# **ML Augmented Prediction for** Labor Exploitation Detection

Stanford Data Science ×



August 14, 2024



## **Our Team**



Enkhjin Munkhbayar DSSG Fellow



Leon Reilly DSSG Fellow





Kyler Shu DSSG Fellow



## **Our Mentors**



Dr. Benjamin Seiler **Technical Mentor** 



Dr. Kim Babiarz **Technical Mentor** 





# Background

### Modern Slavery. Brazil. Charcoal. Our Goal.





## **Modern Slavery**

- **50 million** exploited annually.
- Victims **trapped** by threats and coercion.
- **Data gaps** hinder effective policy.
- Global efforts lack data-driven impact.

## **HTDL's Brazil Focus**

#### Over 1 million

trapped in modern slavery.

#### **Robust data** from record-keeping and transparency laws.

### Why Brazil?



#### Strong collaboration

 with Brazil's Federal Labor Prosecution Office.

## **HTDL's Charcoal Focus**

Labor-Intensive Production Process  $\triangleright$ 

#### Exploitation Risk $\triangleright$

- >
- **Detection Challenges**  $\triangleright$
- Satellite Tracking  $\triangleright$

### Why Charcoal?





#### **Environmental and Economic Factors**

## · · · Charcoal Site Detection Process

#### Satellite Imagery

Remote Detection Model (CHAR)

Human Post-Processing



#### Task Force Inspection

## · · · Charcoal Site Detection Process

Remote Detection Model (CHAR)

## What We Seek









## What We Seek



High Resolution Image



#### Training Image

## **Charcoal Site Detection Process**

#### Satellite Imagery

Remote Detection Model (CHAR)

ML Model with Geospatial Covariates

#### Task Force Inspection

## Our Goal

**Elevate** the human post-processing.



Develop ML Models

Explore Geospatial Data



Expand Training Data





# Feature Engineering

GeoPandas Pipeline. Distance. Density.



## **Charcoal Site Data**

### **5278 Sites**

Flagged by the CHAR model from satellite images of Maranhão. Threshold of 0.9.

### 478 True Sites

Manually labelled and confirmed as charcoal sites.

## Month

Images from 7/23 to 3/24.

### Geometry

Includes precise location of the flagged site.

### **Model Score** Model score from CHAR is included.

### **Tiling** Satellite imagery grouped by unique tile ID.





### Roads

Charcoal needs to be transported to steel mills.

## Model Intuition

## Villages

Charcoal sites may want to be far away from villages to avoid detection.

### Deforestation

Charcoal is made from cutting down trees.

## Other Sites

Expect some clustering of charcoal sites.

## **Feature Construction**



## **Data Source**

EDA and thinking to determine relevant data which may have signal.

## **Appropriate Metric**

Determine which metric to construct. Shortest distance to, feature count within a radius, within municipality, etc.

### GeoPandas

Create pipeline to query database and construct features to be fed into the model.



## **Feature Construction**



### **Data Source**

EDA and thinking to determine relevant data which may have signal.

#### SmartLab: $\triangleright$

• Contains survey data of every municipality in Brazil. Includes data like literacy rate, poverty rate, number of workers rescued, and so on.



#### **Geographic Features**:

• Geometries (locations) of roads, lakes, towns, indigenous lands, deforestation permits.

#### **MapBiomas** Alerts: >

• Geometries of deforestation alerts that are updated every two weeks by the Brazilian government.



## **Feature Construction**



## **Appropriate Metric**

Determine which metric to construct. Shortest distance to, feature count within a radius, within municipality, etc.



 $\triangleright$ It makes sense to ask how many lakes are within 10 km of a charcoal site and how close a charcoal site is since the number and distance of lakes may have a bearing on whether to setup a charcoal site or not.



### GeoPandas

Create pipeline to query database and construct features to be fed into the model.

## **Initial Results**

In general, data aligns with expectations. Watermass is proxying for other features



## **Initial Results**

Discernment between FP and TP sites exists. Suggests there is signal here for the model to pick up on.





Distance to nearest watermass (km)

### 14 Distance Variables

Shortest straightline distance to feature

## Full Feature Construction

### 3 Density Variables

Feature count within 10 km radius 38 Total



### 12 Landcover Categories

Forest plantation, savannah formation, etc.

### 9 Survey Variables

From SmartLab data on poverty, literacy rate, rescued workers, etc.

# Machine Learning Model

Architectures. Analytics. Performance.





## Implementation

Grouping and Stratification

Model Architectures

Hyperparameter Tuning and Result Analysis

# Data Handling



## Grouping

Group datapoints by location to prevent train/test knowledge leakage.

## **Stratification**

Balance by label to ensure sufficient training points and consistent evaluation.

## Splitting

1/6 Holdout set, remaining 5/6 broken into 5-fold cross validation.

## **Model Architectures**

### **Tree-based models**

Gradient Boosting, Random Forest

### **Transformer-based models** TabPFN







## Hyperparameter Tuning



## **Model Performance** On validation set, at threshold 0.25.





### F1 Score

**Precision** 







#### **Model Analytics** 700 600 500 400 Count 300 700 200 100 600 0. 500 400 tung 25 300 20 200 15 Count 100 10 0 -0.4 0.6 1.0 0.2 0.8 0.0 proba 5 0 -0.0

### **Ground Truth**





# Feature Importance

### Built-in Gradient Boost (top 10)



#### TreeSHAP

model score Distance to nearest rural settlements Char alerts within 10km Distance to nearest biomas alert Distance to nearest watermass Distance to nearest indigenous lands Other non Vegetated Areas Savanna Formation Sum of 32 other features



# Cluster Analysis

Geospatial. Full Feature.



# **Geospatial Cluster Analysis**

DBSCAN Clustering with Buffer Zones



- ➢ Total True Charcoal Sites: 86
- Unique Clusters Identified: 26
- Max Clustering Distance: 20 km
- Min Sites per Cluster: 2

## Feature Cluster Analysis



# Conclusion

### Future Work. Acknowledgements.



# **Future Work**

## Image feature embeddings

Enrichen the information from the first stage of the model.

## Improved time-series modeling

"Hotspot" feature, deforestation chronology

## Feedback from fieldwork

Brazil FLPO task force deployment this August



# Acknowledgements

Dr. Ben Seiler

Dr. Mike Baiocchi

Dr. Kim Babiarz, Jonas Junnior, and the HTDL Lab

Shilaan Alzahawi, Dr. Balasubramanian Narasimhan, Dr. Annie Lamar, and the whole DSSG team

