Class 16: Going viral

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Sociology 204: Social Networks
Princeton University

Last class:

- experimental approaches can measure the effect we have on each other

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- voting is contagious & emotional valence of word use is contagious

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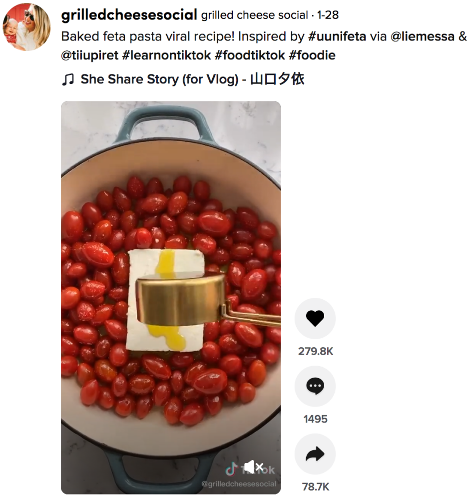
- experimental approaches can measure the effect we have on each other
- voting is contagious & emotional valence of word use is contagious
- two designs: 1) intervene and spillover; 2) edge-control
- some of these experiments raise ethical questions (e.g., Kramer et al.)

- Mon: Experimental approaches to studying contagion
- Today: Going viral
- Next 5 classes (up to Thanksgiving): Social media

Community minute

Think-pair-share: What's an example of something that people say has gone viral?

What does it mean to go viral?



https://www.tiktok.com/@grilledcheesesocial/video/6922946148760030469

Similarities between the papers

- Both papers deal with a similar empirical phenomena and both struggle to figure out what is the **right question**

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- Both papers are in Pasteur's quadrant (motivated by use and seeking fundamental understanding)

Quest for fundamental understanding?	Consideration of use? No	Consideration of use? Yes
Yes	Pure basic research (Bohr)	Use-inspired basic research (Pasteur)
No		Pure applied research (Edison)

For more information, see Salganik (2018): `https://www.bitbybitbook.com/en/1st-ed/running-experiments/making/partner/`

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- Both papers include small and big cascades offering a systematic approach
- Both papers require data that was not possible until recently
- The papers end up with different ways of approaching the problem: descriptive vs predictive

The Structural Virality of Online Diffusion

Sharad Goel, Ashton Anderson
Stanford University, Stanford, California, 94305 {scgoel@stanford.edu, ashton@cs.stanford.edu}
Jake Hofman, Duncan J. Watts
Microsoft Research, New York, New York 10016 {jmh@microsoft.com, duncan@microsoft.com}

What is virality?

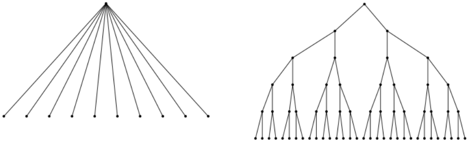


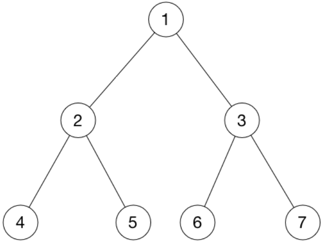
Figure 1 **A schematic depiction of broadcast versus viral diffusion, where nodes represent individual adoptions and edges indicate who adopted from whom.**

Wiener index (from chemistry):

$$\nu(T) = \frac{1}{n(n-1)} \sum_{i=1}^{n} \sum_{j=1}^{n} d_{ij}$$

where $d_{i,j}$ is the length of the shortest path between i and j

In other words, expected path length between two randomly chosen points



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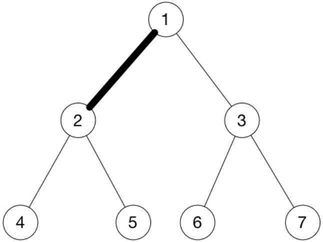

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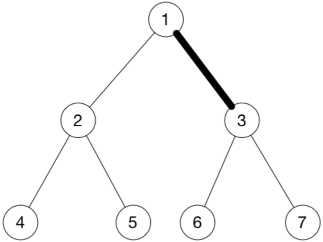

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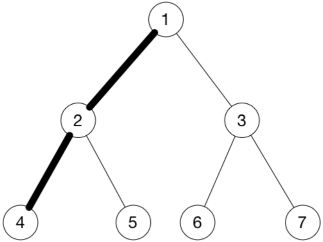

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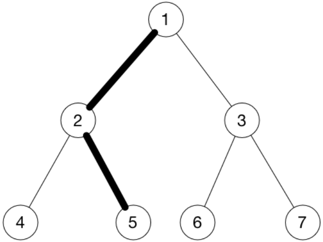

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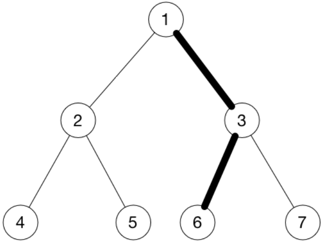

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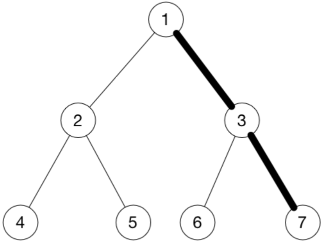

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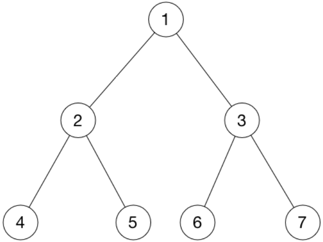

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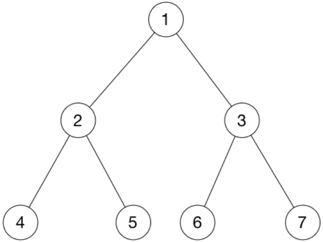

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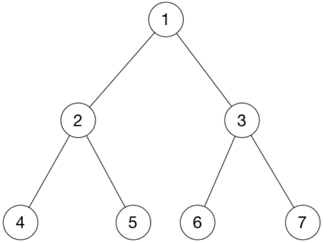

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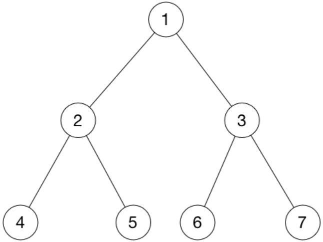

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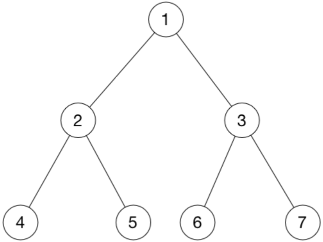

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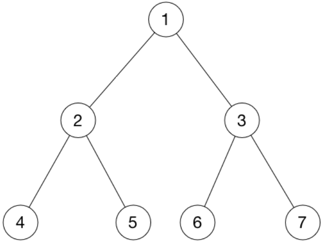

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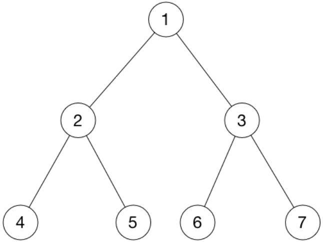

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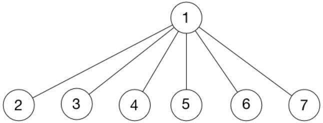
$$\nu(T) \approx 2.29$$



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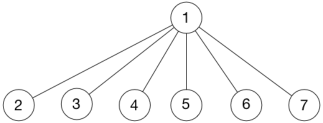

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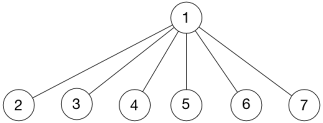

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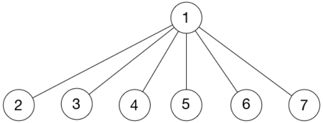

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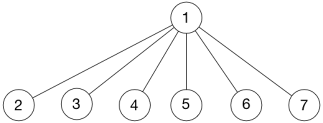

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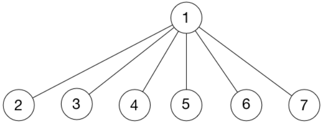

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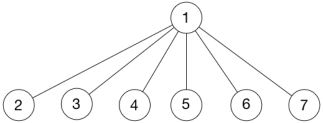

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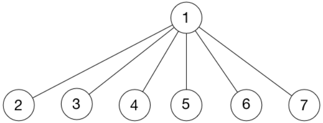

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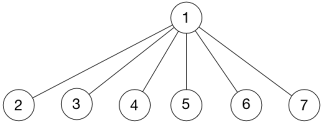

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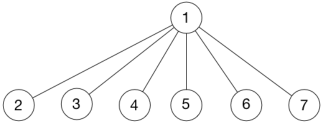

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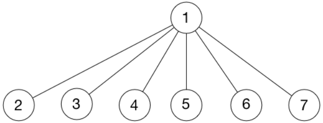

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- meets the three properties they want (e.g, for a fixed total number of adoptions in a cascade, structural virality should increase with the branching factor of the structure)

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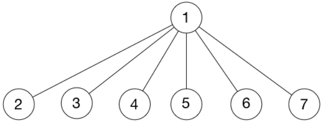
- avoids problems of other measures (e.g., depth can be impacted by a single long path)
- does not depend on any assumed generative model



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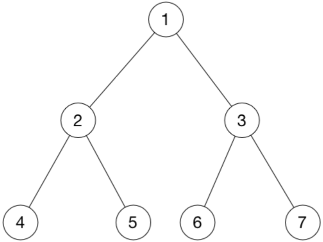

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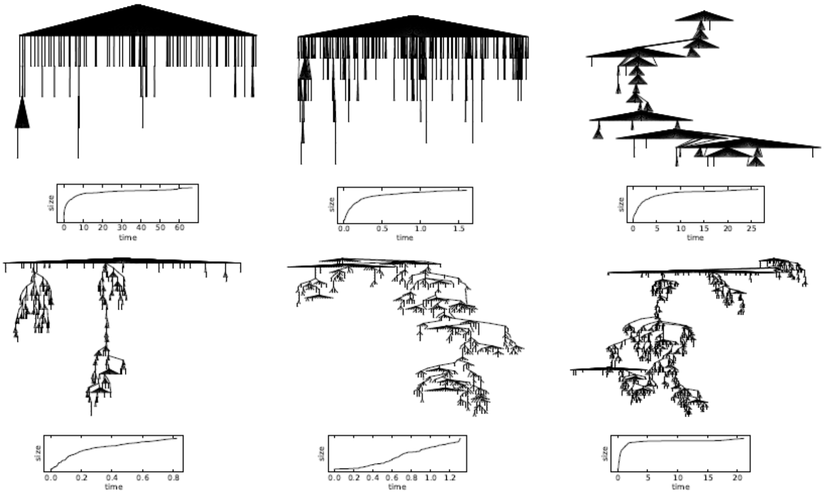


Figure 3 A random sample of cascades stratified and ordered by increasing structural virality, ranging from 2 to 50. For ease of visualization, cascades were restricted to having between 100 and 1000 adopters. Cumulative adoption curves (i.e., total cascade size over time) are shown below each cascade, with time indicated in hours.

describing outcomes vs describing generative process

What do viral cascades look like?

- 622 million unique pieces of content (links) shared via Twitter
- 1.2 billion adoptions (posting of content)
- videos, images, news stories, and petitions

"Big data" is needed because large cascades are very, very rare.

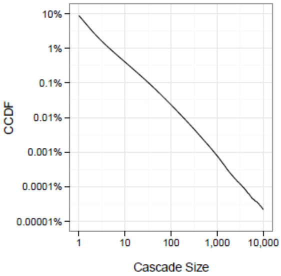
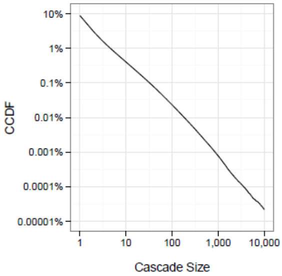


Figure 2 Distribution of cascade sizes on a log-log scale, aggregated across the four domains we study: videos, news, pictures, and petitions.

- Most things don't grow (99% of adoptions are accounted for by the root node and the immediate followers of the root node)



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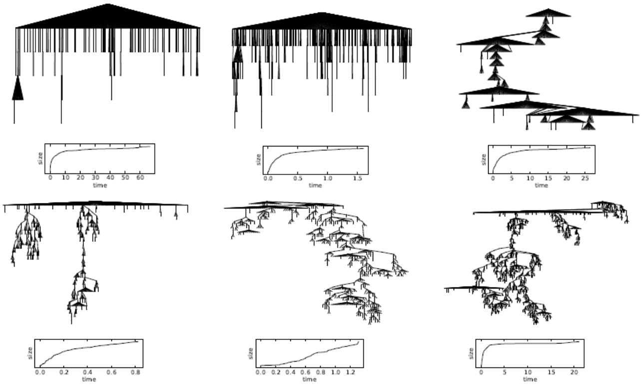
- Most things don't grow (99% of adoptions are accounted for by the root node and the immediate followers of the root node)
- They focus on the cascades that include at least 100 nodes (1 in 4,000 events).



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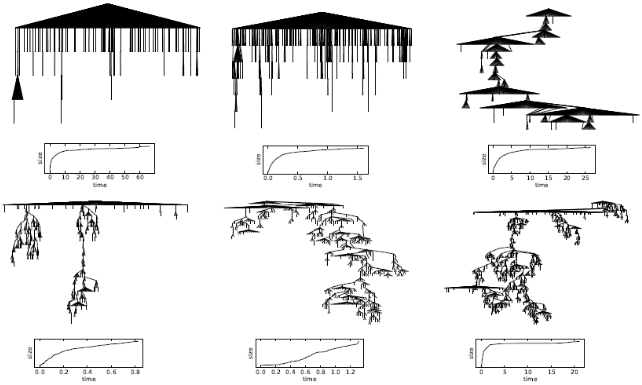
- Examples of different structural virality



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- Examples of different structural virality
- Structural virality captures something different from speed of adoption and diffusion curves

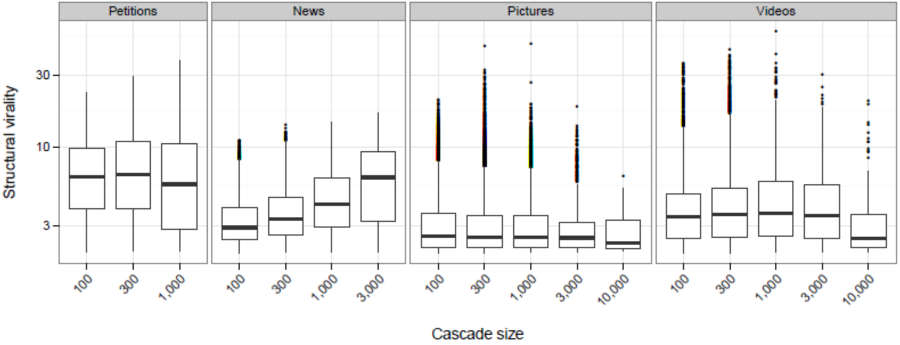

Figure 5 **Boxplot of structural virality by size on a log-log scale, separated by domain. Lines inside the boxes indicate median structural virality, while the boxes themselves show interquartile ranges.**

Knowing the size of a cascades reveals little about structural virality. This is true for all 4 types of content (but a bit less true for news).

What combination of spreading process and network structure is consistent with these results?

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SIR model on network with power law degree distribution

How might the ideas in this paper be used?

https://www.youtube.com/watch?v=wSw0szoHuoI

Now we have a sense of what cascades can look like, but can they be predicted?

Can cascades be predicted?

Justin Cheng
Stanford University
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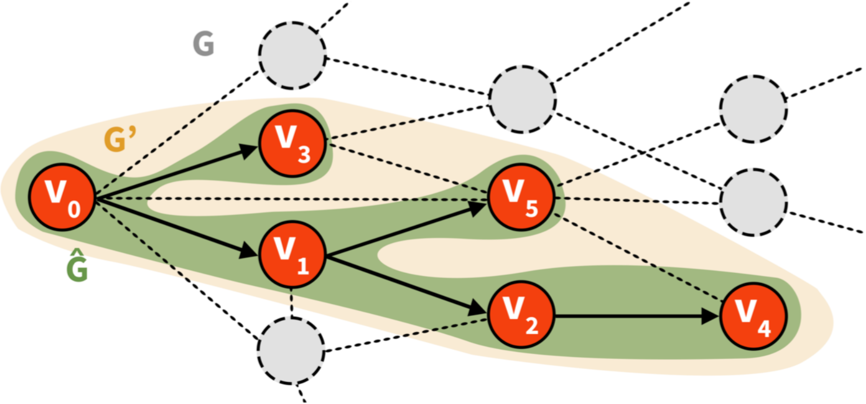
Lada A. Adamic
Facebook
ladamic@fb.com

P. Alex Dow
Facebook
adow@fb.com

Jon Kleinberg
Cornell University
kleinber@cs.cornell.edu

Jure Leskovec
Stanford University
jure@cs.stanford.edu



Reshare cascades of images on Facebook in June 2013

Two ways of posting the same question (in this case):

- Given a cascade that current has size k, will grow beyond the median size of $f(k)$?
- Given a cascade of size k, will the cascade double in size and reach at least $2k$ nodes?

We therefore propose the following *cascade growth prediction problem*: given a cascade that currently has size k, predict whether it grow beyond the median size $f(k)$. (As we show later, the prediction problem is equivalent to asking: given a cascade of size k, will the cascade double its size and reach at least $2k$ nodes?) This implicitly defines a family of prediction problems, one for each k. We can thus ask how cascade predictability behaves as we sweep over larger and larger values of k. (There are natural variants and generalizations in which we ask about reaching target sizes other than the median $f(k)$.) This problem formulation has a number of strong advantages over standard ways of trying to define cascade prediction. First, it leads to a prediction problem in which the classes are balanced, rather than highly unbalanced. Second, it allows us to ask for the first time how the predictability of a cascade varies over the range of its growth from small to large. Finally, it more closely approximates the real tasks that need to be solved in applications for managing viral content, where many evolving cascades are being monitored, and the question is which are likely to grow significantly as time moves forward.

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Why might we need to manage viral content?

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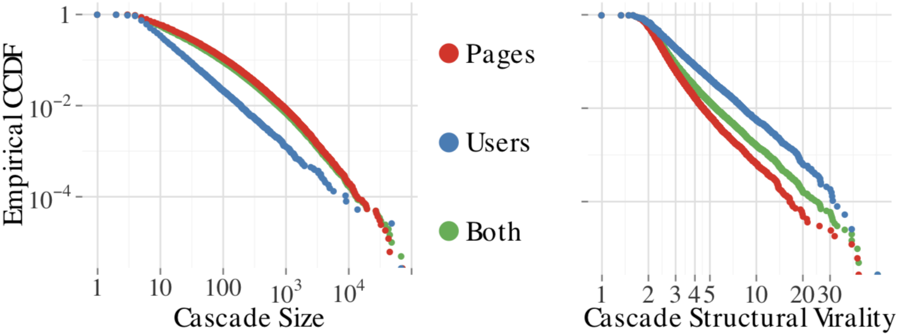
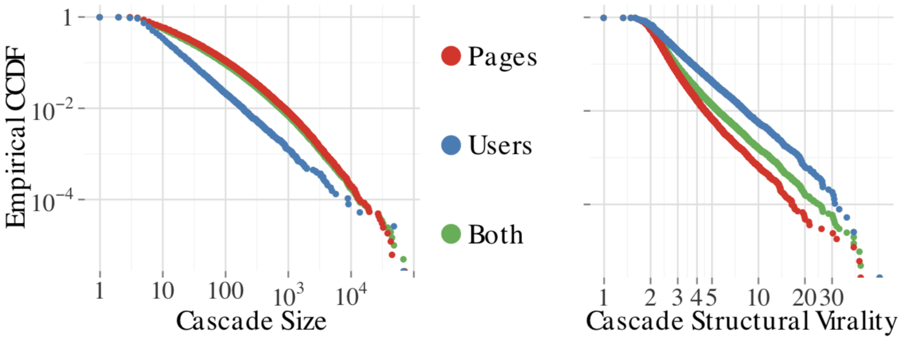
Why might we need to manage viral content?

- Amplify virality
- Check and possible pull things that appear likely to go viral



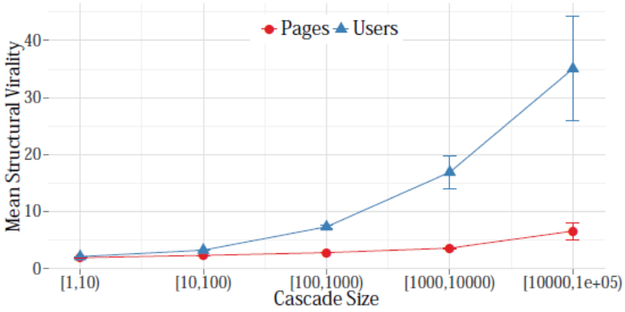
Difference between pages (media, celebrities) and users (organic):

- user cascades are small than page cascades

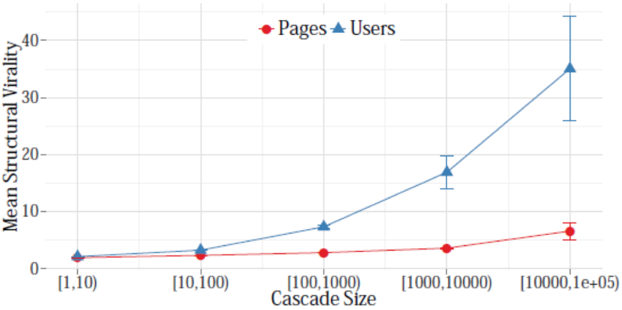


Difference between pages (media, celebrities) and users (organic):

- user cascades are small than page cascades
- user cascades tend to have higher structural virality



Pages
Users
Mean Structural Virality
40
30
20
10
0
[1,10)
[10,100)
[100,1000)
[1000,10000)
[10000,1e+05)
Cascade Size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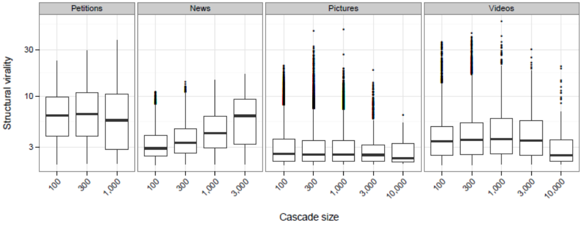
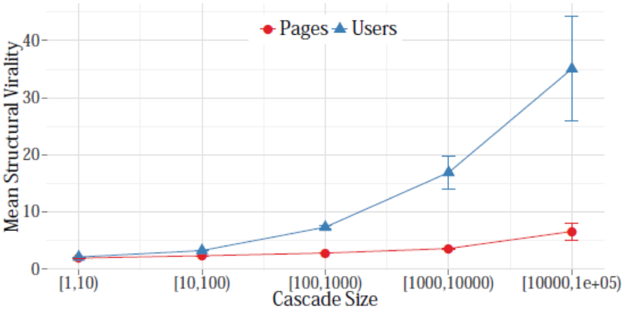

Petitions
News
Pictures
Videos
Structural virality
30
10
3
100
300
1,000
3,000
10,000
Cascade size



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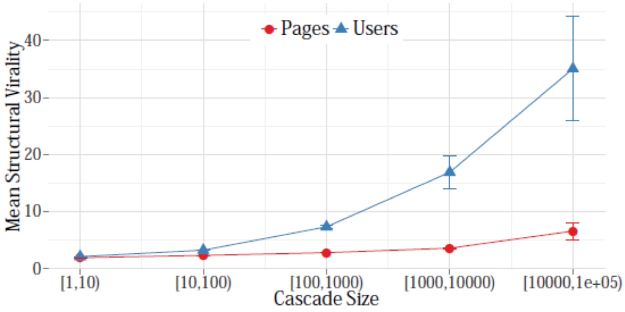

- For page cascades, there is a weak relationship between size and virallity (similar to Goel et al)
- For user cascades, there is a strong positive relationship between size and virallity (different to Goel et al)

Machine learning approach (e.g., COS 424) to predicting if a cascade will double

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Content Features	
$score_{food/nature/\ldots}$	The probability of the photo having a specific feature (food, overlaid text, landmark, nature, etc.)
is_en	Whether the photo was posted by an English-speaking user or page
$has\_caption$	Whether the photo was posted with a caption
$liwc_{pos/neg/soc}$	Proportion of words in the caption that expressed positive or negative emotion, or sociality, if English
Root (Original Poster) Features	
$views_{0,\ k}$	Number of users who saw the original photo until the kth reshare was posted
$orig\_is\_page$	Whether the original poster is a page
$outdeg(v_0)$	Friend, subscriber or fan count of the original poster
age_0	Age of the original poster, if a user
$gender_0$	Gender of the original poster, if a user
fb_age_0	Time since the original poster registered on Facebook, if a user
$activity_0$	Average number of days the original poster was active in the past month, if a user
Resharer Features	
$views_{1..k-1,\ k}$	Number of users who saw the first $k-1$ reshares until the kth reshare was posted
$pages_k$	Number of pages responsible for the first k reshares, including the root, or $\sum_{i=0}^{k} \mathbb{1}\{v_i \text{ is a page}\}$
$friends_k^{avg/90p}$	Average or 90th percentile friend count of the first k resharers, or $\frac{1}{k}\sum_{i=1}^{k} outdeg_{friends}(v_i)\mathbb{1}\{v_i \text{ is a user}\}$
$fans_k^{avg/90p}$	Average or 90th percentile fan count of the first k resharers, or $\frac{1}{k}\sum_{i=1}^{k} outdeg(v_i)\mathbb{1}\{v_i \text{ is a page}\}$
$subscribers_k^{avg/90p}$	Average or 90th percentile subscriber count of the first k resharers, or $\frac{1}{k}\sum_{i=1}^{k} outdeg_{subscriber}(v_i)\mathbb{1}\{v_i \text{ is a user}\}$
$fb\_ages_k^{avg/90p}$	Average or 90th percentile time since the first k resharers registered on Facebook, or $\frac{1}{k}\sum_{i=1}^{k} fb\_age_i$
$activities_k^{avg/90p}$	Average number of days the first k resharers were active in July, or $\frac{1}{k}\sum_{i=1}^{k} activity_i$
$ages_k^{avg/90p}$	Average age of the first k resharers, or $\frac{1}{k}\sum_{i=1}^{k} age_i$
$female_k$	Number of female users among the first k resharers, or $\sum_{i=1}^{k} \mathbb{1}\{gender_i \text{ is female}\}$
Structural Features	
$outdeg(v_i)$	Connection count (sum of friend, subscriber and fan counts) of the ith resharer (or out-degree of v_i on $G = (V, E)$)
$outdeg(v_i')$	Out-degree of the ith reshare on the induced subgraph $G' = (V', E')$ of the first k resharers and the root
$outdeg(\hat{v}_i)$	Out-degree of the ith reshare on the reshare graph $\hat{G} = (\hat{V}, \hat{E})$ of the first k reshares
$orig\_connections_k$	Number of first k resharers who are friends with, or fans of the root, or $\lvert\{v_i \mid (v_0, v_i) \in E,\ 1 \le i \le k\}\rvert$
$border\_nodes_k$	Total number of users or pages reachable from the first k resharers and the root, or $\lvert\{v_i \mid (v_i, v_j) \in E,\ 0 \le i, j \le k\}\rvert$
$border\_edges_k$	Total number of first-degree connections of the first k resharers and the root, or $\lvert\{(v_i, v_j) \mid (v_i, v_j) \in E,\ 0 \le i, j \le k\}\rvert$
$subgraph_k'$	Number of edges on the induced subgraph of the first k resharers and the root, or $\lvert\{(v_i, v_j) \mid (v_i, v_j) \in E',\ 0 \le i, j \le k\}\rvert$
$depth_k'$	Change in tree depth of the first k reshares, or $\min_\beta \sum_{i=1}^{k} (depth_i - \beta i)^2$
$depths_k^{avg/90p}$	Average or 90th percentile tree depth of the first k reshares, or $\frac{1}{k}\sum_{i=1}^{k} depth_i$
did_leave	Whether any of the first k reshares are not first-degree connections of the root
Temporal Features	
$time_i$	Time elapsed between the original post and the ith reshare
$time_{1..k/2}'$	Average time between reshares, for the first $k/2$ reshares, or $\frac{1}{k/2-1}\sum_{i=1}^{k/2-1}(time_{i+1} - time_i)$
$time_{k/2..k}'$	Average time between reshares, for the last $k/2$ reshares, or $\frac{1}{k/2-1}\sum_{i=k/2}^{k-1}(time_{i+1} - time_i)$
$time_{1..k}''$	Change in the time between reshares of the first k reshares, or $\min_\beta \sum_{i=1}^{k-1}(time_{i+1} - time_i) - \beta i)^2$
$views_{0,k}'$	Number of users who saw the original photo, until the kth reshare was posted, per unit time, or $\frac{views_{0,\ k}}{time_k}$
$views_{1..k-1,\ k}'$	Number of users who saw the first $k-1$ reshares, until the kth reshare was posted, per unit time, or $\frac{views_{1..k-1,k}}{time_k}$

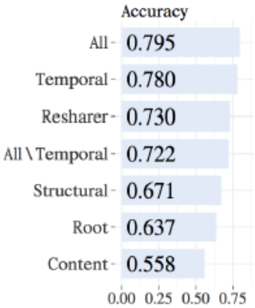
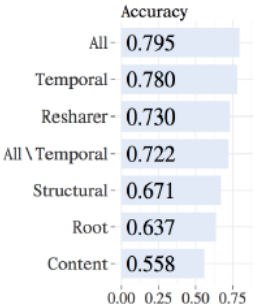


Figure 4: Using logistic regression, we are able to predict with near 80% accuracy whether the size of a cascade will reach the median (10) after observing the first k =5 reshares.

- Temporal features are most predictive (things that spreading fast are likely to keep spreading)



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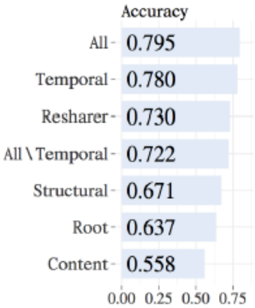

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- Temporal features are most predictive (things that spreading fast are likely to keep spreading)
- Content features least predictive
- Temporal features are more predictive than everything else put together

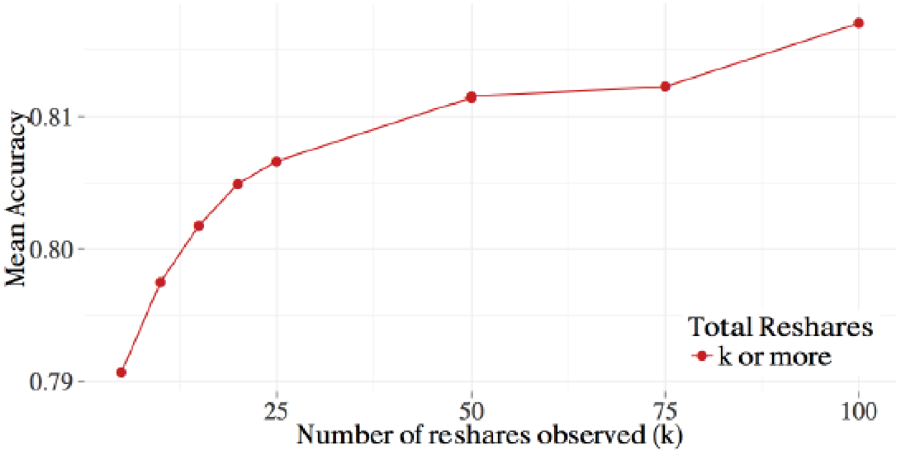
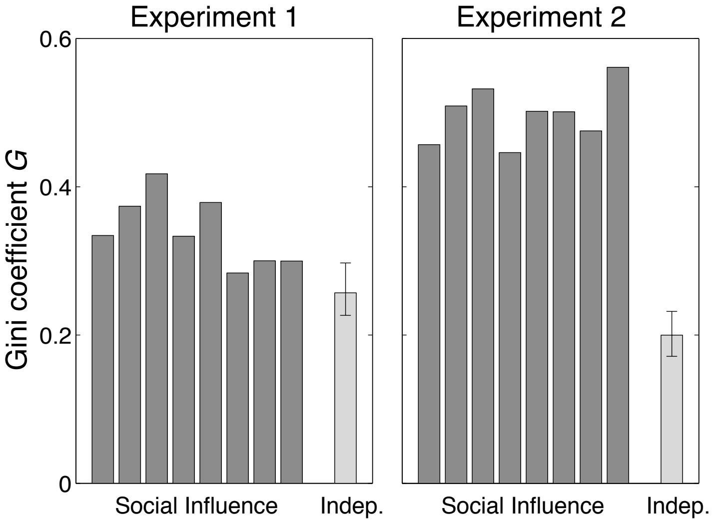


Figure 5: If we observe the first k reshares of a cascade, and want to predict whether the cascade will double in size, our prediction improves as we observe more of it.


SUP BRO

gini coefficient: 0.787!


Experiment 1
Experiment 2
0.6
0.4
0.2
0
Gini coefficient G
Social Influence
Indep.
Social Influence
Indep.

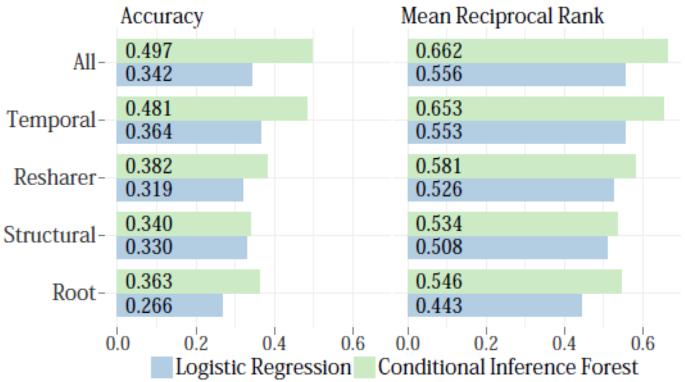


Figure 10: In predicting the largest cascade in clusters of 10 or more cascades of identical photos, we perform significantly above the baseline of 0.1.

We can somewhat predict which of the identical seeds will spread, if we observe the beginning of each cascade

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Summary:

- asking the right question can be very important in research
- almost nothing posted on Twitter and Facebook creates a large cascades
- tweets and photos from FB pages show little relationship between structural virality and cascades size; photos from FB users that create large cascades are structurally viral
- there are many different ways to ask interesting questions about going viral

What is all this stuff going viral?

Next 5 classes will be about social media

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- Social media and society
- Social ads in social media
- Fixing social media
- The Facebook Files

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Assignments 7, 8 and 9 will be about self-experimentation and social media.

For next class:

- Kross, E. et al. (2020). Social media and well-being: Pitfalls, progress, and next steps. *Trends in Cognitive Science*.
- Carey, B. (2019). This is your brain off Facebook. *New York Times*.
- Allcott, H. et al. (2020). The welfare effects of social media. *American Economic Review*.
- Baym, N.K. et al. (2020). Mindfully scrolling: Rethinking Facebook after time deactived. *Social Media + Society*.