Imperial College London

BEng Individual Project - Final Report

jSCAPE - Java Self-assessment Center of Adaptive Programming Exercises

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Abstract

Abstract here...

Acknowledgements

Thanks to...

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Chapter 1

Introduction

1.1 Motivation

- The rise in MOOCs such as Coursera, Udacity shows that there is a real interest in learning programming.
- Programming is considered "difficult" to learn and it can only be learnt effectively through lots and lots of practice.
- This is even more apparent when students are introduced to other programming languages with different paradigms such as Haskell and Prolog, or more low level programming languages such as C.
- Hence, the need to provide a platform for students to practice their programming skills and understanding of programming concepts.
- Having a lecturer come up with all the exercises by himself can be both time consuming and ineffective: some exercises may not be challenging enough for certain top students, or on the contrary too difficult for struggling students, which can be discouraging.
- Lecturers can only rely on a few homework assignments to get an idea of how students are doing. Having a way for lecturers to gather large amounts of data about students' performances would be beneficial. Allows for supplementary material, exercises, etc...

1.2 Objectives

Having identified the problems associated with teaching and learning programming, we were lead to formulating objectives in order to make the project successful and useful to the parties involved.

The main objective of the project was to produce a web-based teaching infrastructure to complement the introductory first year programming classes. Four key features were identified:

- **Programming questions/exercises -** The web platform should allow students to practice their programming skills and understanding of programming concepts. There should be no limit to the number of questions a student can answer, so that if a student desires more practice, then he should be able to do that. Additionally, it should be possible for a specific set of people, such as lecturers and tutors, to add questions/exercises to the system.

- **Progress tracking -** Designated people, such as lecturers and tutors, should have access to detailed statistics about the students performances. This will provide them with useful information about difficulties particular students, or the entire class, may be facing. In addition, the system should give feedback to the students, in the form of simple statistics, allowing them to identify their weak areas and thus improve on them.

- **Adaptive difficulty -** The questions or exercises presented to the students should be suited to their ability. Not only will this stimulate the learning process, but it will also give a better indication of a student's understanding of the programming concepts being tested.

- **Automated generation -** There should be a mechanism to allow for some degree of automated or semi-automated generation of exercises. This will provide a large supply of "fresh" questions, so that students don't end up answering the same questions and memorizing the answers to them.

While investigating existing solutions (Section 2.4 - Related Work) we found out that some of these features were less common than others. The availability of programming exercises and progress tracking are very essential in such systems, therefore many of the related software we looked at implemented these features. On the other hand, relatively few tools integrated some form of adapting the questions to the students' ability. Finally, almost none of the tools featured automated generation of questions, opting instead to allow exercises to be added manually to the system.

1.3 Contributions

Within the context given above, this project makes the following contributions:

1.4 Report Structure

Chapter 2

Background

Add an opening comment here to talk a bit about what we will be presenting in this chapter.

2.1 Computer Based Tests

CBT abbreviation - offers advantages such as being able to display higher quality visuals such as pictures, videos, graphs, etc... - low paperwork, everything is stored on the computer - automatic grading, less work for teachers - generation of statistics is made easier by the fact that the data can be processed by the computer - nowadays a lot of learning is done on computer systems, and children are used to dealing with computers so assessment through this medium is advantageous.

CBTs are typically "fixed-item" tests where all the students answer the same set of questions, usually provided by the person responsible for the assessment. This isn't ideal since students can be presented with questions that are too easy or too difficult for them to answer. Consequently, the results of the test won't give a very accurate representation of a student's ability, and for this reason, these types of tests aren't extremely useful. This problem lead to research and the development of computerized adaptive testing (CAT).

2.2 Computerized Adaptive Testing

Computerized adaptive testing (CAT), also called *tailored testing*, is a form of computer-based testing which administers questions (referred to as *items* in the psychometrics literature) of the appropriate difficulty by adapting to the examinee's ability. For example, if an examinee answers an item correctly, then the next item presented will higher on the difficulty scale. On the other hand, if they answer incorrectly, they will be presented with an item lower on the difficulty scale.

From an architectural perspective, a computerized adaptive test (CAT) consists of five components [3]:

1. Calibrated item pool

An item pool is needed to store all the items available for inclusion in a test. This item pool must be calibrated with a psychometric model. During this phase, the item parameters are estimated according to the chosen model and scaled to fit with already existing items. Usually, the psychometric model employed in these systems is called Item Response Theory (IRT) (section 2.3.4). Calibration is a complex process, and to be done accurately it requires a considerable amount of data. Typically, it is performed by psychometricians, aided by expensive and sophisticated calibration software.

2. Starting point

Initially, when zero items have been administered, no information is known about the examinees and so the CAT is unable to estimate their ability. As a result, the item selection algorithm will fail to choose the next item to be administered. If there is previous information available, for example an examinee's ability estimate in a closely related subject, then this can be input into the system to form the starting point configuration. Often this data isn't available or too costly to collect, so the CAT's initial ability estimate for the examinee corresponds to the mean on the ability scale - hence the first item presented will be of average difficulty.

3. Item selection algorithm

The item selection algorithm chooses the next item to present to the examinee based on the ability estimate of the examinee up to that point. Several methods exist and largely depend on the psychometric model in use. One of the most commonly used methods is the *maximum information method* (section 2.3.4), which selects the item which maximizes the information function with respect to the estimated ability at that point.

4. Scoring algorithm

The scoring algorithm refers to the steps taken to update the examinee's ability estimate after an item has been answered. The two most commonly used methods are *maximum likelihood estimation* (section 2.3.4) and *Bayesian estimation* (section 2.3.4).

5. Termination criterion

The termination criterion specifies when the CAT should finish. For example the CAT can terminate when the change in the ability estimate after each iteration is below a certain threshold, or when time has run out, or when N items have been administered, etc... Obviously, the CAT shouldn't be terminated too early, so as to allow enough time to estimate the examinee's ability with acceptable accuracy.

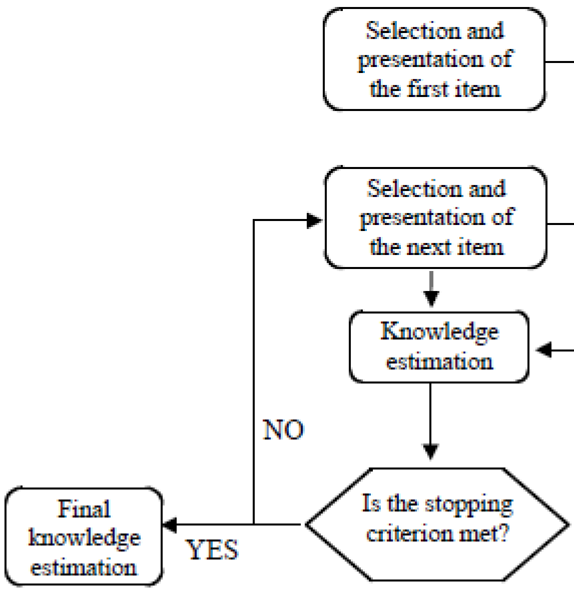


Figure 2.1: Flowchart of an adaptive test. Adapted from [1].

The flowchart in figure 2.1 corresponds to components 2-5, and illustrates the basics of the algorithm implemented in CAT. [2] gives a more detailed description of the procedure:

1. The pool of items that haven't been administered yet is searched to determine the best item to present to the examinee, according to the current estimation of his ability.

2. The chosen item is presented to the examinee, who then answers it correctly or incorrectly.

3. The ability estimate is updated, based upon this new piece of information and the previous ability estimate.

4. Steps 1–3 are repeated until a termination criterion is met.

5. The algorithm returns a final ability estimate for the examinee's performance along with a confidence level: a percentage value indicating how accurate the estimate is.

CATs offer several advantages over traditional CBTs. As a result CATs have been used in many areas[4], such as education, job hiring, counselling, clinical studies, etc... Since CATs administer items by adapting to the examinee's ability, the test-taking experience ends up being a more positive one. Indeed, examinees won't have to deal with answering items which are too difficult or too easy compared to their ability level, a problem which appears in traditional CBTs.

In addition, by administering only those items which will yield additional information, CATs end up being more accurate in estimating an examinee's ability level. This contrasts with CBTs which usually provide the best precision for examinees of medium ability, whereas extreme scores end up being less accurate.

Lastly, CATs can come up with an ability estimate much quicker and with fewer administered items when compared to traditional CBTs. Indeed, an adaptive test can typically be shortened by 50% and still maintain a higher level of precision than a fixed version.[5]

Despite the advantages mentioned above, CATs have some limitations. A frequent complaint is that an examinee isn't allowed to go back and change his answer to a past item. This limitation exists to prevent the examinee from intentionally answering items incorrectly to make subsequent items easier, and then going back and selecting the correct answers to achieve a perfect score. For similar reasons, it isn't possible to skip items, the examinee must select an answer to move on to the next item.

The second issue has to do with the items themselves. First of all, there is the need for a large bank of items to cater to all ability levels. Developing an item pool of sufficient size can be very time consuming. David J. Weiss writes in [6] that item pools with 150-200 items are to be preferred, although 100 high quality items can sometimes be enough to achieve adequate estimations of ability levels.

Secondly, for the CAT to be of good quality the item pool needs to be calibrated accurately. This requires pre-administering the items to a sizeable sample and then simultaneously estimating all the item parameters for each item. The guidelines in [7] suggest that sample sizes may be as large as 1000 examinees. This phase is costly, time consuming and often times simply unfeasible.

Lastly, item exposure is a possible security concern. Sometimes particular items may be presented too often and become overused. This may result in examinees becoming familiar with them and sharing them to other examinees of the same ability level, thus corrupting the results of the test. This problem can be solved to some extent by modifying the item selection algorithm to include some exposure control mechanism.

A brief overview of CATs was given in this section. All of these concepts will be explored in more detail in item response theory (section 2.3.4) and in the implementation of adaptive testing in jSCAPE (section 5.??).

2.3 Probabilistic Test Theory

In the previous section we listed some of the components necessary for the development of CATs. Many of these components, especially the item selection and scoring algorithms, rely heavily on probabilistic concepts. Therefore, in this section we go over a few topics in probability and how they can be implemented in a psychometric model to be used in computerized adaptive testing.

2.3.1 Probability Theory

Probability theory provides us with a means to model uncertainty in data and to infer information from observed data. This is especially useful when it comes to estimating latent variables, i.e. variables that are not directly observed, instead they are inferred from other observed variables. For instance, examinee ability is a latent variable, hence the reason for section 2.3.

The probability of an event E occurring is a numerical value between 0 and 1, indicating how probable it is that we will observe event E. It is denoted as $P(E)$ and $0 < P(E) < 1$. The value 1 indicates total certainty, whereas the value 0 indicates impossibility.

In addition, there is the concept of conditional probability where the probability of an event E_1 occurring, given that event E_2 has occurred, can be denoted as $P(E_1|E_2)$. This concept is also important in statistical inference because it allows us to update prior beliefs given additional observed data. This is explained in more detail in sections 2.3.2 and 2.3.3.

2.3.2 Likelihood and Maximum Likelihood Estimation

Although the terms probability and likelihood are used interchangeably in every day life, in statistics a distinction can be made.

For any stochastic process, let us denote the observed outcomes as x and the set of parameters as θ. When we say probability, we want to calculate $P(x|\theta)$, i.e. the probability of observing the outcomes x given specific values for the set of parameters θ.

However, sometimes we do not know the specific values for θ, instead, we have observed some outcomes x, and want to find out how likely a particular value of θ is given the observed outcomes x. We call this the likelihood or likelihood function, and it is denoted as $L(\theta|x)$. The likelihood of a set of parameter values, θ, given outcomes x, is equal to the probability of those observed outcomes given those parameter values, i.e. $L(\theta|x) = P(x|\theta)$.

To highlight the distinction we illustrate with an example of how the two terms are used. If we consider a dice, a possible parameter is the fairness of the dice, while possible outcomes are which values are displayed after a roll. For instance, if a fair dice is rolled 5 times, what is the *probability* that a 6 will show up on every roll? If a dice is rolled 5 times and lands on 6 every roll, what is the *likelihood* that the dice is fair?

Maximum likelihood estimation refers to a method of statistical inference where one can find the set of parameter values (θ) which are most *likely* given the observed outcomes (x). As mentioned in the name of the method, this is done by finding the parameter values which maximize the likelihood function $L(\theta|x)$.

2.3.3 Bayesian inference

Bayesian inference is a method of statistical inference where Bayes' theorem is used to update the probability estimate for a hypothesis after observing additional events or outcomes.

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{2.1}$$

Let us consider a small example: There is a 60% chance of it snowing on Thursday. If it snows on Thursday, there is a 20% chance of it snowing on Friday. If it didn't snow on Thursday, there is a 70% chance it will snow on Friday.

Before observing any additional data, we can say that the probability of it snowing on Thursday is 60%. But, we are given additional information, namely that it snowed on Friday. How we can we update the probability that it snowed on Thursday to reflect this observation?

We can do this by using Bayes' theorem shown in equation (2.1). Let A be the event "snowing on Thursday" and B be the event "snowing on Friday". Then we have:

$$P(A|B) = \frac{0.2 \times 0.6}{0.2 \times 0.6 + 0.7 \times 0.4} = 0.3$$

This example shows how additional observed data can affect one's prior beliefs. The observation that it snowed on Friday reduced the probability that it snowed on Thursday from 60% to 30%.

However, in the context of this project, we are interested in Bayesian inference of the probability distributions of parameters.

$$P(\theta|x) = \frac{P(x|\theta)P(\theta)}{P(x)}$$

The prior distribution, $P(\theta)$, is the distribution of the parameters θ before any data is observed. $P(x|\theta)$ is the distribution of the observed data conditioned on the parameters. The posterior distribution, $P(\theta|x)$, is the probability distribution of the parameters after considering the new information brought by the observed data.

2.3.4 Item Response Theory

We mentioned in section 2.2 that Item Response Theory (IRT) is usually the psychometric model of choice when developing a CAT, e.g. the Graduate Record Examination (GRE) and Graduate Management Admission Test (GMAT). CATs can still be implemented with Classical Test Theory but they offer less sophistication and less information to evaluate/improve the reliability of the test, making IRT the superior choice.

In psychometrics, an item is a generic term used to refer to a question or an exercise. For instance, in a mathematics exam, "What is the square root of 81?" is a possible item.

Item Response Theory gets its name from focusing on analyzing the items themselves as opposed to Classical Test Theory, which considers the test as a whole. Indeed, Classical Test Theory judges an examinee's ability simply on the number of correct answers obtained, totally disregarding which items were answered correctly or incorrectly, thereby making the assumption that all items possess identical properties.

IRT hinges on the idea that it is possible to model, as a mathematical function, the probability of a certain response to an item given the item parameters and the examinee's ability level. IRT is based on a set of strong assumptions[8]:

1. A unidimensional trait denoted by θ;
2. Local independence of items;
3. The response of a person to an item can be modelled by a mathematical *item response function* (IRF).

The unidimensionality of the trait means that the items are supposed to measure one characteristic of the person, generally their ability, and that this trait should account for most of the variance in the test score. The trait level is denoted as the Greek letter theta (θ), and typically it has a mean of 0 and a standard deviation of 1. For example, in the context of this project, theta (θ) will represent an examinee's ability level in a particular programming subject (e.g. arrays, binary trees, etc...). Ability is a latent variable (section 2.3.1) because it isn't directly observable, therefore it must be inferred from the observable, concrete data such as examinee responses.

The local independence of items states that an examinee's responses to items are independent of one another. This property of conditional independence is crucial to estimating examinee trait levels as we will see later on in this section.

Several IRT models have been developed over the years to address the different types of tests that exist, e.g. multiple choice exams, agreement questionnaires (Likert scale), etc... These models all seek to achieve the same goal, modelling the examinee's ability on some ability scale, but they differ in the number of parameters associated with each item. We shall note that we only consider unidimensional IRT models which deal with dichotomously scored items, i.e. scored as correct or incorrect, in a multiple choice question for instance. We now take a look at these different models in more detail.

The one-parameter logistic model

Every IRT model is defined by two elements: a set of item parameters, and a mathematical item response function. This function plots the probability that an examinee of a given ability will answer a particular item correctly. The one-parameter logistic (1PL) model is the simplest IRT model because in this model items are only characterized by one parameter: the difficulty parameter b_i, where the subscript i identifies item i. This has the effect of making the item response function quite simple.

$$P_i(\theta) = \frac{1}{1 + \mathrm{e}^{-(\theta - b_i)}} \tag{2.2}$$

Equation (2.2) shows the item response function for the 1PL model. θ is the examinee's ability level, $P_i(\theta)$ is the probability of answering item i at all ability levels, and as mentioned above, b_i is the item difficulty.

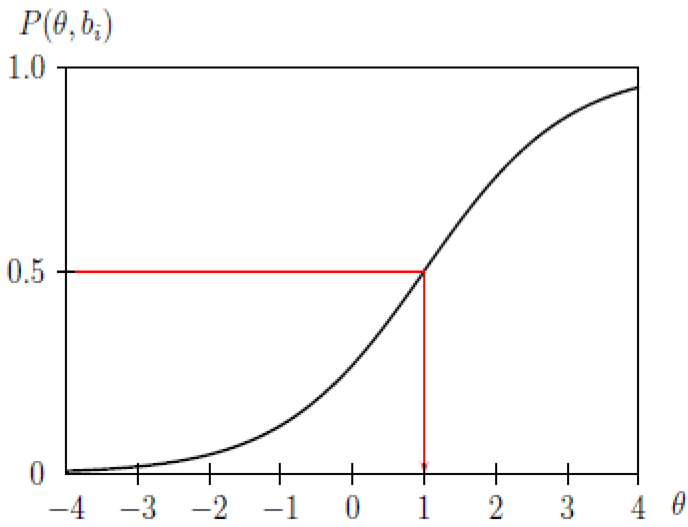


Figure 2.2: The item response function of the 1PL model. (Source:[10]).

Figure 2.2 shows the probability of answering an item correctly for all ability levels. In the 1PL model, the item difficulty is the point at which a correct response and an incorrect response are equally probable. In the figure this is shown in red, and in this case, the item has difficulty parameter $b_i = 1$. This highlights one of IRT's attractive properties, the fact that examinee ability and item difficulty are both measured on the same scale. The ability scale is a design choice, in this case it ranges from -4 to +4.

Ability (θ)	-4	-3	-2	-1	0	1	2	3	4
$P_1(\theta)$	0.007	0.018	0.047	0.119	0.269	0.5	0.731	0.881	0.953
$P_2(\theta)$	0.047	0.119	0.269	0.5	0.731	0.881	0.953	0.982	0.993

Table 2.1: Probabilities of a correct answer for two items in the 1PL model.

Table 2.1 shows the probability values for two 1PL items. $P_1(\theta)$ corresponds to the probability of answering item 1 (the item in figure 2.2) correctly. $P_2(\theta)$ corresponds to the probability of answering item 2 (with difficulty $b_2 = -1$) correctly. It can be seen that as the ability level of the examinee increases, so does the probability of him answering the item correctly. The difficulty parameter shifts the item response function to the left or to the right depending on its value.

Although the 1PL model provides a good basis for IRT it is rather simplistic and fairly limited. For instance, the model assumes that at low ability levels the examinee has close to no chance to answer the item correctly. However, in multiple choice questions there is always the option of guessing randomly. These existing limitations bring us to considering the next model.

The two-parameter logistic model

The two-parameter logistic (2PL) model builds upon the 1PL model by adding a new item parameter: the discrimination (a_i), where the subscript i identifies item i. Discrimination refers to an item's capacity to distinguish between examinees of different ability levels. Graphically, the discrimination parameter corresponds to the slope of the item response function, and typically it ranges from -2.8 to 2.8.

$$P_i(\theta) = \frac{1}{1 + \mathrm{e}^{-1.7a_i(\theta - b_i)}} \tag{2.3}$$

Equation (2.3) shows the item response function for the 2PL model. It is very similar to the equation of the 1PL model (Equation (2.2)), except for the inclusion of the discrimination parameter (a_i) and a constant of 1.7 to control the shape of the curve.

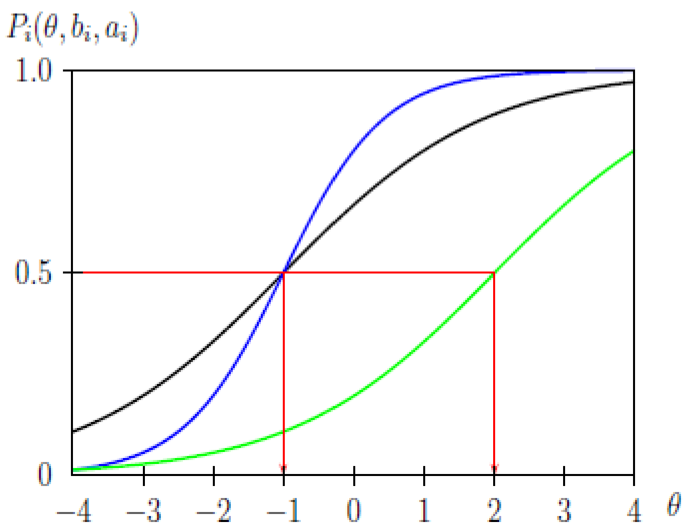


Figure 2.3: The item response functions of three items in the 2PL model. (Source:[10]).

Figure 2.3 shows the item response functions of three items in the 2PL model. As in the 1PL model, the item difficulty is still located where $P_i(\theta) = 0.5$, shown in the red lines. The item represented by the black curve and the item represented by the green curve both have the same discrimination, but different difficulty. As mentioned before, all this does is shift the item response function to the right or to the left, depending on which item you take as the reference point.

The black and blue curves illustrate the other scenario. The item represented by the black curve and the item represented by the blue curve have different discrimination, but identical difficulty. This has the effect of making the blue curve much steeper than the black one, thus affecting the probabilities over the ability scale. Indeed, the item represented by the blue curve discriminates quite well between respondents. Examinees of low ability have a much lower probability of answering the item correctly than examinees of higher ability. Compare this to the item represented by the black curve, where examinees of low ability still have a fair chance of getting the item correct.

The three-parameter logistic model

The three-parameter logistic (3PL) model takes into account the possibility of guessing a correct response to an item. This model is especially convenient for tests where multiple choice questions are present. In IRT, this parameter is called the pseudo-guessing or chance parameter, and it is denoted as c_i, where the subscript i identifies item i. Graphically, it corresponds to a lower asymptote, i.e. $P_i(-\infty) = c_i$. The guessing parameter does not vary as a function of the examinee's ability. Indeed, whether they be of low ability or high ability, examinees both have the same probability of guessing the correct answer to an item.

$$P_i(\theta) = c_i + (1 - c_i)\frac{1}{1 + \mathrm{e}^{-1.7a_i(\theta - b_i)}} \tag{2.4}$$

Equation (2.4) shows the item response function for the three-parameter logistic model (3PL). The addition of c_i defines a lower asymptote at that value, whereas $1 - c_i$ acts as a weighting factor towards the 2PL model equation (Equation (2.3)). Typically the pseudo-chance parameter ranges from 0 to 0.35, greater values being considered unacceptable. Lastly, if $c_i = 0$ then we are simply left with a normal 2PL model.

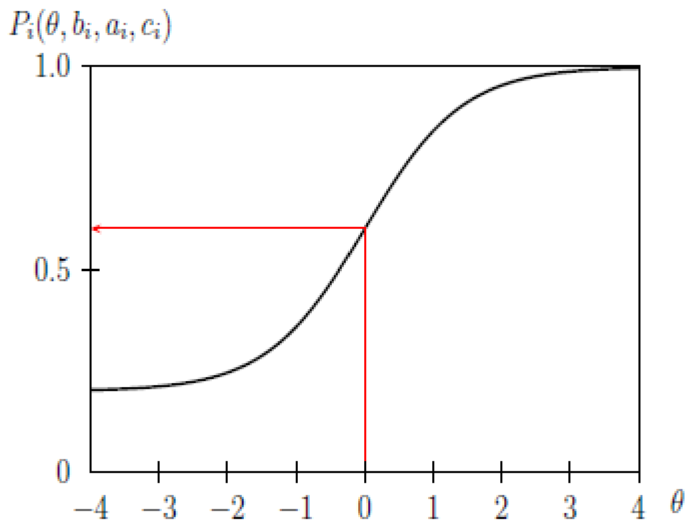


Figure 2.4: The item response function of the 3PL model. (Source:[10]).

Figure 2.4 shows the item response function of an item in the 3PL model. This item has parameters $a = 1.4$, $b = 0$ and $c = 0.2$. Now it can be seen that the guessing phenomenon is taken into account by this IRT model. Indeed, at the lowest possible ability ($\theta = -4$), the probability of a correct answer is $P(-4) = 0.200059$, which is very close to the guessing parameter of the item.

Something to note is that $P_i(b_i) \neq 0.5$, i.e. the probability of a correct response at the ability level equal to the item difficulty is no longer 0.5. Instead, we have $P_i(b_i) = c + \frac{1-c}{2}$, and in figure 2.4 we have $P(0) = 0.6$. If we consider a multiple choice question, adapted to the examinee's ability level, then it makes sense that the probability of them getting it correct would be greater than 0.5, to account for the possibility of getting it right merely through guessing.

Item information

In section 2.2, when discussing item selection algorithms, we mentioned the maximum information method as a possible implementation. This method relies on the IRT concept of item information.

In psychometrics and statistics, the term *information* is defined as the reciprocal of the precision with which a parameter can be estimated[9]. Therefore, item information is the precision in the ability estimate that the item provides, at all ability levels. It is also an indication of the quality of the item in terms of how well that item can discriminate between several respondents.

The item information function for the 1PL model is calculated as

$$I(\theta) = P_i(\theta)Q_i(\theta),$$

where $Q_i(\theta) = 1 - P_i(\theta)$.

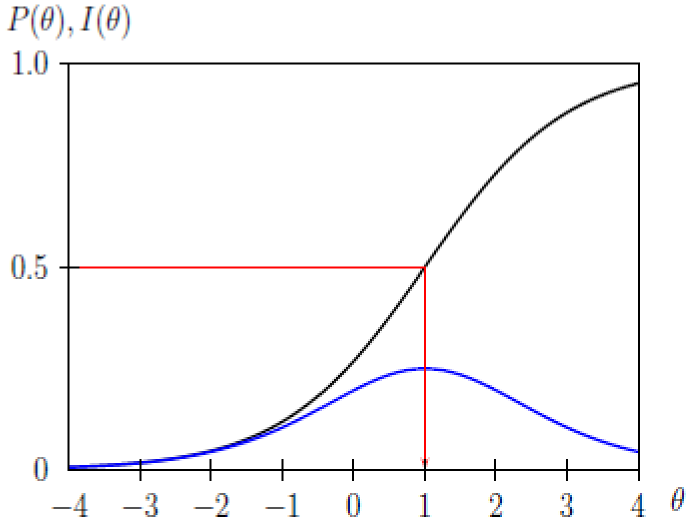


Figure 2.5: Item response function and item information function for the 1PL model. (Source:[10]).

In figure 2.5, two curves are plotted. The black curve is the item response function of an item, and the blue curve is the associated information function for that item. In the 1PL model, the maximum value of item information occurs where the probability of a correct answer and the probability of an incorrect answer are both equal to 0.5. This point is indicated by the red line. If we recall earlier, this point also represents the difficulty of the item, i.e. item parameter b_i. Thus, the item provides the most information for those examinees whose ability is equal to the difficulty of the item, 1 in this case. This means that administering this item will give more precise ability estimates for examinees whose true ability is at that particular level. Presenting this item to examinees not at that particular level, examinees of ability -2 for instance, will not yield very much precision to subsequent ability estimates.

The item information function for the 2PL model is calculated as

$$I(\theta) = a_i^2 P_i(\theta)Q_i(\theta),$$

where $Q_i(\theta) = 1 - P_i(\theta)$. In the 2PL and 3PL models, the discrimination parameter, a_i, plays a significant role in the function, as it appears squared in the function.

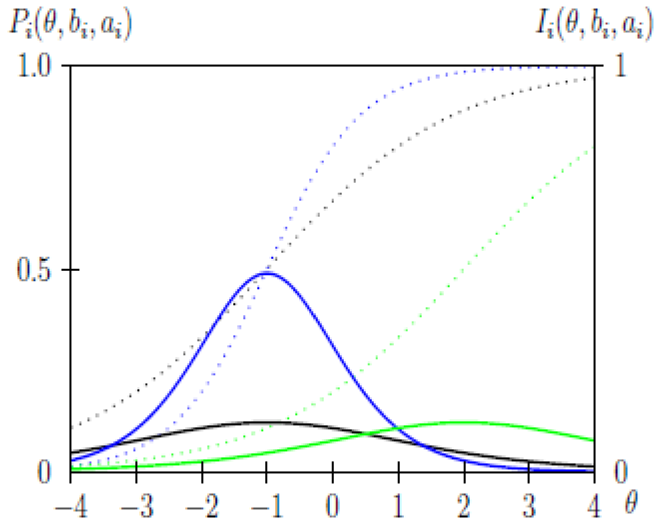


Figure 2.6: Item response functions and item information functions for three items in the 2PL model. (Source:[10]).

Figure 2.6 shows three 2PL item response functions, in dotted lines, matched in color with the corresponding item information functions in solid lines. Like in the 1PL model, items still reach their maximum information at the point where ability is equal to the difficulty of the item. However, the amount of information provided at that ability level can now vary depending on how large the discrimination parameter is.

The items represented by the black and blue curves both have the same difficulty parameter. But, the item represented by the blue curve has a higher discrimination parameter, and therefore this affects the item information function. Higher discrimination values lead to more item information, whereas lower discrimination values make the item less informative.

The items represented by the black and green curves both have the same discrimination parameter, so the maximum information value will be the same for these items. However, these items do not share the same difficulty parameter. All this does is shift the curve along the ability axis, thus changing the location of maximum information for that item.

The item information function for the 3PL model is calculated as

$$I(\theta) = a_i^2 \cdot \frac{(P_i(\theta) - c_i)^2}{(1 - c_i)^2} \cdot \frac{Q_i(\theta)}{P_i(\theta)},$$

where $Q_i(\theta) = 1 - P_i(\theta)$.

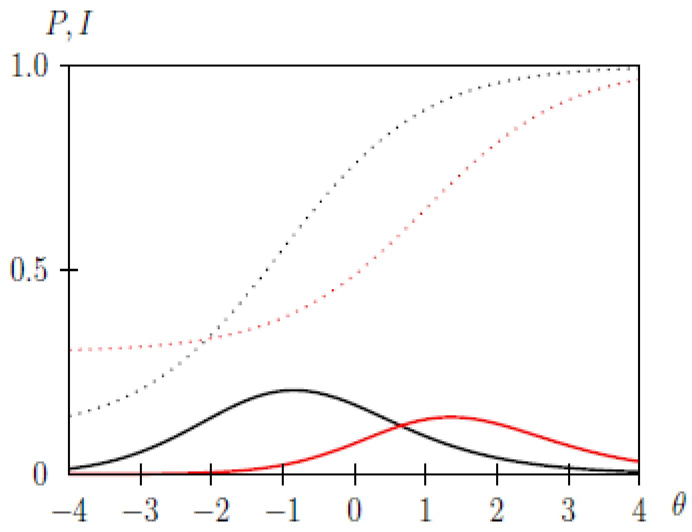


Figure 2.7: Item response functions and item information functions for two items in the 3PL model. (Source:[10]).

Figure 2.7 shows two 3PL item response functions, in dotted lines, matched in color with the corresponding item information functions in solid lines. In the 3PL model, the maximum of item information functions is no longer at the point where ability is equal to the difficulty of the item. Here, the guessing or pseudo-chance parameter (c_i) plays a role in the shape of the item information function. Higher guessing parameters lead to less item information, whereas lower guessing parameters lead to more item information. For instance, the item represented by the black curve has $c_i = 0.1$, and the item represented by the red curve has $c_i = 0.3$, which explains why the item represented by the black curve yields more information.

Estimating the ability

In section 2.2, when discussing scoring algorithms, we saw that the two most common methods for ability estimation were *maximum likelihood estimation* and *Bayesian estimation*.

In the *maximum likelihood estimation* method, we need to define a likelihood function in terms of the ability level (θ) we are trying to estimate:

$$L(\theta|\mathbf{u}) = L(\theta|u_1, ..., u_n) = \prod_{i=1}^{n} P_i(\theta)^{u_i}(1 - P_i(\theta))^{(1-u_i)},$$

where $\mathbf{u} = (u_1, ..., u_n)$ is called the response vector for an examinee, that is $u_i = 1$ if the examinee answers the i^{th} item correctly, and $u_i = 0$ if the examinee answers the i^{th} item incorrectly. $P_i(\theta)$ corresponds to the probability of answering the i^{th} item correctly when the ability level is θ, and thus $1 - P_i(\theta)$ gives the probability of answering the i^{th} item incorrectly when the ability level is θ.

Now that the likelihood function is defined, we can apply maximum likelihood estimation to find the ability level which is most likely given the examinee's response vector. Let us illustrate with a very simplistic example where ability levels are discrete values between -1 and $+1$. We would iterate through these ability levels and compute the following values, for example:

$$L(\theta = -1|\mathbf{u}) = 0.001$$
$$L(\theta = +0|\mathbf{u}) = 0.017$$
$$L(\theta = +1|\mathbf{u}) = 0.058$$

The likelihood function is maximized when $\theta = +1$, and so this is the maximum likelihood estimate for θ. In a CAT, and based on the examinee's response vector $\mathbf{u}$, the system would assign $+1$ as the ability level for that examinee.

In the *Bayesian estimation* method, the CAT maintains a *knowledge distribution* $P(\theta)$, which represents the probability that the examinee's ability is θ. In the absence of any additional information, the CAT considers the examinee's initial knowledge distribution to be a uniform distribution.

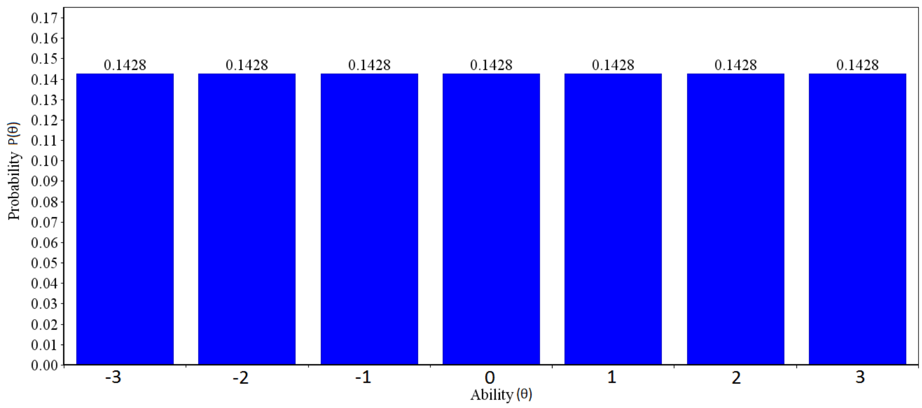


Figure 2.8: Initial examinee knowledge distribution.

For example, figure 2.8 shows the initial examinee knowledge distribution in a CAT having discrete ability levels ranging from -3 to 3. Continuous knowledge distributions are certainly possible as they allow for, in theory, infinitely more ability levels. However, they are more complex and require the use of integration to compute probabilities, thus for the purposes of illustration, we will only consider discrete knowledge distributions.

The *Bayesian estimation* method relies on Bayesian inference to derive the posterior knowledge distribution according to Bayes' rule:

$$P(\theta|\mathbf{u}) = \frac{P(\mathbf{u}|\theta)P(\theta)}{P(\mathbf{u})},$$

where, again, $\mathbf{u}$ is the examinee's response vector and θ corresponds to the possible ability levels.

The posterior distribution is the result of updating the prior knowledge distribution, $P(\theta)$, with observed data, $P(\mathbf{u}|\theta)$, i.e. the examinee's response pattern. We can express this using the likelihood function:

$$P(\theta|\mathbf{u}) \propto L(\theta|\mathbf{u}) \cdot P(\theta)$$

After computing the posterior knowledge distribution, the CAT can estimate the ability estimation for the examinee. This is equal to the mode of the knowledge distribution, i.e. the ability associated with the highest probability value.

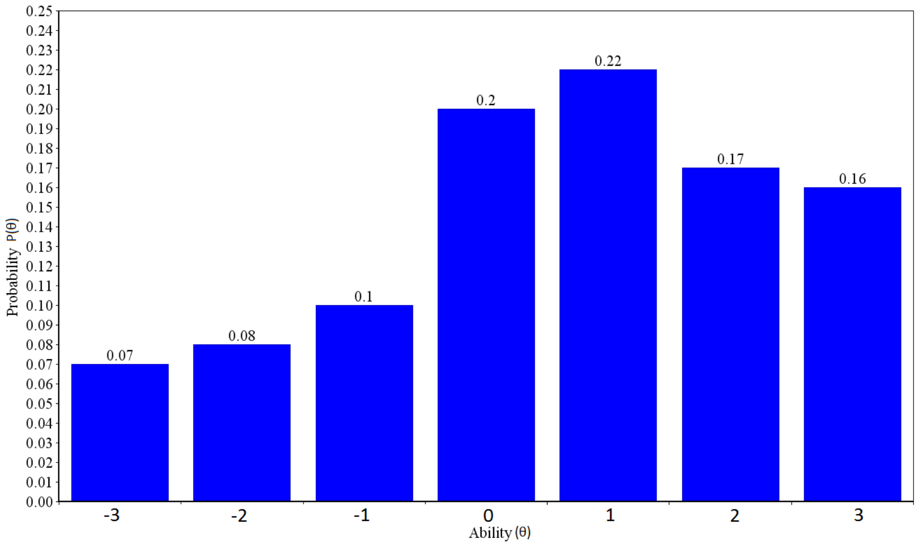


Figure 2.9: Examinee knowledge distribution after answering an item correctly.

For example, figure 2.9 shows the knowledge distribution of an examinee after being shown an item of medium difficulty and answering it correctly. It can be seen that lower ability levels have become less likely, whereas higher ability levels are now more probable.

The ability level associated with the highest probability is $\theta = 1$, thus this becomes the estimated ability. Over time, after the examinee answers more items, the estimation will become associated with even higher probability values. These probabilities indicate how confident the CAT is in that particular ability estimation.

2.4 Summary

In this section, the relevant background literature and theory for this project was discussed.

Firstly, we discussed types of computer based assessment and how they differ from regular assessment techniques. We then looked at an improvement over traditional computer tests in the form of computerized adaptive testing (CAT), where the difficulty of the questions in the test is adapted to fit the student's ability.

We provided an overview of the probability concepts necessary to understand Item Response Theory, and explained in quite some detail the techniques behind Item Response Theory. These will become the basis of one of the adaptive difficulty algorithms in jSCAPE. In the context of Item Response Theory, we have seen three models designed to calculate the probabilities of answering questions correctly, and knowledge estimation techniques in those particular models.

In the next chapter we take a look at related work which will help us in developing jSCAPE. We focus on how these works approach the design of some of the components of such a system, i.e. providing exercises, exercise generation, collecting statistical data, adapting the difficulty, etc...

Chapter 3

Related Work

Web-based/Computer based education and adaptive web-based assessment systems are a “hot” research area, and as a result, numerous tools, environments and infrastructures have emerged over the years. There are common features to all, however some distinguish themselves by having not so common features. Automated exercise generation in these tools is usually non-existent or very limited. Moreover, the tools are more focused on assessing students rather than self-assessment, i.e. students take tests which count towards their final grade on these systems.

There are many components involved in this project, two of the more important ones are adaptive difficulty and automated generation of exercises, so there are many tools which exist which do one or the other, very rarely both.

In this section we look at related software and evaluate them with respect to the objectives listed at the beginning of the development of jSCAPE.

3.1 Environment for Learning to Program

Environment for Learning to Program (ELP) is an interactive web based environment for teaching programming to first year Information Technology students at Queensland University of Technology (QUT).

3.2 CourseMarker

CourseMarker is a re-design of Ceilidh, a computer based assessment system used at the University of Nottingham for 13 years. Ceilidh was quite a complete system, providing coursework, the management of modules and the presentation of module content.

3.3 AEGIS

The Automatic Exercise Generator with Tagged Documents based on the Intelligence of Students (AEGIS)

3.4 Programming Adaptive Testing

PAT[11] is a web-based adaptive testing system, developed in ActionScript/Flash, for assessing students' programming knowledge in Greek high schools.

The assessment is carried out by presenting students with 30 questions from various chapters of the introductory programming course. Some of the questions supported by the PAT system are true/false questions, multiple choice questions, gap filling in a piece of code, questions involving diagrams and questions where one has to determine the behaviour of a piece of code.

In PAT, questions are classified into different difficulty categories. Category A is for easy questions, category B is for intermediate questions and category C is for difficult questions. PAT seeks to adapt the difficulty of the questions to the student's ability, by choosing questions of the appropriate difficulty category.

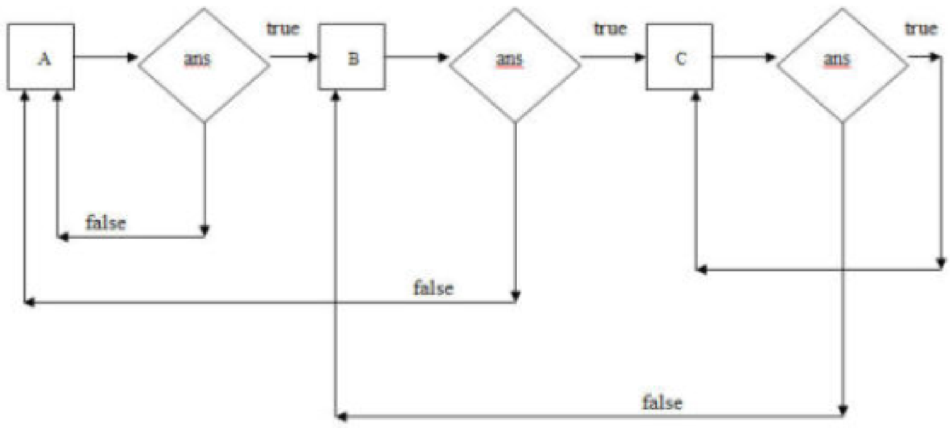


Figure 3.1: Adaptive sequence of questions in PAT. (Source:[11])

Figure 3.1 shows the possible adaptive sequences. This algorithm is quite simplistic, every correct answer leads to a promotion to the next level of difficulty until no further promotions are possible. Likewise, every incorrect answer leads to a demotion to a lower level of difficulty until no further demotions are possible.

At the end of the test, the system shows the student's total number of correct answers out of 30 and how well the student performed on each chapter. Also, PAT classifies the student into one of three programming skill levels based on their final score and a weighted score, where the difficulty of the questions answered correctly is considered. These results are available to both students and teachers so that they can be used to improve performance later on in the school year.

We feel that the adaptive algorithm increases the difficulty of questions too quickly and doesn't take into account guessing or possible slip ups from students. This limitation can be circumvented by, for instance, requiring a number of correct answers at the current difficulty level before progressing to the next one.

PAT only provides assessment at specific times throughout the school year and no opportunity for students to practice and self-assess in their own time. In addition, it isn't possible for teachers to upload their own questions to the system. The question bank remains static and contains 443 questions. Lastly, the authors of PAT admit that the statistical data available to students and teachers is fairly limited, and that improvements should be pursued in future work.

3.5 Adaptive Self-Assessment Master

Adaptive Self-Assessment Master (ASAM) is an extension to CourseMarker, which improves upon it by administering questions which are suited to the student's ability.

3.6 SIETTE

SIETTE[12] (System of Intelligent Evaluation Using Tests for Tele-education) is a web based environment for generating and constructing adaptive tests. It has been used with great success in courses from the computer science engineering school, the telecommunication engineering school and the philosophy faculty, all at the University of Malaga, Spain.

SIETTE is a vast system, and at the time of publication (2005) it contained information about 15000 student test sessions, and the knowledge base contained 84 subjects, 1852 topics, 3820 question and 220 tests.

SIETTE is designed to be used by both students and teachers. Teachers use the system to create tests, define the subject topics, the questions and their parameters. Students use the system to take the tests specified by the teachers. The tests can be used for self-assessment, where the correction is shown immediately after the student has answered. Hints and more extensive feedback are also available in this mode. Or, the tests can be used as exams, where the score counts towards the student's final grade. In this mode, hints and feedback aren't provided. It is important to note that tests have a fixed number of questions, thus, new tests must be created every time a student runs out of practice.

As mentioned earlier, SIETTE constructs adaptive tests, therefore, when a student answers a question, his ability is re-estimated and the next question is selected accordingly. Implementation of this is done by using item response theory in the computerized adaptive testing framework.

SIETTE uses the three-parameter logistic (3PL) model and measures the student's knowledge in terms of a discrete random variable θ, which ranges from 0 to $K-1$, where K is the number of discrete knowledge levels. When it comes to creating items, the guessing parameter c is determined automatically, whereas the other two parameters must be entered by the teacher. The discrimination parameter (a) must be a number between 0.5 and 1.5. The difficulty parameter must be a natural number between 0 and $K-1$. A few years after the SIETTE paper was published, the authors added an item calibration tool because teacher estimates of item parameters are never very accurate.

To estimate students' knowledge level, SIETTE uses the Bayesian estimation method (section 2.3.4) with a knowledge distribution per student, per topic. Also, SIETTE provides teachers with the option of choosing different item selection procedures for tests, such as random selection, difficulty-based selection and bayesian selection.

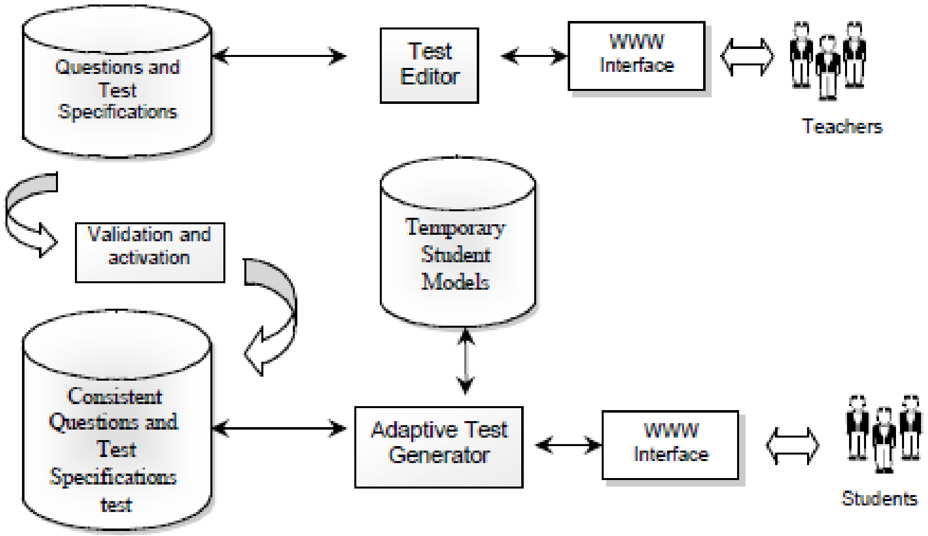


Figure 3.2: SIETTE Architecture. (Source:[1])

Figure 3.2 gives on overview of the SIETTE architecture. The system is comprised of several components[13]:

- The *knowledge base*: where tests, topics and questions are stored. Some supported question types are true/false, multiple choice, multiple response and fill-in-the-gap. More interactive questions also exist, implemented as Java applets, where one has to color parts of a map, or move around objects so that they appear chronologically, for example.
- The *student model repository*: a collection of student models, where information about students' knowledge level estimation, which questions they answered, etc... is stored.
- The *student workspace*: a web interface where students take tests.
- The *test editor*: a tool where teachers can define tests, topics, questions.
- The *result analyzer*: a tool which presents graphical data about students' performance, knowledge estimation levels, etc...
- The *item calibration tool*: a module used to calibrate items by determining the item parameters (difficulty, discrimination and pseudo-chance).

SIETTE is a large and complex system, containing many useful features relevant to the area of web-education, and going through all of these wouldn't be possible. Since SIETTE has been used to such success in university courses we decide to inspire ourselves from this system, especially the implementation of the adaptive difficulty component. Details about the algorithms used in SIETTE, and hence jSCAPE, can be found in section 5.XX, with Java code to illustrate.

3.7 Summary

We have looked at some of the relevant work in the field of computer based education and assessment. We saw that SIETTE provided many of the features we set out to replicate in jSCAPE, therefore particular parts of our implementation will be inspired by SIETTE.
SIETTE the most complete system we have come across while doing research for this project.
Moreover, examining these existing solutions has given us insight into the most common features available in these types of systems.
We hope to have shown in this section that developing such systems is quite difficult since the depth of some features can be pushed quite far. Instead we decide to create a system which we deem as complete, having the main features present in the system but only the very basics of the feature, e.g. feedback is simple as opposed to complex feedback which would be more useful.
In the next chapter we present the system developed as part of this project: jSCAPE.

Chapter 4

The jSCAPE System

The jSCAPE system is designed for two distinct groups of users: students and teachers/lecturers. This separation of roles lead to the development of the main application for students, and an administrator tool for teachers/lecturers.

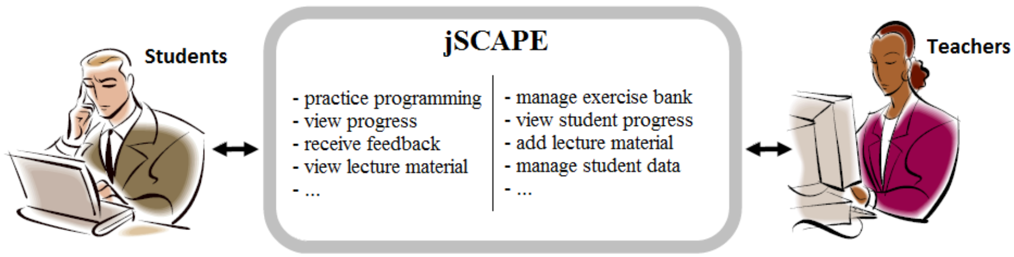


Figure 4.1: Use case diagram of the jSCAPE system.

Figure 4.1 shows some of the main capabilities of the jSCAPE system. Students can practice their understanding of programming concepts by answering exercises provided by the lecturers, and receive feedback while doing so. In addition, students can track their progress by viewing various graphs and charts of their performance on particular exercise categories. Finally, students can access lecture notes and website links provided by the teacher.

Teachers can manage the exercise bank, whether it be adding exercises manually or automatically generating new ones based on templates. They can keep track of their students' progress and thereby identify any difficulties particular students are having. Finally, teachers are responsible for adding lecture material, website links and creating student profiles to store in the database.

In the rest of this chapter we take a closer look at the current available features of jSCAPE.

At the time of writing this report, we would like to note that the screen shots of the application do not represent the final version of jSCAPE, in particular, the graphics and logos haven't been finalized.

4.1 Student view

4.1.1 Login screen

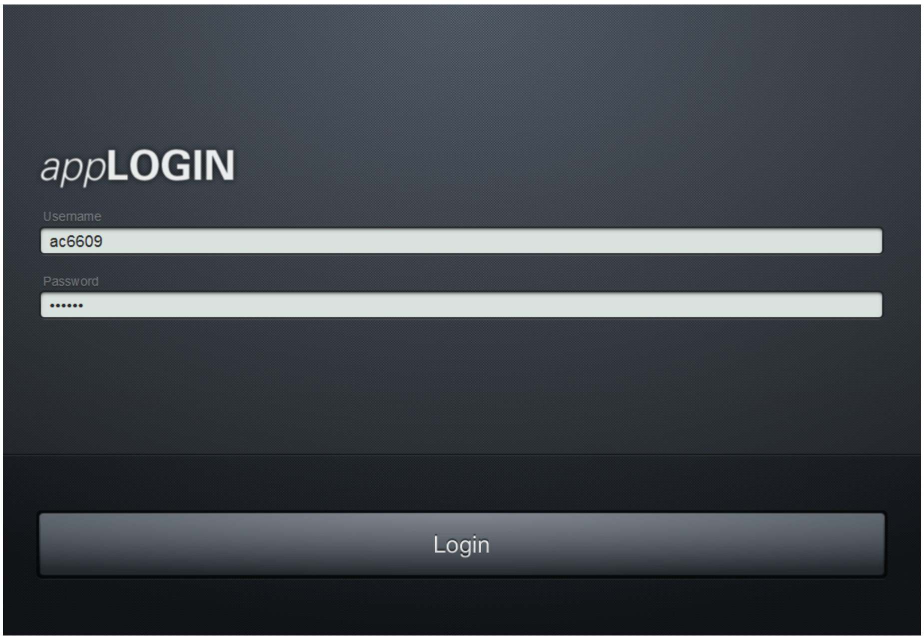


Figure 4.2: The jSCAPE login screen.

For a student to use jSCAPE, they need to be in possession of login credentials, usually acquired by asking the appropriate teacher or lecturer. A connection to the jSCAPE system will be rejected if the entered login details are incorrect. Otherwise, the student can proceed to jSCAPE and access its features.

4.1.2 Practising programming

One of the main features of jSCAPE is the ability to practise programming through answering exercises. Selecting the Practice tab brings the student to a window where exercise categories, defined by the teacher, are displayed. These categories exist to separate exercises so that students can focus on practising one particular concept at a time.

Figure 4.3 gives an overview of the Practice tab in jSCAPE. In this case, seven exercise categories have been defined by the teacher: Arrays, Loops, Syntax, Conditionals, Binary Trees, Strings and Objects. Order is irrelevant, students simply choose what type of exercise they want to practice.

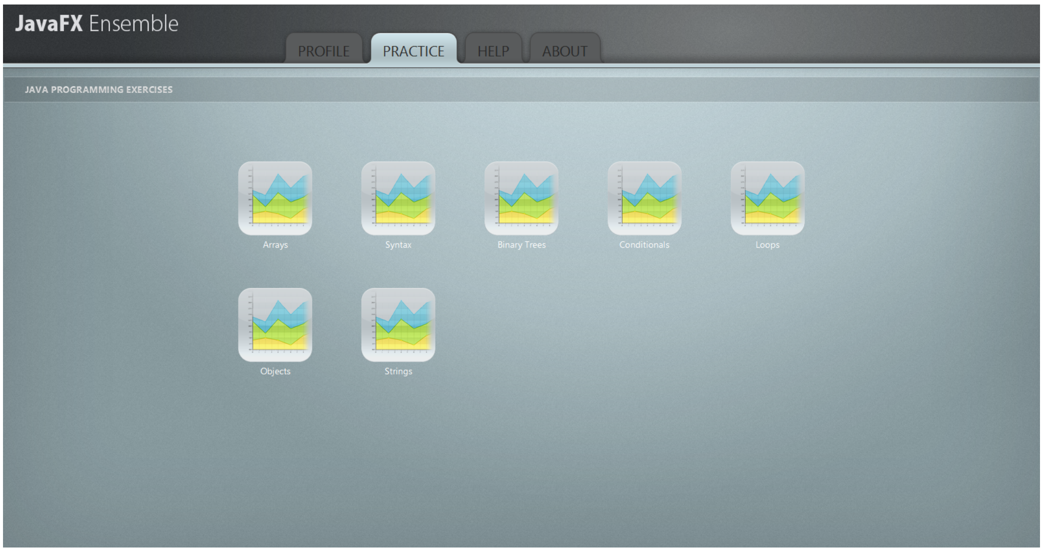


Figure 4.3: An overview of the Practice tab in jSCAPE.

Clicking one of the exercise categories will bring the student to a new window, with an exercise and some helpful information about the chosen exercise category. Figures 4.4 and 4.5 give examples of what this exercise view can look like.

In the case of the binary tree exercise (figure 4.4), exercise data, in the form of a binary tree, is displayed on the left of the window. On the right side of the window is the exercise itself, in this case it asks what should be printed if the binary tree is traversed using the in-order algorithm, and gives four options to choose from. It can be seen that the student has attempted to answer the exercise and has selected the wrong answer. This is indicated to the student in the form of “wrong answer” in red. A correct answer would display “correct answer” in green. Moreover the solution to the exercise is provided immediately after the student has answered it.

Example exercises

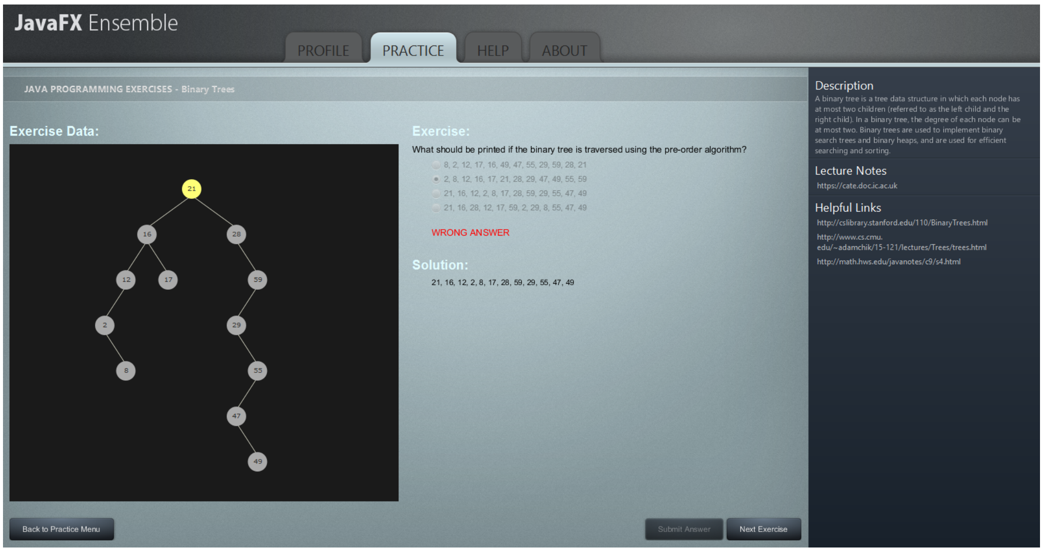


Figure 4.4: The Practice tab view showing an exercise on binary trees.

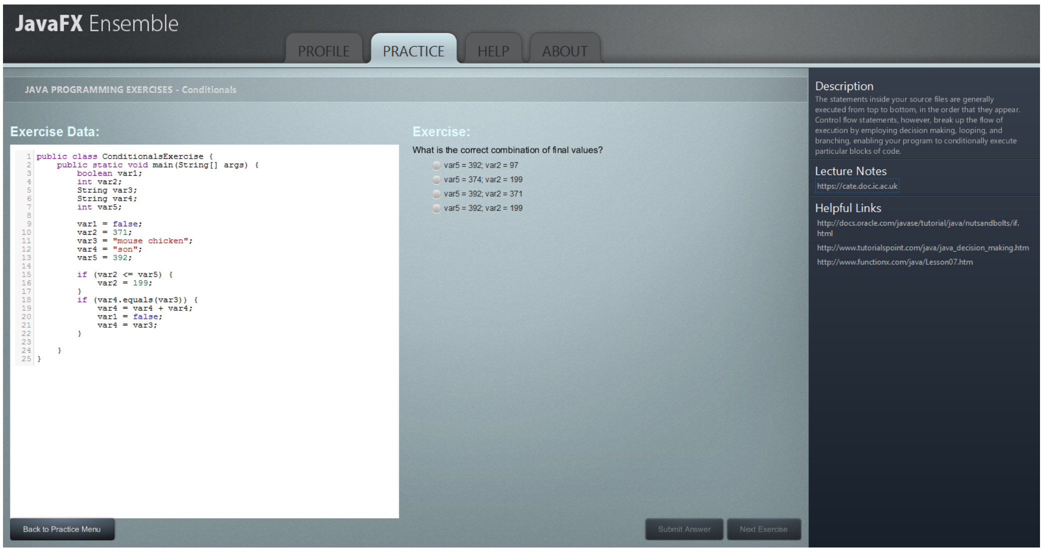


Figure 4.5: The Practice tab view showing an exercise on conditionals.

In the case of the exercise on conditionals (figure 4.5), exercise data, in the form of a code fragment, is displayed on the left of the window. On the right side of the window is the exercise itself, in this case it asks the student to examine the code and to determine the final values of two variables, and provides again four options to choose from.

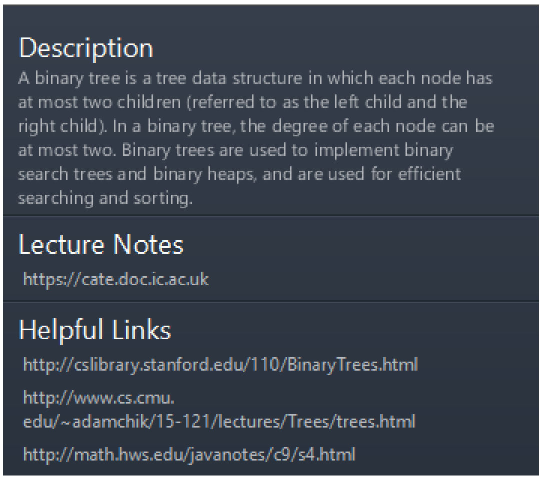


Figure 4.6: An example sidebar in the Practice tab.

On the far right of every exercise, there is a dark blue sidebar which displays a description of the programming concept or construct being practised, links to university or course lecture notes and some other websites on the Internet if further help is needed. An example sidebar is shown in figure 4.6, in this case the sidebar for the “Binary Trees” exercise category.

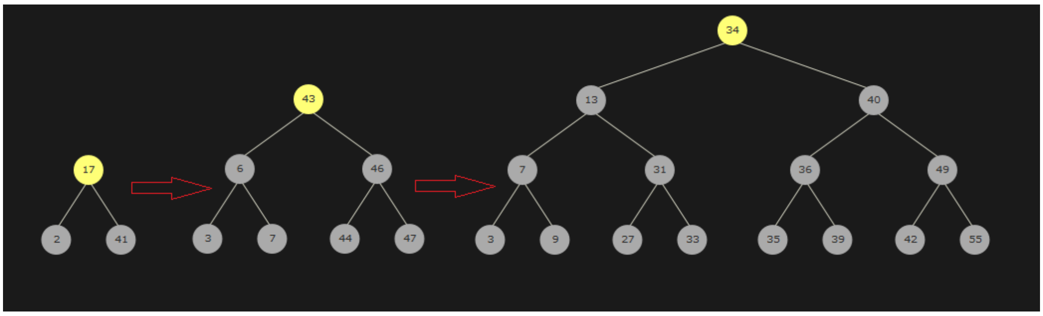


Figure 4.7: Progression of binary tree exercises.

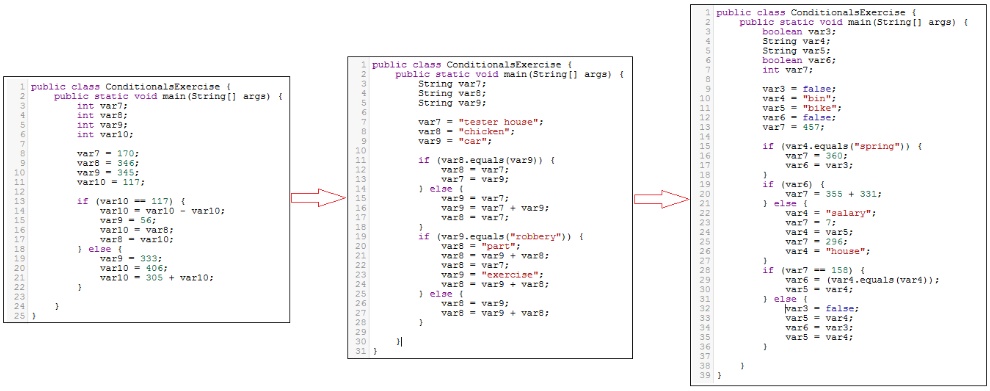


Figure 4.8: Progression of conditionals exercises.

4.1.3 Tracking progress through statistical data

After a successful login the student lands on the Profile tab which presents information about the student, as well as statistical data on the student's performance and usage of the system.

```java
public class ConditionalsExercise {
    public static void main(String[] args) {
        int var7;
        int var8;
        int var9;
        int var10;

        var7 = 170;
        var8 = 346;
        var9 = 345;
        var10 = 117;

        if (var10 == 117) {
            var10 = var10 - var10;
            var9 = 56;
            var10 = var8;
            var8 = var10;
        } else {
            var9 = 333;
            var10 = 406;
            var10 = 305 + var10;
        }

    }
}
```

```java
public class ConditionalsExercise {
    public static void main(String[] args) {
        String var7;
        String var8;
        String var9;

        var7 = "tester house";
        var8 = "chicken";
        var9 = "car";

        if (var8.equals(var9)) {
            var8 = var7;
            var7 = var9;
        } else {
            var9 = var7;
            var9 = var7 + var9;
            var8 = var7;
        }
        if (var9.equals("robbery")) {
            var8 = "part";
            var8 = var9 + var8;
            var8 = var7;
            var9 = "exercise";
            var8 = var9 + var8;
        } else {
            var8 = var9;
            var8 = var9 + var8;
        }

    }
}
```

```java
public class ConditionalsExercise {
    public static void main(String[] args) {
        boolean var3;
        String var4;
        String var5;
        boolean var6;
        int var7;

        var3 = false;
        var4 = "bin";
        var5 = "bike";
        var6 = false;
        var7 = 457;

        if (var4.equals("spring")) {
            var7 = 360;
            var6 = var3;
        }
        if (var6) {
            var7 = 355 + 331;
        } else {
            var4 = "salary";
            var7 = 7;
            var4 = var5;
            var7 = 296;
            var4 = "house";
        }
        if (var7 == 158) {
            var6 = (var4.equals(var4));
            var5 = var4;
        } else {
            var3 = false;
            var5 = var4;
            var6 = var3;
            var5 = var4;
        }

    }
}
```

Figure 4.9: Progression of conditionals exercises.

Figure 4.10: An overview of the Profile tab in jSCAPE.

Figure 4.10 shows the Profile tab after the student has logged in to the system. Profile information for the student is listed on the left hand side, in the light-blue rectangle. This information includes the student's first name, last name, user name, which class the student is in, the last time the student logged in, and the last time the student answered an exercise.

The main part of the Profile tab is split horizontally between statistical data in the form of pie charts and tables, and graphical data in the form of bar charts.

Figure 4.11 shows the performance of the student in a particular exercise category, in this case "Arrays". In the example, the student has gotten 60% of array exercises correct and thus 40% of them wrong. The student can view the performance pie chart for other exercise categories by changing the selected category in the combo box.

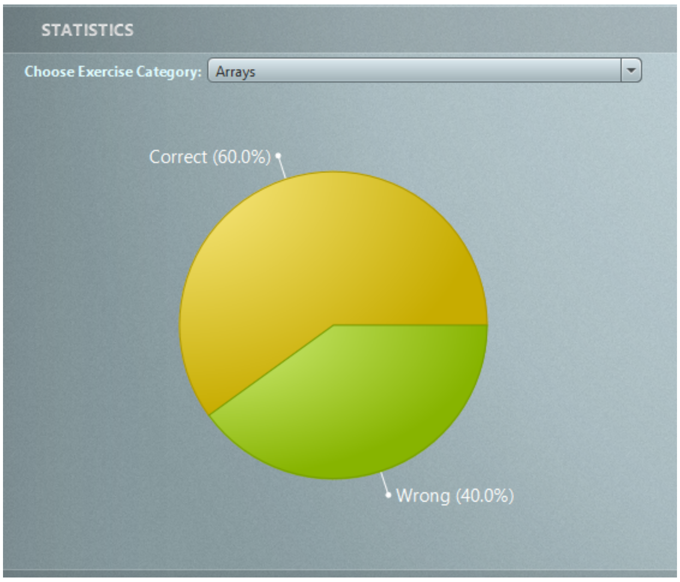


Figure 4.11: Pie chart statistics for exercise category.

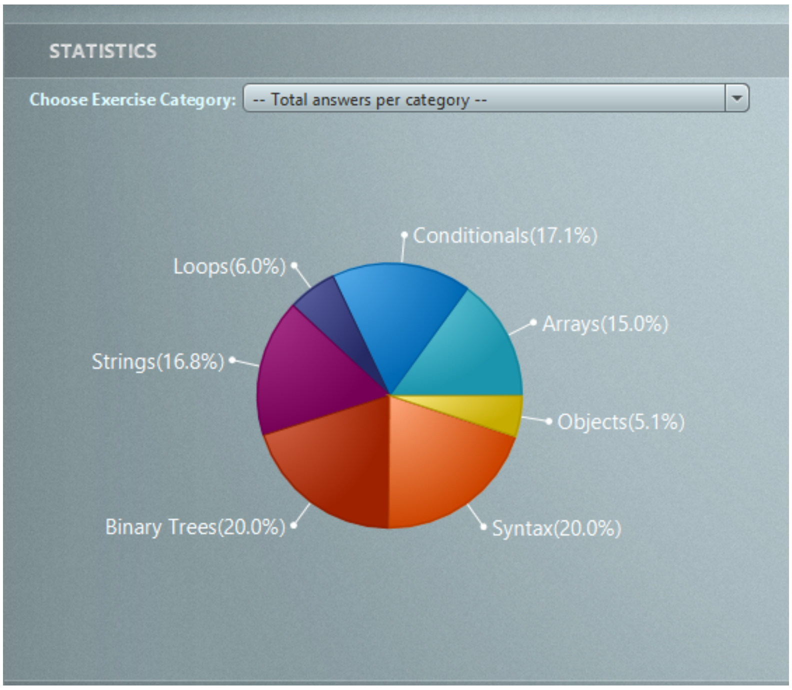
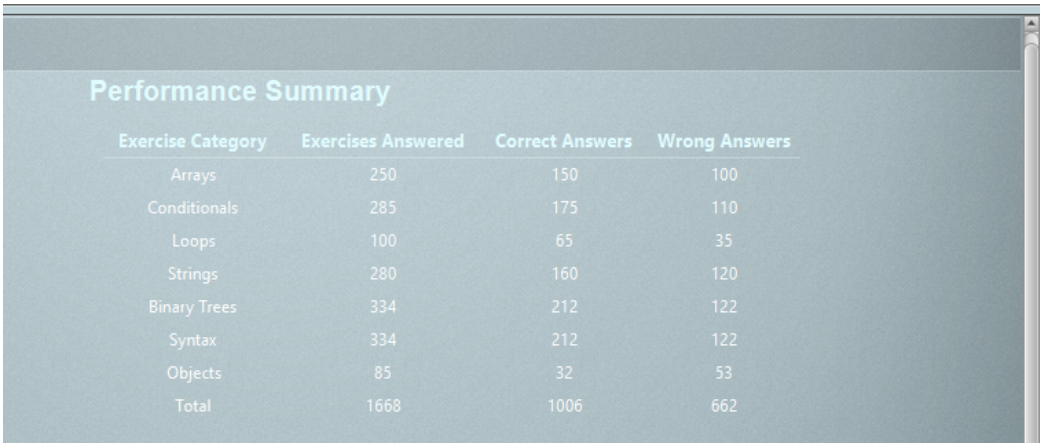


Figure 4.12: Pie chart statistics for distribution of answers.

Another type of pie chart available in jSCAPE can be seen in figure 4.12. This pie chart shows the distribution of answers per exercise category. This is a useful feature when a student is trying to get a balanced amount of practice in all exercise categories.

Next, performance data is presented to the student in the performance summary table, shown in figure 4.13. In this table, there is a row for every exercise category and a row for the total of each column. Each row contains the number of exercises answered, the number of correct answers and the number of wrong answers associated with a particular exercise category.



Performance Summary

Exercise Category	Exercises Answered	Correct Answers	Wrong Answers
Arrays	250	150	100
Conditionals	285	175	110
Loops	100	65	35
Strings	280	160	120
Binary Trees	334	212	122
Syntax	334	212	122
Objects	85	32	53
Total	1668	1006	662

Figure 4.13: Performance summary table.

In the lower half of the Profile tab there is the possibility to view performance data in the form of stacked bar charts.

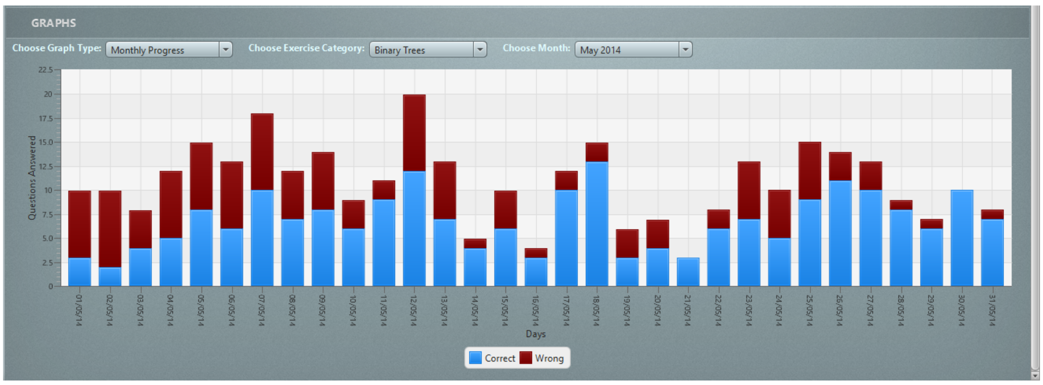


Figure 4.14: Graph data of monthly progress.

Figure 4.14 shows the monthly progress of a student for the month of May 2014 and for the exercise category "Binary Trees". The number of correct answers (in blue) and wrong answers (in red) are graphed for each day where the student answered exercises. The student can view his monthly progress in other exercise categories and other months by manipulating the appropriate combo boxes. This historical data goes back to the first month in which the student answered an exercise.

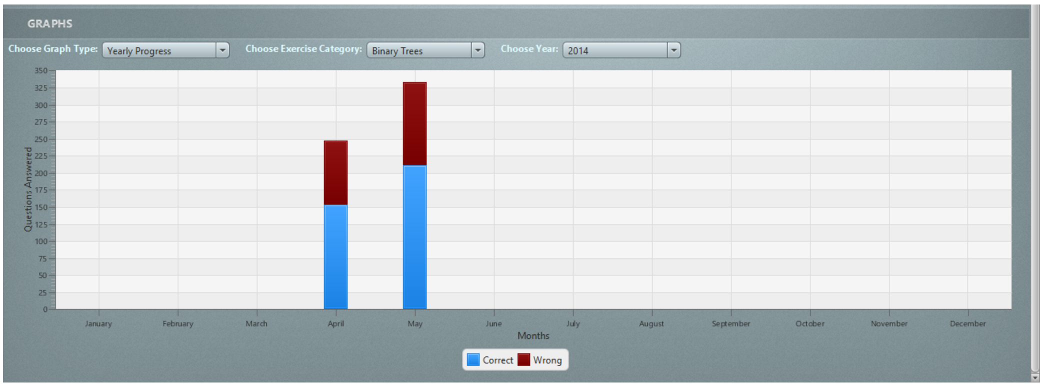


Figure 4.15: Graph data of yearly progress.

Figure 4.15 shows the yearly progress of a student in 2014 for the exercise category "Binary Trees". For each month where the student answered exercises, a stacked bar can be found containing the total number of correct answers (in blue) and the total number of wrong answers (in red) for that particular year and exercise category. The student can view his yearly progress in other exercise categories and other years by manipulating the appropriate combo boxes. This historical data goes back to the year in which the student first started answering exercises.

4.2 Teacher view

The teacher's main access to the system is through the jSCAPE admin tool. Essentially it provides an interface to the database where all information about students, performance, exercise categories and exercises is stored. This tool was developed to allow teachers, not familiar with SQL, to still be able to retrieve useful data about students in a presentable way and to facilitate management of the exercise bank.

4.2.1 Tracking student progress

Figure 4.16: An overview of the Analyze tab in the jSCAPE admin tool.

The jSCAPE admin tool provides teachers with the ability to track student progress and performance over time. Figure 4.16 gives an overview of the Analyze tab, where statistical data about selected students can be displayed. The information displayed is identical to that displayed in the jSCAPE Profile tab (section 4.1.3). On the left hand side of the window, the light blue box contains options to filter which data is displayed in the main window. A close up of the filter options is shown in figure 4.17.

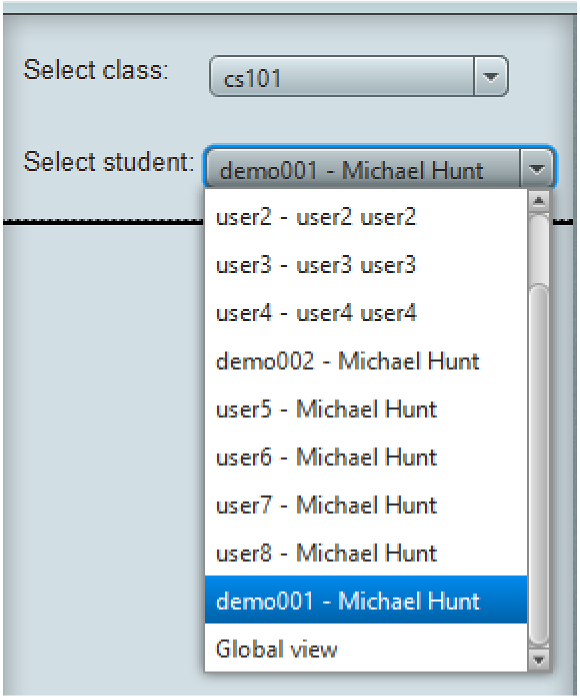


Figure 4.17: Selection possibilities in the Analyze tab.

The jSCAPE system includes support for multiple classes to allow for both the separation of students and the separation of exercises available to a class. A teacher can select a class to view statistics about those students taking the class. This will update the list of students in the combo box, allowing the teacher to focus his attention on the performance of one particular student.

Selecting a student will show their profile information in the light blue window, along with the date of their last login, and the date of their last exercise answered. In addition, the pie charts, performance table and progress graphs will be updated to reflect the performance of the selected student. Finally, there is an option to obtain a global view of the class' performance by selecting the "Global view" option.

Student Name	Exercises Answered	Correct Answers	Correct Percentage	Wrong Answers	Wrong Percentage
demo001	334	212	63.47	122	36.53
demo002	334	212	63.47	122	36.53
user5	334	212	63.47	122	36.53
user6	334	212	63.47	122	36.53
user7	334	212	63.47	122	36.53
user8	334	212	63.47	122	36.53

Figure 4.18: Global statistics view of a class.

Figure 4.18 shows the table that is displayed after selecting the global view option. This table shows all the students who have answered exercises in a particular exercise category. In the example above, the data shown is for the "Syntax" exercise category. The student user names are listed along with the number of exercises they have answered, and a detailed breakdown of the number of correct and wrong answers in terms of raw values and percentages.

There is a combo box to select which exercise category to display, but this isn't shown in the picture to minimize the size of it. The global view feature is useful for teachers to identify which students may be facing difficulties. They can then select the student in the Analyze tab to get more detailed statistics and information about the student's progress.

4.2.2 Managing the exercise bank

A central feature of jSCAPE is providing programming exercises to students. The Exercise tab of the admin tool allows teachers to manage the exercise bank and perform functions such as adding new exercise categories, viewing existing exercises, adding new exercises manually and automatically generating more exercises.

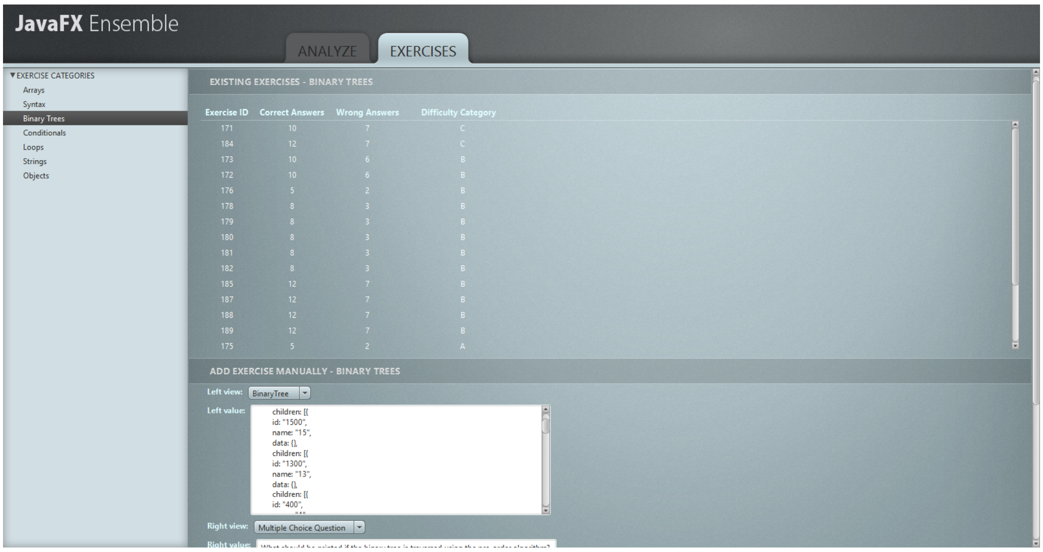


Figure 4.19: An overview of the exercise bank management tab.

Figure 4.19 gives an overview of the Exercise tab. The light blue window on the left contains all existing exercise categories allowing the teacher to select which category they want to manage. In this case, the teacher has selected to view the exercise category "Binary Trees", which displays the appropriate information in the main part of the tab, on the right.

Managing exercise categories

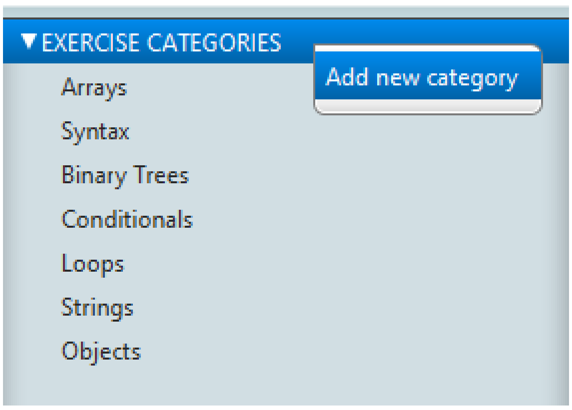


Figure 4.20: Adding a new exercise category.

Figure 4.20 shows a close up of the light blue window. It lists all the existing exercise categories and selecting them will update the information displayed.

Right-clicking on the root of the list opens up a context menu showing the possibility of adding a new exercise category. The definition of a new exercise category involves adding a description of the programming construct, some links to lecture notes and other helpful websites. These are of course optional. This information appears as part of the sidebar to an exercise as in figure 4.6.

There is also the possibility of choosing whether to make an exercise category visible or not to students. This is a useful feature if the class isn't ready to answer exercises of a particular category because the relevant material hasn't been taught yet, but the teacher still wants to prepare the exercises in advance to save time.

Viewing existing exercises

Once an exercise category has been selected from the list, several pieces of information are displayed.

EXISTING EXERCISES - BINARY TREES

Exercise ID	Correct Answers	Wrong Answers	Difficulty Category
171	10	7	C
173	10	6	B
175	5	2	A
172	10	6	B
174	5	2	A
176	5	2	B
177	5	2	A
178	8	3	B
179	8	3	B
180	8	3	B
181	8	3	B
182	8	3	B
183	8	3	A
184	12	7	C
185	12	7	B

Figure 4.21: Viewing information about existing exercises.

Figure 4.21 shows one such piece of information. It is a table listing all the existing exercises of the selected exercise category which have been answered at least once by some student. The table lists some useful information about each exercise such as the exercise ID, the number of correct answers, the number of wrong answers and some information about difficulty.

At the time of writing this report, the feature of double clicking a row to show the actual exercise description hasn't been implemented. We think that this would be a useful feature to have, enabling a teacher to view exactly which exercises students are getting right and wrong. However, a teacher competent with SQL and familiar with the jSCAPE system can still use the exercise ID as an index into the database table to retrieve further information about the exercise, including the actual exercise description.

Automatically generating exercises

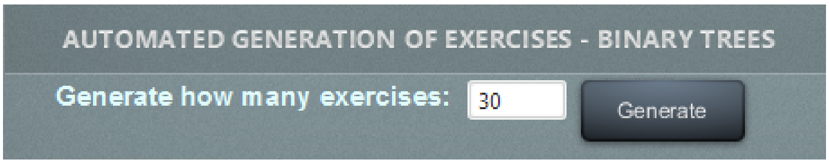


Figure 4.22: Automatically generating a number of new exercises for the Binary Tree exercise category.

In jSCAPE teachers can automatically generate new exercises for a selected exercise category. The teacher inputs the number of exercises he wishes to generate, clicks the Generate button which will call the appropriate exercise generator, create the exercises and add them to the exercise bank. For more details about the implementation of the automated exercise generation process, refer to section 5.??.

Adding an exercise manually

Although automatically generating exercises is a useful feature, it lacks the control offered by adding exercises manually. Indeed, the manual addition of exercises allows teachers to define exercises to target any identified student weaknesses. It also allows for more complex exercises which the automatic exercise generator wouldn't be able to produce.

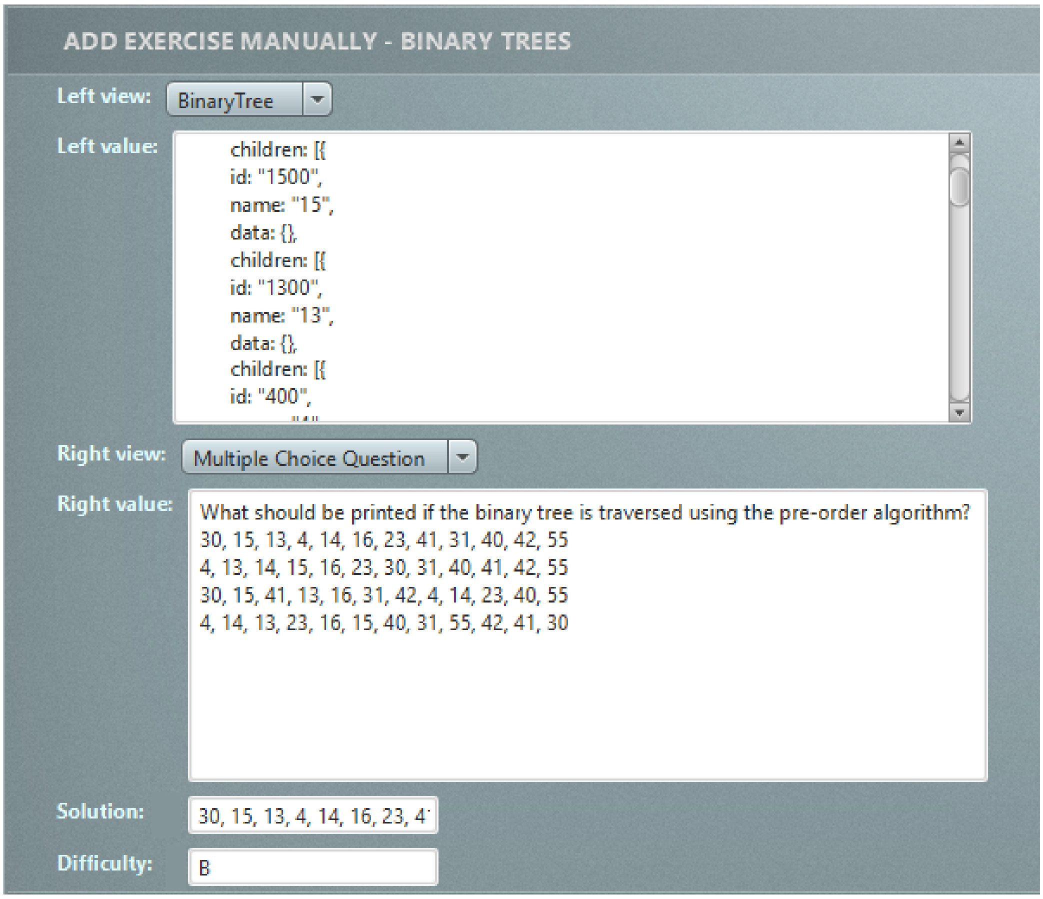


Figure 4.23: Adding an exercise on binary trees manually.

Figure 4.23 shows an example of a teacher adding an exercise on binary trees to the exercise bank. Adding a new exercise manually consists in filling special tags which the jSCAPE system will recognize when trying to display the exercise to the student. These tags are:

- **Left view:** The name of the "handler" that should be used in the left side of the exercise window. At the moment, two handlers exist. One is called BinaryTree for binary tree exercises, and another is called CodeEditor for exercises wishing to display pieces of code in the left view.

- **Left value:** Code or text used by the handler to generate what appears in the left view. In the case of a binary tree exercise, it is the binary tree encoded in a JSON format. For code exercises, it is simply the code snippet to be displayed to the student.

- **Right view:** The format of the exercise. Currently the system only supports multiple choice questions, but it would be quite easy to extend the system to support other types of exercises (section 7.?? FUTURE WORK).
- **Right value:** The exercise description and the four possible choices.
- **Solution:** The solution to the exercise.
- **Difficulty:** Some attributes to indicate difficulty.

For more details about the implementation of exercises and the various possibilities offered by the jSCAPE exercise format, refer to section 5.??

Once these fields have all been filled in, the teacher can click the Add button and the exercise will be stored in the exercise bank and made available to students.

4.3 Summary

In this section we gave an overview of the two applications developed as part of this project: jSCAPE and the jSCAPE admin tool.

We showed that jSCAPE provided an infrastructure for students to practice their understanding of programming concepts through exercises and to view their progress thanks to the extensive amount of statistical data collected by the system.

In addition, we presented the jSCAPE admin tool, which allows teachers to define exercise categories, and add or generate exercises to create an environment suitable for student self-assessment. Finally, we showed features that enabled teachers to track student progress through the same statistical data displayed in the main application.

In the following chapter, we talk more about the design of the system and various interesting implementation details and difficulties faced during the development of this project.

Chapter 5

Design and Implementation

Talk about design choices such as only multiple choices, no exercises asking to write code, writing custom server, etc...
Mention three tier architecture
implemented as a JavaFx applet javafx provides useful statistics package....pie charts, graphs, tables...
list tools+technology and evaluate advantages/disadvantages
java programming exercises, binary trees and code exercises to show the capabilities of the system, that it can handle multiple types of exercises.
server implementation, message codes, objectin/out streams, serverthread, show example array payload method to transfer stuff between client and server
showing feedback immediately after the exercise....cite source, shown to be most effective way of learning
piece of code + exercise involving the behaviour of the code have been found efficient (lister 2001) as far as student's assessment on their ability to read and understand the code's semantics. (NOT MY OWN WORDS) Lister, R. (2001). Objectives and objective assessment in CS1. ACM SIGCSE Bulletin, Vol. 33, No. 1, pp. 292-296.

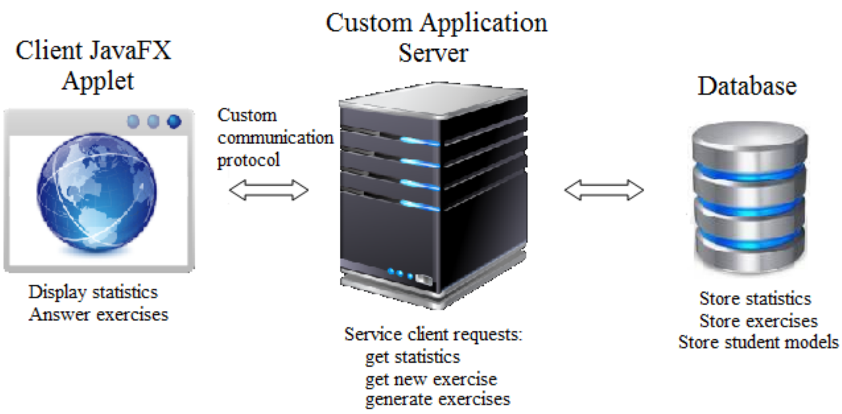


Figure 5.1: Three tier architecture of the jSCAPE system.

CAT development, we refer back to the five components of a CAT...what item selection algorithm we use, what scoring procedure, no termination criterion, entry point is average knowledge distribution initially and attempts at a calibrated item pool, currently with teacher providing the parameters since obtaining a high quality calibrated item pool isn't something I can do.

```java
private double itemInformation(int thetaEstimate, Item item) {
    double information;

    double a = item.getA();
    double c = item.getC();

    double aSquared = Math.pow(a, 2);
    double p = probabilityCorrectAnswer(thetaEstimate, item);
    double q = 1 - p;

    information = aSquared * (q / p);

    double numerator = p - c;
    double denominator = 1 - c;

    information = information * Math.pow(numerator / denominator, 2);

    return information;
}
```

Listing 5.1: Item information algorithm.

```java
private double probabilityCorrectAnswer(int theta, Item item) {
    double a = item.getA();
    double b = item.getB();
    double c = item.getC();

    double probability = (1 - c) / (1 + Math.exp(-1.7 * a * (theta - b)));
    probability = c + probability;

    return probability;
}
```

Listing 5.2: Item response function algorithm.

```
<note>
    <to>Tove</to>
    <from>Jani</from>
    <heading>Reminder</heading>
    <body>Hello world</body>
</note>
```

Listing 5.3: Example exercise illustrating the XML format.

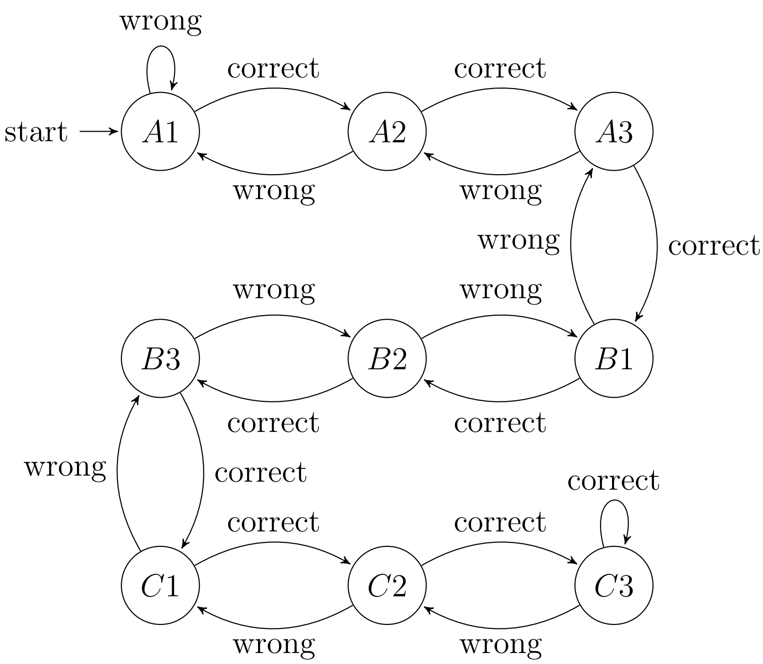


Figure 5.2: State machine of adaptive difficulty categories.

Chapter 6

Evaluation

Mention how our developed system performs against the advantages and disadvantages of CAT.
The evaluation stage will address mostly these two aspects:

- The system has correctly modelled the ability of students
- The system is useful in helping students to learn programming and helping lecturers with getting feedback on their teaching, in the form of statistics.

6.1 Qualitative

- Surveys to get feedback from students on interface, usability, etc...
-

6.2 Quantitative

- Statistical analysis to evaluate item calibration and modelling of student's abilities
-

evaluate the fact that teachers have to enter the parameters of items.

Chapter 7

Conclusion

7.1 Future Work

We have a few ideas of where to orient the project next...
The main limiting factor was time and insufficient means to collect the large amounts of data required to obtain a high quality calibrated item pool.

- Very flexible system so other programming languages could be offered, i.e. cSCAPE, for C and hSCAPE for Haskell.
- Working more extensively on the adaptive component of the system, i.e. improving the algorithm which selects questions for students based on their estimated ability.
- Extend system to allow admins to provide their own question templates, maybe come up with a template grammar which then allows questions to be automatically generated. Or at least allow pluggable function references which will be called to generate the exercise component.
- Add support for more question types. JavaFX is very good in that sense since it can play audio clips, video clips, show animations, the webview component has endless possibilities thanks to the inclusion of Javascript.
- Future Work as a research project vs future work as a commercial product
- JavaFX applications are based on the model-view-controller pattern, so a nice split can be done in the code, however I only learnt about this two weeks into the project, so all the of the GUI components are created in the code as opposed to in the FXML file.

- add more robust security: hashing for login/password and ssl connections between the server and client, and server database, because this communication could reveal solutions to the exercises..

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Appendix A

User Manual