"Whodunit?"

Using Machine Learning Techniques to Predict Perpetrators of Militant Attacks

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AGENDA

01\. Question & Approaches & Motivation

02\. Key Results

03\. Methods & Limitations

04\. Ethical Considerations $ Next Steps

Question

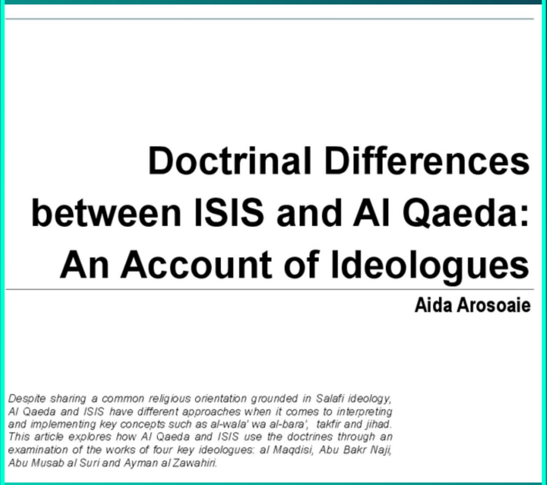
Using the START-UMD Global Terrorism Database (GTD), can we configure a set of features to accurately predict whether an incident is conducted by:

1. ISIS/ISIS-aligned group

OR

2. al-Qaeda/al-Qaeda-aligned group?

Non-ML Approaches



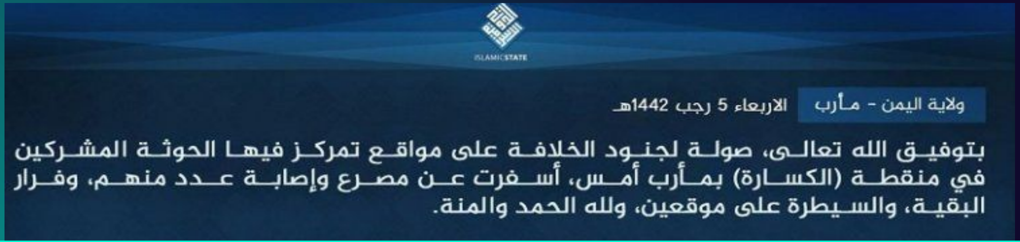
Doctrinal Differences between ISIS and Al Qaeda: An Account of Ideologues

Aida Arosoaie

Despite sharing a common religious orientation grounded in Salafi ideology, Al Qaeda and ISIS have different approaches when it comes to interpreting and implementing key concepts such as al-wala' wa al-bara', takfir and jihad. This article explores how Al Qaeda and ISIS use the doctrines through an examination of the works of four key ideologues: al Maqdisi, Abu Bakr Naji, Abu Musab al Suri and Ayman al Zawahiri.

Source

AQAP claims to have killed Houthi militant by sniper fire in Mayfa area of al-Bayda, Yemen (Feb 2022)



ISIS claims to have killed or injured several Houthi militants and captured position in al-Kasara area of Marib, Yemen (Feb 2021)

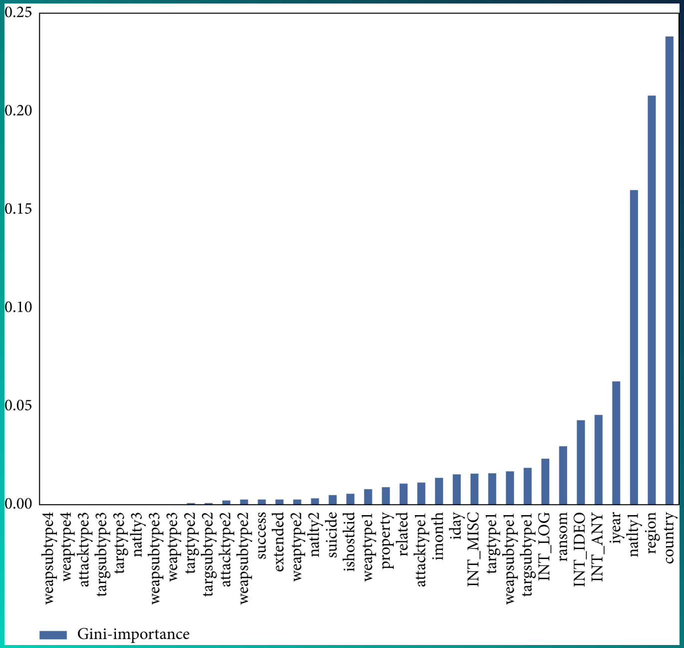
Existing ML Approaches

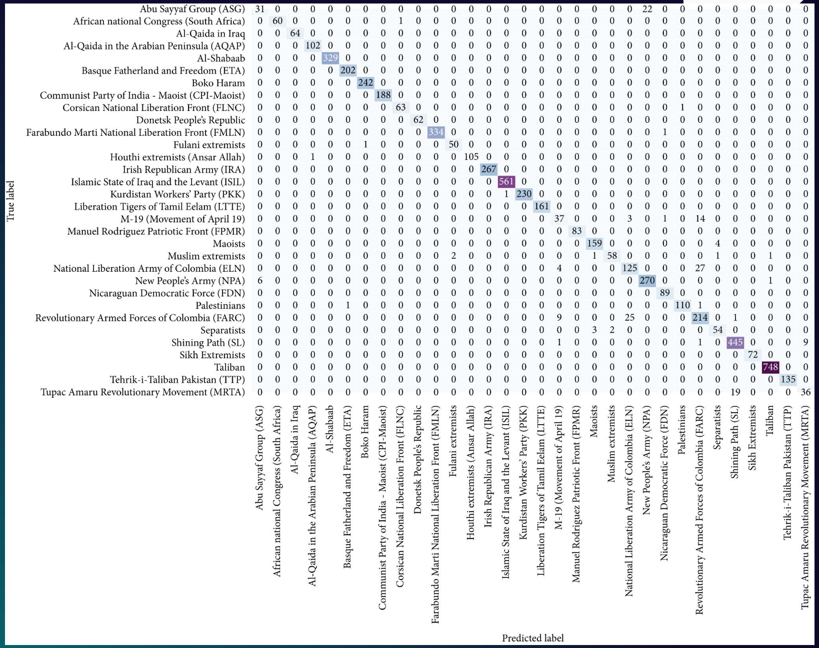
- Xiaohui (2021)
  - Exploits 36 features of GTD data to predict whether an incident is committed by one of 32 most represented militant groups
  - Features engineering through domain expertise and ExtraTrees classifier
  - Attains 97% accuracy using XGBoost and random forest classifiers

- Xiaohui (2021) serves as starting point, but I intend to:
  - Feature engineering to only include immediately ascertainable features
  - Leverage additional domain expertise to test rhetorical basis of “ISIS camp” vs. “AQ camp” groups
  - Consider smaller subset of groups which fall within these two camps

Xiaohui Pan, "Quantitative Analysis and Prediction of Global Terrorist Attacks Based on Machine Learning", Scientific Programming, vol. 2021, Article ID 7890923, 15 pages, 2021. https://doi.org/10.1155/2021/7890923

Existing ML Approaches





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Motivation

From Rhetoric to Tactics

- Ideology is difficult to quantify, requires extensive domain expertise to track

Quantify Differences

- Center quantifiable on-the-ground evidence as a distinguishing factor

Examine Decision-Making

- Exploit the GTD to study the decisions these groups make with regard to the nature of their actions and how other actors categorize them

Key Results & Impact

High Perpetrator Predictability

- Up to 95% accuracy in predicting ISIS vs AQ-affiliated incidents

Feature Set Suggests Potential for Early Perpetrator Detection

- Official claims release days later
- Model uses features easily attainable moments after an incident takes place
- Expedites opportunities to act faster on intelligence

Methods & Limitations

- Dataset
- Preprocessing
- Models
- Limitations

Dataset

Global Terrorism Database

200,000+

Incidents of domestic and international terrorism between 1970 and 2019

- Contains features such as the incident's location, attack type, relevant perpetrators, targets, and weapons involved.

- The START-UMD data set includes incidents aligning with the following definition of terrorism:

The threatened or actual use of illegal force and violence by a non-state actor to attain a political, economic, religious, or social goal through fear, coercion, or intimidation

Source

Dataset

Observation Examples

- Original dataset contains 135 features, relatively sparse.
- Many features only knowable from incident's aftermath & not useful for immediate predictions.

Incident 1: Middle East+ Yemen+Bombing+Explosives used+ Religious figure or institution targeted = ISIS incident

NYT: "3 Suicide Bombings Target Shiite Rebel Mosques in Yemen"

Incident 2: Middle East+Yemen+Assassination+Firearms used+ Government targeted = AQ incident

Xinhua: "Yemeni Intelligence Official Assassinated"

Index	country	targtype1	weaptype1	region	attacktype1
20552	228	15	6	10	3
3027	228	2	5	10	1

20552	1
3027	0

Features

Target

Data Preprocessing

01

Filter Data
Filter data for incidents from 2014 onward

02

Classify Groups
Use domain expertise to classify 700+ unique entities into ISIS/AQ camps

03

Create Dummy Variable Label
0 represents AQ camp, 1 represents ISIS camp

04

Build Classifiers

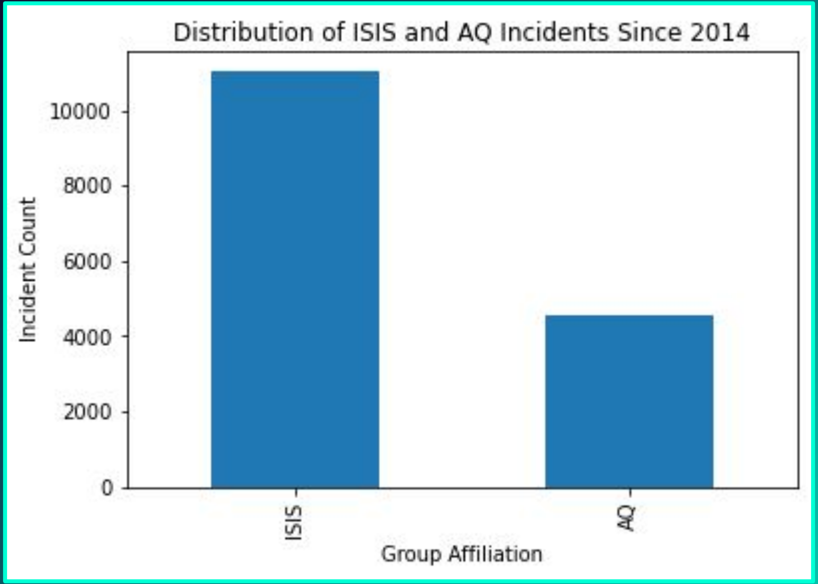
Filtered Incidents (2014-2019)

11,025
ISIS-affiliated incidents

4,542
AQ-affiliated incidents

Imbalanced classification limitation

Incidents conducted by neither these two camps were filtered outside the scope of this project



Features & Models

<u>Features</u>

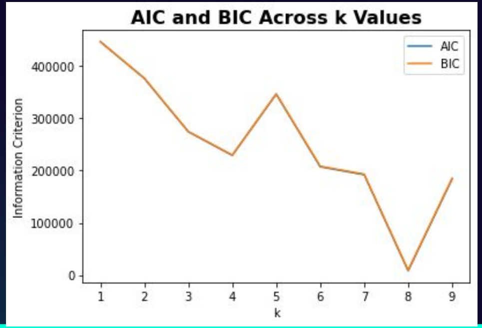
Country
Region (of the world)
Primary Target Type
Primary Weapon Type
Primary Attack Type

70/30 Train-Test Split

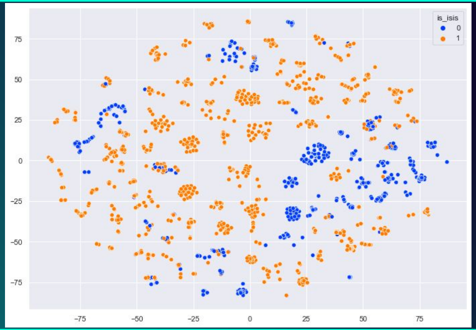
	Accuracy Score	Example Confusion Matrix
Naive Bayes (Categorical)	~95%	[[1209 150] [56 3256]]
SVM (poly kernel)	~87%	[[977 382] [223 3089]]

Limitations

1. Relatively high accuracy scores, but unresolved issues include:
   a. Imbalanced classification problem with ISIS incidents represented more than 2:1 against AQ incidents
2. Possible collinearity between predictors
   a. Dependent relationship between geographic features
   b. Possible dependency between “weapon type” and “attack type”
3. Two classes are perhaps not ideal number of classes to model this problem.



Example: Using an EM Gaussian Mixture model to visualize ideal k-value



Example: T-SNE plot to depict high-dimensional data

Risks & Ethical Considerations

Biased Data

Immense risk in the domain of terrorism and militancy

- Data compiled with a single definition of terrorism
- For example, this definition excludes potentially illegal activity conducted by state actors and militaries.

Reliance on Primary Sources

Dataset curated from various sources

- Compounding ML, human error/ bias
- Collection from media-dense environments
- Ignores incidents unreported, misreported or not collected by GTD team
- Reporting reflects source bias

Impact on Marginalized Communities

Disparate treatment and disparate impact

- Track record of dangers of military, intelligence sectors operationalizing ML against marginalized populations
- Impact on communities should be prioritized and studied prior to deployment

Next Steps

Validate Models
Using data from post-2019 incidents originating outside the GTD curation team

Additional Feature Engineering
Do other features better describe the data?
Would deep learning forgo the costly human-run process?

Replicability in Other Conflict Contexts
Investigate whether these models transfer to predicting perpetrators in other conflicts

THANKS

Do you have any questions?

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