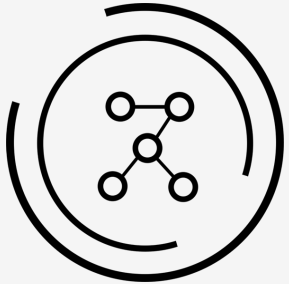
Petition Data Analysis

DSS x Change.org



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Agenda

01 Background

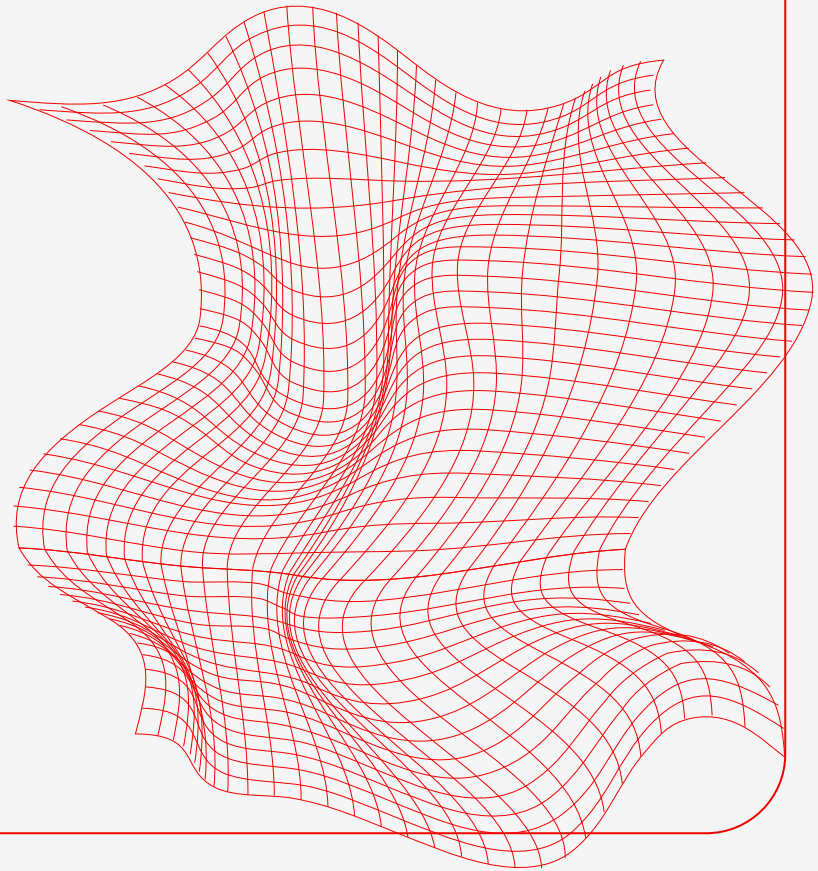
02 Petition Analysis

03 Harmful Data

04 Challenges + Future Work

01

Background



Our Tasks

Analyze Petitions

Find factors that contribute to petition growth/signatures

Predict Success

Use features to build a model that can predict a petition's # of signatures

Examine Harmful Data

Investigate patterns in harmful/spam petitions to improve content regulation

Key Terms

Correlation

Strength of the relationship between two variables, between -1 and 1

Modeling

Using data on existing petitions to predict how many signatures future petitions will get

Overdispersion

When data is very spread out so the variance is greater than the mean

NLP

Natural Language Processing → using code to analyze text

Technical Limitations

Our Barriers

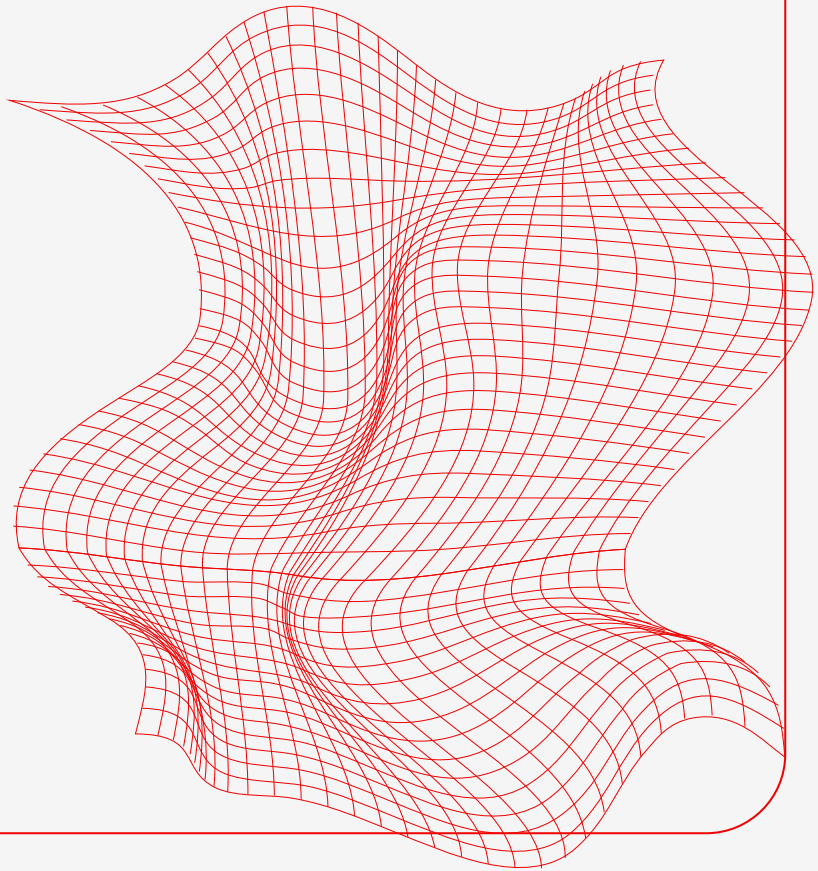
- Deepnote could not handle all 1.6 million rows of data
- Cannot download the data to run locally due to security concerns

Our Solutions

- Initially ran analysis on 1000 rows, but then received 1.6 million later
- From 1.6 million rows, randomly sampled a smaller portion of data
- Think of our project as a test-run of data analysis on the full dataset!

02

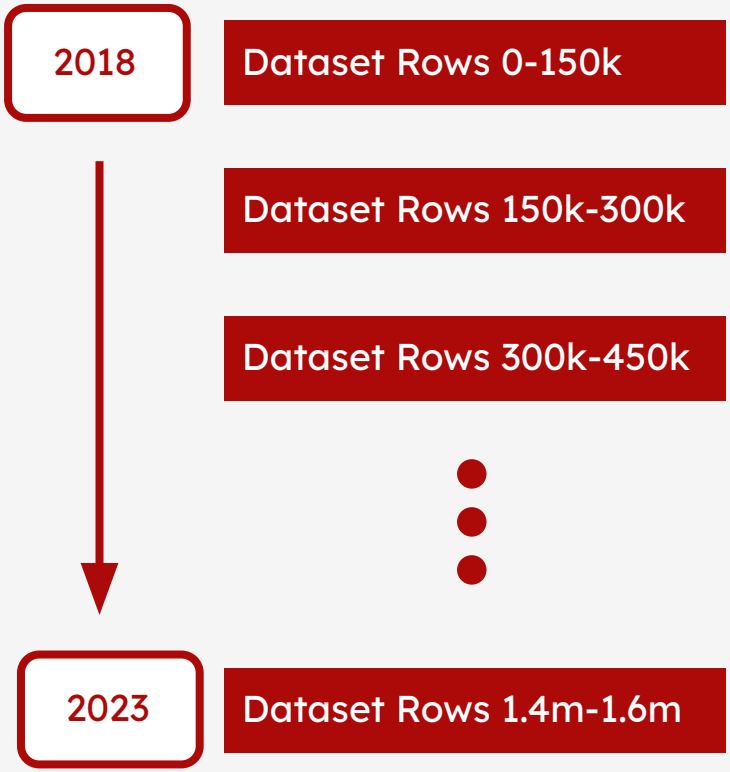
Petition Analysis



Getting the Data

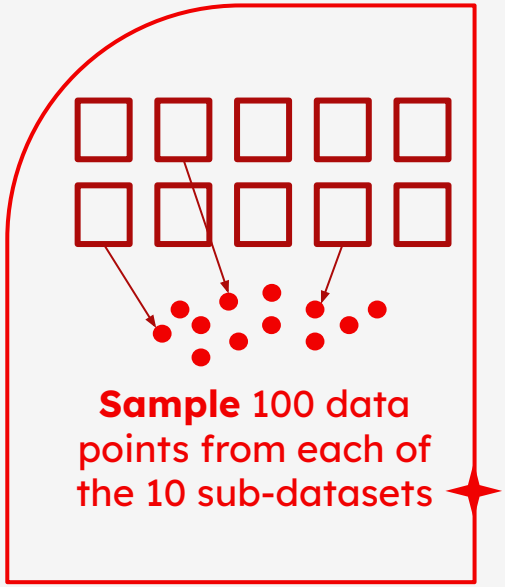
How we attempted using all of our data.

- 1.6 million rows of data total
- Full dataset could only be imported into Deepnote in sub-datasets
- Each dataset has around 100k-200k rows
- Sorted chronologically

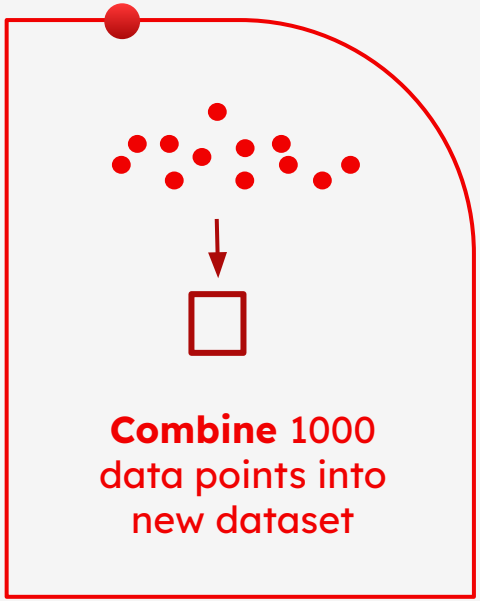


Random Sampling

On all the different combinations of data points



Sample 100 data points from each of the 10 sub-datasets



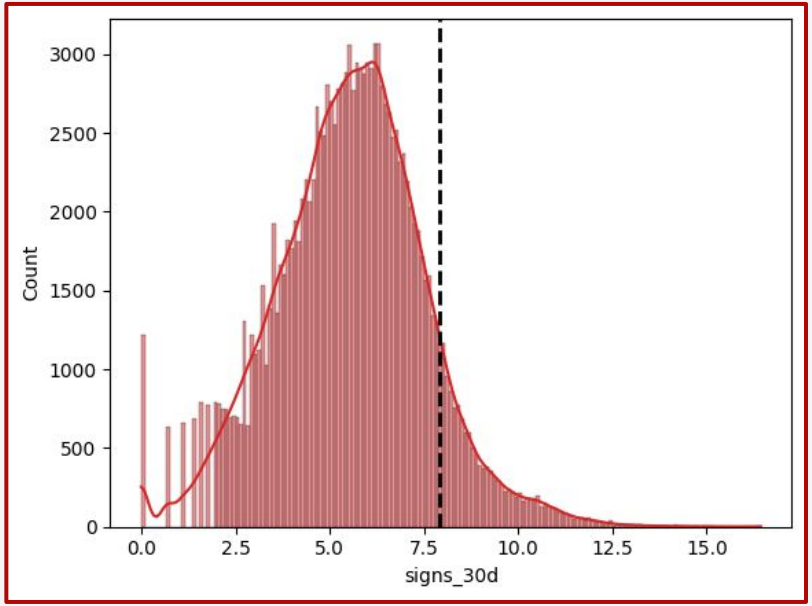
Combine 1000 data points into new dataset

Creating a Success Metric

Existing ‘status’ column does not always signify high success

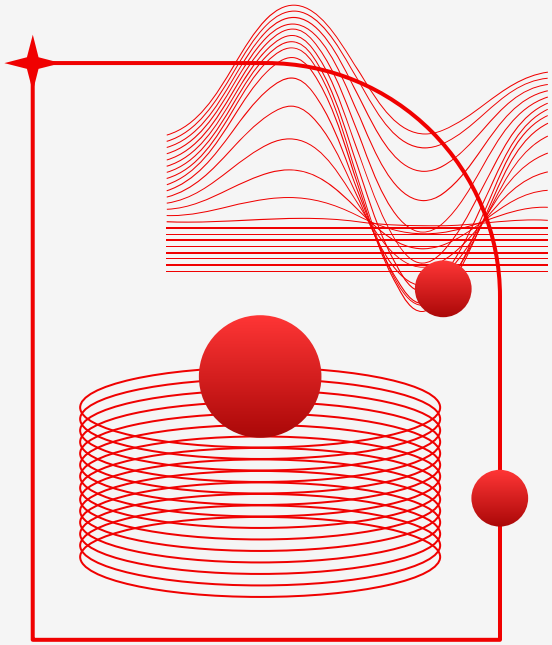
Success metric:

Petitions with # of signatures after 30 days that are above the 90th percentile



Histogram of Log of Number of Signatures on Day 30 Among All Petitions

Factors of Growth



Polarity

Calculated if petition descriptions had a “positive, negative, or neutral” sentiment

01

Subject Matter

Identified the most important keywords amongst petitions

02

Model

Experimented with various types of model to find the best predictor of petition success

03

Polarity Score

Measures the overall sentiment of a particular text, ranged from [-1.0, 1.0] with -1.0 being negative and 1.0 positive.

Polarity Scores

POSITIVE SENTENCE:

"Petitions **empower** communities and **foster** change by **enhancing** voices of individuals **hoping** for a **better** world."

Polarity score:

{'neg': 0.0, 'neu': 0.695, 'pos': 0.305, 'compound': 0.6908}

NEGATIVE SENTENCE:

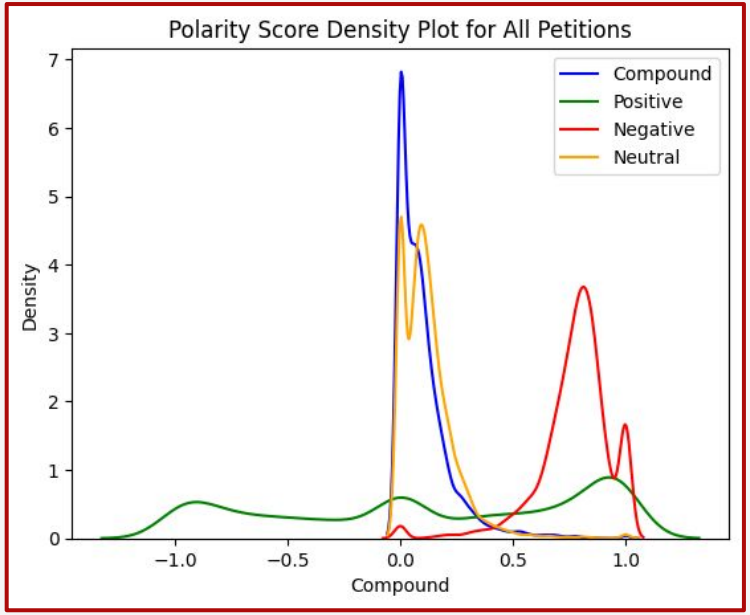
“Petitions can be **disregarded** and face **obstacles**, **dampening** the **hopes** of those seeking **meaningful** change.”

Polarity score:

{'neg': 0.244, 'neu': 0.516, 'pos': 0.239, 'compound': -0.0258}

Polarity Scores

- **Compound:** central around 0, leaning towards more positive
- **Positive:** low, but spread throughout most petitions
- **Negative:** skewed to the right
- **Neutral:** similar to compound



Kernel Density Plot of Polarity Score on 10,000 randomly sampled rows

Polarity Scores

- **10% of petition descriptions have polarity score = -1.0**
  - Changes with random sample
- **There existed petitions that contained spam content**
  - Might skew the polarity scores for petitions

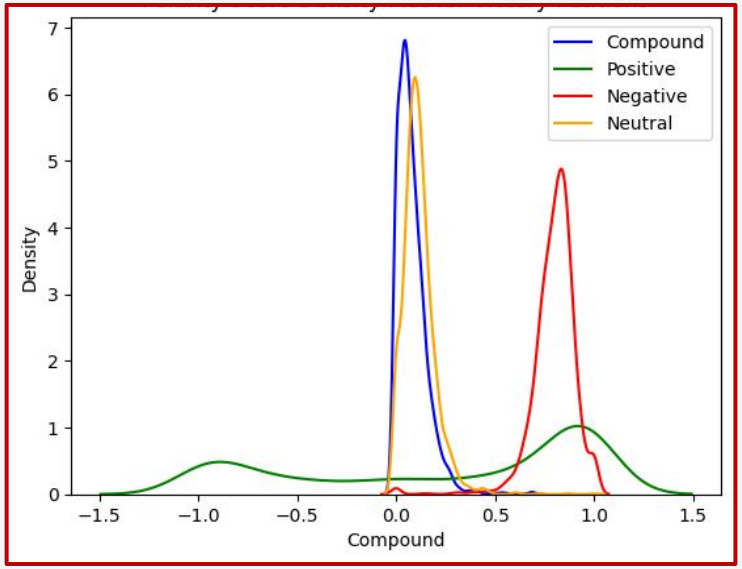
Example Table:

Title	Description
<: aaa	aaa
MLB: Get MLB to remove...	Let Pete back in baseball!
Yes	Its me

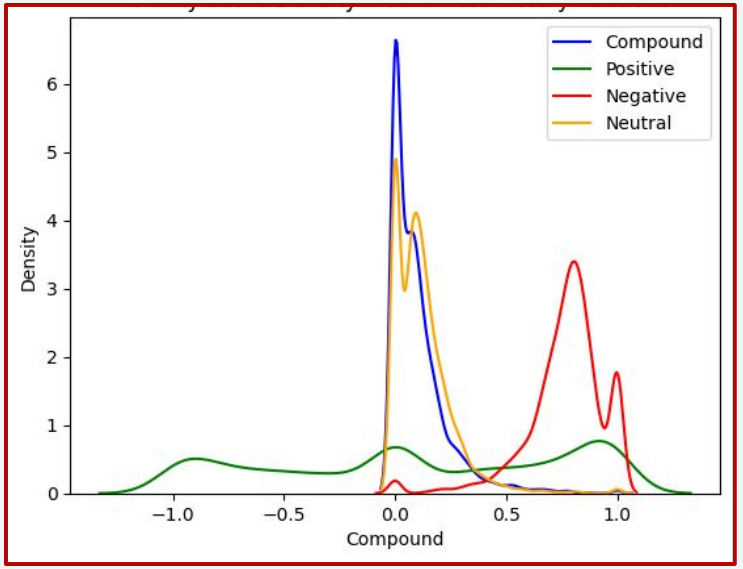
Polarity Scores

Factors of High-Signature Petitions:
1. Strong wording
2. Acting *against* or *preventing* something

‘Successful’ Petitions



‘Unsuccessful’ Petitions



Keyword Extraction with Yake:

Yet Another Keyword Extractor

"unsupervised automatic keyword extraction method"

1. Text Pre-Processing

cleaning and normalizing the text,
tokenizing text

2. Feature Calculation

calculating term frequency, position of
word, degree of word

3. Keyword Scoring

calculate score based on steps 1 & 2

Yake

in action

"Save the Gibson House Museum"

"Stop the "Adventure Park"

"Make BULLYING a criminal offense"

"Gibson House Museum"	0.0007
"Park"	0.206
"Criminal"	0.588

Deduplication Threshold: **0.1**
Max # of Words per Keyword: **3**
Language = **English**
**low deduplication due to the smaller example*

Yake

ask column

animal	0.175
kids	0.174
Home	0.169
Give	0.168
Parents	0.162

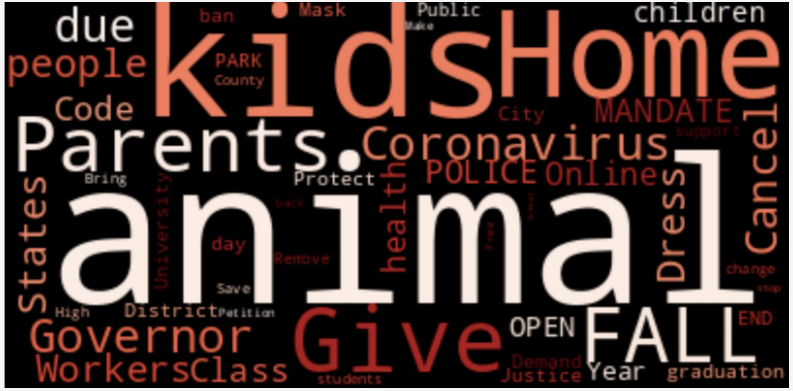
Top 5 Successful Keywords

MOD	0.0034
states	0.0034
time	0.0033
National	0.0032
ENDLESS	0.0032

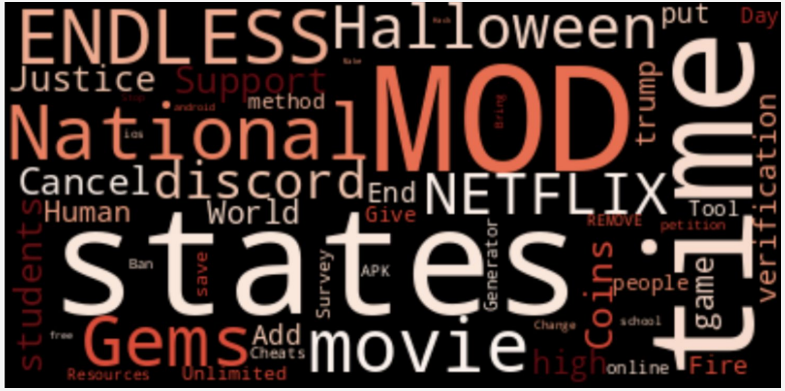
Top 5 Unsuccessful Keywords

Yake WordClouds

ask column

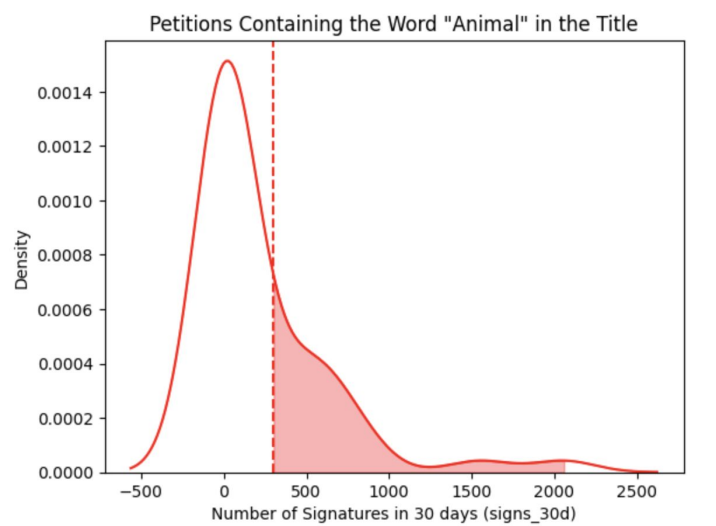


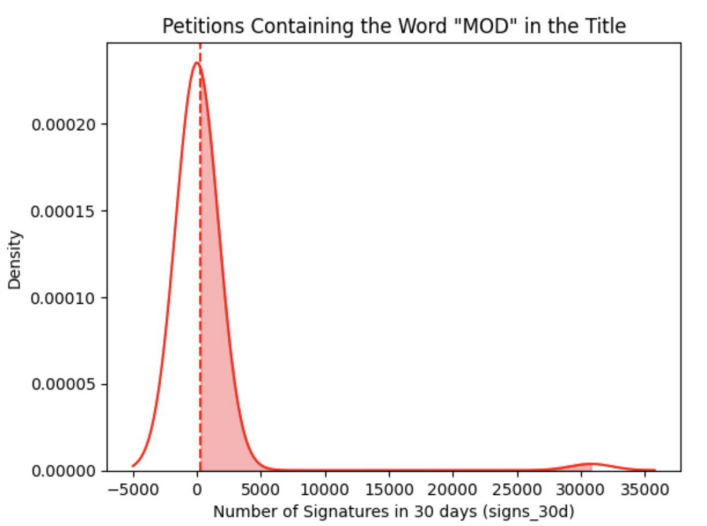
Successful Petitions



Unsuccessful Petitions

Validating Success w/ Yake





Type: Successful Keyword
Success Rate: 0.255 or 25.5%

Type: Unsuccessful Keyword
Success Rate: 0.034 or 3.4%

Regression Models

Input petition features and predict the # of signatures after 30 days

Linear

Pro:
Very high accuracy
Training $R^2 = 0.8396$
Testing $R^2 = 0.8586$

Con:
Could be overfitting

Poisson

Pro:
Useful for non-normal distributions

Con:
Assumptions not met due to overdispersion

Negative Binomial

Pro:
Accounts for overdispersion

Con:
Needs more data & text variables

Key Takeaways: Linear Regression

- Accuracy of predicting successful petition: 85.86%
- Training accuracy is smaller than testing indicating that the **model is good predictor for the data**
- High correlation between signs_30d and signs_7d compared to other predictors
    - Additional influential features needed to decrease weight of single predictor
- Used solely numerical variables, could improve accuracy through categorical (such as user/staff tags)

Analysis of Features: Neg Binomial

Feature	7-Day Signatures	1-7 Day Signatures Ratio	Compound Ask Polarity Score	Number of User Tags	Number of Profanity Words	Amount of Punctuation	Ask Length
Weight in Model	0.002	0.050	0.285	0.027	-1.358	-0.001	0.014
p-value	~~0	~~0	~~0	0.109	~~0	0.868	~~0

Weights: average change of '30-Day Signatures' associated with a one unit increase in each feature

Analysis of Features

Strong Features

- 7 Day Signatures
- 1-7 Day Signatures Ratio
- Compound Ask Polarity Score
- # of Profanity Words
- Ask Length
- Has either a staff tag or user tag
- Has a photo

Weak Features

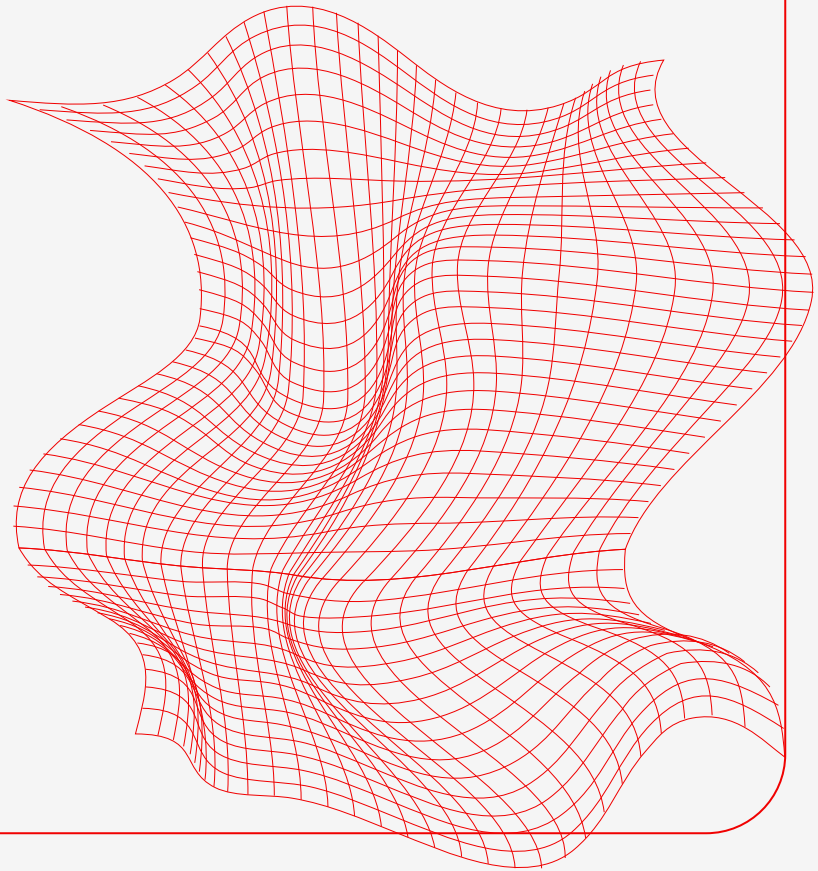
- Number of User Tags
- Amount of Punctuation
- Description Length
- Having zero signatures at 7 Days

Key Takeaways:
Negative Binomial Regression

- Accuracy of predicting successful petition: 0.8128%
- We found some good features!
  - *Not consistent with every random sample
- Log-likelihood is very small indicating that the **model is poor fit for the data**
- Used a Frequentist approach, could have more potential with a Bayesian approach
  - Updating beliefs using observed data

03

Harmful Petitions

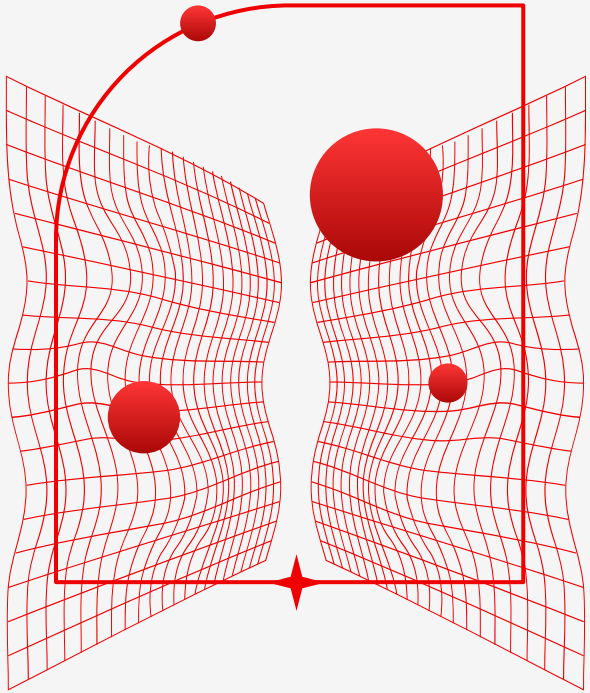


Harmful Petitions - Background, Thought Process

1. “Harmful” / “Abusive” Meaning?
2. The Complexity of “Harm”
3. Freedom of Speech
4. Minimizing Flagging of Good Petitions

Overview of Our Data Analysis

Perspective API

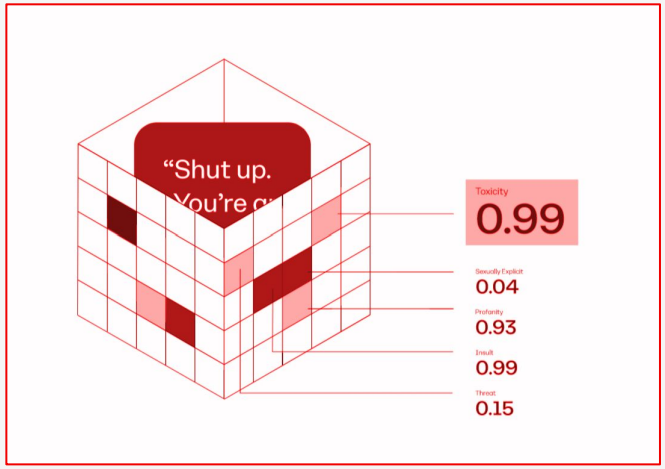


Toxicity Scoring

- Identify and filter online content that may be considered "toxic" or harmful
- **Natural language processing (NLP)** algorithms to analyze text and assign a toxicity score
- Returns **probability (0-1)** of the content containing abusive, threatening, or offensive language

Text:	Toxicity Score:
“Safety in Rockingham County Public Schools”	0.006345861
“Derek should shut the f*ck up❤️”	0.9029226

How Perspective API Works



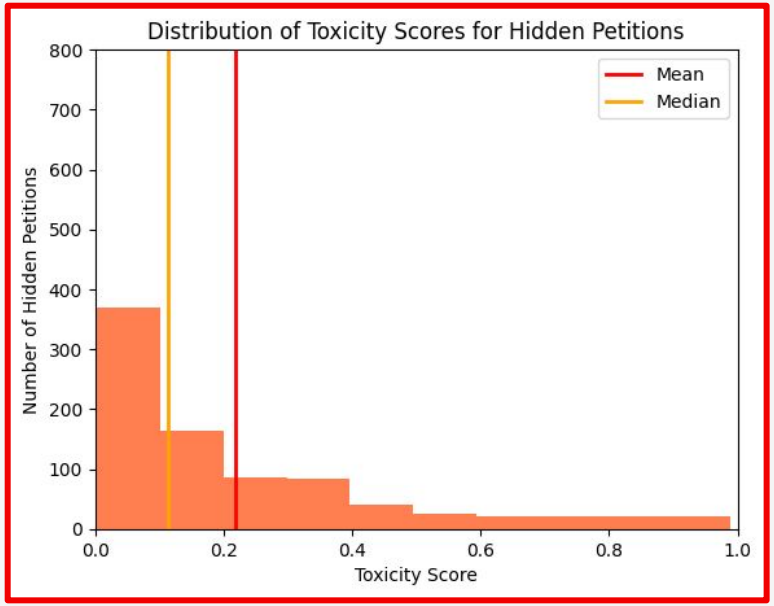
1. Severe toxicity
2. Insult
3. Profanity
4. Identity Attack
5. Threat
6. Sexually Explicit

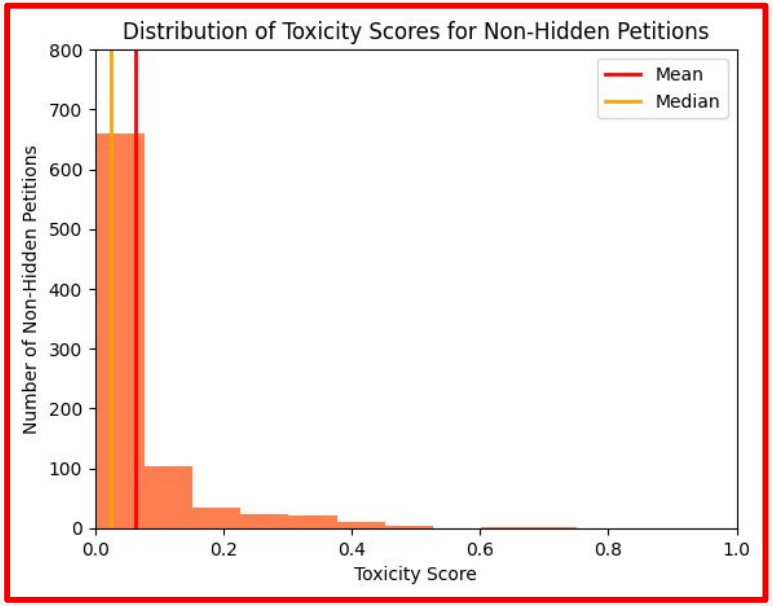
Categories as defined by Perspective API

Toxicity Level	Description of level
Very Toxic	A comment that is very hateful, aggressive, disrespectful, or otherwise very likely to make a user leave a discussion or give up on sharing their perspective.
Toxic	A comment that is rude, disrespectful, unreasonable, or otherwise somewhat likely to make a user leave a discussion or give up on sharing their perspective.
Not Toxic	A neutral, civil, or even nice comment very unlikely to discourage the conversation.
I'm not sure	The comment could be interpreted as toxic depending on the context but you are not sure.

Category	Definition
Profanity/ Obscenity	Swear words, curse words, or other obscene or profane language.
Identity-based negativity	A negative, discriminatory, stereotype, or hateful comment against a group of people based on criteria including (but not limited to) race or ethnicity, religion, gender, nationality or citizenship, disability, age, or sexual orientation.
Insults	Inflammatory, insulting, or negative language towards a person or a group of people. Such comments are **not** necessarily identity specific.
Threatening	Language that is threatening or encouraging violence or harm, including self-harm.

Hidden vs. Non-Hidden Toxicity Scores





Mean: 0.218
Median: 0.114

Mean: 0.062
Median: 0.025

0.1549 - 0.1562

Difference between hidden and non-hidden toxicity scores

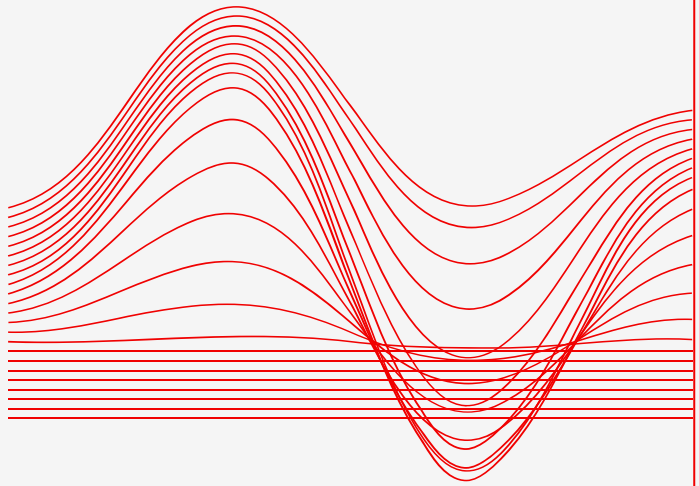
Challenges:

01 Not openly accessible to use: must request access from Google

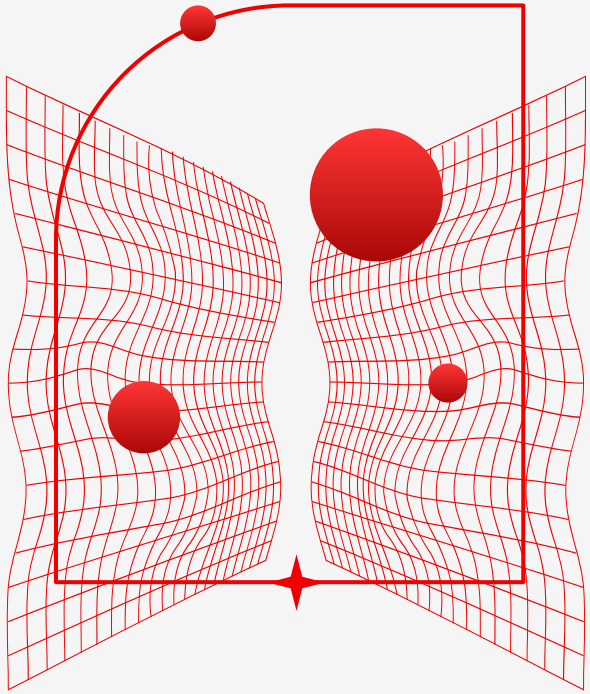
02 Server request error: standard API Package cannot process large-scale requests

Future Exploration:

Use as a feature, linear modeling



Profanity Exploration



Petitions with 1+ Profanity Word (1 sample)

46/826 = **5.7%**

hidden

44/9084 = **0.5%**

non-hidden

Petitions with 1+ Profanity Word: Bootstrap

~ 5.3-5.6% difference

[5.80%, 5.99%]

hidden

[0.37%, 0.42%]

non-hidden

Hidden petitions are ~**13-15 times** more likely to have 1+ profanity word (95% confidence, 200 samples, 10000 rows)

Synthesizing Results: Perspective + Profanity Analysis

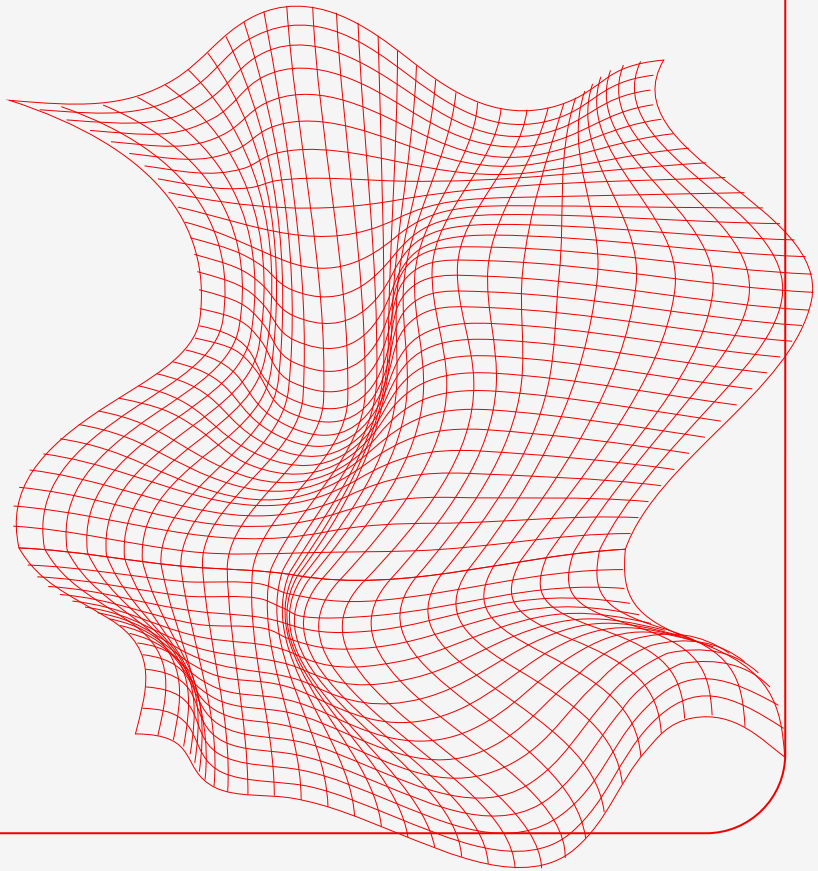
Perspective Alone: reasonably large toxicity difference for hidden vs non-hidden

Profanity Analysis Alone: somewhat large profanity difference for hidden vs non-hidden

Perspective + Profanity Analysis: other factors may play larger role into “toxicity”/harm than profanity. Profanity alone may just be a small factor.

04

Challenges and Future Work



Challenges

Runtime

Large amount of data took an extremely long time to run through the cloud

Modeling

Tested many different types of modeling before landing on final model

Updating Data Pipelines

Had to update code with every new file of data sent

Defining Harmful

Had to research and define the boundaries of what makes content harmful

Next Steps

Improve NLP

Create staff tags for every description

Modeling

Unsupervised categorization to create tag categories for a semi-supervised model

Server Change

Move work to platform with more computing power

Location Analysis

Look more into how location impact petition signatures

Key Takeaways

Petition Analysis

Best Features Associated with Success:

- 7 Day Signatures
- Compound polarity score

Predicting Success

Best Models:

- Negative Binomial
- Linear Regression

Harmful Data

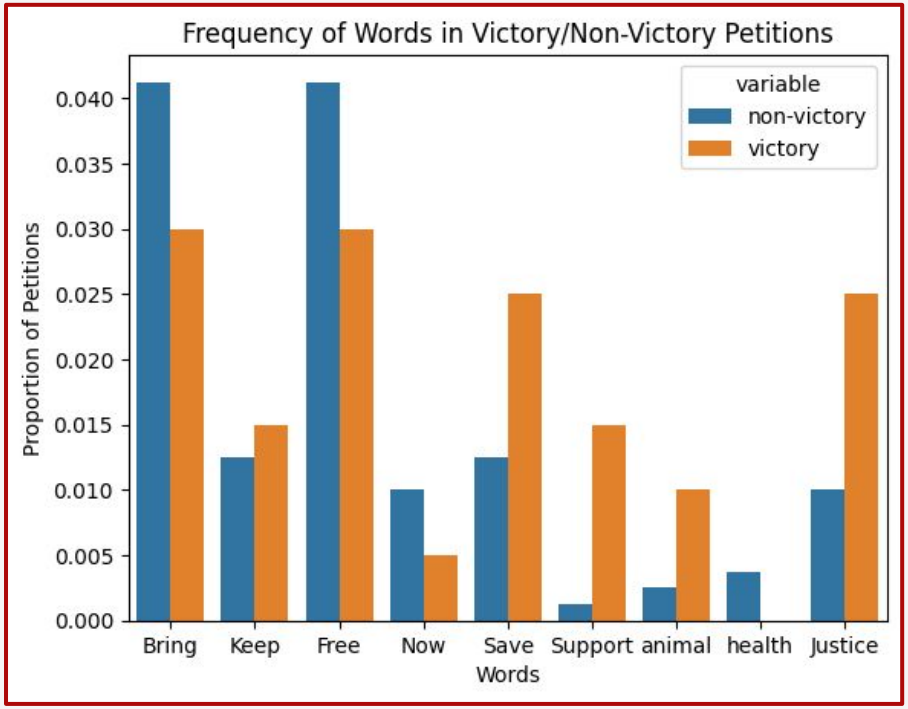
- Harm is multifaceted
- ‘Hidden’ should be examined further as a metric of harm
- Toxicity scores may be good indicators of harm

Thank you!
Questions?

Appendix

Slides We Didn’t Present

Word Frequency



Titles of Petitions: 'ask'

- Looking for visual comparisons between proportion of petitions
- Themes among successful petitions
  - **Keep, Save, Support, Animal, Justice**

Analysis of Features: Neg Binomial

Feature	7-Day Signatures	1-7 Day Signatures Ratio	Compound Ask Polarity Score	Number of User Tags	Number of Profanity Words	Amount of Punctuation	Ask Length
Correlation w/ 30-Day Signatures	0.893	0.102	-0.005	0.166	0.007	0.036	0.060

Analysis of Features: Neg Binomial

Generalized Linear Model Regression Results

Dep. Variable:	signs_30d	No. Observations:	5020
Model:	GLM	Df Residuals:	5008
Model Family:	NegativeBinomial	Df Model:	11
Link Function:	Log	Scale:	1.0000
Method:	IRLS	Log-Likelihood:	-25408.
Date:	Wed, 03 May 2023	Deviance:	1.0732e+08
Time:	06:04:40	Pearson chi2:	1.80e+05
No. Iterations:	100	Pseudo R-squ. (CS):	0.9675
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	1.8423	0.048	38.631	0.000	1.749	1.936
signs_7d	0.0020	5.44e-06	364.888	0.000	0.002	0.002
signs_ratio	0.0502	0.001	71.651	0.000	0.049	0.052
Compound_ask	0.2847	0.078	3.656	0.000	0.132	0.437
num_user_tags	0.0272	0.017	1.603	0.109	-0.006	0.060
profanity_count	-1.3582	0.189	-7.197	0.000	-1.728	-0.988
punctuation_count	-0.0005	0.003	-0.166	0.868	-0.007	0.006
description_len	3.69e-06	4.88e-06	0.756	0.450	-5.88e-06	1.33e-05
ask_len	0.0142	0.001	15.160	0.000	0.012	0.016
has_tag	0.7303	0.038	19.262	0.000	0.656	0.805
has_photo	0.6428	0.037	17.397	0.000	0.570	0.715
no_signs	-0.0033	0.076	-0.043	0.966	-0.153	0.146

Log-likelihood very low, indicating poorly fitted model.

Word Cloud: Hidden vs. Non-Hidden

Hidden

Non-Hidden