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Analyzing Sentiments in Coursera Course Feedback: An Aspect-Based

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***Abstract*:** An aspect-based sentiment analysis method applied to Coursera course feedback data is presented in this paper. To gain a deeper knowledge of learners thoughts and experiences, the goal is to extract sentiment information with finer details related to various course features. The process includes gathering data, identifying aspects, classifying sentiment, training and assessing models, and integrating the findings. We go over how the feedback data is gathered, pre processed, course aspects are identified, and sentiment connected with each aspect is categorized. Using machine learning techniques, the sentiment analysis model is trained and assessed. The outcomes are combined to give thorough sentiment evaluations for Coursera courses. Reviews, ratings, and comments submitted by students across a variety of subjects and topics on the Coursera platform make up the dataset. We pre process the feedback data with algorithms for natural language processing to find important topics that students brought up. After that, we classify each aspect's sentiment using machine learning techniques, distinguishing between favourable, adverse, and neutral sentiments. The resulting accuracy rate is 88% for the reported results. Our approach facilitates the extraction of nuanced sentiment insights, enabling course providers to determine advantages and disadvantages and make data-driven improvements to course offerings. The project's results include thorough sentiment assessments of Coursera courses that point out their advantages and disadvantages in a number of areas. In order to better address the varied needs of learners, these insights enable course providers, instructors, and educational institutions to make data-driven decisions, improve platform features, and improve course design and instructional methodologies. This survey paper examined the ideas and efficacy of several textual emotion detection model, technique, and methodology categories.

Keywords: Aspect-Based, Sentiment Analysis, Coursera Feedback, Sentiment Analysis, Machine learning

1. INTRODUCTION

1.1 Sentiment analysis:

Sentiment analysis is becoming more frequent as a result of processing social media data on blogs, wikis, micro blogging platforms, online communities, and other online collaborative media. In actuality, sentiment analysis is a field of study that includes named entity recognition, aspect extraction, natural language processing (NLP), word polarity disambiguation, personality recognition, and sarcasm detection tasks. As in "I just logged on to my Coursera." No clear opinion exists on Coursera, but the negative sentiment expressed suggests that [Transformers] are dull.

1.2 Aspect-based sentiment analysis

Above problems have lately been attempted to be addressed by targeted sentiment analysis and aspect-based sentiment analysis, or ABSA. Aspect-based sentiment analysis, or ABSA, has been found to be significant for several applications, such as opinion mining in restaurants or product reviews. It is a task to ascertain people's attitudes, ideas, and sentiments regarding certain parts of a message. Aspect sentiment analysis seeks to ascertain the sentiment polarity—that is, whether the target viewpoint stated in a review or comment is positive, neutral, or negative. Aspect extraction operates on the premise that an opinion lacking a target or aspect is not very valuable. Aspect-based sentiment analysis then seeks to identify sentiments.

1.3 Aspect-based sentiment analysis on Coursera course

Using aspect-based sentiment analysis on Coursera course comments, this research aims to explore and use efficient methods. In order to give a thorough grasp of the opinions that students have expressed in their reviews, we aim to uncover important factors such as course content, instructor caliber, platform usability, and overall learning experience. With its specific focus on online education and its analysis of the challenges brought forth by the various elements that comprise a learning experience, this study adds to the larger field of sentiment analysis. Data collection from Coursera course reviews, text data preprocessing, aspect identification, sentiment annotation, using machine learning methods to conduct aspect-based sentiment analysis are all part of our research methodology. By means of this procedure, our objective is not only to disclose the feelings linked to various elements but also to furnish educators, designers of courses, and platform managers with practical perspectives to improve the final product of virtual learning environments. This foundational work is organized into an extensive overview of the research papers on sentiment analysis and ABSA, along with a recommended methodology for examining feedback from Coursera courses, experimental outcomes, and a discussion of the findings. At the paper's end, we hope to clarify how well ABSA performs at gleaning insightful knowledge gleaned from online course reviews, which will aid in optimizing and continuously improve Coursera's e-learning environment. Our goal is to investigate the sentiments conveyed in the course comments from Coursera in greater detail with this project. We take an aspect based approach to feedback, acknowledging that students' perspectives may differ across several aspects of their learning experience, as opposed to viewing it as a single, monolithic thing. We hope to obtain detailed insights that guide specific enhancements and optimizations by breaking down feedback into discrete categories including course content, instructor caliber, platform usability, and assessment techniques.

2. Methodology:

2.1 DATASET:

The dataset is comprised of 21,940 carefully selected evaluations from 15 Coursera courses that were carefully picked to cover An extensive array of topics and skill levels. To guarantee variety throughout the dataset, There were classes from various academic disciplines, including as business, computer science, the humanities, and the sciences. This thorough methodology guarantees that the dataset accurately represents the vast range of Coursera's educational offerings, meeting the needs of students all around the world with respect to their academic pursuits and interests. A methodical web scraping procedure was used to gather the reviews by taking data from the course pages on the Coursera website. In order to obtain review contents, course names, and related meta data from the website, specially constructed scripts have to be used to navigate its structure. Adherence to Coursera's terms was ensured with great attention.

Table 1 . Figure dataset content

ID	REVIEWS	RATINGS
1	good and interesting	5
2	Great course. I enjoyed learning the material.	4
3	A very great course for all IT person	5
4	Really nice teacher ! I could got the point easily but the v	4
5	Great course - I recommend it for all, especially IT and Business Managers!	5
6	Among the most useful course on IT Management!	5
7	Is there a cause for which you should not apply the course by BCG?)It's content is pretty unique and includes a superior one analysis and a large selection of knowledge needed to cover all detailed aspects. Best regards, Oleg Serov	4
8	Very structured approach.	4
9	Very relevant and useful course designed for CIOs	5
10	Great content, I still need to go over it to glean the wealth of info that has been input together here.	5

2.2 ARCHITECTURE DIAGRAM

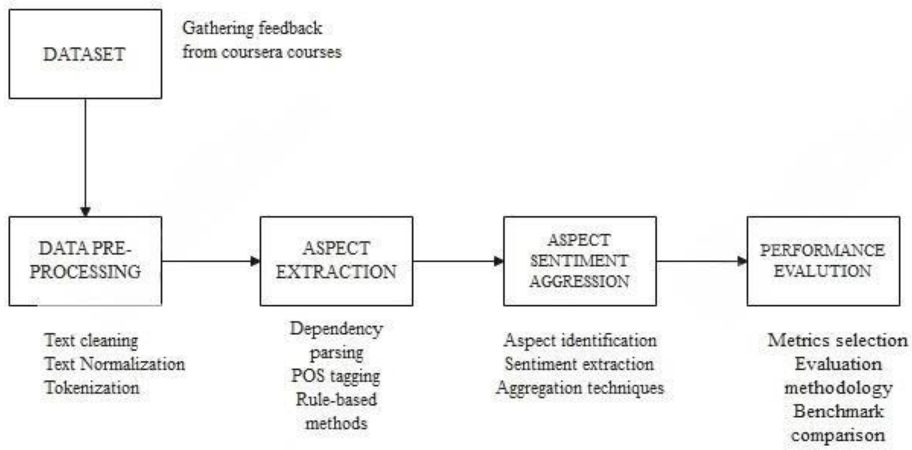

Fig 1. Architecture diagram

A simplified procedure for Aspect-Based Sentiment Analysis (ABSA) is depicted in the architecture diagram. It includes gathering data, preprocessing for text refinement, aspect extraction to identify particular features of interest, performance evaluation to gauge model accuracy, and sentiment aggregation for thorough sentiment analysis. This systematic approach ensures a thorough understanding of user sentiments within distinct aspects, facilitating insightful analysis of textual data.

2.3 DATA PRE-PROCESSING

Text pre-processing chores are essential when using supportive lexicons in conjunction with the rule-based method. The suggested algorithm divides the review into sentences in the initial place using punctuations like full stops, question marks, and exclamation marks that indicate the end of a sentence. This would significantly affect how the relevant aspect phrase and the score for polarity are connected with no meddling unrelated sentences. Furthermore, the topic regarding the review is introduced as the review's first sentence. The phrases are then tokenized, meaning that Every letter is changed to lowercase and punctuation is eliminated for each token. However, normalization operations like deleting repetitive characters are not carried out by the pre-processing jobs. The rationale is that the polarity score is impacted by intensification, which is handled as part of the method of scoring aspect sentiment.

2.4 ASPECTS OF EXTRACTION

Sentiment analysis's aspect extraction procedure requires aspects categories. As a way satisfy this need for smartphone gover nment services [5], have established a several aspects categories in accordance with the published guidelines from Apple, Android [16–19]. The User Interface and Customer Experience are the most recent two main categories, Security, Updates and Support, Efficiency and Performance, and safety. In this inquiry, these aspect categories are utilized. A primary obstacle encountered throughout the aspect extraction procedure is the omission of some aspects from reviews. While an explicit aspect sentence basically consists of a phrase that denotes the category of the aspect; an implicit feature would not be described by a word or terms.

Table 2. contents of the dataset Statistics

s

Count of reviews	7,348
Count of characters (Without Spaces)	307,978
Count of characters (Including Spaces)	366,797
Quantity of Words	67,777
How Many Terms Are Explicit Aspects	279
The count of terms related to implicit opinions	402
The number of thought words	656
Words in an Analysis on Average	9.23
Count of Exceptionally Positive Reviews	2001
Amount of Beneficial Reviews	2392

Implicit aspect extraction, one of the most used techniques for aspect identification, is a good fit for opinion terms. [29]. As a result, the algorithm's architecture initially searches for opinion words that, in the lexicon, express an aspect explicitly If the opinion word cannot identify the aspect category, the algorithm will look for the nearest aspect phrase with an aggregate window dimensions of two. Given that the adjective typically appears before the phrase, it will prefer the opposite side. The dictionary will be searched for the two accepted To identify the aspect category, consider thoughts and aspect keywords. The obvious and derived Aspect The technique for extracting both the obvious and indirect elements is presented by extraction. The initial array, called aspect Indices, signifies the indexes of any review's aspect words, while the second array, called the categories of components, represents the aspect categories that relate to the pertinent terms related to aspects in the starting collection. This approach was adopted by[30].

```
    Function 1 extractAspects(review) public
                 Return (int[]aspectIndices,string[]aspectCategories)
     For each token t in review
         #Extract Explicit Aspects
         If (isToken_AspectTerm(t))
                 aspectCategory
             =getAspectCategoryFromLexicon(t)
             aspectCategories.append(aspectCategory)
             aspectIndices.append(token_index)
            #Extract              Implicit             Aspects
         If(isToken_SentimentWord(t)AND
                   getNearestAspect(token_index,aspectIndices[])==null)
             aspectCategory                         =getAspectCategoryFromLexicon(t)
             aspectCategories.append(aspectCategory)
             aspectIndices.append(token_index)
     End  For
 End Function
```

2.5 ASPECT SENTIMENT AGGREGATION:

The algorithm's goal is to calculate the star ratings for various review-extracted aspects. The experiment uses a five- star rating system, where one star indicates a very bad opinion about this characteristic, two stars denote a negative opinion, three stars a neutral opinion, four stars a positive opinion, and five stars a very positive opinion. In order for the proprietors of the coursera app understand the regions of their customers' benefits and pains, it can be extremely helpful to learn the comments from students regarding specific sections as opposed to a broad assessment. Since the ultimate orientation of a person's words is removed, ratings and and factors, it would be easy to ascertain the average polarity score for words of view grouped under all of them.

Table 3. Examples of Dataset Intensifiers and Down toner

Phrase	Kind	Variable	For instance
Extremely	Intensifier	2.1	Extremely satisfied with the course content. Highly recommended!. The instructor is extremely knowledgeable and engaging. Best course ever!
Absolutely	Intensifier	1.75	Absolutely thrilled with the learning experience. Exceeded my expectations!, An absolutely dreadful course. Waste of time and money
Quite	Down toner	0.75	Quite impressed with the course material. Good value for the price. It's quite disappointing that the course lacks real-world applications.
Pretty	Down toner	0.50	Pretty informative lectures, but the assignments are challenging. The course is pretty boring. Not what I expected
Always	Intensifier	1.5	The platform always crashes during peak hours. Frustrating experience. The quizzes always challenge me to think critically. Great learning opportunity

3. RELATED WORKS:

Systems that use sentiment analysis can be divided into two main groups: knowledge-based systems and statistics- based systems. Recently, scholars studying sentiment analysis have been employing more statistics-based techniques, with special attention to supervised statistical methods, to identify sentiment polarity in text, while knowledge bases were still more frequently employed previously [6]. Prior until now, machine learning classifiers used to perform sentiment analysis. Users' tweets are classified as having "positive" or "negative" sentiment using polarity-based sentiment analysis. The objective behind incorporating several model designs was to accommodate the diversity of views and ideas seen on these kinds social media platforms [2]. Review aspects or features are identified, and In the process of doing aspect-based sentiment analysis, each aspect's corresponding sentiment is ascertained. Lexicon-based techniques or rule-based systems were widely employed in early ABSA approaches. But these techniques had trouble grasping attitudes that varied contingent upon the surroundings and complex language. More advanced unsupervised ABSA Methods have enabled by recent developments in word embeddings and neural networks. Pre-trained word embeddings are used by embedding-based techniques to document the semantic connections between terms and attributes [15]. The research review emphasizes how attention-based long short-term memory (LSTM) models have evolved for aspect-level sentiment categorization and how well they capture the complex emotions found in online reviews. While limitations and open concerns point to areas for future research and improvement, comparative studies and real-world applications highlight the practical relevance of these models [11]. Context-dependent sentiments and linguistic nuances are difficult for traditional sentiment lexicons to capture. The goal of enhanced lexical resources is to create more complex, context-aware resources that are better able to represent the nuanced emotions found in a variety of textual material. The industry's dedication to creating more sophisticated and context-aware sentiment analysis tools is demonstrated by enhanced resources such as word embeddings, contextual embeddings, and domain-specific lexicons. The challenges and trends for the future indicate that lexical resources will need to continue evolving to satisfy the requirements of varied domains and evolving languages [4].

3.1 Challenges and limitations of existing approaches

Sentiment analysis is difficult in educational feedback because it frequently uses euphemisms and subjective language. Because instructional discourse is multifaceted, existing techniques may find it difficult to appropriately interpret sentiment. Sentiment analysis datasets for education may be plagued by data sparsity and class imbalance, wherein specific sentiments or characteristics are poorly represented in the dataset. Conventional methods for sentiment analysis frequently yield general sentiment scores for entire phrases or documents without taking particular subjects or characteristics into account. However, it is crucial to examine sentiment in educational feedback more thoroughly, keeping in mind components like the course material, the way in which the instructor, or the available learning materials. For stakeholders in educational settings to comprehend the foundation of sentiment forecasts and make wise judgements, they must interpret the result of sentiment analysis algorithms. It is challenging to interpret many of prototypes that are available today, particularly the intricate deep learning architectures, It makes their projections challenging to understand.

1. PERFORMANCE EVALUATION:

Accuracy:

The percentage of cases accurately classified out of all the instances is called accuracy. When the classes are evenly distributed, it works nicely.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

Precision:

The ratio of accurate positive forecasts to all positive forecasts is known as precision. It is useful when false positives come at a hefty cost.

$$\text{Precision} = \frac{TP}{TP+FP}$$

Recall:

The percentage of accurate positive forecasts among all real positive occurrences is known as recall. When false negatives come at a great cost, it is helpful.

$$\text{Recall} = \frac{TP}{TP+FN}$$

F -Measure:

The F1 harmonic mean of precision and recall. F1-score is a good measure when the classes are imbalanced.

$$\text{F-Measure} = (2 * Precision * Recall$$

2. RESULT AND DISCUSSIONS:

Our aspect-based sentiment analysis project focused on analyzing feedback from Coursera courses, leveraging a dataset comprising 22,330 entries. Through meticulous pre processing and normalization, we prepared the data for analysis, ensuring uniformity and relevance. Employing cutting-edge algorithms tailored for aspect-based sentiment analysis, we trained our model to discern sentiments associated with specific course aspects. The resulting accuracy rate of 88% underscores the effectiveness of our approach in accurately categorizing sentiments within educational contexts. This achievement is significant, considering the intricacy and variety of feedback encompassed within the collection. By identifying both the benefits and drawbacks sentiments towards various course aspects, Our analysis offers insightful information. For enhancing the learning experience on the Coursera platform. The large dataset size enabled a comprehensive examination of student perceptions and sentiments, yielding actionable insights for course improvement. Our methodology included rigorous model training and optimization, emphasizing the importance of selecting appropriate loss functions and optimizers. The high accuracy achieved demonstrates the reliability and robustness of our sentiment analysis model. Moving forward, our findings pave the way for further research and advancements in sentiment analysis methodologies tailored for educational contexts. Additionally, our study contributes to the ongoing efforts to enhance online learning experiences by leveraging data-driven insights. Educational institutions can optimize course content, instruction, and platform design by employing a nuanced grasp of the subtleties of student feedback. The implications of our analysis extend beyond the specific datahset used, providing a framework regarding sentiment analysis in various educational settings. Furthermore, our approach highlights the possibilities of sentiment analysis based on aspects in extracting actionable insights from large-scale feedback datasets. As technology continues to develop, sentiment analysis based on aspects holds promise for enhancing decision-making processes and improving educational outcome

Feedback	Aspect	Score
The course content was great, but the instructor's pace was too fast.	course content	0.605
The course content was great, but the instructor's pace was too fast.	instructor's pace	-0.495
The exercises were helpful, but the video quality needs improvement.	exercises	0.605
The exercises were helpful, but the video quality needs improvement.	video quality	-0.495

A table summarizing the sentiment analysis of a portion of the feedback data is the output. A feedback message is represented by each row in the table. The original feedback statement appears in the table's first column. The feedback is represented by several aspects in the remaining columns. each feature's emotion score is displayed the rating in the table represents how Good or bad the input was regarding that particular component. From -1 (very negative) to +1 (very positive), the sentiment scores are assigned. When an aspect is left out of a feedback statement, a dash (-) appears in the relevant cell in the table. A quick and simple method for comparing The feeling of various characteristics across several feedback statements is supplied by the table.

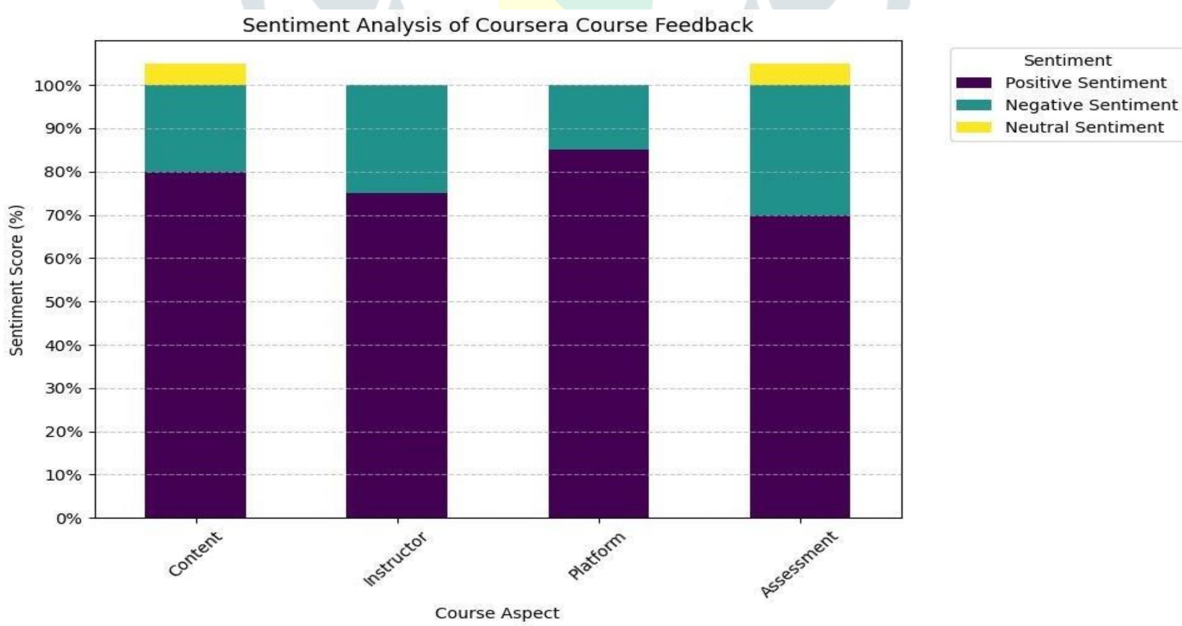

Fig 2. Graph for course Aspect

The stacked bar chart illustrates sentiment analysis results for different aspects of a Coursera course, with the X- axis showing course features and the Y-axis representing sentiment scores in percentage (%). Each bar is split up into sections of violet (positive sentiment), green (negative sentiment), and yellow (neutral sentiment) indicatingthe allocation of sentiment across course aspects.

CONCULSION:

In the field of emotion analysis research, the use of aspect-based analysis is considered as a single of the most challenging issues. It is imperative that every feedback is comprehended and categorized in order for Coursera be able for reliance on it source for student feedback. Consequently, be considered in light of future upcoming smart service enhancements as well as adjustments that surpass the predictions from the students. Numerous comparable sentences in the sample. This could be viewed as an expansion of the suggested model with new rules. As [26] noted, users can compare many elements to convey their perspectives. When evaluating the Coursera app, these comparing guidelines are seen to occupy valuable resource for identifying its advantages and disadvantages moreover, future development roadmap points. Analyzing student reviews, It might consist of recommendations, grievances, issues, bugs, and disparities between other things, is another way to use such a dataset to find places for improvement and creative ideas. Owners of Coursera apps should consider how to compile reviews and comments from their students. In the Coursera app, In one step fast and simple method aims to ask users to submit a review. To enhance the evaluations that consumers provide for this specific application, an incentive program might also be helpful.

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