Anticipating Viral Topics on Twitter by Detecting Micro-Influencers, Using a Combination of Social Network Analysis and AI

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Abstract. *Detecting potentially viral topics on Twitter has been the subject of numerous studies, and several monitoring platforms offer alerts for emerging topics to their users. However, solutions based on semantic analysis of publications are often imprecise and ineffective. In this article, which results from a research project, we propose a methodology based on the application of AI to metrics from Social Network Analysis, which analyses the dynamics of exchanges on social networks. We identified 'micro-influencers' who are active on six societal topics. Micro-influencers are interested in new topics ahead of opinion leaders, and their activism allows them to be picked up outside their communities: they are therefore precursors to the virality of new emerging topics in the public sphere. By applying AI to the dozens of metrics offered by the Gephi Social Network Analysis software, we defined a machine learning model capable of successfully identifying these micro-influencers. To do this, we used an innovative tool that makes it possible to compare the effectiveness of several dozen machine learning models.*

DOI: 10.5604/01.3001.0053.9583
http://dx.doi.org/10.5604/01.3001.0053.9583

Keywords: Artificial Intelligence, micro-influencers, weak signals, Social Network Analysis

Introduction

The online digital traces left by internet users, which provide information on real social activity[1], are extremely numerous and rich on social networks such as Facebook, Twitter, and LinkedIn, which have hundreds of millions of daily users worldwide, and several tens of millions in France. **These services store data on user-posted messages and related interactions, making them amenable to quantitative and automated analyses on large data sets**[2].

[1] R. Rogers, Digital Methods for Web Research, *Emerging Trends in the Social and Behavioral Sciences, MIT Press*, 2015.

[2] M. Cha, H. Haddadi, F. P. Gummadi, *Measuring User Influence in Twitter: The Million Follower Fallacy*, Conference: Proceedings of the Fourth International Conference on Weblogs and Social Media, ICWSM, 2010, Washington DC, USA, May 23–26.

However, the volumes of information from social networks are growing exponentially, making their analysis using traditional methods very complex. **While social networks themselves offer dedicated tools, these are often biased and effectively black boxes**, meaning that information is not equally disseminated to their users.

The algorithms of social networks, especially Twitter, determine which publications will and which will not receive visibility, and are therefore potentially viral.[3] **This particularly favours emotional reactions to current events**[4], and controversy between two irreconcilable camps.[5]

The real-time subjects highlighted by social networks often correspond to hot reactions exploitable only in crisis management. Interpreting events through online data, especially those from social networks[6], must also be approached with caution: depending on the topic and context, the interpretation of this data must be adapted. Several studies have been conducted and tools developed to anticipate trends or analyse opinions, particularly through semantic analysis of the text of publications (Boyadjian, Velcin, 2017). **Automatically analysing the polarity of messages, especially identifying sarcasm and irony, is extremely complex**, and even researchers may have divergent interpretations. Under these conditions, the results brought by AI will be at best generic and therefore poorly suited to detecting new information.[7]

In this article, we have chosen a different approach: the analysis of interactions between profiles generated by publications on Twitter. **More than the content of the message, it is the resulting dynamic between individuals who exchange, question, support, or confront each other that interests us**. This dynamic, which takes different forms, can be found regardless of the language or terms used. **It will highlight specific characteristics of individuals essential to the virality of information, and thus anticipate weak signals announcing a potentially viral subject**. Through the characteristics of information diffusion, which can be mathematically described via social network analysis, and by precisely analysing actors in different data sets, **we will show that it is possible to train a machine learning model to identify these micro-influencers, often at the origin of virality on Twitter**. Thus, without focusing on the content of posted messages or the personal data of those who share them, it is possible to identify new thematics likely to become viral.

As part of a research project conducted between October 2019 and June 2020, we studied several Twitter data sets. This project was funded by the CHEMI (Centre des Hautes Etudes du Ministère de l'Intérieur) and followed by the

[3] T. Jammet, *Vers une communication de marque dictée par les algorithmes? Les relations publiques 2.0 face au Big Data,* 'Communication et organisation', 2018, No. 54, pp. 93–105.

[4] C. Alloing, J. Pierre, *Le Web Affectif: Une économie numérique des émotions*, INA, 2017.

[5] D. Antolinos-Basso, N. Flaminia Paddeu, N. Blanc, *Pourquoi le débat #EuropaCity n'a pas pris sur Twitter?: Analyse de la mobilisation autour d'une controverse environnementale sur le réseau social,* 'Reset', 2017, No. 7, Vol. 1–1.

[6] D. Boullier, *Les sciences sociales face aux traces du big data: Société, opinion ou vibrations?*, 'Revue française de science politique', 2015, No. 5, Vol. 65, pp. 805–828.

[7] J. Boyadjian, *Analyser les opinions politiques sur Internet. Enjeux théoriques et défis méthodologiques*, Paris, 2016.

ENSP (Ecole Nationale Supérieure de la Police). The data from these data sets were qualified using a methodology presented in an article on training machine learning models to identify signals related to information becoming viral. More than technological resources, **it is the understanding of these interactions combined with the comparison of different algorithms that will allow for the effective training of a functional AI**. The first part of the project explains our methodology for identifying micro-influencers. **It involves combining social network analysis and the study of human economic networks to precisely identify certain actors who push a subject and ultimately propel its virality**. The second part describes the process of analysis and manual qualification of data used through the detailed analysis of one of the data sets with the Gephi social network analysis tool. After defining the Twitter accounts at the origin of the virality of the information in the test data sets, the use of the DataRobot data intelligence tool makes it possible to compare the effectiveness of dozens of open-source machine learning models. Finally, the third part involves using AI through the **competition of several dozen machine learning algorithms**. This innovative methodology removes any limitation to a single type of AI for identifying the micro-influencers at the origin of the virality of exchanges.

Combining social network analysis and analysis of human networks

This work proposes to combine the tools of Social Network Analysis and a renewed analysis of human networks, both of which highlight different forms of leadership specific to the globalisation of economies, where traditional hierarchical approaches no longer work. The goal is to better understand the dynamics of the network and the exchanges of emitter accounts. The analysis is not so much interested in opinion leaders who are capable of mobilising strongly, since their messages will then be quickly picked up by their networks, generating a certain virality that will nevertheless be limited to this network. **The analysis aims instead to identify barely visible influencers, or 'micro-influencers'**. These are generally defined as **actors with few followers on Twitter, but influential among different communities with whom they generate more interactions than accounts with a similar number of followers.**[8] It is indeed when several communities pick up on information that it becomes viral on Twitter.[9]

The study of the role of micro-influencers on the Twitter social network mobilises economic and social literature that deals with **go-between leaders, highlighted by the role of 'weak ties' in different human networks: organisations,**

[8] M. Rakoczy, A. Bouzeghoub, A.L. Gancarski, K. Wegrzyn-Wolska, *In the search of quality influence on a small scale: micro-influencers discovery*. OTM 2018: On the Move to Meaningful Internet Systems Conferences, Oct., 2018, Valletta, Malta. pp. 138–153.

[9] D.J. Watts, E. Bakshy, J.M. Hofman, W.A. Mason, *Everyone's an influencer: quantifying influence on twitter*, Proceedings of the fourth ACM international conference on Web search and data mining, February 2011.

communities or companies.[10] In these complex networks, there are multiple connections between actors that the go-between leader will connect.[11] These go-between leaders, or 'information passers', have been less studied than economic leaders because the latter are at the origin of product and organisational innovations thanks to their ability to impart a long-term vision to the network.[12] However, these two types of leader are complementary in complex societies where information and knowledge play an increasingly important role. This type of leadership constitutes 'a bridge' between different networks of actors, by circulating information and thus increasing the number of interactions between actors, which promotes the emergence of a consensus specific to leading concrete actions.[13]

In particular, **the go-between leader thinks about the best way to bring actors together to create immediate actions with the support of several communities**, whose interests may be different, but who unite for specific actions over time.[14] To do this, the go-between leader mobilises three key competencies: knowing how to connect different weak ties, knowing how to create a common mindset that compensates for long-term goal divergences, and knowing how to initiate measurable and step-by-step concrete actions.[15] To achieve this, the leader relies on various tools: disseminating information beyond his or her network, progressive action, and defining intermediate objectives to be achieved.[16] The characteristics of go-between leaders are found on the Internet among micro-influencers because they too are highly involved in different networks that can be complementary or opposed. The latter are particularly capable of contributing to the virality of a subject on Twitter and on the Internet, when initially this subject remained limited to a few communities.

Exploiting the algorithms of the Gephi tool (research software dedicated to social network analysis)

The field of research in Social Network Analysis uses a community analysis tool through information mapping: Gephi (Bastian, Heyman, Jacomy, 2009). **This free and open-source tool is increasingly used by social network analysis professionals, as it allows for very effective and precise interpretation of large Twitter data sets**. By providing a mapping of Twitter exchanges based on tweets and mentions

[10] Ms. Granovetter, *The strength of weak ties*, 'American Journal of Sociology', 1973, Vol. 78, Issue 6, pp. 1360–1380.

[11] M. Crozier, *L'Acteur et le Système* (in collaboration with E Friedberg), Paris, Le Seuil, 1977.

[12] P.F. Drucker, *What Makes An Effective Executive*. *On leadership*, *HBR's 10 Must Reads*, Boston, Massachusetts, Harvard Business Review Press, 2004, reprint 2011, pp. 23–36.

[13] R. Goffee, J. Gareth, *Why Should Anyone Be Led by You?' On leadership, HBR's 10 Must Reads*, Boston, MA, Harvard Business Review Press, reprint 2011, pp. 79–96.

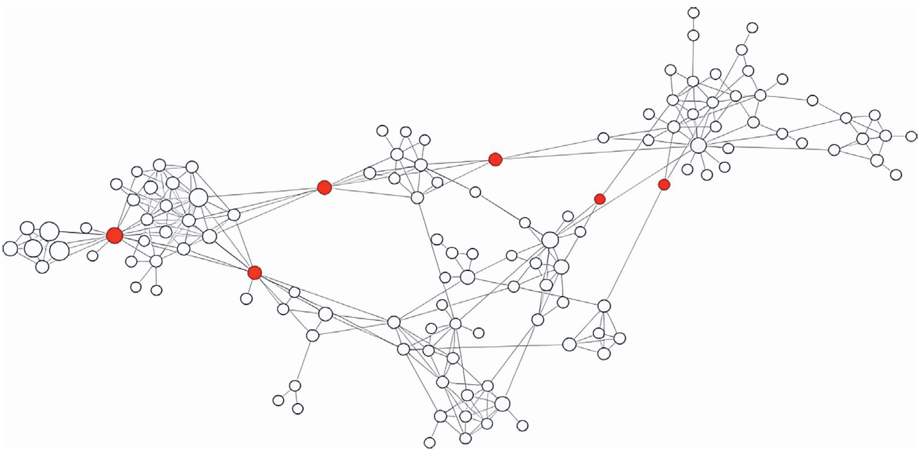
[14] P.F. Drucker, *What Makes…, op. cit.*

[15] C. Baulant, *The Role of Networks for Helping Firms and Countries Invent New Competitive Strategies Well Adapted to the World Knowledge Economy*, 'Journal of Economics Issues', 2015, Vol. 49, Issue 2, pp. 563–573.

[16] C. Baulant, *How Happiness can lead to more Efficiency: A New Paradigm Adapted to the World Knowledge Economy*, 'The American Review of Political Economy, 2017, pp. 110–125.

from accounts, **Gephi provides a visualisation of the network of actors.**[17] The position of Twitter accounts is determined by the Force Atlas 2 spatialisation algorithm[18] which highlights communities corresponding to interactions. **By analysing retweets and mentions, we can precisely analyse the relationships between actors on a given subject on Twitter, especially on specific topics**.[19] Gephi's algorithms are able to calculate several metrics to analyse interactions between the studied tweets, in particular the Betweenness Centrality, which identifies the actors at the centre of exchanges between the different communities of a corpus of tweets, who are not highly retweeted. Micro-influencers correspond to these actors (Fig. 1).[20]

Fig. 1. Representation of micro-influencers in a network (highlighted in red)



Source: Authors' own elaboration.

Combining Gephi's algorithms through filters enables more precise analysis elements for identifying the types of influencers contributing to information propagation (Sylvestre, 2017). If we focus on Twitter accounts capable of disseminating information to other communities and thus contributing to virality, we will first look for those who are both influential within their own community and in other communities. These are 'global' opinion leaders (**Tab. 1.**). However, **accounts with low influence within their own community but also outside are also essential to information diffusion**: these are micro-influencers. It is these that we will seek to identify automatically through machine learning models in this article.

[17] M. Grandjean, *A social network analysis of Twitter: Mapping the digital humanities community*, *Cogent Arts & Humanities,* 2016.

[18] M. Jacomy, T. Venturini, S. Heymann, M. Bastian, *ForceAtlas2, a Continuous Graph Layout Algorithm for Handy Network Visualization Designed for the Gephi Software*. *PLoS ONE* 9(6): e98679. doi: 10.1371/journal.pone.0098679, 2014.

[19] N. Smyrnaios, P. Ratinaud, *Comment articuler analyse des réseaux et des discours sur Twitter : L'exemple du débat autour du pacte budgétaire européen*, 'Tic&société', 2014, Vol. 7, No. 2.

[20] R.A. Hanneman, M. Riddle, *Introduction to social network methods*, 2005, http://faculty.ucr.edu/~hanneman/nettext/index.html.

Tab. 1. Identification of influencer types on Twitter via Gephi

	Shared by other communities	Shared only by their own community
Significant influence in a large community	**Global opinion leader:** (Economic leader): Twitter account highly influential on the topic studied (Viral information, transpartisan…) increasingly rare. **Classic opinion leader**: Twitter account heavily retweeted by their subscribers but does not extend beyond its network.	**Classical opinion leader**: Heavily retweeted by their community but very rarely outside it, into other communities.
Significant influence in a small community	**Micro-influencer (go-between leader):** Twitter account modestly influential in its network but capable of being replicated punctually (expertise, viral information…)	**Classic Twitter user**

Source: Authors' own elaboration.

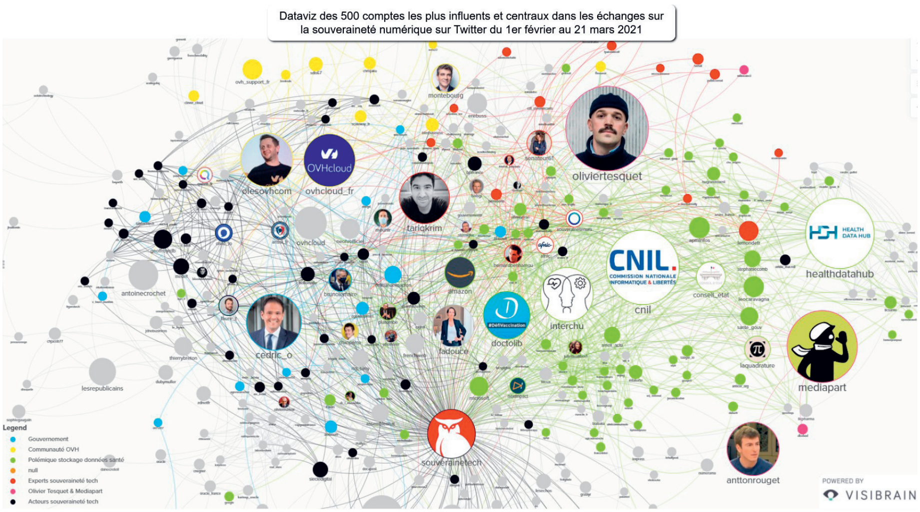
Importance of micro-influencers in Twitter exchanges

Classic opinion leaders are not relevant for defining an algorithm to detect the virality of exchanges. **Their messages are quickly picked up by their followers but generate increasingly weaker virality outside their community**. With the power of networks, any user can now become influential on Twitter by involving their community.[21] Activist actors, even with little influence, by benefiting from strong engagement from their community, can be picked up by other nearby communities and therefore spread their messages more widely. We are interested in the specific role of **micro-influencers, who are both closer to their network and more suited to long-term influence-building processes**. They have the ability to quickly build a network, sometimes from profiles with aliases, as soon as they publish interesting or quality content. For example, the Twitter account **@souverainetech** became a reference on the French Twitter in technological sovereignty at the end of 2020 (**Fig. 2.**) and was picked up by experts in the sector, politicians, and IT actors.[22]

[21] D.J. Watts, P.S. Dodds, *Influentials, Networks, and Public Opinion Formation*, 'Journal of Consumer Research', December 2007; D.J. Watts, E. Bakshy, J.M. Hofman, W.A. Mason, *Everyone's an influencer: quantifying influence on twitter*, Proceedings of the fourth ACM international conference on Web search and data mining, February 2011.

[22] G. Sylvestre, Les politiques s'intéressent de plus en plus à la souveraineté numérique sur Twitter, mais peu d'entre eux développent une vision sur le sujet, 2021, https://cartorezo.wordpress.com/2021/04/06/les-politiques-sinteressent-de-plus-en-plus-a-la-souverainete-numerique-sur-twitter-mais-peu-dentre-eux-developpent-une-vision-sur-le-sujet.

Fig. 2. Gephi mapping of the 500 most influential Twitter accounts (calculated by Eigenvector) on digital sovereignty between 1/02/2021–21/03/2021



Source: Authors' own elaboration.

Micro-influencers on the Internet, like go-between leaders in the real economy, play a key role in a knowledge society because they have the ability to connect different human networks with divergent interests within social networks on the Internet or within competitiveness clusters in the real economy. **Opinion leaders need intermediary leaders (go-betweens/micro-influencers) to translate these long-term objectives into concrete practices in the short and medium term**, and to ensure that all network members will have a stake in collaborating to achieve this objective.[23] These leaders, who have an intermediate position in the network (**Tab. 1.**), are often difficult to identify because they use their personal and human relationships, which remain non-linear.[24]

Identification and analysis of micro-influencer characteristics on different data sets

In the context of our research work with CHEMI, we decided to analyse data related to various societal topics. Indeed, whether it is classical activism, the dissemination of false information, or influence operations, **this type of topic always has the characteristic of emerging from actors with little influence, occasionally**

[23] C. Baulant, *Rethinking the links between Human Relationships and Economic Efficiency using the Local Micro institutions: the case of two emerging countries*, 'Journal of Economics Issues', 2017, Vol. 51, No. 3, pp. 651–662.

[24] A. Damasio, *Spinoza avait raison*, Paris, 2003, Odile Jacob, Edition Poche, 2005.

relayed by opinion leaders, with uneven success. We have therefore chosen topics that have been widely discussed, in order to analyse and identify the role of micro-influencers in making them viral. The choice of Twitter data was made according to the following four criteria:

- Publications correspond to a subject or issue championed by an activist movement seeking to influence the public;
- Speed of virality of the tweets, which can vary over time;
- Diversity of subjects: local issues, fake news, societal problems, *etc.*, in order to verify that the subject or actors as such do not influence the virality;
- Temporal proximity to the topics, here between November 2018 and January 2020.

The analysis of the different data sets allowed us to step back from the virality of social networks and to understand the context and actors involved. The objective of this work is not to propose a detailed analysis of the context and actors of these various mobilisations. **Rather, the goal is to compare the communities at work and identify micro-influencers. We will then seek to identify these leaders through AI**. The aim is to minimise the analysis biases, which are often very frequent in AI applications, when the context of the data being analysed is not taken into account (Alkhatib, Berstein, 2019). The analysis thus seeks a diversity of actors and issues to verify the ability of AI to identify micro-influencers, regardless of the subject of the data corpus. All tweets were analysed using the same methodology, exploiting Gephi algorithms (**Tab. 2.**).

Tab. 2. Different data sets studied by themes and periods

Subject	Themes	Periods
Anti-speciesism Environment	Environment/animal rights	September 2018–May 2019
Marrakech Pact	Far right/Immigration	November–December 2018
EuropaCity	Environment/opposition to a national project	September–October 2019
Extinction Rebellion in Italy 2	Environment	August–October 2019
Extinction Rebellion and Lafarge	Environment/opposition to a local project	January–March 2020
ZAD Dune	Environment/opposition to a local project	January–March 2020

Source: Authors' own elaboration.

The data sets of tweets were compiled by **selecting relevant keywords and hashtags for the chosen subject over an extended period to accurately target the analysis of active communities**. Simultaneously, the data was checked to ensure that errors did not prevent the collection of essential tweets for analysis. Most research on Twitter targets hashtags (Rambukkana, 2015) or terms defined within a limited framework that may not necessarily be suitable for user practices.

Such an analysis of communities using Gephi will thus be partially biased if all modes of expression of the studied subject are not captured. To ensure extended collection of tweets for each subject studied, students from the Angers Master's degree in Economic Intelligence[25] conducted an analysis of the context to identify the main actors, their themes, and the chronology of the subject under the supervision of the authors. **Most research targeting Twitter data relies on its free Application Programming Interface, which provides access only to part of Twitter data**.[26] Therefore, this collection leads to specific biases in the studied corpus.[27]

We used paid access to Twitter's Firehose via the Visibrain[28] monitoring platform. Twitter is the only social network to monetise access to the entirety of its public data. This exhaustive access is thus guaranteed by contract. One of the authors of this study developed with Visibrain a tool to export Twitter data adapted to Gephi, which allowed us to empirically verify the quality of the analyses.

The example of the Marrakech Pact fake news was chosen for our micro-influencer qualification method. **The viral impact of this fake news forced the French Elysée to refute it, indicating the crucial importance of being able to identify potential successes of influence actions beforehand**. The analysis of the Marrakech Pact corpus carried out to identify micro-influencers and thus qualify the data before applying AI will be presented. The same methodology was employed for the other Twitter data sets.

Fake News about the Marrakech Pact on migration issues

The 'Global Compact for Safe, Orderly and Regular Migration' (Marrakech Pact) was signed during an intergovernmental conference held from December 10 to 11, 2018, in Marrakech. Its objective was to clarify migration issues at the international level and was the result of several months of work by United Nations (UN) member states. **In several countries, relying on the limited media coverage of the subject, anti-immigrant parties and politicians spread rumours about the consequences of this pact: a surrender of sovereignty to the UN on migration issues, complete opening of borders**, *etc.* This strategy of manipulating information, carried out by far-right activists, allowed this subject to take on such

[25] The Twitter data corpus was tested and analysed by the students of the Master's degree program in Competitive Intelligence and Strategic Intelligence (M2 IESC) at Angers during the academic year 2019–2020, as part of their supervised project conducted by the authors of this article.

[26] D. Antolinos-Basso, N. Flaminia Paddeu, N. Blanc, *Pourquoi le débat #EuropaCity n'a pas pris sur Twitter?: Analyse de la mobilisation autour d'une controverse environnementale sur le réseau social,* 'Reset', 2017, Vol. 1–1, No. 7.

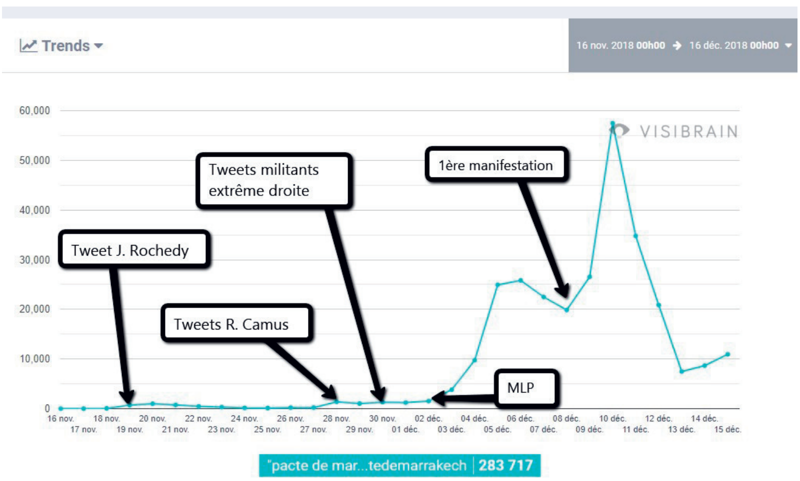
[27] F. Morstatter, J. Pfeffer, H. Liu, K.K. Carley, *Is the Sample Good Enough? Comparing Data from Twitter's Streaming API with Twitter's Firehose*, 2013, *Arxiv*, https://arxiv.org/abs/1306.5204.

[28] https://www.visibrain.com/fr/.

a magnitude in just a few weeks that a yellow vest demonstration was organised on December 8, 2018 (Fig. 3), and the official website of the Elysée had to deny the 'Fake News' on December 10, 2018.

On Twitter, the hashtag #Pactedemarrakech appeared on November 18, 2018, through the Belgian far-right party Vlaams Belang, which was opposed to the signing of the Pact. In France, before the appearance of the hashtag, it was the far-right activist Julien Rochedy who first gave the subject visibility. **The Marrakech Pact was then regularly mentioned by small communities linked to the far right, until the subject was taken up by national elected officials from December 3 onwards**, becoming viral until the first demonstration was organised in Belgium on December 8 (Fig. 3.). In total, nearly 300,000 tweets in French mentioned the Marrakech Pact in three weeks.

Fig. 3. Analysis of the spread of tweets about the Marrakech Pact via the Visibrain software between 16/11/2018–16/12/2018



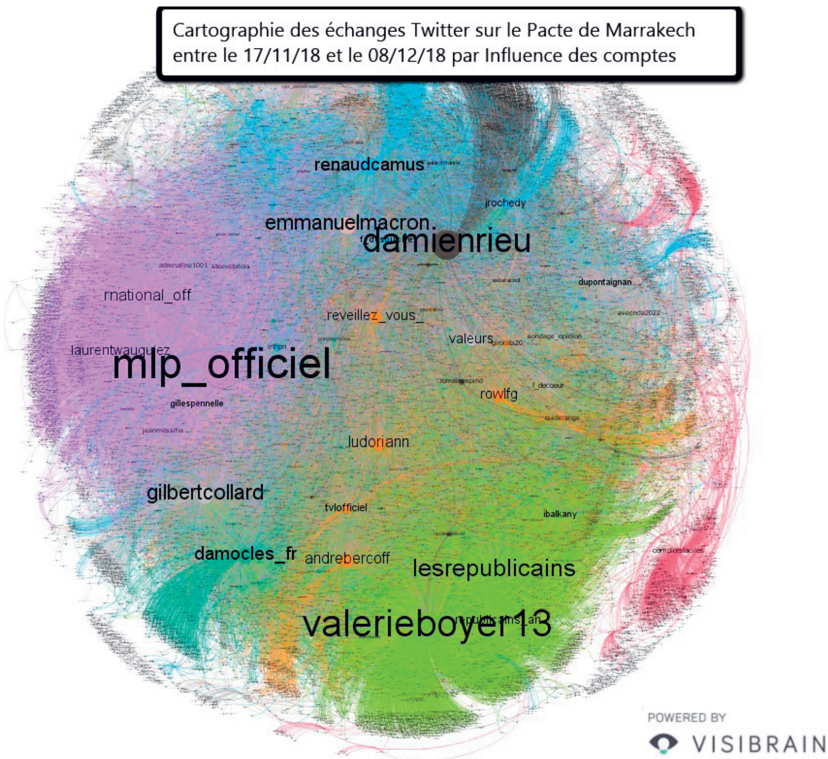
Source: Authors' own elaboration.

Fig. 3 shows that despite the initial involvement of far-right leaders such as J. Rochedy and R. Camus, it took several weeks for this fake news to be relayed in the media, notably through M. Le Pen

Micro-influencers proved to be essential in the spread of this fake news

From November 17th to December 8th, 2018, 67,450 tweets mentioning the Marrakech Pact were disseminated by 16,335 active Twitter accounts. Using the Gephi Social Network Analysis software, **it is possible to identify 700 communities, the top 8 representing more than 70% of the Twitter accounts** (**Fig. 4.**). Only communities with influential leaders (opinion leaders) were influential and got a significant number of retweets. **The two main communities, in purple and green, respectively, correspond to supporters of the far right party Rassemblement National and the French conservative party Les Republicains**. Their weight is similar, around 16% of the total Twitter accounts. The different communities have here a specific discourse, a discourse that is always found on any viral controversy topic[29]: Valerie Boyer (LR) is surprised that the subject does not lead to more debate and mentions the Yellow Vests, while Marine Le Pen attacks more directly using the hashtag **#immigrationdemasse.**

Fig. 4. Gephi mapping of the 100 most influential Twitter accounts (Eigenvector calculation) on the Marrakech Pact between 17/11/2018–8/12/2018

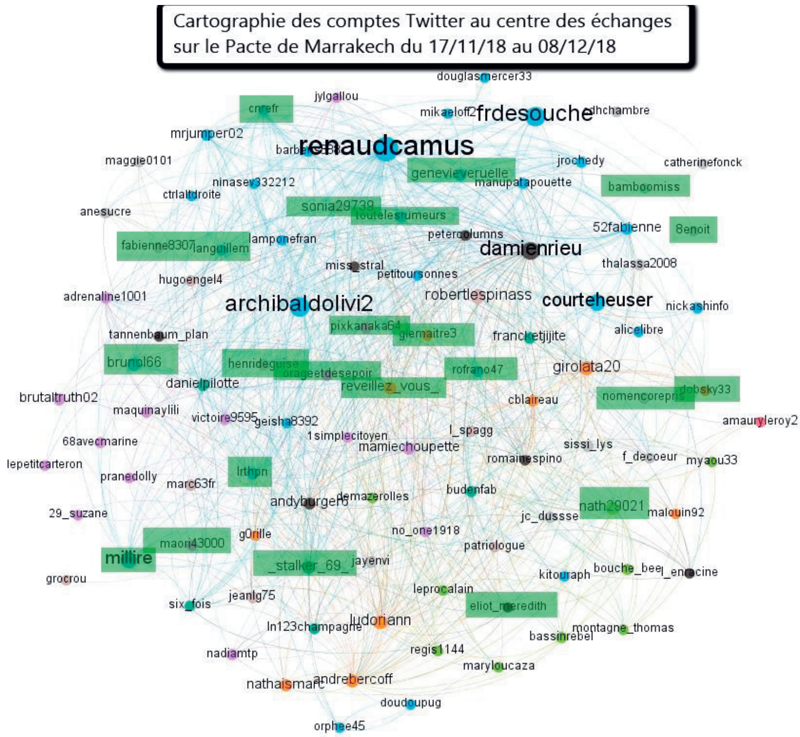


Source: Authors' own elaboration.

This mapping of the most mentioned accounts does not identify the accounts at the origin of the virality of this fake news. By applying the betweenness centrality calculation (**Fig. 5–A. and 5–B.**) and a filter, **it is possible to highlight the accounts at the centre of the exchanges, that is to say, the micro-influencers**. We have highlighted in green the accounts that were actually active before December 2 — the day the subject went viral:

29 N. Smyrnaios, P. Ratinaud, *Comment articuler analyse des réseaux et des discours sur Twitter : L'exemple du débat autour du pacte budgétaire européen*, 'Tic&société', 2014, Vol. 7, No. 2.

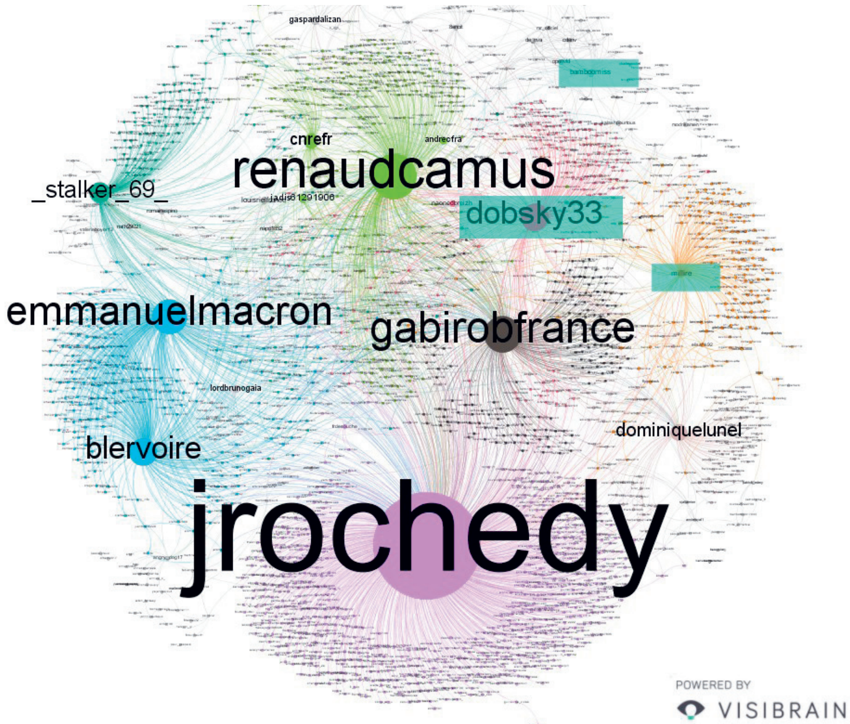
Fig. 5–A. Gephi mapping of the 100 Twitter accounts most central to exchanges (Betweenness centrality calculation) on the Marrakech Pact between 17/11/2018–8/12/2018



Source: Authors' own elaboration.

We can observe that the majority of micro-influencers do not belong to the main political communities, but to activist groups outside of them. The accounts highlighted in green have few followers but are very active and especially very retweeted by their communities, which have exchanged with each other on this subject. In the first three weeks from November 17, 2018 to December 2, 2018, 8,226 tweets were shared by 3,894 users. **It was this short period that was decisive in attracting the attention of various political leaders to the Marrakech Pact and making it go viral**. A second analysis of the publications was therefore conducted on this specific period. **The Gephi mapping of this corpus identifies 30 communities, which is consistent with an emerging and invisible topic in the public sphere. The first three communities in green, blue, and purple represent 50% of the exchanges** (**Fig. 5-B.**). These three communities communicate in different ways, but they mention each other through their micro-influencers, which multiplies their effectiveness: one highlights a 'UN pact on migration', another calls out far-right personalities, and the last is Belgian but relayed by their French network. **Whereas the communities of opinion leaders do not communicate with each other, micro-influencers on the same subject mention each other to get more reach.**

Fig. 5–B. Mapping via Gephi of the 100 Twitter accounts most central in exchanges (calculated with Betweenness Centrality) on the Marrakech Pact between 17/11/2018–2/12/2018



Source: Authors' own elaboration.

The Aix-la-Chapelle Treaty of cooperation between France and Germany, signed a few weeks after the Marrakech Pact on January 22, 2019, **confirms the importance of micro-influencers in the virality of fake news**. Bernard Monot, a member of the European Parliament for the Centre-Massif Central region, ex-National Front and member of Debout la France, posted a video on Facebook and YouTube on January 11, 2019, announcing that the treaty would lead to the cession of Alsace to Germany. **The information was widely shared by some far-right national politicians, but the micro-influencers who spread the fake news about the Marrakech Pact did not disseminate it**. The information remained confined to more or less isolated communities, preventing it from achieving the same virality as the Marrakech Pact, most likely because the subject did not interest them. This shows that opinion leaders alone are not always capable of spreading a message widely: **the participation of micro-influencers to reach multiple communities is essential. These 'ordinary influencers' are one of the keys to virality on Twitter.**[30]

[30] D.J. Watts, P.S. Dodds, 'Influentials…, *op. cit.*; Watts D.J., Bakshy E, Hofman J.M., Mason W.A., 'Everyone's…, *op. cit.*

However, the use of Social Network Analysis algorithms alone is not sufficient to detect them: **the betweenness centrality score, which is the most appropriate choice, generates numerous false positives that require manual verification of the accounts in question**. We therefore propose a detection model using machine learning to more easily identify micro-influencers.

Detecting micro-influencers using AI

The various data sets analyses carried out in this research have enabled us to identify active micro-influencers before the subjects become viral. By analysing the properties of these actors with Social Network Analysis, we will train an AI to recognise micro-influencers by exploiting all the algorithms of social network analysis.

Methodology for data qualification and preparation

We used AI in a supervised learning framework, meaning we indicated the goals we are looking to achieve with the algorithms. We performed the same analyses for each corpus as for the Marrakech Pact to identify the micro-influencers behind the virality of each topic. We then indicated them as targets in the processing file for machine learning (**Tab. 3.**).

All personal data of Twitter accounts were removed for analysis, with each account given a random identifier. **This allows us to use AI while respecting the GDPR (General Data Protection Regulation) since only variables related to the dynamics of exchanges on a topic are relevant for the analysis**. Twitter accounts of nationally influential personalities or organisations, and therefore opinion leaders, are not selected as targets for the algorithm. **They are still indicated in the corpus to verify their potential relevance, knowing that the dynamics of propagating a topic cannot be explained solely by their intervention**. This methodology ensures that the AI tool will seek to identify the properties of micro-influencers above all.

Tab. 3. Determining the number of micro-influencer targets for AI per data set and their role

Subject	Total # of Twitter accounts	Number of targets	Role
Anti-speciesism Environment	1,863	30	Training
Pact of Marrakech	4,671	58	Training / Holdout
EuropaCity	4,051	101	Training
Extinction Rebellion Italie 2	3,186	35	Training / Holdout
Extinction Rebellion and Lafarge	4,422	75	Validation
ZAD Dune	658	25	Validation
TOTAL	18,851	324	

Source: Authors' own elaboration.

For each data set, we obtained between 50 and 100 targets for the AI, out of a total of 1,000 to 4,000 values. **It is therefore a very limited data set that is used to define the most sensitive alert thresholds possible**. The importance of accessing the Twitter Firehose to train a predictive AI model on Twitter is inherent to the functioning of machine learning: not having access to all the data will further limit the capabilities of the AI, which will work on a biased statistical model.

All micro-influencers have a betweenness centrality score on Gephi greater than zero. However, this value alone is not enough to define an account capable of disseminating information widely among important communities. The challenge of applying AI is, therefore, to identify other criteria than betweenness centrality, based on the various algorithms and calculations proposed by Gephi.

To effectively train the AI, we then exploited all the metrics available with Gephi, which allowed us to measure the importance of each for selecting targets. The algorithms used were: Indegree, Outdegree, Degree, Weighted degree, Weighted Indegree, Weighted Outdegree, Eccentricity, closnesscentrality, harmonic-closnesscentrality, betweennesscentrality, Clustering Coefficient, pageranks, componentnumber,strongcompnum,Clusterclustering,eigencentrality,Authority,andHub.

As it is very difficult to identify the right machine learning model for an innovative research project, **we chose to use the Datarobot tool, which automates the application of dozens of machine learning models to identify those that offer the most relevant results**. This developing approach makes the application of machine learning more accessible by reducing the need for data scientist expertise and limiting the risk of project failures due to the choice of an inappropriate algorithm[31]. This innovative approach provides a significant time saving for research projects and proofs of concepts related to AI.

Data analysis procedure with machine learning

The analysis model was built with a data scientist from the Mydral company, an expert in the Datarobot software, which allows the use of dozens of machine learning algorithms. Several dozen machine learning models are used in parallel by Datarobot and compared with each other to select the best model. **We divided the six data sets corresponding to the analyses of each corpus as follows: four sets for training the machine learning models, two sets for validating and classifying the models according to their efficiency, and two sets for hold-out validation, which verifies the correct treatment of the data** (**Tab. 3.**). The objective is to detect micro-influencers as accurately as possible while limiting the number of false positives.

Implementation of machine learning models

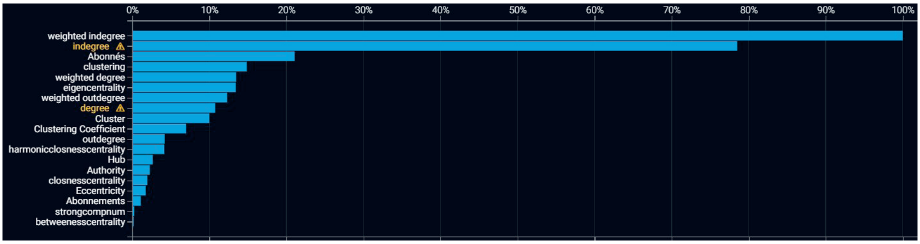
All micro-influencers have a betweenness centrality score greater than zero, which determines their ability to reach other communities. This therefore creates

[31] Truong, A., Walters, A., Goodsitt, J., Hines, K., Bayan Bruss, C., Farivar, R. *Towards Automated Machine Learning: Evaluation and Comparison of AutoML Approaches and Tools,* 2019., Arxiv, https://arxiv.org/pdf/1908.05557&ved=2ahUKEwjS0Zes2ermAhUqTt8KHdCFAhkQFjAGegQIBxAS&usg=AOvVaw0b_JUomS-A1rtsy7v5ZA64.pdf.

a dependency on betweenness centrality for the AI processing. This poses a problem, as we are looking for other properties that can identify a micro-influencer.

We therefore set aside the betweenness centrality score for processing by machine learning algorithms to improve the prediction model (**Fig. 6**). We identified metrics that make it possible to detect micro-influencers (in addition to betweenness centrality): quantity of mentions ('weighted indegree'), number of incoming links (mentions, 'indegree'), number of followers of an account, concentration in a cluster, and number of indirect links ('eigencentricity').

Fig. 6. Comparison of the weight of each variable calculated through Gephi in the detection of micro-influencers after removing the betweenness centrality variable



Source: Authors' own elaboration.

Low impact of the number of subscribers on tweet virality

Accounts with a high number of subscribers bias the reality of the distinction between a target and a non-target account. The artificiality of these accounts in a network is confirmed by the fact that statistically, centrality indicators are observed after qualifying the account as a target or not. **This result confirms that the number of subscribers does not affect influence.**[32] We were able to formalise an inverse relationship between **the average probability of being a micro-influencer and the number of subscribers of the account, which clearly confirms the work on the importance of 'weak links'** by Granovetter (1973) and Crozier (1977). Similarly, there is an inverse relationship between the concentration of the community to which an account belongs and its average probability of being a micro-influencer. By applying undersampling of negative target values over-represented in the test data sets, we developed a model that can identify 100% of true micro-influencers with a false positive rate ranging only between 22% and 27%.

Effectiveness of the machine learning regression model

The algorithm that yielded the best results corresponds to a descent direction model, designed to minimise a differentiable real function defined on a Euclidean

[32] M. Cha *et al.*, *op. cit.*; Beauvisage *et al.,* 2011.

space or, more generally, on a Hilbert space. This model corresponds to the Elastic-Net Classifier.[33] **It is part of the family of machine learning models by regression, which operate by seeking to retrieve precise numerical values from related variables** (Fig. 7). It is by exploiting the different Gephi algorithms to enrich the data corpus that this machine learning model was able to have enough elements to find the targets.

Fig. 7. Functioning of the Elastic-Net Classifier

Source: Authors' own elaboration.

The algorithm is iterative and proceeds through successive improvements. At each point, a movement is made along a descent direction in order to decrease the function. The movement along this direction is determined by the numerical technique known as linear search. In order to reduce overfitting, the algorithm used integrated penalties, known as L1 and L2 regularisation (L2: Ridge/L1: Lasso).

Conclusion

We characterised micro-influencers by exploiting the betweenness centrality algorithm proposed by Gephi, which nonetheless generates many false positives to filter out. Once the Twitter accounts playing the role of micro-influencers were identified, we were able to 'train' an automated system for AI-based detection, which uses several dozen AI models in parallel. **It is therefore possible to set up a system for detecting emerging topics driven by micro-influencers using the metrics of social network analysis**.

On the studied data sets, corresponding to different actors and contexts, with national or local scope, we were able to demonstrate that micro-influencers transmit information from one community to another and are the source of the virality of certain topics. They cannot be detected by simple algorithms as their characteristics need to be verified. Therefore, by providing already qualified data sets to a supervised learning AI, it is possible to find them using Gephi variables.[34]

Two avenues can be explored to extend this type of work. **The first would apply to the detection of influence operations or information manipulation**. For example, the Computational Propaganda Research Project at the University

[33] M. Blondel, S. Kazuhiro, U. Kuniaki, *Block coordinate descent algorithms for large-scale sparse multiclass classification*, 'Machine Learning', 2013, Vol. 93, pp. 31–52.

[34] Not all variables will be relevant, however. Enriching the data too much will pose problems for the AI if the additional variables are not coherent with the rest of the corpus, or more simply, if the calculations proposed by the tool turn out to be incorrect.

of Oxford has defined a 'Twitter manipulation coefficient' which makes it possible to evaluate whether exchanges on the social network have been manipulated on a specific topic.[35] **By combining this algorithm with the detection of micro-influencers, it would then become possible to greatly refine the detection of the spread of fake news**[36]. The second avenue would be to distinguish between retweets and mentions in the analysed Twitter data sets. In this context, Visibrain has implemented this functionality in its data exports in 2021, which distinguishes supporters (retweets) and critics (mentions) within a community. **This distinction would allow for better consideration of the role of micro-influencers in AI training and their respective weights in exchanges**, as demonstrated by the study of the Marrakech Pact.

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***Streszczenie.** Wykrywanie potencjalnie popularnych tematów na Twitterze było przedmiotem wielu badań, kilka zaś platform monitorujących oferuje swoim użytkownikom alerty dotyczące pojawiających się tematów. Jednakże, rozwiązania oparte na analizie semantycznej publikacji są często nieprecyzyjne i nieskuteczne. W artykule, powstałym w związku z prowadzonym projektem badawczym, proponujemy metodologię opartą na zastosowaniu sztucznej inteligencji do metryk z Social Network Analysis, która analizuje dynamikę wymiany w sieciach społecznościowych. Zidentyfikowaliśmy 'mikroinfluencerów', przejawiających aktywność w sześciu tematach społecznych. Mikroinfluencerzy są zainteresowani nowymi tematami przed* *liderami opinii, a ich aktywność pozwala im być odbieranym poza ich społecznościami: są zatem prekursorami wiralności nowych pojawiających się tematów w sferze publicznej. Stosując sztuczną inteligencję do dziesiątek wskaźników oferowanych przez oprogramowanie Gephi Social Network Analysis, zdefiniowaliśmy model uczenia maszynowego zdolny do skutecznej identyfikacji tych mikroinfluencerów. W tym celu wykorzystaliśmy innowacyjne narzędzie, które umożliwia porównanie skuteczności kilkudziesięciu modeli uczenia maszynowego.*

Resumen. *La detección de temas potencialmente populares en Twitter ha sido objeto de numerosas investigaciones; diversas plataformas de monitorización ofrecen a sus usuarios alertas sobre temas emergentes. Ahora bien, las soluciones basadas en el análisis semántico de las publicaciones suelen ser imprecisas e ineficaces. En el presente artículo, que es el producto de un proyecto de investigación, proponemos una metodología basada en la aplicación de la inteligencia artificial a las métricas del Social Network Analysis, que examina la dinámica de los intercambios en las redes sociales. Identificamos 'microinfluenciadores' activos en seis temas sociales. Los microinfluenciadores se interesan por los nuevos temas antes que los líderes de opinión, y su activismo les permite ser percibidos fuera de sus comunidades: son, por tanto, los precursores de la viralidad de los nuevos temas emergentes en la esfera pública. Al aplicar la inteligencia artificial a las decenas de indicadores que ofrece el software Gephi Social Network Analysis, definimos un modelo de aprendizaje automático capaz de identificar eficazmente a estos microinfluenciadores. Con este fin, hemos utilizado una herramienta innovadora que permite comparar la eficacia de decenas de modelos de aprendizaje automático.*

Zusammenfassung. *Die Erkennung der potenziell populärer Themen auf Twitter ist der Gegenstand zahlreicher Forschungsarbeiten, und mehrere Überwachungsplattformen bieten ihren Nutzern Warnmeldungen zu aufkommenden Themen. Lösungen, die auf der semantischen Analyse von Veröffentlichungen basieren, sind jedoch oft ungenau und ineffektiv. In diesem Artikel, der das Ergebnis eines laufenden Forschungsprojekts ist, wird eine Methodik vorgeschlagen, die auf der Anwendung der künstlicher Intelligenz auf Metriken aus Social Network Analysis basiert, die die Dynamik des Austauschs in sozialen Netzwerken analysiert. Wir haben «Mikro-Influencer» identifiziert, die sich in sechs sozialen Themenbereichen engagieren. Microinfluencer interessieren sich für neue Themen noch vor den Meinungsbildnern, und ihre Aktivität ermöglicht es ihnen, außerhalb ihrer Gemeinschaften aufgegriffen zu werden: Sie sind daher Vorläufer der Viralität von neu aufkommenden Themen in der Öffentlichkeit. Durch die Anwendung von künstlicher Intelligenz auf die Dutzenden von Indikatoren, die von der Software Gephi Social Network Analysis angeboten werden, haben wir ein maschinelles Lernmodell definiert, das in der Lage ist, diese Mikro-Influencer effektiv zu identifizieren. Dazu haben wir ein innovatives Tool verwendet, mit dem wir die Wirksamkeit von Dutzenden von maschinellen Lernmodellen vergleichen können.*

Резюме. *Выявление потенциально популярных тем в социальной сети Twitter является предметом многочисленных исследований, а ряд мониторинговых платформ предлагает своим пользователям сообщения о появлении новых тем. Однако решения, основанные на семантическом анализе сообщений, часто оказываются неточными и неэффективными. В данной статье, являющейся результатом проводимого исследовательского проекта, мы предлагаем методику, основанную на применении искусственного интеллекта к метрикам Social Network Analysis, которая исследует динамику обмена информацией в социальных сетях. Мы выявили «микроинфлюенсеров», проявляющих активность по шести социальным темам. Микроинфлюенсеры интересуются новыми темами раньше чем лидеры обсуждений, и их активность позволяет им быть замеченными вне своих сообществ: таким образом, они являются прекурсорами вирусности новых появляющихся тем в публичном пространстве. Применив искусственный интеллект к десяткам показателей, предлагаемых программой Gephi Social Network Analysis, мы определили модель машинного обучения, способную эффективно выявлять таких микрофлюенсеров. Для этого мы использовали инновационный инструмент, позволяющий сравнивать эффективность десятков моделей машинного обучения.*