UCSD POLI 179 Effect of Community Events on Online ISIS Sympathizer Activity.

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GitHub Code Repository:
https://github.com/Ldelatorre81/Poli_179_final_project.git

1 Introduction

In today's world social media platforms such as Twitter and Facebook continue to be woven into the functioning of our society. However, despite their ability to revolutionize the speed and ease with which we communicate with one another, there still lies room for misuse. Social media platforms have accidentally had the effect of also making it easier for online Jihad extremist sympathizers to recruit and inspire others thus raising serious concern for future terrorist attacks. This is why in 2011, the Obama administration initiated a counter-radicalization strategy that focused on empowering local partners to prevent violent extremism in the United States. The program sought to do this by collaborating with local governments via community engagement events that focused on Jihad-inspired extremism. Although these events were closed to the public, the hope was that word would spread throughout the community and thus deter individuals from spreading extremism or acting in a violent extremism manner. These community-led events, which took place primarily between 2014 and 2016, will serve as the foundation for the following research. Much of this and more was covered by Tamar Mitts' paper Countering Violent Extremism and Radical Rhetoric which our research draws heavy inspiration from. In the following project, we used social media posts of Islamic State sympathizers from 2015-2016 to determine whether or not these counter-extremism community-led events affected the way Islamic State sympathizers acted online. Specifically, we used text-based analytical approaches such as word embedding and topic modeling to answer the question "How do counter-extremism efforts influence the evolution of extremist rhetoric on social media platforms?". We will go on to answer this question by comparing tweets from before the community events to tweets after. Additionally, we decided to provide additional comparative analysis on the content of tweets from those with more followers compared to those with fewer followers.

2 Hypothesis

Before conducting our research, we hypothesized that the counter-extremism efforts would result in ISIS sympathizers changing the content of their future tweets. More specifically we believed that the contents of their tweets would be more broadly related to ISIS and less extreme, if at all, thus meaning the community events were effective in deterring online extremist activity. We believe this change in online activity would be a direct result of the increased fear on behalf of the sympathizers caused by the prevalence of community events. By believing they are being more closely watched, they would most likely choose to strategically modify their tweets to not get into trouble with the law. ETS from those with more followers compared to those with fewer followers.

3 Data

In this project, we made use of a dataset produced by Five Tribe titled "How ISIS uses Twitter". This dataset, which was released in November of 2019, contains 17,410 English or English-translated tweets from January 2015 to May 2016 from "ISIS fanboys" The dataset is made up of the following metadata for each tweet: 1) Name 2) Username 3) Description 4) Location 5) Followers at the time of the tweet 6) Number of statuses from user at the time the tweet was downloaded 7) Date and time of the tweet 8) Content of the tweet itself (what they tweeted).

3.1 Data Prepossessing

To better tailor the data to the needs of our research we applied common preprocessing methods such as removing all stop words, making all words lowercase, and removing numbers/symbols. Additionally, after initial analysis, we decided to remove "http" from all tweets as this word was skewing our subsequent results. After completing the above, we then subsetted our dataset into four smaller ones. The first pair are time-related with one encompassing all tweets from 2015 and the other, all tweets from 2016. The second pair is follower-related with one subset being for users having over the median follower count for the dataset and the other being below the media follower count. Lastly, we finalized our preprocessing by turning all four subsets into document-feature matrices for further analysis. For our research, we did not make use of any metadata not otherwise mentioned.

4 Methodology

For our methods, we began by using a topic modeling approach by running a latent Dirichlet allocation (LDA) analysis on both pairs of subsets to retrieve the top five topics from each subset. Five topics were used as this yielded the highest average coherence score across all datasets. The results of the LDA for the 2015 and 2016 subsets were visually represented by a word cloud while the findings of the median follower datasets were visually represented by a histogram. Following our LDA analysis, we employed a second method to validate and expand upon our initial findings. This was done using word embeddings via a Word2Vec model. In our Word2Vec model, we looked for words similar to: 1) Isis 2) Syria 3) Attack

4) Allah for both the 2015/2016 datasets and the follower datasets too. Lastly, we also completed a time series for topic prevalence over time for the 2015 and 2016 datasets.

5 Results & Findings

Below are our results from the LDA analysis for the 2015 and 2016 data:

A key similarity we see is how for both years, we see similarities in words related to: propaganda, information spreading as seen with 'rt' showing up a lot, geographical focus with words such as 'russia', 'syria' and 'aleppo' showing up both years, and religious discourse with words such as 'allah' showing up. Both years have many words that are seen in both years, yet we argue that 2016 has more words related to violent events and military action. The difference is not huge but still can be seen.

5.1 LDA Analysis

LDA Analysis: The results from the LDA analysis for the 2015 and 2016 data give us the following findings, which can be found in figure 1.

Before examining the findings, we hand-labeled each of the 5 topics for both datasets which are as follows.

2015 Dataset: Topic 1: Military Operations and Conflict Zones Topic 2: Causal Discussion and Media Coverage Topic 3: Geopolitical Dynamics Between ISIS Topic 4: Social Media Religious Discourse Topic 5: ISIS Activity

2016 Dataset: Topic 1: French Discussion on ISIS (Omitted From Analysis) Topic 2: International Involvement in Syria Topic 3: Battles and Political Figures in Syria Topic 4: Religious/Social Discussion Topic 5: Updates on Military/ISIS Incidents

The topics the LDA analysis produced indicate a change in the rhetoric used before and after the community engagement events, although this change isn't as drastic as initially predicted. To begin, the topics between the two datasets seem to share more similarities than differences. In both years, there seems to have been consistent discussion revolving around military action, ISIS, and key geographical locations. Additionally, topics generated by both datasets display similar tones and focus on geopolitical factors. Despite this, some changes between the topics can be identified, mainly that the 2016 topics indicate a shift toward more specific rather than general discussion.

As for the LDA analysis in figure 2 for the and above median voter datasets, the following results and hand-labeled topics were produced.

Above Median Followers Data: Topic 1: Casualties From Conflict Topic 2: Islamic State Discussion Topic 3: Middle Eastern Politics of IS Topic 4: Syrian Conflict Topic 5: French Discussion (Omitted From Analysis)

Below Median Followers Data: Topic 1: Islamic State Discussion Topic 2: Conflict Updates/News Topic 3: Specific Conflict Events Topic 4: IS Support on Social Media Topic 5: Religious/Conflict Related

As with the 2015 and 2016 LDA analyses, both of the datasets share similarities mainly between themes and various religious references. However, there are clear differences between the results of the LDA analysis. Tweets from accounts with above median followers tend to be more detailed and specific by covering particular conflicts, geopolitical contexts, locations, etc. This differs from the tweets from accounts with below median followers who tend to be more general in their discussion which is evident by broader statements covering religion, IS support, etc. Overall results from both LDA analyses' indicate differences between the comparing datasets mainly between the specificity of the tweets or lack thereof.

5.2 Visual Representations

The visual representation for the 2015 and 2016 datasets was done in the form world cloud producing illustrations that make the above findings easier to identify and subsequently support. Those are seen in Figures 3 and 4. As for the visual representations for the follower datasets, this was completed in the form of a histogram which has been attached in Figure 5. The results of this show that above-median follower accounts tend to cover all topics evenly while giving more attention to topic three than accounts with below-median followers who tend to give more attention to topic 2.

5.3 Time Series

In addition to the LDA analysis and word cloud done for the yearly datasets, a time series was done to help identify topic prevalence over time. Attached in Figure 6 is a time series that shows prevalence in topics beginning around September 2015 which is when tweet-level data for this dataset began to be collected (only the data from a few users). All topics show relatively the same prevalence except for topic 0 which is notably higher and topic 1 which is notably lower. This continued until the beginning of 2016 when the prevalence of these two topics reversed as tweets containing topic 0 drastically decreased when compared to tweets containing topic 1 which dramatically increased. Findings continue through the peak of tweet data collection around April of 2016 when topics 1 and 3 are the highest.

5.4 Word Embedding

To further elaborate and complement the findings of the LDA analysis, word embeddings were carried out via Word2Vec. The results from the 2015 and 2016 dataset word embeddings once again show a shift from more broad and general discourse in 2015 to more specific in 2016. The results of the world embeddings also indicate a notable shift in the way people speak online with greater inclusion of social media and subsequent technological terminologies as alluded to by the inclusion of various user handles and slang. In addition to this, both years still show a strong focus on military action, geopolitical conflict, and subsequent impacts of that conflict. These results are seen in Figure 7.

The results of the word embeddings for the above and below median follower subsets also seem to have produced similar results. Once again we can see that both datasets show a big focus on ISIS, regional impacts, and military words. Meanwhile, I would argue that above median followers tend to be more specific with military strategies and equipment. On the other hand, the accounts under the median focus more on alliances and other opposition groups to ISIS, and even talk a bit more about the basics of regional conflicts such as Afghanistan. These results are seen in Figure 8.

6 Conclusion

For the LDA analysis, our findings show that while Propaganda, information sharing, geographical focus, and religious discourse stayed fairly similar for both years, we saw a change in how ISIS sympathizers started to switch to a more specific discussion about the military, breaking news, and violent events.

For the word embeddings, our findings show that ISIS sympathizers switched to more particular tweets. These include particular attacks, military movements, and other terrorist groups. Before the tweets were more ideological.

Thus, our overall conclusion is that the counter-extremism events did end up changing how ISIS sympathizers use social media. They started being more strategic with their tweets and tweeting more around ISIS on tactical and military aspects rather than ideology like before the events.

7 Appendix

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Top words for 2015 Data:
Topic 1: islamicstate, iraqi, army, ramadi, amp, soldiers, west, city, know, aleppo
Topic 2: akhijibran, lol, amp, like, somaliyyah, killed, ishmael, media, syrian, regime
Topic 3: rt, syria, isis, al, ramiallolah, russia, killed, abu, muslims, sheikh
Topic 4: allah, rt, soon, wilayathalab, akhi, new, twitter, ya, statement, coming
Topic 5: islamic, state, wilayatninawa, know, syria, rt, fighters, just, news, did
Coherence Score for 2015 Data: 0.38870966790050004
Top words for 2016 Data:
Topic 1: rt, la, le, est, isis, twitter, les, des, je, pas
Topic 2: rt, syria, isis, amp, turkey, ypg, al, ramiallolah, aleppo, russia
Topic 3: isis, rt, syria, state, assad, islamic, aleppo, palmyra, killed, saa
Topic 4: rt, allah, al, amp, muslims, islam, don, people, like, know
Topic 5: rt, killed, isis, iraq, army, al, today, iraqi, near, soldiers
Coherence Score for 2016 Data: 0.5468517250449392
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Figure 1: Figure one is a LDA analysis divided into five topics from 2015 and 2016 datasets. Five topics yielded the highest average coherence score, which is why it was used.

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Top words for Above Median Followers Data:
Topic 1: killed, isis, rt, iraq, al, army, soldiers, iraqi, today, near
Topic 2: rt, islamic, state, amp, al, syria, yes, assad, lol, people
Topic 3: rt, amp, isis, al, assad, muslims, iran, islam, saudi, time
Topic 4: syria, rt, isis, aleppo, assad, ypg, rebels, turkey, army, amp
Topic 5: le, la, est, rt, les, je, pas, des, et, en
Coherence Score for Above Median Followers Data: 0.5504254775642664
Top words for Below Median Followers Data:
Topic 1: rt, al, amp, allah, know, muslims, people, islam, just, said
Topic 2: islamicstate, army, rt, amaqagency, breaking, al, iraqi, killed, area, state
Topic 3: rt, isis, syria, ramiallolah, killed, iraq, assad, amp, al, today
Topic 4: rt, muslims, new, islamic, state, support, twitter, al, abu, account
Topic 5: rt, allah, islamic, state, al, follow, akhi, city, amp, mosul
Coherence Score for Below Median Followers Data: 0.4242624959720088
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Figure 2: Figure two is an LDA analysis divided into five topics from the top words above the median followers, and below the median followers.

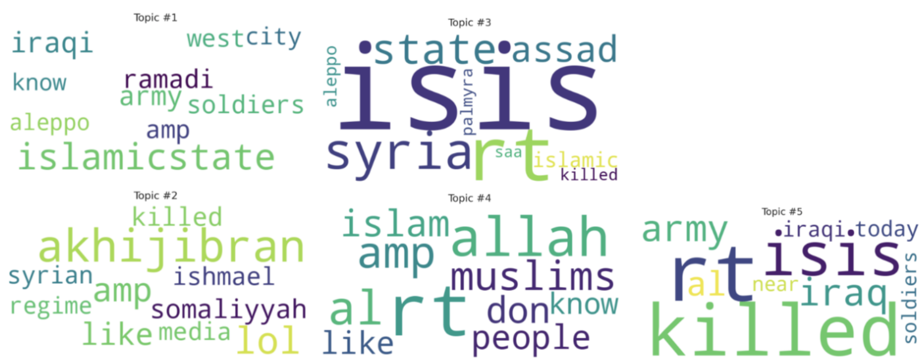

Figure 3: Figure three shows a word cloud from the LDA analysis, visualizing us the results of the most used words in 2015 by topic.

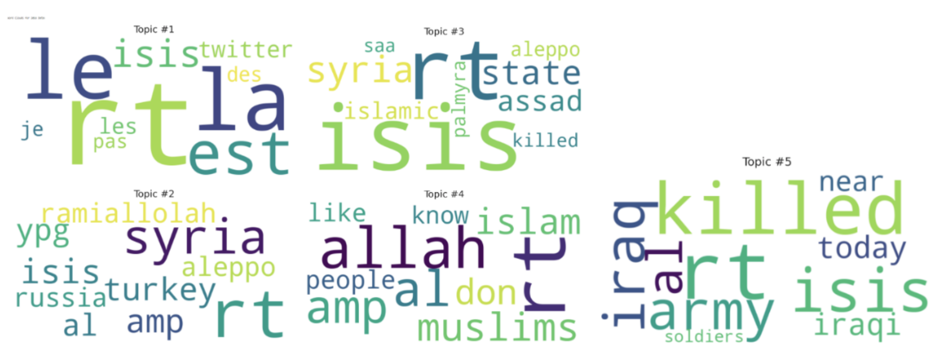

Figure 4: Figure four is a word cloud from the LDA analysis, visualizing us the results of the most used words in 2016 by topic.

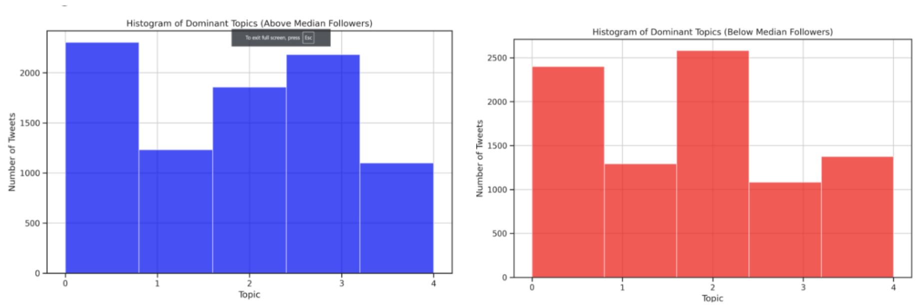

Figure 5: Figure five shows us two histograms, showing us the number of tweets for every word by topic. The histogram on the left shows the amount of tweets per topic for those above the median follower count, and the one on the right counts the amount of tweets per topic for those below the median follower count. This comes from the LDA analysis.

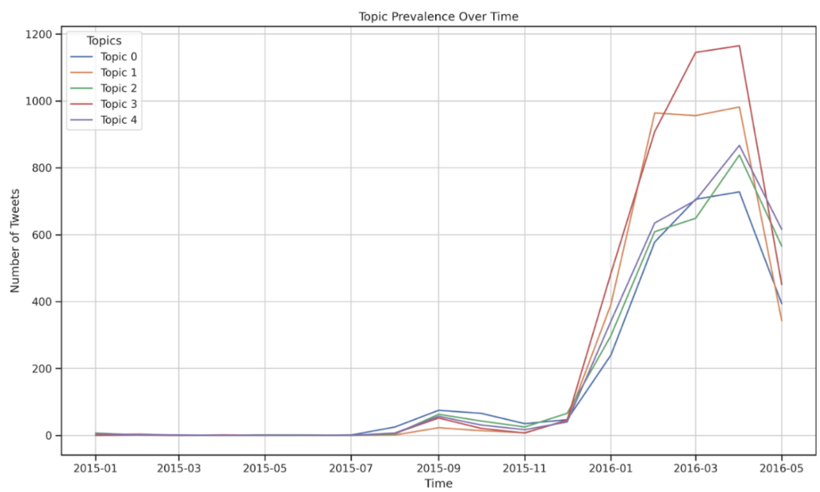

Figure 6: Figure six is a time series showing us the number of tweets per month for every topic. There is one line per topic, and it comes from the year dataset.

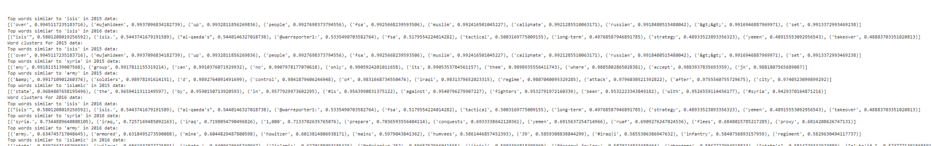

Figure 7: Figure seven shows us the results from the word embedding. It shows us the words most similar to 'isis', 'syria', 'army' 'islamic' from the 2015 and 2016 data.

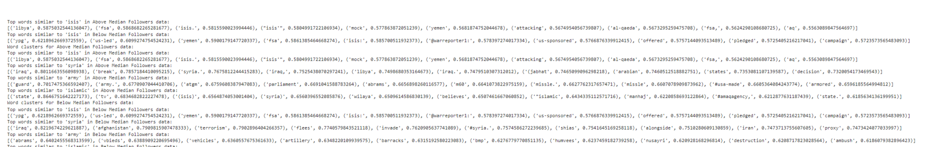

Figure 8: Figure seven shows us the results from the word embedding. It shows us the words most similar to 'isis', 'syria', 'army' 'islamic' from the above median follower count and below median follower count data.

8 References

"How ISIS Uses Twitter." Www.kaggle.com, www.kaggle.com/datasets/fifthtribe/how-isis-uses-twitter.

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