A Yelp for Universities

Text Mining Online Student Reviews of Postsecondary Institutions Using Large Language Models (LLMs)

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Introduction

- College searching and enrollment decisions are critical for students and families. Increasingly, they are turning to online school reviews as a source of information, in addition to schools and social networks.
- Yet, the usage of online school ratings diverges significantly among SES backgrounds, influencing how parents gather and leverage information for educational decisions.¹
- College information not only facilitates better decision-making but also enhances student satisfaction and success in college.²
- Topic modeling and sentiment analysis are popular ways to extract opinions from texts. LLMs and other natural language processing techniques can be employed in this context.³

Research Questions

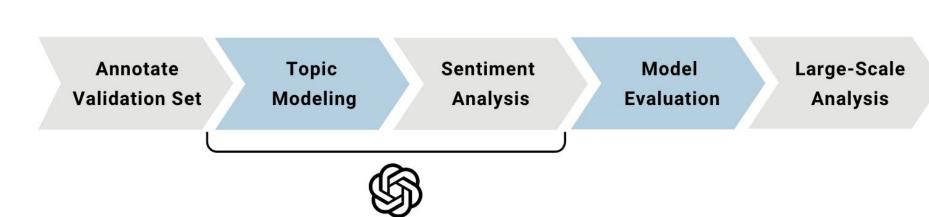
- How accurately can an AI model (like GPT) identify the main topics and opinions in university reviews?
- Is there a relationship between the mention of specific topics in reviews and the schools' overall ratings?

Data

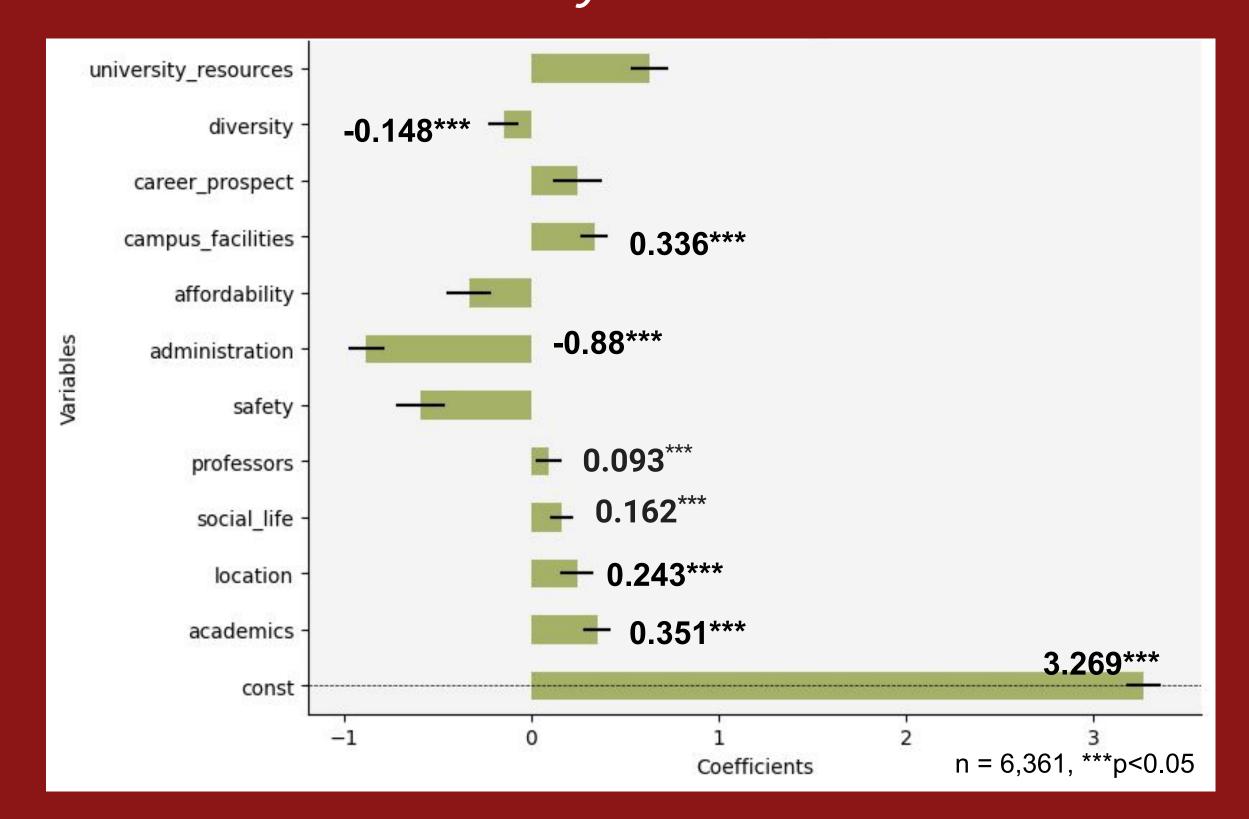
- 94 four-year non-for-profit postsecondary institutions
- 6,361 user-generated reviews from a popular college review site
- Each institution has a mean of 64 reviews with a std. of 14.
- A total of 285 reviews are manually labeled for evaluation
- Distribution of reviews by rating category at a scale of 1-5:



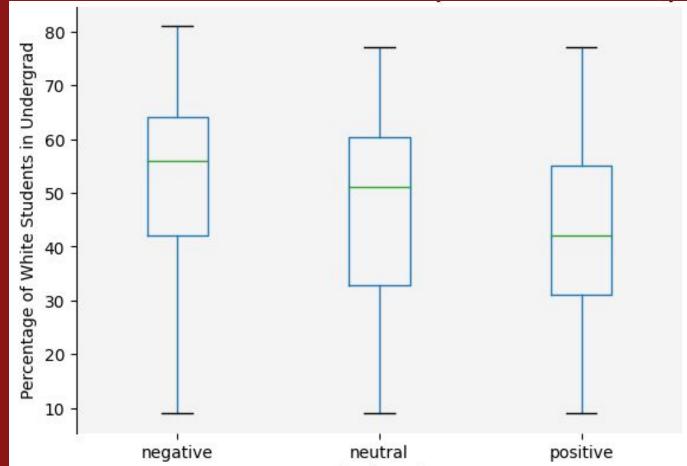
Methods

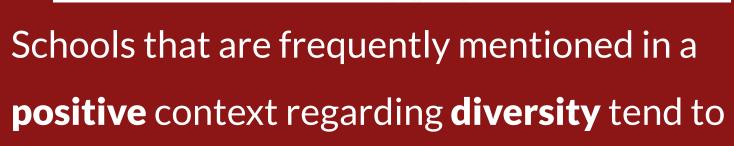


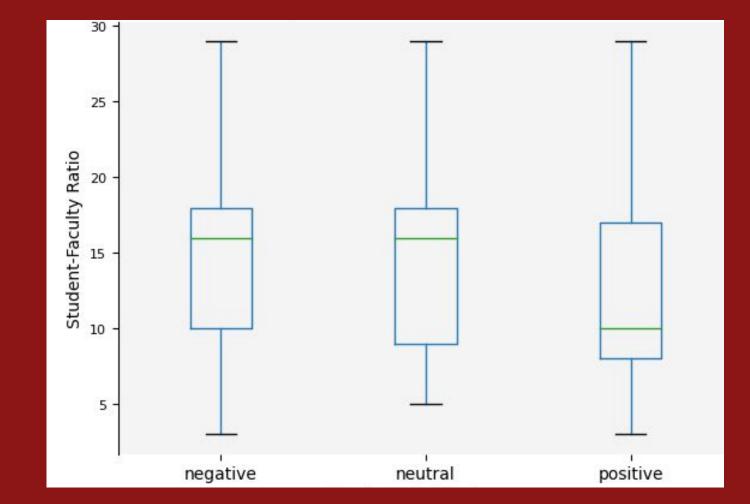
Students show **positive** feelings about *facilities*, academics, and social life, while discussions of administration and diversity often reflect dissatisfaction.



The **sentiments** expressed in online reviews mirror the **characteristics of universities**, such as the *diversity of student population*, *student-faculty ratio*, etc.







Schools that are frequently mentioned in a **positive** context regarding **professors** tend to

have **less homogenous** student body (n = 1,071). have a **lower student-faculty ratio** (n = 1,669).

ANOVA test: F-statistic = 58.08, p-value = 1.13e-24*** ANOVA test: F-statistic = 37.63, p-value = 1.06e-16***

Methods: Prompt Engineering

You are an assistant who reviews school reviews and identifies the main topics mentioned. Please, define the main topics in the review separated by {delimiter}. The assigned topic label should be strictly within this list: ['academics', 'location',...,'university_resources']. The output should be a list with the following format: [<topic1>, <topic2>]. School review: {delimiter} {review} {delimiter} An example of defining topics in review: {delimiter} School review: {example_1} Output: {output_1} {delimiter}

System Prompt User Prompt Input Example

Results

GPT-3.5 Turbo with zero-shot prompting reports a
decent performance in multi-label classification of topics
(F1 score = 0.66) and is highly accurate in determining
positive or negative sentiments (F1 score = 0.97).

Discussions and Conclusion

- GPT-based topic classification achieves up to 66% overlap with topic labels tagged by human annotators, demonstrating the capability of consistently creating outputs in the domain of university reviews.
- The analysis of reviews highlights a strong correlation between the diversity of the population and the perceived school climate, emphasizing the role of inclusivity in shaping student satisfaction.
- Online reviews provide valuable insights into academics and college experiences. This is particularly beneficial for students from underrepresented backgrounds who lack social networks.

References

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- 2. Cabrera, A.F. and La Nasa, S.M. (2000), Understanding the College-Choice Process. New Directions for Institutional Research, 2000: 5-22.
- 3. Chumakov, S., Kovantsev, A., & Surikov, A. (2023). Generative approach to Aspect Based Sentiment Analysis with GPT Language Models. Procedia Computer Science, 229, 284–293.

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