# Top-down Planning and Bottom-up Perception in a Problem-solving Task

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**Abstract**

In this paper we study the roles of top-down planning and the bottom-up elements in problem-solving tasks. We investigate how factors, such as conceptual understanding, perceptual representation and previous experience with the task, influence the action selection. The cognitive and perceptual aspects of problem-solving task are studied within the environment of card game SET. The discussion is provided on cognitive and perceptual demands on the game, and the difference between novice and expert players is analyzed with respect to two types of processes. The hypotheses proposed in this paper are tested on data obtained through an eye tracking experiment. Based on findings the ACT-R model of human player is implemented and compared to human performance.

**Keywords:** cognitive architecture; visual attention; cognitive control; games; ACT-R, problem solving.

## Introduction

Human performance in complex tasks is often a combination of internal planning and responding appropriately to the environment. Nevertheless, cognitive models of complex tasks typically focus on the mental planning aspects, and fail to consider possible influence of an external world on the control of behavior. The role of the environment was first recognized in robotics (Brooks, 1991) but was later extended to human cognition in the *embodied cognition* approach (e.g., Clark, 1997; Kirsh & Maglio, 1994). The challenge is to understand how control is shared between goal-driven planning and processes that are driven by perceptual input. The approach we will take is to assume two parallel processes: a bottom-up visual process that scans the visual field on the basis of saliency and similarity, and a top-down planning process that tries to achieve the goal, but also biases the bottom-up process.

Finding an appropriate task to study the cognitive aspects of human behavior in real-life situation is not easy. However, games provide environments that often require the same type of complex processes that are usually involved in real-world situations. This has the advantage that behavior of a player can be studied in a controlled environment. These qualities make games on a computer an ideal tool for studying complex cognitive processes. One such game is the card game SET[1].

The SET card deck consists of 81 cards. Each card differs from other cards by a unique combination of four attributes: Color, Number, Shape and Shading. Each attribute can have one of three distinct values: Red, Green and Blue for the Color attribute; Open, Solid and Textured for the Shading attribute; One, Two and Three for the Number attribute; Oval, Rectangle and Wiggle for the Shape attribute.

The gameplay for SET is relatively simple. At any moment in the game, 12 cards are dealt open (Figure 1). Players should find any combination of three cards, further referred to as a set, satisfying the main rule stating that in the three cards the values for a particular attribute should be all the same or all different. The number of different attributes in set cards is further referred as a *level* of the set. As such, the set, in which only one attribute is different, is level 1 set. Correspondingly, there can be levels of 2, 3 or 4. Figure 1 shows examples of level 1 (different shape) and level 4 sets (all attributes are different). In the regular game, if a player finds a set, he or she picks up the three cards that form a set, and replaces them with new cards from the deck. After the deck runs out the player with most cards wins.

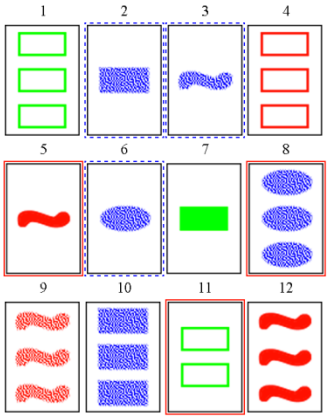


Figure 1: An example array of 12 cards. The cards with the solid highlight form level 4 set (all attributes are different), and cards with dashed highlight form level 1 set (Shape is different).

There are several advantages of choosing SET as a target game of study. SET has very simple rules to follow and relatively static game environment. Despite the simplicity, SET requires complex cognitive processes including pattern recognition, visuospatial processing and decision making. It is our hypothesis that in SET both cognitive and perceptual processes are equally important to play the game. As such, SET provides an excellent opportunity to study the dynamics of such processes in a relatively simple game

[1] SET is a game by Set Enterprises (www.setgame.com)

environment. Finally, the game is unpredictable requiring dynamic and real-time decision making. There are $7*10^{13}$ possible combinations of 12 cards and 220 possible choices of three cards out of the array of 12 cards. It makes the detailed strategy planning impossible. With this regard SET is quite similar to Tetris (Kirsh & Maglio, 1994). In Tetris a player's behavior is not determined by specific strategy, but the player reacts to the next available block. Similarly, in SET the players cannot really decide the strategy unless all the cards are seen. The players have to come up with the strategy on the fly after viewing the cards. Furthermore, the need to find the sets of different levels forces the players to change the strategy as the game progresses. Such dynamic and unpredictable nature of the game makes SET an interesting target of a study.

### Related Works on SET

A study by Jacob and Hochstein (2008) argued that the players prefer to look at perceptually similar cards, and, for comparison step, they mainly rely on processes at the perceptual level. According to the authors, bias to perceptual similarity and bottom-up processes explains why the players need less time to find lower level sets than higher level sets. Taatgen et al. (2003) also reached the conclusion that the perceptual elements play a greater role in finding lower level sets. They suggested a strategy where a player looks at an arbitrary first card then at a second card that shares an attribute value. Next, the player predicts the third card and determines whether that card is one of the remaining ten cards. Taatgen et al. also hypothesized that the choice of the first card might not be arbitrary in some cases. They proposed that the players try to find the set among the cards that have attribute value occurring in more than half of 12 cards (if there are many red cards, it is attractive to search for a set among those cards). Taatgen et al. implemented this strategy in an ACT-R model. However, the data they collected did not have enough detail to determine whether subjects use such a strategy.

Jacob and Hochstein (2008) proposed a generalization of Taatgen's strategy based on notions of the most abundant value (MAV) and the most abundant value group (MAVG). The former refers to an attribute value that occurs most, and the latter refers to the group of cards that have the MAV. They found that the sets belonging to the MAVG are preferred to the sets outside of the MAVG. In addition, the time required to find the set in the MAVG decreased as the size of the MAVG increased. MAVG was preferred to any other value group independently of the attribute type. Jacob and Hochstein suggested dimension reduction strategy where players try to reduce the four dimensional search space into three by choosing to look at the cards that have one attribute value in common. As authors claimed, the dimension reduction primarily occurs with MAV.

There is very little discussion on aspects that result in difference between novice and expert players. Taatgen et al. (2003) argued that the experts have optimized comparison process of cards. Such optimization happens through the gradual transition from the declarative knowledge to procedural knowledge resulting in a faster comparison of the cards. The Taatgen et al. model was able to learn through proceduralization and make a transition from the novice player to the expert player.

## Research Objectives

Taatgen et al. (2003) used questionnaires and reaction times to gain understanding about player's behavior, while Jacob and Hochstein (2008) used combinatorial analysis of reaction time. We hope to gain more insight in the underlying cognitive and perceptual processes through an eye tracking experiment. Other studies have shown that eye movement protocols at least indirectly reflect cognitive processes and amount of cognitive load (Rayner, 1995).

### Cognitive and Perceptual Processes

Even though earlier studies suggest similarity plays an important role in the game, we aim to provide more direct evidence of such by studying the sequence of eye movements people make.

Despite the importance of the similarity-based perceptual processes, as it was shown by Jacob and Hochstein (2008), it is still unclear how the higher level set are found. The players cannot rely on the perceptual similarity and have to deliberately search for the dissimilar cards. This is where we should see evidence of how a top-down process can influence the bottom-up visual scanning process.

Another objective is to study in greater detail the differences between the novice and the expert players. We will investigate what aspects at the cognitive and the perceptual levels result in differences between two groups of players. It might be the case that the novice players rely more on perceptual processes for decision-making, while the expert players rely more on conceptual aspects of the game. For the novice players the choice of the cards to look at might be driven by perceptual similarity, in contrast, the expert player might be driven more by a top-down process, such as a specific strategy.

### Improved ACT-R model

The ACT-R model created by Taatgen et al. (2003) was able to closely approximate the human player's reaction times. It is, however, uncertain whether the model can also predict eye-movement patterns, because it has a purely top-down strategy. It also does not incorporate the recent finding by Jacob and Hochstein demonstrating the importance of bottom-up elements of the game. Our aim is to test whether more complex model with greater emphasis on perceptual elements of the game can explain the human data.

## Experiment

### Design and Procedure

In total, 14 subjects have participated in the experiment. The age of the subjects ranged from 20 to 30 years. All subjects

were either students or staff members of University of Groningen. The subjects' previous experience with SET varied greatly: from few played games to several years of experience. Hence, the reaction times were chosen as an indicator of subject's overall experience.

Every subject was asked to do 60 trials. The group of 60 trials was same for all subjects. Each trial consisted of 12 cards shown on a computer screen and arranged to an array similar to one show in Figure 1. Each trial had exactly one combination of three cards that formed the set.

All 60 trials were randomly generated with constraint that all four levels of difficulty were equally represented in the experiment. In 30 trials one of the set cards was highlighted with the red border. The highlighted card belonged to the set and served as a clue for the subject to find the other two cards. The summary of the trials is shown in Table 1.

Table 1: The summary of the trials.

| | | Trial level | | | | Total |
|---|---|---|---|---|---|---|
| | | Level 1 | Level 2 | Level 3 | Level 4 | |
| Trial type | With highlighted card | 7 | 8 | 8 | 7 | 30 |
| | No highlighted card | 8 | 7 | 7 | 8 | 30 |
| Total | | 15 | 15 | 15 | 15 | 60 |

In each trial, the subject was asked to find the cards forming the set and select them with the mouse. After successful selection of all set cards or expiration of a time limit of 180 s, the next trial was automatically shown to the subject. In case of failure to find the set, the reaction time for that trial was recorded as 180 s. The sequence of trials was determined randomly for every subject.

The subjects' eye movement data was collected using an EyeLink 1000 eye. It is a desktop-mounted remote eye tracker with monocular sampling rate of 500Hz and spatial resolution of $< 0.01^{\circ}$ RMS. The card images were shown on monitor with screen size of 1024×768 pixels. The card images had size of 124×184 pixels with 80 and 70 pixels of horizontal and vertical distances in between. The average viewing distance is 70 centimeters. The calibrations of the eye tracker were performed at the start and during the experiment, if necessary, with average accuracy of $0.8^{\circ}$ being considered as an acceptable measure.

## Results

**Reaction Times** Subjects differed significantly in terms of RT, reflecting their different levels of expertise in SET as it is shown in Figure 2.a. All subjects were categorized into groups of expert, intermediate and beginner players based on their mean reaction times (Figure 2.a).It can be seen from Figure 2.b that having a highlighted card as a clue decreases the RT by more than twice. This effect can be observed in all three groups of subjects and in all levels. Secondly, it is clear that RT is largely dependent on the level.

**Grouping by Attribute Value** To demonstrate how subjects use the dimension reduction strategy we first look at a particular example. In the example trial the subject had to find a level 3 set. The MAV is Oval value with the MAVG size of eight cards. It should be noted that the Oval is the only value which is the same among the cards that make up the set. Figure 3.a shows subject's fixation sequence diagram for the trial. Within the diagram, the subject's fixation sequence is represented four times (four separate lanes), each time from the perspective of one of four attribute types. One unit on x-axis represents fixation on one particular card, while the corresponding bars on four lanes represent the attribute values of that card. The consecutive fixations on the cards with the same attribute value are shaded with solid color if the probability of such fixation subsequence occurring by chance is equal to or below 0.01. The probability is calculated as $P_{ij} = \frac{n_{ij}}{11} * \left(\frac{n_{ij}-1}{11}\right)^{k-1}$ where $k$ is the length of the block, and $n_{ij}$ is a number of cards that have a value $i$ for an attribute $j$.

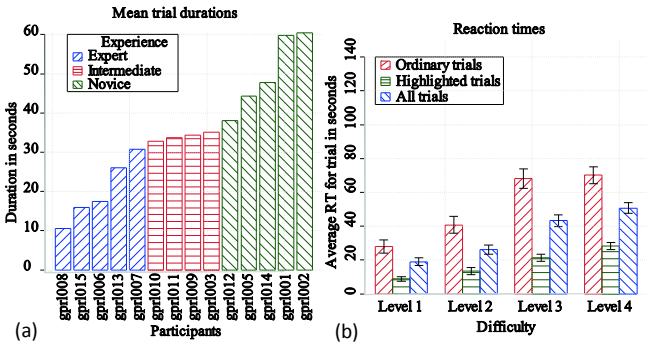


Figure 2: The graph (a) depicts the mean reaction times averaged over all trials for each subject. The graph (b) shows the mean RT in ordinary and highlighted trials clustered by the levels and averaged over all subjects.

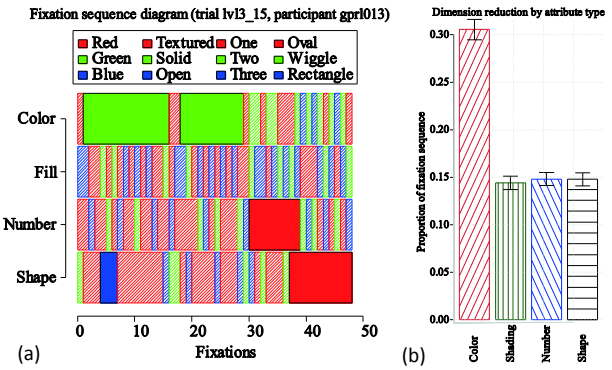


Figure 3: (a) the fixation sequence diagram for trial lvl3_15 and subject gprl007; (b) mean proportions of attribute types used in dimension reduction strategy (overall for all subjects and trials with no highlighted card).

The figure shows that the subject used the dimension reduction strategy at least three times and each time with respect to the different attribute value: Green, One and Oval consecutively. It is a nice example of players using values

other than the MAV for dimension reduction. The example shown in Figure 3.a is not an isolated case. In fact, in 75% of all the fixation sequences the dimension reduction strategy is used. Figure 3.b shows how 75% distributes over the four attribute types.

The fact that the first attribute used for the dimension reduction is the Green color contradicts with Jacob and Hochstein's claim that the choice of the value depends only on the group size and not on the attribute type. Studies found that people prefer to operate on colors rather than on shapes (Kim & Cave, 1995; Pomplun et al., 2001). Likewise, Figure 3.b indicates that for the dimension reduction the SET players prefer to use Color twice as much as the other attributes.

**Search Subsequences** Subjects use a dimension reduction strategy to reduce the complexity of finding a set. However, it is not yet clear how a similarity-based approach can eventually find sets with many different attribute values. We will therefore now analyze the trials in which one of the cards in the solution was already highlighted. Inspection of the data revealed that subjects look back to that card approximately every five card fixations, presumably to refresh their memory and to restart a new search subsequence. Breaking down a trial in separate subsequences allows us to analyze the similarity between the highlighted card and the currently fixated card based on which subsequence it is, and the position within that subsequence.

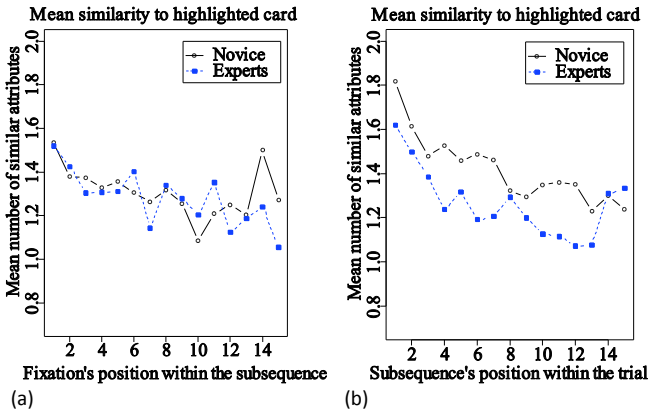


Figure 4: (a) The mean perceptual similarity of each fixation in a subsequence to a highlighted card (b) The mean perceptual similarity of cards in a particular subsequence to a highlighted card.

Figure 4.b shows that with each subsequence (i.e., each attempt to find a set with a highlighted card) the similarity (measured in the number of equal attribute values) between fixated cards and the highlighted card decreases. The same tendency can be observed for the fixations within a subsequence itself (Figure 4.a) although not so obvious.

In the beginning of a trial the subjects clearly prefer to look at the cards that are perceptually similar to the highlighted card. This is in conformance with the Jacob and Hochstein's results. However, the graph shows that, over the time, the subjects tend to look at the cards that are less similar to highlighted card. There is a gradual transition from the search among the cards that are similar to the search among the cards that are dissimilar. In addition, novice players are more biased to the search based on the perceptual similarity than expert players.

**Analysis with Linear Mixed-Effect Regression Model** We analyzed this effect and several other factors of interest with a mixed-effect regression analysis (Baayen, Davidson & Bates, 2008).

Table 2: The fixed effects' coefficients, t and p values.

| Fixed Effects | Coefficients | Standard Errors | t values | p values |
|---|---|---|---|---|
| Intercept | 0.329 | 0.139 | 2.359 | 0.01 |
| Fixation | -0.100 | 0.029 | -3.441 | 0 |
| Subsequence | -0.319 | 0.035 | -9.131 | 0 |
| Experience | 0.063 | 0.022 | 2.827 | 0 |
| ColorCount | 0.134 | 0.021 | 6.272 | 0 |
| FillCount | 0.096 | 0.015 | 3.779 | 0 |
| NumberCount | 0.113 | 0.019 | 6.126 | 0 |
| ShapeCount | 0.071 | 0.018 | 5.659 | 0 |

The dependent variable in the regression model is the value of the perceptual similarity (the number of same attribute values) of the next fixated card to the corresponding highlighted card. Predictors that significantly contributed to this similarity are shown in Table 2.

*Subsequence* is position of a subsequence in a fixation sequence (values of x axis in Figure 4.b), and *Fixation* is the position of a fixation within a subsequence (values of x axis in Figure 4.a). Both predictors have negative coefficients. This supports our postulate that there is a transition from tendency to look at the cards that are perceptually similar to the highlighted card to tendency to look at the cards that are dissimilar. The fact that *Fixation* also has significant negative coefficient indicates that transition occurs not only within fixation sequence as whole, but also within individual subsequences.

The variable *Experience* represents the subject's level of expertise in playing SET (1 for expert group; 2 for intermediate group; 3 for novice group). The predictor's positive coefficient indicates that less experienced players rely more on similarity-based strategy than more experienced ones.

The variables *ColorCount*, *FillCount*, *NumberCount* and *ShapeCount* indicate the number of cards in trial that have same Color, Shade, Number and Shape values as the highlighted card. The positive coefficients for those variables indicate that a bigger group of cards, that are perceptually similar to highlighted card, encourages more to use perceptual similarity-based search than a smaller group of cards. This is consistent with our analysis in the previous section and claims by Jacob and Hochstein. The fact that *ColorCount* has the highest coefficient value is also

consistent with our theory that Color dominates the other attribute types.

## Discussion

Both the descriptive and mixed-effect regression analysis of the fixation sequences indicate that the subjects' basic strategy of playing SET is similarity based. Subjects prefer to look for a set among the cards that are similar to each other. One specific instance of similarity-based strategy is a dimension reduction strategy. The dimension reduction strategy can be used more than once (Figure 3) within the same trial and each time with different attribute value. The player chooses one attribute value, the guiding attribute value or GAV, and starts looking for a set among the cards that share the GAV. If the player fails to find a set with the current GAV, then another GAV is chosen, and the new group of cards is defined as the next search space. This part of the strategy is top-down, but the choice of the GAV is heavily influenced by two bottom-up elements: (1) the size of the group of cards that share the value and (2) its attribute type. The importance of group size (Table 2) was also found by Jacob and Hochstein. However, contrary to their conclusion, we have found that the attribute type also plays an important role (Figure 3.b & Table 2) in choosing the value for the dimension reduction. Particularly, Color is preferred to any other attribute type.

Another interesting finding is the gradual reduction in reliance on similarity (Figure 4 & Table 2). This gradual reduction explains the positive correlation between level of the set and time required to find it. At the beginning of the game the subjects prefer to use similarity based search, such as dimension reduction. However, as the game progresses, the players increasingly look at more dissimilar cards more suitable for finding higher level sets.

Consistent with this, we found that the expert players are less dependent on similarity than the novice players (Figure 4 & Table 2). This result implies that the expert players exercise more top-down control than the novice players.

The strategy of reducing the search space with one value can also be used to find higher level sets. Let's assume that player fails to find a set among cards that share the same Color. In this case the player might choose, for example, one red card and look for the second and third cards among blue and green cards. Here the search space is again reduced since all but one card with a red value are ignored. Players may choose to use this only when dimension reduction strategy fails to find a set. The alternation between the dimension reduction and this strategy, with initial preference on former, can explain the gradual transition from similarity to dissimilarity.

Finding the dissimilar attributes requires an explicit understanding of specific SET rules such as "Given Rectangle and Wiggle the third value should be Oval". Such rule-based cognitive processes are costlier than similarity-based perceptual processes. Most likely this is the reason the novice players prefer to rely on similarity-based perceptual processes. However, the need to find higher level sets forces players to use top-down cognitive processes. Eventually, through training-induced learning the cost of cognitive processes can be reduced (rules get rehearsed and better understood). The expert players rely more on cognitive processes and less on perceptual elements. As a result, expert players are less biased to similarity-based search than novice players.

## An ACT-R Model of a SET Player

### Model Design Decisions

We have implemented the model in the ACT-R cognitive architecture (Anderson, 2007). In each trial, the model is presented with 12 cards. One card is always highlighted indicating that it belongs to a set. The model has to find the other two cards forming a set. The trials from the experiment were used to test the model. Although the model can be generalized to play with trials without highlighted cards, we only provide a broad outline of the more specific model, given the space limitations, and the strategy it uses.

The model largely follows the strategies that we have found in the data. At first, the model attends a highlighted card. Next, it chooses a GAV and scans through the cards satisfying the GAV criteria. While scanning, the model chooses the second card from the ones that have already been fixated with cards fixated earlier being preferred to ones fixated latter on. When the second card is selected, the search criterion for the third card is determined. The specificity of the criterion depends on the experience of the model. Given all three cards, the model verifies if the cards make a set. If there is no set then the model goes back to visual scanning. Model considers every card satisfying the GAV criteria at least once as a possible member of set. If set is still not found then model interrupts the scanning and refixates on the highlighted card to choose another GAV.

The attribute value which is most salient at the time is chosen as the GAV. The saliency of an attribute value depends on its attribute type (fitted parameters for Color and Number are more salient than for Shape and Shading), the number of cards with that particular value (positive correlation modeled with a logarithmic equation with fitted coefficients) and whether it belongs to a highlighted card (fitted parameter for ACT-R spreading activation). The saliency of a value is temporarily suppressed after it has been selected in order to make sure different values are tried in future attempts.

The model consists of two parallel processes (threads; see Salvucci & Taatgen, 2008) reflecting the top-down and bottom-up nature of the task. The bottom-up thread is responsible for visual processes such as deciding the visual scanpath or shifting attention from one card to another. The top-down thread is responsible for the higher-level processes such as deciding the GAV and comparing cards. Both threads can influence each other's processes indirectly. For example, the top-down thread chooses a GAV based on what has already been tried earlier in the trial. However, the choice is also influenced by the bottom-up features such as

what cards are visible or which card is being fixated.

The model is implemented with novice and expert modes. The experience of the model defines how the model performs visual search and comparison (checking if three cards form a set). In the novice model, once the top-down thread chooses the GAV, the visual scanpath is defined by the bottom-up thread only. As a consequence, the selection of the third card is dominated by similarity, making it harder for this model to find higher level sets. The expert model on the other hand has rules in the top-down thread that influence the selection of the third card, directing it to cards with an attribute value that is different from the first two when appropriate (e.g., a rule that biases it towards green cards if the first two cards are blue and red). Although in this case the rules are hard-coded into the expert model, it is in principle possible for it to learn these rules in the same way as the Taatgen et al. (2003) model did.

## Results

In both novice and expert modes the model had to play through 10 blocks. Each block consisted of 30 trials with highlighted cards. The trials were taken from the experiment with the human subjects. The model's mean reaction times are presented in Figure 5.a. In the figure, the model's reaction times (dashed lines) are compared to corresponding mean reaction times of human subjects (solid lines). The model closely reproduces the RT of both novice and expert human players. The model also shows the tendency to have increasing RT with increasing difficulty of a set. As a whole, the model is very good at reproducing human RT.

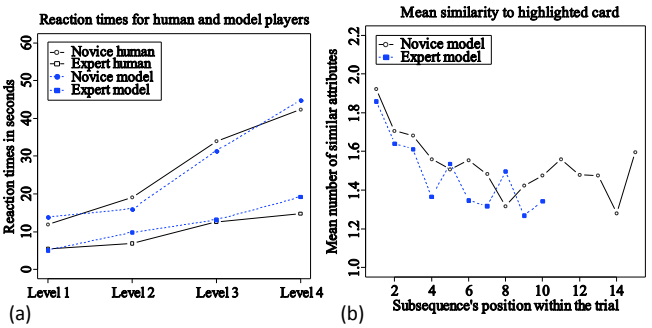


Figure 5: (a) RT of the novice and expert models comparing to the RT of the human players; (b) The mean of perceptual similarity of subsequences to highlighted card.

To test whether the model exhibits the same pattern of behavior as the human players, the similarity between the highlighted card and cards within a certain subsequences is shown in Figure 5.b (compare to Figure 4.b). It shows the transitions from a similarity-based search to a dissimilarity-based search for both expert and novice models. The model fixates first on a highlighted card and then decides the GAV. The attribute values that belong to highlighted card have more chance to be chosen as GAV than attribute values that do not. However, over time the attribute values belonging to highlighted card get inhibited due to high frequency of use, and other values get a chance to become GAV. In this case, the model starts searching for a set with dissimilar values of the chosen attribute. This effect results in gradual decrease in similarity observed in Figure 5.b.

## Conclusion

In this paper we have studied the importance of perceptual and cognitive processes in complex tasks requiring both internal planning and reaction to perceptual stimulus from environment. Our experiment and cognitive model show that both types of processes are involved in decision-making, and there is a complex interaction between them. In our model a major improvement in performance comes not from the optimization of one or another process, but from learning at the top-down level and finding an optimal balance between bottom-up and top-down processes. Indeed, it is very likely that the same processes are happening in human subjects.

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