An Analysis of Response Times in Adaptive Practice of Geography Facts

Jan Papoušek
Masaryk University Brno
jan.papousek@mail.muni.cz

Radek Pelánek
Masaryk University Brno
xpelanek@mail.muni.cz

Jiří Řihák
Masaryk University Brno
thran@mail.muni.cz

Vít Stanislav
Masaryk University Brno
slaweet@mail.muni.cz

ABSTRACT

Online educational systems can easily measure both answers and response times. Student modeling, however, typically focuses only on correctness of answers. In this work we analyze response times from a widely used system for adaptive practice of geography facts. Our results show that response times have simple relationship with the probability of answering correctly the next question about the same item. We also analyze the overall speed of students and its relation to several aspects of students' behaviour within the system.

1. INTRODUCTION

When students use computerized educational systems, we can easily store and analyze not just their answers and their correctness, but also the associated response times. Response times carry potentially useful information about both cognitive and affective states of students.

Response times have been studied thoroughly in item response theory in the context of computerized adaptive testing, for an overview of used models see [5]. But testing and learning settings differ in many aspects, including response times – for example we would expect students to think for longer time in the case of high stake testing than in practice session (there are differences even between high-stakes and low-stakes testing [2]).

Response times have been used previously in the context of student modeling for intelligent tutoring systems, e.g., for modeling student knowledge in the extension of Bayesian Knowledge Tracing [6] or for modeling student disengagement [1]. But overall the use of response times has been so far rather marginal. In this work we analyze response times from an adaptive system for practice of facts, which is a specific application domain where response times have not been analyzed before.

2. THE USED SYSTEM AND DATA

For the analysis we use data from an online adaptive system `slepemapy.cz` for practice of geography facts (e.g., names and location of countries, cities, mountains). The system uses student modeling techniques to estimate student knowledge and adaptively selects questions of suitable difficulty [4]. The system uses open questions ("Where is Rwanda?") and multiple-choice questions ("What is the name of the highlighted country?") with 2 to 6 options.

The system uses a target success rate (e.g., 75 %) and adaptively selects questions in such a way that the students' achieved performance is close to this target [3]. The system also collects users' feedback on question difficulty – after 30, 70, 120, and 200 answers the system shows the dialog "What is the difficulty of asked questions?", students choose one of the following options: "Too Easy", "Appropriate", "Too Difficult".

For the reported experiments we used the following dataset: 54 thousand students, 1458 geography facts, over 8 million answers and nearly 40 thousand feedback answers.

3. RESULTS

We provide basic analysis of response times, and their relation to student knowledge and to students' behaviour within the adaptive practice system.

3.1 Basic Characterization of Response Times

Distribution of response times is skewed, in previous work it was usually modeled by a log-normal distribution [5]. Our data are also approximately log-normal, therefor as a measure of central tendency we use median or mean of log times.

Response times clearly depend on the type of question and on specific item. Our results for example show, that response times are higher for cities and rivers than for countries and regions (states are larger than cities on the used interactive map and therefore it is easier to click on them). Response times are also on average higher for countries in Asia than in South America (there is larger number of countries on the map of Asia).

For the below presented analysis we use percentiles of response times over individual items – these are not influenced by skew and provide normalization across different items.

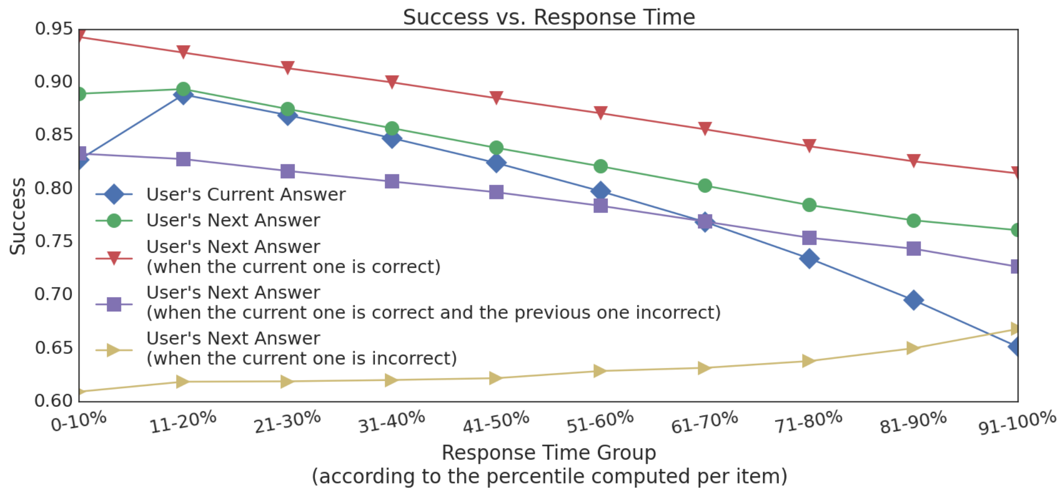

Figure 1: Response times and probability that the (next) answer is correct.

3.2 Response Times and Students Knowledge

Figure 1 shows the relationship between response times and correctness of answers. The relationship between response time and correctness of the *current* answer is non-monotonic – very fast responses combine "solid knowledge" and "pure guessing", long responses mostly indicate "weak knowledge". The highest change of correct answers is for response times between 10th and 20th percentile, i.e., answers that are fast, but not extremely fast.

We get a more straightforward relationship when we analyze correctness of the *next* answer (about the same item) based on both the correctness and response time for the current answer. If the current answer is correct then the probability of correct next answer is linearly dependent on the response time – it goes from 95% for very fast answers to nearly 80% for slow answers. If the current answer is incorrect then the dependence on response time is weaker, but there is still (approximately linear) trend, but in this case in the other direction. When the current answer is incorrect, longer response time actually means higher chance that the next answer will be correct!

A limitation of the current analysis is that we do not take into account types of questions (the number of available choices and the related guess factor) or the adaptive behaviour of the system (the system asks easier questions when knowledge is estimated to be low). However, we do not expect these factor to significantly influence the reported results, which quite clearly show that response times are useful for modeling knowledge and that it is important to analyze response times separately for correct and incorrect answers.

3.3 Speed of Students

As a next step we analyze not just response times for single answers, but over longer interaction with the system. Statistics of response times may indicate affective states or characterize a type of student. For this preliminary analysis we have classified students as fast/slow depending on their median response time and we analyzed correlations with other aspects of their behaviour (in similar way and with analogical results we have also analyzed variance of response time). The reported results do not necessary imply direct relationship as they may be mediated by other factors (like difficulty of presented items).

Slower students answer smaller number of questions in the system. In fact the overall time in the system is nearly the same for students with different speeds, i.e., slower students just solve smaller number of questions during this time. Faster students have higher prior skill and are more likely to return to the system to do more practice. In the feedback on question difficulty slower students report more difficult impression. Possible application of these results is incorporation of students' speed into the algorithm for adaptive selection of questions (e.g., by selecting easier questions for slower students).

4. REFERENCES

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