Visual and Predictive Analytics on Singapore News: Experiments on GDELT, Wikipedia, and ^STI

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Abstract. The open-source Global Database of Events, Language, and Tone (GDELT) is the most comprehensive and updated Big Data source of important terms extracted from international news articles. We focus only on GDELT’s Singapore events to better understand the data quality of its news articles, accuracy of its term extraction, and potential for prediction. To test news completeness and validity, we visually compared GDELT (Singapore news articles’ terms from 1979 to 2013) to Wikipedia’s timeline of Singaporean history. To test term extraction accuracy, we visually compared GDELT (CAMEO codes and TABARI system of extraction from Singapore news articles’ text from April to December 2013) to SAS Text Miner’s term and topic extraction. To perform predictive analytics, we propose a novel feature engineering method to transform row-level GDELT from articles to a user-specified temporal resolution. For example, we apply a decision tree using daily counts of feature values from GDELT to predict Singapore stock market’s Straits Times Index (^STI). Of practical interest from the above results is SAS Visual Analytics’ ability to highlight the various impacts of June 2013 Southeast Asian haze and December 2013 Little India riot on Singapore. Although Singapore is unique as a sovereign city-state, a leading financial centre, has strong international influence, and consists of a highly multi-cultural population, the visual and predictive analytics reported here are highly applicable to another country’s GDELT data.

Keywords: GDELT, Big Data, Singapore, Visual Analytics, Predictive Analytics

1 Introduction

The Global Data on Events, Location and Tone (GDELT) provides one of the best opportunities to perform Big Data analytics on news and events [1]. GDELT [2]:

– is freely available and uses a variety of international news sources with daily updates
contains more than 250 million events from 1979 to present
is CAMEO-coded [3], uses TABARI system for events [4], GeoNames for
decoding, and regularly introduces new enhancements to the data

We focus our analytical efforts only on Singapore which is a relatively small
and peaceful country in the world, compared to parts of the Middle East [1] and
Africa [5]. One benefit is that, as authors of this paper, we know recent Sin-
pore's key events well; and another benefit is that we have to experiment with
machine learning (such as building of decision trees) beyond conflict, violence,
or protests using GDELT. Below are 4 questions and our corresponding answers
after performing initial experiments:

1. Can GDELT be used to understand Singapore better? Yes, to a certain
extent. We were able to highlight some key events by exploring different
analytical approaches
2. Is GDELT’s news complete and valid? The news sources are comprehensive,
but not all articles were valid for our analytical objectives
3. Can GDELT’s term extraction be improved? There can be additional in-
sights from using natural language processing, on top of CAMEO codes and
TABARI system
4. Can GDELT be used to predict non-political outcomes? We propose a novel
feature engineering algorithm to transform GDELT into a machine learning
dataset. For experimental purposes, we attempt to naively predict an index
of the Singapore stock market

With reference to 1st and 2nd columns of Figure 1, we retrieved only Sin-
pore GDELT articles using ActionGeo_CountryCode [3]. Next, we extract and
merge key Singapore events (ground truth) from Wikipedia’s Timeline of Sin-
gaporean history, Wikipedia’s List of major crimes in Singapore, BBC Singa-
pore chronology of key events, and TimelinesDB Singapore timeline. Third,
we exported the Straits Times Index (STI) from Yahoo Finance. We chose
STI as target variable, over interest rates/flat resale price index/unemployment
rate/GDP per capita, because it has daily data and it can be slightly influenced
by the previous day’s news.

At 3rd column of Figure 1, we joined articles and key events (1979-2013)
into a 717,124-row dataset if they shared the same date. Next, we crawled the
sourceURL column’s hyperlinks (1 April 2013 to 31 December 2013) using boil-
erplate detection [6]; and managed to extract 30% of URLs (8,498 out of 28,177).
Third, we use DERIVEFEATURES Algorithm (Sub-section 4.1) to engineer

1 How Computers Can Help Us Track Violent Conflicts - Includ-
ing Right Now in Syria, http://themonkeycage.org/2013/07/09/
how-computers-can-help-us-track-violent-conflicts-including-right-now-in-syria/
(2013)
2 The Arab Spring and GDELT, http://blog.gdelt.org/2013/10/02/
the-arab-spring-and-gdelt/
3 How to both download and read GDELT using just R, http://blog.gdelt.org/
2013/09/02/how-to-both-download-and-read-gdelt-using-just-r/
features, joined them to STI indices (1988-2013) with a 1-day lag, to create a 68,514-row dataset.

The last 2 columns in Figure 1 show that visual analytics (Section 2) and predictive analytics (Section 4) were performed. The visualizations are possible using SAS Visual Analytics (VA) [7]. VA provides a robust set of business intelligence capabilities and approachable analytics, enabling different types of users to gain insights from any size of data through data visualization and exploratory analysis. Text analytics (Section 3) was performed using SAS Text Miner (TM) [8]. TM discovers information buried in collections of text. By automatically reading text data and delivering algorithms for rigorous, advanced analyses, the solution makes it possible to grasp future trends and act on new opportunities more precisely and with less risk.

2 Data Quality of News Articles

Due to space constraints, Figures 7 to 15 in Appendix provides sufficient background to our choice of bubble plot and geomap analysis to understand GDELT’s data quality.

2.1 Bubble Plot Analysis

Figure 2 shows a bubble plot from April to December 2013 (sourceURL only existed from April 2013) with the following criteria:

1. QuadClass = Material Conflict
2. event = 1 (months where key Singapore events occurred)
3. IsRootEvent = true (GDELT events were parsed in the first paragraph of the news article)

Big bubbles at bottom left or top right ends of the plot are interesting. For example, the highlighted bubble at the bottom left is Singapore news articles in July 2013, upon closer inspection of its sourceURL column, show a large number of news sources linking to the locally well-known Kovan double murder on 12 July 2013.

Visually, we see only a small number of the key Singapore events clearly highlighted in the GDELT GoldsteinScale trends (large bubbles on the extreme ends). This is usually caused by many other less important and random events occurring near or during the duration (7 days before or 14 days after) of the key Singapore events. To test the validity of Singapore GDELT data, a much more detailed list of key Singapore events is required.
2.2 Geomap Analysis

Figure 3 is the geomap of Singapore GDELT articles from December 2013 (1 month only). The highlighted circle corresponds to GDELT articles about the Little India riot which happened on 8 December 2013 - it was the first Singapore riot in over 40 years. This circle does not stand out very much from among others. This shows that not all significant events in Singapore can be clearly discovered using GDELT.

3 Accuracy of Term Extraction

Although TABARI provides effective machine coding using lead sentences, one of its weaknesses is the dependence on details available in the actor dictionaries [4]. We propose the following use of natural language processing to complement machine coding.

From sourceURL column in our Singapore GDELT dataset, we are able to retrieve a set of news articles’ text from April 2013 to December 2013. We perform two text analytics tasks on this set of articles, namely concept link exploration and topic analysis.

Due to space constraints, Tables 1 to 3 are available in the Appendix.
3.1 Concept Link Exploration

Using the concept link exploration feature, we are able to visually analyze which terms co-occur with a given term most frequently in the same document. The terms are visualized using nodes and the thickness of the links represent the degree of co-occurrence.

![Concept link illustrating term association for “Shanmugam”, “government”, and “oil”.

The term “Shanmugam” is one of the most frequent terms in our set of articles. A politician and lawyer, K. Shanmugam is Singapore’s Minister for Foreign Affairs and Minister for Law who frequently gives public speeches and interviews. We study the term “Shanmugam” in more detail using concept link exploration.

Figure 4 illustrates the process and the output. We start by visualizing the top 9 terms that are most closely related to the term “Shanmugam”. Among these terms, we are most interested in the “government” and explore further by expanding it in the concept link graph. It is easy to identify that many terms that have strong co-occurrence with the term “government” are closely related to “oil”. If we explore the term “oil” further, we find terms that are related to Indonesian forest fires which resulted in the Southeast Asian haze - it caused record high levels of air pollution in Singapore of which some days were hazardous to health. Putting them together, it makes sense because Shanmugam was the main politician who gave public statements to the Indonesian government, and requested cooperation and collaboration.

3.2 Topic Analysis

Topic analysis provides ways to define, discover and modify sets of topics contained in the collection of texts. A topic is defined by a set of terms that are
strongly associated with a subset of the text collection. Each document can contain zero, one, or many topics. Terms that are used to describe and define one topic can be used in other topics.

To conduct topic analysis, the number of topics has to be provided as an input parameter. Heuristically, we choose to generate 25, 50, 75 and 100 topics for each run. The results of 25-topic analysis is shown in Appendix’s Table 1. Due to space constraints, we show, among many others, 3 key variables for each topic including the top 5 topic terms, the number of topic terms, and the number of documents in the topic. We provided a few key Singapore events in the “Description” column.

We also conducted similar studies for 50, 75 and 100 topics. Due to space constraints, we omit the detailed results. Across the four sets of results, we have other interesting observations. We are able to identify 8 breaking news from the set of articles as shown in Appendix’s Table 2. The topics on Little India riot and Southeast Asian haze exist in all the four result sets. In addition, we discover more topics common to all four sets of results as shown in Appendix’s Table 3. Even with much increase in the number of topics to be identified, the number of common topics does not increase as much.

We have also performed topic analysis on Singapore GDELT articles in quarters 3 and 4 of 2013 separately. Our results show that the haze topic has gone down from 11th place in quarter 3 to 14th in quarter 4 in terms of number of documents on the topic. Over the same period, it can be observed that the topic of Little India riot emerged quickly to 11th in quarter 4. These results are consistent with the chronological order of the two key Singapore events (Southeast Asian haze in June and Little India riot in December 2013).

4 Potential for Prediction

4.1 Feature Engineering using DeriveFeatures Algorithm

In most transactional datasets, there might be multiple records which correspond to a single temporal unit. To roll up the multiple records on the daily level to have exactly one record per day, we need to create a set of new variables to represent the combination of the original variable and its corresponding values. For example, when working with the GDELT dataset, it is often useful to aggregate the records and find out how many events with the value Material Conflict for the Quadclass variable happened on a given day. Such derived information can be used as an important feature for various data analytics/mining tasks such as predictive modeling and clustering. Unfortunately, it is often tedious and error-prone to generate such features manually. Here, we describe a novel and generic feature engineering method.

Algorithm[1] assumes that the input dataset $s$ contains $n+1$ variables $V_0, \ldots, V_n$ of which $V_0$ is a date/time variable which has $m$ distinct values, and $V_1, \ldots, V_n$ are either nominal or numeric variables. The output dataset $s'$ contains $m$ observations, one for each distinct value of $V_0$. The variables of $s'$ include $V_0$ and
Algorithm 1 DeriveFeatures(s)

Require: A dataset s with variables V₀, . . . , Vₙ of which V₀ is a date/time variable which has m distinct values, and V₁, . . . , Vₙ are either nominal or numeric variables

Ensure: Returns a dataset s’ of m observations, one for each distinct value of V₀, and n sets of variables F₁, . . . , Fₙ

1: s’ ← a dataset containing only the m distinct observations of variable V₀
2: for all i = 1 to n do
3:   if Vᵢ is a nominal variable then
4:     dᵢ ← distinctValues(Vᵢ)
5:     Expand s’ by adding dᵢ + 1 variables Vᵢ₀, . . . , Vᵢₜ
6:     for all j = 0 to dᵢ do
7:       for all v₀ ∈ V₀ do
8:         if j = 0 then
9:           Vᵢ,j(v₀) ← selectCount(v₀, Vᵢ, MissingValue)
10:          else
11:             Vᵢ,j(v₀) ← selectCount(v₀, Vᵢ, vᵢ,j)
12:     else if Vᵢ is a numeric variable then
13:       (b₁, . . . , bₙ) ← binning(Vᵢ, l)
14:       Expand s’ by adding l + 1 variables Vᵢ₀, . . . , Vᵢₙ
15:       for all k = 0 to l do
16:         for all v₀ ∈ V₀ do
17:           if k = 0 then
18:             Vᵢ,k(v₀) ← selectCount(v₀, Vᵢ, MissingValue)
19:           else
20:             Vᵢ,k(v₀) ← selectCountFromBin(v₀, Vᵢ, bₖ)
21: return s’

another n sets of variables F₁, . . . , Fₙ, one set for each of V₁, . . . , Vₙ such that each set contains a set of feature variables derived from their corresponding original variable.

The output dataset s’ is constructed as follows. For each nominal variable Vᵢ (lines 3 to 11), we find out the number of distinct values (dᵢ) for the variable in the input dataset (line 4) and create dᵢ + 1 new variables for the output dataset (line 5). Then the value of the variable for the time/date unit in the output dataset is the number of records with that particular value for the variable for the time/date unit in the input dataset (line 11). We need one extra variable to keep track of the number of records with a missing value for the variable for the time/date unit in the input dataset (line 9). We perform the similar procedures for numeric variables (lines 12 to 20), except that for each of the variables we create l bins by using either equal-interval binning or equal-frequency binning method on the all the values of the variable. Similarly we create l + 1 new variables for the output dataset, one for each bin and the extra one for those records with a missing value. For consistency, we have illustrated the algorithm using the same selection function as the one we used for nominal variables: more specifically, counting the number of records in the corresponding bin for the
given date/time unit in the input file. To create other possibly useful features, summation and averaging can also be used as alternative ways for aggregation.

4.2 Prediction using Decision Tree Algorithm

Due to space constraints, Figure 16 is available in the Appendix.

Figure 5. Decision tree constructed using independent variables of Singapore GDELT articles at day $t$ and target variable of STI adjusted close price at day $t+1$ from 13 June 2013 to 27 June 2013 (2 weeks). The Southeast Asian haze started from 13 June 2013 and subsided around 27 June 2013.

Figure 6. Decision tree constructed using independent variables of Singapore GDELT articles at day $t$ and target variable of STI adjusted close price at day $t+1$ from 8 December 2013 to 22 December 2013 (2 weeks). The Little India riot happened on 8 December 2013 and the media coverage continued approximately for the next 2 weeks.

Figure 5 shows the top-3 variables (out of 1,100), during the haze period, to predict $\hat{\text{STI}}$ adjusted close price are $\text{ActionGeo\_Fullname} = \text{Toa Payoh}$, $\text{ActionGeo\_Fullname} = \text{Singapore}$, and $\text{ActionGeo\_Fullname} = \text{Geylang}$. Toa Payoh and Geylang are in central parts of Singapore. The former had good news coverage on a facial mask distribution drive for its aged population, and the latter...
had a number of reports of haze over its skyline and negative impact on outdoor businesses.

Figure 6 shows the top-3 variables (out of 1,100), during the riot period, to predict \( \hat{STI} \) adjusted close price are \( \text{Actor1CountryCode} = \text{Pakistan} \), \( \text{mainURL} = \text{zeenews.india.com} \), and \( \text{ActionGeo_CountryCode} = \text{Singapore} \). It shows there was extensive news coverage of the Little India riots by Pakistani, Indian, and Singaporean media.

5 Conclusion

From this initial work on Singapore GDELT articles, we now have a better understanding of the GDELT’s data quality, content, and potential applications. We will track GDELT’s developments through its blog\(^4\) and future work could include forecasting using GDELT\(^9\).

References


Appendix

\(^4\) Blogging about GDELT (gdelt.utdallas.edu), http://blog.gdelt.org/
Fig. 7. Line chart showing number of Singapore GDELT articles from 1979-2013, aggregated by month [10]. It makes sense to build visualizations and analyses only from 2006-2013 because there is a significantly larger number of GDELT articles compared to 1979-2005. There are some months within 2006-2013 with much fewer Singapore GDELT articles.
Fig. 8. Line charts, each with different aggregate functions on monthly GoldsteinScale [11], grouped by QuadClass [2] from 2006-2013. Top left - Sum(GoldsteinScale), top right - Count(GoldsteinScale), and bottom - Avg(GoldsteinScale). Each of these aggregations have their own advantages and disadvantages. Sum(GoldsteinScale) gives the ability to observe overall impact for an aggregated time period; however, a time period with several small low-impact events can overshadow a time period with only one big event. Count(GoldsteinScale) shows the number of events but masks their intensity. Avg(GoldsteinScale) allows us to look at the impact for an aggregated time period if the variance in impact between individual events is not large; but it masks big events in a time period if there are other smaller events in the same period. Visual comparisons of all 3 line charts is necessary to evaluate the GoldsteinScale over time. For example, according to GDELT, Singapore is a relatively peaceful country which experiences mostly Verbal Cooperation (such as occurrence of dialogue-based meetings) and Material Cooperation (such as receiving or sending aid). There is an obvious false positive where December 2012 Sum(GoldsteinScale) spike in Material Conflict was the result of international media focus on a crime victim who was flown into Singapore's Mount Elizabeth Hospital for treatment.
Fig. 9. Dual-axis bar line chart where the bar is an occurrence of a key Singapore event (such as it being listed in Wikipedia) with a 1 month window and line is the $\text{Sum} \left( \text{GoldsteinScale} \right)$ on Singapore articles from 2006-2013, with focus on July 2012 to December 2013. This approach can be tedious as it requires manual trend observation; furthermore if the line is separated into 4 lines using QuadClass, it could be more challenging to detect actual trends. Here, no obvious relationship seems to exist between ground truth events and the $\text{GoldsteinScale}$.
Fig. 10. Treemap of EventHierarchy and GoldsteinScale on Singapore GDELT articles from 2006-2013. EventHierarchy consists of EventRootCode (21 distinct values), EventBaseCode (139 distinct values), and EventCode (224 distinct values). Size of each box - Count(GoldsteinScale) and color of each box - Sum(GoldsteinScale). This treemap confirms that news about Singapore are mostly positive.

Fig. 11. Word cloud of EventCode on Singapore GDELT articles from 2006-2013. Size of words - Count(EventCode) and color of words - Sum(GoldsteinScale). Again, this word cloud confirms that news about Singapore are mostly positive.
Fig. 12. Network diagram of names that appear in both Actor1Name and Actor2Name; and their interactions within Singapore GDELT articles from 2006-2013. Most of the actors are current or past Singapore Cabinet ministers (including K. Shanmugam), with a few companies which are part of the "STI."
Fig. 13. Bubble plot on monthly Singapore GDELT articles from 2006-2013. This plot uses all 3 aggregate functions on the GoldsteinScale. $x$-axis - $\text{Avg}(\text{GoldsteinScale})$, $y$-axis - $\text{Sum}(\text{GoldsteinScale})$, size of bubble - $\text{Count}(\text{GoldsteinScale})$, and bubble (represents a particular month from 2006-2013). To interpret any such plot, bubbles that are at the extreme top right (most positive impact) or bottom left (most negative impact) would indicate interesting months. This bubble plot shows that Singapore is a relatively peaceful country as the bubbles mostly occupy the positive parts of both axes.
Fig. 14. Geomap of Singapore GDELT articles from 2006-2013. The size and color of the bubble is dependent on $\text{Sum(GoldsteinScale)}$ in that location. More than 90% of the data points have been filtered out because the locations of those data points was in the center of Singapore (the geographical location captured was simply Singapore and not a specific location within Singapore). Because of the long time period of 8 years, the visualization is too cluttered.

Fig. 15. Geomap of Singapore GDELT articles from November 2013 (1 month only). With reference to the sourceURL column, the highlighted big red bubble is about the Anonymous hacker cyber attack on the Ang Mo Kio town council website - a key Singapore event; and the big blue bubble near Clementi is due to the opening of a new corporate lab by National University of Singapore (NUS) and Keppel Corporation, and various other NUS scholarship launches - not a key Singapore event.
### Table 1. Topic analysis results for 25 topics

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### Table 2. Breaking news identified from the articles

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<tr>
<td>+haze,+fire,indonesia,pollution,sumatra</td>
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<td>tpp,intellectual,wikileaks,+proposal,+property</td>
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### Table 3. Number of common topics

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<td>75</td>
<td>50</td>
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<tr>
<td>#Unique Common Topics</td>
<td>20</td>
<td>18</td>
<td>15</td>
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Fig. 16. Decision tree constructed using advanced growth strategy (p242), independent variables of Singapore GDELT articles at day $t$, and target variable of $\hat{STI}$ adjusted close price at day $t+1$, from 1988-2013 (weekends are excluded - 31% of data). The top-3 variables (out of 1,100) to predict $\hat{STI}$ adjusted close price are $Actor2Geo_Lat = NULL$, $Actor1CountryCode = Netherlands$, and $Actor2EthnicCode = Scottish$. This result does not seem to much sense to us. All decision tree results reported in this paper are limited because it uses only features created from news article a day before and did not use target variable as input variables (such as for forecasting).