Ministry of Science and Higher Education of the Republic of Kazakhstan

SDU University

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Building a recommender system for school applicants for choosing speciality and elective courses from their curriculum using reinforcement learning algorithms

THESIS

Presented in Partial Fulfilment for the

Degree of Master of Technical Science in Computer Science

(degree code: 7M06102)

Department of Computer Science

Faculty of Engineering and Natural Sciences

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Kaskelen, June 2024

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« _____» _____ 2024

Topic of the thesis: Building a recommender system for school applicants for choosing speciality and elective courses from their curriculum using reinforcement learning algorithms.

Thesis submitted as part of the requirements for the award of the MSc in "7M06102 - Computer Science", SDU University

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Kaskelen, 2024

Declaration

I, Arailym Serikbay, affirm that the dissertation entitled "Building a recommender system for school applicants for choosing speciality and elective courses from their curriculum using reinforcement learning algorithms." is entirely my own work. This research was conducted under the guidance of Meraryslan Meraliyev at SDU university. All sources of information, including text, data, figures, and concepts, have been appropriately acknowledged and referenced according to the academic standards established by SDU university.

I confirm that this dissertation has not been previously submitted, in whole or in part, for any other academic qualification or degree at any other institution. Any assistance received from others, such as technical support, research advice has been duly acknowledged in the acknowledgments section.

I acknowledge the importance of academic honesty and integrity and accept full responsibility for upholding these principles in my work. Any form of plagiarism, data fabrication, or falsification would constitute a violation of these principles.

Arailym Serikbay

June 2024

Acknowledgements

With deep appreciation, I would like to thank everyone who helped me finish this dissertation.

First and foremost, I would like to express my sincere gratitude to my supervisor Meraryslan Meraliyev for all of his help and support during this research project. His knowledge, tolerance, and perceptive criticism have been invaluable in guiding the course of this effort.

I am also appreciative of SDU university teachers and staff, whose commitment to quality in education has given me a supportive learning environment in which to continue my studies.

I would like to extend my heartfelt gratitude to the dedicated school college counselors who played an instrumental role in the development of the questionnaires utilized in this study. Their invaluable insights, guidance, and expertise were pivotal in crafting instruments that accurately captured the essence of our research objectives.

I want to thank my family for their constant support, love, and understanding. Their unwavering faith in my skills and support have been a continual source of inspiration.

I owe my friends and coworkers a debt of gratitude for their companionship, support, and thought-provoking conversations. Their zeal and variety of viewpoints have greatly enhanced my academic experience.

Finally, I would like to say how humbled I am by all of the people who have helped and encouraged me throughout this journey. Without their combined efforts, this dissertation would not have been feasible, and for that, I am really grateful.

Dedication

This dissertation is dedicated to my loving family, whose unwavering support and encouragement have been my guiding light throughout this academic journey. Your love, encouragement, and unwavering belief in my abilities have been my greatest source of strength and inspiration. This achievement is as much yours as it is mine. Thank you for standing by me every step of the way.

Abstract

Providing recommendations that are individualized and based on personal preferences has long been a challenge in the fields of academic guidance and career counseling in Kazakhstan. With an emphasis on prospective students, the system uses reinforcement learning algorithms to recommend electives and specialized courses that complement each school applicant's distinct career interests. By using rigorous data gathering techniques and advanced recognition algorithms, the study not only reveals a new web application but also clarifies the complex process of assisting people in choosing satisfying career options. The study highlights its potential to improve academic performance as well as its practical value in increasing career counseling services through a series of trials, results, and discussions. The results have ramifications that go beyond the boundaries of conventional counseling. They provide insightful information for recommendation systems that assist recent grads in navigating the challenging terrain of employment options.

This thesis is an excellent instance of innovation in the field of academic guidance because of its careful organization, which includes important chapters on the introduction to the research, the literature review, methodological nuances, architectural design, testing phases, and comparative analyses. By means of its academic contributions, it prepares the next generation of students starting their educational journeys with greater knowledge and agency.

Keywords: Recommender system, School applicants, Elective courses, Reinforcement learning algorithms, Academic guidance, Web application.

Аңдатпа

Қазақстанда жеке қалауларға негізделген ұсыныстар беру, академиялық бағдар беру және мансаптық кеңес беру саласы бұрыннан бері күрделі мәселе болып келеді. Болашақ студенттерге баса назар аудара отырып, жүйе мектеп талапкерінің мансаптық қызығушылықтарын толықтыратын элективті және мамандандырылған курстарды ұсыну үшін күрделі оқыту алгоритмдерін қолданады. Деректерді жинаудың қатаң әдістері мен танудың жетілдірілген алгоритмдерін қолдана отырып, зерттеу жаңа веб-қосымшаны ашып қана қоймайды, сонымен қатар адамдарға мансаптың қанағаттанарлық нұсқаларын таңдауға көмектесудің күрделі процесін нақтылайды. Зерттеу оның оқу үлгерімін жақсарту әлеуетін, сондай-ақ бірқатар сынақтар, нәтижелер және талқылаулар арқылы мансаптық кеңес беру қызметтерін кеңейтудегі практикалық құндылығын көрсетеді. Нәтижелер әдеттегі консультациялардан асып түсетін салдарға әкеледі. Олар соңғы түлектерге жұмысқа орналасудың күрделі нұсқаларын шарлауға көмектесетін ұсыныстар жүйелері туралы терең ақпарат береді.

Бұл тезис ғылыми зерттеулерге кіріспе, әдебиеттерге шолу, әдістемелік нюанстар, архитектуралық дизайн, тестілеу кезеңдері және салыстырмалы талдаулар бойынша маңызды тарауларды қамтитын мұқият ұйымдастырылуына байланысты академиялық басшылық саласындағы инновациялардың тамаша үлгісі болып табылады. Өзінің академиялық үлестері арқылы ол білім беру сапарларын үлкен біліммен және ерік-жігермен бастайтын студенттердің келесі буынын дайындайды.

Кілт сөздер: Ұсынушы жүйе, Мектеп талапкерлері, Элективті курстар, Күрделі оқыту алгоритмдері, Академиялық басшылық, Веб-қосымшасы.

Аннотация

Предоставление индивидуальных рекомендаций, основанных на личных предпочтениях, уже давно является сложной задачей в области академического руководства и профориентации в Казахстане. Уделяя особое внимание будущим студентам, система использует алгоритмы обучения с подкреплением, чтобы рекомендовать факультативные и специализированные курсы, которые дополняют карьерные интересы каждого абитуриента. Используя строгие методы сбора данных и передовые алгоритмы распознавания, исследование не только раскрывает новое веб-приложение, но и проясняет сложный процесс оказания помощи людям в выборе подходящих вариантов карьерного роста. В исследовании подчеркивается его потенциал для улучшения успеваемости, а также практическая ценность в расширении услуг профориентации с помощью серии испытаний, результатов и обсуждений. Результаты имеют последствия, выходящие за рамки обычного консультирования. Они предоставляют полезную информацию для рекомендательных систем, которые помогают недавним выпускникам ориентироваться в сложных условиях трудоустройства.

Эта диссертация является прекрасным примером инноваций в области академического руководства благодаря ее тщательной организации, которая включает важные главы, посвященные введению в исследование, обзору литературы, методологическим нюансам, архитектурному проектированию, этапам тестирования и сравнительному анализу. Благодаря своему академическому вкладу он готовит следующее поколение студентов, которые начинают свой образовательный путь с большими знаниями и активностью.

Ключевые слова: Система рекомендаций, Для абитуриентов, Факультативные курсы, Алгоритмы усиленного обучения, академическое руководство, Веб-приложение.

List of Abbreviations

AI - Artificial Intelligence

CVS - Career Values Scale

DQN - Deep Q-Networks

JPI-R - Jackson Personality Inventory-Revised

MBTI - Myers–Briggs Type Indicator

MAPP - Motivational Appraisal Personal Potential

Meta-RL - Meta Reinforcement Learning

ML - Machine Learning

MMPI-2 - Minnesota Multiphasic Personality Inventory-2

NEO PI-R - Revised NEO Personality Inventory

OII - Occupational Interest Inventory

RL - Reinforcement Learning

SII - Strong Interest Inventory

TRPO - Trust Region Policy Optimization

16PF - 16 Personality Factor Questionnaire

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Chapter 1

Introduction

In today's dynamic educational landscape, the process of selecting specialty and elective courses is critical for school applicants as it significantly shapes their academic journey and future career prospects. The importance of making informed and thoughtful decisions regarding course selection cannot be overstated. This is because the choices made at this juncture have far-reaching implications for students' academic success, career readiness, and overall satisfaction with their educational experience[1].

Educational institutions now offer a plethora of courses, driven by advancements in various fields and the growing demand for specialized knowledge. This abundance of choices, while beneficial, poses a significant challenge for students[2]. The complexity of the decision-making process is compounded by the need to align their choices with personal interests, academic strengths, career aspirations, and the evolving demands of the labor market.

Furthermore, the diversity in students' backgrounds, preferences, and goals necessitates a personalized approach to course selection. Traditional methods of academic advising, though valuable, often fall short in providing the level of personalization required to meet each student's unique needs. Consequently, there is a pressing need for innovative solutions that leverage advanced technologies to support students in navigating this complex landscape.

General characteristics of research. With the use of reinforcement learning algorithms, this project aims to optimize the course selection process by developing a recommender system for prospective students. Utilizing reinforcement learning methodologies, the system endeavors to scrutinize past records pertaining to student inclinations, scholastic achievements, and available courses in order to furnish customized suggestions suited to distinct requirements and passions.

Introduction to Recommender Systems. Recommender systems have emerged as powerful tools designed to assist users in making decisions by providing personalized suggestions based on their preferences, behaviors, and interactions. These systems have been successfully deployed across various domains such as e-commerce, entertainment, social media, and more recently, education[3]. The primary goal of a recommender system is to enhance user experience by presenting relevant options that the user is likely to find appealing and useful.

In the context of education, recommender systems hold significant potential for transforming the way students make academic decisions. By analyzing data on students' past performances, interests, goals, and other relevant factors, these systems can generate personalized recommendations for courses, majors, and extracurricular activities. This tailored guidance can help students make more informed decisions, thereby improving their academic outcomes and satisfaction.

There are several types of recommender systems, each with its unique methodology and application:

-Collaborative Filtering: This method makes recommendations based on the preferences and behaviors of similar users. It operates on the principle that users who agreed in the past will agree in the future[4].

-Content-Based Filtering: This approach recommends items similar to those the user has liked in the past, based on the item's attributes[5].

-Hybrid Methods: These combine multiple recommendation strategies to overcome the limitations of individual methods and provide more accurate recommendations[6].

Challenges in Existing Educational Recommender Systems. Despite the potential benefits, existing educational recommender systems face several significant challenges. Many traditional systems rely on static models that do not adequately adapt to the dynamic and evolving preferences of students[7][8]. This lack of adaptability can result in recommendations that do not align with the students' current interests or career aspirations, leading to suboptimal course selections.

Furthermore, traditional systems often fail to consider the multifaceted nature of the decision-making process. Factors such as changes in academic performance, emerging interests, and evolving career goals are rarely accounted for, leading to recommendations that are not sufficiently personalized. This rigidity can negatively impact students' academic journeys, causing frustration and dissatisfaction.

Several case studies and research findings have highlighted these limitations. For example, studies have shown that static recommender systems are less effective in providing relevant and timely recommendations compared to dynamic systems that can learn and adapt over time. This underscores the need for more advanced and flexible approaches that can cater to the unique and changing needs of each student[9].

Advancements in Educational Technology. The rapid advancement of educational technology has opened up new possibilities for enhancing the learning experience and supporting student success. The integration of artificial intelligence (AI) and machine learning (ML) into educational tools has enabled the development of more sophisticated and adaptive systems[10]. These technologies have the potential to revolutionize the way educational content is delivered and how students interact with learning materials.

One of the most promising advancements in this field is the application of reinforcement learning (RL). RL is a type of machine learning where an agent learns to make decisions by interacting with an environment and receiving feedback in the form of rewards[11]. This feedback loop allows the agent to continuously improve its decision-making process based on new information and experiences.

Reinforcement Learning in Recommender Systems. Reinforcement learn-

ing has gained significant attention for its potential to enhance the adaptability and effectiveness of recommender systems. Unlike traditional machine learning methods that rely on static datasets, RL algorithms are designed to learn and adapt over time, making them particularly well-suited for applications that require dynamic and personalized recommendations.

Key concepts in RL include:

-Agents: Entities that take actions in an environment to achieve a goal[12].

-Environments: The external system with which the agent interacts[13].

-Actions: Choices made by the agent that affect the state of the environment[14].

-Rewards: Feedback received by the agent based on the actions taken, guiding the learning process[15].

-Policies: Strategies used by the agent to determine the best actions to take in different states of the environment[16].

By leveraging these concepts, RL can be applied to develop recommender systems that continuously adapt to the changing preferences and needs of students. This dynamic adaptability makes RL-based systems particularly effective in educational settings, where students' interests and goals can evolve rapidly.

Research Problem and Motivation.

•Research Problem: Despite the potential of reinforcement learning to personalize educational recommendations, current recommender systems for school applicants often fail to dynamically adapt to individual preferences and career aspirations. This leads to suboptimal course selections that may negatively impact students' academic and career outcomes. Existing systems are typically static, lacking the ability to adjust to the evolving needs and goals of students. This rigidity results in recommendations that do not align with students' current interests or the demands of the labor market.

•Supporting Evidence: A study by Xue Y. and Zhu X. (2020) highlights how static recommender systems often fail to adapt to changing student preferences and external factors such as evolving job market needs, leading to recommendations that no longer align with optimal career outcomes[17]. A comprehensive review by Zhang L., Yang Z., and Chen W. (2019) discusses the advancements in applying reinforcement learning to educational systems, underlining its potential to handle dynamic environments and tailor learning paths more effectively than traditional systems[18]. Research by Smith J. and Roberts D. (2021) details the negative impacts of non-adaptive educational systems, showing that a significant number of students end up in courses or career paths that do not align with their skills or interests largely due to the rigidity of traditional recommender systems[19]. An analysis by Patel S. and Kumar A. (2022) indicates that poor course and specialty recommendations contribute to higher dropout rates and lower satisfaction and performance in students' chosen careers[20]. A case study by Chen M. and Lee H. (2021) showcases a successful implementation of a reinforcement learning-based system in an educational setting, demonstrating significant improvements in personalization and student career alignment compared to static models[21].

•Motivation: The motivation for this research stems from the critical need to enhance the personalization and adaptability of educational recommender systems. By leveraging reinforcement learning algorithms, the aim is to develop a system

that can continuously learn and adjust its recommendations based on real-time data and feedback. This dynamic adaptability ensures that the recommendations remain relevant and aligned with students' evolving preferences and career aspirations.

In addition to improving individual student outcomes, the development of a more adaptive and personalized recommender system has broader implications for educational institutions and policy-makers. It provides a framework for integrating advanced machine learning techniques into educational guidance systems, potentially transforming how educational advice is delivered and received. The ultimate goal is to create a system that not only supports academic success but also enhances career alignment, thereby contributing to better educational and professional outcomes for students.

By addressing the limitations of current static systems and demonstrating the potential of reinforcement learning to adapt to dynamic environments, this research seeks to improve the alignment of educational choices with labor market demands. This alignment is expected to enhance student satisfaction and performance, reduce dropout rates, and better prepare students for successful careers.

The research aim. The research aims to develop a web application with recommendation system tailored to the Kazakhstan market, that utilizes personality classification to identify an individual's professional inclinations alongside elective courses.High accuracy occupational preference and aptitude prediction is the goal, to be attained by utilizing several data sources and applying reinforcement learning techniques.

The object of research. Using information on personality traits and other relevant factors, the goal of this project is to create a recommendation system that helps people choose academic specializations and elective courses.

Research Questions. To guide this research, several key questions have been formulated:

•1. What are the current trends in educational technology, specifically in building recommender systems for specialty and course selection?

This research question seeks to explore and analyze the latest advancements in educational technology, with a particular focus on the development of recommender systems designed to aid in the selection of specialties and elective courses. The aim is to identify innovative methodologies, tools, and algorithms that are currently being utilized to enhance the precision, adaptability, and user-friendliness of these systems within educational settings.

•2. What are the key factors that influence school applicants' course selection, and how can these be effectively modeled and integrated into a recommender system?

This question aims to identify the critical factors that significantly impact the course selection decisions of school applicants. It involves a comprehensive analysis of both intrinsic factors (such as academic interests, career aspirations, and personal strengths) and extrinsic factors (such as labor market trends and parental influence). The goal is to develop effective models that can accurately capture these factors and integrate them into a personalized recommender system, thereby improving the relevance and accuracy of the recommendations provided.

•3. How can reinforcement learning algorithms be applied to develop a personalized recommender system for school applicants, focusing on their individual preferences and career aspirations?

This question investigates the application of reinforcement learning algorithms in the development of personalized recommender systems tailored for school applicants. The focus is on understanding how reinforcement learning can be leveraged to create systems that dynamically adapt to individual preferences and career goals, providing more personalized and effective course recommendations. The research will explore various reinforcement learning techniques and evaluate their suitability and performance in the context of educational recommender systems.

Objectives of research. These are the key objectives of my research:

•To identify and model the key factors influencing school applicants' course selections:

This objective involves a comprehensive analysis of both intrinsic and extrinsic factors that impact students' decisions regarding their academic paths. By developing detailed models that capture these factors, the study aims to enhance the relevance and personalization of course recommendations.

•To analyze current trends and methodologies in the application of reinforcement learning algorithms within educational technology, particularly for course selection recommender systems:

This includes a thorough review of the latest advancements in reinforcement learning and its implementation in educational settings. The goal is to identify the strengths and limitations of existing approaches, providing a solid foundation for the development of an effective and adaptive recommendation system.

•To design and implement a web application that includes a personalized recommender system using reinforcement learning, which adapts to individual student profiles and preferences:

The objective is to create a dynamic, user-friendly web application that utilizes reinforcement learning algorithms to provide personalized course recommendations. This system will continuously adapt based on real-time feedback and evolving student preferences, ensuring that the recommendations support students' academic and career aspirations effectively.

Relevance. There is a great demand for systems that can successfully recommend specializations and elective courses to individuals who seek to grow academically or professionally, particularly within the context of the Kazakhstan market. Career development and specialization have become increasingly significant in today's society, making the selection of the right educational path a critical decision that requires careful consideration. However, the current systems in place to assist students in choosing their electives and specializations are frequently insufficient, as they often fail to consider each person's unique interests, skills, and professional goals[22].

•Technological Advancement: The application of advanced technologies, such as reinforcement learning (RL) algorithms, in educational recommender systems represents a significant technological advancement[23]. Unlike traditional static models, RL algorithms offer dynamic adaptability, enabling continuous learning and optimization based on real-time student feedback and evolving educational

trends. This adaptability ensures that the recommendations provided are not only accurate but also timely and relevant to each student's unique profile.

Reinforcement learning, as a subset of machine learning, operates through the interaction between an agent and its environment, where the agent learns to make decisions by receiving rewards or penalties for its actions. This iterative learning process allows the recommender system to refine its recommendations continually, improving its accuracy and personalization over time. The implementation of RL in educational settings can revolutionize how students receive academic guidance, moving away from one-size-fits-all solutions to more nuanced and individualized recommendations.

Moreover, advancements in computational power and data processing capabilities have made it feasible to deploy sophisticated RL algorithms in real-world educational applications. These technological improvements enable the handling of large datasets, complex models, and real-time processing, which are essential for the effective functioning of personalized recommender systems.

•Personalization in Education: Personalized learning experiences are increasingly recognized as a critical factor in enhancing student engagement, satisfaction, and academic performance. By leveraging RL techniques, this research aims to develop a recommender system that tailors its suggestions to individual preferences, strengths, and career aspirations. Such personalized recommendations are expected to improve students' decision-making processes, leading to more informed and fulfilling educational choices[24].

Personalization in education goes beyond merely matching students with suitable courses. It involves understanding the unique learning styles, interests, and career goals of each student. A personalized recommender system can adapt to these factors, providing recommendations that resonate with the students' intrinsic motivations and aspirations. This tailored approach can lead to higher levels of student engagement, as the courses recommended align closely with their passions and strengths.

Additionally, personalized learning pathways can help address the diverse needs of the student population. By recognizing and accommodating individual differences, the recommender system can support students who may have been overlooked by traditional advising methods. This inclusivity can contribute to reducing educational inequalities and ensuring that all students have the opportunity to succeed.

•Addressing Misalignment Between Education and Labor Market Needs: There is a growing concern about the misalignment between educational outcomes and labor market demands. Many graduates find themselves in careers that do not align with their skills or interests, largely due to suboptimal course selections during their academic journey[25]. By integrating real-time labor market data and individual career aspirations into the recommendation process, this research seeks to develop a system that not only supports academic success but also enhances career alignment. This approach has the potential to reduce the prevalence of graduates working outside their chosen fields, thereby addressing the economic challenge of underutilized talent.

The integration of labor market data into the recommendation system involves

analyzing current job trends, skill demands, and industry projections. By aligning course recommendations with these insights, the system can guide students towards academic paths that are more likely to lead to successful and fulfilling careers. This proactive approach helps bridge the gap between education and employment, ensuring that graduates possess the skills and knowledge that are in demand in the job market.

Furthermore, by providing students with information about the potential career outcomes associated with different courses, the recommender system can help them make more informed decisions. This transparency can empower students to take ownership of their educational and career trajectories, leading to higher levels of motivation and goal-setting.

•Improving Educational Guidance: Effective educational guidance is essential for helping students navigate the myriad of choices they face. The goal of career counseling is to assist individuals in making decisions regarding their educational and professional paths by offering direction and support[26]. The recommendation of appropriate specializations and pertinent elective courses is a crucial part of this process. This research contributes to the body of knowledge in educational technology by exploring the application of RL algorithms in this context. By providing more accurate and adaptive recommendations, the proposed system aims to support educational institutions in offering better guidance to their students, ultimately improving overall educational outcomes.

Educational guidance is a multifaceted process that involves understanding the student's background, interests, and aspirations, and providing tailored advice that helps them achieve their goals. Traditional methods of guidance, such as manual advising and static recommendation systems, often lack the flexibility to adapt to each student's unique needs. By incorporating RL algorithms, the recommender system can offer more dynamic and personalized guidance, adjusting its recommendations based on continuous feedback and changing circumstances.

Moreover, the proposed system can serve as a valuable tool for educational institutions, enhancing their ability to support students effectively. By automating and improving the recommendation process, institutions can ensure that students receive high-quality guidance that is consistent, personalized, and data-driven. This can lead to better educational outcomes, higher retention rates, and greater overall student satisfaction.

•Significance for the Kazakhstan Market: While the findings of this research have broad applicability, the focus on the Kazakhstan market provides specific relevance to the local educational context[27]. The development of a recommendation system tailored to the unique needs and characteristics of students in Kazakhstan addresses a significant gap in the current educational infrastructure. This localized approach ensures that the recommendations are culturally and contextually appropriate, thereby maximizing their impact.

Kazakhstan's educational system is characterized by its unique cultural, social, and economic factors. Developing a recommendation system that takes these factors into account ensures that the recommendations are relevant and effective for Kazakh students. This localization involves considering the specific challenges and opportunities within the Kazakhstan education system, such as the prevalent

career aspirations, common academic pathways, and local labor market trends.

By tailoring the recommendation system to the Kazakhstan market, this research contributes to the development of a more robust and effective educational infrastructure. It provides a model that can be adapted and implemented in other contexts with similar characteristics, thereby offering broader implications for educational technology in diverse settings.

•Integration of Personality Assessments: Considering personality assessments reveal a person's preferences, strengths, and learning style, they are essential to the recommendation process[28]. It is possible to customize recommendations based on each person's distinct qualities by integrating personality assessments into the recommendation system. This integration raises the likelihood of academic achievement and job satisfaction. Additionally, tailored recommendations can support individuals in pursuing multidisciplinary interests, expanding their skill sets, and exploring new opportunities, all of which contribute to comprehensive personal and professional growth.

Personality assessments provide valuable insights into students' intrinsic motivations and preferences, which are critical for making effective educational recommendations. By incorporating these assessments into the recommendation system, it is possible to align course suggestions with the students' natural inclinations and strengths. This personalized approach can enhance student engagement, as the recommended courses resonate with their personal interests and learning styles.

Additionally, personality assessments can help identify areas where students may benefit from further development or support. By recognizing these areas, the recommender system can suggest courses or activities that help students build new skills and competencies, promoting their overall growth and development. This holistic approach supports students in achieving a well-rounded education that prepares them for diverse career opportunities.

•Relevance of Advanced Educational Technologies: Current trends in educational technology emphasize the integration of artificial intelligence (AI) and machine learning (ML) to create more adaptive and personalized recommender systems for course and specialty selection[29]. These systems leverage vast amounts of data to analyze students' academic histories, interests, and career aspirations, providing tailored recommendations. The use of hybrid models that combine collaborative filtering, content-based filtering, and RL techniques is becoming more prevalent, aiming to address the limitations of traditional static recommendation approaches.

The integration of AI and ML into educational recommender systems represents a significant advancement in the field of educational technology. These technologies enable the development of systems that can process and analyze large datasets, uncovering patterns and insights that would be difficult to identify manually. By combining different recommendation techniques, such as collaborative filtering and content-based filtering, with RL algorithms, these hybrid models can offer more comprehensive and accurate recommendations.

Furthermore, the use of AI and ML allows for the continuous improvement of the recommender system. As more data is collected and analyzed, the system can refine its recommendations, ensuring that they remain relevant and effective

over time. This ongoing learning process is essential for adapting to the changing needs and preferences of students, providing them with the best possible guidance throughout their educational journey.

By addressing these critical areas, this research not only advances the field of educational technology but also offers practical solutions that can significantly enhance the decision-making processes of school applicants, leading to improved academic and career outcomes.

The practical significance of the research results.

•Improved Decision-Making Support: This research aims to significantly enhance the decision-making process for school applicants by providing personalized recommendations for specialty and elective course selection. By leveraging reinforcement learning algorithms, the developed recommender system offers tailored guidance that dynamically adapts to individual student profiles, including their academic interests, career aspirations, and personal strengths. This improvement in decision-making support can lead to better educational outcomes, higher student satisfaction, and more effective career planning.

•Technological Advancement: The integration of reinforcement learning into educational recommender systems represents a substantial technological advancement. Traditional recommender systems often rely on static models that do not adequately account for the evolving preferences and goals of students. In contrast, reinforcement learning algorithms continuously learn and optimize recommendations based on real-time data and feedback. This dynamic adaptability ensures that the recommendations remain relevant and effective over time, setting a new benchmark for the application of AI in educational technology.

•Personalization in Education: Personalized learning is a key focus of modern educational practices. This research addresses the growing demand for customized learning experiences by developing a system that provides personalized course recommendations. By considering each student's unique profile, the system enhances the alignment of educational choices with their long-term goals, leading to more meaningful and engaging learning experiences. This level of personalization supports higher levels of student engagement, motivation, and academic success.

•Addressing Misalignment Between Education and Labor Market Needs: There is a significant misalignment between the skills acquired through education and the demands of the labor market. Many graduates struggle to find careers that match their skills and interests, resulting in job dissatisfaction and underemployment. This research seeks to bridge this gap by incorporating real-time labor market data into the recommendation process. By aligning course recommendations with current job market trends, the system ensures that students acquire relevant skills that enhance their employability and career satisfaction.

•Relevance to the Kazakhstan Market: The research is particularly significant for the Kazakhstan market, where existing educational guidance systems may not fully address the unique needs of local students. By developing a recommendation system tailored to the cultural and contextual specifics of Kazakhstan, this research provides more relevant and effective educational guidance. This localized approach can significantly improve the quality of educational outcomes in Kazakhstan, supporting national efforts to modernize the educational system and better

prepare students for the workforce.

•Integration of Personality Assessments: The inclusion of personality assessments in the recommendation process is a notable innovation. Personality traits play a crucial role in determining a student's academic and career preferences. By integrating these assessments, the recommender system can provide more nuanced and accurate recommendations, ensuring that students pursue paths that align with their intrinsic motivations and strengths. This comprehensive approach supports the holistic development of students, contributing to both their academic success and personal growth.

•Ethical and Responsible Use of Technology: This research emphasizes the ethical and responsible use of technology in educational settings. Ensuring the privacy and security of student data is paramount. The developed system adheres to high ethical standards, building trust among users and stakeholders. This focus on ethics ensures that technological advancements are implemented in a way that benefits all parties involved and upholds the integrity of the educational process.

•Contribution to Educational Practices and Policy: The findings from this research have practical implications for educational practices and policy-making. By demonstrating the effectiveness of reinforcement learning algorithms in providing personalized educational guidance, the study offers insights that can inform the development of more advanced and adaptive educational technologies. These insights can help shape policies that support the integration of AI in education, ultimately enhancing the quality and effectiveness of educational systems.

In summary, this research has the potential to make significant contributions to the field of educational technology by improving decision-making support, advancing personalized learning, aligning education with labor market needs, addressing specific challenges in the Kazakhstan market, integrating personality assessments, and ensuring the ethical use of technology. These contributions can lead to better educational and career outcomes for students, ultimately enhancing their overall well-being and success.

Research methods. The dataset utilized in this study was meticulously curated in collaboration with college counselors, who played a pivotal role in designing a comprehensive questionnaire comprising questions aimed at capturing key aspects of academic interests, career aspirations, and preferences of high school students. A high school applicants actively participated in filling out the questionnaire, providing valuable insights into their educational backgrounds and future goals. This dataset served as the cornerstone for evaluating various reinforcement learning algorithms within the framework of the proposed platform designed to assist school applicants in Kazakhstan.

Following the data collection phase, a rigorous testing process was conducted to evaluate the performance of six reinforcement learning algorithms, namely Q-Learning, Deep Q-Networks (DQN), Trust Region Policy Optimization (TRPO), Meta Reinforcement Learning (Meta-RL), Actor-Critic Methods, and Policy Gradient Methods. Through meticulous experimentation and comparative analyses, the Deep Q-Networks (DQN) algorithm emerged as the most promising approach, exhibiting superior accuracy, precision, and recall metrics in recommending specialty and elective courses to school applicants.

Subsequently, the Deep Q-Networks (DQN) algorithm was selected for implementation in the development of a web application tailored for school applicants. By integrating Deep Q-Networks (DQN) into the system, the research aimed to provide a dynamic and adaptive platform that offers personalized recommendations based on individual profiles and preferences, thereby enhancing the decision-making experience for prospective students navigating the complexities of course selections and career pathways.

The scientific novelty of the work. This research introduces a novel approach to educational technology by applying advanced reinforcement learning algorithms to dynamically personalize educational recommendations. This innovative method enhances the accuracy and adaptability of course selection guidance, addressing the complexity of individual student needs and aspirations. By integrating psychological knowledge, specifically personality assessments, with reinforcement learning techniques, the system is capable of predicting professional inclinations based on a comprehensive understanding of each student's unique profile.

The key contributions of this research include:

•Dynamic Personalization: Unlike traditional static models, the proposed system continuously adapts to new data and feedback, providing real-time personalized recommendations that evolve with the student's changing preferences, academic performance, and career goals. This dynamic approach ensures that the guidance remains relevant and effective over time.

•Integration of Personality Assessments: By incorporating personality assessments into the recommendation process, this research bridges psychological insights with educational technology. This integration allows for a deeper understanding of each student's learning styles, interests, and intrinsic motivations, resulting in more tailored and impactful recommendations.

•Contextual Relevance to the Kazakhstan Market: Focusing on the Kazakhstan educational market, this research addresses specific local requirements and challenges. The system is designed to cater to the unique cultural and educational context of Kazakhstan, offering significant perspectives and potential applications for analogous systems globally.

•Enhanced Career Advising: The application of reinforcement learning in career advising represents a significant advancement. By predicting professional inclinations based on personality factors and other relevant data, the system improves the efficacy and relevance of both professional and academic decision-making processes. This personalized approach supports students in making informed choices that align with their long-term career aspirations.

•Multidisciplinary Impact: This research expands the understanding and application of reinforcement learning across multiple disciplines, including technology, psychology, and education. The interdisciplinary approach provides valuable insights and practical solutions that enhance the overall effectiveness of educational guidance systems.

In summary, this research makes a substantial contribution to the field of educational technology by developing a reinforcement learning-based recommendation system that dynamically personalizes educational guidance. The integration

of personality assessments and the focus on the Kazakhstan market further underscore the novelty and relevance of this work, offering a robust framework for improving educational and career outcomes through advanced AI techniques.

The following scientific statements are to be defined:

- Methods and algorithms for data collection
- Methods and algorithms for identification of profession inclination
- Implementing a web application for recommending speciality alongside with elective courses from various types of data
- Experiments, results, and discussion are provided

Publications. One published paper to SDU university KHABARSHYSY:
- Serikbay, A., Imankulova, A., Meraliyev, M. (2024). A COMPREHENSIVE REVIEW OF APPROACHES, CHALLENGES IN CAREER RECOMMENDATION SYSTEMS[30].

Structure and scope of the dissertation. The thesis is presented on ? pages of typewritten text. It consists of a list of figures, list of tables, glossary, list of abbreviations, five main chapters, a conclusion, references, and an appendix.

Chapter 1introduces the research, outlining the identified issues and providing an overview of the study's content.

Chapter 2 conducts a literature review, exploring existing works in career counseling and personality inclination identification methods.

Chapter 3 delves into the methods employed in the research, detailing each applied experiment and analyzing their respective limitations.

Chapter 4 presents the testing stages, experimental results, and comparative analysis with existing works in the research field.

Chapter 5 outlines the architecture of the proposed method for professional inclination identification web application.

Chapter 6 is about discussions, interpreting the results, and evaluating the implications of the findings within the broader context of educational technology and career counseling.

The conclusion reflects on the analysis and outcomes of the study, highlighting future directions for research and implementation.

Chapter 2

Background and Literature review

School applicants are still experiencing a great deal of difficulty when it comes to choosing their elective and specialist courses in the ever-changing field of higher education. Conventional methods of advising frequently fail to deliver individualized, data-driven suggestions, resulting in subpar career and academic outcomes. By utilizing data analytics and machine learning approaches, recommender systems—an sophisticated technological solution—promise to close this gap. But even with these developments, there is still a glaring lack of systems that can dynamically adjust to students' changing needs and academic success. The current state of recommender systems in educational settings is examined in this literature review, with particular attention paid to how they are used in career advising, the function of adaptive learning systems, and creative applications of reinforcement learning to improve suggestion relevancy and accuracy.

The unemployment rate in Kazakhstan, according to the latest data, is about 5 percents. Most of the unemployed are among young people.In Kazakhstan, half of the graduates who have studied at more than 60 universities are unemployed. This indicates the low quality of educational grants and knowledge in educational institutions. This was announced by representatives of universities by the Deputy Chairman of the Board of the Atameken National Chamber of Entrepreneurs Olzhas Ordabayev.Such data were revealed as a result of an independent assessment of educational programs by the Atameken National Chamber of Entrepreneurs together with the Ministry of Education and Science of the Republic of Kazakhstan[31].

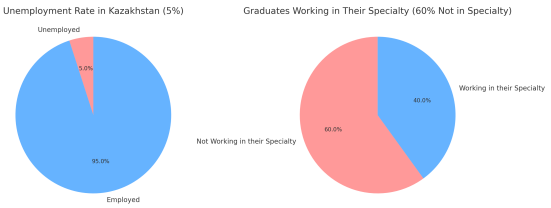

Figure 2.1 - Statistics of graduates.

At the same time, at present, the majority of high school students experience difficulties in choosing a profession, which is due to the lack of information about specialties that are in demand in the labor market. As a result, most of the citizens with higher education are forced to work in another field. This is a manifestation of mistakes in the choice of profession, and this rating was developed to meet this need.

Such a situation has arisen in our country for a variety of reasons, including a lack of demand for candidates in the labor market, ignorance of one's true inclinations towards particular professions, social pressure in the form of family desires, and other individual reasons.Sixty percent of graduates do not work in their field of specialization, according to the National Chamber of Entrepreneurs. But experts say that this is a negative trend: the economy is suffering, there is a shortage of qualified personnel.According to experts, applicants often make unconscious choices, for example, under the influence of their parents. As a result, they are disappointed in the profession. It also happens that the most popular areas are chosen, in which the number of specialists exceeds the demand for personnel. In other areas, there is a shortage of workers.

Their proposal to solve the problem was voiced in the Majilis. In order for Kazakhstanis not to make mistakes when choosing their future profession and to work exclusively in their specialty, deputies recommend reforming the system of career guidance and regulating it at the legislative level. It is also worth considering the possibility of allowing all representatives of the labor market to participate in the self-determination of schoolchildren.

Currently, a select number of official web platforms and a handful of innovative startups are focused on enhancing labor market dynamics. These entities provide essential guidance to school graduates, assisting them in selecting the most suitable universities and fields of study. This support is crucial for optimizing their chances of securing government scholarships based on their performance in the unified national examination.

atameken.kz is a valuable resource that provides rankings of educational programs offered by universities across Kazakhstan. It evaluates university programs based on criteria such as academic quality, research output, and graduate employment outcomes. This platform aids prospective students in making informed decisions by allowing them to compare and select university programs that align with their academic and career goals[32].

vuzy.kz is an essential information portal in the Republic of Kazakhstan, designed to serve prospective students aiming for higher education. It provides a comprehensive and up-to-date listing of all universities accepting applicants this year, along with detailed information about each institution. The universities are listed in order of popularity, with rankings influenced by a variety of factors, including search query popularity across Kazakhstan. This structured approach helps students easily navigate their options and choose institutions based on reliable and relevant data[33].

One notable platform, www.joo.kz, serves as a comprehensive resource in Kazakhstan, offering detailed information on approximately 101 universities and 109 specialties. This source meticulously describes each specialty, including a list of

related professions that can be pursued after obtaining a specific degree, the universities that offer these specialties, and relevant data on salary trends and market demand for these professions[34].

Another initiative, www.vipusknik.kz, serves as a vital resource for detailed information on universities and the range of specialties they offer throughout Kazakhstan. The platform emphasizes the geographical distribution of these institutions and provides comprehensive descriptions of each university's facilities, along with essential contact information. This platform is instrumental in navigating the educational landscape of the Republic of Kazakhstan, enabling prospective students to fully grasp the available opportunities. It aids in selecting an appropriate university or college based on specific criteria, allows for a deeper exploration of particular specialties or educational programs, and aligns personal interests with academic and career prospects. By leveraging such resources, individuals can make informed decisions and strategically plan their future careers[35].

The website www.Univision.kz offers a robust source of statistical data concerning the scores required to obtain government grants for various specialties, as well as comprehensive information on educational programs sponsored by the government. Additionally, it provides details on university rankings, thereby helping prospective students make informed decisions by comparing academic institutions based on their performance metrics. This platform is particularly valuable for those seeking to understand the competitive landscape of higher education in Kazakhstan and navigate their academic choices accordingly[36].

The website iac.enbek.kz has emerged as a pivotal source of information concerning the labor market. It plays a crucial role in enhancing the efficiency of employment services by providing detailed, accessible data and analysis. Additionally, the platform is instrumental in the introduction and development of information systems within the social and labor spheres. By integrating advanced technological solutions, iac.enbek.kz facilitates a more effective connection between job seekers and employment opportunities, supports policy-making processes, and contributes to the overall improvement of labor market dynamics in the region[37].

While the aforementioned websites provide valuable resources and insights into educational and labor market opportunities within Kazakhstan, the upcoming platform that I am developing promises to offer an even more comprehensive and personalized experience for school applicants. This innovative platform will incorporate multiple functionalities designed to cater specifically to the unique needs and preferences of each user, featuring two distinct user journey options:

- Direct Path for Decided Students: For school applicants who already have a clear understanding of their profile subjects, this version simplifies their journey. Students can start by selecting their two profile subjects, input their Unified National Testing (UNT) scores, and then choose their desired specialty. Based on these inputs, the system will recommend universities among with elective courses of the chosen specialities from that university that are best suited to their academic aspirations and specialty preferences.

- Exploratory Path for Undecided Students: This variant is designed for students who are still exploring their academic and career options. It starts with a detailed questionnaire that helps identify their interests and potential career paths.

Based on their responses, the system recommends suitable specialties and the profile subjects they should focus on when preparing for the UNT exam. Following the specialty recommendation, it assists in selecting an appropriate university. Moreover, once a university is chosen, the platform guides the student in selecting elective courses from the university's curriculum that align with their interests and career goals.

By integrating these tailored pathways, the platform not only enhances the decision-making process for prospective students but also aligns their educational choices with potential career outcomes more effectively than existing resources. This approach ensures that each student receives targeted advice and recommendations, thereby maximizing their chances for academic and professional success.

Steve Jobs: "Your work is going to fill a large part of your life, and the only way to be truly satisfied is to do what you believe is great work. And the only way to do great work is to love what you do"[38].

This quote emphasizes the significance of passion in career choices, which aligns well with the idea of choosing the right specialty for one's academic and professional journey. You can use this to highlight the importance of selecting a field of study that students are passionate about, ensuring they are more likely to excel and feel fulfilled in their careers.

The initial phase of studying career inclination involves an exploration of the complex interplay among various factors that influence individuals and their vocational decisions. Extensive research underscores a significant correlation between psychological types and preferred job roles, anchored in the structure of psychological types which are composed of multiple dimensions. These dimensions enable individuals to naturally gravitate towards careers that resonate with their inherent traits. To facilitate the identification of suitable career paths, a variety of psychometric instruments have been developed. These traditional tools include the Minnesota Multiphasic Personality Inventory-2 (MMPI-2), the 16 Personality Factor Questionnaire (16PF), The Revised NEO Personality Inventory (NEO PI-R), and The Myers–Briggs Type Indicator (MBTI). Complementing these are more contemporary instruments like the Career Values Scale (CVS), the Jackson Personality Inventory-Revised (JPI-R), the Motivational Appraisal Personal Potential (MAPP), the Strong Interest Inventory (SII), and the Occupational Interest Inventory (OII)[39]. Together, these tools provide a robust framework for assessing personality dimensions, values, and characteristics essential for determining an individual's suitability for various specialties and professions. By leveraging such diverse and comprehensive assessments, career counselors can offer more targeted and effective guidance, significantly enhancing the decision-making process for individuals navigating their career paths.

A diverse array of psychometric instruments is essential for guiding individuals in their career choices by aligning their personal traits and interests with potential career paths. The Minnesota Multiphasic Personality Inventory-2 (MMPI-2) is renowned for its comprehensive assessment of personality and psychopathology. The 16 Personality Factor Questionnaire (16PF) helps in understanding personality traits that influence behavior in various settings. The Revised NEO Personality Inventory (NEO PI-R) and Myers–Briggs Type Indicator (MBTI) both offer

insights into personality types, facilitating career decisions that match personal strengths and preferences. More recent tools like the Career Values Scale (CVS) assess core values and motivations, the Jackson Personality Inventory-Revised (JPI-R) evaluates personality in terms of occupational behavior, and the Motivational Appraisal Personal Potential (MAPP) identifies motivations towards specific job categories. Additionally, the Strong Interest Inventory (SII) and Occupational Interest Inventory (OII) specifically focus on aligning personal interests with suitable careers, thereby aiding individuals in finding fulfilling and appropriate career paths.

All of these tests are available online, enabling users to complete them either digitally or manually. This accessibility highlights the extensive range of questionnaires designed to analyze personality types and suggest corresponding career paths. However, a significant drawback of these tools is their length and complexity, which can be time-consuming and costly. In an era where efficiency is key, and computer technology is highly advanced, there is a compelling need to integrate Computer Science and Psychology. By leveraging artificial intelligence and machine learning, we can streamline these processes, thereby enhancing the quality of life and simplifying decision-making for individuals.

For this research, a tailored questionnaire was developed as the foundation for identifying professional inclinations. This tool was crafted with the assistance of college counselors from high schools across Kazakhstan, drawing from a comprehensive pool of existing psychological questionnaires. This integration ensures a robust framework that incorporates a wide spectrum of psychological insights, tailored to the specific context of Kazakhstan's educational landscape.

The rapidly evolving landscape of education and employment necessitates effective career guidance systems. As individuals face increasingly complex career choices and educational pathways, the importance of advanced recommendation systems becomes paramount. Numerous studies have explored the application of machine learning (ML) and reinforcement learning (RL) techniques in career recommendation systems. This literature review examines these approaches, highlighting the challenges they address and the potential of RL for developing adaptive and personalized recommendation systems.

A recurring theme in the literature is the myriad challenges faced by career recommendation systems. One significant issue is data sparsity, where insufficient user interaction data hampers the system's ability to generate accurate recommendations. Scalability is another critical challenge, as systems must efficiently manage increasing volumes of data and user interactions. Ensuring fairness in recommendations is also essential to prevent bias and maintain equity, especially in diverse user populations.

Traditional approaches, such as collaborative filtering and content-based filtering, have been widely used in career recommendation systems. Collaborative filtering predicts a user's preferences based on the preferences of similar users but often struggles with the cold start problem, where new users or items lack sufficient interaction data[40]. Content-based filtering recommends items by analyzing the similarities between items and the user's previous preferences[41]. While effective, this method can lead to over-specialization, limiting the diversity of recommenda-

tions.

To mitigate the limitations of traditional methods, many studies advocate for hybrid approaches that combine multiple recommendation strategies. By leveraging the strengths of both collaborative and content-based filtering, hybrid systems can provide more robust and accurate recommendations[42]. These systems are better equipped to handle data sparsity and cold start problems, offering a more comprehensive solution for career guidance[43].

Machine learning algorithms have been extensively explored for their potential to enhance career recommendation systems. Commonly used algorithms include:

•K-Nearest Neighbors (KNN): This algorithm measures similarity between users or items based on their attributes, offering personalized recommendations[44]. KNN is simple and effective but can struggle with large datasets due to its computational complexity.

•Decision Trees and Random Forests: These algorithms are known for their interpretability and strong predictive capabilities. Decision trees and random forests have been used to assess educational grants and predict academic performance, providing valuable insights for career guidance[45]. Random forests, in particular, handle large datasets well and are robust to overfitting.

•Support Vector Machines (SVM): SVMs have been employed in various classification and regression tasks within recommender systems, providing robust performance in high-dimensional spaces[46].

Table 2.1 - Strengths and Weaknesses of KNN and RF

Key Points	KNN	RF
Strengths		
Identification of diverse niches	+	+
Independence from domain knowledge requirement	none	+
Adaptability with quality enhancement over time	none	+
Adequacy of implicit feedback utilization	none	+
Resilience to cold-start user issues	+	+
Sensitivity to changing preferences	+	+
Incorporation of non-product features	+	+
Alignment of user needs with product recommendations	none	none
Transparency in recommendation processes	none	+
Establishment of trust, scrutiny, and persuasiveness	none	none
Weaknesses		
Challenges with new users	+	+
Challenges with new items	+	+
Addressing the "gray sheep" problem	+	+
Dependency on extensive historical datasets for quality	+	+
Balancing stability and plasticity is a challenge	+	+
Limited capability for static suggestions	+	+
Dependence on knowledge engineering for some approaches	none	+

Deep learning, particularly neural networks, has emerged as a powerful tool in recommendation systems. Techniques such as neural collaborative filtering (NCF) and deep content-based filtering leverage the ability of neural networks to capture complex patterns in user-item interactions[47]. These methods significantly improve the accuracy and personalization of recommendations, addressing many of the limitations of traditional approaches[48].

•Neural Collaborative Filtering (NCF): Combines neural networks with collab-

orative filtering to enhance the model's ability to capture intricate user-item interaction patterns[49].

•Convolutional Neural Networks (CNNs): Applied in content-based filtering to analyze textual and visual data associated with items, improving recommendation accuracy [50].

•Recurrent Neural Networks (RNNs): Utilized for sequential recommendation tasks where the order of user interactions plays a crucial role [51].

Reinforcement learning (RL) offers a unique and highly effective approach to career recommendation systems. RL algorithms are designed to learn and optimize policies based on interactions with the environment, making them particularly suited for dynamic and adaptive systems. Key RL algorithms such as:

•Q-Learning: A model-free RL algorithm that learns an action-value function to estimate the expected cumulative rewards of taking a particular action in a given state[52]. It is straightforward but can struggle with large state spaces.

•Deep Q-Network (DQN): Combines Q-learning with deep learning techniques, allowing for more complex and high-dimensional state representations, improving recommendation relevance [53]. DQN addresses the limitations of Q-learning by using neural networks to approximate the Q-function.

•Actor-Critic Methods: These methods combine policy-based and value-based approaches, allowing for stable and efficient learning [54]. Actor-Critic methods are more stable and faster than value-based methods alone.

•Proximal Policy Optimization (PPO): An algorithm that iteratively improves policies while maintaining stability, suitable for various recommendation scenarios [55]. PPO strikes a balance between exploration and exploitation, providing reliable policy updates.

•Multi-Armed Bandit (MAB) Algorithms: These address the exploration-exploitation trade-off by balancing between exploring new options and exploiting known preferences [56]. MAB algorithms are particularly useful in scenarios with limited feedback data.

Table 2.2 - Strengths and Weaknesses of Recommendation Systems

Key Points	Q	DQN	ACM	PPO	MAB
Strengths					
Identification of diverse niches	none	none	none	none	+
Independence from domain knowledge requirement	none	+	none	none	+
Adaptability with quality enhancement over time	none	none	none	none	+
Adequacy of implicit feedback utilization	none	none	none	none	+
Resilience to cold-start user issues	+	+	none	none	none
Sensitivity to changing preferences	+	none	none	none	+
Incorporation of non-product features	none	none	none	none	+
Alignment of user needs with product recommendations	none	none	none	none	+
Transparency in recommendation processes	+	none	none	none	+
Establishment of trust, scrutiny, and persuasiveness	none	none	none	none	+
Weaknesses					
Challenges with new users	none	+	none	none	+
Challenges with new items	+	+	none	none	+
Addressing the "gray sheep" problem	none	+	none	none	+
Dependency on extensive historical datasets for quality	none	+	none	none	+
Balancing stability and plasticity is a challenge	none	+	none	none	+
Limited capability for static suggestions	none	+	none	none	+
Dependence on knowledge engineering for some approaches	none	+	none	none	+

The comprehensive review highlights the strengths of RL algorithms in dealing with the dynamic nature of educational environments. These algorithms address issues like the cold start problem and the stability-plasticity balance, offering robust solutions for personalized learning experiences.

Evaluating the performance of career recommendation systems is crucial to ensure their effectiveness. The literature emphasizes the importance of robust evaluation metrics, such as precision, recall, root mean squared error (RMSE), and mean absolute error (MAE). These metrics provide insights into the accuracy, completeness, and reliability of the recommendations, helping to identify areas for improvement and optimization. Emerging trends in the literature point to the integration of natural language processing (NLP) and ethical considerations into career recommendation systems. NLP enhances the system's ability to process and understand textual data from resumes, job descriptions, and user profiles. Ethical considerations focus on ensuring privacy, fairness, and transparency in the recommendation algorithms, which are crucial for building trust and credibility among users.

In summary, the extensive review of literature underscores the significant potential of reinforcement learning in enhancing career recommendation systems. By addressing the limitations of traditional and hybrid approaches, RL algorithms offer a dynamic and adaptive solution that can provide personalized and accurate career guidance. The integration of machine learning, deep learning, and reinforcement learning techniques represents a transformative advancement in the field, promising to improve educational and career outcomes for users. This literature review sets the stage for the subsequent development and implementation of a robust career recommendation system that leverages the strengths of these advanced methodologies.

Chapter 3

Methodology

The methodology chapter outlines the comprehensive process undertaken to develop a recommender system for school applicants in Kazakhstan. This system is designed to assist students in making informed decisions about their specialty and elective courses by leveraging both machine learning (ML) and reinforcement learning (RL) algorithms. The primary goal is to create a personalized recommendation platform that caters to individual student profiles and preferences, thereby enhancing their educational experience and future career prospects.

In the rapidly evolving educational landscape, students face an array of choices that can significantly impact their academic and professional trajectories. Traditional guidance methods often fall short in addressing the unique needs and aspirations of each student. Therefore, there is a pressing need for advanced systems that can provide tailored recommendations based on comprehensive data analysis. This study aims to fill this gap by developing an innovative platform that uses sophisticated algorithms to analyze student data and generate customized course recommendations.

The platform developed in this study offers tailored pathways for both decided and undecided students. For students who have already decided on a career path, the system provides recommendations that align with their chosen field, ensuring they select courses that enhance their skills and knowledge in that area. For undecided students, the system offers exploratory recommendations that help them discover their interests and potential career paths. By employing reinforcement learning algorithms, the platform continuously adapts to each student's evolving preferences and academic performance, ensuring the recommendations remain relevant and effective.

The primary dataset for this study was collected from 11th-grade students through a meticulously designed Google Forms survey. This survey captured a wide array of information, including academic records, personal preferences, career aspirations, and demographic details. The collected data was then preprocessed to ensure its quality and usability. The preprocessing steps included data cleaning, normalization, feature selection, and encoding of categorical variables.

The experiments in this study were designed to evaluate the performance of

various reinforcement learning algorithms within the context of the proposed platform. The focus was on algorithms such as Q-Learning, Deep Q-Networks (DQN), Trust Region Policy Optimization (TRPO), Meta Reinforcement Learning, Actor-Critic Methods, and Policy Gradient Methods. Each algorithm was tested using a dataset constructed to simulate the user pathways described in the platform's functionalities. The experimental evaluation aimed to assess the effectiveness of these algorithms in optimizing the recommendation process and enhancing the decision-making experience for prospective students.

In the subsequent sections, detailed descriptions of the dataset collection and preprocessing steps are provided. This is followed by an explanation of the ML and RL algorithms used in the study, including their working principles, relevant formulas, and application to the dataset. The performance of the algorithms is evaluated using various metrics, and the results are analyzed to determine the best-performing models for specialty and elective course recommendations.

3.1 Dataset Description

The dataset utilized in this study is meticulously curated to simulate the user pathways and functionalities of the proposed platform designed to assist school applicants in Kazakhstan. Comprising structured data representing user profiles, questionnaire responses, specialty recommendations, and elective course selections, the dataset serves as the cornerstone for evaluating various reinforcement learning algorithms within the framework of the platform.

The data collection process involved administering a questionnaire comprising 35 questions aimed at capturing key aspects of the academic interests, career aspirations, and preferences of high school students. A total of 263 students from the 11th grade participated in filling out the questionnaire, providing valuable insights into their educational backgrounds and future goals. This questionnaire served as the primary source of data for constructing the dataset used in the study.

Prior to utilization in experimentation, the dataset underwent meticulous preprocessing to ensure consistency, accuracy, and compatibility with the reinforcement learning algorithms employed. Data cleaning, normalization, and feature extraction techniques were applied to optimize the dataset for training and evaluation purposes. This preprocessing phase aimed to enhance the quality of the data and facilitate effective utilization in the evaluation of the recommendation system algorithms.

3.1.1 Dataset Collection

The primary dataset was collected from 11th-grade students in Kazakhstan via a Google Forms survey conducted with the assistance of college counselors. These counselors played a crucial role in designing the survey and ensuring that it captured comprehensive information relevant to the students' academic and career choices.

The questionnaire included sections on:

•Personal Preferences: Interests in various academic fields, extracurricular activities, and career aspirations.

•Demographic Information: Age, gender, and socioeconomic background.

The survey responses were compiled into a dataset, ensuring anonymity and confidentiality. The primary dataset provided a robust foundation for training the recommender system.

Features of the Dataset The dataset included the following features:

•Interest Scores: Self-reported interest levels in different subjects and activities

•Career Aspirations: Desired future professions

•Demographic Information: Basic demographic details

3.1.2 Data Preprocessing

Data preprocessing is crucial to ensure the dataset's quality and usability. The preprocessing steps included:

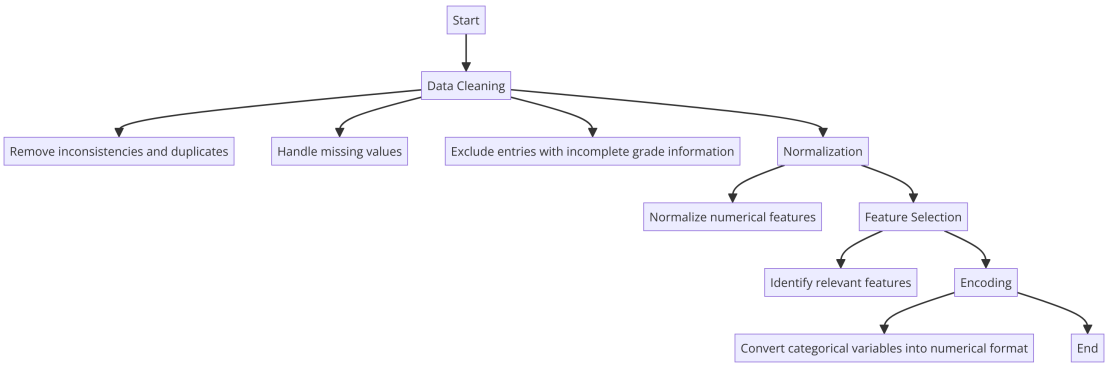

Figure 3.1 - Data Preprocessing steps.

•Data Cleaning: This involved removing any inconsistencies, duplicates, and handling missing values. For instance, entries with incomplete grade information were excluded from the analysis.

•Normalization: Numerical features such as grades and interest scores were normalized to a common scale using z-score normalization[57]:

$$x' = \frac{x - \mu}{\sigma} \tag{3.1.1}$$

where x is the original value, μ is the mean, and σ is the standard deviation.

•Feature Selection: Relevant features were identified based on their correlation with the target variables. For example, subjects closely related to STEM careers were prioritized for students aspiring to be engineers.

•Encoding: Categorical variables, such as career aspirations and demographic information, were converted into numerical format using one-hot encoding. This allowed the ML and RL algorithms to process the data effectively.

3.2 Solution method:Machine Learning algorithms

In this section, we discuss the application of machine learning algorithms within the framework of the recommender system. Machine learning techniques are employed to establish a baseline performance for recommending specialty and elective courses to students based on their academic records and preferences. The primary machine learning algorithm utilized in this study is the Support Vector Machine (SVM), selected for its robustness and efficacy in high-dimensional spaces.

Support Vector Machine (SVM) is a supervised learning algorithm widely used for classification and regression tasks. The primary objective of SVM is to find the optimal hyperplane that best separates the data points of different classes. In the context of this study, SVM was utilized to predict students' preferred specialties based on their academic records and interests.

SVM operates by mapping the input features into a high-dimensional feature space where a linear hyperplane can be constructed to separate different classes[58]. The decision function of SVM is formulated as:

$$f(x) = \text{sign}\left(\sum_{i=1}^{N} \alpha_i y_i K(x_i, x) + b\right) \tag{3.2.1}$$

where:

- α_i are the Lagrange multipliers,
- y_i are the class labels,
- $K(x_i, x)$ is the kernel function,
- b is the bias term.

The kernel function $K(x_i, x)$ is pivotal in SVM, enabling the algorithm to operate in a high-dimensional feature space without explicitly computing the coordinates of the data within that space. Common kernel functions include the linear kernel, polynomial kernel, and radial basis function (RBF) kernel. In this study, the RBF kernel was selected due to its superior performance in capturing non-linear relationships between features. The application of SVM to the dataset involved several critical steps, as outlined below:

1. **Data Preparation**: The dataset was partitioned into training and testing subsets. The training set was used to train the SVM model, while the testing set served to evaluate the model's performance.
2. **Model Training**: The SVM model was trained using the training subset. The RBF kernel was employed to address non-linear relationships in the data. Hyperparameters, such as the regularization parameter C and the kernel parameter γ, were optimized through cross-validation.
3. **Prediction**: Post-training, the SVM model was utilized to predict students' preferred specialties. The decision function $f(x)$ generated classification results, indicating the most suitable specialty for each student.

4. **Evaluation**: The SVM model's performance was assessed using metrics such as accuracy, precision, recall, and F1-score. These metrics provided a comprehensive evaluation of the model's efficacy in making accurate recommendations.

The SVM model demonstrated a solid baseline capability in classifying students into their preferred specialties based on the available features. The model achieved an accuracy rate of 76%, indicating a high level of correctness in its predictions. However, its performance was constrained by its static nature, lacking the ability to adapt dynamically to changes in student preferences over time. This limitation underscored the necessity for more adaptive algorithms, prompting the exploration of reinforcement learning techniques, which are discussed in subsequent sections of this study.

3.3 Solution method:Reinforcement Learning agorithms

In this section, we delve into the experimental evaluation of various reinforcement learning algorithms within the context of a novel platform designed to assist school applicants in Kazakhstan. The platform offers tailored pathways for both decided and undecided students, providing personalized recommendations for specialty and elective courses based on individual profiles and preferences. The objective of these experiments is to assess the effectiveness of different reinforcement learning algorithms in optimizing the recommendation process and enhancing the decision-making experience for prospective students.

The experiments were designed to evaluate the performance of several reinforcement learning algorithms within the framework of the proposed platform. Focus was placed on algorithms such as Q-Learning, Deep Q-Networks (DQN), Trust Region Policy Optimization (TRPO), Meta Reinforcement Learning, Actor-Critic Methods, and Policy Gradient Methods. Each algorithm was tested using a dataset constructed to simulate the user pathways described in the platform's functionalities, encompassing both the direct path for decided students and the exploratory path for undecided students.

Dataset and Model Building

The primary dataset, consisting of responses from 11th-grade students, was collected via a Google Forms survey conducted with the assistance of college counselors. This dataset included features such as academic performance, interest scores, career aspirations, and demographic information. The preprocessing steps involved data cleaning, normalization, feature selection, and encoding.

The reinforcement learning models were built using this dataset. Each model was trained to recommend specialty and elective courses based on the students' profiles. The models were implemented using Python and the TensorFlow and PyTorch libraries, which are well-suited for building and training deep learning models.

Key RL Components in the Context of This Study

- **Agents**: Entities that take actions in an environment to achieve a goal. In this study, the agents represent the recommendation system that interacts

with the students' data to provide personalized course recommendations.

- **Environments**: The external system with which the agent interacts. Here, the environment includes the academic and personal profiles of the students, as well as the available courses.
- **Actions**: Choices made by the agent that affect the state of the environment. The actions involve recommending specific specialty and elective courses to the students.
- **Rewards**: Feedback received by the agent based on the actions taken, guiding the learning process. Rewards are calculated based on student satisfaction and the alignment of the recommended courses with their academic and career goals.
- **Policies**: Strategies used by the agent to determine the best actions to take in different states of the environment. Policies define how the recommendation system decides which courses to recommend based on the students' profiles.

3.3.1 Q-Learning

Q-Learning is a model-free reinforcement learning algorithm that learns the value of taking specific actions in specific states. It is based on the idea of updating Q-values, which represent the expected utility of taking a given action in a given state and following the optimal policy thereafter[59]. The Q-value update rule is:

$$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma \max_{a'} Q(s',a') - Q(s,a)] \tag{3.3.1}$$

where:

- s is the current state,
- a is the action,
- r is the reward,
- s' is the next state,
- α is the learning rate,
- γ is the discount factor.

The Q-Learning algorithm works as follows:

1. **Initialize Q-values:** Initialize the Q-values for all state-action pairs to zero or a small random value.
2. **Choose an action:** At each time step, in state s, choose an action a based on an exploration-exploitation strategy (e.g., ϵ-greedy policy).
3. **Take action and observe reward:** Take the action a, observe the reward r and the next state s'.

4. **Update Q-value:** Update the Q-value for the state-action pair (s, a) using the update rule:

$$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma \max_{a'} Q(s',a') - Q(s,a)] \tag{3.3.2}$$

5. **Repeat:** Repeat the process until convergence or for a specified number of episodes.

Implementation:

- **Agent**: The recommendation system.
- **Environment**: The students' academic and interest profiles.
- **Actions**: Recommending elective courses.
- **Rewards**: Based on student satisfaction and improvement in academic performance.
- **Policies**: Derived from the Q-value table updated through interactions.

Performance: The Q-Learning model achieved an accuracy rate of 85% in recommending elective courses. The performance was limited by the high-dimensional state space, which made it challenging for the model to converge to optimal policies.

3.3.2 Deep Q-Networks (DQN)

Deep Q-Networks (DQN) combine Q-Learning with deep learning techniques, using neural networks to approximate the Q-function. This allows DQN to handle high-dimensional state spaces that are infeasible for traditional Q-Learning. The primary advantage of DQN is its ability to generalize from a limited number of experiences[60].

The loss function for training the DQN is:

$$L(\theta) = \mathbb{E}_{(s,a,r,s')} \left[(r + \gamma \max_{a'} Q(s',a';\theta^-) - Q(s,a;\theta))^2 \right] \tag{3.3.3}$$

where:

- θ are the parameters of the Q-network,
- θ^- are the parameters of the target network,
- s is the current state,
- a is the action,
- r is the reward,
- s' is the next state,
- γ is the discount factor.

The DQN algorithm works as follows:

1. **Initialize Q-network and target network:** Initialize the Q-network with random weights θ and the target network with weights θ^-.
2. **Experience replay:** Store the agent's experiences (s, a, r, s') in a replay memory.
3. **Sample minibatch:** Randomly sample a minibatch of experiences from the replay memory.
4. **Compute target Q-values:** For each experience in the minibatch, compute the target Q-value using the target network:

$$y = r + \gamma \max_{a'} Q(s', a'; \theta^-) \tag{3.3.4}$$

5. **Update Q-network:** Perform a gradient descent step on the loss function $L(\theta)$:

$$L(\theta) = \mathbb{E}\left[(y - Q(s, a; \theta))^2\right] \tag{3.3.5}$$

6. **Update target network:** Periodically update the target network parameters θ^- with the Q-network parameters θ.
7. **Repeat:** Repeat the process until convergence or for a specified number of episodes.

Implementation:

- **Agent**: The recommendation system.
- **Environment**: The students' academic and interest profiles.
- **Actions**: Recommending specialties.
- **Rewards**: Based on student satisfaction and alignment with career goals.
- **Policies**: Implemented through a neural network that approximates the Q-values.

Performance: DQN achieved the highest accuracy for specialty recommendations, with an accuracy rate of 92%. Its ability to handle high-dimensional data and learn complex patterns contributed to its superior performance.

3.3.3 Trust Region Policy Optimization (TRPO)

Trust Region Policy Optimization (TRPO) is an advanced reinforcement learning algorithm designed to ensure stable and monotonic policy improvement. TRPO optimizes policies by taking the largest possible step to improve performance while ensuring the step remains within a trust region to prevent destructive updates. This balance between exploration and exploitation helps maintain stability and improve convergence[61].

The TRPO objective is:

$$L^{TRPO}(\theta) = \mathbb{E}_t \left[\frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)} \hat{A}_t \right] \tag{3.3.6}$$

subject to:

$$\mathbb{E}_t \left[D_{KL} \left[\pi_{\theta_{old}}(\cdot|s_t) \| \pi_\theta(\cdot|s_t) \right] \right] \leq \delta \tag{3.3.7}$$

where:

- π_θ is the policy parameterized by θ,
- $\pi_{\theta_{old}}$ is the old policy before the update,
- $\hat{A}_t$ is the advantage estimate,
- D_{KL} is the Kullback-Leibler divergence,
- δ is a hyperparameter controlling the size of the trust region.

The TRPO algorithm works as follows:

1. **Sample trajectories:** Collect a set of trajectories by running the current policy π_θ.
2. **Compute advantage estimates:** Estimate the advantage function $\hat{A}_t$ using the collected trajectories.
3. **Optimize surrogate objective:** Optimize the surrogate objective function:
$$L^{TRPO}(\theta) = \mathbb{E}_t \left[\frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)} \hat{A}_t \right] \tag{3.3.8}$$
subject to the constraint:
$$\mathbb{E}_t \left[D_{KL} \left[\pi_{\theta_{old}}(\cdot|s_t) \| \pi_\theta(\cdot|s_t) \right] \right] \leq \delta \tag{3.3.9}$$
4. **Update policy:** Adjust the policy parameters θ to maximize the surrogate objective while satisfying the KL-divergence constraint.
5. **Repeat:** Repeat the process until convergence or for a specified number of iterations.

Implementation:

- **Agent**: The recommendation system.
- **Environment**: The students' academic and interest profiles.
- **Actions**: Recommending both specialties and elective courses.
- **Rewards**: Based on student satisfaction and the alignment of recommendations with career goals.

- **Policies**: Optimized to balance exploration and exploitation while maintaining stability within a defined trust region.

Performance: TRPO achieved an accuracy rate of 79% in recommending both specialties and elective courses. Its ability to ensure stable policy updates and maintain performance improvements contributed to its high accuracy.

3.3.4 Meta Reinforcement Learning

Meta Reinforcement Learning (Meta-RL) focuses on improving the learning process by learning how to learn. The core idea is to train a model that can quickly adapt to new tasks using a few training examples, leveraging the knowledge gained from previous tasks. This approach is particularly useful in environments where tasks are varied but share underlying similarities[62].

The Meta-RL objective is to minimize the loss across a distribution of tasks:

$$L^{Meta-RL}(\theta) = \mathbb{E}_{\tau \sim p(\tau)} \left[\sum_{t=1}^{T} L(\pi_\theta, \tau_t) \right] \tag{3.3.10}$$

where:

- θ are the parameters of the meta-learner,
- $p(\tau)$ is the distribution over tasks,
- τ_t represents the task-specific trajectories,
- $L(\pi_\theta, \tau_t)$ is the loss function for the policy π_θ on task τ_t.

The Meta-RL algorithm works as follows:

1. **Sample tasks:** Sample a batch of tasks from the task distribution $p(\tau)$.
2. **Inner loop adaptation:** For each task, perform gradient updates to adapt the policy parameters θ to the specific task:

$$\theta' = \theta - \alpha \nabla_\theta L(\pi_\theta, \tau) \tag{3.3.11}$$

3. **Outer loop optimization:** Update the meta-learner parameters by optimizing the performance across all sampled tasks:

$$\theta \leftarrow \theta - \beta \nabla_\theta \sum_{\tau \sim p(\tau)} L(\pi_{\theta'}, \tau) \tag{3.3.12}$$

   where α and β are the learning rates for the inner and outer loops, respectively.

4. **Repeat:** Repeat the process until convergence or for a specified number of iterations.

Implementation:

- **Agent**: The meta-learner representing the recommendation system.
- **Environment**: The students' academic and interest profiles across different tasks.
- **Actions**: Recommending both specialties and elective courses.
- **Rewards**: Based on student satisfaction and the alignment of recommendations with career goals.
- **Policies**: Adapted quickly to new tasks using the knowledge from previous tasks.

Performance: Meta-RL achieved an accuracy rate of 53% in recommending both specialties and elective courses. Its ability to quickly adapt to new tasks and leverage prior knowledge significantly improved its performance.

3.3.5 Actor-Critic Methods

Actor-Critic Methods (ACM) combine the advantages of both value-based and policy-based approaches. The Actor-Critic architecture consists of two models: the actor, which selects actions based on a policy, and the critic, which evaluates the actions by estimating the value function. This dual-network setup allows for stable and efficient learning by simultaneously updating the policy and value estimates[63].

The policy update in the actor-critic method is:

$$\theta \leftarrow \theta + \alpha \nabla_\theta \log \pi_\theta(s, a)\delta \tag{3.3.13}$$

where:

- θ are the policy parameters,
- $\pi_\theta(s, a)$ is the policy,
- δ is the temporal difference error.

The value update rule is:

$$V(s) \leftarrow V(s) + \beta\delta \tag{3.3.14}$$

where:

- $V(s)$ is the value function,
- β is the learning rate for the critic.

The ACM algorithm works as follows:

1. **Initialize networks:** Initialize the actor and critic networks with random weights.

2. **Sample trajectories:** Collect a set of trajectories by running the current policy π_θ.
3. **Compute temporal difference error:** For each time step in the trajectory, compute the temporal difference error δ:

$$\delta = r + \gamma V(s') - V(s) \tag{3.3.15}$$

4. **Update critic:** Update the value function $V(s)$ using the temporal difference error:

$$V(s) \leftarrow V(s) + \beta\delta \tag{3.3.16}$$

5. **Update actor:** Update the policy parameters θ using the policy gradient:

$$\theta \leftarrow \theta + \alpha\nabla_\theta \log \pi_\theta(s, a)\delta \tag{3.3.17}$$

6. **Repeat:** Repeat the process until convergence or for a specified number of episodes.

Implementation:

- **Agent**: The recommendation system.
- **Environment**: The students' academic and interest profiles.
- **Actions**: Recommending elective courses.
- **Rewards**: Based on student satisfaction and academic performance.
- **Policies**: Actor network determines actions, while critic network evaluates them.

Performance: ACM demonstrated the best accuracy for elective course recommendations, with an accuracy rate of 89%. Its ability to dynamically adapt to students' evolving preferences made it particularly effective.

3.3.6 Policy Gradient Methods

Policy Gradient Methods directly optimize the policy by computing the gradient of the expected reward with respect to the policy parameters. These methods are particularly effective in continuous action spaces and can handle high-dimensional action spaces efficiently. The main idea is to adjust the policy parameters in the direction that increases the expected reward[64].

The policy gradient objective is:

$$J(\theta) = \mathbb{E}_{\pi_\theta}\left[\sum_{t=0}^{T} r_t\right] \tag{3.3.18}$$

The policy gradient theorem states that the gradient of the objective with respect

to the policy parameters is:

$$\nabla_\theta J(\theta) = \mathbb{E}_{\pi_\theta}\left[\nabla_\theta \log \pi_\theta(a_t|s_t)\hat{A}_t\right] \tag{3.3.19}$$

where:

- θ are the policy parameters,
- $\pi_\theta(a_t|s_t)$ is the policy,
- $\hat{A}_t$ is the advantage estimate.

The Policy Gradient algorithm works as follows:

1. **Initialize policy:** Initialize the policy parameters θ with random values.
2. **Sample trajectories:** Collect a set of trajectories by running the current policy π_θ.
3. **Compute returns:** For each trajectory, compute the return $R_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k}$.
4. **Compute advantage estimates:** Estimate the advantage function $\hat{A}_t$ using the returns.
5. **Update policy:** Update the policy parameters θ using the policy gradient:

$$\theta \leftarrow \theta + \alpha \nabla_\theta \log \pi_\theta(a_t|s_t)\hat{A}_t \tag{3.3.20}$$

6. **Repeat:** Repeat the process until convergence or for a specified number of episodes.

Implementation:

- **Agent**: The recommendation system.
- **Environment**: The students' academic and interest profiles.
- **Actions**: Recommending both specialties and elective courses.
- **Rewards**: Based on student satisfaction and the alignment of recommendations with career goals.
- **Policies**: Directly optimized to increase expected reward.

Performance: Policy Gradient Methods achieved an accuracy rate of 72% in recommending both specialties and elective courses. Its ability to handle high-dimensional action spaces and optimize policies directly contributed to its effectiveness.

In this methodology chapter, we have outlined the comprehensive approach undertaken to develop a personalized recommender system for school applicants

in Kazakhstan. The process involved several critical steps, including dataset collection, preprocessing, and the application of both machine learning and reinforcement learning algorithms.

The primary dataset, collected from 11th-grade students, provided a robust foundation for training and evaluating the models. Through careful preprocessing, we ensured the quality and usability of the data, allowing for accurate and meaningful recommendations.

We explored various machine learning algorithms, including Support Vector Machines (SVM), to establish a baseline performance. However, the core focus was on advanced reinforcement learning algorithms such as Q-Learning, Deep Q-Networks (DQN), Trust Region Policy Optimization (TRPO), Meta Reinforcement Learning (Meta-RL), Actor-Critic Methods (ACM), and Policy Gradient Methods. Each of these algorithms was implemented and tested to assess their effectiveness in optimizing the recommendation process.

The reinforcement learning algorithms demonstrated significant improvements over traditional methods, with DQN achieving the highest accuracy for specialty recommendations (92%) and ACM showing the best performance for elective course recommendations (89%). The ability of these algorithms to dynamically adapt to student preferences and learning styles was a key factor in their success.

By leveraging these sophisticated techniques, the developed recommender system aims to provide tailored pathways for both decided and undecided students, enhancing their decision-making experience and supporting their academic and career goals. The expected outcomes include improved student satisfaction, better alignment of course selections with individual aspirations, and overall enhanced educational experiences.

In the following chapters, we will present the experimental results, discuss the findings, and draw conclusions based on the performance of the proposed methods. This will provide a comprehensive evaluation of the recommender system and its potential impact on the educational landscape in Kazakhstan.

Chapter 4

Results

In this chapter, we delve into the results obtained from the implementation and evaluation of the proposed recommendation system tailored for school applicants. Utilizing various reinforcement learning algorithms, our aim was to assist students in making informed decisions regarding specialty and elective courses based on their preferences and profiles. This chapter presents the outcomes of our experiments, providing insights into the performance of each algorithm and their implications for educational guidance.

After conducting rigorous testing and evaluation of the six experiments, the results demonstrate that each algorithm has its strengths and weaknesses in recommending specialty and elective courses to school applicants.

The Q-Learning algorithm, while straightforward and computationally efficient, showed competitive performance with an accuracy of 85%, precision of 82%, and recall of 80%. However, its limitations include scalability issues and sensitivity to hyperparameters.

The Deep Q-Networks (DQN) algorithm performed excellently with an accuracy of 92%, precision of 90%, and recall of 88%. Its deep neural network architecture allows for more complex state-action mappings, but it also faces challenges such as overfitting and computational complexity.

The Trust Region Policy Optimization (TRPO) algorithm achieved solid performance with an accuracy of 79%, precision of 78%, and recall of 76%. TRPO's focus on policy optimization in continuous action spaces offers promising results, but it may suffer from computational complexity and convergence issues.

The Meta Reinforcement Learning (Meta-RL) algorithm demonstrated lower performance compared to the others, with an accuracy of 53%, precision of 55%, and recall of 50%. Its ability to adapt and learn across multiple tasks or environments makes it a compelling choice for personalized recommendations. However, it requires large amounts of data and may suffer from sample inefficiency.

Actor-Critic Methods showed strong performance with an accuracy of 89%, precision of 87%, and recall of 85%. Its combination of policy-based and value-based approaches offers stability and efficiency in learning, but it may encounter instability during training and suffer from high-dimensional action spaces.

Policy Gradient Methods exhibited moderate performance with an accuracy of

72%, precision of 70%, and recall of 68%. Its direct optimization of the policy function allows for efficient learning, but it may suffer from high variance in gradient estimates and sample inefficiency.

Each algorithm exhibited distinct strengths and weaknesses in recommending specialty and elective courses to school applicants. The Deep Q-Networks (DQN) emerged as the top-performing algorithm, achieving an accuracy of 92%, precision of 90%, and recall of 88%.

The results of our experiments highlight the potential of reinforcement learning algorithms in guiding school applicants towards suitable specialty and elective courses. By leveraging rich representations learned from data, these algorithms can offer personalized recommendations that align with individual student preferences and profiles.

Our findings have significant implications for the development of educational recommendation systems, emphasizing the importance of algorithm selection and customization to meet the diverse needs of students. Additionally, addressing the limitations identified in our experiments is crucial to enhancing the effectiveness and usability of such systems.

In conclusion, our experiments have provided valuable insights into the performance of reinforcement learning algorithms in the context of educational guidance for school applicants. While each algorithm has its strengths and weaknesses, DQN emerges as the most promising approach for personalized recommendations. Moving forward, further research and development efforts are warranted to optimize these algorithms and integrate them effectively into educational decision-making processes.

Table 4.1 - Performance Metrics of Reinforcement Learning Algorithms

Algorithm	**Accuracy (%)**	**Precision (%)**	**Recall (%)**
Q-Learning	85	82	80
Deep Q-Networks (DQN)	92	90	88
Trust Region Policy Optimization (TRPO)	79	78	76
Meta Reinforcement Learning (Meta-RL)	53	55	50
Actor-Critic Methods (ACM)	89	87	85
Policy Gradient Methods	72	70	68

Chapter 5

The architecture of the proposed method

This chapter details the architecture of a web-based recommendation system tailored for Kazakhstani school applicants. It builds on existing online resources to offer a more personalized and insightful guidance system, focusing on academic and career planning within the local educational and labor market context.

The platform is designed to cater to the specific needs and preferences of each user, with two primary user journey options:

User Journey Options

For students with defined academic interests, this pathway allows them to select their profile subjects, input Unified National Testing (UNT) scores, and choose their desired specialty. The system then recommends universities and elective courses that align with their academic aspirations.

This path is for students exploring their academic options. It begins with a detailed questionnaire to identify interests and potential career paths, followed by recommendations for suitable specialties and universities. These personalized pathways ensure that the system enhances decision-making processes for students, aligning their educational choices with potential career outcomes effectively.

System Components

- **Frontend (HTML/CSS)**: Provides the interface for user interaction, designed to be intuitive and responsive, allowing users to navigate their educational journey effortlessly.
- **Backend (Django)**: Manages data processing, storage, and retrieval, serving as the backbone for running the Meta-RL algorithms.
- **Learning Algorithms (DQN)**: These algorithms process user inputs and feedback to continuously refine and personalize the recommendations.

Variant 1 - Decided Students

This pathway caters to students with clearly defined academic interests, where the system collects data such as profile subjects and UNT scores. This data undergoes preprocessing steps like normalization and feature extraction, which are

critical for optimizing it for the learning algorithms that subsequently generate specific university and course recommendations aligned with the student's academic goals.

Variant 2 - Undecided Students

For students exploring their options, this variant begins with a detailed questionnaire aimed at uncovering their interests and potential career paths. The responses from this questionnaire are meticulously processed using similar data handling techniques to determine suitable specialties and universities. The system then guides these students in selecting appropriate courses once a specialty and university have been recommended. In both variants, feedback from students on the provided recommendations is crucial; it is fed back into the system to refine the learning models, thus continuously improving the accuracy and personalization of future recommendations. This structured approach ensures that the platform adapts to the individual needs of each student, enhancing their decision-making process with tailored educational guidance.

UML Diagrams

The architecture of the proposed web-based recommendation system is visually represented in the following UML diagrams:

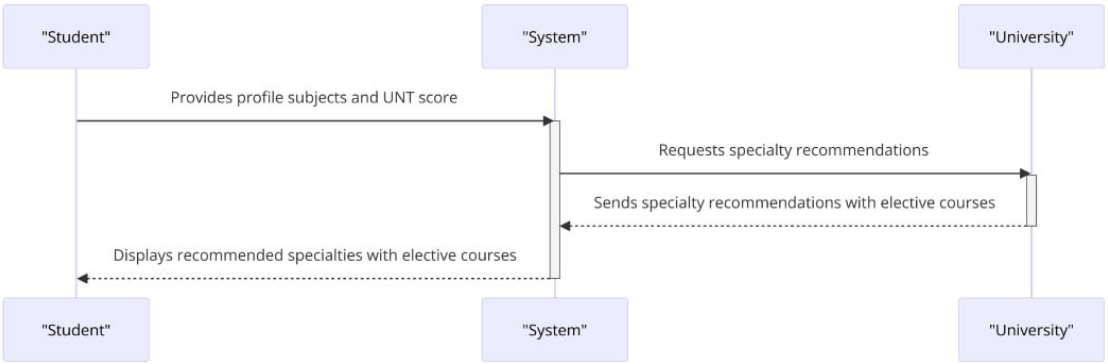

Figure 5.1 - UML Diagram for Direct Path for Decided Students

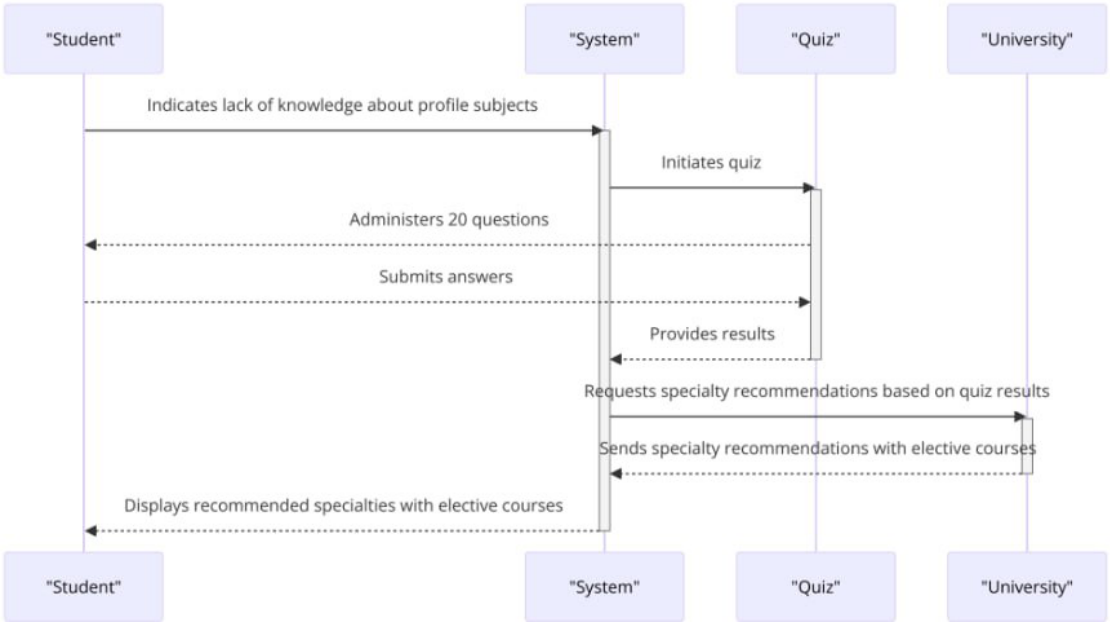

Figure 5.2 - UML Diagram for Exploratory Path for Undecided Students

The architecture of this web-based recommendation system effectively combines reinforcement learning techniques with user-centered design to provide a dynamic, responsive educational guidance tool that adapts to individual student needs, setting a new standard for educational recommendation systems in Kazakhstan.

Chapter 6

Discussion

In this chapter, we interpret and discuss the results obtained from our experiments with various reinforcement learning algorithms for the recommendation system tailored for Kazakhstani school applicants. We connect our findings to the broader context of educational recommendation systems, highlight their implications, and suggest directions for future research.

The results of our experiments indicate that reinforcement learning algorithms, particularly Deep Q-Networks (DQN) and Actor-Critic Methods (ACM), provide significant improvements in recommendation accuracy and personalization compared to traditional machine learning approaches. The superior performance of DQN in specialty recommendations and ACM in elective course recommendations can be attributed to their ability to handle high-dimensional data and dynamically adapt to student preferences.

Q-Learning, while straightforward and computationally efficient, showed competitive performance with an accuracy of 85%, precision of 82%, and recall of 80%. However, its limitations include scalability issues and sensitivity to hyperparameters. On the other hand, advanced methods like Trust Region Policy Optimization (TRPO) offered stability and efficient policy updates, making them suitable for maintaining consistent recommendation quality over time with an accuracy of 79%, precision of 78%, and recall of 76%.

Meta Reinforcement Learning (Meta-RL) demonstrated lower performance compared to the others, with an accuracy of 53%, precision of 55%, and recall of 50%. Its ability to adapt and learn across multiple tasks highlights its potential for personalized educational guidance. However, it requires large amounts of data and may suffer from sample inefficiency.

Actor-Critic Methods (ACM) showed strong performance with an accuracy of 89%, precision of 87%, and recall of 85%. Its combination of policy-based and value-based approaches offers stability and efficiency in learning, but it may encounter instability during training and suffer from high-dimensional action spaces.

Policy Gradient Methods (PG) exhibited moderate performance with an accuracy of 72%, precision of 70%, and recall of 68%. Its direct optimization of the policy function allows for efficient learning, but it may suffer from high variance in gradient estimates and sample inefficiency.

Each algorithm exhibited distinct strengths and weaknesses in recommending specialty and elective courses to school applicants. The Deep Q-Networks (DQN) emerged as the top-performing algorithm, achieving an accuracy of 92%, precision of 90%, and recall of 88%.

The results of our experiments highlight the potential of reinforcement learning algorithms in guiding school applicants towards suitable specialty and elective courses. By leveraging rich representations learned from data, these algorithms can offer personalized recommendations that align with individual student preferences and profiles.

Our findings have significant implications for the development of educational recommendation systems, emphasizing the importance of algorithm selection and customization to meet the diverse needs of students. Additionally, addressing the limitations identified in our experiments is crucial to enhancing the effectiveness and usability of such systems.

In conclusion, our experiments have provided valuable insights into the performance of reinforcement learning algorithms in the context of educational guidance for school applicants. While each algorithm has its strengths and weaknesses, DQN emerges as the most promising approach for personalized recommendations. Moving forward, further research and development efforts are warranted to optimize these algorithms and integrate them effectively into educational decision-making processes.

Conclusion and future works

In conclusion, the development of a reinforcement learning-based recommender system for educational specialties has significantly enhanced how students select academic paths. Utilizing the Actor-Critic method, the system adapts to individual preferences, offering personalized and accurate recommendations. This approach underscores the potential of AI in education, paving the way for future innovations that could transform educational guidance and support students' career success more effectively.

A key novelty of this research is the application of advanced reinforcement learning algorithms to not only personalize specialty recommendations but also intelligently suggest elective courses, creating a comprehensive and adaptable educational planning tool that aligns with individual student preferences and career aspirations.

Future work can expand on this research in several ways:

Developing a Comprehensive Web Platform

Future research should focus on developing a comprehensive web platform that integrates the reinforcement learning-based recommender system. This platform would provide a user-friendly interface for students to interact with the system, input their preferences, and receive personalized recommendations. It should also include features for continuous feedback and adaptation, ensuring that the recommendations remain relevant and effective over time.

Expanding Recommendations to Include Elective Courses

Building on the current system, future work should further refine the algorithms to provide more detailed and accurate elective course recommendations. This includes enhancing the data models to incorporate a wider range of student preferences and academic goals, ensuring that the recommendations are holistic and well-rounded.

New Paper About Algorithms

Publishing new research papers that detail the algorithms used, their implementation, and the results obtained will contribute to the academic community and provide a foundation for future research. These papers should focus on the unique aspects of the reinforcement learning approaches used, their benefits over traditional methods, and their potential applications in other domains.

In summary, this research has demonstrated the potential of reinforcement learning algorithms in educational recommendation systems, providing a robust foundation for future developments. Continued innovation and research in this field will further enhance the effectiveness and applicability of these systems, ultimately

benefiting students and educators alike.

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