Adaptive Theory: Limited Neural Resource, Attention and Risk Taking

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This paper presents a new descriptive theory for decision making under risk, called adaptive theory, which deals with how the brain adapts the distribution of limited neural resources to encode subjective utility(SV) for efficient use in different contexts. This distribution affects the relative utilities between each payoff, and finally determines the brain's risk attitude. We propose that the adaptation of distribution can be divided into two dimensions, the location and the degree of neural resources concentration. By introducing four assumptions on the distribution, this paper studies how those two dimensions vary according to contexts, and finally determines risk attitude. By specifying these two parameters as a function of payoffs, our theory provides a novel and unified account of a large number of empirical phenomena. Our theory also yields new predictions that distinguish it from prospect theory and the salience theory. In addition, the implications of our theory may provide new directions for decision theories based on the concept of decision utility.

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I. Introduction

Economists always have to make different assumptions about the marginal utility in their models to deal with different risk attitude(Schoemaker 1982). This demand not only reflects the existence of different utility functions in corresponding decision contexts but may also reflect that the neural system encoding decision utility cannot use an identical scale to encode utility in all decision contexts. The neural system cannot keep this scale identical in different decision contexts, it also cannot keep it identical on different goods which are identical in nature but only different in the relationship with the decision maker. The scale of encoding utility will be adapted to the decision context. The need for such adaptation comes from the conflict between the limited amount of neural resource and a relatively unlimited amount of objects to be encoded. This conflict becomes a problem because a perceptible encoding requires at least a certain amount of neural resources. If we keep the scale identical in all decision contexts, we can not make a meaningful decision in most of the contexts based on our perception, because the difference between most options could not be perceived. Therefore, an adaptive encoding system is necessary for effective decision making. Marginal utility decreasing or increasing is the result of this meaningful adaptive encoding according to the decision contexts. In this paper, we try to build an analytical framework to model how a neural system with limited representation resources adapt its encoding scale to encode unlimited objects and the consequence of this adaption on risk attitude.

Attention is a mechanism, intentionally or unintentionally used by the neural system, to guide its adaptive encoding in the decision context to avoid the conflict from the limitations of the neural system mentioned above. The encoding system adjusts the distribution of neural resources by taking two dimensions of attention into account. The first one is to allocate more resources when the position is nearer from the attention and to allocate lesser when the position is farther from the attention, according to the location of attention; The second is to allocate more resources to the position nearer from attention when the degree of attention is higher, according to the degree of attention. Similarly, we consciously or passively experienced the adjustment of visual attention every day. We not only adjust the location of our visual attention, but we also adjust our distance from the object being attended(Bundesen 1990). Our analytical framework can be used to study how the decision-making context affects the distribution of neural resources by adjusting the two dimensions of attention, and thus the effects of individual utility functions and behaviors. We first apply some of the robust attention determination mechanisms found in psychological research to make an assumption about attention determination in a given decision context, based on which we give a prediction about risk attitude in that context. We also use the assumption that individuals avoid imperceptible encoding to determine the degree of attention, which tells the story about risk coefficiency.

The location of attention is usually determined by two mechanisms, the top-down mechanism, and the bottom-up mechanism(Buschman and Miller 2007). We will note that the default position is assumpted at 0, determined by a top-down mechanism, which may be a goal to earn some money in the experiment. We then focused on the impact of bottom-up mechanisms on attention. We assume that a potential extreme outcome may capture attention when its salience is big enough. We define the salience by the ratio of the utility of potential outcome to the utility of the expected value, under the initial utility function with the default attention. When the salience is large enough, attention may be captured by the potential extreme outcome, leading to an attention shifting. Otherwise, it remains unchanged. This assumption about attention determination tells a good story about the common consequence effect and the common ratio effect. It also has the ability to distinguish them from the peanut effect, for the salience is the key to attention shifting. Our assumptions about the determination of attention under this framework can also be used for studying the reference point in the Prospect theory. Our results also enrich the study of the Prospect theory.

In our framework, a change in the degree of attention leads to a change in the degree of concentration of neural resources distribution, which will be reflected in the change in the utility of a given payoff. A change in utility of a given payoff is an external manifestation of a change in neural resources distribution. This means that almost any change in utility of a given payoff will inevitably be an indication of a change in the utility function. This will lead to a change in the absolute risk aversion coefficient(ARAC). When the utility of a given payoff increases, the ARAC increases. When the utility decreases, the ARAC decreases. We conclude that any discount in the utility of a given payoff caused by external factors will lead to a reduction in the ARAC. For example, our framework predicts that time discounting will lead to a less risk aversion. These predictions cannot be explained by the Prospect theory. This is a new direction that a theory can contribute to and our framework did well in this direction.

In terms of changes in the utility of a given value, we first consider the effect of the upper limit of the decision set on the degree of adaptation. On the assumption that the neural resources for representation are limited, the change of the utility of a given value means a change of the distribution, which finally affects the individual's absolute risk aversion coefficient. In our theory, the change of the utility of a given value represents the adaptation of the distribution of resources. Thus, the size of this utility represents the degree of attention. When the upper limit of the decision set increases, the utility of a given value will decrease, so the absolute risk aversion coefficient of the decision maker will decrease. On the contrary, when the upper limit of the decision set decreases, the utility of the given value will increase, so the absolute risk aversion coefficient of the decision maker will increase. This property of a change in the utility of a given value shows a new approach to understand Rabin's criticism of expected utility theory. Rabin's critique is based on the assumption of a stable utility function, which implies that the distribution is stable. In this case, all the effects induced by changes in utility must be attributed to a subjective probability function. Our theory, however, argues that some unusual decision-making practices and unusual value to the decision maker result in a change of neural resources distribution, leading to a violation of the expected utility theory.

The encoding system will adapt to the size of payoff values in the degree of attention. Generally, when the payoff is large, the degree of attention does not need to be too high to make the payoff be perceived. When the payoff goes smaller, the degree of attention goes low correspondingly. Therefore, when the payoff is different, the difference in the degree of attention will result in a difference in ARAC. When the upper limit of the decision set increases, the utility of a given value will decrease, so the absolute risk aversion coefficient of the decision maker will decrease. On the contrary, when the upper limit of the decision set decreases, the utility of the given value will increase, so the absolute risk aversion coefficient of the decision maker will increase. This property of a change in the utility of a given value shows a new approach to understand Rabin's criticism of expected utility theory. Rabin's critique is based on the assumption of a stable utility function, which implies that the distribution is stable. In this case, all the effects induced by changes in utility must be attributed to a subjective probability function. Our theory, however, argues that some unusual decision-making practices and unusual value to the decision maker result in a change of neural resources distribution, leading to a violation of the expected utility theory.

The article proceeds as follows. In Section II, we will first propose our model and explain the psychophysiology foundation of this model. In Section III, we will demonstrate the most basic economic implications of this theory. In Section IV, we consider the determination of attention, and on this basis explain some common violations of the theory of expected utility. In Section V, we will consider the degree of attention changes corresponding to the stake sizes of the tasks. In this section, we will also explain the new decision situations which our theory can be applied in. In Section VI, we will discuss the advantages and disadvantages of our theory as a descriptive model, as well as the implications for the normative model. Section VII concludes.

II. The Model

A. The Decision Model

Our theory is that the individual chooses between lotteries so as to maximize the mathematical expectation of decision utility. We may define the expected utility E_i of lottery L_i, by:

$$E_i = \sum_j u_j p_j$$

Faced with a choice between lotteries L_i and L_k, the individual will prefer L_i, prefer L_k or be indifferent between them according to whether E_i is greater than, less than or equal to E_k. This model of expected value is identical to the classical expected utility model in its expression. The difference is that the utility in our theory has different properties compared with the utility in the expected utility model. We will explicate our ideas about utility below.

B. Utility Function, Attention and Density Function

Our theory assumes that the decision utility is encoded by the neural activity in the relevant brain regions and this process consumes an amount of limited neural activity resource. This assumption is based on the fact that neural activity can reveal individual preferences in advance, which is one of the most important findings and foundations in neuroeconomics(Smith et al. 2013). This assumption is also supported by other findings in related topics in neuroscience, that is, the subjective perceptions reported by individuals in multiple sensory systems are linearly related to the measured neural activity(Johnson, Hsiao, and Yoshioka 2002,Anderson et al. (2003),Bartels and Zeki (2004),Jackson, Meltzoff, and Decety (2005),Sabatinelli et al. (2005),Walter et al. (2008)). Decision utility is the subjective motivation intensity perceived by the individual, and it is a kind of perception. Therefore, we assume that the intensity of neural activation can encode the strength of decision utility, and the two have a linear relationship. The decision utility that a given object can cause can be reflected in the amount of neural resource needed to encode the utility.

On this assumption, in order to encode the decision utility of a given added value v, $v \in R$, the neural resource must be distributed over the entire real space R in which the added value lies. The neural resource accumulated on this added value under this distribution, the intensity of the neural activity caused by it, is the decision utility of this added value. If we denote this distribution by density function $f(x)$, the decision utility of the added value can be precisely defined as the integral of the distribution function over the range of the added value.

Definition 1: Assuming that the current payoff value is w, the decision utility of an added value v to w is given by the integral of density function $f(x)$ over that interval of $[w, w+v]$, which is

$$U(v|w) = \int_{w}^{w+v} f(x)d(x)$$

We should carefully examine the characteristics of the distribution of neural resources, i.e., the features of the density function $f(x)$. This density function $f(x)$ is mathematically equivalent to the marginal utility function in previous studies because it is exactly the first derivative of the utility function. However, the marginal utility functions in those models are often relatively simple and less studied. We highlight this density function here because we need to pay special attention to the limitations and features of this function, which is key to differ our theory from previous theories. First, we will list four basic assumptions about the density function. We will then review the literature on the psycho-physiological foundations of these assumptions.

Definition 2: Attention is a mechanism, intentionally or unintentionally used by the neural system, to guide its adaptive encoding in the decision context, by allocating more neural resource to the location closer to the attention point, to enhance the discrimination of the attention point.

Definition 2': The degree of Attention. The degree of attention is higher when more neural resources have been allocated to the nearby of the attention point.

A higher degree of attention means a higher degree of neural resource concentration. We now turn to the definition of the density function. The definition we give for the density function is as follows:

Definition 3. The neural resource density function for a given context is a continuous and bounded function $f(x)$ that satisfies four conditions:

A1. Non-negativity. Given $\forall a \in R$ and $\forall d \in R^+$, we have $f(x) \geq 0$.

A2. Strictly Unimodality. Given any a, the first derivative of $f(x)$ is positive for $x < a$, negative for $x > a$, and zero only at $x = a$.

A3. Finity. The neural resource can be used to represent stimulus is limited is unity, which is

$$\int_{-\infty}^{+\infty} f(x)dx = 1$$

A4. A minimum resource requirement for perception. If a difference, for example, $n - m$, should be perceived, the minimum resource allocated on this range should be larger than a given amount e.

$$\int_{m}^{n} f(x) > e$$

These four basic assumptions are actually common constraints for all neural perceptions of the external world. For example, our senses(hearing, vision, taste, smell, touch) related neural system satisfy these four constraints. The psychophysiology foundation behind these assumptions is therefore quite solid, as we will discuss in the next section. We will then give an example function that satisfies the above assumptions to provide an intuitive explanation of the economic implications of these hypotheses.

C. An Example Utility Function

Based on assumptions A1-A3, we give an example of the density function. Assumption A4 is not like A1-A3, which is a factor that an individual needs to consider when he/she wants to percept a difference, so it is not a feature of the distribution function itself. And this assumption is not considered in the example function. However, we reserve a parameter d in this density function, which can give us the possibility to consider assumption A4 later. In this function, a indicates the location of attention and d indicates the degree of attention. As follows:

$$f(x) = \frac{d}{(x-a)^2 + d^2}$$

This density function satisfies assumptions A1-A3 required by Definition 1 $\forall a \in R$ and $\forall d \in R^+$.

For instance, in this formular, because $d > 0$, and for $\forall x$ and $\forall a$, $(a-x)^2 + d^2 > 0$, we have $f(x) > 0$ for all a in the real numbers domain, which is requirement 1, Non-negativity.

Therefore, based on this density function, we have a utility for a value x:

$$U(x) = \int_0^x f(x)d(x) = \arctan((x-a)/d) + \arctan(a/d)$$

If we want to reflect assumption A4 in this density function, we can adapt d for a given combination x, a to satisfy A4.

D. Psychophysiology Foundations of the distribution

In this part, we will review some literature on the psychophysiology foundation of the four assumptions of distribution. Those assumptions are of great importance to guide how the neural resource is distributed on the whole range of the external world. Therefore, it is needed to clarify why we should build our theory on these assumptions.

Minimum Requirement for Perception

A large number of neuroscience experiments, psychological measurements, and neural measurements, in particular, use of psychometric-neurometric comparisons (correlational research), investigate both the psychophysical responses and neurobiological measurements of a particular, externally quantifiable variable and test whether the influences are in a similar manner (Kable and Glimcher 2007). One example is to assess the relationship between the contrast increment threshold and neural activity in the human visual cortex. Boynton et al. (1999) measured BOLD signals in the visual cortex and associated them with the changes in visual stimulus contrast. They find that the contrast increment is detected by human subjects when the fMRI responses in the early visual areas increased by a criterion amount, a visual barrier. Furthermore, while two different contrast levels evoke different magnitudes of fMRI responses, subjects are only able to discriminate these two contrast levels when the BOLD signal difference in the visual cortex is larger than a specific value. Such evidence attests to the ability of BOLD signal changes as reasonable predictors of variations in contrast threshold. It also is a piece of evidence to suppose the A4.

Limited Resource

The neural resource used to represent utility is limited. The limitation of representation resource comes from two aspects. The first one is imposed by the fixed amount of overall energy available to the brain and by the high energy cost of the neuronal activity. Neurons firing relies on metabolic resources (oxygen and glucose) carried by the bloodstream. The metabolic cost of brain activity is high, so the maximum frequency of firing of individual neurons is limited. This literature indicates that firing rates in a system result from a controlled usage of metabolic resources. The second limitation is imposed by the fixed amount of neurons available to represent utility at any given point in time. This claim is also supported by the phenomenon of neuroplasticity. This discovery of a stimulus-dependent alteration in the brains??? macroscopic structure contradicts the traditionally held view that cortical plasticity is associated with functional rather than anatomical changes. This phenomenon shows that more neurons are needed to represent the object more clearly.

Limited Resource Allocation and Attention

Because the neural resource is limited and the neural system has the minimum necessary resource requirements to process information, the neural resources could not be evenly distributed over all external world. As a result, there are more neural resources in some parts and less in others. This difference in distribution is the result of the different location of attention. Attention selectively allocates limited neural resources effectively according to their goals, and the attended part receives more neural resources than the unattended parts. (see Knudsen, 2007 for a review). In previous decision models in economics, the way to model attention is to employ a weighting function, which puts more weight on the attended part and less weight on the unattended part. This modeling approach is similar to the spotlight model in spatial attention studies and has important applications in multi-attribute decision models. A decision maker may focus on different attributes in different environments, resulting in different attributes receiving different weights, so as to make different choices. However, this modeling approach does not adequately address the effects of feature-based attention. For example, at present, there are two amounts of money, what if the small amount of money receives attention? In this case, an individual may choose the small one other than the big one due to the weights on them. In the prospect theory, the weighting function is incorporated into the probability function. The over-weight of small-probability events in the original prospect theory is substantially equivalent to saying that the small-probability events are overweight, which leads to a violation of stochastic dominance. Therefore, in the cumulative prospect theory, such attention can only be put on high ranking outcomes with small probabilities. The rank-dependent weighting function only allows the big one to receive attention. Without this restriction, this modeling approach of attention has its weakness.

We here in this paper take another approach to model attention, which can be applied to model inseparable feature-based attention. The amount of money is different from the separable objects in the space, money is inseparable. A small amount of money is always an inseparable part of a large amount of money in terms of values. Attention on a given amount of money is attention to a given degree of the same feature. The purpose of this feature-based attention is to discriminate the attended degree of that feature and other degrees of that feature. Therefore, the effect of this kind of attention is that more neural resources will be distributed at the point of attention. When a degree of that feature is closer to the attended degree of that feature, more resources will be distributed at this degree. This pattern of neural resource allocation can make sure that the attended degree is effectively discriminated from other degrees. In this modeling approach, we do not need restrictions imposed by their rank.

III. Basic Implications

A. Stochastic dominance

Our new method to incorporate attention into utility ensures that no matter where attention is, the property of stochastic dominance will be kept. According to the decision model and the utility's definition based on the four assumptions, our theory satisfied the principle of stochastic dominance. Firstly, let us consider the first and second derivative of this utility function. Because the density function is the first derivative of the utility function, and none-negativity is the first condition that the density function should satisfy, the utility function $u(x)$ is a nondecreasing function, which means that $f(x+\varepsilon) \geq f(x)$ for $\forall \varepsilon > 0$. Therefore, in a risky decision situation without distortions in probabilistic decision weights, a decision maker evaluates a prospect L_i as:

$$V(L_i) = \sum_i p_i \cdot u(x_i).$$

Our theory do not have to resort to any forms of rank-dependent subjective probability function. This rank-dependent weighting function is a necessary component in other non-expected utility theories(Quiggin 1992,Kahneman, Knetsch, and Thaler (1991)). Without implementing this rank-dependent weighting function, those theories will ignore the effect induced by the attention. However, we will argue that this rank-dependent weighting function is just an approaching method to stimulate the effects predicted by our theory later in this article.

B. *Location of Attention and Reflection effect*

Now, let us consider the second derivative of this utility function. Because the density function is the first derivative of the utility function, the first derivative of the density function will be the second derivative of the utility function. According to the strictly unimodality assumption, the utility function has only one inflection point, where the second derivative of $u(x)$, $u''(x)$ is 0 at $x = a$. The assumption A1 ensures that the first derivative of the utility function is always non-negative, $u'(x) > 0$. Therefore, we have $u'(x) > 0$ and $u''(x) > 0$ for $x < a$ and $u'(x) > 0$ and $u''(x) < 0$ for $x > a$. This property implies the reflection effect.

To illustrate this property, let us exam the second derivative of the example utility function:

$$\frac{\partial^2}{\partial x^2}\left(\arctan\left(\frac{x-a}{d}\right) + \arctan\left(\frac{a}{d}\right)\right) = \frac{2\,(a-x)\,d}{\left((x-a)^2 + d^2\right)^2}$$

Our prediction is the same as the prospect theory if the reference point in their theory is the attention point in our theory and the subjective probability function is a linear function. For instance, given any gamble G yielding x_1 or x_2 with $x_1 > x_2 > 0$, if the agent's attention is at $a = x_1$, then he/she will be risk seeking. When his/her attention is at $a = 0$, he/she will be risk aversion.

The key factor that determines risk attitude is the location of attention in a decision context. This property implies that if attention is changed, the risk attitude will change accordingly. We will list two ways of determining where attention is in Section IV.

C. Degree of Attention and Relative Utility

We will discuss in this part how a change in utility of a given value will affect relative utilities between two given values. For simplicity, we first consider the situation where the attention point is kept at zero, $a = 0$. We will assume that the effect and aim of increasing a utility of a given value are to better distinguish the differences between the attended and non-attended parts, and the effect and aim of reducing utility are to appropriately reduce such discrepancies between the attended and non-attended parts. Because of assumption A3, the change in the distribution function only means that changes in how to allocate neural resources, rather than changes in the total amount of resources. Therefore, increased neural resources for attended parts come from sources that are left for remote potentials parts which are absent right now; Reduced neural resources for attended parts will be left for remote potentials parts which are absent right now. This assumption implies that if the utility increase, the increased neural resources per value unit increase as they become closer to attention; Conversely, as the utility decreases, the decreased neural resources per value unit increase as they become closer to attention. We should ensure all distribution functions still satisfying our assumptions A1-A3.

We denote the original distribution function as $o(x)$, And the modified distribution function as $m(x)$. Thus, we can denote the difference between these two distributions by $k(x) = m(x) - o(x)$. Since $\int_a^\infty m(x) - \int_a^\infty o(x) = 0$, we have $\int_a^\infty k(x) = \int_a^\infty (m(x) - o(x)) = 0$. This means that there is at least one x_i, such that $k(x_i) = 0$. And if $m(x)$ denotes the distribution function of the increased utility, we have $\int_a^{x_i} k(x) > 0$ and $\int_{x_i}^\infty k(x) < 0$. Our assumption implies that there exists $x_j, x_j\ in(x_i, \infty)$ and we have $k(x) = m(x) - o(x)$ monotonically decreasing in (a, x_j) and monotonically increases in (x_j, ∞). And, in (a, ∞), there is only one point $x_i \in (a, x_j)$ such that $k(x_i) = 0$. Under our assumptions A1˜A4, and above, we have the following theorem:

- As the utility of a given value increases, the decision maker's absolute risk aversion coefficient (ARAC) becomes larger. Conversely, ARAC gets smaller as the utility of a given value decreases.

Proof: According to Cauchy's median value theorem and our assumptions about the changes in distribution, we have our theorem.

Remark: This theorem shows that a change in utility of a given value, the estimated absolute risk aversion coefficient will change accordingly. When a value is given at y, a larger utility of this value means a more concentrated distribution of neural resources around the attention(when attention is in $[0, y]$). This theorem shows that the degree of attention determines absolute risk aversion coefficient. Because the amount of neural resources is finite, more resources being allocated to a given value means fewer resources left for the parts which do not contain this given value. Therefore, the greater the utility of a given value has, the fewer resources will be left for other parts, which leads to a change in relative utilities of two given values.

Corollary: Given that there are two values, $y > x > a = 0$, we denote the utility of x as $u_o(x)$ and the utility of y as $u_o(y)$ in context o. In another context, we denote the utility of x as $u_m(x)$ and the utility of y as $u_m(y)$. (1): We have, if $u_m(x) > u_o(x)$, then, $u_m(y) > u_o(y)$. (2): if $u_m(x) > u_o(x)$, then, $u_m(y)/u_m(x) > u_o(y)/u_o(x)$

Remarks: This corollary says that any change in utility will result in a change in relative utilities of two given values. Exceptions: if $y = 2x = 2a$, then a change in utility will not lead to a change in its relative utilities.

ABSOLUTE RISK AVERSION IN THE EXAMPLE UTILITY FUNCTION

Recall the definition of the coefficient of absolute risk aversion (ARA), we can calculate ARA of this utility function.

$$ARA = -\frac{u''}{u'} = \frac{2\left(x-a\right)}{\left(a-x\right)^2+d^2}$$

Let's first see the concave part of this utility function, in which we have $x > a$.

$$\frac{\partial ARA}{\partial x} = -\frac{2\left(a^2-2ax-d^2+x^2\right)}{\left(a^2-2ax+d^2+x^2\right)^2} = -\frac{2\left(\left(a-x\right)^2-d^2\right)}{\left(\left(a-x\right)^2+d^2\right)^2}$$

The numerator of this expression determines whether the overall expression $\partial ARA/\partial x$ is greater than zero or less than zero. When $|x-a| < |d|$, which is when $x \in (a-d, a+d)$, we have$\partial ARA/\partial x > 0$; Otherwise, we have $\partial ARA/\partial x < 0$.

$$\frac{\partial ARA}{\partial d} = \frac{4\left(-x+a\right)d}{\left(\left(a-x\right)^2+d^2\right)^2}$$

when $x < a$, we have $ARA(X)$ decreases with d, because $\left(\left(a-x\right)^2+d^2\right)^2 > 0$ and $a-x<0$ when $x>a$,$\partial ARA/\partial d < 0$; when $x < a$, $\partial ARA/\partial d > 0$.

D. *Implications for anomalies in Risky Choice*

The probability used in our decision model is the original objective probability, which means that all violations of the expected utility theory come from the density changes in utility function in this theory. We show above that, if attention a and the degree of adaptation d (reflecting the utility of a given value) stay the same, there would be no violations of EUT.

However, a change in the attention a or a change in the degree of adaptation d will lead to a change in risk attitude. Those changes in attention or/and degree of adaptation are reasons for violations of expected utility model. In the following parts of this article, we will discuss the specific impact of changes in attention and utility on risk attitudes.

IV. adaptive in the location of Attention

Because the distribution of neural resource should satisfy assumption A3 and A4, the attention point could not always remain in one position. If the attention point is fixed at one place, no matter what the degree of adaptation d is, A4 will not be satisfied in a large set of decision situations. If you stay in one place, you will never see the difference between two objects beyond your sight. You will never know there are decisions that you can make. An animal that stays at a place without moving cannot detect possible food far away from the place it stays. Therefore, attention must be adjusted in order to better finish the tasks of different requirements. That is, we will adjust our attention according to our goals.

In risk decision making, we have at least two potential competing goals. The first goal is to get some money, which is the same as to avoid ignoring the minimum possible money. The second goal is to get the maximum possible outcome. Participants will have different risk attitudes when one of the two goals wins the attention. When the first goal wins, the decision maker will be risk averse; When the second goal wins, the decision maker will be risk seeking.

A. Goals and Attention

A large body of literature in the field of psychology shows that attention is usually determined in a top-down way, while a bottom-up stimulation may also capture individuals' attention. In our theory, we assume that attention is initially allocated in a top-down way because our attention is directed by our goals in a specific task. A goal is usually the most important source of the top-down attention regulation. Often, for participants who come to an economic experiment, their goals could be regarded as to make some money instead of to get the maximum possible money. Thus, we can assume that the initial purpose of participants is to gain some revenue and avoid losses, which is a relatively general goal for most people. In this case, the attention will be at $a = 0$. This attention can make sure that the decision maker could notice as many potential targets as possible, which can ensure that we get some income.

For example, when we walk around, we should put our attention on the road, so we can avoid both small and big obstacles. If you look at the sky and put your attention there, you can avoid big obstacles but neglect small obstacles. If we keep doing this, we will ignore many small obstacles. This will also make us hard to walk around. On the contrary, when you put your attention at 0, you will never ignore large gains, although these large gains may be under-evaluated. Therefore, it is acceptable for an individual to put attention on point 0, as this will allow he/she to survive by detecting as many gains as possible. The negative side of putting attention at 0 is that it may weaken the power of the biggest potential outcome.

Other potential goals can also capture attention by its salience in contexts. The goal of getting the maximum possible outcome is a potential goal in a risk decision. This goal can be activated by its salience relative to expected values of the lotteries.

Previous studies in Psychology focused on the impact of different types of external stimuli on attention in those bottom-up attention studies. These studies found that if the bottom-up stimulus wants to capture the attention, the stimulus should be selected by the salience filter. For example, some stimuli are critical to the existential for an organism, which will be encoded in the attention system of the organism. Those stimuli could be selected by the salience filter of the organism, which can help the organism to survive by detecting those particular stimuli when needed. Another way to capture attention through the bottom-up way is by enhancing the intensity of the stimulus to reach a certain standard, which could also be selected by the salience filter.

Although monetary stimulus differs from these stimuli studied in those experiments, monetary stimulus is a kind of stimuli. A stimulus capturing attention through a bottom-up way needs to meet two basic conditions: The first one is that this stimulus is important to the individual, and the second one is that its strength should surpass the background stimuli in terms of neural activities. Those two conditions are necessary for an individual to switch attention from the current point to the salient new one. When different types of stimuli compete for attention resources, different types of stimuli require special salience filters; Successfully competing for attention from the same feature through the bottom-up way is usually most likely due to its higher intensity. Of course, we do not deny that a change in attention could be caused by other reasons, we currently only consider the change in attention caused by its relative strength with the background stimulus in terms of neural activities.

This neural activity is based on the initial distribution with attention at the initial place $a = 0$. Under this distribution, if the utility of the maximum possible outcome surpasses the utility of expected value of the lotteries quite a lot based on the initial distribution, the alternative goal of getting the maximum possible outcome will be so salient that capture the attention. That requirement is, $u(x_{max})/u(ev) > \lambda$. We can illustrate this requirement in the example utility function.

For example, the attention point is initially assumed at $a = 0$. The expected value of the gamble is ev, and the maximum possible outcome is x_{max}. Whether the maximum possible outcome could be regarded as the new attention point depends on whether its utility surpasses the utility of the expected value ev for a great deal. For a given d and λ, we have

$$r = \arctan(x_{max}/d)/\arctan(ev/d) > \lambda \tag{1}$$

d indicates the degree of adaptation, reflected in the utility of given value. λ

is used to indicate the surpass required to change attention. Indeed, the salience function provided in this section does not cover all possible situations. This leaves a gate for future research.

B. Implications of attention shifting

If attention will be changed according to the way we suggested above, we have following theorem.

- If the utility of the expected value of the lotteries ev is larger or equal than λ, $u(ev) > 1/\lambda$, there is no attention shifting according to the way suggested.
- If the maximum possible outcome x_{max} is given, the possibility of x_{max} being attention increases as ev decreases.
- If the utility of a given value increases, the possibility of x_{max} being attention increases.

Remarks: The first point of this theorem indicates that, with an increase of ev, the possibility of x_{max} being attention decreases. This means that a decision maker will be more likely to keep risk aversion when the expected value is large enough.

The common consequence effect and Allais paradox

Corollary: Increasing the value of the common result increases the expected value of the lotteries. A decreasing in the common consequence of two lotteries will increase the possibility of x_{max} being attention. Therefore, An decreasing in the common consequence increase the possibility of the decision maker being risk-seeking.

When the common consequence is small, $u(ev)$ is small, the attention will be x_{max} if the requirement is satisfied. In this case, the decision maker shows risk seeking. When the common consequence increases to a certain value, the requirement will no longer be satisfied and the attention will be kept at 0. In this case, the decision maker will show risk aversion.

Suppose that there are two independent prospects $L_1 = (x_1, p_1; x_\alpha, 1 - p_2)$ and $L_2 = (x_2, p_2; x_\alpha, 1 - p_2)$, in which $1 \geq p_2 > p_1 > 0$ and $|x_2| \geq |x_\alpha| \geq 0$. If there exist a common consequence $x_\alpha{}^*$, such that when $x_\alpha = x_\alpha{}^*$, we have $L_1 \sim L_2$, then,

Common consequence effect: if $x_1 > x_2 > 0$, when $x_\alpha < x_\alpha{}^*$ we have $L_1 \succ L_2$ and when $x_\alpha > x_\alpha{}^*$ we have $L_1 \prec L_2$;

Reverse common consequence effect: if $x_1 < x_2 < 0$, when $x_\alpha > x_\alpha{}^*$ we have $L_1 \prec L_2$ and when $x_\alpha < x_\alpha{}^*$ we have $L_1 \succ L_2$.

First, we will put the question in the positive domain, where $x_1 > x_2 > 0$. When x_α increases, the expected value ev the decision maker can get from this choice increases. Therefore, the probability of $a = x_{max} = x_1$ decreases. This makes decision makers choosing L_1 over L_2 when $x_\alpha < x_\alpha{}^*$, and choosing L_2 over L_1 when $x_\alpha > x_\alpha{}^*$. This is the pattern called common consequence effect.

In the negative domain, where $x_1 < x_2 < 0$, the expected value decreases with x_α decreasing. There would be a$x_\alpha{}^* < 0$, when $x_\alpha < x_\alpha{}^*$, $a = 0$, L_1 would be chosen; and when $x_\alpha > x_\alpha{}^*$, $a = x_2$, L_2 would be chosen. This is the pattern called reverse common consequence effect.

Let's recall that subjects are asked to choose between the two lotteries:

$$L_1(x_\alpha) = (2500, 0.33; \quad x_\alpha, 0.66; \quad 0, 0.01)$$

$$L_2(x_\alpha) = (2400, 0.34; \quad x_\alpha, 0.66)$$

When $x_\alpha = 0$, the expected value reaches its lowest point in this structure, a will be x_1 in this situation, and risk-seeking would be shown. This is Problem 1 in Kahneman and Tversky (1979). When $x_\alpha = 2400$, the expected value reaches its highest point, a will be 0 in this situation, and risk aversion would be shown.

This is Problem 2 in Kahneman and Tversky (1979).

Common ratio effect

Corollary: Increasing the common ratio increases the expected value of the lotteries. A decreasing in the common ratio of two lotteries will increase the possibility of x_{max} being attention. Therefore, An decreasing in the common ratio increase the possibility of the decision maker being risked seeking.

When the common ratio is small, $u(ev)$ is small, the attention will be x_{max} if the requirement is satisfied. In this case, the decision maker shows risk seeking. When the common ratio increases to a certain value, the requirement will no longer be satisfied and the attention will be kept at 0. In this case, the decision maker will show risk aversion.

Suppose that there are two independent prospects, $L_3 = (x_3, \lambda \cdot p)$ and $L_4 = (x_4, p)$, in which, $1 \geq p > 0$ and $1 > \lambda > 0$. To a population, if there is a probability p^*, such that, when $p = p^*$, there are 50 percents people in this population will choose X_i and the others will choose X_k, implying that $X_i \sim X_k$. Then we have,

Common ratio effect: if $x_3 > x_4 > 0$, when $p < p^*$ we have $L_3 \succ L_4$ and when $p > p^*$ we have $L_3 \prec L_4$;

Reverse common ratio effect: if $x_3 < x_4 < 0$, when $p < p^*$ we have $L_3 \prec L_4$ and when $p > p^*$ we have $L_3 \succ L_4$.

First, we will see the positive domain, where $x_3 > x_4 > 0$. When p increases, the expected value the decision maker can get from this choice increases. Therefore, the probability of $a = x_{max} = x_3$ decreases. This makes decision makers choosing L_3 over L_4 when $p < p^*$, and choosing L_4 over $L_3$when$p > p^*$. This is the pattern called common ratio effect.

In the negative domain, where $x_3 < x_4 < 0$, the expected value increases with p decreasing. There would be a p^*, when $p > p^*$, $a = 0$, L_3 would be chosen; and when $p < p^*$, $a = x_3$, L_4 would be chosen. This is the pattern called reverse common ratio effect.

Let's recall that subjects are asked to choose between the two lotteries:

$$
\begin{aligned}
L_3(p) &= (4000, 0.8 \cdot p; \quad 0, 1 - 0.8 \cdot p) \\
L_4(p) &= (3000, p; \quad 0, 1 - p)
\end{aligned}
\tag{2}
$$

When $p = 1$, (commonratio) will be Problem 3 in (Kahneman1979); and when $p = 0.25$, (commonratio) will be Problem 4 in (Kahneman1979). In problem 3, decision maker choose between $x_3 = 4000$ with $p = 0.8$ and $x_4 = 3000$ with $p = 1$. In this case, the expected value is $ev = 3150$, making $x_3 = 4000$ not been a and $a = 0$. Therefore, L_4 was being selected by the majority. In problem 4, decision maker choose between $x_3 = 4000$ with $p = 0.2$ and $x_4 = 3000$ with $p = 0.25$. In this case, the expected value is $ev = 750$, making $x_3 = 4000$ been selected as a and $a = 4000$. Therefore, L_3 was being selected by the majority. This is typical common ratio effect.

The peanuts effects

Corollary: This is a direct application of the theorem. When the smallest possible expected value is large enough, its utility will larger than $1/\lambda$, which ensures that the requirement could not be satisfied. In this case, the maximum possible outcome could never be the attention point, and attention will be kept at 0. Therefore, when the smallest possible expected value is big enough, there is no attention shifting.

The common ratio effect shows that when the common probability is small, decision makers show more risk seeking. However, this is not true for all stake size. Several studies find that the relative risk aversion is affected by stake size, and the pattern could not be accounted for by prospect theory(Weber and Chapman 2005). For instance, decision makers are more risk seeking for small-stakes gambles than for large-stakes gambles. This pattern cannot be accounted by the salience theory by Bordalo, Gennaioli, and Shleifer (2012), in which they show that large-stakes induce more risk seeking. This kind of example of risk-seeking behavior for small stakes was first noted by Markowitz (1952). Also, there are experiments concerning such effects.

Let‘s see two problems in Li (1995)'s experiments, Problem 1 and Problem 2.

$$\begin{aligned} A &= (\$5, 1) \\ B &= (\$5000, 0.001; \quad 0, 0.999) \end{aligned} \tag{3}$$

$$\begin{aligned} C &= (\$5000, 1) \\ D &= (\$5000000, 0.001; \quad 0, 0.999) \end{aligned} \tag{4}$$

These two choice problems are designed to question the subjective weighting probability function by (Kahneman1979). Therefore, if the overweighting of very low probabilities can give rise to risk seeking in the positive domain, when presented with a choice between (a) a monetary gamble and (b) a sure thing that is equal to the expected dollar value of the gamble, the overweighting of the small probability p = 0.001 would predict that the gamble should still be chosen over the sure gain. Problems 1 is identical to Problems 1 except that the expected value of the gamble is 1,000 times larger. However, the percentage of choosing A in problem 1 is 42% with N=95, and 74% with N=403 in problem 2. This result cannot be explained by prospect theory.

In our model, when the payoff magnitude is small, it's easy for participants to adjust and have a full adaptation. However, when the payoff magnitude is extremely big, participants have no past experiences of dealing those payoffs, so it's hard for them to adjust. Recall the attention function in section 2, we know that d has an impact on which extreme payoff is the salient one. The \$5,000 in problem 1, rather than \$5,000,000 is more likely to be selected as the salience.

Therefore, A is more likely to be selected in problem 1, not in problem 2.

V. adaptive in the degree of Attention

While the adaptation in attention(attention shifting) can play a part in making it possible that the distribution of neural resource can satisfy both assumptions A4 and A3 on some decision occasions, adaptation in the utility of a given value are necessary for this purpose. The adaptation in the location of attention and the adaptation in the utility of a given value are the two aspects of distribution adaptation, which are indispensable. In this section, we will focus on the impact of the adaptation in the utility of a given value on risk attitudes.

The necessity of adaptation in utility comes from the fact that the neural distribution should satisfy both assumptions A3 and A4 at the same time. The requirements of A3 and A4 are in many cases conflicting, which makes it difficult for the decision maker's distribution function to stabilize over the entire range of the external objects. This means that in different decision contexts, the distribution has different parameters. For example, the adaptation parameter d in the example utility function cannot be consistent with a single value in any situations. If d remains the same at a given value in every decision situations, assumptions A3 and A4 cannot be satisfied at the same time in most cases. For example, when a decision maker encounters a range with a very small amount of goods, A4 may not be satisfied. In contrast, In the case of a very large amount of values, a very big value which is far from the attention point will be neglected by the decision maker if d being kept at a given value, for assumption A4 has not been satisfied for that value. d being kept at a given value will cause a very big amount of good that is distant from the attention not be perceived. A more intuitive example is that, as we usually read books with a font size between 10 and 12, the distance between our eyes and the book is always maintained at a distance about 40cm, and the image size in the retina is relatively stable at a level. If we keep the distance same at about 40 cm, a book with a font size of 120 may be unreadable.

We should adjust our visual distance, in this case, so the representation of a given value will also change accordingly. Obviously, this adjustment will help us reach our goal.

As we illustrated in Section III, when the utility of a given value changes, the relative utilities between two given values will change accordingly. This adaptation will lead to a change in the relative utility. Therefore, an adaptation of distribution will lead to a change in the ARAC. It is definitely by nature that the utility of a given value can be adapted to a larger one or to a lesser one. One direction will have a corresponding change in ARAC. When the utility of a given value increases, the ARAC will increases. When the utility of a given value decreases, the ARAC will decrease.

A. *Local Sufficient Adaptation and Stable Utility Function*

Context-based adaptation does not mean that decision maker cannot form a stable distribution of neural resource under any circumstances. In fact, this stable representation exists, so a stable utility function exists. For example, a decision maker may be able to create a relatively stable distribution of neural resources when dealing with her/his routine tasks. The point is this stable distribution exists within a limited range. Therefore, this stable utility function only exists in a limited range. Within this range, both assumptions A3 and A4 are satisfied at the same time. When all the possible outcomes fall in this range, and when the distribution of neural resources remains unchanged, we say that this distribution is fully adapted to this range. For example, when we read, we form a stable reading distance at which the usual size fonts are readable. Besides, in this usual range of font size, we do not need to adjust our reading distance. In decision making, stable distribution of neural resource comes from the habituation of outcome sets of the decision tasks. Repeated exercising gives a decision maker a relatively stable representation of the set of amount of money that they are familiar with. The distribution function corresponding to this stable representation can satisfy both the requirements of assumption A3 and A4 at the same time when the number of goods is within the familiar set.

In order to facilitate our analysis, we assume that the set mentioned here is just a point, e.g. x. Under this assumption, a stable distribution can be defined as a state where, given any set(a point), the neural resource allocated on this value is given at an amount of $s, s < 1$. In our example utility function, a full adaptation based on this definition means that there is a linear relation between d and x with a fixed coefficient, for example, $d = k \times x$. This assures that our neural resource can be used to represent any set of values after full adaptation. Therefore, we can assume that each decision maker i has its own stable set x_i. If attention keeps constant at a, this full adaptation will ensure that all decisions in this range consistent with the expected utility theory. This prediction tells that the expected utility theory is a special case of our theory.

Because the amounts of different stimuli that we normally experienced are different varies, the stable distributions of neural resources over those stimuli will be different from each other. Thus, for different stimuli, our stable utility function corresponds to different degrees of adaptation. This also means that the utilities of the same amount of different stimuli are different. In the meantime, the utility size of a given value has an impact on the absolute risk aversion coefficient(ARAC), the ARAC will be different for each stimulus. Below, we will discuss the different risk attitudes that individuals exhibit under different but related decision contexts. We will show that our theory can explain some seemingly conflicting experimental results.

Asymmetrical Adaptations and Loss Aversion

Loss aversion, in our theory, may come precisely from the familiarity difference between gains and losses experienced by people in their day-to-day decisions. Often, people are more familiar with the gains, not the losses, because, in most of the decisions we made in our daily lives, we deal with gains, not losses. Thus, people tend to use a more neural resource to represent the world. We can imagine that an individual lives in a situation where he always needs to deal with losses rather than gains. How could he survive in this situation? There is no basis for their survival. People can only live when their gains are larger than their losses. Therefore, our familiarities to gains differ from our familiarities to losses. This familiarity difference is reflected in our sample utility function given in this article as $d_{loss} < d_{gain}$. Therefore, compared with gains, a more amount of neural resources will be distributed to the losses, thus showing the phenomenon of loss aversion.

Based on this interpretation, we predict that people will show the diminishing loss aversion as their experience of losses increases. Unfamiliarity induced distribution will be re-adapted by As people become familiar with losses, people can adapt to losses. Their assessment of the loss tends to be stable at a lower level compared with their initial assessment. In this case, people will be less loss aversion. This change has been investigating in several studies. For example, List et al's field experiment found that familiarity in the market lessens the degree of loss aversion.

We have other implictions about the asymmetry between gains and losses. According to Theorem 1, the utility of a given value has an impact on ARAC. We infer that the ARAC is bigger in the loss domain than that in the gains domain. This prediction is contradicted by the prediction given by the prospect theory.

Discounting and Risk attitude

In many cases, a utility will be discounted by many factors. For example, a common assumption in psychology and behavioral economics is that the utility of an outcome is discounted as temporal distance from the outcome increases (see, e.g., Ainslie, 1975; Loewenstein & Prelec, 1992; Rachlin, Brown, & Cross, 2000). This pattern has been illustrated in many experiments, which is quite stable. For instance, future 100 USD has less utility than current 100 USD. When people make decisions with hypothetical money. Other people's money, that utility will be discounted. Our theory predicts that, if the utility of a given value decreases, the absolute risk aversion decrease, implying that the decision maker will be less risk aversion. Because a change in utility will lead to a change in relative utility, which may lead to a shift of attention to the maximum from original attention at zero. In this case, the decision maker will be risk seeking.

Corollary 3: When the utility is discounted, the individual will be less risk aversion; in some cases, the decision maker will be risk seeking.

Remarks: The prediction of this model is different from that of the construal-level theory on the impact of psychological distance on risk attitudes. The construal-level theory reasons that an increase in psychological distance leads to individual attention shifting form probability of concrete level to reward of the general level. Thus, the weight will be put on the reward other than the probability, and the decision maker will be risk seeking. In the construal-level theory, the decision maker will always be risk-seeking when the lotteries are psychological distant. In our theory, only when the utility of the maximum possible outcome surpass the utility of the expected value quite a lot and the attention shifting to the maximum possible outcome, the decision maker will be risk seeking. Otherwise, the decision maker will be just less risk-averse.

This corollary can explain a series of experimental results in related fields. Research on decision making has shown that people often take more risk and feel more confident about the more distant future (Gilovich, Kerr, & Medvec, 1993; Nisan, M., & Minkowich, A. (1973),Shelley 1994;Onculer, A., & Onay, S. (2009);Keren, G., & Roelofsma, P. (1995);Sagristano, Trope, & Liberman, 2002). Individuals exhibit less risk aversion when making decisions for the future. Similarly, when people evaluate other person's utility, there is a discount. For example, Hsee, C. K., & Weber, E. U. (1997) find that there is a fundamental prediction error: Self–others discrepancies in risk preference. When making decisions with hypothetical money, they also show less risk averse(Holt and Laury 2002). None of these results can be explained by the prevailing decision-making model in economics.

Its impact on Attention

According to Theorem 1, the greater the utility of the maximum possible value exceeds the utility of expected value, the more likely the maximum possible outcome to be the new attention point. A change in utility of a given value leading to a change in its relative utility. Therefore, a change in utility of a given amount of money may cause a shifting of attention. If the utility of the expected value decrease, the more likely the maximum possible outcome to be the new attention point in case of the utility of the maximum possible outcome surpass the utility of expected values. In this case, the decision maker will be risk seeking.

Corollary: A decrease in the utility of a given value will increase the possibility of the maximum possible outcome being the new attention point.

Proof: According to Theorem 1 above, a change in the utility of a given amount of money will lead to a change in the relative utility. According to Theorem 2, the relative utility of the maximum possible outcome and the expected value will affect where the attention would be. Therefore, a change in utility of a given amount of money may lead to a change in risk attitude. When the utility decreases, the utility of the maximum possible outcome will be more salient. This leads to a fact that the maximum possible outcome is more likely to be the new attention point.

This corollary indicates that a utility discounting will lead a decision maker from risk averse to risk seeking.

B. Insufficient Adaptation

We will next discuss one of the most common insufficient adaptation, namely, insufficient adaptation due to unfamiliarity with the amount of a given stimulus. This kind of insufficient adaptation means that this amount of stimulus is not in the range which the decision maker has already fully adapted with and that the decision maker has not yet adapted to that amount of stimulus. In this case, the local full adaptation of this decision maker will no longer applicable to this new amount of stimulus. This adaptation is similar to the case when we are reading. When the character font is large, the reading distance will be adapted to a little further; When the character font is small, the reading distance will be adapted to a little closer. However, we did not sufficiently adjust the size of the font in the retina to the same size for all sizes of fonts, but rather the image of a larger font size was still relatively larger, while the image of a smaller font size was still relatively smaller. When the amount of the stimulus is smaller than the normal range, if the neural resources are distributed to fit the normal range, this amount of stimulus may not be clearly represented, because the accumulated resources allocated on this stimulus are too small; When the amount of the stimulus is larger than the normal range, if the neural resources are distributed to fit the normal range, some amounts of stimulus may not be clearly represented, because the resources left to represent those stimuli are too small.

Therefore, for a decision with outcomes that are not in a familiar range, the degree of adaptation of a decision maker will be somewhere between the full adaptation associated with the familiar range of the decision maker and the full adaptation associated with the new decision context. Thus, if the full adaptation associated with the familiar range of the decision maker, x, is d_x and the full adaptation associated with the new decision context, x_{new}, is d_{new}, an insufficient adaptation has a degree of adaptation $d_{insufficient}$ with $d_{insufficient} \in (d_x, d_{new})$ if $d_x < d_{new}$ and $d_{insufficient} \in (d_{new}, d_x)$ if $d_x > d_{new}$. According to our definition and demonstration of the local sufficient adaptation in previous parts, if $d_x = k \times x$, we have $d_{insufficient} = k \times (\alpha x + (1-\alpha) x_{new})$. $1-\alpha$ in this function indicates the process to fully adaptation associated the new decision context, x_{new}. This process to fully adaptation means that the utility of a given value when not fully adapted is greater than its utility when fully adapted when $x_{new} > x_i$, and the utility is smaller than that when $x_{new} < x_i$.

Another issue that needs to be highlighted is that the process to full adaptation, $1 - \alpha$, is associated with the times of repetition. When the times of repetition is different, the process $1 - \alpha$ will be different. Generally, for an unfamiliar stimulus, the result of repetitive experiences is to bring the degree of adaptation closer to the full adaptation associated with the task. The more repetitions, the closer the adaptation is to the full adaptation corresponding to the task. For example, the habituation of the neural response to repeated stimuli has been well demonstrated (Fischer et al., 2003). In this example, the intensity of the external stimulus used in the experiment is significantly larger than that of usual external stimulus participants experienced in daily lives. This evidence suggests that the initial neural response to the stimulus of an individual is significantly greater than the neural response when the stimulus is habituated, which supports our assumption of the process of adaptive. This evidence also suggests that when the decision maker is not familiar with the set of stimulus, its representative resource distribution would be not stable. Therefore, the utility function in this process will change regularly.

This process of adaptive indicates that the utility of a given value will change accordingly to the decision contexts. This change in utility will lead to a change in absolute risk aversion coefficient(ARAC). In the case of small value, the individual will appropriately increase the neural resources so that the utility given by the individual is greater than the utility under the usual stable utility function. In the case of greater value, the individual may appropriately reduce the amount of neural resource, leaving the individual less effective than usually stabilizing the utility function. Therefore, ARAC will change accordingly with the decision contexts. In the following parts, we will study several classical cases that contains insufficient adaptation.

Description experience gap

In the description treatment, participants are told to make only a few decisions. In some experiments, Individuals have only one chance to do the task in the description treatment. However, in the experience treatment, participants have to make a lot of decisions. This repetition makes decision maker feel less utility for the same amount of money.

In our model, given an amount of money, the absolute risk aversion is small in the context where the utility of this amount of money is small, and the absolute risk averse is big in the context where the utility is big. Therefore, we predict that in the description treatment, the absolute risk averse is big; and in the experience treatment, the absolute risk aversion is small. In some cases where the maximum possible outcome is very salient in the experience treatment, decision-makers will be risk seeking if attention being shifted to the maximum possible outcome. This model can tell the description-experience gap by the difference between the utility of a given amount of money. Because constant repetition of one thing will reduce the resources we allocate for a given Good. Other models concerning risk aversion in economics could not tell this difference. In our model, we can attribute the description-experience gap as the difference between decision makers' familiarity and unfamiliarity to the amount of value and tasks used in the experiments.

Preference Reversal

Preference Reversals (PRs) were first discovered by Lichtenstein and Slovic (1971) and Lindman (1971), and were brought to the attention of economists by Grether and Plott (1979). PRs occur when subjects are confronted with two prospects, a p-bet which offers a relatively large sum of money, but a relatively small probability of winning, and a P-bet, which offers a more modest sum of money, but a greater probability of winning. Subjects are then asked to perform three tasks: to choose between the two prospects and to attach a certainty equivalent to each prospect. The typical finding is that subjects prefer the P-bet, while paradoxically, the p-bet is given the higher valuation. The opposite pattern, choosing the p-bet but valuing the P-bet higher, is rarely observed(Bleichrodt and Wakker 2015). Let's see Table 8 in Bleichrodt and Wakker (2015), in which, the p-bet is $\{18, 30\%; 0, 70\%\}$ and P-bet is $\{8, 60\%; 0, 30\%\}$.

When these two bets are evaluated separately, the d for each bet is $d(18)$ and $d(8)$, respectively. Therefore, the the equivalent sum of money for the p-bet is given by:

$$equal(\pounds - bet) = 18 \cdot \tan(0.3 \cdot \arctan(18/18)) \approx 4.32$$

the equivalent sum of money for the P-bet is

$$equal(P - bet) = 8 \cdot \tan(0.6 \cdot \arctan(8/8)) \approx 4.08$$

In this situation, we have $equal(\pounds - bet) = 4.32 > 4.08 = equal(P - bet)$. However, when they are evaluated together, the d will be $d(18)$, and in this case we have:

$$0.3 \cdot \arctan(18/18)) < 0.6 \cdot \arctan(8/18)$$

This shows that, when evaluated separately, p-bet has a higher equivalent sum of money. However, when evaluated together, p-bet is less attractive than the P-bet. This is the PRs, and caused by the degree of adaptation in different contexts(tasks), in our model.

Rabin's Concern

When the stake sizes in different decision contexts are not in a range in which a stable distribution could be reached, the degree of adaptation will be different across contexts. ARAC is different because of the different degree of adjustment. Therefore, stake size can affect ARAC.

We can see two impacts on ARAC of stake sizes. One is the large stake size with larger d and less resource concentration, so the ARAC is smaller when Stake size is larger. Second, if we make a full adjustment under each decision, the decision maker's risk appetite will not change because of the same structure's decision-making (the stake ratio increases proportionally), because the change of stake size will not cause the change of utility at this moment. However, in the case of inadequate adjustment, the larger stake is accompanied by a greater utility, and thus the risk coefficient of the individual is greater under the assumption of isomorphic risk with larger stake size. Third, because stake size can cause a change in distribution, policymakers do not anticipate Rabin's predictions.

Contrast effect and Regret theory

One of the definitive features of regret theory is that, the value of choosing something is dependent on the nature of the things simultaneously rejected(Loomes and Sugden 1982, Landman (1987)). In other words, there is an addition of a regret term to the classical utility function. According to a typical regret theory, the expected utility of choice X is a multiplicative function of the probability of X and the value of X plus or minus the amount of regret for not-X, some possible alternative not chosen(Landman 1987). Actually, the effect of this additional regret term in utility function is similar with the contrast effect, which was a fundamental principle of perception and widely found in many areas.

For instance, there are two amounts of money x and y, $x > y$, and have their own the degree of adaptation separately, d_x and d_y, general $d_x \geq d_y$ for a given agent at a time. However, When two amounts of money being evaluated together, the degree of adaptation d, generally, will not be separated for each of the two amounts anymore. In this case, if $d_x \neq d_y$

Before comparing, the separated utility for x is $u(x) = \arctan(x/d_x)$ and y, $u(y) = \arctan(y/d_y)$. Therefore, the relevant will be $\arctan(x/d_x)/\arctan(y/d_y)$ if being evaluated separately. However, the ratio will be $\arctan(x/d)/\arctan(y/d)$ when being evaluated together.

$$r(d) = \frac{\arctan(x/d_x)}{\arctan(y/d_y)} \cdot \frac{\arctan(y/d)}{\arctan(x/d)}$$

And we have, $\partial r(d)/\partial d < 0$ when $x > y$ and $d > d_y$.

This property implies that as the common d increases, the relevant utility of the bigger amount $u(x)$ increases, generating the same effect as adding an additional regret term to the original utility function. Therefore, in terms of relevant utility, our utility function could be applied in the classical regret theory.

VI. Discussion

A. *New insights as a descriptive model*

This article is based on the most fundamental hypothesis of neuroeconomics that the degree of neural activities can be used to represent the utility used in decision models. For the first time, under this assumption, we propose to construct utility by investigating accumulated neural resources distributed on the target product. Therefore, how neural resources are distributed over the whole range of objects is critical to figure out the amount of neural resource accumulated on the target. Because the overall neural resource for representing utility is limited (assumption A3), and there is a resource barrier for perception (assumption A4), the distribution of neural resource should not be fixed at any contexts. Studying how the distribution varies across contexts is of great importance in this sense.

Our theory proposes to investigate the distribution function of neural resource other than utility function when we study decision making under risk. This investigation could help us to understand those violations of expected utility theory deeply. Our theory focuses on how context features will affect the distribution of the neural resource. This means that there is no stable utility function across all contexts. We do not insist that there is no stable utility function at all. In fact, we assume that there is a range in which the decision maker will keep a stable distribution function, a stable utility function. This range cannot cover all possible decision contexts designed by experimental economists and psychologists. Therefore, the expected utility theory could not deal with all behavior patterns in lab experiments. From the perspective of our theory, a stable utility function can only exist within a limited range. Thus, the expected utility theory can be and can only be supported in a given decision situation within a range with familiar outcomes. When facing decisions with outcomes in this range, the decision maker does have a stable utility function and can make decisions according to this stable utility function. Beyond this range, the stable utility function no longer exists. The classical experiments design by Allais effectively introduced a decision context that exceeds most participants' familiar decision range, which requires a redistribute of the neural resource. In this case, of course, the decision maker will violate the expected utility theory.

Prospect theory uses an S-shaped rank-dependent subjective probability function that exactly mimics the phenomenon of distributional changes induced by attention shifting in our theory. The reason why rank-dependent subjective probability functions can approach this phenomenon is that this function captures a major feature of attentional shifting, namely, from the initial place at zero to the most likely alternative, the maximum possible outcome. Thus, a rank-dependent subjective probability function places more emphasis on the effect of large outcomes than that of small probabilities, although a small probability is necessary. In fact, we can also see this emphasis from the differences between OPT and CPT, in which the decision maker only overweight a small probability with high ranked outcomes. This combination of small probability and high ranked outcomes in an actuarially fair choice always contains a fact that the utility of the maximum outcome is much larger than the utility of the expected values. In this case, the decision maker will shift his/her attention, so the risk attitude will change accordingly. In this paper, we only show this mechanism of attention shifting, for it may be the main reason for a rational decision maker to make a change. Thus, the S-shaped rank-dependent subjective probability function can capture the impact of attention shifting in the neural resource distribution on risk attitude. However, our theory predicts that not all similar combination will lead to this change in attention. In our theory, a change in attention induced by this combination is the difference between the utility of the maximum possible outcome and the utility of the expected value, not the difference between those values. Therefore, the prediction of our theory when all the values in the choices are quite large is different from the prediction given by the prospect theory. The peanuts effect support our theory, which indicates that the rank-dependent subjective probability function is not always successful.

Our model expands our understanding of utility. In previous models, without taking the limitation of neural resources into account, the authors could not identify the relative utility changing caused by the utility changing of a given value. In our model, due to the limited neural resource of the total amount of resources, the utility changing of a given value is not just a linear translation of a given curvature curve, but a changing of the utility function. Therefore, the utility of a given value in our model not only shows the size of the utility of that value itself but more importantly, indicates the degree of distortions of neural resource allocation. As a result, neglecting this limitation neglects the effect of differences in utility size on risk attitudes. Our model can consider the changes in attitudes toward risk resulting from changes in utility over a range of decision-making scenarios.

Previous decision models also did not consider the minimum resource requirement for discriminating different motivations. As a result, these models do not need to adjust the distribution of resources according to the context adjustment. This makes the past models assume that there should be a stable utility function in different scenarios. Rabin concludes that utility function alone could not explain the risk aversion in small risks. This leads to the subjective probability becoming a necessary device to explain the risk aversion under small risks. In our model, the minimum requirement requires the brain to adapt neural resource distribution according to the context. The utility changes reflect distribution changes in our model, which leads different risk attitudes. This article provides a different mechanism to explain risk attitudes in small stakes rather than Rabin.

Our model extends existing methods of modeling attention in decision making theories. Previous models incorporate attention by inducing a weighting function or through subjective probability functions. We provide a way to internalize the effects of attention into utility, which could also be used to model attention to any inseparable features. This method to incorporate attention has many advantages. One of them is that we do not need rank-dependent subjective probability functions anymore. In addition, we do not need to construct additional weighting functions, so we do not need to model probabilistic effects with probabilistic subjectivity.

We provide an example utility function according to our model, and that utility function only contains two parameters, the degree of adaptation and attention point. If we need to estimate the parameters in this model, we only have two parameters, the number of which is much less than that of the previous models. For instance, in the Prospect theory, we have to estimate at least three parameters, two for the utility function and one for the weighting function. Even though this is just a parsimony approach, the explanation power is significant.

Our model provides a new perspective on understanding behavioral anomalies in risky decisions. To those anomalies, our model has different interpretations. For example, the Allais Paradox, in the prospect theory, is explained by overweighting small probabilities and underweight big probabilities. In our model, when the common result is small, the expected value is small, and thus the utility of the maximum possible return is far greater than the utility of the expected value in those lotteries, resulting in an attention shifting from the original zero to the maximum possible outcome. In this case, the decision maker may be risk seeking. When the common result is large, the expected value is large, and thus the utility of the maximum possible return exceeds the expected value not too much. In this case, there is no attention shifting. The attention remains at zero, so the decision makers are still risk-averse. Therefore, in our model, the risk attitudes depends on the difference between the maximum possible outcome and expected value in terms of utility. This logic also applies to the common ratio effect. When the common ratio is small, the expected value is smaller, and thus the utility of the maximum possible outcome is far greater than the utility of the expected value, resulting in an attention shifting from the original point at zero to the maximum possible outcome. In this case, the decision maker is risk seeking. When the common ratio is larger, the expected value is larger. Therefore, the utility of the maximum possible outcome exceeds the utility of expected value not so much. In this case, there is no attention shifting and the attention keeps at zero. The decision maker is risk-averse. The effects of attention shifting in our model have been interpreted as overweighting small probabilities and underweight big probabilities in prospect theory.

As a result, some inconsistencies between our model and previous models can arise. For example, prospect theory predicts a so-called fourfold pattern. However, our model argues that only when the decision maker's utility of the maximum possible outcome surpasses the utility of an expected value for a great deal, the so-called fourfold pattern would come out. If in terms of utility, the maximum possible outcome surpasses the expected value not large enough, the decision maker will still be risk-averse while keeping attention at zero. As a result, our model and previous theories will make a huge difference in the prediction of individual risk attitudes in those scenarios. Our model does not always predict the so-called fourfold pattern unless a transfer of attention has taken place.

Another important property of this model is that it can be applied to many decision situations in which previous models cannot work. The utility of a given value has an impact on decision maker's absolute risk aversion and finally the attention point. This connection between utility and risk attitude can be used to predict risk attitude in many decision situations. Previous models did not tell this connection, so they have no predictions in this kind of situations.

Our theory attributes the violations of expected utility theory to the changes of the distribution function of neural resource, including changes in attention and changes in the utility of a given value. Therefore, our theory can only deal with those anomalies induced by the changes of these two factors. Including changes in attention and utility, other factors may also lead to changes in risk attitudes. For example, a decision maker's misunderstanding and miscalculation of tasks may lead to a violation of rational axioms. For another example, the attitude of decision-makers on the risk itself will also affect its risk behavior. Therefore, although having shown that our theory provides certain predictions and explanations that the other theories mentioned do not, we should make it clear that we are not claiming that adaptive theory can explain all of the behavioral regularities revealed by experimental research into choice under uncertainty.

In this article, we only consider several main factors that lead to a change in the attention point and the utility of a given value. There are other factors that will have an impact on attention and the degree of adaptation, which has not been included in this paper. For example, other than the relative utilities mentioned in this article may cause changes in attention, other factors may also lead to a change in attention. Simple repetition of an outcome may capture the attention of the decision maker, making the decision maker put more weight on those outcomes. This may serve as an explanation for the split effect in risk decision making. The visual impact of the split may lead the decision maker to focus directly on those split outcomes, resulting in an attention shifting from the initial attention point discussed in this article to the split outcomes. If only attending on those split outcomes, the decision maker may show a split effect. In addition, emotions may also lead to changes in attention. For example, optimistic people may be more likely to pay attention to the maximum possible results and pessimists are more likely to pay attention to the smallest possible outcome. Emotions also have an impact on the utility of a given value, leading to a change in the relative utilities between two given values. Therefore, by changing the attention and utility of a given value, other factors will have an impact on risk attitudes, which has not been investigated in this article.

B. Suggestions for normative thinking

Our model may help build a bridge between descriptive and normative models. As a descriptive model, our model shows that violations of expected utility theory in risk decision-making come from changes in neural resource distribution, including changes in attention and changes in the degree of adaptation(the utility of a given value). A change in attention can lead to a change in risk attitude; a change in the degree of adaptation will lead to a change in relative utilities of two given values and the absolute risk aversion coefficient. At the same time, our model states that a change in relative utility may also lead to a change in attention, so a change in utility of a given value may also lead to a change in risk attitude. Therefore, if there is no change in the distribution of neural resource, that is, if both the attention and the utility of a given value remain unchanged, the individual's risk attitude and absolute risk aversion coefficient will not change. Because our interpretation of the violations of expected utility theory does not rely on subjective probabilistic weights, this invariance will lead our model to be a classical expected utility model. In this case, our model is consistent with the classical expected utility theory and satisfies the three axioms of rational decision making suggested by many economists, which means that the expected utility model is a special case of our theory.

Attention and the utility of a given value can only be kept fixed in a small range. This means that a stable distribution function can and can only exist in a small range and that the rational axioms can be applied in this range. As we suggested, repetitions may form a relatively stable distribution of the neural resource. Therefore, for a familiar decision task and a familiar range of money, a decision maker can form a relatively stable neural resource distribution and then a stable utility function. Within this range, the density distribution function of the decision makers will not change with upside limits of specific decision sets. Thus, in this case, individuals can satisfy the three axioms. This also explains the fact that satisfying the rational axioms can be learned by repetition. However, this stable distribution induced by familiarity can only exist in a small range and cannot cover all the extreme data that may appear in experiments. A stable distribution requires assumptions A3 and A4 being satisfied at the same time, which is impossible over the whole range if the utility is represented by the neural resource. As suggested by the proponents of the expected utility theory, the violations of EUT in experiments are some of the decisions that are hard to come by in everyday life. From the perspective of our theory, those classical experiments provided participants with unfamiliar tasks and unmanageable extreme values (a simple choice immediately determines whether you got \$ 0 or \$ 1000), resulting in a failure to hold a stable distribution. Any change in the distribution will lead to a deviation from the expected utility theory. Therefore, the three axioms of rational decision making can only be applied in a small range in which the distribution is stable and this kind of rationality may be just local rationality.

Therefore, whether normative requirements by the three axioms are feasible for individuals is a more fundamental issue that should be discussed before discussing normative issues. Generally, a normative theory usually discusses what you should do and a descriptive theory focuses on what you actually did.
Since our theory takes the assumption A4 into account, we need to add a dimension to the discussion, that is, whether we human beings can obey the three axioms on all occasions. This same question in our theory is could the decision maker apply the same stable distribution function on all occasions? The next question will be whether he/she should fix his distribution on all occasions? If utility for an individual is represented by neural resources, the physiological aspects of the nervous system must impose its limitation on the representation. Therefore, the importance of feasibility issues is particularly prominent, because

the normative issues can only be discussed if the feasibility is guaranteed. From our previous analysis, we can see that it is impossible to maintain a consistent and stable distribution across the entire decision space. A fixed distribution across all possible decision space means the decision maker should give up most of his possible decisions. This just likes the case that a person who stands on a point without moving his eyes and fixes his positions should give up seeing most sights in the earth. Thus, keeping all three axioms in all decision-making space means giving up a large part of the overall decision-making space.

Therefore, the normative implication of our model is that individuals should satisfy the three axioms when it is possible to form a stable distribution of the neural resource. In a larger decision space in which a fixed distribution cannot be satisfied, an individual who insists on the rational axioms will lose his/her decisions entirely because he/her can hardly percept the utilities in those decisions. There are some decisions which will never be familiarized for ordinary people. For example, when facing a choice between A: to get 20 bottles of purified water for sure and B: 10 percent to get 10,000 bottles of purified water, 90 percent to get nothing, which one will you choose? If you are currently in a city where purified water is not scarce, which one will you choose? Or if you are currently in a desert where 20 bottles of purified water can make you survive, which one will you choose? We can assume that in both cases you have 10000 bottles of purified water at your home in another city as your wealth. Should a rational decision maker choose the same option in those two cases? No! We can imagine that the choice pattern violating the three axioms will be corrected in the subsequent introspection when a stable distribution of neural resource can be formed. In the absence of a stable distribution, when a decision maker reflects his/her choice pattern that violates the three axioms, they will still insist on the chosen pattern that violating the three axioms.

The assumption A3 and A4 make it hard and complex to think of what is rationality and whether should we insist on the three axioms. The complexity of the environment itself makes the distribution of neural resource should be adapted according to the goals of the decision maker in each particular environment. This makes the stable distribution of the representation cannot be guaranteed. The three axioms of reason can only be applied when there is a stable distribution. Therefore, the three axioms can only be satisfied in the stable distribution within a local decision space. A good normative decision model can only suggest a decision maker obey the three axioms when a stable distribution could be realized in a local context. Indeed, the three axioms are a necessary condition for a decision maker to make good decisions if there is a stable utility function. Without a stable utility function, insisting the three axioms will lead the decision maker to make bad decisions. Therefore, the three axioms can only be rational within a certain range. On other occasions, it is reasonable to violate the three axioms of rationality.

VII. Conclusion Remarks

In this paper, based on the assumption that the strength of neural activities can represent subjective utility, we imposed four key assumptions on the basic assumption, which systematically regulates individual decision making in the risky domain. The idea of using neural activities to represent subjective utility is not a new in economics, which is precisely the basis of neuroeconomics and gradually accepted by economics. This trend makes us consider the impact of the neural system on subjective utility and we propose a density function for the distribution of neural resource representing subjective utility. We identified four important assumptions about the distribution of neural resource that a system should obey, two of which are significant. The first one is all neural system only have limited resources, and the second one is that a perceptible motivation requires a minimum amount of neural activities. Those assumptions need the brain allocating representative resources and adaptive distribution accordingly. Thus, this adaptation of distribution may have a significant impact on all behavioral studies which definitely are determined by neural resources. This article gives new interpretations of the anomalies in risk decision making and new predictions about risky behavior in new situations. And, all those new interpretations and predictions come from the four assumptions about the distribution of neural representative resources.

Our model deals with how limited nerve resource is distributed in different contexts. We also show that the changes of the utility of a given value reflect the changes of the distribution. We find that the changes of the utility of a given value will affect its relative utility with that of another value. This property has significant implications for decision making theories that taking utility as their currencies. Notably, the relative utility change is related to all models related to utility discounts. Relative utility change is a kind of utility discounts. Therefore, if we ignore this effect, this effect will be misunderstood. Because, if different values correspond to different discounts, changes in relative utility size will correspond to different results. For example, in the intertemporal selection model, a reduction in long-term utility leads to a change in relative utility, and the measured discount rate also changes. In the social preference discount model, the return of others relative to their own earnings smaller, the relative impact of the utility will be different. Therefore, the model of this paper is of great significance to a series of problems considered in economics. And may change our deeper understanding of the behavioral foundations of the visions that emerge from our past models.

The new method of modeling attention provides an additional approach to think about the effect of attention on behavior. This new method proposes a model approach to inseparable feature attention, which has not been considered before in decision making theories. Previous models incorporating attention mainly focus on separable attention. Our model completes those models. This model also provides the most fundamental part of attention between different features. Attention in a given feature has an impact on the precepted relative size in that feature, finally determining which feature is important to the decision among several features. For example, there are several models deal with attention between different features. Our model for attention can help to figure out which feature is significant for those models. Thus, if decision maker relies on the relative size of amounts of the same feature, our approach to attention should not be ignored for separable attentions. The competition between different features, the inherent law should give priority to explore the same characteristics of the size of the characterization. Therefore, it is fundamental to examine this issue.

In our model, rational consistency requires the decision maker to stick a fixed distribution in every context. This means that the attention and scales should be fixed in the same and could not be adjusted as the environment changes. This requirement will lead to many problems in decision-making. Therefore, should we define rationality as consistency at the behavioral level is an open question? The behavioral level consistency requires at least two levels consistencies, one is the relationship between internal representation and behavior, and another one is the relationship between outside world and internal representation. This article suggests that the behavior consistency in the canonical model should be replaced by the consistency of utility in the descriptive model. If the relationship between outside world and internal representation keeps constant, the decision maker will not identify the importance in different contexts. In this case, the decision maker may not survive in some contexts. For surviving, the decision maker should notice the relative importance of goods in different situations. Therefore, we should reconsider the meaning of rationality of decision making.

Our model could also shed light on the research about the relationship between neural activities and subjective feelings in the psychophysiology. Previous research on the neuro basis of perception and behavior provide a solid foundation for understanding this relationship. For example, Several rules or laws are proposed to model these relations, such as Weber's law, Weber-Fechner law, and Stevens' power law, etc. Our model may provide a new approach to understand those unclear mechanical behind that psychology-law, by clarifying the impacts of limitation of neural resources. Our model uses the evidence found in these studies and combines their implications to reach new predictions. In addition, we can also use the same rules for them to study probability. Thus, our model helps understand the understanding of the visions that emerge in psychophysiology. Because of these psychological laws are not generally accepted in psychology yet.

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