MASS MOBILIZATION PROJECT

Future Development &
Predictive Applications

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01 INTRODUCTION

In partnership with Binghamton University, University of Notre Dame, the Political Instability Task Force (PITF), and with generous funding from the Central Intelligence Agency, we are here today to discuss the future of the Mass Mobilization project and the following objectives:

MM Researchers	US Government	Data Scientists
• Improve data usability • Identify potential use cases & beneficiaries • Address asks from US government	• Prepare for future protests • Address protester concerns • Resolve protests without violence.	• Inform project direction • Develop predictive solutions with this data.

02 STUDY OVERVIEW

17,145

Protests and Demonstrations

166

Countries

30

Years of Data

02 STUDY OVERVIEW

7
Protester Demands

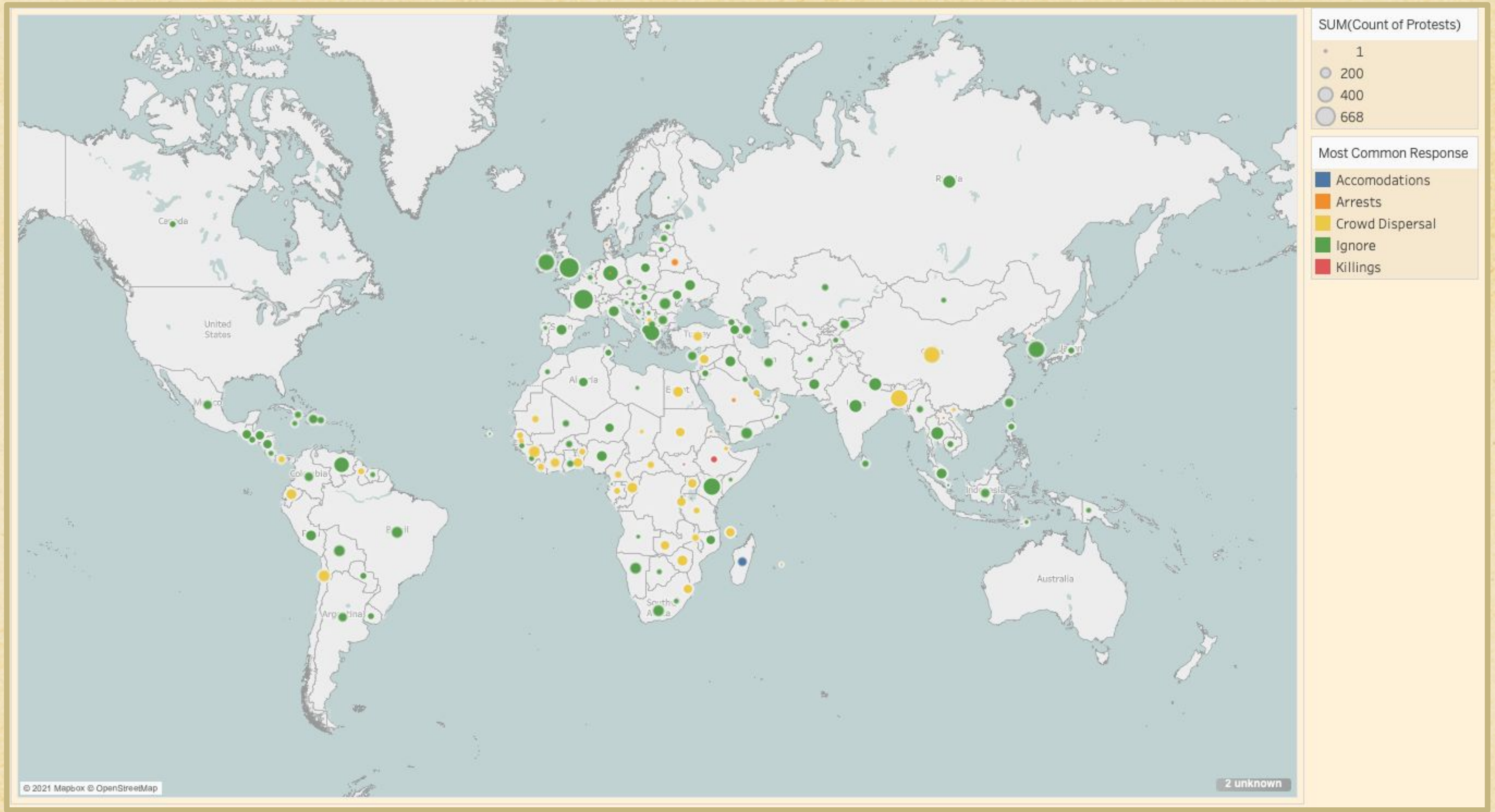
5
Protest Sizes

13
Participant Types

7
State Responses

02 STUDY OVERVIEW

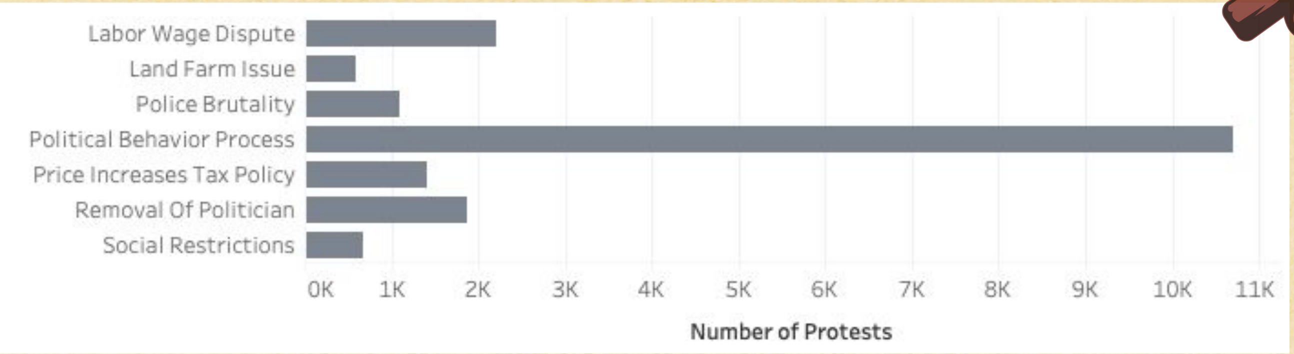
Recorded Protests



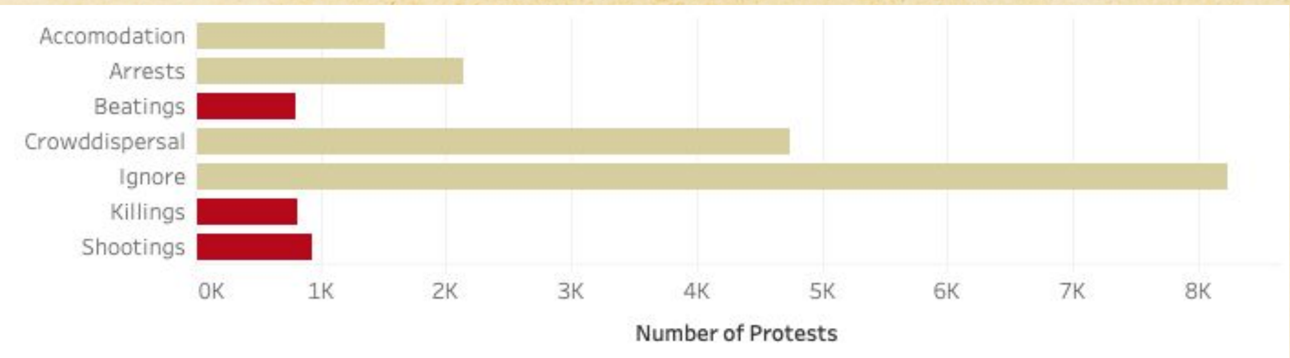
https://public.tableau.com/views/Mass-Protests_ProtestNumMostCommonResponse/Sheet1?:language=en&:display_count=y&:origin=viz_share_link

02 STUDY OVERVIEW

Protest Motivations

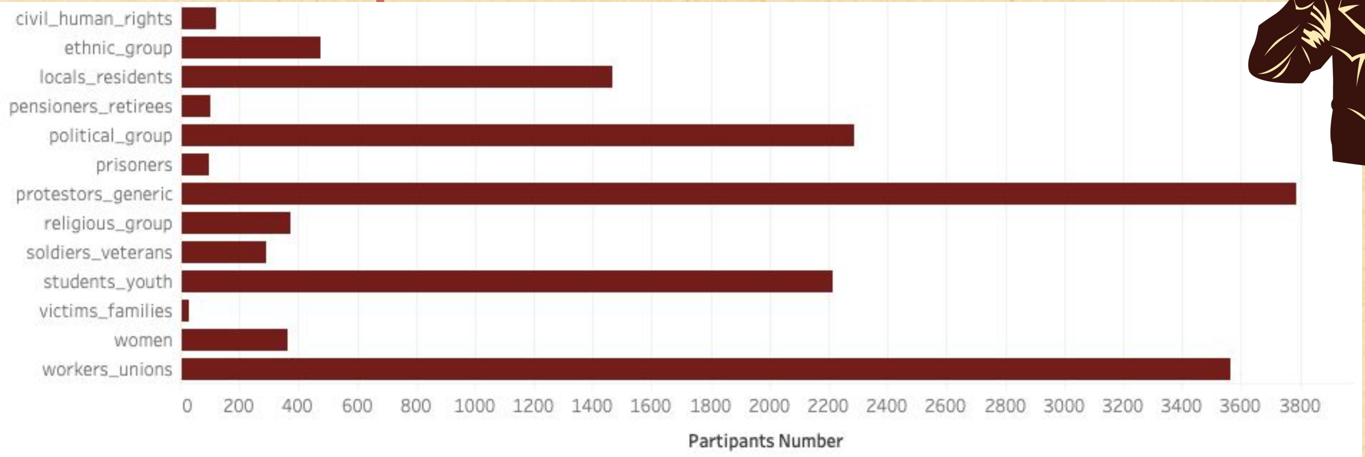


State Responses

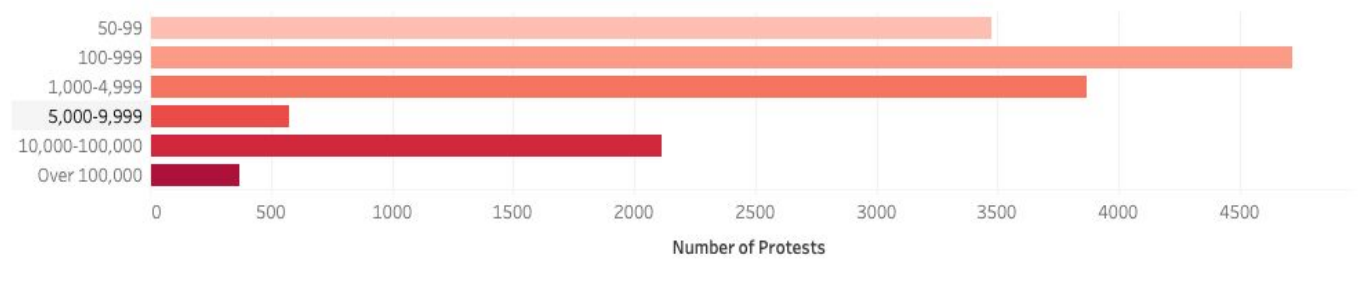


02 STUDY OVERVIEW

Protest Participants



Protest Sizes



03 DATA EVALUATION & CLEANSING

Clean & Complete

Completed Protester Size Ranges,
Transformed text into numbers

Encoding Categories

Countries, Regions, Participants, Protest Size

External Data

Prosperity Index, Population & Density

04 MODELING PROCESS

Data Gathering and Merging

Data Cleaning & Transformation

Feature Engineering & Selection

Model Development

Model Evaluation

Mass Mobilization
UN Country Data

Missing Data
One Hot Encoding

40 Features
7 Targets

04 MODELING PROCESS

MULTI-LABEL

What it does: Predicts multiple targets per observation.

Models Run: Neural Network and Multi-label Classifier (using Random Forest and Bagging)

Results: Neural network was not interpretable. Other models had low scores.

Observation	Prediction
Protest #1	Arrests, Ignore
Protest #2	Shootings
Protest #3	Arrests, Beatings, Killings

04 MODELING PROCESS

MULTI-LABEL

What it does: Predicts multiple targets per observation.

Models Run: Neural Network and Multilabel Classifier (using Random Forest and Bagging Classifier)

Results: Neural network was not interpretable. Other models had low scores due to imbalanced classes.

MULTI-MODEL

What it does: One model per target, predicts binary classification for target

Model Run: Logistic Regression

Results: Logistic regression models perform well for some classes, but imbalanced classes are still an issue.

Observation	Arrests
Protest #1	Yes
Protest #2	No
Protest #3	Yes

Observation	Beatings
Protest #1	No
Protest #2	No
Protest #3	Yes

Observation	Ignore
Protest #1	Yes
Protest #2	No
Protest #3	No

Observation	Shootings
Protest #1	No
Protest #2	Yes
Protest #3	No

04 MODELING PROCESS

MULTI-LABEL

What it does: Predicts multiple targets per observation.

Models Run: Neural Network and Multilabel Classifier (using Random Forest and Bagging Classifier)

Results: Neural network was not interpretable. Other models had low scores due to imbalanced classes.

MULTI-MODEL

What it does: One model per target, predicts binary classification for target

Model Run: Logistic Regression

Results: Logistic regression models performing well on more frequent targets. Imbalanced classes did not perform well.

MULTI-MODEL with TARGET ENGINEERING

Modeled “Ignore” as above. Other state responses only modeled observations with no “Ignore” response. Accounted for imbalances with hyperparameters.

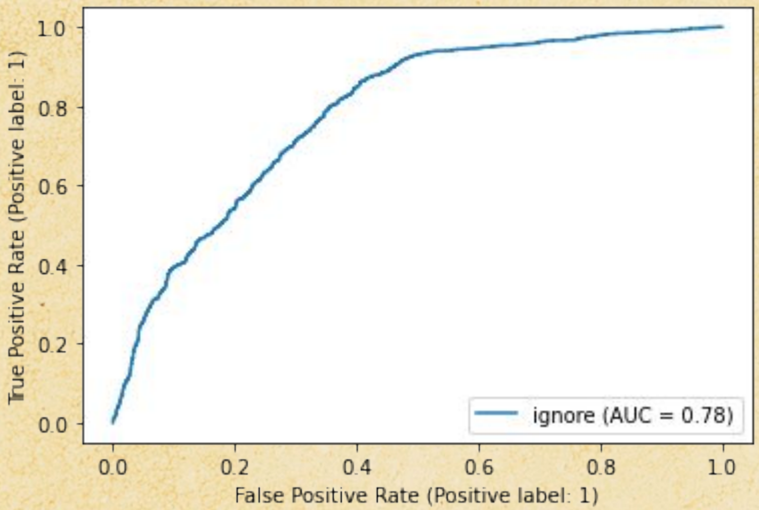
Results: Scores improved across the board.

04 MODELING PROCESS

Evaluation: Model Scores

State Response: Ignored Protest

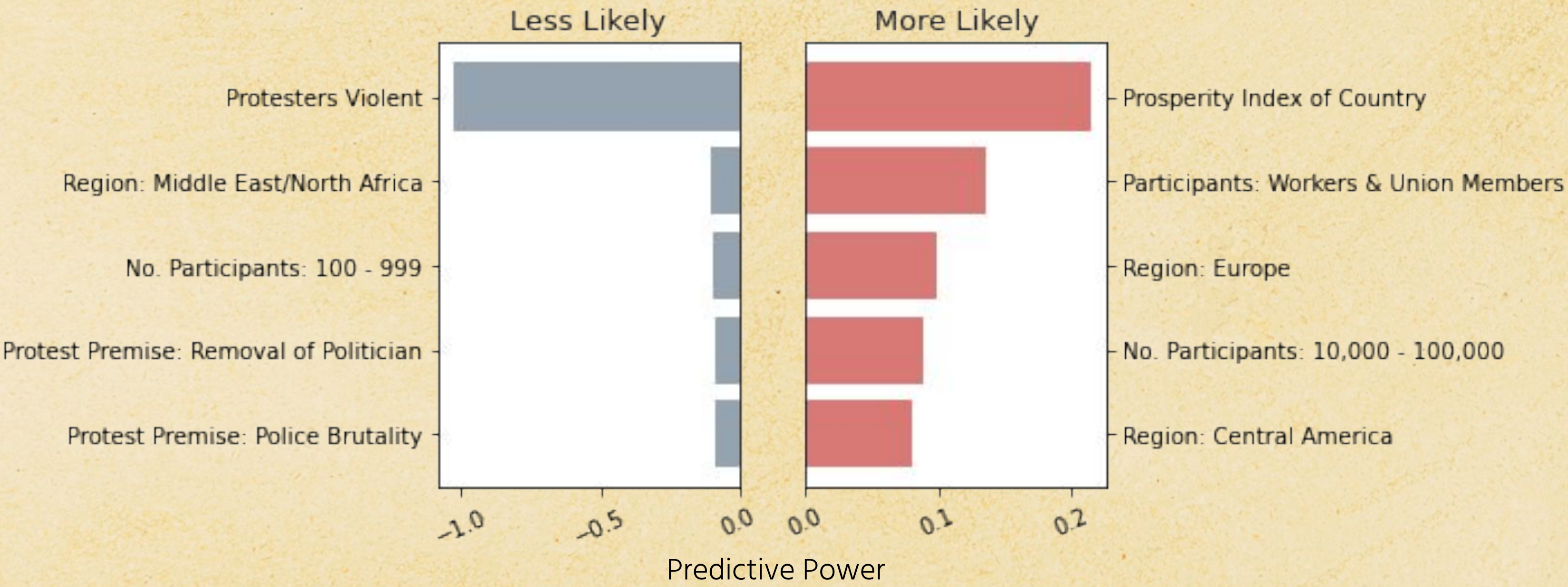
Model Metric	Score
Precision	0.701
Recall/Sensitivity	0.895
Specificity	0.533



04 MODELING PROCESS

Evaluation: Predictive Variables

State Response: Ignored Protest



Note: Positive & Negative Coefficient Predictive Power are not to scale.

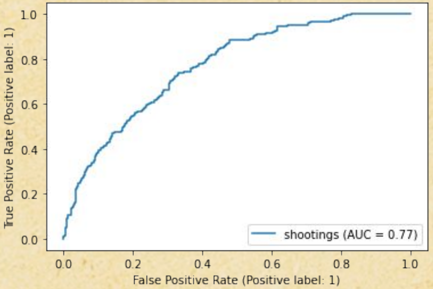
04 MODELING PROCESS

Evaluation

State Response: Violent Responses

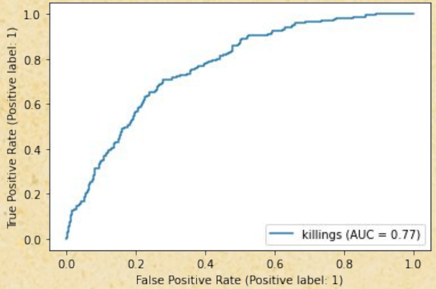
Shootings

Model Metric	Score
Precision	0.247
Recall/Sensitivity	0.840
Specificity	0.611



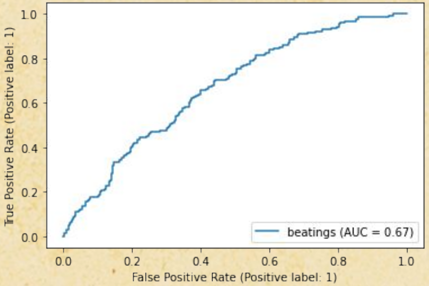
Killings

Model Metric	Score
Precision	0.224
Recall/Sensitivity	0.797
Specificity	0.648



Beatings

Model Metric	Score
Precision	0.180
Recall/Sensitivity	0.726
Specificity	0.584

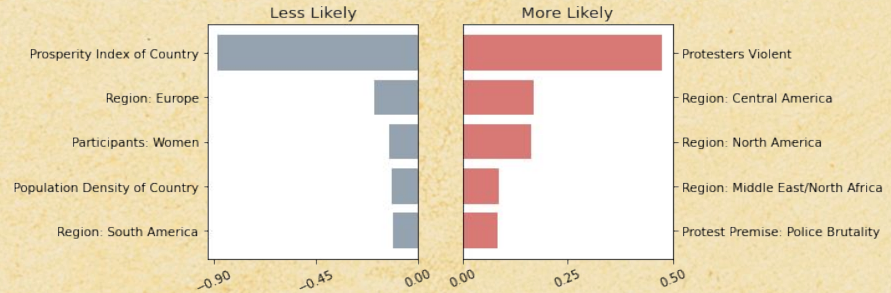


04 MODELING PROCESS

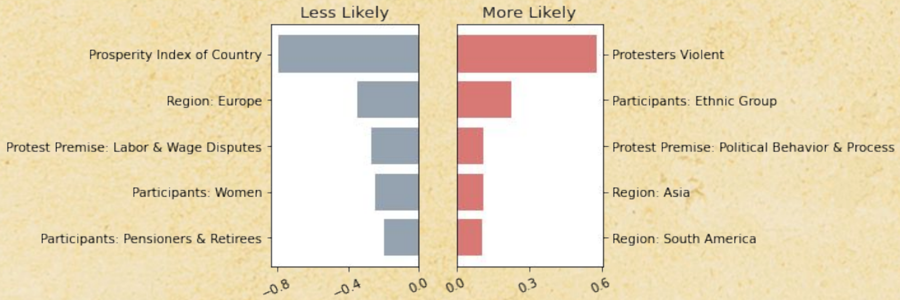
Evaluation

State Response: Violent Responses

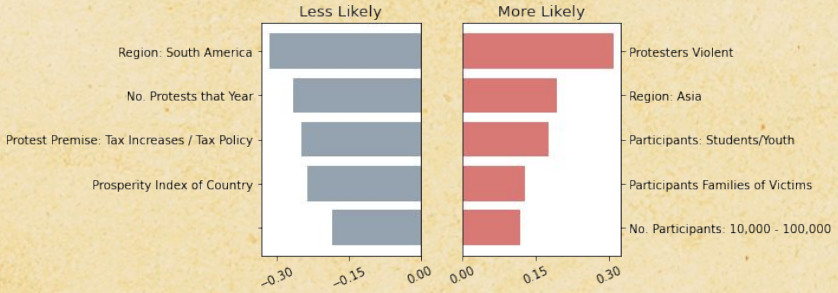
Shootings



Killings



Beatings



04 MODELING PROCESS

Model Application: US Protests

Logistic Regression - Includes all observations, but leads to **imbalanced** classes. Accuracy of predictions is driven by model never predicting underrepresented targets.

	PREDICTED STATE RESPONSE							
	Arrests	Accomodation	Beatings	Crowd Dispersal	Ignore	Killings	Shootings	Violent Response
1999 Seattle WTO Protest	0 ✗	0 ✓	0 ✓	0 ✗	0 ✓	0 ✓	0 ✓	0 ✓
2011 Occupy Atlanta	0 ✗	0 ✓	0 ✓	0 ✗	1 ✗	0 ✓	0 ✓	0 ✓
2018 March For Our Lives	0 ✓	0 ✓	0 ✓	0 ✓	1 ✓	0 ✓	0 ✓	0 ✓
2020 Michigan Covid Lockdown	0 ✓	0 ✓	0 ✓	0 ✓	1 ✓	0 ✓	0 ✓	0 ✓
2021 D.C. Riot	0 ✗	0 ✓	0 ✗	1 ✓	0 ✓	0 ✗	0 ✗	0 ✗

Predicted Positive Response ✓ Correct Prediction ✗ Incorrect Prediction

Model Application: US Protests

Logistic Regression - Includes only protests **WITH** a government response. Accuracy has decreased, but specificity is stronger due to more nuanced predictions.

	PREDICTED STATE RESPONSE						
	Arrests	Accomodation	Beatings	Crowd Dispersal	Killings	Shootings	Violent Response
1999 Seattle WTO Protest	1 ✓	1 ✗	0 ✓	1 ✓	0 ✓	1 ✗	0 ✓
2011 Occupy Atlanta	1 ✓	1 ✗	0 ✓	1 ✓	0 ✓	0 ✓	0 ✓
2018 March For Our Lives	1 ✗	0 ✓	1 ✗	1 ✗	0 ✓	0 ✓	0 ✓
2020 Michigan Covid Lockdown	1 ✗	0 ✓	0 ✓	1 ✗	0 ✓	0 ✓	0 ✓
2021 D.C. Riot	1 ✓	0 ✓	1 ✓	1 ✓	1 ✓	1 ✓	0 ✗

Predicted Positive Response ✓ Correct Prediction ✗ Incorrect Prediction

05 PROJECT RECOMMENDATIONS

Conclusions

- Factors that correlate most strongly with a protest being **ignored**:
  - **Higher prosperity index** for country
  - Protests involving **workers and union** members

- Primary **protester type** and **protester violence** predict **violent state responses** more than other categorical features in the data set.

- Dataset somewhat vague in certain places.
  - Primary recommendation to the research team is more precise mechanisms for collecting and recording data.

- Drawing conclusions from data with highly imbalanced classes makes finding significant results extremely difficult
  - Research teams could help ameliorate this roadblock by recording data in meaningful classes - i.e. recording data in categories instead of continuous categorical variables.

05 PROJECT RECOMMENDATIONS

Next Steps

- Gather data for US protests
    - Add other protest data and potentially other relevant national datasets
- More advanced multi-label modeling techniques
    - Ex: boosting, clustering
- K-Means clustering for unsupervised inferences on data