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Improved Twitter Virality Prediction using Text and RNN-LSTM

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Abstract. The matter of influence and virality in social media has been studied since the popularity explosion of these platforms. A gargantuan amount of news and political messaging transits through Twitter every second, making it a formidable force for the propagation of information. In order to stay competitive, traditional media needs to participate in these platforms and attain influence. We propose a method to predict the influence of news tweets. To this end we use several thousand tweets to train an RNN-LSTM to classify news tweets as influential or not influential using a corpus of 5000 automatically labeled tweets according to their influence. Our method reaches an F1 of 0.845, while training and classifying in under 300 seconds.
Keywords: Twitter influence, Twitter virality, Twitter popularity, Applied deep learning, Social networks.

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1 Introduction

The dawn of the information era brought massive transformations to our society, traditional entities are losing influence as new social paradigms emerge enabling the creation of new entities and the strengthening of others. Rampant nationalism arises in certain points of the globe [1]. Industrial and digital era entities are struggling to preserve their positions of power and influence.

As the power of governments recedes back into the condign and taxation areas [2], new, smaller and numerous entities emerge and thrive in an environment of openness and free flow of information. Traditional mass media were the original eroders of the state's communicational hegemony starting with the first newspaper [3] in the 17th century with ever-growing influence until the last decade of the 20th century, from where their decline began [4].

Conditioned power, influence, persuasion, or leadership is the ability to change people's behaviors through the communication of ideas [5]. This gives rise to the concept of the "fourth estate" coined by Edmund Burke in 1787 [6] and it means that in touching consciences they hold great power, Dutton's "fifth estate" or "networked individuals enabled by the Internet, i.e., social media" [7] brings this concept into the digital era and even more into social media.

The democratization of content production [8] and the possibility for smaller entities to hold influence have provided ever more atomized groups or movements with power in the political and social spheres [9].

With these technologies comes also isolation, the echo chamber phenomenon, and the widespread dissemination of fake news [10]— undesirable effects that come from the lack of quality assurance, accountability, and validation traditional media were subject to.

It is relevant that entities with oversight and credibility remain a relevant counterweight, not exclusively to governments anymore, but to the new actors in social media, so relevance and influence of the traditional media in social media should be preserved and enhanced. Commercially, regaining influence is relevant for the mass media companies themselves as they have lost audience and importance as even behemoths like the New York Times have had to be salvaged by deep-pocket investors [11].

Three social media platforms dominate the news usage according to a Pew poll: Facebook, YouTube, and Twitter [12]. Of these, Twitter has a predominance of news content usage (Fig 1).

In the present work, while preserving the spirit and method, we depart from traditional —and extremely fast— Machine Learning (ML) algorithms towards more computationally expensive and modern Deep Learning algorithms. It is important to say that our experiments with traditional ML where extensive and exhaustive and we achieved excellent results that consumed very little time and computational resources.

Nonetheless, departing from the "fastest possible optimal" paradigm and looking to improve our results further, will not have us running in the direction of using as many resources as possible to speed up the process, but we'll be looking for the local minimum in terms of performance as well, but in a different algorithm search space.

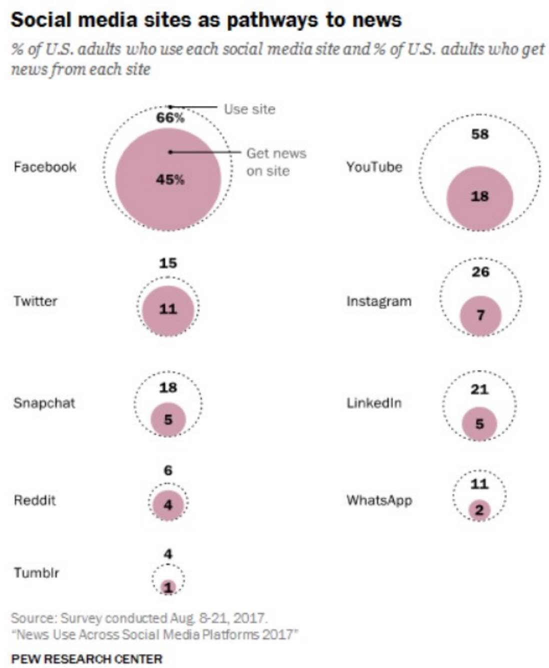

Fig. 1. Social media sites as pathways to news. Credit: Pew Research

2 Related Work

Influence from tweets and news are topics of great interest and importance given their relevance in the era of information and even more in the current days. It is important to notice that while some methods are concerned with the influence of the Twitter user or tweep, we found none on the issue of specific influence of the individual tweet, thus, the works presented here are related to this issue but do not deal with it directly.

The million follower fallacy is an influential article from Cha, Haddadi, Benevenuto, and Gummadi, which explores the issue of popularity in Twitter with the use of graphs and also the observation of behaviors of Twitter users. Dating back to 2010, this paper shows a Twitter that had already consolidated as a leading social network but was still young and devoid of the usage, popularity, and features it has nowadays [13].

Ye and Wu presented *Measuring Message Propagation and Social Influence on Twitter.com* also in 2010. In their comprehensive work they present a statistical and graph-based approach to influence on a single topic, their study is insightful and provided many key notions for the development of our work, nevertheless, the highly theoretical approach also uses a great deal of human analysis, barely touching on the machine learning approach [14].

Everyone's an influencer is an extensive analysis of a massive 1.06 billion corpus of tweets collected over two months by Bakshy, Hofman, Mason, and Watts; they analyze the dispersion rates on 76 million events, tracking 1.6 million tweeps. They concluded that word-of-mouth is —as they admit, intuitively— the main propeller of tweet influence, also finding out that certain actors hold more influence than others according to the size of their audience and the tone they use in their post. This work is important but assumes the linguistic characteristics of the content have little impact or predictive power which was contrary to our own intuition [15]. It is important to mention that this work seeded a previous article of ours about the reach and impact on social media [16].

Bandari, Sitaram, and Huberman in their 2012 work *The pulse of news in social media: Forecasting popularity* offer one of the earliest approaches to predict the influence of news in social media. While their method is precise in terms of prediction reaching precision levels in the vicinity of 84% (similar to our method), it is important to note a great deal of manual work is needed to preprocess, tag the news, and extract the significant features. Machine Learning is used only for the final classification thus making the implementation for industrial purposes almost impossible [17].

In 2013 Sidorov, Miranda-Jiménez, Viveros-Jiménez, Gelbukh, Castro-Sánchez, Velásquez, Díaz-Rangel, Suárez-Guerra, Treviño, and Gordon published *Empirical Study of Machine Learning Based Approach for Opinion Mining in Tweets*. While this work is not geared towards influence, it uses ML to obtain linguistic characteristics of tweets, of course, for the purpose of opinion mining [18].

Cataldi and Aufaure put forward *The 10 million follower fallacy: Audience size does not prove domain-influence on Twitter* [19], with a clear reference to the “One million follower fallacy” article by Cha et al. [13]. They present an updated model and novel conclusions on the size of the audience in relation to influence.

In their 2014 *Understanding Twitter Influence in the Health Domain*, McNeill and Briggs [20] present an applied focus to a specific domain, trying to define how influence operates in Twitter on the context of medical services. Their approach is sociological and psychological, they argue quantitative methods while concurrent with qualitative are limited and have limitations in their descriptive power.

Simmie, Vigliotti and Hankin published their work also in 2014 with the title *Ranking twitter influence by combining network centrality and influence observables in an evolutionary model*. Presenting an elegant and ML oriented model they rank the influence of a tweep according to its node connections [21].

Garcia, Mavrodiev, Casati and Schweitzer released *Understanding Popularity, Reputation, and Social Influence in the Twitter Society* in 2017. They compute network information on a large dataset of 40 million users, creating new global measures of reputation utilizing the D-core decomposition and bow-tie structure of the Twitter follower network ascribing popularity, reputation, and social influence to evaluate a host of behaviors [22].

Ma, Li, Bailey and Wijewickrema present their method in the article *Finding Influentials on Twitter*. Using the temporal influence rate (TIR) they observe and characterize the behaviors of tweeps over a two-month period. They then use ML techniques to identify influential users within the vast network and classify them with a higher accuracy than other, more numerical, approaches [23].

The present work is the development of our previous research on the same topic in 2018 [24], where we designed an initial model which used several linguistic features to characterize tweets including a mixture of regular and POS n-grams and to automatically categorize the tweets using an ad-hoc formula. Finally, we used the Naive Bayes algorithm for classification reaching an F1 of 74.4%. In the next work we fulfilled further experimentation on feature selection and traditional Machine Learning algorithms to achieve an F1 of 78.2% with the Voted Perceptron algorithm for classification [25].

In 2019 a work that uses the idea of infectivity from the field of virology obtains important results. “Infectivity enhances prediction of viral cascades in Twitter” by Li, Cranmer, Zheng and Mucha describes a hybrid model with simulations and real data. The implemented model then gathers the first few time steps of a tweet interaction combined with an infectivity based metric of the user’s network and yields a precision of 70% on real data and 69% on simulation, no F1 measure is presented [26].

Another noteworthy development is the industrial-grade and large-scale system developed in a collaboration between Microsoft Research and the Technological University of Denmark (DTU). It is explained in “Scalable Privacy-Compliant Virality Prediction on Twitter” where the authors Kowalczyk and Larsen present it as consisting of several proprietary technologies including the Azure solutions and APIs and the Twitter Enterprise API Firehose [28]. It is the only work —to our knowledge— that includes the Twitter Privacy Compliance Firehose API. It is significant that the authors—at a great computational and

monetary cost— attempt to predict the exact number of retweets (not categories) claiming to get results 37% over those of Wang et al. in 2018 [27]. It is our opinion that the metrics and method used by the authors in [28] differ too much from those used by Wang, hence, is difficult to compare.
Closer to our work, both in time and features —therefore, making comparison with our method and results possible— is the work of Xiao, Liu, Ma, Li, and Luo entitled *Time sensitivity-based popularity prediction for online promotion on Twitter*. To analyze their results, they do not use the standard F1 metric, but the Geometric Mean from of sensitivity and specificity, sometimes referred to as G-Mean2, achieving 0.6972. In their repository the corpus is heavily preprocessed, so without the original tweet texts it is impossible to test their method which uses different features. In spite of the differences in methodology and result metrics, these researchers use linguistic features and time bins to predict the virality of a tweet. Since these inputs are the same as our inputs and the output is similar to ours, we can say our method and theirs are comparable [29].

3 Method

We developed a tweet influence metric that tries to define the influence of a tweet independently of the influence of the account that posts it. With this measure we classify the tweets in a multi-thousand tweet corpus. As opposed to our previous work, we use plain text of the tweets tagged according to our metric instead of diverse types of n-grams and other representations like bag-of-words (BOW).

This corpus is collected from multiple users related to a specific sector within a variable timeframe based on the frequency of the tweets, then trains a Recurrent Neural Network (RNN) with LSTM (Long Short-term Memory) architecture, with self-adjusting forget gates, from there we proceed to classify.

The optimal classification algorithm was obtained by an experimentation process which included testing 300 different configurations including neural network architectures and flavors as well as internal configurations for the algorithms.

3.1 Corpus

Retrieval of the tweets was necessary since we intended to work with Mexican news media and a corpora of tweets that included all the necessary data for our influence metric was not available. Other sources were either of other locations, scopes, or with partial data.

We collected 133,877 tweets classified from most influential to least influential according to the tweet influence metric and ordered them in a descending order. From these we select 5,000 tweets: the top 2,500 of them as highly influential and the bottom 2,500 as the lowly influential. This reduction allows both for a clear differentiation between the high influence and the low influence tweets and to have balanced categories.

It is noteworthy that our collection method is automatic, during our experimentation we have collected and categorized tweets from 418 corpora totaling 1,001,412 tweets. Most of these corpora are small and task focused, compiled to experiment with other domains and languages of the tweets. Also, it as used to collect tweets of specific topics regardless of their source and to keep record of interesting trending topics, cashtags and hashtags.

Currently, experiments on the news domain but with English-language news-casting accounts from the USA are under development. Smaller corpora are continuously harvested to corroborate the effectiveness of our method at different moments in time.

Our sources for the experimental corpus were 46 influential and active news outlet accounts specific for Mexico. They were selected for their geographical scope —nationwide, not localized—, relevance —using the journalistic expertise of the author as well as consulting specialized websites [36, 37] and periodicity (five or more tweets per day). Accounts from media outlets that presented off-topic tweets (i.e., self-advertisement, promotion of political, governmental, or commercial entities) in a proportion of more than half of their tweet volume were eliminated from the list.

The tweets are in Spanish. The preprocessing process involved eliminating all punctuation symbols thus automatically converting web addresses into linguistic items. While most researchers eliminate web links when preprocessing tweets, we decided to keep them as news accounts frequently re-post links to the same news with different texts. All tweets are converted to lowercase and named entities were preserved.

The list of selected accounts (in no particular order) is given here:

- @reforma
- @larazon_mx
- @lacronicadehoy
- @milenio
- @unomasunomx
- @lajornadaonline
- @capitalmexico
- @elgmx
- @el_universal_mx
- @laprensaoem
- @impactomx
- @elsolde_mexico
- @ddmexico
- @contrareplicamx
- @sdpnoticias
- @eleconomista
- @heraldodemexico
- @diariobasta
- @noticiasmiled
- @excelsior
- @maspormas
- @publimetromx
- @proceso
- @forbes_mexico
- @elarsenalmx
- @20mmexico
- @elfinanciero_mx
- @huellasmx
- @diario24horas
- @lasillarota
- @sinembargomx
- @aristeguionline
- @julioastillero
- @cnnee
- @ntelevisa_com
- @laoctavadigital
- @notimex
- @soycarlosmota
- @_vicenteserrano
- @carlosloret
- @cirogomezl
- @nachorgz
- @lopezdoriga
- @lordmolecula
- @reporte_indigo
- @lpomx

The corpus is presented in two files. The “clean” file has only two columns, the first with the tweet influence metric output rounded to four decimals and the second with the pre-processed tweets. The “complete” file has 11 columns: Username, Tweet ID, Time of Post, Original Tweet, Processed Tweet, Followers, Followed, Retweet, Favorited, Listed, and Ponder (our tweet influence metric, rounded to 4 decimals). The second file is intended to help in forensic analysis.

3.2 Tweet Influence Metric

In order to automatically tag our corpus, we need a simple metric which can help us determine the influence of a tweet using measures provided by the Twitter Search API when retrieving tweets from specific users. These are described in Table 1.

Table 1. Tweet measures obtained from Search API

Measure	Description	Symbol
followers	Number of accounts that follow the user.	w
friends	Number of accounts that the user follows.	d
retweets	Number of retweets (reposts) of a tweet.	r
favorites	Number of favorites (likes) for a single tweet	f

To compare the influence of tweets produced by users with different audience sizes and popularity, we need to have a ratio of the influence of the tweet —its interactions— and the influence of the user itself. This is our rationale.

We sum the number of interactions $r+f$ and use the ratio of r to f to increase the number of interactions if the $f<r$, to hold it the same if $f=r$ and to reduce the interactions if $r>f$. The rationale behind this is that a high number of retweets with few favorites most likely suggests that the tweet is being shared with the purpose of criticizing or making fun of it. An equal number hints a neutral position and a higher number of favorites than retweets likely implies that the tweet is perceived positively. The natural logarithm has the desired property of taking ratios over as positive, at as neutral, and under as negative while providing the robustness of working with large disparities between the numbers without growing out of control.

In order to automatically tag the corpus after it is downloaded, we need to use a metric that does not require ample computational power. This can be achieved at the cost of precision using a small set of arithmetic operations. We can't ignore the fact that many accounts seek followers by participating in fraudulent "follow for follow" dynamics. Also, when an account is followed by less accounts than it follows, the influence should be considered negative as the user is more influenced than it is influential others. To represent this, we subtract *w* from *d* and multiply by its ratio, again using the natural logarithm to tame different values and sum or subtract this to the number of followers as a percentage. We represent those concepts in the following formulas.

Let

$$g = r + f \quad \text{and} \quad h = w - d \quad . \tag{1}$$

We define the *relative* influence of the tweet inf_t as

$$inf_t = g + g\,\frac{\ln\left(\frac{f}{r}\right)}{100} \quad . \tag{2}$$

And the influence of the account as inf_a as

$$inf_a = w + h\,\frac{\ln\left(\frac{w}{d}\right)}{100} \quad . \tag{3}$$

We also define the *absolute* influence of the tweet as

$$inf_{twt} = \frac{inf_t}{inf_a} \quad , \tag{4}$$

which eliminating nested fractions algebraically finally becomes

$$inf_{twt} = \frac{100g + g\,\ln\left(\frac{f}{r}\right)}{100w + h\,\ln\left(\frac{w}{d}\right)} \quad . \tag{5}$$

3.3 Classification

After annotating every tweet according to the measures provided by twitter through the API, using our home-brewed metric as it appears in (4) and selecting the most representative tweets for the *hinf* and *ninf* categories as explained in subsection 3.1, we proceed to train our RNN-LSTM with the annotated corpus and corroborate the training both via traditional training-test sets (for the whole method validation) and also applying 10-fold cross validation (for the experimentation phase).

Finally, we use the trained algorithm for either pre-testing and optimization of new (unsent) tweets or for further corroboration with other sets. It is worth noting that our method includes collecting tweets from users that produce content closely related to the topic of the tweets to which the prediction will be applied. In this work we used Mexican news but our method can be generalized to any language.

4 Results

In this section we present the results and products of our research. First, we present the corpora we made available to the community. A brief description of the corpora is given as well as the link for download. Next, we describe our experimentation, showing the best eight configurations out of the 300 experiment search space. Finally, we present the outcomes of the classification with the best configurations and compare them with the best configuration in our previous work, where we used traditional machine learning, and with ZeroR algorithm without predictive power as a reference.

4.1 Corpus

The compiled corpora includes 133,877 tweets annotated with the value obtained from our metric. We preserved the original files as processed for peer-review purposes. We present screen captures for reference and the files are available for download[1].

Figure 2 gives a partial view of the `133k-compl.csv` file where one can see all the columns mentioned in subsection 3.1. Figure 3 presents a part of the file with cleaned tweets and the value assigned by our metric. It is evident that while the clean file provides promptness to test out the method presented here, doing any sorts of validation on the calculations as well as trying any other method on the same dataset would be impossible.

1 https://drive.google.com/drive/folders/1f078Dlw3JMlQQyGh7fP_fASyikGlLeJZ

0.0001	LAOCTAVADIGITAL	1261204670770343	Fri May 15 08:00:00	#VIDEO | La UIF pre	video la uif presentó	2	4	92478	449	hinf
0.0001	LAOCTAVADIGITAL	1261194352845639	Fri May 15 07:19:00	El abogado de Israel	el abogado de israel	2	5	92478	449	hinf
0	LAOCTAVADIGITAL	1261190326468915	Fri May 15 07:03:00	El diputado local de	el diputado local de	0	2	92478	449	ninf
0.0002	LAOCTAVADIGITAL	1261189572869984	Fri May 15 07:00:00	#VIDEO | Nos estam	video nos estamos p	5	9	92478	449	hinf
0.0001	LAOCTAVADIGITAL	1261184286410985	Fri May 15 06:39:00	El hospital tendrá un	el hospital tendrá un	4	7	92478	449	hinf
0.0001	LAOCTAVADIGITAL	1261179253347045	Fri May 15 06:19:00	.@Tu_IMSS continú	tuimss continúa con	3	6	92478	449	hinf
0	LAOCTAVADIGITAL	1261174473065037	Fri May 15 06:00:00	#VIDEO | Yo estoy d	video yo estoy de ac	2	0	92478	449	ninf
0.0002	LAOCTAVADIGITAL	1261163814898348	Fri May 15 05:17:39	#VIDEO | Recibí la l	video recibí la llama	9	10	92478	449	hinf
0.0001	LAOCTAVADIGITAL	1261161637173694	Fri May 15 05:09:00	Descubre lo que ofre	descubre lo que ofre	3	10	92478	449	hinf
0.0001	LAOCTAVADIGITAL	1261159373327536	Fri May 15 05:00:00	#VIDEO | @AlfredoL	video alfredolecona	3	7	92478	449	hinf
0.0001	LAOCTAVADIGITAL	1261149054228033	Fri May 15 04:19:00	El objetivo de la fies	el objetivo de la fies	2	7	92478	449	hinf
0.0003	LAOCTAVADIGITAL	1261145027981438	Fri May 15 04:03:00	La @UNAM_MX can	la unammx canceló	6	23	92478	449	hinf
0.0004	LAOCTAVADIGITAL	1261142936667877	Fri May 15 03:54:41	#VIDEO | En entrevis	video en entrevista	10	26	92478	449	hinf
0.0001	LAOCTAVADIGITAL	1261139770438119	Fri May 15 03:42:06	#VIDEO I ¿México e	video I méxico está	4	6	92478	449	hinf
0.0002	LAOCTAVADIGITAL	1261138987957149	Fri May 15 03:39:00	Los pacientes graves	los pacientes graves	8	11	92478	449	hinf
0.0002	LAOCTAVADIGITAL	1261136186522898	Fri May 15 03:27:52	#EnVivo | A veces pi	envivo a veces pien	4	13	92478	449	hinf
0.0002	LAOCTAVADIGITAL	1261134135143411	Fri May 15 03:19:43	#EnVivo | Algo que	envivo algo que se	6	12	92478	449	hinf
0	LAOCTAVADIGITAL	1261133954964508	Fri May 15 03:19:00	El @GobiernoJalisco	el gobiernojalisco ya	0	3	92478	449	ninf
0.0002	LAOCTAVADIGITAL	1261132577915600	Fri May 15 03:13:31	#EnVivo | Ese mito c	envivo ese mito de	7	15	92478	449	hinf
0.0003	LAOCTAVADIGITAL	1261132275485298	Fri May 15 03:12:19	Israel Vallarta acusa	israel vallarta acusac	12	13	92478	449	hinf
0.0001	LAOCTAVADIGITAL	1261131930524737	Fri May 15 03:10:57	#EnVivo | Este gobie	envivo este gobierno	4	6	92478	449	hinf
0.0001	LAOCTAVADIGITAL	1261131034805940	Fri May 15 03:07:24	#EnVivo | El Ejército	envivo el ejército y	4	7	92478	449	hinf
0.0001	LAOCTAVADIGITAL	1261130175065886	Fri May 15 03:03:59	#EnVivo | Hay un fra	envivo hay un fraca	3	4	92478	449	hinf
0.0001	LAOCTAVADIGITAL	1261129538504777	Fri May 15 03:01:27	#EnVivo | El propio	envivo el propio pre	3	7	92478	449	hinf
0	LAOCTAVADIGITAL	1261129446314008	Fri May 15 03:01:05	Tomando té de canc	tomando té de canel	2	1	92478	449	ninf
0.0001	LAOCTAVADIGITAL	1261128632468029	Fri May 15 02:57:51	#EnVivo | Yo estoy d	envivo yo estoy de a	3	6	92478	449	hinf

Fig. 2. Partial view of the 133k-compl.csv file of our corpora. Prepared by the authors.

Preserving the complete file will open the door to validating the experiments but also to make comparisons with methods presented in other articles. Since the lack of standardization generates plenty of disparities and difficulties to compare works, this might be a small step towards contributing to establish a gold standard.

4.2 Experimentation

To find the optimal setup, 300 configurations were tested with Convolutional Neural Networks and Recurrent Neural Networks. These two topologies were selected out of a plethora of algorithms after our careful examination of the literature. We then created a matrix of the tweakable parameters and generated scripts to run experiments in batches of ten with an 80-20% training-test split. For the last eight candidates, we used a 10-fold cross validation method. The best eight performing configurations are presented in Table 2.

0.0001	video la uif presentó nuevas denuncias contra garcía luna y luis cárdenas palominohttpstcowzszck5z4o
0.0001	el abogado de israel vallarta aseguró que el estado de salud de su cliente el delicadohttpstcokzyorckx4j
0	el diputado local de sonora por el partido encuentro social carlos navarrete aguirre aseguró que la enfermedad po httpstco5efxjcptwz
0.0002	video nos estamos preparando para enfrentar la fase exponencial que va a ocurrir en estos días en el valle de mé httpstcolocl64paa7
0.0001	el hospital tendrá una capacidad para albergar 40 camas y contará con el equipo necesario para atender a pacientes httpstcokfyqdjkey9
0.0001	tuimss continúa con la aplicación de plasma convaleciente para pacientes con complicaciones respiratorias por el httpstco1hzq1ddgvm
0	video yo estoy de acuerdo con la filosofía de este gobierno de reducir los salarios más altos siempre y cuando httpstcoy0tmnjugav
0.0002	video recibí la llamada de israel el día 12 de mayo y no podía ni respirar me dijo que habían muchos presos enf httpstcob65cltdo6u
0.0001	descubre lo que ofrece la amismx con este seguro de vida gratuito para personal que atiende a pacientes contagiad httpstcoh0u4hibkzx
0.0001	video alfredolecona señaló que la militarización es una traición a los principios que lopezobrador abanderaba httpstco4m1qct8jq3
0.0001	el objetivo de la fiesta es que los asistentes se contagien de covid19 y así obtener la inmunidad de rebaño com httpstcobvvbps55wz
0.0003	la unammx canceló el debate sobre ciencia neoliberal que iba a ser dirigido por johnmackerman httpstcoxfrezt1oth
0.0004	video en entrevista con ricardomraphael la esposa de israel vallarta declaró que el estado de salud de su espo httpstcofbs3a4pr3s
0.0001	video l méxico está listo para el desconfinamiento jeanmarc gabastou asesor de la organización panamericana de httpstcocdxqrdkdix
0.0002	los pacientes graves por coronavirus serán atendidos por doctores del iner respirainer y personal de la httpstcoillavpwckg
0.0002	envivo a veces pienso que el presidente lopezobrador lo que quisiera es desaparecer al ejército por la vía de httpstcom8ktimruoo
0.0002	envivo algo que se hace mal desde la sociedad civil en las campañas contra la militarización es apuntar las bate httpstcoguqe0hgnlq
0	el gobiernojalisco ya está listo para la reactivación gradual de las actividades económicas con la fase0 httpstco2400qxqlgx
0.0002	envivo ese mito de que el presidente se da baños de pueblo tiene que ver con una construcción de un personaje httpstcoihe05k8q2c

Fig. 3. Partial view of the 133k-clean.csv file of our corpora. Prepared by the authors.

As it is noticeable in Table 2, the Recurrent Neural Network configurations showed more promise towards the end of the race. Nonetheless, Convolutional Neural Networks were tested all the way through, since on the first iterations they showed faster performance and comparable precision.

Table 2. Top contender algorithm configurations. Prepared by the authors.

Config. ID	Algorithm	Layer Number	Bi-Direction	Level	Word Format	Epochs	Combiner	Cell Type
92	pllel_cnn	2	no	word	space	5	concat	na
109	pllel_cnn	3	no	word	space	3	concat	na
228	rnn	1	no	word	space	**7**	concat	lstm
232	rnn	1	yes	word	space	7	concat	lstm
246	rnn	2	yes	word	space	5	concat	lstm
251	rnn	2	no	word	space	4	concat	lstm
265	rnn	4	no	word	space	6	concat	lstm
269	rnn	4	yes	word	space	6	concat	lstm

For RNNs it became evident early in the experimentation that LSTMs were necessary for this task. Coming from a background in NLP and having used traditional ML extensively in the past, another surprise was that RNNs take plain text as input.

4.3 Classification

We present our eight best performing configurations along with ZeroR and the Voted Perceptron from our previous work for comparison and as a baseline. The results are presented in Table 3, the configuration with the longest execution time of the fore-runners are highlighted in red.

Table 3. Algorithm configurations. Best result in bold, worst in red, baseline in italics. Prepared by the authors.

Config. ID	Class Size	Correctly Classified	Correctly Classified	All Classes Weighted Average	Time Taken to Build

		Instances	Instances %	Precision	Recall	F1	Model (Seconds)
ZeroR (Reference)	3000	3,000	50.00%	?	0.500	?	0.01
Voted Perceptron (Baseline)	3000	*4,679*	*77.97%*	*0.780*	*0.780*	*0.780*	***1.36***
92	2500	4,219	84.39%	0.8439	0.8439	0.8439	142.00
109	2500	3,989	79.78%	0.7978	0.7978	0.7940	166.00
228	2500	4,008	80.71%	0.8031	0.8031	0.8017	164.00
232	2500	4,037	80.75%	0.8075	0.8075	0.8059	181.00
246	2500	**4,224**	**84.50%**	**0.8450**	**0.8450**	**0.8448**	**224.00**
251	2500	4,048	80.96%	0.8096	0.8096	0.8096	261.00
265	2500	4,011	80.25%	0.8025	0.8025	0.8022	518.00
269	2500	3,983	79.6709%	0.7967	0.7967	0.7967	601.00

A YAML file with the precise configurations for input and output of our model is provided alongside with the corpora[2].

As it can be observed in Table 3, our previous results were solid and an important departure from the reference point of the ZeroR algorithm was shown. This latter non-predictive algorithm classifies randomly and thus showing the of the classes. In our case, as the classes are balanced, the average of several runs tends to 50%. The baseline in our previous work was an F1 of 0.78 using the Voted Perceptron algorithm, which is 28% above random classification.

The exploration of more modern techniques proved useful in improving our F1 to 0.85 which is an improvement of ~7% over baseline and 35% better than random classification. It is a noteworthy improvement showing promise towards better performance provided a more granular search to avoid falling in a possible local minimum. Also, a search within a broader scope in terms of algorithms or parameters might prove beneficial.

There is one specific area where the new algorithm suffers greatly, which is in resource and time consumption. Whilst the Voted Perceptron algorithm managed to both train and classify in a formidable 1.36 seconds time-span (on a Core i7 – 16 GB RAM computer), the RNN-LSTM was ~1,650% slower at the train-classification task (on a Core i7 – 16 GB RAM computer – 980TI GPU) clocking in at 224.0 seconds even when using a GPU —it halted after 18 hours on a GPU-less configuration. This tells us that Voted Perceptron is still suitable on low-resource or time restricted environments where speed is more valuable than precision.

2 https://drive.google.com/drive/folders/1f078Dlw3JMlQQyGh7fP_fASyikGlLeJZ?usp=sharing

With embedded and mobile computers reaching comparable features as mid-low tier desktop platforms (ca. 2021), it is feasible to use traditional machine learning algorithms to reach fast performances on such devices. We find this worth considering.

5 Conclusions

Our best results provided an F1 +6% above the baseline, this is a precision of 84.502%. This result is above the state of the art for textual approaches similar to ours, textual approaches using sentiment analysis and other methods like graph and network analysis. Though as we have mentioned earlier, state of the art methods and success metrics are often disparate and little information provided by other authors makes it difficult to compare results. That is, there is no gold standard in this task.

Given the level of precision, which is presumably improvable through more experimentation, we are prone to conclude that our method can be applied to specific uses within the news, marketing, and public relations industries, as well as used in applications for diverse areas which take advantage of Social Media influence (i.e., through Social Media marketing) for political, commercial and social purposes.

Applications for tweet virality prediction at these levels of accuracy and precision are numerous, our method can be used by any entity interested in presenting its ideas to the world for whatever reason. It is our vision than it can be incorporated into a Generative Adversarial Network as the Adversarial part in order to produce influential tweets automatically.

Our method is of special interest for traditional news outlets which have been receding in influence and reach. It can be employed both as a new business model and as a boost, even a lifeline for their prior business models, in the dire current situation.

On the social front, citizens need to be listened by their authorities. Democracy in real time considered by Laidi and Gelbukh as well as other authors [30, 31, 32] is a two-way process, when the government knows what their citizens want and need. Yes, governments need to apply data mining to Social Media in order to know what people expect of them, but citizens need algorithms that help them achieve more influence, too.

5.2 Reflection upon recent censorship-related events

One of the long-time preoccupations of the authors has been the speed and even the acceleration of power accretion by the “big five” of Silicon Valley. It is noteworthy that each of them has a net-worth larger than the Gross Domestic Product (GDP) of most countries in the world and them taken together are larger than some European countries [33]. Sadly, the “big five” are far from massive tech companies, many other companies populate the list of the richest companies in the world.

Also with the advent of GPT-3 model that costed literally almost 10 million dollars to train [34], academic institutions around world are unable to compete with it. Also, production of knowledge is being seized by these enormous companies. We are, so to say, at their mercy, trusting they will remain respective of our rights and in general providing more benefits than harm.

After the violent incidents on the Capitol [35] which were allegedly fostered from Twitter the —at the moment— still sitting President of the United States, Donald Trump had his personal account canceled. This does not attempt to be a discussion on the actions of Trump, but a clear evidence that the “big five” are willing to overstep the rule of law by taking away such basic human rights as the freedom of speech by imparting their own sentence on a case that had not —at the moment of the cancellation— been ruled by any judicial authority.

It might be arguable whether freedom of speech was canceled, since the person in question can speak in other locations. But still this discussion is necessary because in a hyper-connected world, being prevented from accessing the most prominent spaces of discussion can, indeed, be ostracizing, and thus impede or at least get in the way of the freedom of speech.

It is our opinion that no Terms and Conditions Agreements —of any sort— should be allowed to deprive people of their rights granted by their constitution and national authorities. As computer scientists we tend to be in our own bubble of isolation working on powerful algorithms that might, in the end, promote the accumulation of power.

This narrow and focused worldview should not prevail. We have ownership and responsibility to at least give thought and, if possible, weigh in the discussion, and also to do our best in making our work more accessible for the public.

5.2 Future Work

We favor interdisciplinary research applied to the field of influence to create a standard framework for the future development of the studies on Social Media influence. We need to keep on updating the method to reflect changes in Twitter and on social dynamics, but for this we insist that an interdisciplinary semi-permanent group is of uttermost necessity.

Plans to produce an industrial grade shell product and release it to the public are starting to take form. We also consider an international contest on Social Media influence detection with the intention to further develop standardization for metrics on this specific task.

References

1. Hurrell, A.: Beyond the BRICS: Power, Pluralism, and the Future of Global Order. Ethics & International Affairs. 32, 89–101 (2018).
2. A. Etzioni, "Defining Down Sovereignty", Library of Public Policy and Public Administration, pp. 203-217, 2018.
3. J. Carolus, "Relation: Aller Fuernemmen und gedenckwuerdigen Historien: so sich hin und wider in Hoch- und Nieder-Teutschland, auch in ... verlauffen und zutragen möchte (1609)", Digi.ub.uni-heidelberg.de, 1605. [Online]. Available: http://digi.ub.uni-heidelberg.de/diglit/relation1609.
4. Young, Sally. "The decline of traditional news and current affairs audiences in Australia." Media International Australia 131.1 (2009): 147-159.
5. J. K. Galbraith, The anatomy of power. Transworld Publishers Ltd., 1985.
6. T. Carlyle, On Heroes and Hero Worship and the Heroic in History, 1st ed. London: EVERYMAN'S LIBRARY, 1840, p. 392.
7. W. Dutton, "The Fifth Estate Emerging through the Network of Networks", Prometheus, vol. 27, no. 1, pp. 1-15, 2009.
8. C. Fuchs, Internet and society, 1st ed. New York, N.Y.: Routledge, 2011, pp. 121-129.
9. B. Loader and D. Mercea, "NETWORKING DEMOCRACY?", Information, Communication & Society, vol. 14, no. 6, pp. 757-769, 2011.
10. Gates, W.: Bill Gates on the spread of "fake news" online, https://youtu.be/mYTeeZnf43w. [Accessed: 26- Feb- 2018]
11. S. Rosoff, H. Pontell, R. Tillman and S. Rosoff, Looting America. Upper Saddle River, N.J.: Prentice Hall, 2017, pp. 211-219.
12. "Carlos Slim becomes top New York Times shareholder", U.S., 2018. [Online]. Available: https://www.reuters.com/article/us-new-york-times- warrants-carlos-slim/carlos-slim-becomes-top-new-york-times-shareholder-idUSKBN0KN2M820150114. [Accessed: 6-Mar- 2018].
13. M. Cha, H. Haddadi, F. Benevenuto and P. K. Gummadi, Measuring user influence in twitter: The million follower fallacy. Icwsm, 10 pp. 10-17, (2010).
14. S. Ye and S. Wu, "Measuring Message Propagation and Social Influence on Twitter.com", Lecture Notes in Computer Science, pp. 216-231, 2010.
15. Bakshy, E., Hofman, J.M., Mason, W.A. and Watts, D.J., Everyone's an influencer: quantifying influence on twitter. In Proceedings of the fourth ACM international conference on Web search and data mining (2011) pp. 65-74.
16. Maldonado, C. E. How to Improve the Reach and Impact of Social Media Content. Research in Computer Science, vol. 127. 2016.
17. R. Bandari, A. Sitaram, and B. A. Huberman. "The pulse of news in social media: Forecasting popularity." ICWSM 12 pp. 26-33, 2012.
18. Sidorov G., Miranda-Jiménez S., Viveros-Jiménez, F., Gelbukh A., et. al. Empirical Study of Machine Learning Based Approach for Opinion Mining in Tweets. Lecture Notes in Artificial Intelligence, N 7629, 2013

19. M. Cataldi and M. Aufaure, "The 10 million follower fallacy: audience size does not prove domain-influence on Twitter", Knowledge and Information Systems, vol. 44, no. 3, pp. 559-580, 2014.
20. A. McNeill and P. Briggs, "Understanding Twitter influence in the health domain", Proceedings of the 23rd International Conference on World Wide Web - WWW '14 Companion, 2014.
21. D. Simmie, M. Vigliotti and C. Hankin, "Ranking twitter influence by combining network centrality and influence observables in an evolutionary model", Journal of Complex Networks, vol. 2, 2014.
22. D. Garcia, P. Mavrodiev, D. Casati and F. Schweitzer, "Understanding Popularity, Reputation, and Social Influence in the Twitter Society", Policy & Internet, vol. 9, no. 3, pp. 343-364, 2017.
23. X. Ma, C. Li, J. Bailey and S. Wijewickrema, "Finding Influentials in Twitter: A Temporal Influence Ranking Model", Arxiv.org, 2018. https://arxiv.org/abs/1703. 01468.
24. C. Maldonado-Sifuentes, A. Gelbukh & G. Sidorov. “Automatic Detection of Linguistic Features of Influential News Tweets” Master’s Degree Thesis. (2018).
25. C. Maldonado-Sifuentes, C. Caballero, G. Sidorov & O. Kolesnikova. “Predicción de Viralidad en Twitter utilizando PLN y aprendizaje automático” COMIA. (2020).
26. Wang, K., Bansal, M. and Frahm, J.M., 2018, March. Retweet wars: Tweet popularity prediction via dynamic multimodal regression. In 2018 IEEE Winter Conference on Applications of Computer Vision (WACV) (pp. 1842-1851). IEEE.
27. Kowalczyk, D.K. and Larsen, J., 2018. Scalable Privacy-Compliant
28. Xiao, C., Liu, C., Ma, Y., Li, Z. and Luo, X., 2020. Time sensitivity-based popularity prediction for online promotion on Twitter. Information Sciences.
29. Virality Prediction on Twitter. arXiv preprint arXiv:1812.06034.
30. E. Shearer and J. Gottfried, "News Use Across Social Media Platforms 2017", Pew Research Center's Journalism Project, 2018. [Online]. Available: http://www.journalism.org/2017/09/07/news-use-across-social- media-platforms-2017/. [Accessed: 01- Mar- 2020].
31. Laidi, Z. and Costopoulos, P.J., 2002. Democracy in real time. Journal of Democracy, 13(3), pp.68-79.
32. Poria, S., Gelbukh, A., Cambria, E., Das, D. and Bandyopadhyay, S., 2012, December. Enriching SenticNet polarity scores through semi-supervised fuzzy clustering. In 2012 IEEE 12th International Conference on Data Mining Workshops (pp. 709-716). IEEE.
33. Bonaparte, Y. The Rise and Fall of Banks: What is the Future for Banks?. Available at SSRN 3683222 (2020).
34. Oxford Analytica. "GPT-3 AI language tool calls for cautious optimism." Emerald Expert Briefings oxan-db.
35. Associated Press. “Memphis man charged in U.S. Capitol raid” APNews (2020) Available: https://apnews.com/article/joe-biden-donald-trump-capitol-siege-elections-arrests-42651a7c4bd066126d89e4eede75e098
36. Prensa Escrita, n.d. Periódicos Diarios De Ciudad De México. [online] Prensaescrita.com. Available at: <https://www.prensaescrita.com/america/df.php>
37. Socialbakers.com. 2020. Most popular Twitter accounts in Mexico. [online] Available at: <https://www.socialbakers.com/statistics/twitter/profiles/mexico/media/daily-news/page-1-5> [Accessed 12 August
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