Intelligent Career Recommendation and Personalized Career Guidance System

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Abstract
The choice of a career is a challenging task when the student's knowledge of potential jobs and their requirements is insufficient. The general advice to base decisions on personal strengths, interests, educational attainment, and the characteristics of different positions is, at times, too vague. This paper aims to design an intelligent career recommendation and guidance system. The proposed solution will utilize natural language processing (NLP) to extract meaning from structured and unstructured input data and machine learning (ML) to compare a candidate's description against the descriptions of different careers. It will be possible to input the requirements and personal skills using predefined categories while also entering some textual descriptions, which will be parsed using NLP algorithms. The recommendation component will score different careers according to the entered data and provide the user with a short explanation of why each option was selected and which skills they might be lacking. The paper will propose a rule-based career recommendation baseline and compare its results to an ML-based content recommendation approach. The design and evaluation of the proposed solution will be discussed, and an experiment will be described. The final section will provide results based on the experiment described.

Keywords: Career Recommendation, Natural Language Processing, Machine Learning, Personalized Guidance, Skill Gap Analysis, Content-Based Recommendations.

1. Introduction
Career choices can influence a student's education, range of employment opportunities and career progression. However, students cannot always rely on one-to-one career counselling, nor can they easily link their current skill set to possible careers. Online career information is abundant but fragmented, requiring users to identify which jobs are relevant to their skills, knowledge, qualifications and learning paths before being able to compare them

A recommendation system can help structure this information, by linking a user's profile to relevant career descriptions. Earlier work has looked at recommender systems to support university major and career domain recommendations, showing that recommendation approaches can benefit educational and career counselling [1]. Recent work has additionally looked at the use of artificial intelligence in this domain and identified the need for analysis of the approaches used [2]. This justifies the need for a recommendation system that does more than suggest a career title match, but also considers why an option may be relevant, and what the user would need to learn to achieve this.

The system uses basic profile details along with the information users provide in their own words to suggest suitable career options. NTP aims to support this information, enabling a matching component to identify potential career options, ranked according to relevance. This approach builds an initial suggestion mechanism that can be iterated upon, but which is always framed within the context of career counselling and a student's own decision-making. It is not intended to replace the role of a qualified career counsellor or the user's own decision-making.

1.1 Problem Statement
Students often have time to pick a career that fits their education, their past experiences, their interests, their abilities and their future. A basic list of jobs usually does not show how each career matches what a student needs and what they are good at. Students might also not know which skills they need to get better at or what qualifications are needed for a job. Also, information about careers is spread out over websites, which makes it hard to look at different options and pick the right one. This study focuses on creating a career recommendation system that uses structured user data and descriptions written in natural language. Natural Language Processing (NLP) is used to find the skills, the interests and the career preferences that are important to the user. The system then checks this information against career

profiles, figures out how well each career matches the user and puts the options in order based on the user's profile. It also tries to give students advice about which skills they can work on to become better suited for the careers they want.

1.2 Objectives

- To develop a user's profile including educational background, skills, interests, experience, strengths and career goals.
- To investigate NLP techniques for extracting relevant information from the short descriptions provided by the users.
- To compare the results of the rule-based and content-based approaches to career recommendation.
- To provide the user with the list of recommended careers with accompanying explanations.
- To find out which skills the user already has and which additional skills they need to develop for their chosen career.
- To establish a mechanism for assessing the effectiveness of the designed recommendation system.

1.3 Contributions

The main contribution of this work is to create personalized career guidance. This method uses both information about the user and text that the user writes freely. The design brings together steps in one process. These steps include checking the user's profile matching the user, with careers explaining the recommendations and helping the user improve their skills. The design also sets up a plan and a way to test the approach so that it can be checked in a proper way. These are the design ideas that are being suggested. The real success of these ideas will be shown when they are built and tested.

2. Literature Review

Career guidance systems have used ways to recommend options. These ways range from matching user interests to more complex descriptions of fields or areas. Lahoud et al. Compared systems that help choose university majors and career areas [1]. This paper provides background for the current project, as it underlines the importance of choosing the right recommendation method based on what each person likes. Therefore, this paper supports the suggestion of choosing a way to match the users' attributes, instead of just using one system for all.

A study by Sarmurzin et al. Looks at the use of artificial intelligence in career guidance for students in college [2]. The paper provides insight, by showing what's happening with the use of AI in career guidance. The research is crucial for the work, because it highlights the importance of having good information and clear recommendations when students choose their careers. The current project would benefit a lot by considering the information's quality and clarity, along with any limits it might pose.

The system collects details from users and studies their information to suggest career options that match their skills and interests.TF-IDF weighted terms and cosine similarity are ways to see how similar documents are [3]. These methods can be beneficial, as they make it clear how the matching is done. The Sentence-BERT method makes embeddings to check how similar sentences are [4]. This method could be used in the project as another way to do the matching, if there is enough computer power and time.

The project being worked on benefits a lot from the papers mentioned. The project's goal is to build a system that considers the user's details and how similar texts. Also, the study highlights the importance of explaining the recommendations and checking the students' skills, which can be added to the project. However, the papers do not provide enough reasoning as to why the methods should be used in this project. It is necessary to gather a data set and compare the methods to test the idea.

Table 1. Selected Literature Relevant to the Proposed System

Reference	Focus	Relevance to This Study	Consideration
Lahoud et al. [1]	Career and university course recommendation	Helps understand how recommendation systems can guide students toward careers and study options.	The proposed system needs its data and testing.
Sarmurzin et al. [2]	Use of AI in university career counselling	Provides background on how AI can support career guidance.	The original review should be examined to understand its findings.
Manning et al. [3]	Information retrieval and text processing	Helps explain how TF-IDF can compare users	It may not recognize words with meanings.

		written interests with career descriptions.	
Reimers and Gurevych [4]	Sentence-BERT and text similarity	Helps explore how NLP can identify similarities, between user responses and career descriptions.	The model needs to be tested to determine how well it works for career recommendations.

3. Methodology

The study is set up as a prototype to test and evaluate how well it works. First, it gathers user profiles. Then it gets the data ready. Does text analysis. At the end it gives ranked career suggestions with tips. Before sharing any results we will choose the dataset, set feature weights and decide on testing methods. Everything will be written down. Users provide their details through a questionnaire that includes their educational background, skills, interests, work experience, strengths, and future career goals. Users can also write their descriptions of what they like and what they're good at. Natural Language Processing (NLP) will be used to go through these descriptions. It will find skills, interests and career preferences. Once the data is cleaned and ready the system compares the user profile with saved career profiles. These profiles include job titles, needed qualifications and key skills. We'll start by building a rule-based method as a version. Then we might try a text-matching method using TF-IDF and cosine similarity. This will measure how closely user descriptions match career profiles. The system will use skill matching, education fit, interests and text similarity to rank career options. Along with career picks the system will give short explanations. It will also point out skills the user might want to work on. After everything is built and tested the prototype will be checked using measures, like Precision@K and Recall@K. These will help see if the suggestions are actually relevant. The real results will only be shared after all testing is done.

3.1 System Architecture

Figure 1. Proposed Architecture of the Career Recommendation and Guidance System

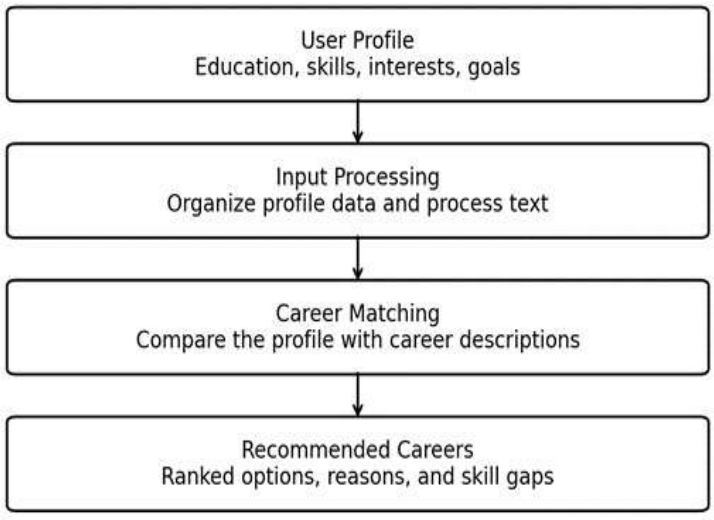


Figure 1 below shows the framework for the career recommendation system. The process begins by gathering the user's data, such as education, skills, personal information and career goals. These details are then. The career recommendation system analyzes the user's text, with natural language processing. After that the framework matches the user's description to the details of occupations. Finally, the career recommendation system lists the best-fitting

careers. Explains why they fit, as well as the areas the user needs to improve for those occupations. The career recommendation system is designed to help people recognize their career options and to make their decision-making process smoother.

3.2 NLP and Recommendation Techniques

The proposed system will apply Natural Language Processing (NLP) to interpret the details students supply regarding their skills, interests, educational background, and career goals. Basic cleaning steps will be carried out before the text is processed. These involve turning text into lowercase, eliminating spaces, and dealing with punctuation as necessary. Nevertheless, key information such as programming languages, technical terms, and professional certifications will be retained. This is because such details can assist the system in delivering career recommendations.

By relying on keywords and a predefined list of career-related terms, the system will identify skills and interests within students' descriptions. This method helps connect the information students provide with what careers require. To compare students' descriptions against career profiles, the system may rely on TF-IDF and cosine similarity [3]. Such methods can help identify careers whose words and ideas align with a student's profile. Sentence-BERT could also be considered as an alternative, since it is able to grasp the meaning behind sentences rather than matching words [4]. The technique ultimately selected will depend on its performance, how easily it can be implemented, and how well it suits the needs of the proposed system.

Career recommendations will be generated by examining a student's skills, interests, educational background, and career goals. By bringing all these details together, the system will rank career options according to how closely they match the student's profile. The weight assigned to each factor. Such as skills or interests. Will be determined while the system is being developed. It will also be evaluated to determine how effectively the system recommends careers that are genuinely relevant.

Along with suggesting careers, the system will provide an explanation for why each career was recommended. For instance, a career might be proposed because it aligns with the student's programming skills, their interest in technology, or where they pursue their studies. The system will also point out skills the student may need to develop and recommend areas for learning. This allows students to see which careers could suit them and what steps they can take to get ready. The recommendations are intended to help students plan their careers, not to guarantee jobs or professional success.

3.3 Dataset Preparation and Profile Representation

The system requires a career-profile collection, which includes at least the career's title, a brief description of the role, skills typical for the position, required education/qualifications (where relevant), and related fields of interest. The user profiles can be gathered using a questionnaire or created as test cases. The source and licensing information of every external career description should be documented. If synthetic profiles are applied during the early stages of development, this should be stated clearly, and it should not be suggested that these are real student data.

Prior to the study, the number of career profiles and their sources, the number of user/test profiles and their sources, the fields included, missing value treatment, text-preprocessing instructions, and deduplication should be reported. If human participants are enrolled in the research, informed consent should be obtained, and only essential personal information should be gathered. No contact information or other identifiers should be collected, as they are not required for the career-matching purpose and pose a risk to privacy.

A small-scale career catalogue can be sufficient for developing a prototype; however, the coverage should be mentioned, as it will affect the recommendation results. The paper should explicitly state that the catalogue does not include all the occupations and industries or labor markets that may be relevant.

3.4 Evaluation Metrics

The quality of the recommendations needs to be checked using an documented way of deciding what is relevant. This could be career options that expert people say are matches or what participants say using a set way to decide. The way we choose what is relevant has to be explained because whether a career is a fit depends on many different things.

- Precision@K: how many of the K recommendations are relevant.
- Recall@K: how many of all the career options are found in the top K recommendations.
- NDCG@K: a way to measure how well the recommendations are ranked, giving value to the ones that are more relevant and appear higher.
- Catalogue coverage: how many of all the career profiles are recommended to least one test profile.

• Explanation and skill-gap review: looking at whether the reasons given and the missing skill indicators match the profile and the career data.
• User feedback if it exists: ratings on how clear, relevant and useful the recommendations. Also, the number of people who took the survey and how it was done.
The metrics need to be calculated using the test cases for both the rule-based system and the new method being tested. The value of K the way relevance is decided and how results are combined should all be clearly stated before looking at the results. If there are no labels or a user study the paper should only talk about how the system works and not claim that it has proven to be a good match for careers.

3.5 Experimental Setup

The prototype can be built using Python. Scikit-learn will handle TF-IDF vectorization, cosine similarity and basic models. A sentence-embedding model can be added as an option for comparison. A simple web interface can gather user input. Show results. A local database can keep the career catalogue and application records. The final paper needs to list the software versions and models that were used.

The planned comparison is between a rule-based baseline that matches skills and interests using clear rules and a content-based approach that mixes structured data with text similarity. Both approaches will use the same list of career options and sample user profiles to evaluate and compare their results. Keep track of the setup score weights, processing choices and any random seeds. If a train/test split is used, describe how it was made and make sure the test set does not affect tuning. At the time this draft was written no experiment was. No confirmed measurements were provided. So, the results table below is a template and needs to be filled with actual values after the prototype is tested.

4. Results

This section should report on the actual output of the implemented system. Do not retain placeholder text in a submitted paper. Both methods will be evaluated using the same performance measures and test cases to ensure a fair comparison of their results. If the study includes a small qualitative review, summarize the review procedure and the observed issues without generalizing beyond the evidence.

Table 2. Results Template to Complete After Evaluation

Method	Precision@K	Recall@K	NDCG@K
Rule-based method	To be measured	To be measured	To be measured
TF-IDF method	To be measured	To be measured	To be measured
Sentence-embedding method	To be measured / N/A	To be measured / N/A	To be measured / N/A

After testing the methods, the results will be compared to identify which method provides more relevant career recommendations. The evaluation will use multiple user profiles and check whether the recommended careers match their skills, interests, and goals. Any unsuitable recommendations will also be noted. The results will be added after testing; no values will be assumed in advance.

5. Discussion

The goal of the proposed design is to link career suggestions to the information that users provide. By combining data with text inputs, the system aims to capture both clearly defined skills and more informal descriptions of interests. The explanation and skill-gap features are meant to make the results more useful than a simple list of job titles. The evaluation in Section 3 will determine whether the proposed system successfully achieves these objectives.
There are limitations to keep in mind. First the quality of recommendations depends heavily on how complete and accurate the career catalogues. Second text similarity might match words than real fit, which could lead to misleading results. Third career choices are shaped by factors that a short questionnaire cannot capture—such as personal life situations, local job availability, money issues and shifting passions. Fourth, the scoring method might unintentionally help users who give detailed profiles even if this isn't fair. To deal with these issues the system should offer explanations to handle missing data carefully, review the career catalogue regularly and collect feedback from users.

The ranked list should not be seen as the answer. Users should be encouraged to look at options check the requirements for each job and talk to people who can offer real-world advice. Later evaluations should also check if the recommendations vary in a way that favors groups and whether the explanation shown to users truly matches what the model used to make its decisions.

6. Conclusion and Future Work

I show the design of a career recommendation and personalized guidance system that uses NLP and machine-learning-based matching. This workflow takes user data and free-text descriptions builds a combined profile compares the combined profile with career descriptions and returns ranked options with reasons and potential skill gaps. TF-IDF with cosine similarity offers a starting point while sentence embeddings can be checked as an optional semantic approach. A rule-based baseline and a transparent evaluation plan are added to support a comparison.

I note that the current manuscript describes a proposed system than a validated deployed solution. I cannot confirm the effectiveness of the career recommendation and personalized guidance system until the career catalogue is ready, the prototype is built and the planned evaluation is finished. Future work can bring an regularly updated career catalogue, feedback from students and career counsellors, multilingual input, better skill extraction and a more detailed learning-resource mapping. I also think further work should look at privacy, fairness, explainability and how users interpret the recommendations.

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