Social Media Stories

Event detection in heterogeneous streams of documents applied to the study of information spreading across social and news media

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En mémoire de Marie-Luce Viaud

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Chapter 1

Introduction

According to the Reuters Institute, 39% of French adults use social media as a source of news in 2020.[1] This evolution of news consumption may reflect a growing appetite for stories that are not usually covered by traditional news media, or are covered in a different way.

In response to the transformation of news consumption, one should expect a change in the production of news by traditional media outlets. McGregor and Molyneux [2018] find that journalists using Twitter as part of their daily work consider tweets to be as newsworthy as headlines from the Associated Press. Does this perception have an effect on the type of stories they choose to report? Does the success of a story on social media impact the news production of traditional news media outlets?

1.1 Objective

In this thesis, we seek to investigate the role of Twitter in the evolution of news production in recent years. Our objective is to find out to what extent events trending on social networks are relayed more by traditional media outlets. The challenge is to precisely quantify and analyze the relationships between the two spheres, in a context of very strong co-dependence of each sphere.

Indeed, stories trending on Twitter always emerge in a context that fosters their propagation, and traditional news media are not isolated from that same context. For example, in the summer of 2018, far-left MP Jean-Luc Mélenchon called for a boycott of French President Emmanuel Macron's speech at the Palace of Versailles by spreading the hashtag #MacronMonarc with other members of his party. Sympathizers were invited to tweet massively on the subject using this hashtag. That strategy was a

[1] `https://reutersinstitute.politics.ox.ac.uk/sites/default/files/2020-06/DNR_2020_FINAL.pdf`

major success on Twitter, as illustrated in Figure 1.1, and many traditional media outlets covered the boycott or mentioned the hashtag when reporting on the speech by the French President. However, one cannot state with certainty that the success of the online hashtag resulted in more articles on the boycott than Jean-Luc Mélenchon's statements alone would have done. At that time, Emmanuel Macron's popularity had dropped to its lowest level since the spring of 2017, and the statements made by his political opponent were closely followed by the media. Hence, the same context that favoured the success of the #MacronMonarc hashtag may have prompted the coverage by mainstream media, without Twitter having any real effect.

For an individual event, it is therefore impossible to disentangle the effects of the context, the intrinsic interest of the news, and the popularity on Twitter, in the choices made by news editors. However, the problem can be approached at an aggregate level: if we have available all the events covered both on Twitter and in the media, it is possible to highlight a systematic effect of popularity on Twitter.

This is the approach we take in this thesis: we build a completely new dataset containing around 70% of all the tweets in French during one year (July 2018 - July 2019) and the content produced online by the French-language general information media outlets during the same time period. We develop algorithms capable of grouping together tweets and news articles related to the same events. Finally, we study whether an event popularity on Twitter impacts the coverage that mainstream media devote to this event.

The originality of this project is its multidisciplinary nature. On the one hand, it consists of an analysis in media economics, in order to determine causal factors that influence the success of news stories. On the other hand, drawing conclusions on all media events over the course of a year, as we propose to do, requires contributions in computer sciences involving the design of novel approaches for tweet collection, event detection and multimodal analysis.

1.2 Scope of the study

Choice of Twitter

Twitter is not the most widely used social network in France. According to the Reuters Intitute, in 2020 it is actually the 4th most-used French social network for the consumption of news (used by 9% of respondents), behind Facebook (43%), YouTube (23%) and Facebook Messenger (12%). Nevertheless, we chose this network for our analysis of the relationships between social networks and traditional news

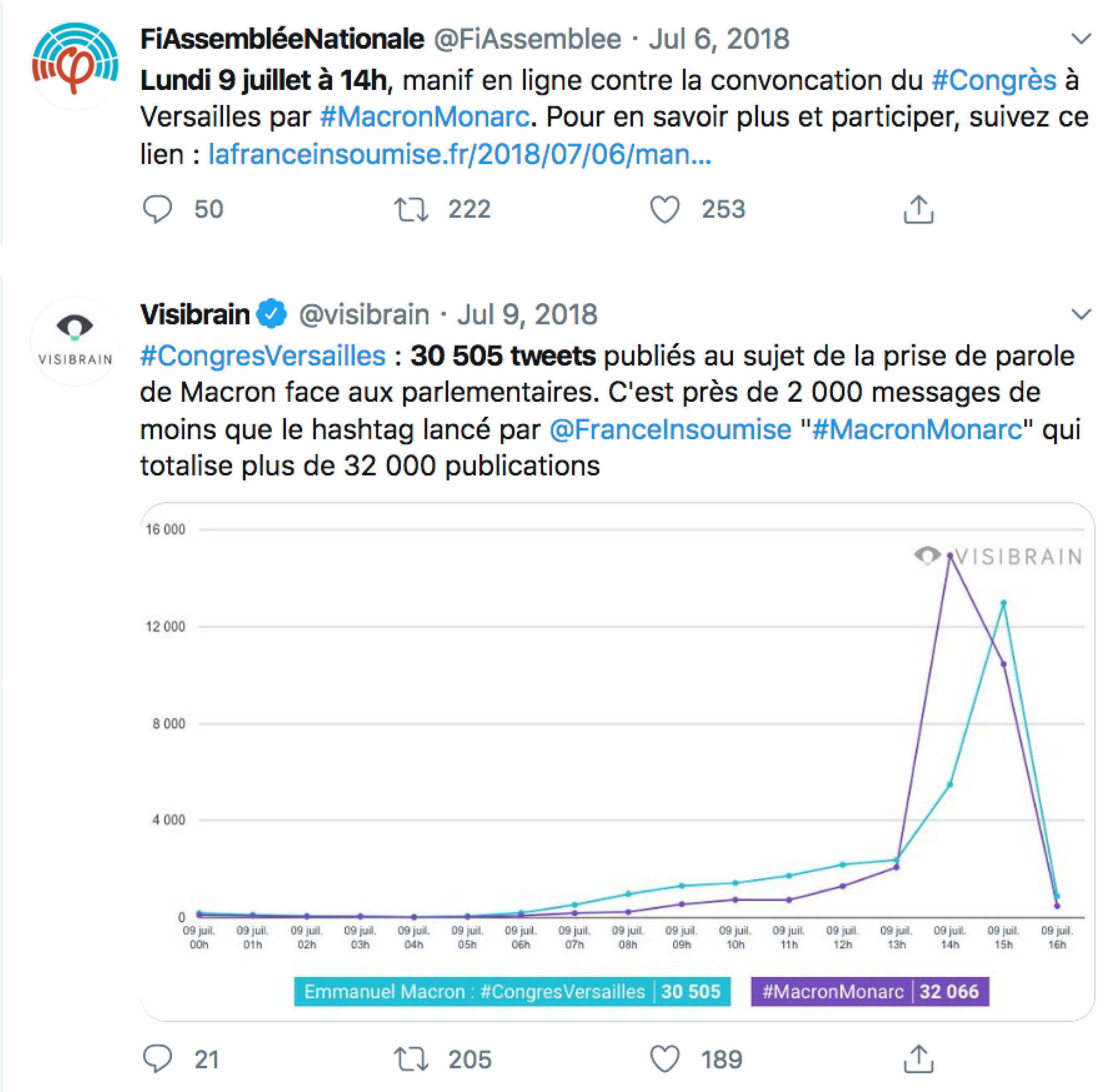

Figure 1.1: Two tweets outlining the propagation history of the hashtag #MacronMonarc. The upper tweet calls for an online protest against the speech of President Macron at the Palace of Versailles. The bottom tweet, published 3 days later, reports on the success of the #MacronMonarc hashtag, compared to the other hashtag used to refer to the speech delivered by Emmanuel Macron.

media for several reasons.

First of all, **the structure of Twitter makes it a privileged tool for sharing news content**. Indeed, it favors public statements rather than private messages to family and friends, and encourages the sharing of external content (reference to other pages through URLs) because of the brevity of tweets. Kwak et al. [2010] even argue that the structure of Twitter makes it similar to a news media.

Secondly, **Twitter has quickly become the preferred network of journalists**, who use it both to easily contact sources and to build a connection with their audience [Swasy, 2016]. In the sample of journalists studied by McGregor and Molyneux [2018], 93% had a Twitter account. A report conducted at the request of the European Commission[2] shows a similar trend in Europe: the journalists interviewed make the distinction between Twitter, mostly used for work, and Facebook, more widely used in private life.

Finally, **Twitter provides a larger access to its data than other social media platforms**. Even though the volume of tweets that can be accessed through Twitter's APIs is limited, the company still provides free access to a large volume of data. Conversely, it is still nearly impossible for researchers outside Facebook to get access to information on users' activity on the platform, with the exception of partnerships with a few rare research teams.

Use of French tweets

This thesis is part of the OTMedia project [Hervé, 2019], a platform for collecting and analysing French media developed at the Institut National de l'Audiovisuel (INA), the French media institute. This project aims to collect all contents published by French media online, regardless of their offline support (TV, radio, press, pure online media and press agencies). From the outset, therefore, the objective of the thesis was to work on the French media and their relationship with social networks, which meant collecting data from French Twitter. However, it is somewhat difficult to determine the country of Twitter users. On Twitter, there are two different ways to identify the location: through the location of the user and through the location of the tweet.

First, users can indicate their location in their profile: nearly two thirds of the $4,222,734$ users in our sample do so. While the information provided is most often a real location (e.g. "Paris, France" or "Val-d'Oise, Ile-de-France"), many users fill in this field with whimsical content (e.g. some users indicate "Gotham City" or "Everywhere and nowhere"). Nonetheless, we parsed this field for all authors of tweets in

[2] http://ec.europa.eu/commfrontoffice/publicopinion/archives/quali/journsm_en.pdf

French in our sample, and, using OpenStreetMap, we associated each user to a country. Of the $2,693,307$ users for whom the location field is filled in, the information provided allowed us to recover the country where the user is located in 72% of the cases. 47% of these users indicate that they are located in France.

Second, users can share their location at the time of their tweet. They can either occasionally decide to assign a location to their tweet, and are then presented with a list of places, or they can decide to automatically "geo-tag" all of their tweets. However, of our $4,222,734$ unique users, only $62,037$ (i.e. 1.5%) share their location in the first of their tweets we observe, and even fewer users "geo-tag" their tweets: only $13,382$ (i.e. 0.32%) do so the first time we observe them, and $13,529$ the last time.

In both cases, filtering French tweets according to their location (or the location of their author) is likely to introduce biases or errors in our sample: on the one hand, the use of Open Street Map probably produces some false results (but we are not able to evaluate how many), and on the other hand, we do not know the factors that drive a user to share their location. They may be correlated with news consumption, for example.

We finally decided to work on all tweets in French, using the language metadata automatically determined by Twitter, without making assumptions about the country. This study has therefore gradually become a work on media production in French-speaking countries, since we have also extended the OTMedia collection to some non-French (but French-speaking) media. The list of all collected media is presented in the Appendix, in Section A.2.

The choices we have made regarding the scope of this study lead in practice to a number of constraints, which we detail in the next section.

1.3 Empirical challenges

Characterization of events

According to the historian Pierre Nora, the emergence of the mass media has transformed the nature of events: *"Press, radio, images are not only means from which events are relatively independent; they are the very condition of their existence."*[3] [Nora, 1972]. The sociologist Patrick Champagne [Champagne, 2000] shares the same view (*"The media build the events they report"*[4]) but highlights the fact that creating

[3] "Presse, radio, images, n'agissent pas seulement comme des moyens dont les événements seraient relativement indépendants, mais comme la condition même de leur existence."

[4] "les médias construisent les événements dont ils rendent compte"

an event is a collective process: one media outlet alone cannot make the news if it is not picked up by others. A media event has thus to be reported by several sources in order to be defined as such.

With the appearance of social media, a new dimension has emerged: traditional news media cannot ignore a topic that is breaking on Facebook or Twitter. In practice, many news events nowadays start on social media. In many cases, social events and media events tend to be the same, which we call *joint events*. However, any conversation or trend on social media cannot be considered an event, but we lack an objective criterion that would allow us to distinguish between everyday conversation and what constitutes an event on Twitter. Empirically we solve this problem by using the event definition proposed by McMinn et al. [2013]:

"*Definition 1.* An *event* is a significant thing that happens at some specific time and place."

"*Definition 2.* Something is *significant* if it may be discussed in the media."

With this definition in mind, we consider that any group of tweets dealing with the same subject can be considered an event, but in practice we only consider joint events, i.e. those that reach traditional media. The main challenge of this thesis in terms of machine learning is the design of a method to optimally detect joint events.

Another issue frequently raised when addressing the notion of event is that of granularity. Indeed, most events can be broken down into sub-events. For example, in a sports tournament, each match can be considered a separate event, or the tournament itself can be considered to be the event. From the point of view of computer science, this question can be reduced to a threshold issue: a low threshold will lead to the detection of small, very homogeneous events, while a higher threshold will lead to the formation of more general events. Choosing a particular threshold will not fundamentally change the validity of our study, as long as some variability in the choice of a threshold does not change our final results.

Working on French tweets

A common empirical challenge for researchers using Twitter data comes from the fact that, because of the limits of the Twitter streaming APIs, only 1% of the global volume of tweets can be collected at any given moment. Perhaps paradoxically, collecting tweets in a language with few speakers compared to English, Japanese or Spanish, which are the three most commonly spoken languages on Twitter – see Figure 2.4 – becomes an advantage here. Indeed, with French tweets, we seek to collect only 1.8% of all tweets posted worldwide, which seems an attainable target using several API access keys.

However, using a dataset of French tweets and news content is also a challenge due to the continued lack of available corpora for Natural Language Processing and tweet analysis in French compared to English. We thus had to manually annotate our own event detection dataset, since the only other existing corpus for this task is in English. In addition, recent machine learning models handling text need to be pre-trained on massive datasets containing hundreds of thousands of examples. As a result, tackling documents written in French rather than in English or Chinese means that the performance of the existing models will never be at the same level as the results described in the international machine learning literature.

Including visual contents

Communication on social networks is increasingly carried by visual supports (image, video or animated GIF). Recently, with the success of deep-learning based approaches and their ability to learn useful data representations [Bengio et al., 2013], various approaches have been proposed for the learning of multi-modal representation with an application to tasks such as Image Captioning, Visual Question Answering or Cross-Modal Image-Text Retrieval. In these tasks, the models are learned on image-text pairs that are aligned: the text is a description of the picture, or the image is an illustration of the text. Under this condition, it is possible to learn a common representation of text and image in the same latent space. However, the text-image relationship on Twitter is rarely of this nature. For example, memes[5] are quite different from illustrations: the same meme image is reused thousands of times in different contexts, associated with a text that gives it a different meaning.

In this thesis, we attempt to address the problem of multimodal representation of tweets by forming joint representations of text and image.

Collecting representative data

By opting for a multidisciplinary thesis, which combines the prerequisites of econometrics with those of machine learning, we set ourselves additional criteria for the quality of our data. In machine learning, a biased dataset is defined relatively to a specific task: a bias in a dataset built to learn a specific task will lead to false conclusions when trying to solve the same task on different data (see for example [Tommasi et al., 2017]).

[5]A meme is an amusing image or video that spreads virally on the Internet, often with slight variations. See Figure 3.2 for a classical example of meme.

However, in order to obtain valid conclusions in econometrics, the definition of bias must be stricter: an unbiased dataset is a subset of the overall population being described that proportionally reflects all the characteristics of that population. Here, considering that our collection of media content reaches virtually the entire universe of French articles, we had to design a method of collecting tweets that would guarantee the absence of bias in tweets. To achieve this, we used as a reference the tweet feed provided by Twitter's Sample API, which provides a random sample of tweets emitted at a given time.

Another key issue here is data completeness: since the author of the first tweet of an event is a critical element for our final conclusions (we are particularly interested in the author's centrality in the Twitter network), it is important that we capture the actual first tweet of each event, not the second or third. Ideally, this means capturing the complete corpus of all tweets published in French. According to our estimates, our collection method yields between 74 and 78% of original tweets (i.e. not retweets), thus guaranteeing the completeness of the data in the vast majority of events.

Designing scalable methods

Finally, as our constraints in terms of completeness led us to collect about 5 million tweets per day for one year, resulting in a final corpus of 1.8 billion tweets, our event detection methods had to be extremely time and memory efficient. One way to speed up processing was to work only on the original tweets (37% of tweets), and to aggregate the retweets a posteriori into events. However, the speed of algorithms remains a central concern of our work.

1.4 Detailed Outline

In order to solve the set of issues presented in the previous section, the thesis is organized as follows.

The first step (see Chapter 2) is the collection of a dataset of tweets representative of daily activity on French Twitter, and as complete as possible. To do so, we design a novel collection method based on neutral words, and compare the obtained corpus to two other French corpora of tweets. We also detail the annotation campaign conducted with three students in Political Sciences in order to label a large number of tweets that refer to events.

Chapter 3 is devoted to the design of algorithms to automatically detect events in Twitter datasets. We test several algorithms, and several types of vector representations of tweets, including multi-modal representations. Our experiments are conducted on two different event datasets: a corpus in English

[McMinn et al., 2013] and the French corpus presented in the previous Chapter. The best-performing method is a clustering algorithm called First Story Detection, which we modify to take into account the brevity and noisiness of tweets.

In Chapter 4, we detail the method used to group together Twitter events and media events inside joint events. We use the First Story Detection approach – presented above – to cluster tweets and news articles separately. We then use a graph community detection algorithm in order to group media events and Twitter events into common joint events. We investigate the role of text-similarity, hashtags, URLs and time features in the performance of our method.

In the last Chapter, we use the detected joint events to investigate the effect of popularity (in terms of number of tweets) of an event on its coverage by traditional media. To isolate the causal impact of popularity, regardless of the intrinsic interest of a story, we rely on the structure of the Twitter network. We use an instrument relying both on user centrality and news pressure at the time of the event to identify a variation in stories popularity that is exogenous to the intrinsic interest of stories. We show that the popularity of a story has a positive effect on media coverage, but that this effect varies depending on the characteristics of media outlets.

Chapter 2

Building a corpus for event detection on Twitter

2.1 Introduction

Research on social media topic detection and tracking (without specification of the type of topics) lacks publicly available tweet datasets to generate reproducible results. This is particularly the case for non-English languages. Some datasets do exist, but they often have different definitions of event or topic than ours: many works centering on event detection are actually focused on burst detection (detecting topics such as natural disasters, terrorist attacks, etc., which cause an unusual volume of tweets) and do not attempt to assess the relative size of events. Therefore, we needed to build our own evaluation corpus that would fit our needs in terms of language (French), representativity of the collected tweets, quality and diversity of the annotated events. This introduction details the properties expected from such a corpus. In the rest of the chapter, we present the existing social media and in particular tweet datasets for event detection, then we detail our tweet collection method and our annotation process. Finally, we propose several ways of evaluating the built corpus.

2.1.1 Representativity and completeness of the collected data

In an ideal world, to compare news production on social media and on mainstream media, one would need the universe – during a given period of time (e.g. the year 2018) and a geographical location (e.g. France, the UK or the US) – of all documents published on the one hand on social media and on the other hand on mainstream media. Unfortunately, given the limitation of the Twitter API, it is not possible for the researcher to capture the universe of the documents (or tweets) published on Twitter. However, the researcher can work on a sample of the documents as long as this sample is “representative”, i.e. the sample matches the characteristics of the real Twitter stream along all variables of interest. Why do we need representativity?

Let us assume that we obtain access to a subsample of the documents published on Twitter, but that this sample is not representative of the overall traffic. For example, let us assume that this sample of tweets is such that the characteristics of the tweets (perhaps because the API provides the researcher with documents tweeted by users with more followers) mean that these documents have a higher probability of making it into the mainstream media. Using this biased subsample will then lead the researcher to overestimate the probability that a news story broken on social media will appear on mainstream media.

The same issue will arise if the researcher wants to tackle the follow-up question: what are the determinants of the success of a news story initially broken on social media? Let us imagine that the researcher is using a selected sample of tweets that is not representative - for example, this sample of tweets comes mainly from journalists working for a given media, e.g. *Le Monde* - and that, at the same time, within the set of tweets posted by *Le Monde*’s journalists, only the successful ones are part of the sample. The results of the empirical analysis will be biased in favor of *Le Monde*. In other words, when the researcher studies the impact of the company for which the journalist works (independent variable) on the probability that the news story will break on Twitter and make it to the mainstream media (dependent variable), the coefficient obtained for *Le Monde* will overestimate the real causal impact of the company.

It appears to be very difficult to correct for the latter kind of biases. One can always control for a number of observable variables, but unobserved confounders will bias the estimation. Hence the necessity to have a representative sample of tweets, i.e. a sample of tweets such that the tweets included in our sample do not differ from the tweets that are not included along all the dimensions that may have a direct impact on the dependent variable of interest.

Representativity is thus critical for the study of news production on social media. However, to study the interaction between social media and mainstream media, we need more than just representativity: in a sense, we need completeness. For example, to determine whether a story emerged on Twitter or was first covered by mainstream media, representativity is not sufficient, because we may miss some tweets posted before the first news articles appeared. It is therefore of utmost importance not only to build a “representative" sample of tweets, but to build one that is as complete as possible.

2.1.2 Quality of the annotated subset

The properties of a given corpus have an impact on the implementation of the detection algorithm: for example, if all events in our corpus tend to grow at a high rate (i.e. people react very quickly to that event on social media), a simple way to increase the performance of our algorithm would be to select groups of tweets that have a high growth rate and discard others as “non-events". However, the resulting approach would be incapable of detecting other types of events and would thus introduce bias in our results. Therefore, the choices made during the creation of the annotated corpus are critical to ensure that our program can detect a large variety of events.

The size of events is also an important parameter that needs to be taken into account: small events that generate few tweets are difficult to detect automatically and this is precisely why they need to be represented in our test corpus. On the other hand, large events, such as the 2018 FIFA World Cup, generate such a large volume of tweets that it is impossible to annotate all of them manually. This is an inevitable flaw in any manually annotated corpus.

It is also necessary to ensure the diversity of events in the corpus in terms of topic (sport, economy, science and technology, etc.) and regarding the origin of events (events having emerged on Twitter vs. events first covered by news media). The diversity of tweets inside each annotated event is also of importance: ideally, tweets should originate from a variety of sources, and not be written only by journalists or media accounts.

The following section details the choices made by the authors of existing datasets with regard to these quality criteria.

tables/July/regression$_{m}edia_{I}V_{P}oisson.tex$

2.2 State of the art: event detection corpora

Twitter gives limited access to its data, but still provides some API endpoints to retrieve tweets (which is not the case with other more popular social networks, in particular Facebook), hence the large number of works based on Twitter datasets. However, few of them provide access to their evaluation corpora. We detail available event detection collections in this section.

McMinn et al. [2013] created the largest available corpus on event detection. They used several methods to generate candidate events: two automatic event detection methods on their set of 120 million tweets

Dataset	Content	Collection method	Collection period	Events	Nb docs collected	Nb docs annotated
McMinn et al. [2013]	tweets	sample API	10/10/2012-07/11/2012	505	120 million	100000
SNOW Papadopoulos et al. [2014]	tweets	filter API: keywords and accounts	25/02/14	59	1 million	230
TREC 2015 Lin et al. [2015]	tweets	sample API	20/07/2015-29/07/2015	51	-	60000
MediaEval 2014 Petkos et al. [2014b]	images + metadata	Flickr API	-	20000	300000	300000
Signal-1M Suarez et al. [2018]	tweets + articles	search API: keywords	01/09/2015-30/09/2015	100	32 million	6000
News Event Mele and Crestani [2019]	tweets + articles	filter API: media accounts	01/03/2016-30/06/2016	57	80000	750
Event2018 Mazoyer et al. [2020]	tweets	sample API + filter API on neutral words	16/07/2018-06/08/2018	240	38 million	95000

Table 2.1: Summary table of existing datasets for event detection on social networks . The number of collected documents only takes tweets (or images for the MediaEval dataset) into account: news articles or RSS-feeds are not taken into account. The Event2018 dataset in the last row is not presented in this state of the art since it is our own dataset.

in English and one method based on query expansion of Wikipedia events. The automatically generated events were then assessed using Amazon Mechanical Turk, first to evaluate if the automatically generated events corresponded to their definition of event, and second to judge if the clustered tweets were all relevant to the event. They finally merged the events from the three candidate generation methods and removed duplicate events. The final corpus consists of more than 100,000 annotated tweets covering 505 events. However, this corpus dates from 2012. Because of tweets being removed and Twitter accounts being closed, a large part of this dataset can no longer be recovered.[1] In August 2018, we could only retrieve 66.5 million tweets from the original collection (55%) and 72,790 tweets from the annotated corpus (72%).

The SNOW dataset [Papadopoulos et al., 2014] can also be used as a test corpus for an event detection task. It is composed of 59 events from the headlines of the BBC RSS newsfeed and from NewsWhip UK published in the course of one day (25th February, 2014). The tweets were collected from the accounts of 5000 “newshounds" (journalists, media outlets, politicians, etc.) and from a list of keywords linked to news events likely to generate comments on that day. However it does not provide comprehensive sets of tweets related to each event, only two to five “representative” tweets from a collection of more than 1 million tweets emitted on that date.

The *Text REtrieval Conference* (TREC) microblog datasets were released in 2014 Lin et al. [2014] and 2015 Lin et al. [2015]. The most recent dataset consists of more than 60,000 tweets posted between July 19th and July 30th, 2015, annotated in relationship with one of 51 topics. These tweets were sent by participants in response to the Microblog TREC tasks, which comprise two scenarios: (a) a “push notification" system returns tweets considered “interesting and novel" to a user having defined a topic of interest, and (b) a daily “email digest" is sent to a user with tweets containing relevant updates concerning

[1] In accordance with Twitter’s terms of use, researchers sharing datasets of tweets do not share the content of the tweets, but only their ids. Using these identifiers, one can query the Twitter API to retrieve the full content of the tweets - but only if they are still online.

her topic of interest. The 51 interest profiles cannot exactly be defined as “events", but rather general themes, such as “Find information about the possibility of the passage of gay marriage laws in Europe", or “Find information about bridge tournaments in the United States in July or August 2015". The tweets sent by participants to the task were then annotated by assessors as “relevant", “not relevant" or “highly relevant". This dataset is an interesting resource for our task, albeit less relevant than that of McMinn et al. [2013], because the annotated tweets have been selected for their “novelty": the dataset therefore includes many tweets announcing “breaking news", and few tweets of conversation or opinion on topics already known.

The datasets from the 2013 and 2014 MediaEval Social Event Detection tasks Reuter et al. [2013]; Petkos et al. [2014b] are also important corpora to test event detection systems, and multimodal systems in particular. The first challenge of this task consists in clustering images of social events so that each cluster matches an event. The events correspond to sport events, protest marches, BBQs, debates, exhibitions, festivals or concerts all registered on the last.fm website[2]. The authors downloaded pictures tagged with the last.fm event ids on Flickr. In total, each dataset contains 300,000 training images from approximately 20,000 events. This corpus is very interesting because of its size and the large number of different events it contains. However, the fact that it contains only “social events" (public gatherings attended by a large number of people) restricts the task to a certain type of topics. The type of images shared on Flickr is also very different from those shared on Twitter: they are mostly photos taken by users themselves, with few duplicate images. Conversely, images on Twitter are very often re-used by several users, sometimes in different contexts, which makes the task more complex.

Finally, let me mention two additional datasets. The Signal-1M corpora consists of a dataset of 1 million news articles from September 2015 [Corney et al., 2016], and of a dataset of tweets related to 100 randomly selected articles [Suarez et al., 2018]. The tweets dataset contains approximately 6,000 annotated tweets. The News Event Dataset [Mele and Crestani, 2019] contains 147,000 documents (including 80,000 tweets) from 9 news channels and published on Twitter, RSS portals and news websites from March to June 2016. 57 media events were annotated on a crowdsourcing platform, to label 4,300 documents, including 744 tweets. These two datasets contain too few tweets to allow a large-scale evaluation of any event detection and tracking system. In addition, events in SNOW, Signal-1M and the News Events Dataset are selected from media sources only. Only the corpus by McMinn et al. [2013] relies on a

[2]last.fm is a music website, used in particular by artists to share the dates of their concerts. Its use has been extended to other types of events, not necessarily related to music.

topic detection step among collected tweets before proceeding to the annotation step. This method allows for a greater variety of events, but is likely to influence the evaluation: indeed, event detection systems similar to those used by McMinn et al. [2013] for corpus creation may get better results when tested on this corpus.

We tried to avoid these biases when creating our own corpus. The methodology used to build our dataset is detailed in the two following sections.

2.3 Tweet collection

Our objective is to collect automatically and continuously as large a set of tweets as possible, and one that is representative of actual Twitter activity. In addition to being **representative**, this corpus must contain a **volume of tweets large enough for media events to be represented** in it, particularly medium and small events. Furthermore, we want to collect enough tweets so as to ensure that events that appear first on Twitter and then on mainstream media also do so in our dataset. Finally, these tweets must be **in French**. The following sections present the methods used to achieve these objectives.

2.3.1 Constraints

There are different ways of collecting large volumes of tweets, although collecting the full volume of tweets emitted during a given period is not possible. Indeed, even though Twitter is known for providing greater access to its data than other social media platforms,[3] the Twitter streaming APIs are strictly limited in terms of volume of returned tweets. These limitations are constraints that we must integrate into our collection procedure.

Sample API: the Sample API[4] continuously provides 1% of the tweets posted around the world at a given moment in time. Once connected to the API at time t_0, the user gets 1% of all tweets emitted after t_0, and receives regular batches of tweets as long as she stays connected. Twitter provides little information on how the sample is generated. However, Kergl et al. [2014] have studied it by analyzing the ids of tweets (based on a timestamp in milliseconds and on a number of series to identify tweets issued during the same millisecond). They show that all tweets provided by the API were issued between the

[3] In particular, despite the research effort recently launched by Facebook, it is still nearly impossible for researchers outside Facebook to get access to information on users' activity on the platform.

[4] `https://developer.twitter.com/en/docs/tweets/sample-realtime/overview/get_statuses_sample`

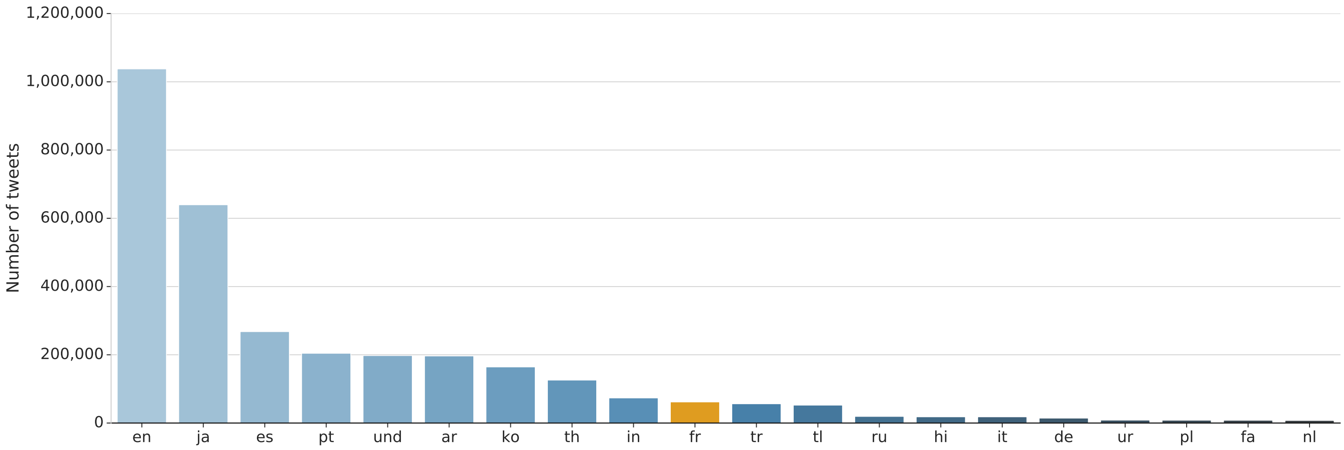

Figure 2.1: Average number of tweets per day in each language collected using the Sample API. This figure plots the average number of tweets collected per day using the Sample API in the 20 most frequent languages on Twitter. The language metadata is provided by Twitter. "und" stands for "undefined" language.

657th and 666th milliseconds of each second, which should guarantee that the user receives a constant stream representing around 1% of the total. Another study done on the distribution of tweets in the Sample API in comparison with another paid API, which provides full access to all emitted tweets, shows no statistically significant difference between the two samples [Morstatter et al., 2014].

This API does not meet our needs, since the proportion of tweets in French is only 1.8% of the total sample on average (Figure 2.1 illustrates the distribution of tweets in different languages). Moreover, according to Liu et al. [2016], the proportion of tweets concerning news is less than 0.2%. If we combine all these restrictions, we could only have access to 92,000 tweets in French a day, and less than 200 tweets a day concerning news if we were simply using the Sample API provided by Twitter.

Filter API: the Filter API[5] continuously provides tweets corresponding to the input parameters (keywords, account identifiers, geographical area). The language of the returned tweets can be selected. Again, the API provides only about 1% of the total flow. However, this is sometimes enough to collect all the tweets containing a relatively little-used keyword, and it is clearly enough to collect all the tweets from a given account. For a language with low representation such as French, this API could theoretically provide us with up to 55% ($\frac{1\%}{1.8\%} = 55\%$) of all the tweets emitted in French. Given this observation, we worked at identifying the keywords that maximize the number of returned French tweets.

[5] `https://developer.twitter.com/en/docs/tweets/filter-realtime/api-reference/post-statuses-filter.html`

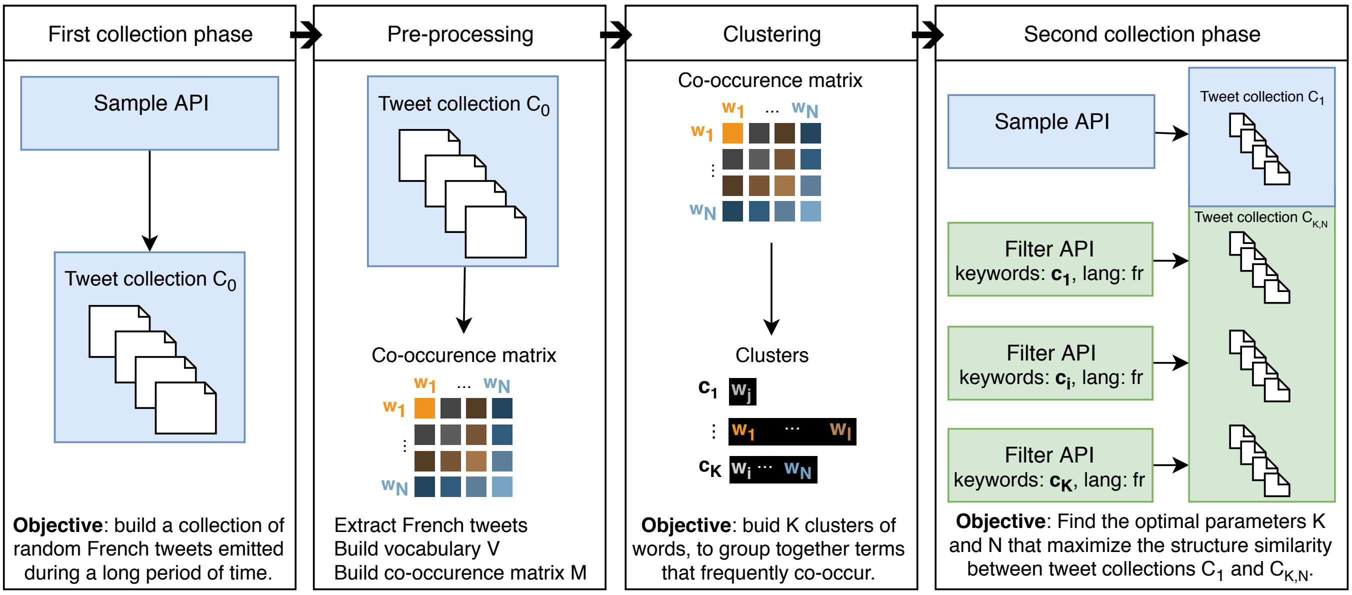

Figure 2.2: Diagram of our methodology to select the best set of keywords for each API key

Joseph et al. [2014] compare five samples collected through the Filter API with the same input keywords at the same time, using five different connection tokens[6]: they find that two connections to the Filter API at the same time with the same keywords as inputs are nearly identical". Hence, it is not useful to try to collect more tweets using a second access token with the same keywords. However, spreading different keywords over several API connections should return a higher number of tweets.

2.3.2 Proposed collection strategy

Given the constraints of the APIs, we decided to collect tweets by using the random stream proposed by the Sample API, but to increase the volume of collected data by using the Filter API as well, with “neutral" terms as keywords parameters, and “French" as the language parameter. In order to further increase the volume, we decided to use multiple tokens to connect to the Filter API.

The choice of the keywords parameters was made with a view to optimizing two metrics: the number of collected tweets, and their representativity of actual Twitter activity. The selected terms thus had to be the most frequently written words on Twitter, and we had to use different terms (and terms that do not co-occur in the same tweets) as parameters for each connection. In this way, the multiple connections would return sets of tweets with little intersection, and thus a greater total volume.

The precise strategy we used is as follows (it is schematized in Figure 2.2): given a set of tweets

[6] To use the Twitter API, a connection token is required. Twitter limits the access to its data by generating only one connection token per Twitter account.

$C_0 = \{t_1, \dots, t_k\}$ collected using the Sample API during a time-interval $I = [d_{t,start}, d_{t,end}]$ we select tweets in French, creating a subset $C_{0French}$ and extract from them a vocabulary $V = \{w_j, \forall j \in [1, \dots, M]\}$ of all unique words appearing in $C_{0French}$. We extract a subset of the N words of V having the highest document-frequency. We build a co-occurrence matrix $\mathcal{M} = (m_{i,j}) \in \mathbb{N}^{N \times N}$ where $(m_{i,j})$ is the number of times w_i and w_j co-occur in the same tweet of $C_{0French}$. Using spectral clustering with $\mathcal{M}$ as adjacency matrix, we extract K clusters of terms. The K obtained clusters of words are then used as parameters of K different connections to the Filter API. By doing so, we aim to separate terms that are not frequently used together and thus to collect sets of tweets with the smallest possible intersection.

Section 2.3.4 presents the method used to evaluate the similarity between $C_{K,N}$ – the set of tweets collected using N keywords spread on K Filter API connections –, and $C_1French$ – the set of French tweets collected with the Sample API during the same period as $C_{K,N}$.

2.3.3 Experimental setup

In practice, we collected our corpus C_0 of sample tweets between $d_{t,start}$ = 2018/01/15 and $d_{t,end}$ = 2018/02/15. The text of the collected tweets was tokenized on white spaces and on punctuation characters (“qu’il" was considered to be two words, “qu" and “il"). The resulting vocabulary V was lowercased and accents were removed, since we noticed that accents and capital letters are not taken into account by the Twitter API. For example, the API returns tweets containing both “à" and “a" if the parameter “a" is given as input. No other pre-processing such as stemming was applied (the vocabulary contains both “mdr" and “mdrrr"[7], for example), since the objective here is not to query the API with semantically different terms, but with the most frequently used terms.

We ran tests with $N \in \{50, 100, 200\}$ and $K \in \{2, 3\}$. This choice was motivated by our storage and CPU capacity. The clusters of terms for the different N and K values are presented in the Appendix A.1.1. The resulting clusters are imbalanced in size: some contain only a few words, while others contain all remaining terms. In order to control for the effect of imbalanced clusters, we instead follow a different method and distribute terms randomly in clusters of size $\frac{N}{K}$. The samples collected using random clustering are denoted $R_{K,N}$. We ran each test for a period of two weeks, during which we also collected tweets from the Sample API and extracted tweets in French. This last set of tweets is denoted $C_{1French}$.

[7]French abbreviations similar to “lol" and “loool". “mdr" stands for “mort de rire", literally “die laughing".

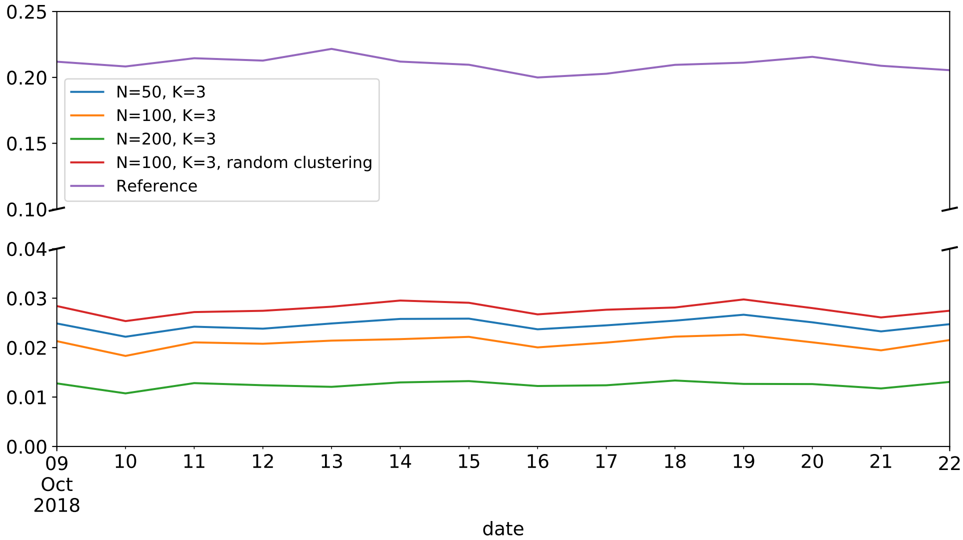

Figure 2.3: Daily evolution of the divergence between collection $C_1French$ and the collections $C_{K,N}$ with $K = 3$. This figure plots the daily evolution of the KL-divergence between the word distribution in collection $C_1French$ and the distribution obtained using 4 collection methods. The "Reference" is obtained by splitting the collection $C_1French$ into two sets and computing the KL-divergence between them. A KL-divergence of 0 indicates a perfect similarity between 2 distributions.

2.3.4 Evaluation of the collection strategy

We compared the sets $C_{K,N}$ and $R_{K,N}$, collected with each collection method, with the set $C_{1French}$, collected with the Sample API during the same time interval, in order to assess the representativity of each test dataset. This approach is comforted by the study of Morstatter et al. [2014], who had access to the entire stream of tweets and compared it with the Sample API. They find that the tweets from the Twitter Sample API are "a representative sample of the true activity on Twitter".

Several comparison methods can be used in order to assess the similarity between two collections of texts. A first approach consists in considering the number of times each word is used in each collection as a probability distribution, and to measure the difference between those distributions. We used Kullback-Leibler divergence [Kullback, 1997] as comparison metric. For two discrete probability distributions P and Q defined on the same probability space χ the Kullback-Leibler divergence is defined as

$$KL(Q\|P) = \sum_{x\in\chi} Q(x) \log\left(\frac{Q(x)}{P(x)}\right). \tag{2.1}$$

This measure is not symmetric, since it is meant to measure the difference between a probability distribution P to a reference distribution Q, which is precisely what we have to evaluate, Q being the distribution

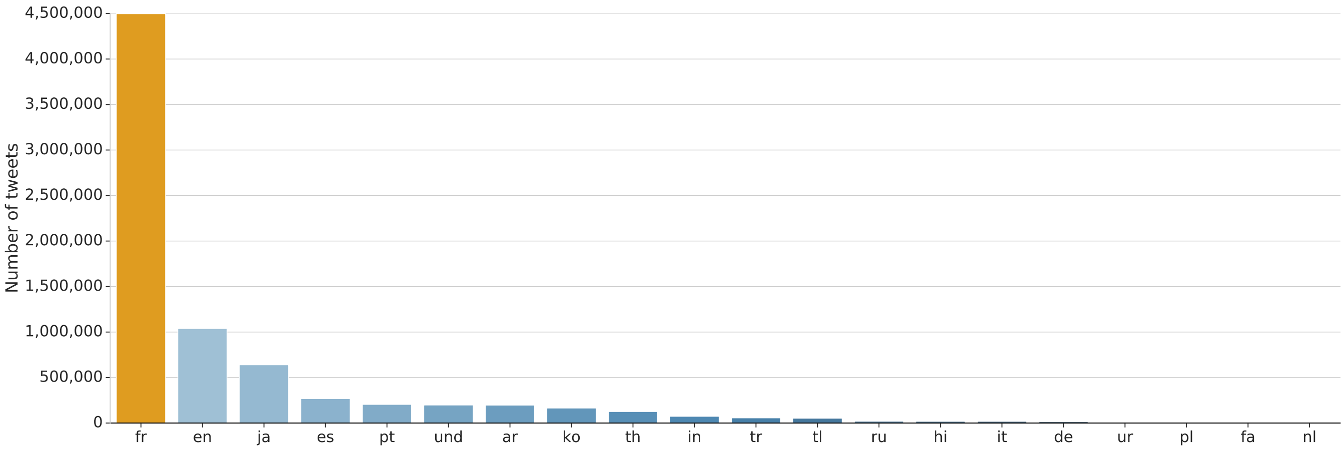

Figure 2.4: Average number of tweets per day in each language collected using the Sample API combined to our best collection method. This figure plots the average number of tweets in the 20 most frequent languages on Twitter. The language metadata is provided by Twitter. "und" stands for "undefined" language.

of words in $C_{1,French}$. For each $(N, K) \in \{50, 100, 200\} \times \{2, 3\}$, we computed the KL-divergence between the word distribution in $C_{K,N}$ and in $C_{1French}$ for the same collection period. In order to have a reference of what level of divergence can be accepted, we also split the corpus $C_{1French}$ into two sets (depending on whether the tweets had an even or odd id) and computed the KL-divergence between those sets. Figure 2.3 presents the results for $K = 3$. Overall, we found that the collection $C_{3,200}$ was the most similar to $C_{1French}$ using KL-divergence as a comparison metric.

We decided to keep $C_{3,200} \cup C_{1French}$ as our main collection method, since its similarity to the random sample was the highest. Figure 2.4 illustrates the new distribution of language we obtain using that method.

2.3.5 Evaluate the share of collected tweets

The tweet collection tool has been running from June 2018 to the present day, allowing us to store around 3 billion tweets. This long collection period allowed us to compare our corpus with other French tweet corpora collected during that time. Two teams were kind enough to give us access to part of their data: the French Internet legal deposit at the INA, and the Médialab at Sciences Po Paris. We also used metrics from Twitter (the number of tweets per user) to estimate the percentage of tweets that we collected, and conversely, the number of tweets we missed.

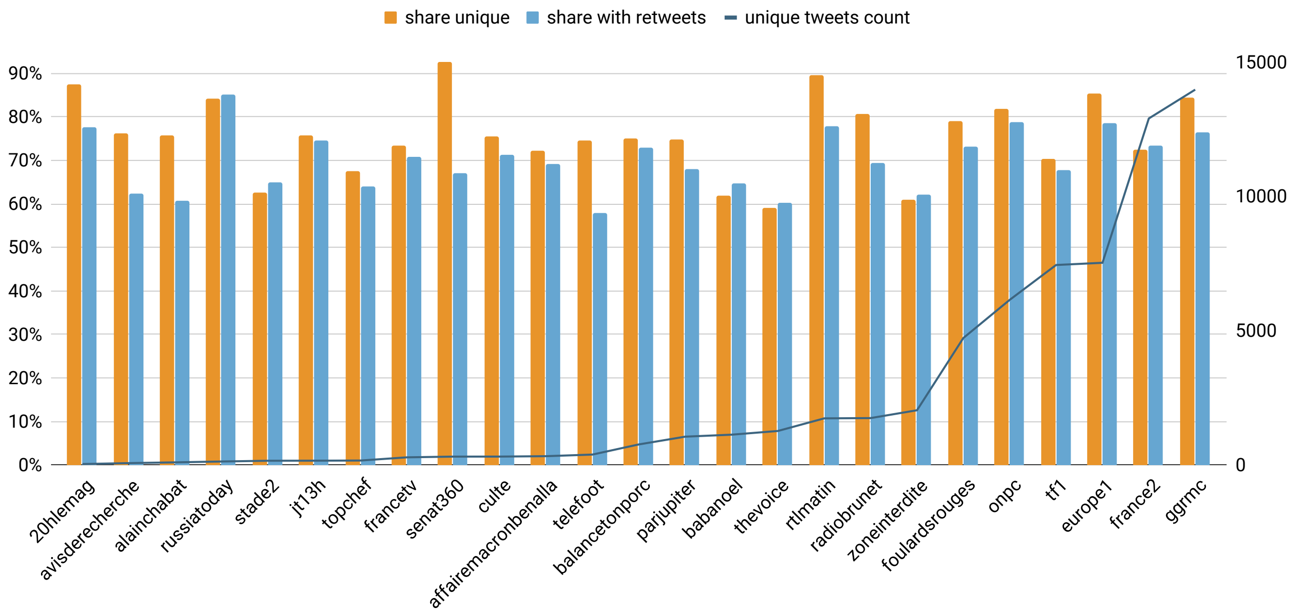

Figure 2.5: Share of DLWeb tweets captured using our collection method for a set of 25 hashtags. Blue columns represent the ratio for all tweets, yellow columns represent the ratio for original tweets (*i.e.* retweets excluded). The grey line shows the number of original tweets (*i.e.* retweets excluded) captured by the DLWeb for each hashtag. Tweets were collected from December 1st to December 31st, 2018.

Corpus provided by the French Internet legal deposit (DLWeb)

The French Internet legal deposit department at the INA (DLWeb) is in charge of archiving French websites related to audiovisual media (television, radio, web TVs). As part of this mission, the team collects tweets concerning audiovisual media and therefore regularly updates a manually curated list of hashtags and Twitter accounts to be captured using the Filter API. The DLWeb team provided us with the tweets collected for 25 of these hashtags over the course of a month (248,037 tweets), and we counted how many of these tweets had been collected over the same time period using our method. The results are presented in Figure 2.5. On average, we collected 74% of the tweets from the DLWeb, and 78% if we exclude retweets. Original tweets are better captured than retweets by our collection method, because each retweet allows us to archive the original tweet to which it refers. Therefore, we only need to capture one of the retweets of a tweet to get the original tweet. Retweets, on the other hand, are not retweeted, so we lose any chance of catching them if they were not obtained at the time they were sent.

It should also be mentioned that the DLWeb does not guarantee the collection of all tweets containing a given hashtag. Capturing tweets with specific hashtags allows the DLWeb to obtain a larger share of the tweets containing these hashtags than we do, but we also captured some tweets that they did not collect. We found 11,595 tweets from our collection (*i.e.* 4.7% of the DLWeb collection) containing one of the 25 selected hashtags that were not present in the DLWeb collection. Overall, since Twitter does not communicate on this subject, it is difficult to evaluate precisely the reasons why the relative performance of the collection methods varies depending on the hashtag. The volume collected by the DLWeb may depend on the popularity of the hashtag, and the popularity of other collected hashtags during the same time period.

In order to validate our collection method with a more stable comparison dataset, we computed the same metrics on a second corpus, presented in the next section.

Corpus provided by the Médialab team

We compared our collection of tweets with the corpus of tweets built by Cardon et al. [2019], which consists of tweets containing URLs from a curated list of 420 French media sources. The Médialab team uses different API endpoints to search for tweets that contain one of the selected domain names, including the Filter API but also the Search API[8] that returns tweets matching a query within the last 7 days. They

[8] `https://developer.twitter.com/en/docs/tweets/search/api-reference/get-search-tweets`

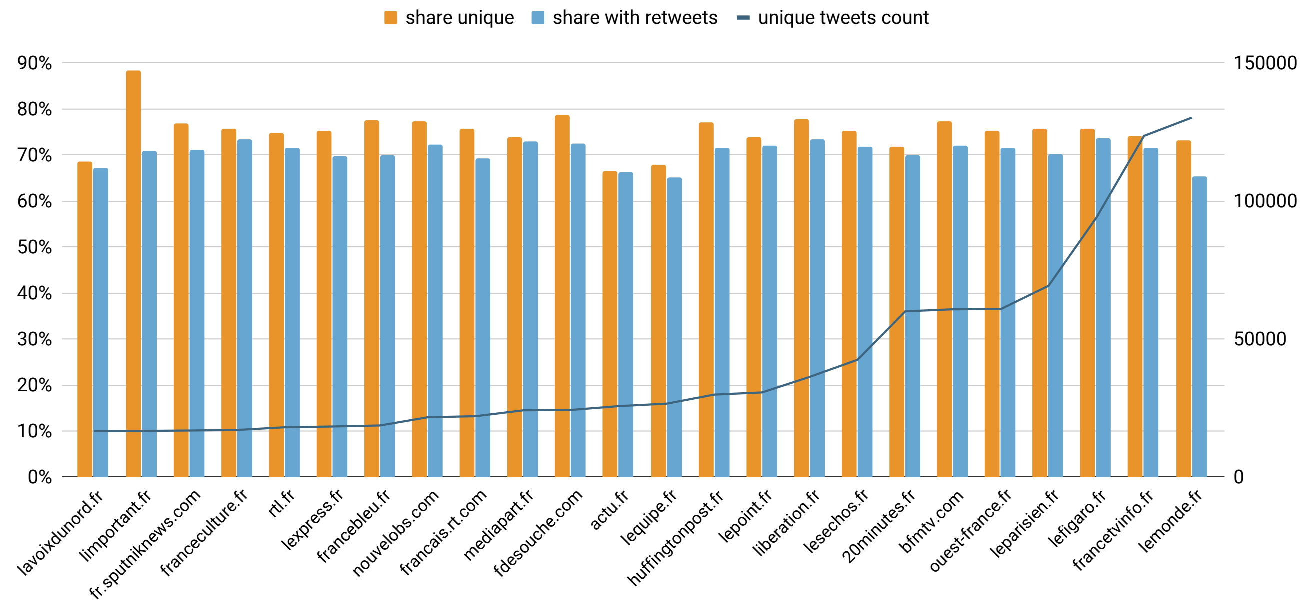

Figure 2.6: Share of tweets from the Médialab also captured using our collection method for 25 domain names. Blue columns represent the ratio for all tweets, yellow columns represent the ratio for original tweets (*i.e.* retweets excluded). The grey line shows the number of original tweets (*i.e.* retweets excluded) captured by the Médialab for each domain. Tweets were collected from December 1st to December 31st, 2018.

gave us access to a part of their dataset, namely all tweets collected between December 1st and 31st, 2018, amounting to 8.7 million tweets.

Among these tweets, we only kept those in French, i.e. 7.3 million tweets. Our sample contains 70% of these tweets in French, and 74% if we exclude retweets. Figure 2.6 shows the percentage of collected tweets for the most important domain names in terms of number of original tweets (*i.e.* retweets excluded) in the Médialab dataset. The Médialab dataset appears to be more complete than the collection from the DLWeb, probably due to the fact that several collection methods are combined: we found only 223,457 tweets from our collection (i.e. 2.6% of the Médialab dataset) containing one of the selected domain names that were not present in the Médialab dataset.

Evaluate the number of tweets per user

A third method can be used to compare our sample with the real number of tweets in French emitted on Twitter. It is based on the total number of tweets sent by a user since the account creation, a metadata that is provided by Twitter for every new tweet. With this metric, we can get an estimate of the total number of tweets emitted by a given user between two of its tweets. We can then compare this value with the number of tweets actually collected for that user.

In practice, we selected the tweets of all users who had written at least 3 tweets in 3 months (from July 1st to September 30th, 2018), retweets included. In order to select users that write mostly in French (tweets written in other languages are not collected with our method), we used the OpenStreetMap API to locate users depending on what they indicate in the "location" field. We obtained 920,000 users localized in France who emitted 241 million tweets in 3 months, according to the "number of tweet" field. With our collection method, we captured 147 million tweets from these users, *i.e.* 61% of the real number of emitted tweet. We found the same percentage with the sample of users who geolocate their tweets in France (27,000 users). This method gives us a high estimate of the real number of emitted tweets in French, since some of these users probably write in other languages than French, even if they are located in France.

All three comparison methods have their flaws; however, they produce close results. We can therefore conclude that we collected between 60% and 75% of all tweets in French sent on Twitter. We were therefore able to build our annotated dataset with the guarantee that our sample of tweets is representative. The next section presents the annotation procedure.

2.4 Tweet annotation

We built our event detection corpus based on tweets collected with our collection method from July 15th to August 6th, 2018. During this period, we collected 38 million original tweets (retweets excluded). We annotated these tweets depending on their relation to Twitter events and media events that took place in France at the time of the annotation.

2.4.1 Media event selection

To select media events, we decided to draw events randomly from the hundreds of events described in the French general information media every day. We drew press articles on a daily basis from July 15th to August 6th, 2018, for a total of 23 days. We did not want to use any automatic detection method to generate events from the collected tweets, since it may have biased the results of our evaluation tests (detection methods similar to the one used to generate events in the test set may be advantaged). In addition, we did not use Wikipedia to select important events (as is the case in McMinn et al. [2013]

and Petrović et al. [2012]), considering that “an event detection system should also be able to detect newsworthy events at a smaller scale" [Hasan et al., 2018]. In particular, we wanted to be able to detect events on social media than never became mainstream media events.

In practice, we drew 30 events a day, two thirds from the Agence France Presse (AFP), which is the third largest news agency in the world, and one third from a pool of major French newspapers (*Le Monde*, *Le Figaro*, *Les Échos*, *Libération*, *L'Humanité*, *Médiapart*). This selection method has the advantage of giving “big" events a higher chance of being selected, since they are covered by all news outlets, while also letting relatively “small" events emerge. Duplicates, i.e. articles covering the same event, were manually removed. We considered 30 events to be the maximum number of events the annotators could process in one day. In reality they did not have time to annotate most of them, and only processed the beginning of the list each day. Since new events were drawn every day, events that continued over several days were considered as separated events at the time of the annotation. We then grouped together these daily events manually.

2.4.2 Twitter events selection

Since our final objective is to measure differences in the coverage of events by news media and Twitter users, we did not want to miss important events in the Twitter sphere that would receive little coverage by traditional news media. We therefore monitored the trending terms on Twitter by detecting unusually frequent terms every day.

We chose a metric called JLH, which is used by Elasticsearch[9] to identify “significant terms" in a subset of documents (*foreground set*) compared to the rest of the collection (*background set*). It simply compares for each term t the frequency of occurrence in the foreground set (p_{fore}) and in the background set (p_{back}). This metric is computed as:

$$f(t,d) = \begin{cases} (p_{fore}(t,d) - p_{back}(t))\frac{p_{fore}(t,d)}{p_{back}(t)} & if\, p_{fore}(t,d) - p_{back}(t) > 0 \\ 0 & elsewhere \end{cases}$$

Where $p_{fore}(t,d) = \frac{tf(t,d)}{u_d}$ (the number of different users mentioning term t on day d divided by u_d the total number of users tweeting on day d) and $p_{back}(t) = \frac{tf(t)}{U}$ (the number of distinct users mentioning term t in the total collection divided by U the total number of users, measured by the number of different authors

[9] https://www.elastic.co/guide/en/elasticsearch/reference/current/search-aggregations-bucket-significantterms-aggre html#_jlh_score

of tweets in our collection). We did not use a standard tf-idf metric because it gave poor results when identifying bursting terms for a given day.

We computed the 20 terms with the best JLH scoring every day and went on Twitter to discover the underlying events causing a burst of these terms. We were then able to group together terms related to the same event. For example the terms “afcbom", “bournemouth", “bouom", “afcbournemouth" - all related to a soccer match between the Association Football Club Bournemouth (AFCB) and the Olympique de Marseille (OM) - were grouped together. We then excluded any events:

- that were artificially amplified using automatic tools. In particular, the Q&A website Curious Cat was used to post the same questions (“Where do you see yourself in tens years from now?", “What is your favorite movie?") to all Twitter users registered on Curious Cat. Many of them responded using the terms of the question (“My favorite movie is...") causing a burst in the frequency of those terms.
- that had already been drawn from the media events selection process.

Once the media events and the Twitter events were selected, the annotators' work could begin. In the following section, we explain the annotation procedure.

2.4.3 Annotation procedure

User interface

We developed a user interface (see Figure 2.7) presenting each event in the form of a title and a description text. For media events we used the title and the first paragraphs of the drawn corresponding press article. For Twitter events was ofthe bursting terms detected with the JLH scoring were used as title, and the description was a tweet manually selected because it described the event clearly. Under the title and the description, a search bar was presented. The user could use that bar to enter keywords and find the collected tweets containing those exact keywords. 12 tweets per page were displayed, starting with the most retweeted one. The user could select or deselect the tweets she considered related to the event. If the tweet contained a URL, the user could click or unclick a button under the tweet to indicate whether the linked page was related to the event as well. Once the user had read all twelve tweets and selected those related to the event, the user could submit her answers and access the next 12 tweets. Displayed tweets were not pre-selected by our program depending on their content, only depending on their publication date (we only displayed tweets emitted on the day of the event.) Retweets were excluded from the annotation

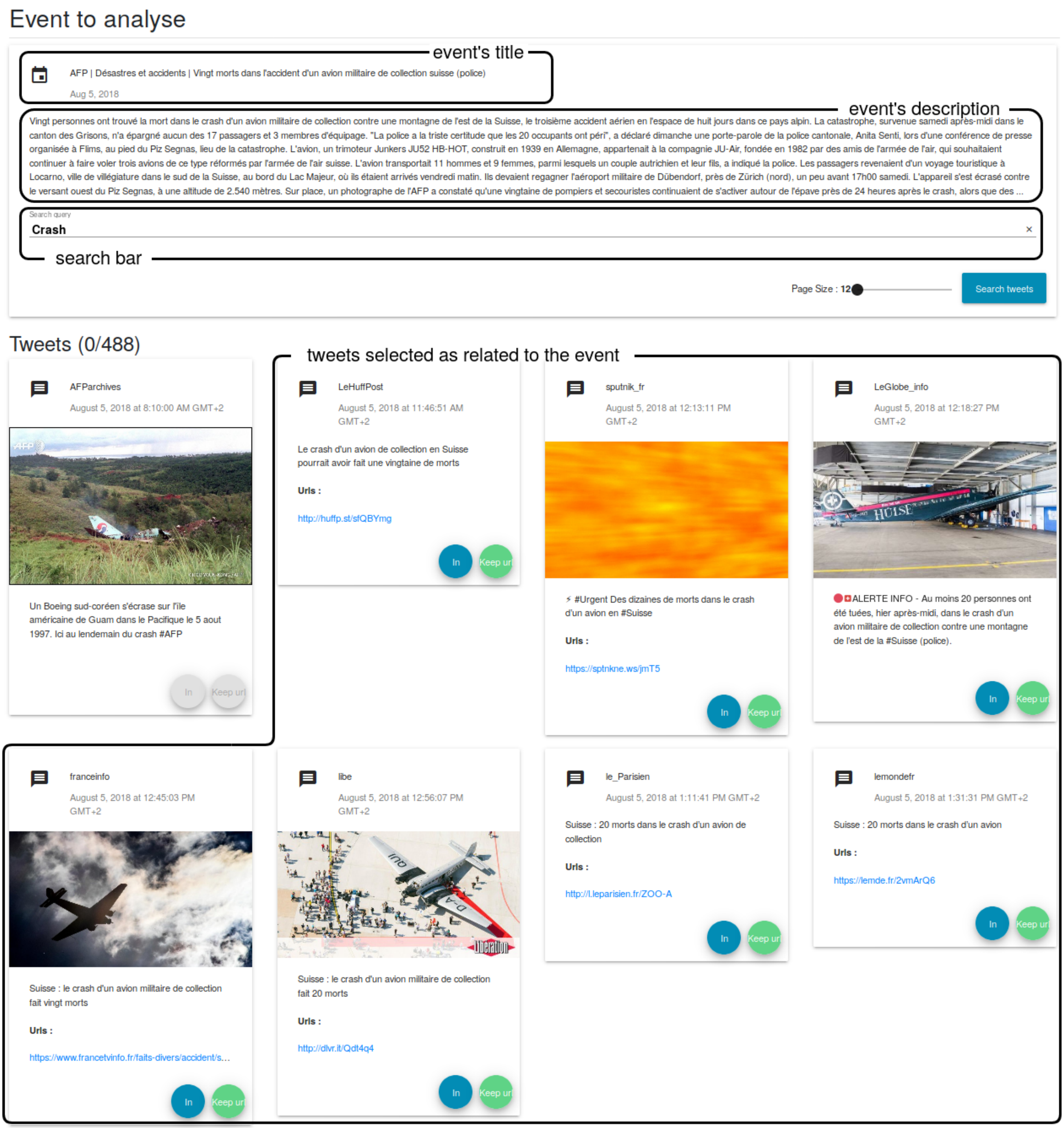

Figure 2.7: View of the annotation interface

interface..

The interface also made it possible to review tweets annotated by other users: once an annotator was done with an event, she could access another page displaying the same event (same title, same description) and the tweets seen by other annotators in relation to the event. The user had to go through all these tweets and annotate them, without knowing if those tweets were marked as relevant or irrelevant to the event by the other users.

Annotation task

Three political science students were hired for a month to annotate the corpus. All three of them were Twitter users and had a good knowledge of news media and the French political landscape. Every day they were presented with the new list of events. On July 16th, 2018, they began annotating events from July 15th. The first day of annotation was not included in the final dataset and served as a day of adaptation. Since the annotators did not work on Saturdays or Sundays, some days between July 15th and August 15th could not be annotated. We made the choice to annotate over a continuous period of time, from July 16th to August 6th.

For every event, they were asked to search for related tweets on the user interface, using a large variety of keywords. We insisted on the importance of named entities (persons, locations, organizations) and on the specificity of Twitter (one person could be referred to using her real name or her Twitter user name, for example). Like McMinn et al. [2013], we asked the annotators to mark tweets as related to the event if the tweet made reference to that event, even implicitly. It became clear that annotators could not treat more than 20 events a day, and often no more than 10 events, depending on the volume of tweets generated by each event. Indeed, some major events would have required days of work in order to be fully treated. We therefore instructed them not to spend more than one hour on each event. This of course had an impact on the maximum number of tweets per event that could be annotated.

In order to ensure that the annotators worked on the same tweets, we stopped the first annotation task after four hours of work every day, and asked them to go to the second part of the user interface, where they could find tweets already seen by at least one of the other annotators. They then had to annotate those tweets without knowing the judgment made by the others. In this way, we could make sure that all tweets would be reviewed by all three students.

Maximizing annotation efficiency

The annotation interface was designed to take advantage of the annotators' intelligence and avoid repetitive tasks. Thus, it seemed unnecessary to have them annotate tweets that contained exactly the same text. For tweets containing the same url, we added a "keep url" checkbox (see the green buttons on Figure 2.7), which was checked by default. If annotators felt that the url present in the tweet did not refer to content related to the event, they had to uncheck the box. For most other tweets (for which the url did refer to an event-related article), tweets containing the same url were no longer shown to the annotators in the interface. Here are all the rules we used to avoid repetition. For a given event:

1. tweets longer than 4 words containing the same text as an already-annotated tweet were no longer displayed;
2. tweets containing the same url as an already-annotated tweet were no longer displayed, unless the "keep url" checkbox was unchecked for that tweet;
3. retweets and responses to a tweet, as well as tweets quoting a previously annotated tweet were not displayed.

These rules played an important role to improve the quality of the corpus in terms of tweet diversity within a given event. The following section details some quality evaluation metrics.

2.5 Evaluation of the created corpus

In this section, we first present the annotator agreement and discuss possible reasons for differences in agreement. We then describe the characteristics of the corpus, including the number of events, their distribution across different categories, and the number of tweets per event.

2.5.1 Corpus characteristics

In total, 137,757 tweets were annotated (found by annotators using search keywords), and 95,796 tweets were considered linked to one or several events by at least 2 users. 327 daily events were selected, including 31 "Twitter events" (detected using the term frequency on Twitter) and 296 "media events" (drawn randomly in our collection of online news). Since the events were discovered day by day, we manually merged some of them to obtain 257 "macro-events". A macro-event contains 376 tweets on average.

	annotated	linked to daily event	linked to macro event
tweet count	137757	95796	95796
event count	327	327	257
mean	428	296	376
std	434	449	1324
min	7	2	2
25%	150	30	22
50%	280	100	76
75%	494	344	241
max	2913	2906	18534

Table 2.2: Distribution of the number of tweets per event. . *annotated* tweets were found by annotators using search keywords but not necessarily considered
as *linked to an event*. *Macro events* were built manually after annotation by grouping *daily events* together.

0.5% of the tweets were linked to several events. Additional descriptive statistics are presented in Table 2.2.

To describe the distribution of events across categories we used the classification by the French news agency AFP. AFP dispatches are labeled using the IPTC Information Interchange Model[10] Media Topics. This taxonomy is used internationally by numerous media companies to apply metadata to text, images and videos. The distribution of events across the 17 top Media Topics is detailed in Table 2.3. Among the 326 selected events, only 209 were drawn from the AFP and had a label. For the remaining 117 events (from other French press outlets or from Twitter events) we attributed a label manually.

2.5.2 Intra-event diversity

The quality of the dataset should also be measured in terms of variety of the tweets within a given event: what proportion of the tweets are simply the headline of the same linked article, for instance? Indeed, the proportion of tweets containing a url is high among the annotated tweets (71%), compared to the entire corpus of 38 million tweets (36%). However, due to the design of the annotation interface (see Section 2.4.3), very few annotated tweets share the same url. Only 4.6% of tweets linked to an event share the same url as another tweet in the same event. However, we did not anticipate during annotation that different urls can be linked to the same page. After redirection, 9.3% of tweets share the same page as another tweet in the same event, but 95% of pages are shared less than 3 times in a given event.

[10] `https://en.wikipedia.org/wiki/IPTC_Information_Interchange_Model`

English categories	French categories	Number of events
arts, culture, entertainment and media	Arts, culture, divertissement et médias	12
disaster, accident and emergency incident	Désastres et accidents	9
economy, business and finance	Economie et finances	47
education	Education	5
environment	Environnement	0
human interest	Gens animaux insolite	8
conflict, war and peace	Guerres et conflits	24
weather	Météo	0
crime, law and justice	Police et justice	71
politics	Politique	53
religion and belief	Religion et croyance	1
health	Santé	6
science and technology	Science et technologie	4
labour	Social	3
society	Société	21
sport	Sport	54
lifestyle and leisure	Vie quotidienne et loisirs	8

Table 2.3: Distribution of events across the 17 top IPTC Information Interchange Model Media Topics.

2.5.3 Annotator agreement

Annotator agreement is usually measured using Cohen's kappa for two annotators. Here we chose to hire three annotators in order to have an odd number of relevance judgments for each tweet. In the case of several annotators, Randolph [2005] recommends using Fleiss' kappa [Fleiss, 1971] in case of "*fixed marginal distributions*" (annotators know in advance the proportion of cases that should be distributed in each category) and free-marginal multirater kappa [Randolph, 2005] if there is no prior knowledge of the marginal distribution. Indeed, we experienced some odd results using Fleiss' kappa on our corpus, in particular for events with a strong asymmetry between categories (when a large majority of tweets were annotated as "unrelated" to the event of interest, or the opposite). We hence decided to use free-marginal multirater kappa, which is also the measure used by McMinn et al. [2013].

If one denotes P_o the proportion of overall agreement among annotators, P_e the proportion of agreement expected by chance, free-marginal multirater kappa is expressed as

$$\kappa_{free} = \frac{P_o - P_e}{1 - P_e}$$

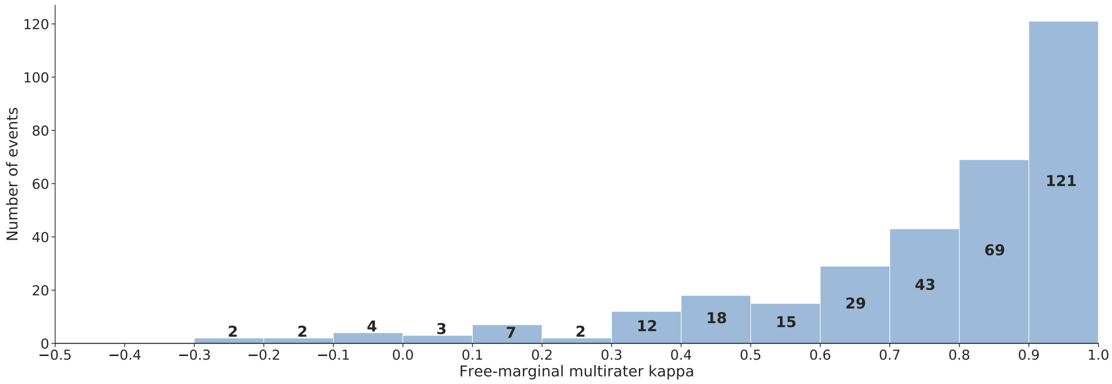

Figure 2.8: Distribution of the events depending on annotators' agreement, measured by free-marginal multirater kappa. In our corpus, 121 events have a free-marginal multirater kappa higher than 0.9, 69 events have a free-marginal multirater kappa between 0.8 and 0.9, etc.

with

$$P_o = \frac{1}{Nn(n-1)}((\sum_{i=1}^{N}\sum_{i=j}^{k} n_{ij}^2) - Nn)$$

and

$$P_e = \frac{1}{k}$$

where N is the total number of cases (here the number of tweets to annotate), n is the number of annotators and k the number of categories (two in our case: *relevant* or *not relevant* to a given event). Its values vary between -1 and 1. A value of 0 indicates a level of agreement that could have been expected by chance, and a positive value indicates a level of agreement that is better than chance. Negative values indicate worse agreement than expected by chance.

In our corpus, $\kappa_{free} = 0.79$ which indicates a strong level of agreement among annotators. We also computed the κ_{free} value for each individual event (taking into account all tweets that have been read by annotators while working on this event). Figure 2.8 describes the distribution of events depending on the κ_{free}. We observe that for some events, the agreement is very low: 8 events have a negative κ_{free} value, and 12 events have a κ_{free} value between 0 and 0.3.

We asked the annotators to come together and re-read the events on which their agreement was particularly low, in order to understand why they did not annotate tweets in the same way. The students admitted some errors in the annotation for 4 of the 17 examined events. For the other events, they explained that they had different views of the events' scope: for example, one article reported the fact that President of Nicaragua, Daniel Ortega, refused to resign in a context of severe crisis in his country. Two of the annotators included in the event those tweets related to the crisis in Nicaragua. One annotator restricted the event to the statement of Daniel Ortega. Faced with these differences in opinion we could decide to remove from the corpus the tweets where the annotators disagreed, or to remove events with a very low kappa. However we found it interesting to see how an algorithm behaves in such borderline cases.

2.6 Conclusion

It is rare in a Machine Learning thesis to devote so much work to the constitution of a corpus: instead, the standard recommendation is to work on existing datasets recognized by the scientific community, and to evaluate performances on a common benchmark. However, there are several reasons why I took the time to set up a reliable collection method, and spent the summer of 2018 annotating tweets.

As I showed in Section 2.2, publicly accessible tweet corpora for event detection are rare, they are generally quite small and do not exist in French. I hope that I have partly remedied this lack, having published my corpus with the ids of the 38 million tweets collected during the summer of 2018. Given the number of annotated tweets and the general quality of the annotation (see Section 2.5) it may be a useful resource for researchers in the future, especially French-speaking ones.

Working on tweets in French was not only an incentive to build my own corpus, but also to set up my own method of collecting tweets, which I detailed in Section 2.3, in order to obtain a sufficient volume of tweets in French. By ruling out the sole use of the Sample API, which ensures a random distribution of collected tweets, I also had to find methods to evaluate the resulting sample, in order to guarantee its representativity. This work allows me, in the continuation of this thesis, to guarantee the reliability of my analyses.

Finally, the architecture for collecting and indexing tweets, implemented in 2018, has been running continuously until today. It is a tool for INA researchers that will serve even after my thesis is concluded. It is currently being used by Nicolas Hervé for a research project on media intensity on the subject of COVID-19 and will hopefully give rise to many other studies.

Chapter 3

Detecting Twitter events

3.1 Introduction

Twitter has been used to detect or predict a large variety of events, from flood prevention [de Bruijn et al., 2017] to stock market movements [Pagolu et al., 2016]. However, the specificity of social network data (short texts, use of slang, abbreviations, hashtags, images and videos, very high volume of data) makes all "general" detection tasks (without specification of the type of topic) very difficult.

Many works on event detection are actually focused on burst detection (detecting topics such as natural disasters, attacks, etc., that cause an unusual volume of tweets), and do not attempt to assess the relative size of events. We seek to detect *all* events, both those that generate a high volume of tweets and those that are little discussed, and to group together *all* tweets related to the same event. With this definition in mind, the topic detection and tracking task is conceptually similar to clustering. Given the size of our tweet collection, the chosen clustering method has to be extremely time-efficient.

As well as deciding on the event detection algorithm, we also have to consider the type of tweet representation: should we only use the text of the tweets, or should we consider the tweet as a multimodal document, composed of text and/or images, videos, hashtags?

In the field of language processing, recent works have made it possible to reach a performance level close to human capacity in several tasks, particularly when evaluating the semantic similarity between two sentences[1]. However, these advances, based on the training of neural networks on very large corpora of texts, may not always be suited to our task. Indeed, despite rapid progress in recent years in the adaptability of language processing models (the GLUE benchmark Wang et al. [2018] consists of 9 different tasks,

[1]See the results on the GLUE benchmark: `https://gluebenchmark.com/leaderboard`

and the models are evaluated according to their average performance on all these tasks), it remains difficult to adapt these models to new tasks. Any transformation of the initial task requires fine-tuning a deep neural network on (at least) a few thousand sentences, which involves hours of manual annotation to create a suitable dataset. In our work we focus on short-text topic similarity (evaluate whether two sentences / short texts address the same subject), which in some cases differs from semantic similarity (evaluate whether two sentences mean the same thing) evaluated in GLUE, and we do not have a corresponding training dataset. Besides, even on a strictly identical task, the performances announced in the literature are perfectly reproducible only on English language corpora.

Finally, most of these models are designed to be used as input to end-to-end systems. For example, to calculate a similarity score between sentences with BERT [Devlin et al., 2018], it is necessary to process sentences in pair instead of individually. Using the example proposed in [Reimers and Gurevych, 2019], to find the two most similar sentences in a corpus of $n = 10,000$ sentences, the number of treatments to be performed is $n\frac{(n-1)}{2} = 49,995,000$ operations, which represents approximately 65 hours of processing with BERT on a V100 GPU. These architectures do not apply well to information retrieval systems that involve comparing hundreds of thousands of sentences. For clustering or information retrieval tasks, it is more efficient to represent each sentence in a vector space where similar sentences are close (so-called *embeddings*), and then apply conventional distance measurements (cosine, euclidean distance, etc.).

With regard to images, recent progress in the field of visual content description due to deep neural networks provides new ways of representing social media documents by including rich visual features. There are cases where image provides decisive information for event detection (see Fig. 3.1). However, dealing with image tweets often requires a contextual knowledge external to the document. Without this knowledge, image can become a source of error for event detection algorithms compared to text alone.

In this chapter, we show that the First Story Detection clustering algorithm is the most suitable for our event detection task. We show that the best vector representation of tweets for the FSD algorithm is the tf-idf approach. We compare this algorithm with another standard algorithm (DBSCAN) and a method from the literature (DMM). We are also testing a two-step clustering method, to group tweets according to their textual content and then according to their visual content.

We conduct our demonstration by starting with a review of the state of the art, then a presentation of the approach we propose. We then detail several concurrent algorithms tested, and we review the different experiments carried out with these algorithms. Finally, we present our results in detail.

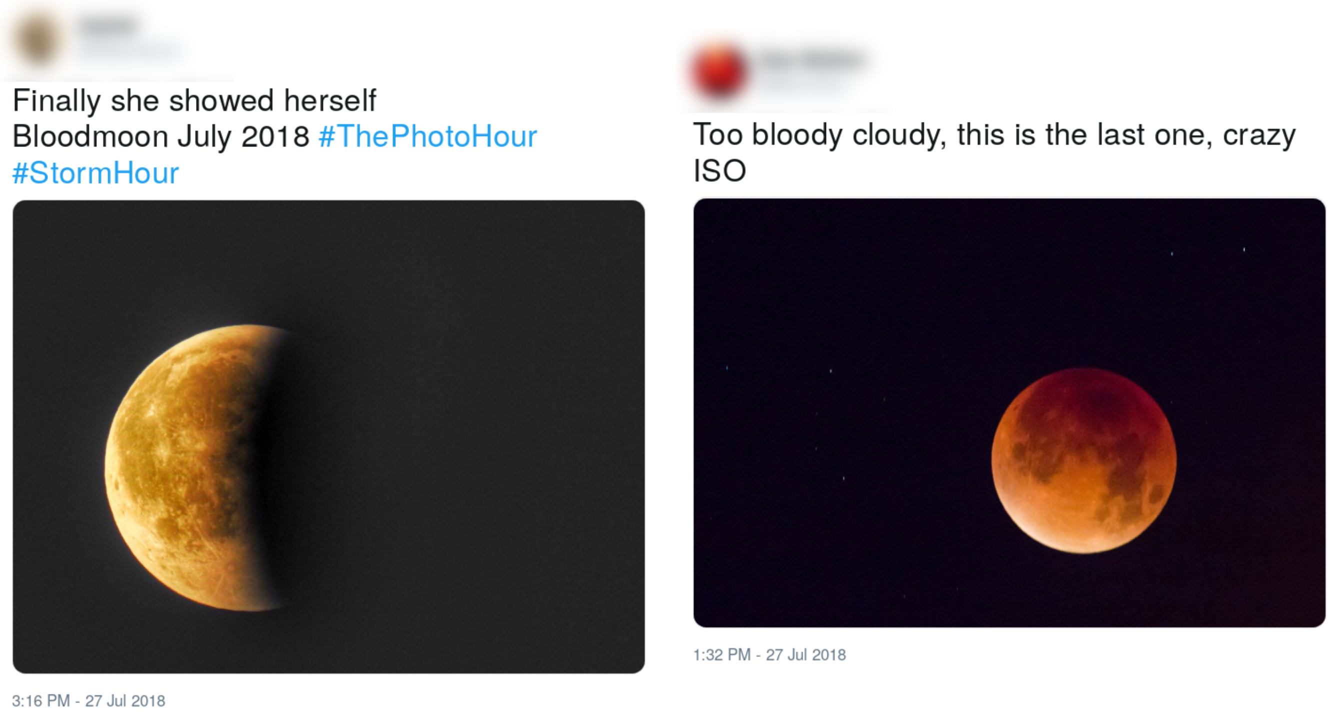

Figure 3.1: Example of a topic (the July 2018 lunar eclipse) where multimedia contents provide critical information for topic detection

3.2 State of the art

3.2.1 Twitter event detection approaches

We divide the event detection methods into three types of approaches: term-weighting-based approaches, topic modeling, and clustering. This is also the classification used in the survey on real-time event detection by Hasan et al. [2018]. The last approach, clustering, is dealt with in more detail in this state of the art, as it is the one we chose to implement for our own event detection tool.

Term-weighting-based approaches

These approaches rely on tracking the terms likely to be linked to an event (often due to a high frequency of some terms during a given time window). They usually return a list of the top k trending events on Twitter, which does not meet our objective of detecting events in an exhaustive manner.

The event detection system TwitterMonitor [Mathioudakis and Koudas, 2010] detects bursty keywords in the Twitter stream by comparing their term frequencies in previous periods to current term frequency. Bursty keywords are then grouped together in “trends" depending on their co-occurrences in recent tweets.

EnBlogue [Alvanaki et al., 2012] measures the correlation of hashtag pairs within a given time window. Emergent topics are then detected among the pairs with the highest shift in their correlation. EnBlogue produces an overall scoring of the topics depending on the shift in correlation and on the total popularity of each topic. This score is smoothed in order to give a higher rank to new topics.

MABED [Guille and Favre, 2015] does not only use the textual content of the tweets: the frequency at which users interact with each other using “mentions" (i.e. the name of another Twitter account preceded by “@") is also taken into account to detect events. The system models the number of tweets that contain word t and at least one mention during a given time-window as a binomial distribution. It detects positive anomalies if the creation of mentions associated to word t is strictly greater than the expectation of the model. The magnitude of impact of an event on a time interval I is computed by integrating the anomaly function on the interval I. For each word associated with a mention, the system finds the interval I that maximizes its magnitude of impact. After other steps of event description and duplicates removal, the events with the highest impact are returned.

The Twitter Live Detection Framework (TLDF) [Gaglio et al., 2016] modifies the Soft Frequent Pattern Mining (SFPM) algorithm [Petkos et al., 2014a] to adapt to the dynamic nature of tweets. The authors use the relevance score of term t proposed for SFPM: the ratio of the likelihood of appearance of the term in the current time-window and in a reference set of tweets. This relevance score is combined with a parameter boosting the score of named entities and multiplied by the tf-idf of term t. Moreover, the size of the detection time-window is not fixed, but is controlled by a sigmoid function depending on the volume of emitted tweets at a given moment.

Topic models

Topic models are widely used techniques in the natural language processing field to discover the topical structure from a corpus of textual documents (news articles, scientific papers, tweets, etc.). Latent Dirichlet Allocation (LDA) is the most common one [Blei et al., 2001]. In this model, each document is considered a mixture of different topics drawn from a topic distribution. In the case of topic detection in a collection of tweets, LDA has several drawbacks:

1) the model does not take into account the fact that topics change over time; 2) the number of topics has to be known in advance; 3) it assumes that a document is a mixture of several topics, which is very rare in short texts such as tweets. There is, however, a vast literature working on strategies to overcome

these limitations.

The first point has been addressed by Blei and Lafferty [2006]; however, they assume that the number of topics remains the same over periods, whereas in a stream of tweets, topics can emerge and disappear in each new period.

With regard to the number of topics, some methods exist to estimate the optimal parameter k [Brunet et al., 2004; Griffiths and Steyvers, 2004; Arun et al., 2010; Greene et al., 2014]. However these methods rely on re-generating topic models for each candidate $k \in [k_{min}, k_{max}]$. This can be achieved for a small number of topics ($k_{max} < 100$), but testing each k in a range $[2100, 10500]$ (between 100 and 500 events a day in our corpus of 21 days) is not an option.

Regarding the third assumption, a number of articles have specifically tackled the issue of applying topic models to short texts. The recent survey by Likhitha et al. [2019] summarizes the topic modeling techniques used to find topics within short text documents.

Based on the assumption made by Nigam et al. [2000] that each document is assumed to be generated from a single topic, i.e. the words within a document are all sampled from the same topic distribution, Yin and Wang [2014] propose the Dirichlet Multinomial Mixture (DMM) model. The generative process of DMM can be described as follows:

1. Choose a proportion of topics $\theta \sim Dirichlet(\alpha)$.
2. For each topic $k \in \{1, \ldots, K\}$:

   Draw a distribution of words linked to this topic $\phi_k \sim Dirichlet(\beta)$.
3. For each document $d \in \{1, \ldots, D\}$:
   (a) Draw a topic $z_d \sim Multinomial(\theta)$.
   (b) For each word w:

       Draw a word $w \sim Multinomial(\phi_{z_d})$

Yin and Wang [2014] provide a collapsed Gibbs Sampling algorithm (GSDMM) to approximate the hidden variables in this generative process. The interest of this method in our case is that over iterations, some clusters (topics) become empty, while others progressively gather more documents. This means that the algorithm can approximate the number of documents in the collection, as long as the initial number of topics (K) is large enough at initialization. DMM is therefore very relevant to our study because it addresses both problem 2 (number of clusters unknown) and problem 3 (only one topic per tweet).

This simple and efficient method has been adapted and improved by several authors: Nguyen et al. [2015] integrates Word2Vec embeddings into DMM by replacing the topic-word Dirichlet multinomial component with a draw from a Bernoulli distribution to determine whether the Dirichlet multinomial component or a word embedding component will be used to draw the word w. Li et al. [2017] propose PDMM, an extension of the DMM model allowing short texts to be generated from one to three topics and drawn from a Poisson distribution, and GPU-PDMM, which exploit word-embeddings to enrich the latent topic learning with external semantic relations.

However, these advances seem to increase calculation times by several orders of magnitude. Li et al. [2017] provide a comparative table of the time efficiency of these different models, which we compare with their accuracy in Table 3.1. According to their experiments (all models are implemented in Java), the extended DMM models seem to multiply by 10 or even 100 the calculation time of plain DMM, on the BaiduQA dataset[2] for an increase in accuracy of 2 to 3 points. Therefore, we decided to use DMM as comparison model with the First Story Detection algorithm rather than more recent approaches.

Model	*K=40*	*K=60*	*K=80*
DMM	0.355	0.566	0.843
LF-DMM	13.0	20.5	31.8
PDMM	11.6	11.7	11.8
GPU-PDMM	37.8	40.7	45.2

(a) Time cost (in seconds) per iteration of each model

Model	*K=40*	*K=60*	*K=80*
DMM	0.523	0.548	0.553
LF-DMM	0.424	0.449	0.487
PDMM	0.553	0.562	0.577
GPU-PDMM	0.545	0.569	0.583

(b) Average classification accuracy of each model

Table 3.1: Comparison of time efficiency and classification accuracy of several DMM-adapted models with different numbers of topics K on the BaiduQA dataset. These values are provided by Li et al. [2017]

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Dynamic clustering

Dynamic clustering approaches do not require a fixed number of clusters. These methods are well fitted for discovering clusters of textual documents dynamically as new documents are added to the collection. For this type of clustering, the algorithms that are often used take into account both the thematic similarity of the documents and their temporal proximity, in order to avoid grouping in the same cluster tweets sent at very distant times. This type of approach generally uses the state-of-the-art First Story Detection (FSD) [Allan, 2002] algorithm as a reference method. In this method (see Algorithm 1), documents are represented using tf-idf (see Section 3.2.2 for a presentation of tf-idf encoding) and their similarity is

[2] a corpus of 648,514 questions from a Chinese Q&A website, containing 35 labels.

evaluated using cosine similarity. The cosine similarity of two vectors u and v is computed as follows:

$$cos(u,v) = \frac{u \cdot v}{\|u\|\|v\|} \tag{3.1}$$

We denote $\delta(u,v)$ the cosine distance between u and v, which is defined as:

$$\delta(u,v) = 1 - cos(u,v) \tag{3.2}$$

Each new document joins the cluster of its nearest neighbor in the collection. If the cosine distance to the nearest neighbor is higher than a pre-defined threshold t, a new cluster is created containing the new document. The oldest documents are dropped from the collection at regular intervals. This insures that each new document is only compared to the most recent documents.

Algorithm 1 “First Story Detection"

Input: threshold t, window size w, corpus C of documents in chronological order
Output: thread ids for each document

$T \leftarrow [\,]\,; i \leftarrow 0$
while document d in C **do**
  if T is empty **then**
    $thread\_id(d) \leftarrow i$
    $i \leftarrow i + 1$
  else
    $d_{nearest} \leftarrow$ nearest neighbor of d in T
    if $\delta(d, d_{nearest}) < t$ **then**
      $thread\_id(d) \leftarrow thread\_id(d_{nearest})$
    else
      $thread\_id(d) \leftarrow i$
      $i \leftarrow i + 1$
    end if
  end if
  if $|T| \geq w$ **then**
    remove first document from T
  end if
  add d to T
end while

Existing works on tweet incremental clustering have adapted this reference method initially developed for streams of news (such as RSS streams) to process much higher volumes of documents, and very short texts. Indeed, the maximum size of a tweet is 280 characters (140 characters before 2018). Changes in that baseline method are made either in the type of text representation or in the clustering algorithm itself. A step of noise filtering is also frequently added before the clustering step, to distinguish event from non-event tweets (according to Liu et al. [2016], the proportion of event tweets in well-established corpora such as that of McMinn et al. [2013] is less than 0.2%). This section explores the variations introduced in the clustering algorithm.

In TwitterStand, Sankaranarayanan et al. [2009] first perform a filtering step, which classifies tweets as either “junk" or “news" using a naive Bayes classifier. Next, their online clustering algorithm associates a vector to each cluster, which is composed from the contained tweets’ terms weighted with tf-idf. Each new tweet is represented using tf-idf and compared to the clusters’ vectors using a modified cosine distance that accounts for the temporal dimension of clusters. The distance formula is

$$\dot{\delta}(t,c) = \delta(t,c) \times e^{\frac{-(T_t - T_c)^2}{2\sigma^2}}$$

where $\delta(t,c)$ is the cosine distance between tweet t and cluster c, T_t is tweet t's publication time and T_c is cluster c's mean publication time. The distance is only computed for clusters with a mean publication time T_c more recent than 3 days, and that have a word in common with t. If $\dot{\delta}(t,c^*) \leqslant \epsilon$ (where c^* is the nearest cluster to t), the tweet t is added to the cluster c^*. Otherwise, a new cluster is created. To speed up the search for the nearest cluster, an inverted index of the cluster’s words is maintained: for each word w, the inverted index stores pointers to the clusters that contain w. The clustering algorithm in TwitterStand is adapted to the noisy nature of tweets by maintaining a list of reputable sources. A cluster is dropped from the list of active clusters if none of the first k tweets are from a reputable source. The system also deals with fragmentation (the fact that several clusters about the same topic are created) by removing duplicate clusters. If a cluster c' is identified as the duplicate of an older cluster c, c' is marked as “slave" of the cluster c, and c as “master" of c'. Any tweet that should be added to c' is now added to c.

Petrović et al. [2010] speed up the standard FSD algorithm by replacing the nearest neighbor search by an approximate nearest neighbor search using Locality Sensitive Hashing. Instead of searching for the nearest neighbor in the full set of documents, the search is done among a small set S of potential nearest neighbors. The set S is the set of documents that have the same hash as current document x:

$$S(x) = \{y : h_{ij}(y) = h_{ij}(x), \exists i \in [1 \dots L], \forall j \in [1 \dots k]\}$$

where L is the number of hash tables, and k the number of hyperplanes in each hash table. The hash functions h_{ij} are defined as:

$$h_{ij}(x) = sgn(u_{ij}^T x)$$

the sign of the scalar product of random vector u_{ij} and x. To reduce the risk of failing to find the nearest neighbor (if the nearest neighbor y does not collide with x in the set $S(x)$), if no nearest neighbor is found, the system starts a search for an exact nearest neighbor through an inverted index containing only the most recent documents. To limit the growth of the sets S (also called buckets), the number of documents in a single bucket is limited to a constant parameter. The oldest documents in the bucket are then removed.

The system proposed by Petrović et al. [2010] was subsequently improved by the same authors [Petrović et al., 2012] using public synonym and paraphrase corpora in order to expand the words of the tweets with all their potential synonyms. This approach is a way to compensate for the scarcity of information contained in tweets and to increase the chances of finding a potential neighbor even if there is no tweet containing the same words in the collection.

Becker et al. [2011b] use the same clustering algorithm as Sankaranarayanan et al. [2009], with each new tweet being represented as a tf-idf vector and compared using cosine similarity to the centroid of each cluster (the centroid is the mean weight of all terms in all tweets contained in the cluster). The specificity of their approach lies in the step following the clustering: instead of processing to a noise/event classification at the tweet level, the classification step takes place at the cluster level. They use a wide range of features in order to run a classification algorithm able to distinguish event clusters from noise clusters. The considered features are temporal features (taking into account the frequency of emission of the tweets in the cluster), social features (percentage of messages being retweets, replies, or mentions), topical features (based on the assumption that event clusters have a smaller diversity of topics), and Twitter-Centric features (hashtag usage, presence of multi-word hashtags).

McMinn and Jose [2015] base their event-detection approach on Part Of Speech (POS) Tagging and Named Entity Recognition (NER). Their first step is to extract named entities (persons, locations and organizations) and lemmatized nouns and verbs from each tweets. They then proceed to an aggressive filtering step (95% of the tweets are removed): the system removes retweets, tweets with no named entities, and tweets containing terms associated with noise (“follow", “watch", etc.). Then two steps are conducted in parallel: a clustering and a burst detection step. The clustering is based on an inverted index of all named entities: for each new tweet, the tweets containing the same named entities are retrieved from the index. The nearest neighbor is searched for among these tweets using tf-idf representation, cosine similarity and a similarity threshold. If a nearest neighbor is found and does not already belong to a cluster, a new cluster is created containing the two tweets. In parallel, the burst detection module looks for bursts in the frequency of the detected entities. Once a burst has been detected, the clusters associated with the given entity are associated to it if the average timestamp of the tweets in the cluster is after the initial burst. The clusters associated to one burst form an event. If an entity associated to another event is mentioned in more than 50% of the event's tweets, the two events are merged.

With Reuters Tracer, Liu et al. [2016] propose an event detection system that is also largely based on POS tagging and NER. This system combines a tweet-level noise filtering and a cluster-level noise filtering. We consider as "noise" all tweets and all clusters of tweets that are not linked to an event (as defined by McMinn et al. [2013]). The clustering algorithm itself is quite different from the standard FSD algorithm. New tweets are added to clusters based on three criteria: (1) Retweets of the same tweets are all added to the same cluster. (2) Tweets containing the same url are all added to the same cluster. (3) Finally, a similarity metric with the existing clusters is computed as follows:

$$S_i = aN_e + bN_n + cN_v + dN_h$$

where N_e, N_n, N_v, N_h are the numbers of matching Named Entities, nouns, verbs and hashtags between the tweet and the cluster, and a, b, c, d are learned parameters. Liu and al. explain that their system is primarily based on named entities ("An event is usually defined by *who*, *where* and *what*" according to McMinn et al. [2013]), and that there is no need for high dimensional tf-idf vectors to compute a good similarity function. The obtained clusters, called "unit clusters" are progressively merged into bigger clusters using the same steps (merging based on retweets, urls, then similarity metric) as the unit clustering step. However, the used a, b, c, d parameters are different.

Hasan et al. [2016] use the technique of First Story Detection with LSH developed by Petrović et al. [2010]. However, they observe that the k independent random vectors in a single hash table need to be updated every time the size of the input tf-idf vectors increases (which happens at a high rate in Twitter data since the vocabulary evolves faster than in traditional news media). To alleviate this problem, they propose a technique using random indexing [Sahlgren, 2005]. This aims to represent terms with fixed-size vectors. Each term t is associated with two vectors: an index vector and a context vector. The index vector is a random vector. The context vector has the same size as the index vector and is initialized with zeroes. When a co-occurrence of the term t with another term t' is observed, the context vector of t is updated by adding the index vector of t'. A tweet can then be represented as an average of the vectors of each term in the tweet. This tweet representation is then used to perform the LSH approximate neighbors search of tweet d. However, once the set S of all documents that collide with d in a hash table is computed, the exact nearest neighbor search is done using cosine similarity on tf-idf vectors, rather than random indexing vectors. Hasan et al. [2016] use this method as a first algorithm in order to detect “non-unique" tweets, which are then clustered using a second algorithm close to that of Sankaranarayanan et al. [2009]: this time, the similarity to the clusters' centroids is computed. Hasan et al. explain the use of this two-step clustering method by the necessity to restrain the number of “one tweet clusters". A defragmentation step is finally performed in order to merge similar clusters.

In these works, tweets are represented in the form of tf-idf vectors in the vast majority of cases [Sankaranarayanan et al., 2009; Petrović et al., 2010; Becker et al., 2011a; Hasan et al., 2016]. Repp and Ramampiaro [2018] test different types of representation of tweets (Word2Vec average, GloVe average, Doc2Vec, Word2Vec average weighted by the idf of each word). However, these representations are only tested on a classification task, and the best representation (the average of Word2Vec) is then used for clustering. We therefore wanted to update this work by testing recent embeddings, and in particular those developed for representation of sentences. The next section details recent advances in text embeddings, from word embeddings to sentence or short-text embeddings.

3.2.2 Text embeddings

The most commonly used “vectorization" method until the 2010s was the tf-idf, introduced by Sparck Jones [1972]. This is an improvement on the principle “bag of words” vectors [Harris, 1954], where each document is described by the number of occurrences of the words it contains ("term frequency"). The tf-idf representation uses the same vectors, but weights each of the words in inverse proportion to the number of documents in which it appears.

Word embeddings

The publication of Word2Vec [Mikolov et al., 2013] and GloVe [Pennington et al., 2014], two methods based on the prediction of the context of each word (or the prediction of each word depending on its context), made it possible to create word vectors carrying semantics other than the word frequency in the corpus. However, these representations lost the ability to describe each document by a single vector. To get around this problem, each document is often represented by an average of word vectors.

With ELMo [Peters et al., 2018] a new generation of models appears, allowing words to be represented not only depending on their usual context (the words with which they are frequently used in the training corpus), but also according to their local context: the word representation is specific to a given sentence. This constitutes an important advance in language processing, since a word no longer has a single representation that aggregates its different meanings, but several representations for each of the contexts in which it is used. ELMo is based on a bi-directional LSTM neural network trained to predict the next word in a sequence in both directions (i.e. to predict the next word in a sentence, but also, given the end of a sentence, to predict the word just before it). However, ELMo is not designed to produce sentence embeddings, but rather to be used as input to task-specific neural models. Nevertheless, the authors test the performance of word vectors directly from the first or second layer of their model (which contains three layers) for a disambiguation task by searching for the first nearest neighbor. The results obtained are close to the state of the art.

BERT [Devlin et al., 2018] is even more generic than ELMo, because this model does not require a specific architecture for each type of task: it can be fine-tuned to a new dataset by simply adding an output layer. BERT is built with a Transformer-type architecture [Vaswani et al., 2017], and pre-trained on two types of pretext tasks: predicting hidden words in a sentence and predicting the next sentence in a text. As in ELMo, the authors of BERT do not intend to create sentence embeddings from their model, but rather to provide an architecture that should be trained differently for each specific task. However, they demonstrate that a simple transfer learning (extraction of word vectors used at the input of a new model without fine-tuning) can match the state of the art for a named entities detection task.

Sentence embeddings

There is a large number of works that attempt to represent sentences by generic vectors that can be used in a wide variety of tasks, especially for transfer-learning. For example, Skip-Thought [Kiros et al., 2015] is based on an encoder-decoder architecture trained to generate the sentences framing a given sentence in a text.

Conneau et al. [2017] show with InferSent, a bi-directional Siamese LSTM network (Siamese means that it takes two sentences as input, but applies the same weights in both parts of the network), that supervised learning provides better results for the creation of generic sentence vectors. InferSent is trained on a classification task using the SNLI dataset [Bowman et al., 2015], which contains $570,000$ pairs of English sentences manually annotated in three categories: the first sentence implies the second, the first sentence contradicts the second, or the first sentence and the second sentence are mutually neutral.

With Universal Sentence Encoder, Cer et al. [2018] apply the results of Kiros et al. [2015] and Conneau et al. [2017] by training a Transformer architecture both on unsupervised tasks, as was done for Skip-Thought, and on the SNLI dataset, like InferSent.

Sentence-BERT [Reimers and Gurevych, 2019] does not provide universal vectors, but a fine-tuning architecture of the BERT model specifically adapted to produce sentence embeddings adapted to certain types of tasks. This model modifies BERT into a Siamese network, with a final layer depending on the type of task on which the network is trained. The authors test their representations on the STS dataset [Cer et al., 2017] ($8,628$ pairs of sentences with a similarity score between 0 and 5) by computing a simple cosine similarity score between the vectors associated with each sentence. They show that the best performances on the STS dataset are obtained by a first fine-tuning on SNLI and then a second fine-tuning on the STS training set.

All these embedding methods are potential ways of representing the text of tweets. We compare their performance in Section 3.6.1. However, we were also interested in the information carried by the image, because communication on social networks is increasingly carried by visual supports. The next section reviews the existing literature on multimodal event detection.

3.2.3 Text-Image event detection

In the last three years, some works on Twitter data have started to use multimodal embeddings to solve various tasks: Lu et al. [2018] incorporate tweet pictures in order to improve Named Entities Recognition in the text of the tweets. Other works combine text and image of tweets in order to recommend hashtags [Zhang et al., 2017] or users' mentions [Ma et al., 2018]. These approaches show that using visual and textual context for tweet-related tasks improves performance in several cases. However, it is unsure whether current visual content description systems can improve Twitter event detection.

We found relatively little work on the joint use of image and text for the specific task of event detection in tweets. Alqhtani et al. [2018] use text and image to detect tweets related to earthquakes. They extract visual features by using scale-invariant feature transform (SIFT) to automatically detect keypoints from

The two images present variations of the same meme, known as “Distracted Boyfriend". It is a classical example of meme, with identical visual content but different captions.

Figure 3.2: Example of a meme

images. These keypoints are then clustered to generate a visual vocabulary. Images are then represented as “bags of visual words". Text is represented using tf-idf vectors. After a step of features selection using PCA, they use a linear combination of two kernels to train a classifier detecting “earthquake tweets" from other tweets. This contribution shows that a kernel fusion of text and image provides better results than text alone on the specific task of detecting earthquakes. However, these results do not give any conclusion on the role of the image in the detection of other types of events.

Zhang et al. [2018] generate image captioning using an encoder-decoder neural architecture to enrich the text of tweets with a description of images. They then apply an improved-LDA algorithm to extract topics. The authors obtain better results with their method than with the tested “text-only" LDA approach. However, the evaluation corpus is rather small (only 10 subjects), and the selected topics favour the contribution of image, as they are subjects for which image captioning tools provide satisfactory results, such as “Giraffe", “Polar Bear" or “Sunrise".

The “MediaEval Social Event Detection" challenges [Reuter et al., 2013; Petkos et al., 2014b] have led to the publication of research articles on social event detection, unfortunately it is based on Flickr datasets. A description of the datasets is provided in Section 2.2. Strictly speaking, Flickr is an image hosting service and not a social network: text plays a very limited role, and the images posted are personal photos rather than memes[3] or images containing text.

[3] A meme is an amusing image or video that spreads virally on the Internet, often with slight variations. See Figure 3.2 for a classical example of meme.

On Twitter, conversely, not all tweets contain images (in our annotated corpus, 23% of tweets contain a visual content - image, video or animated GIF), and a very large share of the images contains text. Chen et al. [2016] find that 35% of the images in their dataset contain text, mainly in the form of memes (37%), photos of text (22%) or tweet screenshots (8%). Due to the high proportion of textual content and memes in Twitter images, the contribution of images to the event detection task may be small or even negative compared to text alone, given that tweets about very different events may contain the same image. In the remainder of this chapter, we test several types of text and image representations, as well as several types of event detection, in order to answer this question.

3.3 Our event detection approach

In this section, we detail our own methodology. We first recall the required properties of our event detection algorithm. We then detail the choices we made to match these requirements.

3.3.1 Requirements

Our algorithm should have the following properties:

- **The number of events can not be a fixed parameter**. The algorithm has to automatically discover the optimal number of topics, which could vary depending on the time of year or due to a specific situation – such as the COVID pandemic, which restricted the number of topics discussed on social networks since the virus was the public's primary concern.

- **Scalable and time-efficient.** Ultimately, we want to process all the tweets resulting from our capture method over a whole year in a period of no more than a few days. Our algorithm must therefore be capable of changing scale, shifting from tests conducted on a few tens of thousands of tweets to an implementation on hundreds of millions of tweets.

- **Able to take into account the time of issue of tweets**. Some subjects appear in the news cyclically (soccer games, TV shows, etc.), often with a similar vocabulary. The date of the related tweets is therefore an important feature for discerning them.

- **Able to deal with noise**. Liu et al. [2017] classify the tweets in different categories: spam, advertisements, mundane/everyday conversation, general information, events, news and breaking news.

In this spectrum, they classify all content from spam to general information as noise. Their experiments show a signal-to-noise ratio of less than 0.2%. We did not conduct a manual assessment to confirm or refute these results, but they tend to indicate that our algorithm should be able to handle the vast majority of non-event-related tweets.

3.3.2 Modified First Story Detection algorithm

In order to match the listed requirements, we model the event detection problem as a dynamic clustering problem, using modified versions of the FSD algorithm.

Mini-batch First Story Detection

Our first change consists in introducing “mini-batches" of b tweets. Strictly speaking, we do not parallel the search for a closer neighbor. We use the fact that computing cosine distances between two sets of documents is essentially a matrix multiplication. In the multiplication of two sparse[4] matrices, it is much more efficient to multiply a matrix $A_{(b,|V|)}$ ($|V|$ is the size of the vocabulary) by a matrix $B_{(|V|,w)}$ (w is the window size, i.e. number of past tweets among which we search for a nearest neighbor) than to multiply b vectors of size $|V|$ by the same matrix $B_{(|V|,w)}$. Indeed, using the SMMP algorithm[5] [Bank and Douglas, 1993], the complexity of sparse matrix multiplication is $o(bZ^2 + max(b, w))$ where Z is the maximum number of non-zero values in a row of A and in a column of B. If we took the documents one-by-one (no batch), computing the cosine similarities for b documents would be of complexity $o(b(Z^2 + max(1, w))$.

Our version of the algorithm also deals with “empty" documents, i.e. documents that contain no words or only stop-words. This is frequently the case in datasets of tweets. Empty documents are not clustered, i.e. labeled as -1. Our version of the algorithm is described in Algorithm 2.

Re-clustering

One way of introducing multimodality into the First Story Detection algorithm is to perform a re-clustering step after the first clustering. More precisely, we proceed as follows: given a stream of tweets represented using a text-only representation, we perform a first clustering using the mini-batch FSD algorithm. We then use an image representation of the tweets to perform a re-clustering: for each cluster c, we take

[4]A sparse matrix is a matrix in which most elements are zeros. This is the case for tf-idf matrices: since each column represents a word in the vocabulary, and since each document only contains a few words, the rows (which represent documents) are therefore mostly composed of zeros. Sparse matrices require a specific format, where only nonzero elements are stored.

[5]This algorithm is implemented for sparse matrix multiplication in the python scipy module.

Algorithm 2 "Mini Batch First Story Detection"

Input: threshold t, window size w, batch size b, corpus $C = \{d_0 \dots d_n\}$ of documents in chronological order
Output: thread ids for each document

$T \leftarrow [\,]\,; i \leftarrow 0; j \leftarrow 0$
while $i < n$ **do**
  $batch = \{d_i, \dots d_{i+b-1}\}$
  for document d in $batch$ **do**
    if d is empty **then**
      $thread\_id(d) \leftarrow -1$
    else
      if T is empty **then**
        $thread\_id(d) \leftarrow j$
        $j \leftarrow j + 1$
      else
        $d_{nearest} \leftarrow$ nearest neighbor of d in T
        if $\delta(d, d_{nearest}) < t$ **then**
          $thread\_id(d) \leftarrow thread\_id(d_{nearest})$
        else
          $thread\_id(d) \leftarrow j$
          $j \leftarrow j + 1$
        end if
      end if
      if $|T| \geq w$ **then**
        remove first document from T
      end if
    end if
    add d to T
    $i \leftarrow i + b$
  end for
end while

all the tweets in c and find their neighbors outside of c that are at a distance lower than a pre-defined threshold t_1. If a proportion p_1 of these neighbors is part of the same cluster c', c and c' are merged. This is repeated until the number of clusters converges.

The distance metric used in the re-clustering part depends on the type of image representation chosen (see the next Section for the detail of tweet representations). For ResNet vectors, we use euclidean distance. For SIFT features, we compute our own distance metric based on the estimated linear transformation between each image and a combination of the matching points similarities.

Irrelevant tweets

In order to be able to process a large number of tweets in an acceptable time frame, we had to introduce some modifications to the "Mini Batch FSD" algorithm. These changes also aim to manage the large volume of "noise" (very short documents, whose subject is difficult to know, even for a human reader) naturally present in a dataset of non-pre-selected tweets. To this end, we introduce the notion of "irrelevant document":

- a document is considered irrelevant if its tf-idf vector does not contain any element with a value greater than a r threshold. In other words, the tweet contains only extremely common words;
- a tweet is also considered irrelevant if it contains less than m words.

Irrelevant documents can be clustered if a nearest neighbor is found, however, if no nearest neighbor is found within a radius t they are excluded from the collection and labelled as -2. Whether they are clustered or not, irrelevant tweets cannot be selected as nearest neighbors in the following iterations of the algorithm.

This method has two advantages: first, it prevents very vague tweets from extending the vocabulary of the cluster to which they are attached. This reinforces the stability of the vocabulary of each cluster. Second, it reduces the number of past tweets to which each tweet must be compared, thus increasing the time efficiency of the algorithm. Indeed, the complexity of the FSD algorithms shifts from $O(nw)$ (with n the number of documents in the collection and w the number of documents in the comparison window) to $O(nwp)$, with p the proportion of relevant tweets in the collection.

This approach cannot be tested on the annotated dataset, since almost all documents selected by our annotators are relevant (since they contain enough significant words to be considered as referring to an event). However, we use this method in order to detect events on the entire, very noisy corpus.

3.4 Other tested approaches

We compare the performance of our approach (mini-batch FSD algorithm with or without re-clustering and irrelevant tweets) with other algorithms existing in the literature. Some of these algorithms are not directly suited to our event detection task, since they take the number of classes or topics as an input, whereas we need an algorithm capable of automatically discovering the optimal number of clusters. This is the case for SVM classifiers, which are instead used to evaluate the quality of different embeddings. In total, we present three methods: SVM classification, DBSCAN, and Dirichlet Multinomial Mixture model.

3.4.1 Support Vector Machines (SVM)

Evaluations of the “quality" of tweet representations can be made according to different approaches: first, test if the representation allows a good separability of the different classes (events). Second, make sure that the vectors produced are suitable for distance measurements, which are used for clustering. To evaluate the separability of classes, we initially reduced the task of unsupervised event detection to a classification task. We used SVM classifiers with two types of kernel: a triangular kernel [Fleuret and Sahbi, 2003] and a Radial Basis Function (RBF) kernel.

The triangular kernel function is the following:

$$k(x, y) = 1 - \|x - y\| \tag{3.3}$$

Our experiments with this type of kernel show that, in addition to being invariant to scale changes [Fleuret and Sahbi, 2003], it can be applied effectively to both dense and sparse vectors. It achieves performance similar to parametric kernels on text classification, with the advantage of not requiring a lengthy grid search process to select the right parameters.

Our first experiments were conducted only with a triangular kernel. However, as this is not a very well-known form, several reviewers have requested further tests to be conducted with a more common kernel. We therefore also conducted classification experiments with an RBF kernel:

$$k(x, y) = \exp(-\gamma\|x - y\|^2) \tag{3.4}$$

3.4.2 DBSCAN

We use the DBSCAN algorithm [Ester et al., 1996] as a baseline since it is a classical clustering algorithm that does not require a fixed number of clusters as input. We use the implementation provided by scikit-klearn.[6]

3.4.3 Dirichlet Multinomial Mixture (DMM) model

We chose DMM as our main comparative approach since it has several interesting properties for our problem:

- it can automatically infer the number of clusters
- it is fast to converge
- it is designed to cope with the highly-dimensional problem of short texts

The generative process of DMM is presented in Section 3.2.1. We use a Python implementation[7] of the Gibbs Sampling for DMM (GSDMM) algorithm presented by Yin and Wang [2014].

3.5 Experimental setup

For each of the tested approaches, we optimize the parameters in order to obtain the best possible results for a given algorithm. In this section, we first present our choice of parameters for each model. We then detail the different types of vector representations of tweets tested with the FSD algorithm. Finally, we justify our choice of evaluation metrics.

3.5.1 Choice of parameters

FSD parameters

The parameters of the FSD algorithm are w, the number of past tweets among which we search for a nearest neighbor, and t, the distance threshold above which a tweet is considered sufficiently distant from past tweets to form a new cluster. The value of w has been set differently for each corpus: it is set to approximately one day of tweet history, based on the average number of tweets per day in each corpus.

[6] https://scikit-learn.org/stable/modules/generated/sklearn.cluster.DBSCAN.html#sklearn.cluster.DBSCAN
[7] https://github.com/atefm/pDMM

We then tested different values of t for each type of representation. Generally speaking, lower t values lead to more frequent clustering, and thus better intra-cluster homogeneity (better precision), but may lead to over-clustering (lower recall).

Re-clustering parameters

In the re-clustering step, the parameters are t_1, the distance among which candidate neighbors are selected, and p_1, the minimum proportion of candidate neighbors from the same cluster necessary to merge two clusters. When testing the second step (re-clustering), it is important that the first clusters have a good homogeneity. This is why, during our experiments, we set the t parameter to 0.6, slightly lower than the best t value for the mini-batch FSD algorithm alone. In this way, at the end of the first step we obtain more homogeneous clusters. The w parameter remains set to the average number of tweets per day in the dataset.

Relevance thresholds

Due to the size of the corpus (38 million tweets), it is not possible to test many different values of the relevance thresholds, since each test takes more than 3 days. The parameters were thus set as follows: m (minimum number of words in a document to consider it as relevant) was set to 5, and r (minimum idf value that one of the elements of a vector must reach to consider it as relevant) to 0.21. The value of r was calculated from our annotated collection C as follows:

$$r = \min_{d \in C} \max_{w \in d} idf(w)$$

Thus, we select the minimum value of r on a dataset where all tweets are considered relevant. Any tweet from the rest of the collection that has no word of at least this significance is considered irrelevant.

SVM parameters

Both RBF and triangular classifiers are trained on a random sample of 50% of the corpus. For the RBF kernel, we perform a grid search to optimize the γ parameter.

DBSCAN parameters

DBSCAN uses 2 parameters: the distance ϵ and the minimum number of points μ that must be within a radius ϵ for these points to be considered a cluster. The ϵ parameter controls the local neighborhood of each point. A too large ϵ leads to different clusters being merged, while a too small ϵ will cause most points to be labelled as “outliers". The μ parameter controls the tolerance to noise. Since we run tests only on the annotated part of the datasets (only event-related tweets), the level of noise is rather low, and small values of μ are sufficient. We test different values of μ and ϵ for each corpus.

The vectors given as input to the DBSCAN algorithm are the same tdidf vectors as for the FSD algorithm (tfidf-all-tweets, see Section 3.5.2 for the detail of textual representations). Therefore, we also selected the cosine distance as metric.

DMM parameters

The different parameters are K the number of clusters at initialization, i the number of iterations of the GSDMM algorithm, the parameter α of the Dirichlet topic distribution, and the parameter β of the Dirichlet topic-word distribution.

Yin and Wang [2014] provide an in-depth analysis of the role of the different parameters. They show that the parameter α has a rather small influence on the performance of the algorithm when set to values between 0 and 1. The value of β has an influence on the number of non-empty clusters, and hence on the homogeneity of GSDMM: higher values of β will result in a lower homogeneity, and a higher completeness. Concerning the number of iterations, GSDMM seems to reach a stable number of clusters within 10 iterations on all 4 tested datasets. Finally, the optimal value of the initial number of clusters K depends on the actual number of topics within the dataset: K has to be significantly larger than the ground truth number of topics. However, setting K to a high value can decrease the time efficiency of the algorithm, since the time complexity of GSDMM is $O(KD\bar{L})$ with D the total number of documents, and $\bar{L}$ the average document length.

Taking into account these different factors, we conducted the experiments by setting $\alpha = 0.1$, $i = 100$, and $\beta \in [0.001, 0.1]$, which seem to be the values for which the algorithm's performance is the best. We set K differently for each corpus: for the French corpus, with 257 events, we set K to 500. For the corpus by McMinn et al. [2013], with 505 events, we set K to 1000. For each corpus, we apply the same preprocessing as for the FSD algorithm with tf-idf (see Table 3.2) : remove mentions, stop-words, urls, long numbers, punctuation, split hashtags on capital letters, lowercase and transpose to ASCII characters.

Figure 3.3: Four clusters created using the vizualisation algorithm t-SNE on the ResNet representation of images from our dataset.

3.5.2 Types of representations

In this part we present the different types of embeddings tested for the mini-batch FSD and re-clustering algorithms. We also report our fine-tuning tests aimed at improving the performance of SBERT on the French corpus. Finally, we detail the text preprocessing applied depending on each model.

Image

1. *ResNet layer.* To create image vectors, we test a CNN model trained on ImageNet as the encoder. More precisely, we experiment with the 50-layer version of the ResNet model [He et al., 2016]. We use the penultimate layer as the vector representation of images. The dimension of the image embedding is $2,048$.

The drawback of this type of representations trained on ImageNet is that the semantic expressed by vectors is categorical: vectors allow distinctions to be made between categories such as “people", “animals", “buildings", but cannot, for example, distinguish easily between two soccer games or two different buildings. Figure 3.3 illustrates this by showing some of the clusters created using the t-SNE visualization algorithm [Maaten and Hinton, 2008] on images from one day of our dataset represented as ResNet layers. All faces tend to produce similar vectors, whether they are the faces of politicians or “memes" such as the little girl to the right of the picture. On the other hand, the Amazon building is not in the same cluster as the press conference of Amazon executives that appears in one of the pictures above, even though a human knowing the company's logo would probably have grouped them together.

2. *SIFT features.* Knowing this characteristic of ResNet vectors, we have also used a standard approach based on bag of local features for image descriptions. This category of image retrieval methods is known to integrate low-level visual information, less semantic and more local than that conveyed by global vectors obtained from deep-learning networks. Thus, it focuses on the existence of visually very similar details, in all or part of the images. The underlying idea of this approach is to enable the detection of places or similar objects between images, which can be useful to create links between the tweets. Figure 3.4 shows an example of the kind of similarities that can be detected using local features.

   All images are described with SIFT features Lowe [1999], which are then compressed to 128-bit binary hash codes. This is done by first computing a principal component analysis in the original feature space followed by a binary quantization. The distance between any two features can then be efficiently approximated by the Hamming distance between the hash codes. To avoid scanning the whole dataset, the hash codes are then indexed in a hash table whose keys are the t-length prefix of the hash codes. At search time, the hash code of a query feature is computed, as well as its t-length prefix. We then use a probabilistic multi-probe search algorithm inspired by that of Joly and Buisson [2008] that efficiently returns the approximate K-Nearest Neighbors (K-NN) of each query feature. The raw visual matches returned by the approximate K-NN search are finally filtered by a spatial consistency checking. We therefore estimate a linear transformation (by a RANSAC algorithm) between the query image and each matched image.

   We did not use SIFT features to create image vectors, and therefore we cannot test this representation with the FSD algorithm. Moreover, the distance between images is only computed between the query image and its neighbors as returned by the approximate K-NN search algorithm. Therefore, we do not have the complete distance matrix of images and cannot compute an adapted version of the FSD algorithm with a custom distance metric. However, we can use the distance metric between an image and its close neighbours in the second step of our re-clustering method (3.3.2).

Figure 3.4: Example of near neighbors detected using SIFT features among the images from our dataset. The first image is used as query, and the following ones are matched neighbors.

Text

We chose models that have both French and English versions. This sub-section details the models used.

1. *Tf-idf.* Due to the inherent brevity of tweets, we simplified the calculation of tf-idf to a simple calculation of idf, since it is rare for a term to be used several times in the same tweet. The form used to calculate the weight of a term t in a tweet is therefore $idf(t) = 1 + log(n + 1/df(t) + 1)$, where n is the total number of documents in the corpus and $df(t)$ is the number of documents in the corpus that contain t.

   We have distinguished two calculation modes for n and $df(t)$: **tfidf-dataset** denotes the method that counts only annotated tweets, and **tfidf-all-tweets** denotes the calculation method that takes into account all tweets in the corpus (38 million tweets) to obtain n and $df(t)$. For each method, we restrict the vocabulary with a list of *stop-words* and a threshold df_{min}, the minimum number of tweets that must contain t for it to be included in the vocabulary. In all our experiments, $df_{min} = 10$. We thus obtain a vocabulary of nearly 330,000 words in English and 92,000 words in French for **tfidf-all-tweets**, and 5,000 words in English and 9,000 words in French for **tfidf-dataset**.

2. *Word2Vec.* We used pre-trained models for English, and trained our own French models. For each corpus, we distinguish between **w2v-twitter**, models trained on tweets, and **w2v-news**, models trained on press articles. For English, w2v-twitter is a pre-trained model published by Godin et al. [2015][8] (400 dimensions) and w2v-news is a model trained on Google News and published by Google[9] (300 dimensions). In French, w2v-twitter was trained with the CBOW algorithm on 370 million tweets collected between 2018 and 2019, and w2v-news was similarly trained on 1.9 million AFP dispatches collected between 2011 and 2019. Both models have 300 dimensions. As Word2Vec provides word embeddings and not sentence embeddings, the representation of tweets is obtained by averaging the word vectors of each word. Two methods were used for averaging: a simple average, and an idf-weighted average using the **tfidf-all-tweets** calculation method.

3. *ELMo.* For English, we used the model published on TensorFlow Hub[10]. For French, a model trained on French published by Che et al. [2018][11]. In each case, we use the average of the three layers of the network as a representation of each word. The representation of a tweet is produced by averaging these vectors (of dimension $1,024$).

4. *BERT.* Google provides an English model and a multilingual model[12]. In order to improve the performance of the multilingual model on French tweets, we continued training for 150,000 steps on tweets collected in June 2018. We refer to the simple multilingual model as **bert** and the model trained on tweets as **bert-tweets**. In each case, we used the penultimate layer of the network (of dimension 768) as embedding, by averaging the tokens to obtain a tweet representation.

[8] `github.com/loretoparisi/word2vec-twitter`
[9] `code.google.com/archive/p/word2vec/`
[10] `tfhub.dev/google/elmo/2`
[11] `github.com/HIT-SCIR/ELMoForManyLangs`
[12] `github.com/google-research/bert` models: bert-large, uncased and bert-base, multilingual cased

5. *Universal Sentence Encoder.* The provided models[13,14] (English and multilingual) are designed to provide sentence embeddings, so we were able to use them as is, without averaging vectors as in the previous representations. The vectors are of dimension 512.

6. *Sentence-BERT* The authors of SBERT provide pre-trained models for English[15]. For French, we had to perform a fine-tuning of the multilingual BERT model, which we present in Section 3.5.2. The vectors obtained are of dimension 768.

Fine-tuning Sentence-BERT for French

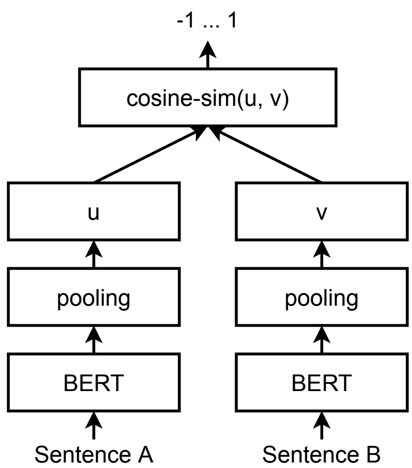


Figure 3.5: SBERT architecture at inference, to compute similarity scores. This architecture is also used during part of the training with mean-square-error as regression objective function. This diagram is provided in the Sentence-BERT paper Reimers and Gurevych [2019].

The SBERT model is specifically trained to provide cosine similarity scores: the architecture presented in Figure 3.5 is used to train the model on the STS corpus. The objective function is a mean-square-error loss between $cosine\text{-}sim(u, v)$ and the similarity score evaluated manually in the dataset. This model seems particularly suitable for a clustering algorithm based on cosine similarity, and indeed, among the sentence embeddings (*Universal Sentence Embedding* and SBERT), it is the one that provides the best clustering results in English.

However, the English pre-trained model is based on fine-tuning on supervised tasks (see 3.2.2 for details of SNLI and STS tasks), which cannot be done in French without an annotated corpus. We have therefore implemented two strategies to perform a fine-tuning of the **bert-tweets** model on French data:

[13] `tfhub.dev/google/universal-sentence-encoder-large/3`
[14] `tfhub.dev/google/universal-sentence-encoder-multilingual-large/1`
[15] `github.com/UKPLab/sentence-transformers`. Model: bert-large-nli-stsb-mean-tokens

first we have used *Cloud Translation API*[16] within the free use limit to translate part of the STS dataset (we obtained $2,984$ pairs of sentences in French). Second, we manually annotated 500 pairs of headlines of selected newspaper articles (we selected headlines that contained common terms). The annotation was done on a scale of 0 to 5, in the same way as for STS. However, instead of indicating the degree of semantic similarity between the sentences, we sought to assess whether the two headlines described the same event. The two types of fine-tuning (translated corpus, or translated corpus + annotated corpus) are designated by **sbert-tweets-sts-short** and **sbert-tweets-sts-long**. The performances of the different representations are described in Section 3.6.

Text-image representation

We build a common vector of text and image by concatenating the ResNet vectors with each type of textual representation. We test several coefficients applied to the image vectors, in order to increase or decrease their weight in the clustering process.

Preprocessing

Each text embedding model takes different text formats as inputs: for example, models able to deal with sentences, such as BERT, Sentence-BERT, ELMo or Universal Sentence Encoder, take the full text with punctuation as input. For Word2Vec and tf-idf models, we lowercase characters and remove punctuation. Table 3.2 summarizes all preprocessing steps depending on the type of model. Each column correponds to a preprocessing step:

- remove mentions: mentions are a Twitter-specific way of referring to another Twitter user in a tweet, so that she is notified that the tweet is talking about her or is addressed to her. Entries take the following form: @name_of_the_user. For tf-idf models, removing mentions is a way to reduce the size of the vocabulary. For most Word2Vec models, mentions are not part of the vocabulary, except for w2v_twitter_en.
- unidecode: we use the Python module unidecode to convert Unicode characters to ASCII characters. In French, for example, all accents are removed: “Wikipédia" becomes “Wikipedia".
- hashtag split: we split hashtags on capital letters. “#HappyEaster" becomes “Happy Easter".

[16] `cloud.google.com/translate/docs/reference/rest/`

model	rm mentions	unidecode	lower	rm punctuation	rm stop-words	hashtag split	rm long numbers	rm repeated chars	rm urls
tfidf_all_tweets	X	X	X	X	X	X	X	X	X
tfidf_dataset	X	X	X	X	X	X	X	X	X
w2v_afp_fr	X	X	X	X		X	X	X	X
w2v_twitter_fr	X	X	X	X		X	X	X	X
w2v_gnews_en	X			X		X	X	X	X
w2v_twitter_en				X		X	X	X	X
elmo						X	X	X	X
bert						X	X	X	X
bert_tweets						X	X	X	X
sbert_sts						X	X	X	X
sbert_nli_sts						X	X	X	X
sbert_tweets_sts_short						X	X	X	X
sbert_tweets_sts_long						X	X	X	X
use						X	X	X	X

Table 3.2: Preprocessing applied for each model

- lower: we set the text in lowercase letters.
- remove long numbers: we remove numbers longer than 4 digits.
- remove repeated characters: we limit the number of repeated characters inside a word to three. “loooooool" becomes “looool".

3.5.3 Evaluation metrics

Classification

The classification is evaluated by the macro average of the F-score of each class. For a given class, if we denote tp the number of true positives (documents that are correctly classified in the class),fp the number false positives (documents that are incorrectly attributed to the class) and fn the number of false negatives (documents that are incorrectly classified into another class), we can define precision, recall and F1-score as follows:

$$precision = \frac{tp}{tp + fp} \tag{3.5}$$

$$recall = \frac{tp}{tp + fn} \tag{3.6}$$

$$F1\text{-}score = 2 \cdot \frac{precison \cdot recall}{precision + recall} \tag{3.7}$$

Event detection

Event detection performance is evaluated by a measure we call “best matching F1". It is defined by Yang et al. [1998]: we evaluate the F1 score of each (cluster, event) pair.[17] Each event is then matched to the cluster for which the F1-score is the best. Each event can be associated to only one cluster. The best matching F1 thus corresponds to the average of the F1-scores of the cluster/event pairs, once the matching is done.

We chose to use this metric, rather than the one defined by McMinn and Jose [2015]: they consider all clusters with more than 75 tweets as candidate events. A candidate is evaluated as true positive if 5% or more than 15 tweets of the candidate's tweets match those of an annotated event. From the detail of their experimental results, we can deduce that all candidates that match with a ground truth's event are counted as true positives, even if several clusters match the same event. Conversely, all candidates that do not match an event from the ground truth are considered false positives.

We decided not to use this metric for two reasons: first, we only have access to the portion of the McMinn et al. [2013] dataset that was not deleted over time. Therefore, we cannot keep the threshold of 75 tweets per event, and we would not be able to compare our results with those obtained by McMinn and Jose. Second, this measure favors over-clustering by not penalizing the fact that several clusters match the same event. We consider the Best Matching F1 score as a better evaluation metric for this task.

3.6 Results

3.6.1 Comparison of text embeddings

Whether for the classification task or for the clustering task, none of the tested models manage to outperform the tf-idf model calculated on the whole corpus (tfidf-all-tweets). However, the relative performance of the models varies by language, and by task.

Classification results

For English, SVM classification results are consistent and robust to kernel change (see Tables 3.3). They show that BERT and ELMo do not provide easily separable short-text vectors. Models intended to be

[17] Clusters are detected by the algorithm, while events are annotated in the ground truth

used as embeddings (Word2Vec, Universal Sentence Encoder, SBERT) obtain better results. The tf-idf vectors remain the best adapted, on a par with weighted w2v-news vectors.

On the French corpus (see Table 3.4), we can make the same conclusions for BERT and ELMo, even for the BERT model further trained on French tweets (bert-tweets): these models do not provide adequate embeddings for sentences or short texts. However, the two kernels do not provide exactly the same results concerning the Universal Sentence Encoder model (use). With the RBF kernel, this model outperforms the other representations while, with the triangular kernel, tf-idf, Word2Vec and Universal Sentence Encoder perform equally well. In both cases, the difference between these latter models is rather small.

	Triangular Kernel			**RBF Kernel**			
Model	*F1*	*precision*	*recall*	γ	*F1*	*precision*	*recall*
bert	74.49 ± 0.41	85.76 ± 0.56	69.42 ± 0.38	0.01	75.31 ± 0.51	85.10 ± 0.62	70.87 ± 0.52
elmo	59.81 ± 0.41	77.17 ± 0.63	53.23 ± 0.25	0.10	57.64 ± 0.36	77.18 ± 0.29	50.55 ± 0.28
sbert-nli-sts	80.55 ± 0.33	87.85 ± 0.35	76.94 ± 0.31	0.01	80.37 ± 0.36	88.53 ± 0.37	76.26 ± 0.32
tfidf-all-tweets	**83.50** ± 0.78	90.87 ± 0.47	79.91 ± 0.78	1.00	**81.86** ± 0.77	90.98 ± 0.32	77.41 ± 0.79
tfidf-dataset	**83.46** ± 0.72	90.28 ± 0.51	80.08 ± 0.71	1.00	**82.70** ± 0.69	89.67 ± 0.51	79.10 ± 0.73
use	80.26 ± 0.38	86.17 ± 0.29	77.59 ± 0.40	1.00	79.92 ± 0.46	85.68 ± 0.45	77.40 ± 0.40
w2v-news	81.35 ± 0.53	88.94 ± 0.40	77.45 ± 0.65	1.00	80.42 ± 0.55	89.09 ± 0.41	75.89 ± 0.64
w2v-news tfidf	**82.39** ± 0.64	89.00 ± 0.35	79.02 ± 0.69	0.01	**81.57** ± 0.73	89.02 ± 0.51	77.64 ± 0.78
w2v-twitter	76.68 ± 0.53	86.82 ± 0.53	72.24 ± 0.52	10.0	77.62 ± 0.62	87.91 ± 0.39	72.71 ± 0.68
w2v-twitter tfidf	81.20 ± 0.48	88.67 ± 0.17	77.54 ± 0.54	0.10	81.07 ± 0.49	88.61 ± 0.29	77.24 ± 0.59

Table 3.3: SVM classification results on the English corpus. Each cell indicates the mean and standard deviation of 5 runs (with different train/test splits), in percentages.

	Triangular Kernel			**RBF Kernel**			
Model	*F1*	*precision*	*recall*	γ	*F1*	*precision*	*recall*
bert	78.46 ± 0.68	90.88 ± 0.78	71.26 ± 0.7	0.01	79.08 ± 0.61	90.95 ± 0.98	72.04 ± 0.56
bert-tweets	81.77 ± 0.7	91.88 ± 0.95	75.73 ± 0.75	0.01	82.68 ± 0.72	91.63 ± 1.08	77.11 ± 0.64
elmo	73.59 ± 0.64	88.53 ± 0.74	65.54 ± 0.61	0.10	74.40 ± 0.70	89.79 ± 1.07	66.21 ± 0.54
sbert-tw-sts-l	86.08 ± 0.86	93.60 ± 0.94	81.16 ± 0.81	0.01	86.43 ± 0.81	94.06 ± 0.89	81.39 ± 0.68
tfidf-all-tweets	**87.79** ± 0.58	95.24 ± 0.91	83.13 ± 0.50	1.00	86.57 ± 0.55	95.20 ± 1.17	81.08 ± 0.36
tfidf-dataset	**87.66** ± 0.69	94.78 ± 1.15	83.14 ± 0.53	1.00	86.42 ± 0.53	94.74 ± 1.06	81.08 ± 0.35
use	**87.45** ± 0.60	93.94 ± 0.56	83.44 ± 0.58	1.00	**88.40** ± 0.75	94.19 ± 0.73	84.65 ± 0.61
w2v-news	**86.59** ± 0.80	92.82 ± 1.03	82.63 ± 0.74	1.00	86.28 ± 0.88	92.84 ± 0.95	82.19 ± 0.91
w2v-news tfidf	**87.51** ± 0.71	92.94 ± 1.06	84.02 ± 0.49	0.01	86.32 ± 0.77	92.63 ± 0.87	82.27 ± 0.69
w2v-twitter	**87.01** ± 0.56	93.40 ± 0.84	83.03 ± 0.58	1.00	86.60 ± 0.60	93.47 ± 0.75	82.33 ± 0.61
w2v-twitter tfidf	**87.73** ± 0.56	93.51 ± 0.99	84.03 ± 0.38	0.01	86.71 ± 0.60	93.32 ± 0.77	82.43 ± 0.58

Table 3.4: SVM classification results on the French corpus. Each cell indicates the mean and standard deviation of 5 runs (with different train/test splits), in percentages.

	English		French	
Model	*t*	*F1*	*t*	*F1*
bert	0.04	39.22	0.04	44.79
bert-tweets	-	-	0.02	50.02
elmo	0.08	22.48	0.20	46.08
sbert-nli-sts	0.39	58.24	-	-
sbert-tweets-sts-long	-	-	0.36	67.89
sbert-tweets-sts-short	-	-	0.38	65.71
tfidf-all-tweets	0.75	**70.10**	0.70	**78.05**
tfidf-dataset	0.65	68.07	0.70	74.39
use	0.22	55.71	0.46	74.57
w2v-news	0.30	53.99	0.25	66.34
w2v-news tfidf-weights	0.31	61.81	0.30	75.55
w2v-twitter	0.16	43.20	0.15	57.53
w2v-twitter tfidf-weights	0.20	53.45	0.25	71.73

Table 3.5: FSD clustering results for each corpus. Performance is assessed using the "Best Matching F1" score. For each model, the best t threshold value was selected by successive tests. The batch size parameter b is fixed to 8. The window-size parameter w is fixed to the average number of tweets per day in each corpus.

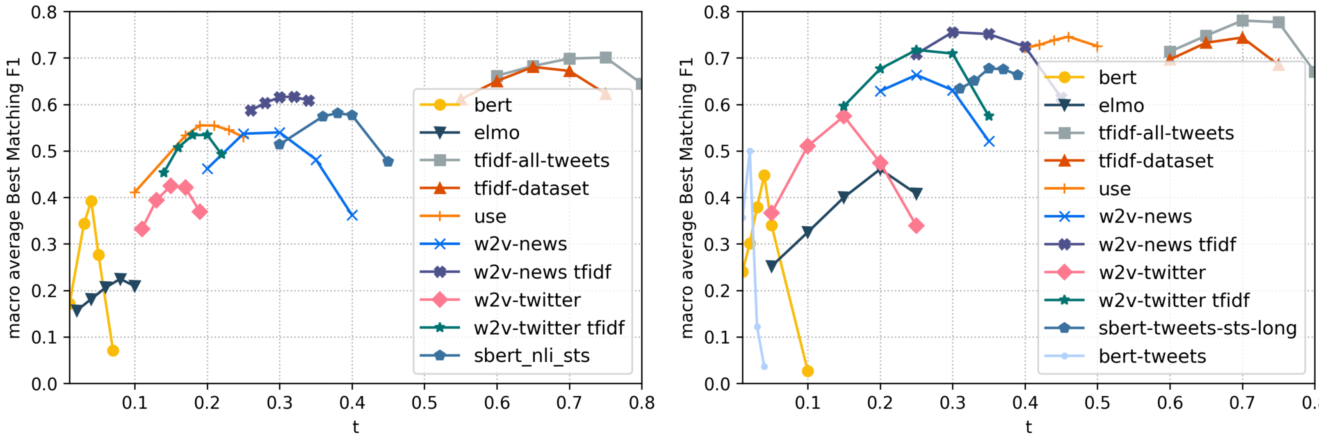
First Story Detection results

The tfidf-all-tweets vectors give the best results for the clustering task (see Table 3.5), even more clearly than for classification. This is due to the shape of the tf-idf vectors, which are particularly well suited for cosine similarity calculations, as well as to the event-specific characteristics of the two datasets: the same terms are obviously widely used among tweets of the same event. These results are consistent with those of Cagé et al. [2020], who came to similar conclusions regarding event detection in press articles.

Concerning neural models adapted to sentence embeddings (SBERT, *Universal Sentence Encoder*), they do not perform better than the tf-idf weighted w2v-news models. On the English corpus, we note that the fine-tuning of *Sentence-BERT* on semantic similarity corpora (sbert-nli-sts) allows slightly better results than the generic vectors of *Universal Sentence Encoder*.

Our own fine-tuning of BERT (sbert-tweets-sts-short and sbert-tweets-sts-long) does not outperform *Universal Sentence Encoder* on the French corpus. However, we note that the thematic similarity corpus (which contains only 500 pairs of sentences) allows to increase the clustering performance by 2 points. Nevertheless, our fine-tuning does not achieve as good results as the English model, due to the fact that it could not be trained on a corpus of similar size to SNLI.

When used with the FSD algorithm, the best embeddings (tf-idf, Word2Vec with tf-idf weights, Universal Sentence Encoder) also have the property of being less sensitive to variations of the threshold t, as shown



(a) English (b) French

Figure 3.6: Best Matching F1 score for FSD clustering depending on the threshold parameter t for each corpus. The batch size parameter b is fixed to 8. The window-size parameter w is fixed to the average number of tweets per day in each corpus.

in Figure 3.6. Moreover, the optimal value of t for a given embedding seems to be approximately the same for each corpus (0.7 for tf-idf). This result may indicate that the First Story Detection algorithm could be applied to other (not annotated) tweet datasets without adapting the threshold value.

It is surprising that Word2Vec models trained on tweets are no better than models trained on news. However, this can be explained by two factors: the content of the datasets, which are made up of tweets referring to news, and whose vocabulary is therefore probably closer to the corpus from the AFP or from Google News than to the average Twitter. The second factor is the great variability in the vocabulary of tweets: it is possible that the w2v_twitter_en model, trained on tweets from 2015, does not correspond to the vocabulary used in the McMinn et al. [2013] corpus, collected in 2012.

The better performance on the French corpus than on the English corpus is probably due to the fact that classification and clustering on the English corpus are more difficult tasks, for several reasons: first, the English corpus is from 2012, and therefore a substantial share of the tweets have been deleted (our last download in November 2019 allowed us to retrieve 72,484 tweets i.e. 72% of the original annotated dataset). This can have important consequences, especially for the FSD algorithm which over-segments clusters if a tweet is missing to link them. Second, it seems that many events in the English corpus could be considered “sub-events" of the same macro event: “Hurricane Sandy in the Bahamas", “Tweets for Praying for people affected by hurricane Sandy", “Superstorm Sandy hits the east coast of the USA", “They all discuss about Sandy Storm" are for example four different events in the corpus by McMinn et al. [2013]. These events with very close topical similarity are probably more difficult to separate for the algorithm.

3.6.2 Comparison of text-image embeddings

Model	t	*F1*	*precision*	*recall*	*weight*
elmo	0.23	50.1	77.5	50.1	
elmo / resnet	0.28	52.5	80.2	50.3	0.05
tfidf-all-tweets	0.79	84.3	92.5	83.7	
tfidf-all-tweets / resnet	0.79	84.6	92.3	84.3	0.005
w2v-news	0.28	75.5	88.1	74.8	
w2v-news / resnet	0.35	76.9	87.2	77.9	0.01
w2v-news tfidf	0.40	81.7	89.1	83.4	
w2v-news tfidf / resnet	0.39	82.1	90.6	82.3	0.01
w2v-twitter	0.17	66.5	85.2	66.0	
w2v-twitter / resnet	0.20	69.2	87.5	66.8	0.01
w2v-twitter tfidf	0.29	79.0	90.4	78.9	
w2v-twitter tfidf / resnet	0.29	79.0	90.4	79.0	0.005

Table 3.6: FSD clustering results on "text only" and "text-image" vectors on the tweets of the French corpus that include visual content. Performance is assessed using the "Best Matching F1" score. For each model, the best t threshold value was selected by successive tests. The batch size parameter b is fixed to 8. The window-size parameter w is fixed to the average number of tweets per day.

The results presented in this section concern only our dataset, as the English dataset does not include enough images: of all the annotated tweets that we were able to retrieve, only 570 contained a link to a video, image or animated GIF. In 2012, the use of smartphones was much less widespread than at present, which probably explains the small number of images.

Conversely, our dataset built up in 2018 contains many visual contents. Out of the 95,796 annotated tweets, we were able to download multimedia content for 22,477 (19.8% photos, 2.5% videos and 1.5% GIFs). In order to get the highest possible number of images, we processed videos and GIFs as images by using the thumbnails provided by Twitter for a static display. We thus obtained 20,481 unique images. We only considered tweets containing visual contents for clustering, which is why the clustering results that we present below are slightly different from those in the previous part, even for the text-only methods.

We present the clustering results in Table 3.6. These results show that visual features do not bring a significantly better performance to the FSD algorithm. Image may improve the results of the textual representations that perform the worst (ELMo). However, this gain is not significant enough to outperform the tf-idf representation. Moreover, the weights applied to the ResNet layer before it is concatenated with textual features are extremely small (0.005 for the tf-idf / ResNet concatenation). This in an indication of

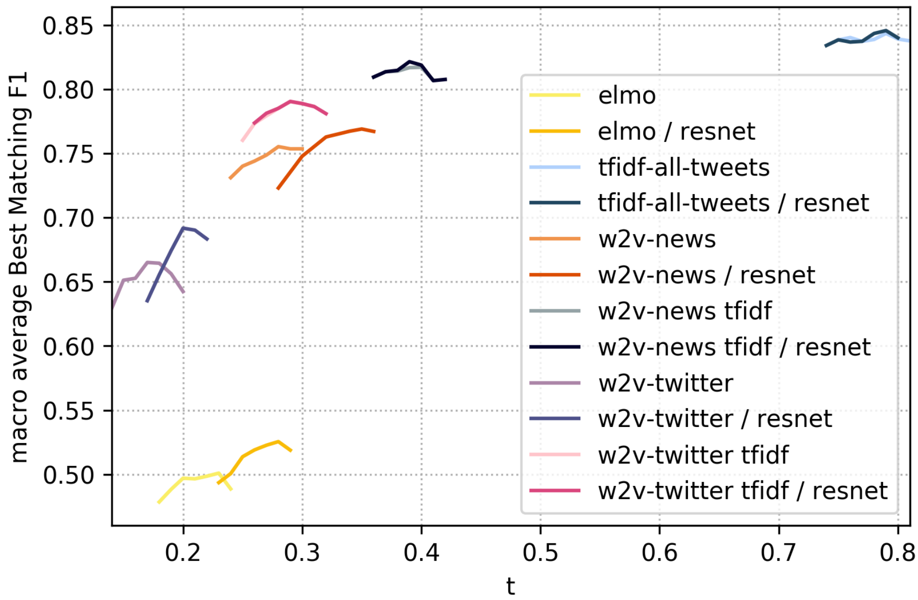


Figure 3.7: Best Matching F1 score for FSD clustering depending on the treshold parameter t for text-only and text-image vectors on the tweets of the French corpus that include visual content. The batch size parameter b is fixed to 8. The window-size parameter w is fixed to the average number of tweets per day.

the very small role played by visual features in the nearest neighbor search. Figure 3.7 illustrates this result more clearly by showing the change in macro-F1 depending on t: ELMo and Word2Vec embeddings are distinctly improved through the concatenation with visual features, whereas the tf-idf embedding provides the same results when it is combined with the ResNet layer.

3.6.3 Comparison of event detection methods

In the previous parts (3.6.1 and 3.6.2) we have determined the best embeddings to serve as input to the FSD algorithm. We now compare our best results with those obtained by other methods: re-clustering, DBSCAN and DMM.

Algorithm	t	t_1	p_1	*F1*	*precision*	*recall*
FSD with tfidf	0.79	-	-	84.3	92.5	83.7
reclustering ResNet	0.60	5	0.8	79.6	91.9	77.3
reclustering SIFT	0.60	-24	0.9	81.1	96.7	74.3

Note: Performance is assessed using the "Best Matching F1" score.
For each model, the best t, t_1 and p_1 values were selected by successive tests.

Table 3.7: Clustering performance of the FSD algorithm and re-clustering algorithms on the tweets of the French corpus that include visual content. Performance is assessed using the "Best Matching F1" score. For each model, the best t, t_1 and p_1 values were selected by successive tests. The batch size parameter b is fixed to 8. The window-size parameter w is fixed to the average number of tweets per day.

Model	*F1*	*precision*	*recall*	α	β	K	i	ϵ	μ	t	w	b
DMM	46.68 $\pm$ 1.44	47.36 $\pm$ 1.05	62.49 $\pm$ 0.37	0.1	0.02	1000	100	-	-	-	-	-
DBSCAN	50.97	86.61	46.16	-	-	-	-	0.4	1	-	-	-
FSD	68.17	81.48	72.52	-	-	-	-	-	-	0.7	2510	1

(a) Results on the English corpus

Model	*F1*	*precision*	*recall*	α	β	K	i	ϵ	μ	t	w	b
DMM	54.26 $\pm$ 2.48	54.65 $\pm$ 1.3	71.74 $\pm$ 2.08	0.1	0.02	500	100	-	-	-	-	-
DBSCAN	57.99	82.42	58.37	-	-	-	-	0.4	3	-	-	-
FSD	79.16	94.07	73.61	-	-	-	-	-	-	0.7	4352	4

(b) Results on the French corpus

Table 3.8: Comparative results of DMM, DBSCAN and FSD algorithms. For each model, the best parameter values were selected by successive tests. See Section 3.5.1 for the definition of each parameter. Since DMM results depend on random initialization, we provide the mean and standard deviation of 5 runs.

Table 3.7 shows the results of the re-clustering approach using each type of visual representation: either a semantic representation, with ResNet vectors, or local features representation, with SIFT similarities. These results indicate that local features tend to perform best to improve the first clustering step. Overall, however, this way of combining representations degrades the performance of the FSD algorithm alone. The very high values selected for the p_1 parameter, which indicate that very few clusters are allowed to merge, seem to indicate that the only way to obtain correct results with the re-clustering algorithm is to minimize the role of the second step. The obtained results are thus close to the results of the FSD algorithm alone with a too low t parameter.

The comparative results of DBSCAN, DMM and FSD are summarized in Table 3.8. The First Story Detection algorithm outperforms the other tested methods by a clear margin. The DMM algorithm appears to be less performant than DBSCAN on both datasets.

3.6.4 Results on the entire collection

All previous experiments were conducted on the annotated part of our dataset. However, the final objective of our study is to detect events in the entire collection of tweets (5 million tweets per day on average) and over a period of several months.

We tested the mini-batch FSD algorithm with and without relevance thresholds on the entire 3 weeks corpus (retweets excluded), i.e. 38 million tweets. The results of both methods are displayed in Table 3.9. The method with relevance thresholds seems to obtain better scores, but these results must be interpreted with caution: indeed, the thresholds "fit" the algorithm to the characteristics of the annotated corpus, resulting in better performance on annotated tweets. This does not tell us whether performance is also better over the entire collection. However, it can legitimately be assumed that these rather low thresholds do not degrade performance, while allowing a gain in time efficiency.

Algorithm	t	m	r	*F1*	*precision*	*recall*
FSD without relevance thresholds	0.6	0	0.00	52.68	74.51	52.63
FSD with relevance thresholds	0.6	5	0.21	59.82	85.07	53.68

Table 3.9: Clustering performance of the FSD algorithm with and without relevance thresholds on the entire (38 million tweets) French corpus. Performance is assessed using the "Best Matching F1" score on the annotated tweets of the collection. The batch size parameter b is fixed to 200. The window-size parameter w is fixed to the average number of tweets per day.

3.7 Conclusion

This chapter does not provide any brand new algorithm, but offers some improvements to the “First Story Detection" algorithm. However, it does allow us to verify, on two tweet corpora, some results already established on news corpora [Cagé et al., 2020]. First, we show that the FSD algorithm is extremely efficient for tweet clustering, more so than topic modeling techniques such as Dirichlet Multinomial Mixture model [Yin and Wang, 2014], or a standard algorithm such as DBSCAN [Ester et al., 1996]. The reason for this superiority probably comes from the very rapid evolution over time of the vocabulary used to talk about a given event. The two previously mentioned algorithms are not designed to take this temporal evolution into account, unlike the FSD algorithm, which allows a gradual evolution of clusters over time.

Second, we show that, out of a large panel of embedding methods, the tf-idf weighting remains the most suitable representation of documents for an algorithm such as FSD, which is based on nearest neighbor search with cosine similarity. In addition, tf-idf is not only the representation that provides the best results, but also the most stable to changes in the algorithm parameter (threshold t). These are important results for us and, I believe, for many researchers who are looking to use vector representations of short texts for Information Retrieval tasks. This does not mean that recent neural embedding methods will not eventually outperform tf-idf for this kind of task as well. In fact, we would like in future work to re-test BERT's fine-tuning (bert-tweets) with a model specially trained on French like CamemBERT [Martin et al., 2020] and not a multimodal model. We would also like to test fine-tuning of Sentence-BERT on a forthcoming French corpus of semantic similarity [Cardon and Grabar, 2020], and further explore the idea that semantic similarity (two sentences have the same meaning) and thematic similarity (two sentences talk about the same subject) are two different things that require different approaches.

Finally, we provide partial results on the role of image for the clustering of tweets. It is true that our two approaches to include multimodality (vector concatenation and re-clustering) in clustering are quite naive and could be improved with a more appropriate text-image fusion method. However, this is a first step, which suggests that image in tweets is more often a source of additional noise than a source of additional information.

Chapter 4

Linking Media events and Twitter events

4.1 Introduction

Detecting common events in heterogeneous collections of documents such as tweets and news articles is a useful task for several reasons. First of all, from the point of view of a reader wishing to learn more about a given event, the two types of documents are complementary. News articles can add contextual information to tweets, which are often too short to fully report on a situation or an event. On the other hand, tweets may help to understand the reactions and comments that the news event generates in the public.

Second, using news articles is a way to improve event detection on tweets alone. Indeed, the brevity of tweets makes it very difficult to group together posts that cover different aspects of the same event. Adding news articles, which are much more detailed, is thus a way to provide contextual information that may help to solve this problem [Phan et al., 2008].

Finally, finding the tweets and news articles that are linked to each other is the only way to study information propagation across news and social media. It is an essential prerequisite for answering a wide range of questions on this subject: what type of Twitter events are considered newsworthy enough to be reported by journalists? What is the share of media events that break on Twitter first? What is the average speed of propagation of a story across both spheres?

Unlike previous approaches that jointly detect events along all document types using topic models, we propose to solve the task in two steps. First, we detect events separately among news articles and tweets. Second, we link together Twitter events and media events that address the same topics. Indeed, a joint detection approach is based on the assumption that all topics within one sphere may also be covered in the other sphere, which is in contradiction with the type of phenomena that observe (events that start on Twitter and never make it to mainstream media, for example). Therefore, we use a clustering approach on tweets and news separately before applying a community detection on the graph resulting from the created clusters.

4.2 Related Work

The task of discovering joint events from news streams including both social and mainstream media has received little attention in the recent literature. In this section, we review existing works on similar tasks: aligning social-media contents with parts or paragraphs of a longer text, matching a tweet with a relevant news article, retrieving tweets related to a news article and, finally, jointly discovering events from heterogeneous streams of documents.

4.2.1 Social content alignment

A first way of linking tweets and news is to associate each part of a text with the corresponding tweets (which are considered as comments or reactions to this specific part). Hu et al. [2012] develop ET-LDA, a Bayesian model that jointly extract topics from a text and a collection of tweets, and perform text segmentation. A segment may consist of one or several paragraphs, and each segment discusses a set of topics. Tweets are “aligned" with one segment if most of their words belong to one of the topics of this segment. Conversely, they are defined as “general tweets" if most of their words belong to general topics. The model is tested on two texts: a speech by President Obama and the transcript of a 2011 Republican Primary debate. The tweets are collected using hashtags (“#MESpeech" and “#ReaganDebate") that unambiguously relate to these events.

4.2.2 Matching tweet-article pairs

Another related task consists in finding the most relevant news article for a given tweet. This research area aims to provide additional context for the reader of a tweet, or for an automatic NLP tool. Guo et al. [2013] propose a graph-based latent variable model that extracts text-to-text correlations via hashtags and named entities in order to enrich the meaning of a short text and help to identify the most related article. They also introduce a dataset of articles from CNN and the New York Times and of tweets containing a link to one of these media outlets. The tweet-news pairs are identified by matching urls, but “trivial" pairs (when the tweet contains the exact title of the article) are removed from the dataset.

Zhao et al. [2019] use an interactive attention deep neural network in order to learn new representations of source and target texts. The representation of the source text is enriched with the target text, considered to be the neighbor information or the context of the source text, and vice-versa. Mutual differences between the original and the new representation are used to produce a similarity score. The model is tested on several applications, including the tweet-article matching task defined by Guo et al. [2013].

Compared to Guo et al. [2013], Danovitch [2020] is interested in the reverse task: from a given news article, find the most relevant tweet (though their architecture seems to be symmetrical and could probably be used for both tasks). They use a deep neural attention network with a Siamese architecture[1] to jointly embed tweet/article pairs. They address the problem of the decreasing weight of tokens with article length in attention-based architectures by using a sparse activation function [Peters et al., 2019]. They also use Star-Transformer [Guo et al., 2019], a lightweight alternative to the fully-connected Transformer architecture [Vaswani et al., 2017] that reduces its complexity from quadratic to linear time. The model is trained with triplet loss. At inference time, this architecture produces embeddings for tweets and articles, making it possible to perform distance computations using cosine similarity.

4.2.3 Social content retrieval

Several articles [Tsagkias et al., 2011; Tanev et al., 2012; Suarez et al., 2018] address the task of linking traditional media and social media as an Information Retrieval problem, which can be formulated as follows: using a given news article, find social media posts that reference it. In this approach, there is no notion of completeness of the retrieved data: these algorithms are often evaluated without taking the “size" of the event (in terms of total number of generated documents) into account. On the other hand, the order of the results is considered important: the most relevant documents should be among the first results. Each article proposes different strategies to model the best queries, i.e. find the keywords that will match relevant tweets, from article title, lead and body.

Wang et al. [2015] depart from this approach, as the goal of their article is not to find the best tweets for a given article, but to associate tweets to clusters of articles. To that end, they perform hierarchical clustering on news articles in order to discover events and sub-events (called “aspects" of an event). Next, a candidate pool of tweets is retrieved using the text, entities and time of each aspect. The top tweets for

[1] See section 3.2.2 for a definition of a Siamese network

each aspect are selected and used as seeds to train a classifier and label more tweets for each aspect.

4.2.4 Joint event detection

Few works address the joint detection of events in tweets and news. However, taking advantage of the richer content of press articles is known to be helpful for discovering events among short texts such as tweets [Phan et al., 2008].

Ning et al. [2015] aim to identify interaction patterns between tweets and news. They only use press articles to perform event detection (which they call “chaining stories"). Tweets containing the url of one of the chained articles are then downloaded and de facto considered as being linked to the event. They then extract the keywords of the top 10 tweets for each event, as well as named entities from news articles, and download an hourly count of the occurrences of these terms from the Twitter API. They then use this hourly count to detect peaks in Twitter activity and infer interaction patterns between the activity on Twitter and the publication of a news article.

Hua et al. [2016] propose the LDA-like *News and Twitter Interaction Topic model* (NTIT) to jointly discover topics from a collection of tweets and news articles. In the NTIT model, tweets are assumed to consist of words that are either sampled from news topics or from Twitter topics. This asymmetric structure (tweets are not generated like news documents) is designed to prevent noisy tweets from degrading the performance of event detection on news articles. The authors propose an algorithm inspired by Gibbs Sampling [Welling et al., 2008] for the inference and parameters estimation of this generative model. The performance of this algorithm is assessed on a dataset composed of 74 events manually selected from the top news outlets of 5 South American countries. The authors retrieve tweets considered relevant to these events by using keywords identified with tf-idf from the title and abstract of news reports. Their relevance to the given news is then manually checked. Finally, hashtags are extracted from the most relevant tweets and used to retrieve additional tweets. The task that the authors propose to solve is close to our own objectives. Furthermore, this is the only case (to our knowledge) of joint event detection where the evaluation dataset does not only contain media tweets or tweets collected because they contain the url of an article. This seems important to ensure that their method is able to handle the language specific to Twitter users. However, the proposed algorithm does not take into account the evolution of subjects over time, which can be problematic if applied over long periods of time.

Mele et al. [2017, 2019] present a variation of Dynamic Topic Model (DTM, [Blei and Lafferty, 2006]) called *dDTM-News*, to discover events in heterogeneous and dynamic streams of news documents (news articles, RSS feeds and tweets). Similarly to DTM, dDTM-News divides the corpus into time-slices and applies LDA to each of them. However, unlike DTM, the number of topics varies with each time slice, and the topics of one slice are independent from the previous slices. The discovered topics are linked to each other using a Hidden Markov Model (HMM) [Rabiner, 1989]. The optimal number of topics and the optimal number of Markov chains are discovered using Bayesian selection models through iteration on these parameters. Topic models represent each document in the form of a distribution over topics, and each document can thus be assigned to the most represented topic in its topics distribution, in order to perform clustering on the discovered topics. The dataset used for their experiments is publicly available [Mele and Crestani, 2019], but the authors do not share their code. It contains 24,157 news articles, 43,381 RSS feeds, and 80,135 tweets issued by 9 popular news outlets (ABC News, Al Jazeera, BBC, CBC, CNN, NBC News, Reuters, United Press International, Xinhua China Agency). However, only 4,307 documents (3,681 unique documents) are annotated, of which 744 are tweets (695 unique tweets). This small number of tweets (17% of the annotated documents) poses a problem because the algorithm by Mele et al. [2017, 2019] makes no distinction in the nature of the documents, and is therefore probably less efficient on tweets, which are much shorter and therefore contain fewer words allowing them to be linked to a topic. In addition, the article does not specify whether the algorithm is run on all the collected data, or just on the annotated data.

We downloaded the dataset and examined it: it seems that the data provided is incomplete, as the authors provide the “events" detected but not “event chains" (grouping of several events). For example, the paper [Mele et al., 2019] cites the case of Muhammad Ali’s death as an example of a chain of events containing 3 sub-events: hospitalization, death and burial (see Figure 4.1). Still, in the annotated dataset, the sub-events have 3 different labels ("ali-muhammad, boxing, champion, hospitalized, respiratory", "boxing, died, louisville, muhammad-ali", "funeral, memorial, muhammad-ali, remembered"). It is therefore unclear how the authors evaluate the chaining of sub-events. Due to the incompleteness of the data provided by Mele et al. [2019], we could not test our algorithm on their dataset.

Compared to the previous works reviewed in this section, our contribution is fourfold:

1. We propose a new detection method capable of taking into account the temporal evolution of events.

2. Our approach deals with articles from traditional media and Twitter separately at first, so as to

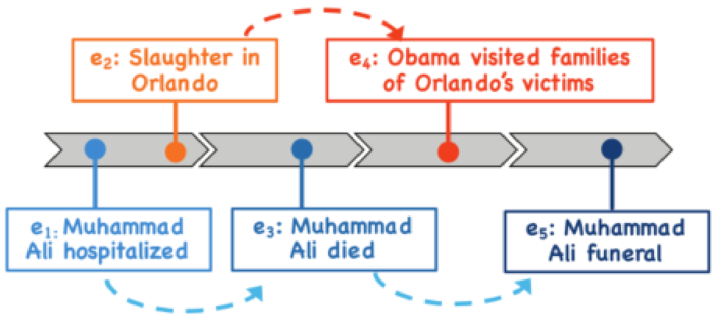


Figure 4.1: Two examples of event chains provided by Mele et al. [2019]. According to the authors, after event detection, the events are connected “based on their evolution" (see dashed arrows). However, the algorithm performing this chaining process is not detailed in the paper, and the event chains are absent from annotated data.

preserve distinctive features of Twitter events. The identification of common events is a second step in the process.

3. We investigate the impact of URLs and hashtags (in addition to word similarity) in joint event detection.

4. We conduct our experiments on a realistic dataset, which is not only composed of tweets that contain URLs, or tweets from media accounts.

We describe the details of our joint event detection method in the following Section.

4.3 Methodology

Our approach can be broken down into three steps: first, we perform the detection of Twitter events and media events separately. Then we represent the similarity between detected events in a weighted bi-partite graph. Finally, we apply a community detection algorithm in order to discover common events across the two spheres.

4.3.1 First Story Detection

Tweets and news articles are quite different in terms of length and type of vocabulary. Detecting joint events directly from a heterogeneous collection of documents may thus lead to a poor performance (see Section 4.5.4). In order to let Twitter-specific and media-specific clusters emerge, we thus perform a first event detection step separately for each type of document. We use the First Story Detection algorithm as described in Algorithm 2, Section 3.3.2, which proved to be efficient both on tweets [Mazoyer et al., 2020] and news articles [Cagé et al., 2020]. Since the total number of news articles is much smaller than the number of tweets, we only use mini-batches for tweets, and not for news articles. Second, since words are likely to be used multiple times in each news article, we use the standard tf-idf formulation for news articles representation while we only compute idf for tweets. The formula of idf and tf-idf are given below:

$$idf(t) = 1 + log(n + 1/df(t) + 1) \tag{4.1}$$

$$tf\text{-}idf(t, d) = tf(t, d) \times idf(t) \tag{4.2}$$

where n is the number of documents in the collection, $tf(t, d)$ is the term frequency, *i.e.* the number of times a term t occurs in a document d and $df(t)$ is the document frequency, i.e. the number of documents in the collection that contain term t.

4.3.2 Event-similarity graph

Once events are detected separately in each sphere, we model the relationships between Twitter events and media events as a weighted bi-partite graph. In the rest of the Chapter, we denote $E_T = \{e_{T,1}, \ldots, e_{T,f}\}$ the set of all Twitter events, and $E_M = \{e_{M,1}, \ldots, e_{M,g}\}$ the set of all media events. A Twitter event is composed of a set of tweets, and a media event is composed of a set of news articles. We explore three types of links between Twitter events and media events: word-similarity, URLs and hashtags.

Word-similarity. In order to compute a word-similarity metric between Twitter events and media events, we represent each event as the average of the tf-idf vectors of all documents it contains. The vocabulary used to compute tf-idf is the union of the two vocabularies (vocabulary of tweets and vocabulary of news). The word-similarity between two events is computed as the cosine similarity between these average vectors and used to weight the edge between the two events:

$$weight_{text}(e_T, e_M) = \frac{\vec{e_T} \cdot \vec{e_M}}{\|\vec{e_T}\|\|\vec{e_M}\|} \tag{4.3}$$

Where $\vec{e}$ is the average of the tf-idf vectors of all documents in e. To facilitate the community detection step (see Section 4.3.3) , we then remove the edges with a too weak cosine similarity. We denote s the similarity threshold.

Hashtags. The graph of hashtag relationships between Twitter events and media events is built as follows: if some of the tweets of a Twitter event and some of the articles of a media event have hashtags in common, we draw an edge between the two events. Thehashtag weight is computed as follows:

$$weight_{htag}(e_T, e_M) = \frac{h(e_T, e_M)}{\max\{h(e_T, e_M) : e_T \in E_T, e_M \in E_M\}} \tag{4.4}$$

where $h(e_T, e_M)$ is the number of times the hashtags common to e_T and e_M appear in the Twitter event e_T. In order to limit the role of one individual hashtag (e.g. #BreakingNews) we remove edges where the number of different hashtags is too low.

URLs. The graph of URLs is constructed in the same way as the graph of hashtags: if tweets within a Twitter event e_T contain a URL pointing to one of the articles in media event e_M, we draw an edge between e_T and e_M. The weight of urls is computed as follows:

$$weight_{url}(e_T, e_M) = \frac{u(e_T, e_M)}{\max\{u(e_T, e_M) : e_T \in E_T, e_M \in E_M\}} \tag{4.5}$$

where $u(e_T, e_M)$ is the number of times urls linking to articles that are part of media event e_M appear in the tweets of Twitter event e_T.

Multidimensional graph. We combine these three different layers into a single multidimensional graph where the weight of the edges is computed as follows:

$$weight(e_T, e_M) = \sum_{i \in \{text, url, htag\}} \alpha_i weight_i(e_T, e_M) \tag{4.6}$$

where $0 \leq \alpha_i \leq 1$ and $\sum_{i \in \{text, url, htag\}} \alpha_i = 1$.

Time of events. In addition to including word similarity, hashtags and urls in the construction of the event similarity graph, we also take into account the time dimension of the events. We therefore introduce a final

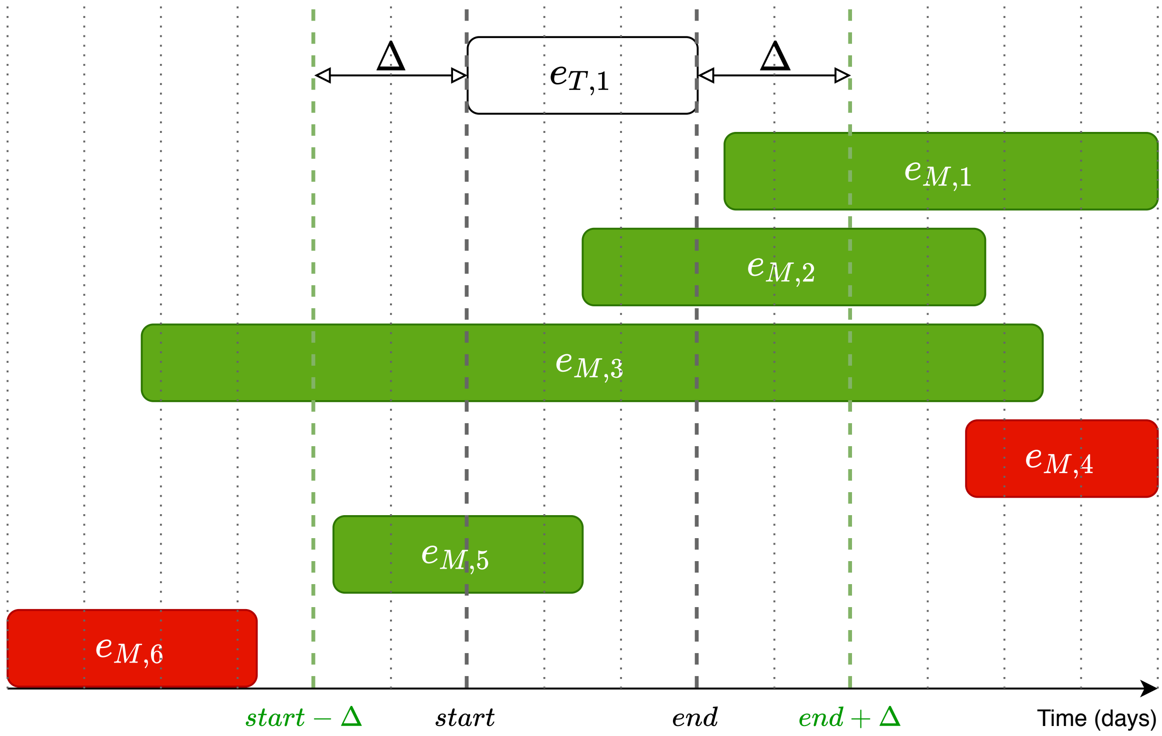


Figure 4.2: Example of different time configurations between a given Twitter event and some media events. Here the value of parameter Δ is set to 2 days. Media events ending before $start - \Delta$ or beginning after $end + \Delta$ appear in red. The edges between these red events and $e_{T,1}$ are removed in the graph.

parameter, Δ, which indicates the maximum time difference (in days) between a pair of events (e_T, e_M). More precisely, if we call $start$ and end the dates of the first and last document of a given event e_T, all media events containing at least one document published between $start - \Delta$ and $end + \Delta$ keep their links with e_T in the graph. Conversely, links between e_T and all other events are removed. Figure 4.2 shows examples of configurations where edges between events are kept, and others where edges are removed.

4.3.3 Community detection

Community detection within a network consists in decomposing the network into sub-groups of highly connected nodes. Researchers have proposed many strategies to solve this task, many of them based on the optimization of a given objective function.

Modularity

The most common of these objective functions is the modularity [Newman and Girvan, 2004] of the partition. The aim of this function is to isolate regions of the network where the density of links is higher than expected by chance. Modularity is defined formally as:

$$Q = \frac{1}{2m} \sum_{i,j} \left[weight(i,j) - \frac{k_i k_j}{2m} \right] \delta(c_i, c_j) \tag{4.7}$$

where

- $weight(i,j)$ represents the weight of the edge between nodes i and j,
- $k_i = \sum_j weight(i,j)$ is the weighted degree of i,
- c_i is the community to which node i is assigned,
- $\delta(x,y)$ is 1 if $x = y$ and 0 otherwise, and
- $m = \sum_{ij} weight(i,j)$ is the weighted sum of all edges in the graph.

The Louvain algorithm [Blondel et al., 2008] is, to the best of our knowledge, the fastest algorithm to find a partition of the nodes that maximizes modularity. We therefore use this algorithm to identify communities within the event-similarity graph.

Surprise

Another metric called surprise outperforms modularity on several benchmarks [Aldecoa and Marin, 2011]. It appears to be more efficient when the network contains communities of different sizes, since the modularity metric does not take into account n_c the number of nodes inside a community and n the total number of nodes, in the calculation of the density of links. Traag et al. [2015] propose an approximation of surprise in large networks, and an algorithm adapted from the Louvain algorithm, in order to maximize the surprise objective function. Their formulation of the function takes the following form:

$$Q = mD(q||\hat{q}) \tag{4.8}$$

where

- $m = \sum_{ij} weight(i,j)$ is the weighted sum of edges,
- $q = \frac{\sum_c m_c}{m}$ is the fraction of internal edges,
- $\hat{q} = \frac{\sum_c \binom{n_c}{2}}{\binom{n}{2}}$ is the expected fraction of internal edges, and
- $D(x||y) = x \log \frac{x}{y} + (1-x) \log \frac{1-x}{1-y}$ is the binary Kullback-Leibler divergence.

Our event similarity graph is expected to contain a lot of very small communities, containing only one (e_M, e_T) pair. However, in the case of long-lasting events with many sub-events, it is likely that the FSD algorithm over-clusters the events in one of the two spheres (and more likely in tweets). The community detection algorithm should then also be able to detect large communities with many nodes. We therefore additionally test the algorithm provided by Traag et al. [2015][2] using surprise as quality function. We detail our experiments in the next Section.

4.4 Experimental Setup

4.4.1 Dataset

We test our approach on the dataset presented in Chapter 2: it contains 95,796 tweets annotated as being related to one of 327 “daily events" (events were drawn day by day and merged afterwards into 257 “macro events"). Among these daily events, 296 are actually news articles drawn randomly from a pool of French daily newspapers. The 31 remaining events were detected by monitoring unusually frequent terms on Twitter every day (see Section 2.4.2). We could manually associate 27 of them to a news article from the OTMedia collection [Hervé, 2019]. Concerning the last 4 events, we consider them to be purely Twitter events that cannot be merged into a joint event, since we could not find any coverage of these events in traditional media. This is not surprising: many Twitter events never lead to an article in mainstream media.

We ran the FSD algorithm on the OTMedia collection in order to automatically group the selected articles with other articles adressing the same topics. From these 323 articles (296 + 27), 167 were automatically clustered with other articles from our pool. In total, we obtained 15,544 news articles from 61 media outlets. We are aware that automatically grouping articles using the FSD algorithm may bias the dataset in favour of our approach, since part of it relies on the FSD algorithm. In order to prove the validity of our approach, we therefore systematically present two type of results: first, results computed on

[2] `https://github.com/vtraag/louvain-igraph`

the entire dataset, second, results computed only on tweets (which were all manually annotated and are therefore not biased).

4.4.2 Evaluation metric

In an approach similar to that of Chapter 3 (see Section 3.5.3), we evaluate the performance of our algorithm using the “best matching" precision, recall and F1 score [Yang et al., 1998] for each event in the ground truth. We then compute the average on all events, to provide a macro-average result.

4.4.3 Parameter tuning

In the first step of our approach (First Story Detection applied on tweets and news articles separately), we use the same parameters as Cagé et al. [2020] for news articles (threshold t of 0.67 and time window w of one day), and the best parameters found in Mazoyer et al. [2020] (see Section 3.6.1: $t = 0.7$ and w set to one day) for tweets.

The graph construction step of our method requires many different parameters, leading to a risk of over-fitting. To test the robustness of our model on different samples, we divide our dataset in 4 subsamples of equal number of documents. The FSD algorithm requires documents to be sorted in chronological order, and for this reason we do not select documents randomly: instead, we split the dataset into 4 different time periods and test each combination of parameters on each subset. We present the role of the different parameters in the next Section.

4.5 Results

We observe a small effect of the choice of the community detection quality metric on the results of our model: surprise outperforms modularity in all cases, however not significantly so (see Figures 4.5 and 4.4). Regarding the choice of parameters, they tend to have similar effects on each subset of our evaluation corpus. We analyze the role of each parameter in greater depth in the rest of this section. We first detail the contribution of the different modalities of event similarity (word similarity, URLs, hashtags). We then present the best choice of Δ and s parameters. Finally, we present the results of our method on the entire dataset.

4.5.1 Effect of word similarity, URLs and hashtags

Figure 4.3 shows the best configuration of parameters α_{text}, α_{url}, α_{htag} and Δ for each subset, with other parameters being fixed ($s = 0.3$ and $l = 3$). Overall, the results are quite stable to the change of parameters, even if the model performs better on all subsets when the weight of word-similarity (α_{text}) is high. URLs and hashtags seem to have a much lower effect, particularly when evaluating the model only on tweets (Figure 4.3b). Increasing α_{url} or α_{htag} may slightly improve the performance on some time periods but there is no configuration that performs equally well on each subset.

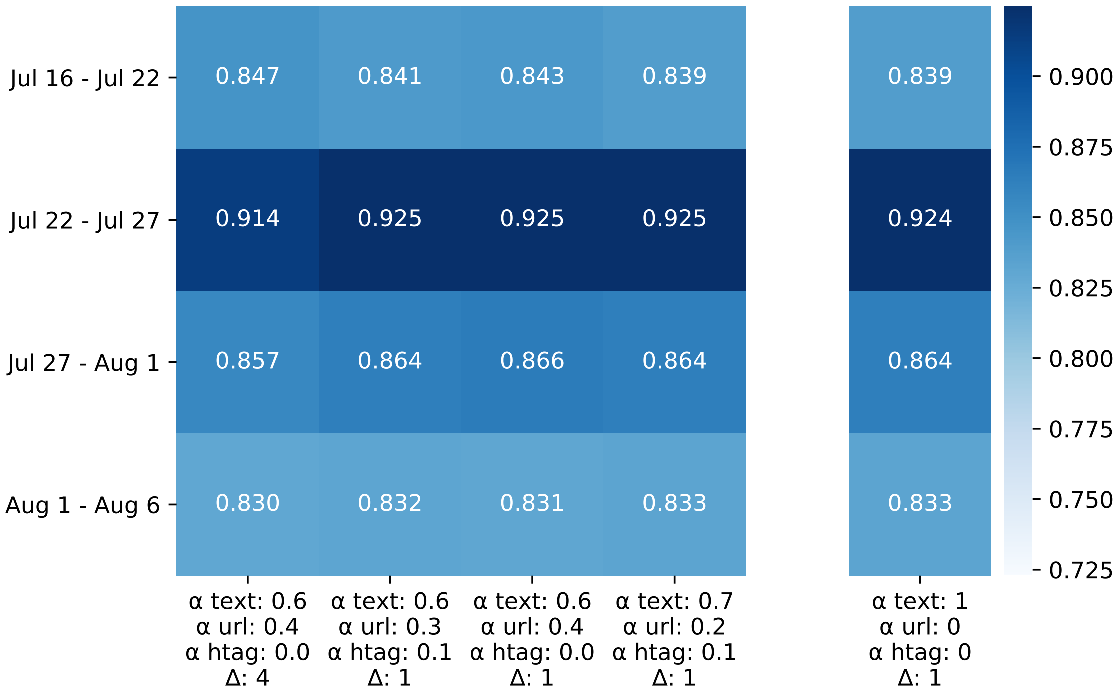
We therefore chose to eliminate these modalities, in order to simplify the graph construction step and to obtain a model that is more stable to the change of dataset. We show the results with a model relying on text only in the right column of Figures 4.3a and 4.3b. The low effect of URLs and hashtags can be explained by the fact that the information carried by these modalities is in most cases already present in the text of the documents.

4.5.2 Effect of the minimum cosine similarity between 2 events (s)

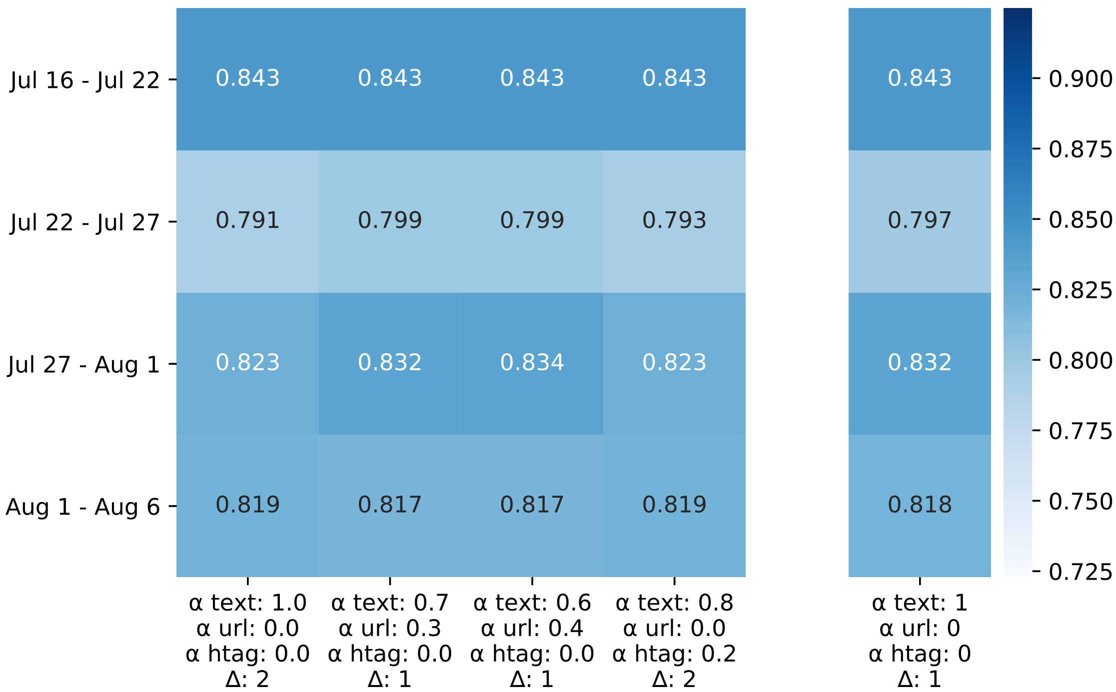
Figure 4.4 shows the average performance of our approach on each subset depending on the value of s. The optimal value of s is 0.3. The choice of the objective function has a real impact for low values of s, i.e. when practically all edges are kept in the event-similarity graph: it seems that the surprise objective function gives better results when the number of edges increases. However, for $s = 0.3$ and higher, the choice of the quality function makes no difference.

4.5.3 Effect of the maximum time distance between 2 events (Δ)

Figure 4.3 suggests that a better performance is obtained with lower values of Δ. However, each subset contains less than 6 days of data, a period during which it is unlikely that two semantically close nodes actually belong to two different joint events. This is why we instead measure the effect of the time distance between events on the entire dataset of 22 days. Figure 4.5 presents the macro F1 score of our model on the evaluation dataset depending on the value of Δ, all other parameters being fixed. We observe that $\Delta = 1$ provides the best results, and that the score is a decreasing function of Δ. Similarly to the effect noted in the previous Section, when the model keeps more edges in the graph – i.e. Δ increases –, the difference in performance between surprise and modularity objective functions is larger: surprise gives better results on denser graphs.



(a) Evaluation on all documents



(b) Evaluation on tweets only

Figure 4.3: Best matching F1 score of our approach on different sub-samples of the dataset. The result of community detection with the best set of parameters for a given sample is displayed on the diagonal of the square matrix. The results of that set of parameters on the other samples are displayed on the corresponding lines. The right column presents the results of community detection on the word-similarity graph only (urls and hashtags are not taken into account). The other parameters are fixed: $s = 0.3$, $l = 3$.

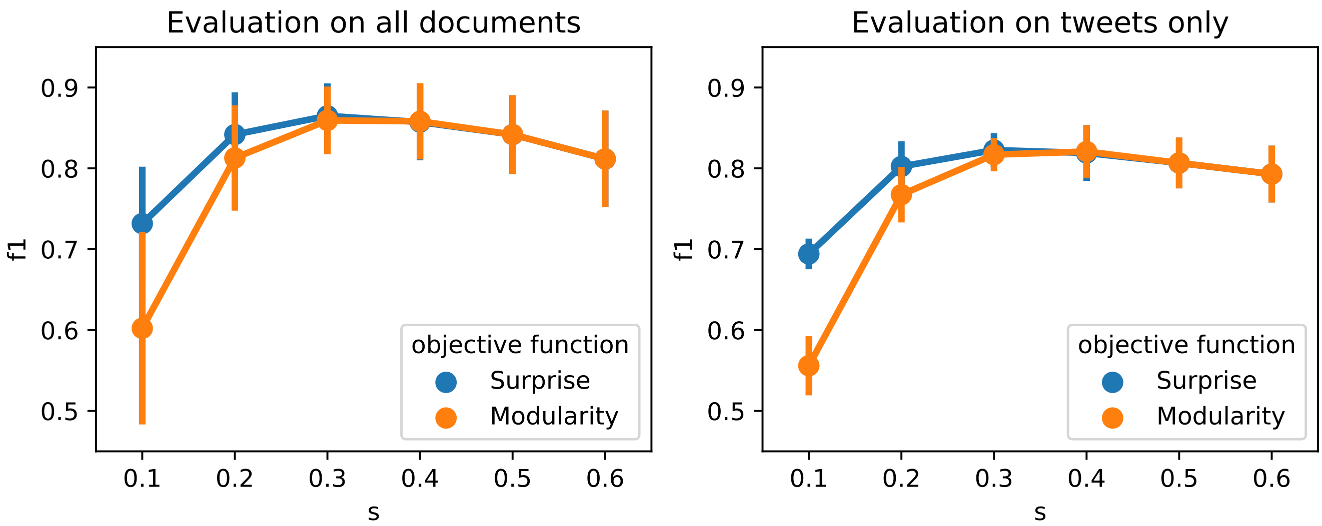


Figure 4.4: Effect of the minimum cosine similarity between 2 events (s) on the performance of our method measured with the best matching F1 score. This Figure plots the average best matching F1 score for the 4 subsets, with standard deviation, depending on s.

4.5.4 Results on the entire corpus

Model	*F1*	*precision*	*recall*
FSD	0.71	0.95	0.61
Proposed	0.82	0.92	0.80

(a) Evaluation on all documents

Model	*F1*	*precision*	*recall*
FSD	0.78	0.94	0.73
Proposed	0.81	0.90	0.80

(b) Evaluation on tweets only

Table 4.1: Results of the proposed approach compared to a joint event detection using the FSD algorithm
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Table 4.1 shows the comparative results of our approach and on a joint clustering approach using the FSD algorithm on the entire dataset. The proposed approach uses surprise as objective function for the community detection step. The choice of parameters is the following: $(\alpha_{text} = 1, s = 0.3, \Delta = 1)$. The important difference in the FSD results between Tables 4.1a and 4.1b can be explained by the fact that the FSD algorithm totally fails to join tweets and news articles inside the same events. As a result, the tweets clusters are consistent, but when we evaluate on the entire dataset, all news articles are missing from the created clusters. Overall, we show that our proposed approach clearly improves the detection of joint events between tweets and news.

figures/.pdf

Figure 4.5: Effect of the of the maximum time distance (Δ) on the performance of our method measured on the entire dataset. This Figure plots the best matching F1 score depending on Δ.

4.6 Conclusion

In this Chapter, we propose a novel event detection and linking method across heterogeneous types of news documents. Our approach is able to take into account the multi-modal relationships (URLs, hashtags, words) between Twitter events and media events. However, we show that using word similarity alone does not significantly decrease performance and simplifies the model in terms of the number of parameters. Overall, our model outperforms a joint clustering algorithm on all tested subsets. Future works should focus on implementing existing methods from the literature [Mele et al., 2017; Hua et al., 2016] in order to prove the superiority of our approach on a realistic dataset.

This work opens the way for an in-depth analysis of the relationships between Twitter and traditional news media, which we present in the next Chapter.

Chapter 5

Social media and newsroom production decisions

5.1 Introduction

Little is known about the impact of social media on the production of news. However, social media not only affect the way we consume news, but also the way news is produced, including by traditional media. First, social media users may report events before traditional media [Sakaki et al., 2010].[1] Second, news editors may use social media as a signal to draw inferences about consumers' preferences. Furthermore, social media compete with mainstream media for consumers' attention, and this may affect publishers' incentives to invest in quality [de Cornière and Sarvary, 2019].

In this chapter, we investigate how editors decide on the coverage for stories, and in particular the role played by social media in their decision. To do so, we have built a completely new dataset including tweets collected during an entire year (July 2018-July 2019) using the collection method described in Chapter 2, Section 2.3 and the content produced online by the French-speaking general information media outlets during the same time period (205 media outlets included, regardless of their offline format).[2] Our dataset contains around 1.8 billion tweets as well as 4 million news articles.

[1] As highlighted by Alan Rusbridger as early as 2010, *"increasingly, news happens first on Twitter."* (...) *"If you're a regular Twitter user, even if you're in the news business and have access to wires, the chances are that you'll check out many rumours of breaking news on Twitter first. There are millions of human monitors out there who will pick up on the smallest things and who have the same instincts as the agencies — to be the first with the news. As more people join, the better it will get."* Source: https://www.theguardian.com/media/2010/nov/19/alan-rusbridger-twitter.

[2] Our dataset includes all the content published online by French general information newspapers, TV channels, radio stations, pure online media, and the news agency AFP as well as the content produced online by 10 French-speaking foreign media outlets such as *Le Temps* (Switzerland).

We use the method presented in Chapter 4 to automatically detect social media events and mainstream media events, and find common events in those two sets. When an event is covered on both social and mainstream media, we determine the origin of the information. For the subset of common events that originate first on social media, we study whether the event popularity on Twitter impacts the coverage that mainstream media devote to this event.

The scale of our dataset (one year of data with several million tweets and news articles) allows us to follow a split-sample approach to relieve concerns about specification search and publication bias [Leamer, 1978, 1983; Glaeser, 2006].[3] Following Fafchamps and Labonne [2016, 2017] and Anderson and Magruder [2017], we first perform our analysis on the July 2018 - September 2018 time period (three months of data). The results in this Chapter rely on this sub-sample that we use to narrow down the list of hypotheses we wish to test and to specify the research plan that we will pre-register.[4] We plan to publish a final version of this Chapter, which will follow the pre-registered plan and perform the empirical analysis on the remainder of the data (October 2018 - July 2019).

The sample we use here (July 2018 - September 2018) includes 417 million tweets and $929,764$ news articles. We identify $5,137$ joint events. Producing these data is our first contribution. It is to the best of our knowledge the most exhaustive dataset on social media and mainstream media events available to researchers. Our second contribution is descriptive: while there is a growing literature focusing on the propagation of fake news on social media [Vosoughi et al., 2017, 2018], little is known about the propagation of information between social media and traditional media outlets. Moreover, while false news only represent a small part of the news we consume, not much is known on the propagation of real information. In this chapter, we investigate the propagation of all news between social and mainstream media, regardless of their topic.

Most importantly, we open the black box of newsroom production decisions, and investigate the extent to which news editors are influenced in their editorial decisions by stories' popularity on social media. Focusing on the subset of news stories that originate first on Twitter ($4,392$ out of the $5,137$ joint events), we investigate how their popularity affects the coverage that traditional media devote to these stories. The popularity of a story on Twitter is measured by the number of tweets about that story published before the first news article devoted to the story appears. We refer to the author of the first tweet in the event as the

[3] We thank Jesse Shapiro for suggesting this approach.

[4] This type of approach is more common in the case of Random Control Trials (RCT). The American Economic Association operated for example a registry for RCT: `www.aeaweb.org/journals/policies/rct-registry`. We will register our research plan on one of these platforms, depending on the journal in which our paper will be published.

seed of the event.

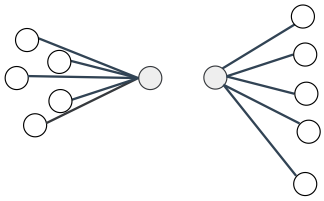
The main empirical challenge here lies in the fact that a story's popularity on Twitter and its media coverage can both be driven by the intrinsic interest of the story, regardless of what happens on social media. Hence, to identify the specific role played by social media, we need to find exogenous sources of variation of a story's popularity on Twitter.To do so, we propose a new instrument that relies on the interaction between the seed's centrality in the Twitter network and the "news pressure" at the time of the event [Eisensee and Strömberg, 2007]. To measure centrality, in the spirit of an intention-to-treat analysis, we compute a measure of the number of "impressions"[5] generated by the previous tweets of the seed's followers: the higher this number, the higher the potential number of retweets, regardless of the tweet's intrinsic interest. We approximate the potential number of "impressions" by the observed number of interactions (retweets/likes/quotes) by the previous tweets of the seed's followers (i.e. by all their tweets before the news event).

Importantly here, we use the average number of interactions generated by the tweets of the seed's followers, not by the tweets of the seed itself, given the former is arguably more exogenous. Figure 5.1 illustrates the intuition behind our empirical strategy. We consider a simple case with two seeds who have an equal number of followers (sub-Figure 5.1a), but the followers of one of the seeds (on the left-hand side of sub-Figure 5.1b) have many more followers those of the other seed (on the right-hand side of sub-Figure 5.1b). As a consequence, regardless of the content of the tweet itself, the tweets emitted by the left-hand side seed have a much lower probability of being retweeted than the tweets emitted by the right-hand side seed, everything else equal (sub-Figure 5.1c).

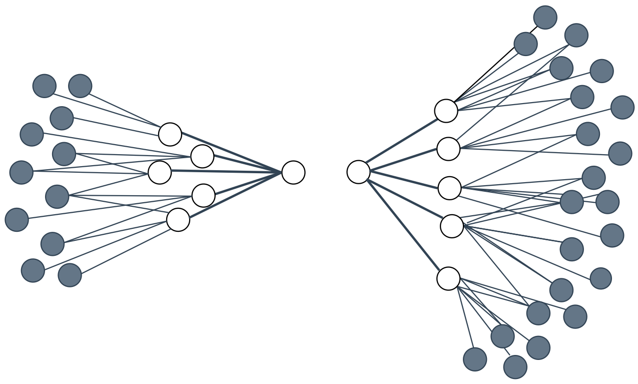
However, the number of impressions generated by the seeds' followers may suffer from the fact that a seed's centrality in the Twitter network may be related to its ability to produce newsworthy content. To relax the exclusion restriction, the instrument we propose is the *interaction* between the seed's centrality in the network (as previously defined) and the news pressure at the time of the tweet (measured by the number of interactions generated by all the tweets published in the hour preceding the tweet), controlling for the direct effect of centrality and news pressure.[6] Our identification assumption is that, once we control for the direct effects of centrality and news pressure, as well as for the seed's number of followers, the interaction between the seed's centrality and news pressure should only affect traditional news production

[5]The number of impressions is a total tally of all the times the tweet has been seen. Unfortunately, this statistics is not directly available to researchers. But we can approximate this number by using the observed number of interactions (retweets/likes/quotes) generated by the tweet.

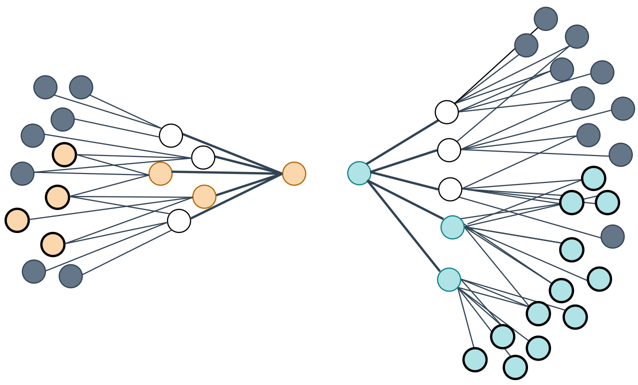
[6]We thank Katia Zhuravskaya for suggesting this approach.



(a) 2 seeds with an equal number of followers...



(b) ... but different numbers of followers' followers



(c) , leading to different numbers of tweet impressions

Notes: The Figure illustrates the IV strategy we develop in this article, in the spirit of an intention-to-treat approach. The thought experiment is described in detail in the text.

Figure 5.1: IV strategy: Illustration

through its effect on the tweet's visibility on Twitter. Furthermore, we show that our results are robust to dropping the news events whose seed is the Twitter account of either a media outlet or a journalist, as well as the events broken by seeds who broke more than one event during our time period, to avoid capturing a celebrity bias as well as tweets by influencers.

Using a first naive estimate, at the event-level, we show that an increase of $1,000$ in the number of tweets published before the first media article appears is associated with an increase of 3.2 in the number of media articles published in the event; this increase is partly driven by a higher number of media outlets covering the event ($+0.4$). These results are robust to controlling for the endogeneity of the event popularity on Twitter. As expected given the direction of the omitted variable bias, the magnitude of the IV estimates is smaller ($1,000$ additional tweets lead to 2 additional media articles) than the one we obtain with the naive approach. Reassuringly, our IV results are robust to controlling for additional characteristics of the seed of the event, and doing so does not affect the magnitude of the estimates.

We then turn to the media-level analysis and investigate the heterogeneity of our results depending on the characteristics of the media outlets. For each of the media outlets in our sample, we collect information on their social media presence, as well as on their business model (e.g. whether they put part of their content behind a paywall and their reliance on advertising revenues). In addition, for a subset of the media, we also gather information on the size of their newsroom, which provides us with a proxy on their investment in news quality. Additionally, we investigate whether there is heterogeneity depending on the offline format of the media. We show that the magnitude of the effect is stronger for the media whose social media presence is relatively higher. Ultimately, we document heterogeneous effects depending on the topic of the event (e.g. sport, international affairs, economics, etc.).

Finally, we discuss the mechanisms that may help rationalizing our findings. First, journalists monitor Twitter. For example, the Muck Rack's "State of Journalism 2019" report reveals that nearly 60% of reporters turn to digital newspapers or magazines as their first source of news, and 22% check Twitter first. For each media outlet in our sample, we compute its number of journalists on Twitter and show that the magnitude of the effect is stronger for the media whose journalists are more present on the social network. However, while this may help us to understand why a number of stories emerge first on Twitter, it does not explain why the intensity of the media coverage (on the intensive margin) also varies with the popularity of a story on Twitter. In the absence of perfect information about consumer preferences, publishers may use Twitter as a signal that allows them to draw inferences about what news consumers are interested in. We investigate whether our results vary depending on the media outlets' business model, in particular their reliance on advertising revenues.

The rest of this chapter is composed as follows: first, we detail our contributions to the literature in the Section below. We then describe our data and specify how we measure popularity on Twitter and media coverage. In Section 5.4, we present our empirical specification, and in particular the new instrument we propose to identify the causal impact of a story's popularity on the subsequent news coverage it receives. We then present our results and analyze various dimensions of heterogeneity in Section 5.5. Finally, we discuss the mechanisms at play in Section 5.6 , and we perform a number of robustness checks in Section 5.7.

5.2 Literature review

We contribute to the growing literature on the impact of the introduction of new media technologies on political participation, government accountability and electoral outcomes (see among others Gentzkow et al. [2011]; Snyder and Stromberg [2010] on newspapers; Strömberg [2004] on radio; Gentzkow [2006]; Angelucci and Cagé [2019]; Angelucci et al. [2020] on television, and Boxell et al. [2018]; Gavazza et al. [2019] on the Internet). There are very few papers examining how social media affects voting [for a review of the literature see Zhuravskaya et al., 2020], and these mainly concentrate on the role played by fake news [Allcott and Gentzkow, 2017]. So far, the focus of this literature has mostly been on news consumption, and little is known about the empirical impact social media have on news production by mainstream media. One exception is a work-in-progress article by Hatte et al. [2020] who study the effect of Twitter on the US TV coverage of the Israeli-Palestinian conflict. Compared to this work, our contribution is threefold. First, we focus on the overall activity on Twitter and collect a large representative sample of about 70% of all tweets rather than the tweets associated with a small number of keywords. Second, we develop an instrument for measuring popularity shocks on Twitter based on the structure of the network that could be of use in different contexts. Finally, we investigate whether there are heterogeneous effects depending on the media characteristics, in particular their business model and their reliance on advertising revenues.

An expanding theoretical literature studies the effects of social media on news. De Cornière and Sarvary [2019] develop a model where consumers allocate their attention between a newspaper and a social platform [see also Alaoui and Germano, 2020, for a theory of news coverage in environments of information abundance]. They document a negative impact on the media's incentives to invest in quality. This literature mainly concentrates on competition for attention between newspapers and social media, and documents a trade-off between the business-stealing and the readership-expansion effect of platforms [Jeon and Nasr, 2016].[7] Here, we highlight the fact that not only are mainstream and social media competing for attention, but also that social media can be used by mainstream media both as a source of news and as a signal to draw inferences on consumers' preferences. We investigate empirically how a story's popularity on Twitter impacts the information produced by traditional media, and in particular the intensity of the coverage they devote to that story.

Our results also contribute to the growing literature in the fields of Economics and Political Science using social media data, and in particular the structure of the social networks – usually Twitter – as a source of information on the ideological positions of actors [Barberá, 2015; Cardon et al., 2019], the importance of ideological segregation and the extent of political polarization [Halberstam and Knight, 2016; Giavazzi et al., 2020], and political language dissemination [Longhi et al., 2019].[8] Gorodnichenko et al. [2018] study information diffusion on Twitter, and Allcott et al. [2019] the spread of false content. While this literature mostly focuses on relatively small corpuses of tweets and on corpuses that are not representative of the overall activity on Twitter [e.g. Gorodnichenko et al., 2018, make requests to collect tweets using Brexit-related keywords], we build a representative corpus of tweets and impose no restriction on the data collection. Furthermore, we contribute to this literature by considering the propagation of information on social media as well as by studying whether and how information propagates from social media to mainstream media (and vice versa). While Cagé et al. [2020] only consider news propagation on mainstream media, we investigate here the extent to which the popularity of a story on social media affects the coverage devoted to this story by traditional media outlets.

The impact of “popularity" on editorial decisions has been studied by Sen and Yildirim [2015] who use data from an Indian English daily newspaper to investigate whether editors expand online coverage of stories which receive more clicks initially.[9] Compared to this previous work, our contribution is threefold. First, we use the entire universe of French general information media online (around 200 media outlets), rather than one single newspaper. Second, we not only identify the role played by popularity, but also investigate whether there is heterogeneity depending on the characteristics of the media outlets, as well

[7] See Jeon [2018] for a survey of articles on news aggregators.

[8] See also Barberá et al. [2019] who use Twitter data to analyze the extent to which politicians allocate attention to different issues before or after shifts in issue attention by the public.

[9] See also Claussen et al. [2019] who use data from a German newspaper to investigate whether automated personalized recommendation outperforms human curation in terms of user engagement.

as the topic of the story. Third, we consider both the extensive and the intensive margin[10], rather than focusing on the subset of stories that receive at least some coverage in the media. Finally, we also contribute to the empirical literature on media by using a split-sample approach; while this approach is increasingly used in economics with the pre-registration of Randomized Controlled Trials, we believe we are the very first to use it with "real-world data" on such a large scale.

In addition to this, we contribute to the broader literature on social media that documents its impact on racism [Müller and Schwarz, 2019], political protests [Enikolopov et al., 2020], the fight against corruption [Enikolopov et al., 2018], and the size of campaign donations [Petrova et al., 2017]. Overall, social media is a technology that has both positive and negative effects [Allcott et al., 2020]. This also holds true for its impact on traditional media: we contribute to this literature by documenting the complex effects social media has on news production, and consequently on news consumption.

Finally, our instrumentation strategy is related on the one hand to the literature that looks at the quantity of newsworthy material at a given moment of time [e.g. Eisensee and Strömberg, 2007; Djourelova and Durante, 2019], and on the other hand to the literature on network interactions [see Bramoullé et al., 2020, for a recent survey]. The main issue faced by researchers willing to identify the causal effects of peers is that the structure of the network itself may be endogenous. Here, we relax the concern of network endogeneity by considering the interaction between the network and news pressure at a given moment of time.

5.3 Data and descriptive statistics

The new dataset we built for this study is composed of two main data sources that we have collected and merged: on the one hand, a representative sample of tweets, and on the other hand, the online content of the general information media outlets. In this section, we describe these two datasets in turn.

5.3.1 Data: Tweets

First, we collect a representative sample of all the tweets in French during an entire year: July 2018 - July 2019. Our dataset, which contains around 1.8 billion tweets, encompasses around 70% of all tweets in French (including retweets) during this time period (see Chapter 2 Section 2.3.5 for a discussion of

[10] The intensive margin here corresponds to whether a story is covered, while on the extensive margin we consider both the total number of articles (conditional on covering the story) and the characteristics of these articles.

the completeness of our dataset). For each of these tweets, we collect information on their “success" on Twitter (number of likes or comments, etc.), as well as information on the user’s characteristics at the time of the tweet (e.g. number of followers).

Filtering the tweets

An important issue on Twitter is the use of bots, i.e. non-human actors and trolls publishing tweets on the social media [see e.g. Gorodnichenko et al., 2018]. In recent years, Twitter has been actively cracking down on bots. In our analysis, we perform some filtering designed to limit the share of tweets from bots in our dataset. However we do not remove all automated accounts: many media accounts, for example, post some content automatically, and are not considered to be bots. Moreover, some types of automatic behaviors on Twitter, such as automatic retweets, may contribute to the popularity of stories and therefore should be kept in our dataset.

Our filtering rules are as follows. First, we use the “source" label provided by Twitter for each tweet.[11] Tweets emanating from a “source" such as “Twitter for iPhone" can be considered valid; however, we excluded sources explicitly described as bots, or referring to gaming or pornographic websites. We also excluded apps automatically posting tweets based on the behaviour of users: for example, many Twitter users (who are human beings and usually publish tweets they have written themselves) post automatic tweets such as “I like a video on Youtube: [url]". The entire list of the excluded sources is presented in Table A.1 of the Appendix.

Second, we filter the users depending on their activity on the network: we only keep users with fewer than 1,000 tweets a day[12], and the users who have at least 1 follower. Finally, we only keep the users who post at least 3 tweets in French between July and September 2018.[13]

[11]Twitter describes this label as follows: “Tweet source labels help you better understand how a Tweet was posted. This additional information provides context about the Tweet and its author. If you don’t recognize the source, you may want to learn more to determine how much you trust the content. [...] Authors sometimes use third-party client applications to manage their Tweets, manage marketing campaigns, measure advertising performance, provide customer support, and to target certain groups of people to advertise to. Third-party clients are software tools used by authors and therefore are not affiliated with, nor do they reflect the views of, the Tweet content. Tweets and campaigns can be directly created by humans or, in some circumstances, automated by an application."

[12]As a matter of comparison, the Twitter account of *Le Monde* publishes on average 88 tweets per day, and that of *Le Figaro* 216.

[13]I.e. users who tweet on average at least once a month.

Descriptive statistics

As highlighted in the introduction, to address concerns about specification search and publication bias [Leamer, 1978, 1983; Glaeser, 2006], we implement a split-sample approach in this paper [Fafchamps and Labonne, 2016, 2017; Anderson and Magruder, 2017]. We split the data into two non-overlapping datasets: July 2018 - September 2018 and October 2018 - July 2019. In this chapter, we use the three-month dataset covering July 2018 - September 2018 to narrow down the list of hypotheses we wish to test.

The final paper will only use data from October 2018 to July 2019. The idea here is to avoid multiple hypothesis testing, which has been shown to be an issue in experimental economics [List et al., 2019] and could also be of concern here. Hence, for the remainder of the chapter, we will rely solely on the first three months of our dataset. This sample includes $417,153,648$ tweets; Table 5.1 presents summary statistics for these tweets.

For each of the tweets, we have information on its length (102 characters on average or 6.2 words), and know whether it is a retweet of an existing tweet or an original tweet. 63% of the tweets in our dataset are retweets; some of these retweets are “quotes", i.e. comment on the retweeted tweet.[14] Of the original tweets, some are replies to other tweets (17% of the tweets in our sample). Finally, 13% of the tweets contains a URL, most often a link to a news media article or to a video.

We also gather information on the popularity of each of the tweets in our sample. On average, the tweets are retweeted 2.3 times, liked 3.7 times, and receive 0.2 replies (these numbers are only computed on the original tweets, given that retweets, likes and quotes are not attributed to the retweets but to the original tweets).[15]

Furthermore, we compute summary statistics on the Twitter users in our sample. Our dataset includes $4,222,734$ unique users between July 2018 and September 2018. Table 5.2 provides these statistics the first time a user is observed in our data.[16] On average, the users tweeted $14,100$ times, liked $7,463$ tweets, and were following 642 other Twitter accounts. The average year of the account creation is 2014 (Twitter was created in 2006). (See Appendix Figure A.2 for the distribution of the users depending on the date on which they created their Twitter account.) On average, users have $2,166$ followers; however, we observe

[14] Quote tweets are much like retweets except that they include a new tweet message.

[15] Appendix Table A.2 shows statistics on the sample of tweets we collect before applying the filters to exclude the bots as described above.

[16] Alternatively, we compute the users' characteristics the last time we observe them. The results are presented in the Appendix Table A.3.

Table 5.1: Summary statistics: Tweets (split-sample, July 2018-September 2018)

	Mean	St.Dev	P25	Median	P75	Max	Obs
Characteristics of the tweet							
Length of the tweet (nb of characters)	102	52	61	98	140	1,121	417,153,648
Number of words	6.2	4.0	3.0	6.0	9.0	269	417,153,648
=1 if tweet contains an URL	0.13	0.33	0.00	0.00	0.00	1	417,153,648
=1 if the tweet is a retweet	0.63	0.48	0.00	1.00	1.00	1	417,153,648
=1 if the tweet is a reply	0.17	0.38	0.00	0.00	0.00	1	417,153,648
=1 if the tweet is a quote	0.19	0.39	0.00	0.00	0.00	1	417,153,648
Popularity of the tweet							
Number of retweets	2.3	111.5	0.000	0.000	0.000	117,389	154,273,618
Number of replies	0.2	6.6	0.000	0.000	0.000	47,892	154,273,618
Number of likes	3.7	172.2	0.000	0.000	0.000	449,881	154,273,619

Notes: The table gives summary statistics. Time period is July 2018-September 2018. Variables are values for all the tweets included in our dataset. Variables for the "popularity of the tweet" are only for the original tweets, given that the retweets/replies/likes are always attributed to the original tweets (hence the lower number of observations). The maximum number of characters (or length of the tweet) is above the 280 Twitter character limit. This is due to the fact that URLs and mentions (e.g. $@BeatriceMazoyer$) contained in the tweets are not included by Twitter in the character limit. We remove the stop-words before computing the "number of words" statistics. The list of stop-words is provided in the Appendix Section A.1.3. Variables are described in more detail in the text.

Table 5.2: Summary statistics: Twitter users

	Mean	St.Dev	P25	Median	P75	Max
User activity						
Total number of tweets	14,100	39,127	192	1,754	11,228	6,020,029
Nb of tweets user has liked	7,463	21,419	95	914	5,414	2,736,965
Nb of users the account is following	642	4,489	76	193	482	1,681,133
User identity						
Date of creation of the account	2014	3	2012	2015	2017	2018
=1 if verified account	0.005	0.073	0	0	0	1
=1 if user is a journalist	0.001	0.034	0	0	0	1
=1 if user is a media	0.0001	0.010	0	0	0	1
User popularity						
Nb of followers	2,166	86,811	24	129	477	58,484,193
Nb of public lists	19	578	0	1	6	1,028,761
Observations	4,222,734					

Notes: The table gives summary statistics. Time period is July 2018-September 2018. Variables are values for all the Twitter users included in our dataset the first time we observe them. Variables are described in more detail in the text.

significant variation: the vast majority of the users have just a few followers, but some of them act as central nodes in the network: the top 1% of the users in terms of followers account for more than 70% of the total number of followers (see Appendix Figure A.3 for the distribution of the number of followers).

0.5% of the users in our sample have a verified account[17], 0.12% are the accounts of journalists, and 0.011% are media outlets' accounts. We have manually identified the Twitter accounts of media outlets. For the Twitter accounts of journalists, we proceed to a semi-manual detection with the following method: first we use the Twitter API to collect the name and description of all accounts that are followed by at least one Twitter media account. Second, we only keep the accounts that have some keywords related to the profession of journalist in their description, such as “journalist", “columnist", “news", etc. Third, we manually select journalists from the remaining accounts by reading their names and description.

5.3.2 Data: News articles

We combine the Twitter data with the online content of traditional media outlets (alternatively called mainstream media) over the same time period, including newspapers, radio channels, TV stations, online-only news media, and the content produced by the Agence France Presse news agency (AFP). See Appendix

[17]According to Twitter, an account may be verified if it is determined to be an account of public interest. Typically this includes accounts maintained by users in music, acting, fashion, government, politics, religion, journalism, media, sports, business, and other key interest areas.

Section A.2 for the list of these media depending on their offline format. The goal here is to gather all the content produced online by the “universe" of French news media, regardless of their offline format. The data is collected as part of the OTMedia research project, a unique data collection program conducted by the French National Audiovisual Institute [Cagé et al., 2020]. Furthermore, we also gather the content produced online by 10 French-speaking (non-French) media outlets such as the daily newspaper *Le Temps Suisse* from Switzerland. This subset of French-speaking media was selected based on the fact that the tweets included in our sample include at least one URL linked to an article published online by these media.

Newsroom characteristics

Our dataset includes 205 unique media outlets, which published $929,764$ online news articles between July 2018 and September 2018. Table 5.3 shows summary statistics for the mainstream media included in our dataset. On average, between July 2018 and September 2018, the mainstream media in our data published $4,152$ news articles (i.e. around 48 articles per day), of which $1,406$ are classified in events (see below for the event definition). 63.4% of the articles come from the newspaper websites, $13,1\%$ from pure online media, 11.1% from the news agency, 8.8% from the radio station websites and the remainder from TV channel websites (see Appendix Figure A.4.)

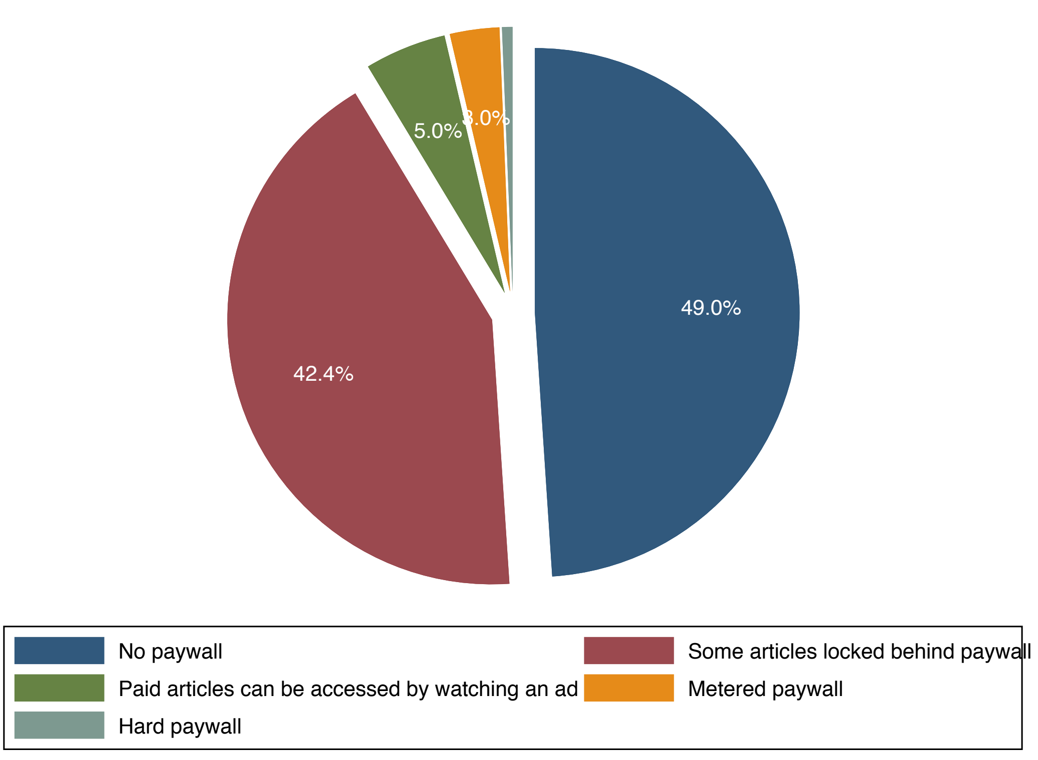
For all the media outlets in our sample, we also collect information on their social media presence. First, we identify their Twitter account(s) (some media only have one Twitter account, while others have many; e.g. *Le Monde*: $@lemondefr$, $@lemondelive$, $@lemonde\_pol$, etc.) and collect information on their popularity (number of followers and public lists, the first time we observe them in our sample), as well as the number of tweets posted by these accounts during our period of interest (July-September 2018). On average, the media outlets in our sample have 3.1 different Twitter accounts. We compute the date of creation of each of these accounts, and report the oldest one in the table. To proxy for the media outlets' social media presence, we also compute the share of the articles the media publishes online that are also on Twitter (see Appendix Figure A.5 for this statistic by media outlet). In addition, for each of the media in our sample, we compute the number of journalists with a Twitter account, as well as the characteristics of these accounts.

Second, to better understand the mechanisms that may be at play, we collect additional information on the media: (i) their year of creation, (ii) the year of creation of their website (2004 on average), as well as

Table 5.3: Summary statistics: Media outlets

	Mean	St.Dev	P25	Median	P75	Max
Content						
Total content (thsd ch)	10,021	25,055	414	1,965	8,045	222,546
Total number of articles	4,152	10,035	185	837	3,366	85,676
Articles classified in events	1,406	4,524	11	114	864	55,932
Number of breaking news	31.8	135.0	0.0	0.0	13.0	1,656
Online audience (daily)						
Number of unique visitors	210,883	301,686	28,843	90,153	227,008	1,282,498
Number of visits	586,269	852,715	72,165	210,473	714,832	3,283,491
Number of page views	1,510,024	2,544,652	160,117	536,866	1,643,809	15,329,183
Social media presence						
% articles on Twitter	17	17	4	10	24	70
Number of Twitter accounts	3.1	5.7	1.0	1.0	2.0	43
Date of Twitter account creation	2009	1.3	2009	2009	2010	2016
Number of tweets	2,874	4,587	455	1,101	3,043	19,730
Nb journalists with Twitter account	211	354	38	81	220	3,086
Other media characteristics						
Year of media creation	1975	39	1945	1986	2008	2018
Year of website creation	2004	7	1998	2004	2010	2018
Year of paywall introduction	2014	5	2013	2015	2018	2020
Number of journalists	147	183	32	90	208	1121
Observations	205					

Notes: The table gives summary statistics. Time period is July 2018-September 2018. Variables are values for media outlets. The observations are at the media outlet/day level for the online audience statistics, and at the media outlet level for the content data and other media characteristics.



Notes: The Figure reports the share of the media outlets in our sample depending on their online business model. 48.1% of the media in our sample do not have a paywall (“no paywall"), and 5.1% condition the reading of the paid articles on the fact of watching an ad (“paid articles can be accessed by watching an ad"). Of the outlets that do have a paywall, we distinguish between three models: hard paywall, metered paywall, and soft paywall (“some articles locked behind paywall").

Figure 5.2: News editors' business model

(iii) information on their business model. In particular, for each of the media outlets, we investigate whether it uses a paywall, the characteristics of this paywall (e.g. soft vs. hard), and the date of introduction of the paywall. This information is summarized in Figure 5.2: while 48.1% of the media outlets do not have a paywall, 43.1% lock at least some of their articles behind a paywall (soft paywall). Metered paywalls and hard paywalls are much less frequent. The media outlets that use a paywall introduced it on average in 2014. Overall, the large majority of the media outlets in our sample rely at least partly on advertising revenues; however, some of them do not (e.g. the pure online media Mediapart).

Third, given that media outlets may react differently to social media depending on their initial investment in quality [see e.g. de Cornière and Sarvary, 2019], we also compute information on the size of the newsroom, and on the average payroll [Cagé, 2016]. This information is available for 68 media outlets in our sample. Finally, for 72 media outlets, we collect daily audience information from the ACPM, the French press organization whose aim is to certify circulation and audience data. The average number of daily visits is $586,269$, and the average number of page views $1,510,024$.

Table 5.4: Summary statistics: Mainstream media articles

	Mean	St.Dev	P25	Median	P75	Max
Length						
Length (number of characters)	2,420	2,224	1,125	1,984	3,184	431,812
Facebook shares						
Number of shares on Facebook	19	336	0	0	1	41,835
Number of comments on Facebook	25	308	0	0	0	19,316
Number of reactions on Facebook	83	1,535	0.00	0.00	0.00	200,136
Observations	929,764					

Notes: The table gives summary statistics. Time period is July 2018-September 2018. Variables are values for the mainstream media articles. The observations are at the article level.

Article characteristics

Table 5.4 presents summary statistics for the $929,764$ articles included in our dataset. On average, articles are $2,420$ characters long. Furthermore, to proxy for the audience received by each of these articles, we compute the number of times they are shared on Facebook.[18]

5.3.3 Detected events

We use the method presented in Chapter 4, Section 4.3 to detect joint events in the corpus. We obtain $5,137$ joint events that encompass over 32 million tweets and $273,000$ news articles. Table 5.5 presents summary statistics on these events that contain on average $6,283$ tweets and 53 media articles published by 17 different media outlets. Of these $5,137$ joint events, $4,392$ break first on Twitter. These articles will be the focus of our analysis in Section 5.4 below. Their characteristics partly differ of those of the events that appear first on mainstream media, as reported in Appendix Table A.4 where we perform a t-test on the equality of means. In particular, they tend to last longer and receive slightly more media coverage.

Using the metadata associated with the AFP distaches, we identify the topic of the joint events. The AFP uses 17 IPTC classes to classify its dispatches. These top-level media topics are: (i) Arts, culture and entertainment; (ii) Crime, law and justice; (iii) Disaster and accidents; (iv) Economy, business and finance; (v) Education; (vi) Environment; (vii) Health; (viii) Human interest; (ix) Labour; (x) Lifestyle and leisure; (xi) Politics; (xii) Religion and belief; (xiii) Science and technology; (xiv) Society; (xv) Sport; (xvi) Conflicts, war and peace; and (xvii) Weather.[19] Figure 5.3 plots the share of events associated with each

[18]Unfortunately, article-level audience data is not available. The number of shares on Facebook is an imperfect yet relevant proxy for this number, as shown in Cagé et al. [2020].

[19]To define the subject, the AFP uses URI, available as QCodes, designing IPTC media topics (the IPTC is the International

Table 5.5: Summary statistics: Joint events

	Mean	St.Dev	P25	Median	P75	Max
Length of the event (in hours)	555	507	161	369	819	2,350
Number of documents in event	6,336	94,618	209	761	2,995	6,486,415
Twitter coverage						
Nb of tweets in event	6,283	94,579	192	728	2,928	6,484,204
Number of different Twitter users	3,288	17,902	163	584	2,220	1,077,929
Average number of retweets of tweets in events	3.2	5.6	1.0	1.8	3.4	149
Average number of replys of tweets in events	0.4	0.5	0.1	0.2	0.5	17
Average number of favorites of tweets in events	4.5	8.0	1.0	2.3	5.0	240
Media coverage						
Number of news articles in the event	53	131	13	20	44	4,538
Number of different media outlets	17	12	9	13	22	98
Observations	5,137					

Notes: The table gives summary statistics. Time period is July 2018 - September 2018. The observations are at the event level.

media topic (given that some events are associated with more than one topic, the sum of the shares is higher than 100%). Nearly one fifth of the events are about “Economy, business and finance", 18% about “Sport", followed by “Politics".“Crime, law and justice" comes fourth.

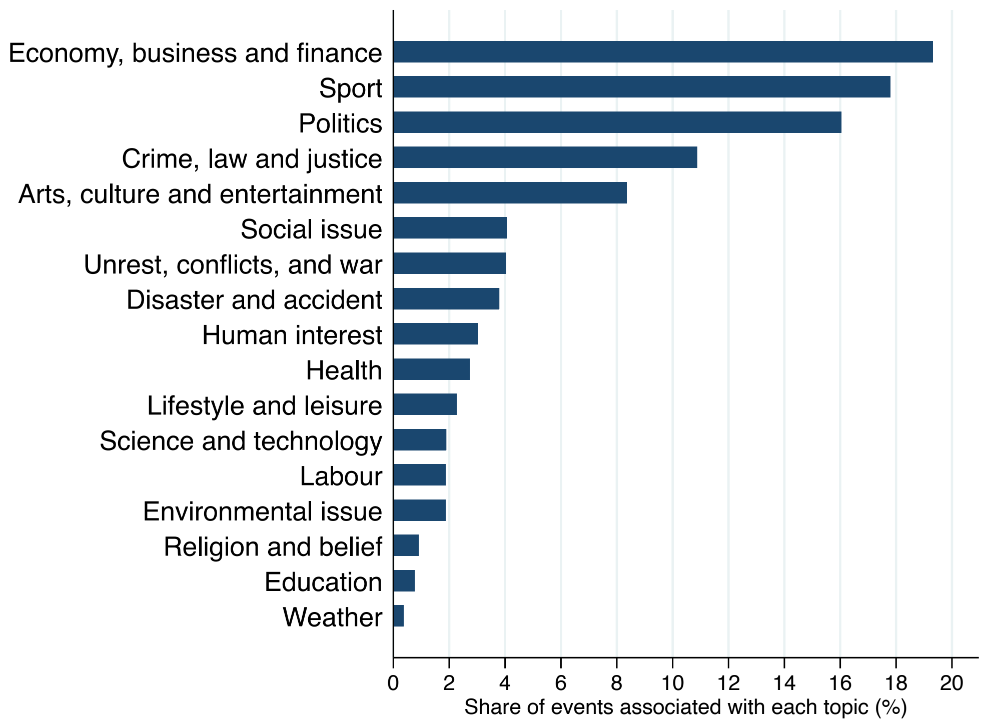
There are several reasons why an event may appear on Twitter first, before being covered by mainstream media. First, an event may be described by a media outlet outside of our corpus, such as an English-language news agency, then be picked up by Twitter users before being relayed by the French media. Second, some Twitter users can witness a “real world" event and film it or talk about it on social networks. This was the case with “the battle of Orly airport", when French rappers Booba and Kaaris got into a fight inside a duty-free store in 2018. Third, some events may originate solely on Twitter, such as the accusations that certain French Youtube influencers had raped minors. These allegations spread in August 2018 with the hashtag #BalanceTonYoutubeur.

5.3.4 Measures of popularity on Twitter and of media coverage

To proxy the popularity of an event on Twitter, we rely on the activity on Twitter and count, in each event, the total number of tweets and the total number of unique users who tweet about the event. For the tweets, we distinguish between the original tweets and the retweets and replies. Furthermore, we compute the average number of followers of the news breaker or seed of the event.

Importantly, to isolate the specific impact of the popularity of a Twitter event e_T on mainstream media

Press Telecommunications Council). An event can be associated with more than one top-level media topic.



Notes: The figure shows the share of joint events associated with each media topic. The topics correspond to the IPTC media topics described in the text. Because some events are associated with more than one topic, the sum of the shares is higher than 100%.

Figure 5.3: Share of the joint events associated with each media topic

coverage we focus on what happens on social media *before* the publication of the first news article; to do so, we compute similar measures but focus only on Twitter activity before the first mainstream media article appears. In the IV strategy described below (Section 5.4.2), to instrument for this popularity, we also compute the average number of interactions generated by the seed's previous tweets, as well as the interactions generated by the tweets of the seeds' followers.[20]

To study the intensity of mainstream media coverage, we look at different dimensions. We use quantitative measures of coverage, in particular the number of articles a given media outlet devotes to the event, as well as the length of these articles. Studying both the intensive and the extensive margin of coverage is of particular importance here given that some media outlets can choose to skip some events while others may decide to follow a more systematic approach. This may depend on the characteristics of the media outlet, but also on the topic of the event.

5.4 Popularity on social media and news editor decisions: Empirical strategy

In the remainder of the paper, we tackle the following question: does the popularity of a story on social media affect, everything else equal, the coverage that mainstream media devote to this story? While the drivers of news editors' decisions remain essentially a black box, understanding the role played by social media in these decisions is of particular importance. In this Section, we present the empirical strategy we develop to tackle this question; the empirical results are presented in the following Section 5.5.

5.4.1 Naive approach

We begin by estimating the correlation between an event popularity on Twitter and its mainstream media coverage. We do so both at the event level and the media level.

Event-level approach At the event-level, we perform the following estimation:

$$\texttt{coverage}_e = \alpha + \mathbf{Z_e'}\beta + \lambda_d + \omega_m + \epsilon_{emd} \tag{5.1}$$

where e index the events, d the day-of-the-week (DoW) of the first tweet in the event, and m the month.

[20] To compute this number of interactions, we also include in our dataset of tweets the period between June 15th 2018 and June 30th 2018. We do so to ensure that we observe at least some tweets before the first event.

Our dependent variable of interest, $\texttt{coverage}_e$, is the intensity of the media coverage that we proxy at the event level by the total number of articles devoted to the event and the number of different media outlets covering the event. Our main explanatory variable, $\mathbf{Z}'_\mathbf{e}$, is a vector that captures the popularity of the event on Twitter *before* the publication of the first article. This vector includes alternatively the total number of tweets in the event and the number of original tweets, retweets and replies. We always control for the seed's number of followers (at the time of the event). We also control for day-of-the-week fixed effects (λ_d) and month fixed effects (ω_m). Given that the dependent variable is a count variable, we use a negative binomial to estimate equation (5.1).

Media-level approach Bias in editorial decisions may vary depending on the characteristics of the media outlet. Furthermore, some media outlets may decide to cover a news event while others do not. To investigate whether this is the case, we then exploit within media outlet variations (in this case, the standard errors are clustered at the event level). Our specification is as follows:

$$\texttt{coverage}_{ec} = \alpha + \mathbf{Z}'_\mathbf{e}\beta + \delta_c + \lambda_d + \omega_m + \epsilon_{ecmd} \tag{5.2}$$

where c index the media outlets and the dependent variable, $\texttt{coverage}_{ec}$, is now alternatively the number of articles published by media c in event e, a binary variable equal to one if the media devotes at least one article to the event and, conditional on covering the event, the average length of media articles. $\mathbf{Z}'_\mathbf{e}$ is the same vector as in equation (5.1) and measures the popularity of the event on Twitter. δ_c, λ_d and ω_m are respectively fixed effects for media, day-of-the-week and month.

5.4.2 IV approach

While estimating equations (5.1) and (5.2) allows us to analyze the relationship between the popularity of a story on Twitter and its coverage on mainstream media, the estimated relationship may be (at least partly) driven by the unobserved characteristics of the story, e.g. its "newsworthiness". Randomizing story popularity on Twitter is not feasible. To identify the causal effect of a popularity shock on Twitter, we thus need to find and exploit exogenous sources of variation in popularity. In this article, we propose a new IV strategy that relies on the structure of the Twitter network interacted with "news pressure" at the time of the event.

In exploiting the structure of the Twitter network, the intention of our identification strategy approach is to mimic a hypothetical experiment that would break the correlation between popularity and unobserved determinants of the story's intrinsic interest. Our source of exogenous variation, in the spirit of an intention-to-treat approach, comes from the number of "impressions" generated by the previous tweets (i.e. before the beginning of the event) of the seed's followers, in the spirit of Figure 5.1 presented in the introduction. The idea is to say that, for two "similar" seeds as defined by their number of followers, everything else equal, the tweets of the seed whose followers themselves have a high number of followers will generate more impressions – and so have a higher probability of being retweeted – than the same tweets by the seed whose followers have just a few followers. Indeed, everything else equal and regardless of the interest of a given tweet, the higher the number of impressions, the higher the potential number of retweets. However, the number of interactions generated by the seeds' followers may suffer from the fact that a seed's centrality in the Twitter network may be related to it's ability to produce newsworthy content.

Hence, our instrument is the interaction between the seed's centrality in the network and the news pressure at the time of the tweet, controlling for the direct effect of centrality and news pressure. We measure news pressure by the number of interactions generated by all the tweets published in the hour preceding the first tweet in the event. The idea, in the spirit of Eisensee and Strömberg [2007], is that, if at the time of the first tweet in the event there are some very popular tweets, then those tweets generate a crowding-out effect: given that they receive a high number of retweets/replies/quotes, they "overfill" the Twitter feed and make the first tweet in the event less visible, regardless of its newsworthiness. In other words, if two equally newsworthy stories are covered on Twitter, we would expect that the story occurring when there is a high number of other stories around would have a lower chance of receiving a large number of retweets than the story occurring when there is little activity on Twitter. We measure the total number of retweets rather than the total number of tweets, because the Twitter API may restrict the number of delivered tweets if it exceeds the threshold of 1% of the global volume. The number of retweets, on the other hand, is known at any time because it is a metadata provided with each collected tweet. Appendix Figure A.7 illustrates our IV strategy: for each minute, we compute the average number of retweets generated by the tweets published during the previous hour.

News pressure alone cannot be a reliable instrument, however: it can indeed affect both Twitter and the media at the same time. This is why our instrument is the interaction between news pressure and centrality in the network as previously defined. Our identification assumption is that, once we control for the direct effects of centrality and news pressure, the interaction between the seed's centrality and news pressure should only affect traditional news production through its effect on the tweet's visibility on Twitter.

This is conditional on controlling for the seed's number of followers, and, we also make sure that our results are robust to dropping the events whose seed is the Twitter account of a media outlet or journalist and/or whose seed is a multiple news breaker, to avoid capturing a celebrity or influencer bias.

Formally, given both our dependent variable (the number of articles) and our main (endogenous) explanatory variable (the number of tweets) are count variable, we rely on Wooldridge [2002, 2013]'s control functions approach. Our first stage and reduced-form specifications, respectively, are (for the event-level approach):

$$\text{number of tweets}_e = \beta_1 \text{interactions}_e \times \text{news pressure}_e + \beta_2 \text{interactions}_e + \beta_3 \text{news pressure}_e + \mathbf{X_e'}\gamma + \lambda_d + \omega_m + \epsilon_{emd} \quad (5.3)$$

$$\text{number of articles}_e = \beta_1 \text{interactions}_e \times \text{news pressure}_e + \beta_2 \text{interactions}_e + \beta_3 \text{news pressure}_e + \mathbf{X_e'}\gamma + \lambda_d + \omega_m + \epsilon_{emd} \quad (5.4)$$

where, in the first stage, number of tweets$_e$ is as before the total number of tweets published in the event e before the publication of the first media article. The instrument interactions$_e \times$ news pressure$_e$ is relevant if $\beta_1 > 0$.

To obtain the second-stage estimates, we follow a two-step procedure. First, we estimate equation (5.3) using a negative binomial and obtain the reduced form residuals $\widehat{\epsilon_{emd}}$. Then, we estimate the following model:

$$\text{number of articles}_e = \zeta_1 \text{number of tweets}_e + \zeta_2 \text{interactions}_e + \zeta_3 \text{news pressure}_e + \zeta_4 \widehat{\epsilon_{emd}} + \mathbf{X_e'}\eta + \lambda_d + \omega_m + \varepsilon_{emd} \quad (5.5)$$

with bootstrapped standard errors. Besides, for robustness, we show that our results are robust to rather using a Generalized Method of Moments estimator of Poisson regression and instrumenting our endogenous variable number of tweets$_e$ by the excluded instrument interactions$_e \times$ news pressure$_e$ [Nichols, 2007].

5.5 Popularity on social media and news editor decisions: Results

In this section, we first present the results of the naive estimations (without instrumenting for event popularity). We then turn to the IV analysis before discussing the heterogeneity of the effects. Each time, we first present the estimates we obtain when performing the analysis at the event level, before turning to the media-level estimations.

5.5.1 Naive estimates

Event-level analysis Table 5.6 reports the results of the estimation of equation (5.1) (event-level analysis). In Columns (1) and (2) the outcome of interest is the total number of articles published in the event, and in Columns (3) and (4) the number of unique media outlets which cover the event. As highlighted above, given that these dependent variables are count variables, we use a negative binomial. We find a positive correlation between the number of tweets published in an event before the first news article ("number of tweets") and the total number of articles published in the event: an increase of $1,000$ in the number of tweets published in the event before the first media article is associated with 3.2 additional articles (Column (1)); this finding is robust to dropping the events whose seed is the Twitter account of a media outlet or journalist and the events whose seed is the Twitter account of a multiple news breaker (as defined above) (Column (2)).

The positive relationship between the popularity of the event on Twitter and the media coverage is driven both by the intensity of the coverage (number of articles) and by the extensive margin: we also find a positive relationship with the number of unique media outlets covering the event (Columns (3) and (4)). An increase of 1,000 in the number of original tweets published in the event before the first media article is associated with an increase of 0.4 in the number of media outlets dealing with the event.

In Table 5.7, we show that the magnitude of this relationship varies with the topic of the event (as defined using the IPTC classes provided by the AFP). In particular, we find that the magnitude of the effect is the strongest for sport and politics, while it is relatively less important for events related to economy as well as culture.

Table 5.6: Naive estimates: Event-level approach

	Number of articles		Number of media	
	(1)	(2)	(3)	(4)
main				
Number of tweets	0.057***	0.057***	0.022***	0.022***
	(0.015)	(0.015)	(0.005)	(0.005)
Seed's number of followers	-0.011	-0.012	-0.011***	-0.011***
	(0.011)	(0.011)	(0.004)	(0.004)
Month & DoW FEs	✓	✓	✓	✓
Drop media		✓	✓	✓
Drop multiple		✓	✓	✓
Observations	4,392	4,313	4,392	4,313
Marginal Effect (tweets)	3.2	3.2	0.4	0.4

Notes: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. The time period is July 2018 - September 2018. Models are estimated using a negative binomial estimation (robust standard errors are reported between parentheses). An observation is a news event. We only consider the subset of news events that appear first on Twitter. All specifications include the seed's number of followers as a control, and day-of-the-week and month fixed effects. Columns (1) and (3) report the estimates for all the events that appear first on Twitter; in Columns (2) and (4) we drop the events whose seed is the Twitter account of a media outlet or journalist ("media") as well as the events whose seed broke more than one event during our time period ("multiple"). The number of tweets is computed *before* the first news article in the event and is given in thousands. More details are provided in the text.

Table 5.7: Naive estimates: Event-level approach, Depending on the topic of the event

	Economy	Sport	Politics	Crime	Culture
	(1)	(2)	(3)	(4)	(5)
Number of news articles in the event					
Number of tweets	0.055	0.103***	0.116***	0.086**	0.006
	(0.042)	(0.023)	(0.038)	(0.044)	(0.015)
Seed's number of followers	-0.029	-0.043*	0.005	-0.014	-0.072**
	(0.024)	(0.023)	(0.023)	(0.030)	(0.036)
Month & DoW FEs	✓	✓	✓	✓	✓
Drop media	✓	✓	✓	✓	✓
Drop multiple	✓	✓	✓	✓	✓
Observations	682	656	572	334	281
Marginal Effect (tweets)	2.7	7.0	8.6	4.7	0.3

Notes: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. The time period is July 2018 - September 2018. Models are estimated using a negative binomial estimation (robust standard errors are reported between parentheses). An observation is a news event. We only consider the subset of news events that appear first on Twitter, and we drop the events whose seed is the Twitter account of a media outlet or journalist ("media") as well as the events whose seed broke more than one event during our time period ("multiple"). All specifications include the seed's number of followers as a control, and day-of-the-week and month fixed effects. The number of tweets is computed *before* the first news article in the event and is given in thousands. More details are provided in the text.

Table 5.8: Naive estimates: Media-level approach

	Number of articles		=1 if at least one article	
	(1)	(2)	(3)	(4)
main				
Number of tweets	0.047***	0.047***	0.015***	0.015***
	(0.011)	(0.011)	(0.003)	(0.003)
Seed's number of followers	-0.016	-0.017	-0.009***	-0.009***
	(0.011)	(0.011)	(0.003)	(0.003)
Media FEs	✓	✓	✓	✓
Month & DoW FEs	✓	✓	✓	✓
Drop media		✓		✓
Drop multiple		✓		✓
Model	Neg bin	Neg bin	Probit	Probit
Observations	839,063	823,974	839,063	823,974
Clusters (events)	4,393	4,314	4,393	4,314
Marginal Effect	0.013	0.013	0.002	0.002

Notes: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. The time period is July 2018 - September 2018. Models are estimated using a negative binomial estimation in Columns (1) and (2) and a Probit in Columns (3) and (4). Standard errors are clustered at the event level. An observation is a media-news event. We only consider the subset of news events that appear first on Twitter. All specifications include the seed's number of followers as a control, and day-of-the-week, month, and media fixed effects. Columns (1) and (3) report the estimates for all the events that appear first on Twitter; in Columns (2) and(4) we drop the events whose seed is the Twitter account of a media outlet or journalist ("media") as well as the events whose seed broke more than one event during our time period ("multiple"). In Columns (1) and (2), the dependent variable is the number of articles published by the media in the event. In Columns (3) and (4) the dependent variable is an indicator variable equal to one if the media outlet publishes at least one article in the event and to zero otherwise. The number of tweets is computed *before* the first news article in the event appears and is given in thousands. More details are provided in the text.

Media-level analysis Table 5.8 shows the estimates when we perform the media-level analysis (estimation of equation (5.2)). The unit of observation is a media-event, and all the media outlets are included in the estimation (even if they do not cover the event; then the value of the number of articles in the event for them is equal to zero). Consistently with the results of Table 5.6, we find a positive relationship between the popularity of the event on Twitter and the media coverage it receives (Column (1)), and this relationship is robust to dropping the events whose seed is the Twitter account of a media / journalist / multiple news breaker (Column (2)). An increase of $1,000$ in the number of tweets published in the event before the first media article appears increases the average number of articles that *each media outlet* publishes in the event by 0.013.

In Columns (3) and (4), our dependent variable is an indicator variable equal to one if the media outlet publishes at least one article in the event (we use a Probit model to perform the estimation). We find that the probability that a media covers the event is also positively associated with the number of tweets in the event before the first media article.

Next, we focus on the media outlets that devote at least one article to the event and investigate the

Table 5.9: Naive estimates: Media-level approach, Conditional on covering the event

	Number of articles		Articles length	
	(1)	(2)	(3)	(4)
main				
Number of tweets	0.02^{***}	0.02^{***}	1.17	1.52
	(0.01)	(0.01)	(2.55)	(2.61)
Seed's number of followers	-0.00	-0.00	3.51	2.84
	(0.01)	(0.01)	(4.12)	(4.17)
Media FEs	✓	✓	✓	✓
Month & DoW FEs	✓	✓	✓	✓
Drop media		✓		✓
Drop multiple		✓		✓
Model	Neg bin	Neg bin	Linear	Linear
Observations	76,703	75,256	76,694	75,246
Clusters (events)	4,393	4,314	4,393	4,314
Marginal Effect	0.06	0.05		

Notes: * p<0.10, ** p<0.05, *** p<0.01. The time period is July 2018 - September 2018. Models are estimated using a negative binomial estimation in Columns (1) and (2), and OLS in Columns (3) to (4). Standard errors are clustered at the event level. An observation is a media-news event, and only the media outlets that devote at least one article to the event are included. Further, we only consider the subset of news events that appear first on Twitter. All specifications include the seed's number of followers as a control, and day-of-the-week, month, and media fixed effects. Columns (1) and (3) report the estimates for all the events that appear first on Twitter; in Columns (2) and (4) we drop the events whose seed is the Twitter account of a media outlet or journalist (“media") as well as the events whose seed broke more than one event during our time period (“multiple"). In Columns (1) and (2), the dependent variable is the number of articles published by the media outlet; in Columns (3) and (4) the average length of these articles. The number of tweets is computed *before* the first news article in the event apears and is given in thousands. More details are provided in the text.

magnitude of the coverage, *conditional on covering* the event. Indeed, the popularity of an event on Twitter can play a role both at the intensive and at the extensive margin. Table 5.9 presents the results. Columns (1) and (2) present the estimations for the number of articles published by the media in the event: we see that the positive impact of popularity appears not only at the extensive margin but also at the intensive margin; there is a positive correlation with the number of articles published (conditional on publishing at least one article in the event). An increase of $1,000$ in the number of tweets is associated with an increase of 0.06 in the number of articles published by each media outlet. However, there is no statistically significant relationship with the length of the article(s) published by the media (Columns (3) and (4)). The length of the articles can be considered a proxy – albeit an imperfect one – for the quality of the articles. We will come back to this point in the mechanisms section below.

Finally, we investigate whether our results vary depending on the offline format of the media outlets we consider. Table 5.10 reports the estimates separately for the national daily newspapers, the local daily newspapers, the weeklies, the pure online media, the websites of the television channels and the websites of the radio stations. First, it is interesting to note that the estimates we obtain are positive and statistically

Table 5.10: Naive estimates: Media-level approach, Depending on the media offline format

	Nat. dail.	Local dail.	Weeklies	Pure online	TV	Radio
	(1)	(2)	(3)	(4)	(5)	(6)
Number of articles						
Number of tweets	0.043***	0.042***	0.048***	0.058***	0.094***	0.041***
	(0.013)	(0.013)	(0.011)	(0.013)	(0.024)	(0.012)
Seed's number of followers	-0.007	-0.019	-0.016	-0.030**	-0.012	-0.007
	(0.011)	(0.015)	(0.011)	(0.013)	(0.013)	(0.012)
Media FEs	✓	✓	✓	✓	✓	✓
Month & DoW FEs	✓	✓	✓	✓	✓	✓
Drop media	✓	✓	✓	✓	✓	✓
Drop multiple	✓	✓	✓	✓	✓	✓
Observations	47,454	120,792	155,304	280,410	30,198	47,454
Clusters (events)	4,314	4,314	4,314	4,314	4,314	4,314
Marginal Effect	0.028	0.016	0.012	0.005	0.107	0.017

Notes: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. The time period is July 2018 - September 2018. Models are estimated using a negative binomial estimation. Standard errors are clustered at the event level. An observation is a media-news event. We only consider the subset of news events that appear first on Twitter, and drop the events whose seed is the Twitter account of a media outlet or journalist ("media") as well as the events whose seed broke more than one event during our time period ("multiple"). All specifications include the seed's number of followers as a control, and day-of-the-week, month, and media fixed effects. In Column (1), we only consider the national daily newspapers, in Column (2) the local daily newspapers, in Column (3) the weekly newspapers, in Column (4) the pure online media, in Column (5) the television channel websites, and in Column (6) the radio station websites. The number of tweets is computed *before* the first news article in the event appears and is given in thousands. More details are provided in the text.

significant for all the offline formats, despite the lower number of observations.

Second, if we turn to the marginal effects, we find that the relationship between the popularity of an event on Twitter and the media coverage it receives is the strongest for the websites of the television stations, followed by the national daily newspapers. Perhaps surprisingly, the magnitude of the correlation is not higher for the pure online media than for the other media outlets. Yet, we will see below that the intensity of the *social media presence* is an important factor explaining why some media outlets react more to what is happening on Twitter than others.

5.5.2 IV estimates

The previous estimates may suffer from the fact that the positive relationship between a story's popularity on Twitter and its media coverage can both be driven by the intrinsic interest of the story, regardless of what happens on social media. Hence, in this section, we report the results of the IV estimates following the strategy described in Section 5.4.2 above. As before, we first report the results of the estimations we obtain at the event level, before turning to the media-level approach.

Event-level approach In Table 5.11, we begin by reporting the results of the reduced-form estimation (equation 5.4) in Columns (1) and (2). The coefficient we obtain for our instrument is positive and statistically significant: the number of previous interactions of the tweets of the seed's followers is positively associated with the number of articles published in the event when the news pressure is low. In Columns (3) to (6), we turn to our two-step procedure. In the first stage, we obtain as expected a positive relationship between the number of tweets in the event (before the first media article appears) and the previous interactions of the tweets of the seed's followers when news pressure is low (Columns (3) and (4)). Columns (5) and (6) show that the findings of Table 5.6 are robust to controlling for the endogeneity of the number of tweets.

Given that the control function method suffers from some drawbacks, we then show that our results are robust to estimating a Poisson regression model with endogenous regressors using generalized method of moments (GMM), following Windmeijer and Silva [1997].[21] Table 5.12 reports the results. In Columns (1) and (2), our endogenous explanatory variable, instrumented as before by interactions$_e$ $\times$ news pressure$_e$, is the total number of tweets in the event before the first media article, and our dependent variable the number of articles published in the event. An increase of $1,000$ in this number is associated with an increase of 2 in the number of news articles published in the event. As expected given the direction of the omitted variable bias, the magnitude of the IV effects is smaller than the one of the naive estimates (increase of 3.2 reported in Table 5.6).

We also find that the increase in the number of media outlets covering the event is robust to instrumenting the number of tweets, but also of smaller magnitude (Columns (3) and (4)). According to our estimates, an increase of $1,000$ in the number of tweets before the publication of the first media article is associated with an increase of 0.37 - 0.38 in the number of outlets covering the event.

Media-level approach We next turn to the media-level estimates. Table 5.13 reports the results of the estimation when we use the Control Function method. As before, in Columns (1) and (2) we report the results of the reduced-form estimation: consistently with the results we obtain when performing the event-level analysis, we find that our instrument is positively associated with the number of articles published by each of the media outlets in the event (controlling for media fixed effects, month fixed effects, and day-of-the-week fixed effects, with standard errors clustered at the level of the events). The estimated coefficients are statistically significant at the five-percent level.

[21] We use the Stata's ivpoisson command.

Table 5.11: IV estimates: Event-level approach, Control Function method

	Reduced form		First stage		Second stage	
	(1) Nb articles	(2) Nb articles	(3) Nb tweets	(4) Nb tweets	(5) Nb articles	(6) Nb articles
main						
Instrument						
Low*Interactions	0.03*	0.04**	0.14***	0.14***		
	(0.02)	(0.02)	(0.05)	(0.05)		
Controls						
Low	0.18**	0.17**	0.17	0.17	0.17**	0.17**
	(0.09)	(0.09)	(0.21)	(0.21)	(0.08)	(0.08)
Interactions	-0.03***	-0.03***	-0.02	-0.03	-0.02	-0.02
	(0.01)	(0.01)	(0.03)	(0.03)	(0.01)	(0.01)
Seed's followers	-0.01	-0.00	-0.04	-0.04	-0.00	-0.00
	(0.01)	(0.01)	(0.04)	(0.04)	(0.01)	(0.02)
Residuals (1st stage)					0.02	0.02
					(0.08)	(0.10)
Second stage						
Number of tweets					0.06***	0.06***
					(0.02)	(0.02)
Month & DoW FEs	✓	✓	✓	✓	✓	✓
Drop media		✓		✓		✓
Drop multiple		✓		✓		✓
Standard errors	Robust	Robust	Robust	Robust	Bootstrap	Bootstrap
Observations	3,435	3,374	3,435	3,374	3,435	3,374
Marginal effect (tweets)					3.3	3.3

Notes: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. The time period is July 2018 - September 2018. An observation is a news event. Robust standard errors are reported between parentheses in Columns (1) to (4). In Columns (5) and (6) we report bootstrapped standard errors. All specifications include the seed's number of followers as a control, and day-of-the-week and month fixed effects. Columns (1) and (2) report the results of the reduced form estimation (the dependent variable is the number of articles), Columns (3) and (4) of the first stage (the dependent variable is the number of tweets), and Columns (5) and (6) of the second stage (the dependent variable is the number of articles). In Columns (2), (4) and (6) we drop the events whose seed is the Twitter account of a media outlet or journalist ("media") as well as the events whose seed broke more than one event during our time period ("multiple"). The number of tweets is computed *before* the first news article in the event appears and is given in thousands. More details are provided in the text.

Table 5.12: IV estimates: Event-level approach, IV Poisson GMM

	Number of articles		Number of media	
	(1)	(2)	(3)	(4)
main				
Number of tweets	0.040***	0.041***	0.022**	0.022**
	(0.010)	(0.010)	(0.009)	(0.009)
Low	0.171*	0.164*	0.087***	0.083***
	(0.091)	(0.092)	(0.030)	(0.031)
Interactions	-0.037**	-0.038**	0.003	0.003
	(0.017)	(0.017)	(0.005)	(0.005)
Seed's followers	0.003	0.005	-0.009*	-0.009*
	(0.017)	(0.017)	(0.005)	(0.005)
Month & DoW FEs	✓	✓	✓	✓
Drop media		✓		✓
Drop multiple		✓		✓
Observations	3,435	3,374	3,435	3,374
Marginal Effect (tweets)	2.03	2.06	0.37	0.38

Notes: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. The time period is July 2018 - September 2018. Models are estimated using a a generalized method of moments (GMM) Poisson regression model with endogenous regressors (Stata's ivpoisson command). An observation is a news event. Robust standard errors are reported between parentheses. All specifications include the seed's number of followers as a control, and day-of-the-week and month fixed effects. In Columns (1) and (2), the dependent variable is the number of articles published in the event. In Columns (3) and (4), the dependent variable in the number of different media outlets covering the event. In Columns (2) and (4) we drop the events whose seed is the Twitter account of a media outlet or journalist ("media") as well as the events whose seed broke more than one event during our time period ("multiple"). The number of tweets is computed *before* the first news article in the event appears and is given in thousands. More details are provided in the text.

Columns (3) and (4) report the first-stage estimates of our two-step procedures, and Columns (5) and (6) the second-stage results. In the first stage, we show that the number of tweets in the event increases with the number of interactions of the previous tweets of the seed's followers when the news pressure is low. In the second stage, we find a positive and statistically significant effect of the popularity of the event on Twitter on the media coverage; the effect is of the same order of magnitude than the one we obtain with the naive estimates, and is robust to dropping the events whose seed is the Twitter account of a media outlet / journalist / multiple news breaker (as previously defined).

We then show that our results are robust to rather estimating a Poisson regression model with endogenous regressors. Table 5.14 presents the results. We estimate the effect separately for each offline media category (as in Table 5.10). We find that the positive relationship between popularity on Twitter and media coverage holds for all the offline types, expect radio stations, but this might be due to the relatively lower number of observations. The magnitude of the effect is the strongest for national daily newspapers and for the websites of the television stations.

Finally, in Table 5.15, we focus on the media outlets that devote at least one article to the event and investigate the magnitude of the coverage, conditional on covering the event. Consistently with the previous results, we show that our effects are robust to instrumenting for the popularity of events on Twitter, and that the magnitude of the IV estimates is slightly lower than the one of the naive estimates. If we consider the national daily newspapers, we find that an increase of $1,000$ in the number of tweets is associated with an increase of 0.055 in the number of articles published in the event by the newspapers that devote at least one article to the event. Furthermore, we find no effect on the length of the articles published by the media outlets.

5.6 Mechanisms

In the previous section, we have documented a positive relationship between the popularity of an event on Twitter and the coverage it receives on mainstream media. In this section, we discuss the different mechanisms at play behind this relationship.

5.6.1 Journalists monitor Twitter

A growing literature in journalism studies highlights the fact that social media play an important role as a news source. For example, von Nordheim et al. [2018] examine the use of Facebook and Twitter as

Table 5.13: IV estimates: Media-level approach, Control Function method

	Reduced form		First stage		Second stage	
	(1) Nb articles	(2) Nb articles	(3) Nb tweets	(4) Nb tweets	(5) Nb articles	(6) Nb articles
main						
Instrument						
Low*Interactions	0.044**	0.045**	0.142***	0.139***		
	(0.021)	(0.021)	(0.046)	(0.047)		
Controls						
Low	0.144*	0.137*	0.169	0.164	0.136*	0.129
	(0.081)	(0.082)	(0.207)	(0.208)	(0.082)	(0.082)
Interactions	-0.025**	-0.026***	-0.025	-0.026	-0.018	-0.018
	(0.010)	(0.010)	(0.030)	(0.031)	(0.012)	(0.012)
Seed's followers	-0.009	-0.007	-0.037	-0.036	-0.005	-0.003
	(0.014)	(0.014)	(0.039)	(0.040)	(0.014)	(0.015)
Residuals (1st stage)					0.051	0.054
					(0.111)	(0.120)
Second stage						
Number of tweets					0.051***	0.051***
					(0.012)	(0.012)
Media FEs	✓	✓			✓	✓
Month & DoW FEs	✓	✓	✓	✓	✓	✓
Drop media		✓		✓		✓
Drop multiple		✓		✓		✓
Observations	656,085	644,434	656,085	644,434	656,085	644,434
Clusters (events)	3,435	3,374	3,435	3,374	3,435	3,374
Marginal effect (tweets)					0.014	0.014

Notes: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. The time period is July 2018 - September 2018. An observation is a media-news event. Standard errors are clustered at the event level. All specifications include the seed's number of followers as a control, and day-of-the-week, month, and media fixed effects. Columns (1) and (2) report the results of the reduced form estimation (the dependent variable is the number of articles), Columns (3) and (4) of the first stage (the dependent variable is the number of tweets), and Columns (5) and (6) of the second stage (the dependent variable is the number of articles). In Columns (2), (4) and (6) we drop the events whose seed is the Twitter account of a media outlet or journalist ("media") as well as the events whose seed broke more than one event during our time period ("multiple"). The number of tweets is computed *before* the first news article in the event appears and is given in thousands. More details are provided in the text.

Table 5.14: IV estimates: Media-level approach, IV Poisson GMM, Depending on the offline format

	Nat. dail.	Local dail.	Weeklies	Pure online	TV	Radio
	(1)	(2)	(3)	(4)	(5)	(6)
Number of articles						
Number of tweets	0.04***	0.03***	0.05***	0.07***	0.04***	-0.44
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(6.12)
Low	0.13	0.20**	0.14	-0.06	0.09	0.30**
	(0.10)	(0.09)	(0.10)	(0.12)	(0.11)	(0.14)
Interactions	-0.03*	-0.02	-0.05**	-0.10**	-0.02	-0.00
	(0.02)	(0.02)	(0.02)	(0.05)	(0.01)	(0.01)
Seed's followers	0.00	0.00	0.01	0.00	0.00	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Media FEs	✓	✓	✓	✓	✓	✓
Month & DoW FEs	✓	✓	✓	✓	✓	✓
Drop media	✓	✓	✓	✓	✓	✓
Drop multiple	✓	✓	✓	✓	✓	✓
Observations	37,114	94,472	121,464	219,310	23,618	37,114
Clusters (events)	3,374	3,374	3,374	3,374	3,374	3,374
Marginal effect (tweets)	0.022	0.011	0.011	0.005	0.016	-0.184

Notes: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. The time period is July 2018 - September 2018. Models are estimated using a a generalized method of moments (GMM) Poisson regression model with endogenous regressors (Stata's ivpoisson command). An observation is a media-news event. We drop the events whose seed is the Twitter account of a media outlet or journalist ("media") as well as the events whose seed broke more than one event during our time period ("multiple"). Standard errors are clustered at the event level. All specifications include the seed's number of followers as a control, and day-of-the-week, month, and media fixed effects. In Column (1), we only consider the national daily newspapers, in Column (2) the local daily newspapers, in Column (3) the weekly newspapers, in Column (4) the pure online media, in Column (5) the television channel websites, and in Column (6) the radio station websites. The number of tweets is computed *before* the first news article in the event appears and is given in thousands. More details are provided in the text.

Table 5.15: IV estimates: Media-level approach, IV Poisson GMM, Conditional on covering the event

	National daily newspapers				Television			
	(1) Nb articles	(2) Nb articles	(3) Length	(4) Length	(5) Nb articles	(6) Nb articles	(7) Length	(8) Length
main								
Number of tweets	0.02***	0.02***	-0.00	-0.00	0.03***	0.03***	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Low	0.07	0.07	0.02	0.02	-0.00	-0.01	0.02	0.02
	(0.08)	(0.08)	(0.02)	(0.02)	(0.09)	(0.09)	(0.02)	(0.02)
Interactions	-0.03***	-0.03***	0.00	0.00	-0.04***	-0.05***	-0.00	-0.00
	(0.01)	(0.01)	(0.00)	(0.00)	(0.02)	(0.02)	(0.01)	(0.01)
Seed's followers	0.01	0.01	-0.00	-0.00	0.02	0.02	0.00	0.00
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.02)	(0.00)	(0.00)
Media FEs	✓	✓	✓	✓	✓	✓	✓	✓
Month & DoW FEs	✓	✓	✓	✓	✓	✓	✓	✓
Drop media		✓		✓		✓		✓
Drop multiple		✓		✓		✓		✓
Observations	8,377	8,229	8,377	8,229	3,885	3,808	3,885	3,808
Clusters (events)	3,178	3,118	3,178	3,118	2,200	2,156	2,200	2,156
Marginal effect (tweets)	0.055	0.058			0.071	0.073		

Notes: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. The time period is July 2018 - September 2018. Models are estimated using a a generalized method of moments (GMM) Poisson regression model with endogenous regressors (Stata's ivpoisson command). An observation is a media-news event, and only the media outlets that devote at least one article to the event are included. Furthermore, we only consider the subset of news events that appear first on Twitter. Standard errors are clustered at the event level. All specifications include the seed's number of followers as a control, and day-of-the-week, month, and media fixed effects. Columns (1) to (4) report the results for the national daily newspapers, and Columns (5) to (8) for television channel websites. In even columns, we drop the events whose seed is the Twitter account of a media or journalist ("media") as well as the events whose seed broke more than one event during our time period ("multiple"). The number of tweets is computed *before* the first news article in the event appears and is given in thousands. More details are provided in the text.

journalistic sources in newspapers of three countries; they show that Twitter is more commonly used as a news source than Facebook.[22] Furthermore, McGregor and Molyneux [2018], who have conducted an online survey experiment on working U.S. journalists, show that journalists using Twitter as part of their daily work consider tweets to be as newsworthy as headlines from the Associated Press.

The use of Twitter crosses many dimensions of sourcing, information-gathering, and production of stories [Wihbey et al., 2019]. Most media organizations actively encourage journalistic activity on social media. Of the $4,222,734$ Twitter accounts for which we have data, 0.12% are the accounts of journalists (see Table 5.2 above); while this might seem low, it is actually rather high compared to the share of the total adult population that journalists represent.

To investigate the role played by monitoring, for all the media organizations included in our sample we compute the list of their journalists present on Twitter and investigate the heterogeneity of the effects depending on this variable. Table 5.16 reports the results of the estimation of the Poisson regression model (Appendix Table A.6 reports the associated naive estimates). We find that the marginal effect is higher for the media that have a high number of journalists with a Twitter account (Columns (4) and (5)) than for those with only a few numbers (Columns (1) and (2)).

However, this finding may be partly driven by the fact that some media simply have *more journalists* than others (independently of the social media presence of these journalists). As highlighted in the data section 5.3.2, for the 68 media outlets for which this information is available, we compute data on the size of their newsroom. In Columns (3) and (6), for this subsample of media outlets, we control for their number of journalists.[23] Doing so does not affect our finding; on the contrary, the marginal effect of the popularity on Twitter becomes even stronger for the media outlets whose journalists are relatively more present on the social network.

Hence, while it cannot entirely explain our findings, the monitoring of Twitter by journalists seems to play a role here. Consistently with this finding, we also show in the Appendix that the magnitude of the effect is stronger for the media that are more present on social media. The intensity of the social media presence is defined with respect to the share of the media outlet's articles that are published on Twitter (Table A.7).

[22] For additional evidence of Twitter as a reporting tool, see Vis [2013].

[23] Note that when we do so, we cannot include media fixed effects given there is no variation, at the media outlet level in the number of journalists.

Table 5.16: IV estimates: Media-level approach, IV Poisson GMM, Depending on the number of journalists with a Twitter account

	Low nb journalists on Twitter			High nb journalists on Twitter		
	(1)	(2)	(3)	(4)	(5)	(6)
Number of articles						
Number of tweets	0.048***	0.048***	0.048***	0.039***	0.039***	0.038***
	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)
Low	0.150	0.141	0.141	0.193**	0.186**	0.188**
	(0.101)	(0.102)	(0.102)	(0.092)	(0.093)	(0.094)
Interactions	-0.042**	-0.044**	-0.044**	-0.034**	-0.035**	-0.034**
	(0.020)	(0.021)	(0.021)	(0.016)	(0.016)	(0.016)
Seed's number of followers	0.002	0.003	0.003	0.005	0.006	0.005
	(0.018)	(0.019)	(0.019)	(0.017)	(0.017)	(0.018)
Number of journalists			0.025***			0.002***
			(0.000)			(0.000)
Media FEs	✓	✓		✓	✓	
Month & DoW FEs	✓	✓	✓	✓	✓	✓
Drop media		✓	✓		✓	✓
Drop multiple		✓	✓		✓	✓
Observations	103,050	101,220	101,220	309,150	303,660	161,952
Clusters (events)	3,435	3,374	3,374	3,435	3,374	3,374
Marginal Effect	0.012	0.013	0.013	0.018	0.018	0.032

Notes: * p<0.10, ** p<0.05, *** p<0.01. The time period is July 2018 - September 2018. Models are estimated using a a generalized method of moments (GMM) Poisson regression model with endogenous regressors (Stata's ivpoisson command). Standard errors are clustered at the event level. An observation is a media-news event. Columns (1) and (4) report the estimates for all the events that appear first on Twitter; in Columns (2), (3), (5) and (6), we drop the events whose seed is the Twitter account of a media outlet or journalist ("media") as well as the events whose seed broke more than one event during our time period ("multiple"). All specifications include the seed's number of followers as a control, and day-of-the-week, month, and media fixed effects. In Columns (3) and (6), we also control for the number of journalists working for the media. In Columns (1) to (3) (respectively (4) to (6), we consider the media with a relatively low (respectively relatively high) number of journalists with a Twitter account. The number of tweets is computed *before* the first news article in the event appears and is given in thousands. More details are provided in the text.

Table 5.17: Naive estimates: Media-level approach, Depending on the reliance on advertising revenues

	No advertising		Advertising	
	(1)	(2)	(3)	(4)
Number of articles				
Number of tweets	0.049***	0.044***	0.048***	0.041***
	(0.010)	(0.011)	(0.009)	(0.007)
Seed's number of followers	0.000*	-0.000**	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Media FEs	✓	✓	✓	✓
Month & DoW FEs	✓	✓	✓	✓
Drop media		✓		✓
Drop multiple		✓		✓
Observations	140,547	104,379	596,260	442,820
Clusters (events)	4,259	3,163	4,259	3,163
Marginal Effect	0.017	0.014	0.011	0.009

Notes: * p<0.10, ** p<0.05, *** p<0.01. The time period is July 2018 - September 2018. Models are estimated using a negative binomial estimation. Standard errors are clustered at the event level. An observation is a media-news event. Columns (1) and (3) report the estimates for all the events that appear first on Twitter; in Columns (2) and (4) we drop the events whose seed is the Twitter account of a media outlet or journalist ("media") as well as the events whose seed broke more than one event during our time period ("multiple"). All specifications include the seed's number of followers as a control, and day-of-the-week, month, and media fixed effects. In Columns (1) and (2) (respectively (3) and (4), we consider the media without online advertising (respectively with advertising revenues). The number of tweets is computed *before* the first news article in the event appears and is given in thousands. More details are provided in the text.

5.6.2 Editorial decisions and popularity

The causal relationship between the popularity of a story on Twitter and its mainstream media coverage can be due to the existence of a clicks bias. This explanation is consistent with the results of Sen and Yildirim [2015] which show, using data from a leading English-language Indian national daily newspaper, that editors' coverage decisions regarding online news stories are influenced by the observed popularity of the story, as measured by the number of clicks received.

In Sen and Yildirim [2015]'s framework (which builds on Latham [2015]), the newspaper cares about the revenue generated by covering a story, which is assumed to be proportional to the number of readers. To test for this hypothesis, we use the fact that our sample of media outlets includes a lot of different media outlets, some of which rely on advertising revenues while others do not. Table 5.17 presents our estimates depending on whether the media rely on advertising revenues (around 80% of the media outlets in our sample do so). The order of magnitude of the estimated effects of popularity on Twitter on media coverage is more or less similar in both cases; if anything, the marginal effects are slightly higher for the media that do not rely on advertising online.

Hence our results do not seem to be driven by short-term considerations generated by advertising revenue-bearing clicks. However, even in the absence of such a consideration, publishers may be willing to cover the stories that resonate the most. In other words, news editors may aim to produce news that consumers are interested in. However, news editors do not know consumers' preferences; hence they can use the popularity of an event on Twitter as a signal that allows them to draw inferences about consumers' preferences.

5.7 Robustness checks and discussion

5.7.1 Robustness

We perform several robustness checks. This section briefly describes them; the detailed results for these tests are available in the Appendix.

French media In this article, we compare the popularity of tweets in French with the coverage that French mainstream media devote to a number of events.[24] However, French is a language not only used in France. Hence, how can we be sure that our tweets in French are twitted by people living in France or consuming French media online?

On Twitter, there are two different ways to identify location: through the location of the user and through the location of the tweet. First, users can indicate their location in their profile ("user-defined location"): nearly two third of the users in our sample do so. While this location is most often a real location (e.g. "Paris, France" or "Val-d'Oise, Ile-de-France"), this is not necessarily the case (e.g. some users indicate "Gotham City" or "Everywhere and nowhere"). We parse this field and, using OpenStreetMap, we obtain coordinates (latitude and longitude) that we attribute to a country. Out of the $2,693,307$ users for which the location field is filled, the information provided allows us to recover the country where the user is located in 72% of the cases. 47% of these users indicate that they are located in France.

Second, users can share their location with Twitter at the time when they tweet. On the one hand, when they decide to assign a location ("place") to their tweet, they are presented with a list of candidate Twitter places. However, out of our $4,222,734$ unique users, only $62,037$ do so for the first of their tweets that we observe. On the other hand, the "place" field is always present when a Tweet is "geo-tagged". However, even fewer users provide their exact location: only $13,382$ (i.e. 0.32%) do so the first time we observe them, and $13,529$ the last time.

[24]We discuss below the issue of the external validity of our results.

While the issue of the location of the users may seem an important one, it is essential to note that this information is also not available to the media; while they may consider the popularity of an event of Twitter at the time of choosing their coverage, and while they can observe whether the users tweet in French or in a different language, journalists cannot (no more than researchers) know where the users tweeting are located. Further, if people do read French – and we can assume here that they do given that they tweet in French –, they can consume French mainstream media even if they are located outside of France. Hence, if what media outlets care about is the number of clicks, they should ignore the location of the users (even if such information may matter for advertisers, depending on where they are located).

With this in mind and as a first robustness check, we re-run our main analysis but only for the media outlets that are located in France (i.e. we drop the content produced by the French-language not-located-in-France media outlets in our sample). Appendix Tables A.8, A.9 and A.10 present the results. Doing so does not affect our main results; if anything, the magnitude of the estimated effects is slightly higher.

Controls In our preferred specification, we only use a reduced set of controls at the event level, including the seed of the event's number of followers. In the Appendix, we show that our results are robust to adding controls; Table A.11 presents the event-level results for the naive estimates and Table A.12 for the Poisson model with endogenous regressors. In both tables, we report in the first columns our preferred specification for the sake of comparison. In Column (2), we control for the time of the day of the first tweet (using an indicator variable in hourly format). Doing so does not affect our main results.

In Column (3), we also control for the reaction time of the first media (i.e. the time interval between the first tweet in the event and the first news article). We do not do so in our preferred specification to avoid a bad controls problem. However, it is interesting to see that even when doing so, we find a positive and statistically significant relationship between the popularity on Twitter and the media coverage. The magnitude of the estimates coefficient is halved however in the naive approach, and also decreases, but to a lower extent, when we estimate the IV Poisson model.

Besides, in Columns (4) and (5), we show that the magnitude of our IV estimates is not affected by the introduction of additional user-level controls: indeed, we find no change in the magnitude of the estimated marginal effects when we introduce in our control set the number of tweets the seed of the event has liked, the number of Twitter accounts she is following, the number of public lists and her total number of tweets (all these characteristics are computed the first time we observe the user in our data).

Sample Finally, we show that our results are robust to changes in our sample of analysis. First, we show that our results are robust to dropping the small events in our sample, i.e. below the 10th percentile in terms of the total number of tweets in the event (Appendix Tables A.13 and A.14). Second, a number of media outlets in our sample produce on average much less articles than others. We verify that our results are robust to dropping the media outlets who produce on average less than one article a day during our period of interest. We find that doing so does not affect our main results, either qualitatively or quantitatively (Appendix Table A.15).

5.7.2 External validity of our results

The results presented in this paper are based on French data and the use of Twitter. Hence, one final question is whether we should expect the patterns we have uncovered in the case of France to be repeated in other contexts and the influence of Twitter to be similar to the one of other social media.

First, it is important to highlight that the choice of France was driven by data considerations. As previously described, the fact of relying on tweets in French language allows us to recover around 70% of all the tweets in French during our period of consideration. This wouldn't have been possible with data from the United States for example, relying on English language. Indeed, given that there is much more activity on Twitter in English than in French, the 1% limitation of the Twitter API makes it impossible to recover a very large (and representative) share of the activity in English.

Should the patterns we obtain with the French data hold in other countries? There are good reasons to think this could be the case. First, while the French media market certainly presents specific features, it is by and large very similar to other Western media markets, whether we consider Internet penetration (87%, like Italy and Spain and only slightly below Belgium – 88% – and Germany – 90%), the use of social media for news (36%, compared to 31% for Germany and 39% for the U.K.), or the proportion of the population who paid for online news (11%, like in Spain, slightly above Germany or Canada – 8% – but below Italy – 12%) [Reuters Institute, 2018]. In France, like in other Western media markets, many publishers offer online news for free and largely rely on advertising. Moreover France, like the U.S., has an international news agency, the AFP, which is the third leading agency in the world after Reuters and Associated Press. From this point of view, the French market is more similar to the U.S. market than the Spanish, Italian, or German markets. Therefore, overall, we believe that the results presented in this paper have implications for other Western countries.

A second concern may come from the fact that we are using Twitter data, while more citizens use Facebook than Twitter. Beforehand, it is important to highlight that Facebook data to a scale similar to what we are using with Twitter is not available to researchers. Besides and more importantly, Twitter is largely used – in particular by journalists – for news. In fact, Twitter is more commonly used as a news source than Facebook [von Nordheim et al., 2018]. Hence, given the focus of this article is on the impact of social media on news production and consequently consumption, it makes more sense to consider Twitter than other social media.

5.8 Conclusion

In this chapter, we focus on an important dimension that has been overlooked in the discussions on the implications of the changes brought by social media: namely how it affects publishers' production and editorial decisions. To do so, we study the effect of the popularity of Twitter events on the coverage of these events by traditional media, independently on their intrinsic interest. We show that an increase of 1000 in the number of tweets inside an event leads to approximately 2 more articles devoted to the story by mainstream media. This effect varies depending on the media offline format (it is stronger for national daily newspapers and TV channel websites) and depending on the topic of events (it is the strongest for sport and politics).

We then discuss the mechanisms that could explain this effect, and show that media outlets in which many journalists have a Twitter account are more likely to cover stories that are popular on Twitter. This effect still holds when controlling for the size of newsrooms. This could reinforce the hypothesis that journalists monitor Twitter to discover potential news stories. However, our second hypothesis – that mainstream media tend to devote more coverage to stories trending on social networks to generate clicks (and therefore advertising revenue) – is not validated by our data: the media that depend on advertising revenues do not seem to be more sensitive to the effect of the popularity of events.

These findings shed a new light on our understanding of how editors decide on the coverage for stories, and have to be taken into account when discussing policy implications of the recent changes in media technologies. In particular, while social media compete with mainstream media for audience attention, they can also be used by journalists as a source of information.

Chapter 6

Conclusion

To conclude this thesis manuscript, we first summarize the work that we have presented, then we put forward some of the research perspectives opened by this work.

6.1 Summary of the thesis

6.1.1 Building a corpus for event detection on Twitter

In Chapter 2, we propose a novel method for collecting random tweets, based on the use of the most frequent words in a given language. We demonstrate that the word distribution of the collected corpus is extremely similar to the word distribution in the sample collected with the Sample API, showing that our method provides a random subset of the entire stream of tweets. Additionally, we show that for a given set of neutral words and a certain number of access tokens to the Twitter API, it is more efficient to group together the terms that frequently co-occurr on the same API key than to randomly distribute words over the API keys.

With our method, we collected around 5 million tweets in French per day from June 2018 to present. Comparing the tweets in our dataset to other corpora collected by French researchers in December 2018, we estimate that we collect between 60% and 75% of all tweets in French sent on Twitter, and between 74% and 78% of all original tweets (i.e. retweets excluded).

Finally, we present an annotated corpus for the task of event detection in tweets, composed of more than 95,000 annotated tweets. This corpus is now publicly available along with the code of our event detection experiments, and should serve as a baseline to test new event detection algorithms. We also published the ids of all original tweets collected between the three weeks of annotation (38 million tweets). This very large volume of tweets can also serve as a training corpus for language models.

6.1.2 Detecting Twitter events

In Chapter 3, we introduce a “mini batch" version of the First Story Detection (FSD) [Allan, 2002] algorithm, which outperforms the Dirichlet Multinomial Mixture (DMM) model [Yin and Wang, 2014] by a large margin for the task of tweets clustering on two different datasets. The FSD algorithm takes as input vector representations of documents (originally tf-idf vectors), which are then grouped together based on cosine similarity. Mini-batches make it possible to speed up the algorithm in the case of sparse vectors such as tf-idf vectors, due to the properties of sparse matrix multiplication.

We also investigate the performance of recent short-text/sentence embedding models including ELMo [Peters et al., 2018], Universal Sentence Encoder [Cer et al., 2018], BERT [Devlin et al., 2018] and Sentence-BERT [Reimers and Gurevych, 2019] when used as input to the FSD algorithm. We show that these representations of tweets do not outperform tf-idf vectors for tweet clustering. Nor do naive text-image representations approaches based on the concatenation of text and image vectors (we tested SIFT [Lowe, 1999] and ResNet [He et al., 2016] models) for a given document.

Finally, we note that the standard FSD algorithm is not designed to filter tweets that are too short or contain too common words. We therefore introduce a new variant of this algorithm to make clusters more stable on "realistic" (i.e. noisy) tweet corpora. Our variant makes it possible to exclude certain tweets from the potential nearest neighbors. It increases both time efficiency, precision and recall compared to the simple “mini batch" FSD when tested on the 38 million-tweet dataset.

6.1.3 Linking Media events and Twitter events

In Chapter 4, we present the approach we use to group together Twitter events and media events. This approach is based on community detection in a weighted graph of various similarities (word similarity, number of hashtags in common, number of URLs in common) between Twitter events and media events. We test our approach with several weight combinations on edges and on several subsets of our corpus. We show that keeping only the word-similarity on the edges of the graph is the simplest approach, and also the most robust to the change of sub-sample. We also show that adding a time-constraint in order to remove edges between events that are too distant in time improves the performance of our method:

our performance results are decreasing with the parameter Δ, which sets the maximum number of days between two events.

6.1.4 Social Media and newsroom production decisions

Finally, in Chapter 5, we apply the algorithms detailed in Chapters 3 and 4 to detect joint events on a corpus of tweets collected between July 2018 and July 2019 (1.8 billion tweets) using our collection method. For the joint events that start on Twitter (i.e. if the first document in the joint event is a tweet), we investigate whether the popularity of Twitter events has an influence on the decisions made by news editors in terms of coverage of the event.

We use an instrumental variable based on the interaction between measures of user centrality and news pressure to isolate a causal effect of story popularity on media coverage. The centrality of the author of the first tweet in the event is estimated through the number of likes, retweets and quotes of the user's previous tweets, while news pressure is measured by the number of likes, retweets and quotes in the entire dataset in the hour before the event.

We show that story popularity has a positive effect on media coverage, but that this effect varies depending on the characteristics of media outlets: the effect is stronger for TV websites than for national daily newspapers, and it is also stronger for media outlets with a high social media presence. However, we do not observe a significant role of advertising revenues (observed by the existence of a paywall) on this effect. These findings shed a new light on our understanding of how editors decide on the coverage for stories.

6.2 Directions for future research

In this section, we propose two different ways to improve our results: first, training text-image vectors depending on topical similarity, and second, better estimating the centrality of users in the network. In addition, we propose longer term perspectives that could add interesting contributions to the present work.

6.2.1 Training text-image vectors using appropriate tasks

In Chapter 3, we fail to build text-image representations of tweets that improve event detection. This is due to the fact that we only concatenate text and image vectors, without training our model to generate useful feature representations from both modalities.

However, the manual annotation of Twitter users that we have performed (see Chapter 5) in order to identify the journalist and media accounts in our dataset can provide us with a good pretext-task[1]: we could train a binary classifier to distinguish between tweets from journalists/media outlets and "regular" users' tweets. Indeed, one can assume that spotting images shared by the media outlets/journalists would allow the model to learn useful text-image features. Alternatively, one could try to predict whether or not the tweet contains an URL.

We could then add a final task to train the obtained network in such a way that the produced sentence embeddings are semantically meaningful and can be compared with cosine-similarity, in the spirit of Reimers and Gurevych [2019] and Danovitch [2020]. To do so, we plan to build a siamese network trained to compute a topical similarity score between two tweets containing images. This last task would require us to annotate pairs of tweets as we did in Chapter 3, Section 3.5.2.

6.2.2 Predicting the followers of a given user

In Chapter 5, we use the centrality of the *seed* (i.e. the author of the first tweet) of an event as a variation of popularity exogenous to the intrinsic interest of the event. Centrality is computed using the total number of retweets, quotes and replies received by the seed's previous tweets. However, a better estimation of a user's centrality would be to measure her distance to a “central node" in the chains of followers in the Twitter network. “Central nodes" could be the accounts of media and journalists, and the account labeled as “verified" by Twitter.

So far we have not been able to obtain the graph of Twitter users' relationships (in terms of who follows whom), as this is one of the most complicated piece of data to obtain using the Twitter API. What we do have in our dataset is the history of interactions between two users (in terms of number of retweets, likes, quotes and mentions since June 2018). We plan to establish a model capable of predicting whether a user follows another user, based on their interactions data.

The model of interrelationships between followers and followees would rely on a Matrix Factorization

[1]A pretext-task in machine learning is an intermediary task used to pre-train neural networks, in order to learn useful representations that should be easily adaptable for other tasks

method. This family of methods consists in projecting two sets of items in a common latent space in order to model their interactions. These methods have been used extensively in the last 10 years by recommender systems, in order to model purchasing decisions based on “implicit feedback" [Hu et al., 2008] such as reading a web page, or clicking on an item. The same type of approach is also used by Rappaz et al. [2019] in order to predict the likelihood of a media outlet to cover a certain type of news events.

6.2.3 Longer term perspectives: patterns of news propagation

In this thesis, we only focused on one type of interaction between Twitter events and media events: the case of events that break on Twitter and are relayed by mainstream media outlets. However, a further research objective would be to identify more complex patterns in the dissemination of information. Ning et al. [2015] propose a first step towards this type of approach by representing interaction patterns as chains of interactions (N: the information goes from News to Twitter, T: the information goes from Twitter to News, B: bi-directional information flow, E: absence of significant information flow) and then clustering interaction patterns into 5 groups.

Instead, we would represent the propagation of information as a graph where the nodes would be groups of actors: mainstream media outlets, Twitter accounts of media outlets, Twitter accounts of journalists, Twitter accounts of potential “sources" (that are followed by a minimum number of journalists), Twitter users that directly follow one of these groups, and other Twitter users.

For each event, we would like to quantify the spread of information among each group of users: we would then be able to know which group shared the information first and whether the other groups also shared the story. This should allow us to identify gaps between different types of Twitter users in the access to information.

Using graph embedding methods such as Graph2Vec [Narayanan et al., 2017] would enable us to learn embeddings of the created graphs and cluster together similar interaction patterns. This type of approach would be an interesting way to investigate how information spreads across social media and traditional news media, and to explore recurrent patterns of dissemination. Using graph embedding methods such as Graph2Vec [Narayanan et al., 2017], we could learn embeddings of the created graphs and cluster together similar interaction patterns. This type of approach would be an interesting way to investigate how information spreads across social media and traditional news media, and what are the recurrent patterns of dissemination.

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Appendix

A.1 Tweet collection: Additional details

A.1.1 Clusters of terms used as tweet collection parameters

These clusters where obtained using spectral clustering with K clusters on the $(N \times N)$ words co-occurrence matrices.

$K = 2$

- $N = 50$
  - a, au, avec, bien, c, ca, ce, cest, dans, de, des, du, elle, en, est, et, faire, fait, il, jai, la, le, les, ma, mais, meme, moi, mon, ne, on, plus, pour, quand, qui, se, si, sur, toi, tout, trop, tu, un, une, va, vous
  - je, me, pas, que, suis
- $N = 100$
  - ah, alors, au, aussi, avec, bah, bien, bon, bonne, c, ca, ce, cette, comme, dans, deja, dire, dit, donc, du, elle, encore, etre, faire, fais, fait, faut, ils, jai, jamais, je, jsuis, la, ma, mais, mdr, me, meme, merci, mes, moi, mon, ne, non, nous, on, oui, par, pas, pour, que, qui, quoi, rien, sa, sais, se, si, son, sont, suis, sur, ta, te, tellement, tes, toi, ton, tous, tout, tres, trop, tu, une, va, vais, veux, vie, voir, vous, vraiment, y, ya, ça
  - a, cest, de, des, en, est, et, il, le, les, lui, ou, plus, quand, quil, un
- $N = 200$

  - 1, 2, 3, ah, ai, aller, alors, ans, apres, as, au, aussi, aux, avant, avec, avoir, bah, beau, beaucoup, belle, bien, bon, bonjour, bonne, c, ca, ce, ces, cetait, cette, chez, comme, comment, compte, contre, coup, cours, crois, d, dans, deja, demain, depuis, deux, dire, dis, dit, donc, du, elle, encore, envie, es, etait, ete, etre, eu, faire, fais, fait, faut, fois, g, genre, gens, grave, gros, il, jai, jaime, jamais, javais, je, jen, jespere, jme, jour, journee, jsuis, juste, jvais, la, lui, ma, mais, mal, mdr, mdrr, mdrrr, me, mec, meme, merci, merde, mere, mes, mieux, moi, moins, moment, mon, monde, ne, nest, non, nous, oh, ok, on, ou, ouais, oui, par, parce, parle, pas, pense, personne, petit, peu, peut, peux, plus, pour, pr, ptdr, ptn, putain, quand, quel, quelle, quil, quoi, quon, rien, rt, sa, sais, sans, se, ses, si, soir, son, sont, suis, super, sur, t, ta, tas, te, tellement, temps, tes, tete, toi, ton, toujours, tous, tout, toute, tres, trop, trouve, tu, une, va, vais, veut, veux, vie, viens, voir, vois, votre, vous, vrai, vraiment, vu, y, ya, ça
  - a, cest, de, des, en, est, et, ils, le, les, leur, ont, passe, pourquoi, que, qui, un

$K = 3$

- $N = 50$
  - a, au, avec, c, ce, dans, de, des, du, elle, en, est, et, faire, fait, il, jai, la, le, les, ma, me, moi, mon, plus, pour, qui, se, sur, tout, trop, un, une, vous
  - bien, ca, cest, mais, meme, ne, on, pas, quand, que, si, toi, tu, va
  - je, suis
- $N = 100$
  - ah, alors, au, aussi, avec, bah, bien, bon, bonne, c, ca, ce, cette, comme, dans, deja, dire, dit, donc, du, elle, encore, etre, faire, fais, fait, faut, ils, jai, jamais, jsuis, la, ma, mais, mdr, me, meme, merci, mes, moi, mon, ne, non, nous, on, oui, par, pas, pour, que, qui, quoi, rien, sa, sais, se, si, son, sont, suis, sur, ta, te, tellement, tes, toi, ton, tous, tout, tres, trop, tu, une, va, vais, veux, vie, voir, vous, vraiment, y, ya, ça
  - a, cest, de, des, en, est, et, il, le, les, lui, ou, plus, quand, quil, un
  - je
- $N = 200$

– a, cest, de, des, en, est, et, ils, le, les, leur, ont, pourquoi, qui, un

– jen, passe, que, tu

– 1, 2, 3, ah, ai, aller, alors, ans, apres, as, au, aussi, aux, avant, avec, avoir, bah, beau, beaucoup, belle, bien, bon, bonjour, bonne, c, ca, ce, ces, cetait, cette, chez, comme, comment, compte, contre, coup, cours, crois, d, dans, deja, demain, depuis, deux, dire, dis, dit, donc, du, elle, encore, envie, es, etait, ete, etre, eu, faire, fais, fait, faut, fois, g, genre, gens, grave, gros, il, jai, jaime, jamais, javais, je, jespere, jme, jour, journee, jsuis, juste, jvais, la, lui, ma, mais, mal, mdr, mdrr, mdrrr, me, mec, meme, merci, merde, mere, mes, mieux, moi, moins, moment, mon, monde, ne, nest, non, nous, oh, ok, on, ou, ouais, oui, par, parce, parle, pas, pense, personne, petit, peu, peut, peux, plus, pour, pr, ptdr, ptn, putain, quand, quel, quelle, quil, quoi, quon, rien, rt, sa, sais, sans, se, ses, si, soir, son, sont, suis, super, sur, t, ta, tas, te, tellement, temps, tes, tete, toi, ton, toujours, tous, tout, toute, tres, trop, trouve, une, va, vais, veut, veux, vie, viens, voir, vois, votre, vous, vrai, vraiment, vu, y, ya, ça

A.1.2 List of the “sources" labels excluded from our dataset

BotDuCul	http://louphole.com
BotGentil	http://www.benjamingibeaux.fr
Botbird tweets	https://slmame.com
Botpoto	https://anthony-dumas.fr
CatenaBot	http://vnatrc.net
CeQuiNeTeBotPas	http://louphole.com/bots/
Cheap Bots, Done Quick!	http://cheapbotsdonequick.com
Comparobot	http://louphole.com/
Curious Cat	https://curiouscat.me
EmergencyPipou0	http://louphole.com
Gamepush2	http://gamepush.fr
Games Trailers	http://gamestrailers.org
Google	https://www.google.com/
Google	http://www.google.com/
H. M. Despladt's BOT	http://vnatrc.net/
JeuDuDicoBot	http://louphole.com
LVRFD Bot	http://twitter.com/LVRFD_Bot
LaCoFD Twitter Bot	https://www.fire.lacounty.gov/
MNBot	http://moringanutrition.fr
ManageTweetBot	https://twitter.com/EasterEd35
MonChatBot	https://mon-chatbot.com
MypornSight autopublish	http://www.mypornsights.com
ONE PIECE TREASURE CRUISE	http://www.bandaigames.channel.or.jp/list/one_...
Paradise Island 2	http://www.game-insight.com/
PsychoAFALISTOBOT	http://www.vnatrc.net/
Radio King LiveTweet	https://www.radioking.com
Random Taxi bot	https://whatever.com
RoboTribz	http://jhroy.ca
Temperature Bot MC901	http://www.notyet.com/
Tweetbot for Mac	https://tapbots.com/software/tweetbot/mac
Tweetbot for iOS	http://tapbots.com/tweetbot
Unfollow.fr	http://www.unfollow.fr/
WizeBot.tv	https://wizebot.tv
bondageartbot_s3	http://121.170.193.209/muse
dtc randposts	http://vnatrc.net/
emploisjob	http://emploisjob.com/
glissantBot	http://www.villaempain.com/en/
gnapblbot	http://vnatrc.net/
lapresse_diff	http://ruebot.net
manuuuuu	https://curiouscat.me/Saphirewall
myfirsttwitbotfabien	http://www.cookngo.paris
porc_bot	https://github.com/clemonster
pyTweetInfoBot	http://www.nilsschaetti.com/index.php/projects...
rakubo2	https://rakubots.kissa.jp/
test essai bot	http://twitter.com/LucieWankel
twitbilbot_	http://bilboeee.fr
twittbot.net	http://twittbot.net/
vnatrcASCIIBOT	http://www.vnatrc.net/

Table A.1: List of the “sources" labels excluded from our dataset

```
STOP_WORDS_FR = ['0', '1', '2', '3', 'a', 'ah', 'ai', 'aime', 'aller', 'alors', 'ans', 'apres', 'après', 'as', 'au',
  'aussi', 'autre', 'autres', 'aux', 'avais', 'avait', 'avant', 'avec', 'avez', 'avoir', 'b', 'bah', 'bcp',
  'beaucoup', 'bien', 'bon', 'bonjour', 'bonne', 'bref', 'c', "c'est", "c'était", 'ca', 'ce', 'cela',
  'celle', 'celui', 'ces', 'cest', 'cet', 'cetait', 'cette', 'ceux', 'chaque', 'chez', 'co', 'comme',
  'comment', 'compte', 'contre', 'coup', 'cours', 'crois', 'cétait', 'c’est', 'd', 'dans', 'de', 'deja',
  'depuis', 'des', 'detre', 'deux', 'dire', 'dis', 'dit', 'dm', 'dois', 'doit', 'donc', 'du', 'déjà',
  'dêtre', 'e', 'eh', 'elle', 'elles', 'en', 'encore', 'entre', 'envie', 'es', 'est', 'estce', 'et', 'etais', 'etait',
  'etc', 'ete', 'etes', 'etre', 'eu', 'f', 'faire', 'fais', 'fait', 'faites', 'faut', 'fois', 'font', 'g',
  'genre', 'gens', 'grave', 'gros', 'gt', 'h', 'hein', 'https', 'i', 'il', 'ils', 'j', "j'ai", "j'aime",
  "j'avais", "j'me", "j'suis", "j'vais", 'jai', 'jaime', 'jamais', 'javais', 'je', 'jen', 'jme', 'jour',
  'journee', 'journée', 'jsp', 'jsuis', 'jte', 'juste', 'jvais', 'jveux', 'jetais', 'jétais', 'j’ai', 'k', 'l', 'la',
  'le', 'les', 'leur', 'leurs', 'lol', 'lui', 'là', 'm', 'ma', 'maintenant', 'mais', 'mal', 'mdr', 'mdrr',
  'mdrrr', 'mdrrrr', 'me', 'mec', 'meme', 'merci', 'merde', 'mes', 'met', 'mettre', 'mieux', 'mis', 'mm',
  'moi', 'moins', 'moment', 'mon', 'monde', 'mtn', 'même', 'n', 'na', 'nan', 'ne', 'nest', 'ni', 'nn',
  'non', 'nos', 'notre', 'nous', 'o', 'of', 'oh', 'ok', 'on', 'ont', 'ou', 'ouais', 'oui', 'où', 'p', 'par',
  'parce', 'parle', 'pas', 'passe', 'pcq', 'pense', 'personne', 'peu', 'peut', 'peutetre', 'peutêtre', 'peux',
  'plus', 'pour', 'pourquoi', 'pq', 'pr', 'prend', 'prendre', 'prends', 'pris', 'ptdr', 'ptdrrr', 'ptn',
  'pu', 'putain', 'q', 'qd', 'qu', "qu'il", "qu'on", 'quand', 'que', 'quel', 'quelle', 'quelque', 'quelques',
  'quelquun', 'qui', 'quil', 'quils', 'quoi', 'quon', 'r', 'rien', 'rt', 's', 'sa', 'sais', 'sait', 'sans',
  'se', 'sera', 'ses', 'sest', 'si', 'sil', 'soir', 'soit', 'son', 'sont', 'suis', 'super', 'sur', 't',
  'ta', 'tas', 'te', 'tellement', 'temps', 'tes', 'tete', 'the', 'tjrs', 'tjs', 'toi', 'ton', 'toujours',
  'tous', 'tout', 'toute', 'toutes', 'tres', 'trop', 'trouve', 'trouvé', 'très', 'tt', 'tu', 'tête', 'u',
  'un', 'une', 'v', 'va', 'vais', 'vas', 'veut', 'veux', 'via', 'vie', 'viens', 'voila', 'voilà', 'voir',
  'vois', 'voit', 'vont', 'vos', 'votre', 'vous', 'vrai', 'vraiment', 'vs', 'vu', 'w', 'wsh', 'x', 'xd',
  'y', 'ya', 'z', 'à', 'ça', 'ça', 'étais', 'était', 'été', 'êtes', 'être', '——', '-', '']
```

Figure A.1: List of stop-words

A.1.3 List of stop words

To compute the average number of words included in the tweets, we have first removed the stop-words listed in Figure A.1.

A.2 News media content data

The content data is from the OTMedia research projet. This projet was subsidized by the *Agence Nationale de la Recherche* (ANR – National Agency for Research), a French institution tasked with funding scientific research. The INA (*Institut National de l'Audiovisuel* – National Audiovisual Institute, a repository of all French radio and television audiovisual archives) was the project leader. The OTMedia research projet used the RSS feeds of the media outlets to track every piece of content they produced online. For the media outlets whose RSS feeds were not tracked by INA, we complete the OTMedia data by scrapping the Sitemaps of their website. Finally, we get all the AFP dispatches directly from the AFP.

Our dataset includes the following media outlets:

Local daily newspapers:

1. *L'Ardennais*;
2. *Aisne Nouvelle*;
3. *Le Berry Republicain*;
4. *La Charente Libre*;
5. *Le Courrier Picard*;
6. *La Depeche Du Midi*;
7. *Est Eclair*;
8. *L'Eveil De La Haute Loire*;
9. *L'Independant Pyrenees Orientales*;
10. *Le Journal De La Haute Marne*;
11. *Le Midi Libre*;
12. *Monaco Matin*;
13. *La Montagne*;
14. *Nice Matin*;
15. *La Nouvelle Republique Des Pyrenees*;
16. *La Nouvelle Republique Du Centre Ouest*;
17. *Ouest France*;
18. *Le Parisien*;
19. *Le Petit Bleu D'Agen*;
20. *La Provence*;
21. *La Republique Des Pyrenees*;
22. *Sud Ouest*;
23. *Le Telegramme*;
24. *L' Union*;
25. *Var Matin*;
26. *La Voix Du Nord*;
27. *Yonne Republicaine*.

National daily newspapers:

1. *La Croix*;
2. *Les Echos*;
3. *L'Equipe*;
4. *Le Figaro*;
5. *France Soir*;
6. *La Gazette Des Communes Des Departements Et Des Regions*;
7. *L'Humanite*;
8. *Liberation*;
9. *Le Monde*;
10. *Le Quotidien De L Art*;
11. *La Tribune*.

Free (national daily) newspapers:

1. *20 Minutes*.

Weekly (national & local) newspapers:

1. *10 Sport*;
2. *Agefi*;
3. *Argus*;
4. *Auto Hebdo*;
5. *L'Avenir De Artois*;
6. *Capital*;
7. *Challenges*;
8. *Closer*;
9. *Courrier International*;
10. *Creuse Agricole Et Rurale*;
11. *L'Echo De La Lys*;
12. *Echo Le Valentinois Drome Ardeche*;
13. *Elle*;
14. *Est Agricole Et Viticole*;
15. *L'Express*;
16. *Grazia*;
17. *Les Inrockuptibles*;
18. *Investir*;
19. *Jeune Afrique*;
20. *Le Journal De Millau*;
21. *Le Journal Du Dimanche*;
22. *L'Hebdo Du Vendredi*;
23. *La Manche Libre*;
24. *Marianne*;
25. *Le Monde Diplomatique*;
26. *Le Moniteur Des Travaux Publics Et Du Batiment*;
27. *L'Obs*;
28. *L'Observateur De Beauvais*;
29. *Paris Match*;

30. *Le Paysan Du Haut Rhin*;
31. *Le Point*;
32. *Point De Vue*;
33. *Le Republicain De L'Essonne*;
34. *La Semaine Dans Le Boulonnais*;
35. *Strategies*;
36. *Tele Z*;
37. *L'Usine Nouvelle*;
38. *Version Femina*;
39. *La Volonte Paysanne De L'Aveyron*.

Monthly (national) newspapers:

1. *Auto Infos*;
2. *Beaux Arts*;
3. *Causeur*;
4. *Connaissance Des Arts*;
5. *Le Courrier De Floride Etats Unis*;
6. *France Amerique Etats Unis*;
7. *Geo*;
8. *GQ Magazine*;
9. *Japon Infos*;
10. *Marie Claire*;
11. *Marie France*;
12. *Mon Viti*;
13. *Premiere*;
14. *Rav*;
15. *La Revue Des Deux Mondes*;
16. *Science Et Vie*;
17. *Sciences Et Avenir*;
18. *Sciences Humaines*;
19. *Tarx*;
20. *Tetu*;
21. *Vogue*;
22. *Zibeline*.

TV:

1. BFM TV;
2. Eurosport;
3. France 24;
4. LCI;
5. Public Senat;
6. TF1;
7. TV5 Monde.

Radio:

1. Europe 1;
2. France Bleu (Radio France);
3. France Culture (Radio France);

4. France Inter (Radio France);
5. France Musique (Radio France);
6. France Info (also TV);
7. Radio Classique;
8. RCF;
9. RFI;
10. RTL;
11. Tendance Ouest.

News agencies:

1. Agence France Presse.

Pure online media:

1. 01 Net;
2. Actu;
3. Aleteia;
4. AOC;
5. Arboriculture Fruitiere;
6. Basta;
7. Boursier Com;
8. Boursorama;
9. Bref Eco;
10. Buzzfeed;
11. C Net;
12. Cfnews;
13. Clubic;
14. Contrepoints;
15. Les Echos Du Touquet;
16. Echos Start;
17. Echosdunet;
18. Foot Mercato;
19. Football;
20. Gamekult;
21. Gamergen;
22. Generation Nouvelles Technologies;
23. Ginjfo;
24. Goodplanet Info;
25. Herault Tribune;
26. Huffington Post;
27. Influenth;
28. Informatique News;
29. L'ADN;
30. Le Libre Penseur;
31. Le Media;
32. Le Tribunal Du Net;
33. L'Explicite;

34. L'Incorrect;
35. L'Internaute;
36. LVSL;
37. Maddyness;
38. Made In Foot;
39. Made In Perpignan;
40. Marsactu;
41. Mashable;
42. Medialot;
43. Mediapart;
44. Meta Media;
45. Minutenews;
46. Mon Cultivar Elevage;
47. Mondafrique;
48. Monde Informatique;
49. Les Moutons Enrages;
50. Myeurop Info;
51. Newsly;
52. Numerama;
53. Numeriques;
54. Ohmymag;
55. Olivieranger;
56. Paris Depeches;
57. Le Petit Journal;
58. Pourquoi Docteur;
59. Pure Medias;
60. Purepeople;
61. Resistance Republicaine;
62. Rue 89 Lyon;
63. Rue89 Bordeaux;
64. Rue89 Strasbourg;
65. Slate;
66. Sputniknews;
67. Toulouse 7;
68. Toute La Culture;
69. La Tribune De L Art;
70. Up Magazine;
71. L'Usine Digitale.

French-speaking foreign media Further, we also gather the content produced online by the following French-speaking foreign media:

1. *20 Minutes Suisse* (Switzerland);

2. Quotidien Canada (Canada);
3. *Temps Suisse* (Switzerland);
4. Lequotidien (pure online media from Quebec);
5. Africa Intelligence;
6. Express Mu Ile Maurice;
7. Nouvelles Caledoniennes;
8. Nouvelle Tribune Benin;
9. Wort Luxembourg;
10. Infohaiti Net Haiti.

A.3 Additional tables

Table A.2: Summary statistics: Tweets – split sample (July 2018 - September 2018), before filters

	Mean	St.Dev	P25	Median	P75	Max	Obs
Characteristics of the tweet							
Length of the tweet (nb of characters)	101	52	60	97	140	1,121	428,338,133
Number of words	6.2	4.0	3.0	6.0	8.0	269	428,338,133
=1 if tweet contains an URL	0.13	0.33	0.000	0.000	0.000	1	428,338,133
=1 if the tweet is a retweet	0.63	0.48	0.000	1.000	1.000	1	428,338,133
=1 if the tweet is a reply	0.17	0.38	0.000	0.000	0.000	1	428,338,133
=1 if the tweet is a quote	0.19	0.39	0.000	0.000	0.000	1	428,338,133
Popularity of the tweet							
Number of retweets	2.2	110.4	0.000	0.000	0.000	117,389	159,932,748
Number of replies	0.2	6.5	0.000	0.000	0.000	47,892	159,932,748
Number of likes	3.7	177.6	0.000	0.000	0.000	449,881	159,932,749

Notes: The table gives summary statistics. Time period is July 2018 - September 2018. Variables are values for all the tweets included in our dataset before we applied the filters to remove the bots. Variables are described in more details in the text.

Table A.3: Summary statistics: Twitter users (full sample; last time the user is observed)

	Mean	St.Dev	P25	Median	P75	Max
User activity						
Total number of tweets	15,174	40,642	286	2,265	12,762	6,183,567
Nb of tweets btw first & last time	99	445	4	9	38	61,203
Nb of tweets user has liked	8,520	23,184	158	1,220	6,655	2,831,010
Nb of users the account is following	688	4549	88	211	519	1672425
User identity						
Date of creation of the account	2,014.469	2.742	2,012	2,015	2,017	2,018
=1 if verified account	0.005	0.074	0	0	0	1
=1 if user is a journalist	0.0012	0.034	0	0	0	1
=1 if user is a media	0	0	0	0	0	1
User popularity						
Nb of followers	2,200	86,685	32	147	515	58,775,462
Nb of public lists	20	578	0	1	6	1,028,438
Observations	4,222,734					

Notes: The table gives summary statistics. Time period is July 2018 - July 2019. Variables are values for all the Twitter users included in our dataset the last time we observe them. Variables are described in more details in the text.

Table A.4: Summary statistics: Joint events – Depending on news breaker

	Media first	Twitter first	Diff/se
Length of the event (in hours)	408	529	-120***
			(15)
Number of documents in event	5,678	4,719	959
			(2,171)
Twitter coverage			
Nb of tweets in event	5,623	4,676	947
			(2,170)
Number of different Twitter users	2,125	2,957	-832
			(467)
Average number of retweets of tweets in events	2.6	2.5	0.0
			(0.1)
Average number of replys of tweets in events	0.3	0.3	-0.0
			(0.0)
Average number of favorites of tweets in events	3.1	3.7	-0.6**
			(0.2)
Media coverage			
Number of news articles in the event	55	43	12***
			(3)
Number of different media outlets	18	16	1**
			(0)
Observations	5,766		

Notes: The table gives summary statistics. Time period is July 2018 - September 2018. The observations are at the event level. Column 1 presents the events that appear first on media. Column 2 presents the results for the events that appear first on Twitter. In column 3, we perform a *t*-test on the equality of means.

Table A.5: Summary statistics: Twitter users – Gatekeepers

	Mean	St.Dev	P25	Median	P75	Max
User activity						
Total number of tweets	65,663	131,782	4,700	21,555	74,287	6,183,567
Nb of tweets July-September 2018	112	580	4	9	43	46,013
Nb tweets user has liked	20,707	53,746	415	2,913	15,874	2,831,010
Nb of users the account is following	11,475	35,916	353	1,053	7,578	1,672,425
User identity						
Date of creation of the account	2012	3	2010	2011	2014	2018
=1 if verified account	39.5	48.9	0.0	0.0	100.0	100
=1 if user is a journalist	8.45	27.82	0.00	0.00	0.00	100
=1 if user is a media	0.757	8.668	0.000	0.000	0.000	100
User popularity						
Nb of followers	115,010	727,425	12,835	26,462	57,461	58,775,462
Nb of public lists	592	4,854	64	175	461	1,028,438
Observations	58,521					

Notes: The table gives summary statistics. Time period is July 2018 - September 2018. Variables are values for all the “gatekeepers" included in our dataset the last time we observe them. Gatekeepers are defined as: **TO BE COMPLETED**

Table A.6: Naive estimates: Media-level approach, Depending on the number of journalists with a Twitter account

	Low nb of journalists with Twitter		High nb of journalists with Twitter	
	(1)	(2)	(3)	(4)
Number of articles				
Number of tweets	0.041***	0.040***	0.044***	0.043***
	(0.011)	(0.010)	(0.011)	(0.011)
Seed's number of followers	-0.023	-0.025	-0.010	-0.012
	(0.015)	(0.015)	(0.011)	(0.011)
Media FEs	✓	✓	✓	✓
Month & DoW FEs	✓	✓	✓	✓
Drop media		✓		✓
Drop multiple		✓		✓
Observations	131,790	129,420	395,370	388,260
Clusters (events)	4,393	4,314	4,393	4,314
Marginal Effect	0.011	0.011	0.022	0.021

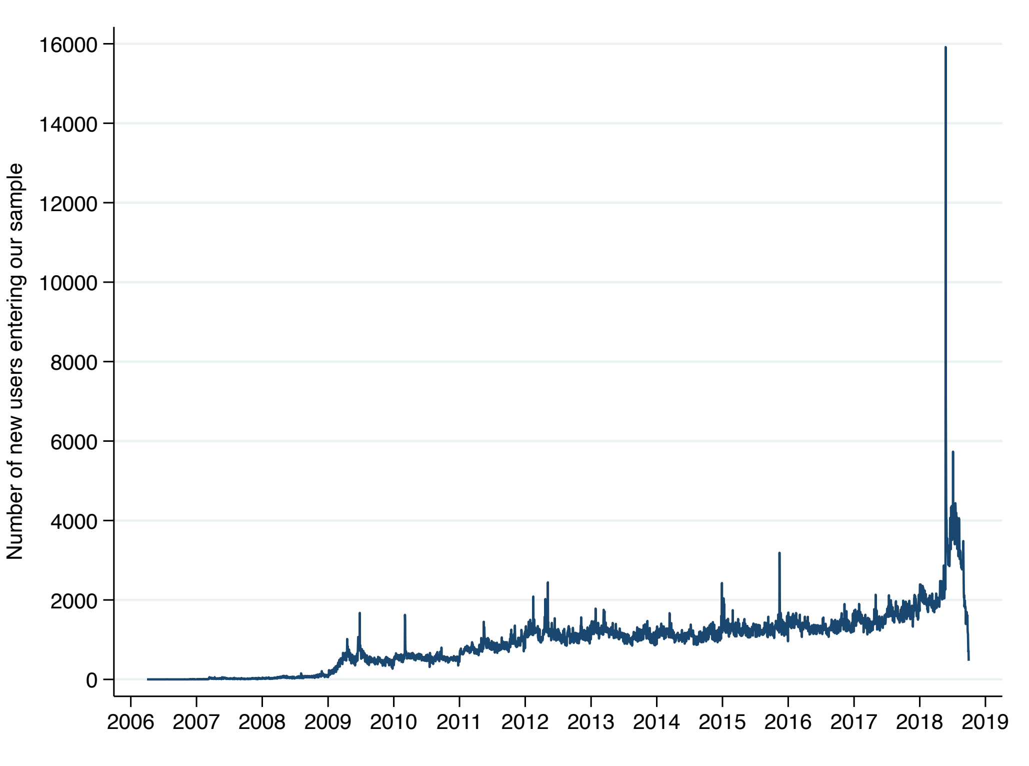
Notes: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. The time period is July 2018 - September 2018. Models are estimated using a negative binomial estimation. Standard errors are clustered at the event level. An observation is a media-news event. Columns (1) and (3) report the estimates for all the events that appear first on Twitter; in Columns (2) and (4) we drop the events whose seed is the Twitter account of a media outlet or journalist ("media") as well as the events whose seed broke more than one event during our time period ("multiple"). All specifications include the seed's number of followers as a control, and day-of-the-week, month, and media fixed effects. In Columns (1) and (2) (respectively (3) and (4), we consider the media with a relatively low (respectively relatively high) number of journalists with a Twitter account. The number of tweets is computed *before* the first news article in the event appears and is given in thousands. More details are provided in the text.

Table A.7: Naive estimates: Media-level approach, Depending on the Social media presence

	Low social media presence			High social media presence		
	(1) Number of articles	(2) Number of articles	(3) Coverage	(4) Number of articles	(5) Number of articles	(6) Coverage
main						
Number of tweets	0.033***	0.033***	0.012***	0.055***	0.054***	0.017***
	(0.008)	(0.008)	(0.003)	(0.013)	(0.013)	(0.004)
Seed's number of followers	-0.017	-0.017	-0.010**	-0.015	-0.017	-0.009***
	(0.011)	(0.011)	(0.004)	(0.011)	(0.011)	(0.004)
Media FEs	✓	✓	✓	✓	✓	✓
Month & DoW FEs	✓	✓	✓	✓	✓	✓
Drop media		✓	✓		✓	✓
Drop multiple		✓	✓		✓	✓
Observations	421,728	414,144	414,144	417,335	409,830	409,830
Clusters (events)	4,393	4,314	4,314	4,393	4,314	4,314
Marginal Effect	0.006	0.006	0.001	0.021	0.020	0.003

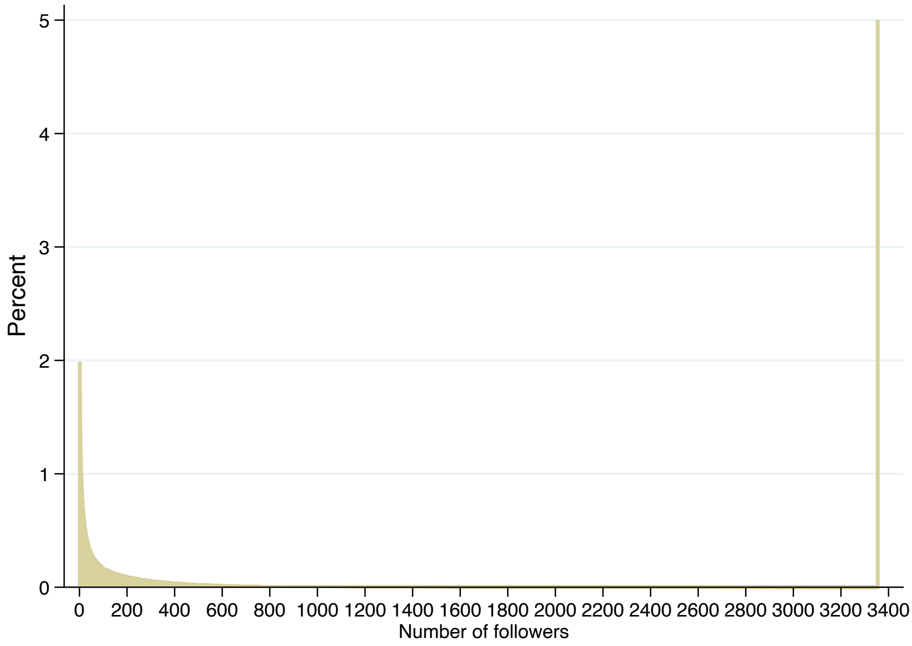
Notes: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. The time period is July 2018 - September 2018. Models are estimated using a negative binomial estimation. Standard errors are clustered at the event level. An observation is a media-news event. We only consider the subset of news events that appear first on Twitter. All specifications include the seed's number of followers as a control, and day-of-the-week, month, and media fixed effects. Columns (1), (3) and (5) report the estimates for all the events that appear first on Twitter; in Columns (2), (4) and (6) we drop the events whose seed is the Twitter account of a media outlet or journalist ("media") as well as the events whose seed broke more than one event during our time period ("multiple"). In Columns (1) and (2) all the media outlets in our sample are included; in Columns (3) and (4) (respectively Columns (5) and (6)) we only consider the media outlets whose social media presence is low (respectively high). High and low social media presence are defined by the share of the media outlet's articles published on social media (above or below the median). The number of tweets is computed *before* the first news article in the event appears and is given in thousands. More details are provided in the text.

A.4 Additional figures

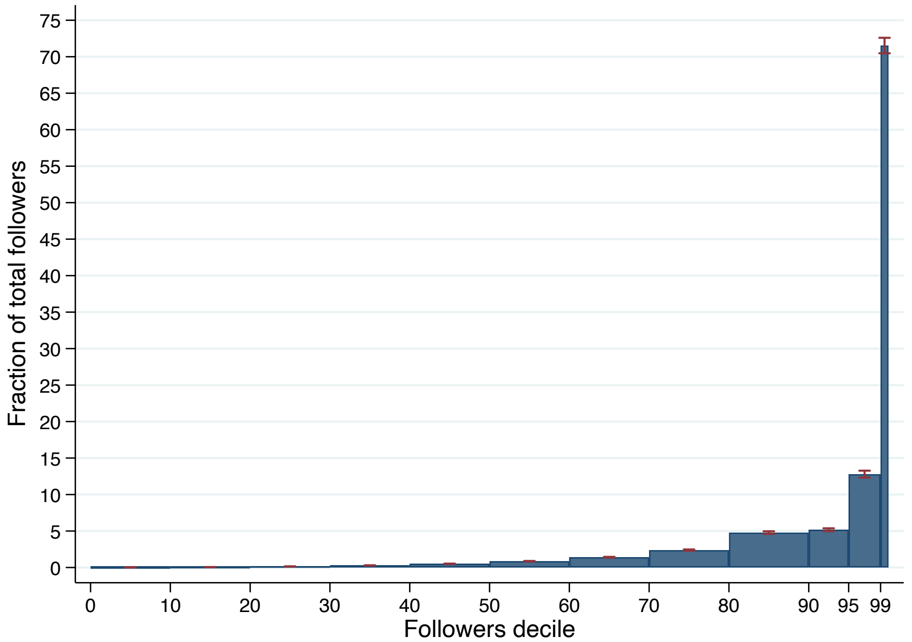


Notes: The figure plots the number of users entering our sample depending on the date of their Twitter account creation.

Figure A.2: Twitter users: Number of followers depending on the date of their account creation



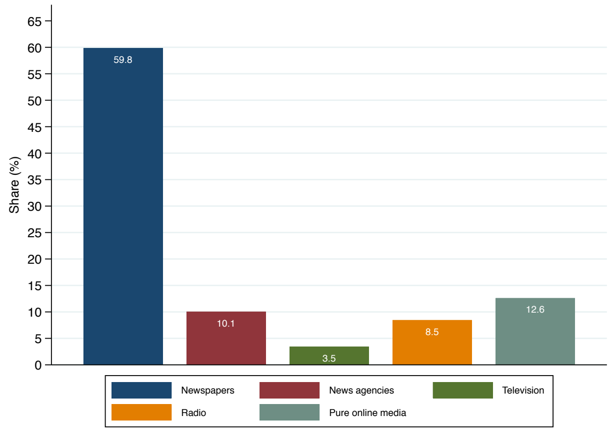
(a) Distribution of the number of followers



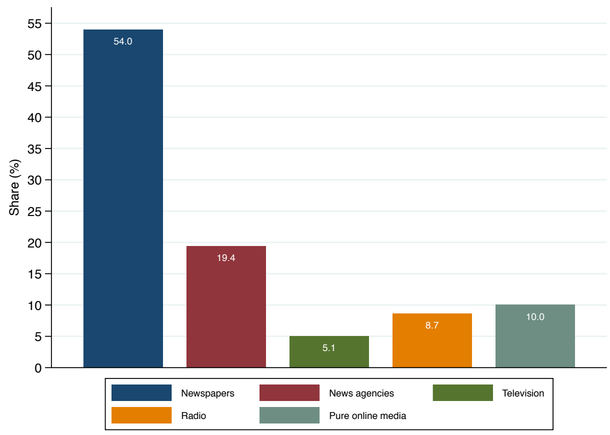
(b) Cumulative distribution of the number of followers

Notes: The upper Figure plots the distribution of the number of followers (winsorized at the 95th percentile, i.e. $3,355$ followers) of the Twitter users in our dataset. The bottom Figure plots the cumulative distribution of the number of followers.

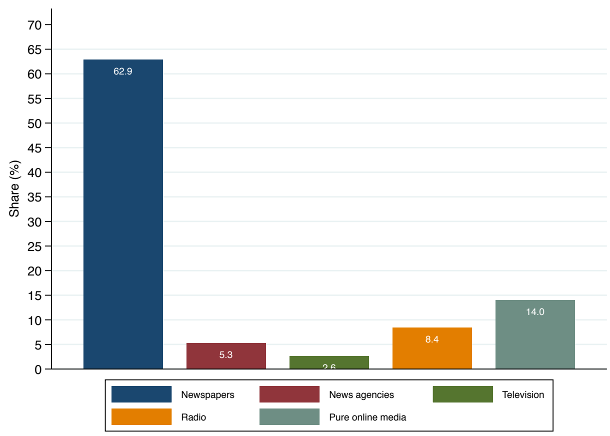
Figure A.3: Twitter users: Distribution of the number of followers



(a) All documents



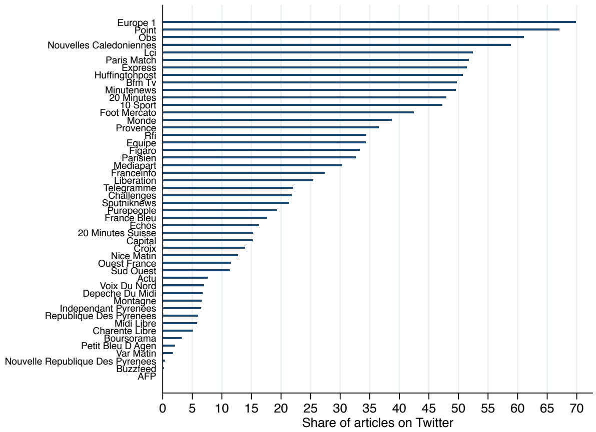
(b) Documents classified in events



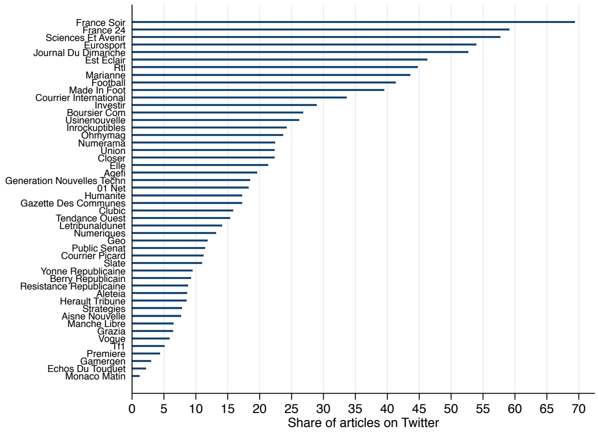
(c) Documents not classified in events

Notes: The figures plot the share of the documents depending on the offline format of the media outlet. The upper figure A.4a plots this number for all the documents; the middle figure A.4b for the documents classified in events; and the bottom figure A.4c for the documents not classified in events. News events are defined in detail in the text, and the list of the media outlets included in each category is given in Section A.2.

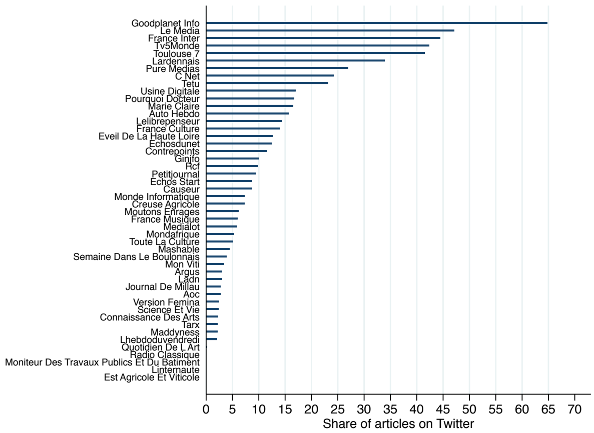
Figure A.4: Share of the documents by offline format



(a) Fourth quartile of the number of articles distribution



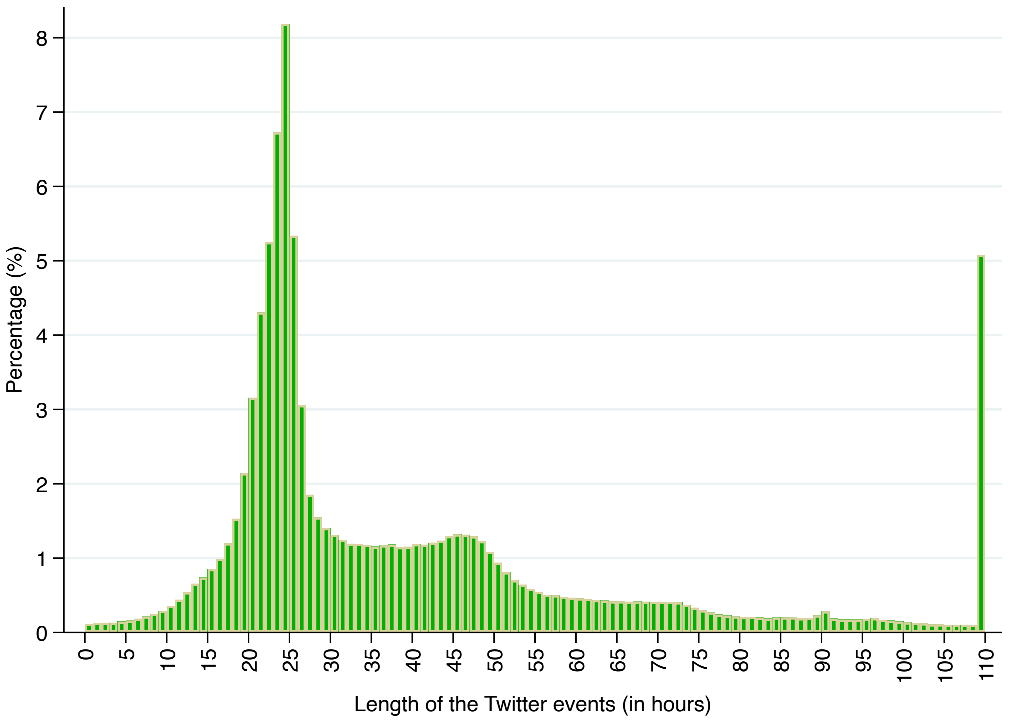
(b) Third quartile of the number of articles distribution



(c) Second quartile of the number of articles distribution

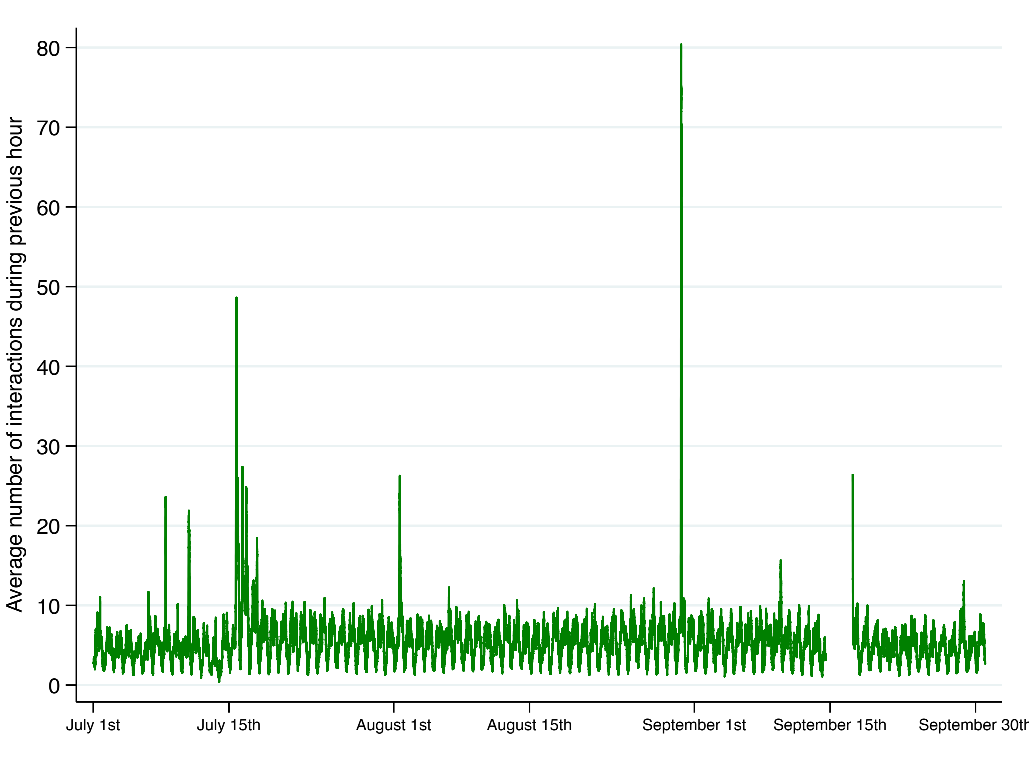
Notes: The Figure plot the share of the articles published online that are on Twitter, depending on the media outlet. Media outlets are ranked depending on the number of articles they publish online between July 2018 and September 2018. The upper Figure plots the share for the media outlets that are in the fourth quartile of the number of articles distribution; the middle Figure for the media outlets that are in the third quartile; and the bottom Figure for the media outlets that are in the second quartile.

Figure A.5: Share of the articles published online that are on Twitter, depending on the media outlet



Notes: The figure plots the distribution of the length of the Twitter events (in hours), Winsorized at the 95th percentile (=105 hours).

Figure A.6: Twitter events: Distribution of the length of the events
Twitter events: Distribution of the length of the events (in hours), Winsorized at the 95th percentile (=109.8 hours)



Notes: The Figure reports the average number of interactions (retweets/replies/favorites) generated by the tweets published during the previous hour. The average number of interactions is computed at the minute-level.

Figure A.7: News pressure: Average number of interactions generated by the tweets published during the previous hour

A.5 Robustness checks

Table A.8: Naive estimates: Media-level approach, Robustness check: Only media outlets located in France

	Number of articles		=1 if at least one article	
	(1)	(2)	(3)	(4)
main				
Number of tweets	0.048***	0.047***	0.016***	0.016***
	(0.011)	(0.011)	(0.003)	(0.003)
Seed's number of followers	-0.016	-0.018	-0.010***	-0.010***
	(0.011)	(0.011)	(0.003)	(0.003)
Media FEs	✓	✓	✓	✓
Month & DoW FEs	✓	✓	✓	✓
Drop media		✓		✓
Drop multiple		✓		✓
Model	Neg bin	Neg bin	Probit	Probit
Observations	799,526	785,148	799,526	785,148
Clusters (events)	4,393	4,314	4,393	4,314
Marginal Effect	0.014	0.014	0.002	0.002

Notes: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. The time period is July 2018 - September 2018. Models are estimated using a negative binomial estimation. Standard errors are clustered at the event level. An observation is a media-news event. Only the media outlets that are located in France are included. We only consider the subset of news events that appear first on Twitter. All specifications include the seed's number of followers as a control, and day-of-the-week, month, and media fixed effects. Columns (1) and (3) report the estimates for all the events that appear first on Twitter; in Columns (2) and(4) we drop the events whose seed is the Twitter account of a media outlet or journalist ("media") as well as the events whose seed broke more than one event during our time period ("multiple"). In Columns (1) and (2), the dependent variable is the number of articles published by the media in the event. In Columns (3) and (4) the dependent variable is an indicator variable equal to one if the media outlet publishes at least one article in the event and to zero otherwise. The number of tweets is computed *before* the first news article in the event appears and is given in thousands. More details are provided in the text.

Table A.9: IV estimates: Media-level approach, Control Function method, Robustness check: Only media outlets located in France

	Reduced form		First stage		Second stage	
	(1) Nb articles	(2) Nb articles	(3) Nb tweets	(4) Nb tweets	(5) Nb articles	(6) Nb articles
main						
Instrument						
Low*Interactions	0.044**	0.045**	0.142***	0.139***		
	(0.020)	(0.021)	(0.046)	(0.047)		
Controls						
Low	0.135	0.128	0.169	0.164	0.126	0.120
	(0.082)	(0.082)	(0.207)	(0.208)	(0.082)	(0.083)
Interactions	-0.024**	-0.025**	-0.025	-0.026	-0.016	-0.016
	(0.010)	(0.010)	(0.030)	(0.031)	(0.012)	(0.012)
Seed's followers	-0.010	-0.008	-0.037	-0.036	-0.006	-0.004
	(0.014)	(0.014)	(0.039)	(0.040)	(0.014)	(0.014)
Residuals (1st stage)					0.046	0.048
					(0.109)	(0.118)
Second stage						
Number of tweets					0.052***	0.051***
					(0.012)	(0.012)
Media FEs	✓	✓			✓	✓
Month & DoW FEs	✓	✓	✓	✓	✓	✓
Drop media		✓		✓		✓
Drop multiple		✓		✓		✓
Observations	625,170	614,068	625,170	614,068	625,170	614,068
Clusters (events)	3,435	3,374	3,435	3,374	3,435	3,374
Marginal effect (tweets)					0.014	0.014

Notes: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. The time period is July 2018 - September 2018. An observation is a media-news event. Only the media outlets that are located in France are included. Standard errors are clustered at the event level. All specifications include the seed's number of followers as a control, and day-of-the-week, month, and media fixed effects. Columns (1) and (2) report the results of the reduced form estimation (the dependent variable is the number of articles), Columns (3) and (4) of the first stage (the dependent variable is the number of tweets), and Columns (5) and (6) of the second stage (the dependent variable is the number of articles). In Columns (2), (4) and (6) we drop the events whose seed is the Twitter account of a media outlet or journalist ("media") as well as the events whose seed broke more than one event during our time period ("multiple"). The number of tweets is computed *before* the first news article in the event appears and is given in thousands. More details are provided in the text.

Table A.10: IV estimates: Media-level approach, IV Poisson GMM, Depending on the offline format, Robustness check: Only media outlets located in France

	Nat. dail.	Local dail.	Weeklies	Pure online	TV	Radio
	(1)	(2)	(3)	(4)	(5)	(6)
Number of articles						
Number of tweets	0.04***	0.03**	0.05***	0.07***	0.04***	-0.44
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(6.12)
Low	0.13	0.19**	0.14	-0.06	0.09	0.30**
	(0.10)	(0.09)	(0.10)	(0.12)	(0.11)	(0.14)
Interactions	-0.03*	-0.02	-0.05**	-0.10**	-0.02	-0.00
	(0.02)	(0.02)	(0.02)	(0.05)	(0.01)	(0.01)
Seed's followers	0.00	0.00	0.01	0.00	0.00	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Media FEs	✓	✓	✓	✓	✓	✓
Month & DoW FEs	✓	✓	✓	✓	✓	✓
Drop media	✓	✓	✓	✓	✓	✓
Drop multiple	✓	✓	✓	✓	✓	✓
Observations	37,114	91,098	121,464	219,310	23,618	37,114
Clusters (events)	3,374	3,374	3,374	3,374	3,374	3,374
Marginal effect (tweets)	0.022	0.010	0.011	0.005	0.016	-0.184

Notes: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. The time period is July 2018 - September 2018. Models are estimated using a a generalized method of moments (GMM) Poisson regression model with endogenous regressors (Stata's ivpoisson command). An observation is a media-news event. Only the media outlets that are located in France are included. We drop the events whose seed is the Twitter account of a media outlet or journalist ("media") as well as the events whose seed broke more than one event during our time period ("multiple"). Standard errors are clustered at the event level. All specifications include the seed's number of followers as a control, and day-of-the-week, month, and media fixed effects. In Column (1), we only consider the national daily newspapers, in Column (2) the local daily newspapers, in Column (3) the weekly newspapers, in Column (4) the pure online media, in Column (5) the websites of the television stations, and in Column (6) the websites of the radio channels. The number of tweets is computed *before* the first news article in the event appears and is given in thousands. More details are provided in the text.

Table A.11: Naive estimates: Event-level approach, Robustness check: Controls

	Number of articles				
	(1)	(2)	(3)	(4)	(5)
Nb articles					
Number of tweets	0.057***	0.058***	0.028***	0.028***	0.028***
	(0.015)	(0.015)	(0.010)	(0.010)	(0.011)
Seed's number of followers	-0.011	-0.011	0.003	0.000	-0.001
	(0.011)	(0.011)	(0.011)	(0.013)	(0.013)
Reaction time 1st media			0.199***	0.202***	0.199***
			(0.018)	(0.018)	(0.018)
Nb of tweets the seed has liked				-0.000*	-0.000*
				(0.000)	(0.000)
Nb of users the seed's account is following				-0.000	-0.000
				(0.000)	(0.000)
Nb of public lists				0.000	0.000
				(0.000)	(0.000)
Seed's total nb of tweets				0.000	0.000
				(0.000)	(0.000)
Month & DoW FEs	✓	✓	✓	✓	✓
Drop media					✓
Drop multiple					✓
Time of the day		✓	✓	✓	✓
Observations	4,392	4,392	4,392	4,392	4,313
Marginal Effect (tweets)	3.2	3.4	1.5	1.5	1.5

Notes: * p<0.10, ** p<0.05, *** p<0.01. The time period is July 2018 - September 2018. Models are estimated using a negative binomial estimation (robust standard errors are reported between parentheses). An observation is a news event. We only consider the subset of news events that appear first on Twitter. All specifications include the seed's number of followers as a control, and day-of-the-week and month fixed effects. In Columns (2) to (4), we also control for the time of the day of the first tweet (using an indicator variable in hourly format), and in Columns (3) to (5) for the reaction time of the first media (i.e. the time interval between the first tweet in the event and the first news article). In Columns (4) and (5) we also control for the characteristics of the seed of the event; these characteristics are computed the first time we observe the seed in our dataset. Columns (1) to (4) report the estimates for all the events that appear first on Twitter; in Columns (5) we drop the events whose seed is the Twitter account of a media outlet or journalist ("media") as well as the events whose seed broke more than one event during our time period ("multiple"). The number of tweets is computed *before* the first news article in the event appears and is given in thousands. More details are provided in the text.

Table A.12: IV estimates: Event-level approach, IV Poisson GMM, Robustness check: Controls

	Number of articles				
	(1)	(2)	(3)	(4)	(5)
Nb articles					
Number of tweets	0.040***	0.033***	0.029**	0.029**	0.030**
	(0.010)	(0.011)	(0.012)	(0.012)	(0.012)
Low	0.171*	0.201**	0.198**	0.197**	0.190**
	(0.091)	(0.095)	(0.095)	(0.095)	(0.096)
Interactions	-0.037**	-0.034**	-0.025	-0.029	-0.030
	(0.017)	(0.017)	(0.018)	(0.020)	(0.020)
Seed's number of followers	0.003	0.003	0.013	0.013	0.014
	(0.017)	(0.017)	(0.017)	(0.019)	(0.019)
Reaction time 1st media			0.206***	0.206***	0.205***
			(0.034)	(0.034)	(0.034)
Nb of tweets the seed has liked				-0.000	-0.000
				(0.000)	(0.000)
Nb of users the seed's account is following				-0.000	-0.000
				(0.000)	(0.000)
Nb of public lists				0.000	0.000
				(0.000)	(0.000)
Seed's total nb of tweets				-0.000	-0.000
				(0.000)	(0.000)
Month & DoW FEs	✓	✓	✓	✓	✓
Drop media					✓
Drop multiple					✓
Observations	3,435	3,435	3,435	3,435	3,374
Marginal Effect (tweets)	2.03	1.67	1.46	1.47	1.49

Notes: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. The time period is July 2018 - September 2018. Models are estimated using a a generalized method of moments (GMM) Poisson regression model with endogenous regressors (Stata's ivpoisson command). An observation is a news event. Robust standard errors are reported between parentheses. All specifications include the seed's number of followers as a control, and day-of-the-week and month fixed effects. In Columns (2) to (4), we also control for the time of the day of the first tweet (using an indicator variable in hourly format), and in Columns (3) to (5) for the reaction time of the first media (i.e. the time interval between the first tweet in the event and the first news article). In Columns (4) and (5) we also control for the characteristics of the seed of the event; these characteristics are computed the first time we observe the seed in our dataset. Columns (1) to (4) report the estimates for all the events that appear first on Twitter; in Columns (5) we drop the events whose seed is the Twitter account of a media outlet or journalist ("media") as well as the events whose seed broke more than one event during our time period ("multiple"). The number of tweets is computed *before* the first news article in the event appears and is given in thousands. More details are provided in the text.

Table A.13: Naive estimates: Event-level approach, Robustness check: Dropping small events

	Number of articles		Number of media	
	(1)	(2)	(3)	(4)
main				
Number of tweets	0.046***	0.046***	0.018***	0.018***
	(0.013)	(0.013)	(0.004)	(0.004)
Seed's number of followers	-0.008	-0.009	-0.009**	-0.009**
	(0.011)	(0.011)	(0.004)	(0.004)
Month & DoW FEs	✓	✓	✓	✓
Drop media		✓	✓	✓
Drop multiple		✓	✓	✓
Observations	3,956	3,886	3,956	3,886
Marginal Effect (tweets)	2.7	2.7	0.3	0.3

Notes: * p<0.10, ** p<0.05, *** p<0.01. The time period is July 2018 - September 2018. Models are estimated using a negative binomial estimation (robust standard errors are reported between parentheses). An observation is a news event. We only consider the subset of news events that appear first on Twitter, and drop events that in the first decile of the distribution in terms of total number of tweets in the event ("small events"). All specifications include the seed's number of followers as a control, and day-of-the-week and month fixed effects. Columns (1) and (3) report the estimates for all the events that appear first on Twitter; in Columns (2) and (4) we drop the events whose seed is the Twitter account of a media outlet or journalist ("media") as well as the events whose seed broke more than one event during our time period ("multiple"). The number of tweets is computed *before* the first news article in the event appears and is given in thousands. More details are provided in the text

Table A.14: IV estimates: Event-level approach, IV Poisson GMM, Robustness check: Dropping small events

	Number of articles		Number of media	
	(1)	(2)	(3)	(4)
main				
Number of tweets	0.040***	0.041***	0.021**	0.022**
	(0.010)	(0.010)	(0.009)	(0.009)
Low	0.175*	0.169*	0.088***	0.085***
	(0.094)	(0.095)	(0.031)	(0.031)
Interactions	-0.041**	-0.042**	0.001	0.000
	(0.017)	(0.018)	(0.005)	(0.005)
Seed's followers	0.006	0.007	-0.008	-0.008
	(0.017)	(0.017)	(0.005)	(0.006)
Month & DoW FEs	✓	✓	✓	✓
Drop media		✓		✓
Drop multiple		✓		✓
Observations	3,087	3,035	3,087	3,035
Marginal Effect (tweets)	2.16	2.20	0.39	0.39

Notes: * p<0.10, ** p<0.05, *** p<0.01. The time period is July 2018 - September 2018. Models are estimated using a a generalized method of moments (GMM) Poisson regression model with endogenous regressors (Stata's ivpoisson command). An observation is a news event. We only consider the subset of news events that appear first on Twitter, and drop events that in the first decile of the distribution in terms of total number of tweets in the event ("small events"). Robust standard errors are reported between parentheses. All specifications include the seed's number of followers as a control, and day-of-the-week and month fixed effects. In Columns (1) and (2), the dependent variable is the number of articles published in the event. In Columns (3) and (4), the dependent variable in the number of different media outlets covering the event. In Columns (2) and (4) we drop the events whose seed is the Twitter account of a media outlet or journalist ("media") as well as the events whose seed broke more than one event during our time period ("multiple"). The number of tweets is computed *before* the first news article in the event appears and is given in thousands. More details are provided in the text.

Table A.15: IV estimates: Media-level approach, IV Poisson GMM, Depending on the offline format, Robustness check: Only media outlets that published over 90 articles between July and September 2018

	Nat. dail.	Local dail.	Weeklies	Pure online	TV	Radio
	(1)	(2)	(3)	(4)	(5)	(6)
Number of articles						
Number of tweets	0.04***	0.03***	0.05***	0.07***	0.04***	-0.44
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(6.12)
Low	0.13	0.20**	0.14	-0.06	0.09	0.30**
	(0.10)	(0.09)	(0.10)	(0.12)	(0.11)	(0.14)
Interactions	-0.03*	-0.02	-0.05**	-0.10**	-0.02	-0.00
	(0.02)	(0.02)	(0.02)	(0.05)	(0.01)	(0.01)
Seed's followers	0.00	0.00	0.01	0.00	0.00	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Media FEs	✓	✓	✓	✓	✓	✓
Month & DoW FEs	✓	✓	✓	✓	✓	✓
Drop media	✓	✓	✓	✓	✓	✓
Drop multiple	✓	✓	✓	✓	✓	✓
Observations	37,114	87,724	107,968	199,066	23,618	37,114
Clusters (events)	3,374	3,374	3,374	3,374	3,374	3,374
Marginal effect (tweets)	0.022	0.012	0.013	0.006	0.016	-0.184

Notes: * p<0.10, ** p<0.05, *** p<0.01. The time period is July 2018 - September 2018. Models are estimated using a a generalized method of moments (GMM) Poisson regression model with endogenous regressors (Stata's ivpoisson command). An observation is a media-news event. Only the media outlets that published over 90 articles between July and September 2018 are included. We drop the events whose seed is the Twitter account of a media outlet or journalist ("media") as well as the events whose seed broke more than one event during our time period ("multiple"). Standard errors are clustered at the event level. All specifications include the seed's number of followers as a control, and day-of-the-week, month, and media fixed effects. In Column (1), we only consider the national daily newspapers, in Column (2) the local daily newspapers, in Column (3) the weekly newspapers, in Column (4) the pure online media, in Column (5) the websites of the television stations, and in Column (6) the websites of the radio channels. The number of tweets is computed *before* the first news article in the event appears and is given in thousands. More details are provided in the text.

Publications

International conferences and workshops

1. Mazoyer, B., Cagé, J., Hervé, N. & Hudelot, C. (2020). “A French Corpus for Event Detection on Twitter”. In “International Conference on Language Resources and Evaluation (LREC 2020)”, 6220–6227

2. Evrard, M., Uro, R., Hervé, N. & Mazoyer, B. (2020). “French Tweet Corpus for Automatic Stance Detection”. In “International Conference on Language Resources and Evaluation (LREC 2020)”, 6317–6322

3. Mazoyer, B., Cagé, J., Hudelot, C., & Viaud, M.-L. (2018). “Real-Time Collection of Reliable and Representative Tweets Datasets Related to News Events”. In “Proceedings of the First International Workshop on Analysis of Broad Dynamic Topics over Social Media (BroDyn 2018) co-located with the 40th European Conference on Information Retrieval (ECIR 2018)”, 23–34

National conferences and workshops

1. Mazoyer, B., Hervé, N., Hudelot, C., & Cagé, J. (2020). “Représentations lexicales pour la détection non supervisée d’événements dans un flux de tweets : étude sur des corpus français et anglais”. In “Extraction et Gestion des Connaissances (EGC 2020)”

2. Mazoyer, B., Turenne, N., & Viaud, M.-L. (2017). “Étude des influences réciproques entre médias sociaux et médias traditionnels”. In “Amsaleg, L., Claveau, V. & Tannier, X. Actes de l’atelier Journalisme Computationnel 2017”, 37–40

In preparation

1. Mazoyer, B., Hervé, N., Hudelot, C., & Cagé, J. (2020). “Short-Text Embeddings for Unsupervised Event Detection in a Stream of Tweets". *In* “Advances in Knowledge Discovery and Management", Vol 10

2. Mazoyer, B., Cagé, J., & Hervé, N. (2020). “Social Media and Newsroom Production Decisions"

Synthèse en français

Cette thèse se donne pour objectif d'étudier le rôle de Twitter dans l'évolution de la production d'information médiatique au cours des dernières années. Notre objectif est de découvrir dans quelle mesure les histoires (que nous désignons en anglais par *stories* ou *events*) populaires sur les réseaux sociaux sont davantage relayés par les médias traditionnels. Le défi est de quantifier et d'analyser précisément les relations entre les deux sphères, dans un contexte de très forte dépendance de chaque sphère vis-à-vis de l'autre. Cette synthèse détaille l'ensemble des étapes nécessaires pour y parvenir.

Construire un corpus pour la détection d'événements sur Twitter

Nous proposons tout d'abord une nouvelle méthode pour collecter un grand volume de tweets aléatoires. En effet, l'API *Sample* de Twitter ne donne accès qu'à 1% de l'ensemble des tweets émis à un moment donné. Notre méthode est fondée sur une autre API, *Filter*, avec pour paramètres de recherche les mots les plus fréquents d'une langue donnée. Nous montrons que la distribution des mots dans le corpus ainsi collecté est extrêmement similaire à celle obtenue avec l'API *Sample* de Twitter, prouvant ainsi que notre méthode permet d'obtenir un échantillon aléatoire de l'ensemble des tweets émis. De plus, nous montrons que pour un ensemble de mots et un certain nombre de clefs d'accès à Twitter, grouper les termes qui sont fréquemment employés ensemble sur la même clef d'accès à l'API donne de meilleurs résultats que de répartir aléatoirement les mots sur chaque clef d'accès.

Notre méthode nous a permis de collecter environ 5 millions de tweets par jour sans discontinuer depuis juin 2018. Nous estimons, en comparant notre jeu de données à d'autres corpus collectés par des chercheurs français dans la période, que nous collectons entre 60% et 75% de tous les tweets en français émis sur Twitter, et entre 74% et 78% de tous les tweets originaux (c'est-à-dire en excluant les retweets).

Enfin, nous présentons un corpus permettant d'évaluer la performance des algorithmes de détection d'événements dans les tweets, composé de plus de 95000 tweets annotés manuellement. Ce corpus, ainsi que le code de nos expériences de détection d'événements, est désormais accessible publiquement afin de servir de référence pour comparer de nouveaux algorithmes. Nous publions également les identifiants de tous les tweets originaux collectés pendant les trois semaines d'annotation (38 millions de tweets). Ce très grand volume de tweets peut également servir à entraîner des modèles de langue.

Détecter les événements sur Twitter

Nous introduisons une version "mini batch" de l'algorithme *First Story Detection* (FSD) [Allan, 2002] qui surpasse largement le modèle *Dirichlet Multinomial Mixture* (DMM) [Yin and Wang, 2014] pour la tâche de détection d'événements sur deux jeux de données différents. L'algorithme FSD prend en entrée des représentations vectorielles de documents (à l'origine des vecteurs tf-idf), qui sont ensuite regroupés en fonction de leur similarité cosinus. Les mini-batchs permettent d'accélérer l'algorithme dans le cas de vecteurs creux tels que les vecteurs tf-idf, du fait des propriétés de la multiplication de matrices creuses.

Nous comparons également le gain qu'apportent différents modèles de plongements sémantiques de phrases/textes courts à l'algorithme FSD. Parmi ces modèles, on trouve ELMo [Peters et al., 2018], Universal Sentence Encoder [Cer et al., 2018], BERT [Devlin et al., 2018] et Sentence-BERT [Reimers and Gurevych, 2019]. Nous montrons que ces représentations de tweets ne font pas mieux que les traditionnels vecteurs tf-idf pour le clustering de tweets. Des représentations texte-image naïves fondées sur la concaténation des vecteurs (pour les vecteurs images, nous testons les modèles SIFT [Lowe, 1999] et ResNet [He et al., 2016]) ne permettent pas non plus d'améliorer les résultats.

Enfin, partant du constat que l'algorithme FSD standard n'est pas prévu pour filtrer les tweets trop courts ou qui contiennent des mots trop communs pour être discriminants, nous introduisons une nouvelle variante de cet algorithme pour rendre les clusters plus stables. Notre variante exclut certains tweets de la recherche de plus proche voisin. Elle permet à la fois de diminuer le temps de calcul, et d'améliorer la précision et le rappel par rapport au simple "mini batch" FSD, lors de nos tests sur le corpus de 38 millions de tweets.

Lier les événements Twitter et les évenements médiatiques

Notre approche pour regrouper les événements est fondée sur la détection de communautés dans le graphe pondéré de la similarité entre événements Twitter et événements médiatiques. Différentes combinaisons linéaires de mesures de similarité (similarité textuelle, nombre de hashtags en commun, nombre d'URLs en commun) sont testées, sur différents sous-ensembles de notre corpus. Nous montrons que l'approche la plus simple est de conserver uniquement la similarité textuelle sur les arêtes du graphe. Cette approche est également la plus robuste aux changements d'échantillon de test. Nous montrons également qu'introduire une contrainte temporelle pour supprimer les arêtes entres des événements trop éloignés dans le temps améliore la performance de notre méthode.

Réseaux sociaux et décisions éditoriales

Enfin, afin de répondre à notre question de recherche, nous appliquons les algorithmes présentés ci-dessus à un corpus de tweets et de pages web de médias collectés entre juillet 2018 et juillet 2019 (1,8 milliards de tweets, 4 millions de pages web). Pour les événements joints qui ont commencé sur Twitter (c'est-à-dire que le premier document de l'événement joint est un tweet) nous étudions si la popularité des événements Twitter a une influence sur la couverture de l'événement par les médias traditionnels.

Nous menons une analyse en termes de variable instrumentale, standard en économétrie, pour isoler l'effet causal de la popularité Twitter d'une histoire sur sa couverture par les médias traditionnels. Notre contribution réside dans le choix d'une variable, qui soit à la fois tout à fait indépendante des choix éditoriaux des médias traditionnels, et qui ait un effet sur la popularité d'un événement sur Twitter. La variable choisie mesure l'interaction entre la centralité des utilisateurs dans le réseau social et la pression médiatique à un moment donné. La centralité de l'auteur du premier tweet de l'événement est estimée par le nombre de likes, retweets et citations de ses tweets avant le début de l'événement. La pression médiatique est mesurée par le nombre de likes, retweets et citations dans l'ensemble du jeu de données dans l'heure qui précède l'événement.

Nous montrons que la popularité d'un événement a un effet positif sur la couverture par les médias traditionnels, mais que cet effet varie en fonction des caractéristiques du média: l'effet est plus important pour les sites des télévisions que pour les sites de la presse quotidienne nationale, et il est également plus fort pour les médias dont les journalistes sont nombreux à avoir un compte Twitter. À l'inverse, nous n'observons pas d'effet significatif des types de revenus (certains médias dépendent uniquement des revenus publicitaires, d'autres protègent l'accès à leur page par un paywall qui incite les lecteurs à s'abonner). Ces résultats jettent un nouvel éclairage sur notre compréhension des décisions éditoriales à l'heure des réseaux sociaux.

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ÉCOLE DOCTORALE
Interfaces:
matériaux, systèmes, usages

Title: Social Media Stories
Event detection in heterogeneous streams of documents applied to the study of information spreading across social and news media

Keywords: Twitter, media, data-mining, event detection, embeddings, multi-modality

Abstract: Social Media, and Twitter in particular, has become a privileged source of information for journalists in recent years. Most journalists monitor Twitter as part of their search for newsworthy stories. This thesis aims to investigate and quantify the effect of this technological change on editorial decisions. Does the popularity of a story affect the way it is covered by traditional news media, regardless of its intrinsic interest?
To highlight this relationship, we take a multidisciplinary approach at the crossroads of computer science and economics: first, we design a novel approach in order to collect a representative sample of 70% of all French tweets emitted during an entire year. Second, we study different types of algorithms to automatically detect tweets that relate to the same stories. We test several vector representations of tweets, looking at both text and text-image representations. Third, we design a new method to group together Twitter events and media events. Finally, we design an econometric instrument to identify a causal effect of the popularity of an event on Twitter on its coverage by traditional media. We show that the popularity of a story on Twitter does have an effect on the number of articles devoted to it by traditional media, with an increase of about 1 article per 1000 additional tweets.

Titre: Social Media Stories
Détection d'événements dans des flux de documents hétérogènes appliquée à l'étude de la diffusion de l'information entre réseaux sociaux et médias

Mots clés: Twitter, médias, fouille de données, détection d'événements, plongements sémantiques, multimodalité

Résumé: Les réseaux sociaux, et Twitter en particulier, sont devenus une source d'information privilégiée pour les journalistes ces dernières années. Beaucoup effectuent une veille sur Twitter, à la recherche de sujets qui puissent être repris dans les médias. Cette thèse vise à étudier et à quantifier l'effet de ce changement technologique sur les décisions prises par les rédactions. La popularité d'un événement sur les réseaux sociaux affecte-t-elle sa couverture par les médias traditionnels, indépendamment de son intérêt intrinsèque ?
Pour mettre en évidence cette relation, nous adoptons une approche pluridisciplinaire, à la rencontre de l'informatique et de l'économie : tout d'abord, nous concevons une approche inédite pour collecter un échantillon représentatif de 70% de tous les tweets en français émis pendant un an. Par la suite, nous étudions différents types d'algorithmes pour découvrir automatiquement les tweets qui se rapportent aux mêmes événements. Nous testons différentes représentation vectorielles de tweets, en nous intéressants aux représentations vectorielles de texte, et aux représentations texte-image. Troisièmement, nous concevons une nouvelle méthode pour regrouper les événements Twitter et les événements médiatiques. Enfin, nous concevons un instrument économétrique pour identifier un effet causal de la popularité d'un événement sur Twitter sur sa couverture par les médias traditionnels. Nous montrons que la popularité d'un événement sur Twitter a un effet sur le nombre d'articles qui lui sont consacrés dans les médias traditionnels, avec une augmentation d'environ 1 article pour 1000 tweets supplémentaires.

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