Models of Meme Transmissions in the Twitterverse

Echo-chambers, Extremism, Transmission processes

Raazesh Sainudiin[†]

[†]Department of Mathematics
Uppsala University, Uppsala, Sweden
http://lamastex.org/lmse/mep/

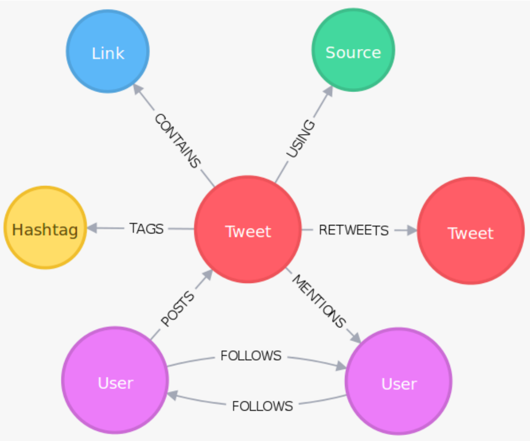
Joint with: Nash, Sahioun and Yogeeswaran, Dept. of Psychology, Univ of Canterbury, Christchurch, NZ

February 10, 2017

1. Motivations and our dataset
   - Why care about the spread of memes on social networks?
   - Media in the Age of Algorithms
2. Data and Statistics
   - Experimental design of twitter streams
   - Empirical Networks: homophily, echo-chambers, hate-anatomy
3. Model
   - The Transmission Process. Sainudiin and Welch, JTB 2016

Twitterverse

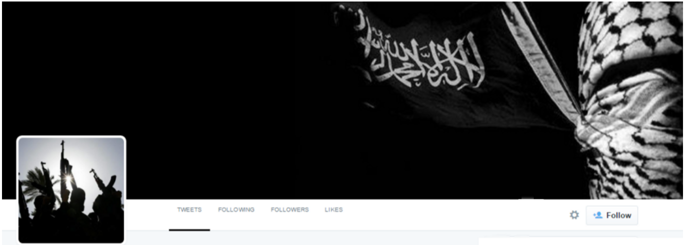
twitter is a micro-blogging service...
What is a tweet? retweet? reply-tweet, etc...



bots, social engineering, etc. – Cambridge Analytica

Extremist Networks

ISIS' Twitter Strategy `http://bit.ly/2gdls4K`



social media is being used by groups such as ISIS to:

- spread their message of hate,
- recruit susceptible youth, and
- project power all over the world.

Extremist Networks

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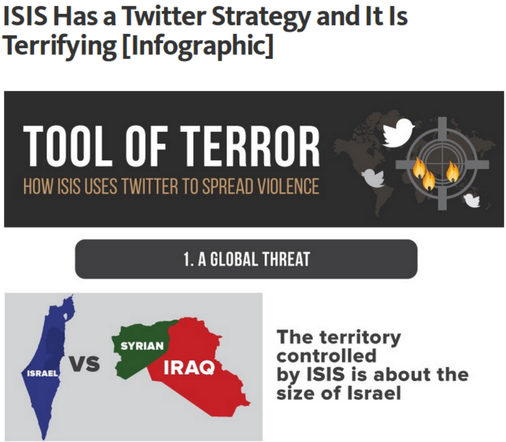

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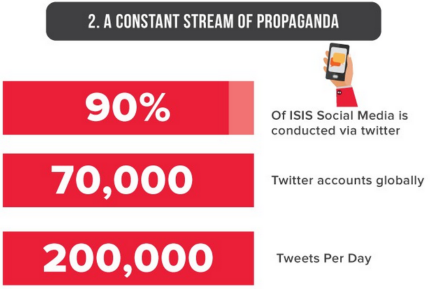

- There are an estimated 21,000 English-language followers alone.
- Most content comes from 2,000 over-performers that tweet in bursts of 50 or more tweets per day
- with each of these over-performers having an average of 1,004 followers.
- The result is an astonishing estimated 200,000 tweets per day.

https://www.brookings.edu/wp-content/uploads/2016/06/isis_twitter_census_berger_morgan.pdf

Extremist Networks

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Extremist Networks

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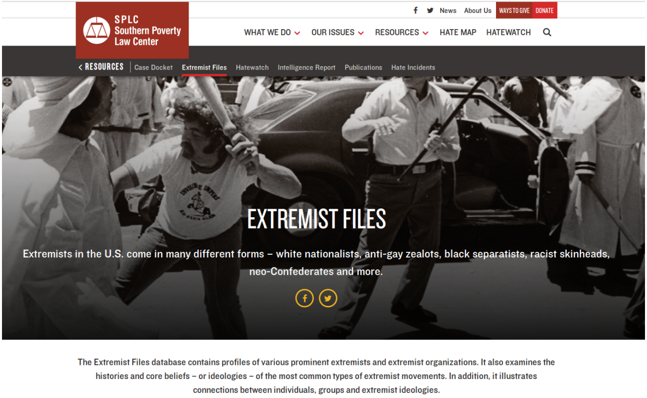
Conclusions of the study by `www.fifthtribe.com`:

- ISIS is essentially crowdsourcing its digital strategy.
- A similar massive operation needs to be developed in order to effectively blunt its outreach efforts.
- Members of the big data community, technologists, creatives, and digital strategists need to come together and coordinate with religious leaders, social media companies, and government agencies to develop an effective counter-messaging effort.

Extremist Networks

US Extremist Groups by SPLC

https://www.splcenter.org/fighting-hate/extremist-files



- https://www.splcenter.org/fighting-hate/extremist-files/ideology
- https://www.splcenter.org/fighting-hate/extremist-files/individual
- https://www.splcenter.org/fighting-hate/extremist-files/groups

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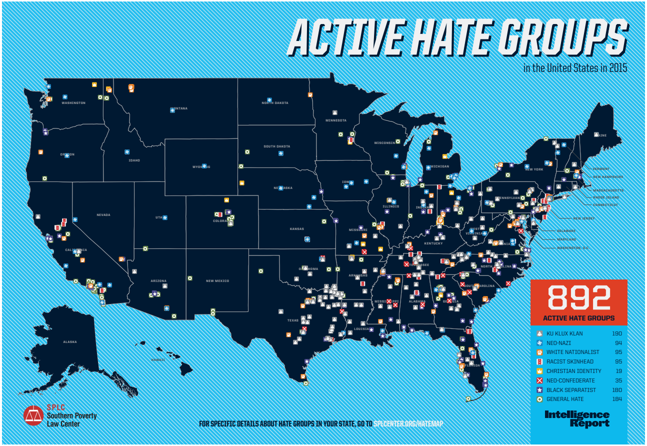

https://www.splcenter.org/hate-map

Extremist Networks

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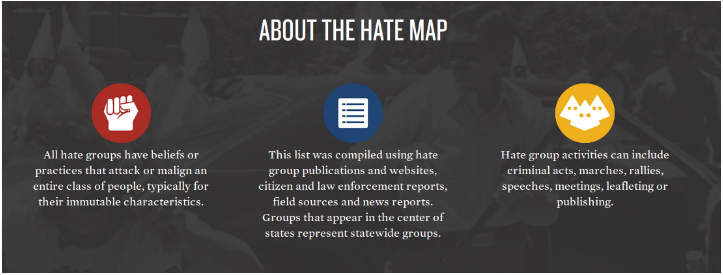

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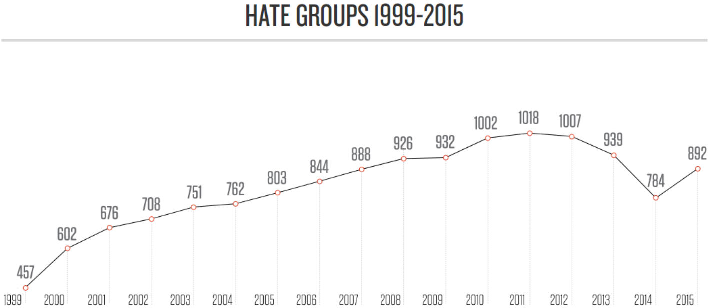

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Extremist Networks

18 US Extremist Ideologies by SPLC

https://www.splcenter.org/fighting-hate/extremist-files

Alternative Right

The Alternative Right, commonly known as the Alt-Right, is a set of far-right ideologies, groups and individuals whose core belief is that "white identity" is under attack by multicultural forces using "political correctness" and "social justice" to undermine white people and "their" civilization...

Anti-Immigrant

Anti-immigrant hate groups are the most extreme of the hundreds of nativist and vigilante groups that have proliferated since the late 1990s, when anti-immigration xenophobia began to rise to levels not seen in the United States since the 1920s.

Anti-LGBT

Opposition to equal rights for LGBT people has been a central theme of Christian Right organizing and fundraising for the past three decades – a period that parallels the fundamentalist movement's rise to political power.

https://www.splcenter.org/fighting-hate/extremist-files/ideology

Extremist Networks

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Anti-Muslim

Anti-Muslim hate groups are a relatively new phenomenon in the United States, most of them appearing in the aftermath of the World Trade Center terrorist attacks on Sept. 11, 2001. Earlier anti-Muslim groups tended to be religious in orientation and disputed Islam's status as a respectable religion.

Antigovernment Movement

The antigovernment movement has experienced a resurgence, growing quickly since 2008, when President Obama was elected to office. Factors fueling the antigovernment movement in recent years include changing demographics driven by immigration, the struggling economy and the election of the first...

Black Separatist

Black separatists typically oppose integration and racial intermarriage, and they want separate institutions -- or even a separate nation -- for blacks. Most forms of black separatism are strongly anti-white and anti-Semitic, and a number of religious versions assert that blacks are the Biblical "...

https://www.splcenter.org/fighting-hate/extremist-files/ideology

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Christian Identity

Christian Identity is a unique anti-Semitic and racist theology that rose to a position of commanding influence on the racist right in the 1980s. "Christian" in name only, the movement's relationship with evangelicals and fundamentalists has generally been hostile due to the latter's belief that...

General Hate

These groups espouse a variety of rather unique hateful doctrines and beliefs that are not easily categorized. Many of the groups are vendors that sell a miscellany of hate materials from several different sectors of the white supremacist movement.

Holocaust Denial

Deniers of the Holocaust, the systematic murder of around 6 million Jews in World War II, either deny that such a genocide took place or minimize its extent. These groups (and individuals) often cloak themselves in the sober language of serious scholarship, call themselves "historical revisionists...

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Ku Klux Klan

The Ku Klux Klan, with its long history of violence, is the most infamous — and oldest — of American hate groups. Although black Americans have typically been the Klan's primary target, it also has attacked Jews, immigrants, gays and lesbians and, until recently, Catholics.

Neo-Confederate

The term neo-Confederacy is used to describe twentieth and twenty-first century revivals of pro-Confederate sentiment in the United States. Strongly nativist, neo-Confederacy claims to pursue Christianity and heritage and other supposedly fundamental values that modern Americans are seen to have...

Neo-Nazi

Neo-Nazi groups share a hatred for Jews and a love for Adolf Hitler and Nazi Germany. While they also hate other minorities, gays and lesbians and even sometimes Christians, they perceive "the Jew" as their cardinal enemy.

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Phineas Priesthood

The Phineas Priesthood is not an actual organization; it has no leaders, meetings, or any other institutional apparatus.

Racist Music

Racist music groups are typically white power music labels that record, publish and distribute racist music in a variety of genres.

Racist Skinhead

Racist Skinheads form a particularly violent element of the white supremacist movement, and have often been referred to as the "shock troops" of the hoped-for revolution. The classic Skinhead look is a shaved head, black Doc Martens boots, jeans with suspenders and an array of typically racist...

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Radical Traditional Catholicism

"Radical traditionalist" Catholics, who may make up the largest single group of serious anti-Semites in America, subscribe to an ideology that is rejected by the Vatican and some 70 million mainstream American Catholics.

Sovereign Citizens Movement

The strange subculture of the sovereign citizens movement, whose adherents hold truly bizarre, complex antigovernment beliefs, has been growing at a fast pace since the late 2000s. Sovereigns believe that they get to decide which laws to obey and which to ignore, and they don't think they should...

White Nationalist

White nationalist groups espouse white supremacist or white separatist ideologies, often focusing on the alleged inferiority of nonwhites. Groups listed in a variety of other categories - Ku Klux Klan, neo-Confederate, neo-Nazi, racist skinhead, and Christian Identity - could also be fairly...

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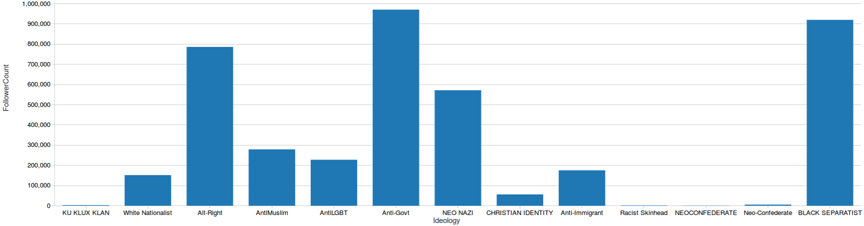

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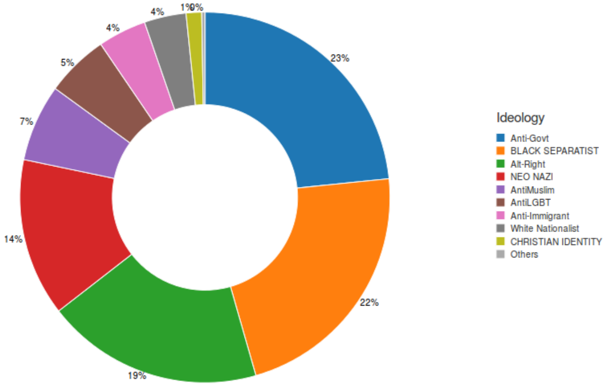

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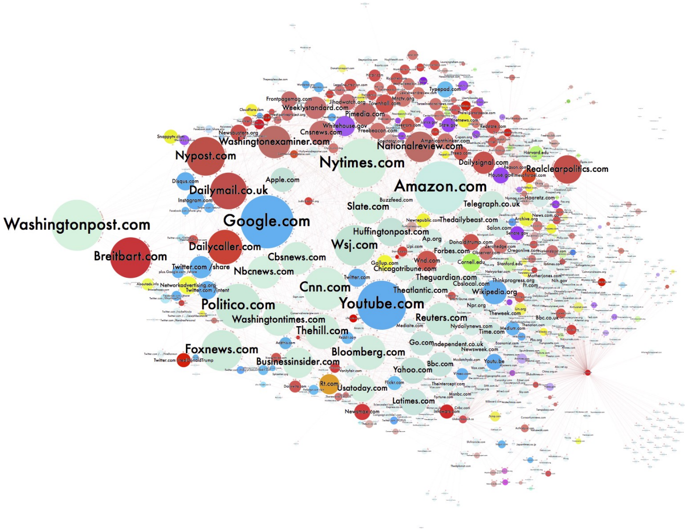
Micro-propaganda network of 117 fake news, viral, anti-science, hoax, and misinformation websites by Jonathan Albright

http://bit.ly/2gidlBW



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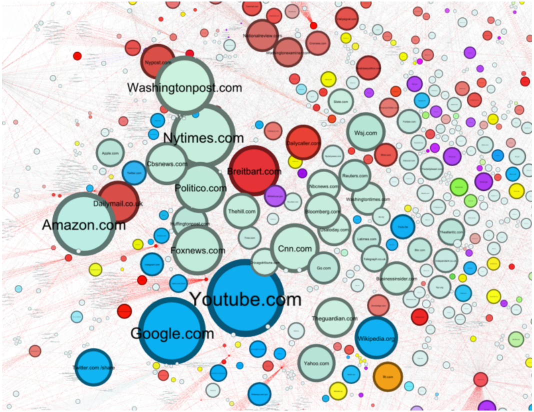

The Targets: Mainstream Media, Social Networks and Wikipedia:

- the sites with the most inbound hyperlinks (the largest circles on the graph) in this 'fake news' propaganda network are Google, YouTube, the NYTimes.com, Wikipedia, and Amazon.com.
- The larger the circle, the more links are coming in from the 117 #MCM network 'fake news' sites.

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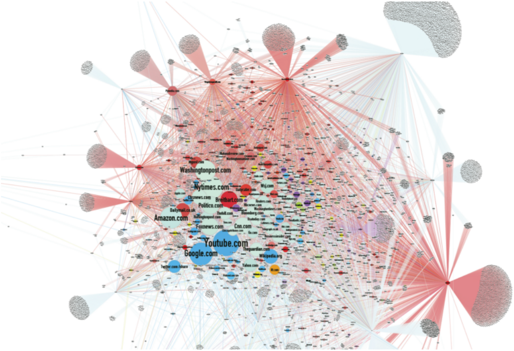

Mainstream Media Are Mostly "Surrounded":

- right-wing, fake news, conspiracy, anti-science, hoax, pseudoscience, and right-leaning misinformation sites **surround** most of the mainstream media
- sites in the fake news and hyper-biased #MCM network have a very small node size — this means they are linking out heavily to mainstream media, social networks, and informational resources
- **every incoming link is not a vote for the popularity of a site** as in Google's page-rank principle — the goal now is to maximize user engagement

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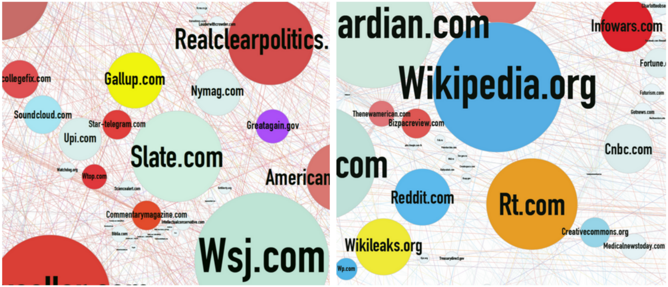

Network "zoom-in" — Gallup polls linked into heavily by MCM sites, as was Wikipedia, Reddit, and Creativecommons.org

Fact Checking and Knowledge Editing:

- #MCM network links heavily to a major poll site, Gallup, and crowdsourced fact-checking and reference resources — most notably Wikipedia, Reddit, and Wikimedia
- Snopes and other fake news verification sites are in the "liberal" side of the network at the top-middle right
- From fantastical falsehoods to outright vandalism, Wikipedians are warring over Trump's inner circle. http://ow.ly/8e4y306hVUn

Social Media Realities

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- Tim O'Reilly's `http://bit.ly/2fpclfZ`:

.... Unfortunately, unlike search, where the desires of the users to find an answer and get on with their lives are generally aligned with "give them the best results", Facebook's prioritization of "engagement" may be leading them in the wrong direction. What is best for Facebook's revenue may not be best for users.

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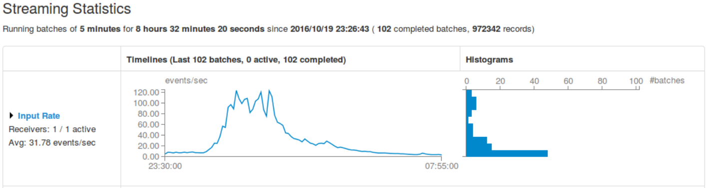
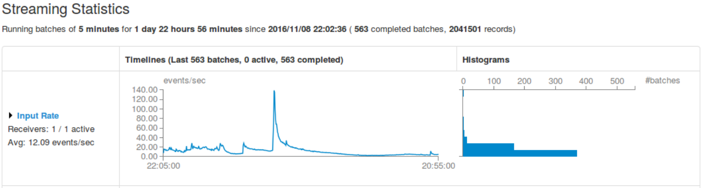
- **GOAL:** Can we shed light on the nature of ideological networks and their effect on "meme" transmissions in the twitterverse? — empirical setting and idealized theoretical setting

US Presidential Election 2016 - Twitter Streams

Twitter Data — 3rd US Presidential Debate



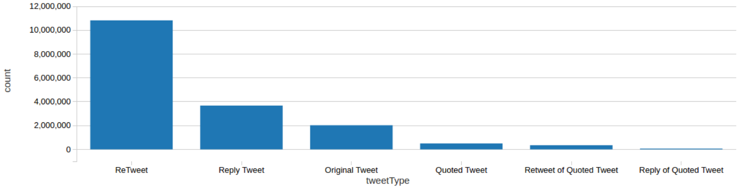
Twitter Data — Last 2 Days Around the End of Election



- User time-line of `@realDonaldTrump`, `@HillaryClinton` and splc-extremists with twitter accounts
- collected data includes all mentions, replies, retweets, etc of these twitter accounts of interest
- Such twitter data was collected every day for about a month around the US Presidential Election

Dataset overview

Data collected around the 2016 US Presidential Election



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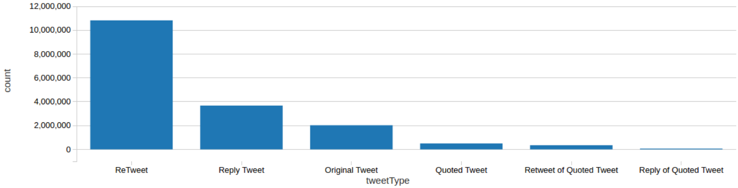

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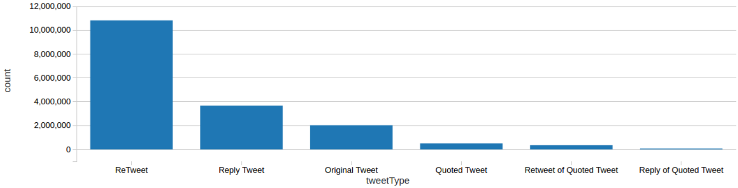

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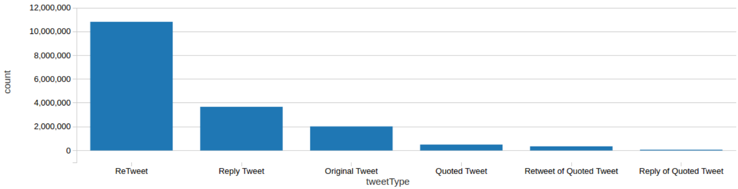

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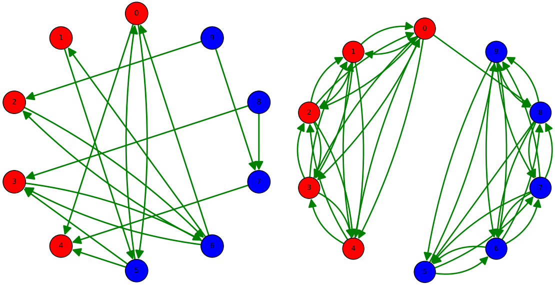
- **Goal:** to gain insights into communications within and across party lines or ideologies & model the effect of social networks on ideological transmissions

Models for Ideological Network Dynamics

- If arc $a_{i,j} = 1$ then we say i ideologically concurs with j



- Just two ideological concurrence networks out of $4,722,366,482,869,645,213,696$ for 9 individuals!
- *homophily* & *confimation bias* can lead to *polarization* or *echo chambers* (for eg. Dandekar, et. al, PNAS, 2013 & iDel Vicario et. al, PNAS 2015), Aldous, Bernoulli 2010

Retweet Network — (3% sample $\#\mathbb{V} = 1205$, $\#\mathbb{E} = 29856$)

Trump-Clinton Retweet Network — a few samples

CPostUserSN	OPostUserSNinRT	OPostUserSNinQT	favouritesCount	followersCount	friendsCount	isVerified	isGeoEnabled	CurrentTweet
georgefayner	realDonaldTrump	null	137811	1466	953	false	true	RT @realDonaldTrump: China is cooking up conspiracy theories that the Olympics are rigged. http://t.co/0ah0hBJt They don't understand why…
KevinCormier10	realDonaldTrump	null	16164	505	367	false	true	RT @realDonaldTrump: EXCLUSIVE: FBI Agents Say Comey 'Stood In The Way' Of Clinton Email Investigation: https://t.co/6n63fHVvNo
thuerta	realDonaldTrump	null	13081	128	345	false	true	RT @realDonaldTrump: 'Trump rally disrupter was once on Clinton's payroll' https://t.co/75oLLuD4SI
tanladyvolfan	HillaryClinton	null	6316	101	200	false	true	RT @HillaryClinton: Our progress is on the ballot. Tolerance is on the ballot. Democracy is on the ballot. Make a plan to vote:…

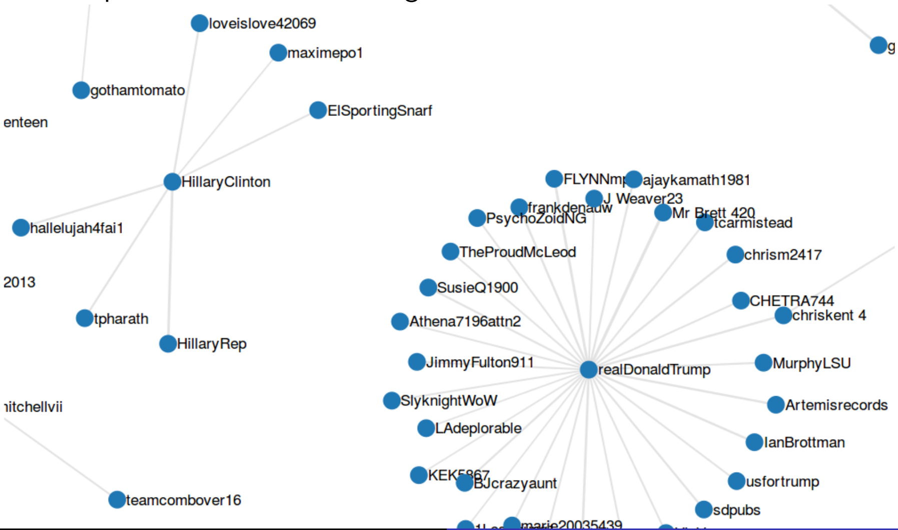
Retweet Network — (3% sample $\#\mathbb{V} = 1205$, $\#\mathbb{E} = 29856$)

Trump-Clinton Retweet Network weighted by Retweet counts

userCreatedAtDate	daysSinceUserCreated	OPostUserSNinRT	CPostUserSN	max(favouritesCount)	max(followersCount)	max(friendsCount)	ReTweetCount
2011-12-13T19:10:28.000+0000	1781	realDonaldTrump	Mr_Brett_420	3294	78	194	190
2016-04-30T00:13:34.000+0000	181	HillaryClinton	HillaryRep	4196	2168	4984	158
2011-03-22T13:09:23.000+0000	2047	realDonaldTrump	FLYNNmpc	1653	48	75	146
2014-08-25T17:02:46.000+0000	795	realDonaldTrump	mikenyr2499	17427	183	155	132
2009-04-26T07:07:03.000+0000	2742	yottapoint	gcommking	5876	797	1826	120
2014-06-20T21:37:39.000+0000	861	BUILDseriesNYC	suzannebuzz	38604	1706	486	112
2009-05-28T15:51:31.000+0000	2710	realDonaldTrump	chriskent_4	838	254	85	112
2009-03-08T12:59:18.000+0000	2791	realDonaldTrump	Artemisrecords	2000	2777	5000	112
2012-09-25T15:09:37.000+0000	1494	realDonaldTrump	IanBrottman	1	89	151	107
2011-03-31T00:54:09.000+0000	2038	realDonaldTrump	frankdenauw	43	45	18	102
2016-07-17T21:30:47.000+0000	103	HillaryClinton	loveislove42069	3818	108	398	98
2015-09-01T18:52:08.000+0000	423	realDonaldTrump	BJcrazyaunt	1064	1296	1433	95
2011-12-24T03:52:02.000+0000	1770	HillaryClinton	tpharath	703	38	183	91
2015-03-08T23:47:05.000+0000	600	HillaryClinton	hallelujah4fai1	16766	227	270	88
2014-06-30T16:44:10.000+0000	851	realDonaldTrump	ajaykamath1981	3309	2667	3010	88
2012-04-29T21:49:38.000+0000	1643	realDonaldTrump	MurphyLSU	65	28	47	84
2010-08-05T16:02:11.000+0000	2276	realDonaldTrump	sdpubs	23674	123	34	83
2011-07-24T19:55:57.000+0000	1923	realDonaldTrump	chrism2417	3012	182	1112	81
2016-02-03T23:58:01.000+0000	268	realDonaldTrump	SusieQ1900	6797	386	415	81

Retweet Network — (3% sample $\#\mathbb{V} = 1205$, $\#\mathbb{E} = 29856$)

Trump-Clinton Retweet Ideological Network



Retweet Network — (3% sample $\#\mathbb{V} = 1205$, $\#\mathbb{E} = 29856$)

Trump-Clinton TIN or (Re)Tweet Ideological Network – Outdegree

```
> display(g.outDegrees.orderBy($"outDegree".desc))
```

id	outDegree
realDonaldTrump	1884
HillaryClinton	1098
wikileaks	479
FoxNews	367
WDFx2EU7	355
TeamTrump	336
DanScavino	320
mitchellvii	295
KellyannePolls	270
JaredWyand	254
mike_pence	246
PrisonPlanet	243
JamesOKeefeIII	220
IngrahamAngle	186
DonaldJTrumpJr	177

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Trump-Clinton TIN or (Re)Tweet Ideological Network

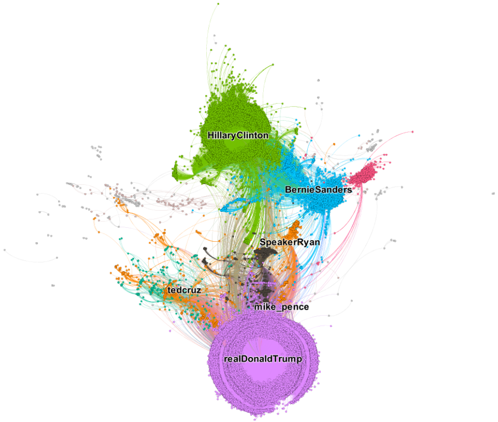
(3% sample $\#\mathbb{V} = 1205$, $\#\mathbb{E} = 29856$) – Indegree

Id	InDegree
theReal_Rebel	46
deuk6767	46
magnifier661	44
neo_zhang16	43
JustBira	43
IndependentHK	41
Anton_Ultron	41
LaurieAnnBaker	40

So, the loudest vessel wins the "being heard match" in the twitterverse! — Whether the vessel is "empty" is less irrelevant than how many can hear it with their specific "emotional needs/fears/etc. soothed"...

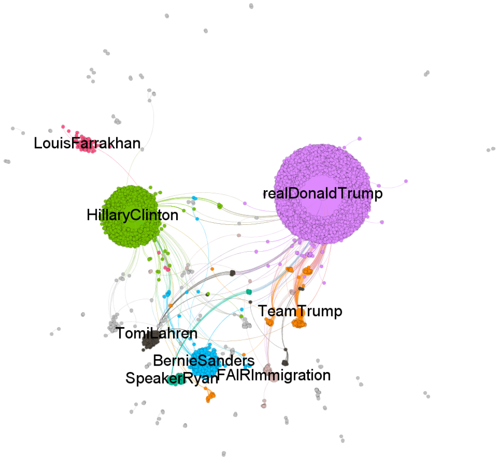
Community Structure of samples of retweet networks

The 3rd US Presidential Debate 22K Retweet Network



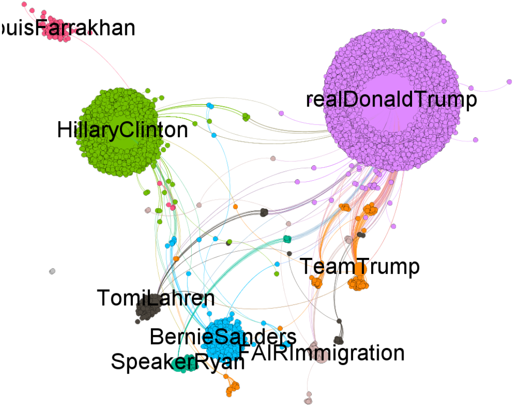
Community Structure of samples of retweet networks

5% random sampled retweet networks for October 19 2016



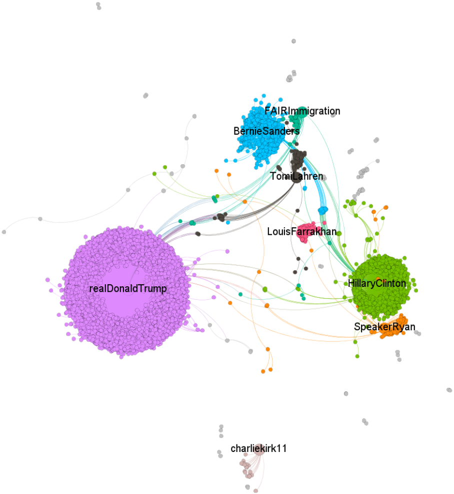
Community Structure of samples of retweet networks

5% random sampled retweet networks for October 19 2016 – top 10



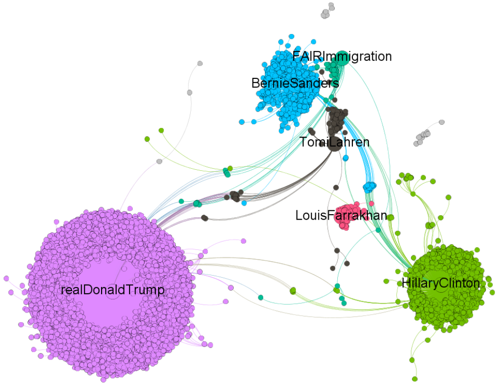
Community Structure of samples of retweet networks

5% random sampled retweet networks for October 24 2016



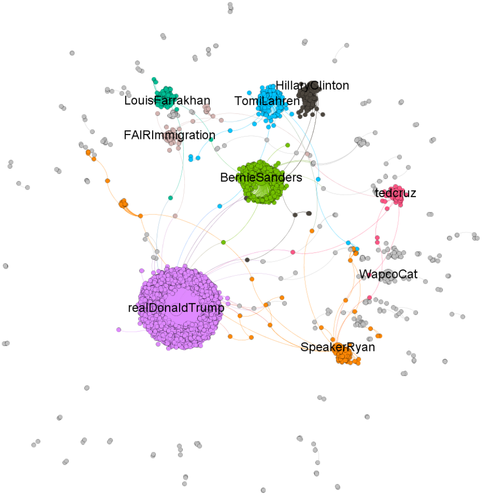
Community Structure of samples of retweet networks

5% random sampled retweet networks for October 24 2016 – top 6



Community Structure of samples of retweet networks

5% random sampled retweet networks for November 15 2016



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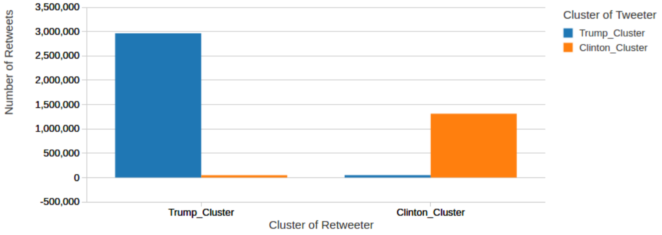
- Step 7: Obtain the sub-graph with the two labels of interest

Number of Retweets Within and Across Ideological Clusters



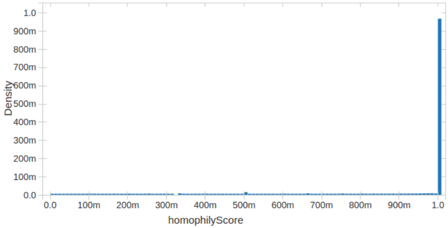
Homophily is reflected by the *probability* h_K *of retweeting tweets that originate in your own cluster* K.

Maximum likelihood estimate of homophily using Bernoilli trials are:

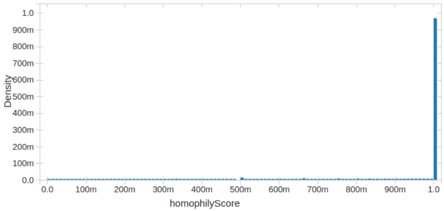
- Trump: $h_T = 0.98373$, 95% CI $(0.98358, 0.98387)$
- Clinton: $h_C = 0.96487$, 95% CI $(0.96456, 0.96518)$
- Both clusters exhibit significantly high levels of homophily
- Reject $H_0 : h_T = h_C$ favoring $h_T > h_C$ (LRTS$= 14279$, p-value < 0.005)

Homophily Estimate for Each Individual in Each Cluster

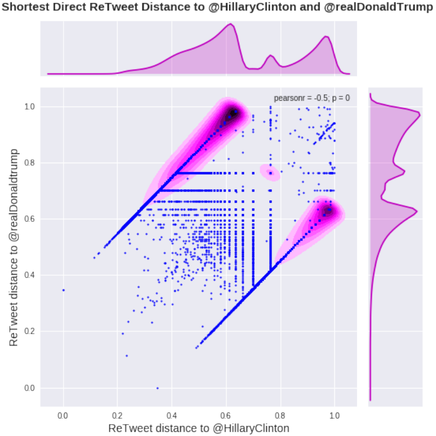
Trump's Echo Chamber



Clinton's Echo Chamber



Shortest RT-weighted paths: Another view of echo-chambers



retweet weights:	0.0	1.0	10.0	100.0	1000.0	2601.0
dissimilarity distances:	1.0	0.764	0.546	0.320	0.0940	0.0

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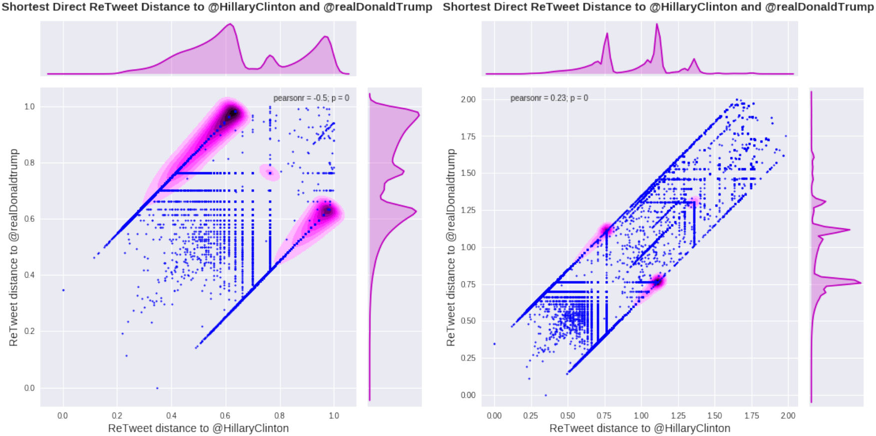

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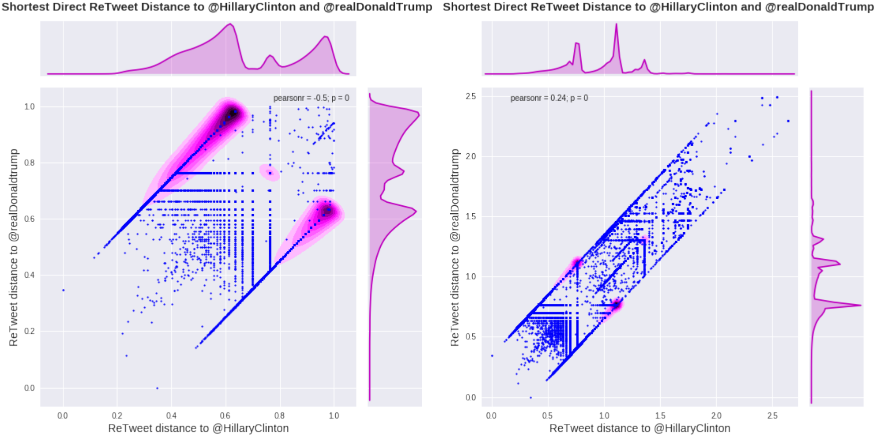

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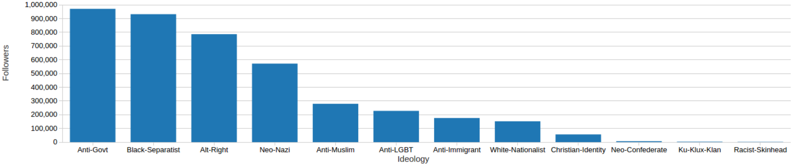
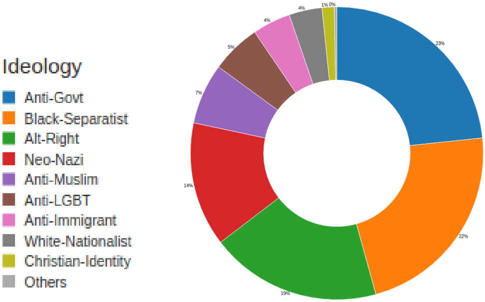
12 SPLC-defined Extremist ideologies

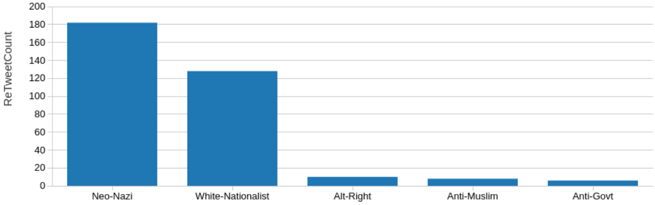
What is publicly tractable in twitter...

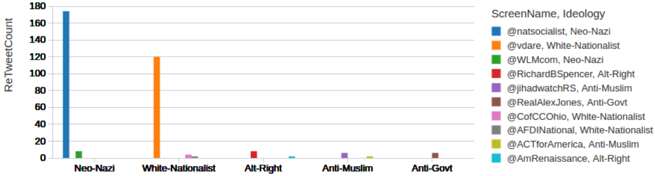


Ideology	Followers
Anti-Govt	970769
Black-Separatist	931736
Alt-Right	786327
Neo-Nazi	571772
Anti-Muslim	279122
Anti-LGBT	227636
Anti-Immigrant	175441
White-Nationalist	151711
Christian-Identity	56191
Neo-Confederate	6628
Ku-Klux-Klan	3070
Racist-Skinhead	1826



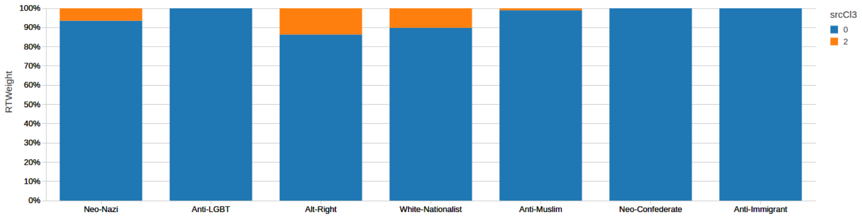
5 SPLC-defined Extremist ideologies retweet Trump





Only showing the first ten series.

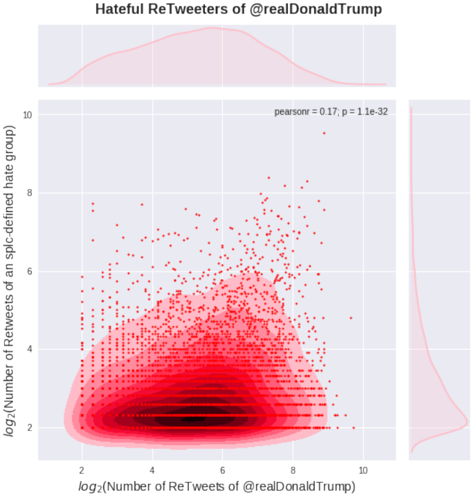
7 SPLC-defined Extremist ideologies Retweet Proportions



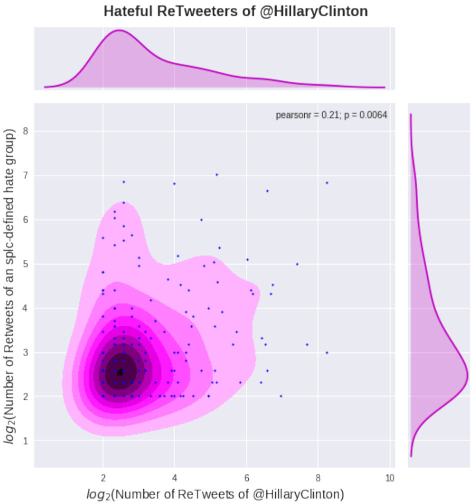
0 = Trump's cluster and 2 = Clinton's cluster

A significant proportion of retweets by leaders of seven extremist ideologies have original tweets in Trump's ideological cluster.

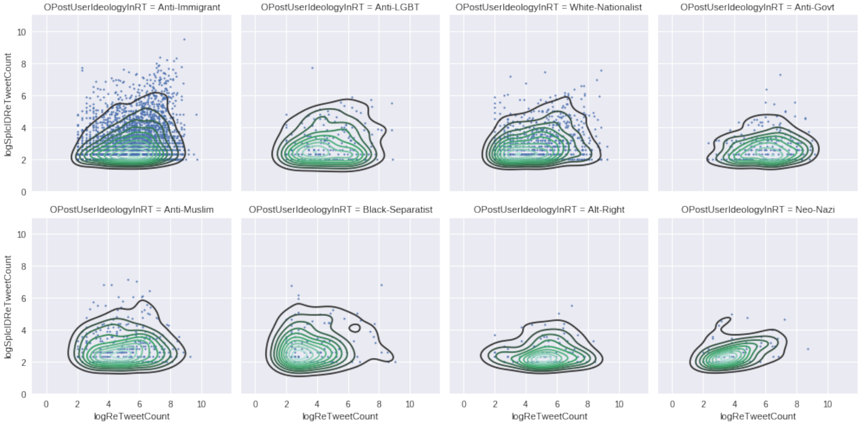
Trump's Hateful Retweeters



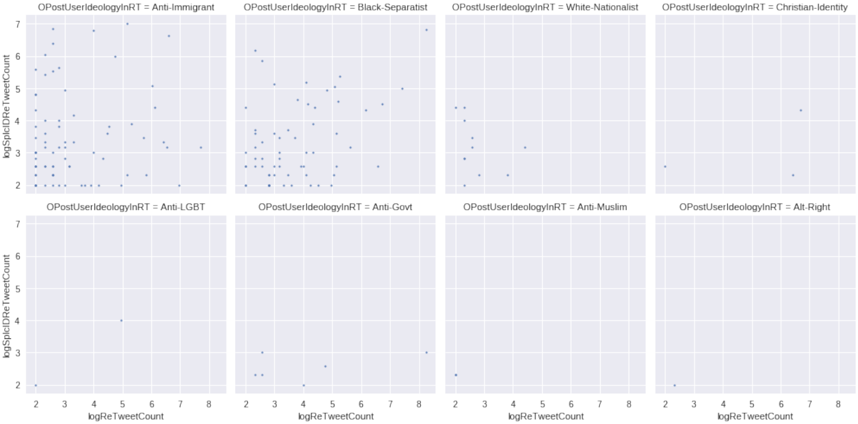
Clinton's Hateful Retweeters



Trump's Hateful Retweeters By Ideology



Clinton's Hateful Retweeters By Ideology



Chi-square tests

Ideology	Donald J Trump	Hillary R Clinton	Chi-Square Statistic	R^2
Alt-Right	1127 (90.7%)	116 (9.3%)	$X^2 = 822.30$, $p < .0001$	$R^2 = 0.662$
Anti-Government	1455 (89.5%)	171 (10.5%)	$X^2 = 1013.93$, $p < .0001$	$R^2 = 0.623$
Anti-Immigrant	15019 (88.6%)	1926 (11.4%)	$X^2 = 10116.65$, $p < .0001$	$R^2 = 0.597$
Anti-LGBT	1621 (88.6%)	209 (11.4%)	$X^2 = 1089.48$, $p < .0001$	$R^2 = 0.595$
Anti-Muslim	2293 (90.8%)	233 (9.2%)	$X^2 = 1679.97$, $p < .0001$	$R^2 = 0.665$
Black-Separatist	1279 (54.9%)	1049 (45.1%)	$X^2 = 22.72$, $p < .01$	$R^2 = 0.009$
Neo-Nazi	1039 (90.7%)	106 (9.3%)	$X^2 = 760.25$, $p < .0001$	$R^2 = 0.664$
White-Nationalist	5103 (89.2%)	616 (10.8%)	$X^2 = 3520.40$, $p < .0001$	$R^2 = 0.616$
Total	28992 (86.5%)	4509 (13.5%)	$X^2 = 18006.72$, $p < .0001$	$R^2 = 0.540$

Chi-square tests

Restricting to retweeters who retweet at least 4 times

Ideology	Donald J Trump	Hillary R Clinton	Chi-Square Statistic	R^2
Alt-Right	936 (98.7%)	12 (1.3%)	X^2 = 900.61, *p* < .0001	R^2 = 0.950
Anti-Government	1388 (98.4%)	23 (1.6%)	X^2 = 1320.50, *p* < .0001	R^2 = 0.936
Anti-Immigrant	12618 (96.6%)	442 (3.4%)	X^2 = 11351.84, *p* < .0001	R^2 = 0.869
Anti-LGBT	1110 (96.0%)	46 (4.0%)	X^2 = 979.32, *p* < .0001	R^2 = 0.847
Anti-Muslim	1866 (98.8%)	22 (1.2%)	X^2 = 1801.03, *p* < .0001	R^2 = 0.954
Black-Separatist	494 (62.5%)	296 (37.5%)	X^2 = 49.63, *p* < .001	R^2 = 0.062
Neo-Nazi	692 (99.4%)	4 (0.6%)	X^2 = 680.09, *p* < .0001	R^2 = 0.977
White-Nationalist	3751 (98.0%)	76 (2.0%)	X^2 = 3529.04, *p* < .0001	R^2 = 0.922
Total	22855 (96.1%)	921 (3.9%)	X^2 = 20234.71, *p* < .0001	R^2 = 0.851

Some mathematical insights

John Guckenheimer: “Everyone’s gut feeling is that the network structure matters, ... but we know surprisingly very little about how it matters.”

Given the structure of these highly polarized ideological networks, can we make some idealizations to make progress on understanding **how “memes” are transmitted from one individual to another**?

Susceptible-Infected Contact Network (SICN) & Transmission Tree (TT)

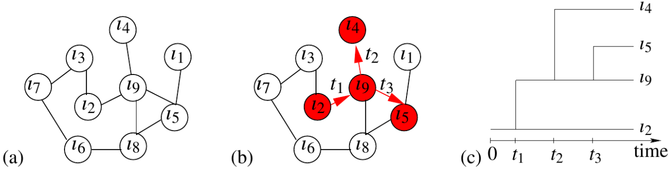


Figure 1: Spread of an epidemic over (a) the contact network of a population as shown by (b) a sub-network where edges representing transmission events are labelled by the time of event and the infected vertices are colored red and (c) the corresponding transmission tree.

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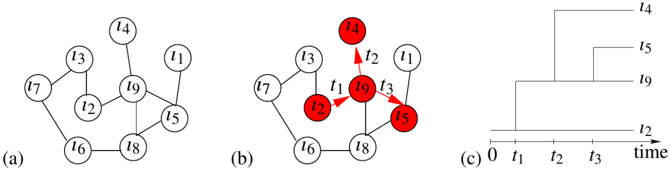

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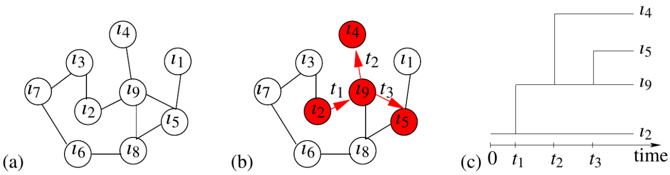

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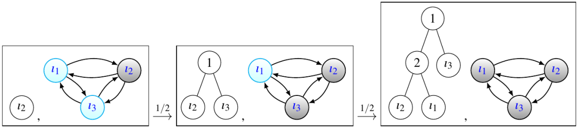
Aldous' ?n: How does the geometry or structure of the SICN afftect the distribution (shape and timing) of the TT?

Answer: It is possible in the simplest setting...

Markov chain on SI Contact Networks × Transmission Trees

- A growing transmission tree on a **complete** SICN in a population of size $n = 3$



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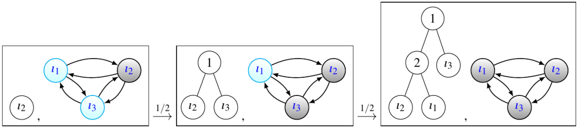

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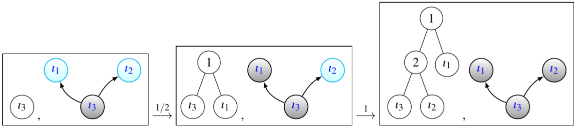

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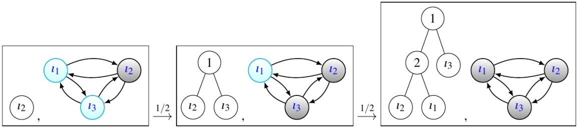

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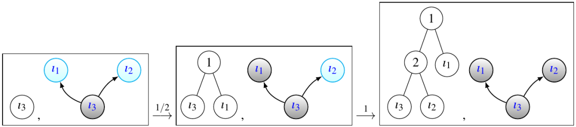
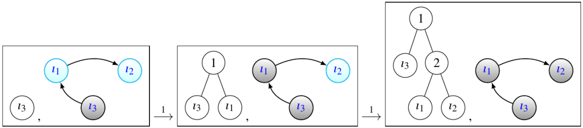


- A growing transmission tree on a **path** SICN in a population of size $n = 3$



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    - where $\tau \in \{$rooted planar ranked leaf-labelled binary trees$\}$
    - Note the poset on 2^{w_n} with unit weights given by $\prec := \subseteq$
    - So the current state of the Markov chain at discrete time z is $(\tau(z), c(z)) \in \mathcal{T}_n \times \mathcal{C}_n$

Transition Probabilities

- One-step transitions for the jump chain

$$\Pr\{(\tau(z+1), c(z+1)) \mid (\tau(z), c(z))\} =$$

$$\frac{\text{the edge-weight from } (z+1)\text{-th infector to the } (z+1)\text{-th infectee}}{\text{Sum of edge-weights from every potential infector to every potential infectee within its susceptible out-neighborhood}}$$

Transition Probabilities

- One-step transitions for the jump chain

$$\Pr\{(\tau(z+1), c(z+1)) \mid (\tau(z), c(z))\} = \frac{\text{the edge-weight from } (z+1)\text{-th infector to the } (z+1)\text{-th infectee}}{\text{Sum of edge-weights from every potential infector to every potential infectee within its susceptible out-neighborhood}}$$

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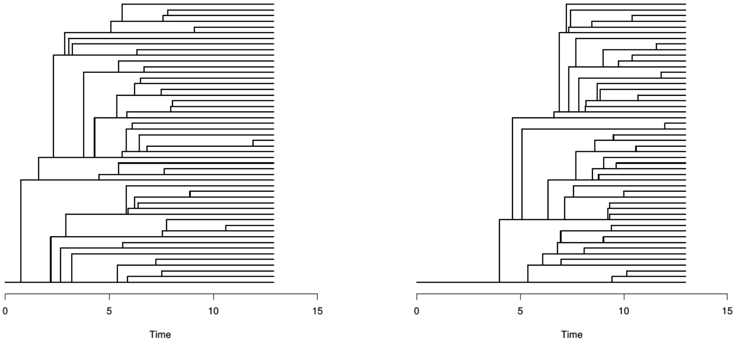
- NOTE: We limit to connected networks with unit weights and undirected edges here

Continuous Time Transmission Process

Two Transmission Trees (TTs) Grown on a Complete Susceptible-Infected Contact Network (SICN) with $n = 50$ individuals



Continuous Time Transmission Process

Branch-lengths of the TTs Grown on Complete SICNs randomly shifted logistic limit

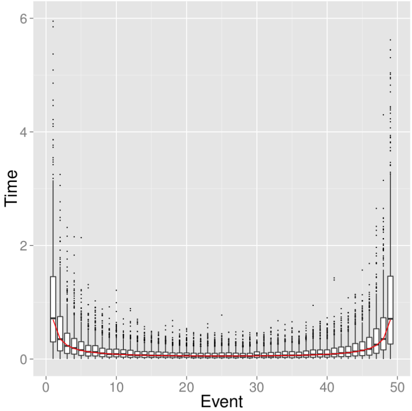


Fig. 6 The sampling distribution of T_z, branch-lengths (times in y-axis) of the transmission tree when there are exactly z infected individuals or between the $(z-1)$-th and z-th infection event (x-axis), where $z \in \{1, 2, \ldots, n-1\}$, from 500 independent simulations of the transmission tree over the complete SI contact network for a population of size $n = 50$ (as box plots) and the median branch-lengths given by $E(T_z)\log 2 = (\lambda z(n-z))^{-1}\log 2$, with $\lambda = 1/(n-1)$ (as red solid line).

for eg. (Aldous, 2013, Eq. 7.13)):

$$T_{\lfloor un \rfloor} - \log n \xrightarrow{d} F^{-1}(u) + G, \quad 0 < u < 1,$$

where, F is the logistic function:

$$F(t) = \frac{\exp(t)}{1+\exp(t)}, \quad -\infty < t < \infty$$

and G has Gumbel distribution with $\Pr(G < x) = \exp(e^{-x})$.

Continuous Time Transmission Process

What is the distribution of transmission trees for an essentially arbitrary contact network?

Transmission Trees on Other Contact Networks

Mean branch-lengths for star, path and complete networks

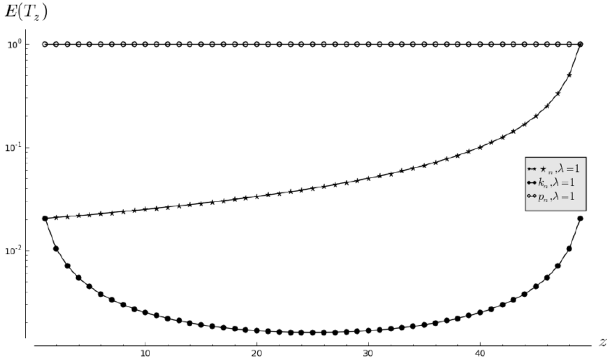
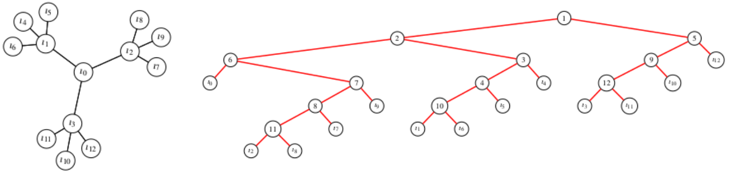
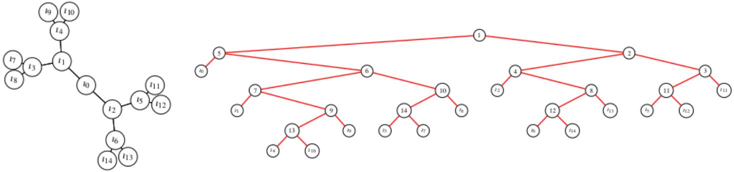


Figure 5: Expected branch-lengths when there are z infection events or $z+1$ infected individuals, $E(T_z)$, for the three cases. Here $n = 50$ and $\lambda = 1$. $E(T_z) = 1/\lambda = 1$ with the path network p_n of Sect. 2.1.3. $E(T_z) = 1/(\lambda(n-z)) = 1/(50-z)$ with the star network $\star_n$ of Sect. 2.1.2 and $E(T_z) = 1/(\lambda z(n-z)) = 1/(z(50-z))$ with the complete network k_n of Sect. 2.1.1 as z ranges in $\{1, 2, \ldots, n-1 = 49\}$.

Transmission Trees on Other Contact Networks

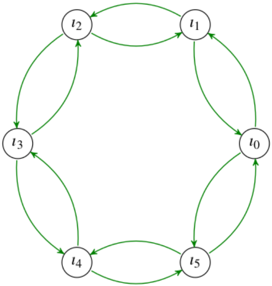
Trees on Balanced Tree Networks

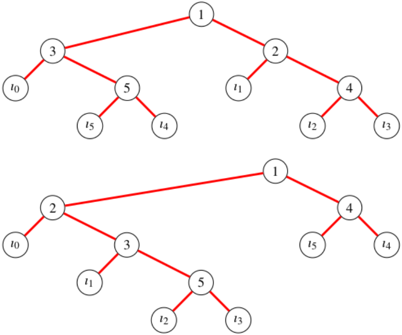




Transmission Trees on Other Contact Networks

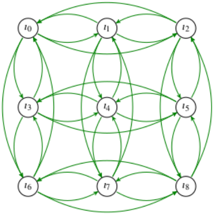
Trees on Bidirectional Circular Networks

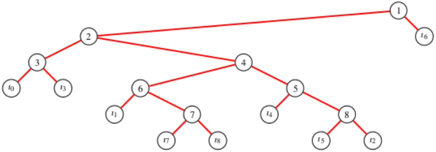


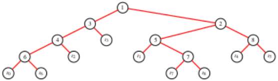


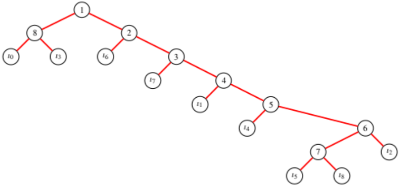
Transmission Trees on Other Contact Networks

Trees on Toroidal Network



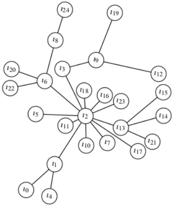


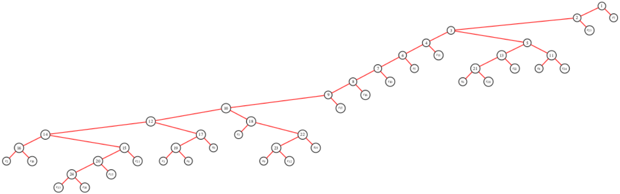




Transmission Trees on Other Contact Networks

Trees on Preferential Attachment Network





Transmission Trees on Other Contact Networks

Real-world networks are quite heterogeneous and are closer to mixtures of various families of deterministic and random contact networks...

What is the distribution of transmission trees for an essentially arbitrary contact network?

Beta-splitting Model

- IDEA: induce distributions on TTs without the SICN

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  - $B_1, B_2, \ldots \overset{iid}{\sim} \mathrm{Beta}(\alpha + 1, \beta + 1)$, $(\alpha, \beta) \in (-1, \infty)^2$

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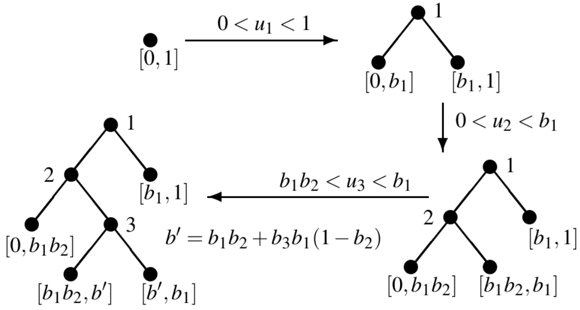
  - $B_1, B_2, \ldots \overset{iid}{\sim} \mathrm{Beta}(\alpha+1, \beta+1)$, $(\alpha, \beta) \in (-1, \infty)^2$
- Beta-splitting construction:



Theorems

Integrating out the interval-valued realizations at the leaf nodes

Theorem 1. *The probability of any discrete transmission tree $\tau(m)$ with m splits and $m+1$ leaves under the integrated Beta-splitting model is:*

$$\Pr\{\tau(m)\} = \prod_{z=1}^{m} \left\{ \frac{1}{B(\alpha+1,\beta+1)} \int_0^1 b_z^{s_z^L+\alpha}(1-b_z)^{s_z^R+\beta} db_z \right\} \times \Pr(\textit{leaf labels})$$

$$= \prod_{z=1}^{m} \frac{B(s_z^L+\alpha+1, s_z^R+\beta+1)}{B(\alpha+1,\beta+1)} \times \Pr(\textit{leaf labels}), \tag{3.4}$$

$$= \prod_{z=1}^{m} \left(\frac{\prod_{j=0}^{s_z^R} \frac{\beta+j}{\beta+j+\alpha} \prod_{i=0}^{s_z^L} \frac{\alpha+i}{\alpha+i+\beta+s_z^R+1}}{\frac{\alpha\beta}{(\alpha+\beta)(\alpha+\beta+1)}} \right) \times \Pr(\textit{leaf labels}), \tag{3.5}$$

Theorems

Beta-splitting model matches distrn on TTs for three example SICNs

- $(\alpha, \beta) = (0, 0) \equiv$ complete SICN,
- $(\alpha, beta) \to (\infty, -1) \equiv$ star SICN
- $(\alpha, beta) \to (-1, \infty) \equiv$ path SICN
- Theorem 2 on MLE expressions
- Theorem 3 on Equivalence class of initialized SICNs with the same (α, β)-specified TT distribution
- Will present a chalk talk in CIM on Feb 14 2017...
- 50 other model parameters simulated...

MLE of α and β from TTs under various SICNs

mean MLEs based on transmission trees simulated from various contact networks indexed by their ID from Table 1.

Beta-projections of various models

ID	Contact network	n	r	trials	$\overline{\hat{\alpha}}$ (s.e.)	$\overline{\hat{\beta}}$ (s.e.)
1	Complete	1,000	1	5	-0.006952 (0.06853)	0.05208 (0.1005)
2	Star	1,000	1	5	∞ (0.0000)	-1.0000 (0.0000)
3	Path	1,000	1	5	-1.0000 (0.0000)	∞ (0.0000)
4	Bidirectional Circular	50	1	5	-0.9880 (0.0006)	1.4584 (0.1534)
5	Bidirectional Circular	50	100	5	-0.9879 (0.0000)	1.5189 (0.0067)
6	BalancedTree(2,9)	1023	1	5	-0.4052 (0.0000)	-0.1477 (0.0000)
7	BalancedTree(3,6)	1093	1	5	-0.06452 (0.0000)	-0.5215 (0.0000)
8	BalancedTree(4,5)	1365	1	5	0.06556 (0.0000)	-0.7109 (0.0000)
9	BalancedTree(6,4)	1555	1	5	0.2350 (0.0000)	-0.8510 (0.0000)
10	BalancedTree(10,3)	1111	1	5	0.9249 (0.0000)	-0.9156 (0.0000)
11	BalancedTree(32,2)	1057	1	5	1.1624 (0.0000)	-0.9853 (0.0000)
12	BalancedTree(999,1)	1000	1	5	∞ (0.0000)	-1.0000 (0.0000)

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13	2D toroidal grid	1024	1	5	-0.8612 (0.008425)	-0.5606 (0.03219)
14	2D toroidal grid	10000	1	5	-0.89346 (0.0022)	-0.6626 (0.0106)
15	3D toroidal grid	1000	1	5	-0.6849 (0.01479)	-0.3515 (0.03451)
16	3D toroidal grid	10648	1	5	-0.7628 (0.007956)	-0.4968 (0.01641)
17	ER(100, 0.030)	100	30	5	-0.6063 (0.01383)	-0.4052 (0.02710)
18	ER(100, 0.040)	100	30	5	-0.5179 (0.01855)	-0.3151 (0.02244)
19	ER(100, 0.050)	100	30	5	-0.4059 (0.02020)	-0.2246 (0.01952)
20	ER(100, 0.10)	100	30	5	-0.1997 (0.03106)	-0.1280 (0.03063)
21	ER(100, 0.20)	100	30	5	-0.1074 (0.03961)	-0.06166 (0.03020)
22	ER(100, 0.40)	100	30	5	0.02247 (0.06603)	0.01541 (0.05499)
23	ER(100, 0.64)	100	30	5	-0.01097 (0.03984)	0.01046 (0.05112)
24	ER(100, 1.0)	100	30	5	-0.001787 (0.04347)	-0.01555 (0.04019)

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25	RandReg(1000, 3)	1000	1	5	-0.7504 (0.004186)	-0.06260 (0.06322)
26	RandReg(1000, 4)	1000	1	5	-0.5530 (0.04513)	-0.002305 (0.09785)
27	RandReg(1000, 6)	1000	1	5	-0.3520 (0.03464)	0.06042 (0.06586)
28	RandReg(1000, 10)	1000	1	5	-0.1939 (0.06167)	0.07274 (0.1238)
29	RandReg(1000, 100)	1000	1	5	0.06378 (0.04519)	0.1084 (0.05844)
30	RandReg(1000, 999)	1000	1	5	-0.01496 (0.08893)	0.006464 (0.04166)
31	$\text{SWRN}^{*,\circ}(50, 2, 0.0)$	50	30	5	-0.9878 (0.0001516)	1.514 (0.01222)
32	$\text{SWRN}^{*}(50, 2, 0.1)$	50	30	5	-0.9618 (0.003047)	-0.4147 (0.03203)
33	$\text{SWRN}^{\circ}(50, 2, 0.1)$	50	30	5	-0.9652 (0.002863)	-0.3828 (0.1171)
34	$\text{SWRN}^{*}(50, 2, 0.2)$	50	30	5	-0.9375 (0.004620)	-0.5683 (0.0193)
35	$\text{SWRN}^{*}(50, 2, 0.5)$	50	30	5	-0.8632 (0.008181)	-0.6471 (0.03722)
36	$\text{SWRN}^{*}(50, 5, 0.1)$	50	30	5	-0.7530 (0.01572)	-0.4751 (0.04671)

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Beta-projections of various models

36	SWRN*(50, 5, 0.1)	50	30	5	-0.7530 (0.01572)	-0.4751 (0.04671)
37	SWRN°(50, 5, 0.1)	50	30	5	-0.7918 (0.01596)	-0.5130 (0.03323)
38	SWRN°(50, 5, 0.2)	50	30	5	-0.6881 (0.03277)	-0.3595 (0.06002)
39	SWRN°(50, 5, 0.5)	50	30	5	-0.5264 (0.04687)	-0.2138 (0.09471)
40	SWRN°(100, 2, 0.2)	100	1	5	-0.9479 (0.01509)	-0.3991 (0.5065)
41	SWRN°(100, 2, 0.2)	100	30	5	-0.9493 (0.003869)	-0.6027 (0.03475)
42	SWRN*(100, 2, 0.5)	100	1	5	-0.9023 (0.03411)	-0.7139 (0.03929)
43	SWRN*(100, 2, 0.5)	100	30	5	-0.8878 (0.006687)	-0.6821 (0.02189)
44	SWRN°(100, 2, 0.5)	100	1	5	-0.8714 (0.05584)	-0.6533 (0.09257)
45	SWRN°(100, 2, 0.5)	100	30	5	-0.8920 (0.005128)	-0.6786 (0.02189)
46	SWRN°(100, 5, 0.99)	100	30	5	-0.5079 (0.02371)	-0.2290 (0.03059)
47	SWRN°(100, 10, 0.99)	100	30	5	-0.2027 (0.07641)	-0.05611 (0.06949)

MLE of α and β from TTs under various SICNs

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48	$\mathrm{PrefAttach}^{*}(100,1)$	100	30	10	-0.3275 (0.04932)	-0.8215 (0.01121)
49	$\mathrm{PrefAttach}^{*}(100,2)$	100	30	10	-0.2443 (0.03283)	-0.6647 (0.01294)
50	$\mathrm{PrefAttach}^{\circ}(100,1)$	100	30	10	-0.3813 (0.04908)	-0.8254 (0.005460)
51	$\mathrm{PrefAttach}^{\circ}(100,2)$	100	30	10	-0.3339 (0.03884)	-0.6743 (0.01657)
52	$\mathrm{PrefAttach}^{\circ}(100,3)$	100	30	10	-0.2545 (0.04181)	-0.5863 (0.01652)
53	$\mathrm{PrefAttach}^{\circ}(100,5)$	100	30	10	-0.1748 (0.04214)	-0.4698 (0.03110)
54	$\mathrm{PrefAttach}^{\circ}(100,10)$	100	30	10	-0.1196 (0.03449)	-0.3089 (0.02663)
55	$\mathrm{PrefAttach}^{\circ}(100,1)$	100	1	5	-0.2472 (0.2698)	-0.7993 (0.05843)

MLE of α and β from TTs under various SICNs

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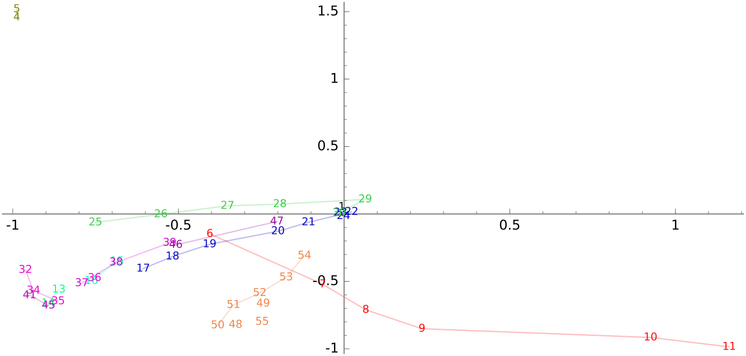
Beta-projections of various models



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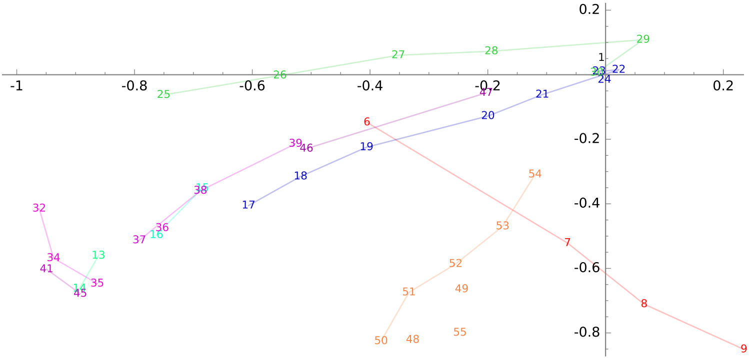

So what? — We can do Bayesian non-parametrics by Beta-splitting mixtures over empirical SICNs/TINs

Summary

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- Distributed computing framework of Apache Spark allows one to handle such large data easily
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- Result 2: strong signals of ideological concurrence between various SPLC-defined extermist groups and ‘@realDonaldTrump‘’s echo-chamber.

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- Need: Markov control processes that allow the Networks themselves to coevolve with transmission trees

The End

Many thanks to:

- Databricks Academic Partners Programme and AWS Educate grant
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    1. Veolia Environnement
    2. French National Museum of Natural History, Paris, France and
    3. Centre for Mathematics and its Applications, Ecole Polytechnique, Palaiseau, France.
- Code Contributors: Ivan Sadikov and Akinwande Atanda
- The Transmission Process: A Combinatorial Stochastic Process for the Evolution of Transmission Trees over Networks, Raazesh Sainudiin and David Welch, Journal of Theoretical Biology, Volume 410, Pages 137–170, 2016 `10.1016/j.jtbi.2016.07.038`
- `http://lamastex.org/lmse/mep`
- Thanks for your Attention :)