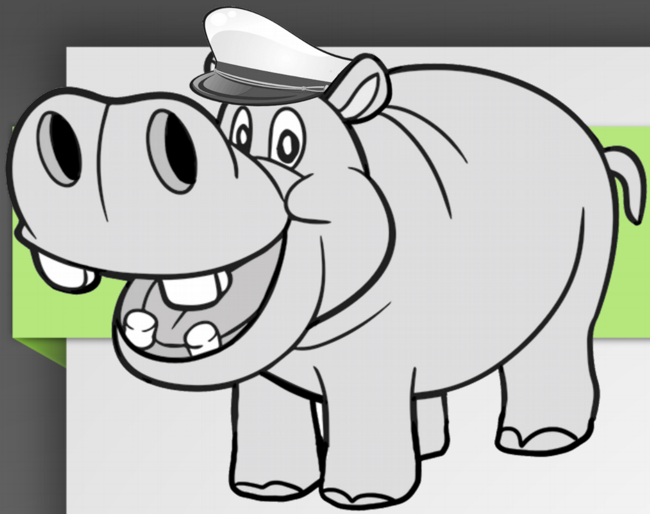


Expecting to be HIP:
modeling Human Behavior in the online environment

Sydney, March 1st, 2018

Marian-Andrei Rizoiu

A new paradigm of human interaction

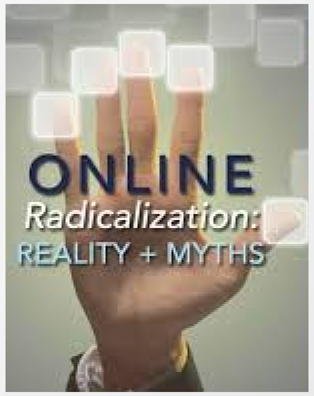
Users are both consumers and producers of information

20% of (US) users get news & information from Social Media

Novel challenges:

Spread of misinformation

SocialBots



Online radicalization

The larger goal

Modeling of information cascades – sequence of human actions

Tool and methods to address novel challenges

Rizoiu, M.-A., Graham, T., Zhang, R., Zhang, Y., Ackland, R., & Xie, L. (2018). #DebateNight: The Role and Influence of Socialbots on Twitter During the 1st U.S. Presidential Debate. **(under review)** (pp. 1–10).

Kong, Q., Rizoiu, M.-A., Wu, S., & Xie, L. (2018). Will This Video Go Viral? Explaining and Predicting the Popularity of Youtube Videos. In 27th **International Conference on World Wide Web Companion - WWW '18** (pp. 1–4).

Rizoiu, M.-A., Mishra, S., Kong, Q., Carman, M., & Xie, L. (2018). SIR-Hawkes: on the Relationship Between Epidemic Models and Hawkes Point Processes. In 27th **International Conference on World Wide Web - WWW '18** (pp. 1–16). Lyon, France. http://doi.org/10.1145/3178876.3186108

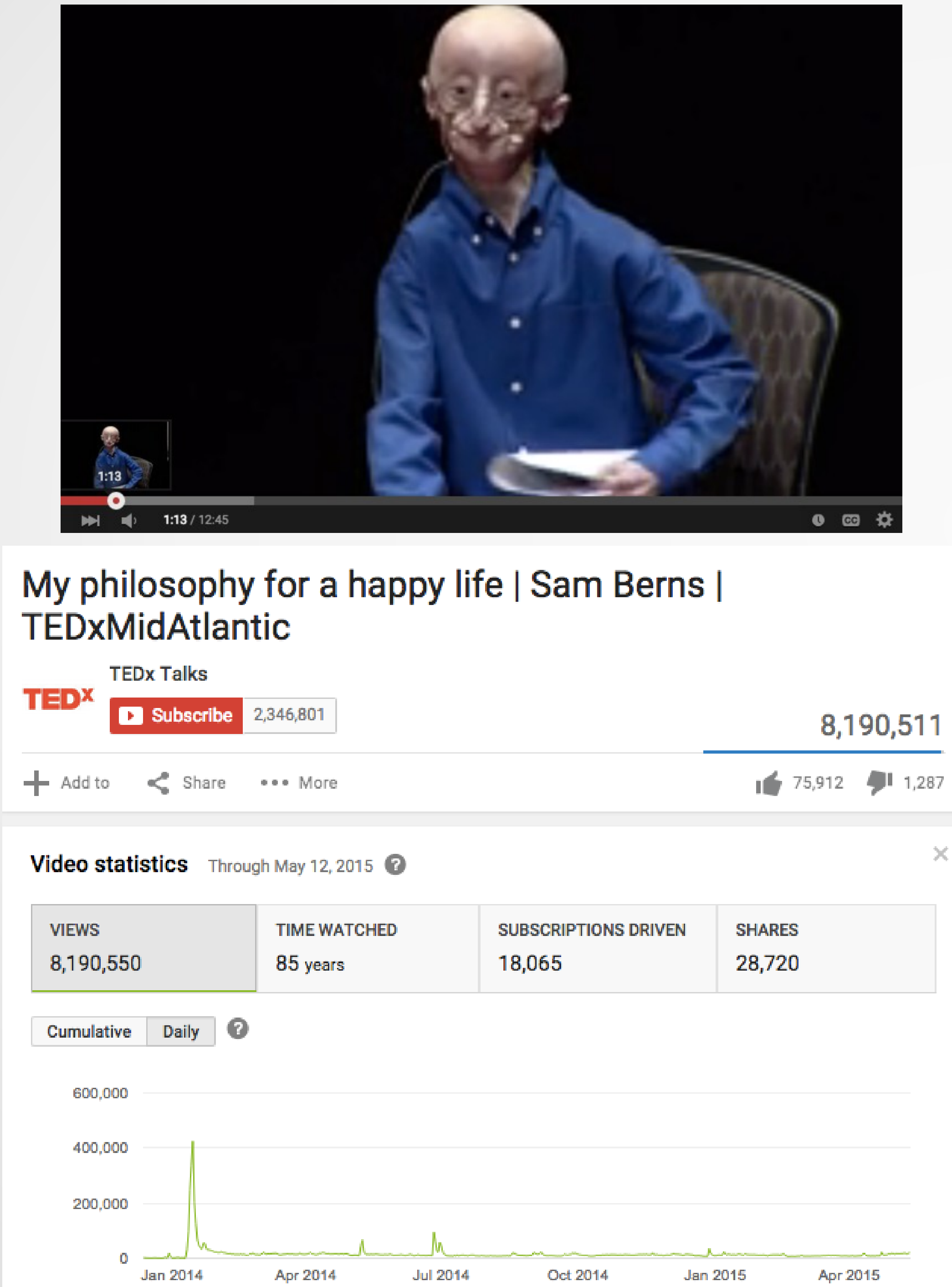
Rizoiu, M.-A., & Xie, L. (2017). Online Popularity under Promotion: Viral Potential, Forecasting, and the Economics of Time. In **International AAAI Conference on Web and Social Media (ICWSM '17)** (pp. 182–191). Canada.

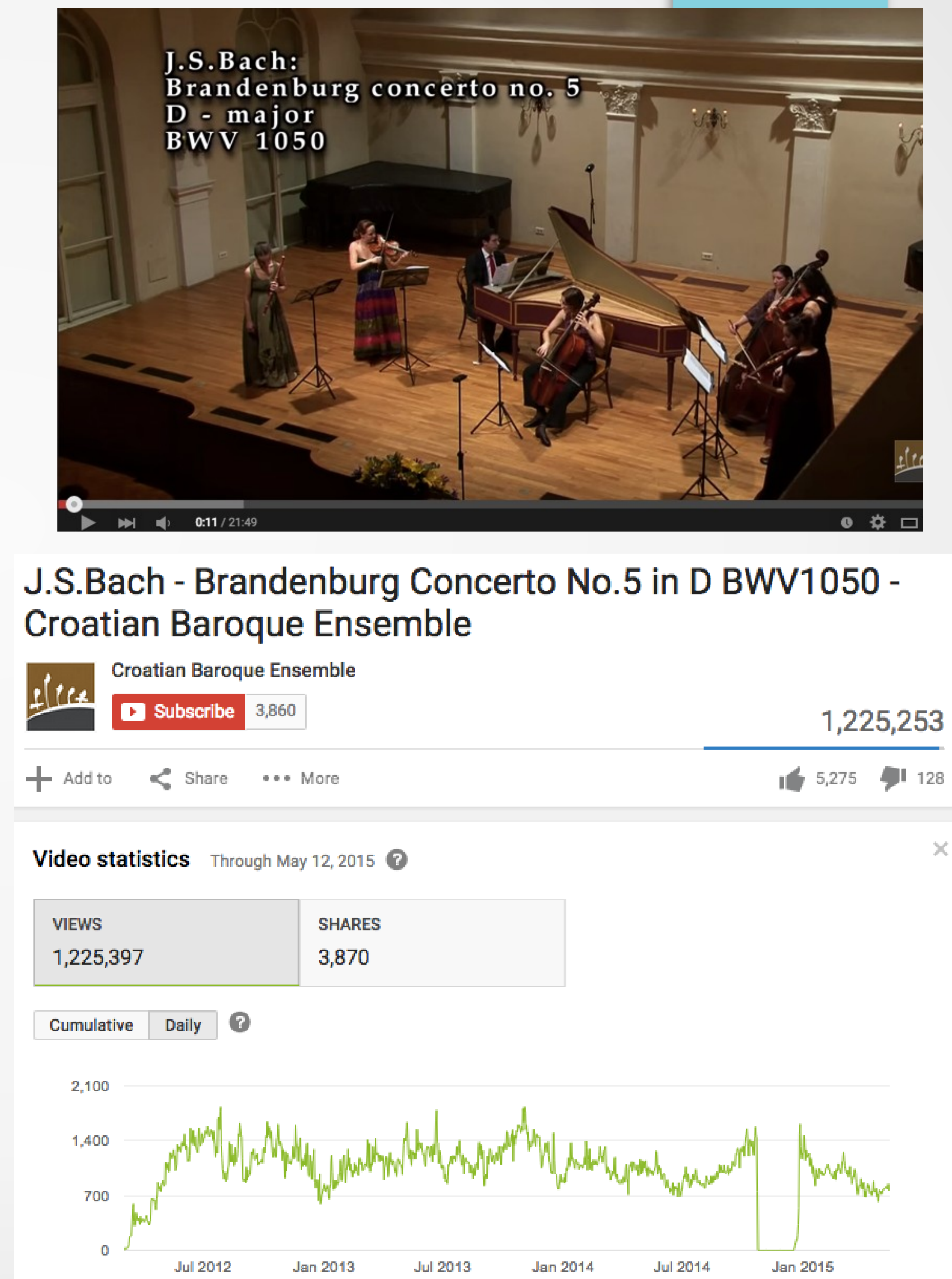
Rizoiu, M.-A., Lee, Y., Mishra, S., & Xie, L. (2017). A Tutorial on Hawkes Processes for Events in Social Media. In S.-F. Chang (Ed.), **Frontiers of Multimedia Research** (pp. 191–218).

Rizoiu, M.-A., Xie, L., Sanner, S., Cebrian, M., Yu, H., & Van Hentenryck, P. (2017). 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.: ACM Press. http://doi.org/10.1145/3038912.3052650

Mishra, S., Rizoiu, M.-A., & Xie, L. (2016). Feature Driven and Point Process Approaches for Popularity Prediction. In Proceedings of the 25th ACM International on **Conference on Information and Knowledge Management - CIKM '16** (pp. 1069–1078). Indianapolis, IN, USA: ACM Press. http://doi.org/10.1145/2983323.2983812

Popularity over time





Why popularity?

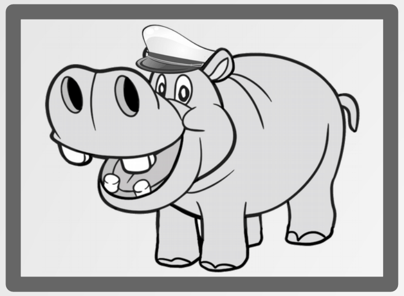
"The fundamental scarcity in the modern world is the scarcity of attention." — Herbert Simon

how does content become popular?
can one predict? can one promote/demote?

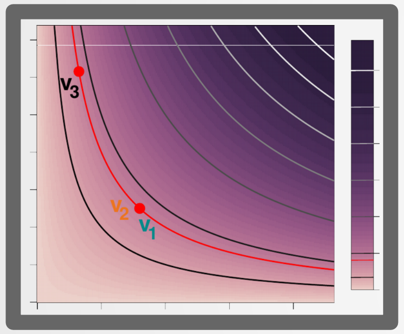
Applications:

- manage information overload
- identify what makes content viral (e.g. fake news)

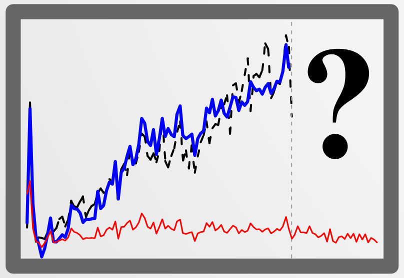
Presentation outline



Modeling popularity with HIP



Content virality and maturity time



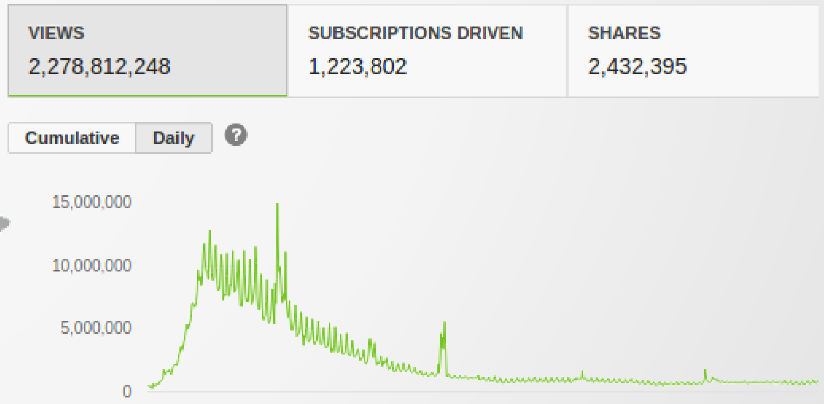
Forecasting popularity under promotion

Promotions schedules and memory lengthening through promotion

Linking exo-endo popularity

exogenous stimuli

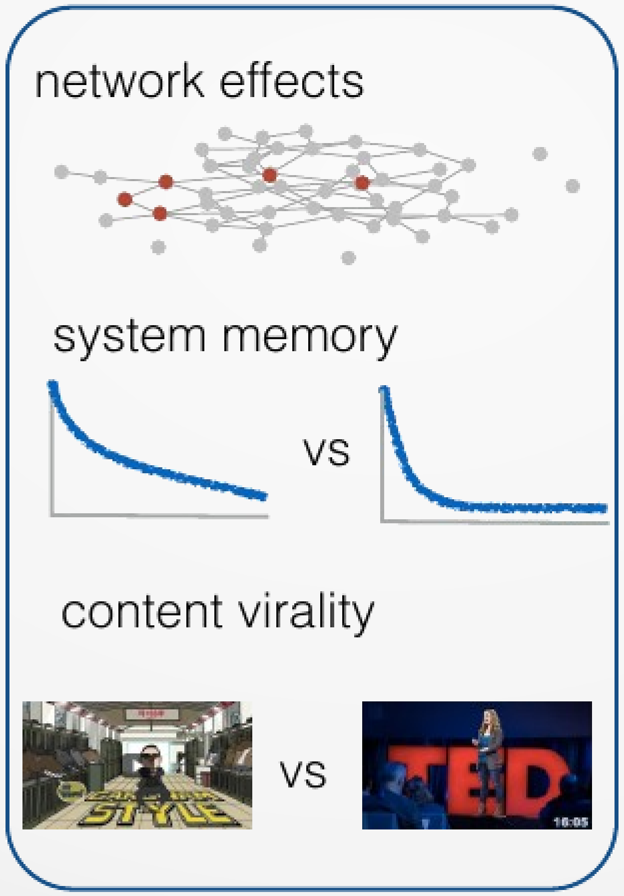
endogenous response



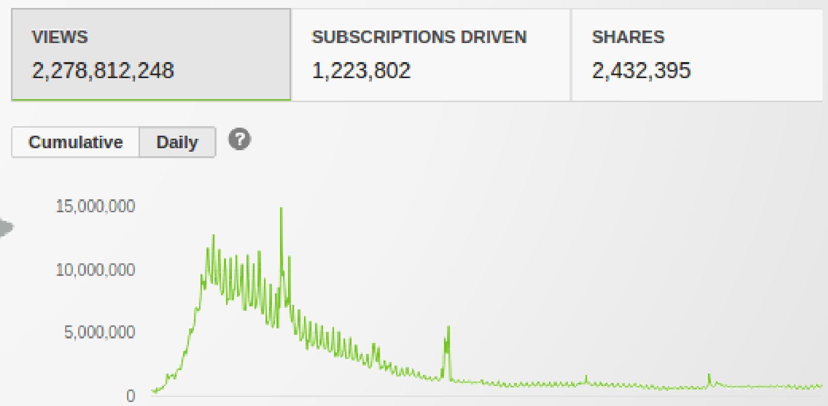
observed popularity

Linking exo-endo popularity

exogenous stimuli



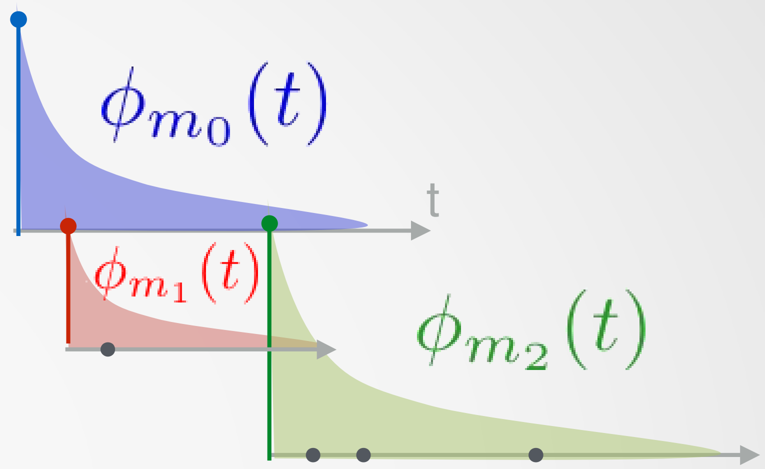
endogenous response



observed popularity

Hawkes Process [Hawkes '71]

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



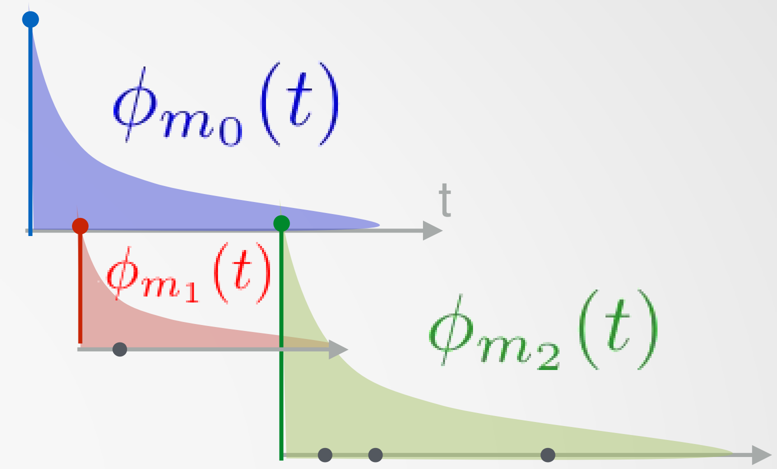
Most state-of-the-art popularity prediction systems require observing individual events.

[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

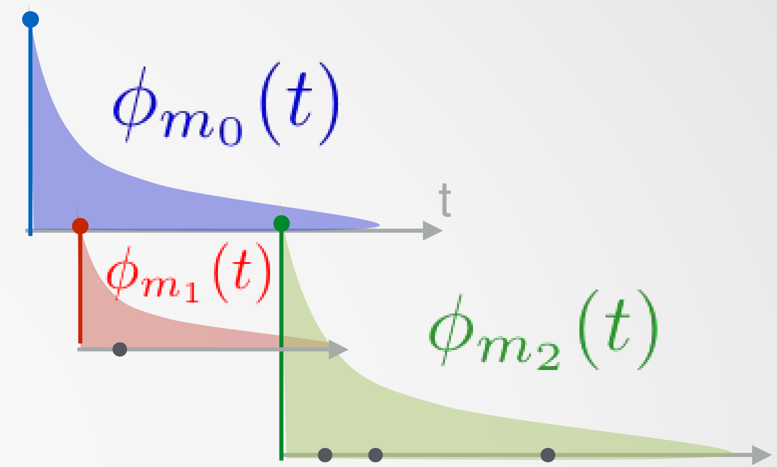
$$\phi_m(\tau) = \kappa\, m^\beta \hat{\tau}^{-(1+\theta)}$$

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

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

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

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

expected number of events

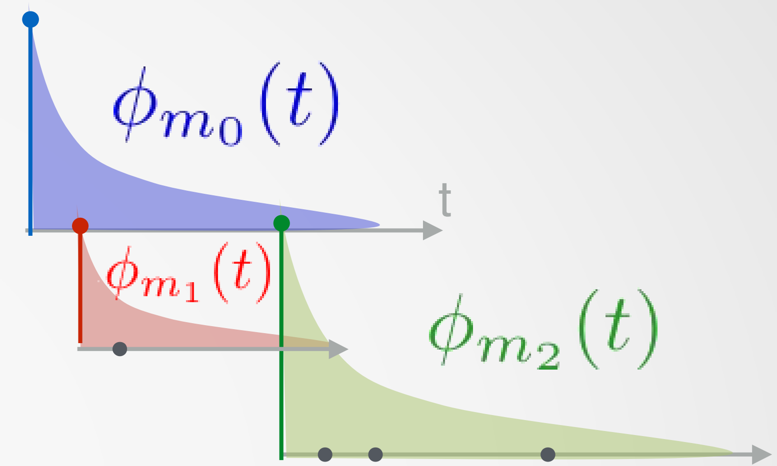
$$\xi(t) = \mu s(t) + C \int_0^t \xi(t-\tau)\hat{\tau}^{-(1+\theta)} d\tau$$

popularity

exogenous stimuli

Hawkes Intensity Process (HIP)

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



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

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

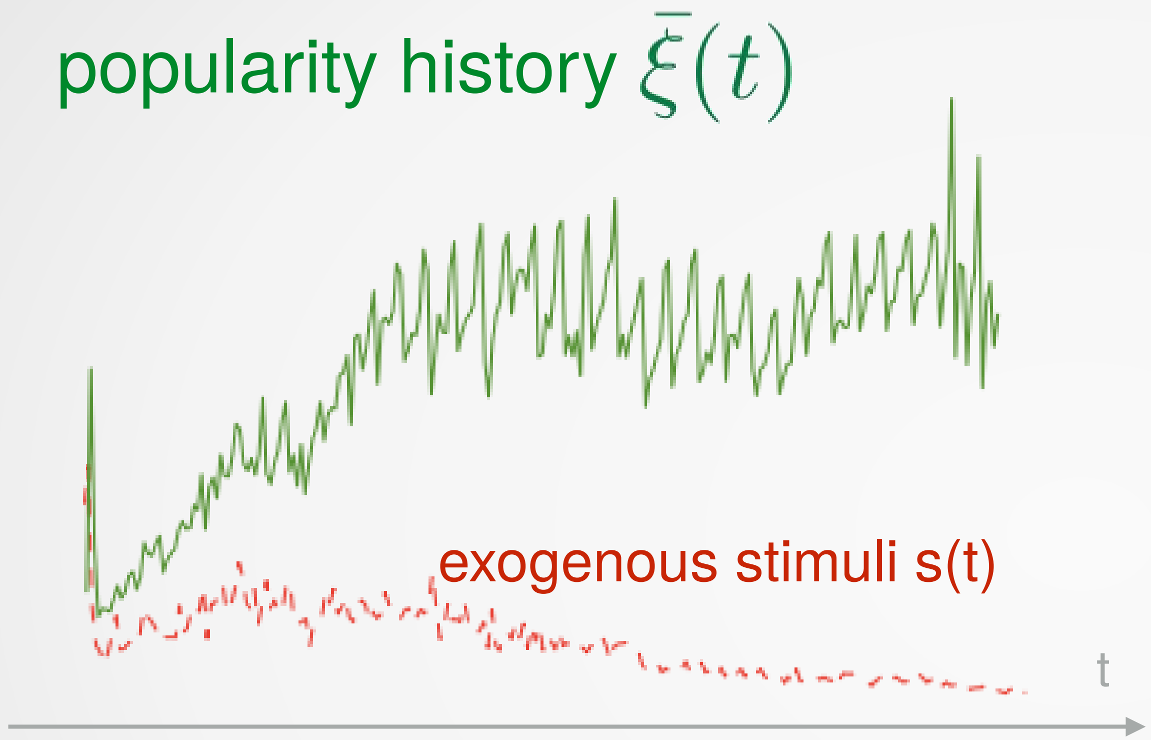
expected number of events

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

popularity

exogenous sensitivity — exogenous stimuli — endogenous reaction

Estimating the HIP model

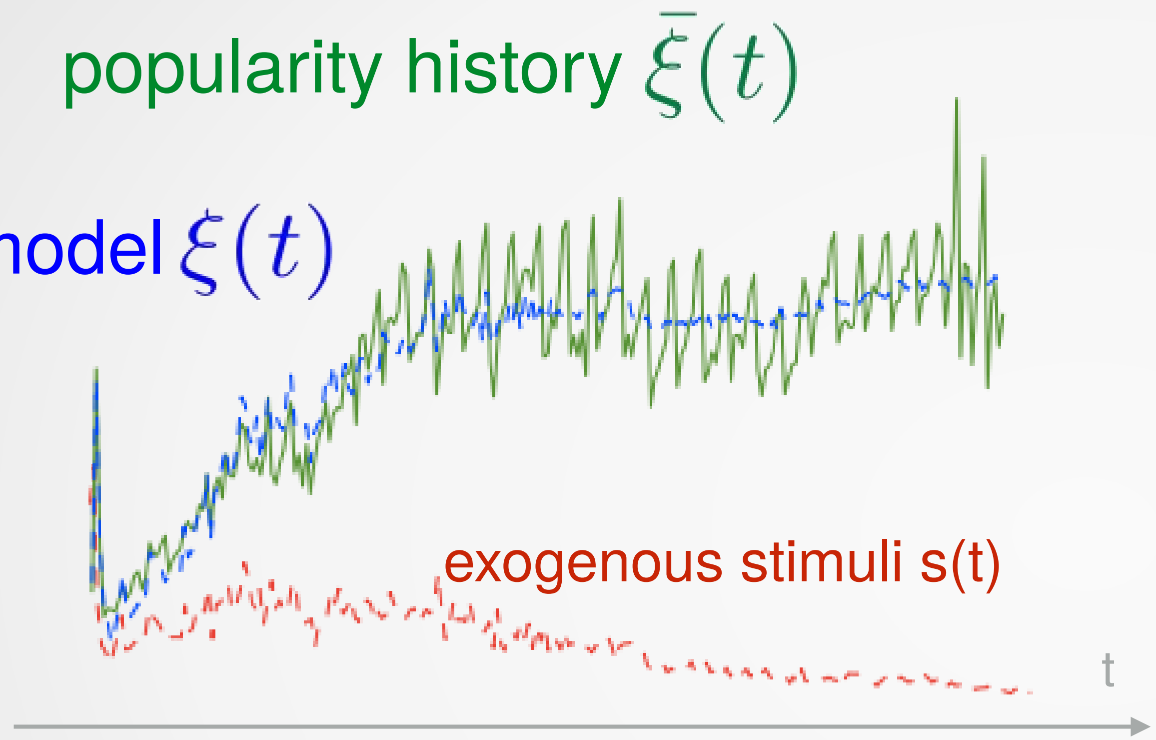


$$\text{find } \{\mu, C, \theta, \ldots\}$$

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

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

Estimating the HIP model



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

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

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

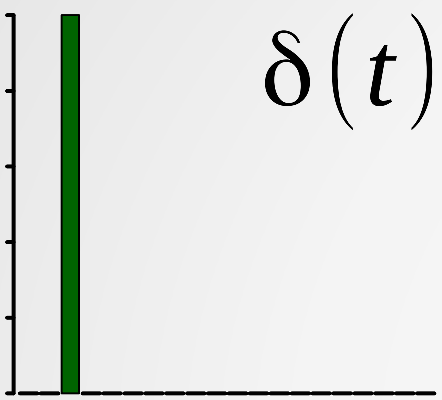
popularity

exogenous sensitivity (μ) exogenous stimuli ($s(t)$)

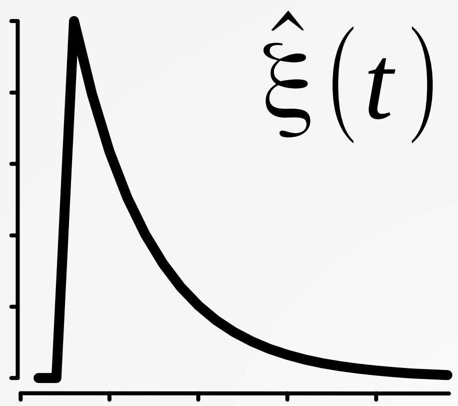
endogenous reaction

HIP as a Linear Time-Invariant system

promotion



response



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

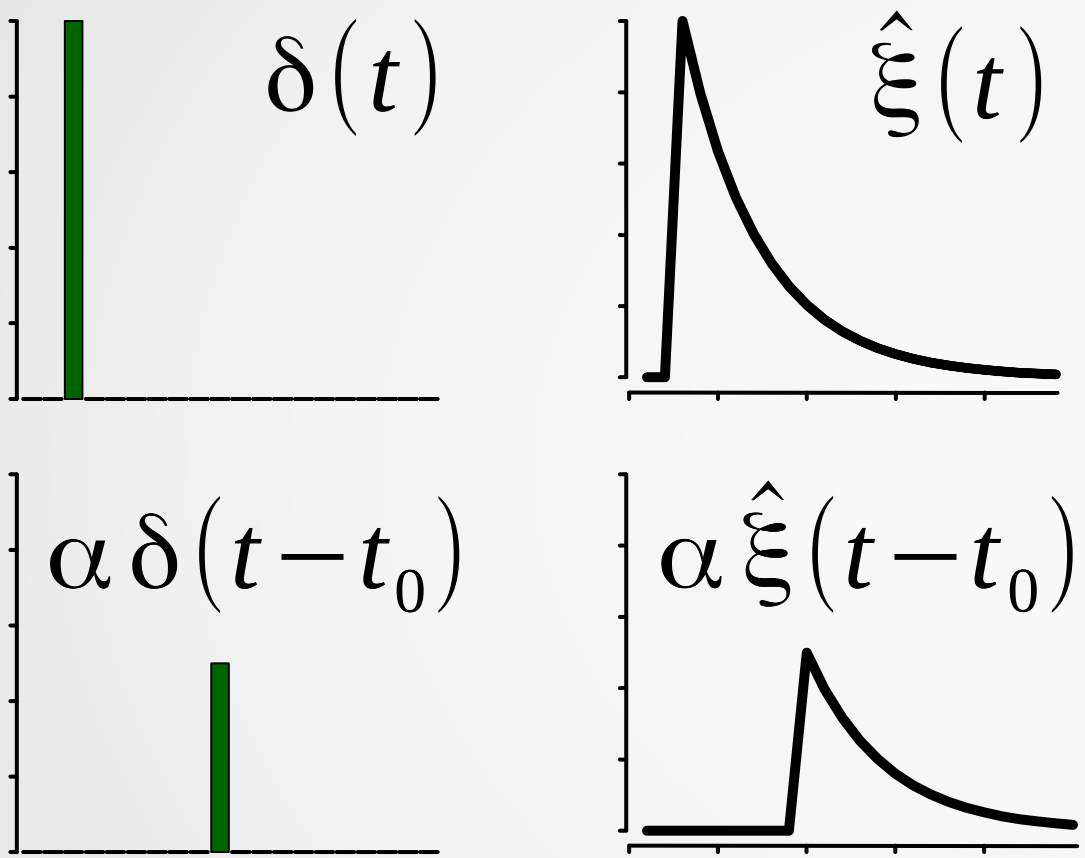
popularity

exogenous sensitivity

exogenous stimuli

HIP as a Linear Time-Invariant system

promotion response



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

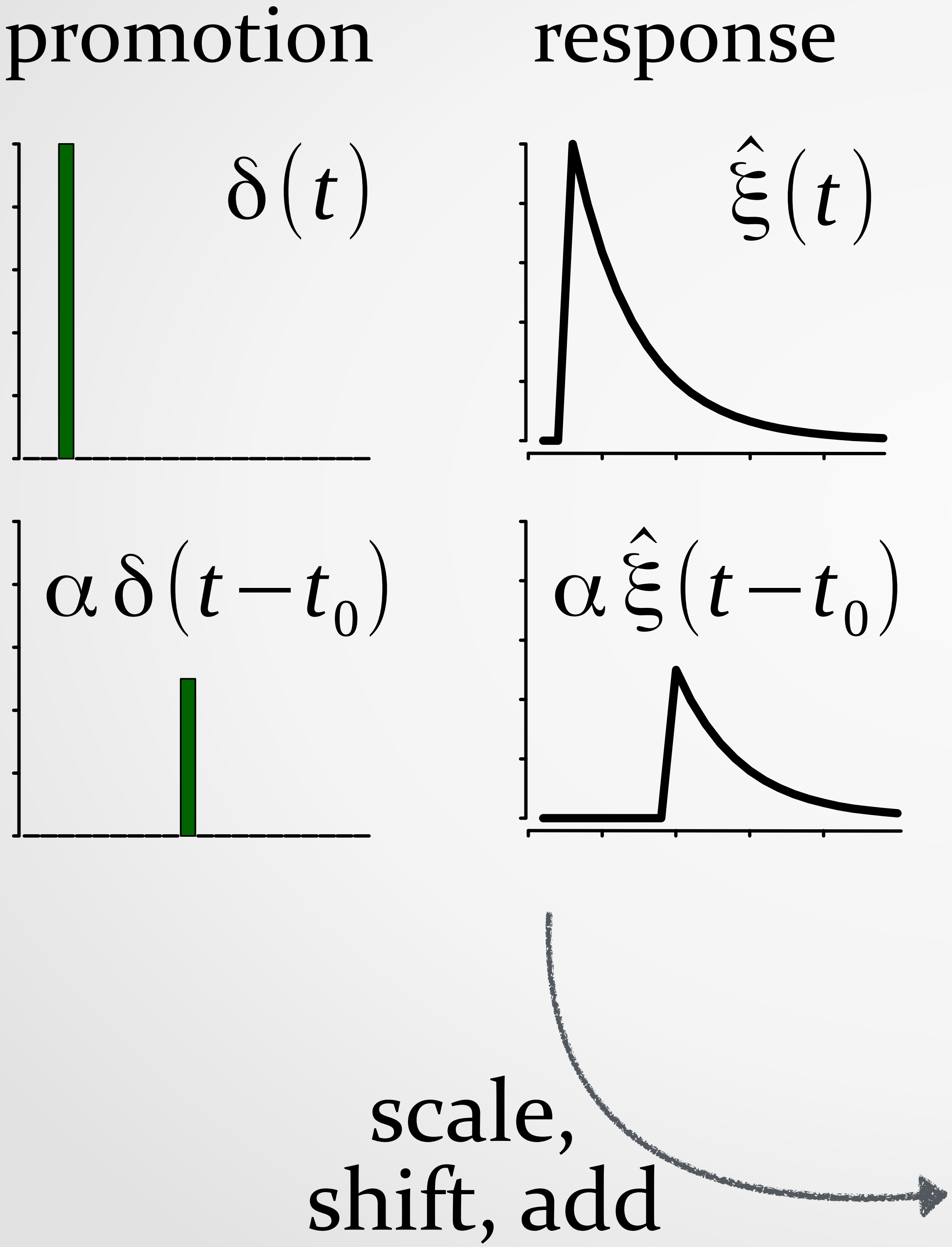
popularity

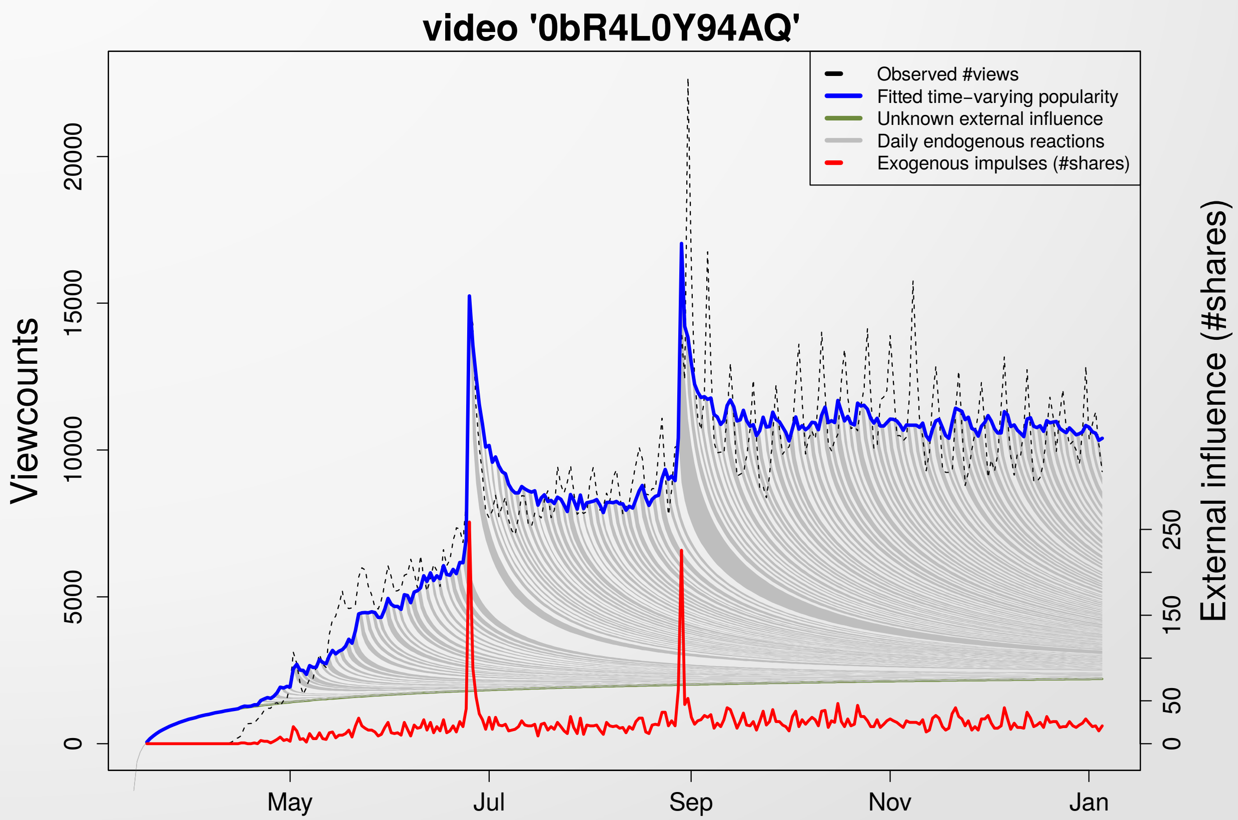
exogenous sensitivity

exogenous stimuli

endogenous reaction

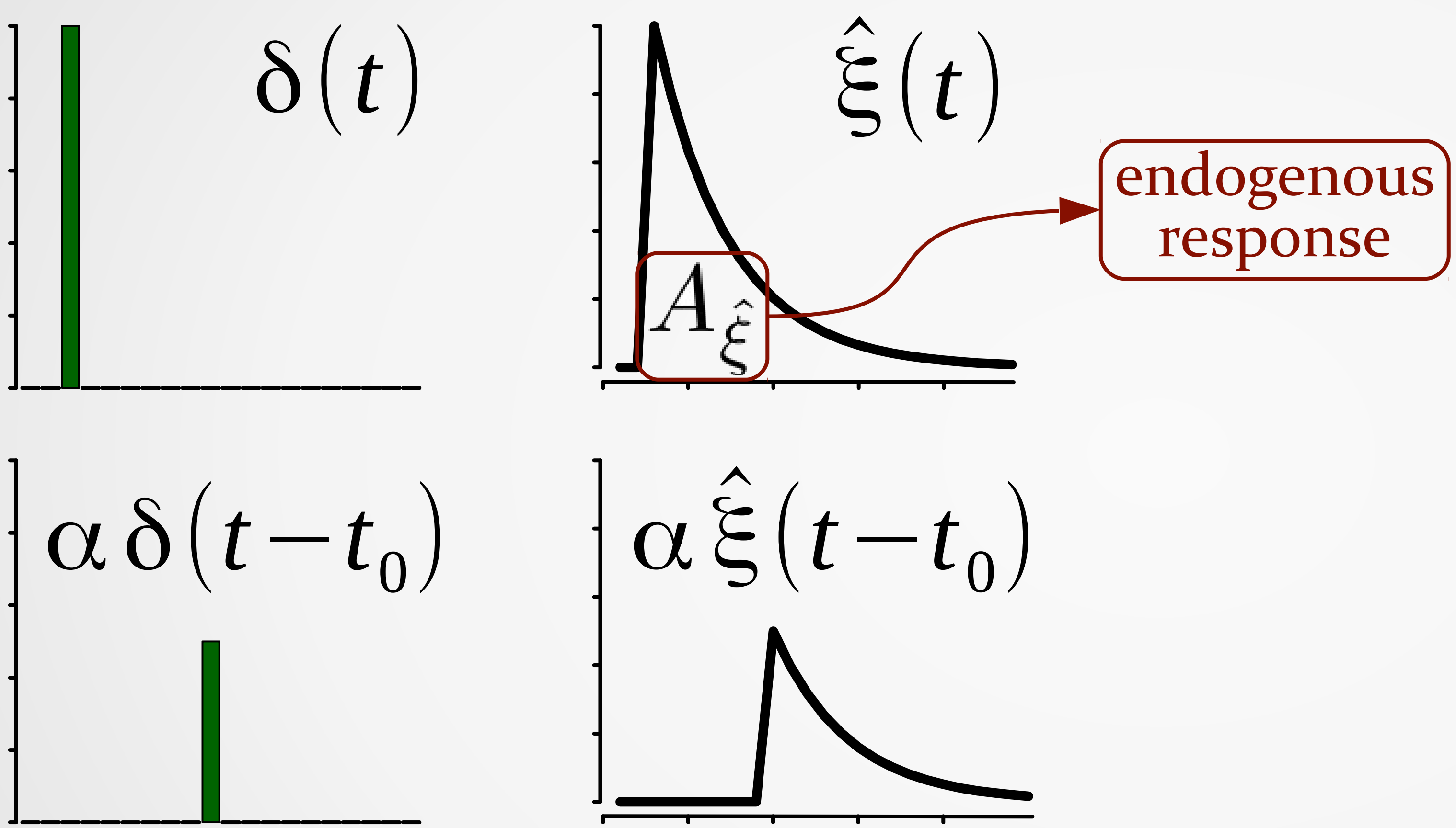
HIP as a Linear Time-Invariant system





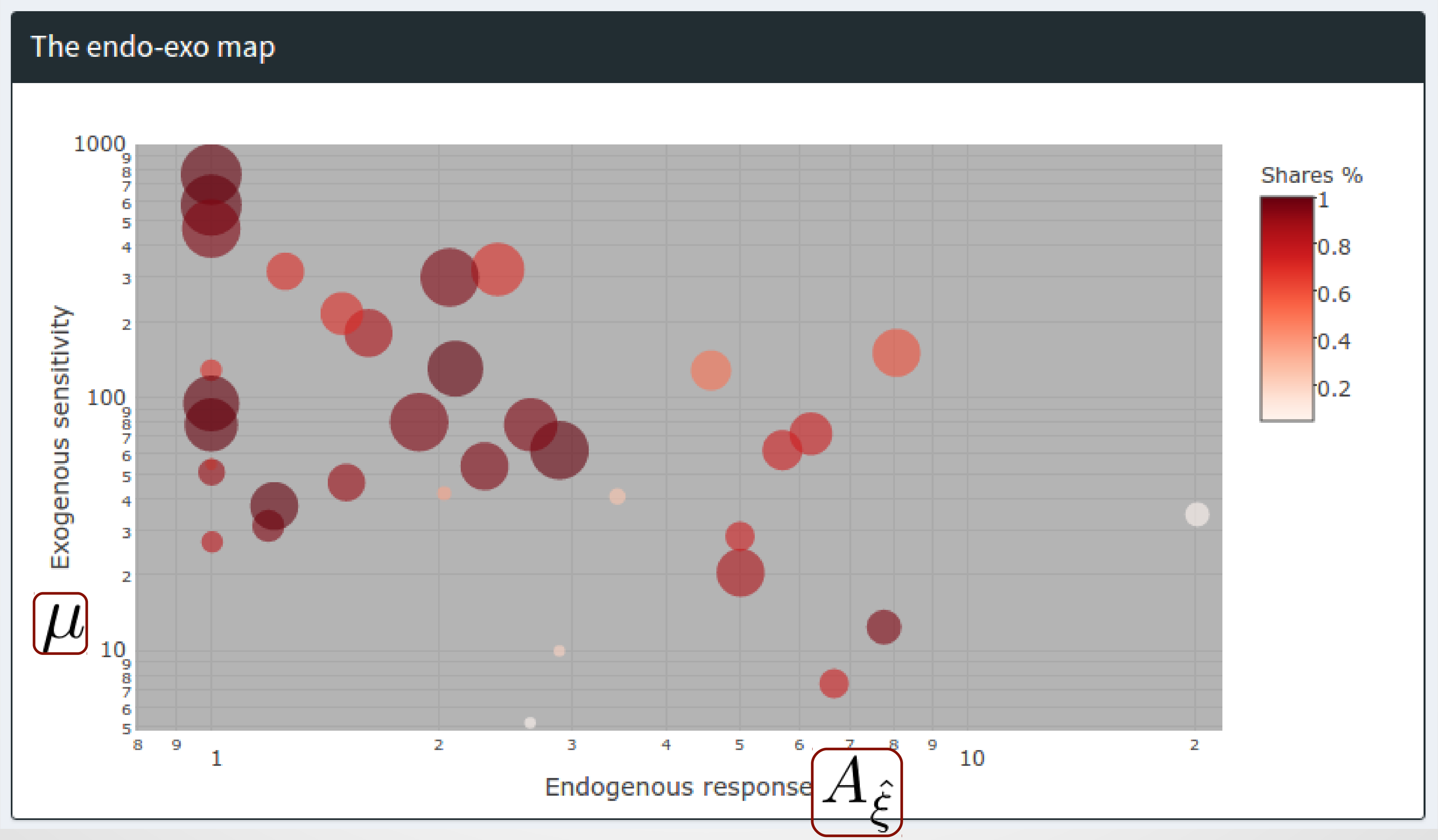
HIP as a Linear Time-Invariant system

promotion response

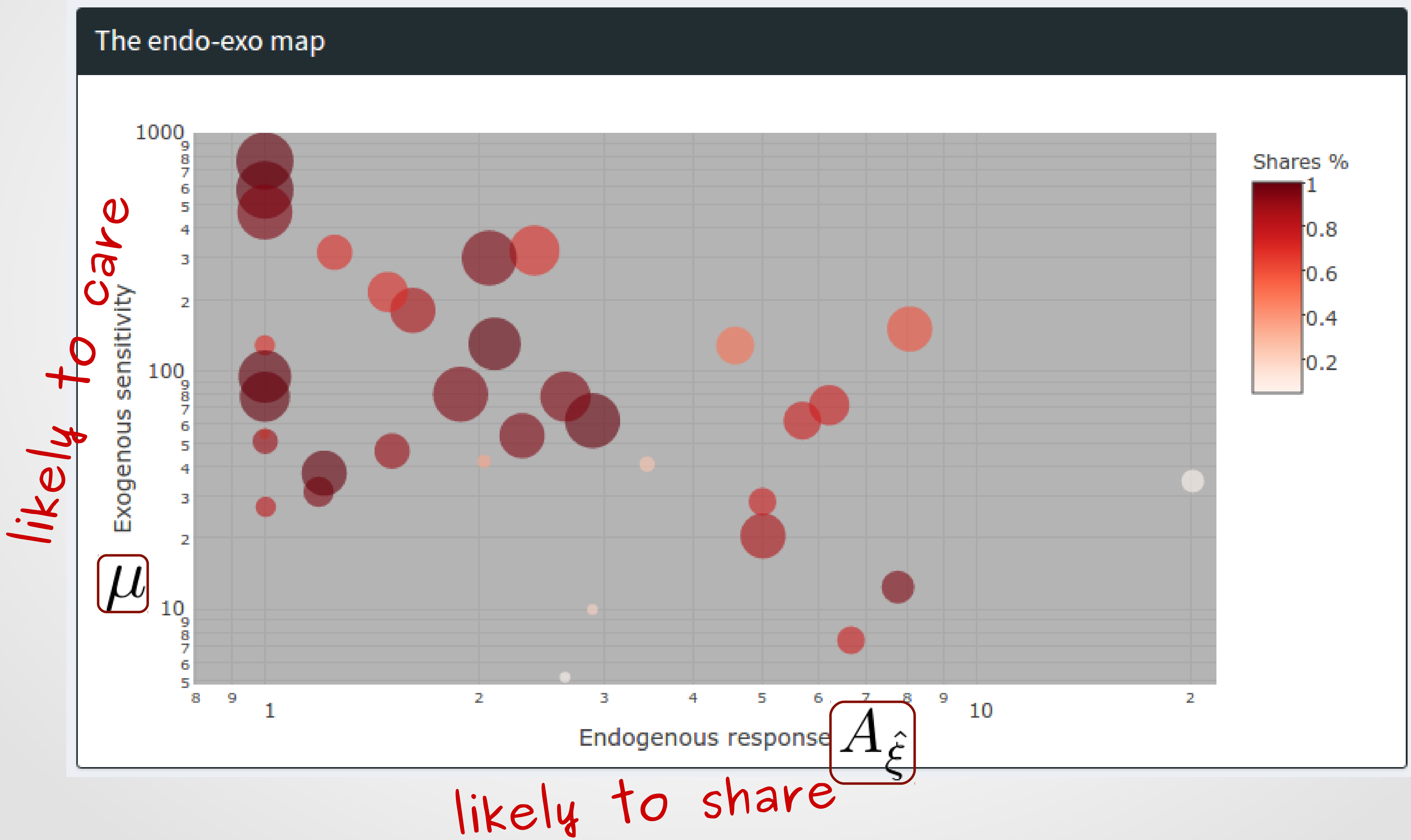


$$\underbrace{\xi(t)}_{\text{popularity}} = \underbrace{\boxed{\mu}}_{\text{exogenous sensitivity}}\underbrace{s(t)}_{\text{exogenous stimuli}} + \underbrace{C\int_0^t \xi(t-\tau)\hat{\tau}^{-(1+\theta)}\,d\tau}_{\text{endogenous reaction}}$$

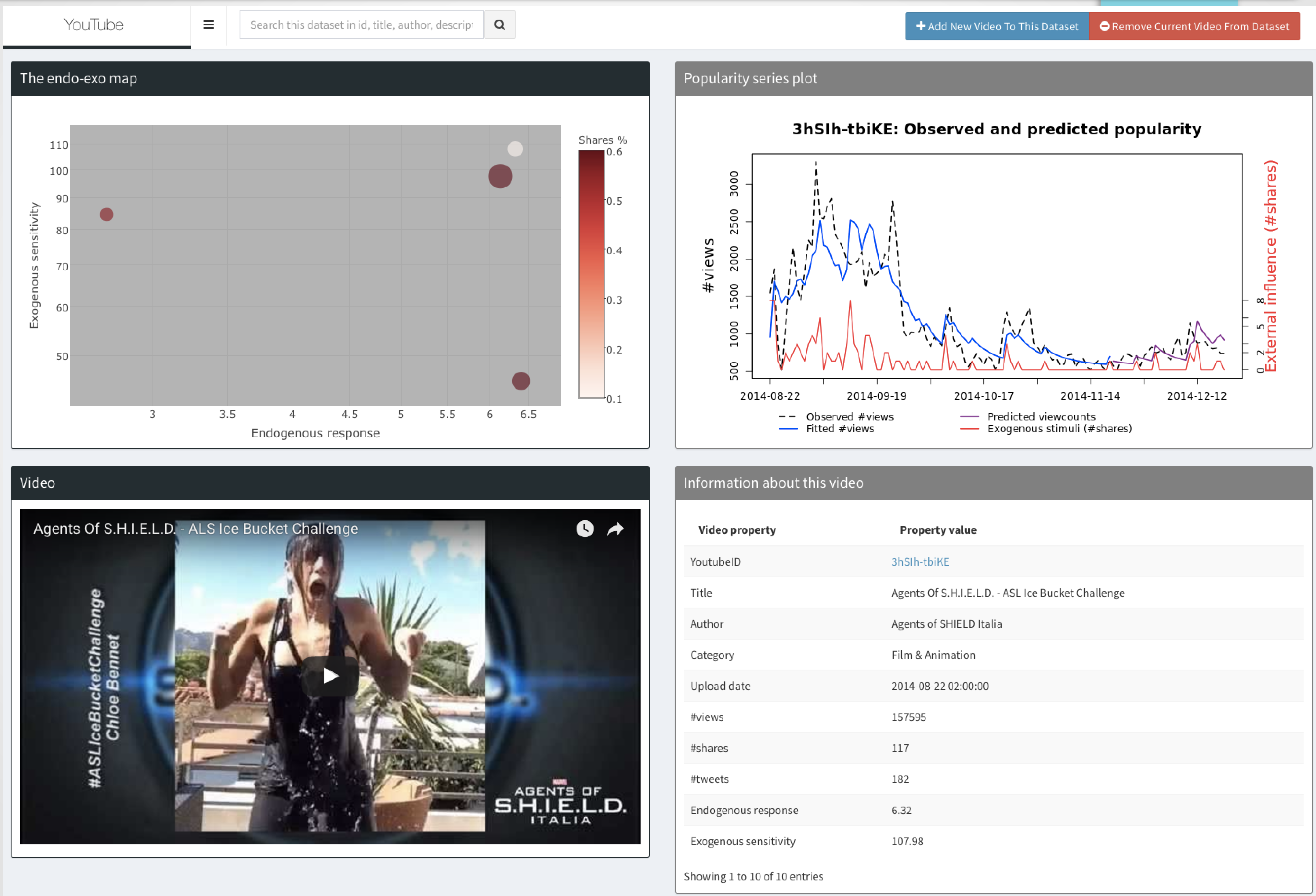
The “endo-exo” map



The “endo-exo” map



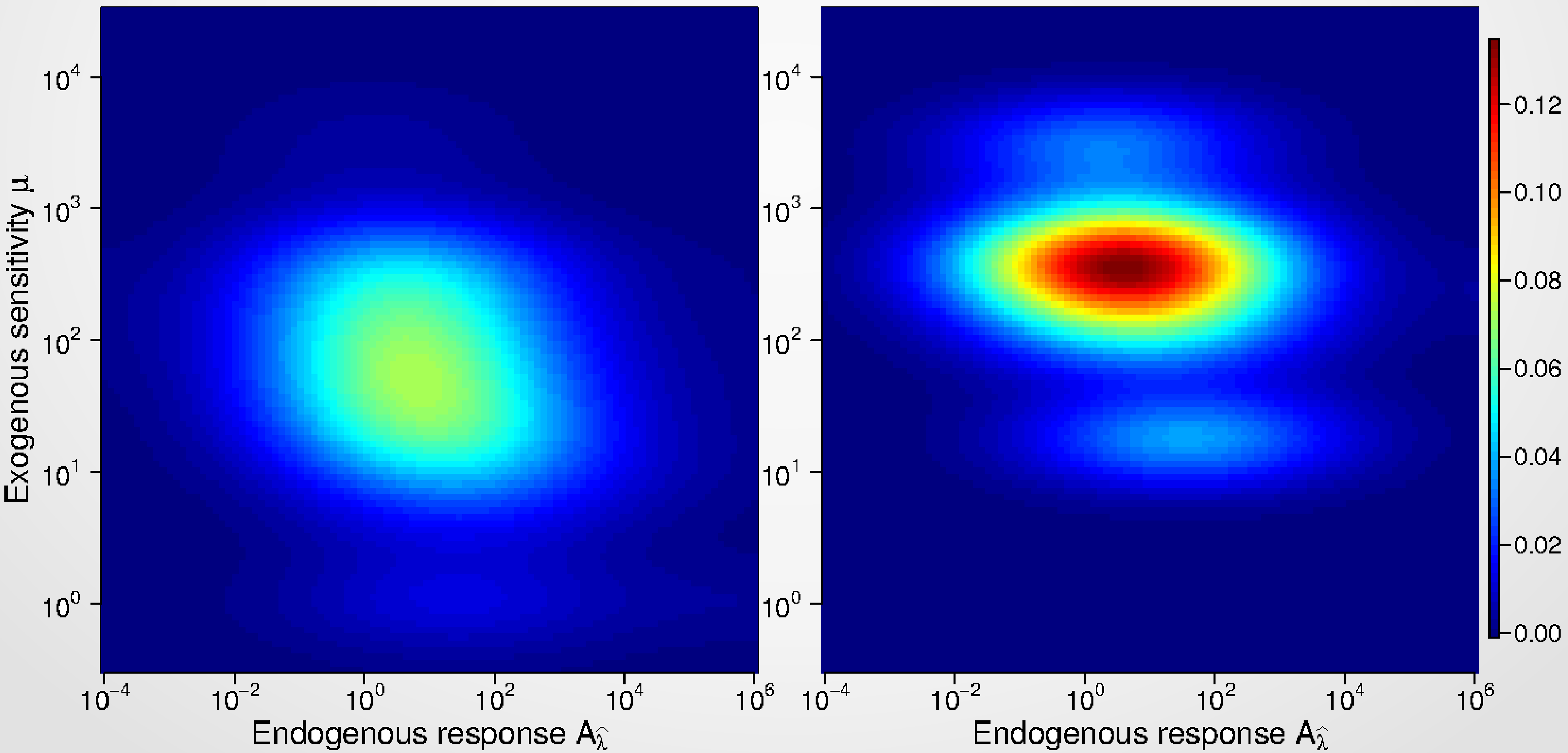
Explain popularity dynamics



Explain popularity – all vs top 5%

Film and Animation:

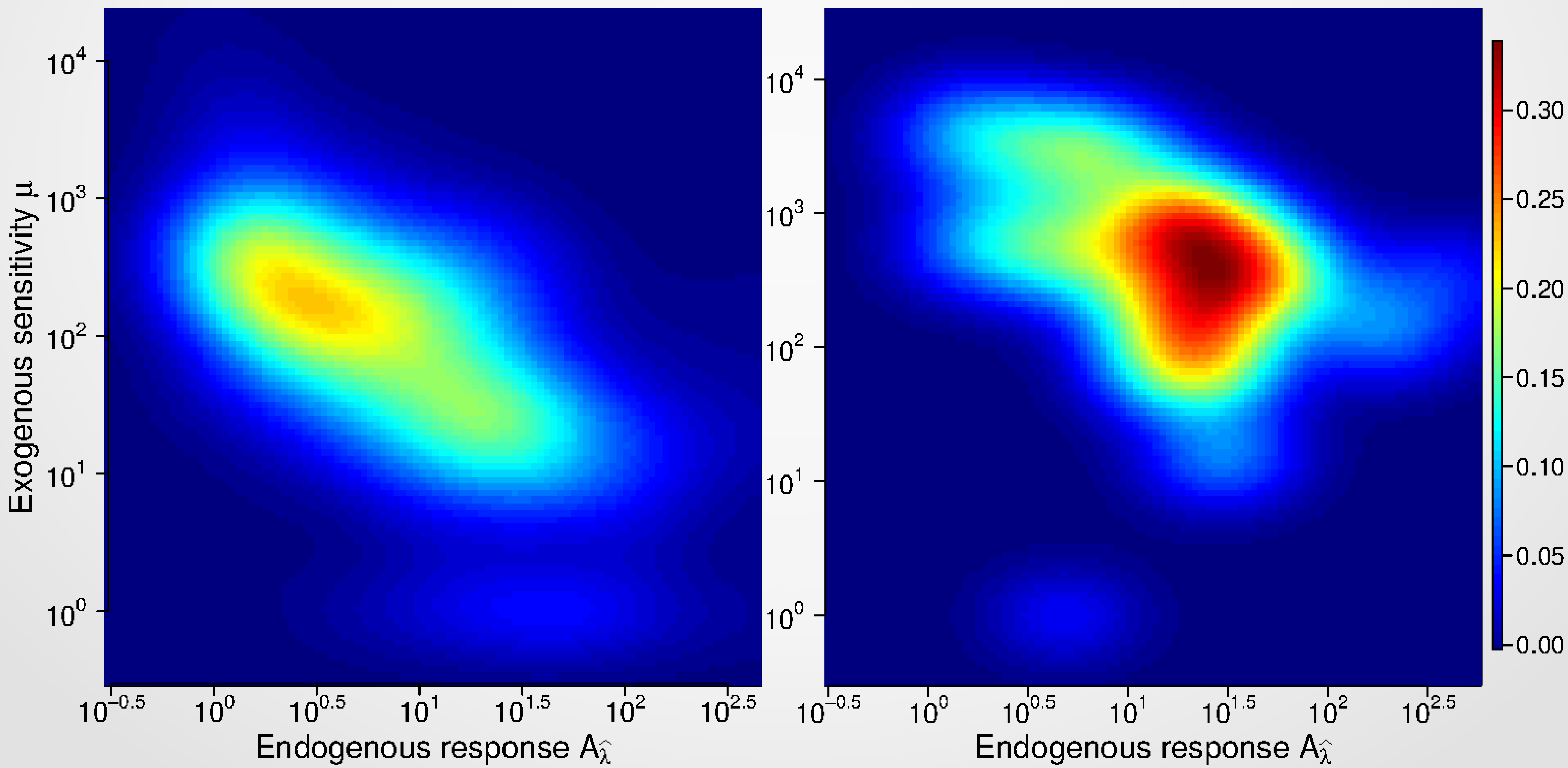
more popular videos have higher sensitivity



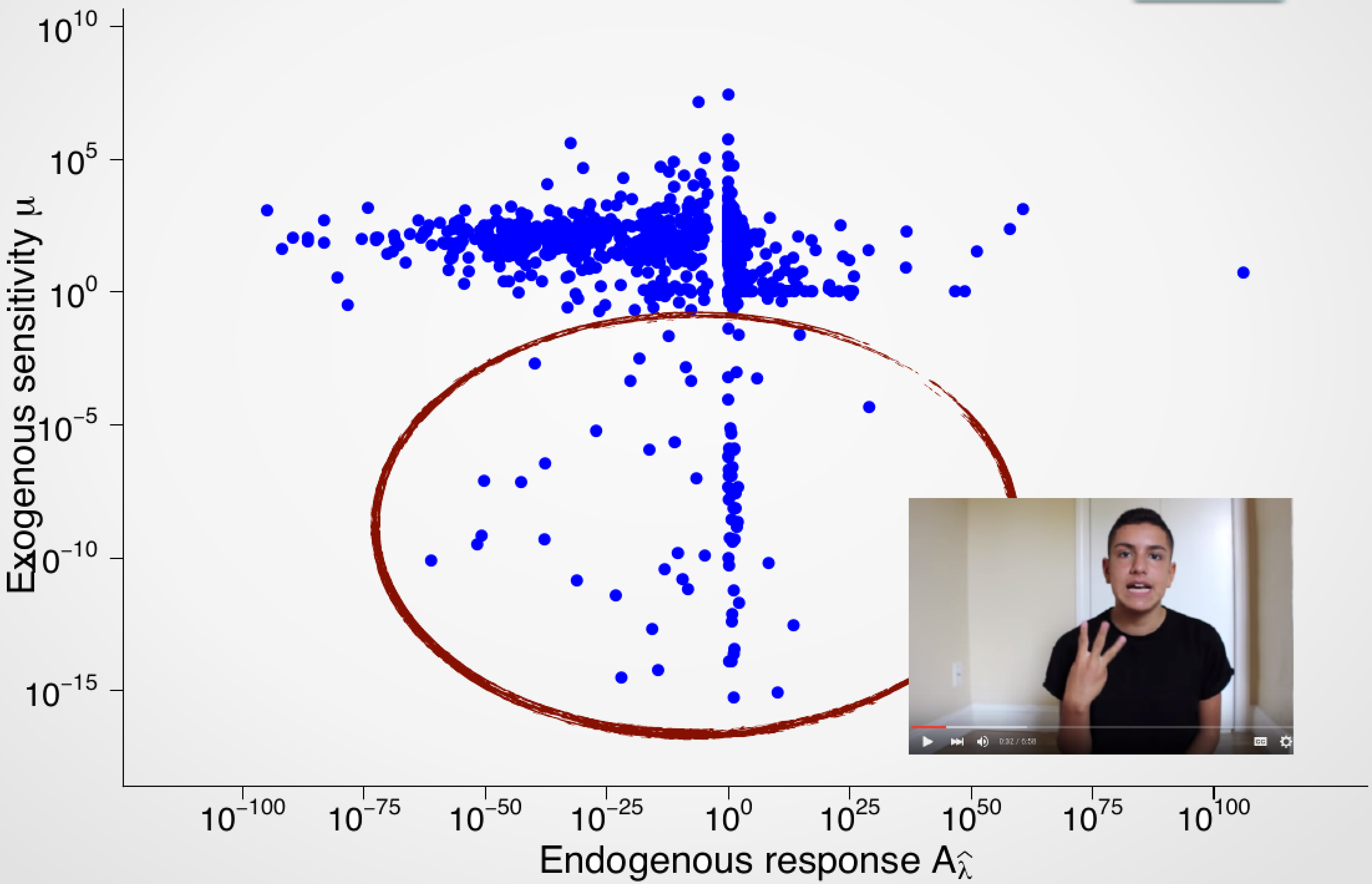
Explain popularity – all vs top 5%

Games:

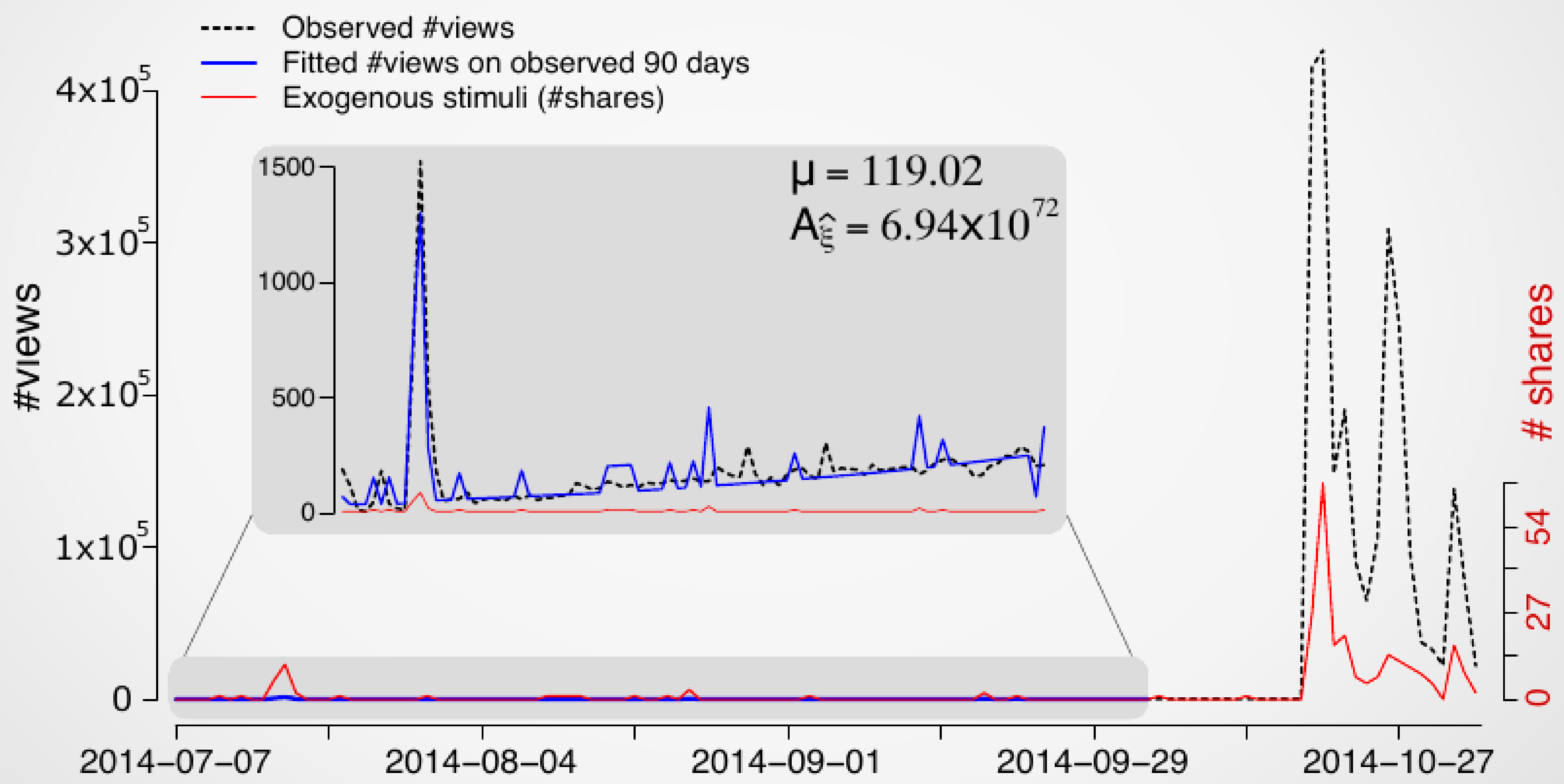
more popular videos have higher endogenous response



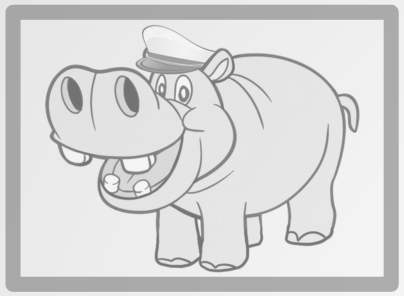
Which videos are un-promotable?



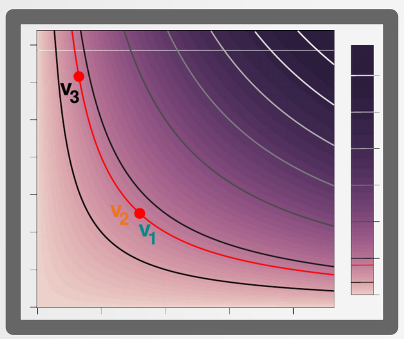
“Potentially viral” video



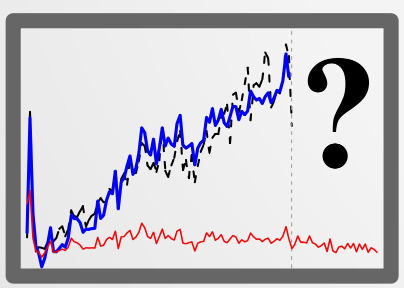
Presentation outline



Modeling popularity with HIP



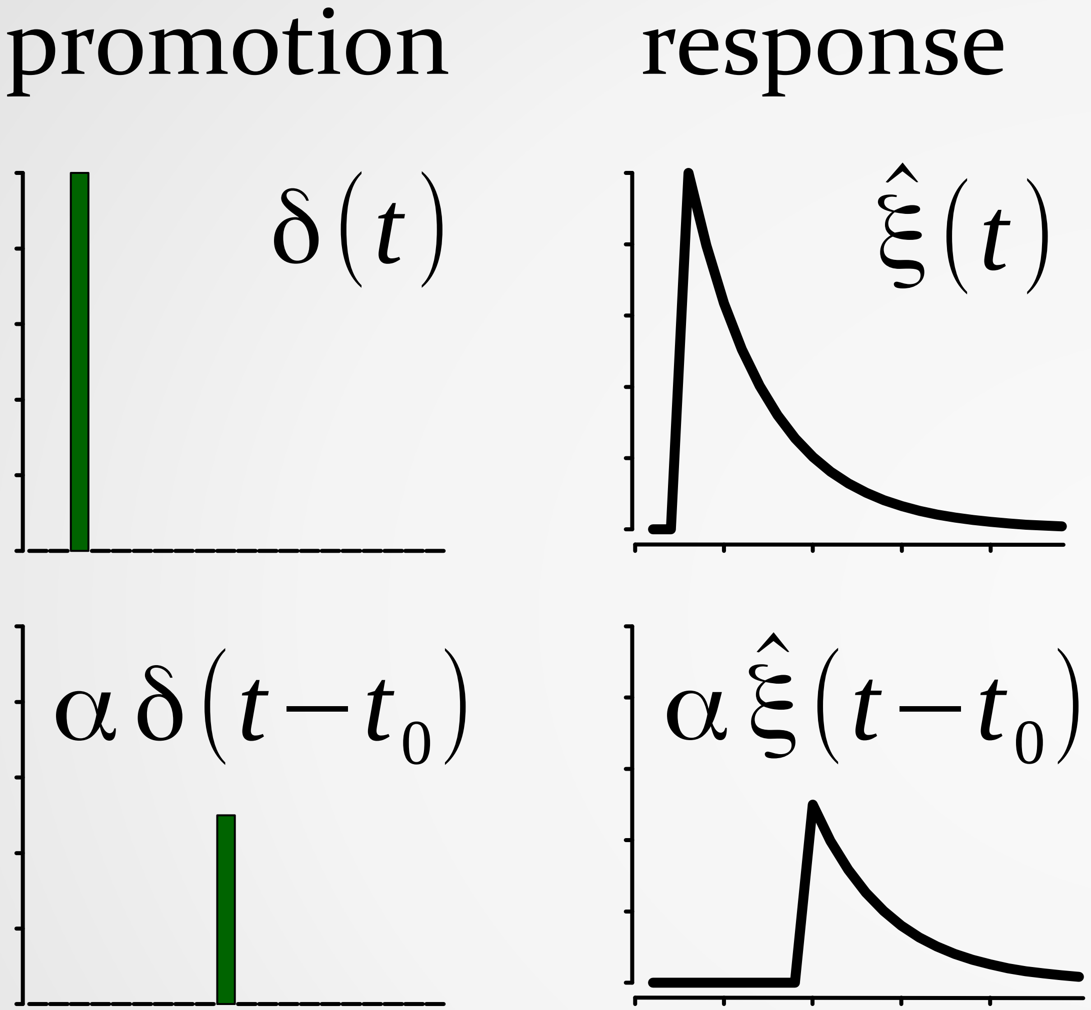
Content virality and maturity time



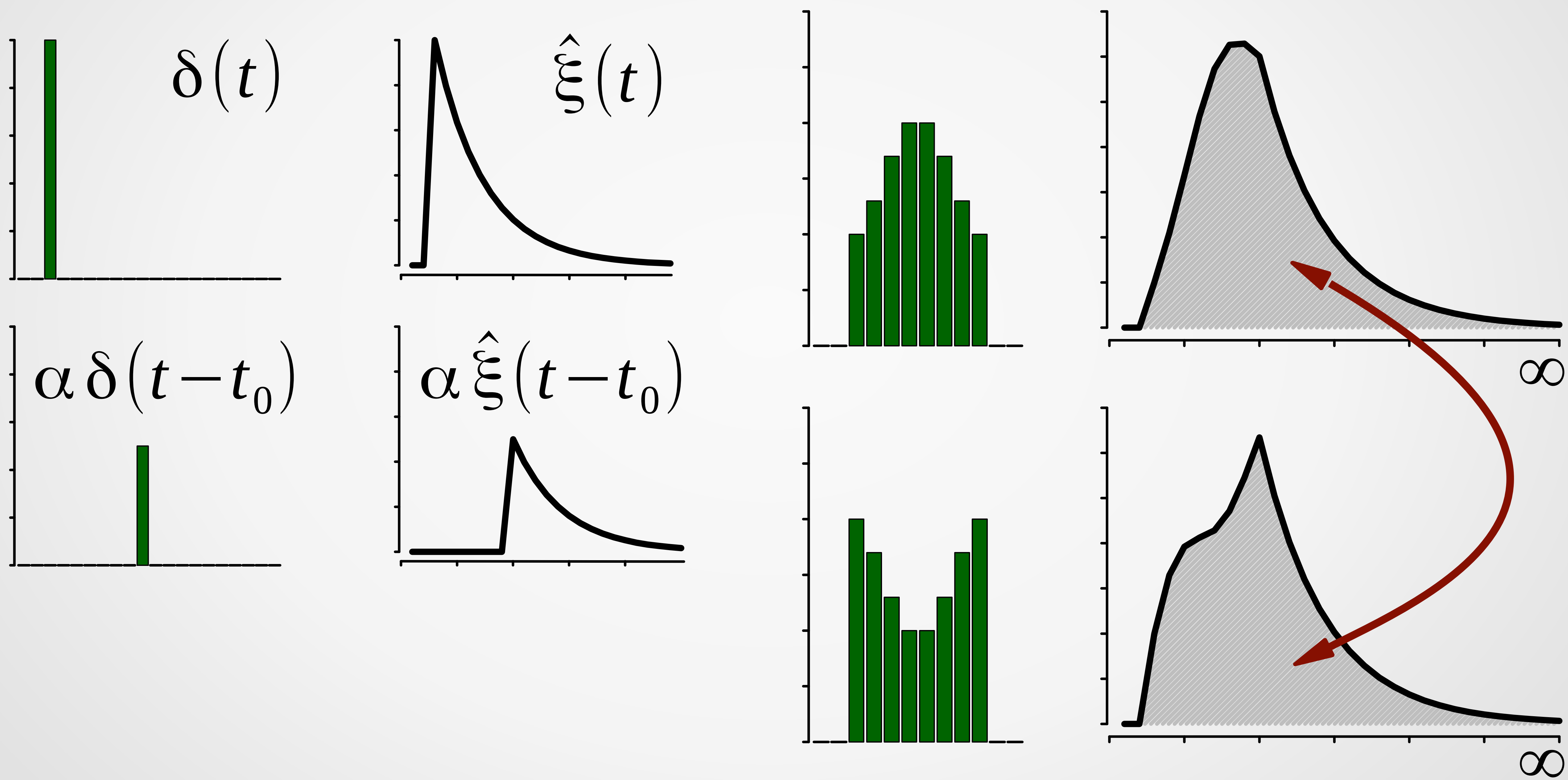
Forecasting popularity under promotion

Promotions schedules and memory lengthening through promotion

HIP as a Linear Time-Invariant system

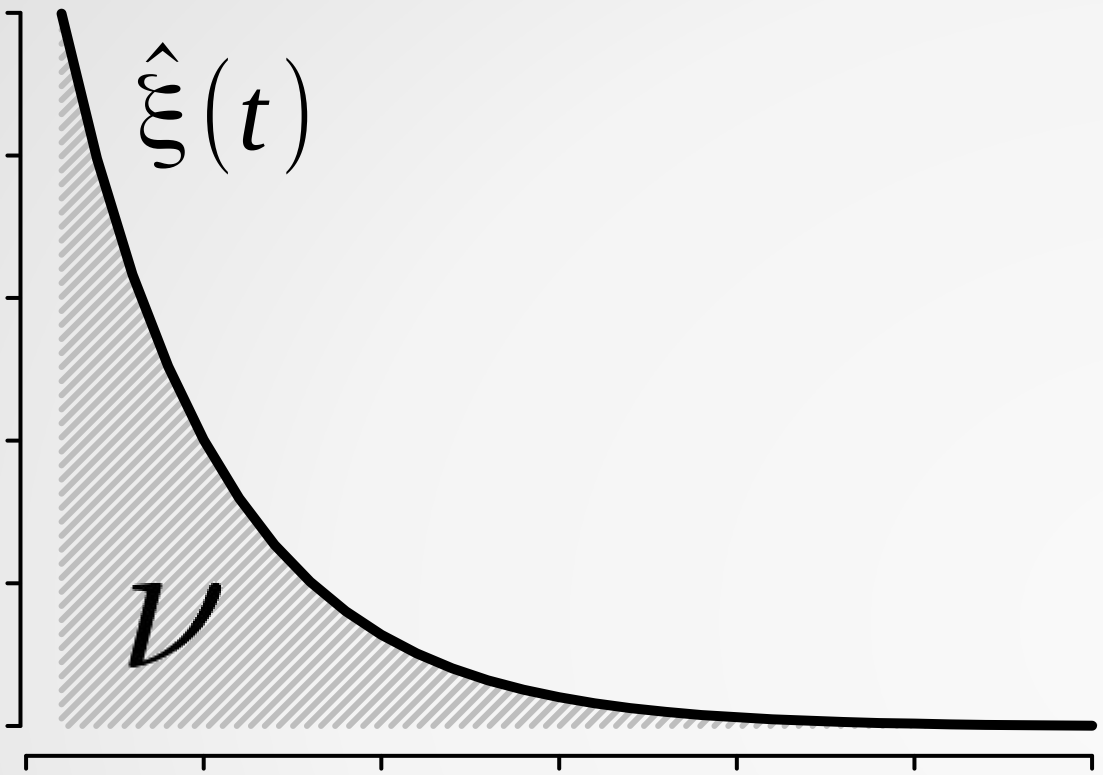


HIP as a Linear Time-Invariant system



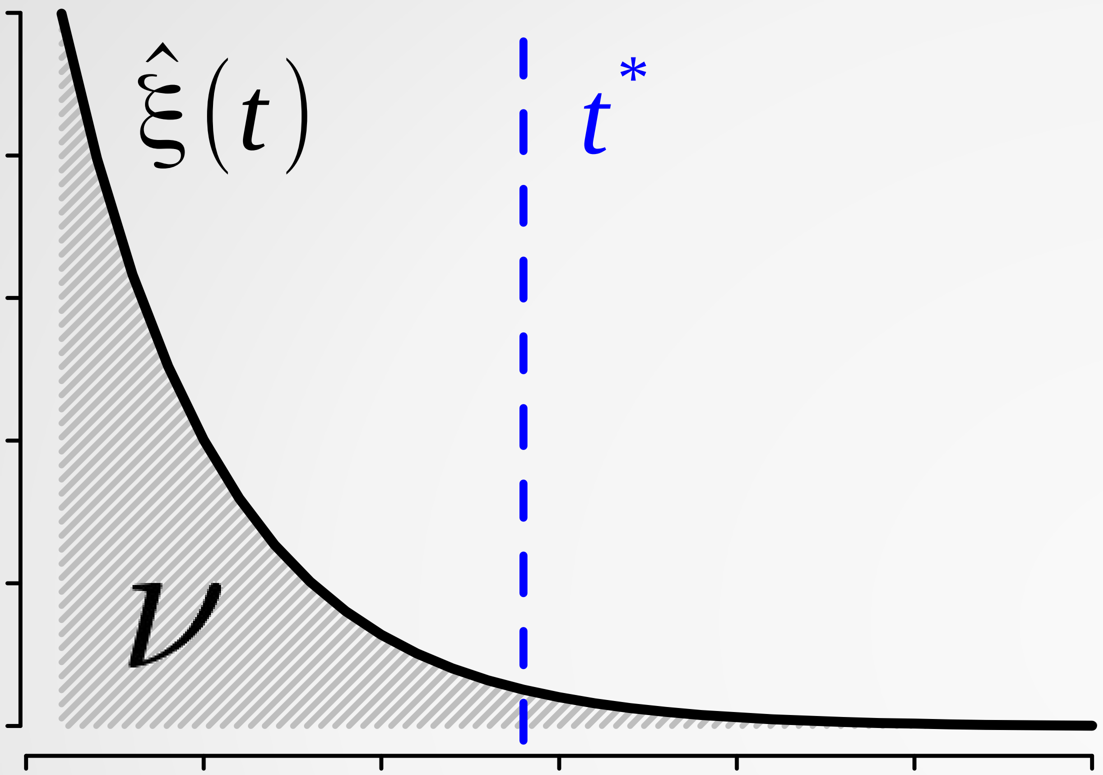
Corollary: same budget → same return

Viral potential and maturity time



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

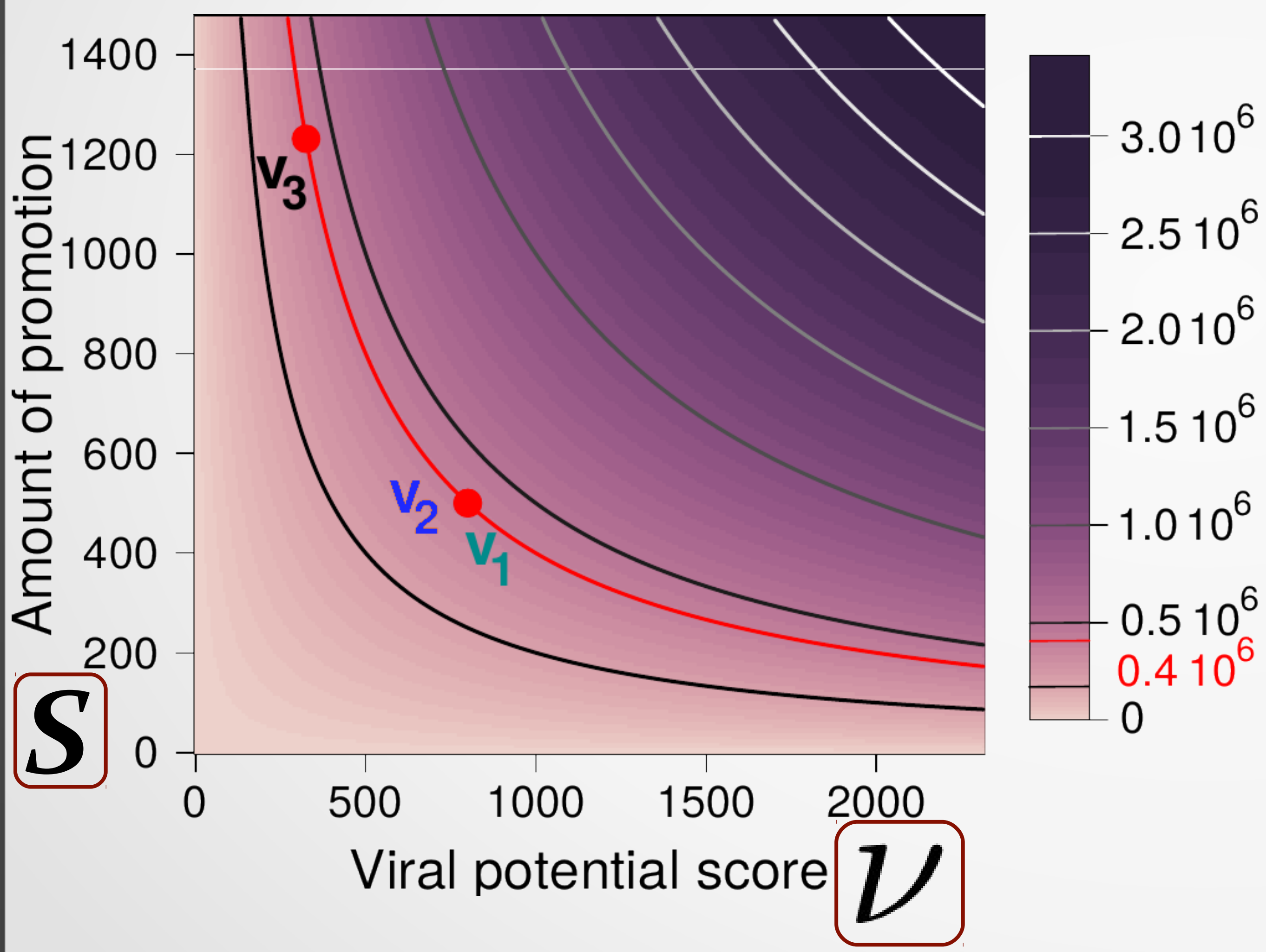
Viral potential and maturity time



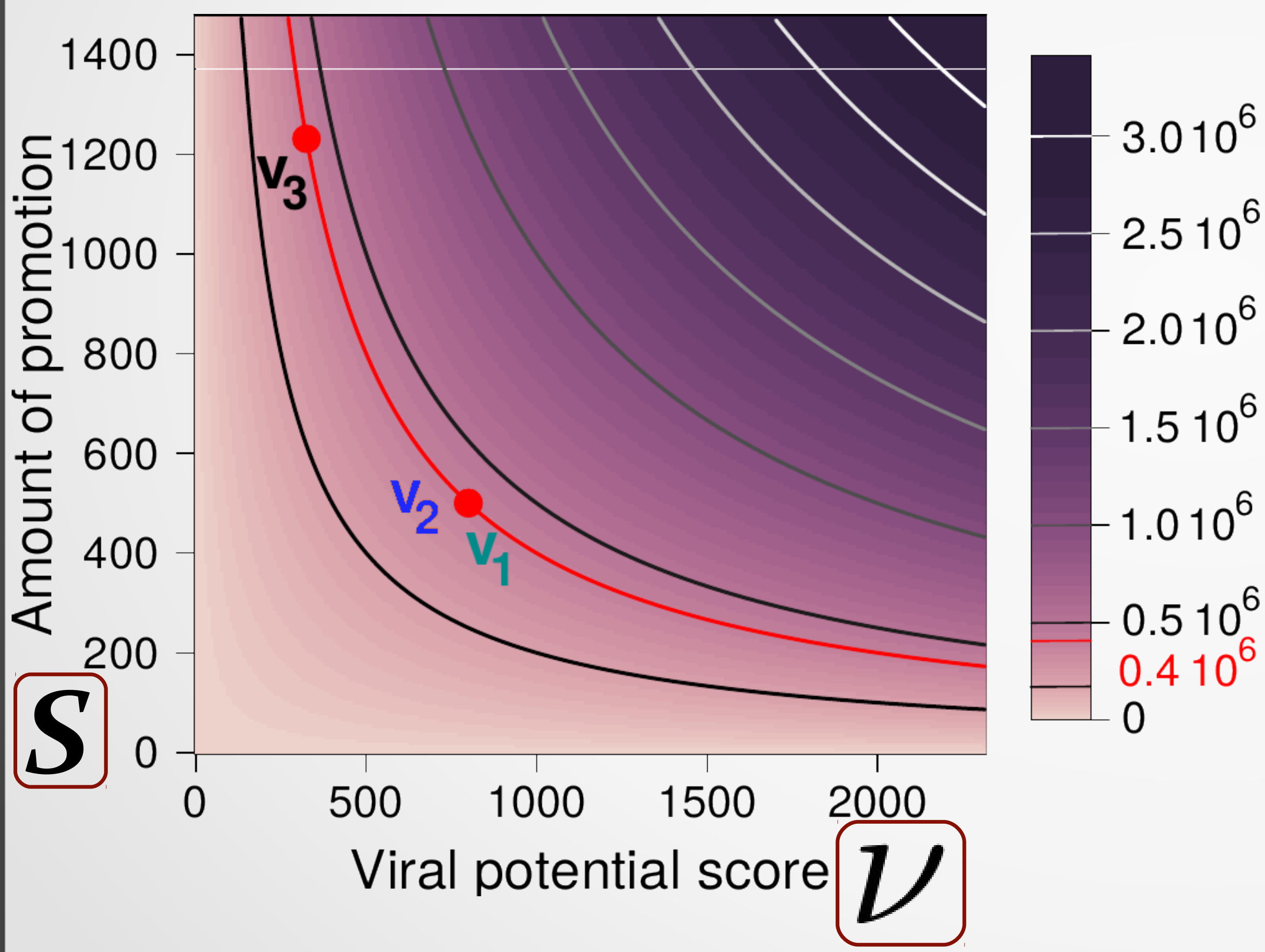
Viral potential score: $$\nu = \int_0^\infty \mu\hat{\xi}(t) = \mu A_{\hat{\xi}}$$

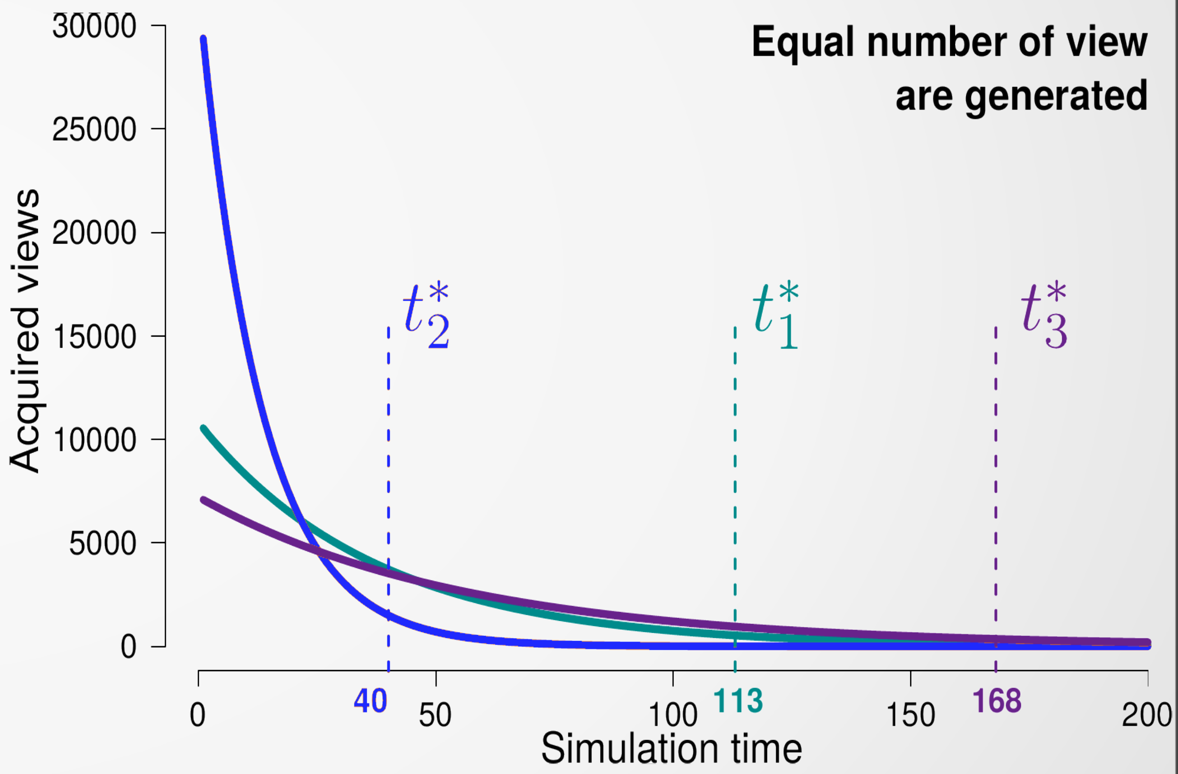
Maturity time: $$t^* = min\left\{t \geq 0 \middle| \int_0^t \hat{\xi}(t)dt \geq 0.95\nu\right\}$$

Virality map

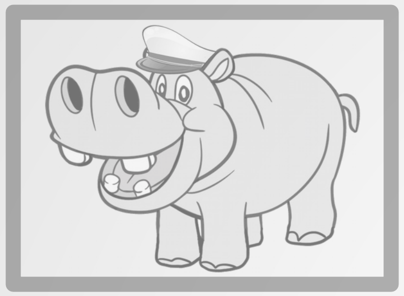


Virality map

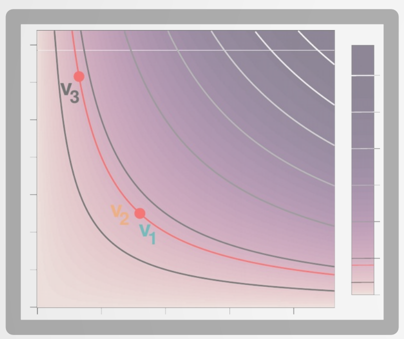




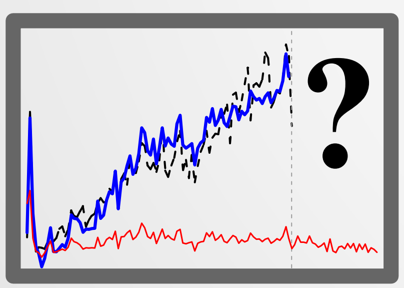
Presentation outline



Modeling popularity with HIP



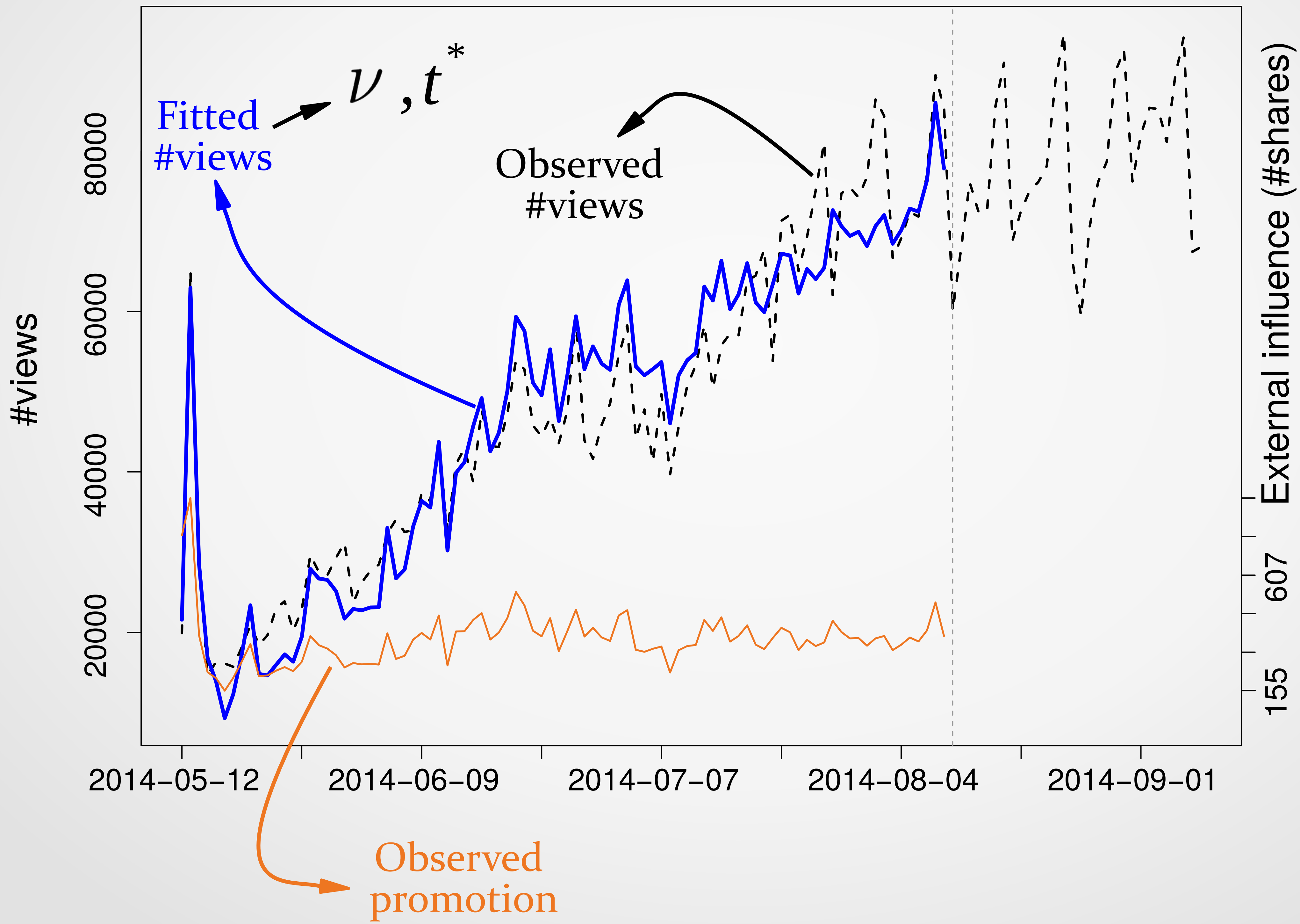
Content virality and maturity time



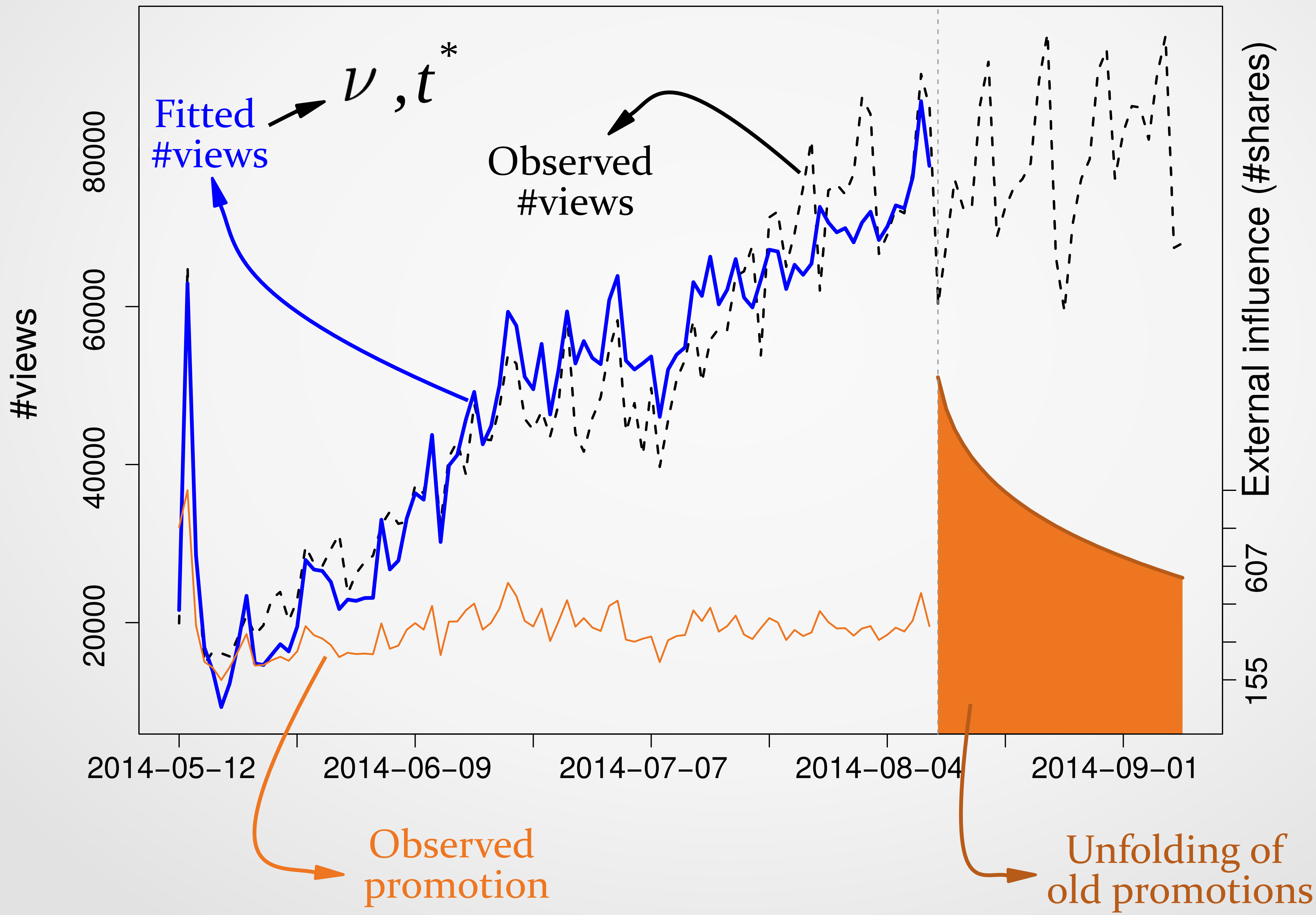
A progression of two problems relating to predicting popularity under promotion

Promotions schedules and memory lengthening through promotion

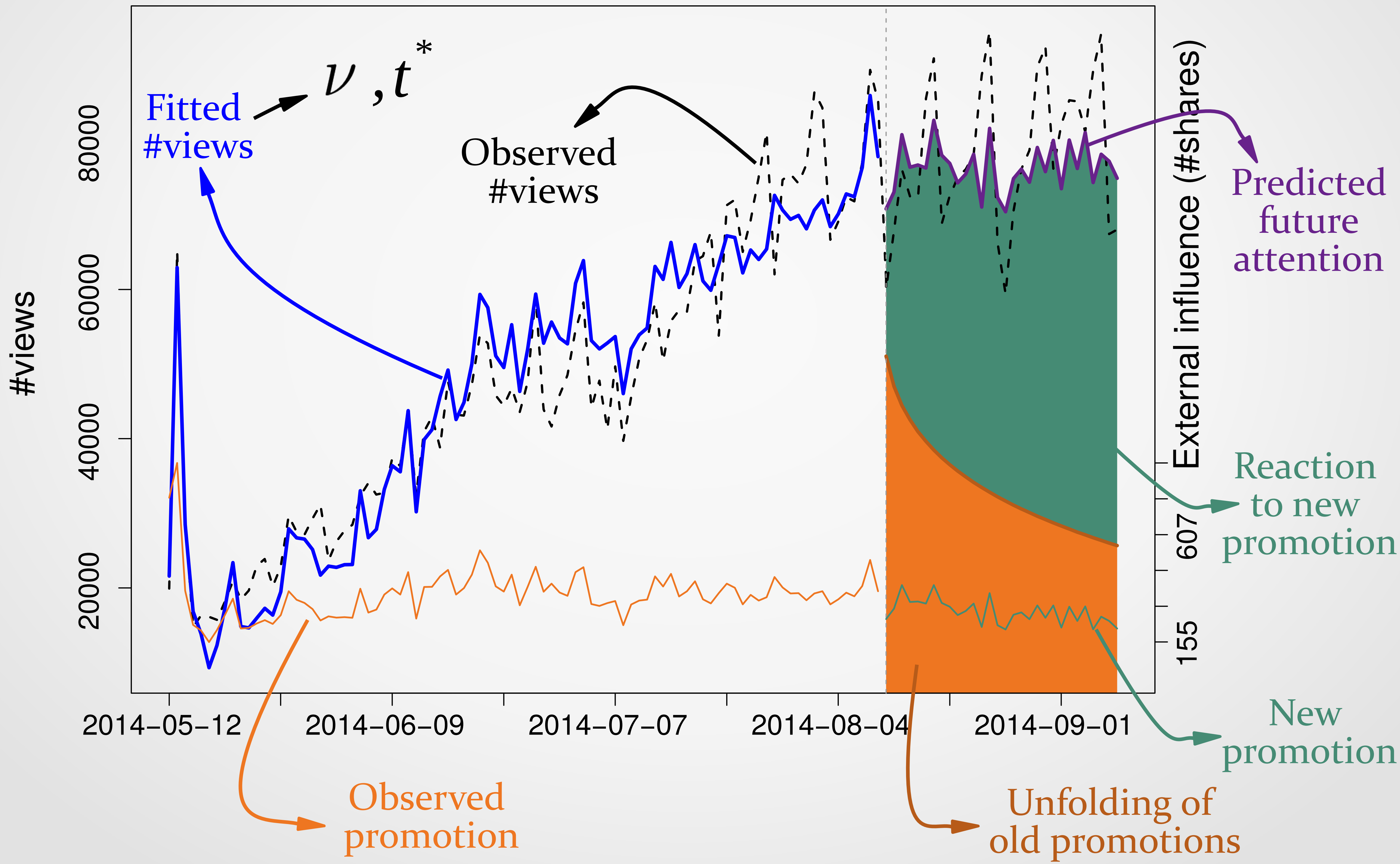
Forecasting future views (1)



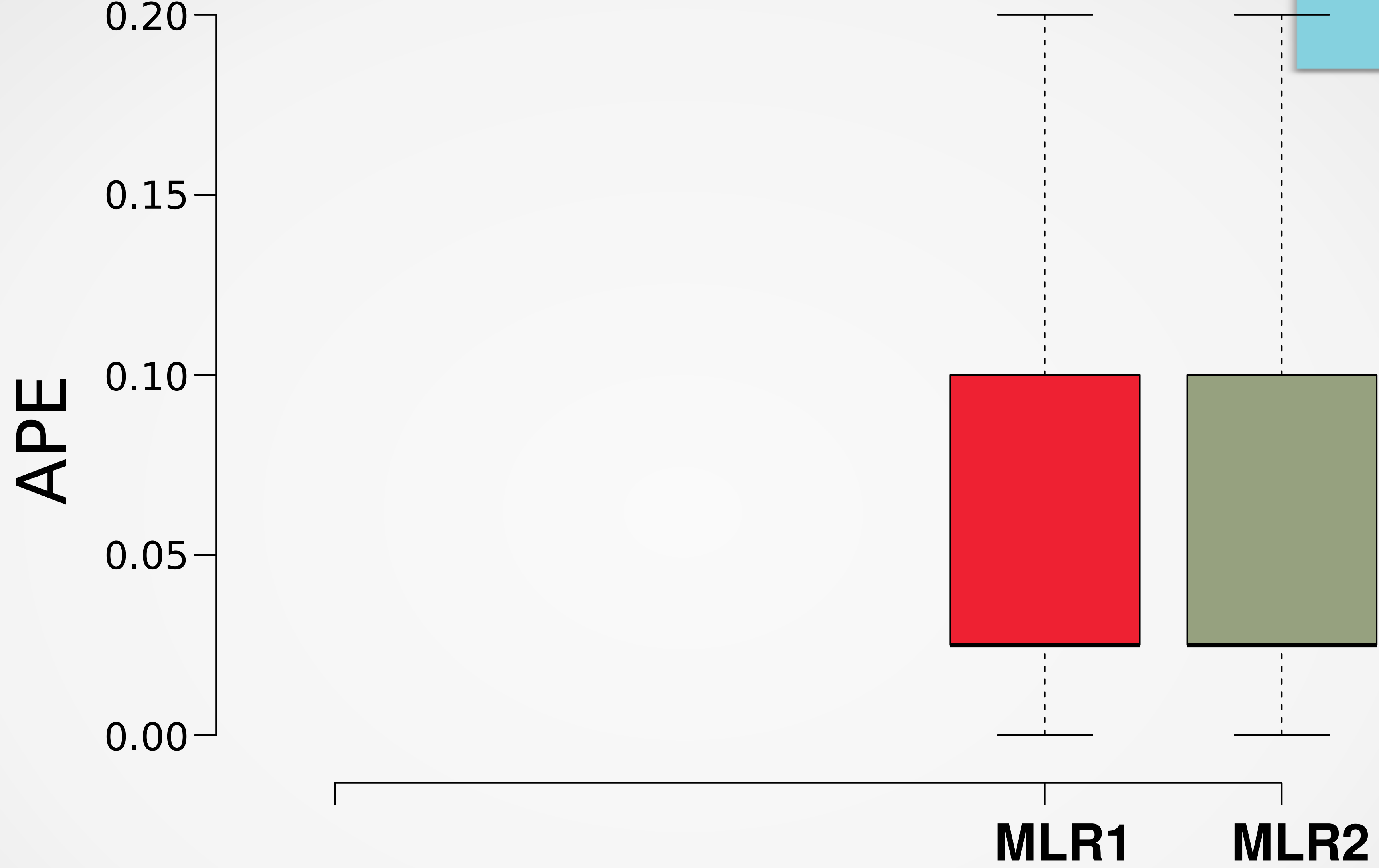
Forecasting future views (1)



Forecasting future views (1)



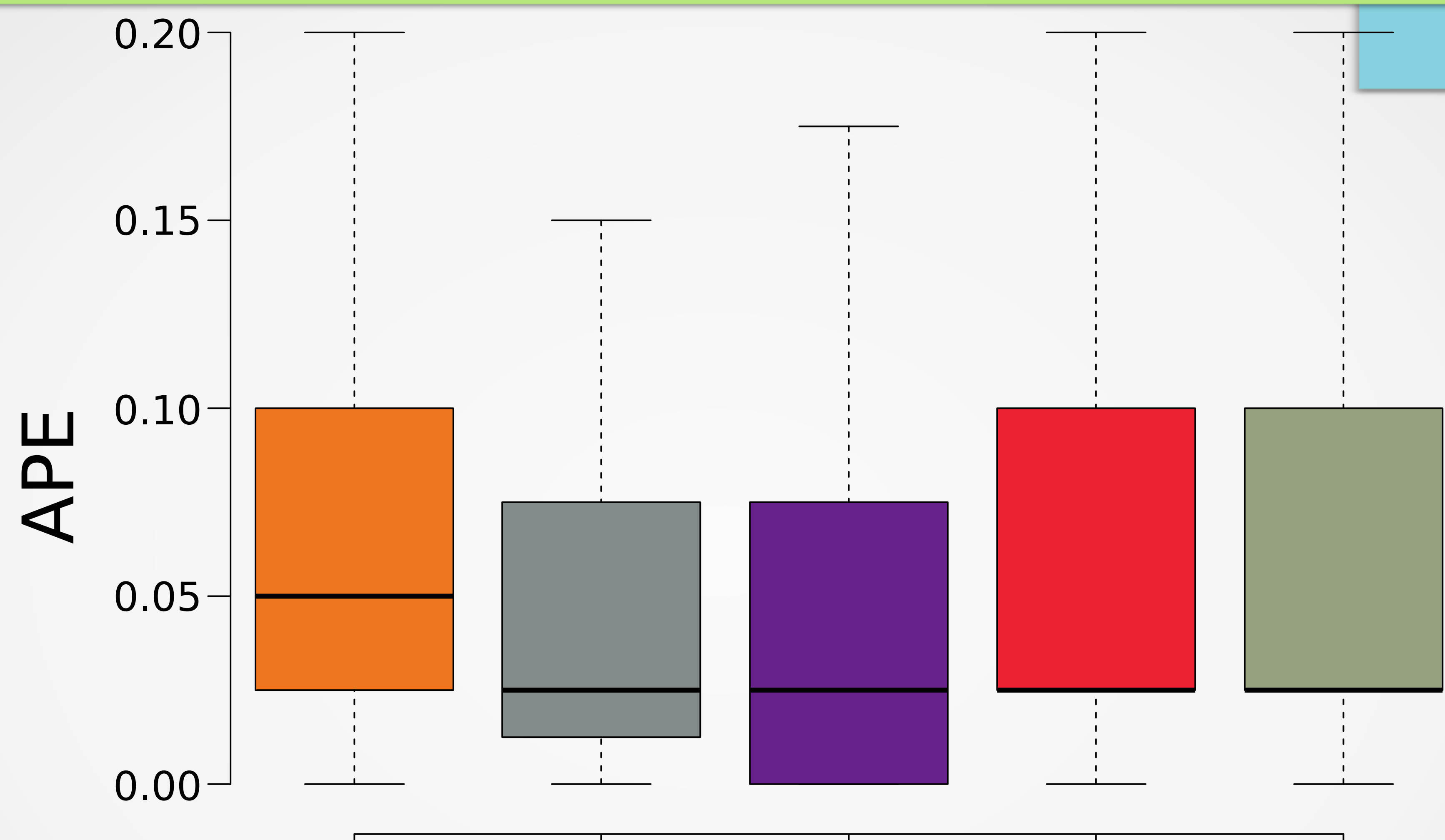
Forecasting future views (2)



[Pinto et al WSDM'13]

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

Forecasting future views (2)

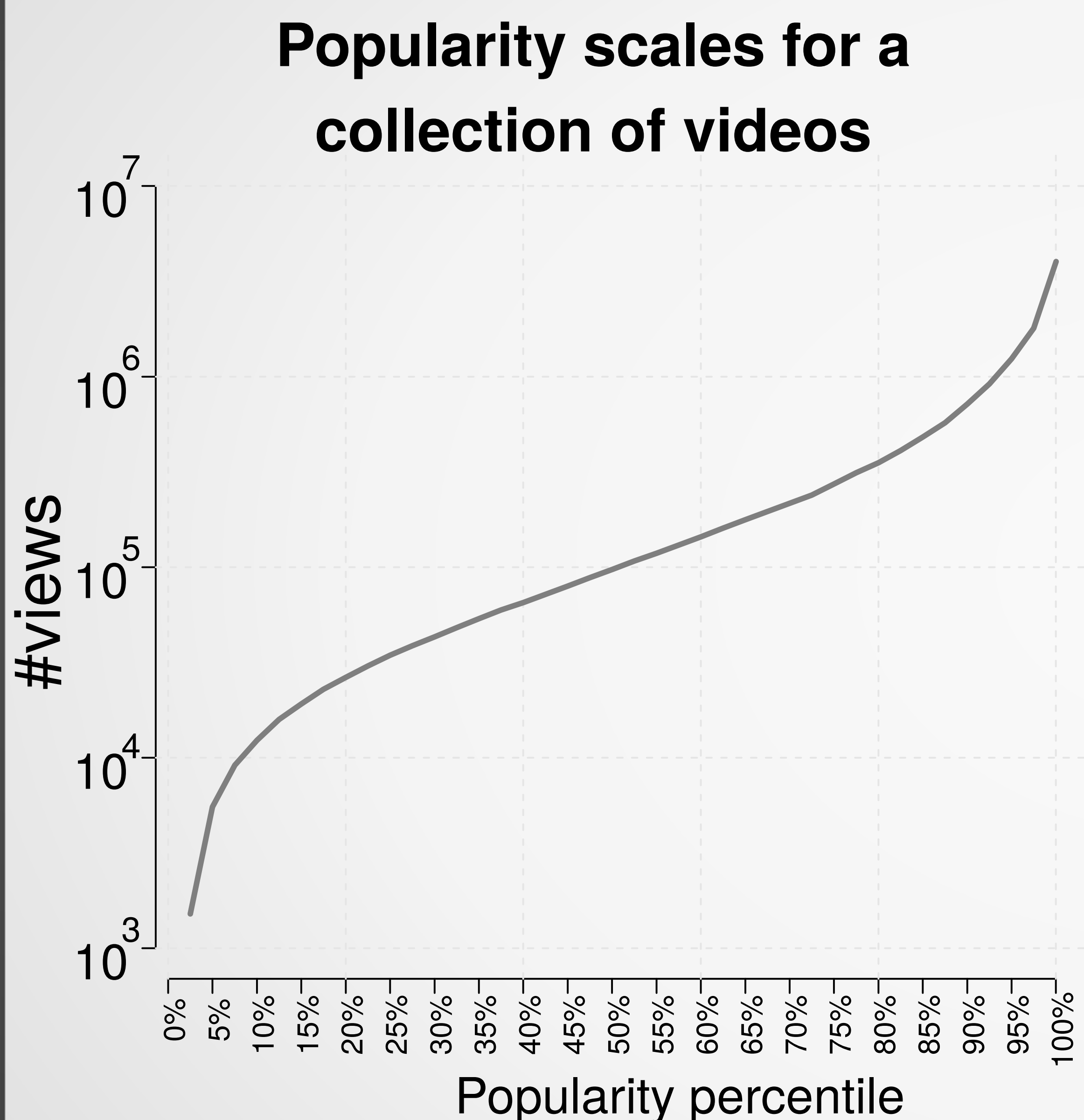


[Rizoiu et al WWW‘17]

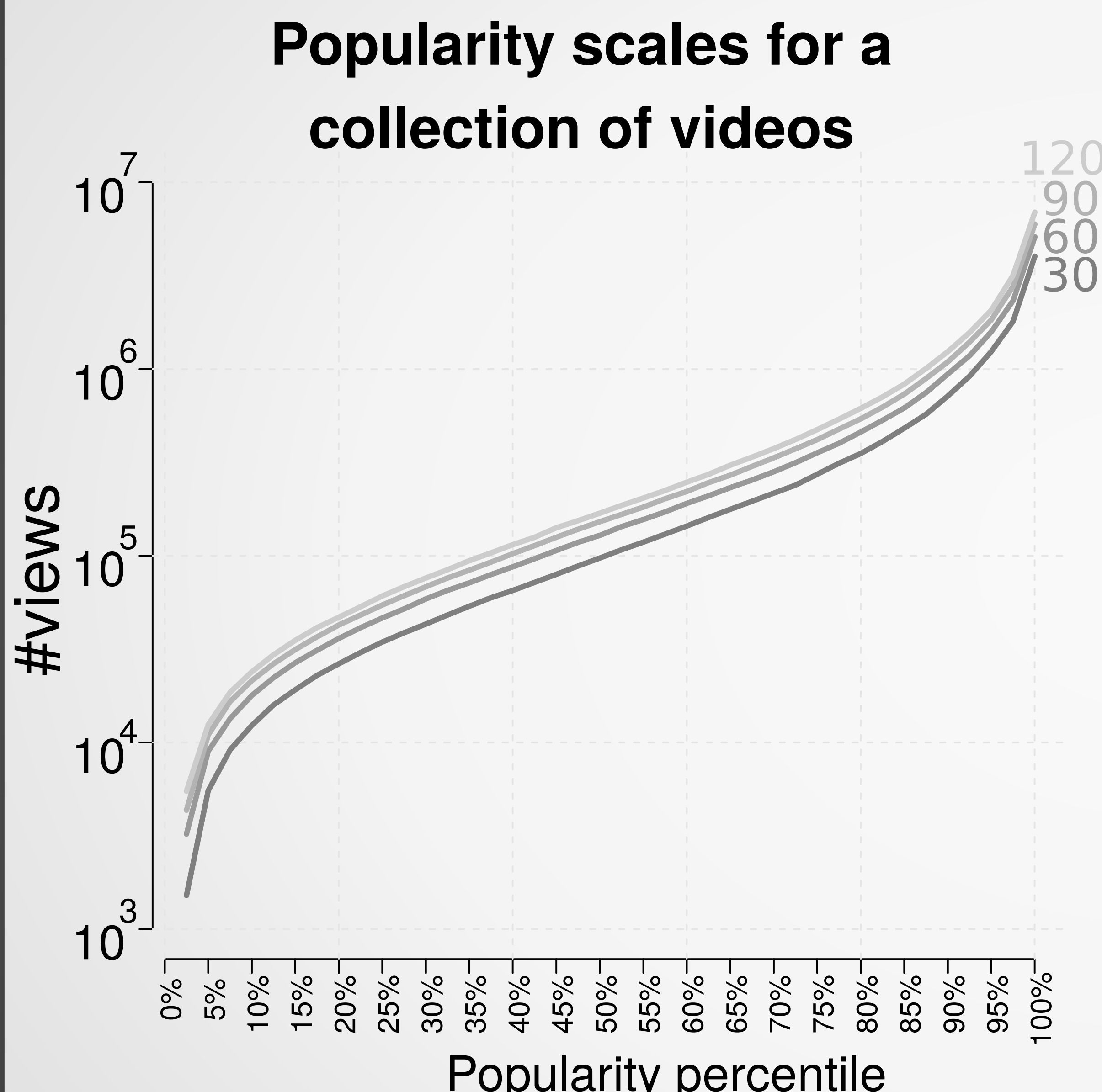
	P1	P2	P3	MLR1	MLR2
History:	✓	✓	✓	✓	✓
Viral potential:	✓	✓	✓		
Promo. volume:		✓	✓		✓
Promo. timing:			✓		✓

[Pinto et al WSDM’13]

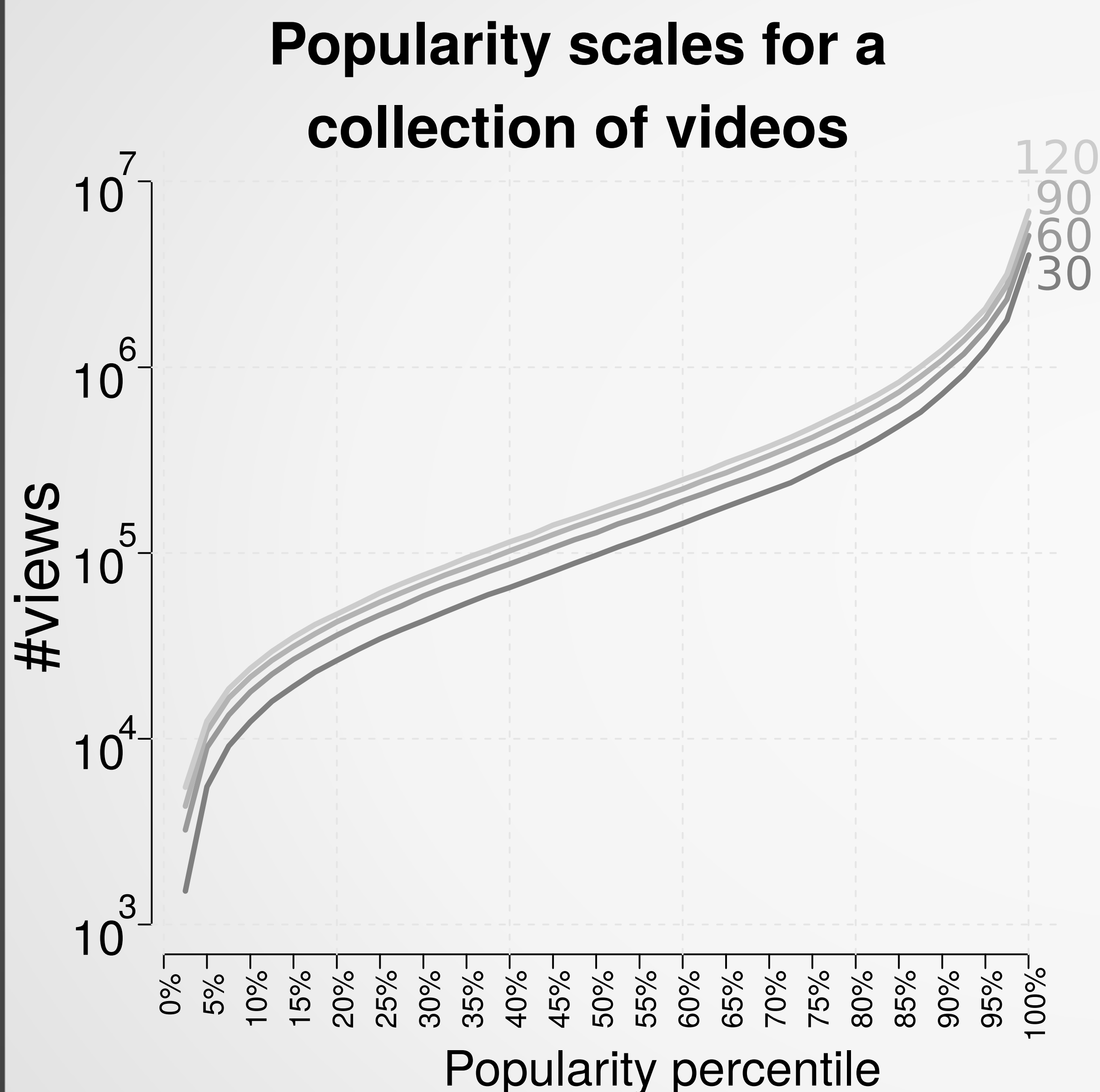
Popularity scales over time

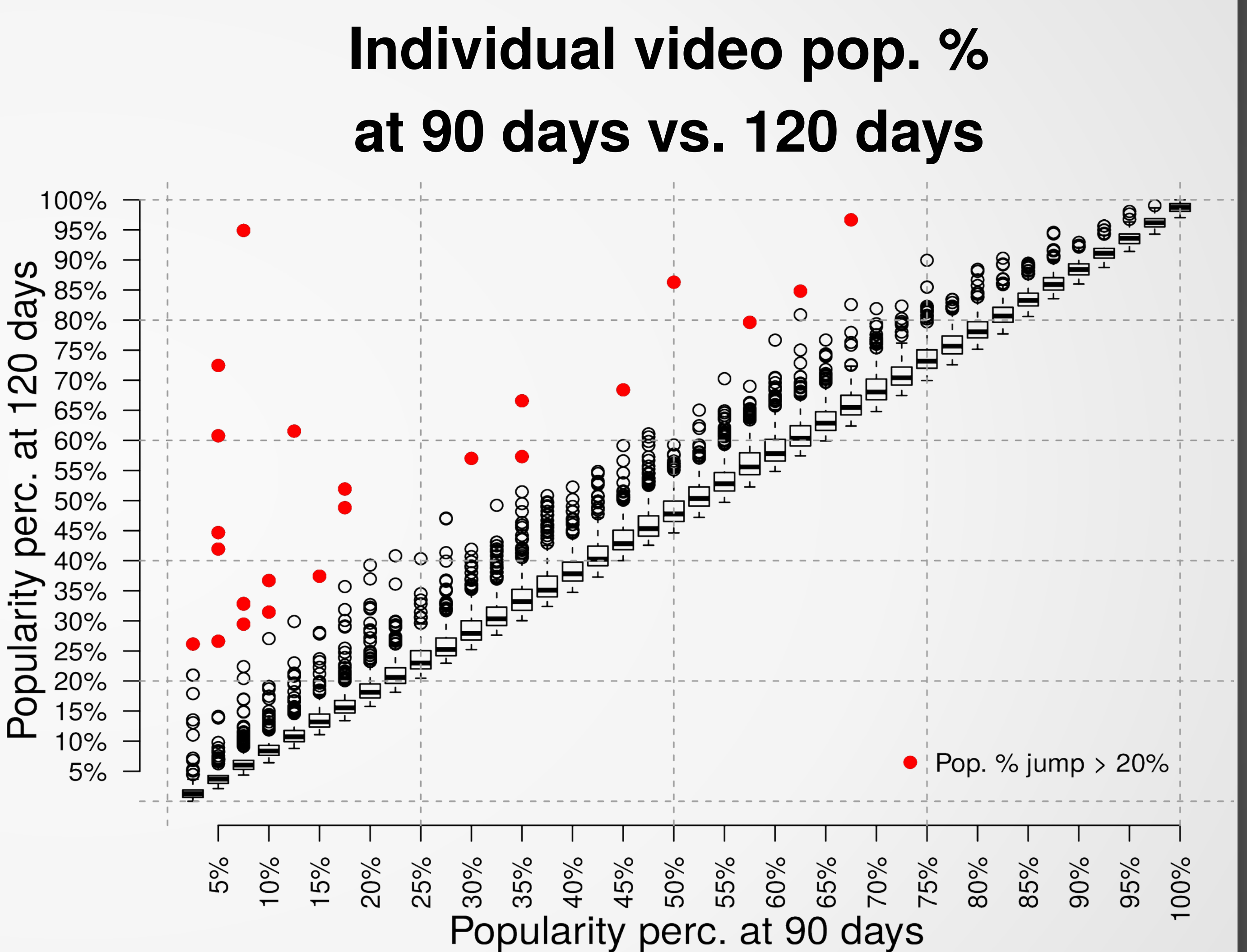


Popularity scales over time



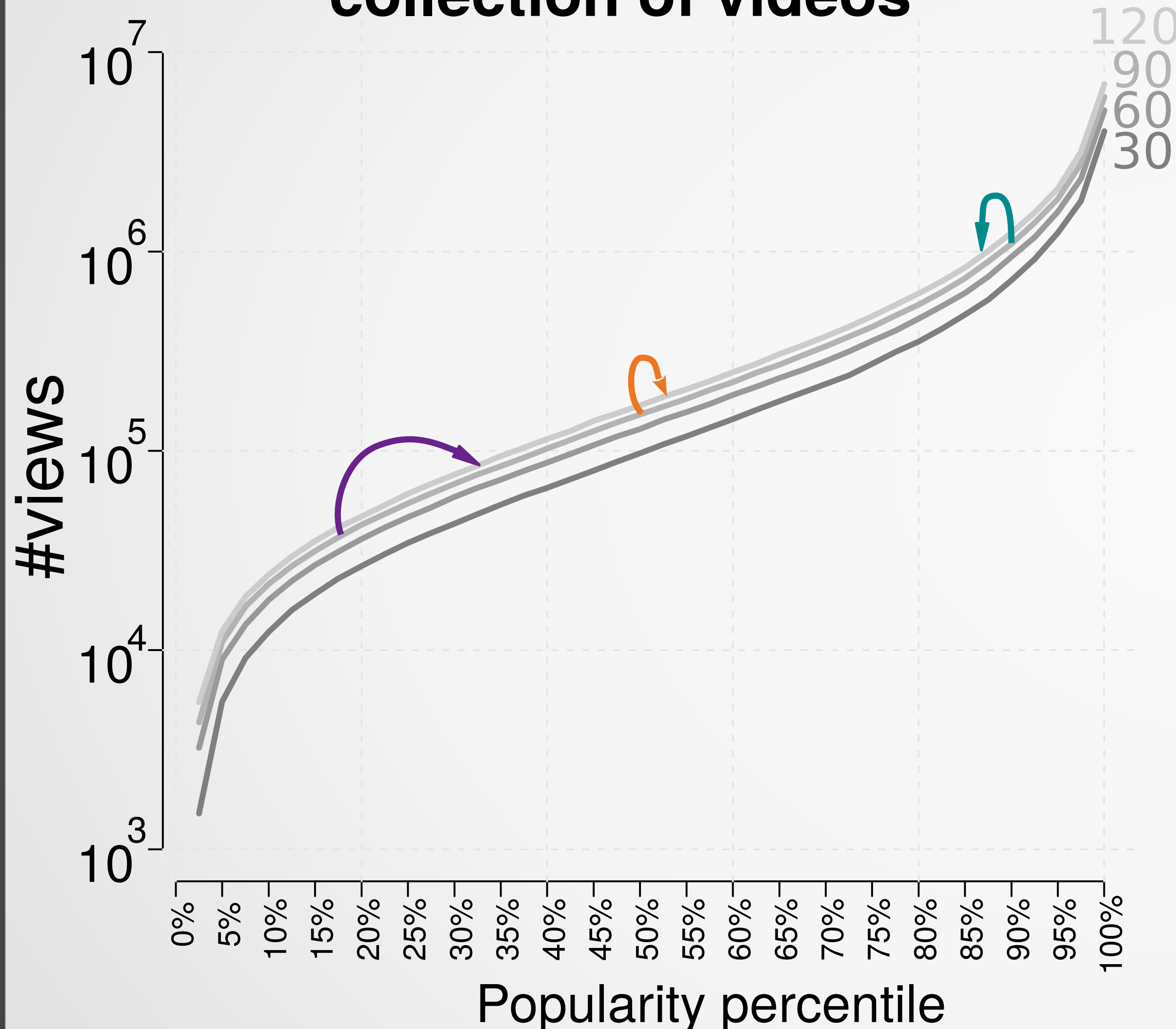
Popularity scales over time



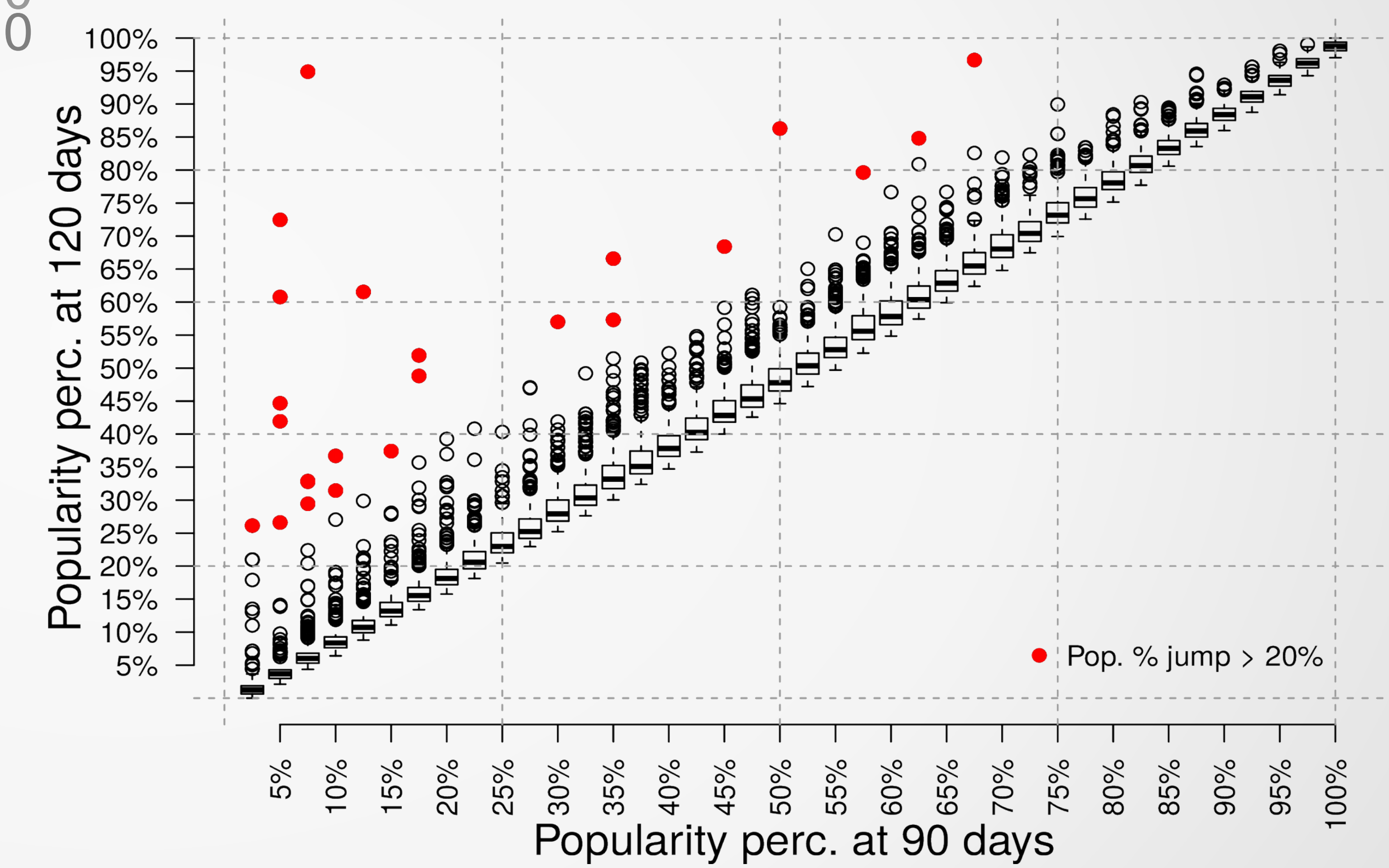


Popularity scales over time

Popularity scales for a collection of videos



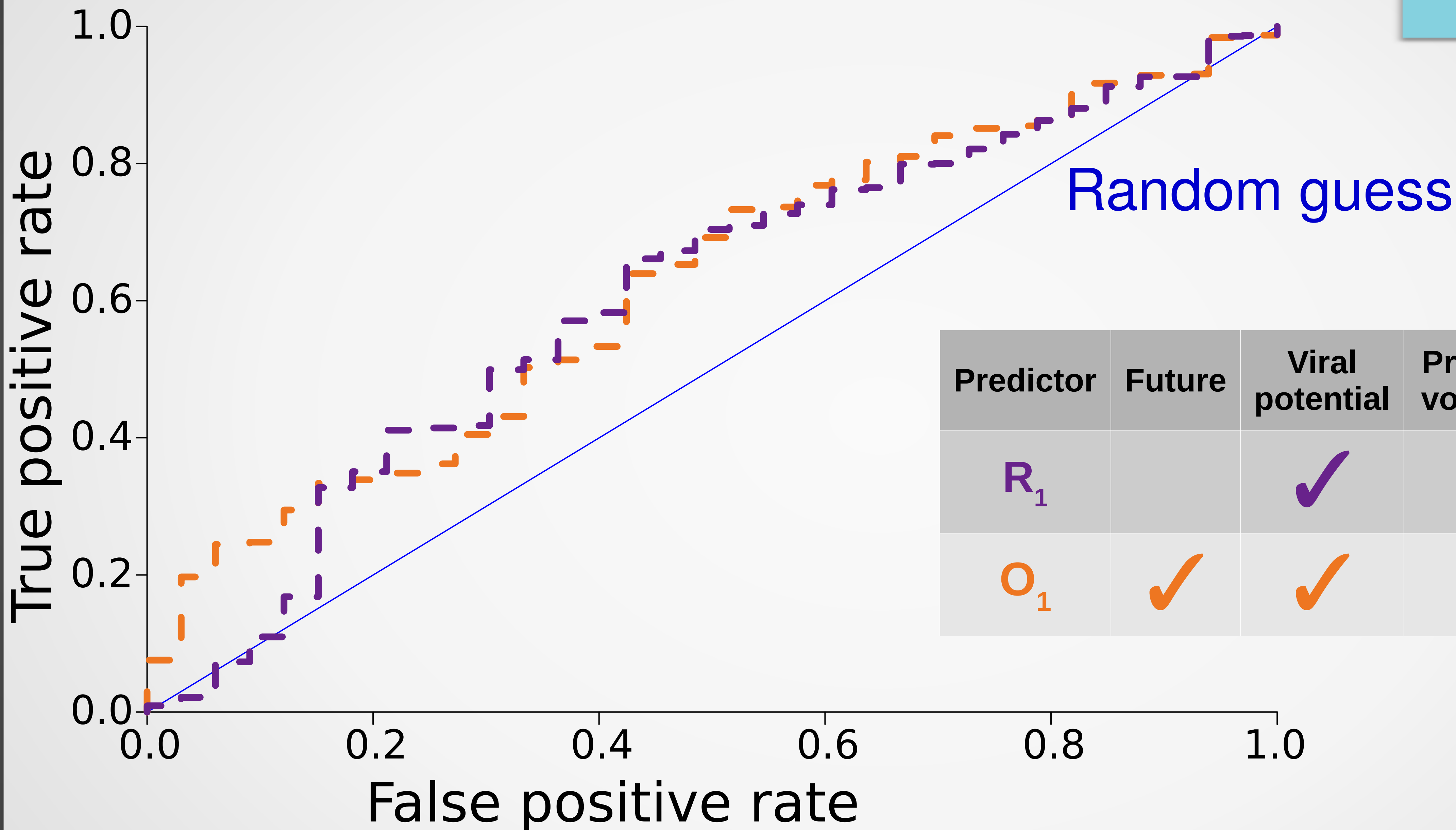
Individual video pop. % at 90 days vs. 120 days



Impact of 40k views:

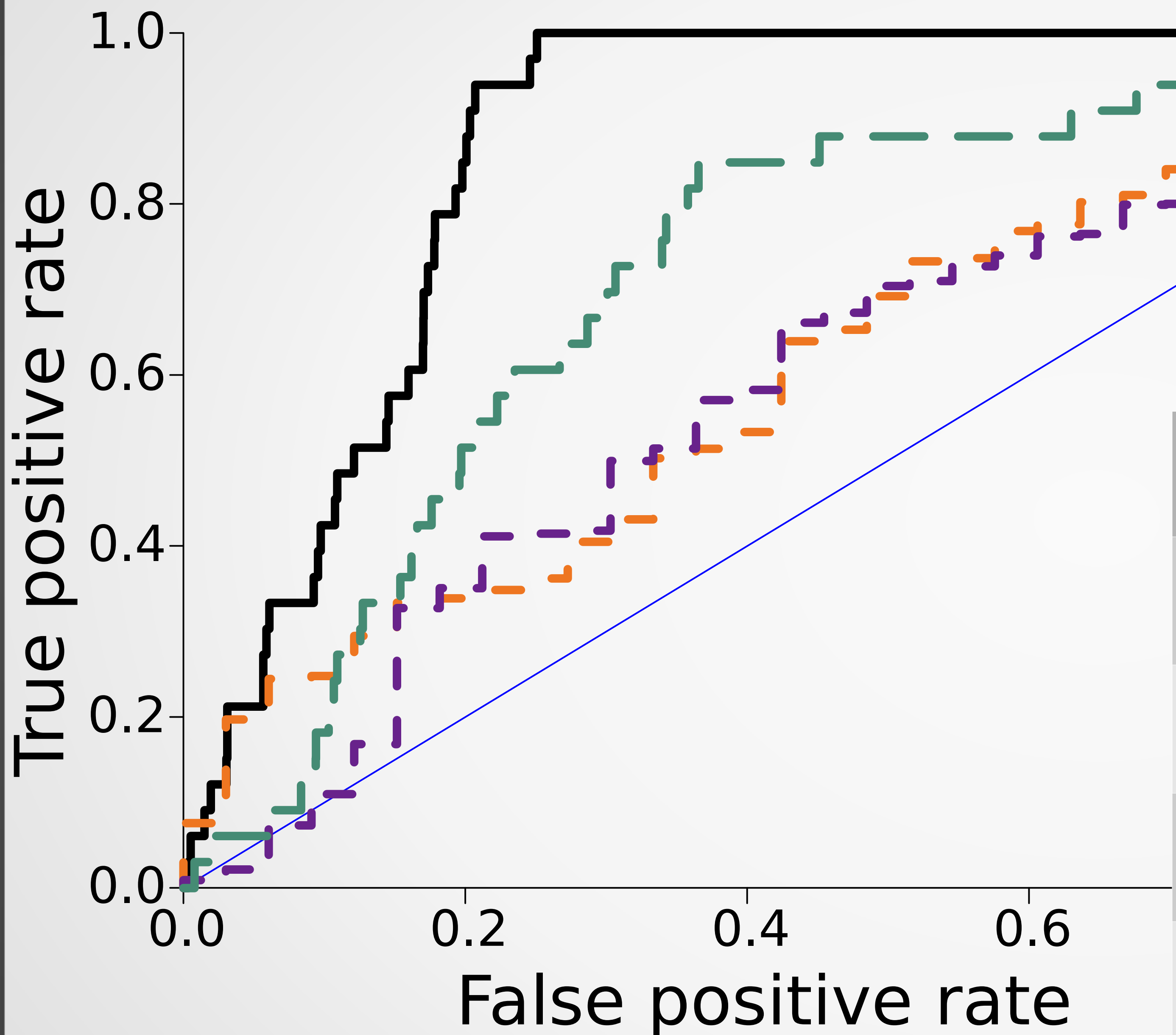
start at 17.5% → +15%   start at 50% → +2.5%   start at 90% → -2.5%

ROC curves for videos that jump



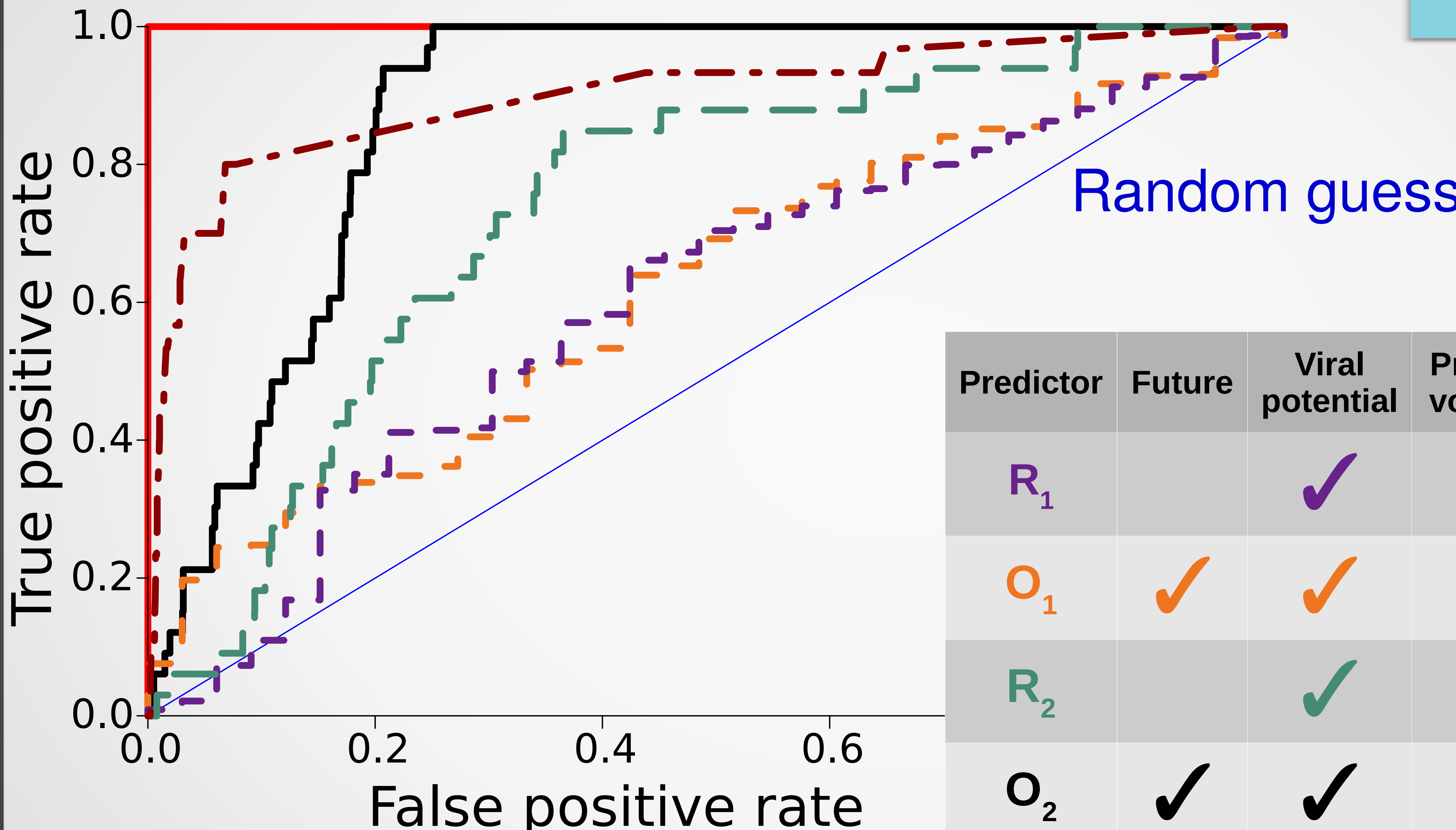
Predictor	Future	Viral potential	Promo. volume	Pop. scale position
R_1		✓		
O_1	✓	✓		

ROC curves for videos that jump



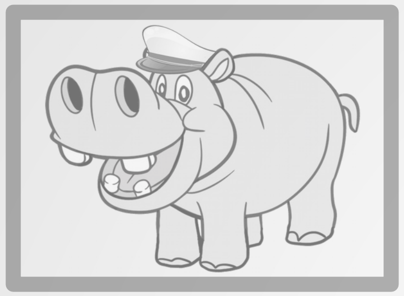
Predictor	Future	Viral potential	Promo. volume	Pop. scale position
R_1		✓		
O_1	✓	✓		
R_2		✓	✓	
O_2	✓	✓	✓	

ROC curves for videos that jump

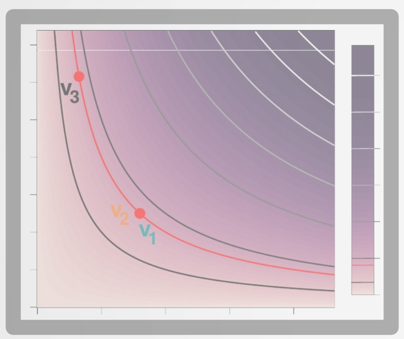


Predictor	Future	Viral potential	Promo. volume	Pop. scale position
R_1		✓		
O_1	✓	✓		
R_2		✓	✓	
O_2	✓	✓	✓	
R_3		✓	✓	✓
O_3	✓	✓	✓	✓

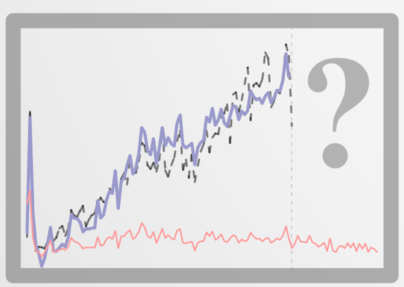
Presentation outline



Modeling popularity with HIP



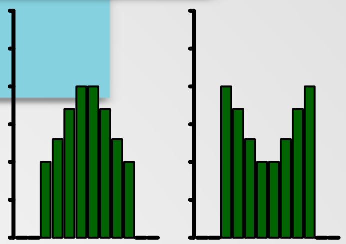
Content virality and maturity time



Forecasting popularity under promotion

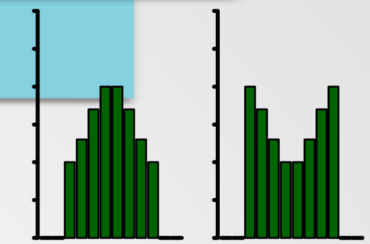
When does promotion timing matter?
Why do people prefer constant promotion?

Designing promotion schedules

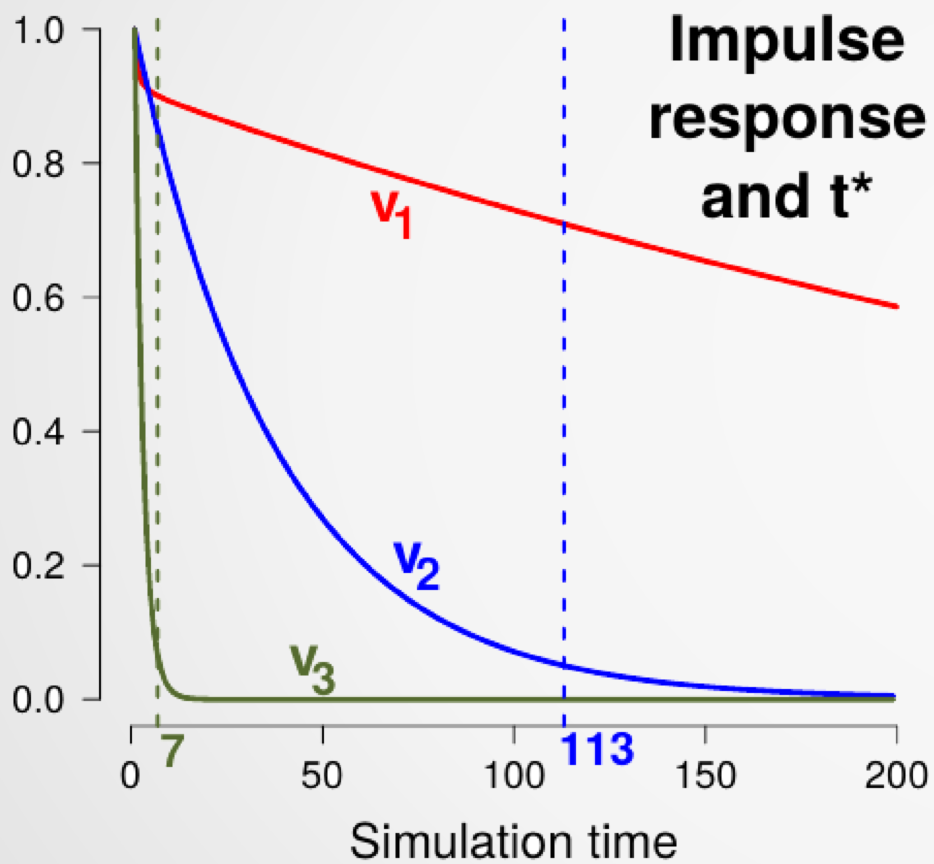


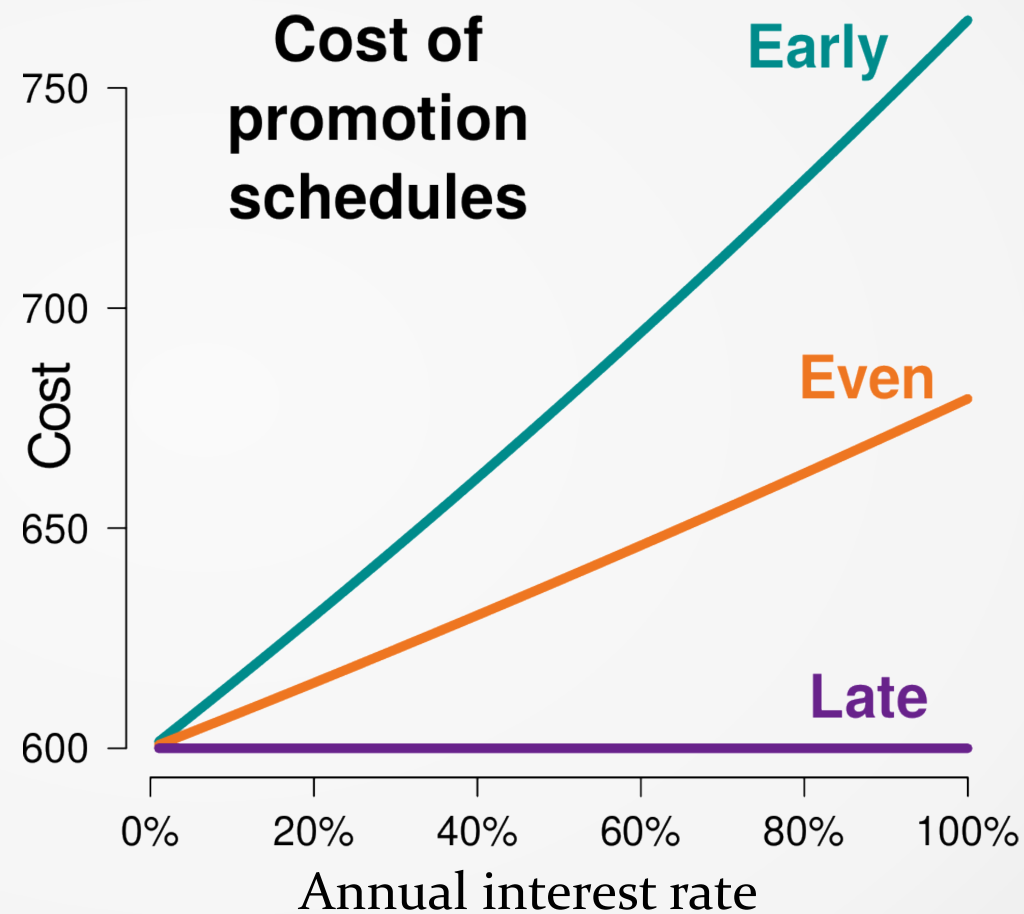
LTI corollary: **same budget, same return!**

Designing promotion schedules

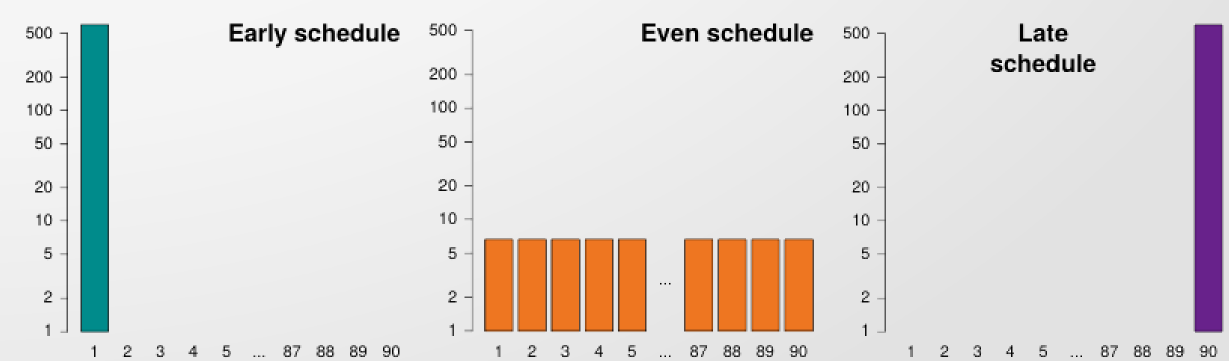


LTI corollary: **same budget, same return!**

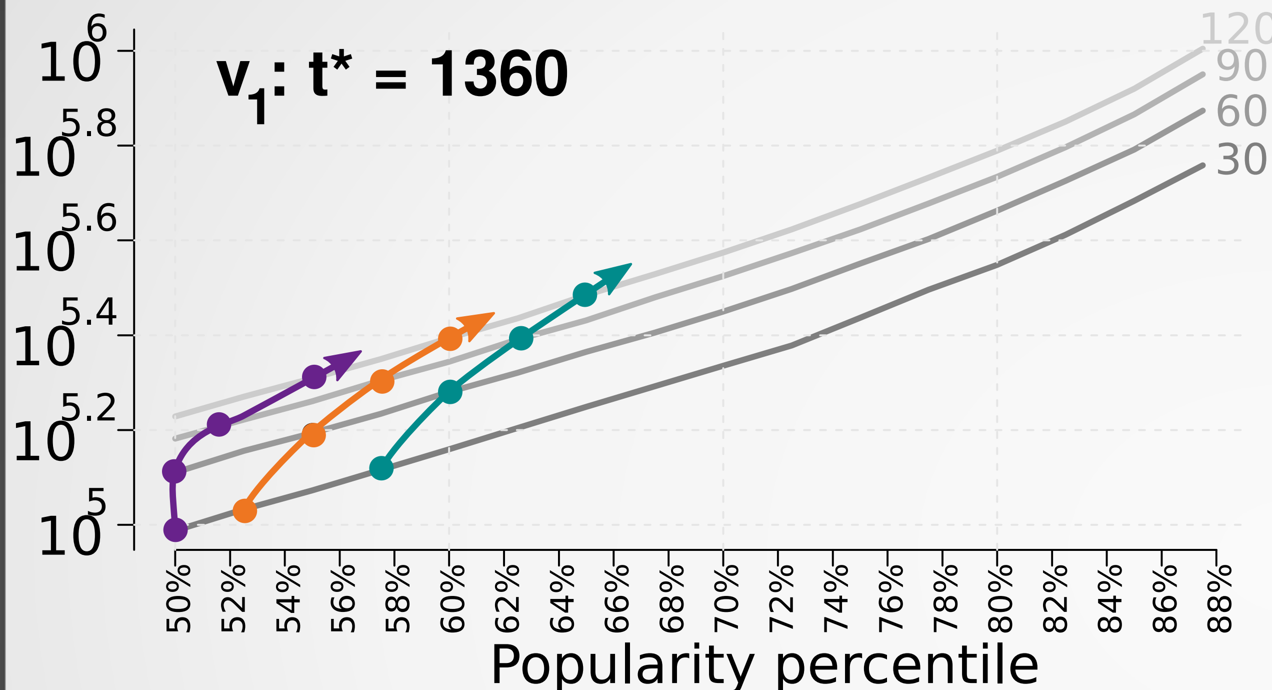


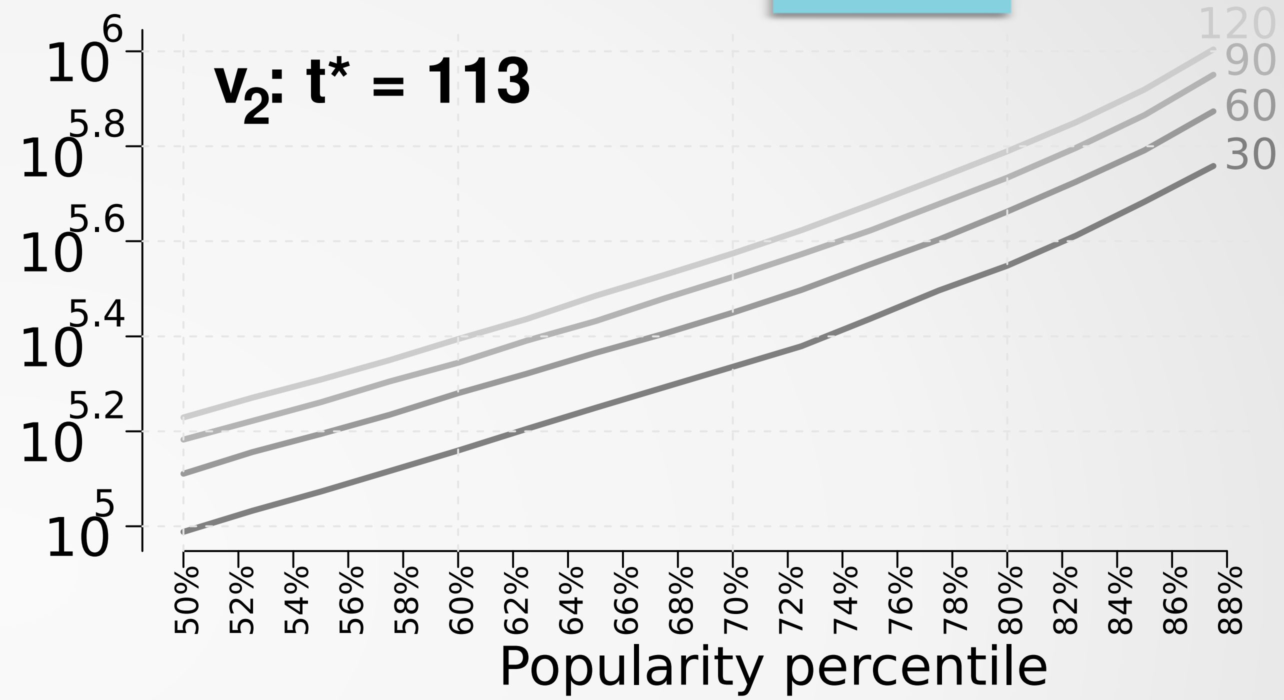


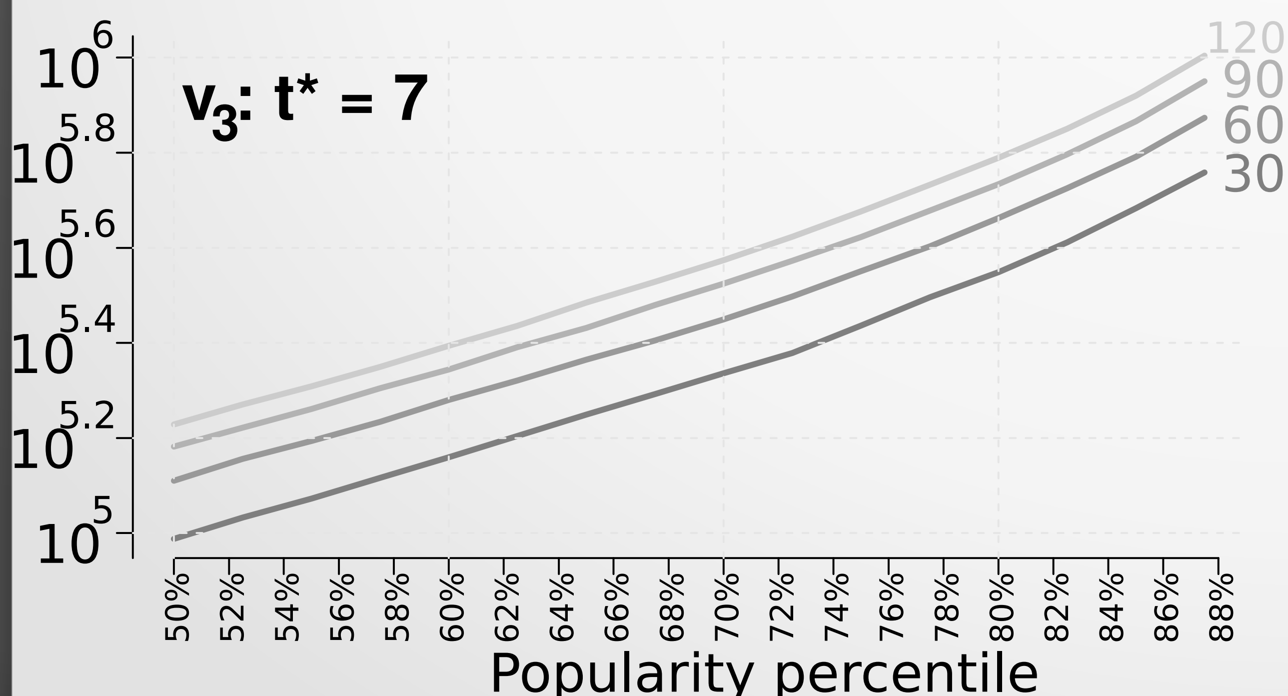
Compounding interest: $cost = (1+a)^k$

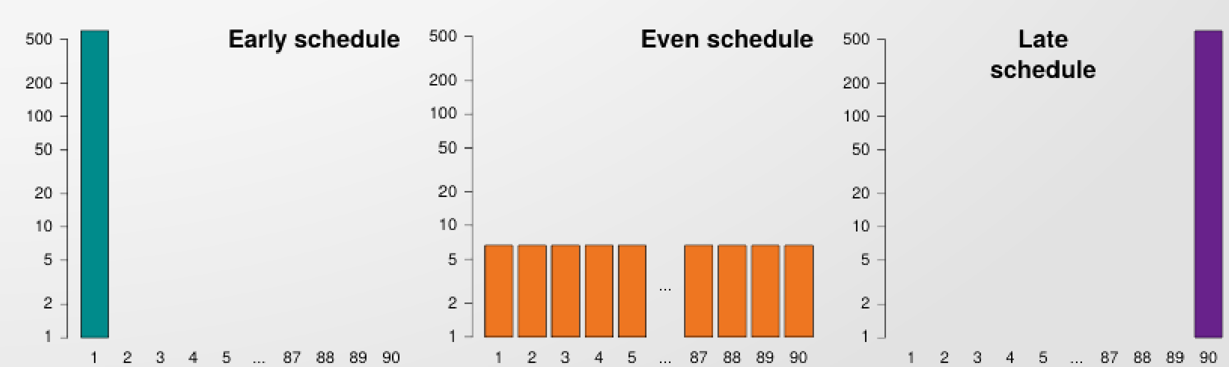


Interplay of 2 temporal factors

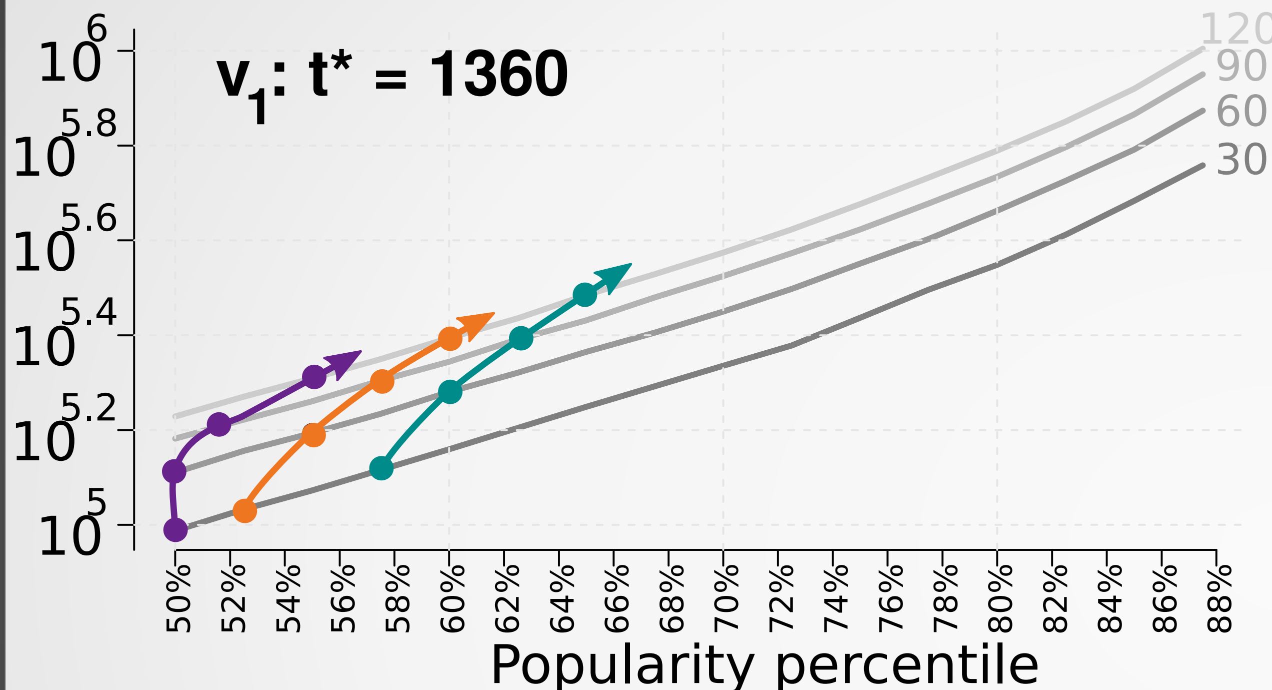


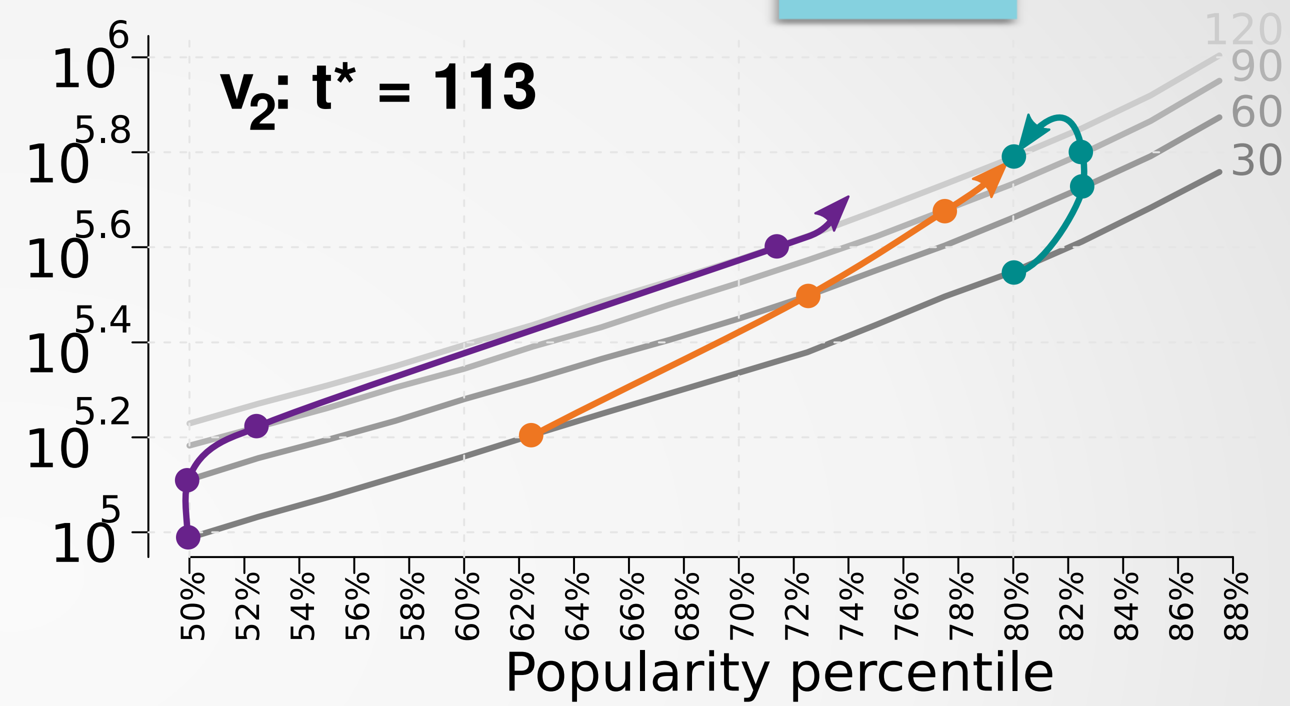


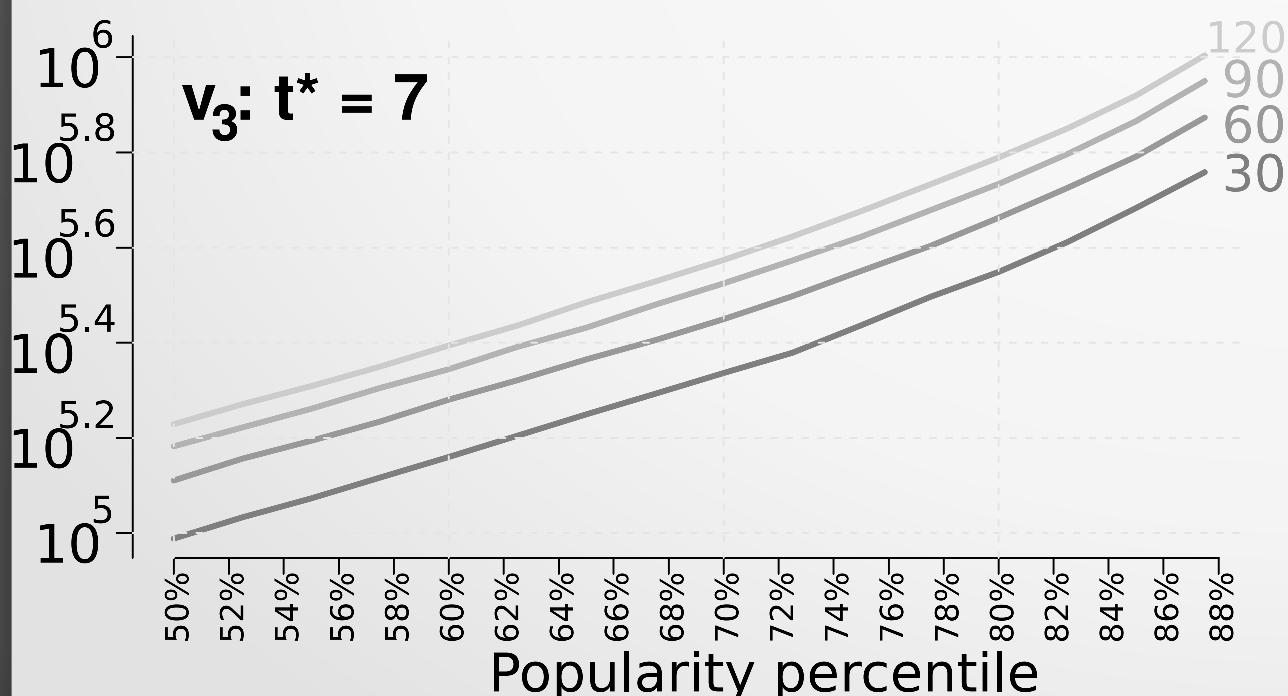


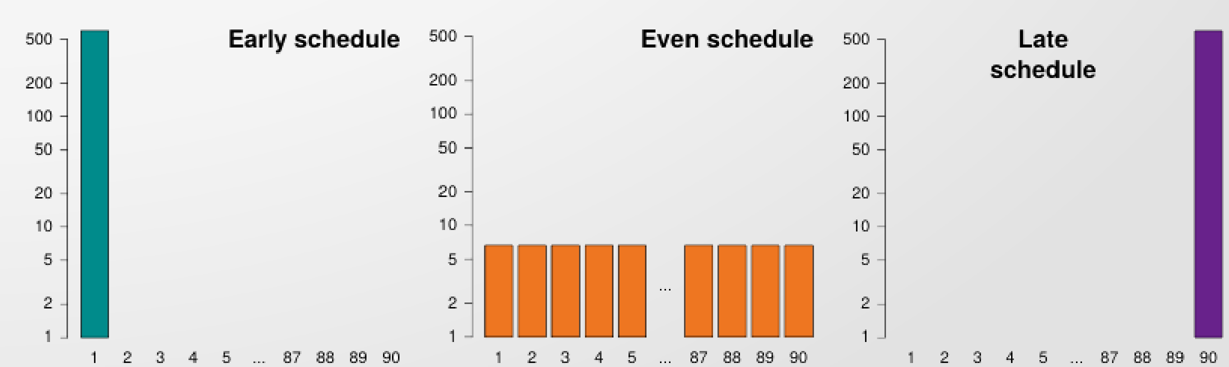


Interplay of 2 temporal factors

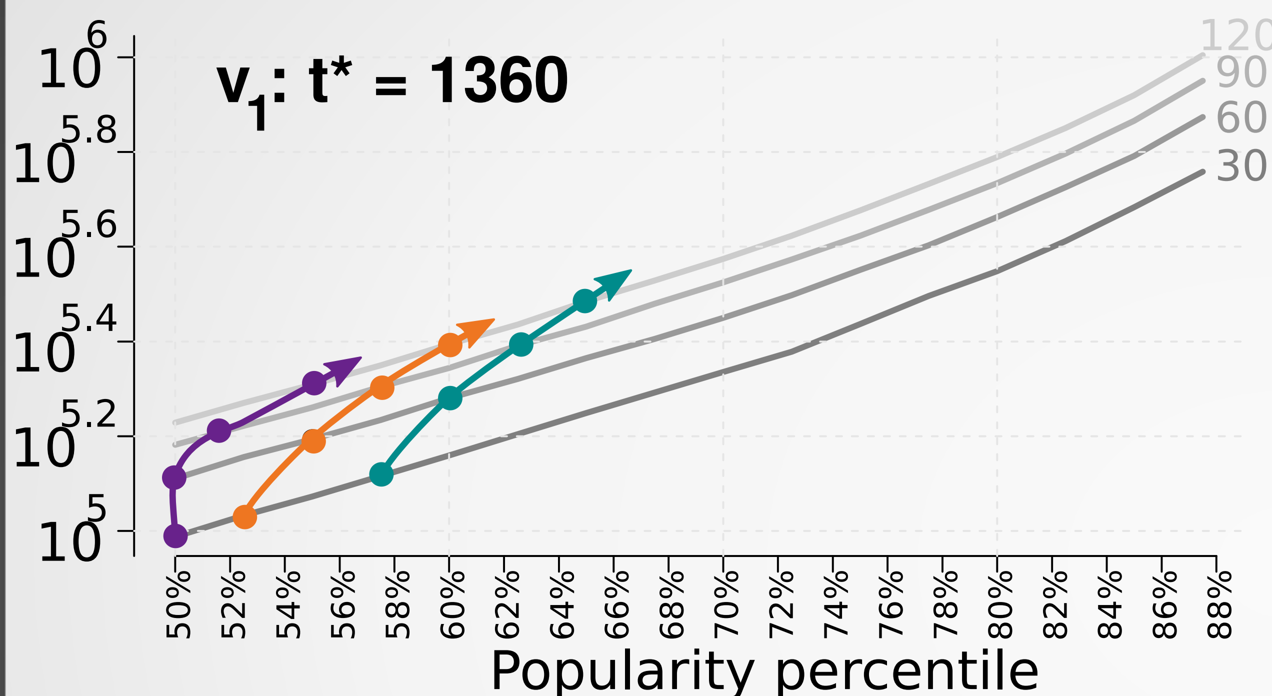


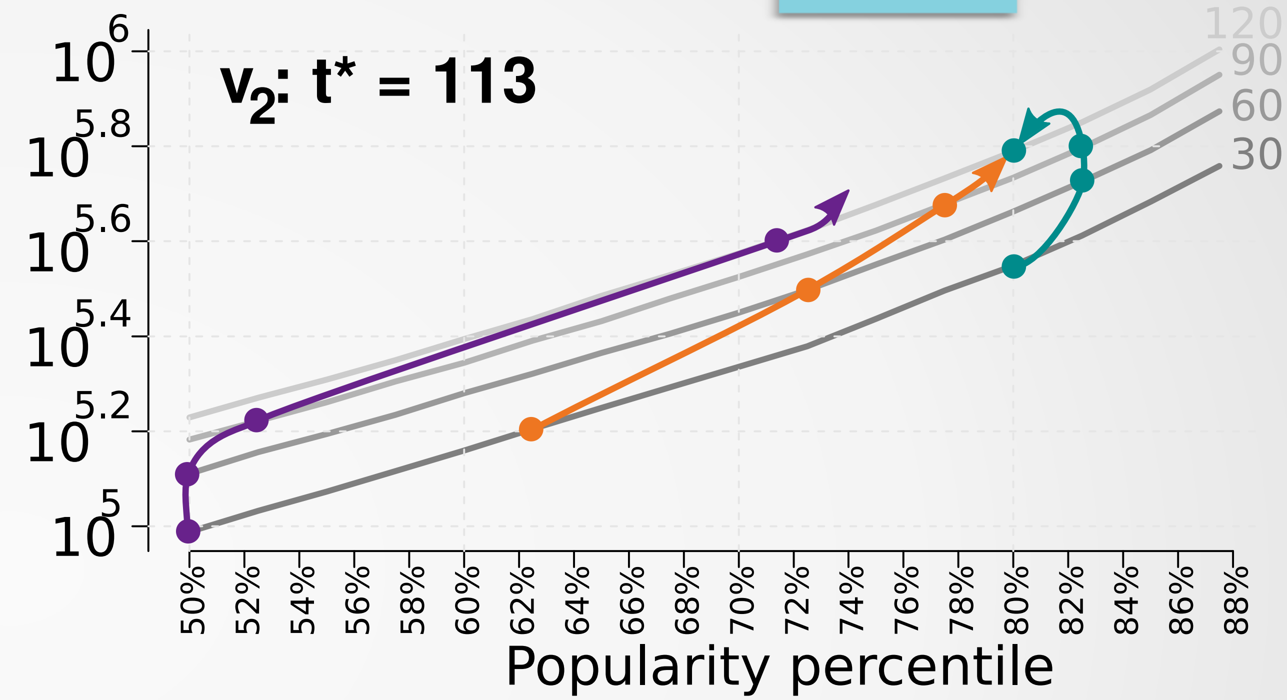


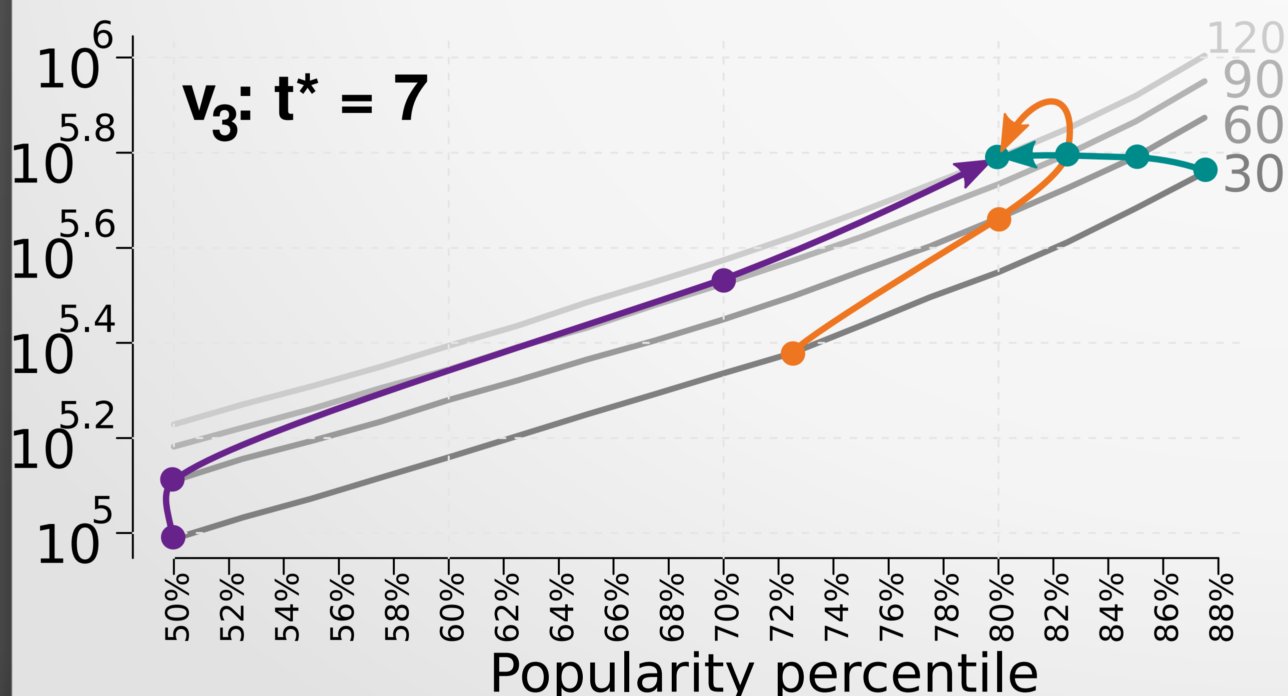


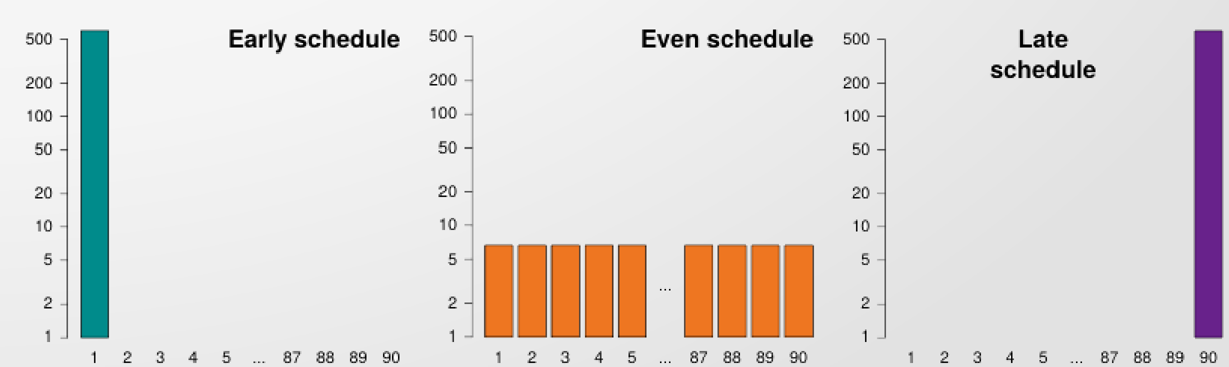


Interplay of 2 temporal factors







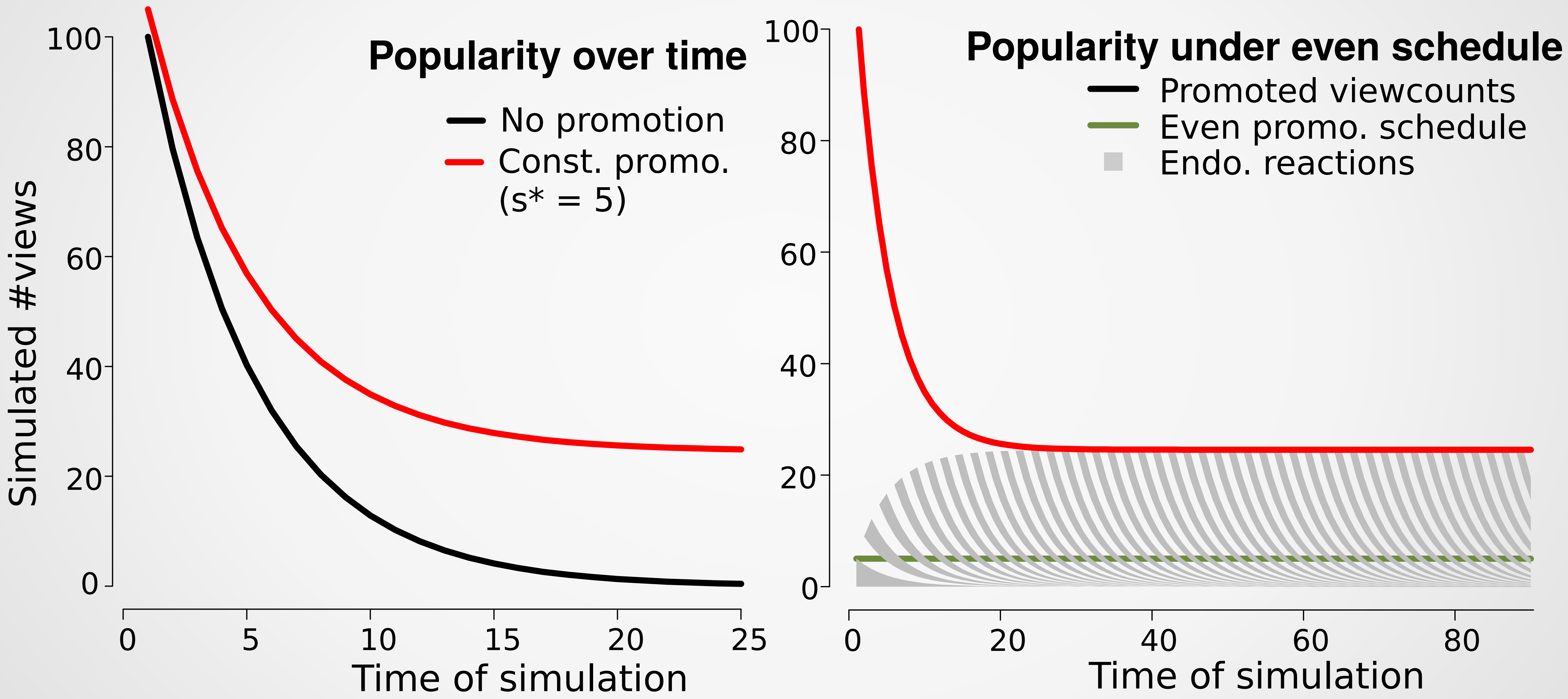


Why is constant promotion desirable?

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

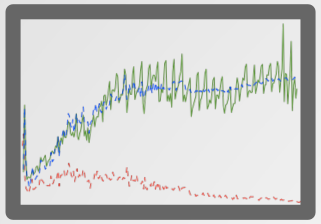
Explains why TV commercials appear at fixed intervals, every day.

Memory lengthening through promotion

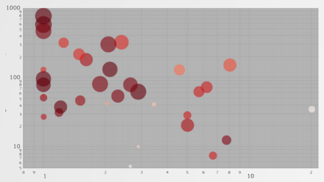


Constant promotion leads to an apparent **memory lengthening.**

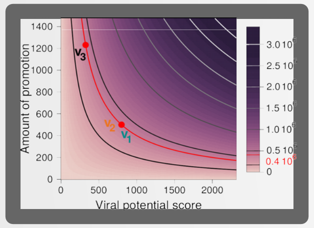
Summary



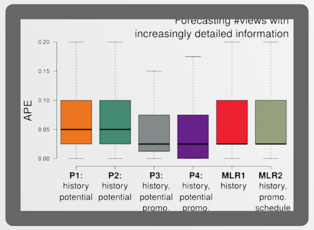
HIP: a mathematical model linking promotion and popularity



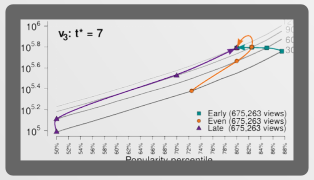
Explain popularity dynamics and identify potentially viral videos



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

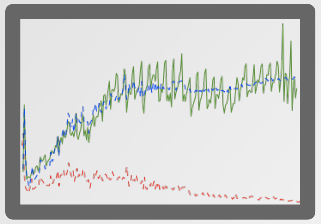


Important factors for forecasting popularity: *virality score*, *promotion volume* and *popularity scale position*

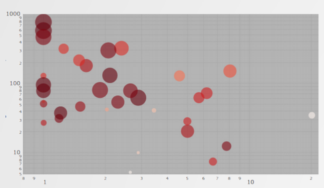


Maturity time influences the cost-effectiveness of promotion schedules

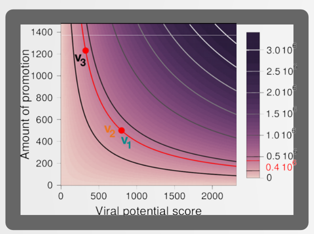
Summary



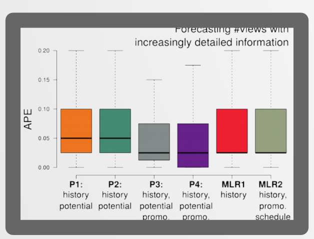
HIP: a mathematical model linking promotion and popularity



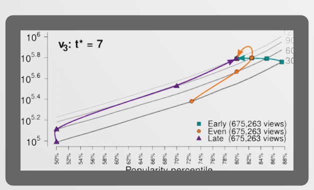
Explain popularity dynamics and identify potentially viral videos



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

Thank you!

Refereces:

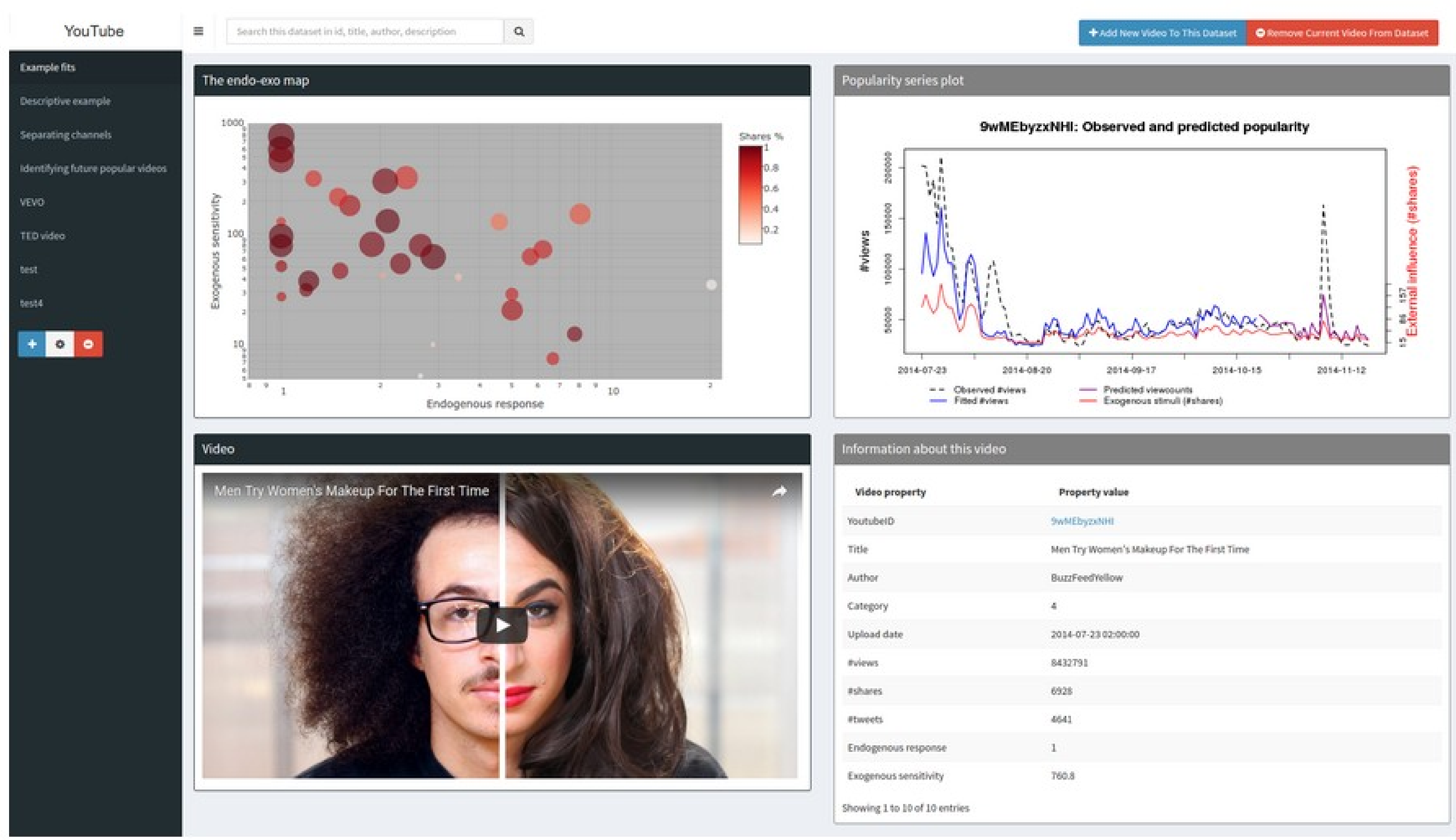
Rizoiu, M.-A., Xie, L., Sanner, S., Cebrian, M., Yu, H., & Van Hentenryck, P. **Expecting to be HIP: Hawkes Intensity Processes for Social Media Popularity**. In *26th International Conference on World Wide Web - WWW '17*, pp. 735-744, Perth, Australia, 2017. doi: 10.1145/3038912.3052650
pdf at arxiv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

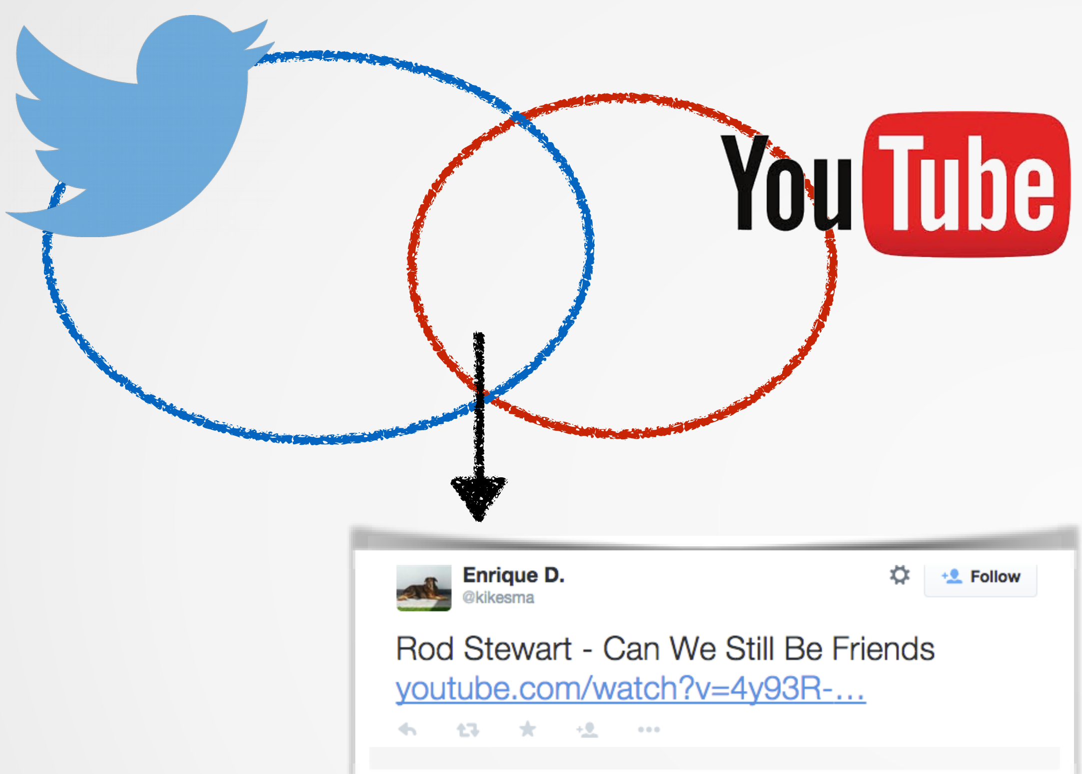


Links:

Code, dataset and interactive visualizer:

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

Twitter videos dataset



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?

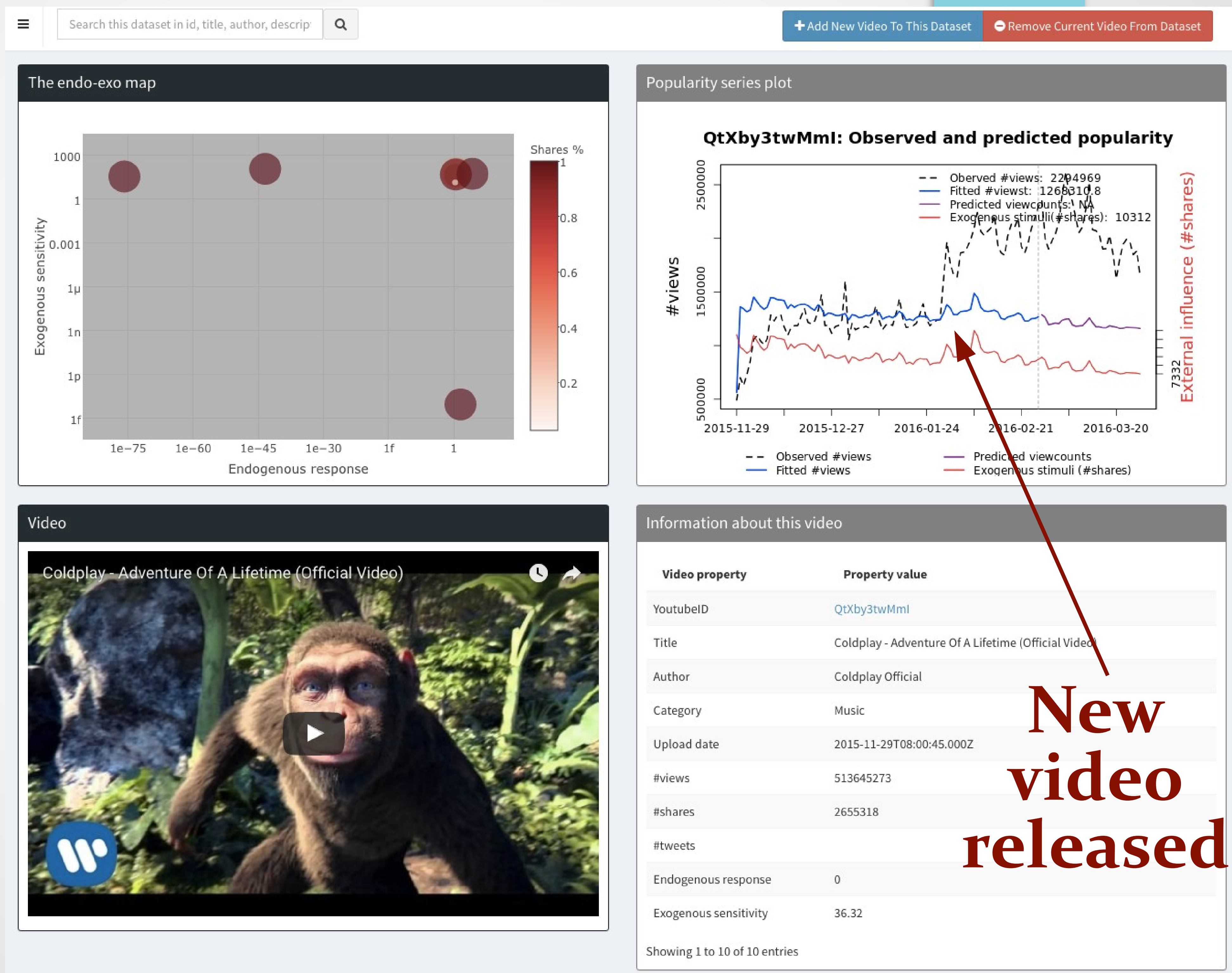
3) Predicting future popularity

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:



New video released

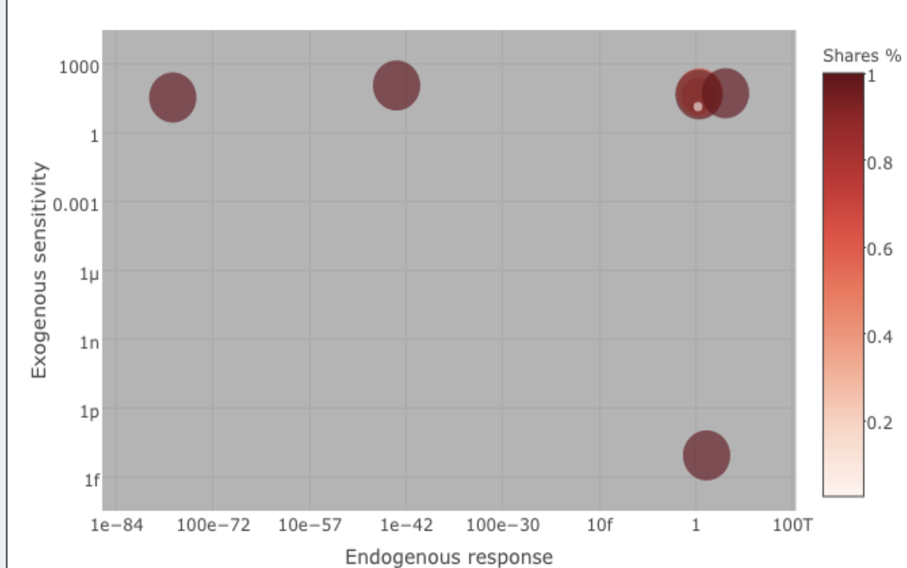
Supp: when HIP fails the fitting (2)

Long term evolutions:

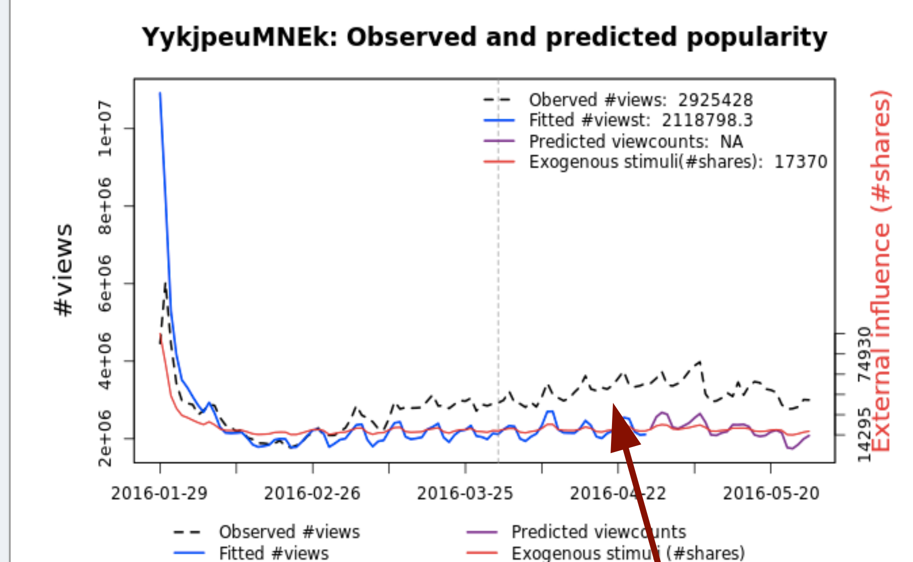
Search this dataset in id, title, author, description

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

The endo-exo map



Popularity series plot



Video

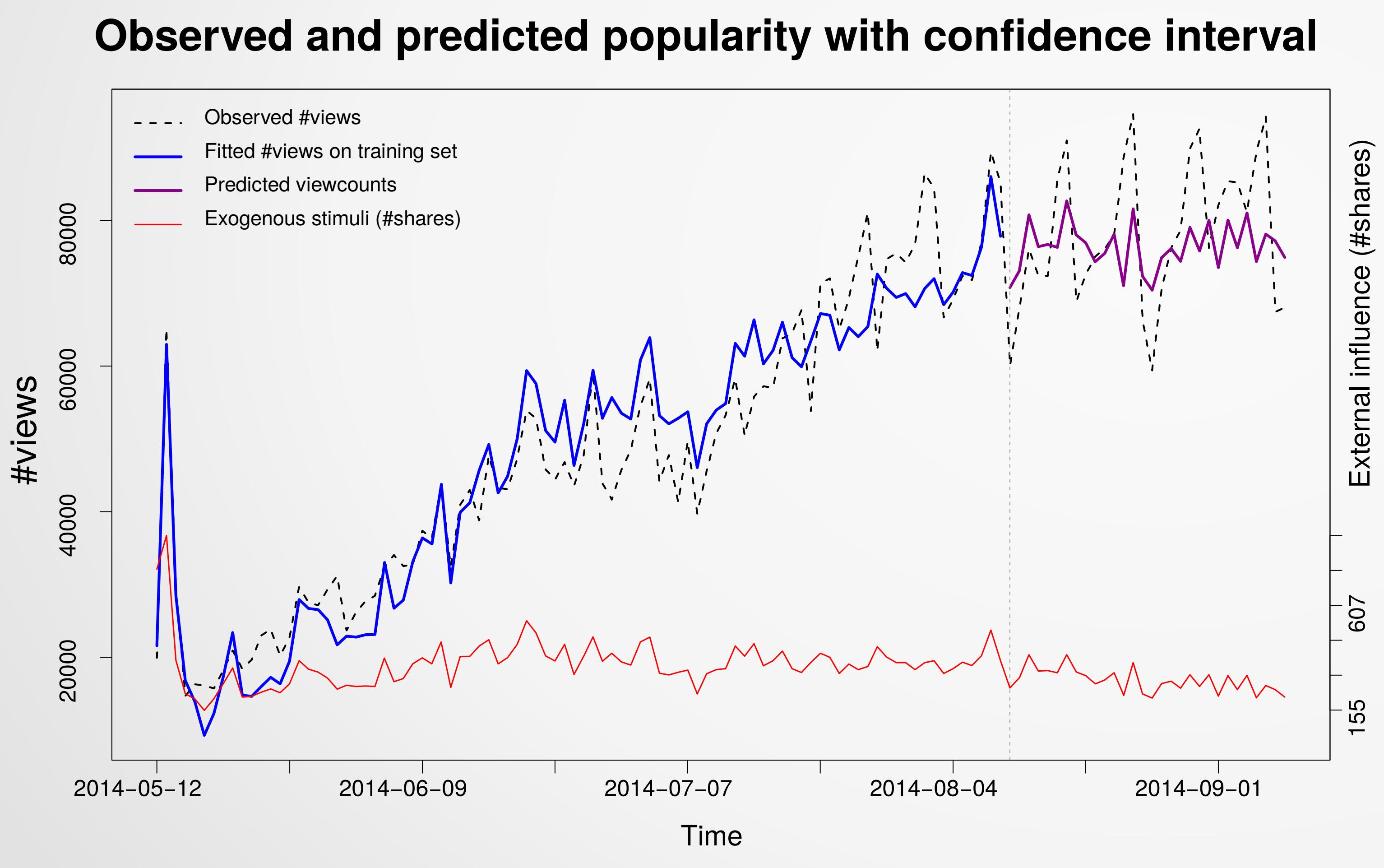
Information about this video

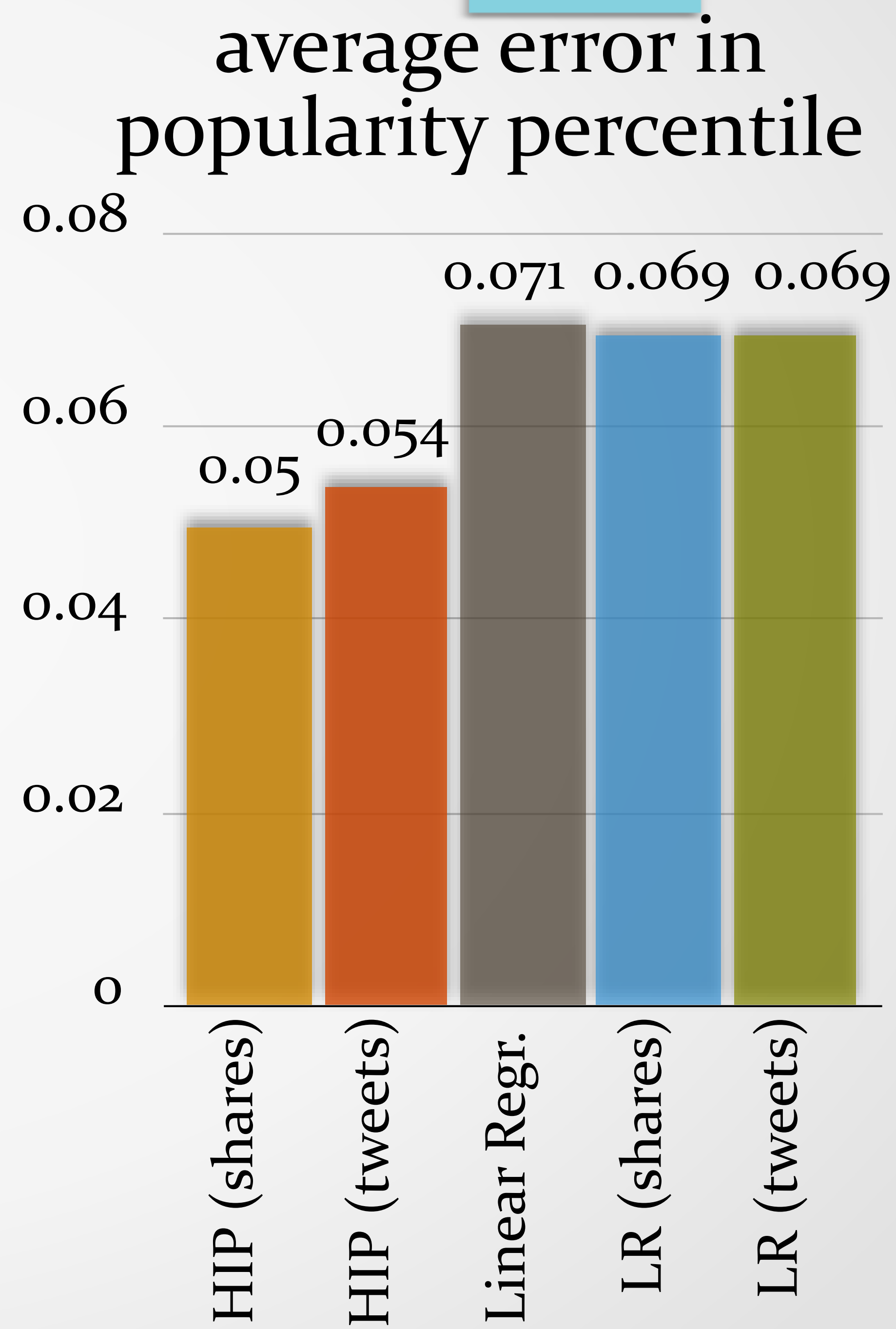
Video property	Property value
YoutubeID	YykjpeuMNEk
Title	Coldplay - Hymn For The Weekend (Official Video)
Author	Coldplay Official
Category	Music
Upload date	2016-01-29T15:00:38.000Z
#views	694792952
#shares	4556631
#tweets	
Endogenous response	0
Exogenous sensitivity	121.18

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]