TERROR ATTACK CLASSIFIER

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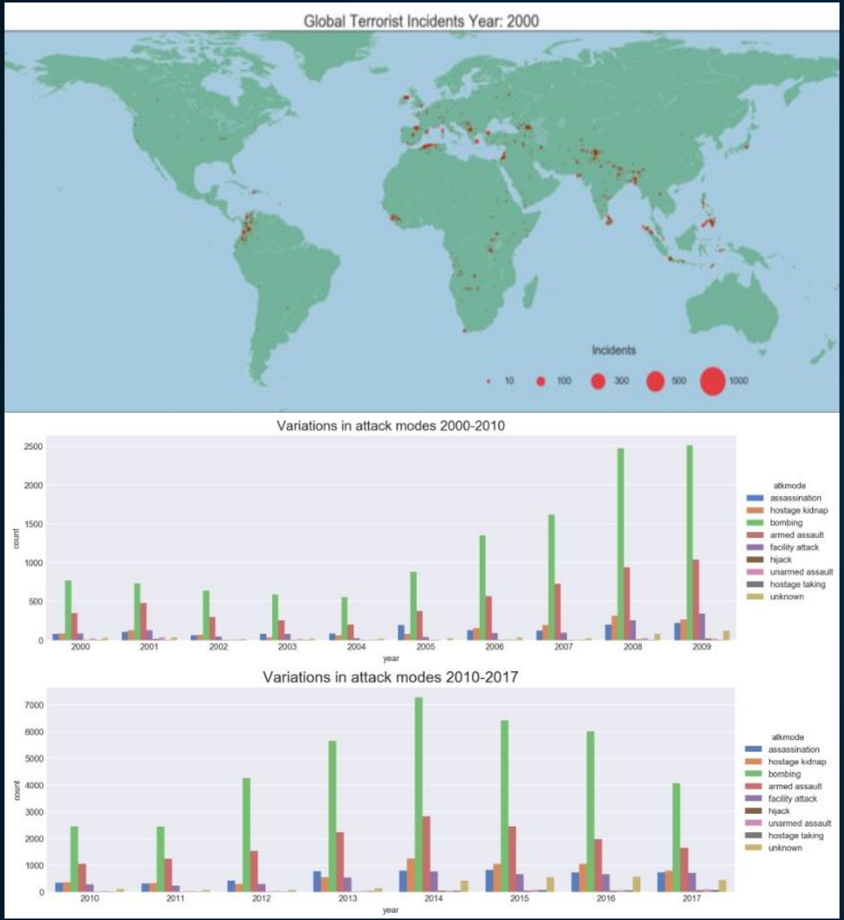
TABLE OF CONTENTS



PROBLEM STATEMENT

Can we predict the probability of a terrorist bombing incident, based on intel text (terror group motive) and alleviate manpower constraints at the same time?

- Counter terrorism relies on intelligence to foil terror incidents.
- The analysis of intel data requires much manpower and training.
- Intel collected has exponential growth with tech advancement
- Bombing (green bar) accounted for more than half of all terror attack modes combined.

PROPOSED SOLUTION

Model to classify expected terrorist incident

- Binary classification; Bomb (positive class) vs. Non-Bomb (negative class)

Model envisaged to:

- augment intelligence analysts
- improve CT efficiency

GTD DATASET

SHAPE

181,691 X 135

CHARACTERISTICS

Maintained by: Uni. Maryland
Size: 150MB
Format: ISO-8859-1
Lineage: 1970-2017
Shifts in data collection:
Jan 1998, Apr 2008, Jan 2012
New Variables: added post-1997
Automated processing: since 2012

Variables describing:
Time, Location,
Perpetrator
(Group, Motive, Weapon used, Incident category)
Target
(Nationality, Name)
Terrorism Criterion (per GTD definition)
Outcome (Success/ Failure)
Casualties / Property Damage

FEATURE OF INTEREST

Time
Location
Perpetrator
Target
Casualties

DATA CLEANING CHALLENGES

Missing Values

- Several variables (post-1997) missing values (> 100,000)
- Inadequate information in some motive texts (blank entries)

Mitigation:
- Drop all except for motive (50561 observations)
- Drop the motive rows w/o sufficient information.

Inconsistent Variable Labels

- Categorical feature names inconsistent with data dict.

Mitigation:
- Defined new set of categorical features

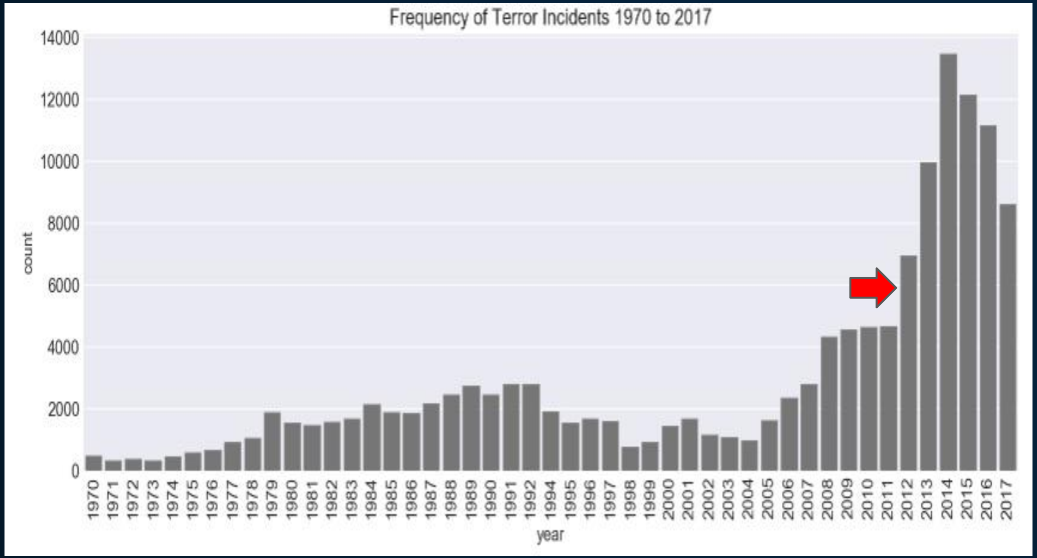
Identifying Features of Interest

- High number of features
- No contextual understanding if go for motive text directly
- New features required for insights (incidents attributable to group, attack modes per group, etc.)

Mitigation:
- Review data dictionary for all 135 variables
- Pare down relevant features for EDA, document decisions made.
- Feature engineer pos/ neg class labels
- Use Groupby, count or sum to derive new features
- Cleaned data shape 32521 x 23 (still sizable for modelling)

EDA

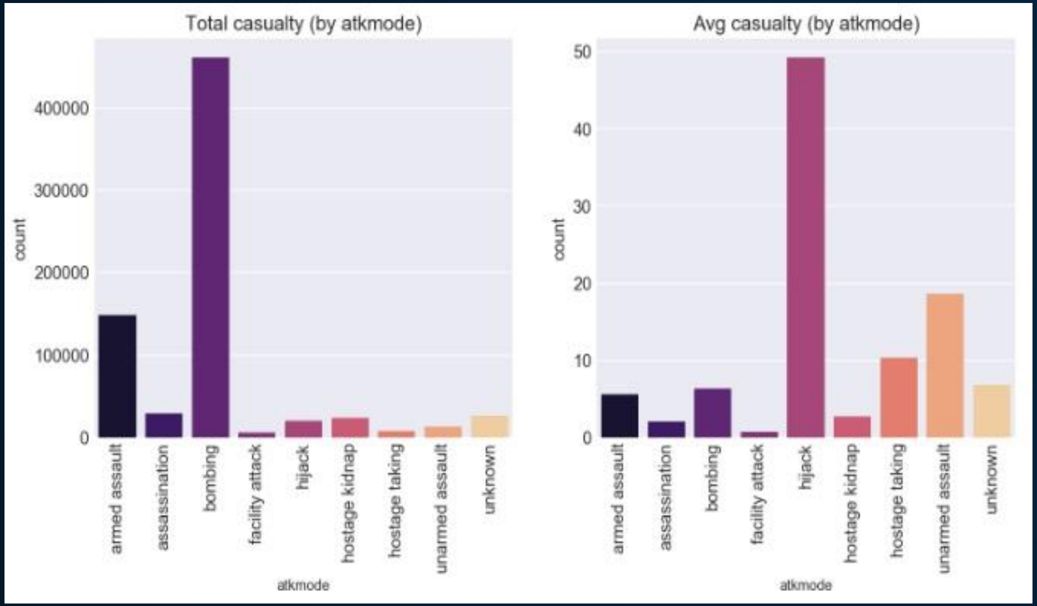
Incident Count over Time



- Sharp increase in incident counts from 2012 onwards

EDA

Bombing Casualties



- From earlier chart, no fundamental shift in the general modes of attacks over the years.
- Bombing remains the favored tactic followed closely by armed assault and kidnapping in more recent years.
- Bombing accounts for highest casualties (total); hijacking accounts for highest average casualties.

EDA

Word Cloud (Motive Text)

- Many factors driving terror incidents (social, ideology, political, sectarian, etc.)
- Common underlying theme being sectarian violence

MODELLING

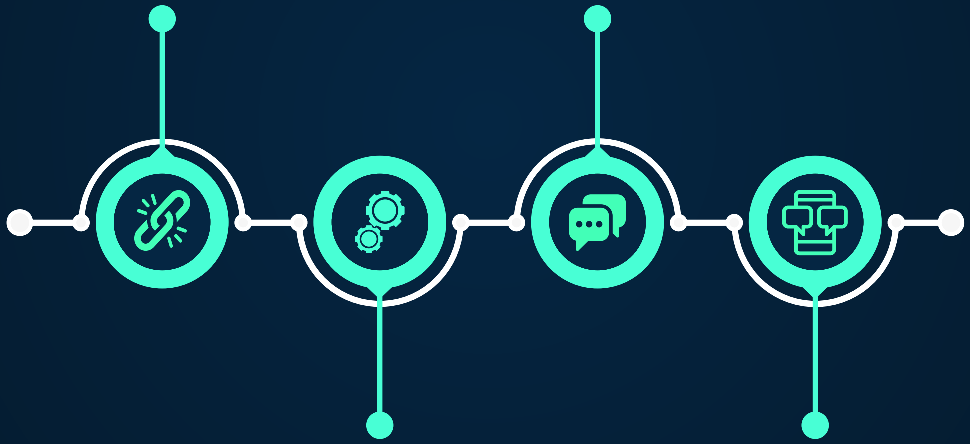
Model Metric
- Sensitivity
- Roc_auc

Positive class
- Bomb (48%)

Processing
- nltk stopwords
- custom stopwords
- nltk porterstemmer

Data
- train, validate, test sets

Pipeline (Train/validate set)
- sklearn CountVectorizer
- Logistic Regression
- Multinomial NaiveBayes



Tuning (Entire train/test)
- custom stopwords

Topic Modelling
- Optimum topics (entire traindata)
- LDA model for classification

Topic Probabilities + Word Vectors
- Production model (train/test set)

Evaluation, Recommendations, Future Work

EVALUATION

Pipeline

Metrics	LR	NB
accuracy	0.6781	0.6593
sensitivity	0.8532	0.8246
roc_auc	0.7460	0.7272

Tuning

Metrics	LR	LR1	LR2
accuracy	0.6898	0.6859	0.6802
sensitivity	0.8584	0.8619	0.8526
roc_auc	0.7620	0.7568	0.7489

Note:
LR1: 50 words contributing to false negative class removed
LR2: overlap words (more than 1200 occurrences) removed

EVALUATION

Topic Modeling

Metrics	Validate	Test
accuracy	0.5820	0.6034
sensitivity	0.8024	0.8106
roc_auc	0.6121	0.6374

Topic Modeling + Word Vectors

Metrics	LR	LR (tm)	LR(tm+wrd vectors)
accuracy	0.6859	0.6034	0.6893
sensitivity	0.8619	0.8106	0.8587
roc_auc	0.7568	0.6374	0.7621

Note:
tm: model using topic probability distributions (tpd)
tm+wrd vectors: model using tpd + word vectors

RECOMMENDATIONS

- Model generalizability using topic modeling for classification demonstrated
- Best model remains the Logistic Regression model using count vectorized word features.

Limitations

- Current model very simplistic; classifies solely on one form of intel (motive text).
- Additional intel sources, political and social trends that could serve as supporting sources of intelligence not considered.

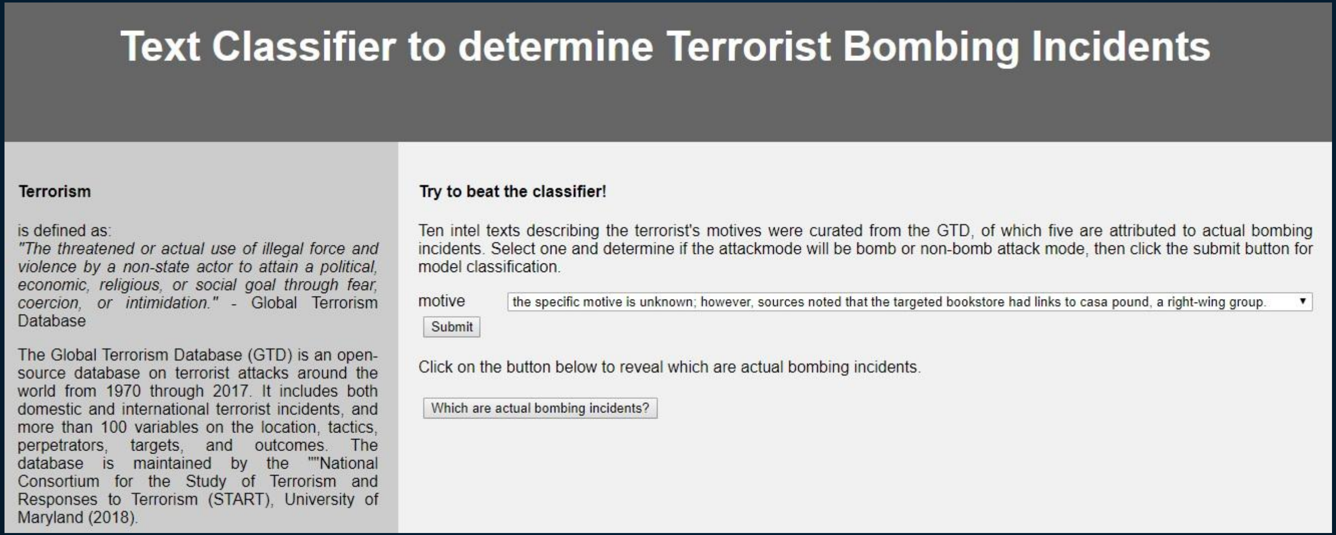
Future Work

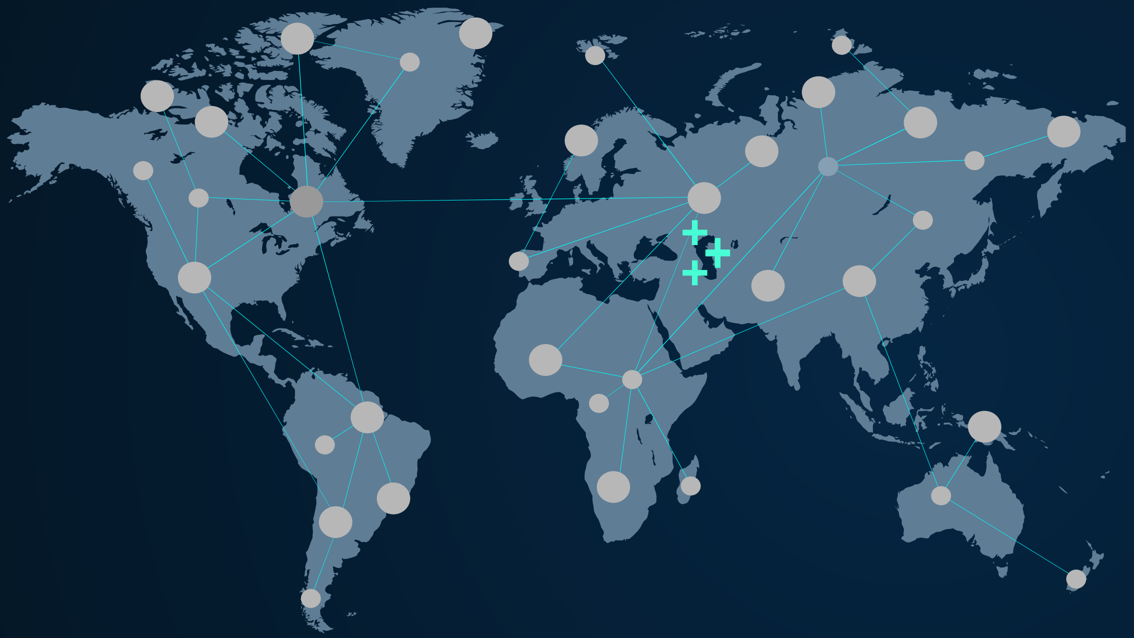
- Additional data to widen perspective
- Feature engineer spatial and temporal aspects (e.g. attacks by region, attacks by decades)
- Explore use of Tfidf vectorizer and spaCy

Deployment

Invitation to try out the classifier at url: https://enigmatic-reef-60524.herokuapp.com/

Appreciate feedback at slack (dm)





THANKS !
QUESTIONS ?

CREDITS

- DSI 14 Instructor and TAs for their patience and guidance
- Work by Marc Kelechava's work on unsupervised nlp topic modeling as a supervised learning input
- Presentation template by Slidesgo
- Icons by Flaticon
- Infographics by Freepik
- Images created by Freepik
- Author introduction slide photo created by Freepik
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