Generating Dynamic Questions Assessing a User's Understanding from Structured Knowledge

GALMAT Honours Project

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ABSTRACT

In general, the current method to analyze how effectively a student has learned information is by assessing their knowledge through the form of a static test. However, static tests do not precisely discover the gap in a user's knowledge. There are various limitations of static tests as they are not adaptable and do not take into account the general knowledge level of an individual student. The questions within a regular test are standardized for everyone, regardless of the fact that some students may be further ahead of others in their understanding of a particular subtopic of a particular topic. Furthermore, the results of a regular test do not necessarily help the student find the relevant content to master the topic. A solution to the problems caused by static tests, is known as Adaptive Learning, and a large component that assists in Adaptive Learning is Automatic Question Generation. Multiple studies have proven that automatically generated adaptive questions are much more beneficial to a learner's learning experience in comparison to traditional static methods, as they not only identify knowledge gaps but also ensure that leaners only receive questions within their realm of knowledge and ability. The purpose of this literature review is to identify and analyse the current algorithms of automatically adaptive question generation from structured knowledge that assess an individual user's understanding of a topic. The positives and drawbacks of each algorithm will be discussed, as well as a potential solution to the problems.

CCS CONCEPTS

•Theory of Computation → Analysis of Algorithms;
•Information Retrieval → Ontologies;
•Information Storage Systems → Structured and Unstructured Knowledge;
•Mathematics of Computing → Probability and Statistics;
•Information Storage System → Learning Knowledge Model;
•Theory of Computation → Automatic Question Generation
•Theory of Computation → Models of Computation

KEYWORDS

Automatic Question Generation; Ontologies; Learner Knowledge Model; Computerized Adaptive Testing; Adaptive Learning.

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1 INTRODUCTION AND MOTIVATION

Learning is a fundamental aspect of all of our lives; thus ensuring that it is maximally efficient is a very desirable goal in general. The current landscape of learning is assessed through static tests in which users simply answer questions and receive a mark based on how many questions they answered correctly. The mark that the learner receives has no other use apart from signaling how many questions the learner answered correctly. As a result, the learner does not benefit from completing the test as they will still receive the same content to learn as usual. This is the problem that generated adaptive learning seeks to solve by automatically generating questions from structured knowledge according to the learner's knowledge level and prior answers to generated questions. The generated questions will also be utilized to generate adaptive learning materials for the learner. This will subsequently fill in the identified knowledge gaps of each individual learner, providing them with an improved learning experience.

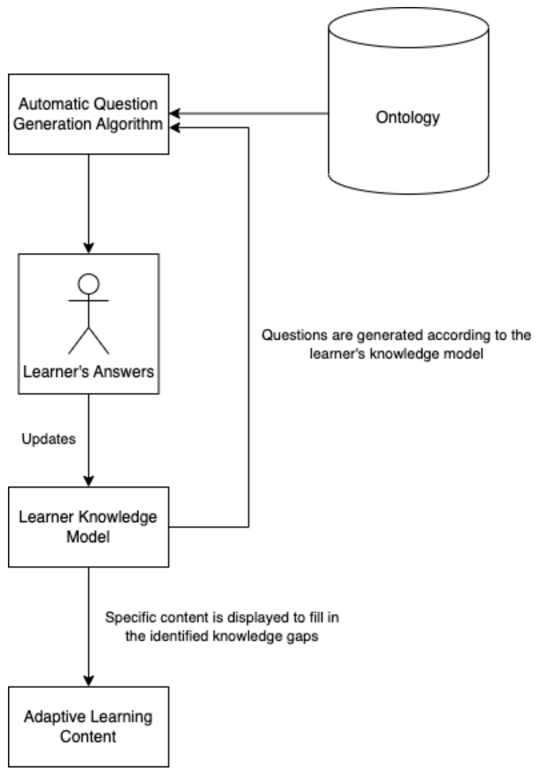

Figure 1: High-level overview of the entire Adaptive Learning process

Generated Adaptive Learning entails automatic question generation from structured knowledge based on a learner's answers to previous questions. The generated questions will be generated according to the learner's knowledge within a topic, which is determined by their answers to previous questions. This would ensure that learners who are more knowledgeable within a specific topic receive harder questions in comparison to a learner who is struggling to understand that same topic. The adaptive learning is introduced here, the algorithm will seek to identify knowledge gaps within each individual learner and will then dynamically update their learning content in an effort to bridge this gap [4]. Thus, every learner will ultimately receive different questions as well as different content. The generated questions and content will be tailored to meet the needs of each learner and will ultimately provide the learner with the most effective learning experience [15]. Figure 1 displays a high-level overview of the overall Adaptive Learning process. The specific area that I am focused on includes the Automatic Question Generation component.

Tests have been carried out to see whether adaptive learning is more suitable for learning than traditional static methods [15]. Although the research is not exhaustive, the results indicate that adaptive learning has greater results. Students who used adaptive learning tended to perform higher than those using static methods of learning. Furthermore, students who initially had low marks tended to have the highest gain in marks once using adaptive learning [15]. This indicates that there is some form of merit to adaptive learning and proves that it fills in a learner's knowledge gaps.

There are a few societal problems involved with static tests, as previously mentioned it does not provide the learner with any real benefit and does not bridge their knowledge gap in any form. Additional problems include the difficulty in creating good multiple-choice questions that subscribe to guidelines that will accurately and efficiently test a learner's knowledge on a topic. Creating effective multiple-choice questions as well as good distractors -possible incorrect options in a multiple-choice question- are time-consuming and difficult [10]. Thus, automatic question generation arises as a solution. However, there are also various problems associated with the automatic question generation solution.

Ontologies are currently used to organize the vast amount of information that currently exists today [17]. Ontologies structure this information in a way that is extremely accessible for other applications to retrieve and make use of [17]. Thus, ontologies are frequently used in Artificial Intelligence, Robotics, Natural Language Processing, and many others [17]. Ontologies are also currently used in automatic question generation. The use of ontologies in automatic question generation is not well-researched and is still relatively new [12]. Thus, there are potential issues such as the generation of questions which require minor or major modification before it is presented to a learner. The extraction of viable information to ask the learner is also a topic that has room for improvement, as although there are multiple methods available for data extraction, none of them are error-free. This leads onto the goal of the literature review, which is to research the current methods of automatic question generation from structured knowledge, as well as explore an alternative that produces much better results. The purpose of the automatically generated questions would be oriented toward effectively assessing learners taking into consideration their respective knowledge levels.

An algorithm that is able to adaptively generate questions from structured knowledge, based on a learner's prior answers to questions is beneficial to the learner as well as society as a whole. It would be a large advancement in the field of education and would provide learners with the ability to identify gaps within their knowledge. It would also largely reduce the amount of effort, time and money that is required to manually create effective questions for learners [10].

This literature review intends on reviewing and researching the existing work within the field of

Automatic Question Generation. Special attention will be paid to the individual components that make Automatic Question Generation possible, the various storage mediums of knowledge as well as the existing question generation algorithms that already exist within the field. An analysis of each of these algorithms will be conducted in order to identify both the pros and cons of them. Special attention will be paid toward the reasons as to why each algorithm does not solve the various societal and computer science problems previously mentioned.

2 PRESENTATION

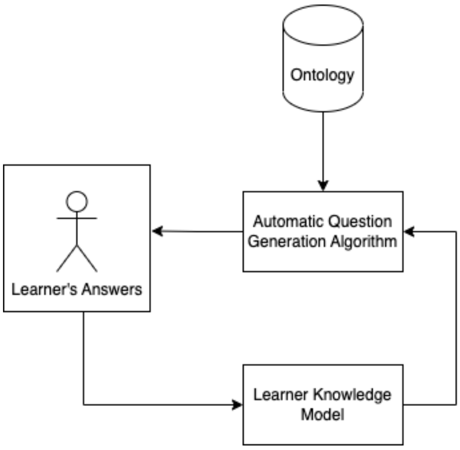

Figure 2: Automatic Question Generation Process

In automatic question generation, there needs to be a source of data from which the questions are created from. The two different sources include structured and unstructured knowledge. Structured knowledge is data that follows some form of structure, thus making it easier to search for data within this knowledge base in comparison to unstructured knowledge [1]. Unstructured knowledge follows no formal structure, thus making it difficult to search for specific items or data [1]. The Generated Adaptive Learning algorithm that we are concerned with will use structured knowledge to create a series of true or false questions.

2.1 STRUCTURED AND UNSTRUCTURED KNOWLEDGE

Structured and unstructured knowledge is not the only consideration that needs to be made regarding automatic question generation. Two sources which are text and ontologies, exist from which questions may be automatically derived [2]. Although text based automatic question generation has a deeper research background [2], there are both advantages and disadvantages associated with it. Text based generation is typically preferable for language-based questions; however, the automatically generated questions do not differ from the content a lot [2], which reduces the difficulty of the questions. Ontology-based generation is the choice of generation for the algorithm that we are concerned with, however there are also both advantages and disadvantages of this method. Ontology-based generation is far less researched in comparison to text-based generation, however ontology-based generation produces questions that differ from the structured or unstructured knowledge [2], thus producing more difficult questions that effectively test the learners understanding of a topic. Ontologies also store knowledge in a shared format that ensures it remains consistent across all learners who are pulling data from the ontology [11].

2.2 ONTOLOGIES

An ontology is a structure of data, and it is the source from where the algorithm will automatically generate questions from. The ontology that is concerned with automatic question generation is referred to as a course ontology [3]. A course ontology is a specific branch of ontologies that stores educational knowledge, such as various concepts as well as the relationships between these concepts [3]. This makes it preferable as a source of question generation, in comparison to a text-based approach, as you are able to extract keywords from the ontologies and place these into questions in a comparatively easier manner [3]. Ontologies, although less researched, suggest that they are preferable for AQG (Automatic Question Generation), as they allow for a more individualized experience for an individual learner [11]. An example of how questions would be automatically generated through this way, would be to extract the relevant keywords from the course ontology, these would then be placed into a question template which follows a certain order. In order to introduce variation to the questions, different categories of questions could be created, each of which would have a different template [3]. These templates would not be limited to one keyword per question, there would actually be no upper limit on the amount of keywords that a question could have. However, it is important to keep in mind the principles and guidelines of what makes a good question when designing the templates.

In order to fill in the templates with keywords, important concepts and information needs to be successfully extracted from the ontology [18]. This is a difficulty associated with automatic question generation from ontologies [4]. An attempt to extract useful keywords from text will use a lexical analyzer and syntactic parser to ignore or remove all filler words, or simply words that provide no real benefit [4]. This would leave only important potential candidates for keywords available however, the algorithm still needs to be able to find a relationship between extracted keywords in order to automatically generate a viable question. Once irrelevant words have been removed or ignored from the structured knowledge, the algorithm will analyze the filtered information using a windowing process - which has been used for text-mining [4]. This windowing process consists of analyzing the filtered information in windows of a predetermined size and taking note of how many times concepts come up together within the same window. Once the windowing process is complete, related concepts will be assessed and those whose relationship score fall under a predetermined threshold will be discarded as a potentially related concept [4]. This process narrows the pool of viable related concepts that may potentially be asked in a question.

2.3 INPUT AND OUTPUT

Automatic Question Generation uses the previously mentioned concepts in order to generate questions. However, the algorithm that we are concerned with also requires different forms of input to produce different forms of output. The primary input of our automatic question generation algorithm would be structured knowledge. This is the structured knowledge or course ontology that will represent the overall learning content from which the user will receive lessons and, subsequently be tested on. This is not the only form of input as the algorithm will dynamically generate questions based on a student's knowledge -which is calculated based on the answers to previous questions. Therefore, the secondary input to our AQG algorithm would be the learner's knowledge model. Every answer that a student gives for a specific question will subsequently update a model that represents their knowledge [5]. This is the knowledge that will assist in generating personalized questions for each individual student. The primary output would be a personalized representation of the learner's knowledge with potential knowledge gaps filled out. This would effectively be the learning content for each individual user, as each user will receive different content that will bridge their individual knowledge gaps determined during the test phase. The secondary output of the algorithm would be the questions generated for each learner. These automatically generated questions would be dynamically generated based on the learner's answers to previous questions, thus the next potential question that a learner receives is decided based on their answer to the previous question. This ensures that learners receive questions that are within their academic ability and prevents learners from having to answer questions that are either too easy or too difficult for them.

2.4 LEARNER KNOWLEDGE MODEL

A core component of Automatic Question Generation is the model that represents each individual student's knowledge. This is an important model that will be created for each individual learner on the system and will store information pertaining to that respective student. This model will store personal information relating to each student, such as their name, surname, and other details. The model will then also store information relating to a learner's academic performance, which will dictate the questions that the algorithm will generate for them [5]. This student knowledge model will also help in generating personalized learning content for each user, learning content that will bridge potential gaps in their knowledge. Therefore, it is important to ensure that the student knowledge model is updated and secure. This model would be updated every time the user begins a test [5], as each question will result in the student knowledge model being updated [7]. If the learner answers a question incorrectly, then the model will be accordingly updated to reflect that the learner potentially does not completely understand that section of the content therefore, the learning content that the learner receives will potentially be updated to further explain that concept and to bridge the learner's knowledge gap [7]. If a learner answers a question correctly, the model will be accordingly updated to reflect that. This may result in the learning content that is dynamically generated for each user being reduced as the learner already understands this concept thus, displaying the information to the learner again is not beneficial and is redundant [5].

3 ALGORITHMS FOR AUTOMATIC QUESTION GENERATION

3.1 MASTERY LEARNING

There are a multitude of different methods regarding Automatic Question Generation. One of the existing methods is known as mastery learning [6]. Mastery learning refers to a method whereby different questions are split up into different categories according to the specific content or learning objective to which they apply. Therefore, questions that test a learner's knowledge on one specific sub-topic will be categorized together. With mastery learning, learners will continuously receive automatically generated questions from the same category until the learner receives a grade over a predetermined threshold signifying that they have mastered the subtopic [6]. Once a learner masters a topic, questions will be generated for a learner based on a different topic.

A potential drawback of mastery learning is that it may be more efficient to quiz a learner on a section that they are the least mastered or knowledgeable in

[6]. The reason behind this is that this forces a learner to learn a wide range of information, as opposed to just a single sub-topic within a topic. Mastery learning also has a tendency of discouraging students [6] as they only move onto a different sub-topic once they have mastered their current topic. Thus, a struggling student may become demotivated if they are repeatedly asked questions on a particular subtopic with no signs of advancement.

3.2 POMDP

A mathematically optimal way of Automatic Question Generation may refer to Partially Observable Markov Decision Process or POMDP [6]. POMDP is a method that predicts a learner's future answers to questions and generates different potential paths that the learner may follow regarding questions. POMDP would then determine the optimal path taking into consideration the learner predictions and will then assign the learner the first question within the chosen path [6]. However, POMDP is difficult to realistically implement and requires extensive modelling of learner knowledge to mathematically compute their predicted answers [16]. These capabilities are often unfeasible and unrealistic.

3.3 BAYESIAN-BASED AQG

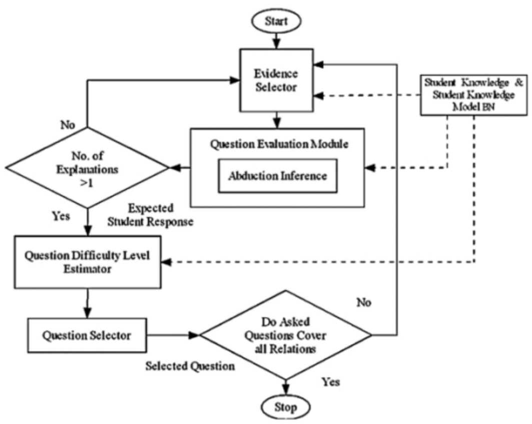

Figure 3: Bayesian-Based AQG [7]

Another method of Automatic Question Generation is known as Bayesian based AQG [7]. The intended goal of this method is to generate questions that, by closely considering the student knowledge model, will generate questions that effectively test their knowledge within a reasonable difficulty level. The five components involved in this method are: the student knowledge estimator, evidence selector, question evaluation module, question difficulty level estimator and the question selector [7]. These five components work together to generate questions according to both the knowledge level of an individual user, as well as according to the difficulty associated with a particular question.

A drawback of the Bayesian-based AQG is that a significant amount of data is required to accurately estimate the difficulty of questions and therefore, assign questions of the right difficulty to learners [7]. The reason that the algorithm requires a large amount of data is that in order to accurately estimate the difficulty of each question, the algorithm analyses the responses of all learners from all of the different knowledge levels to a specific question. It will then use all of this information to mathematically determine the difficulty of that specific question [7].

3.4 META DATA ANNOTATIONS

Another method of Automatic Question Generation includes adding annotations to meta-data [9]. This method consists of semantic interpretation of the annotations within course ontologies in an effort to automatically generate questions that follow similar templates to the templates mentioned in [3]. A drawback of this technique is that the generated questions are not created with a specific difficulty level in mind [9]. Thus, questions would just be automatically generated and not necessarily tailored to individual learners, which is what we are after.

An additional three different methodologies that may be used for extracting keywords from structured knowledge consists of syntax-based, template-based, and semantic-based [12]. Syntax-based simply considers the syntax of the knowledge in order to formulate questions. This method evidently has drawbacks as it may fail to create a viable question for a learner. Template-based was discussed previously, and semantic-based consists of analyzing the semantics of a knowledge structure in order to extract relevant keywords that may be used to form a question for a learner [12].

3.5 CAT

Computerized Adaptive Testing or CAT is a method for Automatic Question Generation that asks each learner a base question which has the purpose of gauging where their current academic ability on a topic stands. From this analysis, future questions are retrieved from an item bank based on the knowledge and ability of the learner [8]. This process is continuously repeated which ensures that the learner receives questions that are best matched with their ability [8]. However, CAT is often very expensive as it requires large amounts of data before questions are generated [8]. The only solution to significantly reduce this cost would be to merge it with an AQG, which would ultimately provide it with the data that it requires. A drawback of this solution is that there is not much evidence of this working, nor of it making CAT significantly less expensive. [8].

Among these different methods of Automatic Question Generation, there are also multiple ways of ensuring different levels of difficulties for the automatically generated questions. A simple method of ensuring different levels of difficulties for questions is to simply extract easier questions from information that is easier to read. In contrast, you would extract harder questions from information that is harder to read [8]. Other methods of determining question difficulty consists of how similar distractors are to the correct answer regarding multiple-choice questions - distractors are the incorrect answers in multiple-choice questions that seek to distract the learner from the correct answer. Another method is the difficulty of the distractor word level, this once again refers to multiple-choice questions [8].

4 DISCUSSION

There are many different methodologies behind automatically generating questions, each of which offer unique advantages and disadvantages. Thus, it is important to understand that different goals will require different methodologies which would produce the best results. These optimal methodologies would be based on the entity within which the knowledge is stored, as well as what type of questions are to be generated. For the AQG algorithm that we are concerned with, an ontology would prove most desirable as a storage medium as it would allow for easy extraction and personalization as concepts are related to each other. Regarding a methodology for data extraction, there are multiple possible options that would produce good results. Ensuring that a learner's knowledge is stored in a model is a necessity as it would provide the ability to extract personalized questions and learning content.

The current success rate of Automatic Question Generation was researched, and the results show that the currently most effective AQG algorithm obtained an acceptance rate of 68.4% [13]. This acceptance rate was calculated by allowing multiple teachers to either accept or reject automatically generated questions. This indicates that only 68.4% percent of the automatically generated questions in [13] were of a suitable quality for learners. This indicates that significant improvements need to be made so that algorithms improve in the extraction of viable keywords to formulate questions. The conducted research shows that although automatically generated questions and adaptive learning significantly improve the learner's ability to learn information, it is by no means perfect within the current landscape and that there is a lot of room for improvement.

There are many algorithms that currently exist for Automatic Question Generation. However, each of these algorithms have certain shortcomings that reduce the potential efficiency and effectiveness that we desire. Thus, there is a need for a better algorithm that successfully solves all of the mentioned problems. The algorithm should take guidance from the successful features of the existing algorithms, whilst avoiding the flawed features. The algorithm should offer an initial standard question to every user, to gauge their knowledge level, and then dynamically adjust the questions based on their previous answers -which would be stored in a student knowledge model. The student knowledge model should be constantly updated with the latest information to accurately reflect the learner's knowledge. This knowledge model should be consulted by the algorithm before generating a question, thus questions that are within the learner's realm of difficulty and understanding are asked. This is a possible way of ensuring that the learner is only asked questions relating to content that they have learned.

It is also important that the algorithm can dynamically adjust the difficulty levels of generated questions. It should increase the difficulty if the learner is continuously answering the questions correctly, and it should decrease the difficulty if the learner is continuously answering the questions incorrectly. A drawback in some of the existing algorithms, such as in [6, 7, 8], was that the algorithms required a large amount of data in order to effectively generate the questions. This is infeasible in many situations and so the future algorithm should be designed in a way that it does not require an unrealistic amount of data to execute efficiently.

5 CRITICAL COMPARISON OF EXISTING WORK

There are many research papers within the field of Automatic Question Generation. However, most of these research papers are not extensively holistic and tend to focus on a particular section of the wide field that is Automatic Question Generation. Some research papers tend to focus on text-based data, whilst others focus on ontologies. The research within the field also differs according to the types of questions that are to be generated, as there are different considerations that need to be made depending on whether you intend on automatically creating multiple-choice questions, true or false questions, fill-in-the word questions, and so forth. The most comprehensive research within the field is [14] and it provides a holistic understanding of AQG.

The existing work suggests that ontologies are the preferable method for storing structured knowledge regarding Automatic Question Generation [14]. Although ontologies within Automatic Question Generation are still relatively new and far less researched, there are still several papers that explain their involvement within AQG [12].

The existing literature suggests that a learner knowledge model is a necessity, as it allows questions to be automatically generated based on a learner's ability to answer that question. Thus, many of the reviewed algorithms, such as those in [6, 7, 8], utilize a learner knowledge model. The manner in which these algorithms update the model is similar in the sense that every question the user answers, whether incorrectly or correctly, updates the learner's knowledge model. This model is then consulted each time that a question is to be automatically generated. This indicates that a learner knowledge model is a key component in any future algorithm regarding automatic question generation.

6 CONCLUSIONS

Automatic Question Generation is a well-researched field and has many different methodologies which one can implement. The research suggests that ontologies are far better than other methods when it comes to Automatic Question Generation. Ontologies allow for important concepts and relationships to be stored in a manner that is accessible to all learners, and ontologies ensure that it is easy to personalize and extract information for learners. However, structured knowledge can be difficult to construct which does lead to potential difficulties regarding ontologies. Despite this, there are existing knowledge graphs available; and we will be working with them.

The effectiveness of Automatic Question Generation in comparison to traditional static forms of testing was also researched. The results of various experiments shown in the research displays that an Adaptive Learning System is much more effective than traditional static forms of learning. Learners tend to learn much more through Adaptive Learning as it allows them to bridge their knowledge gap, something that static learning does not. A large component of Adaptive Learning is Automatic Question Generation, which allows for the knowledge gaps in learners to be identified. The current success rate of AQG was also researched and the results show that there is still room for improvement regarding the generated questions. This emphasizes the need for an improved algorithm that is able to automatically generate questions in a better manner than existing algorithms. Success in doing so would result in a much greater learning experience for learners.

The research has shown that an improved adaptive algorithm that automatically generates questions is possible. This algorithm should make use of ontologies as well as a learner knowledge model. The algorithm should make use of the most efficient generation techniques that do not require an infeasible amount of data to operate, as this will reduce the effectiveness of the algorithm. Many of the existing algorithms have been proven to have strengths, as well as weaknesses.
Therefore, an algorithm that is able to improve on these strengths, whilst addressing the weaknesses, is of great value.

Therefore, the two problems include AQG and Adaptive learning. In order to create an improved Adaptive Learning system, an improved AQG algorithm should be developed which would assist in the generation of content in an Adaptive Learning system, by accurately identifying the knowledge gaps within learners. These two components complement each other, and thus an improvement in both is necessary.

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