Online Popularity under Promotion

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The problem

Cultural Markets seem to be unpredictable. [Salganik et al. Science’06]

1. How well do promotions work?
   [D. Watts ‘11] [Zarezade et al. WSDM ‘17]
   [Zhang et al. WSDM ‘14]

2. When should one promote?
   [Chierichetti et al. SIAM Jour. Comp. ‘14]
   [Bollapragada et al. OR ‘04]

3. How to predict popularity?
   [Rizoiu et al. WWW’17][Kobayashi et al. ICWSM’16]
Presentation outline

Modeling popularity with HIP

Content virality and maturity time

Forecasting popularity under promotion

Promotions schedules and memory lengthening through promotion
HIP: Linking promotion and popularity

\[ \xi(t) = \mu s(t) + C \int_0^t \xi(t - \tau) (\tau + c)^{-(1+\theta)} d\tau \]

shares &

tweets

system memory vs

content virality

network effects

daily views
HIP as a Linear Time-Invariant system

promotion

\[ \delta(t) \]

response

\[ \hat{\xi}(t) \]
HIP as a Linear Time-Invariant system

promotion

\[ \delta(t) \]

\[ \alpha \delta(t-t_0) \]

response

\[ \hat{\xi}(t) \]

\[ \alpha \hat{\xi}(t-t_0) \]
HIP as a Linear Time-Invariant system

**promotion**

\[ \delta(t) \]

\[ \alpha \delta(t-t_0) \]

**response**

\[ \hat{\xi}(t) \]

\[ \alpha \hat{\xi}(t-t_0) \]

Corollary:

same budget

same return
Viral potential and maturity time

Viral potential score:

\[ \nu = \int_0^\infty \hat{\xi}(t) \, dt \]
**Viral potential and maturity time**

Viral potential score: \( \nu = \int_0^\infty \hat{\xi}(t) \, dt \)

Maturity time: \( t^* = \min \left\{ t \geq 0 \left| \int_0^t \hat{\xi}(t) \, dt \geq 0.95\nu \right. \right\} \)
Virality map
Virality map

Viral potential score

Amount of promotion

Acquired views

Equal number of views are generated
Presentation outline

- Modeling popularity with HIP
- Content virality and maturity time
- A progression of two problems relating to predicting popularity under promotion
- Promotions schedules and memory lengthening through promotion
Forecasting future views (1)
Forecasting future views (1)

- **Fitted #views**
- **Observed #views**
- **External influence (#shares)**
- **Unfolding of old promotions**

Legend:
- **ν, t**
- **Observed promotion**
- **Unfolding of old promotions**

Graph details:
- X-axis: Dates from 2014-05-12 to 2014-09-01
- Y-axis: #views ranging from 0 to 80,000
- Observed promotion peak around 2014-07-07
- Fitted #views showing a gradual increase post promotion
- External influence peaks around 2014-08-04
Forecasting future views (1)
Forecasting future views (2)

History:
- Viral potential: ✓
- Promo. volume: ✓
- Promo. timing: ✓

[Pinto et al WSDM’13]
Forecasting future views (2)

History: ✓ ✓ ✓ ✓ ✓
Viral potential: ✓ ✓ ✓ ✓ ✓
Promo. volume: ✓ ✓ ✓ ✓ ✓
Promo. timing: ✓ ✓ ✓ ✓ ✓

[Rizoiu et al WWW’17]
[MLR1]
[MLR2] [Pinto et al WSDM’13]
Popularity scales over time

Popularity scales for a collection of videos
Popularity scales over time

Popularity scales for a collection of videos

Popularity percentile

#views

10^7

10^6

10^5

10^4

10^3

0%
5%
10%
15%
20%
25%
30%
35%
40%
45%
50%
55%
60%
65%
70%
75%
80%
85%
90%
95%
100%
Popularity scales over time

Popularity scales for a collection of videos

Individual video pop. % at 90 days vs. 120 days

Popularity percentile

#views

10^7
10^6
10^5
10^4
10^3

0% 5% 10% 15% 20% 25% 30% 35% 40% 45% 50% 55% 60% 65% 70% 75% 80% 85% 90% 95% 100%

Popularity perc. at 120 days

100%
95%
90%
85%
80%
75%
70%
65%
60%
55%
50%
45%
40%
35%
30%
25%
20%
15%
10%
5%

Popularity perc. at 90 days

5% 10% 15% 20% 25% 30% 35% 40% 45% 50% 55% 60% 65% 70% 75% 80% 85% 90% 95% 100%

Pop. % jump > 20%
ROC curves for videos that jump

Random guess

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Future</th>
<th>Viral potential</th>
<th>Promo. volume</th>
<th>Pop. scale position</th>
</tr>
</thead>
<tbody>
<tr>
<td>R₁</td>
<td>✓</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>O₁</td>
<td>✓</td>
<td>✓</td>
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ROC curves for videos that jump

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<tbody>
<tr>
<td>$R_1$</td>
<td>✔️</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$O_1$</td>
<td>✔️</td>
<td>✔️</td>
<td>✔️</td>
<td></td>
</tr>
<tr>
<td>$R_2$</td>
<td>✔️</td>
<td>✔️</td>
<td>✔️</td>
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</tr>
<tr>
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<td></td>
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<tr>
<td>O_1</td>
<td>✔</td>
<td>✔</td>
<td>✔</td>
<td></td>
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<tr>
<td>R_2</td>
<td>✔</td>
<td>✔</td>
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<tr>
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<td>✔</td>
<td>✔</td>
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<tr>
<td>O_3</td>
<td>✔</td>
<td>✔</td>
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Presentation outline

Modeling popularity with HIP

Content virality and maturity time

Forecasting popularity under promotion

When does promotion timing matter? Why do people prefer constant promotion?
Designing promotion schedules

LTI corollary: same budget, same return!
Designing promotion schedules

LTI corollary: same budget, same return!

Compounding interest: \(cost = (1+a)^k\)
Interplay of 2 temporal factors

$v_1: t^* = 1360$

$v_2: t^* = 113$

$v_3: t^* = 7$
Interplay of 2 temporal factors

\[ v_1: t^* = 1360 \]

\[ v_2: t^* = 113 \]

\[ v_3: t^* = 7 \]
Interplay of 2 temporal factors

\( v_1: t^* = 1360 \)

\( v_2: t^* = 113 \)

\( v_3: t^* = 7 \)
Why is constant promotion desirable?

LTI corollary: *the effects of daily promotion add up over time!*

Explains why TV commercials appear at fixed intervals, every day.
Memory lengthening through promotion

Constant promotion leads to an apparent memory lengthening.
Summary

Two measures: virality score and maturity time

Important factors for forecasting popularity: virality score, promotion volume and popularity scale position

Maturity time influences the cost-effectiveness of promotion schedules
Summary

Two measures: **virality score** and **maturity time**

Important factors for forecasting popularity: **virality score**, **promotion volume** and **popularity scale position**

Maturity time influences the cost-effectiveness of promotion schedules

Limitations & future work: Average over network; Reaction to past and future promotions is the same.
Thank you!

Links:

Papers, code, dataset and interactive visualizer:

https://github.com/andrei-rizoiu/hip-popularity

Reference:

PDF at arXiv with supplementary material

HIP visualization system

This is an Interactive visualization of the plots in the paper: the endo-exo map, observed and fitted popularity series and video metadata. It has additional visualizations of TED videos and VEVO musicians. Furthermore, it allows users to add and compare their own videos.

(access the visualizer by clicking on the thumbnail below)
Supp: Twitted videos dataset

2014.06 - 2014.12
1.061B tweets, 5.89M/day
64.3M users;
81.9M YouTube videos

<table>
<thead>
<tr>
<th>Category</th>
<th>#vids</th>
<th>Category</th>
<th>#vids</th>
</tr>
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<tbody>
<tr>
<td>Comedy</td>
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<td>Music</td>
<td>3549</td>
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<td>Education</td>
<td>298</td>
<td>News &amp; Politics</td>
<td>1722</td>
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<tr>
<td>Entertainment</td>
<td>2422</td>
<td>Nonprofits &amp; Activism</td>
<td>333</td>
</tr>
<tr>
<td>Film &amp; Animation</td>
<td>664</td>
<td>People &amp; Blogs</td>
<td>1947</td>
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<tr>
<td>Gaming</td>
<td>882</td>
<td>Science &amp; Technology</td>
<td>262</td>
</tr>
<tr>
<td>Howto &amp; Style</td>
<td>180</td>
<td>Sports</td>
<td>614</td>
</tr>
<tr>
<td><strong>Total:</strong></td>
<td><strong>13,738</strong></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Supp: when HIP fails the fitting (1)

Relations between videos:

New video released
Supp: when HIP fails the fitting (2)

Long term evolutions:

- Slow drift
**Supp: Hawkes Process** [Hawkes ‘71]

\[
\lambda(t) = \mu(t) + \sum_{t_i < t} \phi_{m_i}(t - t_i)
\]

Most state-of-the-art popularity prediction systems require observing individual events.

[Zhao et al KDD‘15] [Shen et al AAAI‘14]
[Farajtabar et al NIPS‘15] [Mishra et al CIKM‘16]
Supp: Hawkes Process [Hawkes ‘71]

\[ \lambda(t) = \mu(t) + \sum_{t_i < t} \phi_{m_i}(t - t_i) \]

- the rate of ‘daughter’ events
- content virality
- user influence
- memory

\[ \phi_m(\tau) = \kappa m^\beta \hat{\tau}^{-(1+\theta)} \]

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Supp: Hawkes Intensity Process (HIP)

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- the rate of 'daughter' events
- content virality
- user influence
- memory
- expected number of events

\[ \phi_m(\tau) = \kappa m^\beta \hat{\tau}^{-(1+\theta)} \]

\[ \xi(t) = \mu s(t) + C \int_0^t \xi(t - \tau) \hat{\tau}^{-(1+\theta)} d\tau \]

- popularity
- exogenous stimuli
Supp: Hawkes Intensity Process (HIP)

\[ \lambda(t) = \mu(t) + \sum_{t_i < t} \phi_{m_i}(t - t_i) \]

- the rate of ‘daughter’ events
- content virality
- user influence
- memory

\[ \phi_m(\tau) = \kappa m^\beta \hat{T}^{-0(1+\theta)} \]

- expected number of events

\[ \xi(t) = \mu_s(t) + C \int_0^t \xi(t - \tau) \hat{T}^{-0(1+\theta)} d\tau \]

- popularity
- exogenous sensitivity
- endogenous reaction

- exogenous stimuli
Supp: Estimating the HIP model

\[ \xi(t) = \mu s(t) + C \int_0^t \xi(t - \tau) \hat{\tau}^{-(1+\theta)} d\tau \]

find \( \{\mu, C, \theta, \ldots\} \)

s.t. \( \min \sum_t l(\xi(t) - \bar{\xi}(t)) \)
Supp: Estimating the HIP model

\[ \xi(t) = \mu s(t) + C \int_0^t \xi(t - \tau) \hat{\tau}^{-(1+\theta)} d\tau \]

- Model: \( \xi(t) \)
- Popularity history: \( \bar{\xi}(t) \)
- Exogenous stimuli: \( s(t) \)
- Exogenous sensitivity
- Endogenous reaction
Supp: Un-promotable videos
Supp: “Potentially viral” video
Forecasting the effect of promotions

Observed and predicted popularity with confidence interval

Average error in popularity percentile

Observed #views
Fitted #views on training set
Predicted viewcounts
Exogenous stimuli (#shares)

[Pinto et al WSDM'13]
[Szabo & Huberman Comm. ACM'13] [Yu et al ICWSM'15]
HIP as a Linear Time-Invariant system

promotion \[ \delta(t) \]  
response \[ \hat{\xi}(t) \]
HIP as a Linear Time-Invariant system

**promotion**

\[ \delta(t) \]

\[ \alpha \delta(t - t_0) \]

**response**

\[ \hat{\xi}(t) \]

\[ \alpha \hat{\xi}(t - t_0) \]
HIP as a Linear Time-Invariant system

promotion

\[ \delta(t) \]

response

\[ \hat{\xi}(t) \]

scale, shift, add

\[ \alpha \delta(t - t_0) \]

\[ \alpha \hat{\xi}(t - t_0) \]

Observed #views

Fitted time−varying popularity

Unknown external influence

Daily endogenous reactions

Exogenous impulses (#shares)

video '0bR4L0Y94AQ'

Viewcounts

External influence (#shares)
Popularity scales over time

Popularity scales for a collection of videos

#views

Popularity percentile
Popularity scales over time

Popularity scales for a collection of videos
Popularity scales over time

Popularity scales for a collection of videos

Individual video pop. %
at 90 days vs. 120 days

Popularity percentile vs. #views at 90 days vs. 120 days

Pop. % jump > 20%
Popularity scales over time

Popularity scales for a collection of videos

Impact of 40k views:
- start at 17.5% → +15%
- start at 50% → +2.5%
- start at 90% → -2.5%

Individual video pop. %
at 90 days vs. 120 days