Can we Identify Russian Trolls on Twitter?

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Overview

In recent years the media and politicians have been increasingly concerned about foreign influence of US media, especially by Russian Trolls. Social Media platforms such as Twitter provide enormous platforms for trolls to push different agendas. Domestic users of these platforms may be unknowingly bombarded by foreign rhetoric that ultimately affects their views on US politics.

Many users of social media platforms, politicians, and news pundits have argued that the platforms have a responsibility to remove political trolls. But in an age where tweets are posted as rapidly as opinions are formed, how can platforms identify trolls? In my project I have created a learning model that identifies troll tweets from text alone. Using a similar model, social media platforms could remove or flag suspicious tweets as they are posted, helping mitigate the liability and reputation risk posed by trolls.

Data

I pulled my data from several external sources, so I needed to import it and format it inorder to get a single unified dataset. While there was a lot of meta data available, I was mostly concerned with the author, their category (troll/news outlet), and political leaning, and tweet content. Troll tweets were downloaded from FiveThirtyEight, non-trolls were from scraped from twitter with Twarc and data from GWU from a list of mainstream media outlets.

To process the data, I downsampled the original datasets from several million to about 1,000,000. I then discarded tweets where the author or content was missing. I also got rid of non-english tweets, tweets that were simply a link or image with no other context, and tweets that contained only emojis.

Finally, I resampled the data so that I had an equal number of-trolls and non trolls. This helps prevent class imbalances.

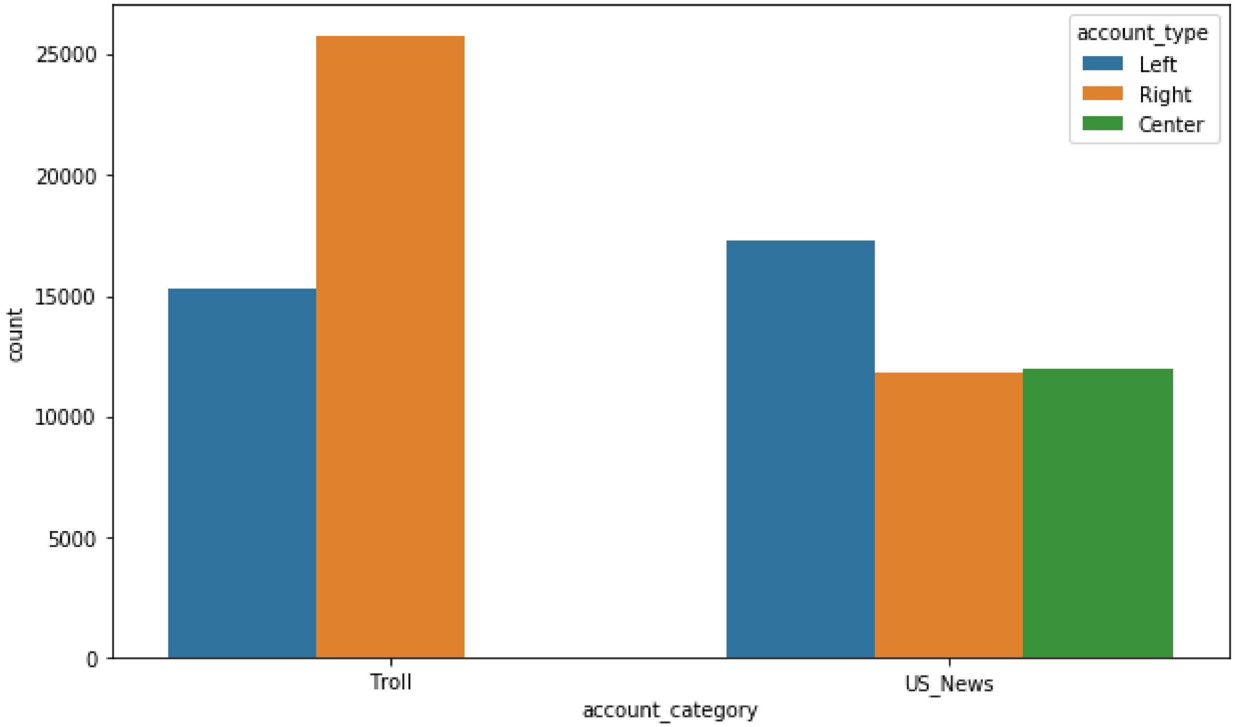
Inital EDA

We want to check how the data is spead out.

A look at how tweets are spread out over category and political leaning.

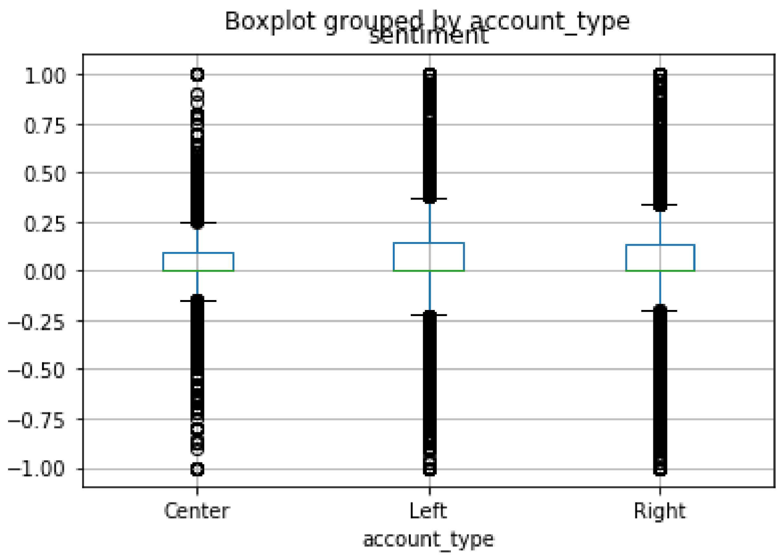
In [4]:

```
plt.subplots(figsize=(10,6));
sns.countplot(x=tweet_data['account_category'], hue=tweet_data['account_type']);
```



Sentiment by political leaning

```
In [7]: tweet_data.boxplot(column='sentiment', by='account_type');
```



Since the boxplots didn't show any significant difference, I'll use groupby to take a deeper dive into sentiment.

The means vary slightly. We can see that center leaning tweets are less positive (more neautral) while Left are more positive.

We can also see troll tweets have slightly higher standard deviation.

In [8]:

```
tweet_data.groupby(by=['account_category', 'account_type']).sentiment.describe()
```

Out[8]:

		count	mean	std	min	25%
account_category	**account_type**					
Troll	**Left**	15314.0	0.071811	0.283470	-1.0	0.0
	Right	25755.0	0.041765	0.299117	-1.0	0.0
US_News	**Center**	11972.0	0.044006	0.221426	-1.0	0.0
	Left	17320.0	0.053626	0.242326	-1.0	0.0
	Right	11777.0	0.047574	0.240826	-1.0	0.0

NLP Preperation

Now to start using NLP. I need to stem the words in the tweet text. This will reduce the number of features and improve the performance of my a model.

In [10]:

```
# Define a function that accepts text and returns a list of stems.
stemmer = SnowballStemmer('english')
def split_into_stems(text):
    text = str(text).lower()
    words = TextBlob(text).words
    return [stemmer.stem(word) for word in words]
```

Now I need to do run the model and evaluate my results. The options for the model I chose were determined by a grid search. with a pipeline. The resulting F1-scores are pretty good, about 85%.

```
In [13]:
vect = CountVectorizer(analyzer=split_into_stems, max_df=1.0, min_df=1, stop_words=stemm
ed_stops, ngram_range=(1,1))
X_train_dtm = vect.fit_transform(X_train)
X_test_dtm = vect.transform(X_test)
nb = MultinomialNB()
nb.fit(X_train_dtm, y_train)
y_pred_class = nb.predict(X_test_dtm)
print(metrics.classification_report(y_test, y_pred_class))
```

```
             precision    recall  f1-score   support

          0       0.81      0.90      0.85     10258
          1       0.89      0.78      0.83     10277

avg / total       0.85      0.84      0.84     20535
```

To get a better look at some of the tweets that were incorretly or correctly classified, I made a function to pull some of the most extreemly rated tweets out.

In [14]:

```
def grab_tweet(tweet):
    print("Author:", tweet['author'])
    print("Probability troll:", tweet['proba_troll'])
    print("Tweet text:", tweet['content'])
    print()
```

News Outlets

Most Troll Like

Author: nytimes | Probability troll: 1.00

Tweet text: RT @jennydeluxe: "Being black in the age of wokeness" is one of my fave episodes to date. Listen & LMK what you think >>>> https://t.co/r4T… (https://t.co/r4T…)

Author: USATODAY | Probability troll: 1.00

Tweet text: "All I really want to do is tell you that I'm feeling great. I'm glad I spent that evening in the hospital, and it did me a lot of good." -Stan Lee https://t.co/JZg09bqS1g (https://t.co/JZg09bqS1g)

Author: FoxNews | Probability troll: 1.00

Tweet text: .@POTUS on Democrats: "I don't think they want to solve the DACA problem. I think they wanna talk about it. I think they wanna obstruct." https://t.co/zBPxHDzk6E (https://t.co/zBPxHDzk6E)

Least Troll Like

Author: politico | Probability troll: 0.00

Larry Kudlow has been widely seen as a leading candidate to replace Gary Cohn, despite his criticism of Trump’s decision to impose a 10 percent tariff on aluminum and 25 percent tariff on steel imports. https://t.co/f3A12AevZU (https://t.co/f3A12AevZU) https://t.co/wpgmLzoh4p (https://t.co/wpgmLzoh4p)

Author: Reuters | Probability troll: 0.00

North Korean leader Kim Jong Un invites South Korean President Moon Jae-in to Pyongyang potentially setting up the first meeting of Korean leaders in more than a decade https://t.co/K7PvzMSyIA (https://t.co/K7PvzMSyIA) @HeeShin @pearswick #PyeongChang2018 https://t.co/kUseNIZ7g2 (https://t.co/kUseNIZ7g2)

Author: HuffPost | Probability troll: 0.00

PyeongChang built itself a brand-new $109 million stadium to host the 2018 Winter Olympic and Paralympic Games. And after just four ceremonial events — including the #OpeningCeremony — PyeongChang plans to tear the place down. 🤔🤔🤔 Here's more: https://t.co/QnNcDktTVs (https://t.co/QnNcDktTVs)

Troll Groups

Most News Like

Author: KANIJJACKSON | Probability troll: 0.00

Confirmed: Michael Cohen received hundreds of thousands of dollars from a Russian oligarch Viktor Vekselberg. The money was paid to a First Republic Bank account Cohen created for Essential Consultants. This is the same bank account Cohen used to pay Stormy Daniels $130,000

Author: IMAPHARRELFAKE | Probability troll: 0.00

Former Cuban President Fidel Castro dies at age 90, his brother, President Raul Castro announces. https://t.co/gHGSyRFlBi (https://t.co/gHGSyRFlBi)

Author: WORLDNEWSPOLI | Probability troll: 0.00

Bao Bao the giant panda leaves Washington zoo for new home in China https://t.co/e6WNrKcrMI (https://t.co/e6WNrKcrMI) https://t.co/QnCVIUb3nQ (https://t.co/QnCVIUb3nQ)

Least News Like

Author: DOROTHIEBELL | Probability troll: 1.0

�#WakeUpAmerica #TeamTrump #CCOT #2A #MAGA�#millenials #MinorityPolitics #tcot �Vote!!��Pols think we are stupid� https://t.co/FHTb098aar (https://t.co/FHTb098aar)

Author: COVFEFENATIONUS | Probability troll: 1.0

'@Acosta @jaketapper @CNN @CNNI @CNNPolitics @CNNSitRoom @WolfBlitzer @JakeTapper @TheLeadCNN @BrianStelter @AnaNavarro @DonLemon @VanJones68 @AndersonCooper @AC360 @JimAcosta CNN IS #FAKENEWS! CNN IS #FAKENEWS! CNN IS #FAKENEWS! CNN IS #FAKENEWS! CNN IS #FAKENEWS! CNN IS #FAKENEWS! #FAKENEWS #MAGA'

Author: PRICEFORPIERCE | Probability troll: 1.0

'@Sandroskeith @Keque_Mage @Always_Woke @MAGA_shopper @AutisteMoM @Dutch_Deplorabl @WanAw000 @jaxon_gator @lordcaccioepepe @HalleyBorderCol @DJTJohnMiller @WDFx2EU95 @mom_vet @ToTheHand @ThomasBernpaine @JonJ_L @HampusSelander @AndrewK_6 @Treeoflife272 @NeonReactionary @LoveUSADawn @nes4america @Silky*Milky* @dualkoondog @this1isno1 @disawooed @reallyyBecky

@polNewsNet @Kekolyte2 @nia4*trump @JJSmithy* @ang_yow @tcburnett @SpaceTrills @xavispar4 @lemuriangirl @whois_John_Galt @SeanLewandowski @pacman522 @Thomas1774Paine @BoozyVonD @tmntiffers @smwrva @Lord_ofthe_Pies @Psyanidex @EvilHillaryPics @JayVanorman @laughingatitall @nancyyvonne87 @VictorOfKadesh https://t.co/IzCYFcd5qV (https://t.co/IzCYFcd5qV)'

Finally, I want to take a look at how each news outlet scored on average:

Outlet	**Mean Score**
Reuters	0.013266
AP	0.018762
chicagotribune	0.039258
ABC	0.041498
politico	0.050556
WSJ	0.052525
NPR	0.079233
CNN	0.087843
USATODAY	0.114722
Forbes	0.116943
nytimes	0.122085
washingtonpost	0.126263
nypost	0.165859
FoxNews	0.168716
HuffPost	0.220815

Conclusions

Overall, I the model works pretty well. Given a 50/50 split, the model is able to predict trolls correctly 84% of the time.

Type	**precision**	**recall**	**f1-score**	**support**
News	0.81	0.90	0.85	10258
Troll	0.89	0.78	0.83	10277

Limitations

- There was no deep dive into links, images (memes), or RTs. So the model does not account for how a tweet could be replying to another comment or promoting an article or even sharing/spreading a meme. However, these contain information that humans understand and can ultimately be influenced by

- I used a limited sample of tweets to compare the trolls to. I.e. I only compared trolls to politicians active at the same time and news articles posted by a select group of outlets. However, in reality a social media platform contains a lot more noise - innocuous meme pages, advertisers, standard users. Not to mention domestic trolls and fake news accounts.

Future work

A great application of the model could be a browser extension that allows users of twitter to quickly asses the likelihood that a tweet if from a troll. It could then allow the model to further train itself by accepting user feedback