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TEAM BUILDING BASED ON A RELATIONAL ANALYSIS ON A PROFILING SYSTEM

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ABSTRACT

In this article, we will show the application of machine learning techniques to develop a recommendation system for employee profiles in order to assign them to specific projects. The aim of this system is to help managers to have a clear idea about the profiles of their collaborators in order to build up a productive team. Our work presents a recommendation system based on a profiling system and relational profile which is based on the publications posted in a professional network. It is made up of two parts. The first part is dedicated to the profiling system based on the extraction of information from internal data and the extraction of interests, psychological profile, and relational profile from the publications exchanged in the professional platform, and the second part is dedicated to the recommendation of profiles corresponds to the requirements of each project.

Keywords: *Recommendation System, Centers Of Interest, Psychological Profile, Relational Profile.*

1. INTRODUCTION

Companies in their pursuit of improvement and increased profitability are undergoing a journey to optimize their management structures and explore innovative solutions. A crucial aspect of this evolution involves finding ways to enhance employee productivity through collaboration and interaction, within groups. Creating an environment that fosters teamwork and trust brings benefits, including increased productivity stimulated innovation efficient problem-solving, and stronger team dynamics. As a result, effective project management necessitates the execution of a process for selecting employees.

Traditionally project leaders heavily relied on judgments when selecting employees for projects. They focused on an individual's perceived trustworthiness and overall competency in managing tasks. However, this approach had limitations as human trust was subjective and lacked foundations. As a result, companies began developing resource (HR) processes that utilized skill assessments and limited historical data to recommend employees for project assignments. However, this approach frequently led to less-than-ideal team formations and project results that were not optimal.

Our belief is based on the understanding that while skills and experience are attributes for project success, they alone are not sufficient. In addition to acquiring skills over time the compatibility between team members along with shared trust, among them can significantly boost project accomplishment by facilitating tasks. As the wise words of Mattie Stepanek remind us " Unity is strength... when there is teamwork and collaboration, wonderful things can be achieved."

To tackle this significant issue, we suggest implementing a profiling system that focuses on relationships. By utilizing advanced data analysis and machine learning techniques, this system will provide recommendations on employees who can work together seamlessly for project completion. The main goal of the profiling system is to simplify the employee selection process by offering information on individual characteristics, skills, experiences, and expertise. In addition, it aims to uncover their interests and gain insight into their psychological motivations. Through harnessing Natural Language Processing (NLP), organizations will be empowered to make well-informed decisions when forming project teams. This approach identifies profiles with strong collaboration potential based on relationship compatibility, ultimately enhancing performance in projects and achieving overall success for the organization.

The main aim of this study is to create and establish a creative system that profiles individuals based on their relationships. The goal of this system is to accurately evaluate employees and assign them roles in specific projects, considering their distinct interests and skills. By doing so, it aims to promote successful collaboration among team members for the successful completion of assigned projects. To

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accomplish this objective, we suggest integrating diverse data sources like HR records, as well as analyzing employee communications published within their professional networks inside the organization.

Our proposed solution combines data analysis and machine learning algorithms to enhance relationship-based profiles. This will enable the identification of patterns, correlations, and insights that help create cohesive project teams and make optimal employee assignments. Our system's intelligent recommendation engine takes into account varying project requirements, employee interests, and individual profiles to ensure the formation of balanced, coherent, and high-performing project teams.

This article delves into the effectiveness of using relationship-based profiles to create cohesive teams for project missions. We conducted a thorough analysis of the existing methodologies and frameworks that are relevant to employee profiling in project management. Our review revealed the shortcomings of current practices, emphasizing the importance of a more systematic and data-driven approach to employee recommendations.

To sum up, this article presents a new approach to project management. It proposes using data to create a profile that matches employees with projects, improving team cohesion and motivation. This method has the potential to transform project management and lead to better outcomes for organizations.

This paper covers different aspects of our research. Section 2 gives an overview of the existing methodologies and frameworks. In the third section, we elucidate the model we have put forward. Section 4 presents the results of our study, highlighting the importance and benefits of our model. Finally, in Section 5, we conclude our research by providing valuable insights into the significance and impact of our relationship-based profile in the field of project management.

2. RELATED WORK

The cornerstone of any project lies in its team, and the thoughtful curation of team members holds the utmost significance in effectively steering a project. Building a proficient team within the organizational framework emerges as a foremost concern for management, as it stands as a pivotal prerequisite for a company's triumph. This concept is supported by [1]. Undoubtedly, a well-structured team possesses the essential vigor to confront hurdles, fulfill predetermined aims, and surpass anticipations. Thus, the meticulous selection of team members, taking into account their competencies and individual traits, emerges as a pivotal task to secure a project's success within a corporate setting. This assures the formation of a high-achieving, unified, and driven team, adept at surmounting challenges and delivering exceptional outcomes, thereby enhancing the company's positive standing in the market.

To mitigate these challenges, businesses have progressively embraced more systematic and equitable methods for selecting collaborators for their projects. They have implemented more structured Human Resources (HR) management procedures founded on potential collaborators' competencies. Utilizing collaborators' Curriculum Vitae (CV) to assess their skills and qualifications presents an unbiased and transparent approach to forming adept teams tailored to the project's requirements [2, 3].

Nonetheless, the judgments made by recruiters are not entirely dependable. Furthermore, due to the substantial volume of CVs received during the selection process to identify the right collaborators for projects, project managers have become unable to thoroughly scrutinize all the details within a limited timeframe. Consequently, despite the utilization of CVs, there might still be constraints on project managers' capacity to fully discern the skills and capabilities of each applicant. Thus, the automation of this procedure becomes imperative. A certain study hinges on objective criteria extracted from candidates' LinkedIn profiles and subjective criteria drawn from their online presence to estimate candidates' relevance scores and infer their personality traits. The ranking of candidates is driven by machine learning algorithms that learn the scoring mechanism from training data supplied by human recruiters. Nevertheless, this approach primarily emphasizes technical skills gleaned from LinkedIn profiles, potentially neglecting other vital attributes such as interpersonal skills or adaptability [4].

Notwithstanding the mechanization of selection processes grounded in objective criteria, a critical element that could be outsourced or inadequately considered in collaborator profiles is the psychological dimension. While technical skills and professional experience can be evaluated with a certain degree of objectivity based on CVs and online platforms, the assessment of personality traits, soft skills, and cultural compatibility remains intricate. A multi-agent team formation mechanism is put forth for a task, taking into account factors like team size, willingness, capability, trust, and the

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reciprocity of the agent. The system is simulated through a case study involving the creation of a virtual medical council using JADE, and the findings demonstrate that our proposed algorithm yields a proficient team of expert agents from a community of agents that are best aligned with the task. Team efficiency is gauged by the collective average willingness, trust, and reciprocity of the team. By tailoring specific parameters for each agent, this approach facilitates the customization of team composition based on each member's distinct traits and skills. This has the potential to lead to teams that are more suited to the precise task at hand. Nevertheless, while the approach may prove efficacious in the specific context of the case study, its generalizability to other scenarios or application domains necessitates further verification. The effectiveness of the approach may fluctuate contingent on the specifics of tasks and contexts [5].

Despite notable progress in team selection and composition, there's a gap in the literature regarding social and collaborative dynamics among team members. This stems from candidates' potential lack of understanding about collaboration, despite their impressive skills. This gap could lead to conflicts and disruptions in projects. To address this, a relational profile creation for collaborators is being explored, leveraging internal company data, interests, and emotions from platform communications. The aim is to identify individuals inclined to collaborate effectively based on shared motivations and project-related interests.

A research paper introduces the logical concept where team constituents are chosen based on criteria like expenses, expertise, and understanding. These criteria are shaped by pragmatic, financial, and alternative rationales, chiefly considering the sway of supply and demand dynamics in the market. The rationale behind this approach is that team members ought to be chosen based on their competencies concerning expertise, abilities, and the accumulation of resources [6].

But another study looks at the personality classification of social network users using the five-factor personality model. The five-factor model of personality (also known as the Big Five) identifies five main personality dimensions: extraversion, agreeableness, conscientiousness, emotional instability, and openness to experience. The researchers explored how these personality traits can be predicted or classified by analyzing user profiles on social networks. The study involved collecting data from social network profiles, such as Facebook, Twitter, or LinkedIn, and analyzing information shared by users, such as posts, photos, social interactions, etc. Using machine learning and classification techniques, the researchers attempted to link online behaviors and profile information to the personality traits of the five-factor model. The results of the study showed that certain characteristics of social network profiles are correlated with certain personality dimensions. For example, users who frequently share photos of parties and social events could be classified as more extroverted. Similarly, people who often interact with other users' publications could be classified as more agreeable [7].

One article explores the processes of group and team formation within social networking platforms such as Facebook or LinkedIn. The authors use real or simulated social network data to create computer models and simulations, aiming to better understand team-building dynamics. It examines different strategies and mechanisms that influence team building in a social network context. These include elements such as friendships, shared interests, previous interactions, and so on. The authors use computer simulations to test various hypotheses about how individuals come together to form teams, and how these teams develop over time [8].

When it comes to building effective project teams, many studies have focused on the importance of considering common characteristics between members, such as their technical skills, past experience, and working styles. However, within this approach, a crucial element has often been overlooked: the individual motivation and interests of each collaborator. It's undeniable that the technical skills and experience shared within a project team play an essential role in achieving objectives. However, ignoring the personal motivations and passions of each member can potentially limit creativity, commitment, and cohesion within the team. Individuals are deeply influenced by their personal interests, aspirations and values. When these elements are taken into account in the composition of a team, significant benefits can result.

First of all, the inclusion of individual motivations can foster a higher level of commitment. When employees work on aspects of the project that correspond to their interests, they are more inclined to invest extra time and effort. This increased involvement can translate into a better quality of work and a greater willingness to collaborate with other team members. What's more, the diversity of motivations and interests within a team can stimulate creativity and innovation. Different perspectives

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from different fields of interest can generate innovative ideas and unexpected solutions to project challenges. Interaction between people with distinct passions can lead to rich discussions and unique approaches to tackling problems. By taking individual motivations into account, project managers can also better tailor each member's responsibilities and tasks. Assigning roles that match each individual's interests and strengths can not only improve efficiency but also enhance a sense of personal accomplishment. Members will feel valued for their specific skills and have the opportunity to contribute in a meaningful way.

3. PROPOSED MODEL AND ALGORITHMS

The methodological requirements of this study encompass three distinct components, each serving a pivotal role in achieving its objectives. Let's delve into these components in detail:

The initial facet of our approach involves crafting a comprehensive personal profile leveraging the collaborator's information sourced from the company's expansive global database. This profile encompasses a spectrum of essential attributes such as identifiers, professional experience, educational background, and more. By amalgamating these insights, we establish a foundational understanding of each collaborator.

Moving forward, the second aspect delves into the realm of natural language processing, a transformative area of exploration. Here, our focus intensifies on refining the profiling process. We embark on an intricate analysis of the collaborator's publications, comments, and if available, dialogues exchanged among colleagues. This analysis uncovers a rich tapestry of information that underpins two key elements:

- ✓ Centers of Interest: Employing a technique known as "Topic Modeling," we uncover the unique spheres of interest for each employee. This reveals the thematic threads that intricately connect their professional pursuits.
- ✓ Psychological Profiles: Through an in-depth "Emotions Analysis," we decipher psychological nuances, shedding light on the emotional fabric that shapes the collaborator's interactions.

Combining the insights garnered from these analyses, we weave an intricate tapestry of a holistic profile for each employee, capturing both their professional interests and emotional inclinations.

Transitioning to the third dimension, we venture into the landscape of relational profiles. Here, our exploration hinges on identifying favored contacts for each collaborator, guided by shared interests, temporal patterns of interaction, and the overall tenor of discussions. This dimension enriches our understanding of interpersonal dynamics within the professional realm.

The culmination of our efforts is manifested in the fourth and final facet. Here, the profiling system steps into its operational role, orchestrating a proactive role in suggesting suitable collaborators for defined periods or new company projects. This integration of comprehensive profiling and project alignment propels a more synergistic and efficient collaboration among team members.

The architectural blueprint for our innovative recommendation system, deeply rooted in the dynamic context of professional social networks, is visualized in Fig 1. This visually encapsulates the journey we undertake, from personal and psychological profiling to relational insights and, ultimately, to purposeful collaboration facilitation.

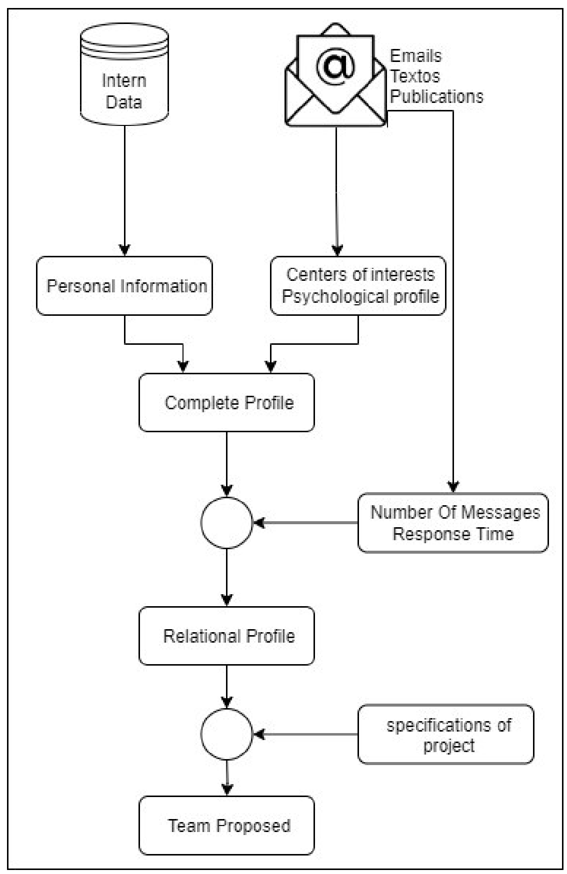

Figure 1: Architectural Diagram

In this manner, our methodological framework navigates through these intricately interwoven stages, culminating in a robust and dynamic

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recommendation system that harmonizes individual profiles with collaborative project needs. The proposed architecture for our recommendation system method based on professional social networks is presented in Fig 1.

3.1 Data Set Overview:

In this endeavor, our project addresses the intricate challenge of profiling and comprehending users of a digital platform. Specifically, our focus lies in discerning user traits and behaviors on a professional online platform by analyzing the content of digital publications. This section elucidates our approach to constructing a comprehensive dataset, pivotal to various stages of our profiling system's development.

3.1.1 Building the Foundational Database

The pivotal objective of our project is to proficiently profile users on a professional platform, leveraging their messages and publications. To facilitate this, we necessitate a meticulously crafted database, brimming with essential attributes that underpin our profiling model. The crucial features encompassed within this dataset are as follows:

- ✓ **User_Id**: The unique identification of the sender.
- ✓ **date_send**: The timestamp of message transmission.
- ✓ **Message**: The textual content of the message transmitted.
- ✓ **User_Receiver_Id**: The unique identification of the message receiver.
- ✓ **response_date**: The timestamp of the message reply.

3.1.2 Harnessing Pertinent Data Sources

For optimum results, we tap into data repositories closely aligned with our domain, such as prominent social media platforms like Facebook and Twitter. Specifically, we capitalize on the "Customer Support Twitter" dataset, which comprises directed networks encompassing interactions between users and companies. This dataset, boasting 2,811,774 entries across 7 columns, becomes a cornerstone in our endeavor [9]. To enhance the authenticity of our dataset, we augment this raw data with "artificial" data generated through meticulous analysis of real-world tweets.

3.1.3 Enriching Dataset with Professional Content

Recognizing the inherent disparity between casual social media content and the nuanced discourse of a professional platform, we embark on a journey to curate a dataset that befits our context. Given the requirement for professional communication, we construct a collection of messages sourced from Wikipedia articles. By carefully selecting relevant topics and extracting sentences from articles of corresponding subjects, we compile a reservoir of meaningful professional messages.

3.1.4 Technical Implementation

The process of dataset enrichment involves sophisticated techniques, including web scraping. Python's Wikipedia library serves as our tool of choice, enabling the extraction of pertinent information. Scrutinizing Wikipedia articles results in satisfactory outcomes, meeting the prerequisite standards of professionalism our project demands.

3.1.5 Data Pre-processing for Enhanced Relevance

An indispensable phase in our analysis is data pre-processing, wherein we refine and structure the dataset for meaningful insights. This stage hinges on a specialized function that orchestrates a series of crucial steps, with a distinct emphasis on message semantics. Notably, the process concentrates on two pivotal columns: date_send and response_date. This intricate treatment ensures that temporal and contextual aspects are accurately captured.

3.2 Centers of Interest

In the pursuit of unveiling the factors and incentives capable of profoundly propelling a collaborator towards wholeheartedly embracing and dedicating their fullest endeavors to attain their objectives, we are reminded of Steve Jobs' assertion that "Passion is the force that propels us forward, even when everything seems impossible." In this context, we hold the conviction that these driving forces align closely with a collaborator's areas of keen interest. To be precise, we advance the notion that every message penned by a user, particularly those imbued with positive sentiments, can serve as a significant indicator of the subjects that authentically captivate the sender.

3.2.1 Introduction to Topic Modeling:

Topic modeling presents a fascinating approach, whereby it aims to distill coherent themes from an unlabeled textual corpus, diverging from the conventional process. The primary objective of this technique is to unveil interpretable representations of documents, enabling the revelation of underlying subjects or structural patterns within a given corpus.

3.2.2 Innovative Approaches to Short Text Topic Modeling:

Current research endeavors are dedicated to innovating thematic modeling techniques for short text content through algorithmic methodologies. The historical progression of this field is examined,

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leading to the formulation of a taxonomy encompassing diverse strategies for modeling subjects within concise textual data. These approaches encompass multinomial mixtures and method-centric self-aggregation techniques.

Taxonomy of Short Text Subject Modeling Methods:

A comprehensive taxonomy is presented, categorizing topic modeling methods into three principal classes:

- ✓ Dirichlet Multinomial Mixture (DMM)-Based [10]: Grounded in the concept that each text originates from a unique latent topic. Enhanced versions like Gibbs collapsed sampling and the Twitter-LDA model have emerged to refine DMM's performance.
- ✓ Global Word Co-occurrences-Based: Certain models leverage global word co-occurrence patterns to infer latent topics. These models incorporate a sliding window mechanism to capture relevant word associations within the corpus.
- ✓ Self-aggregation-Based: These methods address data scarcity issues by amalgamating short texts into larger pseudo-documents. Approaches like SATM [11] and PTM [12] merge topic clustering and modeling, effectively transforming short texts into pseudo-long documents prior to topic inference.

3.2.3 Selection of Dirichlet Mixture Model (DMM)

After careful consideration, the Dirichlet Mixture Model (DMM) emerges as our foundational choice. Functioning as a generative probabilistic model, DMM posits that each document originates from a singular subject, implying that all words within a document are generated using an identical thematic distribution.

3.2.4 Challenges in Evaluating Topic Modeling Algorithms

The evaluation of short text topic patterns poses an ongoing challenge. Existing measures, including coherence metrics, exhibit varied suitability, with some performing well on extensive texts but exhibiting ambiguity for shorter ones. Traditional metrics such as perplexity attempt to estimate the likelihood of preserving test data based on training data parameters, but may not robustly reflect the quality of retrieved subjects [13,14,15,16].

3.2.5 Methodology and Assessment

To comprehensively assess the efficacy of different algorithms, we utilize the Short Text Topic Modeling (STTM) library in Java. We construct a labeled database from our message dataset, enabling us to compare the performance of the four algorithms. This endeavor encompasses the extraction of topics through the application of these algorithms on the message column.

3.2.6 Measuring Success with Accuracy

For our evaluation process, we employ accuracy as a key criterion, which quantifies the proportion of accurate predictions made by a classification model. Formally, accuracy is defined as the ratio of correct document predictions to the total predictions made by the model.

$$Accuracy = \frac{Number of correct predictions}{Total number of predictions}$$

After the application of the latest one, we have obtained the results shown in table 1.

Table 1. Evaluating Topic Modeling Algorithms Through Accuracy with STTM

	DMM	LDA	BTM	PTM
Accuracy	0.878787	0.616161	0.616161	0.616161

Observing that the Dirichlet Mixture Model (DMM) has exhibited promising outcomes in modeling short-text subjects, we have opted to adopt this algorithm for our endeavor. Consequently, we have selected the most prominent topics to serve as focal points of interest.

3.3 Psychological Profile

Within this segment, our attention is directed towards delving into users' psychological profiles, a task achieved through the extraction of predominant emotions from the textual content contributed by each individual. Our approach centers on leveraging the capabilities of EmoNet [17], a neural network-based tool meticulously designed for emotion recognition. This tool proficiently forecasts emotions based on textual input, subsequently classifying them into a spectrum of eight fundamental emotional states. These encompass joy, trust, fear, surprise, sadness, disgust, anger, and anticipation, as visually depicted in Figure 2 for clarity.

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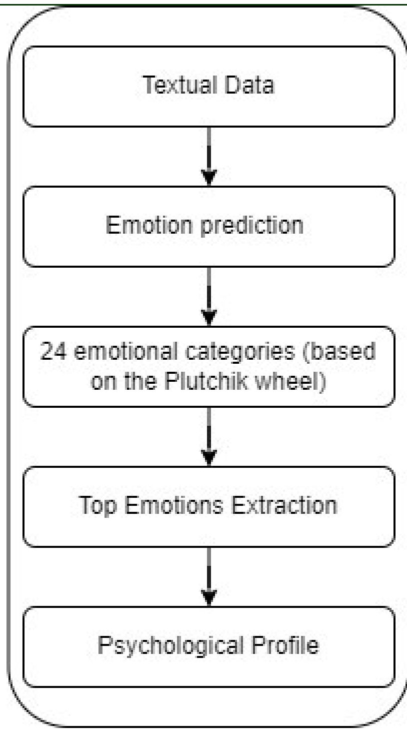

Figure 2: Psychological Profiling Procedure

Nevertheless, our research has undertaken a more intricate approach by refining these emotion categories to harmonize with the 24 distinct emotions outlined in the Plutchik wheel. This wheel extends beyond fundamental emotions, showcasing an extensive array of emotional facets, as illustrated in Figure 3. This adaptation takes into consideration the intricate and multifaceted landscape of human emotions.

Figure 3: Plutchik's Emotion Wheel.

Utilizing EmoNet as our foundation and broadening its classification to encompass the 24 emotions delineated by the Plutchik wheel, our objective is to attain a richer comprehension of users' psychological compositions. This endeavor goes beyond the surface-level emotional states, enabling us to delve into the intricate nuances and intricate interplay of emotions embedded within users' textual expressions.

EmoNet, our chosen tool, meticulously dissects the textual input from users, attributing a distinct score or intensity to each of the 24 emotional categories. These scores serve as indicators of the potency and prevalence of individual emotions within the user's text. Through an amalgamation of these scores across the entirety of a user's generated content, we can ascertain their predominant emotions—the emotions that emerge with the greatest intensity.

This in-depth analysis of psychological profiles via emotion extraction furnishes invaluable insights into users' emotional dispositions and tendencies. It bestows a heightened comprehension of their emotional landscapes, predilections, and leanings. The implications of this understanding span diverse applications, encompassing tailor-made recommendations, precision-targeted marketing approaches, and a more profound comprehension of user conduct.

To encapsulate, our strategy employs EmoNet as the bedrock, augmenting its emotional categories to align with the Plutchik wheel's 24 emotions. This approach facilitates the extraction of dominant emotions from user-generated text, culminating in the creation of a comprehensive psychological profile. This analytical undertaking not only augments our grasp of users' emotional states but also furnishes insights of great worth applicable across a spectrum of domains, including psychology, human-computer interaction, and the social sciences.

3.4 Relational profile

To gain insights into the connections and preferences of a collaborator within a social or professional virtual network, it is crucial to study the structure of their network and the characteristics of their connections. In order to extract the relational profile of each collaborator, we follow a three-step process.

Firstly, we extract the list of users contacted by the collaborator during a specified time period. This provides us with an overview of their network and the individuals they interact with. Additionally, we extract the list of messages exchanged between the collaborator and each contact to further analyze the nature of their interactions.

Secondly, to identify the collaborator's favorite contacts among their recent ones, we consider two factors. The first factor is the time difference between the sending date of the message and the reply date, which helps gauge the responsiveness and engagement of contacts. The second factor is the number of messages exchanged between the collaborator and each contact, indicating the level of communication.

To quantify the preference for specific contacts, we introduce the Top Contacts Coefficient (TCC), calculated as the total number of messages divided by the sum of all response times. This coefficient provides a measure of the collaborator's affinity towards particular contacts based on their responsiveness and the frequency of communication.

$$Top\ Contacts\ Coefficient\ (TCC) = \frac{Totalnumberofmessages}{Responsetime(sumofallresponsetimes)}$$

Finally, we conduct a statistical analysis to determine whether the collaborator's favorite contacts are the most recent ones or if there are distinct patterns indicating their preferred types of individuals to be in contact with. This analysis offers valuable insights into the collaborator's networking preferences and helps identify the characteristics of individuals they are likely to engage.

3.5 Recommendation system

Within this segment, we elucidate the operational dynamics of our recommendation system. Our system stands geared towards the extraction of essential skills from project specifications, followed by an intricate evaluation of how well these skills align with the profiles of our assembled collaborators. This intricate interplay enables us to formulate an ordered catalog of profiles, meticulously ranked based on their alignment with the project prerequisites, visually represented in Figure 4 for clarity.

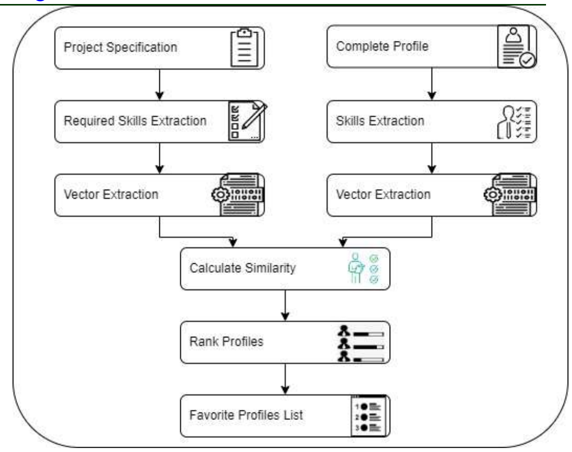

Figure 4: The Process of Creating a Recommendation System

Our innovative recommendation system offers a strategic tool for managers, furnishing them with a meticulously organized list of employees based on their alignment with project prerequisites. This alignment is established by dissecting project requirements to pinpoint the essential competencies and qualifications necessary for project triumph.

Transition to Skill Representation

This transition involves encoding skills into numerical vectors, and translating employee skills and project requirements into a standardized format. Skills can be expressed as binary values (1 denoting possession, 0 otherwise) or as numerical values quantifying proficiency levels.

Leveraging Cosine Similarity

The crux of our approach hinges on employing the cosine similarity formula. This mathematical tool quantifies the likeness between an employee's skill vector and the required skill vector for the project. This calculated similarity score offers a gauge of how well an employee's skills harmonize with the project's demands.

Profiles Sorted for Precision

Sorting employee profiles based on descending cosine similarity scores crafts a ranking system. Higher scores signify enhanced alignment with project requisites. The outcome is a systematically organized list, poised to provide managers with valuable insights.

Facilitating Informed Decision-making

By consulting this ordered list, managers attain a comprehensive overview of potential project candidates. The streamlined access to these profiles empowers managers to efficiently ascertain employees whose skill sets closely dovetail with project specifics. The outcome is more informed decision-making and the strategic deployment of resources.

Enhanced Project Efficiency

The recommendation system revolutionizes employee assignments by presenting managers with a ranked roster. This eliminates the need for time-intensive manual profile assessments, simplifying decision-making. Ultimately, this system enables managers to optimize team composition and elevate project success by strategically selecting employees with the most pertinent skills.

Synthesis

To encapsulate, our recommendation system extracts vital skills from project parameters, evaluating them against employee profiles. This culminates in a tailored list of profiles, meticulously ordered to reflect skill correspondence. The profound insights this list furnishes empower managers to make well-grounded assignment choices, creating a symbiotic alignment between employee expertise and project objectives. This transformative approach streamlines resource allocation, heightening the likelihood of project triumph while fully capitalizing on organizational skill reservoirs.

4. RESULTS AND DISCUSSION

In this segment, we unveil the outcomes garnered through our investigation and engage in a discourse regarding the significance and constraints inherent in our relational profiling system's application for the selection of team members in project implementation.

4.1 Experiment:

The following steps summarize the simulation outcomes:

- ✓ Full-profile extraction: We start by extracting a profile system that encompasses the personal information and skills of each employee. Additionally, we integrate the analysis of interest centers and psychological profiles derived from employees' messages, publications, and comments exchanged on the company's professional networks.

- ✓ Project Skills and Employee Skills: This table showcases the project's required skills and the skills possessed by each employee based on the profiles extracted in the first step. It serves as the foundation for calculating the cosine similarity scores, as shown in Table 2,3.

Table 2. Project Skills

Skill	Presence
Programming	1
Data Analysis	1
Communication	1

Table 3. Employee Skills

Employee	Programming	Data Analysis	Communication
Employee 1	1	1	0
Employee 2	1	0	1
Employee 3	0	1	1
Employee 4	1	1	1
Employee 5	0	0	1

- ✓ Cosine Similarity Scores: This table presents the cosine similarity scores obtained by comparing the project skills with each employee's skills. Higher scores indicate a better match, as shown in Table 4.

Table 4. Cosine Similarity Scores

Employee	Cosine Similarity
Employee 1	0.816
Employee 2	0.577
Employee 3	0.577
Employee 4	1.000
Employee 5	0.577

Based on the cosine similarity scores, we ranked the employee profiles in descending order of compatibility.

- ✓ Ranked Profiles: This table displays the employee profiles sorted by their cosine similarity scores, highlighting the most suitable candidates for the project, as shown in Table 5.

Table 5. Ranked Profiles

Rank	Employee	Cosine Similarity
1	Employee 4	1.000
2	Employee 1	0.816
3	Employee 2	0.577
4	Employee 3	0.577
5	Employee 5	0.577

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These results demonstrate the effectiveness of our recommendation system in identifying employees with the closest match to the required project skills. Employee 4 exhibits a perfect match, while Employee 1 is a good fit with programming and data analysis skills. Employees 2, 3, and 5 show moderate compatibility with the project requirements.

The utilization of cosine similarity as a matching algorithm enables us to provide managers with a ranked list of employee profiles, aiding them in making informed decisions for project assignments. The system offers efficiency by reducing the time and effort required for manual skill assessment and selection.

Overall, the results validate the practical application of our recommendation system and its potential to optimize the employee assignment process within organizations.

4.2 Discussion: Contrasting the Proposed Methodology with Existing Literature

Despite the numerous advancements in team selection and composition, a notable gap remains in the literature concerning the social and collaborative dynamics among team members. This void arises from the observation that while candidates may possess advanced skills and experience, they often lack a profound understanding of collaboration. In the worst-case scenario, conflicts may arise between team members due to a lack of collaboration skills, which can have cascading effects on the project's overall cohesion. Each member might tackle their tasks in isolation, leading to unresolved issues and challenges for other team members.

This realization prompted us to conceive the idea of constructing a relational profile for all collaborators. This profile would be based on a profiling system derived from internal company data, as well as on interests and emotions extracted from the messages and publications within the company's platform. The primary objective is to identify individuals who are more likely to collaborate effectively. We take into account individuals who share similar motivations and interests, ensuring a smoother alignment with project requirements.

In essence, while the literature recognizes the importance of technical skills and experience in team assembly, our proposed approach delves into the realm of interpersonal dynamics. By establishing a relational profile that considers not only expertise but also collaboration potential, we aim to bridge the gap in the existing literature and enhance team interactions. This holistic perspective acknowledges that successful project outcomes are not solely dependent on individual excellence, but also on the harmonious collaboration and alignment of team members' motivations and interests.

4.3 Boundaries and Prospects for Future Endeavors

The current study sheds light on promising avenues for future exploration and refinement. However, several aspects warrant attention in terms of validation and further enhancement.

4.3.1 Validation with Real Data

While our solution demonstrates potential within a controlled environment, future work should prioritize the empirical testing of our approach using actual data. This real-world validation will substantiate the effectiveness of our solution in real scenarios and establish its practical utility.

4.3.2 Emotion-Based Interest Refinement

An avenue for improvement lies in the incorporation of emotions to enhance interest refinement. By infusing emotional factors into the interest assessment process, we can provide a more nuanced understanding of candidate preferences. This could lead to a more accurate matching of candidates with roles that resonate on both technical and emotional levels.

4.3.3 Enhancing Team Compatibility

To further elevate our solution's efficacy, focusing on bolstering team member compatibility is essential. The relational dynamics among team members play a pivotal role in project success. In future iterations, our system can incorporate mechanisms to gauge compatibility and team synergy more comprehensively, thus ensuring well-rounded team formations.

4.3.4 Incorporating Collaborative Analysis

The integration of collaborative analysis via questionnaires presents an exciting avenue for refinement. By introducing targeted questionnaires that probe into the collaborative dynamics among potential team members, we can offer insights into how individuals work collectively. This enriched understanding could significantly inform role assignments, leading to more harmonious and effective team compositions.

In summary, the exploration of our solution's limits and future prospects reveals a multi-faceted roadmap for improvement. Validating our solution's effectiveness with actual data, refining interest assessment through emotional considerations, amplifying team compatibility evaluation, and integrating collaborative analysis mechanisms all

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contribute to a holistic approach that stands to enhance the precision and impact of our role recommendation system.

5. CONCLUSION

In conclusion, this article presents an approach aimed at providing businesses with a solution to aid in the selection of team members for project execution while ensuring team coherence and collaboration among its members. The proposed solution relies on a recommendation system that provides a curated list of preferred candidates for project execution. This is achieved by aligning project specifications with candidate profiles and assessing their collaborative capabilities based on their relational profiles. These profiles are constructed from three key elements: internal company data, interests and emotions extracted from messages exchanged within the company's professional network, and the relational profile based on these factors.

We believe that the relational profile among team members, extracted from their profiles, reveals hidden relationships and shared interests that foster hidden motivations and preferences among them. When team members share motivations and passions, they can collaborate effectively, complementing each other's strengths and weaknesses. This united motivation and collaboration among team members enable them to overcome obstacles. Our approach has yielded promising results with the data we utilized. Nonetheless, we acknowledge the necessity of validating our approach with real-world data to enhance its reliability.

Future work should focus on exploring the feasibility of testing our solution with actual data to validate its effectiveness. Furthermore, improvements can be made by refining interest levels based on emotions and enhancing the relational aspect among candidates to ensure team member compatibility. This can involve incorporating questionnaires to analyze the collaborative aspect among team members.

In summary, our approach underscores the potential to assist businesses in effectively selecting team members for project success. By considering hidden skills and emotional factors, we believe our solution can significantly contribute to enhancing team dynamics and project outcomes. Further research and experimentation with real-world data will validate the robustness of our approach and pave the way for ongoing improvements in this field.

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