Less Is More:

Exploring How People Use Heuristics In Decision Making

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Abstract

For quite a long time, researchers believe that making a decision is a complicated process which includes processing all information and making trade-offs between features. However, recent studies show that people don't make such decisions, they don't collect all the relevant information systematically, or trade off the benefits of attributes. People use heuristics to make decisions, which means that we usually focus on one aspect of a complex problem and ignore others. Heuristic decision making is a simple method for human's mind to process, and it works well under most circumstances.

In this article, we'll talk about the history of decision making theories and heuristics first, then we'll introduce the fast-and-frugal heuristics method which is derived from bounded rationality. To further understand this theory, we'll talk about its two characteristics: stopping rule and ecological validity. The most important part is to introduce its adaptive toolbox – the algorithms of how people make decisions.

Through this article, we hope to provide another thinking about how human make decisions.

Keywords: recognition heuristics, decision making, heuristics, fast and frugal.

A brief history of decision-making theories

The question of how do human make inferences and decisions has been researched for quite a long time, the popular and classical view is that human make inferences based on the laws of probability, statistics and logic. Many contemporary research assumes standard statistical tools to be normative and descriptive models of inference and decision-making, like Multiple regression and Bayes's theorem. Although some later theories propose different views, they all assume that laws of probability and statistics are normative. The problem with the classical views is the inconsistency between the experimental environment and the real-world situation. Many experiments are conducted under simple situations, for example, Bayesian make inferences based on binary hypotheses, the participants of experiments will be provided with all necessary information. However, when put into real world, where there is multiple, redundant information, such rational algorithms require a supercalculator to carry out the computation, which is too complex and intractable for ordinary human minds. (Gigerenzer & Goldstein, 1996, p.1).

In Herbert Simon's (1982) bounded rationality theory, he questioned classical rationality by focusing on psychological and ecological aspects (Gigerenzer & Goldstein, 1996, p.2). He argued that information-processing need to satisfice rather than optimize. The word "satisfice" is combined with "suffice" and "satisfy". Unlike the classical rationality theory which focuses only on the cognitive side, the bounded rationality emphasizes the limitations of human minds as well as the importance of environment in which decision are made, such as limited time, knowledge, or computational capacities.

Gigerenzer and Goldstein (1996) further developed Simon's bounded rationality theory. They introduced the fast and frugal heuristics method and claimed that people use little information and computation to make different kinds of decisions (Gigerenzer & Todd, 1999, p.3).

The visions of different kinds of rationality is shown in figure 1 (Gigerenzer & Selten, 2002, p.2).

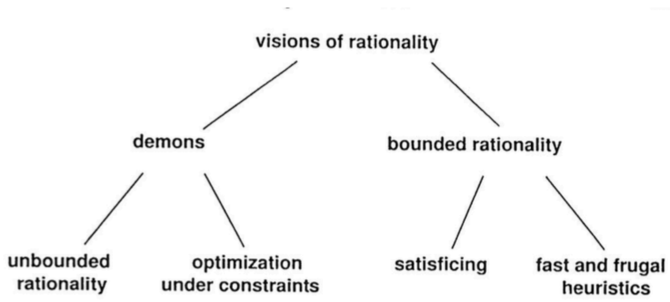

Figure 1: Visions of rationality

What are heuristics

Heuristics are strategies that allow people make judgments quickly and efficiently, they are derived from previous experience with similar problems. Some people likened heuristics to mental shortcuts. Heuristics use readily accessible, though loosely applicable information to process problems in human beings, machines, and abstract issues (Pearl, 1984). Psychologically, heuristics are learned by evolutionary processes.

Heuristics has experienced different status during research history. From its first introduction in 1800s until 1970s, it has been regarded as important cognitive processes for solving problems which may be difficult for probability theory to handle.

However, as statistical tools such as Bayesian methods and ANOVA became more and more popular among psychologists, such cognitive processes were gradually viewed as a "poor replicas" of the optimal and rational strategies (Gigerenzer et al., 2002, p.1).

The fast and frugal heuristics approach is proposed by Gigerenzer and Goldstein in 1996, they use the following definition of heuristics when studying when and why people use heuristics: "Heuristics are adaptive tools that ignore information to make fast and frugal decisions that are accurate and robust under conditions of uncertainty" (Neth & Gigerenzer, 2015, p.6). Instead of focusing on the normative process model, they used psychological mechanisms. Typically, when individuals are faced with decision tasks, they will choose the most ecologically valid heuristics for a particular task to make judgments, despite using such a simple strategy, they still maintain enough accuracy (Oppenheimer, 2003, p.2). The fast-and-frugal study includes three parts: 1. study which heuristics people use and establish an "adaptive toolbox" (collection of heuristics); 2. study when individuals use which heuristics, which is also known as the study of "ecological rationality"; 3. study how to design heuristics tools and environment to improve decision making (Raab & Gigerenzer, 2015, p.2).

The stopping rule

Most classical models aim to find some optimal solutions, take every bit of information into consideration, and consume huge amount of computation of human minds (Gigerenzer el al., 1996, p.3). They are always based on such assumption: when making decisions and inferences, human have unlimited time, unlimited knowledge and unlimited capacity of computation.

However, in real-world situations which are filled with complexity, people will rarely know all the information on which their inferences will be based, their time is always limited and the computation that classical models require is too much even for the most powerful computers (Gigerenzer & Goldstein, 1999, p.2).

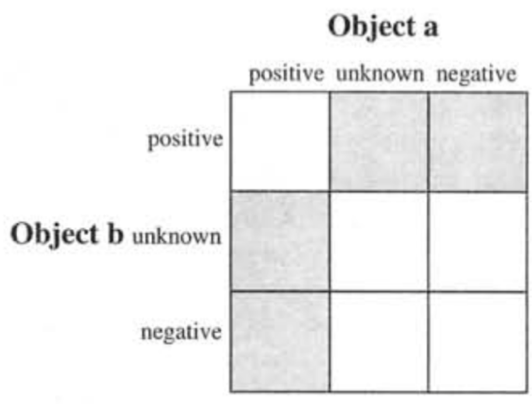

Figure 2: Search through limited knowledge

Thus, limited search has been one of the central features of fast-and-frugal heuristics, which means people don't look up all the available information, only a fraction of the information will influence the final results (Gigerenzer et al., 1999, p.2). Following this, a simple stopping rule is demonstrated by Figure 2. In this figure, both object a and object b have three values: positive, negative and unknown. Search will stop (cue discriminates) only when one object has a positive value while the other does not, which is demonstrated by the shaded knowledge states (Gigerenzer et al., 1996, p.4).

Ecological validity – the order of cues

To make inferences, we not only need cues, something that we can base our inferences on, but also need to know which cues are better than others. This order of cues may be genetically coded (Burnstein, Crandall & Kitayama, 1994, p.13), or may be learned from the social environment (Smith & LaFreniere, 2009). The ecological validity refers to the relative frequency "with which the cue correctly predicts the target" (Gigerenzer et al., 1996, p.5).

Gigerenzer and Goldstein (1996) studied 83 cities in German with more than 100000 inhabitants, with population as the target variable, they established a full model in figure 3. The ecological validity of the nine cues range from 0.51~1.0, which is also the range of "only slightly better than chance" to "certainty".

For the same question, different people has different cue orders according to their perceived validities. People carry out the limited search following this subjective order (Gigerenzer et al., 1999, p.4).

Cue	Ecological validity	Discrimination rate
National capital (is the city the national capital?)	1	0.02
Exposition site (was the city once an exposition site?)	0.91	0.25
Soccer team (does the city have a team in the major league?)	0.87	0.3
Intercity train (is the city on the intercity line?)	0.78	0.38
State capital (is the city a state capital?)	0.77	0.3
License plate (is the abbreviation only one letter long?)	0.75	0.34
University (is the city home to a university?)	0.71	0.51
Industrial belt (is the city in the industrial belt?)	0.56	0.3
East Germany (was the city formerly in East Germany?)	0.51	0.27

Figure 3: Cues, Ecological Validities, and Discrimination Rates

The adaptive toolbox – algorithms that applied in decision making

The adaptive toolbox is formed by a variety of fast-and-frugal heuristics (Oppenheimer, 2003, p.2). Unlike the complicated statistical method, they are simple algorithms following the stopping rule and ecological validity of cues.

To explain how the adaptive toolbox works, we use figure 4 to represent an individual's knowledge about 4 objects: a, b, c, d. Among the 4 objects, a, b and c are recognized (+, positive) by this individual while d is not (-, negative). His knowledge about each object is shown by cues, whose values are binary (0 and 1). The question marks represent missing knowledge of each object (unknown) (Gigerenzer el al., 1999, p.3).

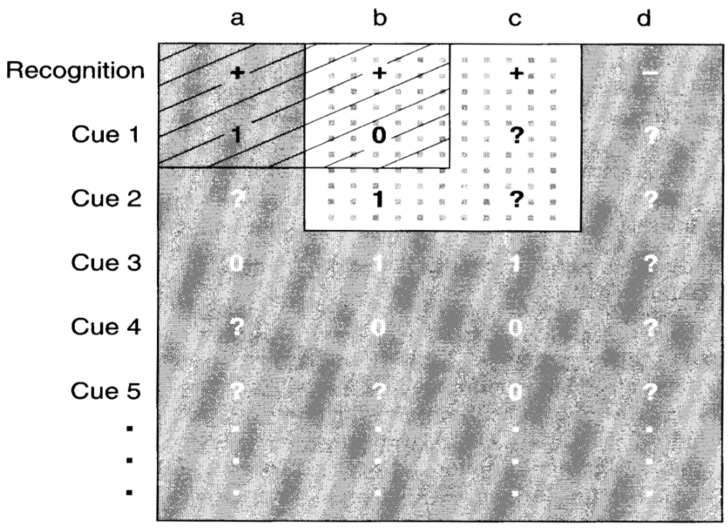

Figure 4: Search through limited knowledge

Assume the 4 objects are 4 cities, which means this individual has some knowledge about city a, b and c, but he has no knowledge about city d. Interpret cue 1 as "whether the city has a soccer team in the major league, interpret cue 2 as "is the city a state capital", etc. Suppose we want to decide which city has the larger population between two cities.

Remember that if one uses classical rationality methods to make inference about which city has the larger population, he will take all the cues into consideration at one time and come to the final result only after he finishes the calculation. Regardless of whether or not he is able to conduct the calculation (if there are quite a lot of cues available) and how long he will spend in calculating, is the classical rationality models more accurate than the simple heuristics method?

First, we'll talk about what methods in making such an inference will be used in fast-and-frugal heuristics.

The recognition heuristic

Recognition heuristic is the simplest strategy which requires minimal cognitive processing (Goldstein et al., 2002). This strategy works under such situation: only one object is recognized and another is not. The recognized object will be judged of higher value (Oppenheimer, 2003, p.2).

For example, in figure 4, city a is recognized by this individual while city d is not, thus this individual will infer that city a has a larger population than city d and ignore all the other information he knows about city a.

In this situation, the judgment is simply made by recognizing one object, it requires almost no calculation. However, Recognition heuristic will not be applied when both cities are recognized, say we want to compare city a and city b. Under this circumstance we need cue-based heuristics.

The Minimalist heuristic

The minimalist heuristic is the simplest strategy among the cue-based inferences. Although this individual has knowledge about city a and b (different cues), he may not be able to know which cue is a better predictor than others. For example, based on our assumption above, he has two cues: “city has a soccer team” and “city is a state capital”. The thing is, when comparing the two cues, he is not sure which cue is a better indicator of a larger population, which means according to his limited knowledge, he doesn’t have a subjective opinion of the ecological validity of the cues.

Thus, this individual will probably look up cues randomly. Among cue 1~5, let’s assume he’ll randomly pick up cue 2 first. To his knowledge, city b is a state capital (positive value), but he doesn’t know if city a is a state capital (unknown). Whatever, the stopping rule is satisfied (only one object has positive value), and the search stops, he judges that city b has a larger population than a and ignore all the other information.

Take the last heuristic

Einstellung effect, first demonstrated by Luchins (1942), describes a phenomenon that in a familiar context, an idea that comes to mind immediately will prevent alternatives to be considered (Bilalić, McLeod & Gobet, 2010). In other words, people tend to refer to their previous experience and methods when solving similar problems.

After an individual uses the minimalist heuristic, the einstellung effect occurs. For example, the individual has used cue 2 to make decisions between city a and city b and he infers city b is larger than a. This time he'll make inference between city b and city c. Since he has already used cue 2, he won't pick up cues randomly again, instead, he'll use cue 2 directly. Like city a, cue 2 indicates that he doesn't know if city c is state capital, the stopping rule is satisfied and search stops. He infers city b is larger than city c.

In conclusion, when there are a series of problems, take the last heuristic will try cues randomly just like the minimalist for the first problem. From the second problem onward, it will begin with the cue which stopped search last time. If this cue can not stop search, then it tries the cue which stopped search the time before last (Gigerenzer et al., 1999, p.4).

Take the best heuristic

Take the best heuristic uses the order of cues, which means this individual has a subjective opinion of the ecological validity of each cue. Again, assume this individual is going to compare the population of city a and city b, based on his previous experience, cue 1~5 has been ordered in his mind according to each cue's ecological validity,

Thus, he will search for cue 1 first (because its ecological validity is the highest), he finds city a has a soccer team in the major league (cue value is 1) but city b doesn't (cue value is 0), the cue discriminates between the two cities, and the search is terminated, the individual infers that city a has larger population than city b, all other information is ignored.

Take city b and city c as another example, he searches cue 1 first and finds a negative value of city b as well as unknown knowledge of city c, the stopping rule is not satisfied and he can't decide with this cue (no positive value), he continues to search for cue 2, this time he finds a positive value of city b and unknown knowledge(again) of city c, he then infers that city b is larger than city c.

This limited search works in a step by step way, when the stopping rule is not met, individuals will continue to search for the next cue, until stopping rule is satisfied.

The less is more effect

Using the take-the-best heuristic, Gigerenzer and Goldstein studied 83 cities and 9 cues in total (1996). Figure 5 shows the correct inferences by take the best algorithm.

The x-axis represents the number of objects recognized, the y-axis represents proportion of correct inferences, the percentage of each curve represents how many cues does this individual know. For example, the curve of 75% means when the individual has knowledge about 75% of all the cues, the value of the proportion of correct inferences changes with the number of how many cities he recognizes.

Let's examine the curve of 100%. We can see that when the individual knows all the cues (100%), the highest value of correct inference proportion occurs when he recognizes 60~70 cities. Counterintuitively, when he recognizes more than 70 cities, the correct rate goes down. This phenomenon is more obvious when he knows less cues. This striking result shows that the maximum correct inference proportion is not achieved when this individual knows all the cities and all the cues, rather, the limited knowledge helps him to make better inference.

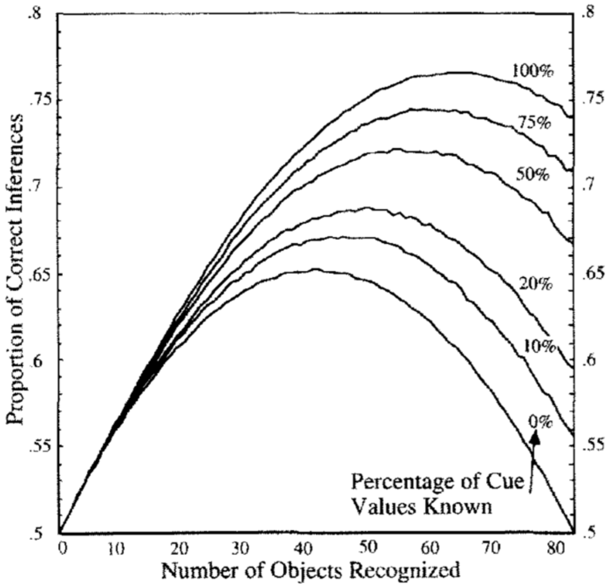

Figure 5: Correct inferences by Take the best algorithm (Gigerenzer et al., 1996)

Is it accurate?

The algorithms discussed above help to speed up decision making greatly, however, how accurate it would be comparing to the classical models? We are not going to dig further about the accuracy of fast-and-frugal heuristics in this article, only a quick review.

Gigerenzer, Goldstein and Todd (1999) compared these simple algorithms to the complex decision models, their research is shown in Figure 6 and Figure 7. From the two figures we can see that these heuristics methods don't have a significant loss of accuracy, instead, they even show higher correct rate in some certain cases.

Martignon and Schmitt (1999) has also proved the robustness of fast-and-frugal heuristics by evaluating the performance of three important classes of models: lexicographic trees, linear modes and Bayesian networks. They claimed that take the best is even simpler than Naive Bayes and concluded such a simple model is rational.

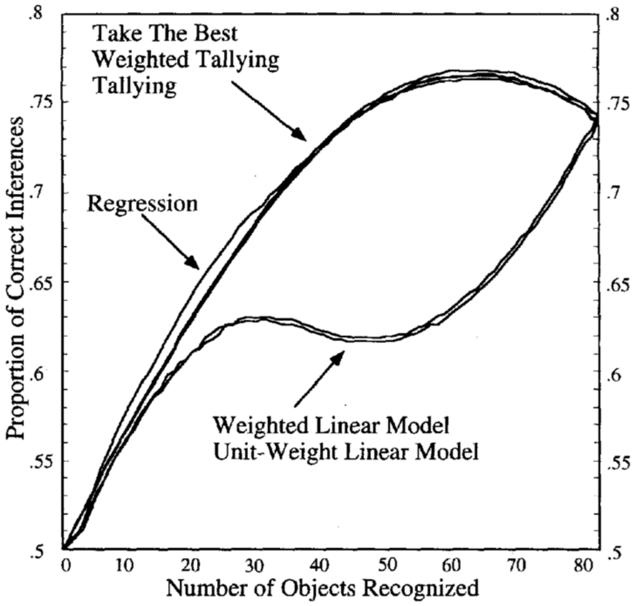

Figure 6: Correct inferences when using classical rationality (Gigerenzer et al., 1996)

	Percentage of cue values known					
Algorithm	10	20	50	75	100	Average
Take The Best	0.621	0.635	0.663	0.678	0.691	0.658
Weighted tallying	0.621	0.635	0.663	0.679	0.693	0.658
Regression	0.625	0.635	0.657	0.674	0.694	0.657
Tallying	0.62	0.633	0.659	0.676	0.691	0.656
Weighted linear model	0.623	0.627	0.623	0.619	0.625	0.623
Unit-weight linear model	0.621	0.622	0.621	0.62	0.622	0.621
Minimalist	0.619	0.631	0.65	0.661	0.674	0.647
Take The Last	0.619	0.63	0.646	0.658	0.675	0.645

Figure 7: Average proportion of correct inferences (Gigerenzer et al., 1996)

Intuitive Design

Fast and frugal tree

Fast and frugal tree is another adaptive tool developed by Green and Mehr (Bibace, 2005), it is used to solve the problem of coronary car unit allocation and is claimed to be more accurate than physician's decisions and the expert system (Koehler & Harvey, 2008).

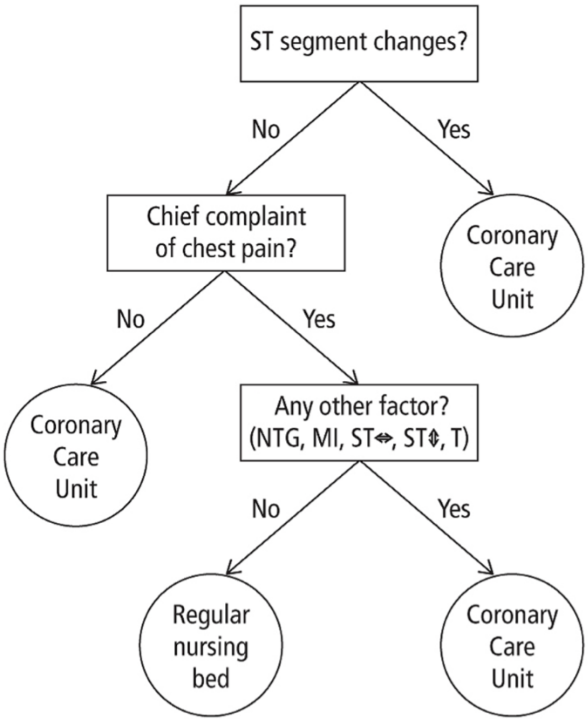

Figure 8: fast and frugal tree for coronary care unit allocation (Raab et al., 2015)

A fast and frugal decision tree is composed with several questions, each question has one exit while the final question has two. Like figure 8, it shows a quick and simple way for physicians to decide whether to send a patient with chest pain to CCU or a regular nursing bed with only three questions. Its accuracy is confirmed by a hospital who claimed such method led to fewer misses and a better false-alarm rate than their traditional HDPI (a chart with about 50 probabilities and a pocket calculator) (Raab et al., 2015).

Such a simple decision model is also used for diagnosing depression (Jenny, Pachur, Williams, Becker & Margraf, 2013) or detecting vulnerable banks (Neth, Meder, Kothiyal & Gigerenzer, 2014) , etc. Thus, I think it is also possible to use the fast and frugal tree to evaluate the usability of a website.

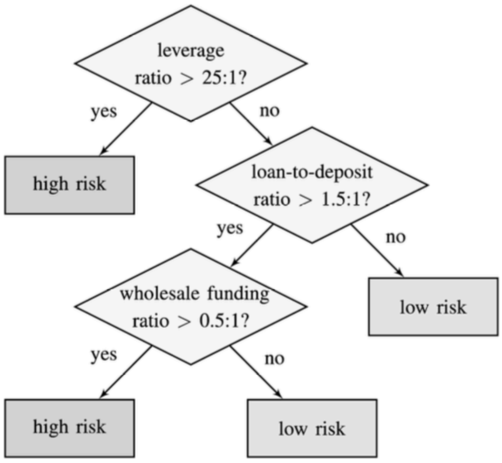

Figure 9: determine the risk of bank failure (Neth, Meder, Kothiyal & Gigerenzer, 2014)

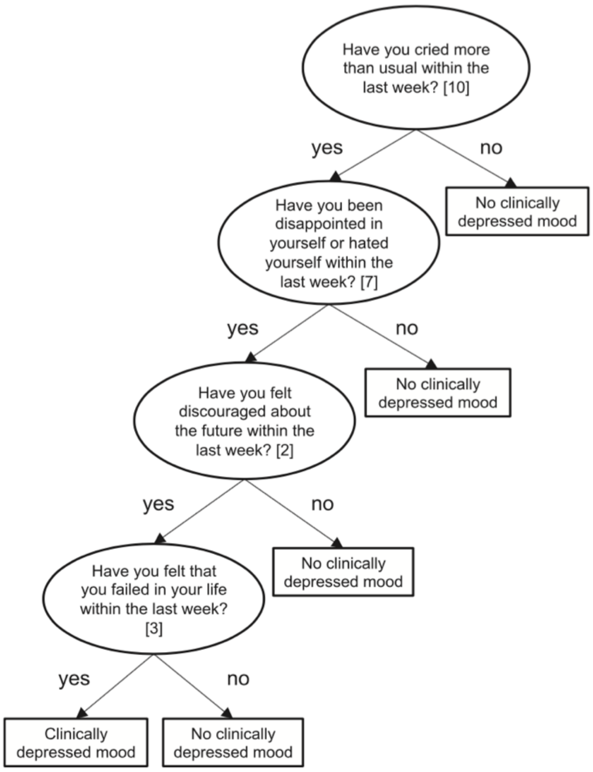

Figure 10: detect depressed mood

The current method to access a website

Many researchers use AVONA to assess a website. For example, Based on Microsoft Usability Guidelines (MUG), Agarwal and Venkatesh (2002) developed a method which includes weights and ratings to assess the usability, the key point of their theory is shown in figure 11.

Categories and Subcategories	Category Weight	Subcategory Weights	Rating (1 to 10)	Weighted Rating	Maximum Rating
Content	45				
Relevance		15	8	120	150
Media use		10	4	40	100
Depth/breadth		10	5	50	100
Current information		10	7	70	100
Ease of use	30				
Goals		15	4	60	150
Structure		10	10	100	100
Feedback		5	5	25	50
Promotion	5	5	10	50	50
Made-for-the-medium	15				
Community		10	8	80	100
Personalization		0	N/A	0	0
Refinement		5	8	40	50
Emotion	5				
Challenge		0	N/A	0	0
Plot		0	N/A	0	0
Character strength		5	7	35	50
Pace		0	N/A	0	0
Overall rating				670	1,000

Figure 11: Use of weights and ratings in determining usability

They added weights to each categories and subcategories of MUG and ask users and investors to rate these categories, with the weighted scores they can further analyze the website.

Similarly, Evans and King (1999) also explored the way of using weighting assessment categories and claimed it to be comprehensive and systemic.

We're not going to discuss further about the pros and cons of these evaluation methods, however, as Gigerenzer and Goldstein (2011) claimed that there are significant individual differences in cognitive strategies, and "analyses based only on means do not allow conclusions about underlying processes" (Gigerenzer et al., 2011), even though a website's final score is at a high level with these methods, it still doesn't mean it's perfect, an overall weighted score ignores all the individual differences of users.

A simple evaluation model with fast and frugal tree

Like all the fast and frugal tree models above, the new evaluation method has a similar structure shown in figure 12.

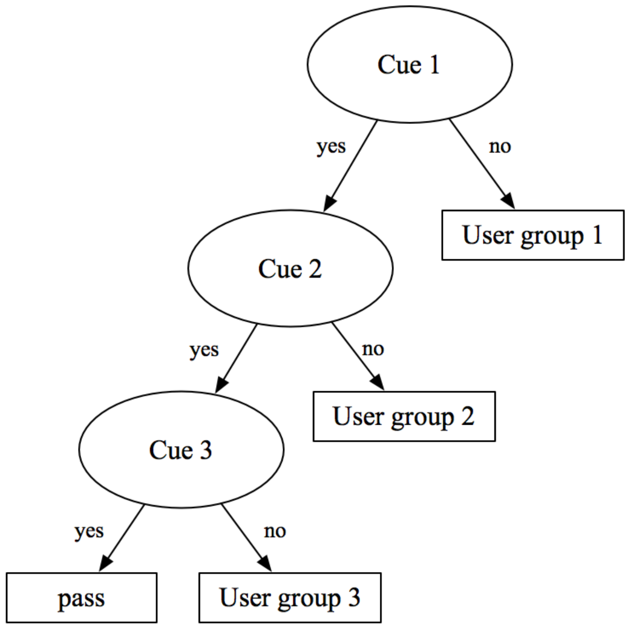

Figure 12: usability test decision tree

We use cue 1~3 to filter out users, for example, when testing a user, we ask: is the content what you expect? If the user says yes, we move on and ask: is it easy to use? However, if the user's answer is no, then he is filtered to User group 1.

Why do we want to filter out users? Spool (2005) presented a model which shows the purpose of website design, shown in figure 13. The "no knowledge" point is where you put those who know absolutely nothing about your website, and the "all knowledge" point is where you put those who know everything, these people are probably designers in your team. The distance from the left side means how much a user knows about your design, which is represented by the “current knowledge” point, another point is called “target knowledge” point, which means how much the user needs to know in order to accomplish their objective. The distance between “current knowledge” and “target knowledge” is called “knowledge gap”.

For a designer, he doesn’t design for the left part of the current knowledge point, because that area is what the user already knows. He doesn’t design for the right part of the target knowledge point either, because that part is not the user’s goal. The design happens in the knowledge gap, designer should design to narrow the knowledge gap.

Their further study showed that by “plotting our different users”, there are very clear clusters, which means “bunches of users that share extremely similar current knowledge”.

Thus, this is the purpose of filtering out users. By using the fast and frugal tree, we find out users who have different level of knowledge, which means they have different current knowledge point. For each user group filtered out by different cues, we study their knowledge separately, and consider how to narrow the group’s knowledge gap. The whole process is demonstrated in figure 14.

Through this method, we define and study user groups who have similar current knowledge, instead of calculating the overall score of a website and ignore all the details, each group need to be examined uniquely so that we can find out how huge is the knowledge gap, did our previous design help user’s current knowledge move forward, or did we reduce the necessary knowledge for users to complete their objects.

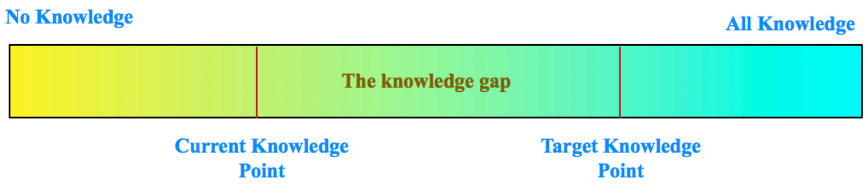

Figure 13: the knowledge gap between users and their targets

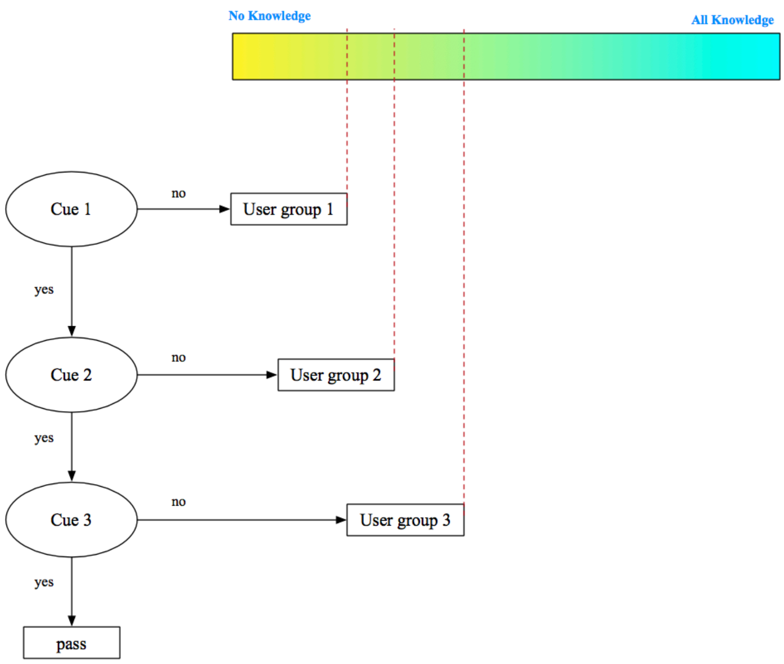

Figure 14: find out users' current knowledge point

This model still need to be further developed, for example, how to choose different cues to distinguish user groups correctly, how to order these cues, how many users should be tested.

Conclusion

In this article, we discussed four fast-and-frugal heuristics methods. In fact, there are still many other heuristics identified in recent studies, such as: Hiatus heuristic (2008), Default heuristic (2003), fast-and-frugal trees (2003), Fluency heuristic (2005) and so on (Neth et al., 2015, p.9).

We emphasize that “Behavior is a function of cognition and environment in tandem” (Neth et al., 2015, p.14). People make decisions under limited time, limited knowledge and limited computation capacity, thus sometimes making a quick and good enough decision is much more important than making the optimal decision.

Fast-and-frugal heuristics provides a simple and quick way for people to make decisions as well as ensures accuracy.

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