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HOW RUGBY MOVED THE MOOD OF NEW ZEALAND

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ABSTRACT

A method for quantifying the collective mood of New Zealanders using mainstream online news content and comments is outlined. Mood is quantified using a text mining pipeline built with the Natural Language Toolkit [1] in Python to measure the sentiment of articles and comments. Intervention analysis is applied to identify statistically significant events which cause a permanent shift in the quantified mood. This technique builds on the well-known ARIMA models, and has been successfully applied in finance to understand the reaction of stock markets to external events. This two-step process shows the impact on the mood of New Zealanders after their national team, the All Blacks, won the 2015 Rugby World Cup (RWC). We find that the All Blacks victory over Australia had a statistically significant, positive impact on the overall mood of New Zealanders.

Keywords: Sentiment, Intervention Analysis, Rugby Union

BACKGROUND

New Zealanders are passionate about rugby union. This oval-ball winter sport contested by 15 players per team over 80 minutes is generally accepted as the nation's number one sport. Since the inaugural tournament in 1987, the Rugby World Cup (RWC) has held every four years between the top international teams. From 1999 the top 20 teams have competed, with the winner of this tournament awarded the Webb Ellis Cup. Anecdotally, there is a suspicion that losses in major sporting events lead to an increase in domestic violence (e.g. [2-5]). However, is the performance in a sporting event sufficient to substantially shift the mood of a nation? More importantly, do positive outcomes correlate with a positive shift in sentiment?

Edmans *et. al.* [6] investigated stock market reactions to sudden changes in investor mood. Their research was motivated by psychological evidence of a strong link between soccer outcomes and mood. Match outcome served as a proxy for mood. Chang *et. al.* [7] used a similar approach exploring National Football League (NFL) game outcomes and the return patterns of NASDAQ firms headquartered geographically near the NFL teams and found that a loss led to lower next-day returns for locally headquartered stocks. That impact was amplified in critical or shock losses. More recently, Gratch *et. al.* [8] used sentiment analysis to examine tweets during the 2014 Soccer World Cup and found that excitement related to expressions of negative emotion. Ljajić *et. al.* [9] explored methods for quantifying sentiment on sports comments alone.

Hong and Skiena [10] explored the relationship between public sentiment regarding team performance and bookmaking odds in the NFL. They found that including sentiment using textual data sourced from four distinct text streams (LiveJournal blogs, RSS blog feeds captured by Spinn3r, Twitter and traditional news media) identified the winner roughly 60% of the time between 2006 and 2008.

Whilst sentiment in sport has been assessed previously as outlined above, the applications have tended to be focused on creating objective proxies based on match results, quantifying the impacts of losses, or improving betting accuracy. Here, we want to assess the collective mood of the nation, independent of any specific reference to sport. To assess the mood of New Zealand, we use proprietary sentiment routine, the Moodalizer [11]. The Moodalizer is a bespoke tool built from publicly-available data sets [12-14]. Reproducing these results is possible by training a similar model with the interfaces discussed by Buitinck *et. al.* [15] and the protocol described at http://scikit-learn.org/stable/tutorial/text_analytics/working_with_text_data.html.

Moodalizer harvests publicly available, mainstream written content from the internet. Natural language processing determines the overall daily sentiment of the nation which is converted into a score using a non-linear transformation. Applying an intervention model enables us to detect any statistically significant shocks in the mood, either positive or negative. The most prevalent headline topics on that date enable us to determine the event that caused the statistically significant shift, thereby enabling a practically significant interpretation of events that influence New Zealand's mood to be assessed.

DATA COLLECTION & PROCESSING

Data collection and scoring is implemented with the Natural Language Toolkit (NLTK) [1]. Articles and reader comments from New Zealand media outlets were extracted by polling RSS feeds and extracting content from the source web pages. Specifically, data from NZ Herald (www.nzherald.co.nz) and Stuff (www.stuff.co.nz) is extracted and utilised. These sites are New Zealand's major news providers.

A sentiment analysis classifier was implemented using training data that combined datasets provided by [12-15]. These labelled documents were processed into shallow text features and fed as both unigrams and bigrams into the model.

The routines for scoring sentiment rely on datasets sourced from movie and product reviews posted on public websites. While the domain is different in our case, the model has proven to be effective at classifying the sentiment for other forms of content that is intended for a general web audience [13]. Chua *et. al.* [16] achieved accuracy of 79% with use of the NLTK to detect sentiment for internet stock message boards.

Post-processed articles and comments are chunked into sections of 10 sentences. Each section is tokenised and scored independently. This allows us to track a document's sentiment as it progresses, which provides richer avenues for analysis.

Articles and comments are processed separately. An article is defined as the content produced by the main author of a webpage, who is a journalist or news reporter. A comment is defined as a third party contribution to that article, often made by a member of the public. Every article may have zero or more comments, often numbering hundreds of comments for notable articles. As a consequence, comments are higher volume and have a general tendency to be negative. More emphasis is placed on articles by giving that syndicated content a higher weight in the routine that combines sentiment from articles and comments. The raw score is then scaled using historical observations to create a score with a mean of approximately 0 and standard deviation of 30. This means that the most likely range for Moodalizer observations is between -60 (predominately negative sentiment) to 60 (predominately positive sentiment). Figure 1 shows the Moodalizer for the period 1st September 2015 to 31st August 2016. A loess function is overlaid.

METHODOLOGY

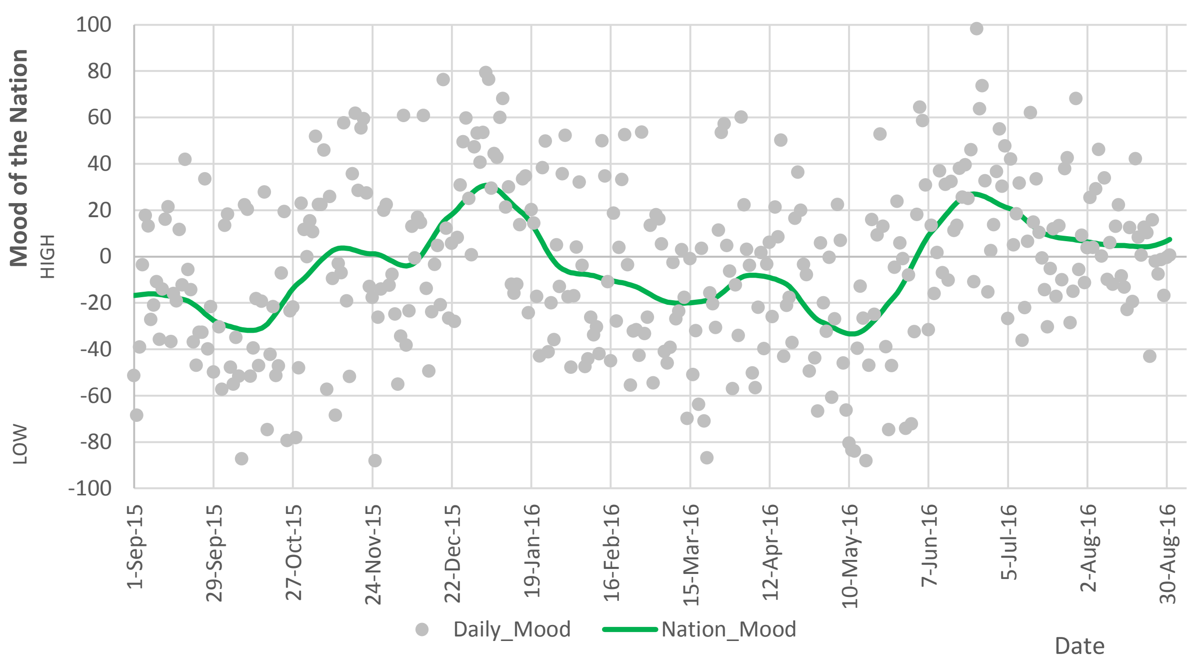
Here we outline our approach for detecting statistically significant shifts in mood observed via mainstream web content.

A key component of the analysis is the extraction of a mid-term trend from the mood time series. We employed a standard seasonal decomposition technique implemented by the 'StatsModels' Python library. The underlying naïve additive model is:

$$Y(t) = T(t) + S(t) + e(t)$$

The seasonal component *S(t)* has a period of seven days, reflecting a weekly cycle in the time series. The residuals *e(t)* represent unexplained noise, which does not exhibit autocorrelation on a scale longer than one week. The trend line *T(t)* shows how the mood evolves when the weekly cycle and short-term noise are removed. It is virtually identical to a rolling average computed over a window of seven days, except that the trend line has a shorter lag time. These three components sum to give the mood time series, *Y(t)*, shown in Figure 1.

Figure 1. Daily Moodalizer with loess function overlaid for 1 September 2015 to 31 August 2016.



Identification of mood-shifting events

Two methods have been developed for identifying the temporal location of mood-shifting events. The first involves examining the slope of the trend line to find regions where the mood shifted significantly in a short period of time (no more than five days). This method cannot be applied to the most recently collected data as it requires the existence of a reliable trend line. However, we find it to be the most reliable method for detecting events older than one week.

Another method which gives provisional information about the most recent events is to examine the mood time series itself for outlying data points. Outliers may be defined as those points lying further than some number of standard deviations from the trend line. The standard deviation itself varies significantly, and should be computed over a rolling window. This method allows potential mood-shifting events to be identified as soon as they occur, but after a week has passed it should be confirmed using the more reliable trend line analysis.

A third method, scanning for events using intervention analysis, did not immediately yield reliable results.

Aggregation of topics from headlines

Where a mood-shifting event has been identified, the headlines from a 7-day window centred on the event are scanned for recurring topics. For the most part this is accomplished using Python's built-in capability for string manipulation, supplemented by some basic features of the Natural Language Toolkit (NLTK), such as word stemming. This allows us to construct a ranked list of headline topics near the mood-shifting event, and infer which topics may have been drivers of mood change.

Intervention analysis

To test the hypothesis that the All Blacks' 2015 RWC tournament success produced a lasting shift in the mood of the nation, we employ a technique called intervention analysis. This technique builds on the well-known autoregressive integrated moving average (ARIMA) models, and has been successfully applied in finance to understand the reaction of stock markets to external events. For events which occurred at a known time in the past, intervention analysis essentially constructs possible response profiles and confirms or refutes these by linear regression. The response profiles themselves are generated by an ARIMA process where the usual white noise input is replaced by a step function or delta function with support at the time of the event. This method naturally incorporates transient and residual effects, possible time lags, and any underlying processes intrinsic to the variable being measured. The 'PyFlux' Python library provides an implementation called ARIMAX [17].

In the case of the RWC final which took place on October 31st 2015, we adopted the intervention model:

$$Y_t = \beta_0 + \omega_0 B I_{t-T} + \frac{\omega_1 B}{1 - 0.9B} I_{t-T} + \frac{1 - \theta_1 B}{1 - \varphi_1 B} a_t$$

where B is the backshift operator ($BX_t = X_{t-1}$), I_t is a step function centered at time 0, a_t is a white noise process, and the Greek letters denote regression coefficients. The first term on the right hand side is just a constant offset, and the second term corresponds to a permanent shift in mood beginning the day after the RWC final. The third term is a transient effect, taking the shape of an initial pulse which decays within a month. The final term is an Autoregressive Moving Average (ARMA) model of order (1,1). The order parameters dictate the number of time lags in the autoregressive (AR) and moving average (MA) terms respectively; the associated regression parameters are φ_1 and θ_1. ARMA models are a special case of the more general ARIMA models, which also incorporate differencing of the time series. We employ the ARMA term to model the stochastic background mood process unrelated to the RWC. The two response functions are illustrated in Figure 2 (note the response functions are not shown to scale).

FEATURES IN THE MOOD DATA

Using the above methods, a number of interesting features are identified in the mood of the nation data which we explore next.

Weekly cycle

Figure 3 indicates that the collective sentiment of New Zealanders tends to be most negative early in the working week, increasing from Thursday onwards as the weekend approaches.

Trend line

Visualization of mood-shifting events is shown in Figure 4. A red line is drawn at the midpoint of each region where a statistically significant slope was detected in the trend line.

The yellow bands represent school holidays. The blue lines are public holidays. The plot also shows 20 bootstraps of the trend line generated by resampling the residuals in the seasonal decomposition.

Figure 2. Intervention analysis illustration for the Rugby World Cup Final, 31 October 2015

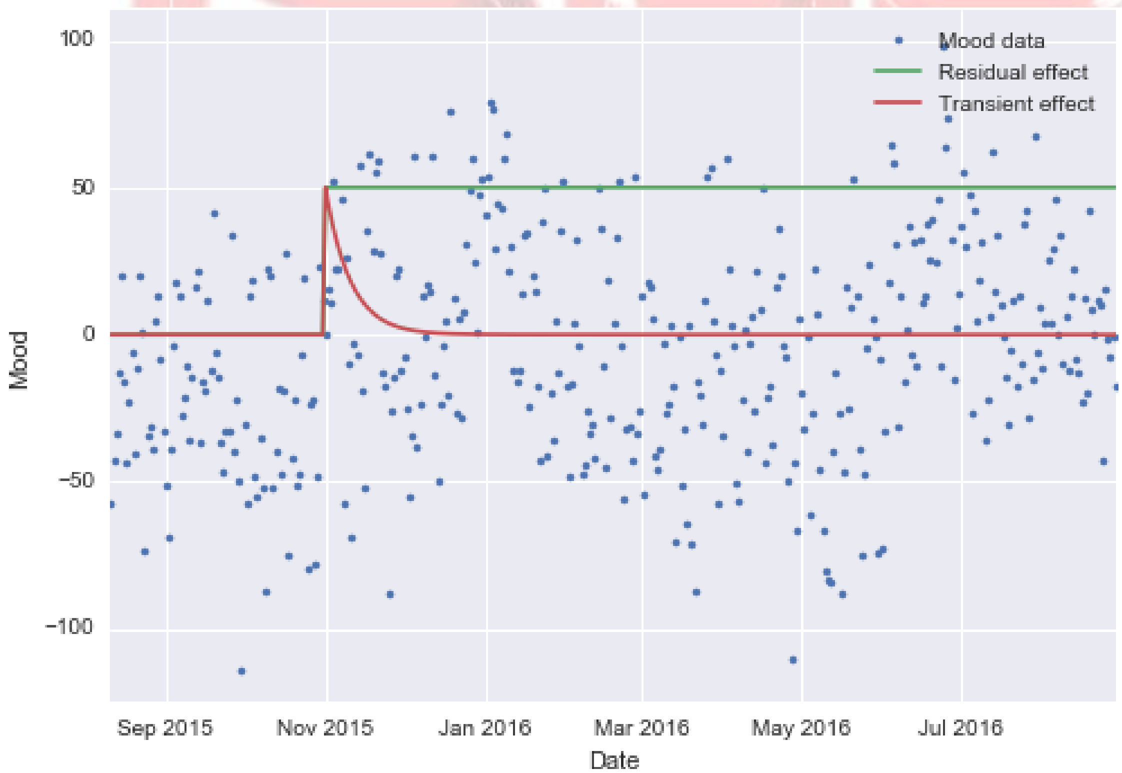


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Figure 3. Weekly mood cycle produced by seasonal decomposition

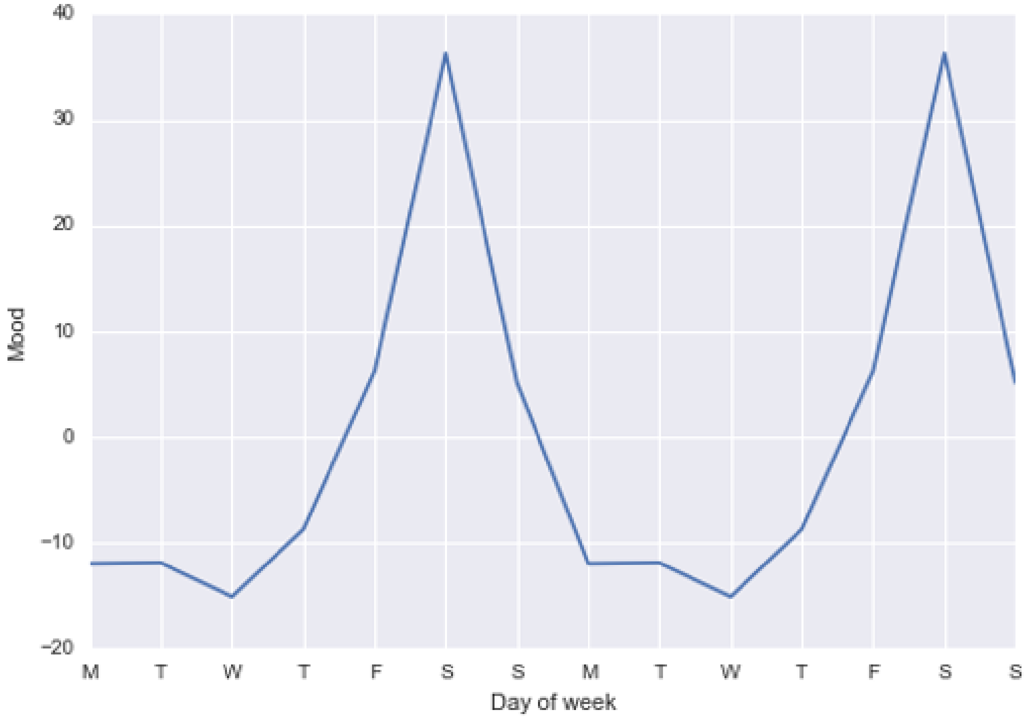

Figure 4. Moodalizer trend line for the period September 2015 to September 2016 with holidays and other statistically significant interventions overlaid

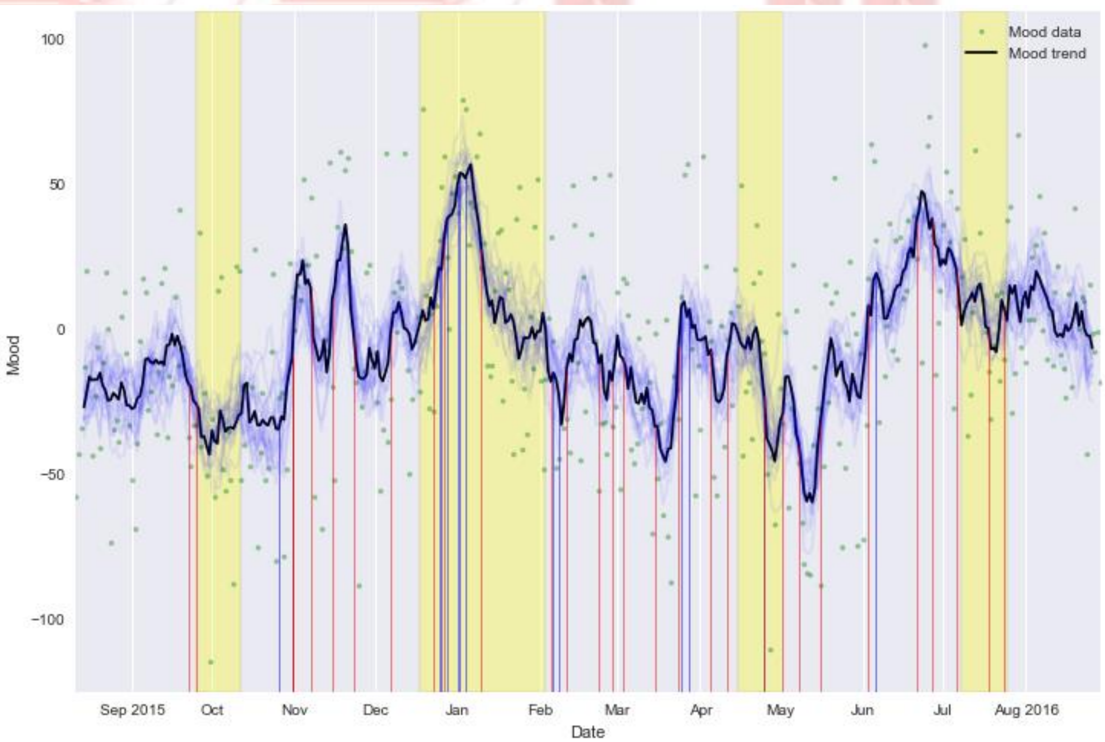

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Table 1: Most prevalent headlines during periods.

Date	Headlines	Direction	Topic
2015-09-22	world, cup	Negative	Rugby World Cup 2015 (NZ beat Argentina 26-16)
2015-09-25	world, cup	Negative	Rugby World Cup 2015 (NZ beat Namibia 58-14)
2015-10-31	world, cup	Positive	Rugby World Cup 2015 (NZ won Final)
2015-11-07	black, recipe	Negative	Black Caps in Australia (Beaten by 208 runs by Australia)
2015-11-23	wellington, attack	Negative	Paris attacks, Jonah Lomu dies (All Black 1994-2002)
2015-12-07	world, christmas	Positive	Christmas, Paris climate change conference
2015-12-23	christmas, year	Positive	Christmas
2015-12-27	christmas, year	Positive	Christmas, cricket
2016-01-10	bowie, david	Negative	Singer-songwriter David Bowie dies
2016-02-05	waitangi, tppa	Negative	NZ signs Trans-pacific partnership agreement
2016-02-11	christchurch, open	Positive	NZ Golf Open build-up (played in Christchurch)
2016-02-28	oscar, super	Positive	Oscars, Super Rugby begins (Rugby Tournament)
2016-03-15	world, wellington	Negative	Wellington council spending, Wellington housing market
2016-03-24	world, easter	Positive	Easter, Brussels attacks
2016-04-05	wellington, panama	Negative	Panama papers, low NZ business confidence
2016-04-25	prince, anzac	Negative	Singer-songwriter Prince dies
2016-05-02	kiwi, league	Positive	Warriors prescription drug scandal
2016-06-03	open, Ali	Positive	French Open, Muhammad Ali dies
2016-06-27	brexit , black	Negative	Britain votes to exit European Union
2016-07-06	house, police	Negative	NZ housing crisis
2016-07-18	attack, police	Negative	Pokemon Go, Baton Rouge attack
2016-07-24	olympics, police	Negative	Russian Olympics doping scandal

Headline topics near mood-shifting events

Table 1 identifies the major headlines and topics identified via intervention analysis and highlighted in Figure 4.

Impact of Rugby World Cup 2015 final

The intervention analysis described above yielded the values in Table 2 for the regression coefficients. As the confidence interval for the constant, ω_0, is positive and does not contain 0 we can state with greater than 95% confidence that the All Blacks' RWC success produced a residual positive shift in the mood of the nation.

Table 2: Coefficients for Intervention Analysis for the days immediately following the final.

Coefficient	Value	95% confidence interval
β_0	-11.7	(-20.4, -3.02)
ω_0	11.1	(1.96, 20.3)
ω_1	0.216	(-0.305, 0.737)
φ_1	0.475	(0.218, 0.731)
θ_1	-0.132	(-0.425, 0.162)

Weather

Initial attempts to correlate mood with NZ-wide temperature data did not reveal a statistically significant effect at a 5% level of significance.

DISCUSSION

This analysis highlights several international, national and sporting events that are perceived to be of national significance. Among these events that correlated with a substantial shift, either positive or negative, were the co-ordinated terrorist attacks on Paris, France on 13th November, 2015. The Trans-Pacific Partnership (TPPA), signed on 4th of February, 2016 caused local unrest. The deaths of singer-songwriters David Bowie and Prince, as well as All Black icon Jonah Lomu, also had a material impact. These results highlight that New Zealand is not purely focused on rugby union and highlights the wider applicability of the Moodalizer. That said, the public perception of relatively poor performances of the All Blacks in pool play of the RWC had a negative impact upon sentiment, particularly the victories against Argentina (26-16) and Namibia (58-14). We hypothesise this reaction was due to the subjective benchmarking of All Black performances against other title contenders, such as Australia. However, when the All Blacks lifted the Webb Ellis Cup at the conclusion of defeating Australia 34-17 in the final to become the first team to defend a Rugby World Cup title, it had a statistically significant, positive impact upon New Zealand's overall sentiment.

CONCLUSION

Not surprisingly, to New Zealand rugby union fans, rugby is a big deal. Previous studies have shown a correlation between sports results and other events. However, we sought to understand if sentimental attachment to the national representative side is sufficient to affect the mood of the nation, by quantifying sentiment for articles and comments from New Zealand's two major news outlets (www.nzherald.co.nz and www.stuff.co.nz). This quantification of sentiment manifests as a proprietary data product, the Moodalizer. Importantly, within this data product we assessed the sentiment across all article types, not just sport.

To test the hypothesis that the All Blacks' World Cup success produced a lasting shift in the mood of the nation, we employed a technique called intervention analysis. This technique builds on the well-known ARIMA models, and has been successfully applied in finance to understand the reaction of stock markets to external events. For events which occurred at a known time in the past, intervention analysis essentially constructs possible response profiles and confirms or refutes these by linear regression.

Our analysis highlighted several international, national and sporting events that were of perceived national significance. Among these events that correlated with a substantial shift in sentiment were: the co-ordinated terrorist attacks on Paris, the signing of the Trans-Pacific Partnership (TPPA) and the death of singer-songwriter David Bowie. These results highlight that New Zealand is not purely focused on rugby union and highlights the wider applicability of the Moodalizer. Most importantly, when the All Blacks beat Australia to win their third Rugby World Cup title, it had a statistically significant, positive impact upon New Zealand's overall sentiment.

Consequently, in a geographically isolated community, such as New Zealand, major sporting achievements have the ability to significantly shift the mood of the nation. Additionally, these result also indicate that other rugby tournaments (Super Rugby) as well as other sporting teams and events (Olympics, Black Caps and NZ Warriors) can have a statistically significant impact on national sentiment which highlights the wider applicability of this approach.

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