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Price, Perceived Value and Customer Satisfaction: A Text-Based Econometric Analysis of Yelp! Reviews

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Abstract

We examine the antecedents of customer satisfaction in the restaurant sector, paying particular attention to perceived value and price level. Using Latent Dirichlet Allocation, we extract latent topics from the text of Yelp! reviews, then analyze the relationship between these topics and satisfaction, measured as the difference between review rating and user average review rating.

Acknowledgments

First, I would like to thank my readers, Professor Pedace and Winston Chei-Wei Ou, for bearing with me through this process. Professor Ou was the first to suggest that I attempt a machine-learning thesis, and that suggestion initiated a fantastic journey of discovery.

I also extend my deep gratitude to my parents, Mark Joseph Dwyer and Marion Rupp Dwyer, who have nurtured and supported me in all aspects of life, and without whom I would not be attending Scripps. I hold you both dearly in my heart and my mind as I finish my time at Scripps and embark upon my journey into real life.

Finally, I thank Corey Hayes. Your constant encouragement, freely-given tech support, and continued interest in my findings (feigned or not) have meant more to me than you will ever know. I love you.

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0.1 Introduction

Imagine yourself, content and perhaps a bit over-full, basking in the afterglow of a lovely meal at a local restaurant. Then, the extravagant bill arrives. Does this high cost reenforce your belief that this meal was valuable and thereby improve your recollection of it? Or does the cost of the meal overshadow your enjoyment of it and leave you wishing you had chosen a simple meal at a better price point? For that matter, what features must an expensive restaurant provide you over a bargain one to justify the extra cost? In this thesis we hope to examine questions like these and determine the effect of restaurant price on customer satisfaction by performing text-based analysis of Yelp restaurant reviews in several U.S. cities.

In order to distill the reviews into more informative data, we will use a Latent Dirichlet Allocation (LDA) model to classify each review word's likely topic (eg. food, service, price, ambience, anecdotes, miscellaneous). Then, using linear regression, we will reveal the topics that most inform customer satisfaction (defined as the difference between a review's star rating and the reviewer's average star rating), and examine how the factors that influence customer satisfaction differ across restaurant price levels.

Both theory and research suggest that perceived value (perceived benefits relative to perceived costs) should have an effect on costumer satisfaction. But because perceived value is such a tricky parameter to measure, marketers, restauranteurs and economists often overlook it, instead focusing on objective restaurant price and quality's effect on customer satisfaction. Thus, with access to the actual text of Yelp reviews written by customers, we have a somewhat novel opportunity to evaluate how subjective perceptions of restaurant value combined with actual restaurant price inform customer satisfaction. Moreover, because customer satisfaction and perceived value are such inherently subjective matters, a machine-learning approach is particularly suited to this task. Traditional data analysis methods would have explicitly selected key words to represent expected satisfaction-influencing factors, and survey methods would have explicitly selected attributes to inquire about. By using LDA to extract factor keywords, we hope to more accurately capture reviewers' subjective expression of their experiences in our analysis.

0.2 Literature Review

Traditional economic thought revolves around the downward-sloping demand curve. Ceteris paribus we tend to assume that inexpensive goods are always preferable to apparently similar expensive goods. A buyer's willingness to pay for any of a set of comparable goods is thought to be fixed; thus, the larger the gap between price willing to pay and price paid, the larger the consumer surplus and the greater the consumer's satisfaction. However, price may serve as an indicator of quality, leading customers to subjectively evaluate more expensive products as superior and thus, preferable. Both theory and empirical evidence from fields such as behavioral economics, psychology, psychophysiology, and marketing suggest that there is a more complicated relationship between price and costumer satisfaction than it first would seem.

The most salient theory we must consider is that of price-dependent preferences, which suggests that preferences are influenced by price even outside of the budget constraint. Pollak (1977) provides a survey of the price-dependent preference literature and also constructs demand models predicated on price-dependent preferences. According to Pollak, the snob hypothesis that high prices might be attractive to snobbish consumers was popularized by Thorstein Veblen (1899). Veblen suggested that more expensive objects carry added value due to the social status that their purchase conveys, and particularly focused on *Veblen goods*: luxury goods whose demand is proportional to their price. If expensive restaurant meals are Veblen goods, then "snobbish" customers might prefer expensive dinners simply because they enjoy the social status their purchase conveys. Scitovsky (1951) extended this idea beyond luxury items, theorizing that because consumers are not experts on the goods they purchase they rely on price to indicate quality. While market prices are the prices customers consider in their budget constraint, Pollak defines *normal prices* as the subjectively perceived prices which influence preferences. The author suggests a normal price function that constructs normal prices from a combination of current and past prices. Thus, normal prices are relative to the prices of other goods, and money illusion does not impact price-dependent preferences. Moreover, Pollack outlines several demand functions incorporating nominal price, demonstrating that it is possible to incorporate this theory and preserve conventional demand function traits. Scitovsky's theory suggests that inexpert restaurant customers' expectations about food quality will be shaped by the restaurant's normal price.

But how does the quality-signalling aspect of price interact with a consumer's purchasing decision? Dodds (1991) constructs a theoretical model of consumer product quality evaluation and perceived value (as well as willingness to buy), dependent on product price and store name information. He assumes that buyers have some acceptable price floor as well as an acceptable price ceiling for a given item. Dodds proposes that this acceptable price floor stems from consumers' perception of poor quality in items that seem too cheap. Echoing Scitovsky's theory, he proposes that this can be explained by a rational belief that competitive market forces will tend to make better products more expensive, and inferior products less expensive. Thus, objective price increases willingness to purchase by positively influencing perceived quality, while still decreasing willingness to purchase by increasing the perceived monetary sacrifice required to purchase the item. In his framework, Dodds unites these dual effects of price on willingness to purchase with the concept of perceived value, representing "the link between the cognitive attitudes of perceived quality and perceived monetary sacrifice." Perceived value is then critical to our understanding of customer satisfaction in restaurants, because perceived value influences the customer's willingness to pay when selecting a restaurant, while the customer's post-meal valuation of their restaurant experience may differ from this initial perception. Thus, customers' satisfaction is likely a measure of how well their initial perceived value of the restaurant, possibly signaled through restaurant price, is matched or exceeded by their experience.

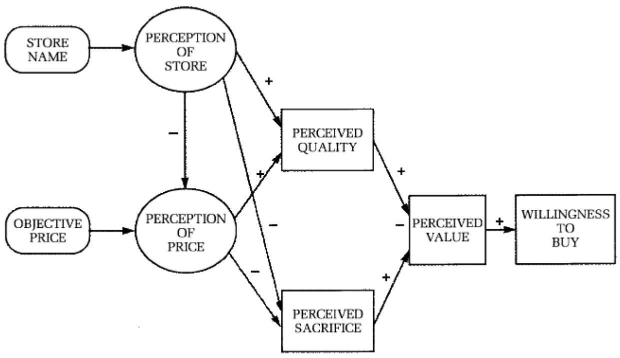

Figure 1: Dodds (1991)

An illustration of Dodds' framework around perceived value appears in Figure 1, above. Note that the positive signs indicate substitutive relationships between variables, while negatives indicate complementary ones. While Dodds also discusses the impact of store name on perceived value (and ultimately, willingness to buy), in this paper we disregard this factor, as store name preference surely varies hugely across individuals, and thus our large-scale aggregation of data would not capture these preferences. Nevertheless, we expect to capture some information about how restaurants' brands are perceived via their average Yelp! Rating.

Dodds further posits that consumers only rely on price to infer quality information because they have incomplete information of the product's quality before purchasing it. This makes the issue of price quality signaling particularly interesting in the case of restaurants because consumers agree to purchase food for a given price before even seeing the food, reducing the factors that can inform their expectation of its quality. We would expect this to increase their reliance on price as an indicator of quality. On the other hand, restaurant patrons may obtain more quality information about restaurants and dishes from reviews, influencing their perceived value and therefore their baseline fair price. Moreover, as the data we are using in this paper are reviews written on Yelp!, it seems likely that the vast majority of review writers had looked at other Yelp! reviews before making the decision to eat at a particular restaurant. Additionally, repeat customers will likely rely entirely on past experiences for quality information. However, this is complicated by the fact that their past quality assessment might have originally incorporated price information. These exposures to non-price signals about the restaurant's quality might lessen the dependence of perceived value (and consequent consumer satisfaction) upon perceived price.

Anderson and Sullivan (1993) illuminate the role of perceived value as an antecedent of customer satisfaction. This study sought to test competing models of the determinants of customer satisfaction using a nationally representative database. The data consists of telephone survey results from customers of 57 prominent companies in Sweden (representing wide-ranging industries and cumulatively making up a 70% market share). Respondents reported values from 1 (low) to 10 (high) indicating their satisfaction, repurchase intentions, expectations, how much their expectations were fulfilled, how easy it is to evaluate the quality of the good purchased, the good's "quality given price", and "price given quality." Perceived quality was calculated as the square root of the product of the latter two variables. Since this measure incorporates both perceived costs and perceived quality, it is not the same perceived quality as previously discussed; rather, it is analogous to Dodd's concept of perceived value. Thus, we will refer to this measure as perceived QUAL (the authors' assigned variable name) from now on to avoid confusion with our more customary conception of perceived quality. The authors examine a multitude of hypotheses related to the determinants of customer satisfaction and repurchase intentions, but we will focus on those most directly relevant to our topic.

The authors begin by considering existing theories regarding satisfaction's antecedents, including some of these theories in their model and using others as alternative hypotheses to those they select. First, they address the prevailing Expectancy-Disconfirmation model described by Oliver (1980), which suggests that consumers construct value expectations of a good or service before purchasing it, then conclude their perceived QUAL after consuming or experiencing it. The difference between post- consumption perceived QUAL and pre-consumption expectations of quality is disconfirmation, which is positive if the customers' expectations were lower than their perceived QUAL and negative if the converse is true. Oliver's Expectancy-Disconfirmation model essentially proposes that customer satisfaction is an increasing function of perceived QUAL and expectations. This is because it incorporates the idea of assimilation: when the difference between objective quality and expectations is relatively small, perceived QUAL is directly influenced by, and assimilates to, expectations. In other words, positive expectations will slightly increase perceived QUAL and negative expectations will slightly decrease perceived QUAL when actual quality falls within an acceptable range of expectations. Evaluating previous studies' evidence for and against the Expectancy-Disconfirmation hypothesis, Anderson and Sullivan find insufficient support for the direct impact of expectations on satisfaction, and thus construct an alternative Quality-Disconfirmation hypothesis, which serves as the basis for their model.

Their model, pictured below in Figure 2, eliminates the direct link between expectations and satisfaction, positing instead that satisfaction is an increasing

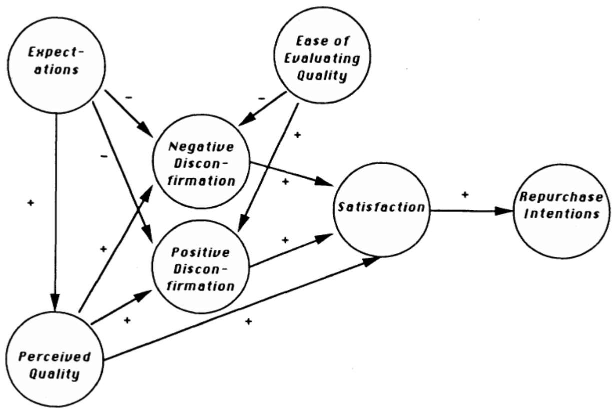

Figure 2: Anderson and Sullivan (1993)

function of perceived QUAL and disconfirmation, which both incorporate the effects of expectation. Moreover, the authors implement the Assymetric-Disconfirmation hypothesis in their model, suggesting that negative disconfirmation decreases satisfaction more than positive disconfirmation increases satisfaction. Additionally, the authors consider theories regarding the effect of quality ambiguity (the difficulty of definitively assessing product quality during and post-consumption) on perceived QUAL convergence to expectations. They ultimately decide to incorporate the Evaluation hypothesis into their model. This hypothesis suggests that greater product quality ambiguity leads customers to rely on their expectation more when constructing perceptions of QUAL. Thus, assimilation plays a greater role when quality is difficult to evaluate. Finding this to be a likely hypothesis, Sullivan and Anderson incorporate ease of evaluating quality in their model as a factor that is positively correlated with the magnitude of disconfirmation; in other words, as the ease of evaluating a good increases, negative disconfirmations become more pronouncedly negative, and positive disconfirmations become more pronouncedly positive.

Finally, Anderson and Sullivan evaluated the strength of each component hypothesis of their model against alternative hypotheses. They do so by estimating regressions for each hypothesis once for each year and each firm in the data. Because customers that report high good quality are more likely to also report positive disconfirmation and high satisfaction, the authors expect dependence of errors for these regressions. To correct for this, the authors use a SUR method proposed by Zellner (1963) for their regressions. The authors examine the data and find no strong evidence of bias in the data. Both a restricted-unrestricted Chow test and a likelihood-ratio test were performed for each regression, yielding the same resulting F statistics. These measures seem appropriate for ensuring quality statistical analysis.

As expected, the authors find that expectations are positively related to perceived QUAL. The Quality-Disconfirmation hypothesis was validated by the data, while the constraint imposed by the Expectancy-Disconfirmation hypothesis was rejected. Thus, expectations affect satisfaction primarily indirectly, through perceived QUAL, and satisfaction is positively related to both perceived QUAL and disconfirmation. To clarify, positive disconfirmation is positively correlated with satisfaction, while negative disconfirmation is inversely correlated with it, as predicted. Nevertheless, perceived QUAL is more strongly correlated with satisfaction than either form of disconfirmation, across almost every firm's regression. The Assimilation Hypothesis is weakly validated, as the constraint imposing no relationship between expectations and perceived quality is rejected after yielding an F statistic of 15.44. However, the authors caution that the R^2

for the Assimilation Hypothesis model is only 0.08, implying that expectations only explain a small amount of the variation in perceived quality. This finding is especially relevant to our inquiry, as it suggests that even if restaurant price signals quality and influences customer expectations, the customers' ultimate evaluation of the value of their experience will only be slightly impacted by this quality expectation. The Assymetric-Disconfirmation hypothesis was also supported by the study's findings in aggregate. This implies that restaurant patrons who enjoy their meal more than they expected to will not gain as much satisfaction as disappointed patrons lose. Finally, Anderson and Sullivan also find that the data supports the evaluation hypothesis. This suggests that in the restaurant sector, where quality is multifaceted and relatively difficult to evaluate, customers' perceptions of quality are more likely to be influenced by their quality expectations than in a sector with less ambiguity in quality evaluation.

Unlike the previously discussed authors, McDougall (2000) does not consider price as a quality signal while empirically testing a model of customer satisfaction across four different service sectors. Nevertheless, this study lends support to Dodds' proposition that perceived value influences customer satisfaction. McDougall's model proposes two primary antecedents to customer satisfaction in service industries: perceived value and perceived service quality. He further breaks perceived service quality down into two components: customer perceptions of core quality (the degree to which the service provider fulfills the basic promised service) and relational quality (the experience surrounding the fulfillment of the service). In the restaurant industry, for instance, core quality might encapsulate the flavor and quality of the food as well as whether it was delivered in a reasonable timeframe, while relational quality might refer to ambience and waitstaff demeanor. McDougall selects the dissimilar restaurant, dentist, auto service, and hairstylist industries to ensure that they differ sufficiently to allow generalizability of the study's results; however, we will focus on the restaurant sector results. Data was collected through questionnaires distributed to a large church congregation, and the restaurant survey had 133 responses (at a response rate of 81.1 percent). The survey asked questions about the respondents' most recent restaurant experience, designed to measure their perception of core service quality, relational service quality, perceived value, satisfaction and future intentions. It also asked demographic questions and questions about past experience with the restaurant in question.

This survey methodology is problematic because it asks respondents to recall a restaurant experience that they have had in the past, and their memories might not be true to their past experience. Moreover, the survey respondents are both geographically and demographically similar, leading to potential biases. Another potential issue emerged once the data was collected; 90 percent of respondents to the restaurant questionnaire based their responses on a restaurant that they went to about half the time they went out to eat. This fact suggests that the data might only be representative of good restaurant experiences, as most people will not repeatedly eat at a restaurant they did not enjoy the first time. While McDougall's findings thus do not tell us much about dissatisfaction, they still may be able to reveal which of the considered factors most influence restaurant customer satisfaction. And indeed, after establishing a LISREL model to relate variables and testing the model's fit, the author concludes that perceived value is the largest factor in determining restaurant customer satisfaction. Moreover, of the four service areas examined, restaurants exhibited the highest connection between perceived value and customer satisfaction.

Few studies have experimentally examined the relationship between perceived value (through perceived price and quality) and customer satisfaction in the restaurant industry alone. One of the only statistically robust of these studies was performed by Han and Ryu (2009). In this study, they investigate the relationship between customers' price perception, various features of a restaurant's physical environment, and customer satisfaction and loyalty. They measure price perception as the customer's subjective evaluation of the *appropriateness* of the price for the restaurant experience. Han and Ryu evaluate perceived price both as a stand-alone factor and as a mediating factor between physical environment features and satisfaction and loyalty, as shown in the figure to the left. It is reasonable to assume that customers' perception of price fairness is largely influenced by the restaurant's appearance and physical environment, as restaurants of different price levels often cultivate particular appearances to signal their price level. Unsurprisingly, then, confirmatory factor analysis revealed that this model fit the data well.

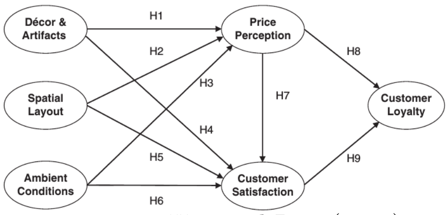

Figure 3: Han and Ryu (2009)

Han and Ryu elicited survey data from customers at three geographically separated restaurants, and obtained a response rate of 58.74% (279 customers). They performed a battery of statistical tests, correcting for slight negative skewness in all variables using a square root transformation, after which their data fit the standard assumptions of normality, linearity and homoscedasticity. Finally, they use correlation measures between each pair of variables to test for relationships, finding the greatest correlation between customer satisfaction and price perception. They also conclude that physical environment factors influenced customer satisfaction and loyalty, largely through influencing price perception. These findings suggest that perception of price appropriateness is a very useful variable in measuring customer satisfaction, especially as it mediates several other influential variables. This is consistent with Dodds' proposal that customers gain greater satisfaction from restaurant experiences whose prices fall within their acceptable range. While Han and Ryu took great care with their statistical analysis, their sample size is troubling as their data only incorporates information from three restaurants, which may not be enough to truly examine the wide range of price perceptions customers have at other restaurants. In this paper, we will not focus on the effect of physical restaurant environment on customer satisfaction; nevertheless, Han and Ryu's research provides some support for the importance of restaurant price signaling in shaping customer satisfaction.

We hope to add to the existing literature by providing a statistically robust analysis of the antecedents of customer satisfaction in the restaurant industry. Unlike most other studies on this topic, we do not use surveys asking customers to quantify their perceived value, expectations and satisfaction. This means that no respondent misunderstandings of these concepts will cloud our data. Moreover, our dataset is far larger than a survey methodology would allow, giving our results more robustness. Nevertheless, we are limited in our approach, as we must use proxy variables to evaluate relationships between these factors of interest. By separately examining the determinants of customer satisfaction for expensive and inexpensive restaurants, we hope to clarify whether price acts as a quality signal to restaurant patrons, and whether expectations shaped by this signal are assimilated into post-consumption evaluations of value.

0.3 Model Selection

Latent Dirichlet Allocation (LDA) is a powerful topic modelling technique especially well-suited to topic classification in text analysis. Blei et al. first proposed

LDA in 2003 as an improvement on Hofmann's probabilistic Latent Semantic Indexing model. We will use the representations and variable names originally used by Blei et al. unless otherwise specified in this paper. Blei et al. use words as base-units, each represented as an N-dimensional vector (where N is the number of words appearing in the corpus). For instance, the vth word is represented as a vector containing all zeroes, except for the vth entry, which takes on a value of 1. We will use the same representation in this paper. Moreover, Blei et al. refer to documents (collections of text) and corpora (collections of documents). In our case, each document is a Yelp! Restaurant review, and our corpus is the amassed collection of reviews. Our base units are individual review words.

Essentially, LDA is a generative probabilistic model; this class of model is usually used to distill content from text. It is generative because it assumes that the document as a whole has a mixture distribution θ governing the joint probabilities of some k latent (i.e. hidden) topics in the document, and that this mixture distribution is generated by some latent probability distribution. Specifically, LDA assumes that the frequency of topics in a document is sampled from a multinomial distribution with k-dimensional parameter vector θ, and that θ itself is sampled from a Dirichlet distribution prior with latent parameter α and known dimensionality k. (The dimensionality k represents the number of latent topics in the corpus; this is a parameter that we will select for our model.) This is convenient because the Dirichlet distribution is the conjugate prior for the multinomial distribution. This means that using the Dirichlet prior ensures that, after incorporating a new set of observations, the posterior distribution will also be Dirichlet. While generative models are often used to predict new observations given an underlying distribution, here we will do the converse, using LDA to perform latent factor analysis. Factor analysis uses previous observations of random variables to infer information about the latent distribution generating these random variables. We hope to discover the latent distribution that governs the probability mixture of review words. Moreover, LDA assumes that word probabilities for each topic are governed by a matrix of conditional probabilities β, such that the (i,j)th entry is the probability that an observation is word j, given that the topic of the observation is topic i. Thus, LDA can be represented as a hierarchichal model (specifically a parametric empirical Bayes model) of a corpus. Figure 3 reflects this hierarchical structure. The large outer box represents the collection of all M documents within a corpus, and the smaller inner box represents the collection of N words within a document. Every parameter in the figure is located at a particular level (corpus, document or word); any parameter at a given level is sampled once for each instance of that level (i.e. once for the corpus level, M times for the document level and N times for the word level). The parameter α is a corpus-level parameter governing the Dirichlet prior for the joint topic probabilities represented by the vector θ. Similarly, β is a corpus-level parameter, representing the matrix of word probabilities, given topics. Meanwhile, θ is a document-level variable, drawn from the Dirichlet distribution with parameter α once for each of the M documents. The value z represents a list of N vectors $\{z_1, z_2, \ldots, z_N\}$, so that the vector z_d includes k values $\{z_{d1}, z_{d2}, \ldots, z_{dk}\}$ representing the topic variables. The N vectors $\{z_d\}$ then each contain the probabilities that the d^{th} word is of topic $1, 2, \ldots, k$. The N-length vector of words w in the document has elements $\{w_1, w_2, \ldots, w_N\}$. Both the z_{dn} and the w_n are considered word-level variables.

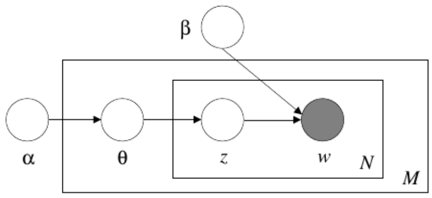

Figure 4: Blei et al. (2003)

Blei et al. note that the soundness of the LDA model rests upon the de

Finetti theorem, which states that exchangeable observations are conditionally independent, conditioning on a latent parameter of the observations' probability distribution. In the case of text analysis, we view words as exchangeable, and thus conditionally independent and identically distributed, conditioning on the β parameter governing the distribution of words within a topic, as well as the Dirichlet parameter α governing the distribution of topics within a document. Thus the de Finetti theorem suggests that the latent mixture distribution θ that governs topic frequency can be estimated fairly accurately using only the observed frequency of words in a document.

Not only is LDA one of the most widely-used methods for general text classification, but also extremely historically successful when applied to review text, specifically. Brody and Elhadad (2010) used an unmodified 3000-iteration LDA model with default parameters $\alpha = 0.1$ and $\beta - 0.1$ to label each sentence of a review collection with an aspect (what we refer to as a topic). After running their model with varying values of k, they used cluster validation to evaluate which k yielded the most consistent clustering. While word-level LDA sometimes focuses in on *global* topics that distinguish reviews from one another, the authors were able to improve *local* topic classification (where local topics are those that appear frequently within individual reviews), by classifying whole sentences with topics. Since the variables of interest in review analysis are mostly local topics (e.g. food, service, ambience) rather than globaxbl topics (cuisine type, etc.), this approach makes sense. However, it does lose some granularity of information, as sentences including multiple topics of interest (for instance the sentence "I really liked the **food**, and the **service** was great.") are labeled only with the most salient topic. Moreover, sentence-level classification requires more intensive semantic pre-processing. Thus, we do not implement this tactic. Nevertheless, Brody and Elhadad obtained impressive results, with their LDA model inferring topics such as ambience, value, staff/service, main dishes, and wine/drinks.

Moreover, a winning entry in the 2013 Yelp! Dataset Challenge by Huang et al. successfuly implemented LDA topic classification with a corpus of reviews almost exactly like ours. The authors aimed to capture the latent topics in Yelp! restaurant review text to deduce what factors increase Yelp! review stars, and thereby increase restaurant revenue. Thus, their research is of great relevance to our investigation. Moreover, their definitions of the parameters of interest and their consideration of reviews as documents mirror our own. Huang et al. implement LDA using an Online Learning algorithm proposed by Hoffman et al. (2010). This implementation reduces memory requirements, as smaller batches of reviews are processed one at a time, then the LDA topic model incorporates information from each batch and updates. Further, the authors limit the review words considered to the 10,000 most frequently occuring words in the corpus. In implementing this model, the authors find that LDA reveals the most sensible topic distinctions using the parameter $k = 50$ for the number of latent topics. Thus, this is the first value we consider. The authors proceed to apply their findings to the task of predicting average restaurant review stars for each topic. We do not replicate this work, as predicted restaurant quality along topic dimensions is only tangentially related to our inquiry. Nevertheless, the success of this study, and the acclaim it garnered in the Yelp! Dataset Challenge, suggest that our LDA model will successfully uncover the latent topics we seek.

0.4 Methodology

We obtain our data as three .json files, containing information about the businesses in the sample, the users in the sample, and the reviews in the sample. All of our data manipulation is performed using the pandas library for python.

Using pandas, we first convert these files to .csv files, then combine them as follows: we first limit the business data frame to those businesses located in Arizona, Nevada and Wisconsin, as these are the U.S. states included in the dataset. (In fact, the dataset is limited to businesses within the metropolitan areas of Pheonix, Arizona, Las Vegas, Nevada, and Madison, Wisconsin. We divide on state rather than city because businesses list neighborhoods and suburbs as their city, and we are concerned with the metropolitan area.) Next, we limit the business data frame to those businesses whose *type* labels include "restaurant". Then, we include information from the business dataset in the review dataset, merging on *business_id*, and insert information from the user dataset into the review dataset, merging on *user_id*. Thus, each review constitutes an observation in our dataset.

Finally, we separate our data into three datasets, each encompassing one city. We retain 344,318 review observations across 4,655 restaurants for Las Vegas, and 324,468 review observations across 7,439 restaurants for Phoenix, but only 25,824 review observations across 916 restaurants for Madison. In light of this wide gap, we drop Madison from our analysis, focusing on Phoenix and Las Vegas, both of which have plenty of observations for our analysis. These two cities are relatively geographically similar, and thus we cannot be sure that our results are generalizable beyond the southwest United States. Nevertheless, the character of these two cities is somewhat distinct, in that Las Vegas is a major tourist and gambling destination, while Phoenix is not. Thus, we contend that the demographic constitution of these cities is sufficiently varied that any similarities between them will be generalizable.

In addition to *state*, *business_id* and *user_id*, our initial variables of interest include:

- *stars*, the number of stars given by each review, ranging from one to five, and discrete,

- *average_user_stars*, the user's average number of review stars, ranging from one to five and continuous,
- *price_range*, the number of dollar signs Yelp! assigns the restaurant, based on the average cost of a meal there, and
- *text*, the text of the review.

We define a new variable, *satisfaction* as the difference between *stars* and *average_user_stars*. This becomes the primary parameter of interest in our analysis, as we propose that a user will rate a restaurant neutrally (the same as her average rating) if it exactly meets her expectations for it. Thus, we hope to capture a user's satisfaction, relative to her expectations, with this variable. Ideally, we would like to measure satisfaction relative to her average stars for that restaurant's price range, as this would account for differences in expectation for expensive and inexpensive restaurants. However we are limited in this by the fact that we do not have separate user average ratings for each price range. Nevertheless, we tentatively assume that users scale their ratings with their expectations when they review a restaurant on Yelp!; in other words, if a user gives three stars on average, we assume that she awards a $$$$ restaurant three stars if it meets her expectations, just as she does a $, $$ or $$$ restaurant, even though her expectations for the $$$$ restaurant may have been higher than those for other price ranges. We examine the distribution of *satisfaction* in our analysis.

Finally, we begin our latent topic analysis for Phoenix and Las Vegas, using the gensim library's LDA implementation. For each city, we construct a corpus from its review texts, restricting our dictionary to only the 10,000 most common stemmed words in the corpus, after stemming words with Porter's Snowball

Stemmer as implemented in the Natural Language Toolkit python library. To select the appropriate number of topics k, we run the model using a variety of values of k, ranging from 5 to 250. Following the selection process proposed by Huang et al. (2013), for each value of k we manually inspect the words associated with each generated topic, finding that $k = 56$ yields the most apparently cohesive and informative topics. While some of these topics' meanings are unclear (partially due to word stem ambiguity), the majority of them have fairly obvious interpretations. For instance, here are a few LDA-generated topics for $k = 56$, with their top 5 associated words:

City	Topic #	Top 5 Word Probabilities	Our Label
Phoenix	4	0.051*clean 0.047*decor 0.037*modern 0.028*grand 0.028*trendi	ambience
Phoenix	54	0.063*the 0.059*good 0.031*price 0.030*food 0.021*portion	Value
Las Vegas	50	0.092*wait 0.037*minut 0.032*line 0.028*get 0.028*long	Service

Note that the probability associated with each word is the value z_{dk}, where d is the index of that word in the dictionary of 10,000 words, and k is the topic number. Further, note that these words are presented here in their stemmed forms.

We obtain θ, the topic probability distribution for each review from our LDA models, and augment our dataset with 56 columns, each containing the probability that a given review is about that topic. These probabilities serve as our independent variables in our statistical analyses, with *satisfaction* as our dependent variable. We standardize these variables by subtracting their means and dividing by their standard deviations. Moreover, we perform each statistical analysis separately for each price level in each city. Thus, we group our observations by price level.

Finally, we perform ordinary least-squares linear regression. Although the variable *satisfaction* is not normally distributed and thus does not entirely satisfy linear regression's assumptions, it does have a strong central tendency, so linear regression seems fairly appropriate. We use the *statsmodels* python package's ols implementation. We examine the covariance of the data, and do not find any significant multicollinearity concerns.

0.5 Results

To begin, we turn our attention to the distribution of *satisfaction* at each price level, as pictured in the charts below:

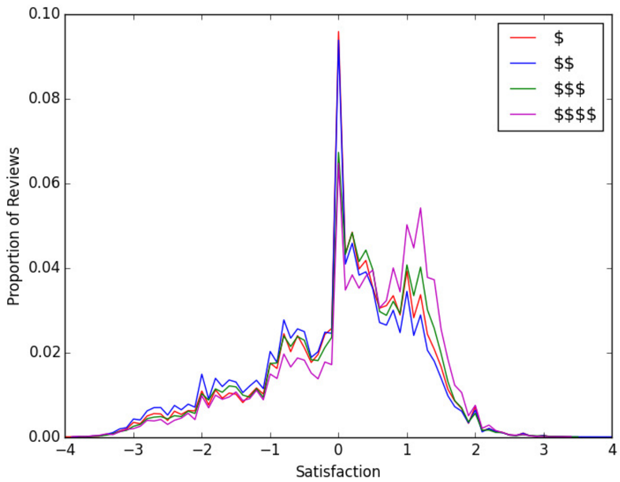

Figure 5: Distribution of *satisfaction* in Las Vegas, NV

These charts show that *satisfaction* is centered around 0, as expected since it is measured as the difference from a reviewer's average star rating. Moreover, *satisfaction* attains a local maximum around 1 and a less prevalent local maximum around -1. Thus, reviewers tend to rate restaurants within a star of their

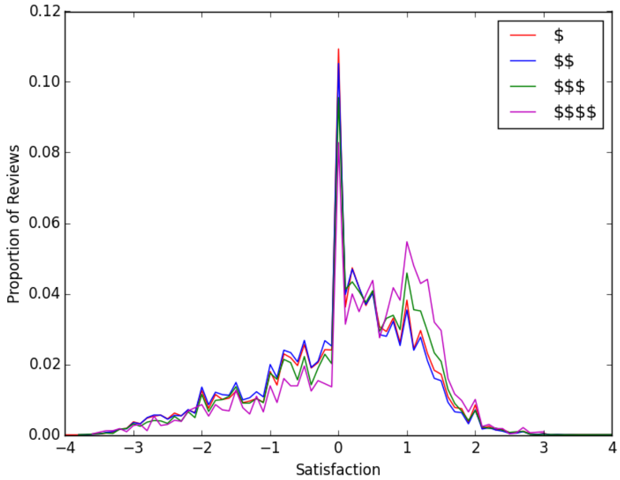

Figure 6: Distribution of *satisfaction* in Phoenix, AZ

average. The heavy left-tail of the distribution is partially due to the fact that average review stars are predominantly contained within the range $[3, 4]$, so the difference between a given review's star rating and the user's average rarely goes above 2. Nevertheless, the greater concentration of dissatisfaction lends some support to the Assymetric-Disconfirmation hypothesis.

We observe that the purple line representing $$$$ reviews lies above the rest for most of the positive values of satisfaction, and below the rest for most negative satisfaction values. Thus, $$$$ reviews are the most likely to exhibit satisfaction and the least likely to exhibit dissatisfaction. This trend is most likely due to $$$$ restaurants providing an objectively better restaurant experience, on average. However, if we hold strongly to our assumption that reviewers calibrate their expectations, and therefore their rating, to the price level, there is another explanation. Under this assumption, this might provide support for the assimilation of perceived quality to expectations, as expensive restaurants signal high quality through price, raising expectations.

Interestingly, it is not the red line for $ reviews, but rather the blue line for $$

reviews that mirrors the $$$$ line. Even compared to $ reviews, $$ reviews are most likely to exhibit dissatisfaction and least likely to exhibit satisfaction. This unexpected trend indicates that satisfaction and perceived quality is primarily a function of disconfirmation for less expensive restaurants. Because expectations should be higher for a $$ restaurant than a $ restaurant, assimilation would predict that $$ reviews would be more satisfied, on average.

We turn now to our linear regressions. The adjusted R^2 values of the linear regressions range from 0.237 to 0.296, meaning that variation in our 56 topic probabilities only accounts for 25-30% of the variation in satisfaction. Because our data is cross-sectional, rather than time-series, these values are sufficiently high to draw meaning from our results. We consider variables' significance at the $\alpha = 0.05$ significance level.

Topic	$	$$	$$$	$$$$
NV_{11}	0.2151	0.2074	0.2278	0.2082
NV_{26}	0.1500	0.1592	0.0968	0.0704
NV_{43}	0.0837	0.1232	0.1598	0.1699
NV_{52}	0.0985	0.1267	0.0870	0.0609
AZ_3	0.2472	0.2513	0.2702	0.2502
AZ_{22}	0.1016	0.0984	0.0619	0.0448
AZ_{26}	0.1798	0.1626	0.1120	0.0442

Table 1: "Positive" Coefficients

First, we examine the coefficients of topics we labeled "Positive", all of which were significant at every price level. The coefficients associated with these topics are, as expected, positive across all price levels. We also examine the coefficients of topics we labeled "Negative". These topics are significant,

Topic	$	$$	$$$	$$$$
AZ_{23}	-0.2509	-0.2229	-0.2122	-0.2275
NV_{44}	-0.1387	-0.1406	-0.1561	-0.1612

Table 2: "Negative" Coefficients

with negative coefficients across all price levels. These results suggest that our linear regressions do indeed fit the data as expected, and also corroborate our topic interpretations.

Next, we turn to the topics we labeled "Comparison and Evaluation." These two topics seem to correspond well to each other, both associated with words such as *would*, *better*, *much*, *like*, *pretty*, *good*, *bad*, *taste*, *place*. All coefficients associated with these topics are negative, and these topics are significant across all price levels. This suggests that reviewers tend to use comparison and evaluation words to describe a restaurant when they find it lacking, rather than when it excels in comparison to other experiences. Additionally, both topics' coefficients for $$$$ are significantly lower than those for other price level. We tentatively suggest that this provides support for the assimilation of perceived value to expectations when expectations are particularly high, as it demonstrates a reduced reliance on evaluation and comparison (and therefore, disconfirmation) for very expensive restaurants.

Topic	$	$$	$$$	$$$$
AZ_{48}	-0.1409	-0.1455	-0.1402	-0.1075
NV_{39}	-0.2102	-0.2478	-0.2799	-0.1612

Table 3: "Comparison and Evaluation" Coefficients

Examining the topics associated with the label "Service," we observe that the coefficients for these topics are uniformly negative, and all significant. This suggests that reviewers primarily discuss service when it does not meet their expectations. Topics AZ_{44} and NV_{38} are characterized by many of the same general service words, such as *order*, *table*, *ask*, *came*, *waitress*,

Topic	$	$$	$$$	$$$$
AZ_{44}	-0.0503	-0.0587	-0.0864	-0.1273
AZ_{53}	-0.1758	-0.2192	-0.2051	-0.2241
NV_{22}	-0.2600	-0.2488	-0.1896	-0.2081
NV_{38}	-0.0415	-0.0763	-0.1072	-0.1322
NV_{50}	-0.0346	-0.0503	-0.0365	-0.0481

Table 4: "Service" Coefficients

didn't, and *back*. Both these topics grow increasingly negative as price level increases. These results suggest that expensive restaurant patrons are more displeased by unsatisfactory service than patrons of inexpensive restaurants. Moreover, AZ_{53} follows this pattern with the exception that its coefficient for $$ is higher than that for $$$, and NV_{50} follows this pattern with the exception that its coefficient for $$ is higher than that for $$$$. Both these topics primarily correspond to wait-related words such as *wait*, *time*, *took*, and *long*, while also corresponding to general service words like *order*, *table* and *service*. These coefficients might suggest that $$ restaurant patrons, and to a lesser extent $$$ and $$$$ restaurant patrons are particularly bothered by slow service. We hypothesize that it is more likely that $$ restaurants simply have particularly slow or bad service, when compared to $$$ and $$$$ restaurants, while $ restaurants are unlikely to have waitstaff at all, reducing wait time as well as the importance of service. However, NV_{22}, complicates these results, with its most negative coefficient at $, then $$, then $$$$ and finally $$$. This topic is associated with the normal service words, but it is also the most markedly negative of the "Service" topics, with associated words like *never*, *even*, *bad*, *horrible*, *didn't* and *tip*. Perhaps the discrepancy between this topic's coefficients and the others' is due to its extremity. Once again, the potential explanation that inexpensive restaurants actually have inferior service would make sense of this result; perhaps the other coefficients captures service dissatisfaction rooted in price-driven expectation disconfirmation, while this variable captures universally displeasing service experiences. Thus, taken together, these topic coefficients do not definitively establish a relationship between restaurant price level and the importance of service. Nevertheless, they somewhat suggest that the negative impact of long waits and worse-than-expected service increases with price level, while the prevalence of truly awful service does not.

We now turn our attention to the topics relating to "ambience." Both AZ_{16} and NV_{45} deal with outdoor restaurant spaces, sharing key words like *patio*, *outside*, *nice* and *seat*. While AZ_{16} is significant for \$, \$\$ and \$\$\$, NV_{45} is significant only for \$ and \$\$. Both topics' coefficients are positive, and largest at \$\$ and smallest at \$. This suggests that patrons of inexpensive restaurants gain considerable satisfaction from the availability of outdoor seating, while outdoor seating does not significantly impact satisfaction at expensive restaurants. Topic NV_{32} is associated with words relating to restaurant layout such as *table*, *room*, *seat*, *group*, and *view*. Once again, it has limited significance, only statistically significant for \$ and \$\$, with increasingly negative coefficients. Thus, complaints about restaurant layout are only a predictor of dissatisfaction at inexpensive restaurants. Similarly, topic AZ_4, associated with general ambience words like *clean*, *décor*, *modern*, *grand* and *trendy*, is only statistically significant at \$\$. Its coefficient is positive, suggesting that reviewers at this price level tend to gain satisfaction from notable ambience and décor. Interestingly, the statistically significant coefficients for all of these "ambience" topics are most extreme for \$\$. One might expect that ambience would be an important determinant of satisfaction at expensive restaurants, but that is not the case, according to our data. Perhaps this is because \$\$\$ and \$\$\$\$ restaurants provide a universally better ambience, reducing variation across this dimension to such a degree that any small differences in ambience negligably affect satisfaction.

Topic	\$	\$\$	\$\$\$	\$\$\$\$
AZ_4	N/S	0.0072	N/S	N/S
AZ_{16}	0.0197	0.0312	0.0250	0.0033
NV_{22}	-0.2600	-0.2488	-0.1896	-0.2081
NV_{32}	-0.0104	-0.0152	N/S	N/S
NV_{45}	0.0188	0.0229	N/S	N/S

N/S = Not Statistically Significant at $\alpha = 0.05$

Table 5: "Ambience" Coefficients

Next, we discuss the coefficients for topics relating to different meals. The topics labeled "Dinner" are both significant with positive coefficients across all price levels. Moreover, both topics' coefficients increase with price level; while AZ_{21}'s coefficient for \$\$\$ is slightly larger than that for \$\$\$\$, the difference is negligible compared to the increase in coefficients from \$ to \$\$ and from \$\$ to \$\$\$/\$\$\$\$. These coefficients suggest that reviewers who discuss dinner are more satisfied than patrons who do not across all price levels. Moreover, dinner experiences seem to grow more satisfying as restaurant price level increases.

Topic	\$	\$\$	\$\$\$	\$\$\$\$
AZ_{21}	0.0102	0.0605	0.1075	0.1042
NV_{14}	0.0153	0.0264	0.0331	0.0542

Table 6: "Dinner" Coefficients

Topic	\$	\$\$	\$\$\$	\$\$\$\$
AZ_2	0.0176	0.0244	0.0189	N/S
AZ_{47}	N/S	N/S	N/S	N/S
NV_{56}	0.0349	0.0147	0.0180	0.0121
N/S = Not Statistically Significant at $\alpha = 0.05$				

Table 7: "Lunch" Coefficients

On the other hand, the topics labelled "Lunch" are not all significant. In fact, AZ_{47} is not significant at any price level. Meanwhile, AZ_2 and NV_{56}'s p-values increase with price level, remaining significant except for \$\$\$\$. Where these topics are significant, their coefficients are positive. While AZ_2's coefficient is highest at \$\$, with the coefficient for \$\$\$ only slightly above that for \$, NV_{56}'s coefficients follow the exact opposite of this pattern. Thus, we cannot infer a relationship between lunch-related satisfaction and price level from the coefficients. Similarly, of the

Topic	\$	\$\$	\$\$\$	\$\$\$\$
AZ_{36}	N/S	0.0188	N/S	N/S
NV_{49}	N/S	0.0166	0.0285	N/S
N/S = Not Statistically Significant at $\alpha = 0.05$				

Table 8: "Breakfast" Coefficients

two topics labeled as "Breakfast", AZ_{36} is significant only for $$, and NV_{49} is significant only for $$ and $$$. Both topics' significant coefficients are positive.

The fact that all three meals have only positive coefficients implies that positive reviews tend to spend more space describing the meal in question: reviews with words clearly associated with breakfast, lunch, or dinner, are more likely to simply describe their individual restaurant experience, rather than universal restaurant topics such as service or ambience. Clearly, we cannot infer preferences for one meal over another at different price levels from these coefficients, as they are all positive. Nevertheless, the p-values do illuminate a certain relationship: while dinner is important at any price level, lunch is either not served, or not particularly appreciated at expensive restaurants, and breakfast is only relevant to satisfaction at $$ and $$$ restaurants.

We turn next to some of the most relevant topics to our investigation, which we labeled "Value." The words associated with NV_{12}, like *good*, *food*, *price*, *service*, *pretty*, *really*, *decent*, *quality*, *average*, *cheap*, *expense* deal with the general perceived value of a restaurant experience. An interesting pattern emerges from this variable's coefficients: at $, NV_{12} has a statistically significant, positive coefficient, losing significance at $$, then regaining significance for $$$ and $$$$ with increasingly negative coefficients. This reveals an unsurprising trend: reviewers are more likely to comment positively on value-for-money at inexpensive restaurants, and negatively on value-for-money at expensive restaurants. Reviews evaluating perceived value relative to expectations demonstrate an inverse relationship between *satisfaction* and price level, while we expect that restaurant price level and expectations are positively cor-

Topic	$	$$	$$$	$$$$
AZ_{54}	-0.0438	-0.0658	-0.1260	-0.1235
NV_2	0.0321	0.0224	N/S	N/S
NV_{12}	0.0158	N/S	-0.0238	-0.0524

N/S = Not Statistically Significant at $\alpha = 0.05$

Table 9: "Value" Coefficients

related. Thus, this pattern suggests that perceived value does not assimilate to expectations, but rather is a function of the difference between experience and expectations, indicating that satisfaction is primarily a function of disconfirmation.

The next variable of interest, AZ_{54}, is associated with some of the same words as NV_{12}, like *good*, *price*, *food*, *service*, and *decent*, but also with portion-size words like *portion*, *little*, *size*, and *expect*. This topic's linear regression coefficients are all negative and statistically significant. As this topic clearly is associated with reviewers' expectations relative to their experiences, the negative sign of the coefficients supports the Assymetric-Disconfirmation hypothesis, which proposes that negative disconfirmation has a stronger effect on satisfaction than positive disconfirmation. Moreover, its coefficients grow increasingly negative with price level, with the exception that the coefficient for $$$ is very slightly larger than that for $$$$; nevertheless, both are almost 2 times greater than the coefficient for $$. This evidence corroborates half of the trend established from NV_{12}, in that reviewers are more disappointed with insufficient value and portion size for expensive restaurants.

Finally, topic NV_2, associated almost exclusively with portion-size words like *portion*, *size*, *large*, *small*, and *share*, only attains significance at $ and $$, with decreasingly positive coefficients. This supports the other half of NV_{12}'s pattern, as it suggests that portion size only increases satisfaction for inexpensive restaurants. Perhaps these trends are simply due to expensive restaurants serving less food than inexpensive ones. However, the strength of the trend across these variables suggests that there is more to it than that, and that this is due at least in part to a difference in perception. What is clear is that reviewers gain satisfaction from value-for money at inexpensive restaurants, while tending towards dissappointment in the value they get from expensive restaurants.

0.6 Conclusion

We determine several factors that exhibit price level-dependent correlations with satisfaction. Unsurprisingly, dissatisfaction correlates more strongly with poor service and long wait times at expensive restaurants. On the other hand, the impact of ambience on satisfaction is inversely correlated with price level. We find that satisfaction is more strongly correlated with lunch for inexpensive restaurants, dinner at expensive restaurants, and breakfast at moderately priced restaurants, while dinner remains the most important meal for satisfaction overall.

There is mixed evidence for the relationship between price level and satisfaction. On one hand, some of our results provide limited evidence for the neoclassical model and the negative impact of price level on perceived value. Our analysis of "Value" topic results finds a distinct increase in value-related dissatisfaction, as well as a decrease in value-related satisfaction, with price level. We find that "Comparison and Evaluation" topics are least strongly correlated with dissatisfaction at very expensive ($$$$) restaurants, suggesting that reviewers of these restaurants are less likely to derive dissatisfaction from comparing their actual experience to their expectations and previous experiences. In other words, reviewers of expensive restaurants seem less susceptible to disconfirmation. A likely explanation for this phenomenon is that expensive restaurants simply measure up to expectations more than their inexpensive counterparts. However, it is also possible that perceived value assimilates to expectations more at extremely expensive restaurants; this might be because individuals who partake in an unusually expensive meal are more reluctant to acknowledge that they "wasted" money than patrons at more moderately priced restaurants. Moreover, the distribution of *satisfaction* itself for different price levels suggests that assimilation may play a role in constructing perceived value, as satisfaction is higher for more expensive restaurants. This is complicated by the fact that $ reviews exhibit higher average satisfaction than $$ reviews; perhaps disconfirmation plays a greater role when choosing between cheap and inexpensive restaurants. Indeed, it is likely that bargain-conscious patrons of $$ restaurants expect a better experience than they would at a $ restaurant, and are disappointed when these expectations are disconfirmed. The fact that "Service" topic coefficients are most strongly associated with dissatisfaction at $$ restaurants corroborates this interpretation. Meanwhile, $$$$ restaurants yield distinctly more satisfaction than their $$$ counterparts, suggesting that, for expensive restaurants, perceived value assimilates to increased expectations, formed by a higher price-level.

Ultimately, we tentatively conclude that perceived value, and thereby satisfaction, are more likely to assimilate to high expectations at particularly or unusually expensive restaurants. Correspondingly, we find that perceived value and satisfaction are most negatively impacted by disconfirmation of expectations for inexpensive to moderate restaurants. We suggest that future research consider low-to-mid-priced restaurants separately from mid-to-high-priced restaurants in order to more accurately assess the relationship between restaurant price level and satisfaction. Moreover, we posit that this effect may carry over into other goods with large price and quality ranges, and suggest this as another area for future inquiry.

List of Figures

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Topics for Phoenix, AZ

1: steak / meat?
0.204*steak + 0.075*rare + 0.067*medium + 0.038*cook + 0.037*cart + 0.025*nacho + 0.024*durant + 0.022*california + 0.020*pink + 0.017*done + 0.017*vega + 0.017*rail + 0.016*filet + 0.015*maggiano + 0.014*lentil + 0.013*king + 0.012*well + 0.012*such + 0.011*persian + 0.010*ear

2: Lunch / Italian
0.135*salad + 0.031*pasta + 0.025*chicken + 0.024*the + 0.024*tomato + 0.019*dress + 0.019*fresh + 0.017*lunch + 0.017*chees + 0.013*italian + 0.012*also + 0.011*bread + 0.011*spinach + 0.011*soup + 0.010*side + 0.010*delici + 0.010*lettuc + 0.010*order + 0.009*grill + 0.009*great

3: positive
0.052*love + 0.040*amaz + 0.035*place + 0.034*best + 0.032*the + 0.025*delici + 0.023*ever + 0.021*tri + 0.018*great + 0.016*food + 0.013*everyth + 0.013*favorit + 0.012*perfect + 0.012*one + 0.012*awesom + 0.012*this + 0.011*absolut + 0.011*recommend + 0.011*time + 0.010*friend

4: ambience / decor
0.051*clean + 0.047*decor + 0.037*modern + 0.028*grand + 0.028*trendi + 0.025*bright + 0.024*interior + 0.023*restaur + 0.021*bathroom + 0.017*bonus + 0.015*upscal + 0.014*courteous + 0.012*nice + 0.012*tourist + 0.011*southern + 0.011*nonetheless + 0.011*the + 0.010*mmm + 0.010*korean + 0.009*rough

5: sushi
0.202*roll + 0.181*sushi + 0.032*tuna + 0.021*teriyaki + 0.018*spici + 0.016*fish + 0.016*fresh + 0.014*chef + 0.012*salmon + 0.011*california + 0.010*sapporo + 0.010*the + 0.009*rice + 0.009*wasabi + 0.007*piec + 0.007*octopus + 0.007*construct + 0.007*avocado + 0.006*restur + 0.006*hawaii

6: middle eastern food
0.073*pita + 0.065*hummus + 0.040*gyro + 0.036*greek + 0.025*jungl + 0.024*chicken + 0.023*platter + 0.018*plate + 0.016*middl + 0.015*eastern + 0.014*express + 0.014*meat + 0.014*lamb + 0.013*mediterranean + 0.013*falafel + 0.013*panda + 0.012*tammi + 0.011*baba + 0.011*wrap + 0.010*coe

7: bbq / meat / comfort food
0.034*the + 0.028*chicken + 0.028*meat + 0.027*bbq + 0.026*rib + 0.026*pork + 0.023*chees + 0.023*sauc + 0.015*beef + 0.015*side + 0.014*mac + 0.014*flavor + 0.011*good + 0.011*corn + 0.011*tender + 0.010*like + 0.009*brisket + 0.009*fri + 0.008*tast + 0.008*grill

8: past visits and plans to visit in the future
0.064*had + 0.052*look + 0.047*back + 0.039*forward + 0.034*tri + 0.024*groupon + 0.023*went + 0.022*next + 0.019*away + 0.019*time + 0.018*will + 0.016*soon + 0.016*go + 0.015*first + 0.014*return + 0.013*blown + 0.012*grandma + 0.011*trip + 0.011*tonight + 0.011*flatbread

9: purchases
0.080*store + 0.050*groceri + 0.044*coupon + 0.043*buy + 0.042*ring + 0.033*gift + 0.028*deli + 0.026*product + 0.025*cupcak + 0.025*card + 0.024*onion + 0.022*squar + 0.018*period + 0.017*bought + 0.016*use + 0.013*cannoli + 0.012*bewar + 0.011*shop + 0.011*slam + 0.010*bang

10: dessert
0.052*coffe + 0.051*cooki + 0.042*chocol + 0.036*cake + 0.034*dessert + 0.018*sugar + 0.015*pastri + 0.013*bake + 0.012*donut + 0.012*cup + 0.011*sweet +

0.010*cinnamon + 0.010*gelato + 0.010*chip + 0.009*almond + 0.009*shop +
0.008*bread + 0.008*tiramisu + 0.008*croissant + 0.008*cafe

11: holiday/ show/ theme
0.062*it + 0.042*dont + 0.029*cant + 0.024*cowboy + 0.023*vacat + 0.023*yard +
0.023*holi + 0.023*crappi + 0.021*killer + 0.021*ive + 0.021*knock + 0.020*crap +
0.020*downsid + 0.018*sing + 0.018*wont + 0.018*packag + 0.016*drank + 0.015*hurt
+ 0.015*devour + 0.013*sooo

12: yelp review / service
0.027*review + 0.019*restaur + 0.019*owner + 0.014*custom + 0.013*make +
0.012*experi + 0.012*new + 0.011*visit + 0.010*year + 0.009*know + 0.009*staff +
0.008*see + 0.008*manag + 0.008*feel + 0.007*star + 0.007*thank + 0.007*establish
+ 0.007*busi + 0.007*read + 0.007*say

13: twenty-somethings
0.055*school + 0.053*lol + 0.041*parent + 0.034*rock + 0.034*tequila + 0.031*organ
+ 0.022*shake + 0.021*cloth + 0.021*creme + 0.020*key + 0.020*low + 0.018*yay +
0.015*regret + 0.014*mmmm + 0.013*legit + 0.012*pretend + 0.011*starbuck +
0.011*old + 0.011*brule + 0.010*suit

14: family
0.095*mom + 0.079*quesadilla + 0.035*mother + 0.034*dad + 0.032*brother +
0.027*terrif + 0.027*mari + 0.025*bloodi + 0.020*law + 0.018*gotta + 0.016*gringo
+ 0.015*everytim + 0.014*boot + 0.014*lil + 0.013*camelback + 0.011*arcadia +
0.010*lisa + 0.010*southwestern + 0.009*proud + 0.009*paradis

15: Mexican food
0.054*mexican + 0.046*taco + 0.038*salsa + 0.035*chip + 0.030*bean + 0.026*the +
0.024*food + 0.023*margarita + 0.022*burrito + 0.018*tortilla + 0.018*enchilada +
0.017*good + 0.015*rice + 0.013*chees + 0.012*sauc + 0.012*chicken + 0.009*red +
0.009*chile + 0.009*flavor + 0.009*order

16: outdoor spaces / ambience
0.036*patio + 0.034*the + 0.030*outsid + 0.024*park + 0.023*seat + 0.020*nice +
0.020*insid + 0.018*sit + 0.017*bar + 0.017*area + 0.015*tabl + 0.014*place +
0.013*lot + 0.010*outdoor + 0.010*great + 0.009*littl + 0.009*enjoy + 0.008*there
+ 0.008*cool + 0.008*friend

17: flavor / food quality
0.073*fresh + 0.066*fish + 0.053*ingredi + 0.032*dish + 0.030*chef + 0.029*cook +
0.028*qualiti + 0.026*prepar + 0.022*oven + 0.019*flavor + 0.015*tast + 0.014*the
+ 0.012*perfect + 0.011*brick + 0.011*signatur + 0.010*kitchen + 0.010*serv +
0.010*japanes + 0.009*char + 0.009*present

18: chicago style hot dogs / smoking ?
0.136*hot + 0.050*dog + 0.037*chicago + 0.025*guac + 0.016*tempura + 0.012*cigar +
0.011*truth + 0.011*ideal + 0.010*pipe + 0.009*del + 0.009*capit + 0.009*generic +
0.009*creation + 0.008*tacki + 0.008*tucson + 0.008*style + 0.008*factori +
0.007*squash + 0.007*butternut + 0.007*lousi

19: ?
0.053*duck + 0.037*spring + 0.032*peanut + 0.027*yelper + 0.026*train +
0.024*pomegran + 0.021*hasn + 0.021*fellow + 0.019*trader + 0.018*eateri +
0.017*def + 0.017*butter + 0.012*cuban + 0.012*poblano + 0.011*colleagu +
0.011*espresso + 0.011*timer + 0.011*hub + 0.010*tongu + 0.010*avenu

20: inexpensive desserts

0.071*pie + 0.046*crepe + 0.033*rosemari + 0.029*jam + 0.028*rosa + 0.025*appl +
0.024*inexpens + 0.023*meatbal + 0.022*nutella + 0.021*sprout + 0.019*snickerdoodl
+ 0.018*pistachio + 0.015*cilantro + 0.014*yogurt + 0.013*rustic + 0.012*banana +
0.012*thanksgiv + 0.011*subway + 0.011*exot + 0.011*lime

21: fancy dinner words / ositive
0.040*wine + 0.028*the + 0.027*dinner + 0.022*menu + 0.020*great + 0.018*restaur +
0.017*night + 0.016*servic + 0.013*dine + 0.013*excel + 0.013*glass + 0.013*enjoy
+ 0.012*experi + 0.011*food + 0.011*select + 0.010*date + 0.010*list +
0.009*special + 0.009*server + 0.009*buffet

22: repeat customer / positive
0.078*alway + 0.045*time + 0.029*food + 0.026*get + 0.022*love + 0.022*year +
0.019*good + 0.018*never + 0.018*the + 0.017*locat + 0.017*favorit + 0.017*servic
+ 0.016*great + 0.015*come + 0.014*one + 0.014*usual + 0.014*everi + 0.013*place +
0.011*eat + 0.010*friend

23: negative
0.015*one + 0.013*like + 0.011*get + 0.010*would + 0.009*even + 0.009*eat +
0.009*place + 0.009*want + 0.009*know + 0.008*ask + 0.008*star + 0.008*the +
0.008*could + 0.007*never + 0.007*order + 0.007*give + 0.007*say + 0.007*food +
0.007*ever + 0.007*and

24:
0.036*asada + 0.031*carn + 0.029*los + 0.028*prosciutto + 0.027*band + 0.020*pear
+ 0.020*fav + 0.018*cave + 0.018*kobe + 0.018*deseo + 0.016*creek + 0.013*cracker
+ 0.013*angel + 0.012*guacamol + 0.012*execut + 0.012*festiv + 0.012*champagn +
0.011*jazz + 0.010*eleg + 0.010*goat

25: seafood
0.086*boyfriend + 0.074*salmon + 0.059*sangria + 0.046*pesto + 0.034*sea +
0.034*ahi + 0.027*tuna + 0.019*smoke + 0.016*bass + 0.015*stingray + 0.015*scallop
+ 0.013*babi + 0.012*sirloin + 0.012*wasnt + 0.011*risotto + 0.010*baja +
0.009*cellar + 0.009*sandwhich + 0.008*flip + 0.008*prix

26: positive
0.119*great + 0.074*food + 0.060*place + 0.053*good + 0.043*servic + 0.040*the +
0.035*friend + 0.022*atmospher + 0.020*love + 0.019*staff + 0.018*realli +
0.018*nice + 0.015*price + 0.014*awesom + 0.014*back + 0.012*this + 0.012*lunch +
0.011*excel + 0.009*recommend + 0.009*definit

27: ambience / anecdote
0.016*citi + 0.015*upon + 0.013*ride + 0.011*charm + 0.009*photo + 0.009*pretenti
+ 0.009*oper + 0.009*chain + 0.009*trick + 0.009*histori + 0.008*overlook +
0.008*old + 0.008*million + 0.008*stumbl + 0.008*success + 0.008*travel +
0.007*fool + 0.007*afraid + 0.007*rais + 0.007*weekday

28: TexMex food / fruit
0.108*green + 0.087*chili + 0.047*fruit + 0.035*juic + 0.031*mahi + 0.027*patti +
0.023*queso + 0.022*lime + 0.021*chile + 0.018*denni + 0.017*southwest +
0.017*natur + 0.016*stew + 0.016*machaca + 0.014*mango + 0.013*swim + 0.012*yellow
+ 0.012*orang + 0.012*pineappl + 0.010*pic

29: Italian / Olive Garden
0.047*mozzarella + 0.040*oliv + 0.028*oil + 0.023*eggplant + 0.022*garden +
0.017*balsam + 0.014*foodi + 0.014*calzon + 0.013*ricotta + 0.012*basil +
0.012*calori + 0.012*challeng + 0.011*vinegar + 0.011*antipasto + 0.010*san +

0.010*mike + 0.009*arugula + 0.009*microwav + 0.008*cross + 0.008*class

30: seafood / sushi
0.099*shrimp + 0.046*crab + 0.039*seafood + 0.032*lobster + 0.022*bobbi + 0.014*fusion + 0.014*oyster + 0.014*fish + 0.013*ginger + 0.012*sauc + 0.012*sashimi + 0.012*sake + 0.011*scallop + 0.009*shell + 0.009*sesam + 0.009*leg + 0.009*dumpl + 0.009*rub + 0.008*soy + 0.008*clam

31: fast food
0.112*fez + 0.043*hype + 0.042*chino + 0.032*bell + 0.028*pollo + 0.025*dough + 0.022*bandido + 0.021*chipotl + 0.017*mcdonald + 0.015*anim + 0.015*sick + 0.013*chimi + 0.013*ill + 0.012*stomach + 0.012*finger + 0.012*current + 0.011*golf + 0.011*ultim + 0.010*soggi + 0.009*hmmm

32: elp website + ?
0.059*yelp + 0.054*com + 0.041*http + 0.040*select + 0.039*www + 0.034*scottsdal + 0.028*biz_photo + 0.026*airport + 0.026*club + 0.023*steakhous + 0.022*chris + 0.020*weak + 0.013*impecc + 0.012*wiseguy + 0.011*brazilian + 0.010*blt + 0.010*factor + 0.009*spell + 0.009*bucket + 0.009*spotti

33: food / flavor / positive
0.027*the + 0.025*ice + 0.022*cream + 0.021*sweet + 0.021*potato + 0.018*perfect + 0.016*dessert + 0.015*tea + 0.014*chees + 0.012*flavor + 0.010*delici + 0.009*top + 0.009*serv + 0.008*for + 0.008*meal + 0.008*cake + 0.007*start + 0.007*also + 0.007*butter + 0.007*sauc

34: location / directions / anecdote
0.068*drive + 0.067*local + 0.040*street + 0.038*market + 0.034*dive + 0.031*across + 0.028*downtown + 0.023*citi + 0.018*support + 0.018*thru + 0.018*phoenix + 0.017*glendal + 0.016*ale + 0.014*joe + 0.013*car + 0.011*worthi + 0.011*draw + 0.009*wide + 0.009*client + 0.009*artist

35: holidays / ?
0.077*indian + 0.041*san + 0.035*philli + 0.034*christma + 0.031*breweri + 0.022*gal + 0.022*chilli + 0.022*hospit + 0.019*diego + 0.017*eve + 0.016*4th + 0.016*blu + 0.016*udupi + 0.016*juli + 0.015*aka + 0.015*barbequ + 0.014*dosa + 0.013*naan + 0.012*masala + 0.011*german

36: breakfast (positive)
0.090*breakfast + 0.052*egg + 0.028*coffe + 0.027*brunch + 0.025*morn + 0.022*bacon + 0.022*toast + 0.020*pancak + 0.017*the + 0.014*sunday + 0.012*omelet + 0.011*brown + 0.011*potato + 0.010*muffin + 0.010*wait + 0.010*french + 0.009*gravi + 0.008*scrambl + 0.008*good + 0.008*fresh

37: Comfort Food
0.084*sauc + 0.079*bread + 0.038*garlic + 0.038*bianco + 0.037*the + 0.028*dip + 0.022*fri + 0.021*chicken + 0.014*pepperoni + 0.013*good + 0.013*calamari + 0.012*order + 0.012*son + 0.010*batter + 0.010*spaghetti + 0.010*greas + 0.009*marinara + 0.009*hubbi + 0.009*tast + 0.008*got

38: dietary restrictions / ?
0.182*free + 0.073*guacamol + 0.058*pho + 0.039*irish + 0.037*gluten + 0.034*resort + 0.031*fajita + 0.026*wheat + 0.019*broth + 0.013*noon + 0.012*cow + 0.012*allergi + 0.012*marg + 0.012*same + 0.011*dairi + 0.011*fleme + 0.010*code + 0.010*grain + 0.009*tripl + 0.009*option

39: romantic evening / special couple event
0.091*yum + 0.032*wed + 0.024*salami + 0.024*anniversari + 0.021*gorgeous +

0.019*gnocchi + 0.019*memor + 0.018*partner + 0.017*fox + 0.014*funki +
0.014*greatest + 0.013*gay + 0.013*marri + 0.012*scrumptious + 0.012*quarter +
0.012*winter + 0.012*mariachi + 0.012*steal + 0.011*flower + 0.010*towner

40: Chinese food / Asian Food / flavor
0.057*chicken + 0.042*rice + 0.028*chines + 0.026*dish + 0.024*the + 0.022*soup +
0.022*food + 0.019*fri + 0.018*order + 0.016*spici + 0.015*sauc + 0.013*thai +
0.013*bowl + 0.012*good + 0.012*noodl + 0.010*beef + 0.010*veggi + 0.010*flavor +
0.010*like + 0.009*asian

41: Happy hour / deals
0.220*hour + 0.213*happi + 0.046*drink + 0.027*special + 0.023*price + 0.017*great
+ 0.017*appet + 0.015*half + 0.014*bagel + 0.014*menu + 0.013*deal +
0.011*margarita + 0.010*martini + 0.009*bar + 0.008*app + 0.008*good + 0.008*day +
0.008*they + 0.007*get + 0.006*tuesday

42: comfort food / burgers
0.168*burger + 0.127*fri + 0.026*the + 0.022*waffl + 0.018*good + 0.017*chees +
0.016*order + 0.015*potato + 0.014*hash + 0.014*bun + 0.013*sweet + 0.013*onion +
0.012*french + 0.012*bacon + 0.012*grill + 0.009*get + 0.008*hamburg + 0.008*they
+ 0.008*chicken + 0.008*also

43: hours of operation / visit logistics
0.026*lunch + 0.025*get + 0.024*time + 0.023*order + 0.015*place + 0.014*call +
0.014*day + 0.013*work + 0.012*open + 0.012*close + 0.011*take + 0.011*they +
0.011*one + 0.008*vegan + 0.007*sinc + 0.007*next + 0.007*make + 0.007*still +
0.007*week + 0.006*right

44: service / negative?
0.033*order + 0.019*came + 0.015*ask + 0.013*back + 0.013*got + 0.012*tabl +
0.012*didn + 0.011*server + 0.011*said + 0.011*would + 0.009*friend + 0.009*went +
0.009*one + 0.009*the + 0.009*meal + 0.008*waitress + 0.008*our + 0.008*time +
0.008*took + 0.008*she

45: fast food? / ?
0.051*jerk + 0.048*sub + 0.041*mill + 0.037*lux + 0.033*dirti + 0.032*colleg +
0.032*par + 0.021*soda + 0.018*chick + 0.018*clean + 0.018*ave + 0.015*student +
0.015*restroom + 0.014*pond + 0.013*asu + 0.013*fountain + 0.012*wash +
0.011*ethiopian + 0.011*ranch + 0.010*bull

46: sports bar
0.128*bar + 0.055*game + 0.051*watch + 0.032*sport + 0.029*sum + 0.029*dim +
0.029*chelsea + 0.016*pool + 0.014*bartend + 0.012*footbal + 0.011*pitcher +
0.011*velvet + 0.011*tvs + 0.010*lee + 0.010*entertain + 0.010*play + 0.010*coast
+ 0.010*event + 0.010*screen + 0.009*fun

47: lunch food / sandwiches
0.356*sandwich + 0.049*bread + 0.044*turkey + 0.026*lunch + 0.020*mayo +
0.020*dave + 0.016*chees + 0.015*hog + 0.014*meat + 0.014*john + 0.012*chip +
0.011*club + 0.010*bum + 0.008*ham + 0.008*till + 0.007*cobbler + 0.006*counter +
0.006*swiss + 0.006*today + 0.006*snicker

48: comparison
0.043*like + 0.036*place + 0.034*good + 0.029*realli + 0.019*the + 0.017*food +
0.014*pretti + 0.014*tri + 0.013*think + 0.013*get + 0.012*thing + 0.012*would +
0.012*much + 0.010*better + 0.009*someth + 0.009*want + 0.009*tast + 0.009*look +
0.009*didn + 0.009*bad

49: crowd / other patrons / ambience?
0.017*tabl + 0.015*peopl + 0.011*kid + 0.010*room + 0.009*jade + 0.009*make +
0.009*you + 0.009*like + 0.008*line + 0.007*walk + 0.007*see + 0.007*get +
0.007*one + 0.006*two + 0.006*and + 0.006*around + 0.006*there + 0.006*front +
0.005*sit + 0.005*show

50: pizza
0.286*pizza + 0.048*crust + 0.033*wing + 0.026*chees + 0.025*thin + 0.022*sauc +
0.022*slice + 0.020*top + 0.018*good + 0.017*the + 0.017*pizzeria + 0.014*sausag +
0.013*order + 0.010*like + 0.008*pie + 0.008*style + 0.007*margherita +
0.007*great + 0.007*tast + 0.006*crispi

51: bar / atmosphere
0.093*beer + 0.048*night + 0.042*bar + 0.039*drink + 0.035*music + 0.020*select +
0.016*good + 0.016*bartend + 0.014*live + 0.014*crowd + 0.014*friday + 0.013*fun +
0.013*play + 0.011*great + 0.011*tap + 0.010*the + 0.010*loud + 0.010*four +
0.010*they + 0.009*peak

52: under-known restaurant / ??
0.033*wall + 0.017*hole + 0.010*old + 0.009*carnita + 0.009*floor + 0.009*like +
0.009*guy + 0.009*cool + 0.009*blue + 0.008*girl + 0.008*the + 0.008*drunk +
0.007*place + 0.007*drink + 0.007*look + 0.007*ass + 0.007*coke + 0.007*alright +
0.006*wear + 0.006*bathroom

53: service / wait
0.051*wait + 0.039*food + 0.031*servic + 0.025*time + 0.022*the + 0.021*minut +
0.020*get + 0.018*tabl + 0.015*order + 0.011*place + 0.010*back + 0.010*long +
0.010*drink + 0.009*server + 0.009*manag + 0.009*took + 0.009*never + 0.008*come +
0.008*busi + 0.008*good

54: portion / value / expectation
0.063*the + 0.059*good + 0.031*price + 0.030*food + 0.021*portion + 0.021*servic +
0.019*star + 0.018*would + 0.017*pretti + 0.016*littl + 0.016*bit + 0.011*size +
0.011*nice + 0.011*small + 0.010*overal + 0.009*reason + 0.009*meal + 0.009*much +
0.009*decent + 0.009*expect

55: fancy food ?
0.065*matt + 0.061*cibo + 0.057*delux + 0.036*lamb + 0.023*gourmet + 0.023*snack +
0.022*daughter + 0.020*roast + 0.019*adventur + 0.015*mint + 0.015*fianc +
0.015*carb + 0.013*squash + 0.013*fluffi + 0.012*divers + 0.012*pot + 0.012*diablo
+ 0.010*combin + 0.010*mapl + 0.010*frost

56: location / surrounding area
0.046*place + 0.044*phoenix + 0.040*best + 0.035*restaur + 0.030*food + 0.023*this
+ 0.021*the + 0.018*one + 0.017*find + 0.017*area + 0.016*valley + 0.016*scottsdal
+ 0.015*town + 0.014*locat + 0.010*live + 0.010*authent + 0.010*found + 0.009*mall
+ 0.009*great + 0.009*new

Topics for Las Vegas, NV

1: past visits
0.094*time + 0.080*star + 0.033*first + 0.032*year + 0.029*give + 0.026*last + 0.023*back + 0.022*visit + 0.016*went + 0.016*second + 0.015*place + 0.014*ago + 0.014*rate + 0.014*would + 0.013*next + 0.012*review + 0.012*tri + 0.012*food + 0.011*still + 0.010*sinc

2: portion size
0.214*portion + 0.096*size + 0.070*huge + 0.059*small + 0.050*larg + 0.038*big + 0.029*loung + 0.017*share + 0.015*smaller + 0.012*fusion + 0.010*bigger + 0.010*ihop + 0.008*father + 0.008*aspect + 0.007*outfit + 0.006*feed + 0.006*tree + 0.006*enough + 0.006*whiskey + 0.006*parm

3:
0.072*box + 0.049*carpaccio + 0.042*pig + 0.036*flight + 0.031*tap + 0.026*sooooo + 0.024*wheat + 0.024*flip + 0.023*sun + 0.022*hook + 0.018*skeptic + 0.018*automat + 0.015*subpar + 0.013*utensil + 0.013*hire + 0.012*offici + 0.012*bento + 0.012*advis + 0.011*offic + 0.011*student

4: Steakhouse
0.087*steak + 0.032*lobster + 0.029*potato + 0.021*side + 0.019*order + 0.019*cook + 0.019*good + 0.018*mash + 0.017*the + 0.015*medium + 0.014*filet + 0.014*bull + 0.014*perfect + 0.013*rare + 0.013*dinner + 0.011*salad + 0.010*well + 0.010*scallop + 0.010*steakhous + 0.008*meal

5: pizza / low key italian
0.116*pizza + 0.043*slice + 0.036*chees + 0.033*crust + 0.026*pie + 0.026*thin + 0.020*the + 0.018*top + 0.017*order + 0.016*bagel + 0.015*good + 0.015*mozzarella + 0.012*tomato + 0.012*sold + 0.012*pesto + 0.012*sauc + 0.010*sausag + 0.009*style + 0.009*like + 0.009*basil

6: lunch / coupons & deals
0.173*salad + 0.058*lunch + 0.025*dress + 0.024*caesar + 0.019*the + 0.019*mall + 0.018*coupon + 0.017*lamb + 0.014*special + 0.012*good + 0.011*dinner + 0.010*maggiano + 0.010*side + 0.010*groupon + 0.009*fresh + 0.009*deal + 0.008*chop + 0.008*also + 0.008*lettuc + 0.008*meal

7: italian food
0.088*pasta + 0.062*italian + 0.047*oliv + 0.040*com + 0.033*yelp + 0.030*http + 0.029*select + 0.027*www + 0.023*gnocchi + 0.022*oil + 0.019*biz_photo + 0.017*bread + 0.015*sauc + 0.014*dish + 0.011*beet + 0.011*calamari + 0.011*balsam + 0.011*langoustin + 0.010*vinegar + 0.010*eateri

8: casino?
0.049*bay + 0.046*mandalay + 0.024*tapa + 0.017*skirt + 0.015*tequila + 0.015*laugh + 0.015*divin + 0.014*pink + 0.013*outrag + 0.012*rais + 0.011*life + 0.011*spoil + 0.009*oper + 0.009*excalibur + 0.009*aria + 0.009*pleasur + 0.009*bed + 0.008*nowher + 0.008*day + 0.008*butt

9:
0.019*get + 0.018*walk + 0.016*you + 0.015*make + 0.013*like + 0.012*guy + 0.012*take + 0.012*place + 0.011*know + 0.010*look + 0.009*see + 0.009*work + 0.008*need + 0.008*one + 0.008*want + 0.008*right + 0.007*even + 0.007*peopl + 0.007*sure + 0.006*face

10: fancy food / casino
0.120*venetian + 0.079*miso + 0.057*quail + 0.043*caviar + 0.028*christma + 0.023*complement + 0.023*dough + 0.023*bitter + 0.020*seabass + 0.017*holiday +

0.017*arugula + 0.016*vietnames + 0.014*beach + 0.014*tao + 0.012*prais +
0.009*ador + 0.009*public + 0.009*aquaknox + 0.008*enthusiast + 0.008*wok

11: positive
0.092*best + 0.057*love + 0.056*ever + 0.054*vega + 0.053*place + 0.042*amaz +
0.030*tri + 0.028*one + 0.027*this + 0.019*must + 0.019*delici + 0.018*eat +
0.018*everyth + 0.017*favorit + 0.016*definit + 0.016*the + 0.015*food +
0.014*everi + 0.014*awesom + 0.011*die

12: value / price / comparison
0.159*good + 0.091*food + 0.064*price + 0.043*servic + 0.036*pretti + 0.032*place
+ 0.028*realli + 0.026*the + 0.019*reason + 0.019*decent + 0.017*qualiti +
0.012*get + 0.011*star + 0.010*fast + 0.010*nice + 0.010*veri + 0.010*averag +
0.010*cheap + 0.008*expens + 0.007*quick

13: Asian food / dim sum
0.141*dim + 0.133*sum + 0.047*sea + 0.039*bass + 0.035*fleur + 0.033*band +
0.031*sorbet + 0.021*pho + 0.016*spring + 0.015*sprout + 0.015*roll + 0.014*dumpl
+ 0.013*palm + 0.013*lys + 0.010*brussel + 0.010*dimsum + 0.010*poker +
0.008*memphi + 0.008*mountain + 0.008*foam

14: general (nice) dinner words
0.019*menu + 0.019*order + 0.016*meal + 0.014*cours + 0.013*dinner + 0.013*one +
0.013*dish + 0.012*restaur + 0.010*time + 0.009*appet + 0.009*two + 0.008*came +
0.008*even + 0.008*foie + 0.008*would + 0.008*gras + 0.008*got + 0.008*night +
0.007*the + 0.007*entre

15: Seafood / ?
0.134*crab + 0.083*pari + 0.046*mon + 0.042*king + 0.031*villag + 0.027*gabi +
0.026*leg + 0.023*german + 0.016*alaskan + 0.015*catfish + 0.015*flower +
0.014*asia + 0.014*shell + 0.011*joe + 0.010*philli + 0.009*thousand + 0.009*capit
+ 0.009*voucher + 0.008*dan + 0.008*hanger

16: Asian food
0.045*noodl + 0.030*rice + 0.029*dish + 0.026*chines + 0.021*the + 0.019*fri +
0.018*order + 0.018*thai + 0.017*soup + 0.017*chicken + 0.016*beef + 0.015*food +
0.014*good + 0.013*restaur + 0.013*pork + 0.012*shrimp + 0.011*asian + 0.011*like
+ 0.010*spici + 0.010*curri

17: Italian food
0.052*ball + 0.050*pair + 0.038*veal + 0.031*penni + 0.028*meatbal + 0.028*cherri
+ 0.028*chop + 0.027*michelin + 0.022*cowboy + 0.018*hurri + 0.017*jar +
0.016*shave + 0.016*cotta + 0.015*panna + 0.015*cloth + 0.014*ingredi +
0.011*legit + 0.010*unusu + 0.010*dent + 0.010*tho

18: Cheese
0.208*chees + 0.062*mac + 0.040*truffl + 0.037*blue + 0.023*grill + 0.022*candi +
0.019*bacon + 0.016*goat + 0.015*tamal + 0.013*craftsteak + 0.011*raspberri +
0.011*pretzel + 0.010*cheddar + 0.009*brioch + 0.008*prosciutto + 0.008*loui +
0.008*chorizo + 0.008*mushroom + 0.008*tomato + 0.008*cotton

19: dessert
0.047*dessert + 0.044*cream + 0.036*ice + 0.036*chocol + 0.021*cake + 0.017*sweet
+ 0.016*the + 0.016*like + 0.015*banana + 0.014*creme + 0.013*strawberri +
0.011*tea + 0.011*brule + 0.010*tast + 0.009*pie + 0.009*top + 0.009*good +
0.009*tart + 0.009*cheesecak + 0.008*pastri

20: food?

0.134*kobe + 0.071*indian + 0.034*donut + 0.032*ramen + 0.026*wagyu + 0.023*noisi + 0.021*daniel + 0.016*monkey + 0.015*such + 0.014*obnoxi + 0.013*tandoori + 0.012*chutney + 0.010*tamba + 0.010*japanes + 0.009*masala + 0.009*lamb + 0.008*mole + 0.008*die + 0.008*battl + 0.008*languag

21: barbecue / flavor / famous Dave's
0.068*sauc + 0.045*spici + 0.043*shrimp + 0.034*yum + 0.034*hot + 0.026*bbq + 0.023*dave + 0.018*love + 0.018*famous + 0.016*sweet + 0.016*bomb + 0.015*dip + 0.014*lucill + 0.011*good + 0.010*hall + 0.010*concert + 0.010*tri + 0.010*spice + 0.010*get + 0.008*like

22: service / negative
0.021*order + 0.019*food + 0.016*got + 0.016*get + 0.014*back + 0.013*one + 0.013*never + 0.011*even + 0.010*ask + 0.009*servic + 0.009*said + 0.008*eat + 0.008*charg + 0.008*bad + 0.008*horribl + 0.008*took + 0.007*didn + 0.007*tip + 0.007*like + 0.007*manag

23: Mexican food
0.062*taco + 0.047*chip + 0.042*margarita + 0.036*nacho + 0.034*mexican + 0.029*salsa + 0.025*the + 0.023*bean + 0.018*good + 0.016*guacamol + 0.014*order + 0.014*tortilla + 0.013*burrito + 0.013*fish + 0.010*food + 0.010*enchilada + 0.008*like + 0.008*green + 0.008*chili + 0.008*rice

24: Comfort food / wings
0.287*chicken + 0.083*fri + 0.036*wing + 0.033*slider + 0.030*order + 0.017*buffalo + 0.015*finger + 0.015*the + 0.013*ranch + 0.012*wrap + 0.012*sauc + 0.011*breast + 0.010*ketchup + 0.010*good + 0.010*lemonad + 0.008*got + 0.008*crispi + 0.008*dip + 0.007*also + 0.007*dri

25: flavor / food quality / positive
0.054*the + 0.041*bread + 0.030*perfect + 0.027*sauc + 0.027*flavor + 0.021*delici + 0.018*fresh + 0.016*good + 0.013*sweet + 0.012*roast + 0.012*butter + 0.011*love + 0.011*tender + 0.011*tast + 0.011*light + 0.011*crispi + 0.010*cook + 0.010*mouth + 0.010*season + 0.010*melt

26: positive / repeat customer
0.053*alway + 0.037*place + 0.031*the + 0.029*time + 0.027*great + 0.027*food + 0.022*friend + 0.020*good + 0.019*get + 0.018*love + 0.018*come + 0.017*they + 0.014*servic + 0.014*staff + 0.012*this + 0.011*favorit + 0.011*make + 0.011*usual + 0.010*eat + 0.009*one

27: buffet / seafood
0.125*buffet + 0.023*crab + 0.022*select + 0.021*seafood + 0.020*dessert + 0.019*wynn + 0.018*leg + 0.015*dinner + 0.015*food + 0.015*station + 0.014*the + 0.012*line + 0.012*bellagio + 0.011*varieti + 0.010*they + 0.010*shrimp + 0.010*lunch + 0.010*oyster + 0.009*vega + 0.009*qualiti

28: ambience / nightlife
0.034*fun + 0.032*night + 0.029*danc + 0.028*music + 0.024*beer + 0.023*drink + 0.022*play + 0.021*bar + 0.020*gilley + 0.017*countri + 0.016*club + 0.016*place + 0.015*watch + 0.013*island + 0.011*cool + 0.011*girl + 0.010*loud + 0.010*peopl + 0.010*crowd + 0.010*like

29: nice food?
0.111*pork + 0.080*cake + 0.060*red + 0.047*belli + 0.032*tenderloin + 0.029*son + 0.028*surf + 0.028*nyc + 0.027*gift + 0.024*turf + 0.022*cupcak + 0.022*forest + 0.021*greatest + 0.019*luxor + 0.018*terrac + 0.016*bakeri + 0.015*velvet + 0.014*baguett + 0.013*reuben + 0.012*albacor

30: anecdote + ?
0.109*fountain + 0.054*tempura + 0.034*carnegi + 0.027*croissant + 0.025*cousin + 0.019*pate + 0.019*lake + 0.018*cornbread + 0.016*octopus + 0.016*north + 0.016*valley + 0.013*studio + 0.013*rainbow + 0.012*gazpacho + 0.012*bucket + 0.011*tacki + 0.011*spank + 0.010*former + 0.009*golf + 0.009*viva

31: event / anecdote
0.102*duck + 0.042*citi + 0.034*sin + 0.032*dad + 0.025*cod + 0.025*mai + 0.025*cirqu + 0.022*express + 0.020*karaok + 0.016*flan + 0.016*confit + 0.016*raffl + 0.013*drunken + 0.013*rick + 0.011*panda + 0.010*heel + 0.009*preserv + 0.009*hilari + 0.009*bao + 0.008*soo

32: ambience / restaurant layout / decor
0.045*tabl + 0.029*room + 0.028*seat + 0.028*parti + 0.027*reserv + 0.018*group + 0.017*peopl + 0.016*show + 0.015*the + 0.013*bar + 0.011*sit + 0.011*view + 0.010*watch + 0.010*larg + 0.010*area + 0.009*restaur + 0.009*dine + 0.008*get + 0.008*one + 0.007*they

33: flavor
0.021*the + 0.013*dish + 0.010*serv + 0.010*menu + 0.009*one + 0.009*flavor + 0.007*well + 0.007*tast + 0.006*meal + 0.006*restaur + 0.006*like + 0.005*two + 0.005*bit + 0.005*star + 0.005*top + 0.005*would + 0.005*chef + 0.005*meat + 0.005*quit + 0.005*dine

34: anecdote / vacation
0.209*vega + 0.092*las + 0.037*strip + 0.037*trip + 0.028*beer + 0.025*best + 0.022*wine + 0.019*visit + 0.017*restaur + 0.013*select + 0.011*frite + 0.011*ami + 0.011*list + 0.010*local + 0.009*one + 0.008*find + 0.008*tourist + 0.007*bottl + 0.007*glass + 0.007*live

35: comfort food / flavor
0.122*soup + 0.068*onion + 0.031*pot + 0.026*bowl + 0.026*french + 0.019*chili + 0.016*tomato + 0.016*clam + 0.016*order + 0.013*hot + 0.013*pastrami + 0.012*ring + 0.012*mushroom + 0.012*pickl + 0.010*salti + 0.010*the + 0.009*good + 0.009*came + 0.009*chowder + 0.008*pepper

36: dinner and a show? / entertainment
0.060*old + 0.031*mirag + 0.029*school + 0.022*tom + 0.014*accord + 0.013*cheer + 0.011*everybodi + 0.011*bewar + 0.011*afraid + 0.010*bird + 0.010*pant + 0.009*wind + 0.009*colleg + 0.009*scale + 0.009*buzz + 0.009*fire + 0.008*neat + 0.008*hawaii + 0.008*frontier + 0.008*finest

37: burger joint
0.241*burger + 0.155*fri + 0.027*bun + 0.015*top + 0.014*dog + 0.014*coast + 0.014*shake + 0.013*patti + 0.012*potato + 0.011*hamburg + 0.010*bacon + 0.010*chees + 0.009*sweet + 0.009*west + 0.009*east + 0.008*order + 0.008*beef + 0.007*hot + 0.007*juici + 0.007*joint

38: service
0.037*server + 0.037*ask + 0.033*order + 0.027*tabl + 0.026*came + 0.025*waiter + 0.023*waitress + 0.021*servic + 0.021*our + 0.016*the + 0.015*she + 0.014*said + 0.014*drink + 0.012*check + 0.012*friend + 0.012*didn + 0.012*back + 0.011*would + 0.011*took + 0.011*told

39: flavor / expectations & comparison
0.038*the + 0.030*food + 0.030*like + 0.029*good + 0.022*realli + 0.021*place + 0.017*would + 0.016*better + 0.015*much + 0.014*pretti + 0.014*didn + 0.014*wasn +

0.013*tast + 0.012*think + 0.012*eat + 0.011*get + 0.011*bad + 0.010*noth + 0.010*expect + 0.009*thing

40: hapy hour / coctails
0.104*drink + 0.095*bar + 0.065*hour + 0.063*happi + 0.044*bartend + 0.029*cocktail + 0.017*martini + 0.012*card + 0.011*vodka + 0.011*gold + 0.011*alcohol + 0.008*mojito + 0.007*app + 0.007*venu + 0.006*shot + 0.006*strong + 0.006*drank + 0.005*sat + 0.005*reward + 0.004*passion

41: anecdote
0.058*drive + 0.038*hubbi + 0.037*shop + 0.029*planet + 0.027*sooo + 0.025*wall + 0.025*hollywood + 0.023*hole + 0.020*stumbl + 0.018*palazzo + 0.017*jean + 0.016*mile + 0.015*blt + 0.014*mom + 0.013*thru + 0.013*cube + 0.013*locat + 0.011*3am + 0.010*jalap + 0.010*home

42: sushi
0.108*sushi + 0.082*roll + 0.035*tuna + 0.034*fish + 0.022*salmon + 0.019*bouchon + 0.018*order + 0.018*fresh + 0.018*sashimi + 0.015*eat + 0.014*japanes + 0.013*chef + 0.013*the + 0.011*place + 0.011*rice + 0.009*good + 0.009*ayc + 0.008*like + 0.008*spici + 0.008*menu

43: positive / dinner
0.058*the + 0.033*food + 0.032*servic + 0.027*restaur + 0.023*great + 0.020*excel + 0.018*experi + 0.017*wine + 0.016*amaz + 0.015*dine + 0.014*recommend + 0.014*high + 0.013*bellagio + 0.012*perfect + 0.011*meal + 0.010*delici + 0.010*top + 0.010*beauti + 0.010*vega + 0.010*view

44: negative / flavor / cheesecake factory
0.035*disappoint + 0.034*dri + 0.028*the + 0.023*tast + 0.023*lux + 0.022*bland + 0.022*cold + 0.020*factori + 0.018*grand + 0.018*cheesecak + 0.017*store + 0.017*frozen + 0.013*tasteless + 0.012*recal + 0.012*overcook + 0.012*qualiti + 0.011*flavorless + 0.011*sad + 0.011*lasagna + 0.011*improv

45: ambience / outdoor area
0.063*the + 0.042*nice + 0.022*restaur + 0.015*outsid + 0.015*decor + 0.013*seat + 0.013*friend + 0.013*enjoy + 0.012*patio + 0.012*insid + 0.012*area + 0.011*littl + 0.011*atmospher + 0.010*bit + 0.010*realli + 0.010*good + 0.009*like + 0.009*feel + 0.008*sit + 0.008*ambianc

46: hotel?
0.061*mgm + 0.035*free + 0.031*deli + 0.025*yellowtail + 0.022*grand + 0.022*pineappl + 0.021*juic + 0.018*sensi + 0.017*culinari + 0.016*gluten + 0.015*almond + 0.014*orang + 0.014*mint + 0.014*fiamma + 0.013*flatbread + 0.012*parfait + 0.012*master + 0.011*franc + 0.011*orchid + 0.011*exquisit

47: hotel / location & convenience
0.036*hotel + 0.035*locat + 0.030*strip + 0.030*casino + 0.028*night + 0.028*vega + 0.027*place + 0.025*stay + 0.023*late + 0.018*open + 0.013*this + 0.013*cafe + 0.010*close + 0.010*it + 0.009*find + 0.009*one + 0.009*right + 0.009*get + 0.009*spot + 0.009*conveni

48: event?
0.065*rock + 0.038*con + 0.026*theme + 0.024*pros + 0.022*anim + 0.019*perform + 0.018*spaghetti + 0.017*palac + 0.017*craft + 0.017*signatur + 0.015*design + 0.014*crystal + 0.014*watermelon + 0.014*airport + 0.012*scrumptious + 0.012*mass + 0.012*art + 0.012*access + 0.012*squar + 0.012*produc

49: breakfast / brunch

0.114*breakfast + 0.060*brunch + 0.045*crepe + 0.040*coffe + 0.029*egg + 0.025*omelet + 0.024*morn + 0.023*cafe + 0.019*benedict + 0.016*sunday + 0.015*omelett + 0.014*day + 0.013*waffl + 0.013*fruit + 0.012*mimosa + 0.010*fresh + 0.010*juic + 0.010*the + 0.008*lunch + 0.008*serv

50: wait time / service
0.092*wait + 0.037*minut + 0.032*line + 0.028*get + 0.028*long + 0.027*time + 0.025*food + 0.022*seat + 0.022*hour + 0.018*order + 0.014*tabl + 0.014*the + 0.011*got + 0.011*around + 0.011*took + 0.010*come + 0.009*take + 0.009*peopl + 0.008*servic + 0.007*busi

51: yelp reviews
0.032*review + 0.025*know + 0.024*like + 0.018*say + 0.012*one + 0.012*make + 0.012*place + 0.011*but + 0.010*read + 0.010*thing + 0.010*and + 0.010*let + 0.009*want + 0.008*think + 0.008*someth + 0.008*said + 0.008*write + 0.007*way + 0.007*yelp + 0.007*go

52: positive
0.311*great + 0.095*food + 0.080*servic + 0.031*back + 0.028*love + 0.027*atmospher + 0.020*fantast + 0.019*had + 0.018*place + 0.017*friend + 0.013*definit + 0.013*wife + 0.012*amaz + 0.011*will + 0.011*delici + 0.010*recommend + 0.010*the + 0.009*went + 0.007*root + 0.007*veri

53: breakfast
0.112*egg + 0.065*french + 0.062*toast + 0.048*breakfast + 0.047*bacon + 0.038*hash + 0.034*potato + 0.032*muffin + 0.031*pancak + 0.027*sausag + 0.024*brown + 0.022*corn + 0.017*denni + 0.016*gravi + 0.016*ham + 0.015*waffl + 0.015*biscuit + 0.013*beef + 0.012*bloodi + 0.012*scrambl

54: barbecue / meat / flavor
0.112*rib + 0.056*meat + 0.052*prime + 0.048*bbq + 0.030*the + 0.023*pork + 0.022*beef + 0.019*good + 0.016*side + 0.016*brisket + 0.015*short + 0.013*like + 0.013*cut + 0.012*tender + 0.011*dri + 0.010*smoke + 0.010*pull + 0.008*bean + 0.008*corn + 0.008*flavor

55: dietary restrictions / menu variety
0.060*option + 0.056*authent + 0.055*vegetarian + 0.041*vegan + 0.039*veggi + 0.035*out + 0.027*cheeseburg + 0.020*doubl + 0.016*fast + 0.015*employe + 0.015*healthi + 0.015*food + 0.014*menu + 0.014*thanksgiv + 0.014*tea + 0.010*gourmet + 0.010*cross + 0.009*penn + 0.009*fresh + 0.009*like

56: lunch
0.127*sandwich + 0.024*turkey + 0.019*order + 0.016*bread + 0.016*lunch + 0.015*got + 0.012*club + 0.011*tri + 0.011*bite + 0.009*eat + 0.009*good + 0.008*one + 0.008*quick + 0.007*get + 0.007*look + 0.007*stop + 0.007*like + 0.007*the + 0.006*half + 0.006*decid

Phoenix, $
OLS Regression Results

Dep. Variable:	y	R-squared:	0.237
Model:	OLS	Adj. R-squared:	0.237
Method:	Least Squares	F-statistic:	447.1
Date:	Sun, 22 Mar 2015	Prob (F-statistic):	0.00
Time:	16:11:43	Log-Likelihood:	-1.1120e+05
No. Observations:	80500	AIC:	2.225e+05
Df Residuals:	80444	BIC:	2.230e+05
Df Model:	56		
Covariance Type:	nonrobust		

topic	coef	std err	t	P>|t|	[95.0% Conf.	Int.]
const	-5.619e-20	5.53e-21	-10.159	0.000	-6.7e-20	-4.53e-20
x1	-0.0046	0.004	-1.297	0.195	-0.011	0.002
x2	0.0176	0.004	4.777	0.000	0.010	0.025
x3	0.2472	0.004	69.714	0.000	0.240	0.254
x4	0.0065	0.004	1.838	0.066	-0.000	0.013
x5	-0.0122	0.004	-3.433	0.001	-0.019	-0.005
x6	0.0076	0.004	2.110	0.035	0.001	0.015
x7	0.0117	0.004	3.152	0.002	0.004	0.019
x8	0.0109	0.003	3.154	0.002	0.004	0.018
x9	-0.0066	0.004	-1.823	0.068	-0.014	0.000
x10	0.0243	0.004	6.591	0.000	0.017	0.032
x11	0.0117	0.004	3.265	0.001	0.005	0.019
x12	0.0185	0.004	4.906	0.000	0.011	0.026
x13	0.0183	0.004	5.143	0.000	0.011	0.025
x14	0.0155	0.004	4.290	0.000	0.008	0.023
x15	0.0157	0.004	4.118	0.000	0.008	0.023
x16	0.0197	0.004	5.405	0.000	0.013	0.027
x17	0.0099	0.004	2.733	0.006	0.003	0.017
x18	0.0166	0.004	4.635	0.000	0.010	0.024
x19	0.0020	0.004	0.549	0.583	-0.005	0.009
x20	0.0138	0.004	3.874	0.000	0.007	0.021
x21	0.0102	0.004	2.891	0.004	0.003	0.017
x22	0.1016	0.003	29.191	0.000	0.095	0.108
x23	-0.2509	0.004	-61.207	0.000	-0.259	-0.243
x24	0.0082	0.004	2.232	0.026	0.001	0.015
x25	-0.0013	0.004	-0.365	0.715	-0.008	0.006
x26	0.1798	0.003	52.197	0.000	0.173	0.187
x27	0.0092	0.004	2.398	0.016	0.002	0.017
x28	0.0002	0.004	0.069	0.945	-0.007	0.007
x29	-0.0095	0.004	-2.603	0.009	-0.017	-0.002
x30	0.0113	0.004	3.047	0.002	0.004	0.019
x31	-0.0237	0.004	-6.571	0.000	-0.031	-0.017
x32	-0.0070	0.003	-2.122	0.034	-0.014	-0.001
x33	0.0255	0.004	6.790	0.000	0.018	0.033
x34	-0.0074	0.004	-2.084	0.037	-0.014	-0.000
x35	0.0052	0.004	1.492	0.136	-0.002	0.012
x36	0.0051	0.004	1.398	0.162	-0.002	0.012
x37	0.0059	0.004	1.644	0.100	-0.001	0.013
x38	0.0159	0.004	4.524	0.000	0.009	0.023
x39	0.0259	0.004	7.192	0.000	0.019	0.033
x40	0.0082	0.004	2.173	0.030	0.001	0.016
x41	0.0002	0.003	0.055	0.957	-0.007	0.007
x42	0.0281	0.004	7.709	0.000	0.021	0.035

x43	0.0154	0.004	4.093	0.000	0.008	0.023
x44	-0.0503	0.004	-12.857	0.000	-0.058	-0.043
x45	-0.0182	0.004	-5.005	0.000	-0.025	-0.011
x46	0.0002	0.004	0.043	0.965	-0.007	0.007
x47	0.0069	0.004	1.816	0.069	-0.001	0.014
x48	-0.1409	0.004	-36.859	0.000	-0.148	-0.133
x49	0.0160	0.004	3.904	0.000	0.008	0.024
x50	0.0266	0.004	7.474	0.000	0.020	0.034
x51	-0.0034	0.004	-0.922	0.356	-0.011	0.004
x52	-0.0113	0.004	-2.943	0.003	-0.019	-0.004
x53	-0.1758	0.004	-46.998	0.000	-0.183	-0.168
x54	-0.0438	0.004	-12.299	0.000	-0.051	-0.037
x55	0.0183	0.004	5.129	0.000	0.011	0.025
x56	0.0972	0.004	26.997	0.000	0.090	0.104

Omnibus:	1500.663	Durbin-Watson:	1.998
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1710.512
Skew:	-0.295	Prob(JB):	0.00
Kurtosis:	3.403	Cond. No.	2.25e+15

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 9.52e-26. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

Phoenix, $$
OLS Regression Results

Dep. Variable:	y	R-squared:	0.265
Model:	OLS	Adj. R-squared:	0.265
Method:	Least Squares	F-statistic:	1040.
Date:	Sun, 22 Mar 2015	Prob (F-statistic):	0.00
Time:	16:11:51	Log-Likelihood:	-2.1860e+05
No. Observations:	161148	AIC:	4.373e+05
Df Residuals:	161092	BIC:	4.379e+05
Df Model:	56		
Covariance Type:	nonrobust		

topic	coef	std err	t	P>|t|	[95.0% Conf. Int.]	
const	-1.075e-19	2.34e-21	-45.947	0.000	-1.12e-19	-1.03e-19
x1	-0.0010	0.002	-0.397	0.691	-0.006	0.004
x2	0.0244	0.003	9.170	0.000	0.019	0.030
x3	0.2513	0.002	101.580	0.000	0.246	0.256
x4	0.0072	0.002	2.918	0.004	0.002	0.012
x5	-0.0046	0.003	-1.840	0.066	-0.010	0.000
x6	0.0042	0.002	1.780	0.075	-0.000	0.009
x7	0.0133	0.003	5.226	0.000	0.008	0.018
x8	0.0151	0.002	6.274	0.000	0.010	0.020
x9	-0.0039	0.002	-1.553	0.121	-0.009	0.001
x10	0.0100	0.003	3.866	0.000	0.005	0.015
x11	0.0075	0.002	3.032	0.002	0.003	0.012
x12	0.0181	0.003	6.935	0.000	0.013	0.023
x13	0.0071	0.002	2.907	0.004	0.002	0.012
x14	0.0125	0.002	5.016	0.000	0.008	0.017
x15	-0.0120	0.002	-4.812	0.000	-0.017	-0.007
x16	0.0312	0.003	12.277	0.000	0.026	0.036
x17	0.0056	0.003	2.193	0.028	0.001	0.011
x18	-0.0091	0.003	-3.643	0.000	-0.014	-0.004
x19	0.0012	0.002	0.482	0.630	-0.004	0.006
x20	0.0157	0.002	6.375	0.000	0.011	0.021
x21	0.0605	0.003	24.097	0.000	0.056	0.065
x22	0.0984	0.002	41.051	0.000	0.094	0.103
x23	-0.2229	0.003	-80.268	0.000	-0.228	-0.217
x24	0.0111	0.003	4.366	0.000	0.006	0.016
x25	-0.0013	0.002	-0.508	0.611	-0.006	0.004
x26	0.1626	0.002	68.061	0.000	0.158	0.167
x27	-0.0024	0.003	-0.909	0.363	-0.008	0.003
x28	-0.0006	0.002	-0.254	0.800	-0.006	0.004
x29	-0.0037	0.003	-1.430	0.153	-0.009	0.001
x30	0.0135	0.003	5.349	0.000	0.009	0.018
x31	-0.0154	0.003	-6.162	0.000	-0.020	-0.011
x32	-0.0002	0.002	-0.105	0.916	-0.005	0.004
x33	0.0422	0.003	15.070	0.000	0.037	0.048
x34	-0.0049	0.003	-1.937	0.053	-0.010	5.8e-05
x35	0.0057	0.002	2.332	0.020	0.001	0.011
x36	0.0188	0.002	7.588	0.000	0.014	0.024
x37	-0.0019	0.003	-0.761	0.447	-0.007	0.003
x38	0.0077	0.002	3.210	0.001	0.003	0.012
x39	0.0109	0.003	4.295	0.000	0.006	0.016
x40	0.0096	0.003	3.836	0.000	0.005	0.015
x41	0.0075	0.002	3.097	0.002	0.003	0.012
x42	0.0141	0.002	5.719	0.000	0.009	0.019

x43	0.0124	0.003	4.921	0.000	0.007	0.017
x44	-0.0587	0.003	-20.473	0.000	-0.064	-0.053
x45	-0.0222	0.003	-8.743	0.000	-0.027	-0.017
x46	-0.0025	0.002	-1.010	0.313	-0.007	0.002
x47	0.0038	0.003	1.533	0.125	-0.001	0.009
x48	-0.1455	0.003	-55.276	0.000	-0.151	-0.140
x49	0.0073	0.003	2.601	0.009	0.002	0.013
x50	0.0334	0.002	13.415	0.000	0.029	0.038
x51	0.0158	0.003	6.195	0.000	0.011	0.021
x52	-0.0066	0.003	-2.473	0.013	-0.012	-0.001
x53	-0.2192	0.003	-81.967	0.000	-0.224	-0.214
x54	-0.0658	0.002	-26.583	0.000	-0.071	-0.061
x55	0.0173	0.003	6.834	0.000	0.012	0.022
x56	0.0757	0.002	30.351	0.000	0.071	0.081

Omnibus:	2502.883	Durbin-Watson:	1.991
Prob(Omnibus):	0.000	Jarque-Bera (JB):	2914.638
Skew:	-0.255	Prob(JB):	0.00
Kurtosis:	3.416	Cond. No.	2.25e+15

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 2.06e-25. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

Phoenix, $$$

OLS Regression Results

Dep. Variable:	y	R-squared:	0.271
Model:	OLS	Adj. R-squared:	0.268
Method:	Least Squares	F-statistic:	90.95
Date:	Sun, 22 Mar 2015	Prob (F-statistic):	0.00
Time:	16:11:52	Log-Likelihood:	-18548.
No. Observations:	13761	AIC:	3.721e+04
Df Residuals:	13705	BIC:	3.763e+04
Df Model:	56		
Covariance Type:	nonrobust		

topic	coef	std err	t	P>|t|	[95.0% Conf. Int.]	
const	5.287e-19	1.09e-19	4.849	0.000	3.15e-19	7.42e-19
x1	0.0187	0.009	2.111	0.035	0.001	0.036
x2	0.0189	0.009	2.066	0.039	0.001	0.037
x3	0.2702	0.008	31.910	0.000	0.254	0.287
x4	-0.0081	0.008	-0.961	0.336	-0.025	0.008
x5	0.0050	0.009	0.554	0.580	-0.013	0.023
x6	-0.0079	0.009	-0.921	0.357	-0.025	0.009
x7	0.0271	0.009	3.013	0.003	0.009	0.045
x8	0.0138	0.008	1.638	0.101	-0.003	0.030
x9	0.0102	0.009	1.190	0.234	-0.007	0.027
x10	0.0153	0.009	1.654	0.098	-0.003	0.033
x11	0.0180	0.008	2.147	0.032	0.002	0.034
x12	0.0066	0.009	0.736	0.462	-0.011	0.024
x13	0.0064	0.008	0.778	0.436	-0.010	0.023
x14	0.0108	0.008	1.289	0.197	-0.006	0.027
x15	0.0074	0.009	0.817	0.414	-0.010	0.025
x16	0.0250	0.009	2.929	0.003	0.008	0.042
x17	0.0265	0.010	2.780	0.005	0.008	0.045
x18	0.0060	0.009	0.682	0.496	-0.011	0.023
x19	-0.0013	0.009	-0.146	0.884	-0.019	0.016
x20	0.0152	0.009	1.747	0.081	-0.002	0.032
x21	0.1075	0.009	12.003	0.000	0.090	0.125
x22	0.0619	0.008	7.651	0.000	0.046	0.078
x23	-0.2122	0.010	-21.831	0.000	-0.231	-0.193
x24	0.0109	0.009	1.221	0.222	-0.007	0.029
x25	0.0011	0.009	0.127	0.899	-0.017	0.019
x26	0.1120	0.008	13.714	0.000	0.096	0.128
x27	0.0102	0.009	1.125	0.261	-0.008	0.028
x28	0.0026	0.009	0.298	0.766	-0.015	0.020
x29	-0.0091	0.009	-0.990	0.322	-0.027	0.009
x30	0.0091	0.010	0.958	0.338	-0.010	0.028
x31	-0.0184	0.008	-2.171	0.030	-0.035	-0.002
x32	0.0075	0.009	0.838	0.402	-0.010	0.025
x33	0.0920	0.011	8.486	0.000	0.071	0.113
x34	-0.0072	0.009	-0.827	0.408	-0.024	0.010
x35	0.0009	0.008	0.104	0.917	-0.016	0.017
x36	-0.0062	0.009	-0.713	0.476	-0.023	0.011
x37	-0.0118	0.008	-1.424	0.155	-0.028	0.004
x38	0.0095	0.008	1.160	0.246	-0.007	0.025
x39	0.0312	0.009	3.416	0.001	0.013	0.049
x40	-0.0214	0.009	-2.480	0.013	-0.038	-0.004
x41	0.0002	0.008	0.029	0.977	-0.016	0.017
x42	-0.0055	0.009	-0.642	0.521	-0.022	0.011

x43	-0.0159	0.009	-1.858	0.063	-0.033	0.001
x44	-0.0864	0.010	-8.578	0.000	-0.106	-0.067
x45	-0.0303	0.009	-3.517	0.000	-0.047	-0.013
x46	0.0065	0.009	0.753	0.451	-0.010	0.023
x47	-0.0078	0.009	-0.894	0.371	-0.025	0.009
x48	-0.1402	0.009	-15.856	0.000	-0.158	-0.123
x49	0.0042	0.010	0.436	0.663	-0.015	0.023
x50	-0.0127	0.008	-1.597	0.110	-0.028	0.003
x51	0.0134	0.008	1.659	0.097	-0.002	0.029
x52	-0.0173	0.009	-1.936	0.053	-0.035	0.000
x53	-0.2051	0.009	-22.734	0.000	-0.223	-0.187
x54	-0.1260	0.009	-14.489	0.000	-0.143	-0.109
x55	0.0035	0.009	0.397	0.692	-0.014	0.021
x56	0.0509	0.009	5.960	0.000	0.034	0.068

Omnibus:	331.064	Durbin-Watson:	2.001
Prob(Omnibus):	0.000	Jarque-Bera (JB):	391.293
Skew:	-0.331	Prob(JB):	1.08e-85
Kurtosis:	3.494	Cond. No.	2.25e+15

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 2.09e-26. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

Phoenix, $$$$

OLS Regression Results

Dep. Variable:	y	R-squared:	0.277
Model:	OLS	Adj. R-squared:	0.262
Method:	Least Squares	F-statistic:	18.13
Date:	Sun, 22 Mar 2015	Prob (F-statistic):	5.86e-146
Time:	16:11:52	Log-Likelihood:	-3726.4
No. Observations:	2704	AIC:	7565.
Df Residuals:	2648	BIC:	7895.
Df Model:	56		
Covariance Type:	nonrobust		

topic	coef	std err	t	P>|t|	[95.0% Conf. Int.]	
const	6.176e-19	5.2e-19	1.187	0.235	-4.03e-19	1.64e-18
x1	-0.0237	0.021	-1.140	0.255	-0.064	0.017
x2	-0.0243	0.022	-1.102	0.270	-0.067	0.019
x3	0.2502	0.020	12.325	0.000	0.210	0.290
x4	-0.0133	0.020	-0.676	0.499	-0.052	0.025
x5	0.0211	0.021	0.982	0.326	-0.021	0.063
x6	-0.0204	0.020	-1.019	0.308	-0.060	0.019
x7	-0.0144	0.023	-0.620	0.535	-0.060	0.031
x8	-0.0284	0.019	-1.471	0.141	-0.066	0.009
x9	0.0178	0.021	0.852	0.394	-0.023	0.059
x10	0.0185	0.024	0.779	0.436	-0.028	0.065
x11	0.0045	0.020	0.220	0.826	-0.036	0.045
x12	0.0306	0.023	1.349	0.177	-0.014	0.075
x13	-0.0152	0.021	-0.732	0.464	-0.056	0.026
x14	-0.0141	0.021	-0.684	0.494	-0.055	0.026
x15	-0.0217	0.018	-1.190	0.234	-0.057	0.014
x16	0.0033	0.020	0.163	0.871	-0.036	0.043
x17	0.0442	0.023	1.893	0.058	-0.002	0.090
x18	-0.0005	0.021	-0.023	0.982	-0.041	0.040
x19	0.0327	0.023	1.419	0.156	-0.012	0.078
x20	0.0144	0.021	0.673	0.501	-0.028	0.056
x21	0.1042	0.023	4.435	0.000	0.058	0.150
x22	0.0448	0.019	2.379	0.017	0.008	0.082
x23	-0.2275	0.023	-9.839	0.000	-0.273	-0.182
x24	0.0179	0.023	0.774	0.439	-0.027	0.063
x25	0.0190	0.022	0.881	0.379	-0.023	0.061
x26	0.0442	0.019	2.293	0.022	0.006	0.082
x27	0.0293	0.022	1.325	0.185	-0.014	0.073
x28	0.0238	0.022	1.087	0.277	-0.019	0.067
x29	0.0190	0.023	0.825	0.409	-0.026	0.064
x30	0.0028	0.023	0.124	0.901	-0.042	0.047
x31	-0.0802	0.022	-3.655	0.000	-0.123	-0.037
x32	-0.0049	0.018	-0.265	0.791	-0.041	0.031
x33	0.1381	0.029	4.688	0.000	0.080	0.196
x34	0.0016	0.022	0.075	0.940	-0.041	0.044
x35	0.0027	0.019	0.140	0.889	-0.035	0.040
x36	0.0229	0.021	1.074	0.283	-0.019	0.065
x37	-0.0237	0.020	-1.210	0.227	-0.062	0.015
x38	-0.0232	0.020	-1.141	0.254	-0.063	0.017
x39	0.0295	0.021	1.399	0.162	-0.012	0.071
x40	-0.0108	0.020	-0.526	0.599	-0.051	0.029
x41	0.0158	0.020	0.802	0.423	-0.023	0.054
x42	-0.0060	0.020	-0.298	0.766	-0.046	0.034

x43	-0.0008	0.021	-0.040	0.968	-0.042	0.040
x44	-0.1273	0.024	-5.287	0.000	-0.175	-0.080
x45	0.0261	0.023	1.160	0.246	-0.018	0.070
x46	-0.0006	0.020	-0.029	0.977	-0.040	0.039
x47	-0.0349	0.021	-1.670	0.095	-0.076	0.006
x48	-0.1075	0.022	-4.941	0.000	-0.150	-0.065
x49	0.0412	0.024	1.711	0.087	-0.006	0.088
x50	-0.0272	0.021	-1.324	0.186	-0.068	0.013
x51	-0.0091	0.020	-0.458	0.647	-0.048	0.030
x52	-0.0345	0.023	-1.517	0.129	-0.079	0.010
x53	-0.2241	0.021	-10.739	0.000	-0.265	-0.183
x54	-0.1235	0.021	-5.951	0.000	-0.164	-0.083
x55	-0.0036	0.024	-0.150	0.880	-0.050	0.043
x56	0.0526	0.020	2.639	0.008	0.014	0.092

Omnibus:	136.406	Durbin-Watson:	1.771
Prob(Omnibus):	0.000	Jarque-Bera (JB):	166.323
Skew:	-0.521	Prob(JB):	7.65e-37
Kurtosis:	3.625	Cond. No.	1.50e+16

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.18e-28. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

Las Vegas, $
OLS Regression Results

Dep. Variable:	y	R-squared:	0.264
Model:	OLS	Adj. R-squared:	0.263
Method:	Least Squares	F-statistic:	401.8
Date:	Sun, 22 Mar 2015	Prob (F-statistic):	0.00
Time:	16:12:02	Log-Likelihood:	-84965.
No. Observations:	62842	AIC:	1.700e+05
Df Residuals:	62786	BIC:	1.705e+05
Df Model:	56		
Covariance Type:	nonrobust		

topic	coef	std err	t	P>|t|	[95.0% Conf. Int.]	
const	-4.663e-19	3.52e-20	-13.252	0.000	-5.35e-19	-3.97e-19
x1	-0.0306	0.004	-7.762	0.000	-0.038	-0.023
x2	0.0321	0.004	8.105	0.000	0.024	0.040
x3	0.0069	0.004	1.713	0.087	-0.001	0.015
x4	0.0135	0.004	3.510	0.000	0.006	0.021
x5	0.0375	0.004	9.538	0.000	0.030	0.045
x6	-7.844e-07	0.004	-0.000	1.000	-0.008	0.008
x7	-0.0102	0.004	-2.690	0.007	-0.018	-0.003
x8	-0.0204	0.004	-5.055	0.000	-0.028	-0.012
x9	0.0284	0.004	6.492	0.000	0.020	0.037
x10	0.0008	0.004	0.186	0.852	-0.007	0.009
x11	0.2151	0.004	56.179	0.000	0.208	0.223
x12	0.0158	0.004	4.094	0.000	0.008	0.023
x13	-0.0164	0.004	-4.102	0.000	-0.024	-0.009
x14	0.0153	0.004	3.737	0.000	0.007	0.023
x15	0.0054	0.004	1.404	0.160	-0.002	0.013
x16	0.0186	0.004	4.288	0.000	0.010	0.027
x17	0.0106	0.004	2.661	0.008	0.003	0.018
x18	-0.0037	0.004	-0.930	0.352	-0.012	0.004
x19	0.0305	0.004	7.511	0.000	0.023	0.038
x20	0.0343	0.004	8.525	0.000	0.026	0.042
x21	0.0462	0.004	11.625	0.000	0.038	0.054
x22	-0.2600	0.004	-60.468	0.000	-0.268	-0.252
x23	0.0236	0.004	5.887	0.000	0.016	0.031
x24	-0.0128	0.004	-3.108	0.002	-0.021	-0.005
x25	0.0936	0.004	22.207	0.000	0.085	0.102
x26	0.1500	0.004	38.474	0.000	0.142	0.158
x27	-0.0098	0.004	-2.457	0.014	-0.018	-0.002
x28	0.0081	0.004	2.005	0.045	0.000	0.016
x29	0.0106	0.004	2.727	0.006	0.003	0.018
x30	0.0004	0.004	0.093	0.926	-0.008	0.008
x31	0.0023	0.004	0.591	0.555	-0.005	0.010
x32	-0.0104	0.004	-2.600	0.009	-0.018	-0.003
x33	-0.0628	0.005	-13.300	0.000	-0.072	-0.054
x34	0.0657	0.004	16.519	0.000	0.058	0.074
x35	-0.0118	0.004	-2.920	0.004	-0.020	-0.004
x36	0.0045	0.004	1.124	0.261	-0.003	0.012
x37	0.0179	0.004	4.262	0.000	0.010	0.026
x38	-0.0415	0.004	-9.958	0.000	-0.050	-0.033
x39	-0.2102	0.004	-51.848	0.000	-0.218	-0.202
x40	0.0046	0.004	1.158	0.247	-0.003	0.012
x41	0.0138	0.004	3.542	0.000	0.006	0.021
x42	0.0057	0.004	1.443	0.149	-0.002	0.013

x43	0.0837	0.004	21.878	0.000	0.076	0.091
x44	-0.1387	0.004	-35.371	0.000	-0.146	-0.131
x45	0.0188	0.004	4.755	0.000	0.011	0.027
x46	0.0059	0.004	1.470	0.142	-0.002	0.014
x47	0.0255	0.004	6.299	0.000	0.018	0.033
x48	-0.0010	0.004	-0.245	0.806	-0.009	0.007
x49	0.0018	0.004	0.447	0.655	-0.006	0.010
x50	-0.0346	0.004	-8.684	0.000	-0.042	-0.027
x51	-0.0522	0.004	-11.766	0.000	-0.061	-0.043
x52	0.0985	0.004	26.063	0.000	0.091	0.106
x53	-0.0018	0.004	-0.441	0.659	-0.010	0.006
x54	-0.0111	0.004	-2.815	0.005	-0.019	-0.003
x55	0.0259	0.004	6.467	0.000	0.018	0.034
x56	0.0349	0.004	8.618	0.000	0.027	0.043

Omnibus:	1385.074	Durbin-Watson:	1.987
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1606.250
Skew:	-0.321	Prob(JB):	0.00
Kurtosis:	3.448	Cond. No.	2.25e+15

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 7.26e-26. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

OLS Regression Results

Dep. Variable:	y	R-squared:	0.291
Model:	OLS	Adj. R-squared:	0.290
Method:	Least Squares	F-statistic:	1107.
Date:	Sun, 22 Mar 2015	Prob (F-statistic):	0.00
Time:	16:12:09	Log-Likelihood:	-2.0814e+05
No. Observations:	151427	AIC:	4.164e+05
Df Residuals:	151371	BIC:	4.170e+05
Df Model:	56		
Covariance Type:	nonrobust		

topic	coef	std err	t	P>|t|	[95.0% Conf.	Int.]
const	9.397e-21	2.69e-21	3.490	0.000	4.12e-21	1.47e-20
x1	-0.0226	0.003	-8.781	0.000	-0.028	-0.018
x2	0.0224	0.003	8.529	0.000	0.017	0.028
x3	0.0022	0.003	0.857	0.392	-0.003	0.007
x4	0.0235	0.003	9.002	0.000	0.018	0.029
x5	0.0366	0.003	14.165	0.000	0.032	0.042
x6	0.0087	0.003	3.395	0.001	0.004	0.014
x7	-0.0137	0.003	-5.344	0.000	-0.019	-0.009
x8	-0.0166	0.003	-6.281	0.000	-0.022	-0.011
x9	0.0213	0.003	7.572	0.000	0.016	0.027
x10	0.0050	0.003	1.935	0.053	-6.47e-05	0.010
x11	0.2074	0.003	81.818	0.000	0.202	0.212
x12	0.0047	0.003	1.871	0.061	-0.000	0.010
x13	-0.0071	0.003	-2.727	0.006	-0.012	-0.002
x14	0.0264	0.003	9.557	0.000	0.021	0.032
x15	-0.0022	0.003	-0.858	0.391	-0.007	0.003
x16	0.0254	0.003	9.431	0.000	0.020	0.031
x17	0.0019	0.003	0.738	0.461	-0.003	0.007
x18	-0.0030	0.003	-1.087	0.277	-0.008	0.002
x19	0.0342	0.003	12.808	0.000	0.029	0.039
x20	-0.0029	0.002	-1.161	0.246	-0.008	0.002
x21	0.0587	0.003	22.541	0.000	0.054	0.064
x22	-0.2488	0.003	-86.149	0.000	-0.254	-0.243
x23	-0.0160	0.003	-6.337	0.000	-0.021	-0.011
x24	0.0024	0.003	0.928	0.353	-0.003	0.008
x25	0.0840	0.003	29.102	0.000	0.078	0.090
x26	0.1592	0.003	62.641	0.000	0.154	0.164
x27	0.0307	0.003	11.951	0.000	0.026	0.036
x28	0.0128	0.003	4.838	0.000	0.008	0.018
x29	0.0159	0.003	6.220	0.000	0.011	0.021
x30	0.0031	0.003	1.157	0.247	-0.002	0.008
x31	0.0030	0.003	1.157	0.247	-0.002	0.008
x32	-0.0152	0.003	-5.593	0.000	-0.021	-0.010
x33	-0.0706	0.003	-22.486	0.000	-0.077	-0.064
x34	0.0534	0.003	20.593	0.000	0.048	0.059
x35	-0.0005	0.003	-0.190	0.849	-0.006	0.005
x36	0.0010	0.003	0.397	0.692	-0.004	0.006
x37	0.0352	0.003	13.043	0.000	0.030	0.040
x38	-0.0763	0.003	-26.420	0.000	-0.082	-0.071
x39	-0.2478	0.003	-92.127	0.000	-0.253	-0.243
x40	-0.0020	0.003	-0.737	0.461	-0.007	0.003
x41	0.0241	0.003	9.395	0.000	0.019	0.029
x42	0.0468	0.003	17.613	0.000	0.042	0.052
x43	0.1232	0.003	48.502	0.000	0.118	0.128

x44	-0.1406	0.003	-55.059	0.000	-0.146	-0.136
x45	0.0229	0.003	8.641	0.000	0.018	0.028
x46	0.0025	0.003	0.966	0.334	-0.003	0.008
x47	0.0104	0.003	3.969	0.000	0.005	0.016
x48	-0.0077	0.003	-2.929	0.003	-0.013	-0.003
x49	0.0166	0.003	6.059	0.000	0.011	0.022
x50	-0.0503	0.003	-18.814	0.000	-0.056	-0.045
x51	-0.0439	0.003	-15.139	0.000	-0.050	-0.038
x52	0.1267	0.002	50.915	0.000	0.122	0.132
x53	0.0149	0.003	5.401	0.000	0.009	0.020
x54	-0.0018	0.003	-0.698	0.485	-0.007	0.003
x55	0.0097	0.003	3.788	0.000	0.005	0.015
x56	0.0147	0.003	5.735	0.000	0.010	0.020

Omnibus:	1971.685	Durbin-Watson:	1.980
Prob(Omnibus):	0.000	Jarque-Bera (JB):	2188.755
Skew:	-0.245	Prob(JB):	0.00
Kurtosis:	3.328	Cond. No.	2.25e+15

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.78e-25. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

Las Vegas, $$$
OLS Regression Results

Dep. Variable:	y	R-squared:	0.297
Model:	OLS	Adj. R-squared:	0.296
Method:	Least Squares	F-statistic:	301.0
Date:	Sun, 22 Mar 2015	Prob (F-statistic):	0.00
Time:	16:12:11	Log-Likelihood:	-53106.
No. Observations:	39888	AIC:	1.063e+05
Df Residuals:	39832	BIC:	1.068e+05
Df Model:	56		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[95.0% Conf. Int.]	
const	-1.281e-19	1.54e-20	-8.333	0.000	-1.58e-19	-9.8e-20
x1	-0.0232	0.005	-4.848	0.000	-0.033	-0.014
x2	-0.0052	0.005	-1.044	0.297	-0.015	0.005
x3	0.0188	0.005	3.788	0.000	0.009	0.029
x4	0.0573	0.005	11.018	0.000	0.047	0.068
x5	-0.0105	0.005	-2.179	0.029	-0.020	-0.001
x6	-0.0029	0.005	-0.596	0.551	-0.013	0.007
x7	-0.0163	0.005	-3.203	0.001	-0.026	-0.006
x8	-0.0268	0.005	-5.341	0.000	-0.037	-0.017
x9	0.0415	0.005	7.870	0.000	0.031	0.052
x10	-0.0027	0.005	-0.538	0.590	-0.013	0.007
x11	0.2278	0.005	48.048	0.000	0.219	0.237
x12	-0.0238	0.005	-5.101	0.000	-0.033	-0.015
x13	0.0136	0.005	2.746	0.006	0.004	0.023
x14	0.0331	0.005	6.126	0.000	0.023	0.044
x15	0.0195	0.005	4.062	0.000	0.010	0.029
x16	-0.0059	0.005	-1.190	0.234	-0.016	0.004
x17	0.0096	0.005	1.886	0.059	-0.000	0.020
x18	-0.0031	0.005	-0.579	0.563	-0.014	0.007
x19	0.0347	0.005	6.446	0.000	0.024	0.045
x20	0.0036	0.005	0.706	0.480	-0.006	0.013
x21	0.0292	0.005	5.980	0.000	0.020	0.039
x22	-0.1896	0.005	-35.572	0.000	-0.200	-0.179
x23	-0.0066	0.005	-1.335	0.182	-0.016	0.003
x24	0.0154	0.005	3.158	0.002	0.006	0.025
x25	0.0947	0.006	16.073	0.000	0.083	0.106
x26	0.0968	0.005	20.471	0.000	0.088	0.106
x27	0.1187	0.006	21.372	0.000	0.108	0.130
x28	0.0163	0.005	3.240	0.001	0.006	0.026
x29	0.0131	0.005	2.737	0.006	0.004	0.022
x30	-0.0025	0.005	-0.512	0.609	-0.012	0.007
x31	0.0055	0.005	1.104	0.269	-0.004	0.015
x32	0.0005	0.005	0.105	0.917	-0.010	0.011
x33	-0.0749	0.006	-12.445	0.000	-0.087	-0.063
x34	0.0298	0.005	6.099	0.000	0.020	0.039
x35	-0.0140	0.005	-2.779	0.005	-0.024	-0.004
x36	0.0051	0.005	1.043	0.297	-0.005	0.015
x37	0.0045	0.005	0.893	0.372	-0.005	0.015
x38	-0.1072	0.005	-19.750	0.000	-0.118	-0.097
x39	-0.2799	0.005	-55.586	0.000	-0.290	-0.270
x40	0.0146	0.005	3.004	0.003	0.005	0.024
x41	0.0068	0.005	1.424	0.154	-0.003	0.016
x42	0.0079	0.005	1.581	0.114	-0.002	0.018

x43	0.1598	0.005	32.529	0.000	0.150	0.169
x44	-0.1561	0.005	-32.241	0.000	-0.166	-0.147
x45	0.0069	0.005	1.393	0.164	-0.003	0.017
x46	0.0060	0.005	1.161	0.246	-0.004	0.016
x47	0.0183	0.005	3.778	0.000	0.009	0.028
x48	0.0023	0.005	0.462	0.644	-0.007	0.012
x49	0.0285	0.005	5.425	0.000	0.018	0.039
x50	-0.0365	0.005	-7.172	0.000	-0.046	-0.026
x51	-0.0547	0.005	-10.255	0.000	-0.065	-0.044
x52	0.0870	0.005	18.816	0.000	0.078	0.096
x53	0.0115	0.005	2.189	0.029	0.001	0.022
x54	0.0058	0.005	1.145	0.252	-0.004	0.016
x55	0.0076	0.005	1.592	0.111	-0.002	0.017
x56	0.0180	0.005	3.760	0.000	0.009	0.027

Omnibus:	1019.578	Durbin-Watson:	1.998
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1150.903
Skew:	-0.365	Prob(JB):	1.21e-250
Kurtosis:	3.399	Cond. No.	2.25e+15

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 5.2e-26. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

Las Vegas, $$$$
OLS Regression Results

Dep. Variable:	y	R-squared:	0.286
Model:	OLS	Adj. R-squared:	0.284
Method:	Least Squares	F-statistic:	145.2
Date:	Sun, 22 Mar 2015	Prob (F-statistic):	0.00
Time:	16:12:12	Log-Likelihood:	-27910.
No. Observations:	20326	AIC:	5.593e+04
Df Residuals:	20270	BIC:	5.638e+04
Df Model:	56		
Covariance Type:	nonrobust		

topic	coef	std err	t	P>|t|	[95.0% Conf. Int.]	
const	2.184e-18	1.07e-18	2.043	0.041	8.87e-20	4.28e-18
x1	-0.0208	0.007	-2.989	0.003	-0.034	-0.007
x2	0.0039	0.007	0.534	0.593	-0.010	0.018
x3	0.0070	0.007	1.021	0.307	-0.006	0.021
x4	0.0781	0.008	9.713	0.000	0.062	0.094
x5	-0.0089	0.007	-1.273	0.203	-0.023	0.005
x6	0.0048	0.007	0.672	0.502	-0.009	0.019
x7	-0.0155	0.008	-1.990	0.047	-0.031	-0.000
x8	-0.0173	0.007	-2.316	0.021	-0.032	-0.003
x9	0.0570	0.008	7.417	0.000	0.042	0.072
x10	0.0114	0.014	0.826	0.409	-0.016	0.038
x11	0.2082	0.007	29.399	0.000	0.194	0.222
x12	-0.0524	0.007	-7.638	0.000	-0.066	-0.039
x13	0.0064	0.008	0.825	0.409	-0.009	0.022
x14	0.0542	0.008	6.411	0.000	0.038	0.071
x15	0.0039	0.007	0.526	0.599	-0.011	0.018
x16	-0.0037	0.007	-0.533	0.594	-0.017	0.010
x17	0.0063	0.008	0.755	0.450	-0.010	0.023
x18	0.0105	0.008	1.240	0.215	-0.006	0.027
x19	0.0357	0.009	3.949	0.000	0.018	0.053
x20	0.0223	0.007	3.185	0.001	0.009	0.036
x21	0.0182	0.007	2.626	0.009	0.005	0.032
x22	-0.2081	0.008	-27.065	0.000	-0.223	-0.193
x23	-0.0260	0.007	-3.742	0.000	-0.040	-0.012
x24	-0.0042	0.007	-0.604	0.546	-0.018	0.009
x25	0.0940	0.009	10.555	0.000	0.077	0.111
x26	0.0704	0.007	10.399	0.000	0.057	0.084
x27	0.0263	0.007	3.682	0.000	0.012	0.040
x28	-0.0098	0.007	-1.316	0.188	-0.024	0.005
x29	0.0174	0.007	2.465	0.014	0.004	0.031
x30	0.0004	0.007	0.056	0.955	-0.014	0.015
x31	-0.0024	0.008	-0.315	0.753	-0.017	0.013
x32	-0.0015	0.008	-0.192	0.848	-0.016	0.014
x33	-0.0788	0.010	-8.124	0.000	-0.098	-0.060
x34	0.0272	0.007	3.708	0.000	0.013	0.042
x35	-0.0180	0.007	-2.438	0.015	-0.033	-0.004
x36	0.0009	0.007	0.122	0.903	-0.013	0.015
x37	0.0130	0.007	1.906	0.057	-0.000	0.026
x38	-0.1322	0.008	-16.497	0.000	-0.148	-0.116
x39	-0.2869	0.007	-38.943	0.000	-0.301	-0.272
x40	0.0222	0.007	2.970	0.003	0.008	0.037
x41	0.0026	0.007	0.367	0.713	-0.011	0.017
x42	0.0397	0.007	5.341	0.000	0.025	0.054

x43	0.1699	0.007	23.119	0.000	0.156	0.184
x44	-0.1612	0.007	-22.947	0.000	-0.175	-0.147
x45	-0.0010	0.007	-0.138	0.891	-0.015	0.013
x46	0.0032	0.008	0.385	0.700	-0.013	0.020
x47	-0.0002	0.007	-0.033	0.973	-0.014	0.014
x48	0.0202	0.007	2.767	0.006	0.006	0.035
x49	0.0055	0.007	0.793	0.428	-0.008	0.019
x50	-0.0481	0.007	-6.567	0.000	-0.062	-0.034
x51	-0.0325	0.008	-4.130	0.000	-0.048	-0.017
x52	0.0609	0.007	8.992	0.000	0.048	0.074
x53	0.0025	0.007	0.333	0.739	-0.012	0.017
x54	0.0151	0.007	2.072	0.038	0.001	0.029
x55	-0.0017	0.007	-0.247	0.805	-0.015	0.012
x56	0.0121	0.007	1.722	0.085	-0.002	0.026

Omnibus:	833.569	Durbin-Watson:	1.873
Prob(Omnibus):	0.000	Jarque-Bera (JB):	995.230
Skew:	-0.469	Prob(JB):	7.74e-217
Kurtosis:	3.544	Cond. No.	2.32e+15

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 2.94e-26. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

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