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A comparison of recommender systems for crowdfunding projects

Work presented in partial fulfillment
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“The question of whether computers can think
is like the question of whether submarines can swim.”
— EDSGER W. DIJKSTRA

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LIST OF ABBREVIATIONS AND ACRONYMS

RS Recommender System

CBF Content-based filtering

CF Collaborative filtering

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1 INTRODUCTION

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 recommendation problem can be formulated in a number of ways. Aggarwal et al. (AGGARWAL, 2016) gives the following main models:

- *Prediction version of problem*: In this approach we try to predict the rating value for a user-item combination. The training data is given by an incomplete R_{MxN} matrix, where M is the number of users and N the number of items. The observed values, which indicates user preferences for items, are used to train a model which will try to fill in the missing or unobserved ratings in the matrix. Since we have an incompletely specified matrix of values, this problem is sometimes referred to as the *matrix completion problem*.
- *Ranking version of problem*: For many applications it is not necessary to obtain absolute values for the predicted ratings. Instead, we are more interested in obtaining the top-k items to recommend to a user, or the top-k users to promote a particular item. Both methods are exactly analogous, with the former being much more common in practice. This problem is often referred to as the *top-k recommendation problem*.

The first formulation of the problem is more general, since it is possible to derive the second one by predicting ratings for every item and then ranking the predictions. However, in many cases it is easier and more practical to solve the ranking problem directly.

Along with the definition of the problem, it is important to define the desired operational and technical characteristics of recommender systems. The main goals of any recommendation algorithm are as follows:

- *Relevance*: The main goal in recommender systems is to provide recommendations that are relevant to the user at hand. Users are much more likely to consume items which they find interesting and are tailored for them.
- *Novelty*: Users are much more engaged when confronting items they haven't seen in the past. Recommending the same items over and over, however good the recommendations may be, is not a good strategy.
- *Serendipity*: Serendipity in recommender systems happens when recommendations are somewhat surprising or unexpected to the user, as opposed to obvious recommendations. It differs from the concept of Novelty in that it doesn't simply recommend items the user didn't know about before, but allows the user to discover entirely new areas of interest. For example, recommending a new spicy Mexican restaurant to someone who regularly visits Mexican restaurants may be novel, but it is not surprising at all. Recommending a Thai restaurant instead might allow the user to discover a whole new interest, increasing sales diversity and user satisfaction.
- *Diversity*: Recommender systems usually suggest a list of top-k items to the user. If all the recommended items are similar, there is an increased chance that the user won't like any of the items. On the other hand, if we show diversified items there is a higher change that the user will like at least one of them.

The sort of items recommended by such systems can vary tremendously. Apart from the most well known examples such as Amazon, which recommends products, and Netflix with movies, RSs are also used to recommend social connections in platforms such as Facebook, as well as news in news aggregators like Google News. Table 1.1 shows a list of recommender systems used in real-world applications. Some of these systems will be discussed in further details in the next chapter.

Table 1.1: Example of recommended products by various real-world applications

System	*Product*
Amazon.com	Books and other products
Netflix	DVDs, Streaming Video
Jester	Jokes
GroupLens	News
MovieLens	Movies
last.fm	Music
Google News	News
Google Search	Advertisements
Facebook	Friends, Advertisements
Pandora	Music
YouTube	Online videos
Tripadvisor	Travel products
IMDb	Movies

Source: (AGGARWAL, 2016)

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 different categories are online and available for backing in Catarse. 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. Therefore, a user-tailored recommendation system is expected to greatly increase user satisfaction and is fundamental to stay competitive in this market.

1.3 Goals

This work aims to implement and compare the main strategies used in RSs in the context of a large-scale Crowdfunding website. Several metrics will be used to determine the best approach, which will then be used in production. Our primary goal is to find a strategy that is at least better than the current popularity ranking, which is usually hard to beat in realistic scenarios.

2 RELATED WORK

2.1 GroupLens Recommender System

One of the first recommender systems to be developed, Grouplens was used for recommendations of Usenet news. It worked by collecting ratings from many Usenet readers in order to recommend new articles to users, a technique now known as Collaborative Filtering. This approach was later extended to other settings such as books and movies, referred to as Booklens and Movielens respectively. One important contribution of this research was the release of several data sets of user ratings to the community, which were not easily available at the time. One of these data sets, Movielens, is still widely used in RS research to this day.

2.2 Netflix Recommender System

Netflix recommendations are obtained through user ratings on a 5-point scale as well as implicit ratings, such as the action of watching a movie. One interesting aspect of their system is in the quality of explanations provided to the recommendations. For instance, a list of recommendations can be pinpointed to having watched a specific movie. This approach can help users in deciding what to watch and improve customer loyalty and retention.

The Netflix Prize contest was a competition organized by Netflix that ran from 2006 to 2009. Contestants were given a data set of existing user ratings and were expected to outperform Netflix's own recommendation algorithm, Cinematch. This contest was responsible for many notable contributions to recommendations research, such as latent factor models.

2.3 Kickstarter Recommender System

Kickstarter initial implementation of its recommender system used a Collaborative Filtering approach, written entirely in MySQL. Later, Content-Based recommendations based on the similarity of the text was used, computed by Latent Semantic Indexing (LSI). Both these approaches were later combined into the current Hybrid system. For the initial

tests, the popular projects ranking was used as a baseline for comparing new algorithms.

3 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.

3.1 Recommender Systems

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, such as relevant keywords, 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. It is important to notice that Content-Based models also use the ratings matrix in most cases, however the model usually focus on the ratings of a single user, instead of attempting to discover inter-user relationships. These two methods are sometimes combined into what is known as Hybrid Recommender Systems. Hybrid systems can combine the strengths of various models in order to perform more robustly in a wide variety of settings.

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.

3.1.1 Collaborative filtering

Collaborative filtering is based on the principle that similar users will share similar interests. Assuming that ratings are highly correlated across various users and items, it is possible to predict a rating not yet given by the user. For example, if the algorithm

identifies that user Alice and Bob have similar tastes, it is likely that the ratings in which only one of them has given a rating will also be similar. 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 is to try to predict the missing ratings, for this to be possible most models focus on leveraging inter-item or inter-user correlations.

CF algorithms can be further divided into Memory-Based and Model-Based approaches. Memory-Based algorithms, also referred to as *neighborhood-based collaborative filtering algorithms*, use a dataset of user-item pairs to identify groups of similar users or items, which are in turn used to make predictions of preference for new items. These where among the earliest CF methods proposed. Although very simple to implement, these methods often have trouble with very sparse matrices.

In Model-Based methods, machine learning and data mining algorithms are used to develop a model that will be used to predict user ratings. Some examples include decision trees, rule-based models, Bayesian methods and latent factor models. 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 3.1.

3.1.1.1 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.

3.1.1.2 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:

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

3.1.1.3 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 alleviated 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

Figure 3.1: 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)

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.

3.1.2 Content-based filtering

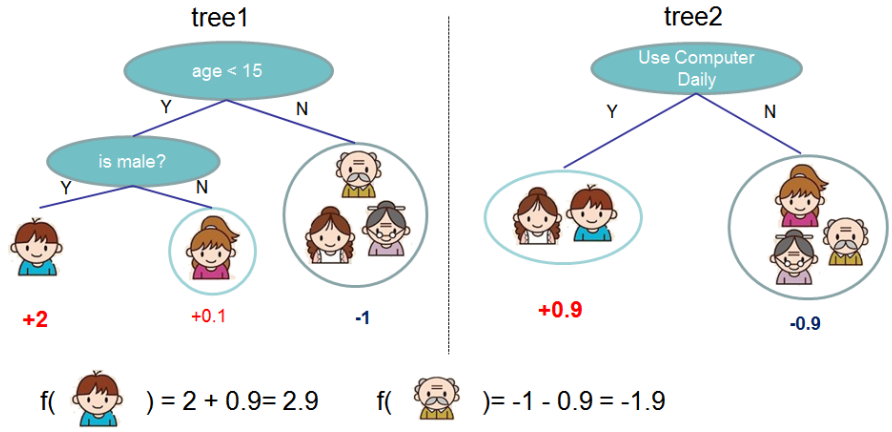
In this approach a description of each item is constructed using structured data or some sort of item presentation algorithm such as Latent Dirichlet Allocation (LDA) or TF-IDF. This representation is then compared to the user profile and the best-matching items are recommended. The user profile can 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. For instance, if user Bob rated movie A but no other ratings are available for the movie, it is still possible to recommend other movies based on the attributes of movie A, such as genre keywords or release date. 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. Finally, while CB methods excel in recommending new items, they are not effective when it comes to new users. This is because the training model requires a rating history in order to make robust predictions.

3.1.2.1 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

Figure 3.2: GbTree example



Source: XGBoost official site

is summed up to get the final score 3.2. Our model can then be defined as

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

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

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

3.1.2.2 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 some simplification our objective function becomes:

$$obj^* = -\frac{1}{2}\sum_{j=1}^{T} \frac{G_j^2}{H_j + \lambda} + \gamma T$$

Finally, we compute the score gain obtained by splitting a leaf into two leaves. Our model is then trained by optimizing for one level of the tree at a time:

$$Gain = \frac{1}{2}\left[\frac{G_L^2}{H_L + \lambda} + \frac{G_R^2}{H_R + \lambda} - \frac{(G_L + G_R)^2}{H_L + H_R + \lambda}\right] - \gamma$$

4 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.

4.1 Data preparation

The dataset D for our Content-Based model 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.

The dataset used for the Collaborative Filtering model is a simple list of User ID and Project ID pairs, one for each contribution in the database. With this information, we build a R_{nxm} matrix where N is the number of users and M the number of projects. The rows indexes represents the User ID, while the columns indexes represents the Project ID. A specific entry $R_{i,j}$ will be 1 if there exists a contribution made by user with ID i to project with ID j, and 0 otherwise. At the time of writing, the cardinality of N was 900k and M 75k, resulting in a matrix R with 67.5 billion entries. To achieve reasonable memory consumption, R is converted to a sparse representation.

4.2 Evaluation Metrics

There are basically 3 ways RSs can be evaluated: offline, online and empirically. Offline measures are those computed based on a given static 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. Evidently,

in this imaginary scenario a RS would be pointless in the first place, consequently 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, let Y be the number of times a user clicked on at least one of the recommended items in N. CTR is then defined as Y/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. To achieve this, a test page with each proposed algorithm along with the existing popularity ranking was made available and a survey was sent to 14 members of the Catarse team. The following questions were asked:

- *1*: Of the available algorithms, which one do you feel gave the best recommendations?
- *2*: Of the available algorithms, which one showed projects you would most likely back?
- *3*: Of the available algorithms, which one gave the most surprising recommendations?
- *4*: Of the available algorithms, which one would you use more often?
- *5*: General observations

4.3 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.

5 RESULTS

In this chapter we give results for our offline, online and empirical metrics. The computed offline metrics were accuracy, recall, and precision. Accuracy is simply a ratio of correctly predicted observation to the total observations. Recall is defined as $tp/(tp + fn)$, where tp is the number of true positives and fn the number of false negatives. Finally precision is given by $tp/(tp + fp)$ where tp is the number of true positives and fp the number of false positives.

5.1 Content-Based

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. In order to understand how each feature affects the outcome prediction in our model, we plot the SHAP (LUNDBERG; LEE,) values of every feature for every sample in figure 5.1. From this plot we can draw some interesting conclusions: the most important feature in determining backing probability is the number of backed projects in the same category, followed closely by the project progress in the first 3 days. We can also see that having a low number of available rewards decreases backing probability.

To determine how individual features effect the output of the model, let's take our most significant feature, $category\_count$, and plot its value against the corresponding SHAP value for all examples in our dataset. Vertical dispersion shows the interaction between features, in this case how $category\_count$ relates to $reward\_count$. The result is shown in figure 5.2.

This approach gave exceptional results in every computed offline metric, as seen on table 5.2. This, however, should be considered with care: our dataset is intrinsically predictable to the point that any method should give great results. For example, a simple test to check if the $category\_count$ feature is greater than zero already yields us an accuracy of 94.5%. This is due to the fact that most users only back one project in one category.

Figure 5.1: Feature importance in Gradient Boosting Tree

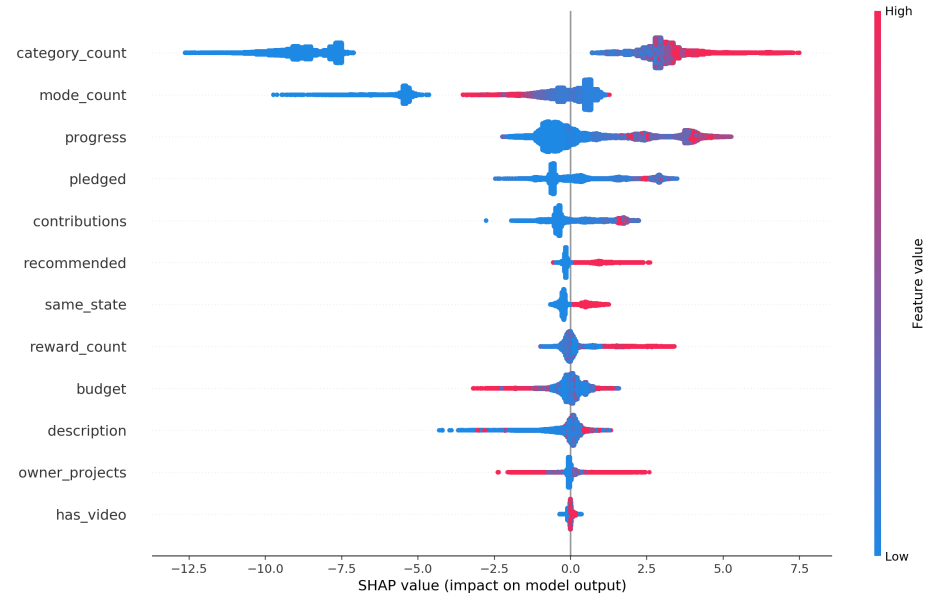


Figure 5.2: Dependence plot for category_count

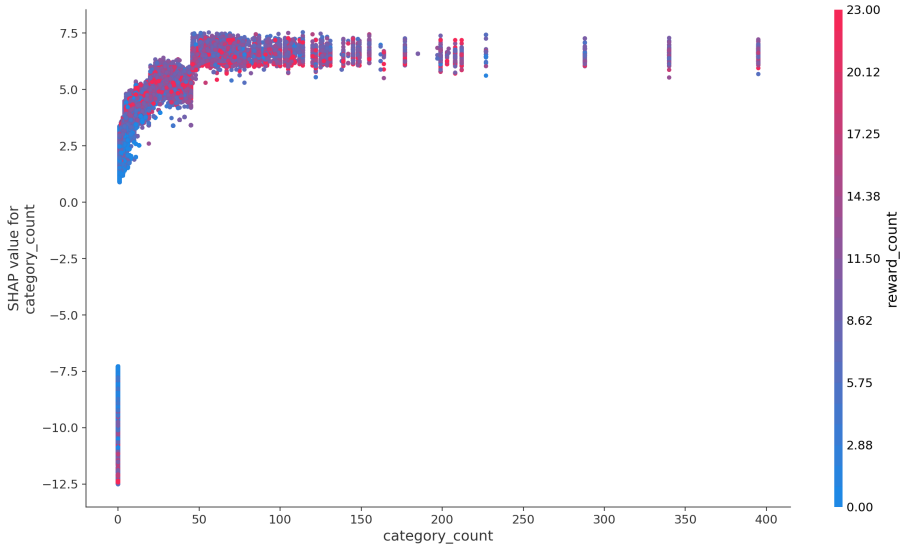


Table 5.1: Content-Based Offline metrics

Recall	*Accuracy*	*Precision*
0.990450	0.986260	0.982813

5.2 Collaborative Filtering

Our Collaborative Filtering model was implemented using the LightFM library. As depicted on table 5.2, every offline metric performed much worse than its Content-Based counterpart. This was expected due to our dataset characteristics: since most users only back one project in their lifetime there is not enough rating data for CF to perform well. However, testing with real users provided much better results.

Calculating error metrics poses a problem for CF algorithms that produce ranked recommendations. The values returned in our prediction function possess no meaning whatsoever; they are used for ranking purposes only. Therefore it is impossible to compute an error metric since we don't have two sets of comparable values to test for equality. However, it is possible to obtain an error metric in the context of our hybrid approach: in order to multiply the prediction values of both algorithms we first normalize CF predictions so they stay in the $0 - 1$ range. We then consider any normalized prediction greater than 0.5 to be in the positive class, and negative otherwise. This gives us an accuracy of approximately 93%, or equivalently an error of 7%.

Table 5.2: Collaborative Filtering Offline metrics

Recall@5	*Recall@10*	*Precision@5*	*Precision@10*
0.06500372900657606	0.0925860086205232	0.015118373	0.010974493

5.3 Hybrid

Hybrid ratings were computed by multiplying the ratings obtained by the CB method by the normalized CF ratings. By doing this, we hope to compensate any weaknesses in the original techniques and sum its strengths.

5.4 Comparison

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@10 for each proposed algorithm.

Table 5.3: Offline metrics

Method	*Recall*	*Accuracy*	*Precision*
Content-Based	0.990450	0.986260	0.982813
Collaborative Filtering	0.08933075	0.9329*	0.010246
Hybrid	0.08933075	Val 3	0.010246

6 CONCLUSION

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