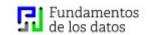


# Disinformation and network analysis

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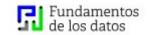
### **Motivation**

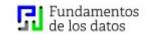
- Our approach: To develop AI techniques and models that enhance the understanding of various issues on social networks, grounded in data-based evidence.
- Areas of study: Phenomena on online social networks (such as bots, polarization dynamics, controversies, and fake news).
- Research based on graph representations, modeled either using representation learning techniques or classical models combined with natural language processing.
- Strong interdisciplinary interaction between computer science and other fields such as communication studies and sociology.
- Teamwork, coordinated with interdisciplinary research at IMFD.

#### Fundamentos de los datos

## **Agenda**

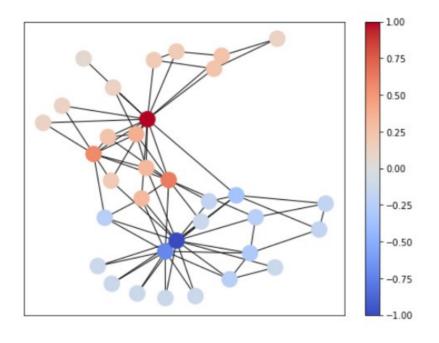
- Definitions and basic concepts.
- Bot detection.
- Disinformation dynamics.
- Perspectives in the era of ChatGPT.





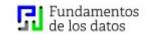
### Social networks:





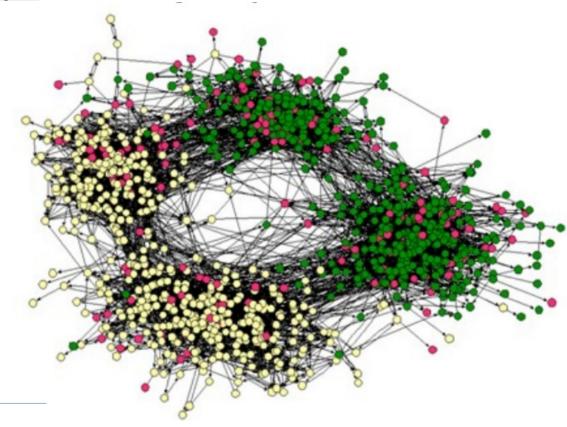


Zachary, W. (1977). An information flow model for conflict and fission in small groups. *Journal of Anthropological Research*, 33, 452–473.



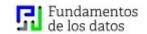
Homophily:

Social interactions Who works with whom?



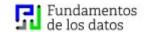


Moody, J. Race, school integration, and friendship segregation in America. American Journal of Sociology, 2001

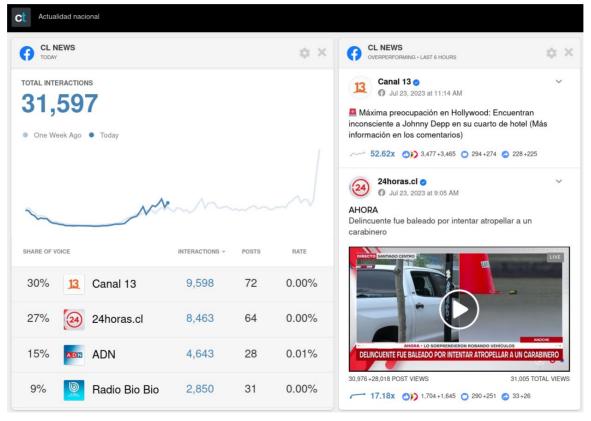


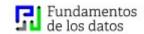
**Online social networks**: Digital social networks where you can write and comment. Some networks establish specific mechanisms for interaction such as likes, retweets, emojis, and so forth.



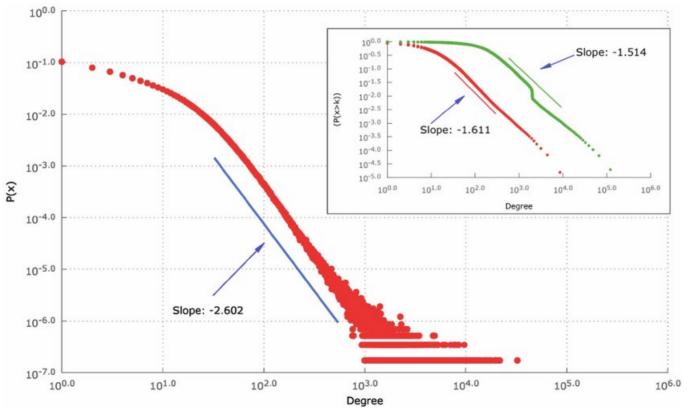


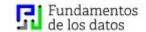
Online social networks: They serve as a massive source of information.





Structure: node degrees can vary widely.





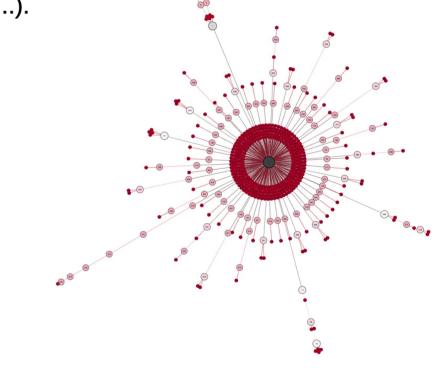
**Hierarchy of relevance:** Certain accounts are significantly more visible than others (e.g., celebrities, influencers, media outlets, ...).

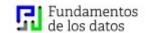




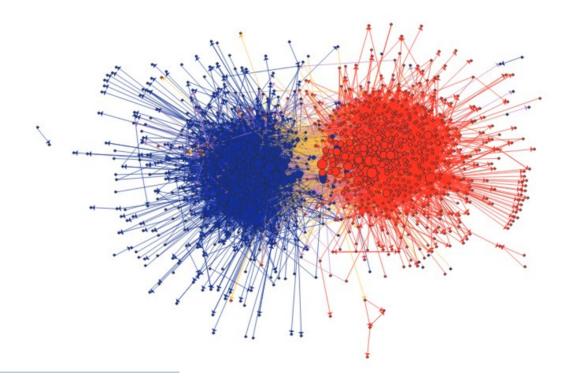
**Hierarchy of relevance:** Certain accounts are significantly more visible than others (e.g., celebrities, influencers, media outlets, ...).

Presidente Boric defiende reconocimiento a Garzón v delimita gesto a su labor "contra la impunidad" El Mandatario señaló que la medalla en cuestión no apunta a "otras gestiones que él ya ha realicomo jurista" Q 508 🙆 💟 🚹 🗟 18 de Julio de 2023 | 14:07 | Por María Luisa Cisternas. Emol Cerrando su paso por Bélgica, el Presidente, Gabriel Boric, realizó un punto de prensa en el frontis del edificio Atomium de Bruselas Allí el Mandatario defendió el polémico reconocimiento que entregó en Madrid al ex juez Baltasar Garzón, apuntando que el gesto " es producto del trabajo que él ha hecho en contra de la impunidad en materia global y en particular en el caso que todos conocemos del juicio a Pinochet, y no por otras gestiones que él ya ha realizado como jurista". que si alguien tiene un pronunciamiento al especto, se pronuncie respecto a ese caso que fue el motivo por el cual se entregó a él y peregrinaje de los partidos a Joan Manuel Serrat una medalla de conmemoración por los 50 años del quiebre que lo de Ucrania "es una condecoración a Garzó de la democracia en Chile". "Incomoda a su canciller able" y pide destrabar "ofende a una parte de Chile "Creo que es un momento importante para reflexionar en conjunto sobre la importancia y el valor que le damos a la democracia ante Ine ripenne mue peta enfronta deede todos los sectores" agrega-





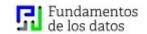
**Echo chambers:** homophily drives towards echo chambers.



Who is speaking — with whom

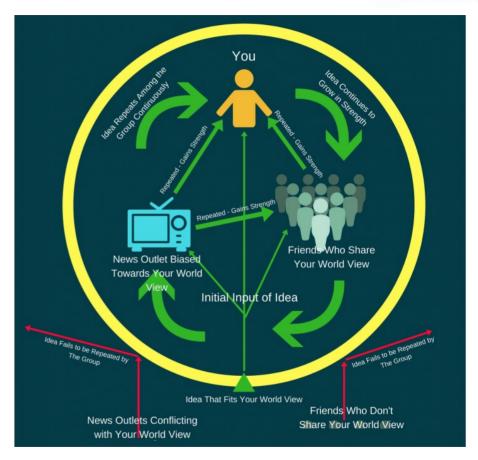


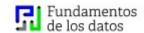
Adamic, L., & Glance, N. (2005). The political blogosphere and the 2004 u.s. election: Divided they blog. In 3rd International Workshop on Link Discovery, LinkKDD 2005 - in conjunction with 10th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (pp. 36–43).



**Echo chambers:** homophily drives towards echo chambers.

The Impact of an Echo
Chamber





**Misinformation**: "A piece of information whose content contradicts the epistemic consensus achieved through the systematic application of a methodology" [1].

**Disinformation**: "A specific type of misinformation aimed at manipulating public opinion" [2].

**Rumor**: "A piece of information whose truthfulness has not been verified at the time of publication" [3].

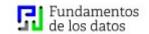
Fake News: "False news published on a digital and/or traditional information medium" [2].



[1] Swire-Thompson B, Lazer D (2020) Public health and online misinformation: challenges and recommendations. *Annu Rev Public Health* 41(1):433–451.

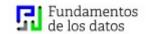
[2] Zhou X, Zafarani R (2020) A survey of fake news: fundamental theories, detection methods, and opportunities. *ACM Comput Surv* (CSUR) 53(5):1-40.

[3] Zubiaga A, Aker A, Bontcheva K, Liakata M, Procter R (2018) Detection and resolution of rumours in social media: a survey. ACM Comput Surv 51(2):32:1-32:36.



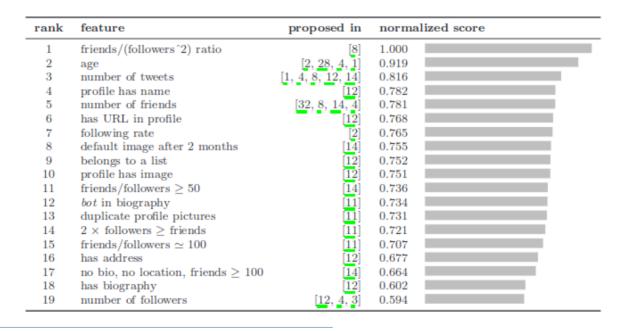
Fake News: a <u>fabricated</u> content designed to disinform.





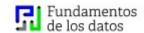
A story about influence. Accounts with the highest visibility have a greater impact on social networks. Malicious actors gain traction through fake followers, often automated (bots) or hired (hyper-partisan individuals).

Numerous studies have aimed to curb the influence of malicious actors





Cresci, S. Fame for sale: efficient detection of fake Twitter followers, 2015.



### The Ecosystem of bots:

**Astroturfers**: These are bots used to support political campaigns. They are employed for electoral propaganda and are managed by organizations or companies that control botnets.

**Fake followers**: These bots increase the visibility of an account by retweeting its posts.

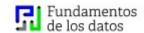
Cashbots: These are bots that assist fundraising campaigns, mainly dealing with bitcoins.

**Spammers**: These bots generate automated content, typically delivering repetitive messages.

**Self-declared**: These are bots that manage chatbot sessions and openly declare themselves as such. Most of these are benign.



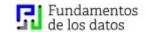
Cresci, S.: A decade of social bot detection. Commun. ACM63(10): 72-83 (2020).



#### The Ecosystem of users.

**Groups**: An institutional mechanism designed to cultivate echo chambers. These groups often incite and escalate radicalization.

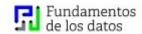




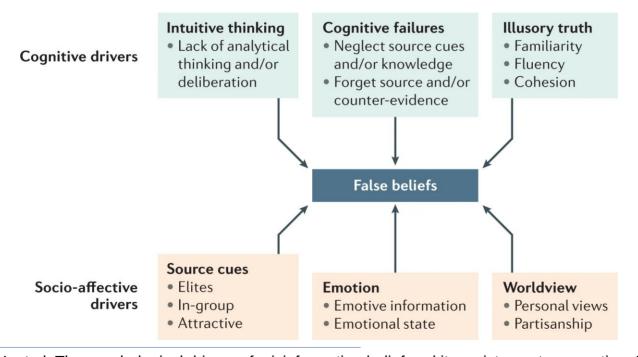
**Confirmation bias:** The veracity of information isn't as relevant as the extent to which it supports your own beliefs and viewpoints.



19

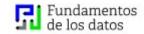


**The psychology of fake news:** There's an assumption that fake news exacerbates polarization. But it might be the case that polarization exacerbates fake news.

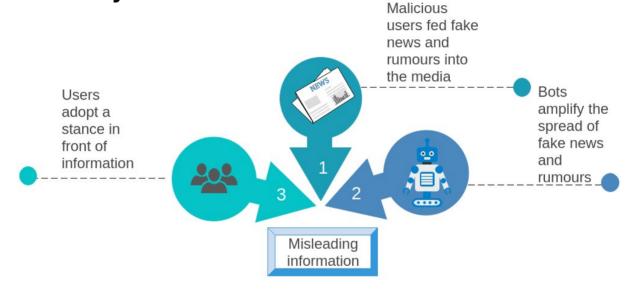




Ecker, U. et al. The psychological drivers of misinformation belief and its resistance to correction, Nature reviews psychology, 2022.

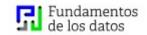


## A disinformation ecosystem:

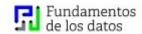




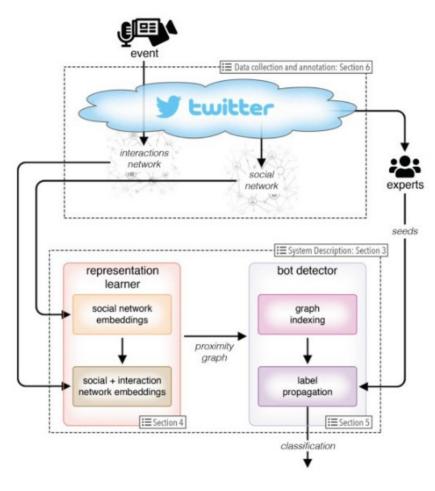
Providel, E., Mendoza, M. (2021). Misleading information in Spanish: a survey, Social Network Analysis and Mining, 11:36

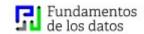


- Bot detection -

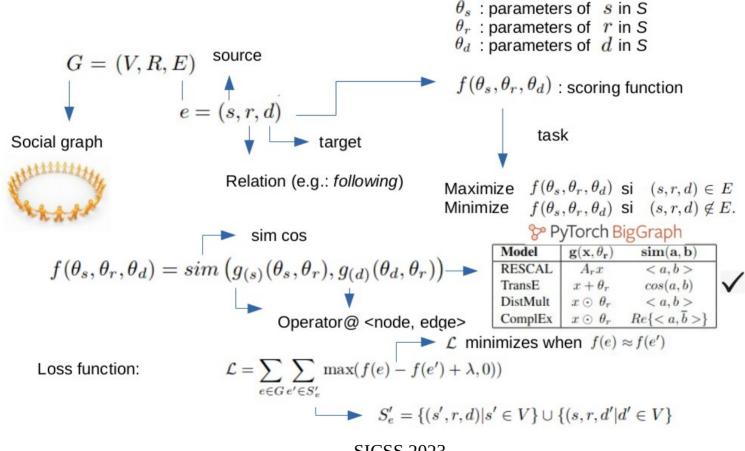


## **Bots**



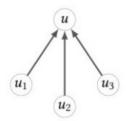


### **Bots**

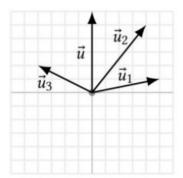


#### Fundamentos de los datos

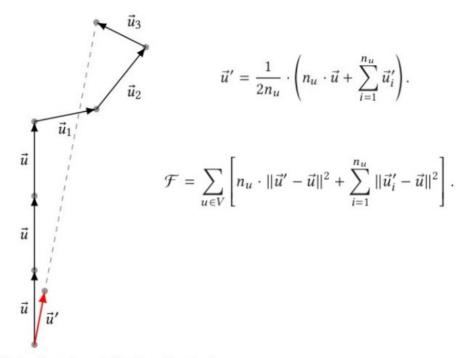
### **Bots**



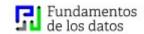
(a) Interaction network of u.



(b) Social network embeddings of u,  $u_1$ ,  $u_2$ ,  $u_3$ .



(c) Retro-fitting  $\vec{u}$  to u's neighborhood in the interaction network.  $\vec{u}'$  (red-colored) is obtained by combining the social network embedding of u with those of the users with whom it interacted.

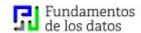


### **Bots**

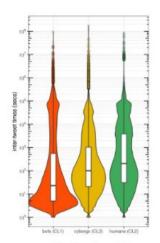
		evaluation metrics							
technique	type	precision	recall	accuracy	F1	MCC	AUC		
comparisons									
Botometer [20, 64]	supervised	0.6951	$0.3098^{\bullet}$	0.5830°	$0.4286^{\bullet}$	0.2051	0.6889		
Social fingerprinting [12]	supervised	0.6562	0.8978°	$0.7114^{\bullet}$	0.7582°	0.4536°	0.7501°		
HoloScope [39]	unsupervised	0.2857°	0.0049	$0.4908^{\bullet}$	$0.0096^{\bullet}$	$-0.0410^{\bullet}$	_		
RTbust [41]	unsupervised	$0.9304^{\circ}$	$0.8146^{\bullet}$	0.8755°	0.8687°	0.7572°	-		
our contributions									
social network	semi-supervised	0.8461	$0.8918^{\bullet}$	0.8773°	$0.8684^{\bullet}$	0.7658°	0.8263		
social + interaction networks	semi-supervised	0.9102	0.9594	0.9386	0.9342	0.8778	0.9245		

<sup>•:</sup> p < 0.01, °:  $p \ge 0.1$  Best results in each evaluation metric are shown in **bold**, second-bests are <u>underlined</u>. Statistical significance results are related to differences between evaluation metrics computed for the best-performing technique (last row) with respect to all the others.

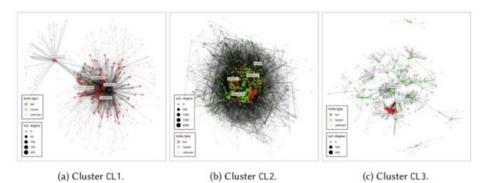
~ 7% de bots



### **Bots**



Distribution of intertweet times for accounts labeled as bots in CL1 and CL2 and for accounts labeled as humans in CL2.



Top-10 Accounts with the Largest In-degree (Most Retweets Received), per Cluster

	CL1		CL2	CL2		
rank	account	label	account	label	account	label
1	@Valerio_Scanu	human	@BTS_ITALIA	bot	@IsabellaF1890	bot
2	@ArmataScanu	bot	@BTSItalia_twt	unknown	@RCCDM90	bot
3	@RaiDue	unknown	@taegijkook	unknown	@RITAPRR9099	unknown
4	@mammaraffy	bot	@GOT7_italia	unknown	@JNYROD	bot
5	@ItaliaCharleroi	unknown	@justignorance_	human	@MARCOFF3	bot
6	@Diletta123	bot	@BLVRRYTAEGI	bot	@VFRR1962	bot
7	@OptiMagazine	unknown	@fjfthseason	unknown	@RAVAG68	bot
8	@dada_loi	unknown	@RaiRadio2	human	@JLSESI90	bot
9	@FrancescaDivs	bot	@BTS_ITALIA_ARMY	unknown	@lisaf881	bot
10	@GammaStereoRoma	unknown	@NonnaHaozi	bot	@ansla54	bot

The analysis of most retweeted accounts quickly reveals the goals of the different groups of bots.



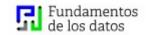
Marcelo Mendoza, Maurizio Tesconi, Stefano Cresci.

Bots in Social and Interaction Networks: Detection and Impact Estimation, ACM Transactions on Information Systems (TOIS), 39(1):5:1--5:32, 2020

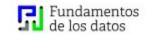
SICSS 2023 27

humans in CL2

accounts labeled as bots in CL1



- Disinformation dynamics -



"Fact-checking, in the broadest sense, refers to any analysis that publicly challenges a given account or statement".

Lucas Graves, Deciding What's true The rise of political Fact-Checking, American Journalism.

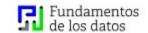
#### Fundamentos de los datos

## **Fact-checking**



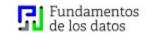
Definition or validation protocols, standards, and methodologies for the accreditation of fact-checking agencies.

- Commitment to transparency.
- Commitment to fairness.
- Commitment to openly disclose sources.
- Commitment to transparently explain the methodology.
- Commitment to clearly indicate the agency's funding sources.
- Commitment to openly present corrections.



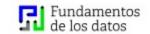
Topic	Fast Check	Decodificador	FactCheckingUC	Total
Social outbreak	102	16	12	130
Covid-19	214	53	86	353
2021 Elections	67	12	0	79
Constitution	57	36	39	132
Other	216	52	38	306
Total	656	169	175	1000

Table 1: Topics per fact checker.



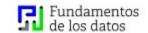
Veracity	Fast Check	Decodificador	FactCheckingUC	Total
True	284	38	53	375
False	250	86	37	373
Imprecise	122	42	85	249
Unverifiable	0	3	0	3
Total	656	169	175	1000

Table 2: Veracity checks per fact checker.



Topic	True	False	Imprecise	
Social outbreak	20 (8.8%)	15 (0.0%)	7 (10.5%)	
Covid-19	43 (17.6%)	37 (45.4%)	14 (21.0%)	
2021 Elections	7 (8.8%)	19 (9.0%)	1 (15.7%)	
Constitution	20 (17.6%)	23 (18.0%)	29 (15.7%)	
Other	39 (41.2%)	19 (27.2%)	14 (36.8%)	
Total	129	113	65	

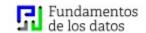
Table 4: Veracity per topic in Twitter.



## **Lingüistic analysis**

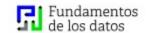
Oninia litavatuva	Feature	Social out.	Covid-19	2021 Elect.	Constitution	Other
Crisis literature	Length	↓ 2561	4179	4907	4815	4774
	Words	↓ 422	690	807	783	788
	Emoticons	0	0.02	0	0	0
	Entropy	-4.24	-4.25	-4.29	-4.25	-4.28
	Sentiment	5.68	5.87	5.94	6.03	6.09
	Arousal	5.33	5.25	5.26	5.25	5.29
	Dominance	5.05	5.12	5.15	5.16	5.17
	Verbs	↓ 37.4	61.5	69.1	68.1	65.5
	Dets	↓ 60.1	98.4	106.8	117.3	111.2
	Nouns	↓ 89.5	143.7	159.6	161.1	162.7
	Propns	↓ 54.2	79.4	121.1	94.1	104.8
	Adps	↓ 78.8	121.9	148.2	138.1	146.7
	Persons	6.31	7.39	<b>↑ 18.9</b>	10.7	11.1
	Locations	↓ 6.28	12.1	11.3	9.3	13.1
	Organizations	6.43	7.72	12.3	13.1	11.5
	Miscs	10.7	16.7	20.5	20.1	19.6

Table 5: Content profiling (average over source and replies in Twitter). Dets: Determiners, Propns: Proper-nouns, Adps: adpositions, Miscs: Miscelaneous.



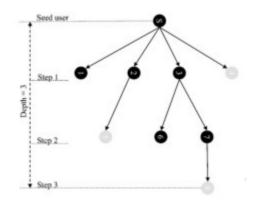
## **Readability indices**

			False			Imprecise			True		
	Metric	mean	std	median	mean	std	median	mean	std	median	
1	Number of characters	214	67.48	200	214.27	62.52	214	216.59	76.28	233	
2	Number of words	31.8	11.67	34	31.94	11.01	33	31.54	12.9	34	
3	Letters per word*	5.87	0.95	5.73	5.89	1.21	5.7	6.04	1.05	5.94	
4	Number of sentences	3.42	2.69	3	2.53	1.29	2	2.76	1.4	2	
5	Total sentences*	3.43	2.13	3	2.88	1.82	2	2.74	1.64	2	
6	TTR	0.9	0.07	0.9	0.89	0.07	0.89	0.9	0.07	0.89	
7	LWF	7.07	4.42	6	8.69	4.96	8	8.91	5.53	7.17	
8	GFOG	25.3	5.14	23.99	26.25	4.98	25.48	26.75	5.62	27.24	
9	DCRS	11.1	1.66	10.96	11.28	1.6	11.14	11.47	1.74	11.49	
10	ARI*	15.2	5.65	13.7	16.3	6.5	15	17.28	6.33	16.4	
11	FKG*	11.5	3.87	10.6	12.15	4.26	11.9	12.67	4.69	12.3	
12	DW	12.9	4.34	13	13.16	4.54	13	13.15	5.03	13	
13	CLI*	17.5	5.69	16.81	17.6	7.14	15.73	18.72	6.38	18.09	
14	FRE	40.1	19.99	45.72	39.74	23.22	46.13	36.16	23.12	38.82	
15	IFSZ	67.3	15.5	67.56	64	18.62	66.57	68.33	13.46	69.86	

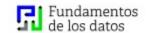


Depth	Mean	Std	Min	Max
True	$\downarrow 6.92$	8.54	1	78
False	9.13	11.54	1	88
Imprecise	9.92	10.10	1	60

Table 9: Depth of the propagation trees in Twitter (replies). KS-tests: false and true:  $D=0.168, p\sim0.08$ , false and imprecise:  $D=0.124, p\sim0.70$ , true and imprecise:  $D=0.275, p\sim0.01$ .

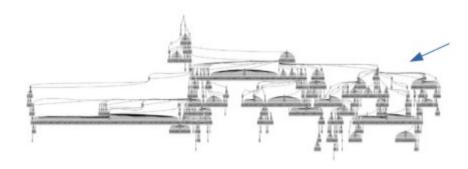


Truthful content often lacks the depth found in other types of content.

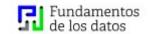


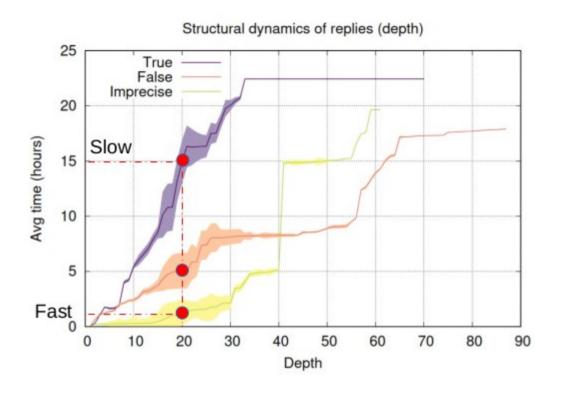
Size	Mean	Std	Min	Max
True	485	1701	3	14237
False	457	669	2	3570
Imprecise	<b>↑679</b>	1101	4	5321

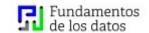
Table 10: Size of the propagation trees in Twitter (replies). KS-tests: false and true:  $D = 0.206, p \sim 0.01$ , false and imprecise:  $D = 0.152, p \sim 0.45$ , true and imprecise:  $D = 0.195, p \sim 0.17$ .

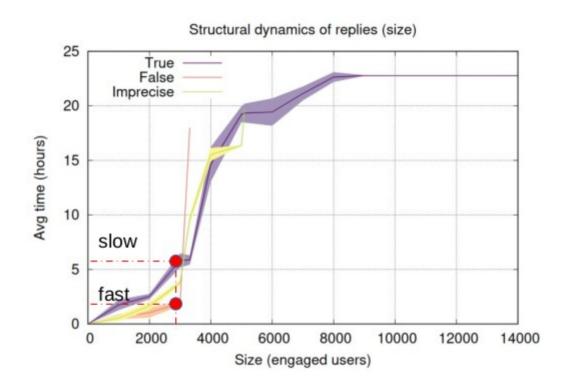


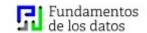
Imprecise content generates more replies than other types of content.











The study can be found at:

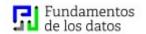


It includes a free online course on the subject matter.

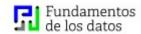
You can review the complete version of the study in the following citation:



Marcelo Mendoza, Sebastián Valenzuela, Enrique Núñez-Mussa, Fabián Padilla, Eliana Providel, Sebastián Campos, Renato Bassi, Andrea Riquelme, Valeria Aldana, Claudia López: A Study on Information Disorders on Social Networks during the Chilean Social Unrest and the COVID-19 Pandemic. Applied Sciences, Vol. 13, Issue 9, 2023.

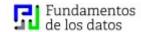


- Perspectives in the era of ChatGPT -



Generative AI, in the hands of malicious actors, opens up new possibilities for disinformation.



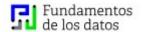


Generative AI, in the hands of malicious actors, opens up new possibilities for disinformation.





43 Deep fakes



Tech Social Media

# Twitter's new API pricing is killing many Twitter apps that can't pay \$42,000 per month

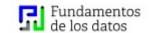
"Hobbyists" can pay \$100. Have an app with more than a few users? You'll likely be paying Twitter \$42,000 per month.

By Matt Binder on March 30, 2023



Twitter appears to have put the nail in the coffin for any indie developer running a Twitter-based app. Credit: Jakub Porzycki/NurPhoto via Getty Images



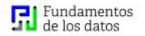


- There are alternatives to Twitter analysis, such as Facebook, Instagram, and TikTok via scraping.
- These are challenging times, filled with numerous hurdles for developing methods of detecting disinformation campaigns. With limited or highly expensive access to data, the gap in data accessibility widens instead of narrowing.
- The challenges are even greater due to the ease with which bad actors can generate content using generative AI. This capability allows them to paraphrase comments, making malicious interactions even more difficult to detect.

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# Disinformation and network analysis

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