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Development of Recommendation System Based on Ai Techniques to Exchange Items Between Users

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ABSTRACT

Online bartering is becoming more and more commonplace as the Internet becomes more accessible. There are numerous parallels between recommending deals on an online bartering platform and conventional techniques to recommending products, including the requirement to model user preferences and product features. Bartering difficulties are intriguing and hard for various reasons, including the statement that users are providers and consumers, as well as the dynamic nature of the trading environment. Bartering needs us to understand more than simply the preferences of users, but also the dynamics of who trades with whom and at what time. We provide three new datasets from online bartering platforms to suggest new models for bartering-based recommendations. Existing solutions function poorly on real-world platforms because they depend on idealistic assumptions that are not supported by actual barter data. A Matrix Factorization-based technique is used to simulate the reciprocal interest that users have in each other's things. Social and temporal relationships between members also have a significant impact, thus we expand our model to include these aspects. Our strategy is tested on a variety of markets, including book, video game, and beer transactions, and we see positive results compared to other strategies.

Keywords : Matrix Factorization-Based Technique, Online Bartering Platform Conventional Techniques

I. INTRODUCTION

A. Overview

This may be understood as a conflict in between the self-interest of its members and the greater good of society as a whole in large-scale dispersed ecosystems Mechanisms that give incentives and encourage cooperation are often required to control the participants' conduct to minimize the possibly unfavorable availability consequences that may follow from individual activities. Economics has a long and varied history of ways to encourage collaboration. Bartering incentive patterns provide an ideal basis for a simple and resilient kind of trade for re-allocating resources in this thesis. Bartering is one of the oldest forms of commerce in the world, yet it still amazes us in many ways. The barter system's success and long-term viability make it a good model to analyze.

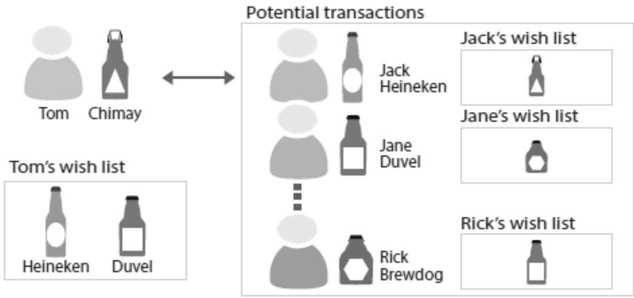


Fig. 1: Trade items with Barter System

B. Background Of Barter System

In Jackson Hole, Wyoming, in August 2000, the world's economic leaders convened for an annual policy summit. The chiefs of the central banks of Japan, Britain, and some other nations were in attendance, including Alan Greenspan.

"Mervyn King, Deputy Governor of the Bank of England," was one of the guests who reflected on the influence of internet commerce and the future of money.

There is no reason why items and services cannot be exchanged directly by consumers and suppliers via a system of direct exchange–effectively a huge barter economy, as he concluded, as cited below. Only a common account and sufficient computational capacity are needed to ensure that all transactions may be completed instantly.

- Payments would be made electronically between individuals, bypassing any intermediary that we could identify as a bank.
- Central banks and money as we know them would vanish.
- Barter is defined in a standard dictionary as the exchange of items or services without the use of cash.

C. Big Barter Networks

The following are a few instances of amazing deals:

"Fujitsu laser printers were exchanged for 1.7 million units of military ready-to-eat (RTE) meals, which were then sold to relief groups for urgent use in the hurricane-ravaged states of Florida and Hawaii. Due to conflicts in the Persian Gulf, there was no need for the RTEs."

"An arrangement signed by PepsiCo, Inc. in April 1990 was the biggest trade transaction between a U.S. firm and the former Soviet Union, bringing in more than $3 billion in total retail sales for the two countries."

To establish hundreds of bottling operations and "Pizza Hut" locations in the "Coalition of Independent States," PepsiCo will be able to utilize foreign currency credits from vodka sales.

In exchange for practically nothing, the Lexington Hotel in New York City received a cutting-edge computer system.

Computers were purchased in 1991 by a barter business in return for more than $300,000 in "hotel room credits" that the firm could use or, with the hotel's consent, sell or trade for other products or services.

Bartering extra office space for products and services is another new trend.

Advertisement time, hotel rooms, and office equipment are just a few of the items that SGD and ICON3 exchange for spare space.

The fabled purchase of an island by "Peter Minuit" in 1626, in which he traded 60 gold pieces worth of trade items for an island known as Manhattan, is an example of the power of barter.

D. Introduction To The Ideal Model

The economy is believed to have been barter-based from its start [1]. The introduction of money as a means of trade and a unit of measurement facilitated the valuation of assets and shaped current economic practices. Barter has re-emerged in the lives of 21st-century consumers as a result of extensive digital communication [2]. Economic models have been resurrected based on the premise that things may be extended to service numerous owners, or that users can get access to obscure or difficult-to-obtain items. Swapping CDs, DVDs, books, and other media may be done on a variety of platforms, including swapacd.com, swapadvd.com, readitswapit.co.uk, and bookmooch.com[3].

E. Scenarios Of The Bartering Approach

A long and diverse history of economic incentives for cooperation. In this thesis, bartering incentive patterns give a simple and robust way to re-allocate resources. The earliest method of business, bartering, still impresses us. Barter's success and longevity make it a valuable model to study. Throughout this thesis, we have specified three relevant situations in which the bartering approach may be used. Let's start with a well-known bartering arrangement:

- An Internet directory service application is used to demonstrate how a bartering–based technique might be used.
- We explain how agents, utilizing bartering, may acquire benefits in commodities without altruistic agents having to be present.
- In a bartering environment, we show the cost of dealing with selfish agents, as well as the impact on performance indicators like topology and disclosed information.

II. LITERATURE REVIEW

A. Priority work on the Best Barter Exchange Strategies, Begin as Early as Possible

The kidney exchange dilemma [4, 5] sparked early work on exchange market algorithm design [6]. For patients with incompatible live donors, algorithms have been devised to identify cross-matched patient-donor combinations in the regional transplant pool. By employing The Top Trading Cycles and Chains mechanism, Roth et al. [7] have addressed the issue Haddawy et al. [8] addresses the issue of identifying a balanced match between buyers and sellers in the setting of barter trade exchanges, which is an important study. There is an intermediary in charge of managing the transactions, and the parties are matched according to their supply and demand information and their credit in terms of a private-labeled currency. On a network, a least-cost circulation issue is modeled. And last but not least, the work of Mathieu [9] attempts to solve the challenge of locating bartering rings in an online marketplace by using weighted trees to compare the similarity of search and offer queries.

B. Circular Exchange Of A Single Item (Csem)

A bartering network's exchange cycles are more complex than the kidney exchange dilemma. Users in a standard exchange market have numerous products to give away and perhaps multiple incoming items, rather than receiving and giving one item (a kidney). A directed network with nodes representing users and edges tagged with item IDs is used by Abassi et al. [10]. It is up to the users to decide what they want to buy and what they want to give away. Potential transactions may be seen in this graph by looking for directed cycles.

C. The Binary Value Exchange Model (Bvem)

"Su et al. [3] address the item exchange issue for "cycles of length two, which is a distinct approach (i.e., swaps). Competitive online situations such as online games with a heavy real-time updating schedule may benefit from the system. For this reason, the value to be optimized is the sum of all possible gains for each of the users. Many recommender systems use Matrix Factorization (MF). The low-rank approximation is used to estimate user preferences that are not seen in the user settings and the item set [11]. MF guesses these preferences using a sparse interaction n matrix R R|U||I|. An item's compatibility with a user is determined by the dot product of the user's interaction with the item and the low-dimensional space in which the user and the item are placed. To address social interactions and temporal dynamics, we mostly draw upon existing theories that extend the MF to integrate social regularisation [12] and "temporal dynamics in recommender system" (RS) recommendations [13].

D. The Bayesian Language (BPR)

Rendle and co-authors [14] have developed an optimization process called Bayesian personalized ranking that directly optimizes a ranking measure. [15] (AUC). Implicit feedback is readily handled by this method since it simply analyses interactions that are 'positive' between the user and the object, while not distinguishing between observations that are negative or absent. Users prefer products they have seen over those they haven't, and this intuition is crucial. Matrix Factorization or "Adaptive k-Nearest-Neighbors" may be used in combination with this pairwise optimization strategy.

III. THE PROPOSED MODEL

A. Notations

Table 1 is showing notation used in the thesis:

Table 1.1: Notation Used in Thesis

Notation	Description
R	Interaction matrix $\in \mathbb{R}^{\lvert U\rvert \times \lvert I\rvert}$
I	Item set
U	User set
u_j	User $u_j \in U$
i_k	Item $i_k \in I$
$r_{u_j i_k}$	Entry in R (for user u_j and item i_k)
W_j	Wish list of user u_j
G_j	Give-away list of user u_j
H_j^g	History of given item for user u_j
H_j^r	History of received item for user u_j
$\hat{y}_{u_j i_k}$	Predicted preference of user u_j for item i_k
$\mathbb{1}$	Heaviside step function

B. Application of the system

In the beginning, restrict deals to friends since successful bartering takes expertise and practise. It's simple to overvalue the object you want and undervalue your own. On the plus side, bartering has several benefits. Bartering does not need money. Bartering also allows for flexibility. For example, portable tablets may be swapped for laptops. For example, lawn mowers may be swapped for TVs. Homes may now be traded for trips, saving both parties money. The buddies may swap their house for a week or so, in return for your parents letting them stay at your home while on a family vacation. Another benefit of negotiating is that no tangible objects are exchanged. Instead, trade a service for an object. To get a skateboard, for example, you may offer to mend your friend's bicycle in return for the skateboard. Bartering allows two people to receive what they desire from each other without spending money [18]. On the technological side, the effort brings together findings from the following fields:

- Grid, peer–to–peer, and other distributed systems
- Agent-Based Simulation
- Complexity and Markets
- Economic Models
- Market Dynamics
- Scalability and performance issues
- Novel applications
- Dynamics of economic Networks
- Self–Organization/Adaptation of Multi-Agent Systems
- Cooperation, Competition, and Autonomy

C. Motivation

"Social and artificial societies" both rely on trade as a fundamental economic principle. The exchange theory covers a wide range of topics:

- Sociology assumes that all social life may be understood as a kind of transaction between agents.
- Exchanges between people and those who have political power are referred to as "politics."
- The exchange of commodities and services is the basis of economics

D. Aim, Purpose, and Objective

The three sections of the thesis all have the same goal:

- It's possible to create a distributed directory service that relies on barter.
- A bartering phenomenon: a series of bargaining agreements that transform a paperclip into a home.
- Resource distribution between self-interested, rational, and autonomous individuals in a bartering framework Because of the following reasons, these sections have a high degree of complexity:

- The theoretical framework and system creation and evaluation are used to study the numerous hopes on bartering.
- The environment's collection of conflicting traits and entities (such as its popularity and its lack of resources)
- Finding a way to go from low-value objects to high-value ones in dynamic and selfish environments.
- With the barter principle in mind, the design of content distribution algorithms is severely limited. Dealing with selfish actors rather than cooperative ones results in efficiency losses, and the means to trade, in our case a bartering technique, is the price to pay [16].

IV. PROPOSED METHODOLOGY

A. Data Analysis

To test our technique, we first performed an empirical investigation by gathering the following datasets:

- **Swap** is a CD exchange platform
- **/r/gameswap** is a self-organized subreddit made forusers to exchange video games.
- **Bookmooch** is a book exchange platform.
- **ReaditSwapit** is a book exchange platform.
- **Swapadvd** is a DVD exchange platform.
- **Ratebeer** is a beer exchange platform.

The rightmost column displays the proportion of people who, based on their public listings, have at least one trade opportunity. There are limited trade partners available to users on most sites. Table 2 provides some basic information about the datasets. Our primary emphasis is on datasets 4, 5, and 6 since they all include transaction histories.

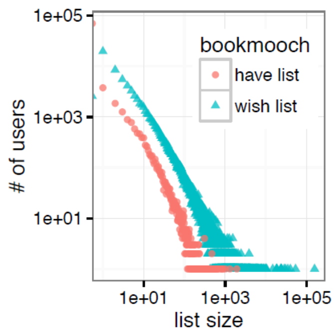
Table 2: Statistics for Some Platform

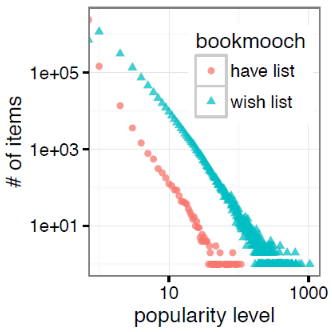
Platform	user count	item count	transaction count	% of users w/ at least one swapping partner
Bookmooch	84,989	2,098,699	148,755	0.2%
Ratebeer	2,215	35,815	125,665	65.9%
/r/gameswap	9,888	3,470	2,008	-
Swapacd	4,516	244,893	-	0.5%
Swapadvd	7,562	91,241	-	0%
ReaditSwapit	33,151	94,399	-	4.2%

B. The Datasets

For example, in Fig. 3.2, you can see how the size of users' wish lists and give-aways, as well as the popularity of each item in terms of how many users possess it and the number of users that want it, are distributed across users (right column). According to these numbers, there are 'power users' [17] on the sites, since they seem to roughly follow power laws. Swapadvd Read and Swapacd

Table 2 shows that even with vast user bases like Bookmooch, there is a scarcity of exchanging partners. However, Ratebeer is an exception to the rule, which may be explained by the itSwapit, which yields comparable findings but was deleted for the sake of saving space.





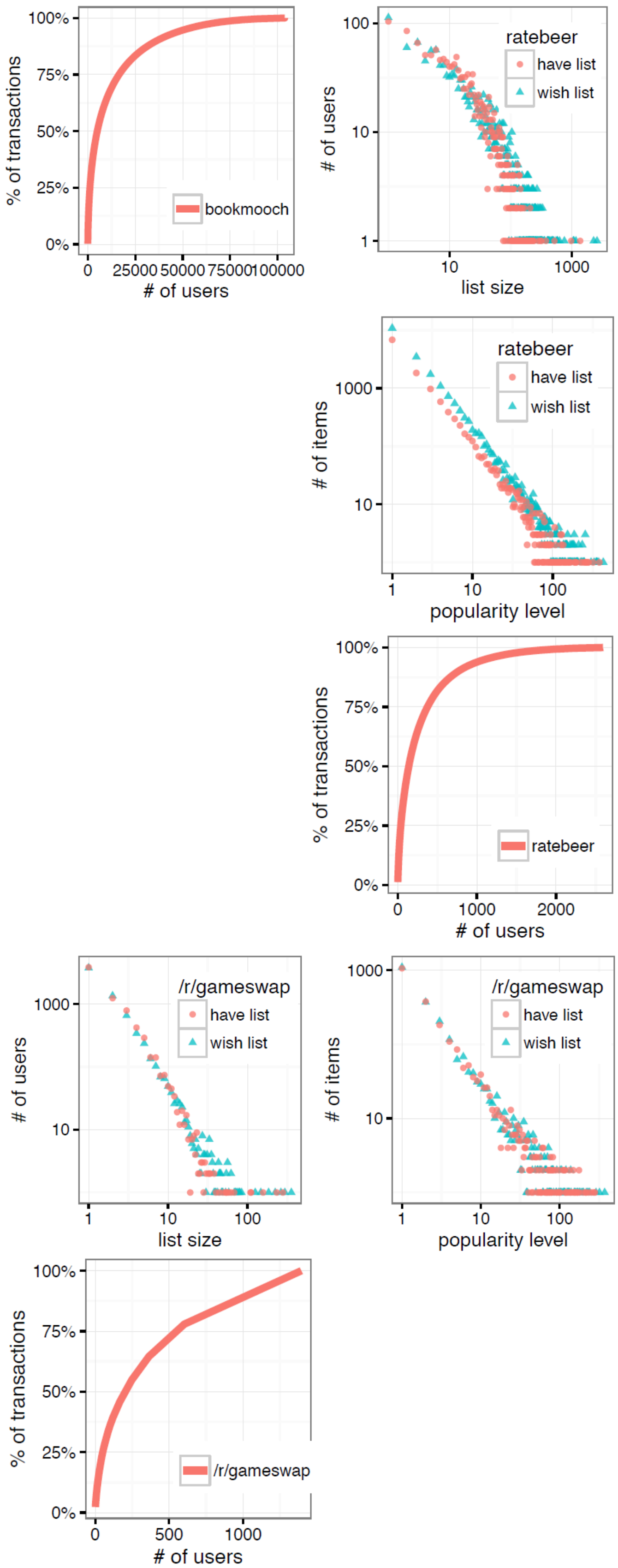


Fig. 2: When it comes to item list lengths and popularity, a power-law distribution holds across the three platforms under consideration. "(top: Bookmooch; middle: Ratebeer; bottom: /r/gameswap)."

Using the CDF plots on the right, we can see how many swap operations each user does. Power users dominate all three platforms, as seen by the high volume of transactions.

C. Few Eligible Swapping Partner Pairs

If both users want goods on the other's giveaway list, they might be trading partners. Table 2 summarises the proportion of users with at least one qualified switching partner for the snapshots of the swapping sites analyzed. /r/gameswap does not appear in the chart because the threads' organization prevented us from obtaining a precise snapshot of all users' haves and 'wants' at a given moment.

Uj's preferences may have changed after they posted their item lists at time t, but it is incorrect to presume that they haven't changed since uk posted their item lists at time D. (rendering the lists stale, they may have exchanged items). Hence, only those users who were active in the thread when the snapshot was taken may be included in the snapshot at t + d.

Table 2 shows that even with big user bases, such as Bookmooch's, the lack of appropriate exchanging partners is an issue. For Ratebeer, there is an exception to the norm, which may be because the platform is many years older and has a worldwide user base.

BVEM [20] and CSEM [19] do not perform well on this data, producing too few (or no) suggestions per user due to the aforementioned scarcity. These algorithms match people entirely based on the content of give-away lists and desire lists. Despite this, as we'll see in the examples below, numerous exchanges occur between people who aren't necessarily eligible?

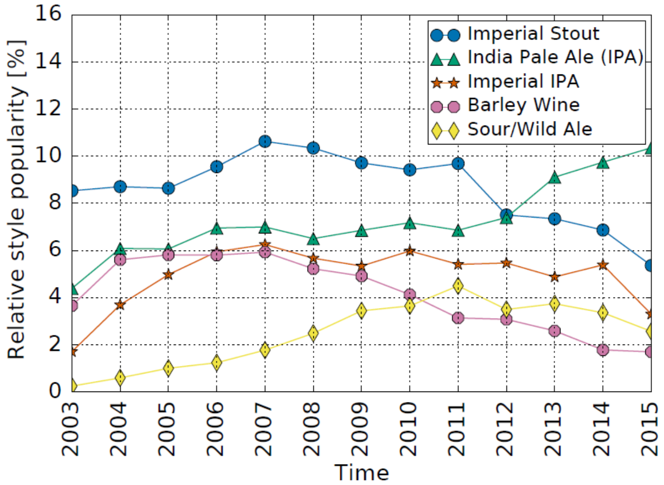


Fig. 3 shows the rise and fall in popularity of the world's most popular beers throughout time (using the Ratebeer dataset).

D. Wish Lists Don't include all of the Preferences that People Have

Bookmooch provides weekly database snapshots, allowing users to see how many of the books they get when trading on the site was already on their want lists. We were able to arrive at an average percentage of 33.2% per user using Bookmooch's snapshots. There is a clear connection between this and the requirement for a recommender that can deduce a user's inclinations toward products that they aren't aware of (or didn't expressly indicate in their wish list) and instead find by chance. This is an important problem that hasn't been addressed before.

E. Trades with the Same Person may be done Several Times

An observation we make regarding transaction events supports our intuition that successful trading pairings are likely to trade again. Bookmooch, Ratebeer, and /r/gameswap are the three most popular places for people to exchange with one another. Social relationships may have a significant influence in deciding the trading partner of a user, and successful trading partners are more likely to trade again in the future, based on this research.

F. Transaction Volume and Time-Dependent Popularity

A bartering platform's dynamic ecosystem is vulnerable to temporal trends. Figure 3 shows how the popularity of beer genres changes over time, as assessed by the number of times they are traded. For example, by 2013, IPAs have overtaken Imperial Stouts as the most popular beer style, although Imperial Stouts had been the most popular before that time.

Another sort of time-dependent behavior is seen in Fig. 3. In each transaction, there is either a focus on the object itself (bottom plot) or the person who is transacting the item (top plot). The Y-value is determined by the number of days that have transpired since the last transaction by the specific user. On the other hand, goods and people with less frequent contact are represented in less active ways in Fig. 3.3.

Fig. 3.3 is showing the cumulative frequency plot of the Bookmooch transactions. However, it is important to keep in mind that although a small group of strong users (i.e., t 100) performs numerous transactions each day, most other things are exchanged less often.

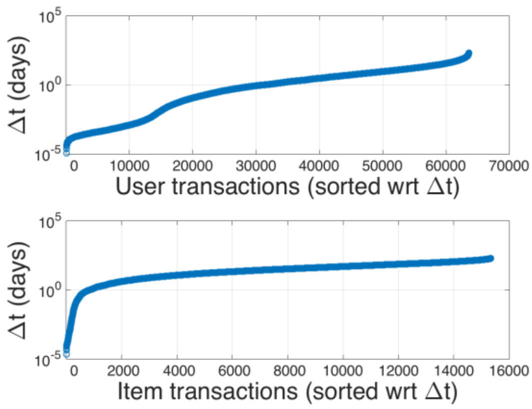


Fig. 3: Shows the cumulative frequency plot of the Bookmooch transactions.

G. Prior Work Limitations

The primary drawbacks of the previously stated techniques are due to the limitations they impose on their implementation. Because the "Circular Single-Item Exchange Model (CSEM)" [10] mandates that a user and their item be suggested to just one other user at a time, this limits the likelihood that an item will be transferred. A limitation like this would make it much more difficult to find swapping partners, as a user's suggestion of an item would be contingent on whether or not the item had previously been suggested to another person. Ideally, a product should be suggested to as many people as possible who may be interested in purchasing it. However, the BVEM, which more properly simulates the trade recommendation issue, needs an assumption that the item list length is limited to a certain amount for it to be tractable (say, less than 50).

Table 3: No of BVEM suggestions for different settings of the price "matching parameter" Each suggestion is addressed to two separate people.

	$\beta = 0.6$	$\beta = 0.7$	$\beta = 0.8$	$\beta = 0.9$
Total recommendations	113	111	110	110
Distinct users	155	152	150	150

The primary disadvantage of both prior techniques is that they examine only stated user preferences, which are far from full. Neither CSEM [18] nor BVEM [19] make advantage of implicit preference information contained in users' transaction histories, but instead offer suggestions based purely on the things expressly included in a user's wish list.

To substantiate the latter point, we evaluated the performance of BVEM [3] on the Bookmooch dataset, which is the only one that has the requisite item price information. The number of suggestions generated using this technique is shown in Table 3 for a dataset of 84,989 users, based on a September 2015 snapshot. Due to the rarity of 'wants' that coincide, only a few people (a maximum of 155) get suggestions under BVEM (see Table 2). We noticed that 3,864 different users acquired books through trades in the four months after the September snapshot, a substantially greater amount than the number of users who received recommendations. To make matters worse, BVEM's recommendations on Swapadvd would be nonexistent owing to a lack of eligible switching partners, therefore the system's total number of proposals is very low (a maximum of 113).

H. Proposed Methodology

Once the fundamental principles are established, the following step is to transform this generic model into a concrete one. Then, using the overall model as a guide, the sorts of concerns to examine in such bartering worlds included the following:

- What is the cost of the difference between bilateral and Pareto optimum allocation? (i.e. the reduction in allocation efficiency, and is there a reduction?)
- What is the "cost of dealing with selfish agents" vs. "altruistic agents" in dispersed environments?
- What circumstances must exist in a market for a decision-maker to convert a non–value item into a valuable one?
- How many decision-makers following a similar pattern can accomplish this goal?
- Can bartering be used in a real-world scenario? Is it beneficial?
- How does the distribution of requests influence the stability of the knowledge obtained via bartering and, if so, in what manner?

I. Conceptualisation

The following summarises the technique of agent-based computational economics [19]:

- The researcher then creates a fictitious economic universe comprised of groupings of actors.
- Conduct an initial investigation to ascertain the nature of the issue to be resolved.
- The modeler then allows the world to grow naturally without additional interference from outside.
- The modeler establishes the world's beginning circumstances, such as the world's trade laws, the agents' characteristics, and the learning model, which serve as the experiment's preconditions.
- The researcher analyses and tries to interpret the data collected using economic principles or

makes policy recommendations to influence future actions.

V. MODEL AND SIMULATION

A. Model

Three new online bartering datasets are provided to assist our new "bartering-based recommendation algorithms." Existing solutions are not supported by real-world platforms since they are built on idealistic notions. User mutual interest in each other's goods is represented via Matrix Factorization. So now our model is temporally aware and socially taking into consideration members' social connections and trading periods. Compared to previous ways, ours works better for video games, novels, and alcohol. Refer to the notation is described the Table 3.1.

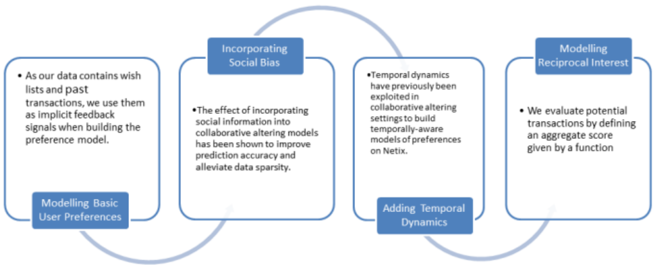


Fig. 4.1: A Proposed Model

B. Problem Definition and Notation

"The setting of the bartering platforms presently considered is described by a set of users $U = \{u_1, u_2, \dots u_m\}$, and a set of items $I = \{i_1, i_2, \dots i_n\}$ known at any time t. Each user uj has a wish list Wj and a give-away list Gj , both of which are available for all members to see. Wj is a subset of I containing items which uj wishes to obtain, while Gj is a subset of I with items to be given away by uj."

C. Modeling Basic User Preferences

Our model's initial objective is to assess a user's preference for a single item. Due to the presence of wish lists and previous transactions in our data, we utilize them as "implicit feedback signals" [20] while developing the preference model. According to Hu et al[21] .'s technique, the "user-item interaction" matrix R is constructed as follows using implicit feedback signals:

$$r_{u_j i_k} = \begin{cases} 1, & \text{if } i_k \in W_j, \text{ or } (*, i_k) \in H_j^r \\ 0, & \text{otherwise} \end{cases}$$

D. Adding Temporal Dynamics

User preferences may change over time or vary regularly. Time-dependent dynamics have already been utilized in collaborative filtering contexts, for example, to construct temporally aware preference models on the networked information system Netix. Taking into consideration the available data, we extend our model from Equation 2 to account for the temporal dynamics of bartering platforms.

E. Incorporating Social Bias

It has been shown that adding social data into collaborative changing models improves prediction accuracy and alleviates data scarcity. As noted the users prefer to trade with a specific subset of peers regularly on "the observed bartering platforms," indicating that their selections are heavily influenced by social (or simply trust) factors. Additionally, this demonstrates that a simple low-rank decomposition of the interaction matrix R is incapable of completely capturing the dynamism of user behavior.

F. Experiments And Discussion

Because our input data contains implicit preference signals, the performance of our approaches should be geared towards appropriately rating items relative to one another, rather than successfully predicting missing values from the interaction matrix R. Rendle et al. [17] developed the BPR optimization approach specifically for this sort of optimization issue. The update rules for this setting are specified as follows, using the notation used by Rendle et al. [17]:

$$\theta \leftarrow \theta + \alpha \cdot (\sigma(-\hat{x}_{u_j i_k i_m}) \frac{\partial \hat{x}_{u_j i_k i_m}}{\partial \theta} + \lambda_\theta \Omega'(\theta)),$$

where an is the Heaviside function and b is "the Heaviside function." Negative user-item combinations (uj, in) are selected at random from an unobserved interaction set for user uj. This statistic indicates how effectively the model classifies goods that the user got via withholding transactions during training vs objects with which the user has not engaged or does not have an explicit desire.

To minimize verbose notation, we have written the AUC above in terms of our "simplest preference model" (yuj im). The preceding statement, however, may be altered to incorporate any of the previously specified models.

Table 4: AUC values for our technique (larger values are better)

Dataset	(1) MF	(2) MF+B	(3) MF+B+S	(4) MF+B+T	(5) MF+B+S+T	(6) B impr.	(7) B+S impr.	(8) B+T impr.	(9) Total impr.
Bookmooch	0.758	0.798	0.849	0.938	**0.958**	+2.0%	+9.15%	+18.06%	+19.98%
/r/gameswap	0.790	0.842	0.863	0.890	**0.903**	+5.19%	+7.31%	+9.99%	+11.29%
Ratebeer	0.824	0.892	0.962	0.969	**0.983**	+6.79%	+13.84%	+14.55%	+15.87%

The best technique for each dataset is boldfaced. MF stands for Matrix Factorization, B for Bidirectional Model, S for Social Bias, and T for Temporal Dynamics.

Users choice processes may be impacted by external variables, such as social relationships and item availability. In such a case, the success of a transaction cannot be completely described by a low-rank decomposition that represents unilateral preferences of users toward products. Bidirectionality (MF+B) greatly enhances the score over MF and leads to comparable gains in conjunction with the other models.

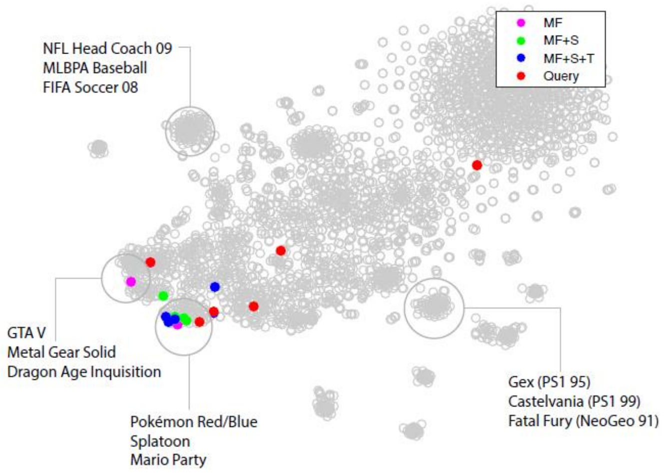


Fig. 4: t-SNE [28] embedding of the /r/gameswap dataset's latent variables. The colored dots in Table 5 represent the projection of suggestions.

The implications of this are that a strong signal created by one of the traders may be able to compensate for a weak signal generated by random sampling performed on the fly. Following that, the hyperparameters are kept constant throughout the testing phase, during which a new train/test split is drawn in the same way at the conclusion of each round. After that, the process is repeated. Table 4.2 summarises the outcomes from five rounds. We discovered that the optimum models for /r/gameswap and Ratebeer have 40-dimensional latent variables while Bookmooch has 100-dimensional latent factors.

G. Results

Table 4 illustrates the performance of our approach's numerous implementations. Our technique outperforms 'standard' matrix factorization by an average of 15.71 percent across the three datasets we examine. Each model addition (temporal dynamics, social bias, and bidirectionality) significantly improves our method's performance, delivering cumulative performance improvements of 4.66 percent, 5.44 percent, and 5.61 percent, respectively (respectively). On all three datasets, the AUC of "the final model (MF+B+S+T)" is more than 0.9. Table 4: An illustration of the suggestions generated by the models in Table 4.1

User's wish list	MF			MF + S			MF + S + T		
	Recommendations (ranked)	#own	most recent activity	Recommendations (ranked)	owner activity	past trans.	Recommendations (ranked)	owner activity	past trans.
Super Mario World									
Sonic Generation									
Kirby's Dream Land	Sonic Generations	19	56 wks.	Kid Icarus	24 wks.	2	Fire Emblem	<1 wk.	0
Metroid: Zero Mission	Earthbound	14	22 wks.	Final Fantasy	24 wks.	2	Contra	<1 wk.	0
Super Mario 64	Super Mario Sunshine	26	22 wks.	Beyond: Two Souls	24 wks.	2	Monster Hunter	<1 wk.	1
Mario Kart: Super Circuit	Grand Theft Auto V	253	<1 wk.	Fire Emblem	92 wks.	1	Bayonetta 2	<1 wk.	1
Sly 3: Honor Among Thieves	Fire Emblem	28	<1 wk.	Paper Mario	92 wks.	1	Mario Kart 7	<1 wk.	1

VI. DISCUSSION

Our method does not limit proposed trades to things on users' wish lists, which is consistent with our finding that only 33.2 percent of products received by users are explicitly mentioned. Our technique, which uses Matrix Factorization to capture user preferences, may predict users' interests in items they haven't explicitly expressed an interest in, allowing for potentially serendipitous suggestions. A user's wish list, with most of the goods being Nintendo console games. Recommendations are the correct word. Fig. 3.6 shows that all approaches successfully identify games that are connected. When social terms (MF+S) are added, the system suggests trades with previous trading partners, but many of them have been inactive for some time; when the temporal term (MF+S+T) is added, the system finally identifies relevant games amongst active users, some of whom were prior trading partners.

VII. CONCLUSIONS AND FUTURE WORK

The goal of this thesis has been to examine how bartering mechanisms might be used to allocate resources in “large-scale distributed networks” without the presence of altruistic actors. In addition to the chapter-by-chapter summaries, we’ve compiled a comprehensive table of contents for this thesis. A common thread running across all of the research reported in this thesis is a desire to better understand how selfish, rational, and autonomous individuals with partial knowledge interact with one another to maximize their anticipated utility via bartering. A theoretical scenario, a use case, and a real-world application have been the focus of our research. Bartering in electronic contexts may be evaluated using any one of these case studies. However, each situation has distinct characteristics that make it stand out. In the future, we want to test our technique in a variety of situations where reciprocal interest plays a significant role, such as e-dating platforms, online video game partner matchups, etc. It’s also our goal to investigate the issue of trading things that have big price discrepancies and to investigate more complicated preference aggregation systems for simulating the bidirectionality of interest between possible trade partners.

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