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A comparison of recommender systems for crowdfunding projects

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“The question of whether computers can think
is like the question of whether submarines can swim.”
— EDSGER W. DIJKSTRA

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS AND ACRONYMS

RS	Recommender System
CBF	Content-based filtering
CF	Collaborative filtering

CONTENTS

1 INTRODUCTION

1.1 About Catarse

Launched in January 2011, Catarse was the first crowdfunding platform for creative projects in Brazil. With over 7000 successfully financed projects raising R$77m from 480.000 people, it's currently the largest national platform of its kind. It works similarly to most crowdfunding platforms: the project owner presents his or her idea and specifies the required investment as well as the cutoff date for the project, while offering rewards for those who back it. Projects are divided into 3 main categories: all-or-nothing, flexible and recurrent. In the first type, projects are available for backing up to 60 days and the project owner only receives the raised amount if the project's goal is met, otherwise all the money is returned to its original backers. On flexible projects, the owner receives the raised amount whether the goal is reached or not. Recurrent projects are subscription based and the owner can collect the money monthly.

1.2 Motivation

As of April 2018, over 1500 projects in 18 categories are online and available for backing. It would be unreasonable to expect users to browse through all projects before deciding which ones to back, as such some sort of ranking is fundamental when showing projects to users, and there is no doubt that the choice of this ranking will greatly affect conversion rates and successful funding of projects. At the time of writing, several ranking strategies are in use. Firstly, on the home page projects are shown ordered by popularity, defined simply by the pledged amount in the last 48 hours. Another section shows projects backed by Facebook friends, for those users who opted to connect their Facebook account. Finally, on the explore page, we also have filters for projects expiring soon. It should be noted that none of these sections, with the exception of backed by friends section, are tailored for each specific user: every user will see the same projects in the same order.

Given the above, project recommendation can be considered a crucial aspect of Catarse's business model. We can expect any marginal improvement in this regard to be of great benefit to the company and its users. As such, a user-tailored recommendation system is expected to greatly increase user satisfaction and is fundamental to stay competitive in this market.

2 THEORETICAL BACKGROUND

In this chapter the main concepts behind Recommender Systems will be reviewed. We will study the most common approaches used in the industry today, and give a detailed comparison of their general characteristics, as well as provide insights relevant to our particular case. For each approach, we give descriptions of the most used algorithms along with state-of-the-art techniques that were used in this work.

2.1 Recommender Systems

Since time immemorial, people have relied on recommendations from many sources to base their decisions on, be it spoken word, magazines, travel guides and so forth. The decision to buy a new book, for example, is often based on the opinions of a close group of friends; employers count on recommendation letters for recruiting; and when selecting a movie to watch, people rely on movie critics they have read. Recommender systems aim to augment this social process in order to assist people in sifting through an ever growing list of movies, books and all sorts of items. RSs are widely used in the industry today to provide useful suggestions to end-users in a completely automated manner. They are ubiquitous in modern e-commerce Web sites (SCHAFER; KONSTAN; RIEDL, 2001), where new products can be recommended based on a customer's interests and preferences, and in many other fields such as movies (Netflix) and music (Spotify). Its importance can't be overstated: the effectiveness of targeted recommendations, as measured by click-through and conversion rates, far exceed those of untargeted content (LINDEN; SMITH; YORK, 2003). By customizing recommendations for each user, search effort is greatly reduced, leading to greater customer loyalty, higher sales and advertising revenues, and better targeted promotions (ANSARI; ESSEGAIER; KOHLI, 2000).

The basic idea behind any recommender system is to obtain a utility function to estimate a user preferences towards an item. The meaning of this function will differ for each context; it could mean how likely a user will want to watch a specific movie or listen to a song, or the likelihood of buying a particular product. In our case, the goal is to find projects the customer is most likely to back given his backing history and other characteristics.

Recommender systems can be broadly divided into two categories: content-based methods and collaborative filtering methods (RAKESH; LEE; REDDY, 2016). The former utilizes the content features of users or items in order to recommend items to users. In collaborative filtering methods, user ratings are used in order to calculate similarities between users or items, which are then ranked to show the most relevant recommendations. These two methods are sometimes combined into what is known as Hybrid Recommender Systems.

2.1.1 Collaborative filtering

Collaborative filtering is based on the principle that similar users will share similar interests. In the traditional approach, each customer is represented by a N-dimensional vector of items, where N stands for the number of available items, and each vector component corresponds to the user rating of the item. These ratings can be obtained explicitly - e.g. star rating or "likes" - or implicitly - e.g. a user buying an item or listening to a song can be considered a positive rating. By collecting ratings from each user, we build a R_{nxm} matrix which is the starting point for CF. For most applications, R will be extremely sparse, our job then is to try to predict the missing ratings.

CF algorithms can be further divided into Memory-Based and Model-Based approaches. Memory-Based algorithms use a dataset of user-item pairs to identify groups of similar users, which are in turn used to make predictions of preference for new items. In Model-Based methods, machine learning algorithms are used to develop a model that will be used to predict user ratings. These methods can solve some of the shortcomings of Memory-Based approaches, such as the need for large rating matrices. Finally, both approaches can be combined into Hybrid Recommenders. A overview of these techniques is depicted in figure 2.1.

2.1.1.1 Neighbourhood methods

Neighborhood methods take rows or columns of R and compute a similarity value between them. If the rows correspond to users and the columns to items, we can obtain the similarity between two users u and v by computing the correlation between $R(u)$ and $R(v)$. In the same fashion, similarity between items i and j can be computed by taking $R^T(i)$ and $R^T(j)$.

For User-Based CF, given users u and v one common method to compute similarity is the cosine measure given by:

$$sim(u,v) = \cos(u,v) = \frac{u \cdot v}{||u|| \cdot ||v||} = \frac{\sum_{i \in I_{uv}} r_{ui} r_{vi}}{\sqrt{\sum_{i \in I_u} r_{ui}^2} \sqrt{\sum_{i \in I_v} r_{vi}^2}}$$

where I_u and I_v are the sets of items rated by user u and v respectively and $I_{uv} = I_u \cap I_v$. To get a rating prediction $\check{r}_{ui}$ given by the user u to item i, we aggregate ratings from the subset of users most similar to u. One such function could be:

$$\check{r}_{ui} = n \sum_{u' \in U'} sim(u,u') r_{u'i}$$

where n is a normalizing factor.

2.1.1.2 Item-Based CF

Item-Based CF works almost exactly the same as User-Based CF. One important distinction is that item-based CF retrieves recommendations directly from the similarity matrix and does not require R to be kept in memory. A major reason for the adoption of this approach is that in most systems users are much more numerous than items, leading to a significantly reduced similarity matrix when using item-based CF (SARWAR et al., 2001). We can redefine our cosine measure for this case like so: let U_i and U_j be the set of users who rated items i and j respectively, and $U_{ij} = U_i \cap U_j$ be the set of users who rated both items i and j, the similarity is then given by:

$$sim(i,j) = \cos(i,j) = \frac{i \cdot j}{||i|| \cdot ||j||} = \frac{\sum_{u \in U_{ij}} r_{ui} r_{uj}}{\sqrt{\sum_{u \in U_i} r_{ui}^2} \sqrt{\sum_{u \in U_j} r_{uj}^2}}$$

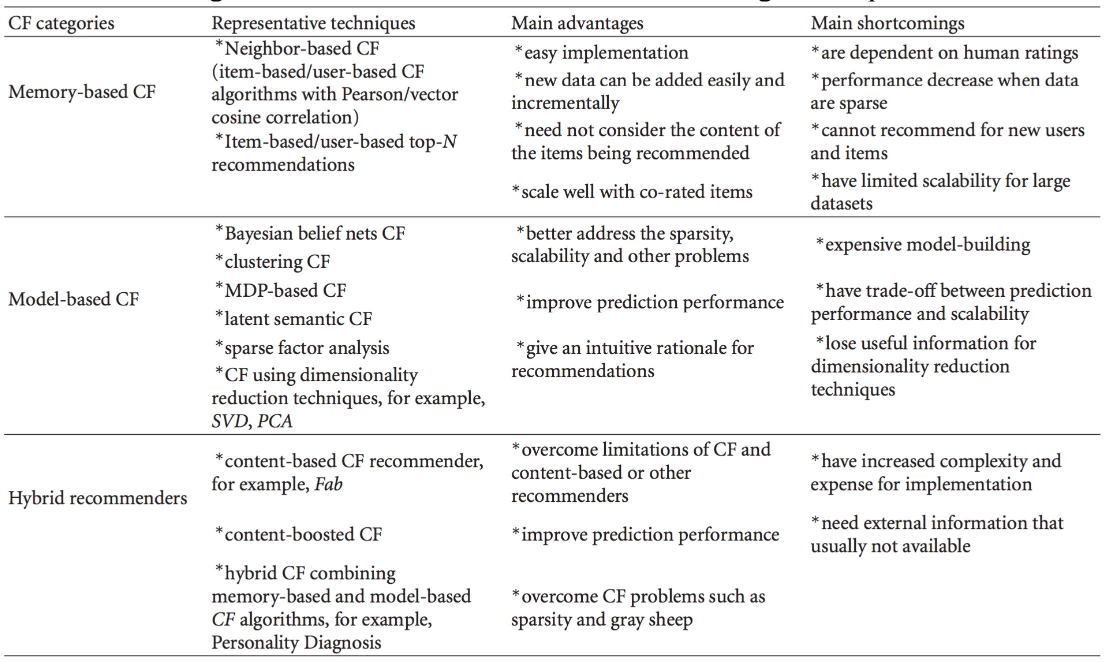
Similarly, we define our rating prediction for item-based CF, considering J to be the set of items j most similar to i, as:

$$\check{r}_{ui} = \frac{\sum_{j \in J} sim(i,j) r_{uj}}{\sum_{j \in J} sim(i,j)}$$

2.1.1.3 Item-to-Item CF

For large databases, CF can be prohibitively computationally expensive. Its worst case performance is $O(MN)$ where M is the number of customers and N is the number of items (LINDEN; SMITH; YORK, 2003), although this problem can be generally alle-

Figure 2.1: Overview of collaborative filtering techniques.



CF categories	Representative techniques	Main advantages	Main shortcomings
Memory-based CF	*Neighbor-based CF (item-based/user-based CF algorithms with Pearson/vector cosine correlation) *Item-based/user-based top-*N* recommendations	*easy implementation *new data can be added easily and incrementally *need not consider the content of the items being recommended *scale well with co-rated items	*are dependent on human ratings *performance decrease when data are sparse *cannot recommend for new users and items *have limited scalability for large datasets
Model-based CF	*Bayesian belief nets CF *clustering CF *MDP-based CF *latent semantic CF *sparse factor analysis *CF using dimensionality reduction techniques, for example, *SVD, PCA*	*better address the sparsity, scalability and other problems *improve prediction performance *give an intuitive rationale for recommendations	*expensive model-building *have trade-off between prediction performance and scalability *lose useful information for dimensionality reduction techniques
Hybrid recommenders	*content-based CF recommender, for example, *Fab* *content-boosted CF *hybrid CF combining memory-based and model-based *CF* algorithms, for example, Personality Diagnosis	*overcome limitations of CF and content-based or other recommenders *improve prediction performance *overcome CF problems such as sparsity and gray sheep	*have increased complexity and expense for implementation *need external information that usually not available

Source: (SU; KHOSHGOFTAAR, 2009)

viated due to the customer vector sparsity. Item-to-item CF is another method proposed by Amazon that tries to minimize these scaling issues by focusing on item instead of user similarity. Each item purchased by the customer is compared to other items in the dataset in order to calculate a similarity metric. The algorithm is shown bellow:

```
for each item in product catalog, I1 do
    for each customer C who purchased I1 do
        for item I2 purchased by customer C do
            Record that a customer purchased I1 and I2;
        end
    end
    for each item I2 do
        Compute the similarity between I1 and I2;
    end
end
```

Algorithm 1: Item-to-item CF

In either case, for this to work large amounts of user data is required. This is known as the cold start problem: new users who haven't rated many items yet will have a reduced recommendation quality. On the other hand, no information about the item itself is needed, making CF specially applicable to collections of hard-to-analyze items such as movies.

2.1.2 Content-based filtering

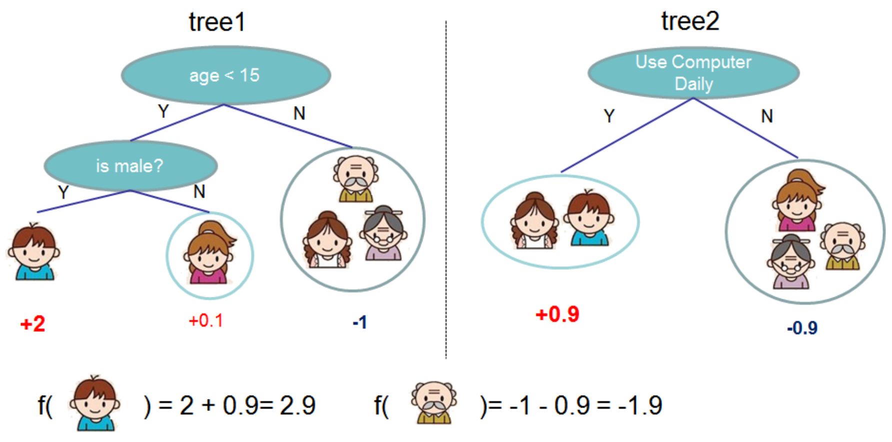
In this approach a description of each item is constructed using structured data or some sort of item presentation algorithm such as Latent Dirichlet Allocation (LDA) or TF-IDF. This representation is then compared to the user profile and the best-matching items are recommended. The user profile can consist of many different types of information: a history of the user's interaction with the system such as page views, searches and purchases is often used to train the model without any explicit user input. Some systems may require the user to explicitly state his interests, however it may be very hard to get users to make this effort, rendering this approach very limited in practice.

As CBF focus on item rather than user similarity, it avoids the cold start problem since little information about user preference is needed. However, since only similar items to those already rated by the user will be considered, CBF strategies tend to suffer from over-specialization (IAQUINTA et al., 2008). This is known as the serendipity problem. Another limitation of CBF algorithms is that items are required to contain enough information in order to distinguish items the user likes from items the user doesn't like. For example, a dataset of songs where only the song name is available would not be enough to make good predictions based on this content only, however this would pose no problem for collaborative filtering methods which rely solely on user similarity.

2.1.2.1 Gradient boosting trees

In recent years, tree boosting has become a increasingly popular method and been shown to give state-of-the-art results for many classification problems (LI,). As in any supervised learning method, our objective is to train a model to predict a target variable y_i given features x_i. Boosting methods are characterized by combining many weak learners into a strong one in a iterative fashion. In this case, our model is an ensemble of trees, more specifically a set of classification and regression trees (CART). Unlike decision trees, where the leafs contain decision values, the leafs on gradient boosting trees contain a score $s \in R$. Multiple simple trees are then constructed and the prediction of each tree is summed up to get the final score 2.2. Our model can then be defined as

Figure 2.2: GbTree example



Source: XGBoost official site

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i), f_k \in \mathcal{F}$$

where K is the number of trees, f is a function in the functional space $\mathcal{F}$, and $\mathcal{F}$ is the set of all possible CARTs (CHEN; GUESTRIN, 2016). Our objective function can the be written as

$$obj(\theta) = \sum_{i}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$$

2.1.2.2 Objective function

Our objective function is used to measure the performance of our model for each set of parameters. We define it as the sum of the training loss function L with the regularization term Ω.

$$obj(\theta) = L(\theta) + \Omega(\theta)$$

In this work we define our loss function as the logistic loss function for logistic regression:

$$L(\theta) = \sum_{i} [y_i \ln(1 + e^{-\hat{y}_i}) + (1 - y_i) \ln(1 + e^{\hat{y}_i})]$$

And our regularization function is defined as follows:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2$$

where w is the vector of scores on leaves and T is the number of leaves.

After defining our objective function, we optimize it in order to train our model.

3 EXPERIMENTAL METHODOLOGY

This chapter describes how we prepared the training data used in our experiment. Later we discuss possible evaluation metrics that are commonly used in recommender systems, listing its main benefits and shortcomings.

3.1 Data preparation

The dataset D was obtained directly from Catarse's production database. Each training example consists of a project-backer pair (p, b) with 12 dimensions presented below:

- *category count*: Number of projects backed by the user b in the same category as project p
- *mode count*: Number of projects backed by the user b with the same mode (aon, flex or sub) as project p
- *same state*: True if the project location is the same as the backer's
- *recommended*: True if project p was manually recommended by an admin
- *has video*: True if the project has uploaded a video
- *budget*: Budget text length in chars
- *description*: Description text length in chars
- *pledged*: Amount pledged in the first 3 days
- *contributions*: Amount of contributions in the first 3 days
- *progress*: Percentage of goal reached in the first 3 days
- *owner projects*: Amount of projects from the same project owner as p
- *reward count*: Number of offered rewards in project p

In order to trim irrelevant data, we remove canceled and draft projects as well as projects with no backers from the dataset. The final cardinality of D was 300000. For the sake of balancing our dataset, we create 300000 more negative instances by randomly combining users with projects they haven't backed. To further emphasize project quality, only successful projects are considered for the positive instances, while only failed projects are used for the negative instances. Finally, due to changes in the platform that occurred in 2015, we ignore data from earlier periods so as to maintain a consistent dataset.

3.2 Evaluation Metrics

There are basically 3 ways RSs can be evaluated: offline, online and empirically. Offline measures are those computed based on a given dataset, generally through techniques such as split validation and cross validation. In these techniques, a subset of the data is withheld to be later used for testing; metrics are then computed for the test set only. According to Herlocker et al. (HERLOCKER et al., 2004), offline metrics can be broadly classified into the following categories: predictive accuracy metrics, such as Mean Absolute Error (MAE) and its variations; classification accuracy metrics, such as precision, recall and F1-measure; rank accuracy metrics, such as Pearson's product-moment correlation, and normalized distance-based performance metric (NDPM). For the sake of completeness, we will provide some of these metrics for each implemented algorithm, however it should be noted that offline metrics are not a good indicator as to how well a RS will actually perform, and trying to optimize for them may actually degrade real-life performance (MCNEE; RIEDL; KONSTAN, 2006). To illustrate this point, lets think about a recommender system for movies. Suppose user Bob likes movies A, B and C. We split our dataset in such a way that movies A and B will be in the train set, while movie C is on the test set. Any kind of offline metric will test in a way or another if movie C was recommended to user Bob, resulting in a higher score if it is recommended and a lower score if other, unrelated movies, are recommended. The problem is that an algorithm that recommends movies D or E could actually be much better than one that recommends movie C, a fact that no offline metric could account for. This can be fundamentally attributed to the fact that, unlike most classification problems, recommender systems work with extremely sparse matrices; this sort of validation strategy would only be valid if we knew the ratings given by the user for every item beforehand. As this is seldom the case in real-life systems, other evaluation strategies are required.

Much more meaningful metrics can be obtained by online evaluation. While much more expensive and time-consuming to perform than offline measurements, live metrics are capable of testing directly whether the RS is achieving its intended purpose. The most common measures are the Click-Through Rate (CTR) and Conversion Rate (CR). CTR is defined as the ratio of users who click on a specific link to the number of users who viewed the page. In our case, if a set of N recommendations is displayed X times, we define CTR as the number of times a user clicked on at least one of the recommended items in N divided by X. For the CR, we require that not only the user click on a specific recommendation, but also back the project. To compare two different RSs in an online setting, the most prominent approach today is A/B-testing. For our experiment, a recommendation algorithm was randomly selected for each user and click-through and conversion rates were measured. This was done for 2 weeks on a live production environment with more than 20 thousand unique visitors per day.

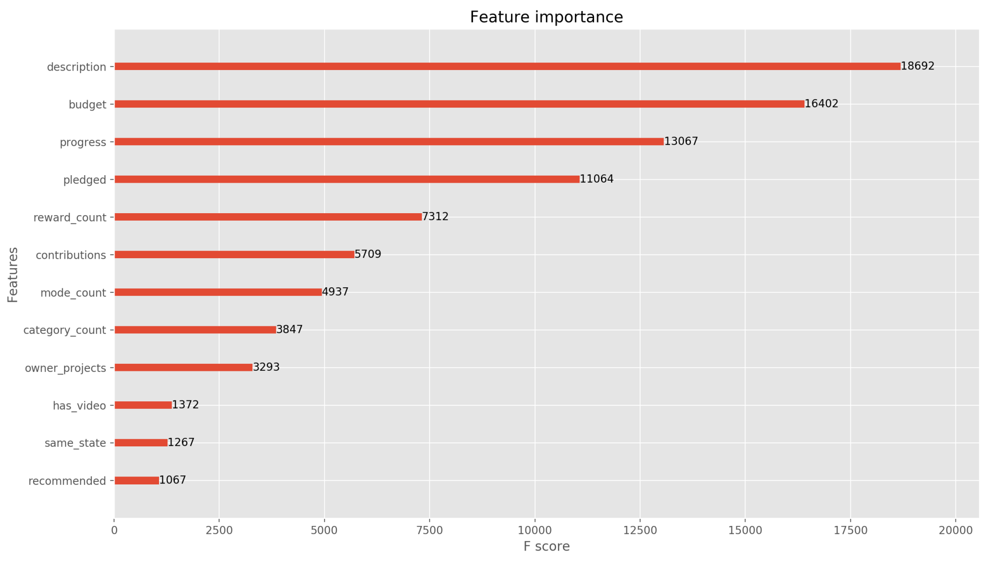
Finally, empirical evaluation - having a person actually look at the results - is equally important in any business setting. Consider a news portal that implemented a RS for its front page news. The RS might start recommending articles about cute cats, which might very well provide higher click-through rates than its more serious articles. This however is probably not what the company had in mind, and such a change in content might hurt the company's reputation in the long run. It is thus paramount to perform sanity checks on recommendation results manually.

The Recall@N metric evaluates whether a item the user has rated in the past is in the top N recommendations from a random set of projects. It works as follows: a set of 100 random projects is augmented with a project the user has interacted previously, we then measure if the interacted project is present in the top N recommendations. For this work, we measure the Recall@5 and Recall@10 for each proposed algorithm.

3.3 Recommending projects

Catarse's dataset is unique in a variety of ways that makes collaborative filtering techniques hard to apply. Firstly, unlike regular e-commerce Web sites such as Amazon where products stay available for many years, crowdfunding projects have a predetermined cutoff date, after which it's no longer possible to make a pledge. It makes no sense to recommend expired projects, limiting our possible recommendations to online projects only. Another challenge is the fact that the majority of Catarse's users only back one project, making it hard to get enough data for CF methods to work properly. Another characteristic of CF systems is that they must be retrained for every new interaction, imposing scalability challenges when implemented on highly dynamic data. Our best choice is then to use content-based methods, this allows us to train our model with the whole dataset to extract backer-project features, and later use this model to search for online projects with the highest backing probability for the current user.

Figure 3.1: Feature weights in gbtree



4 IMPLEMENTATION

The XGBoost python library was used to create our gradient boosting tree model. Hyperparameters were tuned by running 10-fold cross validation while optimizing for negative log-likelihood. No data standardization or normalization was necessary since the base learners are trees.

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