Predicting Students' Satisfaction Towards Online Courses Using Aspect-Based Sentiment Analysis

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Abstract. In recent times, quality of teaching and students' participation is monitored in most of the universities and colleges to improve academic performance. Outcome-based education system also requires experiential learning. Student opinion is one of the powerful mechanisms to evaluate academic activity and quality in education system. It helps to decide on corrective measures towards various entities of teaching and learning process. Many research studies have been carried out in classifying the sentiment polarities of opinions. In educational domain, very limited study is carried out in fetching the key aspects or entities from the students' review. Mining the opinions in a deeper level to fetch the specific aspects confined to the topic will bring productive results. In this paper, aspect-based sentiment analysis is carried out at sentence level to find the students' satisfaction with reference to the online courses using machine learning algorithm. The proposed system has attained improved accuracy than the existing model. From this study, the specific aspects are obtained using both unsupervised and semi-supervised LDA algorithms. Students' satisfaction with specific aspects of the online courses also examined.

Keywords: Aspects · Sentiment analysis · Machine learning · Course reviews · LDA · Education

1 Introduction

Generally, every human [8] prefer to refer the opinion of friends and family before purchasing a product. Researchers and companies tend to use the conventional methods of polling and surveys for collecting information. Common sentiment analyzer that defines [2] the overall sentiment towards the product or service is not enough to describe the entire context of the review. Hence for efficient and fine-grained analysis of user feedback the demand of Aspect-based Sentiment Analysis arises, which would facilitate service providers and product manufacturers to detect the context specific aspects that requires improvement. The Aspect Category Detection process consists of finding every entity E and attribute A pair E#A towards which an opinion is stated in the given review.

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In review summarization procedure, aspect extraction is considered as a significant task [10] to gain a full view about the evaluation of the products or services from the review comments. Sentiment analysis on subjectivity is an essential indicator for developing products and services according to customer's preferences and to satisfy customers in the areas where negative feedback is earned [14].

In this paper, our aim is to suggest a model that facilitates online course providers achieve greater insights and an extensive view of their course takers' requirements. Therefore, the proposed model inspects the course reviews data and improves the course providers' service perspectives. Aspect-based sentiment analysis (ABSA) model is helpful to extract the sentiments thoroughly, from the reviews of electronic products on specific brands. Other relevant sources are discussion forums where people give reviews and share their experiences in using the product [11]. ABSA is widely applied to gain useful insights. Very little number of researches is carried out in analyzing the sentiments at aspect level in education domain. In teaching learning process, students' feedback is an effective [7] tool that gives valuable insights. Handling opinions of students expressed in reviews is a quite laborious and tiresome task. This task may be feasible for small scale courses that involve less amount of students' feedback; it is impractical for large-scale online courses providers like MOOCs. In the teaching–learning process, classifying opinionated texts [5] at document level or at sentence level is helpful but it does not suggest required points for further enhancement. Aspect-Based Sentiment Analysis is quite new field of study [13] and extensive research is must to attain a higher level. Simple sentiment polarity analysis on a particular domain is not sufficient to meet the needs of people and organizations. We should have more understanding on what aspects are presented when the student gives opinion about the teachers. Aspect-based SA is valuable from both user and enterprise point [8] of view. The unsupervised dependency-based methods do not require any [6] human labeled data. Opinions have targets and there exists explicit syntactic relations between opinion words (e.g., "good") and target aspects (e.g., "screen").

In this paper, the specific aspects of the feedback reviews are fetched. It facilitates to acquire discernment on particular entity about the online course which would be helpful to take corrective decisions in course designing. Aspect-Based Sentiment Analysis (or even Text/Opinion Mining in general) on any review may serve well [13] for applying future methodologies to the problem. In document-level sentiment analysis, the mining gives opinion about whole reviews [5]. The overall framework of this paper relies on aspect-level sentiment analysis and focuses on classifying sentiment and polarity expressed in relation to a given aspect associated to the reviews given for the online courses offered by Coursera. The open dataset available in Kaggle repository is taken for research.

The rest of this paper is arranged as follows. Section 2 gives a brief overview of ABSA. Section 3 presents the related work carried out in ABSA. In Sect. 4, objectives and limitation of the research study is presented. System framework is presented in Sect. 5. In Sect. 6, methodology of the study and implication of results are explained. Finally, in Sect. 7, the conclusion is portrayed.

2 Overview of Aspect-Based Sentiment Analysis

Aspect term extraction is an effective method to trace out aspect terms in reviews. Aspects can be categorized as explicit or implicit. Explicit aspects are clearly stated in the review itself; the implicit aspect term is not present in the text [8] but it is implied by another term. Identifying relevant aspects of an entity is very significant [12] to discover the specific areas of improvement. Detecting explicit aspects can be done at ease but implicit aspects detection is cumbersome, without human involvement [10]. Aspect grouping deals with hierarchical alignment of aspects [8]. Aspect weight rating aims to find the importance of each aspect for each entity; this is vital to companies to discover the key aspects of their products from the customers' viewpoint. In aspect-based recommendation, the goal is to produce suggestions for other users based on the aspects examined in existing reviews. Aspect summarization gives an overview of total polarity of aspect groups for each entity.

Aspect extraction and Topics modeling are constantly used [14] in text mining literature which extracts bunch of text features related to a specific topic based on the frequency of words within the sentence. Here one topic can be viewed as a set of words having a similar meaning. Topic model covers the feature that one document can bring on several topics**.** LDA model differs from Seeded-LDA where it allows user to pre-define topics with keywords to carry out context-based analysis of textual data. In the LDA selection model, lots of contextually important words [10] can be missed. Both methods are implemented to distinguish the efficiency in topic categorization. In topic analysis model, topic coherence is useful measure to evaluate the topics extraction. Coherence value decides the quality [10] of the topics by calculating the semantic similarity of the words representing the topics. While using the LDA model, this measure provides an idea of deciding the topics.

3 Related Work in ABSA

Several research papers have been committed to sentiment analysis study. In this section, the literature review of aspect-based sentiment analysis on different domains is carried out which is the focal point of the study. Aspect-based Sentiment Analysis on employer branding domain [1] is carried out for giant companies Amazon, Apple and Google using Glassdoor platform. After preprocessing the reviews using Stanford POS tagger the nouns are extracted and then the keywords are categorized into some of the predefined categories. The keywords in each aspect are verified and each document that holds the keyword is assigned a sentimental score. Performance results are compared for all five aspects where 'career opportunities' aspect has high recall value (92%, 96%, and 94.11%) for all three companies.

The study on Amazon's review data aims at recognizing key smartness dimensions that notably influence the satisfaction of smart speaker users [3] using Latent Dirichlet Allocation (LDA). Initially they identified the smartness elements of smart speakers using actual users' review data and users' star ratings. Feature importance is extracted using SVM, NN, RF and XGBoost algorithms to compare the influences of the topics and find relatively more essential topics. Importance ranking is also done accordingly.

An integrated lexicon and rule-based aspect-based sentiment analysis approach is proposed to extract the aspects of government mobile apps [4] and classify the related implicit and explicit sentiments. Sentiment classification is also done for these aspects. This hybrid method outperformed the lexicon baseline and other rules combinations with a score of 0.81. Two semi supervised models namely, seeded LDA and Newsmap is compared in topic modeling on debate transcripts. The seed words and topics are correlated and compared. The result shows that Newsmap outperformed [9] Seeded LDA model since Newsmap executes multilingual geographical classification of news articles. Knowledge-based seed words and frequency-based seed words are fetched using both models. In this literature, performance measure of teaching evaluation and course evaluation using aspect-based sentiment analysis [5] is done. Concept ontology is applied to eradicate irrelevant terms. Both single and multi-word explicit and implicit aspects are found [11] using Association Rule Mining and finally sentiment classification is done using support vector machine (SVM). In this proposed work, aspect-based sentiment analysis on students' reviews to predict students' satisfaction towards online course is accomplished.

4 Objectives of the Study

This paper includes following notable research contributions:

1. Construction of tagged academic domain dataset using LDA/seeded LDA, consisting of 2397 instances. Each course review is tagged in one of nine aspects including course, content, learning, teaching, instructor, lab/practical, charge/fee, career/job, and grade/test.
2. Building a hybrid model for aspect extraction and sentiment classification using customized lexicon and machine learning classifier.
3. Predicting students' satisfaction of online courses in different aspects based on aspect-based sentiment analysis.

4.1 Limitations of Research

- The study focuses on explicit aspect terms detection and classification alone.
- For sentiment scoring, lexicon-based approach and machine learning approach is used.

5 System Framework

The proposed hybrid model is given in Fig. 1. The text reviews are fed into the system for analysis in the first step. Later, the fine-grained text pre-processing methods are employed on the dataset. It involves removal of stop words, numbers, punctuation marks and white spaces. Then it is transformed into lowercase. Afterwards, the reviews are converted into individual sentences. The sentences were transformed into document feature matrix (DFM). Stanford NLP parser was used to detect meaningful features. From the DFM, the aspects were detected with the help of LDA methods. In order to enhance the detection of sentiment words our own customized lexicon is used and polarity is calculated. Finally, the results are predicted using aspect-based sentiment analysis model using machine learning algorithm.

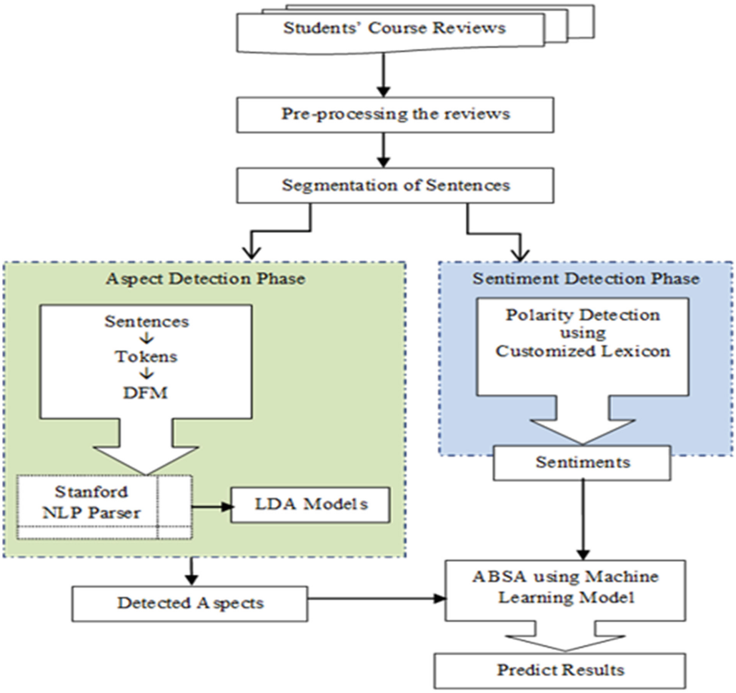

Fig. 1. Proposed hybrid model

6 Methodology and Results

Nowadays, plenty of work is accomplished in sentiment analysis in various domains. It includes hotel reviews, movie reviews, news headlines, online shopping, and online courses. Among these, very few datasets are properly labeled. Real time datasets in education domain are less available with sentiment labels. Apart from sentiment computation, if these datasets give additional inputs on different aspects or entities of educational characteristic it will be productive. This would be possible only through Aspect Based Sentiment Analysis. For the study, the real Coursera dataset available in Kaggle repository is collected through web scraping. Totally 1100 course reviews were randomly chosen from different courses. These reviews are again segmented into sentences for ABSA progression.

Initially in preprocessing, reviews are chopped into sentences which come around 2397. The sentences are converted into same case, punctuation, numbers are removed. After preprocessing the reviews, the text is converted into tokens to derive document features. These features are further tagged with POS tagger. In the proposed model, Stanford NLP parser is used for POS tagging. Since nouns and adjectives mostly contribute towards topic modeling, so the data limited to only terms with these kinds of tags. Different forms of terms are analyzed and classified under different aspects using LDA and seeded LDA algorithm.

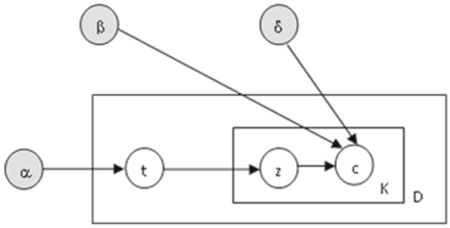

Fig. 2. Proposed plate model for topic modeling

LDA is applied to locate topic with the help of semantic information in unstructured text data [10]. Figure 2 represents the proposed model in plate notation with the modified parameter of δcn where it has topics z and set of K words c with the parameters α and β, the joint distribution of a topic t in document D. Here, δcn denotes a pair wise score of the top n words in a topic. LDA places its own seed words under the topics based on the text features $\mathrm{z_n}$.

The probability of estimating the relevant topic or aspect from the set of topics and words for the given features is given in Eqs. (1) and (2)

$$p(t, z, c|\alpha, \beta) = p(t|\alpha) \prod_{n=1}^{K} p(\mathrm{z_n}|t) p(\delta \mathrm{c_n}|\mathrm{z_n}, \beta) \tag{1}$$

where,

$$\delta \mathrm{c_n} = \sum_{\mathrm{i}<j} \mathrm{score}(\mathrm{c_i}, \mathrm{c_j}) \tag{2}$$

By using seeded LDA, most frequent seed words are introduced occurring in the feature vectors based on topics suggested. The factors that do not fall under the above category are considered as NA. The quality of topic is evaluated using coherence measures. The Hellinger distance is also calculated to find the closely related topics (Fig. 3). In the proposed model, coherence and prevalence score calculation is also carried out to find the best topics/aspects. It is given in Fig. 4.

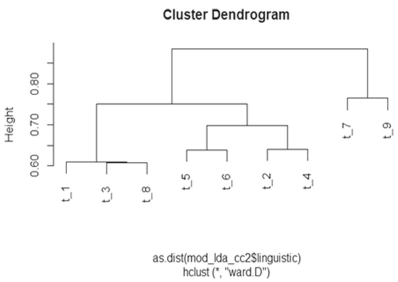

Fig. 3. Hellinger distance measure

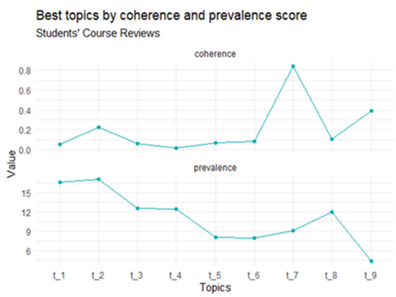

Fig. 4. Coherence vs. prevalence

For this analysis, 1100 course reviews are fetched initially afterwards the reviews were divided into individual sentences with the count of 2397. Few sentences that do not have aspect words were also ignored before analysis. The steps involved for extracting the aspects using both LDA and seeded LDA methods are presented in Algorithm 1a and Algorithm 1b.

```
Algorithm 1a: Aspect mapping using unsupervised algorithm

Input: CR - Course Review sentences, A - Course Aspects
Output: Aspect-based sentences
Start
R ← ~ CR
|F | ←NLP Parser (R)
|T| ← execute LDA (F)
for every T∈F
A →  T
end for
for each A scan F
if F∈T, fetch F and classify
otherwise skip the F and assign Ø
end if
end for
End
```

```
Algorithm 1b: Aspect mapping using semi supervised
algorithm
Input: CR - Course Review sentences, FM – Document- Fea-
ture Matrix, SD – Dictionary of seeded terms, SA - Course
Aspects relevant to seeded terms
Output: Aspect-based sentences

Start
R ← CR9
|F | ← NLP Parser (R)
FM ← F
|ST |← execute seededLDA ∀ SDi ∈ SD in FM
for each ST
SA →  ST
end for
if F∈ST, fetch F and classify
otherwise skip the F and assign Ø
End if
End
```

The Table 1 shows the sample review dataset representation with its resultant aspects and sentiment labels derived using ABSA. The actual reviews are segmented into sentences to add more clarity in terms of fetching the specific aspects and its related sentiment values.

Table 1. Sample dataset representation with identified aspects

Review	Sentences extracted	Aspects Identified using LDA methods	Sentiment Score obtained
Professors need to undergo a presentation and Instruction Design skills. They were talking a lot and everything was going over my head, the reason was there were not visual prompt for the examples, specifically in the last week.	professors need to undergo a presentation and instruction design skills	Teaching	-1
	they were talking a lot and everything was going over my head, the reason was there were not visual prompt for the examples, specifically in the last week.	Instructor	-1

The following Table 2 shows the sentiment polarity count at review and sentence level aspects. Few sentences were ignored in sentence level since they do not comprise any aspects in the given domain. They are under NA category. Aspect-based sentiment polarity is estimated both at review level and sentence level. Among both models, sentence level reveals more clarity in detecting the polarity. It exhibits positive polarity towards 4 aspects.

Table 2. Aspect-specific sentiment count

Aspect	Positive	Negative	Neutral	Overall aspect sentiment	Positive	Negative	Overall aspect sentiment
	Sentence-based classification				Review-based classification		
Career/Job	62	90	44	Negative	51	47	**Positive**
Charge/Fee	55	99	44	Negative	25	73	Negative
Content	71	138	68	Negative	16	84	Negative
Course	275	138	74	**Positive**	96	26	**Positive**
Instructor	71	91	32	Negative	31	46	Negative
Lab	98	70	61	**Positive**	37	57	Negative
Learning	126	67	32	**Positive**	33	55	Negative
Teaching	95	83	41	**Positive**	27	59	Negative
Test/grade	32	119	36	Negative	30	58	Negative

Most frequent words are also fetched to understand the context of reviews which is given in Fig. 5. When the reviews are examined using the Bing lexicon, the results achieve elevated ratio of positive sentiment than the negative sentiment in the reviews. It is depicted in Fig. 6. The sentiment of reviews with specific aspects is also analyzed using proposed customized lexicon.

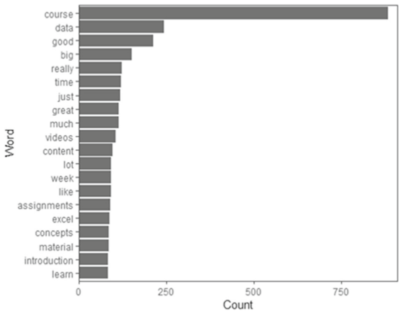

Fig. 5. Word frequency

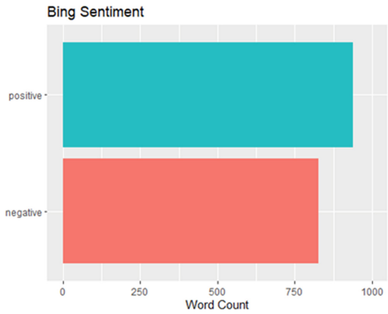

Fig. 6. Bing sentiment

The polarity of various aspects expressed in the sentence is calculated using customized sentiment lexicon (CSL) developed by us and it is shown in Fig. 7. It yields positive polarity for grade/test, instructor, job, learning aspects. For content, course, fee, instructor and teaching it yields negative polarity. The emotions about the course participants are also analyzed using nrc sentiment lexicon and presented in Fig. 8.

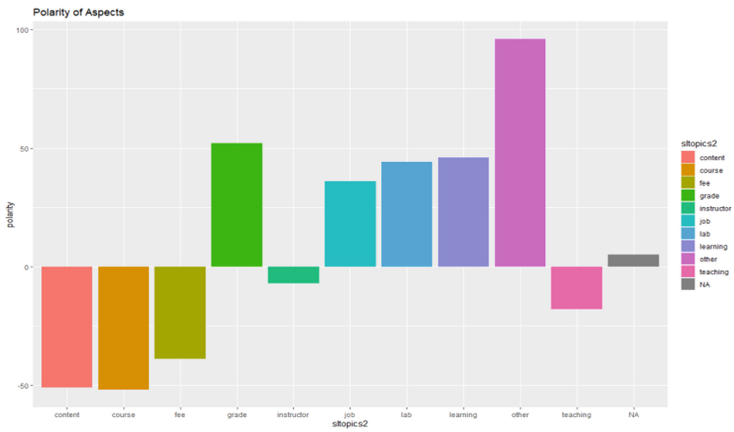

Fig. 7. Polarity of aspects identified using proposed customized lexicon

For few aspects, visualization is presented to find their emotions. Though most of them expresses positive note on emotions still it reveals mixed feelings of students in teaching, learning, test, and course content aspects.

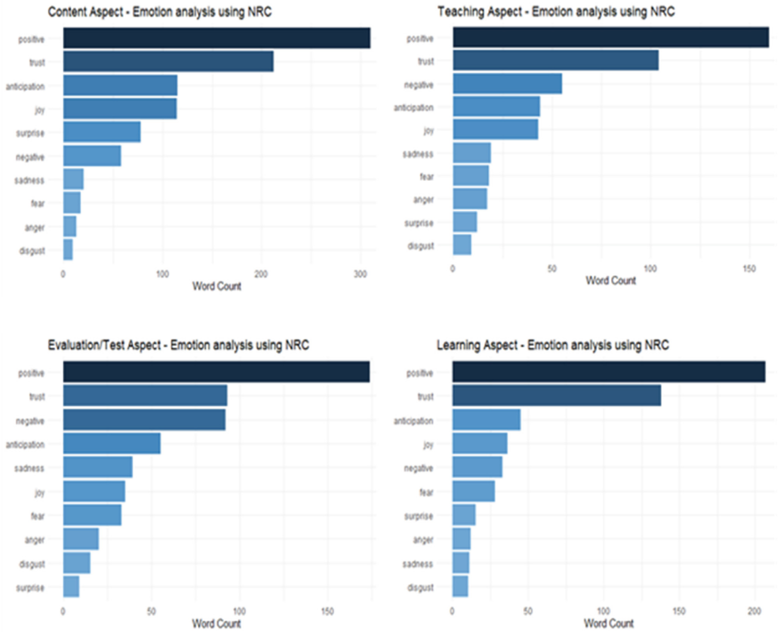

Fig. 8. Emotion analysis using nrc lexicon

After evaluating the optimal number of topics, correlation between two variables word and topic is computed using the phi value for both models. It is depicted as heat map representation in Fig. 9a. and Fig. 9b. Based on visualization of results, it is understood that sentence-based aspect extraction gives more subtle identification of sentiments in aspect-based sentiment analysis. The aspects were fetched using both unsupervised (LDA) and semi-supervised (seeded LDA) model and their efficiency in classifying the aspects are also measured. Seeded LDA covers even implicit aspect words that are relevant to the topic categorization. The detected aspect and its associated feature entities are presented in Table 3. Based on the aspect extraction process, it is indicated that seeded LDA procedure is more accurate than traditional LDA to detect the relevant and related aspect terms. Sentences are tagged with the aspects for further study.

Table 3. Aspect category and variables

Aspect category	Aspect variables fetched using LDA	Seed terms defined in seededLDA
Course	"concepts", "introductory"	"course", "coverage", "rating", "complex"
Content	"videos", "lecture", "slides"	"video", "lecture", "syllabus", "material"
Instructor	"stuff", "basic"	"professor", "intelligent", "approach", "stuff"
Teaching	"teaching", "explanation", "work"	"teaching", "explanation", "presentation", "understand"
Lab	"code", "excel", "exercises"	"programming", "exercises", "code", "tools"
Learning	"concepts", "difficult", "way", "understand"	"learning", "concept", "example"
Job	"skills", "specialization"	"job", "skills", "career", "certificate"
Fee	"money", "material", "weeks"	"cost", "money", "charge", "price"
Grade	"stars", "certificate", project	"test", "practice", "assignment", "quiz"

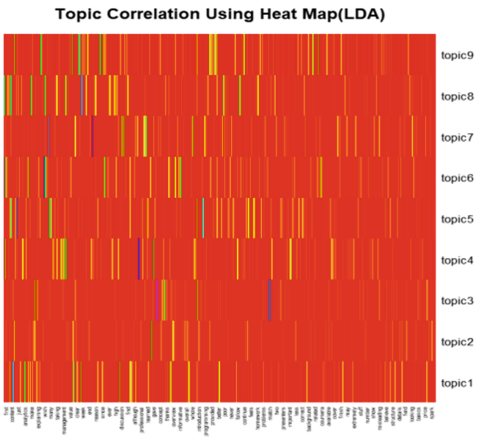

Fig. 9a. LDA results for sentence-based aspect categorization

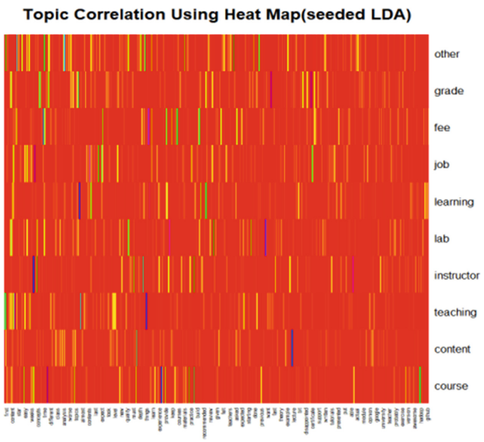

Fig. 9b. seededLDA results for sentence-based aspect categorization

Maximum entropy (MaxEnt) classifier is trained and tested, for estimating the classification accuracy in terms of sentence level aspect-based sentiment classification using hybrid approach. The proposed hybrid aspect-based sentiment classification is done based on the following Algorithm 2.

Algorithm 2: Hybrid aspect-based sentiment classification algorithm

Input: Aspect-labeled course review sentences, and A collection of aspect categories (SA_1, SA_2, …, SA_i)
Output: Predicted results
Start
Step 1: SL ← Aspect-labeled course review sentences
Step 2: For each SL
Step 3: SL_e ← Compute sentiment using CSL
Step 4: Segment the SL_e into train and test set
Step 5: Train and test with machine learning model
Step 6: Classify SL_e
Step 7: end
Step 8: for each SA
Step 9: Compute overall sentiment weight
Step10: Print the predicted results
End

Since maximum entropy classifier is a kind of conditional classifier, the probability of each label is computed using conditional probability. The equation for calculation is given in formula (3). The conditional probability p(c|x) is computed with respect to exponential value of the series of feature weight vectors product (w * f) for labels l with respect to Z topics.

$$\mathrm{p(c|x)} = \frac{1}{\mathrm{Z}}\exp\sum\nolimits_{\mathrm{i}} \mathrm{w_i} * \mathrm{f_i} \tag{3}$$

Basically, maximum entropy classifier starts with least weights and optimizes to find the weights that maximize the likelihood of the data. For that, the target value y is a random variable which can take on C different values matching to the classes' c1, c2…., cC. The feature belongs to a particular class or aspect c is estimated using probability distribution over the classes C. In classification, to select the single-best class, the class that has the maximum probability can be considered using the formula (4).

$$\hat{c} = argmaxP(c|x), \, where \; c \in C \tag{4}$$

The Fig. 10 portrays the accuracy obtained in various aspects. It is a kind of exponential classifier that helps to identify the feature that maximizes the likelihood of the data with respect to the topic it belongs. Aspect Sentiment classification is implemented for test set after training MaxEnt classifier model. The proposed model has achieved improved accuracy results in sentiment classification as 88% for positive, 93.5% for negative and 60.5% for neutral. It is presented in Fig. 11.

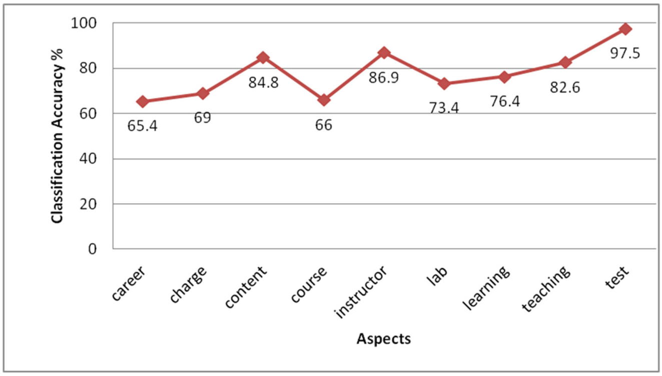

Fig. 10. Aspect classification accuracy of MaxEnt classifier

From the results of sentence level ABSA, it is inferred that sentence level ABSA gives better results than the review level ABSA. And seeded LDA covers most of the domain specific aspects than the LDA model.

6.1 Comparison with Baseline Model

Aspect-based hybrid sentiment classification analysis is carried out using Stanford Twitter Sentiment (STS), [11] Hate Crime Twitter Sentiment (HCTS) and Sanders Twitter

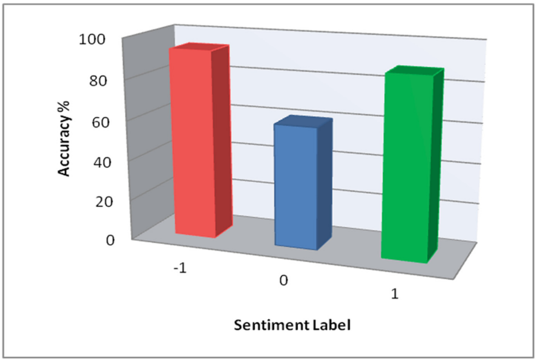

Fig. 11. Sentiment classification using MaxEnt model

Corpus (STC) datasets. Different classification algorithms namely SVM, Random Forest (RF) and Naïve Bayes (NB) are trained along with principal component analysis (PCA) feature selection and Sentiwordnet. Out of these model, SVM classifier attained accuracy % as 76.55, 71.62 and 74.24 respectively for the datasets in aspect-based classification. While comparing with the existing model our proposed hybrid model on course review dataset with the combination of customized sentiment lexicon along with seeded LDA method and Maximum entropy classifier has obtained enhanced accuracy as 80.67% for aspect-based sentiment classification of unigram features. It is shown in Fig. 12. Since ME classifier learns also by non-independent features it helps to trace the uncovered feature vectors in the document. This rationale improves the classification performance of the proposed model than other baseline methods.

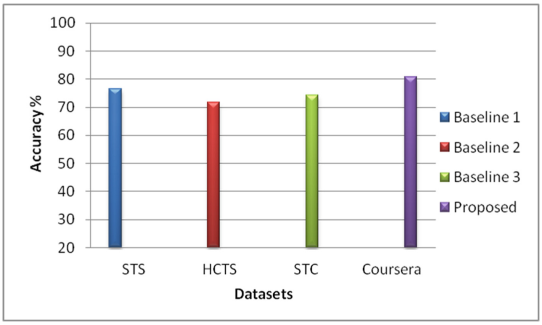

Fig. 12. Comparison of sentiment classification accuracy with other models

6.2 Predicted Results of the Proposed Hybrid Model

According to the proposed hybrid aspect-based sentiment analysis held using the dataset; nine different aspects are considered to trace out the issues in various courses undertaken by the students. As per the results shown in Table 4, on the whole students are satisfied in few aspects such as grade/test, instructor, job, learning aspects based on the sentence level aspect and sentiment analysis model.

Table 4. Results of proposed ABSA model

Aspect	Sentiment
Course	Positive
Content	Negative
Instructor	Negative
Teaching	Positive
Lab	Positive
Learning	Positive
Job	Negative
Fee	Negative
Grade	Negative

As per the proposed model, in few aspects, certain expectations of students are not met out to some extent and predicted as negative. This aspect-based sentiment analysis on course reviews helps us to find the aspects on which the students are really satisfied. It is also helpful to locate the area where the course providers need to give more attention. Few aspects also exhibit good quality feedback about the course. Accuracy of the proposed model is also compared with baseline model and shows significant improvement over the model for the aspect sentiment classification using maximum entropy.

7 Conclusion

The aspect-based sentiment analysis is the need of the hour for various online course providers platform. This study can facilitate to fetch notable aspects of feedback, the emotion and sentiment of students towards the enrolled course. The proposed hybrid model exhibits significant improvement over sentence-level aspect detection than the review level. The sentiment polarity detection is also enhanced using the proposed customized lexicon. The seeded LDA contributed well to trace the contextual features under the aspects/topics. While comparing with existing model the proposed model shows improved accuracy in aspect-based sentiment classification and topic modeling using maximum entropy. Students' satisfaction on various explicit aspects is computed through the proposed model. This would be very essential to enhance the quality of courses offered online. The proposed study will also assist to make corrective decisions based on the results achieved and can improve the quality of services by estimating the students' satisfaction level.

For future studies, implicit aspects can also be investigated through word embedding and linguistic analysis methods.

References

1. Dina, N.Z., Juniarta, N.: Aspect based sentiment analysis of employee's review experience. J. Inf. Syst. Eng. Bus. Intell. **6**(1), 79 (2020). https://doi.org/10.20473/jisebi.6.1.79-88
2. Guha, S., et al.: SIEL: aspect based sentiment analysis in reviews. In: Proceedings of the 9th International Workshop on Semantic Evaluation, pp. 759–766. Denver, Colorado, Association for Computational Linguistics (2015)
3. Park, W., et al.: Extracting principal smartness dimensions of smart speakers using topic modeling and sentiment analysis, 2375-9356/20. IEEE (2020). https://doi.org/10.1109/BigComp48618.2020.00-60
4. Alqaryouti, O., Siyam, N., Monem, A.A., Shaalan, K.: Aspect-based sentiment analysis using smart government review data. Appl. Comput. Inf. (2019). https://doi.org/10.1016/j.aci.2019.11.003
5. Chauhan, G.S., Agrawal, P., Meena, Y.K.: Aspect-based sentiment analysis of students' feedback to improve teaching–learning process. In: Satapathy, S.C., Joshi, A. (eds.) Information and Communication Technology for Intelligent Systems. SIST, vol. 107, pp. 259–266. Springer, Singapore (2019). https://doi.org/10.1007/978-981-13-1747-7_25
6. Liu, Q., Liu, B., Zhang, Y., Kim, D.S., Gao, Z.: Improving opinion aspect extraction using semantic similarity and aspect associations. In: Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence (AAAI-16), pp. 2986–2992. Association for the Advancement of Artificial Intelligence (2016)
7. Kastrati, Z., Imran, A.S., Kurti, A.: Weakly supervised framework for aspect-based sentiment analysis on students' reviews of MOOCs, IEEE Access (2020). https://doi.org/10.1109/ACCESS.2020.3000739
8. Mowlaei, M.E., Abadeh, M.S., Keshavarz, H.: Aspect-based sentiment analysis using adaptive aspect-based lexicons. Elsevier Ltd. (2020). https://doi.org/10.1016/j.eswa.2020.113234 0957-4174/
9. Watanabe, K., Zhou, Y.: Theory-driven analysis of large corpora: semi supervised topic classification of the UN speeches. Soc. Sci. Comput. Rev. 1–21 (2020). https://doi.org/10.1177/0894439320907027. SAGE
10. Das, S.Y., Murakami, R., Chakraborty, B.: Development of a two-step LDA based aspect extraction technique for review summarization. Int. J. Appl. Sci. Eng. 1–18 (2020). https://doi.org/10.6703/IJASE.202103_18(1).003
11. Zainuddin, N., Selamat, A., Ibrahim, R.: Hybrid sentiment classification on twitter aspect-based sentiment analysis. Appl. Intell. **48**(5), 1218–1232 (2017). https://doi.org/10.1007/s10489-017-1098-6
12. Sindhu, I., Daudpota, S.M., Badar, K., Bakhtyar, M., Baber, J., Nurunnabi, M.: Aspect-based opinion mining on student's feedback for faculty teaching performance evaluation. IEEE Access **7**, 108729–108741 (2019). https://doi.org/10.1109/ACCESS.2019.2928872
13. Hajrizi, R., Nuçi, K.P.: Aspect-Based Sentiment Analysis in Education Domain. arXiv:2010.01429 [cs.CL] (2020)
14. Soon-Hong, K., Byong-Kook, Y.: Topics and sentiment analysis based on reviews of omni-channel retailing. J. Distrib. Sci. 25–35 (2021). https://doi.org/10.15722/jds.19.4.202104.25