# Using Stochastic Models to Describe and Predict Social Dynamics of Web Users

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- Conclusion



1 What is Social Dynamics of Web Users?

## Definition and Quantization

#### Definition

Predicting popularity of content in social media

#### **Fact**

If one user interests some social media, he/she will **VOTE** it

#### Quantization

 The changing rate of the number of votes at one given time point

•

$$\frac{dN_{\text{vote}}(t)}{dt} \tag{1}$$



Figure: Screenshot of the front page of the social news aggregator Digg



2 Why do they study Social Dynamics of Web Users?

#### Value

Predicting which newly-submitted items will become popular is critically important for both hosts of social media content and its consumers

#### Hosts Level

Accurate and timely prediction would enable social media content hosts to maximize revenue through differential pricing for access to content or ad placement

#### Consumers Level

Prediction would also give consumers an important tool for filtering the ever-growing amount of content



3 What are the challenges they face?

## Challenge

#### Technology Level

Predicting popularity of content in social media, however, is challenging due to the complex interactions between content quality and how the social media site chooses to highlight content

#### Privacy Level

Most social media sites also selectively present content that has been highly rated by similar users, whose similarity is indicated implicitly by their behavior or explicitly by links in a social network 4 How do they collect their data?

#### **Data Collection**

#### Data Collection

- They collected data for the study by scraping Digg's Web pages in May and June 2006
- structure {
  - the number of votes the stories received
  - the location of the stories on the upcoming and front pages as a function of time
  - the names of its early voters
  - }

**5** How do they modeling Social Dynamics of Web Users?

finition Value Challenge Data **Modeling** Solver Result Modify Conclusion

## Prediction System

State diagram of user behavior for a single story

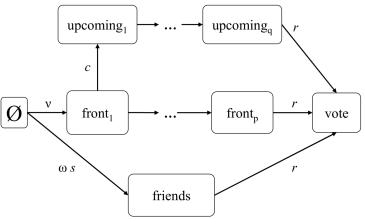


Figure: *vote* = *function* (*upcomings*, *fronts*, *friends*)



## Governing Equation

#### Stochastic Master Equation

$$\frac{d\langle n_k \rangle}{dt} = \sum_{j} \omega_{jk} (\langle \vec{n} \rangle) \langle n_j \rangle - \langle n_k \rangle \sum_{j} \omega_{kj} (\langle \vec{n} \rangle) 
\frac{dN_{\text{vote}}(t)}{dt} = r(\nu_f(t) + \nu_n(t) + \nu_{\text{friends}}(t))$$
(2)

**6** How do they solve the model?

#### Solver

$$f_{\text{page}}(m) = \frac{1}{2} \left( F_m \left( -\mu \right) - \exp \left( \frac{2\lambda}{\mu} \right) F_m \left( \mu \right) \right)$$

$$F_m(x) = \operatorname{erfc} \left( \alpha_m \frac{m - 1 + x}{\mu} \right)$$

$$p(t) = k_f \left( t - T_{\text{promotion}} \right) + 1$$

$$q(t) = k_t t + 1$$

$$\frac{ds}{dt} = -\omega s + a N_{\text{vote}}^{-b} \frac{dN_{\text{vote}}}{dt}$$

$$(3)$$



**7** How is their experimental result?

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### Experimental Result

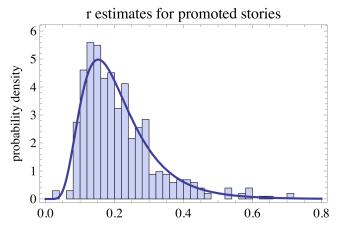


Figure: Distribution of interestingness (i.e., *r* values) for the promoted stories in our data set compared with the best fit lognormal distribution.



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#### Experimental Result

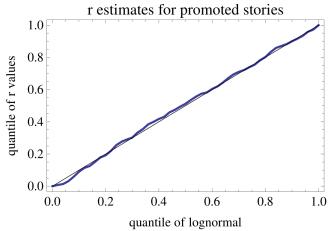


Figure: Quantile-quantile plot comparing observed distribution of r values with the lognormal distribution fit (thick curve)



8 How do they modify this model?

#### Modification

To investigate differences among voters with respect to the friends network, we extend the previous stochastic model to distinguish votes from fans and non-fans. The model considers the joint behavior of users and the location of the story on the web site.

finition Value Challenge Data Modeling Solver Result **Modify** Conclusion

### A Model of Social Voting with Niche Interests

System Architecture

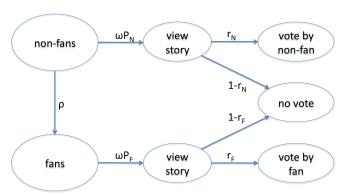


Figure: State diagram for a user. The submitter provides a story's first vote.



## A Model of Social Voting with Niche Interests System Architecture

submission upcoming location: q P(v) front page location: p

Figure: State diagram for a story

## Govern Equation

$$\frac{dv_F}{dt} = \omega r_F P_F F 
\frac{dv_N}{dt} = \omega r_N P_N N 
\frac{dF}{dt} = -\omega r_F P_F F + \rho N \frac{dv}{dt} 
\frac{dB}{dt} = -\omega r_N P_N N - \rho N \frac{dv}{dt}$$
(4)

efinition Value Challenge Data Modeling Solver Result **Modify** Conclusion

#### Parameter Estimation

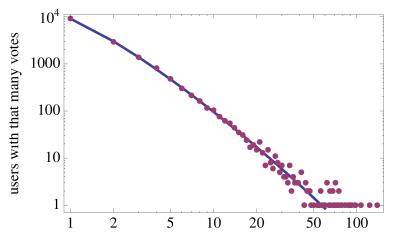


Figure: User activity distribution on logarithmic scales. The curve shows the fit to the model described in the text.



definition Value Challenge Data Modeling Solver Result **Modify** Conclusion

#### Parameter Estimation

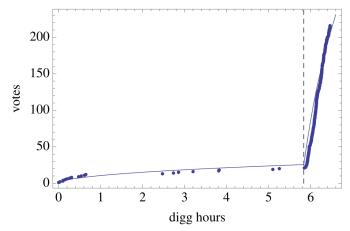


Figure: Voting behavior: the number of votes vs. time, measured in Digg hours, for a promoted story in June 2006.



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## Experimental Result

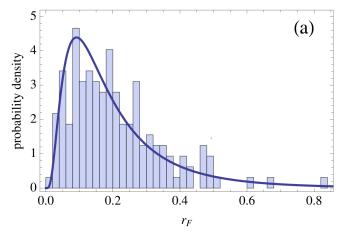


Figure: Distribution of interestingness for (a) fans



## Experimental Result

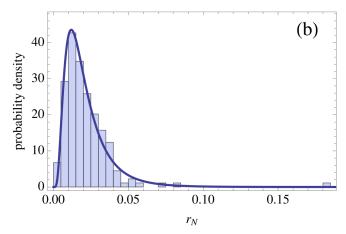


Figure: Distribution of interestingness for (b) non-fans



efinition Value Challenge Data Modeling Solver Result **Modify** Conclusion

#### Experimental Result

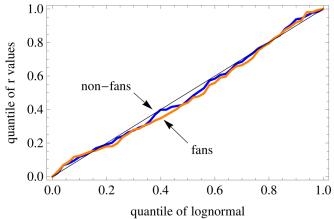


Figure: Quantile-quantile plot comparing the observed distribution for  $r_F$  (fans) and  $r_N$  (non-fans) with the corresponding lognormal distribution fits (thick curves).



finition Value Challenge Data Modeling Solver Result **Modify** Conclusion

#### Model-Based Prediction

a story with no fan votes

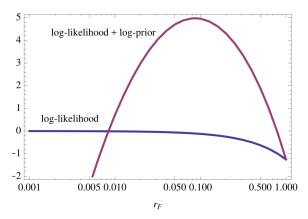


Figure: Comparisonoflog-likelihood(i.e., logP(r-votes)) and log-likelihood plus log(Pprior(r)) for estimating  $r_F$  for a story with no fan votes.





#### Conclusion

Their solution can partially address this prediction challenge by quantitatively characterizing evolution of popularity.

## Thank you