Studying Individual Satisficing-Optimizing Decisions in an Uncertain Explore/Exploit Information Environment

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Abstract: One of the most prevalent cognitive tasks in human-computer interaction (HCI) is seeking information using web searches. Although simple information retrieval is trivial, more complex questions evolve by new meaningful information. The optimal balance to exploit the current resource for gathering the available information or to explore new information is a main topic in Reinforcement Learning Theory (e.g. motion planning for robots), Information Foraging Theory (e.g. improving search engines) and Usability/ UX. Because people are rationally bounded by restricted capacity, information and time, the optimal search strategy is intractable for humans in search decisions under uncertainty. The aim of this short paper is to present and discuss first observations of a calibration test to study empirically the individual satisficing-optimizing relationship.

Keywords: Satisficing, Uncertainty, Optimal Foraging, Web Search

1. Introduction and Aim

1.1 Information Foraging Theory and Satisficing vs. Optimizing

Information Foraging Theory provides a framework where the exploration of the information space is similar to the process when animals search for new food patches, and the exploitation of the information is described as depleting the food patch (Stephens & Krebs 1986; Pirolli & Card 1999). The amount of a single information source is restricted, resulting in switching the food source to explore other patches as information gain diminishes with time. Charnov's Marginal Value Theorem (Charnov 1976) states that a forager should leave the patch when benefits and costs are equal (Olsson & Brown 2006), that is when the gain of the current patch is lower than the average gain. However, the decision to explore/ exploit depends on the information environment and the available resources of the forager (Cohen et al. 2007; Hills et al. 2015).

Human beings are rationally bounded because of limited processing and working memory capacity, restricted information of environmental structure and confined time horizons for finding an optimal solution for a decision task. People therefore do not maximize the reward or expected utility, but are rather satisfied with a sufficient *good enough* solution depending on their aspiration level, a process called satisficing (Simon 1955, Ward 1992). From a computational perspective, optimizing means choosing the best solution after testing all the available options (maximizing). However, searching for the optimum is costly for human beings (Gorod et al, 2017; Shervais & Shannon 2012*)*.

1.2 Aim of Study

The balance between the exploration of new options and the exploitation of available options is a main topic in decision making under uncertainty (Rich & Gureckis 2017). The question is "how do foragers decide *when* to leave a patch?" (Marshall et al. 2013). As most research focuses on the modeling of the exploration/ exploitation trade-off (Wilson et al. 2014), the empirical evidence is rather sparse (Hills et al. 2015; Cohen et al. 2007).

The present study attempts to examine time allocation for the gathering and exploitation of patch information within four different nearby patches arranged in an aggregated environment. Different to existing studies, this setup allows an observation of potential switching-rules between patches separated from the allocation of extra-time for seeking the next feasible patch. It thus reduces the examination to the decision step under exploitation and virtually reduces exploration costs to zero.

It is assumed here that the information complexity of patches correlates with the allocated time and hence information value is quantified. The decision for patch-leaving (skip to next) is examined by a potential interrelation between satisficing, maximizing and the estimation for an optimum. As learning is highly heterogeneous, it is hypothesized here that the point of satisficing might represent an important individual orientation point for optimal patch-leaving.

2. Method Development

The task is to watch and understand a software tutorial presented as four short repeating loops of animated graphical interchange format (GIF) sequences (between 9 and 19 sec.). The four GIF-loops (patches) explain elementary first steps to get started with a given software (e.g. create a new project, upload of images etc.). In task 1 participants were asked to watch the four tutorial loops consecutively and skip to the next GIF when having sufficiently or satisfactorily understood the respective content (satisficed), e.g. when they felt that repetition predominates. Subsequently, the same individuals were asked in the second task to re-visit the same sequence to a duration when almost ~80-90% of respective tutorial content is understood (maximize). Afterwards, participants estimated the optimal time for each GIF loop (task 3) and ranked the complexity in descending order (task 4). Participants were interviewed and shared experiences in a group discussion.

3. First Results

3.1 Subjective Complexity and Intra-Patch Time

The calibration test and interviews comprised seven participants (mean age = 27.3; two female). The median and modus of patch complexity in task 4 is ranked in descending order with 3 > 2 > 1 > 4 where the complexity of the two most complex patches (3 and 2) is paralleled by the highest median exploitation time 97 and 73 seconds, respectively (table 1). The self-paced total time allocation ranges approximately by factor 3 from 148 sec. up to 456 sec. with a mean of 296 sec.

3.2 Relative Satisficed and Maximized Time

First analyses show that the proportion of satisficed/ maximized time is between 0.43 and 0.54 (mean and median 0.49; sd=0.04) depending on information complexity.

Table 1: *Patch number with absolute time: sat = satisficed, max=maximized, opt=estimated optimum time; loop duration in seconds in paranthesis; sd=standard deviation and CV = coefficient of variation.*

patch 1(19)	**sat**	**max**	**sum**	**sat/sum**	**opt**	**opt/sum**
mean	28.71	26.86	55.57	0.54	29.29	0.52
median	22.00	23.00	44.00	0.53	20.00	0.51
sd	12.21	15.22	27.05	0.06	17.28	0.09
CV	0.43	0.57	0.49	0.12	0.59	0.17
patch 2(9)	**sat**	**max**	**sum**	**sat/sum**	**opt**	**opt/sum**
mean	34.14	34.86	69.00	0.49	37.57	0.53
median	35.00	37.00	**73.00**	0.51	40.00	0.50
sd	12.47	11.69	22.30	0.07	17.19	0.12
CV	0.37	0.34	0.32	0.15	0.46	0.23
patch 3(18)	**sat**	**max**	**sum**	**sat/sum**	**opt**	**opt/sum**
mean	45.14	54.43	99.57	0.43	60.00	0.59
median	48.00	49.00	**97.00**	0.45	60.00	0.51
sd	26.87	28.38	52.09	0.09	36.15	0.17
CV	0.60	0.52	0.52	0.20	0.60	0.29
patch 4(13)	**sat**	**max**	**sum**	**sat/sum**	**opt**	**opt/sum**
mean	35.71	35.71	71.43	0.48	37.86	0.53
median	29.00	24.00	59.00	0.45	20.00	0.51
sd	29.56	23.85	52.83	0.08	28.64	0.14
CV	0.83	0.67	0.74	0.16	0.76	0.27

First exploratory results show that optima are aligned to individual satisficing and/ or maximizing values. Assuming the median satisficing value at 50% of information gain, optima are estimated between 35 and 62%. As the estimated averaged optima of patch 3 and 2 are above satisficing (62 and 57%, respectively), patch optima of 4 and 1 are below satisficing at 35 and 45%. Relative metrics are shown in table 2 (see discussion).

Table 2: *Relative satisficed, maximized and estimated optimum (rel_sat, rel_max and rel_opt, respectively) are calculated as the average over individual relative time allocation of all participants per patches. The difference and the ratio of maximized to satisficed (max-sat, max/sat) and the average and sum of relative satisficed and relative maximized time (mean, sum) is shown. (* see discussion)*

	rel_sat	**rel_max**	**mean**	**sum**	**max-sat**	**max/sat**	**rel_opt**
GIF_1	0.23	0.18*	0.2	0,4	-0.05	0.79	0.19
GIF_2	0.26	0.25	0.25	0,5	-0.01	0.96	0.24
GIF_3	0.29*	0.34*	0.32	0,63	0.05	1.18	0.35
GIF_4	0.23	0.23	0.23	0,46	0.01	1.03	0.22

4. Discussion

Although the sample of this calibration group is naturally small, some notes and first observations are discussed here that might be helpful for further designing studies to discover cognitive strategies of satisficing.

First observation suggests that patch-time allocation for satisficing or maximizing in an aggregated resource environment (with virtually no costs for exploring unknown patches), is aligned to a fixed-time rule of 1/4 total time allocation per patch, denoting that learners might equally distribute their time costs to evaluate the rewards (see table 2). This observation partially confirms the results found by Stephens & Krebs (1986) and Nolet et al. (2006). No correlation between complexity or loop length is found (not shown). However, some GIF-loops durations (marked with * in table 2) could be adjusted for a better User Experience (UX) in tutorial learning as the relative deviation from the fixed-time might be inconvenient to the user and motivate to skip pages with relative high cognitive workload. There might be an optimal loop length according to complexity.

Participants allocated absolute time in the range of factor three. The relative metrics are robust. Learners regarded the four patches as an interrelated resource with different information gain per single patch. When revisiting the resource environment for maximizing, after sampling all four patches once, time allocation is shifted according to respective complexity. When complexity or gain of patch is relatively evaluated, then the first patch might function as a self-generated anchor at least for the following patch. It is argued here that the intra-patch time might be comparatively evaluated to the complexity of the last visited patch(es). An interpretation that would explain the flipped order of patch 1 and 4 in most time metrics. Further studies will randomize the order of the sequence to examine a putative effect of a self-generated anchor of the first patch as a kind of priming effect.

Although the definition of the optimum may vary between participants, optima are estimated around +/- 15% of satisficing time. The optima estimates of the more relatively complex patches are +15%, denoting a more directed exploration. Participants shifted more time to the two complex patches by reducing time for the simple patches, without altering total time profoundly.

It might be assumed that satisficing is close to 50% and maximizing close to 80-90% of information gain on a logarithmic scale, as a very first modeling approach of the empirical results, as done by Pirolli & Card (1999). Preliminary results show four distinguishable non-overlapping information sampling curves having no intersections. Alternatively, one can assume that satisficing represents the inflection points of a sigmoidal/ logistic function or the subjective transition point from linear to logarithmic decrease. It is unknown if the structure of the learning curve is logarithmic or linear-logarithmic. Further experiments will focus on a potentially subjectively experienced linear-logarithmic transition point of individual information gain.

Interviews and discussions after the experiment (data not shown) showed that the first sequence of visiting the patch environment under the satisficing policy task equals an exploration of available resources, and thus reduces uncertainty of the environment. Although explorative costs for finding new patches are diminished, exploitation of available resources is a first time exploration. Nevertheless, the forager here exhibits no knowledge about the reward structure of the already available foraged patches and thus exploits the environment first to acquire information. Assigning equal time when having no information is similar to the Principle of Insufficient Reason (PIR) and in accordance with Charnov's Marginal Value Theorem (MVT), because allocating equal time is averaging total time equally.

5. Conclusion and Outlook

First results suggest varying *absolute* individual differences but minor *relative* changes in time allocation of satisficed, maximized and estimated optimum in an uncertain aggregated environment. It is hypothesized here that the assessment of an environmental structure by human beings might be individually elaborated at different pace or thoroughness based on an aspiration level, but the fixed-time rule and the balancing of relative exploration/exploitation might constitute elementary cognitive mechanisms that simplify comparative evaluations.

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