A Psychological Model for Consumption Prediction

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ABSTRACT

The study of consumer psychology reveals two categories of procedures used by consumers to make consumption related choices: compensatory rules and non-compensatory rules. Existing recommendation models such as matrix factorization assume the consumers follow the compensatory rules, which is to make decisions based on a weighted or summated score over different attributes. In this paper, we present a novel model which adopts non-compensatory decision rules. The selected item is superior on the most important attribute and beyond the minimally acceptable level on other attributes. Furthermore, we incorporate ordinal utility in the psychological model for consumption prediction in click sessions. We experimentally demonstrate that this model outperforms state-of-the-art methods.

KEYWORDS

consumer psychology, non-compensatory decision rules, ordinal utility, early prediction

1 INTRODUCTION

Ever since the dawn of psychological science, many attempts have been made to explain human choice behavior. It is well regarded that there are two categories of procedures to make consumption related choices: compensatory rules and non-compensatory rules [?]. Consumers who adopt compensatory rules evaluate every product over multiple relevant aspects and compute a weighted or summated score for each product. Then they will select the products with highest scores. The shortcomings of a product are balanced out by its attractive features. On the contrary, non-compensatory rules do not allow a good performance on one aspect of a product to compensate for poor performances on other aspects. Non-compensatory rules include lexicographic, conjunction and disjunction rules. Under lexicographic rules, products are compared on the most important aspect. Under conjunction and disjunction rules, the consumer imposes requirements for minimally acceptable values on each aspect separately. The conjunction and disjunction rules are often used in conjunction with other decision rules.

One essential goal of recommender systems (RS) is to understand consumption patterns. In the fruitful literature of RS, almost all models are implementations of the compensatory decision rules, i.e. they assume that the probability of a consumption is calculated by a weighted combination of item performances over several hidden aspects [?, ?]. To the best of our knowledge, there is no model that is based on non-compensatory decision making rules.

However, many researches in the field of consumer psychology revealed that users use both compensatory and non-compensatory rules [?]. The selection of decision rules is affected by many factors. For example, a survey [?] pointed out that when the consumer is familiar with the product and the product is low in complexity,

he is most likely to establish a set of evaluative criteria and adopt conjunction rules.

Our first contribution in this work is a novel probabilistic model that represents the cognitive process of consumers following non-compensatory rules. The problem being tackled here is to predict what item the consumer will buy in an activity session (i.e. a click sequence on an e-commerce website). We assume that an item is purchased because (1) it is superior on the aspect which is currently of the most pertinence to the consumer, and (2) it surpasses a minimum level of acceptable performance on other aspects.

A further problem is that an activity session is a behavior sequence. The order of activities could be the result of random error, advertising exposures, or an intentional effort. Decision rules per se can not explain how the order of activities will affect the consumption choice.

According to study of consumer behavior [?], consumers are with limited memory and attention. Our hypothesis in this paper is that a consumer's working memory is only capable of dealing with a limited number of alternatives. In an active session, the consumer will proceed with a series of alternative evaluations in his working memory. Once an evaluation is completed, the main message (i.e. which item is best within this bunch of alternatives) is retained in long-term memory, and the alternative portforlios (i.e. the details of items) are discarded.

Our second contribution in this work is to address the challenge by introducing the concept of evaluation process. Our hypothesis is that in an active session, the consumer will proceed with a series of alternative evaluations. The non-compensatory rules are employed for each alternative evaluation. Once an evaluation is completed, the main message is retained.

The main message of an evaluation is described by ordinal utility. In modern economics, ordinal utility theory is typically applied to study consumer behavior [?]. Suppose there are two items to evaluate, the message to be persist is which item is better, but it is meaningless to keep in mind how much better it is. We present several heuristics to simulate the strategy based on ordinal messages of several evaluations.

This paper is structured as follows. In section 2 we describe the model based on non-compensatory decision rules. In section 3 we discuss the evaluation process based on working memory. In section 4 we analyze our experimental results. In section ?? we briefly review the related work. In section 5 we present the conclusion and outlook of future work.

2 PURCHASE MODEL UNDER NON-COMPENSATORY RULES

Suppose we have the item universe $V = \{v\}$, the user universe $U = \{u\}$, input data $D = \{d\}$ consists of a set of activity sessions. For now, we consider each activity session as a set of activities on items, $d = \{(v, n_v)\}$, where n_v is the number of activities on item v. In each activity session, at least one item will be purchased, thus

d can be divided to two disjoint sets of items, $d = W^d \bigcup L^d$, where W^d is the set of purchases (winners), $L^d = d - W^d$ is the set of remaining items (losers). For example, if we are dealing with user activity sessions on an E-commerce website, W^d will be the set of purchased items, L^d will be the set of clicked but not purchased items, and n is the number of clicks on v.

As with most factor models, we imagine that there are K underlying aspects. Without ambiguity, we use the same notion u, v to denote user preferences and item features. $u, v \in \mathcal{R}^K$. We use subscripts to denote the elements in each vector, i.e. the preference value of user u on the $k-$th aspect is u_k.

The consumer u starts an activity session d with a motivation, which is most pertinent to aspect k. From a probabilistic perspective, we denote the most pertinent aspect by a $1 - of - K$ coding scheme, $g \in \mathcal{R}^K, g_k = 1, \forall k' \neq k, g_{k'} = 0,$. The generation of g is dependent on user preference, $g \sim Mult(u)$. Then the user will follow non-compensatory rules to select the purchased items. The probability of an activity session is denoted by the probability of generating all pairs of winners and losers in the session $p(d|\Theta, g) = \Pi_{w \in W^d, l \in L^d} p(< w, l > |\Theta, g)$, where Θ is other model parameters. Next we introduce the definition of $p(w|d, \Theta, g)$.

According to non-compensatory rules, we have the following two assumptions.

(1) The winner (purchased item) is superior on the most pertinent aspect k (2) The winner is not too bad on other aspects, compared with the losers (remaining items that are viewed but not purchased).

Our model is inspired by the extended BTL model [?] in social science. In the extended BTL model, a ranking $i > j$ is likely to happen if the latent utility score i is relevantly larger than j, $p(i > j) = \frac{i}{i+\theta j}$.

The parameter $\theta > 1$ plays as a tolerance threshold. If the absolute difference between the i and j is not significant $|i - j| \leq \theta$, the user will consider it to be a tie $i = j$, $p(i = j) = \frac{(\theta^2-1)ij}{[i+\theta j][\theta i+j]}$. Note that $p(i > j) + p(i < j) + p(i = j) = 1$.

The usage of parameter θ can be interpreted as the consumer sets a minimally acceptable level of performance, which is controlled by both θ and how well another item j performs, i's performance must be at least better than this cutoff point. Therefore the probability of the winner w being selected in the activity session d is defined as the product of the probability that w outranks other losing items l on the most pertinent aspect $p(i_k > j_k)$ and the probability that w at least tie with other items on other aspects $p(i_{k'} \leq j_{k'})$:
$p(< w, l > |g, \theta, V) = \Pi_{k=1}^K [\frac{w_k}{w_k+\theta v_k}^{g_k} \frac{\theta w_k}{v_k+\theta w_k}^{1-g_k}]$.

Thus we present the likelihood of purchase model under Non-Compensatory Rules (NCR) as follows.

$$p(D|\Theta) = \Pi_{d \in D} \Sigma_g \{\Pi_{w \in W^d, v \in L^d} p(< w, l > |g, \theta, V) p(g|u)\} \quad (1)$$

The model parameters are denoted as $\Theta = \{\theta, v \in V, u \in U)\}$. The inference is implemented by computing a minorization function of the expectation $Q(\Theta) = E_g \ln p(D, G|\Theta)$ in an EM algorithm. For the limited space, we skip the derivation here and present the inference steps.

In the E-step of $t-$th EM round we compute $\gamma(d, k, \Theta^t) = p(g_k = 1|d, \Theta^t)$ according to Equ. 2.

$$\gamma(d, k, \Theta^t) = \frac{u_k \Pi_{w \in W^d, v \in L^d} \frac{w_k}{w_k+\theta^t v_k} \Pi_{k' \neq k} \frac{\theta^t w_{k'}}{v_{k'}+\theta^t w_{k'}}}{\Sigma_{k=1}^K u_k \Pi_{w \in W^d, v \in L^d} \frac{w_k}{w_k+\theta^t v_k} \Pi_{k' \neq k} \frac{\theta^t w_{k'}}{v_{k'}+\theta^t w_{k'}}} \quad (2)$$

In the M-step, we update user preferences u, item features v and minimal level of accepted performance θ by Equ. 3.

$$u_k = \frac{\Sigma_{u(d)=u} \gamma(d, k, \Theta^t)}{\Sigma_{s=1}^K \Sigma_{u(d)=u} \gamma(d, s, \Theta^t)} \quad (3)$$

$$\frac{1}{v_k} = \frac{\Sigma_{d \in W(v)} \Sigma_{v' \in L_d} [\frac{\gamma(d,k,\Theta^t)}{\alpha(v,v',k,\Theta^t)} + \Sigma_{k' \neq k} \frac{\theta^t \gamma(d,k',\Theta^t)}{\alpha(v',v,k,\Theta^t)}]}{\Sigma_{d \in W(v)}|L_d|}$$

$$+ \frac{\Sigma_{d \in L(v)} \Sigma_{v' \in W_d} [\frac{\theta^t \gamma(d,k,\Theta^t)}{\alpha(v',v,k,\Theta^t)} + \Sigma_{k' \neq k} \frac{\gamma(d,k',\Theta^t)}{\alpha(v,v',k,\Theta^t)}]}{\Sigma_{d \in W(v)}|L_d|}$$

$$\theta = \frac{(K-1)\Sigma_d |W_d||L_d|}{\Sigma_d \Sigma_k \gamma(d,k,\Theta^t) \Sigma_{w,v} [\frac{v_k}{\alpha(w,v,k,\Theta^t)} + \Sigma_{k' \neq k} \frac{w_{k'}}{\alpha(v,w,k',\Theta^t)}]}$$

One may argue that number of clicks n_v matters. Intuitively, if a consumer constantly reviews his options, it means that the winner is more appealing and attracts more attentions. Therefore we present two variants of the NCR model: NCR-M and NCR-S.

In NCR-M, we construct $n_w \times n_l$ pairs of winners and losers, and compute the likelihood as in Equ. 4. As $p(< w, l >) \leq 1$, this modification exaggerates the gap between w and l for w with multiple occurrences.

$$p(D|\Theta) = \Pi_{d \in D} \Sigma_g \{\Pi_{w \in W^d, v \in L^d} p(< w, l > |g, \theta, V)^{n_w \times n_l} p(g|u)\} \quad (4)$$

In NCR-S, the likelihood function is Equ. ??, but we modify the winner's probability by multiplying a sigmoid function $s(n_v) = \frac{1}{1+\exp n_v}$, as shown in Equ. ??. Since $s(n_v)$ is monotonic, the more a winner appears, the larger the item feature v should be to generate the observations.

$$p(< w, l > |g, \theta, V) = \Pi_{k=1}^K [\frac{s(n_w)w_k}{s(n_w)w_k + \theta s(n_v)v_k}^{g_k} \frac{\theta s(n_w)w_k}{s(n_v)v_k + \theta s(n_w)w_k}^{1-g_k}] \quad (5)$$

3 PREDICTION STRATEGY

Given the input training data available as described in Section 2, our problem is that for a new activity sequence (i.e. click sequence) $\tilde{d}$, where $\tilde{d}[i]$ is the item at the i-th position of sequence $\tilde{d}$, output a ranking list of most possible purchases. This means that we should assign a numerical value for each item $score(v)$.

Our basic strategy will be treating the activity sequence as a set of items, and directly apply the NCR model to score each item. The first step is to estimate the most possible aspect that the user in this session iis interested on, given the current browsing history $\tilde{d}$. We have

$$p(g_k = 1|\tilde{d}, V) = \frac{\Sigma_{v \in \tilde{d}} v_k}{\Sigma_k \Sigma_{v \in \tilde{d}} v_k} \quad (6)$$

And the possibility of an object being selected is $score(v) = \Pi_{l \in \tilde{d}} p(<v, l> | g, \Theta >)$

We present another type of strategy which is based on sequential evaluations. As discussed in Sec. **??**, our hypothesis is that the consumer conducts a series of alternative evaluations. The evaluation process starts when there are at least two alternatives, and ends at the last item of activity sequence. The evaluation process yields a evaluation sequence, each of which is the result by applying the basic strategy on the current alternatives. For example, as in Fig.'3, for a click sequence (a, b, c, d, e, e), the consumer conducts 5 evaluations on $(a, b), (a, b, c), (a, b, c, d), (a, b, c, d, e)$ and (a, b, c, d, e, e) separately. if the consumer adopts a non-compensatory rule as in model NCR with $\theta = 0.05$, for comparison (a, b), since b is not superior on the pertinent aspect, $score(b) > score(a)$. For comparison (a, b, c, d), d is below the cutoff point on the secondary aspect , so $score(c) > score(a) > score(d) > score(b)$.

Item	Pertinent Aspect	Secondary Aspect
a	0.6	0.4
b	0.4	0.6
c	0.64	0.36
d	0.78	0.22
e	0.65	0.35

Figure 1: A toy example of prediction strategy.

We presume that only the ordinal message of evaluations is kept, i.e. the consumer will only remember which item is the best at each evaluation instead of the exact value of scores. The ordinal message will be $o = (a, c, c, e, e)$. Then the consumer collects the information over all evaluations and scores each item based on how often it is determined to be best. Thus $score(v) = \frac{|\{o[t]=v\}|}{|o|}$. This simple heuristic has one major drawback: there could be multiple items with the same scores. We present three heuristic strategies.

(1) Addictive: In this strategy, Items with equivalent values are re-ordered in timestamp ascending order. In Fig.'3, under the addictive strategy, the output will be c, e, a, b, d. This strategy favors items that perform good and arrive first.

(2) Frequency: This strategy differs with addictive strategy in that, items with equivalent scores will be ranked by their frequencies in $\tilde{d}$. In Fig.'3, under the frequency strategy, the prediction is e, c, a, b, d.

(3) Span: Suppose $l(v) = \max\{i | \tilde{d}[i] = v\}$ is the item's last occurrence and $t(v) = \min\{i | \tilde{d}[i] = v\}$ is the item's first occurrence in the activity session, its total time-span is defined as $s(v) = l(v) - t(v) + 1$. Intuitively an item with large span indicates the consumer is impressive. In Fig.'3, under the span strategy, the prediction is e, c, a, b, d.

4 EXPERIMENT

4.1 Experimental setup

We evaluate our framework over a real data set, the YOOCHOOSE data set [**?**]. The data set is a collection of user activity sessions for a large European e-commerce website over six months. Each activity session consists of a sequence of click event, each click event includes time stamp, item ID, and item category. There are 9,512,786 unique sessions from anonymous users.

In the YOOCHOOSE data set, each activity session might contain any number of purchases (if any). In preprocessing, we filter out sessions without any purchase, and split the remaining records according to the number of purchases. For example, D1 is the set of records with 1 purchase, D6 is the set of records with at least 6 purchases. In each segmentation, we randomly sample about 2800 training records, and about 700 training records without cold-start items. The reported results are averaged over 10 sample sets for each segmentation.

Each session is considered to be the footprint of a new user. θ?

The evaluation metrics are Precision and MRR. Precision is the fraction of correct prediction (purchase) in the top n items of the resulting list, where n is the total number of purchases in the test session. . The mean reciprocal rank (MRR) is the average of the reciprocal ranks of first correct prediction on each test session.

4.2 Decision Rules

Our first goal is to study the performance of different decision rules. We use the following comparative methods. (1) BPR [**?**] is a Bayesian model for optimizing rankings among explicit positive feedbacks and implicit feedbacks . We set the purchased items as positive explicit feedback, and clicked but not purchased items as implicit feedbacks. (2) MF [**?**] is now the most commonly adopted recommendation framework which approximates the ratings of each item. We assign a value 1 to purchased items, and 0.5 to clicked but not purchased items. (3) Linear Regression model is capable of recovering numeric values given a set of features. We assign a value 1 to purchased items, and 0.5 to clicked but not purchased items. (4)GBDT is the gradient boosting decision tree utilized in [**?**] which treats the consumption prediction problem as a binary classification problem. (5) Logistic Regression is yet another classifier which outputs class probabilities. The resulting list is obtained by ranking items based on the probability of being positive. The features for linear regression models, GBDT and logistic regression are extracted ....

From Tab. 1, we have the following observations. (1) MF and BPR can be viewed as implementations of compensatory rules. In all data segments, non-compensatory rules outperform compensatory rules. This shows the massive potential of modeling non-compensatory rules in recommendation systems. (2) Regression and classification models perform better than compensatory rules, as they use global information such as ICR. However, our models are comparable to regression models on D1, and superior on other data segments. (3) Among the three variants, NCR-M is dominating in most data segments. NCR-S performs better than NCR. It verifies our assumption that multiple clicks indicate less convincing item performance. (4) Our model is more suitable for activity sessions with more than 1 purchases. One potential reason is that sessions with only one purchase tend to be shorter, thus the lack of training instances hurt the model performance.

4.3 Evaluation Strategy

Our next goal is to study the performance of prediction strategy. We couple the three strategies with three model variants and report

Table 1: Comparative Performance of Decision Rules

Dataset	Performance	Compensatory rules		Non-compensatory rules			Others		
		BPR	MF	NCR	NCR-M	NCR-S	LinearRegression	GBDT	LogisticRegression
D1	Precision			0.5717	0.6038	0.6354	0.6333	0.6423	**0.67**
	MRR			0.7697	0.7887	0.8046	0.8051	0.812	**0.8244**
D2	Precision			0.6669	**0.7583**	0.7371	0.6785	0.6878	0.6934
	MRR			0.8139	**0.8661**	0.8545	0.8549	0.8597	0.8640
D3	Precision			0.6719	**0.7147**	0.7061	0.6941	0.7079	0.7042
	MRR			0.8383	**0.8869**	0.8721	0.8705	0.8779	0.8788
D4	Precision			0.7014	**0.7360**	0.7284	0.7188	0.7232	0.723
	MRR			0.8581	**0.9044**	0.8889	0.8852	0.8892	0.8904
D5	Precision			0.7192	**0.7522**	0.7461	0.7367	0.7423	0.7402
	MRR			0.8642	**0.9185**	0.90246	0.9039	0.9065	0.9067
D6	Precision			0.7261	**0.7569**	0.7506	0.7454	0.7512	0.7515
	MRR			0.8823	**0.9221**	0.9088	0.9053	0.9072	0.9072

precision at Tab. 2. We can see that (1) the prediction strategies significantly boost the prediction precision, compared with the results in Tab. 1. In general, the frequency strategy is best for most model variants and data segments, again suggesting that multiple views have strong correlation with purchase probability. (2) An optimal combination is model NCR-M or NCR-S with the frequency strategy.

Our final question is to testify the effect of ordinal utility. We compute the average score of each item in each evaluation, and use this cardinal utility as the foundation of three heuristic strategies. We report the performance of cardinal utility based strategy in conjunction with model NCR-M, and compare them with ordinal utility based strategy ensemble with NCR-M. As shown in Tab. 3, cardinal utility does not improve model performance in term of precision. In fact the precisions of all models are reduced for all data segments.

5 CONCLUSION

Table 2: Precision of prediction strategies on model variants

Dataset	Addictive			Frequency			Span		
	NCR	NCR-M	NCR-S	NCR	NCR-M	NCR-S	NCR	NCR-M	NCR-S
D1	0.5804	0.5988	0.6325	0.6648	0.6768	0.6883	0.5728	0.5999	0.6329
D2	0.7176	0.7585	0.7525	0.7570	0.7767	0.7727	0.6952	0.7590	0.7517
D3	0.7697	0.8148	0.8034	0.7837	0.8035	0.7982	0.7503	0.8024	0.7972
D4	0.7969	0.8347	0.8246	0.8138	0.8278	0.8232	0.7845	0.8328	0.8263
D5	0.8083	0.8583	0.8485	0.8265	0.8523	0.8452	0.7934	0.8424	0.8364
D6	0.8277	0.8650	0.8525	0.8452	0.8575	0.8544	0.8196	0.8558	0.8506

Table 3: Comparative performance of cardinal and ordinal utilities

Dataset	Cardinal Utility			Ordinal Utility		
	Addictive	Frequency	Span	Addictive	Frequency	Span
D1	0.5435	0.5614	0.5997	0.6325	0.6883	0.6329
D2	0.6783	0.7379	0.7369	0.7525	0.7727	0.7517
D3	0.7329	0.7980	0.7865	0.8034	0.7982	0.7972
D4	0.7635	0.8272	0.8116	0.8246	0.8232	0.8263
D5	0.7760	0.8512	0.8308	0.8485	0.8452	0.8364
D6	0.8035	0.8649	0.8474	0.8525	0.8544	0.8506