Re-evaluating Restaurant Quality Around McGill Using Text-Based Sentiment Analysis of Google Maps Reviews

I. Problem Definition and Scope

Choosing where to eat around McGill is something most students do almost every day, yet the information we rely on is not always as useful as it seems. Most students rely on Google Maps star ratings and review counts, which compress diverse customer experiences into simplified numerical indicators. However, these indicators do not always reflect what students truly care about, such as price and food quality, which leads us to focus on the concept of value for money.

Star ratings reduce a wide range of opinions into a single number, which can hide many important details. A restaurant may maintain a high average rating despite recent complaints about declining service or overpriced menu items. Similarly, establishments with greater visibility or central locations tend to accumulate more reviews regardless of actual quality. This creates a potential gap between displayed ratings and the real dining experiences of students who are often budget constrained and highly sensitive to perceived quality.

To address this, our project applies text-based sentiment analysis to Google Maps reviews. Instead of relying solely on star ratings, we examine customer language to capture perceptions of quality and value for money, creating a more nuanced and student-focused measure of restaurant performance.

II. Data

Restaurant data were collected using the Google Maps API with Roddick Gates as the central reference point and a 500-meter radius to capture food establishments within walking distance of McGill University. The initial dataset included 108 food-related locations. During data cleaning, three hotels were removed to focus exclusively on restaurants and cafés. In addition, establishments were deduplicated using the unique place_id identifier, which eliminated 15 duplicate entries. After these filtering steps, the final analytical sample consisted of 90 unique restaurants and cafés. For each establishment, exactly five of the most recent reviews were extracted, resulting in a balanced dataset of 450 total reviews. For each establishment, exactly five of the most recent reviews were extracted due to data availability constraints, allowing the analysis to focus on recent customer experiences.

III. Text Analytics Approach & Justification

Text Preprocessing: All reviews were standardized through lowercasing, removal of punctuation and non-alphabetic characters, elimination of English stopwords, and tokenization into individual words. This preprocessing pipeline ensured consistent text formatting and reduced noise prior to sentiment analysis. Reviews containing French expressions were retained in their original form and contributed to sentiment scoring when matching entries in either the VADER dictionary or the custom lexicon, which included selected French terms to reflect Montreal's bilingual context. Only two reviews in the dataset were written entirely in French, representing a minimal share of the total; therefore, French-language content is unlikely to have affected the overall sentiment results.

Sentiment Framework: VADER with GenZ Specific Lexicon: Sentiment analysis was conducted using the VADER framework. To better capture restaurant-specific language and student expressions, VADER was extended with a custom sentiment lexicon developed collaboratively by the team. The custom lexicon

incorporated terms related to food quality, pricing, service experiences, and Generation Z slang observed in the external review dataset. Each term was assigned a polarity weight ranging from -5 (strongly negative) to +5 (strongly positive) based on observed usage and collective judgment of sentiment intensity.
When overlap occurred between VADER's default dictionary and the custom lexicon, priority was given to the custom lexicon values, allowing domain-specific sentiment to override general-purpose polarity scores. This ensured that restaurant-relevant expressions were weighted more accurately within the sentiment calculation.

Review-Level and Restaurant-Level Scoring: Each review's sentiment score was computed by aggregating weighted polarity values and normalizing by review length to control for variation in text size. Restaurant-level sentiment was then calculated as the average score across the five extracted reviews for each establishment. Review-level sentiment was computed by summing matched polarity values and normalizing for review length:

$$ReviewScore_j = \sum_{k=1}^{M_j} SentimentWord_{jk}$$

For example, phrases such as "friendly staff and fresh food" generated positive scores, while "slow service" or "overpriced for the portion size" produced negative values.

Restaurant-level sentiment was then calculated by averaging review scores:

$$RestaurantScore_i = \frac{1}{N_i} \sum_{j=1}^{N_i} ReviewScore_{ij}$$

This yields a continuous, text-derived metric that complements discrete star ratings. Preliminary inspection indicates that some highly rated establishments exhibit more moderate textual sentiment, suggesting that aggregate ratings may mask signals of dissatisfaction.

These sentiment-based quality scores were compared with Google star ratings using correlation and ranking analysis to assess alignment and identify meaningful differences between numerical ratings and textual sentiment.

IV. Results and Findings

The sentiment scores exhibited substantial variation across restaurants, suggesting meaningful differences in perceived quality and value for money. While many highly rated restaurants also showed positive textual sentiment, several establishments with strong star ratings displayed neutral or even negative sentiment in review text, often driven by complaints about portion sizes, high prices, or bad service.

Correlation analysis revealed a moderate positive relationship between Google star ratings and sentiment scores, indicating that while ratings broadly align with customer sentiment, they fail to capture important nuances present in review text. Notably, some moderately rated restaurants ranked among the highest in sentiment due to consistent praise for affordability and food quality, highlighting the importance of textual information for student decision-making. These findings demonstrate that sentiment-based metrics provide complementary insights beyond numerical ratings and can better reflect the concept of value for money emphasized by students.

V. Expected Impact

Although this project focuses on restaurant reviews around McGill, its implications go beyond simply ranking places to eat. The way online reviews are interpreted can influence consumer decisions, shape perceptions of a restaurant, and ultimately affect business outcomes, particularly in markets where price sensitivity plays a central role.

For students, this type of analysis changes how information is consumed by making value for money more transparent. Instead of relying solely on star ratings, students can better understand how price and quality are perceived together. Two restaurants with similar ratings may differ significantly in perceived affordability or portion quality. Sentiment-based insights allow students to assess whether higher prices are justified by better food or service, supporting decisions that align with their budget constraints.

For restaurant owners, review text provides direct signals about how customers evaluate pricing relative to quality. Sentiment analysis helps surface recurring themes related to affordability, portion size, or perceived overpricing, offering clearer guidance on how pricing strategies and quality improvements impact overall customer satisfaction.

At a broader level, platforms like Google Maps influence how consumers evaluate trade-offs between price and quality. Incorporating sentiment-based measures could enhance recommendation systems by better reflecting perceived value for money rather than relying exclusively on aggregate numerical ratings.