Detecting Military Engagements From Social Media Data

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ABSTRACT

Social media posts can be assigned a sentiment score, which is a numerical evaluation of the relative positive or negative emotions displayed in the text. These sentiment scores can be used for prediction of various behaviors, both on an individual and societal scale. This project uses sentiment scores to determine whether or not there is an ongoing military battle in the regions the social media posts reference within an active war zone using data from the ongoing Russo-Ukrainian War. This detection is done using a series of supervised learning models, and is quite successful.

KEYWORDS

Sentiment Analysis, Binary Classification, Military Engagements, Open-Source Intelligence, Supervised Learning, Russo-Ukrainian War

1 Introduction

This project attempts to detect military engagements from Telegram, an instant messaging service, made by Russian and Ukrainian users during the ongoing Russo-Ukrainian War.

Each post is assigned a sentiment score, which is a measure of how positive or negative the sentiment of the text is in a given post. The daily mean sentiment scores of posts about a particular location for both Ukrainian and Russian users is then cross-referenced with the date and location of significant battles to determine if a battle is ongoing in that location on that date.

This data is then explored and modeled using a series of supervised learning algorithms (Logistic Regression, Support Vector Machines, Decision Trees, Random Forest, Naive Bayes, and K-Nearest Neighbors) in order to train models that can detect ongoing battles from the sentiment scores of social media posts.

The long term goal of this project, and further work, is to provide advanced warning to civilians and rescue and aid organizations, so that the affected region can be evacuated or supplied appropriately. When civilians are unaware of a military's future actions they can become caught up in military engagements, which can unnecessarily increase the number of civilian casualties.

2 Previous Work

Sentiment analysis of social media data has been used for numerous purposes with varying degrees of effectiveness.

Previous work in this particular area: prediction of large scale social events, as opposed to individual behaviors, has been predominantly focused on predicting social unrest in the form of political protests or similar actions.

Some models can be quite large, with one attempt by the IMF using 340 indicators drawing from various economic and social metrics.[1]

Several attempts have been intended to be predictive and used semi-supervised algorithms.[2,3,4] However, results are often ambiguous.[5]

To my knowledge, there have been no previous attempts to predict or detect military engagements using these methods.

3 Data Collection

A set of messages from Ukrainian and Russian social media posts made on the instant messaging platform Telegram was scraped using a script utilizing the Selenium Python library from an archive created by OSINTUkraine.[5] These scrapes came in the form of HTML files.

These HTML files were then cleaned using the BeautifulSoup Python library to extract the text of the social media posts and the date that they were posted. A data frame was created from that data with two columns: datetime, and text.

The data frame was then enriched by appending an additional “location” column, which was found by extracting any mentions of either a city or region within the text of the post.

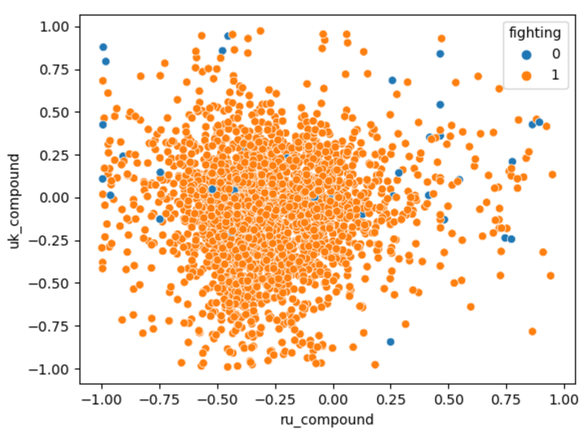
The locations were cross-referenced with a list of major combat events and battles pulled from the wikipedia page, “List of military engagements during the Russian invasion of Ukraine”.[6] This was used to append a column to the data frame with a binary value of 1 or 0, with 1 indicating that there was an ongoing battle in the mentioned region, and 0 indicating that there was not.

4 Sentiment Analysis

For the sentiment analysis portion of the project, the nltk Python library was selected. The pretrained Sentiment Intensity Analyzer, trained on the ‘vader’ lexicon, was used. This model returns a set of four scores for each piece of text: negativity, neutrality, positivity, and compound. The compound score is an overall assessment of how positive, negative, or neutral the given text is. This is the score that was used for this analysis.

5 Data Exploration

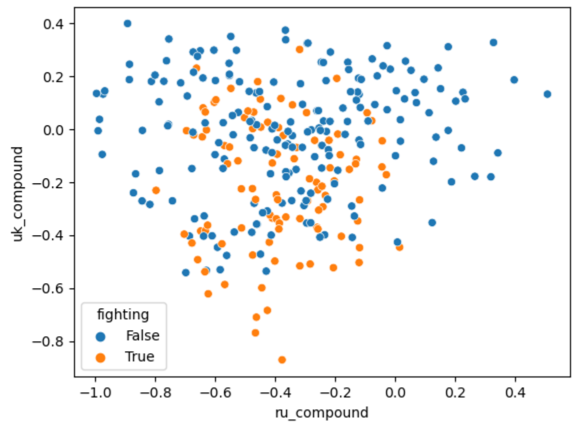
Looking at the data as a whole, we can produce the following scatterplot:



This plot shows the daily mean compound sentiment scores for each date, with the Russian compound score on the x-axis, and the Ukrainian compound score on the y-axis. The data points are color coded with 1 in orange, meaning that there is an ongoing battle in the relevant region on that date, and 0 in blue, meaning there is not an ongoing battle in the relevant region on that date. The key detail to notice from this plot is that the data points overlap heavily, so much so that deriving any meaningful insights from the plot is nearly impossible. As such, we can separate out a representative sample for exploration.

5.1 Exploring Kharkiv Data

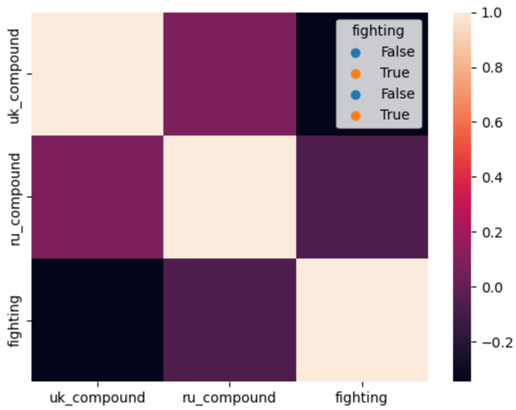
Below we see the same scatter plot produced using only data whose location is ‘Kharkiv’.



From this scatterplot we can see that, in general, when there is an ongoing battle, Ukrainian scores are lower than when there is not an ongoing battle. This makes sense: we should expect people to have negative sentiments about a region in which a battle is occuring.

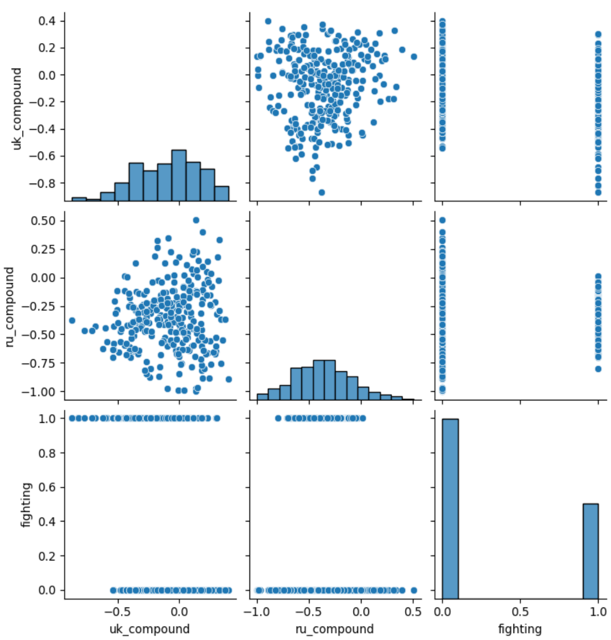
Interestingly, Russian scores are also noticeably lower during an ongoing battle. This is promising from a modeling perspective as it indicates a possible relationship to use for detecting ongoing battles.

If we look at the correlation of our three variables: Ukrainian compound sentiment scores, Russian compound sentiment scores, and whether or not there is an ongoing battle, we can produce the following correlation heatmap:



Brighter colors indicate a stronger correlation. We can see that there are no especially strong correlations here. Optimistically, however, we might think that this is also promising from a modeling perspective because it indicates a lack of collinearity in our variables that may have made our models less reliable.

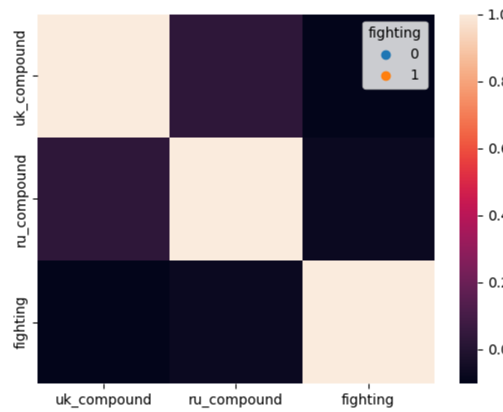
Taking a closer look, we can examine the following pairplot:



Again, we can see that there is not an obvious correlation between our sentiment scores. However, we can see that the "fighting" variable has a notable distribution. Relative to the Ukrainian sentiment score, we can see that data points where "fighting" has a value of True tend to cluster around more negative scores, and that the same is true of the Russian sentiment scores. This reinforces our intuition from the initial scatterplot that lower sentiment scores from both populations are associated with ongoing battles, and gives us something to look for in the larger data set.

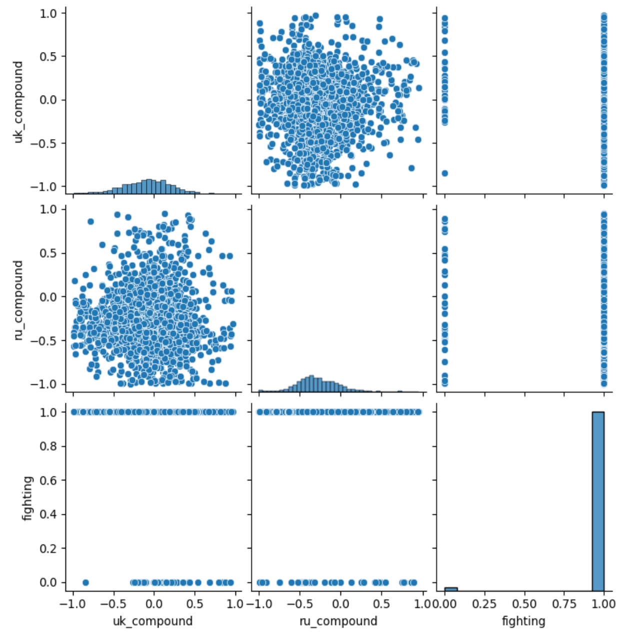
5.2 Exploring The Full Data Set

Next, we recreate our correlation heatmap from above with the full data set:



We see here that our correlations actually get weaker in the full data set than they were in the Kharkiv subset. Again, this may be a boon for modeling because it indicates a lack of collinearity.

Below, we have the pairplot for the full data set:



Here we see the same key features that we found in the Kharkiv subset. There is no clear relationship between the Ukrainian and Russian sentiment scores, but there does appear to be a relationship between sentiment scores and the "fighting" variable. However, this relationship appears to be somewhat weak when viewed individually for each variable.

This seems to suggest that modeling will necessitate the use of both sets of sentiment scores, and that modeling using only the Ukrainian sentiment scores or only the Russian sentiment scores would be less successful at detecting battles.

6 Modeling

Modeling for this project was conducted in three stages. First, an exploratory regression was performed in order to justify the usefulness of the two predictor variables: Ukrainian compound sentiment scores and Russian compound sentiment scores.

Next, a series of models were trained to detect battles from those predictors. The methods used were: Logistic Regression, Support Vector Machines, Decision Trees, Random Forest, Naive Bayes, and K-Nearest Neighbors. The implementations are taken from the Sci-Kit Learn Python library.

The goal of training multiple models was to determine which, if any, type of model was most effective for our purpose.

These models were first trained on the Kharkiv data as a proof of concept, and then trained on the complete data set.

6.1 Exploratory Regression

The results of the exploratory regression can be seen below:

```
Regression Results
==============================================================================
Dep. Variable:          fighting           R-squared:              0.015
Model:                  OLS                Adj. R-squared:         0.015
Method:                 Least Squares      F-statistic:            19.30
Date:                   Mon, 03 Apr 2023   Prob (F-statistic):     4.83e-09
Time:                   11:42:33           Log-Likelihood:         1659.6
No. Observations:       2472               AIC:                    -3313.
Df Residuals:           2469               BIC:                    -3296.
Df Model:               2
Covariance Type:        nonrobust
===============================================================================
              coef     std err   t         P>|t|    [0.025    0.975]
-----------------------------------------------------------------
Intercept     0.9734   0.003     289.129   0.000    0.967     0.980
uk_compound   -0.0391  0.008     -5.070    0.000    -0.054    -0.024
ru_compound   -0.0288  0.008     -3.422    0.001    -0.045    -0.012
==============================================================================
Omnibus:                3251.496           Durbin-Watson:          1.756
Prob(Omnibus):          0.000              Jarque-Bera (JB):       354899.117
Skew:                   -7.598             Prob(JB):               0.00
Kurtosis:               59.698             Cond. No.               3.64
==============================================================================
```

The most notable features here are the p-values for the two predictors and the p-value for the F-statistic.

The p-value for the effect of the Ukrainian sentiment score was approximately 0. The p-value for the effect of the Russian sentiment score was approximately 0.001. This indicates that the effect of each of these predictors is statistically significant.

The p-value for the F-statistic is also approximately 0, indicating that the Regression model performs better than chance.

6.2 Modeling Kharkiv

The results of predictive modeling for the Kharkiv data are given below:

	Accuracy	**Precision**	**Recall**
Logistic Regression	**0.685**	**0.375**	**0.529**
Support Vector Machines	**0.685**	**0.375**	**0.529**
Decision Trees	**0.603**	**0.5**	**0.414**
Random Forest	**0.726**	**0.542**	**0.591**
Naive Bayes	**0.658**	**0.417**	**0.476**
K-Nearest Neighbor	**0.671**	**0.542**	**0.5**

Notably, accuracy is not terribly high, but it is better than chance. Precision, however, is quite low, and recall is not significantly better than chance.

The Random Forest model performs best here. The Decision Trees model is substantially worse than the other models. In modeling the complete data set, attention should be paid to see if this remains the case.

As a predictive model, none of these are successful in a way that would be useful to individuals involved in a conflict, nor to researchers. However, as a proof of concept, the results do imply that a successful predictive model is possible.

6.3 Modeling the Full Data Set

The results of modeling the full data set are given below:

	Accuracy	Precision	Recall
Logistic Regression	0.983	1	0.983
Support Vector Machines	0.983	1	0.983
Decision Trees	0.971	0.986	0.984
Random Forest	0.980	0.996	0.984
Naive Bayes	0.977	0.991	0.985
K-Nearest Neighbor	0.983	1	0.983

Here, accuracy is substantially improved. Precision and recall are also much improved. Notably, the variation in success of the models is significantly diminished, with no particular model appearing to be substantially better or worse than any other.

The huge leap forward in quality is a testament to the importance of large data sets, but may also indicate a quirk in the underlying data. In particular, a precision of 1 implies that there were no false positives at all in the Logistic Regression, Support Vector Machines, or K-Nearest Neighbor models.

A precision score this high may imply that there is something wrong with the implementation or the underlying data. With more time, these models could be explored more thoroughly and re-trained on shuffled data to verify the reliability of these results.

Overall, these results are extremely promising, and this project is a tremendous success based on its intended goal.

6 Conclusion

This project has successfully trained a series of models to detect ongoing battles from social media data. An early goal of the project was to attempt to predict battles in advance, however, that was deemed infeasible due to the limited data set and time constraints of this project, but this should remain a key goal for future work.

Given the success of this project, an applied implementation of these models appears worthwhile. I take the outcome of this project to be a persuasive proof of concept for the application of supervised models to combat detection in war zones for civilian purposes.

7 Future Work

The apparent success of this project in detecting battles from social media data leads to a few reasonable next steps for future work.

7.2 Replication on Larger Data Set

The most obvious next step would be to attempt to replicate this success on a larger data set. The data set used here consisted solely of the Telegram posts archived by OSINTUkraine between April of 2022 and February of 2023.

A future study could look at more recent social media data, as well as at posts on other social media platforms.

7.2 Replication in Other Regions

Another clear next step is to attempt to replicate these results on social media data from other regions or in other conflicts. Social media posts from Syria, Myanmar, or elsewhere, may be similarly scraped and processed in order to attempt to detect combat in those regions.

7.2 Prediction of Battles

Perhaps the most exciting possibility for future work is to attempt to predict battles or major conflicts in advance. It may be that escalating tensions in the days or weeks before a large battle can be detectable in social media data, and that this could be used not only to detect ongoing battles, but to predict them before they begin.

Such predictions would allow aid workers to know in advance where they will be most needed and provide an early warning system to civilians who may need to be evacuated or seek shelter.

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