Masaryk University

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Techniques for measuring similarity of educational items

Bachelor's Thesis

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Declaration

Hereby I declare that this paper is my original authorial work, which I have worked out on my own. All sources, references, and literature used or excerpted during elaboration of this work are properly cited and listed in complete reference to the due source.

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Acknowledgements

These are the acknowledgements for my thesis, which can span multiple paragraphs.

Abstract

This is the abstract of my thesis, which can span multiple paragraphs.

Keywords

similarity, measure, keyword2, . . .

Contents

Introduction

Tutoring systems are computer-based systems designed to introduce users into various domains. They usually hold a large number of items which enables them to provide a personalized experience. To maintain this large pool of items efficiently we need to be able to decide which items are useful and which are not.

Besides Introduction and Conclusion chapters, this thesis is structured into three additional chapters. First chapter talks in general about the problem of measuring the similarity of educational items and advantages of using similarity. This chapter also describes previous work and different proposed measures for computing similarity. Later we explain different types of data available in tutoring systems. The second chapter then advances level deeper and describes observed problems specific to data we are using. The last chapter gives an overview of many experiments that were concluded and summarizes results.

April 25, 2018

1 Similarity

In this chapter, we talk in general about items (questions) in tutoring systems and computing their similarity. At the beginning of the chapter, we focus on better explaining basic terms like tutoring system, item, and similarity which will be used all through the work. We also describe different kinds of data available about items and possible measures for calculating similarity. The last section of this chapter describes data used in our experiments. In particular, we describe used dataset and outline ways of simulating artificial data.

1.1 Tutoring systems

Tutoring systems are computer systems which purpose is to teach its users (students) some knowledge or skill. These systems do this autonomously to some degree. The degree of automation may vary for each tutoring system.

Many different aspects of learning may be implemented into the system or they may also be left out. The most common task which tutoring systems solve is choosing a most beneficial item from the pool of items available for users to solve. This can be done in some simple way or system may also adapt to each of the users choosing more challenging and interesting items to users who are more skilled in a specific area. While presenting users who struggle with more basic items. This is beneficial for maximizing learning aspect of the system. [CITE?] Another aspect which can tutoring systems solve is providing hints and feedback to students. When there are teachers interacting with the system we can also provide feedback about their students progress and so on.

One closely related area are recommender systems which differ from tutoring systems only slightly. Both areas are observing users and items. The main difference is that our main source of information is a performance of users while solving specific item and recommender systems mostly use rating of the items. Which in fact are still only numbers representing slightly different things so we can still share some of the techniques. Although different goals bring different problems specific to each area.

One difference is that we can use some additional data about items. There are item statements and solutions of students which can in some contexts give us really useful information about items.

1.2 Items

In this work, we use the term "items" which may refer to problems, questions, assignments in different systems. Item is a single entry in an educational system which users can answer to. Since many aspects of this work are generally applicable we decided to use this broad term. Complexity of single item in tutoring system can differ greatly. In some tutoring systems, this may refer to simple choice from two options while in other one item is complex tasks which user solves in a matter of minutes.

To further specify the context of our research, we will describe characteristics of items. Computing similarity may be performed by different measures, but they all have to use data which are available for each item. Therefore we first describe sources of data that can be utilized for measuring the similarity of items.

- **Item statement** is some specification of the item for a learner to solve, e.g., a natural language description of the task. Another commonly used format is a grid. Many systems focusing on logic puzzles and programming problems use it.

- **Item solutions** may provide us with additional information about an item. There will usually be some sample solution provided by the author and we can also utilize all the solutions from users.

- **User's performance** consists of information provided indirectly by users. Performance of items may represent user solving times, correctness of the answers, number of attempts required.

Structure of both item statement and solutions differ greatly based context of tutoring system. However, in general, it is still possible to convert data into some standard form and use one of a few standard measures despite original representation.

This description of an item is broad enough to cover most of the tutoring systems. End of this chapter discusses more closely tutoring system used for our results.

The most important property of tutoring systems is that they contain educational items which are solved by users. However, amount of items in systems may vary. Some tutoring systems require a large number of items. This is especially true when they practice simple facts instead of skills. In personalized tutoring systems, the need for a large pool of items is even higher. When providing personalized questions we need a wider set of items to choose from.

Dealing with a large pool of items may not be easy. To maintain a pool of items efficiently we need to be able to easily decide which items are useful and which are not. One possible tool which can help us here is similarity of items.

1.2.1 Measuring similarity

The following section is explaining general approach to measuring and using similarity of educational items.

In general, we can compute the similarity of items in many ways. We define measures for computing similarity for two items. Then when we want to use similarity for some specific use-case we compute pairwise similarities for all pair of items.

Items in our context are commonly represented as vectors of numeric values. For performance data, this is a vector of correctness or time from all users to given item. Other properties of items like question statement may also be represented as a vector, e.g., by using bag-of-words.

When we have vectors for each item we can compare them pairwise to get similarity using some standard similarity measures like Pearson correlation coefficient, cosine similarity, Sokal measure or Euclidean distance.

Another possible way to measuring similarity is counting edits which would convert one item to another. This is called edit distance and there are standard ways of computing it for both strings and trees. Edit distance can be then converted into similarity using something like $1/(1 + \text{edit distance})$. So this covers another common group of information we can encounter.

1.2.2 Elements of standard pipeline

To we can wrap it up. There are a few data structures and few calculations involved in the standard pipeline for computing similarity of educational items.

1. **Feature matrix** is matrix (items × features) containing source data. As we said previously this can represent any property of the items. This matrix consists of one vector for each item and it may represent item statement, solution or solutions of the item and naturally even users performance.

2. **Measuring similarity** may involve some similarity measure or edit distance. This step is used to compute the similarity between all pairs of items. In other words, we transform feature matrix into similarity matrix.

3. **Similarity matrix** is matrix (item × item) where each value represents similarity of pair of items.

4. **Dimensionality reduction** is used to transform similarity matrix into a projection. Techniques like PCA or t-SNE may be used for this.

5. **Projection** is more compact representation (item × 2) of similarity matrix used for visualizations for end users.

1.2.3 Why is similarity of items useful

As we mentioned previously key part of learning is solving educational items. Defining some measures for computing similarity of items can then be used for different purposes.

First, most direct, usage is a recommendation of items for a student to solve. We do not want to recommend very similar items to those that were solved without any problems. However when user struggled system should consider recommending more of the similar problems to strengthen users knowledge.

Another possible usage is generating hints by selecting examples which are similar to the item which is currently solved. Examples are selected from a database of examples. This usage of similarity was used by [CITE Hosseini; Brusilovsky].

Two previous use cases were using problem similarity to automatically make some choices inside tutoring system. Another approach is to bring humans into the decision-making loop [CITE]. This approach provides authors of tutoring system with visualizations which should inform them what changes may be useful. E.g. detecting redundant problems and pointing out where there are not enough similar problems.

One possible way of achieving this is plotting problems to plane and displaying it to the author. This still can not be used for a very large amount of items. But we choose this approach for our specific data as they contain a large number of items but can be divided into item-sets which are solved independently in the system.

One of the use cases of visualizations is a detection of outsiders - items which behave differently than others. This behavior is directly shown in projection and such items lie far away from others.

There is one more usage of similarity which we won't be discussing further. The similarity of items can be utilized for automatic construction of clustering and hierarchical categorization. Even when author already has items categorized he can compare it to computed categorization to verify that groups are formed correctly and refine them if needed.

2 Used data and techniques

The first half of this chapter focuses on used sources of data. It describes both simulated data and dataset from the actual system. We outline structure of tutoring system and focus on exercises and its objects that are useful for our work. Another section includes basic statistics about data from *Umíme česky*. We also summarise previous work using the same dataset.

After that second half of the chapter gives a detailed description of pipeline used in our experiments when calculating similarity and projections. At the end of the chapter, you can find an example of the simple projection and description of what properties should it have to be useful.

In our analysis, we use both real data from the educational system and simulated data. Reason for this is that real-world data are useful for concluding any practical results. However, evaluation of this data is often complicated as we do not know the truth about many of its aspects. That is why we also use simulated data for validating some of our conclusions.

2.1 Simulated data

So when simulating data we are trying to generate results which are similar to real tutoring system. However, we use much simpler model.

The result of the simulation consists mainly of performance matrix with items as columns and users as its rows. First, we have to generate items. For each item, we choose its difficulty and skill required to solve this item. The difficulty of item is value drawn from normal distribution $\mathcal{N}(0, 1)$.

After that, we continued with the construction of users. We generate skills for all users - a matrix of u users and all used skills. This matrix is also filled with random values from normal distribution $\mathcal{N}(0, 1)$.

Next, we simulate each user answering to each item. User answers correctly whenever is a random value higher than a logistic function of the difference of item difficulty and user skill. When it is not given

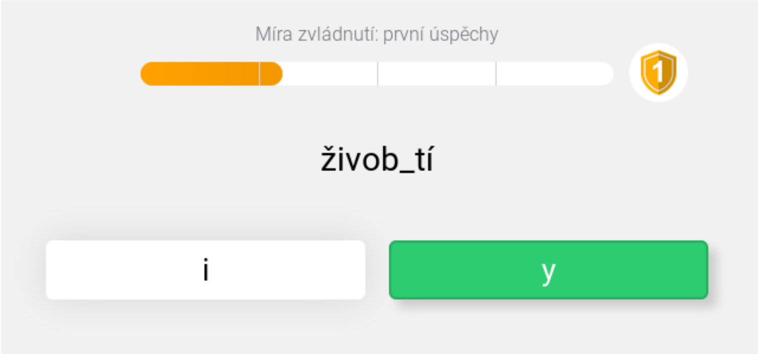

Figure 2.1: “fill-in-the-blank” example question

answer is incorrect. User skill is one of the skills which corresponds to the skill required for given item.

We will talk more in depth about how we generated simulated data in next chapter when describing how we used them specifically. In all experiments using simulated data, we altered this basic simulation in some way to achieve results corresponding to some attribute of real data.

2.2 *Umíme česky*

Umíme česky is a system for practice of Czech grammar. The system contains multiple exercise types, but in our analysis, we use only one exercise type - simple “fill-in-the-blank” with two possible answers. A user is asked to choose one of them.

Although we focused only on “fill-in-the-blank” exercise it can still be used to train various concepts of Czech grammar. The exercise contains many questions and they are divided into item-sets. Each item-set consists of items practicing a different aspect of language, e.g., “Vyjmenovaná slova po B” or “Velká písmena: státy, oblasti”. This item-sets are arranged into hierarchical categorization as seen in the user interface. As our analysis works only with item-sets separately this categorization into different aspects is important to our work. We consider results from each item-set as it has uniform items, but we do not compare them against each other.

Table 2.1: Basic statistics

	Items	Users	Answers	Item-user answers
"Fill-in-blank"	6 037	46 128	10 421 521	7 264 763
One item-set	273	14 207	1 216 403	888 748

Items in item-sets are then divided into levels. Where higher levels are intended for solving by more experienced users as they contain more difficult questions. In general, there are three difficulty levels but not all item-sets have all three of them. Some easy item-sets include only first level. On another hand, there are item-sets which have all three levels or only higher levels.

The used dataset contains multiple sources of information about items. In "item statement" group it is a statement of the question with one missing spot and two possible answers to fill in there. We also know answers from all the users. Then in performance group of information, it is correctness of user answers and response time.

It is not possible to use response time directly. We need to normalize it in some clever way as raw response time is greatly affected by both lengths of questions and users reading speed. Also, it is a good idea to use logarithm of time instead of time itself. This is shown by [CITE]. Only then it would be useful to use data about response times. This is a reason why we are using mostly correctness of user answers.

We choose this tutoring system because, as we explained before, we are focusing on problems which are most important for systems with a large number of items. Also provided dataset has a large number of users and answers which is great for the stability of results.

2.2.1 Basic statistics

This section provides some basic statistics about the size of dataset and users of the system. Table 2.1 shows number of items, users and answers. Statistics are both global and for one selected item-set which is the one most commonly used for analysis. This item-set has most answers from users, therefore, it is ideal for analysis as results are more stable. We used this item-set by default but we also confirmed observed behavior on other item-sets. The last column ("Item-user answers") contains a count of unique item-user pair which were answered. This number differs from all logged answers because users can answer the same item multiple times. In this case, we use only one of the answers for further analysis.

A primary group of users using *Umíme česky* are children studying at primary and secondary school. Users can have individual accounts but the system also allows teachers to create a virtual class and assign students to it. A teacher is then able to select some exercises and give them to students to solve until some deadline. Each week about 200 classes visit the system.

2.3 Previous work

Dataset from *Umíme česky* was used previously in few articles and thesis. Most of the work relevant to our problem comes from article Measuring Similarity of Educational Items Using Data on Learners' Performance [CITE].

They compared few chosen similarity measures to each other. The result was that some of the similarity measures correlate greatly and some do not. It was also determined which similarity measures it is best to use for the stability of results. Especially that using Pearson correlation coefficient is a good default choice.

We are also using it for several reasons. The described article showed that it has good enough results in producing distinct clusters on performance data. Another reason is that Pearson correlation is easy to use as many computational environments already contain fast implementation.

The article also showed that using "second level of similarity" improves the stability of results further. However, we choose not to use it as our dataset is large enough to be sable even with a simpler measure. Using straightforward measure is also beneficial when explaining results and this factor is important to our work.

2.4 Projection

Projections come in handy when it is hard to understand data directly because there is way too much of them. And this is our case as we focus on systems which consist of thousands of solvable items and even more users. Projections are results of dimensionality reduction techniques. We project many-dimensional data into 2 thoughtfully chosen dimensions to simplify them.

In general, we want projection which puts similar items together. This can be achieved in many different ways. The following section explains choices we made when selecting a source of data, a method of processing them prior to applying dimensionality reduction, and dimensionality reduction technique itself.

2.4.1 Computation of item similarity

To better understand how were projections created we have to understand steps of their computation. We call this process a default pipeline and it is used in most cases. When some of the further analysis modify it slightly it is pointed out in the corresponding section. Whenever we don't specify so all projections were produced using this default pipeline.

The first step we have to take is converting raw logged information about user answers into **performance matrix**. Columns of the matrix are items in the educational system and each row of the matrix contains data about single user's performance. In our case, we used correctness of first users answer to specific item as his performance. This means value 1.0 in case of the correct answer and 0.0 for incorrect. It is worth mentioning that performance matrix is relatively sparse as it is not common for users to solve all the items in the system.

Next step is computing **similarity matrix**. It is filled with a pairwise correlation of all items from the performance matrix. For this was chosen Pearson correlation coefficient based on previous work. Values produced by correlation are between -1 and $+1$. Each value in this matrix represents similarity of two items. This gives matrix some properties - matrix is symmetric and all values at main diagonal are 1.0.

The last step is producing 2D **projection**. The similarity matrix is useful for a computer to directly make a decision based on it. However, this matrix still contains way too many values for a human to interpret. As some of our goals are explaining data to authors of the system. We continue with a dimensional reduction to produce a more compact representation of data. This can be achieved by using any dimensional reduction technique.

We decided to use Principal component analysis (PCA) and first two principal components are then used for 2D visualizations. We choose PCA over other commonly used technique t-SNE (which can produce better-looking results) for one important reason. Results of PCA are deterministic. It produces the same result for same input each time it is run. This is not true for t-SNE which is technique using machine learning and gradient descent for finding some local extreme. Stable results are more suitable for understanding data as there is no variation to results caused by the algorithm. And it is much easier to compare results when altering measure used for computing item similarities.

We choose this specific pipeline as we think it is utilizing data about items which hold most information about their similarity. Other possible choices are using item statement and solutions provided by students. However, they do not hold as much information in our specific tutoring system. Item statements in our observed exercise consist only of few Czech words with one missing spot. And student solution is basicly only selection from two provided options. Item statement and solutions can be used more effectively in other contexts like programming, mathematics, or physics where item statements are much more complex.

This choice of a pipeline is also relatively easy to understand. As it consists only of few steps which can be studied separately and interchanged.

2.5 Visible properties of projections

Figure 2.2 shows how can resulting projection look like. This particular projection shows 273 items (single item-set). Each item is represented as one dot in the image and its proximity to others represents how similar they are.

As projections are meant to be used for managing item pool this puts some constraints on how ideal projection should look like.

We want similar items to end as close to each other as possible. When we use performance as data source we can also interpret as

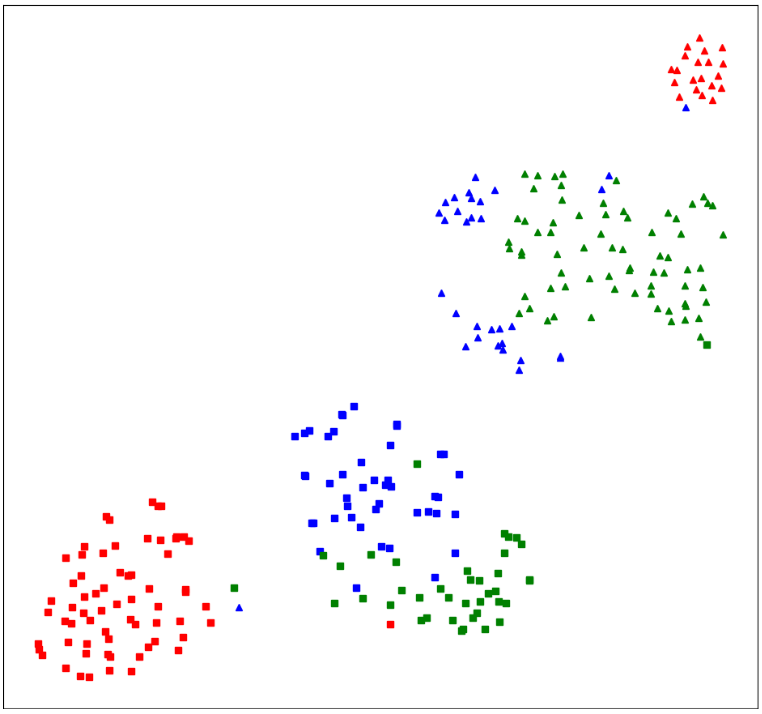

Figure 2.2: Basic t-SNE projection of one item-set

items which require same skills are projected near each other - their answers from each user correlate. For example, when we look at our selected item-set we can see that all words starting with "bio" are close to each other. This group consists of words which are indeed similar because they are based on a single word with added suffix. But remember, there is no information about item statement presented to the similarity measure.

2.6 Regularities

After looking back at figure 2.2 you can notice some regularities. Items depicted with same colors and items using same markers form clusters of same colors and markers. But so far you have no idea what this properties of items represent. This section is talking about it.

2.6.1 Level regularity

Figure 2.2 contains items of three different colors. As you already know item-sets in system *Umíme česky* are divided into multiple levels of difficulty. For this particular item-set, there are three difficulty levels. The first level is depicted using red (with 110 items), second green (with 86 items), and third blue (with 77 items). You can see a visible pattern in our data - each cluster consists mostly of items item from one level.

As we mentioned before, only data about user performance (correctness of answers) are used when composing projections. And there is not a direct reason for this clusters of same levels to form as no information about belonging to a particular level is presented to the algorithm.

This phenomenon is not suitable for analysis of item similarity as it can cause misleading results about similarity. One particular example is when similar words are displayed far away from one another just because they belong to different levels. Such example is pair of words "bič" and "bičík" in item-set "Vyjmenovaná slova po B".

2.6.2 Answers regularity

Another property of items in figure 2.2 is a marker used. One type of marker (rectangle) shows items with correct answer "i" and another marker (triangle) shows items with correct answer "y". Again, there is no direct information about this presented to measure of similarity.

3 Evaluation

The chapter is explaining factors that can affect resulting projections produced from real-world data. We are focusing on higher level factors that can cause a formation of clusters in projection. On a low level, it is apparent that items which performance correlates will be similar (close to each other) in projection. But we focus on higher-level factors in tutoring systems that can cause this correlation.

3.1 Basic

The first section is focusing on experiments which determine a range of this behavior - whether distinct clusters of different answers and levels are still present when altering parameters of pipeline used to calculate projection.

3.1.1 First and last users answer

Our performance matrix contains only one value for each item-user pair. But users can possibly answer to the item multiple times. This raises a question about which of user answers to use. [CITE]

We tried using both first users answer and last in performance matrix. However, there is no visible difference in results. This is clear when we compare first and last answers of users. There is only 5% different answers between them. So at least with a large number of items in the system it does not really matter which one is chosen as only a few items are answered multiple times.

3.1.2 Quality of clusters on different item-sets

When introducing the problem of unneeded clusters in section 2.6 we showed that one particular item-set shows this behavior. However, we still do not know whether this is true for all the item-sets. We decided it may be useful to quantify how recognizable are this clusters on all item-sets.

Quantification of quality of clusters in the projections is executed by comparing its k-means clustering to correct level and answer of items. We ask k-means clustering algorithm to find *levels* × *correct answers* clusters. Quality of clustering is then evaluated using Rand index. So value 1.0 represents that k-means divide all items into same clusters as correct classification (clusters created as a combination of item level and correct answer). On other hand, lover values represent it is hard to divide items correctly and there are no distinct clusters. This process is repeated multiple times to account for random initialization of k-means algorithm.

Table 3.1 describes quality of clusters on different item-sets. Results show that many item-sets have distinct clusters of different levels and answers. But there are some item-sets with an obscure structure of projection. This mostly occurs when item-set have a large number of possible answers.

We were looking at both clusters of answers and levels simultaneously. Another possible choice would be to somehow quantify both qualities of levels and answers separately but this straightforward approach would not work there. Simplest example showing why would consists of two levels and two correct answers - where correct answers are divided evenly into each level. When we ask k-means to create two clusters for levels and two clusters for answers it will return the same clustering in both cases because a number of clusters is the only used parameter. This will result in one metric returning high value but other one small even when clusters are really distinct.

So we can conclude that this behavior is present in all item-sets.

3.1.3 Different similarity measures

In another experiment we inter exchanged four different measures for computing similarity of items to verify that previous results aren't specific to a single measure. Especially whether they all preserve smaller similarity of items with different levels and correct answer.

Figure 3.1 shows four different similarity measures used on same data. Resulting projections are different. However, they all preserve information which is causing items from the same level and answer to form clusters. Different colors represent different levels and markers different answers.

Table 3.1: Quality of clusters in different item-sets

	min	median	max
delka-samohlasek-i	0.272173	0.572914	0.733154
delka-samohlasek-u	0.179007	0.218907	0.278768
koncovky-mi-my-ma	0.173923	0.378383	0.574999
koncovky-ovi-ovy	-0.022328	1	1
koncovky-podstatnych-jmen-muzsky-rod	0.460326	0.526986	0.652672
koncovky-podstatnych-jmen-stredni-rod	0.444935	0.859304	0.880381
koncovky-podstatnych-jmen-zensky-rod	0.358566	0.423671	0.501532
koncovky-pridavnych-jmen	0.431434	0.500458	0.558587
me-mne-samostatne-zajmeno-ja	-0.012182	0.289142	1
predlozky-s-z	0.31752	0.413021	0.455101
psani-be-bje	-0.009319	0.671716	1
psani-me-mne-ve-slove	0.646219	0.733133	0.733133
psani-nn-a-n	0.305013	0.409739	0.462562
psani-s-c-s-z	0.288553	0.353498	0.44766
psani-ve-vje	-0.013296	1	1
shoda-podmetu-s-prisudkem	0.189355	0.245732	0.306245
sklonovani-zajmen-jez-jenz-nimz-ji	-0.01751	0.121347	0.353978
slovesa-podminovaci-zvratna	0.06066	0.10416	0.173317
tvrde-a-mekke-souhlasky	0.135091	0.257167	0.832182
vyjmenovana-slova-po-b	0.385475	0.597867	0.637596
vyjmenovana-slova-po-l	0.575217	0.641585	0.837544
vyjmenovana-slova-po-m	0.478953	0.928013	0.943975
vyjmenovana-slova-po-p	0.641131	0.832391	0.88884
vyjmenovana-slova-po-s	0.373571	0.421781	0.446662
vyjmenovana-slova-po-v	0.483608	0.678045	0.722796
vyjmenovana-slova-po-z	0.528562	0.565708	0.657444

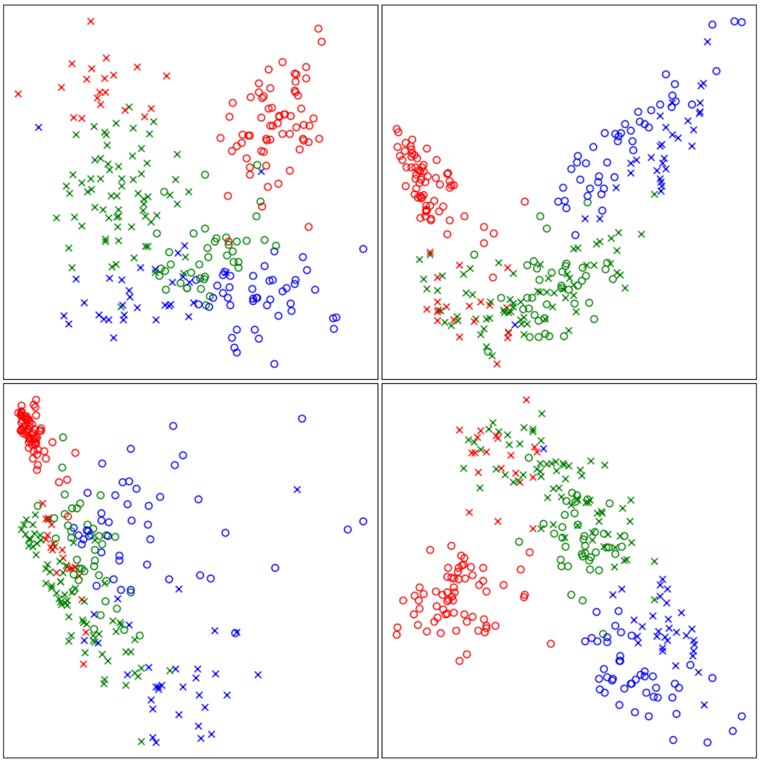

Figure 3.1: Comparison of four similarity measures

Table 3.2: Attributes of boolean similarity measures

	incorrect	correct
incorrect	a	b
correct	c	d

When we encounter performance matrix which contains only two (boolean) values, we can summarize the performance of all users on items i and j by using just four values. See table 3.2.

- **Pearson** ($(ad - bc)/\sqrt{(a+b)(a+c)(b+d)(c+d)}$) is commonly used. It correlates well with much simpler measure **Yule** ($(ad - bc)/(ad + bc)$).
- **Jaccard** differs visibly from other measures.

  TODO:

  The similarity of items is not greater in one group of questions (based on correct answer).

  Similarities provided by Jaccard measure differ greatly from other measures. Resulting projection still shows same clusters of level and items are split based on a correct answer but information is kept in another way than in correlation-based measures like Pearson.
- **Sokal** shows best that different similarity measures can highlight different aspects of item performance. The similarity of items depends heavily on the performance of items when using Sokal. (Where performance of item is a number of correct answers divided by all answers.) Items with higher performance are much more similar than items with lower performance. This is causing a packed cluster of items from a first level (easy) and a spread out cluster of items from third level (harder).
- **Cosine** similarity produces projection similar to Jaccard.

So we can conclude that clusters are present despite used similarity measure.

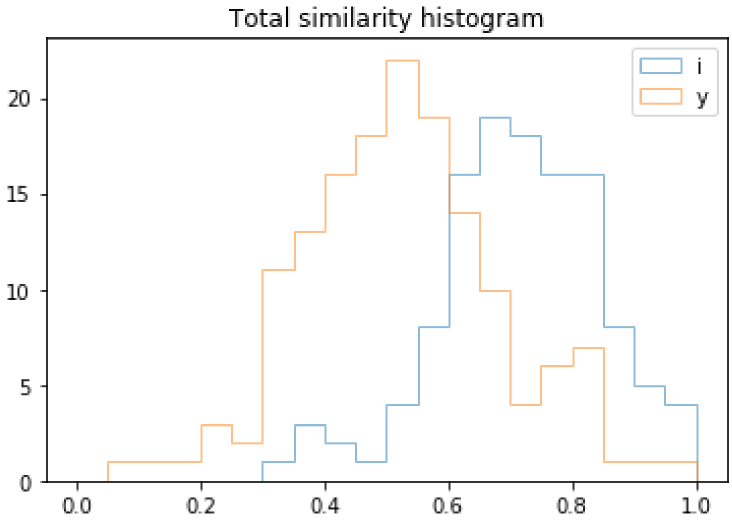

Figure 3.2: Histogram of similarities

3.2 Answers regularity

3.2.1 Total similarity of items

We define another property of items - total similarity. It is a sum of one items vector of similarities to other items. (One column of similarity matrix). This property is normalized to range 0.0-1.0 and tells us how much is item similar to other items.

This is not specific to only one item-set (which was used in previous images), almost all item-sets display similar pattern. Although for some item-sets, it's more distinct than for others. Sets consisting of items with many possible answers does not behave this way. But that is to be expected.

We picked few item-sets which have very distinct clusters of answers and looked whether the answer with higher similarity is located on left or on right in the user interface. Our finding was that there are item-set with a preferred answer on both left and right button. In particular in concept "Vyjmenovaná slova" which have possible answers "i" (left) and "y" (right) the preferred one is the left answer. But for concept "Koncovky přídavných jmen" which has the same possible answers is preferred one "y" on the right.

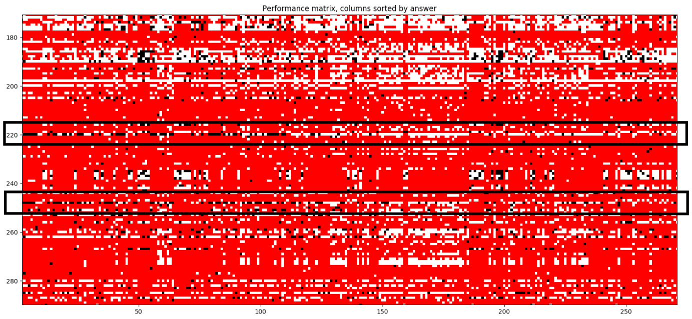

Figure 3.3: Performance matrix ordered by correct answer

This experiment tells us only that there is some underlying difference between items with different correct answers but does not tell us what.

3.2.2 Performance matrix

After looking at performance matrix we can see that there are some rows which behavior differs greatly on different answers. This can be seen in figure 3.3. Each column in image depicts answers to one item. Each row corresponds to one user and colors represent correctness of answer (white is correct, black incorrect) or missing answer (red). Items are ordered in a way that all items having first of the answers as correct are on the left and items with another correct answer on the right.

After exploring performance matrix some more we can see that there are users who have much higher performance on items with one answer than another. There are even users who almost anyways use one of the answers. Such users are highlighted in the image. They answered almost all items with one answer (right) correctly and items with another answer (left) incorrectly.

3.2.3 Default answer

Our guess was that there are users who prefer using one answer by default when they do not know the answer. Firstly we wanted

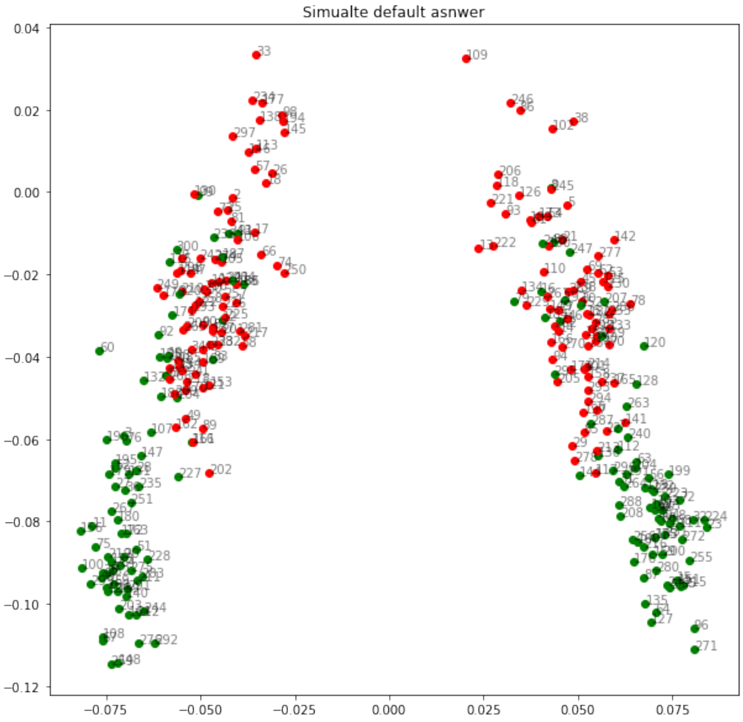

Figure 3.4: Simulation of default answer

to determine whether preferring one answer over another can affect projection and create clusters of different answers.

We used simulation for this. Simulation is extended over basic simulation described in second chapter 2.1. There are a few differences over basic simulation. For each item, we also choose a correct answer. This is used to offset logistic function higher or lower to simulate higher chance of succeeding when solving items which correct answer is the users preferred one. In this experiment, we used offset 0.2 which corresponds to 20% higher chance to answer correctly one answer and 20% lower on items with another answer. Also, there are no missing values in performance matrix - simulated users answer to all items.

This specific simulation is using two uncorrelated skills and two answers. They are distributed in a way that there is the same amount of each combination (1/4 of items). We included different skills in this simulation to better illustrate conditions of real data - as such clusters of levels exist there.

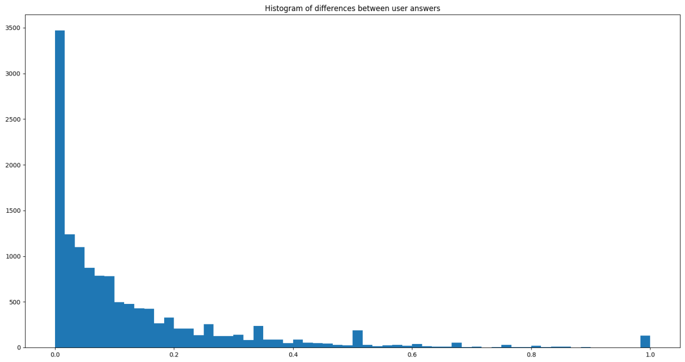

Figure 3.5: Histogram of users differences of performance on different correct answers

When we look at resulting projection 3.4 of simulated performance data we can see that it has same properties as our real data. There are clusters (in this case caused by uncorrelated skills) which have items separated by the correct answer (represented by different colors).

So users proffering one answer over another can cause items to separate by correct answer in projection.

3.2.4 Filter users

The previous simulation showed that preferred answer can cause separation of items. Now we have to show that users like this exist in our real dataset.

We observed before that whole dataset uses both answers approximately the same, but for a single user this may not be true. In this experiment, we want to quantify whether each user prefers some answer or not. For this, we used a difference of performance of items with each correct answer. TODO toto povedata nejak rozumenjsie, aka vymysliet term

For each possible answer and each user, we calculate a ratio of correct answers to all answers on items with given answer. Then we combine this set of values to one using their variation. This gives us single value representing a difference of performance on different answers.

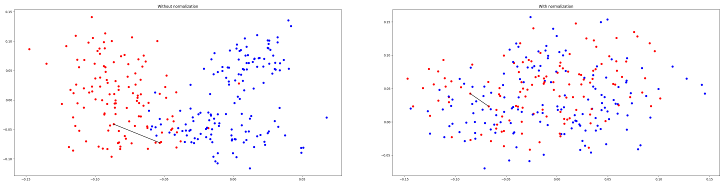

Figure 3.6: Effect filtering out subnormal users

Figure 3.5 shows histogram of this values calculated for each user on one item-set. There are few visible groups of users. The largest group have uniform performance on all answers (represented by values close to 0.0). On the other end of the spectrum are users who use only one answer (values close to 1.0). And in the middle, there are users who probably prefer one answer but use both answers. You can see that there is quite a large amount of users with a small preference for one of the answers. (It does not matter which one.)

We can use this to filter out users which difference in performance is too large. We thought that this will remove the separation of items based on a correct answer from a projection. And it does. Figure 3.6 shows projection before and after filtering users based on their difference in answers. In this particular case, we consider that user should be filtered out when his difference on answers is greater than 0.06 which is median value.

Figure 3.6 shows original projection and projection modified by removing part of the users. Colors in this particular image represent correct answers of items.

In section 2.6.1 of the second chapter we also mentioned that there are words in different levels which should be more similar. This is also shown in figure 3.6 with the black straight line connecting such two items. You can see that distance between them shrank.

When we use only half of users which performance is more uniform separation of items with same answers is gone. Its half of users because we compare their difference to median difference. Apparent question is whether a smaller amount of users removed may not be enough.

We look at the performance of items instead of usage of each answer because it is a performance that directly affects calculated similarity of items. However, they should correlate somewhat. Another reason is that it is closer to simulated experiment so we can compare results directly.

To sum it up. When we simulated users we gave them all habit to use one answer more commonly. This divided items by their corresponding correct answer. But not all users have a habit of using one answer by default in real-world data. Yet there is quite a large amount of users who do. We can filter them out to stop them affecting projections.

3.3 Levels regularity

3.3.1 Missing values

As we mentioned before, performance matrix is relatively sparse. Though missing values are not distributed randomly - they form a distinct pattern. Our question is whether this pattern of missing values can affect similarity of items and projections.

Items in each item-set of the system are divided into up to three levels. As the difficulty of levels is differs users in the system usually do not solve all of the available levels. Less experienced users tend to solve only first or first two levels. Still, more experienced users solve only higher levels. This is causing visible pattern in performance matrix. Some user rows contain information only about specific levels and are missing all values of other levels.

Based on this we can divide users into 8 groups. All groups are listen in table 3.3. First three columns say whether this group contains users who solved particular levels. We say that user solved level when he answered at least 30 items (which is 1/3 of questions for observed item-set). We added color to each group so we can distinguish them in following plots easily. Groups are not represented in data uniformly. Most of the users fall into two groups. These two groups are users who either solve only first or only second level.

Once again, we used simulated data to gather more information about this. A simulation was concluded in the same way as we explained before in section 2.1. The only difference is that resulting performance matrix will now contain missing values. We wanted to recreate missing data in a similar way that this occurs in real performance matrix. This is achieved by simulated users not solving all items.

Table 3.3: Groups of users

1	2	3	Color	Users
no	no	no	black	35%
yes	no	no	red	31%
no	yes	no	green	9%
no	no	yes	blue	8%
yes	yes	no	yellow	7%
no	yes	yes	cyan	2%
yes	no	yes	magenta	2%
yes	yes	yes	light gray	7%

Each user starts with solving one level and then with some probability continues to another. So most users solve only one level, some users solve 2 levels and only a few users solve all 3 levels. Order in which they answer levels is chosen at random as users are not required to continue chronologically. This is also visible in real data - there are users who solve only second or only highest difficulty level.

Figure 3.7 shows projection of our simulated data with missing answers. Projection on left shows first two principal components of PCA, projection on right shows second and third component of PCA. So there are 3 dimensions shown effectively. Colors in the first image depict difficulty of items (dark are difficult, light simple items). The second image is colored by levels as usual.

You can notice that first dimension corresponds pretty well with difficulty of items and next two dimensions (second image) distinguish belongingness to each level.

So how does this happen? TODO find good explanation :D I do not have any with which I am 100% happy with right now.

3.3.2 Item performance

As we know items are divided into in such manner that difficulty of levels raises. Question is whether this is directly projected into similarity of items.

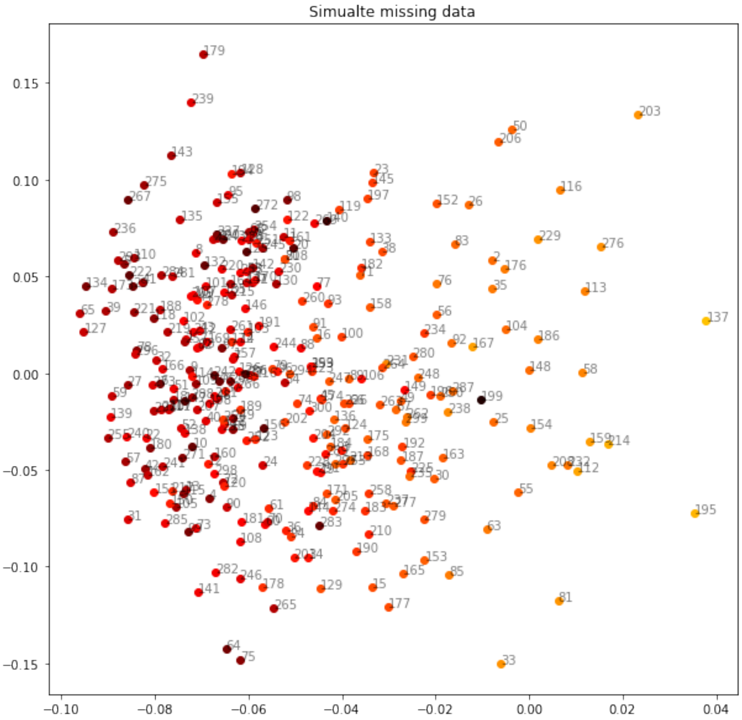

Figure 3.7: First two components of PCA on simulated data

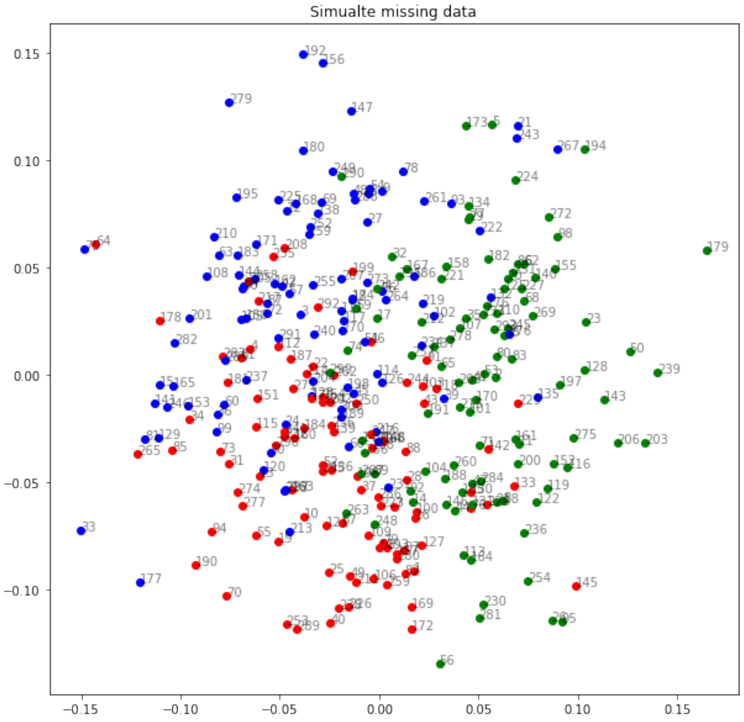

Figure 3.8: Second and third components of PCA on simulated data

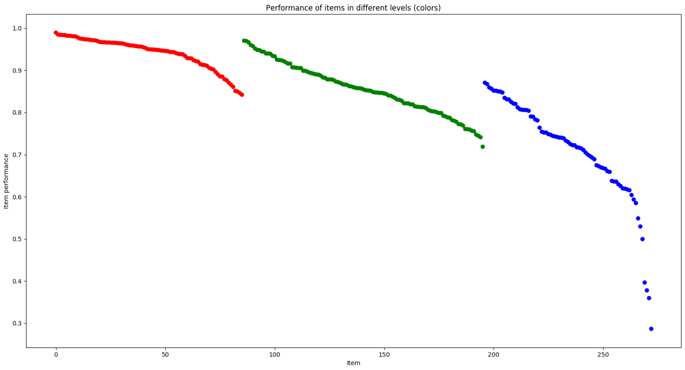

Figure 3.9: Mean performance of items in three levels

Figure3.9 shows mean performance of items from one item-set. Horizontal axis contains items sorted by level and mean their performance. The vertical axis shows a performance of each item. Given item-set contains three item-sets with mean performance 94%, 86%, 71% respectively.

4 Conclusion

We can conclude some recommendations. While trying to explain patterns in our particular used data we run into multiple situatutions hwich can repeat even when explaing some different data using similalr techniques.

determining range of effect.. its stupidly simple, but can be forgotten whenfacig some problem and may help you greatly

Technique we used for calculating projections is quite common in area of Adaptife learning and recommender systems. CITE.

Following section will summarize recommendations useful for explaining results

it is useful to look at both item and user similarity - some patterns in data can be results of habbits of users. - we are using unsupervsed learning like techniques - we obtain some results but it is hard to explain why they are like they are.. one possibility how to explain results is using simulations - we explained one possible way of simulating performance matrix - data fome from users so identifing groups of users who behave same may be useful - we rhink most common groups which can be vosibke in data coming from online tutoring system are eager users and trolls - Main grohp of users tend to answer to quesrions in some regullar patrern based on their knowledge while trolls follow different pattern (for exampla use same answer on all questions) - looking at total similarity of items - typicaly correlates with first dimension of PCA - variance of performance entries of items

4.1 Limitations

- only one exercise - only performane was used for computing similarity of items, other sources of data were ignored .. as we thought there results here are most unexpected .. hovewer there may arise other problems when using different sourcess of data - we used only correctness of answers and ignore response time. It make sense in studied tutoring system but may be important in other systems.

A An appendix

Here you can insert the appendices of your thesis.