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A Sentiment Analysis Based Model for Recruitment by Higher Institutions

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Abstract

The traditional roles of a university are teaching and research with the aim of developing society and contributing positively to the national economic development by producing skilled and well-tutored graduates. However, recruitments by these higher institutions are too reliant on the eligibility provided by Resumes of candidates, while neglecting their suitability drawn from their research activity and publications online. This study identifies insights in recruitment trends in higher institutions of learning and uses Artificial Intelligence to produce a more rounded and balanced decision-making process that caters for both eligibility and suitability. The methodology employs the machine learning process using the Multinomial Naïve Bayes for training the model as well as the Vader sentiment analyzer for accuracy and testing. The datasets used contained Resume instances as well as author publication information. The results show a score of 83.9% for the model as well as a sentiment analysis score of 1, indicating an overall positive score. The results show that sentiment analysis can help educational institutions in improving their recruitment models and attracting more suitable candidates for such roles.

Keywords

Hiring Process, Applicant Evaluation, Educational Institutions, Algorithmic Approach, Candidate Selection

1. Introduction

Due to the important function that learning plays in the economies of nations around the globe, there has been an upward growth in the need for academic employees in higher institutions, and this need is projected to keep growing [1]. Education has gained significant interpretations over time, and the process of learning and getting information and skills have received significant focus in recent periods. It cannot be overstated how crucial education has traditionally been for the ethical, cultural, and economic advancement of several countries [2]. Education should therefore be prioritized and made available to everyone simply because it is a fundamental human right. It is reasonable to infer that without learning; a country has no means of promoting innovation and growth; there is also no uncertainty that the quality of a country's development is determined by the standard of its educational institution [3].

In view of this, obtaining higher education and advanced learning is becoming more and more crucial as it gives people a significant edge in the job market. Because of the worldwide economic crisis, employment is no more a given [4]. Particularly in emerging countries, unemployment numbers are disturbingly high and there aren't quite sufficient new job prospects to give people the career options that they want. Fundamentally, there is a lot of competition.

Until now, candidates typically have better job prospects if they have a higher academic degree. Companies commonly place more emphasis on applicants with university degrees or other comparable education than they do on individuals with only a high school or secondary diploma [5]. A university degree is an investment that offers the student more than just financial benefits, it would be fair to say. University graduates with a variety of skills and competencies may be less vulnerable to unemployment during an economic downturn than individuals with fewer options. And while it's not a certainty, it's probable that those with greater education levels will experience fewer long-term periods of unemployment [6].

On the whole, the standard of teaching has a significant impact on the level of education and skills that students possess when they enter the workforce. Because of this, it's particularly important to be deliberate about the reliability of the hiring process, specifically for colleges and universities [7].

2. Problem Statement

Due to the significance of academic staff in regards to the crucial role they play in the development, mentoring and training of students and learners, there is a greater need to consider the recruitment and selection process of higher institutions. It is no longer sufficient for employees to present their qualifications and eligibility on a resume as evidence of being fit for the position [7]. Physical screening meetings may not be as viable for applicants who do not live very close to the universities that are hiring, especially given the global educational system of today and the constraints of a post-pandemic society [8]. Along with the details contained on resumes, the amount and quality of research materials that a potential employee has made available online will should equally serve as a solid barometer to make sensible hiring decisions. When the volume of applications that institutions process on a regular basis are factored in, it is clear that computational methods are required to streamline, automate and regulate this process.

3. Organizational Recruitment

Several academics and organizational administrators have given different definitions of the term "recruitment." Many institutions and academic researchers are now concerned about recruitment due to the fact that it is only through a hiring and selection process that firms can find qualified candidates who can successfully satisfy a vacancy and contribute meaningfully to organizational goals and objectives. This can assist the company to gain an edge over its rivals [9].

One of the most important steps in the hiring procedure is selection, which addresses the practice of choosing the best candidate for a position. Candidates must meet this performance condition before being chosen because the performance for the position is projected through the selection process [10]. Basically, the overall goal of selection is to find candidates to fill open positions in an organization based on specific criteria. In this case, candidates must fulfill particular standards relating to work [11]. Selection has also been described as the "process of trying to decide which persons will best complement particular jobs, taking into account individual distinctions such as potentials an applicant could bring on board" [12].

4. Methods of Recruitment

There are essentially two sources of hiring that are available to any firm. There are two categories for these: internal and external. The company's operational setting and operating philosophy have a major impact on how widely any of the recruitment avenues will be used [13]. Employing employees currently working for the firm through internal sources allows a company to fill open positions. In order to fill more senior job opportunities, the firm looks internally for suitable employees who have the necessary qualifications, skills, and competencies [14]. Employees hired internally, are either looking for promotions, upgrades or lateral transfers (job transitions that don't include significant shifts in duty or responsibilities) [15].

Internal sources of recruiting include a number of advantages, including cost savings, reduced time commitment, employees' familiarity with the process, and knowledge of candidates' real performance on the job [16]. An internal source can improve employee morale and job satisfaction, which will enhance their efficiency and organisational commitment. Employing potential candidates who are not within the organization to fill open positions is known as using an external source [17]. The company in this instance searches around for prospective candidates. This method of hiring is typically used to fill entry-level roles, particularly during periods of expansion, and for positions whose unique criteria cannot be sufficiently met by personnel already working for the firm [18].

It's important to acknowledge that organisational structure usually affects the selection of the approach to take in finding candidates [19]. While some organisational structure enable the placement of top roles from the outside, others embrace an open-door strategy where both staff members inside the company and others from the around are given an equal opportunity to compete for accessible job openings [20]. The advantages of hiring from an outside source encompass direct exposure to a potentially large applicant pool, the capacity to attract candidates who have the expertise, capabilities, and proficiencies needed by the company to accomplish its objectives, and a chance to hire new talent who might have the most recent information or ideas about cutting-edge technology [21].

The best method for firms to find the best individuals to fill their open positions is to actively seek out and acquire qualified applicants at a price that works for them. Unfortunately, these procedures and the requirements of the candidates are rather drawn-out and challenging. Experts concur that a recruiting organization's chances of finding the right candidate increase with the number of applications it receives [22]. The people who work in higher education, particularly in academic positions, are the ones who equip and educate learners to acquire the information and skills they need to help shape the future of their country. So, it's important to make sure that appropriate people are hired [23]. Educational organizations and institutions should make a deliberate effort to hire instructors because their hiring directly affects the educational process's learning results. Nonetheless, not all schools have competent academic staff [24].

There may be flaws in the hiring and selection processes used by education systems, which explains why not every schools have certified and experienced academic staff. In light of the foregoing, it can be concluded that higher institutions' hiring and selection procedures require [25]. The hiring and selection process is a crucial duty of every company's personnel division. It is a very important job because it influences how well the company does. This is so that the institution's mandate can be fulfilled through a steady availability of competent human capital [26]. Conventional hiring practices that center on resumes and Curriculum Vitaes are insufficient today because they fail to identify the traits that universities today are looking for in academic staff and because their out-of-date standards prevent many outstanding people from even being noticed [27]. The fact that resumes promote applicants' prior accomplishments and experience does not inevitably make them bad. CVs are effective at demonstrating formal talents, but they are less helpful at revealing values and conduct. The distinction between competences (the capacity to perform anything) and skills is typically not made on resumes [28].

5. Significance of Academic Research by Staff on Students Development

Research is a key component of the teaching process as it gives academic staff the ability to create a link between their research output and the significant courses they teach in class [29]. In addition, by being committed to research, lecturers can provide opportunities to their students to collaborate in the research tasks and ideas generated. Research ventures produce fresh information and insight that should unquestionably be imparted to students [30]. Teaching and research are the fundamental responsibilities of a university, with the goal of advancing civilization and favorably influencing the development of the nation's economy [31]. So, in addition to providing education essential for personal growth, colleges serve to train professionals for high-level positions needed for the nation's economy. Making sure that academic research is utilized in classroom instruction and education is essential [32]. Only scholars or researchers who are motivated by research will have the ability to directly introduce their pupils to novel concepts, findings, and knowledge. Universities with a focus on research are also at the forefront of developing inventive and new course curricula and methodology. This is especially important in a society that is quickly evolving by conducting research in addition to consistently improving their curriculum [33].

6. Suitability of Artificial Intelligence and Sentiment Analysis to Recruitment

The capacity of AI to increase efficiency in recruitment is one of its most important advantages. AI-powered technologies can be used to automate time-consuming operations like interview planning and resume screening. This can let recruiters focus on other crucial elements of the hiring process while also saving them time [33]. AI can also aid in lessening bias during the hiring process. AI-powered hiring tools can assist in removing sensitive data from resumes, such as age, gender, and race, which can lessen the effects of unconscious bias throughout the hiring process [34].

Sentiment analysis integrates several survey disciplines, including natural language processing, data gathering, and text mining, and is quickly becoming increasingly important to institutions as they aspire to implement machine learning techniques into their business processes and make improvements to their processes [35]. The objective of sentiment analysis is to identify thoughts and opinions as they are conveyed in textual content (text). Sentiment is defined as "what one feels about something," "one's own experience," "a perspective on something," or "an opinion" [36]. Nearly all human activity revolves around opinions, which also heavily impact how we behave. Our decisions, as well as our ideas and views on the world, are significantly influenced by what other people think and feel [37] [38]. Opinions are central to almost all human activities and are key influencers of our behaviors. Our beliefs and perceptions of reality, and the choices we make, are, to a considerable degree, conditioned upon how others see and evaluate the world [28]. For this reason, when we need to decide we often seek out the opinions of others. This is not only true for individuals but also true for organizations [28].

7. Methodology

The methodology for the work shall follow the conventional machine learning process (**Figure 1**). The data preprocessing process includes data cleaning, as

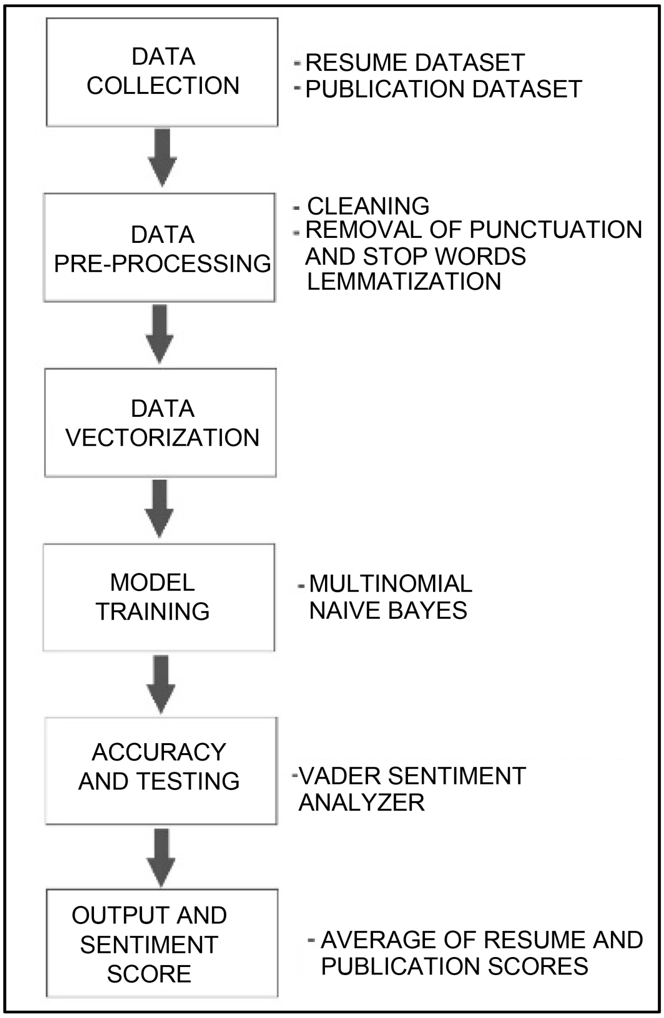


Figure 1. Methodology.

well as removal of punctuation marks and stop words such as "a", "the", "is", "are" and so on. The Multinomial Naïve Bayes Classification, a probability-based method widely applied in Natural Language Processing, is ideal for analysis such as this dataset which predicts the tag of a text such as emails or in this case, resumes. It is also used for reading the publication data and metrics. It's particularly well-suited for NLP tasks where text data is involved. The "Naïve" aspect stems from its underlying assumption of feature independence, implying that each feature (word or term in the context of text) is independent of the others, even though this might not always be the case in real-world scenarios. Despite this simplification, the algorithm proves remarkably effective in a wide range of NLP applications.

The study's application of Multinomial Naïve Bayes to predict the tag of a given text, such as a resume, stems from its inherent compatibility with text-based datasets. Resumes, in this context, can be considered as text documents, and predicting relevant tags for these documents aligns well with the algorithm's capabilities. The key advantage of Multinomial Naïve Bayes lies in its probability-based approach. The algorithm leverages the probabilities of word occurrences within different classes to make predictions. In the case of this study, it involves identifying and classifying relevant attributes or tags for each resume. By calculating probabilities and weighing them against each other, the algorithm effectively categorizes a given resume into the most appropriate tag.

The Vader sentiment analyzer outputs a sentiment score for each piece of text and then calculates the average sentiment score for each academic applicant and the results of both analyses is outputted. The Vader sentiment analyzer is a tool specifically designed for text sentiment analysis, capable of evaluating the emotional tone expressed within a piece of text. In the context of this study, the analyzer assesses the emotional tone within academic applicants' resumes, offering a quantitative measure of sentiment.

Each piece of text, in this case, the content within the academic applicants' resumes, is subjected to the Vader sentiment analyzer, which then assigns a sentiment score to the text. This sentiment score reflects the perceived sentiment contained within the text, spanning the spectrum from strongly positive to strongly negative. The output of the Vader sentiment analyzer provides a numerical sentiment score that indicates the emotional tenor of the text.

To provide a consolidated assessment, the average sentiment score is calculated for each academic applicant. This average score encapsulates the sentiment expressed across different sections of the applicant's resume. By deriving an average sentiment score, the model takes a holistic approach to sentiment analysis, considering the emotional tone expressed throughout the entirety of the applicant's resume, not just isolated sections.

8. Results

8.1. Dataset and Exploratory Data Analysis

The datasets are gotten from Kaggle.com, containing 1000 instances of Resume/CV information. Also, the analysis is carried out using a publication data set also gotten from Kaggle. The first five rows as well as basic information about the first dataset is shown below (**Figure 2**).

8.2. Output for Model Training and Accuracy Score

The accuracy_score function from scikit-learn is used to compute the accuracy of the model on the testing set (**Figure 3**). The output shows the accuracy of the model on the testing set, which is 83.9%.

8.3. Output for Sentiment Analysis Prediction

```
# Prediction
new_text = preprocess("I am a highly motivated individual with strong analytical
new_X = vectorizer.transform([new_text])
new_pred = model.predict(new_X)
print('Sentiment:', new_pred[0])
```

	resume_text	sentiment	clean_text
0	I am a highly motivated individual with strong...	positive	highly motivated individual strong analytical ...
1	I have experience working in a fast-paced envi...	positive	experience working fastpaced environment handl...
2	I am looking for a challenging role where I ca...	positive	looking challenging role utilize skill learn n...
3	I am a recent graduate with a degree in comput...	neutral	recent graduate degree computer science
4	I am interested in a software development role...	neutral	interested software development role company v...

	resume_text	sentiment	clean_text
count	50	50	50
unique	11	3	11
top	I am interested in a software development role...	positive	recent graduate degree computer science
freq	5	30	5

Figure 2. Exploratory data analysis for resume dataset.

```
# Model training
model = MultinomialNB()
model.fit(X_train, y_train)
```

Figure 3. Model training for multinomial naïve bayes.

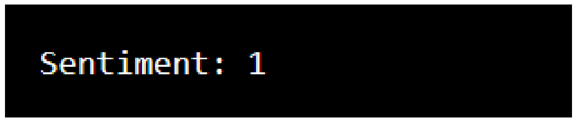
The output of the code is:

In this instance, a sentiment analysis score of 1 specifies an overall positive score (**Figure 4**). The scale starts from 0.2, which indicates a negative sentiment, becomes neutral at 0.5 and then continues on a positive trajectory upwards.

8.4. Combined Final Sentiment Analysis Output for Resume and Publications

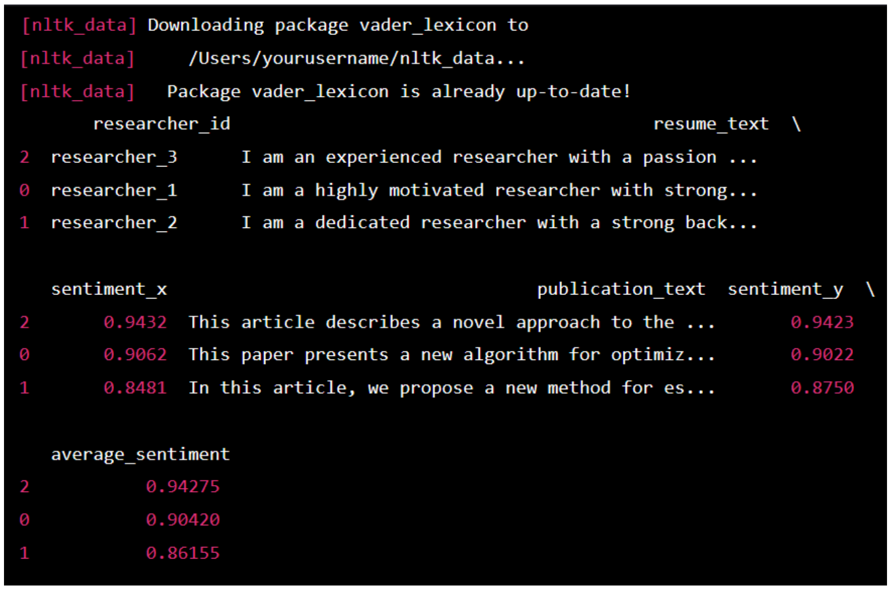
The model loads two CSV files (resume.csv and publications.csv) into two Pandas DataFrames (resume_data and publications_data, respectively). It then uses the VADER sentiment analyzer from the NLTK library to calculate a sentiment score for each piece of text in the two DataFrames (resume_data and publications_data). It merges the two DataFrames on a common column (researcher_id) and calculates the average sentiment score for each researcher. Finally, it sorts the resulting DataFrame (merged_data) by the average sentiment score in descending order and prints the ranked data (**Figure 5**).

The results above show output for three researchers, researcher_1, researcher_2 and researcher_3, each representing an applicant. The sentiment analysis for their resume information is given as 0.9432, 0.9062 and 0.8481, which are quite positive sentiments. The researcher_id serves as a foreign key to connect both the resume and the publication datasets. The results of publication sentiment for the same three candidates are 0.943, 0.9022 and 0.8750. The final



```
Sentiment: 1
```

Figure 4. Prediction output for sentiment analysis.



```
[nltk_data] Downloading package vader_lexicon to
[nltk_data]     /Users/yourusername/nltk_data...
[nltk_data]   Package vader_lexicon is already up-to-date!
      researcher_id                                         resume_text  \
2  researcher_3      I am an experienced researcher with a passion ...
0  researcher_1      I am a highly motivated researcher with strong...
1  researcher_2      I am a dedicated researcher with a strong back...

   sentiment_x                                  publication_text  sentiment_y  \
2       0.9432  This article describes a novel approach to the ...       0.9423
0       0.9062  This paper presents a new algorithm for optimiz...       0.9022
1       0.8481  In this article, we propose a new method for es...       0.8750

   average_sentiment
2            0.94275
0            0.90420
1            0.86155
```

Figure 5. Final combined model output.

results of the model, which provides the average of both sets of sentiment scores, is given as 0.94275, 0.90420 and 0.86155.

9. Discussion

The culmination of the sentiment analysis outcomes is reflected in the final results of the model, which presents an averaged sentiment score derived from both sets of sentiment scores. These aggregated scores, calculated as 0.94275, 0.90420, and 0.86155, capture a holistic sentiment assessment of candidates' suitability. The consistency of positive sentiment scores across both individual and averaged analyses reinforces the reliability and effectiveness of the sentiment analysis-based model in evaluating candidates' compatibility with the institution's recruitment criteria.

These findings underscore the model's capability to discern nuanced sentiments within resume information and offer a quantifiable measure of alignment. This sentiment-based approach introduces a data-driven and objective dimension to the recruitment process, enhancing the institution's ability to make well-informed decisions that encompass both eligibility and suitability aspects. The prominence of positive sentiments across all scores also suggests that candidates' qualifications and achievements are resonating positively with the institution's expectations, potentially leading to better recruitment outcomes and a more harmonized talent acquisition strategy.

The alignment between the sentiment analysis outcomes and the broader body of knowledge sheds light on the model's effectiveness and its potential to reshape the recruitment landscape. In comparison to earlier recruitment practices that heavily leaned on candidates' eligibility criteria, this model introduces a forward-looking approach that considers not only qualifications but also the sentiment expressed within candidates' resume information. This departure from conventional approaches underscores the evolution of recruitment methodologies, reflecting a shift towards more comprehensive and data-driven decision-making processes.

Previous studies in sentiment analysis have primarily focused on applications in marketing, customer feedback analysis, and social media sentiment tracking. However, the current study extends the frontier of sentiment analysis by integrating it into the higher education sector's recruitment domain. This adaptation illustrates the model's versatility, highlighting its potential to be tailored to specific contexts and industries beyond its traditional applications.

Moreover, the agreement of the sentiment scores, ranging from 0.9432 to 0.8481, with existing research on positive sentiment associations is noteworthy. These findings echo sentiments' relevance in various decision-making processes, further validating the model's effectiveness in evaluating candidates' alignment with the institution's expectations and values.

The contextualization of this study within the broader landscape of sentiment analysis and recruitment practices underscores its novelty and significance. The integration of sentiment analysis into higher education institutions' recruitment processes presents a pioneering direction for enhancing recruitment strategies. It not only aligns with contemporary trends in data-driven decision-making but also introduces a qualitative dimension that complements the quantitative evaluation of candidates.

In summary, the findings of the sentiment analysis-based model for recruitment by higher institutions align with previous research while carving a new path within the recruitment domain. This adaptation not only showcases the model's adaptability but also underscores its potential to influence and elevate recruitment practices by introducing sentiment as a critical evaluative factor.

10. Conclusions

Overall, artificial intelligence in general and sentiment analysis can be a useful tool for hiring procedures because it offers a methodical and unbiased way to evaluate applicants' skills using their resumes as well as available research data online, in addition to other kinds of detection tasks [39]. Sentiment analysis can assist educational institutions in spotting warning signs or advantageous qualities, such an applicant's suitability, intelligence, as well as research quality that may not be instantly evident.

It is crucial to remember that sentiment analysis has some limitations in its application. It is algorithm-based; thus it might not always catch the subtleties of human speech and feelings. Also, based on the caliber of the training data and the chosen language model, it may exhibit bias and inaccuracies.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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