The impact of campaign features on crowdfunding success in contemporary visual public art: A machine-learning application[1]

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Version of 25 July 2022

Abstract

This paper aims to shed light on the use of crowdfunding in the contemporary art market by studying the impact of main features of crowdfunding campaigns on their success for less tangible contemporary visual artistic expressions which might be more difficult to be traded through traditional art market channels, such as art public art. In order to disentangle possible benefits of crowdfunding for visual artists, we apply a machine-learning methodology to an ad-hoc taxonomy we elaborated, based on the general literature on crowdfunding benefits. An original dataset was built starting from Kickstarter category "Public Art" for the period 2009-2022. Using Data Robot, we estimated 36 ML models to predict raised funding amount in the public arts crowdfunding campaigns. Out of the estimated models, the Light Gradient Boosted Trees Regressor (Gamma Loss) (4 leaves) performed the best. Feature impact and feature fits were estimated after this model. Main results show that having a direct link of project realisation on the Kickstarter page, number of pledge levels, types of rewards, number of project updates, and number of backed projects by creator are top five features influencing the raised funding amount.

Keywords: Contemporary art market; Crowdfunding; Gatekeeping; Machine learning.

1 Introduction

The art market is a typically for-profit and traditional sector in the creative and cultural industries. For their income, visual artists have mainly relied on trade ensured by intermediaries, such as galleries, dealers, auctions, fairs and, more recently, online platforms. Public and charity financial support is rather limited to public projects and commissions and museum acquisitions. Correspondingly, in the system of the contemporary art market, financing strategies are closely linked to these intermediaries, which act as real gatekeepers in establishing also artistic taste and trends.

Artistic creation is by definition constantly experimenting new ways of expression. Since last century, contemporary visual art has seen an increasing freedom of media, such as installations, performances, mixed media, etc. From a product perspective, these new creative processes have considerably expanded the palette of artworks from solely tangible permanent stockable artworks (e.g., paintings, sculptures, drawings, photography, etc.) only, to also

[1] Paper submitted to the Tenth European Workshop on Applied Cultural Economics, Turin, 8-10 September 2022 – please do not cite without authors' consent.
This research has benefited of the support of the Research Council of Norway under the project CROWDCUL - Funding Culture, https://crowdcul.org.
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perishable, temporary and ephemeral live media (e.g., installations, performance art, public art etc.). These new creative processes have not seen the development of new artistic movements, such as, for instance, Land Art, but also, from an economic perspective, new market challenges (Ginsburgh & Penders, 1997). Eventually, these new media have spread, to be adopted also by more "traditional"-media artists, such as painters, possibly increasing the relevance of the issue of better ensuring financially viable solutions also for these art media that, by their features, are less marketable through more conventional ways.

In the last years, the combination of digitisation, crowdsourcing and entrepreneurship has seen the emergence crowdfunding as suitable mode of funding mode also in the cultural and creative industries, thanks to crowdfunding benefits outscoring their possible barriers (Lazzaro & Noonan, 2020, 2021). Although the use of crowdfunding is less straightforward for the visual art and in particular for the art market for its features we have presented above, which also explains a remarkable gap in the literature.

This paper aims to shed light on new financing and marketing strategies of contemporary visual artists, and especially to what extent artists recur to crowdfunding, therefore contributing original evidence on possible benefits of crowdfunding in supporting a more diverse artistic expression of living visual artists. Our analysis draws on and empirically tests the taxonomy of crowdfunding benefits in visual-art new media that Lazzaro & Nordgård (forthcoming), elaborated on the basis of theoretical and empirical literature. Our paper empirically contributes on: possible substitutional effects and disintermediation in the art market; the impact of crowdfunding on the art-market value chain and on the role of commercial intermediaries in artists' income; a possible freedom of artists from traditional gatekeepers and, more in general, the impact of crowdfunding on artists' aesthetic practices.

Overall, our paper aims to disentangle what role crowdfunding plays and can play on the contemporary art market, and in particular: to what extent crowdfunding is used to fund media novel visual art that are financially less viable on traditional art market channels, such as public art? What are the main features of these crowdfunding campaigns? Can crowdfunding ultimately be considered an alternative or rather complementary on the art market? For this purpose, we apply a rather novel empirical approach of machine-learning

The paper is organised as follows. Section 2 introduces what is crowdfunding for the arts, Section 3 presents the dataset. Section 4 illustrates the empirical approach. Section 6 presents the results.

2 Crowdfunding in the arts and culture

Crowdfunding is a form of crowdsourcing and of alternative or complementary finance. It allows the collection of small amounts of money (pledges) for a given amount (goal) by a large number of people (crowd). It has been possible by the application of digitisation, that substantially reduces associated transaction costs. Crowdfunding is typically employed to fund a project or venture, rather than in structural finance. It first originated in the US to finance IT ventures, to span also social entrepreneurship. Two main forms of crowdfunding exist in the cultural and creative industries, to support creative projects and startups: reward crowdfunding, where symbolic goods are given to thank pledgers; and, to a lesser extent donation crowdfunding, where nothing is given in exchange. Examples of rewards include limited editions, tours, networking sessions and prototypes. Other forms of crowdfunding, such as equity and lending crowdfunding are instead more common in financial markets.
Overall, crowdfunding is increasing, in the cultural sector too. This is also to due to shrinking of public and private funding. The two major markets for crowdfunding activity are the US and Europe, although crowdfunding is growing worldwide. It has been estimated that more that

600 crowdfunding platforms more or less specialised in the cultural and creative industries operate just in Europe (European Commission, 2017) for an annual turnover of more than US$4m. Further arguments in support of crowdfunding point to it favouring community engagement, audience development, co-creation, entrepreneurial skills development, promotion, information and market research (Lazzaro & Noonan, 2020, 2021). Direct and indirect benefits from crowdfunding have been identified.

Direct benefits can be found in the lowering of transaction costs for fundraising and increased project viability. It informs public projects and goals and fosters match-funding. It may also provide improved information, and reduced uncertainty (Block et al, 2017; Kromidha & Robson, 2016) and can be used for market research and prototypes testing. Further, crowdfunding provides the potential for more interaction between creator and prospective backers through various ways of communicating and interacting. Crowdfunding provides better outreach and larger audience and markets, geographical spread and specialisation (Noonan, Breznitz & Mabool, 2020).

Indirect benefits can be found in Crowdfunding's democratisation of funding and the increased chances of attraction of traditional capital. It fosters entrepreneurship and developments of professional skills and it increases community involvement (Agrawal, Catalini & Goldfarb, 2015) and co-creation with audiences (Thomas Claus et al., 2018).

3 Data

We built an original dataset of completed crowdfunding campaigns run on the internationally most popular and specialised arts crowdfunding platform, namely Kickstarter.[3] Data were collected between June 2021 and May 2022, in two rounds. Kickstarter is a US-based platform that follows an "all-or-nothing" reward model. According to this model, campaigners are funded if they succeed to fetch the declared goal from the pledges collected from the crowd. Pledgers typically receive symbolic rewards against the pledges they make, if the campaign is successful. All campaigns included in the dataset have reached their financial goal and all campaigns are completed, although in some cases the project has yet to be finalized. We collected information on all successfully completed Kickstarter campaigns from all over the world since its launch in 2009. We focused on Kickstarter art category "Public Art" (3,564 campaigns) and corresponding most funded campaigns larger than $20,000. In a further step, we manually checked for real projects of contemporary public visual art, in order to exclude different types of projects, such as infrastructure, performing arts, heritage, publications, etc. to control for Kickstarter's categorisation. We finally obtained 155 campaigns. Campaigns run in currencies other than US$ were historically converted to US$. We integrated Kickstarter data with information on artists' bios and campaigned art projects available on the general internet.

4 Inputs to the Automated machine learning model

We aim to study how the amount of money raised by each campaign (dependent variable) is explained by the campaign features (explanatory variables) as detailed below. These campaign features, and corresponding measures and hypotheses presented below draw on the taxonomy elaborated by Lazzaro & Nordgård (forthcoming).

[3] www.kickstarter.com

- The campaigner or artist are institutionalised artists/creators (i.e., belong to the conventional art market circuit of galleries, museums, etc.): institutionalised artists, as they also bear recognition, should attract more pledges than artists or campaigners unknow to the system.
- Rewards are the art project: if the campaigned project aims to produce and sell objects, this could be interpreted as not really as public art, but rather as a mere commercial operation, thus possibly hindering the campaign.
- Project labelled as Kickstarter-Art Basel: This was a collaboration between Kickstarter and the most important contemporary art fair worldwide that lasted until 2016; this label should positively affect campaigns.
- Kickstarter's "Project we love" label: also this label put by the platform itself should positively communicate the goodness of a project from a crowdfunding and possibly artistic perspective.
- "Kickstarter.art" project: this further label should increase confidence about quality and hence favour pledges.
- Artist/creator still active: This is a further indicator the artist is a professional one.
- Country of campaign: other conditions being equal, some countries could be favoured, for instance the US (country of Kickstarter) and other English-speaking countries.
- Information on project realisation on KS vs outside (internet, social media): evidence of the project being realised outside Kickstarter platform should support the credibility of the project and campaigner.
- Number and quality of updates and comments: this variable refers to the crowdfunding benefit of fostering interaction with backers, community involvement and co-creation with audiences, and is expected to be positively correlated with the campaign success.
- Artist is campaign creator: this relates to the marketing, financial and entrepreneurial skill of the artist in crowdfunding.
- Number of campaigns per artist/creator, that accounts for the crowdfunding experience of the artist.
- Number of of pledge levels and types of rewards: this input accounts for the articulation and customisation of campaign rewards.

  Table 1 displays descriptive statistics for the different inputs.

Table 1: Descriptive statistics

	Var Type	Unique	Missing	Mean	Std Dev	Median	Min	Max
Proj we love	Categorical	2	0					
KS_art	Categorical	2	0					
Art Basel	Categorical	2	0					
Country of project realisation in USA	Categorical	2	0					
Collaborator is a serial backer (e_g_ backerclub)	Categorical	2	0					
Proof of project realisation found outside KS page=1	Categorical	2	0					

Institutional artist (i_e_ also in known museums/galleries)	Categorical	2	0					
Rewards are the true project (e_g_ Aimee Golant)	Categorical	2	0					
No_ of collaborators	Numeric	6	0	0.30	0.83	0.00	0.00	5.00
No_ of successful projects by Creator	Numeric	8	0	1.73	1.43	1.00	1.00	8.00
No_ of backed projects by creator	Numeric	35	0	9.47	15.36	3.00	0.00	84.00
Raised	Numeric	152	0	42131.00	45129.00	28106.00	20003.00	462872.00
No_ of pledge levels	Numeric	26	0	13.85	6.33	13.00	4.00	43.00
Types of rewards	Numeric	20	0	12.17	4.22	12.00	4.00	31.00
No_ of days campaign	Numeric	33	0	34.84	10.07	30.50	15.00	60.00
No_ of updates	Numeric	32	0	11.18	7.98	10.00	0.00	58.00

5 Methods

In general, there have been limited applications of machine learning models in predicting the success of crowdfunding campaigns (Yeh and Chen, 2020; Oduro, Yu and Huang, 2022; Shi, Yang, Xu and Wang, 2021), and rarely in the context of predicting raised funding amount in cultural crowdfunding. While machine learning models are useful, researchers are often limited to the applications of one to five ML models in one study. Recent developments in the ML space, known as automated machine learning (AutoML) mitigates these limitations and allows application of hundreds of ML models within a short period of time (Hutter, Kotthoff, and Vanschoren, 2019). AutoML saves time and simplifies the application of ML methods by eliminating the repetitive tasks from ML applications such as data pre-processing and feature engineering (Truong et al., 2019). In this study, we utilized the Data Robot[4] AutoML tool, a cloud-based platform.

Using Data Robot, we estimated 36 ML models to predict raised funding amount in the public arts crowdfunding campaigns. Out of the estimated models, the Light Gradient Boosted Trees Regressor (Gamma Loss) (4 leaves) performed the best. The performance of the 10 top performing models is reported in Table 2. In the table, the first three models are Light Gradient Boosted Trees (LGBT) Regressor (Gamma Loss) (4 leaves) but with varying sample sizes. For instance, the third model has a validation sample with 63.64% observations of the sample, while the first model used 100%. DataRobot starts training models with 63.64% of the observations, and increases sample size for models that provides promising performance, which improves efficiency of the AutoML modelling by reducing computing time. For the same reason, r-squared values of only model one is computed for the holdout sample. R-squared values indicate model performance; the higher the better.

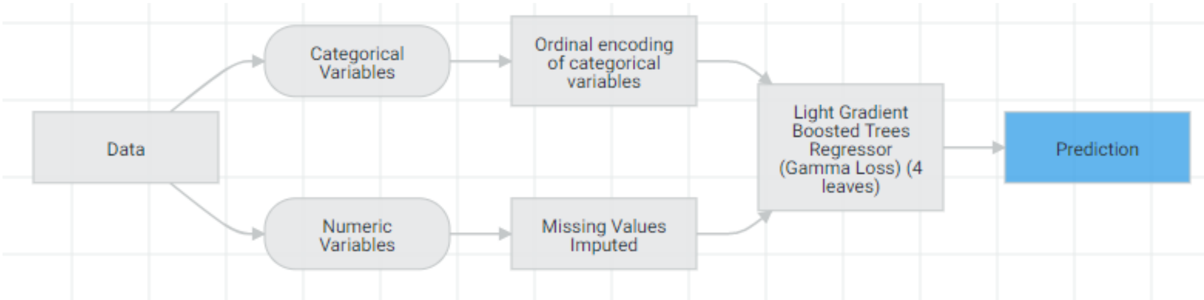
[4] See https://www.datarobot.com/, last accessed on July 25, 2022.

Table 2: Top five performing models

NO	ML Models	Model Source	Sample	R-squared (Validation)	R-squared (Cross-validation)	R-squared (Holdout)
1	**Light Gradient Boosted Trees Regressor (Gamma Loss) (4 leaves)**	**LightGBM model**	100 %	0.2358	0.1785	0.1662
2	Light Gradient Boosted Trees Regressor (Gamma Loss) (4 leaves)	LightGBM model	79.87%	0.2317	0.1628	-
3	Light Gradient Boosted Trees Regressor (Gamma Loss) (4 leaves)	LightGBM model	63.64%	0.1145	0.0958	-
4	Eureqa Regressor (Quick Search: 250 Generations)	Eureqa model	63.64%	0.0432	0.1378	-
5	RandomForest Regressor	Python model	63.64%	0.1512	0.0871	-
6	eXtreme Gradient Boosted Trees Regressor (Poisson Loss)	XGBoost model	63.64%	0.2730	0.0857	-
7	eXtreme Gradient Boosted Trees Regressor (Gamma Loss)	XGBoost model	63.64%	0.3304	0.0855	-
8	eXtreme Gradient Boosted Trees Regressor	XGBoost model	63.64%	0.2400	0.0634	-
9	Elastic-Net Regressor (L2 / Gamma Deviance) with Binned numeric features	DataRobot model	63.64%	0.2704	0.0590	-
10	eXtreme Gradient Boosted Trees Regressor (Gamma Loss) with Unsupervised Learning Features	XGBoost model	63.64%	0.2161	0.0456	-

Each of the ML models estimated using DataRobot follows a blueprint that explains the mechanism of the model. Figure 1 present the blueprint of the LBGT Regressor (Gamma Loss) (4 leaves). As demonstrated in the blueprint, caterogical variables were ordinal encoded and for numerical values any missing values were imputed. Then, the LGBT Regressor algorithm with gamma loss has been estimated by DataRobot. The estimated model can be used to predict funding amount raised in any future public arts campaign given the values of the independent variables.

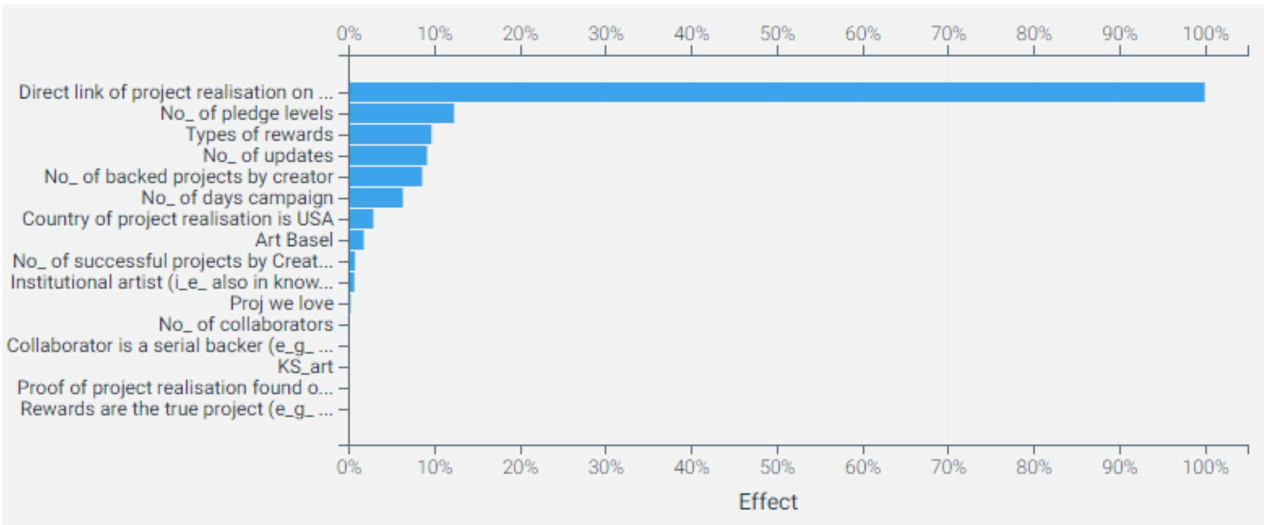
Figure 1: LBGT Regressor (Gamma Loss) (4 leaves)



6 Results

Using the overall best fit model, that is, the Light Gradient Boosted Trees Regressor (Gamma Loss) (4 leaves), feature impact and feature fits are estimated. Feature impact provides the relative influence of each input feature (i.e., independent variable) on the target or outcome feature (dependent variable). Figure 2 reports the feature impacts of the estimated model for predicting raised funds in public arts campaigns. Having a direct link of project realisation on the Kickstarter page, number of pledge levels, types of rewards, number of project updates, and number of backed projects by creator are top five features influencing the raised funding amount.

Figure 2: Feature impact



To explore the influence of each input feature on the target feature, we estimated the feature effects (see Figure 3. a-p). Typically, feature effects provide three ways to explore the influence of each input feature on the target feature: (1) actual, (2) predicted, and (3) partial dependence. Actual shows the influence of an input feature on target feature based on actual data, predicted shows based on the estimated model parameters. Partial dependence also shows the same based on estimated model parameters but considering the influence of other input features included in the model. Partial dependence illustrates how a change in a input feature's value, impacts a model's target feature predictions while keeping all other features as they were (DataRobot, 2022).

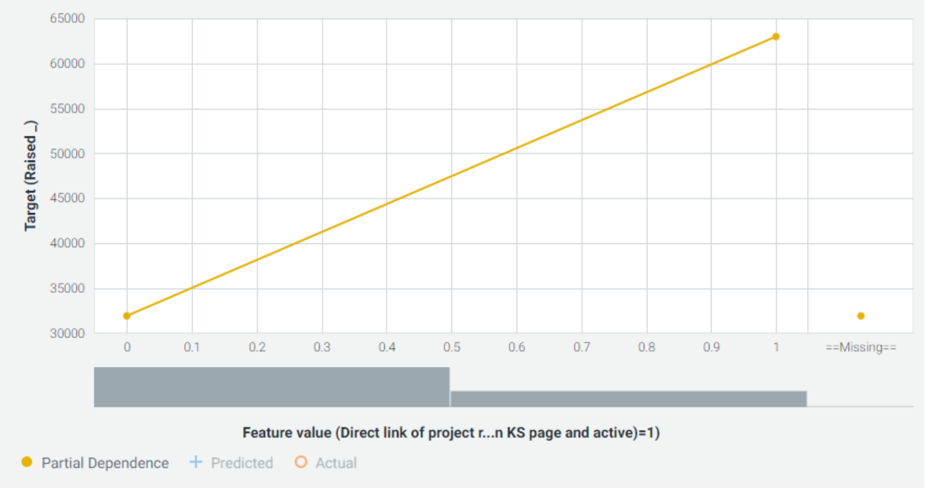
Since partial dependence is the most relevant while understanding the influence of each feature on raised funding, Figure 3(a-p) reports the feature effects of independent variable under consideration. From Figure 3(a), it is evident that having a direct link in the of project realisation on the KickStarter page can increase raised funding amount by approximately USD 30,000. Meanwhile, the optimum number of pledges is between 13 and 15, see Figure 3(b). Funding amount raised increased steadily with the increase in types of reward, see Figure 3(c). The cut-off points for number of pledges are 11 and 19, both of which follows a sharp increase in funding raised. In terms of project updates, the artists or campaign owners should publish between 6 and 15 updates as below six and above 15 follows lower funding amount (Figure 3.d).

In terms of number of projects backed by the campaign creator, they should either back very little (one or less) or 20 or more, see Figure 3(e). Number of days of campaign length is positively associated with funds raised. Campaign longer than 45 days upto 60 days raised the highest funds, see Figure 3(f). Surprisingly, campaigns outside US attracted relatively higher amounts of funds, see Figure 3(g). Campaign collaborations with the international prestigious Art Basel fair raised approximately USD 500 more on average than those which do not (Figure 3.h). More than one successful campaign of the creator reduces funds raised by approximately USD 600 on average, see Figure 3(i). To some extent, if an artist belongs to the traditional art-market channels and is represented by art galleries and in museums will tend to raise relatively less funds than non-institutional artists (Figure 3.j). The number of collaborators in a project as well as Kickstarter label “Project we love” is likely to reduce funds raised, see Figure 3k-l.

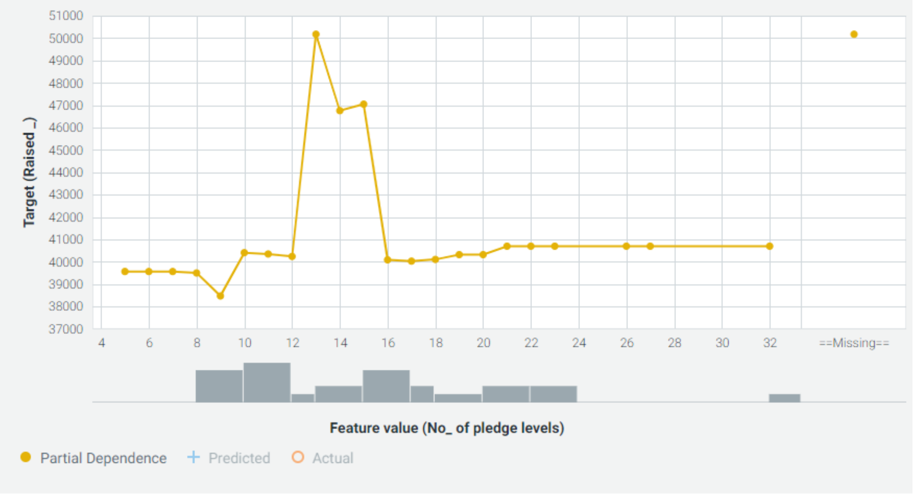
Whether a campaign is categorized as Kickstarter Arts project, the campaign creator is a serial backer, proof of project realisation can be found outside Kickstarter, and the rewards are true projects, do not have any influence on the fund raised.

Figure 3: Feature effects on funds raised

(a)Direct link of project realisation on Kickstarter page

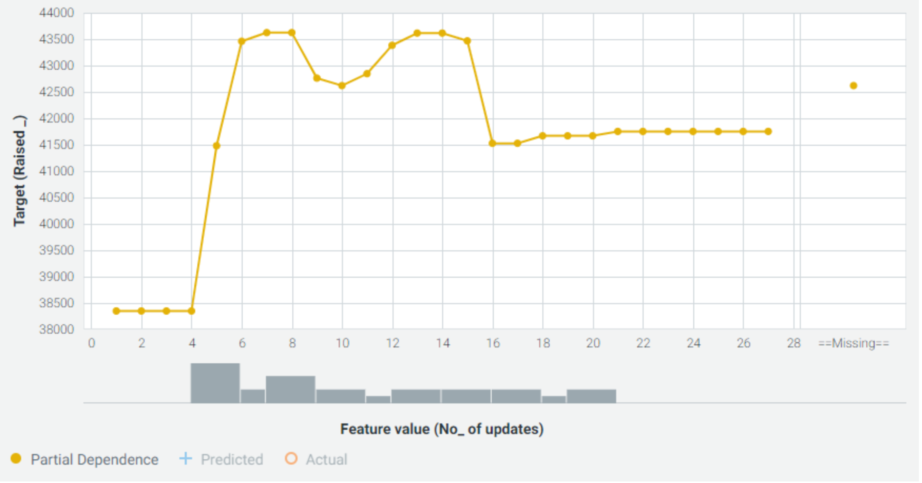


(b) Number of pledge levels

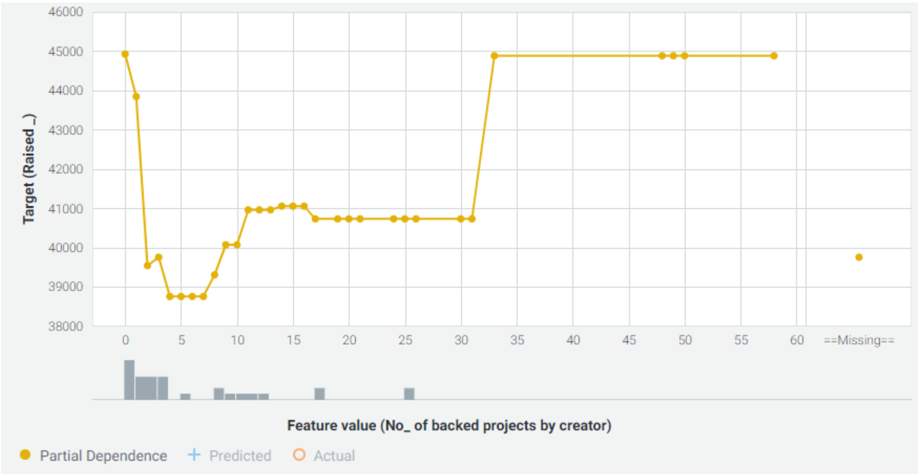


(c) Types of rewards

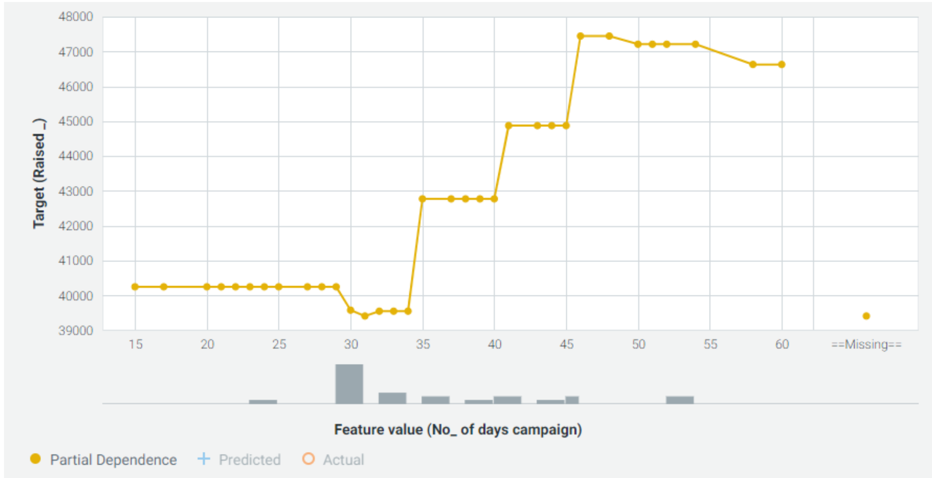
(d) Number of updates



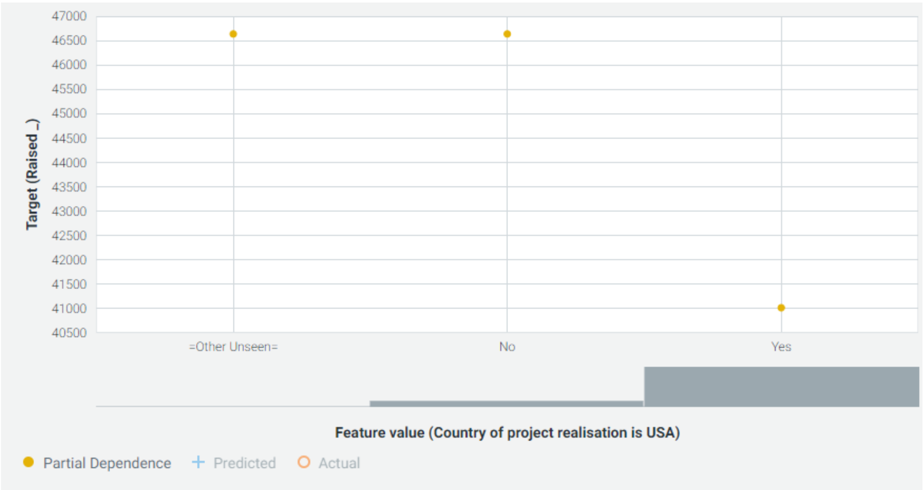
(e) Number of projects backed by the creator



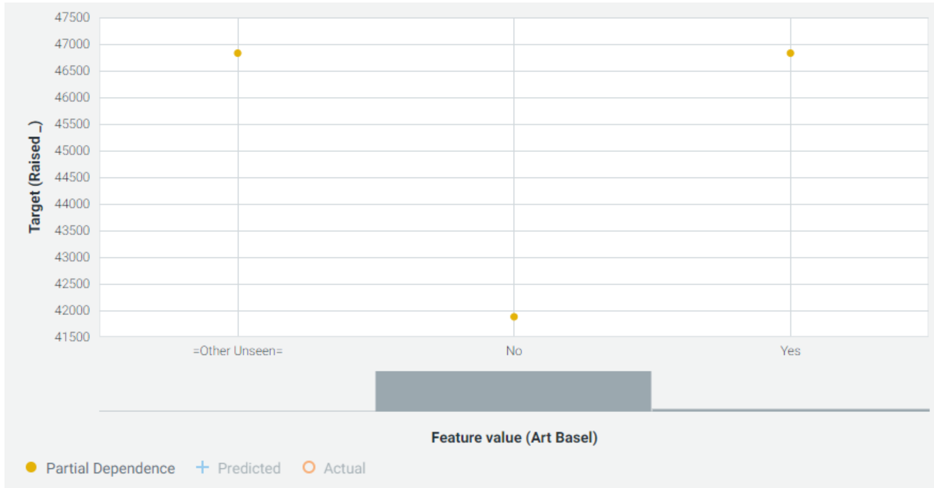
(f) Days of campaign



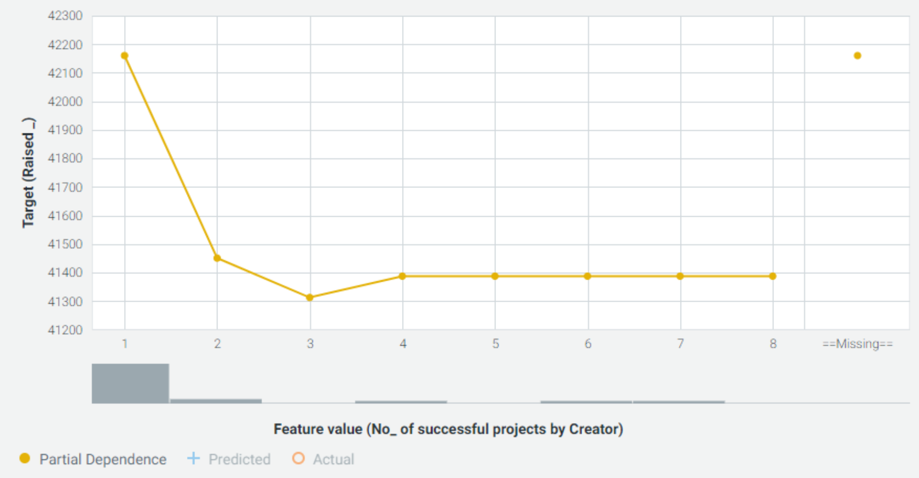
(g) Country of project campaign is in the USA



(h) Campaign in collaboration with Art Basel fair

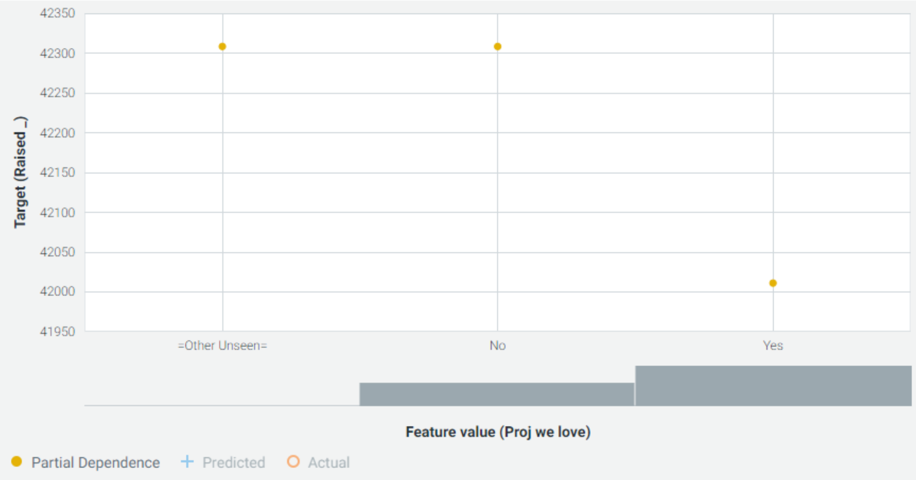


(i) Number of successful campaigns by creator

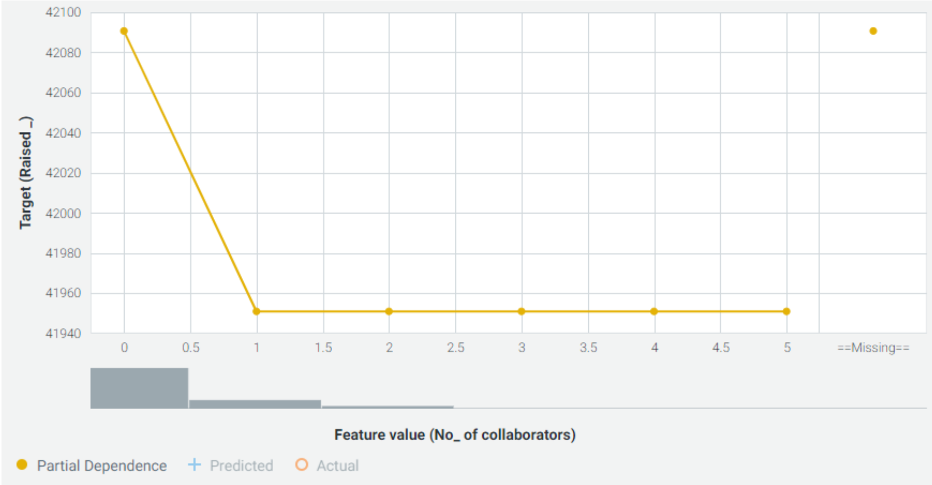


(j) Institutional artist

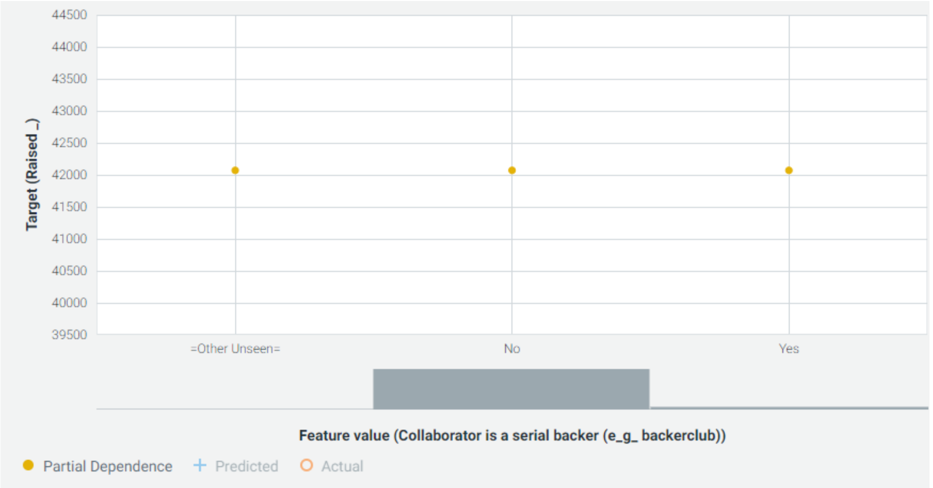
(k)Projects we love categorisation by Kickstarter



(l) Number of campaign collaborators

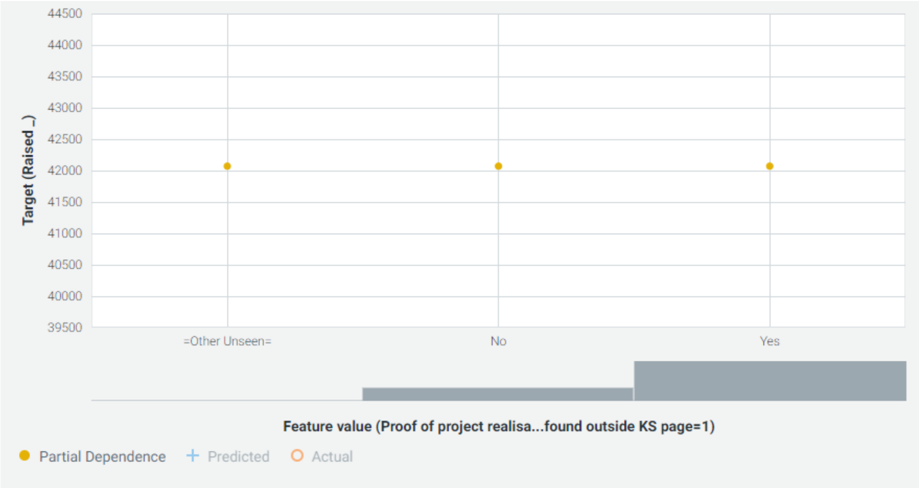


(m) Collaborator is a serial backer

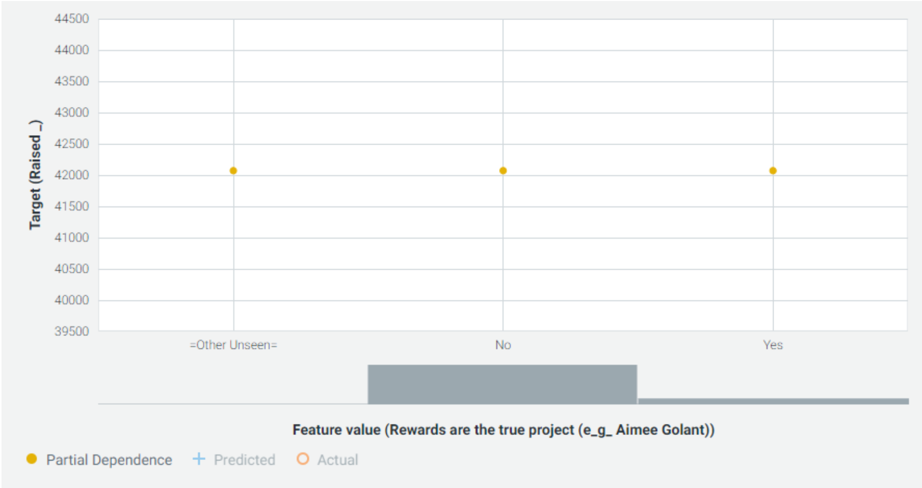


(n) Kickstarter art classification

(o) Proof of project realisation outside Kickstarter platform



(p) Rewards are the true project



7 Conclusions

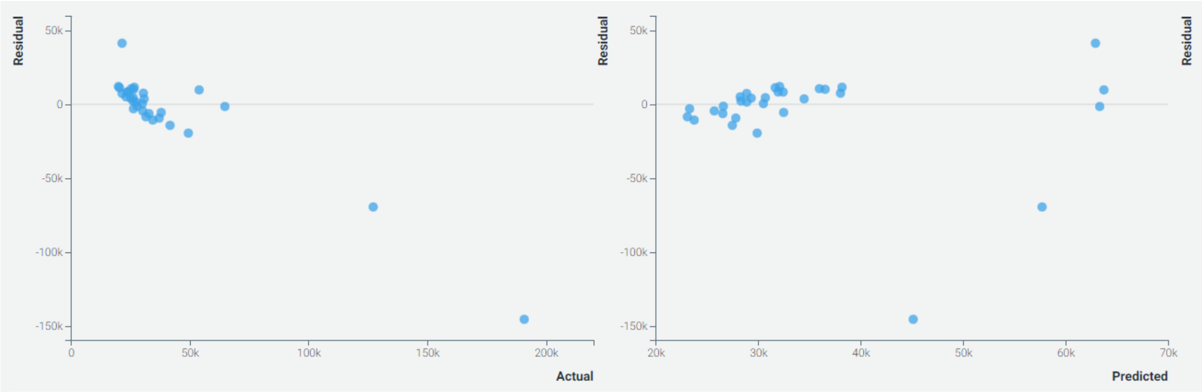
This paper had shed light on the use of crowdfunding in the contemporary art market by studying the impact of main features of crowdfunding campaigns on their success for less tangible contemporary visual artistic expressions which might be more difficult to be traded through traditional art market channels, such as art public art. In order to disentangle possible benefits of crowdfunding for visual artists, we have applied a machine-learning methodology to an ad-hoc taxonomy we elaborated, based on the general literature on crowdfunding benefits.

We built an original dataset starting from Kickstarter category “Public Art” for the period 2009-2022. Using Data Robot, we estimated 36 ML models to predict raised funding amount in the public arts crowdfunding campaigns. Out of the estimated models, the Light Gradient Boosted Trees Regressor (Gamma Loss) (4 leaves) performed the best. Feature impact and feature fits were estimated after this model.

Main results have shown that having a direct link of project realisation on the Kickstarter page, number of pledge levels, types of rewards, number of project updates, and number of backed projects by creator are top five features influencing the raised funding amount.

Appendix

Figure 4: Residuals of estimated LBGT Regressor (Gamma Loss) (4 leaves)



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