivery platforms in percentage in urban, suburban, and rural areas in the U.S. in 2020	2 platforms 3 regions	Grubhub: 30% in urban, 21% in rural, 16% in suburban areas DoorDash: 24% in urban, 43% in rural, 43% in suburban areas	Edison Trend [15]
Food delivery transactions by population density in different regions in the U.S.	Monthly food delivery transactions by population density in percentage in urban, suburban and rural areas in the U.S. from Jan 2019 to Apr 2021	3 regions 28 months	Range for urban: 37% (202104) to 50% (201901) Range for suburban: 48% (201901) to 60% (202104) Range for rural: 2% (201901) to 3% (202104)	McKinsey [5]
COVID impact of moving out in different regions in the U.S. in 2021	Median COVID impact per 1000 of moving out by different regions from principal urban center to rural areas in the U.S. in 2021	6 regions	Min data: -8.35 (principal urban center) Max data: 5.01 (semirural)	CBRE [16]
Change in the propensity to move by life modes in bps in the U.S. in 2021	Change in the propensity to move by life modes from uptown individuals to GenxXurban in bps in the U.S. in 2021	14 life modes	Min data: -182 (GenXurban) Max data: 952(uptown individuals)	CBRE [16]

2.2 Prediction Models

The annual net income of Grubhub is a good index for evaluating Gruhub's performance each year. Its calculation is relevant to yearly revenue, the number of orders, active users, etc. In this study, we only consider variables that have decade-long datasets to achieve more accurate results. With the statistics displayed in Table 2, we can run the prediction.

Four machine learning methods, namely Linear Regression, Support Vector Regression, Bayesian Ridge Regression, and Elastic Net, are used in this study to predict Grubhub's net income in 2019 and 2020 based on the dataset in Table 2 collected from [10-13].

Table 2: Dataset used for prediction

Year	Annual Net Income (in million U.S. dollars)	Annual Revenue (in million U.S. dollars)	Average orders per day by year	Active users worldwide by year (in millions)
2011	15.21	60.61	45700	0.69
2012	7.92	82.3	62000	0.99
2013	6.75	137.14	107900	3.42
2014	24.26	253.87	182800	5.03
2015	38.08	361.83	227100	6.75
2016	49.56	493.33	274800	8.17
2017	98.98	683.07	334000	14.46
2018	78.48	1007.26	435900	17.69
2019	-18.57	1312.15	492300	22.62
2020	-155.86	1819.98	622700	31.42

The training data is data from 2011 to 2018, covering 80% of the data. While data from 2019 and 2020 accounting for the remaining 20% is assigned to test data in all four models. By comparing the predicted results to the true values, we can tell how the company performed during the COVID-19 pandemic. The calculations are done using Python.

2.2.1 Linear Regression

The Linear regression is probably one of the most widely chosen and well-understood algorithms in machine learning. It assumes a linear relationship between the input and output variables and can be employed to build a model to explain that relationship by estimating the parameters [17]. If any unseen input variables are introduced, the fitted model can be used to predict new output variables.

2.2.2 Support Vector Regression

The Support Vector Regression is based on Support Vector Machine (SVM), where support vectors are basically closer points towards the generated hyperplane in an n-dimensional feature space that distinctly segregates the data points about the hyperplane [18]. It is effective for prediction in solving both linear and nonlinear problems. Another advantage of it is that its computational complexity does not depend on the number of input variables. Additionally, it has excellent generalization capability, with high prediction accuracy [19].

2.2.3 Bayesian Ridge Regression

The Bayesian Ridge Regression model is a probabilistic model as it is in the Bayesian framework. Like other regression models, once it is fitted, it then can be adopted for prediction. The use of Bayesian Ridge regression provides high adaptability with small data parameters and its ease of usage in a regularization problem and hyperparameters tuning [20].

2.2.4 Elastic Net

The Elastic Net is a linear regression method that carries out variable selection and regularization at the same time. Elastic Net regularization implements both L1- normalization and L2-normalization regularization to penalize the coefficients in a regression model [21]. The algorithm eliminates redundant information and transforms high-dimensional data into low-dimensional data while retaining the effective information of the original data [22].

3. Results and Discussion

3.1 Performances of prediction models

3.1.1 Results of prediction

By running the four prediction models mentioned above, we obtained the outcomes presented in Table 3. The "Difference" columns in Table 3 present the absolute values of computed results of predicted values subtracted from the actual net incomes. The smaller the difference is, the more accurate the prediction is.

Table 3: Results of Prediction Models

Model name	Predicted value of net income in 2019 (Million U.S. dollars)	Predicted value of net income in 2020 (Million U.S. dollars)	Difference (2019) (Million U.S. dollars)	Difference (2020) (Million U.S. dollars)
Linear Regression	112.853	153.581	131.423	309.441
Support Vector Regression	33.176	31.998	51.746	187.858
Bayesian Ridge Regression	103.157	132.248	121.727	288.108
Elastic Net	112.853	153.581	131.423	309.441

Grubhub's net income for 2019 and 2020 are -18.57 and -155.86 million dollars. The negative number shows that Grubhub faced a net loss in both years. However, the predicted net incomes generated by the four models for 2019 and 2020 are all positive.

Moreover, it can be seen from the last two columns of Table 3 that the predicted results differ largely from the actual values. The predicted value of net income yielded by the Support Vector Regression model was the closest to the real net income for both years, with the differences being 51.746 million dollars for 2019 and 187.858 million dollars for 2020. While the other three models: the Linear Regression model, Bayesian Ridge Regression model, and Elastic Net model, generated accuracies of over one hundred for 2019, with 129.180, 121.727, and 131.423 million dollars respectively, and for 2020, the figures even attain around 300.

3.1.2 Discussion

The difference in the sign between the predicted results and the actual net income indicates an unusual recession in Grubhub's business in 2019 and 2020. In addition, the more striking difference between the predicted values and the values of net income for 2020 reveals that the downturn has become more severe in 2020. This seems abnormal especially when the whole food delivery industry had more than doubled during the COVID-19 pandemic [5]. We will focus on whether the geographic factors play a role here in the following part.

3.2 Analysis of business data

3.2.1 Results of data visualization

To find the geographic factors for Grubhub's decline, the changes in Grubhub's market share of the U.S. food delivery market during the COVID-19 pandemic and the COVID-19 impact on the U.S.

moving rate were further examined. The data about Grubhub was compared to its better-performing competitor, DoorDash. The following charts Figure 1-5 were drawn based on the dataset in Table 2 collected from [5, 14-16] for data visualization.

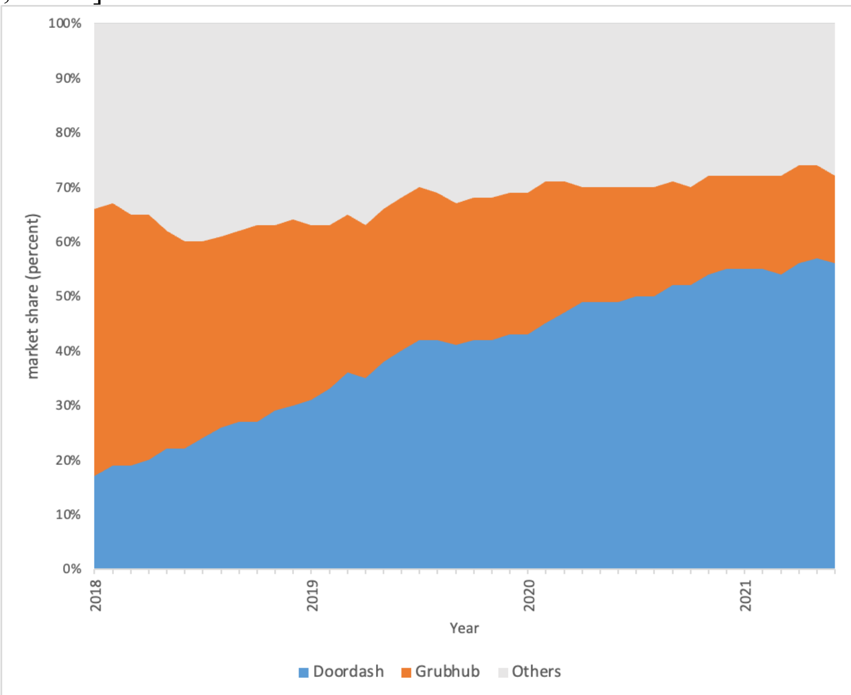

Figure 1: Market share of Grubhub and DoorDash in the U.S. from Jan 2018 to June 2021

Figure 1 illustrates the dataset of the market share of Grubhub and DoorDash in the U.S. In January 2018, before the start of the epidemic, Grubhub captured almost half (49%) of the U.S. takeaway market. However, Grubhub's leadership was gradually overtaken by DoorDash. In June 2021, long after the COVID-19 outbreak, Grubhub's market share dropped directly to just under 30% of DoorDash's.

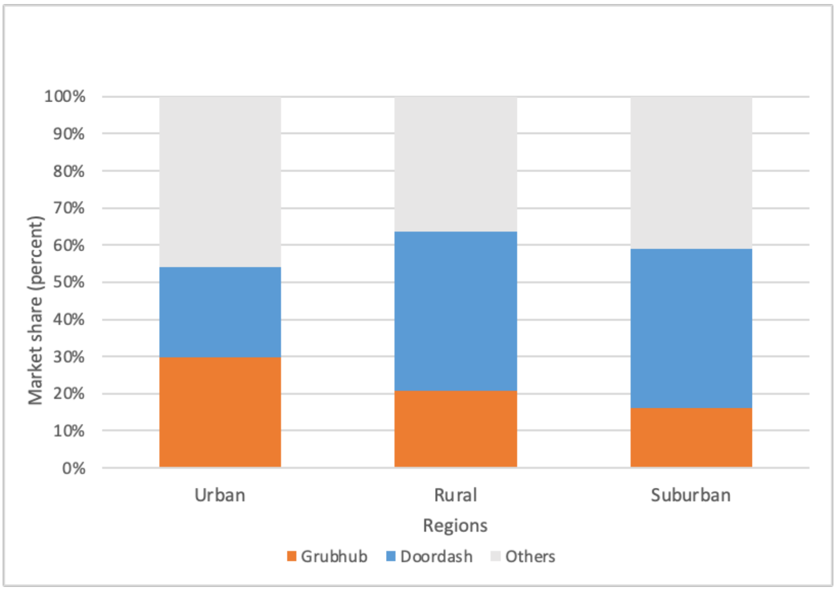

Figure 2: Market shares of Grubhub and DoorDash in different regions in the U.S. in 2020

To evaluate the performance of Grubhub in urban, suburban and rural areas, Figure 2 was drawn to show the dataset of market shares of Grubhub and DoorDash in different regions in the U.S. in 2020. Grubhub still maintained the highest market share among food delivery platforms in urban areas. But in suburban and rural areas, Grubhub was far less competitive than DoorDash.

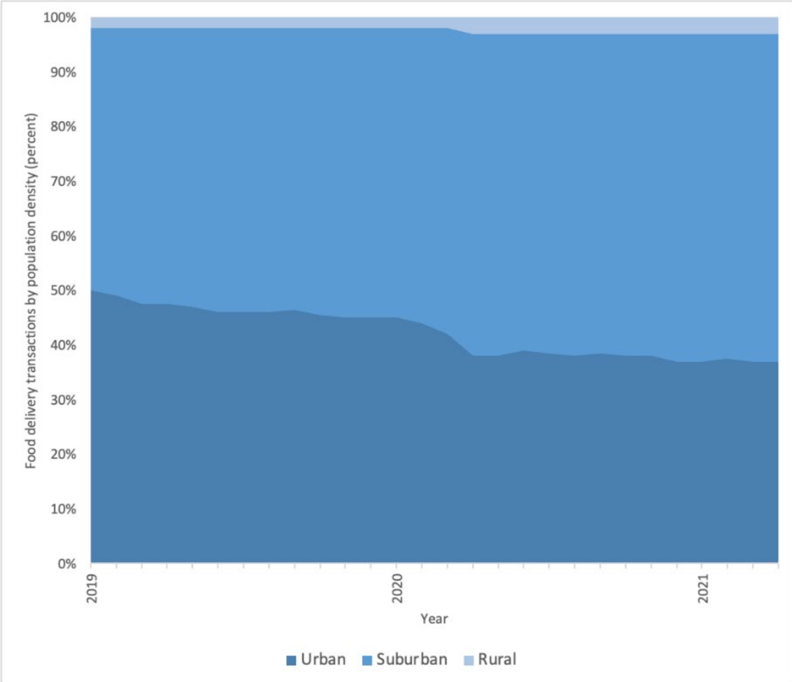

Figure 3: Food delivery transactions by population density in different regions in the U.S. from Jan 2019 to Apr 2021

Regarding the demand for U.S. take-out services, the dataset of food delivery transactions by population density in different regions in the U.S. was interpreted in Figure 3. The take-out transactions in suburban and rural areas had risen over the past two years, representing the growing demand for food delivery services outside of cities during COVID-19.

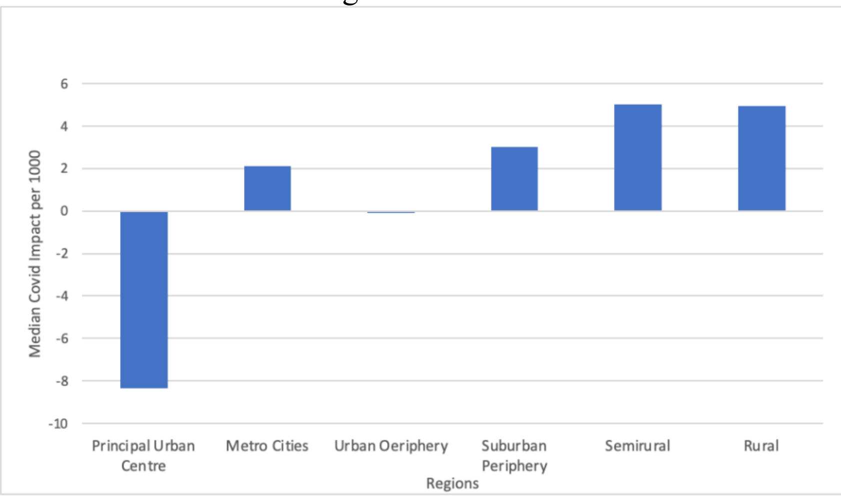

Figure 4: Median COVID impact per 1000 of moving out by different regions in the U.S. in 2021

Moreover, data on the movement of the U.S. population during the COVID was studied. According to Figure 4, which was based on the dataset of the COVID impact of moving out in different regions in the U.S. in 2021, more people are moving out than moving in in most urban areas, but the opposite is true in suburban and rural areas.

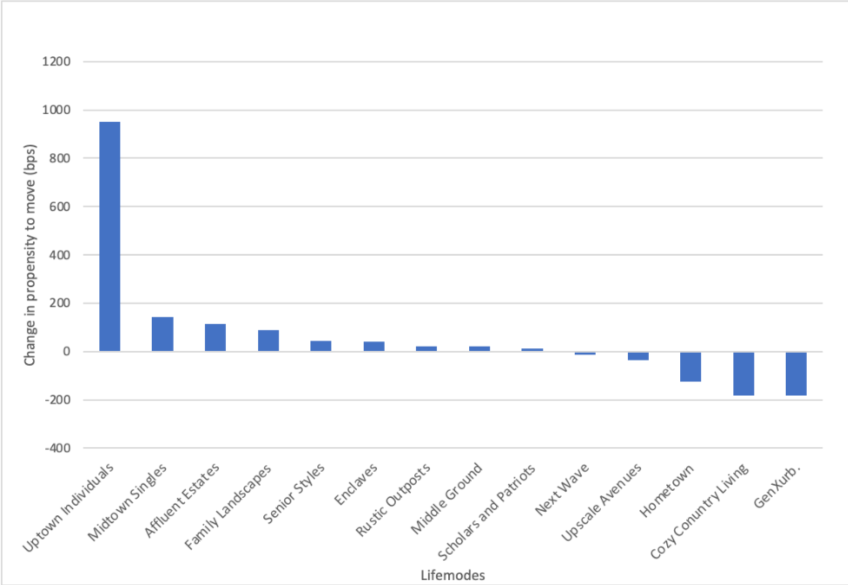

Figure 5: Change in the propensity to move by life modes in bps in the U.S. in 2021

The demographic factor was also used to analyze the movement of the population. Through the result of the dataset of change in propensity to move by life modes in bps in the U.S. in 2021 shown in Figure 5, young, educated, and wealthy "uptown individuals" were much more likely to leave the city during the COVID-19 pandemic.

3.2.2 Discussion

The data visualizations give a conspicuous display of Grubhub's market share before and after the COVID-19 outbreak, and the key factor is its competitiveness in different regions in the U.S. In contrast to Grubhub, DoorDash chose to move to suburban and rural areas before the outbreak began. The two platforms are now showing very different outcomes in Figure 1: DoorDash's market share is rising rapidly, while Grubhub's market share is falling.

To corroborate whether this change in market share is related to geographic factors, Figure 2 and Figure 3 were used to analyze the performance of the U.S. food delivery platforms in urban, suburban, and rural areas. Even though Figure 3 shows the growing demand for food delivery services outside of cities during COVID-19, Figure 2 illustrates that Grubhub owns much less market share in suburban and rural areas than in urban areas. Also, through the result of a Statista study on the familiarity of consumers with Grubhub services in the U.S. by regions [23], Grubhub's popularity in urban areas far exceeds that outside of cities, as almost half of the consumers in suburbs and countryside are unfamiliar with Grubhub. This all suggests that COVID-19 has driven the growth of the food delivery market in suburban and rural America, bringing with it a whole new set of opportunities. However, Grubhub has not previously had a strong presence outside of urban areas. Even though more people are ordering takeout after the pandemic [5], a smaller proportion is using Grubhub, leading DoorDash, which has the opposite geographical advantage, to capitalize on the trend and overtake Grubhub later.

To analyze whether the shift of the food delivery market towards out-of-town areas will be a long-term trend, the tendency of Americans to move during the epidemic was analyzed in Figure 4 and Figure 5. According to Figure 4, COVID-19 accelerates a pre-existing trend in the U.S.: people are moving out of the urban areas and into the suburbs and countryside. Those who leave cities are mostly young, educated, and wealthy "uptown individuals" by Figure 5 since they can afford to relocate and are content to work remotely in a better living environment [16]. These "uptown individuals" are familiar with online food delivery services and have the financial means to order take-out, but Grubhub is missing out on these potential customers. This trend of the wealthy population leaving cities will continue as the epidemic progresses, which is highly detrimental to Grubhub's growth from both geographical and demographic factors.

4. Conclusions

In this work, several prediction models were created to identify the operational decay of Grubhub during the COVID-19 pandemic and data visualization was used to analyze the geographic factors contributing to its current state. All four different prediction models show that Grubhub's financial performance has been anomalous in the last two years. Besides, analysis of the data visualization confirms our suspicion that Grubhub did not seize on the shift of the take-out market to suburban and rural areas in the U.S. during the epidemic because it was previously underdeveloped outside of urban areas. This is a major geographical factor for Grubhub's decline in the past two years. Further study can be done by using correlation analysis or other statistical methods if more relevant data is available in the future.

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