Reviewing Reviews: A Seeded LDA Analysis of Danish Restaurant Reviews

Exam in Introduction to Cultural Data Science

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Abstract

(Kristina) The restaurant-scene is an important part and reflection of the cultural scene of a geographical location (Bertan, 2020; Wood & Muñoz, 2007). This paper investigates the restaurant-scene in the context of restaurant-reviews from TripAdvisor in ten of the largest Danish cities. A seeded LDA topic model is conducted to look at which topics that typically comprise restaurant-reviews in Denmark. Furthermore, the topic-model is used to illuminate differences in topic-distributions for highly and lowly rated reviews. Moreover, an inspection of differences between ten of the largest cities in Denmark provided insights into a potential cultural differences at a geographical level. Findings showed a strong indication of Atmosphere, Food, Service, Price, and Location as the factors that generally comprise restaurant-reviews in Denmark. Furthermore, these topics varied in relevance across good and bad reviews with Location and Food making up larger portions of the badly rated reviews and Atmosphere, Service, and Price being more constitutive of highly rated reviews. An explorative inspection of geographical differences suggested that the general tendency of topic-distributions was the same across all of Denmark, but that further analyses could potentially unravel minor variations in feature-importance across different geographical locations in Denmark. Lastly, the general workflow and pipeline of this study is proposed as an applicable ready-available tool for restaurateurs to use for insight-gathering of their customers' perception of their restaurant.

Keywords

Seeded LDA Topic Modelling, Restaurant Reviews, Cultural Differences in Restaurant Reviews

Introduction

(Gustav) The overall aim of this paper is to investigate the role of different topics in restaurant reviews. It is widely known that there are certain topics that generally compose restaurant reviews (Gan et al., 2017**.** This knowledge is used as grounds to hypothesize that the internal ratio of these topics vary across rating-level. Thus, it is proposed that the general relationship of these topics are different for highly-rated reviews and lowly-rated reviews. Furthermore, it is hypothesized that these topic-relationships might vary across geographical locations.

Theoretical background

(Kristian) In the study that has partly inspired the study at hand, Gan et al., (2017) conduct a literature review in which they find that "Ambience, Food, Price, and Service" are the ubiquitous topics that underlie most restaurant-reviews. They propose that the context in which a restaurant-goer visits a restaurant should be accounted for as well. Hence, a person who goes to a restaurant because they are celebrating their birthday might review a restaurant differently than a person who visits the same restaurant solely to get something to eat. In the study at hand, we conduct a topic model in which we model the topics with point of departure in the topics proposed by Gan et. al. (2017). The four ubiquitous topics; Ambience, Food, Price, And Service are used as categories with the addition of the topic "Location". The category "Ambience" is in our framework changed to "Atmosphere". It is argued by the researchers that by altering the category "Ambience" it is possible to introduce a fifth topic (Location) that makes it possible to account for even more variability in the text-based review analyses. Thus, the integration of a word frequency analysis with the already existing framework of Gan et. al., (2017) produces a slightly altered framework with five different categories. The model in the present paper does not take into account the "context" of the restaurant-visits as it is argued that the added topic "location" in cooperation with atmosphere better compartmentalizes the topics that make up a typical restaurant-review.

Cultural Relevance

(Gustav) Restaurants are an important reflection of cultures and inherently mirror the cultural origins of the foods served in them. In a study on alignment between the portrayal of Australian culture in American media and restaurant experiences in the restaurant chain "Outback Steakhouse" in USA, researchers reported that customers were more inclined to buy into the cultural concept of the individual restaurants if they were aligned with the portrayal of Australian culture perpetuated by American media (Wood & Muñoz, 2007). This, among other things, suggests a cultural relevance of restaurants. In a study on gastronomic tourism and the role of restaurants herein. Bertan (2020) argues that restaurants are propellers of cultural heritage in the sense that they demonstrate inherent trademarks of cultures to tourists that travel to get insights into cultures different to their own. In the present study, an analysis is conducted to investigate cultural trademarks of restaurants in various Danish geographical areas.

Aim of study

(Kristian) The study at hand had multiple purposes. Each purpose will for the remainder of the paper be referred to with its accompanying abbreviation (e.g. "P1"). Firstly, to find general topics that meaningfully summarise restaurant-reviews in Denmark. Secondly, to investigate whether reviews with high and low ratings typically differ in which topics that constitute them. Thirdly, to explore any potential geographical differences for topic-distributions. Lastly, it is attempted to make a ready-available tool for restaurant owners to gain insights into the behavior of their consumers. This is done to enable insights for potential restaurateurs interested in opening new restaurants in Denmark, as well as to provide a tool to help existing restaurants optimize their venues based on quantitative analyses of their reviews.

The study at hand seeks to analyze various characteristics of restaurant-reviews by making quantitative text analysis on reviews for Danish restaurants found on Tripadvisor (*Tripadvisor*, 03.12.2021). Previous studies have, almost exclusively, utilized scant metadata information such as numeric reviews (Gan et al., 2017). However, analyses of textual data from e.g. online reviews have the potential to elucidate more nuanced and complex insights into consumer experiences (Ganu et al., 2013). Therefore, this study will attempt to highlight consumer behavior characteristics by analysing textual data in the form of online restaurant reviews from Tripadvisor.

Advantages of Seeded LDA Topic Modeling

(Gustav) The TripAdvisor reviews were analysed by using a topic model. A topic model enabled the investigation of whether reviews of different ratings typically consist of different topics. For instance, are reviews with low ratings more often composed of topics like 'food' and 'service' than reviews with high ratings or vice-versa? To ensure that the topic model evaluated the reviews on the relevant topics presented in the introduction, a seeded LDA analysis was selected as the method of choice (Latent Dirichlet Allocation). A seeded LDA analysis takes a dictionary as input in which predefined topics and associated words for each topic can be specified (Jagarlamudi et al., 2012). A seeded LDA analysis thereby enables exploitation of prior knowledge of the structure of the reviews while simultaneously making sure that the outcome topics are meaningful for the intended analysis.

Methods

Data Specifics

(Kristian) Using the package "BeautifulSoup4" (Richardson, 2007) in the programming language Python (Van Rossum & Drake, 2009), 188,091 online customer reviews were scraped from 3,877 different restaurants. The restaurants scraped were distributed across 10 different larger cities in Denmark. The reviews were overall in Danish and English (more details about the influence of bilingual reviews can be found in the "Methodological considerations"-section of this paper). All plots and figures were colored with the *wesanderson* color palette (Ram & Wickham, 2018).

Scraping of the Data

(Gustav) The scraping process was twofold. First, all tripadvisor URLs for restaurants in a specific geographical area were collected and gathered in text files. Second, all restaurant urls were looped through and all reviews, ratings, and relevant metadata were extracted and stored in CSV files using the csv library in Python (Van Rossum, 2020). Before extracting the reviews the *selenium* webdriver (Salunke, 2014) was used to interact with the Tripadvisor webpage from the Python-console. The default behavior of TripAdvisor is to display only a set length of a review. In the case of longer reviews, the full review can be displayed by clicking a “more” button. Since the BeautifulSoup4 library only extracts data from the raw HTML code the undisplayed part of the review cannot be extracted unless the more button is firstly pushed which is why the selenium webdriver was used to interact with the TripAdvisor webpage before scraping it. This ensured that the reviews were extracted in their full length.

Preprocessing of the Data

(Kristian) The text analysis was conducted with R (R Core Team, 2020) in Rstudio (RStudio Team, 2020). The data was imported and preprocessed using the tidyverse framework (Wickham et al., 2019). The preprocessing of the data consisted of several steps. First step was to remove all duplicates. Then all reviews from restaurants that had fewer than five reviews were removed. This reduced the data set to 130,718 reviews distributed across 2,815 restaurants.

The next step of the preprocessing involved correcting errors in restaurant names. Several restaurant names were mistyped or not formatted similarly. Some restaurants would for instance interchangeably be spelled with “oe” and “ø”. This meant that the same restaurant in the analysis would be counted as two distinct restaurants if not corrected. The errors were detected using the “stringdist” library (Loo, 2014). All restaurant names were compared and given a score that reflected how distinct they were. The strings were compared using the *optimal string alignment distance* parameter. The string scores were then arranged in ascending order which made it possible to manually inspect the restaurant names that the algorithm rated as being most similar. The comparisons were inspected manually and mistakes detected were corrected by hardcoding replacement statements.

The last step of the preprocessing involved cleaning the actual textual data from the reviews. The R package for quantitative analysis of textual data, “quanteda” (Benoit et al., 2018) was used for this. All punctuation, numbers, and symbols were removed.Then all characters were transformed into lowercase and stop words were removed. As the corpus contains reviews in both Danish and English, both Danish and English stop words were removed. The English stop word list was gathered from the “stopwords” package (Benoit et al., 2021), while the Danish stopword list was gathered from a list created by the GitHub user “berteltorp” (Torp, 2020). Finally, very frequent and very infrequent words were removed. All of these steps were done to isolate the parts of the text that contained relevant semantic meaning for the analysis.

Seeded LDA Analysis

(Gustav) The seeded LDA analysis was conducted using the "seededlda" package (Watanabe & Xuan-Hieu, 2021). Before the analysis was conducted a dictionary of topics and associated words was created. Word lists were created for five different topics: *Atmosphere*, *Food*, *Price*, *Service* and *Location*. The dictionary was created by eyeballing the most frequent words in the corpus. A word from the frequent word list, would be added to a topic in the dictionary if it was assessed as stereotypically associated with a given topic. If a word was assessed as representative for a topic, the *lemma* of the word (the root of the word) would be added to the dictionary and the model would look for all forms of the word when analysing the text. The final dictionary feeded to the model can be seen in table 1. Once the dictionary had been created the seeded LDA analysis was conducted. The seeded LDA analysis provides five estimates for each review, one for each topic. This means that all reviews are given a score of how much they consist of each topic. The sum of the five scores add to 1. The most frequent terms in each category can be seen in table 2. Upon eyeballing the most frequent words for each topic, it was concluded that the model was extrapolating well from the feeded dictionary and associating the different topics with topic relevant words; meaning that the feeded words enabled the model to successfully gather semantically related words.

```
Dictionary object with 5 key entries.
- [Service]:
  - service*, betjening*, friendly, staff, venlig, personale*, qualit*, kvalitet*, tjener*
- [Food]:
  - mad*, menu*, ret*, smag*, dish*, qualit*, kvalitet*
- [Atmosphere]:
  - oplevelse, time*, hyggelig, atmosphere*, atmosfære*, stemning*, cozy*
- [Location]:
  - sted*, place*, hotel, udsigt*, tæt, local*, lokal*
- [Price]:
  - pris*, pebret*, dyr*, billig*, betal*, regning*
```

Table 1: The dictionary fed to the seeded LDA model. The table shows the five different topics and which words were associated with each topic.

	Service	Food	Atmosphere	Location	Price
[1,]	"quality"	"mad"	"atmosphere"	"hotel"	"pris"
[2,]	"betjening"	"maden"	"time"	"local"	"prisen"
[3,]	"venlig"	"dishes"	"times"	"places"	"priser"
[4,]	"personale"	"made"	"cozy"	"sted"	"priserne"
[5,]	"betjeningen"	"dish"	"hyggelig"	"locals"	"betale"
[6,]	"personalet"	"retter"	"stemning"	"stedet"	"dyrt"
[7,]	"tjener"	"smagte"	"oplevelse"	"steder"	"billig"
[8,]	"tjeneren"	"quality"	"atmosfære"	"lokale"	"billigt"
[9,]	"servicen"	"smag"	"stemningen"	"placed"	"dyr"
[10,]	"tjenere"	"ret"	"timer"	"tæt"	"dyre"
[11,]	"tjenerne"	"kvalitet"	"atmosfæren"	"udsigt"	"billige"
[12,]	"serviceminded"	"return"	"timely"	"lokaler"	"betalte"
[13,]	"services"	"menus"	"timers"	"lokalet"	"betaler"
[14,]	"kvalitet"	"smager"	"timed"	"locally"	"regningen"
[15,]	"servicemindede"	"menuen"	"atmosphere-"	"placeret"	"betalt"
[16,]	"kvaliteten"	"retters"	"stemningsfuldt"	"lokalerne"	"regning"
[17,]	"service-minded"	"kvaliteten"	"stemningsfyldt"	"lokal"	"dyrere"
[18,]	"servicemindet"	"smagt"	"stemningsfuld"	"placering"	"billigere"
[19,]	"personalets"	"smage"	"atmosfærer"	"udsigten"	"betaling"
[20,]	"tjenerens"	"retterne"	"atmosphere.more"	"stedets"	"prisniveau"

Table 2: This table shows the words that occurred most frequently in each topic in the seeded LDA analysis.

Findings

Inspecting the Data

(Kristian) The estimates of the seeded LDA analysis were evaluated by inspecting the mean values for the different topics. In figure 1, the mean values are plotted along with the standard deviation as error bars. In this plot it can be seen that the mean values for the five topics are relatively similar with the exception of atmosphere which is a bit higher. This indicates that the model is using all five topics more or less evenly, and that all topics are represented in the reviews.

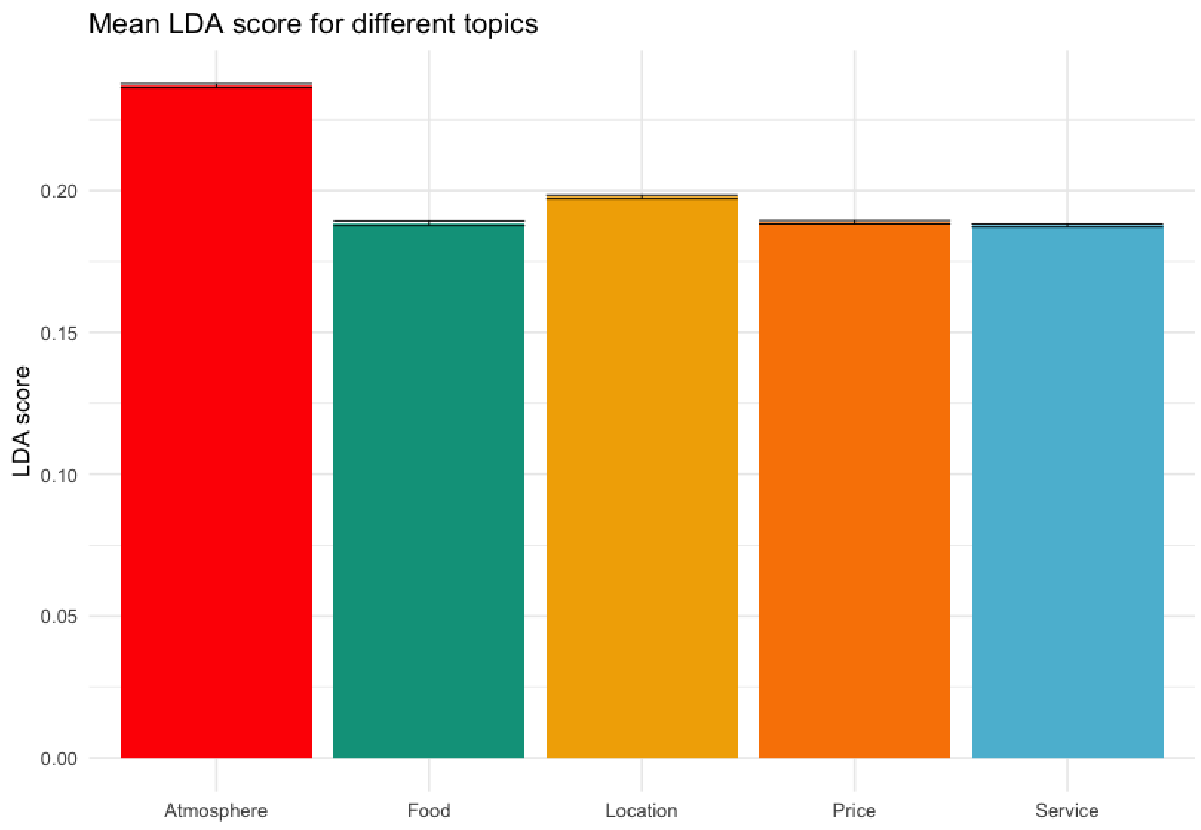

Figure 1: Mean LDA scores for each topic for all reviews in the corpus.

For the remaining analyses the reviews are split into "High Ratings" and "Low Ratings". This is done by utilizing the numeric rating-score provided by TripAdvisor. When a user reviews a restaurant they are required to rate the experience on a scale from 1-5 with 1 being a reflection of a bad experience and 5 being a great experience. For the coming analyses all the reviews with a rating of 1 and 2 are categorized as "Low Ratings" while analyses with the ratings 4 and 5 are categorized as "High Ratings". Ratings of 3 are categorized as "Neutral Ratings" and ignored for the remainder of the paper.

P1: Do the topics summarise the textual data well?

(Gustav) To verify that our chosen categories were significantly influential on the ratings of the restaurant reviews, a mixed-effects linear model was run. The model had all the chosen topics as predictors and had random intercepts for cities. In effect, this means that it was illuminating the influence of all the topics on the rating-value while taking into account the inherent differences that could be in different cities. The fitted model had the following syntax:

Rating ~ 0+Atmosphere*Food*Service*Location*Price + (1|City).

A highly significant 5-way interaction was found for all the five topics: [-2.729e+03] = t(1.307e+05) = -4.252, $p < 0.001$. A five-way interaction is extremely hard to interpret, but the fact that there is an interaction statistically means that the topics should not be interpreted in relation to rating by themselves but together with the rest of the parameters. Intuitively this makes sense as a restaurant-review is not made up of just one or two topics but the sum of all the parameters. In our framework, we have a zero-sum game in which our five topics together constitute the entirety of a review. The individual relationships for the five topics is what can vary. One could imagine a scenario in which a person has reviewed a restaurant poorly, but has complimented the chef and location. Perhaps the waiter was so bad that the review earned an overall bad rating score despite a talented chef and a great location. That the interaction effect is significant means that all the topics are meaningful for the overall rating of the restaurant visits. In other words, the topics numerically summarise the textual reviews well. Thus, the first purpose of this paper that pertained to the meaningful summarisation of general topics in restaurant-reviews has been successfully achieved.

P2: Do reviews with different rating levels differ in topic distribution?

(Kristian) The second purpose of the paper was investigated by visual inspection. In figure 2 the summarised means for each topic for different rating levels are plotted. It is visualised that there is a clear difference in how much the different categories make up of the reviews across good and bad ratings. Thus, *Atmosphere* makes up a significantly higher portion of the reviews in the high-rating category. The same is true for *Service*. On the other hand, *Location*, *food*, and *price* seem to be the principal topics of discussion in the lowly rated reviews.

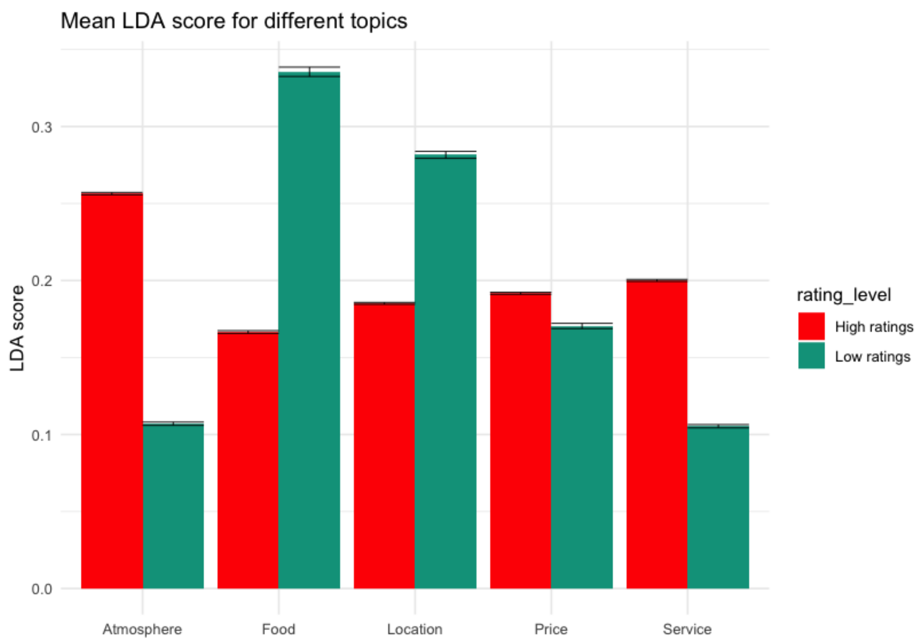

Figure 2: Showing the mean LDA score for the five topics for both high and low ratings with error bars depicting the standard deviation.

(Gustav) There is a clear hierarchy in features that make up a good restaurant (Heung, 2002)**.** Thus, a general tendency is that quality of food is the most contributing factor for the success of a restaurant visit (Kivela, 1997). From our findings it is visibly obvious that some of the topics make up more of the textual reviews than others. Furthermore, it is clear that the distribution of these topics vary for low and high ratings. Keeping in mind that there is a hierarchy of importance for restaurant features in a good restaurant experience, one possible hypothesis that could be made for the differences in topics for good and bad ratings could be that some things need to be in order before less important things can be taken into account by a reviewer. Thus, *food* and *location* seem to comprise more of the text in the reviews when the ratings are bad. It could therefore be suggested that *food* and *location* do not impress a restaurant-goer it could influence the rating negatively. On the other hand, if food and location are great, a reviewer will be more likely to also talk about atmosphere, service, and price. In sum, a restaurant-visit is rated based on a hierarchy in which *food* and *location* need to be ticked off satisfactorily before other features such as *atmosphere*, *price*, and *service* can be credited and influence the rating of a review positively.

The second aim of the study that wanted to investigate differences in topic-distribution across low and high ratings has thus been touched upon. There is a clear difference in the topic-distribution across ratings and this is in turn used to suggest a potential dynamic in the hierarchy of features in order to achieve a good restaurant-visit.

P3: Are there geographical differences in topic distributions

(Kristian) The third purpose of this paper was to investigate whether there were any geographical differences in topic distributions for the restaurant reviews. This was investigated by grouping the data by cities and then plotting the distribution of topics for each city. The resulting plot can be seen in figure 3. By eyeballing the plot it does not seem like there are any notable differences between topic distributions for the different cities. The structure of the topic distributions are similar to that of the summarised data seen in figure 2, where reviews with high ratings typically consist of the topics *atmosphere* and *service* where reviews with low ratings typically consist of the topic *food*. The direction of the topics are similar across the cities, but the size does vary, although rarely enough to change the direction. Therefore, we conclude that we did not find any geographical difference between topic distributions, but that subtle, geographical differences might be present and could be the point of further investigation.

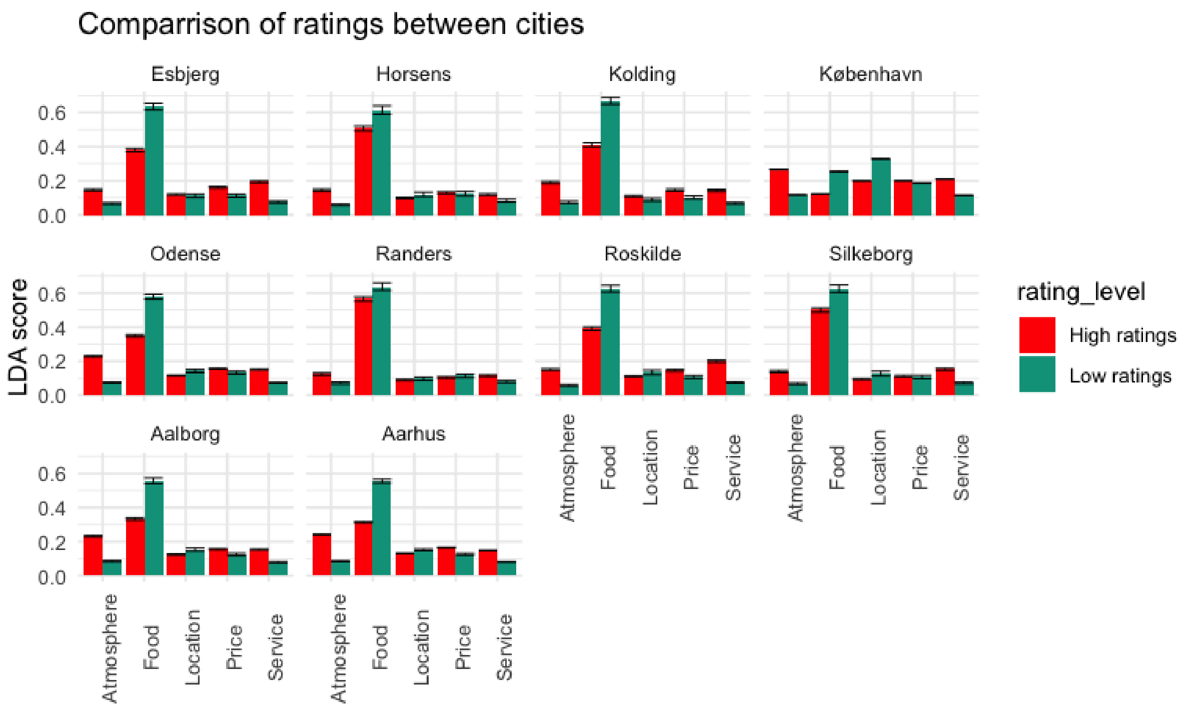

Figure 3: Topic distribution for reviews of high and low ratings for the different cities. The mean LDA scores are plotted with error bars depicting the standard deviation.

P4: A tool for restaurateurs

(Gustav) We argue that our framework has an applicable use for restaurant-owners who want to gain insights into customer-perception of individual restaurants. Thus, a restaurant owner would be able to look at the distribution of topics for their own restaurant in general as well as across good reviews and bad reviews. Thereby, a restaurant owner might be able to see what comprises the good reviews and therefore which things their particular restaurant is getting positive recognition for. Similarly, a restaurateur would be able to shed light on which aspects of their restaurant that needs tending to in order to get better ratings. An example of such an application can be seen in figure 4 where the topic distributions for a specific, arbitrarily chosen, restaurant are visualised. A restaurateur would also be able to use our framework to get an insight into the consumer behavior for a specific geographical area.

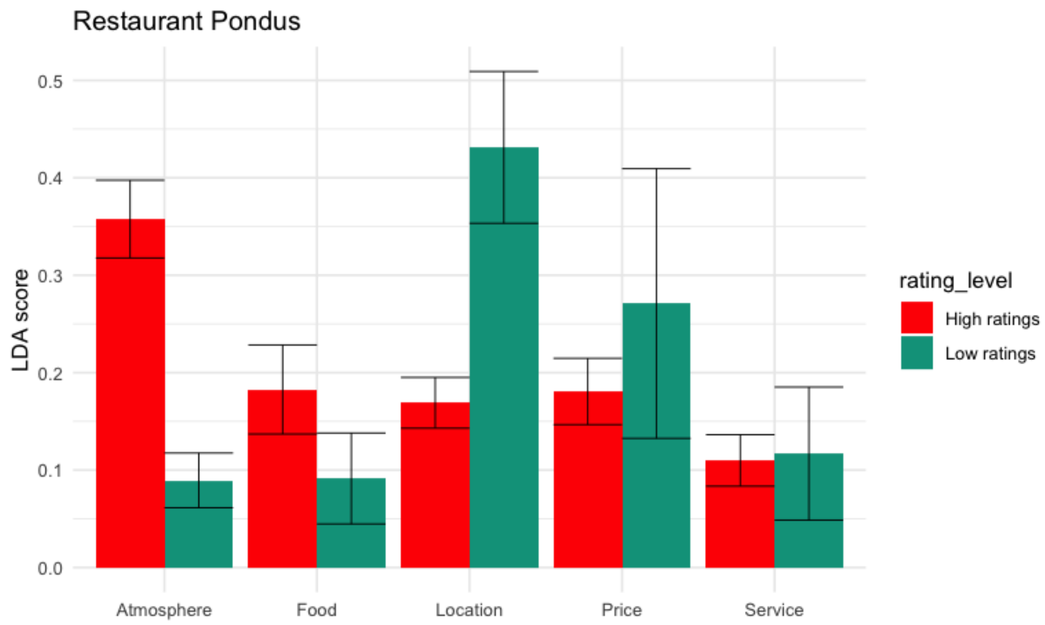

Figure 4: Distribution of topics for reviews of high and low ratings for 'Restaurant Pondus' in Aarhus.

Methodological Considerations

(Kristian) The quality of the results of this paper is limited by the quality of the methods, which is why the methods are the next point of scrutiny. There are especially three aspects of the methods that should be critically assessed. The first is that the reviews both consist of Danish and English reviews. Having several languages in the corpus makes it difficult for the LDA model to find common terms within the categories, hence there will very rarely be any word overlaps between Danish and English reviews even though they concern the same topic. We have tried to account for language differences by removing stop words in both languages and adding both English and Danish words in the topic dictionary. The model would, however, probably perform the best if the corpus only consisted of reviews in one language.

(Gustav) The second aspect of the method that could be improved on are the type of restaurants that are included in the corpus. For instance, it would be sensible to differentiate between fast-food restaurants and regular restaurants, as the reviews might be inherently different.

(Kristian) A third methodological consideration is that the dictionary fed to the seeded LDA model is made manually. The model might therefore be influenced by any subjective opinions on what words are associated with what topics. This can heavily influence the model output and reduce replicability of the results. It can however, still be argued that the results from the analysis are meaningful since all reviews are assessed on the same dictionary.

In line with this point, a further implication could be the internal dynamics of the model topics. The model-framework within this paper rests on an assumption that the five categories constitute 100% of the text-reviews and that only the proportion of the topics in relation to each other is allowed to differ. One could imagine that other features such as *temperature* and *hygiene* could in themselves be topics for inspection. However, it is argued that the initial breakdown of Gan et. al.'s (2017) *ambience* into *location* and *atmosphere* serves as larger umbrella-terms for subcategories of these.

Conclusion

(Gustav) This paper has shed light on different aspects of the Danish restaurant-scene. The different topics that typically comprise a restaurant-review have been discussed. Furthermore, the internal relationship between these topics has been investigated across good and bad ratings. Lastly, geographical differences have been explored. As discussed in the introduction of this paper, the restaurant-scene is widely regarded as a reflection of culture (Bertan, 2020; Wood & Muñoz, 2007)**.** Therefore, the geographical exploration of topic-distributions serves as an investigation into cultural differences in Denmark. All in all, this paper therefore provides cultural insights by investigating the specific sector of the cultural scene that is the restaurant-business.

GitHub

The entire pipeline for the workflow of this paper can be found at this GitHub-repository:
https://github.com/ghelms/restaurants_in_lakeland

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