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ORIGINAL ARTICLE

Recent advances in applications of machine learning in reward crowdfunding success forecasting

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Abstract

Entrepreneurs and small businesses have increasingly used reward-based crowdfunding to raise capital for their creative projects, whose success is central to this industry. Thus, predicting the success of crowdfunding campaigns is a topic of great importance for entrepreneurs and platform managers. The literature that employs monolithic classifiers and static ensemble learning for crowdfunding success prediction are scarce. In contrast, the dynamic selection (DS) algorithm, which belongs to the ensemble learning category, deserves a particular remark since it has overcome traditional monolithic classifiers and static ensembles in many applications. This paper proposes a dynamic selection framework for reward crowdfunding prediction. DS algorithms select a competent subset of the classifier per query instance. This procedure is performed during the generalization, and the subset is composed of local experts, favoring an increase in accuracy. Fifteen machine learning models are evaluated using three metrics (accuracy, area under the ROC curve and F-score), and ensemble learning obtained better results than traditional classifiers. In particular, Meta-DES, which performs dynamic selection, obtains the best overall results among the evaluated models. Furthermore, since usually interpreting the output of ML models is considered to be very difficult due to their complex "black box" architecture, we also use Shapley additive explanations to interpret the perdition's outputs. Among variables evaluated in our models, the textual sentiment of the mass media, the number of pledges, and the target amount of the campaign deserve a highlight when predicting the campaign's success. The source-code and further details about the experimental analysis are available at https://github.com/las33/Crowdfunding.

Keywords Crowdfunding · Machine learning · Ensemble learning · Multiple classifier systems · Dynamic selection · Explainable AI

1 Introduction

Crowdfunding has occupied a growing space in the literature of several fields of knowledge, from finance [1, 2] to art [3] and information systems [4–6] thus demonstrating society's interest in this modality of fast and flexible financing [7, 8] around the world [9]. Therefore, predicting the success of crowdfunding campaigns is a topic to which researchers around the world have dedicated efforts [10–12]. Historically, the prediction of success of crowdfunding reward campaigns has focused on traditional methods, such as linear regression or logit, which are

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largely dependent on parameterization and a set of assumptions. As a consequence, model results may end up being not very robust [13–16]. In parallel, machine learning (ML) techniques have been pointed out as a means to obtain more accurate predictions for the success of campaigns. However, research on this topic is still virtually rare [17–20].

Many ML models are available, and choosing one that best fits a given problem is challenging. Thus, instead of adopting only one model, multiple classifier system (MCS) [21] or ensemble learning employs many models to mitigate the uncertainties related to choosing a single/monolithic model. The fundamental idea is combining the performance of different models to improve the overall accuracy. MCS has proven its ability to obtain better precision in comparison to single machine learning models [22], and it can be divided into static and dynamic types. The former combines all the models to predict a test instance, while the latter dynamically selects a subset of the best models per test instance to perform the prediction. Among the MCSs, dynamic selection (DS) has obtained promising results [23, 24].

DS does not combine all the trained classifiers to predict an unknown instance; in contrast, it selects and combines only a subset of classifiers composed of the most competent classifiers. Since this selection is performed on-the-fly and depends on the instance under analysis, it is likely to select a different subset of classifiers per instance composed of local experts, which is an advantage since classifiers that are not experts for the specific instance are not considered.

Based on that, we claim DS as a promising alternative to effectively predict the success of crowdfunding campaigns and propose a dynamic selection framework to that end. To the best of our knowledge, this is the first work to address this task employing dynamic selection techniques and performing a comprehensive evaluation using monolithic classifiers, static and dynamic ensemble learning.

A crowdfunding campaign is commonly represented using various factors, such as project campaign information, geographic aspects, and categories of the projects [25, 26]. However, textual campaign information is rarely studied for analyzing crowdfunding successes [17, 27], and textual information extracted from the mass media is virtually absent from the literature. This topic interests researchers, regulators, and other stakeholders in the crowdfunding industry and its role [28–31]. Moreover, researchers are interested in new methods and new variables that predict campaign success [32]. To fill this gap, we extract sentiment information of the news from the most prominent newspaper news in circulation in Brazil and information from the X (formerly Twitter) social media platform, measured on the day of the campaign's launch. This information is combined with other variables that measure campaign, and geographic localization attributes to compose each campaign's feature vector. So, in this context, our study is a pioneering one that considers market sentiment reflected in mass media.

We perform a comprehensive set of experiments on the Brazilian reward crowdfunding platform Catarse dataset composed of 4193 campaigns. Fifteen machine learning models are evaluated using three metrics: Accuracy, Area Under the Receiver Operating Characteristic (ROC) Curve, and F1-Score. The main theoretical and empirical contributions to the crowdfunding literature are summarized as follows:

- The proposal of a dynamic selection framework for predicting crowdfunding success.
- An empirical study showing that the choice of machine learning algorithms matters for classification performance. Different machine learning algorithms belonging to monolithic classifiers, static and dynamic ensemble learning are evaluated using three metrics (accuracy, area under the ROC curve and F-score).
- Ensemble learning algorithms obtain better accuracy than monolithic classifiers. In particular, Meta-DES [33], a dynamic selection algorithm, deserves a remark since it obtains the best overall accuracy.
- An analysis using SHAP [34] explainable AI to understand better how the machine learning model's predictions behave shows the importance of the variables for the campaign's success. The proposed mass media sentiment information deserves a relevant position among the most prominent ones.

The rest of this paper is structured as follows: Sect. 2 presents the fundamentals and related literature, Sect. 3 shows the framework for reward crowdfunding prediction, and Sect. 4 describes the experimental protocol showing the data, the variable and the machine learning algorithms. In Sect. 5, we present our results, including SHAP-based explanations, to understand the main results of the model with the best fit. We also summarize the results for various models based on different ML algorithms. Finally, Sect. 6 presents our concluding remarks, with suggestions for future research.

2 Related literature

2.1 Reward crowdfuding campaign success forecasting

In terms of core theory, we focus on the emerging agenda that explores the role played by contextual aspects on funding decisions, specifically on the willingness of individuals to make capital contributions to reward crowdfunding campaigns [35].

In accordance with the theoretical fundamentals of crowdfunding [60], the prediction of reward crowdfunding campaign success is critical to the development of the crowdfunding industry. This is because the prediction of success can assist individuals and organizations in their decision-making regarding the allocation of campaign resources and in recommending more successful campaigns for individual supporters. According to [60], campaign success can be defined as follows. The entrepreneur is first asked to describe the following three elements of his or her campaign on the platform's public webpage: (i) a description of the reward to the consumer, which is typically the entrepreneur's final product; (ii) a pledge level p; and (iii) a target amount TA.

After describing these elements, the crowdfunding campaign starts, and for a fixed period, a consumer (backer or pledger) can pledge an amount p to support the campaign financially. During the campaign, the platform provides accurate information on the current aggregate level of pledges so that a consumer can, in principle, condition his or her decision to pledge on the contributions of previous consumers. After the campaign ends, the platform compares the target amount TA to the sum of pledges $P \equiv n \cdot p$, where n is the number of pledging consumers (backers). If aggregate pledges P fall short of target level TA, the platform declares the crowdfunding campaign a failure.

To the best of our knowledge, the literature (Table 1) has not taken into consideration the determinants of campaigns to attain amount $P \geq TA$ based on the Machine Learning procedure, which is the main reason that this study is considered relevant since it contributes to the development and consolidation of the theory of reward crowdfunding success. There are two particularly relevant aspects in estimating the success of campaigns: the classes of the explanatory variables adopted in the models and the classes of the models employed to estimate success.

Regarding the variables, the literature points to various levels of analysis, ranging from the country level [61] to the individual level [48, 62, 63]. Here, we address campaign characteristics and the cities where they are located to test the ability of machine learning models to predict campaign success [11].

[19] proposed a static combination of neural networks to predict the success of crowdfunding and show that their system outperforms three monolithic classifiers, namely, linear regression, logistic regression, and artificial neural networks. We go further and explore a literature set of methods (called dynamic selection methods) and show that they attain better accuracy rates than static combination methods.

Table 1 Literature related to reward crowdfunding campaign success forecasting and methods

Authorship	Platforms (country)	Method	AoN
[36]	Journalism (USA)	2SLS	No
[37]	Startnext (GER)	P	Yes
[38]	Kickstarter (USA)	L	Yes
[39]	Kickstarter (USA)	T and P	Yes
[40]	Indiegogo (USA)	L	No
[41]	Kickstarter (USA)	L	Yes
[42]	Kickstarter (USA)	DA	Yes
[10]	Catarse (Brazil)	OLS	Yes
[43]	Jing Dong (CH)	L	Yes
[17]	Dreamore (CH)	ML	Yes
[44]	Kickstarter (USA)	L and P	Yes
[45]	Kickstarter (USA)	L and T	Yes
[46]	zhongchou.com (CH)	HMR	No
[47]	Kickstarter (USA)	L	Yes
[48]	Startnext (GER)	P	Yes
[49]	Kickstarter (USA)	HMR	Yes
[50]	Indiegogo (USA)	P	No
[51]	Kickstarter (USA)	L	Yes
[52]	Kickstarter (USA)	P	Yes
[53]	Kickstarter (USA)	L	Yes
[54]	Dreamore (CH)	L	Yes
[55]	Makuake (Japan)	L	Yes
[19]	Indiegogo (USA)	ML	Yes
[56]	Tencent GongYi (CH)	OLS	Yes
[57]	Kickstarter (USA)	NBR	Yes
[7]	Catarse (Brazil)	SA	Yes
[31]	Catarse (Brazil)	L	Yes
[19]	Indiegogo (n.a.)	ML	No
[58]	Kickstarter (USA)	ML	No
[59]	Kickstarter (many countries)	ML	No
This study	Catarse (Brazil)	ML	Yes

Methods: SA = Survival Analysis, OLS = Ordinary Least Square, L = Logit, P = Probit, DA = Discriminant Analysis, T = Tobit, HMR = Hierarchical Multiple Regression, 2SLS = Two-Stage Least Squares, NBR = Negative Binomial Regression, ML = Machine Learning. Countries: USA = United States of America, GER = Germany, CH = China, FIN = Finland. AoN (All-or-Nothing): fundraising type

2.2 Machine learning algorithms

Machine learning is a class of algorithms that extracts information from data. Typical algorithms are decision trees, multilayer perceptrons, support vector machines, k-nearest neighbor and random forests [64]. These data-driven algorithms map the input to the desired prediction, and commonly only one algorithm (monolithic classifier) is applied to the given task. However, MCS, which combines many learning algorithms, has been proven to outperform monolithic classifiers in a myriad of domains [24, 65–67].

MCS has three phases [23]: (i) generation: the training set is used to generate a pool of classifiers; (ii) selection: a subset of the pool of classifiers is selected to perform the classification; (iii) combination/integration: the predictions of the selected classifiers are combined to output the final decision.

Concerning the selection phase, it can be static or dynamic. In the static approach, no selection is performed to obtain the generalization; in other words, all the classifiers defined during the training process are combined to predict the label of the query instance. In contrast, the dynamic selection approach aimed at finding the best subset of classifiers per query instance, and such a procedure is randomly performed.

Dynamic selection (DS) can be divided into dynamic classifier selection (DCS) and dynamic ensemble selection (DES). DCS selects only one classifier per new test sample, and DES selects one or more classifiers for classifying each new test sample. DS deserves special attention since it has achieved superior performance compared with monolithic classifiers and traditional static combination approaches [24, 33, 68, 69].

Meta-DES [33, 70] is a DES framework that achieves state-of-the-art performance. This framework is based on meta-learning, and its main contribution is to use a meta-classifier to assess and select the best subset of the classifier pool instead of using static selection rules as in other algorithms, such as overall local accuracy (OLA) [71] and k-nearest Oracle (KNORA) [68].

2.3 Machine learning explainability

Explainability is a significant concern in machine learning research since it aims to unfold the often called black-box ML models. Methods such as Local Interpretable Model-agnostic Explanation (LIME) and SHaply Additive exPlanation (SHAP) are used to assess the variable's contribution to the prediction. Given that local interpretations using LIME are prone to sampling variability and instability [72], we herein use SHAP [34, 73, 74].

SHAP is a method to explain individual predictions based on the game's theoretically optimal Shapley values [75]. The SHAP's goal is to explain the prediction of an instance x by computing the contribution of each feature to the prediction. The SHAP explanation method computes Shapley's values using coalitional game theory.

The aim is to fairly determine the effect of every single player on the overall team result. It is assumed that n players play a cooperative game. The outcome of the game is referred to as $V(D)$, where $D = \{1, \ldots, n\}$ denotes the aggregated set of players. Φ is each player's contributed value to the game's outcome. An intuitive method is the leave-one-out (LOO) method [76], in which the game is first played with all players, and then with the entire set of players but without the player at interest i. It is shown in Eq. 1 that the value of each player is the difference between the game result with the entire dataset minus the game result without the player at interest.

$$\Phi_i = V(D) - V\left(D \backslash \{i\}\right) \tag{1}$$

To fairly distribute the values of all players, the sum of all individual values Φ_i is required to correspond to the team's overall result, which can be seen in Eq. 2. The LOO method does not meet this criterion.

$$V(D) = \sum_{i=1}^{n} \Phi_i \tag{2}$$

The Shapley values offer an alternative approach that fulfills this criterion. To fairly distribute the values of the players, each Shapley value considers all subsets S of players. The weighted sum of the individual performance in the subsets then gives the player's overall performance. Shapley values are thus defined according to Eq. 3.

$$\Phi_i = \sum_{S \subseteq D \backslash \{i\}} \frac{V\left(S \cup \{i\}\right) - V(S)}{\binom{n-1}{|S|}} \tag{3}$$

The feature values of a data instance act as players in a coalition. Shapley values show how to distribute the "payout" (= the prediction) among the features fairly. A player can be an individual feature value, e.g., for tabular data. A player can also be a group of feature values. For example, to explain an image, pixels can be grouped into superpixels, and the prediction is distributed among them. Using the Python SHAP package,[1] it is possible to visualize feature attributions such as Shapley values as *forces*. Each feature value is a *force* that either increases or decreases the prediction. The prediction starts from the baseline, and the baseline for Shapley values is the average of all predictions. We use SHAP to explain individual predictions, following [77].

Difficulties in interpreting machine learning (ML) models and their predictions limit the practical applicability of and confidence in ML in various fields, especially in reward crowdfunding literature, as can be observed in the works listed in Table 1). The SHAP approach enables the identification and prioritization of features that determine compound classification and activity prediction using any ML model [77, 78]. This is achieved by explaining the model's outcome using the concept of additive feature

[1] https://github.com/slundberg/shap.

attribution [79]. Machine learning algorithms extract information from data, and a major concern is understanding how a specific model operates, i.e., how the model makes the decision.

3 Framework for reward crowdfunding prediction

This paper evaluates single/monolithic classifier and multiple classifier systems (ensemble learning) to predict the crowdfunding campaign's success. A limited number of literature papers applied single classifiers and static ensemble learning for this task, as described in Sect. 2.1.

In particular, to the best of our knowledge, an important type of ensemble learning, called dynamic selection (DS), was not previously evaluated for such a task. DS algorithms select the most competent classifiers per query instance from the pool of classifiers. This selection is performed on-the-fly, i.e., during the generalization phase, and is based on the assumption that different classifiers trained for a problem are experts on different local regions of the feature space [33].

Based on that, this section describes a dynamic selection framework (Fig. 1) for reward crowdfunding prediction. The framework comprises two main phase: training (Sect. 3.1) and testing (Sect. 3.2).

3.1 Training phase

Given a training set (**T**) with many campaigns, the first module is "Feature Engineering" that aims at representing each campaign as a vector of features/variables. The variables used in this study were selected considering the literature on the success of reward crowdfunding campaigns predictions. Three groups of variables are extracted to represent each campaign: campaign attributes, geographic localization attributes, and market sentiment, and are detailed in Sect. 4.2.

After representing each campaign as a feature vector, the "Overproduction" module generates a pool of n classifiers. The pool can be homogeneous when all the classifiers are trained using the same learning algorithm or heterogeneous when the classifiers can be trained using different learning algorithms. Herein, only homogeneous pools are evaluated since this topic is more mature in the dynamic selection literature.

The pool of homogeneous classifiers is generated using the Bagging algorithm [80], which is able to generate diverse classifiers by selecting different bootstraps of the training data. To put it differently, each classifier is an expert in a different region of the feature space since it only have access to part of the whole training data. Other

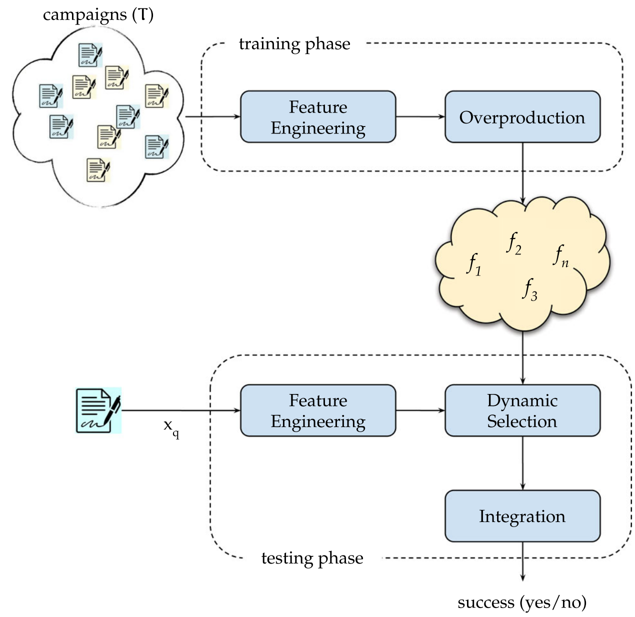


Fig. 1 Dynamic selection framework for reward crowdfunding prediction. The framework comprises two phases: training and testing. **T** is the campaign training dataset, x_q is the query instance, and $f_i \in P$ is a classifier of the pool

alternatives, such as Random Subspace [81], and self-generate hyperplanes [82] can also be used in the Overproduction module.

So, the output of this phase is a pool of classifiers ($P = \{f_1, f_2, \ldots, f_n\}$) trained using **T**.

3.2 Testing phase

After the training phase, a pool of classifiers ($P = \{f_1, f_2, \ldots, f_n\}$ is used to predict the class of an unknown instance x_q. The first module, similar to the training phase is "Feature Engineering" that represents x_q as a feature vector.

The "Dynamic Selection" module selects a subset $P' \subset P$ containing the most competent classifiers to classify x_q. The definition of competence depends on the DS algorithm and can be categorized into accuracy, probabilistic, oracle, meta-learning, and others, as described by [24]. For instance, the dynamic selection OLA algorithm [71] works as follows. First, it finds the k most similar instances to x_q in the validation dataset, this subset of instance is called Region of Competence. Afterward, the OLA algorithm selects the classifier f_i with the best accuracy in the Region of Competence. So, this algorithm relies on the assumption that the best classifier to predict the class of the instances close to x_q should be an excellent choice to classify x_q. All the DS algorithms evaluated in this paper are listed in Sect. 4.3.

Whether the "Dynamic Selection" module selects only one classifier ($P' = \{f_i\}$), this classifier is used to predict the class of x_q. However, if more than one classifier are selected ($|P'| > 1$), the answers of the classifiers in P' applied to x_q must be aggregated. This combination is performed by the "Integration" module.

Among the alternatives to combine the outputs of the classifiers, the Majority vote was chosen. It is a nontrainable rule that does not assume prior knowledge about the classifiers. It can be used with any classifier because it is a hard-level combination rule in contrast to soft-level combination rules that require classifier probabilities estimation.

The output of the "Integration" module is the predicted class (success or unsuccess) of the campaign x_q.

4 Methodology

This section details the data (Sect. 4.1) from a Brazilian reward crowdfunding platform, the variable (Sect. 4.2) used to represent each campaign, and the machine learning algorithms and metrics (Sect. 4.3).

4.1 Data

The data collection used herein was obtained from the Brazilian reward crowdfunding platform Catarse, which is the largest crowdfunding community in the country. Since the beginning of its operations in 2011, it has raised more than R$ 136 million (approximately USD 43.8 million) through the financing of approximately 13,500 campaigns. The fundraising system on this platform is of the AoN (All-or-Nothing) type [83], i.e., if the financial target *TA* established by the entrepreneurs is not reached within the stipulated period, the campaign is canceled and the pledgers receive their resources back or are given credit to finance other campaigns. On the other hand, entrepreneurs of unsuccessful campaigns do not receive any financial resources.

We considered 4193 campaigns that raised more than R$ 38 million (approximately USD 12.3 million) between 2011 and 2015. Table 2 shows the number of successful and unsuccessful campaigns per year. Despite the increase in the number of campaigns over the years (2011 had 298 campaigns, while 2015 had 1404), the classes are balanced, i.e., the two classes (success and unsuccess) have a similar number of instances.

The experimental evaluation is conducted using four different scenarios that aim to evaluate the behavior of the models under different sizes for the training and testing datasets. In the first scenario (I), all the campaigns of 2011 are used to train the models, and the campaigns from 2012 to 2015 are used for evaluating the models. For the second scenario (II), the training dataset is from the years 2011 and 2012, and the testing dataset is composed of the years from 2013 to 2015. The other two scenarios follow the same rationale, and in the last scenario, all years are used to train the models except 2015, which is then used to evaluate the machine learning algorithms. Table 3 shows the number of campaigns for each of the four scenarios.

4.2 Variables

We work with three main groups of independent variables: (i) campaign attributes, (ii) geographic localization attributes (see the geographic localization of the reward crowdfunding campaigns shown in Fig. 2 that represents 415 Brazilian cities), and (iii) Market sentiment.

The first group presents the attributes of the campaigns: $\#$ *of Pledges*$_i$, *Goal*$_i$, *Rewards*$_i$, *Category*$_i$, and *Duration*$_i$. The second group of variables concerns geographic aspects that characterize the campaign's localization: *GDP per Capita*$_i$, *Gini*$_i$, *Elderly population*$_i$, % *of Illiteracy*$_i$, *Population*$_i$, and *City area*$_i$. The third group of variables refers to the Sentiment of the pledger [85] measured from mainstream (*MMNS*) and social media (*SMNS*) at Day d, when campaign i is launched. We use mass media as a proxy for the sentiment of the pledger because, besides serving as a powerful mood stimulus, changes in the news are plausibly exogenous and orthogonal to attributes of crowdfunding campaigns, yielding a promising identification strategy. Each variable is defined as follows.

Campaign success$_i$ is the dependent variable that informs a campaign's success (treated as the achievement of the financial goal *TA*). It is a dummy variable, and we assign 1 to it if the amount collected was equal to or greater than the target amount (i.e., the financial goal) *TA*, and 0 otherwise [60].

Table 2 Number of campaigns (instances) per year

	2011	2012	2013	2014	2015
Number of campaigns	298	531	762	1198	1404
Sucess	156	294	464	650	652
	(52%)	(55%)	(61%)	(54%)	(46%)
Unsucess	142	237	298	548	752
	(48%)	(45%)	(39%)	(46%)	(54%)

This table shows the number of successful and unsuccessful campaigns per year. Despite the increase in the number of campaigns over the years (2011 had 298 campaigns, while 2015 had 1404), the classes are quite balanced, i.e., the two classes (success and unsuccess) have a similar number of instances. The whole dataset contains a total of 4193 campaigns

Table 3 Four different scenarios for dividing the dataset into training and testing

Scenario	Years (number of campaigns)	
	Training	Testing
I	2011 (298)	2012–2015 (3895)
II	2011–2012 (829)	2013–2015 (3363)
III	2011–2013 (1591)	2014–2015 (2602)
IV	2011–2014 (2789)	2015 (1404)

This table shows the number of campaigns for each one of the four scenarios. In the first scenario (I), all the campaigns that occurred in 2011 are used to train the models, and the campaigns from 2012 to 2015 are used for evaluating the models. In the second scenario (II), the training dataset is composed of the campaigns from the years 2011 and 2012, and the testing dataset is composed of campaigns from 2013 to 2015. The other two scenarios follow the same rationale, and in the last scenario, all years are used to train the models except 2015 which is used to evaluate the machine learning algorithms

$Goal_i$ is the ln of the amount (in R$) targeted for the financing of the i-th campaign. This variable was chosen to compose the model because it is believed that the goal is an element that can influence the success of the collective collection of financial resources [38, 86, 87].

$\#$ *of Pledges*$_i$ is the ln of the number of supports received by the campaigns at the end of the fundraising campaign. It was selected because it can be considered an element that attracts contributions and reduces uncertainty about the fundraising process by crowdfunding [39, 88].

$Rewards_i$ is the number of rewards offered during the i campaign fundraising period. According to [89], material rewards (or not) can serve to attract more pledgers to fund campaigns.

$Category_i$ indicates the campaign's classification according to the financing campaigns managed by the Catarse platform. Thus, the campaigns were grouped according to the following categories: music (814), cinema and video (753), theater (388), literature (342), comics (272), community (222), art (215), photography (109), games (109), dance (61), circus (12), architecture and urbanism (34), carnival (39), science and technology (80), design (60), education (146), sport (60), events (152), gastronomy (7), journalism (103), environment (66), mobility and transport (26), fashion (26) and social businesses (97); where the number in parenthesis refers to the number of campaigns per category in the used dataset.

$Duration_i$ is the number of days the campaign takes to reach the target amount TA.

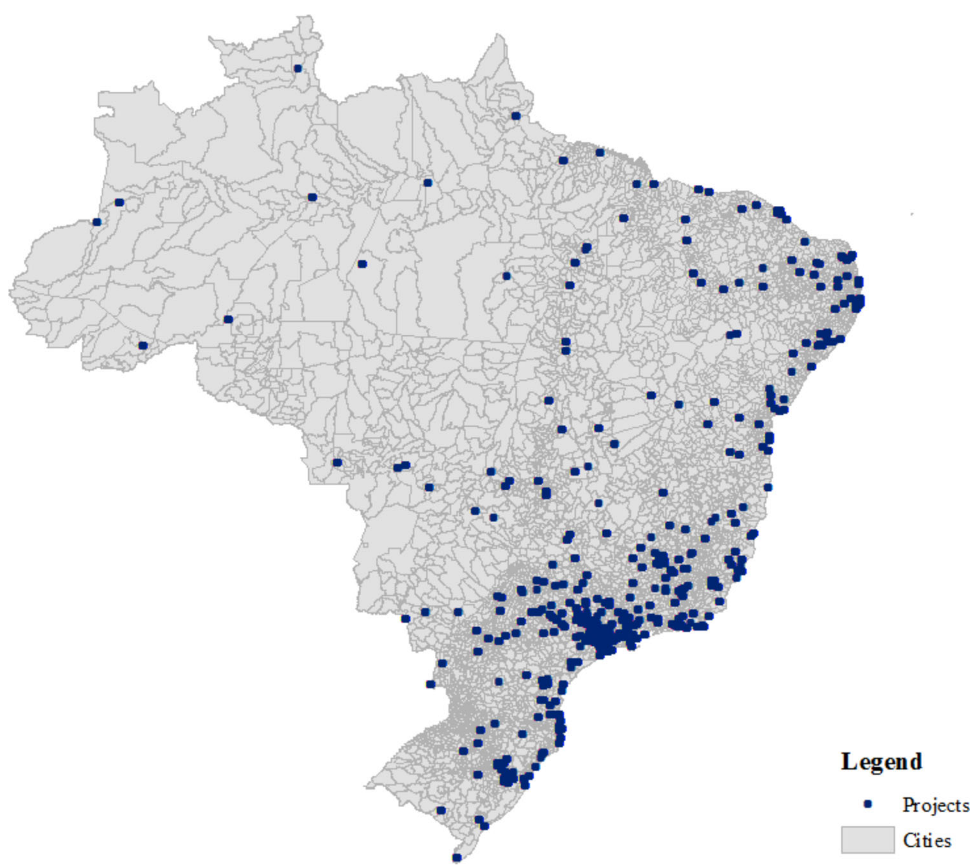


Fig. 2 Geographical distribution of reward crowdfunding campaigns in Brazil. Source: Prepared by the authors, based on data obtained from the Catarse platform, using the ArcGIS ArcMap 10.0 tool [84]. *Note* This figure shows the spatial dispersion of 4193 crowdfunding campaigns on the Catarse platform in the period 2011–2015. See also Table 1)

GDP per Capita$_i$ is the ln of the wealth (in R$) produced in the individual's city that contributes financially to a crowdfunding campaign. We followed the arguments of [38], which suggested that wealthier areas may participate more in funding by crowdfunding. Accordingly, we included this variable because we believe that individuals residing in wealthier regions can make more significant contributions [10]. In addition, we think regions with different income levels should have different dynamics for the success or failure of crowdfunding.

Gini$_i$ is the proxy for the concentration of household income per capita in the cities that are the headquarters of the campaigns seeking collective financing. This variable was extracted from the last census conducted by the Brazilian Institute of Geography and Statistics (IBGE). According to [9, 38], information concerning income and spatial location can help to understand the disproportionate concentration of collective enterprises and should reveal important economic information about the dynamics of crowdfunding.

Elderly population$_i$ is the percentage of the elderly population in each city where crowdfunding campaigns were developed. This variable was considered because demographic variables, such as age group, can influence the rewards model [90]. In general, entrepreneurs are young and with limited availability of capital [90], and these entrepreneurs are likely to count on financial support from people with some financial independence in their financing campaigns. In this way, it makes sense to think that older people with some income can contribute to the projects, especially if they maintain a family relationship with the entrepreneur [91].

% of Illiteracy$_i$ is the percentage of illiteracy in the city of origin of the crowdfunding enterprise. This variable was selected in the modeling because, according to [92], human capital must have a minimum level of education to improve its importance in society and the economy of a given region. In other words, it is reasonable to think that the level of education of individuals in a city can influence their participation in crowdfunding, whether as an entrepreneur or investor.

Population$_i$ is the ln of the estimated population of the city where the campaign takes place [86, 93], according to official data from IBGE census in 2015. *City area$_i$* is the ln the geographic area in (km^2) of the city of origin of the campaign [10].

We use two different proxies for the net sentiment of the pledger's textual sentiment, measured on the day d on which the i campaign is launched on the crowdfunding platform, by using Natural Language Processing-NLP [94]: (i) Mainstream Media Net Sentiment ($MMNS_d$), calculated based on the news captured on mainstream media, and (ii) social media Net Sentiment ($SMNS_d$) based on social media posts. We used the feeling of the backer (pledger) on the day d when the campaign was launched, measured through textual analysis of traditional and social media news content daily relying on the arguments of [31, 85, 95]. This proxy captures sentiment and confidence in the national context through the news with a positive or negative tone. In this sense, we design two variables: an indicator of backer sentiment on the day the campaign was launched via traditional media news of broad reach by the largest newspaper in circulation in Brazil and a variable based on one of the largest social media platforms, X (formerly Twitter). We used the procedure adopted in [96], which in accordance with [97] presents advances concerning the pioneering work of [98], which proposed the method for carrying out the analysis of the speech content based on the frequency of words and assigning a mathematical weight $W_{j,k}$ to the terms found in text content, according to Eq. 4.

$$W_{j,k} = \begin{cases} \dfrac{1+\log(tf_{j,k})}{1+\log(a_k)} & \text{if } tf_{j,k} \geq 1 \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

Given a set of documents $D = \{d_1, d_2, \ldots, d_k, \ldots, d_N\}$ with N documents, the index k refers to the document d_k. Thus, in Eq. 4, $W_{j,k}$ is the weight of the term of a word j in the document with index k, $tf_{j,k}$ is the total number of events of the j word in a d_k document, a_k is the proportion of words counted in the d_k document, and df_j is the total number of documents with at least of one occurrence of the word j. Thus, we measure the pledger of reward crowdfunding campaigns via social and traditional media, based on the largest newspaper published in Brazil, *O Estado de São Paulo* (`@Estadao`), and on the activity of access and filing in the directory of the X (formerly Twitter) Streaming API service, from more than 101 thousand tweets published on the campaign launch dates. We accessed the official X (formerly Twitter) account of this newspaper, which disseminates and shares news, texts, and opinions on economics, politics, culture, and society, to elaborate our social media dataset. With this procedure, we obtained two proxies for the net effect of the textual sentiment based on the tone of the positive and negative news on the day the campaigns are launched. The 1,054 daily news published in mainstream media used for the pledgers' sentiment analysis on the launching day campaigns were manually collected from the cover of the newspaper *O Estado de São Paulo* [99]. Founded in 1870, this newspaper has an average daily circulation of 300,000 copies [100], is available in electronic format on the `estadao.com` domain, and is located in the financial center of Latin America. This newspaper is part of a private news agency

Table 4 The hyperparameter grid considered for the experiments

Method	Hyperparameters
DT	Criterion: [gini, entropy]
	Splitter: [best, random]
	Max-depth: [3, 4, 5, 6, 8, 10, 12, 15] and none
RF	# estimators: [100, 200, ..., 500]
	Max-depth = max-depth: [3,4, 5, 6, 8, 10, 12, 15] and none
XGB	# booster: decision tree learning-rate: [0.05, 0.10, 0.15, 0.20, 0.25, 0.30]
	Max-depth: [3,4, 5, 6, 8, 10, 12, 15]
AdaBoost	Base-estimator: decision tree learning-rate: [0.05, 0.10, 0.15, 0.20, 0.25, 0.30]
	Max-depth: [3,4, 5, 6, 8, 10, 12, 15]
	# Estimators: [10,50,250,1000]
MLP	Hidden-layer-sizes: [50, 100, 200]
	Activation function: [identity, logistic, tanh, relu]
	Solver: [lbfgs, sgd, adam]
	Alpha: [0.0001, 0.001, 0.01, 0.05, 0.5, 1.0]
	Learning-rate: [constant, invscaling, adaptive]
SVM	kernel:[poly, sigmoid, rbf]
	Gamma: [1,0.1,0.01,0.001]
	c: [0.1,1, 10, 100]
SGD	Penalty: [L2, L1, elasticnet]
	Alpha: [0.0001, 0.001, 0.00001, 0.01]
	Loss: [squared_epsilon_insensitive, hinge, log, modified_huber, squared_hinge, perceptron]
KNN	n_neighbors: [1, 3, 5, 7, 9, 13]
	Weights: [uniform, distance]
Static Selection, Single Best	# estimators: [10, 20, 30, 50, 70, 100]
	Base_estimators: [DecisionTree, Perceptron, LogisticRegression, GuassianNB]
OLA, LCA, KNORAU, KNORAE, Meta-DES	k: [3, 7, 5, 9, 13]
	dfp: [True, False] # estimators: [10, 20, 30, 50, 70, 100]
	Base_estimators: [DecisionTree, Perceptron, LogisticRegression, GuassianNB]

Table 4 presents the hyperparameter values considered for each classifier model. For each model, the fivefold cross-validation procedure was performed on the training set, and the hyperparameter configuration that obtained the best performance was selected. KNN = k-Nearest Neighbors, SVM = Support Vector Machines, MLP = Multilayer Perceptron Neural Network, SGD = Stochastic Gradient Descent, DT = Decision Trees, ADA = AdaBoost, RF = Random Forest, XGB = XGBoost, SB = Single Best, StaticS = Static Selection, OLA = Overall Local Accuracy, LCA = Local Class Accuracy, KNORAU = k-Nearest Oracle Union, KNORAE = k-Nearest Oracle-Eliminate, Meta-DES = Meta Learning Dynamic Ensemble Selection

(*Grupo Estado*), with teh extensive capacity to replicate information of a varied nature throughout the Brazilian territory, dealing with economic, political, social, and cultural issues.

4.3 Machine learning algorithms

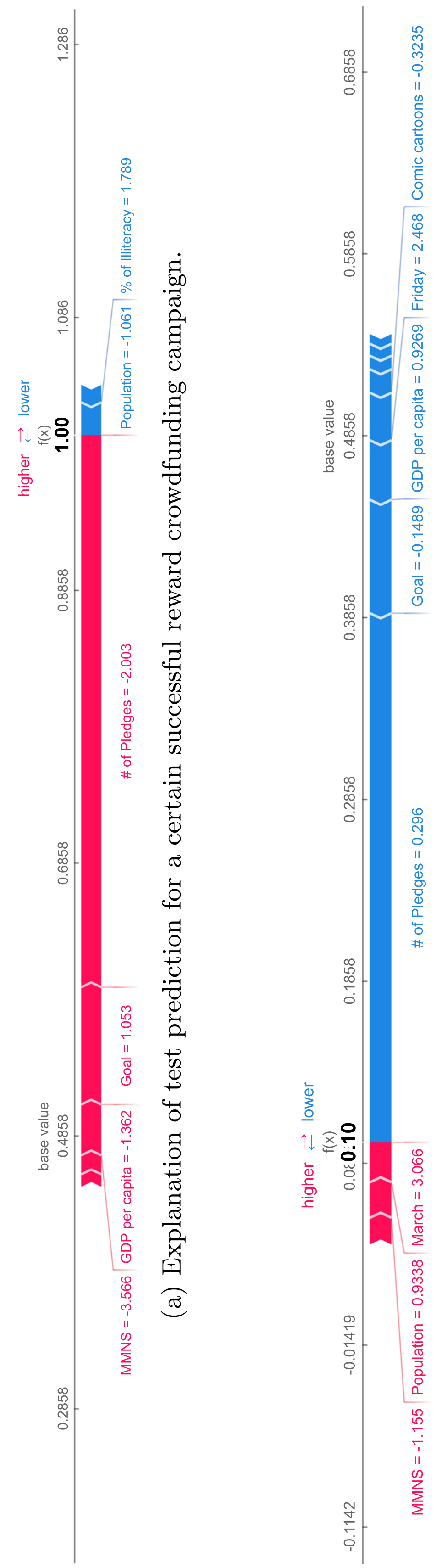
We considered the following learning algorithms in this study: k-Nearest Neighbors (kNN), Support Vector Machines (SVM), Multilayer Perceptron Neural Network (MLP), SGD, Decision Trees (DT), AdaBoost (ADA), Random Forest (RF), and XGBoost (XGB). We also evaluated multiple classifiers systems, such as Single Best (SB) [24], Static Selection (StaticS) [24], Overall Local Accuracy (OLA) [71], Local Class Accuracy (LCA) [71], k-Nearest Oracle Union (KNORAU) [68], k-Nearest Oracle-Eliminate (KNORAE) [68], and Meta-DES [33]. These models were selected since they belong to different families of learning machines, and they are among the best general purpose classification techniques as reported in [64]. Multiple classifier systems, in particular, dynamic selection techniques [24] have been shown to outperform single classifiers [21, 22, 101]. Moreover, to the best of our knowledge, dynamic selection techniques are evaluated herein for the first time to predict campaign success. We used the implementation provided by scikit-learn [102] and the DESlib library [103].

We used a grid search to find the best set of hyperparameters for each machine learning model. Table 4 shows the hyperparameter values considered for each classifier

Table 5 Classifiers' results per scenario

Models	ACC				AUC				F1			
	I	II	III	IV	I	II	III	IV	I	II	III	IV
1. KNN	73.76	73.45	68.13	66.95	81.16	81.60	76.35	76.43	76.40	76.85	72.95	70.89
2. SVM	90.91	88.49	88.39	88.74	**97.14**	95.19	97.06	**97.83**	**91.67**	89.21	89.27	88.96
3. MLP	89.83	89.29	90.19	90.24	96.49	95.99	97.39	97.67	90.43	89.82	90.79	90.27
4. SGD	87.44	88.28	89.39	89.88	91.97	94.82	**97.76**	97.07	88.13	88.79	90.26	89.79
5. DT	88.52	89.89	88.97	88.88	90.55	94.29	95.36	94.84	89.51	90.85	89.73	88.92
6. ADA	89.21	90.54	90.08	88.88	95.47	96.57	96.57	96.56	90.12	91.32	90.74	89.09
7. RF	86.54	87.78	87.89	88.60	93.37	94.75	95.19	96.01	87.80	89.10	88.88	88.81
8. XGB	89.57	91.05	90.69	89.67	96.38	96.86	97.15	97.75	90.37	91.69	91.29	89.70
9. SB	**90.93**	90.60	90.04	90.17	96.94	96.80	97.35	97.80	91.55	91.21	90.68	90.19
10. StaticS	90.50	91.11	90.31	90.38	96.96	95.94	95.34	97.75	91.15	91.76	90.97	90.37
11. OLA	90.65	91.08	90.04	90.52	96.85	97.04	97.46	97.63	91.19	91.75	90.73	90.43
12. LCA	89.34	90.33	89.35	89.60	96.59	97.04	97.17	97.67	90.04	91.11	90.01	89.67
13. KNORAU	90.57	91.46	90.62	**90.81**	96.58	96.25	95.67	97.64	91.20	92.09	91.23	**90.79**
14. KNORAE	89.80	91.31	90.54	90.66	96.72	95.37	96.07	97.67	90.48	91.89	91.16	90.59
15. Meta-DES	90.60	**91.61**	**90.81**	90.66	97.02	**97.15**	95.66	97.71	91.20	**92.19**	**91.39**	90.66

This table presents the accuracy (ACC), area under the receiver operating characteristic-ROC curve (AUC), and F1-score (F1) per scenario for each model. The best and second best results per scenario are in bold and underlined respectively. KNN= k-Nearest Neighbors, SVM = Support Vector Machines, MLP = Multilayer Perceptron Neural Network, SGD = Stochastic Gradient Descent, DT = Decision Trees, ADA = AdaBoost, RF = Random Forest, XGB = XGBoost, SB = Single Best, StaticS = Static Selection, OLA = Overall Local Accuracy, LCA = Local Class Accuracy, KNORAU = k-Nearest Oracle Union, KNORAE = k-Nearest Oracle-Eliminate, Meta-DES = Meta Learning Dynamic Ensemble Selection. For information regarding scenarios I, II, III and IV, see Table 3



(a) Explanation of test prediction for a certain successful reward crowdfunding campaign.

(b) Explanation of test prediction for a certain failed reward crowdfunding campaign.

◀**Fig. 3** Explanation of two test predictions for the scenario IV generated by the Meta-DES model. This figure shows the force SHAP plot for two test instances (i.e., reward crowdfunding campaigns) extracted from scenario IV (see Table 3) using the Meta-DES model. The associated Shapley value of a feature is visualized using the length of an arrow. Feature expressions with large Shapley values have strong effects on the individual prediction and are shown in the middle of SHAP force plots. **a** SHAP force plots show that the individual prediction, via Meta-DES prediction, ($f(x) = 1.0$) consists of the sum of all feature Shapley values and the average model prediction (base value = 0.4858). **b** SHAP force plots show that the individual prediction, via Meta-DES prediction, ($f(x) = 0.10$) consists of the sum of all feature Shapley values and the average model prediction (base value = 0.4858). Thus, for both **a**, **b**, red variables push the result higher than the "base value", while blue variables push the result lower

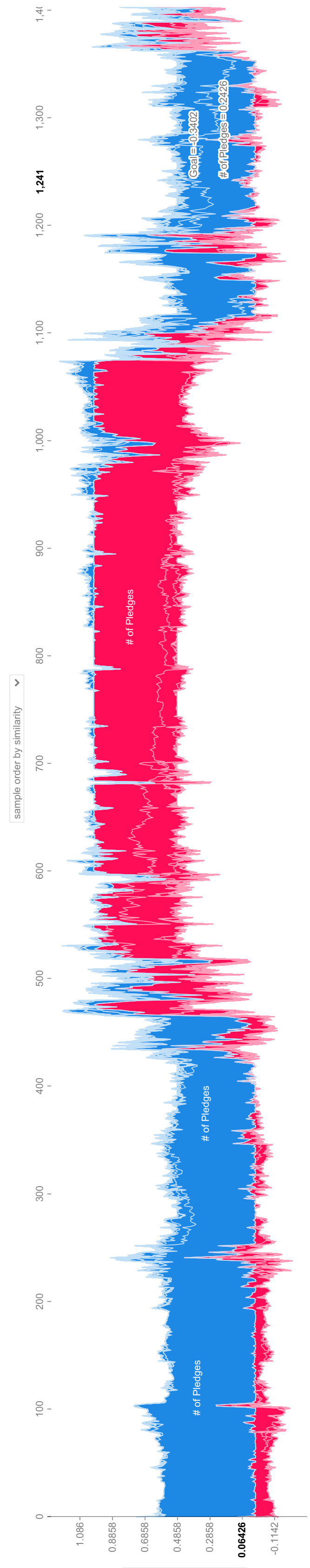
model. For each model, the five fold cross-validation procedure was performed on the training set, and the hyper-parameter configuration that obtained the best performance was selected.

All the experiments were evaluated using three measures: accuracy, area under the ROC Curve (AUC), and F-score (F1). Accuracy is a commonly used measure for classification tasks, and it is defined as the ratio between the number of correctly classified instances and the total number of evaluated instances. The ROC curve is a graph that shows the trade-off between the true positive rate and the false-positive rate for different classification thresholds. In contrast to the ROC curve that provides a 2-dimensional plot, AUC provides a model's performance measure over all possible classification thresholds. F1 is calculated as a combination of precision and recall.

5 Results

The prediction results can be classified into four categories: (i) true positive, when an occurrence is correctly predicted; (ii) true negative, when a nonoccurrence is correctly predicted; (iii) false-positive, when a nonoccurrence is incorrectly predicted; and (iv) false negative, when an occurrence is incorrectly predicted. For the test dataset, the performance of the optimized ML models was evaluated based on three measures: accuracy (ACC), area Under the ROC curve (AUC), and F-score (F1).

Optimized ML models were evaluated using the test dataset and the results are shown in Table 5. Independent of the scenario and used model, all the results show a strong performance for all evaluation metrics (i.e., ACC, AUC, and F1). The best results per scenario are highlighted in bold, and the second-best results are underlined. Among the single classifiers, SVM obtained good accuracy for all scenarios, especially for the AUC metric. Overall, all the



◀ **Fig. 4** Explanation of the whole test dataset predictions for scenario IV generated by the Meta-DES model. This is stacked SHAP explanations clustered by explanation similarity. Each position on the x-axis is an instance of the data, and the y-axis is the model output value. Red SHAP values increase the prediction, and blue values decrease it. This figure shows the whole test set, where the 1404 test instances are sorted by the explanation similarity. When the *# of Pledges* are low, the model tends to indicate that the campaign will not be a success. However, when the *# of Pledges* are high (represented in red at the middle of the plot), the model tends to predict that the campaign will be a success. Three cluster stands out. On the left and right are two groups with a low predicted campaign success

machine learning algorithms achieve very competitive rates, except the k-nearest Neighbor (kNN). RF, XGB, and AdaBoost obtained better results than DT, in general. Thus, given that they use DT as base classifiers, we can infer that these algorithms benefit from using many DTs to predict the instance's label.

Compared to the single classifiers, the multiple classifier systems deserve special attention since they received, in general, the best results. In particular, for the ACC and F1 measures, the best results for all four scenarios were reached by combining the classifiers. Among the combination strategies, Meta-DES was the technique with the best overall result.

Scenario IV (Table 3) is a more realistic scenario since it predicts the outcomes for the next year using all the past data, i.e., the training process uses 2789 campaigns (from 2011 to 2014) to predict the outcomes of 1404 campaigns from 2015. KNORAU obtained the best rates for accuracy and F-score, 90.81 and 90.79, respectively, followed by the Meta-DES. More precisely for the accuracy measure, Meta-DES correctly classified 1273 campaigns and 131 campaigns had their labels predicted incorrectly. The errors are distributed as follows: 112 successful campaigns were classified as unsuccessful, and 19 unsuccessful were classified as successful.

5.1 Discussion

In this section, we analyze how the model's outcome and predictions relate to the variables used to train the 15 different ML models. This analysis is conducted based on the computation of the Shapley values. Consequently, we use the SHAP library[2] in Scenario IV (see Table 3), and the selected model was the Meta-DES (see Table 4) since it obtained the best results (see Table 5). SHAP does a great job in decoding the strength of the influence of the input variables in the predictions. SHAP values determine the feature importance of a feature by comparing what a model

[2] https://github.com/slundberg/shap.

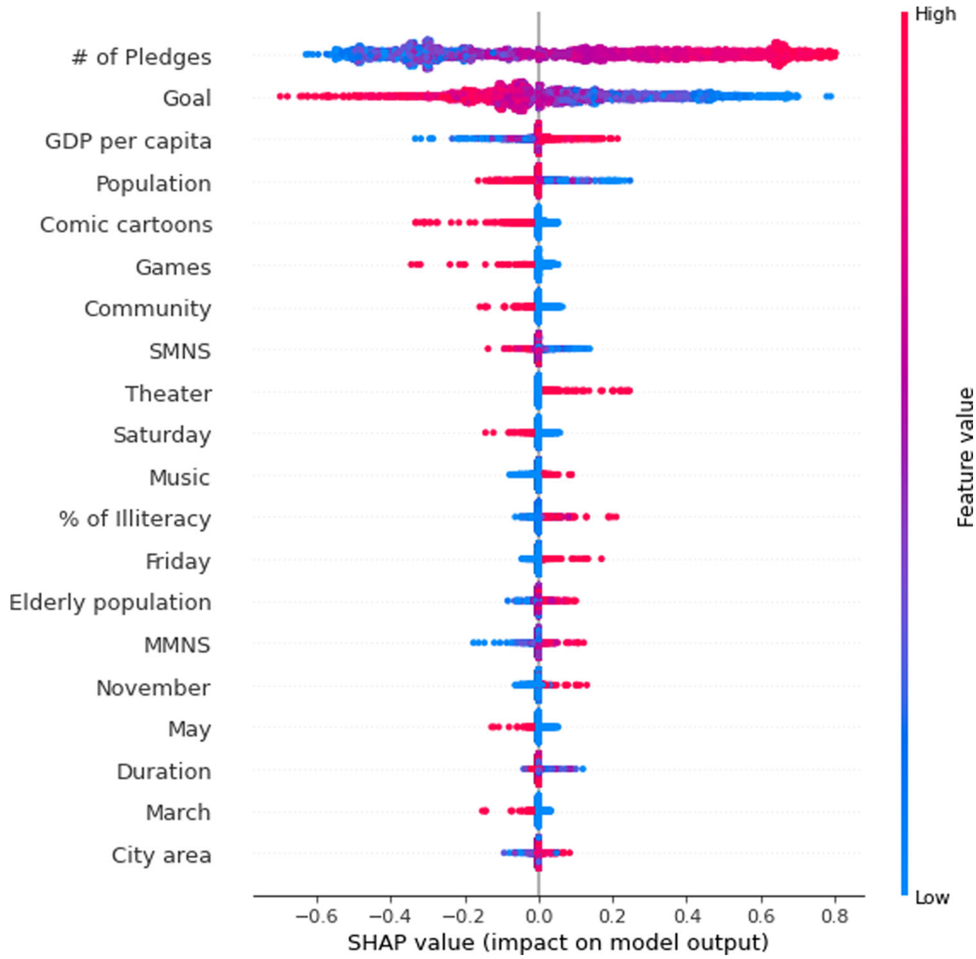


Fig. 5 SHAP summary plot for the Meta-DES model. This figure visualizes Shapley values as the success of the reward crowdfunding campaign and is (one dot per campaign) dependent on feature values for a subset of features of the Meta-DES model applied to scenario IV (Table 3). This figure shows the SHAP summary plot that combines feature importance with feature effects, and shows a global view of the instances. Thus, in this figure, each point visualizes a Shapley value for one subject and one feature. The position on the *y*-axis is determined by the feature and on the *x*-axis by the Shapley value. The color represents the value of the feature from low to high. In other words, the color of the points depends on the feature values, and the *x*-axis shows the calculated Shapley values. The *y*-axis represents both the features, ordered by the mean absolute Shapley values and their distribution. *Comic cartoons*, *games*, *community*, *theater*, *music* are the campaign categories defined by the entrepreneur based on a typology adopted by the crowdfunding platform. We also added a variable to express the day of the week and the month the pledge occurred, with the goal of checking for some kind of calendar effect on the backers' behavior

predicts with and without the feature. We now explain how SHAP can help us to obtain a local knowledge, i.e., how the likelihood of obtaining a higher/lower reward crowdfunding success of each observation is formulated. Explanations obtained by the deep SHAP method are represented graphically.

Figure 3a shows, for a certain successful campaign, the force SHAP plot for one test instance extracted from scenario IV using the Meta-DES model. This plot shows how each feature contributes to the model prediction having the mean model prediction over the training dataset as a baseline. Likewise, Fig. 3b shows the force SHAP plot for one test instance extracted from scenario IV using the Meta-DES model, but for a failed campaign. These plots show how each feature contributes to the model prediction with the mean model prediction over the training dataset as a baseline. For the campaign represented by Fig. 3b, the base value (which is considered to be the mean model prediction over the training dataset) is 0.4858, and the Meta-DES model prediction for the test instance, $f(x)$, is 0.10. Thus, red variables push the result higher than the "base value", while blue variables push the result lower. In other words, the blue variables, such as *#of Pledges* (0.296) and *GDP per capita* (0.9269), are associated with the attribution of negative SHAP values, i.e., the *Campaign success*$_i$ is expected to decrease consequently. In contrast, the red variable, *MMNS* (−1.155), *Population* (0.9338), and campaigns started in *March* (3.066) are

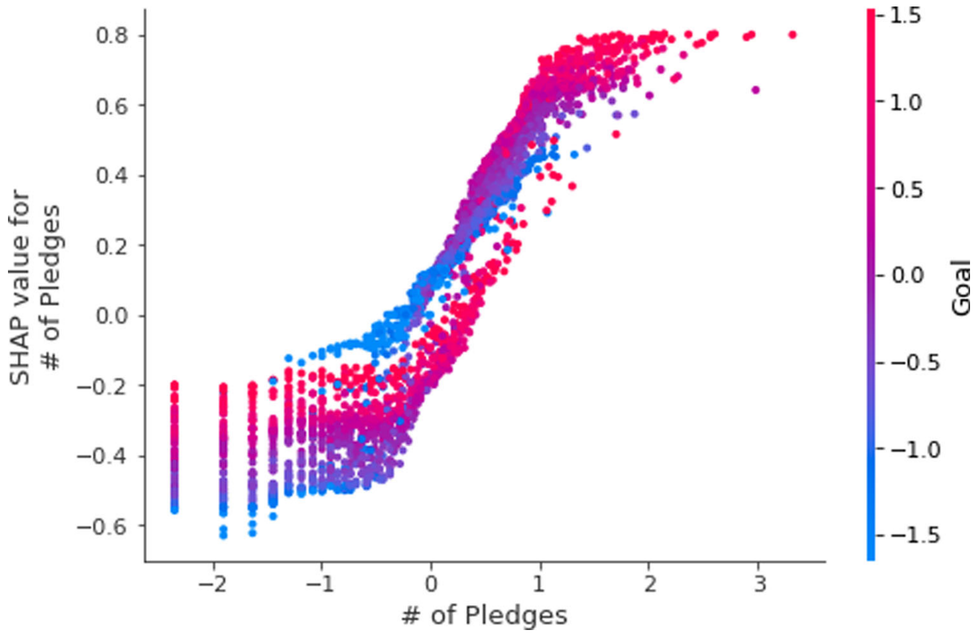


Fig. 6 SHAP feature dependence plot for the predicted outcome of the Meta-DES model, observing two variables, *Goal* and *# of Pledges* for scenario IV. This figure shows the marginal effect that the variables, *# of Pledges* and *Goal*, have on the predicted outcome of the Meta-DES model. Thus, this plot shows that there is an approximately linear and positive trend between the # of Pledges and the target variable; moreover, it is one can observe that the *# of Pledges* interacts with *Goal* frequently

associated with the attribution of positive SHAP values, i.e., the *Campaign* $success_i$ is expected to increase.

In contrast to Fig. 3a, b that show the prediction of a single test instance, Fig. 4 shows the whole test set, where the 1404 test instances are sorted by the explanation similarity. When the *# of Pledges* are low, the model tends to indicate that the campaign will not be a success. However, when the *# of Pledges* are high (represented in red at the middle of the plot), the model tends to predict that the campaign will be a success.

Figure 5 shows the SHAP summary plot that combines feature importance with feature effects with a global view of the instances. Thus, in this Figure, each point is a Shapley value for a feature and an instance. The position on the *y*-axis is determined by the feature and the position on the *x*-axis is determined by the Shapley value. The color represents the value of the feature from low to high. Overlapping points are spread in the *y*-axis direction and as result, we obtain a sense of the distribution of the Shapley values per feature. The features are ordered according to their importance. We are able to see the importance of the features using all the points in the training data, and the variables are ranked in descending order. Thus, *#of Pledges* and the $Goal_i$ are the most relevant attributes to predict a campaign's success. The horizontal spread per feature shows the direction of the impact on the model output. For instance, higher values of *# of Pledges* (red) are more strongly associated with *Campaign success*. On the other hand, the $Goal_i$ feature is inversely proportional to the success of a campaign, i.e., a low $Goal_i$ likely leads to a successful campaign. This finding is compatible with previous intuitions and scientific knowledge, which tells us that the larger a pledge, the more prone to success a crowdfunding campaign [10].

The SHAP dependence plot (Fig. 6) shows the marginal effect that the variable, *# of Pledges* and $Goal_i$, have on the predicted outcome of the Meta-DES model. Thus this plot shows that there is an approximately linear and positive trend between *# of Pledges* and the target variable; moreover, it is possible to observe that the *# of Pledges* interacts with $Goal_i$ frequently. It is worth mentioning that even for campaigns having low values for the *# of Pledges* variable, it is possible to reach a high $Goal_i$; the red dots at the lower left of the plot confirm this.

6 Concluding remarks

Concerns about reward crowdfunding campaign success and its drivers have risen in recent years in developed and emerging countries. Several studies address the crowdfunding campaign success forecasting problem, using techniques that range from traditional statistical approaches to more recent ones such as machine learning models, which have proven useful in this framework (see Table 1). However, there is still a gap between the information provided by these models and the needs of the stakeholders. Not only is an accurate model needed but also a model that provides interpretable results on reward crowdfunding campaigns success and their drivers. Concerning the interpretation of the prediction of reward crowdfunding campaign success, results show that the *# of Pledges* has the greatest impact on the predictions, being directly proportional to reward crowdfunding campaigns success (see

Fig. 5). This is aligned with the current understanding of the phenomena under study.

We show that among the fifteen machine learning models evaluated the results obtained by the Meta-DES model [33], which is a framework that employs a dynamic selection of the models per test instance, compare favorably to the other models. In general, models based on ensemble of classifiers obtain better accuracy compared to monolithic models, such as multilayer perceptrons, decision trees, k-nearest neighbor, random forest, and others. So, multiple classifier systems present as a valuable alternative to predict the campaign success, in particular, those that dynamically select the most competent models per campaign.

After analyzing the influence of variables using SHAP, a method to explain the model's predictions, we have observed that campaigns that attract fewer pledges and set higher revenue targets tend to have more difficulty obtaining success. These two variables turn out to be the main predictors of campaign success, although there are other relevant variables such as the city's gross domestic product per capita, population, and also media sentiment on the campaign launch day.

Finally, we find a light explanatory power in textual sentiment, both in terms of mainstream media and social media. Discussing the effects of mass media on the success of the reward crowdfunding campaign can be a future research around this topic to promote the development of the machine learning and crowdfunding literature. Entrepreneurs and platform managers can learn from our results, as we bring new results about predicting campaign success. Regulators and policy-makers can benefit from our results for the design of public policies that can promote and disseminate the use of crowdfunding reward platforms as a fast and flexible financing channel within the space of FinTechs, especially in the economies of developing countries [104–106]. Furthermore, crowdfunding can be a valuable tool to promote the resilience of communities by allowing quick access to the capital needed to react in times of crisis, such as pandemics and catastrophic events, whether caused by man or natural events [107–109].

Data availability All data supporting the findings of this study are available upon request.

Code availability Source code and supplementary data can be found in the GitHub repository: https://github.com/las33/Crowdfunding.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

1. Sorenson O, Assenova V, Li G-C, Boada J, Fleming L (2016) Expand innovation finance via crowdfunding: crowdfunding attracts venture capital to new regions. Science 354:1526–1528
2. Duan Y, Hsieh T-S, Wang RR, Wang Z (2020) Entrepreneurs' facial trustworthiness, gender, and crowdfunding success. J Corp Finan 64:101693
3. Maechling L, Cunnane V, Corcoran N (2018) Creation and crowdfunding: the marketing of arts. In: Cunnane V, Corcoran N (eds.), European conference on social media. 436–443
4. Bogusz CI, Teigland R, Vaast E (2019) Designed entrepreneurial legitimacy: the case of a Swedish crowdfunding platform. Eur J Inf Syst 28:318–335
5. Bogusz C, Laurell C, Sandström C, Sandström C (2020) Tracking the digital evolution of entrepreneurial finance: The interplay between crowdfunding, blockchain technologies, cryptocurrencies, and initial coin offerings. IEEE Trans Eng Manag 67:1099–1108
6. Sutanto J, Wenninger H, Duriana H (2021) Warm-glow giving, hedonism, and their influence on muslim user engagement on loan-based crowdfunding platforms. J Assoc Inf Syst 22:7
7. Felipe IJ, Mendes-Da-Silva W, Leal CC, Braun Santos D (2022) Reward crowdfunding campaigns: time-to-success analysis. J Bus Res 138:214–228
8. Luo X, Ge L, Wang CA (2022) Crowdfunding for microfinance institutions: the new hope? MIS Quarterly. 46
9. Burtch G, Ghose A, Wattal S (2014) Cultural differences and geography as determinants of online prosocial lending. MIS Q Manag Inf Syst 38:773–794
10. Mendes-Da-Silva W, Rossoni L, Conte BS, Gattaz CC, Francisco ER (2016) The impacts of fundraising periods and geographic distance on financing music production via crowdfunding in Brazil. J Cult Econ 40:75–99
11. Yan J et al (2018) Mining social lending motivations for loan project recommendations. Expert Syst Appl 111:100–106
12. Kim C, Kannan P, Trusov M, Ordanini A (2020) Modeling dynamics in crowdfunding. Mark Sci 39:339–365
13. Tsang EW, Kwan K-M (1999) Replication and theory development in organizational science: a critical realist perspective. Acad Manag Rev 24:759–780
14. Honig B, Samuelsson M (2015) Replication in entrepreneurship research: a further response to delmar. J Bus Ventur Insights 3:30–34
15. Ethiraj SK, Gambardella A, Helfat CE (2016) Replication in strategic management. Estrat Manag J 37:2191
16. Babin BJ, Ortinau DJ, Herrmann J-L, Lopez C (2021) Science is about corroborating empirical evidence, even in academic business research journals. J Bus Res 126:504–511
17. Yuan H, Lau RY, Xu W (2016) The determinants of crowdfunding successDtext analytics approach. Decis Support Syst 91:67–76
18. Shafqat W, Byun Y-C, Park N (2020) Effectiveness of machine learning approaches towards credibility assessment of crowdfunding projects for reliable recommendations. Appl Sci 10:9062
19. Yeh J-Y, Chen C-H (2020) A machine learning approach to predict the success of crowdfunding fintech project. J Enterprise Inf Manag 35:1678
20. Peng N, Zhou X, Niu B, Feng Y (2021) Predicting fundraising performance in medical crowdfunding campaigns using machine learning. Electronics 10:143
21. Kuncheva LI (2014) Combining pattern classifiers: methods and algorithms. Wiley

22. Woźniak M, Graña M, Corchado E (2014) A survey of multiple classifier systems as hybrid systems. Inf Fusion 16:3–17
23. Britto AS, Sabourin R, Oliveira LE (2014) Dynamic selection of classifiers–a comprehensive review. Pattern Recogn 47:3665–3680
24. Cruz RM, Sabourin R, Cavalcanti GD (2018) Dynamic classifier selection: recent advances and perspectives. Inf Fusion 41:195–216
25. Yin C, Liu L, Mirkovski K (2019) Does more crowd participation bring more value to crowdfunding projects? The perspective of crowd capital. Internet Res 29:1149–1170
26. Kaminski JC, Hopp C (2020) Predicting outcomes in crowdfunding campaigns with textual, visual, and linguistic signals. Small Bus Econ 55:627–649
27. Wang W, Zhu K, Wang H, Wu Y-CJ (2017) The impact of sentiment orientations on successful crowdfunding campaigns through text analytics. IET Software 11:229–238
28. Carvajal M, García-Avilés JA, González JL (2012) Crowdfunding and non-profit media: the emergence of new models for public interest journalism. J Pract 6:638–647
29. Stiver A, Barroca L, Minocha S, Richards M, Roberts D (2015) Civic crowdfunding research: challenges, opportunities, and future agenda. New Media Soc 17:249–271
30. Chen Y, Dai R, Yao J, Li Y (2019) Donate time or money? The determinants of donation intention in online crowdfunding. Sustainability 11:4269
31. Mendes-Da-Silva W, Felipe I, Leal CC, Aguiar MO (2022) How the tone of mass media news affects pledge amounts in reward crowdfunding campaigns. J Small Bus Manag 62:254
32. Stasik A, Wilczyńska E et al (2018) How do we study crowdfunding? An overview of methods and introduction to new research agenda. J Manag Bus Admini Central Eur 26:49–78
33. Cruz RMO, Sabourin R, Cavalcanti GDC, Ren TI (2015) Meta-DES: a dynamic ensemble selection framework using meta-learning. Pattern Recogn 48:1925–1935
34. Lundberg SM, Lee SI, Inc CA (2017) A unified approach to interpreting model predictions. In: International conference on neural information processing systems. 4768–4777
35. Dushnitsky G, Sarkar S (2022) Here comes the sun: the impact of incidental contextual factors on entrepreneurial resource acquisition. Acad Manag J 65:66–92
36. Burtch G, Ghose A, Wattal S (2013) An empirical examination of the antecedents and consequences of contribution patterns in crowd-funded markets. Inf Syst Res 24:499–519
37. Crosetto P, Regner T (2014) Crowdfunding: Determinants of success and funding dynamics. Tech. Rep., Jena Economic Research Papers. http://hdl.handle.net/10419/108542
38. Mollick E (2014) The dynamics of crowdfunding: an exploratory study. J Bus Ventur 29:1–16
39. Colombo MG, Franzoni C, Rossi-Lamastra C (2015) Internal social capital and the attraction of early contributions in crowdfunding. Entrep Theory Pract 39:75–100
40. Hörisch J (2015) Crowdfunding for environmental ventures: an empirical analysis of the influence of environmental orientation on the success of crowdfunding initiatives. J Clean Prod 107:636–645
41. Zvilichovsky D, Inbar Y, Barzilay O (2015) Playing both sides of the market: success and reciprocity on crowdfunding platforms. Available at SSRN 2304101
42. Hobbs J, Grigore G, Molesworth M (2016) Success in the management of crowdfunding projects in the creative industries. Internet Res
43. Shi M, Guan L (2016) An empirical study of crowdfunding campaigns: evidence from Jing dong crowdfunding platform. In: International conference on service systems and service management. 1–5
44. Courtney C, Dutta S, Li Y (2017) Resolving information asymmetry: signaling, endorsement, and crowdfunding success. Entrep Theory Pract 41:265–290
45. Skirnevskiy V, Bendig D, Brettel M (2017) The influence of internal social capital on serial creators success in crowdfunding. Entrep Theory Pract 41:209–236
46. Bi S, Liu Z, Usman K (2017) The influence of online information on investing decisions of reward-based crowdfunding. J Bus Res 71:10–18
47. Chan CR, Park HD, Patel P, Gomulya D (2018) Reward-based crowdfunding success: decomposition of the project, product category, entrepreneur, and location effects. Ventur Cap 20:285–307
48. Crosetto P, Regner T (2018) It's never too late: funding dynamics and self pledges in reward-based crowdfunding. Res Policy 47:1463–1477
49. de Larrea GL, Altin M, Singh D (2019) Determinants of success of restaurant crowdfunding. Int J Hosp Manag 78:150–158
50. Lagazio C, Querci F (2018) Exploring the multi-sided nature of crowdfunding campaign success. J Bus Res 90:318–324
51. Oo PP, Allison TH, Sahaym A, Juasrikul S (2019) User entrepreneurs' multiple identities and crowdfunding performance: effects through product innovativeness, perceived passion, and need similarity. J Bus Ventur 34:105895
52. Da Cruz JV (2018) Beyond financing: crowdfunding as an informational mechanism. J Bus Ventur 33:371–393
53. Zhou MJ, Lu B, Fan WP, Wang GA (2018) Project description and crowdfunding success: an exploratory study. Inf Syst Front 20:259–274
54. Wang N, Li Q, Liang H, Ye T, Ge S (2018) Understanding the importance of interaction between creators and backers in crowdfunding success. Electron Commer Res Appl 27:106–117
55. Yeh T-L, Chen T-Y, Lee C-C (2019) Investigating the funding success factors affecting reward-based crowdfunding projects. Innovation 21:466–486
56. Ba Z, Zhao YC, Song S, Zhu Q (2021) Understanding the determinants of online medical crowdfunding project success in china. Inf Process Manag 58:102465
57. Tafesse W (2021) Communicating crowdfunding campaigns: how message strategy, vivid media use and product type influence campaign success. J Bus Res 127:252–263
58. Oduro MS, Yu H, Huang H (2022) Predicting the entrepreneurial success of crowdfunding campaigns using model-based machine learning methods. Int J Crowd Sci 6:7–16
59. Raflesia SP, Lestarini D, Kurnia RD, Hardiyanti DY (2023) Using machine learning approach towards successful crowdfunding prediction. Bull Electr Engin Inf 12:2438–2445
60. Strausz R (2017) A theory of crowdfunding: a mechanism design approach with demand uncertainty and moral hazard. Am Econ Reve 107:1430–76
61. Glazer A, Konrad KA (1996) A signaling explanation for charity. Am Econ Rev 86:1019–1028
62. Fisk RP et al (2011) Crowd-funding: transforming customers into investors through innovative service platforms. J Serv Manag 22:443–470
63. Hu M, Li X, Shi M (2015) Product and pricing decisions in crowdfunding. Mark Sci 34:331–345
64. Fernández-Delgado M, Cernadas E, Barro S, Amorim D (2014) Do we need hundreds of classifiers to solve real world classification problems? J Mach Learn Res 15:3133
65. Dietterich TG (2000) Ensemble methods in machine learning. In: International Workshop on Multiple Classifier Systems, Springer 1–15
66. Kuncheva L (2002) A theoretical study on six classifier fusion strategies. IEEE Trans Pattern Anal Mach Intell 24:281–286

67. Polikar R (2006) Ensemble based systems in decision making. IEEE Circuits Syst Mag 6:21–45
68. Ko AH, Sabourin R, Britto AS Jr (2008) From dynamic classifier selection to dynamic ensemble selection. Pattern Recogn 41:1718–1731
69. Souza MA, Cavalcanti GD, Cruz RM, Sabourin R (2019) Online local pool generation for dynamic classifier selection. Pattern Recogn 85:132–148
70. Meta-learning and feature selection for dynamic ensemble selection (2017) Cruz, R. M., Sabourin, R. & Cavalcanti, G. D. Meta-DES. Oracle. Information Fusion 38:84–103
71. Woods K, Kegelmeyer W, Bowyer K (1997) Combination of multiple classifiers using local accuracy estimates. IEEE Trans Pattern Anal Mach Intell 19:405–410
72. Lundberg S, Erion G, Chen H et al (2020) From local explanations to global understanding with explainable ai for trees. Nat Mach Intell 2:56–67
73. Bloch L, Friedrich CM (2021) Data analysis with shapley values for automatic subject selection in alzheimer's disease data sets using interpretable machine learning. Alzheimer's Res Therapy 13:1–30
74. Vriens M, Vidden C, Bosch N (2021) The benefits of shapley-value in key-driver analysis. Appl Mark Anal 6:269–278
75. Shapley LS (2016) 17. A Value for n-Person Games, 307–318. Princeton University Press
76. Cook RD (1977) Detection of influential observation in linear regression. Technometrics 19:15–18
77. Rodríguez-Pérez R, Bajorath J (2020) Interpretation of machine learning models using shapley values: application to compound potency and multi-target activity predictions. J Comput Aided Mol Des 34:1013–1026
78. Vega García M, Aznarte JL (2020) Shapley additive explanations for no2 forecasting. Eco Inform 56:101039
79. Cha Y et al (2021) An interpretable machine learning method for supporting ecosystem management: application to species distribution models of freshwater macroinvertebrates. J Environ Manag 291:112719
80. Breiman L (1996) Bagging predictors. Mach Learn 24:123–140
81. Ho TK (1998) The random subspace method for constructing decision forests. IEEE Trans Pattern Anal Mach Intell 20:832–844
82. Souza MA, Cavalcanti GDC, Cruz RMO, Sabourin R (2017) On the characterization of the oracle for dynamic classifier selection. In: International joint conference on neural networks. 332–339
83. Hemer J (2011) A snapshot on crowdfunding. Tech. Rep., Arbeitspapiere Unternehmen und Region. http://hdl.handle.net/10419/52302
84. Zieg J, Zawada DG (2021) Improving esri arcgis performance of coastal and seafloor analyses with the python multiprocessing module. J Coast Res 37:1288
85. Shafi K, Mohammadi A (2020) Too gloomy to invest: weather-induced mood and crowdfunding. J Corp Finan 65:101761
86. Giudici G, Guerini M, Rossi-Lamastra C (2018) Reward-based crowdfunding of entrepreneurial projects: the effect of local altruism and localized social capital on proponents success. Small Bus Econ 50:307–324
87. Li G, Wang J (2019) Threshold effects on backer motivations in reward-based crowdfunding. J Manag Inf Syst 36:546–573
88. Josefy M, Dean TJ, Albert LS, Fitza MA (2017) The role of community in crowdfunding success: evidence on cultural attributes in funding campaigns to save the local theater. Entrepreneurship Theory Pract 41:161–182
89. Frydrych D, Bock AJ, Kinder T, Koeck B (2014) Exploring entrepreneurial legitimacy in reward-based crowdfunding. Ventur Cap 16:247–269
90. Gamble JR, Brennan M, McAdam R (2017) A rewarding experience? exploring how crowdfunding is affecting music industry business models. J Bus Res 70:25–36
91. Agrawal A, Catalini C, Goldfarb A (2015) Crowdfunding: Geography, social networks, and the timing of investment decisions. J Econ Manage Strat 24:253–274
92. Florida R (2002) The economic geography of talent. Ann Assoc Am Geogr 92:743–755
93. Giudici G, Guerini M, Rossi Lamastra C (2013) Why crowdfunding projects can succeed: the role of proponents' individual and territorial social capital. Available at SSRN 2255944
94. Li Y, Ma Thomas, Liu D (2020) From semantics to pragmatics: where is can lead in natural language processing (nlp) research. Eur J Inf Syst 30:569
95. Yuan X, Wang L, Yin X, Wang H (2021) How text sentiment moderates the impact of motivational cues on crowdfunding campaigns. Financ Innov 7:1–26
96. Loughran T, McDonald B (2011) When is a liability not a liability? textual analysis, dictionaries, and 10-ks. J Financ 66:35–65
97. Kearney C, Liu S (2014) Textual sentiment in finance: a survey of methods and models. Int Rev Financ Anal 33:171–185
98. Tetlock PC (2007) Giving content to investor sentiment: the role of media in the stock market. J Financ 62:1139–1168
99. Nascimento SS, Rodrigues GM, Kraemer L (2015) A utilização da lei de acesso à informação pela imprensa: análise dos jornais folha de s. paulo, o estado de s. paulo e o globo. *Rumores***9**, 225–248
100. Estadao. Estadão: Publicidade e oportunidades comerciais: Mídia kit (2021). https://www.publicidadeestadao.com.br/. Accessed 16 Nov 2021
101. Kittler J, Hatef M, Duin RPW, Matas J (1998) On combining classifiers. IEEE Trans Pattern Anal Mach Intell 20:226–239
102. Pedregosa F et al (2011) Scikit-learn: machine learning in python. J Mach Learn Res 12:2825–2830
103. Cruz RMO, Hafemann LG, Sabourin R, Cavalcanti GDC (2020) Deslib: a dynamic ensemble selection library in python. J Mach Learn Res 21:1–5
104. Cumming D, Zhang Y (2016) Alternative investments in emerging markets: a review and new trends. Emerg Mark Rev 29:1–23
105. Knewtson HS, Rosenbaum ZA (2020) Toward understanding fintech and its industry. Manag Financ
106. Dorfleitner G, Oswald E-M, Röhe M (2020) The access of microfinance institutions to financing via the worldwide crowd. Q Rev Econ Financ 75:133–146
107. Lemos A, Ramos I (2016) Crowdfunding and resilience of communities: a case study [crowdfunding e resiliência das comunidades: Estudo de caso]. (ed.CAlg) , Vol. 16, 212–230
108. Behl A, Dutta P (2020) Engaging donors on crowdfunding platform in disaster relief operations (dro) using gamification: a civic voluntary model (cvm) approach. Int J Inf Manag.54
109. Trovato M (2021) An axiology of residual green urban areas. Environments. 8