The impact of shock activism on climate change sentiment on Twitter
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Abstract

Climate Change is considered one of the most important issues of our time, and the debate around it and how to combat it is a constant of today's era. Previous studies have shown that it is possible to detect stance and sentiment regarding climate change on social media, and some have studied their evolutions during major natural disasters, but not during political events. The most recent years have seen the rise of shock climate activism that sparked global reactions, such as the Climate Strikes that made Greta Thunberg famous, or more recently the soup-throw on a Van Gogh in London. For these events, we collected data from Twitter posts and classified their aggressiveness, sentiment, and stance on climate change. We observe the evolutions of these reactions during these events, and focus more particularly on stance. We show that such events usually spark a more denial-oriented mean stance on the day they happen, which usually fades away quickly after. These results hold when only accounting for people who already post about climate change, but become less significant, particularly when compensating for people posting much more than others.

1 Introduction

Climate Change is arguably one, if not the, most pressing issues facing society this century, and the perception of it by the general population influences greatly our ability to counter it. Social media provide access to enormous amounts of data related to the treatment of this issue by the general public and how people discuss it. Concurrently, there has been a lack of research regarding the impact of climate activism on actual climate change, says (Fisher and Nasrin, 2021), and the first step is to assess what impact these have on society. Recent articles from, for example, the New York Times [1], only deal with the subject using quotes from their readership to collect opinions, but there hasn't been so far a big data analysis of the impact of these events.

In this study, we use data from the social platform Twitter to study the perception of Climate Change in the general population during and following major political and climate activism events.

We considered the following events:

- The global climate strike of March 2019.
- The global climate strikes of September 2019, the 20th and 27th. Inspired by Greta Thunberg, these events gathered respectively 4 and 2 million people across the globe.[2]
- The soup-throw of October 14 2022.

The primary content type to study discussions around this issue is text, and models to assess stance and sentiment on text have already been developed, for example for (Effrosynidis et al., 2022b), in which they used it to assemble a major corpus of tweets related to cliamte change until October 2019. We augment this data with a new dataset assembled ourselves, and reclassify stance, sentiment and aggressivity of the tweets. We show the classifier we created performs better than the one used in the original dataset.

Finally, we use this new dataset to observe how aggressivity, sentiment, and especially stance on climate change evolve around these major events. We show they induce significant changes in stance during and after the events, particularly in the population of Twitter users who regularly post about climate change.

Our results are more significative for the soup-throw of October 2022, as we collected more data than in (Effrosynidis et al., 2022a), which allowed us to filter it more.

[1] https://www.nytimes.com/2022/12/02/climate/climate-protests-museum-artwork.html

[2] https://www.wikiwand.com/en/September_2019_climate_strikes

2 Literature Review

The study of climate change on Twitter and in the NLP community has already seen some work done, particularly on sentiment and stance detection, but also on data collection and analysis of global discourse around natural events.

In (Effrosynidis et al., 2022b), the authors assembled a dataset of 15 million tweets published between 2006 and 2019, using state-of-the-art NLP models to assess and quantify various aspects of each tweet, and in particular stance, sentiment, and aggressiveness. Similarly, (Koenecke and Feliu-Fabà, 2019) have analyzed the evolution of climate change sentiment before and after major natural disaster events in the USA, using individual tweets from Twitter, while (Vaid et al., 2022) leveraged datasets called ClimateStance and ClimateEng to classify tweets based on user stance and various climate-related categories.

On the technical aspects, techniques such as LDA for topic modeling, BERT and VADER for sentiment analysis, and dedicated models for stance detection. For example, (Effrosynidis et al., 2022a) and (Koenecke and Feliu-Fabà, 2019) created dedicated stance detection models based on BERT, while (Jiang et al., 2017) used LDA and SentiWordNet for topic determination and sentiment analysis in news media stories. Additionally, some linguistic analysis has been conducted in (Vaid et al., 2022) and (Effrosynidis et al., 2022b), showing that climate-affirming online users tend to use the term "climate change" more than "global warming" and discuss more about organizations and governments.

The literature points at the fact that there is still room for improvement and further exploration in this area, like cross-language studies, or refined stance classification - which we attempt at furthering in this paper. Deeper analysis of the impact of climate-related events on sentiment and stance, and study of the influence of news treatment on public perception are also pointed as future leads.

And finally, as (Fisher and Nasrin, 2021) points out, there is also a need for studies related to particular events, such as climate activism actions. This is the object of study here.

3 Datasets

3.1 The 2019 Climate Strikes

We leveraged The Climate Change Dataset assembled in (Effrosynidis et al., 2022a), [3]. This 2.09 GB dataset contains about 15 million tweets collected between 2006 and 2019.

In this dataset, we used the following columns:

- *id* - The unique tweet ID, an integer to find the tweet online.
- *created_at* - A timestamp of when the tweet was posted.
- *sentiment* - A floating point ranging from -1 to 1 with values closer to 1 being translated to positive sentiment, values closer to -1 representing a negative sentiment while values close to 0 depicting no sentiment or being neutral.
- *stance* - A string taking one of three values: "believer" if the tweet supports man-made climate change theories, "denier" if it denies it, "neutral" if there's nothing supporting nor deying it.
- *aggressivity* - A string taking on of two values: "not aggressive" or "aggressive".

Coordinates of posting, topic (uncovered with LDA) and gender (estimated) were also present in the dataset but not used for this study.

Per Twitter's privacy policy, the text of said tweets was not made available. We thus rehydrated the texts ourselves as we deemed it necessary for the following part of the study. We only did so for tweets posted 2 weeks within the strikes of 2019, collecting about 25,000 tweets total.

3.2 The soup-throw of October 2022

The aforementionned events were picked as they are the two biggest events present in the timespan of the Climate Change Dataset, and it was the first time such a strike made global headlines, making famous its most prominent figure Greta Thunberg. More recent events have sparked even more global reactions, such as the soup throw of October 2022. On October 14 2022, young activists of the organization Just Stop Oil threw soup on the Sunflowers of Van Gogh in London, with the intention

[3]https://data.mendeley.com/datasets/mw8yd7z9wc/

of putting climate change in the headlines with a shock action.

This event, which was not present in The Climate Change Dataset, prompted us to assemble a new dataset ourselves. We pulled 350,000 tweets from Twitter in the 4 weeks between October 1st and October 28th, querying for tweets containing either "climate change" or "global warming". According to (Stede and Patz, 2021), these keywords usually allow to query efficiently a majority of the content posted on Twitter around climate change.

We also ensured these 350,000 tweets are neither retweets nor replies, in the hope we collect straight the thoughts of people without giving too much weight to tweets that go viral and would bias our results - in the case of retweets - or conversations that create a lot of answers that react more to the original message and not the current context - in the case of replies.

In the following, we used subsets of this larger corpus. First, so that we have less tweets to classify using the method described later (which can be expensive), and secondly to filter for users who stay active on the subject of climate change before, during and after an event.

4 Methods

4.1 Reclassifying tweets stance

The accuracy of 74% for the stance classification reported by (Effrosynidis et al., 2022b) was confirmed by a self-performed annotation of a sample of tweets from the Climate Change Dataset. As we also resolved to download a new batch of data for the soup-throw of Oct 2022, we needed to use a method to classify the tweets' stance ourselves and used the opportunity to try to improve on their classifier based on BERT.

We used a more recent transformer-based model, building on the finding that these models performed better in the study of The Climate Change Dataset. More specifically, we picked gpt3.5-turbo from OpenAI and designed specific prompts to classify tweets.

We designed two prompts, one that only sent the text of the tweet, the other also contained the author's self-written description on their account. We hoped this would improve the classifier's accuracy, but our results showed otherwise.

Ultimately, we picked the prompt that used only the tweet's text. The resulting classifier had an accuracy of 0.88 on an annotated sample of tweets

Model	**Accuracy**
Original BERT	0.74
GPT-3.5 Prompt 1	0.88
GPT-3.5 Prompt 2	0.8

Table 1: Accuracies of the three classifiers we used. The values were computed after annotating by hand a sample of 50 hydrated tweets from the Climate Change Dataset

from The Climate Change Dataset, vs 0.74 for their original classifier. OpenAI charging about 0.2 cents for 1000 tokens, we ended up paying only 2$ to classify $\approx 12,000$ tweets.

The results are summarized in table 1 and the prompts are put in the appendix for reference.

4.2 Time series analysis around events

For all the events mentioned previously, we performed a time series analysis of the evolution stance in the 2 weeks leading to and following the events we will be studying, inspired by the approach of (Koenecke and Feliu-Fabà, 2019). Like them, we also compared the distribution of stances before and after the event to observe if there is a significant change. We however computed p-values using a statistical Chi-squared test.

This analysis was performed in multiple steps:

First, for each event we wanted to study, we grouped tweets together per day to get a daily distribution of stance, sentiment and aggressiveness, from which we can compute mean and standard deviation. We compare this distribution in the 2 weeks before an event, the day of the event, and 2 weeks after.

While at first we consider all accounts that tweeted in our datasets, we leverage the large amount of data we had for the soup-throw of October 22 to filter for a subset of tweets posted by authors who posted about climate change before, the day of, and after the event (so at least 3 times). We started with 350,000 tweets, and ended up with 36,000 tweets posted by authors of multiple tweets. Among these, we only kept the authors in the 75% percentile of number of tweets posted, which is under 11 tweets posted on climate change over the course of 4 weeks. We justify this decision with the fact that some accounts were posting a lot, which may indicate the presence of bots, but also simply data that might bias our result towards the most active accounts.

This accounts ultimately for 12,500 tweets, a

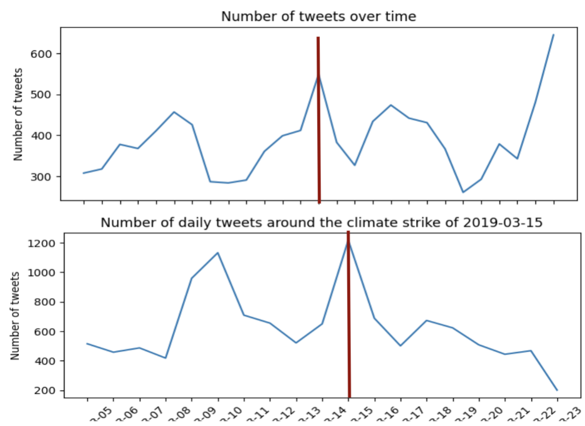


Figure 1: Daily tweet count around March 15 2019 and September 20 2019. The red bar indicates the day of the event.

number comparable to the two previous datasets we had for the 2019 strikes, but containing only data from what we'll call in the rest "usual posters" about climate change.

5 Results

We first observed the amount of tweets generated in the events of interest for us to observe the platform's reaction to the event. In figure 1 we can see the amount of tweet doubles during the two Climate Strikes of 2019.

5.1 Sentiment and aggressiveness

We observe that sentiment and aggressiveness don't vary in a significant nor consistent way across our 3 events, on the day of the event. If there is a change induced by the action, we can't notice it on our data. Plots showing the daily evolution of these two metrics are represented in figure 2.

5.2 Stance shifts towards denial on the day of events

The most striking results in this study are related to climate change stance in the overall population tweeting on climate change. On all 3 of our events, we noticed a significant decrease in the days leading (if the event can be anticipated), and in particular on the day of the event, of the mean stance. This can be clearly noticed on Figure 3.

In the case of the September 2019 strikes, they spanned two weekends, which seems to explain why the drop in stance last a bit longer.

We observe that comparing before and after the event, there is no significant change. We reject the hypothesis that there is a significant change with $p = 0.7$.

5.3 Evolution of stance in the usual posters population

While the previous results confirm that stance is seeing changes, we wanted to confirm this result more consistently by looking at users who post regularly about climate change, and a least once before the event, during, and after it. This section is only using our own assembled dataset of tweets around the soup-throw of October 22, as we didn't have enough data for such an analysis in the Climate Change Dataset.

Plotting the stance along the axis of time around October 14 for these usual posters, we observe a stance increase towards the end of the month, as one can see in Figure 4. An analysis using GPT3.5 to determine common topics reveals that several events happened around that time that could explain why it was this high, including a major UN report and the upcoming COP27.

We thus restricted for an analysis of only the two weeks around the event (the one before and the one after).

We find that these usual posters do experience a significant decrease in stance on the day of an event ($p = 0.001$). However, like in the previous section, we observe that stance does not remain significantly lower in the week after the soup ($p = 0.41$).

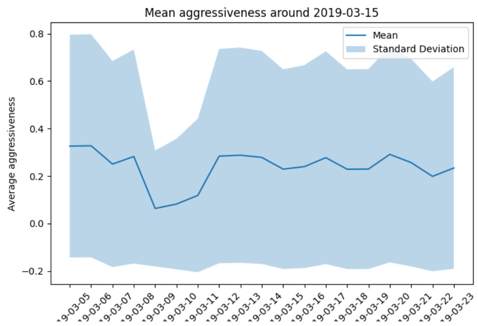
We visualize the three distributions in figure 5.

5.4 Aggregating tweets per usual poster

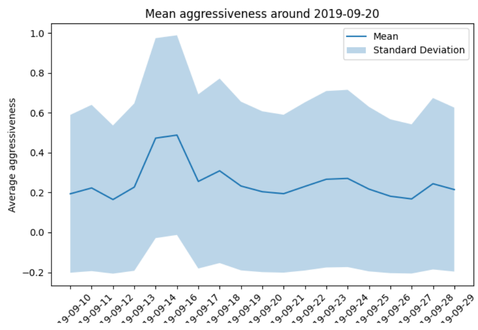
Realizing that each user could still appear multiple times in a day and skew the distribution, we weighed each user's contribution so that their stance average only counts once during one day. Adjusting for that fact, we have our daily stance means get slightly closer, and our chi-squared test to observe if there's a significant difference between the stance on soup day and before, in the usual posters population, fails with $p = 0.10$ (with mean before 0.679 on that day 0.658). There is still no clear difference between before and after the event - $p = 0.27$.

6 Discussion

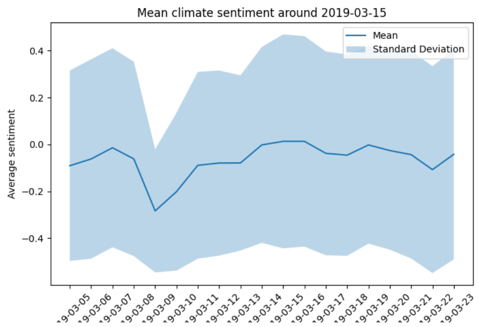
In this study, we show that we can observe major shifts in reactions to climate change on Twitter posts. But the these changes are not significant for all possible reactions and populations.



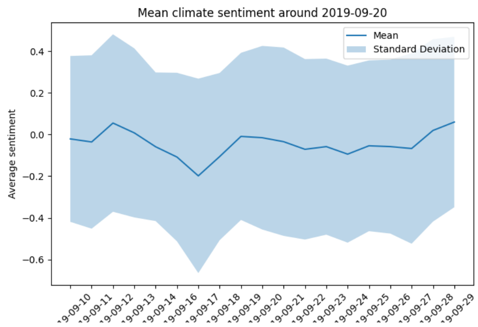
(a) Aggressiveness around the March 15 Climate Strike



(b) Aggressiveness around the Sept 20 and 27 Climate Strike



(c) Sentiment around the March 15 Climate Strike



(d) Sentiment around the Sept 20 and 27 Climate Strike

Figure 2: Evolution of sentiment and aggressiveness in March and September 2019. The light blue area represents the standard deviation. We don't observe a noticeable difference around the center of the plot, which is the date of the event studied.

A first finding was that we don't see observe any significant or consistent change in sentiment or aggressiveness. Because this study focused more on stance, we didn't go further down that path.

6.1 Global stance varies on big events day

However, we do observe that the stance twitter users have - or seem to have - on climate change, varies significantly around these events. On the day of such an event, we see a consistent, significant drop in mean stance, associated with a major increase of twitter posts and also a major increase in stance standard deviation.

This seems to indicate that on these days, as one could expect, many more people express themselves on the subject, but in particular that they tend to be more in denial of the issue. This could be explained by the fact that a shock action would trigger more conservative people to express themselves on Twitter.

In the days after, however, the global mean stance goes back to its previous distribution, and we don't see a lasting impact of the event's outrage on the global stance of Twitter, even for a really shocking event like the Soup Day.

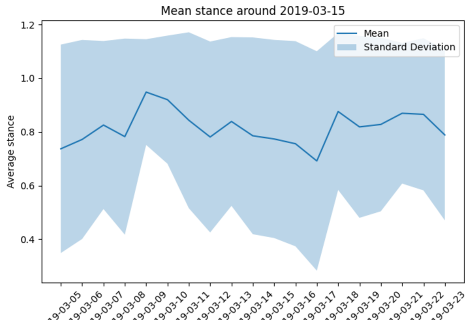
6.2 Usual posters stance also varies, but with a catch

Because deniers come in mass on big events to talk on Twitter, we try to take them out of the loop by only studying the usual posters that have already expressed themselves on the subject before.

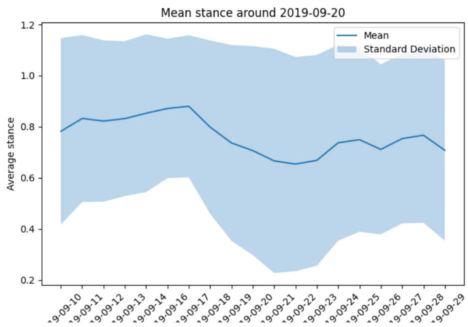
Interestingly, we still observe a drop in stance: even the population of people who usually post about climate change still seems to have a denial spike on Soup Day.

However, we find that this change may be, at least in part, due to the increase in tweets posted by some of these posters, who may be deniers, on the event day. When accounting for that fact, the distribution shift becomes statistically insignificant, although with a p-value that is still a bit low.

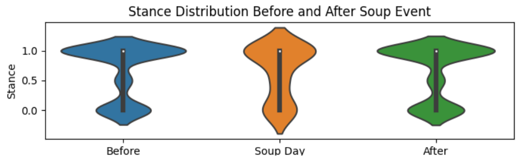
The result could become more significant if we filter or subset for more specific populations, which could allow us to see if some populations really "go mad" on such a day.



(a) Stance around the March 15 Climate Strike



(b) Stance around the Sept 20 and 27 Climate Strike



(c) Distributions before, during and after the October 2022 soup throw

Figure 3: Evolution of stance in March and September 2019 and distribution around October 2022. The plots show that the distribution on the "day of the soup" is particularly skewed towards denial, more so than the average in the two weeks before and after, which are much closer - and in fact indistinguishable.

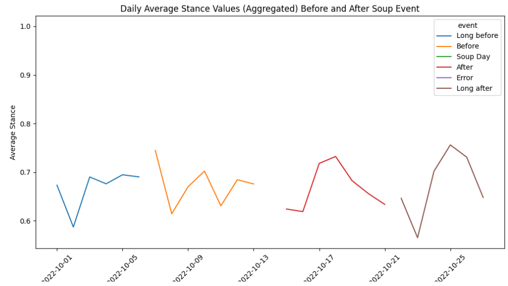


Figure 4: Evolution of daily stance, aggregated by user, around October 14 2022 - the soup day - in the 4 weeks around the event. The last period has an unusually high plateau of stance.

7 Limitations

This study offers a first look at potential answers regarding how shock climate activism effects global stance worldwide. As such, it also highlights many challenges and limitations that arose when attempting this work.

7.1 Classification

Natural Language Processing is advancing extremely fast nowadays, and the stance classification used for the Climate Change Dataset - published a year ago - was easily improved upon by our model based on GPT3.5. However, the accuracy is still not perfect, and considering how close some of our p-values were to 0.05, an improvement in the classification could very well result in a modification of our conclusions.

It is also worth noting that the accuracy was computed after self annotating the tweets, and not more than 50. We took the fact that our computed accuracy for the BERT model was similar to the one reported in (Effrosynidis et al., 2022b) as a sign that it was enough to get a good first picture. A deeper study such as done by (Vaid et al., 2022), leveraging recent advancements in Large Language Models, would be better.

7.2 The climate news move fast

Numerous times in this study we encountered other events that happened close to the ones we had in mind. While they don't necessarily pertain to the same climate activism category we're studying, the impact they have on climate stance was clear.

For example, in the Soup Day dataset, the last days see a rise in climate believers that seemed caused by a combination of a new UN report and the incoming COP27. In the September 2019 study, a major shift a week before the climate strike in aggressiveness, sentiment, and maybe stance, may be explained by American political events linked to figures that are vocal about climate change but also often under social fire by conservatives, such as Alexandria Ocasio-Cortez.

These frequent shifts in the people's attention make it all the much harder to draw conclusions on the long run about the impact of climate activism events such as the soup day on the global stance about climate. In this study, we found it is not the case, but it is worth noting that changing the length of time before and after the event for stance distribution comparison sometimes produced the opposite outcome.

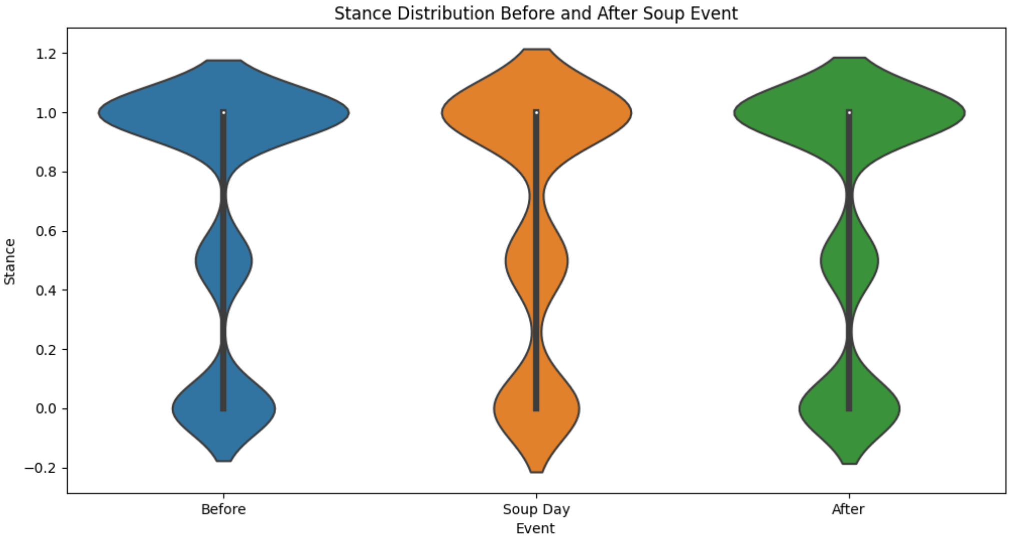


Figure 5: Visualization of distributions of stance for the usual posters - weighed so that each poster counts at most once for each day - in the week before, on the day of, and the week after the soup day. The mean stance before is 0.681, on soup day it is 0.655, and the week after it is 0.668.

7.3 Other events

The events we took are ones of many worth studying and were picked because of their impact in global media. However, that's what made them easily replaceable in global attention span. Picking other events that are more likely to spark a long, unaltered reaction from a population well-represented on Twitter, might allow to get clearer results.

7.4 Transferability

Our results apply first and foremost to the platform from which the data was extracted: Twitter. Whether they would also apply to everyone in the real world that learns about a new shocking climate activism event remains to be proven. However, because we only pulled pure tweets that are neither retweets nor replies, we hope our results would transfer more easily as they don't rely on these features that are very typical of online platforms but don't have equivalent in real life - not on a large scale. If pure tweets are but ways of expressing your opinion, then our results based on the soup day dataset, could be more easily transferable.

8 Ethical Considerations

8.1 Data Privacy

Most of the data posted on Twitter is deemed public, but Twitter does have a Privacy Policy and Terms of Services to ensure, in particular, the right to be forgotten. As such, we can't release the text content of the tweets we have pulled from Twitter without further exchanges.

8.2 Environment

As a study closely related to environmental issues related to Climate Change, including in particular CO2 emissions, it seems important us to provide information regarding the impact of computations performed for this work. Fortunately, all of the work was performed on the author's personal modern Apple laptop without the need for a virtual machine in the cloud. The only external service used here was OpenAI's API, which we sent requests to sequentially for at most 10 hours (to be conservative). Considering an A100 GPU emits 160g of CO2 every hour of compute, that amounts at about 1.6kgCO2 emitted for this study.

This study is thus largely within resaonable bounds, as this is the carbon emitted for a (good) meal.

8.3 Inference about political orientations

We would like to state that reflections made in the Discussion section of this paper regarding who might be pushing the mean stance more towards denial, are not grounded in a thorough examination of the tweets texts and authors. We wrote that we believe they are from more conservative people as research showed they are more likely to be climate deniers (cf (McCright et al., 2016)) and political divide is one of the major drivers of discourse on Twitter.

9 Authorship statement

The author (Axel Peytavin) assumed full ownership of all the work done for this study, including designing the research process, performing it, collecting and assembling the data, designing, implementing, and using the classifiers used for this study, analyzing their output and annotating it, and finally analyzing all the data and writing the paper.

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