Predicting the Success of a GoFundMe Campaign

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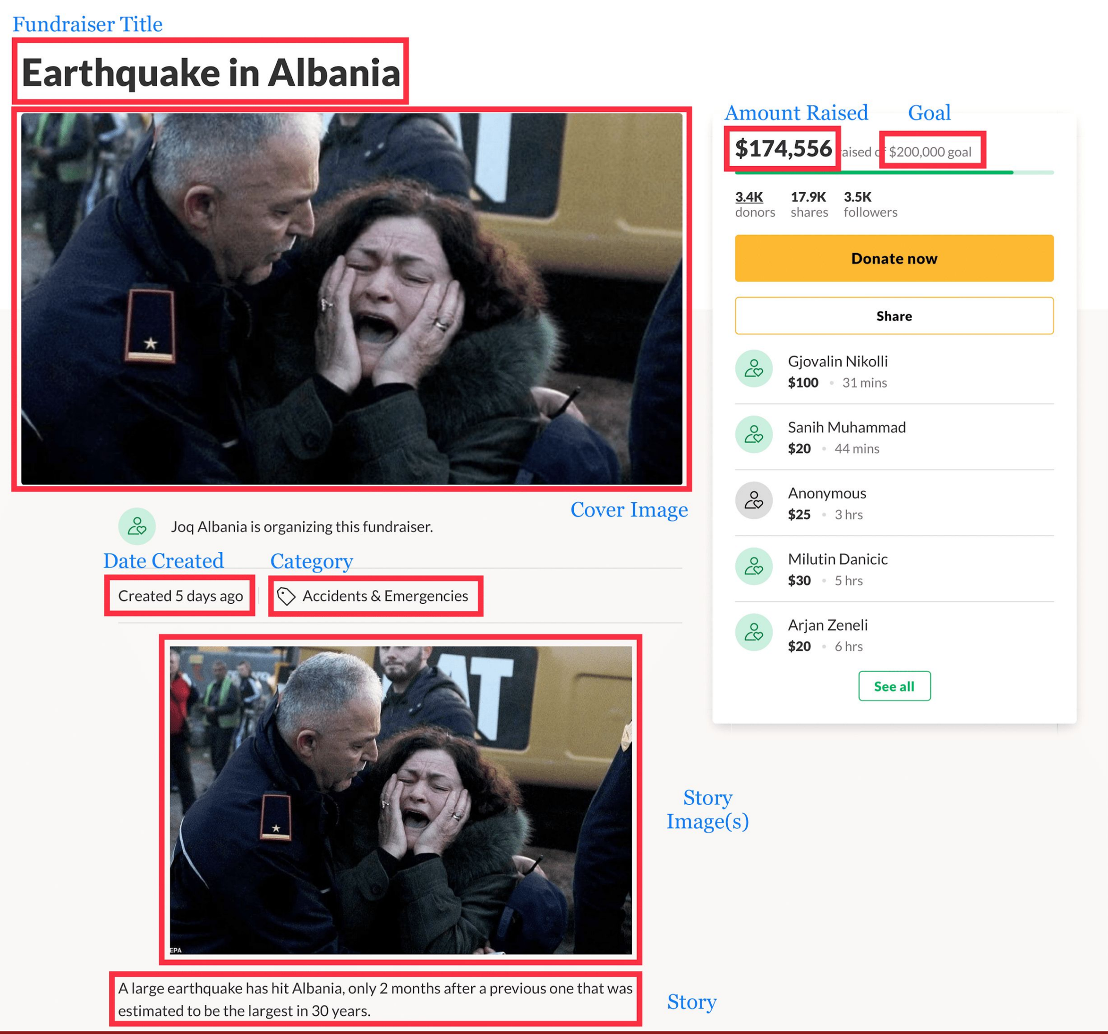
Abstract

What makes a successful GoFundMe campaign? We independently collected data from over 1 million campaigns and compared several techniques to predict how much money campaigns will raise based on factors that campaign creators can control, such as the goal amount, title, story, and images. We trained and tested several models and found that support vector regression (SVR) produced the best predictions. All models beat a baseline linear regression model.

Background & Data

- Individuals and organizations need help **making their fundraising campaigns successful** in a time when potential donors are inundated with alternatives.
- **Goal:** Design a model that predicts how much a fundraising campaign will raise on the popular crowdfunding site **GoFundMe**, given basic information used to populate a fundraising call to action.



- **Data:** We scraped nearly **1.3 million** GoFundMe fundraising pages to extract the information specified in the adjacent figure. Images were scraped as URLs and were later downloaded separately.

Methodology

Feature representation

- All scraped fields were incorporated into our model.
- Text was featurized into vectors outputted from three different language representation models: average **word2vec**, **doc2vec**, and **BERT.**
- Images are summarized using a parallelized, pre-trained "Show and Tell" image captioning model and then vectorized as text features.

Models

- Models were trained to predict a dollar amount raised.
- We built four different models: ***linear regression*** (baseline), ***random forest regression***, ***SVR***, and ***MLP***.
- The models were trained on 500,000 campaigns. We are in the process of running experiments on all 1.3 million campaigns.
- The models were trained on a machine with 32 GB RAM, Ryzen 3600 6c/12t CPU, and an NVIDIA 2070 Super GPU.

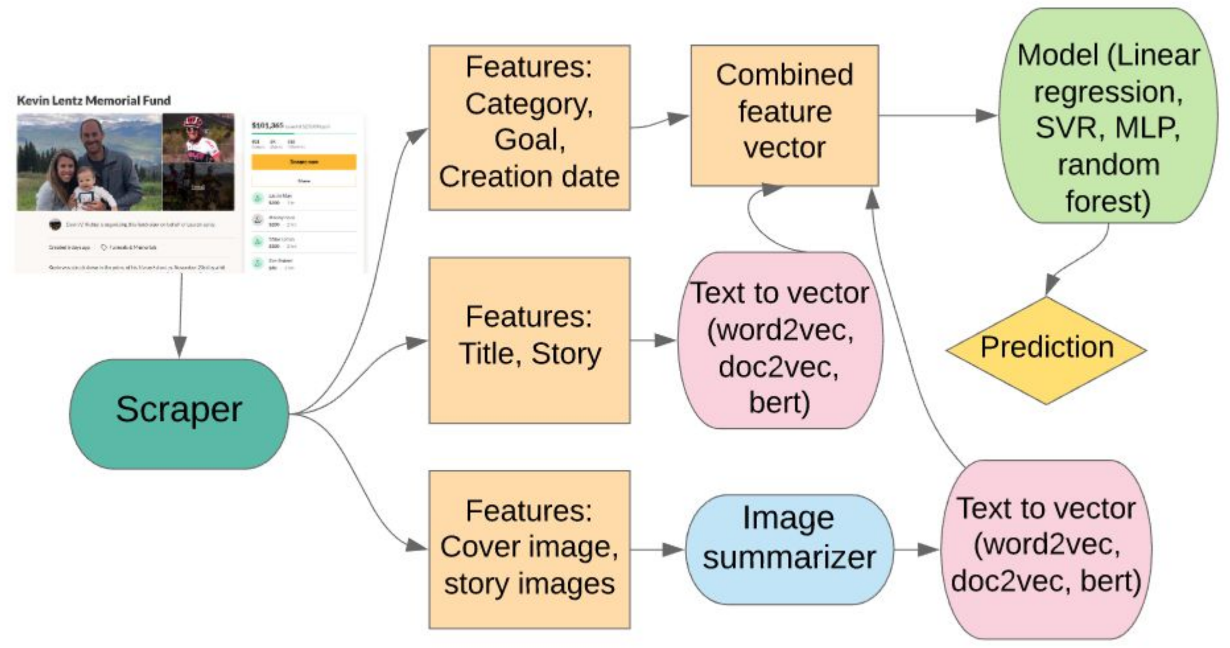


Diagram of experiment and model architecture

Challenges

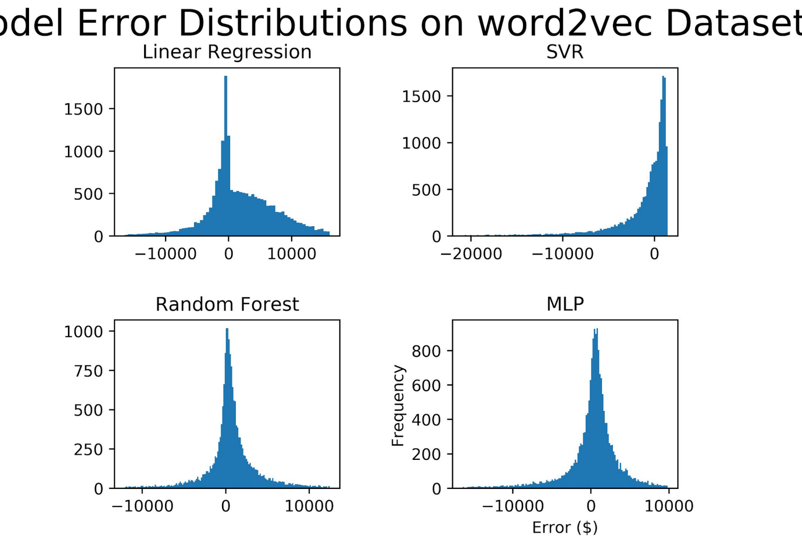
- Image captioning required painstaking debugging. Performance issues with the captioning necessitated parallelization.
- At **17 GB**, we had trouble fitting our dataset into memory while parallelizing experiments across hyperparameters.
- Not a lot of prior work regarding effective document embedding techniques for this application.

Results & Analysis

Mean absolute error comparison				
		Text embedding technique		
Model type	**Dataset size**	word2vec Title and Story	BERT Title and doc2vec Story	doc2vec Title and Story
Linear Regression	250000	6557	7515	5660
	500000	9092	11038	9691
Random Forest	250000	3688	5350	3775
	500000	6592	6601	6883
Support Vector Regression	250000	3280	3310	3310
	500000	4463	4510	4508
Multi-Layer Perceptron	250000	4757	5842	5194
	500000	8083	6798	8358

Mean absolute errors of various models

Model Error Distributions on word2vec Dataset



Test set error histograms for each model type trained on word2vec embeddings

- Across dataset sizes and document embedding techniques, **SVR > Random Forest > MLP > Linear Regression** in terms of error.
- SVR likely performs better than other models because margin maximization is fundamentally built into the model (it inherently "ignores" outliers).
- The error distributions shown above only include the 2.5th-97.5th percentiles. There were significant outliers (one campaign made upwards of $20 million!), which raised the average error. The average campaign on the other hand raises ~$3,000.
- Surprisingly, despite the state of the art improvements in NLP tasks with the advent of this language representation model, using BERT to create feature vectors from text did not result in lower errors relative to its alternatives (more data/different models may be necessary to maximize performance).
- Our experiments using image captioning data are in progress. Because images play an important role in affecting purchasing behavior, we expect these experiments to show improved prediction accuracy.

References

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https://github.com/UKPLab/sentence-transformers

https://github.com/KranthiGV/Pretrained-Show-and-Tell-model