Risk-aware Recommendation based on Prospect Theory

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ABSTRACT

People make lots of decisions under risk in their daily life, especially for e-commerce. For example, one may think that a product is a good match when placing the order, but may instead feel dissatisfied when the product is received. Since people have different tolerance of risks, their purchase decisions can be influenced by their risk attitudes. Economists have studied consumer risk attitudes for decades. The studies reveal that consumers are not always rational enough when making decisions, and their risk attitudes may change in different circumstances. For instance, established behavioral economic theories have shown that most people may underweight outcomes that are merely probable, in comparison with outcomes that are obtained with certainty, which contributes to risk aversion in choices involving sure gains, and to risk seeking in choices involving sure losses. In addition, there is a nonlinear transformation of the probability scale in consumer psychology, which means that consumers will over-weigh events of small probabilities, and under-weigh events of moderate or high probabilities. In other words, people's intuitive feeling about the probability of events can be skewed from the true happening probability of events.

In this paper, we propose a novel risk-aware recommendation framework, which integrates machine learning and behavior economics, and aims to learn the risk mechanism behind users' purchasing behaviors. Specifically, we first develop statistical methods to estimate the risk distribution of each item, and then we draw the Nobel-award winning Prospect Theory into our model to learn how users choose between probabilistic alternatives that involve risks, where the probability of the outcomes are uncertain. Experiments on real-world e-commerce datasets show that by taking user risk preferences into consideration, our approach is able to achieve better performance than many classical recommendation approaches, and further analyses also verify the advantages of risk-aware recommendation beyond accuracy.

KEYWORDS

Recommendation Systems; Personalization; Risk Attitudes; Prospect Theory; Computational Economics

1 INTRODUCTION

Designing personalized recommender systems can help users find relevant items efficiently in the context of web information overload. A well-informed recommender system is capable of not only saving consumers' exploration time, but also benefiting the revenue of various online economic platforms. Traditional recommendation algorithms mostly focus on optimizing rating- or ranking-oriented metrics. Specifically, rating prediction algorithms, including matrix factorization [13, 15, 23] and deep learning approaches [10, 28, 30], devise models to optimize for the prediction accuracy in terms of RMSE. Meanwhile, top-N recommendation algorithms such as pairwise learning to rank [8, 21, 31] propose models to optimize for ranking performance in terms of Precision, Recall, and F1, etc.

However, previous recommendation algorithms seldom consider users' economic incentives when modeling the user behaviors and generating recommendations. Actually, consumers' economic incentives play an important role when making decisions in online economic systems such as e-commerce. One thing to point out here is that online shopping could be risky. More specifically, making purchase decisions online involves potential risks of dissatisfaction. A common observation in practical systems is that people may spend money purchasing an item that they has expected to match their preferences when placing the order. However, they may eventually find themselves unsatisfied with the decision when the item is received, and then it will result in lower ratings towards the item or even a refund request. In this case, online purchasing can be regarded as a process of decision-making under risk/uncertainty.

In fact, users with different risk attitudes could make different decisions even when faced with the same situation. Specifically, risk-averse consumers would more likely to buy products that are "safe choices", i.e., that have many good reviews, while risk-appetite consumers may more likely try new products even though they yet to have sufficiently many good reviews. Meanwhile, based on real-user psychological experiments, behavior economists have revealed that most consumers will over-weigh small probability gains and under-weigh moderate or high probability losses. For instance, when facing 1% probability to win \$500 or 99% probability to win \$5, most people would take the risk and choose the first choice; however, when facing 1% probability to lose \$500 or 99% probability to lose \$5, most people would mitigate the risk and choose the second one. Thus, understanding consumer decisions under risk can assist researchers to better build personalized recommendation algorithms according to users' risk preferences, so that an informed recommendation system with risk-awareness can provide appropriate recommendations that make consumers comfortable. Fortunately, integrating machine learning and established economic principles can help to model the risk attitudes of user decisions based on large-scale user transaction logs.

In this paper, we propose a novel risk-aware recommendation framework, which takes users' risk attitudes into consideration according to several behavioral economic principles. In particular, we simulate the risk distribution of each item based on its rating distribution by conventional statistical methods. Combining the Nobel-prize winning theory in economics — the Prospect Theory [11] — with machine learning algorithms, our model learns to predict the consumer decisions with risk-awareness.

The key contributions of the paper can be summarized as follows:

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- We take consumers' risk attitudes and weighted event probability into our model consideration for economic recommendation, which better simulates the real-world online economic environment, where users have to make decisions under potential risks of dissatisfaction.
- Our model can be considered as a personalized version of the Prospect Theory, i.e., unlike the original Prospect Theory, which assumes a general risk function form for all subjects, our method tries to learn the personalized risk preference for each user, which enhances the economic theory to adapt to different risk attitudes of different users.
- Experimental results on several real-world e-commerce datasets verify that our approach not only achieves better recommendation performance than both classical and economic recommendation baselines, but also successfully adapts the Prospect Theory to learn user's personalized risk attitudes.

The following contents of the paper will be organized as follows: we first review some related work in section 2, and then introduce the key economic preliminaries in section 3 to prepare readers with the basic economic backgrounds used in this work. The proposed model and recommendation strategy are introduced in section 4, followed by experimental results in section 5. Finally, we conclude the work with possible future research directions in section 6.

2 RELATED WORK

In this section, we will briefly introduce some background knowledge to help the readers get a better understanding of the areas that are related to our work.

2.1 Collaborative Filtering

Collaborative Filtering (CF) has always been one of the most dominant approaches to recommender systems. Because of its long history and wide scope of literature, it is almost impossible to cover all its aspects, so we review some representative methods in this subsection. Early approaches to CF consider the user-item rating matrix and conduct rating prediction with user-based [12, 22] or item-based [17, 24] collaborative filtering methods. In these methods, user and item rating vector is considered as the representation vector for each user and item.

With the development of dimension reduction methods, latent factor models such as matrix factorization are later widely adopted in recommender systems, such as singular value decomposition (SVD) [14], non-negative matrix factorization [16], and probabilistic matrix factorization [20]. In these approaches, each user and item is learned as a latent factor representation to calculate the matching score of the user-item pair.

With the development of deep neural networks, deep models have been further extended to collaborative filtering methods for recommendation in recent years. The relevant methods can be broadly classified into two sub-categories: similarity learning approach, and representation learning approach. The similarity learning approach adopts simple user/item representations (such as one-hot) and learns a complex prediction network as the similarity function to calculate user-item matching scores [9, 10], while the representation learning approach learns rich user/item representations and adopts a simple similarity function (e.g., inner product) for matching score calculation [28, 32, 36].

Another important research direction is learning to rank for recommendation, which learns the relative ordering of items instead of the absolute preference scores. The most representative method on this direction is perhaps Bayesian personalized ranking (BPR) [21], which is a pair-wise learning to rank method for recommendation. It is also further generalized to take other information sources such as images [8] and text [31].

2.2 Economic Recommendation

For a long time, recommendation system research focused on the above mentioned rating- or ranking-related tasks such as rating prediction and top-N recommendation. However, the related methods seldom consider the economic value that a recommendation list could bring to the user or the system, although it is one of the most important goals for real-world recommendation systems. Some recent research on economic recommendation has begun to take care of the economic value of personalized recommendation. For example, [29] studied user's sense of value in terms of utility in recommender systems, and [34] conducted large-scale experiments with real-world users to validate the consumer's sense of utility for personalized promotion. [33] further bridged economic principles and machine learning to maximize the social surplus for recommendation, and [35] proposed to learn the substitutive and complementary relations between products for utility maximization. Although current economic recommendation approaches may improve the economic value, their basic motivation is to maximize a total utility function for each user to generate recommendations. However, established behavioral economic principles show that consumers usually make decision under risk conditions, and the risk attitude/preference of different users could be different, which may influence their decisions in economic systems [11], which motivates us to estimate the risk preference of the users for economics-driven risk-aware recommender systems.

2.3 Decision-Making Under Uncertainty

The real-world is filled with plenty of uncertainties, and it involves various different risk factors. People have to make a large number of decisions under uncertainty in their daily life, such as making purchases or investments. As a result, decision-making under risk is one of the most fundamental research subjective for economists. There have been two major types of theory on decision-making under risk, and the key difference between them is how to understand the definition of uncertainty. The first type of theory holds the view that uncertainty is objective, which means that the uncertainty of an event is can be represented as an objective probability distribution of all possible outcomes. One representative theory of this view is the von Neumann-Morgenstern Expected Utility Theory [26]. The other type of risk theory believes that the uncertainty of events is not objective, but it is based on people's subjective judgments of all possible outcomes. In particular, Savage [25] puts forward a theory of subjectivity based on personal probability and statistics, which constitutes the research line underlying Bayesian statistics.

Overall, there exist more than one economic theories on risk modeling, and among them the Expected Utility Theory was generally adopted and practically applied due to its intuition and convenience. However, these theories still cannot properly explain all the known consumer behaviors, and most importantly, researchers gradually realized the limitations of these theories, because of the emerging of several classical paradoxes out of the theories, which were raised by Bernoulli [2], Allais [1], and Ellsberg [4]. To solve these paradoxes, Daniel Kahneman and Amos Tversky renewed the study based on human behaviors and proposed the Prospect Theory [11] in the year of 1979 to model the user risk preferences, and later in 2002, Kahneman was awarded the Nobel Prize in Economics for the success of Prospect Theory in modeling consumer risks in economic behaviors.

3 PRELIMINARIES

In this section, we introduce some basic economic preliminaries to help readers better understand the proposed model.

3.1 Expected Utility Theory

In conventional microeconomics, rational decision-making under uncertainty is an important and extensively study research problem, and one important risk modeling approach developed out of these research is the von Neumann-Morgenstern Expected Utility Theory [26], which has been widely used in micro-economics, game theory, and decision theory. The expected utility theory concerns consumer's preferences with regard to the choices that may have uncertain outcomes, and it states that the subjective value associated with an individual's gamble is the statistical expectation of that individual's valuations of the outcomes on that gamble.

Expected utility measures customers' preference in uncertain circumstances. When an individual has to make a decision under uncertainty, it is rational to make a choice with the highest expected utility, which is also called the von Neumann-Morgenstern (VNM) utility [6, 27]. Assuming that U is the utility function for random variable X, then the expected utility (EU) is

$$EU(X) = \sum_{x \in X} U(x)P(x) \tag{1}$$

In this paper, the detailed estimation of the probability distribution $P(x)$ for one given item is discussed in section 4.2.

3.2 Risk Attitudes

Users usually have to take the risk for their own choices when making decisions under uncertainty. In recommender systems, consumers hardly know for sure if they would be satisfied with a product or not, because a purchase that is believed to be a good match may still result in dissatisfaction due to various factors, such as the quality or delayed shipment, which can be considered as potential risk factors in e-commerce. As we have discussed before, different people may have different attitudes towards risk. In general, consumer risk attitudes can be divided into three categories, which are introduced as follows:

Risk Aversion: Even though there exist a lot of methods to describe individual's risk aversion attitude, the essence of them are the same, i.e., comparing all of the possible returns under different choices that have the same expected value, a risk-aversion consumer would always prefer the certain returns.

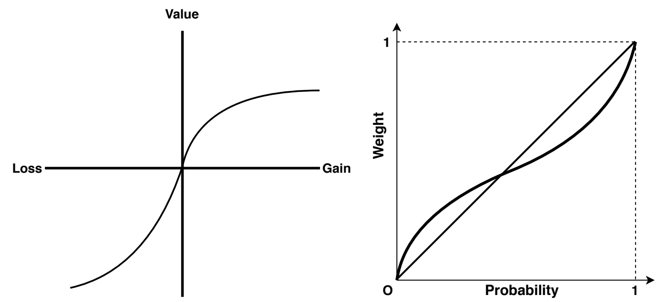


Figure 1: Illustration of the Prospect Theory functions. The left figure shows the value function. For gains, the function is concave to show risk-aversion, and for loss, it is convex to show risk-appetite. Also, as mentioned before, people have stronger feelings for losses than for gains, thus, the loss function is usually steeper than the gain function. The right figure is a weight function, showing that consumers usually over-weigh small probability events and under-weigh high probability events for both losses and gains.

Risk Appetite: The definition of risk appetite is counter part against risk aversion, i.e., comparing all of the possible returns under different choices that have the same expected value, a risk-appetite consumer would always prefer the risky returns.

Risk Neutral: Risk neutral is a mindset where an individual is indifferent to risk when making a decision under uncertainty.

It would be easier to understand the difference of different risk preferences with an example. Suppose there are two choices in a gamble, one is to win either \$100 or \$0 with 50% probability each, and the other choice is to get \$50 with 100% probability. Though the expected utility of both choices are the same (\$50), different users may make different choices based on their risk attitude. A risk-aversion user would prefer to choose a certain \$50 reward, and a risk-appetite user would prefer to risk for a potential \$100 reward, while a risk-neural user is indifferent to the two choices.

3.3 Prospect Theory

Prospect theory is a commonly accepted and widely applied economic principle in behavioral economics, which describes consumer's decision making process between probabilistic alternatives involving risks. Prospect theory believes that people have different evaluations for gain and loss, and it describes the decision making process in two steps:

First, people will divide all potential outcomes as gain or loss by setting a reference point that they consider as indifferent. Specifically, those outcomes that are smaller than the reference point are considered as losses, and those greater than the reference point are considered as gains. Second, people actually have different value functions for gain and loss, respectively, which are their subjective evaluations for certain values of gain or loss. With this, consumers will calculate a prospect value based on all the possible outcomes and their respective probabilities, and finally take the choice with highest prospect value.

According to Kahneman [11], the prospect value is a product of the value function and the weight function, where value function is used to measure the satisfaction of the gain or loss, which can be either positive or negative, respectively. It should be noted that value function is different from utility function commonly used in various utility models, where the latter is usually used to measure the absolute satisfaction of a choice. We will use $v(x)$ to denote the value function in the following parts to distinguish it from the normal utility function $u(x)$.

Through a large number of psychological experiments, prospect theory depicts some general consumer psychological principles and summarizes that people usually are risk aversion for gains and risk appetite for losses, because they have stronger feelings for losses than for gains, i.e., the hurt of losing \$10 is usually much higher than the happiness out of gaining \$10. The hypothesis of value function is based on the above observations and is shown in Fig.1(a). However, there exist researches [18] showing that the loss value function may not always be steeper than the gain value function. We will discuss the issue in detail in the paper though machine learning modeling and experiments.

According to the observations of many behavioral economic experiments [3], there is also a tendency showing that consumers are more risk averse for high-probability gains or low-probability losses, and more risk appetite for low-probability gains or high-probability losses. This trend, which is not reflected in the value function, can be reflected by the individual differences in the elevation of the weighting function. Specifically, people usually over-weigh the low probabilities and under-weigh the high probabilities for both gains and losses. Based on these observations, the weight functions for gains and losses have similar shape, and the hypothesis of the weight function is shown in Fig.1(b). Basically, it shifts the original probability of an event by increasing small probabilities and decreasing large probabilities.

4 THE FRAMEWORK

In this section, we further discuss how to bridge the fundamental economic concepts with machine learning algorithms to establish a riak-aware recommendation framework.

4.1 Prospect Value

According to Kahneman and Tversky's work in 1979 [11], we can get a simple mathematical formula to calculate the prospect value.

$$V = \sum_{i=1}^{n} v(x_i)\pi(p_i) \tag{2}$$

where V represents the prospect value for a certain choice, which consists of $v(x)$ as the value function and $\pi(p)$ as the weight function; $x_1, \cdots, x_n$ are the value of gains or losses for all potential outcomes, and $p_1, \cdots, p_n$ are the corresponding probabilities.

4.1.1 The Value of Gain or Loss. To compute the overall prospect value of certain alternate, it is necessary to get the value of gains or losses for its all potential outcomes. However, e-commerce is different from gambling that uses the certain amount of money to represent gains and losses. In e-commerce, the outcomes of purchasing an item are usually reflected by its rating scores. Therefore, rating, which is usually in $\{1, 2, 3, 4, 5\}$, can be used as an important signal to evaluate the value of gains or losses.

Suppose that the reference point is $\hat{r}$, for every possible outcome that is $r = 1, \cdots, 5$ (i.e., user rates a certain item with score 1, 2, ..., or 5), the value of gains or losses can be designed as

$$x = \tanh(r - \hat{r}) \tag{3}$$

In this formula, the value is positive for gains (i.e., the rating is greater than the reference point) and negative for losses (i.e., the rating is less than the reference point), and $\tanh(\cdot)$ is the hyperbolic tangent function to normalize the values into $[-1, 1]$.

4.1.2 The Value Function. According to the report of Galanter and Pliner [5], the marginal value of both gains and losses usually decrease with the magnitude. For example, people will get more satisfaction by improving the value from \$5 to \$10 than from \$100 to \$105. Similarly, the difference between loss of \$5 and loss of \$10 is greater than the difference between the loss of \$100 and \$105. Therefore, economic principle usually assumed that the value function is concave for gains and convex for losses. Since people have different feelings about gains and losses, the value function should be vary depending on the whether the variable is a gain or a loss. For the value of gain or loss discussed above, the value function can be designed as follows:

$$v(x) = \begin{cases} \alpha \log(1 + x) & \text{if } x \geq 0 \\ -\beta \log(1 - x) & \text{if } x < 0 \end{cases} \tag{4}$$

where α and β are positive parameters.

4.1.3 The Weight Function. The weight function is used to represent the decision weight for all possible outcomes based on their corresponding probabilities. According to the basic ideas of Prospect Theory, we use the following function $\pi(p)$ as the weight function.

$$\pi(p) = \begin{cases} \dfrac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{1/\gamma}} & \text{for gain} \\ \dfrac{p^\delta}{(p^\delta + (1-p)^\delta)^{1/\delta}} & \text{for loss} \end{cases} \tag{5}$$

where p is the probability of the gain (or loss); $\pi(0) = 0$ and $\pi(1) = 1$; γ and δ are positive parameters used to control the shape of the weight function, which will be learned in the model. It should be noted that decision weights are not probabilities any more, and they only represent the important of a gain/loss for the user.

4.2 Estimation of Risk Distribution

Shopping online is risky because consumer may be unsatisfied with the purchased items. Rating score is an important indicator to reflect the satisfaction of the consumer towards a certain item. Usually satisfaction scores should be continuous, but for the sake of convenience, many e-commerce platforms, such as Amazon, choose to approximate the discrete rating score from 1 to 5. We assume that the continuous satisfaction should follow the Gaussian distribution and the probabilities of all potential outcomes should depend on the quality and the purchase history of the item. Given the purchase history of an item $r_i, i = 1, \cdots, N$ (i.e., the rating scores r given by user i), the estimation of the parameters of Gaussian distribution, i.e., the mean and variance, are as follows:

$$\hat{\mu} = \frac{1}{N}\sum_i r_i,\ \hat{\sigma}^2 = \frac{1}{N}\sum_i (r_i - \hat{\mu})^2 \tag{6}$$

Given the above estimation, the Gaussian distribution of a given item should be $\mathcal{N}(\hat{\mu}, \hat{\sigma})$. However, since rating is a discrete value, which represents the approximation of the user satisfaction, we use the integral of certain intervals of the estimated Gaussian distribution as the probabilities of the potential outcomes. More specifically, $P_n = \Pr(r = n) = \int_{n-0.5}^{n+0.5} \mathcal{N}(\hat{\mu}, \hat{\sigma})\mathrm{d}r$ is the probability that the rating score of item j is n (n = 1, 2, 3, 4 or 5, for n = 1, integral lower bound is $-\infty$ and for n = 5, upper bound is $+\infty$).

4.3 Risk-aware Recommendation Model (RAM)

In this work, we propose an optimization framework based on Multinomial Logistic Model (MLM) for our risk-aware recommendation learning framework (RAM). Online shopping requires consumers choosing their desired items among alternatives, which can be considered as a discrete choice problem. Discrete choice problem describes a situation when a consumer chooses an option between two or more discrete alternatives. More formally, suppose that at time point t, consumer i chooses item j over a set of some other alternative products $\Omega_{it}(j)$. We define the total choice set as $\Pi_{it} = \{j, \Omega_{it}(j)\}$ and its k-th element is Π_{it}^k ($\Pi_{it}^1 = j$). The probability that consumer i chooses alternative j is denoted as P_{ij}.

Researchers in economics have utilized Random Utility Models (RUM) to deal with this problem [35]. Different from traditional RUMs, in this paper, we adapt the idea of choosing the alternative item that provides the highest utility into choosing the alternative item with the highest prospect value, without violating the budget constraint. In this way, we have:

$$\hat{V}_i(\Pi_{it}^k) = V_i(\Pi_{it}^k) + \epsilon_k \tag{7}$$

where $V_i(\Pi_{it}^k)$ represents the true prospect value of a product combination, and $\hat{V}_i(\Pi_{it}^k)$ represent the observed prospect value. ϵ_k is a random variable capturing the impact of all unknown factors. Thus, the probability a customer chooses Π_{it}^1 (item j) over other alternatives is:

$$P_{ij}\left(\hat{V}_i(\Pi_{it}^1) > \hat{V}_i(\Pi_{it}^k)\right) = P_{ij}\left(\epsilon_k - \epsilon_1 < V_i(\Pi_{it}^1) - V_i(\Pi_{it}^k)\right) \tag{8}$$

where $k = 2, \ldots, |\Pi_{it}|$. If ϵ_1 and ϵ_k obey an i.i.d. extreme value distribution, then we have,

$$P_{ij}(y_{it} = 1) = P_{ij}\left(\hat{V}_i(\Pi_{it}^1) > \hat{V}_i(\Pi_{it}^k)\right) = \frac{\exp(V_i(\Pi_{it}^1))}{\sum_{k=1}^{|\Pi_{it}|}\exp(V_i(\Pi_{it}^k))} \tag{9}$$

where y_{it} is an indication function that,

$$y_{it} = \begin{cases} 1 & V_i(\Pi_{it}^1) > V_i(\Pi_{it}^k) \quad \forall k \neq 1 \\ 0 & \quad Otherwise \end{cases} \tag{10}$$

Given the observed transactions and multinomial logistic model, the model parameter can be learned by maximizing the probability of choosing the purchased items.

$$\max \sum_{(i,j)\in\mathcal{R}} \frac{\exp(V_i(\Pi_{it}^1))}{\sum_{k=1}^{|\Pi_{it}|}\exp(V_i(\Pi_{it}^k))} - \lambda\|\Phi\|^2 \tag{11}$$

where $\mathcal{R}$ is the training dataset; Φ is the parameter set to be learned in the corresponding loss function, which will be crystallized in the following section.

4.4 Model Specification

Economic principles mainly focus on finding out the general rules for the majority of people, however, with the help of machine learning and massive available data, we now can build the model to fit the personalized preference of each individual. To obtain the personalized measurements, each user-item pair will have a set of parameters. In particular, each parameter (except for the reference point) can be decomposed into the global bias, user bias, item bias, and K-dimensional latent factors of user and item. For example, the parameter α in the value function (Eq.(4)) can be rewritten as:

$$\alpha_{ij} = a + b_i + l_j + \mathbf{p}_i^T\mathbf{q}_j \tag{12}$$

where a is the global bias, b_i is the user bias, l_j is the item bias, $\mathbf{p}_i$ and $\mathbf{q}_j$ are K-dimensional latent factors of user i and item j. We think that each consumer has his/her own reference point, so the reference point $\hat{r}_i$ of each consumer i also needs to be learned. As a result, we set the reference point for each consumer as a parameter and learn it by Stochastic Gradient Descent (SGD) in our model.

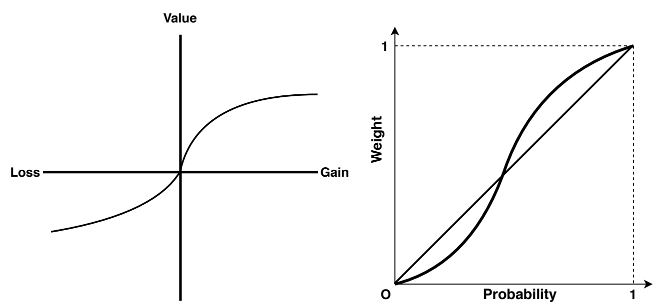


Figure 2: An alternative value function. Similar to the value function in Prospect Theory, for gains, the function is concave and for loss, it is convex. Since there could be a minority group of people that have stronger feelings for gain than for loss, the loss function may looks flatter than the gain function. The right figure shows the corresponding weight function, i.e., some consumers may over-weigh high probability events and under-weigh low probability ones.

The original prospect theory points out that most people usually have stronger feeling about the loss, so that the loss value function is steeper than the gain value function (i.e. $\alpha < \beta$ in Eq.(4)), as shown in Fig.1(a). However, not everyone user follows this rule, and it is possible for some of them to feel the opposite way [18], as shown in Fig.2(a). For the purpose of personalization, we do not apply any constraint on the relationship between α and β, and rely on our model to learn their values automatically.

The weight function still reflects the risk attitudes of different users. According to Kahneman [11], people tend to be risk aversion for gains, and meanwhile, people are risk appetite for lower probability events of gains, so they will over-weigh the lower probabilities and under-weigh larger probabilities, as shown in Fig.1(b). However, since not all consumers are risk aversion for gains [18], we should make sure the weight function has the ability to learn the preferences for these consumers. In particular, they may underweigh lower probabilities and over-weigh the higher probabilities, as shown in Fig.2(b). Similar to the treatment of value function, we do not apply any constraint to the relationship between γ and δ in Eq.(5), so that the framework has the ability to learn the different preferences for diffident users.

4.5 Top-K Recommendation

Once we learned the model parameters r_{ij}, α_{ij}, β_{ij}, γ_{ij} δ_{ij} and $\hat{r}_i$ according to our model, we can then calculate the prospect value V_{ij} for each user-item pair. We rank all products for a user according to their prospect values, and select the top items whose price is within the user's budget to generate the top-K recommendation list, where in this work, a consumer's budget is considered as the highest price that the consumer had ever spent in his/her purchasing history.

5 EXPERIMENTS

5.1 Dataset Description

We use the consumer transaction data from Amazon[1] [7, 19] in our experiments. The dataset includes user transaction (user id, item id, rating, etc.) and item metadata (item id, price, related item, etc.) on twenty-four product categories lasting from May 1996 to July 2014. We take three categories (Movies, Electronics and Books) that have different size and data sparsity for experiments.

Some basic statistics of the experimental datasets are shown in Table 1. For each dataset, we sort the transactions of each consumer according to the purchase timestamp, and then split the records into training, validation, and testing sets chronologically by 3:1:1, namely, the first 60% items of each user are used for training, the following 20% are for validation, and the last 20% are used for testing[2].

Table 1: Basic statistics of the experimental data sets.

Dataset	#users	#items	#interactions	sparsity
Movies	25,431	10,470	726,857	0.273%
Electronics	40,983	16,286	556,227	0.083%
Books	74,520	21,066	2,005,029	0.128%

5.2 Experimental Setup

We compare our model with the following baselines, including both economic and non-economic methods. For economic methods, we involve baselines that do not consider risk preferences to illustrate the importance of risk consideration.

CF: Collaborative Filtering based on matrix factorization is a representative method for rating prediction. In this experiment, we use CF based on latent factor modeling [14].

BPR: Bayesian Personalized Ranking [21] is one of the most representative ranking-based methods for top-N recommendation.

MPUM: Multi-Product Utility Maximization for recommendation [35], which is an economic recommendation approach that maximizes the utility of product combinations for recommendation.

[1] http://jmcauley.ucsd.edu/data/amazon/

[2] Code and data will be released on publication

Expected Utility (EU): Expected Utility Maximization for recommendation, which is an economic recommendation approach that maximizes the expected utility of items for recommendation. Inspired by Zhang [33], we use KPR utility in EU, which is $u(x) = \alpha_{ij} ln(Q_{ij} + 1)$. Same as our learning framework, we just replace prospect value with expected utility, which can be calculate with Eq.(1) and KPR utility, and try to maximize it. The loss function of EU can be summarized as follows:

$$\max \sum_{(i,j)\in\mathcal{R}} \log\left(\frac{exp(EU_i(\Pi^1_{it}))}{\sum_{k=1}^{|\Pi_{it}|} exp(EU_i(\Pi^k_{it}))}\right) - \lambda \|\Phi\|^2 \tag{13}$$

PT without weight Function (PTWF): Prospect theory for recommendation without using the weight function, which is a variant of our model that does not consider the different risk attitude introduced by weight function.

For each dataset, we use the validation set to tune the model and find the best parameters of each method.

5.3 Experimental Results

Key experimental results are shown in Table 2, and we also plot the hit rate in Figure 3 under different recommendation length K (from 1 to 10). We analyze and discuss the results in terms of the following three perspectives.

5.3.1 **Personalized Prospect Theory:** Thanks to machine learning and massive data mining, we now can build a model that fits every consumers' preference. The results show something different from the traditional prospect theory, therefore we call it Personalized Prospect Theory.

The Value Function: According to the prospect theory, most people should have stronger feeling about loss (i.e. $\beta > \alpha$). However, for *Movies*, the parameters learned from our model show that 99.94% of the user-item pairs have stronger feeling for gains. This is because the traditional prospect theory is based on the experiments of gambling, where the loss is actual monetary loss, while the loss in e-commerce is usually just dissatisfaction, meanwhile, lots of online shopping platforms also have refund policy, which will help to reduce the consumer feeling of loss. According to the learned reference points shown as histogram in Fig.4(a), we find that most consumers have low reference points, with an average of 1.46, which indicates that they usually feel gains and only feel the loss in some very extreme cases (rating = 1). Furthermore, we analyze the situations mentioned in the original prospect theory, when consumers have stronger feeling for losses than for gains. We compare the price of all the items in both situation and plot the histogram Fig.5(a). The average price for stronger loss is $27.7 while the average price for stronger gain is $18.3 (statistically significant at $p = 0.001$). It shows that when consumers have stronger feeling for losses, the price of items are relatively higher, which is reasonable because consumers with feel upset when spending a lot of money on an item and only to find that it is not very satisfactory.

For *Electronics*, 39.75% of user-item pairs have stronger feeling about losses, and this ratio is larger than the other two datasets. The reference point distribution shown in Fig.4(b) (average = 1.481) is not significantly difference from other datasets. However, according to the price distribution shown in Fig.5(b), the average price for stronger loss is $83.5 while the average price for stronger gain is

Table 2: Summary of the performance. We evaluate for ranking (Precision, Recall and F_1, in percentage (%) values), and K is the length of recommendation list. When RAM is the best, its improvements against the best baseline are significant at p=0.001.

Dataset	Movies								
Measures	Precision(%)			Recall (%)			F_1 Measure (%)		
K	1	5	10	1	5	10	1	5	10
CF	2.9177	2.4647	2.2079	0.5427	2.2922	4.1068	0.9152	2.3753	2.8719
BPR	4.6479	3.8205	3.3565	0.8645	3.5531	6.2432	1.4579	3.6820	4.3659
MPUM	5.5208	3.8897	3.4246	1.0269	3.6175	6.3697	1.7317	3.7487	4.4543
EU	4.5220	3.6208	3.2051	0.8411	3.3673	5.9616	1.4184	3.4895	4.1689
PTWF	7.2628	3.6703	3.0306	1.3509	3.4134	5.6369	2.2781	3.5372	3.9418
RAM	**8.3402**	**4.3278**	**3.6129**	**1.5513**	**4.0249**	**6.7201**	**2.6160**	**4.1708**	**4.6993**

Dataset	Electronics								
Measures	Precision(%)			Recall(%)			F_1 Measure(%)		
K	1	5	10	1	5	10	1	5	10
CF	4.7483	3.0652	2.3078	2.1051	6.7945	10.2313	2.9170	4.2246	3.7661
BPR	6.9956	3.8460	2.7607	3.1014	8.5253	12.2390	4.2975	5.3007	4.5051
MPUM	7.3713	3.8904	2.8451	3.2680	8.6238	12.6133	4.5284	5.3619	4.6429
EU	6.7467	3.5634	2.7145	2.9911	7.8990	12.0346	4.1447	4.9113	4.4299
PTWF	9.6772	4.0973	2.8468	4.2903	9.0825	12.6209	5.9449	5.6471	4.6457
RAM	**10.6996**	**4.1539**	**2.8692**	**4.7435**	**9.2079**	**12.7204**	**6.5730**	**5.7251**	**4.6823**

Dataset	Books								
Measures	Precision(%)			Recall(%)			F_1 Measure(%)		
K	1	5	10	1	5	10	1	5	10
CF	3.6849	2.6860	2.1927	0.7310	2.6643	4.3500	1.2200	2.6751	2.9157
BPR	3.9882	3.2662	2.7326	0.7912	3.2398	5.4209	1.3204	3.2530	3.6335
MPUP	6.0199	3.4412	2.7472	1.1942	3.4134	5.4500	1.9931	3.4273	3.6530
EU	3.6903	3.0043	2.5921	0.7321	2.9800	5.1422	1.2218	2.9921	3.4467
PTWF	**6.9283**	3.5115	2.7303	**1.3745**	3.4832	5.4164	**2.2939**	3.4973	3.6305
RAM	6.8867	**3.5416**	**2.8396**	1.3662	**3.5130**	**5.6334**	2.2801	**3.5272**	**3.7759**

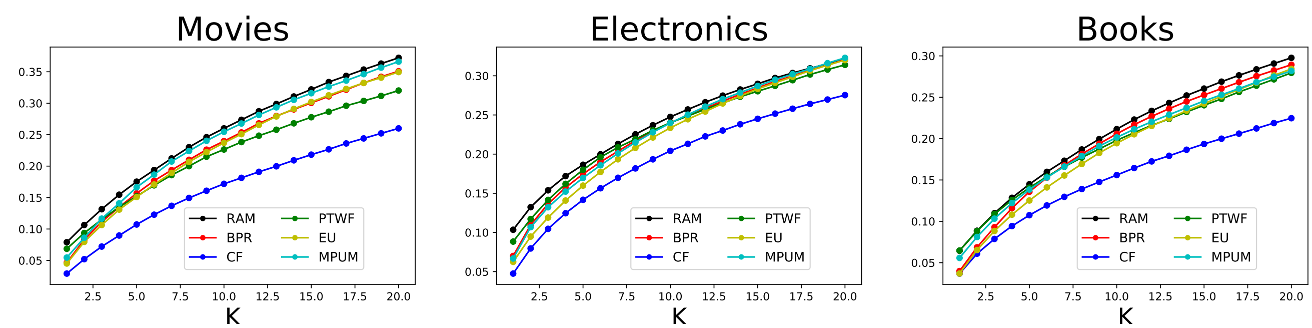
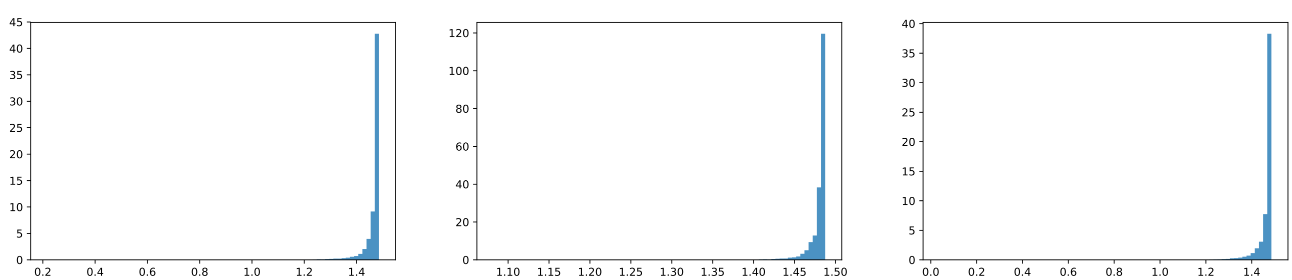
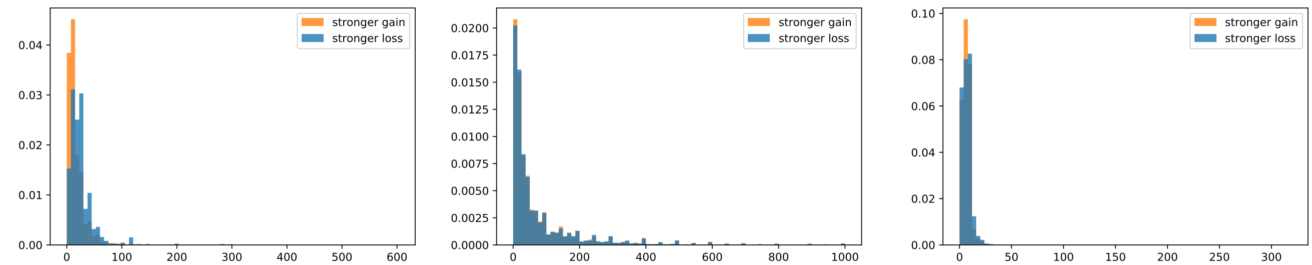


Figure 3: Hit rate on three datasets. x-axis is the length of the recommendation list and y-axis is the hit rate.



(a) Movies (b) Electronics (c) Books

Figure 4: The distribution of reference points on the above three datasets.



(a) Movies (b) Electronics (c) Books

Figure 5: The histogram of item price in two situations on three datasets.

\$80.4. Based on this observation, the price of items in Electronics is more expensive than other categories, which means that more severe losses might be caused by dissatisfaction. Considering that electronics may cause more severe losses than movies since they are more expensive and time consuming to refund, and that our model can indeed reflect the difference in the learned value functions for the two domains (the percentage of users that have stronger feelings about losses on *Electronics* is 39.75%, while for *Movies* it is only 0.06%), it shows that our model can automatically learn the different risk preferences of consumers for more informed recommendation. Similar observations are seen in the *Books* domain.

The observations above have verified based on large-scale data that, the assumption made in the original prospect model that every consumer has a stronger feeling for losses than gains is not always true [18], and the proportion of consumers obey that rule is usually related to the price of the products, since expensive products will cause more loss than a cheaper one. As a result, an informed recommendation model should have the ability to make adaptive adjustments of its value function for different users.

The Weight Function: The experiments of prospect theory showed that most people is risk aversion for gains and risk appetite for losses. People also have different risk attitudes for small probability events represented by the weight function as Fig.1(b).

According to the parameters learned from the *Movies* dataset, 99.99% user-item pairs follow that rule of gains and losses depicted in the original prospect theory. For gains in *Movies*, the parameter histogram and the weight function are shown in Fig.6(a) and Fig.6(b), while for losses, the parameter histogram and the weight function are shown in Fig.6(c) and Fig.6(d), respectively. Based on Fig.6(b) and Fig.6(d), we see that most of the learned weight functions (darker areas) follow the observation in the original prospect theory, i.e., small probabilities are over-weighed, while higher probabilities are under-weighed. However, there indeed exist some inverse-shaped weight functions (on the other side of the $y = x$ line), which means that a small portion of pairs may have different risk attitudes. Also, even for those weight functions that have similar shapes, they may have different curvatures, which means that the degree of risk-aversion/appetite of users can be different.

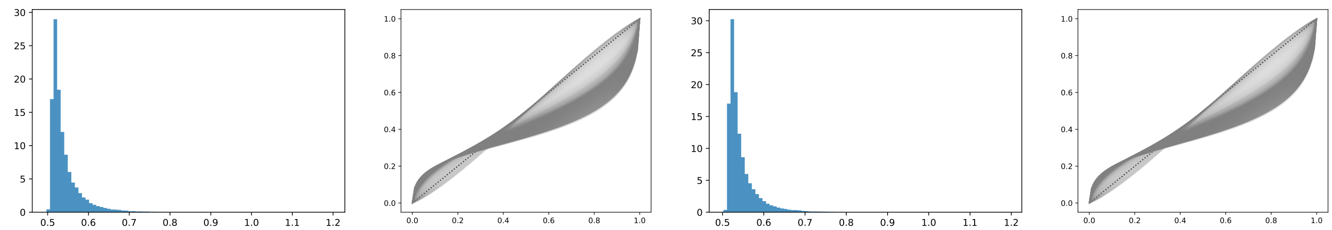
For *Electronics*, only a tiny portion of pairs have inverse-shape weight functions. The distributions and weight functions for gains and losses are shown in Fig.7. And the parameters are more concentrated compared with the other two datasets. Based on the fact that the average price of electronic products is much higher than the other two, this means that individual differences will reduce under large amount of gains or losses. Similarly for *Books*, only 0.0047% of pairs have inverse-shaped weight functions, where gains and losses have same percentage. The parameters histogram and weight function are shown in Fig.8(a) and Fig.8(b) for gains and Fig.8(c) and Fig.8(d) for losses.

Based on above observations, we can see that most people comply with the hypothesis of the original Prospect Theory in terms of risk distribution. However, there indeed exist individual differences. Combining the information in Fig.5, Fig.6, Fig.7 and Fig.8, we find that the difference between consumer risk-attitudes decreases when the price of products increases.

5.3.2 **Recommendation Performance:** As shown in Table 2, among the baseline models, all pair-wise learning methods (BPR, EU and PTWF) are better than the point-wise CF method, which shows the superiority of pair-wise methods on top-K ranking tasks. Furthermore, our RAM approach achieves the best top-K recommendation performance against all baselines in most cases. For example, when averaged across all datasets and recommendation lengths, we get 27.81% improvement than BPR. In particular, the improvement is 79.44% for Precision@1 on the *Movies* dataset against BPR. For hit rate, we get 9.40% improvement than the BPR baseline when averaged across K on all of the three datasets, and the largest improvement (69.88%) is achieved when $K = 1$ on *Movies* dataset. Among the three datasets, our model gets the largest improvement (12.87%) on the *Movies* dataset against BPR on average. Compared with the economic recommendation baseline MPUM, our model gets 15.70% improvement on Precision in average, and especially a 51.07% improvement for Precision@1 on *Movies* dataset. Meanwhile, our model gets 6.76% improvement than MPUM for hit rate on average and the largest improvement (55.04%) occurs when $K = 1$ on the *Electronics* dataset.

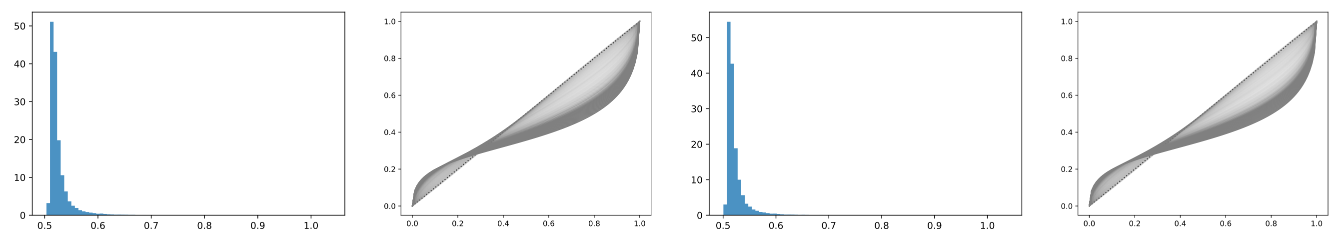
The observations imply that by modeling user behaviors under uncertainty based on established risk-aware principles, our model is able to better capture the user preferences for recommendation.

5.3.3 **Risk Awareness vs. Risk Unawareness:** Basically, the personalized risk attitudes in our model are mainly represented by the weight functions. When we use the original probability without the weight function, the whole method is noted as PTWF (Prospect Theory w/o Weight Function) in the baselines. According to the Table 2, our RAM model has better performance against PTWF. When averaged across all datasets and recommendation



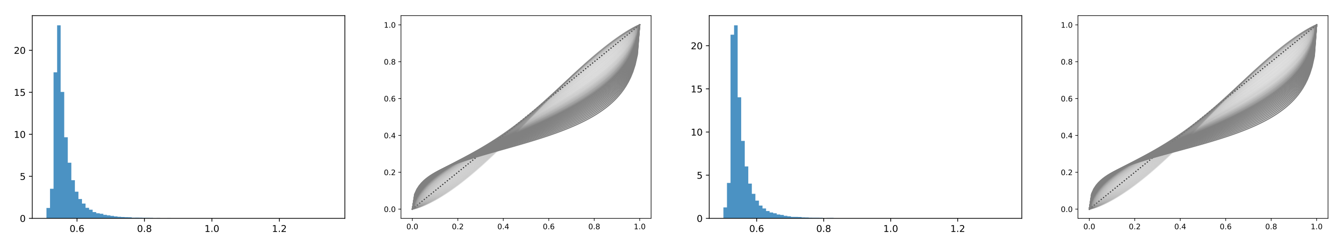
(a) γ Distribution (b) weight function for gains (c) δ Distribution (d) weight function for losses

Figure 6: The histogram for the parameters of the weight function for gains and losses, and the different shapes of the learned weight function for gains and losses, where darker color means more frequent occurrences on the *Movies* dataset.



(a) γ Distribution (b) weight function for gains (c) δ Distribution (d) weight function for losses

Figure 7: The histogram for the parameters of the weight function for gains and losses, and the different shapes of the learned weight function for gains and losses, where darker color means more frequent occurrences on the *Electronics* dataset.



(a) γ Distribution (b) weight function for gains (c) δ Distribution (d) weight function for losses

Figure 8: The histogram for the parameters of the weight function for gains and losses, and the different shapes of the learned weight function for gains and losses, where darker color means more frequent occurrences on the *Books* dataset.

lengths, we get 7.66% improvement than PTWF. Meanwhile, the largest improvement is 19.21% for Precision@10 on *Movies* dataset. For hit rate, the average improvement against PTWF is 8.48% and the largest improvement (17.1%) occurs when $K = 1$ on *Electronics* dataset. However, PTWF is slightly better on *Books* dataset when $K = 1$. It is partly because the products in books category are relatively cheaper and most consumers may have the same or similar risk attitudes. Thus, it is less useful to consider the impact of individual risk attitudes in the books domain.

Expected Utility Theory (EU) is also a classic economic approach, while the prospect theory is used to solve the paradoxes that could not be addressed by expected utility theory. When comparing with EU baseline, out model gets 34.62% improvement on Precision in average, especially a significant improvement (86.62%) on Precision@1 for *Books* dataset. For the hit rate, RAM gets 13.80% improvement against EU in average. The largest improvement (74.8%) achieves when $K = 1$ on the *Books* dataset.

6 CONCLUSIONS AND FUTURE WORK

In this paper, we introduce risk attitudes into personalized recommendation systems and propose risk-aware recommendation. In particular, we bridge prospect theory and machine learning algorithms together to predict individual risk attitudes. We believe that online shopping could be risky with uncertainty, and the risk attitudes of different consumers may affect their decision making processes under uncertainty/risk. Understanding the risk attitude of consumers can help the system accurately predict human behaviors for better services. Meanwhile, we advance prospect theory into a personalized version based on machine learning over large-scale consumer transaction logs. Experimental results verified the effectiveness of our model in terms of top-K recommendation. In the future, we will consider user risk attitudes in other online systems beyond e-commerce recommendation, and consider other economic principles and learning methods to benefit recommendation systems both effectively and economically.

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