Demographics, Weather and Online Reviews: A Study of Restaurant Recommendations

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ABSTRACT

Online recommendation sites are valuable information sources that people contribute to, and often use to choose restaurants. However, little is known about the dynamics behind participation in these online communities and how the recommendations in these communities are formed. In this work, we take a first look at online restaurant recommendation communities to study what endogenous (i.e., related to entities being reviewed) and exogenous factors influence people's participation in the communities, and to what extent. We analyze an online community corpus of 840K restaurants and their 1.1M associated reviews from 2002 to 2011, spread across every U.S. state. We construct models for number of reviews and ratings by community members, based on several dimensions of endogenous and exogenous factors. We find that while endogenous factors such as restaurant attributes (e.g., meal, price, service) affect recommendations, surprisingly, exogenous factors such as demographics (e.g., neighborhood diversity, education) and weather (e.g., temperature, rain, snow, season) also exert a significant effect on reviews. We find that many of the effects in online communities can be explained using *offline* theories from experimental psychology. Our study is the first to look at exogenous factors and how it related to online online restaurant reviews. It has implications for designing online recommendation sites, and in general, social media and online communities.

1. INTRODUCTION

Taking a trip to someplace warm in the middle of winter, or being outdoors when spring arrives, can be particularly beneficial. Research shows that pleasant weather improves mood and memory and broadens cognitive performance, thinking and judgement [41, 59]. Low levels of humidity and high levels of sunlight are associated with high mood [8, 40, 48, 50]. Demographics of a region have been associated with people's spending time online [21, 22]. A common underlying aspect of these observations is that they study *exogenous* factors – that are generally not considered when studying people's online activities such as participation in recommendation communities.

*This work was done before Partha Kanuparthy joined Yahoo.

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In this paper, we ask the question: might these phenomena documented in psychology studies also affect[1] large-scale online behavior? Could weather and local demographics of restaurants drive how we rate them online?

Review and recommender sites are highly popular online resources. People contribute content in the form of recommendations to these communities. A recent work by Anderson and Magruder [2] found that an extra half star rating on Yelp causes restaurants to sell out 19% more frequently. People increasingly base their decisions on input from such online reviews and ratings. A recent survey found that 64% of consumers search for online reviews before spending on services [7], and 85% of them are more likely to purchase services when they can find online recommendations. The same study found that 87% of consumers say that positive online reviews reinforce their decisions, while 80% say that negative online reviews have led them to change their minds. These findings imply significant returns on an extra half-star rating or more number of reviews and suggest that restaurants have strong incentives to improve their online reviews and ratings.

Despite their widespread use, little is known about the *dynamics* of participation and of contributions by people in online recommendation sites. For example, would factors such as weather conditions, that are shown to influence mood and behavior, affect people's participation and recommendations? Are restaurants from neighborhoods with high education levels more likely to receive reviews? Are restaurants in highly populated urban neighborhoods more likely to be reviewed rather than restaurants in regions with lower population density? What is the role, if any, of racial diversity in a restaurant's neighborhood in shaping online participation?

Our insights could help consumers better understand online reviews and ratings, and aid review sites in calibrating recommendations. For example, exogenous factors may introduce systematic bias in online ratings of a highly-reviewed restaurant in San Fransisco, compared to a similar restaurant in a rural area. Our study aims to understand such differences – what factors can influence the likelihood of being reviewed in a region?

Three primary aspects of a restaurant are available to consumers via online reviews: user *evaluation* (overall rating), user *participation* (number of reviews, which also indicates *popularity*) and the reviews themselves (i.e., the text and rating of each review). We study the effect of these aspects of three broad classes of factors: *restaurant attributes*, *local demographics* and *local weather conditions at the date of visit*. Our study is the first to look at exogenous factors and how they affect online ratings. We explain the importance of these classes and why we choose them in our related work.

[1]We use the term "effect" in this paper to refer to the statistical effect measured by regression, and not causality.

We study 840,000 restaurants spread across 32,402 cities and towns in the US. We collect over 1.1 million reviews and the corresponding ratings across these restaurants, spanning 10 years. We combine this with data on demographic information and daily weather conditions local to each restaurant. While this is certainly not an exhaustive compilation of factors, we show that the models presented here have significant explanatory power.

All told, we find the following:

- Restaurants that are marked online as "low-price" tend to get fewer reviews and lower ratings. At the same time, online promotions are related with higher number of reviews, but not necessarily higher ratings.
- Specific features of a restaurant, such as having a bar might be associated with higher number of reviews but does not affect the ratings. The same relationship holds for restaurants that are featured via online advertisements.
- Service related factors such as delivery and carry-out are strongly tied with the population density of the neigborhood, and the interplay of the two can influence the number of reviews and ratings.
- Restaurants that are in neighborhoods with higher population density and higher education levels are more likely to be reviewed. The education level does not seem to affect ratings.
- Restaurants in some regions of United States (e.g. Pacific and Northeast) are more likely to receive reviews compared to other regions (Midwest and South).
- There is a seasonal pattern among rating and reviews, showing lower ratings and higher number of reviews in months of July and August.
- Weather conditions are significantly associated with ratings. Reviews written on warm or cool days are more likely to be rated high than those written in cold or hot days. Reviews written on rainy or snowy days tend to have lower ratings than those written on days without rain or snow.

We perform conditional analyses on our data and show examples of online review text where feasible to substantiate our claims. Our study looks at the effect of several factors on online reviews, but at the same time, opens a number of research directions for future work. We discuss some of these towards the conclusion of the paper.

2. RELATED WORK

There has been significant body of work that studied endogenous factors behind participation in online communities, and psychology of diners in the offline context. An interesting and not yet understood socio-technical system that bridges both research areas is online restaurant recommendation sites. Our work complements online studies by being the first to do a large-scale study of restaurant recommendation communities, and the first to look at effects of exogenous factors on ratings and reviews. Our work complements theories from experimental psychology by validating them in online communities.

Online communities: Several research efforts studied the factors behind people's participation in online communities. These studies focused on factors that are endogenous to the online community and its members. Ridings et al. [44] studied various types of communities to understand why people participate in them. They report that participation is usually a factor of the community type; and that the common reasons behind participation include information exchange, social support and friendship. Social loafing, a theory that shows the effect of group size on an individual's motivation to contribute [29], has been observed in online communities [51].

Class	Example variables
Food	cuisine, vegetarian, fine dining
Atmosphere	ambience (romantic, quiet, view, etc.)
Service	delivery, carryout
Monetary	menu prices, promotions
Advertising	*featured* on websites
Location	latitude-longitude, city/town, neighborhood
Miscellany	name

Table 1: Restaurant attributes in our data.

Researchers have looked at factors affecting participation in specific online communities. Lakhani and Wolf [32] studied contributors to Open Source Software (OSS) projects and found that career benefits and intellectual stimulation drive OSS community members to contribute to the projects. Nov studied motivations behind significant contributors to Wikipedia content [39] and found that having fun, learning and emotional aspects are significant drivers of contributions. Lampe et al. studied member participation in the Everything2 online encyclopedia [33] and found that a sense of belonging to the online community was a significant factor towards participation, while social interaction was not a strong motivator. To our knowledge, our work is the first to look at online restaurant recommendation communities which are highly popular. While prior work only considers endogenous predictors of online participation, we also consider exogenous predictors (i.e., factors not related to the community or its members), and we show that they play a role in community participation.

An integral part of an online recommendation community is reviews written by people. Researchers have analyzed review text and found some interesting features. Two prior studies have shown that review text has temporal correlation patterns [18, 60] and gender differences [43]. David and Pinch found evidence of duplicate reviews between products [11]; and Feng et al. found common patterns in deceptive reviews [16]. Certain patterns were also discovered among helpfulness evaluation of reviews [9]. Language analysis of review text showed a significant association between language features and sales [17]. A related research thread focuses on analysis of review text to identify and predict features: for example, identifying fake reviews, and summarizing and predicting product ratings [28, 36, 38, 43]. In this work, we consider reviews and ratings as they are available to users on recommendation sites, since users make choices based on these reviews.

Offline psychology: Consumers have many dining choices, and tend to consider many factors when making their decisions [55]. Traditionally, diners have traded recommendations using *offline* methods (e.g., word-of-mouth). In this context, there has been a significant effort in experimental psychology to understand, using in-person experiments, how people perceive dining and the effect of different factors. Our work shows that these observations of behavior in the offline world also hold true in online recommendation communities.

Experimental psychologists proposed theories of hedonic and utilitarian consumer experiences to understand the effect of prices, service and restaurant ambience on consumer behavior. For example, it has been shown that 91% of consumers dissatisfied with service do not revisit a restaurant, and further, tell eight to ten others about their negative experience [42]. Studies [15, 57] have found that consumers relate to ambience in an emotional (hedonic) terms, rather than cognitively. A similar effect of price was demonstrated by Wakefield et al. [58].

Researchers have also studied the effect of promotions on consumers, which can be summarized into three classes of approaches. The first approach consists of analytical and empirical approaches which studied the effects of the price change or incentives on aggregate metrics such as sales or market share. For example, a recent study found that online Groupon promotions can have a negative effect on subsequent online ratings [5]. The second approach looks at demographics of consumers who respond better to promotions [4]. The third approach studies psychological effect of promotions on consumers' behavior [12].

There has been work on consumers' perceptions of quality, price and value [62]. The authors showed that consumers perceive quality and value as being similar. A study on the perception of food showed that food can be considered as a social concept, one that defines social status, based on the quality, cost and presentation of food [3].

Exogenous factors affecting mood and behavior. Psychologists have long known - in the offline world - that sunlight, and weather in general, influences people's moods, thinking and judgement [41, 59]. Both seasonal and daily variations in weather have been documented to have effects on mood, depression and behavior [23, 30, 46]. In a study that manipulated temperature, Allen and Fischer [1] found that performance on a paired association memory task peaked at $72^oF(22^oC)$ and declined with warmer or cooler temperature. Sinclair et al. [52] found that days that were sunny and warm were associated with more heuristic and less systematic processing than cloudy and cool days. In some studies, low levels of humidity [48], high levels of sunlight [8, 40, 50] and high temperature [8, 27] have been associated with high mood. However, high temperature has also been associated with low mood [20] and low potency (low potency is similar to low mood [27]).

Changes result from physical characteristics of environment, often without the organism's awareness [45]. Cunnigham [8] found that weather also has an affect on helping behavior. In the study the weather was found to have an effect on the size of the tips that people left a waitress in a restaurant and the waitress's self reported mood. The study also suggested that sunshine levels affect mood through the symbolic connections it has with pleasant events. Therefore sunshine could increase a person's mood by stimulating thoughts of positive and pleasant activities such as swimming, outdoor outings/activities and picnics.

Weather and lunar cycles have been found to have an effect on stock market as well [14, 19, 25, 34, 49, 56, 61]. Saunders [49] shows that the NYSE rises more on sunny days in New York City, resulting in lower stock returns on cloudy days.

In addition to the outside weather, differences in the indoor lighting environment (levels, spectral distribution, temporal patterns, etc.) have been found to affect people in various ways. Daurat et al. [10] found that subjects reported a more positive mood under 2000 Lux compared to being under 300 Lux. Belcher and Kluczny [31] proposed a model in which mood, visual performance and decision-making strategy are affected by the visual environment and compete for mental processing capacity.

Demographics is an important factor in usage of the Internet [21, 22], and so it might affect the online behavior and level of activities.

Our work builds on this research by looking for the first time at exogenous factors affecting the online reviews. We connect the anecdotal, experimental and theoretical studies of mood and behavior in psychology with the participation in online communities.

3. DATASET

We consider three broad classes of variables: (1) *control variables:* restaurant attributes, including reviews and ratings; (2) *demographics* near the restaurant; and, (3) *weather conditions* at the time of visit, near the restaurant. Our data spans 2002 to 2011 (inclusive). We do not consider data after 2011, since we want to allow

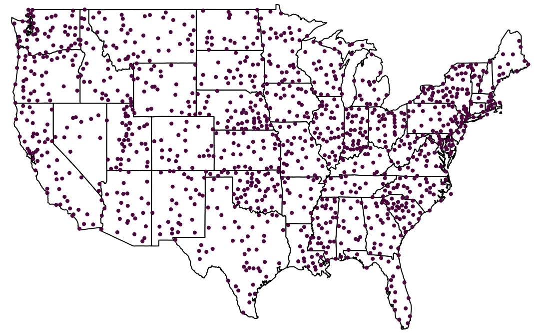


Figure 1: Locations of weather stations in our data. We consider restaurants located within a 20-mile radius of each station.

sufficient duration for formation of opinions via online reviews. We have a total of 840,000 restaurants across 32,402 towns/cities and 50 (+DC) states in United States, comprising a total of 1.1 million text reviews and ratings across the restaurants. Our data contains 46 dimensions which span the restaurant, demographics and weather classes. We expand on the data variables in subsections below. Note that our study is geographically limited to the US, since we have access to data for the region; we leave a study across other geographic regions for future work.

Our data collection process is as follows. First, we mark (possibly) overlapping regions in US that have a radius of 20 miles. We choose the centers of these regions as the locations of 1,219 weather monitoring stations operated by the United States Historical Climatology Network (USHCN). At a given time, we expect that the weather conditions are stationary in a 20-mile radius around each station. We note that weather monitoring stations are deployed in regions that contain a reasonable population (and hence include a reasonable number of restaurants). Second, we find all restaurants that are located in each region of interest, and mine their attributes, reviews and ratings. Third, we mine demographic information in the neighborhood of each restaurant. Figure 1 shows the locations of weather stations in our data.

3.1 Restaurants and Reviews

We collect restaurant-related data using the CityGrid API[2] between 2002 and 2011 (inclusive). The CityGrid database indexes up-to-date restaurant snapshots from several popular online business information and recommendation websites such as Citysearch, AllMenus, Foursquare, GrubHub, Demandforce, Factual, GoMobo, InfoUSA, SpaFinder and TripAdvisor. We extract restaurant data from CityGrid[3]. Specifically, for each USHCN weather monitoring station, we find all restaurants located in a radius of 20 miles[4] of the station. We ensure that each restaurant is associated with its nearest weather station. We collect data for 840,000 restaurants in 50 (+DC) states across United States. Large cities are divided into *neighborhoods*, giving us a total of 32,402 neighborhoods, towns and cities.

Restaurants. Each restaurant in our data contains several attributes of its online presence. These attributes can be divided into seven classes; Table 1 gives examples in each class.

[2]http://docs.citygridmedia.com/display/citygridv2/CityGrid+APIs

[3]We do not consider Yelp data in this study since the API does not give us sufficient variables for analysis.

[4]The restaurant location is specified as a latitude-longitude pair, and we use the Haversine formula to compute distances.

Type	Variable	min	mean	median	max	std.dev	Distribution
Restaurant	number of reviews*	0	1.23	0	595	5.19	
	restaurant rating	0	7.8	8	10	2.03	
Review	review rating	0	7.26	8	10	3.11	
	polarity	-1	0.26	0.25	1	0.22	
	subjectivity	0	0.57	0.57	1	0.13	
Demographics	median income*	0	52.0K	46.9K	278K	26.8K	
	population density*	0	3.9K	2.4K	69.4K	5.3K	
	diversity index	0	0.46	0.51	0.86	0.22	
	higher education	0	0.27	0.22	1	0.19	
Weather	mean temperature	0	29.43	23	104.5	30.48	
	precipitation*	0	5.68	0	823	27.49	
	snow*	0	0.46	0	640	5.57	

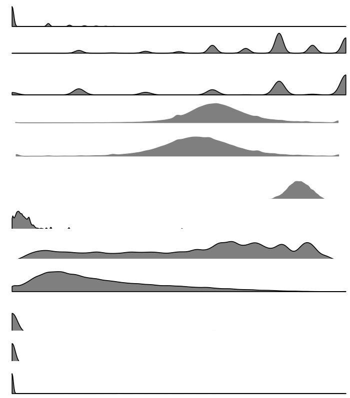


Table 2: Distributions of quantitative variables used in this paper. Variables marked with '*' are log transformed.

Note that some of the data may not be available for a restaurant; we mark such data as missing data. We pre-process the dataset to exclude missing data, assuming that missing data occurs at random.

Reviews. For each restaurant, we collect all available user reviews and ratings using the CityGrid API. Hence, each restaurant is associated with a *number of reviews* attribute, which quantifies online user participation for that restaurant. Each review is associated with a unique author (online user), restaurant and timestamp tuple. For each review, we collect the complete review text and *rating*. The rating is an integer between 0 (low) and 10 (high). We collect a total of 1.1 million reviews.

We post-process the review text for each review to quantify the *subjectivity* (between 0 and 1) and *polarity* (between -1 and 1) of the text using the Pattern Toolkit [53].

3.2 Demographics

We expect that demographics may have an impact on online reviews and ratings of a restaurant as it is an important factor in usage of the Internet [21, 22]. For each restaurant, we collect four dimensions of demographics at the restaurant location (latitude-longitude or neighborhood) as follows.

First, we collect the *median income* for residents in the location (latitude-longitude). We represent median income (in USD) as a categorical variable with five values: less than 25K, 25K-50K, 50K-100K, 100K-200K and greater than 200K.

Second, we collect the *education level* for that location, defined as the fraction of residents who have a bachelors degree or higher. We use the US National Broadband Map[5] for this purpose. We represent the education level as a categorical variable with the following values: less than 10%, 10-25%, 25-50% and higher than 50%.

Third, we collect the *diversity index* for the city/town where each restaurant is located. The diversity index for an area is defined by the US Census Bureau as the probability (on a scale of 0-1) that two randomly chosen people from the area will have different racial (or Hispanic/non-Hispanic) backgrounds. We use the USA Today Census database [6] to collect diversity data. We represent diversity index as a categorical variable with values corresponding to: less than 0.3, 0.3-0.5, 0.5-0.7 and greater than 0.7.

The fourth dimension of demographics data is the population density, defined as population of the neighborhood per square mile. We define population as a categorical variable based on density, with intervals starting with densities 1000, 2500, 5000 and 10000.

3.3 Weather Conditions

For each review for a restaurant, we collect several weather variables at the time of review. We choose weather-related factors, since they have been shown to affect human behavior and mood [13] – and among others, retail sales [54] and the stock market [49]. We assume that the day when a review is written is representative of the day when the reviewer formed her opinions of the restaurant.

A restaurant is associated with a unique USHCN weather monitoring station. We collect data about weather conditions for each of the 1,219 weather monitoring stations in our dataset (Figure 1) using the USHCN Daily Dataset [37]. The USHCN weather data is provided at the granularity of a day, which works well for our purpose.

We collect the following weather variables for each restaurant review: (1) the minimum temperature in Farenheit ($T_{\min}$) in the 24 hour period, (2) similarly, the maximum temperature ($T_{\max}$), (3) precipitation in hundredth of inches, quantifying rainfall, and (4) snow in tenth of inches. Since $T_{\min}$ and $T_{\max}$ quantify extreme conditions that last for a small duration in the day, we process the temperature data to calculate a mean temperature estimate, $\bar{T} = (T_{\min} + T_{\max})/2$, on the day of the review. We then categorize temperature into four buckets that describe better how humans perceive temperature: *very cold* $\bar{T} \in [0, 20]$, *cold* $\bar{T} \in (20, 40]$, *cool* $\bar{T} \in (40, 70]$, *warm* $\bar{T} \in (70, 100]$ and *hot* $\bar{T} > 100$. Unless otherwise mentioned, we measure temperature in degree Farenheit.

We also categorize precipitation into three groups of *no* precipitation $prcp = 0$, *medium* precipitation $prcp \in (0, 100]$ and *high* precipitation $prcp > 100$. We process snow into a binary variable showing whether there was snow $snow > 0$ or there was no snow $snow = 0$.

We use temperature, precipitation and snow to quantify weather conditions during a diner's restaurant visit. Distribution of quantitative variables are summarized in Table 2.

4. MODELING REVIEWS AND RATINGS

In this section, we describe our statistical models for the number of reviews and ratings. We then summarize the results of each model by comparing effects of different factors.

[5]http://www.broadbandmap.gov/

[6]http://developer.usatoday.com/docs/read/Census

Model	θ	Resid. df	2 x log-lik.
ed model	0.16	846466	-1937755
ed+ex model	0.19	846443	-1903529
Summary			
LR.stat		34225.65	
degrees of freedom		23	
Pr(>Chisq)		< 2.2e-16	

Table 3: Summary of the models from equation 2 and 4, θ is the shape parameter of negative binomial distribution, Resid. df is the residuals degree of freedom for the fitted model. The chi-square test rejects the hypothesis and so the model with exogenous variables is significant.

4.1 Modeling Reviews

The number of reviews is a *count* variable. We model number of reviews using negative binomial regression, on two classes of independent variables: restaurant attributes (endogenous) and local demographics (exogenous). Negative binomial regression is well-suited for *overdispersed* distributions of *count* dependent variable [6]. We use negative binomial regression instead of Poisson regression since the variance of the dependent variable is larger than the mean ($\mu = 1.23$, $\sigma = 5.19$). We use overdispersion to test whether Poisson or negative binomial regression should be used. This test was suggested by Cameron and Trivedi [6], and involves a simple least-squares regression to test the statistical significance of the overdispersion coefficient.

The negative binomial regression models the *expected* number of reviews y for a restaurant as a function of endogenous and exogenous independent variables. We construct two regression models to evaluate the *impact* of endogenous and exogenous variables: first to model endogenous variables alone (ed model), and the second to model both exogenous and endogenous variables (ed+ex model). The reduction in deviance from the full model to the endogenous-only model shows the significance of exogenous variables on explaining the number of reviews.

The first model uses restaurant attributes (endogenous variables ed) as predictors of the number of reviews a restaurant receives.

$$ln(y) = I + \Sigma_i^{x_i \in ed} \beta_i x_i \quad (1)$$

where I is the intercept for the model and the endogenous sum is computed using the following restaurant-related attributes:

$$\begin{aligned}\Sigma_i^{x_i \in ed} \beta_i x_i = \beta_{price} x_{price} + \beta_{offers} * x_{offers} + \beta_{bar} * x_{bar} \\ + \beta_{delivery} * x_{delivery} + \beta_{carryout} x_{carryout} \\ + \beta_{meal} x_{meal} + \beta_{featured} * x_{featured}\end{aligned} \quad (2)$$

This model allows us to understand the effect on the number of reviews of endogenous variables alone.

We then model the impact of exogenous factors (local weather and demographics) on the number of reviews as follows. We construct a second model that includes both restaurant attributes and exogenous attributes as predictors. We also include predictors for the interaction between some pairs of the independent variables.

$$ln(y) = I + \Sigma_i^{x_i \in ed} \beta_i x_i + \Sigma_j^{x_j \in ex} \beta_j x_j \quad (3)$$

where, the endogenous sum is taken from equation 2 and exogenous sum is computed using demographics variables and interaction between endogenous and demographic variables:

$$\begin{aligned}\Sigma_j^{x_j \in ex} \beta_j x_j = \beta_{region} x_{region} + \beta_{pop} x_{pop} + \beta_{income} x_{income} \\ + \beta_{edu} x_{edu} + \beta_{diversity} x_{diversity} \\ + \beta_{carryout*pop} x_{carryout} x_{pop} + \beta_{delivery*pop} x_{delivery} x_{pop}\end{aligned} \quad (4)$$

Model	no. param	AIC	log-Lik
ed model	25	3031064	-1515507
ed+ex model	71	3028808	-1514333
Summary			
LR.stat		2348.1	
degrees of freedom		46	
Pr(>Chisq)		< 2.2e-16	

Table 4: Summary of the ed and ed+ex models for review ratings. The Chi-square test on the difference between deviances in the models shows significance of ed+ex compared to ed model.

Here, x_{pop} is the categorical variable for population density and x_{edu} is the catgeorical variable representing ranges of percentage of population in the neighborhood with higher education.

The regression coefficients β allow us to understand the effect of an independent variable on the number of reviews (note that to be able to compare coefficients, we z-score all numerical variables before performing regression).

In order to choose which subset of independent variables should be included in the number of reviews model, we use the *Akaike Information Criterion (AIC)*. AIC is a measure of the relative quality of one model against another, and is defined as following:

$$AIC = -2L + 2k$$

where, k is the number of parameters and L is the maximum log-likelihood of the model. The smaller the value of AIC, the better the fit of the model. Starting with a full set of independent variables listed in the data section, and all possible interactions of those, we use a step-wise procedure to select the model that minimizes AIC. Using the model with minimum AIC also reduces the chances of choosing a model that overfits the data.

We test coefficients of all independent variables for the null hypothesis of a zero-valued coefficient (two-sided). This method is based on standard errors of coefficients, which is analogous to the *t-test* used in conventional regression analyses. We use a Chi-squared test with one degree of freedom to test the hypothesis that each coefficient β_j is zero. To do this, we compute the following term:

$$\chi^2 = \frac{b_j^2}{(SE_j)^2}$$

where, b_j is the estimate of β_j and SE_j is the standard error of the coefficient β_j. Table 6 shows the β coefficients and the p-values from the Chi-squared test. We see that almost all independent variables (and interaction variables) have coefficients that are statistically significant.

We use the deviance goodness of fit test to assess our regression fit [24]. The deviance is expressed as:

$$D = 2 \sum_{i=1}^{n} (\zeta(y_i; y_i) - \zeta(\mu_i; y_i))$$

with $\zeta(y_i; y_i)$ indicating a log-likelihood function with every value of μ given the value y in its place. The $\zeta(\mu_i; y_i)$ is the log-likelihood function for the model being estimated.

The deviance is a comparative statistic. We use the *Chi-square test* to find the significance of the regression model, with the value of deviance and the degrees of freedom as two Chi-square parameters. The degrees of freedom is the number of predictors in each model. Table 3 summarizes the model parameters and the goodness of fit test results, showing that the regression models are a good fit for our data.

4.2 Modeling Ratings

Users specify ratings as an integer on a scale of 0 to 10. We model ratings using a *cumulative link model*, also known as *ordered logistic regression* [26] on the endogenous and exogenous independent variables for a review (restaurant attributes, demographics and weather conditions), since the model is well-suited for ordinal dependent variables and dichotomous dependent variables.

A cumulative link model is a model for an ordinal response variable, Y_i that can fall in $j = 1, ..., J$ categories. Then Y_i follows a multinomial distribution with parameter π where π_{ij} denotes the probability that the i'th observation falls in response category j. We can write the cumulative probabilities as follows:

$$\gamma_{ij} = P(Y_i \leq j) = \pi_{i1} + ... + \pi_{ij}$$

The logit function is defined as $logit(\pi) = log(\frac{\pi}{1-\pi})$ and cumulative logits follow:

$$logit(\gamma_{ij}) = log\frac{P(Y_j \leq j)}{1 - P(Y_i \leq j)}, j = 1, .., J - 1 \quad (5)$$

Note that the cumulative logits are defined for all but the last category. A cumulative link model with a logit link is a regression model for cumulative logits:

$$logit(\gamma_{ij}) = \theta_j - x_i^T \beta$$

where x_i is a vector of independent variables for the i'th observation and β is the corresponding vector of regression coefficients. The θ_j variables provide the j'th cumulative logit with its own intercept. A key point is that the regression part $x_i^T \beta$ is independent of j, so β has the same effect for each of the $J - 1$ cumulative logits.

The regression coefficients β allow us to understand the effect of an independent variable on the rating (we scale numeric variables as before). Most of the weather-related distributions (see Table 2) have a heavy tail; we hence consider the logarithm and scale for zero mean before using as input to regression.

In order to understand the effect of exogenous variables on ratings, we build two models for ratings, along the lines of the models for number of reviews. These include logit regression to model effect of endogenous variables (ed model), and a logit regression to model the effect of both endogenous and exogenous variables (ed+ex model). For each model, we choose the set of independent variables that give us a statistical model with the lowest AIC value.

Similar to the reviews model, we use deviance to test for the goodness of fit of the ratings regression models. The deviance asymptotically follows as χ^2 distribution with degrees of freedom equal to the number of predictors in each model. We use the Chi-square test to find the significance of the regression model, as before. Table 4 summarizes the model parameters and their significance, showing that the regression models are a good fit for our data.

5. EFFECT OF RESTAURANT ATTRIBUTES (ENDOGENOUS)

The first class of variables we study are our control variables, i.e., restaurant attributes. In particular, we look at the effect of monetary attributes, atmosphere, service and online advertising on recommendations. Understanding the effect of endogenous factors is a critical part of this work, since such a study provides a framework for evaluating the effects of exogenous factors.

Table 6 summarizes the regression coefficients β of the negative binomial and cumulative link models with and without the exogenous variables (both ed and ed+ex models). The models' significance is summarized in Tables 3 and 4.

We choose a subset of restaurant attributes that we expect would not have collinearity between them based on observations from the data. For example, we find that the restaurant type "steak and seafood" is correlated with the higher price range, while "hamburger joints" are correlated with lower price range. This is also the case with dining type; for example, the "*cheap eats*" and "*fine dining*" types are not independent of price range. Hence, when we talk about effect of price range, we control for restaurant and dining types as well. In our model, we do not consider other restaurant attributes such as cuisine and ambience, since we find that the price range is generally correlated with these variables in our dataset; hence, price range could be treated as representative of these variables.

Next, we look at the effect of different endogenous variables on user reviews and ratings.

Price range. Price range is characterized using a scale of four in websites: "$" (low) to "$$$$" (high). Our regression model for both number of reviews and ratings consider the lowest price range ($) as the reference to evaluate effect of each category on number of reviews and ratings. The results show that the higher price range restaurants are more likely to be reviewed by online users and they are more likely to receive higher ratings. For example the restaurants with price range "$$$$" receive on average 10.9 times more reviews than the restaurants of price range "$" ($\beta_{\$\$\$\$} = 2.39$, $IRR = 10.9$[7]). We see similar effect for the other two price ranges: for "$$$" $\beta = 2.19$, $IRR = 8.93$, and for "$$" $\beta = 1.77$, $IRR = 5.87$.

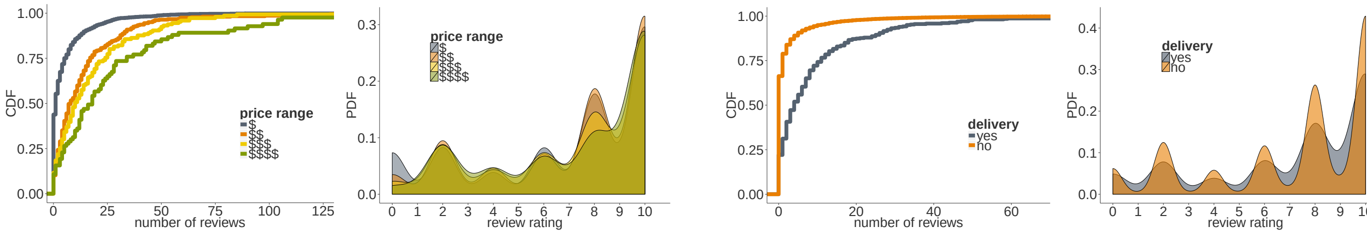
One reason for the low number of reviews for "$" compared to the higher price ranges could be that diners do not look for a complete dining experience in low-priced restaurants, and this may mean a lower propensity to spend time reviewing online. The dining atmosphere, which makes for a more complete experience, is correlated with the price range – suggesting that "$" restaurants may be focused towards quick or self-service and not a complete dining experience. We found in our data that more than 95% of the quick serve and family dining restaurants have a price range "$".

Our observations confirm market research studies by Wakefield et al. [58] who found that consumers become less sensitive to prices when they are looking for a hedonic experience (as opposed to functional experience). For example, a diner of a "$$$$" restaurant admits in the review that although the place is expensive, the dining experience is enjoyable:

> *"Yes it is expensive, but we enjoy eating here. Great service, great food and a very nice wine list with something for everyone."* (Rating: 10/10)

The strong effect of restaurant price which is correlated with ambience may be explained by experimental psychology. Ambience is related to consumers' hedonic experiences (fantasy and emotional aspects) of dining. Wakefield and Blodgett found that consumers look for hedonic consumption to experience pleasure and excitement [58]. The "Servicescape" theory [15, 57] argues that hedonic purposes are more involved than utilitarian (functional) purpose in consumers. Research shows that the degree of pleasure that consumers experience in a hedonic consumption has a significant effect on their degree of satisfaction and subsequent behavior [35, 47]. For example, celebrating a special occasion may have a strong hedonic purpose, and hence, the dining perception is likely to be

[7]We use IRR to refer to *Incidence Rate Ratio*. We compute IRR for a categorical independent variables x as the ratio of amount of change in the dependent variable (outcome) for x relative to a reference level of x.



(a) Effect of price range.

(b) Effect of service (delivery).

Figure 2: Effect of restaurant attributes: conditional analysis showing impact on reviews and ratings. We control for the geographical region (metro Chicago in this case), so that we consider the same population and demographics across restaurants in the controlled sample.

"positive." For example, the following review demonstrates an emphasis on ambience than price:

> "*Took my wife here for a romantic dinner. Service was excellent. Ambiance exceptional (decor, lighting, view). Food exquisite. Very pricey.*" (Rating: 9/10)

Another example of review that emphasizes on ambience:

> "*What a delightful evening! My boyfriend and I decided to treat ourselves to a romantic French dinner and couldn't have picked a better restaurant to do so. The ambiance, the decor and the service were impeccable.*" (Rating: 10/10)

To illustrate further, we control for location to demonstrate the effect of price range on online reviews and ratings. We consider all restaurants in metro Chicago. Conditioning the data on a city ensures that the sample of restaurants we consider will be less biased by demographics such as population or education level (which can affect number of reviews). Figure 2(a) shows the distribution of number of reviews and ratings for each price range. We see that only the lowest price range ("$") restaurants show a small number of reviews and low ratings. We repeated this experiment on other cities in US and saw similar distributions. Further, higher price ranges show a median increase of 10, 21 and 23 reviews; and 0.52, 0.89 and 0.93 mean rating over the lowest price.

Special restaurant features. Some restaurants have a bar, which is a separate section of the restaurant that prepares and serves drinks. Our regression models show that the presence of a bar has a positive relationship with the number of reviews ($\beta = 0.82, IRR = 2.27$), but a negative relationship with the rating ($\beta = -0.16$). The positive effect on number of reviews may be because the restaurant attracts customers who visit the bar, as the following review indicates:

> "*I have been going for drinks for a while because I love the bar scene.*"(Rating: 4/10)

Service. We collect two service attributes for restaurants: delivery and carry-out. We find that delivery has a positive effect ($\beta = 0.68$) on the number of reviews, while carry-out has a negative effect ($\beta = -0.77$). Delivery does not have a strong effect on the ratings ($\beta = -0.04$), but carry-out has a negative effect ($\beta = -0.46$). We speculate that this may be because customers have expectations regarding time with delivery and carry-out services. For example, a reviewer is not happy with a carry-out service:

> "*The staff is the worst thing about this restaurant. Placed a carryout order, which was promised in 15 minutes - was not ready even 45 minutes later - when I complained to the staff, I got a rude response. Then to top it all off, the food...*" (Rating: 2/10)

It may be argued that delivery and carry-out may be affected by population, since they are popular in certain regions; for example, large cities may have a higher fraction of delivery services due to higher demand than small towns. We test this hypothesis in the next subsection, when we study the effect of demographics.

Service pace is an important factor shaping impressions of the reviewers. While we did not have a quantified measure of service delays in our dataset, we observed several instances of poor ratings because of slow pace of service. For example, one reviewer emphasizes on poor service:

> "*If you are a masochist and love poor waitress service, waiting forever for your bill, indifferent management (I complained twice and never felt that I was listened to) and a restaurant that likes to violate the law*" (Rating: 2/10)

Advertisement. Restaurants can attract new customers by online advertising or by online incentives such as promotions. We look at two such instances of online "image building". First, restaurants may be "featured" on online recommendation sites. We found that being featured has a strong positive effect on the number of reviews ($\beta = 1.38, IRR = 3.97$). This means that restaurants that are featured on the site are 3.97 times more likely to receive reviews, compared to those that are not featured. Being featured does not seem to have a strong effect on ratings ($\beta = 1.38, IRR = 3.97$). We note here a limitation of this observation: restaurants may *pay* recommendation websites to be featured, or restaurants may be featured after they are *already popular* on the website. We do not have data to distinguish between the two scenarios, and we leave a causal analysis of such advertising to future work.

Second, restaurants may use online promotions such as coupons and offers to attract customers. Promotions (offers) have a positive effect on number of reviews ($\beta = 1.69, IRR = 5.42$) and on the rating ($\beta = 0.45$).

6. EFFECT OF DEMOGRAPHICS AND WEATHER (EXOGENOUS)

We collect demographic data from two public databases, the US Census Bureau and the US National Broadband Map and weather data from USHCN weather monitoring stations. We ask whether local weather conditions and demographics of the neighborhood affect online reviews participation and evaluation. We find that both demographics and weather conditions play a role.

Predictor	ref. category	ed model β	ed model p	ed+ex model β	ed+ex model p
(Intercept)		0.23	<e-15	-0.97	<e-15
$\beta_{featured}$	not featured	1.38	<e-15	1.33	<e-15
$\beta_{price=\$\$}$	price=$	1.77	<e-15	1.59	<e-15
$\beta_{price=\$\$\$}$	price=$	2.19	<e-15	1.93	<e-15
$\beta_{price=\$\$\$\$}$	price=$	2.39	<e-15	2.10	<e-15
β_{bar}	no bar	0.82	<e-15	0.72	<e-15
$\beta_{carryout}$	no carryout	-0.77	<e-15	-0.41	<e-15
$\beta_{delivery}$	no delivery	0.68	<e-15	0.28	<e-5
β_{offers}	no offers	1.69	<e-15	1.43	<e-15
$\beta_{meal=breakfast}$	meal=others	0.40	<e-15	0.33	<e-15
$\beta_{meal=brunch}$	meal=others	1.52	<e-15	1.32	<e-15
$\beta_{meal=latenight}$	meal=others	1.92	<e-15	1.55	<e-15
$\beta_{meal=lunch}$	meal=others	0.77	<e-15	0.58	<e-15
$\beta_{region=mountain}$	region=midwest			0.22	<e-15
$\beta_{region=northeast}$	region=midwest			0.23	<e-15
$\beta_{region=pacific}$	region=midwest			0.60	<e-15
$\beta_{region=south}$	region=midwest			-0.08	<e-15
$\beta_{pop\in(1000,2500)}$	pop<1000			0.20	<e-15
$\beta_{pop\in(2500,5000)}$	pop<1000			0.39	<e-15
$\beta_{pop\in(5000,10000)}$	pop<1000			0.32	<e-15
$\beta_{pop>10000}$	pop<1000			0.21	<e-15
$\beta_{edu\in(10\%,25\%)}$	edu<10%			0.31	<e-15
$\beta_{edu\in(25\%,50\%)}$	edu<10%			0.71	<e-15
$\beta_{edu>50\%}$	edu<10%			1.02	<e-15
$\beta_{diversity\in(0.3,0.5)}$	diversity<0.3			0.13	<e-15
$\beta_{diversity\in(0.5,0.7)}$	diversity<0.3			0.18	<e-15
$\beta_{diversity>0.7}$	diversity<0.3			-0.12	<e-15
$\beta_{carryout*pop\in(1000,2500)}$				-0.26	<e-15
$\beta_{carryout*pop\in(2500,5000)}$				-0.27	<e-15
$\beta_{carryout*pop\in(5000,10000)}$				-0.09	<e-3
$\beta_{carryout*pop\in>10000}$				0.03	0.42
$\beta_{delivery*pop\in(1000,2500)}$				0.13	0.07
$\beta_{delivery*pop\in(2500,5000)}$				0.28	<e-5
$\beta_{delivery*pop\in(5000,10000)}$				0.31	<e-3
$\beta_{carryout*pop>10000}$				0.70	<e-14
$\beta_{polarity}$				0.84	<e-15
$\beta_{subjectivity}$				0.13	<e-15

Table 5: Regression coefficients and their statistical significance for both models describing the number of reviews. The reference category refers to the category of the variable that each factor was compared against. For the interaction predictors, the reference can be determined by using the reference category of each of the variables.

Predictor	ref. category	ed model β	ed model p	ed+ex model β	ed+ex model p
$\beta_{featured}$	not featured	0.07	<e-6	0.06	<e-6
$\beta_{price=\$\$}$	price=$	0.30	<e-15	0.29	<e-15
$\beta_{price=\$\$\$}$	price=$	0.38	<e-15	0.37	<e-15
$\beta_{price=\$\$\$\$}$	price=$	0.43	<e-15	0.42	<e-15
β_{bar}	no bar	-0.16	<e-15	-0.16	<2-15
$\beta_{carryout}$	no carryout	-0.46	<e-15	-0.54	<e-15
$\beta_{delivery}$	no delivery	0.04	<e-4	-0.20	<e-5
β_{offers}	no offers	0.45	<e-15	0.42	<e-15
$\beta_{meal=breakfast}$	meal=others	-0.04	0.08	-0.04	0.10
$\beta_{meal=brunch}$	meal=others	0.00	0.78	-0.00	0.69
$\beta_{meal=latenight}$	meal=others	0.10	<e-13	0.09	<e-11
$\beta_{meal=lunch}$	meal=others	0.11	<e-15	0.09	<e-15
$\beta_{region=mountain}$	region=midwest			0.05	<e-8
$\beta_{region=northeast}$	region=midwest			-0.07	<e-15
$\beta_{region=pacific}$	region=midwest			-0.02	<e-2
$\beta_{region=south}$	region=midwest			0.02	<e-2
$\beta_{pop\in(1000,2500)}$	ppp<1000			0.00	0.92
$\beta_{pop\in(2500,5000)}$	pop<1000			0.03	<e-3
$\beta_{pop\in(5000,10000)}$	pop<1000			0.02	0.03
$\beta_{pop>10000}$	pop<1000			0.04	<e-05
$\beta_{edu\in(10\%,25\%)}$	edu<10%			0.01	<e-2
$\beta_{edu\in(25\%,50\%)}$	edu<10%			0.03	<e-4
$\beta_{edu>50\%}$	edu<10%			0.04	<e-8
$\beta_{diversity\in(0.3,0.5)}$	diversity<0.3			-0.01	<e-2
$\beta_{diversity\in(0.5,0.7)}$	diversity<0.3			-0.01	0.26
$\beta_{diversity>0.7}$	diversity<0.3			0.002	0.83
$\beta_{carryout*pop\in(1000,2500)}$				-0.01	0.44
$\beta_{carryout*pop\in(2500,5000)}$				0.09	<e-8
$\beta_{carryout*pop\in(5000,10000)}$				0.26	<e-15
$\beta_{carryout*pop\in>10000}$				0.34	<e-15
$\beta_{delivery*pop\in(1000,2500)}$				0.03	0.62
$\beta_{delivery*pop\in(2500,5000)}$				0.26	<e-7
$\beta_{delivery*pop\in(5000,10000)}$				0.26	<e-6
$\beta_{carryout*pop>10000}$				0.26	<e-7
$\beta_{temp\in(20,40)}$	temp<20			0.29	< e-16
$\beta_{temp\in(40,70)}$	temp<20			0.34	< e-16
$\beta_{temp\in(70,100)}$	temp<20			0.54	<e-12
$\beta_{temp>100}$	temp<20			-0.18	<e-13
$\beta_{prcp\in(1,100)}$	prcp=0			-0.32	<e-9
$\beta_{prcp>100}$	prcp=0			-0.34	<e-7
β_{snow}	snow=0			-0.23	<e-7
$\beta_{polarity}$		0.84	<e-16	0.82	<e-15
$\beta_{subjectivity}$		0.13	<e-16	0.16	<e-15

Table 6: Regression coefficients and their statistical significance for both models describing the ratings.

We consider three demographics dimensions in our study; these dimensions are categorical variables defined over a geographic region such as a city or town (for larger cities we consider neighborhoods as a unit of geography): (1) population density (per square mile), (2) education level, (3) diversity index. We also considered median income (dollars) in initial models, but the predictor did show any significance and was suggested inefficient by the model. Hence we removed income as a predictor to both models. Education level is defined as the fraction of population who have a bachelor degree or higher in the region. Diversity index (or "diversity") is defined by the US Census Bureau as the probability that two randomly selected people from the region have different racial or Hispanic/non-Hispanic backgrounds.

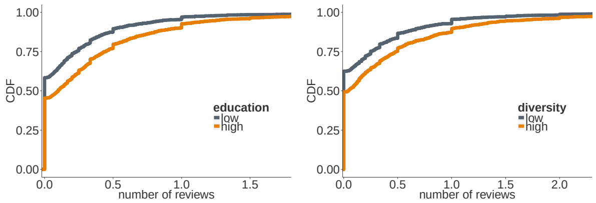
Population. We begin with the question: Does population density in the region of a restaurant shape the online review participation and ratings?

We represent population density as a categorical variable in our model (with buckets starting at 0, 1000, 2500, 5000 and 10000). We use the first bucket (0-1000) as a reference category. Hence, all β coefficients are compared against the reference category.

We see from our regression models that the effect of neighborhood population on number of reviews is positive but not too large (β between 0.20 and 0.39). Restaurants in regions with density between 1000 and 2500 have the largest number of reviews while regions with lower population densities (less than 1000) are the ones with fewer number of reviews. Restaurants in the most dense areas (> 10000), however, do not get the highest number of reviews. The effect of population is not as large as some other demographic factors such as education, which we will discuss later.

The effect of population on rating is small and negligible; in other words, the higher populated areas do not necessarily impact the ratings of restaurants in the neighborhood.

We also look at interaction effects between endogenous service factors (carryout and delivery) and the (exogenous) neighborhood population. We find that regions with higher population and availability of delivery service have higher chances of being reviewed ($\beta_{delivery*pop>10000} = 0.7$, $IRR = 2.0$). Restaurants in regions with population density between 1000 and 10000 are likely to be rated lower than those in low density regions (less than 1000) and high density regions (greater than 10000). The effect on ratings of interaction between the carryout attribute and local population is relatively more significant. A case in point is restaurants with car-



(a) Effect of education level. (b) Effect of diversity.

Figure 3: Effect of demographics: controlled analyses showing distribution of number of reviews for pairs of restaurants in neighborhoods having similar population densities but highly dissimilar education and diversity levels. We control for population since it has a strong effect on the number of reviews.

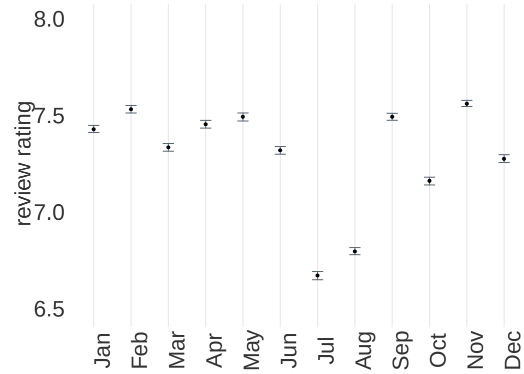


Figure 4: Confidence intervals for average ratings in a month.

ryout service that are located in neighborhoods with density greater than 10000: they are more highly rated than restaurants in other regions. This finding emphasizes on importance of studying the interplay between endogenous and demographic factors.

Region. We group states of US into five geographical regions: Midwest, South, Northeast, Mountain and Pacific, based on census bureau designated areas. Note that this variable would not be correlated with restaurant-local demographics and weather variables, since it captures relatively coarse-grained region effects. We estimate the effect of regional properties on reviews and ratings. We use Midwest as our reference region category. Our results show that region plays a role in explaining the variance in number of reviews. Restaurants in the Pacific region are 1.8 times more likely ($\beta = 0.60, IRR = 1.82$) to receive reviews compared to the ones in Midwest. On the other hand, while Mountain and Northeast regions are more likely to receive reviews compared to Midwest, the South region is relatively less likely. When it comes to ratings, however, we find that regions have a negligible effect on ratings.

Education. We see that region has a relationship with number of reviews. What factors in a region are behind these effects? We find that education shows a strong positive effect on the number of reviews. More specifically, neighborhoods with high percentage of college degrees (greater than 50%) are highly likely to have restaurants with high number of reviews. The reference category for education is neighborhoods with percentage of higher education less than 10%. Neighborhoods with highly educated residents receive 2.78 times more reviews ($\beta = 1.02$, $IRR = 2.78$). Neighborhoods with 10-25% higher degree penetration ($\beta = 0.31, IRR$) and 25-50% penetration ($\beta = 0.18, IRR$) are more likely to receive reviews than neighborhoods with less than 10% of higher-educated population. In general, the higher the education level in a region, the higher are the chances of restaurants in that region being reviewed online. Higher education level, however, has relatively lesser effect on ratings.

Racial diversity. Another demographic factor we considered in our study is the role of racial diversity (as defined by the US Census Bureau). We divide regions into four categories in terms of diversity, and use the lowest diversity category as our reference. We find that medium diversity positively impacts the number of reviews ($\beta_{diversity \in (0.3,05)} = 0.13, IRR = 1.14$ and $\beta_{diversity \in (0.5,0.7)} = 0.18, IRR = 1.20$); while the effect of high diversity is less than the effect for reference category. We do not see significant effect of diversity on ratings.

Weather. Weather conditions at the time of review are an attribute of a review. Hence, we can only test the effects of weather on ratings. Our results show that in all cases of precipitation greater than 0 (rainy days) the rating is affected negatively. This is inline with previous studies showing sunshine having positive affect on mood while cloudy weather having negative affect [8, 40, 50]. Specifically, we find that when it rains but the precipitation is less than 100, users rate restaurants lower than when it does not rain ($\beta = -0.32$). When precipitation is greater than 100, the same relationship holds ($\beta = -0.34$).

For temperature we use the the very cold category (0-20°F) as the reference category. We find that when the temperature is in the 20-100°F range, it positively affects the rating ($\beta_{temp \in (20,40)} = 0.29, \beta_{temp \in (40,70)} = 0.34, \beta_{temp \in (70,100)} = 0.54$); but at high temperatures (over 100°F), the ratings given by users are lower than the reference category ratings ($\beta_{temp>100} = -0.18$). In other words, the ratings for a restaurant when the user visited it in moderate (cold, cool and warm) weather conditions are likely to be higher than ratings when the visit was during very cold or very hot weather. Users tend to give the highest ratings when the weather is warm (between 70-100°F). A related study by Allen and Fischer [1] found that temperature can affect humans - in particular, performance on a paired association memory task peaked at 72°F (22°C) and declined with warmer or cooler temperature.

During days when it snows (snow is a binary variable), we see that users rate restaurants lower than other days ($\beta = -0.23$). Note that the binary snow variable is not necessarily correlated with temperature; hence, we can use the two variables as predictors in our model.

Seasonal trends. Taking a closer look at the data, we find two interesting temporal patterns of online reviews (see Figure 4). First, we find that the number of reviews as well as ratings change with the month of the year (across 2002 to 2011). Specifically, diners tend to give lower ratings to restaurants in the Summer months of July and August. We also find that the number of reviews shows an opposite trend, increasing in the months of Summer (June, July and August) and a month in Fall (November).

7. DISCUSSION

Restaurant-goers are increasingly using and relying on social recommendation communities to make their dining choices. Understanding the dynamics of participation on social recommendation sites is vital to improving such services, and to calibrate recommendations. Prior research has focused on endogenous factors, which are based on the recommendation community and its users. In this paper, we augment prior work by studying the effects of exogenous factors and comparing them with endogenous factors.

Our findings show that exogenous factors affect user behavior, and highlight the importance of exogenous factors in recommendation systems. This could be a foundation for understanding how people recommend businesses on online communities, and what factors influence these recommendations.

In ths work, we take a holistic view of online recommendations of restaurants by considering several endogenous and exogenous factors that can play a role. We showed that several endogenous factors related to restaurants influence how users review and rate the restaurants online. We found that the price bracket in which a restaurant operates, the type of meal it offers, and the nature of service have a significant correlation with how strongly the restaurant is recommended (or not) online.

Our work is the first to show that exogenous factors such as demographics of a restaurant's neighborhood and weather conditions at the time of the review, can play an important role in online recommendations for that restaurant. We found that restaurants located in neighborhoods with higher education levels are much more likely to receive reviews. We also found that weather conditions when a user reviews a restaurant can play a role in the user's online recommendation. We saw that reviews written in warm days are more likely to be higher rated relative to more extreme temperature conditions. We found that reviews written on non-rainy days and non-snowy days are higher rated than those written on rainy and snowy days. We controlled for all restaurant and demographics-related factors in our analysis.

We also showed that certain endogenous and exogenous factors are inter-related. For example, service-related factors such as delivery and carryout are inter-related with population density; and their impact is better understood when the neighborhood demographics are taken into account.

We believe that this is only an initial step, and that there is a rich landscape of research directions and open questions in this area. Our findings have implications for the design of recommendation systems. Recommendation sites can account for, and correct bias, that is systematically related to demographics and weather. For example, a restaurant with N reviews in New York City may not describe the same popularity as one with N reviews in a small suburban area.

Limitations and Future Work. Our work is purely quantitative and based on observations we had from data. Our approach is useful in describing what factors affect restaurant reviews and ratings, but without a corresponding qualitative approach, we can only speculate on *why* these factors matter. Further, the statistical methods we used examine only a small segment of what is available on the review sites (for example, a large-scale analysis of review text can complement our work).

Future work can establish models to further understand impact. First, we note that our analysis does not necessarily establish *causality* between all of these dimensions and reviews or ratings. Second, modeling dynamics of interaction on social recommendation sites may highlight aspects of how particular restaurants become popular on recommendation sites. Third, *what-if* and *how-to* models are useful to predict online reviews and ratings in new scenarios and to help business owners understand how to improve (or correct) ratings of their restaurants. Finally, models similar to the ones in our study can be built for other review sites or online communities. For example, the CityGrid database indexes data about shopping.

Open questions. There are some interesting questions that can be answered with the dataset. First, we have not looked at the effect of *culture* on online ratings of restaurants. Can we validate our models for online recommendations in other geographic areas? Second, a fine-grained demographics analysis of ratings is necessary to understand how users rate online, and how a particular user demographic perceives different restaurants (as opposed to demographics of the restaurant neighborhood). This would require demographic data about online reviewers (or inference of such dimensions from available information). Third, we have shown some interesting but preliminary visualizations of time trends among ratings and reviews. Additional work is required to understand these trends. We are happy to share our rich dataset[8] with the community for future work.

8. CONCLUSION

Online recommendation sites are important sources of information for people to choose restaurants. In this work, we take a first look at online restaurant recommendation sites to study what endogenous (i.e., related to either the community, its members or entities being reviewed) and exogenous factors influence people's participation and their recommendations. Online participation and recommendations have been modeled in general as functions of endogenous factors. Using models constructed from a corpus of 840K restaurants and their 1.1M associated reviews, we find that while endogenous factors such as restaurant attributes (e.g., price and service) affect recommendations, surprisingly, exogenous factors such as demographics (e.g., neighborhood diversity, education) and weather (temperature, precipitation, snow, season) also exert a significant effect on recommendations. Many of these online effects can be explained using (offline) theories from experimental psychology. Our work has implications for online recommendation systems design; for example how online communities could calibrate recommendations or project reviews for new restaurants with few reviews.

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