Social Media Analysis – RUOK Day

ASSIGNMENT 2

Contents

Introduction

Mental Health is an epidemic, according to the guardian, the world is living in a new age crisis of "monumental suffering" – where if properly addressed, 13.5 million lives could be saved each year (The Guardian, 2019).

Australia is touted as the "second most depressed country in the world", (SciMax, 2017) and in a 2013 report, they were described to be at "the forefront of mental health care innovation" due to their progression towards community-based mental health solutions (OECD, 2013)

Specifically related to community-based care programs, since 2009, the RUOKDay mental health movement began to take flight (RUOK.org, 2019). Originally inspired by Gavin Larkin, a man who lost his father to suicide, Gavin proposed a question to the world, to hopefully protect others from the same anguish he endured.

That question was "Are you okay?".

Data Collection

To begin with, since the goal of the group was to obtain information about a particular trending topic happening out in the world, obtaining tweets via Twitter was deemed a natural solution to this problem.

The main package utilised for data collection was Tweepy. Some investigations were also held using the twarc to gather the "replies of tweets". This led to some interesting reply chain graphs detailed later.

Given the start date of the assignment was only three days prior to RUOK Day itself (12th of September), the window to collect data was limited. Utilising the REST API, tweets were gathered in regards to RUOKDay from the 3rd of September, until the 4th of October, spanning a total of 33 days.

The search queries utilised for producing this analysis were:

- #ruok
- #ruokday
- #ruokday2019
- @ruokday

In order to collect data on RUOKDay, tweets were pulled wherever possible between the dates of 3rd of September and 4th of October (the only time limit imposed, was that of the Twitter API itself). All tweets retrieved were those in the English language, as this was the focus of our analysis. The tweet mode utilised was the "extended" tweet mode, as this allowed the retrieval of the entire, untruncated tweet content.

Our tweet database was routinely updated through weekly queries into csv files, dated with the time the command was triggered to pull additional tweets. These tweets were all placed into a folder for later processing. A total of 24,000 tweets were obtained using this method.

Pre-processing and Data Cleaning

Pandas and numpy packages were used for data cleaning. The most common steps utilised for data cleaning were the removal of strange characters in text fields. Most notably "b'" and single quotation marks surrounding screen_name and full_text fields.

There was an additional exercise undertaken to properly extract location geocodes from tweets. Due to the method used for extraction. Location (or place) geocodes were found embedded in a column along with many other place related information. Each place had a set of four x and y coordinates. The average of these was taken and used as a point estimate for the given place.

The "time" package was used throughout all scripts to help with performance measurement of certain processes. Processes which took significantly longer to run were earmarked for optimisation. Most optimisation-based solutions tended to be exporting data, to allow for quick re-import later on during the process.

In ensuring that our tweet collection gathered over several queries maintained integrity, as part of the re-combination process, duplicates were removed using the tweet Id column. To ensure the most recent data of each tweet was kept (i.e. number of retweets) only the last unique tweet was retained from the removal of duplicates.

A custom list of stopwords was curated to help with sentiment analysis and topic modelling. This was done on an ad-hoc basis as initial analysis revealed words that either didn't make sense (i.e. non UTF-8 characters) or words that didn't add value (i.e. the). This was also combined with the standard list of English stopwords provided by the NLTK package.

Through using the twarc package, reply chains were obtained. This was a timely and difficult process to both construct and run. In the end, the information provided was quite strong, however reply chains were not able to be retrieved for RUOK Day itself. The information still wound up useful for an interesting graph analysis.

Analysis Approach

Upon successful retrieval of all required data, the team needed to make additional decisions relating to the analysis about to be undertaken.

Selection of Lexicon

The VADER and the NRC Emotion Lexicons are applied to help capture the opinions in our collected tweets. Due to the theme of RUOK Day, these relevant tweets could be potentially rich in emotional experiences and sharing. Therefore, other than analysing positive and negative sentiments from these tweets, we also employ another lexicon, NRC, to learn the emotions behind each tweet.

The VADER sentiment analysis is especially designed for determining sentiment expressed in social media. Apart from rating words based on their semantic orientation as either positive and negative, it also considers the effect from lexical features such as capitalisations, conjunctions, degree modifiers, and punctuations when scoring the sentiment. In this study, we look at the compound sentiment scores, which sums up the lexicon ratings of each tweet and normalizes it between -1 (most negative) and 1 (most positive). A compound sentiment score at 0 indicates neutral sentiment.

The NRC Emotion Lexicon developed by the National Research Council of Canada covers over 14,000 words, with each word associated under two sentiments: negative and positive, and eight basic emotions: anger, anticipation, disgust, fear, joy, sadness, surprise and trust. We look at the word-emotion associations part for this study. Each tweet is assigned a score under each of the eight emotions by a ratio of how many words associated with that emotion compared to the total word count of that tweet.

Selection of topic modelling approach

In order to obtain perplexity, and likelihood scores, sklearn was utilised. However, there was additional potential to identify coherence scores to help support identifying the optimal number of topics. To achieve this, the team needed to gather understanding of using the genism topic modelling package to unpack additional diagnostics required to make a robust topic model.

Selection of Graph modelling method

The Networknx graph library was selected as a natural progression from material provided within RMIT held laboratory sessions. This was used in unison with gephi to help further visualise relationships between graph nodes. These two libraries utilised together allowed the team to successfully present account-reply activity in relation to RUOK Day.

Initial Insights

Qualitative Analysis

Account Tweet Distribution

We can see that the distribution of accounts tweeting about RUOKDay shows a long tail. We have a small handful of accounts tweeting the most, and only three accounts have tweeted more than 100 times. Every account in the distribution only appears to tweet a handful of times. Only the top 200 accounts are shown.

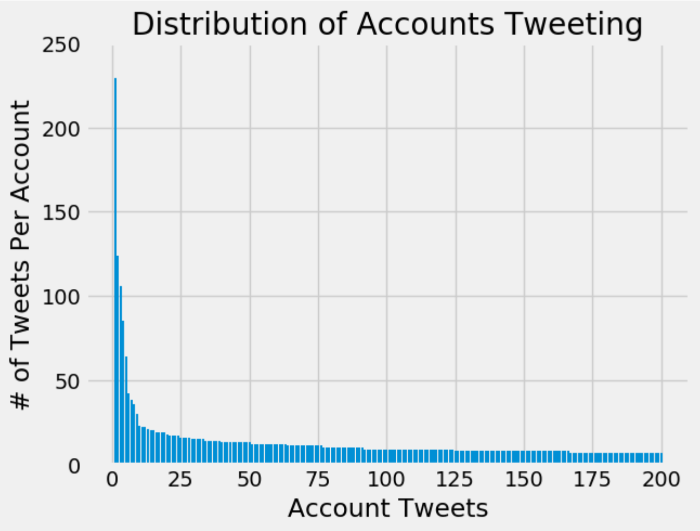


Figure 1

Frequency Graph – Top 10 account tweet metrics

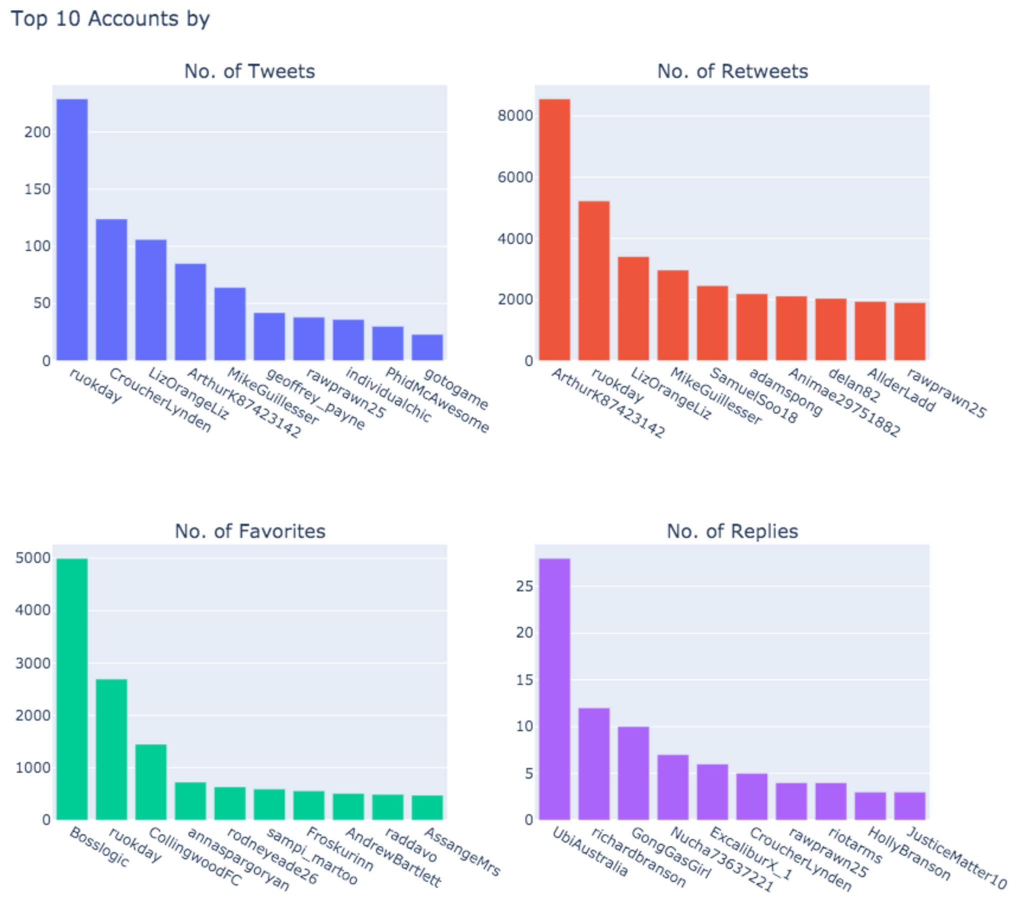


Figure 2

The above graphs provide some interesting insights:

Tweets: As expected, the RUOKDay account has the most tweets on RUOKDay.

Retweets: RUOKDay is second. Another account (ArthurK87432142) has more retweets.

Favorites: RUOKDay is second, however we see some interesting entries (such as Collingwood FC)

Replies: The account with most replies is UbiAustralia, while RUOKDay is only ranked 12th

Frequency Graph – Top 10 location tweet metrics

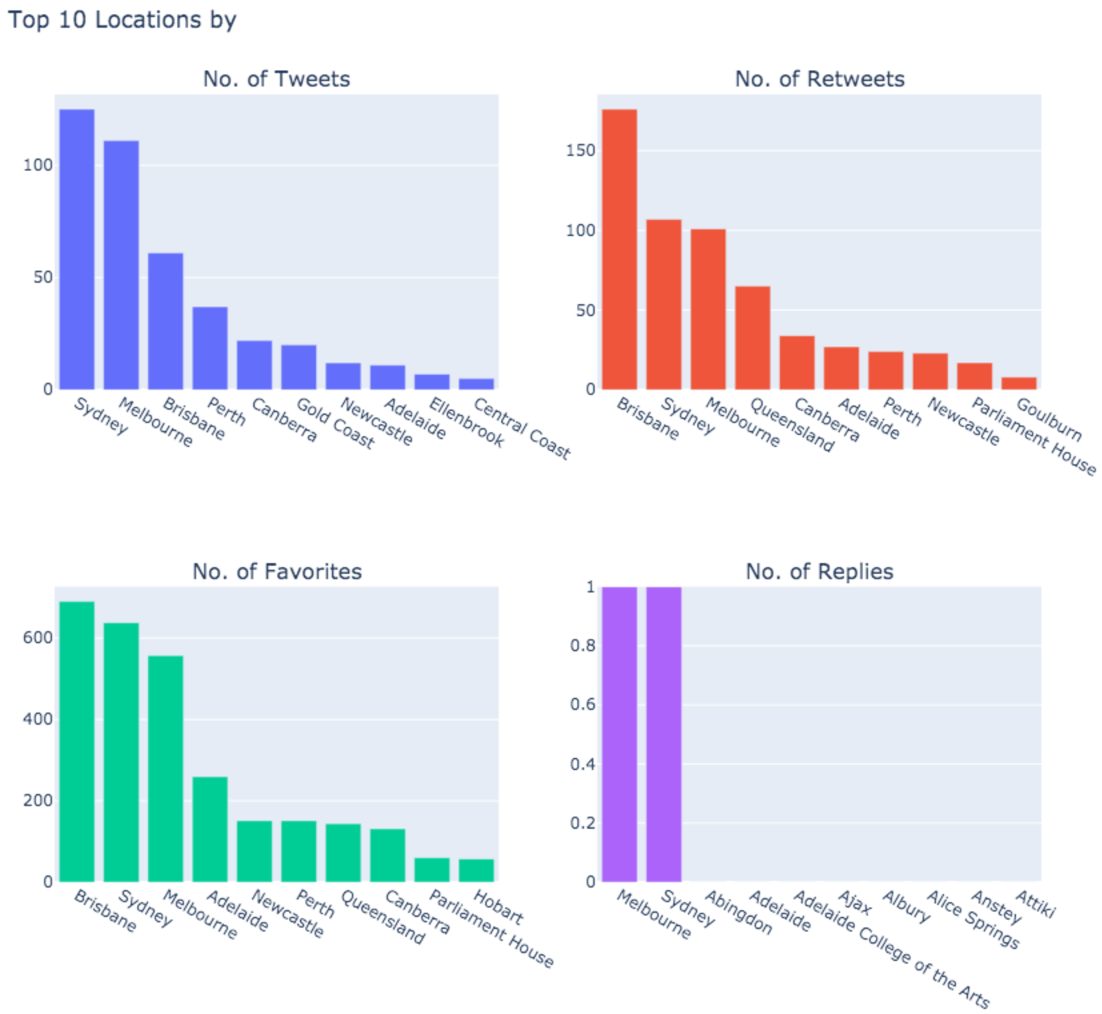


Figure 3

Visible from the above graphs, is that Sydney and Melbourne dominate the total number of tweets, although interestingly enough, Brisbane is the location that has the most number of retweets and favorites associated with tweets. Number of replies in turn does not provide adequate data. This is due to the data sparsity issue of accounts which make their location known, as well as the amount of reply data which was able to be retrieved via the twarc package.

Heat Map – Number of Tweets

As shown in the below heat map (figure 4), even though RUOK Day is originated from Australia in the year 2009, we can see that now after ten years of development, its influence has spread to other parts of the world, with mostly English-speaking countries such as US, UK, and New Zealand, and other countries such as India, Namibia, Nigeria, Papua New Guinea, United Arab Emirates, and Finland.

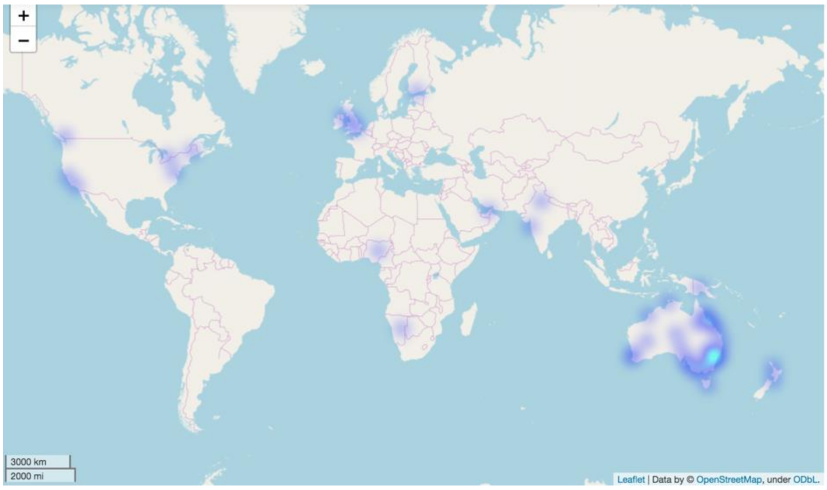


Figure 4

Time Series Analysis

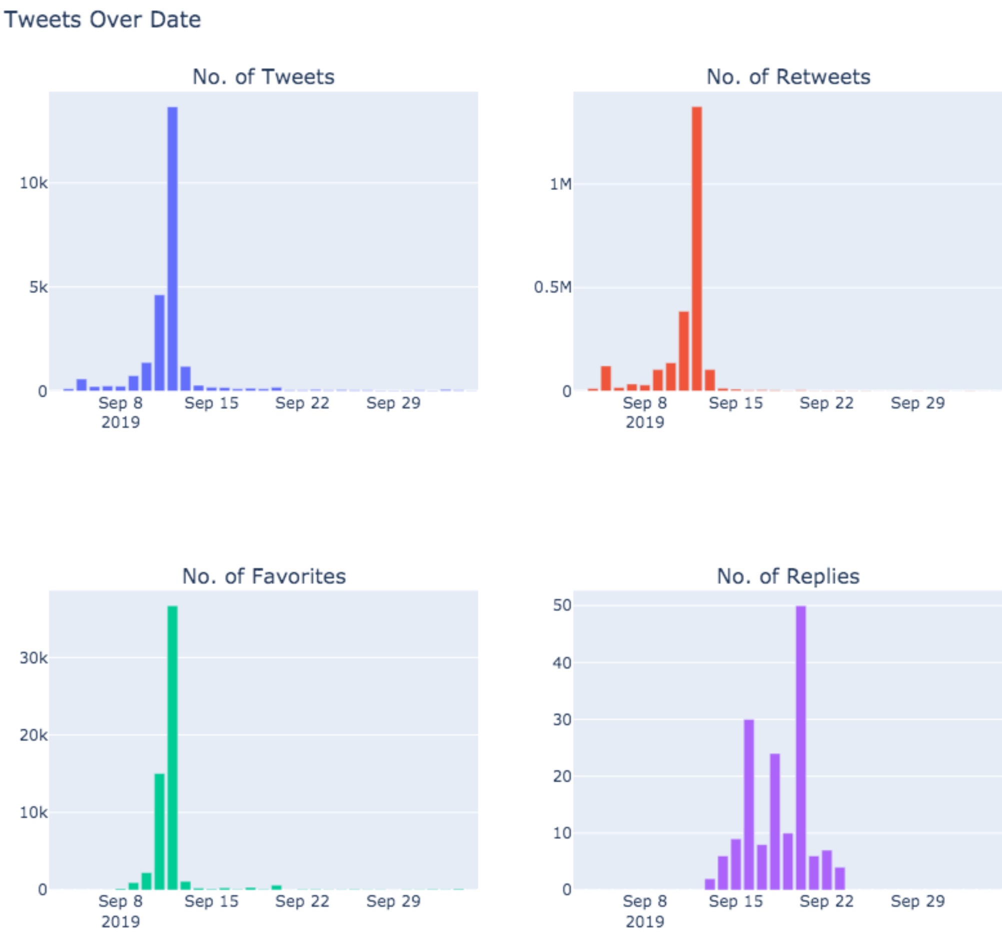


Figure 5

Visible in the above facet graph, is the large peak in activity around September 12 which is the data of RUOKDay. Data was retrieved for all days during the periods shown in the x-axis, however the amount of activity dropped significantly after the day took place.

One finding not to be misinterpreted are the low numbers of replies around September 12. Reply data was only able to be retrieved after this date, so total replies to tweets made on RUOKDay will unfortunately be left unknown, unless manually obtained.

Sentiment Analysis

Types of Sentiment and Emotions

According to the VADER sentiment analysis, the positive sentiment is most common. 66.1% of the tweets are positive. There are almost 5 times more tweets categorized as positive than negative.

Amongst all tweets, the trust emotion dominates, followed by anticipation and joy. The trust emotion could be a sign of people showing support to RUOK Day. The proportions of anger and surprise emotions are relatively low, with similar proportions between 0.0005 and 0.001. The proportion is the ratio of how many words associated with the emotion compared to the total word count, as stated in the "Selection of Lexicon" section above.

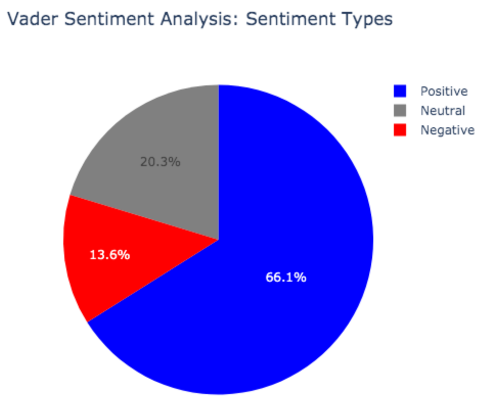


Figure 6

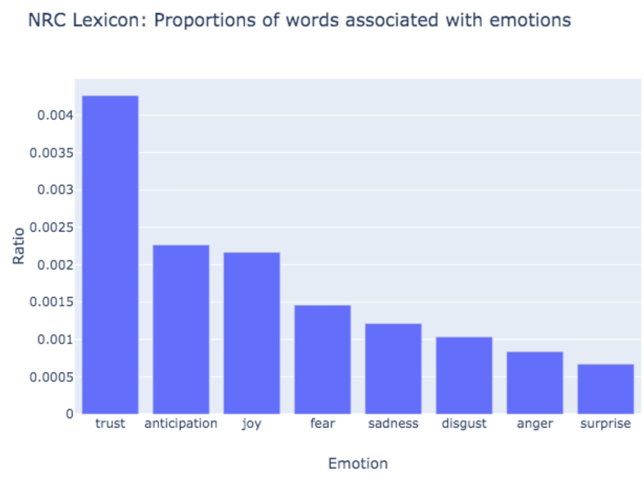


Figure 7

Sentiment and Emotions by Time

Figure 8 shows the trend of average compound sentiment scores grouped by date. Although this sentiment trend fluctuates and slightly goes down, the average scores keep above 0 during a nearly one-month period from 3 Sep to 5 Oct 2019, which again confirms the domination of positive tweets. On the other hand, the trend of average compound sentiment scores grouped by the hour also stays above 0 throughout the day. The sentiment trend picks up from 6 pm and reaches the peak at 9 pm.

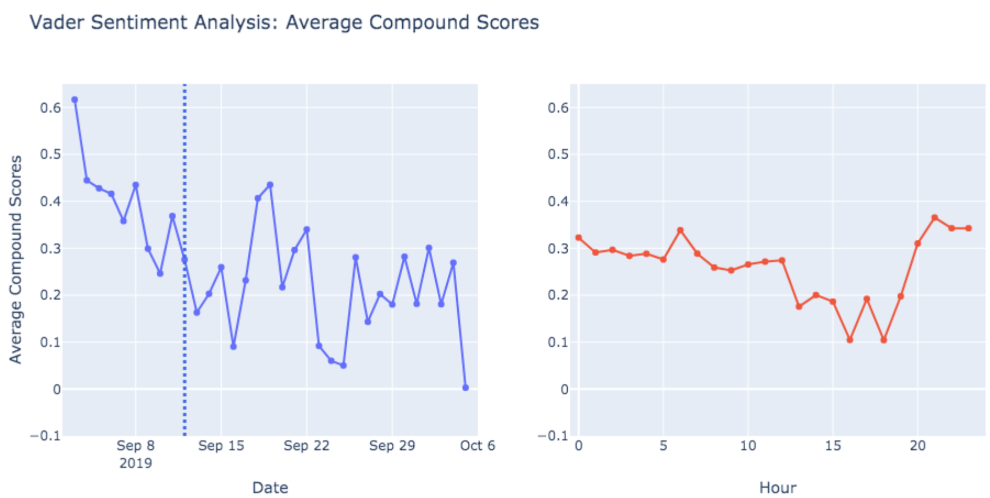


Figure 8

Figure 9 shows the trends of the eight basic emotions over date. It is interesting to see that the anticipation and joy emotions seem to move together most of the time, and so do the fear and sadness emotions. Anticipation exists with joy, while fear exists with sadness in our collected tweets.

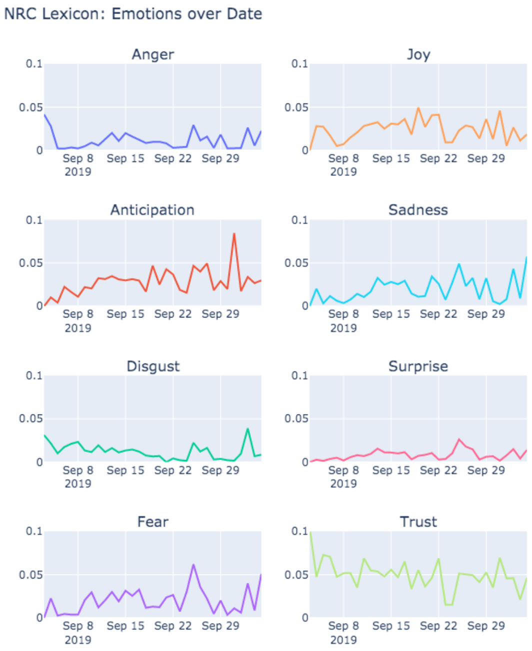


Figure 9

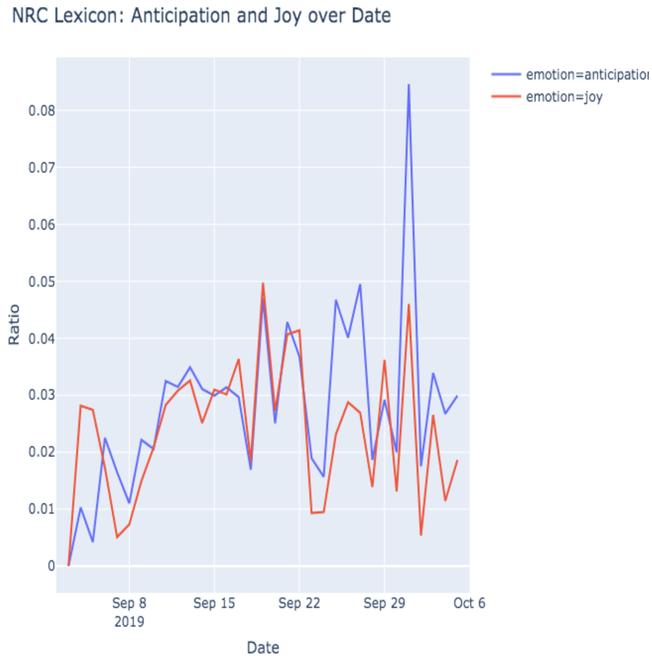


Figure 10

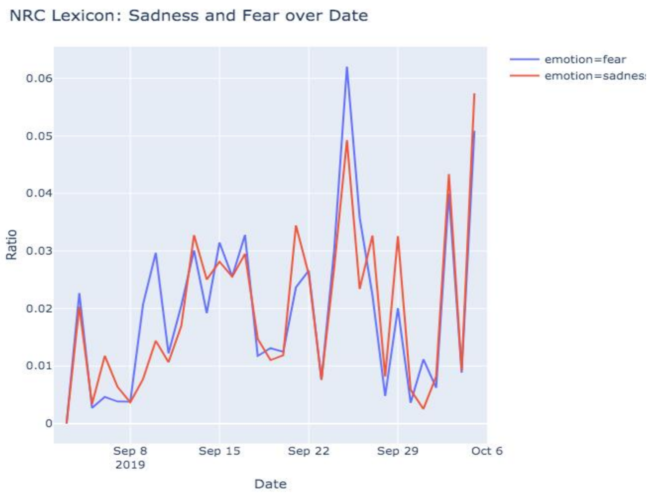


Figure 11

Sentiment and Emotions by City

Figure 12 shows the sum of compound sentiment scores in some cities of Australia. In this plot, when several tweets belong to the same city, the rectangles are stacked on top of one another. Other than the number of tweets, this plot also takes the value of sentiment scores into account. Gold Coast seems to have an equal share of the positive and negative sentiments. Melbourne is more critical towards RUOK Day than Sydney. The numbers of tweets from the two cities are similar, however, the share of negative sentiment is larger in Melbourne.

Figure 13 compares the average emotion levels across major cities in Australia. It is notable that trust, joy, and anticipation take up most of the weights among the eight emotions and are relatively consistent from city to city with only slight differences in magnitude. The sadness emotion seems to exhibit the most variance across the cities.

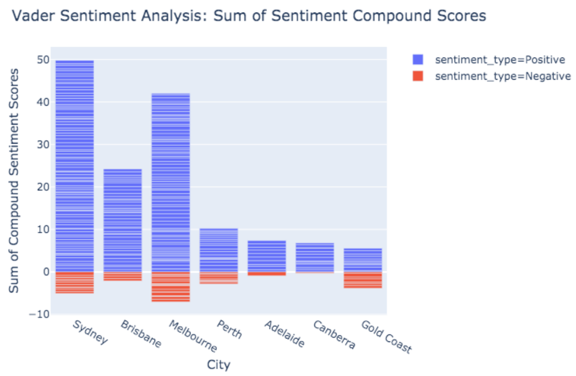


Figure 12

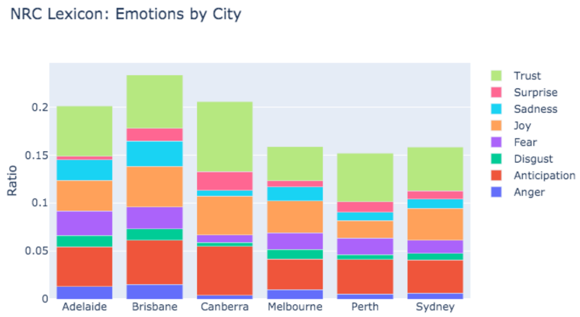


Figure 13

Sadness Emotion map of RUOK Day

Figure 14 is a screenshot of the interactive map that shows locations of the tweets that contained sadness emotions, where a larger-sized red circle marker means a higher sadness emotion level. The sadness level here is measured by the average proportion of sadness words contained in the tweets from the location.

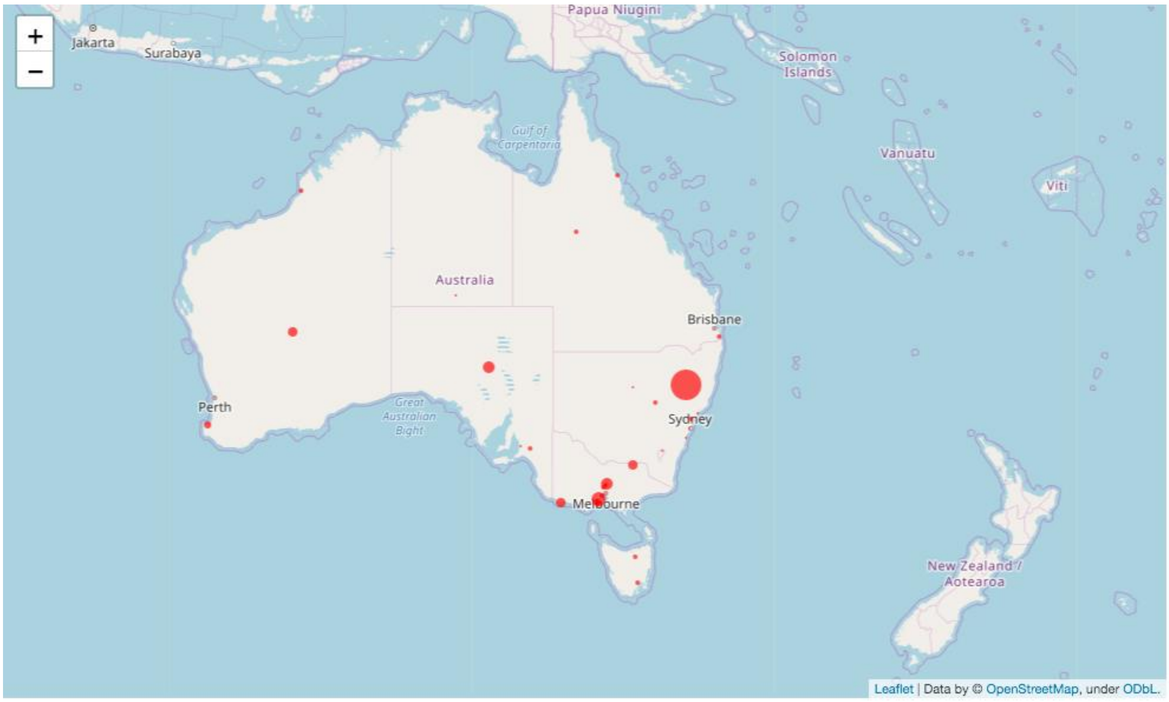


Figure 14

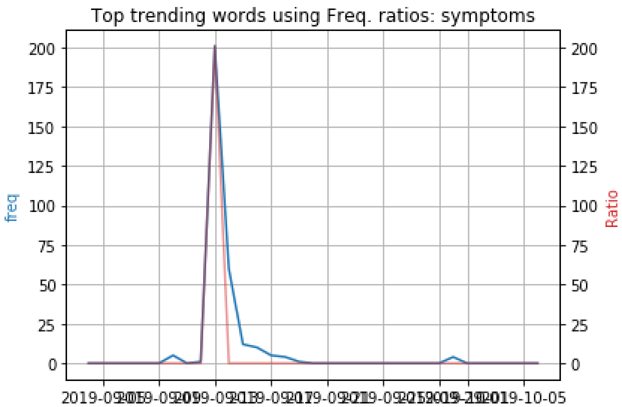
Event Detection – Does RUOKDay register as an event?

Both the simple frequency ratio and burstiness score approaches were used. Most used keyword found in both diagnostic tests was revealed to be “symptoms”. Also featured, were the words “united”, “nations”, “wear” and “action”.

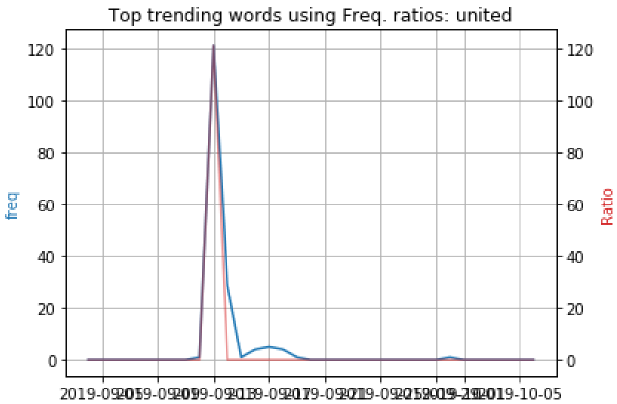
Keywords

Simple Frequency Ratio

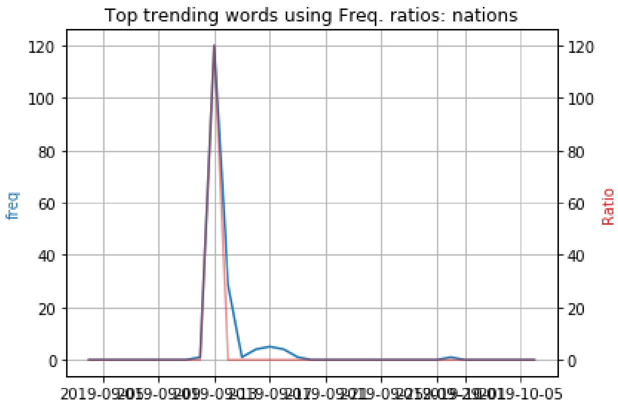
“symptoms”



“united”

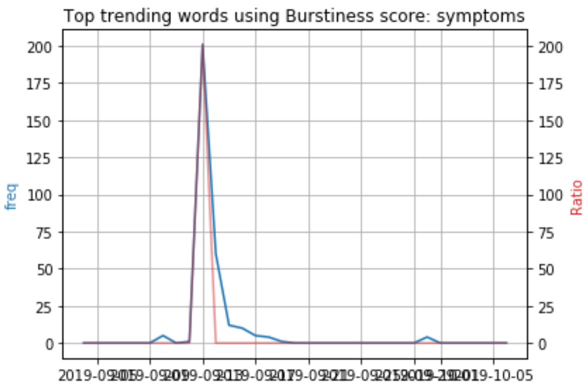


“nations”

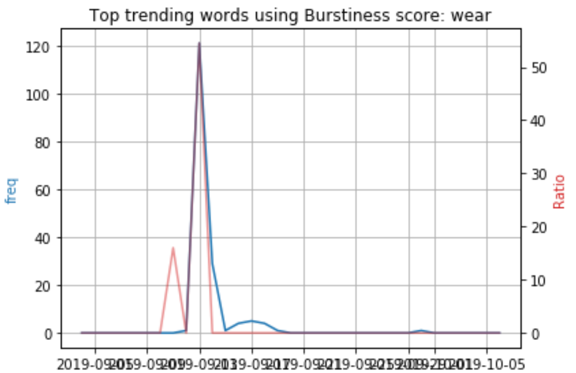


Burstiness Score

“symptoms”



“wear”



“action”

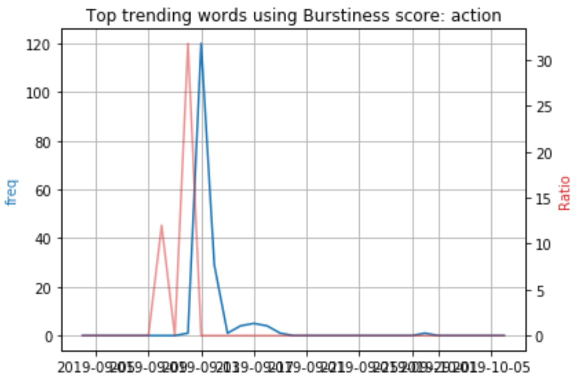


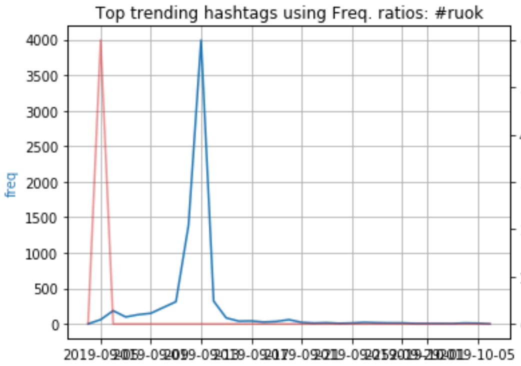
Figure 15

Hashtags

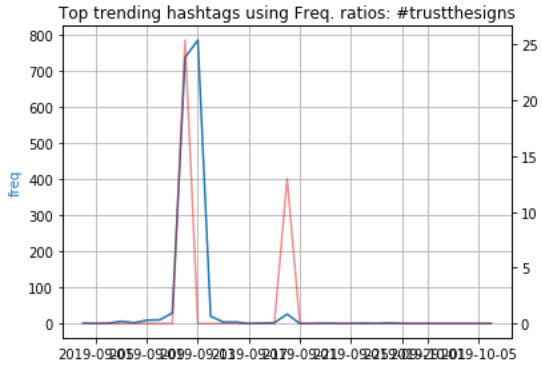
This section actually exposed a lot of related hashtags we did not expect from the analysis. "#trustthesigns" was not a hashtag we were originally aware of, and it has come out in 2nd in the simple frequency ratio, and 1st in the burstiness score ratio.

Simple Frequency Ratio

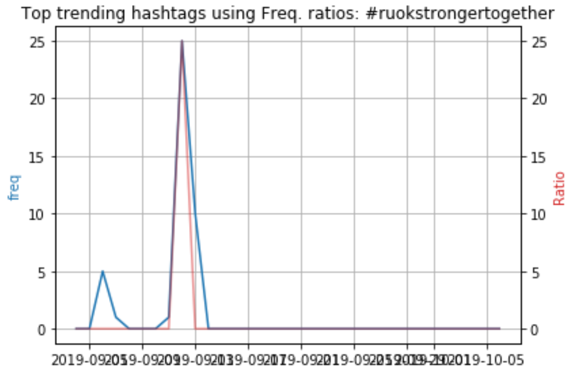
#ruok



#trustthesigns

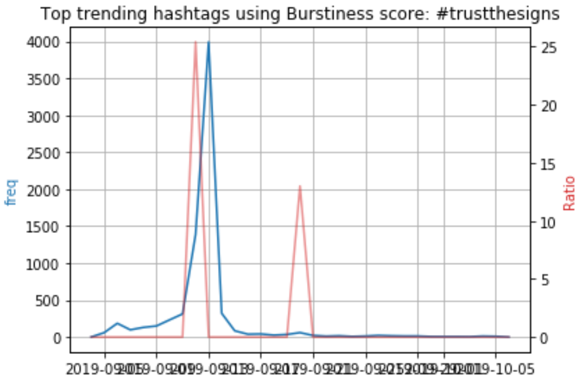


#ruokstrongertogether

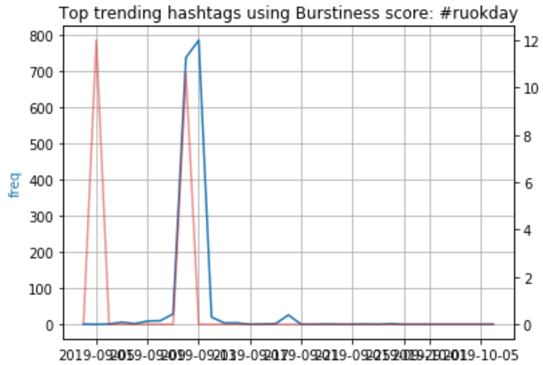


Burstiness Score

#Trustthesigns



#ruokday



#ruok

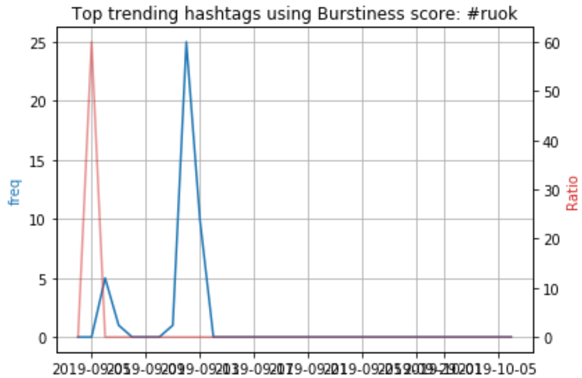


Figure 16

Mentions

Analysing mention frequency was rather eye-opening. Of all topics, Collingwood Football club rated highest on both ratios. Does this mean Collingwood football club was a great proponent of RUOKDay and active in the mental health sphere of raising awareness. Further analysis is required.

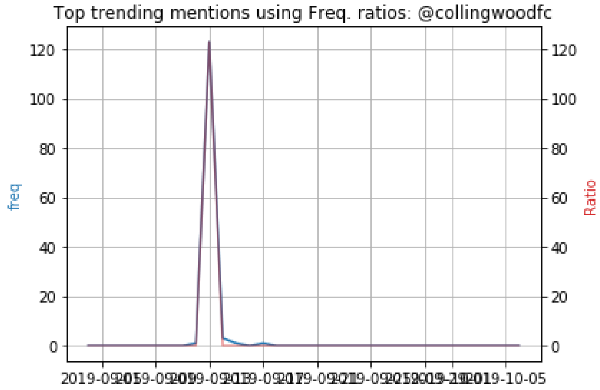
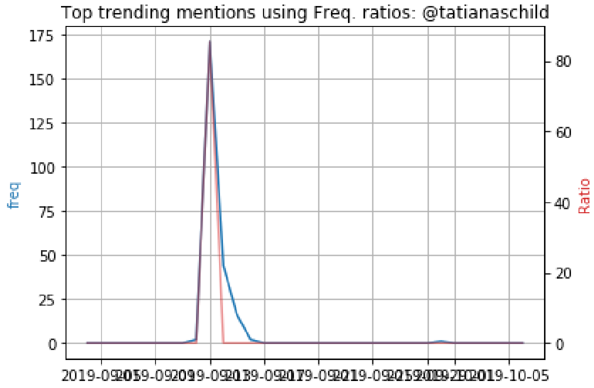
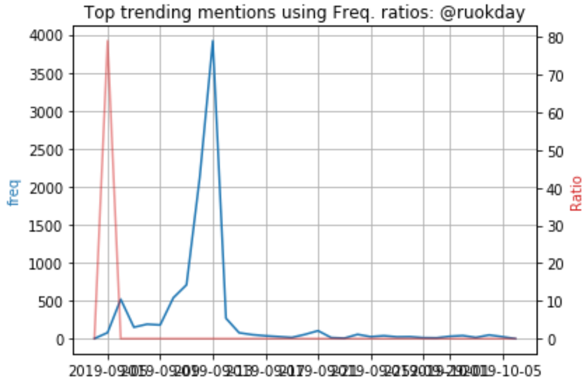
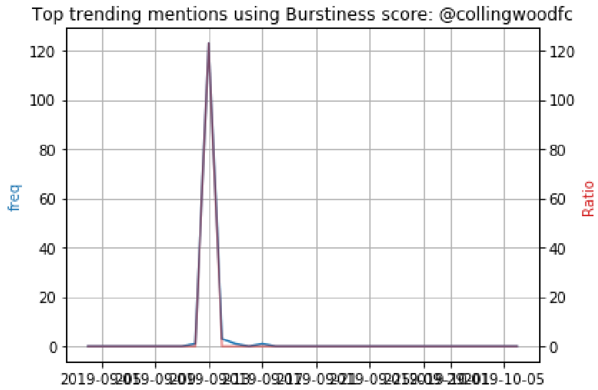
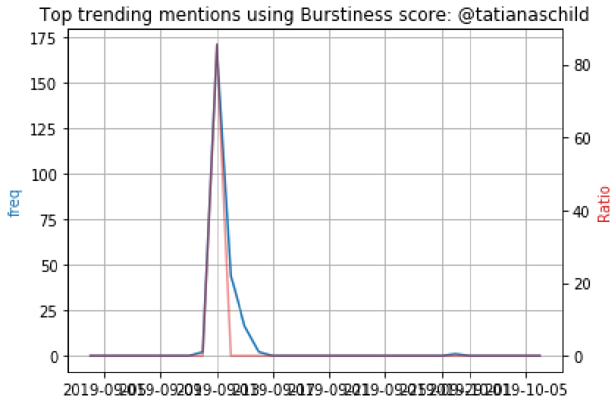
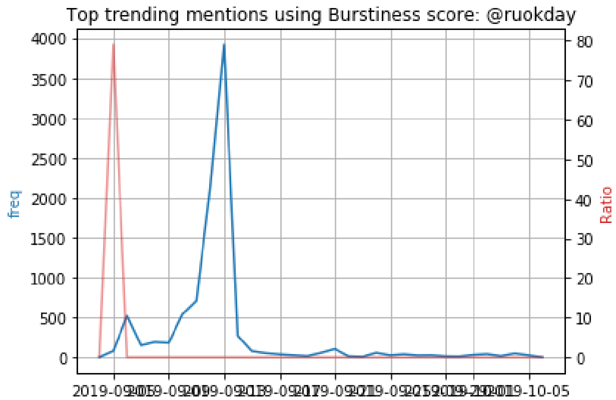
Simple Frequency Ratio		
@collingwoodfc 	@tatianaschild 	@ruokday 
Burstiness Score		
@collingwoodfc 	@tatianaschild 	@ruokday 

Figure 17

Event Detection – Section Outcomes

The United Nations and RUOKDay

Many mentions of the United Nations and RUOKDay originated from retweets of one particular tweet launched by the twitter account "Solitary Confinement Causes Mental Damage". What didn't show up in event detection, was that this tweet was about Julian Assange being mentally tortured. The group used the hashtag #RUOKday to help spread awareness about the atrocity.

Solitary Confinement Causes Mental Damage
@surf_key

#RUOKday
#RUOKDay2019
#JulianAssange is gravely ill and was found by United Nations to have all symptoms of psychological #torture. He is being tortured in solitary confinement now in imprisonment that is illegal under international law.

He may die.

#FreeAssangeNOW #Unity4j

1:47 PM · Sep 12, 2019 · Twitter Web App

166 Retweets **184** Likes

(Solitary Confinement Causes Mental Damage, 2019)

Collingwood and RUOKDay

Collingwood Football club's sudden burstiness score originated from their Twitter post spreading awareness about RUOKDay.

(Collingwood FC, 2019)

Collingwood wasn't the only AFL club to post about RUOKDay, however the heightened response they received was likely due to the emotive nature of the picture within the tweet. Below is a tweet posted by the Essendon Football club, which only garnered approximately 10% of the likes attained by Collingwood.

(Essendon FC, 2019)

Topic Modelling

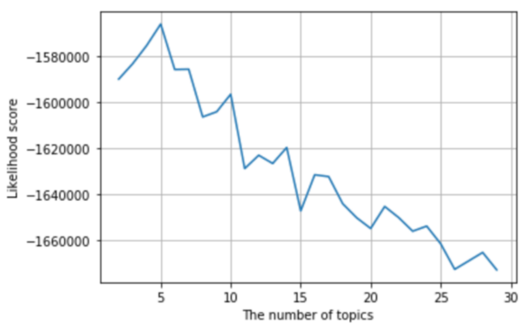
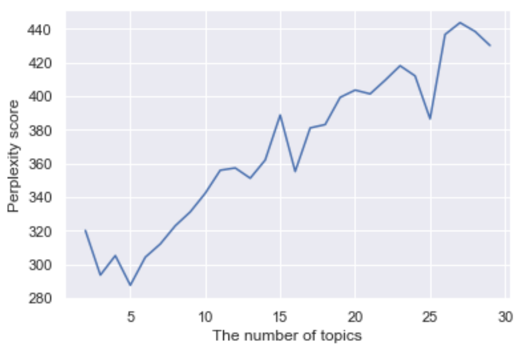
In this section, we perform topic modeling on our data to find out what are the topics that people tweet about in relation to RUOKDAY. One of the topic modeling techniques, Latent Dirichlet Allocation (LDA) is used to help us find the hidden thematic structure in the text. Firstly, we develop our topic model using Sklearn's LDA and perform topic model evaluation using log-likelihood and perplexity. In the second part, we use GenSim's LDA model so that we can evaluate the topic models using the measure of topic coherence (intrinsic evaluation metric).

Topics found via SKlearn's LDA model

Figure 18

In our first LDA model attempt, we apply 10 number of topics for discovery. The result has showed by using word clouds (figure 18) so that we can visualise the most important words for each topic. By looking at figure 18, it shows 10 topics are very similar, mainly because of the data that we collected are about RUOKDAY. Then, we use log-likelihood and perplexity to check our model performance, this LDA model has log-likelihood score of -1604631.32 and perplexity score of 335.55. In practice, we want our model with higher log-likelihood score and lower perplexity score.

Evaluate number of topics using likelihood scores and perplexity score

Log-likelihood score	**Perplexity score**
 *Figure 19*	 *Figure 20*
Optimal Topics: 5	Optimal Topics: 5

Since we want a larger likelihood with minimal number of topics and a lower perplexity with minimal number of topics, both plots above appear 5 topics is the good selection. On the other hand, "perplexity might not be the best measure to evaluate topic models because it doesn't consider the context and semantic associations between words" (Machine Learning Plus, 2019). In addition, "perplexity and human judgement are often not correlated" (Kapadia, n.d.) which means that using perplexity to find optimal number of topics may not produce human interpretable topic. Hence, we will also use topic coherence measure to evaluate our topic model later.

Analysing optimal LDA model results

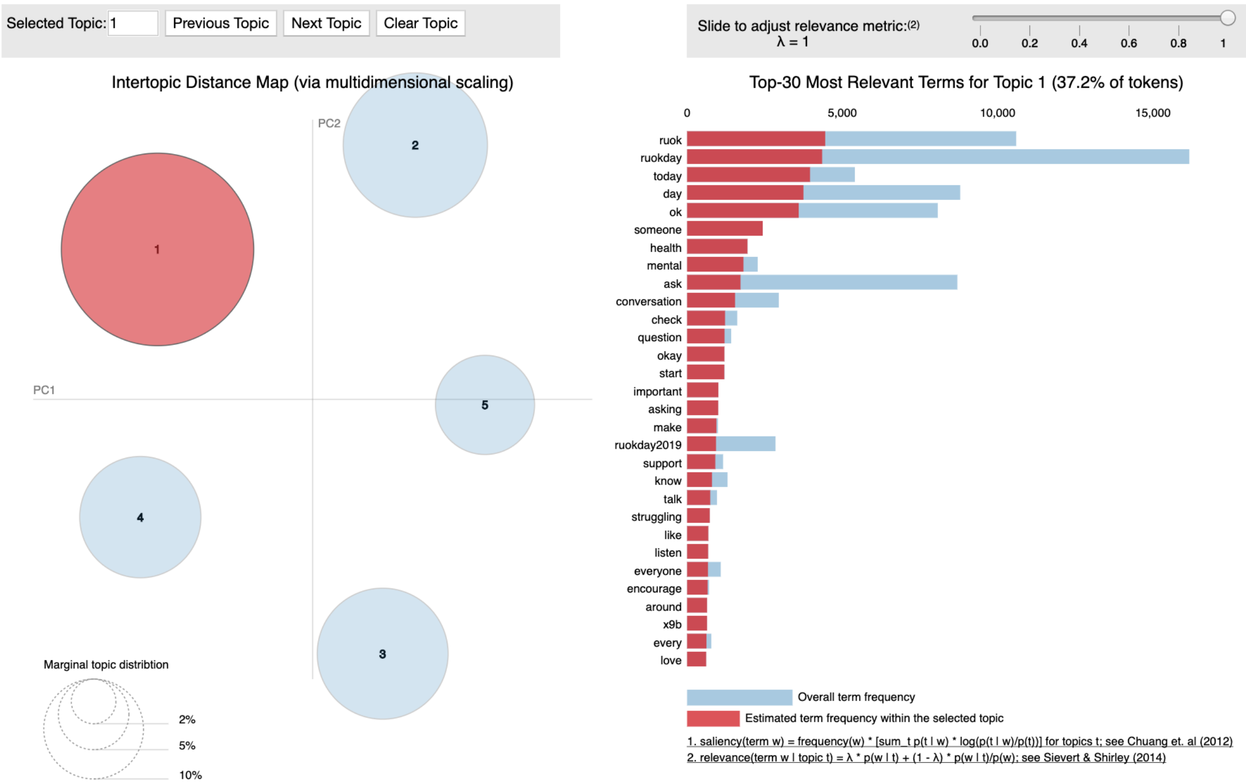


Figure 21

We conclude that 5 topics is a good topic model since there is no overlapping between the circles in figure 21. Let's interpret the result from what we see in pyLDAvis:

Most relevant terms for each topic	Interpretation of topic
Topic 1: Ruok, ruokday, today, day, ok, someone, health, mental, ask, conversation, check, question, okay, etc.	R U OK? Day, the "national day of action dedicated to reminding everyone to ask "Are you okay?" and to remember everyday day of the year to support people who may be struggling with life's ups and downs." (RUOK?, 2019)
Topic 2: Ruokday, people, friends, suicide, time, family, ok, help, one, take, etc.	Promote suicide prevention, increase people's awareness about mental health issue.
Topic 3: Life, ok, change, could, ask, ruokday, today, conversation, simple, small, notice, matter, save, need, etc.	Encourage people to have conversation with someone you know and you feel something is different with this person as one conversation may save or help someone.
Topic 4: Ruokday, day, ask, ruok, reminder, action, trusthesigns, national , learn, September, needed, etc.	RUOK? organisation promotes the Trust the Signs Tour and welcome everyone to join the event.
Topic 5:	RUOKDay, motivate people to ask "Are you okay?" to support people around.

Trust, gut, signs, ruokday, ruok, ask, ok, want, mental, encouraging, everyone, etc.	

Word Embeddings to visualise topics

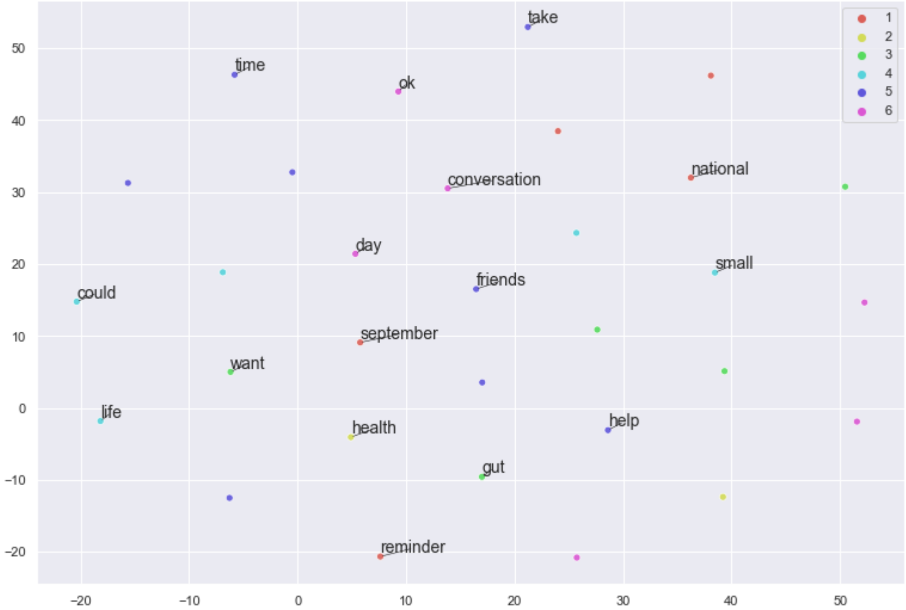


Figure 22

In figure 22, we see the words such as “day”, “September”, “want”, “conversation”, “friends” are similar, therefore they are plotted close to each other in the centre. These words are likely related to topic of RUOK organisation inspire people to make conversations in RUOK? Day (12 September 2019). While words such as “take”, “help”, “small” are considered as dissimilar, therefore we can see they are far from each other in the plot.

Topics found via GenSim’s LDA model

We train the LDA model with 5 topics since 5 is the optimal topic that we obtained from first part in this section. The table below shows the result from LDA model: keywords from each topic and we judge what the topic is about:

Keywords from each topic	Judge what the topic is about
Topic 1: Depression, great, week, lose, member, show, anxiety, help, collingwoodfc, andrewbartlett	The Australian Football League, Collingwood and Andrew Bartlett, an Australian politician and social campaigner are spreading awareness about RUOKDay.
Topic 2: Ruok, day, ask, ruokday, amp, help, September, conversation, life, friend	RUOKDAY.
Topic 3: Today, suicide, someone, mental, health, people, know, need, want, make	Depression, mental health.
Topic 4: Sign, trust, gut, care, everyone, come, tomorrow, answer, trustthesigns, moment	“Trust the Signs Tour”, the campaign run by RUOK organisation.
Topic 5:	Self-empowerment.

Learn, xb, small, matter, ruo, podcast, stigma, expert, business, young	The words "xb" and "ruo" are included in the stopword list and they supposed to be removed.

Visualise the topic-keywords using pyLDAvis

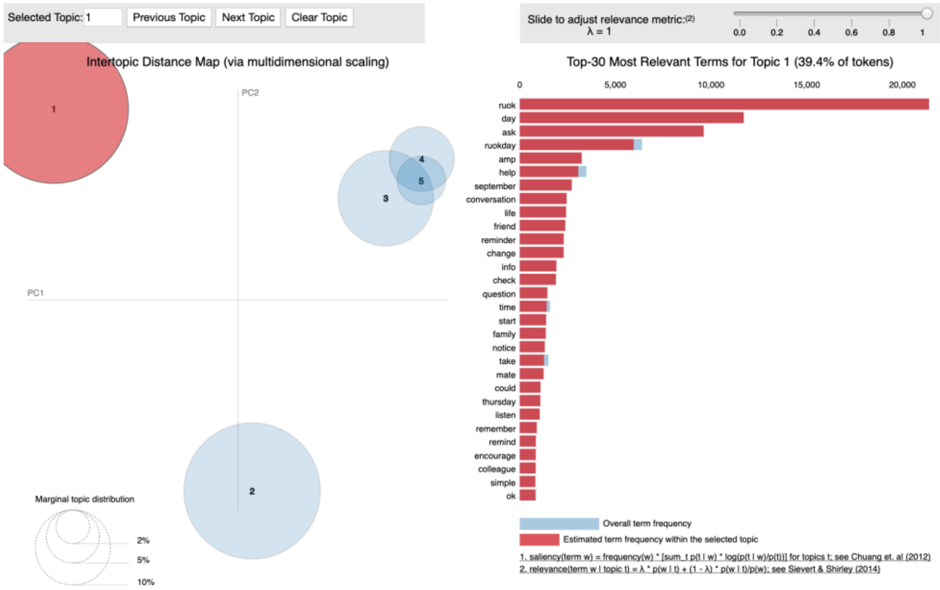


Figure 23

Figure 23 shows there are overlapped between topic 3, 4, 5 and being clustered in one quadrant which indicate this topic model is not good. Hence, we need to improve our model by selecting the most appropriate number of topics.

Evaluate number of topics using coherence score

Next, we implement Gensim's inbuilt version of the LDA algorithm, Mallet because "it is known to run faster and gives a better quality of topics" (Machine Learning Plus, 2018). Before the implementation of LDA Mallet model, the coherence score was 0.407 and it has decreased to 0.372 which is unreasonable. Hence, we find the optimal number of topics for LDA model that has the highest coherence score.

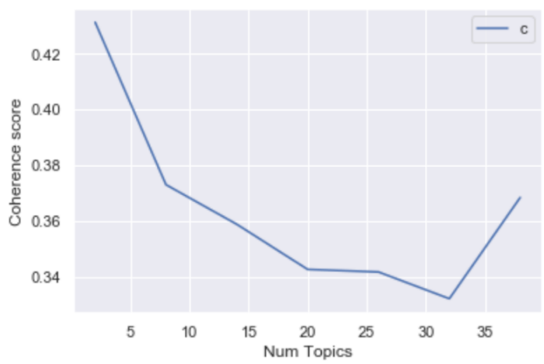


Figure 24

```
Num Topics = 2  has Coherence Value of 0.4313
Num Topics = 8  has Coherence Value of 0.373
Num Topics = 14  has Coherence Value of 0.3588
Num Topics = 20  has Coherence Value of 0.3426
Num Topics = 26  has Coherence Value of 0.3417
Num Topics = 32  has Coherence Value of 0.3321
Num Topics = 38  has Coherence Value of 0.3684
```

Figure 25

By computing c_v coherence in the range of topic number, the result shows that the highest coherence value is 0.4313 with the topic number of 2.

Lastly, we apply 2 topics into our final LDA model and we obtain:

Keywords from each topic	Judge what the topic is about
Topic 1: Ruokday, ruok, day, amp, trust, reminder, friend, gut, sign, action	RUOKDAY
Topic 2: Today, conversation, life, mental, people, health, check, start, question, support	Increase people's awareness of mental health problem.

Since the data is collected based on the query that associated to RUOKDAY, we do not find another topic that is not related to RUOKDAY. In the beginning of this section, we review the LDA model with 10 topics and find that most of the topics are very similar. Then, we evaluate the model using log-likelihood and perplexity and obtain the outcome of 5 topics is the most appropriate model.

However, when result is analysed using pyLDAVis, the topics are still very similar to each other and some of the topics are not meaningful. Lastly, when the GenSim's LDA model is implemented, the highest coherence score is achieved, which points to two topics.

To sum up, we recommend 2 topics for the model because the topics are clearer and more meaningful based on human-interpretability. A five topic model is also good, however the five topics tend to share a lot of themes with one another.

Graph Modelling

Community Detection – Reply Chains

Upon using the twarc package, the team was able to retrieve tweet reply chains between users over the course of one week of RUOKDay.
Note: The resulting account reply chain graph of replies between September 16 and September 22 is found below.

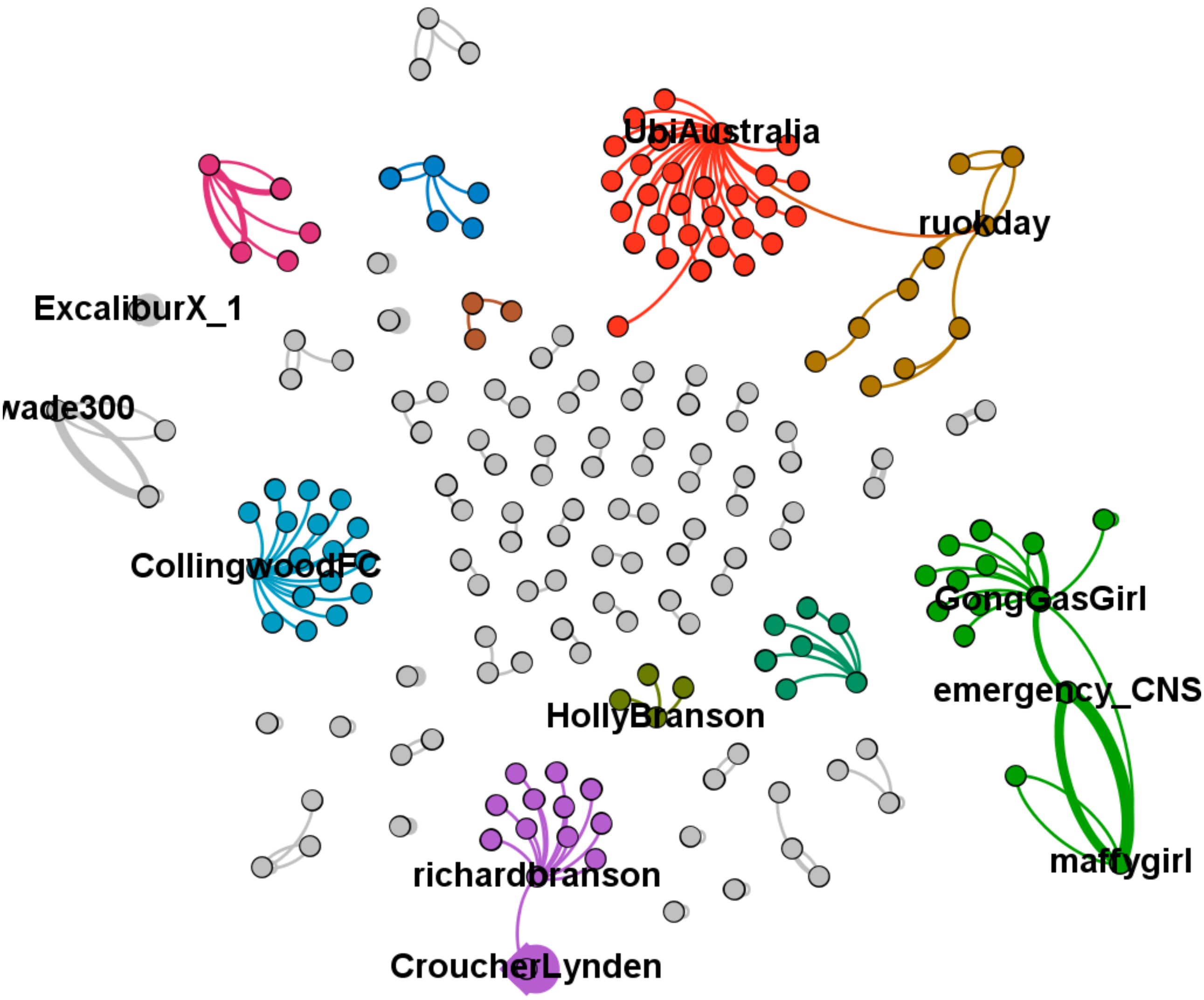


Figure 26

It is quite clear from the above graph structure, there are many fragmented communities- 56 different communities in total. There are many communities made up of only one, two or three nodes, where the most common relationship, is a single account posting, with a single account replying to them, which is visible from observing the grey nodes in the middle of the graph structure.

Reply Chain Graph – Summary Statistics – Centrality Measures

Metric/Measure	In degrees	Out degrees	Degree Centrality	Eigenvector Centrality	Katz Centrality	Closeness Centrality	Betweenness Centrality
Mean	2.068966	0.7241	0.013966	1.90E-02	0.076541	0.011758	0.000045
St. Dev	3.662485	0.7422	0.018957	1.06E-01	0.023172	0.020102	0.000169
Min	1	0	0.005	2.61E-24	0.068659	0	0
25th Percentile	1	0	0.005	2.61E-24	0.068659	0.005	0
50th Percentile	1	1	0.01	2.94E-11	0.069353	0.005	0
75th Percentile	1	1	0.01	8.10E-11	0.071428	0.01	0
Max	28	3	0.145	7.37E-01	0.239906	0.137619	0.001055

Using both a visual analysis of the graph, and the above summary statistics table, it seems relatively obvious that all measures of centrality are rather low, with the exception of some higher-end outliers.

Presence of outliers can also be detected when comparing the difference between mean scores, standard deviation and max scores. These higher end outliers however, when considered in the broader topic of graph analysis, are still very low scores, and speaks volumes to the overall dysconnectivity of the network.

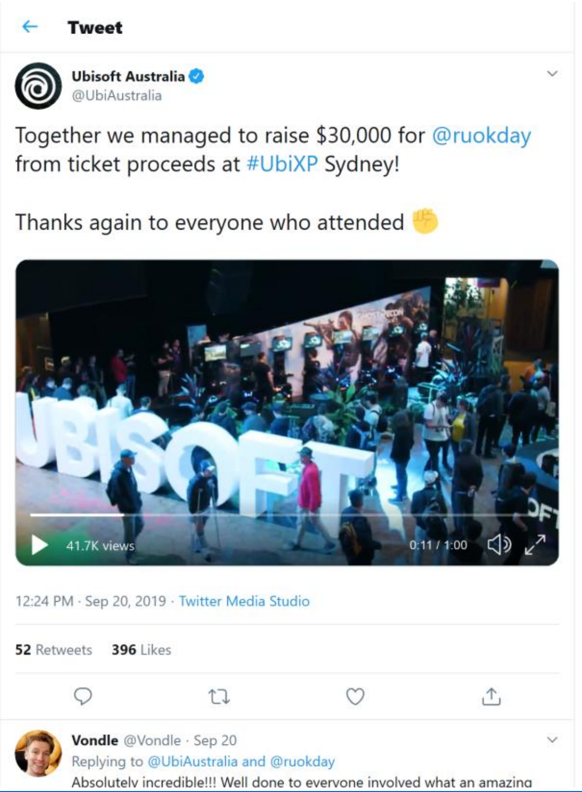
Since mathematical observation has indicated this dataset contains many outliers, it is worth delving into the only most extreme of these values, to decipher the reasoning behind this phenomenon.

Most popular accounts by centrality score

user_screen_name	in_degrees	out_degrees	degree_centrality
UbiAustralia	28	1	0.145
CollingwoodFC	16	0	0.08
GongGasGirl	11	2	0.065
richardbranson	12	0	0.06
ruokday	4	2	0.03

The centrality score calculates the amount of edges per node. Although the above centrality scores are relatively low, one can see both UbiAustralia and CollingwoodFC with the highest score.

UbiSoft are a company known for creating video games. They achieved the highest score as they ran a fundraiser in preparation for RUOKDay. This was the tweet everyone was replying to.

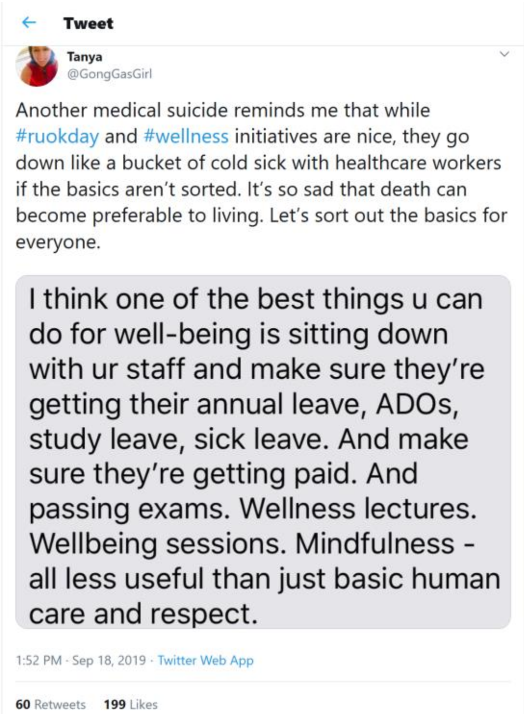


(UbiSoft Australia, 2019)

Highest betweenness centrality score

user_screen_name	betweenness_centrality
GongGasGirl	0.001055276
UbiAustralia	0.000854271
maffygirl	0.000653266
ruokday	0.000502513
mindsetinterest	0.000201005

GongGasGirl achieved the highest betweenness centrality score. Upon checking her tweet, it was evident that although she successfully sparked discussion on RUOKDay, unlike others, she was an active participant with those who replied to her tweets.



(GongGasGirl, 2019)

UbiAustralia also scored quite highly on this metric, likely because they were the only large community to receive a reply from another large community – from the RUOKDay account itself.

Betweenness centrality

user_screen_name	betweenness_centrality
GongGasGirl	0.001055276
UbiAustralia	0.000854271
maffygirl	0.000653266
ruokday	0.000502513
mindsetinterest	0.000201005

A factor not seen too often in the subject graph, is a level of interactivity between users. The betweenness centrality metric identifies those accounts that act as a “bridge” to connect other accounts. Due to GongGasGirl’s high amount of accounts interacting with herself from different directions, she scored highest on this metric with 0.001.

Self-replies

Not so much a graph measure, but rather a twitter specific metric – some accounts have been observed constructing lengthy posts by discussing their own thoughts within a reply chain to their own tweets. These accounts did not score highly on these metrics as their tweets have not garnered any replies, despite the amount of activity made with themselves.

CroucherLynden and ExcaliburX_1 are two examples of this phenomenon. This is seen in the graph, where there are two nodes with incoming edges surrounding the node itself.

Conclusion

Delving deeper into the content of RUOKDay, through utilising techniques suited for social media analysis, has allowed a greater state of understanding the totality of the story behind RUOKDay, and those tweeting about it.

In terms of emotions portrayed through the NRC lexicon analysis, it has been observed that trust, anticipation and joy exists alongside one another, and that overall positivity expressed by users on RUOKDay, diminishes after the day itself.

Event detection highlighted unexpected themes typically not associated with RUOKDay, such as the psychological abuse of Julian Assange, and a large show of support from Australian Football fans, through Collingwood football club spreading awareness of the day.

Topic modelling revealed a multitude of alternate topics in regards to RUOKDay, such as the trustthesigns movement, involving driving across Australia spreading awareness. Modelling the correct number of topics proved itself difficult, due to conflicting diagnostic recommendations for topics. The model recommended by the team was the two-topic model, although a five topic model also explains the overall landscape of tweets quite well.

A detailed reply chain analysis of reply revealed that the majority of posts about the day do not create effective conversation about the day. Many reveal a one-to-one relationship, others reveal a single post that reaches many users, however does not inspire conversation.

A recommendation to make to RUOKDay itself in order to increase engagement with users, would be to post emotive stories and recollections from people's own struggle with mental health, to coax other users to continue the discussion.

In retrospect, a more effective analysis of RUOKDay and it's impact on Australian twitter users could have been better to obtain tweets just from Australia, and then check to see the presence of tweets related to RUOKDay itself.

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