



Predicting the Success of Crowdfunding Campaign Using ML

Mr. Mohit Peshwani, Abhishek Odrani, Richa Sharma,
Saurav Kalaskar, Daksh Ramchandani, Rohini Temkar
Dept. Of Computer Engineering
VESIT
Mumbai, India

Abstract—Crowdfunding websites provide an accessible platform for creators, innovators and entrepreneurs to get funding directly from their customers in return for tangible rewards such as special packages, etc. Most of these crowdfunding campaigns are a success, although some of them also fail. The reasons behind their success and failure include communication of campaign ideas to the customers, customer excitement, social media marketing, domains, websites, countries they live in, etc. Our Machine Learning model aims to analyze these various factors and find the correlation between them and the success/failure of a campaign. We present this information to potential creators, innovators, entrepreneurs so that they can make a better decision as to what campaigns they can launch, how to successfully market them, etc. All of this is done by finding out which set of algorithms works best for our datasets and how much accuracy can be expected from different domains.

Keywords—Crowdfunding, campaigns, creator, admin, entrepreneur, machine learning model, innovation

I. INTRODUCTION

Crowdfunding is the practice of financing a venture or venture by raising little sums of cash from an expansive number of individuals, regularly through the Web[1]." This present day crowdfunding demonstration is for the most part based on three sorts of components - the venture initiator who proposes the thought or extend to be financed, people or bunches who back the thought, and a directing organization (the "stage") that brings the parties together to dispatch the thought. In spite of the fact that crowdfunding has been proposed to be profoundly connected to supportability, observational approval has appeared that maintainability plays as it were a fractional part in crowdfunding. The primary critical occasion of online crowdfunding was within the music industry in 1997, when fans of the British shake band Marillion raised US \$60,000 in gifts by means of a Web campaign to guarantee a complete U.S. visit. The band hence utilized this strategy to finance their studio collections. This built on the victory of crowdfunding by means of magazines, such as the 1992 campaign by the Veggie lover Society that crowdfunded the generation of the Truth or Dairy video documentary. Within the film industry, autonomous writer/director Mark Tapio Kines outlined a website in 1997 for his then-unfinished film Remote Journalists. By early 1999, he had raised more than US\$125,000 on the Web from at least 25 fans, giving him the reserves to total his film[2]. The "Free Blender" campaign was an early computer program crowdfunding forerunner in 2002 [3]. The campaign pointed to open-sourcing the Blender 3D computer illustrations program by collecting €100,000 from the community, whereas advertising extra benefits for giving individuals. The Crowdfunding Centre's May 2014 report distinguished two essential sorts of crowdfunding: Rewards crowdfunding: Business people pre offer an item or benefit to dispatch a commerce concept without causing obligation or relinquishing equity/shares. Equity crowdfunding: The sponsor gets offers of a company, more often than not in its early stages, in trade for the cash vowed. The primary company to lock in in this trade show was the U.S. website ArtistShare (2001). As the show developed, more crowdfunding destinations begun to seem on the internet such as Kiva (2005), The Point (2008, forerunner to Groupon), IndieGoGo (2008), Kickstarter (2009), GoFundMe (2010), Microventures (2010), and YouCaring (2011) [4]. Our model aims to provide entrepreneurs with the best insight in the factors behind the success of a crowdfunding campaign based on their current circumstances and the vision they want to execute. These insights will be based on factors such as domain, project



description, websites/platforms used, age group targeted, countries where they were launched/marketed, etc. This will help them in coming up with a suitable campaign idea and then marketing it properly through use of appropriate platforms and communication channels.

II. LITERATURE SURVEY

Prediction of Crowdfunding Campaigns considering the impact of targeting and marketing aspects is a tricky part of any business venture, even for the most seasoned and experienced of business-strategist teams[5]. An accurate Campaign Success Prediction Model can prove to be a crucial insight for aspiring innovators and entrepreneurs. Targeting the campaign towards different audience demographics can mean using wildly different marketing techniques. This review article has investigated what has been done on the predicting success of a crowdfunding campaign through machine learning in the literature.

[6] Michael J. Ryoba , Shaojian Qu , Ying Ji and Deqiang Qu. This paper investigated campaign success contributions of various phased communication aspects from updates and comments, the best of which can help creators to successfully manage campaigns by focusing on the important communication aspects.

[7] Binbin Jin, Hongke Zhao, Enhong Chen. In this paper the authors have noticed that the implicit factor of distribution of backing behaviors has a positive impact on estimating the success time of the crowdfunding campaign.

[8] Chaoran Cheng, Fei Tan, Zhi Wei. Rich visual images are utilized in several project profiles for attracting backers little work that has been conducted to evaluate their efforts towards success prediction. Author designed and evaluated advanced neural network schemes that combine information from different modalities to study the influence of sophisticated interaction among textual, visual data for prediction.

[9] Alex Kindler, Sorin Solomon. The mechanism of spreading social collective action and funding is not well understood yet. Social networks play an important role for spreading misinformation or behaviour which propagates through people to people. Kickstarter campaigns are analysed. "The predictor model uses an algorithm which underlying the success of a campaign depends less on the backers influencing one another ("virality") but rather on the campaign appealing to a particular class of high-pledge backers."

[10] G Alan Wang, Baozhou Lu, Weiguo (Patrick) Fan. Model can predict an accuracy rate of 73% which is 15% more than the baseline model. This idea is among the primary to investigate crowdfunding with a center on the data substance of venture portrayals.

[11] Yan Li, Vineeth Rakesh, Chandan Reddy [6] Author built a system that ranks the projects based on their expected success date, thus the investors can choose the best project to invest in. The model also helps the failed projects in building a robust prediction model to perform better next time.

III. METHODOLOGY

Data Cleaning: If data is incorrect, outcomes and algorithms applied will be unreliable. Data cleaning involves removing incorrect, corrupted and duplicate data from the dataset.

Data Reduction: It increases storage efficiency and performance by reducing data storage cost. Data reduction eliminates the invalid data.

Data Transformation: Process of converting the data from one format to another. It organizes the data which makes it easier to understand.

Categorizing: It is creating subclasses for a specific domain such as business, brand or tech that follow the same pattern / trend.



Model Training: Applying the dataset to the model and training the supervised algorithm for prediction.

Evaluating the model: Predicting the success or failure of the crowdfunding campaign and the factors affecting it.

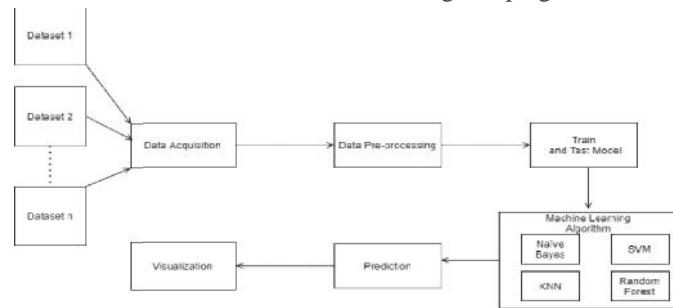


Fig 1. Block Diagram

IV. PROPOSED SOLUTION

To accurately predict the success or failure of a crowdfunding campaign, we performed data analysis on crowdfunding data using six algorithmic models to discover which model gives the highest accuracy. The dataset for this was acquired from Kaggle website and contains records of the campaigns and various factors pertaining to them such as success and failure but also country of origin, no. of backers, etc. We then preprocessed this data and performed data encoding to convert the data into numeric values, since working with strings is costly. We also encoded the launch date and deadline into string objects so they will be easier to transform into numeric format (previously being in date and time format). Then, this encoded data was split into the training set and testing set in a ratio of 4:1 i.e., 80 % of the data was used as a training set and the remaining 20 % as testing set. Upon completion of these steps, we implemented the following six algorithmic models on the data with varying degrees of success:

- 1) Decision Tree Classifier: We used Decision Tree Classifier MODEL ON THE training set and acquired 99.897 percent accuracy.
- 2) Gaussian Naive-Bayes: We used the Gaussian Naive-Bayes model on the training set and acquired 70.744 percent accuracy.
- 3) K-NN: With the five nearest clusters, we acquired an accuracy of 99.944 percent.
- 4) SVM with linear kernel: 99.996 percent.
- 5) Logistic Regression: Accuracy 99.994 percent.
- 6) Random Forest Classifier: Accuracy 99.622 percent



```

140) def RFC_model(features, X_train, X_test, y_train, y_test):
    rfc = RandomForestClassifier(
        n_estimators=100,
        min_samples_split=10,
        min_samples_leaf=10,
        bootstrap=True,
        random_state=42)

    rfc.fit(X_train, y_train)

    y_pred = rfc.predict(X_test)

    accuracy = accuracy_score(y_test, y_pred)

    print('Accuracy: %f' % accuracy)

    return accuracy

141) def print_feature_importance(features, rfc):
    feature_importance = rfc.feature_importances_

    for i in range(len(features)):
        print('%s: %f' % (features[i], feature_importance[i]))

142) def print_top_features(features, rfc):
    sorted_indices = np.argsort(feature_importance)[::-1]

    top_features = features[sorted_indices[:5]]

    print('Top 5 features: %s' % top_features)

143) def plot_feature_importance(features, rfc):
    plt.figure(figsize=(10, 5))

    plt.bar(features, feature_importance)

    plt.title('Feature Importance')

    plt.show()

144) def main():
    # Load data
    X_train, X_test, y_train, y_test = load_data()

    # Train model
    accuracy = RFC_model(X_train, X_test, y_train, y_test)

    # Print feature importance
    print_feature_importance(features, rfc)

    # Print top features
    print_top_features(features, rfc)

    # Plot feature importance
    plot_feature_importance(features, rfc)

if __name__ == '__main__':
    main()
    
```

FIG 2. RFC MODEL

```

In [140]: from sklearn.metrics import classification_report
          classification_report(rfc.predict(X_test), y_test)
          precision    recall  f1-score   support

0.00:         1.00         0.00         0.00         1.00
1.00:         0.00         1.00         0.00         1.00
avg / total         1.00         1.00         1.00         2.00
          weighted avg
          precision    recall  f1-score   support

0.00:         1.00         0.00         0.00         1.00
1.00:         0.00         1.00         0.00         1.00
avg / total         1.00         1.00         1.00         2.00
          weighted avg
    
```

FIG 3. Classification Report for Decision Tree

```

In [141]: classification_report(rfc.predict(X_test), y_test)
          precision    recall  f1-score   support

0.74:         0.77         0.77         0.77         1.00
1.00:         0.77         1.00         0.88         1.00
avg / total         0.77         0.89         0.83         2.00
          weighted avg
    
```

FIG 4. Classification Report for G N-B

```

In [142]: classification_report(rfc.predict(X_test), y_test)
          precision    recall  f1-score   support

1.00:         1.00         1.00         1.00         1.00
1.00:         1.00         1.00         1.00         1.00
avg / total         1.00         1.00         1.00         2.00
          weighted avg
    
```

FIG 5. Classification Report for K-NN

```

In [143]: classification_report(rfc.predict(X_test), y_test)
          precision    recall  f1-score   support

1.00:         1.00         1.00         1.00         1.00
1.00:         1.00         1.00         1.00         1.00
avg / total         1.00         1.00         1.00         2.00
          weighted avg
    
```

FIG 6. Classification Report for SVM

```

In [144]: classification_report(rfc.predict(X_test), y_test)
          precision    recall  f1-score   support

1.00:         1.00         1.00         1.00         1.00
1.00:         1.00         1.00         1.00         1.00
avg / total         1.00         1.00         1.00         2.00
          weighted avg
    
```

FIG 7. Classification Report for Logistic Regression

```

In [145]: classification_report(rfc.predict(X_test), y_test)
          precision    recall  f1-score   support

1.00:         1.00         1.00         1.00         1.00
1.00:         1.00         1.00         1.00         1.00
avg / total         1.00         1.00         1.00         2.00
          weighted avg
    
```

FIG 8. Classification Report for Random Forest Classifier



From the above analysis, we discovered that SVM with a linear kernel provided the highest amount of accuracy among the algorithmic models we selected. However, save for Gaussian Naïve-Bayes, all models provided only slightly varying accuracies and hence shouldn't be eliminated from future-use prospects in situations where, for e.g., one algorithmic model is not able to accommodate a certain factor but the other can.

V. RESULTS

We tested six different algorithmic models on our data and created a prediction using SVM with a linear kernel model. This system discovered the campaigns that successfully utilized social media platforms in marketing to the correct target audiences were able to reach their goals successfully. Also, it was discovered that campaigns that are based in European and North American countries tended to be successful more often than in countries on other continents. In future, we aim to include more factors into the prediction system to analyze whether inclusion of a given factor increases or decreases a campaigns chances of success. We are also open to utilizing four out of the other five algorithmic models for these features if the present system doesn't accommodate them well; since excluding Gaussian Naïve-Bayes all models delivered results with only slightly varying accuracies.

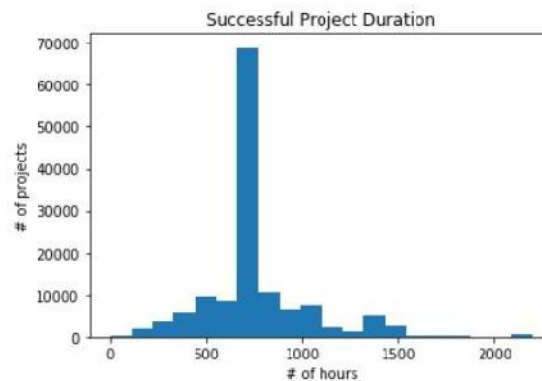


Fig 3. Successful projects with specific duration

VI. CONCLUSION

Crowdfunding is increasingly becoming a viable source for entrepreneurs as an alternative financing method. More and more creators and innovators are looking for platforms to launch their products from. It would not be an exaggeration to say that crowdfunding could very literally be the next frontier for innovation which encourages creativity over corporate bureaucracy. However there is a gap between the expectation and reality of funding goals, where creators are not able to meet the expected funding requirements. In this project, we aim to close this gap which can be caused by various factors in the campaign's execution.

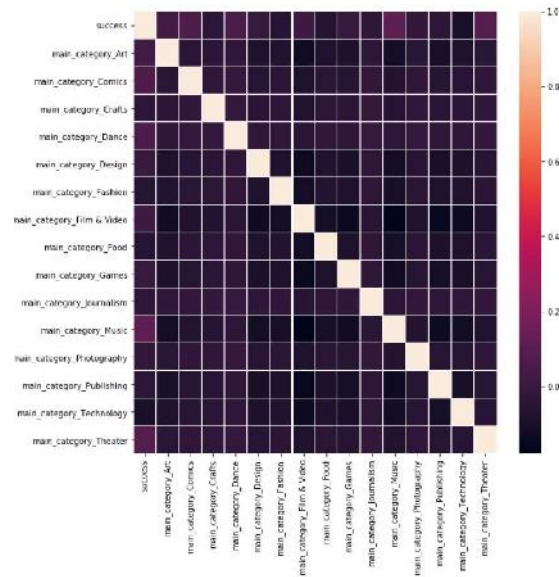


Fig 4. Correlation between sphere of project and success

We aim to create a Machine Learning model that will accurately display what factors influenced the success or failure of a crowdfunding campaign and predict whether another campaign having similar and other factors will be a success or not. By feeding our Machine Learning model with data of various factors of crowdfunding campaigns over the years, the model will be trained to predict whether the campaign will be a success or not depending on various factors. Thus the entrepreneur will be better informed as to what product to launch in their campaign and how to market their campaign for the maximum success. This will not only allow innovative products to enter the market and get a chance to be popular, but also allows talented and creative minds to not be slowed down in realising their vision.



Fig 5. Successful Campaign



Fig 6. Failed Campaign

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