AI4ED

TOWARDS AN Artificial Intelligence (AI) DRIVEN EDUCATIONAL PROCESS
INTEGRATING MODERN CAREERS IN THE EDUCATIONAL SYSTEM

Deliverable

D 2.3 - AI4Ed Report on the 3 AI Models

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Glossary

AI	Artificial Intelligence
AU-ROC	Area Under – Receiver Operating Characteristic
KPI	Key Performance Indicator
LMS	Learning Managment Systems
ROC	Receiver Operating Characteristic

EXECUTIVE SUMMARY / ABSTRACT

Abstract	Artificial Intelligence Models for Education and Training: Functionality, Ethics, and Data Analysis. This document describes three AI models addressing education challenges: dropout risk, content recommendation, and personalized training suggestions. Ethical considerations and data analysis are considered to ensure responsible usage and transparency.
Keywords	AI, data lifecycle, data structure, AI models

1 Introduction

1.1 Objective of the document

The main objective of this document is to provide a detailed description of three artificial intelligence models developed within the framework of the AI4Ed project. These models have been created with the purpose of addressing different challenges related to education and continuous training. Throughout this report, the artificial intelligence models designed to calculate the risk of dropout, recommend content, and suggest new training actions for individuals to enrol in will be presented.

In addition to presenting the artificial intelligence models and their functionalities, this document will also encompass a comprehensive discussion of the ethical considerations considered during their development and deployment. Ethical considerations play a crucial role in ensuring that the AI models are designed and used responsibly, respecting user privacy, and avoiding bias or discrimination.

Furthermore, the document will delve into the data fields derived from the Key Performance Indicators (KPIs) described in *D2.1 KPIs on personalised tutoring, active learning, and dropout prevention* and used in training and evaluating the AI models. These data fields will be meticulously analysed to shed light on the information used by the models to make predictions and recommendations. By providing insights into the data fields derived from the KPIs, it will be possible to gain a deeper understanding of the factors that influence the model's outputs and decisions.

In the current context, where access to education and continuous training plays a fundamental role in the personal and professional development of individuals, the implementation of artificial intelligence techniques has become essential. These models aim to enhance the quality of education and facilitate the decision-making process by providing personalized and accurate recommendations.

The first model focuses on the idea of promoting active learning. Active learning is a pedagogical approach that encourages students' active participation in their own learning process, fostering exploration, reflection, and critical thinking. By recommending educational content in a personalized manner, we provide students with a study path that adapts to their specific needs, interests, and goals. This involves providing a selection of relevant materials and resources that align with their current level of knowledge, as well as their areas of interest and strengths.

The second model will concentrate on recommending new courses that individuals can enrol in. The diversity of educational options can be overwhelming, so this model will offer personalized recommendations based on each individual's interests, skills, and objectives, helping them make informed decisions about their educational and professional development.

Finally, the third model will tackle the challenge of calculating the risk of dropout, identifying students who may abandon their studies before completion. This model will enable educational institutions to intervene early, providing additional support and retention strategies to at-risk students, thus improving their completion rates.

Throughout this document, the approaches used to develop each model will be described in detail, including the architecture, datasets used, training and evaluation processes, as well as the results and metrics obtained. Additionally, the potential applications and benefits of these models will be discussed, along with their limitations and areas for improvement.

In summary, this project represents a significant effort to harness the power of artificial intelligence in the educational field. The developed models aim to personalize the learning experience, facilitate decision-making regarding course selection, and improve student retention. We hope that this report provides a clear and comprehensive overview of the achievements made, as well as valuable recommendations for future research in this constantly evolving field.

For our artificial intelligence project focused on education, we have encountered an interesting and challenging situation: our partners and collaborators have very different realities. This diversity of contexts and conditions is essential to understand the complexity of the challenges we face and has forced us to adapt our strategies and models to address the specific needs of each of them.

One of the reasons why the partners have different realities is due to the technologies they use for e-learning. Each partner has different technological infrastructures and educational platforms; some partners use more advanced Learning Management Systems (LMS), while others rely on simpler solutions. These technological differences influence how educational data is collected, processed, and stored.

Moreover, the educational actions provided by the partners also vary significantly. Each educational institution or collaborating entity has different pedagogical approaches, curricula, teaching methodologies, and learning activities. Some partners focus on formal education, offering structured educational programs, while others concentrate on active learning-based educational programs. These differences in educational actions affect the available data and behaviour patterns that can influence content recommendation models and dropout prediction.

Here is a summary of the reality of each partner:

1.1.1 IMH

IMH has adopted Moodle as its primary Learning Management System (LMS). Moodle is used as a comprehensive tool to support teaching and learning. Within Moodle, students can access different modules and lessons in a predefined order. Each lesson may contain various types of content and practical activities related to the subject matter.

1.1.2 SCSKZ

SCSKZ uses Microsoft Teams and eAsistent as tools to manage the educational aspect. They utilize Microsoft Teams as an online collaboration platform for students and teachers to communicate, share files, and participate in video calls. On the other hand, eAsistent is an educational management system used at the state/governmental level. Its main function is to enable effective tracking of students' grades, attendance, and educational progress. Thanks to this tool, SCSKZ can record and keep students' grades updated quickly and accurately. Additionally, the system facilitates monitoring students' attendance in classes.

1.1.3 BREMEN

BREMEN uses a platform developed in the Erasmus+ context in collaboration with entities such as CECIMO (European Association of the Machine Tool Industries), Tknika, IMH, etc. This platform offers a variety of content and tests, and students have the freedom to consume the content in the order they choose. They can access different educational materials and take tests to assess their understanding. The learning content is migrated to Moodle to smoothen the application of AI and to exploit the broad experience by AlchemyML.

1.1.4 CENFIM

CENFIM has implemented Moodle as its main Learning Management System. Moodle plays a fundamental role in supporting teaching and learning. In the Moodle platform, students have access to various modules and lessons presented in a predefined order. Each lesson offers a variety of content and practical activities related to the course topic.

1.2 Ethical Considerations

Being an AI project in the educational field, certain ethical considerations have been considered. Below are the most important ones:

- **Clear definition of objectives**: This refers to establishing clear goals and purposes in the educational context. Both students and teachers should clearly understand what is expected to be achieved in the teaching and learning process.
- **Student and teacher-centred approach**: Education should focus on the well-being and development of both students and educators. Ensuring a favourable learning environment and supporting the professional growth of teachers is essential.

- **Transparency and responsible use**: Emphasize the importance of transparency in educational management and the responsible use of available resources. This includes clear communication of education-related policies and decisions and the ethical use of resources.
- **Privacy and data security**: Safeguarding the privacy and security of personal and educational information of students and teachers is crucial. Measures must be implemented to protect the data and ensure its usage aligns with privacy standards.
- **Involvement of teachers**: Recognizing the significance of active participation and collaboration of teachers in curriculum design, development, and educational decision-making. Involving educators helps ensure that educational policies and practices are more effective and appropriate.
- **Inclusivity**: Education should be accessible and suitable for all students, regardless of their differences or particular needs. Inclusivity aims to eliminate barriers and ensure equal opportunities for all students to learn and develop.

In conclusion, when implementing AI models in the educational field, it is essential to address ethical considerations related to the mentioned points. By doing so, the ethical and responsible use of AI can be ensured for the benefit of students and educational development.

1.3 Dataset

Regarding data collection, the educational cycle is generally divided into three distinct parts: before the start of the course, during the course, and at the end of the course. Each of these stages has specific characteristics and objectives, and relevant information is collected in each one for the development and evaluation of the educational process.

1.3.1 Before the start of the course

During this stage, students will fill out forms to provide personal information. This form might contain the following questions even it is extremely important that the partners try to gather most part of the purposed information:

1. *Date of birth*
2. *Gender*
3. *What is your nationality?*
4. *Are you a native of the country where the course is being offered?*
5. *What is your current level of education?*
6. *What was your final grade at your current level of education?*
7. *When did you completed your last level of education?*
8. *What is your current employment status?*
9. *What is your area of study or expertise?*
10. *Which is your main motivation for taking the course?*
11. *What is the level of motivation you have for the training?*
12. *What are your expectations of the results you wish to achieve?*
13. *Are you afraid of failure or reluctant to follow the course comfortably?*
14. *Special conditions that we should be aware of?*
15. *Do you have availability to meet the course schedule?*
16. *Do you have any time constraints during the course period?*
17. *Do you think the course program is clear enough?*
18. *Do you have stable access to a digital device and the internet?*
19. *What is your skill level with computer tools?*
20. *Do you have specific technical knowledge required for the course you are enrolling in?*
21. *How do you get this specific technical knowledge?*
22. *What is your level of oral communication skills?*

23. *What is your level of written communication skills?*
24. *How would you rate your ability to work in a team?*
25. *How confident are you in your abilities to successfully complete the course?*
26. *How do you usually react when facing unpredictable situations?*
27. *How do you usually react when facing problems to solve?*
28. *What is the approach that most motivate you in the development of learning activities?*
29. *How do you describe yourself as a learner?*

1.3.2 During the course

During the course, information related to students' performance will be collected. This information will be automatically gathered from the specific educational management systems of each partner.

From the educational management systems, the following data will be obtained:

- *Students*
- *Training programs*
- *Subjects*
- *Activities*
- *Contents*
- *Enrolments*
- *Consumed contents*
- *Grades*

1.3.3 Upon finishing the course

Upon finishing the course, during this final stage, partners chose from or adapt the following questions related to the course evaluation even it is extremely important that the partners try to gather most part of the purposed information.

EXPECTATIONS

1. *Did the course meet your expectations?*
2. *How would you rate the relevance of the course to your personal/professional needs and goals?*
3. *Do you believe the course provided you with the necessary knowledge and skills to face challenges related to the topic?*
4. *What was the level of practical utility of the course in your personal or professional life?*
5. *What was the overall impact of the course on your personal or professional development?*
6. *Would you recommend this course to others interested in the topic?*

AUTOEVALUATION

7. *What level of commitment did you have during the course?*
8. *To what extent do you believe you dedicated enough time to complete the tasks and activities of the course?*
9. *To what extent do you believe you dedicated enough effort to complete the tasks and activities of the course?*
10. *How responsible do you consider yourself in meeting the deadlines and expectations of the course?*
11. *How would you rate your level of self-discipline during the course to maintain the pace of study and participation?*
12. *How committed were you to actively participate in the discussions and activities of the course?*
13. *Have you got enough time to finish the activities of the course?*

COURSE CONTENT

14. *Was the course content relevant and applicable to your needs or interests?*
15. *Was the course content well-structured and clearly organized?*

16. *Were the support materials (manuals, presentations, additional resources, etc.) useful for understanding the course content?*
17. *How often did you need to review the contents and learning resources?*
18. *Do you think that the learning resources and guidance allowed you to progress autonomously throughout the study?*
19. *Do you think that you needed more support from the tutor/trainer?*
20. *Did the assessment tools and methods seem appropriate to you?*
21. *Was the feedback from this assessment always fast and clear?*
22. *Did the feedback from this assessment facilitated your progression in learning?*

1.4 Technological Context

1.4.1 Software

In the development of this project, the Python programming language has been used along with the packages Pandas, NumPy, and Scikit Learn. Python has become a popular choice in the field of data analysis and artificial intelligence due to its readable syntax and wide range of libraries and tools.

The Pandas package has been fundamental for processing and analysing the data used in this project. It provides efficient data structures, such as DataFrames, which allow for loading, cleaning, and transforming data effectively. With Pandas, we have been able to perform operations such as removing missing data, selecting relevant columns, and grouping data to obtain statistical summaries. Additionally, Pandas offers flexible methods for data manipulation and filtering, which has facilitated the exploration and analysis of educational datasets.

On the other hand, the NumPy package has been essential for performing efficient numerical calculations on arrays and matrices. With its mathematical functions and tools for numerical data processing, we have been able to carry out statistical and algebraic operations necessary to deeply understand educational data. NumPy has allowed us to calculate descriptive statistics, perform matrix operations, and carry out complex data manipulations with ease and efficiency.

Furthermore, we have employed the Scikit Learn package to build artificial intelligence models and perform predictive analysis in this project. Scikit Learn is a machine learning library that offers a wide range of algorithms and tools. We have used different classification models from Scikit Learn to predict student dropout, and for the content recommender, we have utilized collaborative filtering techniques. These algorithms have allowed us to train models using historical data and make predictions about the future behaviour of students. We have also leveraged Scikit Learn's evaluation functions and metrics to measure the performance and accuracy of our models.

In summary, the use of the Python programming language and the packages Pandas, NumPy, and Scikit Learn has been fundamental in this project. These tools have allowed us to load, clean, and transform educational data, perform numerical and statistical calculations, and build artificial intelligence models for dropout prediction and content recommendation. Python and its associated packages are a powerful and versatile combination for the analysis of educational data and the development of machine learning models.

1.4.2 Hardware

The initial steps have been developed under this hardware configuration:

The project has been deployed on a server featuring the following specifications:

The server runs on Ubuntu 20.10 (Groovy Gorilla), equipped with a storage capacity of 500 GB and an additional 500 GB for backup.

It also boasts 32 GB of RAM and a 6-core/12-thread processor.

Furthermore, it provides a high-speed internet connection with 1 Gbps bandwidth.

1.5 Data Ingestion and Results Delivery

In the current project, a unification has been carried out in the data ingestion process for the partners using Moodle, while the other partners have provided their data in CSV format. This unification ensures that all data is in a homogeneous format to facilitate subsequent processing and analysis.

For partners using Moodle, the data is extracted directly from the Moodle database. Next, these data are cleaned and pre-processed to eliminate redundant or irrelevant information and ensure they are ready for analysis. Once the data is prepared, it is stored in a CSV file with the same format as the files provided by the other partners. Unifying the formats in the CSV files simplifies and standardizes the final stage of data ingestion.

As for the results obtained through the models, currently, they are stored in the database. However, the method of delivering the results to the partners is still under consideration and will be defined in later stages of the project.

It is essential to highlight that this unification in data ingestion and storage allows for better collaboration between partners, facilitates the exchange of information, and ensures that all analyses and models are based on the same reliable and coherent data source.

2 Foundations of Artificial Intelligence and necessary context for the developed models.

Artificial Intelligence (AI) is a branch of computer science that focuses on the development of systems and programs capable of performing tasks that would typically require human intelligence. These tasks range from learning and problem-solving to environment perception, reasoning, pattern recognition, decision-making, and understanding human language.

Machine Learning, on the other hand, is a subfield of Artificial Intelligence that involves creating mathematical models to enable machines to learn. Examples of machine learning include algorithms that play video games, recognize faces, or classify users into different groups.

The field of machine learning addresses a wide range of problems, which is why it is divided into two main groups: supervised models (with target variables) and unsupervised models (without target variables).

In this case, supervised classification algorithms have been used to obtain the probabilities of student dropout. Additionally, collaborative recommendation algorithms based on items and users have been employed for content and course recommendations.

2.1 Supervised Classification Algorithms

Supervised classification algorithms are a set of machine learning techniques used to predict the membership of a specific class within a dataset. In these algorithms, a set of training examples is available, and each example is labelled with its corresponding class. The objective is to learn a model that can generalize and classify new examples that have not been seen during training. Among all the available algorithms for classification problems, two popular algorithms in this category are Random Forest and Logistic Regression.

2.1.1 Random Forest

Random Forest is a supervised learning algorithm that uses the ensemble learning method to combine multiple decision trees, thereby achieving more accurate and robust classification, see Figure 1. The "randomness" in Random Forest comes from two main sources:

Random sample selection: For each tree in the forest, a subset of samples from the training set is selected using the bootstrap method. This means that each tree is trained on a slightly different data set.

Random feature selection: In each node split in the trees, a random subset of features is selected. This ensures that the trees are decorrelated and that the final model is more robust.

The process of constructing a Random Forest involves creating a large number of decision trees. Each tree is trained on a random subset of the training data and uses only a random subset of features for each node split. During classification, each tree casts a "vote" for the class of interest, and the class with the most votes becomes the final prediction of the model.

One of the advantages of Random Forest is its usefulness for large and complex datasets. It tends to perform well in most situations and is less prone to overfitting compared to a single decision tree. This is because the final model is the average of many trees, which helps to smooth predictions and avoid overfitting to the training data.

In addition, Random Forest provides a measure of feature importance, which can be useful for feature selection and for gaining a better understanding of the factors driving the model.

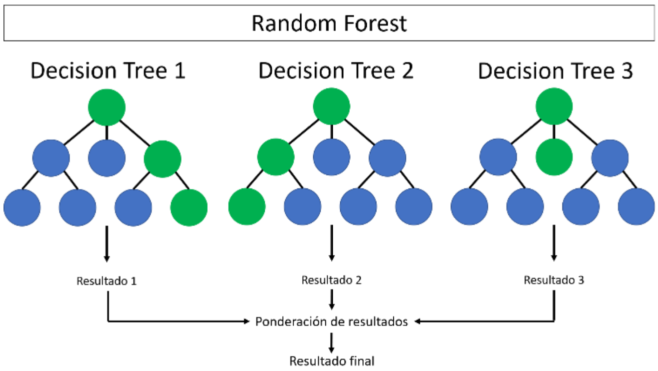

Figure 1 - Schematic view of a Random Forest supervised algorithm

2.1.2 Logistic Regression

Despite its name, Logistic Regression is a binary classification algorithm used for problems where the target variable or dependent variable is categorical and consists of two distinct classes, see Figure 2. Logistic Regression is based on the logistic function that transforms the linear output into a value between 0 and 1, representing the probability of an example belonging to one of the two classes.

During training, the algorithm adjusts the coefficients of the input features to find the best separation curve between the two classes, maximizing the probability that the observed data belongs to their respective classes. Once trained, the model can predict the probability of belonging to a specific class for new examples.

Logistic Regression is widely used due to its simplicity, interpretability, and computational efficiency. While mainly used for binary classification problems, it can be extended to address multiclass classification problems using approaches such as "one-vs-all" or "one-vs-one."

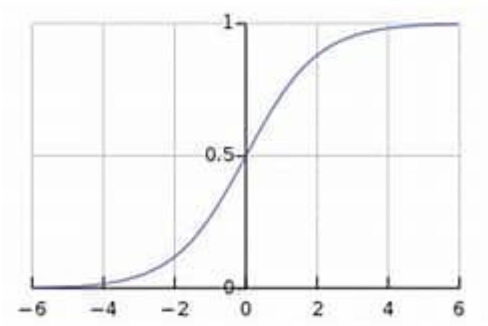

Figure 2 - Schematic view of Logistic Regression representation

2.1.3 Obtaining Probabilities

Both Random Forest and Logistic Regression allow obtaining the probabilities of belonging to a specific class for a new example. In the case of Random Forest, probabilities are obtained by averaging the votes of individual trees. To get the probability of belonging to a class, the number of times the class appears as the result of the trees' votes is counted and divided by the total number of trees.

In Logistic Regression, the sigmoid function is used to transform the linear outputs into probabilities. The probability of an example belonging to a specific class is simply the value of the sigmoid function applied to the linear combination of the features.

This probability will be used as the probability of a student leaving the education program.

2.1.4 Metrics for the Evaluation of Classification Models

Evaluation metrics are critical tools for measuring the performance and effectiveness of classification models. These metrics provide an objective way to compare different models and determine how well they are performing in the classification task.

The confusion matrix is a fundamental tool in evaluating classification models, and it helps in calculating various evaluation metrics. The confusion matrix is a table that summarizes the performance of a classification model on a set of test data for binary or multiclass classification problems.

For a binary classification problem, the confusion matrix has four elements:

- True Positives (TP): The number of correctly predicted positive examples.
- False Positives (FP): The number of negative examples incorrectly predicted as positive.
- True Negatives (TN): The number of correctly predicted negative examples.
- False Negatives (FN): The number of positive examples incorrectly predicted as negative.

Here are some of the most common metrics used for the evaluation of classification models:

- **Accuracy**: Accuracy is a basic metric that indicates the proportion of correct predictions over the total number of examples in the dataset. It is useful when classes are balanced, meaning they have roughly the same number of samples. However, it can be misleading when classes are imbalanced, as a model could achieve high accuracy by always predicting the majority class.
- **Precision**: Precision measures the proportion of true positive examples (correctly classified positive samples) to all positive predictions (true positives + false positives). It is a useful metric when the cost of false positives is high, as it focuses on the quality of positive predictions.
- **Recall or Sensitivity**: Recall measures the proportion of true positive examples to all actual positive examples (true positives + false negatives). It is useful when the cost of false negatives is high, as it focuses on the model's ability to find all positive examples.
- **Specificity**: Specificity measures the proportion of true negative examples (correctly classified negative samples) to all actual negative examples (true negatives + false positives), see Figure 3. It is useful when the cost of false positives is high, and we want to ensure the model has a low false positive rate.

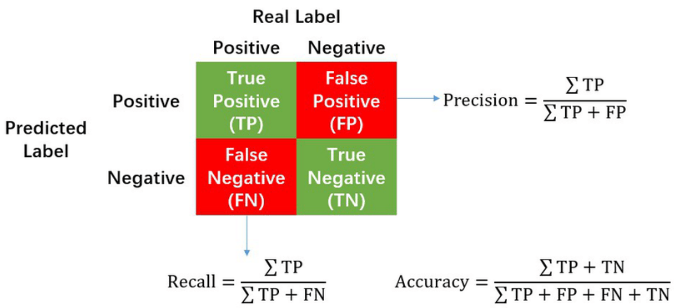

Figure 3 - Schematic view of how to calculate specificity

- **ROC Curve (Receiver Operating Characteristic Curve)**: The ROC curve is a graphical representation of the performance of a classification model as the decision threshold varies. The curve shows the true positive rate (sensitivity) against the false positive rate (1-specificity). An area under the ROC curve (AUC-ROC) close to 1 indicates better model performance, see Figure 4.

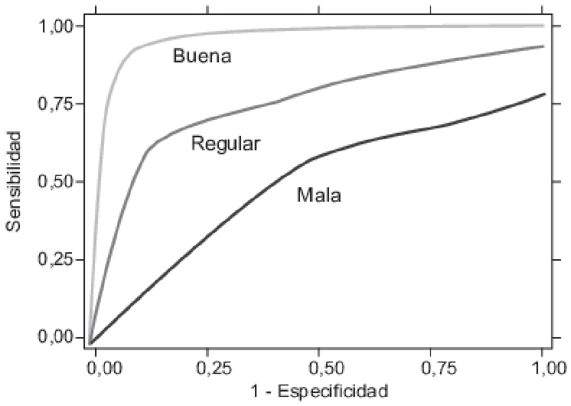

Figure 4 - Example of a ROC curve

2.2 Collaborative Recommendation Algorithms

Collaborative recommendation systems are algorithms that use data from multiple users to make personalized suggestions. Their goal is to predict and recommend items or content that a user may find interesting based on similarity with other users or items, see Figure 5.

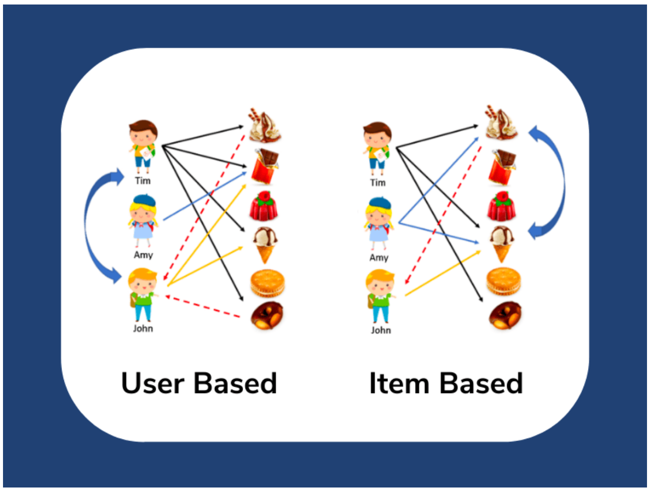

Figure 5 - Example of Collaborative Recommendation Algorithms

2.2.1 Item-Based Collaborative Recommendation Algorithms

The item-based approach in recommendation systems focuses on the similarity between items or content. Similarity is calculated based on past interactions of users with the items, see Figure 6.

Collaborative filtering based on items uses information about user interactions with items to make recommendations. It identifies items similar to those a user has shown interest in and suggests items that the user has not seen yet.

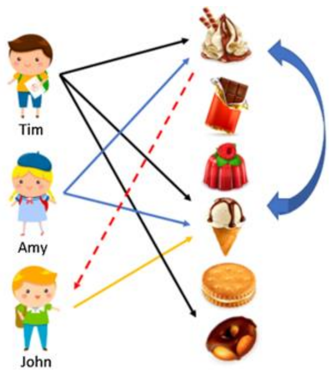

Figure 6 - Example of Item-based Collaborative Recommendation Algorithms

2.2.2 User-Based Collaborative Recommendation Algorithms

The user-based approach in recommendation systems focuses on the similarity between users. It identifies users with similar tastes and preferences and uses their past interactions to make recommendations, see Figure 7.

Collaborative filtering based on users uses ratings and interactions of similar users to make recommendations for a particular user. If User A has similar interests to User B, the algorithm suggests to User A items that User B has positively rated and that User A has not seen yet.

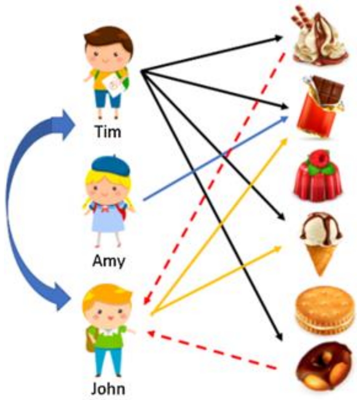

Figure 7 - Example of User-based Collaborative Recommendation Algorithms

2.2.3 Metrics for the Evaluation of Recommendation Models

To evaluate the performance of a collaborative recommendation model based on items, you can use various metrics depending on your objectives and the type of data you are handling. Some of the most common metrics are:

- **Top-N Accuracy**: This metric measures the proportion of relevant recommendations present in the list of the top N recommended items. For example, if you are recommending 10 items, the top-10 accuracy will tell you how many of those items were genuinely relevant to the user.
- **Top-N Recall**: Recall measures the proportion of relevant items that were retrieved in the list of the top N recommended items. This metric helps you understand how well your model captures all relevant items for a user in the recommendation list.
- **Coverage**: Coverage measures the proportion of unique elements that have been recommended at least once in a set of users. High coverage means that your model is recommending a wide variety of elements.
- **Diversity**: Diversity measures how varied the recommendations your model offers are. It is important to ensure that the same items are not always recommended to different users.
- **Novelty**: Novelty measures how new or unexpected the recommended items are for a user. It is useful for evaluating whether the model suggests different elements or if it sticks to the most popular options.

3 Artificial Intelligence model for Active Learning

3.1 Challenges in Content Recommendation

Developing an artificial intelligence system capable of recommending content to students can have various benefits and challenges. Here are some key aspects to consider in the development process:

- Data Collection: It is essential to collect and store a wide range of relevant data about students, their preferences, learning history, and other relevant factors. This may include educational performance, specific interests, and browsing behaviours.
- Data Analysis and Processing: Once the data is collected, data analysis and machine learning techniques are required to extract meaningful information. This involves identifying patterns, trends, and correlations in the data to better understand individual students' preferences and needs.
- Recommendation Algorithm Design: The system should use recommendation algorithms to provide personalized suggestions to students. These algorithms can be based on different approaches, such as collaborative filtering, content-based filtering, or hybrid systems that combine several techniques.
- Evaluation of Recommendation Quality: It is important to evaluate the quality and effectiveness of the recommendations generated by the system. This involves using metrics and evaluation techniques, such as recommendation accuracy, student acceptance rate, and feedback received.
- Implementation and Continuous Improvement: Once the system is developed, it should be implemented on a platform accessible to students. Additionally, continuous monitoring should be performed to gather more data and user feedback, allowing for continuous improvement and refinement of the system over time.
- Ethical and Privacy Considerations: Handling students' personal data requires ensuring information privacy and security. Data protection regulations and best practices should be followed to ensure the system meets ethical and legal standards.

3.2 Traditional Methods and Their Limitations

These are the typical methods for recommending content to students:

- **Teacher Recommendations**: Teachers, as experts in their fields, often recommend relevant content for the subjects they are teaching. These recommendations are based on their experience and knowledge of available materials.
- **Standard Curricula**: Educational programs and established curricula prescribed by educational institutions or regulatory entities often provide a list of specific content and materials considered relevant for a particular course or subject.
- **Tutoring or Mentoring Programs**: Tutoring or mentoring programs can offer personalized content recommendations to students. Tutors or mentors, based on their experience and expertise, suggest content to help students understand and delve into specific topics.
- **Peer Recommendations**: Students can share content recommendations they found useful for their studies with each other. These recommendations are based on students' personal experiences and their perception of content relevance and quality.

However, these traditional methods often have the following limitations:

- **Lack of Personalization**: Traditional educational content recommendation methods often rely on general approaches that do not consider individual students' needs and preferences. This may hinder delivering study materials that are relevant and suitable for each student's level of knowledge and learning style.

- **Resource Diversity Limitations**: Traditional approaches may be limited by the availability and variety of recommended resources. Content recommendation based on static materials may not be sufficient to address the various ways students learn and access information today.
- **Lack of Instant Feedback**: Traditional methods usually lack a quick and effective way to collect and analyse student feedback on recommended content. This may hinder identifying strengths and weaknesses of materials and adapting recommendations to enhance the learning experience.

3.3 Key Stages from Data Collection to Model Implementation

The following are the most important stages for implementing the content recommendation model:

- **Data Collection and Preparation**: Relevant data sources for the recommendation system, such as student activity records, grades, content interactions, etc., have been identified. The data has been cleaned and pre-processed to treat missing values and ensure it is in a suitable format for the model.
- **Recommendation System Design**: The type of collaborative filtering model to be used has been defined, which is a combination of user-based and item-based collaborative filtering.
- **Dataset Splitting**: The data has been divided into training, validation, and test sets, allowing for objective model performance evaluation and avoiding overfitting.
- **Collaborative Filtering Model Creation**: The model has been implemented using the Scikit-Learn library in Python. The model's hyperparameters have been fine-tuned using cross-validation to optimize its performance.
- **Model Evaluation**: Finally, various evaluation metrics will be used to measure the model's precision and performance on the test set. Some of the metrics used include precision, recall, and coverage.

3.4 Model Description

The implemented mixed collaborative filtering model is a recommendation system that utilizes both item-based and user-based approaches to provide personalized recommendations to students. It combines information on item similarity and user similarity to generate predictions about which content may be of most interest to each student.

3.5 Model Architecture

The architecture of the mixed collaborative filtering model consists of two main components:

- **Item-Based Collaborative Filtering**: Item similarity has been calculated using measures such as Pearson correlation or cosine similarity. For each item, the most similar items have been identified based on the calculated similarity. The number of user visits has been used to generate a prediction for each item based on similar items.
- **User-Based Collaborative Filtering**: User similarity has been calculated using measures such as Pearson correlation or cosine similarity. For each user, the most similar users have been identified based on the calculated similarity. The historical visits of the target user and visits of similar users have been used to generate predictions for items the user has not visited yet.

The model combines the predictions generated by both approaches to obtain a final list of recommendations for each student.

3.6 Dataset

The dataset used for training and evaluating the model consists of historical records of student visits and/or interactions with different content. Each record contains information about which student interacted with which content, along with the type of interaction performed.

3.7 Model Training and Evaluation

The dataset has been split into training, validation, and test sets. The training set has been used to fit the model's parameters and learn relationships between students and content. The validation set has been used to fine-tune hyperparameters and prevent overfitting, while the test set has been used to evaluate the final model performance.

3.8 Results and Evaluation Metrics

Once the model has been trained and evaluated on the test set, various evaluation metrics will be used to measure its performance:

- **Top-N Precision**
- **Top-N Recall**
- **Coverage**
- **Diversity**
- **Novelty**

The model's performance will be assessed based on these metrics to determine its ability to provide accurate and personalized recommendations to students.

4 Artificial Intelligence model for Personlaised Tutoring

4.1 Challenges in Content Recommendation

The development of an artificial intelligence-based content recommendation system can face several challenges. Some of them are as follows:

- **Data Quality and Quantity**: AI-based recommendation systems require large amounts of data to function effectively. It is important to have relevant and up-to-date datasets that represent the diversity of users and content. Data collection and processing can be challenging, especially when there is a lack of sufficient high-quality data.
- **Bias and Lack of Diversity**: Recommendation systems can be affected by inherent biases in the training data. If the data exhibits biases related to gender, race, culture, or other aspects, the system may perpetuate and amplify those disparities in its recommendations. It is essential to actively address bias and ensure that the recommendations are fair and diverse.
- **Explainability and Transparency**: AI-based recommendation systems, such as machine learning models, can be complex and difficult for users to understand. The lack of explainability can lead to mistrust, as users may feel uncomfortable accepting recommendations without understanding how they are generated. It is crucial to develop recommendation systems that are transparent and provide clear explanations about the recommendation process.
- **Changes in Tastes and Preferences**: User preferences can change over time, and recommendation systems must be able to adapt to these changes. The dynamic nature of preferences and the evolution of user interests can pose challenges in keeping recommendations updated and relevant.
- **Privacy and Data Security**: AI-based recommendation systems need access to personal and behavioural data of users to generate accurate recommendations. The privacy and security of this data are paramount, and appropriate measures must be implemented to protect sensitive information and comply with privacy regulations.
- **Feedback and Continuous Evaluation**: Recommendation systems should have mechanisms to collect and analyse user feedback. This feedback is essential to assess the quality and effectiveness of recommendations, identify areas for improvement, and make continuous adjustments to the recommendation model.
- **Adaptation to New Content and Contexts**: Recommendation systems must be capable of continuous learning and adaptation as new content, changes in user interests, and new contexts emerge. Keeping recommendation models updated and flexible to incorporate new data and changes in the environment is a significant challenge.

Addressing these challenges requires a combination of strong technical expertise, ethical approaches, and careful attention to data quality and user experience. It is essential to tackle these challenges to develop reliable, equitable, and effective AI-based content recommendation systems.

4.2 Traditional Methods and their Limitations

Traditional methods for recommending courses to students often include:

- **Educational Advising**: Educational advisors are education professionals who provide guidance and recommendations on courses and study programs. Based on a student's goals, interests, and educational requirements, advisors can suggest specific courses that align with their needs.
- **Course Catalogues**: Educational institutions typically provide course catalogues describing various available courses in detail. Students can explore these catalogues and select courses based on their areas of interest and educational requirements.

- **Recommendations from Teachers**: Teachers can recommend specific courses to students based on their expertise and knowledge in a particular field. Drawing on a student's educational background and objectives, they can offer personalized recommendations.
- **Previous Experiences of Other Students**: Students can obtain recommendations from peers who have taken similar courses. Sharing experiences and opinions about specific courses can help students make informed decisions.
- **Institutional Information**: Educational institutions often provide detailed course information, including objectives, content, prerequisites, and instructor profiles. Students can use this information to evaluate whether a course fits their needs.

However, these traditional methods also have limitations, including:

- **Lack of Personalization**: Traditional methods may not consider individual student preferences and needs. Recommendations may be based on general approaches and may not consider each student's specific interests.
- **Outdated Information**: Course catalogues and institutional information can become outdated and may not reflect changes and updates made to study programs. This can lead to students not having access to up-to-date and accurate information when making course decisions.
- **Limited Feedback**: Traditional methods may lack dynamic and updated feedback on the quality and effectiveness of courses. Students may not have access to opinions or ratings of courses from other students, making it challenging to make informed decisions.

4.3 Key Stages from Data Ingestion to Model Implementation

The most important stages in the implementation of the course recommendation model are as follows:

- **Data Collection and Preparation**: Relevant data sources for the recommendation system, such as course information, student activity records, grades, interactions with content, etc., have been identified. The data has been cleaned and pre-processed to treat missing values and ensure it is in an appropriate format for the model.
- **Design of the Recommendation System**: The type of collaborative filtering model to be used has been defined, which is a combination of user-based and item-based collaborative filtering.
- **Dataset Splitting**: The data has been divided into training, validation, and test sets, allowing for an objective evaluation of the model's performance and preventing overfitting.
- **Creation of the Collaborative Filtering Model**: The model has been implemented using the Python Scikit-Learn library. The model's hyperparameters have been tuned using cross-validation to optimize its performance.
- **Model Evaluation**: Different evaluation metrics will be used to measure the accuracy and performance of the model on the test set. Some of the metrics used include precision, sensitivity, and coverage.

4.4 Model Description

The implemented mixed collaborative filtering model is a hybrid recommendation system that combines techniques from user-based and item-based collaborative filtering. The objective is to provide course recommendations to students based on the similarities between users and courses, allowing for personalized suggestions and improving the accuracy of the recommendations.

4.5 Model Architecture

The mixed collaborative filtering model consists of two main components: user-based collaborative filtering and item-based collaborative filtering.

- User-Based Collaborative Filtering: This component analyses the similarity between users based on their past interactions with courses. It uses similarity measures, such as cosine distance or correlation coefficient, to determine which users are similar to each other. It then recommends courses that are enjoyed or interacted with by similar users to a given user.

- Item-Based Collaborative Filtering: This component focuses on finding similarities between courses based on users' past interactions with those courses. Once users with similar behaviour patterns are identified, the model recommends courses that these similar users have enjoyed or interacted with to other users with similar profiles.

The recommendation system combines the information provided by both approaches to enhance the quality and diversity of the recommendations, resulting in a more enriching experience for the students.

4.6 Dataset

The dataset used to train the model contains information about student interactions with courses. The data includes details such as student identifiers, course identifiers, information about student enrolments in courses, etc. This data is essential for identifying behaviour patterns and establishing connections between users and courses.

4.7 Model Training and Evaluation

For training the model, a supervised learning technique has been used, where the model parameters are adjusted to minimize the error between the provided recommendations and the actual course enrolments by users. The dataset has been split into a training set and a test set to validate the model's performance.

During the training process, the model learns to calculate the similarity between users and courses and how to combine this information to make accurate recommendations.

4.8 Results and Evaluation Metrics

As this is a recommendation model similar to the content recommendation model, the same metrics will be used to evaluate the model's performance. These metrics allow measuring the quality and performance of the model in the task of recommending courses to students.

5 Artificial Intelligence model for Dropout Prevention

5.1 Description of the Dropout Problem

The issue of dropout in the educational context, referring to students leaving their studies before completion, has been addressed. This phenomenon has negative consequences both at an individual level and at a systemic level, impacting students' personal development and the overall efficiency of the education system. In this project, an Artificial Intelligence (AI) model has been developed to predict the risk of dropout, enabling the identification of vulnerable students and the implementation of timely interventions to mitigate this risk.

5.2 Traditional Methods and Limitations

There are several traditional methods used to measure and prevent dropout rates. Some of them are as follows:

- **Dropout Rates**: Used to measure the percentage of students who leave school within a specific period. These rates can be calculated at the school, district, or country level, providing a quantitative measure of the problem.
- **Attendance and Educational Performance Tracking**: Regularly monitoring students' attendance and educational performance can help identify those at risk of dropping out. A decline in attendance or educational performance can serve as an early warning sign.
- **Interviews and Questionnaires**: Individual or group interviews and questionnaires can be used to collect qualitative information about the reasons leading students to drop out. These techniques allow exploration of socioeconomic, familial, personal, or educational factors that may contribute to dropout.
- **Follow-up Programs and Tutoring**: These programs focus on providing additional support to students at risk of dropping out. They may include educational tutoring, vocational guidance, emotional counselling, and extracurricular activities.

However, these traditional methods have some limitations:

- **Delay in Detection**: Some risk indicators may go unnoticed until the student is already in the process of leaving school. Traditional indicators may not be sensitive enough to detect problems in a timely manner.
- **Non-Real-Time Data Collection**: In many cases, information on attendance, educational performance, and other indicators is collected periodically, such as at the end of each semester or school year. This means there can be a significant delay between the emergence of dropout risk and its official detection.
- **Reactive Approach Instead of Preventive**: These methods are often used once students are already at risk of dropping out. Implementing early prevention strategies that address risk factors before they become significant issues would be more effective.

In general, it is important to combine traditional approaches with more innovative and student-adapted strategies to effectively address the dropout problem in education.

5.3 Key stages from data ingestion to model implementation

In this project, several key stages have been carried out from data ingestion to model implementation:

- **Data Collection and Preprocessing**: Relevant data about the students, such as their educational history, engagement, and behaviour, has been collected. This data has undergone a cleaning and preparation process, where outliers have been removed, and transformations have been applied to ensure data quality.

- **Feature Selection**: Careful feature selection has been conducted, identifying those considered most relevant for predicting the risk of dropout. These features may include educational performance in different subjects, engagement, and participation in activities.
- **Data Set Split**: The data set has been divided into training and testing sets, using 80% of the data for training and 20% for validation, to evaluate the model's performance and generalization.
- **Model Development and Training**: An AI classification model using the Random Forest supervised machine learning technique has been developed. The model has been trained using the training data set, adjusting its parameters based on the input data analysis.
- **Model Evaluation**: Once trained, the model will be evaluated using the testing data set, which was not used during the training process. This evaluation measures the model's performance in terms of its ability to accurately predict the risk of dropout.

5.4 Model Description

The dropout prediction model is based on the Random Forest classification algorithm, a machine learning technique that has proven effective in predicting binary events like school dropout. The primary goal of this model is to accurately identify students at risk of dropping out and provide timely preventive measures.

As mentioned earlier, the Random Forest algorithm works by constructing multiple decision trees. Each tree is trained using different random subsets of features and training data, which helps avoid overfitting and improve model generalization. The results from each tree are then combined to obtain a final joint prediction.

During the training phase, the model uses labelled historical data indicating whether a student dropped out or not to learn patterns and relationships between features and school dropout. As trees are developed and adjusted, the model looks for important features that have a greater impact on predicting school dropout.

Once the model has been trained, it can be used to predict the risk of school dropout for new students. By providing the relevant student data to be evaluated, the model uses the pertinent features and decision trees to generate a score indicating the probability of the student dropping out.

5.5 Model Architecture

Using a Random Forest model, static parameters are not specified because the model automatically adjusts and adapts to new data during the retraining process. This provides the ability to maintain accurate and up-to-date performance as more data is generated and features change. As the model is retrained with new data, the optimal parameters may vary, allowing the model to continuously adjust to capture the most relevant and accurate relationships in the updated data.

5.6 Dataset

The data set used for training the models is specified in the Data Set section. These data have been pre-processed to be fed into the models and optimize their performance.

5.7 Model Training and Evaluation

In a binary classification problem like this (dropout or no dropout), the Random Forest assigns each sample a probability of belonging to each class. To determine the probability of a student's dropout, the estimated probability associated with the "dropout" class (usually labelled as class 1) is taken.

Since there are far fewer dropout cases in the training data, meaning class imbalance, typical evaluation metrics like accuracy may not provide an accurate picture of the model's performance.

The most suitable metric to address class imbalance is the ROC Curve and the Area Under the ROC Curve (AUC-ROC). The ROC curve is a graphical representation that shows how the true positive rate (sensitivity) changes with the false positive rate (1 - specificity) when varying the model's classification threshold.

The AUC-ROC is a numerical metric calculated from the ROC curve, providing an aggregated measure of the model's performance across the entire range of thresholds. The AUC-ROC takes values between 0 and 1, where a value closer to 1 indicates better model performance in terms of its ability to distinguish between the two classes, even in the presence of imbalance.

In this case, both the ROC curve and the AUC-ROC will be used to evaluate the model's performance.

6 Conclusions

6.1 Summary of Proposed Artificial Intelligence Models

In summary, this document describes three artificial intelligence models developed within the framework of the AI4Ed project. The first model aims to calculate the risk of student dropout, allowing educational institutions to intervene early and provide additional support and retention strategies to at-risk students.

The second model is a content recommendation system that personalizes students' learning experiences.

The third model recommends new educational actions that individuals can enrol in, adapting to the individual needs of the students.

Throughout the document, the approaches used to develop each model have been described in detail, including the architecture, datasets used, training and evaluation processes, etc.

6.2 Final Considerations and Recommendations for Future Research

Finally, it is highlighted that the artificial intelligence models developed in the AI4Ed project represent a significant effort to harness the power of AI in the educational field. It is expected that these models can enhance student retention, personalize the learning experience, and facilitate decision-making regarding course selection. However, the limitations and areas for improvement of the models have also been mentioned, such as the need to enhance the diversity of recommended resources and provide instant feedback.

It is recommended that future research focus on addressing these limitations and improving the accuracy and effectiveness of artificial intelligence models for education. Exploring new applications of AI in education, such as early detection of learning problems and personalization of education for students with special needs, is also suggested.

Overall, it is expected that this document provides a clear and comprehensive overview of the progress achieved in the AI4Ed project and serves as a starting point for future research in this constantly evolving field.

7 References

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