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Detection of Fraudulent Campaigns on Donation-Based Crowdfunding Platforms using a combination of Machine Learning and Rule-Based Classifier

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ABSTRACT

In today's world where acts of kindness are seldom and rare, there are still many people who are able and willing to help their fellow human beings. One such way of doing that is donating to a crowdfunding campaign. People in need of financial assistance describe their stories on a crowdfunding platform and generous people donate to these campaigns. Even in such a noble cause, there are malicious actors who post fake campaigns and misuse the donations made to the campaign. In this study, we propose a fraud detection method to classify a campaign as genuine or fake. We have collected the details of non-fraudulent campaigns from ww.GoFundMe.com and we are collecting details of fraudulent campaigns from www.GoFraudMe.com. We propose a combination of machine learning classifier and a rule-based classifier to classify a campaign as genuine or fake. We have based our rule-based classifier on theories in deception which uses cognitive load, certainty, emotion, and distancing strategy depicted in a text. We then aggregate the results of these two classifiers to label a

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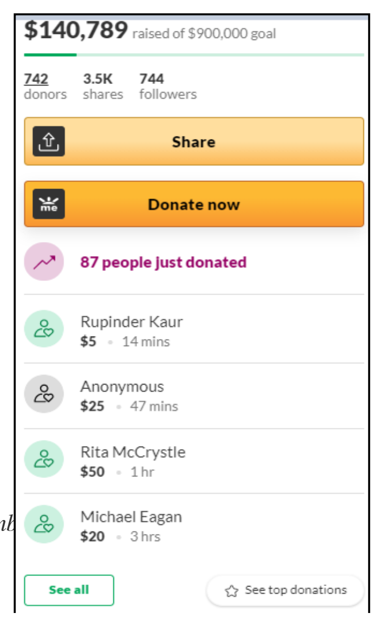
campaign as genuine or fake. Fraudulent campaigns add up to $30M and hence their detection has significant practical use.

Keywords: donation-based crowdfunding, fraud detection, machine learning, rule-based classifier, deception

INTRODUCTION

The rapid rise of social media technologies in the last two decades has led to multiple online social-economical platforms where individuals carry out economic exchange. Crowdfunding is one of these online platforms which facilitates economic exchange and is extensively used as a tool for funding resources, goods, and services online. It uses the Internet as a platform to rally the crowd for collective funding (Burtch et al. 2013; Zvilichovsky et al. 2013). Over $17 billion is generated yearly through crowdfunding in North America and the crowdfunding market is projected to grow to $300 billion by 2030 (Freedman and Jin 2018).

Online crowdfunding model is generally based on three types of actors: the project initiator who proposes the idea or project to be funded, individuals or groups who support the idea, and a moderating organization (the platform) that brings the parties together to launch the idea (Ordanini et al. 2013). There are four common types of crowdfunding models – donation-based, lending-based, reward-based, and equity-based (Agrawal et al. 2014). We focus our study on the donation-based model. The donation-based model (e.g., GoFundMe, Inc) gives no return to donors and is often used for fundraising for causes such as disaster relief, medical care, and poverty alleviation.



In this model, the investor who will now be referred to as a donor decides to donate to campaign(s) on a donation-based crowdfunding platform based on her willingness to donate. A key feature of this model is that the donor has no financial incentive. When a donor goes to a crowdfunding platform, he/she sees several campaigns.

Each campaign has an image with a brief description about the campaign. Upon clicking on any of these campaigns, the potential donor can then read more about the description and get the latest information about the campaign as shown in Figure 1 which indicates the information that the donor sees. This information comprises of the launch date, category of campaign, campaign organizer, the target amount, the amount donated so far, and the last few donations amounts and donors.

At its core, the donation-based crowdfunding platform enables people in need of financial support to be funded by able and willing people. The platform keeps a percentage of the total donations as platform fee, and the campaign organizer receives the remaining amount. A campaign organizer can start a campaign for herself or for someone else as well which makes sense since if a person is hospitalized and needs money immediately for surgery, then she can't launch a campaign herself. The platform is primarily responsible for doing the background checks and the verifications of the campaigns posted. The platforms have their own constraint of making it easier for people to start a campaign since the platform makes money only if donations are made, and donations will be made only if there are campaigns visible on the platform. This creates room for fraudulent actors who create and post fake campaigns on these platforms and play with the emotions of good people trying to help society.

Fraudulent Campaigns

Although a top online crowdfunding platform claims that only 1 in 10000 campaigns are fake, the issue of fake campaigns on donation-based crowdfunding campaigns needs scrutiny for reasons pertaining to a) Financial implications which are too high given that online crowdfunding is estimated to be a 300B dollar industry by 2030 and even a small fraction of that amount is significantly large, b) Societal Goodwill which can get eroded when the donors and potential donors realize that the donation they made actually went to a scammer; which in turn can lead them to refrain from donating in future and eventually depriving the genuine requests, and c) Platforms do not have enough incentive to identify and publicize the fake campaigns since there is a cost to the platform associated with publicizing in terms of a decrease in trust in the platform itself and translating to financial as well as reputational loss.

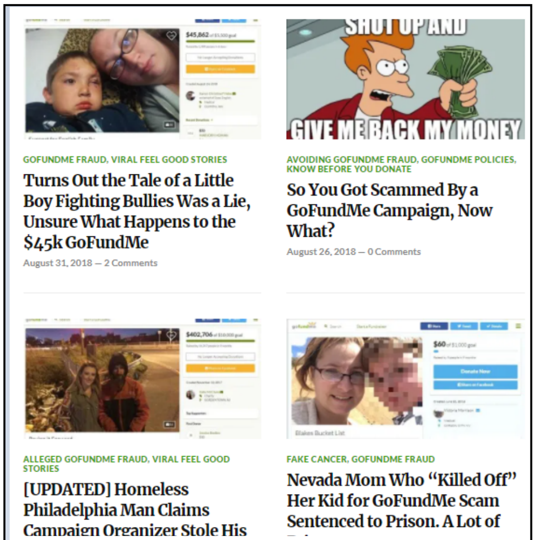


Figure 2. Fake Campaigns

The number of fraudulent cases has been so high that there is a website www.GoFraudme.com which constantly calls out fraudulent campaigns. A large portion of the messages www.GoFraudMe.com gets are from people asking for help in shutting down scam campaigns or campaigns that are fraudulent, misleading, inaccurate, or dishonest. Figure 2 shows a few cases posted on www.GoFraudme.com.

The striking resemblance between a genuine and fake campaign leaves not enough room for the potential donor to scrutinize and carefully do the background checks for the campaign. Since there is no personal financial incentive for the donors, instead of doing a thorough background verification of the campaign, they might rely on the platforms which claim to be highly vigilant. The nature of the Internet as well as the specific characteristics of crowdfunding platforms make it especially hard to detect deceivers since the environment of such Internet platforms is characterized by low entry barriers, spatial and temporal separation, and anonymity (Xiao et al. 2011). This leads us to our first research question, R1: What would be a robust mechanism to identify fraudulent donation-based crowdfunding campaigns?

In this paper, we seek to answer this question by using i) A machine learning based classifier, and ii) a rule-based text classifier based on theories of deception. We attempt to do this by looking for characteristics which differentiate a genuine and a fake campaign. More specifically, we look at cues from the most prominent feature of a campaign –the campaign description (text file). The need for a rule-based classifier arises from our argument that traditional classification approaches that rely on keywords only without looking at their relationship or other cues may miss some fraudulent campaigns. We review different textual and linguistic features and examine their distributions and how they contribute to campaign fraud. In their meta-analysis of linguistic cues to deception, Hauch et al. (2014) report that relative to truth-tellers, liars experienced greater cognitive load, expressed more negative emotions, distanced themselves more from events, expressed fewer sensory–perceptual words, and referred less often to cognitive processes. However, liars were not more uncertain than truth-tellers. This leads us to our second research question: R2: How can linguistic cues in the text description of a campaign be utilized in distinguishing between a fake and a genuine campaign? We have referred to Hauch et. al's meta-analysis to identify these linguistic cues. We posit that the status of a campaign (genuine or fake) is reflected in cognitive load, certainty, emotion, and distancing strategies depicted in the description.

A combination of Machine Learning Classifier and Rule-Based classifier performs better in classification (Chau et al. 2020). This leads us to our third research question, R3: In donation-based crowdfunding, would a combination of a Machine Learning based classifier and a rule-based classifier perform better than individual classifiers? To calculate the probability of a campaign being fraud, we calculate an aggregated score from the campaign's textual and linguistic cues. We seek to answer our third research question by expressing this score for each campaign as a linear combination of standardized Machine Learning Classifier score and rule-based score. More specifically, we will be optimizing the value of fraction 'f' in the following equation in such a way that the combined classifier score most accurately predicts the probability of a campaign being fraud:

Combined classifiers Score = f*(Machine Learning Based classifier score) + (1-f) *(Rule-Based classifier score).

We then compare the classification results derived from combined classifiers scores with those derived from individual classifiers.

LITERATURE REVIEW

Our work derives from the work of Siering et al (2016) who discuss the role of linguistic and content-based cues in detecting fraudulent behavior on crowdfunding platforms. However, our work differs from them in two ways a) they have proposed the mechanism for a reward-based platform. We argue that a donor's mindset is different when he has no incentive like in a donation-based campaign than when he has a reward or an incentive in the donation. b) in their classification, all the campaigns which have been suspended are called fraudulent. Cancellation of a campaign does not necessarily mean it being fraudulent. To reduce this gap, we label campaigns as fake only if they are a confirmed fraudulent campaign. Our research differs from

Perez et al.'s work in progress on fraud detection in crowdfunding platforms in that our work is not just data driven. We combine a rule-based classifier with a Machine Learning Classifier.

Fraud detection theories

The act of trying to get someone to believe something untrue is deceit. Table 1 summarizes three theories in fraud detection and the relevant insights of these theories for our research work.

Table 1. Relevant Ideas from Fraud Detection Theories

Fraud detection Theories	Key points relevant to detecting fraudulent crowdfunding campaigns
Information Manipulation Theory [McCornack et al]	Deceivers tend to use too little or too much information, quantitatively.
	Information presented is not completely relevant to the topic at hand or comprehensible within the context
	The information being communicated is equivocal rather than being clear and succinct
Four-Factor Theory (FFT) [Zuckerman et al]	Deceivers feel anxiety and arousal (e.g., word repetition).
	Deceivers have mixed emotional responses (e.g., guilt, duping delight) while lying.
	Cognitive burden encountered to conceal the lie is also reflected outwardly (e.g., using general statements).
Interpersonal Deception Theory [Buller et al]	Deceivers manipulate information in terms of completeness, accuracy, and relevance.

Based on IDT and FFT, we postulate that linguistic cues as well as contextual cues like - Language Complexity, Lexical Diversity, expressivity, non-immediacy, affect, and sentiment can contribute significantly in the creation of a rule-based classifier for identification of fraudulent campaigns. Table 2 summarizes each of the above linguistic and context-based cues to be used to create a rule-based classifier.

Table 2. Linguistic and Context Based Cues

Linguistic and content based cues	Features and explanations
Language Complexity	Average sentence length - Average number of words per sentence.
	Average word length - Average number of letters per word.
	Pauses - Ratio of number of marks (periods, commas, exclamation marks etc) to the number of sentences
Diversity	Lexical Diversity - Ratio of number of unique words to the total number of words.
Expressivity	Emotiveness - Number of emoticons.
Non - immediacy	Self-references - Ratio of first-person (me, I, myself etc.) words to total words.
	Group references - Ratio of words connected to group (we, us, ourselves etc.) to total words.
	Reader references - Ratio of words related to the readers (you, your) to total words.
Affect	Positive affect ratio - Ratio of positive words to total words
	Negative affect ratio - Ratio of negative words to total words
Sentiment	Sentiment score - Overall sentiment of the document based on five basic emotions (sadness, joy, fear, disgust, and anger)
	Tone - Confidence score for seven possible tones (frustration, satisfaction, excitement, politeness, sadness, and sympathy)
Informality	Typos - Ratio of number of incorrectly spelled words to total words.

The study is still in the early stage of data collection and annotation.

RESEARCH METHODOLOGY

Figure 3 shows the data collection and analysis process of the study. We collect data for two types of campaigns- Genuine and Fake through a web crawler which scrapes the data of genuine campaigns from various donation-based crowdfunding platforms and the data of fake campaigns from www.GoFraudMe.com which has various proven fraudulent campaigns sorted by their type (e.g., crime, alleged GoFundMe spam, etc.) Next, we create a training dataset. The features selected through Genetic Algorithm are fed to the machine learning classifier, whereas those described in Table 2 are fed to a rule-based classifier. We then aggregate these two results using the optimized value of 'f' and classify a campaign as genuine or fake. In the future, we plan to use the research process shown to classify campaigns as genuine or fake.

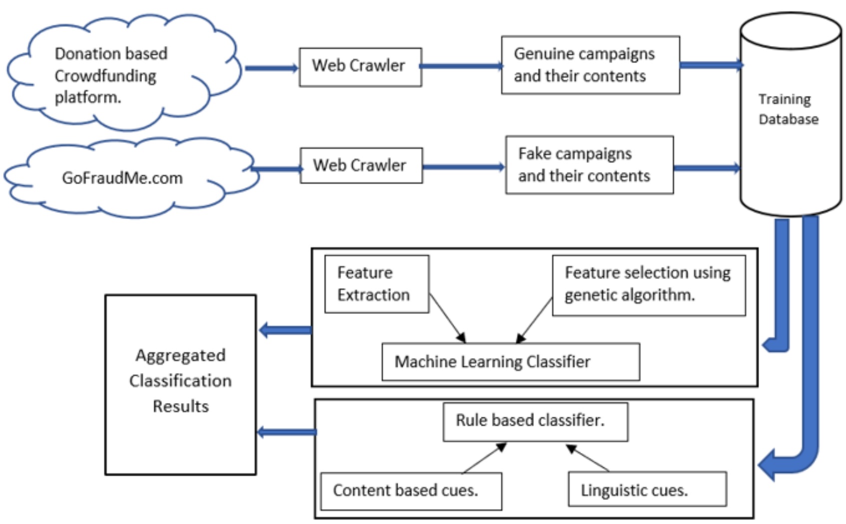


Figure 3. Research process

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