A Review on Explanations in Recommender Systems

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This report discusses the explanations in the domain of recommender systems: A review of the research papers in the domain, the different explanation interfaces and the evaluation criteria, our vision in this domain and its application on the e-learning project “METAL”.

1. Introduction

Recommender Systems (RSs) are software tools and techniques providing suggestions for items to be of use to a user. Recommender systems have become increasingly popular in recent years, and are utilized in a variety of areas including movies, music, news, books, research articles, search queries, social tags, and products in genera[9].

Recommender systems supply users with new suggested items, but they are sometimes considered as black boxes where no explanatory information about them is provided. Thus these recommendations could be accompanied by explanations that describe why a specific item is recommended. Explaining the recommendations usually make it easier for users to make decisions, increasing conversion rates and leading to more satisfaction and trust in the system. An explanation is a description that justifies the recommendations and makes users better realize if the recommended item is relevant to their needs or not. [15]. Providing explanations along with recommendations would lead to better understand the recommender system and establish a "sense of forgiveness" when users do not like the new recommended items [16]. The need of justifications and explanations have started to gain attention during the last decade, being nowadays more crucial due to shilling attacks favoring a given item [3].

There is increasing awareness in recommender systems research of the need to make the recommendation process more transparent to users [8]. In recent years, the question of how to automatically generate and present system-side explanations has attracted increased interest in research. Today some basic explanation facilities are already incorporated in e-commerce web sites such as Amazon.com [5].

Explanations are represented through different explanation interfaces that interpret them. Traditional explanation interfaces are usually textual explanations, tag-based explanations, histograms, radar graphs, pie charts, tree graphs and other graphical representations. There are 7 defined criteria for the evaluation of explanations in recommender systems: transparency, scrutability, efficiency, effectiveness, persuasiveness, satisfaction and trust. These measures evaluate the quality of the explanations and are considered as advantages that explanations may offer to recommender systems answering the question of why to explain [14]. The report is structured as follows, the second section discusses the state of the art in the domain of explanations in recommender systems including the read research papers in the domain, the different explanation interfaces and the evaluation criteria, the third section discusses our proposed work in the domain of explanation and explanations in METAL, the student indicators and their explanations and the recommendations and their explanations, and the fourth section discusses the conclusion.

2. State of the art in the domain of explanations in recommender systems

2.1. Research papers in the domain of explanations in recommender systems

Herlocker and his colleagues [6] address explanation interfaces for automatic collaborative filtering systems. They presented a model for explanations based on the user's conceptual model of the recommendation process, they then present experimental results demonstrating what components of an explanation are the most compelling. Thy performed two experiments, the first one for investigating the model and the second one for acceptance and filtering performance.

In the first experiment, they measured how users of an ACF system respond to different explanations. 21 different explanation interfaces were provided for movie recommendations and were compared, and the ones having the highest ranks were histograms of the neighbor's ratings, past performance and similarity to other items in the user's profile. In the second experiment, they tested if adding explanation interface to automatic collaborative filtering system will improve the acceptance of the system among users and will improve the performance of filtering decisions made by users of the system. There was a positive feedback regarding the addition of explanation interfaces to recommender systems. Their experimental results showed that certain styles of explanation for collaborative filtering increased the likelihood that the user would adopt system's recommendations.

Bilgic and his colleagues (Bilgic et al., 2005) discussed that the most important contribution of explanations is not to convince users to adopt recommendations (promotion), but to allow them to make more informed and accurate decisions about which recommendations to utilize (satisfaction). They presented two new methods for explaining recommendations, collaborative filtering and content-based recommendations and experimentally showed that they actually improve user's estimation of item quality. They evaluated 3 different approaches to explaining recommendations according to how well they allow users to accurately predict their true opinion of an item, neighbor style recommendation which is partly or purely collaborative and show how active user's CF neighbors rated the recommended item, keyword style explanation which explains content-based recommendations where it presents content information about an item that caused it to be recommended, and influence style explanations which presents ratings previously provided by the user that caused an item to be recommended. To evaluate the 3 forms of explanations, they designed a user study where users rate the recommendations after being provided by explanations, and then after trying the item. Their results demonstrate that the “neighborhood style” explanation for collaborative filtering systems previously found to be effective at promoting recommendations [6], actually causes users to overestimate the quality of an item which leads to mistrust in the system. Keyword-style explanations or influence-style explanations were found to be significantly more effective at enabling accurate assessments.

Gedikli and his colleagues [5] discussed their study that reveals that the content-based tag cloud explanations are particularly helpful to increase the user-perceived level of transparency and to increase user satisfaction even though they demand higher cognitive effort from the user. In their user study, users of a recommender system were provided with 10 different explanation types to be evaluated with respect to the quality factors, efficiency, effectiveness, persuasiveness, perceived transparency and satisfaction in parallel. They conducted a laboratory study in which they compare several existing explanation types from the literature with tag-based explanation approach. They also detected the interdependencies between more than 2 quality dimensions, and based on the dependencies between the different effects of explanation types, they derived a set of guidelines for the design of effective and transparent explanations for recommender systems and they were validated through a qualitative interview-based study. They found that satisfaction is a prerequisite of trust, user-perceived transparency is important for user satisfaction and trust where efficiency doesn’t have an important effect on satisfaction and trust and positive and negative persuasiveness can cause the loss of trust from the users. The guidelines that they defined included using domain specific content data to boost effectiveness, using explanation concepts that users are already familiar with, increasing transparency for higher user satisfaction,and considering that explanation types should not primarily be optimized for efficiency. Their analysis also revealed a strong relationship between transparency and satisfaction. They concluded that explanation types have different effects on users such as quicker decisions, higher transparency or higher satisfaction and that tag cloud interfaces are good interfaces for building trustworthy explanations.

Cleger and his colleagues [2] studied whether the general idea of learning from explanations works and showed that explanations can be considered as a valuable source of knowledge that can be exploited by a recommender system. Their research focuses on using neighbors' opinions about items previously rated by the user in the explanations. They demonstrated that relevant data can be gathered from this type of explanation and they can use machine learning strategies to change this data into knowledge and induce general rules about the user's actions from a set of observed instances. They learned a regression model from the information presented in these explanations that can change the recommendation of a target item when needed. They have identified a series of features that can be used for prediction purposes like the recommendation or predicted rating, the error in prediction, the entropy that measures the uncertainty in the distribution of the ratings given by the selected neighbors to the item. These features can be used to improve recommendations for around 30% of users by considering previous user experiences. They concluded that it is possible to learn from a set of explanations, although this is highly user-dependent, and an automatic procedure can be used to analyze the role of the different features presented in an explanation.

In this subsection, I described the literature review in the domain of explanations in recommender systems with the different approaches, models and experiments presented.

2.2. Explanation interfaces

An explanation interface is a representation of the explanation provided for a recommended item suggested by a recommender system. There are various explanation interfaces used in the literature, some of them are traditional and can be applied and adapted to all domains, and others are specific for each domain.

Some of the explanation interfaces presented contains data in the form of ratings. When creating an educational dashboard for students, it is hard to ask students, especially under the age of 18, to frequently rate items as it would be a boring task for them and there would be a risk that they will stop using our system. As a result, these kinds of interfaces don't fit in our case as we can't have data in the form of ratings. Some examples of the most commonly used explanation interfaces for recommender systems are described below.

- Histogram of ratings

  One of the traditional and most used explanation interface is the histogram of ratings that displays the ratings of similar users to the target user for the recommended item. It is usually used for explaining the recommendations of suggested movies or items to buy. It could be a histogram representing the ratings from 1 to 5 separately as in Figure 1 or a histogram with grouping representing a group of good ratings and another of bad ratings as Figure 2.

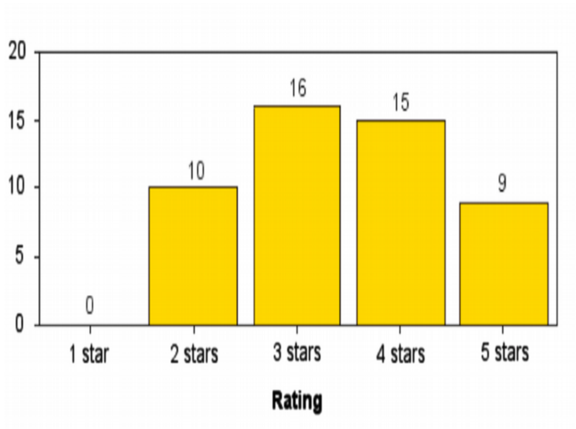

Fig-1-Histogram of rating

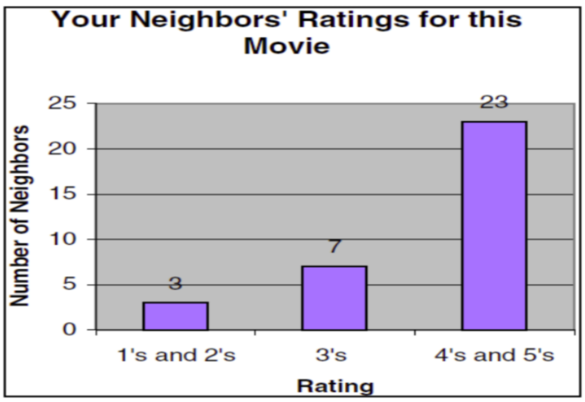

Fig-2-Histogram with grouping

- Table of neighbors rating

  This explanation interface represents a table that contains the data about ratings of the neighbor users to the target user as in Figure 3.

Rating	Number of Neighbors
★	1
★★	2
★★★	7
★★★★	14
★★★★★	9

Fig-3-Table of neighbors rating

- Pie chart based interface

  This explanation interface represents a pie chart that displays the ratings of neighbor users to the target user with their percentages.

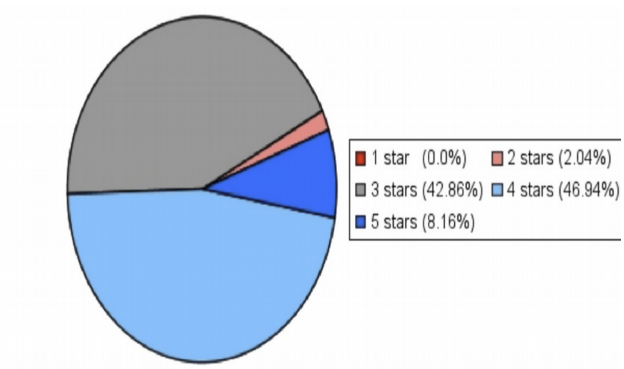

Fig-4-Pie chart of ratings

- Another kind of explanation interface is tag cloud based explanations. It is a way of visualizing explanations in recommender systems. Each recommended item can be characterized as a set of tags or keywords that are provided by the user community or automatically extracted from external resources. There are 2 kinds of tag clouds, non-personalized tag cloud that contains a set of user-provided keywords (tags) that are relevant for a recommended item, and personalized tag cloud where the visualization integrated additional information if a user has a positive, negative, or neutral sentiment towards the concept behind each tag. Examples of the 2 kinds are provided in Figure 5 and Figure 6. In our project, as it is in the domain of e-learning and dealing with school students, it is difficult to obtain tags from the students or any kind of explicit feedback, so this kind of explanation interface is not found to be practical in our work.

Fig.5 Non-personalized tag cloud

Fig.6 Personalized tag cloud

- The percentage of confidence in the prediction is a commonly used explanation interface that provides trust in the recommendation by providing percentages of the cases where the recommendations of the systems were proved to be correct. An example of this explanation interface is found in Figure 7. This explanation interface could be used in our project, and it provides confidence in the provided recommendations, but its disadvantage is that it can only be used after a training phase where recommendations are provided for students and then students try the recommended items to check if the prediction of the system was correct or not. This process needs time before the system is able to provide these explanations.

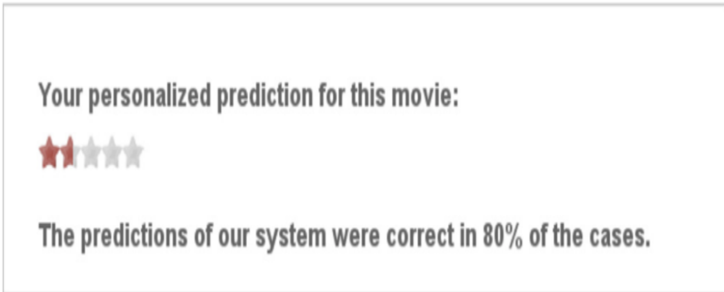

Fig.7 Confidence display

- One of the traditional explanation interfaces is the explanation in the form of a textual description that states in natural language the reasons for providing these recommendations. The advantage of this explanation interface is that it fits all domains and can be used in all cases as it is the least risky interface used. An example of this interface is displayed in figure 8.

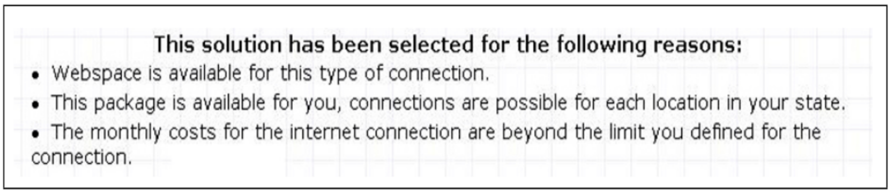

Fig.8 Textual explanation

There are also other types of explanation interfaces that are used like complex graphs with counts, ratings and similarities, ratings with percentage of agreement with closest neighbors, overall average rating, similarity to other rated items and others.
In this section, I displayed various examples of explanation interfaces, their applications in different domains and their possibility of application to our domain with their advantages and disadvantages.

2.3. General domains of application of explanations in recommender systems

In the previously described state of the art of the domain, we find that explanations in recommender systems is mainly applied in the domain of e-commerce especially in the domains of movie recommendations, tourism and various recommended items for customers to be bought. The explanations to the recommendations are provided to attract more users, to convince users to buy items and to gain more money.

As to my knowledge so far, there is no work done on the explanations in recommender systems in the domain of e-learning. The challenge is to provide explanations to recommendations in this domain. In our project, the aim is to develop a recommender system that recommends academic resources to students. This case is critical and risky as it deals with students and their success where any inconvenience or misinterpretation may cause a student failure; thus the explanations should be good in all its measures and aspects.

2.4 Evaluation measures of explanation interfaces

As mentioned previously, recommendations were considered as a black-box and this may be the reason why they have gained much less acceptance in high-risk domains such as holiday packages or investment portfolios than in low risk domains such as Cd's or movies. Here comes the importance of providing explanations to the recommendations so that they are more reliable and make users feel more confident in the system. There are 7 criteria to evaluate the quality of explanations of recommendations, efficiency, effectiveness, satisfaction, transparency, scrutability, trust and persuasiveness. The 7 criteria are discussed below.

- Transparency: Does the explanation give the user a clear idea on how the system works taking into consideration the ethical, privacy, understandability and motivation aspects?

Transparency explains how the system works. It is the capability of a system to expose the reasoning behind a recommendation to its users [6]. There are two kinds of transparency, objective transparency where the recommender reveals actual mechanism of the underlying algorithm and user-perceived transparency which is based on the subjective opinion of the users about how good the system is capable of explaining its recommendation logic.

- Efficiency: Does the explanation help the user take a faster decision for choosing the best item?

  Efficiency measures the decision time required by the user, that is the time needed to perform the same task with or without an explanation facility [10], or with different explanation interfaces. There are 2 types of efficiency, item-based efficiency which is measuring the decision time required by a user to evaluate a single candidate item at a time given a set of explanations, and list-based efficiency which is measuring the decision time having a list of recommendations [5]. Efficiency is a criterion that can be automatically evaluated by measuring the decision time, this makes it a criterion that can be automatically evaluated, and this is more practical in our domain because we deal with kids, and it would be boring and unmotivating for them to be asked to fill questionnaires to evaluate the explanations.
- Effectiveness: Does the explanation help the user take a better decision for choosing among the recommended items?

  Effectiveness is measuring how much people still like an item they have bought after consuming it. Effective explanations support the users in correctly determining the actual quality or suitability of the recommended items and filter out uninteresting items [1]. It is the criteria that is most closely related to accuracy measures such as precision and recall [12]. Effectiveness can be measured by liking the recommended item prior to and after consumption or to test the same system with or without an explanation facility [13], measuring the difference in ratings of users before and after being provided by an explanation, or measuring the difference between the user's estimate of the quality of a recommended item and the actual quality of the item. Therefore, effectiveness is also a criterion that can be automatically evaluated.

- Scrutability: Does the explanation let the user tell when the system is wrong or certify the recommendation?
  Scrutability allows the user to tell the system that it is wrong [13]. Explanations should be part of a cycle, where the user understands what is going on in the system and exerts control over the type of recommendations made, by correcting system assumptions where needed [11].
- Trust: Does the explanation provide trust and confidence to the user in the system?
  Trust increases user's confidence in the system. It is sometimes linked with transparency and could also depend on the accuracy of the recommendation algorithm [7]. Trust can be measured by getting feedback from the users concerning their confidence in the recommender system after being provided with explanations to the recommendations, by measuring the differences in user's sales on the system before and after the explanations, or by checking the behavior of the user on the system after being provided by explanations.
- Persuasiveness: Does the explanation convince the user to accept or disregard a recommended item?
  Persuasion can be measured as the difference in likelihood of selecting an item [13]. It is the ability of an explanation to convince the user to take a decision concerning a recommended item. It can be calculated as the difference between two ratings of the same item before and after being provided with an explanation interface [4]. The explanations that lead users to overestimate the quality of items can be risky because users may think that the system is cheating; on the other hand, the explanations that lead users to underestimate the quality of items may make the user think that the system fails to generate accurate recommendations. Therefore, positive and negative persuasiveness can cause loss of trust from users in the recommender system.

- Satisfaction: Does the explanation increase the satisfaction and the interest of the user in the recommended item? Satisfaction is when the item best fits the user's needs. Satisfaction with the explanations increases the overall satisfaction with the system. It is a prerequisite for trust (Cosley et al., 2003); a user who is not satisfied in a system will not probably find it trustworthy. Satisfaction can be measured by asking users whether they prefer the system with or without explanations, and if the system is fun to use [13]. Transparency was proved to have a positive effect on satisfaction [5].

  Out of the 7 evaluation criteria previously discussed, efficiency and effectiveness can be automatically evaluated; the remaining criteria can generally be evaluated by questionnaires filled by users. In our project, as it is difficult to ask students to frequently fill questionnaires, we can measure them by evaluating the students' behaviors and following their traces of activities to infer the results.

  In this section, I discussed the 7 different criteria of evaluating explanations in recommender systems.

3. Our proposed work in the domain

3.1. <u>Explanations in our e-learning project "METAL"</u>

As previously mentioned, the explanations in the domain of e-learning is critical and risky as it is directly related to the students' success. In our project, we have to provide 2 explanations, explanations to the indicators that display the students academic levels, and explanations to the recommendations of external resources provided to the students to help them improve their level. As we deal with students under the age of 18, it is more difficult to provide good explanations that suits their level of knowledge and thinking. Therefore, we determined some criteria that should be respected in building the explanations to the indicators and the recommendations as well.

First, the explanations should be simple. Generally, kids may not be able to understand complex information and prefer to be provided with simple information that doesn't require much time to understand. If the information is complex, there is a risk that students would not use the system and consider it complicated. Therefore, the explanations should be simple, but at the same time useful and contain all the sufficient information. The explanations should also be positive. Even for students being at risk of failure, the explanations should always be positive to encourage the student to work harder. They should explain to their students, in a positive way, their points of weakness that they need to work on to improve their level. The explanations should also be coherent. The explanation interfaces provided for students should be coherent so that they don't get lost with too much information or various kinds of information among different explanation interfaces. The coherency could be in the similarity of interfaces or similarity in the measures provided (like percentages or average ratings) among different interfaces. Finally, the explanations should be motivating. They should motivate the student to use these recommended resources to work harder and improve. If students are not motivated by the explanations provided to them, they may stop using the system. Therefore, the explanations should be interesting enough to motivate students to use the system to improve their academic level.

3.2. Student indicators and their explanations

3.2.1 Student indicators

In our project, our aim is to design indicators for students; these indicators display the academic level of students,that is a good, average or low (at risk) level. The aim of these indicators is to help students determine their level and understand better their academic situation. The indicators should be simple, positive and motivating as well. To build successful indicators for students, it is important to determine the best periods of time for students to display them, which kinds of indicators to be displayed and what information they should contain.

To be able to understand when to display the indicators and what information is used, first we will plan meetings with the students to discuss with them some points like what kinds of indicators they prefer to have on the dashboard, whether they prefer graphics or other representations, what information they would like to know about, whether they prefer detailed or brief information and whether they prefer one indicator or more than one indicator displayed as additional information upon request. Second, we set some parameters that should be taken into consideration when designing the indicators as follows: periods of time (morning, day, week, time remaining until the end of the course) when the indicators are displayed on the screen or the interfaces of the indicators are changed, tracking evolution of the student level through time, measuring the performance level of the student on the dashboard and thus determining the level of the student in each subject and his overall level.

To decide on the kind of displayed indicators, we set a list of possible indicators to be displayed for students. During our meeting with the students, we will display these different kinds of indicators to them so that they help in choosing what are the best ones. The list of suggested indicators is described below.

- Traffic lights: It is a traditional indicator whose result is displaying one of the 3 lights, red, yellow and green; these lights indicate students at risk, student with an average level and students with a good level respectively, an example is displayed in figure 9. One light is set at a time for each student indicating his level, and the light could be changed across the semester through defined periods according to the change in the level of the student.

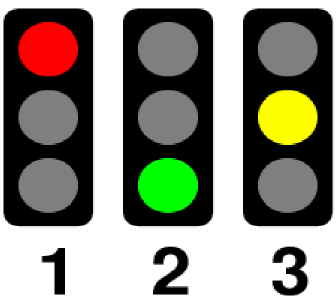

Fig-8-traffic light indicator[1]

- Radar chart: Another suggested indicator is a radar chart including the grades of all the subjects registered by the student. In this case, the student would be able to view information on each subject not just an overall view of his level which makes him able to determine his weakness more precisely. An example of a radar chart indicator for a student registered in 5 subjects is displayed in figure 9.

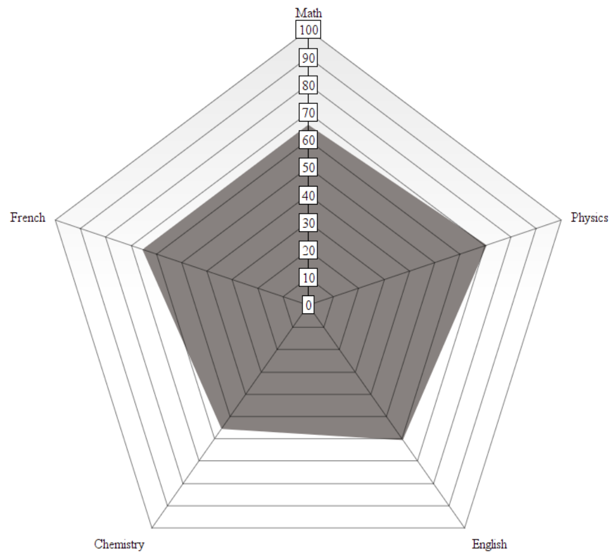

Fig-9-radar chart indicator

- Line chart: It is an option of a simple indicator to be provided to students. It displays the evolution of the average grade of student throughout the semester, or up to the present period of the semester when the indicator is provided. The student would be able to view his progress through time clearly and also to view his academic level at a specific period of time during the semester. An example of a line chart for a student displaying the

1 https://wikipedia.org

evolution of his average grade throughout his 12-week semester is displayed in figure 10.

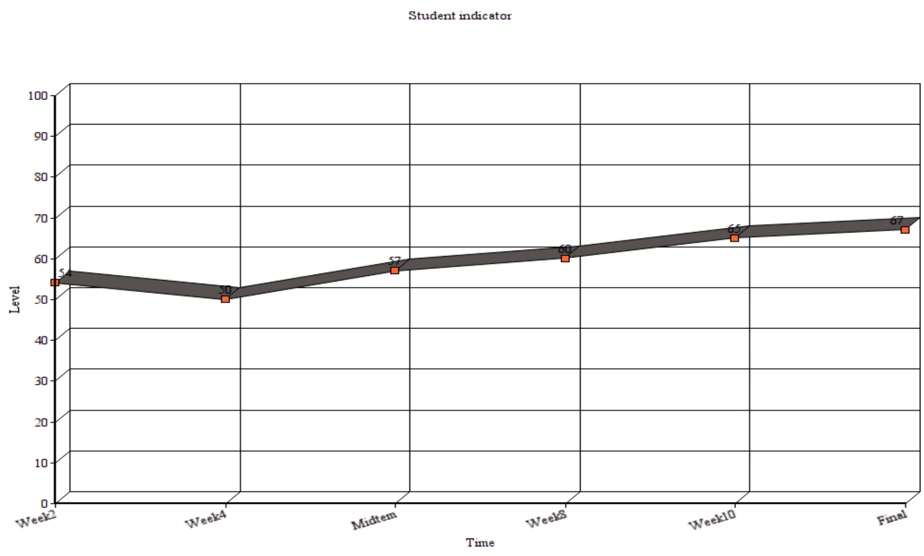

Fig-10- line chart indicator

- Histogram: It is a traditional indicator which is frequently used. Usually, it is a histogram of ratings in the cases where data in the form of ratings can be provided. In our case, the histogram would display the grades of the students in all his registered subjects where each bar represents the grade in a subject. An example of a histogram is displayed in figure 11.

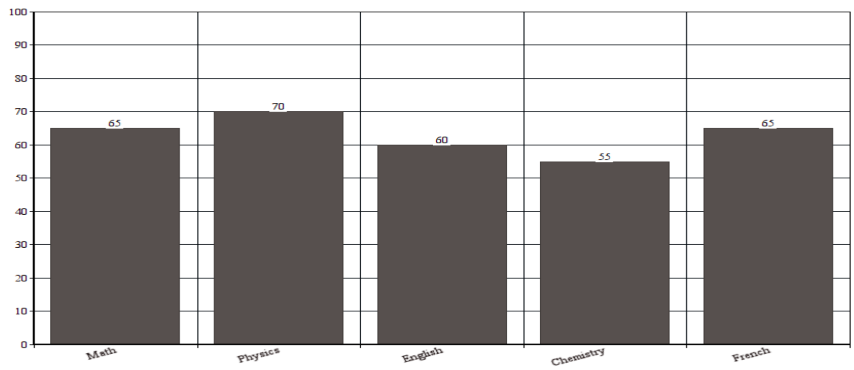

Fig-11- histogram indicator

- Table of grades: It is another traditional indicator in the form of a table that shows each subject registered by a student with its overall grade to have a detailed view of his level in each subject. It is clear and simple to understand and everyone is usually used to such a traditional interface. An example of this indicator is displayed in figure 12.

Subject	Grade
Overall	63,4
Math	70
Physics	55
Chemistry	60
French	65
English	67

Fig-12- Table indicator

- Traffic light on main screen: One of the 3 traffics lights could be displayed on the top of the main page of the student dashboard. In this case, the student would be able to have a general idea of his level without having to go to a specific page, and he clicks on the light if he needs additional information; the additional information could be in the form of one of the other defined indicators or simply a textual explanation describing his academic level. An example of this indicator is displayed in figure 13.

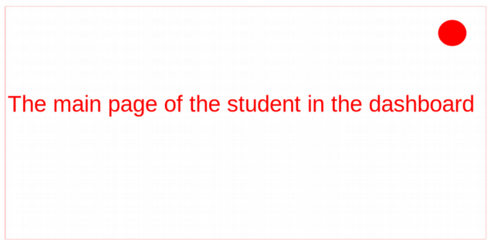

Fig-12- Traffic light on main screen

- Shade of colors: This indicator could be in the form of a shade of colors between the 3 traffic lights to indicate the student's level, with a pointer pointing to the color that represents the student level. Additional information about the academic level could be provided for the student upon his request. An example of this indicator is displayed in figure 14.

Fig-11- shade of colors indicator

- Range of percentages: It is a similar indicator to the shade of colors where the range of percentages is displayed with a pointer pointing to the percentage indicating the academic level of students.
- Traffic light per subject: This indicator is in the form of circles representing each subject registered by the student, and each circle is colored with one of the 3 traffic lights indicating the level of the student in this subject. It is a simple graphical representation that is easy to understand by students.

In this subsection, I presented suggested indicators that could be displayed for students.

3.2.2. Explanations to the indicators

After displaying the indicators for students showing them their academic level, it is important as a further step to provide explanations to these indicators. The explanations help students have more confidence in the system when provided with additional information and interpretations, understand the reasons of the results displayed in the indicator which makes them better understand their points of weakness and thus become more motivated to improve their level.

Each indicator may need different explanations; thus for each of the suggested indicators in the previous section, I will provide suggested explanation interfaces that could fit best this indicator.

The explanation of the traffic light indicator depends on the light that represents the level of the student. If the light is green, it means that the student has a good academic level, and doesn't need detailed explanations unless required; thus, an explanation displaying the overall average would be sufficient. The additional information provided when requested would be the averages of all the courses registered by the student. If the light is yellow, it means that the student has an average level, and if he doesn't work harder, he may become at risk of failing. In this case, the explanation could be information about the subjects that he is weak at to improve his level or his performance through the past period. If the light is red, this means that the student is at risk of failing; thus detailed explanations should be provided for him. Explanations could be the grades in all the subjects he is registered at accompanied with textual explanation about his exact level and his performance during the past period with expectations to his performance and grades in the coming period.

The radar chart, histogram and table of grades indicators provide detailed information on the averages in all subjects registered by the user. This kind of indicator gives the student a view of his level in all courses. The explanation could be additional information on the academic level of the student in a specific parts of the subjects that he got low grades at. For example, if a student gets a failing grade in chemistry, the explanation would be his academic level in organic and inorganic chemistry separately so that he knows exactly where his point of weakness in this subject lies.

The indicator displaying the evolution of the level of students throughout the semester or until the present period of the semester contains detailed and sufficient information for the student to understand his overall level. The explanation could be providing information about the average grades in all his subjects.

The shade of colors and range of percentages indicators provide an overview of the level of students. The explanations to these indicators could be providing information about the average grades in all his subjects.

3.3. Recommender systems and their explanations

3.3.1. Recommender systems

After providing the students with the indicators and their explanations so that they have a clear idea in their mind about their academic level which should make them motivated to work harder, we provide them with recommendations that help improve their level. The recommendations are additional external resources like lectures, books, chapters, exercises or exams; they are recommended to students based on their level and the subjects that they need to improve at. The recommendations could be one or more resources suggested to the student in each subject that he is registered at, taking into consideration the different level of students and thus the different needs of recommendations. A student having a good academic level would need a recommendation that is not urgent, however it could be in a subject that he is interested to know more about. Average and low-level students would need the recommendations to help them improve their level and increase their average in order to succeed. Traditionally in recommender systems, more than one item is recommended from the same source, and the student chooses what suits him out of these recommended items. In the domain of e-learning and especially when dealing with students under 18 years old, providing more than one item from the same source will make the student lost and not able to decide which recommendation is the best for him; in addition, if we provide students with top 5 recommendations, as it is related to their success and they would not risk it, they would definitely choose the top first recommendation to ensure his success. Therefore, we propose to provide different items from different sources to provide a variety that suits all kinds of students and their different needs. The different kinds of resources provided could be one of the following:

- Resources provided by different teachers who are teaching the same program and subject, in case the student's problem is that he doesn't prefer the way of teaching of his own teacher.
- Resources followed by past students who improved their level and succeeded after following them.
- Resources followed by similar students to the target student which were found useful to them and helped them increase their level.
- Resources that were statistically proved to be useful for students.

3.3.2. Explanations to recommendations

As previously mentioned, in the domain of e-learning and when dealing with students under 18 years old, it is complicated to provide them with similar recommendations coming from the same source. Therefore, the recommendations must be different, and the difference should be clear and understandable for students to choose what suits them. As a result, it is important to provide explanations to the recommendations that describe these differences between them. 5 different explanation examples are provided below:

- I recommend you this exercise because 100% of the students who performed it succeeded in the exam, but it is difficult.
- I recommend you this exercise because 80% of the students who performed it succeeded in the exam, and it is not difficult.
- I recommend you this exercise because similar students who performed it succeeded in the exam.
- I recommend you this exercise because it is not provided by your teacher, but by a different teacher who is teaching the same program and class as yours.

- I recommend you this exercise because past students who already succeeded have performed it during this time of the semester.

  In this subsection, I discussed our proposed work for the recommendations and their explanations.

4. Conclusion

In conclusion, the domain of explanations in recommender systems is an important domain with increased interest. Our aim is to apply it in the domain of e-learning; it is a challenge as it is a critical domain where there should be no risk because it directly deals with the success of students. Our aim is to provide indicators of the academic level of students with explanations to these indicators and to design a recommender system that recommends external resources for students to help them improve their level along with the explanations to these recommendations to make the system more understandable and trustworthy for the students.

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