SET LEARNING: A CASESTUDY OF TOP-DOWN LEARNING IN A BOTTOM-UP PERCEPTUAL TASK

Bachelorproject

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Abstract: In this article, we look at the game Set as a casestudy of learning. This game is particularly useful for this cause because it has both perceptual and cognitive processes, and the interaction between these two in a single task. To study these processes, we asked subjects to play the game against a computer. We looked at different possible explanations for how the players transition from a novice to an expert player, and in particular in which of the processes these changes manifest themselves.

1. Introduction

Learning is the process of changing behavior as a result of gaining experience. Initially, complex tasks often require a lot of conscious effort when trying to solve them. However, for someone who has a lot of experience with the task, it may require almost no effort to solve at all. An example of such a task is (perceptual) categorization (Ashby & Madox, 2005). The task we use is the game Set, invented by Marsha Jean Falco in 1974 (Set Enterprises Inc.; homepage: www.setgame.com). This game is very suitable because it consists of both perceptual and cognitive processes, and the interaction between both. It is also easily studied and has relatively simple rules.

1.1. The game of Set

Set is a game in which players are presented with 12 cards at a time, from which they have to identify a Set of 3 cards. When they do, 3 new cards will be added from the deck to complement the remaining cards. The cards differ from one another along 4 different attributes: color, count, shape and filling. Each of these attributes has 3 possible values (red, green or blue; 1, 2 or 3; oval, wiggle or rectangle; empty, half-filled or filled). As all cards are unique, there is a total of (3x3x3x3) 81 cards. The game ends when the deck is empty and there are no more Sets left within the remaining cards.

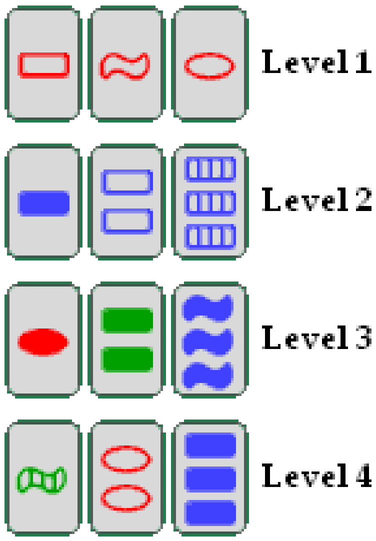

Figure 1: Examples of different levels of Set: (1) Shape has different values (2) Count and filling have different values (3) Color, count and shape have different values (4) All attributes have different values

A combination of 3 cards is considered a Set if and only if within each of the 4 dimensions the values are either *all different* or *all alike*. We distinguish between 4 different basic types of Set: those with 1, 2, 3 and 4 different values. The more similar the cards within a Set are, the easier they are considered to be found. See figure 1 for examples of the different types of Set.

1.2. Earlier Set research

In Taatgen, van Oploo, Braaksma, and Niemantsverdriet (2003) the authors presented subjects (4 novices and 4 experts) with 20 different situations of a selection of

12 cards. Each of these selections contained exactly 1 Set and were presented in a random order, different for every subject. These 20 Sets had different difficulties (level 1-4). They concluded that higher level Sets required more time to solve than lower level Sets. They also concluded that expert players were particularly better in high level Sets.

Another study on Set (Jacob & Hochstein, 2008) has resulted in many findings. In their first experiment, they simply let people play a computer version of the game Set. In this version of the game, it was made sure that there was at least 1 Set available within the 12 cards. One conclusion was that more similar Sets were found more often than dissimilar Sets, compared to their combinatorially expected count. The reaction times (RT), as Taatgen *et al.* (2003) had also found, of these lower level Sets were concluded to be lower.

Jacob & Hochstein also looked at the effect of the number of sets present on RT. They suggested that RT can be approximated by the *Horse race model*. According to this model, when multiple Sets are competing for a player's attention, the result can be performance facilitation according to probability summation. This follows from the processes being independent from one another.

Another interesting factor to look at is the *Most Abundant Value* (MAV). This is the value (blue, two, full, etc.) that is present the most among 12 cards. Subjects were found to look preferentially within the MAV-group. Subjects also found Sets within the MAV-group quicker than those outside. Jacob & Hochstein suggested that this was because players tend to first look within the MAV-group, and only after they fail to find a Set there they consider Sets outside the MAV-group.

In a second experiment by Jacob & Hochstein, they looked at dimensional salience; the preference for similarity in one dimension over similarity in another. Individual subjects were found to prefer one dimension over another, but different subjects had different preferences.

In their third experiment, Jacob & Hochstein looked at Learning and Generalization. Their subjects played Set for 3 sessions for a total of 9-12 games. They looked at the RT of different levels over the course of the games. Throughout the first 3 games, there was a lot of improvement in RT, but after that it remained fairly stable.

After these 9-12 games, when no more progress appeared to occur, Jacob & Hochstein changed the shapes on the cards to circles, triangles and squares. The colors were also different. However, subjects did not show any change in performance (RT), even in their first games with the new shapes and colors. Even though they had not practiced with the new dimension values, they scored the same. This suggests that the players learned the cognitive rules of what constitutes a Set, rather than perceptual stimuli, such as oval or blue. Jacob & Hochstein concluded that the learning effect generalized to playing the game with new values. However, they stated that the generalization may occur because of the fact that the subjects did not yet reach a stabilized “automatic” level (Goldstone, 1998; Treisman, Vieira, & Hayes, 1992).

1.3. An ACT-R model of Set

Nyamsuren & Taatgen (2011) have improved upon a model of Set in the ACT-R architecture (Anderson, 2007), originally by Taatgen *et al.* (2003). The model consists of two parallel processes, to reflect the bottom-up and top-down nature of the task. The bottom-up process is responsible for the visual scanpath as well as for switching attention from one card to another. The top-down process is used to make higher-level decisions, such as choosing the guiding attribute value (GAV). The model tries

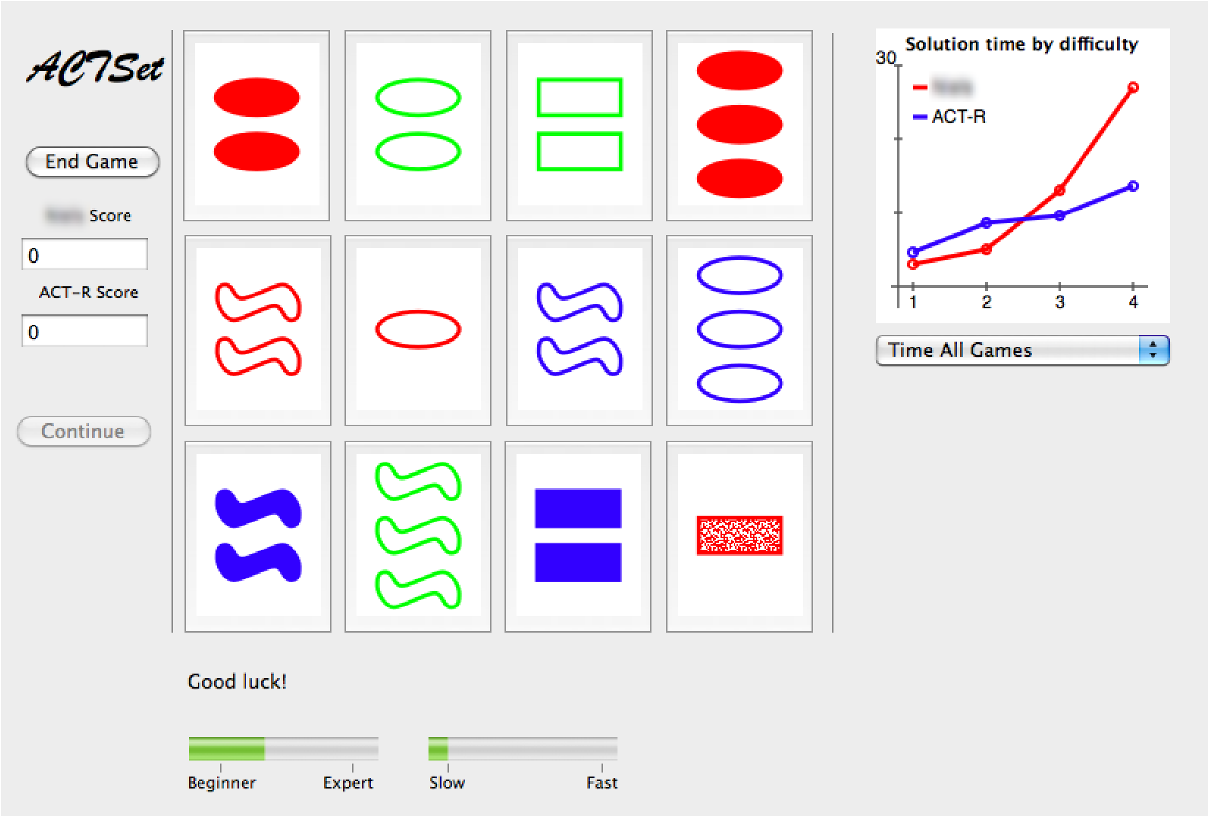

Figure 2: The user interface of the ACT-R Set Model showing the cards, the parameters and the average solution time for different Set levels.

looking for a Set among cards that share this GAV. The two processes can also influence eachother. For instance, a higher-level decision may depend on what card the bottom-up process is currently fixating on.

The model makes use of some of the discussed strategies. However, contradicting Jacob and Hochstein's results, Nyamsuren and Taatgen concluded that some dimensions were universally preferred over others. In particular, color was preferred over other dimensions. Therefore, they concluded that attribute type does play a role in choosing the GAV.

1.4. Research objectives

While many strategies have been covered, very little attention has been given to learning. Jacob and Hochstein did look at RT of subjects accumulating experience, but that was about the extent of the research on learning effects. It would also be interesting to see what strategies/preferences are used by a novice player, what strategies/preferences are used by an expert, and how this usage changes in the transition from novice to expert. We expect that novice players will use many low-level, perceptual strategies to find their Sets, whereas expert players may use higher-level, cognitive strategies. We expect this because, as stated by Taatgen *et al.*, experts are better at finding higher level Sets than novices, which requires top-down processes. This implies that there is a top-down learning effect.

So the main question of interest is: What are the top-down learning effects in a bottom-up perceptual task?

As will be described in more detail in the method section, we will let subjects to play Set against a computer model. With the gathered data, we will look at RT per level, the Most Abundant Value, what level of Set is preferred in the presence of multiple Set levels, dimensional salience and the ratio of found Sets. Of all of these we will look at how they change over time, to attempt to see where the learning effects manifest themselves. Finally, we will look at the learning rates of different levels of Set, which might give insight into whether learning takes place at a high level (top-down) or at a low-level (bottom-up).

2. Method

To answer our main question, we will let subjects play the Set game against the generalized version of the ACT-R model of Nyamsuren & Taatgen (2011). The players have to select 3 cards to form a Set, out of 12 displayed cards. If they fail to do so quickly enough, the computer opponent will find it. Selecting cards that do not form a Set does not result in a penalty. See figure 2 for the game's user interface.

The model uses a speed-parameter and an expert-parameter. The speed-parameter is increased when the player finds a Set and decreased when the model finds a Set. The expert-parameter works similarly, but only changes if a higher level Set (level 3 or 4) is found. The decrease of a parameter is slightly larger than the increase, so the player has an advantage over the model and remains motivated. The presence of the parameters is necessary so the model's strength remains enough to be able to keep the player challenged. Also, the model opponent limits outliers by finding the Set when the player is taking a long time.

Each subject will play the game for at least 5 hours spread over sessions of at least 1 hour and at most 2.5 hours, in order to limit the effects of fatigue. This results in approximately 40 games for each of the 12 subjects, which should be enough to reach a stabilized "automatic" level. In total, 6300 Sets were found. All subjects are required to have little to no previous experience with the game Set. This is necessary to accurately see the learning effects in the transitioning from a new to an experienced player. If the player did not know the rules, it was explained to them and they were given examples of right and wrong Sets before starting to play against the model.

All of the subjects' actions and performance, as well as the model (speed and expert) parameters and the currently present cards and Sets, are logged. These logs are used to create dataframes from which all kinds of information can be extracted, such as average reaction time and usage of different strategies (or an index to represent this strategy) over time. This shows us the differences between novice and expert players and in what manner the transition from a novice to an expert occurs. We also use the gathered data for analysis with a Linear Mixed-Effect Regression Model.

3. Analysis and Results

In this section, we describe how we analyzed the potential factors in finding a Set, and show the results of this analysis. We will describe this for each of those factors individually, starting with the reaction time per level. At the end of this section, we will describe a linear mixed effect regression model, in which we use any factors that are found to have a significant effect.

3.1. Reaction Time per Level

As Taatgen *et al*. have already found, lower level Sets are found more quickly than higher level Sets. However, it is still useful and necessary to look at it in this study as well, as it is the most apparent predictor for reaction time. Also, we will use this data to compare it to the LME regression model, to see how well it's approximated.

3.1.1 Analysis

In order to analyse the reaction time per level (over time), we first sorted the data on the level of the Set. Afterwards, we split the data into 10 bins of half an hour, in chronological order. We used the median

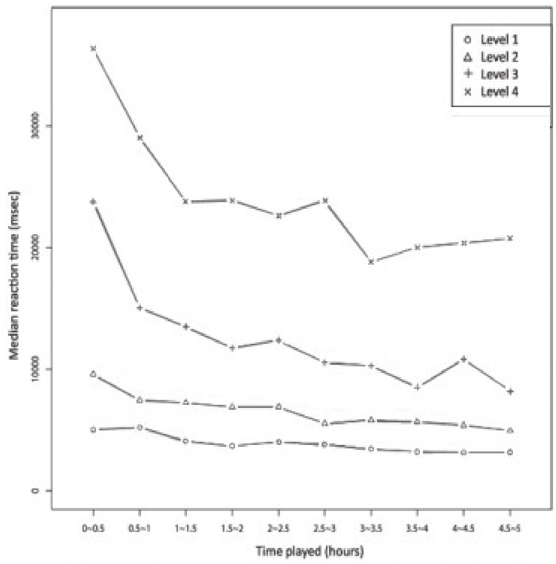

Figure 3: Reaction time for the 4 different levels, plotted over time. The learning in lower level Sets is less apparent in this figure due to the scaling, but it is there, albeit less than the learning on high levels.

reaction time of each of these bins, in order to limit the influence of outliers.

3.1.2 Results

As expected, higher level Sets take a lot longer to find than lower level Sets. This is the case especially for novice players. For expert players the difference is a lot less, but there is still learning on the lower levels as well. See figure 3.

3.2. Most Abundant Value

The MAV is the value of any of the dimensions (blue, two, oval) that occurs the most among the 12 cards that are present. A Set is said to be in the MAV-group (MAVG) if each of the cards in the Set shares the same MAV. Jacob & Hochstein already looked at the MAV, but we also looked at how the MAVD changes over time, to see if there are learning effects relevant to the MAV.

3.2.1 Analysis

In order to analyse the MAV-dependency (MAVD), we looked at all the situations out of the 6300 Sets found where there is both a Set inside and a Set outside the MAVG. We

$$MAVD = \begin{cases} \dfrac{totalSets}{setsInMAVG} & set \in MAVG \\ 0 & otherwise \end{cases}$$

Formula 1: MAVD calculation

calculated an index (MAVD) that shows the MAV-dependency. If the found Set is not in the MAVG, this index is given a value of 0. If the Set is in the MAVG, it's value is the total number of Sets divided by the number of Sets inside the MAVG. This is the inverse of the chance a player would pick a Set within the MAVG if they had no particular MAV-related preference at all. If this were to be the case, the average index would be 1. See formula 1.

For example, if there are 5 Sets available, 2 of which are in the MAVG, if a Set in the MAVG were found, MAVD would get appointed a value of 2,5. If players have no preference and this scenario occurs several times, on average they would find a Set within the MAVG 2/5 of the time. So the index would get 2,5 points twice, and 0 points in the other cases. This averages out to 1. If the MAVD is higher than 1, Sets in the MAVG are preferred. If it is lower than 1, Sets outside of the MAVG are preferred. For instance, if the MAVD is 2, Sets in the MAVG are chosen twice as often as expected if there were no preference.

3.2.2 Results

After drawing a smooth curve through the collected MAVD datapoints (figure 4), we can see that the MAVD stays above 1. This means that players show a preference for sets within the MAVG, as Jacob & Hochstein have also concluded. The figure also shows that the MAVD does not change much over time, meaning that it is unlikely that learning takes place regarding the MAV. Novices and experts show very little difference in their MAV usage. The strong increase towards the end is likely caused by the smoothing procedure.

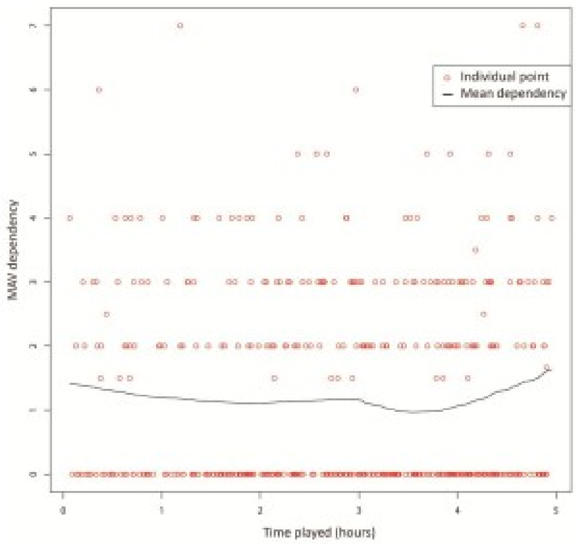

Figure 4: The mean MAV-dependency plotted against time. A MAVD above 1 means Sets within the MAVG are preferred over Sets outside of the MAVG.

3.3. Level 4 Preference

Another point of interest is what Set players will choose in the presence of multiple Sets of different levels. However, because of the sheer amount of different combinations, we only looked at one simple case: if there is at least 1 level 4 Set, and at least 1 lower level Set, how often will the level 4 Set get picked? In the absence of a better term, we will call this "level 4 preference".

3.3.1 Analysis

In order to analyse the level 4 preference, we first filtered all the Sets found to include only those Sets found when there was both a level 4 and a lower level Set available. The index (l4preference) for level 4 preference is calculated similarly to the MAVD, as shown in formula 2.

$$l4preference = \begin{cases} \dfrac{totalSets}{level4Sets} & found\ level = 4 \\ 0 & otherwise \end{cases}$$

Formula 2: Level 4 preference calculation

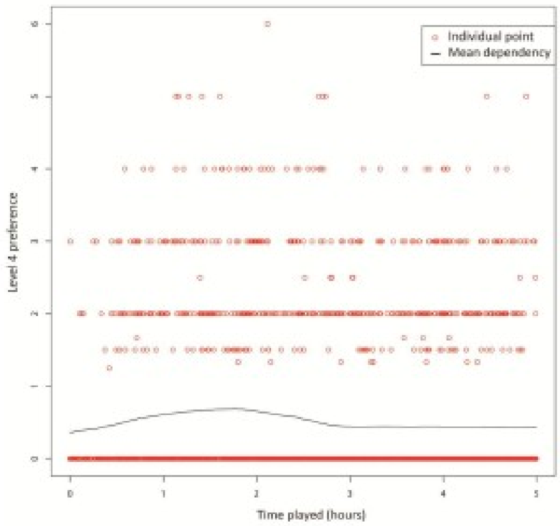

Figure 5: The mean l4preference plotted against time. An l4preference under 1 means lower level Sets are preferred over level 4 Sets.

As was the case for MAVD, an index of 1 means that a player has no particular preference for level 4 or lower levels, when both are available. An index of 0,5 means that level 4 Sets are found half as often as expected if the player had no particular preference.

3.3.2 Results

The curve drawn through the relevant datapoints (the ones where both a level 4 and a lower level Set are available), shown in figure 5, shows us that the l4preference is below 1 at all times. There is a small bump the first 3 hours, after which the l4preference stabilizes at slightly above 0,4. This means that level 4 Sets are found 2,5 times less often than would be expected from a player with no level 4 preference. In other words, there is a very strong aversion towards level 4 Sets. This aversion is less at the bump around 1,5 hours.

3.4. Dimensional Salience

The dimensions in Set are color, count, shape and filling. Dimensional salience is the term that describes which of these dimensions has the largest influence in making a Set easy or hard to find, or the

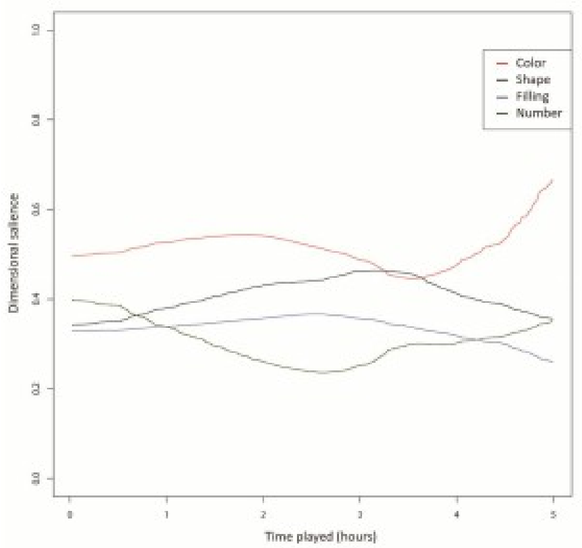

Figure 6: The dimensional salience over time. There is some fluctuation, but overall the dimension color is more salient than the other dimensions.

term that describes how much a dimension "pops out". Both Jacob & Hochstein and Nyamsuren & Taatgen have looked at dimensional salience, but they found different results. In addition to (in)validating their results, we also looked at how the salience changes over time.

3.4.1 Analysis

In order to analyse dimensional salience, we looked at the number of Sets that have a dimension in common. For instance, a level 2 Set may have color and count in common. For each Set, there is a datapoint for each of the dimensions, which is either 0 or 1, depending on whether the dimension is shared by the cards in the Set. Each datapoint was put on the timeline at the time the Set was found. Finally, these datapoints were averaged to form a smooth curve.

3.4.2 Results

Just like Jacob & Hochstein, we found that different subjects had different preferences. However, like Nyamsuren & Taatgen we found that in general, color is preferred over the other dimensions. See figure 6.

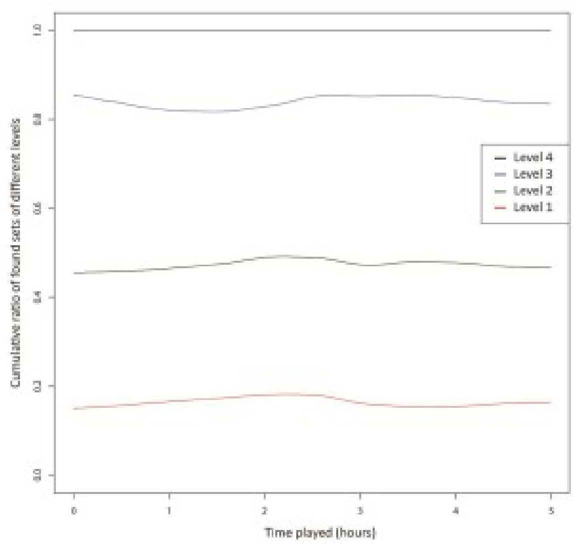

Figure 7: The cumulative ratio of the different levels of Set. The space in between two lines represents the ratio at a particular point in time.

3.5. Level Ratio

Level ratio is the ratio of occurrence of the 4 different Set levels. In this section we looked at this ratio, and how the found ratio compares to the expected ratio. Also, we looked at how the ratio changes over time.

3.5.1 Analysis

In order to analyse level ratio, we looked at each of the 6300 Sets found. If a Set is level 1, then level 1 will get the value 1, while all other Sets get awarded the value 0. As a result, when averaging the datapoints the levels have an average ratio of 0,25. Any deviation from this means the Set level is found more or less often. The datapoints were plotted with respect to time, so we can see if any changes occur in the transition from novice to expert (see Figure 7).

To compare the found data against the expected data, we first had to calculate the ratio of occurrence. This is done according to formula 3, which is the general equation of Set occurrence from Jacob & Hochstein (2008). This formula lead to a total of 1080 Sets, so in order to accommodate it to our data, we had to multiply the results by 6300/1080.

$$levelRatio=\frac{3^4\cdot\binom{4}{level}*2^{level}}{3!}$$

Formula 3

Table 1: Difference between expected and found number of Sets per level

Level	Expected	Found	Relative Diff.
1	630	1034	1,64
2	1890	1965	1,04
3	2520	2290	0,91
4	1260	1011	0,80

3.5.2 Results

As shown in table 1, lower level Sets were found more often than expected by occurrence, while higher level Sets were found less. Figure 7 shows that that these ratio's stay about the same throughout all games, except for a slight bump in level 4 around 1.5 hours in, which corresponds to the bump found earlier, in level 4 preference.

3.6. LME Regression Model

In the LME Regression Model, we wanted to model the reaction time of a Set, given data such as the level and the time played.

3.6.1 Analysis

For the model to work well, we needed to find as many elements as possible that significantly improve the predictions of the model. To do this, we used an Analysis of Variance to see if an added element improved the performance of the model. If the improvements from an added element were too small, the element was discarded, to prevent overfitting to the dataset. The elements of the model equation that we used all come from the factors discussed in previous sections.

3.6.2 Results

The fixed effects of our model can be found in table 2, and the random effects can be found in table 3. The final model has the logarithm of the RT as it's dependent variable. The logarithm was used because it showed more accurate predictions, and also so outliers would have less influence. Each of the independent variables will be discussed separately.

Intercept is the base case. In other words, a level 1 Set without practice, etcetera. All the other fixed effects have to be added to this coefficient. It should be noted that even effects with small coefficients have a large impact, because the dependent variable is logarithmic.

Time is the time the subject has practiced. This negative coefficient means that with more practice, the reaction time becomes lower. We used the logarithm of *time* because of the nature of learning: the first hour has a bigger effect than the following hours.

TotalSets is the number of Sets currently present. We also used the logarithm of *TotalSets*, because the previously described *Horse Race Model* has a logarithmic character.

Color is when the three cards in the Set share the same color. The other dimensions were shown not to be significant. If the color is shared, the Set is more easily found.

Level 2, 3 and *4* apply for different levels of Set. It shows that higher level Sets take longer to find.

Log(time):Level shows the interaction between time and level. These coefficients show that different levels have different learning rates. Higher level Sets have a higher learning rate. Interestingly enough, level 3 appears has a much higher learning rate than level 4, though.

Figure 8 shows how the model fits the actual reaction times. For each of the 6300 Sets found, the model used the described elements to predict the RT.

Table 2: Fixed effects of the LME Regression Model

Fixed effects	Coefficients	t-value	p-value
Intercept	9.290	100.54	0
Log(time)	-0.103	-4.09	0
Log(totalSets)	-0.586	-31.57	0
Color	-0.198	-9.26	0
Level 2	0.511	13.12	0
Level 3	0.962	25.17	0
Level 4	1.310	27.53	0
Log(time):Level 2	-0.113	-3.47	0
Log(time):Level 3	-0.174	-5.55	0
Log(time):Level 4	-0.097	-2.53	0.01

Table 3: Random effects of the LME model

Groups	Variance	Std. Deviation
subj	0.085	0.291
Residual	0.528	0.727

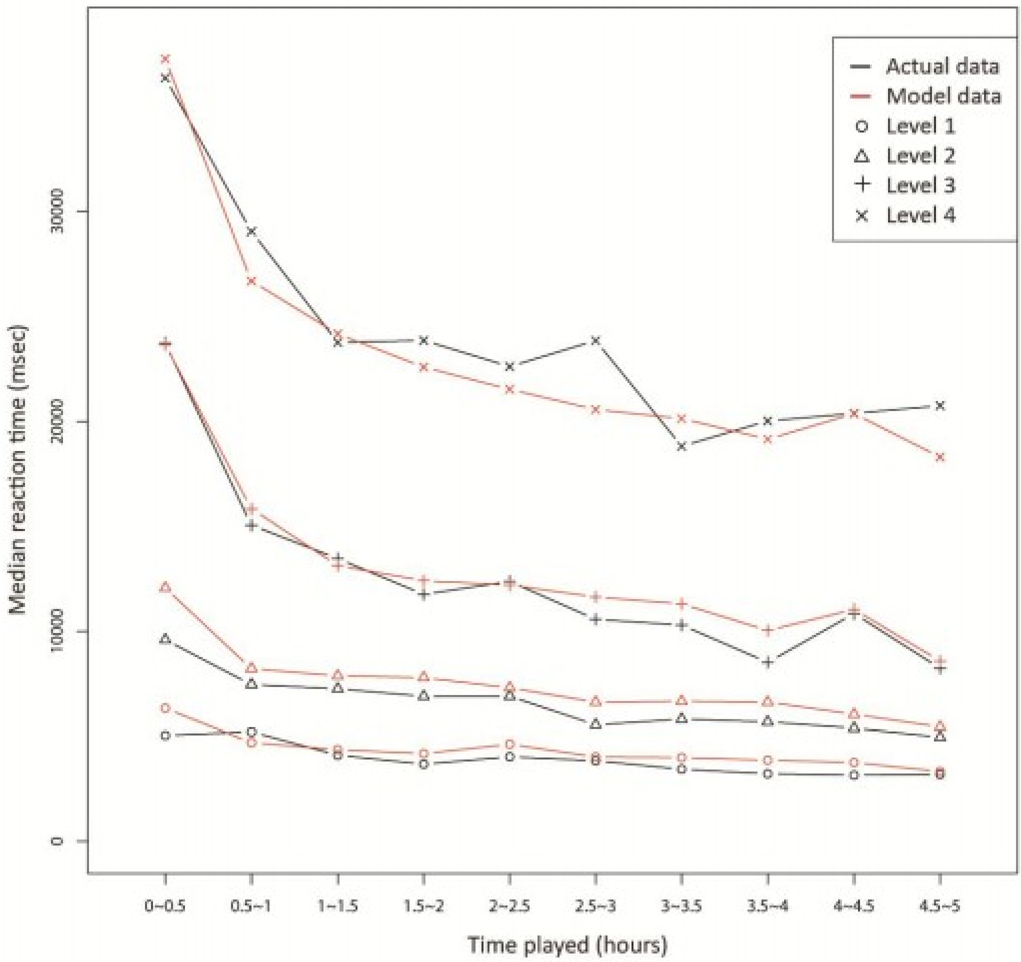

Figure 8: The LME model fitting the actual reaction times, using the elements from table 2 as predictors.

3.7. Computer opponent parameters

A final thing of interest is the speed-parameter and expert-parameter of the opponent mentioned above, and how it is affected by time.

3.7.1 Analysis

We will start off with an analysis of how the speed-parameter and expert-parameter change over time. We will look at this by plotting the parameters against time. We use the data of all subjects, sorting the datapoints on time spent playing.

We use these datapoints to create an LME model in which time spent playing is used to predict the values of the speed and expert-parameter.

Finally, we will look at the correlation between the two parameters. We will try answering whether all players follow the same pattern or whether they have different progressions in the two parameters. To do this, we look at the difference in parameters between after 1 hour and after 5 hours for each individual. With this we create a scatterplot that will show any trends in the correlation of the two parameters.

3.7.2 Results

As shown in figure 9, the speed-parameter slightly increases (meaning slower finding of Sets) at first, and gradually declines afterward. The initial increase can be explained by the fact that the initial parameter settings are an estimation of the skill of a novice player. Apparently this estimation was slightly off. The decline seems to be heading towards an asymptote, as expected.

In figure 10, a similar plot is shown for the expert-parameter. This shows that the parameter consistently rose until it hit the

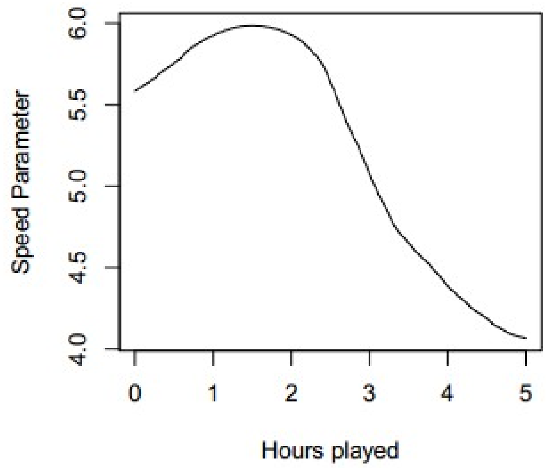

Figure 9: The changes of the speed-parameter over time.

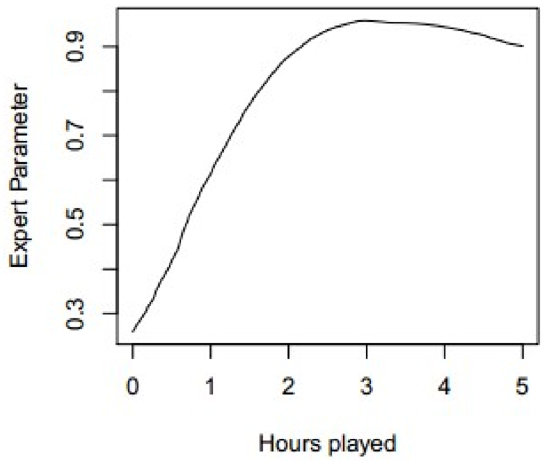

Figure 10: The changes of the expert-parameter over time.

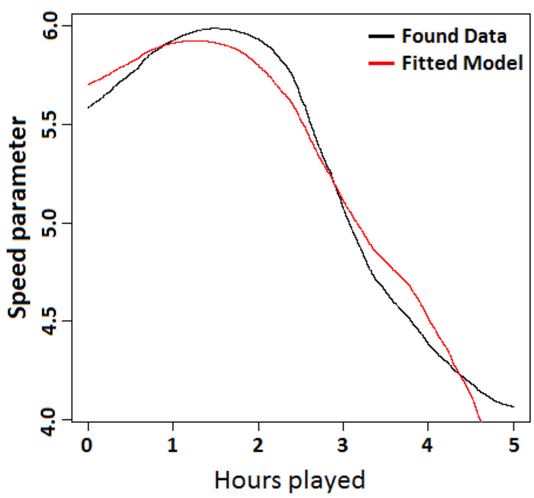

Figure 11: The fitted model of the speed-parameter

maximum. This implies that subjects learn higher level sets in a consistent fashion. However, we have already seen that the reaction times lower in a logarithmic manner, so perhaps this seemingly linear progression is caused by the model becoming better logarithmically as well.

Figure 11 and figure 12 show the graph of a model for the parameters in addition to the actually found data. The only predictors are time and Log(time). As the figures show, the model's graph closely follows the actual data. The only difference in shape is near the end and is likely caused by the smoothing function. The fixed and random effects of the two models are shown in table 4, 5, 6 and 7.

Finally, figure 13 shows the scatter-plot for correlation between the two parameters. The twelve data-points represents each individual subject. Keep in mind that a lower value for the speed-parameter means the subject is faster.

While the points in the scatter-plot are not very clustered, the scatter-plot still shows that subjects who learn more in one parameter learn less in the other.

4. Discussion

Our main question was what the top-down learning effects are in the perceptual task of Set. In order to help answer this, we looked at what changes between novices and experts we could find to explain where the learning effects manifest themselves.

We first looked at the MAV-dependency. It was shown that Sets within the MAVG were found more easily than those outside of the MAVG. However, MAV-dependency did not change over time. Also, MAV was statistically proven to not be a significant factor in predicting RT.

A possibly explanation for this is that the model already included other factors that made the MAV redundant.

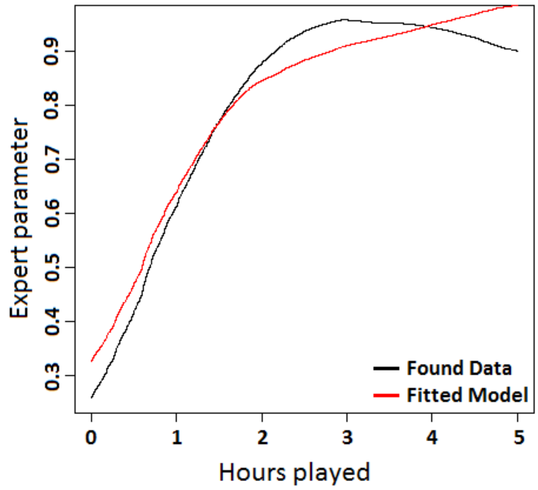

Figure 12: The fitted model of the expert-parameter.

Table 4: Fixed effects of the speed-parameter model

Fixed effects	Coefficients	t-value	p-value
Intercept	7.372	12.70	0
Log(Time)	0.546	12.87	0
Time	-0.719	-27.71	0

Table 5: Random effects of the speed-parameter model

Groups	Variance	Std. Deviation
subj	4.020	2.005
Residual	1.668	1.292

Table 6: Fixed effects of the expert-parameter model

Fixed effects	Coefficients	t-value	p-value
Intercept	0.714	29.69	0
Log(Time)	0.257	60.19	0
Time	-0.034	-13.06	0

Table 7: Random effects of the expert-parameter model

Groups	Variance	Std. Deviation
subj	0.007	0.082
Residual	0.017	0.130

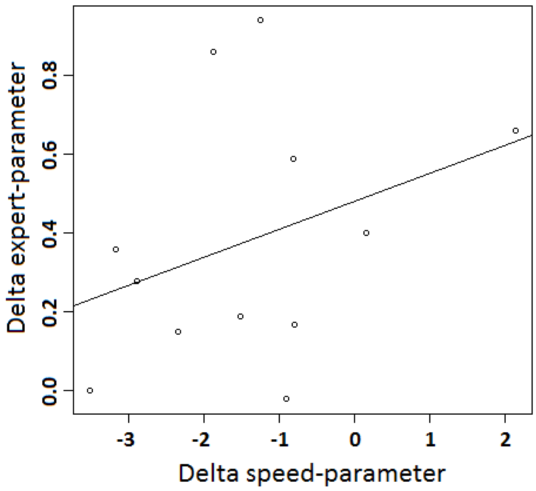

Figure 13: Scatter-plot showing the correlation between improved speed and expert-parameters between 1 and 5 hours. More improvement in one parameter generally means less improvement in the other.

In particular, the presence of levels may have done this. It has been shown that level 4 Sets are found much slower than low level Sets. In order for a Set to be part of a MAVG, it's cards must share some dimension. Because the cards of a level 4 Set do not share any dimension, it is impossible to be in the MAVG. This explains why Sets in the MAVG are found more easily: they are, on average, a lower level. Besides the restriction on level that the MAV-dependency enforces, there is no proof for the MAV to play any role.

Next, we looked at level 4 preference. As expected, level 4 Sets were more difficult to find than lower level Sets. There was little change in the level 4 preference, though, except for a small bump around the 1,5 hour mark. A possible explanation for this would be that at the start, players are not proficient at finding level 4 Sets yet, but when they start to understand them, they overlearn and put too much focus on level 4 Sets. Eventually, it balances out and they will focus more on the easier levels again. When we looked at level ratio's, except this bump there were no changes noticed.

Unlike Jacob & Hochstein, but like Nyamsuren and Taatgen, we found that color is significantly more salient than the other dimensions. If the cards in a Set share color, the RT of finding the Set will be lower on average. However, the dimensional preference is different for different individuals.

We also constructed an LME model. This model allowed us to prove that there are different learning rates for different levels of Set. Higher level Sets were found to have a higher learning rate than lower level Sets. As stated by Jacob & Hochstein and Nyamsuren & Taatgen, these high level Sets require cognitive processes. This shows that most of the learning comes from improvements in cognition, rather than perception.

Finally, we looked at the computer opponent parameters. We found that the more someone improves their expert-parameter between after 1 and 5 hours of playing, the less they improve their speed-parameter in this time. The explanation for this is as follows:

Figure 10 shows us that subjects reach the maximum expert-level very quickly, and afterward stay at the maximum. The speed-parameter on the other hand does not start increasing significantly until after the expert-parameter reached it's maximum. The stronger players managed to maximize their expert-parameter after about an hour already, meaning that the difference between after 1 hour and after 5 hours is very small. However, these are also the players that spent the most time improving the speed-parameters, whereas a weaker player will take longer maximizing their expert-parameter and thus have less time to improve their speed-parameter.

In short, players maximize the expert-parameter first, and once it is maximized they start lowering the speed-parameter.

More time spent on the expert-parameter means less time spent on the speed-parameter.

Some of the results obtained can be explained by how the opponent-model works, rather than how the players learn the game. In these cases, more useful conclusions could be drawn when the issues of the opponent-model that were pointed out are resolved.

5. Conclusion

While we looked at many possible factors that potentially influenced RT, none of these factors accounted for the change in performance over time. However, we did show that training on higher level Sets was larger than the training on low level Sets. While part of the learning may come from perceptual improvements, there must also be cognitive, top-down improvements to explain the larger learning effects in higher level Sets.

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