## **Kickstarter Dataset...**

# ... when a crowdfunding campaign will be profitable?



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## THE TEAM



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## Kickstarter Dataset

#### **Exploring the Platform Landscape**

Kickstarter is a dynamic global crowdfunding platform dedicated to bringing creative projects to life.

With \$1.9 billion in pledges from 9.4 million backers, it has fueled 257,000 diverse projects, from films to technology.



It serves as the driving force behind transforming creative visions into reality worldwide...

... but not every project is able to reach the goal...

## **Kickstarter Dataset**

#### The Purpose

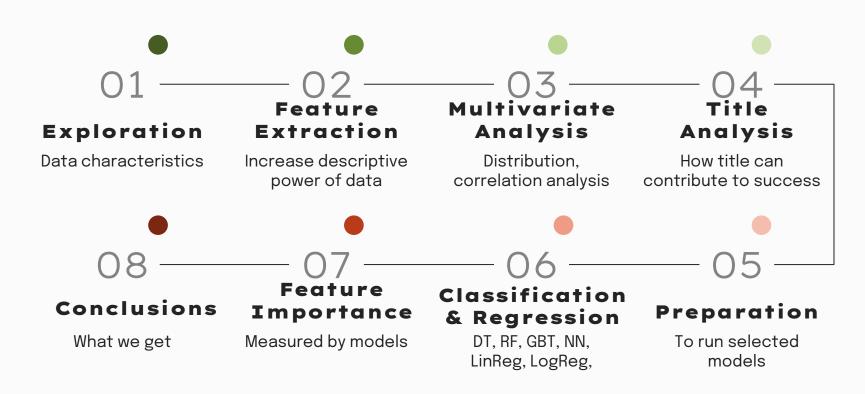
Only about **35**% of the total projects have raised **successful** fundings

Then, which projects can successfully achieve their goal?



Are there any **key project characteristics** that increases the chances of success?

#### WORKFLOW



#### **Feature Extraction**

Deadline

• year
• month
• time

day of launch

• time interval

• use of "?!"

Country

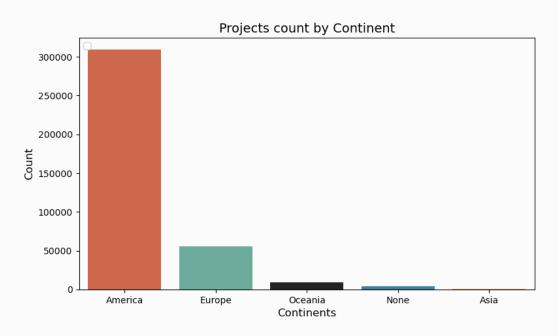
**Title** 

continent

length

## CONTINENT EXTRACTION & ANALYSIS

Looking for the continent with the highest number of projects



America dominates over other continents

Data are from Kickstarter, so these proportion don't match reality

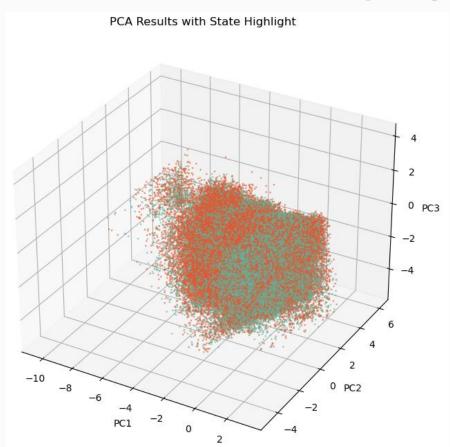
#### **PCA - 3 Components**

#### Features used

Goal - Year - Month Day of week - Time interval Length of title - Use of ?! Category - Main Category Currency - Continent

- Fail
- Success

Not very interesting...



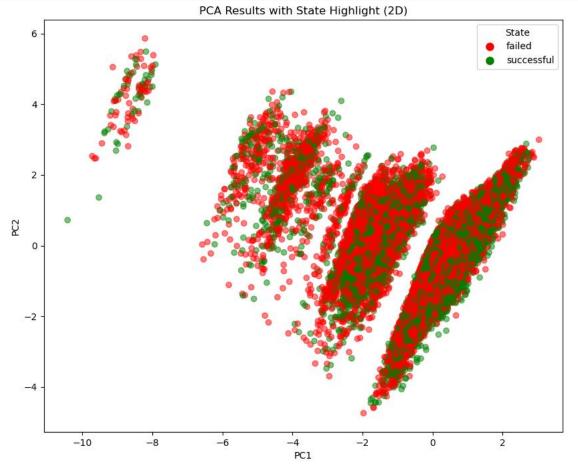
PCA - 2 Components

#### Features used

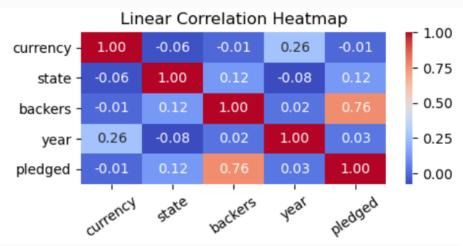
Goal - Year - Month -Day of week - Time interval -Length of title - Use of ?! -Category - Main Category -Currency - Continent

We can notice a **clear separation** between some areas of the points

Maybe some clustering technique can explain them better

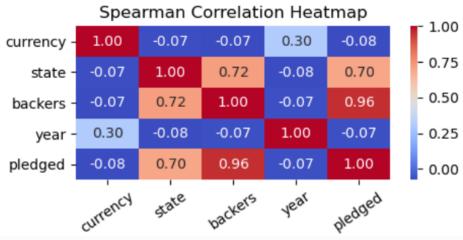


### **Correlation Analysis**

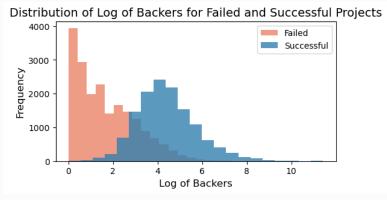


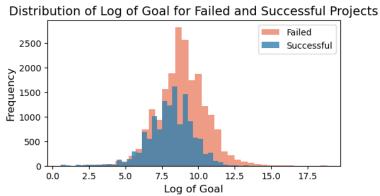
Which variables are linearly correlated?

Can we find other variables non-linear correlated?



### Correlation Analysis – Insight





0.72 correlation with number of backers

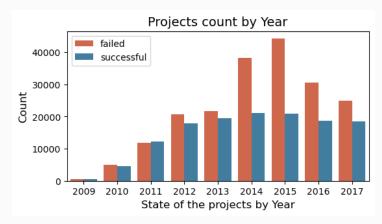
More supporters raise the probability of success

-0.22 correlation with the goal

Very high fundraising goals are difficult to achieve

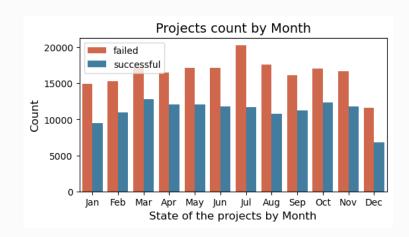
#### **Temporal Analysis**

How the **period** and the **duration** of a campaign influence the outcome?



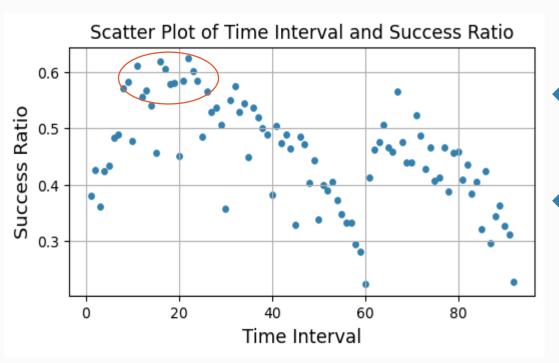
Less interesting information can be extrapolated from a seasonal analysis

## Crowdfunding platforms have followed a growing trend



#### **Temporal Analysis**

Relation between the duration and the success rate



The bivariate distribution shows a bimodal behavior

A short-medium interval seems to be the best choice

## Categories Analysis – A Big Picture

Best and worst categories for success/fail ratio

Rank	Category	Success/Fail Ratio	
1	Dance	1.9	niche but very attractive (3500 projects)
2	Theater	1.8	(0000 projects)
14	Journalism	0.32	more frequent but less attractive
15	Technology	0.31	(27000 projects)

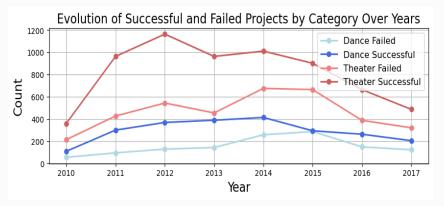
Niche categories gather more support while the more widespread ones have a lower success rate

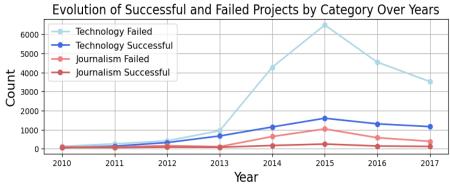
#### Categories Analysis - Trend

Examining category success growth over the years, distinguishing successful from unsuccessful, two patterns emerge:

Less frequent categories remain stable over time, maintaining a consistent success/failure ratio

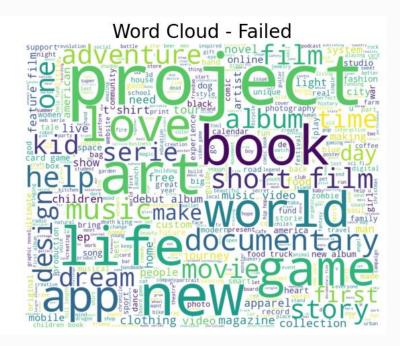
Popular categories align with the overall trend each year: failures exceed successes in growth





#### Title Analysis - most used words



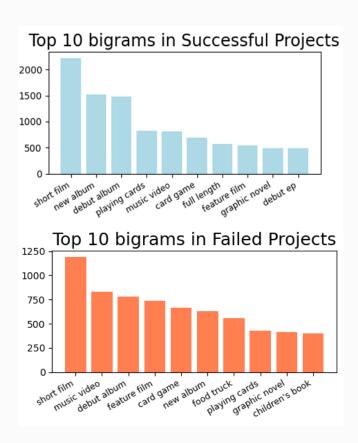


### Title Analysis - Bigrams

Bigrams are two consecutive words that appear in a sentence

Similar bigrams but different frequencies

Bigram	Success rate	Fail rate
new album	70.8%	29.2%
debut album	65.4%	34.6%
short film	65.1%	34.9%



### Classification - performance

- Hyperparameter tuning: Grid search with Cross Validation (4 folds)
- Backers, Pledged are a posteriori info: excluded from input features

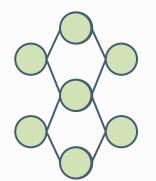
MODEL	F1-score	AUROC	Accuracy
<b>Decision Tree</b>	0.56	0.65	0.67
Gradient Boosting Trees	0.68	0.75	0.69
Neural Network	0.63	0.68	0.64
Logistic Regression	0.59	0.65	0.62

### Classification - Insight

#### **Neural Network**

Lack of flexibility in hidden's activation functions

Hidden layers: (6,4,2) stepsize = 0.01

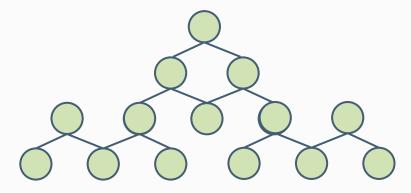


#### DT & GBT

Few descriptive features. Shallow Tree structure

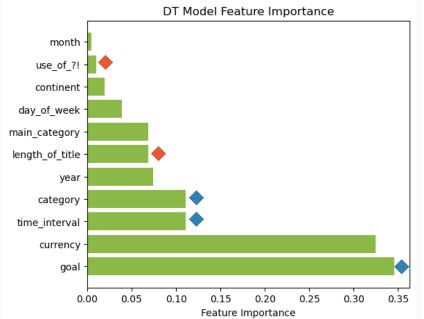
parameters

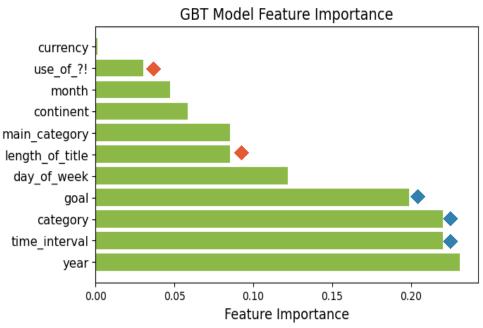
DT depth = 15 MinInstancePerNode = 80 GBT depth = 5 stepsize = 0.2



#### Classification - Feature Importance







- goal, time\_interval, category are the most important for both models
- ◆ Feature extracted from title don't influence the outcome of a project

#### **Linear Regression**

Features not considered: continent and backers

#### **Performance**

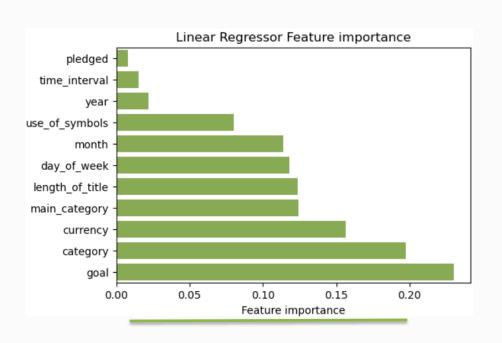
RMSE	0.36
R^2	0.48

Features not considered: continent, backers and pledged

Additional parameter: **regularization value**.

#### **Performance**

RMSE	0.49
R^2	0.004



Feature importance

#### Conclusion

Our analysis tells an insightful story about crowdfunding projects, from 2011 to 2018

- Annual and seasonal trends reveal significant shifts in the ratio between fundraisers and backers
- Some categories outperform, particularly niche ones (Dance, Theater and Comics)
- The title words and punctuation do not influence donors
- Fundraiser tip: Choose goal and duration wisely

However, training a model to **predict** campaign outcomes in advance is **challenging**, due to the **limited** availability of project **informations** 



## Thanks! Questions?