A Theory of How People Make Decisions with Visualised Data: The Role of Emergent Strategies

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ABSTRACT

In this paper, we report a new theory of how people make decisions with visualized data. For example, how they determine whether or not it will rain today given a weather map. The theory is based on the assumption that using a visualisation to make a decision is an example of a Partially Observable Markov Decision Problem (POMDP). Two important properties of this kind of problem are (1) the visualised data allows only partial observations through foveated vision, which covers only 1-2 degrees of visual angle, and (2) the outcomes are partly random (sometimes it rains and sometimes it does not) and are partly determined by the users decisions (which part of the visualisation the user chooses to focus on). We illustrate the theory with a model of how a person determines the likelihood of credit card fraud given a number of different situation variables, called cues, including the location of a transaction, its amount, and customer history. Each of these variables may have a different validity and users may weight their relevance to a decision accordingly. The model, which is sensitive to human information processing constraints and the task environment, solves the POMDP by learning patterns of eye movements over a visualization of the data. We also compare the model predictions to human performance using a visualisation of credit card transactions. The extent to which the visualization provided the participant with an overview of the decision variables was a key factor. We show that the model does a good job of predicting human performance, and therefore at predicting the value of the visualization.

Author Keywords

information filtering; cognitive modeling; visual search; eye movements; Markov Decision Process; reinforcement learning; interaction science

ACM Classification Keywords

H.5.2 Theory and methods: H.1.2 User/Machine Systems: Human Information Processing

INTRODUCTION

While storage, aggregation and management of data is becoming easier by the day, an outstanding issue remains how to design interfaces that help people use it to make decisions. Data mining and machine learning offer methods to turn a deluge of data into an intelligible and manageable stream of information. However, in many domains where such methods are employed, there remain people in the loop which have to make decisions based on the information made available to them. An example for such a domain is credit card fraud detection: here, machine learning is employed on a large scale across millions of transactions in order to extract fraudulent patterns from transaction attributes that can easily enumerate to 100 or more. Once a potentially fraudulent transaction is detected (which occurs in near-realtime), a decision needs to be taken as to whether or not the credit card is blocked and the transaction flagged. Such a decision is often best made given multiple sources of information pertaining to the transaction.

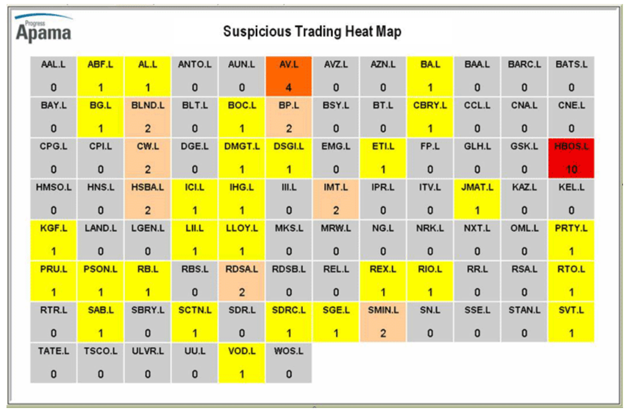

Figure 1: Apama uses a heat map to visualise suspicious trading activity in real time. The heat map is based on the event processing visualization platform by SL Corporation. Figure from `http://www.thecepblog.com/2008/01/02/apama-fraud-detection-and-heat-maps/`.

Working with large amounts of information can be supported with visualization, such as the colour block visualisation in Figure 1, and current design questions concern both the user interface layout and data representation. In terms of the interface layout, the designer may have to choose between a single-screen display like a dashboard, or multiple-screen displays in which information has to be revealed, such as in a menu or through data query. In terms of data representation, the choice can fall between the provision of the exact data, or the provision of abstracted and interpreted data represented for example in a traffic light color coding, for example, red, amber, green or heat maps, for example, with varying color intensity or hue. This design space is illustrated by a number of recent efforts to provide visualisation based decision aids. Several companies, for example SL Corporation, StreamBase, Apama, Gartner Group have developed software to provide real-time monitoring and visualization services to support people making real-time decisions with large amounts of visualized data. Apama, for example, uses heat maps to visualise suspicious trading activity in real time (Figure 1) in the domain of stock market trading. Heat maps have the advantage of bypassing the interpretive step of a decision maker: the color already encodes the meaning of the information sources, so the visualization is easy and quick to interpret for an observer. The downside of this visualization is that an observer cannot fact-check the display or get a detailed understanding of the margins which caused the heat map to take on a specific color; hence it is impossible to detect cases at the boundaries of specifications; the representation does no communicate uncertainty of a categorization. The heat map is a common type of information visualization used in a range of applications. Similarly, heat maps are used in other control environments, such as games and business monitoring: in an example case, they are used to summarize the activity of players and creatures in the HERO gaming environment. The visualized information is used to tune the gaming engine applications in real-time. In business activity monitoring dashboards containing key performance indicators are used to provide assurance and visibility of performance.

There is a substantial literature assessing the viability of different types of visualizations. For example, visualization techniques for comparative analysis [38] allow the analyst to quickly find answers to questions like: 'is the web traffic increasing or decreasing?' Visualizations have been designed to help users effectively track multiple targets at the same time [9]. In the current paper, we are interested in color-block visualizations, such as that in Figure 1, that are used to support the recognition of complex patterns from a number of different cues. Two advantages of color-block visualizations are (1) the simplified format of individual data items (color versus text), (2) the fact that an overview of multiple items is presented intuitively to users. The combination of these dimensions is intended to support users in directly perceiving patterns in the data. This *direct perception* is assumed to result in faster search and decision times for users. Color-block visualizations epitomize the way that visualization technologies attempt to support higher level decision making by taking full advantage of human perceptual mechanisms. Understanding how they work, or fail to work, requires understanding both human visual perception and higher level human decision making.

In the current paper, we suggest that a deeper understanding of how to design visualisations could be based on a cognitive model of how visualisations are used in service of decision making. Our approach is based on the assumption that user strategies are adaptive to a range of constraints [35, 33, 15, 24, 26, 20]. In this approach a sequence of user actions is predicted from an analysis of what it is rational for a user to do given a interface design and given known constraints on human cognition. These analyses take into account the costs and benefits of each action to the user so as to compose actions into efficient behavioural sequences. Perhaps the most pertinent example of this approach is Card's cost of knowledge function. Examples also include models of the search for information on the web in which the benefits include information gain [36]. In addition, there are models of multitasking in which the time spent on each of two or more tasks is determined by their relative benefits and time costs [37]. More recently, it has been suggested that menu search can be understood as a Partially Observable Markov Decision Problem (POMDP) [6]. Two important properties of this kind of problem are (1) the visualised data allows only partial observations through foveated vision, which covers only 1-2 degrees of visual angle, and (2) the outcomes are partly random (the outcomes of a decision are not always known) and are partly determined by the users decisions (which part of visualisation the user chooses to focus on).

The contribution of the work is in providing a new model of how people make decisions with visualisations that has potential to predict the value of a visualisation for a task. Subsequently, we report a model of information gathering and decision making which shows how decision making behavior is an emergent consequence of adaptation to the design choices made in the visualization. Critically, the model does not make any a priori assumptions about decision strategy, rather the strategy emerges through learning. The paper also contributes an empirical test of the theory designed to reveal the functional role of color blocks in active vision and decision making. Detailed comparisons to human performance metrics (including performance time and eye movements) are provided.

BACKGROUND

In the psychology literature, while there has been little work on visualisation, extensive studies have been conducted to understand how people gather information in service of decision making. One influential approach is based on the idea of fast-and-frugal heuristics [13, 12]. This approach makes a strong commitment to the heuristic theory of decision making [11] which assumes that people use simple rules in order to make good decisions fast, rather than computing exact probabilities based on all available information. One prominent decision heuristic has received great attention: the take-the-best (TTB) heuristic[13]. The TTB heuristic consists of a set of rules concerning the most important aspects of information gathering: the search rule, the stopping rule and the decision rule. This requires knowing the validity of cues. Validity is the probability that the information represented by a cue will lead an observer to the correct decision. A validity of 1 will always lead to the correct decision, whereas a validity of 0.5 will result in chance performance. A person using TTB searches from the most useful information (with the highest validity) to the information with the lowest validity (the search rule). Information search terminates once a cue discriminates between the considered options or once all cues have been examined (the stop rule); at which point the model chooses the option favoured by the discriminating cue (the decision rule). For example, when people are asked to determine whether Berlin has a higher population than Neuss, they might use a high validity cue (recognition) to tell them that, as they have not heard of Neuss, Berlin must be bigger. However, if they are asked whether Stuttgart is bigger than Nuremburg, both of which are recognised, then they may move to the next best cue, say whether or not they have heard of a football team from that city.

Following [12] who showed how Take-The-Best (TTB), could describe human information gathering and decision making behaviours, a number of articles offered empirical investigations into which heuristics people choose [22, 23, 5, 4, 19]. A particular concern in this research has been whether people use a heuristic, Take-The-Best (TTB), that uses information selectively, or a heuristic such as Weighted-ADDitive (WADD) that integrates all information [28, 27]. While this debate has been waged in the psychology literature, it is highly relevant to understanding how information visualisations are used by people, and therefore to how visualisations should be designed. If people use TTB and not WADD then they may make use of a much smaller part of the displayed information than if they use WADD.

Visualization

When confronted with a collection of data with different provenance, reliability and salience to their task, analysts need to engage in a number of processes to ascertain the most appropriate sources to use and the most appropriate tasks to apply these sources. These processes carry with them a cost, and the cost structure can be considered in terms of the resources available to the user and the methods that they could apply to exploit these resources [17]. The resources themselves could relate to the content and visual appearance of information sources (external resources) and to the knowledge, effort and ability of the user (internal resources). The methods relate to the actions that can be performed to access, interpret and collate the content of the information sources. For Russell et al. [29] the main cost arises from data extraction. The implication is that the design of visualization can have an impact on this data extraction cost, such that it should be possible to elicit differences in extraction cost (e.g., measured by search time) from different layouts, content or features in the visualization. In previous work (in intelligence analysis), it has been shown how users engage in parallel, overlapping explorations of data and often work with minimal and sketchy frames to explain these data [1]. This work shows that we might anticipate that users will use a subset of the of available information, partly in an effort to reduce the cost associated with information access, partly as a result of the incremental construction of an explanatory frame to model the data, and partly as a result of the methods that they apply.

Visual Perception

Studies of visual perception show that perceiving a pattern such as that in Figure 1, involves a complex sequence of eye movements to gather information and maximize the utility of the decision [35, 33, 15, 24]. This is a process of active vision. People move their eyes to seek out items within a visual scene that are relevant to the task or question they are engaged in. Eye movements are necessary since only a very small area of what we look at is visible at high resolution at any one point in time. This area covers only 1-2 degrees visual angle and is called 'foveal' vision: the fovea has the highest density of daylight/color vision receptor cells. With increasing eccentricity, there is a sharp drop off in the density of these cells, and hence vision becomes rapidly blurred. To guide eye movement from one item to the next, people are generally believed to use information gathered from peripheral vision to guide saccadic eye movements (ref!! this is all still controversial and not well understood, where to look next). The periphery, covering a much larger area than the fovea, still contains useful information despite the reduced acuity. It is well known that peripheral vision plays a key role in guiding eye movements during visual search [10, 18] but less is known about the role of eye movements in the use of visualizations for decision making. Therefore, it is important to understand the strengths and limitations of designing displays that enable the use of peripheral vision in visual search.

TASK

Before introducing our theory of decision making with visualisations, we briefly described a task, the credit card fraud detection task, which will be used to illustrate the theory.

The task is motivated by a real-world task that is known to be extremely difficult for people. Credit card fraud detection analysts attempt to identify fraudulent patterns in transaction datasets, often characterised by a large number of samples, many dimensions and online updates[8]. Despite the use of automated detection algorithms, there continue to be key roles for people to play in the analysis process. These roles range from defining and tuning the algorithms that automatic systems deploy, to triaging and screening recommendations from such systems, to contacting customers (either to query a transaction or to explain a decision). In terms of triaging and screening, we assume that an automated detection process is running and that this process has flagged a given transaction (or set of transactions) as suspicious and a user will engage in some form of investigation to decide how to respond to the flag. Based on interviews and discussions with credit card fraud analysts and organisations, we believe that there are several ways in which the investigation could be performed. In some instances, the investigation could involve direct contact with the card-holder, in which the caller follows a predefined script and protocols that do not involve investigative capabilities. In some cases, the investigation could involve the analysis of a set of transactions on an account, with the analyst seeking to decide whether or not to block the card (this is the approach assumed in this paper). In this instance, the analyst would take a more forensic approach to the behavior of the card holder and the use of the card, relative to some concept of normal activity. In some cases, investigation could be at the level of transactions, in which the analyst seeks to identify patterns of criminal activity involving several cards. In this instance, the analysis would be looking for evidence of stolen details or unusual patterns of use of several cards, say multiple transactions in different locations within a short timeframe. Other functions that people can perform in the fraud detection process include: risk prioritisation, fast closure of low risk cases, documentation of false positives [25], and identification of risk profiles and fraud patterns [31, 16].

Below, we use a simplified version of the fraud detection in which the task is to decide whether a transaction should be blocked (prevented from being authorized) or allowed. Participants are provided with 9 sources of information (cues) and these are presented using one of 4 display designs (visualisations). The cues differ in the reliability with which they determine whether or not a transaction is a fraud and the participants must discover these validities with experience and decide which cues are worth using to make a decision. Further details are provided below.

THEORY

In order to model how people use visualizations in credit card fraud detection we build on a previous model of visual search [6, 36]. In this approach eye movement strategies, scan paths and stopping rules, are an emergent consequence of the visualization and the limits of human vision. The assumption is that people choose which cues to look at first and when to stop looking at cues informed by the reward that they receive for the decisions they make. Better decisions will receive higher rewards, which will reinforce good eye movement strategies.

This approach is known as reinforcement learning and it makes use of optimal control and Machine Learning methods [3, 30, 34]. A key contribution of this literature has been to provide a formal basis for learning a strategy, including eye movement strategies, given only a definition of the reward function, the state space, and the action space. The strategy learnt (the control knowledge) is then that which determines what-to-do-when. In the case of information gathering in service of decision making, it concerns where to get information and when to make the decision. Importantly, the aim of this behavior work is that behaviours, such as search rules, stopping rules and decision rules, should emerge from theoretical assumptions, rather than being encoded/assumed by the researchers.

In this framework, the expected value of an action given a state is the sum of an immediate reward plus the rewards that would accrue from subsequent actions if that action were selected. This simple assumption has provided a means of deriving human visual search strategies in well-known laboratory tasks [7] and menu search tasks [6]. It also provides a means by which to derive credit card fraud detection strategies given assumptions given different visualization techniques, but only if the decision making problem can be defined as a reinforcement learning problem. We report a model that does just that.

In the following paragraphs, we first report the learning problem and then report pilot data that tests the model predictions.

Problem formulation

We assume that the problem faced by a decision analyst can be modelled as a Partially Observable Markov Decision Process (POMDP). The process is partially observable because the true state (the values of the cues) is unknown to the analyst and can only be observed through a noisy and uncertain foveated visual system. The process is Markovian because the outcomes are partly random (on some trials are frauds and some are not) and partly determined by the users decisions (where to look and whether or not to block a transaction).

A decision can be made by choosing from scanning and choice actions, $a \in \mathcal{A}$. The action selections are dependent on the observations, the history, and knowledge. At each moment, the environment is at one state $s \in \mathcal{S}$. The state is not fully observed by the analyst. Instead, by interacting, observations, $o \in \mathcal{O}$, and rewards, $r \in \mathcal{R}$ are received from the environment, i.e., the environment is partially observable. This action-observation-reward sequence happens in cycles indexed by $t = 1, 2, 3, ...$ The action-observation sequence is used to update the estimate of the belief about the true state using Sequential Bayesian updating (explained below). Q-learning is used to learn which action to do next (e.g., to gather more information or to make a decision) given the current belief about the state. It does so by learning the belief-action values through simulated experience. Belief-action values are updated incrementally (learned) as reward and cost feedback is received from the interaction during the simulated experience. For example, if the model looks at cue A and subsequently makes an incorrect decision, then the value of cue A to the model will decrease. With enough simulation trials, the optimal strategy will emerge and the model will take the best actions given the beliefs.

In the following sections more detail is provided about how the belief update and optimal controller work.

A POMDP is defined by the following elements.

- $\mathcal{S}$: At each time t, the environment is in a state $s_t \in \mathcal{S}$. A state represents an true information pattern presented on the user interface. As shown in Figure 2, nine attributes associated with credit card transactions are presented on the interface. According to the experiment to be modelled, the value of each attribute was discretised as two levels, representing 'fraudulent' and 'normal' respectively. For example, one of the states is a 9 element vector as follows: [F N N F F F N F N], each item of which represents the value for one attribute (F for fraudulent and N for normal). Therefore the size of the state space is $2^9 = 512$.

- $\mathcal{A}$: A set of actions that the decision analyst can take. It consists of the information gathering actions (i.e., which attribute to fixate at, i.e., $f_i(i \in 1, 2, 3, ...9)$) and decision making actions (i.e., block/allow transaction). Therefore, the size of the action space is 11.

- $\mathcal{O}$: A set of observations that can be made. The observation at step t is defined as the information gathered up until t for all the information sources. Information is gathered through both foveated vision and peripheral vision. The observation is a 9 element vector. Each element has three levels, F (fraudulent), N (normal) and U (unknown). For example, one of the observation is [F N U, F U U, U N N], each element of which represents the information gathered for one attribute. Therefore the upper bound of observation space is $3^9 = 19683$.

- $\mathcal{R}(S, A)$: A set of rewards generated by the environment. At any moment, the environment that occupies in one of the

(a) Covered Text (CT) (b) Covered Color (CC)

(c) Visible Text (VT) (d) Visible Color (VC)

Figure 2: Four interface variants for credit fraud detection. The text is not intended to be readable. What is important is that information cues are represented with text (left panels) or colour (right panels) and that the information is either immediately available (bottom panels) or revealed by clicking (top panels).

states s, generates a reward $r \in \mathcal{R}$ in response to the action taken a. The reward for the information gathering actions is the time cost. The time cost includes both the dwell time on one sub-window and the saccadic time cost travelling across sub-windows. More details about the time cost is provided in subsection 'Time Cost' below. The reward for a correct decision was +10; the penalty for an incorrect selection was -20.

- $T(S_{t+1}|S_t, A_t)$: This transition function describes how the state changes based on the actions taken. In the current task the information pattern (i.e. the state) across time steps (within one trial) did not change. Therefore, $T(S_{t+1}|S_t, A_t)$ equals to 1 only when $S_{t+1} = S_t$. $T(S_{t+1}|S_t, A_t)$ equals 0 otherwise. That is, the state transition matrix is the identity matrix.

- $p(O_t|S_t, A_t)$: This observational function describes how states and actions combine to yield observations. In the experiment, the information was represented on the interface by either color blocks or text. It is known that an object's color is more visible in the periphery than the object's text label. In our model, the observation model is based on the acuity functions reported in [18]. The observational model is explained in more detail in next subsection "Observation Model".

The basic concept in POMDPs is following: the states cannot be directly observed by the agent. Instead, the decision maker receives two signals from the environment: (1) observations, determined by the observation model, and (2) the rewards, determined by the reward function. The goal is for the agent to choose actions at each time step that maximise its expected future discounted reward. Many POMDP algorithms have been proposed to find the optimal policy to do so. In our model, we used Q-learning algorithm to learn the optimal strategy. More details are given below.

Because the agent does not directly observe the environment's state, the agent must make decisions under uncertainty of the true environment state. By interacting with the environment and receiving observations, the agent update its belief in the true state. Below we describe how this belief update is computed. An example update from $t = 0$ to $t = 1$ is given, which could be generalised to from t to $t + 1$.

At $t = 0$, the environment occupies in a state $s \in \mathcal{S}$ we have an initial belief, $\vec{B}_{t=0}$, that is assumed to be a uniform distribution over all possible states. This means that without any evidence, the model believe that the environment is equally in one of the possible states. At $t = 1$, the agent takes an action a_1, which causes the environment to transition to state s' with probability $T(s' \mid s, a)$. After reaching $s' \in \mathcal{S}$, the agent observes o_1 with probability $P(o_1 \mid s', a_1)$. An agent needs to update its belief upon taking the action a_1 and observing o_1.

$$B_1(s') = \frac{\sum_{s \in S} B_0(s) \times T(s' \mid s, a_1) \times p(o_1 \mid s', a_1)}{\sum_{s' \in S} p(o_1 \mid s', a_1) \sum_{s \in S} T(s' \mid s, a_1) B_0(s)} \quad (1)$$

As mentioned above $p(s'|s, a_1) = 1$ only if $s' = s$, and 0 otherwise, Equation (1) can be simplified as Equation (2):

$$B_1(s) = \frac{B_0(s) \times p(o_1 \mid s, a_1)}{\sum_{s \in S} p(o_1 \mid s, a_1) B_0(s)} \quad (2)$$

At each time t, a belief $\vec{B}_t$ vector consists of a probability for each of possible states, $B_t(s_i)$, where $i \in 1, 2, 3, ...$ Each element $B_t(s_i)$, of the belief vector is updated independently. The estimate of the state (i.e., belief) is summarised in the vector, $\vec{B}_t$. We use this as a prior for next update when a_{t+1} and o_{t+1} is receiving.

Observation Model

The observation obtained is constrained by the human visual system. In the experiment, the information was presented either by color blocks or in texts. It is known that color plays an key role in visual search [32, 18]. As that it can be perceived from a wide range of eccentricity, it often serves as a guide of the eye movements [14]. In contrast, the text recognition would require a fixation on the texts unless the text is very large [18]. In our model, the observational is implemented based on the acuity function reported in [18].

Peripheral vision

Our model assumed that the semantic of the text information was obtained only when it was fixated. The color acuity was specified as a quadratic psychophysical function from [18]. This function was used to determine the availability of the color in each cue given the eccentricity and the size of the item. In our model, the acuity function was represented as the probability that each visual feature of the item was recognised.

$$P(available) = P(s + X > threshold) \quad (3)$$

where $threshold = a \times e^2 + b \times e + c$; $X \sim \mathcal{N}(s, v \times s)$; s is the item size; e is eccentricity. In the model, the function were set with parameter values of v=0.7, b=0.1, c=0.1, a=0.035 as in [18]. The objection size s was chosen according to our experiment. The color blocks used in the experiment is about 4 degrees in visual angle. These parameter settings resulted in the acuity function shown in Figure 3. On each fixation, the availability of the color information was determined by these probabilities.

Time Cost

Saccade duration

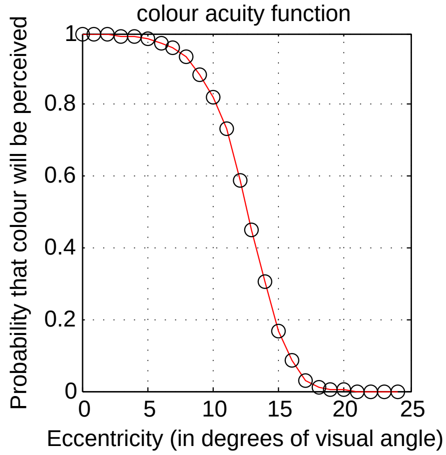

Figure 3: The color acuity function used in the optimal control model.

The saccade duration D (in milliseconds) was determined with the following equation [2]:

$$D = 37 + 2.7A \quad (4)$$

where A is the amplitude (in terms of visual angle in degrees) of the saccade between two successive fixations.

Fixation duration

The fixation durations used in the model were from the measurements from the empirical experiment (Figure 8).

Learning

The control knowledge is represented as a mapping between the beliefs and actions, which is learnt with a reinforcement learning algorithm, Q-learning. Further details of the algorithm can be found in any standard Machine Learning text (e.g.[34]), e.g., the optimality guarantee of the Q-learning, and its conditions.

Before learning, an empty Q-table was assumed in which the values (i.e., Q-values) of all belief-action pairs were zero. The model therefore started with no control knowledge and action selection was entirely random. The model was then trained until performance plateaued (requiring 10^5 trials). The model explored the action space using an ϵ-greedy exploration. This means that it exploited the greedy/best action with a probability $1 - \epsilon$, and it explored all the actions randomly with probability ϵ. ϵ was set to 0.1 in our model. Q-values of the encountered belief-action pairs were adjusted according to the reward and cost feedback, as shown in Equation (5).

$$Q(b, a) \leftarrow Q(b, a) + \alpha[r + \gamma \max_{a'} Q(b', a') - Q(b, a)] \quad (5)$$

where Q(b,a) is the Q-value for one belief-action pair (b, a), r is the immediate reward/cost obtained while the action a is taken, α is called learning rate, and γ is called discounted factor. The idea is that, these Q-values are learned (or estimated) by simulated experience of the interaction tasks. The true Q-values are estimated by the sampled points encountered during the simulations. The optimal policy acquired through this

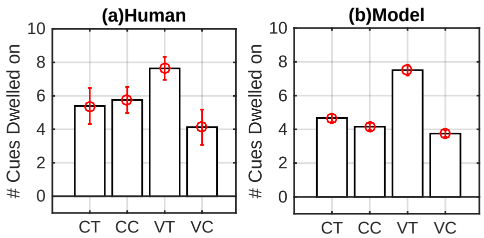

Figure 4: Information Sources used by the participants and the model

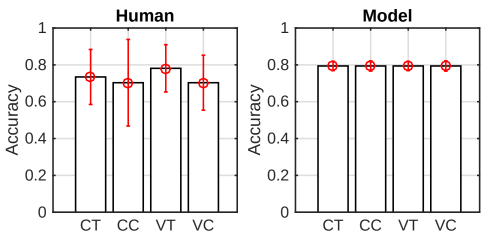

Figure 5: Accuracy achieved by the participants and the model

training was then used to generate the predictions described below.

While we used Q-learning, any reinforcement learning algorithm that is guaranteed to converge on the optimal policy is sufficient to derive the rational adaptation [34]. The Q-learning process is not a theoretical commitment. Its purpose is merely to find the optimal policy. It is not to model the process of learning and is therefore used to achieve methodological optimality and determine the computationally rational strategy [20].

In summary, Q-learning was used to learn (or estimate) the value of each belief-action pair by simulated experience of the interaction tasks. The optimal policy is then the greedy policy given the Q-values. The model was implemented in Matlab and can be downloaded on request from the first author.

RESULTS

Information used and accuracy

As shown in the left panel of Figure 4, the model predicted that more cues should be used in the 'visible/text' (VT) condition than in the other conditions. This is because the information in the visible conditions is much cheaper, compared with covered/color (CC) and covered/text (CT) where it had 1.5 seconds delay for each cue (based on the experiment design). However, because of the difference between the acuity function for colour and text, fewer cues were fixated by the model in the visible/colour condition than in the visible/text condition.The model achieved about 79% accuracy across the four conditions. In contrast, the model predicts the same level of accuracy is achieved in all conditions (Figure 5). The accuracy level is near ceiling given the available cue validities and is likely to reflect the importance of accuracy given the high temporal cost of an incorrect decision.

decision strategy

We examined the action sequences generated by the model to determine whether they corresponded to a Take-the-best strategy (TTB) or a weighted-additive strategy (WADD). TTB would be indicated by the participants selecting just the very best cue (which in our interface always discriminates) and then making a fraud/no-fraud decision. WADD would be indicated by the participants using all of the available cues. In fact, the number of decision cues used (Figure 4) is at neither of these extremes and, in addition, our informal inspection of the action sequences suggests that people use a range of intermediate strategies; they examing a few of the best cues, integrate information and then make a decision. Further analysis is provided in the results of the study reported below.

Decision time distribution

Long-tail left-skewed distributions are a signature feature of human decision times (e.g. a review in [21]). Figure 6 shows the response time distributions for the model. The distributions are interesting because despite the fact that the no skewed distributions are assumed in the model performance they do emerge as a consequence of adaptation to the constraints.

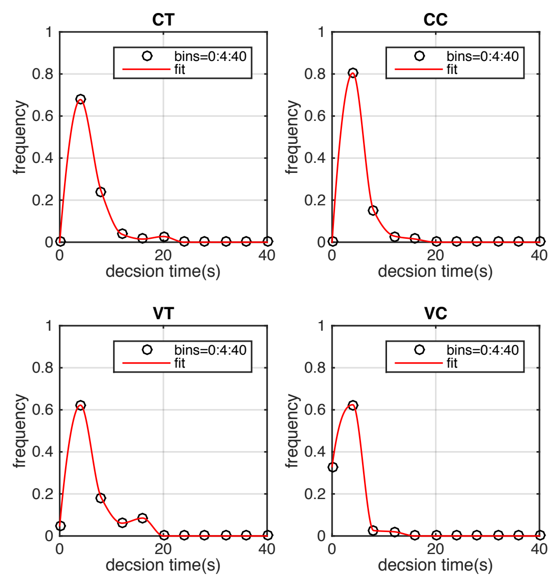

Figure 6: Model decisionTime

EXPERIMENT: CREDIT CARD FRAUD ANALYSIS

Subjects

Sixteen participants (11 males, a mean (SD) age of 31.6 (7.5) years) from staff and students at University of XXXX voluntarily participated the experiment. No financial or other incentives were given. Participants were equally and randomly assigned to four experimental groups which are detailed below.

Apparatus

A custom user interface was created in Matlab (The MathWorks). The participants were seated in front of 22 inch

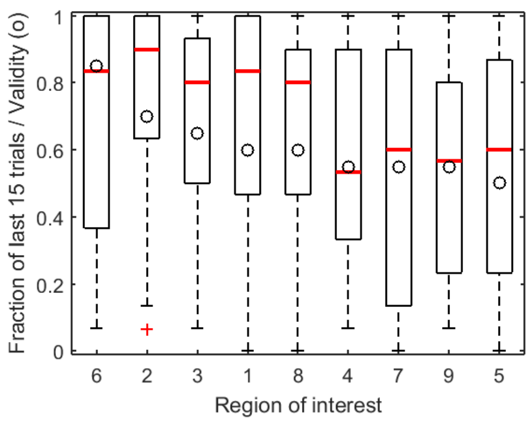

Figure 7: Frequency of cue use ordered by cue validity. Region of interest (ROI) 6 had the highest cue validity, ROI 2 the next highest validity etc. Box plots represent frequencies and circles represent cue validities.

screen instrumented with an eye tracker (X2-60, Tobii, Sweden) recording gaze data at 60 Hz. The eye tracker was operated through Matlab using the Tobii SDK and Matlab binding.

Design

The participants were asked to take on the role of a credit card fraud analyst at a bank. The task was to decide whether the transactions should be blocked (prevented from being authorized) or allowed. As shown in each sub window of Figure 2 , nine panels laid out in a 3 x 3 grid. Each panel provides an information source of a transaction. An operation panel is presented on the right side of the interface, e.g., Block/Allow buttons, feedbacks.

The nine credit card transaction attributes, as shown in Table 1, were selected as relevant to the detection of credit card fraud based on the literature and discussions with domain experts from FICO, FeedZai and the UK Cards Association. Information for each source was presented in binary terms based on rules for fraudulent and non-fraudulent behavior (As shown in Table1), which was provided to the participants. The cues had *validities* [0.85, 0.7, 0.65, 0.6, 0.6, 0.6, 0.55, 0.55 and 0.55], where validity was defined as the probability that the cue indicated fraud given that the ground truth of the transaction is fraudulent. Validities were arbitrarily assigned to the nine cues and do not reflect cue validity in the real world. The location of each information source on the interface was assigned randomly for each participant and stayed constant across all trials. Participants were told that in making their predictions they should try to work out which pieces of information were most useful as not all the pieces were equally informative. They were asked to complete 100 correct trials as quickly as possible, so that errors were operationalized as time cost.

Table 1: the information for these 9 information sources. The values that assigned to be fraudulent/normal for the information sources with star sign (*) were counterbalanced across participants.

Info Sources	Normal	Fraudulant	Validities
Transaction Amount	≤ 500	> 510	0.6
Transaction History	3 small amounts in a row	N/A	0.7
Card Present	YES	NO	0.65
CVV Entered	YES	NO	0.55
Card Issued Bank*	Hanford	NorthWest	0.6
Purchase Made in*	Europe	USA	0.85
Card Expiry Check	≥ 5 days	$\leq$ 4days	0.55
Transaction Time	6:00-20:00	20:00-6:00	0.60
Type of Goods*	Travel agent	Electrical goods	0.55

The experiment was a 2×2 design. The independent two factors were *format* and *availability*. (1) the *format* had two levels: text vs. color; (2) the *availability* had two levels: visible vs. covered. Figure 2 shows the representative user interface of each of the four experimental conditions. In panel (a), it is the covered/text (**CT**) condition, where the information was presented in text. In order to check each the information source, the participants had to click on the associated button on each information source and wait for 1.5 seconds while a blank screen was shown (Figure 2). In panel (b) (covered/color (**CC**)), the information was presented by color (green for possibly normal, red for possibly fraudulent). The same information revealing process applied. In panels (c) and (d), an overview of the information was given; one was presented by text (visible/text (**VT**)) and the other is presented by color (visible/color (**VC**)).

Procedure

Participation in the study started with reading/signing the information sheet and consent form, followed by reading the detailed written study instructions. Study instructions were modified to suit each of the four experimental conditions. After eye-tracker calibration, the participant then worked through the first transaction with the opportunity to ask any clarifying questions. After this, participants worked through transactions at their own pace.

The workflow for evaluating a transaction was as follows. On each trial, they are told to use as much information as they see fit (up to 9) by clicking the 'reveal' buttons or by fixating at the information panels depends on the conditions they were assigned to. They then indicated their decisions in the right panel by clicking 'Allow transaction' or 'Block transaction' button. The participants were then instructed to tick the information sources using the provided checkboxes that they deemed most important for making the decision. Following this, the 'submit' button had to be clicked in order to receive feedback regarding the correctness of the decision. By clicking 'OK', the UI was then saved and the next transaction could be called up using an interim screen that had the button 'next transaction'. The button was placed in the top right corner of the UI above the workflow panel to not confound initial gaze data above any of the nine information sources. At intervals of 15 minutes, participants were offered the opportunity to take a short break if they wished.

RESULTS

The participants' performance below was analyzed based on their last 15 trials.

Information cues used and accuracy

We estimated how much information was used in each condition. Figure 4 shows the number of cues participants dwelled on before making decisions in the four conditions (the left panel). This analysis is based on a cutoff of 200 ms, i.e., the number of cues that was dwelled on for longer than the cutoff.

A mean of 7.64 (std=1.6) cues was dwelled on in the 'visible/text' (VT) condition, which is more than that in the other three conditions. This is because that the information in the visible conditions is much cheaper, compared with covered/color (CC) and covered/text (CT) where the participants had to click on a button and wait for 1.5 seconds for the information to reveal. In contrast, participants learnt to be relatively economical in the 'covered' conditions because of the increased information access cost (CT: mean=5.29; CC: mean=5.75). However, because they could take advantage of color peripheral vision in visible/color (VC) condition , the number of cues dwelled on is not higher than *covered* conditions (VC: mean=4.12).

However, while participants fixated on more cues in the visible/text (VT) condition, they did so without any noticeable increase in accuracy (the left panel of Figure 5). This suggests that the overview/text (VT) design is the worst of the 4 conditions considered. Participants achieved about 75% accuracy, which our analyses suggest is close to optimal given the cost of action and the validity of the cues (Figure the left panel of Figure 5)).

Did participants use the highest validity cues?

In order to further understand the decision strategy used by participants, we also analysed which decision cues they used (rather than just how many). The quality of cues is determined by the validities. In Figure 7 the frequency with which cues were used in the last 15 trials is plotted in order of cue validity, with the highest validity cues on the left. What can be seen is that the participants used all of the highest validity cues more frequently than they used all of the lower validity cues. In addition, it can be seen that they did not only use the highest validity cue. Therefore, participants, appear not to be using either Take-the-Best heuristic, nor a weighted additive strategy; the very best cue is not used any more frequently than any of the other best 5 cues and, even though all cues always display either fraud or non-fraud (there is no 'unknown' display), on average participants use substantially more than a single cue.

Dwell times

As shown in Figure 8, the effect of the experimental condition on the *dwell time* varied across information sources. For '**Transaction history** and '**Card expiry check**', the two conditions where the information was presented in text format resulted in a longer dwell time than the corresponding conditions displaying in color. However, interestingly, YES/NO text was used differently to other text and that it can be better than color. This can be found in two cues (**CardPresent** and **CVV Entered**), where the information is given as YES/NO in text conditions and Green/Red in color conditions. For the remaining information sources, dwell times were very similar across conditions.

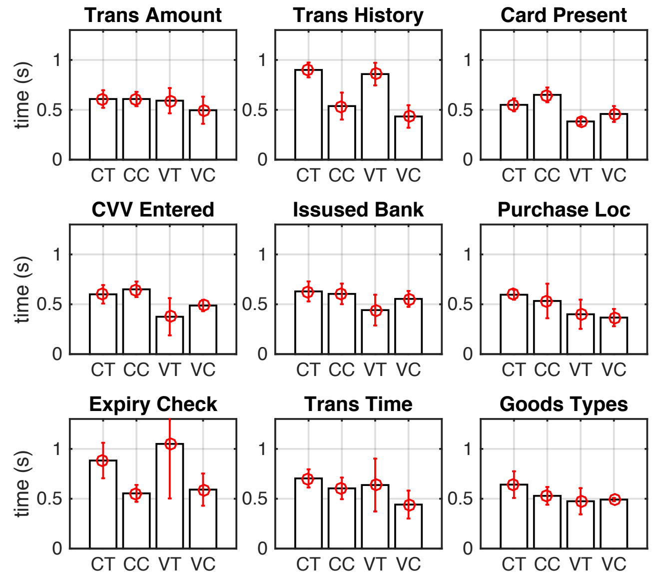

Figure 8: Human dwell time for each cue

Decision time distribution

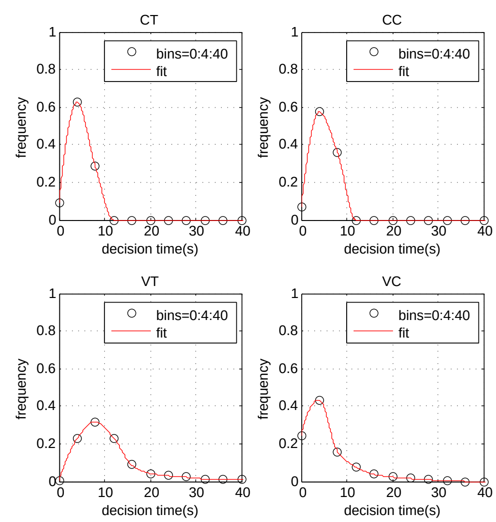

Figure 9: human decisionTime

Long-tail left-skewed distributions are a signature feature of human decision times (e.g. a review in [21]). Figure 9 shows that human decision times on our experiment have this feature.

DISCUSSION

We have reported a new model of how people use information visualisation to make decisions. The model shows how different types of information visualisation lead to the emergence of different user strategies. In particular, it shows how when colour block visualisations were made available without the need for mouse clicks to reveal the data, more use should be made of peripheral vision to gather information. This result is a consequence of the fact that emergent strategies for information gathering can take advantage of the different human acuity functions associated with colour and with text; whereas colour information can be obtained from the periphery, text must be foveated to be understood.

In addition, the model predicts that people should use neither the Take-the-Best (TTB) nor the Weighted-Additive (WADD) decision strategies. These strategies have been extensively studied in the human decision making literature, but more recent work has suggested that people exhibit a more flexible range of strategies. Instead of assuming TTB or WADD, our model derived the optimal strategy given a POMDP problem formulation; this strategy involved using a weighted integration of the optimal number of the best cues. These cues provide the right information at a time cost that is best given the trade-off between time and accuracy imposed in the experiment.

The fact that the model is able to predict the *strategies* that people use is a departure from models that are programmed with strategies and predict performance time. This is important because it suggests how the theory might be developed in the future so as to rapidly evaluate the usability of a broader range of visualisations for a broader range of decision tasks. A key factor here is that the model is based on a very general modeling framework. The model is based on a specification of the decision *problem* faced by a people with foveated vision and it is not based on a specific set of decision heuristics. Strategies for a specific visualisation are then learnt through interaction. It should therefore be possible to apply the model to a broad range of visualisation technologies and automatically derive predictions for their usability.

ACKNOWLEDGMENTS
This research was supported by XXXXXXXX

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