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Twitter Sentiment Analysis: What does Social Media tell us about coronavirus concerns in the UK?

Data Science Working Party / IFoA COVID-19 Action Taskforce

Melanie Zhang, FIA
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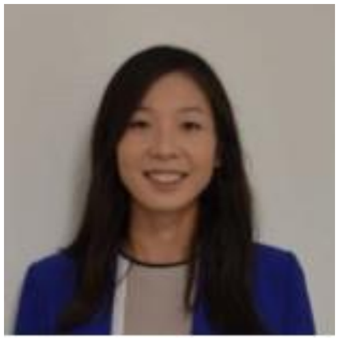
24 July 2020

Speakers' Biography



Melanie is Head of Property Innovation at AXIS Capital, having previously worked in actuarial pricing, reserving and business planning roles in the London insurance market since 2011. Melanie has recently completed her Master's degree at UCL in Computational Statistics and Machine Learning.

She is a member of the IFoA Data Science Managing Committee, Data science WP Education Workstream Lead and the IFoA Data Science Certificate Committee.

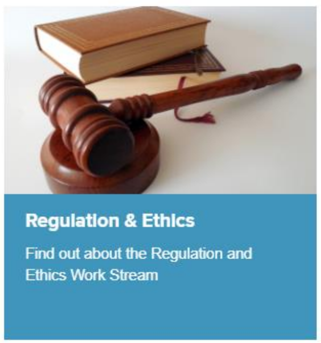
John is Senior Data Scientist at Reinsurance Group of America (RGA), where he provides predictive modelling solutions for internal and external clients on mortality, morbidity, biometrics and digital distribution. In his previous roles he developed end-to-end Automated Machine Learning (AutoML) platform for a range of product lines and deployed advanced pricing optimisation frameworks.

John is a Fellow of Institute of Actuaries, an experienced pharmacist, IFoA Data Science Research Workstream Chair, Data Science Managing Committee member and Deputy Chair of IFoA Health and Care Research sub-committee.

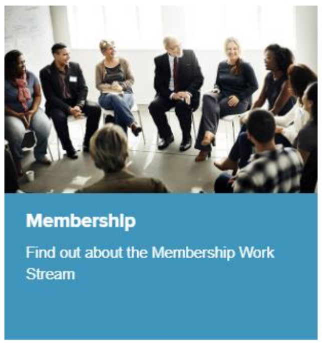
Data Science WP – Managing Committee

The overall objective of the Data Science Working Party (WP) is to be a platform of delivering Case Studies, Webinars, Events, GIRO sessions and integrating data science applications within our IFoA educational system, in order to supply actuaries and data practitioners with credible techniques that can be used within industry.

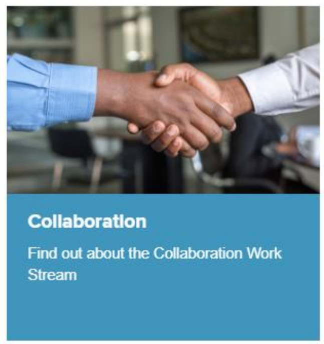
- Asif John (Chair)



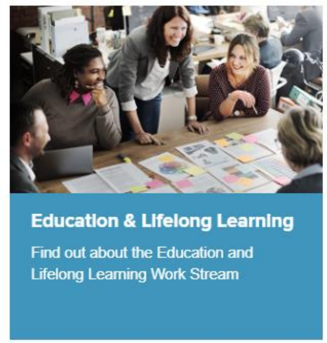
- Matthew Byrne



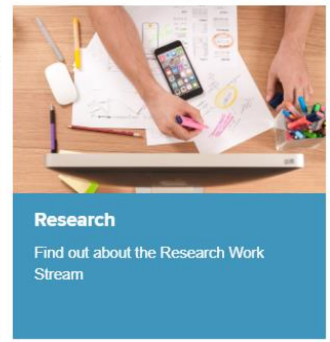
- Alex Labram
- Stelio Passaris



- Biren Dhir
- Alexis Iglauer



- Melanie Zhang
- David Tudor-Griffith
- Ankush Agarwal
- Alex Hanks



- John Ng

New COVID-19

Managing Committee

Agenda

- Introduction
- Data Preparation
- Sentiment Analysis Models
- Sentiment Analysis on Historical UK Tweets
- Limitations and Summary
- Appendix

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Introduction

What is Sentiment Analysis?

Sentiment analysis, also known as ***opinion mining*** or ***emotion AI***, refer to the use of *Natural Language Processing (NLP)* and *text analytics* to automatically determine the overall feeling a writer is expressing in a piece of text.

Sentiment classification is often framed as binary (positive/negative), ternary (positive/neutral/negative) or multi-class (for example neutral, happy, sad, anger, hate).

Sentiment analysis is used in many applications:

- Monitor and analyse online and social media content around a specific topic
- Evaluating survey response
- Voice of the customer analysis, leading to value proposition
- Product analytics: e.g. categorising product reviews
- Improve Customer Support and feedback analysis
- Reputation and Brand management
- Market Research, Competitor Analysis

Research Aims

In this work, we consider the problem of classifying sentiment of UK Twitter messages on COVID-19 using Natural Language Processing (NLP) and supervised Machine Learning techniques

Our research considers the following:

- Labelling sentiments using emoticons (a noisy method)
- Data enrichment using a non-COVID Twitter dataset (sentiment140)
- NLP pipeline for pre-processing Twitter data
- Encoding methods: Bag-of-words (BoW),Term Frequency-Inverse Document Frequency (TF-IDF), GLoVE (Global Vectors for Word Representation)
- Comparison of 'out-of-the-box sentiment classifier' vs Machine Learning predictive models: Random Forest, Logistic Regression, Support Vector Machines, Naive Bayes, XGBoost
- Visualisation of time-series results for overall UK Twitter sentiment, and for Tweets relating to key words, such as **'*nhs*' '*stayathome*'**, **'*work*'**, **'*government*'**

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Data Preparation

Data Source

We chose the "**COVID-19 Twitter chatter dataset for scientific use**" published by Georgia State University's Panacea Lab

- 1st January – 11th March 2020: tweets containing key words *coronavirus*, *2019nCoV*
- 11th March – 25th April 2020: tweets containing more COVID-related key words, such as: *COVD19, CoronavirusPandemic, COVID-19, 2019nCoV, CoronaOutbreak,coronavirus, covid19, coronaviruspandemic, covid-19, 2019ncov, coronaoutbreak,*
- New tweets are added on a daily basis, and there are weekly updates released with the full history (versions 1.0, 2.0, 3.0, ….)

We used Version 7.0 from this dataset, which contains relevant twitter IDs from 1st January 2020 to 26th April 2020:

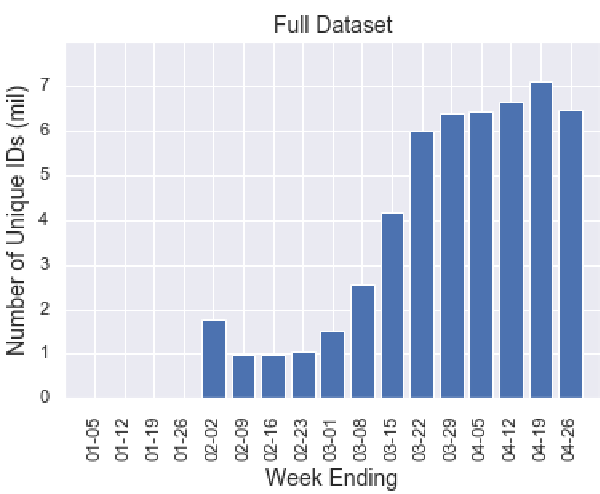
- Cleaned version with no retweets: **52,026,197 unique twitter IDs**
- In line with Twitter's terms of use, only the twitter IDs are provided and these need to be hydrated to extract the original tweets and metadata from the IDs, example:

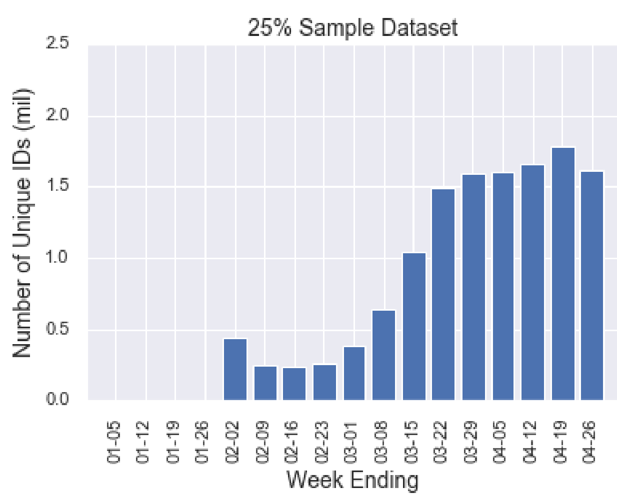
Twitter ID	Hydrated Data
1254259095701520385	{'**created_at**': '2020-04-26', '**favourite_count**': 1, '**lang**': 'en,' '**text**': 'Local man confused here again oh,guys help me…', '**place**': …}

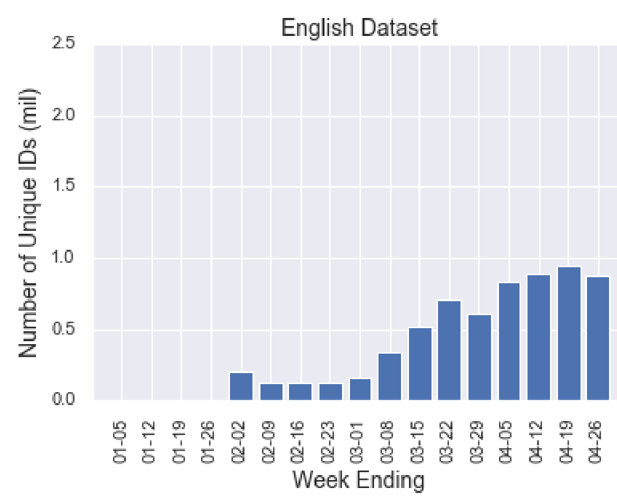
Data Extraction

Twitter applies a **rate limit** on hydrating IDs – i.e. it restricts the number of IDs that can be hydrated within a 15 minute window

- To limit the required time for Twitter hydration, we took a random 25% sub-sample of the full dataset*:* **13,006,549** of **52,026,197** unique twitter IDs
- Hydration took around 4 days for this 25% sample, and we were able to hydrate **11,406,801** Twitter IDs, as we couldn't get results for Tweets that have since been deleted
- Filtered for English language tweets only to obtain **6,458,776** Tweets







Country Classification

There are 3 data fields in the hydrated metadata that provide information about user location, with differing levels of fill rate for the English Tweets dataset:

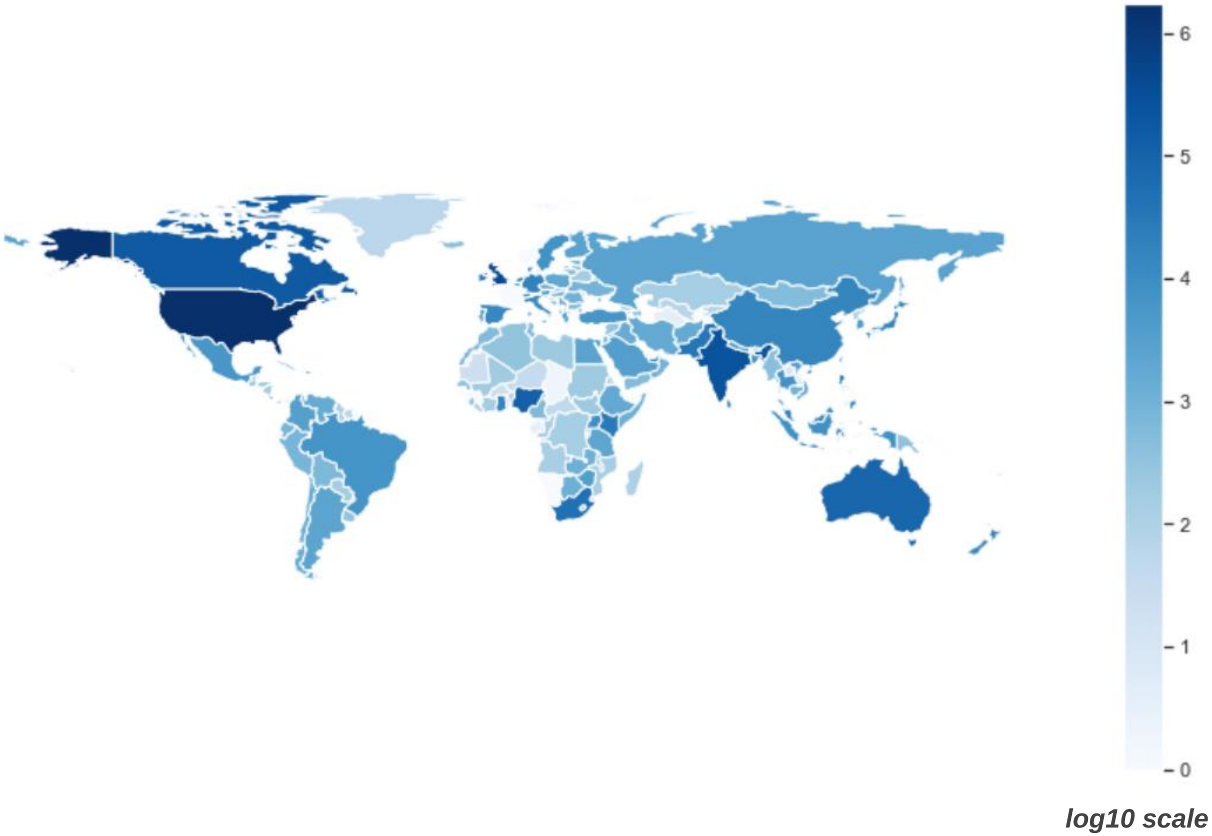
- "**coordinates**": latitude-longitude of user location (**0.1% filled**)
- "**place**": semi-structured field of user location, usually "city, state", or "state, country" or "country" (**3.4% filled**) – with around 20k unique entries
- "**user_location**": free text field filled in by user (**74.0% filled**) – this is the noisiest field with >400k unique entries

We considered 3 methods of extracting country location for each Tweet (with the aim to avoid any manual mapping methods):

1. Look for key location words in "place" and "user_location", e.g. US state names, abbreviations, and various country name representations for US, UK and India (the top 3 countries for COVID Tweet volumes according to Georgia State University's Panacea Lab)
2. Used the semi-structure field "place" to find mappings from low-level places to high-level places (e.g. Los Angeles → CA → US)
3. Used the Google Geocoding API on locations that couldn't be mapped to a country from either of the first 2 methods (limited to the most frequent 20k locations for "user_location")

Able to map 3.3m out of 6.4m (51.7%) Tweets to a specific country

Tweet Volumes by Country



Top 5 countries by volume of English language Tweets related to COVID-19 as at 26 April 2020:

Country	Volume (000s)	% of Total
USA	1,733	51.9%
UK	432	12.9%
India	236	7.1%
Canada	166	5.0%
Nigeria	114	3.4%

Sentiment Labels using Emoticons

7k Training Set Labels:

- 7k Tweets from our UK dataset of English language Tweets relating to COVID-19, automatically labelled ‘positive’ [e.g. 🤣, 😊, 😁, 😉 etc.] or ‘negative’ [e.g. 🤦, 😠, 😥, 🤬 etc.] using a similar method
- This is a <u>noisy labelling method</u>, as there can be examples where there are contradictory sentiments between the text and the emoji present in the Tweet [e.g. “Ah what a shame 🤗 https://...”], but this removes the need for any manual human labelling on a large dataset
- Equal number of positive and negative labels

3k Test Set Labels:

- 3k Tweets from our UK dataset of English language Tweets relating to COVID-19, automatically labelled ‘positive’ or ‘negative’ as above, but then with manual human review to correct cases for sentiment based on the text only
- E.g. “I’ve waited 4/5 months to get back out on the golf course and it’s going to be ruined by the coronavirus🤣⛳” would have been automatically labelled as “positive” but manually overwritten in the test set as “negative”
- 54% negative / 46% positive labels

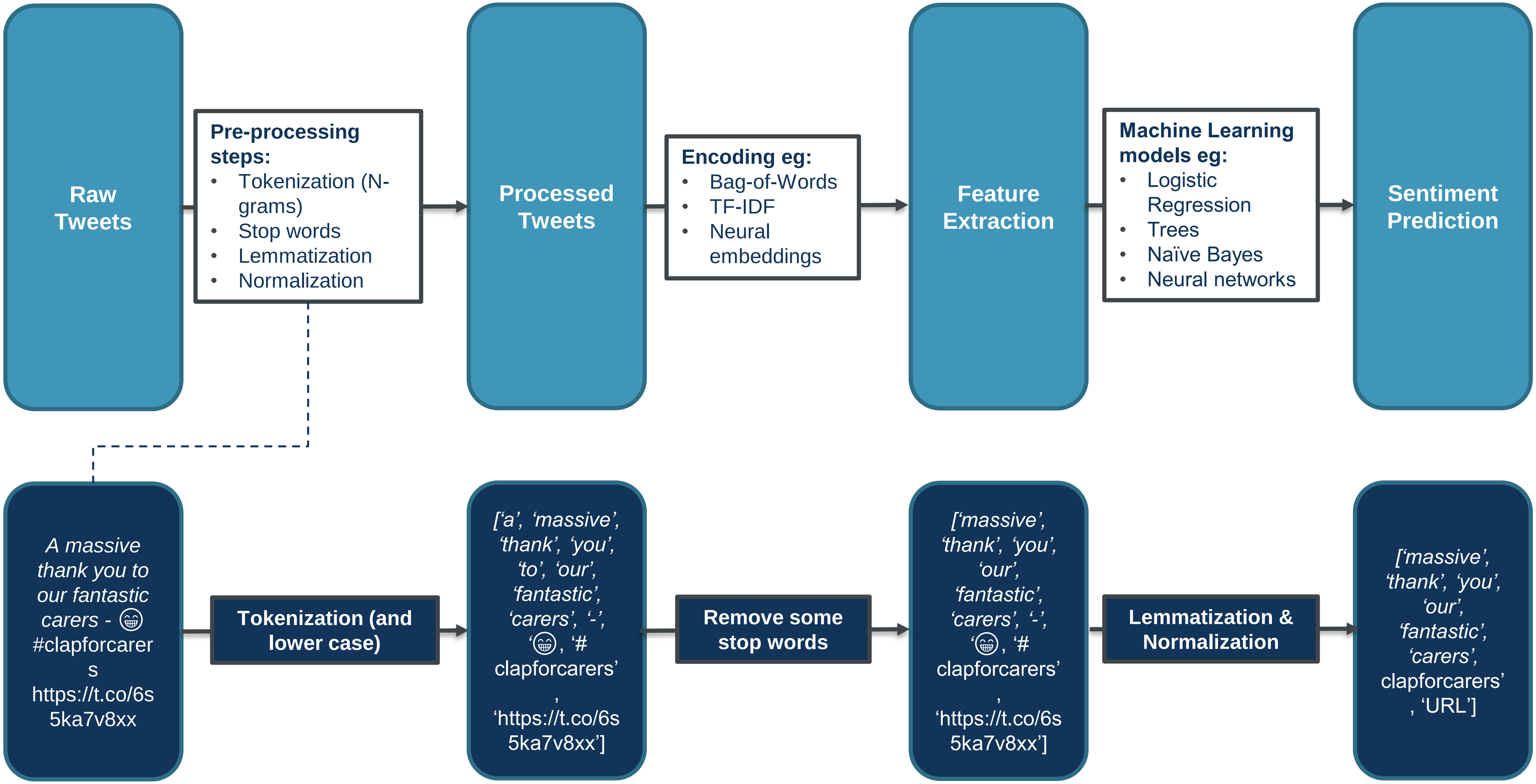
Data Enrichment

Training data of 7k UK English Tweets is relatively small in size. Model performance could potentially be improved by enriching it with other labelled text datasets from the same source (Twitter). More data contributes to a larger vocabulary to be associated with sentiment.

200k Training Set Labels:

- 193k random sample from the sentiment140 dataset, a collection of 1.6m (non-COVID) Tweets, automatically labelled ‘positive’ or ‘negative’, using the presence of positive [e.g. ☺] or negative [e.g. ☹] emoticons
- The above is appended to our 7k UK dataset of English language Tweets relating to COVID-19, resulting in a Training Set with 200k labels
- Equal number of positive and negative labels

NLP Pipeline



Tokenization: N-Grams

N-grams are a sequence of N words, and text can be converted into N-gram tokens before encoding

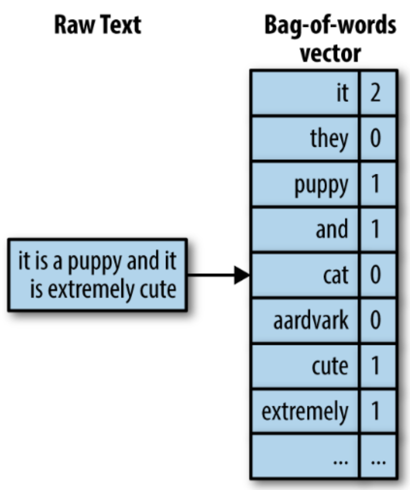
N-Gram Type	Text Tokens
Unigrams (N = 1)	*[‘massive’, ‘thank’, ‘you’, ‘our’, ‘fantastic’, ‘carers’, clapforcarers’, ‘URL’]*
Bigrams (N = 2)	*[‘massive-thank’, ‘thank-you’, ‘you-our’, ‘our-fantastic’, ‘fantastic-carers’, ‘carers-capforcarers’, clapforcarers-URL’]*
Trigrams (N = 3)	*[‘massive-thank-you’, ‘thank-you-our’, ‘you-our-fantastic’, ‘fantastic-carers-clapforcarers’, ‘carers-clapforcarers-URL’]*

Feature Extraction: Encoding

Encoding converts a set of text tokens into a numerical vector, which can be read by ML models

Bag-of-Words (BOW)

- Counts frequency of each token in the text, where the dimension of the vector is the size of the whole vocabulary
- Simple and can be effective, but ignores grammar and order, and often computationally slow to handle



Term Frequency-Inverse Document Frequency (TF-IDF)

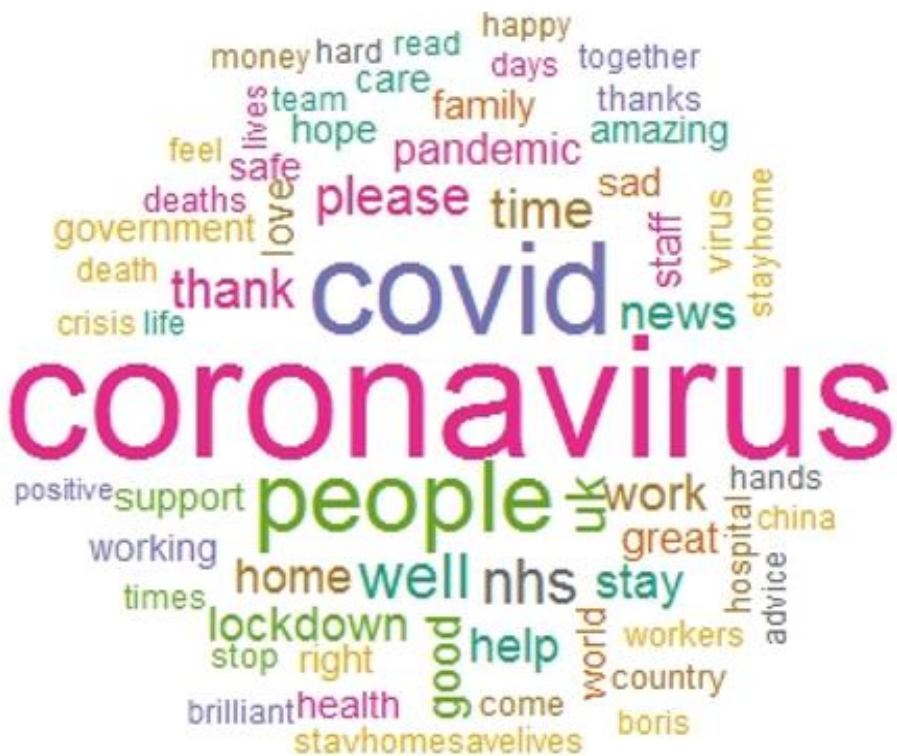
- Commonly used in search engine rankings and other information retrieval settings

- TF-IDF calculates the importance of a word, which increases proportionally to the number of times a word appears in a Tweet, but is offset by the frequency of the word in all Tweets

Neural Embeddings

- A.k.a "semantic vector space", "word feature vector", "vector representation"
- Neural embedding is a representation of a word as a numerical vector that captures semantic meaning (e.g. GloVe)
- For example the word "peace" might be represented as (-0.035, 0.078, 0.022, -0.013)
- 3 primary purposes:
    - Make recommendation by finding nearest neighbour in the embedding space
    - Input for supervised learning
    - Visualisation of concepts and relationships between categories

Word Cloud



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Sentiment Analysis Models

Baseline Models

Running a simple baseline with give a benchmark accuracy to compare other more sophisticated models against. The baseline models below do not require any training on our dataset.

1. SentiWordNet: Positive / Negative Word Count

- Use SentiWordNet, an open source list of words with labelled sentiment scores for positivity, negativity, objectivity
- For each Tweet in the test set, count the number of 'positive' and 'negative' words based on the SentiWordNet label
- Classify Tweet as 'positive' if the number of positive words is greater or equal to the number of negative words

2. TextBlob

- 'Out-of-the-box' sentiment classifier (and can perform other NLP tasks such as Part-of-speech Tagging)
- Pre-trained on a movie review dataset and applies Naïve Bayes on new text
- Can output 'polarity' and 'subjectivity', where polarity indicates sentiment and is a score between -1 (negative) and +1 (positive)
- Classify Tweet as 'positive' if the polarity ≥ 0

Model Performance Metric

Model performance is measured by the AUC (Area Under the ROC Curve).

The Receiver Operating characteristic (ROC) curve is a graph showing the performance of a classification model at all classification thresholds.

AUC shows the capability of model to distinguish positive and negative sentiment classes.

AUC values	Results
0.9 - 1	Excellent
0.8 - 0.9	Good
0.7 - 0.8	Fair
0.6 - 0.7	Poor
0.5 - 0.6	Unsatisfactory

Machine Learning Models

The tables below show AUC performance of models on 3k test data.

Models (except baseline) trained and tuned on 7k training data:

Encoder / Model AUC	SentiWord Net	TextBlob	XGBoost	Linear SVM	Logistic Regression (Regularised)	Naïve Bayes	Random Forest
BOW	0.490	0.724	0.828	0.838	0.851	0.857	0.857
TF-IDF	n/a	n/a	0.815	0.839	0.848	0.856	0.848

Data enrichment - Models (except baseline) are trained and tuned on 200k training data:

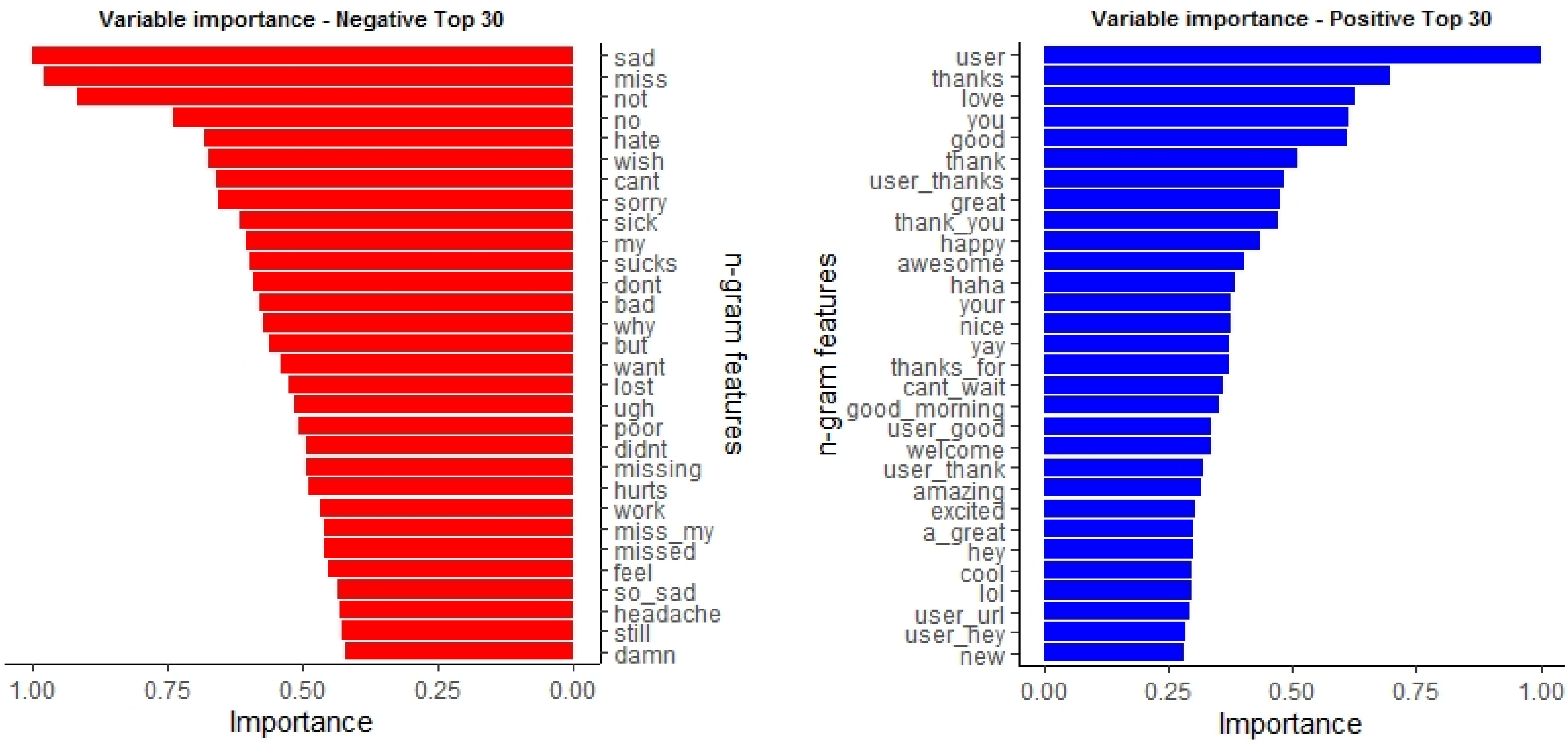
Encoder / Model AUC	SentiWord Net	TextBlob	XGBoost	Linear SVM	Logistic Regression (Regularised)	Naïve Bayes	Random Forest
BOW	0.490	0.724	0.843	0.846	0.858	0.848	0.864
TF-IDF	n/a	n/a	0.834	0.847	**0.859**	0.858	0.858

Selected Model (based on results, run-time, simplicity and transparency) is
<u>Regularised (Ridge) Logistic Regression with TF-IDF trained on enriched data set (200k)</u>

Parameter Tuning and Feature Selection

- Hyper-parameter tuning were performed using **5-fold cross validation** on training data
- Training on 7k data utilised **document-term-matrix of uni-grams** and 6k features.
- Training on 200k data utilised **document-term-matrix of bi-grams**, 80k features (selected from most common ones out of 880k possible bi-grams). **10x weightings** were applied to the subset of 7k COVID-19 related tweets - to improve contextual signals.
- It is essential to work with **sparse matrices** to handle the size of these matrices during computation and to vastly improve speed when training the models.
- **TF-IDF** encoding results were similar to BOW, with small improvements for some supervised algorithms but also small deterioration for others.
- **GloVe** (Global Vectors for Word Representation) by Stanford NLP was explored. It has the potential for encoding some form of meaning/context. While interesting and helpful in unsupervised learning, it had not significantly boost predictive performance of the machine learning algorithms we tried. As such, these features are not included in the final model.

Variable Importance of ML Model



Variable importance is calculated using Agresti method of standardisation

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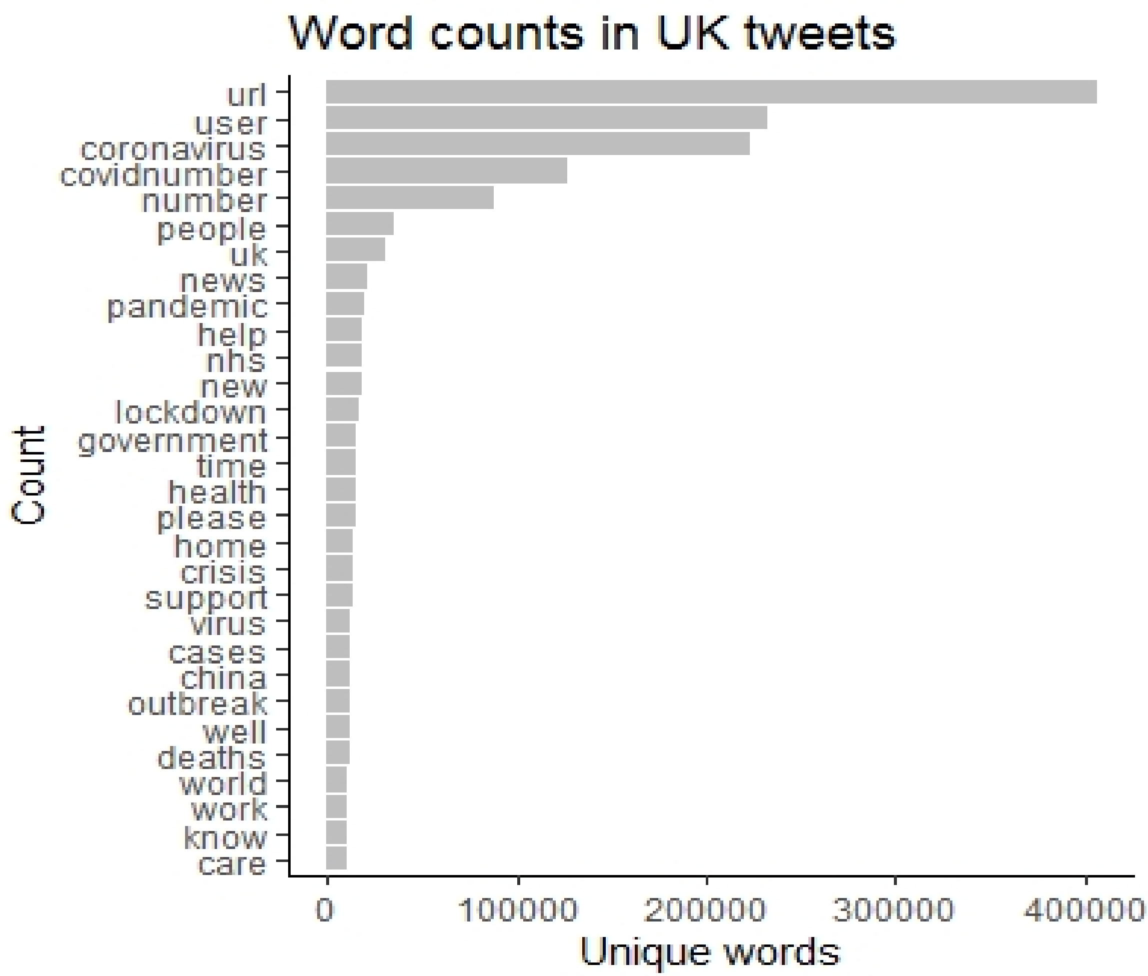
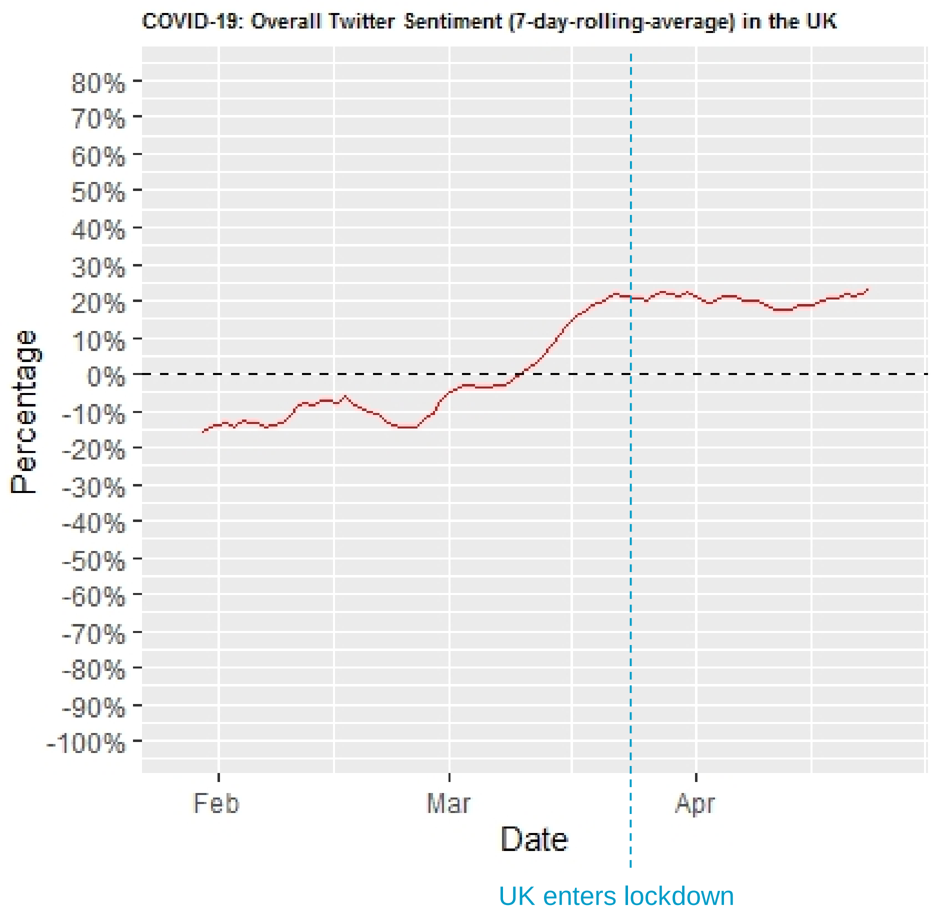
Sentiment Analysis on Historical UK Tweets

Common words in UK Tweets

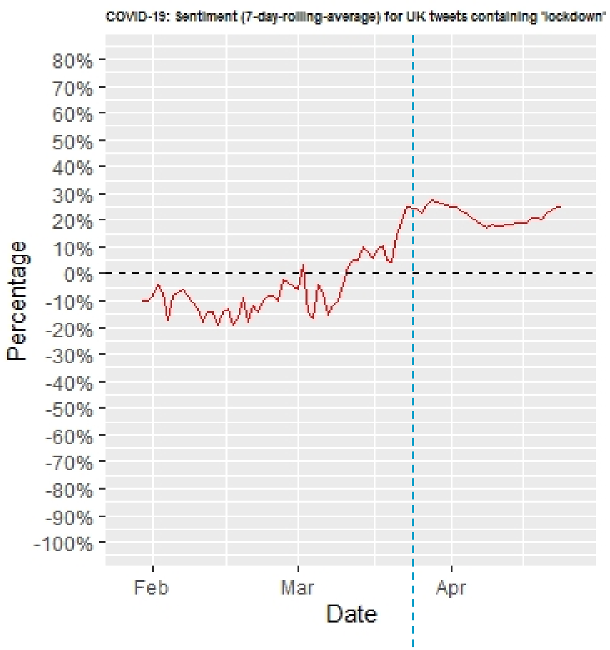


Overall Sentiment Scoring on all UK Tweets

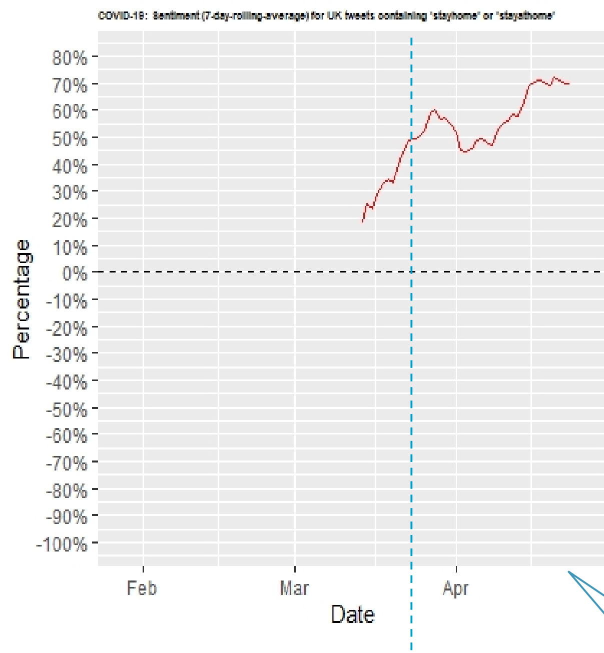


- Sentiment scoring on 432k UK Tweets using machine learning model
- Tweets from end of January till late February generally focused on COVID-19 development in other countries and carried a more negative sentiment
- The inflection point was middle of March where there were more positive sentiments, staying at +20% level until the end of April
- Timeline:
  - 31 Jan - First two cases confirmed
  - 28 Feb - First British death
  - 9 Mar - FTSE 100 plunged by more than 8 percent
  - 11 Mar - Bank of England interest rate cut; Chancellor announces £30 billion measures to protect economy
  - 23 Mar - Lockdown
  - 27 Mar - Both PM Boris Johnson and HS Matt Hancock tested positive
  - 8 April - Estimated peak of hospital deaths

Sentiment of Tweets containing ‘lockdown’ or ‘stayhome’



UK enters lockdown

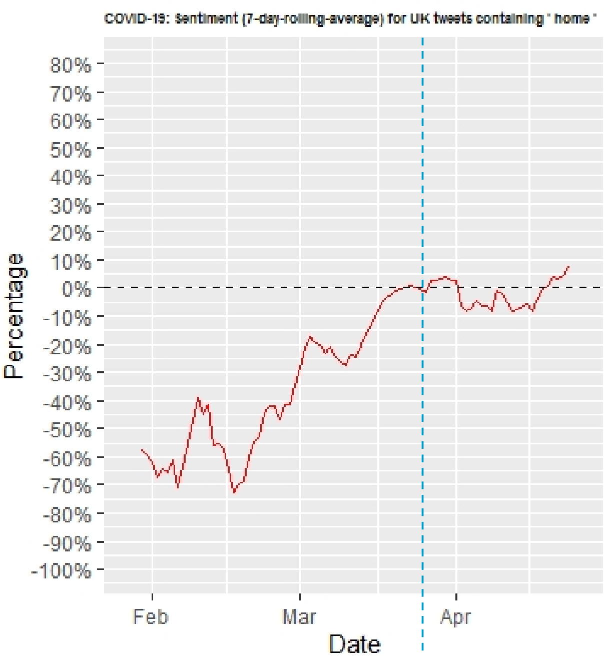


UK enters lockdown

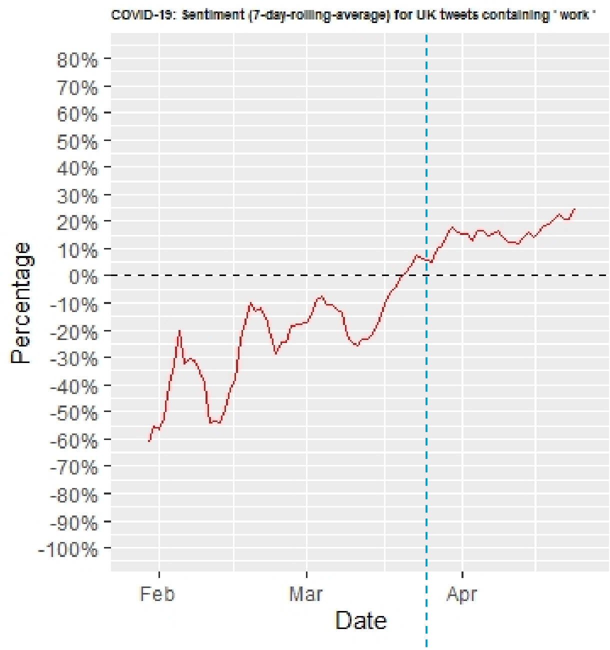
- There was increasingly positive sentiment trend around the period when the lockdown was introduced
- Note the slight dip in sentiment 1-2 weeks after lockdown, possibly because of people feeling exhausted
- Sentiment for “**lockdown**” was very similar to overall sentiment of all UK tweets, in both shape and scale
- The response to the “**stayathome**”/ “**stayhome**” / “**stayhomesavelives**” message was favourable - sentiment scores as high as 70% by end of April

“staying home is the easiest and most effective way to stay safe lets make sure we observe government lockdown and follow the guideline in keeping safe while at home covidNUMBER stayhome”

Sentiment of Tweets containing ‘home’, ‘work’



UK enters lockdown



UK enters lockdown

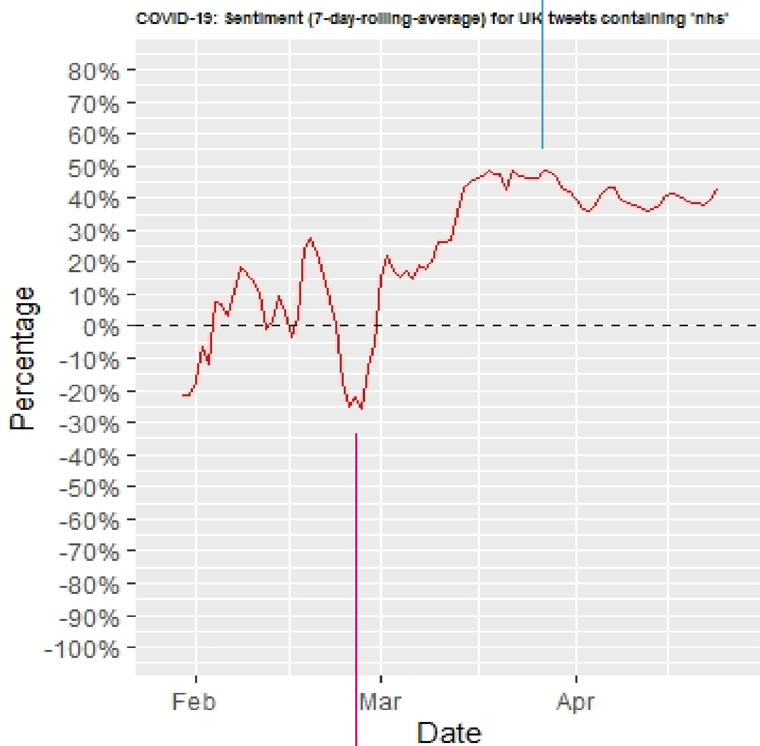
Example Tweets:

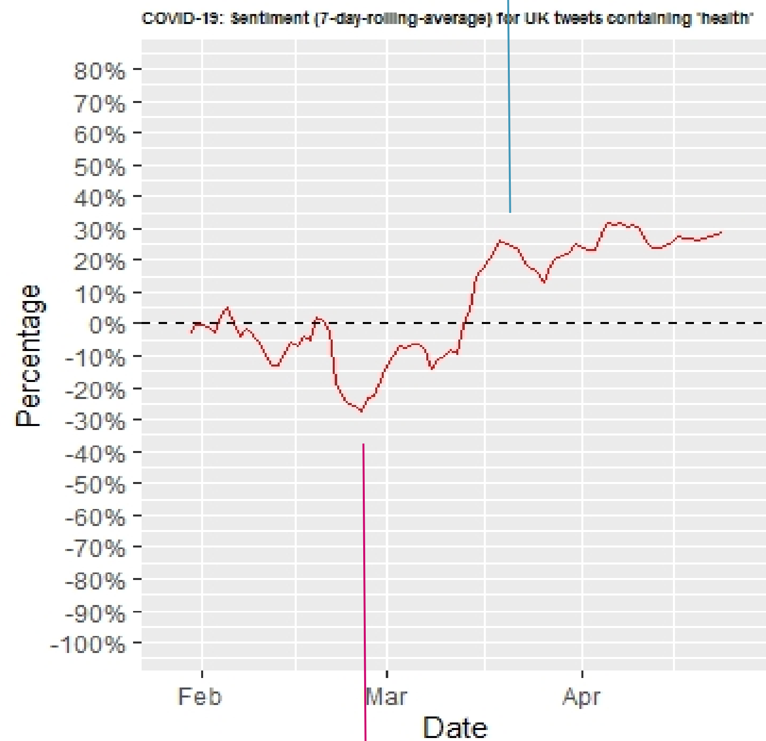
- ‘**Home**‘ - Early Feb
  - “Bring <u>home</u> britons from wuhan”
  - “so worried about a possible coronavirus breakout back <u>home</u>”
- Entering lockdown
  - “people forced to stay at <u>home</u> saying they want to be at <u>work</u> and there are people forced to go to <u>work</u> saying they want to be at <u>home</u>”
- ‘ **Home**‘ - Late April
  - “Staying <u>home</u> keep safe”
  - “my brother was in a nursing <u>home</u> he died .. “
- ‘ **Work**‘ - Late April
  - “Amazing <u>work</u>”
  - “Thank you for your hard <u>work</u>”
    (nhs, key workers, volunteers etc)

Sentiment of Tweets containing ‘nhs’, ‘health’

“nhsheroes heroes nhs nhsthankyou a massive thanks”

“Thank you to all healthcare workers”



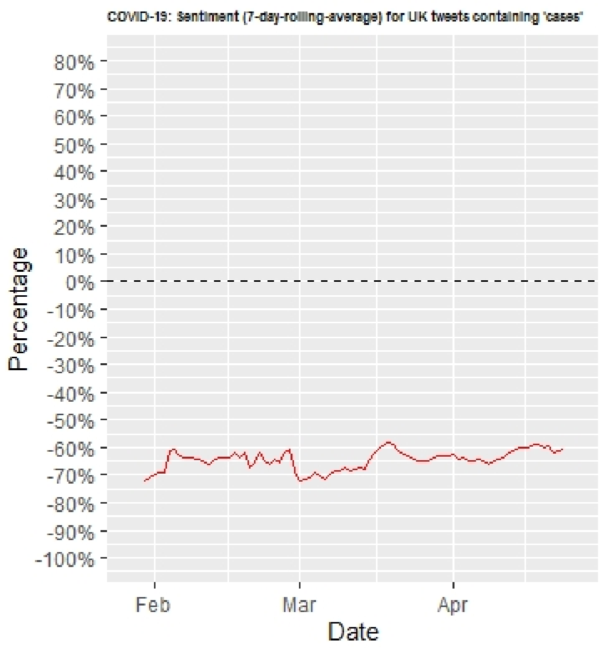


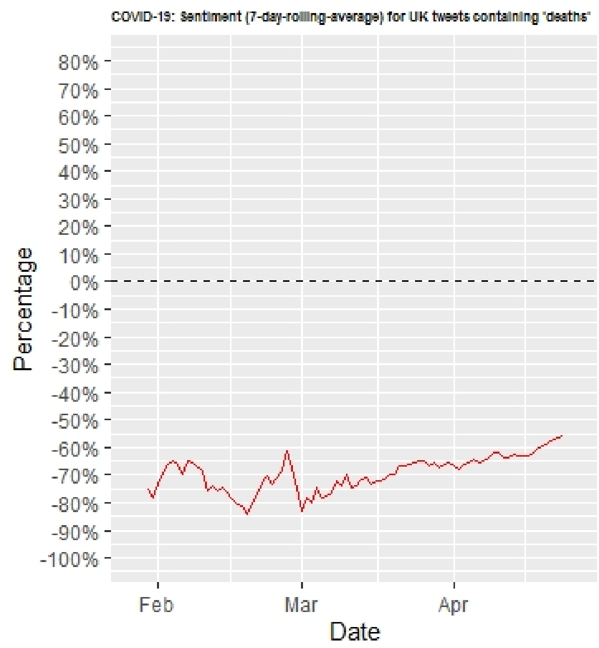
“coronavirus patients could be denied lifesaving care if virus overwhelms nhs hospitals”

“nhs staff shortages too few beds a lack of protective equipment”

“coronavirus declared a serious and imminent threat to public health as cases surpass NUMBER”

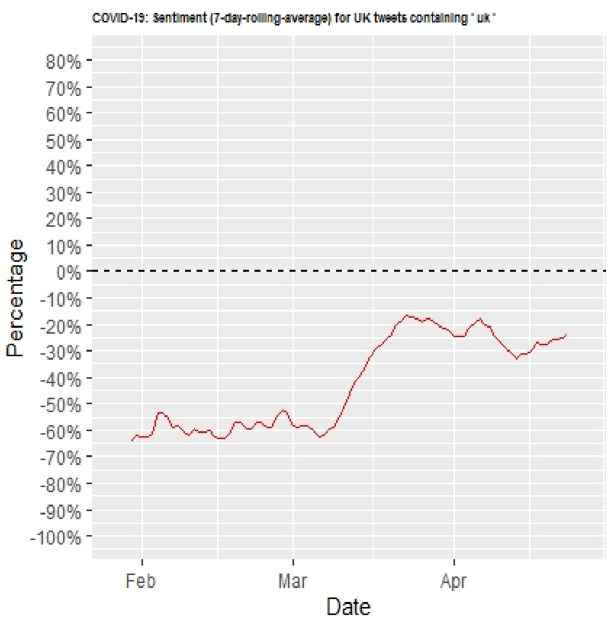
Sentiment of Tweets containing ‘cases’, ‘deaths’

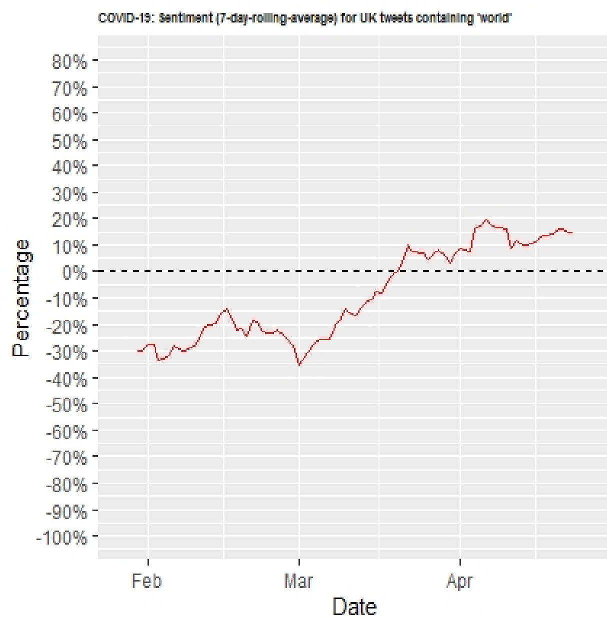




- These Tweets were frequently associated with reported COVID-19 statistics, number of cases and deaths in the UK and around the world
- The sentiment related to “**cases**” and “**deaths**” were overwhelming negative, as one would expect
- Sentiment of “**cases**” hovered around -70%. Sentiment of “**deaths**” was around -80% initially but was improving towards the end of April.

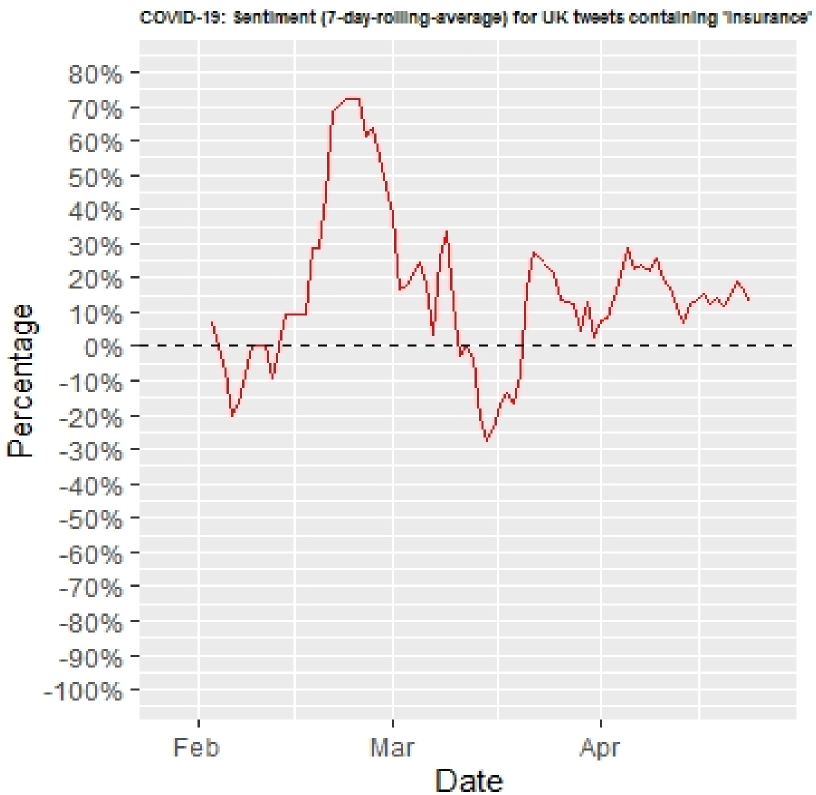
Sentiment of Tweets containing ‘uk’, ‘world’





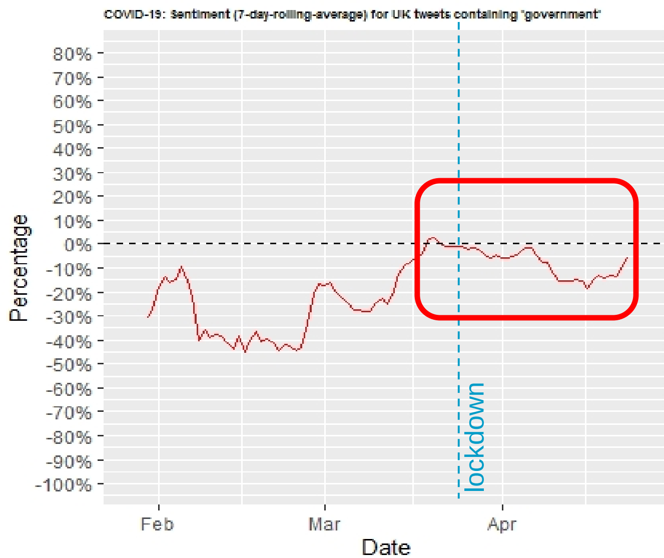
- The sentiment trend for Tweets containing “**uk**” was similar to the overall sentiment of all UK tweets, but scaled down by around 40%
- The sentiment trend for Tweets containing “**world**” was similar to the overall sentiment of all UK tweets, but scaled down by around 10%

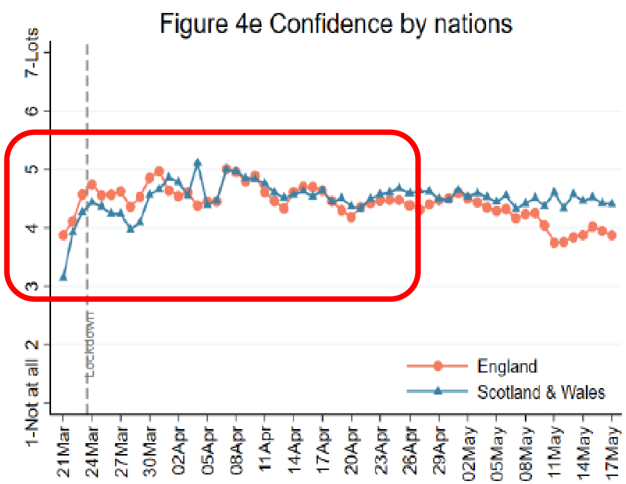
What about sentiment on ‘insurance’?

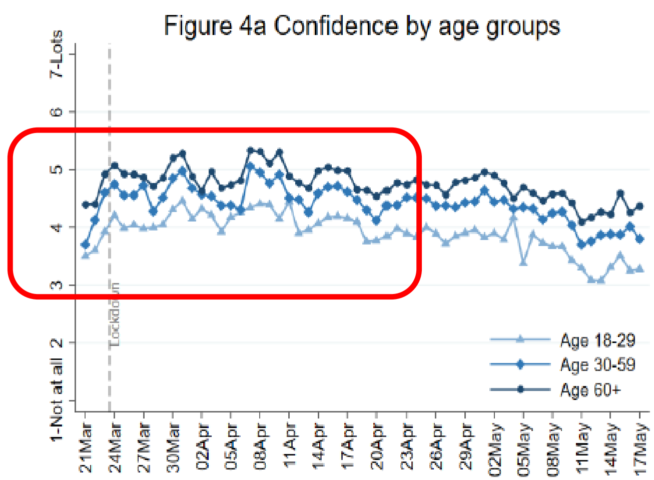


- Positive peak end of Feb was due to a number of very similar tweets pointing to travel insurance advice given on https://www.citizensadvice.org.uk/
- Notice the dip in mid-March (just before UK lockdown):
  - (-) "last night the pm encouraged people to stay away from theatres pubs and restaurants to stem the spread of covidNUMBER but he didn’t formally ask those businesses to close without clear government instruction that leaves them unable to claim insurance and liable to go bankrupt"
- After lockdown (23rd March):
  - (-) “hiscox rejects agency’s coronavirus claim warns pandemic too large”
  - (-) “bbc insurance firms ordered to pay out or explain”
  - (-) “wedding insurance companies won’t pay out”
  - (+) “renewals reinsurers showed resilience despite covidNUMBER challenges”
  - (+) “us insurers offer motor premium refunds”
  - (+) “nfu mutual includes covidNUMBER in personal accident and annual travel insurance policies”
  - (+) “these are the times insurance companies are grateful for the existence of reinsurance companies”
  - (+) “thats why people take out insurance”

Sentiment of Tweets concerning ‘government’ vs UCL social study







- The UCL COVID-19 Social Study conducted a panel study of over 90,000 respondents focusing on the psychological and social experiences of adults living in the UK
- One way of validation is to compare the Twitter Sentiment Analysis results against independent findings in the UCL Social Study. The lower plots shows respondents’ confidence in the government, by nations and by age
- The sentiment trend for tweets containing “**government**” post-lockdown (23 March) was generally better than pre-lockdown
- Twitter users have a younger demographics. The “government confidence” is lowest for the youngest age group in the UCL Social Study – note the similarities between Twitter sentiment and people’s confidence on government:
    - Hovers around the neutral level
    - Decent levels 1-2 weeks post-lockdown, and slight decrease after that

Limitations

- **Change in Twitter keyword search**: Data source is more complete for Tweets made after 11th March 2020, when the list of COVID-related keywords were expanded - so there is more uncertainty in the sentiment levels shown prior to this date
- **Noisy labelling**: We use an automated labelling method for sentiment based on emoticons present in Tweets for the training set - whilst this has saved a lot of time, this can lead to mislabelling where there is contradiction between the text and the emoticon sentiment [e.g. “Ah what a shame 🤗 ...”]
- **Lost data in pre-processing:** Due to time limitations and the desire to avoid manual pre-processing steps, we chose to take a 25% sample of the full dataset available, and were able to map 51.7% of all English Tweets to a specific country, effectively discarding the remainder from the analysis - it is assumed that our data sample is representative of the full dataset without any significant bias
- **Ignored neutral sentiment:** In practice, some Tweets are neutral in sentiment, but this has been ignored in our analysis and we have built the models to only predict ‘positive’ or ‘negative’ sentiment
- **Twitter user profile:** Twitter users can have different demographic mix from the general UK population, and insights on sentiment from Twitter may not be representative of the UK as a whole

Summary

- Training and fine-tuning ML models on a COVID Twitter dataset can significantly outperform simple pre-trained baseline models
- Data enrichment for training (using sentiment140 non-COVID Twitter dataset) can improve sentiment prediction results on the test set.
- Selected model was **Regularised (Ridge) Logistic Regression using TF-IDF trained on enriched data set (200k)**, based on accuracy, speed, simplicity and transparency, achieving 0.859 AUC on the 3k test set
- Sentiment analysis on historical UK COVID-19 Tweets suggest:
  – Overall sentiment has become more positive post-lockdown on the 23rd March, with relatively strong positive sentiment reaction to the **'stayathome'** message compared to '**lockdown**'. This is an opportunity for positive behavioural change if there are future waves.
  – Increase in positive sentiment for Tweets relating to **'NHS'** and **'health'**, particularly from late-March, which also coincides with the start of Clap for Carers - some dips in sentiment related to fears about running out of hospital beds and lack of sufficient PPE
  – Sentiment relating to **'UK'** is generally more negative compared to those relating to **'world'**
  – Tweets containing **'government'** have been mostly negative pre-lockdown with some sentiment improvements to neutral level during lockdown. There exists similarities with UCL Social Study results.
  – Tweets containing **'insurance'** show swings in sentiment relating to travel insurance advice, government policy, insurers' responses to COVID-19 coverage and changing market conditions

Potential Future Investigations

- **Update for latest period:** We can update the analysis by mining Twitter data for the period since 26th April 2020 - our work described here uses Georgia State University's Panacea Lab v7.0, whereas the latest released v16.0 contains Tweet IDs up to 27 June 2020
- **Explore Deep Learning architectures:** Recent advances in NLP show that deep neural network architectures, particularly when pre-trained on a large text corpus, can significantly outperform more traditional ML models (such as the ones used in this work), but this will require more computing power
- **Neural Embeddings:** More work can be done to analyse the effectiveness of neural embeddings, as BOW and TF-IDF have a number of limitations:
  - BOW / TF-IDF leads to a <u>high dimensional</u> and <u>sparse feature vectors</u>, due to the size of the Twitter vocabulary and elements only take non-zero values where the corresponding word appears in the Tweet
  - BOW / TF-IDF automatically <u>discards order of words</u> in a Tweet, e.g. "*the pm encouraged people to stay away…*" and "*people encouraged the pm to stay away…*" would have the same representation, which can change the semantic meaning or sentiment of a Tweet
  - Learning is usually <u>more efficient with neural embeddings</u>, which have denser lower-dimensional representations compared to BOW / TF-IDF
- **Visualisation:** Tools such as t-SNE can be used to visualise and group similar types of Tweets together, based on their encoded representations
- **Cleaner Labelling:** We could enlist the help of other volunteers to perform a manual review of the training data labels, to remove some of the noise around using emoticons to detect sentiment

Questions

Comments

Institute and Faculty of Actuaries

Appendix

Token Normalization

Approach to token normalization taken from Badr and Fatima (2015) and Saif et al (2012):

- **Username replacement**: all user mentions are replaced by the token USER
- **Web links replacement**: all URLs are replaced by the token URL
- **Punctuation**: all punctuation marks are removed
- **Emoticons**: all emoticons are removed (after noise labelling use)
- **Hashtags**: the hash symbol # is removed from hashtags and they are treated as regular words
- **Numbers replacement**: all digit characters are replaced by the token NUMBER
- **Word compression**: any sequence of repeated letters is reduced to two letters, e.g. "*coool*" and "*cooool*" are compressed as a single token "*cool*"

References

1) Georgia State University's Panacea Lab
2) Sentiment140 dataset with 1.6 million tweets
3) DocNow Hydrator
4) Using Skipgrams, Bigrams, and Part of Speech Features for Sentiment Classification of Twitter Messages [Badr and Fatima 2015]
5) Alleviating Data Sparsity for Twitter Sentiment Analysis [Saif et al 2012]
6) Twitter Sentiment Classification using Distant Supervision [Go et al 2020]
7) Feature Engineering for Machine Learning [Zheng and Casari 2018]
8) SentiWordNet
9) TextBlob
10) GloVE: GLobal Vectors for Word Representation
11) Sentiment Analysis [Wikipedia]
12) UCL COVID-19 Social Study