Personality-based Hybrid Machine Learning Model for Mentor-Mentee Matching using Collaborative and Content Filtering Methods

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***Abstract*— Mentoring relationships have gained increasing significance in the contemporary business world, serving as a valuable platform for personal and professional growth. This study endeavors to explore the importance and impacts of mentorship relationships within the workplace. It investigates the role of mentorship programs in high school, university, and workplace settings, with an emphasis on the cruciality of aligning mentors and mentees based on shared interests, expertise, and goals. Consideration of factors such as learning and teaching styles becomes essential to cultivate a productive mentor-mentee relationship. To facilitate the identification of suitable mentor-mentee pairings based on skills, goals, and personality types, this study presents a hybrid machine learning model that combines collaborative filtering and content-based filtering algorithms. The analysis of skills and goals aids mentors in guiding mentees in their professional development, while evaluating personality traits helps determine compatibility and communication styles. In conclusion, this study suggests leveraging machine learning algorithms to recommend mentors based on various factors, utilizing personality types as one of the attributes to pair the most compatible mentor and mentee, ultimately leading to successful mentorship programs.**

Keywords—mentor, mentorship, matching algorithm, machine learning, content-based filtering, collaborative filtering

I. INTRODUCTION

In the contemporary world of business, the establishment of strong mentoring relationships is deemed indispensable as they serve as a valuable platform for personal and professional growth [1]. Acknowledging the inherent worth of mentorship for both mentors and mentees holds great significance in such a dynamic work environment. By fostering a mentoring culture, organizations can actively encourage collaboration, knowledge sharing, and continuous learning. This preface sets the stage for a comprehensive exploration of the considerable significance and advantageous impacts that mentoring relationships hold within the workplace.

The mentorship program plays a crucial role in the development and success of high school students, university students, and individuals in the workplace. While the mentorship programs for each group differ in focus, they all serve the purpose of guiding and supporting mentees towards their respective goals.

In high school, mentorship programs are designed to assist students in making decisions about their future after high school [2]. They provide guidance in career exploration, college or vocational training choices, and personal development. It is important to highlight the valuable insights and advice that mentors in high school programs can offer to help students navigate through this significant transitional period.

For university students, mentorship programs have a more focused approach towards academic and professional growth [3]. Mentors can aid in course selection, major declaration, and exploring internship opportunities. It is crucial to emphasize the importance of mentors in helping students make informed decisions about their academic and career paths, as well as providing guidance on networking and developing necessary skills.

In the workplace, mentorship programs aim to support individuals as they navigate their careers and strive for professional growth [4]. Mentors in these programs provide guidance on job-specific skills, industry knowledge, and career advancement strategies. It is essential to underscore the role of mentors in facilitating learning, fostering a sense of belonging, and helping mentees achieve their career goals.

Overall, mentorship programs are vital in different life stages as they provide tailored guidance and support to individuals in high school, university, and the workplace. Despite their differences, these programs all play a significant role in shaping the mentees' development and success.

A. The matching Process

The matching process determines the effectiveness of mentoring, where careful consideration of shared interests, expertise, and goals is essential. A successful mentor-mentee pairing involves evaluating the needs, aspirations, and personalities of both individuals to foster a productive and supportive learning environment for guidance and mentorship, resulting in mutual growth and development [5].

B. The purpose

When considering the pairing of mentors and mentees in a mentorship program, it is crucial to take into account their shared interests, expertise, and goals. This is applicable to high school students, university students, and workplace mentoring. A successful mentor-mentee match involves evaluating the needs, aspirations, and personalities of both individuals. By nurturing a productive and supportive learning environment, the mentorship experience can lead to mutual growth and development [6].

However, it is worth noting that personal factors are often overlooked in the mentorship matching process. Understanding the preferred learning and teaching styles of individuals is essential. Just as different students have different techniques for learning, mentors and mentees may also have varying approaches to teaching. Therefore, it is important to consider the personalities of mentors and mentees to ensure a fruitful and effective mentor-mentee relationship.

Ongoing research endeavours aim to identify the factors that contribute to the best mentor-mentee pairings. While workplace mentorship programs generally match junior and senior employees in the same departments, personal factors are often disregarded. To address this issue, this study will investigate the significance of personality in mentor-mentee matching and assess if it leads to better pairings compared to matching based solely on skills and goals.

The present study examines a NZ based company's mentorship program, which encompasses detailed information about the mentees and mentors, including their job titles, skills, and goals. As part of this study, employees were required to undergo the 16 personality type test, and the results of this test are also incorporated. The collected data was enhanced and subsequently utilized in a hybrid approach that combines the CNN machine learning algorithm and content-based learning. The aim of this approach is to predict the most appropriate mentor for a given mentee based on their skills, goals, and personality types.

II. Literature Review

First, confirm that you have the correct template for your paper size. This template has been tailored for output on the A4 paper size. [7] outlines a comprehensive methodology for effectively matching mentors and mentees. They propose considering deep-level similarities, the career progression needs of mentees, and both parties' input during the matching process to ensure an efficient match. [8] highlights the limitation of a lack of mentors, which hinders the establishment of an efficient matching process. Their study suggests that the mentor-mentee match should involve a multi-stage process to foster personalized mentoring relationships. [9] emphasizes the benefits of mentoring programs in the workforce and the importance of considering the growth and needs of both mentors and mentees. They advocate for including the interests, backgrounds, preferences, and expectations of both parties in the matching process.

Similarly, [10] identify attributes for effective mentoring relationships in the academic industry, focusing on active engagement, communication, and shared interests between mentors and mentees. While they hint at the significance of considering personality, it is not explicitly mentioned. Literature reveals the implementation of mentoring programs across various industries and populations. [11] conducted a qualitative study that showed mentors without vision impairments tended to be younger, more likely to work in a helping profession, and have lower expectations.

However, the attributes, expectations, and mentoring process differ in a community of high-risk probationers. [12] conducted a qualitative study analyzing the perceptions of mentors and mentees involved in a mentoring program for high-risk probationers. Mentees highlighted relatability and support as key issues, and it was found that the best matches were between individuals with similar lived experiences and criminal histories.

[13] found that concordance and discordance in the neuroticism personality trait significantly impacted the perceived success of mentorship relationships in terms of professional advancement. Their research was based on the person-environment (P-E) fit concept. [14] proposes a meeting-based mentoring program that takes into account mentees' and mentors' preferences, communication methods, ethnicity, and not just their goals and interests during the matching process.

There exists a body of literature that explores the pairing and mentoring process through the utilization of machine learning algorithms. [15] conducted a comparative investigation of solution algorithms employed in matching mentors and mentees. They examined approximation algorithms, heuristics, and a two-sided matching approach. Their study revealed that the manipulation methods employed significantly influenced the algorithms, leading to biased solutions.

In another study, [16] compared different algorithms aiming to identify high-quality solutions for matching mentors and mentees. They concluded that a combination of evolutionary heuristics and local search approaches yielded the most favorable outcomes in terms of achieving expected high-quality matches.

[17] analyzed two alternative electronic data processing (EDP)-supported matching processes, namely the "online algorithm" (OA) and the "online search" (OS), in comparison to personal matching (PM) conducted by an experienced expert. They discovered that personal matching performed better than both EDP-supported methods. Considering the investment required in personal matching, the authors concluded that EDP-supported matching could serve as a viable compromise. Nevertheless, the study highlighted the need for further research in developing an efficient EDP-supported matching process.

Although the literature acknowledges the importance of algorithms and the attributes that contribute to an efficient mentor-mentee match, it remains divided and lacks cohesion regarding the specific algorithms and matching processes. While some literature highlights the significance of incorporating personality traits in the matching process to enhance the mentor-mentee relationship, it does not provide technical guidance on implementing such factors in online or digital tools. Notably, no literature was found that pertains to the utilization of machine learning or AI technology for the matching process.

III. Methodology

A. Dataset

A mentorship program is currently being implemented by a New Zealand-based IT company for its permanent staff members. The process of selecting mentors involves a careful evaluation by the leadership team, taking into consideration various attributes such as the skills and goals of the mentees. This ensures that mentor-mentee alignment is achieved based on the compatibility of their skills. It is possible for a mentor to have multiple mentees. The program entails regular meetings with mentors to monitor progress towards achieving yearly goals, which can be both professional and personal in nature. The dataset used for this study encompasses the skills, goals, and personality types of these mentors and mentees. To protect privacy, employee names have been altered, and certain mentor-mentee pairings were omitted due to their potential ease of identification, thus complying with privacy regulations.

The 16 personality types of the Myers-Briggs Type Indicator (MBTI) are grounded in the theories of Carl Jung and serve to comprehend individual discrepancies in how individuals perceive the world and make decisions [18]. Each type is denoted by a combination of four letters: extraversion (E) or introversion (I), sensing (S) or intuition (N), thinking (T) or feeling (F), and judging (J) or perceiving (P).

By comprehending these dichotomies and the subsequent amalgamations, one can obtain insights into their own personality type and how they engage with others. It can serve as a valuable tool for personal advancement, professional guidance, and enhancing communication and comprehension in relationships.

We are proceeding in this study under the assumption that the manual pairing process ensures that each mentor and mentee pairing is the most suitable match within the mentorship program. The evaluation of the machine learning algorithm will be conducted based on this assumption and will be compared to the actual pairing.

B. *Features and Supervised Learning Method*

A Convolutional Neural Network (CNN) is a deep learning algorithm, predominantly utilized for image classification and recognition within the field of machine learning. It draws inspiration from the organizational structure of the visual cortex in the human brain and finds extensive application in various computer vision tasks [19]. The CNN algorithm employs multiple layers of interconnected nodes, which perform convolutions on the input data to extract significant features. Subsequently, these features are subjected to pooling layers that reduce dimensionality while preserving crucial information.

Collaborative filtering is a prevalent recommendation algorithm that aims to predict user preferences for items by leveraging the preferences of similar users [20]. In recent years, the application of CNN for collaborative filtering tasks has demonstrated promising outcomes. Do not use abbreviations in the title or heads unless they are unavoidable.

Convolutional Neural Network (CNN) algorithms are extensively utilized in the field of Natural Language Processing (NLP) owing to their remarkable efficacy in capturing local patterns and hierarchies within textual data [21]. These algorithms operate by applying a sequence of filters to conduct convolution over the input text, thereby extracting pertinent features at varying scales. This unique ability enables CNNs to comprehensively comprehend and analyze the contextual and semantic aspects inherent within the given text.

Content-based filtering is a machine learning technique utilized to recommend items based on their content characteristics. It entails the analysis of item content and comparison with the user's preferences in order to provide personalized recommendations [22].

In the context of mentorship, content-based filtering can be applied to match mentors with mentees by evaluating their shared interests and preferences. This technique examines the attributes of mentors and mentees, such as industry experience, specific skills, educational background, and professional goals, to offer personalized suggestions. By utilizing machine learning algorithms, the system can propose mentors to mentees who possess similar content attributes, enhancing the chances of establishing a successful mentorship relationship. This approach enables mentees to find mentors who possess the desired knowledge and expertise, while mentors can connect with mentees in their specialized areas. Ultimately, content-based filtering empowers both mentors and mentees to engage in meaningful and productive mentorship connections.

C. *Proposed Hybrid Approach*

To develop the CNN-based recommendation system for this study, we applied a hybrid approach that integrates collaborative filtering using CNN and content-based filtering based on skill, goal, and personality types. The use of collaborative filtering assists in capturing user interactions and similarities. In contrast, content-based filtering considers individual user preference [23].

D. *Method*

The data was obtained in a CSV format from the company, wherein each row consists of various details regarding the mentees, such as their name, job title, skills, goals, and personality type. Additionally, the data also includes information about the assigned mentors, encompassing their skills, job titles, and personality type. As part of the data preprocessing steps, any row lacking a personality type was eliminated. Subsequently, the data underwent augmentation and preprocessing in Python, utilizing a dataframe format. A tokenization process was then applied to convert the strings into arrays suitable for insertion into the machine learning model.

Following the tokenization phase, the data was split into an 80/20 ratio, with 80% allocated for training and the remaining 20% reserved for evaluating the model's quality. The subsequent step involved designing a CNN model using the collaborative filtering method, which initially required no layers to determine the model's baseline accuracy. The first input layer was subsequently developed using the content-based filtering approach, incorporating the mentors' skills and the mentees' goals and skills. As a result, in these initial layers, the matching and analysis of these features occur. The machine learning model was then re-executed with the input from the first layer.

The third iteration entailed constructing the personality layer, encompassing the personality types of both mentors and mentees. By reintroducing this layer, the machine learning model underwent another round of execution. Throughout this process, the model's performance was evaluated by predicting the output of the test data. The process is depicted in figure 1.filtering considers individual user preferences [23].

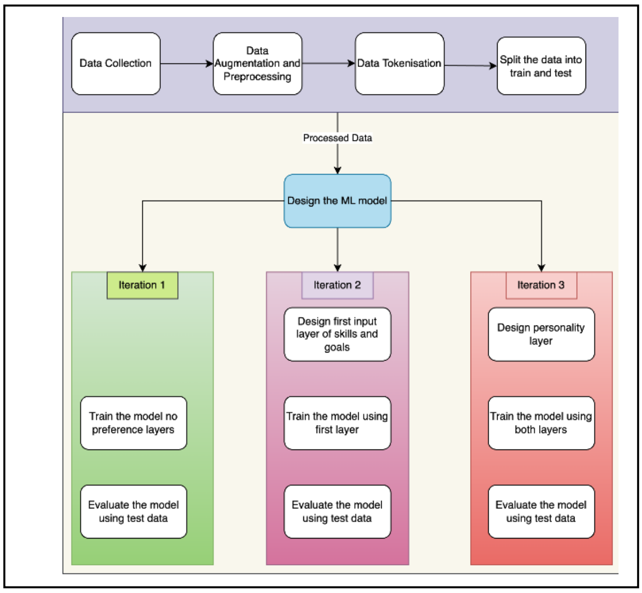

Fig. 1. Overview of the methodology

IV. Results and Discussion

For the purpose of this research, we obtained a dataset containing information about mentors and mentees, including their skills, goals, job titles, and personality types. It should be noted that providing the personality type was not mandatory for the mentorship program, resulting in some pairs without this attribute being excluded from the data. Ultimately, a total of 22 mentor-mentee pairs were included in this study. To ensure the dataset was of sufficient size for analysis, augmentation techniques were applied to expand the data, making it suitable for input into the machine learning model.

The model was executed in three iterations, each with different input. In order to evaluate the quality of the model in each iteration, a cross-validation method was employed. This involved using test data to assess the accuracy of the model. Table 1 illustrates the accuracy rates obtained in each iteration. Given the limited amount of data available, the number of training epochs was set to a relatively low value of 15 to prevent overfitting. This means that the model traversed the entire training dataset 15 times, updating its parameters in order to learn from the data. To further fine-tune the model, a larger batch size of 32 was chosen to reduce noise in the data, particularly in attributes such as skills and goals which initially consisted of free-flowing text columns. In this particular case, a larger batch size of 64 was intentionally avoided to prevent slower convergence of the model.

TABLE I. Accuracy Rate per Iteration

Iteration	Input	Model Accuracy
Iteration 1	Processed data with no layers	49.2%
Iteration 2	Processed data with first input layer of skills and goals	52.0%
Iteration 3	Processed data with first input layers of skills and goals and another layer of personality	78.0%

From the data presented in Table 1, it is apparent that the inclusion of skills and goals as the primary layer resulted in a mere 3% increase in the accuracy of the model, which can still be considered poor. Notably, by introducing another layer pertaining to the personality traits of both mentor and mentee, the accuracy rate improved to 78%, indicating a substantial 26% increase. This addition greatly enhanced the model's precision. However, it is uncertain at this stage whether the significant improvement in accuracy is a result of incorporating personality types, which provide a structured approach to the data, or simply due to the addition of another layer.

Further examination of the accuracy entailed scrutinizing the evaluated data. The comparison of the test output with the predicted output during the third iteration revealed an interesting finding. Specifically, one aspect of the personality traits played a significant role in determining a successful mentor-mentee pairing.

In understanding an individual's personality and their compatibility with others, the traits of intuition and sensing hold key importance. Intuition refers to the ability to perceive patterns, possibilities, and future outcomes. It enables individuals to establish connections between seemingly unrelated information and generate innovative ideas. Conversely, sensing focuses on the present moment and tangible details. It relies on the five senses to gather information and prefers to work with what is directly observable.

Acquiring a comprehension of these personality traits enables individuals to better understand themselves and their preferred approach to processing information and making decisions. For instance, individuals with a strong intuition trait may be inclined to rely on gut instincts, imagination, and possibilities. They often excel in brainstorming and envisioning future scenarios. On the other hand, individuals with a strong sensing trait may prefer concrete data and observable facts. They excel in analysing details and engaging in practical tasks.

Regarding compatibility, individuals with similar personality traits are likely to share common ways of perceiving and processing information. For example, two individuals with a strong intuition trait may enjoy exploring imaginative possibilities and engaging in profound discussions about abstract concepts. Similarly, two individuals with a strong sensing trait may thrive in a relationship where they can focus on the present moment and revel in sensory experiences together.

When analysing the initial pairing data, it was observed that approximately 60% of the pairings were formed based on matching mentees with the intuition personality trait with mentors possessing the same personality trait, and conversely, matching mentors with the sensing personality trait with mentees exhibiting the same trait. This finding supports one of the research points identified in the literature review, highlighting the significance of aligning the learning style and teaching style when pairing a mentor with a mentee. Consequently, the introduction of the personality layer in the machine learning model significantly improved its accuracy rate.

This revelation prompted consideration of solely utilizing the personality trait as a basis for matching mentors and mentees. However, re-running the model by solely incorporating the personality trait was deemed unnecessary. While a high accuracy rate would indicate compatibility between individuals with similar personalities, it would not guarantee that the assigned mentor would effectively guide the mentee. Hence, the amalgamation of skills, goals, and personality type yielded a model with a considerably impressive accuracy rate.

A. Limitation and Future Research

The limitation regarding the data quantity is evident. Enhancing the model can be achieved by incorporating a dataset that encompasses a substantial number of pairings.

As previously emphasized, the evaluation of these pairings is conducted manually by the leadership team. When a new individual joins the organization, the leadership team carefully considers their resume, skills, and other relevant factors to determine the best mentor who can cater to the mentee's specific needs and contribute to their professional growth. It is assumed that these pairings are the most suitable, and thus, the model's results are compared against them to assess its accuracy. However, to delve deeper into the mentor-mentee pairing, the company has the potential to administer an evaluation survey to mentors and mentees after a certain period of time to gather feedback on their satisfaction with the pairing. Analyzing these surveys and comparing them with the machine learning model could further refine the algorithm.

At present, the model provides a binary output, rendering a simple "Yes" or "No" response when subjected to mentor-mentee pairing data. To enhance its efficacy, the output could be transformed into a percentage format that denotes the calculated compatibility between a mentor and a mentee.

Another avenue of exploration could involve developing a recommendation system on top of this model. By prompting mentees to input information regarding their skills, goals, and personality type, the model could generate the top three mentors who are likely to be compatible with the mentee, based on the output percentage.

V. Conclusion

The aim of this study was to develop a hybrid machine learning model utilizing both collaborative filtering and content-based filtering algorithms. The objective was to identify the most suitable mentor-mentee pairings based on their skills, goals, and personality types. The analysis of skills and goals helped assess the current professional positions of the mentors and mentees, enabling mentors to utilize their expertise to guide mentees in enhancing their skills and achieving their yearly objectives within the mentorship program. The consideration of personality traits enabled an examination of mentees' preferred learning styles and mentors' preferred teaching or guidance approaches. Additionally, the personality trait analysis served as an indicator of compatibility between pairs in terms of their communication styles.

To implement the collaborative filtering methods, a CNN model was designed using a dataset consisting of mentor-mentee pairings from an IT company based in New Zealand. Two input layers were created employing content-based filtering: one to match the skills and goals of the pair and another to match their personality traits. The Myers Briggs personality indicator test results were used to calculate the personality traits of the pairs.Evaluating the model revealed an accuracy of 78%, which is quite favorable considering the limited size of the dataset. This hybrid machine learning model demonstrates promising performance in the domain of mentor-mentee pairing analysis.

The existing body of literature extensively covers the subject of effective mentor-mentee matching, highlighting the numerous advantages of a successful pairing and outlining how these factors can be implemented in a mentorship program. From a machine learning perspective, researchers have found evidence that supports the effectiveness of certain algorithms for matching mentors and mentees, paving the way for the development of search engines or recommendation tools to assist mentees in finding suitable mentors. Contrary to existing literature, which relies on the mentee's choice in selecting a mentor, this study employs a machine learning algorithm to recommend the most suitable mentor for a mentee based on their skills, goals, and personality type – factors not currently addressed in the literature.

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