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Prescriptive Decision Making Model for Contextual Intelligence in Human Resource Analytics

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This study also proposes Machine learning algorithms, specifically Logistic Regression and Gaussian Naïve Bayes, for generating recommendations; which exploit user context information to shortlist for the desired job role and also recommend alternative jobs to the candidates. Based on existing skills, new opportunities and possibilities will be introduced, that the candidate wouldn't have explored before. In an innovative approach, it also focuses on formalizing the problem of identifying the additional skills, taking into account the employee's existing skills. Performance of the proposed system is evaluated in terms of classification accuracy and the results are compared with alternative models. With an objective to assist job seekers and recruiters in selecting the perfect jobs and the right candidates to achieve career objectives and desired goals, a bidirectional recommender system is introduced later in this research work. This system comprises: Named Entity Recognition (NER), Similarity techniques and text summarization techniques. In an attempt to tackle the problem of unregistered words for text summarization, a solution called Decoder Attention with Pointer Network (DA-PN) has been introduced. This method incorporates the use of a coverage mechanism to prevent word repetition in the generated text summaries. DA-PN + Cover model with mixed learning objective (MLO) (DA-PN + cover + MLO) is utilized for protecting the spread of increasing errors in generated text summaries

Keywords: Machine Learning Algorithms, Logistic Regression, Gaussian Naïve Bayes, Contextual Recommendations, Job Shortlisting, Alternative Job Recommendations, Skills Identification, Named Entity Recognition (NER).

1. Introduction

In the rapidly evolving landscape of human resource management (HRM), organizations are increasingly turning to data-driven approaches to inform their decision-making processes[1]. The integration of analytics into HRM, commonly referred to as human resource analytics, holds tremendous potential for improving organizational performance, enhancing employee engagement, and driving strategic workforce planning.

However, the complexity and diversity of HR data pose significant challenges in deriving actionable insights that are both relevant and contextualized to the specific needs and dynamics of an organization[2].

This Work presents a prescriptive decision-making model tailored to enhance contextual intelligence in human resource analytics. The model addresses the multifaceted nature of HR data by integrating advanced analytics techniques with a deep understanding of organizational contexts and dynamicsP[3]. By leveraging machine learning algorithms, natural language processing, and predictive modeling, the model aims to analyze diverse data sources and generate actionable recommendations to optimize HR decision-making processes[4][5].

The key objectives of the prescriptive decision-making model are as follows:

Contextual Understanding: The model seeks to deepen the understanding of organizational contexts, industry trends, and cultural factors that influence HR outcomes. By incorporating contextual intelligence into the analytics process, the model can generate insights that are more relevant and actionable for stakeholders[6].

Predictive Analytics: Through the use of machine learning algorithms such as logistic regression and Gaussian Naïve Bayes, the model aims to predict HR outcomes and identify potential areas for intervention. By analyzing historical data and contextual factors, the model can generate recommendations for optimizing HR processes and improving organizational performance[7].

Skills Identification and Recommendations: An innovative aspect of the model is its focus on identifying additional skills and recommending new opportunities for job seekers based on their existing skills. By leveraging techniques such as named entity recognition (NER) and similarity analysis, the model can match candidates with suitable job roles and introduce them to alternative career paths they may not have considered before[8].

Bidirectional Recommender System: To assist both job seekers and recruiters in selecting the perfect jobs and candidates, the model introduces a bidirectional recommender system[9]. This system incorporates NER, similarity techniques, and text summarization to provide personalized recommendations and summaries tailored to the needs of each user.

Evaluation and Comparison: The performance of the proposed model is evaluated in terms of classification accuracy and compared with alternative models[10]. By assessing the effectiveness and reliability of the model, organizations can gain confidence in its ability to support informed decision-making in HRM.

There is an immediate demand for improved personnel decisions globally due to the unpredictable and ever-changing nature of the corporate environment. In order to achieve lasting success, it is crucial to thoroughly analyse data in order to identify the source of issues, implement suitable solutions, and predict future changes using solid evidence. The foundation of any good HR analytics strategy is this procedure[11]. When it comes to HR, big data analytics has shown some encouraging outcomes, particularly in the area of talent acquisition, where organisationsanalyse thousands of resumes each. Data scientists can outperform hiring experts when it comes to speed and accuracy with the help of machine learning. The terms "HR Big Data" and "HR analytics" have recently become popular jargon because they describe the area where analytics may make use of preexisting structured organisational data and Big Data can make use of unstructured heterogeneous data. When it comes to HR decision-support difficulties, in particular, both are huge deals for the HR community[12].

2. Descriptive Analytics

While raw data does not provide any insight into the causes of an event, it can make a difference once gathered. In order for businesses to keep tabs on performance and other trends, descriptive analytics—a more basic kind of analytics—are often used to generate reports, KPIs, and other measures. It takes facts from the past and makes it easier to interpret. As an example, a descriptive analysis is what every employee's report is. If we were to further subdivide it by demographics, it would still fall into the same bucket. Also included in the descriptive category are more complex measures like time-to-fill or turnover rates [3]. Both make use of prior information and seek to clarify the reasons behind past events. Reacting only using descriptive analytics is a low-level strategy. Human resources, which are changing to meet the needs of the company, should prioritise taking the initiative. Data may be turned into valuable insights with the help of diagnostic analytics. It takes into account both internal and external elements that may be impacting patterns, variations, and causal links. After descriptive analytics have shown what happened, diagnostic analytics will show you what caused it [4]. A graphical report ranking the reasons salespeople have left is one such example. The reasons for this might be anything from not meeting the quota to rivals offering better base salary.

Diagnostics get to the bottom of what descriptive data is trying to describe. To better address the issue, it would be helpful to identify its root cause.

3. Prescriptive Analytics

The issue of what to do next follows the prediction of the future. Based on predictions and historical data, prescriptive analytics suggests next steps to take.

During their busiest times of year, businesses may greatly benefit from this kind of study[13]. During the summer, a park may need to know how many employees to hire, and retailers may want to know how many to hire for the holidays. Using a new hire's strengths and abilities as a basis, prescriptive analytics may even advise on the best way to onboard them [6].

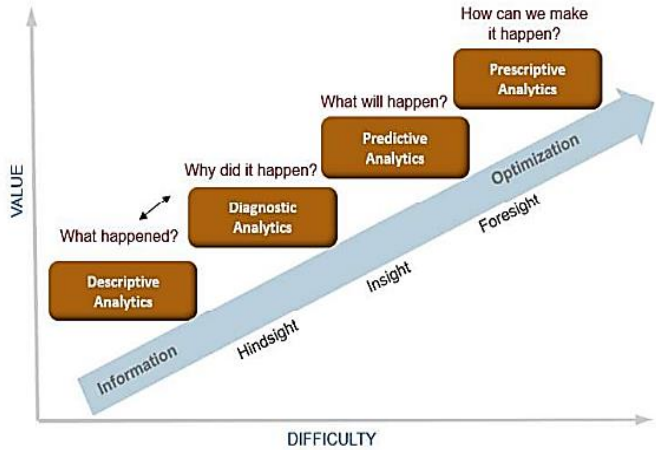

Figure 1. Types of HR Analytic

4. Benefits of Prescriptive Analytics over Predictive analytics

Based on information that is merely connected with each other, predictive analytics assumes that there is a cause-and-effect relationship or that there is some confidence about the outcome of each observed circumstance. On the other hand, HR software may go from a data-only system (Description/Prediction) to one that can prescribe a tailored set of actions based on the same data. In order to propose potential courses of action, prescriptive analytics outperform both descriptive and predictive analytics[14]. As a subfield of business analytics, prescriptive analytics seeks the most applicable and useful strategy for every particular problem; in other words, it turns predictive analytics into actionable insights. Using analytics to foretell how something will probably turn out is known as predictive analytics.

More proactive than predictive analytics, prescriptive analytics suggests courses of action that are likely to provide the intended result. Take the issue of staff retention as an example to illustrate the point that this case illustrates an HR problem. Using predictive analytics, you may find out which workers are most likely to leave your company. The action that has the best chance of keeping these workers would be recommended by prescriptive analytics. In addition to assisting with staff retention, prescriptive analytics may be used to propose training methods that enhance productivity and engagement, among other things. The most effective method to empower the HR manager in whatever area they interact with daily is via prescriptive analytics, provided there is trustworthy and solid data[15].

5. HR Needs Contextual Intelligence

Unstructured data is a bane to human resources. Consider the following: job postings, evaluation comments, social media footprints of candidates, reviews, and more. When presented with such Unstructured Data, current HR automation solutions exhibit significant shortcomings [2]. Every level of HR operations is affected by this critical deficiency. It restricts HR workers' ability to comprehend data that is relevant to them and impacts the company overall. For instance, data pertaining to professionals is handled by human resources. An important component of this is the knowledge and expertise of the people who work for the company, which is a key factor in how well the company does. On a CV, skills are often listed in relation to one another. Experience in the workplace is relative to each person. Details like this are specific to companies. Since their companies and applications are distinct, Company A and Company B have different perspectives on Java capabilities. Organisations want talent analytics for more than just that. Relevant talent analytics are required. The first section of any company strategy that contains items that must be understood in context is human resources. For HR to reap the benefits of data-driven analytics, it must reframe data in a contextual light[7].

With the help of Contextual Intelligence, which drives dynamic discussions, provides more relevant replies, and generates increasingly precise forecasts, people and robots may work together more effectively. Machine learning (ML) relies on context, which is both an essential component and the lone factor preventing it from mimicking human intelligence. Thus, machines may do the following with the help of contextual AI: Generate new knowledge: By analysing data for patterns and characteristics and drawing on information from a small number of supervised learning instances, a contextual AI system may learn more about each given scenario. This paves the way for AI systems to learn without human oversight, approaching new situations with the same individualised approach that humans do.

Transfer knowledge between contexts: What this implies is that AI systems may generalise their learnings from one setting to another, allowing them to perform better on comparable tasks. A contextual AI responsible for transcribing a business conference, for instance, may immediately identify and associate a project name with an earlier reference in a separate meeting.

Infer context to problem-solve: Artificial intelligence systems grow better at taking into account all relevant factors to determine the end-user's actual demands in the present instant as they learn from each encounter. A self-driving automobile, for instance, may detect obstacles on the road, such as people or rain, and slow down accordingly.

6. Methodology and Proposed Architecture

Unstructured data is mostly textual. Either carefully reading it word for word or using certain automated methods to extract the necessary information is necessary for comprehension. Text Mining methods are essential for extracting important information from large amounts of textual data. These approaches convert unstructured material into a structured form, allowing for additional insights, processing, analysis, and visualisations.

The Internet now constitutes the bulk of people's daily lives. But now more than ever, it's essential to use the Internet to identify qualified workers or employment opportunities. It takes a lot of human labour and a lot of time for standard databases to handle a big number of applicant resumes in an unstructured format[11]. Whereas, a candidate resume parsing applicant tracking system should be able to handle the constant expressivity of natural language and undergo continuous training.

Traditionally, recruiting departments have assessed resumes as static records. A hiring manager will often peruse a CV section by section, looking for evidence of relevant abilities and expertise in areas like schooling, projects, and previous work experience. Therefore, having the hiring manager read the whole resume to locate each relevant component for the position substantially increases the time it takes to analyse a resume.

Resumes and curriculum vitaes may take several forms, including text files (txt, doc, pdf, etc.) and a wide range of content and formatting options. Important information is difficult to retrieve due to this variability. A lot of time and energy goes into reviewing resumes by the HR staff in order to extract useful information. After the data is retrieved, choosing the right people who match the job descriptions becomes a breeze. Because of how time-consuming it is, there is an immediate need to standardise and organise the data stored in the skills database. Resume processing involves several levels of analysis to extract relevant information about a candidate. Here are some common levels of processing:

1. Text Extraction: In the initial stage, the system extracts raw text from the resume document. This involves converting various file formats (PDF, Word, etc.) into machine-readable text.

2. Entity Recognition: Use natural language processing (NLP) techniques to recognize entities such as job titles, companies, educational institutions, dates, and locations. This helps in understanding the context and relationships between different pieces of information.

3. Skill Extraction: Identify and extract key skills mentioned in the resume. This involves using predefined lists of skills or employing machine learning models to recognize relevant keywords.

4. Keyword Matching: Match extracted information against predefined criteria or keywords specified by the employer. This helps in identifying candidates who possess the desired qualifications and skills.

5. Ranking and Scoring: Assign scores to candidates based on how well their skills match the job requirements. This step may involve using algorithms to calculate relevance scores

This study suggests a strategy to prevent expected metric deviation by extracting useful information from CVs and resumes and then making suggestions based on the company's preferences and requirements. In order to achieve the target, the whole procedure has been split into three parts. In the first part, we use natural language processing (NLP) to glean relevant data from unstructured documents; in the second part, we analyse and interpret the findings; and finally, we update the count for the keywords in the resume of the chosen applicant.

The proposed effort focuses on one particular area, namely, resumes and candidate profiles. Based on the preferences and needs of the firm, this study suggests a strategy for extracting useful information from resumes and making suggestions. With an emphasis on extracting unique abilities via Natural Language Processing (NLP), it suggests a machine-learning approach to resume phrase matching. Software can now comprehend spoken or written language thanks to natural language processing (NLP), an AI approach.

7. Conclusion

The prescriptive decision-making model presented in this study represents a comprehensive approach to enhancing contextual intelligence in human resource analytics. By leveraging advanced analytics techniques and incorporating a deep understanding of organizational contexts, the model empowers organizations to make data-driven decisions that drive strategic workforce planning, improve employee engagement, and enhance organizational performance. Through further research and empirical validation, this model has the potential to revolutionize HRM practices and contribute to the achievement of organizational objectives in today's dynamic business environment.

Conflicts of Interest

The authors declare that they have no competing interests.

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