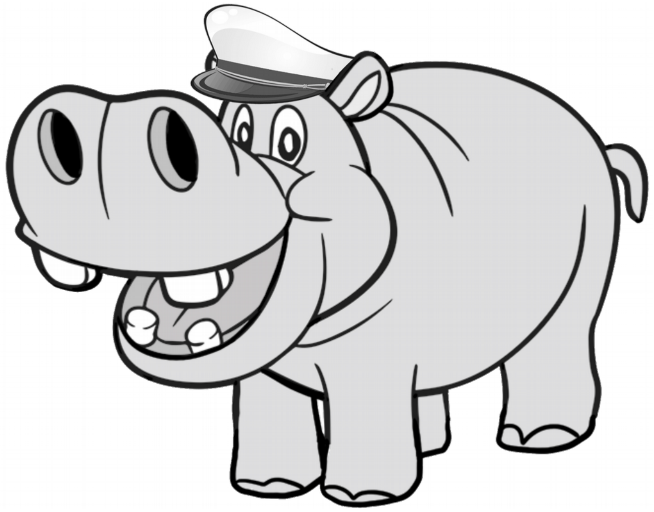
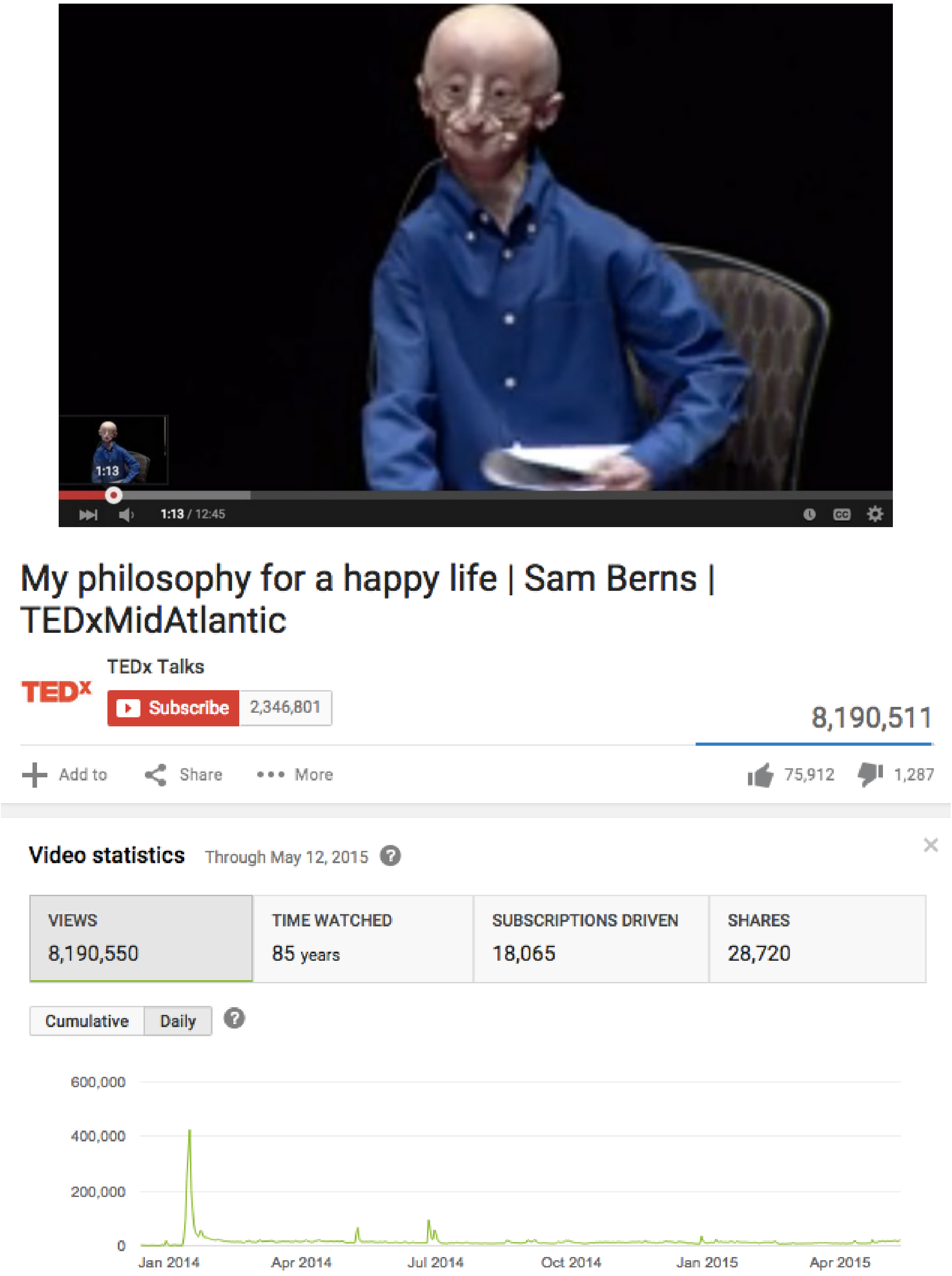


# Expecting to be HIP:
# Hawkes Intensity Processes for modeling online popularity and virality

Marian-Andrei Rizoiu

**ComputationalMedia @ANU:** http://cm.cecs.anu.edu.au

# Popularity over time



My philosophy for a happy life | Sam Berns | TEDxMidAtlantic

TEDx Talks

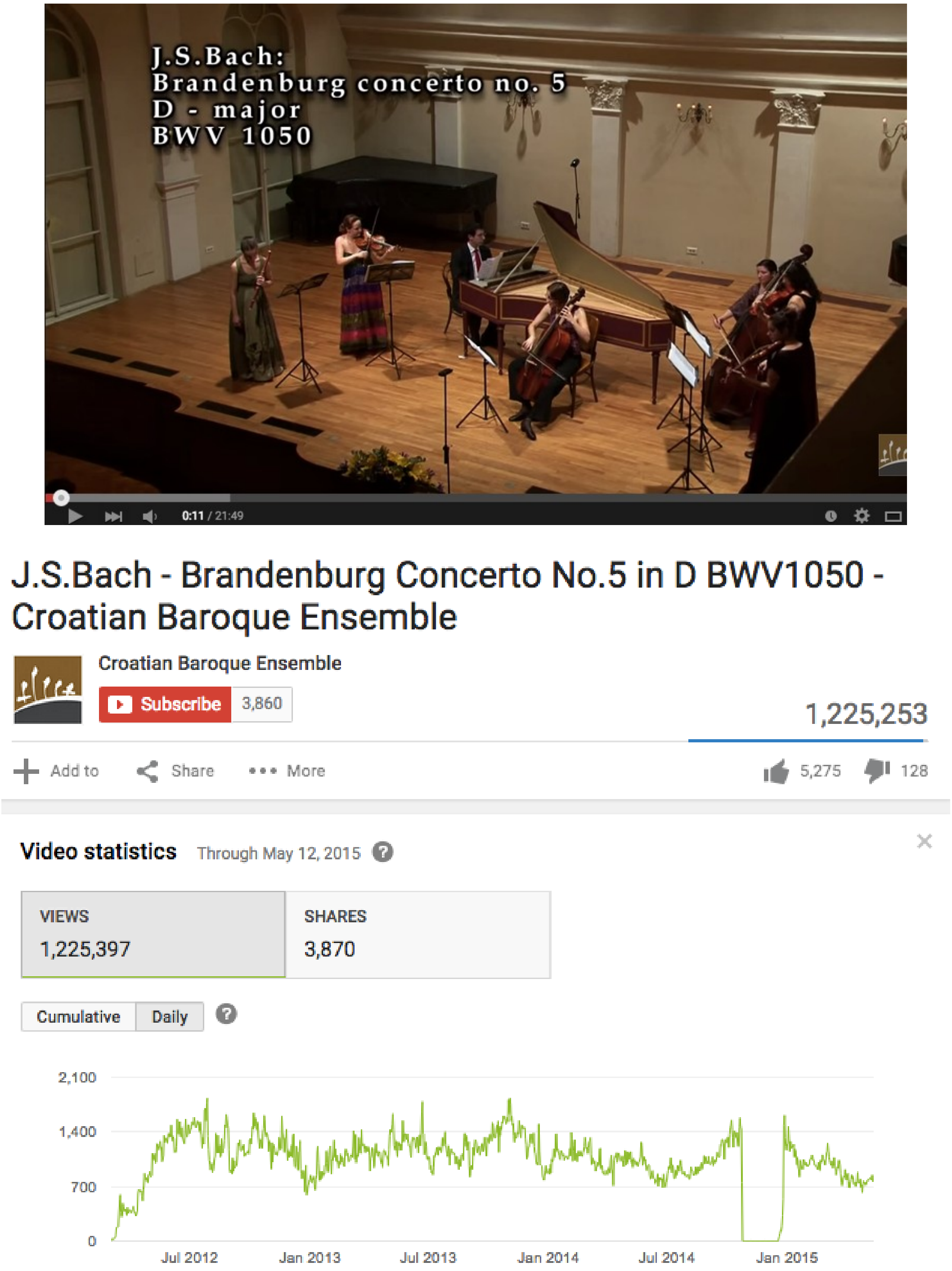
2,346,801

8,190,511

75,912 1,287

Video statistics Through May 12, 2015

| VIEWS | TIME WATCHED | SUBSCRIPTIONS DRIVEN | SHARES |
|---|---|---|---|
| 8,190,550 | 85 years | 18,065 | 28,720 |



J.S.Bach - Brandenburg Concerto No.5 in D BWV1050 - Croatian Baroque Ensemble

Croatian Baroque Ensemble

3,860

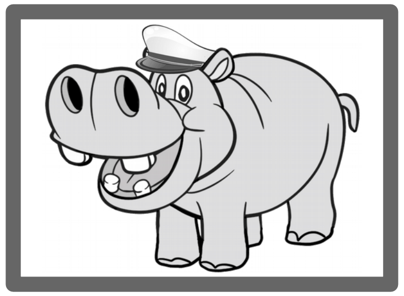
1,225,253

5,275 128

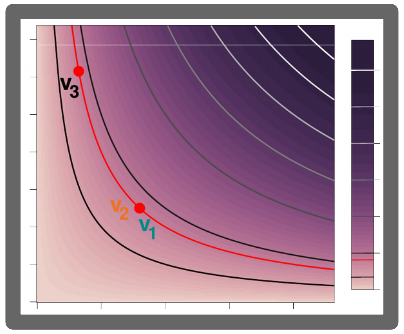
Video statistics Through May 12, 2015

| VIEWS | SHARES |
|---|---|
| 1,225,397 | 3,870 |

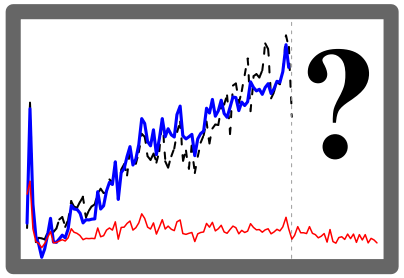
# Presentation outline



Modeling popularity with HIP



Content virality and maturity time



Forecasting popularity under promotion

Promotions schedules and memory lengthening through promotion

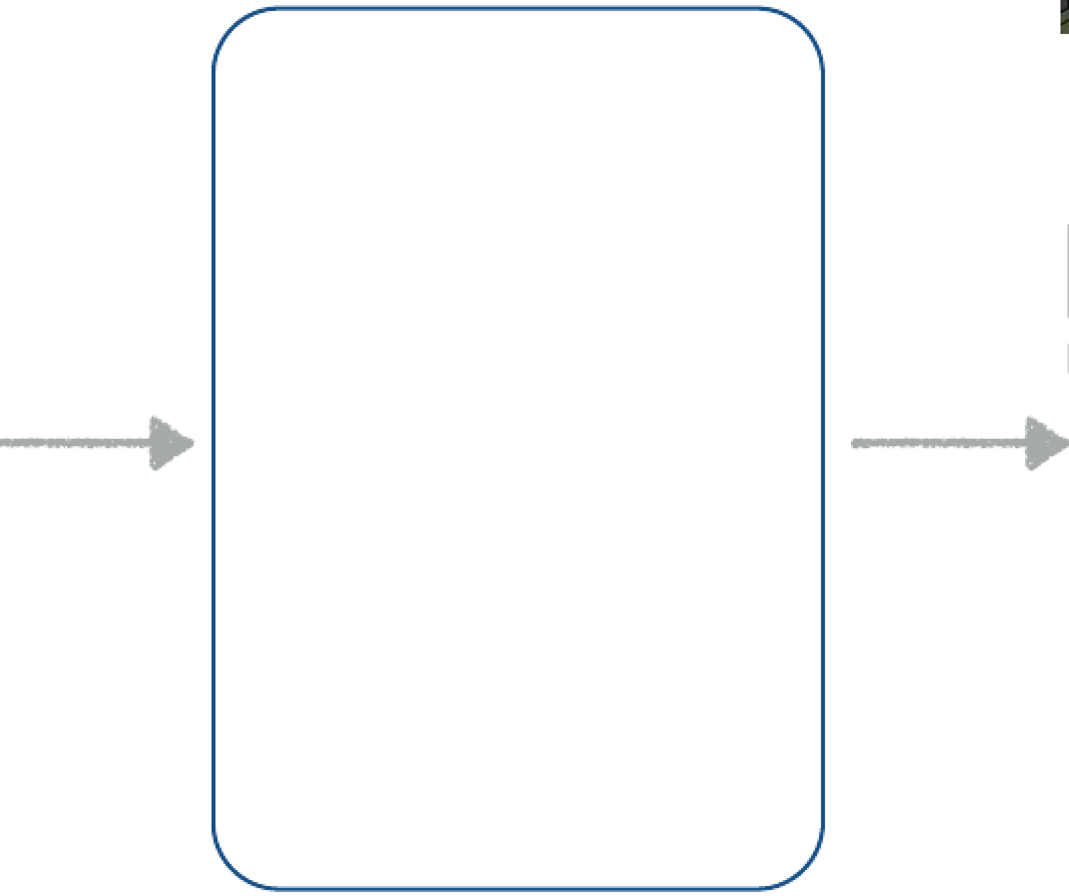
# Linking exo-endo popularity

AFIŞĂRI 2.278.811.434

PE BAZĂ DE ABONAMENTE 1.223.802

NUMĂR DE DISTRIBUIRI 2.432.395

exogenous
stimuli

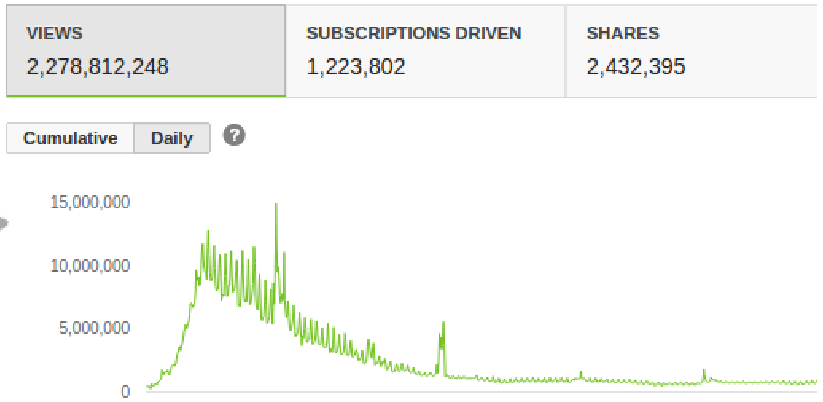


endogenous
response

PSY - GANGNAM STYLE (강남스타일) M/V

officialpsy

2,321,368,075



VIEWS 2,278,812,248

SUBSCRIPTIONS DRIVEN 1,223,802

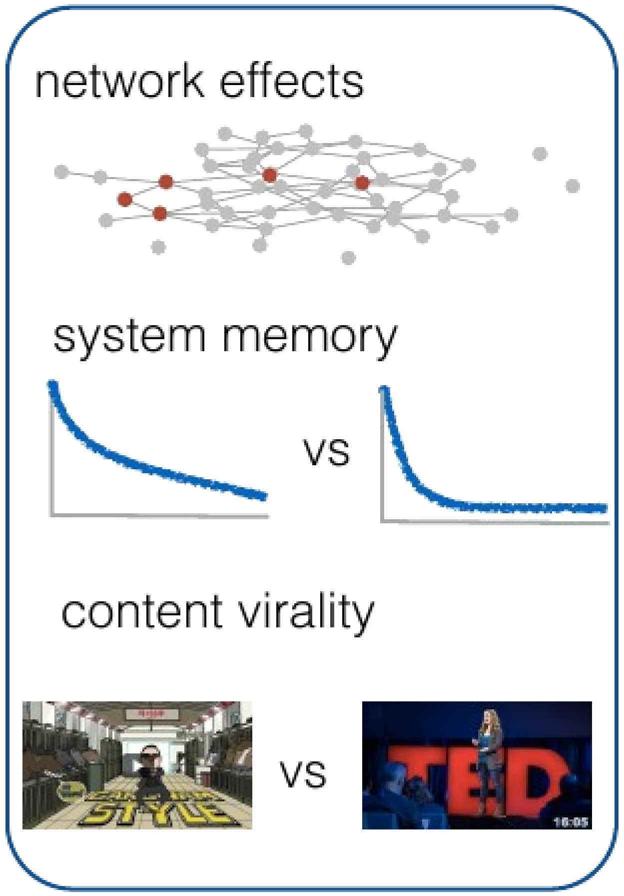
SHARES 2,432,395

observed
popularity

# Linking exo-endo popularity

| AFIŞĂRI | PE BAZĂ DE ABONAMENTE | NUMĂR DE DISTRIBUIRI |
|---|---|---|
| 2.278.811.434 | 1.223.802 | 2.432.395 |

exogenous
stimuli



network effects

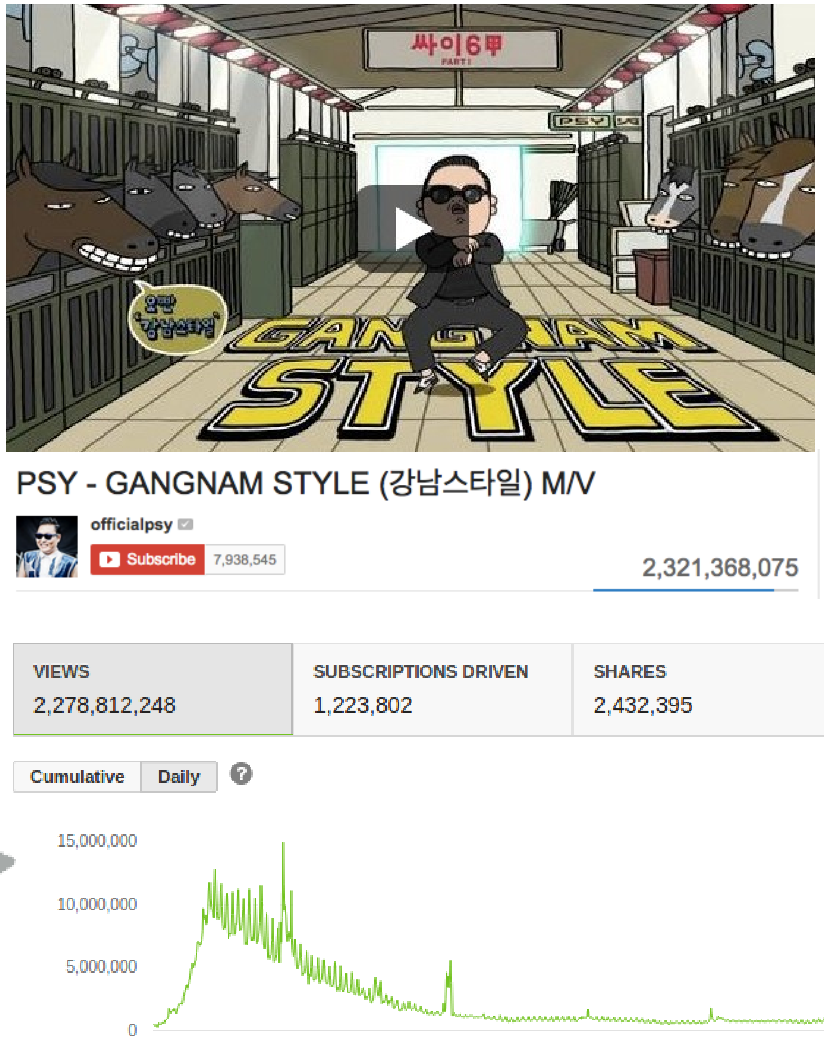
system memory

vs

content virality

vs

endogenous
response



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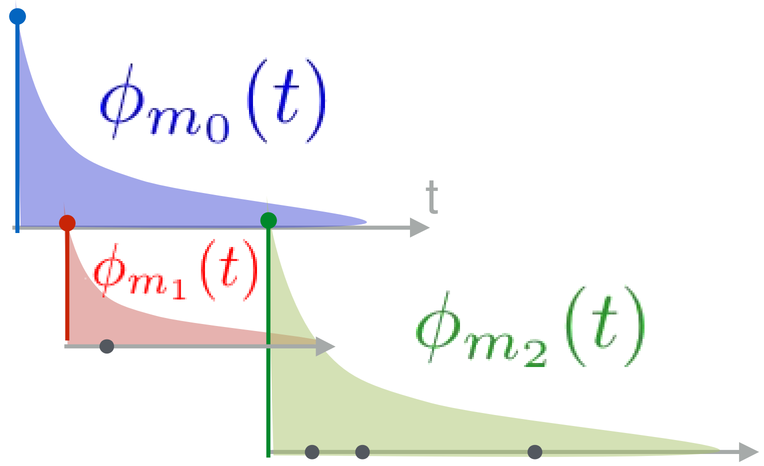
2,321,368,075

| VIEWS | SUBSCRIPTIONS DRIVEN | SHARES |
|---|---|---|
| 2,278,812,248 | 1,223,802 | 2,432,395 |

observed
popularity

# Hawkes Process [Hawkes ‘71]

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

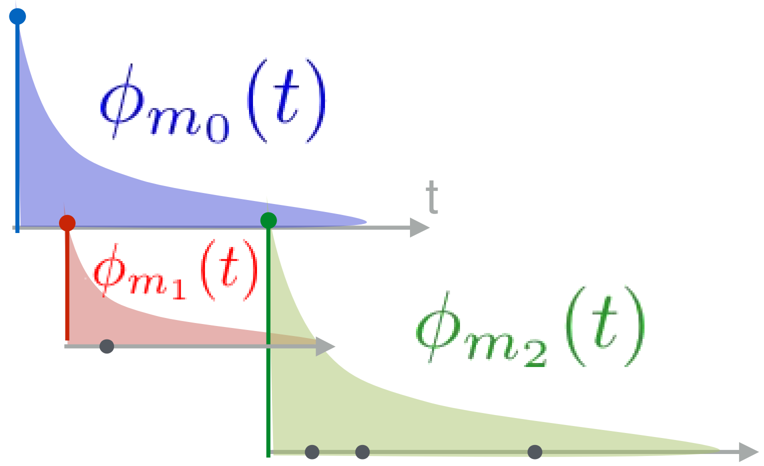


**Most state-of-the-art popularity prediction systems require observing individual events.**

[Zhao et al KDD‘15] [Shen et al AAAI‘14] [Farajtabar et al NIPS‘15] [Mishra et al CIKM‘16]

# 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

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

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

[Zhao et al KDD'15] [Shen et al AAAI'14]

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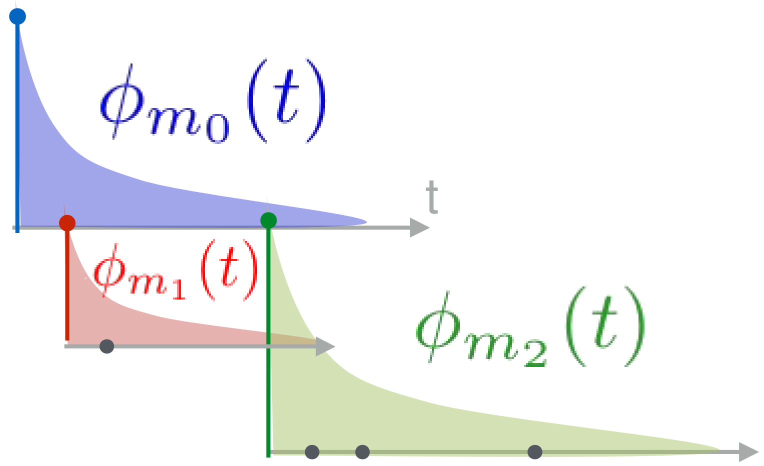
# Hawkes Intensity Process (HIP)

[Rizoiu et al, WWW‘17]

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



the rate of ‘daughter’ events

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user influence

memory

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

expected number of events

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

popularity

exogenous stimuli

# Hawkes Intensity Process (HIP)

[Rizoiu et al, WWW‘17]

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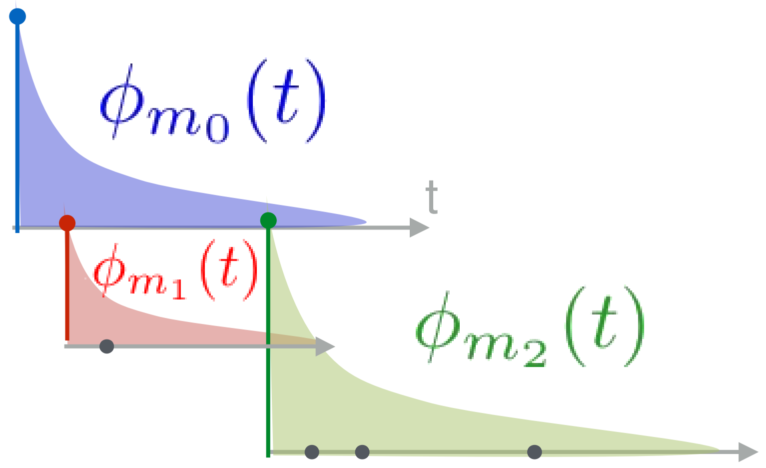

the rate of ‘daughter’ events

content virality

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

expected number of events

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

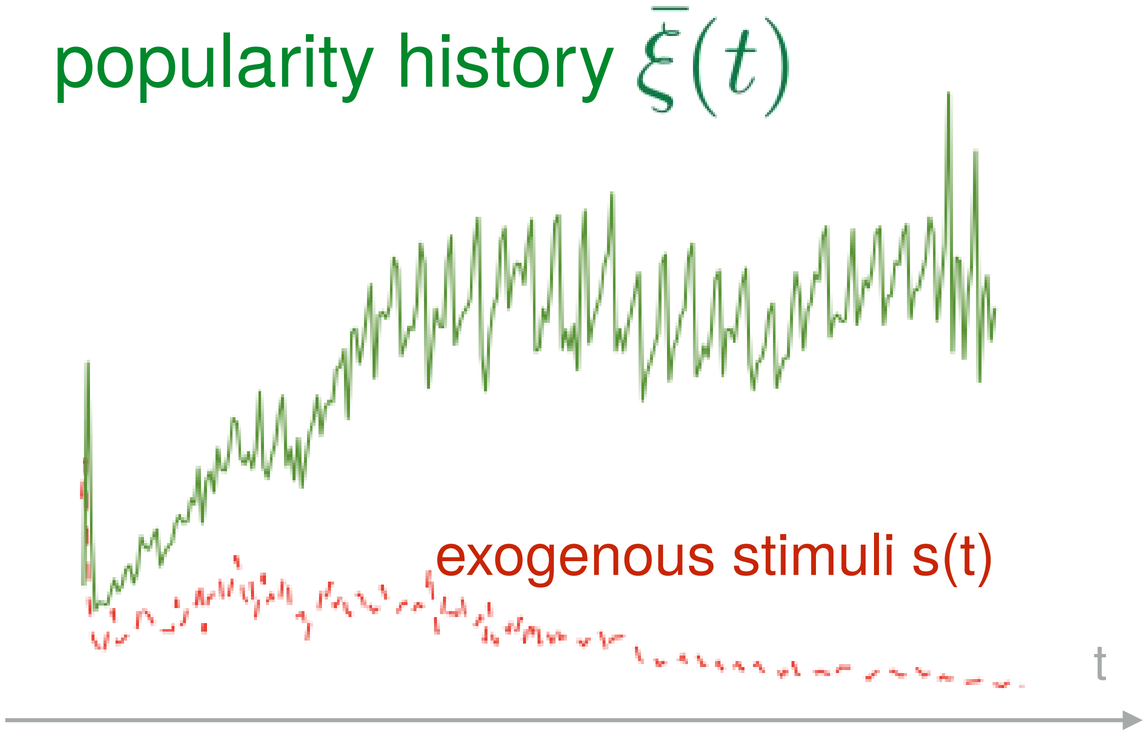
popularity

exogenous sensitivity

exogenous stimuli

endogenous reaction

# Estimating the HIP model



$$\text{find } \{\mu, C, \theta, \ldots\}$$

$$\text{s.t.} \quad \min \sum_t l(\xi(t) - \bar{\xi}(t))$$

$$\xi(t) = \mu s(t) + \underbrace{C \int_0^t \xi(t-\tau)\hat{\tau}^{-(1+\theta)} d\tau}_{\text{endogenous reaction}}$$

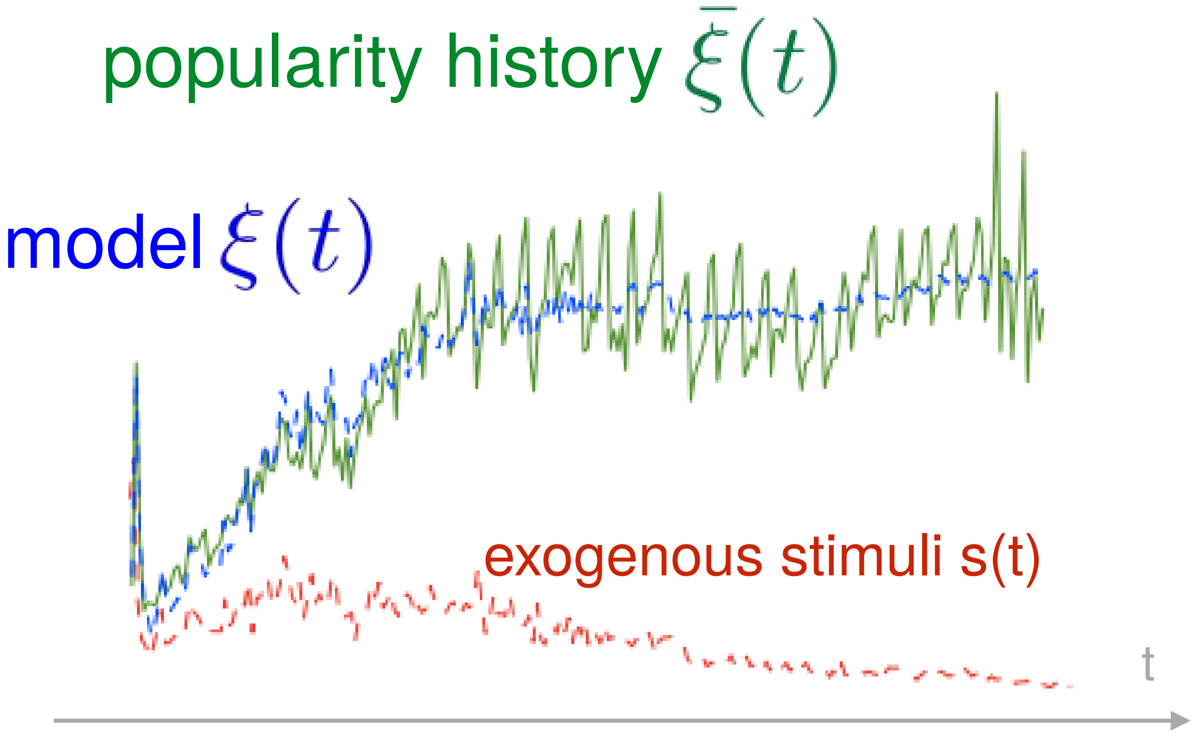
popularity

exogenous sensitivity

exogenous stimuli

endogenous reaction

# Estimating the HIP model



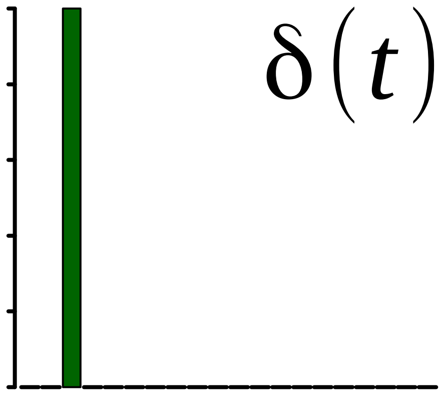
$$\text{find } \{\mu, C, \theta, \ldots\}$$

$$\text{s.t.} \quad \min \sum_t l(\xi(t) - \bar{\xi}(t))$$

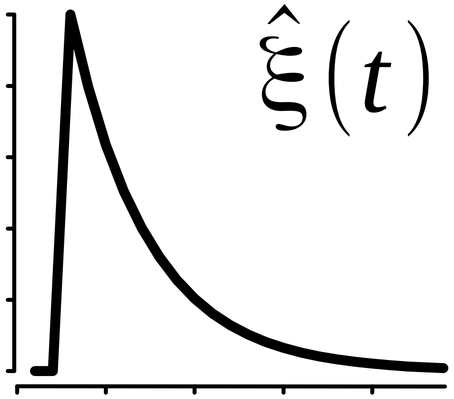
$$\underbrace{\xi(t)}_{\text{popularity}} = \underbrace{\mu}_{\text{exogenous sensitivity}} \underbrace{s(t)}_{\text{exogenous stimuli}} + \underbrace{C \int_0^t \xi(t-\tau)\hat{\tau}^{-(1+\theta)} d\tau}_{\text{endogenous reaction}}$$

# HIP as a Linear Time-Invariant system

promotion

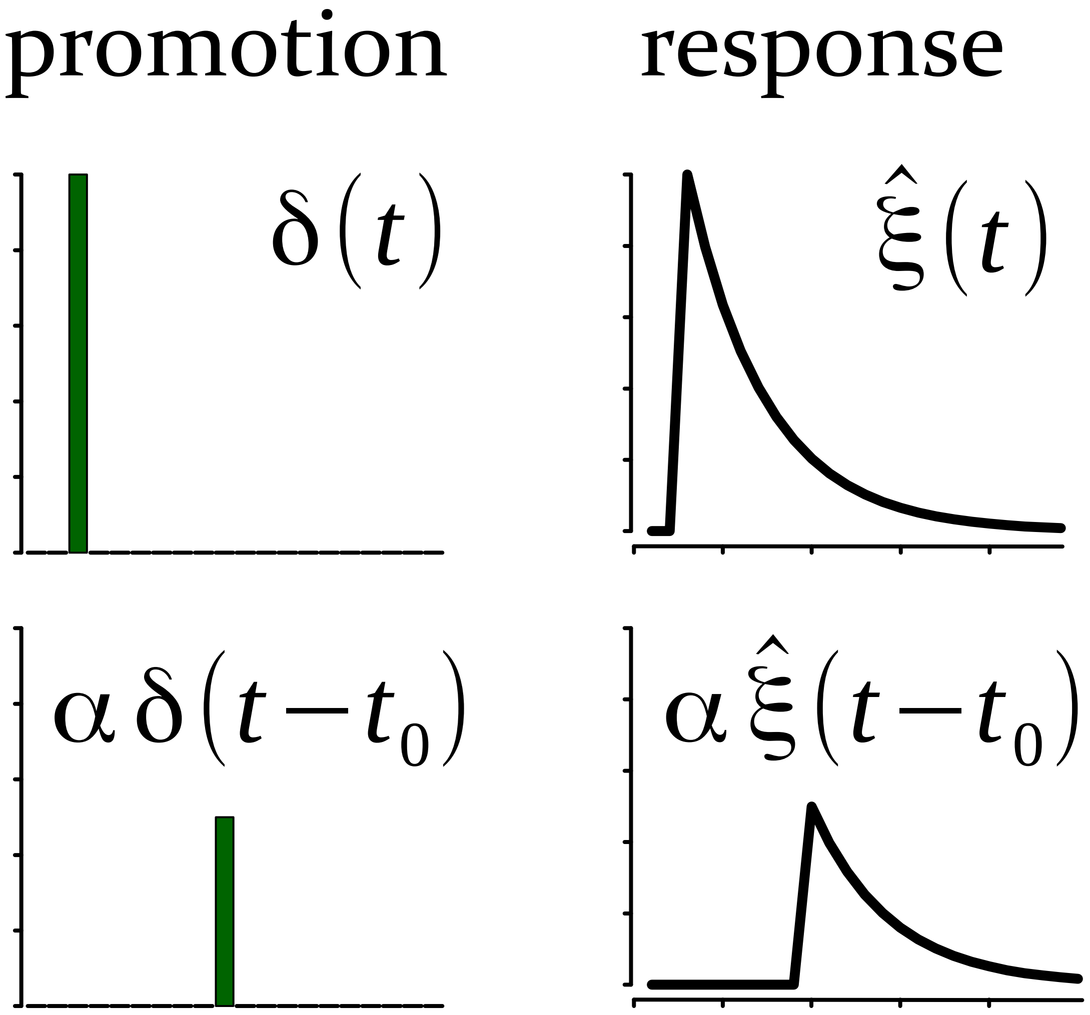


response



$$\underbrace{\xi(t)}_{\text{popularity}} = \underbrace{\mu}_{\text{exogenous sensitivity}} \underbrace{s(t)}_{\text{exogenous stimuli}} + \underbrace{C \int_0^t \xi(t-\tau)\hat{\tau}^{-(1+\theta)} d\tau}_{\text{endogenous reaction}}$$

# HIP as a Linear Time-Invariant system



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

popularity

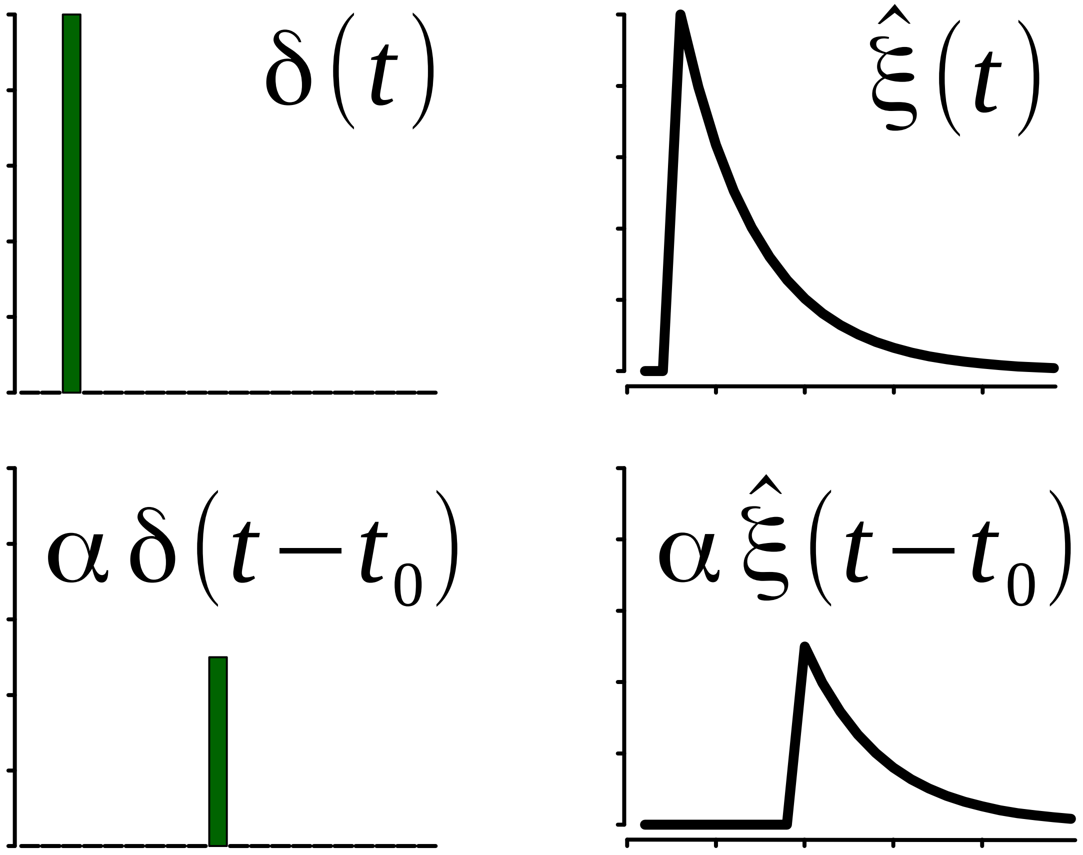
exogenous sensitivity

exogenous stimuli

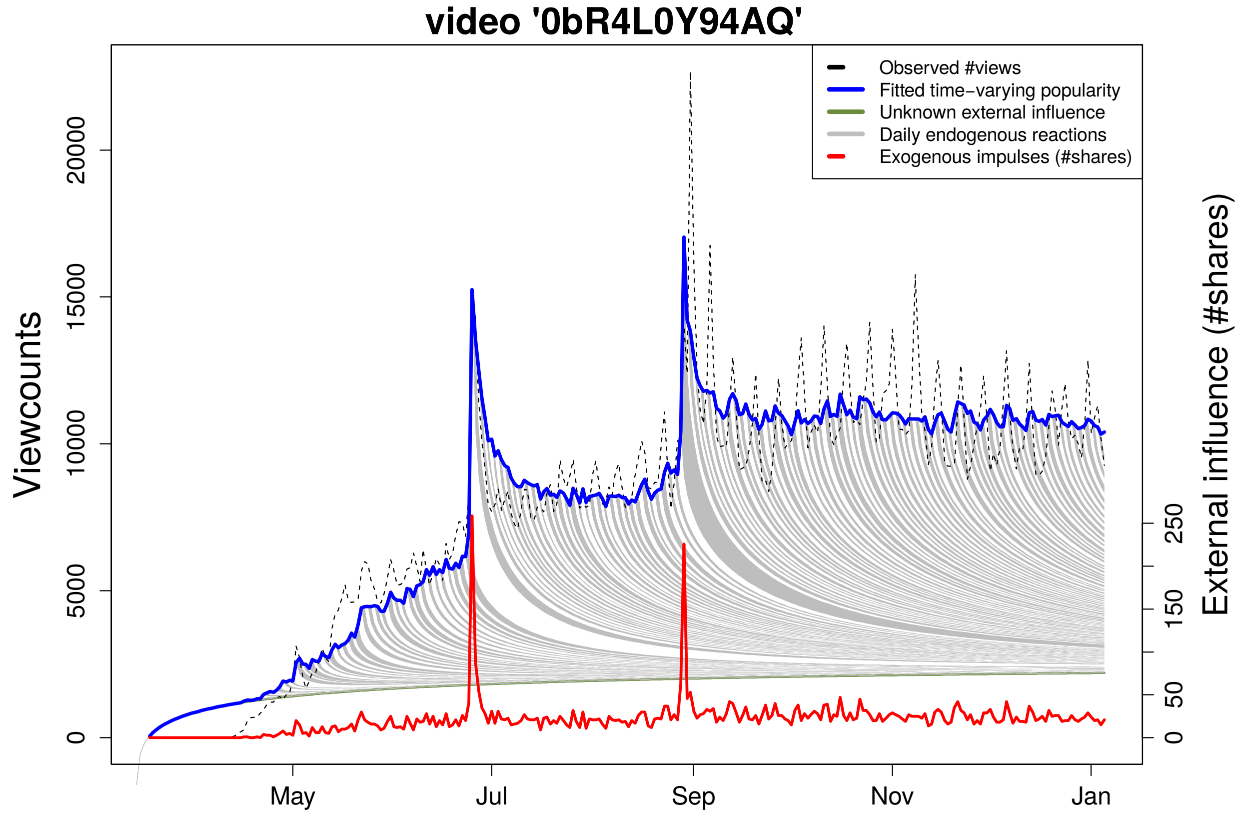
endogenous reaction

# HIP as a Linear Time-Invariant system

promotion response

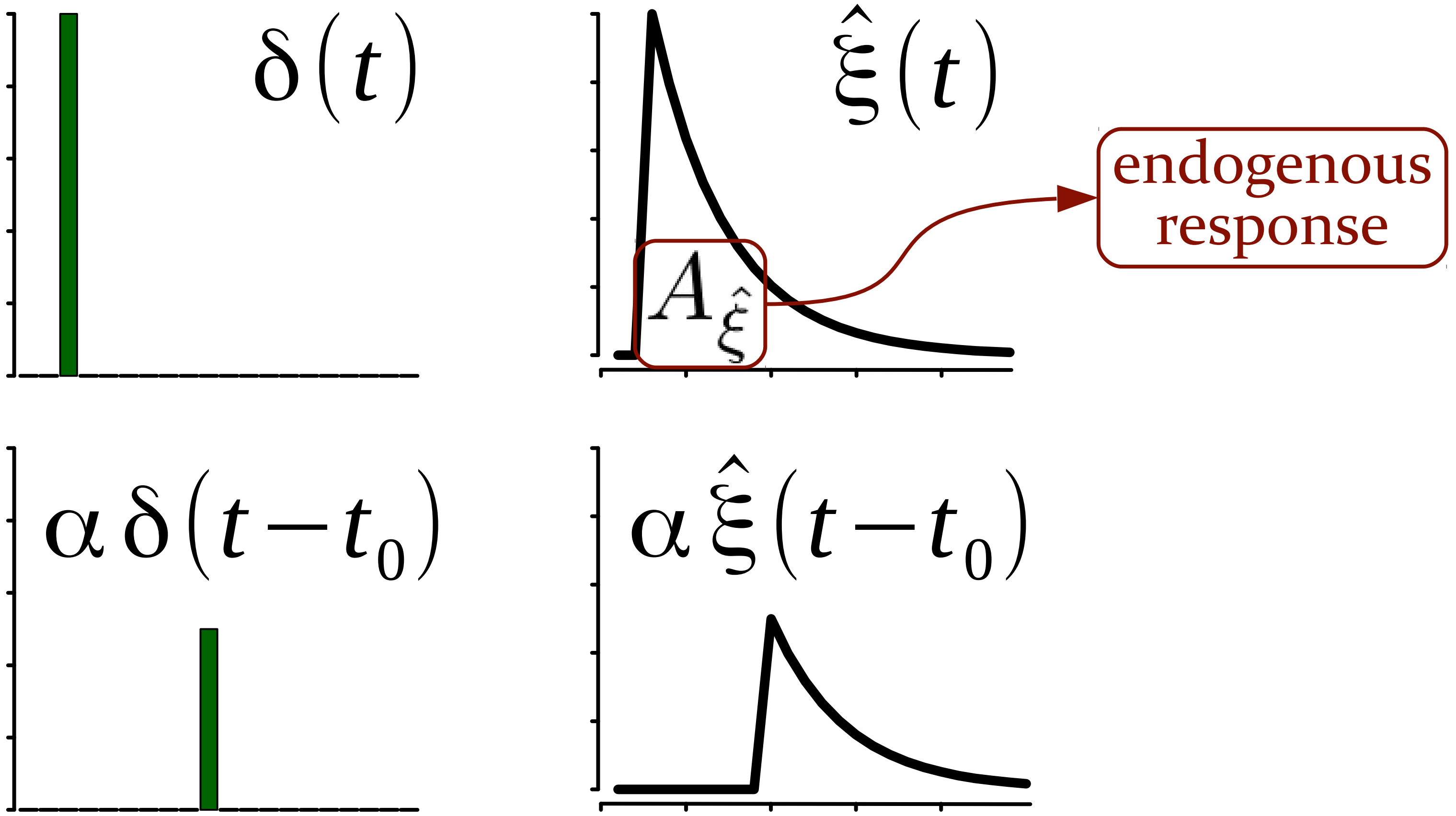


scale,
shift, add



# HIP as a Linear Time-Invariant system

promotion response



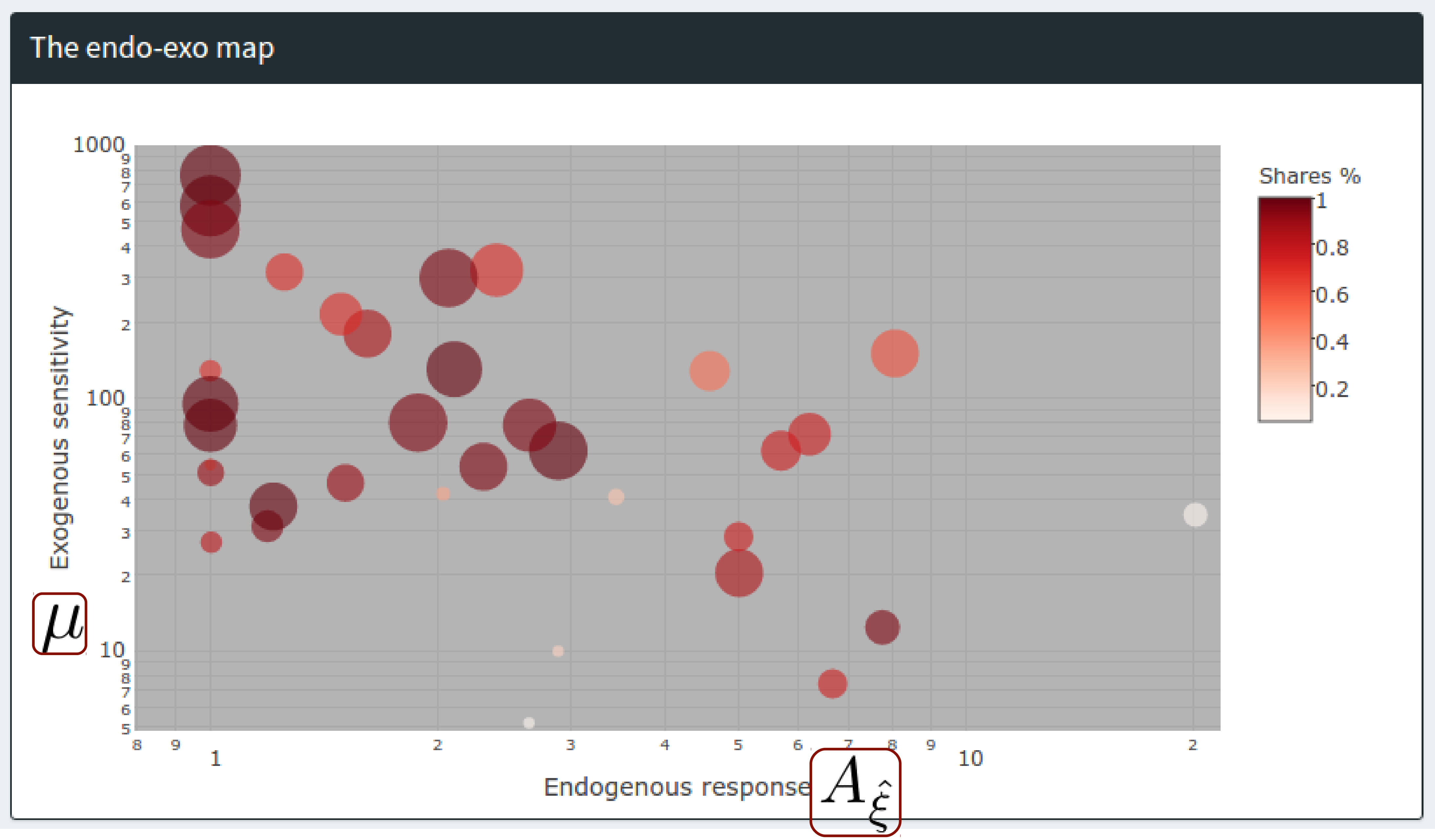
$$\xi(t) = \boxed{\mu} s(t) + C \underbrace{\int_0^t \xi(t-\tau)\hat{\tau}^{-(1+\theta)} d\tau}_{\text{endogenous reaction}}$$

popularity

exogenous sensitivity

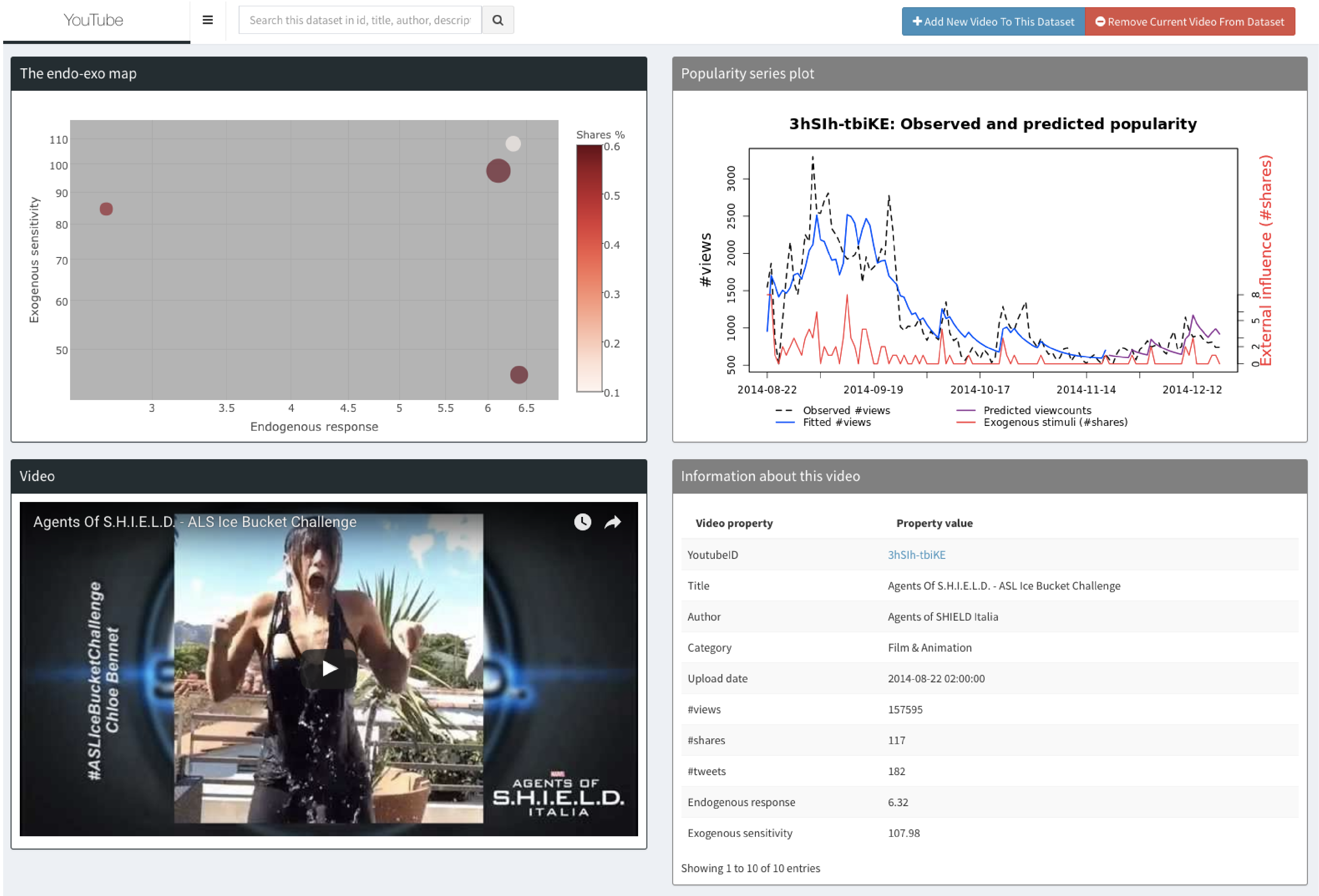
exogenous stimuli

# The “endo-exo” map



# Explain popularity dynamics

[Kong et al, WWW‘18]



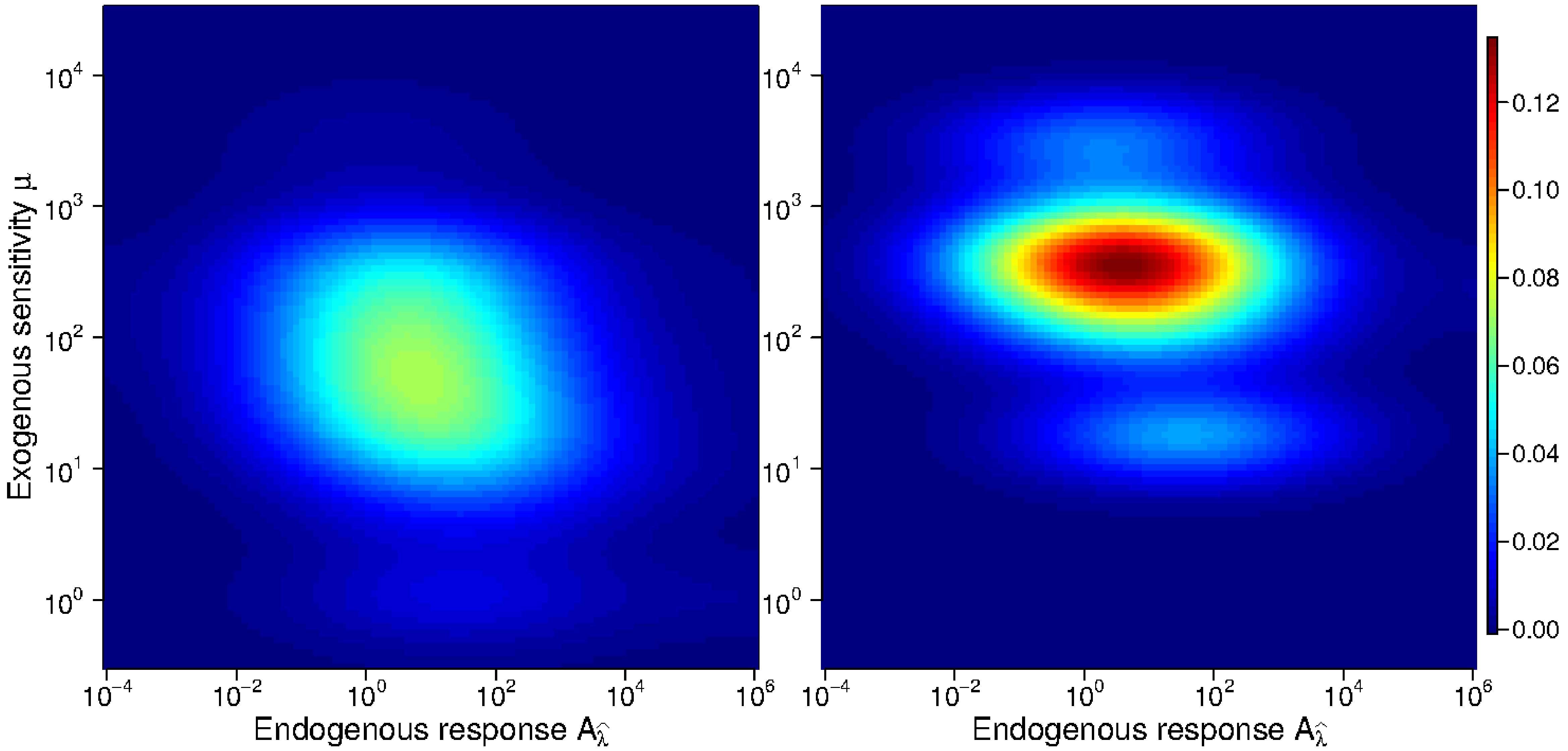
| Video property | Property value |
|---|---|
| YoutubeID | 3hSIh-tbiKE |
| Title | Agents Of S.H.I.E.L.D. - ASL Ice Bucket Challenge |
| Author | Agents of SHIELD Italia |
| Category | Film & Animation |
| Upload date | 2014-08-22 02:00:00 |
| #views | 157595 |
| #shares | 117 |
| #tweets | 182 |
| Endogenous response | 6.32 |
| Exogenous sensitivity | 107.98 |

Showing 1 to 10 of 10 entries

# Explain popularity – all vs top 5%

Film and Animation:

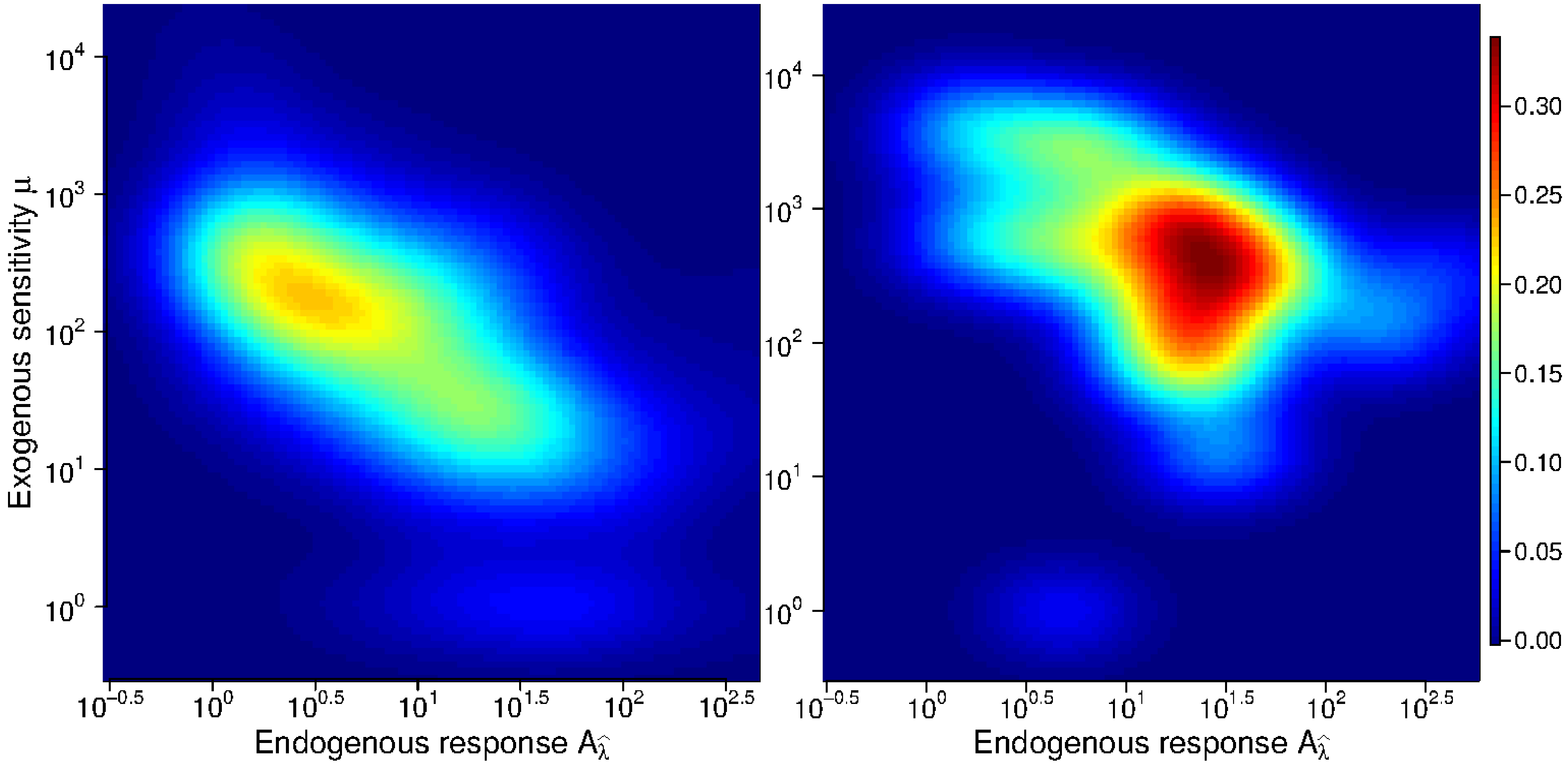
more popular videos have higher sensitivity



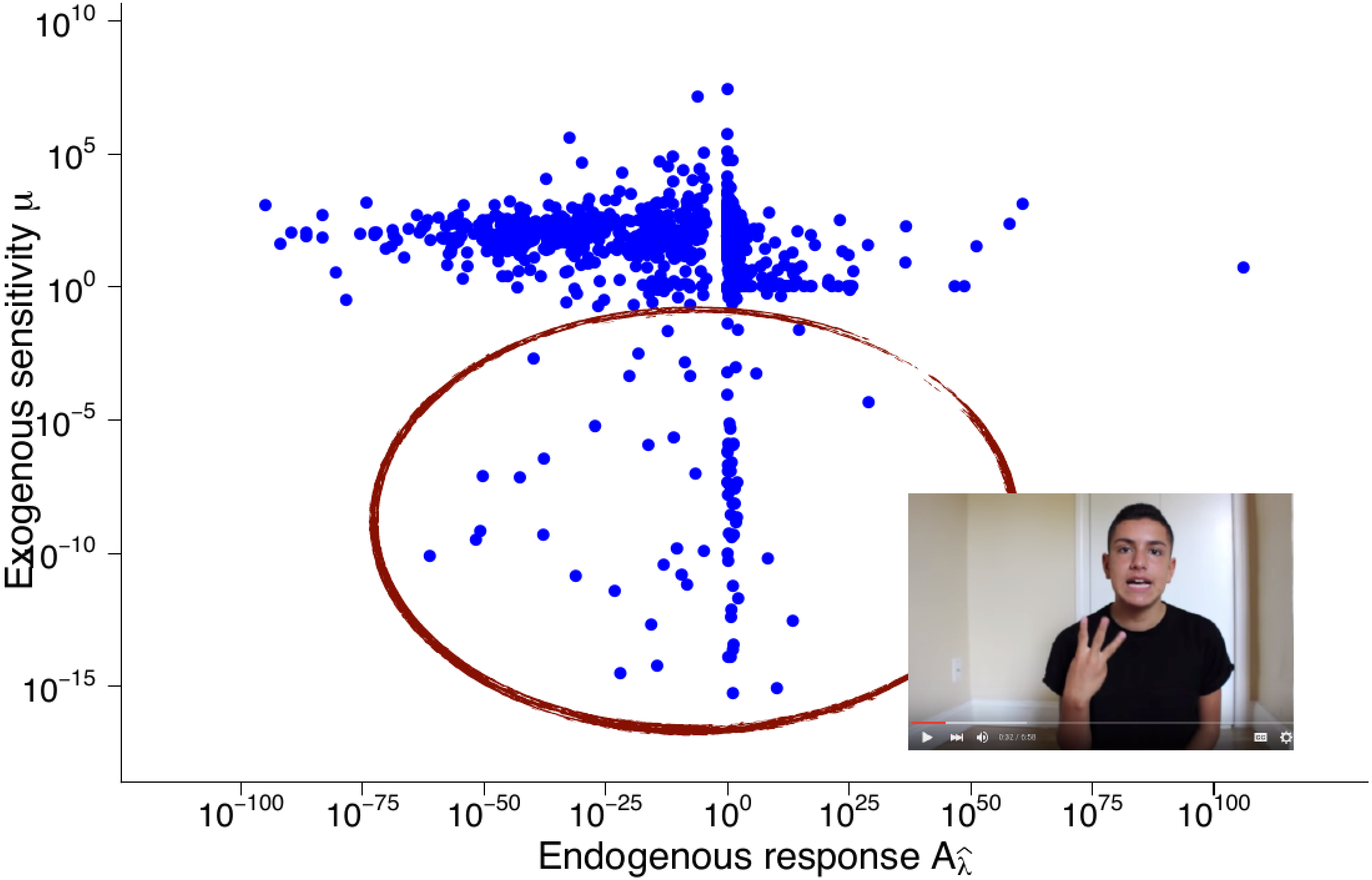
# Explain popularity – all vs top 5%

Games:

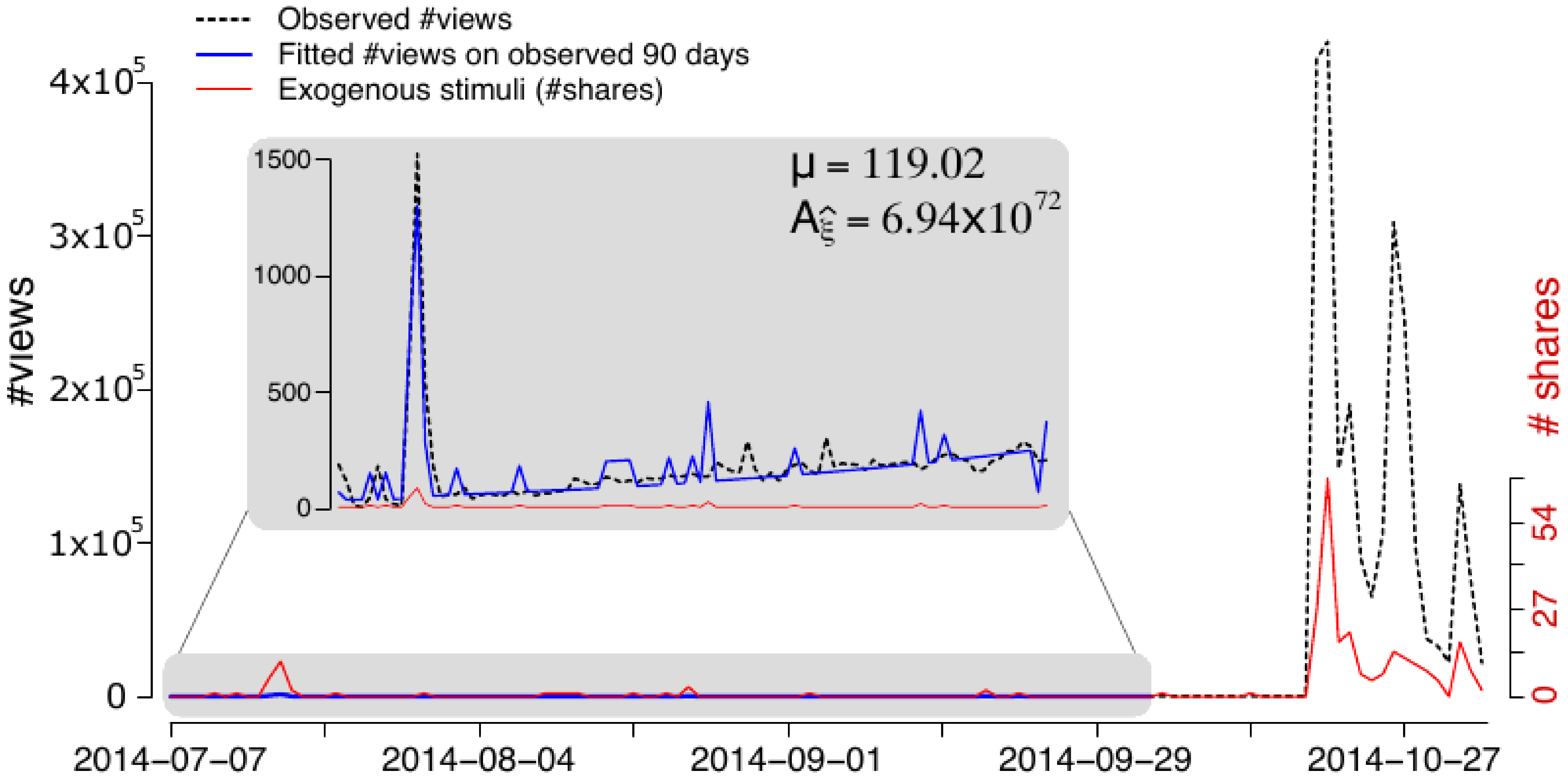
more popular videos have higher endogenous response



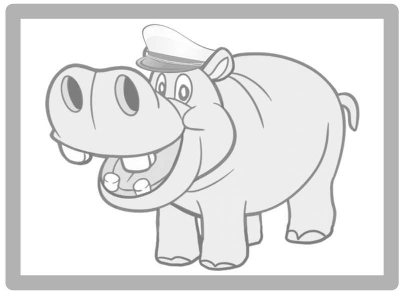
# Which videos are un-promotable?



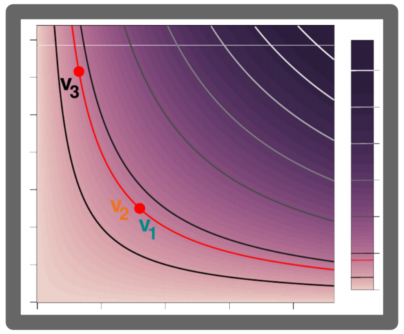
# “Potentially viral” video



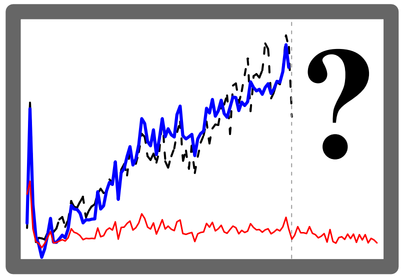
# Presentation outline



Modeling popularity with HIP



Content virality and maturity time

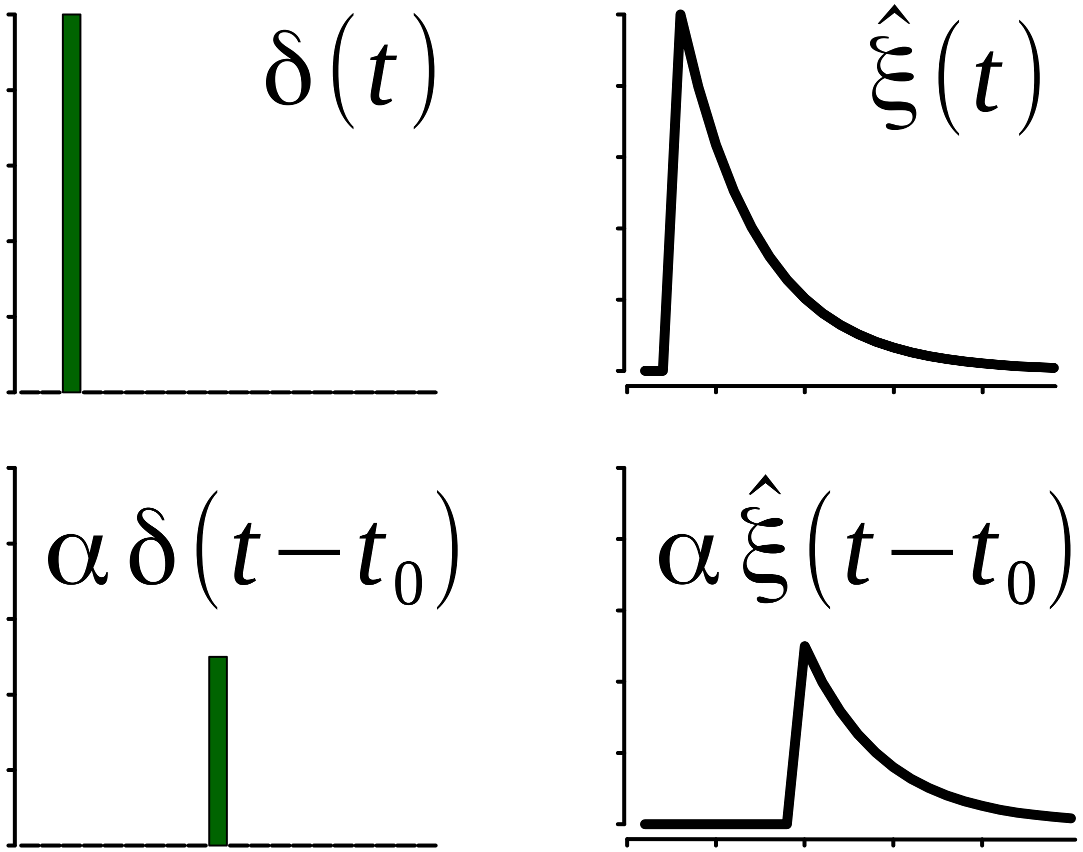


Forecasting popularity under promotion

Promotions schedules and memory lengthening through promotion

# HIP as a Linear Time-Invariant system

promotion response

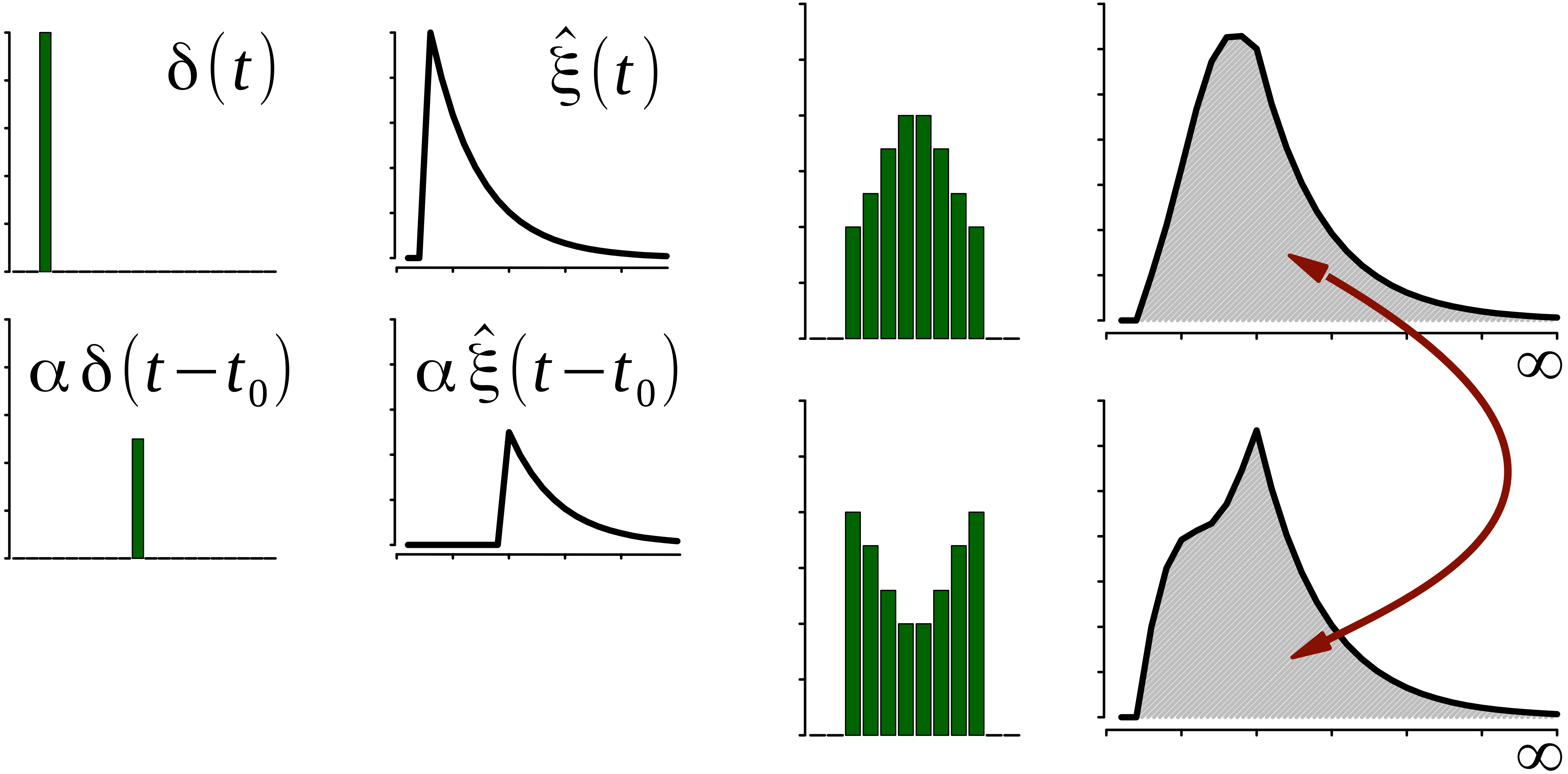


$\delta(t)$ $\hat{\xi}(t)$

$\alpha\,\delta(t-t_0)$ $\alpha\,\hat{\xi}(t-t_0)$

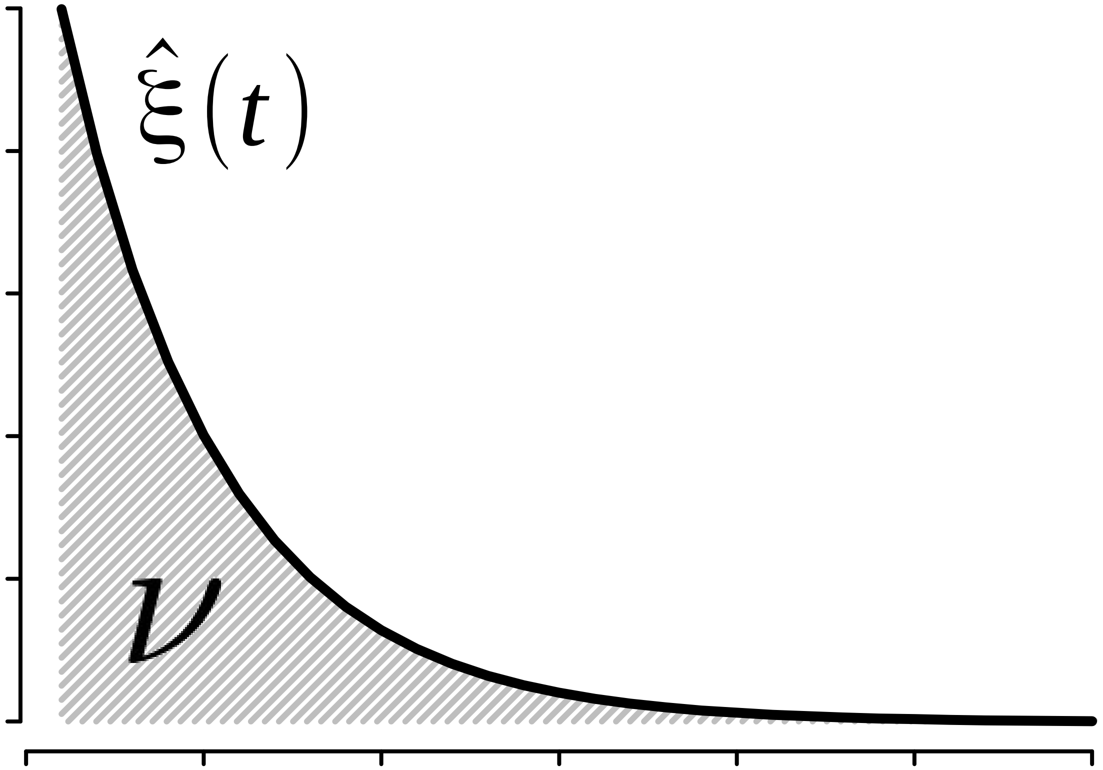
# HIP as a Linear Time-Invariant system

promotion response



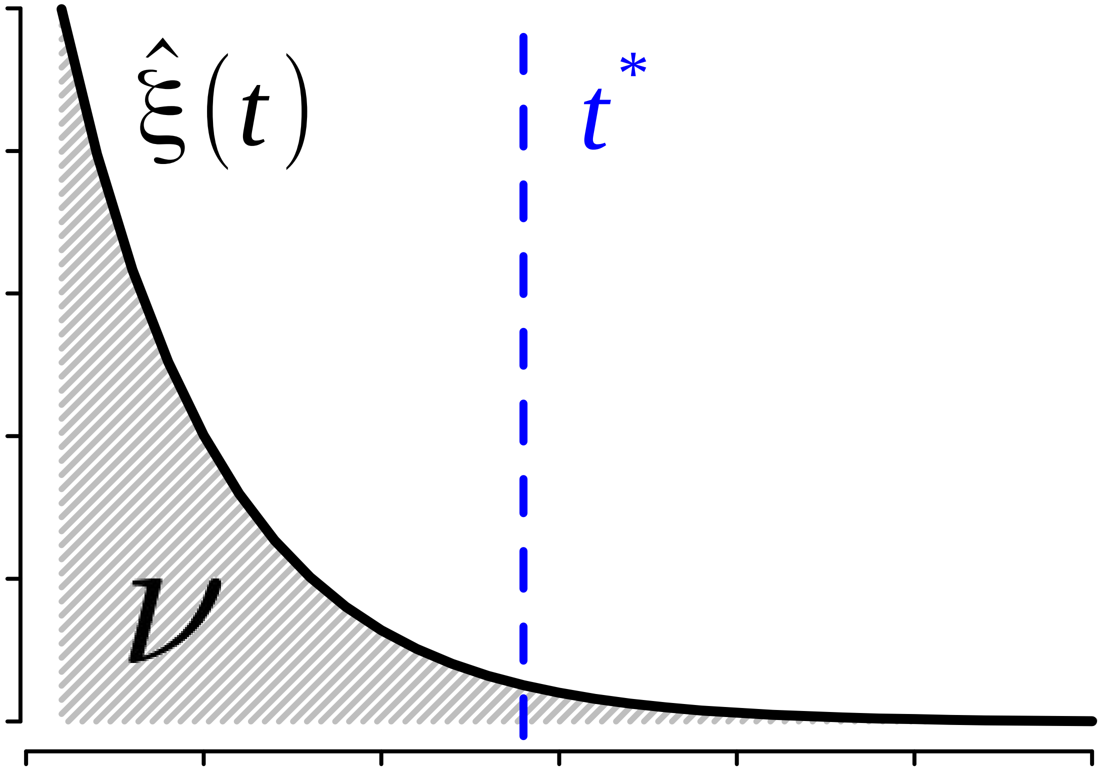
**Corollary:** same budget same return

# Viral potential and maturity time



Viral potential score: $\nu = \int_0^\infty \mu\hat{\xi}(t) = \mu A_{\hat{\xi}}$

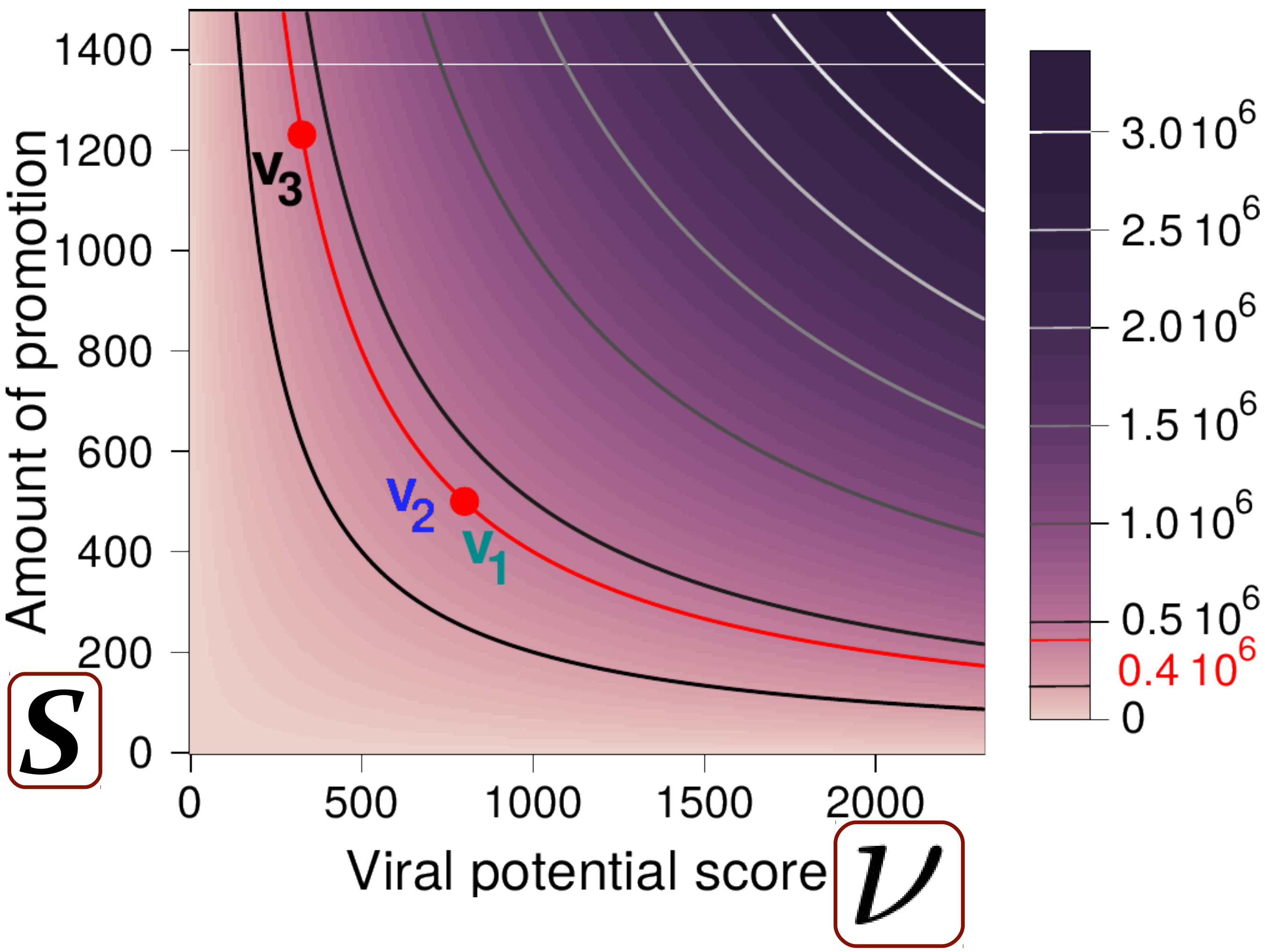
# Viral potential and maturity time



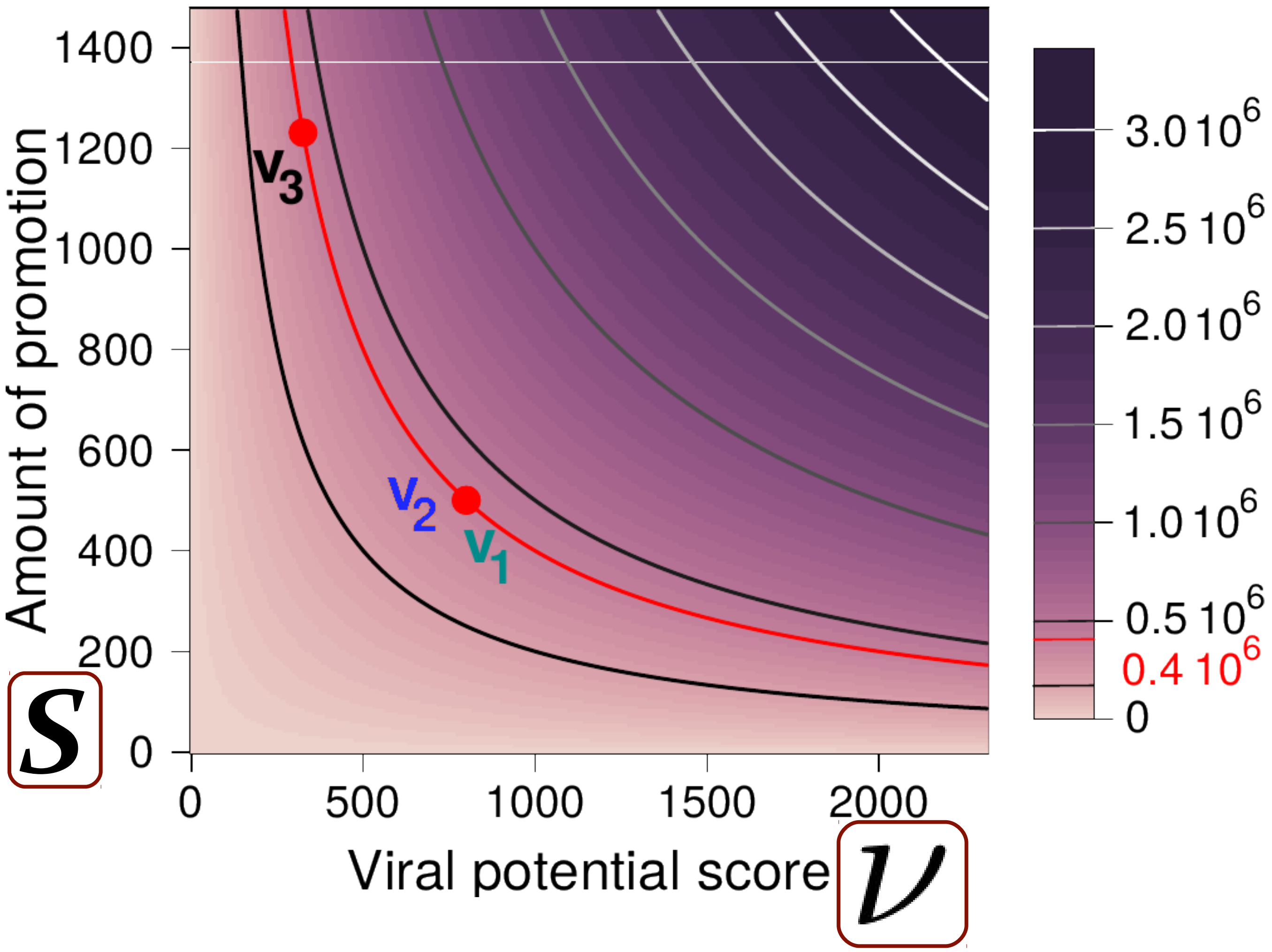
Viral potential score: $\nu = \int_0^\infty \mu\hat{\xi}(t) = \mu A_{\hat{\xi}}$

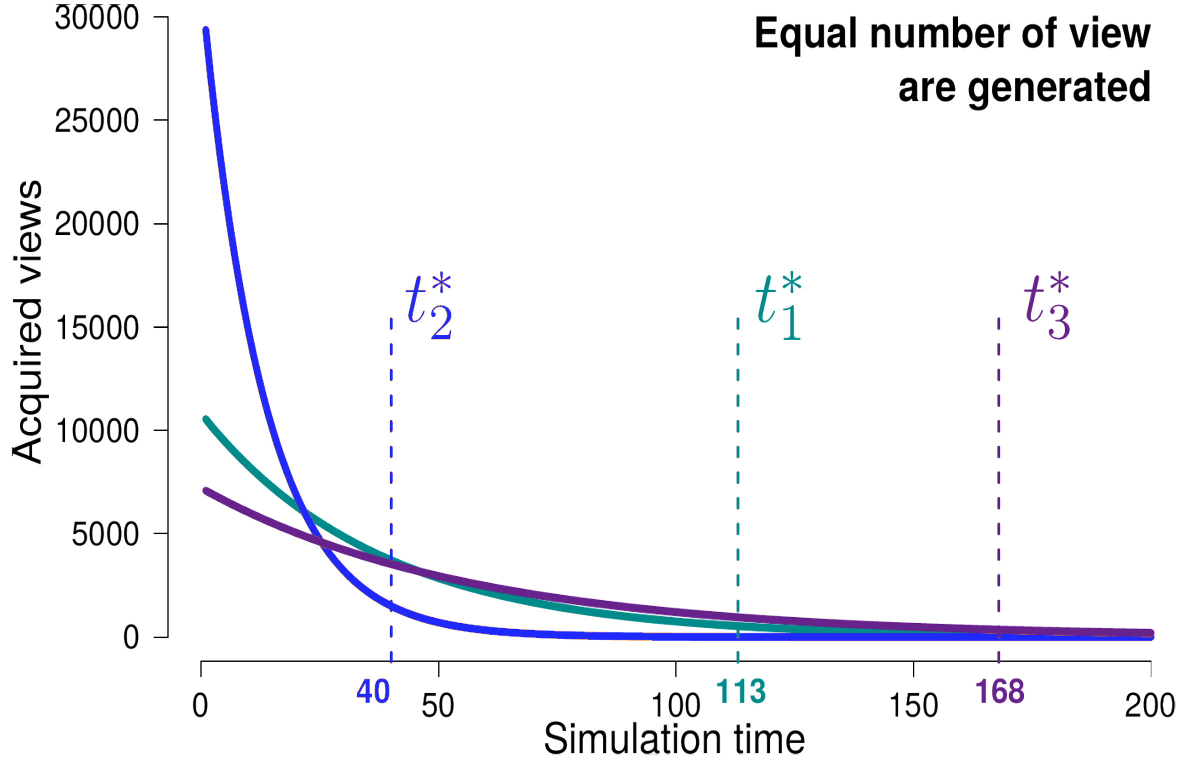
Maturity time: $t^* = min\left\{t \geq 0 \middle| \int_0^t \hat{\xi}(t)dt \geq 0.95\nu\right\}$

# Virality map

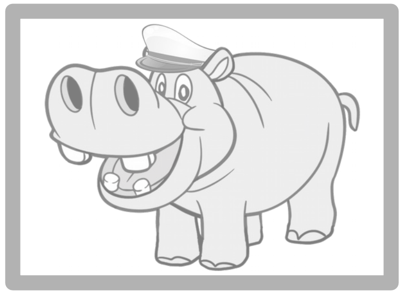


# Virality map

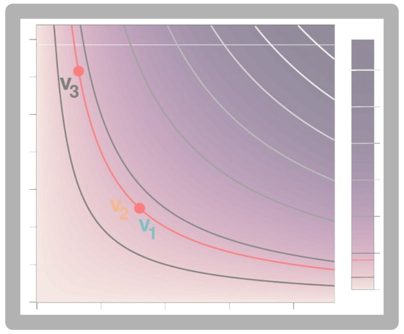




# Presentation outline



Modeling popularity with HIP



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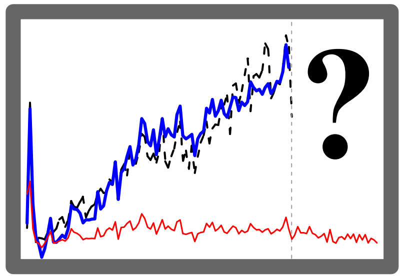
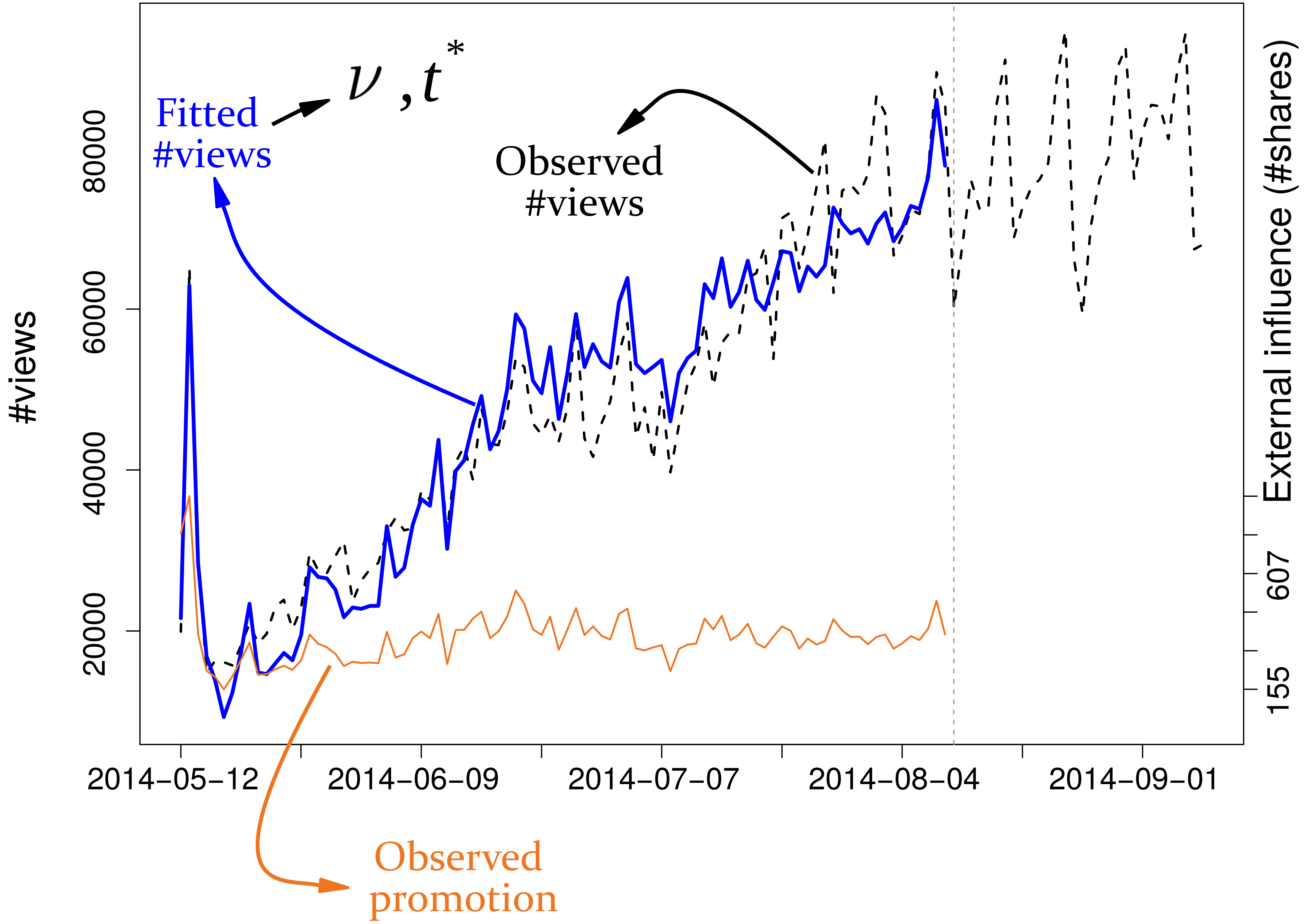


A progression of two problems relating to predicting popularity under promotion

Promotions schedules and memory lengthening through promotion

# Forecasting future views (1)



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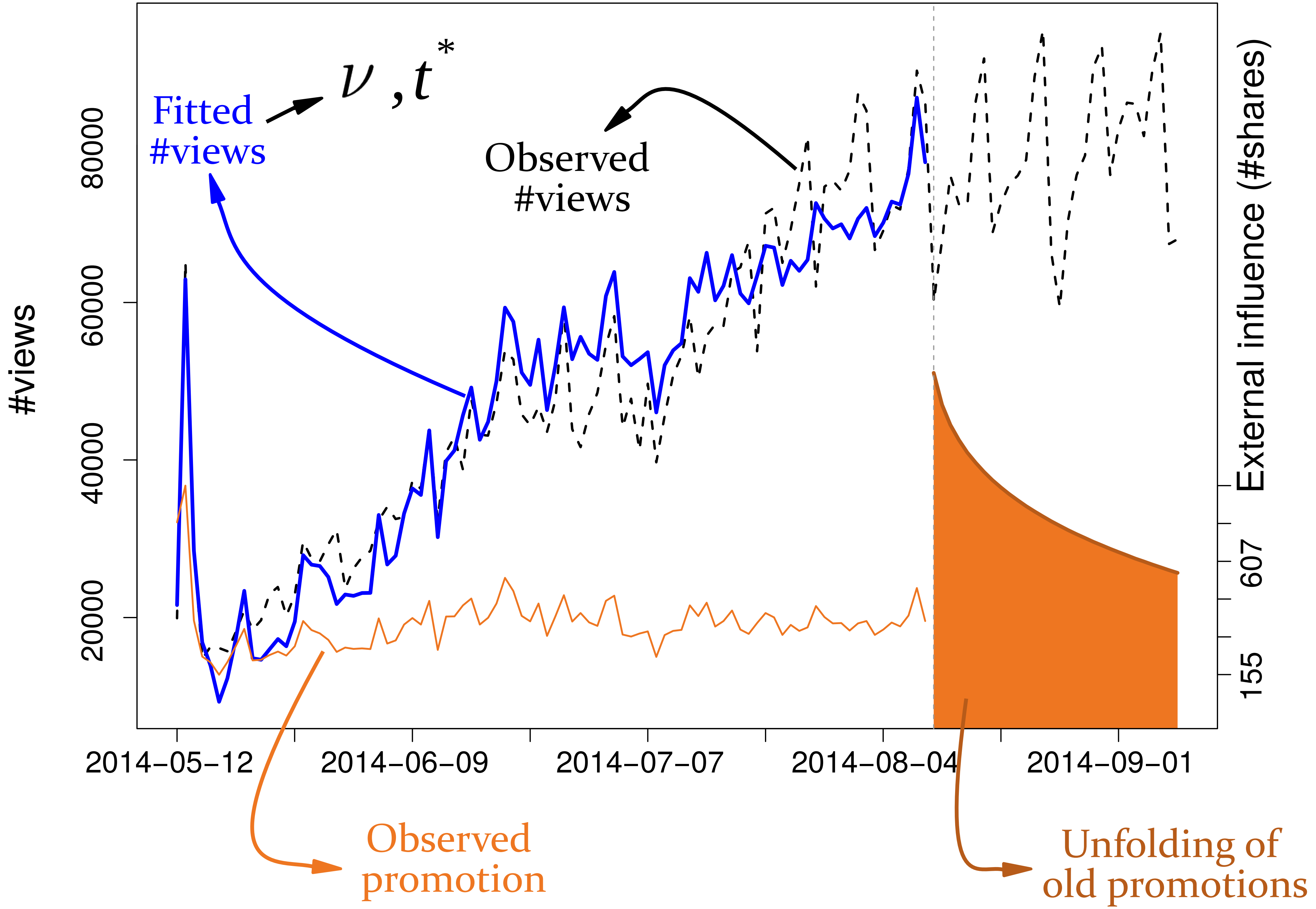

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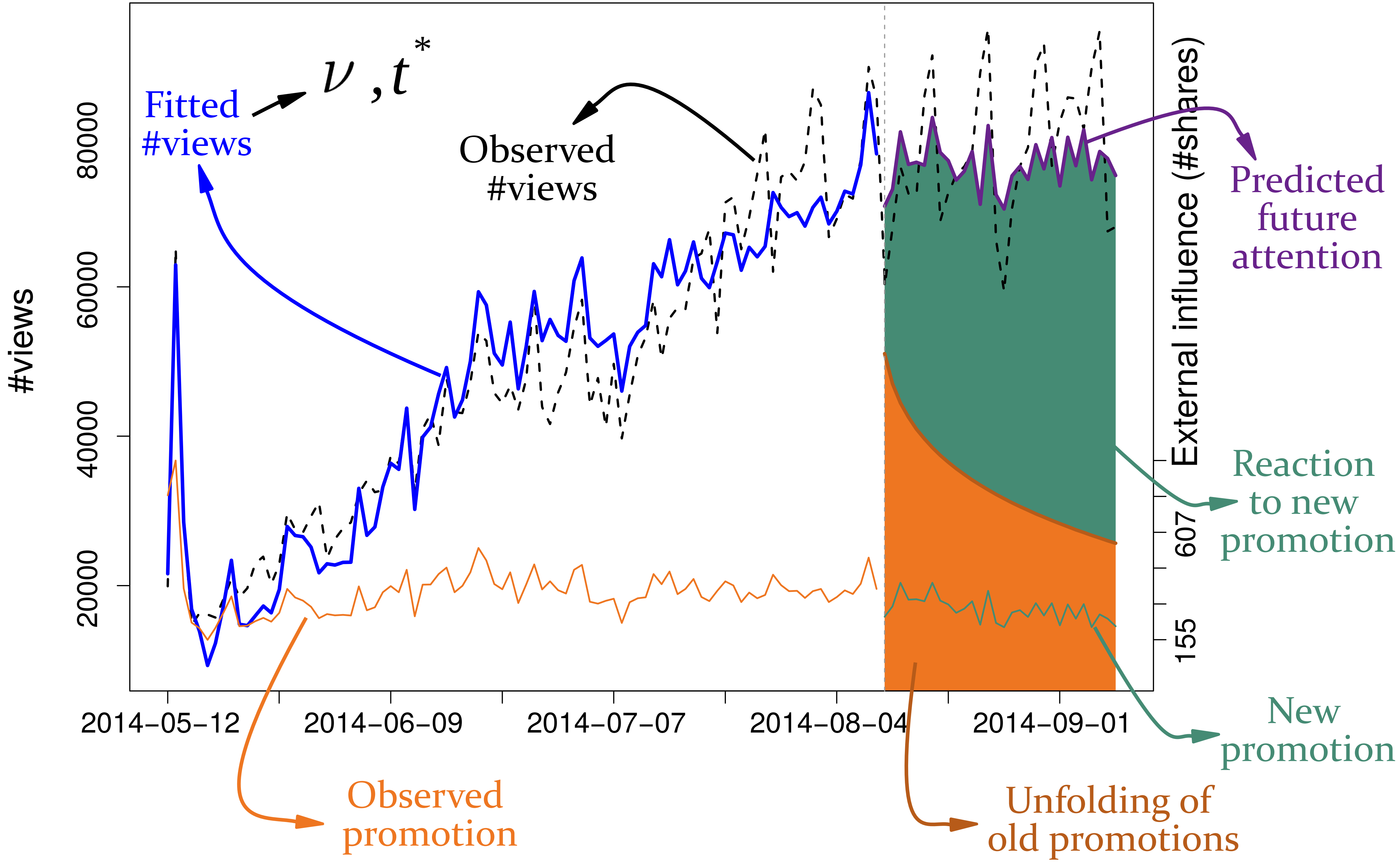


Fitted #views

$\nu, t^*$

Observed #views

Predicted future attention

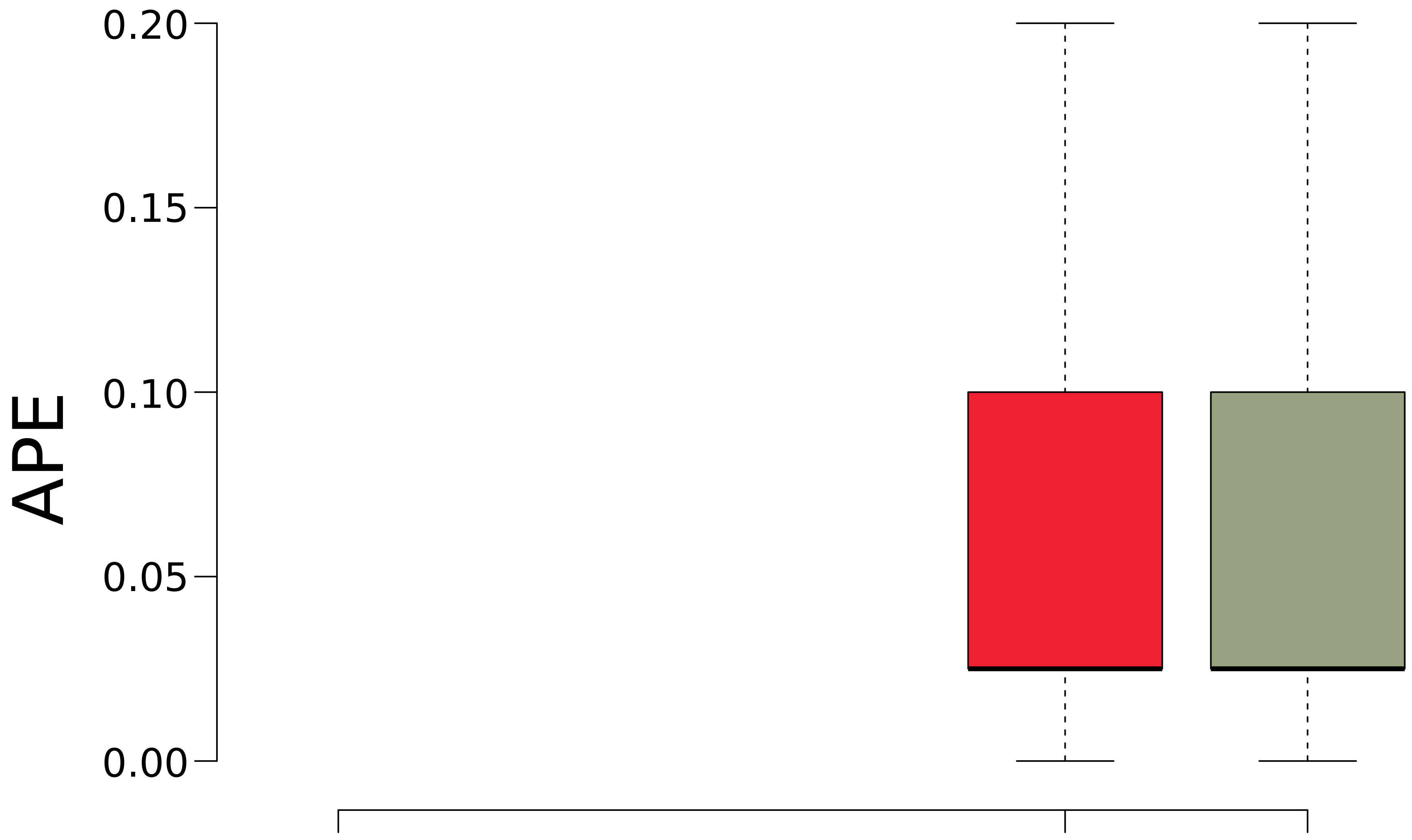
Reaction to new promotion

New promotion

Observed promotion

Unfolding of old promotions

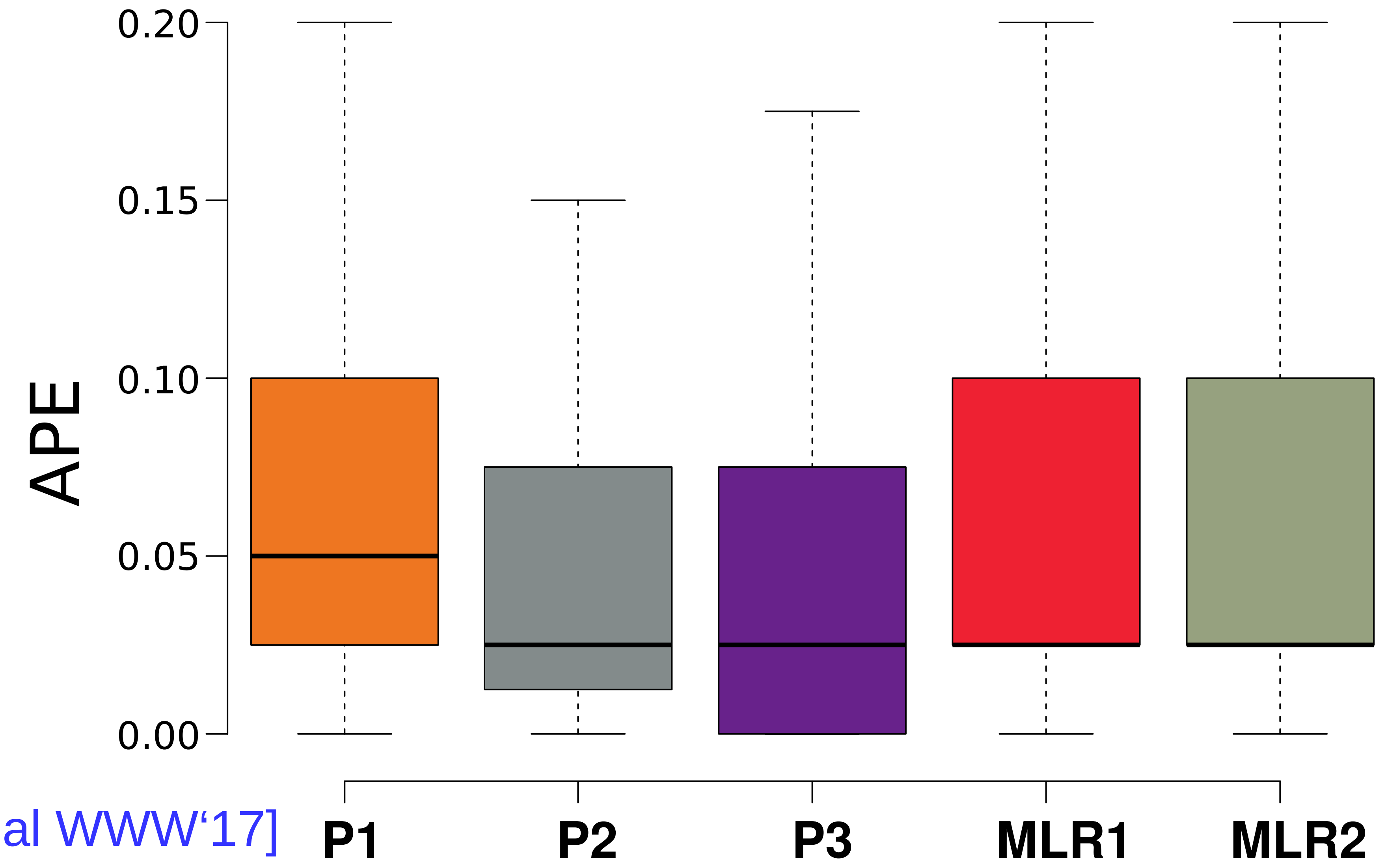
# Forecasting future views (2)



[Pinto et al WSDM'13]

| | MLR1 | MLR2 |
|---|---|---|
| **History:** | ✓ | ✓ |
| **Viral potential:** | | |
| **Promo. volume:** | | ✓ |
| **Promo. timing:** | | ✓ |

# Forecasting future views (2)

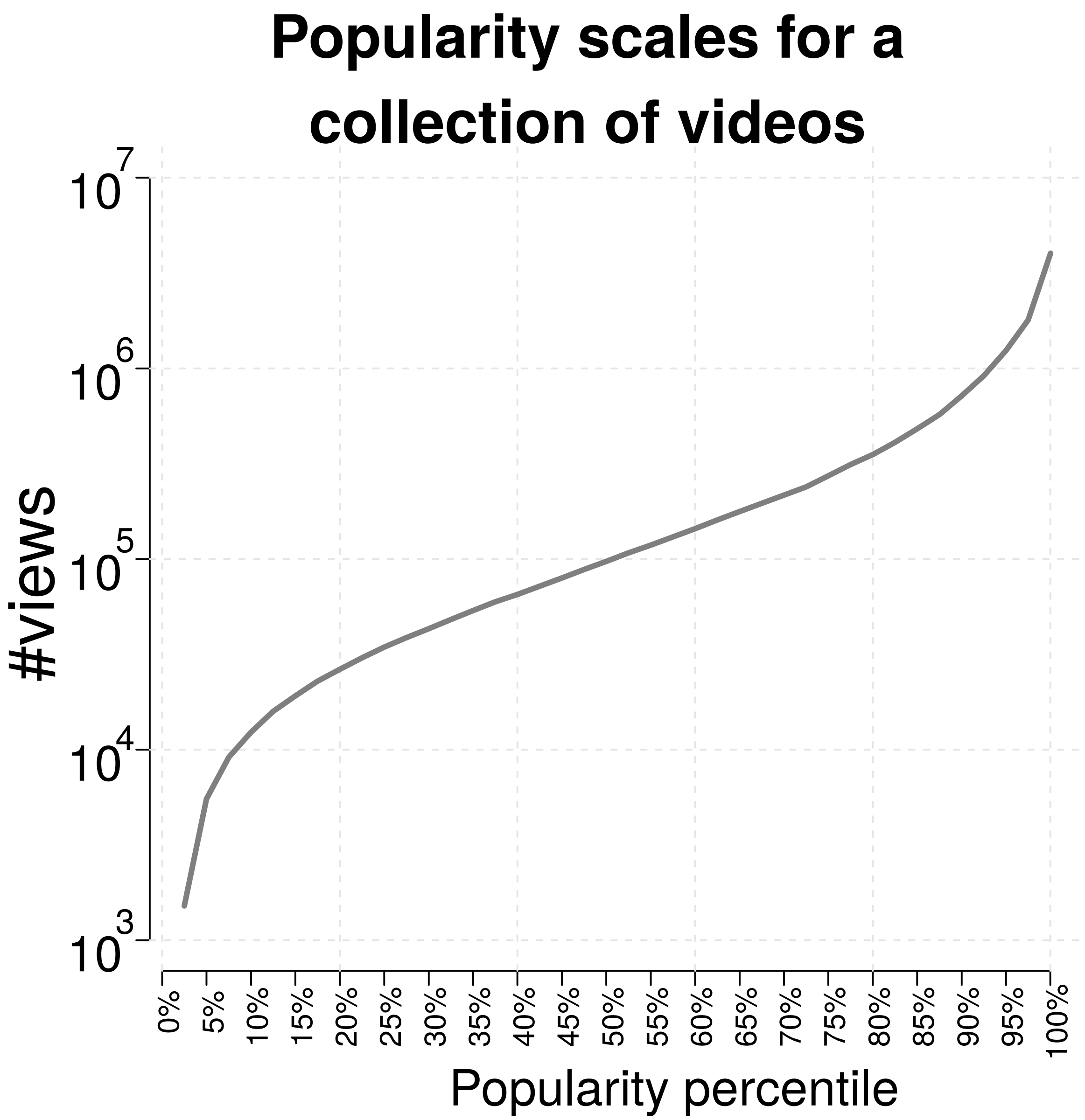


[Rizoiu et al WWW‘17]

[Pinto et al WSDM’13]

| | P1 | P2 | P3 | MLR1 | MLR2 |
|---|---|---|---|---|---|
| **History:** | ✓ | ✓ | ✓ | ✓ | ✓ |
| **Viral potential:** | ✓ | ✓ | ✓ | | |
| **Promo. volume:** | | ✓ | ✓ | | ✓ |
| **Promo. timing:** | | | ✓ | | ✓ |

# Popularity scale over time



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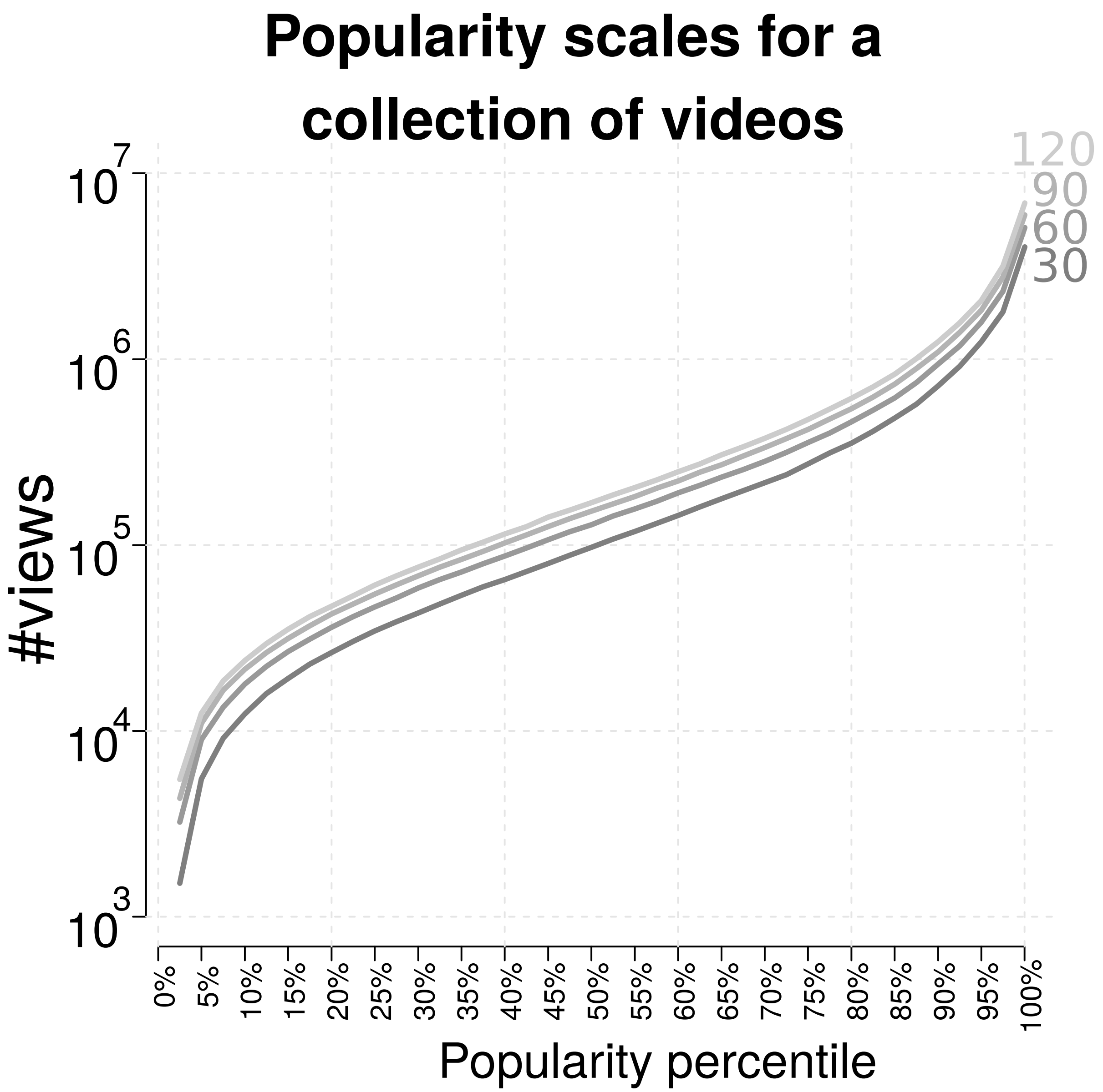

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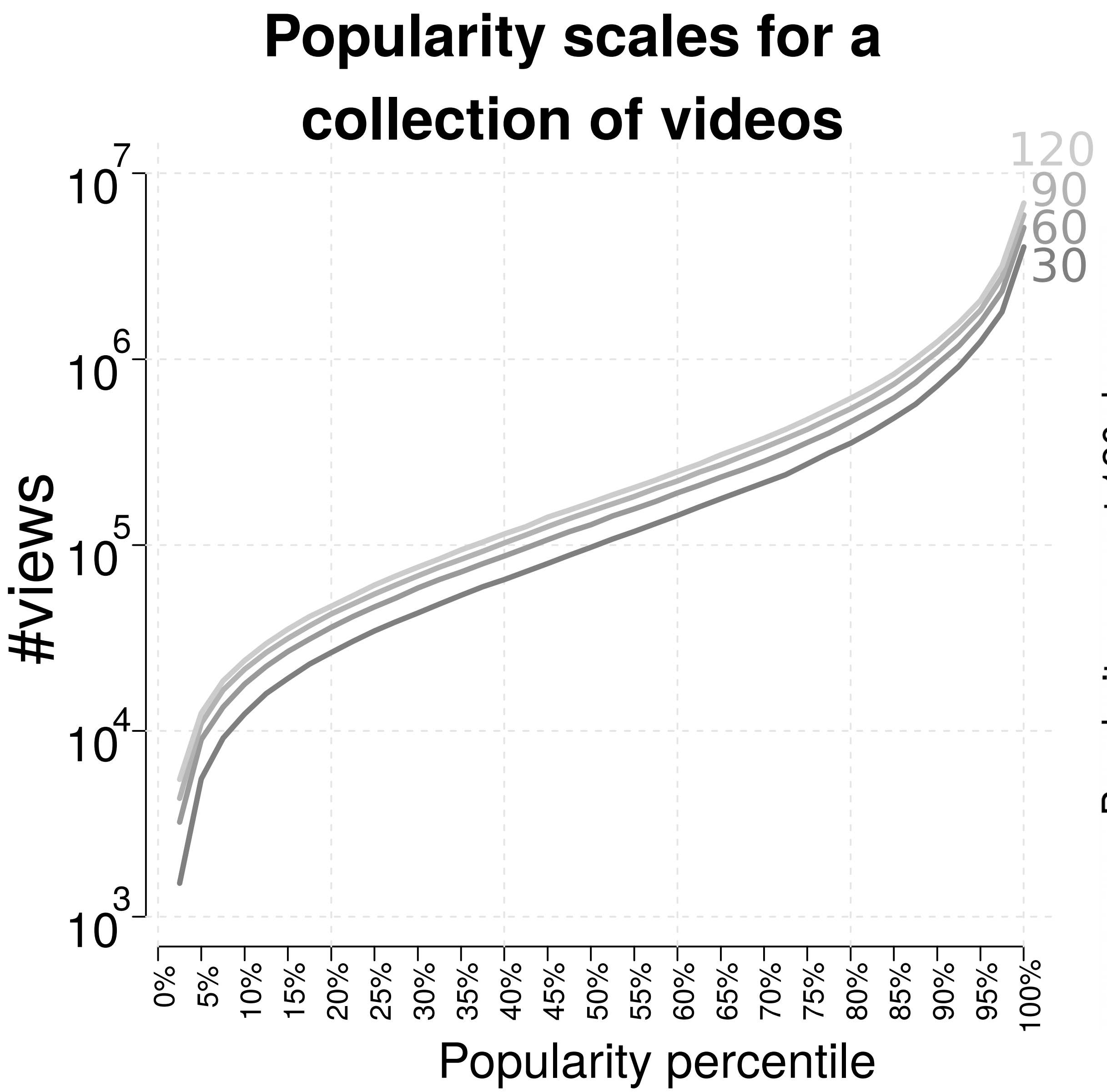

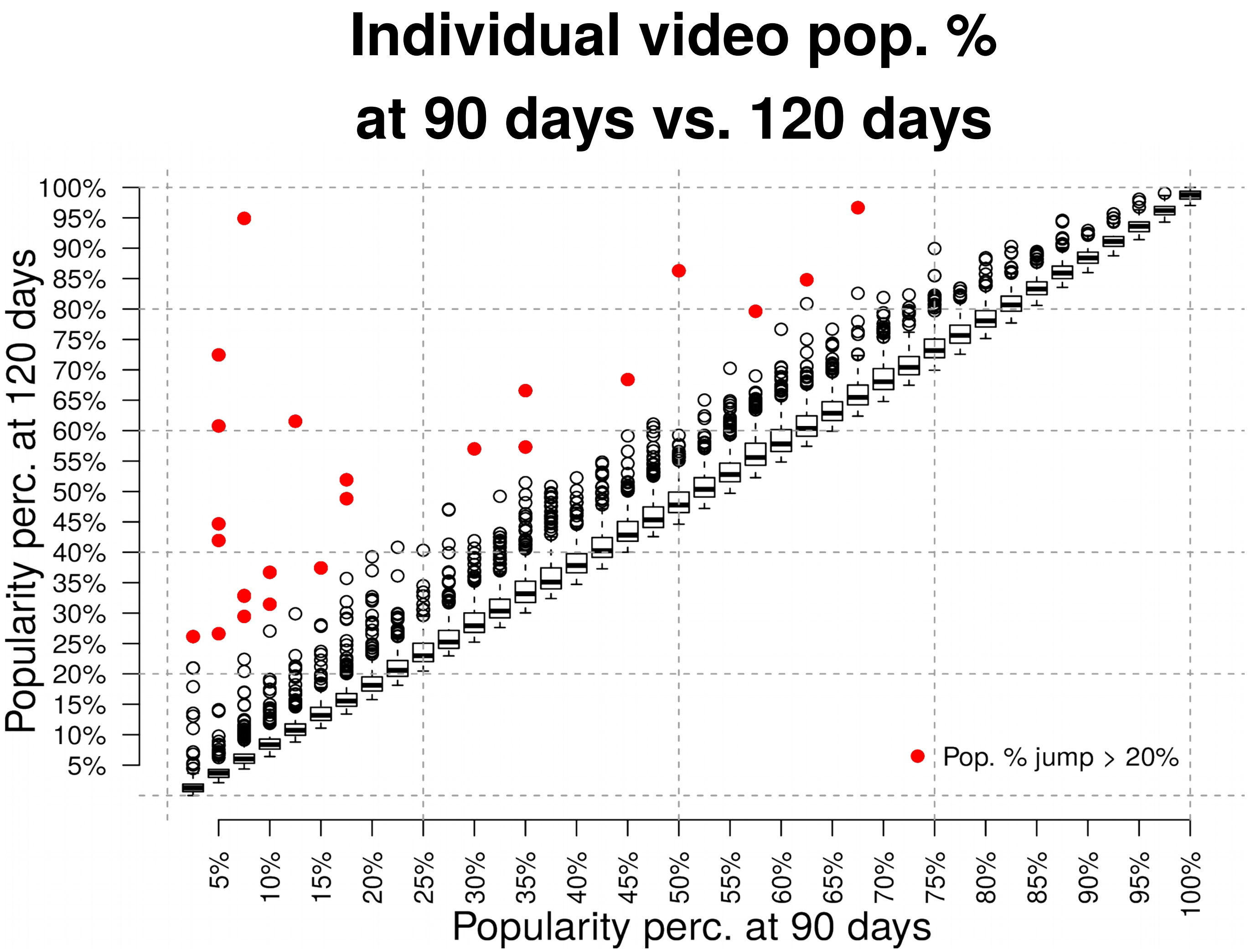

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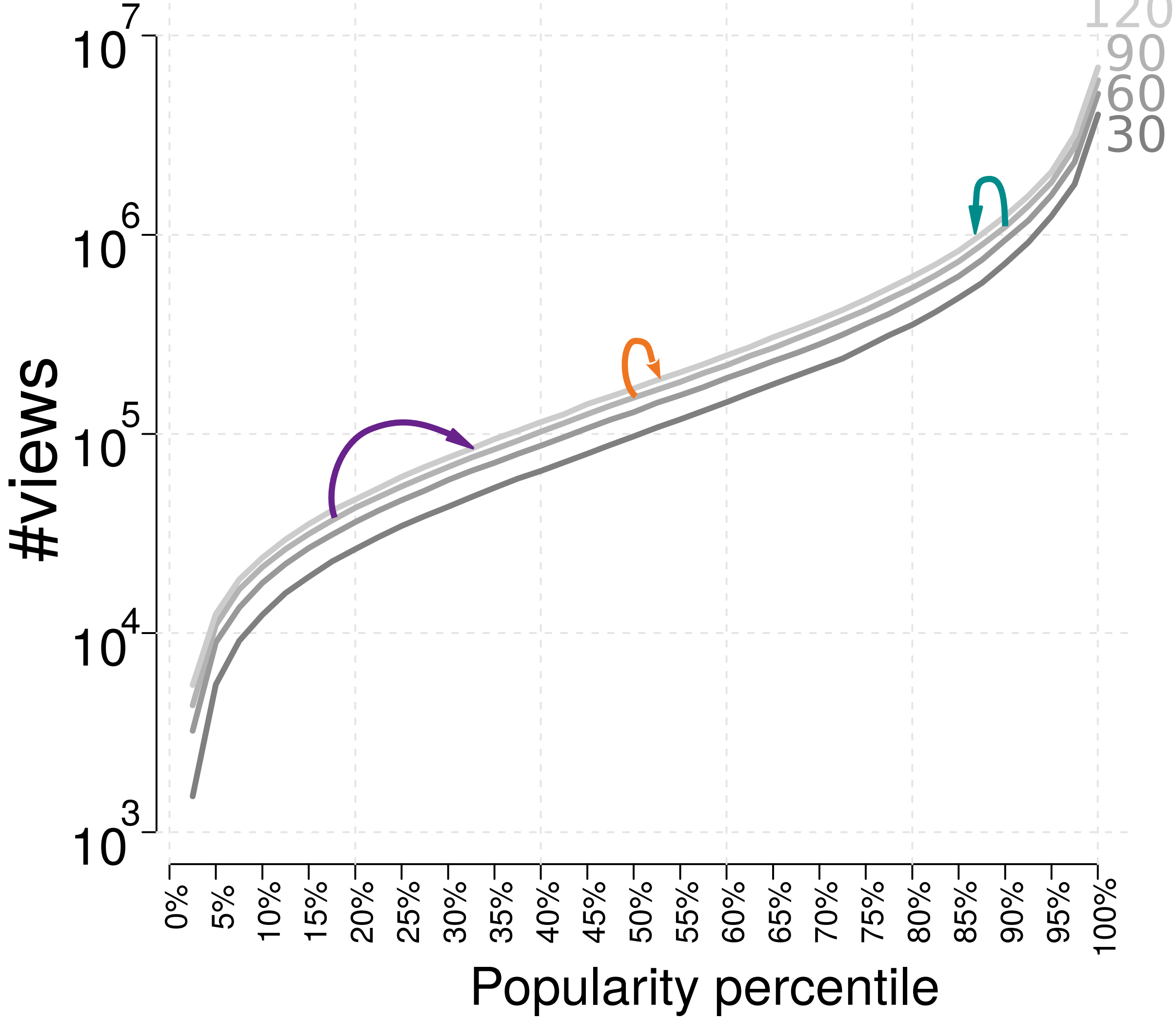
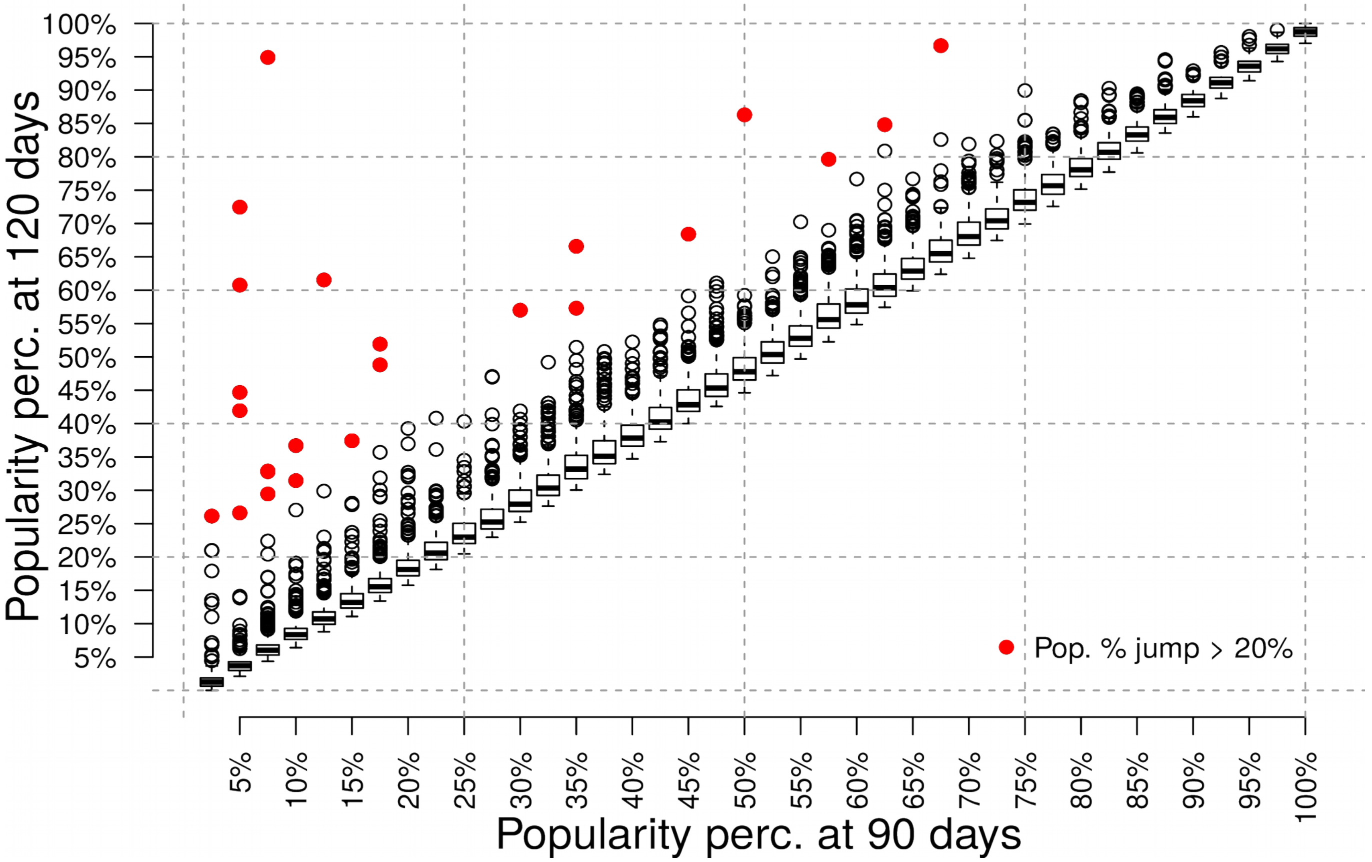


Popularity scales for a collection of videos

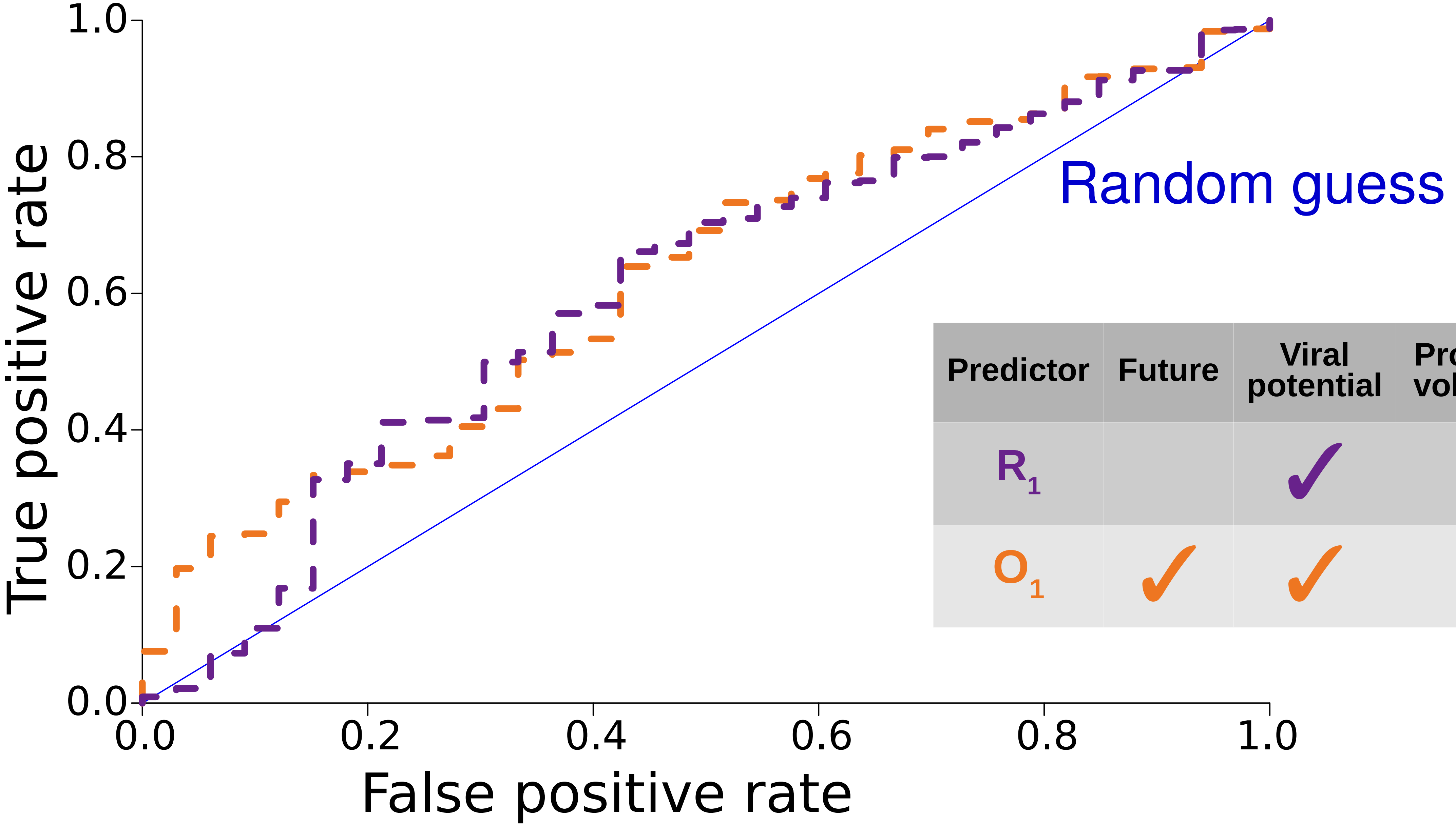


Individual video pop. % at 90 days vs. 120 days

**Impact of 40k views:**

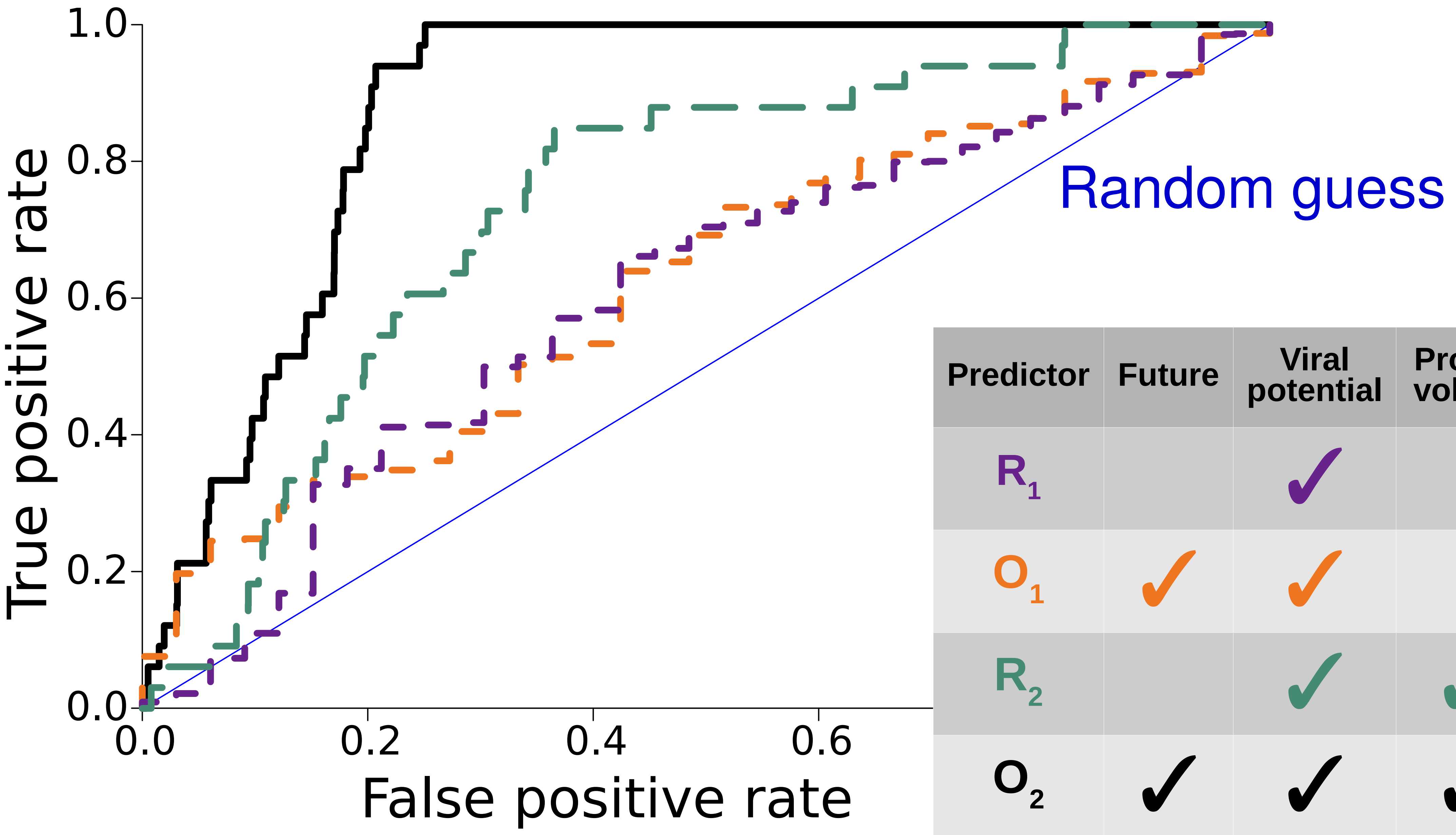
start at 17.5% → +15%    start at 50% → +2.5%    start at 90% → -2.5%

# ROC curves for videos that jump



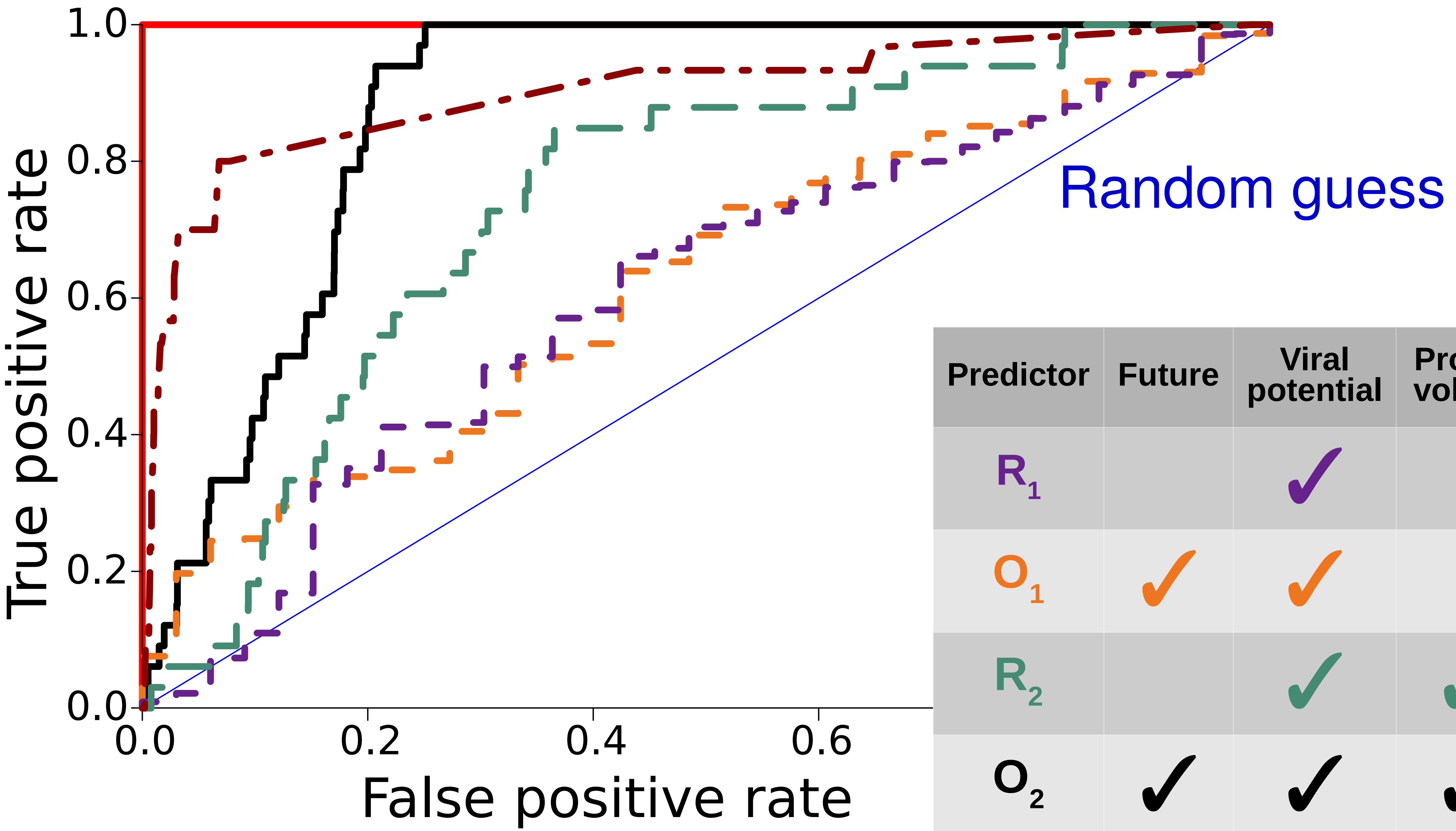
| Predictor | Future | Viral potential | Promo. volume | Pop. scale position |
|---|---|---|---|---|
| $R_1$ |  | ✓ |  |  |
| $O_1$ | ✓ | ✓ |  |  |

# ROC curves for videos that jump



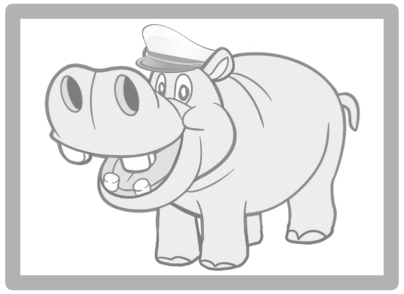
| Predictor | Future | Viral potential | Promo. volume | Pop. scale position |
|---|---|---|---|---|
| $R_1$ |  | ✓ |  |  |
| $O_1$ | ✓ | ✓ |  |  |
| $R_2$ |  | ✓ | ✓ |  |
| $O_2$ | ✓ | ✓ | ✓ |  |

# ROC curves for videos that jump

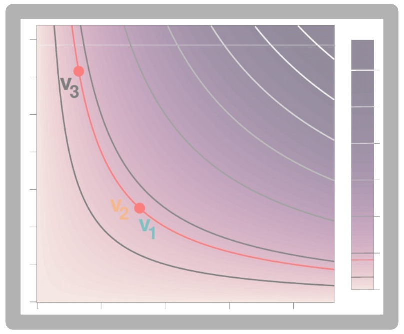


| Predictor | Future | Viral potential | Promo. volume | Pop. scale position |
|---|---|---|---|---|
| $R_1$ | | ✓ | | |
| $O_1$ | ✓ | ✓ | | |
| $R_2$ | | ✓ | ✓ | |
| $O_2$ | ✓ | ✓ | ✓ | |
| $R_3$ | | ✓ | ✓ | ✓ |
| $O_3$ | ✓ | ✓ | ✓ | ✓ |

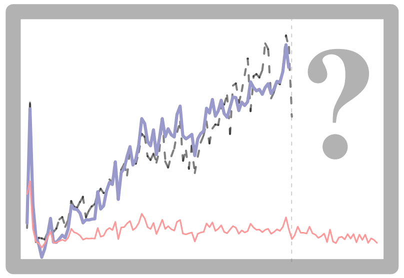
# Presentation outline



Modeling popularity with HIP



Content virality and maturity time

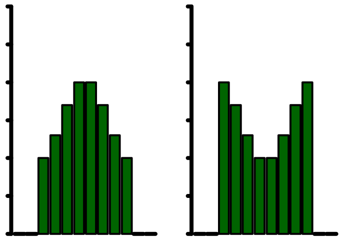


Forecasting popularity under promotion

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

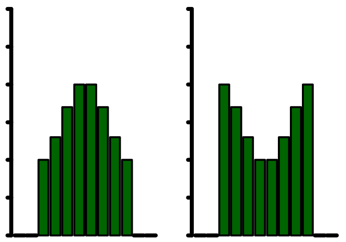
# Designing promotion schedules

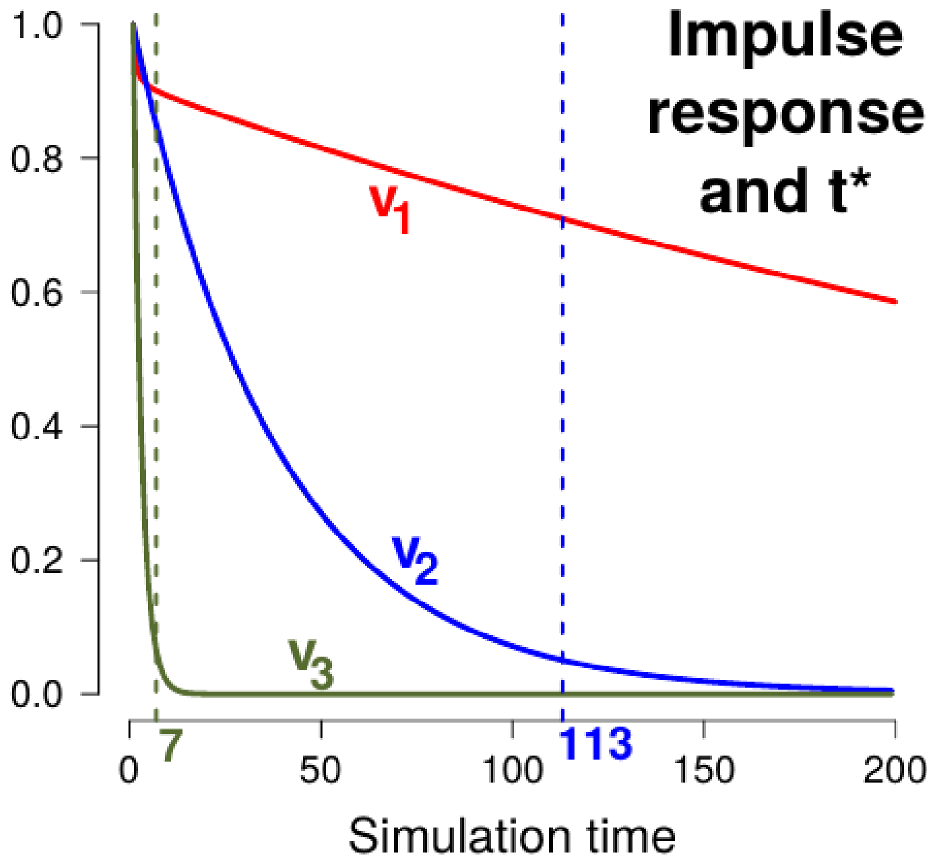
LTI corollary: **same budget, same return!**

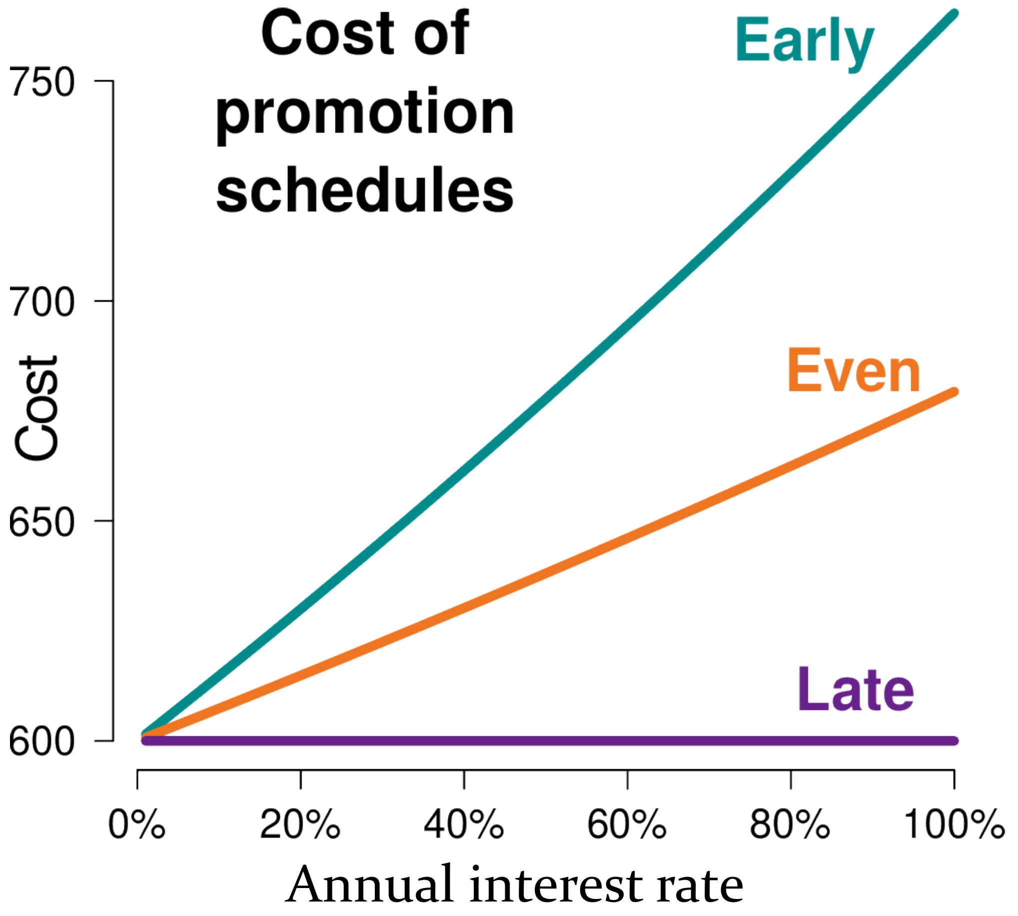


# Designing promotion schedules

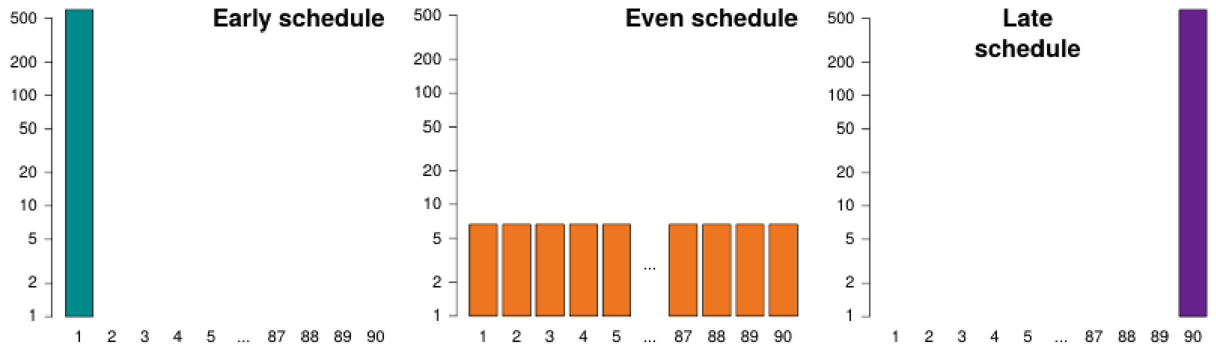
LTI corollary: **same budget, same return!**



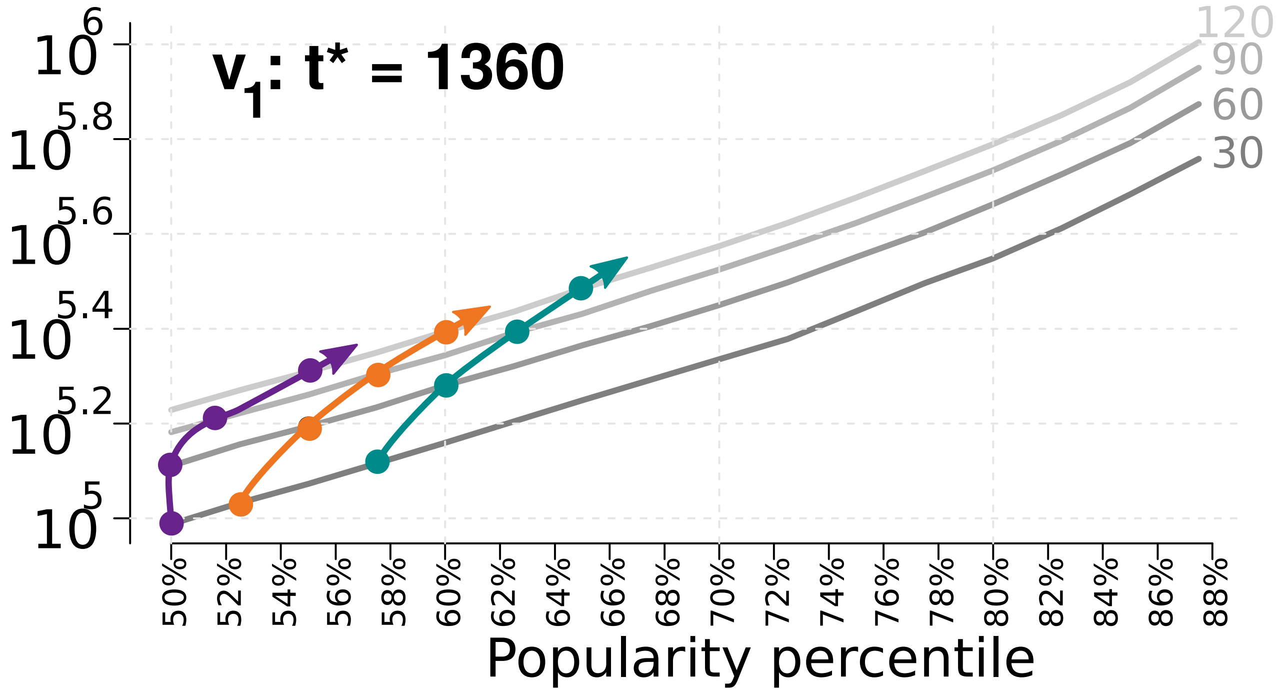


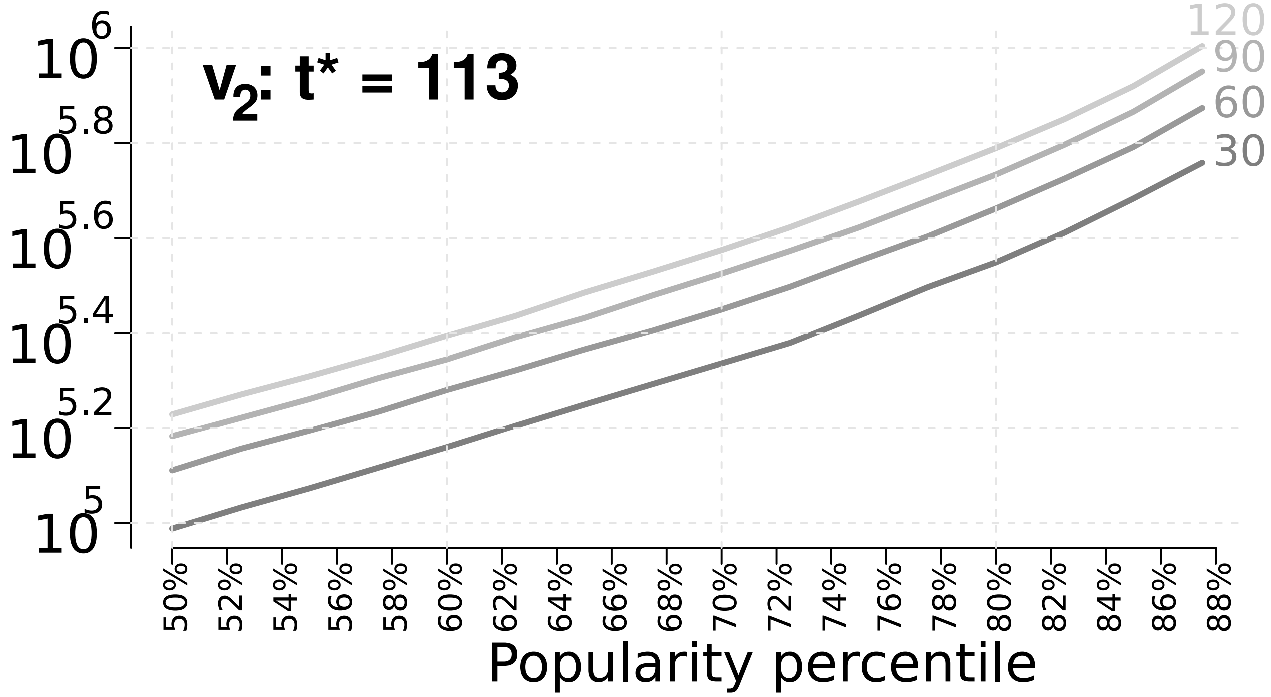


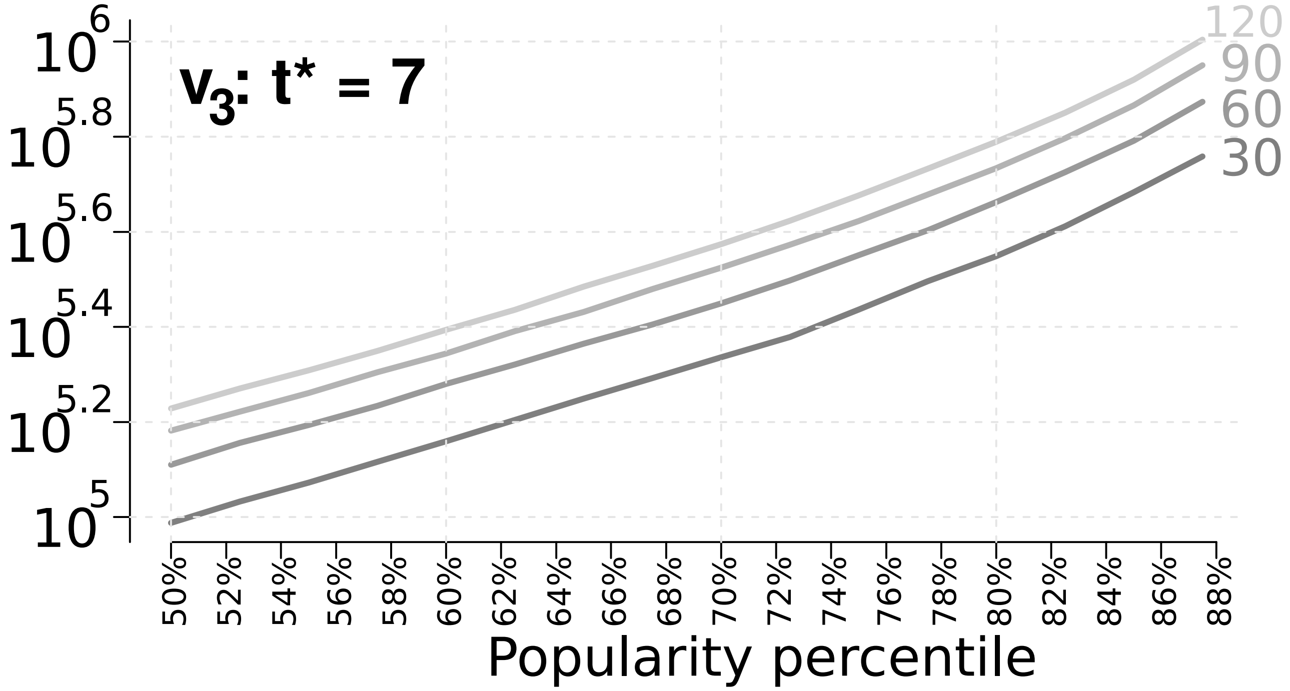
Compounding interest: $cost=(1+a)^k$

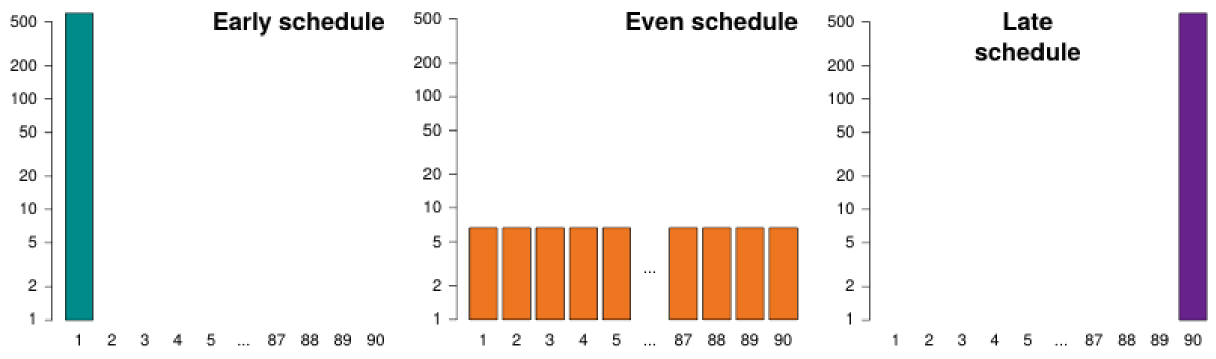


# Interplay of 2 temporal factors

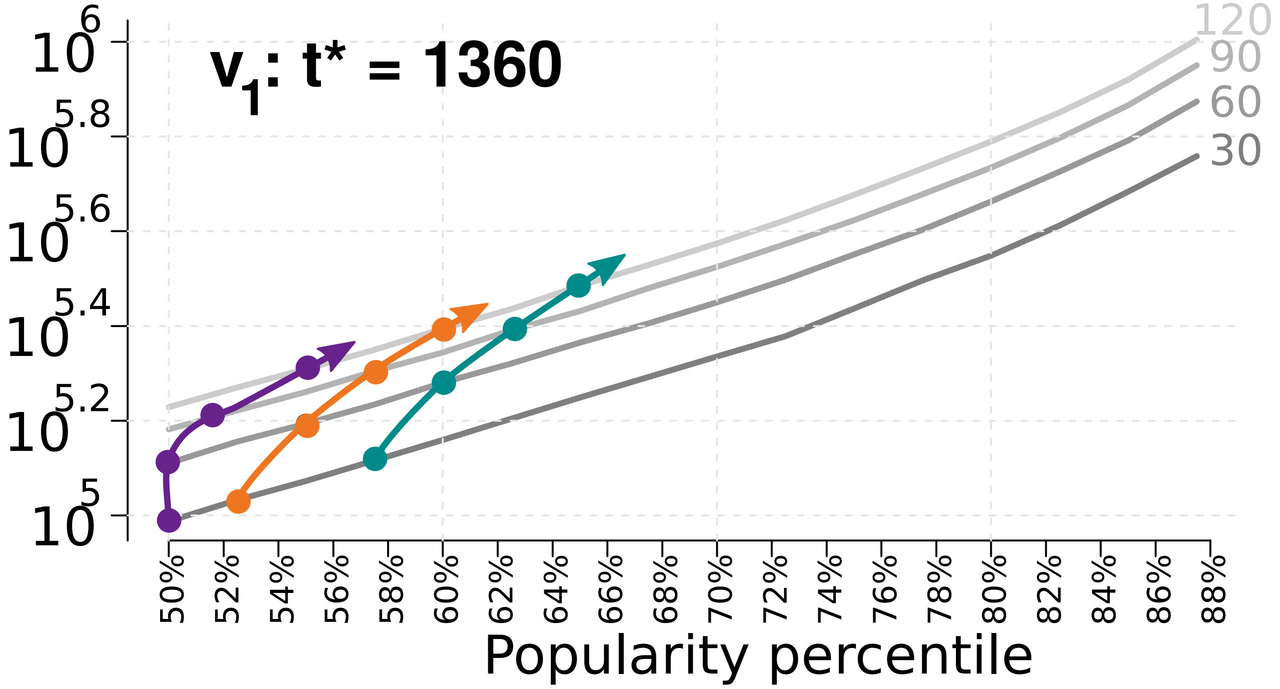


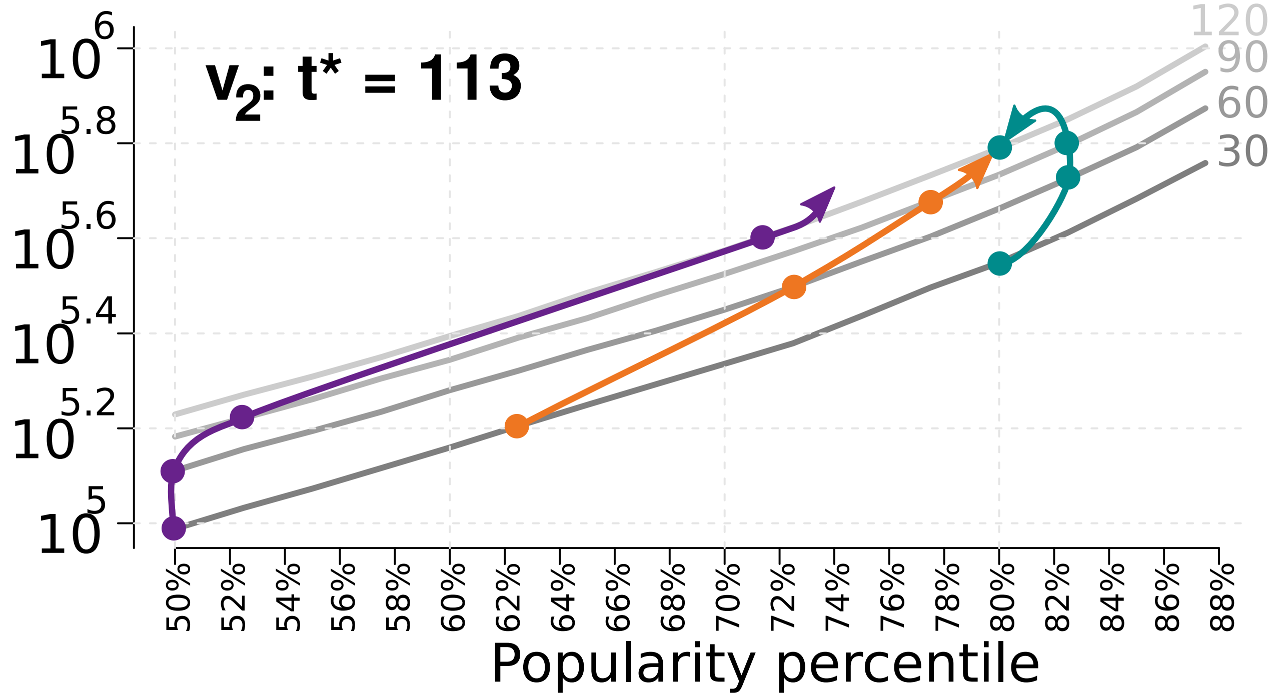


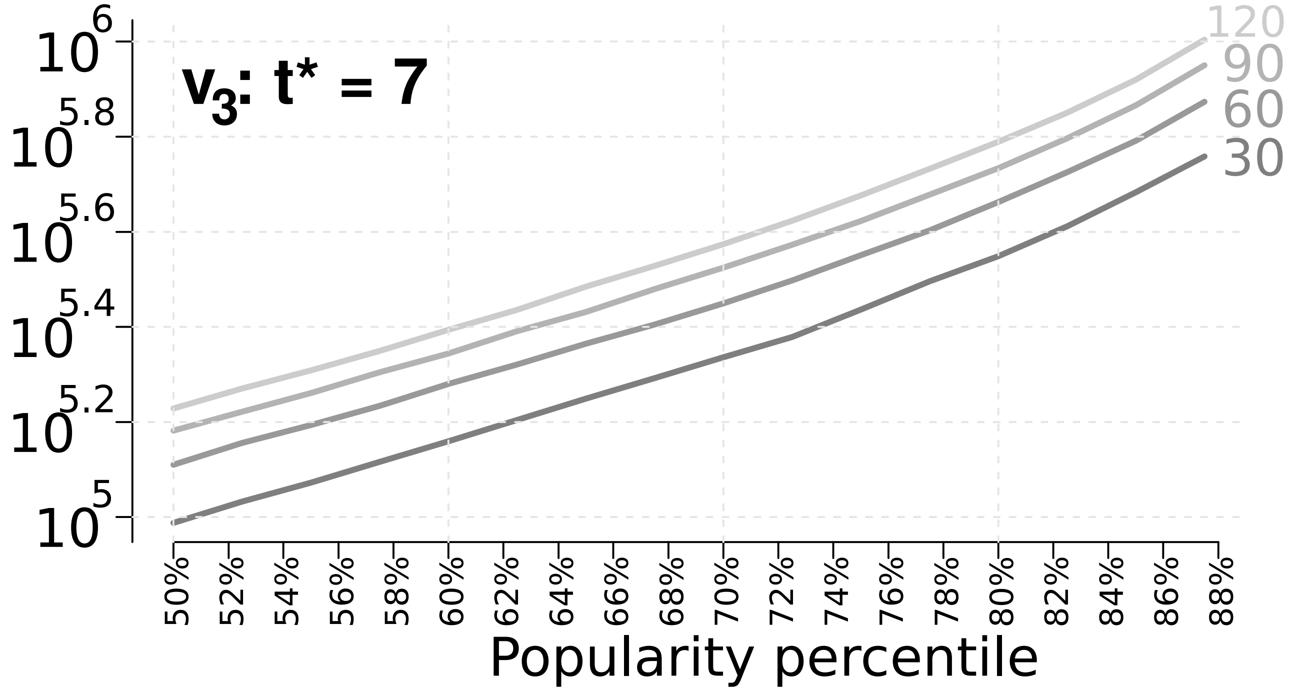


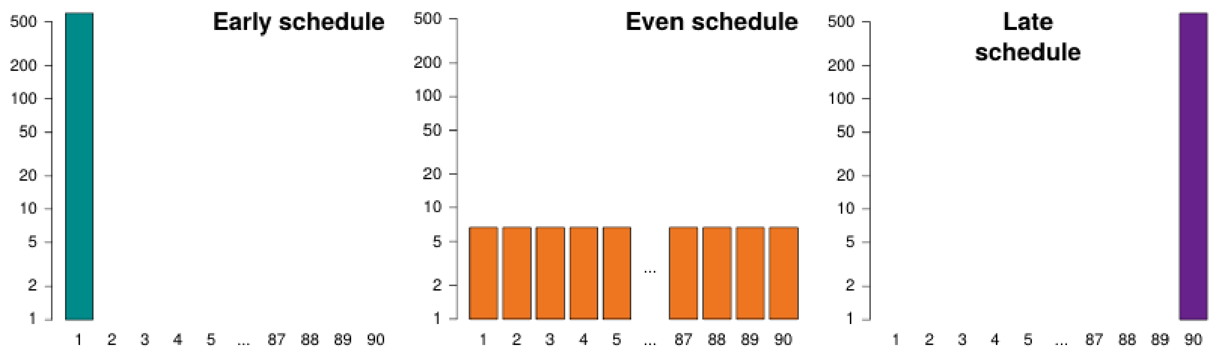


# Interplay of 2 temporal factors

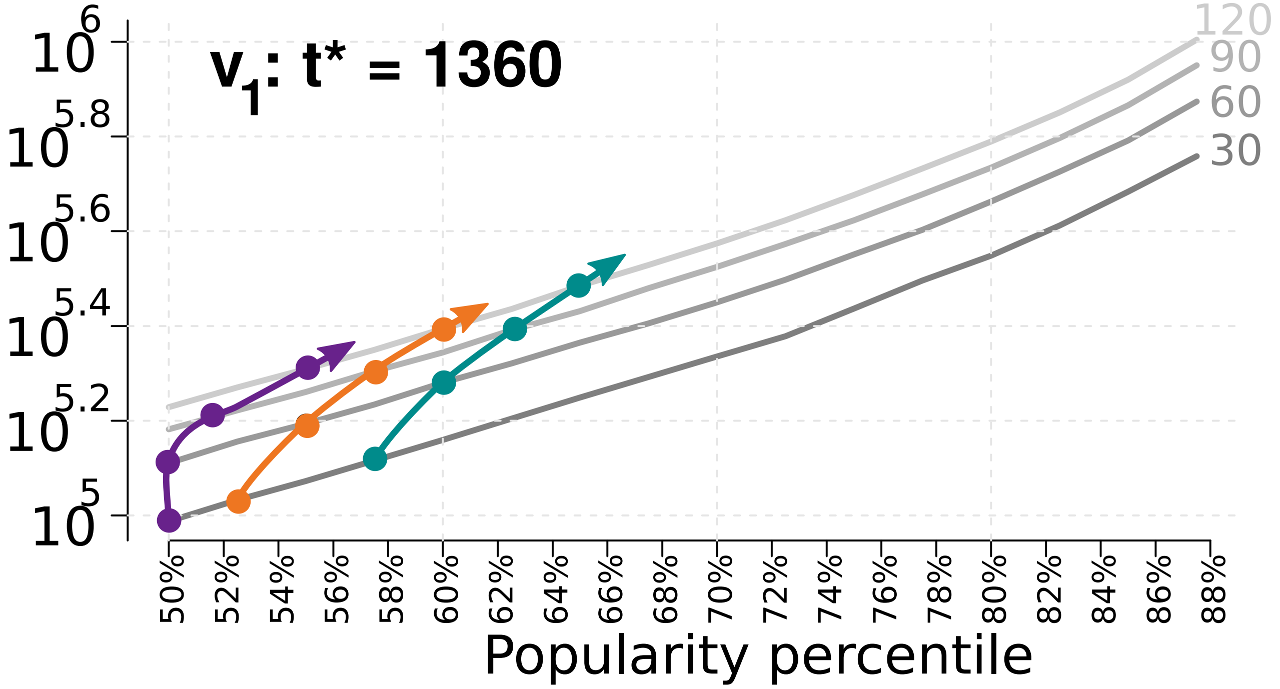


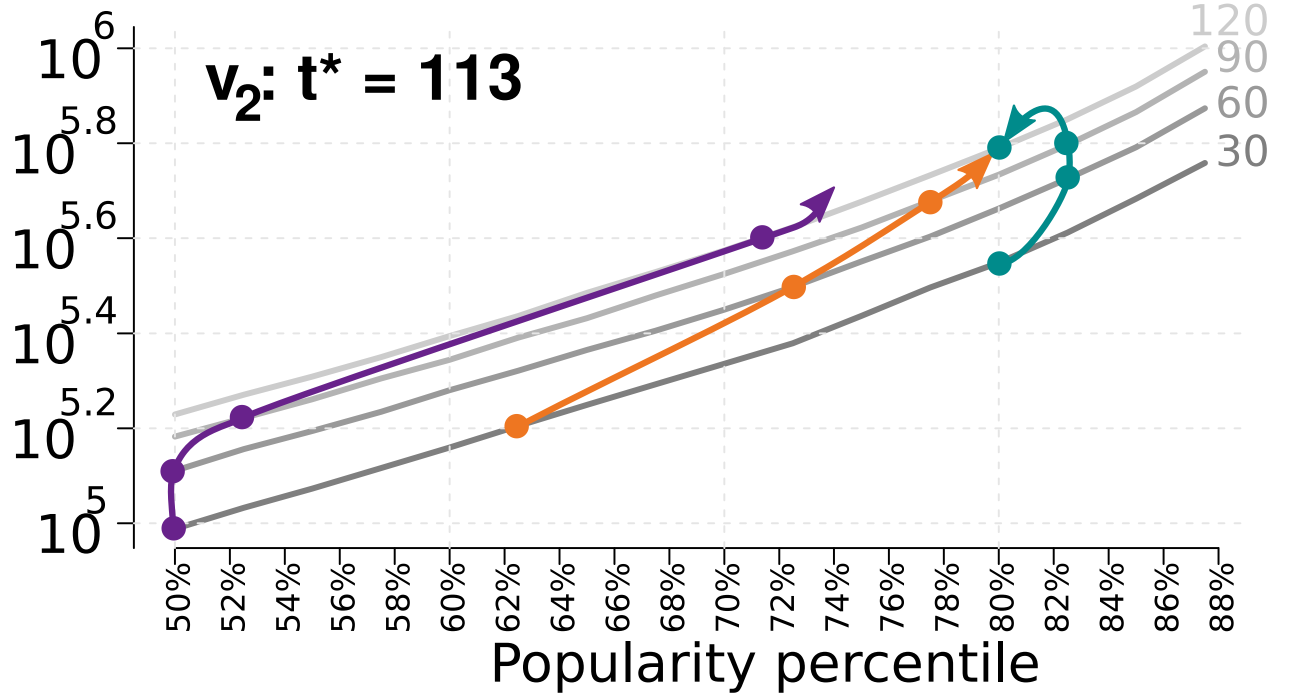


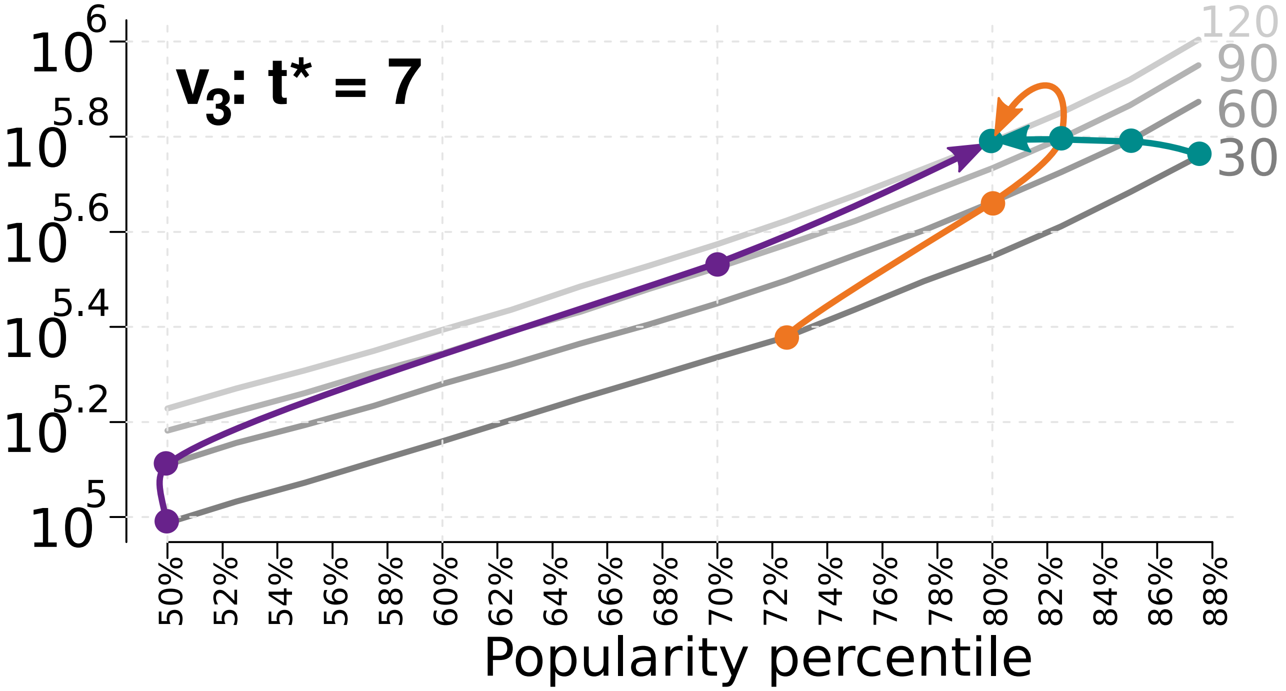


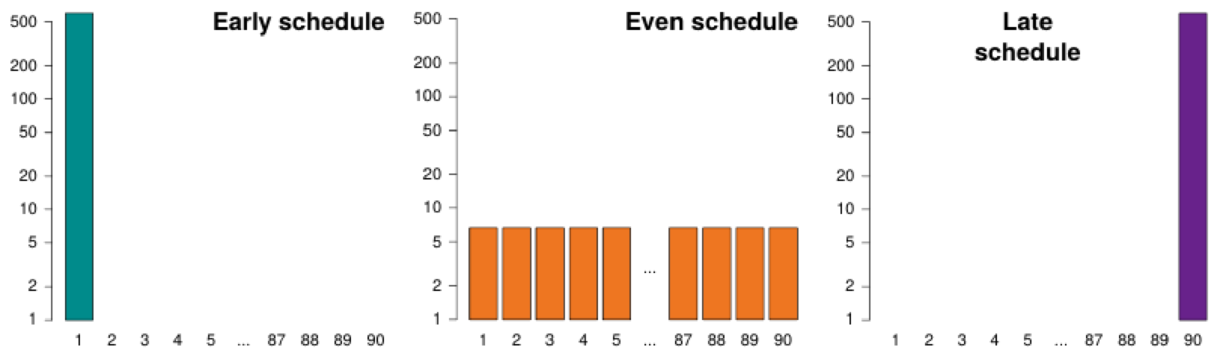


# Interplay of 2 temporal factors







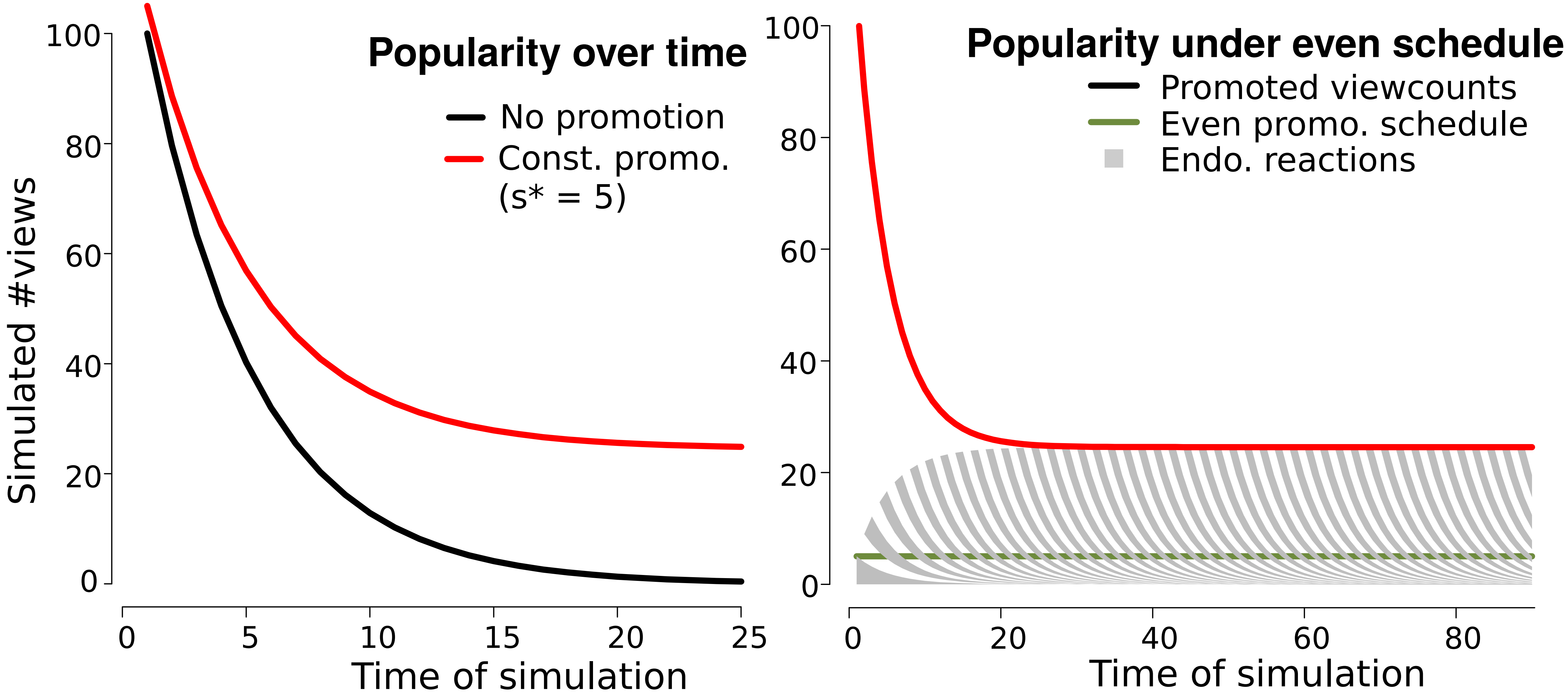


# Why is constant promotion desirable?

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

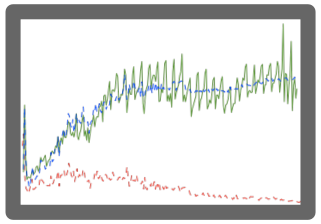
Explains why TV commercials appear at fixed intervals, every day.

# Memory lengthening through promotion

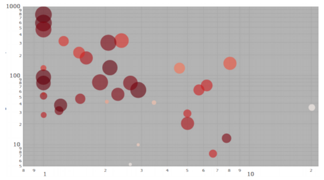


Constant promotion leads to an apparent **memory lengthening.**

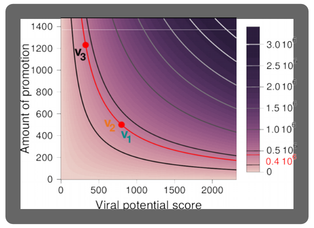
# Summary



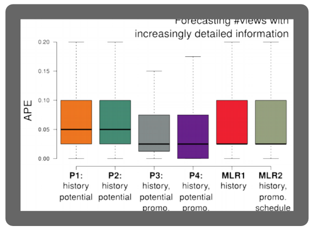
HIP: a mathematical model linking promotion and popularity



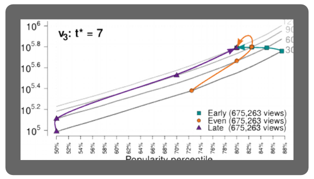
Explain popularity dynamics and identify potentially viral videos



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

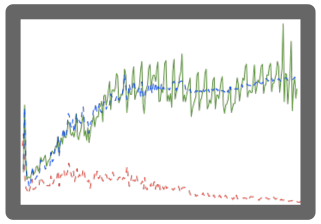


Important factors for forecasting popularity: *virality score*, *promotion volume* and *popularity scale position*

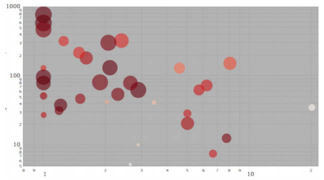


Maturity time influences the cost-effectiveness of promotion schedules

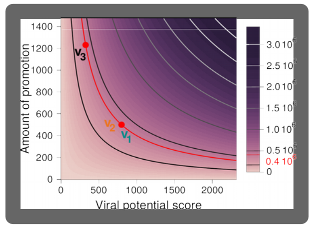
# Summary



HIP: a mathematical model linking promotion and popularity



Explain popularity dynamics and identify potentially viral videos



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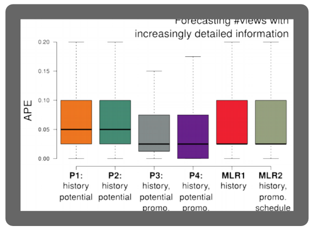

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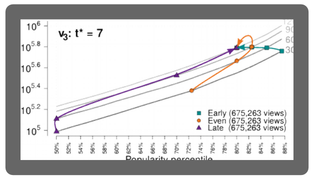


Maturity time influences the cost-effectiveness of promotion schedules

**Limitations & future work:** unobserved sources of external influence, seasonality, network structure, reaction to past and future promotions is the same.

# Thank you!

## Links:

Code, dataset and interactive visualizer:

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

*Refereces*:

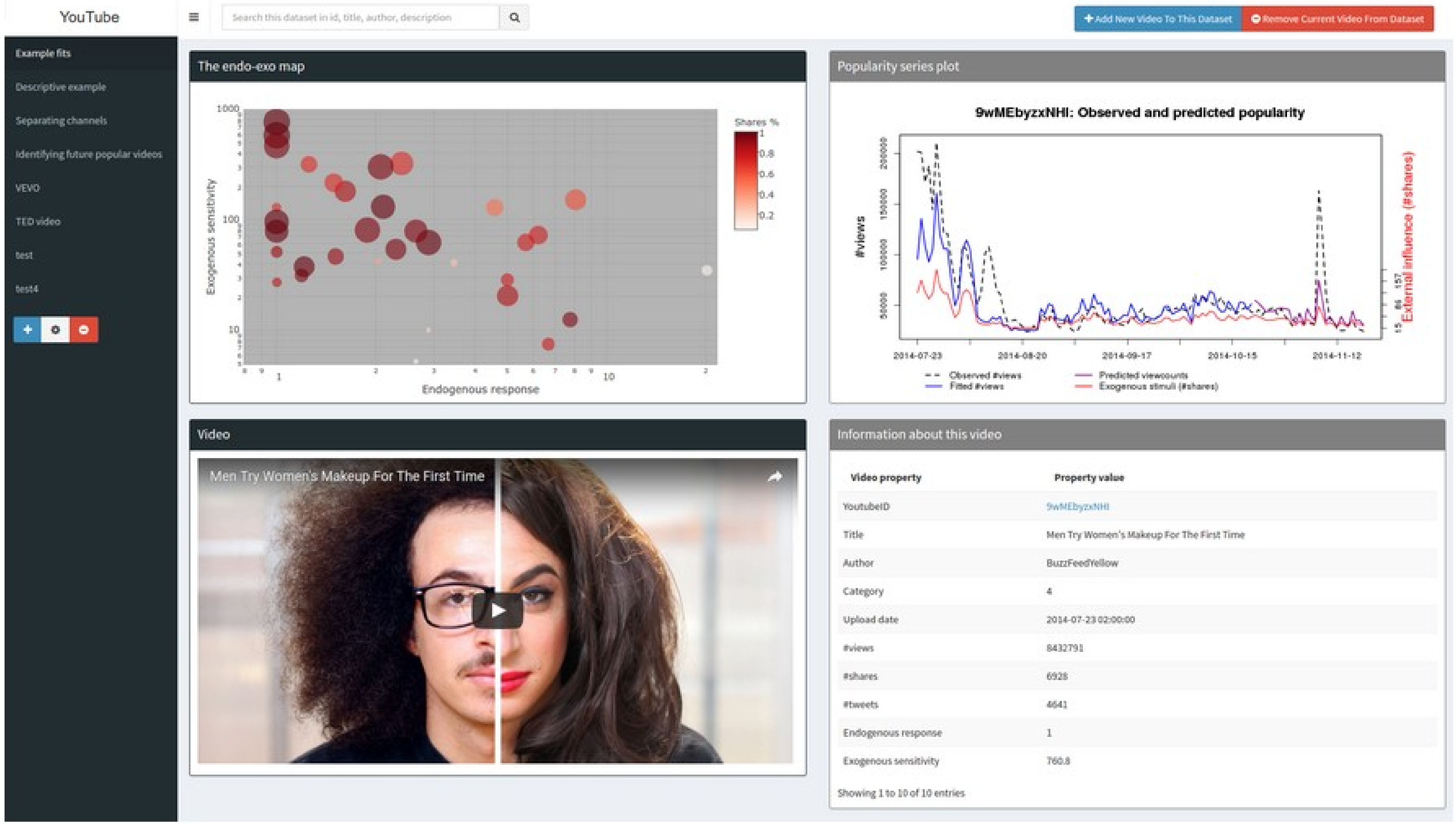
Rizoiu, M.-A., Xie, L., Sanner, S., Cebrian, M., Yu, H., & Van Hentenryck, P. **Expecting to be HIP: Hawkes Intensity Processes for Social Media Popularity**. In *26th International Conference on World Wide Web - WWW '17*, pp. 735-744, Perth, Australia, 2017. doi: 10.1145/3038912.3052650
pdf at arxiv with supplementary material

Rizoiu, M.-A., & Xie, L. (2017). **Online Popularity under Promotion: Viral Potential, Forecasting, and the Economics of Time**. In *11th International AAAI Conference on Web and Social Media - ICWSM '17*, p. 10, Montréal, Canada, 2017.
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)**

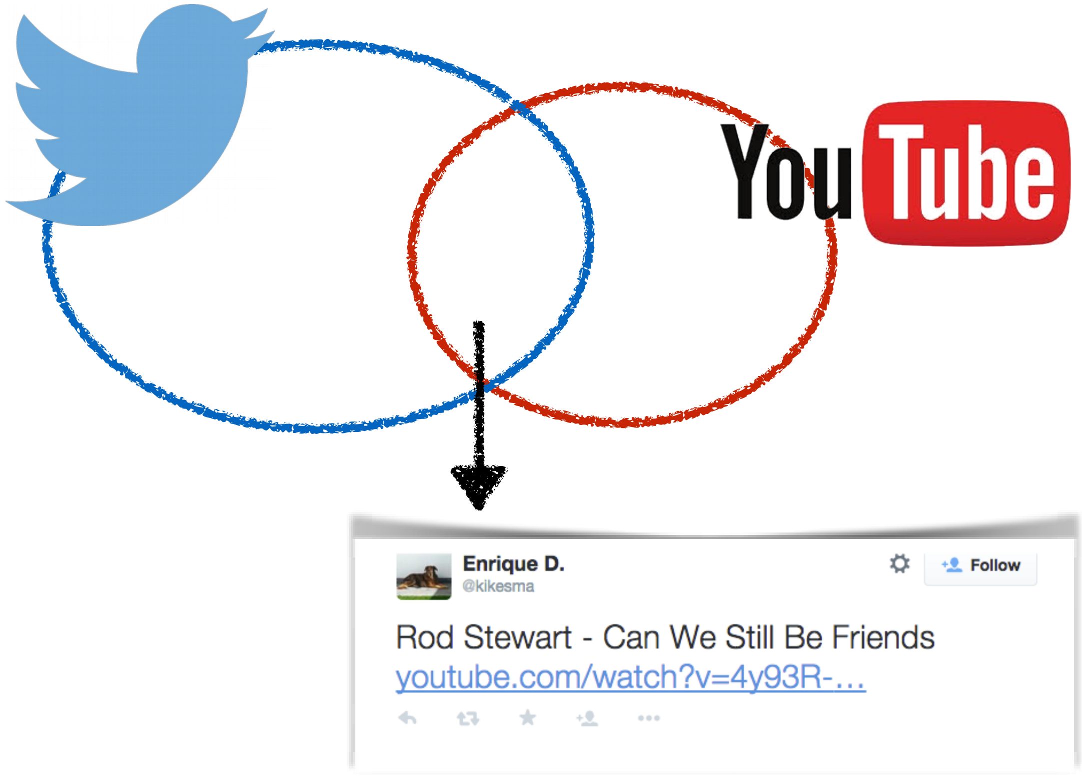


Information about this video

| Video property | Property value |
|---|---|
| YoutubeID | 9wMEbyzxNHI |
| Title | Men Try Women's Makeup For The First Time |
| Author | BuzzFeedYellow |
| Category | 4 |
| Upload date | 2014-07-23 02:00:00 |
| #views | 8432791 |
| #shares | 6928 |
| #tweets | 4641 |
| Endogenous response | 1 |
| Exogenous sensitivity | 760.8 |

Showing 1 to 10 of 10 entries

# Twitter videos dataset



Enrique D.
@kikesma

Rod Stewart - Can We Still Be Friends
youtube.com/watch?v=4y93R-...

| Category | #vids | Category | #vids |
|---|---|---|---|
| Comedy | 865 | Music | 3549 |
| Education | 298 | News & Politics | 1722 |
| Entertainment | 2422 | Nonprofits & Activism | 333 |
| Film & Animation | 664 | People & Blogs | 1947 |
| Gaming | 882 | Science & Technology | 262 |
| Howto & Style | 180 | Sports | 614 |
| Total: | 13,738 | | |

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

# Prior work and gaps

## 1) Modeling popularity

power-law shapes [Crane & Sornette PNAS'08]
power-law decays with periodicity [Matsubara et al KDD'12]
collection of recurrence peaks [Cheng et al WWW'16]

How would popularity evolve under continuous external influence?

## 2) Explaining virality

diffusion history [Cheng et al WWW'14]
positive sentiment [Bakshy et al WSDM'11]

Can something go viral if promoted?

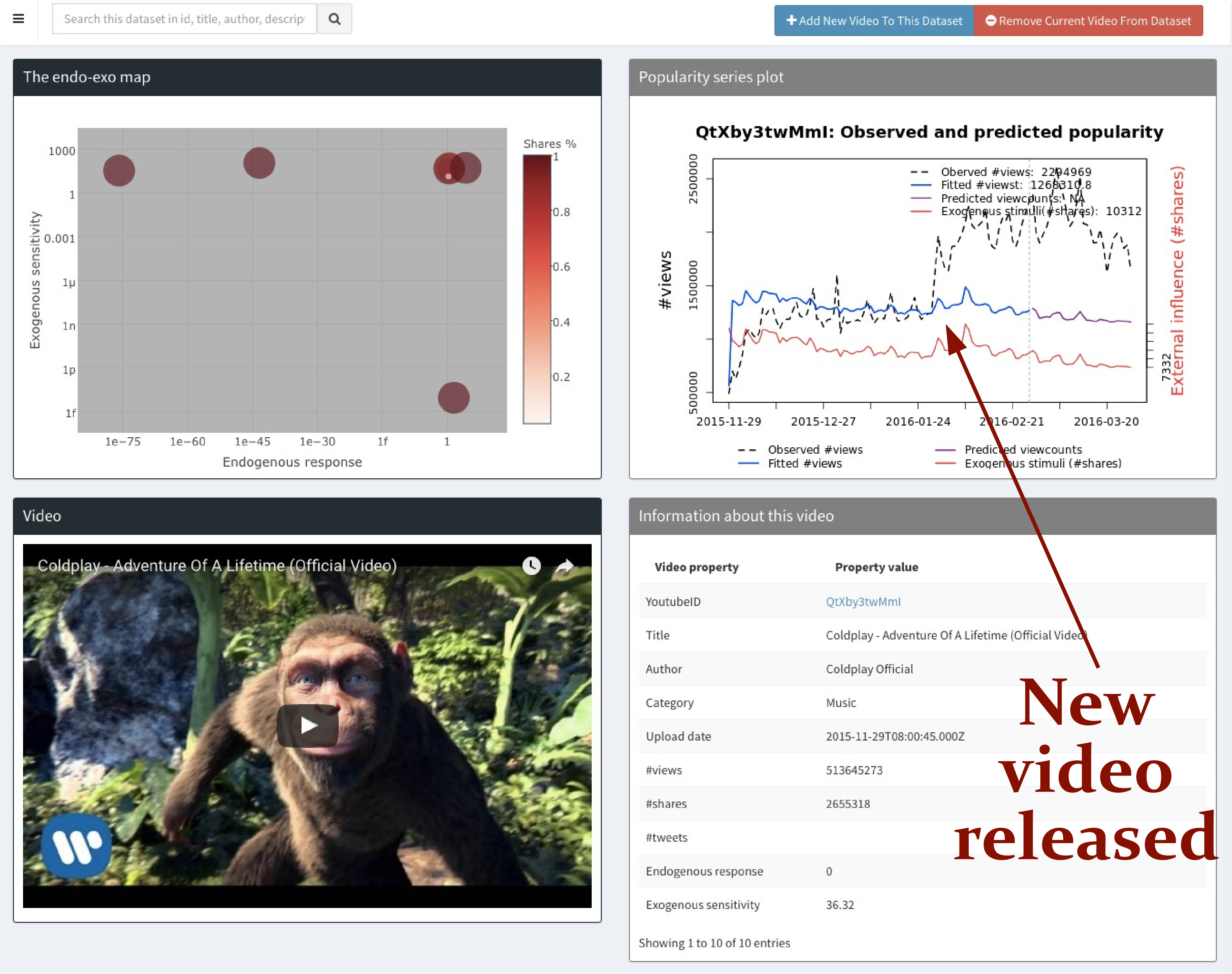
## 3) Predicting future popularity

popularity history [Pinto et al WSDM'13] [Szabo and Huberman Comm.ACM 10]
timing features [Cheng et al WWW'14]

How to forecast future popularity given planned promotions?

# Supp: when HIP fails the fitting (1)

Relations between videos:



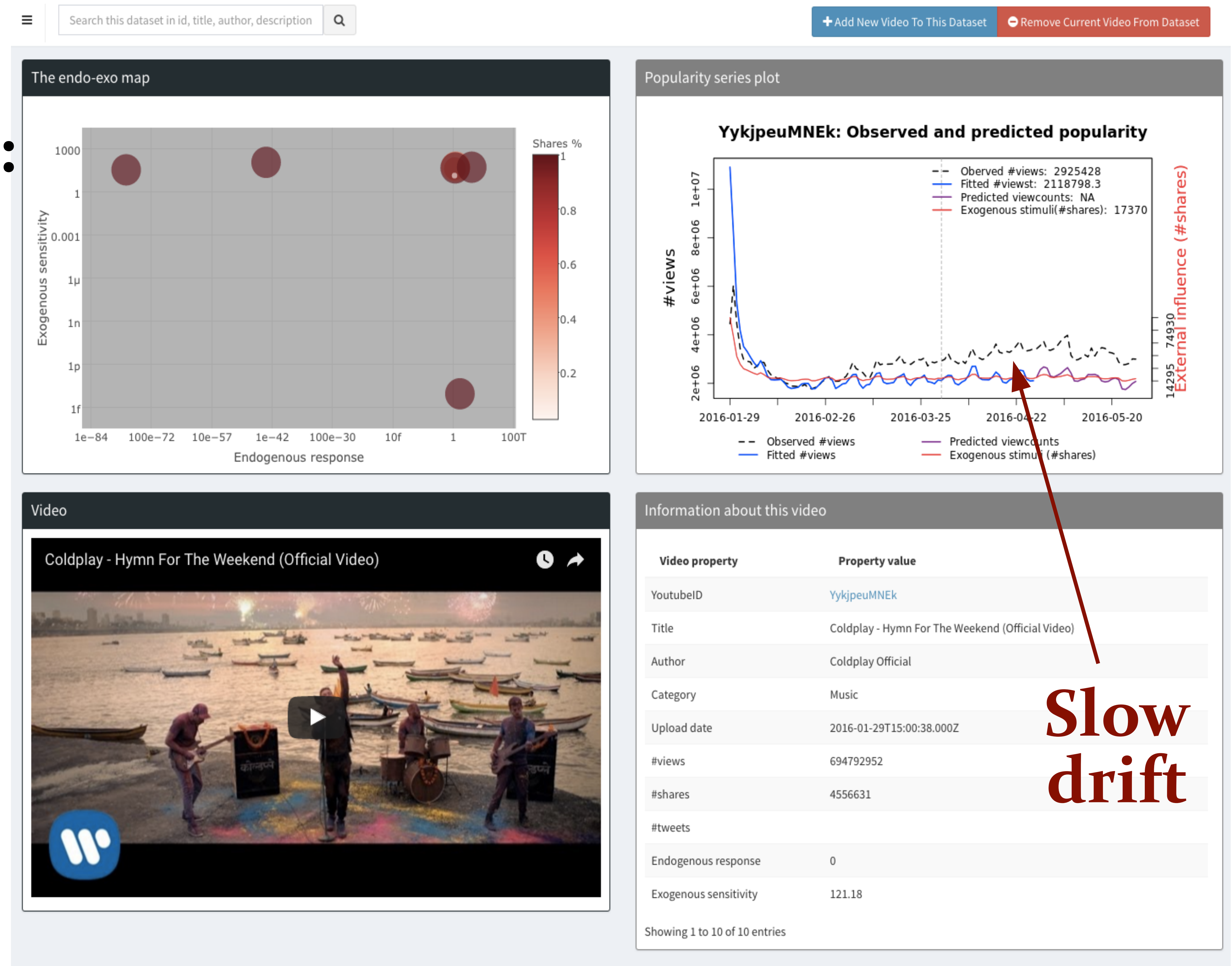
| Video property | Property value |
|---|---|
| YoutubeID | QtXby3twMmI |
| Title | Coldplay - Adventure Of A Lifetime (Official Video) |
| Author | Coldplay Official |
| Category | Music |
| Upload date | 2015-11-29T08:00:45.000Z |
| #views | 513645273 |
| #shares | 2655318 |
| #tweets | |
| Endogenous response | 0 |
| Exogenous sensitivity | 36.32 |

Showing 1 to 10 of 10 entries

New video released

# Supp: when HIP fails the fitting (2)

Long term evolutions:



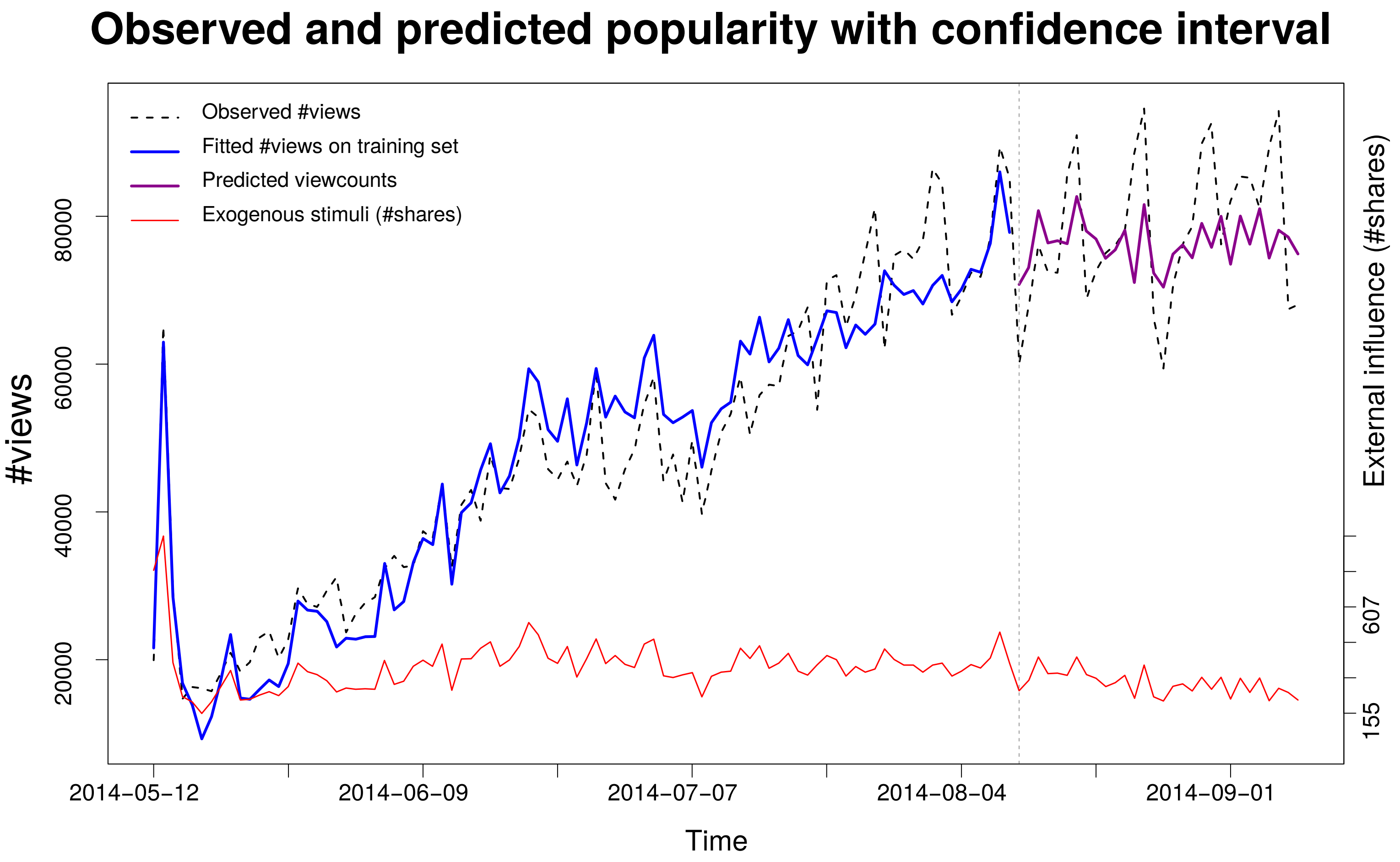
Information about this video

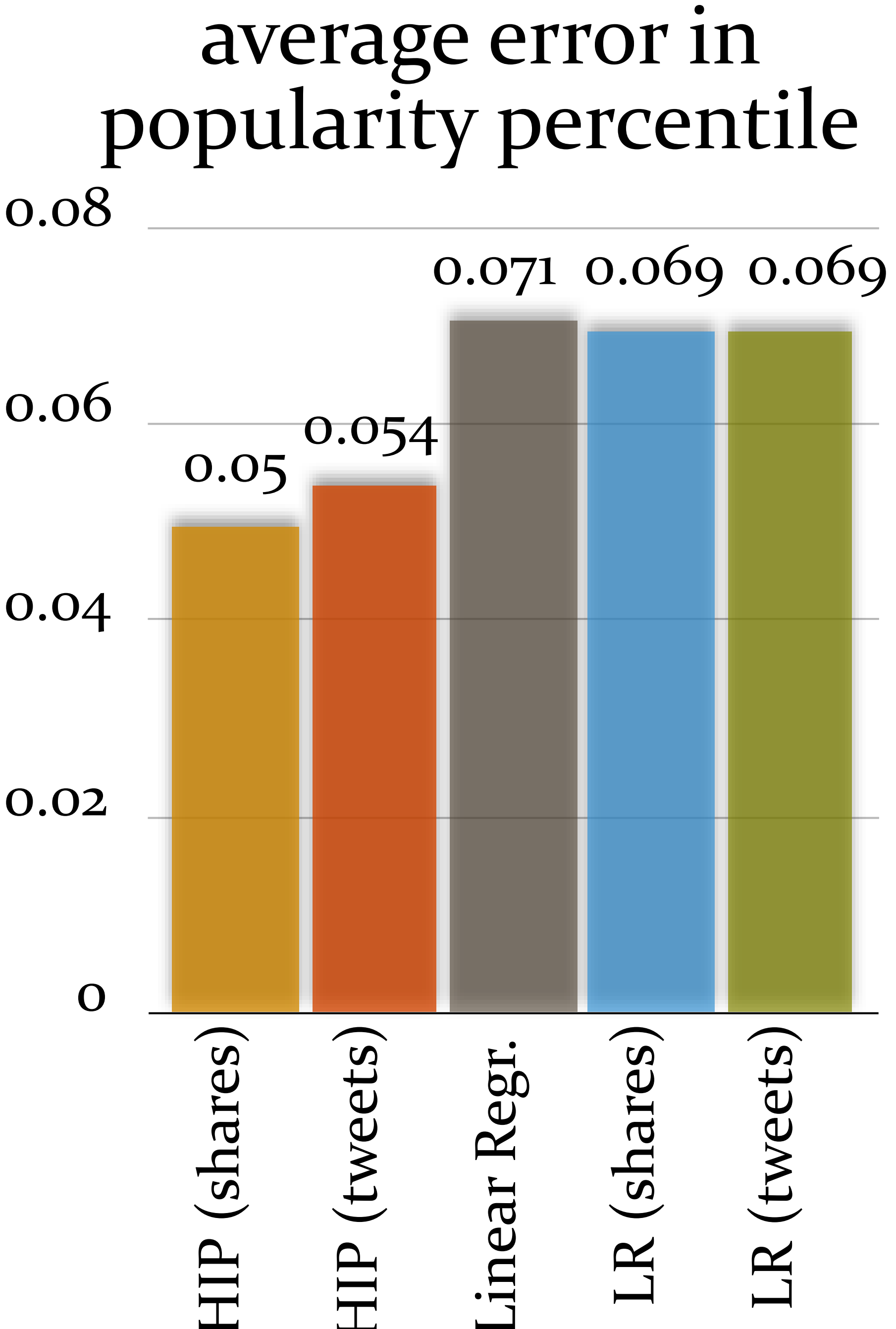
| Video property | Property value |
|---|---|
| YoutubeID | YykjpeuMNEk |
| Title | Coldplay - Hymn For The Weekend (Official Video) |
| Author | Coldplay Official |
| Category | Music |
| Upload date | 2016-01-29T15:00:38.000Z |
| #views | 694792952 |
| #shares | 4556631 |
| #tweets | |
| Endogenous response | 0 |
| Exogenous sensitivity | 121.18 |

Showing 1 to 10 of 10 entries

**Slow drift**

# Forecasting the effect of promotions





[Pinto et al WSDM’13]

[Szabo & Huberman Comm. ACM’13] [Yu et al ICWSM‘15]