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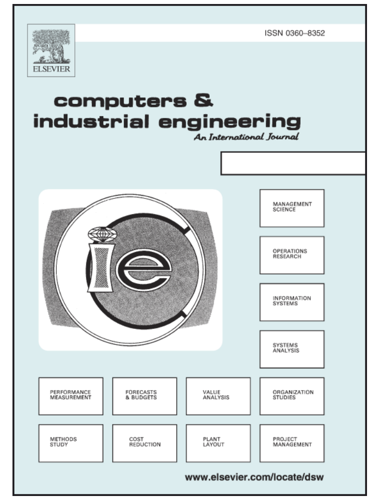

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Topic-based Knowledge Mining of Online Student Reviews for Strategic Planning in Universities

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REVISED MANUSCRIPT

Abstract:

Over the past few years, studies observe a continuous decline in university enrollment and retention rates resulting in millions of dollars in lost revenue. Past research shows that 95% of the students rely heavily on the positive word-of-mouth to select a college. Especially, with the advent of Web 2.0 tools, students are able to make informed decisions due to increased awareness through online reviews. Academic institutions can also leverage this information to understand and improve their students' perception. The objective of this paper is to identify the current strengths, weaknesses, opportunities and threats (SWOT) of a university by analyzing online student reviews using text analytics. Our proposed approach integrates four different techniques: topic modeling, sentiment analysis, root cause and SWOT analyses. First, we introduce an ensemble of Latent Dirichlet Allocation (E-LDA) topic models to automatically identify the key features (topics) that are predominantly discussed by the students and categorize each review sentence into the most related topic. We then detect the opinion associated with each sentence (positive, negative and neutral) using sentiment analysis. Finally, a topic-based opinion summary (TOS) for a university is established to identify its strengths and weaknesses from the students' perspective, and the opportunities and threats are determined by analyzing the TOS of the competitors (or other similar institutions). A case study is used to illustrate the feasibility and application of the proposed approach. The results indicate that the proposed method provides efficient and economic performance summary of a university and its competitors, and could help its leaders in recruitment and retention efforts.

Keywords: Online word-of-mouth; Text mining; Sentiment analysis; Topic modeling; Voice of the customer; SWOT analysis

1. Introduction

The attenuation of student enrollment and retention at the U.S. universities over the past years has been a pressing issue that colleges are trying to address. The enrollment rate at several schools has been declining since 2011, notably from 2015 (National Student Clearinghouse Research Center, 2016). Besides the declining enrollment, student attrition has also become a crucial issue. The National Center for Educational Statistics (2017) highlighted that only 59% of the students graduate from the same university in which they initially registered. Further, about 75% of the students who leave universities are either freshman or sophomore, and 85% of student departures are voluntary, in spite of them maintaining a satisfactory academic performance (Spring and Schonberg, 2001). There are numerous repercussions as a result of low student registration and retention, such as reduced tuition revenue, limited course offerings, closure of academic departments, and elimination of university jobs. Across the US, several flagship universities have eliminated jobs, including full-time, non-tenure track faculty and staff positions due to plummeting enrollment (Irby, 2017, Ciurczak, 2017). To revive the falling enrollment and retention rates, colleges spend millions of dollars on market research, recruiting campaigns and branding programs.

Prospective students choose their universities by going through an emotionally wrenching process and consider several factors, such as academic reputation, financial assistance and tuition fees, to make their choice (Ciurczak, 2017). Nearly 95% of the time, students make final university decisions based on positive word-of-mouth (WOM) from trusted sources such as current students, alumni, family members or selection consultants (Attila, 2016). In particular, about 58% of students rely specifically on online reviews and ratings to choose their future universities (Farrell, 2016). Based on an empirical study, Elliott and Healy (2001) also concluded that current students spreading positive feedback is the most efficient strategy for increasing enrollment. These studies indicate that positive WOM has become an essential differentiator for prospective students to make their final university choice, which can be achieved by enhancing the student experience in areas that are most important to them (e.g., academic support, social life). Therefore, there exists a necessity to capture the voice of customers (students) thereby understanding their perception and achieve positive WOM.

Each university's creation of value to students is perceived by different elements of the academic system in different ways. While the school views the quality of an academic system in terms of the infrastructure, research facilities and qualification of faculty members, students' interpretation of the university image are dissimilar (Akareem and Hossain, 2016; Azoury et al., 2013). For instance, results from a survey conducted across 763 students in eight countries indicate that there is a positive relationship between the cost/quality ratio and the overall image of the university. Several types of research have focused on identifying the determinants of students' perception of education quality by conducting student satisfaction/experience surveys (Elliott and Healy, 2001; Rowley, 2003; Fleming et al., 2005; Markle, 2015). However, Douglas and Douglas (2006) criticized the "tick-box" quantitative survey methods, which can only record the satisfaction ratings without considering the importance of each question.

A recent study shows that online customer reviews (OCR) have helped several businesses to learn about the strengths and weaknesses of their products or services (Salehan and Kim, 2016). These user-generated contents are rapidly increasing, especially with the large-scale usage of Web 2.0 technologies (Guo et al., 2017). Although OCR is purely subjective and only reflects a subset of the customer population, these are considered the second most trustworthy platform for getting product information from a customer's perspective (Nielsen Holdings, 2012). Moreover, negative reviews have a colossal impact on the business as they propagate five to six times faster than positive ones (Salehan and Kim, 2016). Therefore, with the increasing usage of social media, businesses now face the challenge of analyzing online customer reviews to know their product/service performance (Sen and Lerman, 2007). This also paves the way for any organization to improve the quality of its products/services. Thus, it is expected that the educational systems can use the same approach to improve their student experience.

The objective of this paper is to enhance student satisfaction by identifying the current strength, weakness, opportunities and threats of a university through knowledge mining of online student reviews. Each online review discusses a myriad of topics (e.g., faculty, campus location, etc.) and expresses an opinion (positive, negative or neutral) towards each topic. For example, consider the following online review:

"..the professors were incredible and so inspiring. The university offers many opportunities for building your resume through so many clubs, volunteer work, jobs, and internships. Football coaches are biased and unfair"

In the above review, the first two sentences express a positive opinion about the faculty and academic support, respectively. Whereas, the third sentence expresses a negative opinion about football. Thus, the sentences in the above review can be classified (labeled) to three different topics, namely, faculty, academic support, and sports. However, gathering business intelligence using online reviews is challenging due to its dimensions such as high volume, variety and velocity. We propose an approach to automatically mine online reviews for topic identification, sentence labeling, and sentiment classification, and summarize them to conduct SWOT analysis. The proposed approach can serve as a decision support system to assist the university officials in setting goals and priorities focusing on the most important factors that could improve student satisfaction, university reputation, enrollment and retention rates.

The remainder of the paper is organized as follows. A review of some prominent studies in the literature is presented in Section 2. Section 3 provides a detailed discussion of the proposed approach. The case study description along with the results are discussed in Section 4. Finally, the conclusions and scope for future work are given in Section 5.

2. Literature Review

The focus of this paper is to capture the voice of students using online review mining and enable university strategic planning. Therefore, we review some prominent studies on understanding the voice of students (i.e., student expectations, enablers, and obstacles) and online review mining.

2.1 Voice of Students

The academic environment in today's world has enticed students with several options. In order to stay competitive, universities must develop effective strategies to enhance student experience. Fleming et al. (2005) categorized the voice of students into three sections: peer interaction, classroom environment and physical environment. Peer interaction is characterized by the heterogeneous roles (such as roommate, classmate, study partner and competitor) played by the students when interacting with people of different cultural backgrounds, socioeconomic status, and/or different value systems. While peer interaction provides the impetus for student growth in an out-of-classroom environment, in-class experience gives the rite of passage that leads to shaping of individual thoughts. The third and final setting is the physical environment, not necessarily the physical facilities, but also includes other factors such as proximity of residence and type of college town.

Elliott and Healy (2001) examined the different aspects of student's experience affecting student satisfaction and found that student centeredness, campus climate and instructional effectiveness have a strong impact on the overall student satisfaction. Turner and Thompson (2014) specifically focused on understanding the determinants of student perception to increase the retention rates using open-ended interview questions. The authors concluded that freshman activities and events, effectiveness of the study skills and instructor-student relationship are the key elements affecting the student perception of a university. While prior studies explore the relationship between several dimensions of the university and student experience, Markle (2015) used a role-theory perspective to conclude that the graduation persistence rate did not differ by gender hence proving the needlessness to consider the difference in attrition rate between men and women.

Although most prior research conducts empirical studies based on extensive surveys to capture the voice of the customer (student), the categorizations are broad and unique issues about a particular institution may not be captured. For instance, a study conducted in a Midwestern US university concludes that students' perception of instructor preparedness had an impact on the student retention rates (Spring and Schonberg, 2001). Therefore, the need to study the features affecting the university-specific enrollment is evident, as the voice of the customer is the key input to conduct student-centric SWOT analysis.

2.2 Online Review Mining

Online reviews act as a strong link between current and future customers. The customer experience and satisfaction levels (in terms of the product and service quality) posted online turn into feeder information for potential patrons (Xiang, and Gretzel 2010; Munar and Jacobsen, 2014; Ramanathan et al., 2017). Studies proving the importance of online reviews on product sales are abundant (e.g., Hu et al., 2008; Ghose et al., 2011; DeMaeyer, 2012; Cui et al., 2012; Floyd et al., 2014). Online customer reviews not only help manufacturing industries to increase their product sales but have also aided service sectors to maximize their revenue. Chae (2015) proposed a novel Twitter Analytics framework for analyzing supply chain tweets and developing managerial insights. Tan et al. (2015) aimed to improve a firm's innovation capabilities related to supply chain by providing an analytic infrastructure to gain competitive advantage. Singh et al. (2017) were able to identify supply chain issues in food industry by analyzing customer opinions posted in Twitter using support vector machine and hierarchical clustering with multiscale bootstrap resampling.

For instance, Ye et al., (2011) conducted an empirical research to analyze the effect of online WOM on hotel reservation. Their results showed that with 10% increase in user-generated review score, online booking increases by more than 5%. Thus, regardless of any sector, analyzing online WOM is critical to understand the voice of the customer.

Using natural language processing (NLP) for automatically mining key aspects (topics) and customer opinion from online reviews has been a challenging task. Topic model is a statistical approach to extract the hidden semantics that occurs in a collection of documents or reviews. In particular, Latent Dirichlet Allocation (LDA) proposed by Blei et al. (2003) is perhaps the most influential approach for unsupervised topic modeling. It has been widely adopted to identify topics from documents (texts, reviews, tweets, etc.) belonging to various domains (e.g., Leskovec et al. 2009; Weng et al., 2010; Guo et al., 2017). In order to adapt LDA to different problem-specific review analysis and domains, several variants have also been proposed. Titov and McDonald (2008) proposed a multi-grain LDA to identify the global (topics related one particular entity) and local topics (common across all entities in the domain) for three different domains, namely, Mp3 players, hotels and restaurants. Jo and Oh (2011) proposed sentence-LDA by assuming that each word in a sentence corresponded to a single topic and used it to identify key topics in restaurant and electronic domain. Upon identification of features using topic modeling, supervised and unsupervised approaches can be used to categorize review sentences into its most related topic.

Sentiment analysis is a common approach in NLP for mining the overall opinion of the customers as positive, negative or neutral towards a product or service. Most studies on extracting sentiments from online reviews focus on using lexicon-based approach (Ding et al., 2008; Taboada et al., 2011) or machine learning algorithms (Pang et al., 2002; Boiy and Moens, 2009). While lexicon-based approach deals with the use of word dictionaries (positive and negative sentiment words) to capture the polarity and sentiment, machine learning approaches train from features (e.g., bag of words, terms and their frequency, parts of speech) that are manually annotated as positive, neutral or negative. In recent times, Valence Aware Dictionary and sEntiment Reasoning (VADER), a rule-based method for sentiment analysis method proposed by Gilbert (2014), has gained attention due to its consistent outperformance. Few studies have also combined topic modeling and sentiment analysis to provide a topic-based review summary of the product or service (e.g., Pang and Lee, 2008; Lin and Ye, 2009; Xianghua et al., 2013).

2.3 Contribution to the Literature

This research is one of the first to analyze online student reviews (unstructured data) using topic modeling and sentiment analysis. Further, we integrate strategic planning tools, namely, SWOT and root cause analyses, with text mining approaches to capture the voice of the student. Past studies focus on obtaining student feedback using traditional qualitative, quantitative or mixed methods such as questionnaire survey and focus groups. Guo et al. (2017) pointed out that researchers using such traditional methods are forced to make a tradeoff between data collection cost and estimation performance. Further, such an approach may not provide a holistic understanding of customer needs due to the difficulty in capturing emotional responses coupled with the incapacity of discussing any subject matter in detail due to space limitation. These issues do not exist in online review comments posted by students and alumni.

We also deviate from the literature in the domain of text analytics by using an ensemble of LDA models, called the Ensemble Latent Dirichlet Allocation (E-LDA) model, for topic identification and sentence classification. While supervised approaches such as support vector machines and Naïve Bayes have good accuracy for sentence classification, they are computationally expensive and require a large amount of labeled data set for training and testing. Unless the domain-specific annotated data is readily available for training, it is difficult to implement a supervised machine-learning algorithm for sentence classification, as tremendous amount of manual effort is required to label the data. On the other hand, unsupervised approaches require less computational effort and can reduce the need for large amounts of annotated data. For example, a trained LDA can be used as a discriminative model to classify a sentence into a topic (Zhang and Xu, 2016, Jelodar et al., 2017). However, such an approach may not achieve high classification accuracy. Further, prior studies on machine learning have demonstrated the outperformance of ensemble classifiers in comparison to single classifiers both theoretically (Krogh and Vedelsby, 1995) and empirically (Opitz and Shavlik, 1996a; 1996b).

This serves as a motivation for combining the inference of diverse trained LDA models to classify each review sentences into the most related topic.

3. Methodology

The proposed approach will first use a web scraper to extract thousands of publicly available student review archives from online sources. The retrieved data will then be mined to automatically identify the main subject matters (topics) using topic modeling. We use an ensemble of Latent Dirichlet allocation (E-LDA), an unsupervised topic modeling approach, to model the reviews as a mixture of latent topics. Once the E-LDA is sufficiently trained to distinguish the key words corresponding to each topic, we use it for the discriminative task of labeling each review sentence to a most probable topic. In addition, we analyze the student opinion associated with each review sentence by means of lexicon-based sentiment analysis, which derives the sentiment by employing several rules (to capture negation, review intensity, emoticons, etc.) and dictionary of positive and negative words annotated with their semantic orientation (polarity and strength). Finally, a student-centric SWOT analysis is conducted using the topic-based opinion summary (TOS) obtained by combining the student opinion of the predefined topics. Figure 1 provides an overview of the proposed approach.

PLEASE INSERT FIGURE 1 HERE

3.1. Web Scrapping and Text Pre-Processing

The student reviews of the university under study and its competitors are scraped from an online university review site using Python, a programming language that provides the flexibility of both text mining and text analysis. The competitors were chosen based on the similarities of following factors: graduation rate, median SAT scores of admitted students, tuition fee, total student enrollment, and student to faculty ratio. Each student review might not be centered around a single aspect of the university. Therefore, each review is separated as individual sentences and the sentences are treated as independent comments. Following the extraction, the data is cleaned by detecting and removing incomplete, duplicate and irrelevant reviews. Subsequently, the sentences are prepared for topic modeling and sentiment analysis by tokenizing, eliminating special characters and non-English words, stemming inflected words, converting to lower-case characters and removing stop and infrequent words. This is achieved by modules that are available in the Python natural language toolkit (NLTK). In addition to the default English stop words in the NLTK toolkit, we also created a custom set of stop words to filter unnecessary words that do not add value for topic modeling or sentiment analysis. Figure 2 provides a comparison of the actual and pre-processed review sentence.

PLEASE INSERT FIGURE 2 HERE

3.2. Topic Identification using Ensemble of Latent Dirichlet Allocation (E-LDA)

After pre-processing, the review sentences are randomized and split into learning (training) data and held-out data, where the proportion of the learning data is substantially higher. We use the reviews in the training data as inputs to the LDA. To extract the topics, it is assumed that a total of N words constitutes a student review (r) with the word sequence denoted by $w = (w_1, w_2, \ldots, w_N)$. Further, it is also assumed that all the reviews $(r = 1,2, \ldots, R)$ are combined together to form a corpus D, which contain word set $\{w_1, w_2, \ldots, w_R\}$. The generative process of LDA algorithm, given by Blei et al. (2003), for each review in a corpus D is as follows:

1. Choose $N \sim \text{Poisson}(\xi)$
2. Choose $\theta \sim \text{Dir}(\alpha)$
3. For each of the N words w_n:
   (a) Choose a topic $z_n \sim \text{Multinomial}(\theta)$
   (b) Choose a word w_n from $p(w_n|z_n, \beta)$, a multinomial probability conditioned on the topic z_n.

where α and β are hyper-parameters of the Dirichlet prior determined based on the topic distribution and word distribution, respectively, in the review document; θ is the data generating K-dimensional Dirichlet random variable.

The probability density function of the topic distribution θ conditioned on Dirichlet prior parameter α is given by Equation (1).

$$p(\theta|\alpha) = \frac{\Gamma(\sum_{k=1}^{K} \alpha_k)}{\prod_{k=1}^{K} \Gamma(\alpha_k)} \theta_1^{\alpha_1 - 1}, \ldots, \theta_K^{\alpha_K - 1} \quad (1)$$

The joint distribution of a topic mixture θ, a set of N topics z, and a set of N words w is given by Equation (2).

$$p(\theta, z, w|\alpha, \beta) = p(\theta|\alpha) \prod_{n=1}^{N} p(z_n|\theta)\, p(w_n|z_n, \beta) \tag{2}$$

where $p(z_n|\theta)$ is simply θ_i for the unique i such that $z_n^i = 1$. The marginal distribution of a document can be obtained by integrating over θ as shown in Equation (3).

$$p(w|\alpha, \beta) = \int p(\theta|\alpha) \left(\prod_{n=1}^{N} \sum_{z_n} p(z_n|\theta) p(w_n|z_n, \beta) \right) d\theta \tag{3}$$

The probability of a corpus is obtained by taking the marginal probabilities of all documents and is presented in Equation (4).

$$p(D|\alpha, \beta) = \prod_{d=1}^{R} \int p(\theta_d|\alpha) \left(\prod_{n=1}^{N_d} \sum_{z_{dn}} p(z_n|\theta_d) p(w_{dn}|z_{dn}, \beta) \right) d\theta_d \tag{4}$$

The output of the LDA would include a list of words grouped by a topic, where the words are ordered in decreasing probability for being in that topic. However, human effort is required to assign topic title, and is done by interpreting the words in the topic matrix. Since LDA uses Collapsed Gibbs Sampling (CGS) in its implementation, the results (word distribution for each topic) from multiple runs on the same set of reviews are usually different and inconsistent (Groof and Yu, 2017). Thus, to overcome this problem we train multiple LDA models in parallel and store the trained models in a local repository to be used later for sentence labeling. The LDA models are coded using Python with the GENSIM toolkit.

3.3 Sentence Classification

Subsequent to the topic identification process, the LDA can be used for the discriminative task of labeling each review sentence under one of the $K = \{T_1, T_2, \dots, T_K\}$ topics. Given a sentence S, each of the trained LDA models ($l \in L$), provides the topic distribution of that sentence. To classify the sentence to a topic, we first consider a plurality voting of the topics labeled by the LDA models, where each LDA model labels the sentence based on the most probable topic. If $P(T_k|l, S)$ denotes the probability of occurrence of topic k given sentence S and model l, then the most likely topic assigned to S by model l is given by $top_{lS} = \mathrm{argmax}_k\{P(T_k|l, S): k = 1,2, .. K\}$. Based on plurality voting of all the LDA models, the topic for sentence S, is given by $Topic_S = \mathrm{mode}\{top_{lS}: l \in L\}$.

However, if there is a tie (i.e., more than one mode or no mode), then we identify the maximum of the probability of the most likely topic across all LDA models. In other words, we determine the most probable topic and the corresponding probability for a given sentence S across all the LDA models as shown in Equations (5) and (6), respectively.

$$M = \underset{k}{\operatorname{argmax}}\{P(T_k|S): k \in K\} \quad (5)$$

$$P(M|S) = \max_{k}\{P(T_k|S): k \in K\} \quad (6)$$

where $P(T_k|S) = \max\{P(T_k|l, S) : l \in l\}$

We assign the sentence to topic M, if $P(M|S)$ is greater than a threshold parameter γ. Whereas, if $P(M|S)$ less than the threshold parameter, then the sentence is assigned to 'Null' topic, which indicates that S does not belong to any one of the K topics. For example, objective sentences such as "*I am a sociology major*" or "*I live close to campus*" are intended to be classified under the 'Null' category.

A summary of the sentence labeling procedure is given in Equation (7).

$$Topic_S = \begin{cases} \text{mode}\{top_{ls}: l \in L\} & \text{if there exisits a unique mode} \\ M & \text{if } P(M|S) > \gamma \text{ and no unique mode} \\ Null & Otherwise \end{cases} \quad (7)$$

Thus, using the sentence classification procedure, each sentence in the corpus is grouped into any one of the identified topics.

3.4 Testing Procedure

To perform extrinsic evaluation, we compare the LDA inferred topic with the ground truth (actual topic). We use the trained LDA to label the sentences in the held-out data (i.e., data not used for learning). The ground truth is determined by using human annotators, who manually categorize each sentence in the held-out data into a topic. The annotators only have prior knowledge of the list of identified topics and are asked to categorize each sentence under the list of topics given to them. We discard sentences for which we observe discrepancies in the judgments among annotators. Thus, the manually annotated sentences that are in agreement among all the annotators are considered to be the ground truth. To quantitatively evaluate the performance, we consider topic-wise recall, precision and F_1 score, the most commonly used evaluation metrics in text classification (Sokolova and Lapalme, 2009). Precision for a given topic is the proportion of correct classifications of that topic among all the instances, where the

E-LDA model declared that topic. Recall for a topic is the fraction of correct classifications of that topic out of all the cases of that topic in the ground truth. The F_1 score of a topic is the harmonic mean of recall and precision of that topic and is given in Equation (8)

$$F_1\ Score\ for\ topic\ k = 2 \times \frac{precision_k \times recall_k}{precision_k + recall_k} \tag{8}$$

The maximum value for the F_1 score is one, which indicates that the classifier has correctly classified all the instances in the test data.

3.5 Sentiment Analysis

In addition to sentence labeling, the opinion polarity (positive, negative or neutral) associated with each sentence must be determined to obtain the TOS. To determine the sentiment score of each sentence, we use the Valence Aware Dictionary and sEntiment Reasoning (VADER), a rule-based method for sentiment analysis method proposed by Gilbert (2014). VADER has unique advantages over several sophisticated machine learning techniques such as support vector machine (SVM) with respect to computational time and F-1 score accuracy (Gilbert and Hutto, 2014). Another reason for particularly using VADER in this research is its ability to process sentence characteristics along with textual properties to determine sentence score. Moreover, Riberio et al. (2016) compared 24 sentiment analysis methods to identify sentiment polarity (positive, neutral or negative) and found VADER to consistently be the best performer across varying datasets.

For a given sentence, VADER determines the polarity score between -1 to +1, where -1 indicates extremely negative and +1 indicates extremely positive. In addition to retaining the advantages of traditional lexicon-based methods, VADER also uses different rules (heuristic approaches) to calculate the valence (or polarity) score. Using these rules, it accounts for word-order sensitive relationship between terms by considering the following: punctuations (e.g., “Campus is safe!!!” is more intense than “Campus is safe”), capitalization (e.g., “PROFESSORS ARE AMAZING” is more intense than “Professors are amazing”), degree modifiers (e.g., “Campus is *extremely* unsafe” is more intense than “Campus is unsafe”), contrastive conjunction (e.g., “School plans a lot of events *but* needs to advertise better”) and negation identification (“Counselors did *not* show any interest in helping freshmen”). We converted the polarity score to a polarity class by using thresholds.

3.6. SWOT Analysis using Topic-Based Opinion Summary

For each university, the sentiment of all the sentences is combined by their topics to obtain the TOS. These results are then used to conduct student perceived SWOT analysis for the university under study. SWOT is a tool most commonly used for recognizing the strategic factors (both internal and external) that are important to the future of the enterprise (Kurttila et al., 2000). The strengths and weaknesses are identified by analyzing the internal characteristics of the organization, while opportunities and threats constitute the external elements such as competition. The basic framework of SWOT analysis is shown in Figure 3. Such a SWOT assessment highlights the important factors that influence the students' viewpoint of the university and can aid the university in their planning decisions.

PLEASE INSERT FIGURE 3 HERE

4. Case Study

In this section, we illustrate the feasibility of the proposed approach using a case study. First, the parameters related to the case study is discussed. We then validate the performance of the proposed E-LDA, and identify the aspects from online reviews. Finally, we present the results of SWOT analysis and discuss the managerial implications of this research.

4.1 Case Study Parameters

We consider a public university in California with a six-year graduation rate of only 52%. In addition, we also consider six competitors (or similar universities) in the US – three within the same state and three located outside California. Students may prefer in-state colleges due to reduced tuition rate, additional financial aid, and comparatively easier acceptance. However, during recent times many students are migrating to out-of-state university due to various reasons such as specialized program offerings, assistantship opportunities, and greater independence. Therefore, we chose three in-state (Competitor University 1 – 3) and three out-of-state competitors (Competitor University 4 – 6) for our case study. The chosen universities had similar graduation rates (Mean = 51%; SD = 5%), ACT requirement (Mean = 1026, SD = 20.91), tuition fee (Mean = $22,734, SD = $804.68), total enrollment (Mean = 20,818, SD = 4026.08), student to faculty ratio (Mean = 22.60, SD = 7.42). The models were coded using Python programming language and executed on a computer running Windows 10 with i7 processor and 64GB RAM.

In total, we scraped 24,390 reviews posted by students in different fields of study over the last five years from niche.com, an information-rich website with over 100 million student reviews. The mined reviews had approximately 100,000 unique sentences with an average review length of 170 words. Since manual annotation is a time-consuming task, we only held out 10% of the retrieved data for extrinsic evaluation and used the remaining 90% for unsupervised learning. We observed that an ensemble of three LDAs and a threshold parameter (γ) of 0.7 performed well by achieving a good trade-off between accuracy and computational complexity. We also considered a randomly-seeded LDA (traditional LDA) as a benchmark model, which classifies a sentence to the most probable topic only if its probability exceeds the threshold parameter (γ). We used two annotators to manually label the held-out reviews and 8920 review sentences were in complete agreement (i.e., sentences categorized under the same topic by both the annotators). For sentiment analysis using VADER, we consider the sentence sentiment to be negative if the polarity is less than -0.05, positive if the polarity score is greater than +0.05, and neutral if the polarity score is between (-0.05, 0.05).

4.2 Experimental Results

We were able to infer twelve meaningful topics (aspects) based on categorizations from the three LDAs. Table 1 lists the twelve topics along with its brief description and the top five words that have the highest probability conditioned on that topic. We can see that in addition to commonly discussed topics such as academic support and faculty, students frequently post about unexpected subject matters such as parking and transportation.

PLEASE INSERT TABLE 1 HERE

Based on the topics identified, the held-out reviews are independently annotated into one of the 12 student-interested topics as well as a "Null" topic by two volunteers. Figure 4 compares the distribution of topics in ground truth (obtained based on annotators labeling) and E-LDA inferred. It can be observed that the topic distribution inferred by the E-LDA closely matches with the ground truth. We can also see that 'Faculty' is the most discussed topic among the students while all the other topics are almost equally distributed. Yet this does not necessarily highlight the performance of the E-LDA as it does not compare sentence-level agreement. Thus, to quantitatively evaluate the two approaches (randomly-seeded LDA and E-LDA), we compute topic-wise precision, recall and F_1 score. Observing the values of these measures in Table 2, it is apparent that E-LDA consistently outperforms randomly-seeded LDA, which align with the findings in the literature about obtaining better performance with ensemble techniques. Further, a high-value of topic-wise precision and recall value indicates that the E-LDA model is able to accurately label a majority of the sentence to its most probable topic.

PLEASE INSERT FIGURE 4 HERE

PLEASE INSERT TABLE 2 HERE

After verifying the performance of the E-LDA on the held-out review data, we use the trained model to label each of the extracted review sentences to its most probable topic. In other words, all the 100,000 review sentences (i.e., review sentence corresponding to the university under study and its competitors) are classified into one of the identified topics. In addition, we also use VADER method and obtain sentence-level sentiment for all the review sentences.

4.3. Results of SWOT Analysis

Figure 5 presents the TOS for the university under study and highlights the overall positive (strengths) and negative (weaknesses) topics from the student's perspective. It is evident from Figure 5 that a majority of the students comment positively on the following topics: 'Job Prospects', 'Faculty', 'Food', 'Diversity', 'Social Life' and 'Weather'. On the other hand, most students have negative opinions on the following topics: 'Academic Support', 'Financial Aid', 'Housing', 'Safety' and 'Parking & Transportation'. However, a majority of the review sentences consider 'Sports' to be neither positive nor negative.

PLEASE INSERT FIGURE 5 HERE

We further investigate the weaknesses by automatically mining the most frequently occurring bi-grams (i.e., a sequence of two adjacent words) in the review sentences. For each weakness, we filter the review sentences expressing negative opinion, process it (stop words removal, tokenization) and then mine them to obtain the most frequently occurring bi-grams. These bi-grams indicate the underlying problem related to that topic. In addition, it also facilitates manual scrutiny of these sentences using the frequently occurring keywords. We consider a bi-gram to be frequent if it occurs in at least 15% of the review sentences. An example of the most frequently occurring bi-gram for the weakness 'Parking & Transportation' is shown in Figure 6.

PLEASE INSERT FIGURE 6 HERE

Thus by adopting a similar approach, we assess the underlying cause for strong negative opinion of all the weakness. The root cause analysis of student dissatisfaction (negative opinion) is illustrated using the Ishikawa cause and effect diagram (Figure 7). The primary causes are the weaknesses identified using the TOS, and the secondary causes are found using the bi-gram analysis and manual keyword scrutiny of the review sentences. For the *academic support* aspect, the common complaint among the students was the policy to allow non-affiliated individuals into university library resulting in safety issues and lack of seating. Other academic support feedback was related to the lack of user-friendly course registration software, crowded labs and slow computers. Students felt the *financial aid* office at the university under study was inefficient, mainly because the staffs misplace several student documents leading to repetitive, time-consuming tasks. They also criticized excessive paperwork, long processing times and outdated information on the financial aid webpage. As far as *housing* is concerned, students felt that it is unfair to have the same student housing rates for residents living in renovated modern dorms compared to those living in old dorms. Expensive student-housing options and lack of on-campus family housing are few other perceived drawbacks. The secondary causes for the *parking and transportation* aspect are expensive permits, insufficient parking spots and lack of metered parking for students. Students also reported the absence of proper shuttle services within the university. *Safety* is an issue due to its location as there is a substantial presence of homeless people, drug addicts and miscreants on or near campus. Even though the campus police are taking their efforts to control crime, students complain about the lack of surveillance camera near dorms and police patrol near high-risk areas such as garages and ATMs.

PLEASE INSERT FIGURE 7 HERE

We also obtain a TOS for the six competitor universities (shown in Table 3) to investigate the potential opportunities and threats for the university under study. 'Transportation & Parking' is the leading cause of student dissatisfaction for both in-state and out-of-state universities. In addition, 'Housing' is considered as one of the leading factors for student dissatisfaction in most of the universities (Competitor Universities 2, 3, 4 and 6). It can also be observed that students negatively perceive the 'Academic Support' and 'Financial Aid' services provided by the in-state universities. Also, it is interesting to note that the students in all the competitive university are not unhappy with the 'Safety' aspect. Clearly, students in the out-of-state competitor universities (Competitor University 4 – 6) speak positively about their academic support aspect compared to the university under study. Similarly, Competitors 4 and 5 fare better in terms of 'Financial Aid'. The findings presented in Table 3 will allow us to investigate topic-specific reviews rather than examining the entire pool of available reviews.

PLEASE INSERT TABLE 3 HERE

To gather competitive intelligence, we identified the strength and weaknesses of the competitor universities and further analyzed student reviews pertaining to these traits. We uncovered two opportunities. First, we observed that all the competitor universities are underperforming with respect to 'Parking & Transportation' aspect. Therefore, the university under study can capitalize on this aspect by considering innovate solutions to improve parking operations. To partially offset the financial crisis, Competitor University 1 has the student-sponsor program in which faculty-student team provides a customized industry solution to benefactors, and the industry, in turn pays a sponsorship fee, thus benefitting from this low-cost means. Competitor University 1 also has student offices at sponsor sites, and businesses utilize the students as skilled employees. Such a strategy would greatly benefit the university under consideration because of its location in California, a state that headquarters thousands of industries.

There are two main threats that we have observed during our analysis. An overwhelming majority of students at competitor universities 1 and 5 had positively reviewed about the expansion of their residence halls. Nevertheless, construction of new on-campus dormitories for the university under consideration is not feasible due to its location being in concentrated land areas. A substantial number of students in the university under study complained about insufficient financial aid coupled with the high cost of living in California. In addition, the state budget cuts could further worsen this situation. Whereas, students in out-of-state universities (Competitors 4 and 5) did not have many grievances about these issues. Thus, such a trend would be a significant threat as it could adversely affect the enrollment and retention rates.

4.4. Managerial Implications

Based on the TOS in Table 3 and subsequent bi-gram analysis of competitors, we put forth the following managerial implications to improve student satisfaction.

- *Increase lighting throughout the campus*: Based on the reviews, students reported misconducts at parking lots and walkways. On the other hand, students at Competitor University 1 indicated that they felt safe to walk due to a well-lit campus. Therefore, it is recommended to install motion sensor energy efficient lighting fixtures, which can increase campus safety while reducing energy usage.
- *Restricted public access to library*: Since most students complained of homeless people entering the library in the evening, restricting the library access to visitors beyond a certain time could avoid such problems. Based on the student reviews at Competitor University 6, we understand that due to crimes such as armed robbery, the universities have decided to either close their libraries for public access or increase security cameras.
- *Training of financial aid staff*: Several HR departments at universities offer recurring staff training and we advise the same for staffs working at office of financial aids, to increase student satisfaction. Additionally, 5S organization method can be adopted at the financial aid office to reduce misplacing student documents.
- *Crime control*: Even though the university under consideration takes measures to control crimes on campus, students' feedback suggests the lack of foot patrolling by police.

Hence, we strongly recommend patrolling by foot or bicycles. Also, we observed that students from Competitor University 6 boasted about the presence of emergency call boxes on their campus and this would be another option to consider.

- *Online and distance learning programs*: Even though the university offers evening classes, some student reviews express their challenge of continuing their profession while pursuing academic credentials. Our review analysis observed that competitor universities 5 and 6 have distance-learning programs. They prepare lecture recording which provides students the flexibility to plan their study time while employed. We suggest that university can increase the number of online degree program offering to increase enrollment.
- *Renovating dormitories*: According to student reviews, Competitor University 2 is expanding the housing options and Competitor University 5 is renovating its dorms. Given that students complain about old dormitories, we propose that the university renovates the dormitories and add additional floors to enhance students' housing experience.
- *Parking solutions*: Based on the opportunity observed, we advise the use of portable parking meter, an electronic device that uses pre-paid smartcards and is placed on a vehicle's rearview mirror. In addition, class times can be scheduled in such a way that all students are not rushing to campus at the same time.
- *Optimal allocation of Safety Resources:* Many students at the university under study complained on the lack of surveillance cameras and police patrol near high-risk areas. To alleviate this problem, the university must understand the offense patterns and identify crime hotspots by analyzing historical campus crime data. This would enable the university to proactively deploy their resources and targeted placement of surveillance system.

5. Conclusions

Studies have shown that the most efficient means of increasing student enrollment is through positive word-of-mouth from current students. Almost all research on enhancing student satisfaction focused on using social research methods such as conducting surveys to understand the voice of students. However, these methods suffer from limitations such as hardship of capturing emotional responses and incorrect interpretation of questions by respondents. In this study, we proposed an approach to identify the SWOT of a university from the students' perspective using text analytics of online reviews. In our approach, we introduced an ensemble technique, E-LDA, to automatically mine online reviews for identification of key topics and classification of reviews sentences into one of the topics. Supervised approaches for topic identification and sentence classification require a large amount of labeled data set for training and testing, whereas, unsupervised methods may not achieve high classification accuracy. However, the proposed E-LDA achieves a compromise between the two approaches. We then determined the student opinion associated with each topic using VADER sentiment analysis tool. Finally, we used the TOS to conduct SWOT analysis. The strengths and weaknesses of the university were respectively based on student compliments and criticisms, while the opportunities and threats were identified based on examining the online reviews of the competitors.

To illustrate the viability and effectiveness of the proposed approach, we considered a public university in California, and retrieved student review comments from an online source for that university along with six current competitors. Our evaluation of the proposed E-LDA ascertained its ability to automatically identify critical topics and accurately classify the review sentences into its corresponding topics. We identified 12 meaningful topics using the proposed approach and conducted SWOT analysis to determine the critical factors that influence the students' viewpoint of the university. We also put forth several managerial implications to the university's governing bodies that can aid them in their planning decisions to improve student satisfaction, university reputation, and enrollment and retention rates. In addition, our approach provides tremendous value to the university's leaders as it delivers efficient and economic performance summary of the university and its competitors from the student's perspective.

In future research, we would like to extend our approach to capture the voice of the customer as well as the voice of the employee by combining data from multiple sources. We would also like to validate the proposed approach on different domains and datasets.

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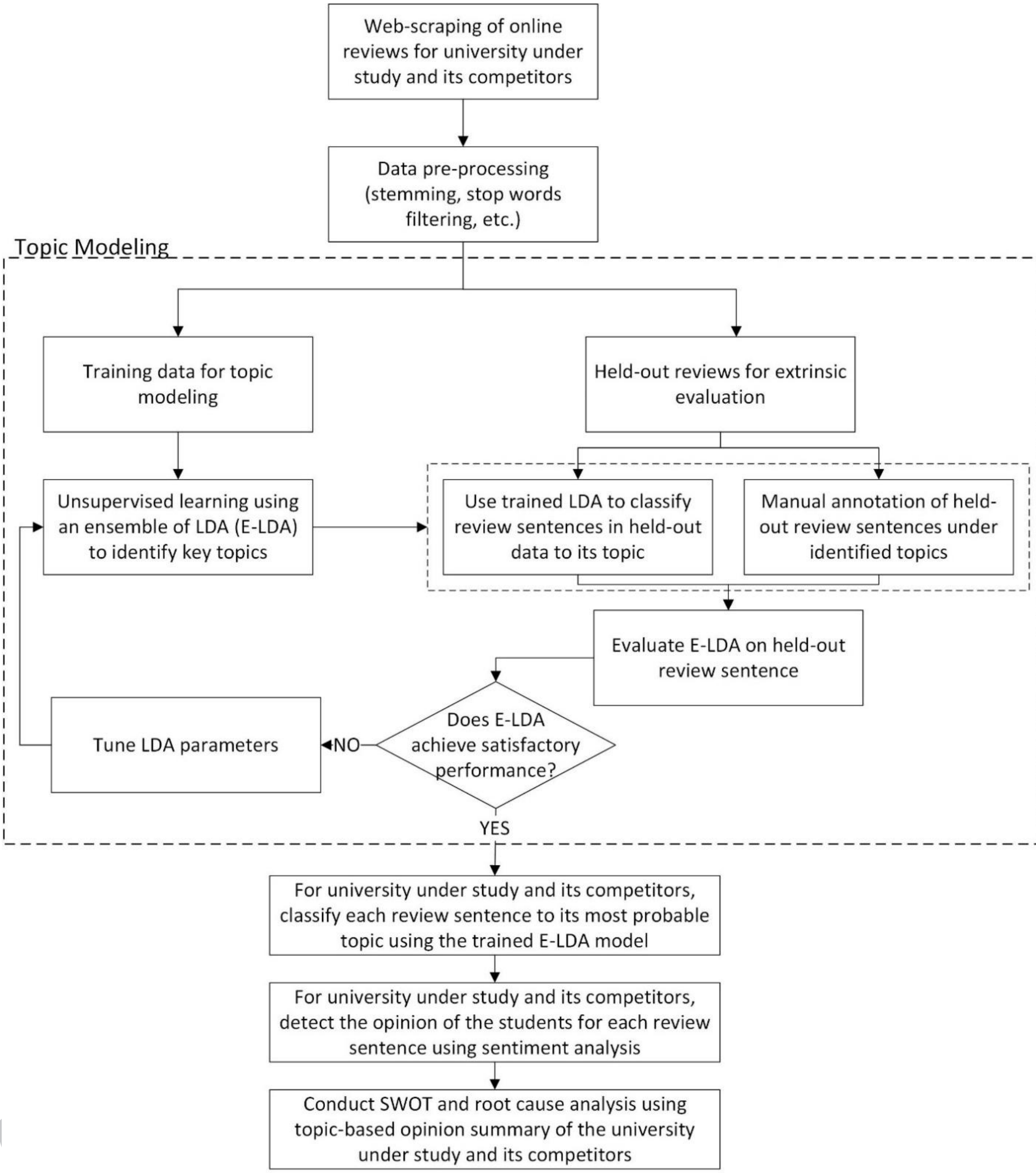

Figure 1: Overview of Methodology

Actual Review: *"The Wait Time for financial aid to process and to receive a notification that the process has been complete takes way too long."*

Pre-Processed Review: [*'wait', 'time', 'financi', 'aid', 'process', 'receiv', 'notif', 'process', 'complet', 'take', 'way', 'long'*]

Figure 2: Comparison of Actual and Pre-Processed Review Sentence

	Strengths	**Weaknesses**
Internal	University services that enrich student's experience and leads to positive WOM (e.g., small class size; friendly staff members)	Qualities and identities of university that lack pride among students (e.g., inefficient operational structure/bureaucracy)
	Opportunities	**Threats**
External	Potential changes that university can adopt to enhance reputation (e.g., introduction of new technologies in market, adapting unique practices followed by similar institutions)	Obstacles that the university faces due to external environment (e.g., economic crisis)

Figure 3: Basic Framework of Student Experience SWOT Analysis

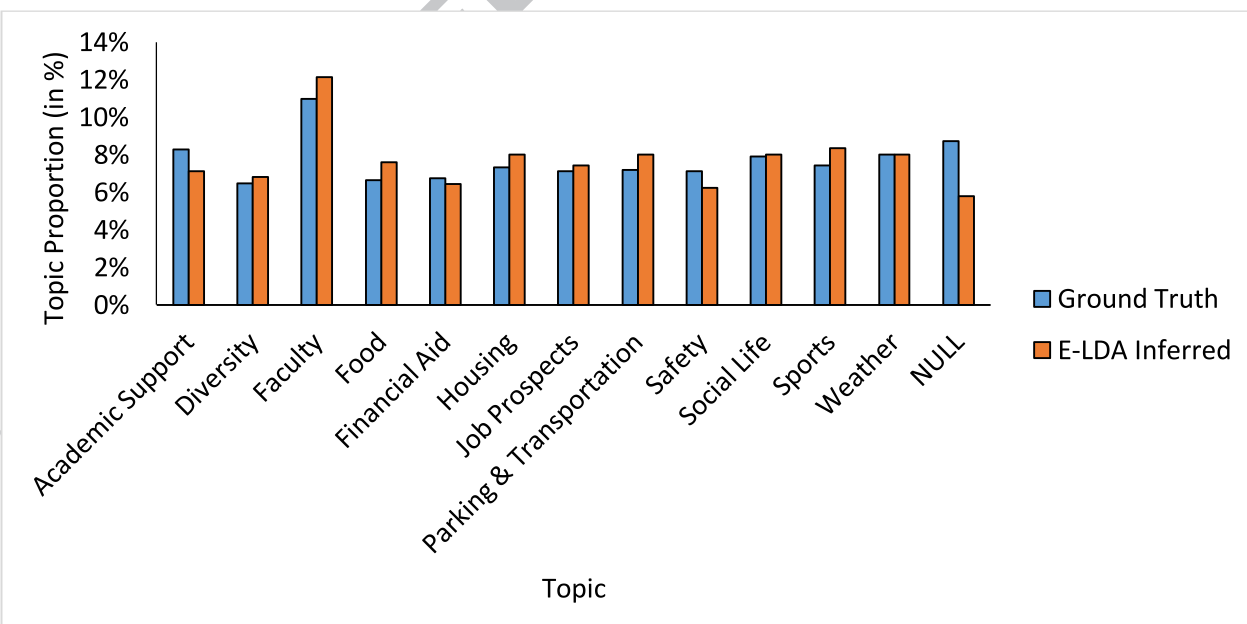

Figure 4: Proportion of Topics in the Ground Truth versus Proportion Inferred by E-LDA

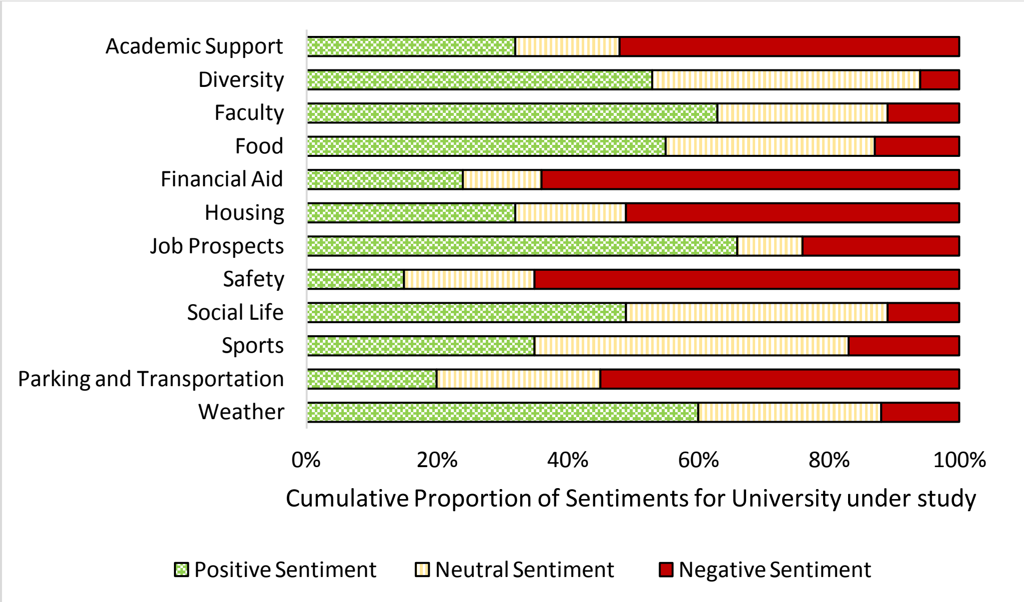

Figure 5: Topic-Based Opinion Summary

('pass', 'expensive'), ('parking', 'problem'), ('parking', 'garage'), ('parking', 'parking'), ('parking', 'permits'), ('parking', 'tickets'), ('time', 'finding'), ('finding', 'parking'), ('constant', 'traffic'), ('permits', 'cost'), ('daily', 'permits'), ('permits', 'expensive')

Figure 6: Frequently occurring bi-grams for negative opinions related to 'Parking & Transportation' topic

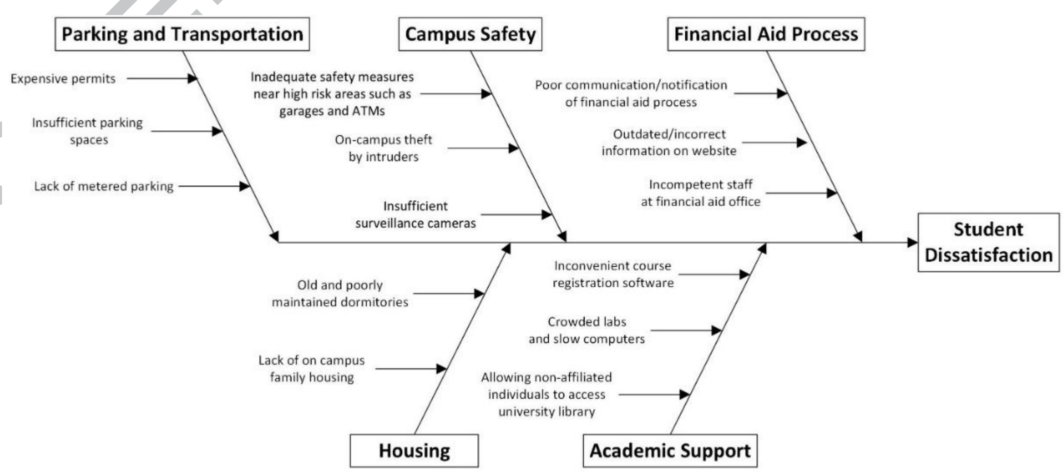

Figure 7: Root Cause Analysis of Topics with Overall Negative Sentiments

LIST OF TABLES

Table 1: Top Five Words According to Aspect (Topics)

Topic	Description	Significant Words
Academic Support	Educational amenities and resource availability for students	Computer, Library, Registration, Lab, Center
Diversity	Distribution of student population with respect to demographics	Diverse, Ethnic, Culture, People, Different
Faculty	Characteristics of faculty such as teaching competency and approachability	Professor, Teacher, Learn, Course, Academics
Food	Attributes of food that is offered on-campus and off-campus, such as quality, variety and price	Food, Eat, Option, Restaurant, Variety
Financial Aid	Resources and services provided by the university to obtain financial aid	Aid, Financial, Time, Process, Office
Housing	Housing options and availability for students	Live, Dorm, House, Apartment, Room
Job Prospects	Potential to be employed after graduation	Job, Internship, Opportunities, Business, Requirements
Safety	Student's perception of campus safety	Safe, Police, Emergency, Crime, Secure
Social Life	Opportunities for doing enjoyable activities	Party, Bar, Social, Nightlife, Fun
Sports	Sports culture of the university and the sports facilities provided by the university	Sport, Team, Athletics, Football, Spirit
Parking & Transportation	Parking facilities and transportation services provided by the university	Parking, Spot, Bus, Permit, Commute
Weather	Weather conditions	Weather, Hot, Sunny, Cold, Winter

Table 2: Topic-wise Performance Measures

Topic	LDA			E-LDA		
	Precision	Recall	F_1 Score	Precision	Recall	F_1 Score
Academic Support	0.74	0.60	0.66	0.82	0.76	0.79
Diversity	0.74	0.54	0.63	0.75	0.79	0.77
Faculty	0.61	0.79	0.69	0.84	0.93	0.88
Food	0.77	0.62	0.69	0.78	0.85	0.81
Financial Aid	0.73	0.67	0.70	0.86	0.81	0.84
Housing	0.78	0.62	0.69	0.77	0.86	0.81
Job Prospects	0.55	0.49	0.52	0.71	0.74	0.72
Safety	0.84	0.53	0.65	0.89	0.72	0.80
Social Life	0.71	0.59	0.65	0.80	0.77	0.79
Sports	0.71	0.59	0.64	0.82	0.82	0.82
Parking & Transportation	0.87	0.59	0.70	0.84	0.91	0.87
Weather	0.84	0.85	0.85	0.84	0.94	0.89
NULL	0.26	0.45	0.33	0.64	0.48	0.55

Table 3: Topic-Based Opinion Summary of All Universities

Topic	University under Study		Competitor University 1		Competitor University 2		Competitor University 3		Competitor University 4		Competitor University 5		Competitor University 6	
	Positive Sentiment	Negative Sentiment	Positive Sentiment	Negative Sentiment	Positive Sentiment	Negative Sentiment	Positive Sentiment	Negative Sentiment	Positive Sentiment	Negative Sentiment	Positive Sentiment	Negative Sentiment	Positive Sentiment	Negative Sentiment
Academic Support	32%	52%	35%	49%	30%	53%	36%	49%	50%	12%	50%	15%	56%	11%
Diversi	53%	6%	54%	5%	59%	6%	56%	6%	53%	7%	53%	8%	57%	8%

ty														
Faculty	63%	11%	68%	11%	66%	11%	61%	14%	66%	11%	66%	11%	69%	10%
Food	55%	13%	51%	11%	46%	10%	48%	12%	43%	13%	50%	13%	46%	11%
Financial Aid	24%	64%	40%	40%	25%	55%	24%	51%	66%	12%	50%	15%	35%	25%
Housing	32%	51%	62%	12%	29%	54%	39%	44%	39%	43%	60%	18%	40%	41%
Job Prospects	66%	24%	60%	6%	68%	13%	61%	8%	53%	10%	54%	8%	53%	10%
Parking	20%	55%	19%	55%	18%	54%	23%	62%	27%	58%	28%	60%	32%	52%
Safety	15%	65%	55%	22%	53%	25%	48%	25%	49%	26%	52%	25%	58%	21%
Social Life	49%	11%	58%	11%	62%	10%	48%	29%	29%	49%	53%	28%	58%	22%
Sports	35%	17%	65%	6%	50%	22%	53%	17%	45%	22%	65%	10%	72%	8%
Weather	60%	12%	59%	12%	65%	9%	58%	16%	38%	32%	33%	45%	33%	43%

Highlights

- Uses text analytics of online student review to identify voice of customers
- Introduces ensemble topic model to extract topics and label reviews automatically
- Integrates four different techniques: topic modeling, opinion mining, RCA, SWOT
- Provides efficient & economic performance summary of university and its competitors
- Helps university leaders in student-centered strategic planning