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# Modeling acceptable novelty using information theory

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**Abstract:** Novelty is an essential factor in design that is deemed attractive and creative by humans. However, an individual's acceptance of novelty depends on their emotions. Knowledge about the range of novelty which ones accept will help to create attractive design targeting certain users. We previously developed a mathematical model of emotional dimensions associated with novelty such as arousal (i.e., surprise) and valence (i.e., positivity and negativity). The model formalized arousal as Bayesian information gain and valence as a function of the arousal based on Berlyne's arousal potential theory. The arousal model was a function of three parameters: prediction error (the difference between expectation and reality), uncertainty (i.e., unpredictability), and external noise. In Berlyne's model, the valence against novelty forms an inversed-U curve and turns from positive to negative when novelty is large. We assumed such a point that the sign of the valence turned showed the range of novelty ones would accept. Here, we derived a prediction error where valence turns from positive to negative. We termed this acceptable novelty and defined it as the range of novelty one can accept. Our model predicted that when the order of uncertainty is larger than external noise, the higher the uncertainty is, the larger the acceptable novelty becomes. This analysis is an update from our previous model and can be a basis of designing products to certain target users.

**Keywords:** *Modeling, Emotion, Novelty, Uncertainty, Prediction error*

## 1. INTRODUCTION

Novelty is fundamental in determining how humans perceive creative and attractive design. Raymond Loewy, a pioneer of industrial design, defined an inflection point between attractiveness of a novelty and fear of the unknown as MAYA ("most advanced, yet acceptable"). This point describes where broad acceptance of a new design may take place within a group of humans [1]. Berlyne added to Lowey's theory, advocating that there is a range which maximizes the pleasantness between familiar and novel, and between simple and complex [2]. As such, the hedonic responses result in an inversed-U curve shape function of arousal potential (Fig. 1). Several experimental studies have supported Berlyne's theory in humans, including studies on aesthetic preference for industrial design [3], food preferences [4], and artistic preferences [5]. However, an individual's perception of novelty greatly depends on their emotional state. In the realm of industrial design or product design, knowledge about the range of novelty which consumers individually accept will help to create attractive design.

We previously developed a mathematical model of emotional dimensions that explains how novelty affects emotions [6]. Emotional dimensions are said to consist of two axes: arousal (or intensity) and valence (i.e., positivity and negativity) [7]. The intensity of surprise corresponds to the intensity of arousal and is in proportion to the intensity of novelty. Therefore, our model considers surprise as an index of the horizontal axis in Berlyne's model. Our model formalized arousal as a function of three parameters: prediction error, uncertainty, and external noise. Furthermore, we formalized valence as a function of arousal based on Berlyne's theory.

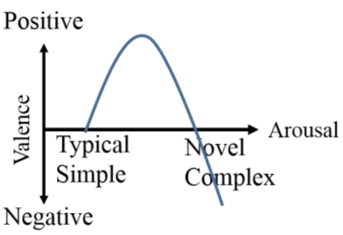


**Figure 1:** Hedonic response to novelty and complexity

Our previous model of the valence was just suggested and left to be analyzed. In this study, we mathematically derived a prediction error where hedonic response (i.e., valence) turns from positive to negative from our previous model. We termed this prediction error "acceptable novelty," defined as the range of novelty one can accept.

We analyzed how uncertainty affected the acceptable novelty.

## 2. MODELING AROUSAL

### 2.1 Arousal as a function of information gain

Following our previously proposed model [6], we assumed valence as a mathematical function of information gain. We defined the amount of information obtained from experiencing a novel event *information gain*. Here, experiencing an event means one exposure. We previously formalized the information gain $G$ as a function of three parameters: prediction error, uncertainty, and noise in equation (1). Information gain is an index of *surprise* [8] and corresponds to arousal.

$$G = \alpha d^2 + \beta$$
$$\alpha = \frac{S_p}{2(S_p + S_l)^2}, \beta = \frac{1}{2}\{log\frac{S_p + S_l}{S_l} - \frac{S_p}{S_p + S_l}\} \qquad (1)$$

where $d$ is the difference between the prior expectation and the peak of the likelihood function, meaning the difference between the expectation and the actual condition. We termed this difference *prediction error* [9]. $S_p$ represents an *uncertainty*, or the difficulty to predict the object, and is dependent upon one's prior knowledge and experience. $S_l$ represents the external noise of stimuli. As equation (1) shows, information gain is a quadratic function of prediction error. The larger the prediction error, the higher the information gain or *surprise*.

### 2.2 Interaction of prediction error and uncertainty on information gain

We analyzed how uncertainty affects information gain or surprise (i.e., arousal level). Using equation (1), we compared any two information gain functions that had different degrees of uncertainty. We held external constant and kept the prediction error positive. If the two functions of different uncertainties have an intersection, then the information gains cross as $d$ increases. While when $d$ is relatively small, the information gain for the larger uncertainty is larger than one for the smaller uncertainty (Fig. 2). Conversely, when $d$ is relatively large, the information gain for the smaller uncertainty is larger than one for the larger uncertainty (Fig. 2). The two information gain functions have an intersection under the following condition:

$$S_{p1}S_{p2} > S_l^2. \qquad (2)$$

For example, the two information gain functions with conditions $(S_p, S_l) = (0.5, 1.0)$ and $(2.5, 1.0)$ have an intersection (Fig. 2).

Generally, the variance of prediction is considered to be larger than the variance of sensing of stimuli input. In that case, information gains as functions of prediction error should cross given different uncertainties. This function model has been supported by experimental results using event-related potential (ERP) P300 of human participants as an index of arousal in which the familiarity and the consistency of musical instruments are controlled [6].

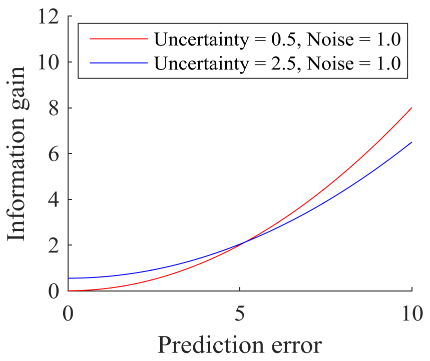


**Figure 2:** Simulated information gain as functions of prediction error for different uncertainties.

## 3. MODELING VALENCE

### 3.1 Inverse-U curve function

Berlyne advocated the arousal potential theory that collative variables such as novelty or complexity have the quality of arousal potential, with highly novel stimuli increasing arousal [2]. A moderate level of arousal potential induces a positive hedonic response, resulting in an inversed-U curve of the hedonic response against arousal potential (Fig. 1). Berlyne assumed that the hedonic response stems from two biological systems: the reward system and the aversion system [10]. Yanagisawa et al. modeled the two systems as sigmoid functions of arousal and defined valence function as the summation of the reward and aversion functions:

$$Valance = Reward + Aversion$$
$$Reward(G) = \frac{K_r}{1 + exp(-A_r(G - G_r))} \qquad (3)$$
$$Aversion(G) = \frac{-K_a}{1 + exp(-A_a(G - G_a))}$$

Where, $G_r, K_r,$ and $A_r$ represent the threshold of the information gain that activates the reward system, the maxima of positive valence levels, and the gradients, respectively. $G_a, K_a, and\ A_a$ represent these in aversion system. The values of reward and aversion across increasing arousal result in a single peak value of arousal located immediately before aversion declines rapidly or reward stabilizes (Fig. 3).

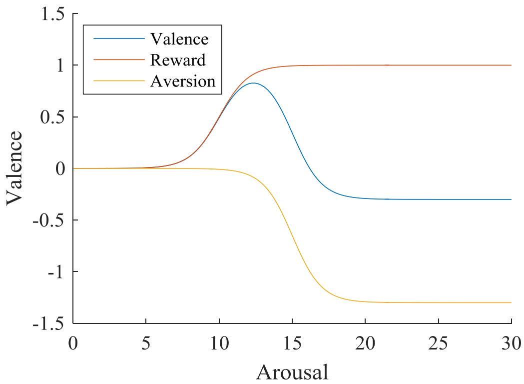


**Figure 3:** Valence modeled as a summation of two sigmoidal functions representing the biological systems of reward and aversion.

### 3.2 Predicting acceptable novelty

We analyzed how uncertainty and prediction error affect the value of the valence. As mentioned in Section 2.2, the arousal function has three variables: prediction error, uncertainty, and external noise. We can describe the valence as a function of prediction error using equations (1) and (3). The valence modeled as a function of prediction error for different values of uncertainty demonstrates that the prediction error at which the valence quality turns from positive to negative varies depending on the uncertainty level (Fig. 4).

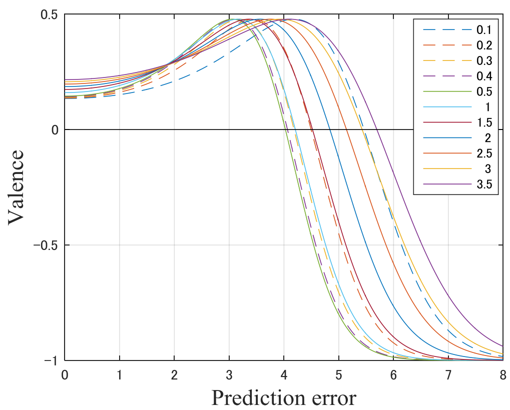


**Figure 4:** Valence modeled as a function of prediction error for different values of uncertainty (ranging from 0.1 to 3.5). External noise is fixed at 0.5.

We defined acceptable novelty as $d_0$, derived as:

$$d_0^2 = 2E\frac{(S_p+S_l)^2}{S_p} - \frac{(S_p+S_l)^2}{S_p}ln(S_p+S_l) + \frac{(S_p+S_l)^2}{S_p}ln\,S_l + S_p + S_l \qquad (4)$$

where $E = -\frac{1}{A}l\,n\left|\frac{K_r-K_a}{K_a e^{AG_r}-K_r e^{AG_a}}\right|$, and $A_r = A_a \equiv A$ is assumed.

In order to analyze the effect of uncertainty on $d_0$, we partially differentiated equation (4) by uncertainty $S_p$ while holding external noise constant, yielding

$$\frac{\partial}{\partial S_p}d_0^2 = g(\alpha) = \frac{\alpha^2-1}{\alpha^2}\left\{2E - ln(\alpha+1) - \frac{\alpha}{\alpha^2-1}\right\} \qquad (5)$$

$$y = 2E \qquad (6)$$

$$y = ln(\alpha+1) + \alpha/(\alpha^2-1) \qquad (7)$$

where $\alpha$ is the uncertainty-to-noise ratio, $S_p/S_l$.

Assuming that valence quality is positive when arousal is none, then $E$ is positive. The sign of equation (5) is determined by the product of $(\alpha^2-1)/\alpha^2$ and $2E - ln(\alpha+1) - \alpha^2/(\alpha^2-1)$. The latter is the difference between equations (6) and (7). The value of $d_0^2$ varies according to the value of $E$. Defining the half of the local minimum of the function (7) as $\tilde{E}$, $\tilde{E}$ nearly equals 0.8639 (Fig. 5). When $E$ is smaller than $\tilde{E}$, $d_0$ decreases as uncertainty increases, whereas when $E$ is larger than $\tilde{E}$, $d_0$ decreases, then increases, and finally decreases as uncertainty increases. Let the inflection points be $\alpha_1$ and $\alpha_2$ $(1 < \alpha_1 < \alpha_2)$ for each. When $\alpha$ is smaller than $\alpha_1$, the lower the uncertainty is, the more acceptable novelty is. When $\alpha$ is between $\alpha_1$ and $\alpha_2$, the higher the uncertainty is, the more the acceptable novelty is. When $\alpha$ is larger than $\alpha_2$, the lower the uncertainty is, the more the acceptable novelty is (Fig. 5).

The inflection points $\alpha_1$ and $\alpha_2$ vary according to the value of $E$ (Fig. 5). $\alpha_2$ largely changes against the rate of the change of $E$. For example, $\alpha_2 \cong 146$ at $E = 2.5$ and $\alpha_2 \cong 22600$ at $E = 5$. Supposing that $E$ is a suitable value, it can be presumed that $E$ is larger than $\tilde{E}$ and $\alpha_2$ is sufficiently large. Based on this assumption, when the arousals, i.e., information gain, under two uncertainty conditions do not have an intersection along with the increase of prediction error, the lower the uncertainty is, the more the acceptable novelty becomes. On the other hand, when the arousals under the two uncertainty conditions have an intersection along with the increase of prediction error, the higher the uncertainty is, the more the acceptable novelty becomes.

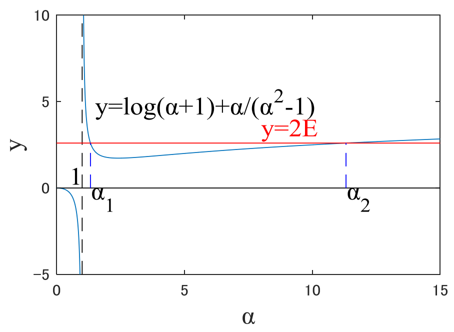


**Figure 5:** The relationship of the two functions $y = 2E$ and $y = ln(\alpha + 1) + \alpha/(\alpha^2 - 1)$. The dashed line indicates $\alpha = 1$ and $\alpha_1$ is considered to nearly equal to 1.

## 5. DISCUSSION

Our model predicts that the acceptable novelty behaves differently depending on whether the arousal levels under two uncertainties cross or not along with the increase of prediction error. When they don't cross, the lower the uncertainty is, the more the acceptable novelty becomes. This can be interpreted that a leeway supported by a high predictability enables ones to accept the prediction error. On the other hand, when they cross, the higher the uncertainty is, the more the acceptable novelty becomes. This can be interpreted that a high predictability leads ones to distinguish the prediction error more clearly, resulting in negative response. Surely, both the responses to the novelty can be considered. However, the intensity of each response may change depending on the uncertainty-to-noise ratio, and the stronger response may be appear finally. In Sylvia's experimental study on arts, the highly trained groups showed ability to understand both simple pictures and complex pictures than the lowly trained groups [5]. This means that ones with low uncertainty showed higher acceptability. Our model can explain the opposite phenomenon, that is, ones with low uncertainty show lower acceptability. For example, those who are very particular about an object may be strict with deviation.

## 6. CONCLUSION

This study proposes a model that describes how prediction error, uncertainty, and external noise affect an individual's acceptance of a novel event, defined as deviation from a prediction. Based on the proposed model, we hypothesized that:

1. When the arousals don't cross under two uncertainty conditions as prediction error increases, the higher the uncertainty, the less the acceptable novelty becomes.
2. When the arousals cross as prediction error increases, the higher the uncertainty, the more the acceptable novelty becomes.

Our model needs experimental supports. However, the proposed model will be a basis or a guide of designing products targeting certain users. We updated the previous model by analyzing the acceptable novelty and provided a potential to explain the strictness of one with a strong preference.

## ACKNOWLEDGMENTS

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