SCIENCES SORBONNE UNIVERSITÉ

Business Intelligence and User Modeling

Conflict Prediction

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Contents

1 Introduction

International Conflicts have always been a prized forecasting objective, world organizations, intelligence communities and diplomatic bodies depend on it. The UN peace keeping initiatives use predictions to orient their focus on unstable countries and prevent these conflicts. In order to better protect their assets, States and multinational corporations are reliant on geopolitical forecasts, it is wiser to invest in a country that remains stable. The general public makes use of such information to make decisions on moving prospects.

These predictions are usually produced by political experts. Yet, while they often provide valuable insights into a region or the relationship between two countries, studies suggest that their predictions are on average no better than random guesses. Moreover, the recent change in the nature of available data, with many initiatives providing very detailed and nearly real time datasets on events happening around the world, makes it very hard or impossible for an expert to make forecasts. Therefore automated warning systems must be developed, this raises a question about the predictability of conflicts.

Our goal through this project is to investigate this question by looking at various sources of data, to make analysis, to choose the best features for determining early warning signs and finally propose a model. To achieve this, we have decided to first look at the socio-economic indicators which consist of economic and social time series and find patterns to determine whether a country is likely to enter a war or not. In the second part, we've chosen to exploit the declarations made by leaders at international summits and gatherings.

2 Economic and Social Side

As they say "money is the root of all evil", History is filled with wars fought over economic reasons, whether it's a country whose newly found wealth attracts others or a state in the decline looking for an opportunity to bounce back, economic reasons are powerful incentives for conflicts. The Anglo-Indian Wars (1766-1849) or The Winter War (1939-1940) are perfect examples of this. Another aspect of conflict triggers that we need to consider is the state of the societies we are investigating. In this section, we'd like to dig into the data to answer some queries we have about the relationship between the social and economic situation of a nation and the triggers of conflicts. The questions are listed below:

1. How do conflicts evolve over time? are they periodical? is there a clear geographical tendency?
2. Do economic recessions have an impact on conflicts? If so, which aspect of the economy is has the biggest impact and for what kind of conflicts?
3. Is a diverse state more prone to civil wars?
4. Is there a link between relying too much on natural resources and instability?

Given this information, we have decided to use these economic indicators:

- External debt stocks (% of GNI) : Total external debt stocks to gross national income. Total external debt is debt owed to nonresidents repayable in currency, goods, or services [5].
- Current account balance (% of GDP) : Current account balance is the sum of net exports of goods and services, net primary income, and net secondary income [4].
- Foreign direct investment, net inflows (% of GDP): Foreign direct investment are the net inflows of investment to acquire a lasting management interest (10 percent or more of voting stock) in an enterprise operating in an economy other than that of the investor [6].
- GDP per capita growth (annual %) :Annual percentage growth rate of GDP per capita based on constant local currency [7].

- Inflation, consumer prices (annual %) : Inflation as measured by the consumer price index reflects the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services that may be fixed or changed at specified intervals, such as yearly [8].
- Unemployment, total (% of total labor force) (modeled ILO estimate) : Unemployment refers to the share of the labor force that is without work but available for and seeking employment [13].
- Total natural resources rents (% of GDP) : Total natural resources rents are the sum of oil rents, natural gas rents, coal rents (hard and soft), mineral rents, and forest rents [12].

For the social part, we considered multiple indicators:

- Mortality rate, infant (per 1,000 live births): Infant mortality rate is the number of infants dying before reaching one year of age, per 1,000 live births in a given year [9].
- Corruption: an index offers an annual snapshot of the relative degree of corruption by ranking countries and territories from all over the globe published by transparency international [2].
- Ethnic, Linguistic and Religious Fractionalization: fractionalization scores based on ethnicity, religious and linguistic data directly from the Encyclopedia Britannica lists [1].

To link all of these indicators to conflicts, we used the UCDP/PRIO Armed Conflict Dataset version 19.1, which lists all armed conflicts from 1946 to 2018. It consists mainly on state based conflicts defined as : *" a contested incompatibility that concerns government and/or territory where the use of armed force between two parties, of which at least one is the government of a state, results in at least 25 battle-related deaths in a calendar year"*. We have decided to keep only events that happened after 1960. The data set lists 4 kinds of events : internal (between a state and a rebel group), extrasymetric (between a state and a rebel group outside its territory), interstate (two states) and internationalized internal (internal but with foreign states interference). There is also a distinction between a minor conflict and a war. For a more detailed definition see [10].
We've also took into account the influence of neighboring countries, to do so we used a borders data-set [3]. The Final data set contains : 13329 rows.

2.1 Datawarehouse

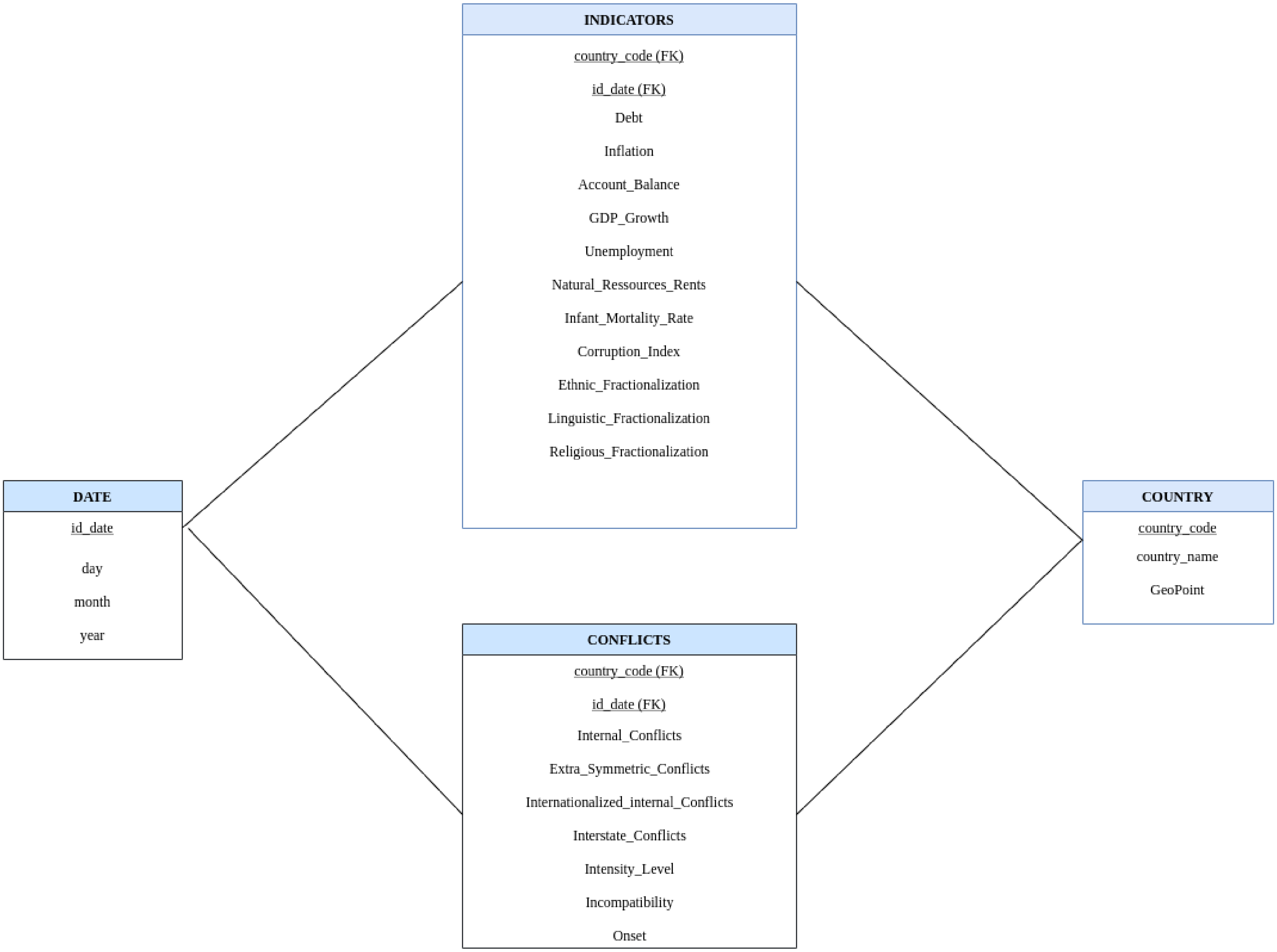


Figure 1: Fact constellation schema

2.1.1 Data warehouse logical data model

Country(country_code, country_name, GeoPoint)

Date(id_date, day, month, year)

Indicators(country_code*, id_date*, Debt, Inflation, Account_Balance, GDP_Growth, Unemployment, Natural_Ressources_Rents, Infant_Mortality_Rate, Corruption_Index, Ethnic_Fractionalization, Liguistic_Fractionalization, Religious_Fractionalization)

Conflicts(country_code*, id_date*, Internal_Conflicts, Extra_Symmetric_Conflicts, Internationalized_Internal_Conflicts, Interstate_Conflicts, Intensity_Level, Incompatibility, Onset)

2.2 Analysis

Before trying to design a model for prediction, we must investigate the relationships between our various data. In this section, we will do so by answering the questions mentioned above.

2.2.1 Question 1 : Evolution of Conflicts

The first question that comes to mind is the evolution of conflicts through time.

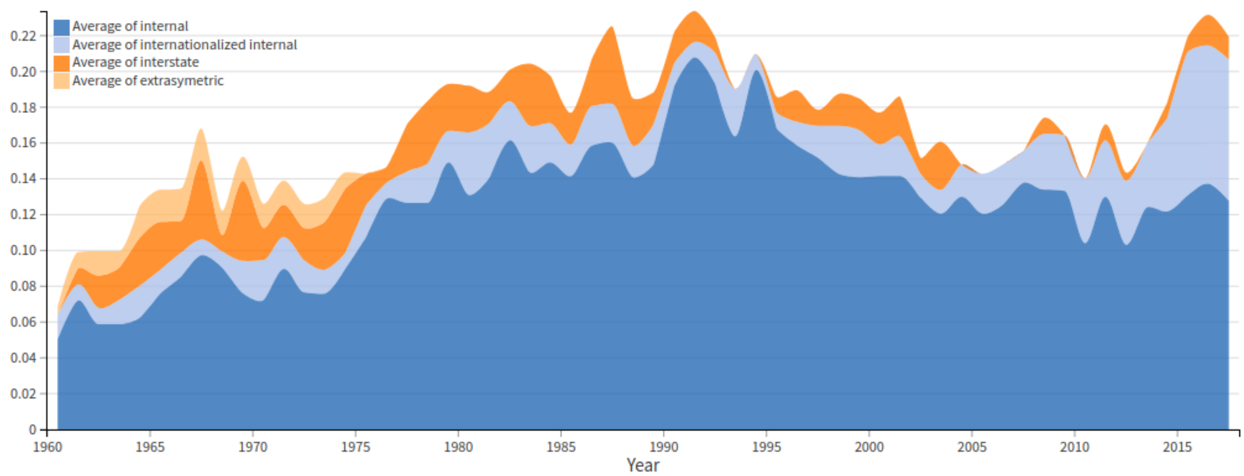


Figure 2: Evolution of conflict types

Figure 2 shows a staked chart of the evolution of conflict types. Overwhelmingly the internal wars or civil wars are the most common type of warfare, closely followed by the internationalized civil wars whose numbers blew up in the last decade. The extrasymmetric kind is only present before 1975. we can also note the variation in the number of conflicts. They peaked in the 90's due to the number of civil wars and also in the 2010's due to the increase in proxy wars. Perhaps certain periods were more favorable for the apparition of conflicts, but there is no clear periodicity here.

To identify the underlying periodic patterns, we transformed the time series into the frequency domain. Afterwards we computed the periodogram. All the features showed the dominant frequency to have a period of one year ie : there is no pattern that repeats itself. The only interesting exceptions are the onset of wars and the onset of conflicts, shown in figure 3.

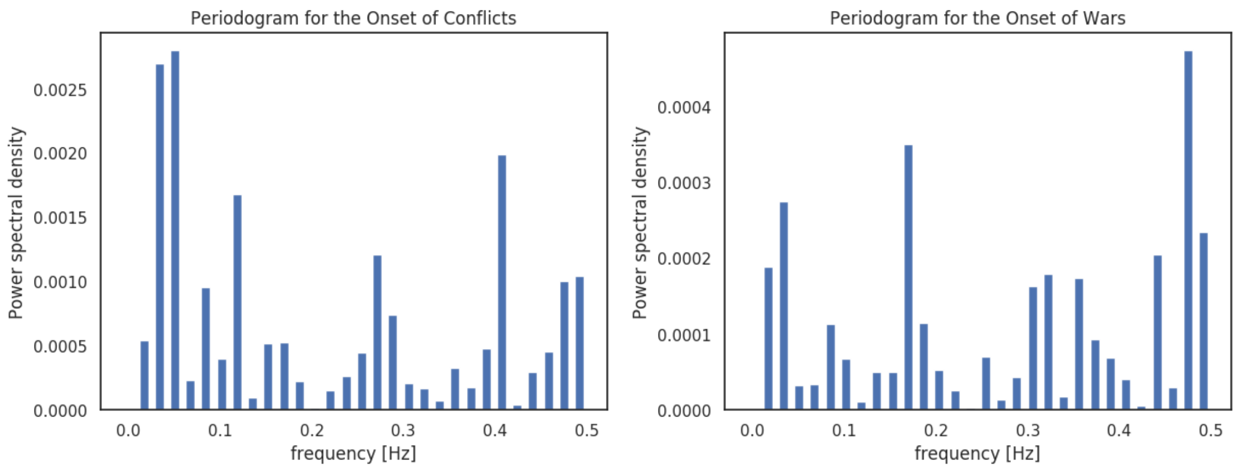


Figure 3: Periodograms for the Onset of Conflicts and Wars in Particular

The most present frequencies for the onset of conflicts have periods of approximately 20 and 2 years, We can see why in figure 4, the number of new conflicts peak every 2, 20 or 30 years. It's not as clear as the periodicity of the new wars, the periodogram indicates the dominant cyclical behavior to have a period of 2 to 6 years. In figure 4, new wars emerge in blocks of 2 to 6 years wide, sometimes taking longer. This means that the emergence of wars are to a degree periodical.

Figure 4: Plot of the new Conflicts (emergence) and new Wars (War emergence) by Year

We also notice the tendency of new wars to be less frequent. To have a better understanding of the distribution of conflict severity, We have plotted in figure 5, the conflicts broken down to minor conflict and war. There is a decrease of 25% in the stake of wars in present day conflicts.

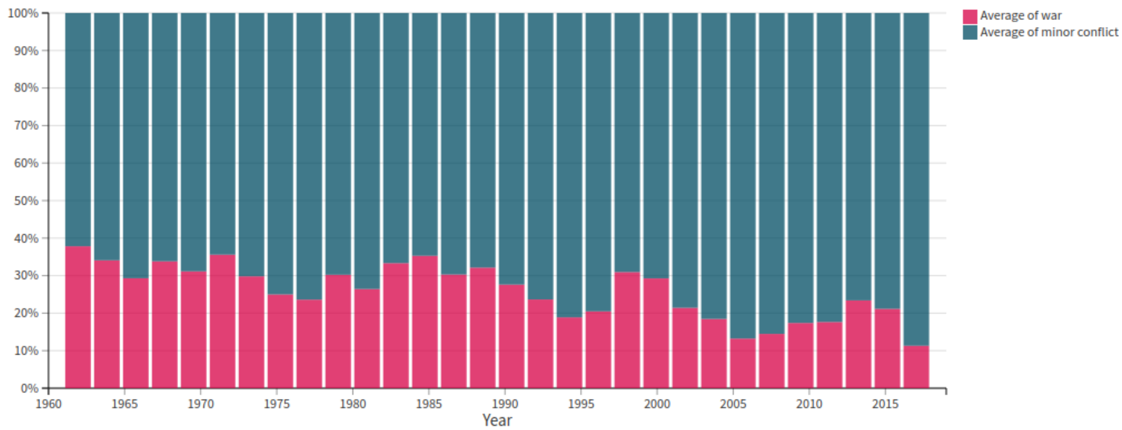


Figure 5: Staked histogram of conflicts broken down to minor conflicts and wars

We compute the auto-correlation and the partial auto-correlation for the average number of wars by year, to see how the time series is correlated with itself.

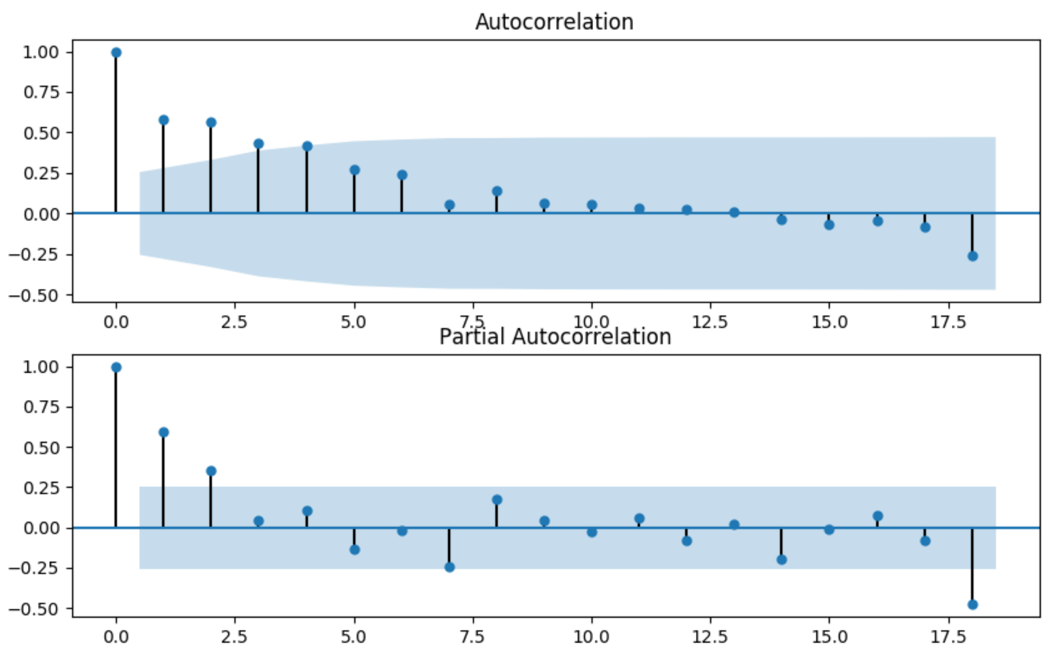


Figure 6: Auto-correlation and partial Auto-correlation

The partial auto-correlation gives us an insight on which previous years affects the current one. The previous two years are the ones that affect the most the current average wars. There is also a negative correlation with the version lagged by 18 years.

Another way to visualize the data is regionally. In figure 7, whole regions don't seem to be affected, the only case for it is the middle east and not in its entirety, it could be that the influence of the neighborhood is greater than that of the region.

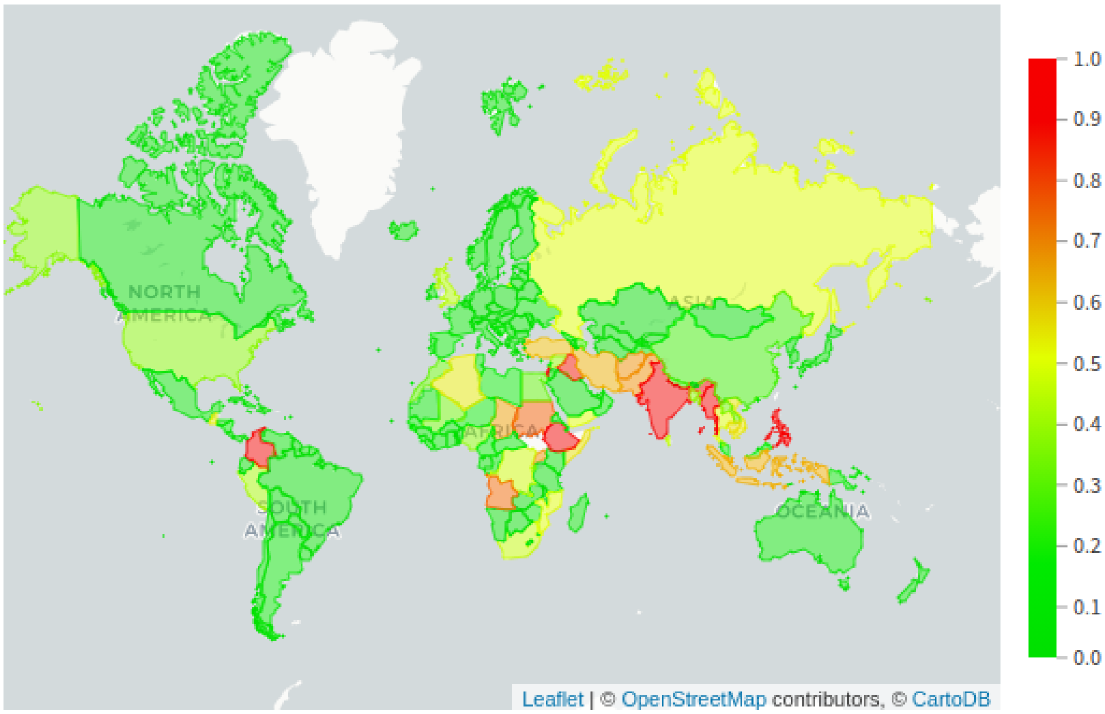


Figure 7: Map showing percentage of conflicted years from 1960 to 2018

In figure 8, we use a bubble map plot, were the size of a bubble indicates the percentage of conflicted years a country has had and the color indicates the percentage of years that its neighbors were in turmoil. The regions most at war all abide by our assumption but lonely states don't always influence the stability of the regions, as is the case for Colombia for example.

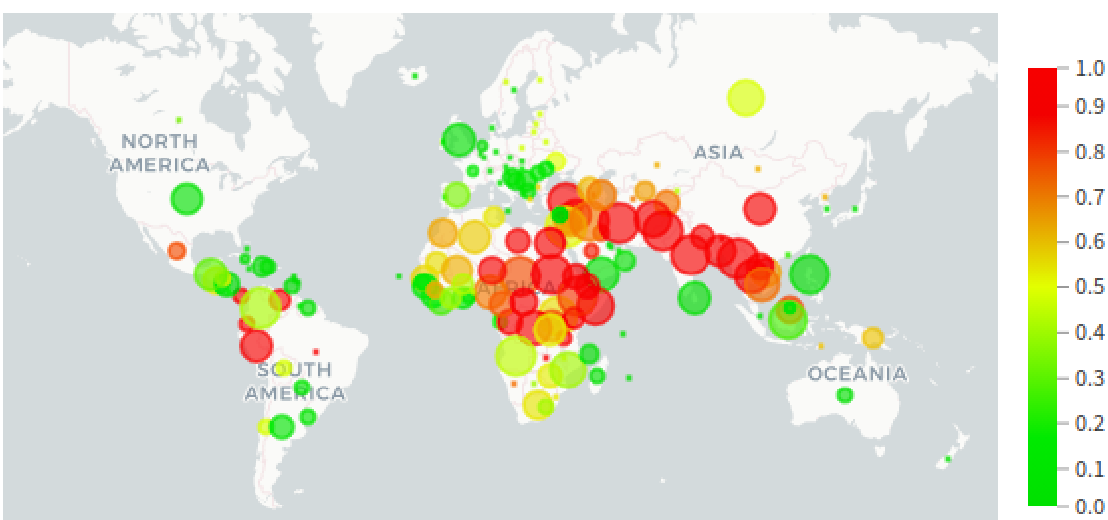


Figure 8: Relation between the conflicts (size) and the neighbors at war (color)

2.2.2 Question 2 : Economic Recessions

What interests us here is how the aggravation of a nation's economic states will influence its stability. Our first hypothesis is that a sudden decay in the economic state worldwide is a recipe for violence. To do this, we will examine how the economic indicators (Debt, GDP, unemployment, etc) affect the state of wars in the world.

Granger Causality

We have a multivariate time series, we cannot simply use the Pearson's correlation because the current conflict state can be a function of past values of other variables. That is why we resort to using the Granger Causality test, which determines how a times series influences another.

The more a change in a time series X triggers a change in a second time series Y, the more the Granger causality approaches 1. The maximum number of lags for this computation was set to 5, meaning that we look to the past 5 years.

In the next figure, we present the Granger causality measurement between the economic indicators and the conflict indicators by year for the whole world.

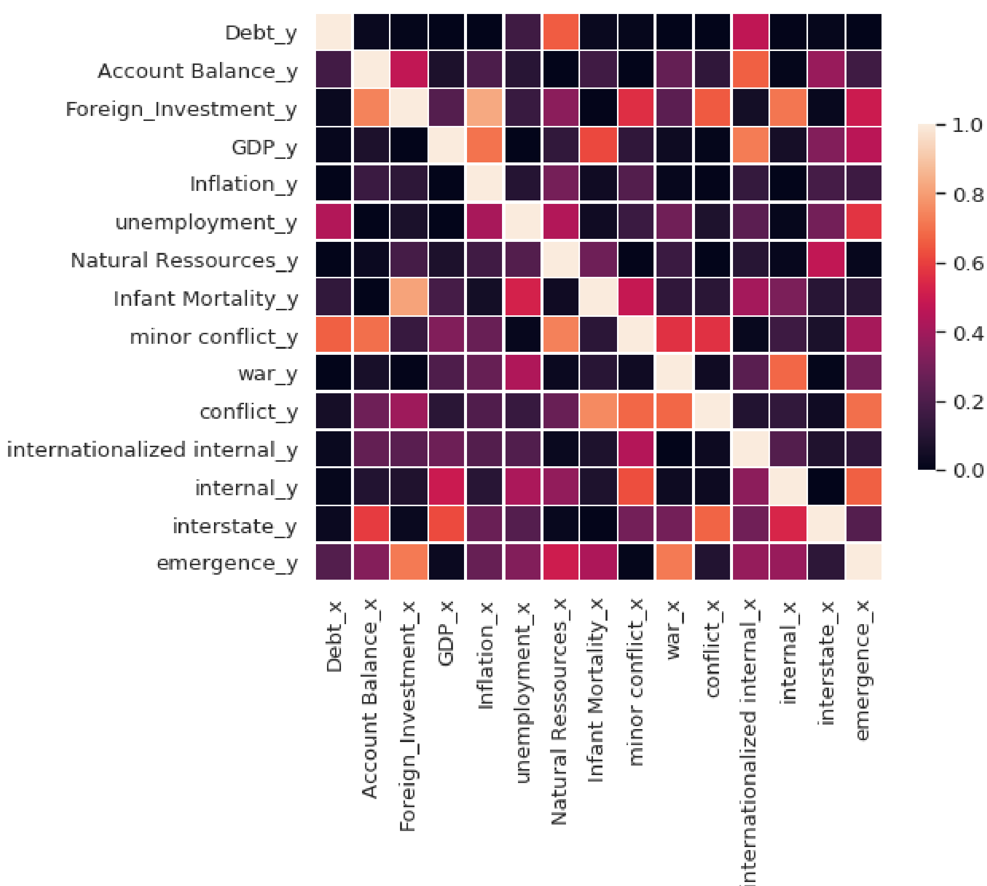
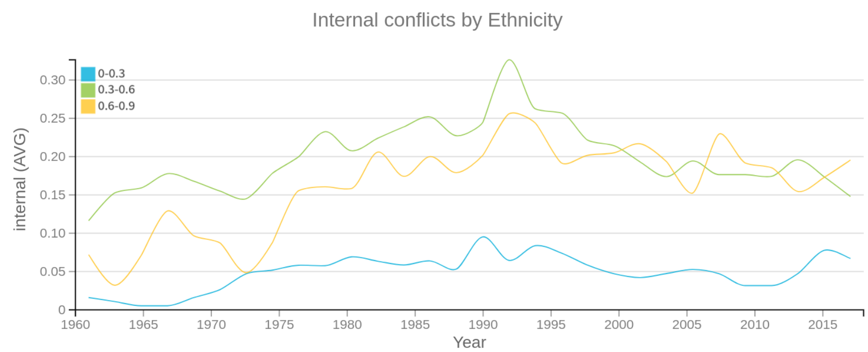


Figure 9: Granger causality measurements for economic indicators and conflicts, X influences Y.

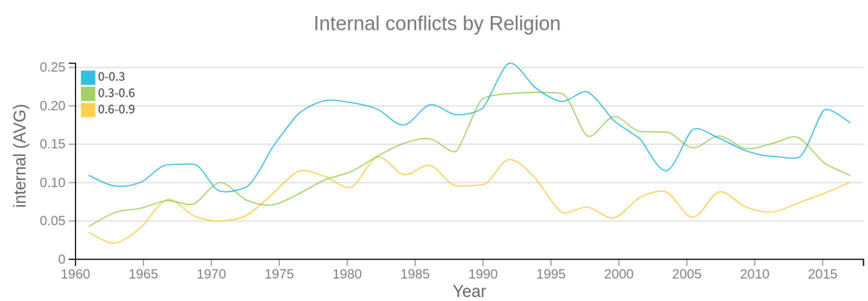
There are many conclusions that we can draw from this measurement. Firstly, the minor conflicts are strongly affected by the debt, the account balance and the Natural resources rents. The conflicts in general are strongly influenced by the infant mortality rates which is an indicator that poverty triggers conflicts in general. The interstate conflicts are triggered by the GDP and the Account balance. There is also a strong link between the foreign direct investments and the onset or "emergence" of new conflicts. These observations seem to validate our hypothesis. We can therefore conclude that the economy has an impact on the conflicts, but different aspects of the economy link to different kinds of warfare.

2.2.3 Question 3 : Diversity and civil wars

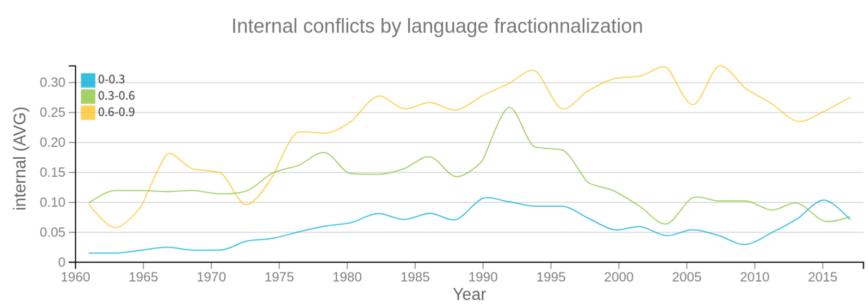
When we think about civil wars, we usually associate it with a fractured society, made up of groups ethnically and religiously different. We want to investigate this claim by using three kinds of diversity indexes : ethnic, religious and linguistic. The higher these indexes are, the more divided a country is. In figure 10, we look at the internal conflicts by year for the three levels of diversity.



(a) Ethnically



(b) Religiously



(c) Linguistically

Figure 10: The internal conflicts each type of fractionalization

We can see that our assumptions were not founded. For the ethnic index, the less diverse countries (0-0.3) are the least affected, but the most diverse ones (0.6-0.9) are not necessarily more prone to civil conflicts than the moderately diverse countries(0.3-0.6).
For the religious diversity, the results are not as we thought either, the more diverse countries seem to have less internal conflicts, while the minimally diverse ones (0-0.3) seem to be the most affected.
Finally, for the linguistic diversity, our assumptions were correct, the more languages a country has, the more it will be subject to internal turmoil. The reason for this is maybe that the language is a very strong binder between populations and not sharing a common language stops communication and favors isolation.
In conclusion, it's not as simple as we thought, diversity in general is not synonym with civil conflicts. However certain aspects of diversity seem to favor civil conflicts.

2.2.4 Question 4 : Natural resources and instability

Another common thought about conflicts is that countries with a lot natural resources are less stable, due to other nations wanting to get control over them, an example of this is Iraq or the Kasai region in Congo. In the next figure, we separated countries whose percentage of revenue coming from natural resources rents didn't exceed 10% of their GDP and the ones who do, we plotted the mean number of conflicts for each group in a given year. For example, on average France gets 0.1% of its revenue from natural resources rents, for Venezuela, it's around 20%.

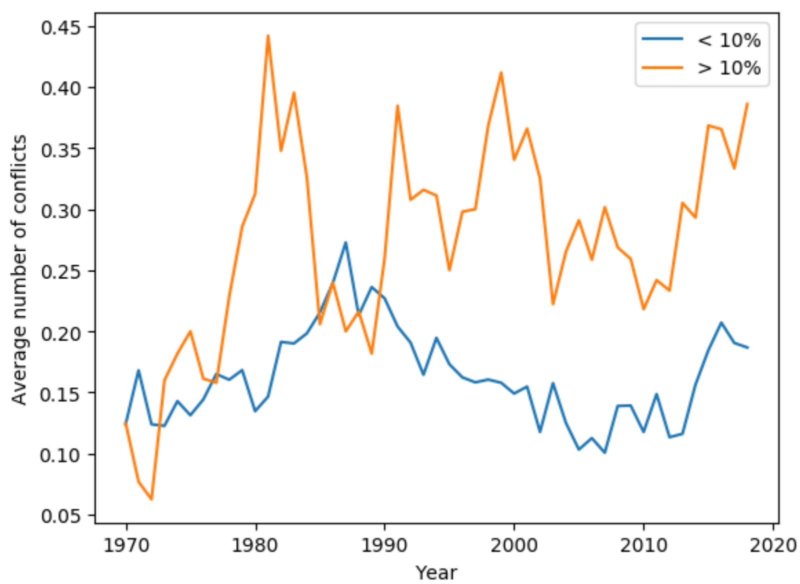


Figure 11: Mean number of conflicts in a year depending on natural resources

There is a clear difference between the two types of economies. Regardless of the year, the countries whose natural resources rents are over 10% of their GDP have significantly more conflicts then the ones with less than 10%. The curve for the ones with more than 10% fluctuates much more, which seem to indicate that these countries seem to change frequently, meaning that they are much more unstable. Our observations still hold if we only consider the major conflicts.

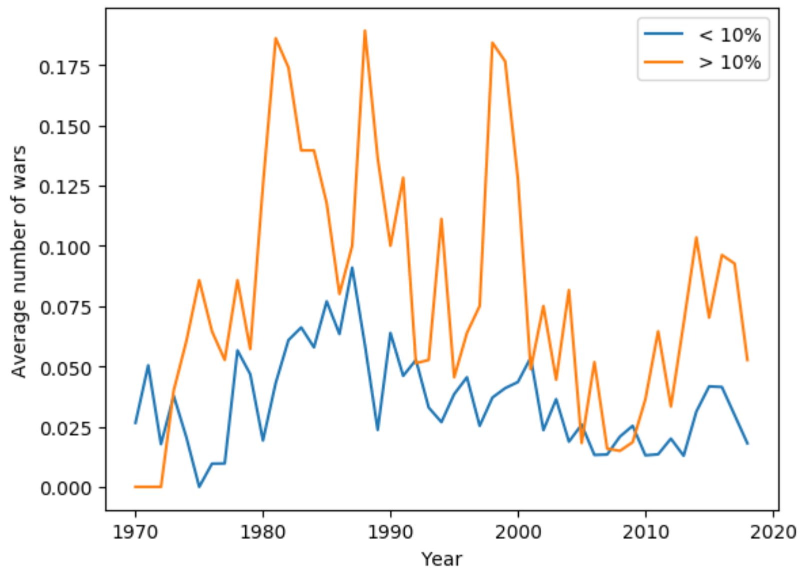


Figure 12: Mean number of wars in a year depending on natural resources

We can see that the situation is the same, the ones with more than 10% are much more unstable. With all of these observations, we can conclude that the more a country's economy is dependent on its natural resources, the more unstable it gets.

2.3 Learning models and prediction

We will consider two aspects of conflicts prediction, the first one will be at the world scale, then we will look at each country separately and make more precise predictions.

2.3.1 Vector auto-regression

To be able to take into account a multivariate time series we have to use vector auto-regression model. A vector auto-regression (VAR) is a stochastic process model used to capture the linear inter-dependencies among multiple time series. VAR models generalize the univariate auto-regressive model (AR model) by allowing for more than one evolving variable. All variables in a VAR enter the model in the same way: each variable has an equation explaining its evolution based on its own lagged values, the lagged values of the other model variables, and an error term. VAR modeling does not require as much knowledge about the forces influencing a variable as do structural models with simultaneous equations: The only prior knowledge required is a list of variables which can be hypothesized to affect each other intertemporally.
Before running this model we have to :

- Check that the time series are stationary by using the **Dickey-Fuller Test** and differentiating them until they become stationary.
- Select the optimal number of lags by applying the model and selecting the order that gives the lowest 'AIC', 'BIC', 'FPE' and 'HQIC' scores.
- Train the model and check for Serial Correlation of Residuals (Errors) using Durbin Watson Statistic: If there is any correlation left in the residuals, then, there is some pattern in the time series that is still left to be explained by the model, which means that there is room for improvement.
- Do the forecasting.

We needed to differentiate the time series one time before reaching stationarity. We determined the optimal number of lags to be 3. The Serial Correlation of Residuals (Errors) using the Durbin Watson Statistic gave scores of 2 for every variable, which is a good evaluation. After applying the model to predict the next 3 years, we present the results in the next figure.

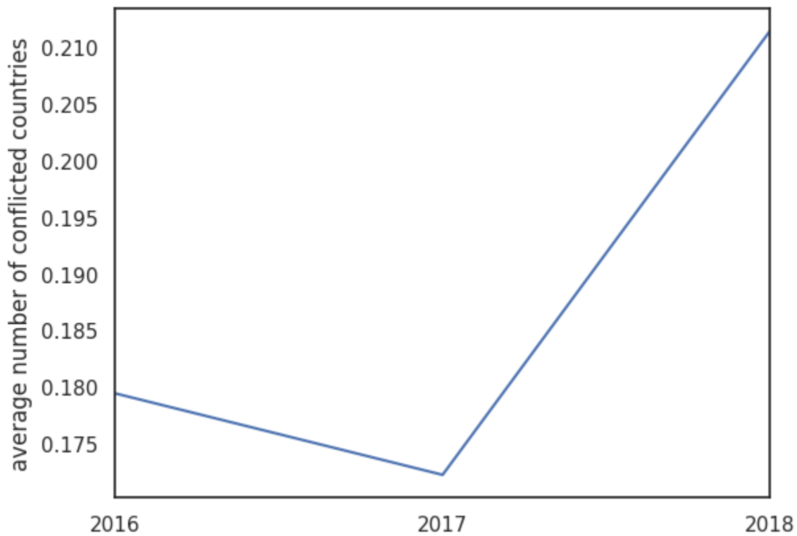


Figure 13: Prediction of the mean number conflicts in the world for the years 2016, 2017 and 2018

The model predicts that in 2018, the number of conflicts will jump by 3%, which is equivalent to 6 more conflicts in the world. We have to stress out the fact that this model is based on aggregated data by year i.e. the model only predicts the average number of conflicts in the entire world, not for a particular country. To do that, we need to use a classification algorithm.

2.3.2 Classification

Our goal here is to determine what country will have a new conflict (minor or major) in the near future. We computed a five year projection by adding variables that indicate if a country is going to be in a conflict in the next five years. We did an 80-20 split on the data and tried multiple models: Logistic Regression, Random Forest, K nearest neighbors, MLP. Because the target variable is unbalanced (the new conflicts are rare events), for the evaluation, we used the F-1 score.

the random forest model is the best on our data, the specifications of the model is given below.

Algorithm	Random forest classification
Number of trees	100
Max trees depth	15
Min samples per leaf	1
Min samples to split	3

The performance of the algorithm is shown in the next figure.

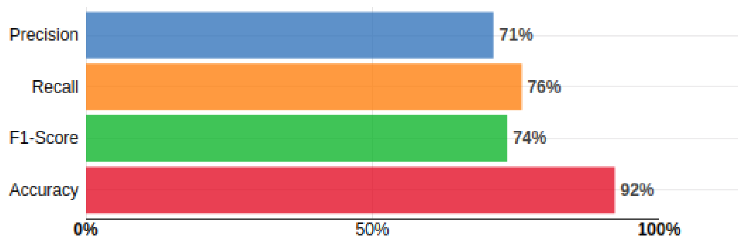


Figure 14: The performance of the random forest model for the prediction of new conflicts

We can see that the model performs fairly well with an F1 score of 74%. In figure 15, we look at what features the model uses to classify.

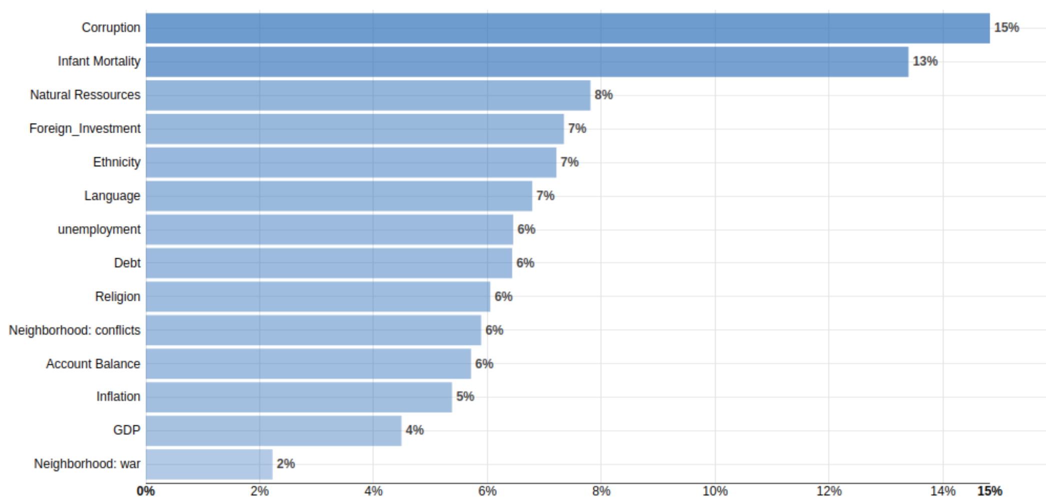


Figure 15: Importance of the features for our model

The most influential features are the Corruption, the infant mortality rate and the Natural resources rents. This means that the model's predictions are based on regime type (corruption) and poverty (Infant mortality) and dependence on resources (Natural resources).

Finally, we feed the data from the latest years (2018 and 2019) to the model to see what country in the world will enter in a new conflict in the next five years (2019-2024). We represent the results in the map below.

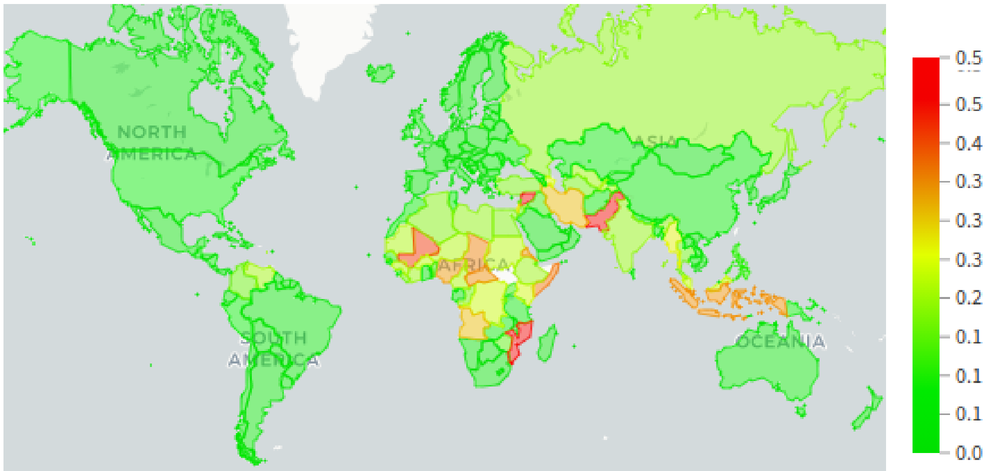


Figure 16: Probability of each country to have a new conflict in the years 2019-2024

The predictions are surprising. Pakistan, which is relatively stable, has a high probability of having a new conflict in the near future. Indonesia, which isn't the first country that comes to mind when thinking about unstable countries is likely to experience a conflict. Other countries that have a history of instability like Mali, Syria and Mozambique seem to be facing a new war or a new minor conflict in the next 5 years. Iran, which has recently been under an immense stress from sanctions and the recent political atmosphere, has a relatively high probability of entering in a new conflict.

3 Political Side

Among the six principal organs of the United Nations,the United Nations Security Council (UNSC) is undoubtedly the most significant. It is charged with the primary responsibility of the maintenance of international peace and security. The Council meets on emerging crises or on matters of significant geopolitical tensions. Studying these debates therefore gives insights into developments of historical importance.
The dataset used in this section allows to trace all public UNSC debates over a 23 year period from 1995 until 2017. Overall, the dataset covers $\sim$ 4400 meetings and includes $\sim$ 65000 speech contributions. The corpus is available here [11].
In this section, we use descriptive statistics and natural language processing to address the following questions:

1. How are the speeches distributed by topic? By country?
2. Can we detect the tension periods by analysing the speeches?
3. Are conflicts discussed of before they happen? does the sentiment change?
4. Are some topics disproportionately talked about? Are the priorities of members different?

3.1 Datawarehouse

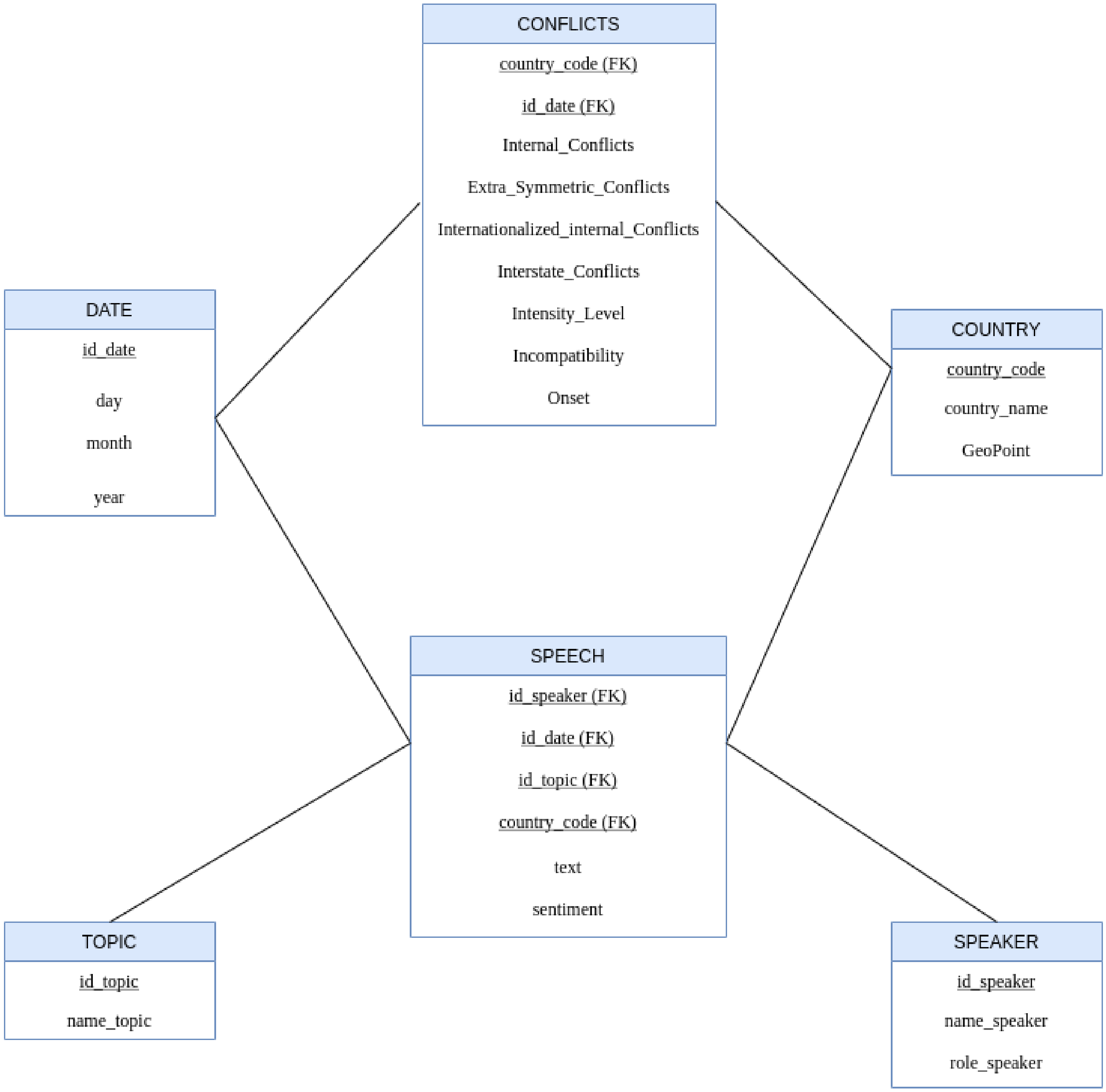


Figure 17: Fact constellation schema

3.1.1 Data warehouse logical data model

Country(<u>country_code</u>, country_name, GeoPoint)

Speaker(<u>id_speaker</u>, name_speaker, role_speaker)

Topic(<u>id_topic</u>, name_topic)

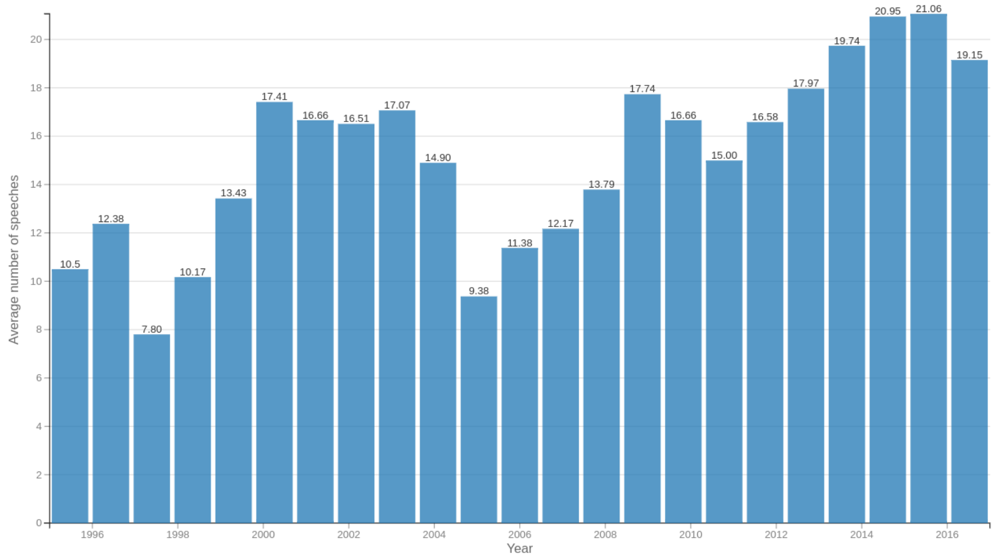
Date(<u>id_date</u>, day, month, year)

Speech(id_speaker*, id_date*, id_topic*, country_code*, text, sentiment)

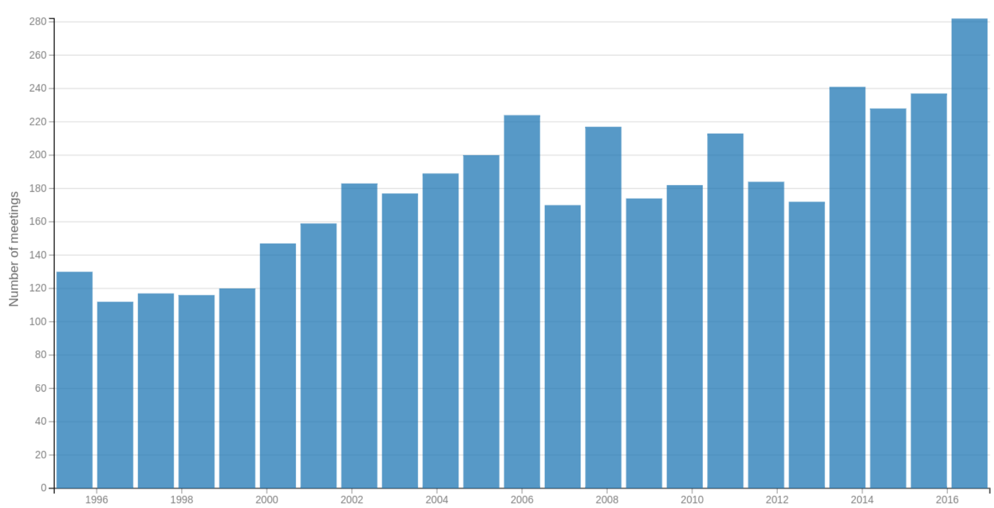
Conflicts(country_code*, id_date*, Internal_Conflicts, Extra_Symmetric_Conflicts, Internationalized_Internal_Conflicts, Interstate_Conflicts, Intensity_Level, Incompatibility, Onset)

3.2 Question 1: Distribution of the speeches

Figure 18 shows how the meetings and the speeches distribute over the years. The number of meetings per year increased over time as well as the number of speeches per meeting, this can be explained by the fact that the period starting in 2000 includes the wars in Afghanistan, Iraq and the Israeli–Palestinian conflict. In particular, one can notice a peak around the Iraq war in 2003. Another possible explanation is the fact that states address new global challenges and therefore, new topics have emerged over time.



(a) Average number of speeches per meeting



(b) Number of meetings per year

Figure 18: Meetings and speeches over time

The UNSC consists of 15 members, of which five are permanent: The United States of America, the United Kingdom, France, Russia and China. As can be seen in figure 19, the permanent members are the top 5 speakers, It should also be noted that UN representatives speak almost as often as the 5 permanent members.

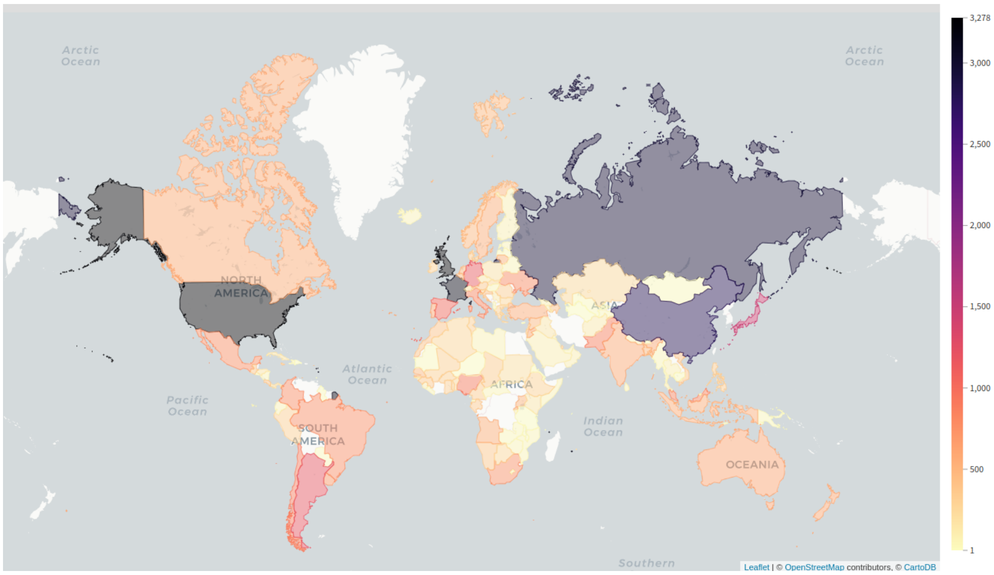


Figure 19: Map showing the number of speeches per country

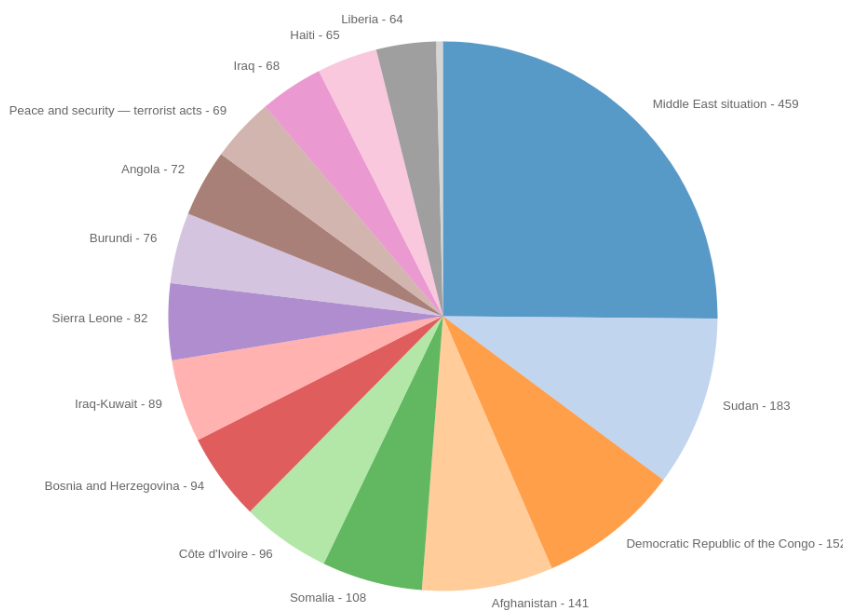


Figure 20: Distribution of topics

Figure 20 shows the 15 most discussed topics in UNSC debates. Almost a quarter of the speeches focus on the situation in the Middle East, which is not surprising given the events that took place there during the 2000s. The other subjects seem to be of equal importance for the UNSC.

3.3 Question 2: Periods of tension using Sentiment analysis

The only relevant speakers in the UNSC are the five permanent members and the UN secretary general. The other countries are not always present and they have less to no power at all when it comes to decisions. For this reason, to determine the periods of tension, we will only look at the five permanent members plus the UN. In the next figure, we count the number of speeches by country from 1995 to 2017. Here, it is

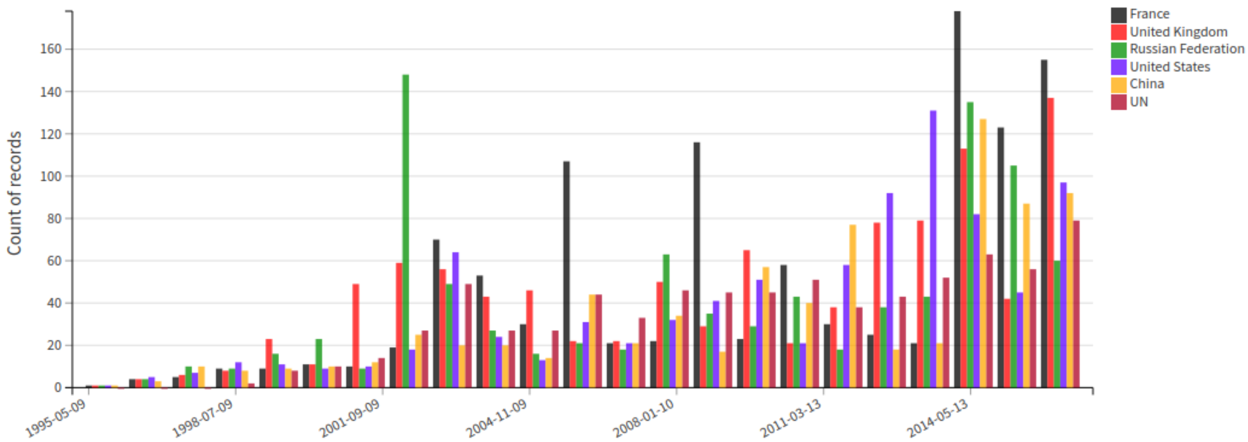


Figure 21: Number of speeches for the most important members of the UNSC

much easier to see the very critical periods. Since 2001, the number of speeches increased by a significant amount. We can already see the periods of tensions, there are peaks every time major events happen, the Iraq invasion in 2003, the libyan, syrian and other revolutions in arab countries, and the terrorist events of the 2010's.

Now, we will use the Sentiment Analysis tool provided by Dataiku to attribute a sentiment, positive or negative to a speech. In the next figure, we plotted the sentiments of the speeches.

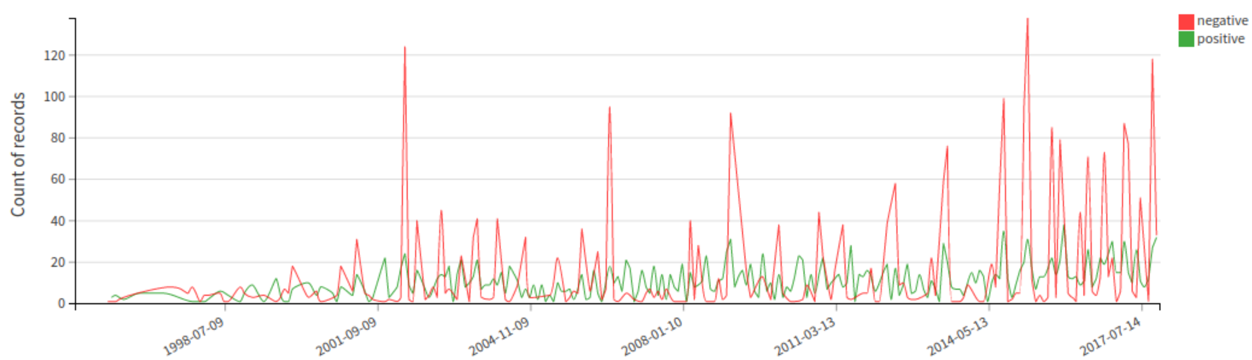


Figure 22: Sentiment of the declarations from 1995 to 2017

The number of positive declarations is much smaller and does not vary very much. On the other hand, the negative speeches vary a lot, there are many very high peaks in negative declarations and they coincide with major event (Iraq in 2003, the Israel–Hezbollah War in 2006, etc ...). This permits us to determine periods of tension just by analyzing the peaks of negative declarations to the UNSC.

3.4 Question 3 : Are conflicts discussed of before they happen?

Obviously, an unforeseen event, like a terrorist attack, can't be mentioned prior to its occurrence. However, for other conflicts that were planned before, they are discussed vividly during the security council's meetings. To illustrate this, we will take two examples of wars and see how the declarations were before the event.

Iraq Invasion

The invasion phase began on March 19^{th} 2003 (air) and March 20^{th} 2003(ground) and lasted just over one month. In figure 23, we look at the dates around the invasion. There is a peak in the number of negative

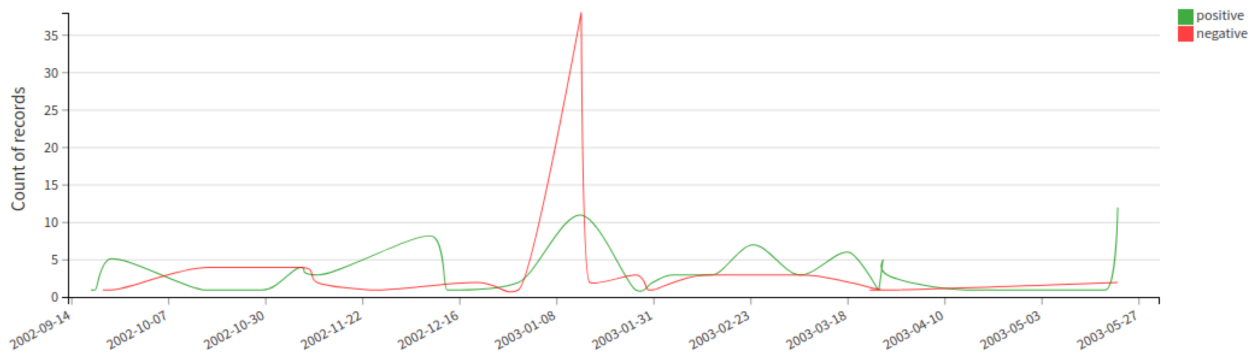


Figure 23: Declarations before the war in Iraq

declarations approximately two months before the event, in January 2003. It is safe to say that for this example, without looking at the content of the speeches and only analyzing their sentiment, we have been able to foresee a major event happening.

The Israel-Hezbollah War

The 2006 Israel-Hezbollah War is a 34-day military conflict in Lebanon, Northern Israel and the Golan Heights. It started on July, 12^{th} 2006. As for the past example, we present the data at the dates surrounding the event.

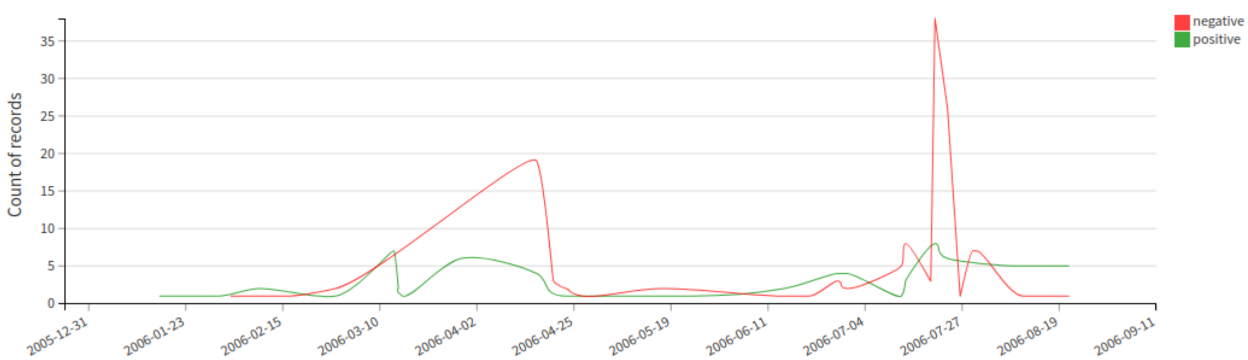


Figure 24: Declarations before the Israel-Hezbollah War

Here it is not as clear as previously. There is a peak after the event and there is another one a few months before, but there is no major peak in the negative declarations right before the event. We cannot conclude that the peak that occurred months before was necessarily about that war.

The conclusion to this analysis is that the predictability of the conflicts using sentiment analysis depends on how the war came to be. If it was planned before but had to be discussed in UN, we can foresee it. However, for sudden and abrupt events, there is nothing in the publicly available diplomatic declarations that allows us to predict them.

3.5 Question 4: Priorities of each member

To answer this question, we generated word clouds, which are rather pleasant ways to look at the term frequencies in a text. We applied the lemmatization process on the declarations and got rid of the stop words.

Firstly, we selected the 30 most frequent words in all the declarations. We obtained the word cloud shown below. The Israeli–Palestinian conflict seem to have the biggest importance, there are mentions of other

Figure 25: Word Cloud for the entire corpus

wars like Iraq and Syria.

We also decided to show how different the priorities of two major super powers (The United States and Russia) are.

(a) Russian Federation

(b) United States of America

Figure 26: Comparison of the important terms

The key difference between the two nations is that each one cites more the conflicts that it is actively engaged in. The rest of the terms are quite similar and it's normal, these are debates, meaning that, if one member mentions an issue, the others have to respond to it. It results in using similar language.

3.6 Learning models and prediction

Our goal here is to use the sentiment analysis calculated previously to perform a regression on the average number of conflicts. We use a five year projection i.e. the model uses actual information to predict the state of the world within the next 5 years. Using an aggregated version of the dataset limits greatly the performances of the model, but we've managed to get a descent enough model using Random Forests of 100 trees and a max depth of 13. The Mean Average Percentage Error is of 10.4%.
We fed the last row of the data set (2017) to our model and obtained the following result:

- The average number of countries in a conflict (major or minor) from 2017 to 2022, will be 19.74%. Which represents a decrease of 3% compared to 2016.

4 Conclusion

Throughout this project, we explored the many intricacies of conflict outbreaks around the world. We analyzed the problem geographically, historically, using past information about a nation's economic and social state. We also examined how the speech patterns and sentiment of the declarations made by diplomats permit us to determine the state of the world in the near future. We made insightful predictions at the country level for the next 5 years, which can be useful for world organisations and multinational corporations.
Our subject remains very much open, there are many paths that could be taken to improve our work. More advanced machine learning architectures could be used, Recurrent neural networks for the first part of the project, Word embeddings for the natural language processing part. We can also consider the financial aspect of war by using data sources on arms deals.

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