Predicting Perpetrators of Unclaimed Terrorist Attacks

ECON 8330 - Business Forecasting Final Presentation

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Agenda

- Define the Problem

 Preview Results
- Diagnosis of Data
- Plan of Action
 - Cleaning the data
 - Selecting our model
- Review Results

Define the Problem



- Thousands of terrorist attacks were committed in Pakistan (2007-2018)
- Some attacks are claimed by the group that committed them
- Can we predict the perpetrators of attacks that go unclaimed?
 - Specifically those of the Tehrik-i-Taliban (TTP)
- Why does this matter?
 - Help understand patterns, possibly prevent future attacks

Results

51.3% of unclaimed attacks likely perpetrated by TTP

- 8,873 unclaimed attacks analyzed
 4,552 likely perpetrated by TTP
- Important variables
 - Location, day and week of attack, number killed, number wounded

- 2,950 claimed attacks
 - TTP committed 44.9% of the claimed attacks

Results



Results - SHAP



Results – SHAP



The Data

- 12,237 attacks between 2007-2018
 - 2,950 claimed
 - 9,287 unclaimed (414 dropped)
- Several variables to describe the location, type of attack, attack details, and number of people killed or wounded

- Columns with many null values
 - Location (text description)
 - Target Subtype
 - Corp1
 - Claimed / claimed mode
 - Weapon Subtype

Selecting Our Training Data

Included

- Date (as day of week, week of year)
- Latitude, longitude
- Multiple, success, suicide
- Attack, target, weapon type (text fields)
- Number killed, wounded (including subset for US affliates and terrorists)

Excluded

- Data with lots of null values
- Region, providence/state, city
- Summary
- Group name, claimed

Cleaning the Data

- Dropped those with null values in the killed/wounded fields
 - 414 rows in all
- Split into Training and Prediction based on gname = Unknown
 - Create dummy variable for TTP claimed attacks
- Merge year, month, day and create datetime fields

 Created lists of categorical fields to avoid issues with categories not in the training data

all_attack = data['attacktype1_txt'].unique()
all_target = data['targtype1_txt'].unique()
all_weapon = data['weaptype1_txt'].unique()

C(attacktype1_txt, levels=all_attack)

Selecting Our Model – Complex Classification Models

Gradient Boosted Tree (GBT)

- GBT generally produce higher accuracy level compared to other models by reducing errors in bias
- GBT works better with fewer input variables, but GBT tends to overfit data with more noise

Random Forest (RF)

- RF produce higher accuracy level by reducing variance in predictions
- RF is less computationally expensive

Compare the Results:

- Similar prediction results (GBT 53.78% VS RF 51.3%)
- GBT has lower in-sample accuracy (GBT 68.5% compared to RF 99.8%)
- RF model includes more variable than GBT does

Random Forest Model

- 99.8% in sample accuracy
- Default 100 trees in model
- Did not limit depth or samples in a split
 - Did not change results much



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