

a summary of

“Influence and Passivity in Social Media”

Daniel M. Romero, Wojciech Galuba,
Sitaram Asur, and Bernardo A. Huberman (2010)



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[Paper linked here](#)

Quantifying 'popularity'

- Social networks are massively popular
- Content consumption with rippling effects
- Twitter spotlight – fast information propagation, growing user base.
- Order within chaos; Individual status vs user passivity
 - two competing forces driving content virality:
- Leverage the dichotomy (inspired by HITS) – potentially mutually reinforcing

This Paper

- Analyze URL propagation on Twitter to describe ‘popularity’
- Status of a user measured by retweet rate in the network, ‘influence’
 - Attention is not all you need
- Bonus points for influence with a *passive* audience
- Novel, builds off of earlier works –
 - Some discussed key influentials, sparse hidden networks
 - Others studied measures of influence, reciprocity and homophily

Twitter & the Dataset

- Tweets/retweets are automatically shared with followers
- Fast interaction rate, increasingly leveraged by businesses & organizations
- 300 hours of Twitter Search API calls for `re.match('http', tweets)`
- 22 Million data points, 1/15 of entire activity.
- User graph contains all public users who posted at least 1 URL
- For each user, a list of followers was fetched once.

The Objective & Assumptions

- Users are majorly passive – often ignore info they receive (tweets, links). 1 in 318 retweet rate on average!
- We want to predict ‘influence’ by A on B \approx B’s *retweet rate* of A’s tweets.

Assumptions:

- Influence score depends on number of people they influence, their passivity, and their dedication.
- Passivity score depends on influence of those they follow, and their relative passivity (in the context of the audience of those they follow.)

Acceptance, Mathematically

- For every arc (i, j) in E , we define acceptance rate $u(i, j)$ by:

$$u_{ij} = \frac{w_{i,j}}{\sum_{k:(k,j) \in E} w_{kj}}$$

- The amount of influence that ‘j’ accepted from ‘i’, normalized by total influence accepted by ‘j’.
- User ‘dedication’

Rejection, Mathematically

- For every arc (i, j) in E , we define rejection rate $v(i, j)$ by:

$$v_{ji} = \frac{1 - w_{ji}}{\sum_{k:(j,k) \in E} (1 - w_{jk})}$$

- The amount of influence that ‘i’ rejected from ‘j’, normalized by total influence rejected from ‘j’ by all users in the network.
- Relative passivity

The IP Algorithm

- We begin with a weighted directed graph $G = (N, E, W)$
 - Each node 'n' in N represents a single user.
 - The weight $w(i,j)$ for each edge (i, j) corresponds to the ratio:
(influence that i successfully exerts on j) to (total influence that i attempted to exert on j),
 - Weight is computed as a ratio of # URLs

We want to define an Influence score and a Passivity score per-node:

$I: N \rightarrow [0, 1]$ and $P: N \rightarrow [0, 1]$

IP is Two Operations

The 'update' step:

$$I_i \leftarrow \sum_{j:(i,j) \in E} u_{ij} P_j$$

$$P_i \leftarrow \sum_{j:(j,i) \in E} v_{ji} I_j$$

- 'I' is the set of influence scores, $I(i)$ is the score of node 'i' (likewise for P)
- Each term on the right corresponds to an assumption we made.

The IP Algorithm

- Straightforward application from here:
 - a. Initialize all I and P scores to 1
 - b. Perform the update step, storing new I and P.
 - c. End after 'm' iterations
- Similar to HITS – uses the mutually reinforcing relationship; Passivity ~ authority score, Influence ~ hub score. However, IP it operates on a weighted graph & considers other properties (acceptance and rejection rate).

Evaluation & Comparisons

- For the 450k node dataset (1 million arcs), IP converged in tens of iterations
- IP-Influence score achieves an R^2 of 0.95 on predicting the upper limit of # of URL clicks, better than PageRank (0.84) or number of followers (0.59)
- h-index (0.05) and number of retweets (0.02) are extremely poor indicators of tweet performance.
- We can predict with 99.9% certainty the ceilings on # retweets, given a user with a large/small IP-influence score.

Wider Applicability

- IP-Influence adaptability – the initial graph $G(N, E, W)$ set weights based on URL clicks; this parameter could be modified for different applications.
- Content ranking – posts could be served and filtered based on their forecasted performance with the IP-influence score.
- Content filtering – Highly passive users tend to be bots/spammers, IP could be extended to perform content filtering (limiting visibility)

Areas for Potential Improvement

- Mentioned in the paper – IP was only evaluated over a fixed 300 hour window; like HITS, new weights/information -> fresh set of updates to node weights.
- IP over time – quantify growth on a platform?
- URL clicks could also mean clickbait – bots and retweet contests ranked high.
Influence does not directly translate to authority
- In the context of misinformation – a catchy URL might elicit clicks; IP operates reliant on external censorship/fact checking.