Understanding Online Hotel Reviews Through Automated Text Analysis

(Service Science)

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Presented by Souk Won Jun

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Motivation for Introducing this Paper

1. To introduce how machine learning works with an econometric model for managerial purpose.
2. To get some idea to use ***Yelp dataset*** from Kaggle, a well-known platform for predictive modeling and analytics competitions.
    - 5,200,000 user reviews
    - Information on 174,000 businesses including restaurant, shopping, food, home services etc
    - The data spans 11 metropolitan areas

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The Use of Customer Feedback in Hotel Industry

- ***Customer feedback*** can be used to improve hotel's operations, competitive positioning, and profitability.
- *Comment cards*, *market surveys*, and *mystery shoppers* has been traditionally used to gain valuable customer feedback.

Source: *https://international.grg.com/*

Figure: The Process of Mystery Shopping

Online Customer Review as Customer Feedback

- Today, the unprecedented approach to ***online hotel reviews*** enables to understand customers' experience.
- However, such reviews are ***voluminous*** and ***unstructured***.
- So, they are hard to implement for direct analysis using traditional methods that were designed for well-structured, quantitative data.

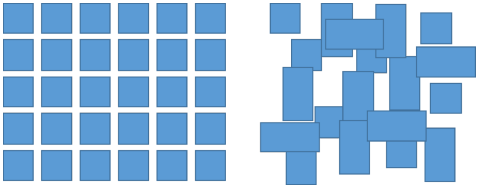

Figure: Comparison of Structured(left) and Unstructured(right) Data Shapes

Purpose and Main Idea of this Paper

Purpose

- To draw actionable managerial insights from consumer reviews to improve their operational effectiveness using a statistical tool.

Main Ideas

1. Designing a statistical model explaining associations between star ratings and variables through various text analysis including not only word count but *topic modeling, sentiment analysis,* and *style of writing.*
2. Extracting "attributes" or "topics" from consumer reviews using a topic modeling approach, a well-established technique called *Latent Dirichlet Allocation (LDA).*
3. Matching topics extracted from consumer reviews to the process from *"Before Arrival"* to *"After Departure"* that a customer goes through, and ultimately suggesting actionable managerial insights.

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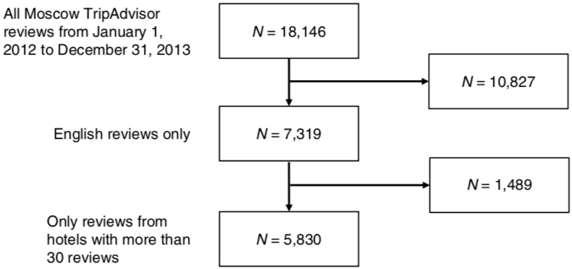
Data

- All consumer reviews are collected from TripAdvisor for hotel in Moscow, Russia from Jan. 2012 to Dec. 2013 inclusive.
- The dataset include the date, customer satisfaction star ratings (1-5 inclusive), title and contents of the review, and types of reviewers.
  - The star ratings range from 1 to 5 inclusive.
  - Each reviewer is categorized as one of business, family, solo, couple, etc.
- No other service quality/excellence index was used, due to the prohibition from identifying the hotel the consumer review is talking about.

Data

- This paper only considers reviews that (a) were written in English, (b) were written for hotels that had 30 or more reviews during this period, and (c) were not duplicates.
- Thus, the final analytical sample comprised 5,830 reviews across 57 hotels.

Figure 1. Sample Construction



The Basic Approach of this Paper

- (Step 1) To better understand the structure of the data and to identify broad trends.
  1. In this step, individual hotels were used as the unit of analysis.
  2. Consumer reviews were preprocessed and analyzed using various techniques : *DW Matrix, sentiment analysis, style of writing, and topic modeling.*
  3. Hotels were seperated into three tiers (low, middle, and high), according to the tertiles of their mean rating scores (taken across all reviews for that hotel).

- (Step 2) To study the relationship of various text-based review features on rating scores.
  1. Individual reviews were used as the unit of analysis.
  2. The results of text analyses and star rating scores were used as the variables of linear regression models.
  3. The data statistics of regression models would be the summary of the results of (Step 1) text analyses.

Fundamental Concepts in Text Analysis –Preprocessing and Text Representation

- ***Document-Word Matrix*** is used to transform unstructured data to a structured, amenable form
- A simple example of Document-Word Matrix is following :

1. We enjoyed dinner at the hotel restaurant.
2. The room was cozy so that we had dinner at the room.
3. We arrived at the midnight.

< Document-Word Matrix of the Example >

Document	D1	D2	D3
We	1	0	1
we	0	1	0
enjoyed	1	0	0
dinner	1	1	0
at	1	1	1
The	0	1	0
the	1	1	1
hotel	1	0	0
restaurant	1	0	0
room	0	2	0
was	0	1	0
cozy	0	1	0
so	0	1	0
that	0	1	0
had	0	1	0
arrived	0	0	1
midnight	0	0	1

Fundamental Concepts in Text Analysis –Preprocessing and Text Representation

- Each document is composed of lots of words, making dimension of document-term matrix too large with lots of zeros.
- This high dimensional matrix with lots of zeros, called a sparse matrix, increases computational and memory costs.
- To alleviate this problem, following steps are standard:

1. Transforming all text into ***lowercase***
2. Removing words composed of less than three characters and very common words called ***Stop Words*** (e.g., the, and, of)
3. Stemming words, which refers to the process of ***removing suffixes***, so that words like values, valued, and valuing are all replaced with "valu"
4. Removing words that occur either ***too frequently or very rarely***.

Fundamental Concepts in Text Analysis
–Preprocessing and Text Representation

< *Before* Preprocessing >

Document	D1	D2	D3
We	1	0	1
we	0	1	0
enjoyed	1	0	0
dinner	1	1	0
at	1	1	1
The	0	1	0
the	1	1	1
hotel	1	0	0
restaurant	1	0	0
room	0	2	0
was	0	1	0
cozy	0	1	0
so	0	1	0
that	0	1	0
had	0	1	0
arrived	0	0	1
midnight	0	0	1

< *After* Preprocessing >

Document	D1	D2	D3
~~We~~	1	0	1
~~we~~	~~1~~	~~1~~	~~1~~
enjoy~~ed~~	1	0	0
dinner	1	1	0
~~at~~	~~1~~	~~1~~	~~1~~
~~The~~	~~0~~	~~1~~	~~0~~
~~the~~	~~1~~	~~1~~	~~1~~
hotel	1	0	0
restaurant	1	0	0
room	0	2	0
~~was~~	~~0~~	~~1~~	~~0~~
cozy	0	1	0
~~so~~	~~0~~	~~1~~	~~0~~
~~that~~	~~0~~	~~1~~	~~0~~
~~had~~	~~0~~	~~1~~	~~0~~
arriv~~ed~~	0	0	1
~~midnight~~	~~0~~	~~0~~	~~1~~

Results of Preprocessing and Text Representation

- Removed were the top five most common words and all words that occurred 10 times or less.
  - The top five most common words were "hotel", "room", "good", "moscow", and "stay".
- As a result, a document-term matrix was made with 5,830 reviews (documents) and 18,106 unique terms.
- The matrix was still very sparse with lots of zeros, 99.673% of all the elements.

Fundamental Concepts in Text Analysis –Sentiment Analysis

- ***Word Count*** and ***Sentiment*** represent the most basic statistics for summarizing a corpus, since they are associated with customer decision making and product sales (Hu *et al.* 2013).
- ***Positive*** and ***negative*** sentiment are respectively measured with validated databases, called dictionaries in text mining domain, to investigate potential nonlinearities in the impact of sentiment.
  - The positive sentiment score was calculated by counting the number of unique words in each review that matched a list of "positive" words in dictionaries.
  - The negative sentiment was calculated analogously.
- The dictionaries used in this literature were created for text analysis of consumer reviews by Liu (2010), Nielsen (2011), Mohammad and Turney (2013).

Results of Sentiment Analysis

- On average, reviews tended to have less negative content than positive content.

Statistics	Positive Sentiment	Negative Sentiment
Mean	$+10.65$	-3.002
SD	7.22	3.65
Median	$+9$	-3
Max.	$+147$	-47

Fundamental Concepts in Text Analysis –Style of Writing

- Readability of each review was used mainly focusing on the reading level of the Flesch-Kincaid grade level (Kincaid et al. 1975)
  - For completeness, various alternative measures of readability are also used and represented in supplemental material at http://dx.doi.org/10.1287/serv.2016.0126.
- the Flesch-Kincaid grade level is linked to US Grade Level using calibrated weights.

$$GradeLevel = 0.39\left(\frac{TotalWords}{TotalSentences}\right) + 11.8\left(\frac{TotalSyllables}{TotalWords}\right) - 15.59$$

Results of Style of Writing

- around 71.1% of the reviews had a style of writing below high school level
- 6.3% of the reviews had a quality indicative of a college degree or higher

Grade level	Review text
< 10 (lowest possible score)	“Best location, well trained friendly staff. Nice restaurant on the top. Clean rooms. What else do you need:)?” “Short and sweet : : : if you can afford to stay here, stay here” “i was in hilton hotel in july and i was so nice trip. quality of rest was high. if you want to have fun you should go to hilton.” “We stayed 4 days with friends. As we hat late flight we came in Da Hostel deep night. The check-in was fast. Rooms are not so big but clean and nice. And we were so lucky to have friendly neighbors from France. We spent nice holidays all together. And we liked design so much!”

Results of Style of Writing

Grade level	Review text
> 16 (highest possible score)	“Beautiful historical hotel conveniently located. The staff are very friendly and accommodating. The price is very reasonable. We’ve enjoyed our stay very much! Highly recommended to everybody traveling to Moscow.” “A typical Swedish style hotel on the banks of the Volga—Very bright, clean and airy—With a free minibar! Continental style breakfast excellent A fair way out from the city centre but not too bad once you have mastered the metro There is a very good pizza restaurant with reasonably priced wine at the end of the road" “Excellent historic hotel in a great location, near several train stations and metro stops. Beautiful lobby, comfortable rooms. Certainly a traveler expecting Western standards in a business hotel will not leave here disappointed.” “Expensive but very luxurious, perfect retreat after a full day of meetings. Service and facilities surpassed all expectations. Not far from many restaurants, try the Azerbaijani restaurant around the corner from the hotel.”

Fundamental Concepts in Text Analysis –Topic Modeling

- This paper uses Latent Dirichlet Allocation (LDA) as a topic modeling technique, an algorithmic technique that recognizes latent patterns in data.
- LDA is a probabilistic model with a corresponding generative process.
- Here, LDA discovers :
  - hidden topics described in a set of documents
  - proportion of the topics within a document
  - the most probable words in topics
- LDA basically assumes that
  - A document is generated by the generative process of LDA.
  - A document exhibits multiple topics.
  - A topic is a distribution over a fixed vocabulary.

(Supplement) Latent Dirichlet Allocation

- LDA working in unsupervised learning regards the writing process as the generative process that a writer
  1. specifies topics to write about, choosing a distribution over topic.
  2. randomly picks a topic over the topic distribution.
  3. randomly chooses a word in relation to the topic from the distribution over the vocabulary.
  4. goes back to step 2 and repeat.
- Thus, we can simply say that the writing process is based on the distributions of topic and vocabulary.
- Since we have words used in a document, this will be a bayesian problem to find out posterior distributions of topic and vocabulary given the words.

Results of Topic Modeling

Term	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
1	***Breakfast***	***Metro***	***Check***	One	***Great***
2	***Free***	***Walk***	***Night***	***Like***	***Staff***
3	***Food***	***Locat***	***Time***	***Price***	Servic
4	***Bed***	***Station***	***Day***	Can	***Excel***
5	Floor	Clean	Back	Time	Locat
6	Bar	Minut	Even	Place	Nice
7	***Wifi***	Close	Book	Will	Red
8	Small	Also	Ask	Much	Best
9	Bathroom	Citi	***Front***	Just	***View***
10	Night	***Restaur***	***Desk***	***Better***	***Recommend***
11	Well	Nice	One	Busi	Location
12	Also	Staff	Servic	***Standard***	Well
13	Restaur	Airport	First	Bit	Help
14	Area	Street	***Arriv***	Star	Perfect
15	Larg	English	Recept	***Get***	Visit
16	Water	Train	Got	Mani	***High***
17	Buffet	Can	Get	Realli	Veri
18	Clean	Near	Taxi	Need	Kremlin
19	Shower	Away	Just	Quit	Realli
20	Use	Just	Made	Expect	Square
21	Includ	Center	Will	***Internet***	Breakfast
22	Nice	Busi	Hour	Lobbi	Love
23	Offer	Shop	Make	Want	Friend
24	Etc	Get	Call	Old	Trip
25	Day	Friend	Never	***Look***	Enjoy
26	English	Around	Russian	Thing	Spacious
27	Comfort	Min	Guest	Feel	Service
28	Drink	Speak	Next	Littl	Definit
29	Smoke	Conveni	Way	Big	Beauti
30	Coffe	Red	Took	Lot	Place

- From the output of LDA, words for each topic were extracted.
- By carefully looking at the words and considering hotel operations, the authors named ;
  - Topic 1 as *Amenities*
  - Topic 2 as *Location*
  - Topic 3 as *Transactions*
  - Topic 4 as *Value*
  - Topic 5 as *Experience*

Fundamental Concepts in Text Analysis –Topic Modeling

Two sets of variables for a review were created from the output θ_i of LDA:

- Dummy variables of topics within a review :

$$Topic_{i,k} = \begin{cases} 1, & \text{if } P(k|i) > \text{median prob. across all reviews \& topics} \\ 0, & \text{otherwise.} \end{cases}$$

- The second variable explains how much a review focuses on each topic. The equation is the following :

$$Focus_i = \sum_{k=1}^{K} P(k|i)^2$$

- Intuitively, reviews with larger values of focus are those review texts that are concentrated on a small number of topics.
- This measure of focus is known in other contexts as *the Herfindahl Index* (Rhoades 1993).

Periods of Guest's Interactions with Hotel & Topics

To suggest actionable managerial insights, this paper ;

- describes *periods of guest's interactions with hotel,*

Periods of Guest's Interactions with Hotel

- and matches them with topics.

	Before Arival	***Check In***	***Stay***	***Check Out***	***After Departure***
Topic 1 : *Amenities*			✓		
Topic 2 : *Location*	✓		✓		✓
Topic 3 : *Transactions*	✓	✓		✓	
Topic 4 : *Value*	✓				✓
Topic 5 : *Experience*		✓	✓	✓	

Summary Statistics

Hotel Level (#)	All (57)	Low (19)	Medium (19)	High (19)
Number of reviews	102.281 (8.137)	65.474 (7.083)	94.526 (10.150)	146.842 (16.610)
Rating score	3.967 (0.057)	3.507 (0.074)	3.986 (0.027)	4.408 (0.045)
Review span (days)	668.702 (9.263)	636.211 (23.924)	686.158 (5.156)	683.737 (10.667)
Word count	145.482 (2.471)	151.121 (4.632)	139.482 (3.240)	145.842 (4.609)
$(Sentiment)^+$	10.454 (0.152)	9.613 (0.234)	10.406 (0.184)	11.344 (0.209)
$(Sentiment)^-$	−3.051 (0.110)	−3.674 (0.218)	−2.874 (0.100)	−2.604 (0.144)
Focus	0.217 (0.000)	0.219 (0.001)	0.216 (0.001)	0.217 (0.001)
FK writing level:				
Below high school	0.711 (0.006)	0.700 (0.013)	0.712 (0.010)	0.723 (0.006)
High school	0.228 (0.007)	0.241 (0.016)	0.226 (0.010)	0.218 (0.007)
College and above	0.060 (0.003)	0.059 (0.006)	0.062 (0.008)	0.059 (0.004)
(Travler type) Business	0.452 (0.024)	0.428 (0.048)	0.521 (0.037)	0.405 (0.035)
(Travler type) Couples	0.202 (0.014)	0.186 (0.022)	0.168 (0.026)	0.252 (0.021)
(Travler type) Family	0.082 (0.006)	0.089 (0.011)	0.066 (0.008)	0.092 (0.013)
(Travler type) Friends	0.099 (0.008)	0.115 (0.019)	0.087 (0.010)	0.095 (0.009)
(Travler type) Solo	0.076 (0.007)	0.088 (0.016)	0.066 (0.009)	0.075 (0.008)
(Travler type) Unspecified	0.091 (0.005)	0.098 (0.008)	0.091 (0.008)	0.083 (0.008)
Topic 1 (amenities) freq.	0.506 (0.016)	0.540 (0.019)	0.553 (0.023)	0.426 (0.028)
Topic 2 (location) freq.	0.561 (0.024)	0.585 (0.030)	0.619 (0.031)	0.478 (0.053)
Topic 3 (transaction) freq.	0.447 (0.016)	0.517 (0.030)	0.413 (0.016)	0.409 (0.030)
Topic 4 (value) freq.	00518 (0.016)	00587 (0.028)	0.518 (0.023)	0.447 (0.024)
Topic 5 (experience) freq.	0.489 (0.029)	0.322 (0.023)	0.445 (0.038)	0.701 (0.040)

Model

Model	Independent variables
1	Hotel level fixed effects, Log(Word count), $(Sentiment)^+$, $(Sentiment)^-$
2	Variables from Model 1, $[(Sentiment)^+]^2$, $[(Sentiment)^-]^2$
3	Variables from Model 1, $[(Sentiment)^+]^2 + [(Sentiment)^-]^2$
4	Variables from Model 3, focus
5	Variables from Model 4, Flesch-Kincaid Grade Levels
6	Variables from Model 5, dummy variables for traveler types
7	Variables from Model 6, dummy variables for topics
8	Variables from Model 7, interaction terms between topic dummies and $(Sentiment)^+$, interaction terms between topic dummies and $(Sentiment)^-$,

- To control fixed effects of hotel level, dummy variables of hotel level was introduced.
- To find out the sensitivity of rating scores to sentiment, quadratic nonlinearities of sentiment were separately entered in Model 2.
- $[(Sentiment)^+]^2 + [(Sentiment)^-]^2$ were added in Model 3 to support the key results of the asymmetric impact of positive and negative sentiment on star ratings.
- To deep dive into the connections between topics and sentiment, (Topic dummies) $\times(Sentiment)^+$ and (Topic dummies) $\times(Sentiment)^-$ were added in Model 8.

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Regression Results

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	3.240 (0.044)***	3.147 (0.041)***	3.041 (0.049)***	3.049 (0.047)***	3.048 (0.047)***	2.981 (0.051)***	3.136 (0.062)***	3.109 (0.076)***
Log(WordCount)	−0.203 (0.026)***	−0.223 (0.021)***	−0.270 (0.024)***	−0.231 (0.022)***	−0.232 (0.022)***	−0.239 (0.022)***	−0.116 (0.020)***	−0.086 (0.020)***
$(\mathit{Sentiment})^{-}$	−0.113 (0.006)***	−0.150 (0.006)***	−0.098 (0.006)***	−0.093 (0.006)***	−0.093 (0.006)***	−0.091 (0.006)***	−0.076 (0.006)***	−0.091 (0.012)***
$(\mathit{Sentiment})^{+}$	0.067 (0.004)***	0.091 (0.005)***	0.088 (0.005)***	0.086 (0.004)***	0.086 (0.004)***	0.085 (0.004)***	0.069 (0.004)***	0.080 (0.007)***
$[(\mathit{Sentiment})^{-}]^2$		0.003 (0.000)***						
$[(\mathit{Sentiment})^{+}]^2$		−0.001 (0.000)***						
$\{[(\mathit{Sentiment})^{-}]^2 + [(\mathit{Sentiment})^{+}]^2\}$			−0.000 (0.000)***	−0.000 (0.000)***	−0.000 (0.000)***	−0.000 (0.000)***	−0.000 (0.000)***	−0.000 (0.000)***
Focus				−0.092 (0.013)***	−0.092 (0.013)***	−0.092 (0.013)***	−0.104 (0.013)***	−0.090 (0.015)***
Flesch-Kincaid Grade Level					0.009 (0.011)	0.008 (0.011)	0.009 (0.011)	0.010 (0.011)
Traveler Type								
Couples						0.153 (0.029)***	0.117 (0.026)***	0.114 (0.025)***
Family						0.190 (0.046)***	0.139 (0.043)***	0.135 (0.041)***
Friends						0.096 (0.038)*	0.063 (0.036)	0.067 (0.036)
Solo						0.118 (0.043)**	0.106 (0.039)**	0.091 (0.038)*
Unspecified						0.060 (0.034)	0.054 (0.036)	0.049 (0.036)

(Continued)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Topics								
Topic 1 (Amenities)							−0.067 (0.021)**	−0.006 (0.044)
Topic 2 (Location)							0.121 (0.021)***	0.182 (0.035)***
Topic 3 (Transactions)							−0.122 (0.026)***	−0.253 (0.037)***
Topic 4 (Value)							−0.177 (0.025)***	−0.268 (0.040)***
Topic 5 (Experience)							0.307 (0.025)***	0.571 (0.046)***
$(Sentiment)^{(\cdot)}$ × Topics:								
$(Sentiment)^{-}$ × Topic 1								0.027 (0.006)***
$(Sentiment)^{-}$ × Topic 2								0.030 (0.011)**
$(Sentiment)^{-}$ × Topic 3								−0.013 (0.007)*
$(Sentiment)^{-}$ × Topic 4								−0.009 (0.009)
$(Sentiment)^{-}$ × Topic 5								−0.008 (0.009)
$(Sentiment)^{+}$ × Topic 1								−0.013 (0.004)**
$(Sentiment)^{+}$ × Topic 2								−0.016 (0.004)***
$(Sentiment)^{+}$ × Topic 3								0.016 (0.004)***
$(Sentiment)^{+}$ × Topic 4								0.010 (0.003)**
$(Sentiment)^{+}$ × Topic 5								−0.024 (0.004)***

Regression Results of Sentiment

	Model 1	Model 2	Model 3	Model 4
$(Sentiment)^-$	−0.113 (0.006)***	−0.150 (0.006)***	−0.098 (0.006)***	−0.093 (0.006)***
$(Sentiment)^+$	0.067 (0.004)***	0.091 (0.005)***	0.088 (0.005)***	0.086 (0.004)***
$[(Sentiment)^-]^2$		0.003 (0.000)***		
$[(Sentiment)^+]^2$		−0.001 (0.000)***		
$\{[(Sentiment)^-]^2 + [(Sentiment)^+]^2\}$			−0.000 (0.000)***	−0.000 (0.000)***
	Model 5	**Model 6**	**Model 7**	**Model 8**
$(Sentiment)^-$	−0.093 (0.006)***	−0.091(0.006)***	−0.076 (0.006)***	−0.091 (0.012)***
$(Sentiment)^+$	0.086 (0.004)***	0.085 (0.004)***	0.069 (0.004)***	0.080 (0.007)***
$[(Sentiment)^-]^2$				
$[(Sentiment)^+]^2$				
$\{[(Sentiment)^-]^2 + [(Sentiment)^+]^2\}$	−0.000 (0.000)***	−0.000 (0.000)***	−0.000 (0.000)***	−0.000 (0.000)***

- Over all models, reviews with *stronger negative (positive) sentiment* scores were associated with *lower (higher)* rating scores.
- *Asymmetric impacts* of sentiment on star ratings; the negative, on average, had grader impact on star ratings.
- An ***"overall" sentiment*** by taking the difference of the pos. and neg. does ***not*** accurately capture the nonlinear impact of these components.

Regression Results of Sentiment (Continued)

	Model 1	Model 2	Model 3	Model 4
$(Sentiment)^-$	-0.113 (0.006)***	-0.150 (0.006)***	-0.098 (0.006)***	-0.093 (0.006)***
$(Sentiment)^+$	0.067 (0.004)***	0.091 (0.005)***	0.088 (0.005)***	0.086 (0.004)***
$[(Sentiment)^-]^2$		0.003 (0.000)***		
$[(Sentiment)^+]^2$		-0.001 (0.000)***		
$\{[(Sentiment)^-]^2 + [(Sentiment)^+]^2\}$			-0.000 (0.000)***	-0.000 (0.000)***

	Model 5	Model 6	Model 7	Model 8
$(Sentiment)^-$	-0.093 (0.006)***	-0.091(0.006)***	-0.076 (0.006)***	-0.091 (0.012)***
$(Sentiment)^+$	0.086 (0.004)***	0.085 (0.004)***	0.069 (0.004)***	0.080 (0.007)***
$[(Sentiment)^-]^2$				
$[(Sentiment)^+]^2$				
$\{[(Sentiment)^-]^2 + [(Sentiment)^+]^2\}$	-0.000 (0.000)***	-0.000 (0.000)***	-0.000 (0.000)***	-0.000 (0.000)***

- In Model 2, the estimated coefficients were reversed in sign, suggesting that the sensitivity of rating scores to sentiment were less pronounced at more extreme values of sentiment.
- In Model 3 to 8, the estimated coefficients of the neg. and pos. sentiments were similar when the sum of square of the negative and positive was controlled.

Regression Results of Word Count & Focus

	Model 1	Model 2	Model 3	Model 4
Log(WordCount)	−0.203 (0.026)***	−0.223 (0.021)***	−0.270 (0.024)***	−0.231 (0.022)***
Focus				−0.092 (0.013)***
	Model 5	**Model 6**	**Model 7**	**Model 8**
Log(WordCount)	−0.232 (0.022)***	−0.239 (0.022)***	−0.116 (0.020)***	−0.086 (0.020)***
Focus	−0.092 (0.013)***	−0.092 (0.013)***	−0.104 (0.013)***	−0.090 (0.015)***

- Across all models, there were negative associations between ratings and word count and between ratings and focus.
- These results suggest that ***longer reviews*** tend to have ***lower ratings*** and that the reviews that focused on ***fewer topics*** are inclined to have ***lower ratings***.

Regression Results of Topics

	Model 7	Model 8
Topic 1 (Amenities)	−0.067 (0.021)**	−0.006 (0.044)
Topic 2 (Location)	0.121 (0.021)***	0.182 (0.035)***
Topic 3 (Transactions)	−0.122 (0.026)***	−0.253 (0.037)***
Topic 4 (Value)	−0.177 (0.025)***	−0.268 (0.040)***
Topic 5 (Experience)	0.307 (0.025)***	0.571 (0.046)***

- Reviews about *Topic 2 (location)* and *Topic 5 (experience)* were significantly associated with *"higher ratings"*, whereas those about Topic 3 (transactions) or Topic 4 (value) were with "lower ratings".
- From these results, authors point that guests tend to write ***more about "value" and "transactions"*** when they are ***dissatisfied***, but tend to write ***more about "location" and "experience"*** when they are ***satisfied***.

Regression Results of Topics (Continued)

	Model 7	Model 8
$(Sentiment)^{-} \times$ Topic 1		0.027 (0.006)***
$(Sentiment)^{-} \times$ Topic 2		0.030 (0.011)**
$(Sentiment)^{-} \times$ Topic 3		−0.013 (0.007)*
$(Sentiment)^{-} \times$ Topic 4		−0.009 (0.009)
$(Sentiment)^{-} \times$ Topic 5		−0.008 (0.009)
$(Sentiment)^{+} \times$ Topic 1		−0.013 (0.004)**
$(Sentiment)^{+} \times$ Topic 2		−0.016 (0.004)***
$(Sentiment)^{+} \times$ Topic 3		0.016 (0.004)***
$(Sentiment)^{+} \times$ Topic 4		0.010 (0.003)**
$(Sentiment)^{+} \times$ Topic 5		−0.024 (0.004)***

- For Topic 1 and Topic 2, the coefficients of their interaction terms (with negative and positive sentiment) were reversed in sign as the respective linear coefficients.
- Reviews about these topics are those whose ratings are more independent from the sentiment of their review, probably indicating these as *"objectivity-enhancing"* topics.
- For Topic 3, the coefficient of its interaction term with negative and positive sentiment had the same sign as the corresponding linear sentiment coefficients.
- Reviews that mention this topic tend to have rating scores that have an accentuated effect of sentiment. Hence, one might think of this topic as being *"objectivity reducing."*

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Managerial Insights for the three primary stakeholders

This paper provides the following managerial insights to the three primary stakeholders, namely, (i) hotel customers, (ii) facility managers, and (iii) travel portals.

- *Hotel customers* using reviews can incentivize the hotels to improve operations and provide better value.
- *Facility Operators* can use the insights, such as the sentiment and topics of reviews, generated from the approach suggested by this study as well as obtained from traditional approaches.
- *Travel portals and social networks* can find customer reviews valuable and provide tools to

Further Research

This paper also suggests four potential directions to extend this research:

- Comparing *cultural effects* using multiple languages,
- Performing an analysis that takes into account *how the reviews evolved over time*,
- Developing *customized dictionaries* fitted into hotel reviews and better analyzing sentiment of the reviews, and
- Improving *a topic modeling technique in cooperation with subject matter experts*, to better fitting the technique into hotel reviews.