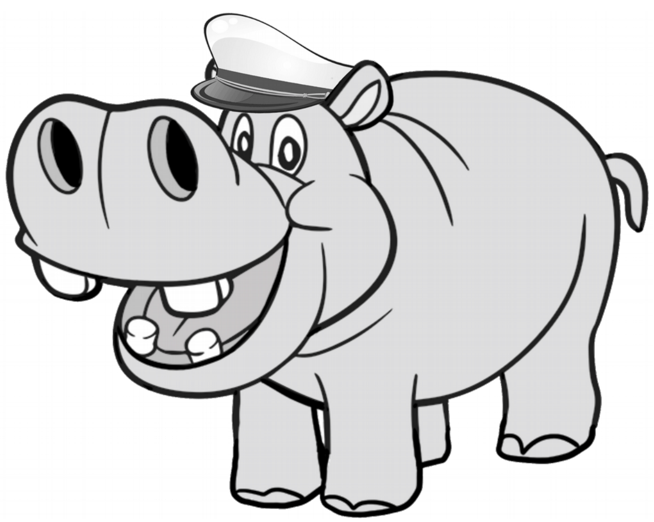
Behavioral Data Science

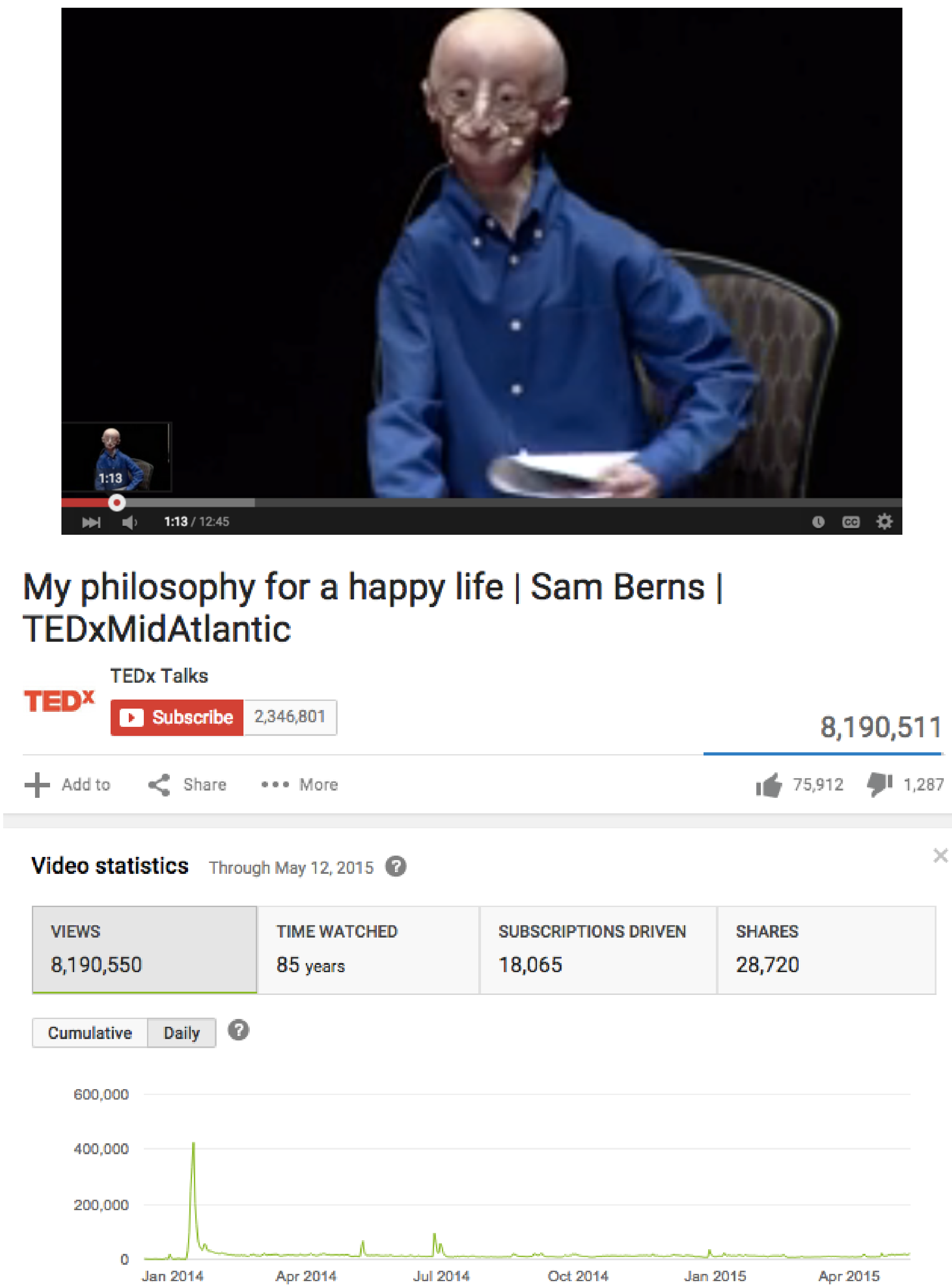
UTS
UNIVERSITY OF TECHNOLOGY SYDNEY

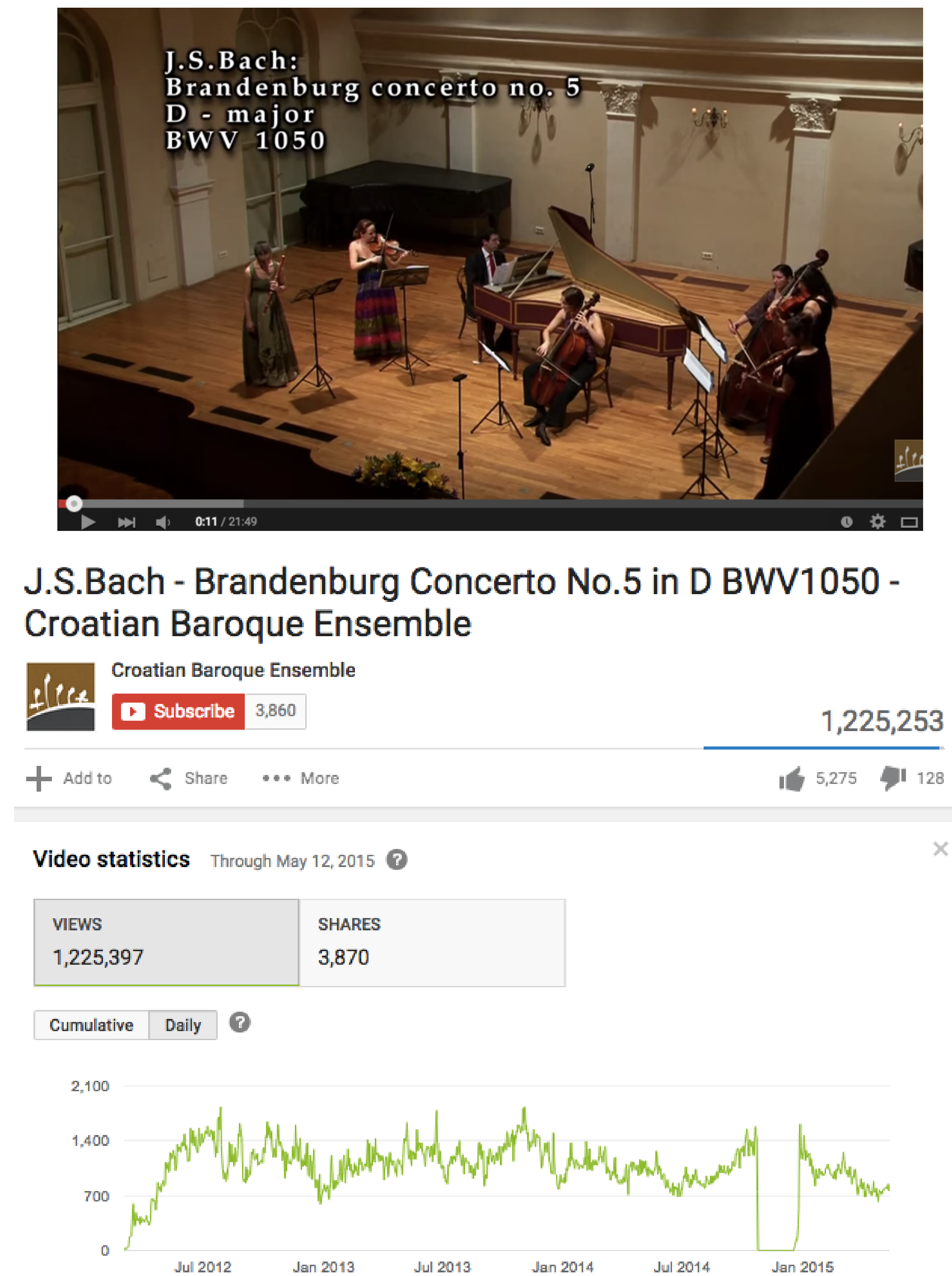


Expecting to be HIP:
Hawkes Intensity Processes for modeling online popularity and virality

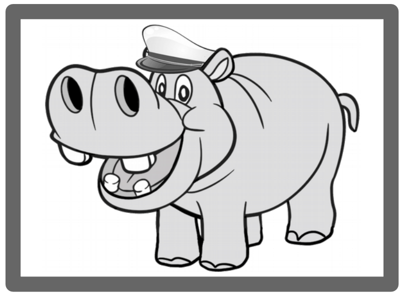
Marian-Andrei Rizoiu

Popularity over time

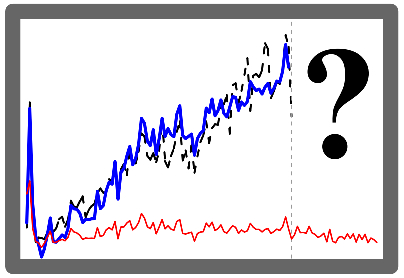




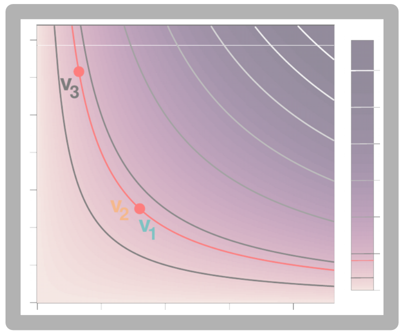
Presentation outline



Modeling popularity with HIP



Forecasting popularity under promotion



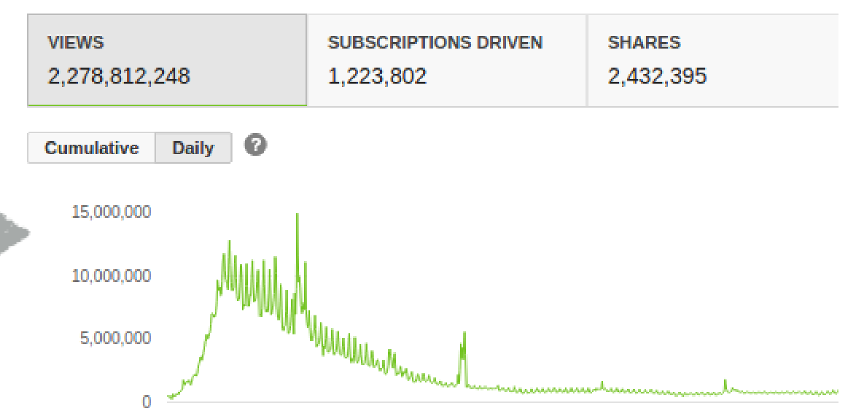
Content virality and maturity time

Promotions schedules and memory lengthening through promotion

Linking exo-endo popularity

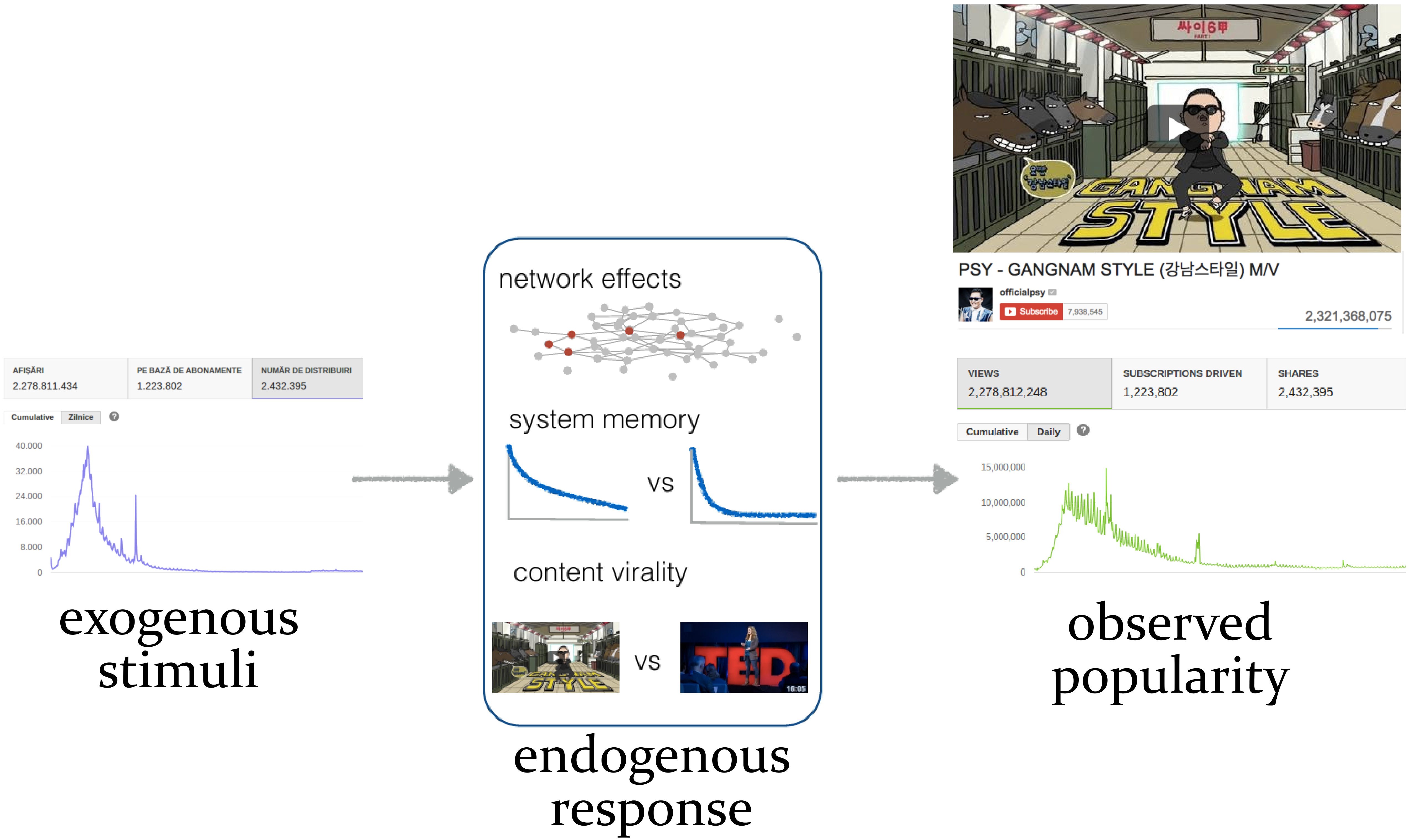
exogenous
stimuli

endogenous
response



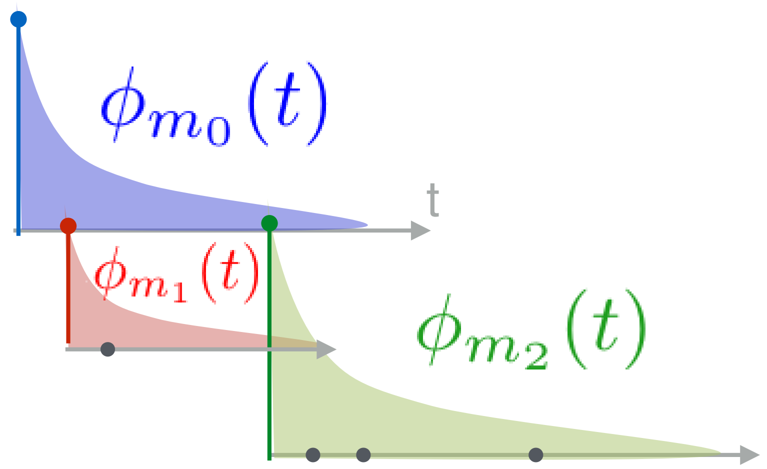
observed
popularity

Linking exo-endo 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]

Hawkes Process [Hawkes '71]

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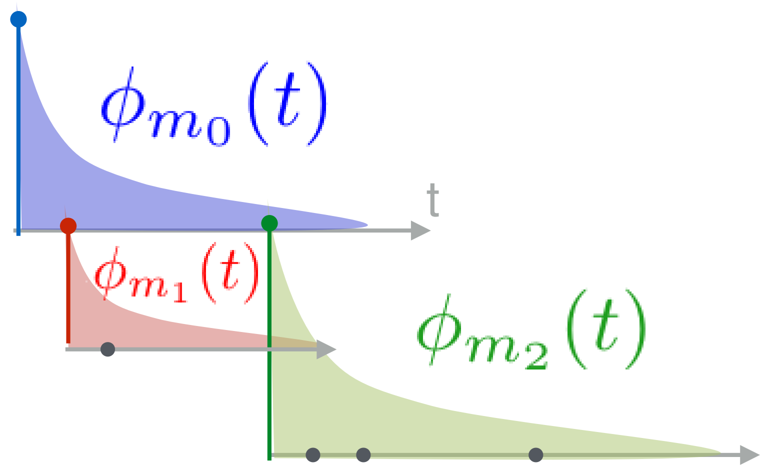

the rate of 'daughter' events | content virality | user influence | memory

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

[Mishra et al CIKM'16]

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

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Hawkes Intensity Process (HIP)

[Rizoiu et al, WWW'17]

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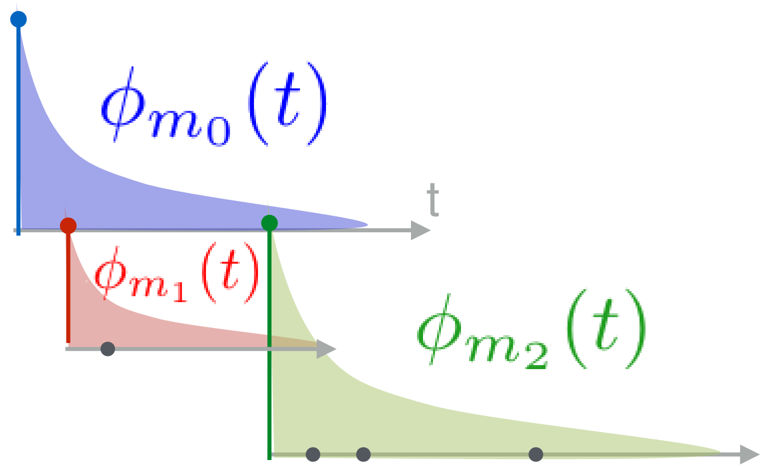

the rate of 'daughter' events

content virality

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

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[Rizoiu et al, WWW'17]

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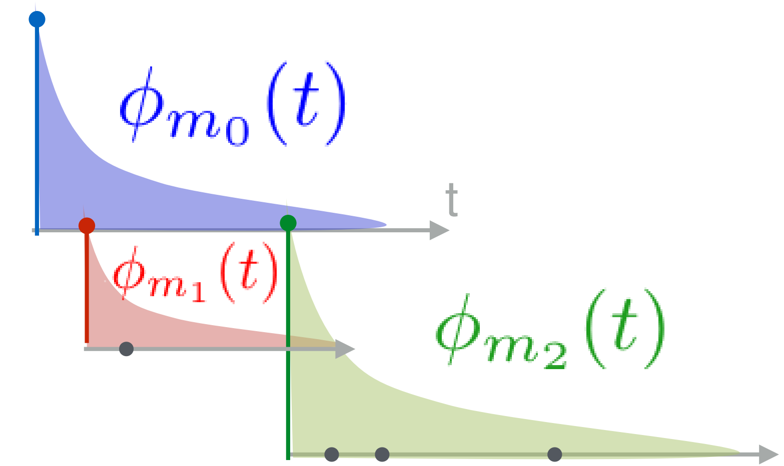

the rate of 'daughter' events | content virality | user influence | memory

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

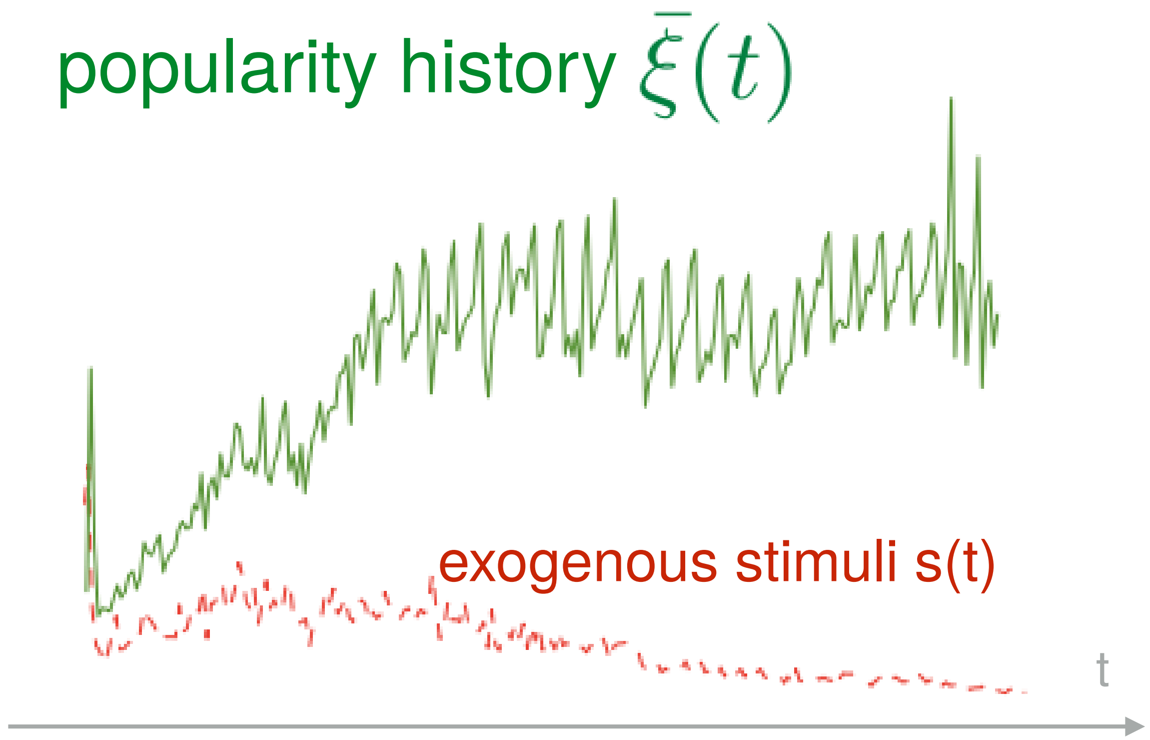
popularity

exogenous sensitivity

exogenous stimuli

endogenous reaction

Estimating the HIP model



$$\text{find } \{\mu, C, \theta, \ldots\}$$
$$\text{s.t.} \quad \min \sum_t l(\xi(t) - \bar{\xi}(t))$$

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

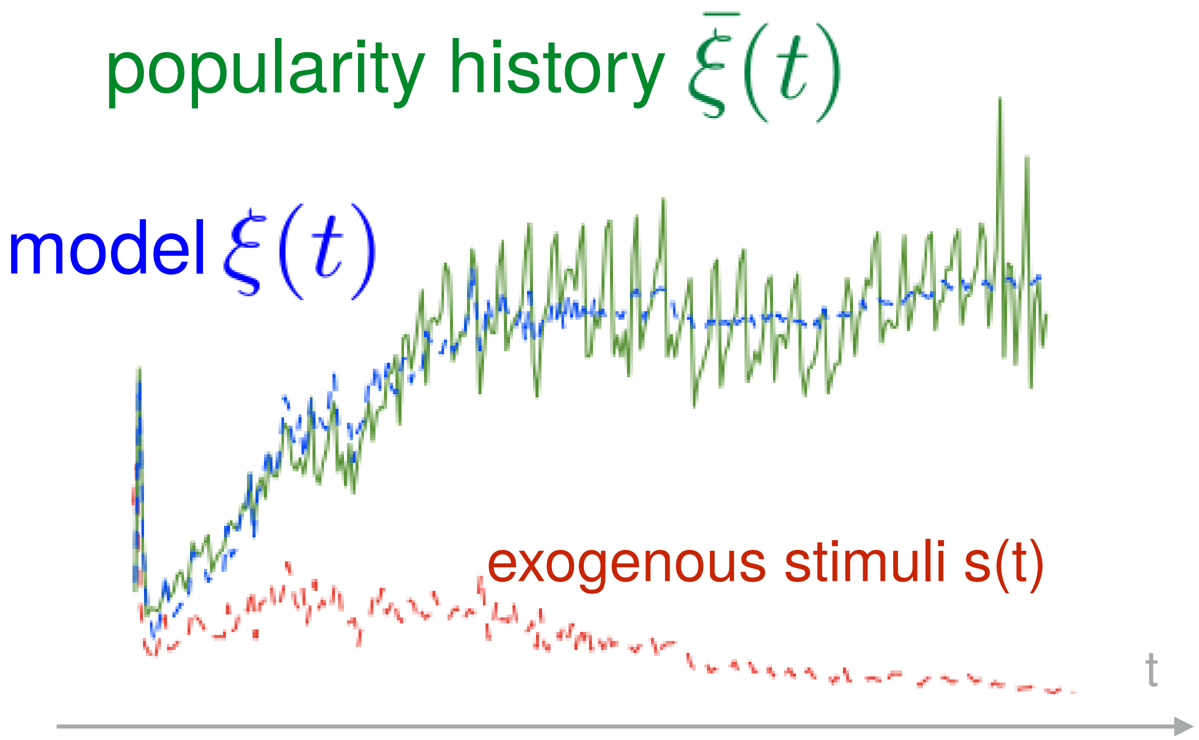
popularity

exogenous sensitivity

exogenous stimuli

endogenous reaction

Estimating the HIP model



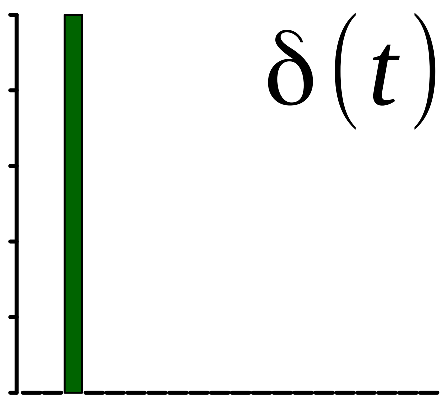
$$\text{find } \{\mu, C, \theta, \ldots\}$$

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

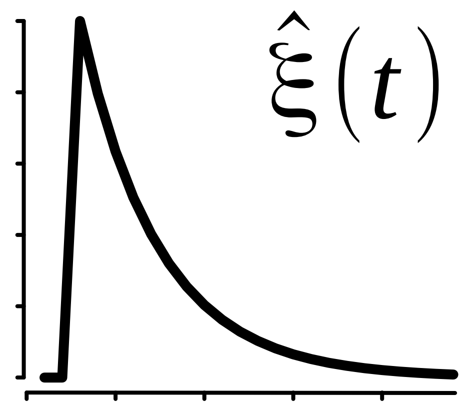
$$\underbrace{\xi(t)}_{\text{popularity}} = \underbrace{\mu}_{\text{exogenous sensitivity}} \underbrace{s(t)}_{\text{exogenous stimuli}} + \underbrace{C \int_0^t \xi(t-\tau)\hat{\tau}^{-(1+\theta)} d\tau}_{\text{endogenous reaction}}$$

HIP as a Linear Time-Invariant system

promotion



response



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

popularity

exogenous sensitivity

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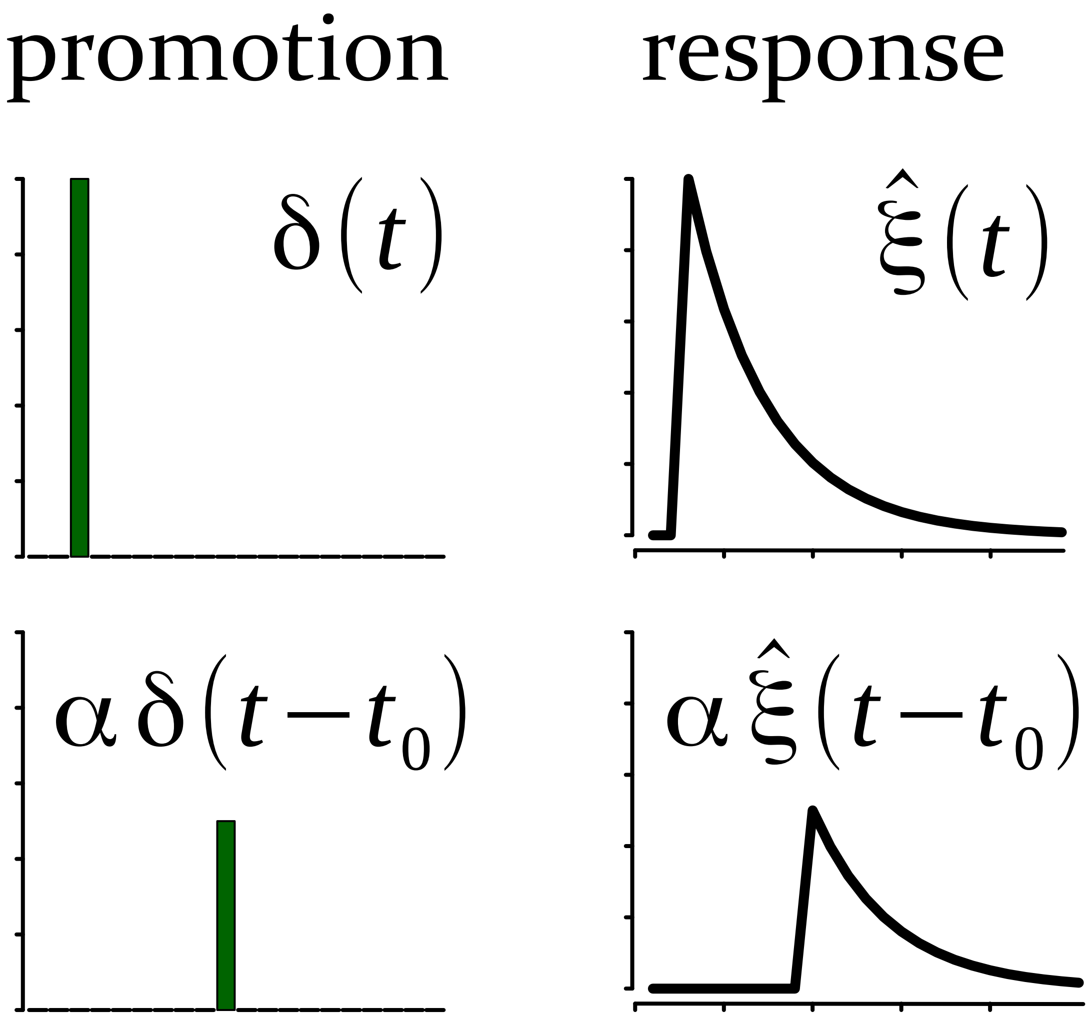
HIP as a Linear Time-Invariant system



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popularity

exogenous sensitivity

exogenous stimuli

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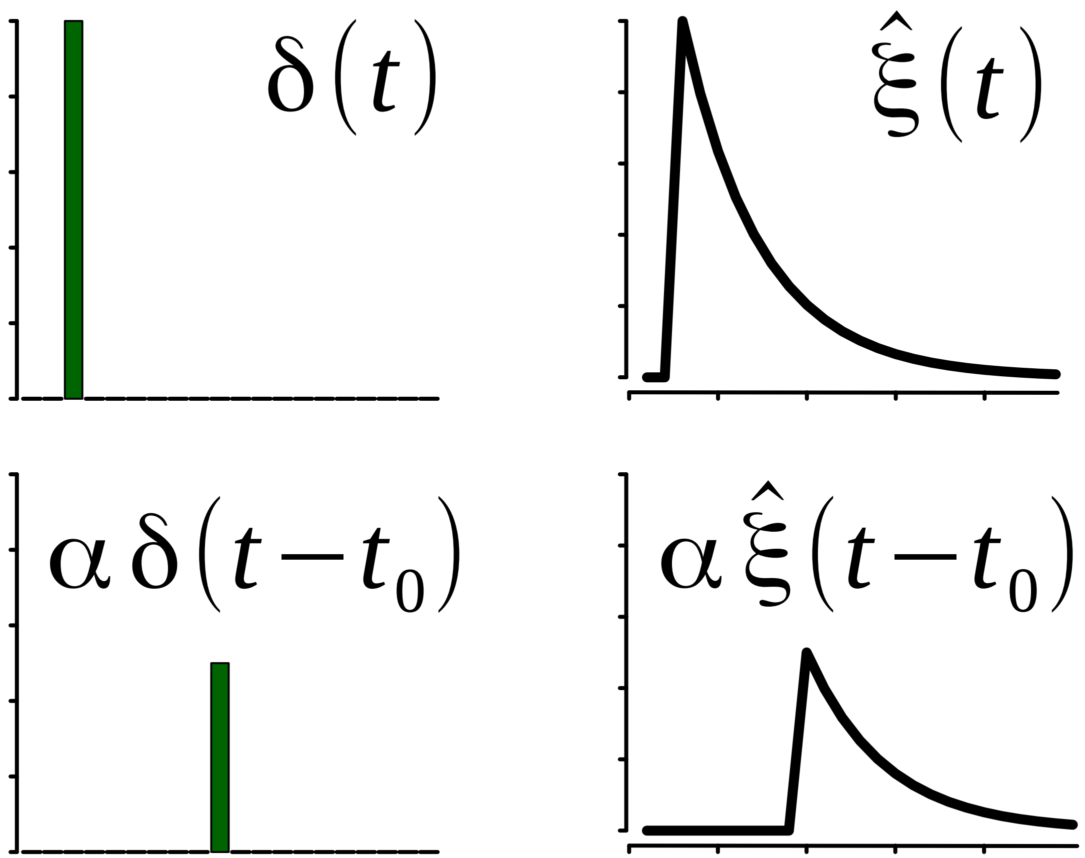
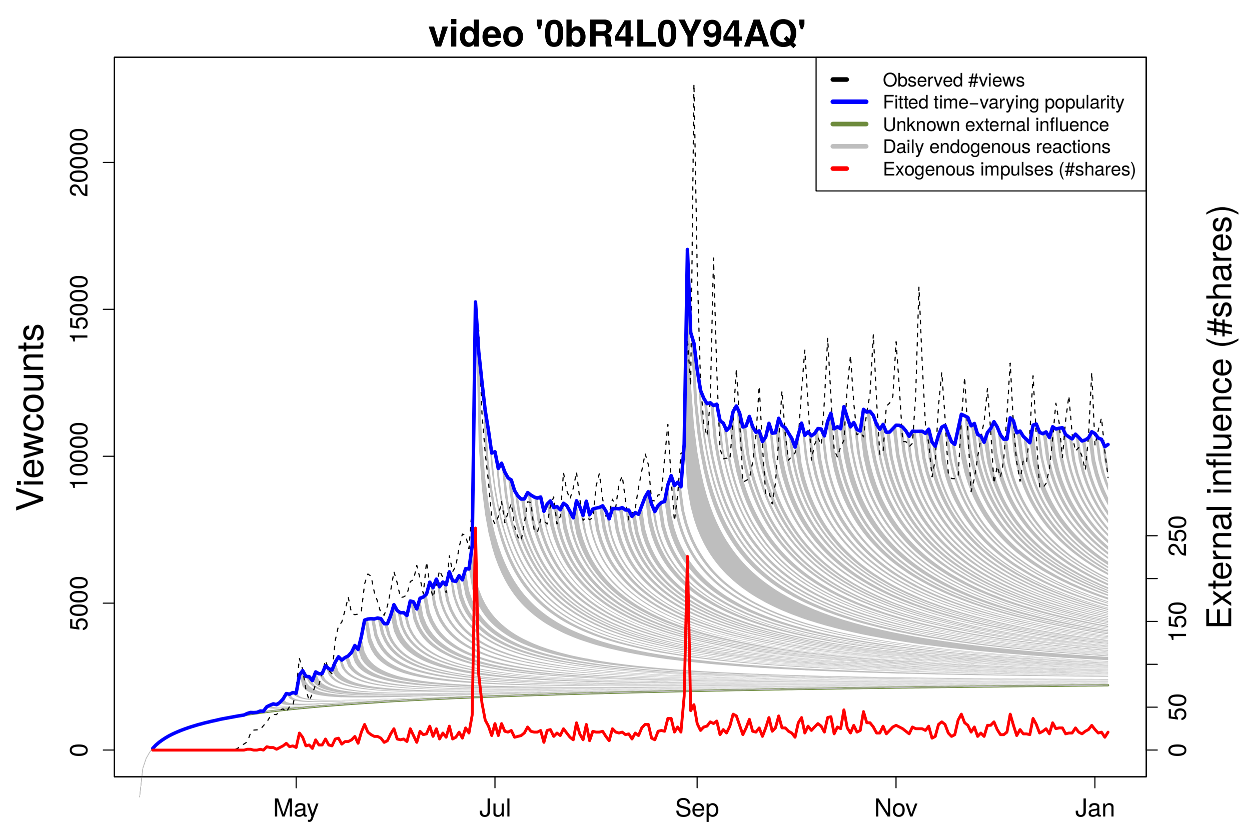
HIP as a Linear Time-Invariant system

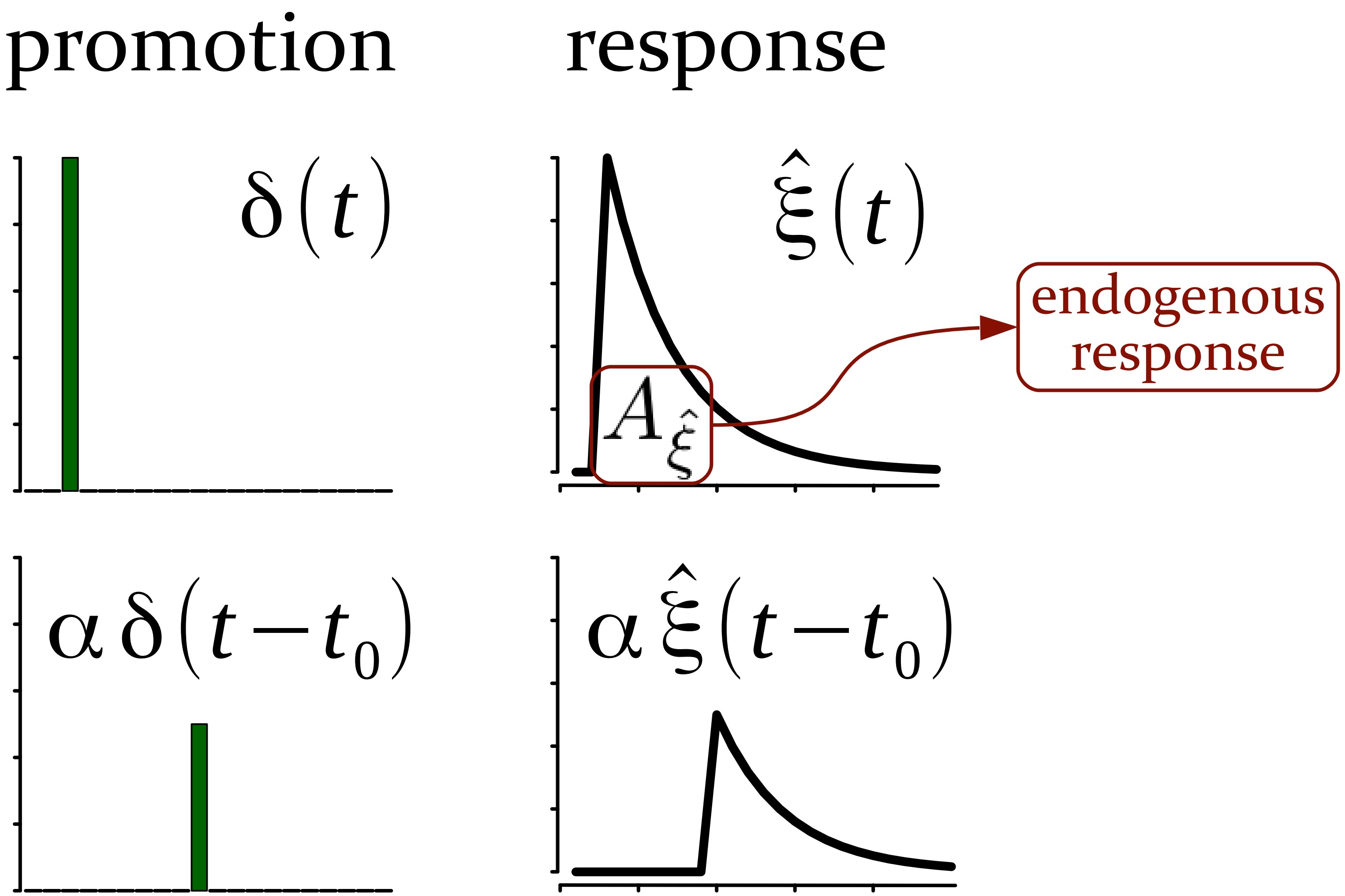
promotion response



scale,
shift, add



HIP as a Linear Time-Invariant system



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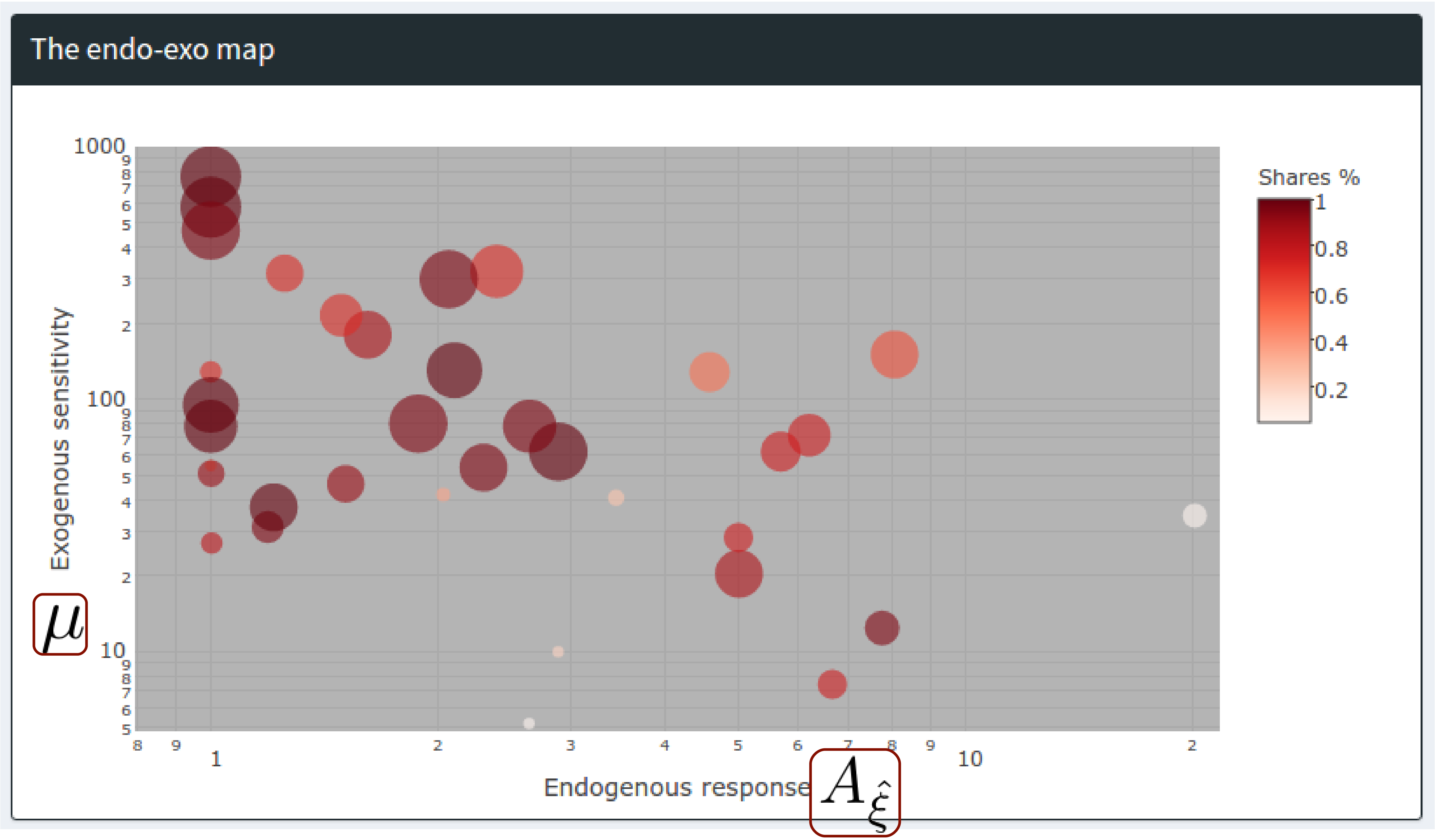
popularity

exogenous sensitivity

exogenous stimuli

The "endo-exo" map



Explain popularity dynamics

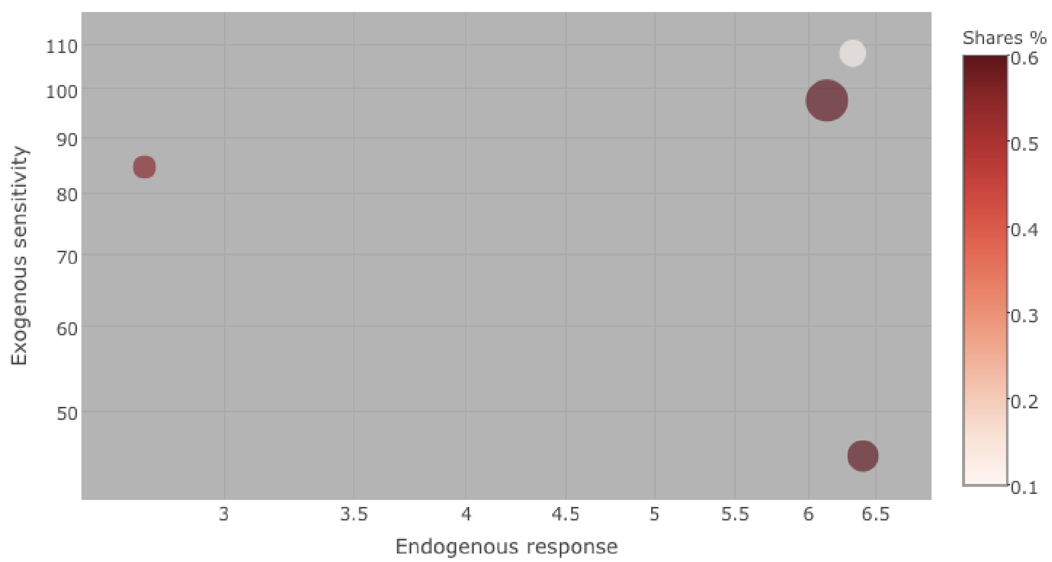
[Kong et al, WWW‘18]

YouTube

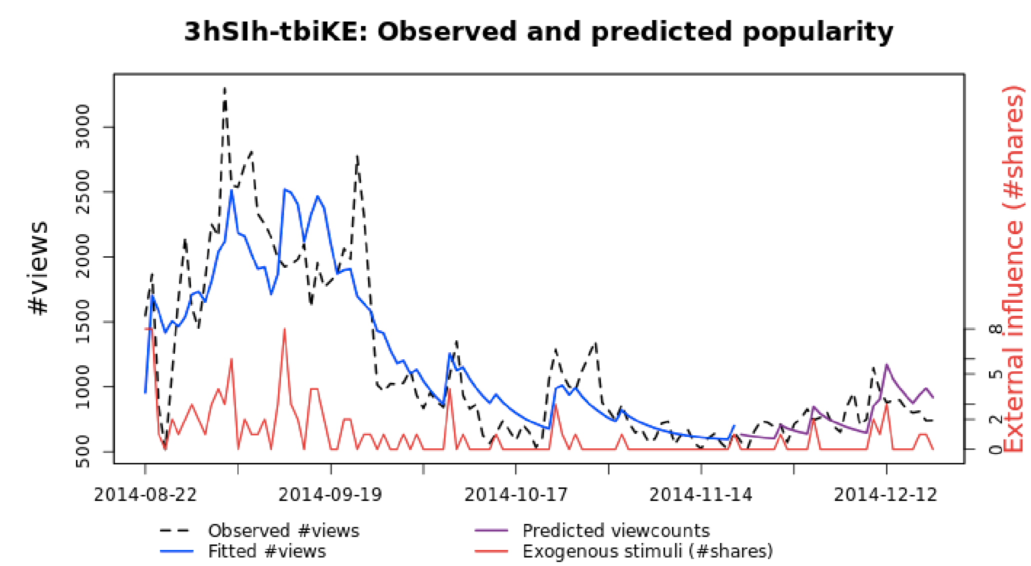
Search this dataset in id, title, author, descrip

+ Add New Video To This Dataset | Remove Current Video From Dataset

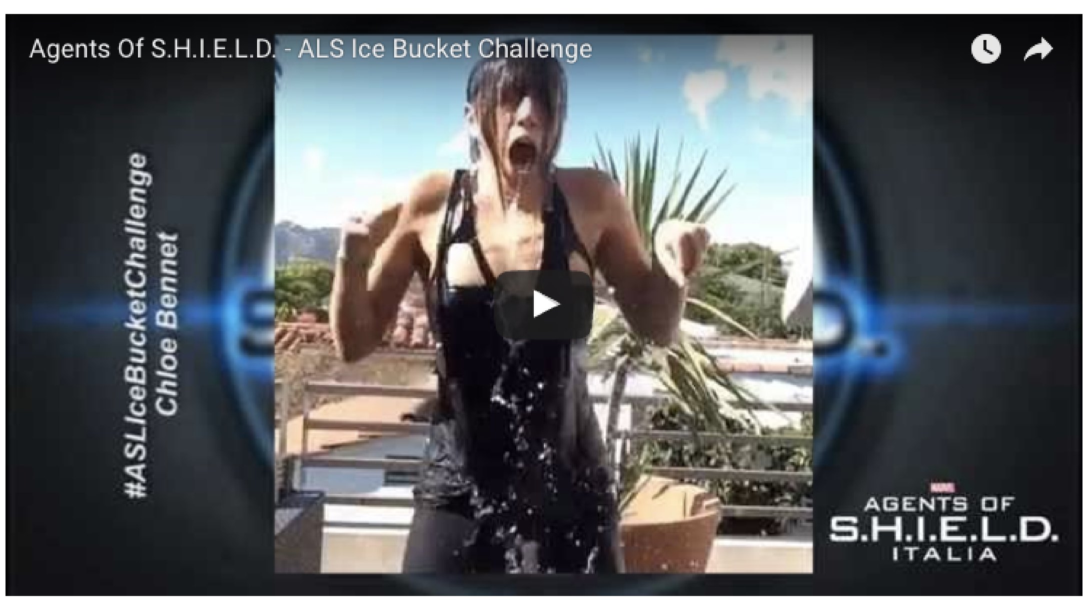
The endo-exo map



Popularity series plot



Video



Information about this video

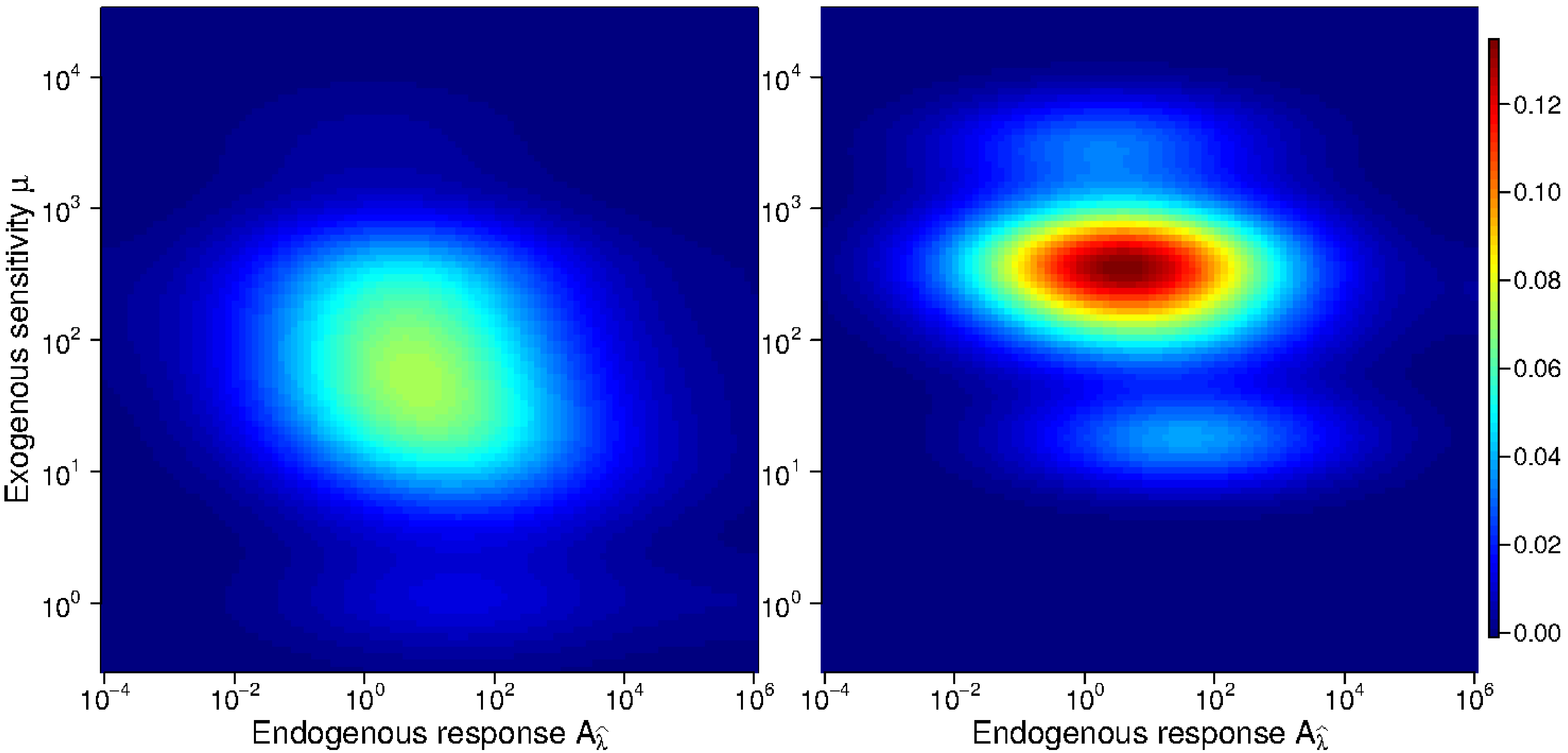
Video property	Property value
YoutubeID	3hSIh-tbiKE
Title	Agents Of S.H.I.E.L.D. - ASL Ice Bucket Challenge
Author	Agents of SHIELD Italia
Category	Film & Animation
Upload date	2014-08-22 02:00:00
#views	157595
#shares	117
#tweets	182
Endogenous response	6.32
Exogenous sensitivity	107.98

Showing 1 to 10 of 10 entries

Explain popularity – all vs top 5%

Film and Animation:

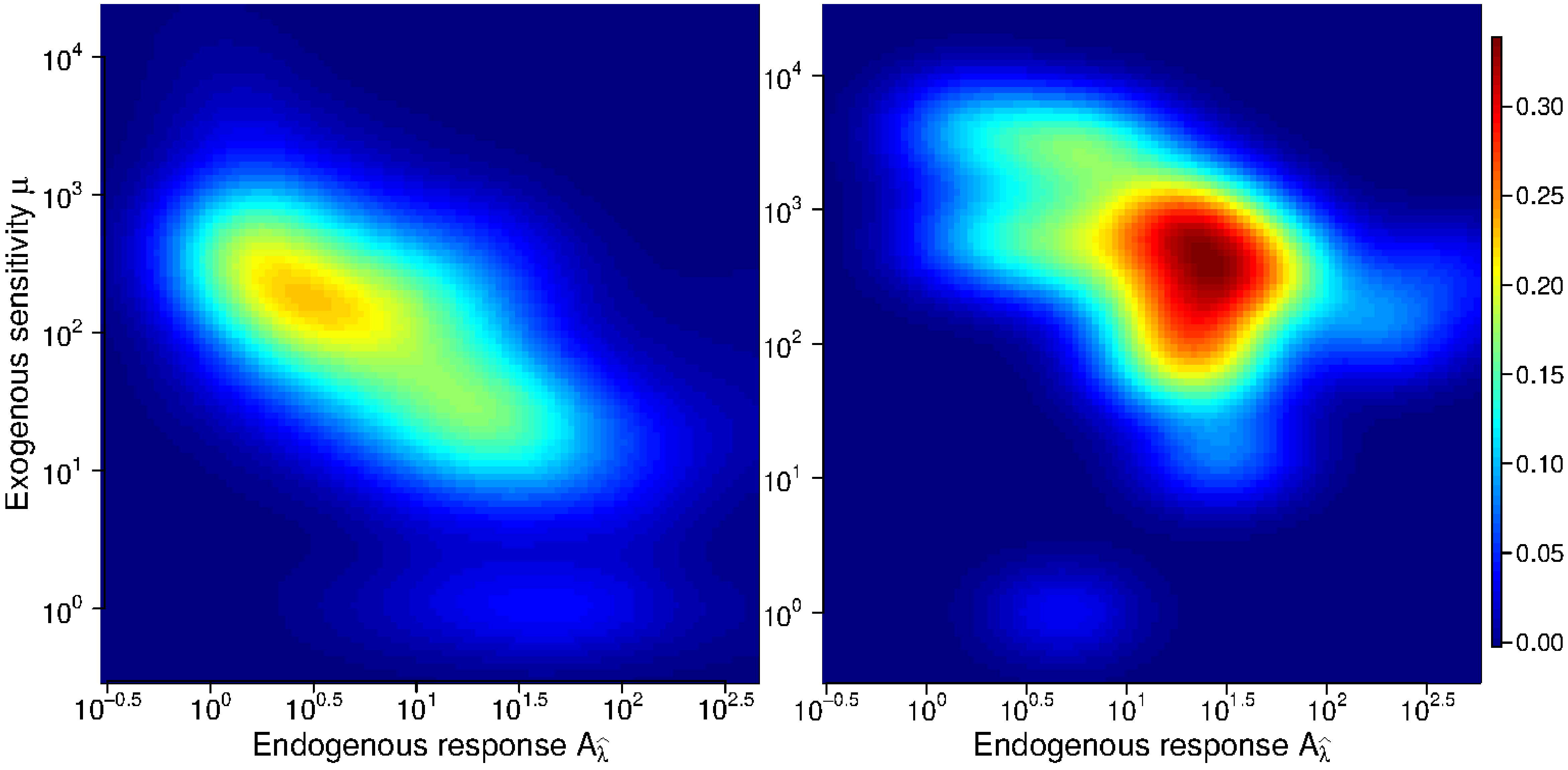
more popular videos have higher sensitivity



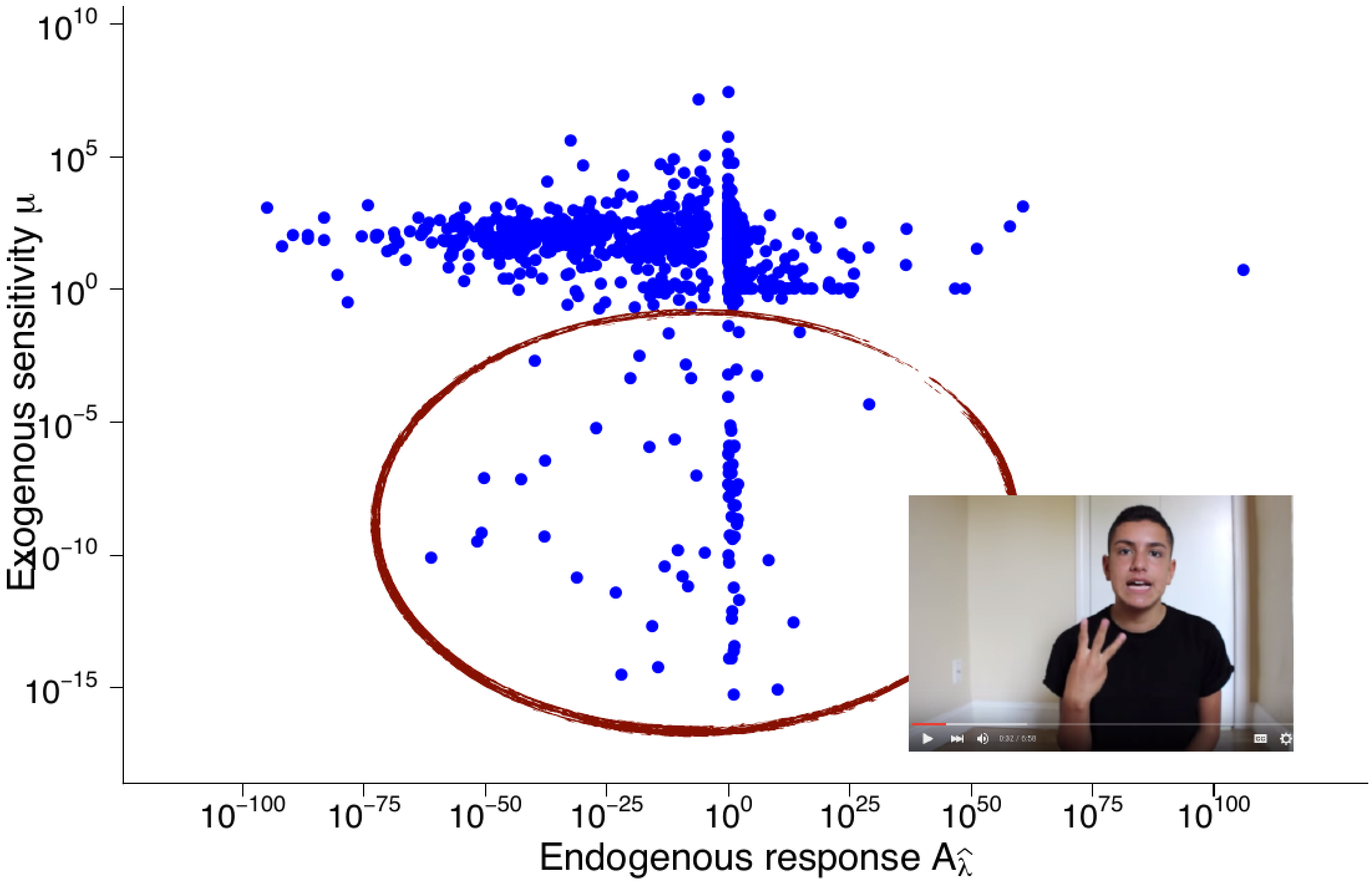
Explain popularity – all vs top 5%

Games:

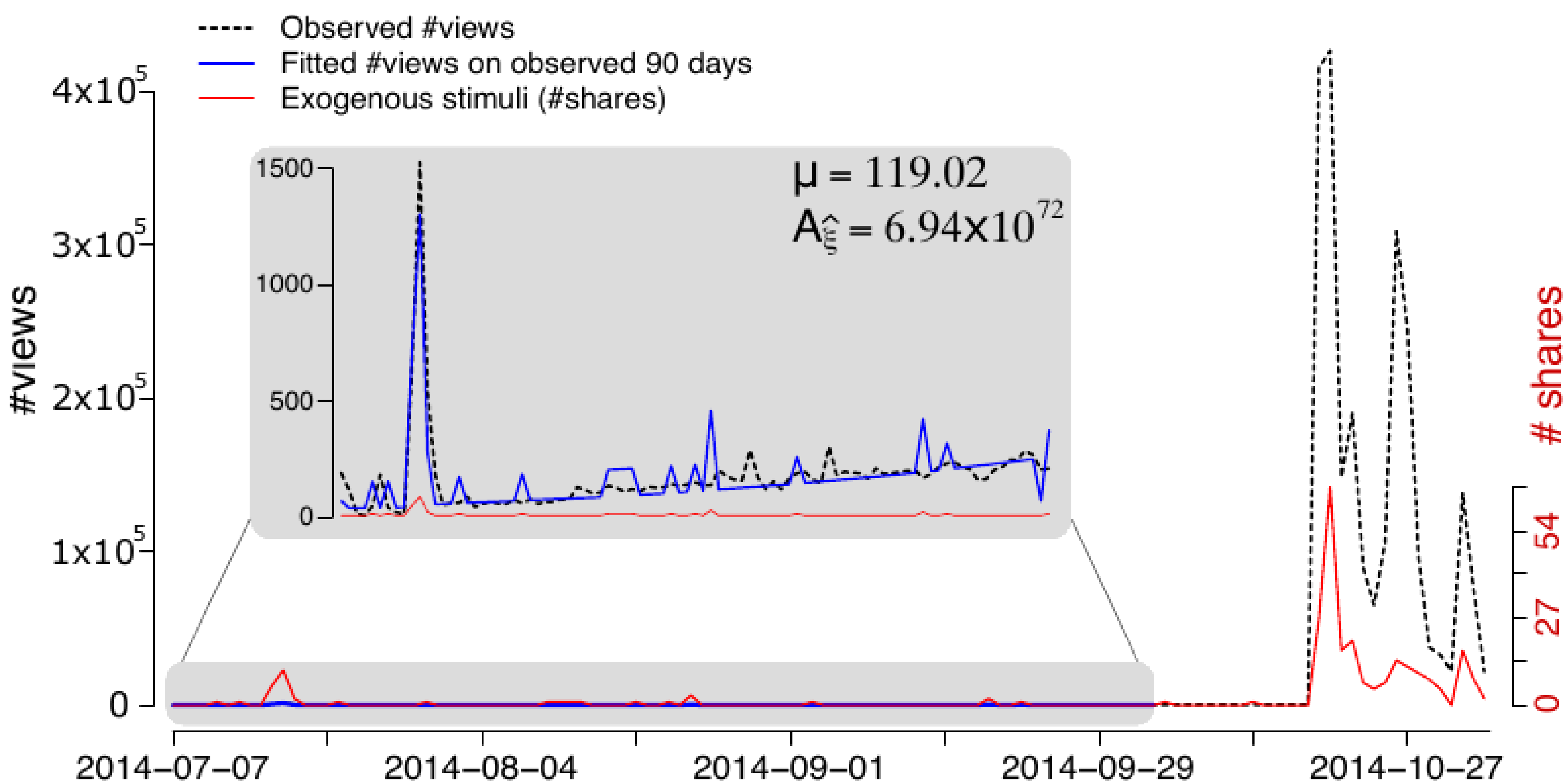
more popular videos have higher endogenous response



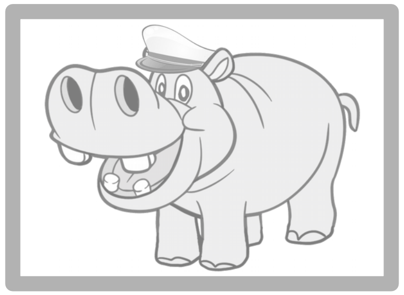
Which videos are un-promotable?



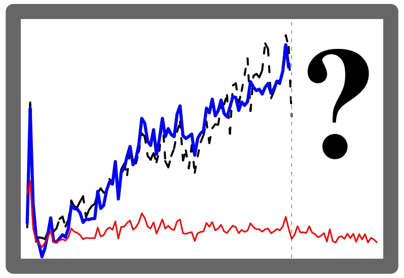
“Potentially viral” video



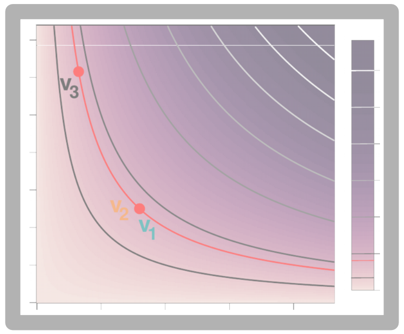
Presentation outline



Modeling popularity with HIP



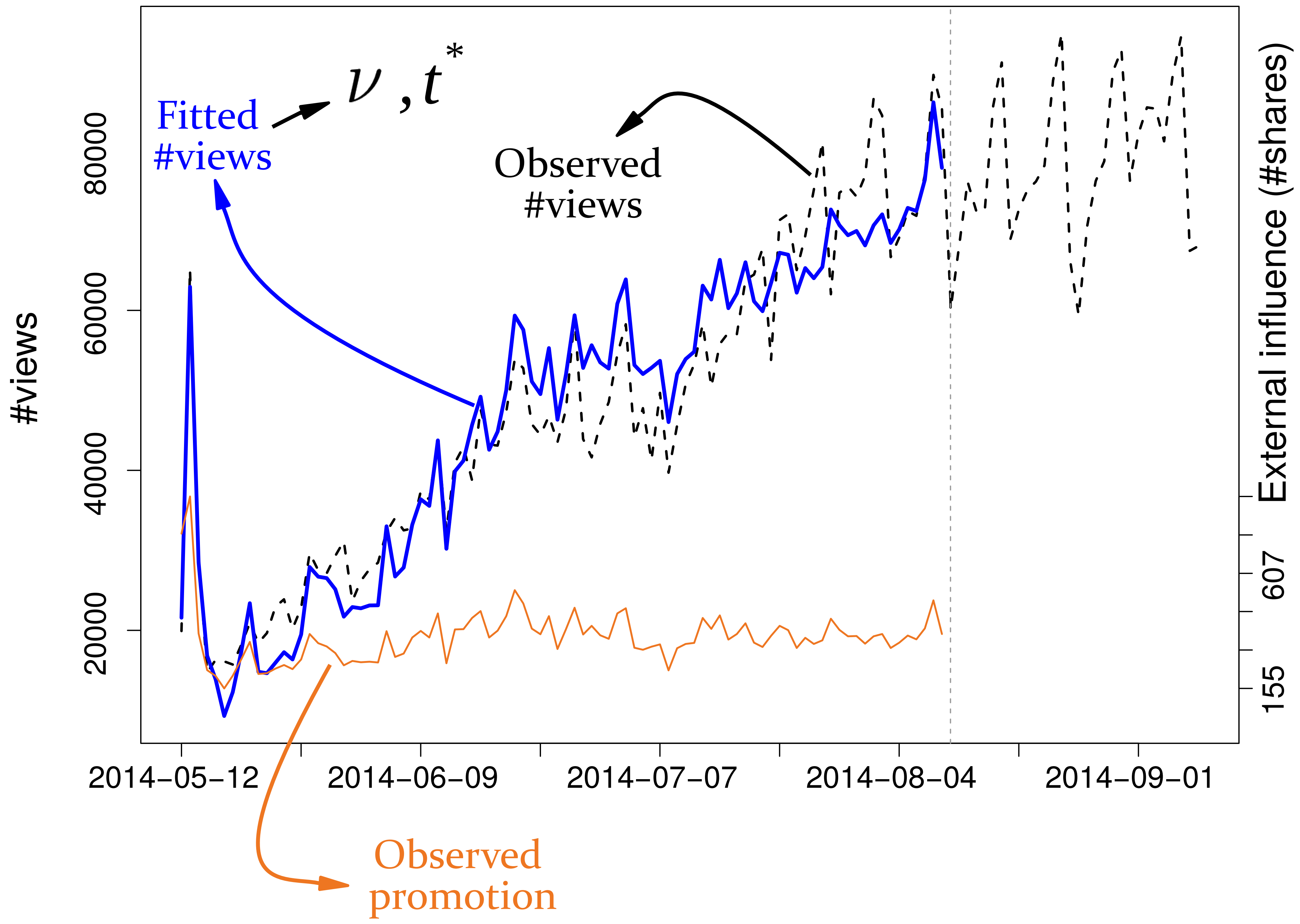
A progression of two problems relating to predicting popularity under promotion



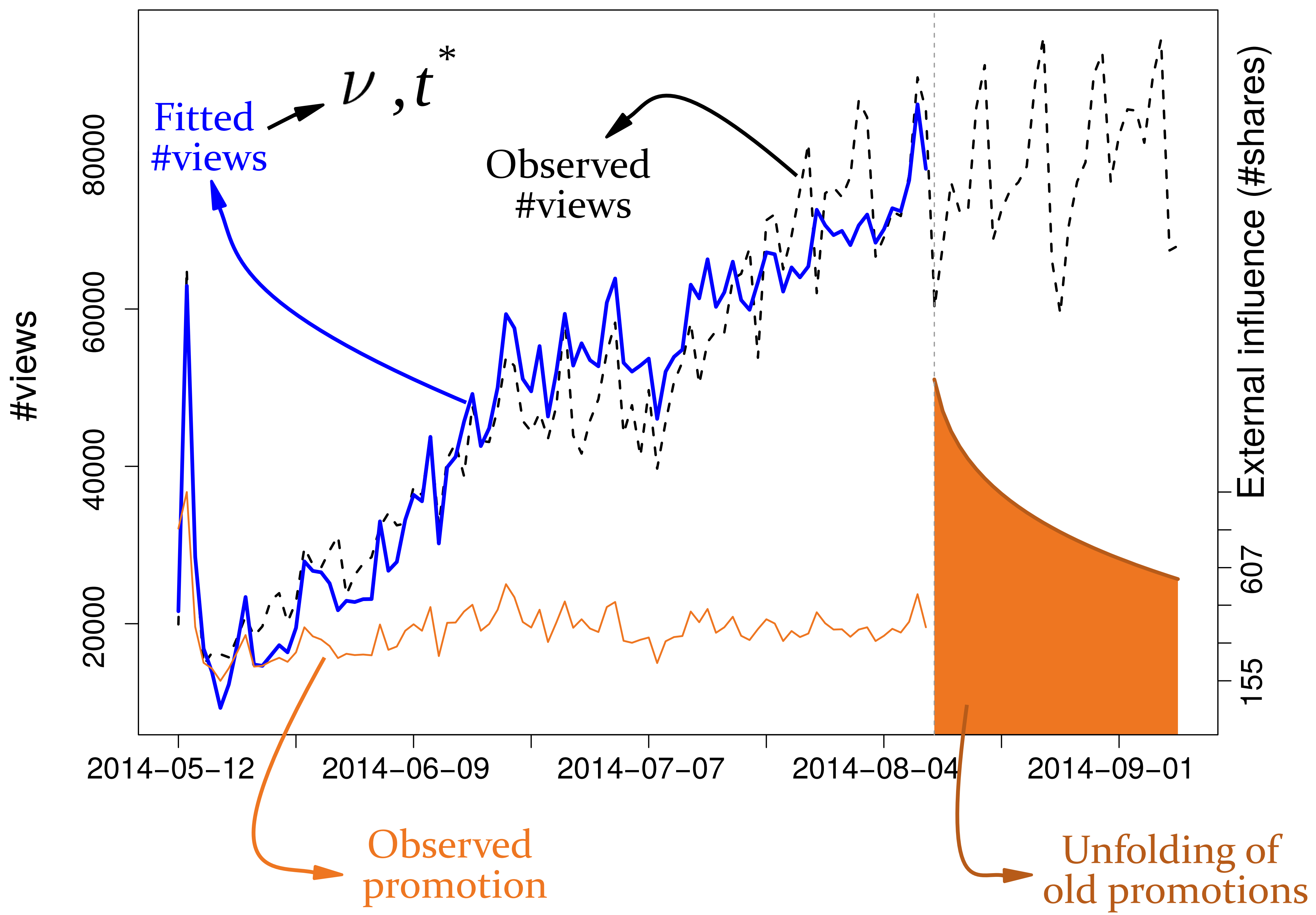
Content virality and maturity time

Promotions schedules and memory lengthening through promotion

Forecasting future views (1)



Forecasting future views (1)



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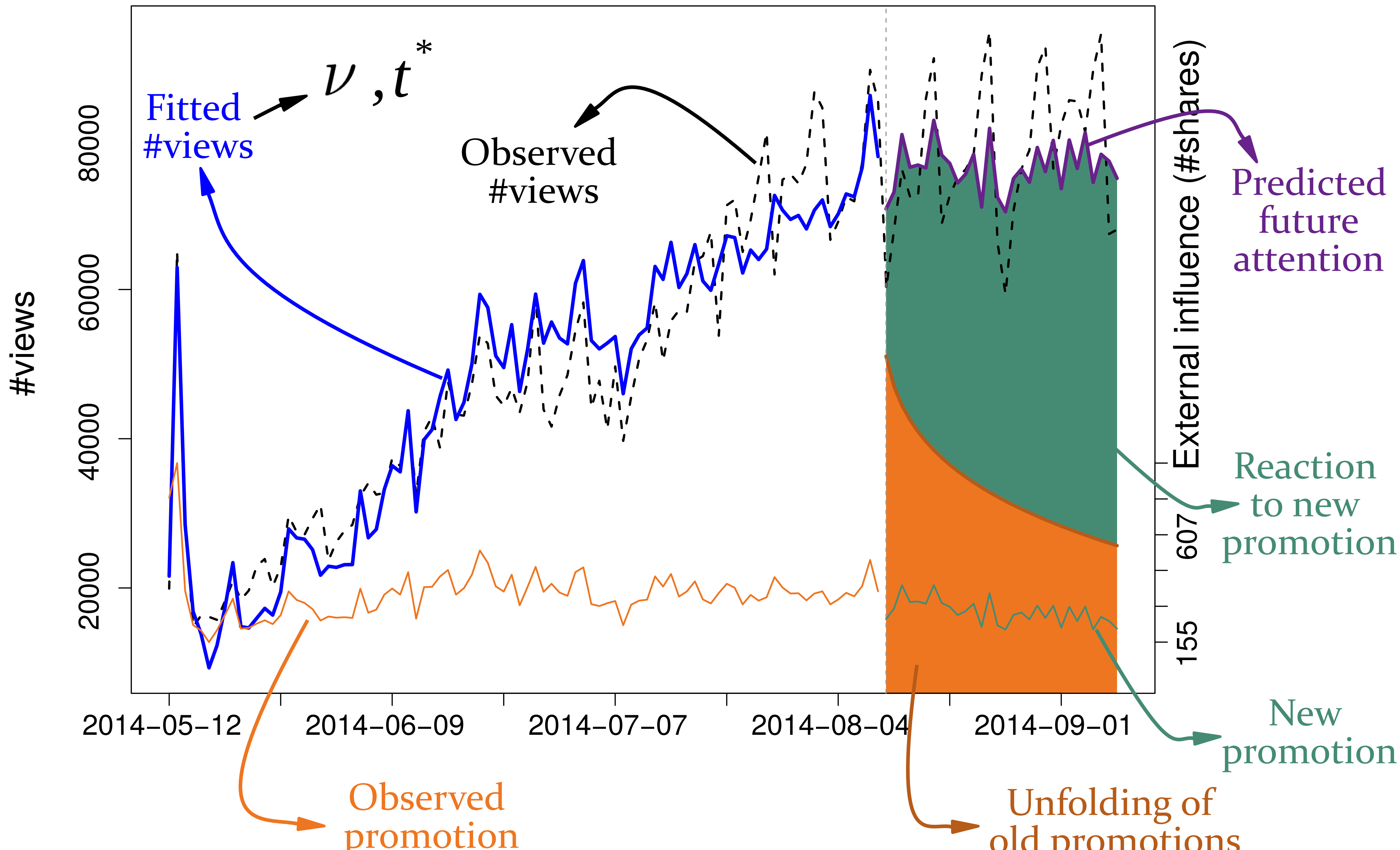
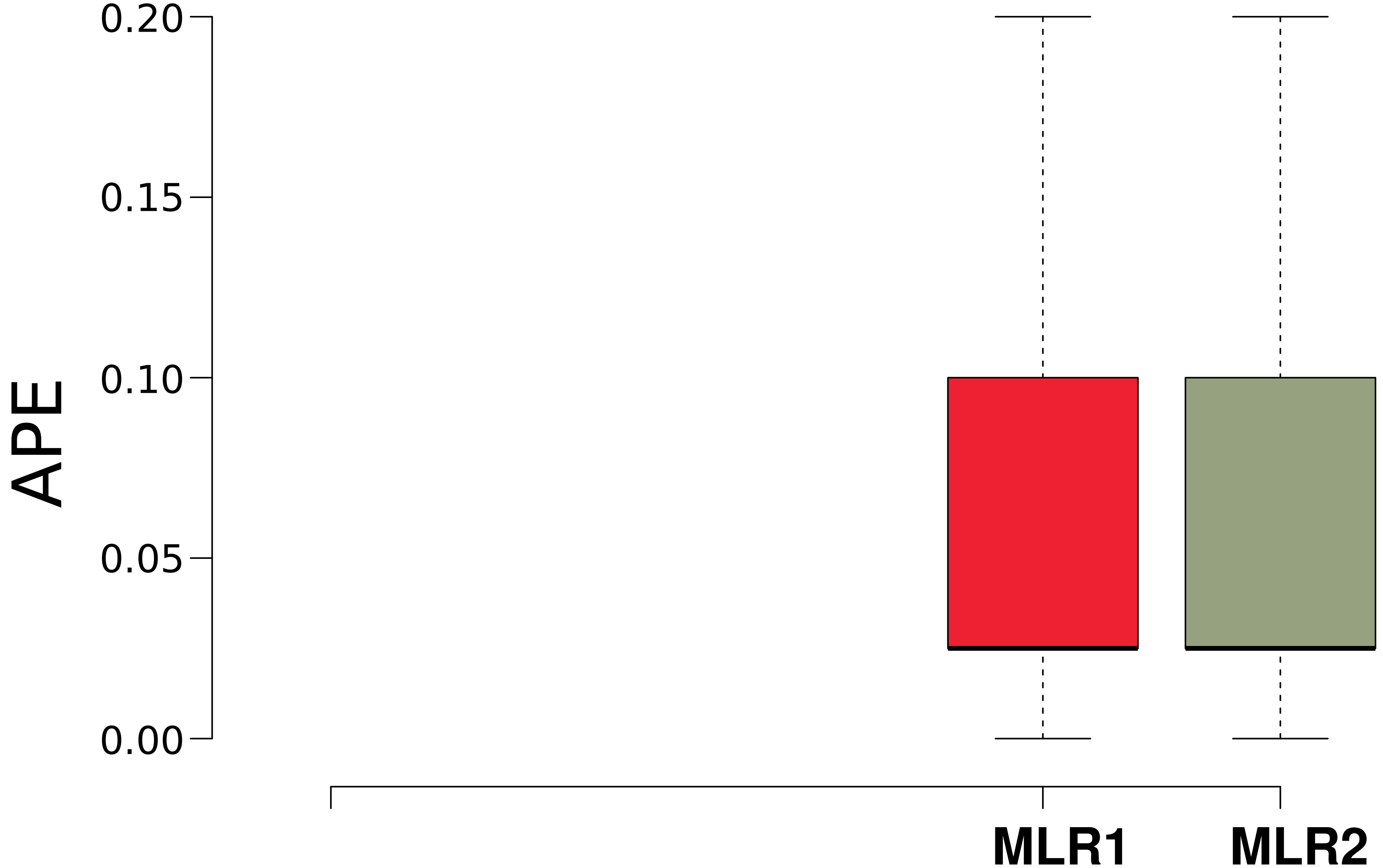


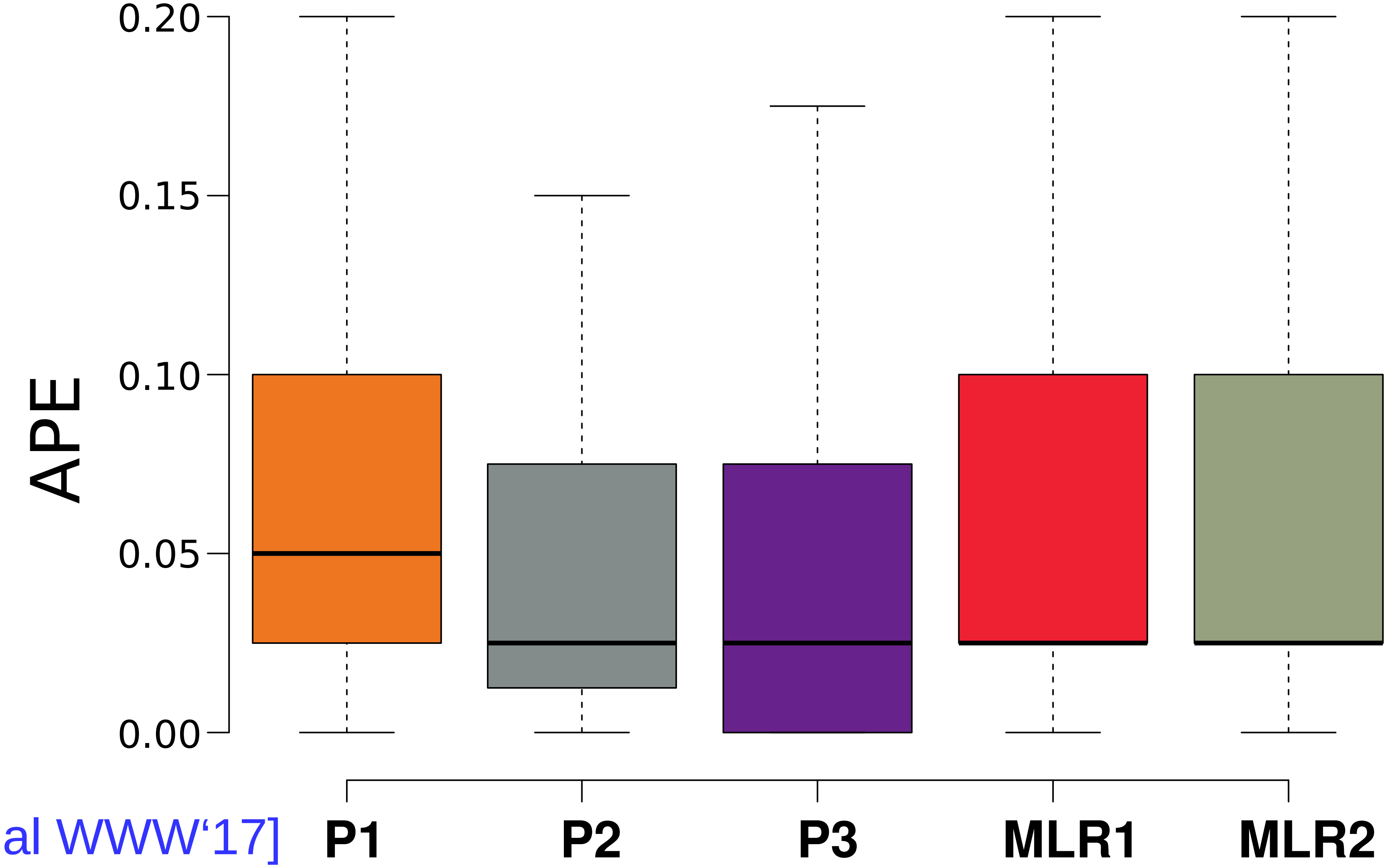
Forecasting future views (2)



[Pinto et al WSDM'13]

	MLR1	MLR2
History:	✓	✓
Viral potential:		
Promo. volume:		✓
Promo. timing:		✓

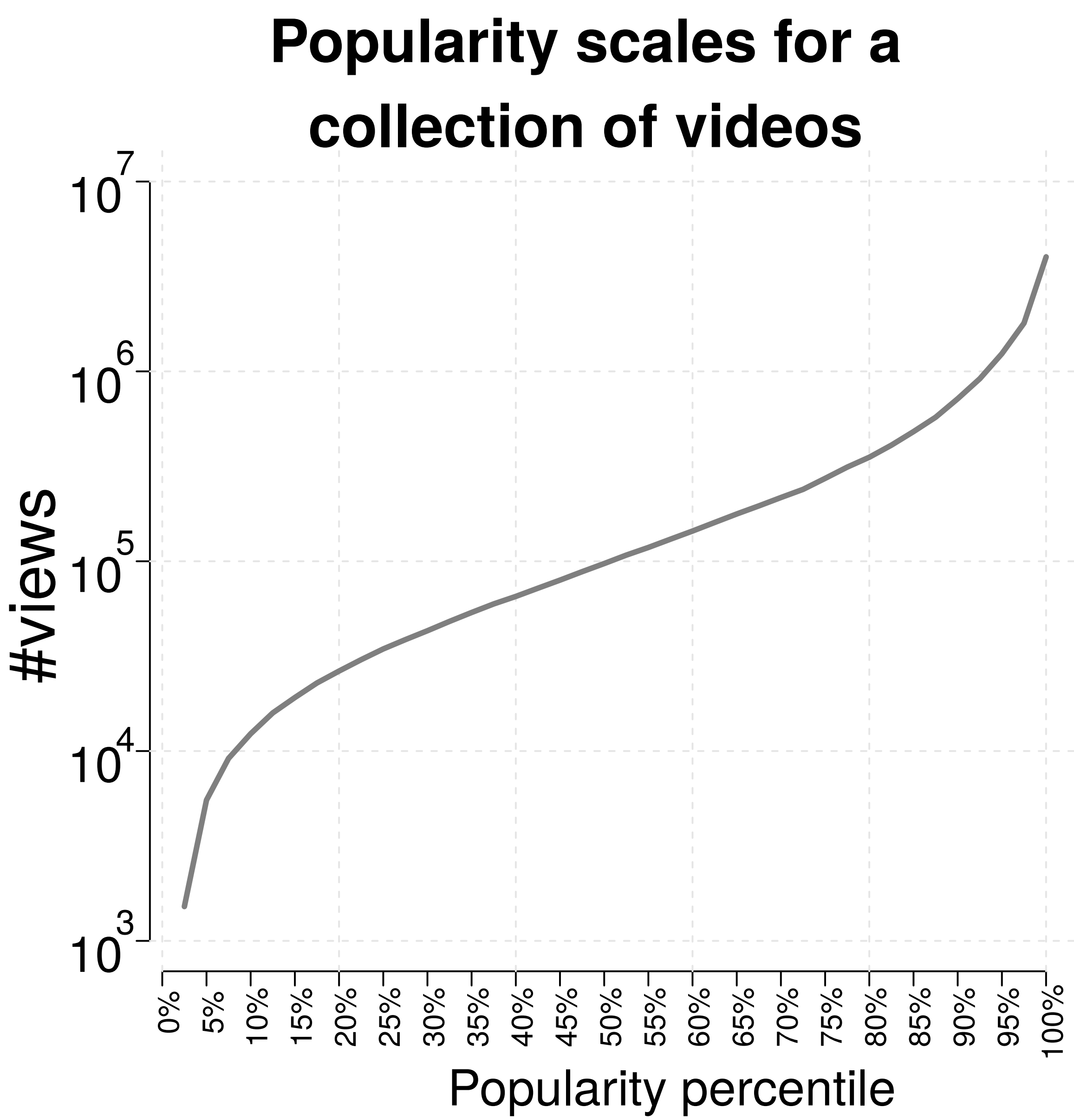
Forecasting future views (2)



[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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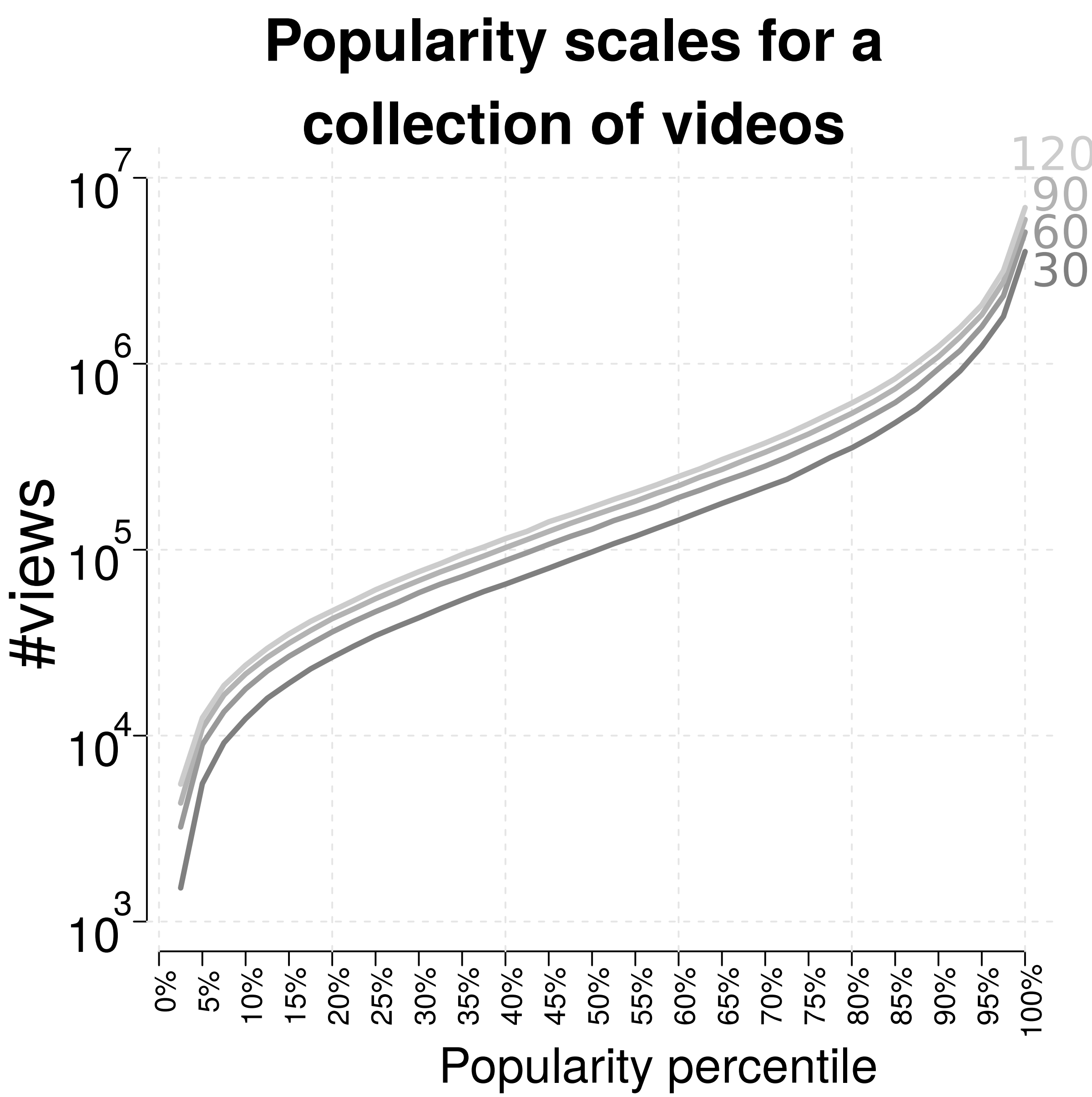

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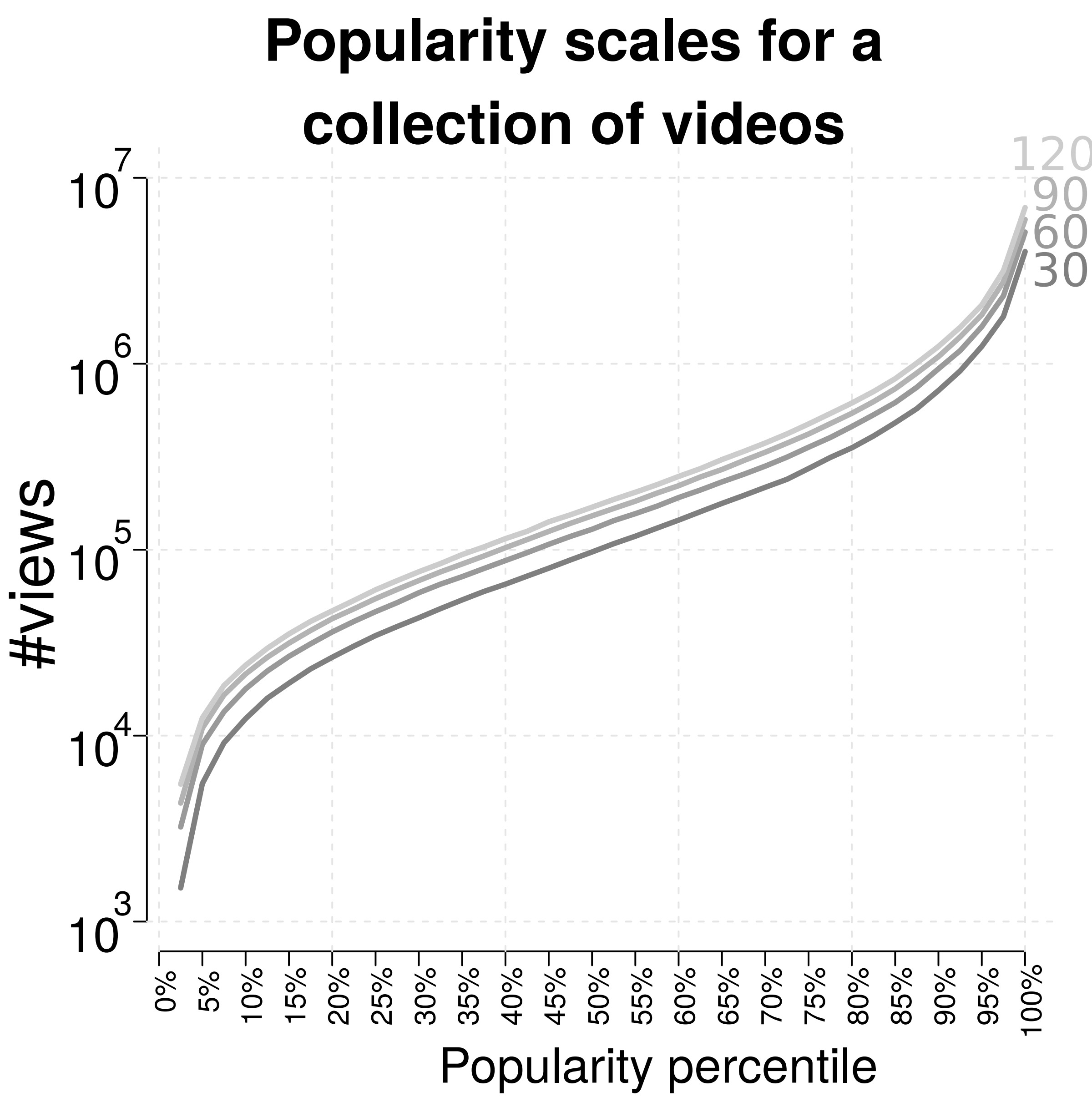

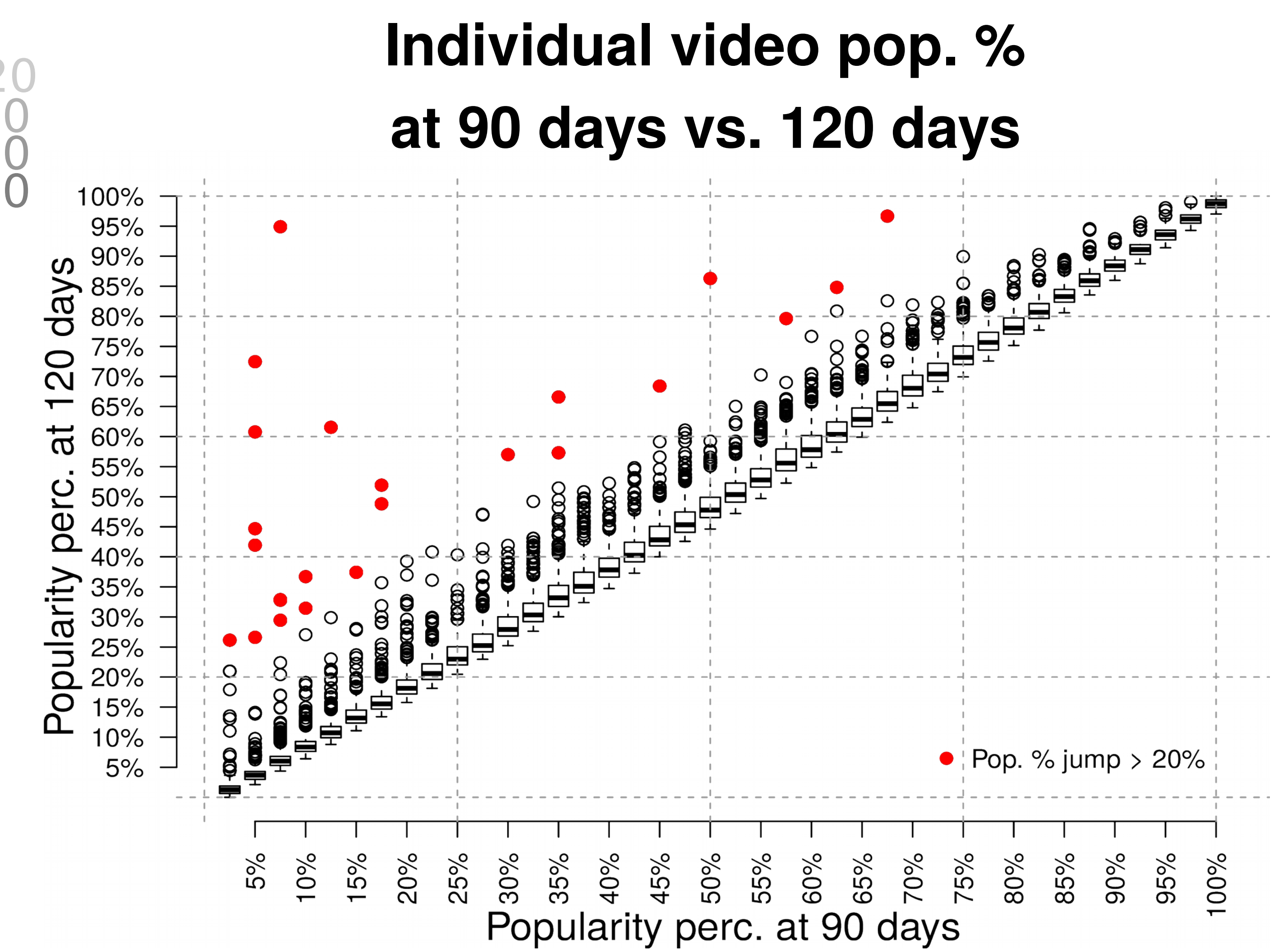

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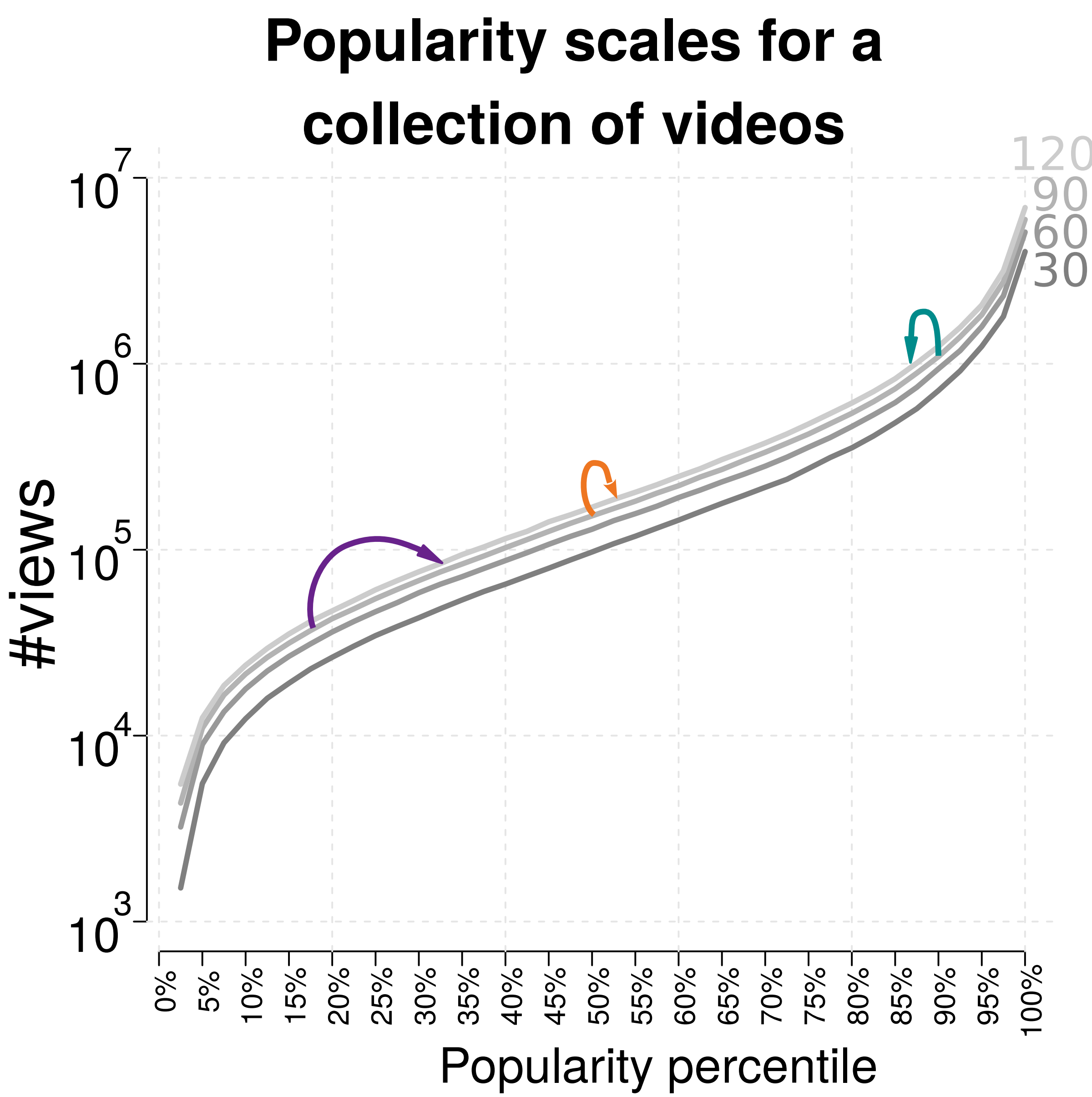
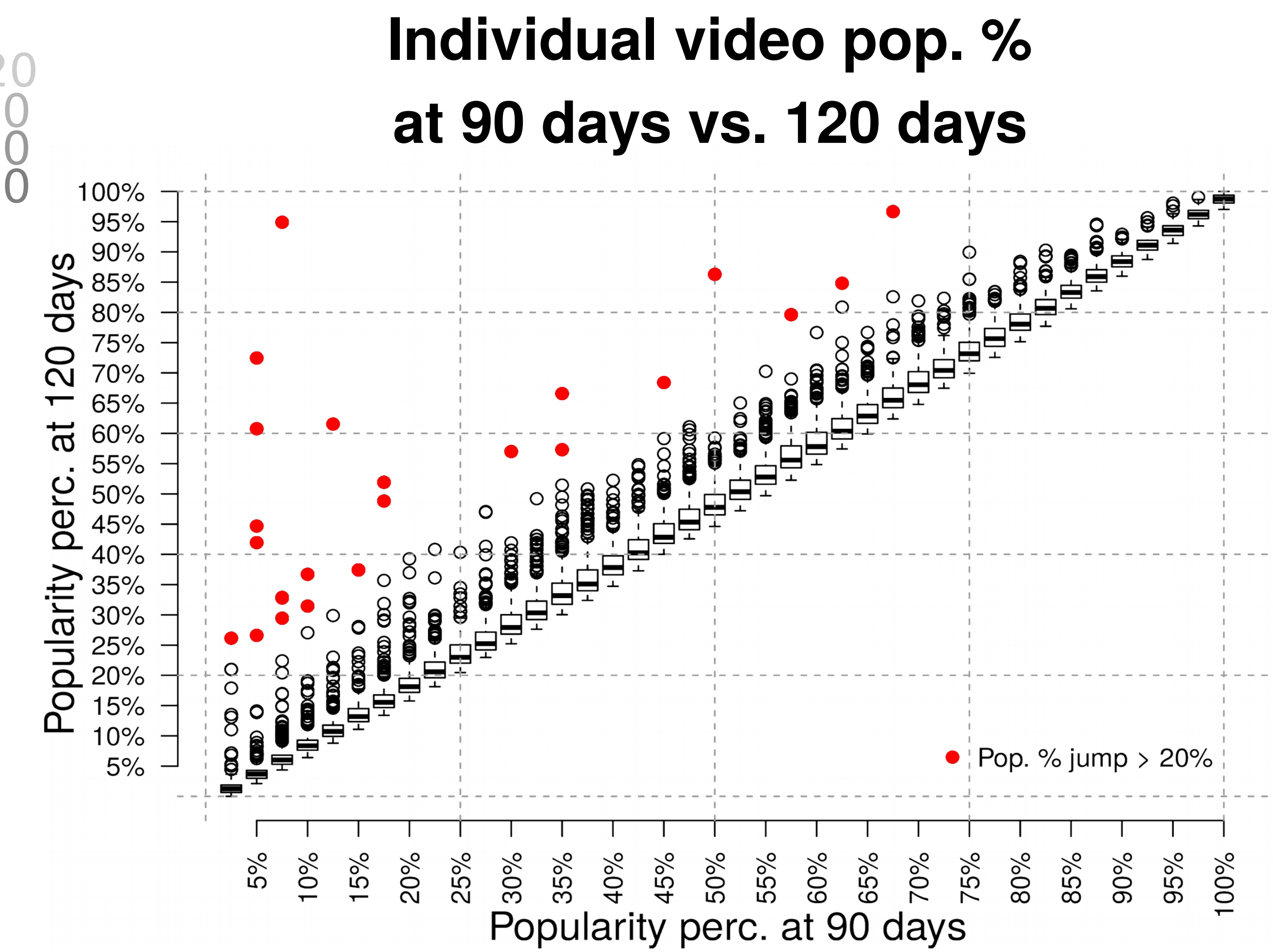
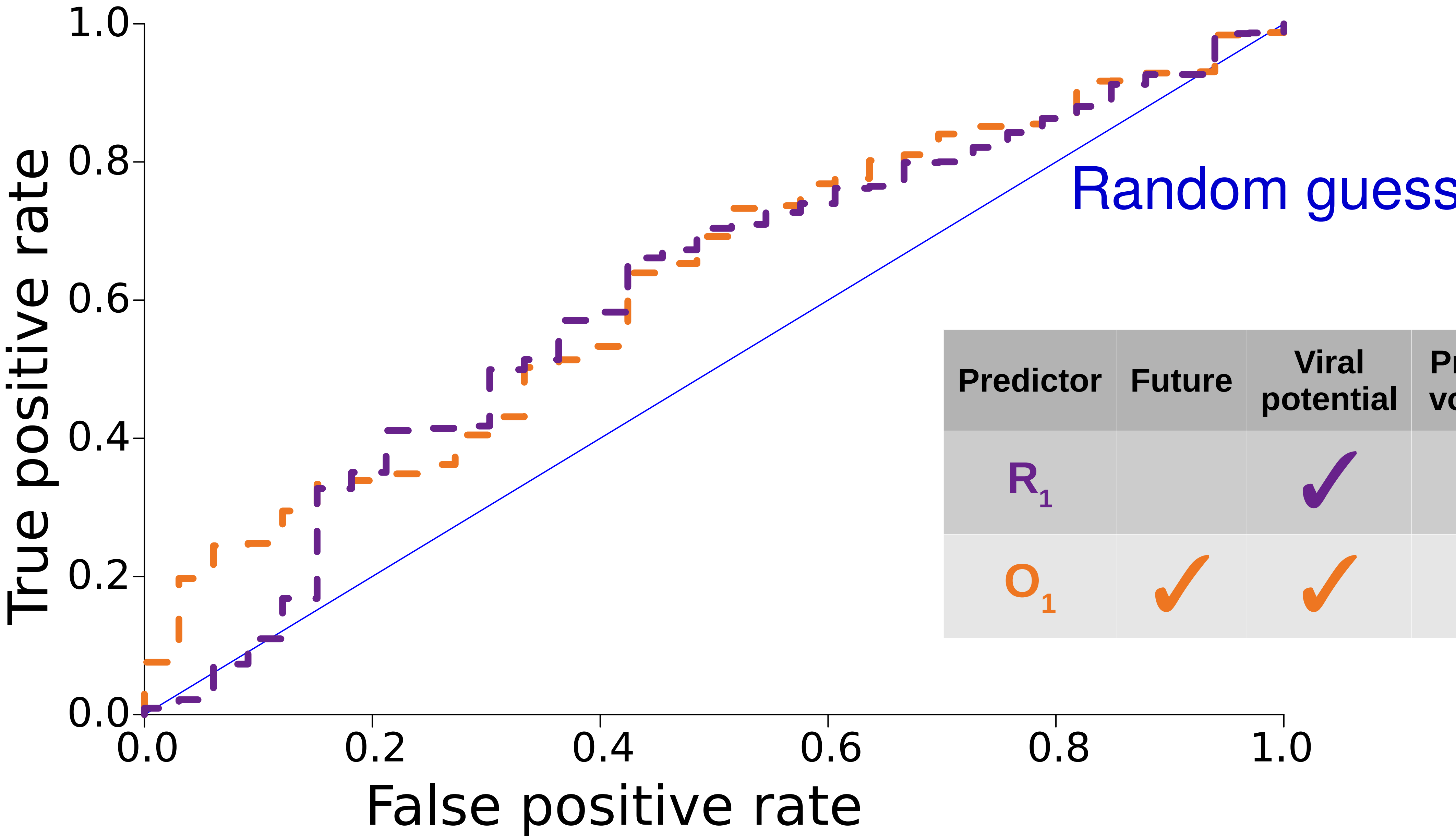




Impact of 40k views:

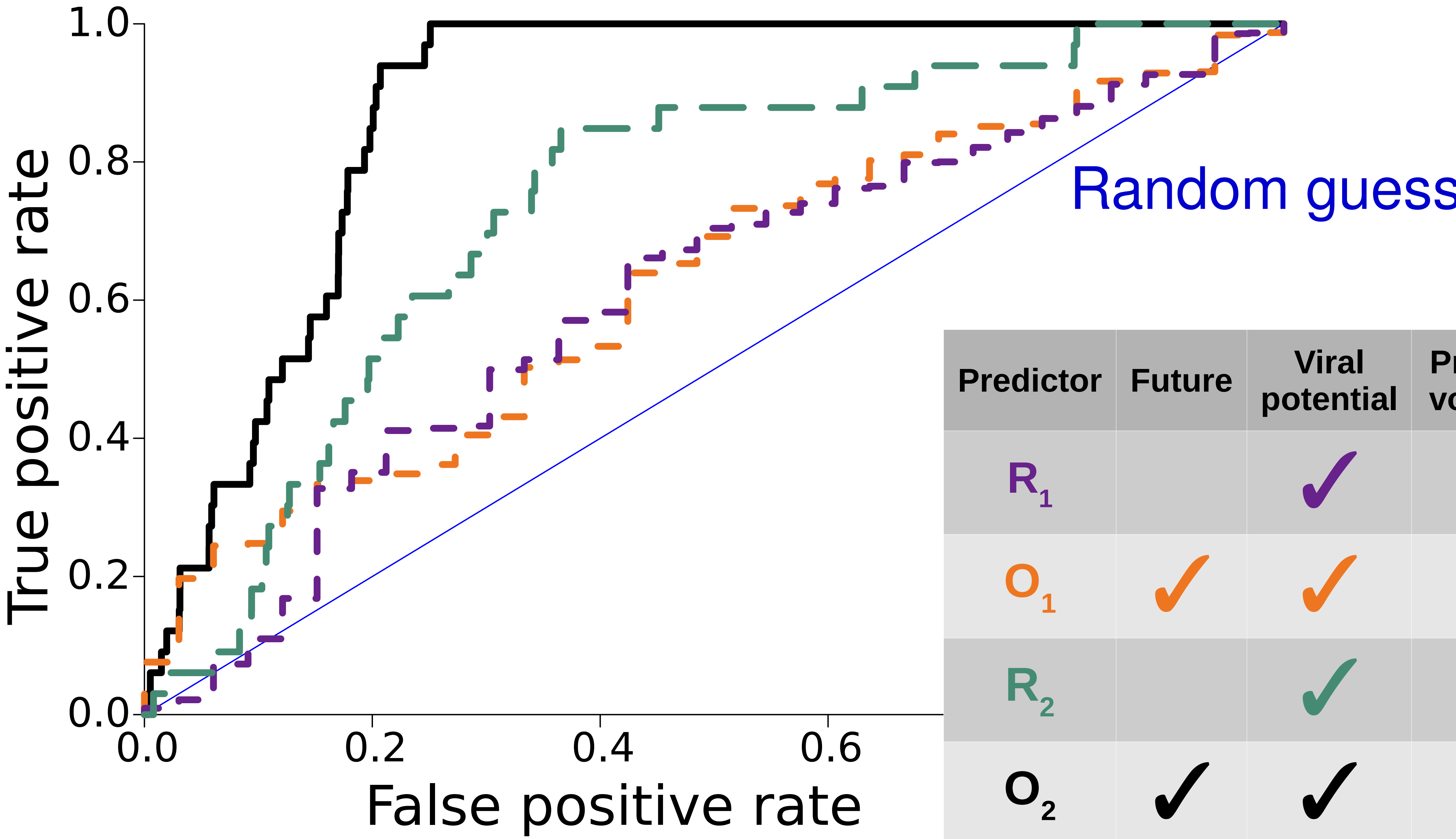
start at 17.5% → +15%   start at 50% → +2.5%   start at 90% → -2.5%

ROC curves for videos that jump



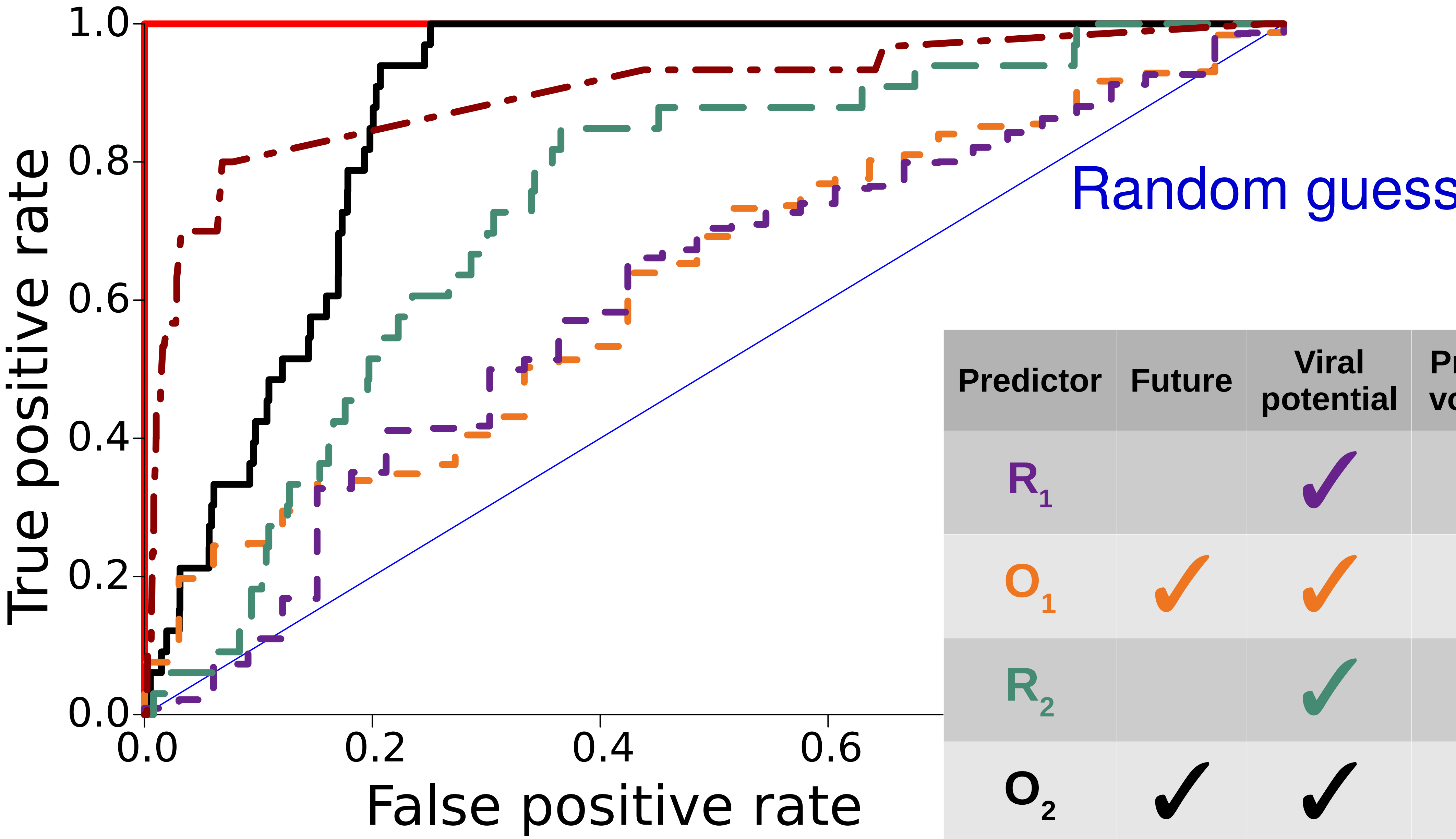
Predictor	Future	Viral potential	Promo. volume	Pop. scale position
R_1		✓		
O_1	✓	✓		

ROC curves for videos that jump



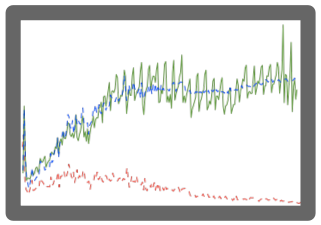
Predictor	Future	Viral potential	Promo. volume	Pop. scale position
R_1		✓		
O_1	✓	✓		
R_2		✓	✓	
O_2	✓	✓	✓	

ROC curves for videos that jump

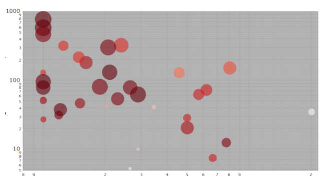


Predictor	Future	Viral potential	Promo. volume	Pop. scale position
R_1		✓		
O_1	✓	✓		
R_2		✓	✓	
O_2	✓	✓	✓	
R_3		✓	✓	✓
O_3	✓	✓	✓	✓

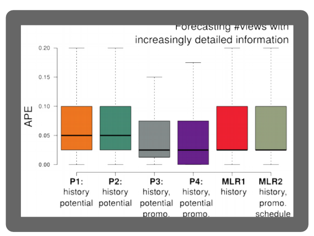
Summary



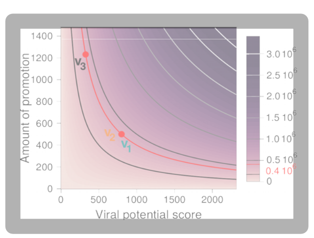
HIP: a mathematical model linking promotion and popularity



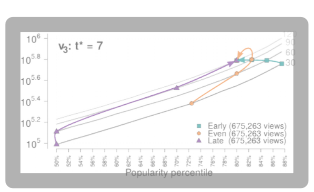
Explain popularity dynamics and identify potentially viral videos



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

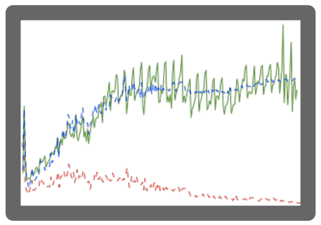


Two measures: *virality score* and *maturity time*

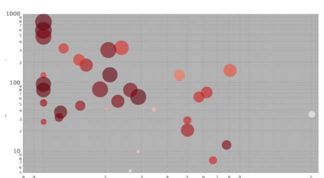


Maturity time influences the cost-effectiveness of promotion schedules

Summary



HIP: a mathematical model linking promotion and popularity



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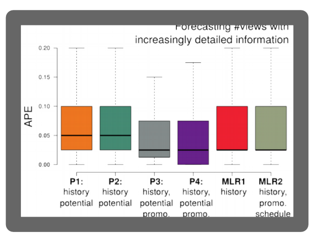

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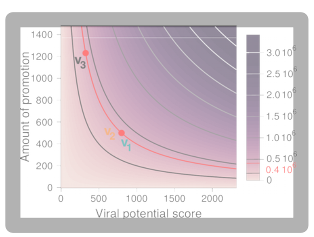

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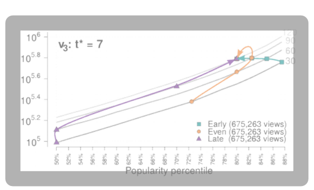


Maturity time influences the cost-effectiveness of promotion schedules

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

Thank you!

Refereces:

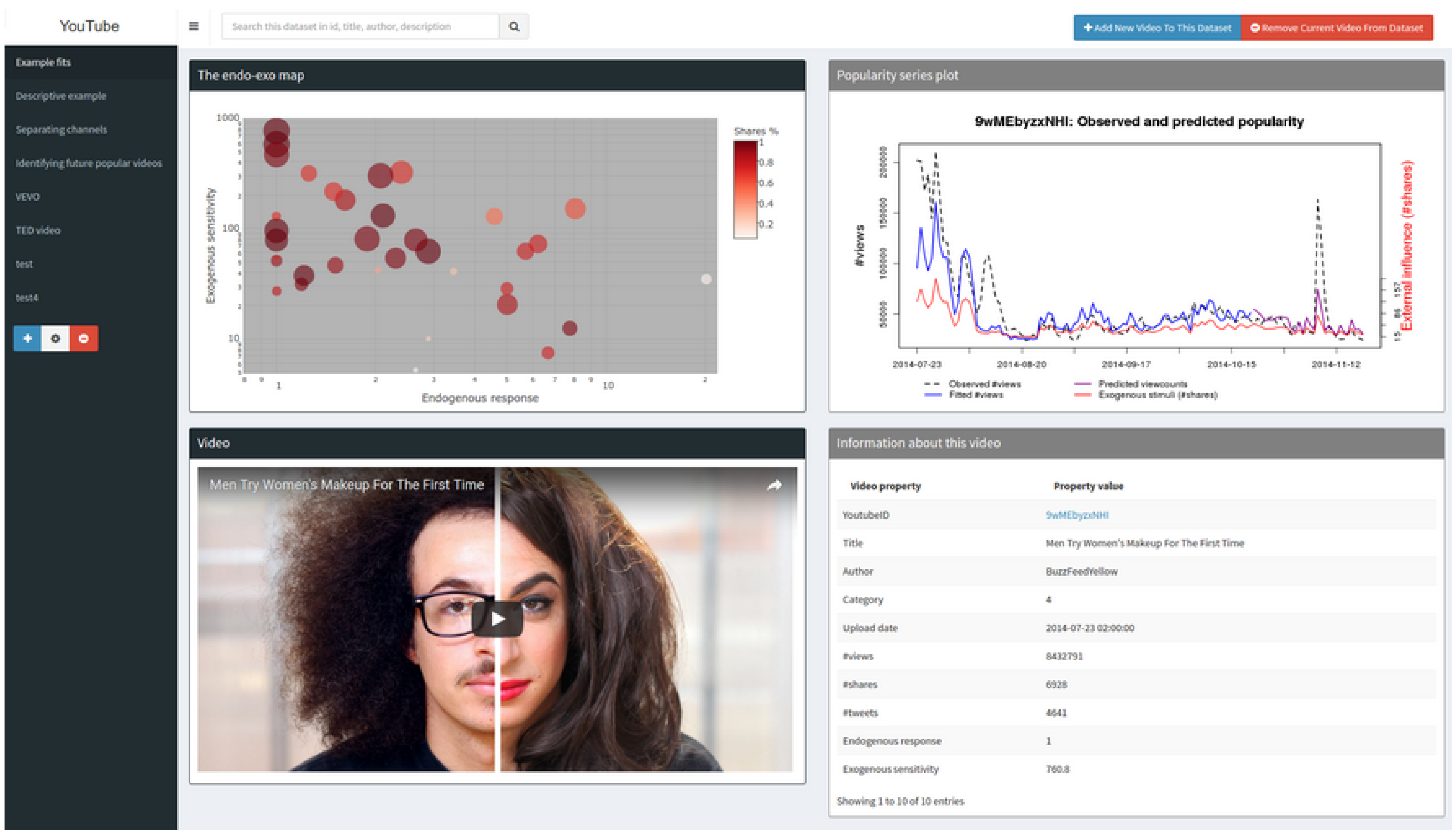
Rizoiu, M.-A., Xie, L., Sanner, S., Cebrian, M., Yu, H., & Van Hentenryck, P. **Expecting to be HIP: Hawkes Intensity Processes for Social Media Popularity**. In *26th International Conference on World Wide Web - WWW '17*, pp. 735-744, Perth, Australia, 2017. doi: 10.1145/3038912.3052650
pdf at arxiv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

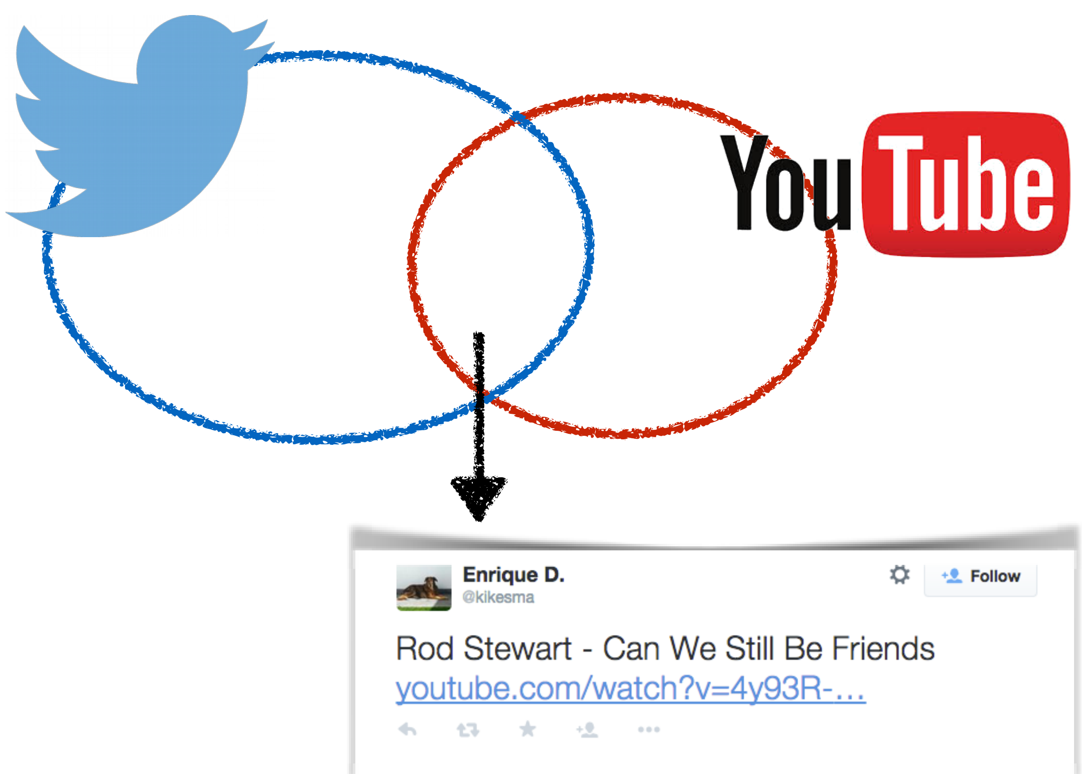


Links:

Code, dataset and interactive visualizer:

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

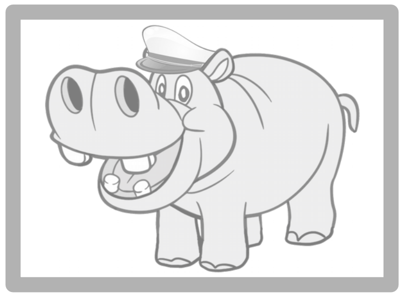
Twitter videos dataset



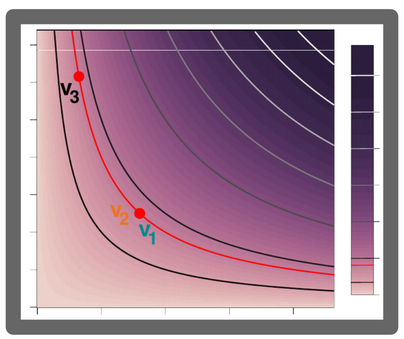
2014.06 - 2014.12
1.061B tweets, 5.89M/day
64.3M users;
81.9M YouTube videos

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		

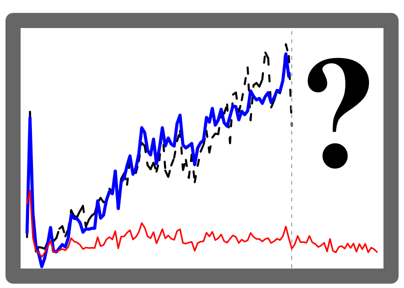
Presentation outline



Modeling popularity with HIP



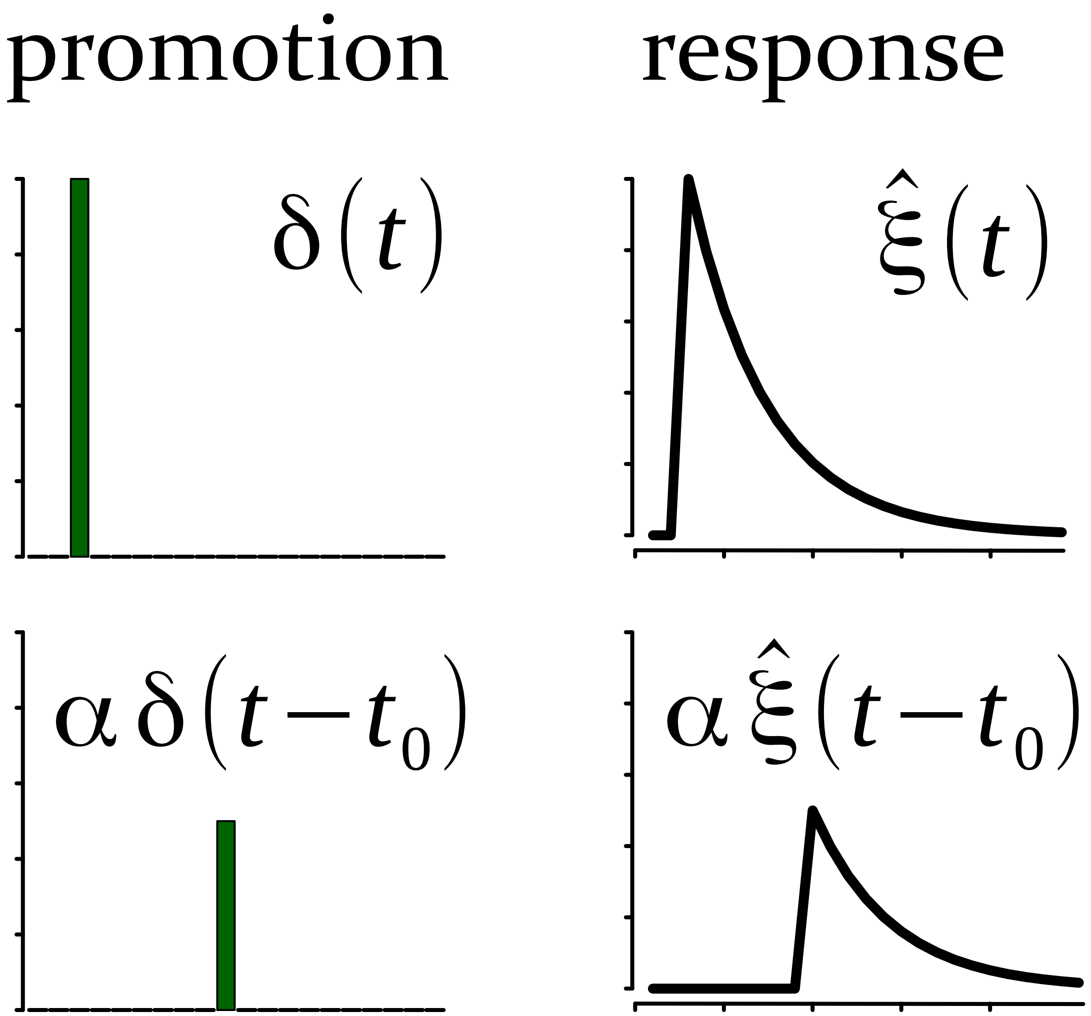
Content virality and maturity time



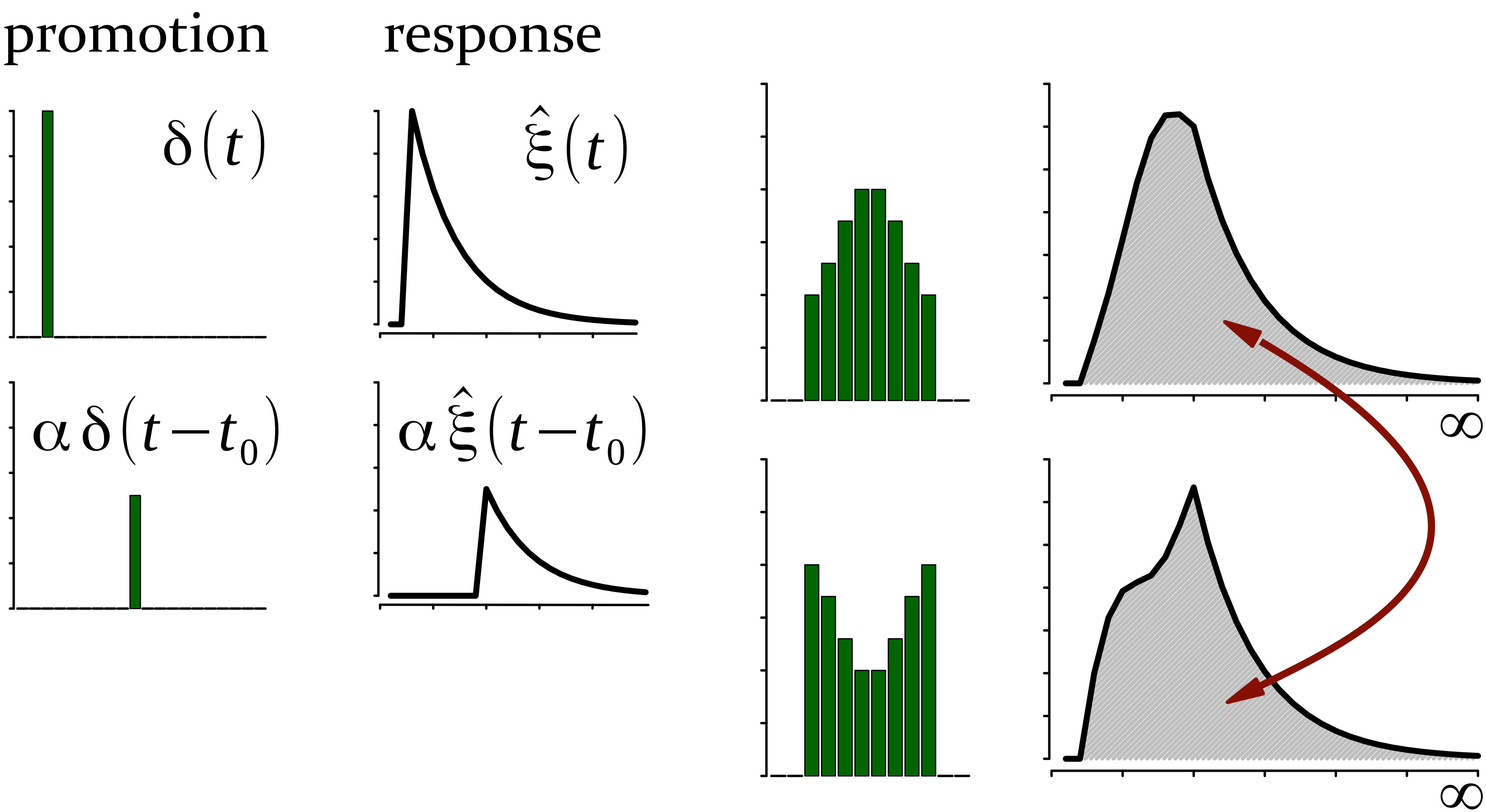
Forecasting popularity under promotion

Promotions schedules and memory lengthening through promotion

HIP as a Linear Time-Invariant system

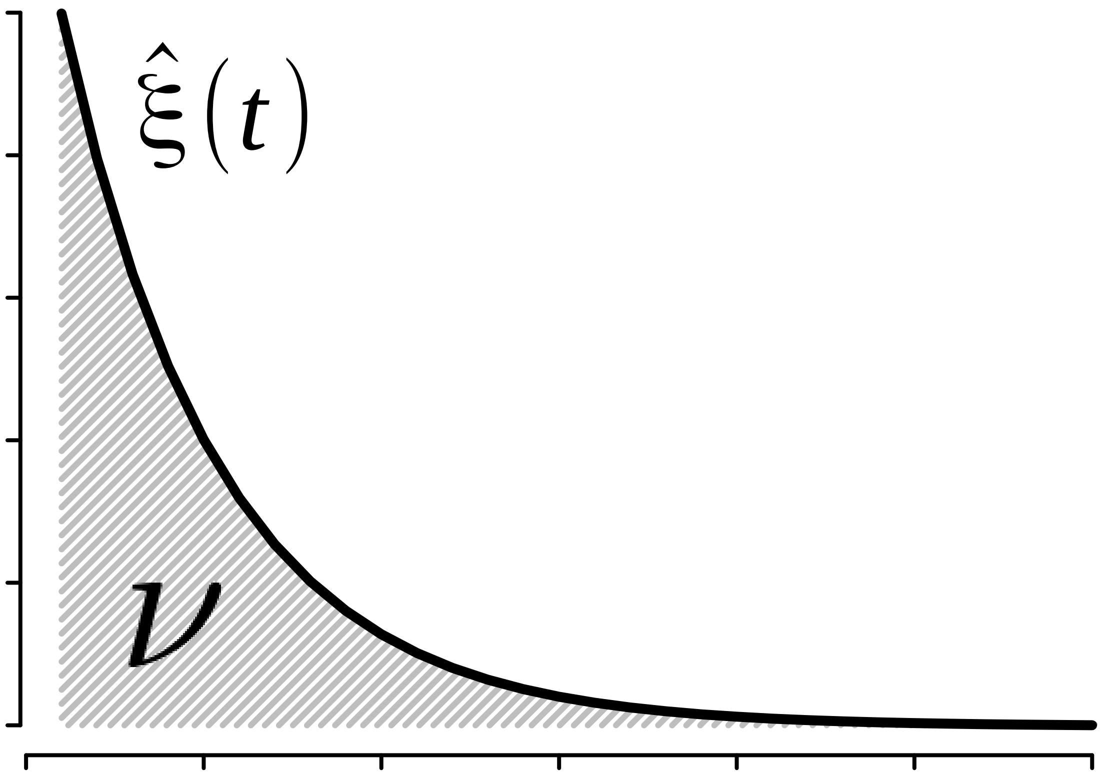


HIP as a Linear Time-Invariant system



Corollary: same budget same return

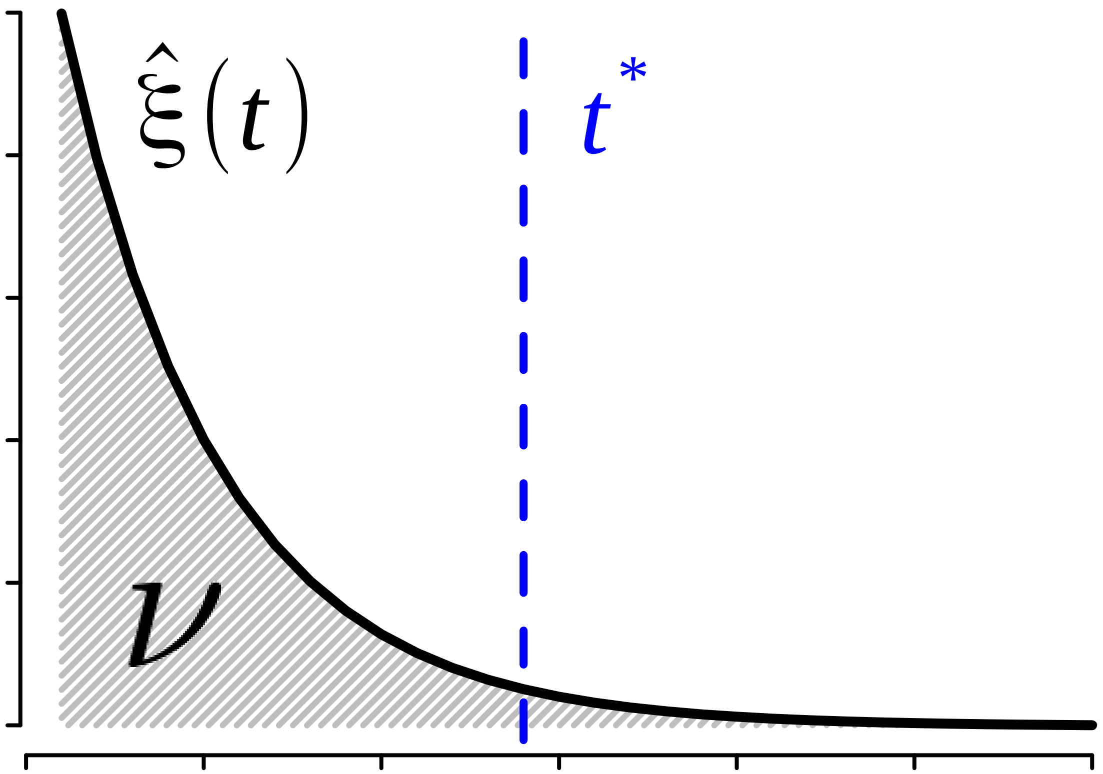
Viral potential and maturity time



Viral potential score:

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

Viral potential and maturity time



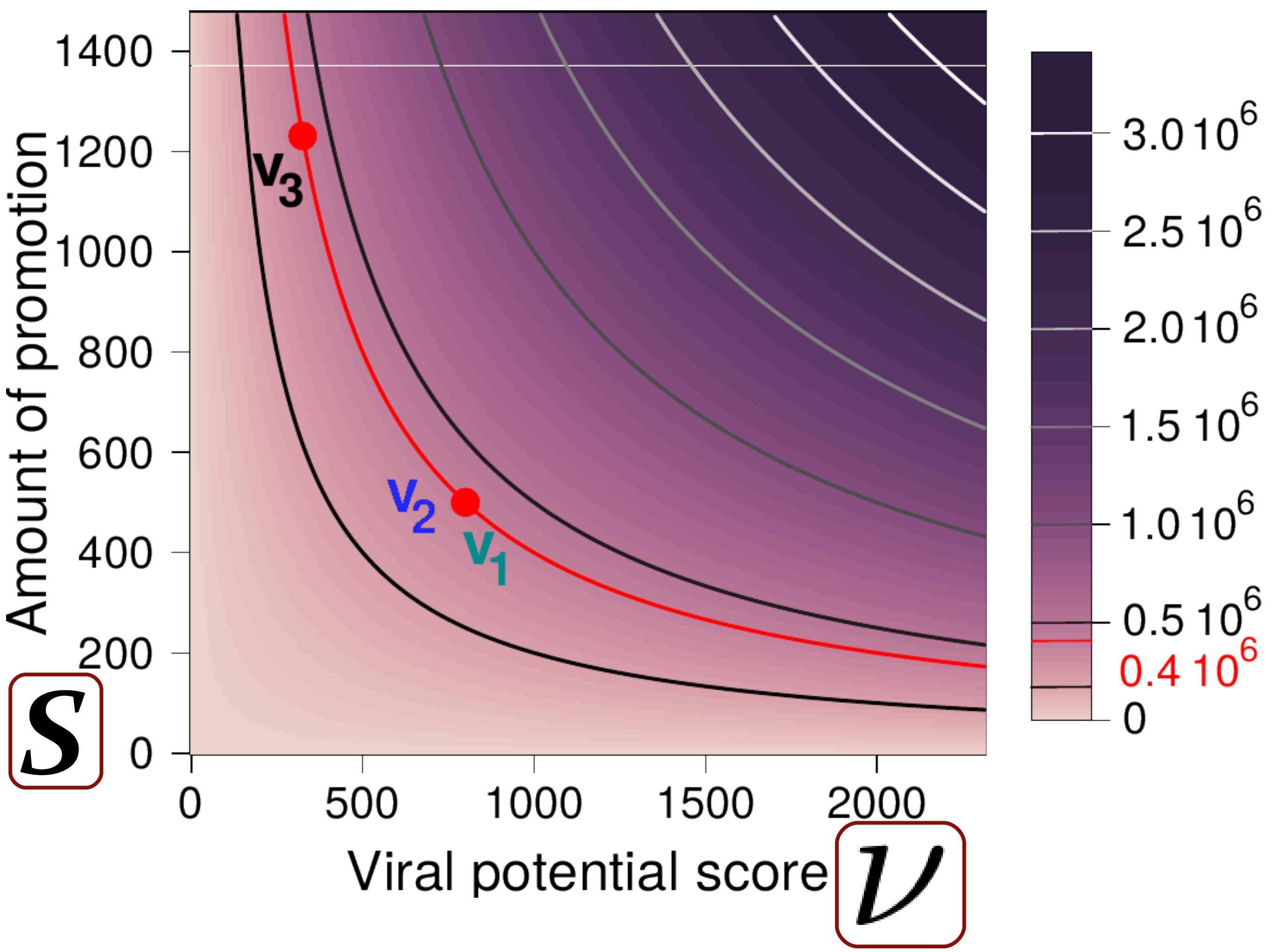
Viral potential score:

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

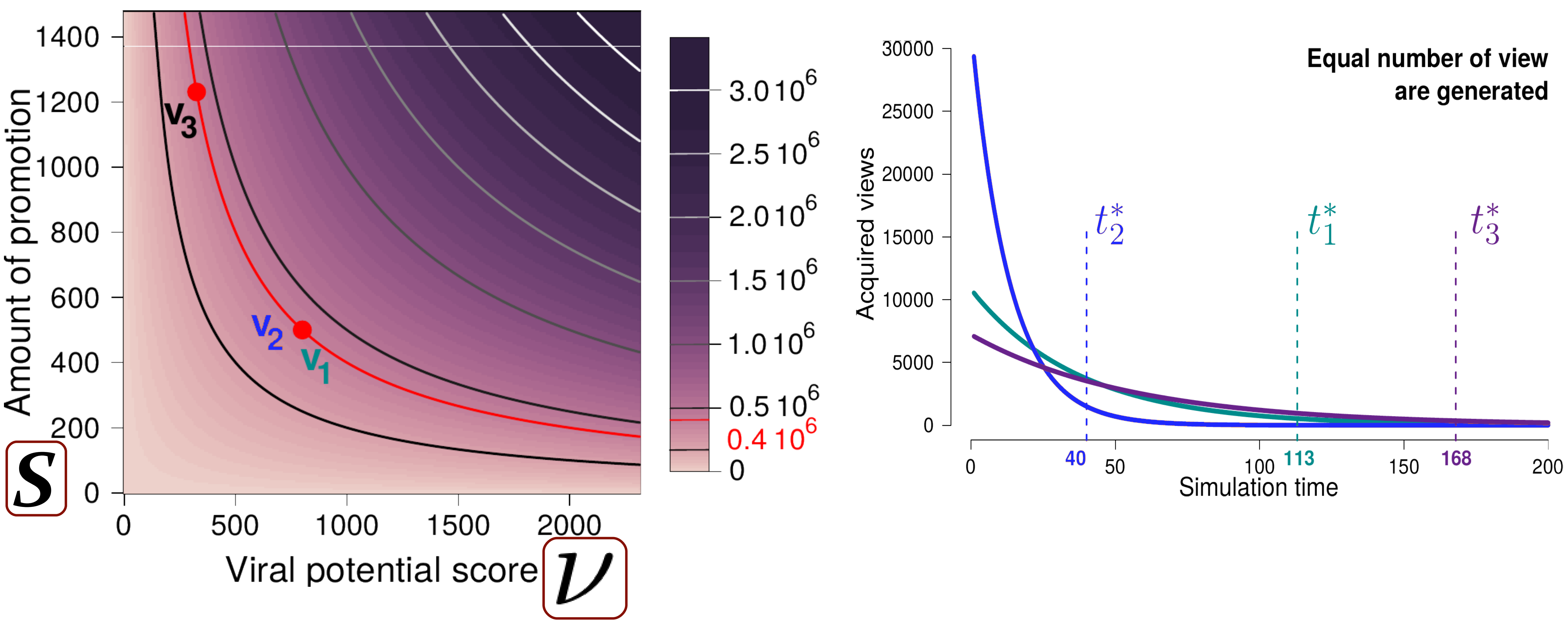
Maturity time:

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

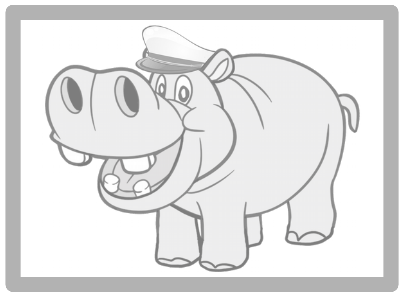
Virality map



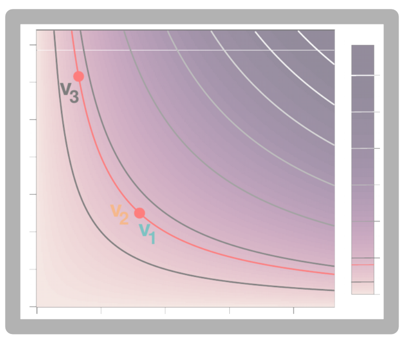
Virality map



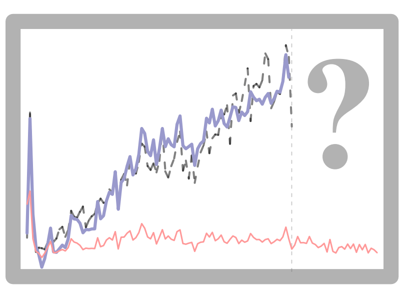
Presentation outline



Modeling popularity with HIP



Content virality and maturity time

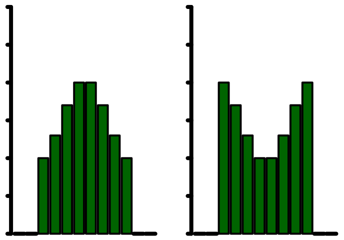


Forecasting popularity under promotion

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

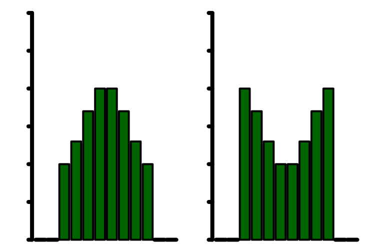
Designing promotion schedules

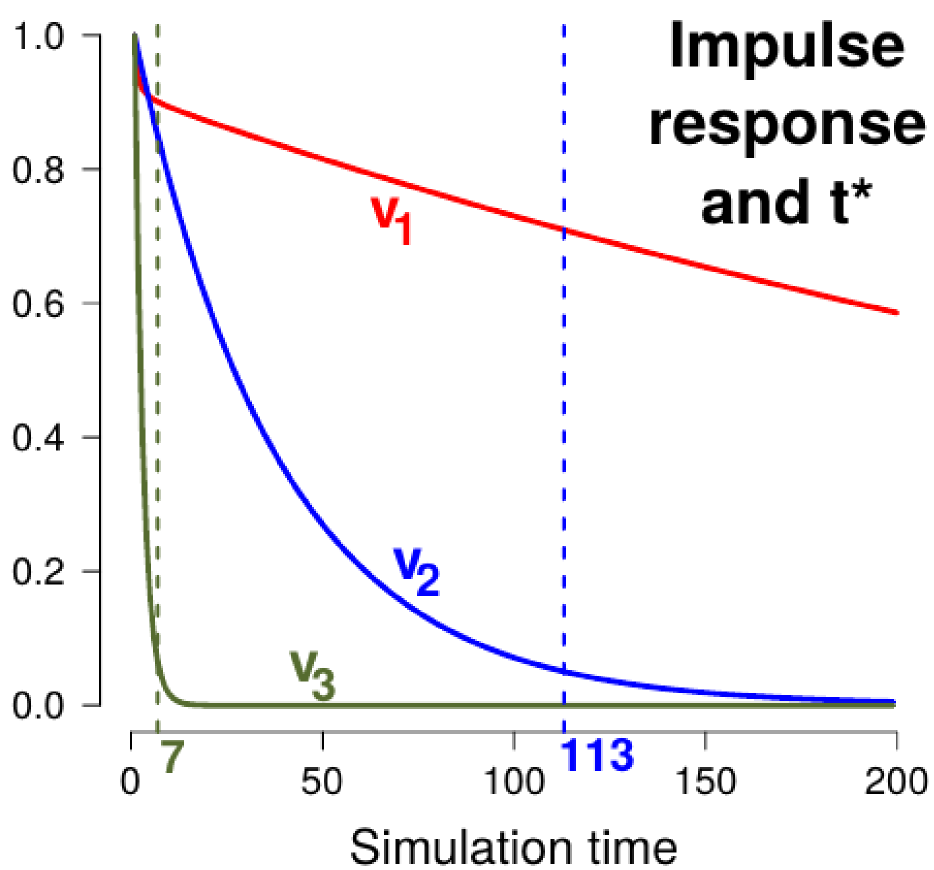
LTI corollary: **same budget, same return!**

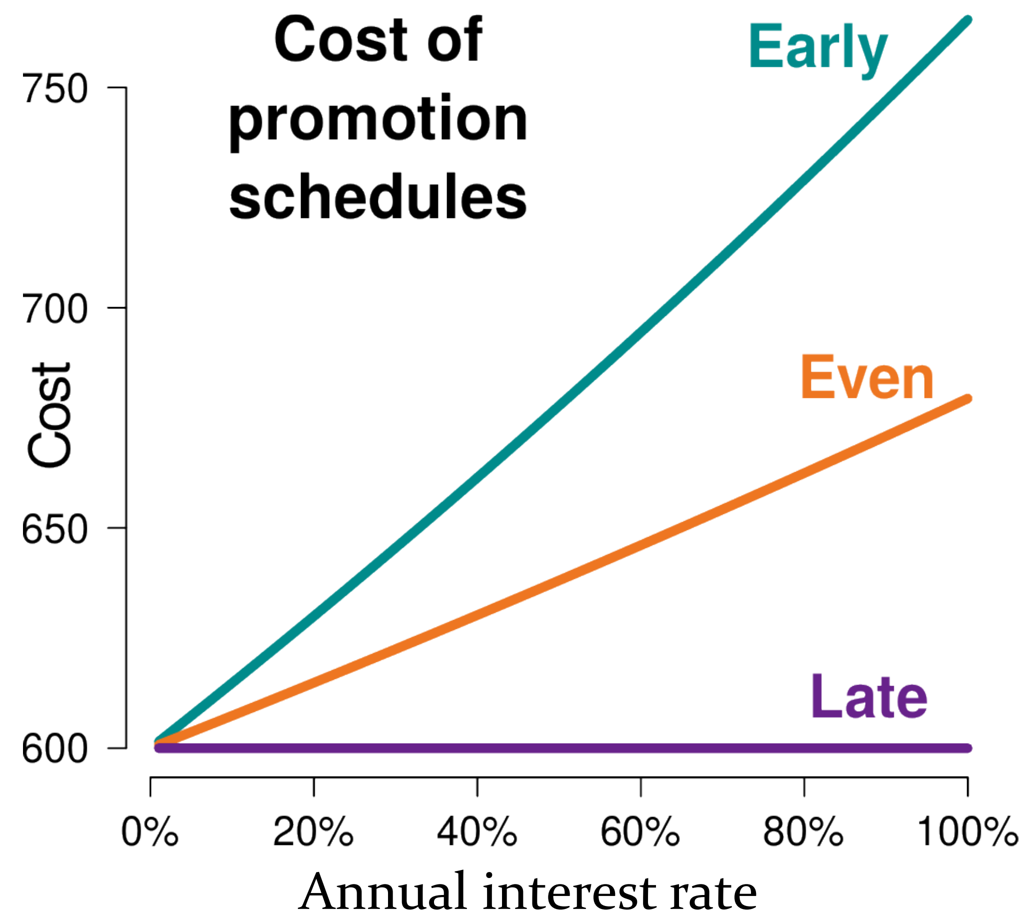


Designing promotion schedules

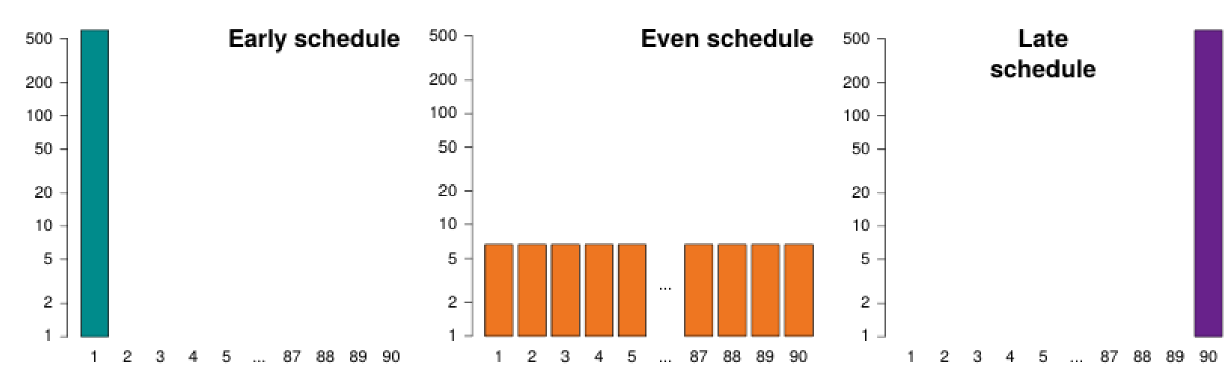
LTI corollary: **same budget, same return!**



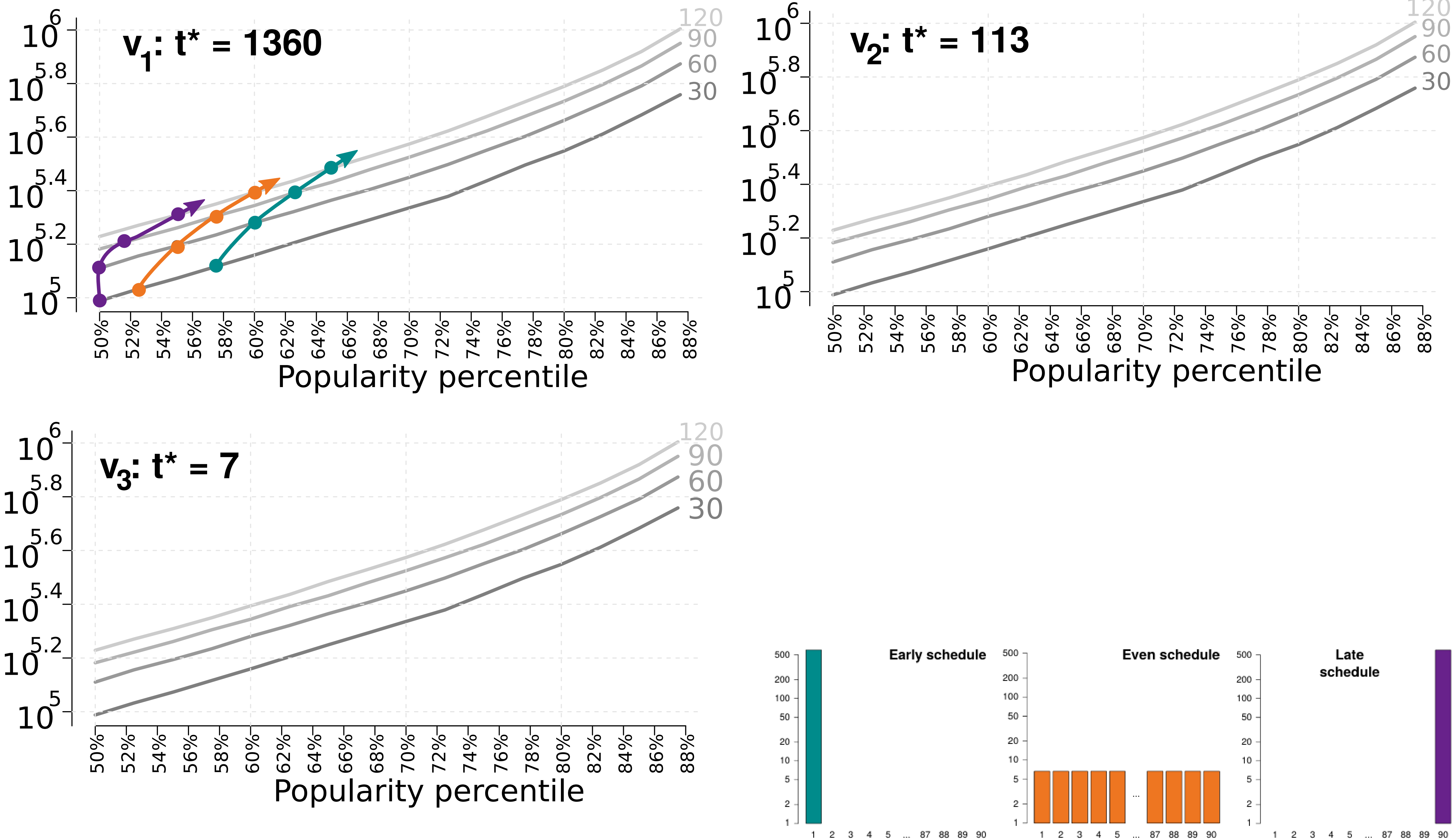




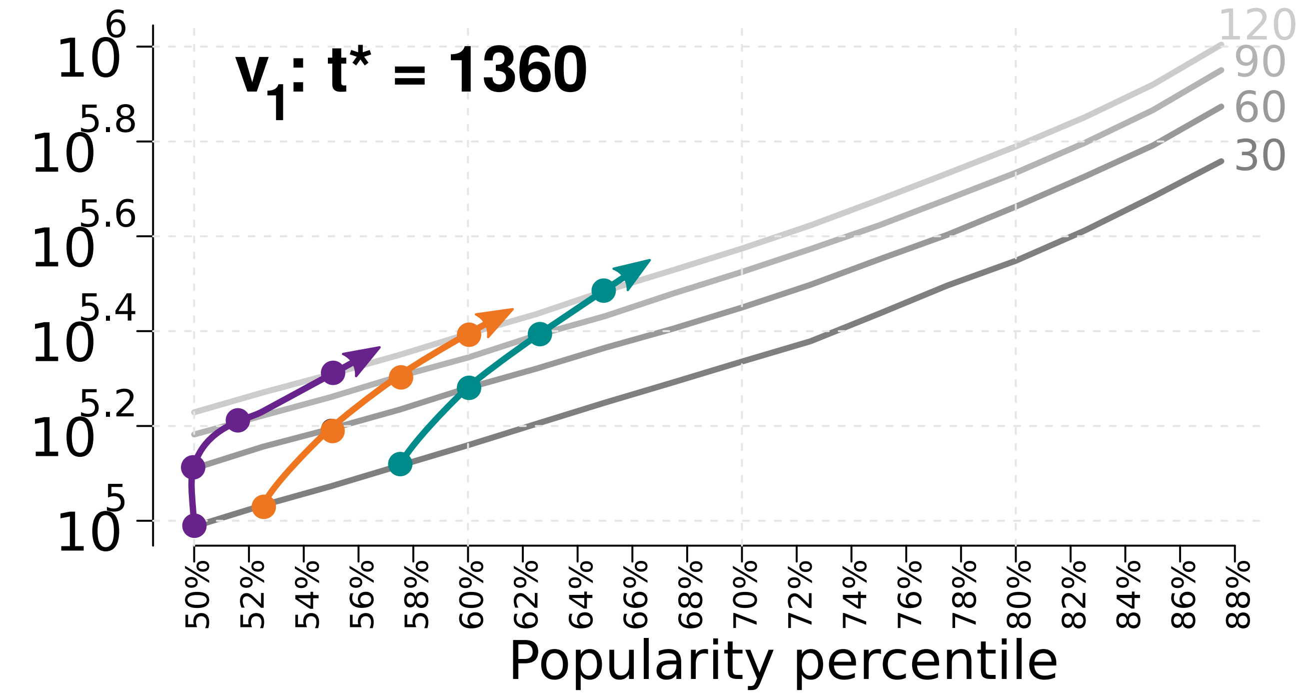
Compounding interest: $cost = (1+a)^k$

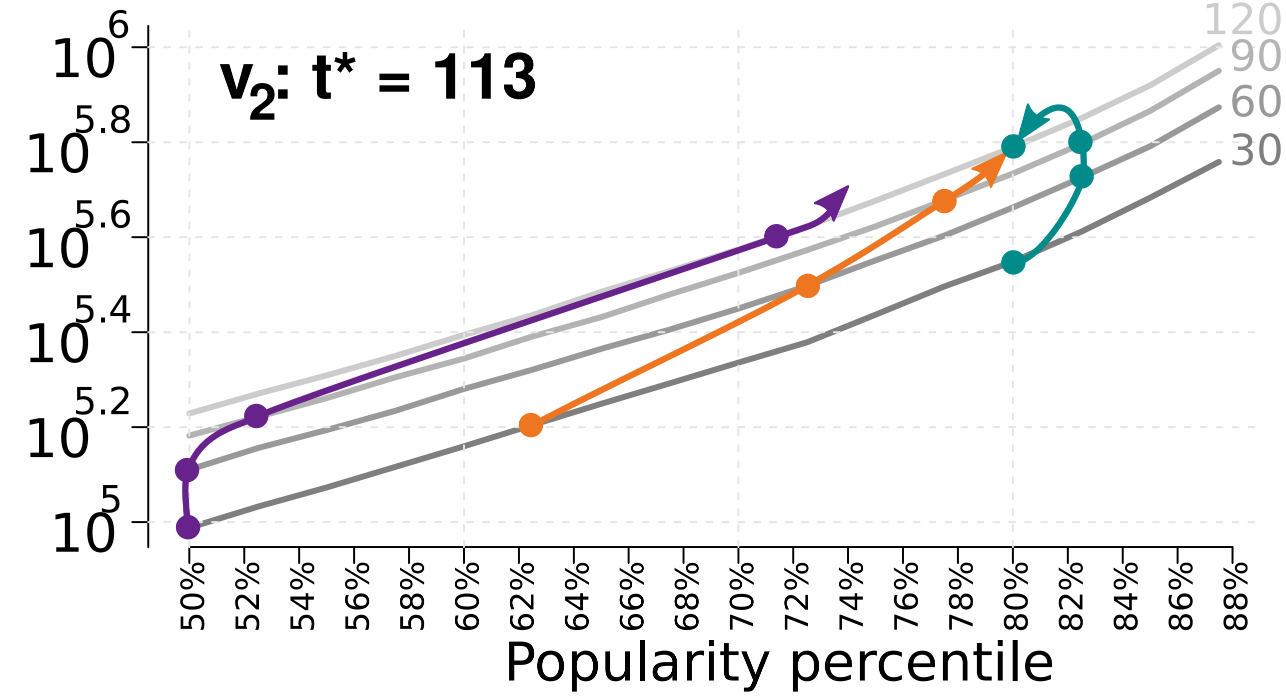


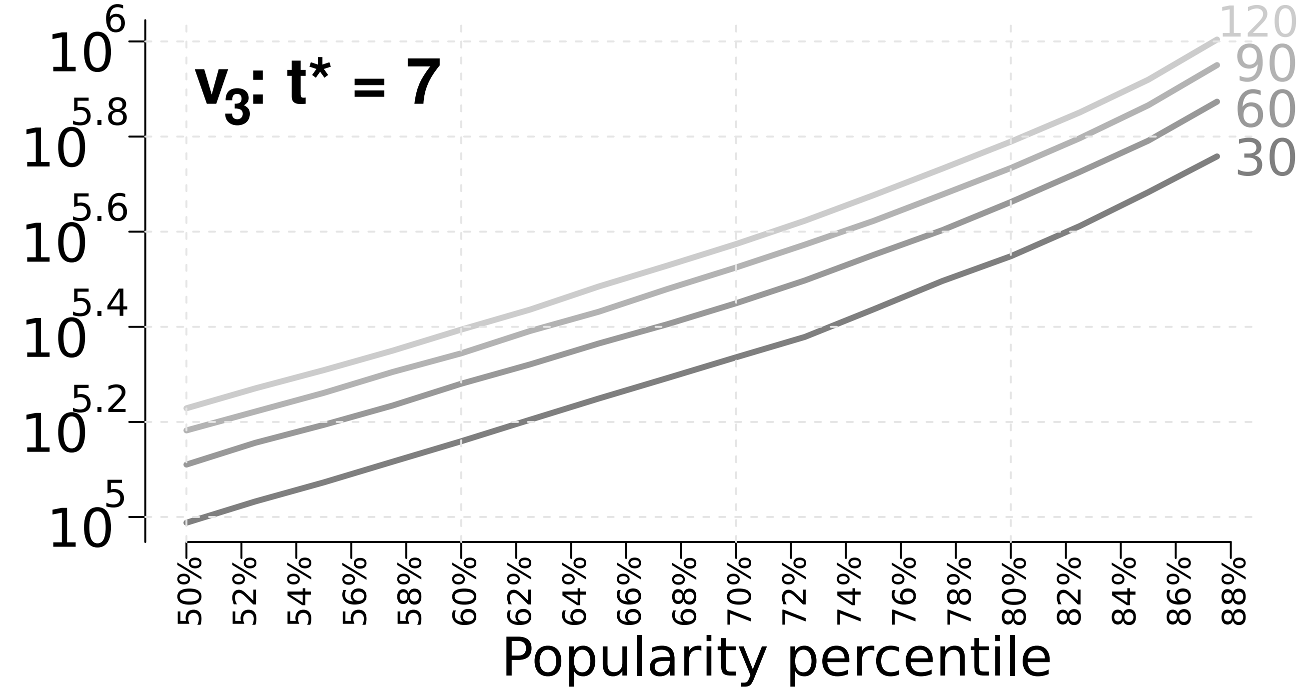
Interplay of 2 temporal factors

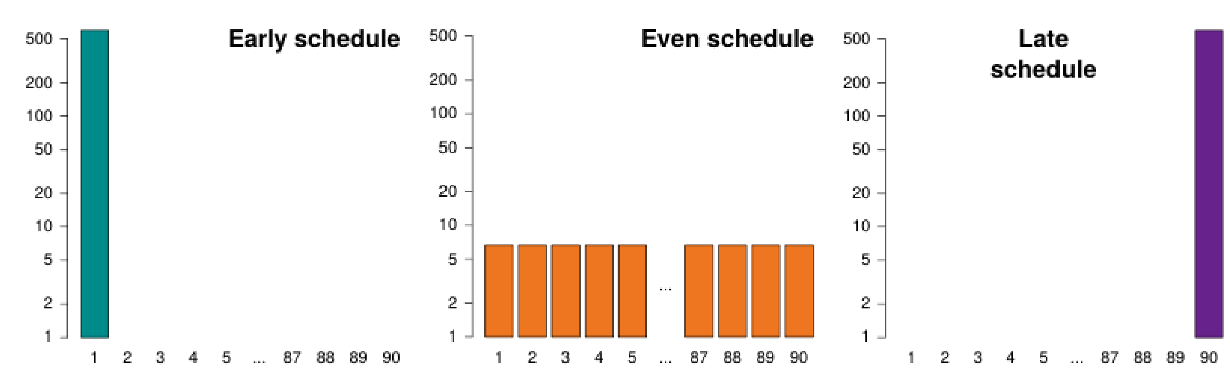


Interplay of 2 temporal factors

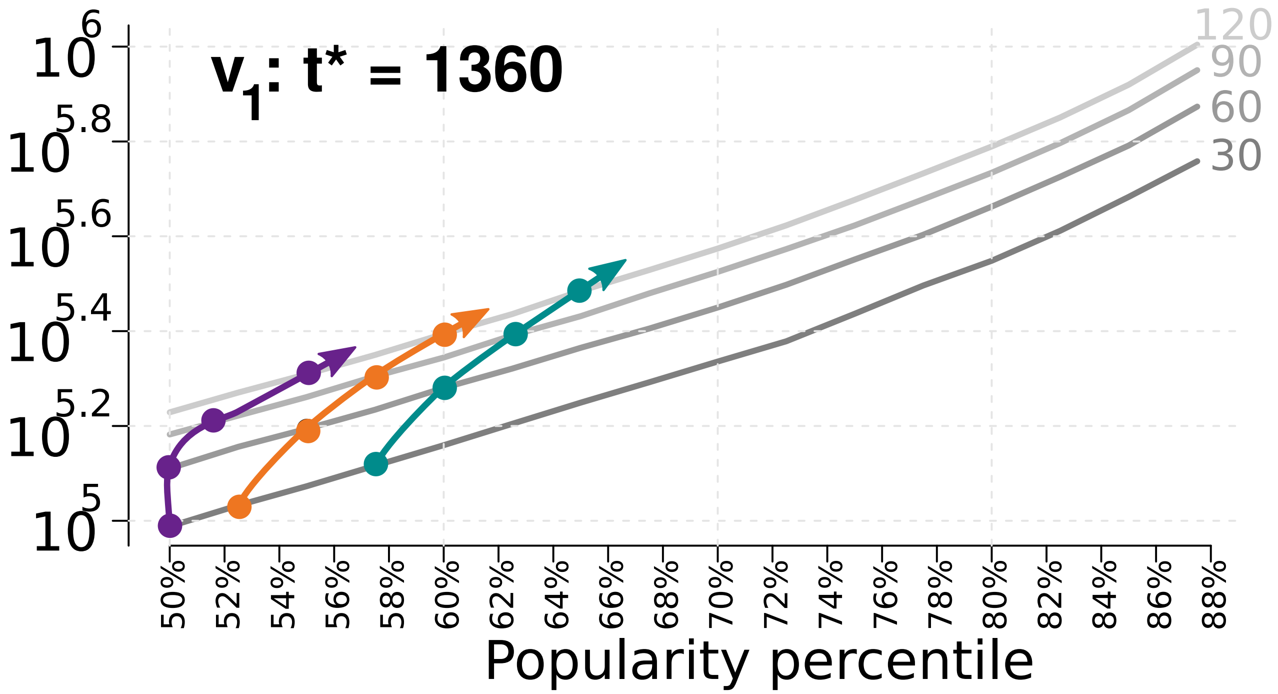


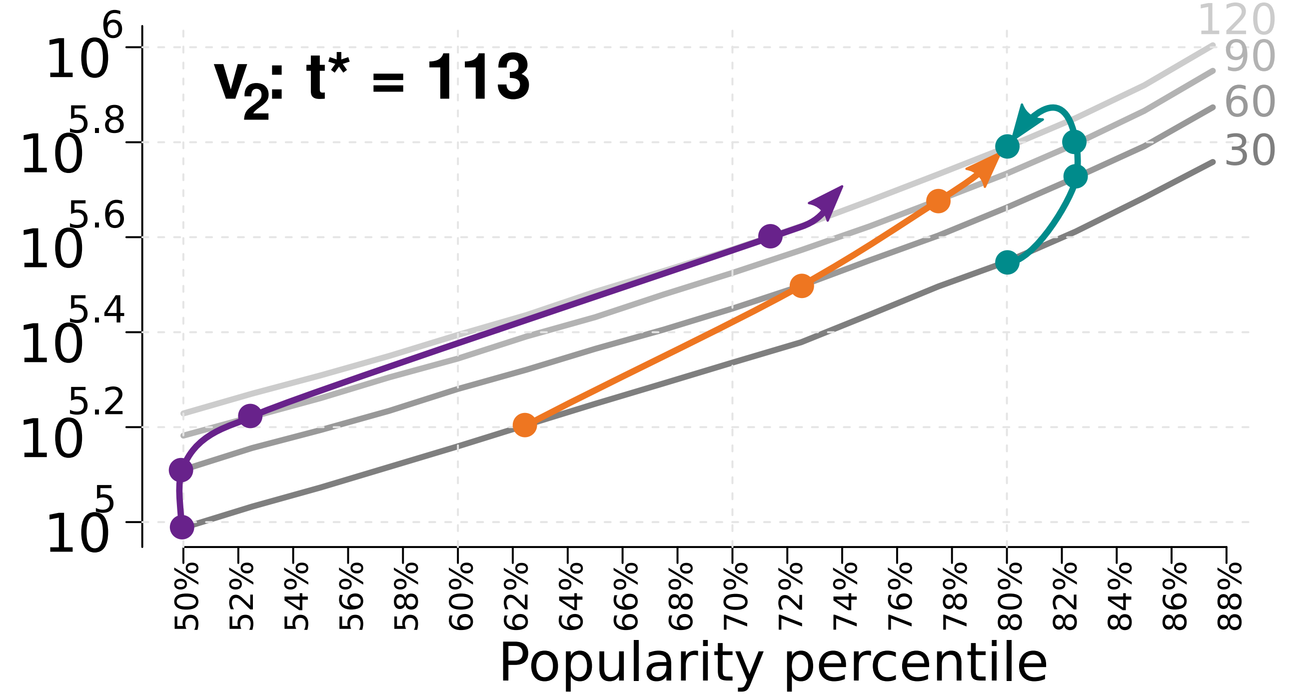


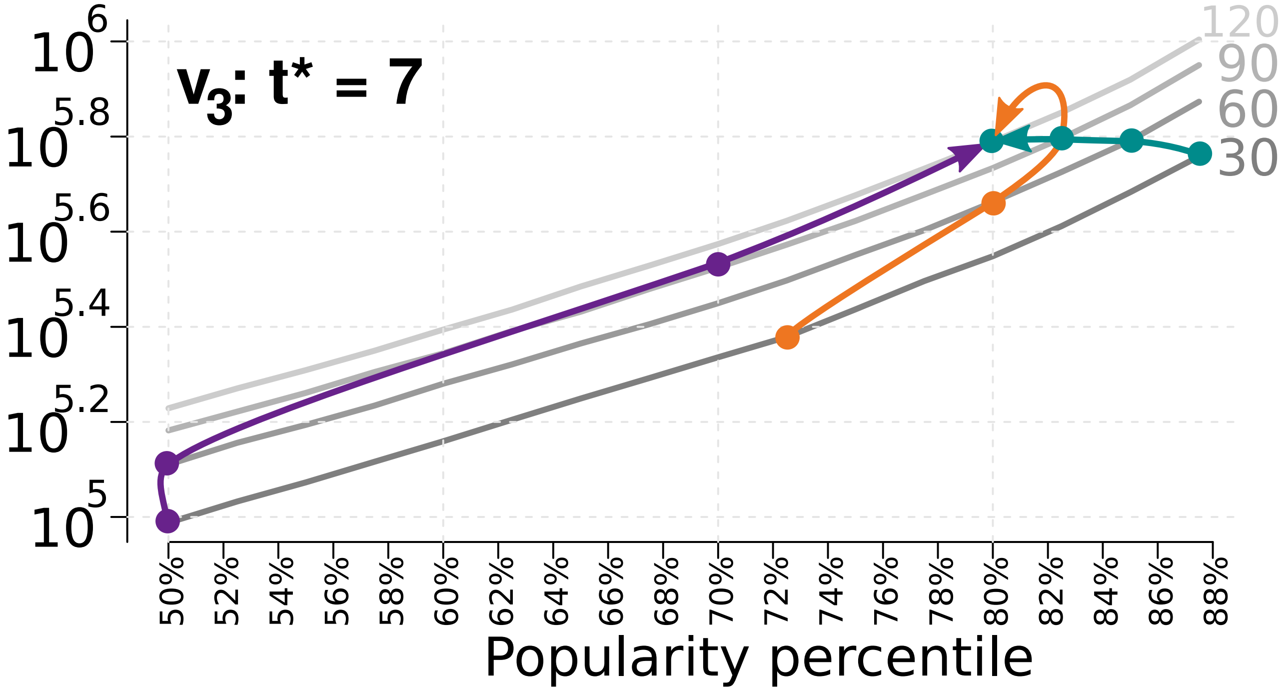


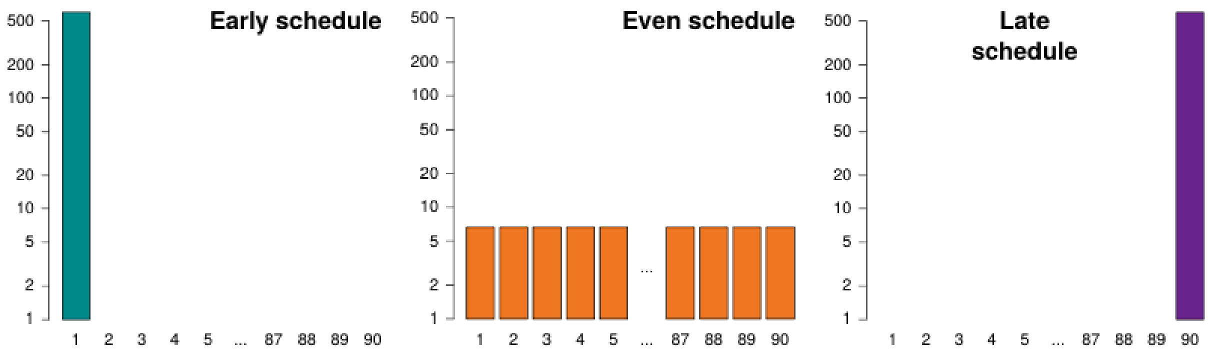


Interplay of 2 temporal factors







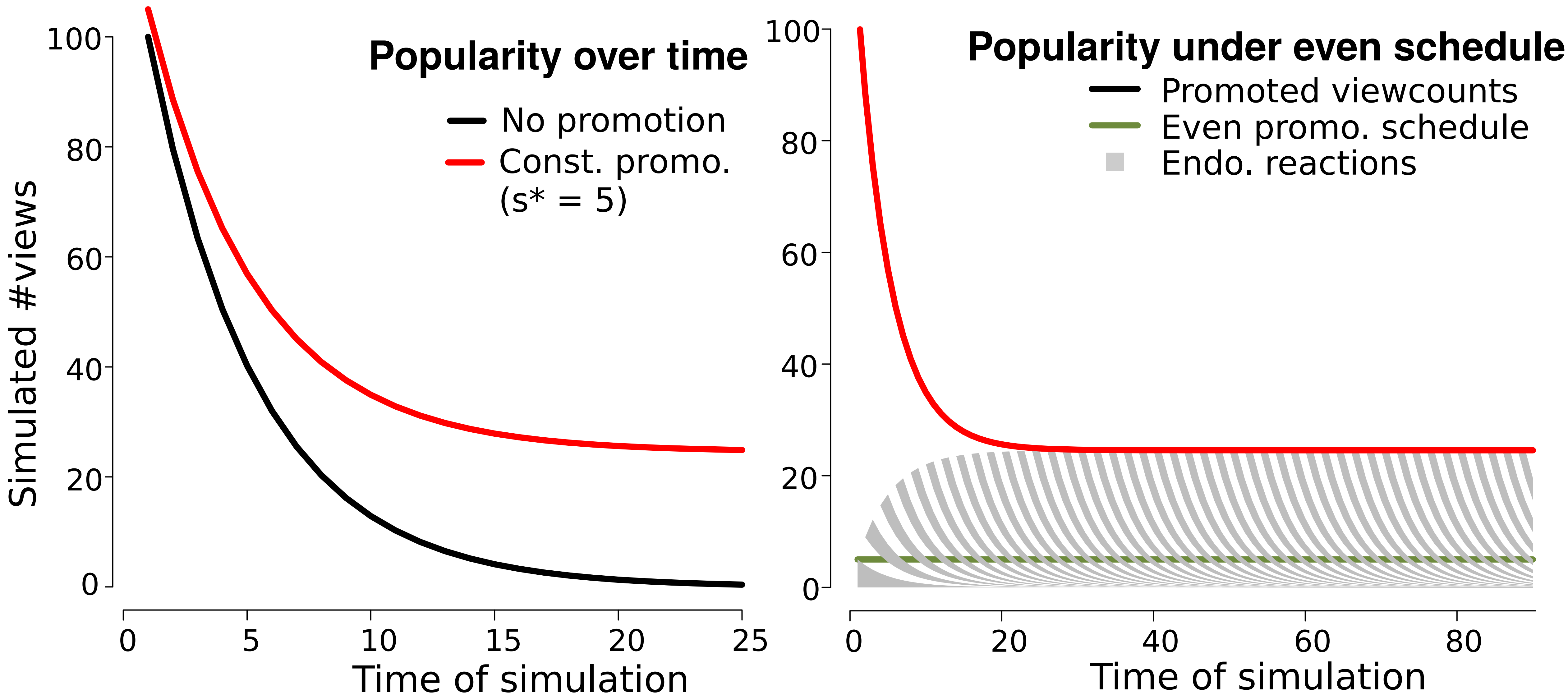


Why is constant promotion desirable?

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.**

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?

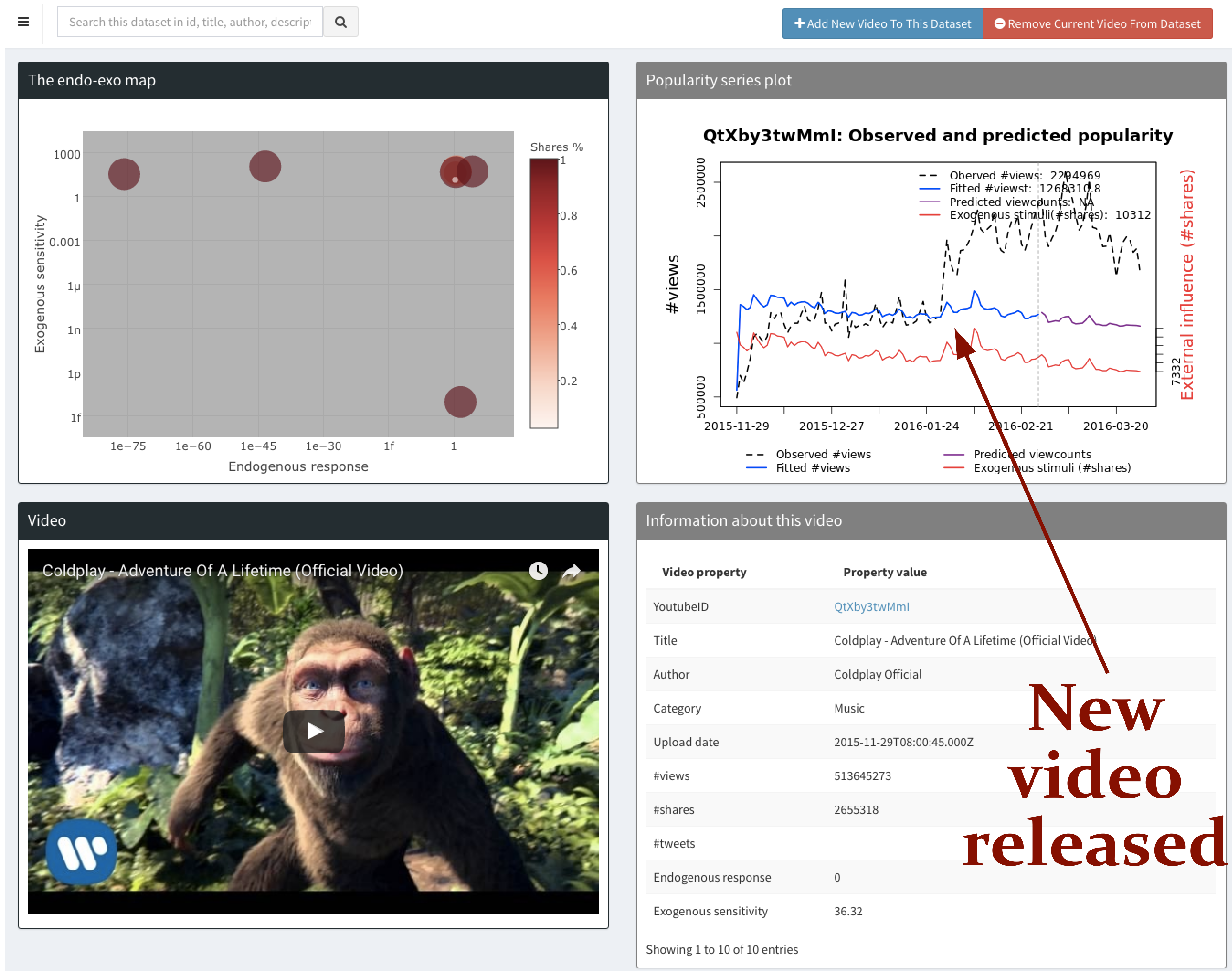
3) Predicting future popularity

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?

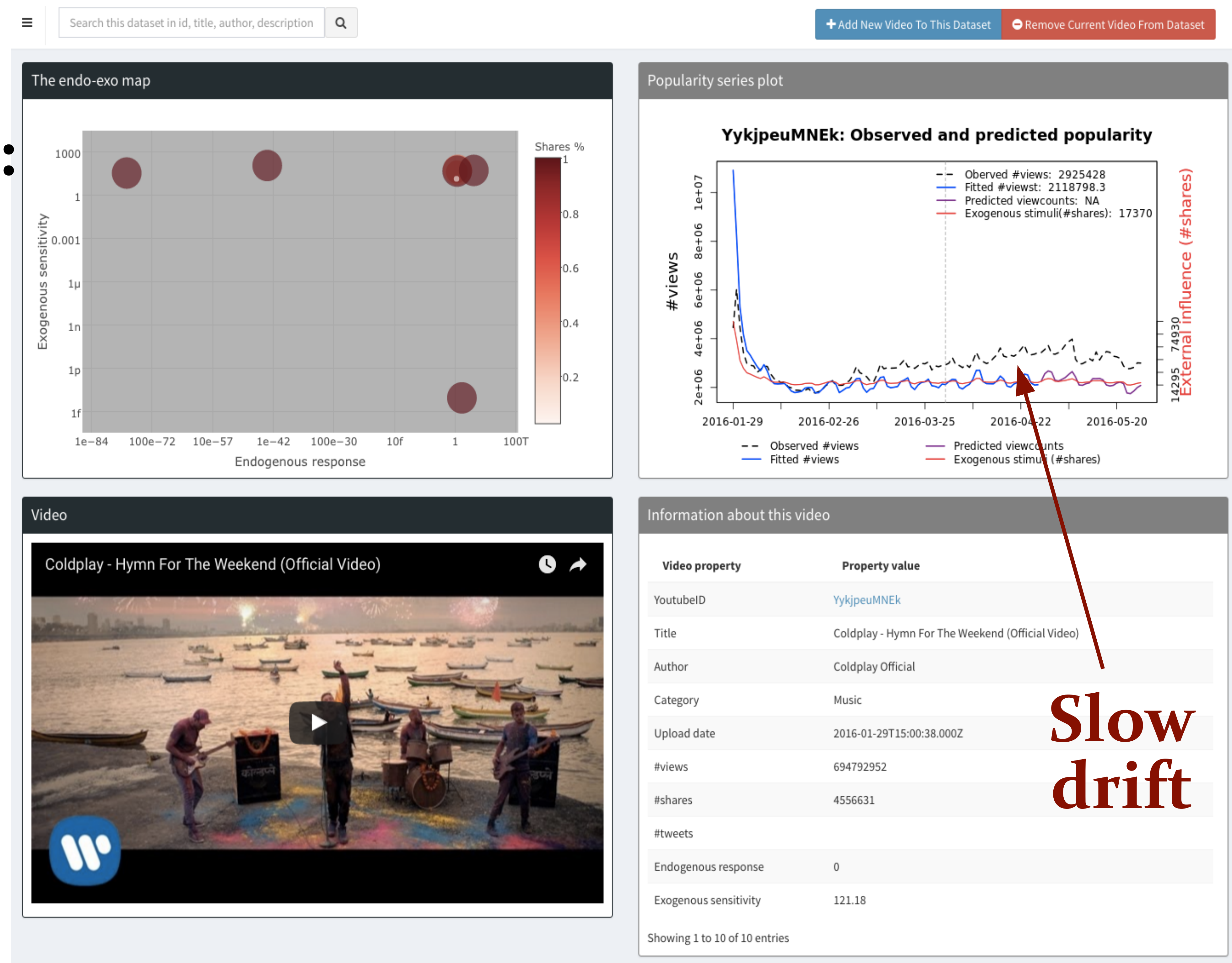
Supp: when HIP fails the fitting (1)

Relations between videos:



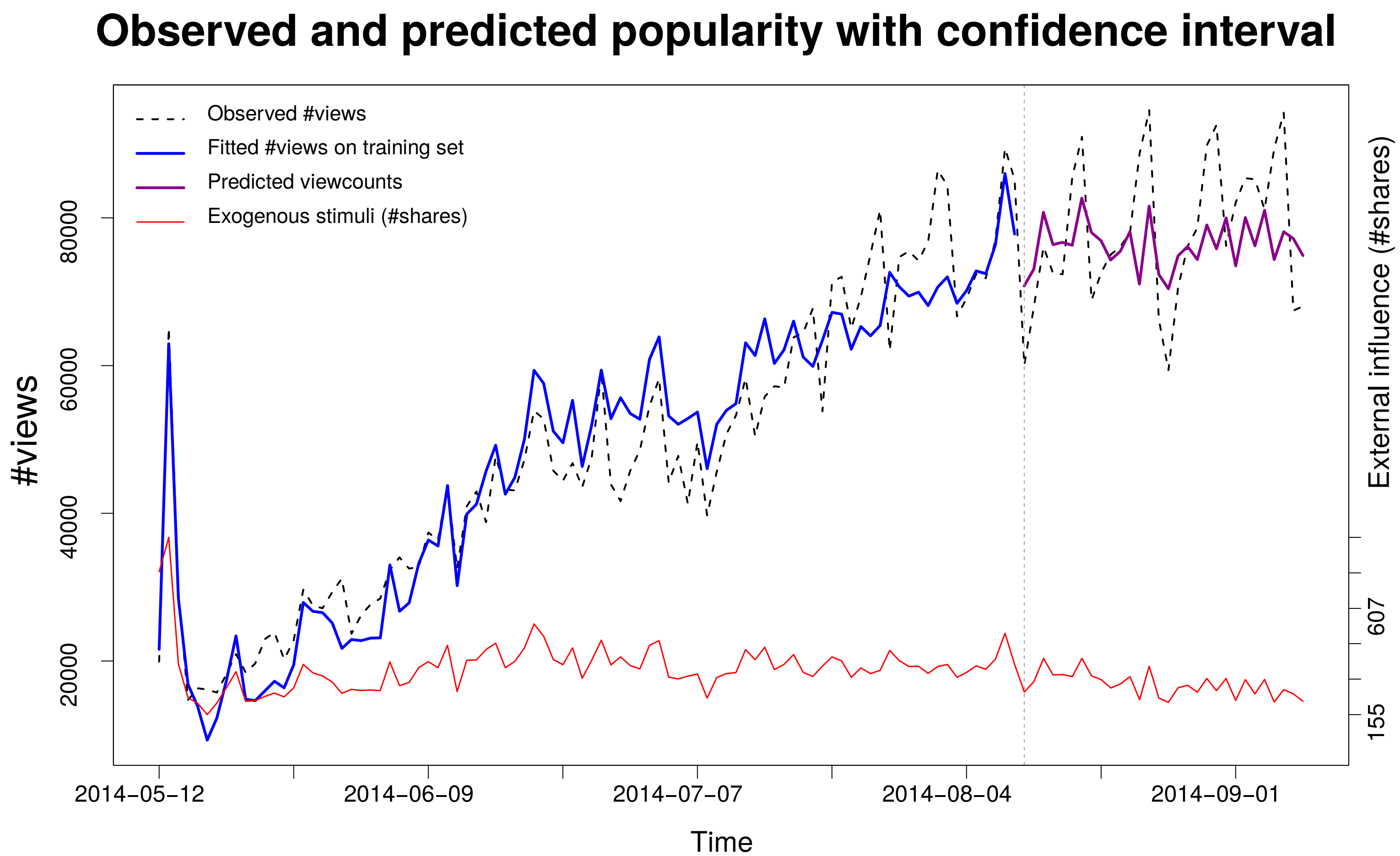
Supp: when HIP fails the fitting (2)

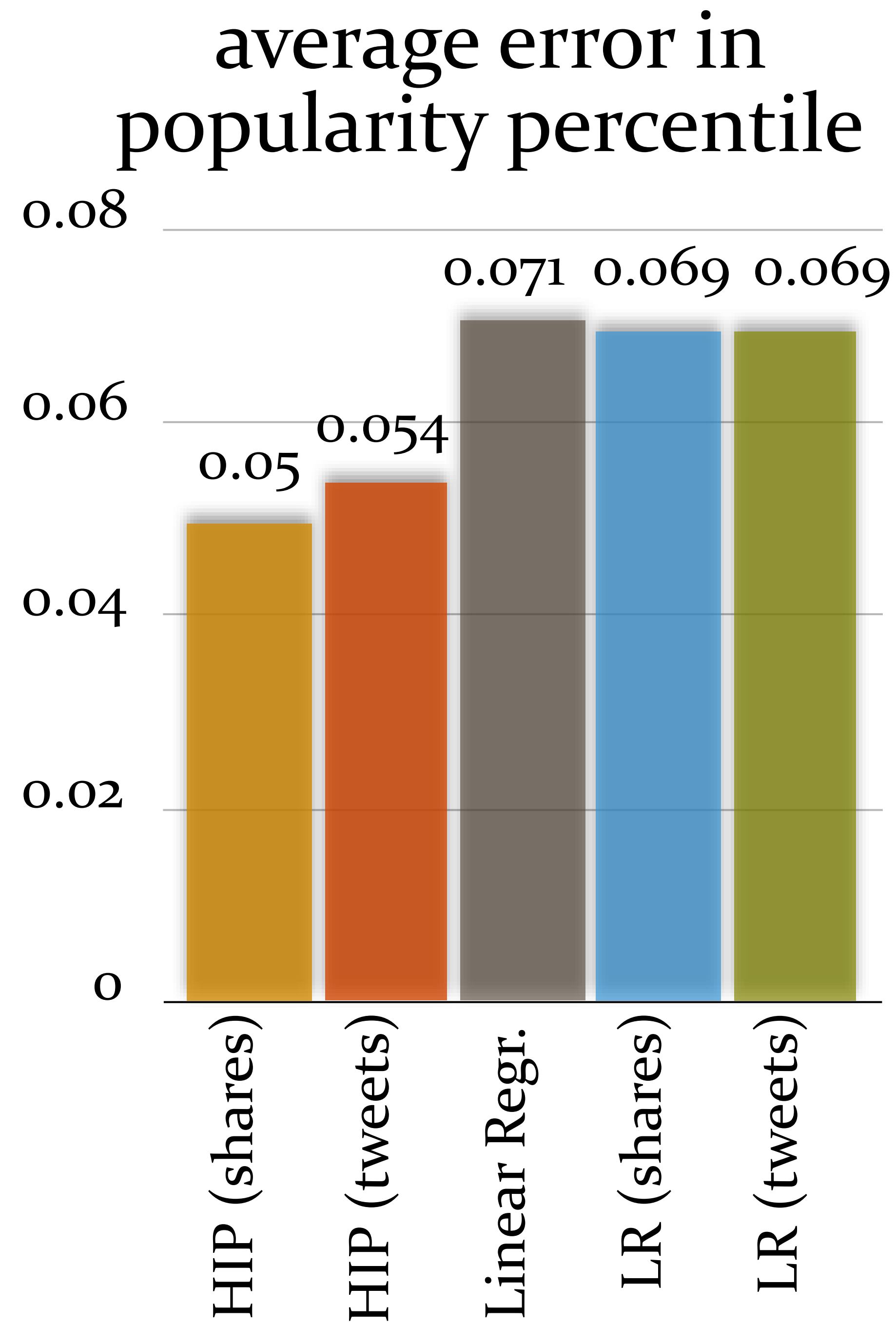
Long term evolutions:



Slow drift

Forecasting the effect of promotions





[Pinto et al WSDM'13]
[Szabo & Huberman Comm. ACM'13] [Yu et al ICWSM'15]