Feeling Under the Weather and Restaurant Rating Tendency: A Tentative NLP Research

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Abstract

Our project investigated how weather conditions impact people's sentiments when they write restaurant reviews on Yelp. By analyzing the connection between the emotional content of the reviews and the weather, we can obtain valuable insights into user behavior and decision patterns. Our primary discoveries revealed that although there is no notable correlation between these factors, there is a noticeable trend of improved sentiment among users as the temperature rises, regardless of precipitation, which is consistent with the previous research.

1 Introduction

The influence of weather on human emotions has been extensively studied (Denissen et al., 2008; Keller et al., 2005; Klimstra et al., 2011), but its impact on online reviews, particularly in the context of restaurant ratings, remains relatively unexplored. This research aims to investigate the correlation between weather conditions (precipitation and temperature) and sentiments expressed in restaurant reviews on Yelp using three different correlation models, PROCESS 4, PROCESS 5, and PROCESS 7. These relationships can provide valuable insights into consumer emotional response and behavior, and thus help restaurant owners and marketers improve customer satisfaction.

2 Dataset Inspection and Preparation

The reviews and restaurants data have been obtained from Yelp Dataset (Inc., 2019) — collection containing businesses, reviews, and user data. The weather data have been obtained though Open-Meteo API (Zippenfenig, 2023) that was used to retrieve the weather conditions at specific coordinates.

2.1 Dataset

The project used two primary files in the dataset: `business.json` (approximately 150,000 instances) and `reviews.json` (approximately 7 million instances). Our initial analysis focused on the establishments dataset.

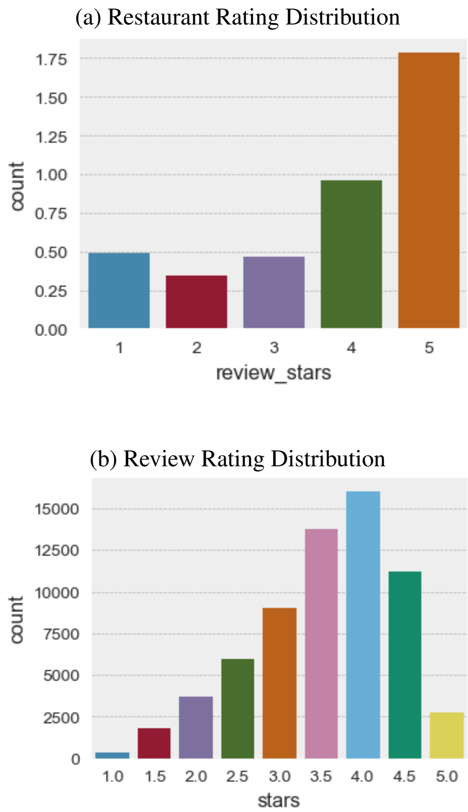

Figure 1: Data Visualizations

No missing values were identified; out of all possible feature groups we chose: *business_id*, *name*, *longitude*, *latitude*, *stars*, and *categories*. The data entries primarily pertained to North America, allowing us to further draw inferences on the weather conditions. With over 1300 cate-

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gories, we decided to narrow down the dataset to include only the ”Restaurant” Category (containing around 50.000 businesses).

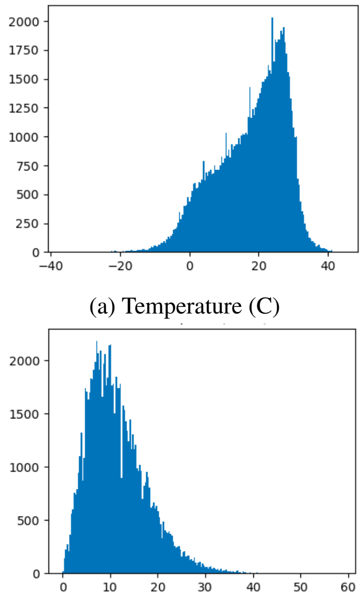
Next, reviews were inspected. The dataset was filtered to include only reviews corresponding to the ”Restaurant” category. Reviews with missing text values (e.g., only star rating) were excluded. The resulting dataframe contained approximately 4 million values, which were then merged back with the business data on *business_id*. Subsequently, considering high computational and temporal limitations, we decided to choose a smaller sample. To preserve the original data distribution, we sampled the data based on the joint conditional probability of business and review rating pairs. We calculated the probabilities for each combination, assigned them to their respective data points in the original dataset, normalized them (ensuring the probabilities summed up to 1), and then sampled 100,000 entries from this distribution.

2.2 Weather Scraping

To explore the relationship between weather patterns and restaurant rating tendencies, we utilized the Openmeteo dataset, which provides historical weather data. The dataset includes essential weather attributes such as temperature, precipitation, weather code, and wind speed. We accessed the weather data for each review by matching the coordinates and dates.

To facilitate the data retrieval process, we developed a Python function called `get_weather_data` in a Jupyter Notebook file named `weather_scraping.ipynb`. This function leveraged the Openmeteo dataset, which is based on reanalysis datasets, to retrieve the weather data associated with each review's latitude, longitude, and date. The Historical Weather API used by Openmeteo (Zippenfenig, 2023) is built upon these reanalysis datasets, which combine various sources of weather observations including weather stations, aircraft, buoys, radar, and satellite data. By utilizing mathematical models, these datasets can estimate the values of weather variables and provide comprehensive historical weather information even for locations without nearby weather stations, such as rural areas or the open ocean.

Using this approach, we successfully obtained weather information for approximately 100,000 reviews. The scraped weather data includes the latitude, longitude, date, temperature, precipitation, weather code, and wind speed. A sample distribution of the scraped weather data is presented below (Figure 2):



(a) Temperature (C)

(b) Wind speed (km/h)

Figure 2: Weather data distribution

By combining the restaurant reviews with the corresponding weather data, we aimed to analyze the potential impact of weather conditions on restaurant ratings. The next section describes the integration of these datasets and the subsequent analysis conducted as part of this research project.

3 Review Inspection

3.1 Preprocessing

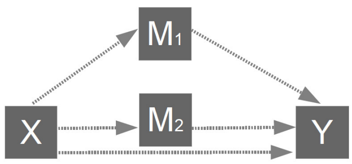
A simple pre-processing pipeline of the reviews before the analysis involved the removal of special characters, numbers, and emojis with Regular Expressions; punctuation and English stopwords have been removed as well. Then, the reviews were lowercased, lemmatized with WordNetLemmatizer, and tokenized with NLTK Word Tokenizer.

3.2 Sentiment Retrieval

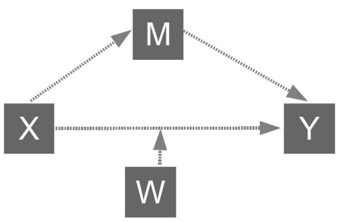
The sentiment of the reviews was analyzed with three different models, vaderSentiment (Kiritchenko et al., 2014), Hedonometer (Dodds and Danforth, 2009; Dodds et al., 2011), and TextBlob (Hazarika et al., 2020). All three models have been previously successfully used for user-generated text involving informal language. The difference between the three lies in how they present the sentiment score. For vaderSentiment results, a compound sentiment score was used, which is a composite score of the positive, neutral, and negative scores ranging from -1 (extremely negative) to +1 (extremely positive). The Hedonometer results are presented on a scale from 0 (extremely negative) to 10 (extremely positive). TextBlob results involved subjectivity and polarity scores, sentiment polarity ranging from -1 (extremely negative) to +1 (extremely positive) was used as the sentiment value. The results of all three models were used for the following correlation analysis.

4 Correlation Identification

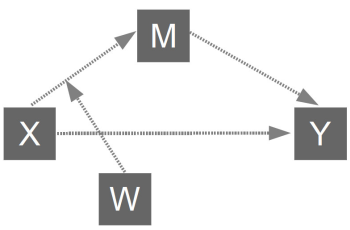
Following the pipeline employed in He et al. (2020), we chose MACRO Process Models (Hayes, 2022) to inspect potential correlation between the weather data and the retrieved sentiments. Specifically, Models 4 (parallel mediation; Figure 3a), Model 5 (mediation with moderated direct path; Figure 3b), and Model 7 (moderated mediation with moderation of the a-path/indirect path but not the c'-path/direct effect; Figure 3c) were used to perform analysis. The target model is linear regression in all cases.



(a) Model 4



(b) Model 5



(c) Model 7

Figure 3: MACRO Models (Regorz, 2023)

4.1 Model 4

Precipitation was used as a focal variable, Sentiment score (vaderSentiment), Hedonometer sentiment score (Hedonometer), and Sentiment Polarity (TextBlob) as a target variables (outcome). The residual data (namely, temperature, windspeed, and weathercodes) were set as mediators. As presented in Table 1, no significant correlation was found within any sentiment through mediation.

Sentiment	Effect	R^2	t-value	p-value
vaderSentiment	0.0015	0.0000	0.7141	0.4752
Hedonometer	0.0004	0.0000	1.2001	0.2301
TextBlob	0.0011	0.0008	0.8189	0.4128

Table 1: Effect Comparison, Model 4

4.2 Model 5

Further, our analysis shifted to examining the indirect effects of the conditions. Instead of focusing on the indirect path and the main variable itself, we investigated the moderated mediation via the direct path (i.e., degree of alteration). Precipitation and Sentiment metrics remained as the focal and target variables, while temperature was selected as the moderator. Although no significant correlation was observed in this model, there was a general trend of improvement with increasing temperature (Table 2). As the temperature parameter rose, the correlation between the variables appeared to strengthen.

Moderator value (temperature)	Effect	p-value
7.7726	0.0004	0.6591
17.8481	0.0017	0.4902
27.9236	0.0030	0.3378

Table 2: Averaged Effect Comparison, Model 5

4.3 Model 7

Finally, we tested for indirect effect of the mediators and moderators explored earlier. The results (Table 3) suggest that the relationship between the precipitation and the sentiment is significantly moderated by temperature ($p << 0.05$, ΔR^2 = 0.0006). Further, the statistic revealed a consistent trend: people generally experience more 'happiness' when the temperature is higher, regardless of the presence or intensity of rain (i.e., precipitation). Additionally, higher temperatures result in more apparent variations in review sentiment among the different precipitation intensities compared to lower temperatures, which is compliant with the previous research.

Sentiment	Effect	R^2	p-value
vaderSentiment	0.0060	0.0002	0.0007
Hedonometer	0.0060	0.0002	0.0000
TextBlob	0.0012	0.0006	0.0000

Table 3: Effect Comparison, Model 7

5 Results and Discussion

The correlation identification analysis using MACRO Process Models provided insights into the potential relationships between weather data and sentiment scores.

In Model 4, results suggest that the weather conditions, as represented by precipitation, did not have a substantial direct or mediated effect on the sentiments expressed in the reviews. In Model 5, there was a general trend of improvement in sentiment scores with increasing temperature. As the temperature parameter rose, the correlation between weather conditions and sentiments appeared to strengthen, indicating a potential relationship between temperature and sentiment perception. Model 7 showed a consistent trend: people generally experienced more positive sentiment (e.g., higher vaderSentiment and Hedonometer scores) when the temperature was higher, irrespective of the presence or intensity of rain.

Overall, the analysis suggests that while there may not be a direct correlation between weather conditions, specifically precipitation, and sentiment scores, there is a potential indirect effect mediated by temperature. Higher temperatures seem to enhance positive sentiment, aligning with previous research by Keller et al. (2005) that pleasant weather tends to make people happier, especially after a long winter when there is a craving for warmth. On the other hand, the presence of rain may influence sentiment perception differently at varying temperatures. It is important to note that extreme heat can also have a negative impact, as summarized by Keller et al. (2005) that excessively hot weather can be perceived as uncomfortable. These findings highlight the importance of considering temperature as a moderator when examining the relationship between weather and sentiment in restaurant reviews.

It is worth noting that the analysis is based on a large dataset of reviews and comprehensive weather data. However, the findings should be interpreted with caution, as they rely on sentiment analysis techniques and statistical models. Further research is needed to validate these findings and explore additional factors that may influence the relationship between weather and sentiment in the context of restaurant reviews.

5.1 Wider context

In the wider context of this project, several factors should be considered when analyzing the relationship between weather and sentiment in restaurant reviews. These factors include the influence of individual personality traits and demographic characteristics on weather perception, the choice of weather variables beyond temperature and wind, the impact of Seasonal Affective Disorder (SAD) on mood, the need to critically evaluate common associations between weather and emotions, and the distinction between seasonal and daily weather changes. By taking these factors into account, researchers can gain a more comprehensive understanding of how weather conditions affect customer experiences and sentiment in restaurant settings, leading to more nuanced and accurate analyses.

6 Author's contribution

Stanislav contributed to the project by conducting preparatory data analysis, creating visualizations, preprocessing the dataset, and facilitating statistical modeling using MACRO Process (with the subsequent result interpretation) in addition to actively participating in researching project strategies, group time management, and presentation making.

Jago contributed by proposing the subject of exploring the relationship of sentiment analysis; creating and managing the git repo together with presentation; and putting the results into a wider perspective. Additionally, she actively participated in discussions, conducted research, and implemented code to access weather data from an API, enhancing the comprehensiveness and credibility of our analysis.

Veronika contributed to the creation of the presentation and research, as well as conducted review preprocessing and sentiment analysis.

Kengo participated in the early stages of the project.

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