Covid or not Covid? Topic Shift in Information Cascades on Twitter

13 December 2020

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Social Media

Easy to understand

Powered by Influencers

COVID-19 TREATMENT AND VACCINE TRACKER

Providing anecdotal evidence



Research Literature



Full of terminology



COVID-19 and cancer



lying to @GailRule1 and @wolfblitzer

frederick schoenfeld @frederickschoe1 · 45m

Ray @revdmann · 47m

How to spot a bot:

Juan J. Ramirez @hotsmartfy · 1h Are you still banning #HydroxyChloroquine? The following media includes potentially sensitive content.

Spreaker #covid_19 #covid_19_pandemic #facema:

oming soon a new line of T-shirts: I attended a naldTrump #SuperSpreaderEvent and everyone go free

#BidenHarris #fbr #doomscroller C C C C @Betsy Man...

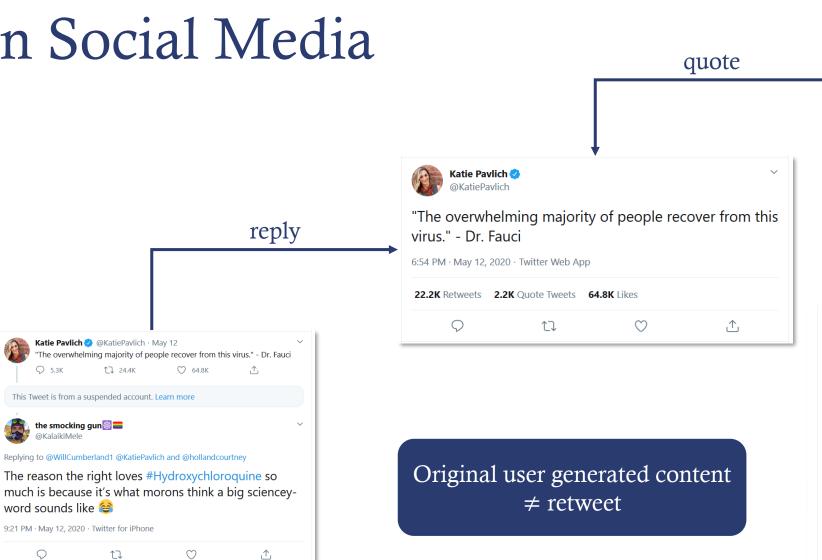
They show up with some generic, quick insult. "You're irrelevant" or "you're fat" etc

New Podcast! "We have the therapeutics to defeat Covid" on

olfblitzer is a hypocrite ...when the #WhiteHouse was briefing the press, @CNN and other "liberal" media outlets lied about them. Anybody remember when the president first about #HydroxyChlo

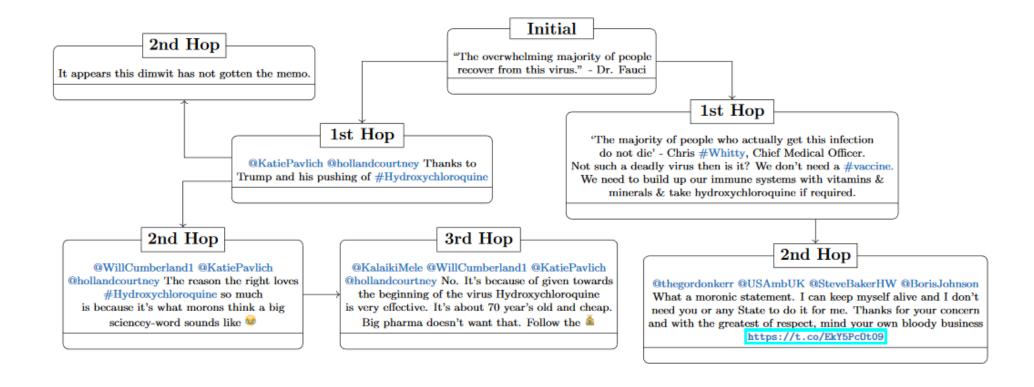
> We have the therapeutics to defeat Covid We are Unintentionally Hurting Our Children and

Information Cascades in Social Media





Information Cascades in Social Media



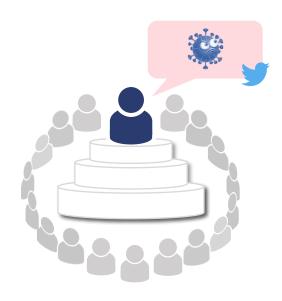


[▶] D.M. Romero, W. Galuba, S. Asur, and B.A. Huberman. 2011. Influence and Passivity in Social Media. In Dimitrios Gunopulos, Thomas Hofmann, Donato Malerba, and Michalis Vazirgiannis, editors, *Machine Learning and Knowledge Discovery in Databases*, pages 18–33, Berlin, Heidelberg. Springer Berlin Heidelberg.

Public Figures on Social Media













Public Figures on Social Media



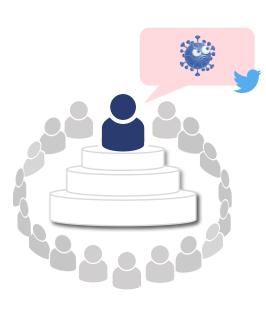
politics

Donald Trump (US President)



healthcare

Dr. Anthony Fauci





art & show business

Scott Adams (Dilbert comics)



journalism

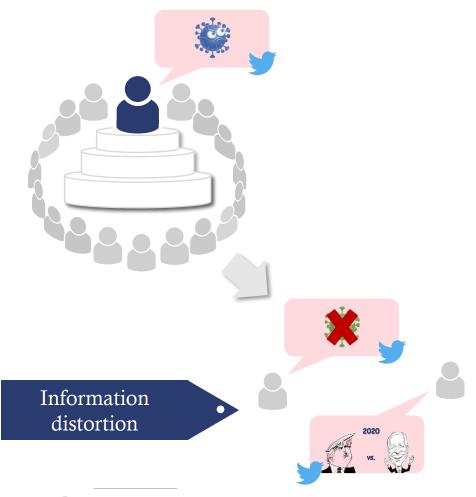
Nail Cavuto (Fox News)



business

Bill Gates

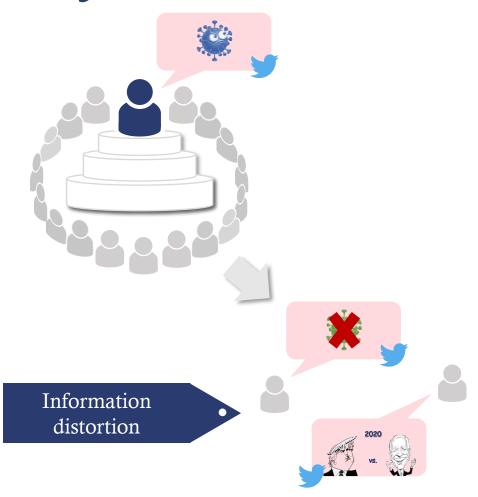
Information Distortion on Social Media





- ▶ J.S. Brennen, F.M. Simon, P.N. Howard, and R.K. Nielsen. 2020. Types, Sources, and Claims of COVID-19 Misinformation. page 13.
- J. Shin, L. Jian, K. Driscoll, and F. Bar. 2018. The diffusion of misinformation on social media: Temporal pattern, message, and source. *Computers in Human Behavior*, 83:278–287, June.
- ▶ G. Pennycook, J. McPhetres, Y. Zhang, J.G. Lu, and D.G. Rand. 2020. Fighting COVID-19 Misinformation on Social Media: Experimental Evidence for a Scalable Accuracy-Nudge Intervention. *Psychological Science*, 31(7):770–780, July. Publisher: SAGE Publications Inc.
- ▶ Horta Manoel Ribeiro, Kristina Gligoric, and Robert West. 2019. Message distortion in information cascades. page 681–692.

Objectives



What are the Public Figures (PF) tweets on healthcare topics that generate information cascades?

How does a transformation of the initial tweet involve misinformation (topic shift)?

Plan

PART 1

Data Collection

✓ Collection of information cascades from the tweets about controversial COVID-19 treatments

PART 2

Topic Shift

☑ Topic shifts within information cascades

PART 3

Semantic Analysis of Topic Shifts

☑ Case study of distortion mechanisms within cascades

☑ Disease related terms and their occurrences

Data Collection: Controversial COVID-19 Treatments

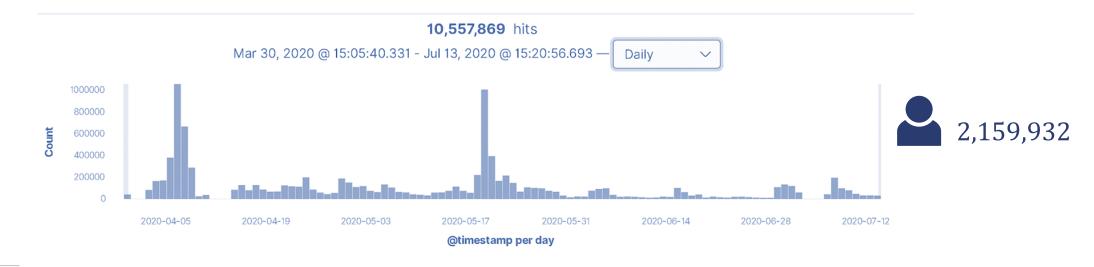






Twitter Streaming

science retraction, chloroquine, hydroxychloroquine, HCQ, Raoult, remdesivir, tocilizumab, favipiravir, Avigan, azithromicyn, azithromicyne, Axemal, Dolquine, Quensyl, Hydroxychloroquinum, Hydroxychloroquin, Hidroxicloroquina, Montagnier, Hydroquin, Quinoric





Data Collection: Controversial COVID-19 Treatments → Cascades



Original tweets (≠ retweet RT)

141,866



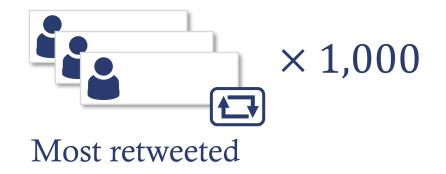


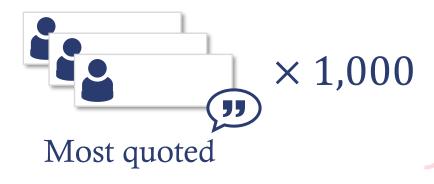
Data Collection: Controversial COVID-19 Treatments → Cascades



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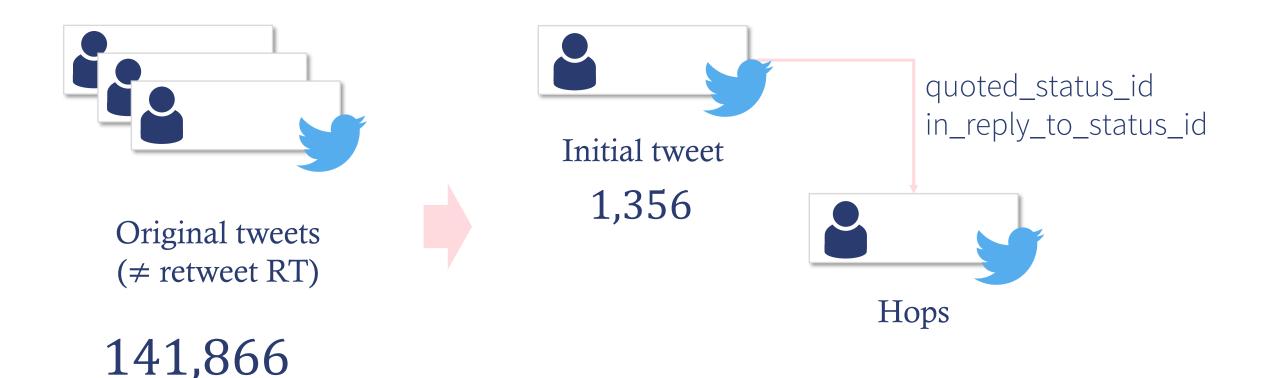






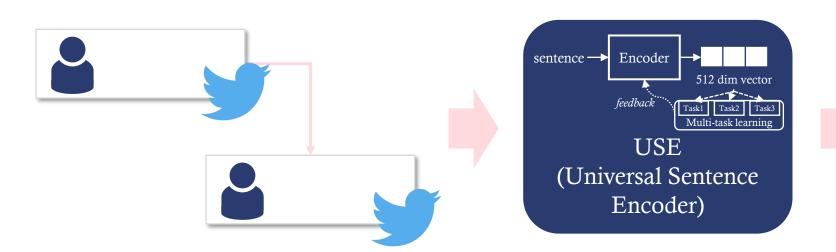
Initial tweet 1,356

Data Collection: Controversial COVID-19 Treatments → Cascades



Max depth = 10 (9 hops)

Topic Shift between Hops and Initial Tweets



between neighbouring hops

$$\Delta^{(i-1)} = 1 - \cos(\overrightarrow{hop_i}, \overrightarrow{hop_{i-1}}) = 1 - \frac{\overrightarrow{hop_i} \cdot \overrightarrow{hop_{i-1}}}{\|\overrightarrow{hop_i}\| \|\overrightarrow{hop_{i-1}}\|}$$

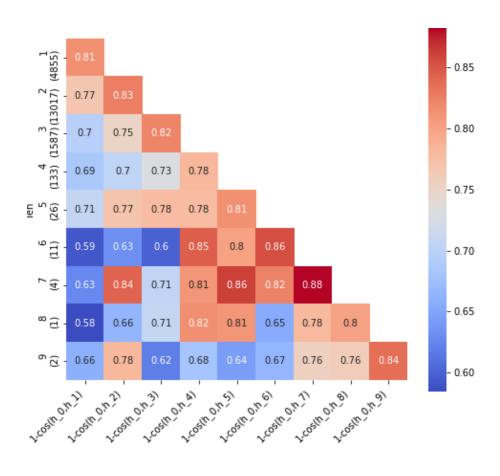
between a hop and initial tweet

$$\Delta^{(0)} = 1 - \cos(\overrightarrow{hop_i}, \overrightarrow{hop_0}) = 1 - \frac{\overrightarrow{hop_i} \cdot \overrightarrow{hop_0}}{\|\overrightarrow{hop_i}\| \|\overrightarrow{hop_0}\|}$$



[▶] Daniel Cer, Yinfei Yang, Sheng-yi Kong, Nan Hua, Nicole Limtiaco, Rhomni St. John, Noah Constant, Mario Guajardo-Cespedes, Steve Yuan, Chris Tar, Brian Strope, and Ray Kurzweil. 2018. Universal Sentence En-coder for English. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 169–174, Brussels, Belgium, November. Association for Computational Linguistics.

Topic Shift between Hops and Initial Tweets: Results



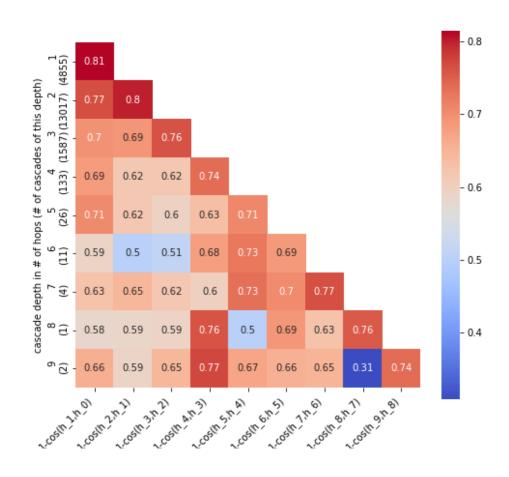
Current vs. Initial Hops

Topic Shift between Hops and Initial Tweets: Results Accumulation of semantic difference

Accumulation of semantic difference - 0.85 - 0.80 0.75 - 0.75 0.8 0.86 - 0.70 0.71 0.86 0.81 - 0.65 0.65 0.71 0.67 0.76

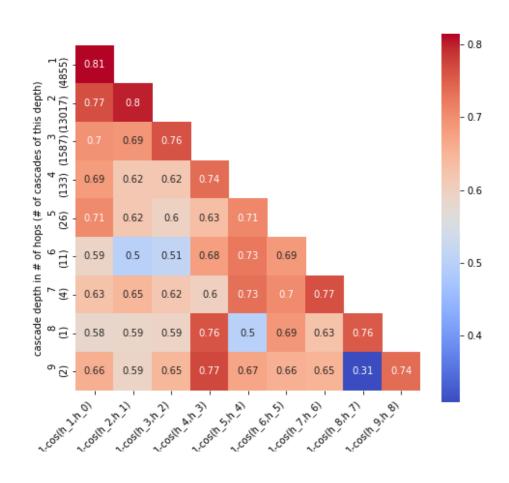
Current vs. Initial Hops

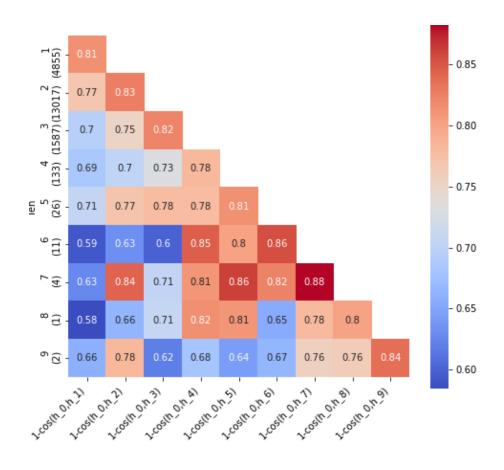
Topic Shift between Hops and Initial Tweets: Results



Neighbouring Hops

Topic Shift between Hops and Initial Tweets: Results

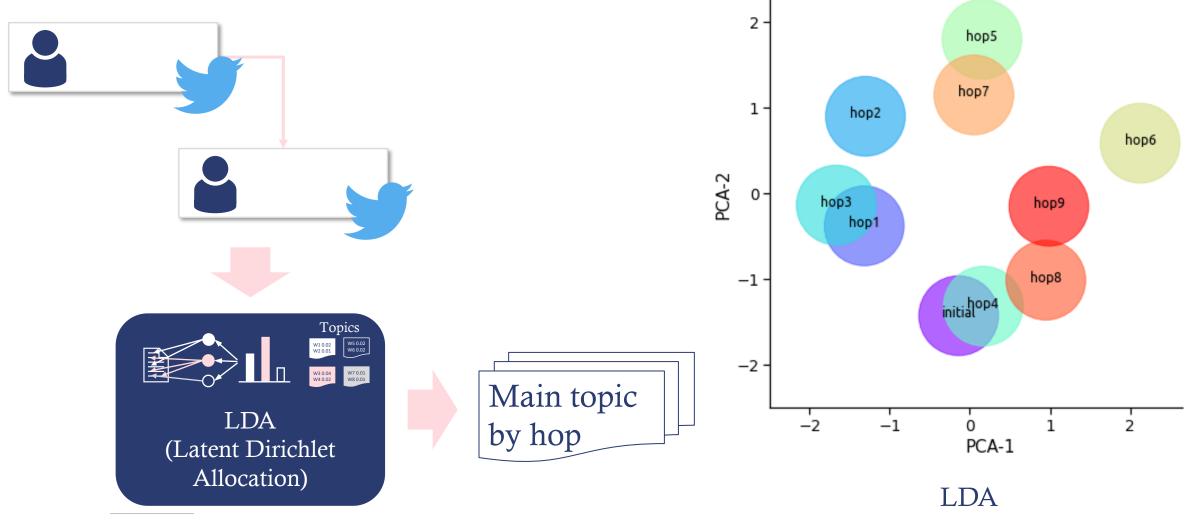




Neighbouring Hops

Current vs. Initial Hops

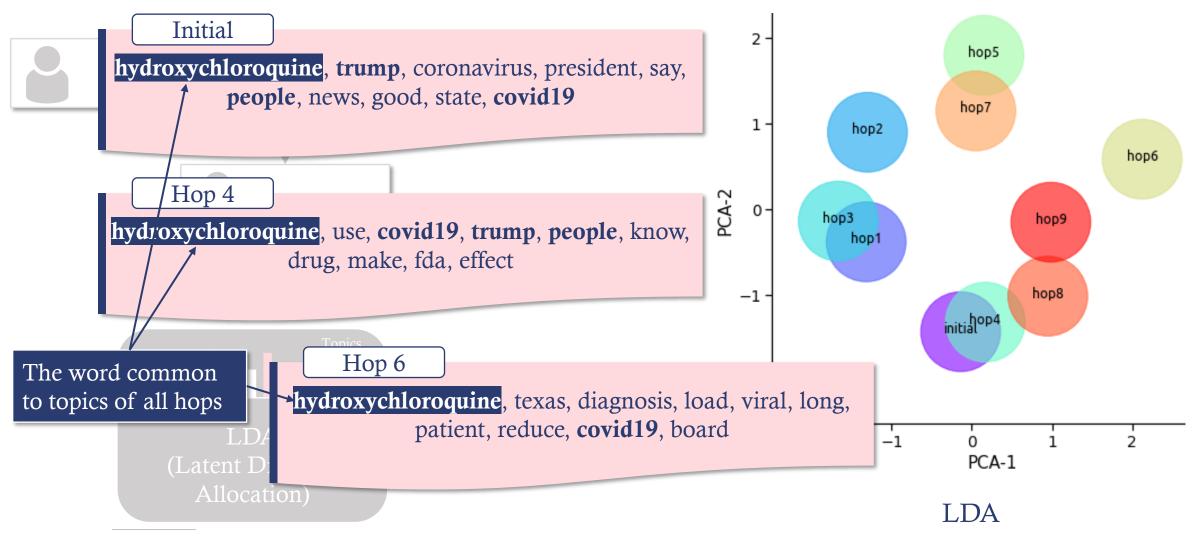
Topic Modelling of Hops





▶ Matthew D. Hoffman, David M. Blei, and Francis R. Bach. 2010. Online learning for latent dirichlet allocation. In *Advances in Neural Information Processing Systems 23: 24th Annual Conference on Neural Information Processing Systems 2010. Proceedings of a meeting held 6-9 December 2010, Vancouver, British Columbia, Canada*, pages 856–864. Curran Associates, Inc.

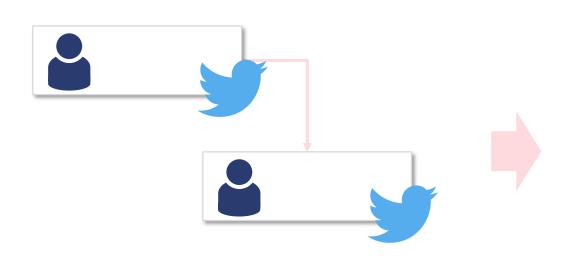
Topic Modelling of Hops





[▶] Matthew D. Hoffman, David M. Blei, and Francis R. Bach. 2010. Online learning for latent dirichlet allocation. In Advances in Neural Information Processing Systems 23: 24th Annual Conference on Neural Information Processing Systems 2010. Proceedings of a meeting held 6-9 December 2010, Vancouver, British Columbia, Canada, pages 856–864. Curran Associates, Inc.

Semantic Analysis



Manual semantic analysis Key term distribution in cascades Context and substitution analysis

Term substitutions

Verification of logical relationships among hops



Distortions w.r.t. the initial tweets

Semantic Analysis: Information Distortion within Information Cascades

Erroneous logical connections

Misuse of medical concepts

Distortion of connections between medical concepts

Insertion of erroneous conclusions

Substitution

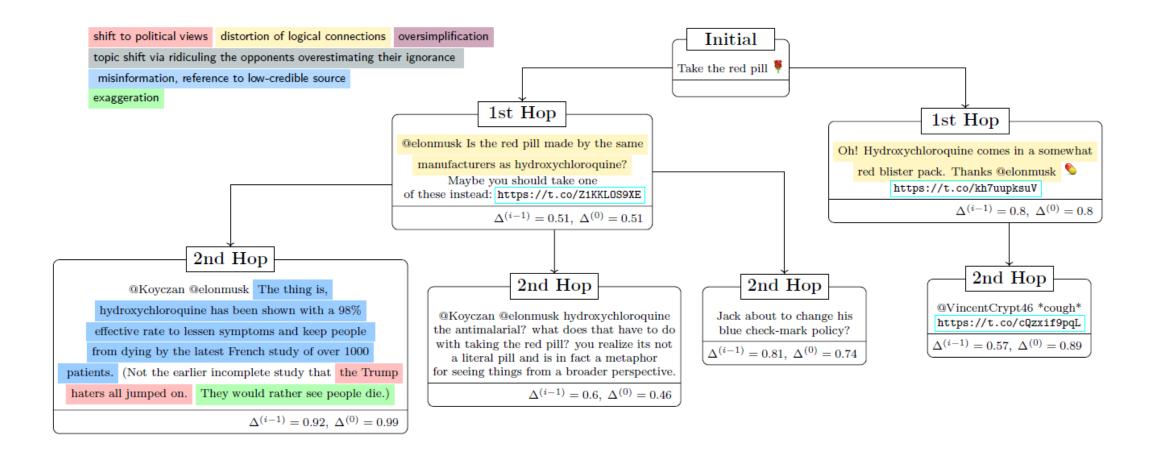
Oversimplification

Omission of facts

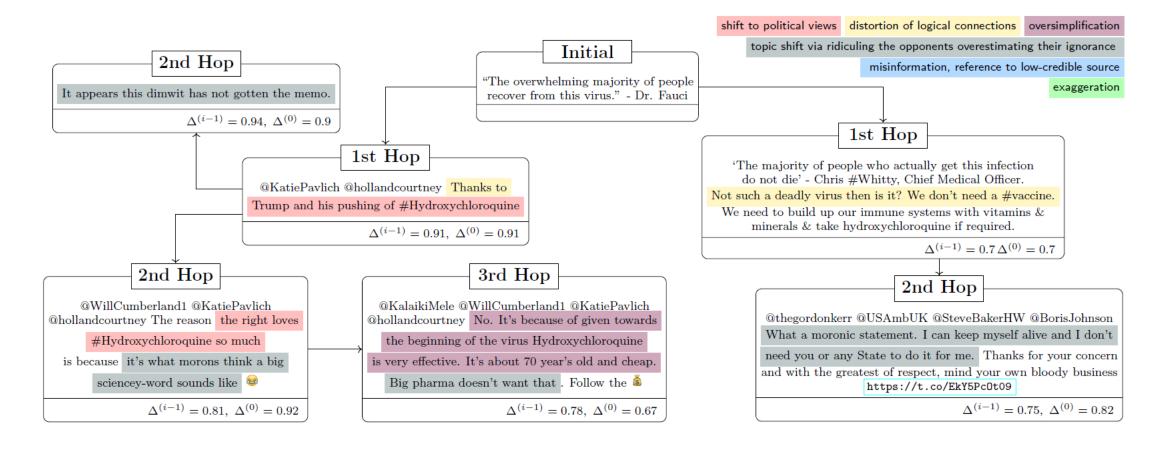
Overgeneralisation

Exaggeration

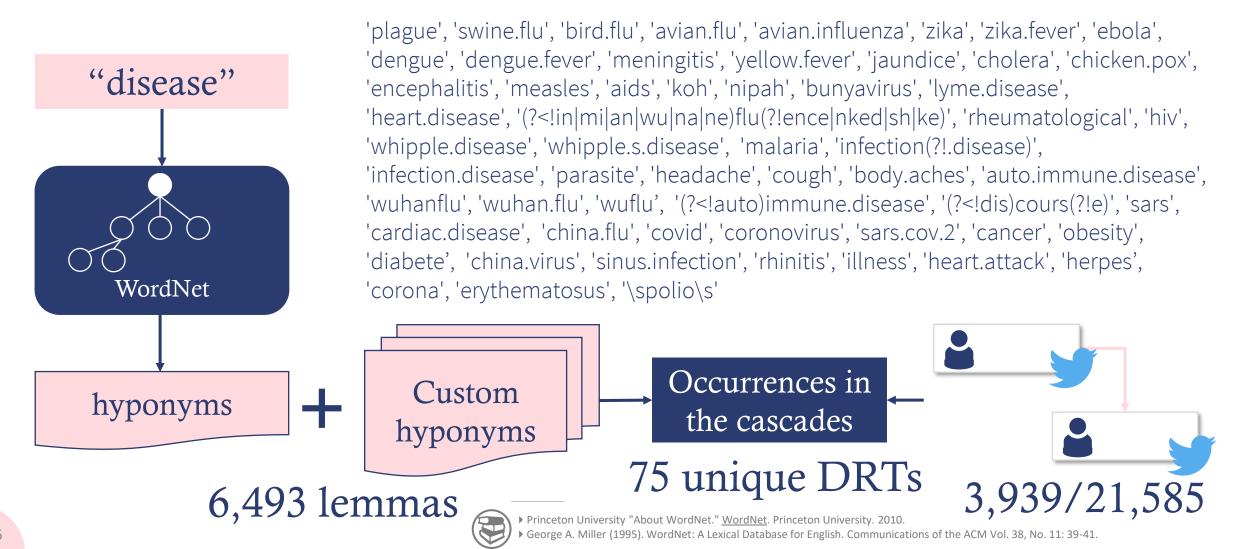
Semantic Analysis: Information Distortion within Information Cascades



Semantic Analysis: Information Distortion within Information Cascades



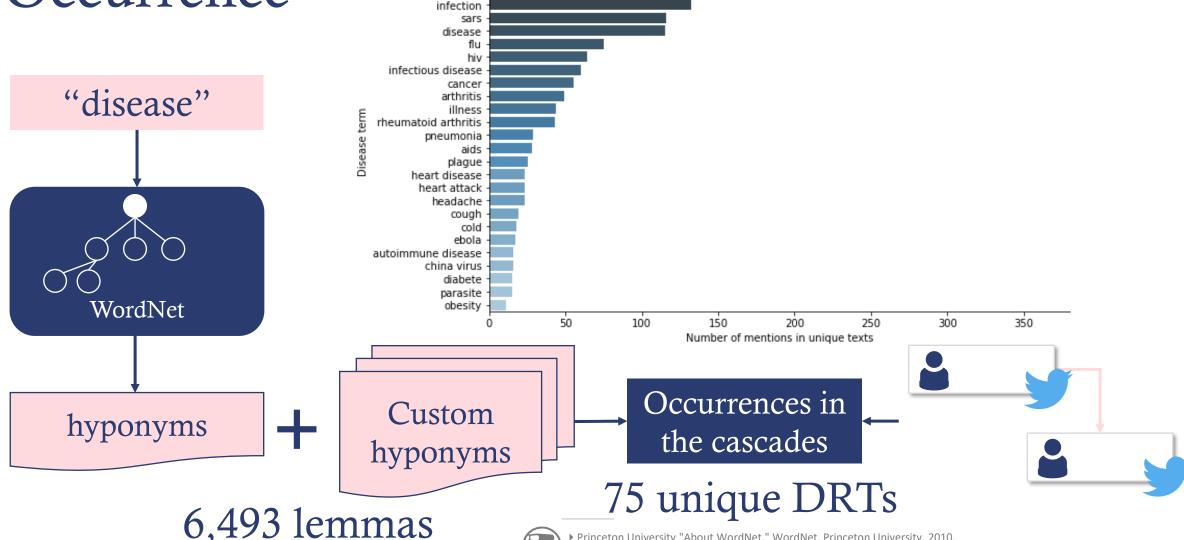
Disease Related Terms (DRTs) and Their Occurrence



Disease Related Terms (DRTs) and Their

malaria lupus

Occurrence



Disease Related Terms (DRTs) and Their Occurrence

75 unique DRTs



14 contexts

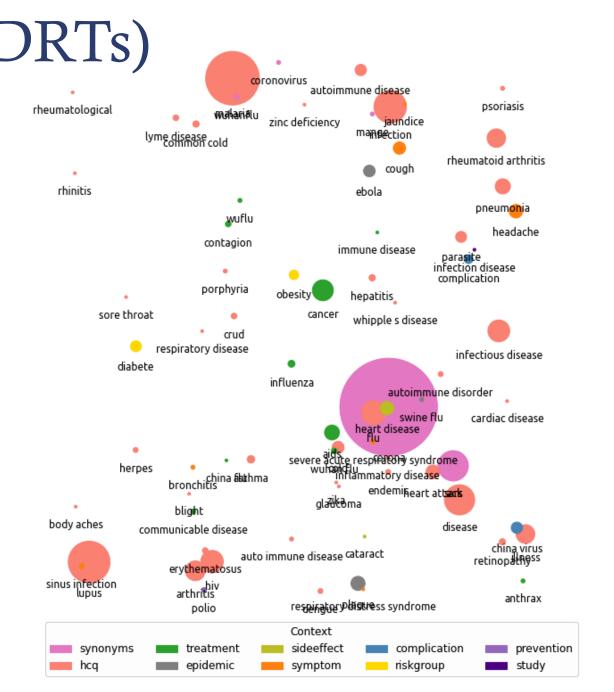
hcq = {hydroxychloroquine, hcq, hc, azithromycin, chloroquine, zpack, z.pac, antimalarial, zinc, sulfate, zithromax} symptom = {symptom, congestion, blood, cough, aches, lungs, fever, antibody, headache, mucus, signs, asymptomatic, respiratory, shortness.of.breath, symptom.free, back.pain, diarrhea, nausea} treatment = {treatment, cure, curing, treat, pill, medicament, remedy, therapy, drug, acetaminophen, prescribe, prescription, breathlessness, medications, diagnos, recovery) prevention = {vaccin, mask, hand.wash, distanc, prevention, detection, test, cover.*mouth, self.isol, prophylaxis, immunity, stayhome, staying.home, stay.home, prophylactic, serum.test, preventative} alternatives = {antibiotic, anti.hiv.drug, analgesics, remdesivir, favipiravir, antiviral.medication, anti.biotic} propagation = {contaminate, contamination, propagation, viral.load, (?<!dead.zone.)\splague(?!.*dead.zone)}</pre> study = {study, control.group, randomi.ed, research, treatment.group, trial, expert, scientific.evidence, success.rate, science, protocol, effective.rate, placebo} complication = {ventilator, complication, transfusion, coma, hospitalization, death, severe.case, critically, critical.condition, severe, urgent.care.center, emergency, icu, intensive.care.unit} epidemic = {epidemic, pandemic, plague, zika, ebola, lockdown, locked.down, outbreak, swine.flu} sideeffect = {side.effect, heart.disease, cardiac.problem, hallucination, psychiatric.symptom, vision.loss, vomiting, loss.of.appetite, dizziness, slow.heartbeat, heart.failure, swelling.ankles} riskgroup = {elderly, diabete, obesity, obese, asthma, comorbidity, 60.plus, 60.year} synonyms = {corona, wuhan.virus, wuhan.disease, sars.cov.2, covid19, covid, c19, coronavirus, chinese.flu, china.flu, cv.19, sars.cov, sars, chinese.plague, coronahoax, wuhanflu} plaguereference = {dead.zone.*plague, 2003.*plague, plague.*dead.zone, plague.*2003, dead.zone} otherissues = {shortage, economic.crisis, economy.crisis}

Disease Related Terms (DRTs) and Their Occurrence

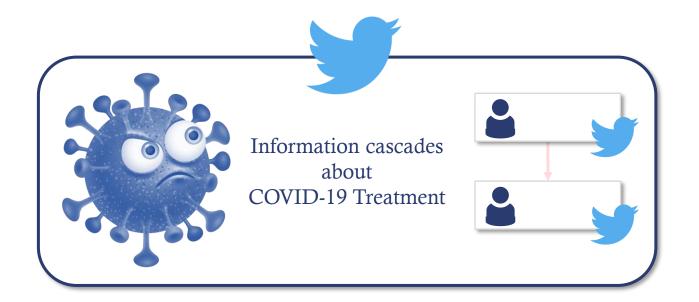
75 unique DRTs



14 contexts



Conclusions



Tweets posted by Public Figures generated multiple information cascades

Topic Shift as a common phenomenon of information cascades about Covid-19 treatments

Substitution & confusion of medical terms

Politisation of the discussions

Oversimplification & distortion of logical links between fact