RecAid: A Sponsorship Recommendation Approach

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Abstract: Non-government organizations play an important role in society, providing access to basic services in culture, education, health, and security for needy people. Some of these organizations raise funds for their social projects through sponsorship programs for people in poverty, deprivation, exclusion and vulnerability. The intensive use of technology for sponsors and beneficiaries matching is paramount to create more lasting bonds, maximizing the likelihood of stronger relationships, consequently raising more resources for projects. In this article we propose and evaluate a learning approach to recommend beneficiaries to sponsors. Particularly, we exploit different recommendation strategies, such as collaborative filtering with matrix factorization, content-based with bag of words and word embeddings and knowledge-based with association rules. Experimental results show that content-based strategies based on word embeddings are more effective, reaching up to 72% of performance in MAP and nDCG. Additionally, it can effectively recommend beneficiaries to sponsors even if there is less feedback information on beneficiaries and sponsors to train recommendation models.

1 INTRODUCTION

Socioeconomic inequality is a worldwide problem. While a large part of economic resources is exclusively available to a small group of people, a large group of people have no access to basic resources for education and health. Particularly in Brazil, this problem is even greater. According to IPEA (Institute for Applied Economic Research), approximately 26 million people lived in poverty in 2014 in Brazil, and another 8 million people lived in extreme poverty.

Many non-government organizations (NGOs) support the social development of communities, delivering an improvement in the quality of life of poor people. The Resolution 288 of the Economic and Social Council of the United Nations defines “non-government organizations” as organizations established by civil society without government agreements (Ferreira, 2005). NGOs often raise funding from civil society and government to support their social development actions, but many of them have no formal strategy for this (da Silva et al., 2016). Nevertheless, one of the strategies adopted by NGOs is to raise funds directly from individual sponsors through sponsorship programs, where donors sponsor beneficiaries by providing financial resources, fostering projects in the community where beneficiaries live.

Attracting and retaining sponsors is a challenging problem and is closely related to the NGOs credibility and theirs ability to effectively allocate funding resources. Previous work reported in literature show that there is a positive correlation between transparency in the application of funds and financing maintenance by sponsors (Portulhak et al., 2016). Furthermore, emotional and practical aspects related to the bonds between sponsor and beneficiary significantly impact the maintenance of donations. For instance, emotional bonds present in the formal communication between sponsor and beneficiary maximize the chance of lasting sponsorship. In this scenario, attracting and retaining sponsors for NGOs projects is paramount to the reduction of global socioeconomic inequality. Thus, the understanding of the emotional and practical aspects that impact the relationship between sponsors and beneficiaries is crucial to promote the creation of long-lasting bonds, maximizing the likelihood of long-term funding.

In this article we propose a learning approach for beneficiary-sponsor recommendation to retain sponsors through the building and maintenance of lasting bonds between them. Particularly, different strategies are used in recommendation, such as collaborative filtering with matrix factorization, content-based with bag of words and word embeddings, and knowledge-

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based with association rules. Experimental results using a new sponsorship recommendation dataset built from funding data provided by ChildFund Brasil[1], an international NGO, show that content-based strategies with word embeddings outperforms the other strategies, reaching up to 72% in MAP and nDCG. Additionally, the content-based strategies performs well even if there is less feedback information on beneficiaries and sponsors to train the recommendation model. The main contributions of this article are:

- SRD, a new sponsorship recommendation dataset for beneficiary-sponsor recommendation built from funding data of ChildFund Brasil, an international NGO.
- RECAID, a learning approach to recommend beneficiaries to sponsors that implements different recommendation strategies, particularly a content-based strategy driven by word embeddings.
- A throughout evaluation of our proposed approach, contrasting the performance of different recommendation strategies.

This article indirectly contributes to improve the NGO fundraising process, presenting concepts and technologies to enhance NGO processes and methods. Moreover, our recommendation approach is designed to be effective in a real-world scenario where most beneficiary-sponsor relationships are one to one. Unlike other recommendation approaches that recommend knowing a large range of choices made by users, RECAID need to be effective in a more restrict universe of knowing choices.

The remaining of this article is divided as follows: Section 2 presents theoretical background on social technologies and recommendation systems. Section 3 presents related work. Section 4, presents our proposed recommendation approach. Section 5 presents experimental setup and results. Finally, Section 6 presents conclusions and directions for future work.

2 BACKGROUND

This section presents the main concepts on social technologies and recommendation systems.

2.1 Social Technologies

The expression "social technology" originates in India from a concept of appropriate technology, used for the first time in the late 14th century by Mahatma Gandhi (Dagnino et al., 2004). In Brazil, this expression became popular in the first decade of the 21st century, mostly due to social actors concerned with the problem of social exclusion. Formally, social technology is a way to use, create, implement and manage technologies to address social and environmental problems, trying to promote social inclusion and sustainable development in a guided way, comprising products, techniques, and methodologies developed for community interaction with the aim of promote social transformation (Dagnino, 2011). Thus, social technologies require action and reflection of individuals to stimulate a more fair, inclusive and sustainable society, emphasizing citizens, neighborhood associations, solidarity economy enterprise, social mobilization and organizations (Costa, 2013).

Typically, social technologies run by social organizations action within social projects. These organizations usually have no links with the public or private sector, do not receive government funding and their projects are sponsored by donations from ordinary contributors (Falcão, 2004; de Albuquerque, 2006). The two key agents in social projects are beneficiaries and sponsors. Beneficiaries are people who are directly benefit from the project's products, services and results. Usually, they are needy people and their needs or rights are not met by public agencies (Culligan et al., 2013). Sponsors are donors in social projects that provide cash, goods or services to the NGOs or directly to a non-profit social project. These sponsors contribute by providing more opportunities and resources for beneficiaries (Belem and Donadone, 2013).

2.2 Recommendation Systems

Recommendation systems, or recommenders, are information retrieval systems that help users to make choices on items in a wide universe of options. Recommendations are generated through explicitly or implicitly preferences expressed by users, and by using items and users properties, including demographic and lifestyle data, visualization statistics, behavioral information and other contextual properties depending on what is recommend (Linden et al., 2003; Massa and Avesani, 2007; Cremonesi et al., 2010).

Until recently recommendation was a personal experience based on people habits and behaviors. From there, it has been evolving to a personal experience based on collective knowledge. Today, there are a huge amount of choices of items in the Web, such as movies, music, food, drinks and other products, making decisions hard for people emerged in their daily routines. Recommenders offer a way to streamline

[1] http://www.childfundbrasil.org.br

decisions, filtering the options based on past choices, common interests and preferences.

Popularity-based is one of the most traditional recommendation strategy widely used in practise, where the only available knowledge used to recommend is the history and popularity of the items. This strategy is based on collective wisdom and typically recommend the most popular items to users, with no customization or personalized experience (Steck, 2011). It does not distinguish groups, providing no targeted recommendations in such a way that it is often ineffective, failing to embody the user's desire.

The collaborative filtering strategy is more sophisticated, providing predictions aimed at the users' interest on items, consolidating filtering based on their preferences history (Linden et al., 2003). These strategies assume the likelihood of users having common interests about items, being able to group users based on the grade they have defined for an item in the past, and infer the user's future choice by understanding the preferences that similar users in the same group made for certain items (Sarwar et al., 2001). Usually, collaborative filtering recommendation is based on the similarity of users (user-based) or on the similarity of items (item-based). In addition, latent models (Sarwar et al., 2000; Aggarwal and Parthasarathy, 2001) reduces the dimensionality inherent in calculating similarity in large matrices of users and items, providing an effective matrix factorization procedure. One of the most popular implementations of latent models is the singular value decomposition (SVD).

The content-based recommendation strategy uses the textual content of users and items to provide predictions. It can recommend new items for users even when there is no feedback data, minimizing the cold-start problem. However, due to the use of text descriptors, it usually provides obvious recommendations (Balabanović and Shoham, 1997; Aggarwal et al., 2016). A hybrid strategy can achieve outperforming recommendation, improving other non-hybrid strategies (Lekakos and Caravelas, 2008). It aims to minimize problems related to cold-start and sparsity by combining different strategies, depending on what kind of item need to be recommended. The hybrid strategy is widely used nowadays due to its effectiveness, resilience and modularity.

Knowledge-based recommendation strategies use explicit contextual knowledge on items, user preferences and recommendation criteria to provide predictions (Burke, 2000). Usually these strategies are suitable for complex domains, where items are not consumed very often by users. Several classifier and regression algorithms can be used to provide the predictions, such as association rules (Osadchiy et al., 2019), support vector machines (Min and Han, 2005) and neural networks (Gupta and Sharma, 2021). Particularly, a recommendation strategy based on neural networks is inspired by the architecture of the human brain, allowing for an important ability to train different classifiers for a higher quality recommendation. Similar to hybrid recommenders, neural network recommenders can combine several architectures and be trained using several data sources to provide an outperforming recommendation. Thus, one can train several neural networks per user, still customizing the user preferences, tastes, and behavior (Ricci et al., 2015).

Recently, novel deep learning architectures have been proposed to generate text embeddings that can be effectively used in several natural language processing problems (Mikolov et al., 2013b; Vaswani et al., 2017; Devlin et al., 2019). For instance, Word2Vec are the first efficient models to learn distributed representations of words from large amount of unstructured text with billions of words (Mikolov et al., 2013a; Mikolov et al., 2013b). Training such models does not involve dense matrix multiplications and can be quickly done with a single machine. Previous work reported in literature show that word embeddings can be effectively used in recommendation (Kannan et al., 2018).

Regardless of strategy, recommendation systems must provide personalized recommendations by using as much information as possible on demographic, lifestyle, groups of friends, areas of interest and any other feature that can define user personality. Providing effective recommendations is paramount to retain users, particularly when they are able to convey a sense of individuality, that is when the user feels that their recommendations are exclusive. By analogy, an effective recommendation system can be associated with an experienced salesperson, that first seeks to understand the customer's needs to then recommend a product that meet the needs. In this sense it is crucial to know historical data and characteristics of users to provide effective recommendations (Zanker and Ninaus, 2010).

3 RELATED WORK

Recommending people (items) to people (users) can be applied in different contexts, such as friendships, dating, educational and professional partnerships. In this context, users lifestyle information is usually an important feature for recommendation and, together with others features, it can provide an approximation of the user's personality, allowing the predictions of user future choices to be filtered in a better way.

For friendship recommendation, (Gurini et al., 2018) proposed a new recommendation approach based on semantic attitudes by using traditional social networks, such as Twitter. In particular, favorable and unfavorable statements are considered in specific matters, thus improving the recommendation results. They extract text from social networks, converting them into unigrams and eliminating irrelevant ones. A three-dimensional matrix factorization model is generated and a temporal dynamics is modeled, improving the accuracy and diversity of the recommender. The experiments carried out by authors with data obtained in the monitoring of the traffic produced by the users allowed the authors to make comparative analyzes with other approaches reported in the literature, such as random recommendation, popularity-based, content-based, and collaborative filtering. The authors divided the datasets into 70% for training and 30% for testing, for the evaluation of results and accuracy, diversity and novelty metrics were measured. Experimental results showed that with the use of implicit feeling, volume and objectivity improves the recommendations. In addition, the proposed approach behaved better than the others in experimental evaluation. Similarly to these work, in our investigation we analyse features that impact the recommendation of people to people. Moreover, we also use a consolidated approach in the literature to try out possibilities. But differently from these work, we use a sponsorship recommendation dataset to infer the likelihood of long-term bond between beneficiaries and sponsors.

In a different vein, (Rahim et al., 2019) propose an approach based on centrality measures between friends of friends and similarity measures of groups and events to recommend new friends for users. The features used by this approach is extracted from two Facebook datasets, the first consisting of seven group of features: friends, events, groups, neighbors, friend events, friend event groups and friend event groups neighbors. The second consisting on friendship relations and used to assess whether both users were able to become true friends. For recommendation, the authors propose different techniques for measuring similarities. The first technique is based on friends of friends relationships, with the five best friends been recommended using each one of the centrality measures separately. The second technique use three measures of similarity based on each user's common group or event: data coefficient, Jaccard similarity, and cosine similarity. Both techniques were evaluated and the authors showed that the recommendations made by them performs almost equally, with an accuracy of 56% for the second technique and 52% for the first technique. In addition, these work presents an interesting comparison between techniques and metrics, creating possibilities for the authors to verify the confidence level of the recommendation.

The aforementioned related approaches that recommend people focus mainly on the interest of new friendships or dating. In the same vein (Edith and Yu, 2018) propose a recommender focused on the building of new friendships. The authors use the k-nearest neighbors algorithm to estimate users' preferences and lifestyle features. They also collected data directly from each user's smartphones, which allowed measuring the similarity between them having a defined context. Experimental results showed that the friends' choices directly reflect the preferences expressed by the users, with the main advantage in recommending friends, the sharing of similar interests on both sides. This work is important to demonstrate how similarities measures of users impact the recommendation of friends, and how estimating similar interests, daily routines, styles, and opinions can help to build users clusters that enhance the recommendation.

Although there are several works reported in the literature on recommending people, none of them address the problem of recommending beneficiaries to donors, a sub-problem that imposes even greater challenges given the properties of the users and items of the recommendation system, and the lack of information on social sponsorship.

4 THE RECAID APPROACH

Recommendation systems can be implemented in different contexts using different recommendation strategies. In this section we present RECAID, our approach to recommend beneficiaries to sponsors in social projects. Figure 1 presents the RECAID architecture.

First, the Processor component creates the Sponsorship dataset by processing the NGO Funding dataset containing sponsor and beneficiary relationships. Part of this processing consists of anonymizing the data of beneficiaries and sponsors. Another part of processing consists of generating sponsor ratings for beneficiaries based on the level of interactions between them. Each case record in the NGO Funding dataset represents an interaction between a sponsor and a beneficiary. In particular, the dataset records eleven types of cases. In one year, at least three cases are record for each beneficiary: progress report, registration update, and initiated letter. Some engaged sponsors have a larger number of cases, usually hav-

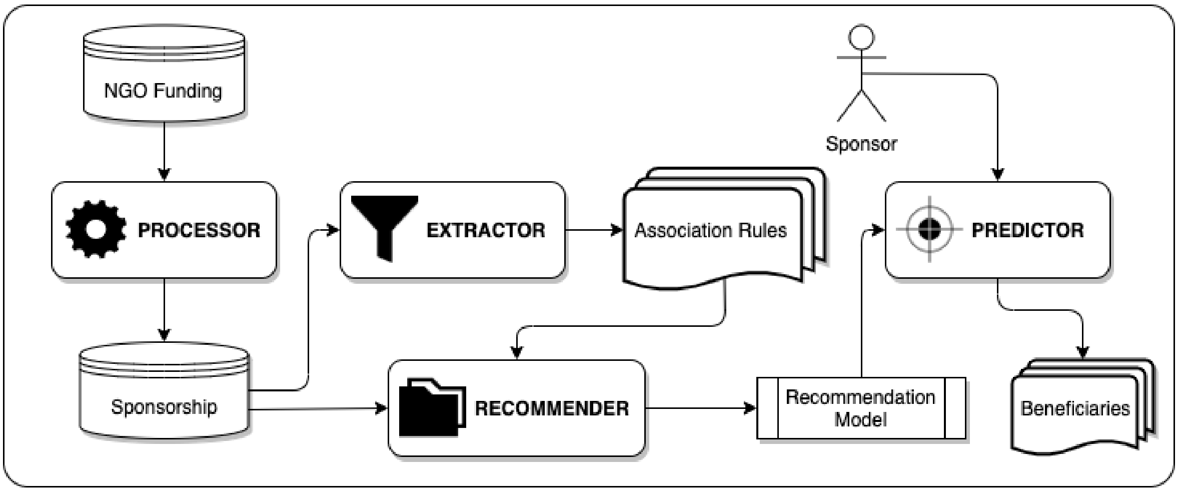

Figure 1: The architecture of the RECAID approach.

ing a longer time bond with their beneficiaries.

Second, the Extractor component extracts association rules with high confidence level (above a configurable threshold) from the Sponsorship dataset. For this, we use sponsor's features, such as city, gender, age and payment, and beneficiary's features as gender, age and illiteracy level. Third, the Recommender component learns from the Sponsorship dataset and association rules a recommendation model using different strategies. In particular, collaborative filtering, content-based, knowledge-based and hybrid strategies are used for this. Finally, the Predictor component recommend a ranked set of beneficiaries to a sponsor using the recommendation model.

5 EXPERIMENTS

In this section, we present the experiments we carried out to evaluate our recommendation approach, including datasets, evaluation metrics and experimental results. Particularly, in our experiments we answer the following research questions: how effective is RECAID to recommend beneficiaries to sponsors in social projects?

5.1 Dataset

The sponsorship recommendation dataset (SRD)[2] proposed in this article was built using funding data provided by ChildFund Brasil, an international NGO. This new dataset contains data of 53 years of social projects development, filling a gap in the lack of datasets for beneficiary-sponsor recommendation systems. Within the funding data we extract seventeen sources of features that bring information on beneficiaries and sponsors, such as their demographic and personal characteristics.

Along with the SRD dataset we provide a short-code showing how to use it for beneficiary-sponsor recommendation, in addition to sponsorship metadata in English and Portuguese. In particular, the SRD dataset contains 11,392 records of beneficiaries, 8,624 of them already being sponsored by any sponsor. In addition, there are 16,923 records of sponsors, 8,299 of them donating infrequently. Moreover, 68% of beneficiary-sponsor links are unique, i.e., one donor sponsor just one beneficiary.

In our experiments, we use four sources of beneficiary-sponsor features: beneficiaries, bonds, cases, and sponsors. To infer sponsor ratings in beneficiaries, we perform the sum of all cases, i.e., the interactions recorded in the sponsorship relationship, and we normalize each beneficiary-sponsor case by the sum of cases.

5.2 Setup

We evaluate four different strategies for recommendation: collaborative filtering, content-based, knowledge-based and a hybrid one. For collaborative filtering we use the cosine similarity as the distance metric used to calculate sponsors and beneficiaries similarity and matrix factorization with singular value decomposition. In our experiments, we refer to this strategy as SVD.

For the content-based strategy, all sponsors and beneficiaries are represented in a vector space using bag of words with TF-IDF schema (BoW) and

[2]http://doi.org/10.5281/zenodo.4540776

Word2Vec representations. For both BoW and Word2Vec we estimate the similarity between the vectors using the cosine similarity. We set the maximum size of each vector of 5,000 words. These words are extracted from the beneficiary and sponsor descriptions. In our experiments, we refer to the content-based strategy with TF-IDF as CB and to the content-based strategy with Word2Vec as W2V. We also combine TF-IDF and Word2Vec vectors in a single vector. In our experiments, we refer to the content-based strategy with combined TF-IDF and Word2Vec as W2VT.

For the hybrid strategy, we multiply the scores from collaborative filtering and content-based strategies previously presented to provide a hybrid ranking. In our experiments, we refer to the hybrid strategy as HB. Additionally, we combine previously presented strategies with a knowledge-based recommendation strategy based on association rules, referring them in our experiments as CB-AR, HB-AR, SVD-AR, W2V-AR and W2VT-AR. We extract all rules with confidence levels between 20% and 75%, filtering from the recommended beneficiaries only those records that follow the association rules.

There are different metrics to evaluate the accuracy of a recommendation system (Beel et al., 2013). In this article, we provide ranking prediction metrics to evaluate the order in which the items should be recommended. For this, we use information retrieval metrics, such as, Mean Average Precision (MAP) and Normalized Discounted Cumulative Gain (nDCG). The MAP calculates the average precision of the scores of a set of queries and the nDCG defines the relevance of the classification of the items recommended in the result set to evaluate the utility or gain based on its position (Geng et al., 2007). In addition, we use the holdout for cross-validation, considering a random sample of 20%, 30%, 40%, 50%, 60% training data,

5.3 Experimental Results

Table 1 presents the MAP metric for each recommendation strategy.

From Table 1 we observe that W2VT outperforms the other approaches. However the performance of HB, HB-AR, and SVD are remarkable. The performance of HB and HB-AR is largely derived from the performance of the SVD. Additionally, we observe that the best performance occurs when the sample rate is 40% for training and 60% for testing. Table 2 presents the nDCG metric for each strategy.

From Table 2 we observe again that W2VT outperforms the other approaches. The CB strategy is the

Table 1: RECAID Performance in MAP.

Approach	20%	30%	40%	50%	60%
CB	0.349	0.313	0.351	0.128	0.048
CB-AR	0.256	0.224	0.173	0.001	0.002
HB	0.555	0.428	0.500	0.500	0.666
HB-AR	0.555	0.428	0.500	0.500	0.666
SVD	0.556	0.428	0.500	0.501	0.666
SVD-AR	0.222	0.142	0.333	0.250	0.000
W2V	0.333	0.364	0.329	0.383	0.322
W2V-AR	0.210	0.235	0.110	0.197	0.181
W2VT	**0.580**	**0.480**	**0.598**	**0.568**	**0.721**
W2VT-AR	0.398	0.428	0.351	0.343	0.390

Table 2: RECAID Performance in NDCG.

Approach	20%	30%	40%	50%	60%
CB	0.666	0.571	0.500	0.250	0.000
CB-AR	0.333	0.285	0.166	0.000	0.000
HB	0.555	0.428	0.500	0.500	0.666
HB-AR	0.555	0.428	0.500	0.500	0.333
SVD	0.556	0.428	0.500	0.500	0.666
SVD-AR	0.222	0.142	0.333	0.250	0.000
W2V	0.556	0.428	0.500	0.500	0.666
W2V-AR	0.322	0.242	0.433	0.250	0.410
W2VT	**0.708**	**0.651**	**0.612**	**0.668**	**0.721**
W2VT-AR	**0.708**	0.480	**0.612**	**0.668**	0.601

most volatile, but with minor differences when compared. The association rules extracted from the base, also do not help in gaining the correctness of the strategy as it was expected to have, we can see, at most in the hybrid strategy, the hits are close, but they do not exceed.

The experimental results show that W2VT outperforms the other strategies in all evaluation metrics. Recalling our research question, these observations attest the effectiveness of RECAID to recommend beneficiaries to sponsors in social projects, especially when we use features that describe a beneficiary, that is, when we opt for content-based strategies.

The content-based strategy that uses the description or attributes of the beneficiaries and thus creates similarities was more efficient. To use this strategy, we used the description field of the beneficiary, using the TF-IDF scheme to calculate the weight of the words in the text, which is a measure to indicate the importance of each word in the description of the beneficiary, and with that, we can verify the links and determine the most similar ones helping to solve the problem we have in the other recommendations to which they present only a 1 to 1 ratio in most cases. The best results come from the TF-IDF Word2Vec, Pattern Factorization and Hybrid strategy, combining two strategies already presented, based on content and pattern factoring (SVD), thereby minimizing problems related to sparsity and cold-start.

By assessing the effectiveness of these strategies, we noticed that the sponsor and beneficiary relationship structure greatly influences the models, keeping them away from improved results, since the history or similarity that are important factors for a good recommendation establish little performance. However, when evaluating the strategies that had a better result, we realized that the description of the beneficiary can establish a path to be followed in the recommendation, finding similarities between them. For the tests, we do not consider the temporal dimension and we consider that all beneficiaries would be available to receive a sponsor in the sponsorship program. It is also not possible to discard other unused base features, which can improve recommendation strategies.

6 CONCLUSION

In the present article we propose RECAID, a recommendation approach that recommends beneficiaries to sponsors in social projects. RECAID aims to improve fundraising and loyalty from sponsors through the construction of lasting bonds. In particular, different recommendation strategies reported in scientific literature on recommender systems for people recommendation were identified, different techniques for recommending beneficiaries to sponsors in social projects were evaluated and the main characteristics of beneficiaries and sponsors that impact on the effectiveness of the proposed recommendation approach were identified.

Experimental results show that the Wor2vec with TF-IDF that exploits descriptive textual content of beneficiaries and sponsors performed better for recommendation. Particularly, with a training rate of 60%, the MAP and nDCG metrics reached 72% accuracy. In addition, other as matrix factorization and hybrid approaches strategy achieved the accuracy of 66% in nDCG. Based on the observed results we intend to explore new techniques for displaying the textual content and new features that describe emotional aspects of beneficiaries and sponsors.

In future work, we also intend to explore a larger set of characteristics of beneficiaries and sponsors to understand what practical and emotional aspects impact the maintenance of lasting bonds. Additionally, we intend to evaluate other strategies recently proposed in the literature, such as those based on neural networks. Moreover, we intend to use a larger set of features, since the current database is unbalanced, with a small number of lasting links between beneficiaries and sponsors. We also intend to explore new approaches based on sentence embeddings to capture neglected semantic aspects to improve the performance of content-based strategies.

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