



Finding Bots and Trolls

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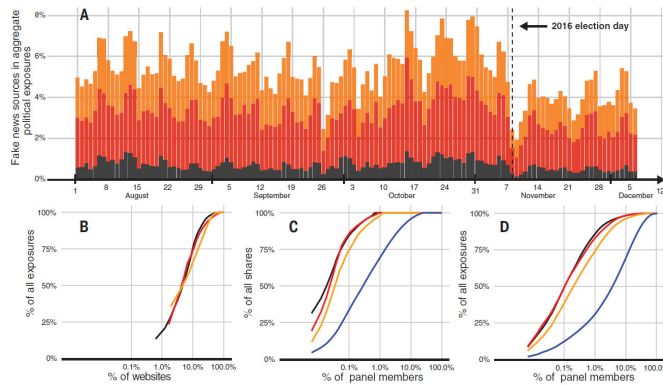


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Disinformation is ubiquitous in online conversations.

Fig. 1. Prevalence over time and concentration of fake news sources. (A) Daily percentage of exposures to black, red, and orange fake news sources, relative to all exposures to political URLs. Exposures were summed across all panel members. (B to D) Empirical cumulative distribution functions showing distribution of exposures among websites (B), distribution of shares by panel members (C), and distribution of exposures among panel members (D). The x axis represents percentage of websites or panel members responsible for a given percentage (y axis) of all exposures or shares. Black, red, and orange lines represent fake news sources; blue line denotes all other sources. This distribution was not comparable for (B) because of the much larger number of sources in its tail and the fundamentally different selection process involved.



Grinberg, N., Joseph, K., Friedland, L., Swire-Thompson, B., & Lazer, D. (2019). Fake news on Twitter during the 2016 U.S. presidential election. *Science*.



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Disinformation is fueled by inauthentic agents—e.g., bots and trolls.

Fig. 4 Impact of bots on humans. **a** Joint distribution of bot scores of accounts that retweeted links to low-credibility articles and accounts that had originally posted the links. Color represents the number of retweeted messages in each bin, on a log scale. **b** The top projection shows the distribution of bot scores for retweeters, who are mostly human. **c** The left projection shows the distribution of bot scores for accounts retweeted by likely humans who are identified by scores below a threshold of 0.4 (black crosses), 0.5 (purple stars), or 0.6 (orange circles). In spite of the threshold, we observe a significant portion of likely bots retweeted by likely humans.

Shao, C., Ciampaglia, G. L., Varol, O., Yang, K., Flammini, A., & Menczer, F. (2018). The spread of low-credibility content by social bots. *Nature Communications*.

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Bots and Trolls

- Bots
 - Automated agents
 - Not necessarily malicious
- Trolls
 - Inauthentic accounts which disrupt online conversations
 - Not necessarily automated

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BotHunter: A Tiered Approach

TABLE I: Four *tiers* of Twitter data collection to support account classification (originally presented in [7])

Tier	Description	Focus	Collection Time per 250 Accounts	# of Data Entities (i.e. tweets)
Tier 0	Tweet text only	Semantics	N/A**	1
Tier 1	Account + 1 Tweet	Account Meta-data	~ 1.9 sec	2
Tier 2	Account + Timeline	Temporal patterns	~ 3.7 min	200+
Tier 3	Account + Timeline + Friends	Network patterns	~ 20 hrs	50,000+

Uyheng, J., Magrawski, T., Villa-Cox, R., Sowa, C., & Carley, K. M. (2019). Interoperable pipelines for social cyber-threat intelligence: Assessing Twitter information operations during NATO Trident Juncture 2018. Computational and Mathematical Organization Theory. Advance online publication.

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Trolls: An Initial Data-Driven Examination

Coefficients of Trollness

Effect	Estimate	Significant
penne_first	~ -0.02	FALSE
penne_second	~ -0.01	FALSE
penne_third	~ -0.01	FALSE
penne_absolutist	~ 0.02	FALSE
penne_non.absolutist	~ 0.01	FALSE
penne_exclusive	~ -0.08	FALSE
penne_abusive	~ 0.04	TRUE
penne_identities	~ 0.02	FALSE
penne_readingDifficulty	~ -0.18	TRUE
penne_euclid	~ 0.25	TRUE
penne_cosine	~ 0.18	FALSE
penne_botTRUE	~ -0.04	FALSE

Forthcoming work on troll detection.

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WHAT DO BOTS AND TROLLS DO?

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Overview of the BEND Framework

- Narrative maneuvers
 - Positive maneuvers
 - Negative maneuvers
- Network maneuvers
 - Positive maneuvers
 - Negative maneuvers

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Bots play the election game.

Table 2. Detected bots with predicted role identities.

Case study	Role identities	Unique users	Detected bots
Philippine elections	Normal	63260 (78.79%)	9073 (11.30%)
	Government	7424 (9.25%)	1189 (1.48%)
	News agency	3538 (4.41%)	510 (0.64%)
	News reporter	2950 (3.67%)	630 (0.78%)
	Company	802 (1.00%)	103 (0.13%)
	Celebrity	2015 (2.51%)	172 (0.21%)
	Sports	300 (0.36%)	44 (0.05%)
Indonesian elections	Normal	21987 (87.48%)	2568 (10.22%)
	Government	722 (2.87%)	95 (0.28%)
	News agency	471 (1.87%)	26 (0.10%)
	News reporter	60 (0.24%)	10 (0.04%)
	Company	1569 (6.24%)	215 (0.86%)
	Celebrity	230 (0.92%)	32 (0.13%)
	Sports	95 (0.28%)	6 (0.02%)
Stand with Okinawa	Normal	31428 (98.09%)	8750 (27.31%)
	Government	103 (0.32%)	30 (0.09%)
	News agency	171 (0.53%)	22 (0.07%)
	News reporter	23 (0.08%)	10 (0.03%)
	Company	261 (0.81%)	55 (0.17%)
	Celebrity	25 (0.08%)	3 (0.01%)
	Sports	29 (0.09%)	2 (0.01%)

Table 4. Super spreaders and super friends.

Case study	Super spreaders	Super friends
Philippine elections	rapplerdotcom* (0.37)	ruddy9 (0.50)
	MARoxas* (0.41)	raincyrainy (0.52)
	ATajum (0.44)	mariaagarciuah (0.42)
	cnphilippines* (0.20)	MayDPoresBeWidU (0.54)
	mariaagarciuah (0.42)	MelLegaspil (0.44)
	AsecMargauxUson (0.51)	AsecMargauxUson (0.51)
	ruddy9 (0.50)	jvejericto* (0.69)
Indonesian elections	BembangBiik (0.37)	BoyoKiss (0.65)
	Sandiuno* (0.47)	Addarul1 (0.57)
	CakKhum (0.25)	HotPepperinTea (0.51)
	Gerindra* (0.53)	abiid_d (0.56)
	Addarul1 (0.57)	abiyu231299 (0.38)
	02Sandiaga (0.45)	Rusydi_riau40 (0.52)
		MangajatsCkp (0.55)
Stand with Okinawa	surumesogeso (0.65)	tkatsumi06j (0.30)
	robkajiwara (0.57)	affluencekana (0.46)
	ISOKO_MOCHIZUKI (0.65)	sabor_sabole (0.74)
	times_henoko (0.35)	robkajiwara (0.57)
	29ryukyu (0.33)	HempHere (0.34)
	mr_naha_das (0.49)	29_momechabo (0.57)
	BFJNews* (0.59)	HIROMI150303 (0.48)
		ActStudge (0.50)

Uyheng, J., & Carley, K. M. (2019). Characterizing bot networks on Twitter: An empirical analysis of contentious issues in the Asia-Pacific. *SBP-BRIMS*. Washington DC, USA.

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Bots impact public conversations.

Granger Statistics for PH

Granger Statistics for ID

Granger Statistics for TW

VAR Coefficients for PH

Uyheng, J., & Carley, K. M. (2020-forthcoming). Bot impacts on public sentiment and community structures: Comparative analysis of three elections in the Asia-Pacific. *SBP-BRIMS*. Washington DC, USA.

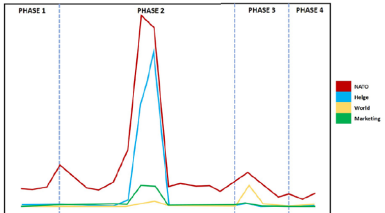
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Bots ride on international influence campaigns.



Topic	Bot activity	
	Number of bot tweets	(%)
Collision of Helge Ingstad	2385	31.97
NATO Trident Juncture	42512	25.63
World politics	3018	20.30
Opportunistic marketing	3799	7.82

We organize rows by percentage of tweets in each topic associated with a predicted bot. The collision topic featured the highest level of predicted bot activity

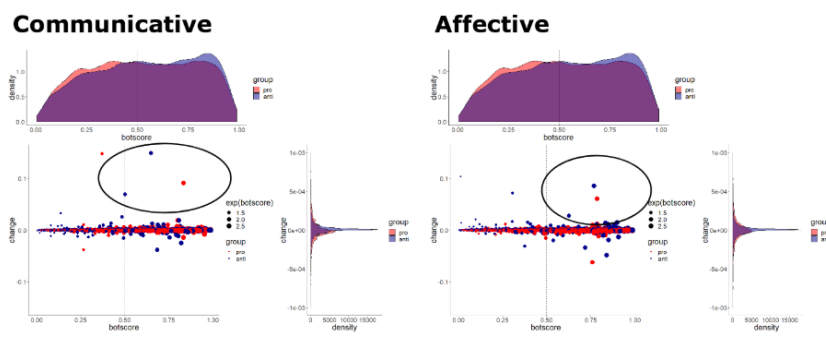
Uyheng, J., Magelinski, T., Villa-Cox, R., Sowa, C., & Carley, K. M. (2019). Interoperable pipelines for social cyber-security: Assessing Twitter information operations during NATO Trident Juncture 2018. Computational and Mathematical Organization Theory. Advance online publication.

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Bots drive polarization.



Communicative **Affective**

Forthcoming work on network polarization.

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