

This is the list of references cited in the papers examined in the „Social Media Bot Detection Research: Review of Literature“ review paper available at: <https://arxiv.org/abs/2503.22838>

1. Abdullah-All-Tanvir, Mahir EM, Akhter S, Huq MR (2019) Detecting fake news using machine learning and deep learning algorithms. In: 7th international conference on smart computing and communications (ICSCC), IEEE, pp 1–5 <https://doi.org/10.1109/ICSCC.2019.8843612>
2. Abdullah-All-Tanvir, Mahir EM, Huda SMA, Barua S (2020) A hybrid approach for identifying authentic news using deep learning methods on popular Twitter threads. In: International conference on artificial intelligence and signal processing (AISP), IEEE, pp 1–6 <https://doi.org/10.1109/AISP48273.2020.9073583>
3. Abu Arqoub O, Abdulateef Elegba A, Efe Özad B, Dwikat H, Adedamola Oloyede F (2022) Mapping the scholarship of fake news research: a systematic review. *J Pract* 16(1):56–86. <https://doi.org/10.1080/17512786.2020.1805791>
4. Ahmed S, Hinkelmann K, Corradini F (2020) Development of fake news model using machine learning through natural language processing. *Int J Comput Inf Eng* 14(12):454–460
5. Aïmeur E, Brassard G, Rioux J (2013) Data privacy: an end-user perspective. *Int J Comput Netw Commun Secur* 1(6):237–250
6. Aïmeur E, Hage H, Amri S (2018) The scourge of online deception in social networks. In: 2018 international conference on computational science and computational intelligence (CSCI), IEEE, pp 1266–1271 <https://doi.org/10.1109/CSCI46756.2018.00244>
7. Alemanno A (2018) How to counter fake news? A taxonomy of antifake news approaches. *Eur J Risk Regul* 9(1):1–5. <https://doi.org/10.1017/err.2018.12>
8. Allcott H, Gentzkow M (2017) Social media and fake news in the 2016 election. *J Econ Perspect* 31(2):211–36. <https://doi.org/10.1257/jep.31.2.211>
9. Allen J, Howland B, Mobius M, Rothschild D, Watts DJ (2020) Evaluating the fake news problem at the scale of the information ecosystem. *Sci Adv.* <https://doi.org/10.1126/sciadv.aay3539>
10. Allington D, Dufy B, Wessely S, Dhavan N, Rubin J (2020) Healthprotective behaviour, social media usage and conspiracy belief during the Covid-19 public health emergency. *Psychol Med.* <https://doi.org/10.1017/S003329172000224X>
11. Alonso-Galbán P, Alemañy-Castilla C (2022) Curbing misinformation and disinformation in the Covid-19 era: a view from cuba. *MEDICC Rev* 22:45–46 <https://doi.org/10.37757/MR2020.V22.N2.12>
12. Altay S, Hacquin AS, Mercier H (2022) Why do so few people share fake news? It hurts their reputation. *New Media Soc* 24(6):1303– 1324. <https://doi.org/10.1177/1461444820969893>
13. Amri S, Sallami D, Aïmeur E (2022) Exmulf: an explainable multimodal content-based fake news detection system. In: International symposium on foundations and practice of security. Springer, Berlin, pp 177–187. <https://doi.org/10.1109/IJCNN.2020.9206973>
14. Andersen J, Sør SO (2020) Communicative actions we live by: the problem with fact-checking, tagging or fagging fake news-the case of Facebook. *Eur J Commun* 35(2):126–139. <https://doi.org/10.1177/0267323119894489>

15. Apuke OD, Omar B (2021) Fake news and Covid-19: modelling the predictors of fake news sharing among social media users. *Telematics Inform* 56:101475.
<https://doi.org/10.1016/j.tele.2020.101475>
16. Apuke OD, Omar B, Tunca EA, Geveer CV (2022) The effect of visual multimedia instructions against fake news spread: a quasiexperimental study with Nigerian students. *J Librariansh Inf Sci*. <https://doi.org/10.1177/09610006221096477>
17. Aswani R, Ghrera S, Kar AK, Chandra S (2017) Identifying buzz in social media: a hybrid approach using artificial bee colony and k-nearest neighbors for outlier detection. *Soc Netw Anal Min* 7(1):1–10. <https://doi.org/10.1007/s13278-017-0461-2>
18. Avram M, Micallef N, Patil S, Menczer F (2020) Exposure to social engagement metrics increases vulnerability to misinformation. *arXiv preprint arxiv:2005.04682*,
<https://doi.org/10.37016/mr-2020-033>
19. Badawy A, Lerman K, Ferrara E (2019) Who falls for online political manipulation? In: *Companion proceedings of the 2019 world wide web conference*, pp 162–168
<https://doi.org/10.1145/3308560.3316494>
20. Bahad P, Saxena P, Kamal R (2019) Fake news detection using bidirectional LSTM-recurrent neural network. *Procedia Comput Sci* 165:74–82.
<https://doi.org/10.1016/j.procs.2020.01.072>
21. Bakdash J, Sample C, Rankin M, Kantarcioglu M, Holmes J, Kase S, Zaroukian E, Szymanski B (2018) The future of deception: machine-generated and manipulated images, video, and audio? In: *2018 international workshop on social sensing (SocialSens)*, IEEE, pp 2–2
<https://doi.org/10.1109/SocialSens.2018.00009>
22. Balmas M (2014) When fake news becomes real: combined exposure to multiple news sources and political attitudes of inefficacy, alienation, and cynicism. *Commun Res* 41(3):430–454. <https://doi.org/10.1177/0093650212453600>
23. Baptista JP, Gradim A (2020) Understanding fake news consumption: a review. *Soc Sci*.
<https://doi.org/10.3390/socsci9100185>
24. Baptista JP, Gradim A (2022) A working definition of fake news. *Encyclopedia* 2(1):632–645.
<https://doi.org/10.3390/encyclopedia2010043>
25. Bastick Z (2021) Would you notice if fake news changed your behavior? An experiment on the unconscious effects of disinformation. *Comput Hum Behav* 116:106633.
<https://doi.org/10.1016/j.chb.2020.106633>
26. Batailler C, Brannon SM, Teas PE, Gawronski B (2022) A signal detection approach to understanding the identification of fake news. *Perspect Psychol Sci* 17(1):78–98.
<https://doi.org/10.1177/1745691620986135>
27. Bessi A, Ferrara E (2016) Social bots distort the 2016 US presidential election online discussion. *First Monday* 21(11-7). <https://doi.org/10.5210/fm.v21i11.7090>
28. Bhattacharjee A, Shu K, Gao M, Liu H (2020) Disinformation in the online information ecosystem: detection, mitigation and challenges. *arXiv preprint arXiv:2010.09113*
29. Bhuiyan MM, Zhang AX, Sehat CM, Mitra T (2020) Investigating differences in crowdsourced news credibility assessment: raters, tasks, and expert criteria. *Proc ACM Hum Comput Interact* 4(CSCW2):1–26. <https://doi.org/10.1145/3415164>

30. Bode L, Vraga EK (2015) In related news, that was wrong: the correction of misinformation through related stories functionality in social media. *J Commun* 65(4):619–638. <https://doi.org/10.1111/jcom.12166>
31. Bondielli A, Marcelloni F (2019) A survey on fake news and rumour detection techniques. *Inf Sci* 497:38–55. <https://doi.org/10.1016/j.ins.2019.05.035>
32. Bovet A, Makse HA (2019) Influence of fake news in Twitter during the 2016 US presidential election. *Nat Commun* 10(1):1–14. <https://doi.org/10.1038/s41467-018-07761-2>
33. Brashier NM, Pennycook G, Berinsky AJ, Rand DG (2021) Timing matters when correcting fake news. *Proc Natl Acad Sci*. <https://doi.org/10.1073/pnas.2020043118>
34. Brewer PR, Young DG, Morreale M (2013) The impact of real news about “fake news”: intertextual processes and political satire. *Int J Public Opin Res* 25(3):323–343. <https://doi.org/10.1093/ijpor/edt015>
35. Bringula RP, Catacutan-Bangit AE, Garcia MB, Gonzales JPS, Valderama AMC (2022) “Who is gullible to political disinformation?” Predicting susceptibility of university students to fake news. *J Inf Technol Polit* 19(2):165–179. <https://doi.org/10.1080/19331681.2021.1945988>
36. Buccafurri F, Lax G, Nicolazzo S, Nocera A (2017) Tweetchain: an alternative to blockchain for crowd-based applications. In: *International conference on web engineering*, Springer, Berlin, pp 386–393. https://doi.org/10.1007/978-3-319-60131-1_24
37. Burshtein S (2017) The true story on fake news. *Intell Prop J* 29(3):397–446
38. Cardaioli M, Ceconello S, Conti M, Pajola L, Turrin F (2020) Fake news spreaders profiling through behavioural analysis. In: *CLEF (working notes)*
39. Cardoso Durier da Silva F, Vieira R, Garcia AC (2019) Can machines learn to detect fake news? A survey focused on social media. In: *Proceedings of the 52nd Hawaii international conference on system sciences*. <https://doi.org/10.24251/HICSS.2019.332>
40. Carmi E, Yates SJ, Lockley E, Pawluczuk A (2020) Data citizenship: rethinking data literacy in the age of disinformation, misinformation, and malinformation. *Intern Policy Rev* 9(2):1–22. <https://doi.org/10.14763/2020.2.1481>
41. Celliers M, Hattingh M (2020) A systematic review on fake news themes reported in literature. In: *Conference on e-Business, e-Services and e-Society*. Springer, Berlin, pp 223–234. https://doi.org/10.1007/978-3-030-45002-1_19
42. Chen Y, Li Q, Wang H (2018) Towards trusted social networks with blockchain technology. *arXiv preprint arXiv:1801.02796*
43. Cheng L, Guo R, Shu K, Liu H (2020) Towards causal understanding of fake news dissemination. *arXiv preprint arXiv:2010.10580*
44. Chiu MM, Oh YW (2021) How fake news differs from personal lies. *Am Behav Sci* 65(2):243–258. <https://doi.org/10.1177/0002764220910243>
45. Chung M, Kim N (2021) When I learn the news is false: how fact-checking information stems the spread of fake news via thirdperson perception. *Hum Commun Res* 47(1):1–24. <https://doi.org/10.1093/hcr/hqaa010>
46. Clarke J, Chen H, Du D, Hu YJ (2020) Fake news, investor attention, and market reaction. *Inf Syst Res*. <https://doi.org/10.1287/isre.2019.0910>

47. Clayton K, Blair S, Busam JA, Forstner S, Glance J, Green G, Kawata A, Kovvuri A, Martin J, Morgan E et al (2020) Real solutions for fake news? Measuring the effectiveness of general warnings and fact-check tags in reducing belief in false stories on social media. *Polit Behav* 42(4):1073–1095. <https://doi.org/10.1007/s11109-019-09533-0>
48. Collins B, Hoang DT, Nguyen NT, Hwang D (2020) Fake news types and detection models on social media a state-of-the-art survey. In: *Asian conference on intelligent information and database systems*. Springer, Berlin, pp 562–573 https://doi.org/10.1007/978-981-15-3380-8_49
49. Conroy NK, Rubin VL, Chen Y (2015) Automatic deception detection: methods for finding fake news. *Proc Assoc Inf Sci Technol* 52(1):1–4. <https://doi.org/10.1002/pra2.2015.145052010082>
50. Cooke NA (2017) Posttruth, truthiness, and alternative facts: Information behavior and critical information consumption for a new age. *Libr Q* 87(3):211–221. <https://doi.org/10.1086/692298>
51. Coscia M, Rossi L (2020) Distortions of political bias in crowdsourced misinformation tagging. *J R Soc Interface* 17(167):20200020. <https://doi.org/10.1098/rsif.2020.0020>
52. Dame Adjin-Tettey T (2022) Combating fake news, disinformation, and misinformation: experimental evidence for media literacy education. *Cogent Arts Human* 9(1):2037229. <https://doi.org/10.1080/23311983.2022.2037229>
53. Deepak S, Chitturi B (2020) Deep neural approach to fake-news identification. *Procedia Comput Sci* 167:2236–2243. <https://doi.org/10.1016/j.procs.2020.03.276>
54. de Cock Buning M (2018) A multi-dimensional approach to disinformation: report of the independent high level group on fake news
55. and online disinformation. Publications Ofce of the European Union Del Vicario M, Quattrocioni W, Scala A, Zollo F (2019) Polarization and fake news: early warning of potential misinformation targets. *ACM Trans Web (TWEB)* 13(2):1–22. <https://doi.org/10.1145/3316809>
56. Demuyakor J, Opatu EM (2022) Fake news on social media: predicting which media format influences fake news most on facebook. *J Intell Commun*. <https://doi.org/10.54963/jic.v2i1.56>
57. Derakhshan H, Wardle C (2017) Information disorder: definitions. In: *Understanding and addressing the disinformation ecosystem*, pp 5–12 Desai AN, Ruidera D, Steinbrink JM, Granwehr B, Lee DH (2022)
58. Misinformation and disinformation: the potential disadvantages of social media in infectious disease and how to combat them. *Clin Infect Dis* 74(Supplement–3):e34–e39. <https://doi.org/10.1093/cid/ciac109>
59. Di Domenico G, Sit J, Ishizaka A, Nunan D (2021) Fake news, social media and marketing: a systematic review. *J Bus Res* 124:329–341. <https://doi.org/10.1016/j.jbusres.2020.11.037>
60. Dias N, Pennycook G, Rand DG (2020) Emphasizing publishers does not effectively reduce susceptibility to misinformation on social media. *Harv Kennedy School Misinform Rev*. <https://doi.org/10.37016/mr-2020-001>

61. DiCicco KW, Agarwal N (2020) Blockchain technology-based solutions to fight misinformation: a survey. In: *Disinformation, misinformation, and fake news in social media*. Springer, Berlin, pp 267–281, https://doi.org/10.1007/978-3-030-42699-6_14
62. Douglas KM, Uscinski JE, Sutton RM, Cichocka A, Nefes T, Ang CS, Deravi F (2019) Understanding conspiracy theories. *Polit Psychol* 40:3–35. <https://doi.org/10.1111/pops.12568>
63. Edgerly S, Mourão RR, Thorson E, Tham SM (2020) When do audiences verify? How perceptions about message and source influence audience verification of news headlines. *J Mass Commun Q* 97(1):52–71. <https://doi.org/10.1177/1077699019864680>
64. Egelhofer JL, Lecheler S (2019) Fake news as a two-dimensional phenomenon: a framework and research agenda. *Ann Int Commun Assoc* 43(2):97–116. <https://doi.org/10.1080/23808985.2019.1602782>
65. Elhadad MK, Li KF, Gebali F (2019) A novel approach for selecting hybrid features from online news textual metadata for fake news detection. In: *International conference on p2p, parallel, grid, cloud and internet computing*. Springer, Berlin, pp 914–925, https://doi.org/10.1007/978-3-030-33509-0_86
66. ERGA (2018) Fake news, and the information disorder. European Broadcasting Union (EBU)
67. ERGA (2021) Notions of disinformation and related concepts. European Regulators Group for Audiovisual Media Services (ERGA)
68. Escolà-Gascón Á (2021) New techniques to measure lie detection using Covid-19 fake news and the Multivariable Multiaxial Suggestibility Inventory-2 (MMSI-2). *Comput Hum Behav Rep* 3:100049. <https://doi.org/10.1016/j.chbr.2020.100049>
69. Fazio L (2020) Pausing to consider why a headline is true or false can help reduce the sharing of false news. *Harv Kennedy School Misinformation Rev*. <https://doi.org/10.37016/mr-2020-009>
70. Ferrara E, Varol O, Davis C, Menczer F, Flammini A (2016) The rise of social bots. *Commun ACM* 59(7):96–104. <https://doi.org/10.1145/2818717>
71. Flynn D, Nyhan B, Reifer J (2017) The nature and origins of misperceptions: understanding false and unsupported beliefs about politics. *Polit Psychol* 38:127–150. <https://doi.org/10.1111/pops.12394>
72. Fraga-Lamas P, Fernández-Caramés TM (2020) Fake news, disinformation, and deepfakes: leveraging distributed ledger technologies and blockchain to combat digital deception and counterfeit reality. *IT Prof* 22(2):53–59. <https://doi.org/10.1109/MITP.2020.2977589>
73. Freeman D, Waite F, Rosebrock L, Petit A, Causier C, East A, Jenner L, Teale AL, Carr L, Mulhall S et al (2020) Coronavirus conspiracy beliefs, mistrust, and compliance with government guidelines in England. *Psychol Med*. <https://doi.org/10.1017/S0033291720001890>
74. Friggeri A, Adamic L, Eckles D, Cheng J (2014) Rumor cascades. In: *Proceedings of the international AAAI conference on web and social media* García SA, García GG, Prieto MS, Moreno Guerrero AJ, Rodríguez
75. Jiménez C (2020) The impact of term fake news on the scientific community. Scientific performance and mapping in web of science. *Soc Sci*. <https://doi.org/10.3390/socsci9050073>

76. Garrett RK, Bond RM (2021) Conservatives' susceptibility to political misperceptions. *Sci Adv.* <https://doi.org/10.1126/sciadv.abf1234>
77. Giachanou A, Rissola EA, Ghanem B, Crestani F, Rosso P (2020) The role of personality and linguistic patterns in discriminating between fake news spreaders and fact checkers. In: *International conference on applications of natural language to information systems.* Springer, Berlin, pp 181–192 https://doi.org/10.1007/978-3-030-51310-8_17
78. Golbeck J, Mauriello M, Auxier B, Bhanushali KH, Bonk C, Bouzaghrane MA, Buntain C, Chanduka R, Cheakalos P, Everett JB et al (2018) Fake news vs satire: a dataset and analysis. In: *Proceedings of the 10th ACM conference on web science*, pp 17–21, <https://doi.org/10.1145/3201064.3201100>
79. Goldani MH, Momtazi S, Safabakhsh R (2021) Detecting fake news with capsule neural networks. *Appl Soft Comput* 101:106991. <https://doi.org/10.1016/j.asoc.2020.106991>
80. Goldstein I, Yang L (2019) Good disclosure, bad disclosure. *J Financ Econ* 131(1):118–138. <https://doi.org/10.1016/j.jfneco.2018.08.004>
81. Grinberg N, Joseph K, Friedland L, Swire-Thompson B, Lazer D (2019) Fake news on Twitter during the 2016 US presidential election. *Science* 363(6425):374–378. <https://doi.org/10.1126/science.aau2706>
82. Guadagno RE, Guttieri K (2021) Fake news and information warfare: an examination of the political and psychological processes from the digital sphere to the real world. In: *Research anthology on fake news, political warfare, and combatting the spread of misinformation.* IGI Global, pp 218–242 <https://doi.org/10.4018/978-1-7998-7291-7.ch013>
83. Guess A, Nagler J, Tucker J (2019) Less than you think: prevalence and predictors of fake news dissemination on Facebook. *Sci Adv.* <https://doi.org/10.1126/sciadv.aau4586>
84. Guo C, Cao J, Zhang X, Shu K, Yu M (2019) Exploiting emotions for fake news detection on social media. *arXiv preprint arXiv: 1903.01728*
85. Guo B, Ding Y, Yao L, Liang Y, Yu Z (2020) The future of false information detection on social media: new perspectives and trends. *ACM Comput Surv (CSUR)* 53(4):1–36. <https://doi.org/10.1145/3393880>
86. Gupta A, Li H, Farnoush A, Jiang W (2022) Understanding patterns of covid infodemic: a systematic and pragmatic approach to curb fake news. *J Bus Res* 140:670–683. <https://doi.org/10.1016/j.jbusres.2021.11.032>
87. Ha L, Andreu Perez L, Ray R (2021) Mapping recent development in scholarship on fake news and misinformation, 2008 to 2017: disciplinary contribution, topics, and impact. *Am Behav Sci* 65(2):290–315. <https://doi.org/10.1177/0002764219869402>
88. Habib A, Asghar MZ, Khan A, Habib A, Khan A (2019) False information detection in online content and its role in decision making: a systematic literature review. *Soc Netw Anal Min* 9(1):1–20. <https://doi.org/10.1007/s13278-019-0595-5>
89. Hage H, Aïmeur E, Guedidi A (2021) Understanding the landscape of online deception. In: *Research anthology on fake news, political warfare, and combatting the spread of misinformation.* IGI Global, pp 39–66. <https://doi.org/10.4018/978-1-7998-2543-2.ch014>

90. Hakak S, Alazab M, Khan S, Gadekallu TR, Maddikunta PKR, Khan WZ (2021) An ensemble machine learning approach through effective feature extraction to classify fake news. *Futur Gener Comput Syst* 117:47–58. <https://doi.org/10.1016/j.future.2020.11.022>
91. Hamdi T, Slimi H, Bounhas I, Slimani Y (2020) A hybrid approach for fake news detection in Twitter based on user features and graph embedding. In: *International conference on distributed computing and internet technology*. Springer, Berlin, pp 266– 280. https://doi.org/10.1007/978-3-030-36987-3_17
92. Hameleers M (2022) Separating truth from lies: comparing the effects of news media literacy interventions and fact-checkers in response to political misinformation in the us and netherlands. *Inf Commun Soc* 25(1):110–126. <https://doi.org/10.1080/1369118X.2020.1764603>
93. Hameleers M, Powell TE, Van Der Meer TG, Bos L (2020) A picture paints a thousand lies? The effects and mechanisms of multimodal disinformation and rebuttals disseminated via social media. *Polit Commun* 37(2):281–301. <https://doi.org/10.1080/10584609.2019.1674979>
94. Hameleers M, Brosius A, de Vreese CH (2022) Whom to trust? media exposure patterns of citizens with perceptions of misinformation and disinformation related to the news media. *Eur J Commun*. <https://doi.org/10.1177/02673231211072667>
95. Hartley K, Vu MK (2020) Fighting fake news in the Covid-19 era: policy insights from an equilibrium model. *Policy Sci* 53(4):735–758. <https://doi.org/10.1007/s11077-020-09405-z>
96. Hasan HR, Salah K (2019) Combating deepfake videos using blockchain and smart contracts. *IEEE Access* 7:41596–41606. <https://doi.org/10.1109/ACCESS.2019.2905689>
97. Hiriyanaiyah S, Srinivas A, Shetty GK, Siddesh G, Srinivasa K (2020) A computationally intelligent agent for detecting fake news using generative adversarial networks. *Hybrid computational intelligence: challenges and applications*. pp 69–96 <https://doi.org/10.1016/B978-0-12-818699-2.00004-4>
98. Hosseinimotlagh S, Papalexakis EE (2018) Unsupervised content-based identification of fake news articles with tensor decomposition ensembles. In: *Proceedings of the workshop on misinformation and misbehavior mining on the web (MIS2)*
99. Huckle S, White M (2017) Fake news: a technological approach to proving the origins of content, using blockchains. *Big Data* 5(4):356–371. <https://doi.org/10.1089/big.2017.0071>
100. Hufaker JS, Kummerfeld JK, Lasecki WS, Ackerman MS (2020) Crowdsourced detection of emotionally manipulative language. In: *Proceedings of the 2020 CHI conference on human factors in computing systems*. pp 1–14 <https://doi.org/10.1145/3313831.3376375>
101. Ireton C, Posetti J (2018) *Journalism, fake news & disinformation: handbook for journalism education and training*. UNESCO Publishing, Paris Islam MR, Liu S, Wang X, Xu G (2020) Deep learning for misinformation detection on online social networks: a survey and new perspectives. *Soc Netw Anal Min* 10(1):1–20. <https://doi.org/10.1007/s13278-020-00696-x>
102. Ismailov M, Tsikerdakis M, Zeadally S (2020) Vulnerabilities to online social network identity deception detection research and recommendations for mitigation. *Fut Internet* 12(9):148. <https://doi.org/10.3390/f12090148>
103. Jakesch M, Koren M, Evtushenko A, Naaman M (2019) The role of source and expressive responding in political news evaluation. In: *Computation and journalism*

- symposium Jamieson KH (2020) *Cyberwar: how Russian hackers and trolls helped elect a president: what we don't, can't, and do know*. Oxford University Press, Oxford.
<https://doi.org/10.1093/poq/nfy049>
104. Jiang S, Chen X, Zhang L, Chen S, Liu H (2019) User-characteristic enhanced model for fake news detection in social media. In: CCF International conference on natural language processing and Chinese computing, Springer, Berlin, pp 634–646.
https://doi.org/10.1007/978-3-030-32233-5_49
 105. Jin Z, Cao J, Zhang Y, Luo J (2016) News verification by exploiting conflicting social viewpoints in microblogs. In: Proceedings of the AAAI conference on artificial intelligence Jing TW, Murugesan RK (2018) A theoretical framework to build trust and prevent fake news in social media using blockchain. In: International conference of reliable information and communication technology. Springer, Berlin, pp 955–962, https://doi.org/10.1007/978-3-319-99007-1_88
 106. Jones-Jang SM, Mortensen T, Liu J (2021) Does media literacy help identification of fake news? Information literacy helps, but other literacies don't. *Am Behav Sci* 65(2):371–388. <https://doi.org/10.1177/0002764219869406>
 107. Jungherr A, Schroeder R (2021) Disinformation and the structural transformations of the public arena: addressing the actual challenges to democracy. *Soc Media Soc*.
<https://doi.org/10.1177/2056305121988928>
 108. Kaliyar RK (2018) Fake news detection using a deep neural network. In: 2018 4th international conference on computing communication and automation (ICCCA), IEEE, pp 1–7
<https://doi.org/10.1109/CCAA.2018.8777343>
 109. Kaliyar RK, Goswami A, Narang P, Sinha S (2020) Fndnet—a deep convolutional neural network for fake news detection. *Cogn Syst Res* 61:32–44.
<https://doi.org/10.1016/j.cogsys.2019.12.005>
 110. Kapantai E, Christopoulou A, Berberidis C, Peristeras V (2021) A systematic literature review on disinformation: toward a unified taxonomical framework. *New Media Soc* 23(5):1301–1326. <https://doi.org/10.1177/1461444820959296>
 111. Kapusta J, Benko L, Munk M (2019) Fake news identification based on sentiment and frequency analysis. In: International conference Europe middle east and North Africa information systems and technologies to support learning. Springer, Berlin, pp 400–409,
[10.1007/978-3-030-36778-7_44](https://doi.org/10.1007/978-3-030-36778-7_44)
 112. Kaur S, Kumar P, Kumaraguru P (2020) Automating fake news detection system using multi-level voting model. *Soft Comput* 24(12):9049–9069. <https://doi.org/10.1007/s00500-019-04436-y>
 113. Khan SA, Alkawaz MH, Zangana HM (2019) The use and abuse of social media for spreading fake news. In: 2019 IEEE international conference on automatic control and intelligent systems (I2CACIS), IEEE, pp 145–148. <https://doi.org/10.1109/I2CACIS.2019.8825029>
 114. Kim J, Tabibian B, Oh A, Schölkopf B, Gomez-Rodriguez M (2018) Leveraging the crowd to detect and reduce the spread of fake news and misinformation. In: Proceedings of the eleventh ACM international conference on web search and data mining, pp 324–332.
<https://doi.org/10.1145/3159652.3159734>

115. Klein D, Wueller J (2017) Fake news: a legal perspective. *J Internet Law* 20(10):5–13
Kogan S, Moskowitz TJ, Niessner M (2019) Fake news: evidence from financial markets. Available at SSRN 3237763
Kuklinski JH, Quirk PJ, Jerit J, Schwieder D, Rich RF (2000) Misinformation and the currency of democratic citizenship. *J Polit* 62(3):790–816. <https://doi.org/10.1111/0022-3816.00033>
116. Kumar S, Shah N (2018) False information on web and social media: a survey. arXiv preprint arXiv:1804.08559
117. Kumar S, West R, Leskovec J (2016) Disinformation on the web: impact, characteristics, and detection of Wikipedia hoaxes. In: *Proceedings of the 25th international conference on world wide web*, pp 591–602. <https://doi.org/10.1145/2872427.2883085>
118. La Barbera D, Roitero K, Demartini G, Mizzaro S, Spina D (2020) Crowdsourcing truthfulness: the impact of judgment scale and assessor bias. In: *European conference on information retrieval*. Springer, Berlin, pp 207–214. https://doi.org/10.1007/978-3-030-45442-5_26
119. Lanius C, Weber R, MacKenzie WI (2021) Use of bot and content flags to limit the spread of misinformation among social networks: a behavior and attitude survey. *Soc Netw Anal Min* 11(1):1–15. <https://doi.org/10.1007/s13278-021-00739-x>
120. Lazer DM, Baum MA, Benkler Y, Berinsky AJ, Greenhill KM, Menczer F, Metzger MJ, Nyhan B, Pennycook G, Rothschild D et al (2018) The science of fake news. *Science* 359(6380):1094–1096. <https://doi.org/10.1126/science.aao2998>
121. Le T, Shu K, Molina MD, Lee D, Sundar SS, Liu H (2019) 5 sources of clickbaits you should know! Using synthetic clickbaits to improve prediction and distinguish between bot-generated and human-written headlines. In: *2019 IEEE/ACM international conference on advances in social networks analysis and mining (ASONAM)*. IEEE, pp 33–40. <https://doi.org/10.1145/3341161.3342875>
122. Lewandowsky S (2020) Climate change, disinformation, and how to combat it. In: *Annual Review of Public Health* 42. <https://doi.org/10.1146/annurev-publhealth-090419-102409>
123. Liu Y, Wu YF (2018) Early detection of fake news on social media through propagation path classification with recurrent and convolutional networks. In: *Proceedings of the AAAI conference on artificial intelligence*, pp 354–361
124. Luo M, Hancock JT, Markowitz DM (2022) Credibility perceptions and detection accuracy of fake news headlines on social media: effects of truth-bias and endorsement cues. *Commun Res* 49(2):171–195. <https://doi.org/10.1177/0093650220921321>
125. Lutzke L, Drummond C, Slovic P, Árvai J (2019) Priming critical thinking: simple interventions limit the influence of fake news about climate change on Facebook. *Glob Environ Chang* 58:101964. <https://doi.org/10.1016/j.gloenvcha.2019.101964>
126. Maertens R, Anseel F, van der Linden S (2020) Combatting climate change misinformation: evidence for longevity of inoculation and consensus messaging effects. *J Environ Psychol* 70:101455. <https://doi.org/10.1016/j.jenvp.2020.101455>
127. Mahabub A (2020) A robust technique of fake news detection using ensemble voting classifier and comparison with other classifiers. *SN Applied Sciences* 2(4):1–9. <https://doi.org/10.1007/s42452-020-2326y>

128. Mahbub S, Pardede E, Kayes A, Rahayu W (2019) Controlling astroturfing on the internet: a survey on detection techniques and research challenges. *Int J Web Grid Serv* 15(2):139–158. <https://doi.org/10.1504/IJWGS.2019.099561>
129. Marsden C, Meyer T, Brown I (2020) Platform values and democratic elections: how can the law regulate digital disinformation? *Comput Law Secur Rev* 36:105373. <https://doi.org/10.1016/j.clsr.2019.105373>
130. Masciari E, Moscato V, Picariello A, Sperlí G (2020) Detecting fake news by image analysis. In: *Proceedings of the 24th symposium on international database engineering and applications*, pp 1–5. <https://doi.org/10.1145/3410566.3410599>
131. Mazzeo V, Rapisarda A (2022) Investigating fake and reliable news sources using complex networks analysis. *Front Phys* 10:886544. <https://doi.org/10.3389/fphy.2022.886544>
132. McGrew S (2020) Learning to evaluate: an intervention in civic online reasoning. *Comput Educ* 145:103711. <https://doi.org/10.1016/j.compedu.2019.103711>
133. McGrew S, Breakstone J, Ortega T, Smith M, Wineburg S (2018) Can students evaluate online sources? Learning from assessments of civic online reasoning. *Theory Res Soc Educ* 46(2):165–193. <https://doi.org/10.1080/00933104.2017.1416320>
134. Meel P, Vishwakarma DK (2020) Fake news, rumor, information pollution in social media and web: a contemporary survey of state-of-the-arts, challenges and opportunities. *Expert Syst Appl* 153:112986. <https://doi.org/10.1016/j.eswa.2019.112986>
135. Meese J, Frith J, Wilken R (2020) Covid-19, 5G conspiracies and infrastructural futures. *Media Int Aust* 177(1):30–46. <https://doi.org/10.1177/1329878X20952165>
136. Metzger MJ, Hartsell EH, Flanagin AJ (2020) Cognitive dissonance or credibility? A comparison of two theoretical explanations for selective exposure to partisan news. *Commun Res* 47(1):3–28. <https://doi.org/10.1177/0093650215613136>
137. Micallef N, He B, Kumar S, Ahamad M, Memon N (2020) The role of the crowd in countering misinformation: a case study of the Covid-19 infodemic. *arXiv preprint arXiv:2011.05773*
138. Mihailidis P, Viotty S (2017) Spreadable spectacle in digital culture: civic expression, fake news, and the role of media literacies in “post-fact society. *Am Behav Sci* 61(4):441–454. <https://doi.org/10.1177/0002764217701217>
139. Mishra R (2020) Fake news detection using higher-order user to user mutual-attention progression in propagation paths. In: *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition workshops*, pp 652–653
140. Mishra S, Shukla P, Agarwal R (2022) Analyzing machine learning enabled fake news detection techniques for diversified datasets. *Wirel Commun Mobile Comput*. <https://doi.org/10.1155/2022/1575365>
141. Molina MD, Sundar SS, Le T, Lee D (2021) “Fake news” is not simply false information: a concept explication and taxonomy of online content. *Am Behav Sci* 65(2):180–212. <https://doi.org/10.1177/0002764219878224>
142. Moro C, Birt JR (2022) Review bombing is a dirty practice, but research shows games do benefit from online feedback. *Conversation*.

<https://research.bond.edu.au/en/publications/review-bombing-is-a-dirty-practice-but-research-shows-games-do-be>

143. Mustafaraj E, Metaxas PT (2017) The fake news spreading plague: was it preventable? In: Proceedings of the 2017 ACM on web science conference, pp 235–239. <https://doi.org/10.1145/3091478.3091523>
144. Nagel TW (2022) Measuring fake news acumen using a news media literacy instrument. *J Media Liter Educ* 14(1):29–42. <https://doi.org/10.23860/JMLE-2022-14-1-3>
145. Nakov P (2020) Can we spot the “fake news” before it was even written? arXiv preprint arXiv:2008.04374
146. Nekmat E (2020) Nudge effect of fact-check alerts: source influence and media skepticism on sharing of news misinformation in social media. *Soc Media Soc*. <https://doi.org/10.1177/2056305119897322>
147. Nygren T, Brounéus F, Svensson G (2019) Diversity and credibility in young people’s news feeds: a foundation for teaching and learning citizenship in a digital era. *J Soc Sci Educ* 18(2):87–109. <https://doi.org/10.4119/jsse-917>
148. Nyhan B, Reifer J (2015) Displacing misinformation about events: an experimental test of causal corrections. *J Exp Polit Sci* 2(1):81–93. <https://doi.org/10.1017/XPS.2014.22>
149. Nyhan B, Porter E, Reifer J, Wood TJ (2020) Taking fact-checks literally but not seriously? The effects of journalistic fact-checking on factual beliefs and candidate favorability. *Polit Behav* 42(3):939–960. <https://doi.org/10.1007/s11109-019-09528-x>
150. Nyow NX, Chua HN (2019) Detecting fake news with tweets’ properties. In: 2019 IEEE conference on application, information and network security (AINS), IEEE, pp 24–29. <https://doi.org/10.1109/AINS47559.2019.8968706>
151. Ochoa IS, de Mello G, Silva LA, Gomes AJ, Fernandes AM, Leithardt VRQ (2019) Fakechain: a blockchain architecture to ensure trust in social media networks. In: International conference on the quality of information and communications technology. Springer, Berlin, pp 105–118. https://doi.org/10.1007/978-3-030-29238-6_8
152. Ozbay FA, Alatas B (2020) Fake news detection within online social media using supervised artificial intelligence algorithms. *Physica A* 540:123174. <https://doi.org/10.1016/j.physa.2019.123174>
153. Ozturk P, Li H, Sakamoto Y (2015) Combating rumor spread on social media: the effectiveness of refutation and warning. In: 2015 48th Hawaii international conference on system sciences, IEEE, pp 2406–2414. <https://doi.org/10.1109/HICSS.2015.288>
154. Parikh SB, Atray PK (2018) Media-rich fake news detection: a survey. In: 2018 IEEE conference on multimedia information processing and retrieval (MIPR), IEEE, pp 436–441. <https://doi.org/10.1109/MIPR.2018.00093>
155. Parrish K (2018) Deep learning & machine learning: what’s the difference? Online: <https://parsers.me/deep-learning-machine-learning-whats-the-difference/>. Accessed 20 May 2020
 Paschen J (2019) Investigating the emotional appeal of fake news using artificial intelligence and human contributions. *J Prod Brand Manag* 29(2):223–233. <https://doi.org/10.1108/JPBM-12-2018-2179>

156. Pathak A, Srihari RK (2019) Breaking! Presenting fake news corpus for automated fact checking. In: Proceedings of the 57th annual meeting of the association for computational linguistics: student research workshop, pp 357–362 Peng J, Detchon S, Choo KKR, Ashman H (2017) Astroturfing detection in social media: a binary n-gram-based approach. *Concurr Comput: Pract Exp* 29(17):e4013. <https://doi.org/10.1002/cpe.4013>
157. Pennycook G, Rand DG (2019) Fighting misinformation on social media using crowdsourced judgments of news source quality. *Proc Natl Acad Sci* 116(7):2521–2526. <https://doi.org/10.1073/pnas.1806781116>
158. Pennycook G, Rand DG (2020) Who falls for fake news? The roles of bullshit receptivity, overclaiming, familiarity, and analytic thinking. *J Pers* 88(2):185–200. <https://doi.org/10.1111/jopy.12476>
159. Pennycook G, Bear A, Collins ET, Rand DG (2020a) The implied truth effect: attaching warnings to a subset of fake news headlines increases perceived accuracy of headlines without warnings. *Manag Sci* 66(11):4944–4957. <https://doi.org/10.1287/mnsc.2019.3478>
160. Pennycook G, McPhetres J, Zhang Y, Lu JG, Rand DG (2020b) Fighting Covid-19 misinformation on social media: experimental evidence for a scalable accuracy-nudge intervention. *Psychol Sci* 31(7):770–780. <https://doi.org/10.1177/0956797620939054>
161. Potthast M, Kiesel J, Reinartz K, Bevendorf J, Stein B (2017) A stylometric inquiry into hyperpartisan and fake news. *arXiv preprint arXiv:1702.05638*
162. Previti M, Rodriguez-Fernandez V, Camacho D, Carchiolo V, Malgeri M (2020) Fake news detection using time series and user features classification. In: International conference on the applications of evolutionary computation (Part of EvoStar), Springer, Berlin, pp 339–353. https://doi.org/10.1007/978-3-030-43722-0_22
163. Przybyla P (2020) Capturing the style of fake news. In: Proceedings of the AAAI conference on artificial intelligence, pp 490–497. <https://doi.org/10.1609/aaai.v34i01.5386>
164. Qayyum A, Qadir J, Janjua MU, Sher F (2019) Using blockchain to rein in the new post-truth world and check the spread of fake news. *IT Prof* 21(4):16–24. <https://doi.org/10.1109/MITP.2019.2910503>
165. Qian F, Gong C, Sharma K, Liu Y (2018) Neural user response generator: fake news detection with collective user intelligence. In: *IJCAI*, vol 18, pp 3834–3840. <https://doi.org/10.24963/ijcai.2018/533>
166. Raza S, Ding C (2022) Fake news detection based on news content and social contexts: a transformer-based approach. *Int J Data Sci Anal* 13(4):335–362. <https://doi.org/10.1007/s41060-021-00302-z>
167. Ricard J, Medeiros J (2020) Using misinformation as a political weapon: Covid-19 and Bolsonaro in Brazil. *Harv Kennedy School misinformation Rev* 1(3). <https://misinforeview.hks.harvard.edu/article/using-misinformation-as-a-political-weapon-covid-19-and-bolsonaro-in-brazil/>
168. Roozenbeek J, van der Linden S (2019) Fake news game confers psychological resistance against online misinformation. *Palgrave Commun* 5(1):1–10. <https://doi.org/10.1057/s41599-019-0279-9>

169. Roozenbeek J, van der Linden S, Nygren T (2020a) Prebunking interventions based on the psychological theory of “inoculation” can reduce susceptibility to misinformation across cultures. *Harv Kennedy School Misinformation Rev.* <https://doi.org/10.37016/mr-2020-008>
170. Roozenbeek J, Schneider CR, Dryhurst S, Kerr J, Freeman AL, Recchia G, Van Der Bles AM, Van Der Linden S (2020b) Susceptibility to misinformation about Covid-19 around the world. *R Soc Open Sci* 7(10):201199. <https://doi.org/10.1098/rsos.201199>
171. Rubin VL, Conroy N, Chen Y, Cornwell S (2016) Fake news or truth? Using satirical cues to detect potentially misleading news. In: *Proceedings of the second workshop on computational approaches to deception detection*, pp 7–17
172. Ruchansky N, Seo S, Liu Y (2017) Csi: a hybrid deep model for fake news detection. In: *Proceedings of the 2017 ACM on conference on information and knowledge management*, pp 797–806. <https://doi.org/10.1145/3132847.3132877>
173. Schuyler AJ (2019) Regulating facts: a procedural framework for identifying, excluding, and deterring the intentional or knowing proliferation of fake news online. *Univ Ill JL Technol Pol’y*, vol 2019, pp 211–240
174. Shae Z, Tsai J (2019) AI blockchain platform for trusting news. In: *2019 IEEE 39th international conference on distributed computing systems (ICDCS)*, IEEE, pp 1610–1619. <https://doi.org/10.1109/ICDCS.2019.00160>
175. Shang W, Liu M, Lin W, Jia M (2018) Tracing the source of news based on blockchain. In: *2018 IEEE/ACIS 17th international conference on computer and information science (ICIS)*, IEEE, pp 377–381. <https://doi.org/10.1109/ICIS.2018.8466516>
176. Shao C, Ciampaglia GL, Flammini A, Menczer F (2016) Hoaxy: A platform for tracking online misinformation. In: *Proceedings of the 25th international conference companion on world wide web*, pp 745–750. <https://doi.org/10.1145/2872518.2890098>
177. Shao C, Ciampaglia GL, Varol O, Yang KC, Flammini A, Menczer F (2018) The spread of low-credibility content by social bots. *Nat Commun* 9(1):1–9. <https://doi.org/10.1038/s41467-018-06930-7>
178. Shao C, Hui PM, Wang L, Jiang X, Flammini A, Menczer F, Ciampaglia GL (2018) Anatomy of an online misinformation network. *PLoS ONE* 13(4):e0196087. <https://doi.org/10.1371/journal.pone.0196087>
179. Sharma K, Qian F, Jiang H, Ruchansky N, Zhang M, Liu Y (2019) Combating fake news: a survey on identification and mitigation techniques. *ACM Trans Intell Syst Technol (TIST)* 10(3):1–42. <https://doi.org/10.1145/3305260>
180. Sharma K, Seo S, Meng C, Rambhatla S, Liu Y (2020) Covid-19 on social media: analyzing misinformation in Twitter conversations. *arXiv preprint arXiv:2003.12309*
181. Shen C, Kasra M, Pan W, Bassett GA, Malloch Y, O’Brien JF (2019)
182. Fake images: the effects of source, intermediary, and digital media literacy on contextual assessment of image credibility online. *New Media Soc* 21(2):438–463. <https://doi.org/10.1177/1461444818799526>
183. Sherman IN, Redmiles EM, Stokes JW (2020) Designing indicators to combat fake media. *arXiv preprint arXiv:2010.00544*

184. Shi P, Zhang Z, Choo KKR (2019) Detecting malicious social bots based on clickstream sequences. *IEEE Access* 7:28855–28862. <https://doi.org/10.1109/ACCESS.2019.2901864>
185. Shu K, Sliva A, Wang S, Tang J, Liu H (2017) Fake news detection on social media: a data mining perspective. *ACM SIGKDD Explor Newsl* 19(1):22–36. <https://doi.org/10.1145/3137597.3137600>
186. Shu K, Mahudeswaran D, Wang S, Lee D, Liu H (2018a) Fakenewsnet: a data repository with news content, social context and spatialtemporal information for studying fake news on social media. *arXiv preprint arXiv:1809.01286*, <https://doi.org/10.1089/big.2020.0062>
187. Shu K, Wang S, Liu H (2018b) Understanding user profiles on social media for fake news detection. In: 2018 IEEE conference on multimedia information processing and retrieval (MIPR), IEEE, pp 430–435. <https://doi.org/10.1109/MIPR.2018.00092>
188. Shu K, Wang S, Liu H (2019a) Beyond news contents: the role of social context for fake news detection. In: *Proceedings of the twelfth ACM international conference on web search and data mining*, pp 312–320. <https://doi.org/10.1145/3289600.3290994>
189. Shu K, Zhou X, Wang S, Zafarani R, Liu H (2019b) The role of user profiles for fake news detection. In: *Proceedings of the 2019 IEEE/ACM international conference on advances in social networks analysis and mining*, pp 436–439. <https://doi.org/10.1145/3341161.3342927>
190. Shu K, Bhattacharjee A, Alatawi F, Nazer TH, Ding K, Karami M, Liu H (2020a) Combating disinformation in a social media age. *Wiley Interdiscip Rev: Data Min Knowl Discov* 10(6):e1385. <https://doi.org/10.1002/widm.1385>
191. Shu K, Mahudeswaran D, Wang S, Liu H (2020b) Hierarchical propagation networks for fake news detection: investigation and exploitation. *Proc Int AAAI Conf Web Soc Media AAAI Press* 14:626–637
192. Shu K, Wang S, Lee D, Liu H (2020c) Mining disinformation and fake news: concepts, methods, and recent advancements. In: *Disinformation, misinformation, and fake news in social media*. Springer, Berlin, pp 1–19 https://doi.org/10.1007/978-3-030-42699-6_1
193. Shu K, Zheng G, Li Y, Mukherjee S, Awadallah AH, Ruston S, Liu H (2020d) Early detection of fake news with multi-source weak social supervision. In: *ECML/PKDD* (3), pp 650–666 13:30
194. Singh VK, Ghosh I, Sonagara D (2021) Detecting fake news stories via multimodal analysis. *J Am Soc Inf Sci* 72(1):3–17. <https://doi.org/10.1002/asi.24359>
195. Sintos S, Agarwal PK, Yang J (2019) Selecting data to clean for fact checking: minimizing uncertainty vs. maximizing surprise. *Proc VLDB Endowm* 12(13), 2408–2421. <https://doi.org/10.14778/3358701.3358708>
196. Snow J (2017) Can AI win the war against fake news? MIT Technology Review Online: <https://www.technologyreview.com/s/609717/can-ai-win-the-war-against-fake-news/>. Accessed 3 Oct. 2020
197. Song G, Kim S, Hwang H, Lee K (2019) Blockchain-based notarization for social media. In: 2019 IEEE international conference on consumer electronics (ICCE), IEEE, pp 1–2 <https://doi.org/10.1109/ICCE.2019.8661978>

198. Starbird K, Arif A, Wilson T (2019) Disinformation as collaborative work: Surfacing the participatory nature of strategic information operations. In: Proceedings of the ACM on human–computer interaction, vol 3(CSCW), pp 1–26 <https://doi.org/10.1145/3359229>
199. Sterret D, Malato D, Benz J, Kantor L, Tompson T, Rosenstiel T, Sonderman J, Loker K, Swanson E (2018) Who shared it? How Americans decide what news to trust on social media. Technical report, Norc Working Paper Series, WP-2018-001, pp 1–24 Sutton RM, Douglas KM (2020) Conspiracy theories and the conspiracy mindset: implications for political ideology. *Curr Opin Behav Sci* 34:118–122. <https://doi.org/10.1016/j.cobeha.2020.02.015>
200. Tandoc EC Jr, Thomas RJ, Bishop L (2021) What is (fake) news? Analyzing news values (and more) in fake stories. *Media Commun* 9(1):110–119. <https://doi.org/10.17645/mac.v9i1.3331>
201. Tchakounté F, Faissal A, Atemkeng M, Ntyam A (2020) A reliable weighting scheme for the aggregation of crowd intelligence to detect fake news. *Information* 11(6):319. <https://doi.org/10.3390/info11060319>
202. Tchechmedjiev A, Fafalios P, Boland K, Gasquet M, Zloch M, Zapilko B, Dietze S, Todorov K (2019) Claimskg: a knowledge graph of fact-checked claims. In: International semantic web conference. Springer, Berlin, pp 309–324 https://doi.org/10.1007/978-3-030-30796-7_20
203. Treen KMd, Williams HT, O'Neill SJ (2020) Online misinformation about climate change. *Wiley Interdiscip Rev Clim Change* 11(5):e665. <https://doi.org/10.1002/wcc.665>
204. Tsang SJ (2020) Motivated fake news perception: the impact of news sources and policy support on audiences' assessment of news fakeness. *J Mass Commun Q*. <https://doi.org/10.1177/1077699020952129>
205. Tschatschek S, Singla A, Gomez Rodriguez M, Merchant A, Krause A (2018) Fake news detection in social networks via crowd signals. In: Companion proceedings of the the web conference 2018, pp 517–524. <https://doi.org/10.1145/3184558.3188722>
206. Uppada SK, Manasa K, Vidhathri B, Harini R, Sivaselvan B (2022) Novel approaches to fake news and fake account detection in OSNS: user social engagement and visual content centric model. *Soc Netw Anal Min* 12(1):1–19. <https://doi.org/10.1007/s13278-022-00878-9>
207. Van der Linden S, Roozenbeek J (2020) Psychological inoculation against fake news. In: Accepting, sharing, and correcting misinformation, the psychology of fake news. <https://doi.org/10.4324/9780429295379-11>
208. Van der Linden S, Panagopoulos C, Roozenbeek J (2020) You are fake news: political bias in perceptions of fake news. *Media Cult Soc* 42(3):460–470. <https://doi.org/10.1177/0163443720906992>
209. Valenzuela S, Muñiz C, Santos M (2022) Social media and belief in misinformation in mexico: a case of maximal panic, minimal effects? *Int J Press Polit*. <https://doi.org/10.1177/19401612221088988>
210. Vasu N, Ang B, Teo TA, Jayakumar S, Raizal M, Ahuja J (2018) Fake news: national security in the post-truth era. *RSIS*
211. Vereshchaka A, Cosimini S, Dong W (2020) Analyzing and distinguishing fake and real news to mitigate the problem of disinformation. In: Computational and mathematical organization theory, pp 1–15. <https://doi.org/10.1007/s10588-020-09307-8>

212. Verstraete M, Bambauer DE, Bambauer JR (2017) Identifying and countering fake news. *Arizona legal studies discussion paper* 73(17-15).
<https://doi.org/10.2139/ssrn.3007971>
213. Vilmer J, Escorcía A, Guillaume M, Herrera J (2018) Information manipulation: a challenge for our democracies. In: Report by the Policy Planning Staf (CAPS) of the ministry for europe and foreign affairs, and the institute for strategic research (RSEM) of the Ministry for the Armed Forces
214. Vishwakarma DK, Varshney D, Yadav A (2019) Detection and veracity analysis of fake news via scrapping and authenticating the web search. *Cogn Syst Res* 58:217–229.
<https://doi.org/10.1016/j.cogsys.2019.07.004>
215. Vlachos A, Riedel S (2014) Fact checking: task definition and dataset construction. In: *Proceedings of the ACL 2014 workshop on language technologies and computational social science*, pp 18–22. <https://doi.org/10.3115/v1/W14-2508>
216. von der Weth C, Abdul A, Fan S, Kankanhalli M (2020) Helping users tackle algorithmic threats on social media: a multimedia research agenda. In: *Proceedings of the 28th ACM international conference on multimedia*, pp 4425–4434.
<https://doi.org/10.1145/3394171.3414692>
217. Vosoughi S, Roy D, Aral S (2018) The spread of true and false news online. *Science* 359(6380):1146–1151. <https://doi.org/10.1126/science.aap9559>
218. Vraga EK, Bode L (2017) Using expert sources to correct health misinformation in social media. *Sci Commun* 39(5):621–645. <https://doi.org/10.1177/1075547017731776>
219. Waldman AE (2017) The marketplace of fake news. *Univ Pa J Const Law* 20:845 Wang WY (2017) “Liar, liar pants on fire”: a new benchmark dataset for fake news detection. *arXiv preprint arXiv:1705.00648*
220. Wang L, Wang Y, de Melo G, Weikum G (2019a) Understanding archetypes of fake news via fine-grained classification. *Soc Netw Anal Min* 9(1):1–17.
<https://doi.org/10.1007/s13278-019-0580-z>
221. Wang Y, Han H, Ding Y, Wang X, Liao Q (2019b) Learning contextual features with multi-head self-attention for fake news detection. In: *International conference on cognitive computing*. Springer, Berlin, pp 132–142. https://doi.org/10.1007/978-3-030-23407-2_11
222. Wang Y, McKee M, Torbica A, Stuckler D (2019c) Systematic literature review on the spread of health-related misinformation on social media. *Soc Sci Med* 240:112552.
<https://doi.org/10.1016/j.socscimed.2019.112552>
223. Wang Y, Yang W, Ma F, Xu J, Zhong B, Deng Q, Gao J (2020) Weak supervision for fake news detection via reinforcement learning. In: *Proceedings of the AAAI conference on artificial intelligence*, pp 516–523. <https://doi.org/10.1609/aaai.v34i01.5389>
224. Wardle C (2017) Fake news. It’s complicated. Online: <https://medium.com/1st-draft/fake-news-its-complicated-d0f773766c79>. Accessed 3 Oct 2020 Wardle C (2018) The need for smarter definitions and practical, timely empirical research on information disorder. *Digit J* 6(8):951–963. <https://doi.org/10.1080/21670811.2018.1502047>
225. Wardle C, Derakhshan H (2017) Information disorder: toward an interdisciplinary framework for research and policy making. *Council Eur Rep* 27:1–107

226. Weiss AP, Alwan A, Garcia EP, Garcia J (2020) Surveying fake news: assessing university faculty's fragmented definition of fake news and its impact on teaching critical thinking. *Int J Educ Integr* 16(1):1–30. <https://doi.org/10.1007/s40979-019-0049-x>
227. Wu L, Liu H (2018) Tracing fake-news footprints: characterizing social media messages by how they propagate. In: *Proceedings of the eleventh ACM international conference on web search and data mining*, pp 637–645. <https://doi.org/10.1145/3159652.3159677>
228. Wu L, Rao Y (2020) Adaptive interaction fusion networks for fake news detection. *arXiv preprint arXiv:2004.10009*
229. Wu L, Morstatter F, Carley KM, Liu H (2019) Misinformation in social media: definition, manipulation, and detection. *ACM SIGKDD Explor Newsl* 21(2):80–90. <https://doi.org/10.1145/3373464.3373475>
230. Wu Y, Ngai EW, Wu P, Wu C (2022) Fake news on the internet: a literature review, synthesis and directions for future research. *Intern Res*. <https://doi.org/10.1108/INTR-05-2021-0294>
231. Xu K, Wang F, Wang H, Yang B (2019) Detecting fake news over online social media via domain reputations and content understanding. *Tsinghua Sci Technol* 25(1):20–27. <https://doi.org/10.26599/TST.2018.9010139>
232. Yang F, Penttala SK, Mohseni S, Du M, Yuan H, Linder R, Ragan ED, Ji S, Hu X (2019a) Xfake: explainable fake news detector with visualizations. In: *The world wide web conference*, pp 3600–3604. <https://doi.org/10.1145/3308558.3314119>
233. Yang X, Li Y, Lyu S (2019b) Exposing deep fakes using inconsistent head poses. In: *ICASSP 2019-2019 IEEE international conference on acoustics, speech and signal processing (ICASSP)*, IEEE, pp 8261–8265. <https://doi.org/10.1109/ICASSP.2019.8683164>
234. Yaqub W, Kakhidze O, Brockman ML, Memon N, Patil S (2020) Effects of credibility indicators on social media news sharing intent. In: *Proceedings of the 2020 CHI conference on human factors in computing systems*, pp 1–14. <https://doi.org/10.1145/3313831.3376213>
235. Yavary A, Sajedi H, Abadeh MS (2020) Information verification in social networks based on user feedback and news agencies. *Soc Netw Anal Min* 10(1):1–8. <https://doi.org/10.1007/s13278-019-0616-4>
236. Yazdi KM, Yazdi AM, Khodayi S, Hou J, Zhou W, Saedy S (2020) Improving fake news detection using k-means and support vector machine approaches. *Int J Electron Commun Eng* 14(2):38–42. <https://doi.org/10.5281/zenodo.3669287>
237. Zannettou S, Sirivianos M, Blackburn J, Kourtellis N (2019) The web of false information: rumors, fake news, hoaxes, clickbait, and various other shenanigans. *J Data Inf Qual (JDIQ)* 11(3):1–37. <https://doi.org/10.1145/3309699>
238. Zellers R, Holtzman A, Rashkin H, Bisk Y, Farhadi A, Roesner F, Choi Y (2019) Defending against neural fake news. *arXiv preprint arXiv:1905.12616*
239. Zhang X, Ghorbani AA (2020) An overview of online fake news: characterization, detection, and discussion. *Inf Process Manag* 57(2):102025. <https://doi.org/10.1016/j.ipm.2019.03.004>

240. Zhang J, Dong B, Philip SY (2020) Fakedetector: effective fake news detection with deep difusive neural network. In: 2020 IEEE 36th international conference on data engineering (ICDE), IEEE, pp 1826–1829. <https://doi.org/10.1109/ICDE48307.2020.00180>
241. Zhang Q, Lipani A, Liang S, Yilmaz E (2019a) Reply-aided detection of misinformation via Bayesian deep learning. In: The world wide web conference, pp 2333–2343. <https://doi.org/10.1145/3308558.3313718>
242. Zhang X, Karaman S, Chang SF (2019b) Detecting and simulating artifacts in GAN fake images. In: 2019 IEEE international workshop on information forensics and security (WIFS), IEEE, pp 1–6 <https://doi.org/10.1109/WIFS47025.2019.9035107>
243. Zhou X, Zafarani R (2020) A survey of fake news: fundamental theories, detection methods, and opportunities. *ACM Comput Surv (CSUR)* 53(5):1–40. <https://doi.org/10.1145/3395046>
244. Zubiaga A, Aker A, Bontcheva K, Liakata M, Procter R (2018) Detection and resolution of rumours in social media: a survey. *ACM Comput Surv (CSUR)* 51(2):1–36. <https://doi.org/10.1145/3161603>
245. H. Liu et al., “Uncovering deception in social media,” *Social Network Analysis and Mining*, vol. 4, no. 1, pp. 1–2, 2014.
246. G. Stringhini, M. Egele, C. Kruegel, and G. Vigna, “Poultry markets: on the underground economy of Twitter followers,” in *Online Social Networks*. ACM, 2012, pp. 1–6.
247. G. Stringhini, G. Wang, M. Egele, C. Kruegel, G. Vigna, H. Zheng, and B. Y. Zhao, “Follow the green: growth and dynamics in Twitter follower markets,” in *Internet Measurement Conference (IMC)*. ACM, 2013, pp. 163–176. 15
248. K. Thomas, D. McCoy, C. Grier, A. Kolcz, and V. Paxson, “Trafficking fraudulent accounts: The role of the underground market in Twitter spam and abuse,” in *22nd USENIX Security Symposium*, 2013, pp. 195–210.
249. K. Lee, J. Caverlee, and S. Webb, “Uncovering social spammers: social honeypots + machine learning,” in *33rd Research and Development in Information Retrieval*. ACM, 2010, pp. 435–442.
250. G. Stringhini, C. Kruegel, and G. Vigna, “Detecting spammers on social networks,” in *26th Annual Computer Security Applications Conference (ACSAC)*. ACM, 2010, pp. 1–9.
251. S. Fortunato, “Community detection in graphs,” *Physics Reports*, vol. 486, no. 3, pp. 75–174, 2010.
252. S. Ghosh, B. Viswanath, F. Kooti, N. K. Sharma, G. Korlam, F. Benevenuto, N. Ganguly, and K. P. Gummadi, “Understanding and combating link farming in the Twitter social network,” in *21st World Wide Web*. ACM, 2012, pp. 61–70.
253. C. Yang, R. Harkreader, and G. Gu, “Empirical evaluation and new design for fighting evolving Twitter spammers,” *IEEE Trans. Information Forensics and Security*, vol. 8, no. 8, pp. 1280–1293, 2013.
254. X. Hu, J. Tang, and H. Liu, “Online social spammer detection,” in *28th AAAI Conference on Artificial Intelligence*, 2014.
255. E. Ferrara, O. Varol, C. Davis, F. Menczer, and A. Flammini, “The rise of social bots,” *Communications of the ACM*, vol. 59, no. 7, pp. 96–104, 2016.

256. M. Jiang, P. Cui, A. Beutel, C. Faloutsos, and S. Yang, "Catching synchronized behaviors in large networks: A graph mining approach," *ACM Trans. on Knowledge Discovery from Data*, vol. 10, no. 4, 2016.
257. K. Li and Y. Fu, "Prediction of human activity by discovering temporal sequence patterns," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 36, no. 8, pp. 1644–1657, 2014.
258. Y. Boshmaf, I. Muslukhov, K. Beznosov, and M. Ripeanu, "The socialbot network: when bots socialize for fame and money," in *27th ACSAC*. ACM, 2011, pp. 93–102.
259. Z. Chu, S. Gianvecchio, H. Wang, and S. Jajodia, "Detecting automation of twitter accounts: Are you a human, bot, or cyborg?" *IEEE TDSC*, vol. 9, no. 6, pp. 811–824, 2012.
260. S. Cresci, R. Di Pietro, M. Petrocchi, A. Spognardi, and M. Tesconi, "Fame for sale: Efficient detection of fake Twitter followers," *Decision Support Systems*, vol. 80, pp. 56–71, 2015.
261. UNKNOWN, "A Criticism to Society (as seen by Twitter analytics)," in *1st International Workshop on Big Data Analytics for Security*. IEEE, June 2014, pp. 194–200.
262. H. Gao, Y. Chen, K. Lee, D. Palsetia, and A. N. Choudhary, "Towards online spam filtering in social networks," in *Network and Distributed System Security Symposium*, 2012.
263. S. Lee and J. Kim, "WarningBird: A near real-time detection system for suspicious URLs in Twitter stream," *IEEE Trans. on Dependable and Secure Computing*, vol. 10, no. 3, pp. 183–195, 2013.
264. K. Thomas, C. Grier, J. Ma, V. Paxson, and D. Song, "Design and evaluation of a real-time URL spam filtering service," in *32nd Symposium on Security and Privacy*. IEEE, 2011, pp. 447–462.
265. H. Gao et al., "Spam ain't as diverse as it seems: throttling OSN spam with templates underneath," in *30th ACSAC*. ACM, 2014, pp. 76–85.
266. Y. Liu, B. Wu, B. Wang, and G. Li, "SDHM: A hybrid model for spammer detection in Weibo," in *Advances in Social Networks Analysis and Mining*. IEEE, 2014, pp. 942–947.
267. Z. Yang, C. Wilson, X. Wang, T. Gao, B. Y. Zhao, and Y. Dai, "Uncovering social network sybils in the wild," *Trans. Knowledge Discovery from Data*, vol. 8, no. 1, 2014, special issue TKDD-CASIN.
268. A. Beutel, W. Xu, V. Guruswami, C. Palow, and C. Faloutsos, "CopyCatch: stopping group attacks by spotting lockstep behavior in social networks," in *22nd World Wide Web*, 2013, pp. 119–130.
269. M. Jiang, P. Cui, A. Beutel, C. Faloutsos, and S. Yang, "Inferring lockstep behavior from connectivity pattern in large graphs," *Knowledge and Information Systems*, pp. 1–30, 2015.
270. M. Giatsoglou et al., "ND-Sync: Detecting synchronized fraud activities," in *Advances in Knowledge Discovery and Data Mining*. Springer, 2015, pp. 201–214.
271. Q. Cao, X. Yang, J. Yu, and C. Palow, "Uncovering large groups of active malicious accounts in online social networks," in *ACM SIGSAC Conference on Computer and Communications Security*. ACM, 2014, pp. 477–488.

272. R. Yu, X. He, and Y. Liu, "GLAD: Group anomaly detection in social media analysis," *ACM Transactions on Knowledge Discovery from Data (TKDD)*, vol. 10, no. 2, pp. 1–22, 2015.
273. M. Ou, P. Cui, J. Wang, F. Wang, and W. Zhu, "Probabilistic attributed hashing," in *AAAI Conference on Artificial Intelligence*, 2015, pp. 2894–2900.
274. F. Ahmed and M. Abulaish, "A generic statistical approach for spam detection in online social networks," *Computer Communications*, vol. 36, no. 10, pp. 1120–1129, 2013.
275. Z. Miller, B. Dickinson, W. Deitrick, W. Hu, and A. H. Wang, "Twitter spammer detection using data stream clustering," *Information Sciences*, vol. 260, pp. 64–73, 2014.
276. S. Cresci, R. Di Pietro, M. Petrocchi, A. Spognardi, and M. Tesconi, "DNA-inspired online behavioral modeling and its application to spambot detection," *IEEE Intelligent Systems*, vol. 31, no. 5, pp. 58–64, 2016.
277. K. L. Gwet, *Handbook of inter-rater reliability: The definitive guide to measuring the extent of agreement among raters*. Advanced Analytics, LLC, 2014.
278. J. R. Landis and G. G. Koch, "The measurement of observer agreement for categorical data," *Biometrics*, pp. 159–174, 1977.
279. M. Avvenuti, S. Bellomo, S. Cresci, M. N. La Polla, and M. Tesconi, "Hybrid crowdsensing: A novel paradigm to combine the strengths of opportunistic and participatory crowdsensing," in *26th World Wide Web Conference, Companion Volume*, 2017.
280. R. Zafarani, M. A. Abbasi, and H. Liu, *Social media mining: an introduction*. Cambridge University Press, 2014.
281. B. Sriram et al., "Short text classification in Twitter to improve information filtering," in *Research and Development in Information Retrieval*. ACM, 2010, pp. 841–842.
282. K. Lee, D. Palsetia, R. Narayanan, M. M. A. Patwary, A. Agrawal, and A. Choudhary, "Twitter trending topic classification," in *Data Mining Workshops (ICDMW)*. IEEE, 2011, pp. 251–258.
283. D. Gusfield, *Algorithms on strings, trees and sequences: computer science and computational biology*. Cambridge Univ. Press, 1997.
284. M. Arnold and E. Ohlebusch, "Linear time algorithms for generalizations of the longest common substring problem," *Algorithmica*, vol. 60, no. 4, pp. 806–818, 2011.
285. L. Chi and K. Hui, "Color set size problem with applications to string matching," in *Combinatorial Pattern Matching*. Springer, 1992, pp. 230–243.
286. T. Fawcett, "An introduction to ROC analysis," *Pattern recognition letters*, vol. 27, no. 8, pp. 861–874, 2006.
287. P. Baldi, S. Brunak, Y. Chauvin, and H. Nielsen, "Assessing the accuracy of prediction algorithms for classification: An overview," *Bioinformatics*, vol. 16, no. 5, pp. 412–424, 2000.
288. S. J. Pan and Q. Yang, "A survey on transfer learning," *IEEE Transactions on knowledge and data engineering*, vol. 22, no. 10, pp. 1345–1359, 2010.
289. G. Palshikar et al., "Simple algorithms for peak detection in timeseries," in *Advanced Data Analysis, Business Analytics and Intelligence*, 2009.

290. V. Lampos and N. Cristianini, "Nowcasting events from the social web with statistical learning," *ACM Transactions on Intelligent Systems and Technology (TIST)*, vol. 3, no. 4, p. 72, 2012.
291. Twitter Inc., "Twitter's IPO filing," Oct 2013, <https://goo.gl/pbXxHh> (Last checked 07/12/16).
292. R. Kohavi and F. Provost, "Glossary of terms," *Machine Learning*, vol. 30, no. 2-3, pp. 271–274, 1998.
293. D. M. W. Powers, "Evaluation: from Precision, Recall and F-Measure to ROC, informedness, markedness and correlation," *International Journal of Machine Learning Technologies*, vol. 2, no. 1, pp. 37–63, 2011.
294. Y. Chen, A. Wan, and W. Liu, "A fast parallel algorithm for finding the longest common sequence of multiple biosequences," *BMC bioinformatics*, vol. 7, no. 4, p. 1, 2006.
295. F. Benevenuto, T. Rodrigues, M. Cha, and V. Almeida, "Characterizing user navigation and interactions in online social networks," *Information Sciences*, vol. 195, pp. 1–24, 2012.
296. B. Viswanath, M. A. Bashir, M. Crovella, S. Guha, K. Gummadi, B. Krishnamurthy, and A. Mislove, "Towards detecting anomalous user behavior in online social networks," in *23rd USENIX Security Symposium*, 2014, pp. 223–238.
297. X. Ruan, Z. Wu, H. Wang, and S. Jajodia, "Profiling online social behaviors for compromised account detection," *IEEE Trans. on Information Forensics and Security*, vol. 11, no. 1, pp. 176–187, 2016.
298. L. Cao, "In-depth behavior understanding and use: the behavior informatics approach," *Information Sciences*, vol. 180, no. 17, pp. 3067–3085, 2010. 16
299. D. P. Kroese, T. Brereton, T. Taimre, and Z. I. Botev, "Why the Monte Carlo method is so important today," *Wiley Interdisciplinary Reviews: Computational Statistics*, vol. 6, no. 6, pp. 386–392, 2014.
300. L. Bergroth, H. Hakonen, and T. Raita, "A survey of longest common subsequence algorithms," in *String Processing and Information Retrieval*, 2000. SPIRE 2000. Proceedings. Seventh International Symposium on. IEEE, 2000, pp. 39–48.
301. Cresci et al. - 2018 - Social Fingerprinting Detection of Spambot Groups.pdf
302. Adikari S, Dutta K (2020) Identifying fake profiles in LinkedIn Akyon FC, Esat Kalfaoglu M (2019) Instagram fake and automated account detection. In: *Proceedings—2019 innovations in intelligent systems and applications conference, ASYU 2019*. <https://doi.org/10.1109/ASYU48272.2019.8946437>
303. Alarif A, Alsaleh M, Al-Salman AM (2016) Twitter turing test: identifying social machines. *Inf Sci*. <https://doi.org/10.1016/j.ins.2016.08.036>
304. Albayati MB, Altamimi AM (2019) An empirical study for detecting fake Facebook profiles using supervised mining techniques. *Inf Slovenia*. <https://doi.org/10.31449/inf.v43i1.2319>
305. Albayati M, Altamimi A (2020) MDFFP: a machine learning model for detecting fake Facebook profiles using supervised and unsupervised mining techniques. *Int J Simul Syst Sci Technol*. <https://doi.org/10.5013/ijssst.a.20.01.11>

306. Aldayel A, Magdy W (2022) Characterizing the role of bots' in polarized stance on social media. *Soc Netw Anal Mining*. <https://doi.org/10.1007/s13278-022-00858-z>
307. Alharthi R, Alhothali A, Moria K (2019) Detecting and characterizing Arab spammers campaigns in Twitter. *Proc Comput Sci* 163:248–256. <https://doi.org/10.1016/j.procs.2019.12.106>
308. Alhassun AS, Rassam MA (2022) A combined text-based and metadatabased deep-learning framework for the detection of spam accounts on the social media platform Twitter. *Processes*. <https://doi.org/10.3390/pr10030439>
309. Ali A, Syed A (2022) Cyberbullying detection using machine learning. *Pak J Eng Technol* 3(2):45–50. <https://doi.org/10.51846/vol3iss2pp45-50>
310. Aljabri M, Aljameel SS, Mohammad RMA, Almotiri SH, Mirza S, Anis FM, Aboulmour M, Alomari DM, Alhamed DH, Altamimi HS (2021a) Intelligent techniques for detecting network attacks: review and research directions. In *Sens*. <https://doi.org/10.3390/s21217070>
311. Aljabri M, Chrouf SM, Alzahrani NA, Alghamdi L, Alfahaid R, Alqarawi R, Alhuthayf J, Alduhailan N (2021b) Sentiment analysis of Arabic tweets regarding distance learning in Saudi Arabia during the covid-19 pandemic. *Sensors* 21(16):5431. <https://doi.org/10.3390/s21165431>
312. Aljabri M, Altamimi HS, Albelali SA, Al-Harbi M, Alhuraib HT, Alotaibi NK, Alahmadi AA, Alhaidari F, Mohammad RM, Salah K (2022a) Detecting malicious URLs using machine learning techniques: review and research directions. *IEEE Access* 10:121395– 121417. <https://doi.org/10.1109/access.2022.3222307>
313. Aljabri M, Alhaidari F, Mohammad RM, Mirza S, Alhamed DH, Altamimi HS, Chrouf SM (2022b) An assessment of lexical, network, and content-based features for detecting malicious urls using machine learning and deep learning models. *Comput Intell Neurosci* 2022:1–14. <https://doi.org/10.1155/2022/3241216>
314. Aljabri M, Alahmadi AA, Mohammad RM, Aboulmour M, Alomari DM, Almotiri SH (2022c) Classification of firewall log data using multiclass machine learning models. *Electronics* 11(12):1851. <https://doi.org/10.3390/electronics11121851>
315. Aljabri M, Mirza S (2022) Phishing attacks detection using machine learning and Deep Learning Models. In: 2022 7th international conference on data science and machine learning applications (CDMA). <https://doi.org/10.1109/cdma54072.2022.00034>
316. Alom Z, Carminati B, Ferrari E (2020) A deep learning model for Twitter spam detection. *Online Soc Netw Media*. <https://doi.org/10.1016/j.osnem.2020.100079>
317. Alothali E, Alashwal H, Salih M, Hayawi K (2021a) Real time detection of social bots on Twitter using machine learning and Apache Kafka. In: 2021a 5th cyber security in networking conference, CSNet 2021a. <https://doi.org/10.1109/CSNet 52717.2021.9614282>
318. Alothali E, Hayawi K, Alashwal H (2021b) Hybrid feature selection approach to identify optimal features of profile metadata to detect social bots in Twitter. *Soc Netw Anal Mining*. <https://doi.org/10.1007/s13278-021-00786-4>
319. Alothali E, Zaki N, Mohamed EA, Alashwal H (2019) Detecting social bots on Twitter: a literature review. In: *Proceedings of the 2018 13th international conference on innovations in information technology, IIT 2018*. <https://doi.org/10.1109/INNOV ATIONS.2018.8605995>

320. Al-Qurishi M, Alrubaian M, Rahman SMM, Alamri A, Hassan MM (2018) A prediction system of Sybil attack in social network using deep-regression model. *Future Gener Comput Syst.* <https://doi.org/10.1016/j.future.2017.08.030>
321. Al-Zoubi AM, Alqatawna J, Faris H (2017) Spam profile detection in social networks based on public features. In: 2017 8th international conference on information and communication systems, ICICS 2017. <https://doi.org/10.1109/IACS.2017.7921959>
322. Andriotis P, Takasu A (2019) Emotional bots: content-based spammer detection on social media. In: 10th IEEE international workshop on information forensics and security, WIFS 2018. <https://doi.org/10.1109/WIFS.2018.8630760>
323. Anwar A, Yaqub U (2020) Bot detection in twitter landscape using unsupervised learning. *ACM Int Conf Proc Series.* <https://doi.org/10.1145/3396956.3401801>
324. Attia SM, Mattar AM, Badran KM (2022) Bot detection using multi-input deep neural network model in social media. In: 2022 13th international conference on electrical engineering (ICEENG), p 71–75. <https://doi.org/10.1109/ICEENG49683.2022.9781863>
325. Barhate S, Mangla R, Panjwani D, Gatkhal S, Kazi F (2020) Twitter bot detection and their influence in hashtag manipulation. In: 2020 IEEE 17th India council international conference, INDICON 2020. <https://doi.org/10.1109/INDICON49873.2020.9342152>
326. Bazm, M. and Asadpour, M. (2020) “Behavioral Modeling of Persian Instagram Users to detect Bots.” Available at: <https://doi.org/10.48550/arXiv.2008.03951> Beğenilmiş E, Uskudarli S (2018) Organized behavior classification of tweet sets using supervised learning methods. *ACM Int Conf Proc Series.* <https://doi.org/10.1145/3227609.3227665>
327. Benkler Y et al (2017) Partisanship, propaganda, and disinformation: online media and the 2016 U.S. presidential election, search issue lab. Issue lab. Available at: <https://search.israelab.org/resource/partisanship-propaganda-and-disinformation-online-media-and-the-2016-u-s-presidential-election.html>. Accessed 9 Oct 2022
328. Bhattacharya A, Bathla R, Rana A, Arora G (2021) Application of machine learning techniques in detecting fake profiles on social media. In: 2021 9th international conference on reliability, Infocom technologies and optimization (trends and future directions), ICRITO 2021. <https://doi.org/10.1109/ICRITO51393.2021.9596373>
329. Bindu K et al (2022) Detection of fake accounts in Twitter using data science. *Int Res J Mod Eng Technol Sci* 4(5), pp. 3552-3556.
330. Cable, J. and Hugh, G. (2019) Bots in the Net: Applying Machine Learning to Identify Social Media Trolls. rep. Available at: <http://cs229.stanford.edu/proj2019spr/report/74.pdf>
331. Caers R, de Feyter T, de Couck M, Stough T, Vigna C, du Bois C (2013) Facebook: a literature review. *New Media Soc.* <https://doi.org/10.1177/1461444813488061>
332. Cai C, Li L, Zeng D (2017a) Detecting social bots by jointly modeling deep behavior and content information. *Int Conf Inf Knowl Manag Proc Part F131841.* <https://doi.org/10.1145/3132847.3133050>
333. Cai C, Li L, Zeng D (2017b) Behavior enhanced deep bot detection in social media. In: 2017b IEEE international conference on intelligence and security informatics: security and big data, ISI 2017b. <https://doi.org/10.1109/ISI.2017.8004887>

334. Cao F, Ester M, Qian W, Zhou A (2006) Density-based clustering over an evolving data stream with noise. In: Proceedings of the sixth SIAM international conference on data mining, 2006. <https://doi.org/10.1137/1.9781611972764.29>
335. Carminati B, Ferrari E, Heatherly R, Kantarcioglu M, Thuraisingham B (2011) Semantic web-based social network access control. *Comput Secur* 30(2–3):108–115. <https://doi.org/10.1016/j.cose.2010.08.003>
336. Chen C, Wang Y, Zhang J, Xiang Y, Zhou W, Min G (2017a) Statistical features-based real-time detection of drifted Twitter spam. *IEEE Trans Inf Forensics Secur*. <https://doi.org/10.1109/TIFS.2016.2621888>
337. Chen Z, Tanash RS, Stoll R, Subramanian D (2017b) Hunting malicious bots on twitter: an unsupervised approach. In: Lecture notes in computer science (including subseries lecture notes in artificial intelligence and lecture notes in bioinformatics), 10540 LNCS. https://doi.org/10.1007/978-3-319-67256-4_40
338. Cresci S, di Pietro R, Petrocchi M, Spognardi A, Tesconi M (2015) Fame for sale: efficient detection of fake Twitter followers. *Decis Support Syst*. <https://doi.org/10.1016/j.dss.2015.09.003>
339. Cresci S, di Pietro R, Petrocchi M, Spognardi A, Tesconi M (2016) DNA-inspired online behavioral modeling and its application to spambot detection. *IEEE Intell Syst*. <https://doi.org/10.1109/MIS.2016.29>
340. Cresci S, Spognardi A, Petrocchi M, Tesconi M, di Pietro R (2017) The paradigm-shift of social spambots: evidence, theories, and tools for the arms race. In: 26th international world wide web conference 2017, WWW 2017 companion. <https://doi.org/10.1145/3041021.3055135>
341. Dan J, Jieqi T (2017) Study of bot detection on Sina-Weibo based on machine learning. In: 14th international conference on services systems and services management, ICSSSM 2017—Proceedings. <https://doi.org/10.1109/ICSSSM.2017.7996292>
342. Daouadi KE, Rebaï RZ, Amous I (2019) Bot detection on online social networks using deep forest. *Adv Intell Syst Comput*. https://doi.org/10.1007/978-3-030-19810-7_30
343. David I, Siordia OS, Moctezuma D (2017) Features combination for the detection of malicious Twitter accounts. In: 2016 IEEE international autumn meeting on power, electronics and computing, ROPEC 2016. <https://doi.org/10.1109/ROPEC.2016.7830626>
344. Davis, C. A., Varol, O., Ferrara, E., Flammini, A., & Menczer, F. (2016). BotOrNot. Proceedings of the 25th International Conference Companion on World Wide Web - WWW . <https://doi.org/10.1145/2872518.2889302>
345. Derhab A, Alawwad R, Dehwah K, Tariq N, Khan FA, Al-Muhtadi J (2021) Tweet-based bot detection using big data analytics. *IEEE Access*. <https://doi.org/10.1109/ACCESS.2021.3074953>
346. Dewan P, Kumaraguru P (2017) Facebook Inspector (FbI): towards automatic real-time detection of malicious content on Facebook. *Soc Netw Anal Mining*. <https://doi.org/10.1007/s13278-017-0434-5>
347. Dey A, Reddy H, Dey M, Sinha N (2019) Detection of fake accounts in Instagram using machine learning. *Int J Comput Sci Inf Technol*. <https://doi.org/10.5121/ijcsit.2019.11507>

348. Dinath W (2021) LinkedIn: a link to the knowledge economy. In: Proceedings of the European conference on knowledge management, ECKM.
<https://doi.org/10.34190/EKM.21.178>
349. Echeverría J, de Cristofaro E, Kourtellis N, Leontiadis I, Stringhini G, Zhou S (2018) LOBO. In: Proceedings of the 34th annual computer security applications conference, p 137–146. <https://doi.org/10.1145/3274694.3274738>
350. Ersahin B, Aktas O, Kilinc D, Akyol C (2017) Twitter fake account detection. Int Conf Comput Sci Eng (UBMK) 2017:388–392. <https://doi.org/10.1109/UBMK.2017.8093420>
351. Eshraqi N, Jalali M, Moattar MH (2016) Detecting spam tweets in Twitter using a data stream clustering algorithm. In: 2nd international congress on technology, communication and knowledge, ICTCK 2015. <https://doi.org/10.1109/ICTCK.2015.7582694>
352. Ezarfelix J, Jeffrey N, Sari N (2022) Systematic literature review: Instagram fake account detection based on machine learning. Eng Math Comput Sci J.
<https://doi.org/10.21512/emacsjournal.v4i1.8076>
353. Fazil M, Abulaish M (2018) A hybrid approach for detecting automated spammers in Twitter. IEEE Trans Inf Forensics Secur. <https://doi.org/10.1109/TIFS.2018.2825958>
354. Fernquist J, Kaati L, Schroeder R (2018) Political bots and the Swedish general election. In: 2018 IEEE international conference on intelligence and security informatics, ISI 2018. <https://doi.org/10.1109/ISI.2018.8587347>
355. Ferrara, E. (2018). Measuring Social Spam and the Effect of Bots on Information Difusion in Social Media. Computational Social Sciences, 229-255.
https://doi.org/10.1007/978-3-319-77332-2_13 Ferrara, E. (2020). What types of COVID-19 conspiracies are populated by Twitter bots?. First Monday, 25(6).
<https://doi.org/10.5210/fm.v25i6.10633>
356. Fonseca Abreu JV, Ghedini Ralha C, Costa Gondim JJ (2020) Twitter bot detection with reduced feature set. In: Proceedings—2020 IEEE international conference on intelligence and security informatics, ISI 2020.
<https://doi.org/10.1109/ISI49825.2020.9280525>
357. Gannarapu S, Dawoud A, Ali RS, Alwan A (2020) Bot detection using machine learning algorithms on social media platforms. In: CITI-SIA 2020—IEEE conference on innovative technologies in intelligent systems and industrial applications, proceedings.
<https://doi.org/10.1109/CITISIA50690.2020.9371778>
358. Gao T, Yang J, Peng W, Jiang L, Sun Y, Li F (2020) A content-based method for Sybil detection in online social networks via deep learning. IEEE Access.
<https://doi.org/10.1109/ACCESS.2020.2975877>
359. Gheewala S, Patel R (2018) Machine learning based twitter spam account detection: a review. In: Proceedings of the 2nd international conference on computing methodologies and communication, ICCMC 2018. <https://doi.org/10.1109/ICCMC.2018.8487992>
360. Gilani Z, Wang L, Crowcroft J, Almeida M, Farahbakhsh R (2016) Stweeler: a framework for Twitter bot analysis. In: WWW 2016 companion—proceedings of the 25th international conference on World Wide Web. <https://doi.org/10.1145/2872518.2889360>
361. Gilani Z, Farahbakhsh R, Tyson G, Wang L, Crowcroft J (2017) Of bots and humans (on Twitter). In: Proceedings of the 2017 IEEE/ACM international conference on advances in

- social networks analysis and mining 2017, p 349–354.
<https://doi.org/10.1145/3110025.3110090>
362. Gorwa R, Guilbeault D (2020) Unpacking the social media bot: a typology to guide research and policy. *Policy Internet* 12(2):225–248. <https://doi.org/10.1002/poi3.184>
 363. Güngör KN, Ayhan Erdem O, Doğru İA (2020) Tweet and account based spam detection on Twitter, p 898–905. https://doi.org/10.1007/978-3-030-36178-5_79
 364. Guofei Gu (no date) Welcome to Guofei Gu's Homepage. Available at: <https://people.engr.tamu.edu/guofei/index.html>. Accessed 12 Oct 2022
 365. Gupta A, Kaushal R (2017) Towards detecting fake user accounts in facebook. In: *ISEA Asia security and privacy conference 2017, ISEASP 2017*. <https://doi.org/10.1109/ISEASP.2017.7976996>
 366. Hakimi AN, Ramli S, Wook M, Mohd Zainudin N, Hasbullah NA, Abdul Wahab N, Mat Razali NA (2019) Identifying fake account in facebook using machine learning. In: *Lecture notes in computer science (including subseries lecture notes in artificial intelligence and lecture notes in bioinformatics)*, 11870 LNCS. https://doi.org/10.1007/978-3-030-34032-2_39
 367. Hayawi K, Mathew S, Venugopal N, Masud MM, Ho PH (2022) DeeProBot: a hybrid deep neural network model for social bot detection based on user profile data. *Soc Netw Anal Mining*. <https://doi.org/10.1007/s13278-022-00869-w>
 368. Heidari M, Jones JH, Uzuner O (2020) Deep contextualized word embedding for text-based online user profiling to detect social bots on Twitter. In: *IEEE international conference on data mining workshops, ICDMW, 2020-November*. <https://doi.org/10.1109/ICDMW51313.2020.00071>
 369. Heidari M, Jones JH, Uzuner O (2021) An empirical study of machine learning algorithms for social media bot detection. In: *2021 IEEE international IOT, electronics and mechatronics conference, IEMTRONICS 2021—Proceedings*. <https://doi.org/10.1109/IEMTRONICS52119.2021.9422605>
 370. Huang, Y., Zhang, M., Yang, Y., Gan, S., & Zhang, Y. (2016) The Weibo Spammers' Identification and Detection based on Bayesian-algorithm. *Proceedings of the 2016 2nd Workshop on Advanced Research and Technology in Industry Applications*. <https://doi.org/10.2991/wartia-16.2016.271>
 371. Inuwa-Dutse I, Liptrott M, Korkontzelos I (2018) Detection of spamposting accounts on Twitter. *Neurocomputing*. <https://doi.org/10.1016/j.neucom.2018.07.044>
 372. Kantartopoulos P, Pitropakis N, Mylonas A, Kylilis N (2020) Exploring adversarial attacks and defences for fake Twitter account detection. *Technologies*. <https://doi.org/10.3390/technologies8040064>
 373. Kantepe M, Gañiz MC (2017) Preprocessing framework for Twitter bot detection. In: *2nd international conference on computer science and engineering, UBMK 2017*. <https://doi.org/10.1109/UBMK.2017.8093483>
 374. Kaplan AM, Haenlein M (2010) Users of the world, unite! The challenges and opportunities of social media. *Bus Horiz*. <https://doi.org/10.1016/j.bushor.2009.09.003>
 375. Kenyeres A, Kovács G (2022) "Conference: XVIII. Conference on hungarian computational linguistics." Available at:

https://www.researchgate.net/publication/358801180_Twitter_bot_detection_using_deep_learning

376. Kesharwani M, Kumari S, Niranjana V (2021) "Detecting fake social media account using deep neural networking. *Int Res J Eng Technol (IRJET)*, 8(7), pp. 1191-1197.
377. Khaled S, El-Tazi N, Mokhtar HMO (2019) Detecting fake accounts on social media. In: *Proceedings—2018 IEEE international conference on big data, big data 2018*. <https://doi.org/10.1109/BigData.2018.8621913>
378. Khalil H, Khan MUS, Ali M (2020) Feature selection for unsuper-vised bot detection. In: *2020 3rd international conference on computing, mathematics and engineering technologies: idea to innovation for building the knowledge economy, ICoMET 2020*. <https://doi.org/10.1109/iCoMET48670.2020.9074131>
379. Knauth J (2019) Language-agnostic twitter bot detection. In: *International conference recent advances in natural language processing, RANLP, 2019-September*. https://doi.org/10.26615/978-954-452-056-4_065
380. Koggalahewa D, Xu Y, Foo E (2022) An unsupervised method for social network spammer detection based on user information interests. *J Big Data*. <https://doi.org/10.1186/s40537-021-00552-5>
381. Kolomeets M, Chechulin A (2021) Analysis of the malicious bots market. In: *Conference of open innovation association, FRUCT, 2021-May*. <https://doi.org/10.23919/FRUCT52173.2021.9435421>
382. Kondeti P, Yerramreddy LP, Pradhan A, Swain G (2021) Fake account detection using machine learning, p 791–802. https://doi.org/10.1007/978-981-15-5258-8_73
383. Kudugunta S, Ferrara E (2018) Deep neural networks for bot detection. *Inf Sci*. <https://doi.org/10.1016/j.ins.2018.08.019>
384. Kumar G, Rishiwal V (2020) Machine learning for prediction of malicious or SPAM users on social networks. *Int J Sci Technol Res*, 9(2), pp. 926-932
385. Lee K, Eof BD, Caverlee J (2011) Seven months with the devils: a long-term study of content polluters on Twitter. *Icwsn 2011*
386. Mahesh, B. (2020) "Machine Learning Algorithms - A Review," *International Journal of Science and Research (IJSR)*, 9(1), pp. 381–386. Available at: <https://doi.org/10.21275/ART20203995>.
387. Martin-Gutierrez D, Hernandez-Penaloza G, Hernandez AB, Lozano-Diez A, Alvarez F (2021) A deep learning approach for robust detection of bots in Twitter using transformers. *IEEE Access*. <https://doi.org/10.1109/ACCESS.2021.3068659>
388. Mateen M, Iqbal MA, Aleem M, Islam MA (2017) A hybrid approach for spam detection for Twitter. In: *Proceedings of 2017 14th international bhurban conference on applied sciences and technology, IBCAST 2017*. <https://doi.org/10.1109/IBCAST.2017.7868095>
389. Mazza M, Cresci S, Avvenuti M, Quattrocioni W, Tesconi M (2019) RTbust: exploiting temporal patterns for botnet detection on twitter. In: *WebSci 2019—proceedings of the 11th ACM conference on web science*. <https://doi.org/10.1145/3292522.3326015>

390. Meshram EP, Bhambulkar R, Pokale P, Kharbikar K, Awachat A (2021) Automatic detection of fake profile using machine learning on Instagram. *Int J Sci Res Sci Technol*. <https://doi.org/10.32628/ijrst218330>
391. Morstatter F, Wu L, Nazer TH, Carley KM, Liu H (2016) A new approach to bot detection: striking the balance between precision and recall. In: 2016 IEEE/ACM international conference on advances in social networks analysis and mining (ASONAM), p 533–540. <https://doi.org/10.1109/ASONAM.2016.7752287>
392. Munoz SD, Paul Guillen Pinto E (2020) A dataset for the detection of fake profiles on social networking services. In: *Proceedings—2020 international conference on computational science and computational intelligence, CSCI 2020*. <https://doi.org/10.1109/CSCI51800.2020.00046>
393. Najari S, Salehi M, Farahbakhsh R (2022) GANBOT: a GAN-based framework for social bot detection. *Soc Netw Anal Mining*. <https://doi.org/10.1007/s13278-021-00800-9>
394. Narayan N (2021) Twitter bot detection using machine learning algorithms. In: 2021 4th international conference on electrical, computer and communication technologies, ICECCT 2021. <https://doi.org/10.1109/ICECCT52121.2021.9616841>
395. Naveen Babu M, Anusha G, Shivani A, Kalyani C, Meenakumari J (2021) Fake profile identification using machine learning. *Int J Recent Adv Multidiscip Topics* 2(6):273–275
396. Oentaryo RJ, Murdopo A, Prasetyo PK, Lim EP (2016) On profiling bots in social media. In: *Lecture notes in computer science (including subseries lecture notes in artificial intelligence and lecture notes in bioinformatics)*, p 10046 LNCS. https://doi.org/10.1007/978-3-319-47880-7_6
397. Orabi M, Mouheb D, al Aghbari Z, Kamel I (2020) Detection of bots in social media: a systematic review. *Inf Process Manag*. <https://doi.org/10.1016/j.ipm.2020.102250>
398. Pierri F, Artoni A, Ceri S (2020) Investigating Italian disinformation spreading on Twitter in the context of 2019 European elections. *PLoS ONE*. <https://doi.org/10.1371/journal.pone.0227821>
399. Ping H, Qin S (2019) A social bots detection model based on deep learning algorithm. In: *Int Conf Commun Technol Proc, ICCT, 2019-October*. <https://doi.org/10.1109/ICCT.2018.8600029>
400. Prabhu Kavin B, Karki S, Hemalatha S, Singh D, Vijayalakshmi R, Thangamani M, Haleem SLA, Jose D, Tirth V, Kshirsagar PR, Adigo AG (2022) Machine learning-based secure data acquisition for fake accounts detection in future mobile communication networks. *Wirel Commun Mob Comput*. <https://doi.org/10.1155/2022/6356152>
401. Pramitha FN, Hadiprakoso RB, Qomariasih N, Girinoto (2021) Twitter bot account detection using supervised machine learning. In: 2021 4th international seminar on research of information technology and intelligent systems, ISRITI 2021. <https://doi.org/10.1109/ISRITI54043.2021.9702789>
402. Pratama PG, Rakhmawati NA (2019) Social bot detection on 2019 Indonesia president candidate's supporter's tweets. *Proc Comput Sci*. <https://doi.org/10.1016/j.procs.2019.11.187>

403. Purba KR, Asirvatham D, Murugesan RK (2020) Classification of instagram fake users using supervised machine learning algorithms. *Int J Electr Comput Eng*. <https://doi.org/10.11591/ijece.v10i3.pp2763-2772>
404. Rahman MA, Zaman N, Asyhari AT, Sadat SMN, Pillai P, Arshah RA (2021) SPY-BOT: machine learning-enabled post filtering for social network-integrated industrial internet of things. *Ad Hoc Netw*. <https://doi.org/10.1016/j.adhoc.2021.102588>
405. Ramalingaiah A, Hussaini S, Chaudhari S (2021) Twitter bot detection using supervised machine learning. *J Phys Conf Series* 1950(1):012006. <https://doi.org/10.1088/1742-6596/1950/1/012006>
406. Rangel F, Rosso P (2019) Overview of the 7th author profiling task at Pan 2019: Bots and gender profiling in twitter. In: *CEUR workshop proceedings*, p 2380
407. Rao S, Verma AK, Bhatia T (2021) A review on social spam detection: challenges, open issues, and future directions. *Exp Syst Appl*. <https://doi.org/10.1016/j.eswa.2021.115742>
408. Rathore S, Loia V, Park JH (2018) SpamSpotter: an efficient spam-mer detection framework based on intelligent decision support system on Facebook. *Appl Soft Comput J*. <https://doi.org/10.1016/j.asoc.2017.09.032>
409. Reddy PM, Venkatesh K, Bhargav D, Sandhya M (2021) Spam detection and fake user identification methodologies in social networks using extreme machine learning. *SSRN Electron J*. <https://doi.org/10.2139/ssrn.3920091>
410. Ren H, Zhang Z, Xia C (2018) Online social spammer detection based on semi-supervised learning. *ACM Int Conf Proc Series*. <https://doi.org/10.1145/3302425.3302429>
411. Rodrigues AP, Fernandes R, Shetty A, Lakshmana K, Shaf RM (2022) Real-time Twitter spam detection and sentiment analysis using machine learning and deep learning techniques. *Comput Intell Neurosci* 2022:1–14. <https://doi.org/10.1155/2022/5211949>
412. Rodríguez-Ruiz J, Mata-Sánchez JI, Monroy R, Loyola-González O, López-Cuevas A (2020) A one-class classification approach for bot detection on Twitter. *Comput Secur*. <https://doi.org/10.1016/j.cose.2020.101715>
413. Sadineni PK (2020) Machine learning classifiers for efficient spam-mers detection in Twitter OSN. *SSRN Electron J*. <https://doi.org/10.2139/ssrn.3734170>
414. Sahoo SR, Gupta BB (2020) Popularity-based detection of malicious content in facebook using machine learning approach. *Adv Intell Syst Comput*. https://doi.org/10.1007/978-981-15-0029-9_13
415. Santia GC, Mujib MI, Williams JR (2019) Detecting social bots on facebook in an information veracity context. In: *Proceedings of the 13th international conference on web and social media, ICWSM 2019*
416. Saranya Shree S, Subhiksha C, Subhashini R (2021) Prediction of fake Instagram profiles using machine learning. *SSRN Electron J*. <https://doi.org/10.2139/ssrn.3802584>
417. Sayyadiharikandeh M, Varol O, Yang KC, Flammini A, Menczer F (2020) Detection of novel social bots by ensembles of specialized classifiers. *Int Conf Inf Knowl Manag Proc*. <https://doi.org/10.1145/3340531.3412698>
418. Sedhai S, Sun A (2015) Hspam14: a collection of 14 million tweets for hashtag-oriented spam research. In: *SIGIR 2015—proceedings of the 38th international ACM SIGIR*

- conference on research and development in information retrieval. <https://doi.org/10.1145/2766462.2767701>
419. Sedhai S, Sun A (2018) Semi-supervised spam detection in Twitter stream. *IEEE Trans Comput Soc Syst* 5(1):169–175. <https://doi.org/10.1109/tcss.2017.2773581>
 420. Sen I, Singh S, Aggarwal A, Kumaraguru P, Mian S, Datta A (2018) Worth its weight in likes: towards detecting fake likes on instagram. In: *WebSci 2018—proceedings of the 10th ACM conference on web science*. <https://doi.org/10.1145/3201064.3201105>
 421. Sengar SS, Kumar S, Raina P (2020) Bot detection in social networks based on multilayered deep learning approach. *Sens Transducers* 244(5):37–43
 422. Shao C, Ciampaglia GL, Varol O, Yang K, Flammini A, Menczer F (2017) The spread of low-credibility content by social bots. *Nat Commun*. <https://doi.org/10.1038/s41467-018-06930-7>
 423. Shearer E, Mitchell A (2022) News use across social media platforms in 2020, Pew Research Center's Journalism Project. Available at: <https://www.journalism.org/2021/01/12/newsuseacrosssocialmediaplatformsin2020>. Accessed 9 Oct 2022
 424. Sheeba JI, Pradeep Devaneyan S (2019) Detection of spambot using random forest algorithm. *SSRN Electron J*. <https://doi.org/10.2139/ssrn.3462968>
 425. Sheehan BT (2018) Customer service chatbots: anthropomorphism adoption and word of mouth. Griffith University, University of Queensland, Queensland
 426. Sheikhi S (2020) An efficient method for detection of fake accounts on the instagram platform. *Revue Intell Artif*. <https://doi.org/10.18280/ria.340407>
 427. Shevtsov A, Tzagkarakis C, Antonakaki D, Ioannidis S (2022) Explainable machine learning pipeline for Twitter bot detection during the 2020 US Presidential Elections. *Softw Impacts* 13:100333. <https://doi.org/10.1016/j.simpa.2022.100333>
 428. Shukla R, Sinha A, Chaudhary A (2022) TweezBot: an AI-driven online media bot identification algorithm for Twitter social networks. *Electron (switzerland)*. <https://doi.org/10.3390/electronic s11050743>
 429. Shukla H, Jagtap N, Patil B (2021) Enhanced Twitter bot detection using ensemble machine learning. In: *Proceedings of the 6th international conference on inventive computation technologies, ICICT 2021*. <https://doi.org/10.1109/ICICT50816.2021.9358734>
 430. Siddiqui A (2019) Facebook 2019 Q1 earnings: The social media giant boasts 2.7 billion monthly active users on its all services, Digital Information World. Available at: <https://www.digitalinformationworld.com/2019/04/facebook-q1-2019-report.html>. Accessed 9 Oct 2022
 431. Singh Y, Banerjee S (2019) Fake (sybil) account detection using machine learning. *SSRN Electron J*. <https://doi.org/10.2139/ssrn.3462933>
 432. Sohrabi MK, Karimi F (2018) A feature selection approach to detect spam in the Facebook social network. *Arab J Sci Eng*. <https://doi.org/10.1007/s13369-017-2855-x>
 433. Subrahmanian VS, Azaria A, Durst S, Kagan V, Galstyan A, Lerman K, Zhu L, Ferrara E, Flammini A, Menczer F (2016) The DARPA Twitter bot challenge. *Computer* 49(6):38–46. <https://doi.org/10.1109/MC.2016.183>

434. Tenba Group (2022) What is Sina Weibo? Know your Chinese social media!, Tenba Group. Available at: <https://tenbagroup.com/whatissinaweiboknowyourchinesesocialmedia>. Accessed 9 Oct 2022
435. Thakur S, Breslin JG (2021) Rumour prevention in social networks with layer 2 blockchains. *Soc Netw Anal Mining*. <https://doi.org/10.1007/s13278-021-00819-y>
436. Thejas GS, Soni J, Chandna K, Iyengar SS, Sunitha NR, Prabakar N (2019) Learning-based model to fight against fake like clicks on Instagram posts. In: *Conference proceedings—IEEE SOUTH-EASTCON*, 2019-April. <https://doi.org/10.1109/SoutheastCon42311.2019.9020533>
437. Thuraisingham B (2020) The role of artificial intelligence and cyber security for social media. In: *Proceedings—2020 IEEE 34th international parallel and distributed processing symposium workshops, IPDPSW 2020*. <https://doi.org/10.1109/IPDPSW50202.2020.00184>
438. van der Walt E, Eloff J (2018) Using machine learning to detect fake identities: bots vs humans. *IEEE Access*. <https://doi.org/10.1109/ACCESS.2018.2796018>
439. Varol O, Ferrara E, Davis CA, Menczer F, Flammini A (2017) Online human-bot interactions: detection, estimation, and characterization. In: *Proceedings of the 11th international conference on web and social media, ICWSM 2017*
440. Wald R, Khoshgoftaar TM, Napolitano A, Sumner C (2013) Predicting susceptibility to social bots on Twitter. In: *Proceedings of the 2013 IEEE 14th international conference on information reuse and integration, IEEE IRI 2013*. <https://doi.org/10.1109/IRI.2013.6642447>
441. Wanda P, Hiswati ME, Jie HJ (2020) DeepOSN: bringing deep learning as malicious detection scheme in online social network. *IAES Int J Artif Intell*. <https://doi.org/10.11591/ijai.v9.i1.pp146-154>
442. Wiederhold G, McCarthy J (1992) Arthur Samuel: Pioneer in machine learning. *IBM J Res Dev* 36(3):329–331. <https://doi.org/10.1147/rd.363.0329>
443. Wu B, Liu L, Yang Y, Zheng K, Wang X (2020) Using improved conditional generative adversarial networks to detect social bots on Twitter. *IEEE Access*. <https://doi.org/10.1109/ACCESS.2020.2975630>
444. Wu Y, Fang Y, Shang S, Jin J, Wei L, Wang H (2021) A novel framework for detecting social bots with deep neural networks and active learning. *Knowl Based Syst*. <https://doi.org/10.1016/j.knosys.2020.106525>
445. Xiao C, Freeman DM, Hwa T (2015). Detecting clusters of fake accounts in online social networks. In: *AISeC 2015—proceedings of the 8th ACM workshop on artificial intelligence and security, co-located with CCS 2015*. <https://doi.org/10.1145/2808769.2808779>
446. Xu G, Zhou D, Liu J (2021) Social network spam detection based on ALBERT and combination of Bi-LSTM with self-attention. *Secur Commun Netw*. <https://doi.org/10.1155/2021/5567991>
447. Yang C, Harkreader R, Gu G (2013) Empirical evaluation and new design for fighting evolving twitter spammers. *IEEE Trans Inf Forensics Secur*. <https://doi.org/10.1109/TIFS.2013.2267732>

448. Yang Z, Chen X, Wang H, Wang W, Miao Z, Jiang T (2022) A new joint approach with temporal and profile information for social bot detection. *Secur Commun Netw* 2022:1–14. <https://doi.org/10.1155/2022/9119388>
449. Yang C, Harkreader R, Zhang J, Shin S, Gu G (2012) Analyzing spammers' social networks for fun and profit: A case study of cyber criminal ecosystem on Twitter. In: WWW'12—proceedings of the 21st annual conference on World Wide Web. <https://doi.org/10.1145/2187836.2187847>
450. Zeng Z, Li T, Sun S, Sun J, Yin J (2021) A novel semi-supervised self-training method based on resampling for Twitter fake account identification. *Data Technol Appl* 56(3):409–428. <https://doi.org/10.1108/dta-07-2021-0196>
451. Zhang W, Sun HM (2017) Instagram spam detection. In: Proceedings of IEEE Pacific Rim international symposium on dependable computing, PRDC. <https://doi.org/10.1109/PRDC.2017.43>
452. Zhang Z, Gupta BB (2018) Social media security and trustworthiness: overview and new direction. *Future Gener Comput Syst*. <https://doi.org/10.1016/j.future.2016.10.007>
453. Zheng X, Zhang X, Yu Y, Kechadi T, Rong C (2016b) ELMbased spammer detection in social networks. *J Supercomput* 72(8):2991–3005. <https://doi.org/10.1007/s11227-015-1437-5>
454. Zheng X, Wang J, Jie F, Li L (2016a) Two phase based spammer detection in Weibo. In: Proceedings—15th IEEE international conference on data mining workshop, ICDMW 2015. <https://doi.org/10.1109/ICDMW.2015.22>
455. Twitter, October 2017. - Online - . Available: <https://investor.twitterinc.com/results.cfm>
456. C. Smith. (2017, November) 400 amazing twitter statistics and facts. - Online - . Available: <https://expandedramblings.com/index.php/>
457. E. Ferrara, O. Varol, C. Davis, F. Menczer, and A. Flammini, "The rise of social bots," *Communications of the ACM*, vol. 59, no. 7, pp. 96-104, 2016.
458. O. Varol, E. Ferrara, C. A. Davis, F. Menczer, and A. Flammini, "Online human-bot interactions: Detection, estimation, and characterization," *arXiv preprint arXiv:1703.03107*, 2017.
459. N. Abokhodair, D. Yoo, and D. W. McDonald, "Dissecting a social botnet: Growth, content and influence in twitter," in *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing*. ACM, 2015, pp. 839-851.
460. V. Subrahmanian, A. Azaria, S. Durst, V. Kagan, A. Galstyan, K. Lerman, L. Zhu, E. Ferrara, A.
461. Flammini, and F. Menczer, "The darpa twitter bot challenge," *Computer*, vol. 49, no. 6, pp. 38- 46, 2016.
462. C. Grier, K. Thomas, V. Paxson, and M. Zhang, "@ spam: the underground on 140 characters or less," in *Proceedings of the 17th ACM conference on Computer and communications security*. ACM, 2010, pp. 27-37.

463. G. Stringhini, C. Kruegel, and G. Vigna, "Detecting spammers on social networks," in Proceedings of the 26th annual computer security applications conference. ACM, 2010, pp. 1-9.
464. A. H. Wang, "Detecting spam bots in online social networking sites: A machine learning approach." DBSec, vol. 10, pp. 335-342, 2010.
465. X. Zhang, S. Zhu, and W. Liang, "Detecting spam and promoting campaigns in the Twitter social network," in Data Mining (ICDM), 2012 IEEE 12th International Conference on. IEEE, 2012, pp. 1194-1199.
466. S. Rathore, P. K. Sharma, V. Loia, Y.-S. Jeong, and J. H. Park, "Social network security: Issues, challenges, threats, and solutions," Information Sciences, vol. 421, pp. 43-69, 2017.
467. M. Shafahi, L. Kempers, and H. Afsarmanesh, "Phishing through social bots on Twitter," in Big Data (Big Data), 2016 IEEE International Conference on. IEEE, 2016, pp. 3703-3712.
468. J. Zhang, R. Zhang, Y. Zhang, and G. Yan, "The rise of social botnets: Attacks and countermeasures," IEEE Transactions on Dependable and Secure Computing, 2016.
469. Y. Boshmaf, I. Muslukhov, K. Beznosov, and M. Ripeanu, "The socialbot network: when bots socialize for fame and money," in Proceedings of the 27th annual computer security applications conference. ACM, 2011, pp. 93-102.
470. A. Gupta, H. Lamba, and P. Kumaraguru, "\$1.00 per rt# bostonmarathon# prayforboston: Analyzing fake content on twitter," eCrime Researchers Summit (eCRS). IEEE, 2013, pp. 1-12.
471. Y. Boshmaf, I. Muslukhov, K. Beznosov, and M. Ripeanu, "Design and analysis of a social botnet," Computer Networks, vol. 57, no. 2, pp. 556-578, 2013.
472. S. Cresci, R. Di Pietro, M. Petrocchi, A. Spognardi, and M. Tesconi, "Fame for sale: efficient detection of fake twitter followers," Decision Support Systems, vol. 80, pp. 56-71, 2015.
473. F. Amato, A. Castiglione, A. De Santo, V. Moscato, A. Picariello, F. Persia, and G. Sperl , "Recognizing human behaviours in online social networks," Computers & Security, 2017.
474. S. Sivanesh, K. Kavin, and A. A. Hassan, "Frustrate twitter from automation: How far a user can be trusted?" in Human-Computer Interactions (ICHCI), 2013 International Conference on. IEEE, 2013, pp. 1-5.
475. G. Laboreiro, L. Sarmiento, and E. Oliveira, "Identifying automatic posting systems in microblogs," Progress in Artificial Intelligence, pp. 634-648, 2011.
476. C. M. Zhang and V. Paxson, Detecting and Analyzing Automated Activity on Twitter. Berlin, Heidelberg: Springer Berlin Heidelberg, 2011, pp. 102-111. - Online - . Available: https://doi.org/10.1007/978-3-642-19260-9_11
477. N. Chavoshi, H. Hamooni, and A. Mueen, "Temporal patterns in bot activities," in Proceedings of the 26th International Conference on World Wide Web Companion. International World Wide Web Conferences Steering Committee, 2017, pp. 1601-1606.
478. Q. Fu, B. Feng, D. Guo, and Q. Li, "Combating the evolving spammers in online social networks," Computers & Security, vol. 72, pp. 60-73, 2018.

479. S. Lee and J. Kim, "Early filtering of ephemeral malicious accounts on twitter," *Computer Communications*, vol. 54, pp. 48-57, 2014.
480. C. Freitas, F. Benevenuto, S. Ghosh, and A. Veloso, "Reverse engineering socialbot infiltration strategies in twitter," in *Proceedings of the 2015 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2015*. ACM, 2015, pp. 25-32.
481. C. A. Davis, O. Varol, E. Ferrara, A. Flammini, and F. Menczer, "Botornot: A system to evaluate social bots," in *Proceedings of the 25th International Conference Companion on World Wide Web*. International World Wide Web Conferences Steering Committee, 2016, pp. 273-274.
482. A. Alarifi, M. Alsaleh, and A. Al-Salman, "Twitter turing test: Identifying social machines," *Information Sciences*, vol. 372, pp. 332-346, 2016.
483. M. Kantepe and M. C. Ganiz, "Preprocessing framework for twitter bot detection," in *Computer Science and Engineering (UBMK), 2017 International Conference on*. IEEE, 2017, pp. 630-634.
484. B. Erşahin, Ö. Aktaş, D. Kılınç, and C. Akyol, "Twitter fake account detection," in *Computer Science and Engineering (UBMK), 2017 International Conference on*. IEEE, 2017, pp. 388-392.
485. A. Mehrotra, M. Sarreddy, and S. Singh, "Detection of fake twitter followers using graph centrality measures," in *Contemporary Computing and Informatics (IC3I), 2016 2nd International Conference on*. IEEE, 2016, pp. 499-504.
486. J. Jia, B. Wang, and N. Z. Gong, "Random walk based fake account detection in online social networks," in *Dependable Systems and Networks (DSN), 2017 47th Annual IEEE/IFIP International Conference on*. IEEE, 2017, pp. 273-284.
487. J. Zhang, R. Zhang, J. Sun, Y. Zhang, and C. Zhang, "Truetop: A sybilresilient system for user influence measurement on twitter," *IEEE/ACM Transactions on Networking*, vol. 24, no. 5, pp. 2834-2846, 2016.
488. Z. Gilani, E. Kochmar, and J. Crowcroft, "Classification of twitter accounts into automated agents and human users."
489. Z. Gilani, L. Wang, J. Crowcroft, M. Almeida, and R. Farahbakhsh, "Stweeler: A framework for twitter bot analysis," in *Proceedings of the 25th International Conference Companion on World Wide Web*. International World Wide Web Conferences Steering Committee, 2016, pp. 37-38.
490. C. Cai, L. Li, and D. Zengi, "Behavior enhanced deep bot detection in social media," in *Intelligence and Security Informatics (ISI), 2017 IEEE International Conference on*. IEEE, 2017, pp. 128-130.
491. N. Chavoshi, H. Hamooni, and A. Mueen, "Debot: Twitter bot detection via warped correlation." in *ICDM*, 2016, pp. 817-822.
492. Z. Chu, S. Gianvecchio, H. Wang, and S. Jajodia, "Detecting automation of twitter accounts: Are you a human, bot, or cyborg?" *IEEE Transactions on Dependable and Secure Computing*, vol. 9, no. 6, pp. 811-824, 2012.

493. K. S. Adewole, N. B. Anuar, A. Kamsin, K. D. Varathan, and S. A. Razak, "Malicious accounts: dark of the social networks," *Journal of Network and Computer Applications*, vol. 79, pp. 41-67, 2017.
494. N. Chavoshi, H. Hamooni, and A. Mueen, "Identifying correlated bots in twitter," in *International Conference on Social Informatics*. Springer, 2016, pp. 14-21.
495. Z. Chu, S. Gianvecchio, H. Wang, and S. Jajodia, "Who is tweeting on twitter: human, bot, or cyborg?" in *Proceedings of the 26th annual computer security applications conference*. ACM, 2010, pp. 21-30.
496. F. Ahmed and M. Abulaish, "A generic statistical approach for spam detection in online social networks," *Computer Communications*, vol. 36, no. 10, pp. 1120-1129, 2013.
497. M. Chakraborty, S. Pal, R. Pramanik, and C. R. Chowdary, "Recent developments in social spam detection and combating techniques: A survey," *Information Processing & Management*, vol. 52, no. 6, pp. 1053-1073, 2016.
498. Kwak, H., Lee, C., Park, H., & Moon, S. "What is Twitter, a social network or a news media?". In *Proceedings of the 19th international conference on World wide web* (pp. 591-600). ACM. 2010.
499. Lee, K., Eoff, B. D., & Caverlee, J. ." Seven Months with the Devils: A Long-Term Study of Content Polluters on Twitter". In *ICWSM.2011*
500. Morstatter, F., Wu, L., Nazer, T. H., Carley, K. M., & Liu, H. " A new approach to bot detection: Striking the balance between precision and recall". In *Advances in Social Networks Analysis and Mining (ASONAM), 2016 IEEE/ACM International Conference on* (pp. 533-540). IEEE. 2016
501. Abel, F., Gao, Q., Houben, G.-J., & Tao, K. (2011a). Semantic enrichment of twitter posts for user profile construction on the social web. In *Extended semantic web conference* (pp. 375–389). Springer.
502. Abel, F., Gao, Q., Houben, G.-J., & Tao, K. (2011b). Semantic enrichment of twitter posts for user profile construction on the social web. In G. Antoniou, M. Grobelnik, E. Simperl, B. Parsia, D. Plexousakis, P. De Leenheer, & J. Pan (Eds.), *The semantic web: Research and applications: 8th extended semantic web conference, ESWC 2011, Heraklion, Crete, Greece, May 29 – June 2, 2011, Proceedings, Part II* (pp. 375–389). Berlin, Heidelberg: Springer Berlin Heidelberg.
503. Abner, L. (2018). Google+ is shutting down for consumers after privacy bug. <https://9to5google.com/2018/10/08/google-plus-shutting-down/>. Accessed: 2018-10-27.
504. Adedoyin-Olowe, M., Gaber, M. M., Dancausa, C. M., Stahl, F., & Gomes, J. B. (2016). A rule dynamics approach to event detection in twitter with its application to sports and politics. *Expert Systems with Applications*, 55, 351–360.
505. Aggarwal, A., Rajadesingan, A., & Kumaraguru, P. (2012). PhishAri: Automatic realtime phishing detection on twitter. In *2012 ECrime researchers summit* (pp. 1–12). IEEE, URL: <http://ieeexplore.ieee.org/document/6489521/>.
506. Ahmed, W. (2020). Using Twitter as a data source: an overview of social media research tools (2019). <https://bit.ly/3f21WDz>. Accessed: 2020-7-5.

507. Ajao, O., Bhowmik, D., & Zargari, S. (2018). Fake news identification on twitter with hybrid cnn and rnn models. In *Proceedings of the 9th international conference on social media and society* (pp. 226–230). ACM.
508. Alexa Internet, Inc. (2018). Alexa top 500 global sites. <http://www.alexa.com/topsites>. Accessed: 2018-10-28.
509. Almaatouq, A., Alabdulkareem, A., Nouh, M., Shmueli, E., Alsaleh, M., Singh, V. K., Alarifi, A., Alfaris, A., & Pentland, A. S. (2014). Twitter: who gets caught? observed trends in social micro-blogging spam. In *Proceedings of the 2014 ACM conference on web science* (pp. 33–41). ACM.
510. Alperin, J. P., Hanson, E. W., Shores, K., & Haustein, S. (2017). Twitter bot surveys: A discrete choice experiment to increase response rates. In *#SMSociety17, Proceedings of the 8th international conference on social media & society* (pp. 27:1–27:4). New York, NY, USA: ACM.
511. Alsaleh, M., Alarifi, A., Al-Salman, A. M., Alfayez, M., & Almuahysin, A. (2014). Tsd: Detecting sybil accounts in twitter. In *Machine learning and applications (ICMLA), 2014 13th international conference on* (pp. 463–469). IEEE.
512. Amleshwaram, A. A., Reddy, A. L. N., Yadav, S., Gu, G., & Yang, C. (2013). CATS: Characterizing automation of Twitter spammers. In *COMSNETS* (pp. 1–10). IEEE.
513. Amnesty International (2018). Troll patrol findings, using crowdsourcing, data science & machine learning to measure violence and abuse against women on twitter. <https://bit.ly/2QAQZk9>. URL: <https://decoders.amnesty.org/projects/troll-patrol/findings> - Online; Accessed 2018-12-30 - .
514. André, P., Bernstein, M., & Luther, K. (2012). Who gives a tweet?: Evaluating microblog content value. In *CSCW '12, CSCW '12*. New York, NY, USA: ACM.
515. Anta, A. F., Chiroque, L. N., Morere, P., & Santos, A. (2013). Sentiment analysis and topic detection of spanish tweets: A comparative study of of NLP techniques. *Procesamiento del Lenguaje Natural*, 50, 45–52.
516. Antonakaki, D., Ioannidis, S., & Fragopoulou, P. (2018). Utilizing the average node degree to assess the temporal growth rate of Twitter. *Social Network Analysis and Mining*, 8(1), 12. *Expert Systems With Applications* 164 (2021) 114006
517. Antonakaki, D., Polakis, I., Athanasopoulos, E., Ioannidis, S., & Fragopoulou, P. (2014). Think before rt: An experimental study of abusing twitter trends. In *International conference on social informatics* (pp. 402–413). Springer.
518. Antonakaki, D., Polakis, I., Athanasopoulos, E., Ioannidis, S., & Fragopoulou, P. (2016). Exploiting abused trending topics to identify spam campaigns in twitter. *Social Network Analysis and Mining*, 6(1), 48.
519. Antonakaki, D., Spiliotopoulos, D., Samaras, C. V., Ioannidis, S., & Fragopoulou, P. (2016). Investigating the complete corpus of referendum and elections tweets. In *2016 IEEE/ACM international conference on advances in social networks analysis and mining (ASONAM)* (pp. 100–105). IEEE.
520. Antonakaki, D., Spiliotopoulos, D., V. Samaras, C., Pratikakis, P., Ioannidis, S., & Fragopoulou, P. (2017). Social media analysis during political turbulence. *PloS One*, 12(10), Article e0186836.

521. Asur, S., & Huberman, B. A. (2010). Predicting the future with social media. In 2010 IEEE/WIC/ACM international conference on web intelligence and intelligent agent technology (pp. 492–499). IEEE, URL: <http://ieeexplore.ieee.org/document/5616710/>.
522. Asur, S., Huberman, B. A., Szabo, G., & Wang, C. (2011). Trends in social media: Persistence and decay. SSRN Electronic Journal, URL: <http://www.ssrn.com/abstract=1755748>.
523. Baccianella, S., Esuli, A., & Sebastiani, F. (2010). Sentiwordnet 3.0: an enhanced lexical resource for sentiment analysis and opinion mining. In *Lrec*, Vol. 10 (pp. 2200–2204).
524. Backstrom, L., Boldi, P., Rosa, M., Ugander, J., & Vigna, S. (2012). Four degrees of separation. In *Proceedings of the 3rd annual ACM web science conference on - WebSci '12* (pp. 33–42). New York, New York, USA: ACM Press, URL: <http://dl.acm.org/citation.cfm?id=2380718.2380723>.
525. Bader, D. A., Kintali, S., Madduri, K., & Mihail, M. (2007). Approximating betweenness centrality. In *Algorithms and models for the web-graph* (pp. 124–137). Berlin, Heidelberg: Springer Berlin Heidelberg.
526. Bakshy, E., Hofman, J. M., Mason, W. A., & Watts, D. J. (2011). Everyone's an influencer. In *Proceedings of the fourth ACM international conference on web search and data mining - WSDM '11* (p. 65). New York, New York, USA: ACM Press.
527. Balahur, A., & Turchi, M. (2013). Improving sentiment analysis in twitter using multilingual machine translated data. In *Proceedings of the international conference recent advances in natural language processing RANLP 2013* (pp. 49–55).
528. Barabási, A. (1999). Emergence of scaling in random networks. *Science*, 286(5439), 509–512, URL: <http://science.sciencemag.org/content/286/5439/509.abstract>.
529. Barbieri, N., Bonchi, F., & Manco, G. (2013). Cascade-based community detection. In *Proceedings of the sixth ACM international conference on web search and data mining* (pp. 33–42). ACM.
530. Barbieri, N., Bonchi, F., & Manco, G. (2014). Who to follow and why: link prediction with explanations. In *Proceedings of the 20th ACM SIGKDD international conference on knowledge discovery and data mining* (pp. 1266–1275). ACM.
531. Barrick, M. R., & Mount, M. K. (1991). The big five personality dimensions and job performance: a meta-analysis. *Personnel Psychology*, 44(1), 1–26.
532. Batrinca, B., & Treleaven, P. C. (2015). Social media analytics: a survey of techniques, tools and platforms. *AI & Society*, 30(1), 89–116.
533. Benevenuto, F., Magno, G., Rodrigues, T., & Almeida, V. (2010). Detecting spammers on twitter. In *Annual collaboration, electronic messaging, anti-abuse and spam conference (CEAS)*.
534. Bird, S., Klein, E., & Loper, E. (2009). *Natural language processing with Python: analyzing text with the natural language toolkit*. "O'Reilly Media, Inc."
535. Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent dirichlet allocation. *Journal of Machine Learning Research (JMLR)*, 3, 993–1022.
536. Bliss, C. A., Frank, M. R., Danforth, C. M., & Dodds, P. S. (2013). An evolutionary algorithm approach to link prediction in dynamic social networks. *CoRR abs/1304.6257*.

537. Bliss, C. A., Kloumann, I. M., Harris, K. D., Danforth, C. M., & Dodds, P. S. (2012). Twitter reciprocal reply networks exhibit assortativity with respect to happiness. *Journal of Computer Science*, 3(5), 388–397.
538. Bollen, J., Mao, H., & Pepe, A. (2010). Determining the public mood state by analysis of microblogging posts. In *Proceedings of the alife XII conference*.
539. Bollen, J., Mao, H., & Pepe, A. (2011). Modeling public mood and emotion: Twitter sentiment and socio-economic phenomena. *lcwsm*, 11, 450–453.
540. Borra, E., & Rieder, B. (2014). Programmed method: developing a toolset for capturing and analyzing tweets. *Aslib Journal of Information Management*, 66(3), 262–278.
541. Bošnjak, M., Oliveira, E., Martins, J., Mendes Rodrigues, E., & Sarmiento, L. (2012). Twitterecho: a distributed focused crawler to support open research with twitter data. In *Proceedings of the 21st international conference on world wide web* (pp. 1233–1240). ACM.
542. Boyd, D., Golder, S., & Lotan, G. (2010). Tweet, tweet, retweet: Conversational aspects of retweeting on twitter. In *System sciences (Hicss), 2010 43rd Hawaii international conference on* (pp. 1–10). IEEE.
543. Bray, P. (2015). Social authority: Our measure of twitter influence. <http://moz.com/blog/social-authority>. - Online; accessed 10-October-2015 - .
544. Brin, S., & Page, L. (1998). The anatomy of a large-scale hypertextual Web search engine. *Computer Networks and ISDN Systems*, 30(1–7), 107–117, URL: <http://dl.acm.org/citation.cfm?id=297810.297827>.
545. Broder, A. (1997). On the resemblance and containment of documents. In *SEQUENCES '97, Proceedings of the compression and complexity of sequences 1997* (p. 21). Washington, DC, USA: IEEE Computer Society, URL: <http://dl.acm.org/citation.cfm?id=829502.830043>.
546. Broniatowski, D. A., Jamison, A. M., Qi, S., AlKulaib, L., Chen, T., Benton, A., Quinn, S. C., & Dredze, M. (2018). Weaponized health communication: Twitter bots and Russian trolls amplify the vaccine debate. *American Journal of Public Health*, 108(10), 1378–1384.
547. Broniatowski, D. A., Paul, M. J., & Dredze, M. (2013). National and local influenza surveillance through twitter: an analysis of the 2012-2013 influenza epidemic. *PloS One*, 8(12), Article e83672.
548. Buccafurri, F., Lax, G., Nicolazzo, S., & Nocera, A. (2016). Interest assortativity in twitter. In *WEBIST (1)* (pp. 239–246).
549. Burnap, P., & Williams, M. L. (2015). Cyber hate speech on twitter: An application of machine classification and statistical modeling for policy and decision making. *Policy & Internet*, 7(2), 223–242.
550. Byrnes, N. (2016). How the Bot-y politic influenced this election. <https://bit.ly/2fBN13R>. Technologyreview.com, Accessed: 2018-12-30.
551. Carvalho, J. P., Rosa, H., Brogueira, G., & Batista, F. (2017). MISNIS: An intelligent platform for twitter topic mining. *Expert Systems with Applications*, 89, 374–388.
552. Cataldi, M., Di Caro, L., & Schifanella, C. (2010a). Emerging topic detection on twitter based on temporal and social terms evaluation. In *Proceedings of the tenth international workshop on multimedia data mining* (p. 4). ACM.

553. Cataldi, M., Di Caro, L., & Schifanella, C. (2010b). Emerging topic detection on twitter based on temporal and social terms evaluation. In *Proceedings of the tenth international workshop on multimedia data mining - MDMKDD '10* (pp. 1–10). New York, New York, USA: ACM Press.
554. Cha, M., Haddadi, H., Benevenuto, F., & Gummadi, K. (2010). Measuring user influence in twitter: The million follower fallacy. In *4th international AAAI conference on weblogs and social media (ICWSM)*.
555. Cha, M., Mislove, A., & Gummadi, K. P. (2009). A measurement-driven analysis of information propagation in the flickr social network. In *Proceedings of the 18th international conference on world wide web - WWW '09* (p. 721). New York, New York, USA: ACM Press.
556. Charalampakis, B., Spathis, D., Kouslis, E., & Kermanidis, K. (2015). Detecting irony on greek political tweets: A text mining approach. In *EANN '15, Proceedings of the 16th international conference on engineering applications of neural networks (INNS)* (pp. 17:1–17:5). New York, NY, USA: ACM.
557. Chavoshi, N., Hamooni, H., & Mueen, A. (2016). Debot: Twitter bot detection via warped correlation. In *ICDM* (pp. 817–822).
558. Chen, Y., Yuan, J., You, Q., & Luo, J. (2018). Twitter sentiment analysis via bi-sense emoji embedding and attention-based LSTM. *arXiv preprint arXiv:1807.07961*.
559. Choi, H.-J., & Park, C. H. (2019). Emerging topic detection in twitter stream based on high utility pattern mining. *Expert Systems with Applications*, 115, 27–36.
560. Choudhury, M. D., Lin, Y.-R., Sundaram, H., Candan, K. S., Xie, L., & Kelliher, A. (2010). How does the data sampling strategy impact the discovery of information diffusion in social media? In *Proceedings of the 4th international AAAI conference on weblogs and social media* (pp. 34–41).
561. Chowdhury, A. (2010). State of Twitter Spam. <https://bit.ly/2QwmB5G>. Twitter.com, Accessed: 2018-12-30.
562. Chu, Z., Gianvecchio, S., Wang, H., & Jajodia, S. (2012). Detecting automation of twitter accounts: Are you a human, bot, or cyborg? *IEEE Transactions on Dependable and Secure Computing*, 9(6), 811–824.
563. Chu, Z., Widjaja, I., & Wang, H. (2012). Detecting social spam campaigns on twitter. In *International conference on applied cryptography and network security* (pp. 455–472). Springer.
564. Chun, H., Kwak, H., Eom, Y.-H., Ahn, Y.-Y., Moon, S., & Jeong, H. (2008). Comparison of online social relations in volume vs interaction. In *Proceedings of the 8th ACM SIGCOMM conference on internet measurement conference - IMC '08* (p. 57). New York, New York, USA: ACM Press.
565. Chung, J. E., & Mustafaraj, E. (2011). Can collective sentiment expressed on twitter predict political elections? In *AAAI*, Vol. 11 (pp. 1770–1771).
566. Cody, E. M., Reagan, A. J., Mitchell, L., Dodds, P. S., & Danforth, C. M. (2015). Climate change sentiment on twitter: an unsolicited public opinion poll. *PloS One*, 10(8), Article e0136092.

567. Colleoni, E., Rozza, A., & Arvidsson, A. (2014). Echo chamber or public sphere? Predicting political orientation and measuring political homophily in twitter using big data. *Journal of Communication*, 64(2), 317–332.
568. Confessore, n., Dance, G. J., Harris, R., & Hansen, M. (2018). The follower factory. <https://nyti.ms/2rJ8YZM>. Accessed: 2018-10-20.
569. Conover, M., Ratkiewicz, J., Francisco, M. R., Gonçalves, B., Menczer, F., & Flammini, A. (2011). Political polarization on twitter. *lcwsm*, 133, 89–96.
570. Constine, J. (2016). Facebook sees 2 billion searches per day, but it's attacking Twitter not Google. <https://tcrn.ch/2aL3jGk>. Accessed: 2018-12-30.
571. Cormack, G. V. (2008). Email spam filtering: A systematic review. *Foundations and Trends in Information Retrieval*, 1(4), 335–455, URL: <http://dl.acm.org/citation.cfm?id=1454707.1454708>.
572. Csardi, G., & Nepusz, T. (2006). The igraph software package for complex network research. *InterJournal, Complex Systems*, 1695, URL: <http://igraph.org>. *Expert Systems With Applications* 164 (2021) 114006
573. Cui, A., Zhang, M., Liu, Y., & Ma, S. (2011). Emotion tokens: Bridging the gap among multilingual twitter sentiment analysis. In *Asia information retrieval symposium* (pp. 238–249). Springer.
574. Daniel, M., Neves, R. F., & Horta, N. (2017). Company event popularity for financial markets using Twitter and sentiment analysis. *Expert Systems with Applications*, 71, 111–124.
575. Davis, C. A., Varol, O., Ferrara, E., Flammini, A., & Menczer, F. (2016). Botornot: A system to evaluate social bots. In *Proceedings of the 25th international conference companion on world wide web* (pp. 273–274). International World Wide Web Conferences Steering Committee.
576. Derczynski, L., Ritter, A., Clark, S., & Bontcheva, K. (2013). Twitter part-of-speech tagging for all: Overcoming sparse and noisy data. In *Proceedings of the international conference recent advances in natural language processing RANLP 2013* (pp. 198–206).
577. Diakopoulos, N. A., & Shamma, D. A. (2010a). Characterizing debate performance via aggregated twitter sentiment. In *Proceedings of the SIGCHI conference on human factors in computing systems* (pp. 1195–1198). ACM.
578. Diakopoulos, N. A., & Shamma, D. A. (2010b). Characterizing debate performance via aggregated twitter sentiment. In *CHI '10, Proceedings of the SIGCHI conference on human factors in computing systems* (pp. 1195–1198). New York, NY, USA: ACM.
579. Dimson, T. (2018). Emojineering part 1: Machine learning for emoji trends. <https://bit.ly/2PcHKBm>. Accessed: 2018-10-7.
580. Ding, X., Liu, B., & Yu, P. S. (2008). A holistic lexicon-based approach to opinion mining. In *Proceedings of the 2008 international conference on web search and data mining* (pp. 231–240). ACM.
581. Djuric, N., Zhou, J., Morris, R., Grbovic, M., Radosavljevic, V., & Bhamidipati, N. (2015). Hate speech detection with comment embeddings. In *Proceedings of the 24th international conference on world wide web* (pp. 29–30). ACM.

582. Dodds, P. S., Harris, K. D., Kloumann, I. M., Bliss, C. A., & Danforth, C. M. (2011). Temporal patterns of happiness and information in a global social network: Hedonometrics and twitter. *PloS One*, 6(12), Article e26752.
583. Dong, A., Zhang, R., Kolari, P., Bai, J., Diaz, F., Chang, Y., Zheng, Z., & Zha, H. (2010). Time is of the essence: improving recency ranking using twitter data. In *Proceedings of the 19th international conference on world wide web* (pp. 331–340). ACM.
584. Duncan, G. (2010). It's not just you: 71 percent of tweets are ignored. <https://bit.ly/2H9hZTr>. - Online; accessed 2018-30-12 - .
585. Duwairi, R. M., Marji, R., Sha'ban, N., & Rushaidat, S. (2014). Sentiment analysis in arabic tweets. In *Information and communication systems (Icics), 2014 5th international conference on* (pp. 1–6). IEEE.
586. Dwi Prasetyo, N., & Hauff, C. (2015). Twitter-based election prediction in the developing world. In *HT '15, Proceedings of the 26th ACM conference on hypertext & social media* (pp. 149–158). New York, NY, USA: ACM.
587. Dzogang, F., Lightman, S., & Cristianini, N. (2018). Diurnal variations of psychometric indicators in twitter content. *PLOS ONE*, 13(6), 1–18.
588. Ediger, D., Jiang, K., Riedy, J., Bader, D. A., & Corley, C. (2010). Massive social network analysis: Mining twitter for social good. In *2010 39th international conference on parallel processing* (pp. 583–593). IEEE, URL: <http://ieeexplore.ieee.org/document/5599247/>.
589. Edwards, C., Edwards, A., Spence, P. R., & Shelton, A. K. (2014). Is that a bot running the social media feed? Testing the differences in perceptions of communication quality for a human agent and a bot agent on twitter. *Computers in Human Behavior*, 33, 372–376.
590. Efron, M. (2010). Hashtag retrieval in a microblogging environment. In *SIGIR '10, Proceedings of the 33rd international ACM SIGIR conference on research and development in information retrieval* (pp. 787–788). New York, NY, USA: ACM.
591. Eom, Y.-H., Puliga, M., Smailovic, J., Mozetic, I., & Caldarelli, G. (2015). Twitter-based analysis of the dynamics of collective attention to political parties. *PloS One*.
592. Eysenbach, G. (2011). Can tweets predict citations? Metrics of social impact based on twitter and correlation with traditional metrics of scientific impact. *Journal of Medical Internet Research*, 13(4), Article e123.
593. Fang, A., Macdonald, C., Ounis, I., & Habel, P. (2016). Using word embedding to evaluate the coherence of topics from Twitter data. In *Proceedings of the 39th international ACM SIGIR conference on research and development in information retrieval* (pp. 1057–1060).
594. Ferrara, E., Varol, O., Davis, C., Menczer, F., & Flammini, A. (2016). The rise of social bots. *Communications of the ACM*, 59(7), 96–104.
595. Finin, T., Murnane, W., Karandikar, A., Keller, N., Martineau, J., & Dredze, M. (2010). Annotating named entities in Twitter data with crowdsourcing. In *Proceedings of the NAACL HLT 2010 workshop on creating speech and language data with amazon's mechanical turk* (pp. 80–88). Association for Computational Linguistics.
596. Finkel, J. R., Grenager, T., & Manning, C. (2005). Incorporating non-local information into information extraction systems by gibbs sampling. In *Proceedings of the 43rd annual*

meeting on association for computational linguistics (pp. 363–370). Association for Computational Linguistics.

597. Flores, M., & Kuzmanovic, A. (2013). Searching for spam: detecting fraudulent accounts via web search. In *Passive and active measurement* (pp. 208–217). Springer.
598. Foroozani, A., & Ebrahimi, M. (2019). Anomalous information diffusion in social networks: Twitter and Digg. *Expert Systems with Applications*, 134, 249–266.
599. Fortuna, P., & Nunes, S. (2018). A survey on automatic detection of hate speech in text. *ACM Computing Surveys*, 51(4), 1–30.
600. Founta, A.-M., Djouvas, C., Chatzakou, D., Leontiadis, I., Blackburn, J., Stringhini, G., Vakali, A., Sirivianos, M., & Kourtellis, N. (2018). Large scale crowdsourcing and characterization of twitter abusive behavior. *arXiv preprint arXiv:1802.00393*.
601. Freelon, D. (2018). Social media data collection tools. <http://socialmediadata.wikidot.com/>. Accessed: 2018-10-21.
602. Freeman, L. (2004). The development of social network analysis. *A Study in the Sociology of Science*, 1.
603. Gabielkov, M., & Legout, A. (2012). The complete picture of the twitter social graph. In *Proceedings of the 2012 ACM conference on CoNEXT student workshop* (pp. 19–20). ACM.
604. Gabielkov, M., Rao, A., & Legout, A. (2014a). Sampling online social networks: an experimental study of twitter. In *Proceedings of the 2014 ACM conference on SIGCOMM* (pp. 127–128). ACM.
605. Gabielkov, M., Rao, A., & Legout, A. (2014b). Studying social networks at scale: macroscopic anatomy of the twitter social graph. In *ACM SIGMETRICS performance evaluation review*, Vol. 42 (pp. 277–288). ACM.
606. Gao, H., Chen, Y., Lee, K., Palsetia, D., & Choudhary, A. (2012). Towards online spam filtering in social networks. In *Symposium on network and distributed system security (NDSS)*.
607. Gao, H., Hu, J., Wilson, C., Li, Z., Chen, Y., & Zhao, B. Y. (2010). Detecting and characterizing social spam campaigns. In *Proceedings of the 10th annual conference on internet measurement - IMC '10* (p. 35). New York, New York, USA: ACM Press.
608. Gayo-Avello, D. (2012). A meta-analysis of state-of-the-art electoral prediction from twitter data. *CoRR abs/1206.5851*. URL: <http://arxiv.org/abs/1206.5851>.
609. Gayo-Avello, D., Metaxas, P. T., & Mustafaraj, E. (2011). Limits of electoral predictions using twitter. In *ICWSM*. The AAAI Press.
610. Ghiassi, M., & Lee, S. (2018). A domain transferable lexicon set for Twitter sentiment analysis using a supervised machine learning approach. *Expert Systems with Applications*, 106, 197–216.
611. Ghosh, S., Viswanath, B., Kooti, F., Sharma, N. K., Korlam, G., Benevenuto, F., Ganguly, N., & Gummadi, K. P. (2012). Understanding and combating link farming in the twitter social network. In *Proceedings of the 21st international conference on world wide web - WWW '12* (p. 61). New York, New York, USA: ACM Press, URL: <http://dl.acm.org/citation.cfm?id=2187836.2187846>.

612. Giachanou, A., & Crestani, F. (2016). Like it or not: A survey of twitter sentiment analysis methods. *ACM Computing Surveys*, 49(2), 28.
613. Gilani, Z., Wang, L., Crowcroft, J., Almeida, M., & Farahbakhsh, R. (2016). Stweeler: A framework for twitter bot analysis. In *Proceedings of the 25th international conference companion on world wide web* (pp. 37–38). International World Wide Web Conferences Steering Committee.
614. Gilbert, C. E. (2014). Vader: A parsimonious rule-based model for sentiment analysis of social media text. In *Eighth international conference on weblogs and social media (ICWSM-14)*.
615. Go, A., Bhayani, R., & Huang, L. (2009). Twitter sentiment classification using distant supervision. In *CS224N project report, Stanford*, Vol. 1.
616. Golbeck, J., & Hansen, D. (2011). Computing political preference among twitter followers. In *CHI '11, Proceedings of the SIGCHI conference on human factors in computing systems* (pp. 1105–1108). New York, NY, USA: ACM.
617. Gonçalves, P., Araújo, M., Benevenuto, F., & Cha, M. (2013). Comparing and combining sentiment analysis methods. In *Proceedings of the first ACM conference on online social networks* (pp. 27–38).
618. Gonçalves, B., Perra, N., & Vespignani, A. (2011). Modeling users' activity on twitter networks: validation of Dunbar's number. *PloS One*, 6(8), Article e22656.
619. González-Ibáñez, R., Muresan, S., & Wacholder, N. (2011). Identifying sarcasm in twitter: A closer look. In *HLT '11, Proceedings of the 49th annual meeting of the association for computational linguistics: human language technologies: Short papers - volume 2* (pp. 581–586). Stroudsburg, PA, USA: Association for Computational Linguistics, URL: <http://dl.acm.org/citation.cfm?id=2002736.2002850>.
620. Grier, C., Thomas, K., Paxson, V., & Zhang, M. (2010). @spam: The underground on 140 characters or less. In *CCS '10, Proceedings of the 17th ACM conference on computer and communications security* (pp. 27–37). New York, NY, USA: ACM.
621. Griffiths, T. L., & Steyvers, M. (2004). Finding scientific topics. *Proceedings of the National Academy of Sciences of the United States of America*, 5228–5235.
622. Hall, M., Frank, E., Holmes, G., Pfahringer, B., Reutemann, P., & Witten, I. H. (2009). The WEKA data mining software: an update. *ACM SIGKDD Explorations Newsletter*, 11(1), 10–18.
623. Han, B., & Baldwin, T. (2011). Lexical normalisation of short text messages: Makn sens a# twitter. In *Proceedings of the 49th annual meeting of the association for computational linguistics: Human language technologies* (pp. 368–378).
624. Han, B., Cook, P., & Baldwin, T. (2012). Automatically constructing a normalisation dictionary for microblogs. In *Proceedings of the 2012 joint conference on empirical methods in natural language processing and computational natural language learning* (pp. 421–432).
625. Hanneman, R. A., & Riddle, M. (2005). *Introduction to social network methods*. University of California Riverside.
626. Harvey, D. (2010). Trust and safety. <https://bit.ly/2LWt3Cl>. Accessed: 2018-12-30.

627. Hashemi, M. (2018). The infrastructure behind twitter: Scale. <https://bit.ly/2qMuujC>. Accessed: 2018-10-21.
628. Haveliwala, T. H., & H., T. (2002). Topic-sensitive PageRank. In Proceedings of the eleventh international conference on world wide web - WWW '02 (p. 517). New York, New York, USA: ACM Press. Expert Systems With Applications 164 (2021) 114006
629. Hernandez-Suarez, A., Sanchez-Perez, G., Toscano-Medina, K., Martinez-Hernandez, V., Sanchez, V., & Perez-Meana, H. (2018). A web scraping methodology for bypassing twitter API restrictions. arXiv preprint arXiv:1803.09875.
630. Herzallah, W., Faris, H., & Adwan, O. (2018). Feature engineering for detecting spammers on Twitter: Modelling and analysis. *Journal of Information Science*, 44(2), 230–247.
631. Hirsch, J. (2005). An index to quantify an individual's scientific research output. *Proceedings of the National Academy of Sciences of the United States of America*, 102(46), 16569–16572.
632. Hong, L., Dan, O., & Davison, B. D. (2011). Predicting popular messages in twitter. In Proceedings of the 20th international conference companion on world wide web - WWW '11 (p. 57). New York, New York, USA: ACM Press.
633. Hong, L., & Davison, B. D. (2010). Empirical study of topic modeling in twitter. In SOMA '10, Proceedings of the first workshop on social media analytics - SOMA '10 (pp. 80–88). New York, NY, USA: ACM.
634. Hong, S., & Nadler, D. (2012). Which candidates do the public discuss online in an election campaign?: The use of social media by 2012 presidential candidates and its impact on candidate salience. *Government Information Quarterly*, 29(4), 455–461.
635. Hopkins, D., & King, G. (2010). A method of automated nonparametric content analysis for social science. *American Journal of Political Science*, 54(1), 229–247.
636. Howlader, P., & Sudeep, K. (2016). Degree centrality, eigenvector centrality and the relation between them in twitter. In 2016 IEEE international conference on recent trends in electronics, information & communication technology (RTEICT) (pp. 678–682). IEEE.
637. Hu, Y., John, A., Wang, F., & Kambhampati, S. (2012). Et-Ida: Joint topic modeling for aligning events and their twitter feedback. In Twenty-sixth AAAI conference on artificial intelligence.
638. Hu, X., Sun, N., Zhang, C., & Chua, T.-S. (2009). Exploiting internal and external semantics for the clustering of short texts using world knowledge. In Proceedings of the 18th ACM conference on information and knowledge management (pp. 919–928).
639. Huang, J., Thornton, K. M., & Efthimiadis, E. N. (2010). Conversational tagging in twitter. In HT '10, Proceedings of the 21st ACM conference on hypertext and hypermedia (pp. 173–178). New York, NY, USA: ACM.
640. Investopedia (2020). How twitter makes money. <https://tinyurl.com/y7q2cehz>. - Online; accessed 2020-15-06 - .
641. Jiang, L., Yu, M., Zhou, M., Liu, X., & Zhao, T. (2011). Target-dependent twitter sentiment classification. In Proceedings of the 49th annual meeting of the association for

- computational linguistics: Human language technologies-volume 1 (pp. 151–160). Association for Computational Linguistics.
642. Jianqiang, Z., & Xiaolin, G. (2017). Comparison research on text pre-processing methods on twitter sentiment analysis. *IEEE Access*, 5, 2870–2879.
 643. Johnson, S., Torres, J. J., Marro, J., & Munoz, M. A. (2010). Entropic origin of disassortativity in complex networks. *Physical Review Letters*, 104(10), Article 108702.
 644. Kanich, C., Kreibich, C., Levchenko, K., Enright, B., Voelker, G. M., Paxson, V., & Savage, S. (2008). Spamalytics: an empirical analysis of spam marketing conversion. In *CCS '08: Proceedings of the 15th ACM conference on computer and communications security* (pp. 3–14). New York, NY, USA: ACM, URL: <http://portal.acm.org/citation.cfm?id=1455770.1455774>.
 645. Kantrowitz, A. (2018). How twitter made the tech world's most unlikely comeback. <https://bit.ly/2M0sOpy>. Accessed: 2018-10-21.
 646. Karami, A., Dahl, A. A., Turner-McGrievy, G., Kharrazi, H., & Shaw, G. (2018). Characterizing diabetes, diet, exercise, and obesity comments on twitter. *International Journal of Information Management*, 38(1), 1–6.
 647. Kaufmann, M., & Kalita, J. (2010). Syntactic normalization of twitter messages. In *International conference on natural language processing*, Kharagpur, India, Vol. 16.
 648. Kim, Y. (2014). Convolutional neural networks for sentence classification. *arXiv preprint arXiv:1408.5882*.
 649. Kleinberg, J. (2000). Navigation in a small world. *Nature*, 406(6798), 845.
 650. Kleinberg, J. M., Kumar, R., Raghavan, P., Rajagopalan, S., & Tomkins, A. S. (1999). The web as a graph: measurements, models, and methods. In *Computing and combinatorics* (pp. 1–17). Springer.
 651. Kleineberg, K.-K., & Boguñá, M. (2014). Evolution of the digital society reveals balance between viral and mass media influence. *Physical Review X*, 4, Article 031046.
 652. Kolchyna, O., Souza, T. T., Treleaven, P., & Aste, T. (2015). Twitter sentiment analysis: Lexicon method, machine learning method and their combination. *arXiv preprint arXiv:1507.00955*.
 653. Kontopoulos, E., Berberidis, C., Dergiades, T., & Bassiliades, N. (2013). Ontologybased sentiment analysis of twitter posts. *Expert Systems with Applications*, 40(10), 4065–4074.
 654. Kouloumpis, E., Wilson, T., & Moore, J. D. (2011). Twitter sentiment analysis: The good the bad and the omg! *lcwsm*, 11(538–541), 164.
 655. Krebs, B. (2018). Twitter bots drown out anti-kremlin tweets. URL: <https://krebsonsecurity.com/tag/maxim-goncharov/>accessed: 2018-12-30.
 656. Kreibich, C., Kanich, C., Levchenko, K., Enright, B., Voelker, G. M., Paxson, V., & Savage, S. (2008). On the spam campaign trail. *LEET*, 8, 1–9.
 657. Kucher, K., Paradis, C., & Kerren, A. (2018). The state of the art in sentiment visualization. In *Computer graphics forum*, Vol. 37 (pp. 71–96). Wiley Online Library.
 658. Kumar, R., Novak, J., & Tomkins, A. (2006). Structure and evolution of online social networks. In *Proceedings of the 12th ACM SIGKDD international conference on knowledge*

- discovery and data mining - KDD '06 (p. 611). New York, New York, USA: ACM Press, URL: <http://dl.acm.org/citation.cfm?id=1150402.1150476>.
659. Kumaraguru, P., Rhee, Y., Acquisti, A., Cranor, L. F., Hong, J., & Nunge, E. (2007). Protecting people from phishing. In Proceedings of the SIGCHI conference on human factors in computing systems - CHI '07 (p. 905). New York, New York, USA: ACM Press.
 660. Kupavskii, A., Ostroumova, L., Umnov, A., Usachev, S., Serdyukov, P., Gusev, G., & Kustarev, A. (2012). Prediction of retweet cascade size over time. In Proceedings of the 21st ACM international conference on information and knowledge management (pp. 2335–2338). ACM.
 661. Kwak, H., Lee, C., Park, H., & Moon, S. (2010). What is Twitter, a social network or a news media? In Proceedings of the 19th international conference on world wide web - WWW '10 (p. 591). New York, New York, USA: ACM Press, URL: <http://dl.acm.org/citation.cfm?id=1772690.1772751>.
 662. Kwok, I., & Wang, Y. (2013). Locate the hate: Detecting tweets against blacks. In AAAI.
 663. Laflin, P., Mantzaris, A. V., Ainley, F., Otley, A., Grindrod, P., & Higham, D. J. (2013). Discovering and validating influence in a dynamic online social network. *Social Network analysis and Mining*, 3(4), 1311–1323.
 664. Lamos, V., Preoȃuc-Pietro, D., & Cohn, T. (2013). A user-centric model of voting intention from social media. In ACL '13, Proceedings of the 51st annual meeting of the association for computational linguistics (pp. 993–1003). URL <http://www.aclweb.org/anthology/P13-1098>.
 665. Lee, K., Caverlee, J., & Webb, S. (2010). Uncovering social spammers. In Proceeding of the 33rd international ACM SIGIR conference on research and development in information retrieval - SIGIR '10 (p. 435). New York, New York, USA: ACM Press.
 666. Lee, K., Eoff, B. D., & Caverlee, J. (2011). Seven months with the devils: A long-term study of content polluters on twitter. In ICWSM. DOI: <https://doi.org/10.1609/icwsml.v5i1.14106>
 667. Leong, E. (2016). New ways to control your experience on Twitter. <https://bit.ly/2b2dtRD>. Accessed: 2018-12-30.
 668. Lerman, K., & Ghosh, R. (2010). Information contagion: An empirical study of the spread of news on digg and twitter social networks. In Fourth international AAAI conference on weblogs and social media (pp. 90–97). URL: <http://arxiv.org/abs/1003.2664>. arXiv:1003.2664.
 669. Leskovec, J., Backstrom, L., Kumar, R., & Tomkins, A. (2008). Microscopic evolution of social networks. In Proceeding of the 14th ACM SIGKDD international conference on knowledge discovery and data mining - KDD 08 (p. 462). New York, New York, USA: ACM Press, URL: <http://dl.acm.org/citation.cfm?id=1401890.1401948>.
 670. Leskovec, J., & Faloutsos, C. (2006). Sampling from large graphs. In Proceedings of the 12th ACM SIGKDD international conference on knowledge discovery and data mining - KDD '06 (p. 631). New York, New York, USA: ACM Press, URL: <http://dl.acm.org/citation.cfm?id=1150402.1150479>.

671. Leskovec, J., Kleinberg, J., & Faloutsos, C. (2005). Graphs over time: densification laws, shrinking diameters and possible explanations. In *Proceeding of the eleventh ACM SIGKDD international conference on knowledge discovery in data mining - KDD '05* (p. 177). New York, New York, USA: ACM Press, URL: <http://dl.acm.org/citation.cfm?id=1081870.1081893>.
672. Leskovec, J., Kleinberg, J., & Faloutsos, C. (2007). Graph evolution: Densification and shrinking diameters. In *TKDD, Vol. 1* (p. 2). ACM.
673. Leskovec, J., Lang, K. J., Dasgupta, A., & Mahoney, M. W. (2008). Statistical properties of community structure in large social and information networks. In *Proceeding of the 17th international conference on world wide web - WWW '08* (p. 695). New York, New York, USA: ACM Press, URL: <http://dl.acm.org/citation.cfm?id=1367497.1367591>.
674. Li, C., Weng, J., He, Q., Yao, Y., Datta, A., Sun, A., & Lee, B.-S. (2012). Twiner: named entity recognition in targeted twitter stream. In *Proceedings of the 35th international ACM SIGIR conference on research and development in information retrieval* (pp. 721–730). ACM.
675. Liu, K.-L., Li, W.-J., & Guo, M. (2012). Emoticon smoothed language models for twitter sentiment analysis.. In *Aaai, Vol. 12* (pp. 22–26).
676. Liu, L., Preotiuc-Pietro, D., Samani, Z. R., Moghaddam, M. E., & Ungar, L. H. (2016). Analyzing personality through social media profile picture choice.. In *ICWSM* (pp. 211–220).
677. LiveStats, I. (2018). Twitter usage statistics - Internet live stats. www.internetlivestats.com/twitter-statistics/. Accessed: 2018-12-30.
678. Lo, S. L., Chiong, R., & Cornforth, D. (2017). An unsupervised multilingual approach for online social media topic identification. *Expert Systems with Applications*, 81, 282–298.
679. Lukasik, M., Cohn, T., & Bontcheva, K. (2015). Estimating collective judgement of rumours in social media. *CoRR abs/1506.00468*. URL: <http://arxiv.org/abs/1506.00468>.
680. Madduri, K., Ediger, D., Jiang, K., Bader, D. A., & Chavarria-Miranda, D. (2009). A faster parallel algorithm and efficient multithreaded implementations for evaluating betweenness centrality on massive datasets. In *2009 IEEE international symposium on parallel & distributed processing* (pp. 1–8). IEEE, URL: <http://ieeexplore.ieee.org/document/5161100/>.
681. Maharani, W., & Gozali, A. A. (2014). Degree centrality and eigenvector centrality in twitter. In *Telecommunication systems services and applications (TSSA), 2014 8th international conference on* (pp. 1–5). IEEE. *Expert Systems With Applications* 164 (2021) 114006
682. Mahata, D., Friedrichs, J., Shah, R. R., & Jiang, J. (2018). Did you take the pill?- detecting personal intake of medicine from twitter. *arXiv preprint arXiv:1808.02082*.
Mangles, C. (2018). Search engine statistics 2018. <https://bit.ly/2Bwhqva>. Accessed: 2018-12-30.
683. Markatos, E., Balzarotti, D., Almgren, M., Athanasopoulos, E., Bos, H., Cavallaro, L., Ioannidis, S., Lindorfer, M., Maggi, F., & Minchev, Z. (2013). The red book. SysSec Consortium.
684. Marketingcharts (2013). Social networking eats up 3+ hours per day for the average American user. <https://bit.ly/1mmPPhB>. Accessed: 2018-12-30.

685. Martínez-Cámara, E., Martín-Valdivia, M. T., Urena-López, L. A., & Montejó-Ráez, A. R. (2014). Sentiment analysis in twitter. *Natural Language Engineering*, 20(1), 1–28.
686. Martinez-Romo, J., & Araujo, L. (2013). Detecting malicious tweets in trending topics using a statistical analysis of language. *Expert Systems with Applications*, 40(8), 2992–3000.
687. Matthews, C. (2013). How does one fake tweet cause a stock market crash?. <https://bit.ly/2FkPjEE>. Times.com, Accessed: 2018-12-30.
688. Mazza, M., Cresci, S., Avvenuti, M., Quattrociochi, W., & Tesconi, M. (2019). Rtbust: Exploiting temporal patterns for botnet detection on twitter. In *Proceedings of the 10th ACM conference on web science* (pp. 183–192).
689. McCallum, A. K. (2002). MALLET: A machine learning for language toolkit. <http://mallet.cs.umass.edu>.
690. Mccord, M., & Chuah, M. (2011). Spam detection on twitter using traditional classifiers. In *International conference on autonomic and trusted computing* (pp. 175–186). Springer.
691. McCoy, D., Pitsillidis, A., Jordan, G., Weaver, N., Kreibich, C., Krebs, B., Voelker, G. M., Savage, S., & Levchenko, K. (2012). Pharmaleaks: understanding the business of online pharmaceutical affiliate programs. In *Proceedings of the 21st USENIX conference on security symposium* (p. 1). USENIX Association.
692. McCreadie, R., Soboroff, I., Lin, J., Macdonald, C., Ounis, I., & McCullough, D. (2012). On building a reusable twitter corpus. In *Proceedings of the 35th international ACM SIGIR conference on research and development in information retrieval* (pp. 1113–1114). ACM.
693. McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual Review of Sociology*, 27, 415–444.
694. Meeder, B., Karrer, B., Sayedi, A., Ravi, R., Borgs, C., & Chayes, J. (2011). We know who you followed last summer: inferring social link creation times in twitter. In *Proceedings of the 20th international conference on world wide web* (pp. 517–526). ACM.
695. Meel, P., & Vishwakarma, D. K. (2019). Fake news, rumor, information pollution in social media and web: A contemporary survey of state-of-the-arts, challenges and opportunities. *Expert Systems with Applications*, Article 112986.
696. Mendoza, M., Poblete, B., & Castillo, C. (2010). Twitter under crisis. In *Proceedings of the first workshop on social media analytics - SOMA '10* (pp. 71–79). New York, New York, USA: ACM Press.
697. Mersch, V. v. d. (2018). Twitter's 10 year struggle with developer relations. <https://bit.ly/2TAG1YR>. Accessed: 2018-10-28.
698. Messias, J., Schmidt, L., Oliveira, R., & Benevenuto, F. (2013). You followed my bot! transforming robots into influential users in twitter. *First Monday*, 18(7).
699. Midha, A. (2014). Study: Exposure to brand tweets drives consumers to take action – both on and off Twitter. <https://bit.ly/2CgY6UV>. - Online; accessed 2018-30-12 - .
700. Milgram, S. (1967). The small world problem. In *Psychology today*, Vol. 2, New York (pp. 60–67).

701. Mislove, A., Marcon, M., Gummadi, K. P., Druschel, P., & Bhattacharjee, B. (2007). Measurement and analysis of online social networks. In *Proceedings of the 7th ACM SIGCOMM conference on internet measurement - IMC '07* (p. 29). New York, New York, USA: ACM Press, URL: <http://dl.acm.org/citation.cfm?id=1298306.1298311>.
702. Mitchell, L., Frank, M. R., Harris, K. D., Dodds, P. S., & Danforth, C. M. (2013). The geography of happiness: Connecting twitter sentiment and expression, demographics, and objective characteristics of place. *PloS One*, 8(5), Article e64417.
703. Morales, A., Borondo, J., Losada, J., & Benito, R. (2014). Efficiency of human activity on information spreading on twitter. In *Elsevier - Social networks*, Vol. 39 (pp. 1–2011). Elsevier.
704. Morales, A., Borondo, J., Losada, J. C., & Benito, R. M. (2015). Measuring political polarization: Twitter shows the two sides of venezuela. *Chaos. An Interdisciplinary Journal of Nonlinear Science*, 25(3), Article 033114.
705. Motamedi, R., Jamshidi, S., Rejaie, R., & Willinger, W. (2020). Examining the evolution of the Twitter elite network. *Social Network Analysis and Mining*, 10(1), 1.
706. Mottl, D. (2020). GetOldTweets3. <https://github.com/Mottl/GetOldTweets3>. - Online; Accessed 2020-7-5 - .
707. Mozetič, I., Grčar, M., & Smailović, J. (2016). Multilingual Twitter sentiment classification: The role of human annotators. *PloS One*, 11(5), Article e0155036.
708. Myers, L. (2014). What Happens in a Twitter Minute? Infographic. <https://louisem.com/6267/twitter-minute-infographic>. Accessed: 2018-12-30.
709. Myers, S. A., Sharma, A., Gupta, P., & Lin, J. (2014). Information network or social network?: The structure of the twitter follow graph. In *Proceedings of the companion publication of the 23rd international conference on world wide web companion* (pp. 493–498). International World Wide Web Conferences Steering Committee.
710. Naaman, M., Becker, H., & Gravano, L. (2011). Hip and trendy: Characterizing emerging trends on Twitter. *Journal of the American Society for Information Science and Technology*, 62(5), 902–918.
711. Nakov, P., Ritter, A., Rosenthal, S., Sebastiani, F., & Stoyanov, V. (2016). SemEval2016 task 4: Sentiment analysis in Twitter. In *Proceedings of the 10th international workshop on semantic evaluation (Semeval-2016)* (pp. 1–18).
712. Narr, S., Hulphenhaus, M., & Albayrak, S. (2012). Language-independent twitter sentiment analysis. In *Knowledge discovery and machine learning (KDML), LWA* (pp. 12–14).
713. Naveed, N., Gottron, T., Kunegis, J., & Alhadi, A. C. (2011). Bad news travel fast: A content-based analysis of interestingness on twitter. In *Proceedings of the 3rd international web science conference* (p. 8). ACM.
714. Newman, M. E. (2002). Assortative mixing in networks. *Physical Review Letters*, 89(20), Article 208701. Newman, M. E. (2005). Power laws, Pareto distributions and Zipf's law. *Contemporary Physics*, 46(5), 323–351.
715. Newman, T. P. (2017). Tracking the release of ipcc ar5 on twitter: Users, comments, and sources following the release of the working group i summary for policymakers. *Public Understanding of Science*, 26(7), 815–825.

716. Nishi, R., Takaguchi, T., Oka, K., Maehara, T., Toyoda, M., Kawarabayashi, K.-i., &
717. Masuda, N. (2016). Reply trees in twitter: data analysis and branching process models. *Social Network Analysis and Mining*, 6(1), 26.
718. Nobata, C., Tetreault, J., Thomas, A., Mehdad, Y., & Chang, Y. (2016). Abusive language detection in online user content. In *Proceedings of the 25th international conference on world wide web* (pp. 145–153). International World Wide Web Conferences Steering Committee.
719. O'Connor, B., Balasubramanyan, R., Routledge, B. R., & Smith, N. A. (2010). From tweets to polls: Linking text sentiment to public opinion time series. In *Proceedings of the international AAAI conference on weblogs and social media*.
720. O'Donovan, J., Kang, B., Meyer, G., Höllerer, T., & Adalii, S. (2012). Credibility in context: An analysis of feature distributions in twitter. In *SocialCom/PASSAT* (pp. 293–301).
721. Omnicore (2018). Twitter by the numbers: Stats, demographics & fun facts. <https://www.omnicoreagency.com/twitter-statistics/>. Accessed: 2018-10-27.
722. Ozdakis, O., Senkul, P., & Oguztuzun, H. (2012). Semantic expansion of hashtags for enhanced event detection in Twitter. In *Proceedings of the 1st International Workshop on Online Social Systems*.
723. Pak, A., & Paroubek, P. (2010). Twitter as a corpus for sentiment analysis and opinion mining. In N. C. C. Chair, K. Choukri, B. Maegaard, J. Mariani, J. Odijk, S. Piperidis, M. Rosner, & D. Tapias (Eds.), *Proceedings of the seventh international conference on language resources and evaluation (LREC'10)*. Valletta, Malta: European Language Resources Association (ELRA).
724. Palachy, S. (2018). A list of Twitter datasets and related resources. <https://bit.ly/2H5P8zu>. URL: <https://github.com/shaypal5/awesome-twitter-data> - Online; Accessed 2018-12-30 - .
725. Patel-Schneider, P. F., Pan, Y., Hitzler, P., Mika, P., Zhang, L., Pan, J. Z., Horrocks, I., & Glimm, B. (2010). Making sense of twitter. In P. F. Patel-Schneider, Y. Pan, P. Hitzler, P. Mika, L. Zhang, J. Z. Pan, I. Horrocks, & B. Glimm (Eds.), *The semantic web – ISWC 2010: 9th international semantic web conference, ISWC 2010, Shanghai, China, November 7-11, 2010, Revised selected papers, Part I* (pp. 470–485). Berlin, Heidelberg: Springer Berlin Heidelberg.
726. Paul, I., Khattar, A., Kumaraguru, P., Gupta, M., & Chopra, S. (2019). Elites tweet? Characterizing the twitter verified user network. In *2019 IEEE 35th international conference on data engineering workshops (ICDEW)* (pp. 278–285). IEEE.
727. Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., & Duchesnay, E. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research (JMLR)*, 12, 2825–2830.
728. Pepe, A., & Bollen, J. (2008). Between conjecture and memento: Shaping a collective emotional perception of the future. In *AAAI spring symposium: Emotion, personality, and social behavior* (pp. 111–116).
729. Perlroth, N. (2013). Fake twitter followers become multimillion-dollar business. *The New York Times*, Accessed: 2018-12-30.

730. Petrović, S., Osborne, M., & Lavrenko, V. (2010). The edinburgh twitter corpus. In Proceedings of the NAACL HLT 2010 workshop on computational linguistics in a world of social media (pp. 25–26).
731. Pfitzner, R., Garas, A., & Schweitzer, F. (2012). Emotional divergence influences information spreading in twitter. ICWSM, 12, 2–5.
732. Potts, C. (2011). Sentiment symposium tutorial: Lexicons. <https://bit.ly/2smM9Zo>. URL: <http://sentiment.christopherpotts.net/lexicons.html>. - Online; Accessed 2018- 12-30 - . Pratikakis, P. (2018). TwAowler: A lightweight twitter crawler. arXiv preprint arXiv: 1804.07748.
733. Preotiuc-Pietro, D., Volkova, S., Lampos, V., Bachrach, Y., & Aletras, N. (2015). Studying user income through language, behaviour and affect in social media. PloS One, URL: <http://research.microsoft.com/apps/pubs/default.aspx?id=258405>.
734. Priyanta, S., Trisna, I. P., & Prayana, N. (2019). Social network analysis of twitter to identify issuer of topic using pagerank. International Journal of Advanced Computer Science and Applications, 10(1), 107–111.
735. Prusa, J. D., Khoshgoftaar, T. M., & Dittman, D. J. (2015). Impact of feature selection techniques for tweet sentiment classification. In The twenty-eighth international flairs conference. Expert Systems With Applications 164 (2021) 114006
736. Quercia, D., Kosinski, M., Stillwell, D., & Crowcroft, J. (2011). Our twitter profiles, our selves: Predicting personality with twitter. In Privacy, security, risk and trust (PAS-SAT) and 2011 IEEE third international conference on social computing (SocialCom), 2011 IEEE third international conference on (pp. 180–185). IEEE.
737. Rübiger, S., & Spiliopoulou, M. (2015). A framework for validating the merit of properties that predict the influence of a twitter user. Expert Systems with Applications, 42(5), 2824–2834.
738. Ratkiewicz, J., Conover, M., Meiss, M., Goncalves, B., Flammini, A., & Menczer, F. (2011). Detecting and tracking political abuse in social media. In Conference on weblogs and social media (ICWSM 2011). URL: <http://www.aaai.org/ocs/index.php/ICWSM/ICWSM11/paper/view/2850>.
739. Reiss, J. (1981). Statistical methods for rates and proportions (2nd ed.). (pp. 212–225). New York: John Wiley and Sons. Riquelme, F., & González-Cantergiani, P. (2016). Measuring user influence on Twitter: A survey. Information Processing & Management, 52(5), 949–975.
740. Ritter, A., Clark, S., & Etzioni, O. (2011). Named entity recognition in tweets: an experimental study. In Proceedings of the conference on empirical methods in natural language processing (pp. 1524–1534). Association for Computational Linguistics.
741. Rizzo, G., & Troncy, R. (2011). Nerd: A framework for evaluating named entity recognition tools in the web of data. In 10th international semantic web conference (ISWC'11), Demo Session, Bonn, Germany (pp. 1–4).
742. Rodríguez-Ruiz, J., Mata-Sánchez, J. I., Monroy, R., Loyola-González, O., & López-Cuevas, A. (2020). A one-class classification approach for bot detection on twitter. Computers & Security, 91, Article 101715.

743. Romero, D. M., Galuba, W., Asur, S., & Huberman, B. A. (2011). Influence and passivity in social media. In *Proceedings of the 20th international conference companion on world wide web - WWW '11* (p. 113). New York, New York, USA: ACM Press.
744. Rosa, H., Batista, F., & Carvalho, J. P. (2014). Twitter topic fuzzy fingerprints. In *2014 IEEE international conference on fuzzy systems (FUZZ-IEEE)* (pp. 776–783). IEEE.
745. Rosa, H., Carvalho, J. P., & Batista, F. (2014). Detecting a tweet's topic within a large number of portuguese twitter trends. In *3rd symposium on languages, applications and technologies. Schloss Dagstuhl-Leibniz-Zentrum fuer Informatik*.
746. Rosen, A., & Ihara, I. (2018). Giving you more characters to express yourself. <https://bit.ly/2fQ2b7W>. Twitter.com, Accessed: 2018-12-30.
747. Ross, B., Rist, M., Carbonell, G., Cabrera, B., Kurowsky, N., & Wojatzki, M. (2017). Measuring the reliability of hate speech annotations: The case of the european refugee crisis. *arXiv preprint arXiv:1701.08118*.
748. Roth, Y., & Harvey, D. (2018). How twitter is fighting spam and malicious automation. <https://bit.ly/2N40umE>. Accessed: 2018-10-20.
749. Sadikov, E., & Martinez, M. M. M. (2009). Information propagation on Twitter. In *CS322 project report*.
750. Said, A., Bowman, T. D., Abbasi, R. A., Aljohani, N. R., Hassan, S.-U., & Nawaz, R. (2019). Mining network-level properties of Twitter altmetrics data. *Scientometrics*, 120(1), 217–235.
751. Saif, H., He, Y., & Alani, H. (2012a). Alleviating data sparsity for twitter sentiment analysis. In *2nd workshop on making sense of microposts (#MSM2012): Big things come in small packages at the 21st international conference on the world wide web (WWW'12)* (pp. 2–9). *CEUR Workshop Proceedings (CEUR-WS.org)*, URL: <http://oro.open.ac.uk/38501/>.
752. Saif, H., He, Y., & Alani, H. (2012b). Semantic sentiment analysis of twitter. In *International semantic web conference* (pp. 508–524). Springer.
753. Seo, Y.-D., Kim, Y.-G., Lee, E., & Baik, D.-K. (2017). Personalized recommender system based on friendship strength in social network services. *Expert Systems with Applications*, 69, 135–148.
754. Severyn, A., & Moschitti, A. (2015). Twitter sentiment analysis with deep convolutional neural networks. In *Proceedings of the 38th international ACM SIGIR conference on research and development in information retrieval* (pp. 959–962). ACM.
755. Shao, C., Ciampaglia, G. L., Varol, O., Yang, K.-C., Flammini, A., & Menczer, F. (2018).
756. The spread of low-credibility content by social bots. *Nature Communications*, 9(1), 4787. Sharma, K., Qian, F., Jiang, H., Ruchansky, N., Zhang, M., & Liu, Y. (2019). Combating fake news: A survey on identification and mitigation techniques. *ACM Transactions on Intelligent Systems and Technology (TIST)*, 10(3), 21.
757. Sheng, S., Wardman, B., Warner, G., Cranor, L. F., Hong, J., & Zhang, C. (2009). An empirical analysis of phishing blacklists. In *Proceedings of sixth conference on email and anti-spam (CEAS)*.
758. Shi, L., Agarwal, N., Agrawal, A., Garg, R., & Spoelstra, J. (2012). Predicting US primary elections with Twitter. <https://stanford.io/2shORiz>. accessed: 2018-12-30.

759. Shrout, P., & Lane, S. (2012). Psychometrics. In M. R. Mehl, & T. S. Conner (Eds.), *Handbook of research methods for studying daily life* (pp. 302–320). New York, NY: Guilford Press. - Google Scholar - .
760. Shuai, X., Pepe, A., & Bollen, J. (2012). How the scientific community reacts to newly submitted preprints: article downloads, twitter mentions, and citations. *PloS One*, 7(11), Article e47523.
761. Sinnenberg, L., Buttenheim, A. M., Padrez, K., Mancheno, C., Ungar, L., & Merchant, R. M. (2017). Twitter as a tool for health research: a systematic review. *American Journal of Public Health*, 107(1), e1–e8.
762. Smith, A., & Anderson, M. (2018). Social media use in 2018. <https://pewrsr.ch/2FDfiFd>. Accessed: 2018-12-30.
763. Snefjella, B., Schmidtke, D., & Kuperman, V. (2018). National character stereotypes mirror language use: A study of canadian and American tweets. *PLOS ONE*, 13(11), 1–37.
764. Snow, R., O'Connor, B., Jurafsky, D., & Ng, A. Y. (2008). Cheap and fast—but is it good?: evaluating non-expert annotations for natural language tasks. In *Proceedings of the conference on empirical methods in natural language processing* (pp. 254–263). Association for Computational Linguistics.
765. Speriosu, M., Sudan, N., Upadhyay, S., & Baldrige, J. (2011). Twitter polarity classification with label propagation over lexical links and the follower graph. In *Proceedings of the first workshop on unsupervised learning in NLP* (pp. 53–63). Association for Computational Linguistics.
766. Sridharan, V., Shankar, V., & Gupta, M. (2012). Twitter games: How successful spammers pick targets. In *ACSAC '12, Proceedings of the 28th annual computer security applications conference* (pp. 389–398). New York, NY, USA: ACM.
767. Stamatelatos, G., Gyftopoulos, S., Drosatos, G., & Efraimidis, P. S. (2020). Revealing the political affinity of online entities through their twitter followers. *Information Processing & Management*, 57(2), Article 102172.
768. Stella, M., Ferrara, E., & De Domenico, M. (2018). Bots increase exposure to negative and inflammatory content in online social systems. *Proceedings of the National Academy of Sciences*, Article 201803470. Stone-Gross, B., Abman, R., Kemmerer, R. A., Kruegel, C., Steigerwald, D. G., &
769. Vigna, G. (2013). The underground economy of Fake Antivirus Software. In *Economics of information security and privacy III* (pp. 55–78). New York, NY: Springer New York. Stringhini, G., Kruegel, C., & Vigna, G. (2010). Detecting spammers on social networks.
770. In *Proceedings of the 26th annual computer security applications conference* (pp. 1–9). ACM. Stringhini, G., Wang, G., Egele, M., Kruegel, C., Vigna, G., Zheng, H., & Zhao, B. Y. (2013). Follow the green: growth and dynamics in twitter follower markets. In *Proceedings of the 2013 conference on internet measurement conference* (pp. 163–176). ACM.
771. Subrahmanian, V., Azaria, A., Durst, S., Kagan, V., Galstyan, A., Lerman, K., Zhu, L., Ferrara, E., Flammini, A., & Menczer, F. (2016). The darpa twitter bot challenge. *arXiv preprint arXiv:1601.05140*.

772. Suh, B., Hong, L., Pirolli, P., & Chi, E. H. (2010). Want to be retweeted? large scale analytics on factors impacting retweet in twitter network. In 2010 IEEE second international conference on social computing (pp. 177–184). IEEE.
773. Talukdar, P. P., & Crammer, K. (2009). New regularized algorithms for transductive learning. In Springer Berlin Heidelberg (pp. 442–457). Springer Berlin Heidelberg.
774. Tang, D., Wei, F., Qin, B., Liu, T., & Zhou, M. (2014). Coooolll: A deep learning system for twitter sentiment classification. In Proceedings of the 8th international workshop on semantic evaluation (SemEval 2014) (pp. 208–212).
775. Tang, D., Wei, F., Yang, N., Zhou, M., Liu, T., & Qin, B. (2014). Learning sentimentspecific word embedding for twitter sentiment classification. In Proceedings of the 52nd annual meeting of the association for computational linguistics (volume 1: long papers), Vol. 1 (pp. 1555–1565).
776. Tausczik, Y. R., & Pennebaker, J. W. (2010). The psychological meaning of words: LIWC and computerized text analysis methods. *Journal of Language and Social Psychology*, 29(1), 24–54.
777. Teevan, J., Ramage, D., & Morris, M. R. (2011). # twitterSearch: a comparison of microblog search and web search. In Proceedings of the fourth ACM international conference on web search and data mining (pp. 35–44). ACM.
778. Telegraph, M. (2018). Twitter to remove ‘like’ tool in a bid to improve the quality of debate. <https://bit.ly/2yExMmK>. Accessed: 2018-11-15.
779. Thelwall, M., Haustein, S., Larivière, V., & Sugimoto, C. R. (2013). Do altmetrics work? Twitter and ten other social web services. *PloS One*, 8(5), Article e64841. Thomas, K., Grier, C., & Paxson, V. (2012). Adapting social spam infrastructure for political censorship. In Presented as part of the 5th USENIX workshop on large-scale exploits and emergent threats.
780. Thomas, K., Grier, C., Song, D., & Paxson, V. (2011). Suspended accounts in retrospect: An analysis of twitter spam. In IMC ’11, Proceedings of the 2011 ACM SIGCOMM conference on internet measurement conference (pp. 243–258). New York, NY, USA: ACM.
781. Thomas, K., Li, F., Grier, C., & Paxson, V. (2014). Consequences of connectivity. In Proceedings of the 2014 ACM SIGSAC conference on computer and communications security - CCS ’14 (pp. 489–500). New York, New York, USA: ACM Press, URL: <http://dl.acm.org/citation.cfm?id=2660267.2660282>.
782. Thomas, K., McCoy, D., Grier, C., Kolcz, A., & Paxson, V. (2013). Trafficking fraudulent accounts: The role of the underground market in twitter spam and abuse. In Proceedings of the 22nd usenix security symposium.
783. Titcomb, J. (2018). Twitter makes first profit in 12-year history. <https://bit.ly/2RD1MtD>. [telegraph.co.uk](https://www.telegraph.co.uk), Accessed: 2018-11-15.
784. Travers, J., & Milgram, S. (1969). An experimental study of the small world problem. In JSTOR - sociometry (pp. 425–443). JSTOR.
785. Tromble, R., Storz, A., & Stockmann, D. (2017). We don’t know what we don’t know: When and how the use of twitter’s public APIs biases scientific inference. Available at SSRN 3079927.

786. Tromp, E., & Pechenizkiy, M. (2011). Senticorr: Multilingual sentiment analysis of personal correspondence. In Data mining workshops (ICDMW), 2011 IEEE 11th international conference on (pp. 1247–1250). IEEE. Expert Systems With Applications 164 (2021) 114006
787. Tumasjan, A., Sprenger, T. O., Sandner, P. G., & Welp, I. M. (2011). Election forecasts with Twitter: How 140 characters reflect the political landscape. *Social Science Computer Review*, 29(4), 402–418.
788. Twitter (2020). Twitter API access that scales with you and your solution. <https://developer.twitter.com/en/pricing>. - Online; accessed 2020-15-06 - .
789. Twitter Help Center (2018). The twitter rules. <https://bit.ly/2j9xU9n>. Accessed: 2018-12-30. Twitter Inc. (2018). Shutting down spammers. <https://bit.ly/2VEEZx1>.
790. Twitter.com, Accessed: 2018-12-30. Twitter official API documentation (2018). Standard API rate limits per window. <https://bit.ly/2REDPCI>. Accessed: 2018-11-15.
791. Twitter Official Blog (2018). Continuing our commitment to health. <https://bit.ly/2tocAOi>. URL: <https://bit.ly/2tocAOi> - Online; Accessed 2018-12-30 - .
792. Twitter official blog (2018). Delivering a consistent twitter experience. <https://bit.ly/2C8KX00>. Accessed: 2018-11-15.
793. Ugander, J., Karrer, B., Backstrom, L., & Marlow, C. (2011). The anatomy of the facebook social graph. arXiv preprint arXiv:1111.4503.
794. Unsvåg, E. F., & Gambäck, B. (2018). The effects of user features on twitter hate speech detection. In Proceedings of the 2nd workshop on abusive language online (ALW2) (pp. 75–85).
795. Vosoughi, S., Roy, D., & Aral, S. (2018). The spread of true and false news online. *Science*, 359(6380), 1146–1151, arXiv:<http://science.sciencemag.org/content/359/6380/1146.full.pdf>. URL: <http://science.sciencemag.org/content/359/6380/1146>.
796. Wang, A. H. (2010). Don't follow me - spam detection in twitter. In SECRIPT (pp. 142–151).
797. Wang, H., Can, D., Kazemzadeh, A., Bar, F., & Narayanan, S. (2012). A system for real-time twitter sentiment analysis of 2012 us presidential election cycle. In Proceedings of the ACL 2012 system demonstrations (pp. 115–120). Association for Computational Linguistics. Wang,
798. T., Chen, Y., Zhang, Z., Sun, P., Deng, B., & Li, X. (2011). Unbiased sampling in directed social graph. *ACM SIGCOMM Computer Communication Review*, 41(4), 401–402.
799. Wang, Y., Feng, Y., Hong, Z., Berger, R., & Luo, J. (2017). How polarized have we become? a multimodal classification of trump followers and clinton followers. In International conference on social informatics (pp. 440–456). Springer.
800. Wang, Y., Liu, J., Qu, J., Huang, Y., Chen, J., & Feng, X. (2014). Hashtag graph based topic model for tweet mining. In Data mining (ICDM), 2014 IEEE international conference on (pp. 1025–1030). IEEE.
801. Waseem, Z., & Hovy, D. (2016). Hateful symbols or hateful people? predictive features for hate speech detection on twitter. In Proceedings of the NAACL student research workshop (pp. 88–93).

802. Washha, M., Qaroush, A., Mezghani, M., & Sèdes, F. (2019). Unsupervised collectivebased framework for dynamic retraining of supervised real-time spam tweets detection model. *Expert Systems with Applications*, 135, 129–152.
803. Waugh, B., Abdipanah, M., Hashemi, O., Abdul Rahman, S., & Cook, D. M. (2013). The influence and deception of twitter: the authenticity of the narrative and slacktivism in the Australian electoral process. In *ECCWS2014-Proceedings of the 13th European conference on cyber warfare and security*. Security Research Institute, Edith Cowan University.
804. Weber, I., Garimella, V. R. K., & Batayneh, A. (2013). Secular vs. islamist polarization in egypt on twitter. In *Proceedings of the 2013 IEEE/ACM international conference on advances in social networks analysis and mining* (pp. 290–297). ACM.
805. Weitzel, L., Quaresma, P., & de Oliveira, J. P. M. (2012). Measuring node importance on twitter microblogging. In *Proceedings of the 2nd international conference on web intelligence, mining and semantics* (pp. 1–7).
806. Weng, J., Lim, E.-P., Jiang, J., & He, Q. (2010). Twitterrank. In *Proceedings of the third ACM international conference on web search and data mining - WSDM '10* (p. 261). New York, New York, USA: ACM Press, URL: <http://dl.acm.org/citation.cfm?id=1718487.1718520>.
807. Wernicke, S., & Rasche, F. (2006). FANMOD: a tool for fast network motif detection. *Bioinformatics* (Oxford, England), 22(9), 1152–1153, URL: <http://bioinformatics.oxfordjournals.org/content/22/9/1152.long>.
808. Wesslen, R., Nandu, S., Eltayeb, O., Gallicano, T., Levens, S., Jiang, M., & Shaikh, S. (2018). Bumper stickers on the twitter highway: Analyzing the speed and substance of profile changes. *SocArXiv*, URL: osf.io/preprints/socarxiv/bx9rm.
809. Wilson, R. E., Gosling, S. D., & Graham, L. T. (2012). A review of facebook research in the social sciences. *Perspectives on Psychological Science*, 7(3), 203–220.
810. Wisniewski, C. (2010). Twitter hack demonstrates the power of weak passwords. <https://bit.ly/2sgQsFi>. Accessed: 2018-12-30.
811. Wong, J. C., & Solon, O. (2018). Google to shut down google+ after failing to disclose user data leak. *The Guardian*, URL: <https://www.theguardian.com/technology/2018/oct/08/google-plussecurity-breach-wall-street-journal>.
812. Wu, S., Hofman, J. M., Mason, W. A., & Watts, D. J. (2011). Who says what to whom on twitter. In *Proceedings of the 20th international conference on world wide web - WWW '11* (p. 705). New York, New York, USA: ACM Press.
813. Wu, Z., Pi, D., Chen, J., Xie, M., & Cao, J. (2020). Rumor detection based on propagation graph neural network with attention mechanism. *Expert Systems with Applications*, Article 113595.
814. Wu, T., Wen, S., Xiang, Y., & Zhou, W. (2018). Twitter spam detection: Survey of new approaches and comparative study. *Computers & Security*, 76, 265–284.
815. Yang, J., & Leskovec, J. (2011). Patterns of temporal variation in online media. In *Proceedings of the fourth ACM international conference on web search and data mining* (pp. 177–186). ACM.

816. Yang, K.-C., Varol, O., Davis, C. A., Ferrara, E., Flammini, A., & Menczer, F. (2019). Arming the public with artificial intelligence to counter social bots. *Human Behavior and Emerging Technologies*, 1(1), 48–61.
817. Ye, S., & Wu, S. (2010). Measuring message propagation and social influence on Twitter. com. In *International conference on social informatics* (pp. 216–231). Springer.
818. Yu, J., & Muñoz-Justicia, J. (2020). Free and low-cost twitter research software tools for social science. *Social Science Computer Review*, Article 0894439320904318.
819. Zhang, L., Ghosh, R., Dekhil, M., Hsu, M., & Liu, B. (2011). Combining lexicon-based and learning-based methods for twitter sentiment analysis, Vol. 89: Technical Report HPL-2011, HP Laboratories.
820. Zhao, J., Dong, L., Wu, J., & Xu, K. (2012). Moodlens: an emoticon-based sentiment analysis system for chinese tweets. In *Proceedings of the 18th ACM SIGKDD international conference on knowledge discovery and data mining* (pp. 1528–1531). ACM.
821. Zhao, W. X., Jiang, J., Weng, J., He, J., Lim, E.-P., Yan, H., & Li, X. (2011). Comparing twitter and traditional media using topic models. In *European conference on information retrieval* (pp. 338–349). Springer.
822. Zou, B., Lamos, V., Gorton, R., & Cox, I. J. (2016). On infectious intestinal disease surveillance using social media content. In *Proceedings of the 6th international conference on digital health conference* (pp. 157–161). ACM.
823. Zubiaga, A., Liakata, M., & Procter, R. (2016). Learning reporting dynamics during breaking news for rumour detection in social media. *arXiv preprint arXiv:1610. 07363*.
824. S. Tavernise, “As fake news spreads lies, more readers shrug at the truth,” Dec 2016. - Online - . Available: <https://www.nytimes.com/2016/12/06/us/fakenewspartisanrepublicandemocrat.html>
825. J. Gottfried and E. Shearer, “News use across social media platforms 2016,” Dec 2017. - Online - . Available: <https://www.journalism.org/2016/05/26/newsuseacrosssocialmediaplatforms2016/>
826. V. Perez-Rosas, B. Kleinberg, A. Lefevre, and R. Mihalcea, “Automatic ´ detection of fake news,” in *Proceedings of the 27th International Conference on computational Linguistics*, 2018, pp. 3391–3401.
827. C. Silverman, “This analysis shows how viral fake election news stories outperformed real news on facebook,” Nov 2016. - Online - . Available: <https://www.buzzfeednews.com/article/craigsilverman/viralfakeelectionnewsoutpermedrealnewsonfacebook>
828. L. H. OWEN, “Facebook is just gonna come out and start calling fake news fake (well, “false”).” - Online - . Available: <https://www.niemanlab.org/2019/10/facebook-is-just-gonna-come-out-and-start-calling-fake-news-fake-well-false/>
829. D. Pomerleau and D. Rao. Fake news challenge stage 1 (fnc-i): Stance detection. - Online - . Available: <http://www.fakenewschallenge.org/>
830. B. Sean, S. Doug, and P. Yuxi, “Talos targets disinformation with fake news challenge victory,” 2017. - Online - . Available: <http://blog.talosintelligence.com/2017/06/talosfakenewschallenge.html>

831. A. Hanselowski, A. PVS, B. Schiller, F. Caspelherr, D. Chaudhuri, C. M. Meyer, and I. Gurevych, "A retrospective analysis of the fake news challenge stance detection task," arXiv preprint arXiv:1806.05180, 2018. (2019)
832. Qatar international fake news detection and annotation contest. - Online - . Available: <https://sites.google.com/view/fakenews-contest>
833. I. Solaiman, "Gpt-2: 1.5b release," Nov 2019. - Online - . Available: <https://openai.com/blog/gpt-2-1-5b-release/>
834. S. Vosoughi, D. Roy, and S. Aral, "The spread of true and false news online," *Science*, vol. 359, no. 6380, pp. 1146–1151, 2018.
835. R. Baly, G. Karadzhov, D. Alexandrov, J. Glass, and P. Nakov, "Predicting factuality of reporting and bias of news media sources," arXiv preprint arXiv:1810.01765, 2018.
836. S. Afroz, M. Brennan, and R. Greenstadt, "Detecting hoaxes, frauds, and deception in writing style online," in 2012 IEEE Symposium on Security and Privacy. IEEE, 2012, pp. 461–475.
837. V. Rubin, N. Conroy, Y. Chen, and S. Cornwell, "Fake news or truth? using satirical cues to detect potentially misleading news," in Proceedings of the second workshop on computational approaches to deception detection, 2016, pp. 7–17.
838. H. Rashkin, E. Choi, J. Y. Jang, S. Volkova, and Y. Choi, "Truth of varying shades: Analyzing language in fake news and political fact-checking," in Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, 2017, pp. 2931–2937.
839. M. Potthast, J. Kiesel, K. Reinartz, J. Bevendorff, and B. Stein, "A stylometric inquiry into hyperpartisan and fake news," arXiv preprint arXiv:1702.05638, 2017.
840. G. Bhatt, A. Sharma, S. Sharma, A. Nagpal, B. Raman, and A. Mittal, "Combining neural, statistical and external features for fake news stance identification," in Companion Proceedings of the The Web Conference 2018. International World Wide Web Conferences Steering Committee, 2018, pp. 1353–1357.
841. L. Borges, B. Martins, and P. Calado, "Combining similarity features and deep representation learning for stance detection in the context of checking fake news," *Journal of Data and Information Quality (JDIQ)*, vol. 11, no. 3, p. 14, 2019.
842. J. G. Fiscus and G. R. Doddington, "Topic detection and tracking evaluation overview," in Topic detection and tracking. Springer, 2002, pp. 17–31.
843. P. Han and N. Zhou, "A framework for detecting key topics in social networks," in Proceedings of the 2nd International Conference on Big Data Technologies. ACM, 2019, pp. 235–239.
844. Y. Cha and J. Cho, "Social-network analysis using topic models," in Proceedings of the 35th international ACM SIGIR conference on Research and development in information retrieval. ACM, 2012, pp. 565–574.
845. T. N. Rubin, A. Chambers, P. Smyth, and M. Steyvers, "Statistical topic models for multi-label document classification," *Machine learning*, vol. 88, no. 1-2, pp. 157–208, 2012.
846. R. Ibrahim, A. Elbagoury, M. S. Kamel, and F. Karray, "Tools and approaches for topic detection from twitter streams: survey," *Knowledge and Information Systems*, vol. 54, no. 3, pp. 511–539, 2018.

847. J. M. Schultz and M. Y. Liberman, "Towards a "universal dictionary" for multi-language information retrieval applications," in *Topic detection and tracking*. Springer, 2002, pp. 225–241.
848. G. Kumaran and J. Allan, "Text classification and named entities for new event detection," in *Proceedings of the 27th annual international ACM SIGIR conference on Research and development in information retrieval*. ACM, 2004, pp. 297–304.
849. S. I. Nikolenko, S. Koltcov, and O. Koltsova, "Topic modelling for qualitative studies," *Journal of Information Science*, vol. 43, no. 1, pp. 88–102, 2017.
850. G. Fuentes-Pineda and I. V. Meza-Ruiz, "Topic discovery in massive text corpora based on min-hashing," *Expert Systems with Applications*, 2019.
851. H.-J. Choi and C. H. Park, "Emerging topic detection in twitter stream based on high utility pattern mining," *Expert Systems with Applications*, vol. 115, pp. 27–36, 2019.
852. D. M. Blei, A. Y. Ng, and M. I. Jordan, "Latent dirichlet allocation," *Journal of machine Learning research*, vol. 3, no. Jan, pp. 993–1022, 2003.
853. M. Rosen-Zvi, T. Griffiths, M. Steyvers, and P. Smyth, "The author-topic model for authors and documents," in *Proceedings of the 20th conference on Uncertainty in artificial intelligence*. AUAI Press, 2004, pp. 487–494.
854. D. Ramage, D. Hall, R. Nallapati, and C. D. Manning, "Labeled lda: A supervised topic model for credit attribution in multi-labeled corpora," in *Proceedings of the 2009 Conference on Empirical Methods in Natural Language Processing: Volume 1-Volume 1*. Association for Computational Linguistics, 2009, pp. 248–256.
855. D. Quercia, H. Askham, and J. Crowcroft, "Tweetlda: supervised topic classification and link prediction in twitter," in *Proceedings of the 4th Annual ACM Web Science Conference*. ACM, 2012, pp. 247–250.
856. K. Kowsari, M. Heidarysafa, D. E. Brown, K. J. Meimandi, and L. E. Barnes, "Rmdl: Random multimodel deep learning for classification," in *Proceedings of the 2nd International Conference on Information System and Data Mining*. ACM, 2018, pp. 19–28.
857. N. Ding, Z. Li, Z. Liu, H. Zheng, and Z. Lin, "Event detection with trigger-aware lattice neural network," in *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, 2019, pp. 347–356.
858. G. Burel, H. Saif, M. Fernandez, and H. Alani, "On semantics and deep learning for event detection in crisis situations," 2017.
859. K. Lee, J. Caverlee, and S. Webb, "Uncovering social spammers: social honeypots+ machine learning," in *Proceedings of the 33rd international ACM SIGIR conference on Research and development in information retrieval*. ACM, 2010, pp. 435–442.
860. Z. Gilani, R. Farahbakhsh, G. Tyson, L. Wang, and J. Crowcroft, "Of bots and humans (on twitter)," in *Proceedings of the 2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2017*. ACM, 2017, pp. 349–354.
861. H. Almerikhi and T. Elsayed, "Detecting automatically-generated arabic tweets," in *AIRS*. Springer, 2015, pp. 123–134.

862. S. Mukherjee and G. Weikum, "Leveraging joint interactions for credibility analysis in news communities," in Proceedings of the 24th ACM International on Conference on Information and Knowledge Management. ACM, 2015, pp. 353–362.
863. Z. Yang, Z. Dai, Y. Yang, J. Carbonell, R. Salakhutdinov, and Q. V. Le, "Xlnet: Generalized autoregressive pretraining for language understanding," arXiv preprint arXiv:1906.08237, 2019.
864. Y. Liu, M. Ott, N. Goyal, J. Du, M. Joshi, D. Chen, O. Levy, M. Lewis, L. Zettlemoyer, and V. Stoyanov, "Roberta: A robustly optimized bert pretraining approach," arXiv preprint arXiv:1907.11692, 2019.
865. J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "Bert: Pre-training of deep bidirectional transformers for language understanding," arXiv preprint arXiv:1810.04805, 2018.
866. M. E. Peters, M. Neumann, M. Iyyer, M. Gardner, C. Clark, K. Lee, and L. Zettlemoyer, "Deep contextualized word representations," arXiv preprint arXiv:1802.05365, 2018.
867. Y. Wang, M. Huang, L. Zhao et al., "Attention-based lstm for aspectlevel sentiment classification," in Proceedings of the 2016 conference on empirical methods in natural language processing, 2016, pp. 606–615.
868. J. Pennington, R. Socher, and C. Manning, "Glove: Global vectors for word representation," in Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP). Doha, Qatar: Association for Computational Linguistics, Oct. 2014, pp. 1532– 1543. - Online - . Available: <https://www.aclweb.org/anthology/D14-1162>
869. J.-J. Lee, P.-H. Lee, S.-W. Lee, A. Yuille, and C. Koch, "Adaboost for text detection in natural scene," in 2011 International Conference on Document Analysis and Recognition. IEEE, 2011, pp. 429–434.
870. T. Chen, T. He, M. Benesty, V. Khotilovich, and Y. Tang, "Xgboost: extreme gradient boosting," R package version 0.4-2, pp. 1–4, 2015.
871. Antropova, M. (2014). Йохан Бекман: В Финляндии формируют банк данных о сторонниках политики Путина - Johan Bäckman: A database of Putin's supporters is formed in Finland - . Notum.info, 23 September. <http://www.notum.info/news/politika/johan-bekman-v-finlyandii-formiruyut-bank-dannyix-o-storonnikax-politiki-putina> Accessed 18 April 2016.131 European View (2016) 15:121–132
872. Aro, J. (2014). Oletko joutunut Venäjän troliarmeijan kohteeksi—kerro kokemuksiasi - Have you become a target of the Russian troll army—Share your experiences - . Yle.fi, 15 September. http://yle.fi/uutiset/oletko_joutunut_venajan_trollarmeijan_kohteeksi_kerro_kokemuksiasi/7470016. Accessed 18 April 2016.
873. Aro, J. (2015a). My year as a pro-Russia troll-magnet: International shaming campaign and an SMS from dead father. Kioski.yle.fi, 9 November. <http://kioski.yle.fi/omat/myyearasaprussiattrollmagnet>. Accessed 18 April 2016.
874. Aro, J. (2015b). This is what pro-Russia Internet propaganda feels like—Finns have been tricked into believing in lies. Kioski.yle.fi, 24 June. <http://kioski.yle.fi/omat/thisiswhatprussiainternetpropagandafeelslike>. Accessed 18 April 2016.

875. Aro, J. (2015c). Yle Kioski investigated: This is how pro-Russia trolls manipulate Finns online—Check the list of forums favoured by propagandists. Kioski.yle.fi, 24 June.
876. <http://kioski.yle.fi/omat/troll-piece-2-english>. Accessed 18 April 2016.
877. Aro, J., & Mäkeläinen, M. (2015). Yle Kioski traces the origins of Russian social media propaganda—Never-before-seen material from the troll factory. Kioski.yle.fi, 20 February. <http://kioski.yle.fi/omat/at-the-origins-of-russian-propaganda>. Accessed 18 April 2016.
878. Facebook. (2016). South Front. <https://www.facebook.com/SouthFrontEnTwo/?fref=ts>. Accessed 7 April 2016.
879. Garmazhapova, A. (2013). Где живут тролли. И кто их кормит - Where the trolls live. And who feeds them - . Novaya Gazeta, 7 September. <http://www.novayagazeta.ru/politics/59889.html>. Accessed 7 April 2016.
880. Giles, K. (2016). Russia's 'new' tools for confronting the West—Continuity and innovation in Moscow's exercise of power. Chatham House. London. 8 April. <https://www.chathamhouse.org/sites/files/chathamhouse/publications/research/20160321russiasnewtoolsgiles.pdf>. Accessed 14 April 2016.
881. Hallamaa, T. (2015). Presidentti Sauli Niinistö infosodasta: me kaikki olemme maanpuolustajia - President Sauli Niinistö on info war: We are all national defenders - . Yle.fi, 17 October. http://yle.fi/uutiset/presidentti_niinisto_infosodasta_me_kaiikki_olemmme_maanpuolustajia/8388624. Accessed 7 April 2016.
882. Illarionov, A. (2014). Challenges of (dis)information war for liberal democratic regime and on possible counter-strategy. XIX Open Society Forum: Soft Power. Tallinn, 18 September.
883. Interfax. (2015). Shoigu: Information becomes another armed forces component. 28 March. <http://www.interfax.com/newsinf.asp?id=581851>. Accessed 7 April 2016.132
884. European View (2016) 15:121–132
885. Jantunen, S. (2016). Information war—Yrittääkö Venäjä horjuttaa Suomea informaatiotosodankäynnin keinoin - Information war—Is Russia trying to destabilise Finland with information war tactics? - . Lecture at the Finnish Club. Helsinki, 11 January.
886. Russian Ministry of Foreign Affairs. (2000). Information security doctrine of the Russian Federation. 9 September. <http://archive.mid.ru/bdomp/ns-osndoc.nsf/1e5f0de28fe77fdcc32575d900298676/2deaa9ee15ddd24bc32575d9002c442b!OpenDocument>. Accessed 7 April 2016.
887. Russkaja Narodnaja Linya. (2014). Йохан Бекман: « Многие финские журналисты являются завербованными сотрудниками американо-прибалтийских спецслужб » - Johan Bäckman: 'Many Finnish journalists are recruited as employees of American–Baltic special services' - . 19 September. http://ruskline.ru/news_rl/2014/09/19/johan_bekman_mnogie_finskie_zhurnalisty_yavlyayutsya_zaverbovannymi_sotrudnikami_amerikanopribaltijskih_specsluzhb/. Accessed 18 April 2016.
888. South Front. (2015). Southfront: The knowledge you can rely on. 21 November. <https://southfront.org/southfront-knowledge-can-rely/>. Accessed 18 April 2016.

889. South Front. (2016). Analysis. Intelligence. <https://southfront.org/>. Accessed 7 April 2016.
890. E. Adar and A. Adamic, Lada. Tracking information epidemics in blogspace. In 2005 IEEE/WIC/ACM International Conference on Web Intelligence, Compiegne University of Technology, France, 2005.
891. S. Aral, L. Muchnik, and A. Sundararajan. Distinguishing influence-based contagion from homophily-driven diffusion in dynamic networks. *Proceedings of the National Academy of Sciences*, 106(51):21544, 2009.
892. E. Bakshy, B. Karrer, and A. Adamic, Lada. Social influence and the diffusion of user-created content. In 10th ACM Conference on Electronic Commerce, Stanford, California, 2009. Association of Computing Machinery.
893. F. M. Bass. A new product growth for model consumer durables. *Management Science*, 15(5):215–227, 1969.
894. R. A. Berk. An introduction to sample selection bias in sociological data. *American Sociological Review*, 48(3):386–398, 1983.
895. L. Breiman, J. Friedman, R. Olshen, and C. Stone. *Classification and regression trees*. Chapman & Hall/CRC, 1984.
896. M. Cha, H. Haddadi, F. Benevenuto, and K. P. Gummadi. Measuring user influence on twitter: The million follower fallacy. In 4th Int'l AAAI Conference on Weblogs and Social Media, Washington, DC, 2010.
897. R. M. Dawes. *Everyday irrationality: How pseudo-scientists, lunatics, and the rest of us systematically fail to think rationally*. Westview Pr, 2002.
898. J. Denrell. Vicarious learning, undersampling of failure, and the myths of management. *Organization Science*, 14(3):227–243, 2003.
899. M. Gladwell. *The Tipping Point: How Little Things Can Make a Big Difference*. Little Brown, New York, 2000.
900. J. Goldenberg, S. Han, D. R. Lehmann, and J. W. Hong. The role of hubs in the adoption process. *Journal of Marketing*, 73(2):1–13, 2009.
901. A. Goyal, F. Bonchi, and L. V. S. Lakshmanan. Discovering leaders from community actions. pages 499–508. ACM, 2008. Proceeding of the 17th ACM conference on Information and knowledge management.
902. D. Gruhl, R. Guha, D. Liben-Nowell, and A. Tomkins. Information diffusion through blogspace. pages 491–501. ACM New York, NY, USA, 2004.
903. E. Katz and P. F. Lazarsfeld. *Personal influence; the part played by people in the flow of mass communications*. Free Press, Glencoe, Ill. 1955.
904. E. Keller and J. Berry. *The Influentials: One American in Ten Tells the Other Nine How to Vote, Where to Eat, and What to Buy*. Free Press, New York, NY, 2003.
905. D. Kempe, J. Kleinberg, and E. Tardos. Maximizing the spread of influence through a social network. In 9th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Washington, DC, USA., 2003. Association of Computing Machinery.

906. A. Kittur, E. H. Chi, and B. Suh. Crowdsourcing user studies with mechanical turk. Proceedings of the twenty-sixth annual SIGCHI conference on Human factors in computing systems, 2008.
907. H. Kwak, C. Lee, H. Park, and S. Moon. What is twitter, a social network or a news media? pages 591–600. ACM, 2010.
908. A. Leavitt, E. Burchard, D. Fisher, and S. Gilbert. The influentials: New approaches for analyzing influence on twitter.
909. J. Leskovec, A. Adamic, Lada, and A. Huberman, Bernardo. The dynamics of viral marketing. ACM Trans. Web, 1(1):5, 2007.
910. D. Liben-Nowell and J. Kleinberg. Tracing information flow on a global scale using internet chain-letter data. Proceedings of the National Academy of Sciences, 105(12):4633, 2008.
911. W. Mason and S. Suri. Conducting Behavioral Research on Amazon’s Mechanical Turk. SSRN eLibrary, 2010.
912. W. Mason and D. J. Watts. Financial incentives and the performance of crowds. Proceedings of the ACM SIGKDD Workshop on Human Computation, pages 77–85, 2009.
913. S. A. Munson and P. Resnick. Presenting diverse political opinions: how and how much. pages 1457–1466. ACM, 2010.
914. R. R. Picard and R. D. Cook. Cross-validation of regression models. Journal of the American Statistical Association, 79(387):575–583, 1984.
915. E. M. Rogers. Diffusion of innovations. Free Press, New York, 4th edition, 1995.
916. V. S. Sheng, F. Provost, and P. G. Ipeirotis. Get another label? improving data quality and data mining using multiple, noisy labelers. pages 614–622. ACM, 2008.
917. R. Snow, B. O’Connor, D. Jurafsky, and A. Y. Ng. Cheap and fast-but is it good? evaluating non-expert annotations for natural language tasks, 2008.
918. E. S. Sun, I. Rosenn, C. A. Marlow, and T. M. Lento. Gesundheit! modeling contagion through facebook news feed. In International Conference on Weblogs and Social Media, San Jose, CA, 2009. AAAI.
919. B. Tomlinson and C. Cockram. Sars: Experience at prince of wales hospital, hong kong. The Lancet, 361(9368):1486–1487, 2003.
920. D. J. Watts. A simple model of information cascades on random networks. Proceedings of the National Academy of Science, U.S.A., 99:5766–5771, 2002.
921. D. J. Watts and P. S. Dodds. Influentials, networks, and public opinion formation. Journal of Consumer Research, 34:441–458, 2007.
922. D. J. Watts and J. Peretti. Viral marketing for the real world. Harvard Business Review, May:22–23, 2007.
923. G. Weimann. The Influentials: People Who Influence People. State University of New York Press, Albany, NY, 1994.
924. J. Weng, E. P. Lim, J. Jiang, and Q. He. Twitterrank: finding topic-sensitive influential twitterers. pages 261–270. ACM, 2010.

925. E. Adar and A. Adamic, Lada. Tracking information epidemics in blogspace. In 2005 IEEE/WIC/ACM International Conference on Web Intelligence, Compiègne University of Technology, France, 2005.
926. S. Aral, L. Muchnik, and A. Sundararajan. Distinguishing influence-based contagion from homophily-driven diffusion in dynamic networks. *Proceedings of the National Academy of Sciences*, 106(51):21544, 2009.
927. E. Bakshy, B. Karrer, and A. Adamic, Lada. Social influence and the diffusion of user-created content. In 10th ACM Conference on Electronic Commerce, Stanford, California, 2009. Association of Computing Machinery.
928. F. M. Bass. A new product growth for model consumer durables. *Management Science*, 15(5):215–227, 1969.
929. R. A. Berk. An introduction to sample selection bias in sociological data. *American Sociological Review*, 48(3):386–398, 1983.
930. L. Breiman, J. Friedman, R. Olshen, and C. Stone. *Classification and regression trees*. Chapman & Hall/CRC, 1984.
931. D. Centola and M. Macy. Complex contagions and the weakness of long ties. *ajs*, 113(3):702–34, 2007.
932. M. Cha, H. Haddadi, F. Benevenuto, and K. P. Gummadi. Measuring user influence on twitter: The million follower fallacy. In 4th Int’l AAAI Conference on Weblogs and Social Media, Washington, DC, 2010.
933. R. M. Dawes. *Everyday irrationality: How pseudo-scientists, lunatics, and the rest of us systematically fail to think rationally*. Westview Pr, 2002.
934. M. Gladwell. *The Tipping Point: How Little Things Can Make a Big Difference*. Little Brown, New York, 2000.
935. J. Goldenberg, S. Han, D. R. Lehmann, and J. W. Hong. The role of hubs in the adoption process. *Journal of Marketing*, 73(2):1–13, 2009.
936. M. S. Granovetter. Threshold models of collective behavior. *American Journal of Sociology*, 83(6):1420–1443, 1978.
937. D. Gruhl, R. Guha, D. Liben-Nowell, and A. Tomkins. Information diffusion through blogspace. pages 491–501. ACM New York, NY, USA, 2004.
938. E. Katz and P. F. Lazarsfeld. *Personal influence; the part played by people in the flow of mass communications*. Free Press, Glencoe, Ill. 1955.
939. E. Keller and J. Berry. *The Influentials: One American in Ten Tells the Other Nine How to Vote, Where to Eat, and What to Buy*. Free Press, New York, NY, 2003.
940. D. Kempe, J. Kleinberg, and E. Tardos. Maximizing the spread of influence through a social network. In 9th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Washington, DC, USA., 2003. Association of Computing Machinery.
941. A. Kittur, E. H. Chi, and B. Suh. Crowdsourcing user studies with mechanical turk. *Proceedings of the twenty-sixth annual SIGCHI conference on Human factors in computing systems*, 2008.

942. H. Kwak, C. Lee, H. Park, and S. Moon. What is twitter, a social network or a news media? pages 591–600. ACM, 2010.
943. A. Leavitt, E. Burchard, D. Fisher, and S. Gilbert. The influentials: New approaches for analyzing influence on twitter.
944. J. Leskovec, A. Adamic, Lada, and A. Huberman, Bernardo. The dynamics of viral marketing. *ACM Trans. Web*, 1(1):5, 2007.
945. D. Liben-Nowell and J. Kleinberg. Tracing information flow on a global scale using internet chain-letter data. *Proceedings of the National Academy of Sciences*, 105(12):4633, 2008.
946. W. Mason and D. J. Watts. Financial incentives and the performance of crowds. *Proceedings of the ACM SIGKDD Workshop on Human Computation*, pages 77–85, 2009.
947. S. A. Munson and P. Resnick. Presenting diverse political opinions: how and how much. pages 1457–1466. ACM, 2010.
948. M. E. J. Newman and D. J. Watts. Scaling and percolation in the small-world network model. *Physical Review E*, 60(6):7332–7342, 1999.
949. R. Pastor-Satorras and A. Vespignani. Epidemic spreading in scale-free networks. *Physical Review Letters*, 86(14):3200–3203, 2001.
950. R. R. Picard and R. D. Cook. Cross-validation of regression models. *Journal of the American Statistical Association*, 79(387):575–583, 1984.
951. E. M. Rogers. *Diffusion of innovations*. Free Press, New York, 4th edition, 1995.
952. T. C. Schelling. Hockey helmets, concealed weapons, and daylight saving: A study of binary choices with externalities. *Journal of Conflict Resolution*, 17(3):381–428, 1973.
953. V. S. Sheng, F. Provost, and P. G. Ipeirotis. Get another label? improving data quality and data mining using multiple, noisy labelers. pages 614–622. ACM, 2008.
954. R. Snow, B. O’Connor, D. Jurafsky, and A. Y. Ng. Cheap and fast, but is it good? evaluating non-expert annotations for natural language tasks, 2008.
955. E. S. Sun, I. Rosenn, C. A. Marlow, and T. M. Lento. Gesundheit! modeling contagion through facebook news feed. In *International Conference on Weblogs and Social Media*, San Jose, CA, 2009. AAAI.
956. B. Tomlinson and C. Cockram. Sars: Experience at prince of wales hospital, hong kong. *The Lancet*, 361(9368):1486–1487, 2003.
957. D. J. Watts. A simple model of information cascades on random networks. *Proceedings of the National Academy of Science, U.S.A.*, 99:5766–5771, 2002.
958. D. J. Watts and P. S. Dodds. Influentials, networks, and public opinion formation. *Journal of Consumer Research*, 34:441–458, 2007.
959. D. J. Watts and J. Peretti. Viral marketing for the real world. *Harvard Business Review*, May:22–23, 2007.
960. D. J. Watts and S. H. Strogatz. Collective dynamics of ‘small-world’ networks. *Nature*, 393(6684):440–442, 1998.

961. G. Weimann. *The Influentials: People Who Influence People*. State University of New York Press, Albany, NY, 1994.
962. J. Weng, E. P. Lim, J. Jiang, and Q. He. Twitterrank: finding topic-sensitive influential twitterers. pages 261–270. ACM, 2010.
963. Pepa Atanasova, Lluís Màrquez, Alberto Barrón-Cedeño, Tamer Elsayed, Reem Suwaileh, Wajdi Zaghouani, Spas Kyuchukov, Giovanni Da San Martino, and Preslav Nakov. 2018. Overview of the
964. CLEF-2018 CheckThat! lab on automatic identification and verification of political claims, task 1: Check-worthiness. In *CLEF 2018 Working Notes. Working Notes of CLEF 2018 - Conference and Labs of the Evaluation Forum, CEUR Workshop Proceedings, Avignon, France*. CEUR-WS.org.
965. Stefano Baccianella, Andrea Esuli, and Fabrizio Sebastiani. 2009. Evaluation measures for ordinal regression. In *Proceedings of the 9th IEEE International Conference on Intelligent Systems Design and Applications, ISDA '09*, pages 283–287, Pisa, Italy.
966. Ricardo Baeza-Yates. 2018. Bias on the web. *Commun. ACM*, 61(6):54–61.
967. Ramy Baly, Mitra Mohtarami, James Glass, Lluís Màrquez, Alessandro Moschitti, and Preslav Nakov. 2018. Integrating stance detection and fact checking in a unified corpus. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT '18*, pages 21– 27, New Orleans, LA, USA.
968. Alberto Barrón-Cedeño, Tamer Elsayed, Reem Suwaileh, Lluís Màrquez, Pepa Atanasova, Wajdi Zaghouani, Spas Kyuchukov, Giovanni Da San Martino, and Preslav Nakov. 2018. Overview of the CLEF-2018 CheckThat! lab on automatic identification and verification of political claims, task 2: Factuality. In *CLEF 2018 Working Notes. Working Notes of CLEF 2018 - Conference and Labs of the Evaluation Forum, CEUR Workshop Proceedings, Avignon, France*. CEUR-WS.org.
969. Ram B Basnet, Andrew H Sung, and Quingzhong Liu. 2014. Learning to detect phishing URLs. *International Journal of Research in Engineering and Technology*, 3(6):11–24.
970. Ann M Brill. 2001. Online journalists embrace new marketing function. *Newspaper Research Journal*, 22(2):28.
971. Kevin R. Canini, Bongwon Suh, and Peter L. Pirolli. 2011. Finding credible information sources in social networks based on content and social structure. In *Proceedings of the IEEE International Conference on Privacy, Security, Risk, and Trust, and the IEEE International Conference on Social Computing, SocialCom/PASSAT '11*, pages 1–8, Boston, MA, USA.
972. Carlos Castillo, Marcelo Mendoza, and Barbara Poblete. 2011. Information credibility on Twitter. In *Proceedings of the 20th International Conference on World Wide Web, WWW '11*, pages 675–684, Hyderabad, India.3537
973. Abhijnan Chakraborty, Bhargavi Paranjape, Kakarla Kakarla, and Niloy Ganguly. 2016. Stop clickbait: Detecting and preventing clickbaits in online news media. In *Proceedings of the 2016 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, ASONAM '16*, pages 9–16, San Francisco, CA, USA.
974. Cheng Chen, Kui Wu, Venkatesh Srinivasan, and Xudong Zhang. 2013. Battling the Internet Water Army: detection of hidden paid posters. In *Proceedings of the 2013 IEEE/ACM*

International Conference on Advances in Social Networks Analysis and Mining, ASONAM '13, pages 116–120, Niagara, Canada.

975. Kareem Darwish, Dimitar Alexandrov, Preslav Nakov, and Yelena Mejova. 2017a. Seminar users in the Arabic Twitter sphere. In *Proceedings of the 9th International Conference on Social Informatics, SocInfo '17*, pages 91–108, Oxford, UK.
976. Kareem Darwish, Walid Magdy, and Tahar Zanouda. 2017b. Improved stance prediction in a user similarity feature space. In *Proceedings of the Conference on Advances in Social Networks Analysis and Mining, ASONAM '17*, pages 145–148, Sydney, Australia.
977. Sohan De Sarkar, Fan Yang, and Arjun Mukherjee. 2018. Attending sentences to detect satirical fake news. In *Proceedings of the 27th International Conference on Computational Linguistics, COL-ING '18*, pages 3371–3380, Santa Fe, NM, USA.
978. Leon Derczynski, Kalina Bontcheva, Maria Liakata, Rob Procter, Geraldine Wong Sak Hoi, and Arkaitz Zubiaga. 2017. SemEval-2017 Task 8: RumourEval: Determining rumour veracity and support for rumours. In *Proceedings of the 11th International Workshop on Semantic Evaluation, SemEval '17*, pages 60–67, Vancouver, Canada.
979. Xin Luna Dong, Evgeniy Gabrilovich, Kevin Murphy, Van Dang, Wilko Horn, Camillo Lugaresi, Shaohua Sun, and Wei Zhang. 2015. Knowledge-based trust: Estimating the trustworthiness of web sources. *Proc. VLDB Endow.*, 8(9):938–949.
980. Sebastian Dungs, Ahmet Aker, Norbert Fuhr, and Kalina Bontcheva. 2018. Can rumour stance alone predict veracity? In *Proceedings of the 27th International Conference on Computational Linguistics, COLING '18*, pages 3360–3370, Santa Fe, NM, USA.
981. Howard Finberg, Martha L Stone, and Diane Lynch. 2002. Digital journalism credibility study. Online News Association. Retrieved November, 3:2003.
982. Jesse Graham, Jonathan Haidt, and Brian A Nosek. 2009. Liberals and conservatives rely on different sets of moral foundations. *Journal of personality and social psychology*, 96(5):1029. Andreas Hanselowski, Avinesh PVS, Benjamin
983. Schiller, Felix Caspelherr, Debanjan Chaudhuri, Christian M. Meyer, and Iryna Gurevych. 2018. A retrospective analysis of the fake news challenge stance-detection task. In *Proceedings of the 27th International Conference on Computational Linguistics, COLING '18*, pages 1859–1874, Santa Fe, NM, USA.
984. Momchil Hardalov, Ivan Koychev, and Preslav Nakov. 2016. In search of credible news. In *Proceedings of the 17th International Conference on Artificial Intelligence: Methodology, Systems, and Applications, AIMSA '16*, pages 172–180, Varna, Bulgaria.
985. Benjamin Horne and Sibel Adali. 2017. This just in: Fake news packs a lot in title, uses simpler, repetitive content in text body, more similar to satire than real news. *CoRR*, abs/1703.09398.
986. Benjamin Horne, Sibel Adali, and Sujoy Sikdar. 2017. Identifying the social signals that drive online discussions: A case study of Reddit communities. In *Proceedings of the 26th IEEE International Conference on Computer Communication and Networks, ICCCN '17*, pages 1–9, Vancouver, Canada.
987. Benjamin D. Horne, William Dron, Sara Khedr, and Sibel Adali. 2018a. Assessing the news landscape: A multi-module toolkit for evaluating the credibility of news. In *Proceedings of the The Web Conference, WWW '18*, pages 235–238, Lyon, France.

988. Benjamin D. Horne, Sara Khedr, and Sibel Adali. 2018b. Sampling the news producers: A large news and feature data set for the study of the complex media landscape. In *Proceedings of the Twelfth International Conference on Web and Social Media, ICWSM '18*, pages 518–527, Stanford, CA, USA.
989. Clayton Hutto and Eric Gilbert. 2014. VADER: A parsimonious rule-based model for sentiment analysis of social media text. In *Proceedings of the 8th International Conference on Weblogs and Social Media, ICWSM '14*, Ann Arbor, MI, USA.
990. Georgi Karadzhov, Pepa Gencheva, Preslav Nakov, and Ivan Koychev. 2017a. We built a fake news & click-bait filter: What happened next will blow your mind! In *Proceedings of the International Conference on Recent Advances in Natural Language Processing, RANLP '17*, pages 334–343, Varna, Bulgaria.
991. Georgi Karadzhov, Preslav Nakov, Lluís Màrquez, Alberto Barrón-Cedeño, and Ivan Koychev. 2017b. Fully automated fact checking using external sources. In *Proceedings of the International Conference on Recent Advances in Natural Language Processing, RANLP '17*, pages 344–353, Varna, Bulgaria.
992. Elena Kochkina, Maria Liakata, and Arkaitz Zubiaga. 2018. All-in-one: Multi-task learning for rumour verification. In *Proceedings of the 27th International Conference on Computational Linguistics, COLING '18*, pages 3402–3413, Santa Fe, NM, USA.3538
993. David M.J. Lazer, Matthew A. Baum, Yochai Benkler, Adam J. Berinsky, Kelly M. Greenhill, Filippo Menczer, Miriam J. Metzger, Brendan Nyhan, Gordon Pennycook, David Rothschild, Michael Schudson, Steven A. Sloman, Cass R. Sunstein, Emily A. Thorson, Duncan J. Watts, and Jonathan L. Zittrain. 2018. The science of fake news. *Science*, 359(6380):1094–1096.
994. Yaliang Li, Jing Gao, Chuishi Meng, Qi Li, Lu Su, Bo Zhao, Wei Fan, and Jiawei Han. 2016. A survey on truth discovery. *SIGKDD Explor. Newsl.*, 17(2):1–16.
995. Ying Lin, Joe Hoover, Morteza Dehghani, Marlon Mooijman, and Heng Ji. 2017. Acquiring background knowledge to improve moral value prediction. *arXiv preprint arXiv:1709.05467*.
996. Jing Ma, Wei Gao, Prasenjit Mitra, Sejeong Kwon, Bernard J. Jansen, Kam-Fai Wong, and Meeyoung Cha. 2016. Detecting rumors from microblogs with recurrent neural networks. In *Proceedings of the 25th International Joint Conference on Artificial Intelligence, IJCAI '16*, pages 3818–3824, New York, NY, USA.
997. Jing Ma, Wei Gao, Zhongyu Wei, Yueming Lu, and Kam-Fai Wong. 2015. Detect rumors using time series of social context information on microblogging websites. In *Proceedings of the 24th ACM International on Conference on Information and Knowledge Management, CIKM '15*, pages 1751–1754, Melbourne, Australia.
998. Jing Ma, Wei Gao, and Kam-Fai Wong. 2017. Detect rumors in microblog posts using propagation structure via kernel learning. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics, ACL '17*, pages 708–717, Vancouver, Canada.
999. Justin Ma, Lawrence K. Saul, Stefan Savage, and Geoffrey M. Voelker. 2009. Identifying suspicious URLs: An application of large-scale online learning. In *Proceedings of the 26th Annual International Conference on Machine Learning, ICML '09*, pages 681–688, Montreal, Canada.

1000. Suman Kalyan Maity, Aishik Chakraborty, Pawan Goyal, and Animesh Mukherjee. 2017. Detection of sockpuppets in social media. In Proceedings of the ACM Conference on Computer Supported Cooperative Work and Social Computing, CSCW '17, pages 243–246, Portland, OR, USA.
1001. Todor Mihaylov, Georgi Georgiev, and Preslav Nakov. 2015a. Finding opinion manipulation trolls in news community forums. In Proceedings of the Nineteenth Conference on Computational Natural Language Learning, CoNLL '15, pages 310–314, Beijing, China.
1002. Todor Mihaylov, Ivan Koychev, Georgi Georgiev, and Preslav Nakov. 2015b. Exposing paid opinion manipulation trolls. In Proceedings of the International Conference Recent Advances in Natural Language Processing, RANLP '15, pages 443–450, Hissar, Bulgaria.
1003. Todor Mihaylov, Tsvetomila Mihaylova, Preslav Nakov, Lluís Màrquez, Georgi Georgiev, and Ivan Koychev. 2018. The dark side of news community forums: Opinion manipulation trolls. Internet Research.
1004. Todor Mihaylov and Preslav Nakov. 2016. Hunting for troll comments in news community forums. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics, ACL '16, pages 399–405, Berlin, Germany.
1005. Tsvetomila Mihaylova, Preslav Nakov, Lluís Màrquez, Alberto Barrón-Cedeño, Mitra Mohtarami, Georgi Karadjov, and James Glass. 2018. Fact checking in community forums. In Proceedings of the Thirty-Second AAAI Conference on Artificial Intelligence, AAAI '18, pages 879–886, New Orleans, LA, USA.
1006. Tomas Mikolov, Wen-tau Yih, and Geoffrey Zweig. 2013. Linguistic regularities in continuous space word representations. In Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT '13, pages 746–751, Atlanta, GA, USA.
1007. Lewis Mitchell, Morgan R Frank, Kameron Decker Harris, Peter Sheridan Dodds, and Christopher M Danforth. 2013. The geography of happiness: Connecting Twitter sentiment and expression, demographics, and objective characteristics of place. PloS one, 8(5):e64417.
1008. Mitra Mohtarami, Ramy Baly, James Glass, Preslav Nakov, Lluís Màrquez, and Alessandro Moschitti. 2018. Automatic stance detection using endtoend memory networks. In Proceedings of the 16th Annual Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT '18, pages 767–776, New Orleans, LA, USA.
1009. Subhabrata Mukherjee and Gerhard Weikum. 2015. Leveraging joint interactions for credibility analysis in news communities. In Proceedings of the 24th ACM International on Conference on Information and Knowledge Management, CIKM '15, pages 353–362, Melbourne, Australia.
1010. Preslav Nakov, Alberto Barrón-Cedeño, Tamer Elsayed, Reem Suwaileh, Lluís Màrquez, Wajdi Zaghouani, Pepa Atanasova, Spas Kyuchukov, and
1011. Giovanni Da San Martino. 2018. Overview of the CLEF-2018 CheckThat! lab on automatic identification and verification of political claims. In Proceedings of the Ninth International Conference of the CLEF Association: Experimental IR Meets Multilinguality, Multimodality, and Interaction, Lecture Notes in Computer Science, pages 372–387, Avignon, France. Springer.3539

1012. An T. Nguyen, Aditya Kharosekar, Matthew Lease, and Byron C. Wallace. 2018. An interpretable joint graphical model for fact-checking from crowds. In *Proceedings of the Thirty-Second AAAI Conference on Artificial Intelligence, AAAI '18*, New Orleans, LA, USA.
1013. Jeff Z. Pan, Siyana Pavlova, Chenxi Li, Ningxi Li, Yangmei Li, and Jinshuo Liu. 2018. Content based fake news detection using knowledge graphs. In *Proceedings of the International Semantic Web Conference, ISWC '18*, Monterey, CA, USA.
1014. Symeon Papadopoulos, Kalina Bontcheva, Eva Jaho, Mihai Lupu, and Carlos Castillo. 2016. Overview of the special issue on trust and veracity of information in social media. *ACM Trans. Inf. Syst.*, 34(3):14:1– 14:5.
1015. Verónica Pérez-Rosas, Bennett Kleinberg, Alexandra Lefevre, and Rada Mihalcea. 2018. Automatic detection of fake news. In *Proceedings of the 27th International Conference on Computational Linguistics, COLING '18*, pages 3391–3401, Santa Fe, NM, USA.
1016. Evaggelia Pitoura, Panayiotis Tsaparas, Giorgos Flouris, Irini Fundulaki, Panagiotis Papadakos, Serge Abiteboul, and Gerhard Weikum. 2018. On measuring bias in online information. *SIGMOD Rec.*, 46(4):16–21.
1017. Kashyap Papat, Subhabrata Mukherjee, Jannik Strötgen, and Gerhard Weikum. 2016. Credibility assessment of textual claims on the web. In *Proceedings of the 25th ACM International on Conference on Information and Knowledge Management, CIKM '16*, pages 2173–2178, Indianapolis, IN, USA.
1018. Kashyap Papat, Subhabrata Mukherjee, Jannik Strötgen, and Gerhard Weikum. 2017. Where the truth lies: Explaining the credibility of emerging claims on the Web and social media. In *Proceedings of the 26th International Conference on World Wide Web Companion, WWW '17*, pages 1003–1012, Perth, Australia.
1019. Kashyap Papat, Subhabrata Mukherjee, Jannik Strötgen, and Gerhard Weikum. 2018. CredEye: A credibility lens for analyzing and explaining misinformation. In *Proceedings of The Web Conference 2018, WWW '18*, pages 155–158, Lyon, France.
1020. Martin Potthast, Johannes Kiesel, Kevin Reinartz, Janek Bevendorff, and Benno Stein. 2018. A stylometric inquiry into hyperpartisan and fake news. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics, ACL '18*, pages 231–240, Melbourne, Australia.
1021. Hannah Rashkin, Eunsol Choi, Jin Yea Jang, Svitlana Volkova, and Yejin Choi. 2017. Truth of varying shades: Analyzing language in fake news and political fact-checking. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, EMNLP '17*, pages 2931–2937, Copenhagen, Denmark.
1022. Marta Recasens, Cristian Danescu-Niculescu-Mizil, and Dan Jurafsky. 2013. Linguistic models for analyzing and detecting biased language. In *Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics, ACL '13*, pages 1650–1659, Sofia, Bulgaria.
1023. Benjamin Riedel, Isabelle Augenstein, Georgios P Spithourakis, and Sebastian Riedel. 2017. A simple but tough-to-beat baseline for the Fake News Challenge stance detection task. *ArXiv:1707.03264*.

1024. Sara Rosenthal, Noura Farra, and Preslav Nakov. 2017. SemEval-2017 task 4: Sentiment analysis in Twitter. In *Proceedings of the 11th International Workshop on Semantic Evaluation, SemEval '17*, pages 502–518, Vancouver, Canada.
1025. Kai Shu, Amy Sliva, Suhang Wang, Jiliang Tang, and Huan Liu. 2017. Fake news detection on social media: A data mining perspective. *SIGKDD Explor. Newsl.*, 19(1):22–36.
1026. James Thorne, Mingjie Chen, Giorgos Myrianthous, Jiashu Pu, Xiaoxuan Wang, and Andreas Vlachos. 2017. Fake news stance detection using stacked ensemble of classifiers. In *Proceedings of the EMNLP Workshop on Natural Language Processing meets Journalism*, pages 80–83, Copenhagen, Denmark.
1027. James Thorne and Andreas Vlachos. 2018. Automated fact checking: Task formulations, methods and future directions. In *Proceedings of the 27th International Conference on Computational Linguistics, COLING '18*, pages 3346–3359, Santa Fe, NM, USA.
1028. James Thorne, Andreas Vlachos, Christos Christodoulopoulos, and Arpit Mittal. 2018. FEVER: a large-scale dataset for fact extraction and VERification. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT '18*, pages 809–819, New Orleans, LA, USA.
1029. Soroush Vosoughi, Deb Roy, and Sinan Aral. 2018. The spread of true and false news online. *Science*, 359(6380):1146–1151.
1030. Arkaitz Zubiaga, Elena Kochkina, Maria Liakata, Rob Procter, Michal Lukasik, Kalina Bontcheva, Trevor Cohn, and Isabelle Augenstein. 2018. Discourseaware rumour stance classification in social media using sequential classifiers. *Inf. Process. Manage.*, 54(2):273–290.
1031. Arkaitz Zubiaga, Maria Liakata, Rob Procter, Geraldine Wong Sak Hoi, and Peter Tolmie. 2016. Analysing how people orient to and spread rumours in social media by looking at conversational threads. *PLoS ONE*, 11(3):1–29.
1032. Jefferson Viana Fonseca Abreu, Célia Ghedini Ralha, and João José Costa Gondim. 2020. Twitter bot detection with reduced feature set. In *2020 IEEE International Conference on Intelligence and Security Informatics (ISI)*. IEEE, 1–6.
1033. Seyed Ali Alhosseini, Raad Bin Tareaf, Pejman Najafi, and Christoph Meinel. 2019. Detect me if you can: Spam bot detection using inductive representation learning. In *Companion Proceedings of The 2019 World Wide Web Conference*. 148–153.
1034. David M Beskow and Kathleen M Carley. 2018. Bot-hunter: a tiered approach to detecting & characterizing automated activity on twitter. In *Conference paper. SBP-BRIMS: International conference on social computing, behavioral-cultural modeling and prediction and behavior representation in modeling and simulation*, Vol. 3.
1035. Stefano Cresci, Roberto Di Pietro, Marinella Petrocchi, Angelo Spognardi, and Maurizio Tesconi. 2015. Fame for sale: Efficient detection of fake Twitter followers. *Decision Support Systems* 80 (2015), 56–71.
1036. Stefano Cresci, Roberto Di Pietro, Marinella Petrocchi, Angelo Spognardi, and Maurizio Tesconi. 2017. The paradigm-shift of social spambots: Evidence, theories, and tools for the arms race. In *Proceedings of the 26th international conference on world wide web companion*. 963–972.

1037. Yushun Dong, Ninghao Liu, Brian Jalaian, and Jundong Li. 2022. Edits: Modeling and mitigating data bias for graph neural networks. In *Proceedings of the ACM Web Conference 2022*. 1259–1269.
1038. Juan Echeverría, Emiliano De Cristofaro, Nicolas Kourtellis, Ilias Leontiadis, Gianluca Stringhini, and Shi Zhou. 2018. LOBO: Evaluation of generalization deficiencies in Twitter bot classifiers. In *Proceedings of the 34th annual computer security applications conference*. 137–146.
1039. Shangbin Feng, Zhaoxuan Tan, Rui Li, and Minnan Luo. 2022. Heterogeneityaware twitter bot detection with relational graph transformers. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 36. 3977–3985.
1040. Shangbin Feng, Zhaoxuan Tan, Herun Wan, Ningnan Wang, Zilong Chen, Binchi Zhang, Qinghua Zheng, Wenqian Zhang, Zhenyu Lei, Shujie Yang, et al. 2022. TwiBot-22: Towards graph-based Twitter bot detection. *arXiv preprint arXiv:2206.04564* (2022).
1041. Shangbin Feng, Herun Wan, Ningnan Wang, Jundong Li, and Minnan Luo. 2021. Satar: A self-supervised approach to twitter account representation learning and its application in bot detection. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*. 3808–3817.
1042. Shangbin Feng, Herun Wan, Ningnan Wang, Jundong Li, and Minnan Luo. 2021. Twibot-20: A comprehensive twitter bot detection benchmark. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*. 4485–4494.
1043. Shangbin Feng, Herun Wan, Ningnan Wang, and Minnan Luo. 2021. BotRGCN: Twitter bot detection with relational graph convolutional networks. In *Proceedings of the 2021 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining*. 236–239.
1044. Emilio Ferrara, Onur Varol, Clayton Davis, Filippo Menczer, and Alessandro Flammini. 2016. The rise of social bots. *Commun. ACM* 59, 7 (2016), 96–104.
1045. Matthias Fey and Jan Eric Lenssen. 2019. Fast graph representation learning with PyTorch Geometric. *arXiv preprint arXiv:1903.02428* (2019).
1046. Qinglang Guo, Haiyong Xie, Yangyang Li, Wen Ma, and Chao Zhang. 2021. Social bots detection via fusing bert and graph convolutional networks. *Symmetry* 14, 1 (2021), 30.
1047. Zhichun Guo, William Shiao, Shichang Zhang, Yozen Liu, Nitesh Chawla, Neil Shah, and Tong Zhao. 2022. Linkless Link Prediction via Relational Distillation. *arXiv preprint arXiv:2210.05801* (2022).
1048. Kadhim Hayawi, Sujith Mathew, Neethu Venugopal, Mohammad M Masud, and Pin-Han Ho. 2022. DeeProBot: a hybrid deep neural network model for social bot detection based on user profile data. *Social Network Analysis and Mining* 12, 1 (2022), 43.
1049. Pengcheng He, Xiaodong Liu, Jianfeng Gao, and Weizhu Chen. 2020. DeBERTa: Decoding-enhanced bert with disentangled attention. *arXiv preprint arXiv:2006.03654* (2020).
1050. Geoffrey Hinton, Oriol Vinyals, and Jeff Dean. 2015. Distilling the knowledge in a neural network. *arXiv preprint arXiv:1503.02531* (2015).

1051. Philip N Howard, Gillian Bolsover, Bence Kollanyi, Samantha Bradshaw, and Lisa-Maria Neudert. 2017. Junk news and bots during the US election: What were Michigan voters sharing over Twitter. *CompProp, OII, Data Memo 1* (2017).
1052. Xiaoqi Jiao, Yichun Yin, Lifeng Shang, Xin Jiang, Xiao Chen, Linlin Li, Fang Wang, and Qun Liu. 2019. Tinybert: Distilling bert for natural language understanding. *arXiv preprint arXiv:1909.10351* (2019).
1053. Thomas N Kipf and Max Welling. 2016. Semi-supervised classification with graph convolutional networks. *arXiv preprint arXiv:1609.02907* (2016).
1054. Maria Kouvela, Ilias Dimitriadis, and Athena Vakali. 2020. Bot-Detective: An explainable Twitter bot detection service with crowdsourcing functionalities. In *Proceedings of the 12th International Conference on Management of Digital EcoSystems*. 55–63.
1055. Sneha Kudugunta and Emilio Ferrara. 2018. Deep neural networks for bot detection. *Information Sciences* 467 (2018), 312–322.
1056. Solomon Kullback and Richard A Leibler. 1951. On information and sufficiency. *The annals of mathematical statistics* 22, 1 (1951), 79–86.
1057. Zhenyu Lei, Herun Wan, Wenqian Zhang, Shangbin Feng, Zilong Chen, Qinghua Zheng, and Minnan Luo. 2022. BIC: Twitter Bot Detection with Text-Graph Interaction and Semantic Consistency. *arXiv preprint arXiv:2208.08320* (2022).
1058. Jure Leskovec and Christos Faloutsos. 2006. Sampling from large graphs. In *Proceedings of the 12th ACM SIGKDD international conference on Knowledge discovery and data mining*. 631–636.
1059. Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Ves Stoyanov, and Luke Zettlemoyer. 2019. Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. *arXiv preprint arXiv:1910.13461* (2019).
1060. Paul Pu Liang, Chiyu Wu, Louis-Philippe Morency, and Ruslan Salakhutdinov. 2021. Towards understanding and mitigating social biases in language models. In *International Conference on Machine Learning*. PMLR, 6565–6576.
1061. Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692* (2019).
1062. Yuhan Liu, Zhaoxuan Tan, Heng Wang, Shangbin Feng, Qinghua Zheng, and Minnan Luo. 2023. BotMoE: Twitter Bot Detection with Community-Aware Mixtures of Modal-Specific Experts. *arXiv preprint arXiv:2304.06280* (2023).
1063. Qingsong Lv, Ming Ding, Qiang Liu, Yuxiang Chen, Wenzheng Feng, Siming He, Chang Zhou, Jianguo Jiang, Yuxiao Dong, and Jie Tang. 2021. Are we really making much progress? revisiting, benchmarking and refining heterogeneous graph neural networks. In *Proceedings of the 27th ACM SIGKDD conference on knowledge discovery & data mining*. 1150–1160.
1064. Zachary Miller, Brian Dickinson, William Deitrick, Wei Hu, and Alex Hai Wang. 2014. Twitter spammer detection using data stream clustering. *Information Sciences* 260 (2014), 64–73.

1065. Moin Nadeem, Anna Bethke, and Siva Reddy. 2020. StereoSet: Measuring stereotypical bias in pretrained language models. arXiv preprint arXiv:2004.09456 (2020).
1066. Lynnette Hui Xian Ng and Kathleen M Carley. 2022. BotBuster: Multi-platform Bot Detection Using A Mixture of Experts. arXiv preprint arXiv:2207.13658 (2022).
1067. Dat Quoc Nguyen, Thanh Vu, and Anh Tuan Nguyen. 2020. BERTweet: A pretrained language model for English Tweets. arXiv preprint arXiv:2005.10200 (2020).
1068. Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, et al. 2019. Pytorch: An imperative style, high-performance deep learning library. *Advances in neural information processing systems* 32 (2019).
1069. Fabian Pedregosa, Gaël Varoquaux, Alexandre Gramfort, Vincent Michel, Bertrand Thirion, Olivier Grisel, Mathieu Blondel, Peter Prettenhofer, Ron Weiss, Vincent Dubourg, et al. 2011. Scikit-learn: Machine learning in Python. *the Journal of machine Learning research* 12 (2011), 2825–2830.
1070. Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. *The Journal of Machine Learning Research* 21, 1 (2020), 5485–5551.
1071. Victor Sanh, Lysandre Debut, Julien Chaumond, and Thomas Wolf. 2019. DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter. arXiv preprint arXiv:1910.01108 (2019).
1072. Michael Schlichtkrull, Thomas N Kipf, Peter Bloem, Rianne Van Den Berg, Ivan Titov, and Max Welling. 2018. Modeling relational data with graph convolutional networks. In *The Semantic Web: 15th International Conference, ESWC 2018, Heraklion, Crete, Greece, June 3–7, 2018, Proceedings* 15. Springer, 593–607.
1073. Shuhao Shi, Kai Qiao, Jie Yang, Baojie Song, Jian Chen, and Bin Yan. 2023. Over-Sampling Strategy in Feature Space for Graphs based Class-imbalanced Bot Detection. arXiv:2302.06900 - cs.CV
1074. Zhaoxuan Tan, Shangbin Feng, Melanie Sclar, Herun Wan, Minnan Luo, Yejin Choi, and Yulia Tsvetkov. 2023. BotPercent: Estimating Twitter bot populations from groups to crowds. arXiv preprint arXiv:2302.00381 (2023).
1075. Petar Veličković, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Lio, and Yoshua Bengio. 2017. Graph attention networks. arXiv preprint arXiv:1710.10903 (2017).
1076. Svitlana Volkova, Yoram Bachrach, Michael Armstrong, and Vijay Sharma. 2015. Inferring latent user properties from texts published in social media. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 29.
1077. Feng Wei and Uyen Trang Nguyen. 2019. Twitter bot detection using bidirectional long short-term memory neural networks and word embeddings. In *2019 First IEEE International conference on trust, privacy and security in intelligent systems and applications (TPS-ISA)*. IEEE, 101–109.
1078. Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, Morgan Funtowicz, et al. 2020. Transformers: State-of-the-art natural language processing. In *Proceedings of the 2020*

- conference on empirical methods in natural language processing: system demonstrations. 38–45.
1079. Jun Wu, Xuesong Ye, and Yanyuet Man. 2023. Bottrinet: A unified and efficient embedding for social bots detection via metric learning. In 2023 11th International Symposium on Digital Forensics and Security (ISDFS). IEEE, 1–6.
 1080. Bencheng Yan, Chaokun Wang, Gaoyang Guo, and Yunkai Lou. 2020. Tinygcn: Learning efficient graph neural networks. In Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. 1848–1856.
 1081. Chao Yang, Robert Harkreader, and Guofei Gu. 2013. Empirical evaluation and new design for fighting evolving twitter spammers. *IEEE Transactions on Information Forensics and Security* 8, 8 (2013), 1280–1293.
 1082. Kai-Cheng Yang, Onur Varol, Pik-Mai Hui, and Filippo Menczer. 2020. Scalable and generalizable social bot detection through data selection. In Proceedings of the AAAI conference on artificial intelligence, Vol. 34. 1096–1103.
 1083. Yingguang Yang, Renyu Yang, Yangyang Li, Kai Cui, Zhiqin Yang, Yue Wang, Jie Xu, and Haiyong Xie. 2022. RoSGAS: Adaptive Social Bot Detection with Reinforced Self-Supervised GNN Architecture Search. *ACM Transactions on the Web* (2022).
 1084. Sen Ye, Zhaoxuan Tan, Zhenyu Lei, Ruijie He, Hongrui Wang, Qinghua Zheng, and Minnan Luo. 2023. HOFA: Twitter Bot Detection with Homophily-Oriented Augmentation and Frequency Adaptive Attention. *arXiv preprint arXiv:2306.12870* (2023).
 1085. Hanqing Zeng, Hongkuan Zhou, Ajitesh Srivastava, Rajgopal Kannan, and Viktor Prasanna. 2019. Graphsaint: Graph sampling based inductive learning method. *arXiv preprint arXiv:1907.04931* (2019).
 1086. Shichang Zhang, Yozen Liu, Yizhou Sun, and Neil Shah. 2021. Graph-less neural networks: Teaching old mlps new tricks via distillation. *arXiv preprint arXiv:2110.08727* (2021).
 1087. Jianan Zhao, Meng Qu, Chaozhuo Li, Hao Yan, Qian Liu, Rui Li, Xing Xie, and Jian Tang. 2022. Learning on large-scale text-attributed graphs via variational inference. *arXiv preprint arXiv:2210.14709* (2022).
 1088. E. Ferrara, O. Varol, F. Menczer, A. Flammini, Detection of promoted social media campaigns, in: Proceedings of the 10th International Conference on Web and Social Media (ICWSM’16), AAAI, 2016, pp. 563–566.
 1089. S. Cresci, Harnessing the Social Sensing revolution: Challenges and Opportunities, University of Pisa, 2018 PhD dissertation.
 1090. J. Ratkiewicz, M. Conover, M.R. Meiss, B. Gonçalves, A. Flammini, F. Menczer, Detecting and tracking political abuse in social media, in: Proceedings of the 5th International Conference on Web and Social Media (ICWSM’11), AAAI, 2011, pp. 297–304.
 1091. S. Cresci, F. Lillo, D. Regoli, S. Tardelli, M. Tesconi, \$FAKE: Evidence of spam and bot activity in stock microblogs on Twitter, in: Proceedings of the 12th International Conference on Web and Social Media (ICWSM’18), AAAI, 2018, pp. 580–583.
 1092. S. Cresci, R. Di Pietro, M. Petrocchi, A. Spognardi, M. Tesconi, The paradigm-shift of social spambots: Evidence, theories, and tools for the arms race, in: Proceedings of the

- WWW'17 Companion, ACM, 2017, pp. 963–972.16 S. Cresci, M. Petrocchi and A. Spognardi et al. /Online Social Networks and Media 9 (2019) 1–16
1093. C. Yang, R. Harkreader, G. Gu, Empirical evaluation and new design for fighting evolving Twitter spammers, *IEEE Trans. Inf. Forensics Secur.* 8 (8) (2013) 1280–1293.
 1094. E. Ferrara, O. Varol, C. Davis, F. Menczer, A. Flammini, The rise of social bots, *Commun. ACM* 59 (7) (2016) 96–104.
 1095. S. Tognazzi, S. Cresci, M. Petrocchi, A. Spognardi, From reaction to proaction: unexplored ays to the detection of evolving spambots, in: *Proceedings of the 27th Web Conference Companion (WWW'18 Companion)*, ACM, 2018, pp. 1469–1470.
 1097. S. Cresci, R. Di Pietro, M. Petrocchi, A. Spognardi, M. Tesconi, DNA-inspired online behavioral modeling and its application to spambot detection, *IEEE Intell. Syst.* 5 (31) (2016) 58–64.
 1098. S. Cresci, R. Di Pietro, M. Petrocchi, A. Spognardi, M. Tesconi, Social fingerprinting: detection of spambot groups through DNA-inspired behavioral modeling, *IEEE Trans. Dep. Secur. Comput.* 4 (15) (2018) 561–576.
 1099. M. Mitchell, *An Introduction to Genetic Algorithms*, MIT Press, 1998.
 1100. X. Hu, J. Tang, H. Liu, Online social spammer detection, in: *Proceedings of the 28th International Conference on Artificial Intelligence (AAAI'14)*, AAAI, 2014, pp. 59–65.
 1101. S. Cresci, R. Di Pietro, M. Petrocchi, A. Spognardi, M. Tesconi, Exploiting digital DNA for the analysis of similarities in Twitter behaviours, in: *Proceedings of the 4th International Conference on Data Science and Advanced Analytics (DSAA'17)*, IEEE, 2017, pp. 686–695.
 1102. D. Gusfield, *Algorithms on Strings, Trees and Sequences: Computer Science and Computational Biology*, Cambridge University Press, 1997.
 1103. M. Arnold, E. Ohlebusch, Linear time algorithms for generalizations of the longest common substring problem, *Algorithmica* 60 (4) (2011) 806–818.
 1104. L. Chi, K. Hui, Color set size problem with applications to string matching, in: *Combinatorial Pattern Matching*, Springer, 1992, pp. 230–243.
 1105. M. Avvenuti, S. Bellomo, S. Cresci, M.N.L. Polla, M. Tesconi, Hybrid crowdsensing: a novel paradigm to combine the strengths of opportunistic and participatory crowdsensing, in: *Proceedings of the 26th International Conference on World Wide Web Companion*, 2017, pp. 1413–1421.
 1106. S. Cresci, R. Di Pietro, M. Petrocchi, A. Spognardi, M. Tesconi, The paradigm-shift of social spambots: evidence, theories, and tools for the arms race, in: *Proceedings of the 26th International Conference on World Wide Web (WWW'17 Companion)*, ACM, 2017, pp. 963–972.
 1107. G. Palshikar, Simple algorithms for peak detection in time-series, in: *Proceedings of the 1st International Conference on Advanced Data Analysis, Business Analytics and Intelligence*, IIMA, 2009.
 1108. V. Lampos, N. Cristianini, Nowcasting events from the social web with statistical learning, *ACM Trans. Intell. Syst. Technol. (TIST)* 3 (4) (2012) 72.

1109. L. Cao, In-depth behavior understanding and use: the behavior informatics approach, *Inf. Sci.* 180 (17) (2010) 3067–3085.
1110. A. Tsakalidis, S. Papadopoulos, A. Cristea, Y. Kompatsiaris, Predicting elections for multiple countries using twitter and polls, *IEEE Intell. Syst.* 30 (2) (2015) 10–17.
1111. K. Li, Y. Fu, Prediction of human activity by discovering temporal sequence patterns, *Pattern Anal. Mach. Intell. IEEE Trans.* 36 (8) (2014) 1644–1657.
1112. H. Liu, J. Han, H. Motoda, Uncovering deception in social media, *Social Netw. Anal. Min.* 4 (1) (2014) 162.
1113. S. Cresci, R. Di Pietro, M. Petrocchi, A. Spognardi, M. Tesconi, Fame for sale: efficient detection of fake Twitter followers, *Decis. Support Syst.* 80 (2015) 56–71.
1114. C. Yang, R. Harkreader, G. Gu, Empirical evaluation and new design for fighting evolving twitter spammers, *IEEE Trans. Inf. Forensics Secur.* 8 (8) (2013) 1280–1293.
1115. M. Jiang, P. Cui, A. Beutel, C. Faloutsos, S. Yang, Catching synchronized behaviors in large networks: a graph mining approach, *ACM Trans. Knowl. Discov. Data (TKDD)* 10 (4) (2016) 35.
1116. X. Hu, J. Tang, H. Liu, Online social spammer detection, in: *Proceedings of the AAAI Conference on Artificial Intelligence*, 2014, pp. 59–65.
1117. P. Van Mieghem, N. Blenn, C. Doerr, Lognormal distribution in the digg online social network, *Eur. Phys. J. B* 83 (2) (2011) 251–261.
1118. C. Wang, B.A. Huberman, Long trend dynamics in social media, *EPJ Data Sci.* 1 (1) (2012) 1–8.
1119. C. Doerr, N. Blenn, P. Van Mieghem, Lognormal infection times of online information spread, *PLoS One* 8 (5) (2013) e64349.
1120. Cresci et al 2019 - On the capability of evolved spambots to evade detection via genetic engineering
1121. H. Liu et al., “Uncovering deception in social media,” *Social Network Analysis and Mining*, vol. 4, no. 1, pp. 1–2, 2014.
1122. G. Stringhini, M. Egele, C. Kruegel, and G. Vigna, “Poultry markets: on the underground economy of Twitter followers,” in *Online Social Networks*. ACM, 2012, pp. 1–6.
1123. G. Stringhini, G. Wang, M. Egele, C. Kruegel, G. Vigna, H. Zheng, and B. Y. Zhao, “Follow the green: growth and dynamics in Twitter follower markets,” in *Internet Measurement Conference (IMC)*. ACM, 2013, pp. 163–176.
1124. K. Thomas, D. McCoy, C. Grier, A. Kolcz, and V. Paxson, “Trafficking fraudulent accounts: The role of the underground market in Twitter spam and abuse,” in *22nd USENIX Security Symposium*, 2013, pp. 195–210.
1125. K. Lee, J. Caverlee, and S. Webb, “Uncovering social spammers: social honeypots + machine learning,” in *33rd Research and Development in Information Retrieval*. ACM, 2010, pp. 435–442.
1126. G. Stringhini, C. Kruegel, and G. Vigna, “Detecting spammers on social networks,” in *26th Annual Computer Security Applications Conference (ACSAC)*. ACM, 2010, pp. 1–9.

1127. S. Fortunato, "Community detection in graphs," *Physics Reports*, vol. 486, no. 3, pp. 75–174, 2010.
1128. S. Ghosh, B. Viswanath, F. Kooti, N. K. Sharma, G. Korlam, F. Benevenuto, N. Ganguly, and K. P. Gummadi, "Understanding and combating link farming in the Twitter social network," in *21st World Wide Web. ACM*, 2012, pp. 61–70.
1129. C. Yang, R. Harkreader, and G. Gu, "Empirical evaluation and new design for fighting evolving Twitter spammers," *IEEE Trans. Information Forensics and Security*, vol. 8, no. 8, pp. 1280–1293, 2013.
1130. X. Hu, J. Tang, and H. Liu, "Online social spammer detection," in *28th AAAI Conference on Artificial Intelligence*, 2014.
1131. E. Ferrara, O. Varol, C. Davis, F. Menczer, and A. Flammini, "The rise of social bots," *Communications of the ACM*, vol. 59, no. 7, pp. 96–104, 2016.
1132. M. Jiang, P. Cui, A. Beutel, C. Faloutsos, and S. Yang, "Catching synchronized behaviors in large networks: A graph mining approach," *ACM Trans. on Knowledge Discovery from Data*, vol. 10, no. 4, 2016.
1133. K. Li and Y. Fu, "Prediction of human activity by discovering temporal sequence patterns," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 36, no. 8, pp. 1644–1657, 2014.
1134. Y. Boshmaf, I. Muslukhov, K. Beznosov, and M. Ripeanu, "The socialbot network: when bots socialize for fame and money," in *27th ACSAC. ACM*, 2011, pp. 93–102.
1135. Z. Chu, S. Gianvecchio, H. Wang, and S. Jajodia, "Detecting automation of twitter accounts: Are you a human, bot, or cyborg?" *IEEE TDSC*, vol. 9, no. 6, pp. 811–824, 2012.
1136. S. Cresci, R. Di Pietro, M. Petrocchi, A. Spognardi, and M. Tesconi, "Fame for sale: Efficient detection of fake Twitter followers," *Decision Support Systems*, vol. 80, pp. 56–71, 2015.
1137. —, "A Criticism to Society (as seen by Twitter analytics)," in *1st International Workshop on Big Data Analytics for Security. IEEE*, June 2014, pp. 194–200.
1138. H. Gao, Y. Chen, K. Lee, D. Palsetia, and A. N. Choudhary, "Towards online spam filtering in social networks," in *Network and Distributed System Security Symposium*, 2012.
1139. S. Lee and J. Kim, "WarningBird: A near real-time detection system for suspicious URLs in Twitter stream," *IEEE Trans. on Dependable and Secure Computing*, vol. 10, no. 3, pp. 183–195, 2013.
1140. K. Thomas, C. Grier, J. Ma, V. Paxson, and D. Song, "Design and evaluation of a real-time URL spam filtering service," in *32nd Symposium on Security and Privacy. IEEE*, 2011, pp. 447–462.
1141. H. Gao et al., "Spam ain't as diverse as it seems: throttling OSN spam with templates underneath," in *30th ACSAC. ACM*, 2014, pp. 76–85.
1142. Y. Liu, B. Wu, B. Wang, and G. Li, "SDHM: A hybrid model for spammer detection in Weibo," in *Advances in Social Networks Analysis and Mining. IEEE*, 2014, pp. 942–947.

1143. Z. Yang, C. Wilson, X. Wang, T. Gao, B. Y. Zhao, and Y. Dai, "Uncovering social network sybils in the wild," *Trans. Knowledge Discovery from Data*, vol. 8, no. 1, 2014, special issue TKDD-CASIN.
1144. A. Beutel, W. Xu, V. Guruswami, C. Palow, and C. Faloutsos, "CopyCatch: stopping group attacks by spotting lockstep behavior in social networks," in *22nd World Wide Web*, 2013, pp. 119–130.
1145. M. Jiang, P. Cui, A. Beutel, C. Faloutsos, and S. Yang, "Inferring lockstep behavior from connectivity pattern in large graphs," *Knowledge and Information Systems*, pp. 1–30, 2015.
1146. M. Giatsoglou et al., "ND-Sync: Detecting synchronized fraud activities," in *Advances in Knowledge Discovery and Data Mining*. Springer, 2015, pp. 201–214.
1147. Q. Cao, X. Yang, J. Yu, and C. Palow, "Uncovering large groups of active malicious accounts in online social networks," in *ACM SIGSAC Conference on Computer and Communications Security*. ACM, 2014, pp. 477–488.
1148. R. Yu, X. He, and Y. Liu, "GLAD: Group anomaly detection in social media analysis," *ACM Transactions on Knowledge Discovery from Data (TKDD)*, vol. 10, no. 2, pp. 1–22, 2015.
1149. M. Ou, P. Cui, J. Wang, F. Wang, and W. Zhu, "Probabilistic attributed hashing," in *AAAI Conference on Artificial Intelligence*, 2015, pp. 2894–2900.
1150. F. Ahmed and M. Abulaish, "A generic statistical approach for spam detection in online social networks," *Computer Communications*, vol. 36, no. 10, pp. 1120–1129, 2013.
1151. Z. Miller, B. Dickinson, W. Deitrick, W. Hu, and A. H. Wang, "Twitter spammer detection using data stream clustering," *Information Sciences*, vol. 260, pp. 64–73, 2014.
1152. S. Cresci, R. Di Pietro, M. Petrocchi, A. Spognardi, and M. Tesconi, "DNA-inspired online behavioral modeling and its application to spambot detection," *IEEE Intelligent Systems*, vol. 31, no. 5, pp. 58–64, 2016.
1153. K. L. Gwet, *Handbook of inter-rater reliability: The definitive guide to measuring the extent of agreement among raters*. Advanced Analytics, LLC, 2014.
1154. J. R. Landis and G. G. Koch, "The measurement of observer agreement for categorical data," *Biometrics*, pp. 159–174, 1977.
1155. M. Avvenuti, S. Bellomo, S. Cresci, M. N. La Polla, and M. Tesconi, "Hybrid crowdsensing: A novel paradigm to combine the strengths of opportunistic and participatory crowdsensing," in *26th World Wide Web Conference, Companion Volume*, 2017.
1156. R. Zafarani, M. A. Abbasi, and H. Liu, *Social media mining: an introduction*. Cambridge University Press, 2014.
1157. B. Sriram et al., "Short text classification in Twitter to improve information filtering," in *Research and Development in Information Retrieval*. ACM, 2010, pp. 841–842.
1158. K. Lee, D. Palsetia, R. Narayanan, M. M. A. Patwary, A. Agrawal, and A. Choudhary, "Twitter trending topic classification," in *Data Mining Workshops (ICDMW)*. IEEE, 2011, pp. 251–258.
1159. D. Gusfield, *Algorithms on strings, trees and sequences: computer science and computational biology*. Cambridge Univ. Press, 1997.

1160. M. Arnold and E. Ohlebusch, "Linear time algorithms for generalizations of the longest common substring problem," *Algorithmica*, vol. 60, no. 4, pp. 806–818, 2011.
1161. L. Chi and K. Hui, "Color set size problem with applications to string matching," in *Combinatorial Pattern Matching*. Springer, 1992, pp. 230–243.
1162. T. Fawcett, "An introduction to ROC analysis," *Pattern recognition letters*, vol. 27, no. 8, pp. 861–874, 2006.
1163. P. Baldi, S. Brunak, Y. Chauvin, and H. Nielsen, "Assessing the accuracy of prediction algorithms for classification: An overview," *Bioinformatics*, vol. 16, no. 5, pp. 412–424, 2000.
1164. S. J. Pan and Q. Yang, "A survey on transfer learning," *IEEE Transactions on knowledge and data engineering*, vol. 22, no. 10, pp. 1345–1359, 2010.
1165. G. Palshikar et al., "Simple algorithms for peak detection in timeseries," in *Advanced Data Analysis, Business Analytics and Intelligence*, 2009.
1166. V. Lampsos and N. Cristianini, "Nowcasting events from the social web with statistical learning," *ACM Transactions on Intelligent Systems and Technology (TIST)*, vol. 3, no. 4, p. 72, 2012.
1167. Twitter Inc., "Twitter's IPO filing," Oct 2013, <https://goo.gl/pbXxHh> (Last checked 07/12/16).
1168. R. Kohavi and F. Provost, "Glossary of terms," *Machine Learning*, vol. 30, no. 2-3, pp. 271–274, 1998.
1169. D. M. W. Powers, "Evaluation: from Precision, Recall and F-Measure to ROC, informedness, markedness and correlation," *International Journal of Machine Learning Technologies*, vol. 2, no. 1, pp. 37–63, 2011.
1170. Y. Chen, A. Wan, and W. Liu, "A fast parallel algorithm for finding the longest common sequence of multiple biosequences," *BMC bioinformatics*, vol. 7, no. 4, p. 1, 2006.
1171. F. Benevenuto, T. Rodrigues, M. Cha, and V. Almeida, "Characterizing user navigation and interactions in online social networks," *Information Sciences*, vol. 195, pp. 1–24, 2012.
1172. B. Viswanath, M. A. Bashir, M. Crovella, S. Guha, K. Gummadi, B. Krishnamurthy, and A. Mislove, "Towards detecting anomalous user behavior in online social networks," in *23rd USENIX Security Symposium*, 2014, pp. 223–238.
1173. X. Ruan, Z. Wu, H. Wang, and S. Jajodia, "Profiling online social behaviors for compromised account detection," *IEEE Trans. on Information Forensics and Security*, vol. 11, no. 1, pp. 176–187, 2016.
1174. L. Cao, "In-depth behavior understanding and use: the behavior informatics approach," *Information Sciences*, vol. 180, no. 17, pp. 3067–3085, 2010.
1175. D. P. Kroese, T. Brereton, T. Taimre, and Z. I. Botev, "Why the Monte Carlo method is so important today," *Wiley Interdisciplinary Reviews: Computational Statistics*, vol. 6, no. 6, pp. 386–392, 2014.
1176. L. Bergroth, H. Hakonen, and T. Raita, "A survey of longest common subsequence algorithms," in *String Processing and Information Retrieval*, 2000. SPIRE 2000. Proceedings. Seventh International Symposium on. IEEE, 2000, pp. 39–48.

1177. Ahmed Nesreen K, Rossi Ryan A, Lee John Boaz, Willke Theodore L, Zhou Rong, Kong Xiangnan, Eldardiry Hoda. role2vec: Role-based network embeddings. In Proc. DLG KDD, 2019;1–7.
1178. Aiello Luca Maria, Deplano Martina, Schifanella Rossano, Rufo Giancarlo. People are strange when you're a stranger: Impact and influence of bots on social networks. In Sixth International AAAI Conference on Weblogs and Social Media, 2012.
1179. Ali Alhosseini Seyed, Bin Tareaf Raad, Najaf Pejman, Meinel Christoph. Detect me if you can: Spam bot detection using inductive representation learning. In Companion Proceedings of The 2019 World Wide Web Conference, 2019;pages 148–153.
1180. Alkulaib Lulwah, Zhang Lei, Sun Yanshen, Lu Chang-Tien. Twitter bot identification: An anomaly detection approach. In 2022 IEEE International Conference on Big Data (Big Data), pages 3577–3585. IEEE, 2022.
1181. Bail Christopher A, Guay Brian, Maloney Emily, Combs Aidan, Hillygus D Sunshine, Merhout Friedolin, Freelon Deen, Volfovsky Alexander. Assessing the Russian internet research agency's impact on the political attitudes and behaviors of American twitter users in late 2017. Proc Natl Acad Sci. 2020;117(1):243–50.
1182. Bojanowski Piotr, Grave Edouard, Joulin Armand, Mikolov Tomas. Enriching word vectors with subword information. arXiv preprint arXiv:1607.04606, 2016.
1183. Brown Tom B, Mann Benjamin, Ryder Nick, Subbiah Melanie, Kaplan Jared, Dhariwal Prafulla, Neelakantan Arvind, Shyam Pranav, Sastry Girish, Askell Amanda, et al. Language models are few-shot learners. arXiv preprint arXiv:2005. 14165, 2020.
1184. Cai Hongyun, Zheng Vincent W, Chen-Chuan Chang Kevin. A comprehensive survey of graph embedding: Problems, techniques, and applications. IEEE Trans Knowl Data Eng. 2018;30(9):1616–37.
1185. Carter Daniel. Hustle and brand: The sociotechnical shaping of influence. Social Media+ Society, 2016;2(3):2056305116666305. 10. Cha Meeyoung, Haddadi Hamed, Benevenuto Fabricio, Gummadi Krishna. Measuring user influence in twitter: The million follower fallacy. In Proceedings of the International AAAI Conference on Web and Social Media, 2010;volume 4.
1186. Chavoshi Nikan, Hamooni Hossein, Mueen Abdullah. Debot: Twitter bot detection via warped correlation. In Icdm, 2016;pages 817–822.
1187. De Domenico Manlio, Altmann Eduardo G. Unraveling the origin of social bursts in collective attention. Sci Rep. 2020;10(1):1–9.
1188. Dong Guozhu, Liu Huan. Feature engineering for machine learning and data analytics. CRC Press, 2018.
1189. Donnat Claire, Zitnik Marinka, Hallac David, Leskovec Jure. Learning structural node embeddings via diffusion wavelets. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, 2018;pages 1320–1329.
1190. Feng S, Wan H, Wang N, Li J, Luo M. Twibot-20: A comprehensive twitter bot detection benchmark. In Proceedings of the 30th ACM International Conference on Information & Knowledge Management, 2021;1:4485–4494.

1191. Deen Freelon, Michael Bossetta, Chris Wells, Josephine Lukito, Yiping Xia, Kirsten Adams. Black trolls matter: racial and ideological asymmetries in social media disinformation. *Soc Sci Comput Rev.* 2020;1:894439320914853.
1192. Freitas Carlos, Benevenuto Fabricio, Ghosh Saptarshi, Veloso Adriano. Reverse engineering socialbot infiltration strategies in twitter. In 2015 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM), pages 25–32. IEEE, 2015.
1193. Gao Hongyu, Chen Yan, Lee Kathy, Palsetia Diana, Choudhary Alok N. Towards online spam filtering in social networks. *NDSS.* 2012;12:1–16.
1194. Goyal Palash, Ferrara Emilio. Graph embedding techniques, applications, and performance: A survey. *Knowledge-Based Syst.* 2018;151:78–94.
1195. Grootendorst Maarten. Bertopic: Leveraging bert and c-tf-idf to create easily interpretable topics., 2020.
1196. Grover Aditya, Leskovec Jure. node2vec: Scalable feature learning for networks. In *Proceedings of the 22nd ACM SIGKDD international conference on Knowledge discovery and data mining*, 2016;pp. 855–864.
1197. Hamdi Tarek, Slimi Hamda, Bounhas Ibrahim, Slimani Yahya. A hybrid approach for fake news detection in twitter based on user features and graph embedding. In *Distributed Computing and Internet Technology: 16th International Conference, ICDCIT 2020, Bhubaneswar, India, January 9–12, 2020, Proceedings 16*, 2020;p. 266–280. Springer.
1198. Henderson Keith, Gallagher Brian, Eliassi-Rad Tina, Tong Hanghang, Basu Sugato, Akoglu Leman, Koutra Danai, Faloutsos Christos, Li Lei. Rolx: structural role extraction & mining in large graphs. In *Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining*, 2012;pages 1231–1239. 24. Hwang Tim, Pearce Ian, Nanis Max. Socialbots: Voices from the fronts. *interactions.* 2012;19(2):38–45.
1199. Kamiński Bogumił, Prałat Paweł, Théberge François. *Mining Complex Networks*. CRC Press, 2021.
1200. Lee Kyumin, Eof Brian, Caverlee James. Seven months with the devils: A long-term study of content polluters on twitter. In: *Proceedings of the international AAAI conference on web and social media.* 2011;5:185–92.
1201. Lee Sangho, Kim Jong. Warningbird: A near real-time detection system for suspicious urls in twitter stream. *IEEE transactions on dependable and secure computing.* 2013;10(3):183–95.
1202. Lehmann Janette, Gonçalves Bruno, Ramasco José J, Cattuto Ciro. Dynamical classes of collective attention in twitter. In *Proceedings of the 21st international conference on World Wide Web*, 2012;p. 251–260.
1203. Magelinski Thomas, Beskow David, Carley Kathleen M. Graph-hist: Graph classification from latent feature histograms with application to bot detection. In *Proceedings of the AAAI Conference on Artificial Intelligence*, 2020;34:5134–5141.
1204. Matwin Stan, Milios Aristides, Prałat Paweł, Soares Amilcar, Théberge François. *Generative methods for social media analysis*. SpringerBriefs in Computer Science, 2023.

1205. Mbona I, Elof-Jan HP. Classifying social media bots as malicious or benign using semi-supervised machine learning. *J Cybersec.* 2023;9(1):015.
1206. Mikolov T, Sutskever I, Chen K, Corrado-Greg S, Dean J. Distributed representations of words and phrases and their compositionality. In: *Advances in neural information processing systems*, 2013;1:3111–3119.
1207. Minnich Amanda, Chavoshi Nikan, Koutra Danai, Mueen Abdullah. Botwalk: Efficient adaptive exploration of twitter bot networks. In *Proceedings of the 2017 IEEE/ACM international conference on advances in social networks analysis and mining 2017*, 2017;pages 467–474.
1208. Monti Federico, Frasca Fabrizio, Eynard Davide, Mannion Damon, Bronstein Michael M. Fake news detection on social media using geometric deep learning. *arXiv preprint arXiv:1902.06673*, 2019.
1209. OpenAI. Gpt-4 technical report, 2023.
1210. Perdana Rizal Setya, Muliawati Tri Hadiah, Alexandro Reddy. Bot spammer detection in twitter using tweet similarity and time interval entropy. *Jurnal Ilmu Komputer dan Informasi.* 2015;8(1):19–25.
1211. Perozzi Bryan, Al-Rfou Rami, Skiena Steven. Deepwalk: Online learning of social representations. In *Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining*, 2014;p. 701–710.
1212. Pham Phu, Nguyen Loan TT, Vo Bay, Yun Unil. Bot2vec: A general approach of intra-community oriented representation learning for bot detection in diferent types of social networks. *Inform Syst.* 2022;103: 101771.
1213. Ribeiro Leonardo FR, Saverese Pedro HP, Figueiredo Daniel R. struc2vec: Learning node representations from structural identity. In *Proceedings of the 23rd ACM SIGKDD international conference on knowledge discovery and data mining*, 2017;385–394.
1214. Rossi Ryan A, Ahmed Nesreen K. Role discovery in networks. *IEEE Trans Knowl Data Eng.* 2014;27(4):1112–31.
1215. Rozin Paul, Royzman Edward B. Negativity bias, negativity dominance, and contagion. *Person Soc Psychol Rev.* 2001;5((4):296–320.
1216. Sayyadiharikandeh Mohsen, Varol Onur, Yang Kai-Cheng, Flammini Alessandro, Menczer Filippo. Detection of novel social bots by ensembles of specialized classifiers. In: *Proceedings of the 29th ACM International Conference on Information & Knowledge Management*, 2020;pages 2725–2732.
1217. Stella Massimo, Cristoforetti Marco, De Domenico Manlio. Infuence of augmented humans in online interactions during voting events. *PLoS ONE.* 2019;14(5): e0214210.
1218. Tan Zhaoxuan, Feng Shangbin, Sclar Melanie, Wan Herun, Luo Minnan, Choi Yejin, Tsvetkov Yulia. Botpercent: Estimating twitter bot populations from groups to crowds. *arXiv preprint arXiv:2302.00381*, 2023. Dehghan et al. *Journal of Big Data* (2023) 10:119
1219. Thomas Kurt, Grier Chris, Ma Justin, Paxson Vern, Song Dawn. Design and evaluation of a real-time url spam filtering service. In *2011 IEEE symposium on security and privacy*, pages 447–462. IEEE, 2011.

1220. Wolf Thomas, Debut Lysandre, Sanh Victor, Chaumond Julien, Delangue Clement, Moi Anthony, Cistac Pierric, Rault Tim, Louf Rémi, Funtowicz Morgan, Davison Joe, Shleifer Sam, von Platen Patrick, Ma Clara, Jernite Yacine, Plu Julien, Xu Canwen, Scao Teven Le, Gugger Sylvain, Drame Mariama, Lhoest Quentin, Rush Alexander M. Transformers: State-of-the-art natural language processing. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, pages 38–45, Online, October 2020. Association for Computational Linguistics.
1221. Woolley Samuel C, Howard Philip N. Computational propaganda: political parties, politicians, and political manipulation on social media. Oxford University Press, 2018.
1222. Yang Kai-Cheng, Varol Onur, Davis Clayton A, Ferrara Emilio, Flammini Alessandro, Menczer Filippo. Arming the public with artificial intelligence to counter social bots. *Human Beh Emerg Technol*. 2019;1(1):48–61.
1223. Ali Alhosseini, S., Bin Tareaf, R., Najafi, P., Meinel, C.: Detect me if you can: Spam bot detection using inductive representation learning. In: 2019 World Wide Web Conference, Companion. p. 148–153. WWW '19, ACM (2019). <https://doi.org/10.1145/3308560.3316504>
1224. Antenore, M., Rodriguez, J.M.C., Panizzi, E.: A comparative study of bot detection techniques with an application in Twitter Covid-19 discourse. *Social Science Computer Review* (2022). <https://doi.org/10.1177/08944393211073733>
1225. Biewald, L.: Experiment tracking with weights and biases (2020), <https://www.wandb.com/>
1226. Cao, Q., Yang, X., Yu, J., Palow, C.: Uncovering large groups of active malicious accounts in online social networks. In: ACM SIGSAC Conference on Computer and Communications Security. pp. 477–488. ACM (2014)
1227. Ceron, A.: Internet, news, and political trust: The difference between social media and online media outlets. *Journal of computer-mediated communication* 20(5), 487–503 (2015)
1228. Cresci, S.: A decade of social bot detection. *Commun. ACM* 63(10), 72–83 (2020)
1229. Cresci, S., Di Pietro, R., Petrocchi, M., Spognardi, A., Tesconi, M.: DNA-inspired online behavioral modeling and its application to spambot detection. *IEEE Intelligent Systems* 31(5), 58–64 (2016)
1230. Cresci, S., Di Pietro, R., Petrocchi, M., Spognardi, A., Tesconi, M.: The paradigm-shift of social spambots: Evidence, theories, and tools for the arms race. In: 26th International Conference on World Wide Web Companion. pp. 963–972. ACM (2017). <https://doi.org/10.1145/3041021.3055135>
1231. Cresci, S., Di Pietro, R., Petrocchi, M., Spognardi, A., Tesconi, M.: Social fingerprinting: Detection of spambot groups through DNA-inspired behavioral modeling. *IEEE Trans. Dependable Secur. Comput.* 15(4), 561–576 (2018)
1232. Cresci, S., Lillo, F., Regoli, D., Tardelli, S., Tesconi, M.: \$FAKE: Evidence of spam and bot activity in stock microblogs on Twitter. In: ICWSM (2018). <https://doi.org/10.1609/icwsm.v12i1.15073>
1233. Cresci, S., Pietro, R.D., Petrocchi, M., Spognardi, A., Tesconi, M.: Dna-inspired online behavioral modeling and its application to spambot detection. *IEEE In-14 Edoardo Di Paolo,*

- Marinella Petrocchi, and Angelo Spognardi tell. Syst. 31(5), 58–64 (2016).
<https://doi.org/10.1109/MIS.2016.29>, <https://doi.org/10.1109/MIS.2016.29>
1234. Efthimion, P.G., Payne, S., Proferes, N.: Supervised machine learning bot detection techniques to identify social twitter bots. SMU Data Science Review 1(2), 5 (2018)
 1235. Feng, S., Wan, H., Wang, N., Li, J., Luo, M.: Twibot-20: A comprehensive Twitter bot detection benchmark. In: CIKM '21. pp. 4485–4494. ACM (2021).
<https://doi.org/10.1145/3459637.3482019>
 1236. Ferrara, E., Varol, O., Davis, C., Menczer, F., Flammini, A.: The rise of social bots. Commun. ACM 59(7), 96–104 (Jun 2016) 15. Gangware, C., Nemr, W.: Weapons of Mass Distraction: Foreign State-Sponsored Disinformation in the Digital Age. Park Advisors (2019)
 1237. Gilmory, R., et al.: Dna-influenced automated behavior detection on Twitter through relative entropy. Scientific Reports 12, 8022 (2022)
 1238. Gu, J., et al.: Recent advances in convolutional neural networks. Pattern Recognition 77, 354–377 (2018). <https://doi.org/https://doi.org/10.1016/j.patcog.2017.10.013>
 1239. Guo, B., Ding, Y., Yao, L., Liang, Y., Yu, Z.: The future of misinformation detection: New perspectives and trends. CoRR abs/1909.03654 (2019), <http://arxiv.org/abs/1909.03654>
 1240. Hayawi, K., et al.: DeeProBot: a hybrid deep neural network model for social bot detection based on user profile data. Soc. Netw. Anal. Min. 12(1), 43 (2022).
<https://doi.org/10.1007/s13278-022-00869-w>
 1241. He, K., Zhang, X., Ren, S., Sun, J.: Deep residual learning for image recognition. CoRR abs/1512.03385 (2015), <http://arxiv.org/abs/1512.03385>
 1242. Jeffrey, H.: Chaos game representation of gene structure. Nucleic Acids Research 18(8), 2163–2170 (04 1990). <https://doi.org/10.1093/nar/18.8.2163>
 1243. Krizhevsky, A., Sutskever, I., Hinton, G.E.: Imagenet classification with deep convolutional neural networks. Commun. ACM 60(6), 84–90 (2017).
<https://doi.org/10.1145/3065386>
 1244. Kudugunta, S., Ferrara, E.: Deep neural networks for bot detection. Information Sciences 467, 312–322 (2018). <https://doi.org/10.1016/j.ins.2018.08.019>
 1245. LA, S., et al.: DNA sequence recognition using image representation. Research in Computing Science 148, 105–114 (2019). <https://doi.org/10.13053/rcs-148-3-9>
 1246. Liu, Z., Mao, H., Wu, C.Y., Feichtenhofer, C., Darrell, T., Xie, S.: A ConvNet for the 2020s. In: Computer Vision and Pattern Recognition. pp. 11966–11976 (2022).
<https://doi.org/10.1109/CVPR52688.2022.01167>
 1247. Mazza, M., Avvenuti, M., Cresci, S., Tesconi, M.: Investigating the difference between trolls, social bots, and humans on Twitter. Computer Communications 196, 23–36 (2022)
 1248. Meel, P., Vishwakarma, D.K.: Fake news, rumor, information pollution in social media and web: A contemporary survey of state-of-the-arts, challenges and opportunities. Expert Systems with Applications 153 (2020).
<https://doi.org/https://doi.org/10.1016/j.eswa.2019.112986>

1249. Mustafaraj, E., Metaxas, P.T.: From obscurity to prominence in minutes: Political speech and real-time search. In: Web Science: Extending the Frontiers of Society On-Line (2010)
1250. Najari S., Salehi M., F.R.: Ganbot: a gan-based framework for social bot detection. Soc. Netw. Anal. Min. 12(4) (2022). <https://doi.org/10.1007/s13278-021-00800-9>, <https://doi.org/10.1007/s13278-021-00800-9>
1251. Olteanu, A., Castillo, C., Diaz, F., Kıcıman, E.: Social data: Biases, methodological pitfalls, and ethical boundaries. Frontiers in Big Data 2, 13 (2019)
1252. Rauchfleisch, A., Kaiser, J.: The false positive problem of automatic bot detection in social science research. PLoS One 15(10) (2020)
1253. Sayyadiharikandeh, M., et al.: Detection of novel social bots by ensembles of specialized classifiers. In: CIKM '20: The 29th ACM International Conference on Information and Knowledge Management. pp. 2725–2732. ACM (2020)
1254. Shao, C., et al.: Anatomy of an online misinformation network. Plos one 13(4), e0196087 (2018)
1255. Simonyan, K., Zisserman, A.: Very deep convolutional networks for large-scale image recognition. In: Bengio, Y., LeCun, Y. (eds.) Learning Representations (2015)
1256. Suarez-Lledo, V., Alvarez-Galvez, J.: Prevalence of health misinformation on social media: Systematic review. J Med Internet Res 23(1), e17187 (Jan 2021). <https://doi.org/10.2196/17187>, <http://www.imir.org/2021/1/e17187/>
1257. Sultana, F., Sufian, A., Dutta, P.: Advancements in image classification using convolutional neural network. In: 2018 Fourth International Conference on Research in Computational Intelligence and Communication Networks (ICRCICN). pp. 122– 129. IEEE (2018), <http://arxiv.org/abs/1905.03288>
1258. Sun, B., Yang, L., Zhang, W., Lin, M., Dong, P., Young, C., Dong, J.: Supertml: Two-dimensional word embedding and transfer learning using imagenet pretrained CNN models for the classifications on tabular data. CoRR abs/1903.06246 (2019), <http://arxiv.org/abs/1903.06246>
1259. Tan, Z., Feng, S., Sclar, M., Wan, H., Luo, M., Choi, Y., Tsvetkov, Y.: BotPercent: Estimating Twitter bot populations from groups to crowds. arXiv:2302.00381 (2023)
1260. Valkenburg, P.M., Peter, J.: Comm research—views from europe | five challenges for the future of media-effects research. International Journal of Communication 7, 19 (2013)
1261. Wei, F., Nguyen, U.T.: Twitter bot detection using bidirectional long shortterm memory neural networks and word embeddings. In: Trust, Privacy and Security in Intelligent Systems and Applications. pp. 101–109 (2019). <https://doi.org/10.1109/TPS-ISA48467.2019.00021>
1262. Wu, Y., Fang, Y., Shang, S., Jin, J., Wei, L., Wang, H.: A novel framework for detecting social bots with deep neural networks and active learning. Knowledge-Based Systems 211 (2021). <https://doi.org/https://doi.org/10.1016/j.knosys.2020.106525>
1263. Yang, C., Harkreader, R., Gu, G.: Empirical evaluation and new design for fighting evolving twitter spammers. IEEE Transactions on Information Forensics and Security 8(8), 1280–1293 (2013). <https://doi.org/10.1109/TIFS.2013.2267732>

1264. Yang, K., Varol, O., Davis, C.A., Ferrara, E., Flammini, A., Menczer, F.: Arming the public with AI to counter social bots. CoRR abs/1901.00912 (2019), <http://arxiv.org/abs/1901.00912>
1265. Yang, Y., Yang, R., Li, Y., Cui, K., Yang, Z., Wang, Y., Xu, J., Xie, H.: RoSGAS: Adaptive social bot detection with reinforced self-supervised GNN architecture search. Trans. on the Web (2022). <https://doi.org/10.1145/3572403>
1266. Yardi, S., Romero, D., Schoenebeck, G., et al.: Detecting spam in a Twitter network. First Monday (2010). <https://doi.org/10.5210/fm.v15i1.2793>
1267. Ying, X.: An overview of overfitting and its solutions. In: Journal of physics: Conference series. vol. 1168, p. 022022. IOP Publishing (2019)
1268. Yu, R., He, X., Liu, Y.: GLAD: Group anomaly detection in social media analysis. ACM Transactions on Knowledge Discovery from Data (TKDD) 10(2), 1–22 (2015)
1269. Limeng Cui, Haeseung Seo, Maryam Tabar, Fenglong Ma, Suhang Wang, and Dongwon Lee. Deterrent: Knowledge guided graph attention network for detecting healthcare misinformation. In Proceedings of the 26th ACM SIGKDD international conference on knowledge discovery & data mining, pages 492–502, 2020.
1270. Youze Wang, Shengsheng Qian, Jun Hu, Quan Fang, and Changsheng Xu. Fake news detection via knowledge-driven multimodal graph convolutional networks. In Proceedings of the 2020 International Conference on Multimedia Retrieval, pages 540–547, 2020.
1271. Yi-Ju Lu and Cheng-Te Li. Gcan: Graph-aware co-attention networks for explainable fake news detection on social media. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 505–514, 2020.
1272. Philip N Howard, Bence Kollanyi, and Samuel Woolley. Bots and automation over twitter during the us election. Computational propaganda project: Working paper series, 21(8), 2016.
1273. Samantha Bradshaw, Bence Kollanyi, Clementine Desigaud, and Gillian Bolsover. Junk news and bots during the french presidential election: What are french voters sharing over twitter? Technical report, COMPROP Data Memo, 2017.
1274. Sippo Rossi, Matti Rossi, Bikesh Upreti, and Yong Liu. Detecting political bots on twitter during the 2019 finnish parliamentary election. In Proceedings of the 53rd Hawaii International Conference on System Sciences, 2020.
1275. Emilio Ferrara. Disinformation and social bot operations in the run up to the 2017 french presidential election. arXiv preprint arXiv:1707.00086, 2017.
1276. Emilio Ferrara, Wen-Qiang Wang, Onur Varol, Alessandro Flammini, and Aram Galstyan. Predicting online extremism, content adopters, and interaction reciprocity. In International conference on social informatics, pages 22–39. Springer, 2016.
1277. William Marcellino, Madeline Magnuson, Anne Stickells, Benjamin Boudreaux, Todd C Helmus, Edward Geist, and Zev Winkelman. Counter-radicalization bot research using social bots to fight violent extremism. Technical report, Rand Corp Santa Monica CA United States, 2020.
1278. Emilio Ferrara. What types of covid-19 conspiracies are populated by twitter bots? arXiv preprint arXiv:2004.09531, 2020.

1279. Wasim Ahmed, Francesc López Seguí, Josep Vidal-Alaball, Matthew S Katz, et al. Covid-19 and the “film your hospital” conspiracy theory: social network analysis of twitter data. *Journal of medical Internet research*, 22(10):e22374, 2020.
1280. Ahmed Anwar, Haider Ilyas, Ussama Yaqub, and Salma Zaman. Analyzing qanon on twitter in context of us elections 2020: Analysis of user messages and profiles using vader and bert topic modeling. In *DG. O2021: The 22nd Annual International Conference on Digital Government Research*, pages 82–88, 2021.
1281. Kai-Cheng Yang, Onur Varol, Pik-Mai Hui, and Filippo Menczer. Scalable and generalizable social bot detection through data selection. In *Proceedings of the AAAI conference on artificial intelligence*, volume 34, pages 1096–1103, 2020.
1282. Kyumin Lee, Brian Eoff, and James Caverlee. Seven months with the devils: A long-term study of content polluters on twitter. In *Proceedings of the international AAAI conference on web and social media*, volume 5, pages 185–192, 2011.
1283. Michele Mazza, Stefano Cresci, Marco Avvenuti, Walter Quattrociocchi, and Maurizio Tesconi. Rtbust: Exploiting temporal patterns for botnet detection on twitter. In *Proceedings of the 10th ACM conference on web science*, pages 183–192, 2019.
1284. Nikan Chavoshi, Hossein Hamooni, and Abdullah Mueen. Debot: Twitter bot detection via warped correlation. In *2016 IEEE 16th International Conference on Data Mining (ICDM)*, pages 817–822. IEEE Computer Society, 2016.
1285. David M Beskow and Kathleen M Carley. You are known by your friends: Leveraging network metrics for bot detection in twitter. In *Open Source Intelligence and Cyber Crime*, pages 53–88. Springer, 2020.
1286. Zi Chu, Steven Gianvecchio, Haining Wang, and Sushil Jajodia. Detecting automation of twitter accounts: Are you a human, bot, or cyborg? *IEEE Transactions on dependable and secure computing*, 9(6):811–824, 2012.
1287. Stefano Cresci, Roberto Di Pietro, Marinella Petrocchi, Angelo Spognardi, and Maurizio Tesconi. The paradigm-shift of social spambots: Evidence, theories, and tools for the arms race. In *Proceedings of the 26th international conference on world wide web companion*, pages 963–972, 2017a.
1288. Stefano Cresci. A decade of social bot detection. *Communications of the ACM*, 63(10):72–83, 2020.
1289. Feng Wei and Uyen Trang Nguyen. Twitter bot detection using bidirectional long short-term memory neural networks and word embeddings. In *2019 First IEEE International Conference on Trust, Privacy and Security in Intelligent Systems and Applications (TPS-ISA)*, pages 101–109. IEEE, 2019.
1290. Sneha Kudugunta and Emilio Ferrara. Deep neural networks for bot detection. *Information Sciences*, 467:312–322, 2018.
1291. Shangbin Feng, Herun Wan, Ningnan Wang, Jundong Li, and Minnan Luo. Satar: A self-supervised approach to twitter account representation learning and its application in bot detection. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*, pages 3808–3817, 2021a.

1292. David Dukic, Dominik Keca, and Dominik Stipic. Are you human? detecting bots on twitter using ´ bert. In 2020 IEEE 7th International Conference on Data Science and Advanced Analytics (DSAA), pages 631–636. IEEE, 2020.
1293. Shangbin Feng, Herun Wan, Ningnan Wang, and Minnan Luo. Botrgcn: Twitter bot detection with relational graph convolutional networks. In Proceedings of the 2021 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, pages 236–239, 2021b.
1294. Seyed Ali Alhosseini, Raad Bin Tareaf, Pejman Najafi, and Christoph Meinel. Detect me if you can: Spam bot detection using inductive representation learning. In Companion Proceedings of The 2019 World Wide Web Conference, pages 148–153, 2019.
1295. Thomas N Kipf and Max Welling. Semi-supervised classification with graph convolutional networks. arXiv preprint arXiv:1609.02907, 2016.
1296. Michael Schlichtkrull, Thomas N Kipf, Peter Bloem, Rianne van den Berg, Ivan Titov, and Max Welling. Modeling relational data with graph convolutional networks. In European semantic web conference, pages 593–607. Springer, 2018.
1297. Shangbin Feng, Zhaoxuan Tan, Rui Li, and Minnan Luo. Heterogeneity-aware twitter bot detection with relational graph transformers. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 36, pages 3977–3985, 2022.
1298. Shangbin Feng, Herun Wan, Ningnan Wang, Jundong Li, and Minnan Luo. Twibot-20: A comprehensive twitter bot detection benchmark. In Proceedings of the 30th ACM International Conference on Information & Knowledge Management, pages 4485–4494, 2021c.
1299. Stefano Cresci, Roberto Di Pietro, Marinella Petrocchi, Angelo Spognardi, and Maurizio Tesconi. Fame for sale: Efficient detection of fake twitter followers. Decision Support Systems, 80:56–71, 2015.
1300. Juan M Banda, Ramya Tekumalla, Guanyu Wang, Jingyuan Yu, Tuo Liu, Yuning Ding, Ekaterina Artemova, Elena Tutubalina, and Gerardo Chowell. A large-scale covid-19 twitter chatter dataset for open scientific research—an international collaboration. Epidemiologia, 2(3):315–324, 2021.
1301. Eduardo Graells-Garrido and Ricardo Baeza-Yates. Bots don’t vote, but they surely bother! a study of anomalous accounts in a national referendum. arXiv preprint arXiv:2203.04135, 2022.
1302. Adrian Rauchfleisch and Jonas Kaiser. The false positive problem of automatic bot detection in social science research. PloS one, 15(10):e0241045, 2020.
1303. Zachary Miller, Brian Dickinson, William Deitrick, Wei Hu, and Alex Hai Wang. Twitter spammer detection using data stream clustering. Information Sciences, 260:64–73, 2014.
1304. Kadhim Hayawi, Sujith Mathew, Neethu Venugopal, Mohammad M Masud, and Pin-Han Ho. Deeprobot: a hybrid deep neural network model for social bot detection based on user profile data. Social Network Analysis and Mining, 12(1):1–19, 2022.
1305. Fred Morstatter, Liang Wu, Tahora H Nazer, Kathleen M Carley, and Huan Liu. A new approach to bot detection: striking the balance between precision and recall. In 2016 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM), pages 533–540. IEEE, 2016.

1306. Chiyu Cai, Linjing Li, and Daniel Zeng. Detecting social bots by jointly modeling deep behavior and content information. In *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management*, pages 1995–1998, 2017.
1307. Jürgen Knauth. Language-agnostic twitter-bot detection. In *Proceedings of the International Conference on Recent Advances in Natural Language Processing (RANLP 2019)*, pages 550–558, 2019.
1308. Ashkan Dehghan, Kinga Siuta, Agata Skorupka, Akshat Dubey, Andrei Betlen, David Miller, Wei Xu, Bogumil Kaminski, and Pawel Pralat. Detecting bots in social-networks using node and structural embeddings. 2022.
1309. Phu Pham, Loan TT Nguyen, Bay Vo, and Unil Yun. Bot2vec: A general approach of intra-community oriented representation learning for bot detection in different types of social networks. *Information Systems*, 103:101771, 2022.
1310. Qinglang Guo, Haiyong Xie, Yangyang Li, Wen Ma, and Chao Zhang. Social bots detection via fusing bert and graph convolutional networks. *Symmetry*, 14(1):30, 2021a.
1311. 12Peter J Carrington, John Scott, and Stanley Wasserman. *Models and methods in social network analysis*, volume 28. Cambridge university press, 2005.
1312. Yiyue Qian, Yiming Zhang, Yanfang Ye, and Chuxu Zhang. Distilling meta knowledge on heterogeneous graph for illicit drug trafficker detection on social media. *Advances in Neural Information Processing Systems*, 34, 2021.
1313. Wei Guo, Rong Su, Renhao Tan, Huifeng Guo, Yingxue Zhang, Zhirong Liu, Ruiming Tang, and Xiuqiang He. Dual graph enhanced embedding neural network for ctr prediction. In *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*, pages 496–504, 2021b.
1314. Can Liu, Li Sun, Xiang Ao, Jinghua Feng, Qing He, and Hao Yang. Intention-aware heterogeneous graph attention networks for fraud transactions detection. In *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*, pages 3280–3288, 2021.
1315. Zhao Li, Haishuai Wang, Peng Zhang, Pengrui Hui, Jiaming Huang, Jian Liao, Ji Zhang, and
1316. Jiajun Bu. Live-streaming fraud detection: A heterogeneous graph neural network approach. In *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*, pages 3670–3678, 2021.
1317. Li Wang, Peipei Li, Kai Xiong, Jiashu Zhao, and Rui Lin. Modeling heterogeneous graph network on fraud detection: A community-based framework with attention mechanism. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*, pages 1959–1968, 2021.
1318. Pushkar Mishra, Helen Yannakoudakis, and Ekaterina Shutova. Modeling users and online communities for abuse detection: A position on ethics and explainability. In *Findings of the Association for Computational Linguistics: EMNLP 2021*, pages 3374–3385, Punta Cana, Dominican Republic, November 2021. Association for Computational Linguistics. doi:10.18653/v1/2021.findings-emnlp.287. URL [https://aclanthology.org/2021.findings-
emnlp.287](https://aclanthology.org/2021.findings-emnlp.287).

1319. Yingdong Dou, Zhiwei Liu, Li Sun, Yutong Deng, Hao Peng, and Philip S Yu. Enhancing graph neural network-based fraud detectors against camouflaged fraudsters. In Proceedings of the 29th ACM International Conference on Information & Knowledge Management, pages 315–324, 2020.
1320. Iraklis Varlamis, Dimitrios Michail, Foteini Glykou, and Panagiotis Tsantilas. A survey on the use of graph convolutional networks for combating fake news. *Future Internet*, 14(3):70, 2022.
1321. Linmei Hu, Tianchi Yang, Luhao Zhang, Wanjuan Zhong, Duyu Tang, Chuan Shi, Nan Duan, and Ming Zhou. Compare to the knowledge: Graph neural fake news detection with external knowledge. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 754–763, 2021.
1322. Rex Ying, Ruining He, Kaifeng Chen, Pong Eksombatchai, William L Hamilton, and Jure Leskovec. Graph convolutional neural networks for web-scale recommender systems. In Proceedings of the 24th ACM SIGKDD international conference on knowledge discovery & data mining, pages 974–983, 2018.
1323. Shiwen Wu, Fei Sun, Wentao Zhang, Xu Xie, and Bin Cui. Graph neural networks in recommender systems: a survey. *ACM Computing Surveys (CSUR)*. Thomas Magelinski, David Beskow, and Kathleen M Carley. Graph-hist: Graph classification from latent feature histograms with application to bot detection. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 34, pages 5134–5141, 2020.
1324. Zhenyu Lei, Herun Wan, Wenqian Zhang, Shangbin Feng, Zilong Chen, Qinghua Zheng, and Minnan Luo. Bic: Twitter bot detection with text-graph interaction and semantic consistency. *arXiv preprint arXiv:2208.08320*, 2022.
1325. Alexander Ratner, Stephen H Bach, Henry Ehrenberg, Jason Fries, Sen Wu, and Christopher Ré. Snorkel: Rapid training data creation with weak supervision. In Proceedings of the VLDB Endowment. International Conference on Very Large Data Bases, volume 11, page 269. NIH Public Access, 2017.
1326. Justus J Randolph. Free-marginal multirater kappa (multirater k - free -): An alternative to fleiss’ fixed-marginal multirater kappa. Online submission, 2005.
1327. Petar Velickovic, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Liò, and Yoshua Bengio. Graph attention networks. In International Conference on Learning Representations, 2018.
1328. Zafar Gilani, Reza Farahbakhsh, Gareth Tyson, Liang Wang, and Jon Crowcroft. Of bots and humans (on twitter). In Proceedings of the 2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2017, pages 349–354, 2017.
1329. Stefano Cresci, Roberto Di Pietro, Marinella Petrocchi, Angelo Spognardi, and Maurizio Tesconi. Social fingerprinting: detection of spambot groups through dna-inspired behavioral modeling. *IEEE Transactions on Dependable and Secure Computing*, 15(4):561–576, 2017b.
1330. Stefano Cresci, Fabrizio Lillo, Daniele Regoli, Serena Tardelli, and Maurizio Tesconi. Fake: Evidence of spam and bot activity in stock microblogs on twitter. In Twelfth international AAAI conference on web and social media, 2018.

1331. Stefano Cresci, Fabrizio Lillo, Daniele Regoli, Serena Tardelli, and Maurizio Tesconi. Cashtag piggybacking: Uncovering spam and bot activity in stock microblogs on twitter. *ACM Transactions on the Web (TWEB)*, 13(2):1–27, 2019.
1332. Kai-Cheng Yang, Onur Varol, Clayton A Davis, Emilio Ferrara, Alessandro Flammini, and Filippo Menczer. Arming the public with artificial intelligence to counter social bots. *Human Behavior and Emerging Technologies*, 1(1):48–61, 2019.
1333. David M Beskow and Kathleen M Carley. Bot-hunter: a tiered approach to detecting & characterizing automated activity on twitter. In *Conference paper. SBP-BRIMS: International Conference on Social Computing, Behavioral-Cultural Modeling and Prediction and Behavior Representation in Modeling and Simulation*, volume 3, page 3, 2018.
1334. David M Beskow and Kathleen M Carley. Its all in a name: detecting and labeling bots by their name. *Computational and Mathematical Organization Theory*, 25(1):24–35, 2019.
1335. Jefferson Viana Fonseca Abreu, Célia Ghedini Ralha, and João José Costa Gondim. Twitter bot detection with reduced feature set. In *2020 IEEE International Conference on Intelligence and Security Informatics (ISI)*, pages 1–6. IEEE, 2020.
1336. Stefano Cresci, Roberto Di Pietro, Marinella Petrocchi, Angelo Spognardi, and Maurizio Tesconi. Dna-inspired online behavioral modeling and its application to spambot detection. *IEEE Intelligent Systems*, 31(5):58–64, 2016.
1337. Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692*, 2019. Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi
1338. Zhou, Wei Li, Peter J Liu, et al. Exploring the limits of transfer learning with a unified text-to-text transformer. *J. Mach. Learn. Res.*, 21(140):1–67, 2020. Phillip George Efthimion, Scott Payne, and Nicholas Proferes. Supervised machine learning bot detection techniques to identify social twitter bots. *SMU Data Science Review*, 1(2):5, 2018.
1339. Mücahit Kantepe and Murat Can Ganiz. Preprocessing framework for twitter bot detection. In *2017 International conference on computer science and engineering (ubmk)*, pages 630–634. IEEE, 2017.
1340. Onur Varol, Emilio Ferrara, Clayton Davis, Filippo Menczer, and Alessandro Flammini. Online human-bot interactions: Detection, estimation, and characterization. In *Proceedings of the international AAAI conference on web and social media*, volume 11, 2017.
1341. Maria Kouvela, Ilias Dimitriadis, and Athena Vakali. Bot-detective: An explainable twitter bot detection service with crowdsourcing functionalities. In *Proceedings of the 12th International Conference on Management of Digital EcoSystems*, pages 55–63, 2020.
1342. Eric Ferreira Dos Santos, Danilo Carvalho, Livia Ruback, and Jonice Oliveira. Uncovering social media bots: a transparency-focused approach. In *Companion Proceedings of The 2019 World Wide Web Conference*, pages 545–552, 2019.
1343. Juan Echeverría, Emiliano De Cristofaro, Nicolas Kourtellis, Ilias Leontiadis, Gianluca Stringhini, and Shi Zhou. Lobo: Evaluation of generalization deficiencies in twitter bot classifiers. In *Proceedings of the 34th Annual Computer Security Applications Conference*, pages 137–146, 2018.

1344. Samaneh Hosseini Moghaddam and Maghsoud Abbaspour. Friendship preference: Scalable and robust category of features for social bot detection. *IEEE Transactions on Dependable and Secure Computing*, 2022.
1345. Kai-Cheng Yang, Emilio Ferrara, and Filippo Menczer. Botometer 101: Social bot practicum for computational social scientists. *arXiv preprint arXiv:2201.01608*, 2022.
1346. Jorge Rodríguez-Ruiz, Javier Israel Mata-Sánchez, Raúl Monroy, Octavio Loyola-González, and Armando López-Cuevas. A one-class classification approach for bot detection on twitter. *Computers & Security*, 91:101715, 2020.
1347. Chao Yang, Robert Harkreader, and Guofei Gu. Empirical evaluation and new design for fighting evolving twitter spammers. *IEEE Transactions on Information Forensics and Security*, 8(8): 1280–1293, 2013.
1348. Ziniu Hu, Yuxiao Dong, Kuansan Wang, and Yizhou Sun. Heterogeneous graph transformer. In *Proceedings of The Web Conference 2020*, pages 2704–2710, 2020.
1349. Qingsong Lv, Ming Ding, Qiang Liu, Yuxiang Chen, Wenzheng Feng, Siming He, Chang Zhou, Jianguo Jiang, Yuxiao Dong, and Jie Tang. Are we really making much progress? revisiting, benchmarking and refining heterogeneous graph neural networks. In *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*, pages 1150–1160, 2021.
1350. Lynnette Hui Xian Ng, Dawn C Robertson, and Kathleen M Carley. Stabilizing a supervised bot detection algorithm: How much data is needed for consistent predictions? *Online Social Networks and Media*, 28:100198, 2022.
1351. Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781*, 2013.
1352. Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Kopf, Edward Yang, Zachary DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. Pytorch: An imperative style, high-performance deep learning library. In H. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alché-Buc, E. Fox, and R. Garnett, editors, *Advances in Neural Information Processing Systems*, volume 32. Curran Associates, Inc., 2019. URL <https://proceedings.neurips.cc/paper/2019/file/bdbca288fee7f92f2bfa9f7012727740-Paper.pdf>. William Falcon and The PyTorch Lightning team. PyTorch Lightning, 3 2019. URL <https://github.com/PyTorchLightning/pytorch-lightning>.
1353. Kay Liu, Yingdong Dou, Yue Zhao, Xueying Ding, Xiyang Hu, Ruitong Zhang, Kaize Ding, Canyu Chen, Hao Peng, Kai Shu, et al. Pygod: A python library for graph outlier detection. *arXiv preprint arXiv:2204.12095*, 2022.
1354. Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Remi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander Rush. Transformers: State-of-the-art natural language processing. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 38–45, Online, October 2020. Association for Computational Linguistics. doi:10.18653/v1/2020.emnlp-demos.6. URL <https://aclanthology.org/2020.emnlp-demos.6>.

1355. Matthias Fey and Jan Eric Lenssen. Fast graph representation learning with pytorch geometric. arXiv preprint arXiv:1903.02428, 2019.
1356. F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830, 2011.
1357. Radim Rehurek and Petr Sojka. Software Framework for Topic Modelling with Large Corpora. In *Proceedings of the LREC 2010 Workshop on New Challenges for NLP Frameworks*, pages 45–50, Valletta, Malta, May 2010. ELRA. <http://is.muni.cz/publication/884893/en>.
1358. Matthew Honnibal, Ines Montani, Sofie Van Landeghem, and Adriane Boyd. spaCy: Industrialstrength Natural Language Processing in Python. 2020. doi:10.5281/zenodo.1212303.
1359. Joshua Roesslein. tweepy documentation. Online <http://tweepy.readthedocs.io/en/v3.5.0/>, 5, 2009.
1360. Wes McKinney et al. pandas: a foundational python library for data analysis and statistics. *Python for high performance and scientific computing*, 14(9):1–9, 2011.
1361. Charles R Harris, K Jarrod Millman, Stéfan J Van Der Walt, Ralf Gommers, Pauli Virtanen, David Cournapeau, Eric Wieser, Julian Taylor, Sebastian Berg, Nathaniel J Smith, et al. Array programming with numpy. *Nature*, 585(7825):357–362, 2020.
1362. Clayton Hutto and Eric Gilbert. Vader: A parsimonious rule-based model for sentiment analysis of social media text. In *Proceedings of the international AAAI conference on web and social media*, volume 8, pages 216–225, 2014.
1363. Guillaume Lemaître, Fernando Nogueira, and Christos K. Aridas. Imbalanced-learn: A python toolbox to tackle the curse of imbalanced datasets in machine learning. *Journal of Machine Learning Research*, 18(17):1–5, 2017.
1364. M. Abdullah, A. Madain, and Y. Jararweh, 2022. “ChatGPT: Fundamentals, applications and social impacts,” 2022 Ninth International Conference on Social Networks Analysis, Management and Security (SNAMS), pp. 1–8. doi:<https://doi.org/10.1109/SNAMS58071.2022.10062688>, accessed 1 June 2023.
1365. Adadi and M. Berrada, 2018. “Peeking inside the black-box: A survey on explainable artificial intelligence (XAI),” *IEEE Access*, volume 6, pp. 52,138–52,160. doi:<https://doi.org/10.1109/ACCESS.2018.2870052>, accessed 1 June 2023.
1366. Addawood, A. Badawy, K. Lerman, and E. Ferrara, 2019. “Linguistic cues to deception: Identifying political trolls on social media,” *Proceedings of the International AAAI Conference on Web and Social Media*, volume 13, pp. 15–25, and at <https://ojs.aaai.org/index.php/ICWSM/article/view/3205>, accessed 1 June 2023.
1367. D. Afchar, V. Nozick, J. Yamagishi, and I. Echizen, 2018. “MesoNet: A compact facial video forgery detection network,” 2018 IEEE international workshop on information forensics and security (WIFS). doi:<https://doi.org/10.1109/WIFS.2018.8630761>, accessed 1 June 2023.
1368. Badawy, E. Ferrara, and K. Lerman, 2018. “Analyzing the digital traces of political manipulation: The 2016 Russian interference Twitter campaign,” 2018 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM), pp. 258–265. doi:<https://doi.org/10.1109/ASONAM.2018.8508646>, accessed 1 June 2023.

1369. F. Benevenuto, G. Magno, T. Rodrigues, and V. Almeida, 2010. "Detecting spammers on Twitter," Collaboration, Electronic messaging, Anti-Abuse and Spam Conference (CEAS), at https://gmagno.net/papers/ceas2010_benevenuto_twitterspam.pdf, accessed 1 June 2023.
1370. D.M. Beskow and K.M. Carley, 2018. "Bot-hunter: A tiered approach to detecting & characterizing automated activity on Twitter," at https://sbpbrims.org/2018/proceedings/papers/latebreaking_papers/LB_5.pdf, accessed 1 June 2023.
1371. Besel, J. Echeverria, and S. Zhou, 2018. "Full cycle analysis of a large-scale botnet attack on Twitter," 2018 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM). Social bot detection in the age of ChatGPT: Challenges and opportunities doi:<https://doi.org/10.1109/ASONAM.2018.8508708>, accessed 1 June 2023.
1372. Bessi and E. Ferrara, 2016. "Social bots distort the 2016 U.S. Presidential election online discussion," First Monday, volume 21, number 11, at <https://firstmonday.org/ojs/index.php/fm/article/view/7090/5653>, accessed 1 June 2023. doi:<https://doi.org/10.5210/fm.v21i11.7090>, accessed 1 June 2023.
1373. Biggio, I. Corona, D. Maiorca, B. Nelson, N. Šrندیć, P. Laskov, P. Laskov, G. Giacinto, and F. Roli, 2013. "Evasion attacks against machine learning at test time," In: H. Blockeel, K. Kersting, S. Nijssen, and F. Železný (editors). Joint European Conference on Machine Learning and Knowledge Discovery in Databases. Lecture Notes in Computer Science, volume 8190. Berlin: Springer, pp. 387–402. doi:https://doi.org/10.1007/978-3-642-40994-3_25, accessed 1 June 2023.
1374. P.B. Brandtzaeg and A. Følstad, 2017. "Why people use chatbots," In: I. Kompatsiaris, J. Cave, A. Satsiou, G. Carle, A. Passani, E. Kontopoulos, S. Diplaris, and D. McMillan (editors). Internet science. Lecture Notes in Computer Science, volume 10673. Cham, Switzerland: Springer, pp. 377–392. doi:https://doi.org/10.1007/978-3-319-70284-1_30, accessed 1 June 2023.
1375. Buciluă, R. Caruana, and A. Niculescu-Mizil, 2006. "Model compression," KDD '06: Proceedings of the 12th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 535–541. doi:<https://doi.org/10.1145/1150402.1150464>, accessed 1 June 2023.
1376. Q. Cao, X. Yang, J. Yu, and C. Palow, 2014. "Uncovering large groups of active malicious accounts in online social networks," CCS '14: Proceedings of the 2014 ACM SIGSAC Conference on Computer and Communications Security, pp. 477–488. doi:<https://doi.org/10.1145/2660267.2660269>, accessed 1 June 2023.
1377. Y. Cao, S. Li, Y. Liu, Z. Yan, Y. Dai, P.S. Yu, and L. Sun, 2023. "A comprehensive survey of ai-generated content (AIGC): A history of generative ai from GAN to ChatGPT," arXiv:2303.04226 (7 March). doi:<https://doi.org/10.48550/arXiv.2303.04226>, accessed 1 June 2023.
1378. V. Chandola, A. Banerjee, and V. Kumar, 2009. "Anomaly detection: A survey," ACM Computing Surveys, volume 41, number 3, article number 15, pp. 1–58. doi:<https://doi.org/10.1145/1541880.1541882>, accessed 1 June 2023.
1379. H.C.H. Chang and E. Ferrara, 2022. "Comparative analysis of social bots and humans during the COVID-19 pandemic," Journal of Computational Social Science, volume 5, pp. 1,409–1,425. doi:<https://doi.org/10.1007/s42001-022-00173-9>, accessed 1 June 2023.

1380. H.C.H. Chang, E. Chen, M. Zhang, G. Muric, and E. Ferrara, 2021. "Social bots and social media manipulation in 2020: The year in review," In: U. Engel, A. Quan-Haase, S.X. Liu, and L. Lyberg (editors). *Handbook of Computational Social Science. Volume 1: Theory, Case Studies and Ethics*. London: Routledge. doi:<https://doi.org/10.4324/9781003024583>, accessed 1 June 2023.
1381. N. Chavoshi, H. Hamooni, and A. Mueen, 2016. "DeBot: Twitter bot detection via warped correlation," 2016 IEEE 16th International Conference on Data Mining, pp. 817–822. doi:<https://doi.org/10.1109/ICDM.2016.0096>, accessed 1 June 2023.
1382. Z. Chu, S. Gianvecchio, H. Wang, and S. Jajodia, 2010. "Who is tweeting on Twitter: Human, bot, or cyborg?" ACSAC '10: Proceedings of the 26th Annual Computer Security Applications Conference, pp. 21–30. doi:<https://doi.org/10.1145/1920261.1920265>, accessed 1 June 2023.
1383. J. Chung, C. Gulcehre, K. Cho, and Y. Bengio, 2014. "Empirical evaluation of gated recurrent neuralSocial bot detection in the age of ChatGPT: Challenges and opportunities networks on sequence modeling," arXiv:1412.3555 (11 December). doi:<https://doi.org/10.48550/arXiv.1412.3555>, accessed 1 June 2023.
1384. S. Cresci, 2020. "A decade of social bot detection," *Communications of the ACM*, volume 63, number 10, pp. 72–83. doi:<https://doi.org/10.1145/3409116>, accessed 1 June 2023.
1385. S. Cresci, R. Di Pietro, M. Petrocchi, A. Spognardi, and M. Tesconi, 2017. "The paradigm-shift of social spambots: Evidence, theories, and tools for the arms race," WWW '17 Companion: Proceedings of the 26th International Conference on World Wide Web Companion, pp. 963–972. doi:<https://doi.org/10.1145/3041021.3055135>, accessed 1 June 2023.
1386. C.A. Davis, O. Varol, E. Ferrara, A. Flammini, and F. Menczer, 2016. "BotOrNot: A system to evaluate social bots," WWW '16 Companion: Proceedings of the 25th International Conference Companion on World Wide Web, pp. 273–274. doi:<https://doi.org/10.1145/2872518.2889302>, accessed 1 June 2023.
1387. J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, 2018. "BERT: Pre-training of deep bidirectional transformers for language understanding," arXiv:1810.04805 (11 October). doi:<https://doi.org/10.48550/arXiv.1810.04805>, accessed 1 June 2023.
1388. Dwork, 2006. "Differential privacy," In: M. Bugliesi, B. Preneel, V. Sassone, and I. Wegener (editors). *Automata, Languages and Programming. ICALP 2006. Lecture Notes in Computer Science*, volume 4052. Berlin: Springer, pp. 1–12. doi:https://doi.org/10.1007/11787006_1, accessed 1 June 2023.
1389. J. Echeverria and S. Zhou, 2017. "Discovery, retrieval, and analysis of the 'Star Wars' botnet in Twitter," ASONAM '17: Proceedings of the 2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2017, pp. 1–8. doi:<https://doi.org/10.1145/3110025.3110074>, accessed 1 June 2023.
1390. Y.H. Ezzeldin, S. Yan, C. He, E. Ferrara, and S. Avestimehr, 2021. "Fairfed: Enabling group fairness in federated learning," arXiv:2110.00857 (2 October). doi:<https://doi.org/10.48550/arXiv.2110.00857>, accessed 1 June 2023.
1391. Ferrara, 2022. "Twitter spam and false accounts prevalence, detection and characterization: A survey," *First Monday*, volume 27, number 12, at

- <https://firstmonday.org/ojs/index.php/fm/article/view/12872/10749>, accessed 1 June 2023.
doi:<https://doi.org/10.5210/fm.v27i12.12872>, accessed 1 June 2023.
1392. Ferrara, 2020. "What types of COVID-19 conspiracies are populated by Twitter bots?" *First Monday*, volume 25, number 6, at <https://firstmonday.org/ojs/index.php/fm/article/view/10633/9548>, accessed 1 June 2023. doi:<https://doi.org/10.5210/fm.v25i6.10633>, accessed 1 June 2023.
1393. E. Ferrara, 2017. "Disinformation and social bot operations in the run up to the 2017 French presidential election," *First Monday*, volume 22, number 8, at <https://firstmonday.org/ojs/index.php/fm/article/view/8005/6516>, accessed 1 June 2023. doi:<https://doi.org/10.5210/fm.v22i8.8005>, accessed 1 June 2023.
1394. E. Ferrara, 2015. "Manipulation and abuse on social media," *ACM SIGWEB Newsletter*, volume 2015, Spring issue, article number 4, pp. 1–9. doi:<https://doi.org/10.1145/2749279.2749283>, accessed 1 June 2023.
1395. E. Ferrara and Z. Yang, 2015. "Quantifying the effect of sentiment on information diffusion in socialSocial bot detection in the age of ChatGPT: Challenges and opportunities media," *PeerJ Computer Science*, volume 1, e26. doi:<https://doi.org/10.7717/peerj-cs.26>, accessed 1 June 2023.
1396. E. Ferrara, O. Varol, C. Davis, F. Menczer, and A. Flammini, 2016. "The rise of social bots," *Communications of the ACM*, volume 59, number 7, pp. 96–104. doi:<https://doi.org/10.1145/2818717>, accessed 1 June 2023.
1397. Fung, C.J.M. Yoon, and I. Beschastnikh, 2020. "The limitations of federated learning in Sybil settings," 23rd International Symposium on Research in Attacks, Intrusions and Defenses (RAID), pp. 301–316, and at <https://www.usenix.org/system/files/raid20-fung.pdf>, accessed 1 June 2023.
1398. X. Gao, E. Ferrara, and J. Qiu, 2015. "Parallel clustering of high-dimensional social media data streams," 2015 15th IEEE/ACM International Symposium on Cluster, Cloud and Grid Computing, pp. 323–332. doi:<https://doi.org/10.1109/CCGrid.2015.19>, accessed 1 June 2023.
1399. S. Gehrmann, H. Strobelt, and A.M. Rush, 2019. "GLTR: Statistical detection and visualization of generated text," arXiv:1906.04043 (10 June). doi:<https://doi.org/10.48550/arXiv.1906.04043>, accessed 1 June 2023.
1400. I.J. Goodfellow, J. Shlens, and C. Szegedy, 2014. "Explaining and harnessing adversarial examples," arXiv:1412.6572 (20 December). doi:<https://doi.org/10.48550/arXiv.1412.6572>, accessed 1 June 2023.
1401. R. Gorwa and D. Guilbeault, 2020. "Unpacking the social media bot: A typology to guide research and policy," *Policy & Internet*, volume 12, number 2, pp. 225–248. doi:<https://doi.org/10.1002/poi3.184>, accessed 1 June 2023.
1402. R. Gorwa, R. Binns, and C. Katzenbach, 2020. "Algorithmic content moderation: Technical and political challenges in the automation of platform governance," *Big Data & Society* (28 February). doi:<https://doi.org/10.1177/2053951719897945>, accessed 1 June 2023.
1403. Grimme, D. Assenmacher, and L. Adam, 2018. "Changing perspectives: Is it sufficient to detect social bots?" In: G. Meiselwitz (editor). *Social Computing and Social Media*. User

Experience and Behavior. Lecture Notes in Computer Science, volume 10913. Cham, Switzerland: Springer, pp. 445–461. doi:https://doi.org/10.1007/978-3-319-91521-0_32, accessed 1 June 2023.

1404. Grimme, J. Pohl, S. Cresci, R. Lüling, and M. Preuss, 2022. "New automation for social bots: From trivial behavior to AI-powered communication," Disinformation in Open Online Media: Fourth Multidisciplinary International Symposium, MISDOOM 2022, Boise, ID, USA, October 11–12, 2022, Proceedings, pp. 79–99. doi:https://doi.org/10.1007/978-3-031-18253-2_6, accessed 1 June 2023.
1405. Q. Guo, H. Xie, Y. Li, W. Ma, and C. Zhang, 2021. "Social bots detection via fusing Bert and graph convolutional networks," Symmetry, volume 14, number 1, 30. doi:<https://doi.org/10.3390/sym14010030>, accessed 1 June 2023.
1406. S. Haider, L. Luceri, A. Deb, A. Badawy, N. Peng, and E. Ferrara, 2023. "Detecting social media manipulation in low-resource languages," WWW '23 Companion: Companion Proceedings of the ACM Web Conference 2023, pp. 1,358–1,364. doi:<https://doi.org/10.1145/3543873.3587615>, accessed 1 June 2023.
1407. N. Hajli, U. Saeed, M. Tajvidi, and F. Shirazi, 2022. "Social bots and the spread of disinformation in social media: The challenges of artificial intelligence," British Journal of Management, volume 33, number 3, pp. 1,238–1,253. doi:<https://doi.org/10.1111/1467-8551.12554>, accessed 1 June 2023. Social bot detection in the age of ChatGPT: Challenges and opportunities
1408. M. Heidari and J.H. Jones, 2020. "Using bert to extract topic-independent sentiment features for social media bot detection," 2020 11th IEEE Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON). doi:<https://doi.org/10.1109/UEMCON51285.2020.9298158>, accessed 1 June 2023.
1409. S. Hochreiter and J. Schmidhuber, 1997. "Long short-term memory," Neural Computation, volume 9, number 8, pp. 1,735–1,780. doi:<https://doi.org/10.1162/neco.1997.9.8.1735>, accessed 1 June 2023.
1410. Holzinger, 2016. "Interactive machine learning for health informatics: When do we need the human-in-the-loop?" Brain Informatics, volume 3, number 2, pp. 119–131. doi:<https://doi.org/10.1007/s40708-016-0042-6>, accessed 1 June 2023.
1411. Holzinger, C. Biemann, C.S. Pattichis, and D.B. Kell, 2017. "What do we need to build explainable AI systems for the medical domain?" arXiv:1712.09923 (28 December). doi:<https://doi.org/10.48550/arXiv.1712.09923>, accessed 1 June 2023.
1412. P.N. Howard and B. Kollanyi, 2016. "Bots, #StrongerIn, and #Brexit: Computational propaganda during the UK-EU referendum," arXiv:1606.06356. doi:<https://doi.org/10.48550/arXiv.1606.06356>, accessed 1 June 2023.
1413. T. Hwang, I. Pearce, and M. Nanis, 2012. "Socialbots: Voices from the fronts," Interactions, volume 19, number 2, pp. 38–45. doi:<https://doi.org/10.1145/2090150.2090161>, accessed 1 June 2023.
1414. Ippolito, D. Duckworth, C. Callison-Burch, and D. Eck, 2020. "Automatic detection of generated text is easiest when humans are fooled," Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pp. 1,808–1,822, and at <http://aclanthology.lst.uni-saarland.de/2020.aclmain.164.pdf>, accessed 1 June 2023.

1415. M. JafariAsbagh, E. Ferrara, O. Varol, F. Menczer, and A. Flammini, 2014. "Clustering memes in social media streams," *Social Network Analysis and Mining*, volume 4, article number 237. doi:<https://doi.org/10.1007/s13278-014-0237-x>, accessed 1 June 2023.
1416. S. Kudugunta and E. Ferrara, 2018. "Deep neural networks for bot detection," *Information Sciences*, volume 467, pp. 312–322. doi:<https://doi.org/10.1016/j.ins.2018.08.019>, accessed 1 June 2023.
1417. K. Lee, J. Caverlee, and S. Webb, 2010. "The social honeypot project: Protecting online communities from spammers," *WWW '10: Proceedings of the 19th International Conference on World Wide Web*, pp. 1,139–1,140. doi:<https://doi.org/10.1145/1772690.1772843>, accessed 1 June 2023.
1418. X. Li, Y. Lang, Y. Chen, X. Mao, Y. He, S. Wang, H. Xue, and Q. Lu, 2020. "Sharp multiple instance learning for deepfake video detection," *MM '20: Proceedings of the 28th ACM International Conference on Multimedia*, pp. 1,864–1,872.
1419. Y. Liu, M. Ott, N. Goyal, J. Du, M. Joshi, D. Chen, O. Levy, M. Lewis, L. Zettlemoyer, and V. Stoyanov, 2019. "RoBERTa: A robustly optimized BERT pretraining approach," *arXiv:1907.11692* (26 July). doi:<https://doi.org/10.48550/arXiv.1907.11692>, accessed 1 June 2023.
1420. L. Luceri, S. Giordano, and E. Ferrara, 2020. "Detecting troll behavior via inverse reinforcement learning: A case study of Russian trolls in the 2016 U.S. election," *Proceedings of the International AAAI Conference on Web and Social Media*, volume 14, pp. 417–427. Social bot detection in the age of ChatGPT: Challenges and opportunities doi:<https://doi.org/10.1609/icwsm.v14i1.7311>, accessed 1 June 2023.
1421. L. Luceri, A. Deb, A. Badawy, and E. Ferrara, 2019. "Red bots do it better: Comparative analysis of social bot partisan behavior," *WWW '19: Companion Proceedings of The 2019 World Wide Web Conference*, pp. 1,007–1,012. doi:<https://doi.org/10.1145/3308560.3316735>, accessed 1 June 2023.
1422. S.M. Lundberg and S.-I. Lee, 2017. "A unified approach to interpreting model predictions," *NIPS'17: Proceedings of the 31st International Conference on Neural Information Processing Systems*, pp. 4,768–4,777.
1423. H.B. McMahan, E. Moore, D. Ramage, S. Hampson, and B.A. y Arcas, 2016. "Communication-efficient learning of deep networks from decentralized data," *arXiv:1602.05629* (17 February). doi:<https://doi.org/10.48550/arXiv.1602.05629>, accessed 1 June 2023.
1424. Min, Z. Jiang, M. Freedman, and R. Weischedel. 2017. "Learning transferable representation for bilingual relation extraction via convolutional neural networks," *Proceedings of the Eighth International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pp. 674–684, and at <https://aclanthology.org/I17-1068/>, accessed 1 June 2023.
1425. M. Mitchell, S. Wu, A. Zaldivar, P. Barnes, L. Vasserman, B. Hutchinson, E. Spitzer, I.D. Raji, and T. Gebru, 2019. "Model cards for model reporting," *FAT* '19: Proceedings of the Conference on Fairness, Accountability, and Transparency*, pp. 220–229. doi:<https://doi.org/10.1145/3287560.3287596>, accessed 1 June 2023.
1426. Mørnsted, P. Sapiezynski, E. Ferrara, and S. Lehmann, 2017. "Evidence of complex contagion of information in social media: An experiment using Twitter bots," *PLoS ONE*,

- volume 12, number 9, e0184148. doi:<https://doi.org/10.1371/journal.pone.0184148>, accessed 1 June 2023.
1427. Morstatter, J. Pfeffer, H. Liu, and K. Carley, 2013. "Is the sample good enough? Comparing data from Twitter's streaming api with Twitter's firehose," *Proceedings of the International AAAI Conference on Web and Social Media*, volume 7, number 1, pp. 400–408. doi:<https://doi.org/10.1609/icwsm.v7i1.14401>, accessed 1 June 2023.
 1428. Muric, Y. Wu, and E. Ferrara, 2021. "COVID-19 vaccine hesitancy on social media: building a public Twitter data set of antivaccine content, vaccine misinformation, and conspiracies," *JMIR Public Health and Surveillance*, volume 7, number 11, e30642. doi:<https://doi.org/10.2196/30642>, accessed 1 June 2023.
 1429. Nghiem, G. Muric, F. Morstatter, and E. Ferrara, 2021. "Detecting cryptocurrency pump-and-dump frauds using market and social signals," *Expert Systems with Applications*, volume 182, 115284. doi:<https://doi.org/10.1016/j.eswa.2021.115284>, accessed 1 June 2023.
 1430. D.C. Nguyen, M. Ding, P.N. Pathirana, A. Seneviratne, J. Li, and H.V. Poor, 2021. "Federated learning for Internet of things: A comprehensive survey," *IEEE Communications Surveys & Tutorials*, volume 23, number 3, pp. 1,622–1,658. doi:<https://doi.org/10.1109/COMST.2021.3075439>, accessed 1 June 2023.
 1431. L. Nizzoli, S. Tardelli, M. Avvenuti, S. Cresci, M. Tesconi, and E. Ferrara, 2020. "Charting the landscape of online cryptocurrency manipulation," *IEEE Access*, volume 8, pp. 113,230–113,245, and at <https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=9120022>, accessed 1 June 2023.
 1432. OpenAI, 2021. "introduction — OpenAI API," at <https://platform.openai.com/docs>, accessed 1 June 2023. Social bot detection in the age of ChatGPT: Challenges and opportunities
 1433. M. Orabi, D. Mouheb, Z. Al Aghbari, and I. Kamel, 2020. "Detection of bots in social media: A systematic review," *Information Processing & Management*, volume 57, number 4, 102250. doi:<https://doi.org/10.1016/j.ipm.2020.102250>, accessed 1 June 2023.
 1434. Pacheco, A. Flammini, and F. Menczer, 2020. "Unveiling coordinated groups behind white helmets disinformation," *WWW '20: Companion Proceedings of the Web Conference 2020*, pp. 611–616. doi:<https://doi.org/10.1145/3366424.3385775>, accessed 1 June 2023.
 1435. Pacheco, P.-M. Hui, C. Torres-Lugo, B.T. Truong, A. Flammini, and F. Menczer, 2021. "Uncovering coordinated networks on social media: methods and case studies," *Proceedings of the International AAAI Conference on Web and Social Media*, volume 15, pp. 455–466. doi:<https://doi.org/10.1609/icwsm.v15i1.18075>, accessed 1 June 2023.
 1436. S.J. Pan and Q. Yang, 2010. "A survey on transfer learning," *IEEE Transactions on Knowledge and Data Engineering*, volume 22, number 10, pp. 1,345–1,359. doi:<https://doi.org/10.1109/TKDE.2009.191>, accessed 1 June 2023.
 1437. J.S. Park, J.C. O'Brien, C.J. Cai, M.R. Morris, P. Liang, and M.S. Bernstein, 2023. "Generative agents: Interactive simulacra of human behavior," *arXiv:2304.03442* (7 April). doi:<https://doi.org/10.48550/arXiv.2304.03442>, accessed 1 June 2023.
 1438. Pierri, L. Luceri, and E. Ferrara, 2022. "How does Twitter account moderation work? Dynamics of account creation and suspension during major geopolitical events,"

- arXiv:2209.07614 (15 September).
doi:<https://ojs.aaai.org/index.php/ICWSM/article/download/22197/21976>, accessed 1 June 2023.
1439. Pozzana and E. Ferrara, 2020. "Measuring bot and human behavioral dynamics," *Frontiers in Physics*, volume 8. doi:<https://doi.org/10.3389/fphy.2020.00125>, accessed 1 June 2023.
 1440. J.R. Quinlan, 1986. "Induction of decision trees," *Machine Learning*, volume 1, number 1, pp. 81–106. doi:<https://doi.org/10.1007/BF00116251>, accessed 1 June 2023.
 1441. Radford, K. Narasimhan, T. Salimans, and I. Sutskever, 2018. "Improving language understanding by generative pre-training," at https://cdn.openai.com/research-covers/languageunsupervised/language_understanding_paper.pdf, accessed 1 June 2023.
 1442. Radford, J. Wu, R. Child, D. Luan, D. Amodei, and I. Sutskever, 2019. "Language models are unsupervised multitask learners," at https://d4mucfpsywv.cloudfront.net/betterlanguagemodels/language_models_are_unsupervised_multitask_learners.pdf, accessed 1 June 2023.
 1443. N.M. Radziwill and M.C. Benton, 2017. "Evaluating quality of chatbots and intelligent conversational agents," arXiv:1704.04579 (15 April). doi:<https://doi.org/10.48550/arXiv.1704.04579>, accessed 1 June 2023.
 1444. Ratkiewicz, M. Conover, M. Meiss, B. Gonçalves, S. Patil, A. Flammini, and F. Menczer, 2011. "Truthy: Mapping the spread of astroturf in microblog streams," *WWW '11: Proceedings of the 20th International Conference Companion on World Wide Web*, pp. 249–252. doi:<https://doi.org/10.1145/1963192.1963301>, accessed 1 June 2023.
 1445. M.T. Ribeiro, S. Singh, and C. Guestrin, 2016. "'Why should I trust you?' Explaining the predictions of any classifier," *KDD '16: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pp. 1,135–1,144. doi:<https://doi.org/10.1145/2939672.2939778>, accessed 1 June 2023.
 1446. Rössler, D. Cozzolino, L. Verdoliva, C. Riess, J. Thies, and M. Nießner, 2019. "Faceforensics++: Social bot detection in the age of ChatGPT: Challenges and opportunities
 1447. Learning to detect manipulated facial images," *2019 IEEE/CVF International Conference on Computer Vision (ICCV)*. doi:<https://doi.org/10.1109/ICCV.2019.00009>, accessed 1 June 2023.
 1448. N. Ruchansky, S. Seo, and Y. Liu, 2017. "CSI: A hybrid deep model for fake news detection," *CIKM '17: Proceedings of the 2017 ACM on Conference on Information and Knowledge Management*, pp. 797–806. doi:<https://doi.org/10.1145/3132847.3132877>, accessed 1 June 2023.
 1449. M. Samory and T. Mitra, 2018. "Conspiracies online: User discussions in a conspiracy community following dramatic events," *Proceedings of the International AAAI Conference on Web and Social Media*, volume 12. doi:<https://doi.org/10.1609/icwsm.v12i1.15039>, accessed 1 June 2023.
 1450. Settles, 2010. "Active learning literature survey," *University of Wisconsin–Madison, Computer Sciences Technical Report*, number 1648, at <https://burrsettles.com/pub/settles.activelearning.pdf>, accessed 1 June 2023.

1451. Shao, G.L. Ciampaglia, O. Varol, K.C. Yang, A. Flammini, and F. Menczer, 2018. "The spread of low-credibility content by social bots," *Nature Communications*, volume 9, number 1, article number 4787. doi:<https://doi.org/10.1038/s41467-018-06930-7>, accessed 1 June 2023.
1452. Sharma, Y. Zhang, E. Ferrara, and Y. Liu, 2021. "Identifying coordinated accounts on social media through hidden influence and group behaviours," *KDD '21: Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*, pp. 1,441–1,451. doi:<https://doi.org/10.1145/3447548.3467391>, accessed 1 June 2023.
1453. Shu, D. Mahudeswaran, S. Wang, D. Lee, and H. Liu, 2018. "FakeNewsNet: A data repository with news content, social context and spatialtemporal information for studying fake news on social media," *arXiv:1809.01286* (5 September). doi:<https://doi.org/10.48550/arXiv.1809.01286>, accessed 1 June 2023.
1454. Solaiman, M. Brundage, J. Clark, A. Askeel, A. Herbert-Voss, J. Wu, A. Radford, and J. Wang, 2019. "Release strategies and the social impacts of language models," *arXiv:1908.09203* (24 August). doi:<https://doi.org/10.48550/arXiv.1908.09203>, accessed 1 June 2023.
1455. Stella, E. Ferrara, and M. De Domenico, 2018. "Bots increase exposure to negative and inflammatory content in online social systems," *Proceedings of the National Academy of Sciences*, volume 115, number 49 (20 November), pp. 12,435–12,440. doi:<https://doi.org/10.1073/pnas.1803470115>, accessed 1 June 2023.
1456. Stringhini, C. Kruegel, and G. Vigna, 2010. "Detecting spammers on social networks," *ACSAC '10: Proceedings of the 26th Annual Computer Security Applications Conference*, pp. 1–9. doi:<https://doi.org/10.1145/1920261.1920263>, accessed 1 June 2023.
1457. V.S. Subrahmanian, A. Azaria, S. Durst, V. Kagan, A. Galstyan, K. Lerman, L. Zhu, E. Ferrara, A. Flammini, and F. Menczer, 2016. "The DARPA Twitter bot challenge," *Computer*, volume 49, number 6, pp. 38–46. doi:<https://doi.org/10.1109/MC.2016.183>, accessed 1 June 2023.
1458. Sundararajan, A. Taly, and Q. Yan, 2017. "Axiomatic attribution for deep networks," *ICML'17: Proceedings of the 34th International Conference on Machine Learning*, volume 70, pp. 3,319–3,328.
1459. Szegedy, W. Zaremba, I. Sutskever, J. Bruna, D. Erhan, I. Goodfellow, and R. Fergus, 2013. "Intriguing properties of neural networks," *arXiv:1312.6199* (21 December). doi:<https://doi.org/10.48550/arXiv.1312.6199>, accessed 1 June 2023. Social bot detection in the age of ChatGPT: Challenges and opportunities
1460. L. Torrey and J. Shavlik, 2010. "Transfer learning," In: E.S. Olivas, J.D.M. Guerrero, M. Martinez-Sober, J.R. Magdalena-Benedito, and A.J. Serrano López (editors). *Handbook of research on machine learning applications and trends: Algorithms, methods, and techniques*. Hershey, Pa.: IGI Global, pp. 242–264. doi:<https://doi.org/10.4018/978-1-60566-766-9.ch011>, accessed 1 June 2023.
1461. Tramèr, A. Kurakin, N. Papernot, I. Goodfellow, D. Boneh, and P. McDaniel, 2017. "Ensemble adversarial training: Attacks and defenses," *arXiv:1705.07204* (19 May). doi:<https://doi.org/10.48550/arXiv.1705.07204>, accessed 1 June 2023.
1462. L. van der Maaten and G. Hinton, 2008. "Visualizing data using t-SNE," *Journal of Machine Learning Research*, volume 9, number 11, pp. 2,579–2,605, and at

<https://www.jmlr.org/papers/volume9/vandermaaten08a/vandermaaten08a.pdf>, accessed 1 June 2023.

1463. Varol, E. Ferrara, C. Davis, F. Menczer, and A. Flammini, 2017. "Online human-bot interactions: Detection, estimation, and characterization," *Proceedings of the International AAAI Conference on Web and Social Media*, volume 11, number 1, pp. 280–289. doi:<https://doi.org/10.1609/icwsm.v11i1.14871>, accessed 1 June 2023.
1464. M. Vasek and T. Moore, 2015. "There's no free lunch, even using Bitcoin: Tracking the popularity and profits of virtual currency scams," In: R. Böhme and T. Okamoto (editors). *Financial Cryptography and Data Security. FC 2015. Lecture Notes in Computer Science*, volume 8975. Berlin: Springer, pp. 44–61. doi:https://doi.org/10.1007/978-3-662-47854-7_4, accessed 1 June 2023.
1465. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A.N. Gomez, L. Kaiser, and I. Polosukhin, 2017. "Attention is all you need," 31st Conference on Neural Information Processing Systems (NIPS 2017), pp. 5,998–6,008, and at https://proceedings.neurips.cc/paper_files/paper/2017/hash/3f5ee243547dee91fbd053c1c4a845aa-Abstract.html, accessed 1 June 2023.
1466. M. Veale, M. Van Kleek, and R. Binns, 2018. "Fairness and accountability design needs for algorithmic support in high-stakes public sector decision-making," CHI '18: *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, paper number 440, pp. 1–14. doi:<https://doi.org/10.1145/3173574.3174014>, accessed 1 June 2023.
1467. S. Vosoughi, D. Roy, and S. Aral, 2018. "The spread of true and false news online," *Science*, volume 359, number 6380 (9 March), pp. 1,146–1,151. doi:<https://doi.org/10.1126/science.aap95>, accessed 1 June 2023.
1468. E.L. Wang, L. Luceri, F. Pierri, and E. Ferrara, 2023. "Identifying and characterizing behavioral classes of radicalization within the QAnon conspiracy on Twitter," *Proceedings of the International AAAI Conference on Web and Social Media*, at <https://arxiv.org/pdf/2209.09339.pdf>, accessed 1 June 2023.
1469. Wang, M. Mohanlal, C. Wilson, X. Wang, M. Metzger, H. Zheng, and B.Y. Zhao, 2012. "Social Turing tests: Crowdsourcing sybil detection," arXiv:1205.3856 (17 May). doi:<https://doi.org/10.48550/arXiv.1205.3856>, accessed 1 June 2023.
1470. M. Wolff and S. Wolff, 2020. "Attacking neural text detectors," arXiv:2002.11768 (19 February). doi:<https://doi.org/10.48550/arXiv.2002.11768>, accessed 1 June 2023.
1471. L. Wu, Y. Rao, H. Jin, A. Nazir, and L. Sun, 2019. "Different absorption from the same sharing: Sifted multi-task learning for fake news detection," arXiv:1909.01720 (4 September). doi:<https://doi.org/10.48550/arXiv.1909.01720>, accessed 1 June 2023.
1472. K.-C. Yang, E. Ferrara, and F. Menczer, 2022. "Botometer 101: Social bot practicum for computationalSocial bot detection in the age of ChatGPT: Challenges and opportunities for social scientists," *Journal of Computational Social Science*, volume 5, number 2, pp. 1,511–1,528. doi:<https://doi.org/10.1007/s42001-022-00177-5>, accessed 1 June 2023.
1473. K.-C. Yang, O. Varol, P.-M. Hui, and F. Menczer, 2020. "Scalable and generalizable social bot detection through data selection," *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pp 1,096–1,103. doi:<https://doi.org/10.1609/aaai.v34i01.5460>, accessed 1 June 2023.

1474. K.-C. Yang, O. Varol, C.A. Davis, E. Ferrara, A. Flammini, and F. Menczer, 2019. "Arming the public with artificial intelligence to counter social bots," *Human Behavior and Emerging Technologies*, volume 1, number 1, pp. 48–61.
doi:<https://doi.org/10.1002/hbe2.115>, accessed 1 June 2023.
1475. Z. Yang, Z. Dai, Y. Yang, J. Carbonell, R. Salakhutdinov, and Q.V. Le, 2019. "XLNet: Generalized autoregressive pretraining for language understanding," *NIPS'19: Proceedings of the 33rd International Conference on Neural Information Processing Systems*, article number 517, pp. 5,753–5,763.
1476. R. Zellers, A. Holtzman, H. Rashkin, Y. Bisk, A. Farhadi, F. Roesner, and Y. Choi, 2019. "Defending against neural fake news," *NIPS'19: Proceedings of the 33rd International Conference on Neural Information Processing Systems*, article number 812, pp. 9,054–9,065.
1477. X. Zhang, J. Zhao, and Y. LeCun, 2015. "Character-level convolutional networks for text classification," *NIPS'15: Proceedings of the 28th International Conference on Neural Information Processing Systems*, volume 1, pp. 649–657.
1478. X. Zhou and R. Zafarani, 2018. "A survey of fake news: Fundamental theories, detection methods, and opportunities," *arXiv:1812.00315* (2 December).
doi:<https://doi.org/10.48550/arXiv.1812.00315>, accessed 1 June 2023.
1479. Stefano Cresci, Roberto Di Pietro, Angelo Spognardi, Maurizio Tesconi, and Marinella Petrocchi, "Demystifying misconceptions in social bots research," *arXiv preprint arXiv:2303.17251*, 2023.
1480. Kai-Cheng Yang, Francesco Pierri, Pik-Mai Hui, David Axelrod, Christopher Torres-Lugo, John Bryden, and Filippo Menczer, "The covid-19 infodemic: Twitter versus facebook," *Big Data & Society*, vol. 8, no. 1, pp. 20539517211013861, 2021.
1481. Onur Varol, Emilio Ferrara, Clayton Davis, Filippo Menczer, and Alessandro Flammini, "Online humanbot interactions: Detection, estimation, and characterization," in *Proceedings of the international AAAI conference on web and social media*, 2017, vol. 11, pp. 280– 289.
1482. Buyun He, Yingguang Yang, Qi Wu, Hao Liu, Renyu Yang, Hao Peng, Xiang Wang, Yong Liao, and Pengyuan Zhou, "Dynamicity-aware social bot detection with dynamic graph transformers," *arXiv preprint arXiv:2404.15070*, 2024.
1483. Kai-Cheng Yang, Onur Varol, Pik-Mai Hui, and Filippo Menczer, "Scalable and generalizable social bot detection through data selection," in *Proceedings of the AAAI conference on artificial intelligence*, 2020, vol. 34, pp. 1096–1103.
1484. Michele Mazza, Stefano Cresci, Marco Avvenuti, Walter Quattrociocchi, and Maurizio Tesconi, "Rtbust: Exploiting temporal patterns for botnet detection on twitter," in *Proceedings of the 10th ACM conference on web science*, 2019, pp. 183–192.
1485. Eleonora D'Andrea, Pietro Ducange, Beatrice Lazzerini, and Francesco Marcelloni, "Real-time detection of traffic from twitter stream analysis," *IEEE transactions on intelligent transportation systems*, vol. 16, no. 4, pp. 2269–2283, 2015.
1486. Feng Wei and Uyen Trang Nguyen, "Twitter bot detection using bidirectional long short-term memory neural networks and word embeddings," in *2019 First IEEE International conference on trust, privacy and security in intelligent systems and applications (TPS-ISA)*. IEEE, 2019, pp. 101–109.

1487. Juglar Diaz, Barbara Poblete, and Felipe Bravo-Marquez, "An integrated model for textual social media data with spatio-temporal dimensions," *Information Processing & Management*, vol. 57, no. 5, pp. 102219, 2020.
1488. Maryam Heidari and James H Jones, "Using bert to extract topic-independent sentiment features for social media bot detection," in *2020 11th IEEE annual ubiquitous computing, electronics & mobile communication conference (UEMCON)*. IEEE, 2020, pp. 0542–0547.
1489. Seyed Ali Alhosseini, Raad Bin Tareaf, Pejman Najafi, and Christoph Meinel, "Detect me if you can: Spam bot detection using inductive representation learning," in *Companion proceedings of the 2019 world wide web conference*, 2019, pp. 148–153.
1490. Shangbin Feng, Herun Wan, Ningnan Wang, and Minnan Luo, "Botrgcn: Twitter bot detection with relational graph convolutional networks," in *Proceedings of the 2021 IEEE/ACM international conference on advances in social networks analysis and mining*, 2021, pp. 236–239.
1491. Shangbin Feng, Zhaoxuan Tan, Rui Li, and Minnan Luo, "Heterogeneity-aware twitter bot detection with relational graph transformers," in *Proceedings of the AAAI Conference on Artificial Intelligence*, 2022, vol. 36, pp. 3977–3985.
1492. Shangbin Feng, Zhaoxuan Tan, Herun Wan, Ningnan Wang, Zilong Chen, Binchi Zhang, Qinghua Zheng, Wenqian Zhang, Zhenyu Lei, Shujie Yang, et al., "Twibot-22: Towards graph-based twitter bot detection," *Advances in Neural Information Processing Systems*, vol. 35, pp. 35254–35269, 2022.
1493. Shuhao Shi, Kai Qiao, Jian Chen, Shuai Yang, Jie Yang, Baojie Song, Linyuan Wang, and Bin Yan, "Mgtab: A multi-relational graph-based twitter account detection benchmark," *arXiv preprint arXiv:2301.01123*, 2023.
1494. Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin, "Attention is all you need," *Advances in neural information processing systems*, vol. 30, 2017.
1495. Werner Zellinger, Thomas Grubinger, Edwin Lughofer, Thomas Natschlager, and Susanne Saminger-Platz, "Central moment discrepancy (cmd) for domaininvariant representation learning," *arXiv preprint arXiv:1702.08811*, 2017.
1496. Kai-Cheng Yang, Emilio Ferrara, and Filippo Menczer, "Botometer 101: Social bot practicum for computational social scientists," *Journal of computational social science*, vol. 5, no. 2, pp. 1511–1528, 2022.
1497. Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov, "Roberta: A robustly optimized bert pretraining approach," *arXiv preprint arXiv:1907.11692*, 2019.
1498. Thomas N Kipf and Max Welling, "Semi-supervised classification with graph convolutional networks," *arXiv preprint arXiv:1609.02907*, 2016.
1499. Petar Velickovic, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Lio, and Yoshua Bengio, "Graph attention networks," *arXiv preprint arXiv:1710.10903*, 2017.
1500. Shangbin Feng, Herun Wan, Ningnan Wang, Jundong Li, and Minnan Luo, "Satar: A self-supervised approach to twitter account representation learning and its application in bot

- detection,” in Proceedings of the 30th ACM International Conference on Information & Knowledge Management, 2021, pp. 3808–3817.
1501. Zhenyu Lei, Herun Wan, Wenqian Zhang, Shangbin Feng, Zilong Chen, Jundong Li, Qinghua Zheng, and Minnan Luo, “Bic: Twitter bot detection with text-graph interaction and semantic consistency,” arXiv preprint arXiv:2208.08320, 2022.
 1502. Yuhan Liu, Zhaoxuan Tan, Heng Wang, Shangbin Feng, Qinghua Zheng, and Minnan Luo, “Botmoe: Twitter bot detection with community-aware mixtures of modal-specific experts,” in Proceedings of the 46th International ACM SIGIR Conference on Research and Development in Information Retrieval, 2023, pp. 485–495.
 1503. Fenyu Hu, Liping Wang, Shu Wu, Liang Wang, and Tieniu Tan, “Graph classification by mixture of diverse experts,” arXiv preprint arXiv:2103.15622, 2021.
 1504. Abidin, C. (2016). “Aren’t These Just Young, Rich Women Doing Vain Things Online?”: Influencer Selfies as Subversive Frivolity. *Social Media + Society*, 2(2), 2056305116641342. <https://doi.org/10.1177/2056305116641342>
 1505. Abidin, C., Lee, J., Barbetta, T., & Miao, W. S. (2021). Influencers and COVID-19: reviewing key issues in press coverage across Australia, China, Japan, and South Korea. *Media International Australia*, 178(1), 114–135. <https://doi.org/10.1177%2F1329878X20959838>
 1506. Anspach, N. M., & Carlson, T. N. (2020). What to believe? Social media commentary and belief in misinformation. *Political Behavior*, 42, 697–718. <https://doi.org/10.1007/s11109-018-9515-z>
 1507. Ashford, N. A. (2021, March 29). Not on Facebook? You’re still likely being fed misinformation. *The New York Times*. <https://nyti.ms/3h1570D>
 1508. Ashley, S., Maksl, A., & Craft, S. (2013). Developing a news media literacy scale. *Journalism & Mass Communication Educator*, 68(1), 7–21. <https://doi.org/10.1177/1077695812469802>
 1509. Ashley, S., Maksl, A., & Craft, S. (2017). News Media Literacy and Political Engagement: What’s the Connection? *Journal of Media Literacy Education*, 9(1), 79–98. <https://doi.org/10.23860/JMLE-2017-9-1-6>
 1510. Austin, E. W., Austin, B. W., Willoughby, J. F., Amram, O., & Domgaard, S. (2021). How Media Literacy and Science Media Literacy Predicted the Adoption of Protective Behaviors Amidst the COVID-19 Pandemic. *Journal of Health Communication*, 1–14. <https://doi.org/10.1080/10810730.2021.1899345>
 1511. Ayers, J. W., Chu, B., Zhu, Z., Leas, E. C., Smith, D. M., Dredze, M., & Broniatowski, D. A. (2021). Spread of Misinformation About Face Masks and COVID-19 by Automated Software on Facebook. *JAMA Internal Medicine*. Advance Online Publication. <https://doi.org/10.1001/jamainternmed.2021.2498>
 1512. Bastick, Z. (2021). Would you notice if fake news changed your behavior? An experiment on the unconscious effects of disinformation. *Computers in Human Behavior*, 166, Article 106633. <https://doi.org/10.1016/j.chb.2020.106633>
 1513. Berryman, R., & Kavka, M. (2017). ‘I guess a lot of people see me as a big sister or a friend’: the role intimacy in the celebrification of beauty vloggers. *Journal of Gender Studies*, 26(3), 307–320. <https://doi.org/10.1080/09589236.2017.1288611>

1514. Boerman, S. C., & van Reijmersdal, E. A. (2020). Disclosing influencer marketing on YouTube to children: The moderating role of para-social relationship. *Frontiers in Psychology*, 10, Article 3042. <https://doi.org/10.3389/fpsyg.2019.03042>
1515. Buchanan, M. (2020). Managing the infodemic. *Nature Physics*, 16(9), 894. <https://doi.org/10.1038/s41567-020-01039-5>
1516. Caldera, C. (2020, July 30). Fact check: Low body fat, healthy lifestyle do not prevent COVID-19. *USA Today*. <https://bit.ly/3wGC4Wp>
1517. Casaló, L. V., Flavián, C., & Guinalíu, M. (2011). Antecedents and consequences of consumer participation in online communities: The case of the travel sector. *International Journal of Electronic Commerce*, 15, 137–167. <https://doi.org/10.2753/JEC1086-4415150205>
1518. Casaló, L. V., Flavián, C., & Ibáñez-Sánchez, S. (2020). Influencers on Instagram: Antecedents and consequences of opinion leadership. *Journal of Business Research*, 117, 510–519. <https://doi.org/10.1016/j.jbusres.2018.07.005>
1519. Chae, J. (2018). Explaining females' envy toward social media influencers. *Media Psychology*, 21(2), 246–262. <https://doi.org/10.1080/15213269.2017.1328312>
1520. De Veirman, M., Cauberghe, V., & Hudders, L. (2017). Marketing through Instagram influencers: The impact of number of followers and product divergence on brand attitude. *International Journal of Advertising*, 36(5), 798–828. <https://doi.org/10.1080/02650487.2017.1348035>
1521. Dibble, J. L., Hartmann, T., & Rosaen, S. F. (2016). Parasocial interaction and parasocial relationship: Conceptual clarification and a critical assessment of measures. *Human Communication Research*, 42(1), 21–44. <https://doi.org/10.1111/hcre.12063>
1522. Dienlin, T., Johannes, N., Bowman, N. D., Masur, P. K., Engesser, S., Kümpel, A. S., Lukito, J., Bier, L. M., Zhang, R., Johnson, B. K., Huskey, R., Schneider, F. M., Breuer, J., Parry, D. A., Vermeulen, I., Fisher, J. T., Banks, J., Weber, R., Ellis, D. A., ... de Vreese, C. (2021). An Agenda for Open Science in Communication. *Journal of Communication*, 71(1), 1–26. <https://doi.org/10.1093/joc/jqz052>
1523. Eyal, K., & Rubin, A. M. (2003). Viewer aggression and homophily, identification, and parasocial relationships with television characters. *Journal of Broadcasting & Electronic Media*, 47(1), 77–98. https://doi.org/10.1207/s15506878jobem4701_5
1524. Ferchaud, A., Grzeslo, J., Orme, S., & LaGroue, J. (2018). Parasocial attributes and YouTube personalities: Exploring content trends across the most subscribed YouTube channels. *Computers in Human Behavior*, 80, 88–96. <https://doi.org/10.1016/j.chb.2017.10.041>
1525. Festl, R. (2021). Social media literacy & adolescent social online behavior in Germany. *Journal of Children and Media*, 15(2), 249–271. <https://doi.org/10.1080/17482798.2020.1770110>
1526. Freimuth, V. S., Musa, D., Hilyard, K., Quinn, S. C., & Kim, K. (2014). Trust during the early stages of the 2009 H1N1 pandemic. *Journal of Health Communication*, 19(3), 321–339. <https://doi.org/10.1080/10810730.2013.81132334>
1527. Gerosa, T., Gui, M., Hargittai, E., & Nguyen, M. H. (2021). (Mis)informed During COVID-19: How Education Level and Information Sources Contribute to Knowledge Gaps.

- International Journal of Communication, 15, 2196–2217.
<https://ijoc.org/index.php/ijoc/article/view/16438/3438>
1528. Gleason, T. R., Theran, S. A., & Newberg, E. M. (2017). Parasocial Interactions and Relationships in Early Adolescence. *Frontiers in Psychology*, 8, Article 255.
<https://doi.org/10.3389/fpsyg.2017.00255>
1529. Gnambs, T., & Batinic, B. (2012). A personality-competence model of opinion leadership. *Psychology and Marketing*, 29(8), 606–621. <https://doi.org/10.1002/mar.20547>
1530. Guess, A. M., & Lyons, B. A. (2020). Misinformation, disinformation, and online propaganda. In N. Persily & J. A. Tucker (Eds.), *Social media and democracy: The state of the field, prospects for reform* (pp. 10–33). Cambridge University Press.
1531. Hakobyan, Z., & Koulovatianos, C. (2019). Populism and polarization in social media without fake news: The vicious circle of biases, beliefs and network homophily (CFS Working Paper No. 626). Center for Financial Studies. <https://dx.doi.org/10.2139/ssrn.3435817>
1532. Hearn, A., & Schoenhoff, S. (2016). From Celebrity to Influencer: Tracing the diffusion of celebrity value across the data stream. In P. D. Marshall & S. Redmond (Eds.), *A Companion to Celebrity* (pp. 194–211). John Wiley & Sons.
1533. Hoffner, C. A., & Bond, B. J. (2022). Parasocial relationships, social media, & well-being. *Current Opinion in Psychology*, 45, Article 101306.
<https://doi.org/10.1016/j.copsyc.2022.101306>
1534. Hopkins, J. (2019). “We connect with people through stories”: Gender and affective labor in momblogging. *International Journal of Communication*, 13, 4702–4721.
<https://ijoc.org/index.php/ijoc/article/view/10997/280735>
1535. Horton, D., & Wohl, R. R. (1956). Mass communication and para-social interaction: Observations on intimacy at a distance. *Psychiatry*, 19(3), 215–229.
<https://doi.org/10.1080/00332747.1956.11023049>
1536. Jakob, N. G. E. (2010). No Alternatives? The Relationship between Perceived Media Dependency, Use of Alternative Information Sources, and General Trust in Mass Media. *International Journal of Communication*, 4, 589–606.
<https://ijoc.org/index.php/ijoc/article/view/615/435>
1537. Janssen, L., Schouten, A. P., & Croes, E. A. J. (2021). Influencer advertising on Instagram: Product-influencer fit and number of followers affect advertising outcomes and influencer evaluations via credibility and identification. *International Journal of Advertising*, 1–27. <https://doi.org/10.1080/02650487.2021.1994205>
1538. Jones-Jang, S. M., Mortensen, T., & Liu, J. (2021). Does media literacy help identification of fake news? Information literacy helps, but other literacies don’t. *American Behavioral Scientist*, 65(2), 371–388. <https://doi.org/10.1177%2F0002764219869406>
1539. Kahne, J., & Bowyer, B. (2017). Educating for a democracy in a partisan age: Confronting the challenges of motivated reasoning and misinformation. *American Educational Research Journal*, 54, 3–34. doi:10.3102/0002831216679817
1540. Katz, E., & Lazarsfeld, P. F. (2006). Personal influence. The part played by people in the flow of mass communications (2nd ed.). Transaction Publishers (Original work published 1955).

1541. Khamis, S., Ang, L., & Welling, R. (2017). Self-branding, 'micro-celebrity' and the rise of Social Media Influencers. *Celebrity Studies*, 8(2), 191–208.
<https://doi.org/10.1080/19392397.2016.121829236>
1542. Kim, D. Y., & Kim, H.-Y. (2021). Trust me, trust me not: A nuanced view of influencer marketing on social media. *Journal of Business Research*, 134, 223–232.
<https://doi.org/10.1016/j.jbusres.2021.05.024>
1543. Lazer, D. M. J., Baum, M. A., Benkler, Y., Berinsky, A. J., Greenhill, K. M., Menczer, F., Metzger, M. J., Nyhan, B., Pennycook, G., Rothschild, D., Schudson, M., Sloman, S. A., Sunstein, C. R., Thorson, E. A., Watts, D. J., & Zittrain, J. L. (2018). The science of fake news. Addressing fake news requires a multidisciplinary effort. *Science*, 359(6380), 1094–1096.
<https://doi.org/10.1126/science.aao2998>
1544. Lee, J. E., & Watkins, B. (2016). YouTube vloggers' influence on consumer luxury brand perceptions and intentions. *Journal of Business Research*, 69(12), 5753–5760.
<https://doi.org/10.1016/j.jbusres.2016.04.171>
1545. Lep, Ž., Babnik, K., & Hacin Beyazoglu, K. (2020). Emotional responses and self-protective behavior within days of the COVID-19 outbreak: The promoting role of information credibility. *Frontiers in Psychology*, 11, Article 1846.
<https://doi.org/10.3389/fpsyg.2020.01846>
1546. Levy, N. (2017). The bad news about fake news. *Social Epistemology Review and Reply Collective*, 6(8), 20–36. <http://wp.me/p1Bfg0-3GV>
1547. Long, J. (2021). Package 'interactions'.
<https://cran.rproject.org/web/packages/interactions/interactions.pdf>
1548. Lou, C., & Kim, H. K. (2019). Fancying the new rich and famous? Explicating the roles of influencer content, credibility, and parental mediation in adolescents' parasocial relationship, materialism, and purchase intentions. *Frontiers in Psychology*, 10, Article 2567.
<https://doi.org/10.3389/fpsyg.2019.02567>
1549. Maloy, A. F., & De Vynck, G. (2021, September 12). How wellness influencers are fueling the anti-vaccine movement. *The Washington Post*. <https://wapo.st/3kqle9z> 37
1550. Mena, P., Barbe, D., & Chan-Olmsted, S. (2020). Misinformation on Instagram: The impact of trusted endorsements on message credibility. *Social Media + Society*, 6(2), 1–9.
<https://doi.org/10.1177%2F2056305120935102>
1551. Newman, N., Fletcher, R., Schulz, A., Andi, S., Robertson, C. T., & Nielsen, R. K. (2021). Reuters Institute Digital News Report 2021. 10th edition. Reuters Institute for the Study of Journalism. https://reutersinstitute.politics.ox.ac.uk/sites/default/files/2021-06/Digital_News_Report_2021_FINAL.pdf
1552. Nunnally, J. C. (1978). *Psychometric theory* (2nd ed.). New York: McGraw-Hill.
1553. Ohanian, R. (1990). Construction and validation of a scale to measure celebrity endorsers' perceived expertise, trustworthiness, and attractiveness. *Journal of Advertising* 19(3), 39–52. <https://doi.org/10.1080/00913367.1990.10673191>
1554. Pennycook, G., & Rand, D. G. (2020). Who falls for fake news? The roles of bullshit receptivity, overclaiming, familiarity, and analytic thinking. *Journal of Personality*, 88(2), 185–200. <https://doi.org/10.1111/jopy.12476>

1555. Phua, J., Lin, J.-S., & Lim, D. J. (2018). Understanding consumer engagement with celebrityendorsed E-Cigarette advertising on instagram. *Computers in Human Behavior*, 84, 93–102. <https://doi.org/10.1016/j.chb.2018.02.031>
1556. Kertscher, Tom (2021, August 3). Facebook Posts: No, exercise and healthy eating are not 'the best way' to avoid getting COVID-19. Politifact. <https://www.politifact.com/factchecks/2021/aug/03/facebook-posts/noexerciseandhealthyeatingarenotenoughhavo/>
1557. Reinikainen, H., Munnukka, J., Maity, D., & Luoma-aho, V. (2020). 'You really are a big sister' - parasocial relationships, credibility, and the moderating role of audience comments in influencer marketing. *Journal of Marketing Management*, 36(3–4), 279–298. <https://doi.org/10.1080/0267257X.2019.170878138>
1558. Rieger, M. O., & He-Ulbricht, Y. (2020). German and Chinese dataset on attitudes regarding COVID-19 policies, perception of the crisis, and belief in conspiracy theories. *Data in Brief*, 33, 106384. <https://doi.org/10.1016/j.dib.2020.106384>
1559. Rojecki, A., & Meraz, S. (2016). Rumors and factitious informational blends: The role of the web in speculative politics. *New Media & Society*, 18(1), 25–43. <https://doi.org/10.1177/1461444814535724>
1560. Roozenbeek, J., Schneider, C. R., Dryhurst, S., Kerr, J., Freeman, A. L. J., Recchia, G., van der Bles, M., & van der Linden, S. (2020). Susceptibility to misinformation about COVID-19 around the world. *Royal Society Open Science*, 7, Article 201199. <http://dx.doi.org/10.1098/rsos.201199>
1561. Rubin, A. M., Perse, E. M., & Powell, R. A. (1985). Loneliness, parasocial interaction and local television news viewing. *Human Communication Research*, 12(2), 155–180. <https://doi.org/10.1111/j.1468-2958.1985.tb00071.x>
1562. Schiappa, E., Allen, M., & Gregg, P. B. (2007). Parasocial Relationships and Television: A Meta-Analysis of the Effects. In R. W. Preiss, B. M. Gayle, N. Burrell, M. Allen, & J. Bryant (Eds.), *Mass media effects research: Advances through meta-analysis* (pp. 301–314). Lawrence Erlbaum Associates Publishers.
1563. Schouten, A. P., Janssen, L., & Verspaget, M. (2020). Celebrity vs. influencer endorsements in advertising: The role of identification, credibility, and product-endorser fit. *International Journal of Advertising*, 39(2), 258–281. <https://doi.org/10.1080/02650487.2019.1634898>
1564. Sherman, S. M., Smith, L. E., Sim, J., Amlôt, R., Cutts, M., Dasch, H., ... & Sevdalis, N. (2020). COVID-19 vaccination intention in the UK: results from the COVID-19 vaccination acceptability study (CoVAccS), a nationally representative cross-sectional survey. *Human Vaccines & Immunotherapeutics*, 17(6), 1–10. <https://doi.org/10.1080/21645515.2020.1846397>
1565. Shin, J., Jian, L., Driscoll, K., & Bar, F. (2018). The diffusion of misinformation on social media: Temporal pattern, message, and source. *Computers in Human Behavior*, 83, 278–287. <https://doi.org/10.1016/j.chb.2018.02.008>
1566. Stehr, P., Rössler, P., Leissner, L., & Schönhardt, F. (2015). Parasocial opinion leadership media personalities' influence within parasocial relations: Theoretical conceptualization and preliminary results. *International Journal of Communication*, 9, 982–1001. <https://ijoc.org/index.php/ijoc/article/view/2717/1350>

1567. Swire-Thompson, B., & Lazer, D. (2020). Public health and online misinformation: Challenges and recommendations. *Annual Review of Public Health*, 41, 433–451. <https://doi.org/10.1146/annurev-publhealth-040119-094127>
1568. Törnberg, P. (2018). Echo chambers and viral misinformation: Modeling fake news as complex contagion. *PLoS ONE*, 13(9), Article e0203958. <https://doi.org/10.1371/journal.pone.0203958>
1569. Valkenburg, P. M., & Peter, J. (2013). The differential susceptibility to media effects model. *Journal of Communication*, 63(2), 221–243. <https://doi.org/10.1111/jcom.12024>
1570. Vosoughi, D., Roy, D., & Aral, S. (2018). The spread of true and false news online. *Science*, 359(6380), 1146–1151. <https://doi.org/10.1126/science.aap9559>
1571. Weeks, B. E., & Gil de Zúñiga, H. (2021). What's next? Six observations for the future of political misinformation research. *American Behavioral Scientist*, 65(2), 277–289. <https://doi.org/10.1177%2F0002764219878236>
1572. World Health Organization. (2020, September 2020). Managing the COVID-19 infodemic: Promoting healthy behaviours and mitigating the harm from misinformation and disinformation. <https://bit.ly/3oTiP9v> 40
1573. Zhong, B. L., Luo, W., Li, H. M., Zhang, Q. Q., Liu, X. G., Li, W. T., & Li, Y. (2020). Knowledge, attitudes, and practices toward COVID-19 among Chinese residents during the rapid rise period of the COVID-19 outbreak: a quick online cross-sectional survey. *International journal of biological sciences*, 16(10), 1745–1752. <https://doi.org/10.7150/ijbs.45221>
1574. Zimmermann, F., & Kohring, M. (2020). Mistrust, disinforming news, and vote choice: A panel survey on the origins and consequences of believing disinformation in the 2017 German parliamentary election. *Political Communication*, 37(2), 215–237. <https://doi.org/10.1080/10584609.2019.1686095>
1575. Zimmermann, D., Noll, C., Gräßer, L., Hugger, K.-U., Braun, L. M., Nowak, T., & Kaspar, K. (2020). Influencers on YouTube: a quantitative study on young people's use and perception of videos about political and societal topics. *Current Psychology*. <https://doi.org/10.1007/s12144020011647>
1576. Smith C (2017) 388 amazing twitter statistics and facts. DMR (February 2017)
1577. Alothali E, Hayawi K, Alashwal H (2020) Characteristics of similar-context trending hashtags in Twitter: a case study. In: *International Conference on Web Services*. 2020. Springer
1578. Gao H et al (2011) Security issues in online social networks. *IEEE Internet Comput* 15(4):56–63
1579. Rathore S et al (2017) Social network security: issues, challenges, threats, and solutions. *Inf Sci* 421:43–69
1580. Gupta A, Lamba H, Kumaraguru P (2013) \$1.00 per rt# bostonmarathon# prayforboston: analyzing fake content on twitter. In: *2013 APWG eCrime researchers summit*. 2013. IEEE

1581. Varol O, et al. (2017) Online human-bot interactions: detection, estimation, and characterization. In: Proceedings of the international AAAI conference on web and social media
1582. Yang C, Harkreader R, Gu G (2013) Empirical evaluation and new design for fighting evolving twitter spammers. *IEEE Trans Inf Forensics Secur* 8(8):1280–1293
1583. Cresci S (2020) A decade of social bot detection. *Commun ACM* 63(10):72–83
1584. Kantepe M, Ganiz MC (2017) Preprocessing framework for Twitter bot detection. in 2017 International conference on computer science and engineering (ubmk). 2017. IEEE
1585. Alarifi A, Alsaleh M, Al-Salman A (2016) Twitter turing test: identifying social machines. *Inf Sci* 372:332–346
1586. Chu Z et al (2012) Detecting automation of twitter accounts: Are you a human, bot, or cyborg? *IEEE Trans Dependable Secure Comput* 9(6):811–824
1587. Goodfellow I et al (2020) Generative adversarial networks. *Commun ACM* 63(11):139–144
1588. Alothali E, et al. (2018) Detecting social bots on twitter: a literature review. In: 2018 International conference on innovations in information technology (IIT). 2018. IEEE
1589. Balaji T, Annavarapu CSR, Bablani A (2021) Machine learning algorithms for social media analysis: a survey. *Comput Sci Rev* 40:100395
1590. Collins B, et al. (2020) Method of detecting bots on social media. A literature review. In: International conference on computational collective intelligence. Springer
1591. Latah M (2020) Detection of malicious social bots: a survey and a refined taxonomy. *Expert Syst Appl* 151:113383
1592. Orabi M et al (2020) Detection of bots in social media: a systematic review. *Inf Process Manage* 57(4):102250
1593. Yang Z et al (2014) Uncovering social network sybils in the wild. *ACM Trans Knowl Discov Data (TKDD)* 8(1):1–29
1594. Geiger RS (2016) Bot-based collective blocklists in Twitter: the counterpublic moderation of harassment in a networked public space. *Inf Commun Soc* 19(6):787–803
1595. Stieglitz S, et al. (2017) Do social bots dream of electric sheep? A categorisation of social media bot accounts. *arXiv preprint arXiv: 1710.04044*.
1596. Grimme C et al (2017) Social bots: human-like by means of human control? *Big data* 5(4):279–293 *Neural Computing and Applications* (2023) 35:8903–89188917123
1597. Brereton P et al (2007) Lessons from applying the systematic literature review process within the software engineering domain. *J Syst Softw* 80(4):571–583
1598. Sengar SS et al (2020) Bot detection in social networks based on multilayered deep learning approach. *Sens Transducers* 244(5):37–43
1599. Zegzhda PD, Malyshev E, Pavlenko EY (2017) The use of an artificial neural network to detect automatically managed accounts in social networks. *Autom Control Comput Sci* 51(8):874–880

1600. Cai C, Li L, Zengi D (2017) Behavior enhanced deep bot detection in social media. In: 2017 IEEE international conference on intelligence and security informatics (ISI). IEEE
1601. Al-Qurishi M et al (2018) A prediction system of Sybil attack in social network using deep-regression model. *Futur Gener Comput Syst* 87:743–753
1602. Wu Y et al (2021) A novel framework for detecting social bots with deep neural networks and active learning. *Knowl-Based Syst* 211:106525
1603. Lingam G et al (2020) Particle swarm optimization on deep reinforcement learning for detecting social spam bots and spaminfluential users in twitter network. *IEEE Syst J* 15(2):2281–2292
1604. Katarya R, et al. (2020) Bot detection in social networks using stacked generalization ensemble. In: *The international conference on recent innovations in computing*. Springer.
1605. Zhao C et al (2020) An attention-based graph neural network for spam bot detection in social networks. *Appl Sci* 10(22):8160
1606. Morstatter F, et al. (2016) A new approach to bot detection: striking the balance between precision and recall. In: 2016 IEEE/ACM international conference on advances in social networks analysis and mining (ASONAM). IEEE
1607. Heidari M, Jones JH (2020) Using bert to extract topicindependent sentiment features for social media bot detection. In: 2020 11th IEEE annual ubiquitous computing, electronics & mobile communication conference (UEMCON). IEEE
1608. Kudugunta S, Ferrara E (2018) Deep neural networks for bot detection. *Inf Sci* 467:312–322
1609. Wu B et al (2020) Using improved conditional generative adversarial networks to detect social bots on Twitter. *IEEE Access* 8:36664–36680
1610. Ping H, Qin S (2018) A social bots detection model based on deep learning algorithm. In: 2018 IEEE 18th international conference on communication technology (icct). IEEE
1611. Halvani O, Marquardt P (2019) An unsophisticated neural bots and gender profiling system. In: *CLEF (Working Notes)*
1612. Luo L, et al. (2020) Deepbot: a deep neural network based approach for detecting Twitter bots. In: *IOP Conference Series: Materials Science and Engineering*. 2020. IOP Publishing
1613. Wei F, Nguyen UT (2019) Twitter bot detection using bidirectional long short-term memory neural networks and word embeddings. In: 2019 First IEEE international conference on trust, privacy and security in intelligent systems and applications (TPS-ISA). IEEE
1614. Pennington J, Socher R, Manning CD (2014) Glove: global vectors for word representation. In: *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)*
1615. Onose C, et al. (2019) A hierarchical attention network for bots and gender profiling. In: *CLEF*
1616. Mou G, Lee K (2020) Malicious bot detection in online social networks: arming handcrafted features with deep learning. In: *Social informatics: 12th International*

- Conference, SocInfo 2020, Pisa, Italy, October 6–9, 2020, Proceedings. 2020, Springer-Verlag: Pisa, Italy. p. 220–236
1617. Dukic D, Keca D, Stipic D (2020) Are you human? Detecting bots on Twitter using BERT. In: 2020 IEEE 7th International Conference on Data Science and Advanced Analytics (DSAA). pp. 631–636
 1618. Martin-Gutierrez D et al (2021) A deep learning approach for robust detection of bots in twitter using transformers. *IEEE Access* 9:54591–54601
 1619. Mohammad S, et al. (2019) Bot detection using a single post on social media. In: 2019 third world conference on smart trends in systems security and sustainability (WorldS4)
 1620. Gao T et al (2020) A content-based method for sybil detection in online social networks via deep learning. *IEEE Access* 8:38753–38766
 1621. Rajendran G et al (2020) Deep temporal analysis of Twitter bots. Springer Singapore, Singapore
 1622. Ilias L, Roussaki I (2021) Detecting malicious activity in Twitter using deep learning techniques. *Appl Soft Comput* 107:107360
 1623. Mazza M, et al. (2019) RTbust: exploiting temporal patterns for botnet detection on Twitter. In: Proceedings of the 10th ACM Conference on Web Science
 1624. Lian Y et al (2019) An internet water army detection supernetwork model. *IEEE Access* 7:55108–55120
 1625. Makkar A, Kumar N (2020) An efficient deep learning-based scheme for web spam detection in IoT environment. *Futur Gener Comput Syst* 108:467–487
 1626. Pei W, Xie Y, Tang G (2018) Spammer detection via combined neural network. In: Machine Learning and Data Mining in Pattern Recognition. Springer International Publishing. pp. 350–364
 1627. Alhosseini SA, et al. (2019) Detect me if you can: spam bot detection using inductive representation learning. In: Companion proceedings of the 2019 world wide web conference. 2019, Association for Computing Machinery: San Francisco, USA. p. 148–153
 1628. Aljohani NR, Fayoumi A, Hassan S-U (2020) Bot prediction on social networks of Twitter in altmetrics using deep graph convolutional networks. *Soft Comput* 24(15):11109–11120
 1629. Farber M, Qurdina A, Ahmedi L (2019) Identifying twitter bots using a convolutional neural network. In: CLEF
 1630. Braker C et al (2020) BotSpot: deep learning classification of bot accounts within twitter. Internet of things, smart spaces, and next generation networks and systems. Springer, pp 165–175
 1631. Staykovski T (2019) Stacked bots and gender prediction from twitter feeds. In: CLEF (Working Notes)
 1632. Lingam G, Rout RR, Somayajulu DV (2019) Deep Q-learning and particle swarm optimization for bot detection in online social networks. In: 2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT). IEEE

1633. Daouadi KE, Rebai RZ, Amous I (2019) Bot detection on online social networks using deep forest. In: Computer science on-line conference. Springer
1634. Ahmed F, Abulaish M (2013) A generic statistical approach for spam detection in online social networks. *Comput Commun* 36(10–11):1120–1129
1635. Davis CA, Varol O, Ferrara E, Flammini A, Menczer F (2016) Botornot: a system to evaluate social bots. In: WWW '16 Companion: Proceedings of the 25th International Conference Companion on World Wide Web, pp. 273–274
1636. Yang K-C, Varol O, Hui P-M, Menczer F (2020) Scalable and generalizable social bot detection through data selection. In: Proceedings of the AAAI conference on artificial intelligence, vol. 34, pp. 1096–1103
1637. Rodriguez-Ruiz J, Mata-Sánchez JI, Monroy R, Loyola-Gonzalez O, Pérez-Cuevas AL, (2020) A one-class classification approach for bot detection on twitter. *Comput Secur* 91:101715
1638. Eiman Alothali, Motamen Salih, Kadhim Hayawi, and Hany Alashwal. 2022.
1639. Bot-MGAT: A Transfer Learning Model Based on a Multi-View Graph Attention Network to Detect Social Bots. *Applied Sciences* 16 (2022). <https://doi.org/10.3390/app12168117>
1640. Adam Badawy, Emilio Ferrara, and Kristina Lerman. 2018. Analyzing the Digital Traces of Political Manipulation: The 2016 Russian Interference Twitter Campaign. In 2018 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM). 258–265. <https://doi.org/10.1109/ASONAM.2018.8508646>
1641. Marco T. Bastos and Dan Mercea. 2019. The Brexit Botnet and User-Generated Hyperpartisan News. *Social Science Computer Review* 37, 1 (2019), 38–54. <https://doi.org/10.1177/0894439317734157> arXiv:<https://doi.org/10.1177/0894439317734157>
1642. Alessandro Bessi and Emilio Ferrara. 2016. Social bots distort the 2016 US Presidential election online discussion. *First Monday* 21, 11 (2016). <https://doi.org/10.5210/fm.v21i11.7090>
1643. Christopher Bouzy. 2018. Bot sentinel, Platform developed to detect and track political bots, trollbots, and untrustworthy accounts. <https://botsentinel.com/>
1644. David A. Broniatowski, Amelia M. Jamison, SiHua Qi, Lulwah AlKulaib, Tao Chen, Adrian Benton, Sandra C. Quinn, and Mark Dredze. 2018. Weaponized Health Communication: Twitter Bots and Russian Trolls Amplify the Vaccine Debate. *American Journal of Public Health* 108, 10 (2018), 1378–1384. <https://doi.org/10.2105/AJPH.2018.304567> arXiv:<https://doi.org/10.2105/AJPH.2018.304567> PMID: 30138075.
1645. Daejin Choi, Selin Chun, Hyunchul Oh, Jinyoung Han, and Ted Kwon. 2020. Rumor Propagation is Amplified by Echo Chambers in Social Media. *Scientific Reports* 10, 310 (2020). <https://doi.org/10.1038/s41598-019-57272-3>
1646. Zi Chu, Steven Gianvecchio, Haining Wang, and Sushil Jajodia. 2012. Detecting Automation of Twitter Accounts: Are You a Human, Bot, or Cyborg? *IEEE Transactions on Dependable and Secure Computing* 9, 6 (2012), 811–824. <https://doi.org/10.1109/TDSC.2012.75>

1647. Stefano Cresci. 2020. A Decade of Social Bot Detection. *Commun. ACM* 63, 10 (sep 2020), 72–83. <https://doi.org/10.1145/3409116>
1648. Stefano Cresci, Roberto Di Pietro, Marinella Petrocchi, Angelo Spognardi, and Maurizio Tesconi. 2017. The paradigm-shift of social spambots: Evidence, theories, and tools for the arms race.. In *26th International Conference on World Wide Web. International World Wide Web Conferences Steering Committee*, 963–972. <https://doi.org/10.1145/3041021.3055135>
1649. Stefano Cresci, Fabrizio Lillo, Daniele Regoli, Serena Tardelli, and Maurizio Tesconi. 2019. \$ FAKE: Evidence of Spam and Bot Activity in Stock Microblogs on Twitter. (2019).
1650. Stefano Cresci, Roberto Di Pietro, Marinella Petrocchi, Angelo Spognardi, and Maurizio Tesconi. 2015. Fame forsale: Efficient detection of fake Twitterfollowers. *Decision Support Systems* 80 (2015), 56–71. <https://doi.org/10.1016/j.dss.2015.09.003>
1651. Stefano Cresci, Roberto Di Pietro, Marinella Petrocchi, Angelo Spognardi, and Maurizio Tesconi. 2016. DNA-Inspired Online Behavioral Modeling and Its Application to Spambot Detection. *IEEE Intelligent Systems* 31, 5 (2016), 58–64. <https://doi.org/10.1109/MIS.2016.29>
1652. Stefano Cresci, Roberto Di Pietro, Marinella Petrocchi, Angelo Spognardi, and Maurizio Tesconi. 2017. Exploiting digital DNA for the analysis of similarities in Twitter behaviour. In *IEEE International Conference on Data Science and Advanced Analytics (DSAA)*. 686–695. <https://doi.org/10.1109/DSAA.2017.57>
1653. Stefano Cresci, Roberto Di Pietro, Marinella Petrocchi, Angelo Spognardi, and Maurizio Tesconi. 2018. Social Fingerprinting: Detection of Spambot Groups Through DNA-Inspired Behavioral Modeling. *IEEE Transactions on Dependable and Secure Computing* 15, 4 (2018), 561–576. <https://doi.org/10.1109/TDSC.2017.2681672>
1654. Stefano Cresci, Maurizio Tesconi, Andrea Cimino, and Felice Dell’Orletta. 2015. A Linguistically-Driven Approach to Cross-Event Damage Assessment of Natural Disasters from Social Media Messages. In *Proceedings of the 24th International Conference on World Wide Web (Florence, Italy) (WWW ’15 Companion)*. Association for Computing Machinery, New York, NY, USA, 1195–1200. <https://doi.org/10.1145/2740908.2741722>
1655. Ilias Dimitriadis, Konstantinos Georgiou, and Athena Vakali. 2021. Social Botomics: A Systematic Ensemble ML Approach for Explainable and Multi-Class Bot Detection. *Applied Sciences* 11, 21 (2021). <https://doi.org/10.3390/app11219857>
1656. Juan Echeverria, Emiliano De Cristofaro, Nicolas Kourtellis, Ilias Leontiadis, Gianluca Stringhini, and Shi Zhou. 2018. LOBO: Evaluation of Generalization Defficiencies in Twitter Bot Classifiers. In *34th Annual Computer Security Applications Conference*. Association for Computing Machinery, 137–146. <https://doi.org/10.1145/3274694.3274738>
1657. Tuğrulcan Elmas, Rebekah Overdorf, and Karl Aberer. 2022. Characterizing Retweet Bots: The Case of Black Market Accounts. In *Proceedings of the International AAAI Conference on Web and Social Media*, Vol. 16. 171–182.
1658. Shangbin Feng, Zhaoxuan Tan, and Minnan Luo Rui L and. 2022. Heterogeneityaware Twitter Bot Detection with Relational Graph Transformers. In *AAAI Conference on Artificial Intelligence*. Association for the Advancement of Artificial Intelligence, 3977–3985. <https://doi.org/10.1609/aaai.v36i4.20314>

1659. Shangbin Feng, Herun Wan, Ningnan Wang, Jundong Li, and Minnan Luo. 2021. SATAR: A Self-supervised Approach to Twitter Account Representation Learning and its Application in Bot Detection. In 30th ACM International Conference on Information & Knowledge Management (CIKM). Association for Computing Machinery, 3808–3817. <https://doi.org/10.1145/3459637.3481949>
1660. Shangbin Feng, Herun Wan, Ningnan Wang, Jundong Li, and Minnan Luo. 2021. TwiBot-20: A Comprehensive Twitter Bot Detection Benchmark. (2021), 4485– 4494.
1661. Shangbin Feng, Herun Wan, Ningnan Wang, and Minnan Luo. 2021. BotRGCN: Twitter Bot Detection with Relational Graph Convolutional Networks. In 2021 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining. Association for Computing Machinery, 236–239. <https://doi.org/10.1145/3487351.3488336>
1662. Emilio Ferrara. 2017. Disinformation and Social Bot Operations in the Run Up to the 2017 French Presidential Election. First Monday 22, 8 (2017). <https://doi.org/10.5210/fm.v22i18.8005>
1663. Emilio Ferrara. 2020. What types of COVID-19 conspiracies are populated by Twitter bots? First Monday (05 2020). <https://doi.org/10.5210/fm.v25i6.10633>
1664. Florian Gallwitz and Michael Kreil. 2021. The Rise and Fall of 'Social Bot' Research. <https://ssrn.com/abstract=3814191>
1665. Florian Gallwitz and Michael Kreil. 2022. Investigating the Validity of Botometerbased Social Bot Studies. arXiv:2207.11474 - cs.SI28 -
1666. Andres Garcia-Silva, Cristian Berrio, and José Manuel Gómez-Pérez. 2019. An Empirical Study on Pre-trained Embeddings and Language Models for Bot Detection. In 4th Workshop on Representation Learning for NLP (Repl4NLP). Association for Computational Linguistics, 148–155. <https://doi.org/10.18653/v1/W19-4317>
1667. Timnit Gebru, Jamie Morgenstern, Briana Vecchione, Jennifer Wortman Vaughan, Hanna Wallach, Hal Daumé Iii, and Kate Crawford. 2021. Datasheets for datasets. Commun. ACM 64, 12 (2021), 86–92.
1668. Zafar Gilani, Reza Farahbakhsh, Gareth Tyson, and Jon Crowcroft. 2019. A Large-scale Behavioural Analysis of Bots and Humans on Twitter. ACM Transactions on the Web 13, 1 (2019). <https://doi.org/10.1145/3298789>
1669. Zafar Gilani, Reza Farahbakhsh, Gareth Tyson, Liang Wang, and Jon Crowcroft. 2017. Of Bots and Humans (on Twitter). In IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining. Association for Computing Machinery, 349–354. <https://doi.org/10.1145/3110025.3110090>
1670. Zafar Gilani, Ekaterina Kochmar, and Jon Crowcroft. 2017. Classification of
1671. Twitter Accounts into Automated Agents and Human Users. In 2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM). 489–496.
1672. Zafar Gilani, Ekaterina Kochmar, and Jon Crowcroft. 2020. Classification of twitter accounts into automated agents and human users. In IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM). 489– 496. <https://doi.org/10.1145/3110025.3110091>

1673. Salvatore Giorgi, Lyle Ungar, and H. Andrew Schwartz. 2021. Characterizing Social Spambots by their Human Traits. In *The Joint Conference of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing*. 5148–5158. <https://doi.org/10.18653/v1/2021.findings-acl.457>
1674. Sandra González-Bailón, Valeria d'Andrea, Deen Freelon, and Manlio De Domenico. 2022. The advantage of the right in social media news sharing. *PNAS Nexus* 1, 3 (07 2022). <https://doi.org/10.1093/pnasnexus/pgac137>
arXiv:<https://academic.oup.com/pnasnexus/articlepdf/1/3/pgac137/45484944/pgac137.pdf>
pgac137.
1675. Yuriy Gorodnichenko, Tho Pham, and Oleksandr Talavera. 2018. Social Media, Sentiment and Public Opinions: Evidence from #Brexit and #USElection. NBER Working Papers 24631. National Bureau of Economic Research, Inc. <https://ideas.repec.org/p/nbr/nberwo/24631.html>
1676. Qinglang Guo, Haiyong Xie, Yangyang Li, Wen Ma, and Chao Zhang. 2022. Social Bots Detection via Fusing BERT and Graph Convolutional Networks. *Symmetry* 14, 1 (2022). <https://doi.org/10.3390/sym14010030>
1677. Maryam Heidari and James H Jones. 2020. Using BERT to Extract Topic-Independent Sentiment Features for Social Media Bot Detection. In *11th IEEE Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON)*. 542–547. <https://doi.org/10.1109/UEMCON51285.2020.9298158>
1678. Loukas Ilias and Ioanna Roussaki. 2021. Detecting malicious activity in Twitter using deep learning techniques. *Applied Soft Computing* 107 (2021).
1679. S. Mo Jang, Tieming Geng, Jo-Yun Queenie Li, Ruofan Xia, Chin-Tser Huang, Hwalbin Kim, and Jijun Tang. 2018. A computational approach for examining the roots and spreading patterns of fake news: Evolution tree analysis. *Computers in Human Behavior* 84 (2018), 103–113. <https://doi.org/10.1016/j.chb.2018.02.032>
1680. Tobias Keller and Ulrike Klinger. 2018. Social Bots in Election Campaigns: Theoretical, Empirical, and Methodological Implications. *Political Communication* 36, 1 (2018), 171–189. <https://doi.org/10.1080/10584609.2018.15262383668>
1681. Maria Kouvela, Ilias Dimitriadis, and Athena Vakali. 2020. Bot-Detective: An Explainable Twitter Bot Detection Service with Crowdsourcing Functionalities. In *Proceedings of the 12th International Conference on Management of Digital EcoSystems (Virtual Event, United Arab Emirates) (MEDES '20)*. Association for Computing Machinery, New York, NY, USA, 55–63. <https://doi.org/10.1145/3415958.3433075>
1682. Sneha Kudugunta and Emilio Ferrara. 2018. Deep neural networks for bot detection. *Information Sciences* 467 (2018), 312–322. <https://doi.org/10.1016/j.ins.2018.08.019>
1683. Kyumin Lee, Brian Eof, and James Caverlee. 2011. A Long-Term Study of Content Polluters on Twitter. In *Fifth International AAAI Conference on Weblogs and Social Media*. Association for the Advancement of Artificial Intelligence, 185–192.
1684. Scott M Lundberg and Su-In Lee. 2017. A Unified Approach to Interpreting Model Predictions. In *Advances in Neural Information Processing Systems 30*, I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett (Eds.). Curran Associates, Inc., 4765–4774.
<http://papers.nips.cc/paper/7062aunifiedapproachtointerpretingmodelpredictions.pdf>

1685. Linhao Luo, Xiaofeng Zhang, Xiaofei Yang, and Weihuang Yang. 2019. Deepbot: A Deep Neural Network based approach for Detecting Twitter Bots. IOP Conference Series: Materials Science and Engineering 719, 1 (2019). <https://doi.org/10.1088/1757-899x/719/1/012063>
1686. Franziska Martini, Paul Samula, Tobias R Keller, and Ulrike Klinger. 2021. Bot, or not? Comparing three methods for detecting social bots in five political discourses. *Big Data & Society* 8, 2 (2021), 20539517211033566. <https://doi.org/10.1177/20539517211033566>
arXiv:<https://doi.org/10.1177/20539517211033566>
1688. David Martín-Gutiérrez, Gustavo Hernández-Peñaloza, Alberto Belmonte Hernández, Alicia Lozano-Diez, and Federico Álvarez. 2021. A Deep Learning Approach for Robust Detection of Bots in Twitter Using Transformers. *IEEE Access* 9 (2021), 54591–54601. <https://doi.org/10.1109/ACCESS.2021.3068659>
1689. Michele Mazza, Stefano Cresci, Marco Avvenuti, Walter Quattrociocchi, and Maurizio Tesconi. 2019. RTbust: Exploiting Temporal Patterns for Botnet Detection on Twitter. In 10th ACM Conference on Web Science. Association for Computing Machinery, 183–192. <https://doi.org/10.1145/3292522.3326015>
1690. Guanyi Mou and Kyumin Lee. 2020. Malicious bot detection in online social networks: arming handcrafted features with deep learning. In International Conference on Social Informatics. Springer, 220–236.
1691. Elon Musk. 2022. Bot Percentage Thread. <https://twitter.com/elonmusk/status/1555950698252181507>
1692. Leonardo Nizzoli, Serena Tardelli, Marco Avvenuti, Stefano Cresci, Maurizio Tesconi, and Emilio Ferrara. 2020. Charting the Landscape of Online Cryptocurrency Manipulation. *IEEE Access* 8 (2020), 113230–113245. <https://doi.org/10.1109/ACCESS.2020.3003370>
1693. Gordon Pennycook, Ziv Epstein, Mohsen Mosleh, Antonio A. Arechar, Dean Eckles, and David G. Rand. 2021. Shifting attention to accuracy can reduce misinformation online. *Nature* 592, 6380 (2021), 590–595. <https://doi.org/10.1038/s41586-021-03344-2>
1694. Francesco Pierri, Alessandro Artoni, and Stefano Ceri. 2020. Investigating Italian disinformation spreading on Twitter in the context of 2019 European elections. *PLoS one* 15, 1 (2020), e0227821. <https://doi.org/10.1371/journal.pone.0227821>
1695. Francisco Rangel and Paolo Rosso. 2015. Overview of the 7th Author Profiling Task at PAN 2019: Bots and Gender Profiling in Twitter. In CLEF Evaluation Labs and Workshop Working Notes Papers.
1696. Adrian Rauchfleisch and Jonas Kaiser. 2020. The False positive problem of automatic bot detection in social science research. *PLOS ONE* 15, 10 (2020), 1–20. <https://doi.org/10.1371/journal.pone.0241045>
1697. Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin. 2016. "Why Should I Trust You?": Explaining the Predictions of Any Classifier. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (San Francisco, California, USA) (KDD '16). Association for Computing Machinery, New York, NY, USA, 1135–1144. <https://doi.org/10.1145/2939672.2939778>

1698. Luigi Rovito, Lorenzo Bonin, Luca Manzoni, and Andrea De Lorenzo. 2022. An Evolutionary Computation Approach for Twitter Bot Detection. *Applied Sciences* 12, 12 (2022). <https://doi.org/10.3390/app12125915>
1699. Cynthia Rudin. 2019. Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nature Machine Intelligence* 1, 5 (01 May 2019), 206–215. <https://doi.org/10.1038/s42256-019-0048-x>
1700. Mohsen Sayyadiharikandeh, Onur Varol, Kai-Cheng Yang, Alessandro Flammini, and Filippo Menczer. 2020. Detection of Novel Social Bots by Ensembles of Specialized Classifiers. In *29th ACM International Conference on Information & Knowledge Management*. Association for Computing Machinery, 2725–2732. <https://doi.org/10.1145/3340531.3412698>
1701. Chengcheng Shao, Giovanni Luca Ciampaglia, Onur Varol, Kai-Cheng Yang, Alessandro Flammini, and Filippo Menczer. 2018. The spread of low-credibility content by social bots. *Nature Communications* 9, 4787 (2018), 1–9. <https://doi.org/10.1038/s41467-018-06930-7>
1702. Chengcheng Shao, Pik-Mai Hui, Lei Wang, Xinwen Jiang, Alessandro Flammini, Filippo Menczer, and Giovanni Luca Ciampaglia. 2018. Anatomy of an online misinformation network. *PloS one* 13, 4 (2018), e0196087. <https://doi.org/10.1371/journal.pone.0196087>
1703. Kai Shu, Deepak Mahudeswaran, Suhang Wang, Dongwon Lee, and Huan Liu. 2020. FakeNewsNet: A Data Repository with News Content, Social Context, and Spatiotemporal Information for Studying Fake News on Social Media. *Big Data* 8, 3 (2020), 171–188. <https://doi.org/10.1089/big.2020.0062>
1704. Massimo Stella, Emilio Ferrara, and Manlio De Domenico. 2018. Bots increase exposure to negative and inflammatory content in online social systems. *Proceedings of the National Academy of Sciences* 115, 49 (2018), 12435–12440. <https://doi.org/10.1073/pnas.1803470115>
1705. M. Buğra Torusdağ, Mucahid Kutlu, and Ali Aydın Selçuk. 2020. Are We Secure from Bots? Investigating Vulnerabilities of Botometer. In *2020 5th International Conference on Computer Science and Engineering (UBMK)*. 343–348. <https://doi.org/10.1109/UBMK50275.2020.9219433>
1706. Twitter. 2021. FORM 10-K. <https://www.sec.gov/Archives/edgar/data/1418091/000141809121000031/twtr-20201231.htm>
1707. Soroush Vosoughi, Deb Roy, and Sinan Aral. 2018. The spread of true and false news online. *Science* 359, 6380 (2018), 1146–1151. <https://doi.org/10.1126/science.aap9559> arXiv:<https://www.science.org/doi/pdf/10.1126/science.aap9559>
1708. Xiujuan Wang, Qianqian Zheng, Kangfeng Zheng, Yi Sui, Siwei Cao, and Yutong Shi. 2021. Detecting social media bots with variational autoencoder and k-nearest neighbor. *Applied Sciences* 11, 12 (2021), 5482.
1709. Magdalena Wischnewski, Rebecca Bernemann, Thao Ngo, and Nicole Krämer. 2021. Disagree? You Must Be a Bot! How Beliefs Shape Twitter Profile Perceptions. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (Yokohama, Japan) (CHI '21)*. Association for Computing Machinery, New York, NY, USA, Article 160, 11 pages. <https://doi.org/10.1145/3411764.3445109>

1710. Liang Wu, Xia Hu, Fred Morstatter, and Huan Liu. 2017. Adaptive Spammer Detection with Sparse Group Modeling. In Eleventh International AAAI Conference on Web and Social Media (ICWSM). Association for the Advancement of Artificial Intelligence, 319–326.
1711. Harry Yaojun Yan, Kai-Cheng Yang, Filippo Menczer, and James Shanahan. 2021. Asymmetrical perceptions of partisan political bots. *New Media & Society* 23, 10 (2021), 3016–3037. <https://doi.org/10.1177/1461444820942744>
arXiv:<https://doi.org/10.1177/1461444820942744>
1712. Chao Yang, Robert Harkreader, and Guofei Gu. 2013. Empirical evaluation and new design for fighting evolving twitter spammers. *IEEE Transactions on Information Forensics and Security* 8, 8 (2013), 1280–1293. <https://doi.org/10.1109/TIFS.2013.2267732>
1713. Kai-Cheng Yang, Onur Varol, Clayton A. Davis, Emilio Ferrara, Alessandro Flammini, , and Filippo Menczer. 2019. Arming the public with artificial intelligence to counter social bots. *Human Behavior and Emerging Technologies* 1 (2019), 48–68.
<https://doi.org/10.1002/hbe2.115>
1714. Kai-Cheng Yang, Emilio Ferrara, and Filippo Menczer. 2022. Botometer 101: Social bot practicum for computational social scientists. arXiv preprint arXiv:2201.01608 (2022).
1715. Kai-Cheng Yang, Onur Varol, Pik-Mai Hui, and Filippo Menczer. 2020. Scalable and Generalizable Social Bot Detection through Data Selection. In AAAI Conference on Artificial Intelligence. Association for the Advancement of Artificial Intelligence, 1096–1103.
<https://doi.org/10.1609/aaai.v34i01.5460>
1716. Chaudhury A, Basuchowdhuri P, Majumder S. Spread of Information in a Social Network Using Influential Nodes. In: Proceedings of 16th Pacific-Asia Conference on Knowledge Discovery and Data Mining, PAKDD 2012, KL, Malaysia, vol. 7302 of LNCS. Springer, 2012. p. 121–132.
1717. Dey N, Borah S, Babo R, Ashour AS. Social Network Analytics: Computational Research Methods and Techniques, Academic Press. 2018.
1718. Guille A, Hacid H, Favre C, Zighed DA. Information diffusion in online social networks: a survey. *ACM SIGMOD Record archive*. 2013; 42(2): 17–28.
1719. Tang J, Chang Y, Liu H. Mining social media with social theories: a survey. *SIGKDD Explorations*. 2014; 15(2): 20–29.
1720. Housley W, Webb H, Williams M, Procter R, Edwards A, Jirotko M, et al. Interaction and transformation on social media: the case of Twitter campaigns. *Social Media and Society*. 2018; 4(1): 1–12.
1721. Tabellion J, Esch F. Influencer Marketing and its Impact on the Advertised Brand. In: Bigne E, Rosengren S, editors. *Advances in Advertising Research X*. Springer Nature, 2019. p. 29–41.
1722. Bouguessa M, Romdhane L. Identifying authorities in online communities. *ACM Transactions on Intelligent Systems and Technology (ACM TIST)*. 2015; 6(3): 30.
1723. Liu N, Li L, Xu G, Yang Z. Identifying domain-dependent influential microblog users: A post-feature based approach. In: 28th AAAI Conference on Artificial Intelligence (AAAI 2014), Quebec, Canada, July 2014, Proceedings; 2014. p. 3122–3123.

1724. State of Influencer Marketing in Vietnam 2020. 7Sat. 2020
<https://resources.7saturday.com/stateofinfluencermarketinginvietnam2020?fbclid=IwAR2AQbGLRs10fxJ4JmfPeOhKm5Q4MuR4dsO23rBBfHfKjYgC2xfJMM4-V3A>
1725. Tomoson: <https://www.tomoson.com/blog/influencer-marketing-study/> (Accessed 01 September 2022).
1726. De Veirman M, Cauberghe V, Hudders L. Marketing through Instagram influencers: the impact of number of followers and product divergence on brand attitude. *International journal of advertising*. 2017; 36 (5): 798–828.
1727. Gonzalez CB, Garcia-Nieto J, Navas-Delgado I, Aldana-Montes JF. A fine grain sentiment analysis with semantics in tweets. *Int J Interact Multimed Artif Intell*. 2016; 3: 22–28.
1728. Serrano-Guerrero J, Olivas JA, Romero FP, Herrera-Viedma E. Sentiment analysis: A review and comparative analysis of web services. *Information Sciences*. 2015; 311: 18–38.
1729. Rokade P, Kumari DA. Business intelligence analytics using sentiment analysis—a survey. *International Journal of Electrical and Computer Engineering (IJECE)*. 2019; 9(1): 613–620.
1730. Laroche M, Habibi MR, Richard M, Sankaranarayanan R. The effects of social media based brand communities on brand community markers, value creation practices, brand trust, and brand loyalty. *Computers in Human Behavior*. 2012; 28: 1755–1767.
1731. Chen W, Lakshmanan L, Castillo C. *Information and Influence Propagation in Social Networks: Synthesis Lectures on Data Management*, Ca: Morgan & Claypool. 2013.
1732. Zimmerman J, Ng D. *Social Media Marketing All-in-One (4th ed.)*, Dummies, Wiley. 2017.
1733. Pulizzi J, Barrett N. *Get Content Get Customers: Turn Prospects into Buyers with Content Marketing*, McGraw-Hill Education. 2009.
1734. Abu-Salih B, Wongthongtham P, Zhu D, Chan KY, Rudra A. Social Big Data: An Overview and Applications. In: *Social Big Data Analytics*. Springer, 2021. p.1–14.
1735. Koob C. Determinants of content marketing effectiveness: Conceptual framework and empirical findings from a managerial perspective. *PLoS ONE*. 2021; 16(4): e0249457. <https://doi.org/10.1371/journal.pone.0249457> PMID: 33793631
1736. Bu Y, Parkinson J, Thaichon P. Digital content marketing as a catalyst for e-WOM in food tourism. *Australasian Marketing Journal*. 2021; 29(2): 142–154.
1737. Liu Y, Luo Q, Shen H, Zhuang S, Xu C, Dong Y, et al. Social Media Big Data-Based Research on the Influencing Factors of Insomnia and Spatiotemporal Evolution. *IEEE Access*. 2020; 8: 41516–41529.
1738. Tadesse MM, Lin H, Xu B, Yang L. Detection of Suicide Ideation in Social Media Forums Using Deep Learning. *Algorithms*. 2020; 13(1): 7.
1739. Cha M, Gao W, Li C. Detecting fake news in social media: an Asia-Pacific perspective. *Commun ACM*. 2020; 63(4): 68–71.

1740. Cai D, Liu J, Zhao H, Li M.: Could social media help newcomers' socialization? The moderating effect of newcomers' utilitarian motivation. *Comput Hum Behav.* 2020; 107: 106273.
1741. Zhao Y, Kou G, Peng Y, Chen Y. Understanding influence power of opinion leaders in e-commerce networks: An opinion dynamics theory perspective. *Information Sciences*, 2018; 426: 131–147.
1742. Al-Garadi MA, Varathan K, Ravana S, et al. Analysis of online social network connections for identification of influential users: Survey and open research issues. *ACM Computing Surveys.* 2018; 51(1): 16.
1743. Riquelme F, Gonzalez-Cantergiani P. Measuring user influence on Twitter: A survey. *Int J Inf Process Manag.* 2016; 52: 949–975.
1744. Erlandsson F, Bro'dka P, Borg A, Johnson H. Finding Influential Users in Social Media Using Association Rule Learning. *Entropy.* 2016; 18(5): 164.
1745. Bonnevie E, Rosenberg SD, Kummeth C, Goldbarg J, Wartella E, Smyser J. Using social media influencers to increase knowledge and positive attitudes toward the flu vaccine. *PLoS ONE.* 2020; 15(10): e0240828. <https://doi.org/10.1371/journal.pone.0240828> PMID: 33064738
1746. Tafti A, Zotti R, Jank W. Real-Time Diffusion of Information on Twitter and the Financial Markets. *PLoS ONE.* 2016; 11(8): e0159226. <https://doi.org/10.1371/journal.pone.0159226> PMID: 27504639
1747. Huynh T, Zelinka I, Pham XH, Nguyen H. Some measures to Detect the Influencer on Social Network Based on Information Propagation. In: 9th International Conference on Web Intelligence, Mining and Semantics (WIMS 2019), Seoul, Korea, June 2019, Proceedings; ACM, 2019.
1748. Jiang J, Wilson C, Wang X, et al. Understanding latent interactions in online social networks. *ACM Transactions on the Web.* 2013; 7: 18.
1749. Lu L, Chen D, Ren XL, et al. Vital nodes identification in complex networks. *Physics Reports.* 2016; 650: 1–63
1750. Li Q, Zhou T, Lu L, Chen D. Identifying influential spreaders by weighted LeaderRank. *Physica A: Statistical Mechanics and its Applications.* 2014; 404: 47–55.
1751. Lu L, Zhang YC, Yeung CH, Zhou T. Leaders in social networks, the delicious case. *PloS One.* 2011; 6: e21202. <https://doi.org/10.1371/journal.pone.0021202> PMID: 21738620
1752. Al-Garadi MA, Varathan KD, Ravana SD. Identification of influential spreaders in online social networks using interaction weighted K-core decomposition method. *Physica A: Statistical Mechanics and its Applications.* 2017; 468: 278–288.
1753. Tran QM, Nguyen HD, Huynh T, et al. Measuring the influence and amplification of users on social network with unsupervised behaviors learning and efficient interaction-based knowledge graph. *Journal of Combinatorial Optimization.* 2021; <https://doi.org/10.1007/s10878-021-00815-0>
1754. Bo H, McConville R, Hong J, Liu W. Social Network Influence Ranking via Embedding Network Interactions for User Recommendation. In: Companion Proceedings of the Web

- Conference 2020 (WWW '20 Companion), Taipei, Taiwan, April 2020. ACM, 2020. p. 379–384.
1755. Riquelme F, Gonzalez-Cantergiani P, Hans D, Villarroel R, Munoz R. Identifying Opinion Leaders on Social Networks Through Milestones Definition. *IEEE Access*. 2019; 7: 75670–75677.
 1756. Nguyen H, Huynh T, Hoang S, Pham V, Zelinka I. Language-oriented Sentiment Analysis based on the grammar structure and improved Self-attention network. In: *Proceedings of the 15th International Conference on Evaluation of Novel Approaches to Software Engineering (ENASE 2020)*, Prague, Czech Public, May 2020. Scitepress, 2020. p. 339–346
 1757. Krouska A, Troussas C, Virvou M. Comparative Evaluation of Algorithms for Sentiment Analysis over Social Networking Services. *Journal of Universal Computer Science*. 2017; 23(8): 755–768.
 1758. Gamal D, Alfonse M, El-Horbaty EM, Salem AM. Implementation of Machine Learning Algorithms in Arabic Sentiment Analysis Using N-gram Features. *Procedia Computer Science*. 2019; 154: 332–340.
 1759. Leeftink W, Spanakis G. Towards Controlled Transformation of Sentiment in Sentences. In: *Proceedings of 11th International Conference on Agents and Artificial Intelligence (ICAART 2019)*, Prague, Czech Public, Feb. 2019. Scitepress, 2019.
 1760. Zainuddin N, Selamat A, Ibrahim R. Hybrid sentiment classification on twitter aspect-based sentiment analysis. *Applied Intelligence*. 2018; 48: 1218–1232.
 1761. Carosia A, Coelho G, Silva A. Analyzing the Brazilian Financial Market through Portuguese Sentiment Analysis in Social Media. *Applied Artificial Intelligence*. 2020; 34(1): 1–19.
 1762. Li W, et al. User reviews: Sentiment analysis using lexicon integrated two-channel CNN–LSTM family models. *Applied Soft Computing*. 2020; 94: 106435.
 1763. Samanta S, Dubey V, Sarkar B. Measure of influences in social networks. *Applied Soft Computing*. 2021; 99: 106858.
 1764. Qiu L, Zhang S, Yu J. Positive Influence Maximization in the Signed Social Networks Considering Polarity Relationship and Propagation Probability. *International Journal of Software Engineering and Knowledge Engineering*. 2021; 31(2): 249–267.
 1765. Do N, Nguyen HD, Selamat A. Knowledge-Based model of Expert Systems using Rela-model. *International Journal of Software Engineering and Knowledge Engineering*. 2018; 28(8): 1047–1090.
 1766. Pham XT, Tran TV, Nguyen-Le VT, Pham V, Nguyen H. Build a search engine for the knowledge of the course about Introduction to Programming based on ontology Rela-model, In: *Proceedings of 2020 12th IEEE International Conference on Knowledge and Systems Engineering (KSE 2020)*, Can Tho, Vietnam, Nov. 2020. IEEE, 2020. p. 207–212.
 1767. Do N, Nguyen H, Hoang L. Some Techniques for Intelligent Searching on Ontology-based Knowledge domain in E-learning. *Proceedings of 12th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management (IC3K 2020)*, Vol. 2: KEOD, Budapest, Hungary, Nov. 2020. Scitepress, 2020. p. 313–320.

1768. Phan T, Pham V, Nguyen H, Huynh A, Tran D, Pham VT. Ontology-based Resume Searching System for Job Applicants in Information Technology. In: Proceedings of 34th International Conference on Industrial, Engineering & Other Applications of Applied Intelligent Systems (IEA/AIE 2021), Kuala Lumpur, Malaysia, July 2021, vol. 12798 of LNAI. Springer, 2021. In press.
1769. Huynh T, Nguyen H, Zelinka I, Dinh D, Pham XH. Detecting the Influencer on Social Networks Using Passion Point and Measures of Information Propagation. *Sustainability*. 2020; 12(7): 3064.
1770. Morente-Molinera JA, Kou G, Peng Y, Torres-Albero C, Herrera-Viedma E. Analysing discussions in social networks using group decision-making methods and sentiment analysis. *Information Sciences*. 2018; 447: 157–168.
1771. An L, Hu J, Xu M, et al. Profiling the Users of High Influence on Social Media in the Context of Public Events. *Journal of Database Management (JDM)*. 2021; 32(2): 36–49.
1772. Tran QM, Nguyen HD, Nguyen BT, Pham VT, Le TT. Influence Prediction on Social Media Network through Contents and Interaction Behaviors using Attention-based Knowledge Graph. Proceedings of 13th International Conference on Knowledge and Systems Engineering (KSE 2021), Bangkok, Thailand, Nov. 2021. IEEE, 2021.
1773. Nguyen H, Do N, Pham V, Selamat A, Herrera-Viedma E. A method for knowledge representation to design Intelligent Problems Solver in mathematics based on Rela-Ops model. *IEEE Access*. 2020; 8: 76991–77012.
1774. Nguyen H, Huynh T, Luu S, Hoang S, Pham V, Zelinka I. Measure of the content creation score on social network using sentiment score and passion point. In: Proceedings of 19th International Conference on Intelligent Software Methodologies, Tools, and Techniques (SOMET 2020), Kitakyushu, Japan, Sep. 2020, vol. 327 of FAIA. IOS press, 2020. p. 425–434.
1775. Nguyen H, Tran K, Le T, Luu S, Hoang S, Phan H. Multi-level Sentiment Analysis of Product Reviews based on Grammar Rules of Language. In: Proceedings of 20th International Conference on Intelligent Software Methodologies, Tools, and Techniques (SOMET 2021), Cancun, Mexico, Sep. 2021. Accepted.
1776. Wallis SA. Binomial confidence intervals and contingency tests: Mathematical fundamentals and the evaluation of alternative methods. *J Quant Linguist*. 2013; 20: 178–208.
1777. De Salve A, Guidi B, Ricci L., Mori P. Discovering Homophily in Online Social Networks. *Mobile Netw Appl*. 2018; 23: 1715–1726. <https://doi.org/10.1007/s11036-018-1067-2>
1778. Salve A, Mori P, Guidi B, et al. Predicting Influential Users in Online Social Network Groups. *ACM Trans. Knowl. Discov. Data*. 2021; 15(3): 1–50.
1779. Carullo G, Castiglione A, De Santis A, Palmieri F. A triadic closure and homophily-based recommendation system for online social networks. *World Wide Web*. 2015; 18(6):1579–1601.
1780. McPherson M, Smith-Lovin L, Cook JM. Birds of a feather: homophily in social networks. *Annu Rev Sociol*. 2001; 27(1):415–444.
1781. Şimşek O , Jensen D. Navigating networks by using homophily and degree. *Proc Natl Acad Sci*. 2008; 105(35):12758–12762 <https://doi.org/10.1073/pnas.0800497105> PMID: 18725637

1782. Hiips: <https://hiip.asia/>(Accessed 17 June 2022)
1783. ViralWorks: <https://viralworks.com/>(Accessed 17 June 2022)
1784. Kartajaya H, Setiawan I, Kotler P. Marketing 5.0: Technology for humanity. John Wiley & Sons 2021.
1785. Girgin BA. Ranking influencers of social networks by semantic kernels and sentiment information. *Expert Systems with Applications* 2021, 171:114599.
1786. Duan J, Zeng J, Luo B. Identification of opinion leaders based on user clustering and sentiment analysis. In: *Proceedings of 2014 IEEE/WIC/ACM International Joint Conferences on Web Intelligence (WI) and Intelligent Agent Technologies (IAT)*, Vol. 1, IEEE, 2014. p. 377–383.
1787. Dihyat MMH, Malik K, Khan MA, Imran B. Detecting Ideal Instagram Influencer Using Social Network Analysis. *CoRR*, 2021. <https://dblp.org/rec/journals/corr/abs-2107-05731>
1788. Nguyen H, Nguyen K, Hoang S, Huynh T. Design a management system for the influencer marketing campaign on social network. In: *Proceedings of 9th International Conference on Computational Data and Social Networks (CSoNet 2020)*, Dallas, USA, Dec. 2020, vol. 12575 of LNCS 12575. Springer, 2020. p. 139–151.
1789. Twitter: <https://twitter.com/>(Accessed 01 September 2022)
1790. Zalo: <https://chat.zalo.me/>(Accessed 01 September 2022)
1791. Instagram: <https://www.instagram.com/>(Accessed 01 September 2022)
1792. Tiktok: <https://www.tiktok.com/en/>(Accessed 01 September 2022)
1793. Ni Y. Sequential seeding to optimize influence diffusion in a social network. *Applied Soft Computing*. 2017; 56: 730–737.
1794. Shah SK, Zhongjun T. Elaborating on the consumer’s intention–behavior gap regarding 5G technology: The moderating role of the product market-creation ability. *Technology in Society*. 2021; 66: 101657
1795. Alfano, Mark, J. Adam Carter, and Marc Cheong. 2018. “Technological Seduction and Self-Radicalization.” *Journal of the American Philosophical Association* 4(4):298–322.
1796. Aliapoulios, Max, Emmi Bevensee, Jeremy Blackburn, Barry Bradlyn, Emiliano De Cristofaro, Gianluca Stringhini, and Savvas Zannettou. 2021. “An Early Look at the Parler Online Social Network.” *arXiv: 2101.03820v3* (<https://doi.org/10.48550/arXiv.2101.03820>).
1797. Allen, Jennifer, Baird Howland, Markus Mobius, David Rothschild, and Duncan J. Watts. 2020. “Evaluating the Fake News Problem at the Scale of the Information Ecosystem.” *Science Advances* 6(14) (<https://doi.org/10.1126/sciadv.aay3539>).
1798. Andreoni, James, Nikos Nikiforakis, and Simon Sigenthaler. 2021. “Predicting Social Tipping and Norm Change in Controlled Experiments.” *Proceedings of the National Academy of Sciences* 118(16) (<https://doi.org/10.1073/pnas.2014893118>).
1799. Anspach, Nicolas M. 2021. “Trumping the Equality Norm? Presidential Tweets and Revealed Racial Attitudes.” *New Media & Society* 23(9):2691–707.
1800. Asimovic, Nejla, Jonathan Nagler, Richard Bonneau, and Joshua A. Tucker. 2021. “Testing the Effects of Facebook Usage in an Ethnically Polarized Setting.” *Proceedings of the National Academy of Sciences* 118(25) (<https://doi.org/10.1073/pnas.2022819118>).

1801. Bail, Christopher. 2021. *Breaking the Social Media Prism: How to Make Our Platforms Less Polarizing*. Princeton, NJ: Princeton University Press.
1802. Bail, Christopher A., Lisa P. Argyle, Taylor W. Brown, John P. Bumpus, Haohan Chen, M. B. Fallin Hunzaker, Jaemin Lee, Marcus Mann, Friedolin Merhout, and Alexander Volfovsky. 2018. "Exposure to Opposing Views on Social Media Can Increase Political Polarization." *Proceedings of the National Academy of Sciences* 115(37):9216–21.
1803. Beauchamp, Nicholas. 2017. "Predicting and Interpolating State-Level Polls Using Twitter Textual Data." *American Journal of Political Science* 61(2):490– 503.
1804. Benkler, Yochai, Robert Ferris, and Hal Roberts. 2018. *Network Propaganda: Manipulation, Disinformation, and Radicalization in American Politics*. New York: Oxford University Press.
1805. Bicchieri, Cristina. 2005. *The Grammar of Society: The Nature and Dynamics of Social Norms*. New York: Cambridge University Press.
1806. Blair, Graeme, Rebecca Littman, Elizabeth R. Nugent, Rebecca Wolfe, Mohammed Bukar, Benjamin Cisman, Anthony Etim, Chad Hazlett, and Jiyoung Kim. 2021. "Trusted Authorities Can Change Minds and Shift Norms during Conflict." *Proceedings of the National Academy of Sciences* 118(42) (<https://doi.org/10.1073/pnas.2105570118>).
1807. Bond, Robert M., Christopher J. Fariss, Jason J. Jones, Adam D. I. Kramer, Cameron Marlow, Jaime E. Settle, and James H. Fowler. 2012. "A 61-Million-Person Experiment in Social Influence and Political Mobilization." *Nature* 489:295–98.
1808. Broockman, David E., and Joshua L. Kalla. 2022. "The Manifold Effects of Partisan Media on Viewers' Beliefs and Attitudes: A Field Experiment with Fox News Viewers." *Open Science Foundation* (<https://osf.io/jrw26/>).
1809. Bursztyn, Leonardo, Georgy Egorov, Ruben Enikolopov, and Maria Petrova. 2019. "Social Media and Xenophobia: Evidence from Russia." NBER, Working Paper 26567.
1810. Bursztyn, Leonardo, Georgy Egorov, and Stefano Fiorin. 2020. "From Extreme to Mainstream: The Erosion of Social Norms." *American Economic Review* 110(11):3522–48.
1811. Caren, Neal, Kenneth T. Andrews, and Todd Lu. 2020. "Contemporary Social Movements in a Hybrid Media Environment." *Annual Review of Sociology* 46:443–65.346
1812. Chatman, Jennifer A., David F. Caldwell, Charles A. O'Reilly, and Bernadette Doerr. 2014. "Parsing Organizational Culture: How the Norm for Adaptability Influences the Relationship between Culture Consensus and Financial Performance in High-Technology Firms." *Journal of Organizational Behavior* 35(6):785–808.
1813. Cinelli, Carlos, Andrew Forney, and Judea Pearl. 2022. "A Crash Course in Good and Bad Controls." *Sociological Methods & Research* (<https://doi.org/10.1177/00491241221099552>).
1814. Cinelli, Carlos, and Chad Hazlett. 2020. "Making Sense of Sensitivity: Extending Omitted Variable Bias." *Journal of the Royal Statistical Society Series B (Statistical Methodology)* 82(1):39–67.
1815. Clayton, Katherine, Nicholas T. Davis, Brendan Nyhan, Ethan Porter, Timothy J. Ryan, and Thomas J. Wood. 2021. "Elite Rhetoric Can Undermine Democratic Norms." *Proceedings of the National Academy of Sciences* 118(23) (<https://doi.org/10.1073/pnas.2024125118>).

1816. Dehghan, Ehsan, and Ashwin Nagappa. 2022. "Politicization and Radicalization of Discourses in the Alt-Tech Ecosystem: A Case Study of Parler." *Social Media + Society* 8(3) (<https://doi.org/10.1177/20563051221113075>).
1817. Demarest, Leila, and Arnim Langer. 2022. "How Events Enter (or Not) Data Sets: The Pitfalls and Guidelines of Using Newspapers in the Study of Conflict." *Sociological Methods & Research* 51(2):632–66.
1818. Dignam, Pierce Alexander, and Deana A. Rohlinger. 2019. "Misogynistic Men Online: How the Red Pill Helped Elect Trump." *Signs* 44(3):589–612.
1819. Druckman, James N., Matthew S. Levendusky, and Audrey McLain. 2018. "No Need to Watch: How the Effects of Partisan Media Can Spread via Interpersonal Discussions." *American Journal of Political Science* 62(1):99–112.
1820. Eggers, Andrew C., Guadalupe Tuñón, and Allan Dafoe. 2021. "Placebo Tests for Causal Inference." Working paper (https://pelg.ucsd.edu/Eggers_2021.pdf).
1821. Enikolopov, Ruben, Alexey Makarin, and Maria Petrova. 2020. "Social Media and Protest Participation: Evidence From Russia." *Econometrica* 88(4):1479–514.
1822. Eshima, Shusei, Kosuke Imai, and Tomoya Sasaki. 2021. "Keyword Assisted Topic Models." arXiv: 2004.05964v2 (<https://doi.org/10.48550/arXiv.2004.05964>).
1823. Fawcett, Edmund. 2020. *Conservatism: The Fight for a Tradition*. Princeton, NJ: Princeton University Press.
1824. Feuer, Alan. 2021. "Did the Proud Boys Help Coordinate the Capitol Riot? Yes, U.S. Suggests." *The New York Times*, February 5 (<https://www.nytimes.com/2021/02/05/nyregion/proudboyscapitolriotconspiracy.html>).
1825. Fisher, Dana R., Kenneth T. Andrews, Neal Caren, Erica Chenoweth, Michael T. Heaney, Tommy Leung, L. Nathan Perkins, and Jeremy Pressman. 2019. "The Science of Contemporary Street Protest: New Efforts in the United States." *Science Advances* 5(10) (<https://doi.org/10.1126/sciadv.aaw5461>).
1826. Foos, Florian, Lyubomir Kostadinov, Nikolay Marinov, and Frank Schimmelfennig. 2020. "Does Social Media Promote Civic Activism? A Field Experiment with a Civic Campaign." *Political Science Research and Methods* 9(3):500–18 (<https://doi.org/10.1017/psrm.2020.13>).
1827. Freelon, Deen, Alice Marwick, and Daniel Kreiss. 2020. "False Equivalences: Online Activism from Left to Right." *Science* 369:1197–201.
1828. Gaudette, Tiana, Ryan Scrivens, Garth Davies, and Richard Frank. 2021. "Upvoting Extremism: Collective Identity Formation and the Extreme Right on Reddit." *New Media & Society* 23(12):3491–508.
1829. Gehl, Robert W. 2015. "The Case for Alternative Social Media." *Social Media + Society* 1(2) (<https://doi.org/10.1177/2056305115604338>).
1830. Gehl, Robert W. 2017. "Alternative Social Media: From Critique to Code." Chapter 18 in *Sage Handbook of Social Media*, edited by J. Burgess, A. Marwick, and T. Poell. London, UK: Sage Publishing.
1831. Goldstein, Matthew. 2022a. "Google's Move to Include Truth Social in App Store Buys Investor Confidence." *The New York Times*, October 13

- (<https://www.nytimes.com/2022/10/13/business/truthsocialgoogledigitalworld.html?searchResultPosition=1>).
1832. Goldstein, Matthew. 2022b. "These Investors Are Putting \$1 Billion Into Trump Media." *The New York Times*, May 24 (<https://www.nytimes.com/2022/05/24/business/investors-trump-truth-social.html>).
 1833. Griffith, Daniel. 1987. *Spatial Autocorrelation: A Primer*. Resource Publications in Geography, Association of American Geographers.
 1834. Grimmer, Justin, and Brandon Stewart. 2013. "Text as Data: The Promise and Pitfalls of Automatic Content Analysis Methods for Political Texts." *Political Analysis* 21(3):267–97.
 1835. Haas, Ryan, Sergio Olmos, and Bradley W. Parks. 2020. "Protesters Fight Using Pepper Spray, Baseball Bats in Portland on Saturday." *Oregon Public Radio*, August 22 (<https://www.opb.org/article/2020/08/22/conservative-protesters-plan-rallies-in-downtown-portland/>).
 1836. Haidt, Jonathan, and Christopher Bail. 2022. "Social Media and Political Dysfunction: A Collaborative Review." Unpublished manuscript, New York University (https://docs.google.com/document/d/1vVA tMCQnz8WVxtSNQev_e1cGmY9rnY96ecYuA j6C548/mobilebasic?usp=gmail).
 1837. Hakim, Danny. 2022. "Company Backed by J.D. Vance Gives Platform for Russian Propaganda." *The New York Times*, October 31 (<https://www.nytimes.com/2022/10/31/us/politics/jdvancepeterthielrubble.html>).
 1838. Hechter, Michael, and Karl-Dieter Opp. 2001. "What Have We Learned about the Emergence of Social Norms?" Pp. 394–416 in *Social Norms*, edited by M. Hechter and K.-D. Opp. New York: Russell Sage.
 1839. Heiss, Raffael, and Jörg Matthes. 2019. "Stuck in a Nativist Spiral: Content, Selection, and Effects of Right-Wing Populists' Communication on Facebook." *Political Communication* 37(3):303–28.
 1840. Herman, Peter, Marissa J. Lang, and Clarence Williams. 2020. "Pro-Trump Rally Descends into Chaos as Proud Boys Roam D.C. Looking to Fight." *The Washington Post*, December 13 (https://www.washingtonpost.com/local/public-safety/proudboysproteststabbingarrest/2020/12/13/98c0f740-3d3f-11eb-8db8-395dedaaa036_story.html).
 1841. Hofstadter, Richard. 1965. *The Paranoid Style in American Politics, and Other Essays*. New York: Alfred Knopf.
 1842. Horne, Christine, and Stefanie Mollborn. 2020. "Norms: An Integrated Framework." *Annual Review of Sociology* 46:467–87.
 1843. Hosseinmardi, Homa, Amir Chasemian, Aaron Clauset, Markus Mobius, David M. Rothschild, and Duncan J. Watts. 2021. "Examining the Consumption of Radical Content on YouTube." *Proceedings of the National Academy of Sciences* 118(32) (<https://doi.org/10.1073/pnas.2101967118>).
 1844. Hsiao, Yuan. 2021. "Evaluating the Mobilization Effect of Online Political Network Structures: A Comparison between the Black Lives Matter Network and Ideal Type Network Configurations." *Social Forces* 99(4):1547–74.

1845. Imai, Kosuke, and In Song Kim. 2021. "On the Use of Two-Way Fixed Effects Regression Models for Causal Inference with Panel Data." *Political Analysis* 29(3):405–15.
1846. Iqbal, Mansoor. 2021. "Facebook Revenue and Usage Statistics (2021)." *Business of Apps*, May 24 (<https://www.businessofapps.com/data/facebook-statistics/>).
1847. Jasser, Greta, Jordan McSwiney, Ed Pertwee, and Savvas Zannettou. 2021. "'Welcome to #GabFam': Far-Right Virtual Community on Gab." *New Media & Society* (<https://doi.org/10.1177/14614448211024546>).
1848. Jasso, Guillermina, and Karl-Dieter Opp. 1997. "Probing the Character of Norms: A Factorial Survey Analysis of the Norms of Political Action." *American Sociological Review* 62(6):947–64.
1849. Katz, Elihu, and Paul Lazarsfeld. 1955. *Personal Influence*. New York: Transaction.
1850. Kim, Yoonsang, Rachel Nordgren, and Sherry Emery. 2020. "The Story of Goldilocks and Three Twitter APIs: A Pilot Study on Twitter Data Sources and Disclosure." *International Journal of Environmental Research and Public Health* 17(3):864 (<https://doi.org/10.3390/ijerph17030864>).
1851. Knox, Dean, Christopher Lucas, and Wendy K. Tam Cho. 2022. "Testing Causal Theories with Learned Proxies." *Annual Review of Political Science* 25:419–41.
1852. Koopmans, Ruud, and Susan Olzak. 2004. "Discursive Opportunities and the Evolution of Right-Wing Violence in Germany." *American Journal of Sociology* 110(1):198–230.
1853. Kor-Sins, Ryan. 2021. "The Alt-Right Digital Migration: A Heterogeneous Engineering Approach to Social Media Platform Branding." *New Media & Society* (<https://doi.org/10.1177/14614448211038810>).
1854. Larson, Jennifer M., Jonathan Nagler, Jonathan Ronen, and Joshua A. Tucker. 2019. "Social Networks and Protest Participation: Evidence from 130 Million Twitter Users." *American Journal of Political Science* 63(3):690–705.
1855. Levy, Ro'ee. 2021. "Social Media, News Consumption, and Polarization: Evidence from a Field Experiment." *American Economic Review* 111(3):831–70.
1856. Little, Andrew T. 2016. "Communication Technology and Protest." *Journal of Politics* 78(1):152–66.
1857. Malik, Momin M., Hemank Lamba, Constantine Nakos, and Jurgen Pfeffer. 2015. "Population Bias in Geotagged Tweets." 9th International AAAI Conference on Weblogs and Social Media pp. 18–27.
1858. Marchetti, Arianna, and Phanish Puranam. 2022. "Organizational Cultural Strength as the Negative Cross-Entropy of Mindshare: A Measure Based on Descriptive Text." *Humanities & Social Sciences Communications* 9:135 (<https://doi.org/10.1057/s41599-022-01152-1>).
1859. Marwick, Alice, Benjamin Clancy, and Katherine Furl. 2022. "Far-Right Online Radicalization: A Review of the Literature." *The Bulletin of Technology & Public Life* (<https://citap.pubpub.org/pub/jq7l6jny>).
1860. McAlexander, Richard, Michael Rubin, and Rob Williams. 2021. "'They're Still There, He's All Gone': American Fatalities in Foreign Wards and Right-Wing Radicalization at Home." *APSA Preprints* (<https://doi.org/10.33774/apsa-2021-70pn3>).

1861. McCormick, Tyler H., Hedwig Lee, Nina Cesare, Ali Shojaie, and Emma S. Spiro. 2017. "Using Twitter for Demographic and Social Science Research: Tools for Data Collection and Processing." *Sociological Methods & Research* 46(3):390–421.
1862. MIT Election Data and Science Lab. 2018. "County Presidential Election Returns 2000–2016." Harvard Dataverse (<https://doi.org/10.7910/DVN/VOQCHQ>).
1863. Mitts, Tamar. 2019. "From Isolation to Radicalization: Anti-Muslim Hostility and Support for ISIS in the West." *American Political Science Review* 113(1):173–94.
1864. Müller, Karsten, and Carlo Schwarz. 2020. "From Hashtag to Hate Crime: Twitter and Anti-Minority Sentiment" (<https://dx.doi.org/10.2139/ssrn.3149103>).
1865. Müller, Karsten, and Carlo Schwarz. 2021. "Fanning the Flames of Hate: Social Media and Hate Crime." *Journal of the European Economic Association* 19(4):2131–67 (<https://doi.org/10.1093/jeea/jvaa045>).
1866. Munger, Kevin, and Joseph Phillips. 2020. "Right-Wing YouTube: A Supply and Demand Perspective." *The International Journal of Press/Politics* 27(1):189–219.
1867. Munn, Luke. 2021. "More Than a Mob: Parler as Preparatory Media for the U.S. Capitol Storming." *First Monday* 26(3) (<https://doi.org/10.5210/fm.v26i3.11574>).
1868. Nicas, Jack, and Davey Alba. 2021. "How Parler, a Chosen App of Trump Fans, Became a Test of Free Speech." *The New York Times*, January 10, Section A.348
1869. Nordbrandt, Maria. 2021. "Affective Polarization in the Digital Age: Testing the Direction of the Relationship between Social Media and Users' Feelings for Out-Group Parties." *New Media & Society* (<https://doi.org/10.1177/14614448211044393>).
1870. Pauwels, Lieven, and Nele Schils. 2016. "Differential Online Exposure to Extremist Content and Political Violence: Testing the Relative Strength of Social Learning and Competing Perspectives." *Terrorism and Political Violence* 28(1):1–29.
1871. Pfeffer, Jürgen, Katja Mayer, and Fred Morstatter. 2018. "Tampering with Twitter's Sample API." *EPJ Data Science* 50(7) (<https://doi.org/10.1140/epjds/s13688-018-0178-0>).
1872. Pustejovsky, James E. 2022. "Cluster-Robust Standard Errors and Hypothesis Tests in Panel Data Models" (<https://cran.r-project.org/web/packages/clubSandwich/vignettes/panel-data-CRVE.html>).
1873. Raleigh, Clionadh, Andrew Linke, Håvard Hegre, and Joakim Karlsen. 2010. "Introducing ACLED: An Armed Conflict Location and Event Dataset." *Journal of Peace Research* 47(5):651–60.
1874. Ribeiro, Manoel Horta, Raphael Ottoni, Robert West, Virgílio A. F. Almeida, and Wagner Meira. 2019. "Auditing Radicalization Pathways on YouTube." *arXiv: 1908.08313v3* (<https://doi.org/10.48550/arXiv.1908.08313>).
1875. Robbins, Blaine G., Aimée Dechter, and Sabino Kornrich. 2022. "Assessing the Deinstitutionalization of Marriage Thesis: An Experimental Test." *American Sociological Review* 87(2):237–74.
1876. Rogers, Richard. 2020. "Deplatforming: Following Extreme Internet Celebrities to Telegram and Alternative Social Media." *European Journal of Communication* 35(3):213–29.

1877. Roose, Kevin. 2019. "The Making of a YouTube Radical." *The New York Times*, June 8 (<https://www.nytimes.com/interactive/2019/06/08/technology/youtube-radical.html>).
1878. Ruisch, Benjamin C., and Melissa J. Ferguson. 2022. "Changes in Americans' Prejudices during the Presidency of Donald Trump." *Nature Human Behavior* 6:656–65.
1879. Scherman, Andrés, and Sebastian Rivera. 2021. "Social Media Use and Pathways to Protest Participation: Evidence from the 2019 Chilean Social Outburst." *Social Media + Society* 7(4) (<https://doi.org/10.1177/20563051211059704>).
1880. Schulze, Heidi. 2020. "Who Uses Right-Wing Alternative Online Media? An Exploration of Audience Characteristics." *Politics and Governance* 8(3):6–18.
1881. Schumann, Sandy, Diana Boer, Katja Hanke, and James Liu. 2021. "Social Media Use and Support for Populist Radical Right Parties: Assessing Exposure and Selection Effects in a Two-Wave Panel Study." *Information, Communication & Society* 24(7):92–940.
1882. Scoville, Caleb, Andrew McCumber, Razvan Amironesei, and June Jeon. 2022. "Mask Refusal Backlash, The Politicization of Face Masks in the American Public Sphere during the Early Stages of the COVID–19 Pandemic." *Socius* 8 (<https://doi.org/10.1177/23780231221093158>).
1883. Sheets, Connor. 2021. "The Radicalization of Kevin Greeson." *ProPublica*, January 15 (<https://www.propublica.org/article/theradicalizationofkevingreeson>).
1884. Siegel, Alexandra A., and Vivienne Badaan. 2020. "#No2Sectarianism: Experimental Approaches to Reducing Sectarian Hate Speech Online." *American Political Science Review* 114(3):837–55.
1885. Steinert-Threlkeld, Zachary C. 2017. "Spontaneous Collective Action: Peripheral Mobilization during the Arab Spring." *American Political Science Review* (111)2:379–403.
1886. Stocking, Galen, Amy Mitchell, Katerina Eva Matsa, Regina Widjaya, Mark Jurkowitz, Shreenita Ghosh, Aaron Smith, Sarah Naseer, and Christopher St. Aubin. 2022. "The Role of Alternative Social Media in the News and Information Environment." *Pew Research* (<https://www.pewresearch.org/journalism/2022/10/06/the-role-of-alternative-social-media-in-the-news-and-information-environment/>).
1887. Sunstein, Cass. 2009. *Republic.com 2.0*. Princeton, NJ: Princeton University Press.
1888. Terren, Ludovic, and Rosa Borge. 2021. "Echo Chambers on Social Media: A Systematic Review of the Literature." *Review of Communication Research* 9:99–118.
1889. Theocharis, Yannis, and Will Lowe. 2016. "Does Facebook Increase Political Participation? Evidence from a Field Experiment." *Information, Communication & Society* 19(10):1465–86.
1890. Tufekci, Zeynep. 2014. "Social Movements and Governments in the Digital Age: Evaluating a Complex Landscape." *Journal of International Affairs* 68(1):1– 18.
1891. Tufekci, Zeynep, and Christopher Wilson. 2012. "Social Media and the Decision to Participate in Political Protest: Observations from Tahrir Square." *Journal of Communication* 62(2):363–79.
1892. Van Dijcke, David, and Austin L. Wright. 2021. "Profiling Insurrection: Characterizing Collective Action Using Mobile Device Data" (<https://dx.doi.org/10.2139/ssrn.3776854>).

1893. Wahlström, Mattias, and Anton Törnberg. 2021. "Social Media Mechanisms for Right-Wing Political Violence in the 21st Century: Discursive Opportunities, Group Dynamics, and Co-ordination." *Terrorism and Political Violence* 33(4):766–87.
1894. Wahlström, Mattias, Anton Törnberg, and Hans Ekbrand. 2021. "Dynamics of Violent and Dehumanizing Rhetoric in Far-Right Social Media." *New Media & Society* 23(11):3290–311.
1895. Weidmann, Nils B., and Espen Geelmuyden Rød. 2019. *The Internet and Political Protest in Autocracies*. New York: Oxford University Press.
1896. Williams, Matthew L., Pete Burnap, Amir Javed, Han Lui, and Sefa Ozalap. 2020. "Hate in the Machine: Anti-Black and Anti-Muslim Social Media Posts as Predictors of Offline Racially and Religiously Aggravated Crime." *The British Journal of Criminology* 60(1):93–117.
1897. Wojcieszak, Magdalena. 2010. "'Don't Talk To Me': Effects of Ideological Homogenous Online Groups and Politically Dissimilar Offline Ties on Extremism." *New Media & Society* 12(4):637–55.
1898. Zhuravskaya, Ekaterina, Maria Petrova, and Ruben Enikolopov. 2020. "Political Effects of the Internet and Social Media." *Annual Review of Economics* 12:415–38.
1899. Adewole, K.S., Anuar, N.B., Kamsin, A., Varathan, K.D., Razak, S.A., 2017. Malicious accounts: dark of the social networks. *J. Netw. Comput. Appl.* 79, 41–67.
1900. Akoglu, L., Tong, H., Koutra, D., 2015. Graph based anomaly detection and description: a survey. *Data Min. Knowl. Discov.* 29 (3), 626–688. Albright, J., 2016. The #election 2016 Micro-propaganda Machine. [https://medium.com /@d1gi/the-election2016-micro-propaganda-machine-383449cc1fba](https://medium.com/@d1gi/the-election2016-micro-propaganda-machine-383449cc1fba).
1901. Aldwairi, M., Alwahedi, A., 2018. Detecting fake news in social media networks. *Procedia Computer Science* 141, 215–222.
1902. Allcott, H., Gentzkow, M., 2017. Social media and fake news in the 2016 election. *J. Econ. Perspect.* 31 (2), 211–236.
1903. Alothali, E., Zaki, N., Mohamed, E.A., Alashwal, H., 2018. Detecting social bots on twitter: a literature review. In: *2018 International Conference on Innovations in Information Technology (IIT)*. IEEE, pp. 175–180.
1904. Anna Escher, A.H., 2016. Wtf Is Clickbait? <https://techcrunch.com/2016/09/25/wtf-is-clickbait/>.
1905. Antoniadis, S., Litou, I., Kalogeraki, V., 2015. A model for identifying misinformation in online social networks. In: *OTM Confederated International Conferences" on the Move to Meaningful Internet Systems"*. Springer, pp. 473–482.
1906. Asano, E., 2017. How Much Time Do People Spend on Social Media? *Social Media Today*, pp. 290–306.
1907. Aslam, S., 2021. Omnicore (2018). Twitter by the numbers: Stats, demographics & fun facts. <https://www.omnicoreagency.com/twitter-statistics/>.
1908. Balestrucci, A., De Nicola, R., Inverso, O., Trubiani, C., 2019. Identification of credulous users on twitter. In: *Proceedings of the 34th ACM/SIGAPP Symposium on Applied Computing*, pp. 2096–2103.

1909. Baly, R., Karadzhov, G., Alexandrov, D., Glass, J., Nakov, P., 2018. Predicting Factuality of Reporting and Bias of News Media Sources arXiv preprint arXiv:1810.01765.
1910. Benevenuto, F., Magno, G., Rodrigues, T., Almeida, V., 2010. Detecting spammers on twitter. In: Collaboration, Electronic Messaging, Anti-abuse and Spam Conference (CEAS), vol. 6, p. 12.
1911. Binham, C., 2019. Companies Fear Rise of Fake News and Social Media Rumours. <http://www.ft.com/content/4241a2f6-e080-11e9-9743-db5a370481bc>.
1912. Bollen, J., Mao, H., Pepe, A., 2011. Modeling public mood and emotion: twitter sentiment and socio-economic phenomena. In: Fifth International AAI Conference on Weblogs and Social Media.
1913. Broder, A., Kumar, R., Maghoul, F., Raghavan, P., Rajagopalan, S., Stata, R., Tomkins, A., Wiener, J., 2000. Graph structure in the web. *Comput. Network.* 33 (1–6), 309–320.
1914. Bulger, M., Davison, P., 2018. The Promises, Challenges, and Futures of Media Literacy.
1915. Bytwerk, R.L., 2010. Grassroots Propaganda in the Third Reich: the Reich Ring for National Socialist Propaganda and Public Enlightenment. *German Studies Review*, pp. 93–118.
1916. Canini, K.R., Suh, B., Pirolli, P.L., 2011. Finding credible information sources in social networks based on content and social structure. In: 2011 IEEE Third International Conference on Privacy, Security, Risk and Trust and 2011 IEEE Third International Conference on Social Computing. IEEE, pp. 1–8.
1917. Carlson, E., 2017. Flagging Fake News. <https://niemanreports.org/articles/flagging-fake-news/>.
1918. Carson, J., 2019. Fake News: what Exactly Is it and How Can You Spot it? <https://www.telegraph.co.uk/technology/0/fake-news-exactly-has-really-had-influence/>.
1919. Cha, M., Haddadi, H., Benevenuto, F., Gummadi, K.P., 2010. Measuring user influence in twitter: the million follower fallacy. In: Fourth International AAI Conference on Weblogs and Social Media.
1920. Chen, H., De, P., Hu, Y.J., Hwang, B.-H., 2014. Wisdom of crowds: the value of stock opinions transmitted through social media. *Rev. Financ. Stud.* 27 (5), 1367–1403.
1921. Chen, Y., Conroy, N.J., Rubin, V.L., 2015. Misleading online content: recognizing clickbait as “false news”. In: Proceedings of the 2015 ACM on Workshop on Multimodal Deception Detection, pp. 15–19.
1922. Christian Reuter, J.K., Hartwig, Katrin, Schlegel, N., 2019. Fake news perception in Germany: a representative study of people’s attitudes and approaches to counteract disinformation. In: 14th International Conference on Wirtschaftsinformatik.
1923. Chu, Z., Gianvecchio, S., Wang, H., Jajodia, S., 2010. Who is tweeting on twitter: human, bot, or cyborg?. In: Proceedings of the 26th Annual Computer Security Applications Conference. ACM, pp. 21–30.
1924. Chu, Z., Gianvecchio, S., Wang, H., Jajodia, S., 2012. Detecting automation of twitter accounts: are you a human, bot, or cyborg? *IEEE Trans. Dependable Secure Comput.* 9 (6), 811–824.

1925. Ciampaglia, G.L., Shiralkar, P., Rocha, L.M., Bollen, J., Menczer, F., Flammini, A., 2015.
1926. Computational fact checking from knowledge networks. *PloS One* 10 (6), e0128193.
Clark, B.. SurfSafe Offers a Browser-Based Solution to Fake News (201b).
<https://thenextweb.com/insider/2018/08/21/surfsafe-offers-a-browser-based-solution-to-fake-news/>.
1927. Clauset, A., Shalizi, C.R., Newman, M.E., 2009. Power-law distributions in empirical data. *SIAM Rev.* 51 (4), 661–703.
1928. Collins, B., Hoang, D.T., Nguyen, N.T., Hwang, D., 2020. Trends in combating fake news on social media—a survey. *Journal of Information and Telecommunication* 1–20.
1929. Constantinides, P., Henfridsson, O., Parker, G.G., 2018. Introduction-platforms and Infrastructures in the Digital Age.
1930. Cresci, S., Di Pietro, R., Petrocchi, M., Spognardi, A., Tesconi, M., 2016. Dna-inspired online behavioral modeling and its application to spambot detection. *IEEE Intell. Syst.* 31 (5), 58–64.
1931. Cresci, S., Di Pietro, R., Petrocchi, M., Spognardi, A., Tesconi, M., 2017. The paradigm-shift of social spambots: evidence, theories, and tools for the arms race. In: *Proceedings of the 26th International Conference on World Wide Web Companion*, pp. 963–972.
1932. Cresci, S., Lillo, F., Regoli, D., Tardelli, S., Tesconi, M., 2019. Cashtag piggybacking: uncovering spam and bot activity in stock microblogs on twitter. *ACM Trans. Web* 13 (2), 11.
1933. Dauphin, Y.N., Fan, A., Auli, M., Grangier, D., 2017. Language modeling with gated convolutional networks. In: *Proceedings of the 34th International Conference on Machine Learning*, vol. 70. JMLR. org, pp. 933–941.
1934. Davis, C.A., Varol, O., Ferrara, E., Flammini, A., Menczer, F., 2016. Botornot: a system to evaluate social bots. In: *Proceedings of the 25th International Conference Companion on World Wide Web. International World Wide Web Conferences Steering Committee*, pp. 273–274.
1935. De Domenico, M., Lima, A., Mougél, P., Musolesi, M., 2013. The anatomy of a scientific rumor. *Sci. Rep.* 3, 2980. DFRLab, 2016. Human, Bot or Cyborg?
<https://medium.com/@DFRLab/humanbotorcyborg41273cdb1e17>.
1936. Dimitriou, T., Michalas, A., 2012. Multi-party trust computation in decentralized environments. In: *2012 5th International Conference on New Technologies, Mobility and Security. NTMS*, pp. 1–5. <https://doi.org/10.1109/NTMS.2012.6208686>.
1937. Dimitriou, T., Michalas, A., 2014. Multi-party trust computation in decentralized environments in the presence of malicious adversaries. *Ad Hoc Netw.* 15, 53–66.
<https://doi.org/10.1016/j.adhoc.2013.04.013>.
1938. Edwards, C., Edwards, A., Spence, P.R., Shelton, A.K., 2014. Is that a bot running the social media feed? testing the differences in perceptions of communication quality for a human agent and a bot agent on twitter. *Comput. Hum. Behav.* 33, 372–376.
1939. Ericsson, K.A., Hoffman, R.R., Kozbelt, A., 2018. *The Cambridge Handbook of Expertise and Expert Performance*. Cambridge University Press.

1940. Erşahin, B., Aktaş, Ö., Kılınç, D., Akyol, C., 2017. Twitter fake account detection. In: 2017 International Conference on Computer Science and Engineering (UBMK). IEEE, pp. 388–392. Fernandes, T., 2019. Liardataset. https://github.com/thiagorainmaker77/liar_dataset.
1941. Ferreira, W., Vlachos, A., 2016. Emergent: a novel data-set for stance classification. In: Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pp. 1163–1168.
1942. Figueira, A., Oliveira, L., 2017. The current state of fake news: challenges and opportunities. *Procedia Computer Science* 121, 817–825. M. for minds. Spread of coronavirus fake news causes hundreds of deaths. <https://www.dw.com/en/coronavirus-misinformation/a-54529310>.
1943. Funke Daniel, F.D., 2019. A Guide to Anti-misinformation Actions Around the World. <https://www.poynter.org/ifcn/anti-misinformation-actions/>.
1944. Gabrovšek, P., Aleksovski, D., Mozetič, I., Grčar, M., 2017. Twitter sentiment around the earnings announcement events. *PloS One* 12 (2).
1945. Gao, J., Liang, F., Fan, W., Wang, C., Sun, Y., Han, J., 2010. On community outliers and their efficient detection in information networks. In: Proceedings of the 16th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. ACM, pp. 813–822.
1946. Garcia, D., Mavrodiev, P., Casati, D., Schweitzer, F., 2017. Understanding popularity, reputation, and social influence in the twitter society. *Pol. Internet* 9 (3), 343–364.
1947. Gazi, M.A., Çetin, M., 2017. The research of the level of social media addiction of university students. *International Journal of Social Sciences and Education Research* 3 (2), 549–559.
1948. T. Khan et al. *Journal of Network and Computer Applications* 190 (2021) 103112
1949. Ghavipour, M., Meybodi, M.R., 2018a. Trust propagation algorithm based on learning automata for inferring local trust in online social networks. *Knowl. Base Syst.* 143, 307–316.
1950. Ghavipour, M., Meybodi, M.R., 2018b. A dynamic algorithm for stochastic trust propagation in online social networks: learning automata approach. *Comput. Commun.* 123, 11–23.
1951. Ghosh, S., Viswanath, B., Kooti, F., Sharma, N.K., Korlam, G., Benevenuto, F., Ganguly, N., Gummadi, K.P., 2012. Understanding and combating link farming in the twitter social network. In: Proceedings of the 21st International Conference on World Wide Web, pp. 61–70.
1952. Giachanou, A., Ghanem, B., 2019. Bot and gender detection using textual and stylistic information. *Pan* 16, 5.
1953. Giatsidis, C., Thilikos, D.M., Vazirgiannis, M., 2013. D-cores: measuring collaboration of directed graphs based on degeneracy. *Knowl. Inf. Syst.* 35 (2), 311–343.
1954. Gibert, D., Mateu, C., Planes, J., 2020. The rise of machine learning for detection and classification of malware: research developments, trends and challenges. *J. Netw. Comput. Appl.* 153, 102526.
1955. Giełczyk, A., Wawrzyniak, R., Chora's, M., 2019. Evaluation of the existing tools for fake news detection. In: IFIP International Conference on Computer Information Systems and Industrial Management. Springer, pp. 144–151.

1956. Gilani, Z., 2018. STCS - Streaming Twitter Computation System. <https://github.com/zafargilani/stcs>.
1957. Gilani, Z., Kochmar, E., Crowcroft, J., 2017. Classification of twitter accounts into automated agents and human users. In: Proceedings of the 2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2017. ACM, pp. 489–496.
1958. Grice, A., 2017. Fake News Handed Brexiteers the Referendum and Now They Have No Idea what They're Doing. <https://www.independent.co.uk/voices/michael-gove-boris-johnson-brexit-eurosceptic-press-theresa-may-a7533806.html>.
1959. Grier, C., Thomas, K., Paxson, V., Zhang, M., 2010. @ spam: the underground on 140 characters or less. In: Proceedings of the 17th ACM Conference on Computer and Communications Security. ACM, pp. 27–37.
1960. Grigorev, A., 2017. Identifying Clickbait Posts on Social Media with an Ensemble of Linear Models arXiv preprint arXiv:1710.00399.
1961. Griswold, A., 2016. Facebook Warned People that a Popular Fake News Detector Might Be “Unsafe”. <https://qz.com/851894/facebook-said-bs-detector-a-plugin-to-detect-fake-news-might-be-unsafe/>.
1962. Gupta, A., Kumaraguru, P., Castillo, C., Meier, P., 2014. Tweetcred: real-time credibility assessment of content on twitter. In: International Conference on Social Informatics. Springer, pp. 228–243.
1963. Hannah Bastl, E.H., 2017. Bjorn Buchhold, Triple Scoring. <https://www.wsdm-cup-2017.org/triple-scoring.html>.
1964. Hanselowski, A., 2017. Team Athene on the Fake News Challenge. <https://medium.com/@andre134679/team-athene-on-the-fake-news-challenge-28a5cf5e017b>.
1965. Haralabopoulos, G., Anagnostopoulos, I., Zeadally, S., 2015. Lifespan and propagation of information in on-line social networks: a case study based on reddit. J. Netw. Comput. Appl. 56, 88–100.
1966. Hartwig, K., Reuter, C., 2019. Trustytweet: an indicator-based browser-plugin to assist users in dealing with fake news on twitter. In: Proceedings of the International Conference on Wirtschaftsinformatik (WI).
1967. Hasani-Mavriqi, I., Kowald, D., Helic, D., Lex, E., 2018. Consensus dynamics in online collaboration systems. Computational social networks 5 (1), 2.
1968. Holton, A.E., Lewis, S.C., 2011. Journalists, social media, and the use of humor on twitter. Electron. J. Commun. 21 (1/2), 1–22.
1969. Hong, L., Dan, O., Davison, B.D., 2011. Predicting popular messages in twitter. In: Proceedings of the 20th International Conference Companion on World Wide Web, pp. 57–58.
1970. Hu, X., Tang, J., Zhang, Y., Liu, H., 2013. Social spammer detection in microblogging. In: Twenty-Third International Joint Conference on Artificial Intelligence. IONOS, D.G., 2018. Social Bots – the Technology behind Fake News. <https://www.ionos.com/digitalguide/online-marketing/social-media/social-bots/>.

1971. Jindal, N., Liu, B., 2007. Review spam detection. In: Proceedings of the 16th International Conference on World Wide Web. ACM, pp. 1189–1190.
1972. Jindal, S., Sood, R., Singh, R., Vatsa, M., Chakraborty, T., 2019. Newsbag: A Multimodal Benchmark Dataset for Fake News Detection.
1973. Kaplan, A.M., 2015. Social media, the digital revolution, and the business of media. *Int. J. Media Manag.* 17 (4), 197–199.
1974. Kaur, R., Singh, S., Kumar, H., 2018. Rise of spam and compromised accounts in online social networks: a state-of-the-art review of different combating approaches. *J. Netw. Comput. Appl.* 112, 53–88.
1975. Khan, T., Jan. 2021. Trust and Believe – Should We? Evaluating the Trustworthiness of Twitter Users. <https://doi.org/10.5281/zenodo.4428240>.
1976. Khan, T., Michalas, A., 2020. Trust and believe - should we? evaluating the trustworthiness of twitter users. In: 2020 IEEE 19th International Conference on Trust, Security and Privacy in Computing and Communications (TrustCom). IEEE Computer Society, Los Alamitos, CA, USA, pp. 1791–1800. <https://doi.org/10.1109/TrustCom50675.2020.00246>.
1977. Kharratzadeh, M., Coates, M., 2012. Weblog analysis for predicting correlations in stock price evolutions. In: Sixth International AAAI Conference on Weblogs and Social Media.
1978. Klyuev, V., 2018. Fake news filtering: semantic approaches. In: 2018 7th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions)(ICRITO). IEEE, pp. 9–15.
1979. Kong, X., Shi, Y., Yu, S., Liu, J., Xia, F., 2019. Academic social networks: modeling, analysis, mining and applications. *J. Netw. Comput. Appl.* 132, 86–103.
1980. Kshetri, N., Voas, J., 2017. The economics of “fake news”. *IT Professional* 19 (6), 8–12.
1981. Kucharski, A., 2016. Study epidemiology of fake news. *Nature* 540 (7634), 525, 525.
1982. Kumar, S., West, R., Leskovec, J., 2016. Disinformation on the web: impact, characteristics, and detection of wikipedia hoaxes. In: Proceedings of the 25th International Conference on World Wide Web. International World Wide Web Conferences Steering Committee, pp. 591–602.
1983. Lazer, D.M., Baum, M.A., Benkler, Y., Berinsky, A.J., Greenhill, K.M., Menczer, F., Metzger, M.J., Nyhan, B., Pennycook, G., Rothschild, D., et al., 2018. The science of fake news. *Science* 359 (6380), 1094–1096.
1984. Lee, S., Kim, J., 2013. Warningbird: a near real-time detection system for suspicious urls in twitter stream. *IEEE Trans. Dependable Secure Comput.* 10 (3), 183–195.
1985. Lee, K., Caverlee, J., Webb, S., 2010. Uncovering social spammers: social honeypots+ machine learning. In: Proceedings of the 33rd International ACM SIGIR Conference on Research and Development in Information Retrieval. ACM, pp. 435–442.
1986. Lee, K., Eoff, B.D., Caverlee, J., 2011. Seven months with the devils: a long-term study of content polluters on twitter. In: Fifth International AAAI Conference on Weblogs and Social Media.
1987. Leskovec, J., Mcauley, J.J., 2012. Learning to discover social circles in ego networks. In: Advances in Neural Information Processing Systems, pp. 539–547.

1988. Leskovec, J., Backstrom, L., Kleinberg, J., 2009a. Meme-tracking and the dynamics of the news cycle. In: Proceedings of the 15th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. ACM, pp. 497–506.
1989. Leskovec, J., Backstrom, L., Kleinberg, J., 2009b. Meme-tracking and the dynamics of the news cycle. In: Proceedings of the 15th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 497–506.
1990. Li, H., Chen, Z., Mukherjee, A., Liu, B., Shao, J., 2015. Analyzing and detecting opinion spam on a large-scale dataset via temporal and spatial patterns. In: Ninth International AAAI Conference on Web and Social Media.
1991. Li, J., Hu, X., Wu, L., Liu, H., 2016. Robust unsupervised feature selection on networked data. In: Proceedings of the 2016 SIAM International Conference on Data Mining. SIAM, pp. 387–395.
1992. Lim, E.-P., Nguyen, V.-A., Jindal, N., Liu, B., Lauw, H.W., 2010. Detecting product review spammers using rating behaviors. In: Proceedings of the 19th ACM International Conference on Information and Knowledge Management. ACM, pp. 939–948.
1993. Litou, I., Kalogeraki, V., Katakis, I., Gunopulos, D., 2016. Real-time and cost-effective limitation of misinformation propagation. In: 2016 17th IEEE International Conference on Mobile Data Management (MDM), vol. 1. IEEE, pp. 158–163.
1994. Liu, Y., Wu, Y.-F.B., 2018. Early detection of fake news on social media through propagation path classification with recurrent and convolutional networks. In: Thirty-Second AAAI Conference on Artificial Intelligence.
1995. Liu, Y., Wu, Y.-F.B., 2020. Fned: a deep network for fake news early detection on social media. *ACM Trans. Inf. Syst.* 38 (3), 1–33.
1996. Liu, S., Liu, S., Ren, L., 2019. Trust or suspect? an empirical ensemble framework for fake news classification. In: Proceedings of the 12th ACM International Conference on Web Search and Data Mining, Melbourne, Australia, pp. 11–15.
1997. Ma, J., Gao, W., Mitra, P., Kwon, S., Jansen, B.J., Wong, K.-F., Cha, M., 2016. Detecting Rumors from Microblogs with Recurrent Neural Networks.
1998. Ma, J., Gao, W., Wong, K.-F., 2017. Detect Rumors in Microblog Posts Using Propagation Structure via Kernel Learning. *Association for Computational Linguistics*.
1999. Maigrot, C., Claveau, V., Kijak, E., Sicre, R., 2016. Mediaeval 2016: A Multimodal System for the Verifying Multimedia Use Task.
2000. Mao, Y., Wei, W., Wang, B., Liu, B., 2012. Correlating s&p 500 stocks with twitter data. In: Proceedings of the First ACM International Workshop on Hot Topics on Interdisciplinary Social Networks Research, pp. 69–72.
2001. Matsu, K.E., Shearer, E., 2018. News Use across Social Media Platforms 2018. *Pew Research Center*, 10.
2002. Michalas, A., Komninos, N., 2014. The lord of the sense: a privacy preserving reputation system for participatory sensing applications. In: *Computers and Communication (ISCC), 2014 IEEE Symposium*. IEEE, pp. 1–6.

2003. Michalas, A., Murray, R., 2017. Keep pies away from kids: a raspberry pi attacking tool. In: Proceedings of the 2017 Workshop on Internet of Things Security and Privacy, IoTSP'17. ACM, New York, NY, USA, pp. 61–62. <https://doi.org/10.1145/3139937.3139953>.
2004. Mitra, E.G., 2016. Tanushree, CREDBANK-Data. <https://github.com/compsocial/CREDBANK-data>.
2005. Mitra, T., Gilbert, E., 2015. Credbank: a large-scale social media corpus with associated credibility annotations. In: Ninth International AAAI Conference on Web and Social Media.
2006. Morris, M.R., Counts, S., Roseway, A., Hoff, A., Schwarz, J., 2012. Tweeting is believing?: understanding microblog credibility perceptions. In: Proceedings of the ACM 2012 Conference on Computer Supported Cooperative Work. ACM, pp. 441–450.
2007. Nasim, M., Nguyen, A., Lothian, N., Cope, R., Mitchell, L., 2018. Real-time detection of content polluters in partially observable twitter networks. In: Companion Proceedings of the the Web Conference 2018, pp. 1331–1339.
2008. Neander, J., Marlin, R., 2010. Media and propaganda: the northcliffe press and the corpse factory story of world war i. *Global Media J.: Canadian Edition* 3 (2).
2009. News, B., 2016. Fact-Checking Facebook Politics Pages. <https://github.com/BuzzFeedNews/2016-10-facebook-fact-check>.
2010. Northman, T., 2019. Instagram Is Removing "Fake News" from the Platform. <https://hypebae.com/2019/8/instagram-fake-news-removing-tool-flagging-misinformation>.
2011. Omidvar, A., Jiang, H., An, A., 2018. Using neural network for identifying clickbaits in online news media. In: Annual International Symposium on Information Management and Big Data. Springer, pp. 220–232.
2012. Oshikawa, R., Qian, J., Wang, W.Y., 2018. A Survey on Natural Language Processing for Fake News Detection arXiv preprint arXiv:1811.00770.
2013. O'Brien, N., Latessa, S., Evangelopoulos, G., Boix, X., 2018. The Language of Fake News: Opening the Black-Box of Deep Learning Based Detectors.
2014. Pan, J.Z., Pavlova, S., Li, C., Li, N., Li, Y., Liu, J., 2018. Content based fake news detection using knowledge graphs. In: International Semantic Web Conference. Springer, pp. 669–683.
2015. Paschen, J., 2019. Investigating the emotional appeal of fake news using artificial intelligence and human contributions. *J. Prod. Brand Manag.*
2016. Perez, S., 2018. Twitter's Spam Reporting Tool Now Lets You Specify Type, Including if It's a Fake Account. <https://techcrunch.com/2018/10/31/twitters-spam-reporting-tool-now-lets-you-specify-type-including-if-its-a-fake-account/>.
2017. Perez-Rosas, V., Kleinberg, B., Lefevre, A., Mihalcea, R., 2017. Automatic Detection of Fake News arXiv preprint arXiv:1708.07104.
2018. Perozzi, B., Al-Rfou, R., Skiena, S., 2014. Deepwalk: online learning of social representations. In: Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 701–710.

2019. Pham, L., 2019. Transferring, Transforming, Ensembling: the Novel Formula of Identifying Fake News.
2020. Posetti, J., Matthews, A., 2018. A short guide to the history of 'fake news' and disinformation. *International Center for Journalists* 7, 2018–07.
2021. Potthast, M., Kiesel, J., Reinartz, K., Bevendorff, J., Stein, B., 2017. A Stylometric Inquiry into Hyperpartisan and Fake News arXiv preprint arXiv:1702.05638.
2022. Potthast, M., Gollub, T., Wiegmann, M., Stein, B., Hagen, M., Komlossy, K., Schuster, S., Fernandez, E.P.G., Jun. 2018. Webis Clickbait Corpus 2017 (Webis-clickbait-17). <https://doi.org/10.5281/zenodo.3346491>. URL <https://doi.org/10.5281/zenodo.3346491>.
2023. Rannard, G., 2020. Australia Fires: Misleading Maps and Pictures Go Viral.
2024. Rayana, S., Akoglu, L., 2015. Collective opinion spam detection: bridging review networks and metadata. In: *Proceedings of the 21th Acm Sigkdd International Conference on Knowledge Discovery and Data Mining*. ACM, pp. 985–994.
2025. Read, D., 2019. Social Media News: Fake News Flagging Tool, Clear Facebook History and More. <https://skedsocial.com/blog/fake-news-flagging-tool/>.
2026. Riedel, B., Augenstein, I., Spithourakis, G., Riedel, S., 2017. A Simple but Tough-To-Beat Baseline for the Fake News Challenge Stance Detection Task *corr abs/1707.03264*.
2027. Rieh, S.Y., Danielson, D.R., 2007. Credibility: a multidisciplinary framework. *Annu. Rev. Inf. Sci. Technol.* 41 (1), 307–364.
2028. Risdal, M., 2017. Getting Real about Fake News. <https://www.kaggle.com/mrisdal/fake-news>.
2029. Rubin, V.L., 2017. Deception detection and rumor debunking for social media. In: *The SAGE Handbook of Social Media Research Methods*. Sage, p. 342.
2030. Rubin, V.L., Chen, Y., Conroy, N.J., 2015. Deception detection for news: three types of fakes. In: *Proceedings of the 78th ASIS&T Annual Meeting: Information Science with Impact: Research in and for the Community*. American Society for Information Science, p. 83.
2031. Rubin, V., Brogly, C., Conroy, N., Chen, Y., Cornwell, S.E., Asubiaro, T.V., 2019. A news verification browser for the detection of clickbait, satire, and falsified news. *The Journal of Open Source Software* 4 (35), 1.
2032. Ruchansky, N., Seo, S., Liu, Y., 2017. Csi: a hybrid deep model for fake news detection. In: *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management*. ACM, pp. 797–806.
2033. Ruiz, E.J., Hristidis, V., Castillo, C., Gionis, A., Jaimes, A., 2012. Correlating financial time series with micro-blogging activity. In: *Proceedings of the Fifth ACM International Conference on Web Search and Data Mining*, pp. 513–522.
2034. Rusu, M.-L., Herman, R.-E., 2019. Legislative measures adopted at the international level against fake news. In: *International Conference KNOWLEDGE-BASED ORGANIZATION*, vol. 25. Sciendo, pp. 324–330.
2035. Santia, G.C., Williams, J.R., Buzzface, 2018. A news veracity dataset with facebook user commentary and egos. In: *Twelfth International AAAI Conference on Web and Social Media*.

2036. Sardarizadeh, S., 2019. Instagram Fact-Check: Can a New Flagging Tool Stop Fake News? <https://www.bbc.com/news/blogs-trending-49449005>.
2037. Saxena, A., Iyengar, S., Gupta, Y., 2015. Understanding spreading patterns on social networks based on network topology. In: Proceedings of the 2015 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2015, pp. 1616–1617.
2038. Schwartz, O., 2018. Your favorite Twitter bots are about die, thanks to upcoming rule changes. <https://qz.com/1422765/yourfavoritetwitterbotsareaboutdiethankstoupcomingrulechanges/>
2039. Sean Baird, Y.P., 2017. Talos Targets Disinformation with Fake News Challenge Victory. <https://blog.talosintelligence.com/2017/06/talos-fake-news-challenge.html>.
2040. Shao, C., Ciampaglia, G.L., Flammini, A., Menczer, F., 2016. Hoaxy: a platform for tracking online misinformation. In: Proceedings of the 25th International Conference Companion on World Wide Web. International World Wide Web Conferences Steering Committee, pp. 745–750.
2041. Shiralkar, P., Flammini, A., Menczer, F., Ciampaglia, G.L., 2017. Finding streams in knowledge graphs to support fact checking. In: 2017 IEEE International Conference on Data Mining (ICDM). IEEE, pp. 859–864.
2042. Shu, K., Sliva, A., Wang, S., Tang, J., Liu, H., 2017. Fake news detection on social media: a data mining perspective. ACM SIGKDD Explorations Newsletter 19 (1), 22–36.
2043. Shu, K., Wang, S., Liu, H., 2018. Understanding user profiles on social media for fake news detection. In: 2018 IEEE Conference on Multimedia Information Processing and Retrieval (MIPR). IEEE, pp. 430–435.
2044. Shu, K., Bhattacharjee, A., Alatawi, F., Nazer, T.H., Ding, K., Karami, M., Liu, H., 2020a. Combating disinformation in a social media age. Wiley Interdisciplinary Reviews: Data Min. Knowl. Discov. 10 (6), e1385.
2045. Shu, K., Mahudeswaran, D., Wang, S., Lee, D., Liu, H., 2020b. Fakenewsnet: a data repository with news content, social context, and spatiotemporal information for studying fake news on social media. Big Data 8 (3), 171–188.
2046. Silverman, C., 2016. This Analysis Shows How Viral Fake Election News Stories Outperformed Real News on Facebook <https://www.buzzfeednews.com/article/craigsilverman/viral-fake-election-news-outperformed-real-news-on-facebook\#.hIVK8Br7G>.
2047. Stahl, K., 2018. Fake News Detection in Social Media, vol. 6. California State University Stanislaus.
2048. Stone-Gross, B., Cova, M., Cavallaro, L., Gilbert, B., Szydlowski, M., Kemmerer, R., Kruegel, C., Vigna, G., 2009. Your botnet is my botnet: analysis of a botnet takeover. In: Proceedings of the 16th ACM Conference on Computer and Communications Security. ACM, pp. 635–647.
2049. Suci, P., 2019, More Americans Are Getting Their News From Social Media. <https://www.forbes.com/sites/petersuci/2019/10/11/more-americans-are-getting-their-news-from-social-media/>

2050. Tacchini, E., Ballarin, G., Della Vedova, M.L., Moret, S., de Alfaro, L., 2017. Some like it Hoax: Automated Fake News Detection in Social Networks arXiv preprint arXiv: 1704.07506.
2051. Tambuscio, M., Ruffo, G., Flammini, A., Menczer, F., 2015. Fact-checking effect on viral hoaxes: a model of misinformation spread in social networks. In: Proceedings of the 24th International Conference on World Wide Web. ACM, pp. 977–982.
2052. Tandoc Jr., E.C., Lim, Z.W., Ling, R., 2018. Defining “fake news” a typology of scholarly definitions. *Digital journalism* 6 (2), 137–153.
2053. Tankovska, H., 2021. Number of Social Network Users Worldwide from 2017 to 2025. <https://www.statista.com/statistics/278414/number-of-worldwide-social-network-users/>.
2054. Thakur, A., 2016. Identifying Clickbaits Using Machine Learning. <https://www.linkedin.com/pulse/identifying-clickbaits-using-machine-learning-abhishek-thakur/>.
2055. G. L. R. D., 2019. The Law Library of Congress, 53K Rumors Spread in Egypt in Only 60 Days, Study Reveals. <https://www.loc.gov/law/help/fake-news/counter-fake-news.pdf>.
2056. Thomas, K., 2013. The Role of the Underground Economy in Social Network Spam and Abuse. Ph.D. thesis. UC Berkeley.
2057. Thomas, K., Grier, C., Ma, J., Paxson, V., Song, D., 2011. Design and evaluation of a real-time url spam filtering service. In: 2011 IEEE Symposium on Security and Privacy. IEEE, pp. 447–462.
2058. Torres, R., Gerhart, N., Negahban, A., 2018. Combating fake news: an investigation of information verification behaviors on social networking sites. In: Proceedings of the 51st Hawaii International Conference on System Sciences.
2059. Tschischholek, S., Singla, A., Gomez Rodriguez, M., Merchant, A., Krause, A., 2018. Fake news detection in social networks via crowd signals. In: Companion Proceedings of the the Web Conference 2018. International World Wide Web Conferences Steering Committee, pp. 517–524.
2060. U. of Eastern Finland, 2019. New Application Can Detect Twitter Bots in Any Language. <https://phys.org/news/2019-06-application-twitter-bots-language.html>.
2061. Vieira, T., 2017. Bs-detector-dataset. <https://github.com/thiagovas/bs-detector-dataset>.
2062. Von Ahn, L., Blum, M., Langford, J., 2004. Telling humans and computers apart automatically. *Commun. ACM* 47 (2), 56–60.
2063. Vosoughi, S., Roy, D., Aral, S., 2018. The spread of true and false news online. *Science* 359 (6380), 1146–1151.
2064. Walsh, P., 2019. Factmata Trusted News Chrome Add-On Has Been Turned off until Further Notice. https://medium.com/@Paul__Walsh/factmata-trusted-news-chrome-add-on-has-been-turned-off-until-further-notice-7566f7312f86.
2065. Wanas, N., El-Saban, M., Ashour, H., Ammar, W., 2008. Automatic scoring of online discussion posts. In: Proceedings of the 2nd ACM Workshop on Information Credibility on the Web. ACM, pp. 19–26.

2066. Wang, A.H., 2010. Don't follow me: spam detection in twitter. In: 2010 International Conference on Security and Cryptography (SECRYPT). IEEE, pp. 1–10.
2067. Wang, W.Y., 2017. Liar, Liar Pants on Fire": A New Benchmark Dataset for Fake News Detection arXiv preprint arXiv:1705.00648.
2068. Wang, Y., Yin, G., Cai, Z., Dong, Y., Dong, H., 2015. A trust-based probabilistic recommendation model for social networks. *J. Netw. Comput. Appl.* 55, 59–67. Webwise, 2019. Explained: what Is Fake News? <https://www.webwise.ie/teachers/what-is-fake-news/>.
2069. Weerkamp, W., De Rijke, M., 2008. Credibility improves topical blog post retrieval. In: Proceedings of ACL-08. HLT, pp. 923–931.
2070. Weimer, M., Gurevych, I., Mühlhauser, M., 2007. Automatically assessing the post quality in online discussions on software. In: Proceedings of the 45th Annual Meeting of the ACL on Interactive Poster and Demonstration Sessions. Association for Computational Linguistics, pp. 125–128.
2071. Weng, J., Lim, E.-P., Jiang, J., He, Q., 2010. Twitterrank: finding topic-sensitive influential twitterers. In: Proceedings of the Third ACM International Conference on Web Search and Data Mining. ACM, pp. 261–270.
2072. Wong, J.I., 2016. Almost All the Traffic to Fake News Sites Is from Facebook. new data show. <https://qz.com/848917/facebook-fb-fake-news-data-from-jumpshot-its-the-biggest-traffic-referrer-to-fake-and-hyperpartisan-news-sites/>. (Accessed 1 January 2020).
2073. Wong, Q., 2019. Fake News Is Thriving Thanks to Social Media Users, Study Finds. <https://www.cnet.com/news/fake-news-more-likely-to-spread-on-social-media-study-finds/>.
2074. Wu, L., Liu, H., 2018. Tracing fake-news footprints: characterizing social media messages by how they propagate. In: Proceedings of the Eleventh ACM International Conference on Web Search and Data Mining. ACM, pp. 637–645.
2075. Wu, X., Feng, Z., Fan, W., Gao, J., Yu, Y., 2013. Detecting marionette microblog users for improved information credibility. In: Joint European Conference on Machine Learning and Knowledge Discovery in Databases. Springer, pp. 483–498.
2076. Wu, L., Hu, X., Morstatter, F., Liu, H., 2017a. Adaptive spammer detection with sparse group modeling. In: Eleventh International AAAI Conference on Web and Social Media.
2077. Wu, L., Hu, X., Morstatter, F., Liu, H., 2017b. Detecting camouflaged content polluters. In: Eleventh International AAAI Conference on Web and Social Media.
2078. Xue, J., Yang, Z., Yang, X., Wang, X., Chen, L., Dai, Y., 2013. Votetrust: leveraging friend invitation graph to defend against social network sybils. In: 2013 Proceedings IEEE INFOCOM. IEEE, pp. 2400–2408.
2079. Yan, J., 2006. Bot, cyborg and automated turing test. In: International Workshop on Security Protocols. Springer, pp. 190–197.
2080. Yang, Z., Wilson, C., Wang, X., Gao, T., Zhao, B.Y., Dai, Y., 2014. Uncovering social network sybils in the wild. *ACM Trans. Knowl. Discov. Data* 8 (1), 2.
2081. Yang, K.-C., Niven, T., Kao, H.-Y., 2019. Fake News Detection as Natural Language Inference.

2082. Yaraghi, N., 2019. How Should Social Media Platforms Combat Misinformation and Hate Speech?
<https://www.brookings.edu/blog/techtank/2019/04/09/howshouldsocialmediaplatformscombatmisinformationandhatespeech/#cancel>.
2083. Ye, S., Wu, S.F., 2010. Measuring message propagation and social influence on twitter. com. In: International Conference on Social Informatics. Springer, pp. 216–231.
2084. Ye, J., Kumar, S., Akoglu, L., 2016. Temporal opinion spam detection by multivariate indicative signals. In: Tenth International AAAI Conference on Web and Social Media.
2085. Zhao, Z., Resnick, P., Mei, Q., 2015. Enquiring minds: early detection of rumors in social media from enquiry posts. In: Proceedings of the 24th International Conference on World Wide Web. International World Wide Web Conferences Steering Committee, pp. 1395–1405.
2086. Zhou, Y., 2017. Clickbait Detection in Tweets Using Self-Attentive Network arXiv preprint arXiv:1710.05364.
2087. Zhou, X., Zafarani, R., 2019. Network-based fake news detection: a pattern-driven approach. ACM SIGKDD Explorations Newsletter 21 (2), 48–60.
2088. 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.
2089. K. S. Adewole, N. B. Anuar, A. Kamsin, K. D. Varathan, and S. A. Razak. Malicious accounts: Dark of the social networks. Journal of Network and Computer Applications, 79:41–67, February 2017.
2090. S. Al-Azani and E.-S. M. El-Alfy. Detection of arabic spam tweets using word embedding and machine learning. In 2018 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies (3ICT'18), Sakhier, Bahrain, pages 1–5. IEEE, November 2018.
2091. S. M. B. K. S. Asis and K. Chattopadhyay. Statistical methods in social science research. Springer, 2018.
2092. U. author. search4faces – service for finding people by photo.
<https://search4faces.com/vk01/index.html> - Online; accessed on June 22, 2021 - , 2021.
2093. N. Chavoshi, H. Hamooni, and A. Mueen. Debot: Twitter bot detection via warped correlation. In Proc. Of the IEEE 16th International Conference on Data Mining serie (ICBM'16), Barcelona, Spain, pages 817–822, December 2016.
2094. C. Chen, Y. Wang, J. Zhang, Y. Xiang, W. Zhou, and G. Min. Statistical features-based real-time detection of drifted twitter spam. IEEE Transactions on Information Forensics and Security, 12(4):914–925, October 2016.
2095. C. A. Davis, O. Varol, E. Ferrara, A. Flammini, and F. Menczer. Botornot: A system to evaluate social bots. In Proc. of the 25th international conference companion on world wide web (WWW'16), Quebec, Montreal, Canada, pages 273–274. ACM, April 2016.
2096. J. P. Dickerson, V. Kagan, and V. Subrahmanian. Using sentiment to detect bots on twitter: Are humans more opinionated than bots? In Pro.of the 2014 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM'14), Beijing, China, pages 620–627. IEEE, August 2014.

2097. G. Dong and H. Liu. Feature engineering for machine learning and data analytics. CRC Press, march 2018.
2098. A. Dorri, M. Abadi, and M. Dadfarnia. Socialbothunter: Botnet detection in twitter-like social networking services using semi-supervised collective classification. In Proc. of the 16th Intl Conf on Dependable, Autonomic and Secure Computing, 16th Intl Conf on Pervasive Intelligence and Computing, 4th Intl Conf on Big Data Intelligence and Computing and Cyber Science and Technology Congress (DASC/PiCom/DataCom/- CyberSciTech'18), Athens, Greece, pages 496–503. IEEE, August 2018.
2099. V. Gomez, A. Kaltenbrunner, and V. L ´ opez. Statistical analysis of the social network and discussion threads in slashdot. In Proc. of the 17th international conference on World Wide Web (WWW'08), Beijing, China, pages 645–654, April 2008.
2100. Google. Vision ai. <https://cloud.google.com/vision> - Online; accessed on June 22, 2021 - , 2021.
2101. C. Grimme, M. Preuss, L. Adam, and H. Trautmann. Social bots: Human-like by means of human control? Big data, 5(4):279–293, December 2017.
2102. A. Grover and J. Leskovec. node2vec: Scalable feature learning for networks. In Proc. of the 22nd ACM
2103. SIGKDD international conference on Knowledge discovery and data mining (KDD'16), California, San Francisco, USA, pages 855–864. ACM, August 2016.
2104. M. Heidari and J. H. Jones. Using bert to extract topic-independent sentiment features for social media bot detection. In Proc. of the 11th IEEE Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON'20), New York, New York, USA, pages 0542–0547. IEEE, October 2020.
2105. M. Heidari, J. H. Jones, and O. Uzuner. Deep contextualized word embedding for text-based online user profiling to detect social bots on twitter. In Proc. of the 2020 International Conference on Data Mining Workshops (ICDMW'20), Sorrento, Italy, pages 480–487. IEEE, November 2020.
2106. C.-C. Hsu, C.-Y. Lee, and Y.-X. Zhuang. Learning to detect fake face images in the wild. In Proc. of the 2018 International Symposium on Computer, Consumer and Control (IS3C'18), Taichung, Taiwan, pages 388–391. IEEE, December 2018.
2107. Z. Jin, J. Cao, Y. Zhang, J. Zhou, and Q. Tian. Novel visual and statistical image features for microblogs news verification. IEEE transactions on multimedia, 19(3):598–608, October 2016.
2108. A. Kamal and M. Abulaish. Statistical features identification for sentiment analysis using machine learning techniques. In Proc. of the 2013 International Symposium on Computational and Business Intelligence (ISCB'13), New Delhi, India, pages 178–181. IEEE, August 2013.
2109. A. Karatas, and S. S, ahin. A review on social bot detection techniques and research directions. In Proc. Int. Security and Cryptology Conference Turkey, pages 156–161, October 2017.
2110. I. Karpov and E. Glazkova. Detecting automatically managed accounts in online social networks: Graph embedding approach. arXiv preprint arXiv:2010.07923, 1357:11–21, October 2020.

2111. V. Kepuska and G. Bohouta. Comparing speech recognition systems (microsoft api, google api and cmu sphinx). *Int. J. Eng. Res. Appl*, 7(03):20–24, March 2017.
2112. M. Kolomeec, A. Chechulin, and I. Kotenko. Methodological primitives for phased construction of data visualization models. *Journal of Internet Services and Information Security*, 5(4):60–84, 2015.
2113. M. Kolomeets. Security datasets. <https://github.com/guardeec/datasets> - Online; accessed on June 22, 2021 - , February 2021.
2114. M. Kolomeets, A. Benachour, D. El Baz, A. Chechulin, M. Strecker, and I. Kotenko. Reference architecture for social networks graph analysis tool. *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications (JoWUA)*, 10(4):109–125, December 2019.
2115. M. Kolomeets, A. Chechulin, and I. V. Kotenko. Social networks analysis by graph algorithms on the example of the vkontakte social network. *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications (JoWUA)*, 10(2):55–75, June 2019.
2116. M. Kolomeets, O. Tushkanova, D. Levshun, and A. Chechulin. Camouflaged bot detection using the friend list. In *Proc. of the 29th Euromicro International Conference on Parallel, Distributed and Network-Based Processing (PDP'21)*, Valladolid, Spain, pages 253–259. IEEE, March 2021.
2117. I. V. Kotenko, I. Saenko, and A. Kushnerevich. Parallel big data processing system for security monitoring in internet of things networks. *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications (JoWUA)*, 8(4):60–74, December 2017.
2118. M. Kuptsov, V. Minaev, S. Yablochnikov, V. Dzobelova, and A. Sharopatova. Some statistical features of the information exchange in social networks. In *Proc. of the 2020 Systems of Signal Synchronization, Generating and Processing in Telecommunications (SYNCHROINFO'20)*, Svetlogorsk, Russia, pages 1–4. IEEE, July 2020.
2119. H. Mansourifar and W. Shi. One-shot gan generated fake face detection. *arXiv preprint arXiv:2003.12244*, March 2020.
2120. T. Mikolov, K. Chen, G. Corrado, and J. Dean. Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781*, January 2013.
2121. A. Minnich, N. Chavoshi, D. Koutra, and A. Mueen. Botwalk: Efficient adaptive exploration of twitter bot networks. In *Proc. of the 2017 IEEE/ACM international conference on advances in social networks analysis and mining (ASONAM'17)*, Sydney, Australia, pages 467–474, July 2017.
2122. L. Nataraj, T. M. Mohammed, B. Manjunath, S. Chandrasekaran, A. Flenner, J. H. Bappy, and A. K.
2123. Roy-Chowdhury. Detecting gan generated fake images using co-occurrence matrices. *Electronic Imaging*, 2019(5):532–1, January 2019.
2124. M. Newman. *Networks*. Oxford university press, July 2018.
2125. M. E. Newman, D. J. Watts, and S. H. Strogatz. Random graph models of social networks. *Proc. of the national academy of sciences*, 99(suppl 1):2566–2572, February 2002.

2126. B. Oberer, A. Erkollar, and A. Stein. Social bots—act like a human, think like a bot. In *Digitalisierung und Kommunikation*, volume 31 of EKW, pages 311–327. Springer, April 2019.
2127. M. Orabi, D. Mouheb, Z. Al Aghbari, and I. Kamel. Detection of bots in social media: a systematic review. *Information Processing & Management*, 57(4):102250, July 2020.
2128. J. Pennington, R. Socher, and C. D. Manning. Glove: Global vectors for word representation. In *Proc. of the 2014 conference on empirical methods in natural language processing (EMNLP’14)*, Doha, Qatar, pages 1532–1543, October 2014.
2129. B. Perozzi, R. Al-Rfou, and S. Skiena. Deepwalk: Online learning of social representations. In *Proc. of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining (KDD’14)*, New York, New York, USA, pages 701–710. ACM, August 2014.
2130. M. Polignano, M. G. de Pinto, P. Lops, and G. Semeraro. Identification of bot accounts in twitter using 2d cnns on user-generated contents. In *Proc. of the CLEF (Working Notes)*, September 2019.
2131. G. Saidov and Y. Zdanovich. Find clone – service for finding people by photo. <https://findclone.ru> - Online; accessed on June 20, 2021 - , 2021.
2132. P. Shi, Z. Zhang, and K.-K. R. Choo. Detecting malicious social bots based on clickstream sequences. *IEEE Access*, 7:28855–28862, February 2019.
2133. K. Skorniakov, D. Turdakov, and A. Zhabotinsky. Make social networks clean again: Graph embedding and stacking classifiers for bot detection. In *Proc. of the 27th ACM International Conference on Information and Knowledge Management (CIKM’18)*, Turin, Italy. ACM, October 2018.
2134. T. Stein, E. Chen, and K. Mangla. Facebook immune system. In *Proc. of the 4th workshop on social network systems (SNS’11)*, Salzburg, Austria, pages 1–8, April 2011.
2135. V. S. Subrahmanian, A. Azaria, S. Durst, V. Kagan, A. Galstyan, K. Lerman, L. Zhu, E. Ferrara, A. Flammini, and F. Menczer. The darpa twitter bot challenge. *Computer*, 49(6):38–46, June 2016.
2136. J. Ugander, B. Karrer, L. Backstrom, and C. Marlow. The anatomy of the facebook social graph. *arXiv preprint arXiv:1111.4503*, November 2011.
2137. P. Wang. thispersondoesnotexist – service for generating photos of non-existent people. <https://thispersondoesnotexist.com> - Online; accessed on June 22, 2021 - , 2021.
2138. F. Wei and U. T. Nguyen. Twitter bot detection using bidirectional long short-term memory neural networks and word embeddings. In *Proc. of the 2019 First IEEE International Conference on Trust, Privacy and Security in Intelligent Systems and Applications (TPS-ISA’19)*, Los Angeles, California, USA, pages 101– 109. IEEE, December 2019.
2139. Norah Abokhodair, Daisy Yoo, and David W McDonald. 2015. Dissecting a social botnet: Growth, content and influence in Twitter. In *Proc. of the 18th ACM Conf. on Computer Supported Cooperative Work & Social Computing*. ACM, 839–851.
2140. Terrence Adams. 2017. AI-Powered Social Bots. *arXiv preprint arXiv:1706.05143* (2017).

2141. Lorenzo Alvisi, Allen Clement, Alessandro Epasto, Silvio Lattanzi, and Alessandro Panconesi. 2013. Sok: The evolution of sybil defense via social networks. In *Proc. IEEE Symposium on Security and Privacy (SP)*. 382–396.
2142. Michael Auli, Michel Galley, Chris Quirk, and Geoffrey Zweig. 2013. Joint Language and Translation Modeling with Recurrent Neural Networks.. In *EMNLP*, Vol. 3. 0.
2143. Gustavo EAPA Batista, Ronaldo C Prati, and Maria Carolina Monard. 2004. A study of the behavior of several methods for balancing machine learning training data. *ACM Sigkdd Explorations Newsletter* 6, 1 (2004), 20–29.
2144. Alessandro Bessi and Emilio Ferrara. 2016. Social bots distort the 2016 US Presidential election online discussion. *First Monday* 21, 11 (2016).
2145. Alex Beutel, Wanhong Xu, Venkatesan Guruswami, Christopher Palow, and Christos Faloutsos. 2013. Copycatch: stopping group attacks by spotting lockstep behavior in social networks. In *Proc. 22nd Intl. ACM Conf. World Wide Web (WWW)*. 119–130.
2146. Qiang Cao, Michael Sirivianos, Xiaowei Yang, and Tiago Pregueiro. 2012. Aiding the detection of fake accounts in large scale social online services. In *9th USENIX Symp on Netw Sys Design & Implement*. 197–210.
2147. Nitesh V Chawla, Kevin W Bowyer, Lawrence O Hall, and W Philip Kegelmeyer. 2002. SMOTE: synthetic minority over-sampling technique. *Journal of artificial intelligence research* 16 (2002), 321–357.
2148. Zi Chu, Steven Gianvecchio, Haining Wang, and Sushil Jajodia. 2010. Who is tweeting on Twitter: human, bot, or cyborg?. In *Proc. 26th annual computer security applications conf*. 21–30.
2149. Zi Chu, Steven Gianvecchio, Haining Wang, and Sushil Jajodia. 2012. Detecting automation of twitter accounts: Are you a human, bot, or cyborg? *IEEE Tran Dependable & Secure Comput* 9, 6 (2012), 811–824.
2150. Eric Clark, Chris Jones, Jake Williams, Allison Kurti, Michell Nortotsky, Christopher Danforth, and Peter Dodds. 2015. Vaporous Marketing: Uncovering Pervasive Electronic Cigarette Advertisements on Twitter. *arXiv preprint arXiv:1508.01843* (2015).
2151. Eric Clark, Jake Williams, Chris Jones, Richard Galbraith, Christopher Danforth, and Peter Dodds. 2016. Sifting robotic from organic text: a natural language approach for detecting automation on Twitter. *Journal of Computational Science* 16 (2016), 1–7.
2152. Stefano Cresci, Roberto Di Pietro, Marinella Petrocchi, Angelo Spognardi, and Maurizio Tesconi. 2017. The paradigm-shift of social spambots: Evidence, theories, and tools for the arms race. In *Proceedings of the 26th International Conference on World Wide Web Companion*. International World Wide Web Conferences Steering Committee, 963–972.
2153. Clayton Allen Davis, Onur Varol, Emilio Ferrara, Alessandro Flammini, and Filippo Menczer. 2016. Botornot: A system to evaluate social bots. In *Proceedings of the 25th International Conference Companion on World Wide Web*. International World Wide Web Conferences Steering Committee, 273–274.
2154. Juan Echeverría and Shi Zhou. 2017. The ‘Star Wars’ botnet with >350k Twitter bots. *arXiv preprint arXiv:1701.02405* (2017).

2155. Aviad Elyashar, Michael Fire, Dima Kagan, and Yuval Elovici. 2013. Homing socialbots: intrusion on a specific organization's employee using Socialbots. In Proc. IEEE/ACM Intl. Conf. on Advances in Social Networks Analysis and Mining. 1358–1365.
2156. Emilio Ferrara. 2015. Manipulation and abuse on social media. ACM SIGWEB Newsletter Spring (2015), 4.
2157. Emilio Ferrara. 2017. Disinformation and social bot operations in the run up to the 2017 French presidential election. First Monday 22, 8 (2017).
2158. Emilio Ferrara, Onur Varol, Clayton Davis, Filippo Menczer, and Alessandro Flammini. 2016. The rise of social bots. Commun. ACM 59, 7 (2016), 96–104.
2159. Michelle C Forelle, Philip N Howard, Andrés Monroy-Hernández, and Saiph Savage. 2015. Political bots and the manipulation of public opinion in Venezuela. (2015).
2160. Daniel Gayo-Avello. 2017. Social Media Won't Free Us. IEEE Internet Computing 21, 4 (2017), 98–101.
2161. Felix A Gers, Jürgen Schmidhuber, and Fred Cummins. 1999. Learning to forget: Continual prediction with LSTM. (1999).
2162. Yoav Goldberg. 2016. A Primer on Neural Network Models for Natural Language Processing. J. Artif. Intell. Res.(JAIR) 57 (2016), 345–420.
2163. Guofei Gu, Junjie Zhang, and Wenke Lee. 2008. BotSniffer: Detecting Botnet
2164. Command and Control Channels in Network Traffic.. In NDSS, Vol. 8. 1–18.
2165. David Gunning. 2017. DARPA: Explainable Artificial Intelligence (XAI). (2017). <https://www.darpa.mil/program/explainable-artificial-intelligence>
2166. Stefanie Haustein, Timothy D Bowman, Kim Holmberg, Andrew Tsou, Cassidy R Sugimoto, and Vincent Larivière. 2016. Tweets as impact indicators: Examining 9the implications of automated “bot” accounts on Twitter. Journal of the Association for Information Science and Technology 67, 1 (2016), 232–238.
2167. Haibo He and Edwardo A Garcia. 2009. Learning from imbalanced data. IEEE Transactions on knowledge and data engineering 21, 9 (2009), 1263–1284.
2168. Cong Duy Vu Hoang, Trevor Cohn, and Gholamreza Haffari. 2016. Incorporating Side Information into Recurrent Neural Network Language Models.. In HLT-NAACL. 1250–1255.
2169. Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. Neural computation 9, 8 (1997), 1735–1780.
2170. Philip N Howard and Bence Kollanyi. 2016. Bots,# strongerin, and# brexit: Computational propaganda during the uk-eu referendum. Browser Download This Paper (2016).
2171. Vineet John. 2017. A Survey of Neural Network Techniques for Feature Extraction from Text. arXiv preprint arXiv:1704.08531 (2017).
2172. Rafal Jozefowicz, Wojciech Zaremba, and Ilya Sutskever. 2015. An empirical exploration of recurrent network architectures. In Proceedings of the 32nd International Conference on Machine Learning (ICML-15). 2342–2350.
2173. Andrej Karpathy, Justin Johnson, and Li Fei-Fei. 2015. Visualizing and understanding recurrent networks. arXiv preprint arXiv:1506.02078 (2015).

2174. Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. 2012. Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems*. 1097–1105.
2175. Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. 2015. Deep learning. *Nature* 521, 7553 (2015), 436–444.
2176. Kyumin Lee, Brian David Eoff, and James Caverlee. 2011. Seven Months with the Devils: A Long-Term Study of Content Polluters on Twitter.. In *Proc. 5th AAAI Intl. Conf. on Web and Social Media*.
2177. Jiwei Li, Xinlei Chen, Eduard Hovy, and Dan Jurafsky. 2015. Visualizing and understanding neural models in nlp. *arXiv preprint arXiv:1506.01066* (2015).
2178. Brian D Loader and Dan Mercea. 2011. Networking democracy? Social media innovations and participatory politics. *Information, Communication & Society* 14, 6 (2011), 757–769.
2179. Panagiotis T Metaxas and Eni Mustafaraj. 2012. Social media and the elections. *Science* 338, 6106 (2012), 472–473.
2180. Tomas Mikolov and Geoffrey Zweig. 2012. Context dependent recurrent neural network language model. *SLT 12* (2012), 234–239.
2181. Zachary Miller, Brian Dickinson, William Deitrick, Wei Hu, and Alex Hai Wang. 2014. Twitter spammer detection using data stream clustering. *Information Sciences* 260 (2014), 64–73.
2182. Silvia Mitter, Claudia Wagner, and Markus Strohmaier. 2013. A categorization scheme for socialbot attacks in online social networks. In *Proc. of the 3rd ACM Web Science Conference*.
2183. Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Alex Graves, Ioannis Antonoglou, Daan Wierstra, and Martin Riedmiller. 2013. Playing atari with deep reinforcement learning. *arXiv preprint arXiv:1312.5602* (2013).
2184. Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Andrei A Rusu, Joel Veness, Marc G Bellemare, Alex Graves, Martin Riedmiller, Andreas K Fidjeland, Georg Ostrovski, et al. 2015. Human-level control through deep reinforcement learning. *Nature* 518, 7540 (2015), 529–533.
2185. Bjarke Mønsted, Piotr Sapieżyński, Emilio Ferrara, and Sune Lehmann. 2017. Evidence of Complex Contagion of Information in Social Media: An Experiment Using Twitter Bots. *Plos One* 12, 9 (2017).
2186. Jeffrey Pennington, Richard Socher, and Christopher D. Manning. 2014. GloVe: Global Vectors for Word Representation. In *Empirical Methods in Natural Language Processing (EMNLP)*. 1532–1543. <http://www.aclweb.org/anthology/D14-1162>
2187. Wojciech Samek, Thomas Wiegand, and Klaus-Robert Müller. 2017. Explainable Artificial Intelligence: Understanding, Visualizing and Interpreting Deep Learning Models. *arXiv preprint arXiv:1708.08296* (2017).
2188. Saiph Savage, Andres Monroy-Hernandez, and Tobias Höllerer. 2016. Botivist: Calling Volunteers to Action using Online Bots. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing*. ACM, 813–822.

2189. Chengcheng Shao, Giovanni Luca Ciampaglia, Onur Varol, Alessandro Flammini, and Filippo Menczer. 2017. The spread of fake news by social bots. arXiv preprint arXiv:1707.07592 (2017).
2190. David Silver, Aja Huang, Chris J Maddison, Arthur Guez, Laurent Sifre, George Van Den Driessche, Julian Schrittwieser, Ioannis Antonoglou, Veda Panneershelvam, Marc Lanctot, et al. 2016. Mastering the game of Go with deep neural networks and tree search. *Nature* 529, 7587 (2016), 484–489.
2191. Tao Stein, Erdong Chen, and Karan Mangla. 2011. Facebook immune system. In *Proc. of the 4th Workshop on Social Network Systems*. ACM, 8.
2192. VS Subrahmanian, Amos Azaria, Skylar Durst, Vadim Kagan, Aram Galstyan, Kristina Lerman, Linhong Zhu, Emilio Ferrara, Alessandro Flammini, and Filippo Menczer. 2016. The DARPA Twitter bot challenge. *Computer* 49, 6 (2016), 38–46.
2193. Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, and Andrew Rabinovich. 2015. Going deeper with convolutions. In *Proceedings of the IEEE conference on computer vision and pattern recognition*. 1–9.
2194. Ivan Tomek. 1976. Two modifications of CNN. *IEEE Trans. Systems, Man and Cybernetics* 6 (1976), 769–772.
2195. Gang Wang, Tristan Konolige, Christo Wilson, Xiao Wang, Haitao Zheng, and Ben Y Zhao. 2013. You are how you click: Clickstream analysis for sybil detection. In *Proc. USENIX Security*. Citeseer, 1–15.
2196. Gang Wang, Manish Mohanlal, Christo Wilson, Xiao Wang, Miriam Metzger, Haitao Zheng, and Ben Y Zhao. 2013. Social turing tests: Crowdsourcing sybil detection. In *Proc. of the 20th Network & Distributed System Security Symposium (NDSS)*.
2197. Dennis L Wilson. 1972. Asymptotic properties of nearest neighbor rules using edited data. *IEEE Transactions on Systems, Man, and Cybernetics* 2, 3 (1972), 408–421.
2198. Samuel C Woolley. 2016. Automating power: Social bot interference in global politics. *First Monday* 21, 4 (2016).
2199. Zhi Yang, Christo Wilson, Xiao Wang, Tingting Gao, Ben Y Zhao, and Yafei Dai. 2014. Uncovering social network sybils in the wild. *ACM Trans. Knowledge Discovery from Data* 8, 1 (2014), 2.
2200. Kudugunta and Ferrara - 2018 - Deep neural networks for bot detection.pdf
2201. Seyed Ali Alhosseini, Raad Bin Tareaf, Pejman Najafi, and Christoph Meinel. 2019. Detect me if you can: Spam bot detection using inductive representation learning. In *Companion Proceedings of The 2019 World Wide Web Conference*, pages 148–153.
2202. Jonathon M Berger and Jonathon Morgan. 2015. The isis twitter census: Defining and describing the population of isis supporters on twitter.
2203. Stefano Cresci. 2020. A decade of social bot detection. *Communications of the ACM*, 63(10):72–83.
2204. Stefano Cresci, Roberto Di Pietro, Marinella Petrocchi, Angelo Spognardi, and Maurizio Tesconi. 2015. Fame for sale: Efficient detection of fake twitter followers. *Decision Support Systems*, 80:56–71.

2205. Stefano Cresci, Roberto Di Pietro, Marinella Petrocchi, Angelo Spognardi, and Maurizio Tesconi. 2016. Dna-inspired online behavioral modeling and its application to spambot detection. *IEEE Intelligent Systems*, 31(5):58–64.
2206. Clayton Allen Davis, Onur Varol, Emilio Ferrara, Alessandro Flammini, and Filippo Menczer. 2016. Botornot: A system to evaluate social bots. In *Proceedings of the 25th international conference companion on world wide web*, pages 273–274.
2207. Ashkan Dehghan, Kinga Siuta, Agata Skorupka, Akshat Dubey, Andrei Betlen, David Miller, Wei Xu, Bogumil Kaminski, and Pawel Pralat. 2022. Detecting bots in social-networks using node and structural embeddings. In *Proceedings of the 11th International Conference on Data Science, Technology and Applications, DATA 2022, Lisbon, Portugal, July 11- 13, 2022*, pages 50–61. SCITEPRESS.
2208. Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.
2209. Kuntal Dey, Ritvik Shrivastava, Saroj Kaushik, and Kritika Garg. 2018. Assessing topical homophily on twitter. In *International Conference on Complex Networks and their Applications*, pages 367– 376. Springer.
2210. Kuntal Dey, Ritvik Shrivastava, Saroj Kaushik, and Vaibhav Mathur. 2017. Assessing the effects of social familiarity and stance similarity in interaction dynamics. In *International Conference on Complex Networks and their Applications*, pages 843– 855. Springer.
2211. John P Dickerson, Vadim Kagan, and VS Subrahmanian. 2014. Using sentiment to detect bots on twitter: Are humans more opinionated than bots? In *2014 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM 2014)*, pages 620–627. IEEE.
2212. Shangbin Feng, Zhaoxuan Tan, Rui Li, and Minnan Luo. 2022a. Heterogeneity-aware twitter bot detection with relational graph transformers. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 36, pages 3977–3985.
2213. Shangbin Feng, Zhaoxuan Tan, Herun Wan, Ningnan Wang, Zilong Chen, Binchi Zhang, Qinghua Zheng, Wenqian Zhang, Zhenyu Lei, Shujie Yang, et al. 2022b. Twibot-22: Towards graph-based twitter bot detection. *arXiv preprint arXiv:2206.04564*.
2214. Shangbin Feng, Herun Wan, Ningnan Wang, Jundong Li, and Minnan Luo. 2021a. Satar: A self-supervised approach to twitter account representation learning and its application in bot detection. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*, pages 3808–3817.
2215. Shangbin Feng, Herun Wan, Ningnan Wang, Jundong Li, and Minnan Luo. 2021b. Twibot-20: A comprehensive twitter bot detection benchmark. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*, pages 4485–4494.
2216. Shangbin Feng, Herun Wan, Ningnan Wang, and Minnan Luo. 2021c. Botrgcn: Twitter bot detection with relational graph convolutional networks. In *Proceedings of the 2021 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining*, pages 236–239.

2217. Yanlin Feng, Xinyue Chen, Bill Yuchen Lin, Peifeng Wang, Jun Yan, and Xiang Ren. 2020. Scalable multi-hop relational reasoning for knowledge-aware question answering. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1295–1309.
2218. Yue Feng, Aldo Lipani, Fanghua Ye, Qiang Zhang, and Emine Yilmaz. 2022c. Dynamic schema graph fusion network for multi-domain dialogue state tracking. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 115–126, Dublin, Ireland. Association for Computational Linguistics.
2219. Matthias Fey and Jan Eric Lenssen. 2019. Fast graph representation learning with pytorch geometric. *arXiv preprint arXiv:1903.02428*. Qinglang Guo, Haiyong Xie, Yangyang Li, Wen Ma, and Chao Zhang. 2021. Social bots detection via fusing bert and graph convolutional networks. *Symmetry*, 14(1):30.
2220. Charles R Harris, K Jarrod Millman, Stéfan J Van Der Walt, Ralf Gommers, Pauli Virtanen, David Cournapeau, Eric Wieser, Julian Taylor, Sebastian Berg, Nathaniel J Smith, et al. 2020. Array programming with numpy. *Nature*, 585(7825):357–362.
2221. Kadhim Hayawi, Sujith Mathew, Neethu Venugopal, Mohammad M Masud, and Pin-Han Ho. 2022. Deeprobot: a hybrid deep neural network model for social bot detection based on user profile data. *Social Network Analysis and Mining*, 12(1):1–19.
2222. Sneha Kudugunta and Emilio Ferrara. 2018. Deep neural networks for bot detection. *Information Sciences*, 467:312–322.
2223. K Lee, BD Eoff, and J Caverlee. 2011. A long-term study of content polluters on twitter. *ICWSM*, seven months with the devils.
2224. Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020. Bart: Denoising sequence-to-sequence pretraining for natural language generation, translation, and comprehension. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 7871–7880.
2225. Bill Yuchen Lin, Xinyue Chen, Jamin Chen, and Xiang Ren. 2019. Kagnet: Knowledge-aware graph networks for commonsense reasoning. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 2829–2839.
2226. Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized BERT pretraining approach. *CoRR*, abs/1907.11692.
2227. Shangwen Lv, Daya Guo, Jingjing Xu, Duyu Tang, Nan Duan, Ming Gong, Linjun Shou, Daxin Jiang, Guihong Cao, and Songlin Hu. 2020. Graph-based reasoning over heterogeneous external knowledge for commonsense question answering. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pages 8449–8456.
2228. Thomas Magelinski, David Beskow, and Kathleen M Carley. 2020a. Graph-hist: Graph classification from latent feature histograms with application to bot detection. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pages 5134–5141.

2229. Thomas Magelinski, David Beskow, and Kathleen M Carley. 2020b. Graph-hist: Graph classification from latent feature histograms with application to bot detection. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 34, pages 5134–5141.
2230. Nikhil Mehta, Maria Leonor Pacheco, and Dan Goldwasser. 2022. Tackling fake news detection by continually improving social context representations using graph neural networks. In Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1363–1380, Dublin, Ireland. Association for Computational Linguistics.
2231. Todor Mihaylov and Anette Frank. 2018. Knowledgeable reader: Enhancing cloze-style reading comprehension with external commonsense knowledge. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 821–832.
2232. Zachary Miller, Brian Dickinson, William Deitrick, Wei Hu, and Alex Hai Wang. 2014. Twitter spammer detection using data stream clustering. *Information Sciences*, 260:64–73.
2233. Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, et al. 2019. Pytorch: An imperative style, high-performance deep learning library. *Advances in neural information processing systems*, 32.
2234. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. 2011. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830.
2235. Zhen Peng, Minnan Luo, Jundong Li, Huan Liu, and Qinghua Zheng. 2018. Anomalous: A joint modeling approach for anomaly detection on attributed networks. In *IJCAI*, pages 3513–3519.
2236. Michael Schlichtkrull, Thomas N Kipf, Peter Bloem, Rianne van den Berg, Ivan Titov, and Max Welling. 2018. Modeling relational data with graph convolutional networks. In *European semantic web conference*, pages 593–607. Springer.
2237. Wen Shi, Diyi Liu, Jing Yang, Jing Zhang, Sanmei Wen, and Jing Su. 2020. Social bots' sentiment engagement in health emergencies: A topic-based analysis of the covid-19 pandemic discussions on twitter. *International Journal of Environmental Research and Public Health*, 17(22):8701.
2238. Gray Stanton and Athirai Aravazhi Irissappane. 2019. Gans for semi-supervised opinion spam detection. In Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, *IJCAI 2019*, Macao, China, August 10-16, 2019, pages 5204–5210. ijcai.org. Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob
2239. Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. *Advances in neural information processing systems*, 30.
2240. Bimal Viswanath, Alan Mislove, Meeyoung Cha, and Krishna P. Gummadi. 2009. On the evolution of user interaction in facebook. In Proceedings of the 2nd ACM Workshop on Online Social Networks, *WOSN '09*, page 37–42, New York, NY, USA. Association for Computing Machinery.

2241. Feng Wei and Uyen Trang Nguyen. 2019. Twitter bot detection using bidirectional long short-term memory neural networks and word embeddings. In 2019 First IEEE International Conference on Trust, Privacy and Security in Intelligent Systems and Applications (TPS-ISA), pages 101–109. IEEE.
2242. Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, Morgan Funtowicz, et al. 2019. Huggingface’s transformers: State-of-the-art natural language processing. arXiv preprint arXiv:1910.03771.
2243. Mingzhou Xu, Liangyou Li, Derek F. Wong, Qun Liu, and Lidia S. Chao. 2021. Document graph for neural machine translation. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 8435–8448, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.
2244. An Yang, Quan Wang, Jing Liu, Kai Liu, Yajuan Lyu, Hua Wu, Qiaoqiao She, and Sujian Li. 2019. Enhancing pre-trained language representations with rich knowledge for machine reading comprehension. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 2346–2357.
2245. Kai-Cheng Yang, Onur Varol, Pik-Mai Hui, and Filippo Menczer. 2020. Scalable and generalizable social bot detection through data selection. In Proceedings of the AAAI conference on artificial intelligence, volume 34, pages 1096–1103.
2246. Yingguang Yang, Renyu Yang, Yangyang Li, Kai Cui, Zhiqin Yang, Yue Wang, Jie Xu, and Haiyong Xie. 2022. Rosgas: Adaptive social bot detection with reinforced self-supervised gnn architecture search. arXiv preprint arX
2247. Seyed Ali Alhosseini, Raad Bin Tareaf, Pejman Najafi, and Christoph Meinel. 2019. Detect me if you can: Spam bot detection using inductive representation learning. In Companion Proceedings of The 2019 World Wide Web Conference. 148–153.
2248. Eiman Alothali, Kadhim Hayawi, and Hany Alashwal. 2023. SEBD: A Stream Evolving Bot Detection Framework with Application of PAC Learning Approach to Maintain Accuracy and Confidence Levels. Applied Sciences 13, 7 (2023), 4443.
2249. Hangbo Bao, Wenhui Wang, Li Dong, Qiang Liu, Owais Khan Mohammed, Kriti Aggarwal, Subhojit Som, and Furu Wei. 2021. Vlmo: Unified vision-language pre-training with mixture-of-modality-experts. arXiv preprint arXiv:2111.02358 (2021).
2250. Florian Brachten, Stefan Stieglitz, Lennart Hofeditz, Katharina Kloppenborg, and Annette Reimann. 2017. Strategies and Influence of Social Bots in a 2017 German state election-A case study on Twitter. arXiv preprint arXiv:1710.07562 (2017).
2251. Nikan Chavoshi, Hossein Hamooni, and Abdullah Mueen. 2016. Debot: Twitter bot detection via warped correlation.. In Icdm, Vol. 18. 28–65.
2252. Stefano Cresci. 2020. A decade of social bot detection. Commun. ACM 63, 10 (2020), 72–83.
2253. Stefano Cresci, Roberto Di Pietro, Marinella Petrocchi, Angelo Spognardi, and Maurizio Tesconi. 2015. Fame for sale: Efficient detection of fake Twitter followers. Decision Support Systems 80 (2015), 56–71.
2254. Stefano Cresci, Roberto Di Pietro, Marinella Petrocchi, Angelo Spognardi, and Maurizio Tesconi. 2017. The paradigm-shift of social spambots: Evidence, theories, and tools

- for the arms race. In Proceedings of the 26th international conference on world wide web companion. 963–972.
2255. Stefano Cresci, Roberto Di Pietro, Angelo Spognardi, Maurizio Tesconi, and Marinella Petrocchi. 2023. Demystifying Misconceptions in Social Bots Research. arXiv preprint arXiv:2303.17251 (2023).
 2256. Anahita Davoudi, Ari Z Klein, Abeed Sarker, and Graciela Gonzalez-Hernandez. 2020. Towards automatic bot detection in Twitter for health-related tasks. AMIA Summits on Translational Science Proceedings 2020 (2020), 136.
 2257. Ashkan Dehghan, Kinga Siuta, Agata Skorupka, Akshat Dubey, Andrei Betlen, David Miller, Wei Xu, Bogumil Kaminski, and Pawel Pralat. 2022. Detecting Bots in Social-Networks Using Node and Structural Embeddings. (2022).
 2258. Yushun Dong, Ninghao Liu, Brian Jalaian, and Jundong Li. 2022. Edits: Modeling and mitigating data bias for graph neural networks. In Proceedings of the ACM Web Conference 2022. 1259–1269.
 2259. David Dukić, Dominik Keča, and Dominik Stipić. 2020. Are you human? Detecting bots on Twitter Using BERT. In 2020 IEEE 7th International Conference on Data Science and Advanced Analytics (DSAA). IEEE, 631–636.
 2260. B Everitt. 1998. The cambridge dictionary of statistics cambridge university press. Cambridge, UK Google Scholar (1998).
 2261. William Fedus, Barret Zoph, and Noam Shazeer. 2021. Switch transformers: Scaling to trillion parameter models with simple and efficient sparsity.
 2262. Shangbin Feng, Zhaoxuan Tan, Rui Li, and Minnan Luo. 2022. Heterogeneity aware twitter bot detection with relational graph transformers. In Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 36. 3977–3985.
 2263. Shangbin Feng, Zhaoxuan Tan, Herun Wan, Ningnan Wang, Zilong Chen, Binchi Zhang, Qinghua Zheng, Wenqian Zhang, Zhenyu Lei, Shujie Yang, et al. 2022. TwiBot-22: Towards Graph-Based Twitter Bot Detection. In Thirty-sixth Conference on Neural Information Processing Systems Datasets and Benchmarks Track.
 2264. Shangbin Feng, Herun Wan, Ningnan Wang, Jundong Li, and Minnan Luo. 2021. Satar: A self-supervised approach to twitter account representation learning and its application in bot detection. In Proceedings of the 30th ACM International Conference on Information & Knowledge Management. 3808–3817.
 2265. Shangbin Feng, Herun Wan, Ningnan Wang, Jundong Li, and Minnan Luo. 2021. Twibot-20: A comprehensive twitter bot detection benchmark. In Proceedings of the 30th ACM International Conference on Information & Knowledge Management. 4485–4494.
 2266. Shangbin Feng, Herun Wan, Ningnan Wang, and Minnan Luo. 2021. BotRGCN: Twitter bot detection with relational graph convolutional networks. In Proceedings of the 2021 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining. 236–239.
 2267. Emilio Ferrara. 2017. Disinformation and social bot operations in the run up to the 2017 French presidential election. arXiv preprint arXiv:1707.00086 (2017).

2268. Emilio Ferrara. 2020. # covid-19 on twitter: Bots, conspiracies, and social media activism. arXiv preprint arXiv: 2004.09531 (2020).
2269. Emilio Ferrara. 2022. Twitter Spam and False Accounts Prevalence, Detection and Characterization: A Survey. arXiv preprint arXiv:2211.05913 (2022).
2270. Matthias Fey and Jan E. Lenssen. 2019. Fast Graph Representation Learning with PyTorch Geometric. In ICLR Workshop on Representation Learning on Graphs and Manifolds.
2271. Claudia Flores-Saviaga, Shangbin Feng, and Saiph Savage. 2022. Datavoidant: An AI System for Addressing Political Data Voids on Social Media. *Proceedings of the ACM on Human-Computer Interaction* 6, CSCW2 (2022), 1–29.
2272. Henrich R Greve, Hayagreeva Rao, Paul Vicinanza, and Echo Yan Zhou. 2022. Online Conspiracy Groups: Micro-Bloggers, Bots, and Coronavirus Conspiracy Talk on Twitter. *American Sociological Review* 87, 6 (2022), 919–949.
2273. Kadhim Hayawi, Sujith Mathew, Neethu Venugopal, Mohammad M Masud, and Pin-Han Ho. 2022. DeeProBot: a hybrid deep neural network model for social bot detection based on user profile data. *Social Network Analysis and Mining* 12, 1 (2022), 1–19.
2274. Chris Hays, Zachary Schutzman, Manish Raghavan, Erin Walk, and Philipp Zimmer. 2023. Simplistic Collection and Labeling Practices Limit the Utility of Benchmark Datasets for Twitter Bot Detection. arXiv preprint arXiv:2301.07015 (2023).
2275. Maryam Heidari and James H Jones. 2020. Using bert to extract topic-independent sentiment features for social media bot detection. In 2020 11th IEEE Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON). IEEE, 0542–0547.
2276. Fenyu Hu, Liping Wang, Shu Wu, Liang Wang, and Tieniu Tan. 2021. Graph classification by mixture of diverse experts. arXiv preprint arXiv:2103.15622 (2021).
2277. Ziniu Hu, Yuxiao Dong, Kuansan Wang, and Yizhou Sun. 2020. Heterogeneous graph transformer. In *Proceedings of The Web Conference 2020*. 2704–2710.
2278. Thomas N Kipf and Max Welling. 2016. Semi-supervised classification with graph convolutional networks. arXiv preprint arXiv:1609.02907 (2016).
2279. Sneha Kudugunta and Emilio Ferrara. 2018. Deep neural networks for bot detection. *Information Sciences* 467 (2018), 312–322.
2280. Tharindu Kumara, Joshua Garland, Amrita Bhattacharjee, Kirill Trapeznikov, Scott Ruston, and Huan Liu. 2023. Stylometric Detection of AI-Generated Text in Twitter Timelines. arXiv preprint arXiv:2303.03697 (2023).
2281. Zhenyu Lei, Herun Wan, Wenqian Zhang, Shangbin Feng, Zilong Chen, Qinghua Zheng, and Minnan Luo. 2022. BIC: Twitter Bot Detection with Text-Graph Interaction and Semantic Consistency. arXiv preprint arXiv:2208.08320 (2022).
2282. Shudong Li, Chuanyu Zhao, Qing Li, Jiuming Huang, Dawei Zhao, and Peican Zhu. 2022. BotFinder: a novel framework for social bots detection in online social networks based on graph embedding and community detection. *World Wide Web* (2022), 1–17.
2283. Paul Pu Liang, Chiyu Wu, Louis-Philippe Morency, and Ruslan Salakhutdinov. 2021. Towards understanding and mitigating social biases in language models. In *ICML*. PMLR, 6565–6576.

2284. Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.11692 (2019).
2285. Linhao Luo, Xiaofeng Zhang, Xiaofei Yang, and Weihuang Yang. 2020. Deepbot: a deep neural network based approach for detecting Twitter bots. In IOP Conference Series: Materials Science and Engineering, Vol. 719. IOP Publishing, 012063.
2286. Jiaqi Ma, Zhe Zhao, Xinyang Yi, Jilin Chen, Lichan Hong, and Ed H Chi. 2018. Modeling task relationships in multi-task learning with multi-gate mixture-of-experts. In Proceedings of the 24th ACM SIGKDD international conference on knowledge discovery & data mining. 1930–1939.
2287. Aman Madaan, Niket Tandon, Dheeraj Rajagopal, Peter Clark, Yiming Yang, and Eduard Hovy. 2021. Think about it! Improving defeasible reasoning by first modeling the question scenario. arXiv preprint arXiv:2110.12349 (2021).
2288. Thomas Magelinski, David Beskow, and Kathleen M Carley. 2020. Graph-hist: Graph classification from latent feature histograms with application to bot detection. In Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 34. 5134–5141.
2289. Zachary Miller, Brian Dickinson, William Deitrick, Wei Hu, and Alex Hai Wang. 2014. Twitter spammer detection using data stream clustering. Information Sciences 260 (2014), 64–73.
2290. Fred Morstatter, Liang Wu, Tahora H Nazer, Kathleen M Carley, and Huan Liu. 2016. A new approach to bot detection: striking the balance between precision and recall. In 2016 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM). IEEE, 533–540.
2291. Moin Nadeem, Anna Bethke, and Siva Reddy. 2021. StereoSet: Measuring stereotypical bias in pretrained language models. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers). Association for Computational Linguistics, Online, 5356–5371. <https://doi.org/10.18653/v1/2021.acl-long.416>
2292. Lynnette Hui Xian Ng and Kathleen M Carley. 2022. BotBuster: Multi-platform Bot Detection Using A Mixture of Experts. arXiv preprint arXiv:2207.13658 (2022).
2293. Javier Pastor-Galindo, Mattia Zago, Pantaleone Nespoli, Sergio López Bernal, Alberto Huertas Celdrán, Manuel Gil Pérez, José A Ruipérez-Valiente, Gregorio Martínez Pérez, and Félix Gómez Mármol. 2020. Spotting political social bots in Twitter: A use case of the 2019 Spanish general election. IEEE Transactions on Network and Service Management 17, 4 (2020), 2156–2170.
2294. F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. 2011. Scikit-learn: Machine Learning in Python. Journal of Machine Learning Research 12 (2011), 2825–2830.
2295. Hao Peng, Roy Schwartz, Dianqi Li, and Noah A Smith. 2020. A Mixture of $h - 1$ Heads is Better than h Heads. arXiv preprint arXiv:2005.06537 (2020).

2296. Huailiang Peng, Yujun Zhang, Hao Sun, Xu Bai, Yangyang Li, and Shuhai Wang. 2022. Domain-Aware Federated Social Bot Detection with Multi-Relational Graph Neural Networks. In 2022 International Joint Conference on Neural Networks (IJCNN). IEEE, 1–8.
2297. Automatic Differentiation In Pytorch. 2018. Pytorch.
2298. Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, Peter J Liu, et al. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. *J. Mach. Learn. Res.* 21, 140 (2020), 1–67.
2299. Sippo Rossi, Matti Rossi, Bikesh Upreti, and Yong Liu. 2020. Detecting political bots on Twitter during the 2019 Finnish parliamentary election. In Proceedings of the 53rd Hawaii international conference on system sciences.
2300. Mohsen Sayyadiharikandeh, Onur Varol, Kai-Cheng Yang, Alessandro Flammini, and Filippo Menczer. 2020. Detection of novel social bots by ensembles of specialized classifiers. In Proceedings of the 29th ACM international conference on information & knowledge management. 2725–2732.
2301. Michael Schlichtkrull, Thomas N Kipf, Peter Bloem, Rianne van den Berg, Ivan Titov, and Max Welling. 2018. Modeling relational data with graph convolutional networks. In European semantic web conference. Springer, 593–607.
2302. Noam Shazeer, Azalia Mirhoseini, Krzysztof Maziarz, Andy Davis, Quoc Le, Geoffrey Hinton, and Jeff Dean. 2017. Outrageously large neural networks: The sparsely-gated mixture-of-experts layer. *arXiv preprint arXiv:1701.06538* (2017).
2303. Shuhao Shi, Kai Qiao, Jie Yang, Baojie Song, Jian Chen, and Bin Yan. 2023. Over-Sampling Strategy in Feature Space for Graphs based Class-imbalanced Bot Detection. *arXiv preprint arXiv:2302.06900* (2023).
2304. Andres Garcia Silva, Cristian Berrio, and José Manuel Gómez-Pérez. 2019. An empirical study on pre-trained embeddings and language models for bot detection. In Proceedings of the 4th Workshop on Representation Learning for NLP (Repl4NLP2019). 148–155.
2305. Kate Starbird. 2019. Disinformation’s spread: bots, trolls and all of us. *Nature* 571, 7766 (2019), 449–450.
2306. Andree Thieltges, Florian Schmidt, and Simon Hegelich. 2016. The devil’s triangle: Ethical considerations on developing bot detection methods. In 2016 AAAI Spring Symposium Series.
2307. Joshua Uyheng and Kathleen M Carley. 2020. Bots and online hate during the COVID-19 pandemic: case studies in the United States and the Philippines. *Journal of computational social science* 3, 2 (2020), 445–468.
2308. Laurens Van der Maaten and Geoffrey Hinton. 2008. Visualizing data using t-SNE. *Journal of machine learning research* 9, 11 (2008).
2309. Onur Varol, Emilio Ferrara, Clayton Davis, Filippo Menczer, and Alessandro Flammini. 2017. Online human-bot interactions: Detection, estimation, and characterization. In Proceedings of the international AAAI conference on web and social media, Vol. 11. 280–289.
2310. Feng Wei and Uyen Trang Nguyen. 2019. Twitter bot detection using bidirectional long short-term memory neural networks and word embeddings. In 2019 First IEEE

International Conference on Trust, Privacy and Security in Intelligent Systems and Applications (TPS-ISA). IEEE, 101–109.

2311. Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander M. Rush. 2020. Transformers: State-of-the-Art Natural Language Processing. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations. Association for Computational Linguistics, Online, 38–45. <https://www.aclweb.org/anthology/2020.emnlpdemos.6>
2312. Jun Wu, Xuesong Ye, and Chengjie Mou. 2023. BotShape: A Novel Social Bots Detection Approach via Behavioral Patterns. arXiv preprint arXiv:2303.10214 (2023).
2313. Jun Wu, Xuesong Ye, and Man Yan Yuet. 2023. BotTriNet: A Unified and Efficient Embedding for Social Bots Detection via Metric Learning. arXiv preprint arXiv:2304.03144 (2023).
2314. Harry Yaojun Yan, Kai-Cheng Yang, Filippo Menczer, and James Shanahan. 2021. Asymmetrical perceptions of partisan political bots. *New Media & Society* 23, 10 (2021), 3016–3037. <https://doi.org/10.1177/1461444820942744> arXiv:<https://doi.org/10.1177/1461444820942744>
2315. Kai-Cheng Yang, Emilio Ferrara, and Filippo Menczer. 2022. Botometer 101: Social bot practicum for computational social scientists. arXiv preprint arXiv:2201.01608 (2022).
2316. Kai-Cheng Yang, Francesco Pierri, Pik-Mai Hui, David Axelrod, Christopher Torres-Lugo, John Bryden, and Filippo Menczer. 2021. The covid-19 infodemic: Twitter versus facebook. *Big Data & Society* 8, 1 (2021), 20539517211013861.
2317. Kai-Cheng Yang, Onur Varol, Pik-Mai Hui, and Filippo Menczer. 2020. Scalable and generalizable social bot detection through data selection. In Proceedings of the AAAI conference on artificial intelligence, Vol. 34. 1096–1103.
2318. Yingguang Yang, Renyu Yang, Hao Peng, Yangyang Li, Tong Li, Yong Liao, and Pengyuan Zhou. 2023. FedACK: Federated Adversarial Contrastive Knowledge Distillation for Cross-Lingual and Cross-Model Social Bot Detection. arXiv preprint arXiv:2303.07113 (2023).
2319. Savvas Zannettou, Tristan Caulfield, Emiliano De Cristofaro, Michael Sirivianos, Gianluca Stringhini, and Jeremy Blackburn. 2019. Disinformation warfare: Understanding state-sponsored trolls on Twitter and their influence on the web. In Companion proceedings of the 2019 world wide web conference. 218–226. Liu et al. - 2023 - BotMoE Twitter Bot Detection with Community-Aware.pdf
2320. Gorwa, R., Guilbeault, D.: Unpacking the social media bot: a typology to guide research and policy. *Policy Internet* 12(2), 225–248 (2020)
2321. Aljabri, M., Zagrouba, R., Shaahid, A., Alnasser, F., Saleh, A., Alomari, D.M.: Machine learning-based social media bot detection: a comprehensive literature review. *Soc. Netw. Anal. Min.* 13(1), 20 (2023)
2322. Loyola-González, O., Monroy, R., Rodríguez, J., López-Cuevas, A., Mata-Sánchez, J.I.: Contrast pattern-based classification for bot detection on twitter. *IEEE Access* 7, 45800–45817 (2019)

2323. Ferrara, E., Varol, O., Davis, C., Menczer, F., Flammini, A.: The rise of social bots. *Commun. ACM* 59(7), 96–104 (2016)
2324. Stieglitz, S., Brachten, F., Ross, B., Jung, A.K.: Do social bots dream of electric sheep? a categorisation of social media bot accounts. *arXiv preprint arXiv:1710.04044* (2017)
2325. Davis, C.A., Varol, O., Ferrara, E., Flammini, A., Menczer, F.: Botornot: a system to evaluate social bots. In *Proceedings of the 25th International Conference Companion on World Wide Web*, pp. 273–274, April 2016
2326. Devlin, J., Chang, M.W., Lee, K., Toutanova, K.: Bert: pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805* (2018)
2327. Zhao, C., Xin, Y., Li, X., Zhu, H., Yang, Y., Chen, Y.: An attention-based graph neural network for spam bot detection in social networks. *Appl. Sci.* 10(22), 8160 (2020)
2328. Shahid, W., Li, Y., Staples, D., Amin, G., Hakak, S., Ghorbani, A.: Are you a cyborg, bot or human?-a survey on detecting fake news spreaders. *IEEE Access* 10, 27069–27083 (2022)
10. Mazza, M., Cresci, S., Avvenuti, M., Quattrociocchi, W., Tesconi, M.: Rtbust: exploiting temporal patterns for botnet detection on twitter. In: *Proceedings of the 10th ACM Conference on Web Science*, pp. 183–192, June 2019
- 142 S. Lopez-Joya et al.
2329. Cresci, S.: A decade of social bot detection. *Commun. ACM* 63(10), 72–83 (2020)
2330. Cresci, S., Petrocchi, M., Spognardi, A., Tognazzi, S.: Better safe than sorry: an adversarial approach to improve social bot detection. In: *Proceedings of the 10th ACM Conference on Web Science*, pp. 47–56, June 2019
2331. Orabi, M., Mouheb, D., Al Aghbari, Z., Kamel, I.: Detection of bots in social media: a systematic review. *Inf. Process. Manage.* 57(4), 102250 (2020)
2332. Haustein, S., Bowman, T.D., Holmberg, K., Tsou, A., Sugimoto, C.R., Larivière, V.: Tweets as impact indicators: examining the implications of automated “bot” accounts on Twitter. *J. Am. Soc. Inf. Sci.* 67(1), 232–238 (2016)
2333. Oentaryo, R.J., Murdopo, A., Prasetyo, P.K., Lim, E.-P.: On profiling bots in social media. In: Spiro, E., Ahn, Y.-Y. (eds.) *SocInfo 2016*. LNCS, vol. 10046, pp. 92–109. Springer, Cham (2016). <https://doi.org/10.1007/978-3-319-47880-76>
2334. Yang, K.C., Varol, O., Davis, C.A., Ferrara, E., Flammini, A., Menczer, F.: Arming the public with artificial intelligence to counter social bots. *Hum. Behav. Emerg. Technol.* 1(1), 48–61 (2019)
2335. Nagaraja, S., Houmansadr, A., Piyawongwisal, P., Singh, V., Agarwal, P., Borisov, N.: Stegobot: a covert social network botnet. In: Filler, T., Pevný, T., Craver, S., Ker, A. (eds.) *IH 2011*. LNCS, vol. 6958, pp. 299–313. Springer, Heidelberg (2011). <https://doi.org/10.1007/978-3-642-24178-921>
2336. Cresci, S., Di Pietro, R., Petrocchi, M., Spognardi, A., Tesconi, M.: The paradigm-shift of social spambots: evidence, theories, and tools for the arms race. In: *Proceedings of the 26th International Conference on World Wide Web Companion*, pp. 963–972, April 2017
2337. Heidari, M., et al.: Bert model for fake news detection based on social bot activities in the covid-19 pandemic. In: *2021 IEEE 12th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON)*, pp. 0103–0109. IEEE, December 2021

2338. Wang, G., et al.: Social turing tests: crowdsourcing sybil detection. arXiv preprint arXiv:1205.3856 (2012) 21. Guo, Q., Xie, H., Li, Y., Ma, W., Zhang, C.: Social bots detection via fusing bert and graph convolutional networks. *Symmetry* 14(1), 30 (2021). <https://www.overleaf.com/project/64072d4f13e3abf8ca3ff145>
2339. Freitas, C., Benevenuto, F., Ghosh, S., Veloso, A.: Reverse engineering socialbot infiltration strategies in twitter. In: *Proceedings of the 2015 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2015*, pp. 25–32, August 2015
2340. Li, S., Zhao, C., Li, Q., Huang, J., Zhao, D., Zhu, P.: BotFinder: a novel framework for social bots detection in online social networks based on graph embedding and community detection. In: *World Wide Web*, pp. 1–17 (2022)
2341. Abou Daya, A., Salahuddin, M.A., Limam, N., Boutaba, R.: BotChase: graph-based bot detection using machine learning. *IEEE Trans. Netw. Serv. Manage.* 17(1), 15–29 (2020)
2342. Cresci, S., Petrocchi, M., Spognardi, A., Tognazzi, S.: The coming age of adversarial social bot detection. *First Monday* (2021)
2343. Morstatter, F., Wu, L., Nazer, T.H., Carley, K.M., Liu, H.: A new approach to bot detection: striking the balance between precision and recall. In: *2016 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*, pp. 533–540. IEEE, August 2016 Bot Detection in Twitter 143
2344. Abokhodair, N., Yoo, D., McDonald, D.W.: Dissecting a social botnet: Growth, content and influence in Twitter. In: *Proceedings of the 18th ACM conference on Computer Supported Cooperative Work & Social Computing*, pp. 839–851, February 2015
2345. Heidari, M., Jones, J.H., Uzuner, O.: Deep contextualized word embedding for text-based online user profiling to detect social bots on twitter. In: *2020 International Conference on Data Mining Workshops (ICDMW)*, pp. 480–487. IEEE, November 2020
2346. Heidari, M., Jones, J.H.: Using bert to extract topic-independent sentiment features for social media bot detection. In: *2020 11th IEEE Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON)*, pp. 0542–0547. IEEE, October 2020
2347. Cresci, S., Di Pietro, R., Petrocchi, M., Spognardi, A., Tesconi, M.: Fame for sale: efficient detection of fake Twitter followers. *Decis. Support Syst.* 80, 56–71 (2015)
2348. Sarzynska-Wawer, J., et al.: Detecting formal thought disorder by deep contextualized word representations. *Psychiatry Res.* 304, 114135 (2021)
2349. Yang, K.C., Varol, O., Hui, P.M., Menczer, F.: Scalable and generalizable social bot detection through data selection. In: *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 34, No. 01, pp. 1096–1103, April 2020
2350. Assenmacher, D., Clever, L., Frischlich, L., Quandt, T., Trautmann, H., Grimme, C.: Demystifying social bots: On the intelligence of automated social media actors. *Social Media+ Society* 6(3), 2056305120939264 (2020)
2351. Dialektakis, G., Dimitriadis, I., Vakali, A.: CALEB: a conditional adversarial learning framework to enhance bot detection. arXiv preprint arXiv:2205.15707 (2022)
2352. Sayyadiharikandeh, M., Varol, O., Yang, K.C., Flammini, A., Menczer, F.: Detection of novel social bots by ensembles of specialized classifiers. In: *Proceedings of the 29th ACM*

- International Conference on Information & Knowledge Management, pp. 2725–2732, October 2020
2353. Cresci, S., Lillo, F., Regoli, D., Tardelli, S., Tesconi, M.: Cashtag piggybacking: uncovering spam and bot activity in stock microblogs on Twitter. *ACM Trans. Web (TWEB)* 13(2), 1–27 (2019)
 2354. Ratkiewicz, J., Conover, M., Meiss, M., Gonçalves, B., Flammini, A., Menczer, F.: Detecting and tracking political abuse in social media. In *Proceedings of the International AAAI Conference on Web and Social Media*, vol. 5, No. 1, pp. 297–304 (2011)
 2355. Subrahmanian, V.S., et al.: The DARPA Twitter bot challenge. *Computer* 49(6), 38–46 (2016)
 2356. Elyashar, A., Fire, M., Kagan, D., Elovici, Y.: Guided socialbots: infiltrating the social networks of specific organizations' employees. *AI Commun.* 29(1), 87–106 (2016)
 2357. Kearney, M.W.: tweetbotornot: R package for detecting Twitter bots via machine learning. Version 0.1.0 - R package - . CRAN (2018). Accessed 24 Mar 2023
 2358. Dukic, D., Keca, D., Stipic, D.: Are you human? Detecting bots on Twitter Using BERT. In: 2020 IEEE 7th International Conference on Data Science and Advanced Analytics (DSAA), pp. 631–636. IEEE, October 2020
 2359. Yang, K.C., Ferrara, E., Menczer, F.: Botometer 101: Social bot practicum for computational social scientists. *J. Comput. Soc. Sci.*, 1–18 (2022)
 2360. Pennington, J., Socher, R., Manning, C.D.: Glove: global vectors for word representation. In: *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pp. 1532–1543, October 2014144 S. Lopez-Joya et al.
 2361. Dorri, A., Abadi, M., Dadfarnia, M.: Socialbothunter: Botnet detection in twitterlike social networking services using semi-supervised collective classification. In: 2018 IEEE 16th Intl Conf on Dependable, Autonomic and Secure Computing, August 2018
 2362. Hwang, T., Pearce, I., Nanis, M.: Socialbots: voices from the fronts. *Interactions* 19(2), 38–45 (2012)
 2363. Chavoshi, N., Hamooni, H., Mueen, A.: Debot: Twitter bot detection via warped correlation. In: *Icdm*, vol. 18, pp. 28–65, December 2016
 2364. HypeAuditor. (n.d.). HypeAuditor. <https://hypeauditor.com/>. Accessed 24 Mar 2023
 2365. Combin. (n.d.). Combin. <https://combim.com/>. Accessed 24 Mar 2023
 2366. FollowerAudit. (n.d.). FollowerAudit. <https://www.followeraudit.com/>. Accessed 24 Mar 2023
 2367. BotSentinel. (n.d.). BotSentinel. <https://botsentinel.com/info/about>. Accessed 24 Mar 2023
 2368. Aelst, P. et al. Political communication in a high-choice media environment: A challenge for democracy?. *Ann. Int. Commun. Assoc.* 41(1), 3–27 (2017).
 2369. Santos, M., & Valenzuela, S. Changing media landscapes and political participation. In M. Giugni and M. Grasso, editors, *The Oxford Handbook of Political Participation*, 841–857. Oxford University Press, (2022).

2370. Castillo, C., Mendoza, M., & Poblete, B. Information credibility on Twitter. In Proceedings of the 20th International Conference Companion on World Wide Web (WWW'11), 675–684. ACM, (2011).
2371. Lewandowsky, S., Ecker, U. & Cook, J. Beyond misinformation: Understanding and coping with the post-truth era. *J. Appl. Res. Mem. Cogn.* 6(4), 353–369 (2017).
2372. Starbird, K. Disinformation's spread: Bots, trolls and all of us. *Nature* 571(7766), 449 (2019).
2373. Lee, K., Caverlee, J., & Webb, S. Uncovering social spammers: social honeypots + machine learning. In Proceeding of the 33rd International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR'10), 435–442. ACM, (2010).
2374. Conover, M., Ratkiewicz, J., Francisco, M., Gonçalves, B., Flammini, A., & Menczer, F. Political polarization on twitter. In Proceedings of the 5th International AAAI Conference on Weblogs and Social Media (ICWSM'11), (2011).
2375. Treré, E. From digital activism to algorithmic resistance (Routledge, In Te Routledge Companion To Media And Activism, 2018).
2376. Cresci, S. A decade of social bot detection. *Commun. ACM* 63(10), 61–72 (2020).
2377. Baraniuk, C. How twitter bots help fuel political feuds. *Scientific American*, 20–30, (2018). 11. Nizzoli, L., Tardelli, S., Avvenuti, M., Cresci, S., & Tesconi, M. Coordinated behavior on social media in 2019 UK General Election. *arXiv:2008.08370*, (2020).
2378. Cresci, S., Petrocchi, M., Spognardi, A. & Tognazzi, S. On the capability of evolved spambots to evade detection via genetic engineering. *Online Soc. Netw. Media* 9, 1–16 (2019).
2379. Cresci, S., Petrocchi, M., Spognardi, A., & Tognazzi, S. Better safe than sorry: An adversarial approach to improve social bot detection. In Proceedings of the 11th International ACM Web Science Conference (WebSci'19), 47–56. ACM, (2019b).
2380. Sayyadiharikandeh, M., Varol, O., Yang, K., Flammini, A., & Menczer, F. Detection of novel social bots by ensembles of specialized classifiers. In CIKM '20: Te 29th ACM International Conference on Information and Knowledge Management, Virtual Event, Ireland, October 19-23, 2020, 2725–2732. ACM, (2020).
2381. Providel, E. & Mendoza, M. Misleading information in Spanish: A survey. *Soc. Netw. Anal. Min.* 11(1), 36 (2021).
2382. Rauchfeisch, A. & Kaiser, J. Te false positive problem of automatic bot detection in social science research. *PLOS One* 15(10), 1–20 (2020).
2383. Lee, K., Eof, B., & Caverlee, J.: Seven Months with the Devils: A Long-Term Study of Content Polluters on Twitter. In Proceedings of the 5th International AAAI Conference on Weblogs and Social Media (ICWSM'11). AAAI, (2011).
2384. Davis, C., Varol, O., Ferrara, E., Flammini, A., & Menczer, F. BotOrNot: A System to Evaluate Social Bots. In Proceedings of the 25th International Conference Companion on World Wide Web (WWW'16), 273–274, (2016).
2385. Velázquez, E., Yazdani, M., & Suárez-Serrato, P. Socialbots supporting human rights, (2017).

2386. Broniatowski, D. et al. Weaponized health communication: Twitter bots and Russian trolls amplify the vaccine debate. *Am. J. Public Health* 108(10), 1378–1384. <https://doi.org/10.2105/AJPH.2018.304567> (2018).
2387. Boichak, O., Hemsley, J., Jackson, S., Tromble, R., & Tanupabrunsun, S. Not the bots you are looking for: Patterns and effects of orchestrated interventions in the u.s. and german elections. *Int. J. Commun.* 15, 2021. <https://ijoc.org/index.php/ijoc/article/view/14866>.
2388. Khaund, T., Al-khateeb, S., Tokdemir, S., & Agarwal, N. Analyzing social bots and their coordination during natural disasters. In *SBP-BRIMS*, (2018).
2389. Santos, J., Ituassu, A., Lifschitz, S., Guimarães, T., Cerqueira, D., Albu, D., Fernando, R., Ferreira, J., Mondelli, M. Das milícias digitais ao comportamento coordenado: métodos interdisciplinares de análise e identificação de bots nas eleições brasileiras. In *Anais do X Brazilian Workshop on Social Network Analysis and Mining*, 187–192. SBC, (2021).
2390. Mazza, M., Cresci, S., Avvenuti, M., Quattrociocchi, W., & Tesconi, M. RTbust: Exploiting temporal patterns for botnet detection on twitter. In *Proceedings of the 11th International ACM Web Science Conference (WebSci'19)*, 183–192. ACM, (2019).
2391. Mendoza, M., Tesconi, M. & Cresci, S. Bots in social and interaction networks: Detection and impact estimation. *ACM Trans. Inf. Syst. (TOIS)* 39(1), 5:1-5:32 (2020).
2392. Lee, M., Vajiac, C., Kulshrestha, A., Levy, S., Park, N., Jones, C., Rabbany, R., & Faloutsos, C. Infoshield: Generalizable informationtheoretic human-trafficking detection. In *2021 IEEE 37th International Conference on Data Engineering (ICDE)*, 1116–1127, Los Alamitos, CA, USA, apr 2021. IEEE Computer Society. <https://doi.org/10.1109/ICDE51399.2021.00101>. <https://doi.ieeecomputersociety.org/10.1109/ICDE51399.2021.00101>.
2393. Yang, K., Varol, O., Hui, P., Menczer, F. Scalable and generalizable social bot detection through data selection. In *The 34th AAAI Conference on Artificial Intelligence (AAAI'20)*. AAAI, (2020).
2394. Feng, S., Wan, H., Wang, N., Li, J., Luo, M. Twibot-20: A comprehensive twitter bot detection benchmark. In *CIKM '21: The 30th ACM International Conference on Information and Knowledge Management, Virtual Event, Queensland, Australia, November 1 - 5, 2021*, 4485–4494. ACM, (2021).
2395. Kudugunta, S. & Ferrara, E. Deep neural networks for bot detection. *Information Sciences* 467, 312–322 (2018). ISSN 0020-0255. <https://doi.org/10.1016/j.ins.2018.08.019>. <https://www.sciencedirect.com/science/article/pii/S0020025518306248>.
2396. Pennington, J., Socher, R., & Manning, C. Glove: Global vectors for word representation. In *Empirical Methods in Natural Language Processing (EMNLP)*, 1532–1543, (2014).
2397. Martín-Gutiérrez, D., Hernández-Peñaloza, G., Hernández, A., Lozano-Diez, A. & Álvarez, F. A deep learning approach for robust detection of bots in twitter using transformers. *IEEE Access* 9, 54591–54601. <https://doi.org/10.1109/ACCESS.2021.3068659> (2021).
2398. Yinhan, L., Myle, O., Naman, G., Jingfei, D., Mandar, J., Danqi, C., Omer, L., Mike, L., Luke, Z., & Veselin, S. Roberta: A robustly optimized BERT pretraining approach. *CoRR* (2019). arxiv:1907.11692.20

2399. Rodríguez-Ruiz, J., Mata-Sánchez, J., Monroy, R., Loyola-González, O. & López-Cuevas, A. A one-class classification approach for bot detection on twitter. *Comput. Secur. textbf91(C)*, (2020).
2400. Echeverría, J., De Cristofaro, E., Kourtellis, N., Leontiadis, I., Stringhini, G., Zhou, S. Lobo: Evaluation of generalization defficiencies in twitter bot classifiers. In *Proceedings of the 34th Annual Computer Security Applications Conference, ACSAC '18*, 137-146, New York, NY, USA, (2018). Association for Computing Machinery.
2401. Castillo, S., Allende-Cid, H., Palma, W., Alfaro, R., Ramos, H.S., Gonzalez, C., Elortegui, C., & Santander, P. Detection of Bots and Cyborgs in Twitter: A Study on the Chilean Presidential Election in 2017. In *Conference of 11th International Conference on Social Computing and Social Media, SCSM 2019*, held as part of the 21st International Conference on Human-Computer Interaction, HCI, in *Lecture Notes in Computer Science*, 11578 LNCS, 311–323. Springer Verlag, (2019).
2402. Pastor-Galindo, J., Zago, M., Nespoli, P., López Bernal, S., Huertas Celdrán, A., Gil Pérez, M., Ruipérez Valiente, J., Martínez Pérez, G., & Gómez Mármol, F. Twitter social bots: Te 2019 spanish general election data. *Data Brief*, 32, 106047 (2020). ISSN 2352-3409.
2403. Loyola-González, O., Monroy, R., Rodríguez, J., López-Cuevas, A. & Mata-Sánchez, J. Contrast pattern-based classification for bot detection on twitter. *IEEE Access* 7, 45800–45817 (2019).
2404. Cresci, S., Di Pietro, R., Petrocchi, M., Spognardi, A., & Tesconi, M. Te Paradigm-Shif of Social Spambots: Evidence, Teories, and Tools for the Arms Race. In *Proceedings of the 26th International Conference Companion on World Wide Web (WWW'17)*, 963–972, (2017).
2405. Rangel, F., & Rosso, P. Overview of the 7th author profiling task at Pan 2019: Bots and gender profiling in twitter. volume 2380. *CEUR-WS*, (2019). Conference of 20th Working Notes of Conference and Labs of the Evaluation Forum, CLEF.
2406. Pizarro, J. Using N-grams to detect Bots on Twitter Notebook for PAN at CLEF 2019. volume 2380. *CEUR-WS*, (2019). Conference of 20th Working Notes of Conference and Labs of the Evaluation Forum, CLEF.
2407. Jimenez-Villar, V., Sánchez-Junquera, J., Montes-Y-Gómez, M., Villaseñor-Pineda, L., Ponzetto, S.P. Bots and gender profiling using masking techniques notebook for pan at clef 2019. volume 2380. *CEUR-WS*, 2019. Conference of 20th Working Notes of Conference and Labs of the Evaluation Forum, CLEF.
2408. Polignano, M., De Pinto, M.G., Lops, P., Semeraro, G. Identification of Bot Accounts in Twitter Using 2D CNNs on User-generated Contents Notebook for PAN at CLEF 2019. volume 2380. *CEUR-WS*, 2019. Conference of 20th Working Notes of Conference and Labs of the Evaluation Forum, CLEF.
2409. Fagni, T., & Tesconi, M. Profiling Twitter users using autogenerated features invariant to data distribution notebook for PAN at CLEF 2019. volume 2380. *CEUR-WS*, 2019. Conference of 20th Working Notes of Conference and Labs of the Evaluation Forum, CLEF.
2410. Ouni, S., Fkih, F., & Omri, M. Toward a new approach to author profiling based on the extraction of statistical features. *Soc. Netw. Anal. Min.* 11(1), 59 (2021). <https://doi.org/10.1007/s13278-021-00768-6>.

2411. Graells-Garrido, E., & Baeza-Yates, R. Bots don't vote, but they surely bother! a study of anomalous accounts in a national referendum. In 14th ACM Web Science Conference 2022, WebSci '22, page 302-306, New York, NY, USA, (2022). Association for Computing Machinery. ISBN 9781450391917. <https://doi.org/10.1145/3501247.3531576>.
2412. Liu, F., Ting, K., & Zhou, Z. Isolation forest. In 2008 Eighth IEEE International Conference on Data Mining, 413–422, (2008).
2413. Ruiz, S., Providel, E., & Mendoza, M. Fake news detection via english-to-spanish translation: Is it really useful? In Social Computing and Social Media: Experience Design and Social Network Analysis - 13th International Conference, SCSM, July 24-29, 2021, Proceedings, volume 12774 of Lecture Notes in Computer Science, 136–148. Springer, (2021).
2414. Cresci, S., Pietro, R., Petrocchi, M., Spognardi, A. & Tesconi, M. Social fingerprinting: Detection of spambot groups through DNA-inspired behavioral modeling. IEEE Trans. Depend. Secure Comput. 15(4), 561–576 (2017).
2415. Varol, O., Ferrara, E., Menczer, F. & Flammini, A. Early detection of promoted campaigns on social media. EPJ Data Sci. 6(1), 13 (2017). 50. Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A., Kaiser, L., & Polosukhin, I. Attention is all you need. In Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, December 4-9, 2017, Long Beach, CA, USA, 5998–6008, (2017).
2416. Redondo, J., Fraga, I., Padrón, I. & Comesaña, M. Te spanish adaptation of anew (affective norms for english words). Behav. Res. Methods 39, 600–605 (2007).
2417. Bojanowski, P., Grave, E., Joulin, A. & Mikolov, T. Enriching word vectors with subword information. Trans. Assoc. Comput. Ling. 5, 135–146 (2017).
2418. Barbieri, F., Espinosa-Anke, L., & Camacho-Collados, J. XLM-T: Multilingual language models in Twitter for sentiment analysis and beyond. In N. Calzolari, F. Béchet, P. Blache, K. Choukri, C. Cieri, T. Declerck, S. Goggi, H. Isahara, B. Maegaard, J. Mariani, H. Mazo, J. Odiijk, and S. Piperidis, editors, Proceedings of the Thirteenth Language Resources and Evaluation Conference, 258–266, Marseille, France, June (2022). European Language Resources Association. <https://aclanthology.org/2022.lrec-1.27>.
2419. Devlin, J., Chang, M., Lee, K., Toutanova, K. BERT: pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT, Minneapolis, MN, USA, June 2-7, 2019, 4171–4186. Association for Computational Linguistics, (2019).
2420. Conneau, A., Khandelwal, K., Goyal, N., Chaudhary, V., Wenzek, G., Guzm'an, F., Grave, E., Ott, M., Zettlemoyer, L., & Stoyanov, V. Unsupervised cross-lingual representation learning at scale. In D. Jurafsky, J. Chai, N. Schluter, and J. Tetreault, editors, Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pp. 8440–8451, Online, July (2020). Association for Computational Linguistics. <https://doi.org/10.18653/v1/2020.acl-main.747>. <https://aclanthology.org/2020.acl-main.747>.
2421. Lunarejo, M., Condori-Fernández, N., & Luaces, M. Towards an automatic requirements classification in a new spanish dataset. In 30th IEEE International Requirements

- Engineering Conference, RE 2022, Melbourne, Australia, August 15-19, 2022, 270–271. IEEE, (2022).
2422. Ribeiro, M., Singh, S., & Guestrin, C. why should I trust you?: Explaining the predictions of any classifier. In B. Krishnapuram, M. Shah, A. Smola, C. Aggarwal, D. Shen, and R. Rastogi, editors, *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, San Francisco, CA, USA, August 13-17, 2016, 1135–1144. ACM, (2016). <https://doi.org/10.1145/2939672.2939778>.
 2423. Camiña, J. et al. Bagging-randomminer: A one-class classifier for file access-based masquerade detection. *Mach. Vis. Appl.* 30(5), 959–974. <https://doi.org/10.1007/s00138-018-0957-4> (2019).
 2424. Vafa, K., Naidu, S., & Blei, D. Text-based ideal points. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, ACL 2020, Online, July 5–10, 2020*, 5345–5357. Association for Computational Linguistics, (2020).
 2425. Bradley, M., & Lang, P. Affective norms of english words (anew), (1999).
 2426. Osgood, C., Suci, G., & Tannenbaum, P. The measurement of meaning, (1957).
 2427. Fraga, I. et al. Attentional processing and recall of emotional words. *Revista Latinoamericana de Psicología* 43(3), 401–418 (2011).
 2428. Adel Alipour S, Orji R, Zincir-Heywood N (2022) Security of social networks: lessons learned on twitter bot analysis in the literature. In: *Proceedings of the 17th international conference on availability, reliability and security*, pp 1–9
 2429. Akyon FC, Kalfaoglu ME (2019) Instagram fake and automated account detection. In: *2019 Innovations in Intelligent systems and applications conference (ASYU)*, pp 1–7. IEEE
 2430. Al-Qurishi M, Alrubaian M, Rahman SMM, Alamri A, Hassan MM (2018) A prediction system of sybil attack in social network using deep-regression model. *Future Gener Comput Syst* 87:743–753
 2431. Arin E, Kutlu M (2023) Deep learning based social bot detection on twitter. *IEEE Transact Inf Forensics Sec* 18:1763–1772
 2432. Baumgartner J, Zannettou S, Keegan B, Squire M, Blackburn J (2020) The pushshift reddit dataset. In: *Proceedings of the international AAAI conference on web and social media*, vol 14, pp 830–839
 2433. Beskow DM, Carley KM (2019) Its all in a name: detecting and labeling bots by their name. *Comput Math Organ Theory* 25(1):24–35
 2434. Beskow DM, Carley KM (2018) Bot-hunter: a tiered approach to detecting & characterizing automated activity on twitter. In: *Conference paper. SBP-BRiMS: international conference on social computing, behavioral-cultural modeling and prediction and behavior representation in modeling and simulation*, vol 3, p 3
 2435. Cai C, Li L, Zengi D (2017) Behavior enhanced deep bot detection in social media. In: *2017 IEEE international conference on intelligence and security informatics (ISI)*, pp 128–130. IEEE
 2436. Chavoshi N, Hamooni H, Mueen A (2016) Debot: twitter bot detection via warped correlation. In: *Icdm*, vol 18, pp 28–65

2437. Clayton J (2022) Doubts cast over Elon Musk's Twitter bot claims. BBC. <https://www.bbc.com/news/technology-62571733>
2438. Cresci S (2020) A decade of social bot detection. *Commun ACM* 63(10):72–83
2439. Cresci S, Lillo F, Regoli D, Tardelli S, Tesconi M (2018) Fake: Evidence of spam and bot activity in stock microblogs on twitter. In: Twelfth international AAAI conference on web and social media
2440. Dimitriadis I, Georgiou K, Vakali A (2021) Social botomics: a systematic ensemble ml approach for explainable and multi-class bot detection. *Appl Sci* 11(21):9857
2441. Feng S, Wan H, Wang N, Li J, Luo M (2021) Twibot-20: a comprehensive twitter bot detection benchmark. In: Proceedings of the 30th ACM international conference on information & knowledge management, pp 4485–4494
2442. Ferrara E (2017) Disinformation and social bot operations in the run up to the 2017 French presidential election. *First Monday*. <https://doi.org/10.5210/fm.v22i8.8005>
2443. Ferrara E, Varol O, Davis C, Menczer F, Flammini A (2016) The rise of social bots. *Commun ACM* 59(7):96–104
2444. Ferrara E, Wang W-Q, Varol O, Flammini A, Galstyan A (2016) Predicting online extremism, content adopters, and interaction reciprocity. In: International conference on social informatics, pp 22–39. Springer
2445. Gera S, Sinha A (2022) T-bot: Ai-based social media bot detection model for trend-centric twitter network. *Soc Netw Anal Min* 12(1):76
2446. Hayawi K, Mathew S, Venugopal N, Masud MM, Ho P-H (2022) Deeprobot: a hybrid deep neural network model for social bot detection based on user profile data. *Soc Netw Anal Min* 12(1):43
2447. Heidari M, James Jr, H, Uzuner O (2021) An empirical study of machine learning algorithms for social media bot detection. In: 2021 IEEE international IOT, electronics and mechatronics conference (IEMTRONICS), pp 1–5. IEEE
2448. Hurtado S, Ray P, Marculescu R (2019) Bot detection in reddit political discussion. In: Proceedings of the fourth international workshop on social sensing, pp 30–35
2449. Kantepe M, Ganiz MC (2017) Preprocessing framework for twitter bot detection. In: 2017 International conference on computer science and engineering (ubmk), pp 630–634. IEEE
2450. Kearney MW (2018) GitHub - mkearney/tweetbotornot: R package for detecting Twitter bots via machine learning — github.com. <https://github.com/mkearney/Tweetbotornot>. - Accessed 06-09-2023 -
2451. Khaund T, Kirdemir B, Agarwal N, Liu H, Morstatter F (2021) Social bots and their coordination during online campaigns: a survey. *IEEE Transact Comput Soc Syst* 9(2):530–545
2452. Kudugunta S, Ferrara E (2018) Deep neural networks for bot detection. *Inf Sci* 467:312–322
2453. Livingstone RM (2022) Trump bots and algorithmic experimentation on twitter. *First Monday*. <https://doi.org/10.5210/fm.v27i11.12392>

2454. Luceri L, Deb A, Giordano S, Ferrara E (2019) Evolution of bot and human behavior during elections. *First Monday*. <https://doi.org/10.5210/fm.v24i9.10213>
2455. Mannocci L, Cresci S, Monreale A, Vakali A, Tesconi M (2022) Mulbot: Unsupervised bot detection based on multivariate time series. In: 2022 IEEE international conference on big data (Big Data), pp 1485–1494. IEEE
2456. Mazza M, Cresci S, Avvenuti M, Quattrociocchi W, Tesconi M (2019) Rtbust: exploiting temporal patterns for botnet detection on twitter. In: Proceedings of the 10th ACM conference on web science, pp 183–192
2457. Minnich A, Chavoshi N, Koutra D, Mueen A (2017) Botwalk: efficient adaptive exploration of twitter bot networks. In: Proceedings of the 2017 IEEE/ACM international conference on advances in social networks analysis and mining 2017, pp 467–474
2458. Murdock I, Carley KM, Yağan O (2023) Identifying cross-platform user relationships in 2020 us election fraud and protest discussions. *Online Soc Netw Med* 33:100245
2459. Ng LHX, Carley KM (2022) Pro or anti? a social influence model of online stance flipping. *IEEE Transact Netw Sci Eng* 10(1):3–19
2460. Ng LHX, Carley KM (2023) Do you hear the people sing? comparison of synchronized URL and narrative themes in 2020 and 2023 French protests. *Front Big Data*. <https://doi.org/10.3389/fdata.2023.1221744>
2461. Ng LHX, Robertson DC, Carley KM (2022) Stabilizing a supervised bot detection algorithm: How much data is needed for consistent predictions? *Online Soc Netw Med* 28:100198
2462. Ng LHX, Carley KM (2023) Botbuster: Multi-platform bot detection using a mixture of experts. In: Proceedings of the international AAAI conference on web and social media, vol 17, pp 686–697
2463. Pacheco D, Hui P-M, Torres-Lugo C, Truong BT, Flammini A, Menczer F (2021) Uncovering coordinated networks on social media: methods and case studies. In: Proceedings of the international AAAI conference on web and social media, vol 15, pp 455–466
2464. Pratama PG, Rakhmawati NA (2019) Social bot detection on 2019 Indonesia president candidate's supporter's tweets. *Procedia Comput Sci* 161:813–820
2465. Rauchfleisch A, Kaiser J (2020) The false positive problem of automatic bot detection in social science research. *PloS one* 15(10):0241045
2466. Saeed MH, Ali S, Blackburn J, De Cristofaro E, Zannettou S, Stringhini G (2022) Trollmagnifer: detecting state-sponsored troll accounts on reddit. In: 2022 IEEE symposium on security and privacy (SP), pp 2161–2175. IEEE
2467. Sayyadiharikandeh M, Varol O, Yang K-C, Flammini A, Menczer F (2020) Detection of novel social bots by ensembles of specialized classifiers. In: Proceedings of the 29th ACM international conference on information & knowledge management, pp 2725–2732
2468. Uyheng J, Ng LHX, Carley KM (2021) Active, aggressive, but to little avail: characterizing bot activity during the 2020 Singaporean elections. *Comput Math Organ Theory* 27(3):324–342

2469. Wu Y, Fang Y, Shang S, Jin J, Wei L, Wang H (2021) A novel framework for detecting social bots with deep neural networks and active learning. *Knowl Based Syst* 211:106525
2470. Yang K-C, Varol O, Davis CA, Ferrara E, Flammini A, Menczer F (2019) Arming the public with artificial intelligence to counter social bots. *Human Behav Emerg Technol* 1(1):48–61
2471. Yang K-C, Varol O, Hui P-M, Menczer F (2020) Scalable and generalizable social bot detection through data selection. In: *Proceedings of the AAAI conference on artificial intelligence*, vol 34, pp 1096–1103
2472. Zarei K, Farahbakhsh R, Crespi N (2019) Typification of impersonated accounts on instagram. In: *2019 IEEE 38th international performance computing and communications conference (IPCCC)*, pp 1–6. IEEE
2473. Charity S, Jacobs Lynnette Hui Xian, Ng Kathleen M, Carley Robert, Thomson Samer, Al-khateeb Annetta, Burger Patrick, Park Aryn, A. Pyke (2023) Social Cultural and Behavioral Modeling 16th International Conference SBP-BRIMS 2023 Pittsburgh PA USA September 20–22 2023 Proceedings Tracking China's Cross-Strait Bot Networks Against Taiwan Springer Nature Switzerland Cham 115-125
2474. Lynnette Hui Xian, Ng Kathleen M, Carley (2023) Defating the Chinese balloon: types of Twitter bots in US-China balloon incident Abstract *EPJ Data Science* 12(1) <https://doi.org/10.1140/epjds/s13688-023-00440-3>
2475. Abokhodair, N., Yoo, D., & McDonald, D. W. (2015). Dissecting a social botnet: Growth, content and influence in Twitter. *Proceedings of the 18th ACM conference on computer supported cooperative work & social computing*. ACM839–851.
2476. Abu-El-Rub, N., & Mueen, A. (2019). Botcamp: Bot-driven interactions in social campaigns. *The world wide web conference*. ACM2529–2535.
2477. Adewole, K. S., Anuar, N. B., Kamsin, A., Varathan, K. D., & Razak, S. A. (2017). Malicious accounts: Dark of the social networks. *Journal of Network and Computer Applications*, 79, 41–67.
2478. Ahmed, F., & Abulaish, M. (2013). A generic statistical approach for spam detection in online social networks. *Computer Communications*, 36(10-11), 1120–1129.
2479. Al-Qurishi, M., Al-Rakhami, M., Alamri, A., Alrubaian, M., Rahman, S. M. M., & Hossain, M. S. (2017). Sybil defense techniques in online social networks: A survey. *IEEE Access*, 5, 1200–1219.
2480. Alarifi, A., Alsaleh, M., & Al-Salman, A. (2016). Twitter turing test: Identifying social machines. *Information Sciences*, 372, 332–346.
2481. Allem, J. P., & Ferrara, E. (2018). Could social bots pose a threat to public health? *American Journal of Public Health*, 108(8), 1005–1006.
2482. Almerexhi, H., & Elsayed, T. (2015). Detecting automatically-generated arabic tweets. *AIRS. Springer*123–134.
2483. Alothali, E., Zaki, N., Mohamed, E. A., & Alashwal, H. (2018). Detecting social bots on Twitter: A litekure review. *2018 International conference on innovations in information technology (IIT)*. IEEE175–180.

2484. AlRubaian, M., Al-Qurishi, M., Rahman, S. M. M., & Alamri, A. (2015). A novel prevention mechanism for sybil attack in online social network. 2015 2nd world symposium on web applications and networking (WSWAN). IEEE1–6.
2485. Amleshwaram, A. A., Reddy, N., Yadav, S., Gu, G., & Yang, C. (2013). Cats: Characterizing automation of Twitter spammers. 2013 Fifth international conference on communication systems and networks (COMSNETS). IEEE1–10.
2486. Andriotis, P., & Takasu, A. (2018). Emotional bots: Content-based spammer detection on social media. 2018 IEEE international workshop on information forensics and security (WIFS). IEEE1–8.
2487. Bara, I. A., Fung, C. J., & Dinh, T. (2015). Enhancing Twitter spam accounts discovery using cross-account pattern mining. 2015 IFIP/IEEE international symposium on integrated network management (IM). IEEE491–496.
2488. Beskow, D. M., & Carley, K. M. (2019). Its all in a name: detecting and labeling bots by their name. *Computational and Mathematical Organization Theory*, 25(1), 24–35.
2489. Bessi, A., & Ferrara, E. (2016). Social bots distort the 2016 us presidential election online discussion. *First Monday*, 21(11).
2490. Bose, I., & Mahapatra, R. K. (2001). Business data mininga machine learning perspective. *Information & Management*, 39(3), 211–225.
2491. Boshmaf, Y., Logothetis, D., Siganos, G., Lería, J., Lorenzo, J., Ripeanu, M., ... Halawa, H. (2016). Íntegro: Leveraging victim prediction for robust fake account detection in large scale OSNS. *Computers & Security*, 61, 142–168.
2492. Boshmaf, Y., Muslukhov, I., Beznosov, K., & Ripeanu, M. (2011). The socialbot network: when bots socialize for fame and money. *Proceedings of the 27th annual computer security applications conference*. ACM93–102.
2493. Boshmaf, Y., Muslukhov, I., Beznosov, K., & Ripeanu, M. (2013). Design and analysis of a social botnet. *Computer Networks*, 57(2), 556–578.
2494. Broniatowski, D. A., Jamison, A. M., Qi, S., AlKulaib, L., Chen, T., Benton, A., ... Dredze, M. (2018). Weaponized health communication: Twitter bots and russian trolls amplify the vaccine debate. *American Journal of Public Health*, 108(10), 1378–1384.
2495. Buczak, A. L., & Guven, E. (2015). A survey of data mining and machine learning methods for cyber security intrusion detection. *IEEE Communications Surveys & Tutorials*, 18(2), 1153–1176.
2496. Budania, H., & Singh, P. K. (2017). Person versus non-person classification of Twitter handle. *International conference on health information science*. Springer 103–114.
2497. Burghouwt, P., Spruit, M., & Sips, H. (2013). Detection of covert botnet command and control channels by causal analysis of traffic flows. *Cyberspace safety and security*. Springer 117–131.
2498. Cai, C., Li, L., & Zeng, D. (2017). Detecting social bots by jointly modeling deep behavior and content information. *Proceedings of the 2017 ACM on conference on information and knowledge management*. ACM 1995–1998.

2499. Cai, C., Li, L., & Zengi, D. (2017). Behavior enhanced deep bot detection in social media. 2017 IEEE international conference on intelligence and security informatics (ISI). IEEE 128–130.
2500. Campos, G. F., Tavares, G. M., Igawa, R. A., Guido, R. C., et al. (2018). Detection of human, legitimate bot, and malicious bot in online social networks based on wavelets. *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM)*, 14(1s), 26.
2501. Carr, C. T., & Hayes, R. A. (2015). Social media: Defining, developing, and divining. *Atlantic Journal of Communication*, 23(1), 46–65.
2502. Caruccio, L., Desiato, D., & Polese, G. (2018). Fake account identification in social networks. 2018 IEEE international conference on big data (big data). IEEE 5078–5085.
2503. Chavoshi, N., Hamooni, H., & Mueen, A. (Hamooni, Mueen, 2016a). Debot: Twitter bot detection via warped correlation. *ICDM*817–822.
2504. Chavoshi, N., Hamooni, H., & Mueen, A. (Hamooni, Mueen, 2016b). Identifying correlated bots in Twitter. *International conference on social informatics*. Springer14–21.
- Chen, Z., & Subramanian, D. (2018). An unsupervised approach to detect spam campaigns that use botnets on Twitter. *arXiv:1804.05232*.
2505. Chen, Z., Tanash, R. S., Stoll, R., & Subramanian, D. (2017). Hunting malicious bots on Twitter: An unsupervised approach. *International conference on social informatics*. Springer 501–510.
2506. Chew, P. A. (2018). Searching for unknown unknowns: Unsupervised bot detection to defeat an adaptive adversary. *International conference on social computing, behavioral-cultural modeling and prediction and behavior representation in modeling and simulation*. Springer357–366.
2507. Chu, Z., Gianvecchio, S., Wang, H., & Jajodia, S. (2010). Who is tweeting on Twitter: human, bot, or cyborg? *Proceedings of the 26th annual computer security applications conference*. ACM21–30.
2508. Chu, Z., Gianvecchio, S., Wang, H., & Jajodia, S. (2012). Detecting automation of Twitter accounts: Are you a human, bot, or cyborg? *IEEE Transactions on Dependable and Secure Computing*, 9(6), 811–824.
2509. Cornelissen, L. A., Barnett, R. J., Schoonwinkel, P., Eichstadt, B. D., & Magodla, H. B. (2018). A network topology approach to bot classification. *Proceedings of the annual conference of the South African Institute of computer scientists and information technologists*. ACM 79–88.
2510. Cresci, S., Di Pietro, R., Petrocchi, M., Spognardi, A., & Tesconi, M. (2015). Fame for sale: Efficient detection of fake Twitter followers. *Decision Support Systems*, 80, M. Orabi, et al. *Information Processing and Management* 57 (2020) 102250 2156–71.
2511. Cresci, S., Di Pietro, R., Petrocchi, M., Spognardi, A., & Tesconi, M. (2016). Dna-inspired online behavioral modeling and its application to spambot detection. *IEEE Intelligent Systems*, 31(5), 58–64.
2512. Cresci, S., Di Pietro, R., Petrocchi, M., Spognardi, A., & Tesconi, M. (Di Pietro, Petrocchi, Spognardi, Tesconi, 2017a). The paradigm-shift of social spambots: Evidence, theories, and tools for the arms race. *Proceedings of the 26th international conference on*

- world wide web companion. International World Wide Web Conferences Steering Committee 963–972.
2513. Cresci, S., Di Pietro, R., Petrocchi, M., Spognardi, A., & Tesconi, M. (Di Pietro, Petrocchi, Spognardi, Tesconi, 2017b). Social fingerprinting: detection of spambot groups through DNA-inspired behavioral modeling. *IEEE Transactions on Dependable and Secure Computing*, 15(4), 561–576.
 2514. Cresci, S., Lillo, F., Regoli, D., Tardelli, S., & Tesconi, M. (2019). Cashtag piggybacking: Uncovering spam and bot activity in stock microblogs on Twitter. *ACM Transactions on the Web (TWEB)*, 13(2), 11.
 2515. Cresci, S., Petrocchi, M., Spognardi, A., & Tognazzi, S. (2019). On the capability of evolved spambots to evade detection via genetic engineering. *Online Social Networks and Media*, 9, 1–16.
 2516. Daouadi, K. E., Rebaï, R. Z., & Amous, I. (2019). Bot detection on online social networks using deep forest. *Computer science on-line conference*. Springer 307–315.
 2517. David, I., Siordia, O. S., & Moctezuma, D. (2016). Features combination for the detection of malicious Twitter accounts. 2016 IEEE international autumn meeting on power, electronics and computing (ROPEC). IEEE 1–6.
 2518. Davis, C. A., Varol, O., Ferrara, E., Flammini, A., & Menczer, F. (2016). Botornot: A system to evaluate social bots. *Proceedings of the 25th international conference companion on world wide web*. International World Wide Web Conferences Steering Committee 273–274.
 2519. Dickerson, J. P., Kagan, V., & Subrahmanian, V. (2014). Using sentiment to detect bots on Twitter: Are humans more opinionated than bots? *Proceedings of the 2014 IEEE/ACM international conference on advances in social networks analysis and mining*. IEEE Press 620–627.
 2520. Dorri, A., Abadi, M., & Dadfarnia, M. (2018). Socialbothunter: Botnet detection in Twitter-like social networking services using semi-supervised collective classification. 2018 IEEE 16th international conference on dependable, autonomic and secure computing, 16th international conference on pervasive intelligence and computing, 4th international conference on big data intelligence and computing and cyber science and technology congress (DASC/PICOM/DATACOM/CYBERSCITECH). IEEE 496–503.
 2521. Echeverria, J., & Zhou, S. (2017). Discovery, retrieval, and analysis of the “star wars” botnet in Twitter. *Proceedings of the 2017 IEEE/ACM international conference on advances in social networks analysis and mining 2017*. ACM 1–8.
 2522. El Naqa, I., & Murphy, M. J. (2015). What is machine learning? *Machine learning in radiation oncology*. Springer 3–11.
 2523. Elyashar, A., Fire, M., Kagan, D., & Elovici, Y. (2013). Homing socialbots: Intrusion on a specific organization’s employee using socialbots. 2013 IEEE/ACM international conference on advances in social networks analysis and mining (ASONAM 2013). IEEE 1358–1365.
 2524. Elyashar, A., Fire, M., Kagan, D., & Elovici, Y. (2016). Guided socialbots: Infiltrating the social networks of specific organizations employees. *AI Communications*, 29(1), 87–106.
 2525. Estellés-Arolas, E., & González-Ladrón-De-Guevara, F. (2012). Towards an integrated crowdsourcing definition. *Journal of Information Science*, 38(2), 189–200. Facebook users

- worldwide, 2019. <https://www.statista.com/statistics/264810/number-of-monthly-active-facebook-users-worldwide/>.
2526. Fazil, M., & Abulaish, M. (2018). A hybrid approach for detecting automated spammers in Twitter. *IEEE Transactions on Information Forensics and Security*, 13(11), 2707–2719.
 2527. Ferrara, E., Varol, O., Davis, C., Menczer, F., & Flammini, A. (2016). The rise of social bots. *Communications of the ACM*, 59(7), 96–104. Forelle, M., Howard, P., Monroy-Hernández, A., & Savage, S. (2015). Political bots and the manipulation of public opinion in venezuela. <https://doi.org/10.2139/ssrn.2635800>.
 2528. Freitas, C., Benevenuto, F., Ghosh, S., & Veloso, A. (2015). Reverse engineering socialbot infiltration strategies in Twitter. 2015 IEEE/ACM international conference on advances in social networks analysis and mining (ASONAM). IEEE25–32.
 2529. Geiger, R. S. (2016). Bot-based collective blocklists in Twitter: The counterpublic moderation of harassment in a networked public space. *Information, Communication & Society*, 19(6), 787–803.
 2530. Gilani, Z., Kochmar, E., & Crowcroft, J. (2017). Classification of Twitter accounts into automated agents and human users. *Proceedings of the 2017 IEEE/ACM international conference on advances in social networks analysis and mining 2017*. ACM 489–496.
 2531. Goga, O., Venkatadri, G., & Gummadi, K. P. (2015). The doppelgänger bot attack: Exploring identity impersonation in online social networks. *Proceedings of the 2015 internet measurement conference*. ACM 141–153.
 2532. Gorwa, R., & Guilbeault, D. (2018). Unpacking the social media bot: A typology to guide research and policy. *Policy & Internet*.
 2533. Grimme, C., Assenmacher, D., & Adam, L. (2018). Changing perspectives: Is it sufficient to detect social bots? *International conference on social computing and social media*. Springer 445–461.
 2534. Grimme, C., Preuss, M., Adam, L., & Trautmann, H. (2017). Social bots: Human-like by means of human control? *Big data*, 5(4), 279–293.
 2535. Gurajala, S., White, J. S., Hudson, B., & Matthews, J. N. (2015). Fake Twitter accounts: Profile characteristics obtained using an activity-based pattern detection approach. *Proceedings of the 2015 international conference on social media & society*. ACM9.
 2536. Halawa, H., Beznosov, K., Boshmaf, Y., Coskun, B., Ripeanu, M., & Santos-Neto, E. (2016). Harvesting the low-hanging fruits: Defending against automated large-scale cyberintrusions by focusing on the vulnerable population. *Proceedings of the 2016 new security paradigms workshop*. ACM 11–22.
 2537. Hegelich, S., & Janetzko, D. (2016). Are social bots on Twitter political actors? Empirical evidence from a ukrainian social botnet. *Tenth international AAAI conference on web and social media* 579582.
 2538. Heidemann, J., Klier, M., & Probst, F. (2012). Online social networks: A survey of a global phenomenon. *Computer networks*, 56(18), 3866–3878.
 2539. Hurtado, S., Ray, P., & Marculescu, R. (2019). Bot detection in reddit political discussion. *Proceedings of the fourth international workshop on social sensing*. ACM30–35.

2540. Igawa, R. A., Barbon Jr, S., Paulo, K. C. S., Kido, G. S., Guido, R. C., Júnior, M. L. P., & da Silva, I. N. (2016). Account classification in online social networks with LBCA and wavelets. *Information Sciences*, 332, 72–83.
2541. Ji, Y., He, Y., Jiang, X., Cao, J., & Li, Q. (2016). Combating the evasion mechanisms of social bots. *Computers & Security*, 58, 230–249.
2542. Ji, Y., He, Y., Zhu, D., Li, Q., & Guo, D. (2014). A multiprocess mechanism of evading behavior-based bot detection approaches. *International conference on information security practice and experience*. Springer75–89.
2543. Ji, Y., Li, Q., He, Y., & Guo, D. (2015). Botcatch: Leveraging signature and behavior for bot detection. *Security and Communication Networks*, 8(6), 952–969.
2544. Kahraman, H. T., Sagioglu, S., & Colak, I. (2010). Development of adaptive and intelligent web-based educational systems. *2010 4th International conference on application of information and communication technologies*. IEEE1–5.
2545. Kantepe, M., & Ganiz, M. C. (2017). Preprocessing framework for Twitter bot detection. *2017 International conference on computer science and engineering (ubmk)*. IEEE630–634.
2546. Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! the challenges and opportunities of social media. *Business horizons*, 53(1), 59–68.
2547. Karataş, A., & Şahin, S. (2017). A review on social bot detection techniques and research directions. *Proceedings of international security and cryptology conference Turkey*156–161.
2548. Kartaltepe, E. J., Morales, J. A., Xu, S., & Sandhu, R. (2010). Social network-based botnet command-and-control: Emerging threats and countermeasures. *International conference on applied cryptography and network security*. Springer511–528.
2549. Khaled, S., El-Tazi, N., & Mokhtar, H. M. (2018). Detecting fake accounts on social media. *2018 IEEE international conference on big data (big data)*. IEEE3672–3681.
2550. Kitchenham, B., & Charters, S. (2007). Guidelines for performing systematic literature reviews in software engineering version 2.3. *Engineering*, 45(4ve), 1051.
2551. Kotsiantis, S. B., Zaharakis, I., & Pintelas, P. (2007). Supervised machine learning: A review of classification techniques. *Emerging Artificial Intelligence Applications in Computer Engineering*, 160, 3–24.
2552. Kudugunta, S., & Ferrara, E. (2018). Deep neural networks for bot detection. *Information Sciences*, 467, 312–322.
2553. Lee, K., Eoff, B. D., & Caverlee, J. (2011). Seven months with the devils: A long-term study of content polluters on Twitter. *Fifth international AAAI conference on weblogs and social media*185–192.
2554. Libbrecht, M. W., & Noble, W. S. (2015). Machine learning applications in genetics and genomics. *Nature Reviews Genetics*, 16(6), 321.
2555. Loyola-González, O., Monroy, R., Rodríguez, J., López-Cuevas, A., & Mata-Sánchez, J. I. (2019). Contrast pattern-based classification for bot detection on Twitter. *IEEE Access*, 7, 45800–45817.

2556. Luxton, D. D., June, J. D., & Fairall, J. M. (2012). Social media and suicide: a public health perspective. *American Journal of Public Health*, 102(S2), S195–S200.
2557. Main, W., & Shekokhar, N. (2015). Twitterati identification system. *Procedia Computer Science*, 45, 32–41.
2558. Minnich, A., Chavoshi, N., Koutra, D., & Mueen, A. (2017). Botwalk: Efficient adaptive exploration of Twitter bot networks. *Proceedings of the 2017 IEEE/ACM international conference on advances in social networks analysis and mining 2017*. ACM467–474.
2559. Mitter, S., Wagner, C., & Strohmaier, M. (2014). A categorization scheme for socialbot attacks in online social networks. *arXiv:1402.6288*. Mohaisen, A., & Kim, J. (2013). The sybil attacks and defenses: a survey. *arXiv:1312.6349*.
2560. Morstatter, F., Wu, L., Nazer, T. H., Carley, K. M., & Liu, H. (2016). A new approach to bot detection: Striking the balance between precision and recall. *2016 IEEE/ACM international conference on advances in social networks analysis and mining (ASONAM)*. IEEE533–540.
2561. Nimmo, B. (2017). #botspot: Twelve ways to spot a bot. <https://medium.com/dfrlab/botspot-twelve-ways-to-spot-a-bot-aedc7d9c110c>.
2562. Pan, J., Liu, Y., Liu, X., & Hu, H. (2016). Discriminating bot accounts based solely on temporal features of microblog behavior. *Physica A: Statistical Mechanics and its Applications*, 450, 193–204.
2563. Ping, H., & Qin, S. (2018). A social bots detection model based on deep learning algorithm. *2018 IEEE 18th international conference on communication technology (icct)*. IEEE1435–1439.
2564. Qi, S., AlKulaib, L., & Broniatowski, D. A. (2018). Detecting and characterizing bot-like behavior on Twitter. *International conference on social computing, behavioral-cultural modeling and prediction and behavior representation in modeling and simulation*. Springer228–232.
2565. Ratkiewicz, J., Conover, M. D., Meiss, M., Gonçalves, B., Flammini, A., & Menczer, F. M. (2011). Detecting and tracking political abuse in social media. *Fifth international AAAI conference on weblogs and social media*297304.
2566. Sebastian, S., Ayyappan, S., & Vinod, P. (2014). Framework for design of graybot in social network. *2014 international conference on advances in computing, communications and informatics (ICACCI)*. IEEE2331–2336.
2567. Shafahi, M., Kempers, L., & Afsarmanesh, H. (2016). Phishing through social bots on Twitter. *2016 IEEE international conference on big data (big data)*. IEEE3703–3712.
2568. Shao, C., Ciampaglia, G. L., Varol, O., Yang, K.-C., Flammini, A., & Menczer, F. (2018). The spread of low-credibility content by social bots. *Nature Communications*, 9(1), 4787.
2569. Shi, P., Zhang, Z., & Choo, K. K. R. (2019). Detecting malicious social bots based on clickstream sequences. *IEEE Access*, 7, 28855–28862.
2570. Singh, A., Toderici, A. H., Ross, K., & Stamp, M. (2013). Social networking for botnet command and control. *International Journal of Computer Network and Information Security*, 5(6), 11.

2571. Stein, T., Chen, E., & Mangla, K. (2011). Facebook immune system. Proceedings of the 4th workshop on social network systems SNS'11 Association for Computing Machinery.
2572. Stella, M., Ferrara, E., & De Domenico, M. (2018). Bots increase exposure to negative and inflammatory content in online social systems. Proceedings of the National Academy of Sciences, 115(49), 12435–12440.
2573. Stieglitz, S., Brachten, F., Ross, B., & Jung, A. K. (2017). Do social bots dream of electric sheep? A categorisation of social media bot accounts. arXiv:1710.04044.
2574. Subrahmanian, V., Azaria, A., Durst, S., Kagan, V., Galstyan, A., Lerman, K., ... Menczer, F. (2016). The darpa Twitter bot challenge. Computer, 49(6), 38–46.
2575. Teljstedt, C., Rosell, M., & Johansson, F. (2015). A semi-automatic approach for labeling large amounts of automated and non-automated social media user accounts. 2015 second european network intelligence conference. IEEE 155–159.
2576. Valliyammai, C., & Devakunchari, R. (2018). Distributed and scalable sybil identification based on nearest neighbour approximation using big data analysis techniques. Cluster Computing, 1–16.
2577. Varol, O., Ferrara, E., Davis, C. A., Menczer, F., & Flammini, A. (2017). Online human-bot interactions: Detection, estimation, and characterization. Eleventh international AAAI conference on web and social media 280289.
2578. Veale, T., Valitutti, A., & Li, G. (2015). Twitter: The best of bot worlds for automated wit. International conference on distributed, ambient, and pervasive interactions. Springer 689–699.
2579. Velayutham, T., & Tiwari, P. K. (2017). Bot identification: Helping analysts for right data in Twitter. 2017 3rd international conference on advances in computing, communication & automation (ICACCA)(fall). IEEE 1–5.
2580. Viswanath, B., Post, A., Gummadi, K. P., & Mislove, A. (2011). An analysis of social network-based sybil defenses. ACM SIGCOMM Computer Communication Review, 41(4), 363–374.
2581. Wang, A. H. (2010). Detecting spam bots in online social networking sites: a machine learning approach. IFIP Annual conference on data and applications security and privacy. Springer 335–342.
2582. Wang, B., Zhang, L., & Gong, N. Z. (2018). Sybilblind: Detecting fake users in online social networks without manual labels. International symposium on research in attacks, intrusions, and defenses. Springer 228–249.
2583. Wang, G., Mohanlal, M., Wilson, C., Wang, X., Metzger, M. J., Zheng, H., & Zhao, B. Y. (2013). Social turing tests: Crowdsourcing sybil detection. 20th annual network and distributed system security symposium, NDSS.
2584. Wang, Y., Wu, C., Zheng, K., & Wang, X. (2018). Social bot detection using tweets similarity. International conference on security and privacy in communication systems. Springer 63–78.
2585. West, D. B. (1996). Introduction to graph theory. Vol. 2. Prentice hall Upper Saddle River.

2586. Wilkie, A., Michael, M., & Plummer-Fernandez, M. (2015). Speculative method and Twitter: Bots, energy and three conceptual characters. *The Sociological Review*, 63(1), 79–101.
2587. Xin, Y., Zhao, C., Zhu, H., & Gao, M. (2018). A survey of malicious accounts detection in large-scale online social networks. 2018 IEEE 4th international conference on big data security on cloud (bigdatasecurity), IEEE international conference on high performance and smart computing,(HPSC) and IEEE international conference on intelligent data and security (IDS). IEEE155–158.
2588. Xu, A., Liu, Z., Guo, Y., Sinha, V., & Akkiraju, R. (2017). A new chatbot for customer service on social media. *Proceedings of the 2017 Chi conference on human factors in computing systems*. ACM3506–3510.
2589. Yang, C., Harkreader, R., & Gu, G. (2013). Empirical evaluation and new design for fighting evolving Twitter spammers. *IEEE Transactions on Information Forensics and Security*, 8(8), 1280–1293.
2590. Yang, C., Harkreader, R. C., & Gu, G. (2011). Die free or live hard? Empirical evaluation and new design for fighting evolving Twitter spammers. *International workshop on recent advances in intrusion detection*. Springer318–337.
2591. Yang, W., Dong, G., Wang, W., Shen, G., Gong, L., Yu, M., ... Hu, Y. (2014). Detecting bots in follower markets. *Bio-inspired computing-theories and applications*. Springer525–530.
2592. Yang, Z., Wilson, C., Wang, X., Gao, T., Zhao, B. Y., & Dai, Y. (2014). Uncovering social network sybils in the wild. *ACM Transactions on Knowledge Discovery from Data (TKDD)*, 8(1), 2.
2593. Yu, H. (2011). Sybil defenses via social networks: A tutorial and survey. *ACM SIGACT News*, 42(3), 80–101.
2594. Zhu, X. J. (2005). Semi-supervised learning literature surveyTechnical Report. University of Wisconsin-Madison Department of Computer Sciences.
2595. M. Pfeiffer, T. Pfeil, Deep learning with spiking neurons: Opportunities and challenges, *Frontiers in Neuroscience* 12 (2018) 774.
2596. J. K. Eshraghian, M. Ward, E. O. Neftci, X. Wang, G. Lenz, G. Dwivedi, M. Bennamoun, D. S. Jeong, W. D. Lu, Training spiking neural networks using lessons from deep learning, *Proceedings of the IEEE* 111 (2023) 1016– 1054.
2597. B. Rueckauer, I.-A. Lungu, Y. Hu, M. Pfeiffer, S.-C. Liu, Conversion of continuous-valued deep networks to efficient event-driven networks for image classification, *Frontiers in Neuroscience* 11 (2017) 682.
2598. R. Midya, et al., Artificial neural network (ANN) to spiking neural network 30(SNN) converters based on diffusive memristors, *Advanced Electronic Materials* 5 (9) (2019) 1900060.
2599. C. Stöckl, W. Maass, Optimized spiking neurons can classify images with high accuracy through temporal coding with two spikes, *Nature Machine Intelligence* 3 (3) (2021) 230–238.

2600. P. Falez, P. Tirilly, I. M. Bilasco, P. Devienne, P. Boulet, Unsupervised visual feature learning with spike-timing-dependent plasticity: How far are we from traditional feature learning approaches?, *Pattern Recognition* 93 (2019) 418–429.
2601. M. Mozafari, M. Ganjtabesh, A. Nowzari-Dalini, S. J. Thorpe, T. Masquelier, Bio-inspired digit recognition using reward-modulated spike-timing-dependent plasticity in deep convolutional networks, *Pattern Recognition* 94 (2019) 87–95.
2602. H. Mostafa, Supervised learning based on temporal coding in spiking neural networks, *IEEE Transactions on Neural Networks and Learning Systems* 29 (7) (2017) 3227–3235.
2603. Y. Wu, L. Deng, G. Li, J. Zhu, L. Shi, Spatio-temporal backpropagation for training high-performance spiking neural networks, *Frontiers in Neuroscience* 12 (2018) 331.
2604. D. Rasmussen, NengoDL: Combining deep learning and neuromorphic modelling methods, *Neuroinformatics* 17 (4) (2019) 611–628.
2605. Y. Guo, W. Peng, Y. Chen, L. Zhang, X. Liu, X. Huang, Z. Ma, Joint A-SNN: Joint training of artificial and spiking neural networks via self-Distillation and weight factorization, *Pattern Recognition* 142 (2023) 109639.
2606. G. Orchard, A. Jayawant, G. K. Cohen, N. Thakor, Converting static image datasets to spiking neuromorphic datasets using saccades, *Frontiers in Neuroscience* (2015).
2607. E. Doutsis, L. Fillatre, M. Antonini, P. Tsakalides, Dynamic image quantization using leaky integrate-and-fire neurons, *IEEE Transactions on Image Processing* 30 (2021) 4305–4315.
2608. A. Javanshir, T. T. Nguyen, M. A. P. Mahmud, A. Z. Kouzani, Advancements in algorithms and neuromorphic hardware for spiking neural networks, *Neural Computation* 34 (6) (2022) 1289–1328.
2609. M. Mazza, S. Cresci, M. Avvenuti, W. Quattrociocchi, M. Tesconi, RTbust: Exploiting temporal patterns for botnet detection on Twitter, in: *Proceedings of the 10th ACM Conference on Web Science*, 2019, pp. 183–192.
2610. S. M. Bohte, J. N. Kok, H. La Poutre, Error-backpropagation in temporally encoded networks of spiking neurons, *Neurocomputing* 48 (1-4) (2002) 17– 37.
2611. J. H. Lee, T. Delbruck, M. Pfeiffer, Training deep spiking neural networks using backpropagation, *Frontiers in Neuroscience* 10 (2016) 508.
2612. D. Huh, T. J. Sejnowski, Gradient descent for spiking neural networks, *Advances in Neural Information Processing Systems* 31 (2018).
2613. W. Zhang, P. Li, Temporal spike sequence learning via backpropagation for deep spiking neural networks, *Advances in Neural Information Processing Systems* 33 (2020) 12022–12033.
2614. N. Perez-Nieves, D. Goodman, Sparse spiking gradient descent, *Advances in Neural Information Processing Systems* 34 (2021) 11795–11808.
2615. Y. Zhu, Z. Yu, W. Fang, X. Xie, T. Huang, T. Masquelier, Training spiking neural networks with event-driven backpropagation, *Advances in Neural Information Processing Systems* 35 (2022) 30528–30541.

2616. T. C. Wunderlich, C. Pehle, Event-based backpropagation can compute exact gradients for spiking neural networks, *Scientific Reports* 11 (1) (2021) 12829.
2617. H. Zheng, Y. Wu, L. Deng, Y. Hu, G. Li, Going deeper with directly-trained larger spiking neural networks, in: *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 35, 2021, pp. 11062–11070.
2618. F. Zenke, S. Ganguli, SuperSpike: Supervised learning in multilayer spiking neural networks, *Neural Computation* 30 (6) (2018) 1514–1541.
2619. S. B. Shrestha, G. Orchard, SLAYER: Spike layer error reassignment in time, *Advances in Neural Information Processing Systems* 31 (2018) 1419–1428.
2620. E. O. Neftci, H. Mostafa, F. Zenke, Surrogate gradient learning in spiking neural networks: Bringing the power of gradient-based optimization to spiking neural networks, *IEEE Signal Processing Magazine* 36 (6) (2019) 51–63.
2621. P. J. Werbos, Backpropagation through time: what it does and how to do it, *Proceedings of the IEEE* 78 (10) (1990) 1550–1560.
2622. B. Yin, F. Corradi, S. M. Boht'e, Accurate and efficient time-domain classification with adaptive spiking recurrent neural networks, *Nature Machine Intelligence* 3 (10) (2021) 905–913.
2623. W. Fang, Z. Yu, Y. Chen, T. Huang, T. Masquelier, Y. Tian, Deep residual learning in spiking neural networks, *Advances in Neural Information Processing Systems* 34 (2021) 21056–21069.
2624. Y. Kim, J. Chough, P. Panda, Beyond classification: Directly training spiking neural networks for semantic segmentation, *Neuromorphic Computing and Engineering* 2 (4) (2022) 044015.
2625. S. R. Kheradpisheh, T. Masquelier, Temporal backpropagation for spiking neural networks with one spike per neuron, *International Journal of Neural Systems* 30 (06) (2020) 2050027.
2626. S. Zhou, X. Li, Y. Chen, S. T. Chandrasekaran, A. Sanyal, Temporal-coded deep spiking neural network with easy training and robust performance, in: *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 35, 2021, pp. 11143–11151.
2627. E. Ferrara, O. Varol, C. Davis, F. Menczer, A. Flammini, The rise of social bots, *Communications of the ACM* 59 (7) (2016) 96–104.
2628. S. Cresci, R. Di Pietro, M. Petrocchi, A. Spognardi, M. Tesconi, The paradigm-shift of social spambots: Evidence, theories, and tools for the arms race, in: *Proceedings of the 26th International Conference on World Wide Web Companion*, 2017, pp. 963–972.
2629. C. A. Davis, O. Varol, E. Ferrara, A. Flammini, F. Menczer, BotOrNot: A system to evaluate social bots, in: *Proceedings of the 25th International Conference Companion on World Wide Web*, 2016, pp. 273–274.
2630. J. Rodriguez-Ruiz, J. I. Mata-S'anchez, R. Monroy, O. Loyola-Gonzalez, A. L'opez-Cuevas, A one-class classification approach for bot detection on Twitter, *Computers & Security* 91 (2020) 101715.

2631. A. Minnich, N. Chavoshi, D. Koutra, A. Mueen, BotWalk: Efficient adaptive exploration of Twitter bot networks, in: *Proceedings of the 2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2017*, 2017, pp. 467–474.
2632. M. Balaanand, N. Karthikeyan, S. Karthik, R. Varatharajan, G. Manogaran, C. B. Sivaparthipan, An enhanced graph-based semi-supervised learning algorithm to detect fake users on Twitter, *The Journal of Supercomputing* 75 (2019) 6085–6105.
2633. Q. Cao, M. Sirivianos, X. Yang, T. Pregueiro, Aiding the detection of fake accounts in large scale social online services, in: *Presented as part of the 9th USENIX Symposium on Networked Systems Design and Implementation (NSDI 12)*, 2012, pp. 197–210.
2634. N. Chavoshi, H. Hamooni, A. Mueen, Identifying correlated bots in Twitter, in: *Social Informatics: 8th International Conference, SocInfo 2016, Bellevue, WA, USA, November 11-14, 2016, Proceedings, Part II 8*, Springer, 2016, pp. 14–21.
2635. S. Gupta, P. Kumaraguru, T. Chakraborty, MalReG: Detecting and analyzing malicious retweeter groups, in: *Proceedings of the ACM India Joint International Conference on Data Science and Management of Data*, 2019, pp. 61–69.
2636. J. Pan, Y. Liu, X. Liu, H. Hu, Discriminating bot accounts based solely on temporal features of microblog behavior, *Physica A: Statistical Mechanics and its Applications* 450 (2016) 193–204.
2637. H. S. Dutta, A. Chetan, B. Joshi, T. Chakraborty, Retweet us, we will retweet you: Spotting collusive retweeters involved in blackmarket services, in: *2018 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*, IEEE, 2018, pp. 242–249.
2638. S. Thorpe, J. Gautrais, Rank order coding, *Computational Neuroscience: Trends in Research*, 1998 (1998) 113–118.
2639. M. Pabian, D. Rzepka, M. Pawlak, Supervised training of siamese spiking neural networks with Earth Mover’s Distance, in: *ICASSP 2022-2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, IEEE, 2022, pp. 4233–4237.
2640. Rogers, E. M. *Diffusion of Innovation* (Free Press, New York, 1995). 2. Watts, D. J. & Peretti, J. Viral marketing for the real world. *Harvard Business Review* 104–112 (May 2007).
2641. Gonzalez-Bailon, S., Borge-Holthoefer, J., Rivero, A. & Moreno, Y. The dynamics of protest recruitment through an online network. *Sci. Rep.* 1, 197 (2011).
2642. Gruhl, D., Liben-Nowell, D., Guha, R. V. & Tomkins, A. Information diffusion through blogspace. *Proc. 13th Intl. WWW Conf.* 491–501 (2004). 5. Muchnik, L., Aral, S. & Taylor, S. J. Social Influence Bias: A Randomized Experiment. *Science* 341, 647–651 (2013).
2643. Liben-Nowell, D. & Kleinberg, J. Tracing information flow on a global scale using Internet chain-letter data. *Proc. Natl. Acad. Sci. USA* 105, 4633–4638 (2008).
2644. Watts, D. J. A simple model of global cascades on random networks. *Proc. Natl. Acad. Sci. USA* 99, 5766–5771 (2002).
2645. Kleinberg, J. Cascading behavior in networks: Algorithmic and economic issues. *Algorithmic Game Theory* 613–632 (Cambridge Univ. Press, Cambridge, 2007).
2646. Castellano, C., Fortunato, S. & Loreto, V. Statistical physics of social dynamics. *Rev. Mod. Phys.* 81, 591–646 (2009).

2647. Gallos, L. K., Rybski, D., Liljeros, F., Havlin, S. & Makse, H. A. How people interact in evolving online affiliation networks. *Phys. Rev. X* 2, 031014 (2012).
2648. Rybski, D., Buldyrev, S. V., Havlin, S., Liljeros, F. & Makse, H. A. Communication activity in a social network: relation between long-term correlations and interevent clustering. *Sci. Rep.* 2, 560 (2012).
2649. Katz, E. & Lazarsfeld, P. *Personal Influence* (Free Press, New York, 1955).
2650. Becker, M. H. Factors affecting diffusion of innovations among health professionals. *Am. J. Public Health* 60, 294–304 (1970).
2651. Galeotti, A. & Goyal, S. Influencing the influencers: a theory of strategic diffusion. *RAND J. Econ.* 40, 509–532 (2009).
2652. Goldenberg, J., Han, S., Lehmann, D. & Hong, J. The role of hubs in the adoption processes. *J. Marketing* 73, 1–13 (2009).
2653. Iyengar, R., Van den Bulte, C. & Valente, T. W. Opinion leadership and social contagion in new product diffusion. *Market. Sci.* 30, 195–212 (2011).
2654. Marsden, P. Seed to spread: How seeding trials ignite epidemics of demand. *Connected Marketing: The Viral, Buzz, and Word of Mouth Revolution* 323 (Butterworth-Heinemann, Oxford, 2006).
2655. Valente, T. W. & Davis, R. L. Accelerating the diffusion of innovations using opinion leaders. *Ann. Am. Acad. Polit. SS.* 556, 55–67 (1999).
2656. Van den Bulte, C. & Joshi, Y. V. New product diffusion with influentials and imitators. *Market. Sci.* 26, 400–421 (2007).
2657. Watts, D. J. & Dodds, P. S. Influentials, networks, and public opinion formation. *J. Consum. Res.* 34, 441–458 (2007).
2658. Kempe, D., Kleinberg, J. & Tardos, E'. Maximizing the spread of influence in a social network. *Proc. 9th ACM SIGKDD Intl. Conf. on Knowledge Discovery and Data Mining* 137–146 (2003).
2659. Pei, S. & Makse, H. A. Spreading dynamics in complex networks. *J. Stat. Mech.* 12, P12002 (2013).
2660. Albert, R., Jeong, H. & Barabási, A.-L. Error and attack tolerance of complex networks. *Nature* 406, 378–482 (2000).
2661. Pastor-Satorras, R. & Vespignani, A. Epidemic spreading in scale-free networks. *Phys. Rev. Lett.* 86, 3200–3203 (2001).
2662. Brin, S. & Page, L. The anatomy of a large-scale hypertextual web search engine. *Comput. Networks ISDN* 30, 107–117 (1998).
2663. Freeman, L. C. Centrality in social networks: Conceptual clarification. *Soc. Netw.* 1, 215–239 (1979).
2664. Seidman, S. B. Network structure and minimum degree. *Soc. Netw.* 5, 269–287 (1983).
2665. Wuchty, S. & Almaas, E. Evolutionary cores of domain co-occurrence networks. *BMC Evol. Biol.* 5, 24 (2005).

2666. Dorogovtsev, S. N., Goltsev, A. V. & Mendes, J. F. F. K-core organization of complex networks. *Phys. Rev. Lett.* 96, 040601 (2006).
2667. Alvarez-Hamelin, J. I., Dall'Asta, L., Barrat, A. & Vespignani, A. How the k-core decomposition helps in understanding the internet topology. *ISMA Workshop on the Internet Topology* cs.ni/0504107; cs.ni/0511007 (2006).
2668. Carmi, S., Havlin, S., Kirkpatrick, S., Shavitt, Y. & Shir, E. A model of Internet topology using k-shell decomposition. *Proc. Natl. Acad. Sci. USA* 104, 11150–11154 (2007).
2669. Kitsak, M. et al. Identification of influential spreaders in complex networks. *Nat. Phys.* 6, 888–893 (2010).
2670. Ghoshal, G. & Barabási, A. L. Ranking stability and super-stable nodes in complex networks. *Nat. Comm.* 2, 394 (2011).
2671. Java, A., Kolari, P., Finin, T. & Oates, T. Modeling the spread of influence on the blogosphere. *Proc. 15th Intl. WWW Conf.* 22–26 (2006).
2672. Lu, L., Zhang, Y. C., Yeung, C. H. & Zhou, T. Leaders in social networks, the delicious case. *PloS One* 6, e21202 (2011).
2673. Guille, A., Hacid, H., Favre, C. & Zighed, D. A. Information diffusion in online social networks: A survey. *ACM SIGMOD Record* 42, 17–28 (2013).
2674. Chen, D. B., Xiao, R., Zeng, A. & Zhang, Y. C. Path diversity improves the identification of influential spreaders. *Europhys. Lett.* 104, 68006 (2013).
2675. Nguyen, T. H. & Szymanski, B. K. Social ranking techniques for the web. *Proc. 2013 IEEE/ACM Intl. Conf. on Advances in Social Networks Analysis and Mining* 49–55 (2013).
2676. Hethcote, H. W. The mathematics of infectious diseases. *SIAM Rev.* 42, 599–653 (2000).
2677. Borge-Holthoefer, J. & Moreno, Y. Absence of influential spreaders in rumor dynamics. *Phys. Rev. E* 85, 026116 (2012).
2678. Centola, D. & Macy, M. Complex contagions and the weakness of long ties. *Am. J. Sociol.* 113, 702–734 (2007).
2679. Goldenberg, J., Libai, B. & Muller, E. Talk of the network: A complex systems look at the underlying process of word-of-mouth. *Market. Lett.* 12, 211–223 (2011).
2680. Jackson, M. O. & Lopez-Pintado, D. Diffusion and contagion in networks with heterogeneous agents and homophily. *arXiv preprint arXiv:1111.0073* (2011).
2681. Aral, S., Muchnik, L. & Sundararajan, A. Engineering Social Contagions: Optimal Network Seeding in the Presence of Homophily. *Netw. Sci.* 1, 125–153 (2013).
2682. Singh, P., Sreenivasan, S., Szymanski, B. K. & Korniss, G. Threshold-limited spreading in social networks with multiple initiators. *Sci. Rep.* 3, 2330 (2013).
2683. Backstrom, L., Huttenlocher, D., Kleinberg, J. & Lan, X. Group formation in large social networks: membership, growth, and evolution. *Proc. 12th ACM SIGKDD Intl. Conf. on Knowledge Discovery and Data Mining* 44–54 (2006).
2684. Liben-Nowell, D., Novak, J., Kumar, R., Raghavan, P. & Tomkins, A. Geographic routing in social networks. *Proc. Natl. Acad. Sci. USA* 102, 11623–11628 (2005).

2685. Grabowicz, P. A., Ramasco, J. J., Moro, E., Pujol, J. M. & Eguiluz, V. M. Social features of online networks: The strength of intermediary ties in online social media. *PloS One* 7, e29358 (2012).
2686. Brandes, U. A faster algorithm for betweenness centrality. *J. Math. Sociol.* 25, 163–177 (2001).
2687. Efron, B. & Tibshirani, R. *An introduction to the bootstrap* (CRC Press, Boca Raton, 1994).
2688. Goel, S., Watts, D. J. & Goldstein, D. G. The structure of online diffusion networks. *Proc. 13th ACM Conf. on Electronic Commerce* 623–638 (2012).
2689. Viswanath, B., Mislove, A., Cha, M. & Gummadi, K. P. On the evolution of user interaction in Facebook. *Proc. 2nd ACM SIGCOMM Workshop on Social Networks (WOSN'09)*, Barcelona, Spain (2009).
2690. McCreadie, R. et al. On building a reusable twitter corpus. *Proc. 35th Intl. ACM SIGIR Conf. on Research and Development in Information Retrieval* 1113–1114 (2012).
2691. Cha, M., Haddadi, H., Benevenuto, F. & Gummadi, K. P. Measuring user influence in twitter: The million follower fallacy. *4th Intl. AAAI Conf. on Weblogs and Social media (icwsm)* 14, 8 (2010).
2692. Honeycutt, C. & Herring, S. C. Beyond microblogging: conversations and collaborations via Twitter. *Proc. 42nd HICSS* 1–10 (2009).
2693. Muchnik, L. et al. Origins of power-law degree distribution in the heterogeneity of human activity in social networks. *Sci. Rep.* 3, 1783 (2013).
2694. Kwak, H., Lee, C., Park, H. & Moon, S. What is Twitter, a social network or a news media? *Proc. 19th Intl. WWW Conf.* 591–600 (2010).
2695. Bakshy, E., Hofman, J. M., Mason, W. A. & Watts, D. J. Everyone's an influencer: quantifying influence on twitter. *Proc. 4th ACM Intl. Conf. on Web Search and Data Mining* 65–74 (2011).
2696. Harold D. Lasswell. (1927). *The theory of Political Propaganda*. *The American Political Science Review*, Vol. 21, No. 3. , pp. 627-631.
2697. Ellul J. (1965). *Propaganda: the formation of Men's attitudes*. Vintage Books, New York chapter I section 3 - Categories of propaganda
2698. Jowett, G., & O'Donnell, V. (1992). *Propaganda and persuasion*. Newbury Park, Calif: Sage Publications.
2699. How to Detect Propaganda. (1938). *Bulletin of the American Association of University Professors*(1915-1955), 24(1), 49-55.
2700. Farkas J. & Neumayer C. (2019). *Disguised Propaganda from Digital to Social Media*. *Second International Handbook of Internet Research*. Springer, Dordrecht.
2701. Woolley, S. C. & Howard, P. N. (2017). *Computational Propaganda Worldwide: Executive Summary*.
2702. Woolley, S. C., & Howard, P. N. (2016). *Political Communication, Computational Propaganda, and Autonomous Agents*. *International Journal of Communication*, 10, 4882–48908.

2703. Kollanyi, B., Howard, P. N., & Woolley, S.C. (2016). Bots and Automation over Twitter during the U.S. Election. Data Memo Oxford, UK: Project on Computational Propaganda.
2704. Badawy, A., Ferrara, E., & Lerman, K. (2018). Analyzing the digital traces of political manipulation: The 2016 Russian interference Twitter campaign. IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM).
2705. Bolsover, G. & Howard, P. (2019). Chinese computational propaganda: automation, algorithms and the manipulation of information about Chinese politics on Twitter and Weibo. *Information, Communication & Society*, 22:14, 2063-2080, DOI:10.1080/1369118X.2018.1476576
2706. Woolley, S. C. & Howard, P. N. (2017). Computational Propaganda Worldwide: Executive Summary.
2707. Corneliu Bjola. (2017). Propaganda in the digital age. *Global Affairs*, 3:3, 189-191, DOI:10.1080/23340460.2017.1427694
2708. Bakir, V. & McStay, A. (2018). Fake News and The Economy of Emotions. *Digital Journalism*, 6:2, 154-175, DOI:10.1080/21670811.2017.1345645
2709. Dagim Afework Mekonnen. (2020). Computational Propaganda : A detriment to Democracy. <https://doi.org/10.25598>
2710. Ferrara, E., Chang, H., Chen, E., Muric, G., & Patel, J. (2020). Characterizing social media manipulation in the 2020 U.S. presidential election. *First Monday*, 25(11). <https://doi.org/10.5210/fm.v25i11.11431>
2711. Howard, P. N & Kollanyi, B. (2017). Bots, #StrongerIn and #Brexit: Computational Propaganda during the UK-EU Referendum. ArXiv:1606.06356 - Physics - . <http://arxiv.org/abs/1606.0635617>.
2712. Woolley, S. C. (2016). Automating power: Social bot interference in global politics. *First Monday*, 21(4). <https://doi.org/10.5210/fm.v21i4.6161>
2713. Metaxas, P. T., & Mustafaraj, E. (2012). Social Media and the Elections. *Science*, 338(6106), 472–473
2714. Woolley, S. C. & Guilbeault, D. R. (2017). Computational Propaganda in the United States of America: Manufacturing Consensus Online. Oxford, UK: Project on Computational Propaganda.
2715. Grimme, C., Preuss, M., Adam, L. and Trautmann, H. (2017). Social bots: Human-like by means of human control? *Big data* 5(4):279-293.
2716. @DFRLab. (2017, September 15). #BotSpot: Twelve ways to spot a bot. Retrieved from <https://medium.com/dfrlab/botspot-twelve-ways-to-spot-a-bot-aedc7d9c110c>
2717. Yan, H. Y, Yang, K. C., Menczer, F. & Shanahan, J. (2020). Asymmetrical perceptions of partisan political bots. *New Media and Society*, 1461444820942744. <https://doi.org/10.1177/1461444820942744>
2718. Ferrara, E., Varol, O., Davis, C., Menczer, F., & Flammini, A. (2016). The rise of social bots. *Communications of the ACM*, 59(7), 96-104. <https://doi.org/10.1145/2818717>
2719. Varol, O., Ferrara, E., Davis, C. A, Menczer, F. & Flammini, A. (2017). Online Human-Bot Interactions: Detection, Estimation, and Characterization. arXiv:1703.03107 - cs.SI -

2720. Chavoshi, N., Hamooni, H. & Mueen, A. (2016). Debot: Twitter bot detection via warped correlation. In *Int. Conf. Data Mining (ICDM)*, 817–822.26.
2721. Cresci, S., Di Pietro, R., Petrocchi, M., Spognardi, A. and Tesconi, M. (2016). Dna-inspired online behavioral modeling and its application to spambot detection. *IEEE Intel. Sys.* 31(5):58–64.
2722. Chen, Z. & Subramanian, D. (2018). An unsupervised approach to detect spam campaigns that use botnets on Twitter. Preprint 1804.05232, arXiv.
2723. Jiang, M., Cui, P., Beutel, A., Faloutsos, C. and Yang, S. (2016). Catching synchronized behaviors in large networks: A graph mining approach. *ACM TKDD* 10(4):35
2724. Ferrara, E. (2017). Disinformation and social bot operations in the run up to the 2017 french presidential election. *First Monday* 22(8).
2725. Stella, M., Ferrara, E. and De Domenico, M. (2018). Bots increase exposure to negative and inflammatory content in online social systems. *PNAS* 115(49):12435–12440.
2726. Yang, K.-C., Varol, O., Hui, P.-M., & Menczer, F. (2020). Scalable and Generalizable Social Bot Detection through Data Selection. *Proceedings of the AAAI Conference on Artificial Intelligence*, 34(01), 1096-1103. <https://doi.org/10.1609/aaai.v34i01.5460>
2727. Guilbeault, Douglas. (2016). Growing Bot Security: An Ecological View of Bot Agency. *The International Journal of Communication*, 10, 5003-5021
2728. Cresci, S. (2020, October 1). A Decade of Social Bot Detection. October 2020 | *Communications of the ACM*. <https://cacm.acm.org/magazines/2020/10/247598-a-decade-of-social-bot-detection/fulltext>
2729. Pacheco, D., Hui, P., Torres-Lugo, C., Truong, B. T., Flammini, A. & Menczer, F. (2021). Uncovering Coordinated Networks on Social Media. In *Proc. AAAI InternationalConference on Web and Social Media (ICWSM)*. Forthcoming. Preprint arXiv:2001.05658
2730. Kelion, B. L. (2020, September 1). Deepfake detection tool unveiled by Microsoft. *BBC News*. <https://www.bbc.com/news/technology53984114>
2731. E. M. Rogers and D. G. Cartano, “Living Research Methods of Measuring Opinion Leadership,” *Public Opinion Quarterly*, vol. 3, no. 26, pp. 435–441, 1962.
2732. E. M. Rogers, *Difussion of Innovations*. 1962.
2733. M. J. Lovett, R. Peres, and R. Shachar, “On brands and word of mouth,” *Journal of Marketing Research*, vol. 50, no. 4, pp. 427–444, 2013.
2734. F. Bodendorf and C. Kaiser, “Detecting Opinion Leaders and Trends in Online Communities,” *2010 Fourth International Conference on Digital Society*, pp. 124–129, Feb. 2010.
2735. D. Eccleston and L. Griseri, “How does Web 2.0 stretch traditional influencing patterns?,” *International Journal of Market Research*, vol. 50, no. 5, pp. 575–590, 2008.
2736. C. Lee, H. Kwak, H. Park, and S. Moon, “Finding influentials based on the temporal order of information adoption in twitter,” *Proceedings of the 19th international conference on World wide web - WWW ’10*, p. 1137, 2010.

2737. H. Kwak, C. Lee, H. Park, and S. Moon, "Finding influentials from the order of information adoption and effective readers in Twitter," in Proceedings of the 19th world wide web conference, 2010.
2738. C. Kiss and M. Bichler, "Identification of influencers – Measuring influence in customer networks," *Decision Support Systems*, vol. 46, pp. 233–253, Dec. 2008.
2739. Tunkelang, D. (2009), A twitter analog to PageRank. <https://thenoisychannel.com/2009/01/13/a-twitter-analog-to-pagerank/l..>
2740. J. Weng, E.-p. Lim, and J. Jiang, "TwitterRank : Finding Topic-Sensitive Influential Twitterers TwitterRank : Finding Topic-sensitive Influential Twitterers," pp. 261–270, 2010.
2741. S. L. Hakimi, "Optimum Locations of Switching Centers and the Absolute Centers and Medians of a Graph," *Operations Research*, vol. 12, no. 3, pp. 450–459, 1964.
2742. G. Sabidussi, "The centrality index of a graph," *Psychometrika*, vol. 31, no. 4, pp. 581–603, 1966.
2743. L. C. Freeman, "A Set of Measures of Centrality Based on Betweenness," *Sociometry*, vol. 40, pp. 35–41, Mar. 1977.
2744. L. Page and S. Brin, "The PageRank Citation Ranking: Bringing Order to the Web," pp. 1–17, 1998.
2745. S. Brin and L. Page, "The anatomy of a large-scale hypertextual Web search engine," *Computer Networks and ISDN Systems*, vol. 30, pp. 107–117, Apr. 1998.
2746. J. M. Kleinberg, "Authoritative Sources in a Hyperlinked Environment," in Proceedings of the ninth annual ACM-SIAM symposium on discrete algorithms, no. May 1997, pp. 668–677, 1998.
2747. D. Kempe, J. Kleinberg, and E. Tardos, "Maximizing the spread of influence through a social network," Proceedings of the ninth ACM SIGKDD international conference on Knowledge discovery and data mining - KDD '03, p. 137, 2003.
2748. M. Granovetter, "Threshold models of collective behavior," *American Journal of Sociology*, vol. 6, no. 83, pp. 1420–1443, 1978.
2749. T. Schelling, *Micromotives and Macrobehavior*. 1978.
2750. T. H. Haveliwala, "Topic-sensitive PageRank," Proceedings of the eleventh international conference on World Wide Web - WWW '02, p. 517, 2002.
2751. L. R. Flynn, R. E. Goldsmith, and J. K. Eastman, "Opinion leaders and opinion seekers: two new measurement scales," *Journal of the Academy of Marketing Science*, vol. 24, no. 2, pp. 137–147, 1996.
2752. Gottfried, J. & Shearer, E. News use across social media platforms 2016. White Paper, Pew Research Center (2016). <http://www.journalism.org/2016/05/26/news-use-across-social-media-platforms-2016/>
2753. Vosoughi, S., Roy, D. & Aral, S. The spread of true and false news online. *Science* 359, 1146–1151 (2018).
2754. Markines, B., Cattuto, C. & Menczer, F. Social spam detection. In Proc. 5th International Workshop on Adversarial Information Retrieval on the Web (AIRWeb) (ACM, New York, 2009).

2755. Mustafaraj, E. & Metaxas, P. T. From obscurity to prominence in minutes: Political speech and real-time search. In Proc. Web Science Conference: Extending the Frontiers of Society On-Line (Raleigh, 2010).
2756. Ratkiewicz, J. et al. Detecting and tracking political abuse in social media. In Proc. 5th International AAAI Conference on Weblogs and Social Media (ICWSM) (AAAI, Palo Alto, 2011).
2757. Howell, L. et al. Digital wildfires in a hyperconnected world. In Global Risks (World Economic Forum, 2013).
2758. Gu, L., Kropotov, V. & Yarochkin, F. The fake news machine: how propagandists abuse the internet and manipulate the public. TrendLabs Research Paper, Trend Micro (2017). https://documents.trendmicro.com/assets/white_papers/wpfake-newsmachinehowpropagandistsabusetheinternet.pdf.
2759. Allcott, H. & Gentzkow, M. Social media and fake news in the 2016 election. J. Econ. Perspect. 31, 211–236 (2017).
2760. Hotez, P. J. Texas and its measles epidemics. PLoS Med. 13, e1002153 (2016).
2761. Ferrara, E., Varol, O., Davis, C., Menczer, F. & Flammini, A. The rise of social bots. Comm. ACM 59, 96–104 (2016).
2762. Lazer, D. et al. The science of fake news. Science 359, 1094–1096 (2018).
2763. Weng, L., Flammini, A., Vespignani, A. & Menczer, F. Competition among memes in a world with limited attention. Sci. Rep. 2, 335 (2012).
2764. Sunstein, C. R. Going to Extremes: How Like Minds Unite and Divide (Oxford University Press, Oxford, 2009).
2765. Pariser, E. The Filter Bubble: How the New Personalized Web Is Changing What We Read and How We Think (Penguin, New York, 2011).
2766. Nikolov, D., Lalmas, M., Flammini, A. & Menczer, F. Quantifying biases in online information exposure. J. Am. Soc. Inform. Sci. Technol. Preprint at <https://arxiv.org/abs/1807.06958> (2018).
2767. Conover, M. D., Gonçalves, B., Flammini, A. & Menczer, F. Partisan asymmetries in online political activity. EPJ Data Sci. 1, 6 (2012).
2768. Conover, M. et al. Political polarization on Twitter. In Proc. 5th International AAAI Conference on Weblogs and Social Media (ICWSM) (AAAI, Barcelona, 2011).
2769. Salganik, M. J., Dodds, P. S. & Watts, D. J. Experimental study of inequality and unpredictability in an artificial cultural market. Science 311, 854–856 (2006).
2770. Hodas, N. O. & Lerman, K. How limited visibility and divided attention constrain social contagion. In Proc. ASE/IEEE International Conference on Social Computing (IEEE Computer Society, Washington, 2012).
2771. Ciampaglia, G. L., Nematzadeh, A., Menczer, F. & Flammini, A. How algorithmic popularity bias hinders or promotes quality. Sci. Rep. 8, 15951 (2018).
2772. Stroud, N. Niche News: The Politics of News Choice (Oxford University Press, Oxford, 2011).

2773. Kahan, D. M. Ideology, motivated reasoning, and cognitive reflection. *Judgm. Decis. Mak.* 8, 407–424 (2013).
2774. Levendusky, M. S. Why do partisan media polarize viewers? *Am. J. Pol. Sci.* 57, 611–623 (2013).
2775. Lippmann, W. *Public Opinion* (Harcourt, Brace and Company, New York, 1922).
2776. Weedon, J., Nuland, W. & Stamos, A. Information Operations and Facebook. White paper, Facebook (2017). <https://fbnewsroomus.files.wordpress.com/2017/04/facebook-and-information-operations-v1.pdf>.
2777. Varol, O., Ferrara, E., Davis, C. A., Menczer, F. & Flammini, A. Online human-bot interactions: detection, estimation, and characterization. In *Proc. Intl. AAAI Conf. on Web and Social Media (ICWSM)* (AAAI, Palo Alto, 2017).
2778. Subrahmanian, V. et al. The DARPA Twitter Bot Challenge. *IEEE Comput.* 49, 38–46 (2016).
2779. Jun, Y., Meng, R. & Johar, G. V. Perceived social presence reduces fact-checking. *Proc. Natl Acad. Sci. USA* 114, 5976–5981 (2017).
2780. Jagatic, T., Johnson, N., Jakobsson, M. & Menczer, F. Social phishing. *Commun. ACM* 50, 94–100 (2007).
2781. Bessi, A. & Ferrara, E. Social bots distort the 2016 US presidential election online discussion. *First Monday* 21, 11 (2016).
2782. Woolley, S. C. & Howard, P. N. Computational propaganda worldwide: Executive summary. Working Paper 2017.11 (Oxford Internet Institute Oxford, 2017).
2783. Ferrara, E. Disinformation and Social Bot Operations in the Run Up to the 2017 French Presidential Election. *First Monday* 22, 8 (2017).
2784. Shao, C. et al. Anatomy of an online misinformation network. *PLoS ONE* 13, e0196087 (2018).
2785. Albert, R., Jeong, H. & Barabási, A.-L. Error and attack tolerance of complex networks. *Nature* 406, 378–382 (2000).
2786. Mosseri, A. News feed fyi: showing more informative links in news feed. Press release, Facebook (2017). <https://newsroom.fb.com/news/2017/06/newsfeedfyishowingmoreinformativelinksinnewsfeed/>
2787. Del Vicario, M. et al. The spreading of misinformation online. *Proc. Natl Acad. Sci. USA* 113, 554–559 (2016).
2788. Lewandowsky, S., Ecker, U. K. & Cook, J. Beyond misinformation: understanding and coping with the “post-truth” era. *J. Appl. Res. Mem. Cogn.* 6, 353–369 (2017).
2789. 38. von Ahn, L., Blum, M., Hopper, N. J. & Langford, J. Captcha: Using hard AI problems for security. In *Advances in Cryptology — Proceedings of EUROCRYPT 2003: International Conference on the Theory and Applications of Cryptographic Techniques* (ed. Biham, E.) 294–311 (Springer, Heidelberg, 2003).
2790. Wardle, C. Fake news. It’s complicated. White Paper, First Draft News (2017). <https://firstdraftnews.com/fake-news-complicated/>

2791. Wojcik, S., Messing, S., Smith, A., Rainie, L. & Hitlin, P. Bots in the twittersphere. White Paper, Pew Research Center (2018). <http://www.pewinternet.org/2018/04/09/bots-in-the-twittersphere/>
2792. Ahmed, F.; and Abulaish, M. 2013. A generic statistical approach for spam detection in online social networks. *Computer Communications*, 36(10-11): 1120–1129.
2793. Alsaleh, M.; Alarif, A.; Al-Salman, A. M.; Alfayez, M.; and Almuhaysin, A. 2014. Tsd: Detecting sybil accounts in twitter. In 2014 13th International Conference on Machine Learning and Applications, 463–469. IEEE.
2794. Antonakaki, D.; Spiliotopoulos, D.; V. Samaras, C.; Pratikakis, P.; Ioannidis, S.; and Fragopoulou, P. 2017. Social media analysis during political turbulence. *PloS one*, 12(10): e0186836.
2795. Arnaudo, D. 2017. Computational propaganda in Brazil: Social bots during elections. Computational propaganda research project - University of Oxford.
2796. Badawy, A.; Ferrara, E.; and Lerman, K. 2018. Analyzing the digital traces of political manipulation: The 2016 Russian interference Twitter campaign. In 2018 IEEE/ACM international conference on advances in social networks analysis and mining (ASONAM), 258–265. IEEE.
2797. Bastian, M.; Heymann, S.; and Jacomy, M. 2009. Gephi: An Open Source Software for Exploring and Manipulating Networks. *International AAAI Conference on Weblogs and Social Media*.
2798. Batista, G. E. A. P. A.; Prati, R. C.; and Monard, M. C. 2004. A Study of the Behavior of Several Methods for Balancing Machine Learning Training Data. *SIGKDD Explor. Newsl.*, 6(1): 20–29.
2799. Bolsover, G.; and Howard, P. 2019. Chinese computational propaganda: automation, algorithms and the manipulation of information about Chinese politics on Twitter and Weibo. *Information, communication & society*, 22(14): 2063–2080.
2800. Bouzy, C. 2021. Bot Sentinel. <https://rb.gy/wfymew>. Accessed: 2021-04-19.
2801. Bovet, A.; and Makse, H. A. 2019. Influence of fake news in Twitter during the 2016 US presidential election. *Nature Communications*, 10(1): 7.
2802. Breiman, L. 2001. Random Forests. *Machine Learning*, 45(1): 5–32.
2803. Broniatowski, D. A.; Jamison, A. M.; Qi, S.; AlKulaib, L.; Chen, T.; Benton, A.; Quinn, S. C.; and Dredze, M. 2018. Weaponized health communication: Twitter bots and Russian trolls amplify the vaccine debate. *American journal of public health*, 108(10): 1378–1384.
2804. Burnap, P.; and Williams, M. L. 2015. Cyber hate speech on twitter: An application of machine classification and statistical modeling for policy and decision making. *Policy & Internet*, 7(2): 223–242.
2805. Byrnes, N. 2016. How the bot-y politic influenced this election. *Technology Rev.*, 100(10).
2806. Chatfeld, A. T.; Reddick, C. G.; and Brajawidagda, U. 2015. Tweeting Propaganda, Radicalization and Recruitment: Islamic State Supporters Multi-Sided Twitter Networks. In *Proceedings of the 16th Annual International Conference on Digital Government Research*,

- dg.o '15, 239–249. New York, NY, USA: Association for Computing Machinery. ISBN 9781450336000.
2807. Chavoshi, N.; Hamooni, H.; and Mueen, A. 2016. Identifying correlated bots in twitter. In *International conference on social informatics*, 14–21. Springer, Springer.
 2808. Chen, T.; and Guestrin, C. 2016. XGBoost: A Scalable Tree Boosting System. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD '16*, 785–794. New York, NY, USA: Association for Computing Machinery. ISBN 9781450342322.
 2809. Chu, Z.; Gianvecchio, S.; Wang, H.; and Jajodia, S. 2010. Who is tweeting on Twitter: human, bot, or cyborg? In *Proceedings of the 26th annual computer security applications conference*, 21–30.
 2810. Chu, Z.; Gianvecchio, S.; Wang, H.; and Jajodia, S. 2012. Detecting automation of twitter accounts: Are you a human, bot, or cyborg? *IEEE Transactions on Dependable and Secure Computing*, 9(6): 811–824.
 2811. Church, K. W. 2017. Word2Vec. *Natural Language Engineering*, 23(1): 155–162.
 2812. Cortes, C.; and Vapnik, V. 1995. Support-vector networks. *Machine learning*, 20(3): 273–297.
 2813. Cresci, S.; Di Pietro, R.; Petrocchi, M.; Spognardi, A.; and Tesconi, M. 2017. The paradigm-shift of social spambots: Evidence, theories, and tools for the arms race. In *Proceedings of the 26th international conference on world wide web companion*, 963–972. ACM.
 2814. Davis, C. A.; Varol, O.; Ferrara, E.; Flammini, A.; and Menczer, F. 2016. BotOrNot: A System to Evaluate Social Bots. In *Proceedings of the 25th International Conference Companion on World Wide Web*, 273–274.
 2815. Dickerson, J. P.; Kagan, V.; and Subrahmanian, V. S. 2014. Using sentiment to detect bots on Twitter: Are humans more opinionated than bots? In *2014 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM 2014)*, 620–627. IEEE/ACM.
 2816. Edwards, C.; Edwards, A.; Spence, P. R.; and Shelton, A. K. 2014. Is that a bot running the social media feed? Testing the differences in perceptions of communication quality for a human agent and a bot agent on Twitter. *Computers in Human Behavior*, 33: 372–376.
 2817. Feng, Y.; Li, J.; Jiao, L.; and Wu, X. 2020. Towards Learning-Based, Content-Agnostic Detection of Social Bot Traffic. *IEEE Transactions on Dependable and Secure Computing*, 7(3): 3.
 2818. Ferrara, E. 2017. Disinformation and social bot operations in the run up to the 2017 French presidential election. *First Monday*.
 2819. Ferrara, E.; Varol, O.; Davis, C.; Menczer, F.; and Flammini, A. 2016. The rise of social bots. *Communications of the ACM*, 59(7): 96–104.
 2820. Fortuna, P.; and Nunes, S. 2018. A survey on automatic detection of hate speech in text. *ACM Computing Surveys (CSUR)*, 51(4): 1–30.

2821. Founta, A.; Djouvas, C.; Chatzakou, D.; Leontiadis, I.; Blackburn, J.; Stringhini, G.; Vakali, A.; Sirivianos, M.; and Kourtellis, N. 2018. Large Scale Crowdsourcing and Characterization of Twitter Abusive Behavior. CoRR, abs/1802.00393: 5.
2822. Fraiser, O.; Cabanac, G.; Pitarch, Y.; Besancon, R.; and Boughanem, M. 2018. #Elysee2017fr: The 2017 French Presidential Campaign on Twitter. In International AAAI Conference on Web and Social Media (ICWSM '18). Garimella, K.; and Weber, I. 2017. A Long-Term Analysis of Polarization on Twitter. icwsm, 145–152.
2823. Gilani, Z.; Kochmar, E.; and Crowcroft, J. 2017. Classification of twitter accounts into automated agents and human users. In Proceedings of the 2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2017, 489–496. IEEE/ACM.
2824. Gilani, Z.; Wang, L.; Crowcroft, J.; Almeida, M.; and Farahbakhsh, R. 2016. Stweeler: A Framework for Twitter Bot Analysis. In Proceedings of the 25th International Conference Companion on World Wide Web, 37–38.
2825. Golovchenko, Y.; Buntain, C.; Eady, G.; Brown, M. A.; and Tucker, J. A. 2020. Cross-Platform State Propaganda: Russian Trolls on Twitter and YouTube During the 2016 US Presidential Election. The International Journal of Press/Politics, 21(3): 1940161220912682.
2826. Hegelich, S.; and Janetzko, D. 2016. Are social bots on Twitter political actors? Empirical evidence from a Ukrainian social botnet. In Proceedings of the International AAAI Conference on Web and Social Media, volume 10.
2827. Howard, P. N.; Bolsover, G.; Kollanyi, B.; Bradshaw, S.; and Neudert, L.-M. 2017a. Junk news and bots during the US election: What were Michigan voters sharing over Twitter. CompProp, OII, Data Memo, 21(3): 8.
2828. Howard, P. N.; Bradshaw, S.; Kollanyi, B.; and Bolsolver, G. 2017b. Junk News and Bots during the French Presidential Election: What Are French Voters Sharing Over Twitter In Round Two? ComProp data memo, 21(3): 8.
2829. Howard, P. N.; Kollanyi, B.; and Woolley, S. 2016. Bots and Automation over Twitter during the US Election. Computational Propaganda Project: Working Paper Series, 21: 8.
2830. Howard, P. N.; Woolley, S.; and Calo, R. 2018. Algorithms, bots, and political communication in the US 2016 election: The challenge of automated political communication for election law and administration. Journal of information technology & politics, 15(2): 81–93.
2831. Hui, P.-M.; Yang, K.-C.; Torres-Lugo, C.; and Menczer, F. 2020. BotSlayer: DIY Real-Time Influence Campaign Detection. In Proceedings of the International AAAI Conference on Web and Social Media, volume 14, 980–982.
2832. Ibrahim, M.; Abdillahi, O.; Wicaksono, A. F.; and Adriani, M. 2015. Buzzer Detection and Sentiment Analysis for Predicting Presidential Election Results in a Twitter Nation. In 2015 IEEE International Conference on Data Mining Workshop (ICDMW), 1348–1353.
2833. Illing, S. 2018. Cambridge Analytica, the shady data firm that might be a key Trump-Russia link, explained. <https://rb.gy/zhcpm0>. Accessed: 2021-04-19.
2834. Jones, M. O. 2019. The gulf information war— propaganda, fake news, and fake trends: The weaponization of twitter bots in the gulf crisis. International journal of communication, 13: 27.

2835. Keller, F. B.; Schoch, D.; Stier, S.; and Yang, J. 2017. How to manipulate social media: Analyzing political astroturfing using ground truth data from South Korea. In Eleventh International AAAI Conference on Web and Social Media, 811–824. AAAI.
2836. Keller, T. R.; and Klinger, U. 2019. Social Bots in Election Campaigns: Theoretical, Empirical, and Methodological Implications. *Political Communication*, 36(1): 171–189.
2837. Krebs, B. 2011. Twitter bots drown out anti-Kremlin tweets. <https://rb.gy/xpaoze>.
2838. Lee, K.; Caverlee, J.; and Webb, S. 2010. Uncovering social spammers: social honeypots+ machine learning. In Proceedings of the 33rd international ACM SIGIR conference on Research and development in information retrieval, 435–442. ACM.
2839. Lightfoot, S.; and Jacobs, S. 2017. Political propaganda spread through social bots. *Media, Culture, & Global Politics*, 8: 1–22.
2840. Loyola-Gonzalez, O.; Monroy, R.; Rodriguez, J.; Lopez- Cuevas, A.; and Mata-Sanchez, J. I. 2019. Contrast pattern- based classification for bot detection on Twitter. *IEEE Access*, 7: 45800–45817.
2841. Luceri, L.; Deb, A.; Giordano, S.; and Ferrara, E. 2019. Evolution of bot and human behavior during elections. *First Monday*.
2842. Lundberg, S.; and Lee, S.-I. 2017. A unified approach to interpreting model predictions. *arXiv preprint arXiv:1705.07874*.
2843. Mazza, M.; Cresci, S.; Avvenuti, M.; Quattrociocchi, W.; and Tesconi, M. 2019. Rtbust: Exploiting temporal patterns for botnet detection on twitter. In Proceedings of the 10th ACM Conference on Web Science, 183–192. ACM.
2844. Neudert, L.; Kollanyi, B.; and Howard, P. N. 2017. Junk news and bots during the german parliamentary election: What are german voters sharing over twitter? *Computational Propaganda - University of Oxford*, 21(3): 8.
2845. Osome. 2020. Botometer (formerly BotOrNot) checks the activity of a Twitter account and gives it a score. Higher scores mean more bot-like activity. <https://rb.gy/0hmi4x>.
2846. Rajaraman, A.; and Ullman, J. D. 2011. *Data Mining*, 1–17. Cambridge University Press.
2847. Rizoiu, M.-A.; Graham, T.; Zhang, R.; Zhang, Y.; Ackland, R.; and Xie, L. 2018. #DebateNight: The Role and Influence of Socialbots on Twitter During the 1st 2016 U.S. Presidential Debate. In International AAAI Conference on Web and Social Media (ICWSM '18).
2848. ScikitLearn. 2022. Scikit-learn function: SelectFromModel. <https://rb.gy/kipojk>.
2849. Seo, H. 2014. Visual propaganda in the age of social media: An empirical analysis of Twitter images during the 2012 Israeli–Hammas conflict. *Visual Communication Quarterly*, 21(3): 150–161.
2850. Shane, S. 2017. The fake Americans Russia created to influence the election. *The New York Times*, 7(09).
2851. Shao, C.; Ciampaglia, G. L.; Varol, O.; Yang, K.-C.; Flammini, A.; and Menczer, F. 2018. The spread of lowcredibility content by social bots. *Nature communications*, 9(1): 1–9.
2852. Shapley, L. S. 1953. A value for n-person games. *Contrib. Theory Games*, 2: 307–317.

2853. Sharma, K.; Qian, F.; Jiang, H.; Ruchansky, N.; Zhang, M.; and Liu, Y. 2019. Combating fake news: A survey on identification and mitigation techniques. *ACM Transactions on Intelligent Systems and Technology (TIST)*, 10(3): 1–42.
2854. Stella, M.; Ferrara, E.; and De Domenico, M. 2018. Bots increase exposure to negative and inflammatory content in online social systems. *Proceedings of the National Academy of Sciences*, 115(49): 12435–12440.
2855. Stukal, D.; Sanovich, S.; Bonneau, R.; and Tucker, J. A. 2017. Detecting bots on Russian political Twitter. *Big data*, 5(4): 310–324.
2856. Subrahmanian, V.; Azaria, A.; Durst, S.; Kagan, V.; Galstyan, A.; Lerman, K.; Zhu, L.; Ferrara, E.; Flammini, A.; and Menczer, F. 2016. The DARPA Twitter Bot Challenge. *Computer*, 49(6): 38–46.
2857. Tibshirani, R. 1994. Regression Shrinkage and Selection Via the Lasso. *Journal of the Royal Statistical Society: Series B (Methodological)*, 58: 267–288.
2858. USBotDetection. 2022. GitHub Repository including code and dataset. <https://github.com/alexdrk14/USBotDetection>.
2859. Varol, O.; Ferrara, E.; Davis, C. A.; Menczer, F.; and Flammini, A. 2017. Online human-bot interactions: Detection, estimation, and characterization. In *International AAAI Conference on Web and Social Media (ICWSM '17)*, 280– 289.
2860. Vosoughi, S.; Roy, D.; and Aral, S. 2018. The spread of true and false news online. *Science*, 359(6380): 1146–1151.
2861. Wald, R.; Khoshgoftaar, T. M.; Napolitano, A.; and Sumner, C. 2013. Predicting susceptibility to social bots on twitter. In *2013 IEEE 14th International Conference on Information Reuse & Integration (IRI)*, 6–13. IEEE.
2862. Waugh, B.; Abdipanah, M.; Hashemi, O.; Rahman, S. A.; and Cook, D. M. 2013. The Influence and Deception of Twitter: the authenticity of the narrative and slacktivism in the Australian electoral process. In *14th Australian Information Warfare Conference*, 28–38.
2863. Yang, K.-C.; Varol, O.; Davis, C. A.; Ferrara, E.; Flammini, A.; and Menczer, F. 2019. Arming the public with artificial intelligence to counter social bots. *Human Behavior and Emerging Technologies*, 1(1): 48–61.
2864. Yang, K.-C.; Varol, O.; Hui, P.-M.; and Menczer, F. 2020. Scalable and Generalizable Social Bot Detection through Data Selection. In *Proceedings of the AAAI Conference on Artificial Intelligence*, 1096–1103. AAAI.
2865. Yaqub, U.; Chun, S. A.; Atluri, V.; and Vaidya, J. 2017. Analysis of political discourse on twitter in the context of the 2016 US presidential elections. *Government Information Quarterly*, 34(4): 613–626.
2866. Zhang, C. M.; and Paxson, V. 2011. Detecting and analyzing automated activity on twitter. In *International Conference on Passive and Active Network Measurement*, 102–111. Springer.
2867. Giovanidis, A., Baynat, B., and Vendeville, A. (2019), Performance analysis of online social platforms, In *Proceedings of the IEEE Conference on Computer Communications (INFOCOM 2019)*, pp. 2413–2421, Paris, France.

2868. Althof, T., Borth, D., Hees, J., and Dengel, A. (2013), Analysis and forecasting of trending topics in online media streams, In Proceedings of the 21st ACM International Conference on Multimedia, p. 907916, Barcelona, Spain.
2869. Xu, Q. A., Chang, V., and Jayne, C. (2022), A systematic review of social media-based sentiment analysis: Emerging trends and challenges, *Decision Analytics Journal* (Open access), 3(2022), 100073.
2870. Aguilar-Gallegos, N., Klerkx, L., Romero-Garca, L. E., Martnez-Gonzlez, E. G., and Aguilar-vila, J. (2022), Social network analysis of spreading and exchanging information on Twitter: The case of an agricultural research and education centre in Mexico, *The Journal of Agricultural Education and Extension*, 28(1), 115–136.
2871. Fuentes-Fernndez, R., Gmez-Sanz, J. J., and Pavn, J. (2012), User-oriented analysis of interactions in online social networks, *IEEE Intelligent Systems*, 27(4), 18–25.
2872. Techopedia (2013), Twitter. <https://www.techopedia.com/definition/4957/twitter>. - Online; Last Accessed: 20-April-2021 - .
2873. Walsh, S. (2022), The top 10 social media sites and platforms 2022. <https://www.searchenginejournal.com/social-media/top-sites-platforms/#close>. - Online; Last Accessed: 27-May-2022 - .
2874. Sehl, K. (2020), Top twitter demographics that matter to social media marketers. <https://blog.hootsuite.com/twitter-demographics/>. - Online; Last Accessed: 27-May-2022 - .
2875. Merriam-Webster, URL. <https://www.merriam-webster.com/dictionary/URL>. - Online; Last Accessed: 21-June-2022 - .
2876. Gil, P. (2020), What is twitter and how does it work? <https://www.lifewire.com/what-exactly-is-twitter-2483331>. - Online; Last Accessed: 27-May-2022 - .
2877. Sayce, D. (2020), The number of tweets per day in 2020. <https://www.dsayce.com/social-media/tweets-day/>. - Online; Last Accessed: 27-May-2022 - .
2878. Martin, N. (2018), How social media has changed how we consume news. <https://www.forbes.com/sites/nicolemartin1/2018/11/30/how-social-media-has-changed-how-we-consume-news/?sh=32c019df3c3c>. - Online; Last Accessed: 20-April-2021 - .
2879. Phan, H. T., Dang, D. T., Nguyen, N. T., and Hwang, D. (2020), A new approach for predicting an important user on a topic on Twitter, In Proceedings of the 2020 International Conference on INnovations in Intelligent SysTems and Applications (INISTA), pp. 1–6, Online conference.
2880. Essaidi, A., Zaidouni, D., and Bellafkih, M. (2020), New method to measure the infuence of Twitter users, In Proceedings of the 2020 Fourth International Conference On Intelligent Computing in Data Sciences (ICDS), pp. 1–5, Online conference.
2881. Liu, N., Li, L., Xu, G., and Yang, Z. (2014), Identifying domain-dependent influential microblog users: A post-feature based approach, In Proceedings of the 28th AAAI Conference on Artificial Intelligence, Vol. 28, pp. 3122–3123, Qubec City, Qubec, Canada.
2882. Bouguessa, M. and Romdhane, L. (2015), Identifying authorities in online communities, *ACM Transactions on Intelligent Systems and Technology*, 6(3), 1–23.

2883. Li, J., Peng, W., Li, T., Sun, T., Li, Q., and Xu, J. (2014), Social network user influence sense-making and dynamics prediction, *Expert Systems with Applications*, 41(11), 5115–5124.
2884. Solis, B. (2012), The pillars of influence and how to activate cause and effect. <https://www.socialmediatoday.com/content/pillars-influence-and-how-activate-cause-and-effect>. - Online; Last Accessed: 27-May-2022 - .
2885. Varol, O., Ferrara, E., Davis, C. A., Menczer, F., and Flammini, A. (2017), Online human-bot interactions: Detection, estimation, and characterization, In *Proceedings of the Eleventh International AAAI Conference on Web and Social Media (ICWSM2017)*, pp. 280–289, Montreal Canada.
2886. ThoughtCo. (2020), What is astroturfing in politics? Definition and examples. <https://www.thoughtco.com/what-is-astroturfing-definition-and-examples-5082082>. - Online; Last Accessed: 20-April-2021 - .
2887. Kempe, D., Kleinberg, J., and Tardos, E. (2003), Maximizing the spread of influence through a social network, In *Proceedings of the Ninth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining(KDD '03)*, p. 137146, Washington, D.C., USA: Association for Computing Machinery.
2888. WolframMathWorld, NP-Hard Problem. <https://mathworld.wolfram.com/NP-HardProblem.html>. - Online; Last Accessed: 21-June-2022 - .
2889. More, J. S. and Lingam, C. (2019), A SI model for social media influencer maximization, *Applied Computing and Informatics*, 15(2), 102–108.
2890. Pal, A. and Counts, S. (2011), Identifying topical authorities in microblogs, In *Proceedings of the fourth ACM international conference on Web search and data mining (WSDM '11)*, Hong Kong, China: ACM.
2891. Zhai, Y., Li, X., Chen, J., Fan, X., and Cheung, W. K. (2014), A novel topical authority-based microblog ranking, In *Proceedings of the Web Technologies and Applications 16th Asia-Pacific Web Conference (APWeb 2014)*, pp. 105–116, Changsha, China: Springer International Publishing.
2892. Riquelme, F. and Gonzalez-Cantergiani, P. (2016), Measuring user influence on Twitter: A survey, *Information Processing and Management*, 52(5), 949 – 975.
2893. Danziger, P., Big O notation. <https://www.cs.ryerson.ca/~mth210/Handouts/PD/bigO.pdf>. - Online; Last Accessed: 20-June-2022 - .
2894. Ding, Z., Jia, Y., Zhou, B., and Han, Y. (2013), Mining topical influencers based on the multi-relational network in micro-blogging sites, *China Communications*, 10(1), 93–104.
2895. Purohit, H., Ajmera, J., Joshi, S., Verma, A., and Sheth, A. (2012), Finding influential authors in brand-page communities, In *Proceedings of the International AAAI Conference on Web and Social Media*, pp. 551–554, Dublin, Ireland.
2896. Ben Jabeur, L., Tamine, L., and Boughanem, M. (2012), Active microbloggers: Identifying influencers, leaders and discussers in microblogging networks, In *Proceedings of the 19th International Conference on String Processing and Information Retrieval (SPIRE 2012)*, pp. 111–117, Cartagena Colombia: Springer Berlin Heidelberg.

2897. Kafeza, E., Kanavos, A., Makris, C., and Vikatos, P. (2014), Predicting information diffusion patterns in twitter, In Iliadis, L., Maglogiannis, I., and Papadopoulos, H., (Eds.), Artificial Intelligence Applications and Innovations, pp. 79–89, Berlin, Heidelberg: Springer Berlin Heidelberg.
2898. Kawamoto, T. (2013), A stochastic model of tweet diffusion on the Twitter network, Physica A: Statistical Mechanics and its Applications, 392(16), 3470–3475.
2899. Yang, J. and Counts, S. (2010), Predicting the speed, scale, and range of information diffusion in Twitter, In Proceedings of the Fourth International Conference on Weblogs and Social Media, pp. 355–358, Washington DC, US.
2900. Ding, Z.-y., Jia, Y., Zhou, B., Han, Y., He, L., and Zhang, J.-f. (2013), Measuring the spreadability of users in microblogs, Journal of Zhejiang University SCIENCE C, 14, 701–710.
2901. Costa, L. F., Rodrigues, F. A., Travieso, G., and Boas, P. R. V. (2007), Characterization of complex networks: A survey of measurements, Advances in Physics, 56(1), 167–242.
2902. Barabási, A.-L. and Albert, R. (1999), Emergence of scaling in random networks, Science, 286(5439), 509–512.
2903. Myers, S. A., Sharma, A., Gupta, P., and Lin, J. (2014), Information network or social network?
2904. The structure of the Twitter follow graph, In Proceedings of the 23rd International Conference on World Wide Web, pp. 493–498, Seoul, Korea.
2905. Weng, J., Lim, E.-P., Jiang, J., and He, Q. (2010), TwitterRank: Finding topic-sensitive influential twitterers, In Proceedings of the Third ACM International Conference on Web Search and Data Mining(WSDM '10), p. 261270, New York, NY, USA: Association for Computing Machinery.
2906. Sharma, P., Agarwal, A., and Sardana, N. (2018), Extraction of influencers across Twitter using credibility and trend analysis, In Proceedings of the 2018 Eleventh International Conference on Contemporary Computing (IC3), pp. 1–3, Noida, India.
2907. Razis, G. and Anagnostopoulos, I. (2014), InfluenceTracker: rating the impact of a Twitter account, In Proceedings of the 2014 Artificial Intelligence Applications and Innovations, pp. 184–195, Rhodes, Greece: Springer Berlin Heidelberg.
2908. Zamparas, V., Kanavos, A., and Makris, C. (2015), Real time analytics for measuring user influence on Twitter, In Proceedings of the 2015 IEEE 27th International Conference on Tools with Artificial Intelligence (ICTAI), pp. 591–597, Vietri sul Mare, Italy.
2909. Puigbo, J.-Y., Sanchez, G., Casabayo, M., and Agell, N. (2014), Influencer detection approaches in social networks: A current state-of-the-art, Frontiers in Artificial Intelligence and Applications, 269, 261–264.
2910. Tsugawa, S. (2019), A survey of social network analysis techniques and their applications to socially aware networking, IEICE Transactions on Communications, E102.B(1), 17–39.
2911. Watts, D. J. and Strogatz, S. H. (1998), Collective dynamics of “small-world” networks, Nature, 393, 440–442.
2912. Seidman, S. B. (1983), Network structure and minimum degree, Social Networks, 5(3), 269–287.

2913. Batagelj, V. and Zaversnik, M. (2003), An $O(m)$ algorithm for cores decomposition of networks, *Clinical Orthopaedics and Related Research (CoRR)* (Online), Vol. cs.DS/0310049.
2914. Wang, K., Cao, X., Lin, X., Zhang, W., and Qin, L. (2018), Efficient computing of radius-bounded k -cores, In *Proceedings of the 2018 IEEE 34th International Conference on Data Engineering (ICDE)*, pp. 233–244, Paris, France.
2915. Govind, N. and Lal, R. P. (2021), Evaluating user influence in social networks using k -core, In *Proceedings of the 5th International Conference on Innovative Computing and Communications*, pp. 11–18, Online Conference: Springer Singapore.
2916. IBM Cloud Education (2020), Machine Learning. <https://www.ibm.com/cloud/learn/machine-learning>. - Online; Last Accessed: 22-June-2022 - .
2917. Breiman, L., Friedman, J., Stone, C., and Olshen, R. (1984), *Classification and Regression Trees*, Taylor & Francis.
2918. Cortes, C. and Vapnik, V. (1995), Support-vector networks, *Machine learning*, 20(3), 273–297.
2919. Aggarwal, C. C. (2018), *An introduction to neural networks*, pp. 1–52, Cham: Springer International Publishing.
2920. MacQueen, J. (1967), Classification and analysis of multivariate observations, In *Proceedings of the 5th Berkeley Symposium on Mathematical Statistics and Probability*, pp. 281–297, California USA.
2921. He, K., Zhang, X., Ren, S., and Sun, J. (2016), Deep Residual Learning for Image Recognition, In *Proceedings of the 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 770–778, Las Vegas, NV, USA.
2922. Zheng, C., Zhang, Q., Long, G., Zhang, C., Young, S. D., and Wang, W. (2020), Measuring time-sensitive and topic-specific influence in social networks with LSTM and self-attention, *IEEE Access*, 8, 82481–82492.
2923. Cossu, J.-V., Dugu, N., and Labatut, V. (2015), Detecting real-world influence through Twitter, In *Proceedings of the 2015 Second European Network Intelligence Conference*, pp. 83–90, Karlskrona, Sweden.
2924. Nargundkar, A. and Rao, Y. S. (2016), InfluenceRank: A machine learning approach to measure influence of Twitter users, In *Proceedings of the 2016 International Conference on Recent Trends in Information Technology (ICRTIT)*, pp. 1–6, Bangalore, India.
2925. Katsimpras, G., Vogiatzis, D., and Paliouras, G. (2015), Determining influential users with supervised random walks, In *Proceedings of the 24th International Conference on World Wide Web*, pp. 787–792, Florence Italy.
2926. Estrada, E. and Rodriguez-Velazquez, J. A. (2005), Subgraph centrality in complex networks, *Physical Review E*, 71(5).
2927. Harary, F. (1969), *Graph Theory*, London: Addison-Wesley.
2928. Lancichinetti, A., Kivela, M., Saramki, J., and Fortunato, S. (2010), Characterizing the community structure of complex networks, *PloS One*, 5(8).

2929. Guimera, R. and Amaral, L. A. N. (2005), Cartography of complex networks: modules and universal roles, *Journal of Statistical Mechanics: Theory and Experiment* (Online), 2005(P02001).
2930. Marr, B. (2021), Klout Score. <https://bernardmarr.com/klout-score/>. - Online; Last Accessed: 24-may-2022 - .
2931. Jones, K. (1972), A statistical interpretation of term specificity and its application in retrieval, *Journal of Documentation*, 60, 493–502.
2932. Torres-Moreno, J., El-Beze, M., and Bellot, P. (2012), Opinion detection as a topic classification problem, In Gaussier, E. and Yvon, F., (Eds.), *Textual Information Access: Statistical Models*, Ch. 9, pp. 337–368, John Wiley & Sons, Ltd.
2933. Dempster, A. P., Laird, N. M., and Rubin, D. B. (1977), Maximum likelihood from incomplete data via the EM algorithm, *Journal of the Royal Statistical Society: Series B (Methodological)*, 39(1), 1–22.
2934. Scholkopf, B., Smola, A. J., Williamson, R. C., and Bartlett, P. L. (2000), New support vector algorithms, *Neural Computation*, 12(5), 1207–1245.
2935. Jagarlamudi, J. and Hal Daume Udupa, R. (2012), Incorporating lexical priors into topic models, In *Proceedings of the 13th Conference of the European Chapter of the Association for Computational Linguistics*, pp. 204–213, Avignon, France.
2936. Hochreiter, S. and Schmidhuber, J. (1997), Long short-term memory, *Neural Computation*, 9(8), 1735–80.
2937. Zheng, C., zhang, Q., Young, S., and Wang, W. (2020), On-demand influencer discovery on social media, In *Proceedings of the 29th ACM International Conference on Information and Knowledge Management (CIKM'20)*, pp. 2337–2340, Online conference.
2938. Schuster, M. and Paliwal, K. (1997), Bidirectional recurrent neural networks, *IEEE Transactions on Signal Processing*, 45(11), 2673–2681.
2939. Melo, F. (2013), Area under the ROC curve, In Dubitzky, W., Wolkenhauer, O., Cho, K.-H., and Yokota, H., (Eds.), *Encyclopedia of Systems Biology*, pp. 38–39, New York, NY: Springer New York.
2940. Truong, Q. D., Truong, Q. B., and Dkaki, T. (2016), Graph methods for social network analysis, In Vinh, P. C. and Barolli, L., (Eds.), *Nature of Computation and Communication*, pp. 276–286, Springer International Publishing.
2941. Tabassum, S., Pereira, F. S. F., Fernandes, S., and Gama, J. (2018), Social network analysis: An overview, *WIREs Data Mining and Knowledge Discovery*, 8(5), e1256.
2942. Wasserman, S. and Faust, K. (1994), *Social Network Analysis: Methods and Applications*, Cambridge: Cambridge Univeristy Press.
2943. Yurchuk, I. and Popereshnyak, S. (2021), Social networks: Analysis, algorithms and their implementation, In *Proceedings of the 5th International Conference on Computational Linguistics and Intelligent Systems*, pp. 811–821, Lviv Ukraine.
2944. Brin, S. and Page, L. (1998), The anatomy of a large-scale hypertextual web search engine, *Computer Networks*, 30(1), 107–117.

2945. Page, L., Brin, S., Motwani, R., and Winograd, T. (1999), The PageRank citation ranking: Bringing order to the web., (Technical Report 1999-66) Stanford InfoLab. - Previous number = SIDL-WP-1999-0120 - .
2946. Kleinberg, J. M. (1999), Authoritative sources in a hyperlinked environment, *Journal of the ACM*, 46(5), 604632.
2947. Pujol, J. M., Sanguesa, R., and Delgado, J. (2002), Extracting reputation in multi-agent systems by means of social network topology, In *Proceedings of the First International Joint Conference on Autonomous Agents and Multiagent Systems: Part 1 (AAMAS '02)*, p. 467474, Bologna, Italy: Association for Computing Machinery.
2948. Tunkelang, D. (2009), A twitter analog to PageRank.
<https://thenoisychannel.com/2009/01/13/a-twitter-analog-to-pagerank/>. - Online; Last Accessed: 04-may-2021 - .
2949. Blei, D. M., Ng, A. Y., and Jordan, M. I. (2003), Latent dirichlet allocation, *The Journal of Machine Learning Research*, 3, 9931022.
2950. Yamaguchi, Y., Takahashi, T., Amagasa, T., and Kitagawa, H. (2010), TURank: Twitter user ranking based on user-tweet graph analysis, In *Web Information Systems Engineering (WISE 2010)*, pp. 240–253, Berlin, Heidelberg: Springer Berlin Heidelberg.
2951. Kong, S. and Feng, L. (2011), A tweet-centric approach for topic-specific author ranking in micro-blog, In *Proceedings of the 7th International Conference on Advanced Data Mining and Applications - Volume Part I*, pp. 138–151, Berlin, Heidelberg: Springer Berlin Heidelberg.
2952. Cano, A. E., Mazumdar, D., and Ciravegna, F. (2012), Social influence analysis in microblogging platforms: A topic-sensitive based approach, *Semantic Web*, 5(5), 357–372.
2953. Chien, O. K., Hoong, P. K., and Ho, C. C. (2014), A comparative study of HITS vs PageRank algorithms for Twitter users analysis, In *Proceedings of the 2014 International Conference on Computational Science and Technology (ICCST)*, pp. 1–6, London, U.K.
2954. Ding, C., He, X., Husbands, P., Zha, H., and Simon, H. (2003), PageRank, HITS and a unified framework for link analysis, In *Proceedings of the 2003 SIAM International Conference on Data Mining (SDM)*, pp. 249–253, San Francisco, CA, USA.
2955. Grover, N. and Wason, R. (2012), Comparative analysis of Pagerank and HITS algorithms, *International Journal of Engineering Research and Technology (IJERT)*, 1(8), 1–15.
2956. Sun, Y., Wong, A. K. C., and Kamel, M. S. (2009), Classification of imbalanced data: A review, *International Journal of Pattern Recognition and Artificial Intelligence*, 23(04), 687–719.
2957. BullGuard, Bots and botnets the most dangerous threat on the internet.
<https://www.bullguard.com/bullguard-security-center/internet-security/internet-threats/bots-and-botnets.aspx>. - Online; Last Accessed: 22-June-2022 - .
2958. Rodriguez-Ruiz, J., Mata-Sánchez, J. I., Monroy, R., Loyola-González, O., and López-Cuevas, A. (2020), A one-class classification approach for bot detection on Twitter, *Computers & Security*, 91, 1–14.

2959. Loyola-Gonzalez, O., Monroy, R., Rodriguez, J., Lopez-Cuevas, A., and Mata-Sanchez, J. I. (2019), Contrast pattern-based classification for bot detection on Twitter, *IEEE Access*, 7, 45800–45817.
2960. Przybyla, P. (2019), Detecting bot accounts on Twitter by measuring message predictability, In *Working Notes of Conference and Labs of the Evaluation Forum (CLEF) 2019*, Lugano, Switzerland.
2961. Shevtsov, A. S. A., Oikonomidou, M., Antonakaki, D., Pratikakis, P., Kanterakis, A., Ioannidis, S., and Fragopoulou, P. (2022), Discovery and classification of Twitter bots, *SN Computer Science*, 3(255).
2962. Verma, M., Divya, D., and Sofat, S. (2014), Techniques to detect spammers in Twitter: A survey, *International Journal of Computer Applications*, 85(10), 27–32.
2963. Ahmed, F. and Abulaish, M. (2013), A generic statistical approach for spam detection in online social networks, *Computer Communications*, 36, 11201129.
2964. Dickerson, J. P., Kagan, V., and Subrahmanian, V. S. (2014), Using sentiment to detect bots on Twitter: Are humans more opinionated than bots?, In *Proceedings of the 2014 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*, p. 620627, Beijing, China: IEEE Press.
2965. Moo-Mena, F., Robles-Sandoval, S., Gonzalez-Magaa, K., and Rodriguez-Adame, O. (2019), Towards bots detection by analyzing the behavior of user data on Twitter, *International Journal of Computer Science Issues*, 16(1), 21–29.
2966. Kabakus, A. T. and Kara, R. (2017), A survey of spam detection methods on Twitter, *International Journal of Advanced Computer Science and Applications*, 8(3), 29–38.
2967. Rijsbergen, C. J. V. (1979), *Information Retrieval*, 2nd ed., USA: Butterworth-Heinemann.
2968. Fawcett, T. (2006), An introduction to ROC analysis, *Pattern Recognition Letters*, 27(8), 861–874.
2969. Zhang, Z., Hou, R., and Yang, J. (2020), Detection of social network spam based on improved extreme learning machine, *IEEE Access*, 8, 112003–112014.
2970. Wang, A. H. (2010), Don't follow me: Spam detection in Twitter, In *Proceedings of the 2010*
2971. *International Conference on Security and Cryptography (SECRYPT 2010)*, pp. 1–10, Athens, Greece.
2972. Lee, K., Caverlee, J., and Webb, S. (2010), Uncovering social spammers: Social honeypots + machine learning, In *Proceedings of the 33rd International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR '10)*, p. 435442, Geneva, Switzerland: Association for Computing Machinery.
2973. Benevenuto, F., Magno, G., Rodrigues, T., and Almeida, V. (2010), Detecting spammers on Twitter, In *Proceedings of the Seventh Conference on Collaboration, Electronic messaging, Anti Abuse and Spam (CEAS 2010)*, Redmond, Washington.
2974. McCord, M. and Chuah, M. (2011), Spam detection on Twitter using traditional classifiers, In *Proceedings of the 8th International Conference on Autonomic and Trusted Computing (ATC'11)*, p. 175186, Banf, Canada: Springer-Verlag.

2975. Lin, P.-C. and Huang, P.-M. (2013), A study of effective features for detecting long-surviving Twitter spam accounts, In Proceedings of the 15th International Conference on Advanced Communication Technology, pp. 841–846, PyeongChang, Korea.
2976. Amleshwaram, A. A., Reddy, A., Yadav, S., Gu, G., and Yang, C. (2013), CATS: Characterizing automation of Twitter spammers, In Proceedings of the 2013 Fifth International Conference on Communication Systems and Networks (COMSNETS), pp. 1–10, Banglore, India.
2977. Yang, C., Harkreader, R., and Gu, G. (2013), Empirical evaluation and new design for fighting evolving Twitter spammers, IEEE Transactions on Information Forensics and Security, 8(8), 1280–1293.
2978. Dickerson, J. P., Kagan, V., and Subrahmanian, V. S. (2014), Using sentiment to detect bots on Twitter: Are humans more opinionated than bots?, In Proceedings of the 2014 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM '14), p. 620627, Beijing, China: IEEE Press.
2979. Chen, C., Zhang, J., Chen, X., Xiang, Y., and Zhou, W. (2015), Six million spam tweets: A large ground truth for timely Twitter spam detection, In Proceedings of the 2015 51st IEEE International Conference on Communications (ICC), pp. 7065–7070, London, UK.
2980. Liu, S., Wang, Y., Chen, C., and Xiang, Y. (2016), An ensemble learning approach for addressing the class imbalance problem in Twitter spam detection, In Proceedings of the 21th Australasian Conference on Information Security and Privacy, Vol. 9722, pp. 215–228, Melbourne, Australia: Springer.
2981. Chen, C., Wang, Y., Zhang, J., Xiang, Y., Zhou, W., and Min, G. (2017), Statistical features-based real-time detection of drifted Twitter spam, IEEE Transactions on Information Forensics and Security, 12(4), 914–925.
2982. Kudugunta, S. and Ferrara, E. (2018), Deep neural networks for bot detection, Information Sciences, 467, 312–322.
2983. Loyola-Gonzalez, O., Monroy, R., Rodriguez, J., Lopez-Cuevas, A., and Mata-Sanchez, J. I. (2019), Contrast pattern-based classification for bot detection on Twitter, IEEE Access, 7, 45800–45817.
2984. Lingam, G., Rout, R., and Somayajulu, D. (2019), Adaptive deep Q-learning model for detecting social bots and influential users in online social networks, Applied Intelligence, 49, 39473964.
2985. Badola, K. and Gupta, M. (2021), Twitter spam detection using natural language processing by encoder decoder model, In Proceedings of the 2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS-2021), pp. 402–405, Online conference.
2986. Derhab, A., Alawwad, R., Dehwah, K., Tariq, N., Khan, F. A., and Al-muhtadi, J. (2021), Tweet-based bot detection using big data analytics, IEEE Access, 9, 65988–66005.
2987. Besel, C., Echeverria, J., and Zhou, S. (2018), Full cycle analysis of a large-scale botnet attack on Twitter, In Proceedings of the 2018 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM), pp. 170–177, Barcelona, Spain.
2988. Echeverria, J. and Zhou, S. (2017), Discovery, retrieval, and analysis of 'Star Wars' botnet in Twitter, In Proceedings of the 2017 IEEE/ACM International Conference on

Advances in Social Networks Analysis and Mining (ASONAM'17), pp. 1–8, Sydney Australia: Association for Computing Machinery.

2989. Echeverria, J., Besel, C., and Zhou, S. (2018), Discovery of the Twitter bursty botnet, In Heard, N., Adams, N., Rubin-Delanchy, P., and Turcotte, M., (Eds.), *Data Science for Cyber-Security*, Vol. 3, pp. 145–159, World Scientific.
2990. Jiang, M., Cui, P., Beutel, A., Faloutsos, C., and Yang, S. (2016), Catching synchronized behaviors in large networks: A graph mining approach, *ACM Transactions on Knowledge Discovery from Data*, 10(4), 1–27.
2991. Shevtsov, A., Oikonomidou, M., Antonakaki, D., Pratikakis, P., Kanterakis, A., Fragopoulou, P., and Ioannidis, S. (2020), Discovery and classification of Twitter bots, *SN Computer Science*, 3(255).
2992. Lingam, G., Rout, R. R., Somayajulu, D., and Das, S. K. (2020), Social botnet community detection: A novel approach based on behavioral similarity in Twitter network using deep learning, In *Proceedings of the 15th ACM Asia Conference on Computer and Communications Security (ASIA CCS '20)*, p. 708718, Taipei, Taiwan: Association for Computing Machinery.
2993. Hub, I. M. (2021), What is Influencer Marketing: An in Depth Look at Marketings Next Big Thing. <https://influencermarketinghub.com/what-is-influencer-marketing/>. - Online; Last Accessed: 20-November-2021
2994. Marta (2019), Top 5 Twitter Influencer Tools. "<https://brand24.com/blog/top-5-twitter-influencers-tools/>". - Online; Last Accessed: 22-August-2021
2995. Hub, I. M. (2021), 20 FREE Influencer Marketing Tools to Find Influencers. <https://influencermarketinghub.com/free-influencer-marketing-tools/>. - Online; Last Accessed: 14-November-2021
2996. Dhiraj (2021), 16 Best Twitter Influencers Tools 2021. <https://www.beginndot.com/best-twitter-influencers-tools/>. - Online; Last Accessed: 15-December-2021
2997. Csutoras, B. (2021), 5 Top Influencer Marketing Tools to Find the Most Influential People. <https://www.searchenginejournal.com/top-influencer-marketing-tools/>. - Online; Last Accessed: 20-November-2021
2998. Amigo, E., Carrillo-de Albornoz, J., Chugur, I., Corujo, A., Gonzalo, J., Meij, E., de Rijke, M., and Spina, D. (2014), Overview of RepLab 2014: Author profiling and reputation dimensions for online reputation management, In Kanoulas, E., Lupu, M., Clough, P., Sanderson, M., Hall, M., Hanbury, A., and Toms, E., (Eds.), *Proceedings of the 5th International Conference of the CLEF Initiative*, pp. 307–322, Sheffield, UK.
2999. Davis, C. A., Varol, O., Ferrara, E., Flammini, A., and Menczer, F. (2016), BotOrNot: A system to evaluate social bots, In *Proceedings of the 25th International Conference Companion on World Wide Web (WWW'16)*, p. 273274, Montral Qubec Canada.
3000. CNetS (2020), Botometer V4. <https://cnets.indiana.edu/blog/2020/09/01/botometer-v4/>. - Online; Last Accessed: 04-may-2021
3001. Davis, C. A. and Yang, K. C. (2020), botometer 1.6. <https://pypi.org/project/botometer/>. - Online; Last Accessed: 20-June-2021

3002. Bhat, A. and Phadte, R. (2017), Identifying Propaganda Bots on Twitter. <https://medium.com/@robhat/identifying-propaganda-bots-on-witter-5240e7cb81a9>. - Online; Last Accessed: 20-June-2021 - .
3003. Bouzy, C. (2018), More than just bots... <https://botsentinel.com/info/about>. - Online; Last Accessed: 20-June-2021
3004. Unhackthevote (2019), A Review of Popular Bot Checkers. <https://www.unhackthevote.com/a-review-of-popular-bot-checkers/>. - Online; Last Accessed: 20-June-2021
3005. Yang, K.-C., Varol, O., Hui, P.-M., and Menczer, F. (2020), Scalable and generalizable social bot detection through data selection, In Proceedings of the 34th AAAI Conference on Artificial Intelligence, p. 10961103, New York, New York, USA.
3006. Zhou, Z. (2018), A brief introduction to weakly supervised learning, National Science Review, 5(1), 44–53.
3007. Engelen, J. and Hoos, H. (2020), A survey on semi-supervised learning, Machine Learning, 109, 373–440.
3008. Settles, B. (2012), Active learning, Synthesis Lectures on Artificial Intelligence and Machine Learning, 6(1), 1–114.
3009. Zhuang, F., Qi, Z., Duan, K., Xi, D., Zhu, Y., Zhu, H., Xiong, H., and He, Q. (2021), A comprehensive survey on transfer learning, Proceedings of the IEEE, 109(1), 43–76.
3010. Kouw, W. M. and Loog, M. (2018), An introduction to domain adaptation and transfer learning, (Technical Report) Department of Intelligent Systems, Delft University of Technology.
3011. Jiang, J. and Zhai, C. (2007), Instance weighting for domain adaptation in NLP, In Proceedings of the 45th Annual Meeting of the Association of Computational Linguistics, p. 264271, Prague, Czech Republic: Association for Computational Linguistics.
3012. Hewahi, N. and Kohail, S. (2015), Learning concept drift using adaptive training set formation strategy, International Journal of Technology Difusion, 4, 33–55.
3013. Cui, P., Wang, X., Pei, J., and Zhu, W. (2019), A survey on network embedding, IEEE Transactions on Knowledge and Data Engineering, 31(5), 833–852.
3014. J.C. Flack, R.M. D’Souza, The digital age and the future of social network science and engineering, Proc. IEEE 102 (12) (2014) 1873–1877.
3015. V.U. Wanniarachchi, A. Mathrani, T. Susnjak, C. Scogings, A systematic literature review: What is the current stance towards weight stigmatization in social media platforms? Int. J. Hum.-Comput. Stud. 135 (2020) 102371.
3016. Z.M. Obeidat, R.S. AlGharabat, A.A. Alalwan, S.H. Xiao, Y.K. Dwivedi, N.P. Rana, Narcissism, interactivity, community, and online revenge behavior: The moderating role of social presence among Jordanian consumers, Comput. Hum. Behav. 104 (2020) 106170.
3017. T. Chen, E.C. Hui, J. Wu, W. Lang, X. Li, Identifying urban spatial structure and urban vibrancy in highly dense cities using georeferenced social media data, Habitat Int. 89 (2019) 102005.
3018. J.R. Quinlan, C4. 5: Programs for Machine Learning, Elsevier, 2014.

3019. E. Alpaydin, *Introduction to Machine Learning*, MIT Press, 2014.
3020. E. Whelan, A.N. Islam, S. Brooks, Applying the SOBC paradigm to explain how social media overload affects academic performance, *Comput. Educ.* 143 (2020) 103692.
3021. S. Buhan, Y. Özkazanç, et al., Wind pattern recognition and reference wind mast data correlations with NWP for improved wind-electric power forecasts, *IEEE Trans. Ind. Inf.* 12 (3) (2016) 991–1004.
3022. T. Kasakowskij, J. Fürst, J. Fischer, K.J. Fietkiewicz, Network enforcement as denunciation endorsement? A critical study on legal enforcement in social media, *Telemat. Inform.* (2019) 101317.
3023. Y. Sun, C. Liang, C.-C. Chang, Online social construction of Taiwan's rural image: Comparison between Taiwanese self-representation and Chinese perception, *Tour. Manag.* 76 (2020) 103968.
3024. Y. Gao, Y. Zhen, H. Li, T.-S. Chua, Filtering of brand-related microblogs using social-smooth multiview embedding, *IEEE Trans. Multimed.* 18 (10) (2016) 2115–2126.
3025. M. Egmont-Petersen, D. de Ridder, H. Handels, Image processing with neural networks—a review, *Pattern Recognit.* 35 (10) (2002) 2279–2301.
3026. C. Orellana-Rodriguez, M.T. Keane, Attention to news and its dissemination on Twitter: A survey, *Comp. Sci. Rev.* 29 (2018) 74–94.
3027. D. Praveen Kumar, A. Tarachand, A. Chandra Sekhara Rao, Machine learning algorithms for wireless sensor networks: A survey, *Inf. Fusion* 49 (2019) 1–25.
3028. M. Li, J. Wei, X. Zheng, M.L. Bolton, A formal machine-learning approach to generating human-machine interfaces from task models, *IEEE Trans. Hum.-Mach. Syst.* 47 (6) (2017) 822–833.
3029. J. Kim, M. Hastak, Social network analysis: Characteristics of online social networks after a disaster, *Int. J. Inf. Manage.* 38 (1) (2018) 86–96.
3030. K. Ravi, V. Ravi, A survey on opinion mining and sentiment analysis: tasks, approaches and applications, *Knowl.-Based Syst.* 89 (2015) 14–46.
3031. J. Bobadilla, F. Ortega, A. Hernando, A. Gutiérrez, Recommender systems survey, *Knowl.-Based Syst.* 46 (2013) 109–132.
3032. Z. Xiang, Q. Du, Y. Ma, W. Fan, A comparative analysis of major online review platforms: Implications for social media analytics in hospitality and tourism, *Tour. Manag.* 58 (2017) 51–65.
3033. D. Ramalingam, V. Chinnaiah, Fake profile detection techniques in largescale online social networks: A comprehensive review, *Comput. Electr. Eng.* (2017).
3034. A. Sarker, R. Ginn, A. Nikfarjam, K. O'Connor, K. Smith, S. Jayaraman, T. Upadhaya, G. Gonzalez, Utilizing social media data for pharmacovigilance: a review, *J. Biomed. Inform.* 54 (2015) 202–212.
3035. B. Batrinca, P.C. Treleaven, Social media analytics: a survey of techniques, tools and platforms, *AI Society* 30 (1) (2015) 89–116.
3036. G. Bello-Orgaz, J.J. Jung, D. Camacho, Social big data: Recent achievements and new challenges, *Inf. Fusion* 28 (2016) 45–59.

3037. G. Harshvardhan, M.K. Gourisaria, M. Pandey, S.S. Rautaray, A comprehensive survey and analysis of generative models in machine learning, *Comp. Sci. Rev.* 38 (2020) 100285.
3038. B. Kavšek, N. Lavrač, APRIORI-SD: Adapting association rule learning to subgroup discovery, *Appl. Artif. Intell.* 20 (7) (2006) 543–583.
3039. S. Muggleton, L. De Raedt, Inductive logic programming: Theory and methods, *J. Log. Program.* 19 (1994) 629–679.
3040. M. Paolanti, E. Frontoni, Multidisciplinary pattern recognition applications: A review, *Comp. Sci. Rev.* 37 (2020) 100276.
3041. Y. Bengio, A. Courville, P. Vincent, Representation learning: A review and new perspectives, *IEEE Trans. Pattern Anal. Mach. Intell.* 35 (8) (2013) 1798–1828.
3042. B. McFee, L. Barrington, G. Lanckriet, Learning content similarity for music recommendation, *IEEE Trans. Audio Speech Lang. Process.* 20 (8) (2012) 2207–2218.
3043. J. Schmidhuber, Deep learning in neural networks: An overview, *Neural Netw.* 61 (2015) 85–117.
3044. I. Goodfellow, Y. Bengio, A. Courville, Y. Bengio, *Deep Learning*, Vol. 1, MIT Press Cambridge, 2016.
3045. P. Dixit, S. Silakari, Deep learning algorithms for cybersecurity applications: A technological and status review, *Comp. Sci. Rev.* 39, 100317,
3046. S. Ting, W. Ip, A.H. Tsang, Is Naive Bayes a good classifier for document classification, *Int. J. Softw. Eng. Appl.* 5 (3) (2011) 37–46.
3047. M.M. Saritas, A. Yasar, Performance analysis of ANN and Naive Bayes classification algorithm for data classification, *Int. J. Intell. Syst. Appl. Eng.* 7 (2) (2019) 88–91.
3048. R. Kohavi, Scaling up the accuracy of naive-bayes classifiers: A decision-tree hybrid, in: *Kdd*, Vol. 96, 1996, pp. 202–207.
3049. F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, et al., *Scikit-learn: Machine learning in Python*, *J. Mach. Learn. Res.* 12 (Oct) (2011) 2825–2830.
3050. G. Mountrakis, J. Im, C. Ogole, Support vector machines in remote sensing: A review, *ISPRS J. Photogramm. Remote Sens.* 66 (3) (2011) 247–259.
3051. S.S. Istia, H.D. Purnomo, Sentiment analysis of law enforcement performance using support vector machine and K-nearest neighbor, in: *2018 3rd International Conference on Information Technology, Information System and Electrical Engineering, ICITISEE*, IEEE, 2018, pp. 84–89.
3052. Y. Guo, M. Wang, X. Li, Application of an improved Apriori algorithm in a mobile e-commerce recommendation system, *Ind. Manage. Data Syst.* (2017).
3053. S. Asur, B.A. Huberman, Predicting the future with social media, in: *2010 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology*, Vol. 1, IEEE, 2010, pp. 492–499.
3054. A. Criminisi, J. Shotton, E. Konukoglu, et al., Decision forests: A unified framework for classification, regression, density estimation, manifold learning and semi-supervised learning, *Found. Trends Comput. Graph. Vis.* 7 (2–3) (2012) 81–227.

3055. K. Zhang, Y. Cheng, Y. Xie, D. Honbo, A. Agrawal, D. Palsetia, K. Lee, W.-k. Liao, A. Choudhary, SES: Sentiment elicitation system for social media data, in: 2011 IEEE 11th International Conference on Data Mining Workshops, IEEE, 2011, pp. 129–136.
3056. S.R. Safavian, D. Landgrebe, A survey of decision tree classifier methodology, *IEEE Trans. Syst. Man Cybern.* 21 (3) (1991) 660–674.
3057. C. Robert, *Machine Learning, A Probabilistic Perspective*, Taylor & Francis, 2014.
3058. M.I. Jordan, T.M. Mitchell, Machine learning: Trends, perspectives, and prospects, *Science* 349 (6245) (2015) 255–260.
3059. J. Chen, K. Li, Z. Tang, K. Bilal, S. Yu, C. Weng, K. Li, A parallel random forest algorithm for big data in a spark cloud computing environment, *IEEE Trans. Parallel Distrib. Syst.* 28 (4) (2016) 919–933.
3060. J. Snoek, H. Larochelle, R.P. Adams, Practical bayesian optimization of machine learning algorithms, in: *Advances in Neural Information Processing Systems*, 2012, pp. 2951–2959.
3061. K. Yu, L. Ji, X. Zhang, Kernel nearest-neighbor algorithm, *Neural Process. Lett.* 15 (2) (2002) 147–156.
3062. J.M. Keller, M.R. Gray, J.A. Givens, A fuzzy k-nearest neighbor algorithm, *IEEE Trans. Syst. Man Cybern.* (4) (1985) 580–585.
3063. R. Vatrupu, R.R. Mukkamala, A. Hussain, B. Flesch, Social set analysis: A set theoretical approach to big data analytics, *IEEE Access* 4 (2016) 2542–2571.
3064. C.K. Emani, N. Cullot, C. Nicolle, Understandable big data: a survey, *Comput. Sci. Rev.* 17 (2015) 70–81.
3065. N.A. Ghani, S. Hamid, I.A.T. Hashem, E. Ahmed, Social media big data analytics: A survey, *Comput. Hum. Behav.* 101 (2019) 417–428.
3066. S.J. Qin, L.H. Chiang, Advances and opportunities in machine learning for process data analytics, *Comput. Chem. Eng.* 126 (2019) 465–473.
3067. R.B. Rutledge, A.M. Chekroud, Q.J. Huys, Machine learning and big data in psychiatry: toward clinical applications, *Curr. Opin. Neurobiol.* 55 (2019) 152–159.
3068. I.H. Witten, E. Frank, M.A. Hall, C.J. Pal, *Data Mining: Practical Machine Learning Tools and Techniques*, Morgan Kaufmann, 2016.
3069. R. Bost, R.A. Popa, S. Tu, S. Goldwasser, Machine learning classification over encrypted data, in: *NDSS*, Vol. 4324, 2015, p. 4325.
3070. J. Davis, M. Goadrich, The relationship between Precision-Recall and ROC curves, in: *Proceedings of the 23rd International Conference on Machine Learning*, 2006, pp. 233–240.
3071. M. Sokolova, G. Lapalme, A systematic analysis of performance measures for classification tasks, *Inf. Process. Manage.* 45 (4) (2009) 427–437.
3072. D. Chicco, G. Jurman, The advantages of the matthews correlation coefficient (MCC) over F1 score and accuracy in binary classification evaluation, *BMC Genomics* 21 (1) (2020) 6.
3073. M. Sokolova, N. Japkowicz, S. Szpakowicz, Beyond accuracy, F-score and ROC: a family of discriminant measures for performance evaluation, in: *Australasian Joint Conference on Artificial Intelligence*, Springer, 2006, pp. 1015–1021.

3074. P. Branco, L. Torgo, R.P. Ribeiro, Relevance-based evaluation metrics for multi-class imbalanced domains, in: Pacific-Asia Conference on Knowledge Discovery and Data Mining, Springer, 2017, pp. 698–710.
3075. S. Cheong, S.H. Oh, S.-Y. Lee, Support vector machines with binary tree architecture for multi-class classification, *Neural Inf. Process.-Lett. Rev.* 2 (3) (2004) 47–51.
3076. V. Labatut, H. Cherifi, Evaluation of performance measures for classifiers comparison, 2011, arXiv preprint arXiv:1112.4133.
3077. D.J. Navarro, J.I. Myung, Model evaluation, in: Wiley StatsRef: Statistics Reference Online, Wiley Online Library, 2014.
3078. E. Costa, A. Lorena, A. Carvalho, A. Freitas, A review of performance evaluation measures for hierarchical classifiers, in: Evaluation Methods for Machine Learning II: Papers from the AAAI-2007 Workshop, 2007, pp. 1–6.
3079. C.N. Silla, A.A. Freitas, A survey of hierarchical classification across different application domains, *Data Min. Knowl. Discov.* 22 (1–2) (2011) 31–72.
3080. C. Maes, L. Schreurs, J.M. van Oosten, L. Vandenbosch, #(me) too much? The role of sexualizing online media in adolescents' resistance towards the metoo-movement and acceptance of rape myths, *J. Adolesc.* 77 (2019) 59–69.
3081. C. McClure, Y.-K. Seock, The role of involvement: Investigating the effect of brand's social media pages on consumer purchase intention, *J. Retailing Consum. Serv.* 53 (2020) 101975.
3082. Y. Qin, L.R. Men, Exploring negative peer communication of companies on social media and its impact on organization-public relationships, *Public Relations Rev.* (2019) 101795.
3083. J.M.N. Gonzalez, J.A. Jimenez, J.C.D. Lopez, et al., Root cause analysis of network failures using machine learning and summarization techniques, *IEEE Commun. Mag.* 55 (9) (2017) 126–131.
3084. S. Shahrapour, A. Rakhlin, A. Jadbabaie, Distributed detection: Finitetime analysis and impact of network topology, *IEEE Trans. Automat. Control* 61 (11) (2016) 3256–3268.
3085. J. Zhao, N. Cao, Z. Wen, Y. Song, Y.-R. Lin, C. Collins, # Fluxflow: Visual analysis of anomalous information spreading on social media, *IEEE Trans. Vis. Comput. Graphics* 20 (12) (2014) 1773–1782.
3086. L. Oneto, F. Bisio, E. Cambria, D. Anguita, Statistical learning theory and ELM for big social data analysis, *IEEE Comput. Intell. Mag.* 11 (3) (2016) 45–55.
3087. N. Cao, C. Shi, S. Lin, J. Lu, Y.-R. Lin, C.-Y. Lin, Targetvue: Visual analysis of anomalous user behaviors in online communication systems, *IEEE Trans. Vis. Comput. Graph.* 22 (1) (2016) 280–289.
3088. M. Stewart, U. Schultze, Producing solidarity in social media activism: The case of my stealthy freedom, *Inf. Organ.* (2019).
3089. M. Leban, Y. Seo, B.G. Voyer, Transformational effects of social media lurking practices on luxury consumption, *J. Bus. Res.* (2019).

3090. S. Sun, C. Luo, J. Chen, A review of natural language processing techniques for opinion mining systems, *Inf. Fusion* 36 (2017) 10–25.
3091. H. Arshada, A. Jantana, G.K. Hoon, I.O. Abiodun, Formal knowledge model for online social network forensics, *Comput. Secur.* (2019) 101675.
3092. L. Thomas, E. Orme, F. Kerrigan, Student loneliness: The role of social media through life transitions, *Comput. Educ.* (2019) 103754.
3093. D. Marengo, I. Poletti, M. Settanni, The interplay between neuroticism, extraversion, and social media addiction in young adult Facebook users: Testing the mediating role of online activity using objective data, *Addict. Behav.* 102 (2020) 106150.
3094. X. Luo, C. Jiang, W. Wang, Y. Xu, J.-H. Wang, W. Zhao, User behavior prediction in social networks using weighted extreme learning machine with distribution optimization, *Future Gener. Comput. Syst.* 93 (2019) 1023–1035.
3095. M. Singh, D. Bansal, S. Sofat, Behavioral analysis and classification of spammers distributing pornographic content in social media, *Soc. Netw. Anal. Min.* 6 (1) (2016) 41.
3096. L. Jin, Y. Chen, T. Wang, P. Hui, A.V. Vasilakos, Understanding user behavior in online social networks: A survey, *IEEE Commun. Mag.* 51 (9) (2013) 144–150.
3097. D. Wang, J. Li, K. Xu, Y. Wu, Sentiment community detection: exploring sentiments and relationships in social networks, *Electron. Commer. Res.* 17 (1) (2017) 103–132.
3098. Y. Wang, A.V. Vasilakos, J. Ma, N. Xiong, On studying the impact of uncertainty on behavior diffusion in social networks, *IEEE Trans. Syst. Man Cybern.: Syst.* 45 (2) (2015) 185–197.
3099. F.E. Ayo, O. Folorunso, F.T. Ibharalu, I.A. Osinuga, Machine learning techniques for hate speech classification of twitter data: Stateofheart, future challenges and research directions, *Comp. Sci. Rev.* 38 (2020) 100311.
3100. E. Politou, E. Alepis, C. Patsakis, A survey on mobile affective computing, *Comp. Sci. Rev.* 25 (2017) 79–100.
3101. E. Cambria, Affective computing and sentiment analysis, *IEEE Intell. Syst.* 31 (2) (2016) 102–107.
3102. Z. Wang, Y. Yang, J. Pei, L. Chu, E. Chen, Activity maximization by effective information diffusion in social networks, *IEEE Trans. Knowl. Data Eng.* 29 (11) (2017) 2374–2387.
3103. Y. Wu, N. Pitipornvivat, J. Zhao, S. Yang, G. Huang, H. Qu, egoslider: Visual analysis of egocentric network evolution, *IEEE Trans. Vis. Comput. Graph.* 22 (1) (2016) 260–269.
3104. R. Zhao, K. Mao, Cyberbullying detection based on semantic-enhanced marginalized denoising auto-encoder, *IEEE Trans. Affect. Comput.* 8 (3) (2017) 328–339.
3105. T. Vafeiadis, K.I. Diamantaras, G. Sarigiannidis, K.C. Chatzisavvas, A comparison of machine learning techniques for customer churn prediction, *Simul. Model. Pract. Theory* 55 (2015) 1–9.
3106. T. Iwata, J.R. Lloyd, Z. Ghahramani, Unsupervised many-to-many object matching for relational data, *IEEE Trans. Pattern Anal. Mach. Intell.* 38 (3) (2016) 607–617.

3107. D.M. Jacoby, R. Freeman, Emerging network-based tools in movement ecology, *Trends Ecol. Evol.* 31 (4) (2016) 301–314.
3108. Z.-Y. Chen, Z.-P. Fan, M. Sun, Behavior-aware user response modeling in social media: Learning from diverse heterogeneous data, *European J. Oper. Res.* 241 (2) (2015) 422–434.
3109. C. Wu, X. Chen, W. Zhu, Y. Zhang, Socially-driven learning-based prefetching in mobile online social networks, *IEEE/ACM Trans. Netw.* 25 (4) (2017) 2320–2333.
3110. D. Ruths, J. Pfeffer, Social media for large studies of behavior, *Science* 346 (6213) (2014) 1063–1064.
3111. A. Lesk, *Introduction to Bioinformatics*, Oxford University Press, 2019.
3112. G. Litjens, T. Kooi, B.E. Bejnordi, A.A.A. Setio, F. Ciompi, M. Ghafoorian, J.A. van der Laak, B. van Ginneken, C.I. Sánchez, A survey on deep learning in medical image analysis, *Med. Image Anal.* 42 (2017) 60–88.
3113. J. Fogel, M. Adnan, Trust for online social media direct-to-consumer prescription medication advertisements, *Health Policy Technol.* (2019).
3114. H. Müller, N. Michoux, D. Bandon, A. Geissbuhler, A review of contentbased image retrieval systems in medical applications—clinical benefits and future directions, *Int. J. Med. Inform.* 73 (1) (2004) 1–23.
3115. M. Młyńczak, E. Migacz, M. Migacz, W. Kukwa, Detecting breathing and snoring episodes using a wireless tracheal sensor—A feasibility study, *IEEE J. Biomed. Health Inform.* 21 (6) (2017) 1504–1510.
3116. A. Budd, M. Corpas, M.D. Brazas, J.C. Fuller, J. Goecks, N.J. Mulder, M. Michaut, B.F. Ouellette, A. Pawlik, N. Blomberg, A quick guide for building a successful bioinformatics community, *PLoS Comput. Biol.* 11 (2) (2015) e1003972.
3117. C.A. Goble, J. Bhagat, S. Aleksejevs, D. Cruickshank, D. Michaelides, D. Newman, M. Borkum, S. Bechhofer, M. Roos, P. Li, et al., myExperiment: a repository and social network for the sharing of bioinformatics workflows, *Nucleic Acids Res.* 38 (suppl_2) (2010) W677–W682.
3118. A. Smiti, When machine learning meets medical world: Current status and future challenges, *Comp. Sci. Rev.* 37 (2020) 100280.
3119. C.D. Smyser, N.U. Dosenbach, T.A. Smyser, A.Z. Snyder, C.E. Rogers, T.E. Inder, B.L. Schlaggar, J.J. Neil, Prediction of brain maturity in infants using machine-learning algorithms, *Neuroimage* 136 (2016) 1–9.
3120. J. Torous, P. Staples, J.-P. Onnela, Realizing the potential of mobile mental health: new methods for new data in psychiatry, *Curr. Psych. Rep.* 17 (8) (2015) 61.
3121. H. Zou, B. Huang, X. Lu, H. Jiang, L. Xie, A robust indoor positioning system based on the procrustes analysis and weighted extreme learning machine, *IEEE Trans. Wireless Commun.* 15 (2) (2016) 1252–1266.
3122. M.M. Mostafa, More than words: Social networks' text mining for consumer brand sentiments, *Expert Syst. Appl.* 40 (10) (2013) 4241–4251.

3123. C. Townsend, D.T. Neal, C. Morgan, The impact of the mere presence of social media share icons on product interest and valuation, *J. Bus. Res.* 100 (2019) 245–254.
3124. X. Xu, X. Wang, Y. Li, M. Haghighi, Business intelligence in online customer textual reviews: Understanding consumer perceptions and influential factors, *Int. J. Inf. Manage.* 37 (6) (2017) 673–683.
3125. E. D’Avanzo, G. Pilato, Mining social network users opinions’ to aid buyers’ shopping decisions, *Comput. Hum. Behav.* 51 (2015) 1284–1294.
3126. V. Stantchev, L. Prieto-González, G. Tamm, Cloud computing service for knowledge assessment and studies recommendation in crowdsourcing and collaborative learning environments based on social network analysis, *Comput. Hum. Behav.* 51 (2015) 762–770.
3127. L.A. Johnson, N. Dias, G. Clarkson, A.M. Schreier, Social media as a recruitment method to reach a diverse sample of bereaved parents, *Appl. Nurs. Res.* (2019) 151201.
3128. X. Sun, C. Zhang, G. Li, D. Sun, F. Ren, A. Zomaya, R. Ranjan, Detecting users’ anomalous emotion using social media for business intelligence, *J. Comput. Sci.* 25 (2018) 193–200.
3129. H. Chen, R.H. Chiang, V.C. Storey, Business intelligence and analytics: From big data to big impact, *MIS Q.* (2012) 1165–1188.
3130. J. Choi, J. Yoon, J. Chung, B.-Y. Coh, J.-M. Lee, Social media analytics and business intelligence research: A systematic review, *Inf. Process. Manage.* 57 (6) (2020) 102279.
3131. W. Fan, M.D. Gordon, The power of social media analytics, *Commun. ACM* 57 (6) (2014) 74–81.
3132. B.K. Chae, Insights from hashtag# supplychain and Twitter analytics: Considering Twitter and Twitter data for supply chain practice and research, *Int. J. Prod. Econ.* 165 (2015) 247–259.
3133. P.F. Kurnia, et al., Business intelligence model to analyze social media information, *Procedia Comput. Sci.* 135 (2018) 5–14.
3134. H. Rui, A. Whinston, Designing a social-broadcasting-based business intelligence system, *ACM Trans. Manage. Inf. Syst.* 2 (4) (2012) 1–19.
3135. Y. Chen, C. Jiang, C.-Y. Wang, Y. Gao, K.R. Liu, Decision learning: Data analytic learning with strategic decision making, *IEEE Signal Process. Mag.* 33 (1) (2016) 37–56.
3136. W. He, H. Wu, G. Yan, V. Akula, J. Shen, A novel social media competitive analytics framework with sentiment benchmarks, *Inf. Manage.* 52 (7) (2015) 801–812.
3137. W. Yuan, P. Deng, T. Taleb, J. Wan, C. Bi, An unlicensed taxi identification model based on big data analysis, *IEEE Trans. Intell. Transp. Syst.* 17 (6) (2016) 1703–1713.
3138. S. Yu, Y. Hu, When luxury brands meet China: The effect of localized celebrity endorsements in social media marketing, *J. Retailing Consum. Serv.* 54 (2020) 102010.
3139. A. Dabbous, K.A. Barakat, Bridging the online offline gap: Assessing the impact of brands’ social network content quality on brand awareness and purchase intention, *J. Retailing Consum. Serv.* 53 (2020) 101966.
3140. M. Egele, G. Stringhini, C. Kruegel, G. Vigna, Towards detecting compromised accounts on social networks, *IEEE Trans. Dependable Secure Comput.* 14 (4) (2017) 447–460.

3141. L. Song, R.Y.K. Lau, R.C.-W. Kwok, K. Mirkovski, W. Dou, Who are the spoilers in social media marketing? Incremental learning of latent semantics for social spam detection, *Electron. Commer. Res.* 17 (1) (2017) 51–81.
3142. I. Frommholz, H.M. Al-Khateeb, M. Potthast, Z. Ghasem, M. Shukla, E. Short, On textual analysis and machine learning for cyberstalking detection, *Datenbank-Spektrum* 16 (2) (2016) 127–135.
3143. M.A. Bryan, Y. Evans, C. Morishita, N. Midamba, M. Moreno, Parental perceptions of the internet and social media as a source of pediatric health information, *Acad. Pediatr.* (2019).
3144. G. Sarna, M. Bhatia, Content based approach to find the credibility of user in social networks: an application of cyberbullying, *Int. J. Mach. Learn. Cybern.* 8 (2) (2017) 677–689.
3145. L.P. Del Bosque, S.E. Garza, Prediction of aggressive comments in social media: an exploratory study, *IEEE Lat. Am. Trans.* 14 (7) (2016) 3474–3480.
3146. M. Spreitzenbarth, T. Schreck, F. Echtler, D. Arp, J. Hoffmann, Mobile–Sandbox: combining static and dynamic analysis with machine-learning techniques, *Int. J. Inf. Secur.* 14 (2) (2015) 141–153.
3147. V. Van Vlasselaer, C. Bravo, O. Caelen, T. Eliassi-Rad, L. Akoglu, M. Snoeck, B. Baesens, APATE: A novel approach for automated credit card transaction fraud detection using network-based extensions, *Decis. Support Syst.* 75 (2015) 38–48.
3148. A. Culotta, Towards detecting influenza epidemics by analyzing Twitter messages, in: *Proceedings of the First Workshop on Social Media Analytics, 2010*, pp. 115–122.
3149. M. Gupta, A. Bansal, B. Jain, J. Rochelle, A. Oak, M.S. Jalali, Whether the weather will help us weather the COVID-19 pandemic: Using machine learning to measure Twitter users' perceptions, *Int. J. Med. Inform.* (2020) 104340.
3150. L. Li, Q. Zhang, X. Wang, J. Zhang, T. Wang, T.-L. Gao, W. Duan, K.K.-f. Tsoi, F.-Y. Wang, Characterizing the propagation of situational information in social media during COVID-19 epidemic: A case study on weibo, *IEEE Trans. Comput. Soc. Syst.* 7 (2) (2020) 556–562.
3151. E. Aramaki, S. Maskawa, M. Morita, Twitter catches the flu: detecting influenza epidemics using Twitter, in: *Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing, 2011*, pp. 1568–1576.
3152. H. Achrekar, A. Gandhe, R. Lazarus, S.-H. Yu, B. Liu, Predicting flu trends using twitter data, in: *2011 IEEE Conference on Computer Communications Workshops, INFOCOM WKSHPs, IEEE, 2011*, pp. 702–707.
3153. M.K. Othman, M.S.N.M. Danuri, Proposed conceptual framework of dengue active surveillance system (DASS) in Malaysia, in: *2016 International Conference on Information and Communication Technology, ICICTM, IEEE, 2016*, pp. 90–96.
3154. S. Lim, C.S. Tucker, S. Kumara, An unsupervised machine learning model for discovering latent infectious diseases using social media data, *J. Biomed. Inform.* 66 (2017) 82–94.

3155. C. Liao, A. Squicciarini, C. Griffin, S. Rajtmajer, A hybrid epidemic model for deindividuation and antinormative behavior in online social networks, *Soc. Netw. Anal. Min.* 6 (1) (2016) 13.
3156. S.A. Sumner, S. Galik, J. Mathieu, M. Ward, T. Kiley, B. Bartholow, A. Dingwall, P. Mork, Temporal and geographic patterns of social media posts about an emerging suicide game, *J. Adolesc. Health* (2019).
3157. M.A. Al-garadi, M.S. Khan, K.D. Varathan, G. Mujtaba, A.M. Al-Kabsi, Using online social networks to track a pandemic: A systematic review, *J. Biomed. Inform.* 62 (2016) 1–11.
3158. R. Singh, R. Singh, A. Bhatia, Sentiment analysis using machine learning technique to predict outbreaks and epidemics, *Int. J. Adv. Sci. Res* 3 (2) (2018) 19–24.
3159. J.L. Marcus, W.C. Sewell, L.B. Balzer, D.S. Krakower, Artificial intelligence and machine learning for HIV prevention: Emerging approaches to ending the epidemic, *Curr. HIV/AIDS Rep.* (2020) 1–9.
3160. J. Xue, J. Chen, C. Chen, C. Zheng, S. Li, T. Zhu, Public discourse and sentiment during the COVID 19 pandemic: Using latent Dirichlet allocation for topic modeling on Twitter, *PLoS One* 15 (9) (2020) e0239441.
3161. Z. Long, R. Alharthi, A. El Saddik, Needfull—a tweet analysis platform to study human needs during the COVID-19 pandemic in new york state, *IEEE Access* 8 (2020) 136046–136055.
3162. C. Comito, A. Forestiero, C. Pizzuti, Twitter-based influenza surveillance: An analysis of the 2016–2017 and 2017–2018 seasons in Italy, in: *Proceedings of the 22nd International Database Engineering & Applications Symposium*, 2018, pp. 175–182.
3163. Z. Xu, H. Zhang, V. Sugumaran, K.-K.R. Choo, L. Mei, Y. Zhu, Participatory sensing–based semantic and spatial analysis of urban emergency events using mobile social media, *EURASIP J. Wireless Commun. Networking* 2016 (1) (2016) 44.
3164. H. Mo, X. Hao, H. Zheng, Z. Liu, D. Wen, Linguistic dynamic analysis of traffic flow based on social media—A case study, *IEEE Trans. Intell. Transp. Syst.* 17 (9) (2016) 2668–2676.
3165. E. D’Andrea, P. Ducange, B. Lazzerini, F. Marcelloni, Real–time detection of traffic from twitter stream analysis, *IEEE Trans. Intell. Transp. Syst.* 16 (4) (2015) 2269–2283.
3166. G. Lin, N. Sun, S. Nepal, J. Zhang, Y. Xiang, H. Hassan, Statistical Twitter spam detection demystified: Performance, stability and scalability, *IEEE Access* 5 (2017) 11142–11154.
3167. G. Mujtaba, L. Shuib, R.G. Raj, N. Majeed, M.A. Al-Garadi, Email classification research trends: Review and open issues, *IEEE Access* 5 (2017) 9044–9064.
3168. A. De, S. Bhattacharya, S. Sarkar, N. Ganguly, S. Chakrabarti, Discriminative link prediction using local, community, and global signals, *IEEE Trans. Knowl. Data Eng.* 28 (8) (2016) 2057–2070.
3169. R. Dreżewski, J. Sepielak, W. Filipkowski, The application of social network analysis algorithms in a system supporting money laundering detection, *Inform. Sci.* 295 (2015) 18–32.
3170. X. Zheng, Z. Zeng, Z. Chen, Y. Yu, C. Rong, Detecting spammers on social networks, *Neurocomputing* 159 (2015) 27–34.

3171. L.A. Maglaras, J. Jiang, T.J. Cruz, Combining ensemble methods and social network metrics for improving accuracy of OCSVM on intrusion detection in SCADA systems, *J. Inf. Secur. Appl.* 30 (2016) 15–26.
3172. L. Derczynski, D. Maynard, G. Rizzo, M. van Erp, G. Gorrell, R. Troncy, J. Petrak, K. Bontcheva, Analysis of named entity recognition and linking for tweets, *Inf. Process. Manage.* 51 (2) (2015) 32–49.
3173. D.T. Nguyen, J.E. Jung, Real-time event detection for online behavioral analysis of big social data, *Future Gener. Comput. Syst.* 66 (2017) 137–145.
3174. F. Buccafurri, G. Lax, A. Nocera, D. Ursino, Discovering missing me edges across social networks, *Inform. Sci.* 319 (2015) 18–37.
3175. M.-A. Kaufhold, M. Bayer, C. Reuter, Rapid relevance classification of social media posts in disasters and emergencies: A system and evaluation featuring active, incremental and online learning, *Inf. Process. Manage.* 57 (1) (2020) 102132.
3176. N. Panagiotou, I. Katakis, D. Gunopulos, Detecting events in online social networks: Definitions, trends and challenges, in: *Solving Large Scale Learning Tasks. Challenges and Algorithms*, Springer, 2016, pp. 42–84.
3177. N.M. Oliver, B. Rosario, A.P. Pentland, A Bayesian computer vision system for modeling human interactions, *IEEE Trans. Pattern Anal. Mach. Intell.* 22 (8) (2000) 831–843.
3178. D.C. Duro, S.E. Franklin, M.G. Dubé, A comparison of pixel-based and object-based image analysis with selected machine learning algorithms for the classification of agricultural landscapes using SPOT-5 HRG imagery, *Remote Sens. Environ.* 118 (2012) 259–272.
3179. M. Sonka, V. Hlavac, R. Boyle, *Image Processing, Analysis, and Machine Vision*, Cengage Learning, 2014.
3180. J.A. Richards, J. Richards, *Remote Sensing Digital Image Analysis*, Vol. 3, Springer, 1999.
3181. S.E. Middleton, L. Middleton, S. Modafferi, Real-time crisis mapping of natural disasters using social media, *IEEE Intell. Syst.* 29 (2) (2014) 9–17.
3182. J. Cao, Y. Zhang, R. Ji, F. Xie, Y. Su, Web video topics discovery and structuralization with social network, *Neurocomputing* 172 (2016) 53–63.
3183. S. Lefèvre, D. Tuia, J.D. Wegner, T. Produit, A.S. Nassaar, Toward seamless multiview scene analysis from satellite to street level, *Proc. IEEE* 105 (10) (2017) 1884–1899.
3184. G. Chiachia, A.X. Falcao, N. Pinto, A. Rocha, D. Cox, Learning person-specific representations from faces in the wild, *IEEE Trans. Inf. Forensics Secur.* 9 (12) (2014) 2089–2099.
3185. L. Liu, C. Xiong, H. Zhang, Z. Niu, M. Wang, S. Yan, Deep aging face verification with large gaps, *IEEE Trans. Multimed.* 18 (1) (2016) 64–75.
3186. D. Wang, C. Otto, A.K. Jain, Face search at scale, *IEEE Trans. Pattern Anal. Mach. Intell.* 39 (6) (2017) 1122–1136.
3187. S. Kulkarni, S.F. Rodd, Context aware recommendation systems: A review of the state of the art techniques, *Comp. Sci. Rev.* 37 (2020) 100255.

3188. S. Rantala, A. Toikka, A. Pulkka, J. Lyytimäki, Energetic voices on social media? Strategic niche management and Finnish Facebook debate on biogas and heat pumps, *Energy Res. Soc. Sci.* 62 (2020) 101362.
3189. X. Zhang, J. Jia, K. Gao, Y. Zhang, D. Zhang, J. Li, Q. Tian, Trip outfits advisor: Location-oriented clothing recommendation, *IEEE Trans. Multimed.* 19 (11) (2017) 2533–2544.
3190. A. Tommasel, D. Godoy, A social-aware online short-text feature selection technique for social media, *Inf. Fusion* 40 (2018) 1–17.
3191. R. Zhang, F. Nie, X. Li, X. Wei, Feature selection with multi-view data: A survey, *Inf. Fusion* 50 (2019) 158–167.
3192. Z. Yuan, J. Sang, C. Xu, Y. Liu, A unified framework of latent feature learning in social media, *IEEE Trans. Multimed.* 16 (6) (2014) 1624–1635.
3193. H. Zhang, X. Shang, H. Luan, M. Wang, T.-S. Chua, Learning from collective intelligence: Feature learning using social images and tags, *ACM Trans. Multimedia Comput. Commun. Appl.* 13 (1) (2017) 1.
3194. S. Poria, E. Cambria, A. Gelbukh, Aspect extraction for opinion mining with a deep convolutional neural network, *Knowl.-Based Syst.* 108 (2016) 42–49.
3195. K. Stepaniuk, The relation between destination image and social media user engagement—theoretical approach, *Procedia-Soc. Behav. Sci.* 213 (2015) 616–621.
3196. S.-E. Kim, K.Y. Lee, S.I. Shin, S.-B. Yang, Effects of tourism information quality in social media on destination image formation: The case of sina weibo, *Inf. Manage.* 54 (6) (2017) 687–702.
3197. M.J. Enright, J. Newton, Tourism destination competitiveness: a quantitative approach, *Tourism Manage.* 25 (6) (2004) 777–788.
3198. M. Elahi, F. Ricci, N. Rubens, A survey of active learning in collaborative filtering recommender systems, *Comp. Sci. Rev.* 20 (2016) 29–50.
3199. J. Lu, D. Wu, M. Mao, W. Wang, G. Zhang, Recommender system application developments: a survey, *Decis. Support Syst.* 74 (2015) 12–32.
3200. S. Raza, C. Ding, Progress in context-aware recommender systems—An overview, *Comp. Sci. Rev.* 31 (2019) 84–97.
3201. K. Gibson, S. Trnka, Young people’s priorities for support on social media: “It takes trust to talk about these issues”, *Comput. Hum. Behav.* 102 (2020) 238–247.
3202. B. Yang, Y. Lei, J. Liu, W. Li, Social collaborative filtering by trust, *IEEE Trans. Pattern Anal. Mach. Intell.* 39 (8) (2017) 1633–1647.
3203. Q. Fang, J. Sang, C. Xu, M.S. Hossain, Relational user attribute inference in social media, *IEEE Trans. Multimed.* 17 (7) (2015) 1031–1044.
3204. Y. Li, Y. Peng, W. Ji, Z. Zhang, Q. Xu, User identification based on display names across online social networks, *IEEE Access* 5 (2017) 17342–17353.
3205. Z. Sun, L. Han, W. Huang, X. Wang, X. Zeng, M. Wang, H. Yan, Recommender systems based on social networks, *J. Syst. Softw.* 99 (2015) 109–119.
3206. A. Daud, M. Ahmad, M. Malik, D. Che, Using machine learning techniques for rising star prediction in co-author network, *Scientometrics* 102 (2) (2015) 1687–1711.

3207. M. Ballings, D. Van den Poel, CRM in social media: Predicting increases in Facebook usage frequency, *European J. Oper. Res.* 244 (1) (2015) 248–260.
3208. X. Song, Z.-Y. Ming, L. Nie, Y.-L. Zhao, T.-S. Chua, Volunteerism tendency prediction via harvesting multiple social networks, *ACM Trans. Inf. Syst.* 34 (2) (2016) 10.
3209. J. Tang, S. Chang, C. Aggarwal, H. Liu, Negative link prediction in social media, in: *Proceedings of the Eighth ACM International Conference on Web Search and Data Mining*, ACM, 2015, pp. 87–96.
3210. S. Jiang, A. Alves, F. Rodrigues, J. Ferreira Jr., F.C. Pereira, Mining point-of-interest data from social networks for urban land use classification and disaggregation, *Comput. Environ. Urban Syst.* 53 (2015) 36–46.
3211. I. Konstas, V. Stathopoulos, J.M. Jose, On social networks and collaborative recommendation, in: *Proceedings of the 32nd International ACM SIGIR Conference on Research and Development in Information Retrieval*, ACM, 2009, pp. 195–202.
3212. C. De Maio, G. Fenza, V. Loia, M. Parente, Time aware knowledge extraction for microblog summarization on twitter, *Inf. Fusion* 28 (2016) 60–74.
3213. W. van Zoonen, G. Toni, Social media research: The application of supervised machine learning in organizational communication research, *Comput. Hum. Behav.* 63 (2016) 132–141.
3214. P. Chunaev, Community detection in node-attributed social networks: a survey, *Comp. Sci. Rev.* 37 (2020) 100286.
3215. X. Deng, J. Zhai, T. Lv, L. Yin, Efficient vector influence clustering coefficient based directed community detection method, *IEEE Access* 5 (2017) 17106–17116.
3216. A. Kumar, S.R. Sangwan, Rumor detection using machine learning techniques on social media, in: *International Conference on Innovative Computing and Communications*, Springer, 2019, pp. 213–221.
3217. J. Wu, L. Dai, F. Chiclana, H. Fujita, E. Herrera-Viedma, A minimum adjustment cost feedback mechanism based consensus model for group decision making under social network with distributed linguistic trust, *Inf. Fusion* 41 (2018) 232–242.
3218. S. Wen, J. Jiang, Y. Xiang, S. Yu, W. Zhou, W. Jia, To shut them up or to clarify: Restraining the spread of rumors in online social networks, *IEEE Trans. Parallel Distrib. Syst.* 25 (12) (2014) 3306–3316.
3219. E.D. Raj, L.D. Babu, An enhanced trust prediction strategy for online social networks using probabilistic reputation features, *Neurocomputing* 219 (2017) 412–421.
3220. J. Zhang, L. Tan, X. Tao, T. Pham, B. Chen, Relational intelligence recognition in online social networks—A survey, *Comp. Sci. Rev.* 35 (2020) 100221.
3221. C. Hu, H. Cao, Aspect-level influence discovery from graphs, *IEEE Trans. Knowl. Data Eng.* 28 (7) (2016) 1635–1649.
3222. S. Stieglitz, M. Mirbabaie, B. Ross, C. Neuberger, Social media analytics—Challenges in topic discovery, data collection, and data preparation, *Int. J. Inf. Manage.* 39 (2018) 156–168.
3223. C. Xu, S. Li, Y. Zhang, E. Miluzzo, Y.-f. Chen, Crowdsensing the speaker count in the wild: Implications and applications, *IEEE Commun. Mag.* 52 (10) (2014) 92–99.

3224. P. De Meo, E. Ferrara, D. Rosaci, G.M. Sarné, Trust and compactness in social network groups, *IEEE Trans. Cybern.* 45 (2) (2015) 205–216.
3225. M.V. Mäntylä, D. Graziotin, M. Kuutila, The evolution of sentiment analysis—A review of research topics, venues, and top cited papers, *Comp. Sci. Rev.* 27 (2018) 16–32.
3226. Q. Ye, Z. Zhang, R. Law, Sentiment classification of online reviews to travel destinations by supervised machine learning approaches, *Expert Syst. Appl.* 36 (3) (2009) 6527–6535.
3227. P. Ducange, M. Fazzolari, M. Petrocchi, M. Vecchio, An effective decision support system for social media listening based on cross-source sentiment analysis models, *Eng. Appl. Artif. Intell.* 78 (2019) 71–85.
3228. M. Ebrahimi, A.H. Yazdavar, A. Sheth, Challenges of sentiment analysis for dynamic events, *IEEE Intell. Syst.* 32 (5) (2017) 70–75.
3229. S. Manca, Snapping, pinning, liking or texting: Investigating social media in higher education beyond Facebook, *Internet Higher Educ.* (2019) 100707.
3230. V. Kagan, A. Stevens, V. Subrahmanian, Using twitter sentiment to forecast the 2013 pakistani election and the 2014 indian election, *IEEE Intell. Syst.* 30 (1) (2015) 2–5.
3231. P. Wang, B. Xu, Y. Wu, X. Zhou, Link prediction in social networks: the state-of-the-art, *Sci. China Inf. Sci.* 58 (1) (2015) 1–38.
3232. E. Lunando, A. Purwarianti, Indonesian social media sentiment analysis with sarcasm detection, in: 2013 International Conference on Advanced Computer Science and Information Systems, ICACIS, IEEE, 2013, pp. 195–198.
3233. P. Nakov, S. Rosenthal, S. Kiritchenko, S.M. Mohammad, Z. Kozareva, A. Ritter, V. Stoyanov, X. Zhu, Developing a successful SemEval task in sentiment analysis of Twitter and other social media texts, *Lang. Resour. Eval.* 50 (1) (2016) 35–65.
3234. L. Ren, B. Xu, H. Lin, X. Liu, L. Yang, Sarcasm detection with sentiment semantics enhanced multi-level memory network, *Neurocomputing* (2020).
3235. B. Charalampakis, D. Spathis, E. Kouslis, K. Kermanidis, A comparison between semi-supervised and supervised text mining techniques on detecting irony in greek political tweets, *Eng. Appl. Artif. Intell.* 51 (2016) 50–57.
3236. C. Chen, Y. Wang, J. Zhang, Y. Xiang, W. Zhou, G. Min, Statistical features-based real-time detection of drifted Twitter spam, *IEEE Trans. Inf. Forensics Secur.* 12 (4) (2017) 914–925.
3237. M. Bouazizi, T. Ohtsuki, A pattern-based approach for multi-class sentiment analysis in Twitter, *IEEE Access* 5 (2017) 20617–20639.
3238. R.G. Guimarães, R.L. Rosa, D. De Gaetano, D.Z. Rodríguez, G. Bressan, Age groups classification in social network using deep learning, *IEEE Access* 5 (2017) 10805–10816.
3239. S. Poria, E. Cambria, A. Gelbukh, F. Bisio, A. Hussain, Sentiment data flow analysis by means of dynamic linguistic patterns, *IEEE Comput. Intell. Mag.* 10 (4) (2015) 26–36.
3240. T.H. Nguyen, K. Shirai, J. Velcin, Sentiment analysis on social media for stock movement prediction, *Expert Syst. Appl.* 42 (24) (2015) 9603–9611.

3241. P. Burnap, O.F. Rana, N. Avis, M. Williams, W. Housley, A. Edwards, J. Morgan, L. Sloan, Detecting tension in online communities with computational Twitter analysis, *Technol. Forecast. Soc. Change* 95 (2015) 96–108.
3242. S. Poria, E. Cambria, A. Hussain, G.-B. Huang, Towards an intelligent framework for multimodal affective data analysis, *Neural Netw.* 63 (2015) 104–116.
3243. A. Muhammad, N. Wiratunga, R. Lothian, Contextual sentiment analysis for social media genres, *Knowl.-Based Syst.* 108 (2016) 92–101.
3244. F. Colace, L. Casaburi, M. De Santo, L. Greco, Sentiment detection in social networks and in collaborative learning environments, *Comput. Hum. Behav.* 51 (2015) 1061–1067.
3245. T. Wang, H. Krim, Y. Viniotis, Analysis and control of beliefs in social networks, *IEEE Trans. Signal Process.* 62 (21) (2014) 5552–5564.
3246. M. Fire, R. Puzis, Organization mining using online social networks, *Netw. Spat. Econ.* 16 (2) (2016) 545–578.
3247. J. Serrano-Guerrero, J.A. Olivas, F.P. Romero, E. Herrera-Viedma, Sentiment analysis: A review and comparative analysis of web services, *Inform. Sci.* 311 (2015) 18–38.
3248. J. Sun, G. Wang, X. Cheng, Y. Fu, Mining affective text to improve social media item recommendation, *Inf. Process. Manage.* 51 (4) (2015) 444–457.
3249. E. Ferrara, O. Varol, C. Davis, F. Menczer, A. Flammini, The rise of social bots, *Commun. ACM* 59 (7) (2016) 96–104.
3250. D.P. Gandhmal, K. Kumar, Systematic analysis and review of stock market prediction techniques, *Comp. Sci. Rev.* 34 (2019) 100190.
3251. P.-Y. Chen, S.-M. Cheng, P.-S. Ting, C.-W. Lien, F.-J. Chu, When crowdsourcing meets mobile sensing: a social network perspective, *IEEE Commun. Mag.* 53 (10) (2015) 157–163.
3252. V. Subrahmanian, A. Azaria, S. Durst, V. Kagan, A. Galstyan, K. Lerman, L. Zhu, E. Ferrara, A. Flammini, F. Menczer, The DARPA Twitter bot challenge, *Computer* 49 (6) (2016) 38–46.
3253. S. Poria, E. Cambria, N. Howard, G.-B. Huang, A. Hussain, Fusing audio, visual and textual clues for sentiment analysis from multimodal content, *Neurocomputing* 174 (2016) 50–59.
3254. A.Y.F. Zhu, A.L.S. Chan, K.L. Chou, Creative social media use and political participation in young people: The moderation and mediation role of online political expression, *J. Adolesc.* 77 (2019) 108–117.
3255. W. Akram, R. Kumar, A study on positive and negative effects of social media on society, *Int. J. Comput. Sci. Eng.* 5 (10) (2017) 351–354.
3256. N. Pitropakis, E. Panaousis, T. Giannetsos, E. Anastasiadis, G. Loukas, A taxonomy and survey of attacks against machine learning, *Comp. Sci. Rev.* 34 (2019) 100199.
3257. N. Vaughan, B. Gabrys, V.N. Dubey, An overview of self-adaptive technologies within virtual reality training, *Comp. Sci. Rev.* 22 (2016) 65–87.
3258. J. Fry, J.M. Binner, Elementary modelling and behavioural analysis for emergency evacuations using social media, *European J. Oper. Res.* 249 (3) (2016) 1014–1023.

3259. K.B. Habersaat, C. Betsch, M. Danchin, C.R. Sunstein, R. Böhm, A. Falk, N.T. Brewer, S.B. Omer, M. Scherzer, S. Sah, et al., Ten considerations for effectively managing the COVID-19 transition, *Nat. Hum. Behav.* 4 (7) (2020) 677–687.
3260. I. Alimova, E. Tutubalina, Automated detection of adverse drug reactions from social media posts with machine learning, in: *International Conference on Analysis of Images, Social Networks and Texts*, Springer, 2017, pp. 3–15.
3261. Vosoughi S, Roy D, Aral S. The spread of true and false news online. *Science*. 2018; 359 (6380):1146-51. doi:10.1126/science.aap9559
3262. MacAvaney S, Yao HR, Yang E, Russell K, Goharian N et al. Hate speech detection: Challenges and solutions. *PloS one*. 2019; 14 (8):e0221152. doi:10.1371/journal.pone.0221152
3263. Cresci S, Di Pietro R, Petrocchi M, Spognardi A, Tesconi M. Social fingerprinting: detection of spambot groups through DNA-inspired behavioral modeling. *IEEE Transactions on Dependable and Secure Computing*. 2017; 15(4):561–576. doi:10.1109/TDSC.2017.2681672
3264. Davis CA, Varol O, Ferrara E, Flammini A, Menczer F. Botornot: A system to evaluate social bots. In: *25th International Conference Companion on World Wide Web*; 2016. pp. 273–274.
3265. Kudugunta S, Ferrara E. Deep neural networks for bot detection. *Information Sciences*. 2018; 467:312–322. doi:10.1016/j.ins.2018.08.019
3266. Yang KC, Varol O, Hui PM, Menczer F. Scalable and generalizable social bot detection through data selection. In: *AAAI Conference on Artificial Intelligence*. vol. 34; 2020. pp. 1096–1103.
3267. Orabi M, Mouheb D, Al Aghbari Z, Kamel I. Detection of bots in social media: a systematic review. *Information Processing & Management*. 2020; 57(4):102250. doi:10.1016/j.ipm.2020.102250
3268. Almerexhi H, Elsayed T. Detecting automatically-generated arabic tweets. In: *Asia Information Retrieval Symposium*; 2015. pp. 123–134.
3269. Halawa H, Beznosov K, Boshmaf Y, Coskun B, Ripeanu M, Santos-Neto E. Harvesting the low-hanging fruits: defending against automated large-scale cyber-intrusions by focusing on the vulnerable population. In: *2016 New Security Paradigms Workshop*; 2016. pp. 11–22.
3270. Cornelissen LA, Barnett RJ, Schoonwinkel P, Eichstadt BD, Magodla HB. A network topology approach to bot classification. In: *Annual Conference of the South African Institute of Computer Scientists and Information Technologists*; 2018. pp. 79–88.
3271. Hurtado S, Ray P, Marculescu R. Bot detection in reddit political discussion. In: *Fourth International Workshop on Social Sensing*; 2019. pp. 30–35.
3272. Ping H, Qin S. A social bots detection model based on deep learning algorithm. In: *2018 IEEE 18th International Conference on Communication Technology*; 2018. pp. 1435–1439.
3273. Wang Y, Wu C, Zheng K, Wang X. Social bot detection using tweets similarity. In: *International Conference on Security and Privacy in Communication Systems*; 2018. pp. 63–78.

3274. Jr SB, Campos GF, Tavares GM, Igawa RA, Jr MLP, et al. Detection of human, legitimate bot, and malicious bot in online social networks based on wavelets. *ACM Transactions on Multimedia Computing, Communications, and Applications*. 2018; 14(1s):1–17. doi:10.1145/3183506
3275. Igawa RA, Barbon Jr S, Paulo KCS, Kido GS, Guido RC, et al. Account classification in online social networks with LBCA and wavelets. *Information Sciences*. 2016; 332:72–83. doi:10.1016/j.ins.2015.10.039
3276. Morstatter F, Wu L, Nazer TH, Carley KM, Liu H. A new approach to bot detection: striking the balance between precision and recall. In: 2016 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining; 2016. pp. 533–540.
3277. Chavoshi N, Hamooni H, Mueen A. Identifying correlated bots in twitter. In: International conference on social informatics; 2016. pp. 14–21.
3278. Cresci S, Di Pietro R, Petrocchi M, Spognardi A, Tesconi M. The paradigm-shift of social spambots: Evidence, theories, and tools for the arms race. In: 26th international conference on world wide web companion; 2017. pp. 963–972.
3279. Wang G, Mohanlal M, Wilson C, Wang X, Metzger M, Zheng H et al. Social Turing Tests: Crowdsourcing Sybil Detection. In: 20th Annual Network and Distributed System Security Symposium; 2013.
3280. Pan J, Liu Y, Liu X, Hu H. Discriminating bot accounts based solely on temporal features of microblog behavior. *Physica A: Statistical Mechanics and its Applications*. 2016; 450:193–204. doi:10.1016/j.physa.2015.12.148
3281. Boshmaf Y, Muslukhov I, Beznosov K, Ripeanu M. Design and analysis of a social botnet. *Computer Networks*. 2013; 57 (2):556–578. doi:10.1016/j.comnet.2012.06.006
3282. Stein T, Chen E, Mangla K. Facebook immune system. In: 4th Workshop on Social Network Systems; 2011. pp. 1–8.
3283. Elyashar A, Fire M, Kagan D, Elovici Y. Homing socialbots: intrusion on a specific organization's employee using socialbots. In: 2013 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining; 2013. pp. 1358–1365.
3284. Freitas C, Benevenuto F, Ghosh S, Veloso A. Reverse engineering socialbot infiltration strategies in twitter. In: 2015 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining; 2015. pp. 25–32.
3285. Grimme C, Preuss M, Adam L, Trautmann H. Social bots: Human-like by means of human control? *Big data*. 2017; 5 (4):279–293. doi:10.1089/big.2017.0044
3286. Cresci S, Petrocchi M, Spognardi A, Tognazzi S. On the capability of evolved spambots to evade detection via genetic engineering. *Online Social Networks and Media*. 2019; 9:1–16. doi:10.1016/j.osnem.2018.10.005
3287. Sayyadiharikandeh M, Varol O, Yang KC, Flammini A, Menczer F. Detection of novel social bots by ensembles of specialized classifiers. In: 29th ACM International Conference on Information & Knowledge Management; 2020. pp. 2725–2732.
3288. Giglietto F, Righetti N, Rossi L, Marino G. It takes a village to manipulate the media: coordinated link sharing behavior during 2018 and 2019 Italian elections. *Information, Communication & Society*. 2020; 23 (6):867–891. doi:10.1080/1369118X.2020.1739732

3289. Pasquetto IV, Swire-Thompson B, Amazeen MA, Benevenuto F, Brashier NM, et al. Tackling misinformation: What researchers could do with social media data. *The Harvard Kennedy School Misinformation Review*. 2020. doi:10.37016/mr-2020-49
3290. Martini F, Samula P, Keller TR, Klinger U. Bot, or not? Comparing three methods for detecting social bots in five political discourses. *Big Data & Society*. 2021; 8 (2):20539517211033566. doi:10.1177/20539517211033566
3291. Gallwitz F, Kreil M. The Rise and Fall of “Social Bot” Research. *SSRN*. 2021.
3292. Rauchfleisch A, Kaiser J. The False positive problem of automatic bot detection in social science research. *PloS one*. 2020; 15(10):e0241045. doi:10.2139/ssrn.3565233
3293. Efthimion PG, Payne S, Proferes N. Supervised machine learning bot detection techniques to identify social twitter bots. *SMU Data Science Review*. 2018; 1 (2):5.
3294. Yang KC, Varol O, Davis CA, Ferrara E, Flammini A, Menczer F. Arming the public with artificial intelligence to counter social bots. *Human Behavior and Emerging Technologies*. 2019; 1 (1):48–61.
3295. Cresci S, Lillo F, Regoli D, Tardelli S, Tesconi M. \$ FAKE: Evidence of spam and bot activity in stock microblogs on Twitter. In: *12th International AAAI Conference on Web and Social Media*; 2018. pp. 580–583.
3296. Cresci S, Lillo F, Regoli D, Tardelli S, Tesconi M. Cashtag piggybacking: Uncovering spam and bot activity in stock microblogs on Twitter. *ACM Transactions on the Web*. 2019; 13 (2):1–27. doi:10.1145/3313184
3297. Mazza M, Cresci S, Avvenuti M, Quattrociochi W, Tesconi M. Rtbust: Exploiting temporal patterns for botnet detection on twitter. In: *10th ACM Conference on Web Science*; 2019. pp. 183–192.
3298. Gilani Z, Farahbakhsh R, Tyson G, Wang L, Crowcroft J. Of bots and humans (on twitter). In: *2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2017*; 2017. pp. 349–354.
3299. Yang C, Harkreader R, Gu G. Empirical evaluation and new design for fighting evolving twitter spammers. *IEEE Transactions on Information Forensics and Security*. 2013; 8 (8):1280–1293. doi:10.1109/TIFS.2013.2267732
3300. Cresci S. Detecting malicious social bots: story of a never-ending clash. In: *1st Multidisciplinary International Symposium on Disinformation in Open Online Media*; 2019. pp. 77–88
3301. Brown TB, Mann B, Ryder N, Subbiah M, Kaplan J et al. Language models are few-shot learners. *arXiv preprint arXiv:200514165*. 2020.
3302. Elkins K, Chun J. Can GPT-3 Pass a Writer’s Turing Test? *Journal of Cultural Analytics*. 2020; 1(1):17212 doi:10.22148/001c.17212
3303. Abokhodair, N.; Yoo, D.; and McDonald, D. W. 2015. Dissecting a social botnet: Growth, content and influence in twitter. In *Proc. of the 18th ACM Conf. on Computer Supported Cooperative Work & Social Computing*, 839–851. ACM.
3304. Agarwal, A.; Xie, B.; Vovsha, I.; Rambow, O.; and Passonneau, R. 2011. Sentiment analysis of Twitter data. In *Proc. of the Workshop on Languages in Social Media*, 30–38. ACL.

3305. Aiello, L.; Deplano, M.; Schifanella, R.; and Ruffo, G. 2012. People are strange when you're a stranger: Impact and influence of bots on social networks. In Proc. 6th Intl. AAAI Conf. on Weblogs & Soc. Media (ICWSM).
3306. Alvisi, L.; Clement, A.; Epasto, A.; Lattanzi, S.; and Panconesi, A. 2013. Sok: The evolution of sybil defense via social networks. In Proc. IEEE Symposium on Security and Privacy (SP), 382–396.
3307. Bakshy, E.; Hofman, J. M.; Mason, W. A.; and Watts, D. J. 2011. Everyone's an influencer: quantifying influence on Twitter. In Proc. 4th ACM Intl. Conf. on Web Search and Data Mining, 65–74.
3308. Berger, J., and Morgan, J. 2015. The isis twitter census: Defining and describing the population of isis supporters on twitter. The Brookings Project on US Relations with the Islamic World 3:20.
3309. Bessi, A., and Ferrara, E. 2016. Social bots distort the 2016 us presidential election online discussion. *First Monday* 21(11).
3310. Bessi, A.; Coletto, M.; Davidescu, G. A.; Scala, A.; Caldarelli, G.; and Quattrociocchi, W. 2015. Science vs conspiracy: Collective narratives in the age of misinformation. *PLoS ONE* 10(2):e0118093.
3311. Beutel, A.; Xu, W.; Guruswami, V.; Palow, C.; and Faloutsos, C. 2013. Copycatch: stopping group attacks by spotting lockstep behavior in social networks. In Proc. 22nd Intl. ACM Conf. World Wide Web (WWW), 119–130.
3312. Bollen, J.; Mao, H.; and Zeng, X. 2011. Twitter mood predicts the stock market. *Journal of Computational Science* 2(1):1–8.
3313. Boshmaf, Y.; Muslukhov, I.; Beznosov, K.; and Ripeanu, M. 2011. The socialbot network: when bots socialize for fame and money. In Proc. 27th Annual Computer Security Applications Conf.
3314. Botta, F.; Moat, H. S.; and Preis, T. 2015. Quantifying crowd size with mobile phone and twitter data. *Royal Society open science* 2(5):150162.
3315. Briscoe, E.; Appling, S.; and Hayes, H. 2014. Cues to deception in social media communications. In Hawaii Intl. Conf. on Syst Sci.
3316. Cao, Q.; Sirivianos, M.; Yang, X.; and Pogueiro, T. 2012. Aiding the detection of fake accounts in large scale social online services. In 9th USENIX Symp on Netw Sys Design & Implement, 197–210.
3317. Chavoshi, N.; Hamooni, H.; and Mueen, A. 2016. Identifying correlated bots in twitter. In Social Informatics: 8th Intl. Conf., 14–21.
3318. Chu, Z.; Gianvecchio, S.; Wang, H.; and Jajodia, S. 2010. Who is tweeting on twitter: human, bot, or cyborg? In Proc. 26th annual computer security applications conf., 21–30.
3319. Chu, Z.; Gianvecchio, S.; Wang, H.; and Jajodia, S. 2012. Detecting automation of twitter accounts: Are you a human, bot, or cyborg? *IEEE Tran Dependable & Secure Comput* 9(6):811–824. DOI: 10.1109/TDSC.2012.75
3320. Clark, E.; Jones, C.; Williams, J.; Kurti, A.; Nortotsky, M.; Danforth, C.; and Dodds, P. 2015. Vaporous marketing: Uncovering pervasive electronic cigarette advertisements on twitter. arXiv preprint arXiv:1508.01843.

3321. Clark, E.; Williams, J.; Jones, C.; Galbraith, R.; Danforth, C.; and Dodds, P. 2016. Sifting robotic from organic text: a natural language approach for detecting automation on twitter. *Journal of Computational Science* 16:1–7.
3322. Danescu-Niculescu-Mizil, C.; West, R.; Jurafsky, D.; Leskovec, J.; and Potts, C. 2013. No country for old members: user lifecycle and linguistic change in online communities. In *Proc. of the 22nd Intl. Conf. on World Wide Web*, 307–318.
3323. Das, A.; Gollapudi, S.; Kiciman, E.; and Varol, O. 2016. Information dissemination in heterogeneous-intent networks. In *Proc. ACM Conf. on Web Science*.
3324. Davis, C. A.; Varol, O.; Ferrara, E.; Flammini, A.; and Menczer, F. 2016. BotOrNot: A system to evaluate social bots. In *Proc. 25th Intl. Conf. Companion on World Wide Web*, 273–274.
3325. Echeverria, J., and Zhou, S. 2017. The ‘star wars’ botnet with 350k twitter bots. *arXiv preprint arXiv:1701.02405*.
3326. Elyashar, A.; Fire, M.; Kagan, D.; and Elovici, Y. 2013. Homing socialbots: intrusion on a specific organization’s employee using socialbots. In *Proc. IEEE/ACM Intl. Conf. on Advances in Social Networks Analysis and Mining*, 1358–1365.
3327. Ferrara, E., and Yang, Z. 2015. Quantifying the effect of sentiment on information diffusion in social media. *PeerJ Comp. Sci.* 1:e26.
3328. Ferrara, E.; Varol, O.; Davis, C.; Menczer, F.; and Flammini, A. 2016a. The rise of social bots. *Comm. ACM* 59(7):96–104.
3329. Ferrara, E.; Varol, O.; Menczer, F.; and Flammini, A. 2016b. Detection of promoted social media campaigns. In *Proc. Intl. AAAI Conference on Web and Social Media*.
3330. Ferrara, E.; Wang, W.-Q.; Varol, O.; Flammini, A.; and Galstyan, A. 2016c. Predicting online extremism, content adopters, and interaction reciprocity. In *Social Informatics: 8th Intl. Conf., SocInfo 2016, Bellevue, WA, USA*, 22–39.
3331. Ghosh, R.; Surachawala, T.; and Lerman, K. 2011. Entropy-based classification of retweeting activity on twitter. In *Proc. of KDD workshop on Social Network Analysis*.
3332. Gjoka, M.; Kurant, M.; Butts, C. T.; and Markopoulou, A. 2010. Walking in facebook: A case study of unbiased sampling of osns. In *Proc. IEEE INFOCOM*, 1–9.
3333. Haustein, S.; Bowman, T. D.; Holmberg, K.; Tsou, A.; Sugimoto, C. R.; and Lariviere, V. 2016. Tweets as impact indicators: Examining the implications of automated “bot” accounts on twitter. *Journal of the Association for Information Science and Technology* 67(1):232–238.
3334. Kloumann, I. M.; Danforth, C. M.; Harris, K. D.; Bliss, C. A.; and Dodds, P. S. 2012. Positivity of the english language. *PLoS ONE* 7(1):e29484.
3335. Lee, K.; Eoff, B. D.; and Caverlee, J. 2011. Seven months with the devils: A long-term study of content polluters on twitter. In *Proc. 5th AAAI Intl. Conf. on Web and Social Media*.
3336. Letchford, A.; Moat, H. S.; and Preis, T. 2015. The advantage of short paper titles. *Royal Society Open Science* 2(8):150266. Lokot, T., and Diakopoulos, N. 2016. News bots: Automating news and information dissemination on twitter. *Digital Journalism* 4(6):682–699.
3337. Maaten, L. v. d., and Hinton, G. 2008. Visualizing data using t-sne. *Journal of Machine Learning Research* 9(Nov):2579–2605.

3338. McAuley, J., and Leskovec, J. 2013. From amateurs to connoisseurs: modeling the evolution of user expertise through online reviews. In Proc. 22nd Intl. ACM Conf. World Wide Web, 897–908.
3339. Mislove, A.; Lehmann, S.; Ahn, Y.-Y.; Onnela, J.-P.; and Rosenquist, J. N. 2011. Understanding the demographics of Twitter users. In Proc. of the 5th Intl. AAAI Conf. on Weblogs and Social Media.
3340. Mitchell, L.; Harris, K. D.; Frank, M. R.; Dodds, P. S.; and Danforth, C. M. 2013. The geography of happiness: Connecting Twitter sentiment and expression, demographics, and objective characteristics of place. PLoS ONE 8(5):e64417.
3341. Mitter, S.; Wagner, C.; and Strohmaier, M. 2013. A categorization scheme for socialbot attacks in online social networks. In Proc. of the 3rd ACM Web Science Conference.
3342. Mocanu, D.; Baronchelli, A.; Perra, N.; Goncalves, B.; Zhang, Q.; and Vespignani, A. 2013. The Twitter of Babel: Mapping world languages through microblogging platforms. PLoS ONE 8(4):e61981.
3343. Morstatter, F.; Pfeffer, J.; Liu, H.; and Carley, K. 2013. Is the sample good enough? comparing data from twitter's streaming api with twitter's firehose. In 7th Int Conf on Weblogs & Soc Med.
3344. Pedregosa, F.; Varoquaux, G.; Gramfort, A.; Michel, V.; Thirion, B.; Grisel, O.; et al. 2011. Scikit-learn: Machine learning in Python. Journal of Machine Learning Research 12:2825–2830.
3345. Ratkiewicz, J.; Conover, M.; Meiss, M.; Goncalves, B.; Flammini, A.; and Menczer, F. 2011. Detecting and tracking political abuse in social media. In 5th Int Conf on Weblogs & Soc Med, 297–304.
3346. Savage, S.; Monroy-Hernandez, A.; and Hollerer, T. 2016. Botivist: Calling volunteers to action using online bots. In Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing, 813–822. ACM.
3347. Subrahmanian, V.; Azaria, A.; Durst, S.; Kagan, V.; Galstyan, A.; Lerman, K.; Zhu, L.; Ferrara, E.; Flammini, A.; Menczer, F.; et al. 2016. The DARPA Twitter Bot Challenge. IEEE Computer 6(49):38–46.
3348. Wald, R.; Khoshgoftaar, T. M.; Napolitano, A.; and Sumner, C. 2013. Predicting susceptibility to social bots on twitter. In Proc. 14th Intl. IEEE Conf. on Information Reuse and Integration, 6–13.
3349. Wang, G.; Konolige, T.; Wilson, C.; Wang, X.; Zheng, H.; and Zhao, B. Y. 2013a. You are how you click: Clickstream analysis for sybil detection. In Proc. USENIX Security, 1–15. Citeseer.
3350. Wang, G.; Mohanlal, M.; Wilson, C.; Wang, X.; Metzger, M.; Zheng, H.; and Zhao, B. Y. 2013b. Social turing tests: Crowdsourcing sybil detection. In Proc. of the 20th Network & Distributed System Security Symposium (NDSS).
3351. Warriner, A. B.; Kuperman, V.; and Brysbaert, M. 2013. Norms of valence, arousal, and dominance for 13,915 english lemmas. Behavior research methods 1–17.

3352. Wilson, T.; Wiebe, J.; and Hoffmann, P. 2005. Recognizing contextual polarity in phrase-level sentiment analysis. In *ACL Conf on Human Language Techn & Empirical Methods in NLP*, 347–354.
3353. Yang, Z.; Wilson, C.; Wang, X.; Gao, T.; Zhao, B. Y.; and Dai, Y. 2014. Uncovering social network sybils in the wild. *ACM Trans. Knowledge Discovery from Data* 8(1):2.
3354. Emilio Ferrara et al. “The rise of social bots”. In: *Commun. ACM* (2016). ISSN: 0001-0782. DOI:10.1145/2818717. URL: <https://doi.org/10.1145/2818717>.
3355. Yazan Boshmaf et al. “Design and analysis of a social botnet”. In: *Computer Networks* 57.2 (2013). Botnet Activity: Analysis, Detection and Shutdown, pp. 556–578. ISSN: 1389-1286. DOI:<https://doi.org/10.1016/j.comnet.2012.06.006>. URL: <https://www.sciencedirect.com/science/article/pii/S1389128612002150>.
3356. Daejin Choi et al. “Rumor propagation is amplified by echo chambers in social media”. In: *Scientific reports* 10.1 (2020), p. 310. DOI:10.1038/s41598-019-57272-3.
3357. Kanghyun Cho, Kihwan Nam, and JaeHwuen Jung. “Blessing or Curse: Impact of Algorithmic Trading Bots Invasion of the Cryptocurrency Market”. In: *ICIS 2022 Proceedings. Dec 12th. International Conference on Information Systems (ICIS). Temple University, Dongguk University: Association for Information Systems (AIS) Electronic Library (AISel), 2022*. URL: <https://aisel.aisnet.org/icis2022/blockchain/blockchain/9>.
3358. William Marcellino et al. *Counter-Radicalization Bot Research: Using Social Bots to Fight Violent Extremism*. Santa Monica, CA: RAND Corporation, 2020. DOI:10.7249/RR2705.
3359. Mattias Wahlström and Anton Törnberg. “Social Media Mechanisms for Right-Wing Political Violence in the 21st Century: Discursive Opportunities, Group Dynamics, and Co-Ordination”. In: *Terrorism and Political Violence* 33.4 (2021), pp. 766–787. DOI:10.1080/09546553.2019.1586676. URL: <https://doi.org/10.1080/09546553.2019.1586676>.
3360. Anatoliy Gruzd and Philip Mai. “Going viral: How a single tweet spawned a COVID-19 conspiracy theory on Twitter”. In: *Big Data & Society* 7.2 (2020), p. 2053951720938405. DOI:10.1177/2053951720938405. eprint: <https://doi.org/10.1177/2053951720938405>. URL: <https://doi.org/10.1177/2053951720938405>.
3361. Mariam Orabi et al. “Detection of Bots in Social Media: A Systematic Review”. In: *Information Processing & Management* 57 (Apr. 2020). DOI:10.1016/j.ipm.2020.102250.
3362. Paige Leskin. Inside the rise of TikTok, the viral video-sharing app wildly popular with teens and loathed by the Trump administration — [businessinsider.com.https://www.businessinsider.com/tiktokapponlinewebsitevideosharing2019](https://www.businessinsider.com/tiktokapponlinewebsitevideosharing2019).
3363. Annalise Baines, Muhammad Ittefaq, and Mauryne Abwao. “Scamdemic, Plandemic, or Scaredemic: What Parler Social Media Platform Tells Us about COVID-19 Vaccine”. In: *Vaccines* 9.5 (2021). DOI:10.3390/vaccines9050421. URL: <https://www.mdpi.com/2076-393X/9/5/421>.
3364. Max Aliapoulos et al. “An Early Look at the Parler Online Social Network”. In: *CoRR abs/2101.03820* (2021). arXiv: 2101.03820. URL: <https://arxiv.org/abs/2101.03820>.
3365. Hitkul et al. “Capitol (Pat)riots: A comparative study of Twitter and Parler”. In: *CoRR abs/2101.06914* (2021). arXiv: 2101.06914. URL: <https://arxiv.org/abs/2101.06914>.

3366. Brett Molina. Parler returns to Apple App Store for iPhone after removal. <https://www.usatoday.com/story/tech/2021/05/17/parler-returns-apple-app-store-iphone-after-removal/5124921001/>. USA Today. 2021.
3367. Nico Grant. Parler returns to Google Play store. <https://www.nytimes.com/2022/09/02/technology/parler-google-play.html>. New York Times. 2022.
3368. David Ingram and Abigail Brooks. Conservative social media app Parler planning to relaunch ahead of 2024 election. <https://www.nbcnews.com/tech/tech-news/parler-app-relaunch-2024-newownershipdownloadtrumpcrna130287>. NBC News. 2024.
3369. Clayton A. Davis et al. "BotOrNot: A System to Evaluate Social Bots". In: CoRR abs/1602.00975 (2016). arXiv: 1602.00975. URL: <http://arxiv.org/abs/1602.00975>.
3370. Kai-Cheng Yang, Emilio Ferrara, and Filippo Menczer. "Botometer 101: Social bot practicum for computational social scientists". In: CoRR abs/2201.01608 (2022). arXiv: 2201.01608. URL: <https://arxiv.org/abs/2201.01608>.
3371. James Schnebly and Shamik Sengupta. "Random Forest Twitter Bot Classifier". In: 2019 IEEE 9th Annual Computing and Communication Workshop and Conference (CCWC) (2019), pp. 0506–0512. URL: <https://api.semanticscholar.org/CorpusID:77393048>.
3372. Eiman Alothali et al. "Detecting Social Bots on Twitter: A Literature Review". In: Nov. 2018, pp. 175–180. DOI:10.1109/INNOVATIONS.2018.8605995.
3373. Philipp Probst, Marvin N. Wright, and Anne-Laure Boulesteix. "Hyperparameters and tuning strategies for random forest". In: WIREs Data Mining and Knowledge Discovery 9.3 (2019), e1301. DOI:<https://doi.org/10.1002/widm.1301>. eprint: <https://wires.onlinelibrary.wiley.com/doi/pdf/10.1002/widm.1301>. URL: <https://wires.onlinelibrary.wiley.com/doi/abs/10.1002/widm.1301>.
3374. Michael Isbitski. Unpacking the Parler Data Breach. <https://salt.security/blog/unpacking-the-parler-databreach>. Salt Security Blog. 2024.
3375. GitHub - KonradIT/parler-py-api: UNOFFICIAL Python API to interface with Parler.com — github.com. <https://github.com/KonradIT/parler-py-api.git>. - Accessed 17-06-2024
3376. Mathieu Bastian, Sebastien Heymann, and Mathieu Jacomy. "Gephi: An Open Source Software for Exploring and Manipulating Networks". In: Proceedings of the International AAAI Conference on Web and Social Media 3.1 (2009), pp. 361–362. DOI:10.1609/icwsm.v3i1.13937. URL: <https://ojs.aaai.org/index.php/ICWSM/article/view/13937>.
3377. Abdullah, Z., Putri, K.Y.S., Raza, S.H., Istiyanto, S.B., 2022. Contrariwise obesity through organic food consumption in Malaysia: a signaling theory perspective. BMC Publ. Health 22 (1). <https://doi.org/10.1186/s12889-021-12480-3>, 99–99.
3378. Abidin, C., 2015. Communicative intimacies: influencers and perceived interconnectedness. Ada: J. Gend. New Media Technol. 8, 1–16. <http://adanewmedia.org/2015/11/issue8-abidin/>.
3379. Ahmed, W., Lopez, ´ S.F., Vidal-Alaball, J., Katz, M.S., 2020. COVID-19 and the "Film your hospital" conspiracy theory: social network analysis of Twitter data. J. Med. Internet Res. 22 (10), e22374 <https://doi.org/10.2196/22374>.

3380. Amra, Elma, 2020. Influencer Marketing Study.
<https://www.amraandelma.com/effect-of-pandemic-on-influencer-marketing/>. Aratani, L., 2020. How did face masks become a political issue in America? June 29
3381. Guardian. From. <https://www.theguardian.com/world/2020/jun/29/face-masks-us-politics-coronavirus>.
3382. Ashuri, T., Bar-Ilan, Y., 2017. Collective action recruitment in a digital age: applying signaling theory to filtering behaviors. *Commun. Theor.* 27 (1), 70–91.
<https://doi.org/10.1111/comt.12108>.
3383. Atkinson, Rosenthal, S., 2014. Signaling the green sell: the influence of eco-label source, argument specificity, and product involvement on consumer trust. *J. Advert.* 43 (1), 33–45. <https://doi.org/10.1080/00913367.2013.834803>.
3384. Baker, S.A., 2022. Alt. Health Influencers: how wellness culture and web culture have been weaponised to promote conspiracy theories and far-right extremism during the COVID-19 pandemic. *Eur. J. Cult. Stud.* 25 (1), 3–24. <https://doi.org/10.1177/13675494211062623>.
3385. Boateng, S.L., 2019. Online relationship marketing and customer loyalty: a signaling theory perspective. *Int. J. Bank Market.* 37 (1), 226–240. <https://doi.org/10.1108/IJBM-01-2018-0009>.
3386. Brandon, D., Long, J., Loraas, T., Mueller-Phillips, J., Vansant, B., 2014. Online instrument delivery and participant recruitment services: emerging opportunities for behavioral accounting Research. *Behav. Res. Account.* 26 (1), 1–23.
<https://doi.org/10.2308/bria-50651>.
3387. Bromwich, J.E., 2020. Fighting over masks in public is the new American pastime. June 30 New Times. <https://www.nytimes.com/2020/06/30/style/mask-america-freed-from-coronavirus.html>.
3388. Carpentier, M., Van Hove, G., Weijters, B., 2019. Attracting applicants through the organization's social media page: signaling employer brand personality. *J. Vocat. Behav.* 115, 103326 <https://doi.org/10.1016/j.jvb.2019.103326>.
3389. Center for Countering Digital Hate, 2021. The disinformation dozen. March 24.
https://www.counterhate.com/files/ugd/f4d9b9_b7cedc0553604720b7137f8663366ee5.pdf.
3390. Chejfec-Ciociano, J.M., Martínez-Herrera, J.P., Parra-Guerra, A.D., Chejfec, R., Barbosa-Camacho, F.J., Ibarrola-Pena, J.C., Cervantes-Guevara, G., Cervantes-Cardona, G.A., Fuentes-Orozco, C., Cervantes-Perez, E., García-Reyna, B., Gonzalez-Ojeda, A., 2022. Misinformation about and interest in chlorine dioxide during the COVID-19 pandemic in Mexico identified using google trends data: infodemiology study. *JMIR Infodemiol.* 2 (1), e29894 <https://doi.org/10.2196/29894>.
3391. Chen, Y., Lu, Y., Wang, B., Pan, Z., 2019. How do product recommendations affect impulse buying? An empirical study on WeChat social commerce. *Inf. Manag.* 56 (2), 236–248. <https://doi.org/10.1016/j.im.2018.09.002>.
3392. Cheung, C.M.K., Xiao, B.S., Liu, I.L., 2014. Do actions speak louder than voices? The signaling role of social information cues in influencing consumer purchase decisions. *Decis. Support Syst.* 65, 50–58. <https://doi.org/10.1016/j.dss.2014.05.002>.

3393. Chung, S., Cho, H., 2017. Fostering parasocial relationships with celebrities on social media: implications for celebrity endorsement. *Psychol. Market.* 34 (4), 481–495. <https://doi.org/10.1002/mar.21001>.
3394. Clark, J.K., Evans, A.T., 2014. Source credibility and persuasion: the role of message position in self-validation. *Pers. Soc. Psychol. Bull.* 40 (8), 1024–1036. <https://doi.org/10.1177/0146167214534733>.
3395. Colombo, O., 2021. The Use of Signals in new-venture financing: a review and research agenda. *J. Manag.* 47 (1), 237–259. <https://doi.org/10.1177/0149206320911090>.
3396. Conklin, A., 2020. How Facebook fact checks work. July 13 Fox Bus. <https://www.foxbusiness.com/technology/how-facebook-fact-checks-work>.
3397. Connelly, Certo, S.T., Ireland, R.D., Reutzel, C.R., 2011. Signaling theory: a review and assessment. *J. Manag.* 37 (1), 39–67. <https://doi.org/10.1177/0149206310388419>.
3398. Culliford, E., Paul, K., 2020. Reuters. May 30. <https://www.reuters.com/article/us-twitter-factcheck/with-fact-checks-twitter-takes-on-a-new-kind-of-task-idUSKBN2360U0>.
3399. Davies, W.E., Giovannetti, E., 2018. Signalling experience & reciprocity to temper asymmetric information in crowdfunding evidence from 10,000 projects. *Technol. Forecast. Soc. Change* 133, 118–131. <https://doi.org/10.1016/j.techfore.2018.03.011>.
3400. Dhanesh, Duthler, G., 2019. Relationship management through social media influencers: effects of followers' awareness of paid endorsement. *Publ. Relat. Rev.* 45 (3), 101765 <https://doi.org/10.1016/j.pubrev.2019.03.002>.
3401. Dickey, C., 2019. The Rise and Fall of Facts. *Columbia Journalism Review*. https://www.cjr.org/special_report/rise-and-fall-of-fact-checking.php.
3402. Dobbs, M., 2012. The rise of political fact-checking how Reagan inspired a journalistic movement: a reporter's eye view. February New Am. Found. <https://www.issueab.org/resources/15318/15318.pdf>.
3403. Elfrink, T., 2021. Man Shot Security Guard at High School Basketball Game during Argument over Wearing Mask. *The Washington Post*. <https://www.washingtonpost.com/nation/2021/03/01/martinus-mitchum-tulane-mask-shooting>.
3404. Faul, F., Erdfelder, E., Buchner, A., Lang, A.-G., 2009. Statistical power analyses using G*Power 3.1: tests for correlation and regression analyses. *Behav. Res. Methods* 41 (4), 1149–1160. <https://doi.org/10.3758/BRM.41.4.1149>.
3405. Faul, F., Erdfelder, E., Lang, A.-G., Buchner, A., 2007. G*Power 3: a flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behav. Res. Methods* 39 (2), 175–191. <https://doi.org/10.3758/BF03193146>.
3406. Fda, 2022. Warning Letter. April 6. Sensory Cloud inc. <https://www.fda.gov/inspections-compliance-enforcement-and-criminal-investigations/warning-letters/sensory-cloud-inc-628897-04062022>.
3407. Fielden, N., Holch, P., 2022. Exploring the influence of social media influencers on intention to attend cervical screening in the UK: utilising the theory of planned behaviour. *Cancer Control* 29. <https://doi.org/10.1177/10732748221079480>, 10732748221079480-10732748221079480.

3408. Freberg, Graham, K., McGaughey, K., Freberg, L.A., 2011. Who are the social media influencers? A study of public perceptions of personality. *Publ. Relat. Rev.* 37 (1), 90–92. <https://doi.org/10.1016/j.pubrev.2010.11.001>. Gallagher, J., 2022. Coronavirus Treatments: what Progress Is Being Made? BBC News.
3409. <https://www.bbc.com/news/health-52354520#comments>. Gao Jin, X., Zhang, Y., 2021. User participation behavior in crowdsourcing platforms: impact of information signaling theory. *Sustainability* 13 (11), 6290. <https://doi.org/10.3390/su13116290>. Graves, L., & Amazeen, M. Fact-Checking as idea and practice in journalism. *Oxf. Res. Encycl. Commun.* Retrieved 15 Nov. 2021, from <https://oxfordre.com/communication/view/10.1093/acrefore/9780190228613.001.0001/acrefore-9780190228613-e-808>.
3410. Geyser, W., 2022. What Is an Influencer? – Social Media Influencers Defined. April 4. Influencer MarketingHub. <https://influencermarketinghub.com/what-is-an-influencer/>.
3411. Gil De Zúniga, H., Barnidge, M., Scherman, A., 2017. Social media social capital, offline social capital, and citizenship: exploring asymmetrical social capital effects. *Polit. Commun.* 34 (1), 44–68. <https://doi.org/10.1080/10584609.2016.1227000>.
3412. Goldberg, E., 2021. Demand Surges for Deworming Drug for COVID, Despite Scant Evidence it Works. *The New York Times*. <https://www.nytimes.com/2021/08/30/health/covid-ivermectin-prescriptions.html>.
3413. Gregory, C.K., Meade, A.W., Thompson, L.F., 2013. Understanding internet recruitment via signaling theory and the elaboration likelihood model. *Comput. Hum. Behav.* 29 (5), 1949–1959. <https://doi.org/10.1016/j.chb.2013.04.013>.
3414. Han, M.C., 2021. Thumbs down on “likes”? The impact of Facebook reactions on online consumers’ nonprofit engagement behavior. *Int. Rev. Publ. Nonprofit Mark.* 18 (2), 255–272. <https://doi.org/10.1007/s12208-020-00271-2>.
3415. Harff, Bollen, C., Schmuck, D., 2022. Responses to Social Media Influencers’ Misinformation about COVID-19: A Pre-registered Multiple-Exposure Experiment. *Media Psychology*. <https://doi.org/10.1080/15213269.2022.2080711> ahead-of-print(ahead-of-print), 1–20.
3416. Heiss, R., Rudolph, L., 2022. Patients as health influencers: motivations and consequences of following cancer patients on Instagram. *Behav. Inf. Technol.* <https://doi.org/10.1080/0144929X.2022.2045358>.
3417. Huang, S., Pickernell, D., Battisti, M., Nguyen, T., 2021. Signalling entrepreneurs’ credibility and project quality for crowdfunding success: cases from the Kickstarter and Indiegogo environments. *Small Bus. Econ.* <https://doi.org/10.1007/s11187-021-00477-6>.
3418. James, G., Witten, D., Hastie, T., Tibshirani, R., 2021. Linear regression. In: *An Introduction to Statistical Learning*. Springer Texts in Statistics. Springer, New York. https://doi.org/10.1007/978-1-0716-1418-1_3.
3419. Jones, J.M., 2020. Americans Struggle to Navigate COVID-19 “infodemic”. Gallup. May <https://news.gallup.com/poll/310409/americans-struggle-navigate-covid-infodemic.aspx>.
3420. Kietzmann, J., Hermkens, K., McCarthy, I., Silvestre, B., 2011. Social media? Get serious! Understanding the functional building blocks of social media. *Bus. Horiz.* 54 (3), 241–251. <https://doi.org/10.1016/j.bushor.2011.01.005>.

3421. Kim, P.H., Buffart, M., Croidieu, G., 2016. TMI: signaling credible claims in crowdfunding campaign narratives. *Group Organ. Manag.* 41 (6), 717–750. <https://doi.org/10.1177/1059601116651181>.
3422. Kirmani, Rao, A.R., 2000. No pain, No gain: a critical review of the literature on signaling unobservable product quality. *J. Market.* 64 (2), 66–79. <https://doi.org/10.1509/jmkg.64.2.66.18000>. Kirmani, 1997. Advertising repetition as a signal of quality: if it's advertised so much, something must Be wrong. *J. Advert.* 26 (3), 77–86. <https://doi.org/10.1080/00913367.1997.10673530>.
3423. Klimchak, Bartlett, A.K.W., MacKenzie, W., 2020. Building trust and commitment through transparency and HR competence A signaling perspective. *Person. Rev.* 49 (9), 1897–1917. <https://doi.org/10.1108/PR-03-2019-0096>.
3424. Kline, R.B., 2004. Principles and practice of structural equation modeling, 2nd ed. Guilford Press. Kock, N., 2017. Common method bias: a full collinearity assessment method for pls-sem. In: Latan, H., Noonan, R. (Eds.), *Partial Least Squares Path Modeling*. Springer. http://doi.org/10.1007/978-3-319-64069-3_11.
3425. Korzynski, P., Mazurek, G., Haenlein, M., 2020. Leveraging employees as spokespeople in your HR strategy: how company-related employee posts on social media can help firms to attract new talent. *Eur. Manag. J.* 38 (1), 204–212. <https://doi.org/10.1016/j.emj.2019.08.003>.
3426. Kromidha, Li, M.C., 2019. Determinants of leadership in online social trading: a signaling theory perspective. *J. Bus. Res.* 97, 184–197. <https://doi.org/10.1016/j.jbusres.2019.01.004>.
3427. Kromidha, Robson, P., 2016. Social identity and signalling success factors in online crowdfunding. *Enterpren. Reg. Dev.* 28 (9–10), 605–629. <https://doi.org/10.1080/08985626.2016.1198425>.
3428. Li, Xie, Y., 2020. Is a picture worth a thousand words? An empirical study of image content and social media engagement. *J. Market. Res.* 57 (1), 1–19. <https://doi.org/10.1177/0022243719881113>.
3429. Lou, C., 2021. Social media influencers and followers: theorization of a trans-parasocial relation and explication of its implications for influencer advertising. *J. Advert.* 1–18. <https://doi.org/10.1080/00913367.2021.1880345>.
3430. Malthouse, Calder, B.J., Kim, S.J., Vandenbosch, M., 2016. Evidence that user-generated content that produces engagement increases purchase behaviours. *J. Market. Manag.* 32 (5–6), 427–444. <https://doi.org/10.1080/0267257X.2016.1148066>.
3431. McQuitty, 2004. Statistical power and structural equation models in business research. *J. Bus. Res.* 57 (2), 175–183. [https://doi.org/10.1016/S0148-2963\(01\)00301-0](https://doi.org/10.1016/S0148-2963(01)00301-0).
3432. Moratis, L., 2018. Signalling responsibility? Applying signalling theory to the ISO 26000 standard for social responsibility. *Sustainability* 10 (11), 4172. <https://doi.org/10.3390/su10114172>.
3433. Navarro, M.A., Molleda, J.C., Khalil, N., Verhoeven, P., 2020. The challenge of new gatekeepers for public relations. A comparative analysis of the role of social media influencers for European and Latin American professionals. *Publ. Relat. Rev.* 46 (2) <https://doi.org/10.1016/j.pubrev.2020.101881>.

3434. Nazar, S., Pieters, T., 2021. Plandemic revisited: a product of planned disinformation amplifying the COVID-19 “infodemic. *Front. Public Health* 9. <https://doi.org/10.3389/fpubh.2021.649930>.
3435. Nyagadza, B., Kadembo, E.M., Makasi, A., 2021. When corporate brands tell stories: a signalling theory perspective. *Cogent Psychol.* 8 (1) <https://doi.org/10.1080/23311908.2021.1897063>.
3436. O’Keefe, D.J., 1990. *Persuasion: Theory and Research*. Sage Publications, London.
3437. Pardes, A., 2020. Wellness influencers sell false promises as health fears soar. *WIRED*. <https://www.wired.com/story/coronavirus-anxieties-soar-wellness-influencers-st ep-in>.
3438. Park, Jiang, H., 2020. Signaling, verification, and identification: the way corporate social advocacy generates brand loyalty on social media. *Int. J. Bus. Commun.* <https://doi.org/10.1177/2329488420907121>.
3439. Pirlott, MacKinnon, D.P., 2016. Design approaches to experimental mediation. *J. Exp. Soc. Psychol.* 66, 29–38. <https://doi.org/10.1016/j.jesp.2015.09.012>.
3440. Pazzanese, C., 2020. Battling the ‘pandemic of misinformation.’. May 8 *Harvard Gazette*. From. <https://news.harvard.edu/gazette/story/2020/05/social-media-used-to-spread-create-covid-19-falsehoods/>.
3441. Rao, Lee, K.B., Connelly, B., Iyengar, D., 2018. Return time leniency in online retail: a signaling theory perspective on buying outcomes. *Decis. Sci. J.* 49 (2), 275–305. <https://doi.org/10.1111/deci.12275>.
3442. Rasmus, K.N., Fletcher, R., Newman, J., Brennen, J.S., Howard, P.N., 2020. Navigating the ‘infodemic’: How People in Six Countries Access and Rate News and Information about Coronavirus. April 15. Reuters Institute for the Study of Journalism. From. <https://www.politico.eu/wp-content/uploads/2020/04/Navigatingthe-Coronavirusinfodemic.pdf>.
3443. Rice, R.E., Atkins, K.A., 2001. *Public Communication Campaigns*, fourth ed. Sage Publications, London. Rim, H., Song, D., 2016. How negative becomes less negative”: understanding the effects of comment valence and response sidedness in social media. *J. Commun.* 66 (3), 475–495. <https://doi.org/10.1111/jcom.12205>.
3444. Saxton, G.D., Gomez, L., Ngoh, Z., Lin, Y.-P., Dietrich, S., 2017. Do CSR messages resonate? Examining public reactions to firms’ CSR efforts on social media. *J. Bus. Ethics* 155 (2), 359–377. <https://doi.org/10.1007/s10551-017-3464-z>.
3445. Simmons-Duffin, S., 2022. CDC Is Criticized for Failing to Communicate, Promises to Do Better. January 7. NPR. <https://www.npr.org/sections/health-shots/2022/01/07/1071449137/cdc-is-criticized-for-failing-to-communicate-promises-to-do-better>
3446. Sinclair, S., Agerstrom, J., 2021. Do Social Norms Influence Young People’s Willingness to Take the COVID-19 Vaccine? *Health Communication*, pp. 1–8. <https://doi.org/10.1080/10410236.2021.1937832>.
3447. Spence, M., 1973. Job market signaling. *Q. J. Econ.* 87 (3), 355–374. Spence, 2002. Signaling in retrospect and the informational structure of markets. *Am. Econ. Rev.* 92 (3), 434–459. <https://doi.org/10.1257/00028280260136200>.

3448. Stein, C.M., Morris, N.J., Nock, N.L., 2012. Structural equation modeling. In: Elston, R., Satagopan, J., Sun, S. (Eds.), *Statistical Human Genetics, Methods in Molecular Biology*, vol. 850. Humana Press. https://doi.org/10.1007/978-1-61779-555-8_27.
3449. Stiglitz, 2002. Information and the change in the paradigm in economics. *Am. Econ. Rev.* 92 (3), 460–501. <https://doi.org/10.1257/00028280260136363>.
3450. Taoketao, E., Feng, T., Song, Y., Nie, Y., 2018. Does sustainability marketing strategy achieve payback profits? A signaling theory perspective. *Corp. Soc. Responsib. Environ. Manag.* 25 (6), 1039–1049. <https://doi.org/10.1002/csr.1518>.
3451. Teubner, T., Adam, M.T.P., Hawlitschek, F., 2019. Unlocking online reputation: on the effectiveness of cross-platform signaling in the sharing economy. *Bus. Info. Syst. Eng.* 62 (6), 501–513. <https://doi.org/10.1007/s12599-019-00620-4>.
3452. Tsui, H., 2012. Advertising, quality, and willingness-to-pay: Experimental examination of signaling theory. *J. Econ. Psychol.* 33 (6), 1193–1203. <https://doi.org/10.1016/j.joep.2012.08.011>.
3453. Tyson, A., Funk, C., 2022. Increasing Public Criticism, Confusion over COVID-19 Response in U.S. Pew Research Center. February 9. <https://www.pewresearch.org/science/2022/02/09/increasingpubliccriticismconfusionovercovid19responseinus/>.
3454. Usrey, Palihawadana, D., Saridakis, C., Theotokis, A., 2020. How downplaying product greenness affects performance evaluations: examining the effects of implicit and explicit green signals in advertising. *J. Advert.* 49 (2), 125–140. <https://doi.org/10.1080/00913367.2020.1712274>.
3455. Wasike, B., 2022. Memes, memes, everywhere, nor any meme to trust: examining the credibility and persuasiveness of COVID-19-Related Memes. *J. Computer-Mediated Commun.* 27 (2) <https://doi.org/10.1093/jcmc/zmac024>.
3456. Xie, G., Kronrod, A., 2012. Is the devil in the details?: the signaling effect of numerical precision in environmental advertising claims. *J. Advert.* 41 (4), 103–117. <https://doi.org/10.1080/00913367.2012.10672460>.
3457. Xu, Y., Margolin, D., Niederdeppe, J., 2021. Testing Strategies to increase source credibility through strategic message design in the context of vaccination and vaccine hesitancy. *Health Commun.* 36 (11), 1354–1367. <https://doi.org/10.1080/10410236.2020.1751400>.
3458. Yin, C., Zhang, X., 2020. Incorporating message format into user evaluation of microblog information credibility: a nonlinear perspective. *Inf. Process. Manag.* 57 (6) <https://doi.org/10.1177/0146167214534733>, 102345–102345.
3459. YouGov, 2021. Game-changers: the Power of Gaming Influencers. October 18. Part 1. https://business.yougov.com/content/38826-international-gaming-report-2021?_ga=2.209938197.1441979521.1651880402-1309465120.1651880402.
3460. Yousuf, H., Corbin, J., Sweep, G., Hofstra, M., Scherder, E., van Gorp, E., Zwetsloot, P.P., Zhao, J., van Rossum, B., Jiang, T., Lindemans, J.W., Narula, J., Hofstra, L., 2020. Association of a public health campaign about coronavirus disease 2019 promoted by news media and a social influencer with self-reported personal hygiene and physical distancing in The Netherlands. *JAMA Netw. Open* 3 (7).

3461. Zhang, M., Zhang, Y., Zhao, L., Li, X., 2020. What drives online course sales? Signaling effects of user-generated information in the paid knowledge market. *J. Bus. Res.* 118, 389–397. <https://doi.org/10.1016/j.jbusres.2020.0>.
3462. Zuckerberg, M., 2016. No Title. Meta. November 8. <https://www.facebook.com/zuck/posts/a-lot-of-you-have-asked-what-were-doing-about-misinformation-so-i-wanted-to-give/10103269806149061/>.
3463. Sami Abu-El-Haija, Bryan Perozzi, Amol Kapoor, Nazanin Alipourfard, Kristina Lerman, Hrayr Harutyunyan, Greg Ver Steeg, and Aram Galstyan. 2019. Mixhop: Higher-order graph convolutional architectures via sparsified neighborhood mixing. In *international conference on machine learning*. PMLR, 21–29.
3464. Seyed Ali Alhosseini, Raad Bin Tareaf, Pejman Najafi, and Christoph Meinel. 2019. Detect me if you can: Spam bot detection using inductive representation learning. In *Companion Proceedings of The 2019 World Wide Web Conference*. 148–153.
3465. Matthew C Benigni, Kenneth Joseph, and Kathleen M Carley. 2017. Online extremism and the communities that sustain it: Detecting the ISIS supporting community on Twitter. *PloS one* 12, 12 (2017), e0181405.
3466. Jonathon M Berger and Jonathon Morgan. 2015. The ISIS Twitter Census: Defining and describing the population of ISIS supporters on Twitter. (2015).
3467. David M Beskow and Kathleen M Carley. 2018. Bot-hunter: a tiered approach to detecting & characterizing automated activity on twitter. In *Conference paper. SBP-BRIMS: International conference on social computing, behavioral-cultural modeling and prediction and behavior representation in modeling and simulation*, Vol. 3.
3468. Deyu Bo, Xiao Wang, Chuan Shi, and Huawei Shen. 2021. Beyond low-frequency information in graph convolutional networks. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 35. 3950–3957.
3469. Chiyu Cai, Linjing Li, and Daniel Zeng. 2017. Detecting social bots by jointly modeling deep behavior and content information. In *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management*. 1995–1998.
3470. Chia-Mei Chen, DJ Guan, and Qun-Kai Su. 2014. Feature set identification for detecting suspicious URLs using Bayesian classification in social networks. *Information Sciences* 289 (2014), 133–147.
3471. Stefano Cresci. 2020. A decade of social bot detection. *Commun. ACM* 63, 10 (2020), 72–83.
3472. Stefano Cresci, Roberto Di Pietro, Marinella Petrocchi, Angelo Spognardi, and Maurizio Tesconi. 2015. Fame for sale: Efficient detection of fake Twitter followers. *Decision Support Systems* 80 (2015), 56–71.
3473. Stefano Cresci, Roberto Di Pietro, Marinella Petrocchi, Angelo Spognardi, and Maurizio Tesconi. 2017. The paradigm-shift of social spambots: Evidence, theories, and tools for the arms race. In *Proceedings of the 26th international conference on world wide web companion*. 963–972.
3474. Stefano Cresci, Roberto Di Pietro, Angelo Spognardi, Maurizio Tesconi, and Marinella Petrocchi. 2023. Demystifying Misconceptions in Social Bots Research. *arXiv preprint arXiv:2303.17251* (2023).

3475. Ashkan Dehghan, Kinga Siuta, Agata Skorupka, Akshat Dubey, Andrei Betlen, David Miller, Wei Xu, Bogumil Kaminski, and Pawel Pralat. 2022. Detecting Bots in Social-Networks Using Node and Structural Embeddings. (2022).
3476. Juglar Diaz, Felipe Bravo-Marquez, and Barbara Poblete. 2022. Language Modeling on Location-Based Social Networks. *ISPRS International Journal of Geo-Information* 11, 2 (2022), 147.
3477. Juglar Diaz, Barbara Poblete, and Felipe Bravo-Marquez. 2020. An integrated model for textual social media data with spatio-temporal dimensions. *Information Processing & Management* 57, 5 (2020), 102219.
3478. Kaize Ding, Zhe Xu, Hanghang Tong, and Huan Liu. 2022. Data augmentation for deep graph learning: A survey. *ACM SIGKDD Explorations Newsletter* 24, 2 (2022), 61–77.
3479. Yushun Dong, Ninghao Liu, Brian Jalaian, and Jundong Li. 2022. Edits: Modeling and mitigating data bias for graph neural networks. In *Proceedings of the ACM Web Conference 2022*. 1259–1269.
3480. David Dukić, Dominik Keča, and Dominik Stipić. 2020. Are you human? Detecting bots on Twitter Using BERT. In *2020 IEEE 7th International Conference on Data Science and Advanced Analytics (DSAA)*. IEEE, 631–636.
3481. Juan Echeverria, Emiliano De Cristofaro, Nicolas Kourtellis, Ilias Leontiadis, Gianluca Stringhini, and Shi Zhou. 2018. LOBO: Evaluation of generalization deficiencies in Twitter bot classifiers. In *Proceedings of the 34th annual computer security applications conference*. 137–146.
3482. David Eppstein, Michael S Paterson, and F Frances Yao. 1997. On nearest-neighbor graphs. *Discrete & Computational Geometry* 17 (1997), 263–282.
3483. Shangbin Feng, Chan Young Park, Yuhan Liu, and Yulia Tsvetkov. 2023. From Pretraining Data to Language Models to Downstream Tasks: Tracking the Trails of Political Biases Leading to Unfair NLP Models. *arXiv preprint arXiv:2305.08283* (2023).
3484. Shangbin Feng, Zhaoxuan Tan, Rui Li, and Minnan Luo. 2022. Heterogeneityaware twitter bot detection with relational graph transformers. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 36. 3977–3985.
3485. Shangbin Feng, Zhaoxuan Tan, Herun Wan, Ningnan Wang, Zilong Chen, Binchi Zhang, Qinghua Zheng, Wenqian Zhang, Zhenyu Lei, Shujie Yang, et al. 2022. TwiBot-22: Towards graph-based Twitter bot detection. *arXiv preprint arXiv:2206.04564* (2022).
3486. Shangbin Feng, Herun Wan, Ningnan Wang, Jundong Li, and Minnan Luo. 2021. Satar: A self-supervised approach to twitter account representation learning and its application in bot detection. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*. 3808–3817.
3487. Shangbin Feng, Herun Wan, Ningnan Wang, Jundong Li, and Minnan Luo. 2021. Twibot-20: A comprehensive twitter bot detection benchmark. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*. 4485–4494.
3488. Shangbin Feng, Herun Wan, Ningnan Wang, and Minnan Luo. 2021. BotRGCN: Twitter bot detection with relational graph convolutional networks. In *Proceedings of the 2021 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining*. 236–239.

3489. Emilio Ferrara. 2017. Disinformation and social bot operations in the run up to the 2017 French presidential election. arXiv preprint arXiv:1707.00086 (2017).
3490. Emilio Ferrara. 2020. # covid-19 on twitter: Bots, conspiracies, and social media activism. arXiv preprint arXiv: 2004.09531 (2020).
3491. Emilio Ferrara, Onur Varol, Clayton Davis, Filippo Menczer, and Alessandro Flammini. 2016. The rise of social bots. *Commun. ACM* 59, 7 (2016), 96–104.
3492. Matthias Fey and Jan Eric Lenssen. 2019. Fast graph representation learning with PyTorch Geometric. arXiv preprint arXiv:1903.02428 (2019).
3493. Selva Dilan GÖLBAŞI and Selma METİNTAS. 2020. Covid-19 pandemisi ve infodemi. *ESTÜDAM Halk Sağlığı Dergisi* 5 (2020), 126–137.
3494. Henrich R Greve, Hayagreeva Rao, Paul Vicinanza, and Echo Yan Zhou. 2022.
3495. Online Conspiracy Groups: Micro-Bloggers, Bots, and Coronavirus Conspiracy Talk on Twitter. *American Sociological Review* 87, 6 (2022), 919–949.
3496. Will Hamilton, Zhitao Ying, and Jure Leskovec. 2017. Inductive representation learning on large graphs. *Advances in neural information processing systems* 30 (2017).
3497. Charles R Harris, K Jarrod Millman, Stéfan J Van Der Walt, Ralf Gommers, Pauli Virtanen, David Cournapeau, Eric Wieser, Julian Taylor, Sebastian Berg, Nathaniel J Smith, et al. 2020. Array programming with NumPy. *Nature* 585, 7825 (2020), 357–362.
3498. Kadhim Hayawi, Sujith Mathew, Neethu Venugopal, Mohammad M Masud, and Pin-Han Ho. 2022. DeeProBot: a hybrid deep neural network model for social bot detection based on user profile data. *Social Network Analysis and Mining* 12, 1 (2022), 43.
3499. Ruining He, Anirudh Ravula, Bhargav Kanagal, and Joshua Ainslie. 2020. Realformer: transformer likes residual attention. arXiv preprint arXiv:2012.11747
3500. Maryam Heidari and James H Jones. 2020. Using bert to extract topic-independent sentiment features for social media bot detection. In *2020 11th IEEE Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON)*. IEEE, 0542–0547.
3501. Thomas N Kipf and Max Welling. 2016. Semi-supervised classification with graph convolutional networks. arXiv preprint arXiv:1609.02907 (2016).
3502. Jürgen Knauth. 2019. Language-agnostic twitter-bot detection. In *Proceedings of the International Conference on Recent Advances in Natural Language Processing (RANLP 2019)*. 550–558.
3503. Sneha Kudugunta and Emilio Ferrara. 2018. Deep neural networks for bot detection. *Information Sciences* 467 (2018), 312–322.
3504. Kyumin Lee, Brian Eoff, and James Caverlee. 2011. Seven months with the devils: A long-term study of content polluters on twitter. In *Proceedings of the international AAAI conference on web and social media*, Vol. 5. 185–192.
3505. Sangho Lee and Jong Kim. 2014. Early filtering of ephemeral malicious accounts on Twitter. *Computer communications* 54 (2014), 48–57.
3506. Zhenyu Lei, Herun Wan, Wenqian Zhang, Shangbin Feng, Zilong Chen, Qinghua Zheng, and Minnan Luo. 2022. BIC: Twitter Bot Detection with Text-Graph Interaction and Semantic Consistency. arXiv preprint arXiv:2208.08320 (2022).

3507. Guohao Li, Chenxin Xiong, Ali Thabet, and Bernard Ghanem. 2020. Deepergcn: All you need to train deeper gcns. arXiv preprint arXiv:2006.07739 (2020).
3508. Qimai Li, Zhichao Han, and Xiao-Ming Wu. 2018. Deeper insights into graph convolutional networks for semi-supervised learning. In *Proceedings of the AAAI conference on artificial intelligence*, Vol. 32.
3509. Paul Pu Liang, Chiyu Wu, Louis-Philippe Morency, and Ruslan Salakhutdinov. 2021. Towards understanding and mitigating social biases in language models. In *International Conference on Machine Learning*. PMLR, 6565–6576.
3510. Derek Lim, Felix Hohne, Xiuyu Li, Sijia Linda Huang, Vaishnavi Gupta, Omkar Bhalerao, and Ser Nam Lim. 2021. Large scale learning on non-homophilous graphs: New benchmarks and strong simple methods. *Advances in Neural Information Processing Systems* 34 (2021), 20887–20902.
3511. Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.11692 (2019).
3512. Yuhao Liu, Zhaoxuan Tan, Heng Wang, Shangbin Feng, Qinghua Zheng, and Minnan Luo. 2023. BotMoE: Twitter Bot Detection with Community-Aware Mixtures of Modal-Specific Experts. arXiv:2304.06280 - cs.SI
3513. Andrew L Maas, Awni Y Hannun, Andrew Y Ng, et al. 2013. Rectifier nonlinearities improve neural network acoustic models. In *Proc. icml*, Vol. 30. Atlanta, Georgia, USA, 3.
3514. Thomas Magelinski, David Beskow, and Kathleen M Carley. 2020. Graph-hist: Graph classification from latent feature histograms with application to bot detection. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 34. 5134–5141.
3515. Michele Mazza, Stefano Cresci, Marco Avvenuti, Walter Quattrociocchi, and Maurizio Tesconi. 2019. Rtbust: Exploiting temporal patterns for botnet detection on twitter. In *Proceedings of the 10th ACM conference on web science*. 183–192. DOI:10.1145/3292522.3326015
3516. Zachary Miller, Brian Dickinson, William Deitrick, Wei Hu, and Alex Hai Wang. 2014. Twitter spammer detection using data stream clustering. *Information Sciences* 260 (2014), 64–73. DOI:10.1016/j.ins.2013.11.016
3517. Amanda Minnich, Nikan Chavoshi, Danai Koutra, and Abdullah Mueen. 2017. BotWalk: Efficient adaptive exploration of Twitter bot networks. In *Proceedings of the 2017 IEEE/ACM international conference on advances in social networks analysis and mining* 2017. 467–474.
3518. Moin Nadeem, Anna Bethke, and Siva Reddy. 2020. StereoSet: Measuring stereotypical bias in pretrained language models. arXiv preprint arXiv:2004.09456 (2020).
3519. Lynnette Hui Xian Ng and Kathleen M Carley. 2022. BotBuster: Multi-platform Bot Detection Using A Mixture of Experts. arXiv preprint arXiv:2207.13658 (2022).
3520. Shashank Pandit, Duen Horng Chau, Samuel Wang, and Christos Faloutsos. 2007. Netprobe: a fast and scalable system for fraud detection in online auction networks. In *Proceedings of the 16th international conference on World Wide Web*. 201–210.

3521. Fabian Pedregosa, Gaël Varoquaux, Alexandre Gramfort, Vincent Michel, Bertrand Thirion, Olivier Grisel, Mathieu Blondel, Peter Prettenhofer, Ron Weiss, Vincent Dubourg, et al. 2011. Scikit-learn: Machine learning in Python. *the Journal of machine Learning research* 12 (2011), 2825–2830.
3522. Hongbin Pei, Bingzhe Wei, Kevin Chen-Chuan Chang, Yu Lei, and Bo Yang. 2020. Geom-gcn: Geometric graph convolutional networks. *arXiv preprint arXiv:2002.05287* (2020).
3523. Automatic Differentiation In Pytorch. 2018. Pytorch.
3524. Mauricio Quezada and Barbara Poblete. 2019. A lightweight representation of news events on social media. In *Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval*. 1049–1052.
3525. Sippo Rossi, Matti Rossi, Bikesh Upreti, and Yong Liu. 2020. Detecting political bots on Twitter during the 2019 Finnish parliamentary election. (2020).
3526. Hernan Sarmiento, Felipe Bravo-Marquez, Eduardo Graells-Garrido, and Barbara Poblete. 2022. Identifying and Characterizing New Expressions of Community Framing during Polarization. In *Proceedings of the International AAAI Conference on Web and Social Media*, Vol. 16. 841–851.
3527. Michael Schlichtkrull, Thomas N Kipf, Peter Bloem, Rianne Van Den Berg, Ivan Titov, and Max Welling. 2018. Modeling relational data with graph convolutional networks. In *The Semantic Web: 15th International Conference, ESWC 2018, Heraklion, Crete, Greece, June 3–7, 2018, Proceedings* 15. Springer, 593–607.
3528. Shuhao Shi, Kai Qiao, Jian Chen, Shuai Yang, Jie Yang, Baojie Song, Linyuan Wang, and Bin Yan. 2023. MGTAB: A Multi-Relational Graph-Based Twitter Account Detection Benchmark. *arXiv preprint arXiv:2301.01123* (2023).
3529. Shuhao Shi, Kai Qiao, Jie Yang, Baojie Song, Jian Chen, and Bin Yan. 2023. Over-Sampling Strategy in Feature Space for Graphs based Class-imbalanced Bot Detection. *arXiv preprint arXiv:2302.06900* (2023).
3530. Kate Starbird. 2019. Disinformation’s spread: bots, trolls and all of us. *Nature* 571, 7766 (2019), 449–450.
3531. Zhaoxuan Tan, Shangbin Feng, Melanie Sclar, Herun Wan, Minnan Luo, Yejin Choi, and Yulia Tsvetkov. 2023. BotPercent: Estimating Twitter bot populations from groups to crowds. *arXiv preprint arXiv:2302.00381* (2023).
3532. Andree Thieltges, Florian Schmidt, and Simon Hegelich. 2016. The devil’s triangle: Ethical considerations on developing bot detection methods. In *2016 AAAI Spring Symposium Series*.
3533. Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. *Advances in neural information processing systems* 30 (2017).
3534. Petar Veličković, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Lio, and Yoshua Bengio. 2017. Graph attention networks. *arXiv preprint arXiv:1710.10903* (2017).
3535. Yu Wang, Yuying Zhao, Yushun Dong, Huiyuan Chen, Jundong Li, and Tyler Derr. 2022. Improving fairness in graph neural networks via mitigating sensitive attribute leakage. In

- Proceedings of the 28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining. 1938–1948.
3536. Feng Wei and Uyen Trang Nguyen. 2019. Twitter bot detection using bidirectional long short-term memory neural networks and word embeddings. In 2019 First IEEE International conference on trust, privacy and security in intelligent systems and applications (TPS-ISA). IEEE, 101–109.
 3537. Keyulu Xu, Chengtao Li, Yonglong Tian, Tomohiro Sonobe, Ken-ichi Kawarabayashi, and Stefanie Jegelka. 2018. Representation learning on graphs with jumping knowledge networks. In International conference on machine learning. PMLR, 5453–5462.
 3538. Kai-Cheng Yang, Onur Varol, Pik-Mai Hui, and Filippo Menczer. 2020. Scalable and generalizable social bot detection through data selection. In Proceedings of the AAAI conference on artificial intelligence, Vol. 34. 1096–1103.
 3539. Yuning You, Tianlong Chen, Yongduo Sui, Ting Chen, Zhangyang Wang, and Yang Shen. 2020. Graph contrastive learning with augmentations. *Advances in neural information processing systems* 33 (2020), 5812–5823.
 3540. Savvas Zannettou, Tristan Caulfield, Emiliano De Cristofaro, Michael Sirivianos, Gianluca Stringhini, and Jeremy Blackburn. 2019. Disinformation warfare: Understanding state-sponsored trolls on Twitter and their influence on the web. In *Companion proceedings of the 2019 world wide web conference*. 218–226.
 3541. Jiong Zhu, Ryan A Rossi, Anup Rao, Tung Mai, Nedim Lipka, Nesreen K Ahmed, and Danai Koutra. 2021. Graph neural networks with heterophily. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 35. 11168–11176.
 3542. Jiong Zhu, Yujun Yan, Lingxiao Zhao, Mark Heimann, Leman Akoglu, and Danai Koutra. 2020. Beyond homophily in graph neural networks: Current limitations and effective designs. *Advances in Neural Information Processing Systems* 33 (2020), 7793–7804.
 3543. Sami Abu-El-Haija, Bryan Perozzi, Amol Kapoor, Nazanin Alipourfard, Kristina Lerman, Hrayr Harutyunyan, Greg Ver Steeg, and Aram Galstyan. 2019. Mixhop: Higher-order graph convolutional architectures via sparsified neighborhood mixing. In *international conference on machine learning*. PMLR, 21–29.
 3544. Open AI. 2022. ChatGPT: Optimizing Language Models for Dialogue. <https://openai.com/blog/chatgpt/>, Accessed: 2023-02-25.
 3545. Open AI. 2023. New AI classifier for indicating AI-written text. <https://openai.com/blog/new-ai-classifier-for-indicating-ai-written-text/>, Accessed: 2023-02-25.
 3546. Seyed Ali Alhosseini, Raad Bin Tareaf, Pejman Najafi, and Christoph Meinel. 2019. Detect me if you can: Spam bot detection using inductive representation learning. In *Companion Proceedings of The 2019 World Wide Web Conference*. 148–153.
 3547. Bo Chen, Jing Zhang, Xiaokang Zhang, Yuxiao Dong, Jian Song, Peng Zhang, Kaibo Xu, Evgeny Kharlamov, and Jie Tang. 2022. GCCAD: Graph Contrastive Learning for Anomaly Detection. *IEEE Transactions on Knowledge and Data Engineering* (2022).
 3548. Eli Chien, Jianhao Peng, Pan Li, and Olgica Milenkovic. 2020. Adaptive universal generalized pagerank graph neural network. *arXiv preprint arXiv:2006.07988* (2020).

3549. Stefano Cresci. 2020. A decade of social bot detection. *Commun. ACM* 63, 10 (2020), 72–83.
3550. Mohd Fazil, Amit Kumar Sah, and Muhammad Abulaish. 2021. Deepsbd: a deep neural network model with attention mechanism for socialbot detection. *IEEE Transactions on Information Forensics and Security* 16 (2021), 4211–4223.
3551. Shangbin Feng, Zhaoxuan Tan, Rui Li, and Minnan Luo. 2021. Heterogeneityaware Twitter Bot Detection with Relational Graph Transformers. *arXiv preprint arXiv:2109.02927* (2021).
3552. Shangbin Feng, Zhaoxuan Tan, Herun Wan, Ningnan Wang, Zilong Chen, Binchi Zhang, Qinghua Zheng, Wenqian Zhang, Zhenyu Lei, Shujie Yang, et al. 2022. TwiBot-22: Towards Graph-Based Twitter Bot Detection. *arXiv preprint arXiv:2206.04564* (2022).
3553. Emilio Ferrara. 2017. Disinformation and social bot operations in the run up to the 2017 French presidential election. *arXiv preprint arXiv:1707.00086* (2017).
3554. Matthias Fey and Jan E. Lenssen. 2019. Fast Graph Representation Learning with PyTorch Geometric. In *ICLR Workshop on Representation Learning on Graphs and Manifolds*.
3555. Qinglang Guo, Haiyong Xie, Yangyang Li, Wen Ma, and Chao Zhang. 2021. Social Bots Detection via Fusing BERT and Graph Convolutional Networks. *Symmetry* 14, 1 (2021), 30.
3556. Kaveh Hassani and Amir Hosein Khasahmadi. 2020. Contrastive multi-view representation learning on graphs. In *International Conference on Machine Learning*. PMLR, 4116–4126.
3557. Maryam Heidari, H James Jr, and Ozlem Uzuner. 2021. An empirical study of machine learning algorithms for social media bot detection. In *2021 IEEE International IOT, Electronics and Mechatronics Conference (IEMTRONICS)*. IEEE, 1–5.
3558. Maryam Heidari, James H Jones, and Ozlem Uzuner. 2020. Deep contextualized word embedding for text-based online user profiling to detect social bots on twitter. In *2020 International Conference on Data Mining Workshops (ICDMW)*. IEEE, 480–487.
3559. Maryam Heidari and James H Jones Jr. 2022. Bert Model for Social Media Bot Detection. (2022).
3560. R Devon Hjelm, Alex Fedorov, Samuel Lavoie-Marchildon, Karan Grewal, Phil Bachman, Adam Trischler, and Yoshua Bengio. 2018. Learning deep representations by mutual information estimation and maximization. *arXiv preprint arXiv:1808.06670* (2018).
3561. Andrzej Jarynowski. 2022. Conflicts driven pandemic and war issues in Social Media via multi-layer approach of German Twitter. (2022).
3562. Yizhu Jiao, Yun Xiong, Jiawei Zhang, Yao Zhang, Tianqi Zhang, and Yangyong Zhu. 2020. Sub-graph contrast for scalable self-supervised graph representation learning. In *2020 IEEE international conference on data mining (ICDM)*. IEEE, 222–231.
3563. Diederik P Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980* (2014).
3564. Thomas N Kipf and Max Welling. 2016. Semi-supervised classification with graph convolutional networks. *arXiv preprint arXiv:1609.02907* (2016).

3565. Johannes Klicpera, Aleksandar Bojchevski, and Stephan Günnemann. 2018. Predict then propagate: Graph neural networks meet personalized pagerank. *arXiv preprint arXiv:1810.05997* (2018).
3566. Sneha Kudugunta and Emilio Ferrara. 2018. Deep neural networks for bot detection. *Information Sciences* 467 (2018), 312–322.
3567. Tingting Li, Ziming Zeng, Shouqiang Sun, and Jingjing Sun. 2022. A novel integrated framework based on multi-view features for multidimensional social bot detection. *Journal of Information Science* (2022), 01655515221116517.
3568. Wenbin Li, Xiaokai Chu, Yueyang Su, Di Yao, Shiwei Zhao, Runze Wu, Shize Zhang, Jianrong Tao, Hao Deng, and Jingping Bi. 2022. FingFormer: Contrastive Graph-based Finger Operation Transformer for Unsupervised Mobile Game Bot Detection. In *Proceedings of the ACM Web Conference 2022*. 3367–3375.
3569. Yangyang Li, Yipeng Ji, Shaoning Li, Shulong He, Yinhao Cao, Yifeng Liu, Hong Liu, Xiong Li, Jun Shi, and Yangchao Yang. 2021. Relevance-aware anomalous users detection in social network via graph neural network. In *2021 International Joint Conference on Neural Networks (IJCNN)*. IEEE, 1–8.
3570. Derek Lim, Felix Hohne, Xiuyu Li, Sijia Linda Huang, Vaishnavi Gupta, Omkar Bhalerao, and Ser Nam Lim. 2021. Large Scale Learning on Non-Homophilous Graphs: New Benchmarks and Strong Simple Methods. *Advances in Neural Information Processing Systems* 34 (2021).
3571. Aaron van den Oord, Yazhe Li, and Oriol Vinyals. 2018. Representation learning with contrastive predictive coding. *arXiv preprint arXiv:1807.03748* (2018).
3572. Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, et al. 2019. Pytorch: An imperative style, high-performance deep learning library. *Advances in neural information processing systems* 32 (2019).
3573. Pandu Gumelar Pratama and Nur Aini Rakhmawati. 2019. Social bot detection on 2019 Indonesia president candidate’s supporter’s tweets. *Procedia Computer Science* 161 (2019), 813–820.
3574. Jiezhong Qiu, Qibin Chen, Yuxiao Dong, Jing Zhang, Hongxia Yang, Ming Ding, Kuansan Wang, and Jie Tang. 2020. Gcc: Graph contrastive coding for graph neural network pre-training. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. 1150–1160.
3575. Chiara Ravazzi, Francesco Malandrino, and Fabrizio Dabbene. 2022. Towards Proactive Moderation of Malicious Content via Bot Detection in Fringe Social Networks. *IEEE Control Systems Letters* (2022).
3576. Mohsen Sayyadiharikandeh, Onur Varol, Kai-Cheng Yang, Alessandro Flammini, and Filippo Menczer. 2020. Detection of novel social bots by ensembles of specialized classifiers. In *Proceedings of the 29th ACM international conference on information & knowledge management*. 2725–2732.
3577. Michael Schlichtkrull, Thomas N Kipf, Peter Bloem, Rianne van den Berg, Ivan Titov, and Max Welling. 2018. Modeling relational data with graph convolutional networks. In *European semantic web conference*. Springer, 593–607.

3578. Chengcheng Shao, Giovanni Luca Ciampaglia, Onur Varol, Alessandro Flammini, and Filippo Menczer. 2017. The spread of fake news by social bots. arXiv preprint arXiv:1707.07592 96 (2017), 104. <https://doi.org/10.48550/arXiv.1707.07592>
3579. Peining Shi, Zhiyong Zhang, and Kim-Kwang Raymond Choo. 2019. Detecting malicious social bots based on clickstream sequences. *IEEE Access* 7 (2019), 28855–28862.
3580. Wen Shi, Diyi Liu, Jing Yang, Jing Zhang, Sanmei Wen, and Jing Su. 2020. Social bots' sentiment engagement in health emergencies: A topic-based analysis of the covid-19 pandemic discussions on twitter. *International Journal of Environmental Research and Public Health* 17, 22 (2020), 8701.
3581. Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. 2014. Dropout: a simple way to prevent neural networks from overfitting. *The journal of machine learning research* 15, 1 (2014), 1929–1958.
3582. New York Times. 2022. Musk Says Twitter Committed Fraud in Dispute Over Fake Accounts. <https://www.nytimes.com/2022/08/04/technology/musktwitterfraud.html>, Accessed: 2023-02-26.
3583. Iraklis Varlamis, Dimitrios Michail, Foteini Glykou, and Panagiotis Tsantilas. 2022. A Survey on the Use of Graph Convolutional Networks for Combating Fake News. *Future Internet* 14, 3 (2022), 70.
3584. Petar Veličković, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Lio, and Yoshua Bengio. 2017. Graph attention networks. arXiv preprint arXiv:1710.10903 (2017).
3585. Wikipedia. 2023. Social bot. https://en.wikipedia.org/wiki/Social_bot, Accessed: 2023-05-30.
3586. Samuel C Woolley. 2016. Automating power: Social bot interference in global politics. *First Monday* (2016).
3587. Keyulu Xu, Weihua Hu, Jure Leskovec, and Stefanie Jegelka. 2018. How powerful are graph neural networks? arXiv preprint arXiv:1810.00826 (2018).
3588. Keyulu Xu, Chengtao Li, Yonglong Tian, Tomohiro Sonobe, Ken-ichi Kawarabayashi, and Stefanie Jegelka. 2018. Representation learning on graphs with jumping knowledge networks. In *International Conference on Machine Learning*. PMLR, 5453–5462.
3589. Kai-Cheng Yang, Pik-Mai Hui, and Filippo Menczer. 2019. Bot electioneering volume: Visualizing social bot activity during elections. In *Companion Proceedings of The 2019 World Wide Web Conference*. 214–217.
3590. Kai-Cheng Yang, Onur Varol, Pik-Mai Hui, and Filippo Menczer. 2020. Scalable and generalizable social bot detection through data selection. In *Proceedings of the AAAI conference on artificial intelligence*, Vol. 34. 1096–1103.
3591. Menghan Zhang, Xue Qi, Ze Chen, and Jun Liu. 2022. Social Bots' Involvement in the COVID-19 Vaccine Discussions on Twitter. *International Journal of Environmental Research and Public Health* 19, 3 (2022), 1651.
3592. Jiong Zhu, Yujun Yan, Lingxiao Zhao, Mark Heimann, Leman Akoglu, and Danai Koutra. 2020. Beyond homophily in graph neural networks: Current limitations and effective designs. *Advances in Neural Information Processing Systems* 33 (2020), 7793–7804.

3593. Peng Luo, Kun Chen, Chong Wu, Measuring social influence for firm-level financial performance, *Electron. Commer. Res. Appl.* 20 (2016) 15–29.
3594. JJ Chen Yun-Bei Zhuang, Zhi-hong Li, Modeling the cooperative and competitive contagions in online social networks, *Phys. Stat. Mech. Appl.* 484 (2017) 141–151.
3595. Linyuan L  u, Duanbing Chen, Xiao Long Ren, Qian Ming Zhang, Yi Cheng Zhang, Tao Zhou, Vital nodes identification in complex networks, *Phys. Rep.* 650 (2016) 1–63.
3596. Yu Yang, Zhefeng Wang, Jian Pei, Enhong Chen, Tracking influential individuals in dynamic networks, *IEEE Trans. Knowl. Data Eng.* 29 (11) (2017) 2615–2628.
3597. Siwar Jendoubi, Arnaud Martin, Ludovic Lieetard, Hend Ben Hadji, Boutheina Ben Yaghlane, Two evidential data based models for influence maximization in twitter, *Knowl. Base Syst.* 121 (2017) 58–70.
3598. Linyuan L  u, Yi-Cheng Zhang, Chi Ho Yeung, Tao Zhou, Leaders in social networks, the delicious case, *PloS One* 6 (6) (2011), e21202.
3599. Guojun Wang, Wenjun Jiang, Jie Wu, Zhengli Xiong, Fine-grained feature-based social influence evaluation in online social networks, *IEEE Trans. Parallel Distr. Syst.* 25 (9) (2014) 2286–2296.
3600. Jun zhang, Research on the Mechanism of Time-Varying Evolution of Internet Public Opinion and It’s Countermeasures, China Social Sciences Press, Beijing, 2020.
3601. I.A. Kovaacs, A.L. Barabaasi, Network science: destruction perfected, *Nature* 524 (7563) (2015) 38–39.
3602. Maksim Kitsak, Lazaros K. Gallos, Shlomo Havlin, Fredrik Liljeros, Lev Muchnik, H Eugene Stanley, Hernaan A. Makse, Identification of influential spreaders in complex networks, *Nat. Phys.* 6 (11) (2010) 888–893.
3603. Flaviano Morone, Gino Del Ferraro, Hernaan A. Makse, The k-core as a predictor of structural collapse in mutualistic ecosystems, *Nat. Phys.* 15 (1) (2019) 95–102.
3604. Linyuan L  u, Tao Zhou, Qian-Ming Zhang, H Eugene Stanley, The h-index of a network node and its relation to degree and coreness, *Nat. Commun.* 7 (1) (2016) 1–7.
3605. Tianlong Fan, Linyuan L  u, Dinghua Shi, Towards the Cycle Structures in Complex Network: A New Perspective. *arXiv Preprint arXiv:1903.01397*, 2019.
3606. Xiang Xu, Cheng Zhu, Qingyong Wang, Xianqiang Zhu, Yun Zhou, Identifying vital nodes in complex networks by adjacency information entropy, *Sci. Rep.* 10 (1) (2020) 1–12.
3607. Zhe Li, Tao Ren, Xiaoqi Ma, Simiao Liu, Yixin Zhang, Tao Zhou, Identifying influential spreaders by gravity model, *Sci. Rep.* 9 (1) (2019) 1–7.
3608. Lawrence Page, Sergey Brin, Rajeev Motwani, Winograd Terry, The PageRank Citation Ranking: Bringing Order to the Web, Technical report, Stanford InfoLab, 1999.
3609. Jon M. Kleinberg, Authoritative sources in a hyperlinked environment, *J. ACM* 46 (5) (1998) 604–632.
3610. Alexis Arnaudon, Robert L. Peach, Mauricio Barahona, Graph Centrality Is a Question of Scale. *arXiv Preprint arXiv:1907.08624*, 2019.

3611. Haewoon Kwak, Changhyun Lee, Hosung Park, Sue Moon, What is Twitter, a social network or a news media ?, in: Proceedings of the 19th International Conference on World Wide Web, 2010, pp. 591–600.
3612. R. Albert, H. Jeong, A.L. Barabasi, Error and attack tolerance of complex networks, *Nature* 406 (6794) (2000) 378.
3613. Xin Chen, Critical nodes identification in complex systems, *Comp. Int. Syst.* 1 (1-4) (2015) 37–56.
3614. Cai Bao Xue, Sheng Dai Fu, Wei Zhan Han, Evaluation method of network invulnerability based on disjoint paths in topology, *Syst. Eng. Electron.* 34 (1) (2012) 168–174.
3615. Duanbing Chen, Linyuan L  u, Ming-Sheng Shang, Yi-Cheng Zhang, Tao Zhou, Identifying influential nodes in complex networks, *Phys. Stat. Mech. Appl.* 391 (4) (2012) 1777–1787.
3616. Suppawong Tuarob, Conrad Tucker, Automated discovery of lead users and latent product features by mining large scale social media networks, *J. Mech. Des.* 137 (7) (2015) 1–13.
3617. Changjun Fan, Li Zeng, Yizhou Sun, Yang-Yu Liu, Finding key players in complex networks through deep reinforcement learning, *Nat. Mach. Int.* 2 (6) (2020) 317–324.
3618. Jiezhong Qiu, Jian Tang, Hao Ma, Yuxiao Dong, Kuansan Wang, Jie Tang, Deepinf: social influence prediction with deep learning, in: Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, 2018, pp. 2110–2119.
3619. Sanjin Pajo, Dennis Vandevenne, R. Joost, Duflou, Automated feature extraction from social media for systematic lead user identification, *Technol. Anal. Strat. Manag.* 29 (6) (2016) 1–13.
3620. I. Roelens, P. Baecke, D.F. Benoit, Identifying influencers in a social network: the value of real referral data, *Decis. Support Syst.* 91 (2016) 25–36.
3621. Chanhun Kang, Sarit Kraus, Cristian Molinaro, Francesca Spezzano, V.S. Subrahmanian, Diffusion centrality: a paradigm to maximize spread in social networks, *Artif. Intell.* 239 (2016) 70–96.
3622. Jain Gu, Sungmin Lee, Jari Saram  aki, Petter Holme, Ranking influential spreaders is an ill-defined problem, *EPL (Europhysics Letters)* 118 (6) (2017) 68002.
3623. Mile Sikicc, Alen Lancicc, Nino Antulov-Fantulin, Hrvoje Stefancicc, Epidemic centrality -is there an underestimated epidemic impact of network peripheral nodes? *Eur. Phys. J. B* 86 (10) (2013) 1–13.
3624. Linton C. Freeman, Centrality in social networks conceptual clarification, *Soc. Network.* 1 (3) (1979) 215–239.
3625. Linton C. Freeman, Stephen P. Borgatti, Douglas R. White, Centrality in valued graphs: a measure of betweenness based on network flow, *Soc. Network.* 13 (2) (1991) 141–154.
3626. W. U. Jun Yue Jin Tan, Hong Zhong Deng, Evaluation method for node importance based on node contraction in complex networks, *Syst. Eng. Theory Prac.* 11 (2006) 79–101.
3627. Sanjin Pajo, Paul Armand Verhaegen, Dennis Vandevenne, R. Joost, Duflou, Fast lead user identification framework, *Proc. Eng.* 131 (2015) 1140–1145.

3628. Feng Li, Timon C. Du, Listen to me | evaluating the influence of micro-blogs, *Decis. Support Syst.* 62 (2) (2014) 119–130.
3629. Nicola Barbieri, Francesco Bonchi, Giuseppe Manco, Topic-aware social influence propagation models, *Knowl. Inf. Syst.* 37 (3) (2013) 555–584.
3630. Chuan Hu, Huiping Cao, Aspect-level influence discovery from graphs, *IEEE Trans. Knowl. Data Eng.* 28 (7) (2016) 1635–1649.
3631. Dawei Zhao, Lixiang Li, Shudong Li, Yujia Huo, Yixian Yang, Identifying influential spreaders in interconnected networks, *Phys. Scripta* 89 (1) (2014), 015203.
3632. F. Liberatore, L. Quijano-Sanchez, What do we really need to compute the tie strength? An empirical study applied to social networks, *Comput. Commun.* 110 (2017) 59–74.
3633. Chunxiao Jiang, Yan Chen, KJ Ray Liu, Evolutionary dynamics of information diffusion over social networks, *IEEE Trans. Signal Process.* 62 (17) (2014) 4573–4586.
3634. Mark S. Granovetter, The strength of weak ties, *Am. J. Sociol.* 78 (2) (1973) 105–130.
3635. T.Q. Phan, X. Chen, R. van der Lans, Uncovering the importance of relationship characteristics in social networks: implications for seeding strategies, *J. Market. Res.* 54 (2) (2017) 187–201.
3636. Johannes Stauder, *The Social Structure of Opportunities for Contact and Interaction and Strategies for Analysing Friendship Networks*, Springer Fachmedien Wiesbaden, 2014.
3637. Yen Liang Chen, Kwei Tang, Chia Chi Wu, Ru Yun Jheng, Predicting the influence of users' posted information for ewom advertising in social networks, *Electron. Commer. Res. Appl.* 13 (6) (2014) 431–439.
3638. Wanqiu Guan, Haoyu Gao, Mingmin Yang, Li Yuan, Haixin Ma, Weining Qian, Zhigang Cao, Xiaoguang Yang, Analyzing user behavior of the micro-blogging website Sina Weibo during hot social events, *Phys. Stat. Mech. Appl.* 395 (2014) 340–351.
3639. Yuchi Zhang, Wendy W. Moe, David A. Schweidel, Modeling the role of message content and influencers in social media rebroadcasting, *Int. J. Res. Market.* 34 (1) (2016).
3640. Henri Tajfel, John C. Turner, *The Social Identity Theory of Intergroup Behavior*, 2004.
3641. Daniel J. Brass, A social network perspective on human resources management, *Res. Person. Hum. Resour. Manag.* 13 (1) (1995) 39–79.
3642. Miller McPherson, Lynn Smith-Lovin, James M. Cook, Birds of a feather: homophily in social networks, *Annu. Rev. Sociol.* 27 (1) (2001) 415–444.
3643. Yung-Ming Li, Cheng-Yang Lai, Ching-Wen Chen, Discovering influencers for marketing in the blogosphere, *Inf. Sci.* 181 (23) (2011) 5143–5157.
3644. C. Kadushin, R.D. Alba, The intersection of social circles: a new measure of social proximity in networks, *Socio. Methods Res.* 5 (1) (1976) 77–102.
3645. Karen S. Cook, Richard M. Emerson, Power, equity and commitment in exchange networks, *Am. Socio. Rev.* 43 (5) (1978) 721–739.
3646. Sancheng Peng, Aimin Yang, Lihong Cao, Shui Yu, Dongqing Xie, Social influence

3647. modeling using information theory in mobile social networks, *Inf. Sci.* 379 (2016) 146–159.
3648. Bibb Latane, The psychology of social impact, *Am. Psychol.* 36 (4) (1981) 343.
3649. C.E. Shannon, A mathematical theory of communication, *Bell Labs Tech. J.* 5 (4) (1948) 3–55.
3650. Thomas Hofmann, Probabilistic latent semantic indexing, in: *International ACM SIGIR Conference on Research and Development in Information Retrieval*, 2004, pp. 56–73.
3651. Domingos Pedro, Matt Richardson, Mining the network value of customers, in: *Proceedings of the 7th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 2001, pp. 57–66.
3652. Yogesh Virkar, Aaron Clauset, Power-law distributions in empirical data, *SIAM Rev.* 51 (4) (2009) 661–703.
3653. Hongfu Liu, Yuchao Zhang, Hao Lin, Junjie Wu, Zhiang Wu, Xu Zhang, How many zombies around you?, in: *Data Mining (ICDM), 2013 IEEE 13th International Conference on IEEE*, 2013, pp. 1133–1138.
3654. Chunhua Ju, Wanqiong Tao, A novel relationship strength model for online social networks, *Multimed. Tool. Appl.* 76 (16) (2017) 17577–17594.
3655. Shixi Liu, Cuiqing Jiang, Zhangxi Lin, Yong Ding, Rui Duan, Zhicai Xu, Identifying effective influencers based on trust for electronic word-of-mouth marketing: a domain-aware approach, *Inf. Sci.* 306 (2015) 34–52.
3656. Yun-Bei Zhuang, *User Influence Evaluation in Online Social Networks Considering Noise Existence*, Economics and Management Press, Beijing, 2020.
3657. Jian-Guo Liu, Jian-Hong Lin, Qiang Guo, Tao Zhou, Locating influential nodes via dynamicssensitive centrality, *Sci. Rep.* 6 (1) (2016) 1–8.
3658. Alkulaib L, Zhang L, Sun Y, et al (2022) Twitter bot identification: an anomaly detection approach. In: *2022 IEEE international conference on big data (big data)*. IEEE, pp 3577–3585
3659. Auten T, Matta J (2023) Retweeting Twitter hate speech after musk acquisition. In: *International conference on complex networks and their applications*. Springer, Berlin, pp 265–276
3660. Bellutta D, Carley KM (2023) Investigating coordinated account creation using burst detection and network analysis. *J Big Data* 10(1):1–17
3661. Blondel VD, Guillaume JL, Lambiotte R, et al (2008) Fast unfolding of communities in large networks. *J Stat Mech Theory Exp* 2008(10):P10008
3662. Breunig MM, Kriegel HP, Ng RT, et al (2000) LOF: identifying density-based local outliers. In: *Proceedings of the 2000 ACM SIGMOD international conference on management of data*, pp 93–104
3663. Bruno M, Lambiotte R, Saracco F (2022) Brexit and bots: characterizing the behaviour of automated accounts on Twitter during the uk election. *EPJ Data Sci* 11(1):17
3664. Chavoshi N, Hamooni H, Mueen A (2016) Debot: Twitter bot detection via warped correlation. In: *Icdm*, pp 28–65 8. Cinelli M, Cresci S, Quattrociocchi W, et al (2022)

- Coordinated inauthentic behavior and information spreading on Twitter. *Decis Support Syst* 160:113819
3665. Confessore N, Dance GJ, Harris R, et al (2018) The follower factory. <https://www.nytimes.com/interactive/2018/01/27/technology/social-media-bots.html> - Online; accessed 04-December-2018 -
 3666. Cresci S (2020) A decade of social bot detection. *Commun ACM* 63(10):72–83
 3667. Cresci S, Di Pietro R, Petrocchi M, et al (2015) Fame for sale: efficient detection of fake Twitter followers. *Decis Support Syst* 80:56–71
 3668. Cresci S, Di Pietro R, Petrocchi M, et al (2017) The paradigm-shift of social spambots: evidence, theories, and tools for the arms race. In: *Proceedings of the 26th international conference on world wide web companion*, pp 963–972
 3669. Cresci S, Di Pietro R, Petrocchi M, et al (2017) Social fingerprinting: detection of spambot groups through dna-inspired behavioral modeling. *IEEE Trans Dependable Secure Comput* 15(4):561–576
 3670. Cresci S, Petrocchi M, Spognardi A, et al (2019) Better safe than sorry: an adversarial approach to improve social bot detection. In: *Proceedings of the 10th ACM conference on web science*, pp 47–56
 3671. Ding J, Chen Z (2023) How to find social robots exactly? In: *Proceedings of the 2023 6th international conference on software engineering and information management*, pp 12–18
 3672. Echeverrià J, De Cristofaro E, Kourtellis N (2018) LOBO: evaluation of generalization deficiencies in Twitter bot classifiers. In: *Proceedings of the 34th annual computer security applications conference*, pp 137–146
 3673. Ferrara E, Varol O, Davis C, et al (2016) The rise of social bots. *Commun ACM* 59(7):96–104
 3674. Goel S, Anderson A, Hofman J, et al (2016) The structural virality of online diffusion. *Manag Sci* 62(1):180–196
 3675. Guess AM, Lyons BA (2020) Misinformation, disinformation, and online propaganda. In: *Social media and democracy: The state of the field, prospects for reform*, vol 10
 3676. Hickey D, Schmitz M, Fessler D, et al (2023) Auditing elon musk’s impact on hate speech and bots. In: *Proceedings of the international AAI conference on web and social media*, pp 1133–1137
 3677. Himelein-Wachowiak M, Giorgi S, Devoto A, et al (2021) Bots and misinformation spread on social media: implications for COVID-19. *J Med Internet Res* 23(5):e26933
 3678. Hristakieva K, Cresci S, Da San Martino G, et al (2022) The spread of propaganda by coordinated communities on social media. In: *Proceedings of the 14th ACM web science conference 2022*, pp 191–201
 3679. Jia J, Wang B, Gong NZ (2017) Random walk based fake account detection in online social networks. In: *2017 47th annual IEEE/IFIP international conference on dependable systems and networks (DSN)*. IEEE, pp 273–284

3680. Le T, Tran-Thanh L, Lee D (2022) Socialbots on fire: modeling adversarial behaviors of socialbots via multi-agent hierarchical reinforcement learning. In: Proceedings of the ACM web conference, pp 545–554
3681. Lee MC, Shekhar S, Faloutsos C, et al (2021) Gen 2 out: detecting and ranking generalized anomalies. In: 2021 IEEE international conference on big data (big data). IEEE, pp 801–811
3682. Li Z, Zhao Y, Hu X, et al (2023) ECOD: unsupervised outlier detection using empirical cumulative distribution functions. *IEEE Trans Knowl Data Eng* 35:12181–12193
3683. Liu FT, Ting KM, Zhou ZH (2008) Isolation forest. In: 2008 eighth IEEE international conference on data mining. IEEE, pp 413–422
3684. Liu Y, Tan Z, Wang H, et al (2023) BotMoE: Twitter bot detection with community-aware mixtures of modal-specific experts. *arXiv preprint. arXiv:2304.06280*
3685. Mannocci L, Cresci S, Monreale A, et al (2022) Mulbot: unsupervised bot detection based on multivariate time series. In: 2022 IEEE international conference on big data (big data). IEEE, pp 1485–1494
3686. Mazza M, Cresci S, Avvenuti M, et al (2019) Rtbust: exploiting temporal patterns for botnet detection on Twitter. In: Proceedings of the 10th ACM conference on web science, pp 183–192
3687. Meeder B, Karrer B, Sayedi A, et al (2011) We know who you followed last summer: inferring social link creation times in Twitter. In: Proceedings of the 20th international conference on world wide web, pp 517–526 Zouzou and Varol EPJ Data Science (2024) 13:62
3688. Mendoza M, Providel E, Santos M, et al (2024) Detection and impact estimation of social bots in the Chilean Twitter network. *Sci Rep* 14(1):6525
3689. Mendoza M, Tesconi M, Cresci S (2020) Bots in social and interaction networks: detection and impact estimation. *ACM Trans Inf Syst* 39(1):1–32
3690. Najafi A, Mugurtay N, Demirci E, et al (2022) # secim2023: first public dataset for studying Turkish general election. *arXiv preprint. arXiv:2211.13121*
3691. Najafi A, Mugurtay N, Zouzou Y, et al (2022) # Secim2023: first public dataset for studying Turkish general election. <https://doi.org/10.7910/DVN/QJA1ZW>
3692. Nizzoli L, Tardelli S, Avvenuti M, et al (2021) Coordinated behavior on social media in 2019 UK general election. In: Proceedings of the international AAAI conference on web and social media, pp 443–454
3693. Pacheco D, Hui PM, Torres-Lugo C, et al (2021) Uncovering coordinated networks on social media: methods and case studies. In: Proceedings of the international AAAI conference on web and social media, pp 455–466
3694. Sayyadiharikandeh M, Varol O, Yang KC, et al (2020) Detection of novel social bots by ensembles of specialized classifiers. In: Proceedings of the 29th ACM international conference on information & knowledge management, pp 2725–2732
3695. Shao C, Ciampaglia GL, Varol O, et al (2018) The spread of low-credibility content by social bots. *Nat Commun* 9(1):1–9 4444

3696. Sharma K, Zhang Y, Ferrara E, et al (2021) Identifying coordinated accounts on social media through hidden influence and group behaviours. In: Proceedings of the 27th ACM SIGKDD conference on knowledge discovery & data mining, pp 1441–1451
3697. Takacs R, McCulloh I (2019) Dormant bots in social media: Twitter and the 2018 us senate election. In: Proceedings of the 2019 IEEE/ACM international conference on advances in social networks analysis and mining, pp 796–800
3698. Tardelli S, Nizzoli L, Tesconi M, et al (2024) Temporal dynamics of coordinated online behavior: stability, archetypes, and influence. *Proc Natl Acad Sci* 121(20):e2307038121 43.
Varol O (2023) Should we agree to disagree about Twitter’s bot problem? *Online Soc Netw Media* 37:100263
3699. Varol O (2023) Who follows Turkish presidential candidates in 2023 elections? In: 2023 31st signal processing and communications applications conference (SIU). IEEE, pp 1–4 45.
Varol O, Davis CA, Menczer F, et al (2018) Feature engineering for social bot detection. In: *Feature engineering for machine learning and data analytics*, vol 311
3700. Varol O, Ferrara E, Davis C, et al (2017) Online human-bot interactions: detection, estimation, and characterization. In: *Proceedings of the international AAAI conference on web and social media*, pp 280–289 47.
Varol O, Uluturk I (2019) Deception strategies and threats for online discussions. *arXiv preprint. arXiv:1906.11371*
3701. Varol O, Uluturk I (2020) Journalists on Twitter: self-branding, audiences, and involvement of bots. *J Comput Soc Sci* 3(1):83–101 49.
Wu L, Morstatter F, Carley KM, et al (2019) Misinformation in social media: definition, manipulation, and detection. *ACM SIGKDD Explor Newsl* 21(2):80–90 50.
3702. Yang KC, Varol O, Davis CA, et al (2019) Arming the public with artificial intelligence to counter social bots. *Hum Behav Emerg Technol* 1(1):48–61 51.
3703. Yang KC, Varol O, Hui PM, et al (2020) Scalable and generalizable social bot detection through data selection. In: *Proceedings of the AAAI conference on artificial intelligence*, pp 1096–1103 52.
3704. Zhang Y, Sharma K, Liu Y (2023) Capturing cross-platform interaction for identifying coordinated accounts of misinformation campaigns. In: *European conference on information retrieval*. Springer, Berlin, pp 694–702