Investigating The Sentiment on Twitter After The Congress Invasion In Brazil

Giovanna Chaves, Lucas Costa Santos, Tobias "Tobinho" Pfeiffer

Barcelona School of Economics

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Introduction

Context

- On January 8, 2023, a group of radical Bolsonaro supporters invaded the Brazilian Congress, Supreme Court and the Presidential Palace in Brasília.
- Brazil's political climate has been polarised since the elections (Oct 30, 2022) and leading up to them.
- In the West, Brazil politics has often been compared to the USA.

Figure: Bolsonaro Supporters Storming The Congress

Methodology

Outlook

Are people from Brasilia more affected by the insurrection than in other cities?

- Are they more politicised?
- Are they more positive/negative?
- Are they more critical of Bolsonaro?

Pipeline

1. **Scrape Twitter**
2. **Preprocess Text**
3. **Classify Tweets**
   3.a LDA
   3.b Naive Bayesian & Random Forest
4. **Regression Analysis**
   4.a Synthetic Difference-in-Difference
   4.b Difference-in-Differences

Scraping Twitter

- Dates: 02/01/2023 - 14/01/2023
- 5 cities:
  - Brasília
  - Sao Paulo
  - Rio de Janeiro
  - Fortaleza
  - Salvador

Challenges:

- Not enough control cities for Synthetic DiD
- 800K tweets to pre-process:
  - Computationally intensive
  - Too large to run through the LDA

Prepocessing Tweets

- Lowercasing
- Removing punctuation, diacritics and links
- Removing stopwords
- Tokenizing

Challenges:

- Translator functions are not fully developed yet
- Most resources (dictionaries, corpuses, etc.) are in English
- Keeping special characters
- Twitter is full of informal language and abbreviations

Classification with LDA

- LDA (Latent Drichlet Algorithm)
- Generative probabilistic model for text
- Discover hidden topics in a corpus
- Treats each document is a mixture of topics, and each topic is a mixture of words
- Uses MCMC

Classification with Naive Bayes and Random Forest

- Used dictionary to get political tweets
- Manually classified 747 tweets by their political bias
- Trained model on 522 of these tweets to test on the other 225
- Predicted on the rest of the dataset

Challenges:

- Dictionary might not adequately capture political tweets
- Enumerator biases
  - Classified independently and considered non-matching classes as neutral
- Very small proportion of classified tweets (too time-consuming)

Results

Tweet Classification (LDA)

- Sample 50,000 Tweets
- Choose 10 Topics in hyperparameters
- Initiate prior (one political & one negative)

How does LDA model topics?

- Approx. 4% of Tweets respectively were negative and politicised

Tweet Classification (Naive Bayes & Random Forest)

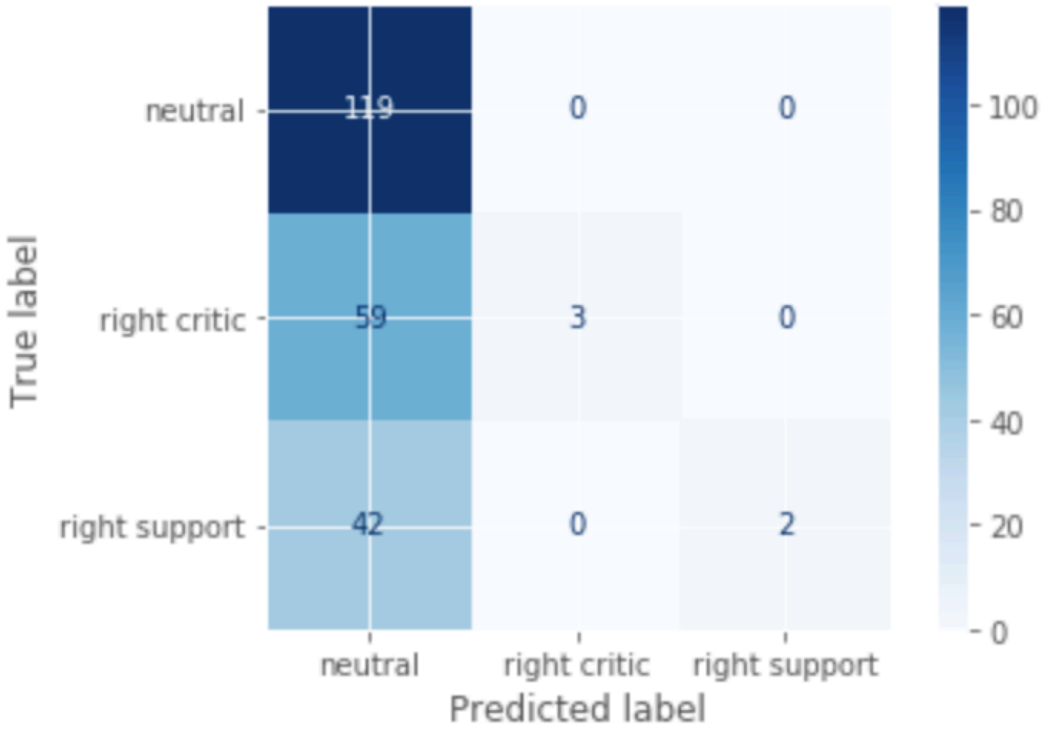
- High precision for anti-Bolsonaro and pro-Bolsonaro tweets in MNB, but very low recall...
- High recall for neutral tweets.
- More balanced with RF, but still not great...

		Multinomial Naive Bayes			Random Forest		
	Metric	**1**	**2**	**Joint**	**1**	**2**	**Joint**
Neutral	Precision	0.52	**0.77**	0.54	0.59	0.55	0.60
	Recall	**1.00**	0.27	**1.00**	0.95	0.52	0.97
	F1-Score	0.68	0.40	0.70	0.73	0.53	**0.74**
Anti	Precision	**1.00**	0.48	**1.00**	0.73	0.52	0.67
	Recall	0.12	**0.97**	0.05	0.34	0.79	0.26
	F1-Score	0.22	**0.64**	0.09	0.46	0.63	0.37
Pro	Precision	**1.00**	**1.00**	**1.00**	0.76	0.73	0.90
	Recall	0.06	0.17	0.05	**0.27**	0.24	0.20
	F1-Score	0.12	0.29	0.09	**0.39**	0.36	0.33

Figure: Performance metrics across classifiers.

Tweet Classification (Naive Bayes & Random Forest)

- Approx. 0.3% of tweets were anti-Bolsonaro and 0.06% pro-Bolsonaro with Naive Bayes.
- Approx. 1.8% of tweets were anti-Bolsonaro and 0.3% pro-Bolsonaro with Random Forest
- Strategy: only classify as anti or pro tweets those which were are certain



Regression Analysis (SDID/LDA)

- What is *Synthetic* Difference in difference?

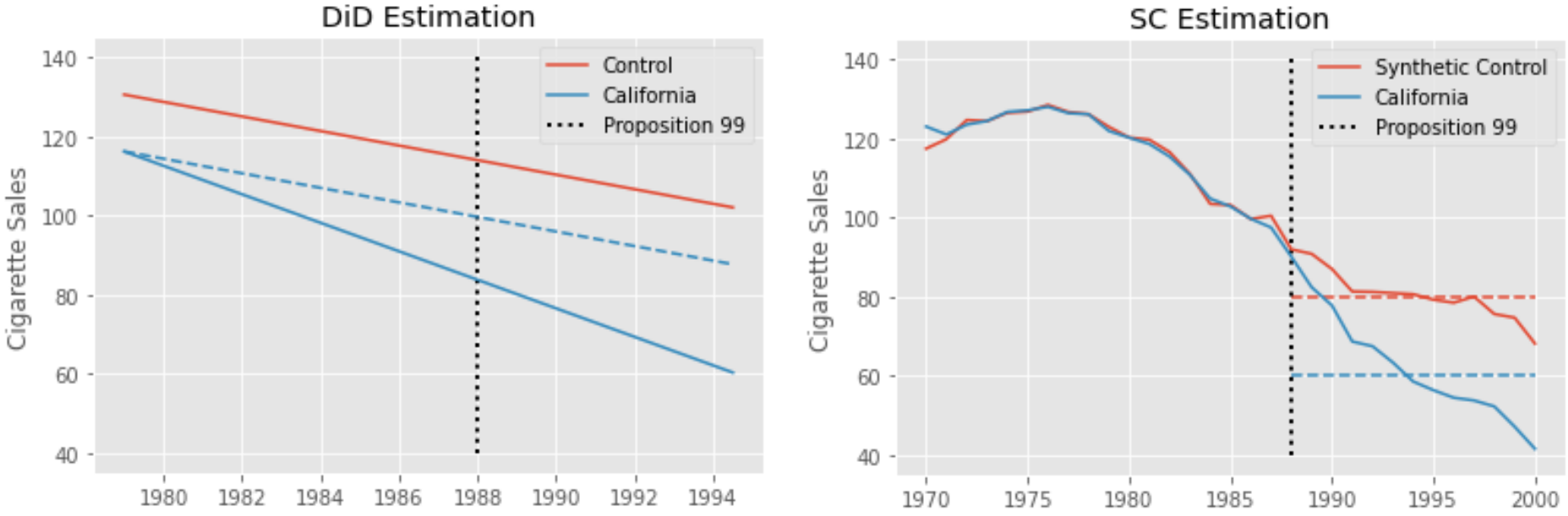


Figure: Intuition behind SDID

Regression Analysis (SDID/LDA)

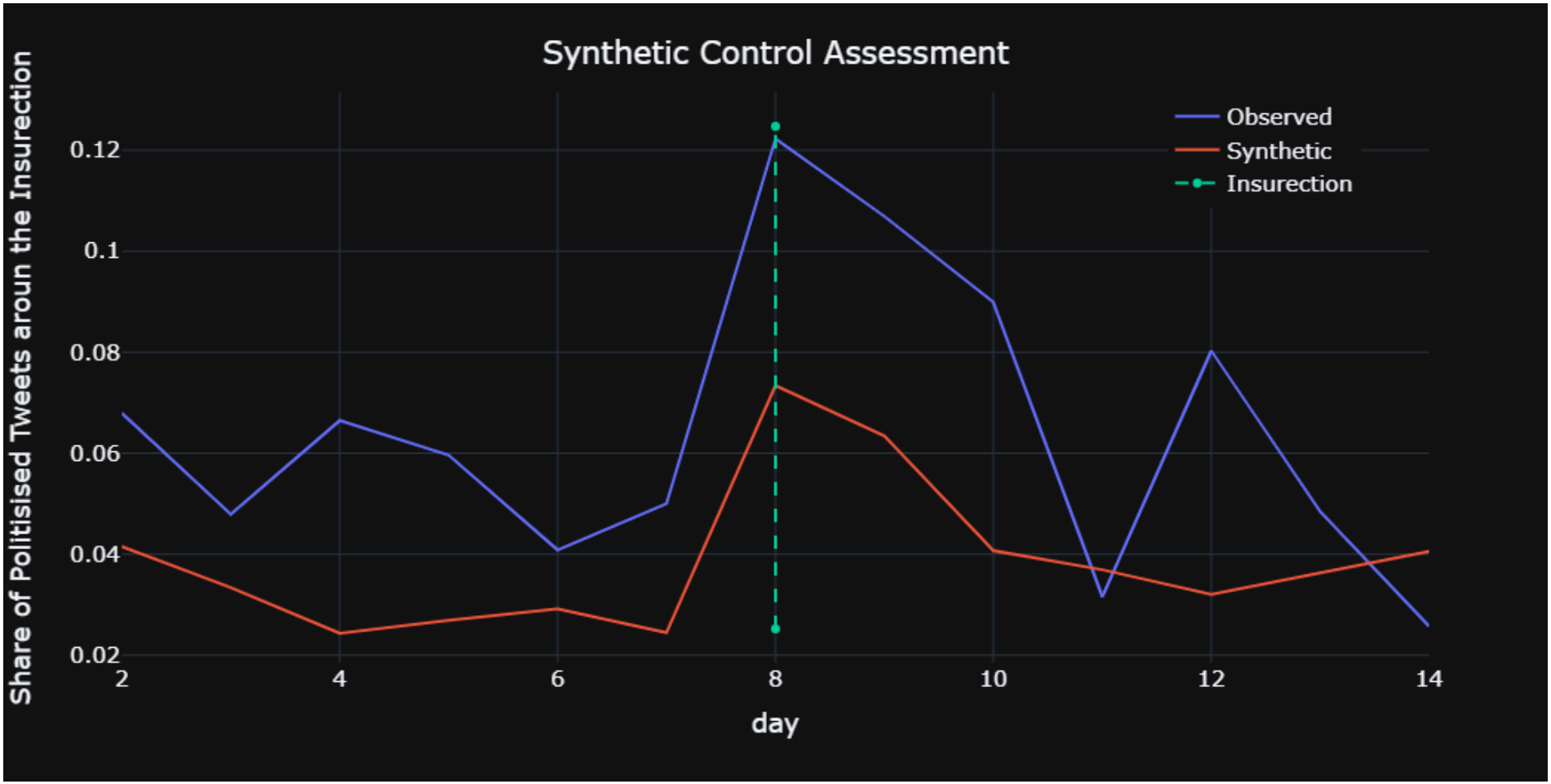


Figure: SDID for politicised Tweets, ATE: 0.08

Regression Analysis (DID/LDA)

$$P_{it} = \beta_0 + \beta_1 \cdot \text{Time}_{it} + \beta_2 \cdot \text{Treated}_{it} + \beta_3 \cdot \text{Time}_{it} \cdot \text{Treated}_{it} + \epsilon_i + u_t + v_{it}$$

OLS Regression Results

Dep. Variable:	political_share	**R-squared:**	0.333
Model:	OLS	**Adj. R-squared:**	0.307
Method:	Least Squares	**F-statistic:**	12.98
Date:	Tue, 21 Feb 2023	**Prob (F-statistic):**	2.68e-05
Time:	19:11:47	**Log-Likelihood:**	137.46
No. Observations:	55	**AIC:**	-268.9
Df Residuals:	52	**BIC:**	-262.9
Df Model:	2		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	0.0388	0.003	12.577	0.000	0.033	0.045
treated_time[T.True]	0.0154	0.006	2.482	0.016	0.003	0.028
treated[T.True]	0.0167	0.009	1.876	0.066	-0.001	0.035
treated_time[T.True]:treated[T.True]	0.0154	0.006	2.482	0.016	0.003	0.028

Omnibus:	2.288	**Durbin-Watson:**	1.335
Prob(Omnibus):	0.319	**Jarque-Bera (JB):**	1.423
Skew:	0.313	**Prob(JB):**	0.491
Kurtosis:	3.479	**Cond. No.**	4.47e+15

Figure: ATT $= 0.015$ (significant)

Regression Analysis (DID/LDA)

- Effect of the insurrection on the share of negative tweets violates the parallel trends assumption.

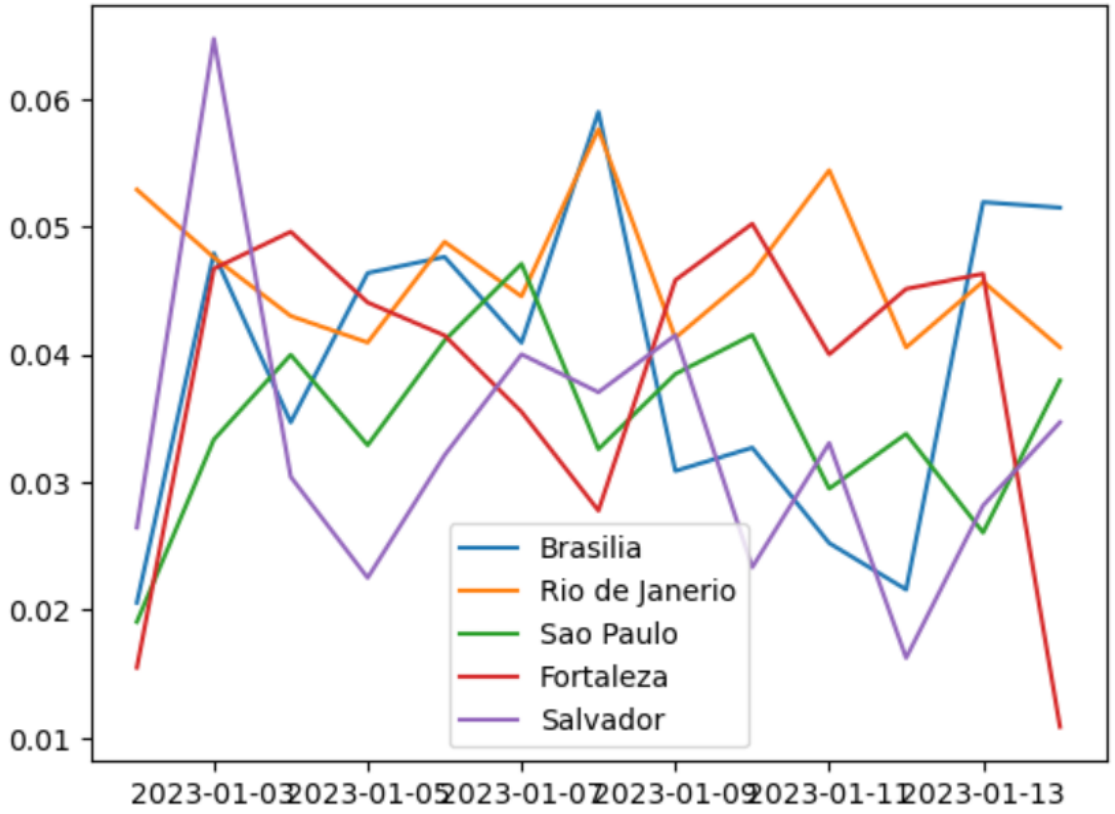


Figure: Share of negative tweets over time

Regression Analysis (DID/MNB)

- Effect of the insurrection on the share of anti-Bolsonaro tweets violates the parallel trends assumption.

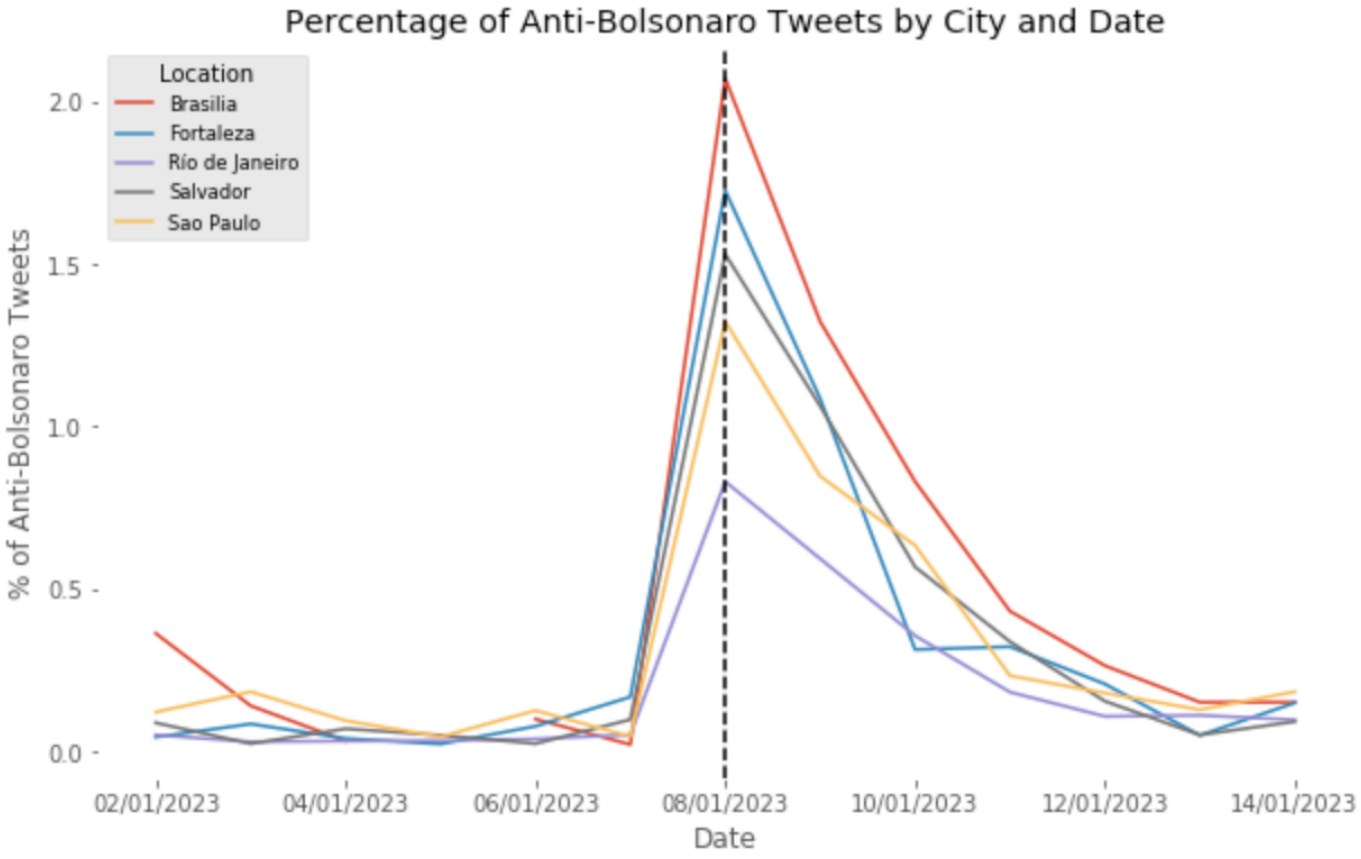


Figure: Share of Anti-Bolsonaro tweets over time

Conclusion & Future Research

Conclusion

- Challenges in adequately pre-processing such a large number of tweets not in English
- Used LDA to identify political and negative tweets
- Trained a classifier to predict political bias
  - Precision vs. recall trade-off
- No effect on negative share or anti-Bolsonaro bias (lower bound)
- 1.5% increase in political tweets in Brasília as a result of the insurrection.

Obrigado Pela Sua Atenção