

Classifying Climate Change Tweets



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Overview

Business Problem



Building the Classifier



Applying the Classifier



Conclusion and Next Steps

Business Problem

- Environmental Defense Fund
- Addressing advertising and promotions expense growth
- Where and when to deploy for most donations



Building the Classifier



The Data

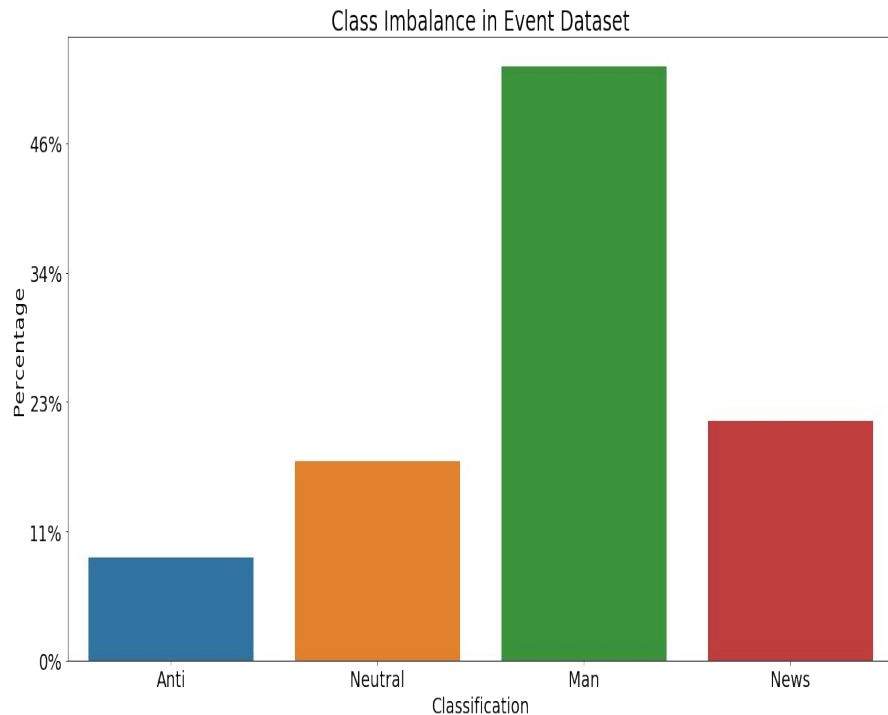
- Kaggle
- 43943 Tweets
- Apr 2015 - Feb 2018
- Four classes
 - Anti Man Made
 - Neutral
 - Man-Made
 - News



Class Imbalance

Metric: F1 Score

**Focus on optimizing
'Anti' class f1 score**



Modeling Process

- 1. Baseline**
- 2. Choosing Best Model**
- 3. Tuning Best Model**

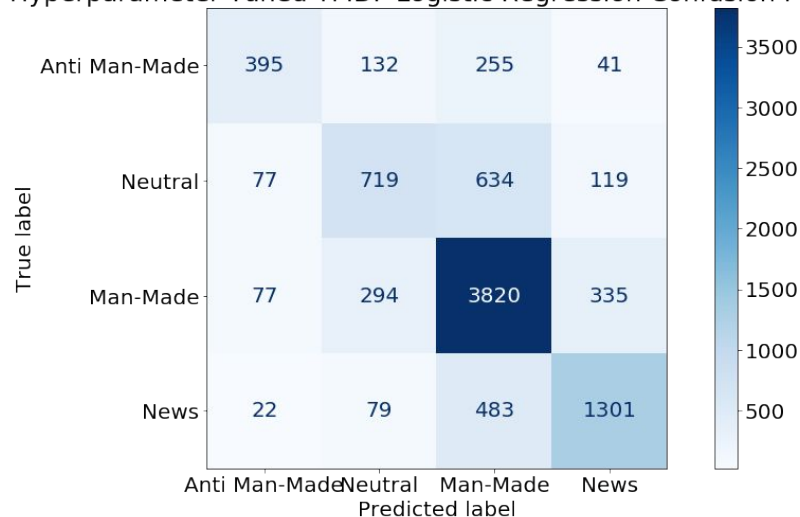
Best Model

Unigram TF-IDF Logistic Regression (Without Added Features)

F1-Scores

- **Man: 0.79**
- **Anti: 0.57**

Hyperparameter Tuned TFIDF Logistic Regression Confusion Matrix



Applying the Classifier

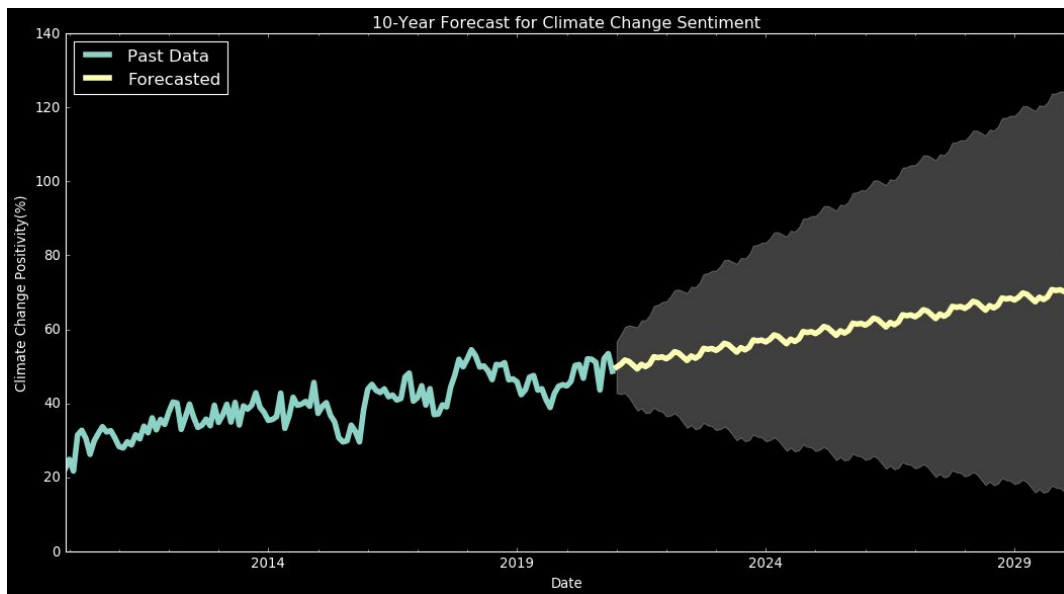


Time Series Analysis

The Assumption

The Data

Analysis



Time Series Findings

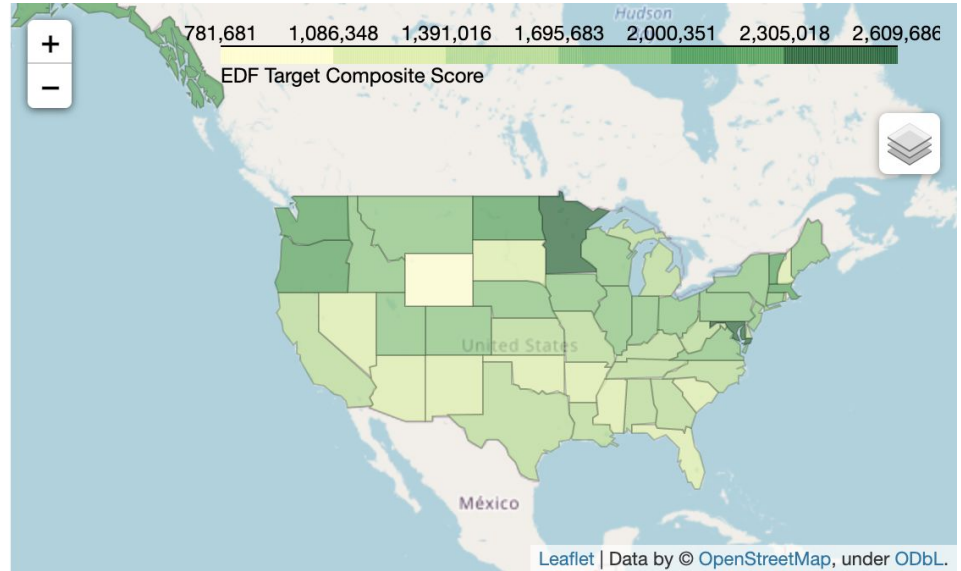
- 1. Donation growth rate of 3.8% year over year**
- 2. Monthly Breakdown:**
 - a. Sentiment average vs season**
 - b. Best month (March)**
 - c. Worst month (August)**

Geographic Analysis

The Assumption

The Data

Analysis



Geographic Findings

Top 5 most likely states for climate change donations:

- 1. Minnesota**
- 2. Maryland**
- 3. Oregon**
- 4. North Dakota**
- 5. Washington**

Recommendations

- **EDF**
 - Cold months (notably March)
 - Top 5 states
- **Environmentally-focused NGO with low budget**

Next Steps

- **Custom scoring metric**
- **Pipeline for auto updating results**
- **Location data by county to pinpoint best areas**

QUESTIONS?

For More Information

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