Application of Data Science to Discover Violence-Related Issues in Iraq

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Abstract

Data science has been satisfactorily used to discover social issues in several parts of the world. However, there is a lack of governmental open data to discover those issues in countries such as Iraq. This situation arises the following questions: how to apply data science principles to discover social issues despite the lack of open data in Iraq? How to use the available data to make predictions in places without data? Our contribution is the application of data science to open non-governmental big data from the Global Database of Events, Language, and Tone (GDELT) to discover particular violence-related social issues in Iraq. Specifically we applied the K-Nearest Neighbors, Naïve Bayes, Decision Trees, and Logistic Regression classification algorithms to discover the following issues: refugees, humanitarian aid, violent protests, fights with artillery and tanks, and mass killings. The best results were obtained with the Decision Trees algorithm to discover areas with refugee crises and artillery fights. The accuracy for these two events is 0.7629. The precision to discover the locations of refugee crises is 0.76, the recall is 0.76, and the F1-score is 0.76. Also, our approach discovers the locations of artillery fights with a precision of 0.74, a recall of 0.75, and an F1-score of 0.75.

Keywords: Iraq, violence, data science, big data, machine learning, classification algorithms

1. Introduction

Data science is the generalizable extraction of knowledge from data [1]. Data is the fuel of data science to discover the places in which help could be provided (for instance, humanitarian aid). However, most data from the Middle East is blocked because of legal or technical restrictions. Specifically, Iraq is one of the countries that is not in the regional ranking regarding to open data [2].

In previous work, thanks to machine learning, a sub-area of artificial intelligence and a key component of data science, it has been possible to discover certain social behaviors or even to predict future events. For instance, in [3] a model was proposed to predict certain levels of violence in districts of Afghanistan. In [4], data science was used to estimate the degree of activity and influence of the USA, China, and USA with respect to politics, economy, trade, culture, the military, among other areas. However, despite the effervescence in the use of machine learning to discover interesting social trends, the lack of data in Iraq makes it difficult to apply this approach in that country.

Our contribution in this research work is the application of data science to open non-governmental big data to discover particular social issues related to violence in Iraq. We are interested in this country because violence, refugee crises, and massacres are constant in its territory [5]. Specifically we applied the K-Nearest Neighbors (KNN), Naïve Bayes, Decision Trees, and Logistic Regression classification algorithms to discover violence-related social issues in the territory of Iraq in terms of refugees, humanitarian aid, violent protests, fights with artillery and tanks, and mass killings. The models were trained with open data from the Global Database of Events, Language, and Tone (GDELT), a project sponsored by Google that contains more than 200 million geolocated events with worldwide coverage regarding news and important events from 1979
GDELT obtains the data from news agencies such as Lexis Nexis, the Agence France-Presse, Reuters, Associated Press, and Xinhua. It also uses the Conflict and Mediation Event Observations (CAMEO) code, which is a content code for electronic news.

In our experiments, the best results were obtained with the Decision Trees algorithm to discover areas with refugee crises and artillery fights. The accuracy value for these two events was 0.7629. The precision, recall, and F1-score values to discover the locations of refugees was 0.76. Also, our approach discovers the locations of artillery fights with a precision of 0.74, a recall of 0.75, and an F1-score of 0.75.

This paper is organized as follows. The second section presents the related work. The third section presents the methodology. The fourth section presents the evaluation results. The fifth section describes the software for classification. The last section presents the conclusions and future work.

2. Related work

Bi, Gao, Wang y Cao used GDELT data to estimate the degree of activity and influence of countries regarding politics, economy, commerce, culture, militia, among others. In their research work, countries such as the United States, China, and Russia stand out. Also, Kumar, Benigni, and Carley used data from GDETL to analyze the perception of the population towards cyber attacks in the United States through graphs. By observing them, they concluded that cyber attacks have decreased in relation to changes in the country’s cyber policy. In another research work, Su, Lan, Lin, Comfort, and Joshi describe the data analysis of the earthquake response in Nepal in 2015. The data were obtained from GDELT and the results show the increase and decrease of people’s interest in contributing through donations. They also explain the support of the government and the effectiveness of international and local organizations. They also describe the importance of careful monitoring and prompt attention after disasters. As far as we know, there is not previous related work about using data science applied to GDELT data to discover social issues related to violence of people in Iraq.

3. Methodology

Data science follows a general process that includes data collection, data cleaning, data analysis, and modeling. In data science, the data obtained is processed differently than in traditional approaches, so a new methodology must be applied to extract the necessary knowledge. In fact, the use of a data-oriented methodology allows analysts to develop and evaluate predictive models in an efficient way. To this end, we used the IBM Foundational Methodology for Data Science, composed of ten stages that represent an iterative process. The first seven stages are described in this section in the context of our research work. The evaluation, deployment, and feedback stages are described in the next sections.

3.1. Problem understanding

According to the Open Data Barometer, there are few countries in the Middle East and North Africa region with open data initiatives. This is due to the low participation of civilians in this kind of initiatives and little pressure of governments to make their data public. In this research work, Iraq was taken as a case study because that is one of the countries in the Middle East with unavailable open data due to legal restrictions.

3.2. Analytic approach

Machine learning was chosen as the mechanism to understand and analyze data regarding refugees, humanitarian aid, violent protests, fights with artillery and tanks, and mass killings in Iraq. These events were selected due to their constant mention in the news from that country. In the experiments, Python was used together with Scikit Learn to program the following machine learning algorithms: KNN, Decision Trees, Naïve Bayes, and Logistic Regression.

1https://scikit-learn.org/stable/
3.3 Data requirements

3.3.1 Data requirements

In this step, a query was executed in Big Query to obtain the GDELT data about the events studied in Iraq. The 42,027 records retrieved during the query include the latitude and longitude in Iraq where the news happened. The query covered data from 2012 to 2015. Specifically, Table 1 shows the description of the variables used in Big Query, where the actor refers to the entity involved in the event. The codes used to get news from particular latitudes and longitudes are also shown.

| Code                        | Description                                      | Type   |
|-----------------------------|--------------------------------------------------|--------|
| ActionGeo_CountryCode       | Country where the event happened and the event   | String |
| Actor1Geo_Lat               | Latitude of the location of the actor            | Float  |
| Actor1Geo_Long              | Longitude of the actor                           | Float  |
| Actor1Type1Code             | Type or role of the actor (e.g. refugees)        | String |
| EventCode                   | Entities related to the event                    | String |
| Year                        | Year of the event                                | Integer|

3.4 Data collection

The results obtained with Big Query were downloaded in the comma separated values (CSV) format. Google Maps was used to get the data from Iraq. The geolocation points that were considered to get the data were the following: latitude greater than 29.12 and lower than 37.29 and longitude greater than 39.22 and lower than 48.48. The ActionGeo_CountryCode corresponds to IZ (Iraq in CAMEO code). Figure 1 shows the limits in terms of extreme latitudes and longitudes of the territory of Iraq. These points were obtained with Google Maps.

![Figure 1: Extreme latitude and longitude points for Iraq.](image-url)
3.5 Data understanding

A query example in Big Query to get data from Iraq from 2012 to 2015 according to the aforementioned latitudes and longitudes is shown in Listing 1.

**Algorithm 1** Query example in Big Query to get the data related to refugees in Iraq from GDELT.

```sql
SELECT Actor1Type1Code , Year , ActionGeo_CountryCode , Actor1Geo_Lat , Actor1Geo_Long , EventCode 
FROM [g delt−bq: full . events ]
WHERE Actor1Type1Code = "REF"
AND (Year > 2011 AND Year < 2016)
AND (Actor1Geo_Lat > 29.12
AND Actor1Geo_Lat < 37.29)
AND (Actor1Geo_Long > 39.22
AND Actor1Geo_Long < 48.48)
AND Actor1Geo_Lat IS NOT NULL
AND Actor1Geo_Long IS NOT NULL
```

Table 2 shows the distribution of the 42,027 records obtained from the query. The CSV file with the results of the query is available online.

| Event | Description | Period 2012-2015 |
|-------|-------------|------------------|
| 073   | Provide humanitarian aid | 10,414 |
| 145   | Violent protests          | 3,068 |
| 194   | Fight with artillery and tanks | 13,247 |
| 202   | Engage in mass killings   | 1,822 |
| REF   | Refugees                | 13,476 |
| **Total number of records** | **42,027** |

3.5 Data understanding

We used Google Maps to understand the data obtained from GDELT. The results of these events are shown in Figure 2 to Figure 6. Some points in the maps exceed the limits established for latitude and longitude in Iraq. This is because these distances were obtained manually using the extreme limits on the map, as described in the previous step (see Figure 1). In the maps, the violence-related events studied in this research work have a greater incidence in the north and east of the country. It is also interesting to see that news related to humanitarian aid and artillery fights cover most of the country.

Although the simple visualization of the data can be used to find patterns, it is important to notice that there are areas where data is not available according to the events studied (i.e., blank areas). It is where machine learning comes into play to discover violence-related issues in areas with insufficient data.

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2https://drive.google.com/drive/folders/0B6LEG8jNFAY9MEJBTkZoYlRIZHc
3https://www.google.com/maps/d/edit?hl=es&authuser=0&mid=1uEeGUsxz38AdaYyYeHCjdWt5m&ll=33.137338087845784%2C43.81860000000006&z=6
3.5 Data understanding

Figure 2: Map of news related to refugees.

Figure 3: Map of news related to humanitarian aid.

Figure 4: Map of news related to violent protests.
3.6 Data preparation and Modeling

The String GDELT code values were converted to Integer values to run the experiments (see Table 1). It was a necessary step because machine learning algorithms work with numerical data. Specifically, the ACTIONGEO_COUNTRYCODE code value for Iraq had a String data type that was converted to Integer. Moreover, the values for the ACTOR1TYPE1CODE code had the String data type as returned by GDELT. The values for this variable were also converted to Integer values (for instance, the REF actor type code was converted to 0). Also, the following Integer values were assigned to the EVENTCODE code: for the refugees event, the value is 0; for the humanitarian aid event, the value is 073; for the violent protests event, the value is 145; for the fights with artillery and tanks event, the value is 194; and for the engage in mass killings event, the value is 202.

In the modeling step, predictive models were generated with machine learning, using the following classification algorithms: KNN, Naive Bayes, Decision Trees, and Logistic Regression. These algorithms were chosen because they are popular in supervised learning [14] and are also insensitive to outliers [15, 16, 17, 18].

To train the models, the studied events were used as classes and the latitude and longitude values were considered as features.

4. Evaluation

The evaluation was performed on a Lenovo laptop with the following characteristics: AMD A8-7410 APU processor with AMD Radeon R5 Graphics, 8 GB RAM, and Windows 10, 64-bits operating system. Also,
Table 3: Number of instances per dataset with different combinations of events.

| Events          | Number of Instances |
|-----------------|---------------------|
| **Two events**  |                     |
| 73, 145         | 13,482              |
| 73, 194         | 23,661              |
| 73, 202         | 12,236              |
| 0, 73           | 23,890              |
| 145, 194        | 16,315              |
| 145, 202        | 4,890               |
| 0, 145          | 16,315              |
| 194, 202        | 15,069              |
| 0, 194          | 26,723              |
| 0, 202          | 15,298              |
| **Three events**|                     |
| 73, 145, 194    | 26,729              |
| 73, 145, 202    | 15,304              |
| 0, 73, 145      | 26,958              |
| 73, 194, 202    | 25,483              |
| 0, 73, 194      | 37,137              |
| 0, 73, 202      | 25,712              |
| 145, 194, 202   | 18,138              |
| 0, 145, 194     | 29,791              |
| 0, 145, 202     | 18,366              |
| 0, 194, 202     | 28,545              |
| **Four events** |                     |
| 73, 145, 194, 202| 28,551             |
| 0, 73, 145, 194| 40,205              |
| 0, 73, 145, 202| 28,780              |
| 0, 73, 194, 202| 38,959              |
| 0, 145, 194, 202| 31,613             |

Python version 2.7.12 was used along with Anaconda version 4.2.0, which contains Pandas and Numpy. The dataset was split into two groups: 70% of the instances or records were used for training and the remaining 30% for evaluating the model.

The experiments consisted in applying the KNN, Decision Trees, Naïve Bayes, and Logistic Regression algorithms to the dataset obtained from GDELT. We calculated all the possible combinations of available events for each experiment based on the following equation:

$$C(n, r) = \binom{n}{r} = \frac{n!}{r!(n-r)!}$$

In this equation, \(n\) stands for the number of entities that can be chosen in a particular experiment and \(r\) is the way in which these events can be chosen. 26 combinations of events were obtained, which is equivalent to 26 datasets that combine the 4 events studied (i.e., the classes). With these datasets, training was carried out with each algorithm, reaching a total of 104 tests (i.e., 4 classification algorithms multiplied by 26 datasets). The files that include the dataset of the experiments are available online.

Table 3 shows the combinations obtained from the events and the number of instances per combination.

\(^4\text{https://drive.google.com/drive/folders/0B6LEG8jNIAY9MEJBTkZoYlRIZhc}\)
4.1 Experiment 1 - KNN algorithm

The results obtained in the experiments were evaluated in terms of accuracy, precision, recall, and F1-score. With respect to accuracy, the expected value to approve the classification model had to be as close as possible to the value of 1 in order to obtain the highest accuracy in the classification [19]. For precision and recall values, values close to 1 were also considered appropriate to obtain a correct classification. Specifically, a low value in precision indicates a high number of false positives [20]. A low recall value indicates a high number of false negatives [21].

The experiments carried out with the refugee and fight with artillery and tanks events obtained the best results in terms of accuracy, precision, recall and F1-score. The results of the experiments with two events that obtained the best scores are described in the following subsections. The source code of the programs that were used in the experiments is available online.

4.1.1 Experiment 1 - KNN algorithm

When using KNN, the best result was obtained with two events (or classes) for the dataset of refugees (event 0 with 4,105 instances) and artillery fight (event 194 with 3,912 instances) with a total of 8,017 instances. Table 4 describes the average of the results with respect to precision, recall, and F1-score. In this experiment, an accuracy of 0.7545 and the results for the precision, recall, and F1-score measurements were appropriate in this study.

Table 4: Results of the KNN algorithm - refugees (event 0) and fights with artillery and tanks (event 194).

| Event | Precision | Recall | F1-score |
|-------|-----------|--------|----------|
| 0     | 0.75      | 0.75   | 0.75     |
| 194   | 0.74      | 0.74   | 0.74     |

4.2 Experiment 2 - Decision Trees algorithm

In the second experiment, the Decision Trees algorithm was applied. The best result corresponded to the classification of the refugee event (event 0, with 4,105 instances) and the fight with artillery and tanks event (event 194, with 3,912 instances). An accuracy of 0.7629 was obtained and the precision, recall, and F1-score values were between 0.74 and 0.76, as shown in Table 5. There is a similarity of these results compared to the ones in the experiments with the KNN algorithm in Table 4.

Table 5: Results of the Decision Tree algorithms - refugees (event 0) and the fights with artillery and tanks (event 194).

| Event | Precision | Recall | F1-score |
|-------|-----------|--------|----------|
| 0     | 0.76      | 0.76   | 0.76     |
| 194   | 0.74      | 0.75   | 0.75     |

4.3 Experiment 3 - Näive Bayes algorithm

In the third experiment, the Näive Bayes algorithm was used. The best result was obtained by applying this classifier to the provide humanitarian aid event (event 73 with 3,124 instances) and the engage in mass killings event (event 202 with 513 instances). For these events, the accuracy value was 0.8510. However, the values for precision, recall, and F1-score in the engage in mass killings event was 0, as shown in Table 6.

Table 6: Results of Näive Bayes algorithm - provide humanitarian aid (event 73) and engage in mass killings (event 202).

| Event | Precision | Recall | F1-score |
|-------|-----------|--------|----------|
| 73    | 0.85      | 1.00   | 0.92     |
| 202   | 0.00      | 0.00   | 0.00     |

5https://drive.google.com/drive/u/0/folders/0B6LEG8jNIAAY9cUNT99mK4WFU
4.4 Experiment 4 - Logistic Regression algorithm

The Näive Bayes algorithm was also used to create a model for the refugee event (event 0 with 4,116 instances) and the violent protests event (event 145 with 915 instances). An accuracy value of 0.8145 was obtained. However, the accuracy in the case of the protest violently event was 0, as shown in Table 7. This demonstrates that a high value in accuracy is not enough for the selection of the algorithm as stated in related work [22].

| Event | Precision | Recall | F-score |
|-------|-----------|--------|---------|
| 0     | 0.82      | 1.00   | 0.90    |
| 145   | 0.00      | 0.00   | 0.00    |

Table 7: Results of the Näive Bayes algorithm - refugees (event 0) and violent protests (event 145).

4.4. Experiment 4 - Logistic Regression algorithm

In this experiment, the Logistic Regression algorithm was applied to the fight with artillery and tanks event (event 194 with 4,022 instances) and engage in mass killings event (event 202 with 499 instances). The generated model obtained an accuracy value of 0.8896. However, the engage in mass killings event obtained low values in terms of precision, recall, and F1-score as shown in Table 8.

| Event | Precision | Recall | F1-score |
|-------|-----------|--------|----------|
| 194   | 0.89      | 1.00   | 0.94     |
| 202   | 0.00      | 0.00   | 0.00     |

Table 8: Results of the Logistic Regression algorithm - fight with artillery and tanks (event 194) and engage in mass killings (event 202).

4.5. Discussion

According to the experiments presented in the last sections, the Decision Trees algorithm stands out for the classification of the refugee event (event 0) and fight with artillery and tanks event (event 194) - see Section 4.2. By applying this algorithm, an accuracy of 0.7629 was obtained. The refugee event is classified with a precision value of 0.76, a recall value of 0.76, and a F1-score value of 0.76. The fight with artillery and tanks event (event 194) was classified with a precision value of 0.74, a recall value of 0.75, and a F1-score value of 0.75. Due to these results, the predictive model created with the Decision Trees was selected to carried out the classifications of violence-related social issues in Iraq.

To corroborate the validity of the model created with the Decision Trees algorithm, in addition to the cross-validation evaluation presented in the previous section, the results of the classification model were compared with the geolocation results obtained from maps. First, we compared the results of the model with the High Commissioner of Nations United (UNHCR) map for refugees in Iraq (see the blue areas in Figure 7). Second, we compared the results of the model with the Liveumap (Live Universal Awareness Map) in terms of zones of fights with artillery and tanks (see Figure 8). The icons in this map indicate the places of the most outstanding news.
Figure 7: UNHCR map of refugees in Iraq [5].

Figure 8: Liveumap map of fight with artillery and tanks in Iraq [23].

Figure 9 shows the classification results of the areas with the highest number of refugees by district in Figure 7 (the zones with darker zones). These points correspond to: Hilla, Suleimaniya, Saladin, Tal Afar, Ninawa, Kerbala, and Erbil. In the experiments, the software correctly classifies the refugees areas compared to the official map of the UNHCR. Figure 10 shows the classification results of the areas with points related to fights with artillery and tanks based on Figure 8. These points correspond to the following cities: Ramadi, Bagdad, Kirkuk, Al-Hawija, Border Al-Kaim, Ambar, and Rawa. The software correctly classifies this event in these locations.
4.5 Discussion

Figure 9: Classification of refugees areas in Iraq: a) Duhok, b) Hila, c) Sulem, d) Saladino, e) Tel Afar, f) Ninaua, g) Kerbala, and h) Erbil.
4.5 Discussion

Figure 10: Classification of fights with artillery and tanks areas in Iraq: a) Ramadi, b) Bagdad, c) Kirkuk, d) Al-Hawija, e) Border Al-Kaim, f) Ambar, and g) Rawa.
5. Deployment and Feedback

During the deployment phase, a software was created to classify the areas of Iraq related to the events obtained with the Decision Trees algorithm, for refugees and combat events with artillery and tanks. The software was built with Python 2.7.12 and the user interface was created with the TKinter library.

Figure 11 presents the use case diagram of this software. The use cases are described as follows: 1) run classifier: the data scientist creates a classification model with the decision trees algorithm; 2) evaluate classifier: the data scientist evaluates the classification model by means of cross validation; 3) input longitude and latitude: the end user inputs in the graphical user interface the latitude and longitude of Iraq that he/she wishes to classify; 4) read the model for classification: the algorithm processes the input longitude and latitude values; 5) obtain the classification: the software obtains the classification of the area. A video shows the software in action.\[6]

![Use case diagram](https://vimeo.com/268047670)

Figure 11: Use cases diagram.

6. Conclusions and Future Work

In this research work we applied data science to discover violence-related issues in Iraq despite the lack of open governmental data. Specifically we applied the KNN, Naïve Bayes, Decision Trees, and Logistic Regression classification algorithms to discover violence-related social issues in Iraq with open data from GDELT in terms of refugees, humanitarian aid, violent protests, fights with artillery and tanks, and mass killings. The best results were obtained with the Decision Trees algorithm to discover areas with refugee crises and artillery fights. A software prototype was created to show the feasibility of our approach. This software classifies the zones of Iraq with available or unavailable data by using the latitude and longitude values of the area to be studied. The results were compared with official maps. The results are promising when comparing the results of the classifier with these maps.

As future work we expect to extend the analysis to other countries in the Middle East. Also, we are planning to use Apache Spark to process GDELT data in real time via stream processing. In addition, we are working on improving the software interface. Specifically, we want the user interface to show a dynamic map in which the user will be able to make classifications by clicking on an area of interest on the map.

Declaration of Competing Interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

\[6\]https://vimeo.com/268047670
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