Branching Processes and their Application to Popularity Dynamics

Two Short Stories

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sfi
Fondúireacht Eolaíochta Éireann
Dá bhfuil romhainn
Science Foundation Ireland
For what's next

Outline of Today's Talk

- What is a **branching process**?
- Modelling **random-copying** mechanisms.
- How they can be used to model **diffusion on social media**.
- What they offer in terms of **predictability** of cascades.
- **Conclusions**.

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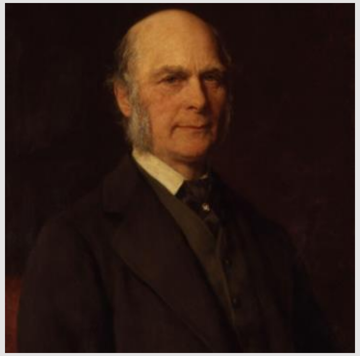
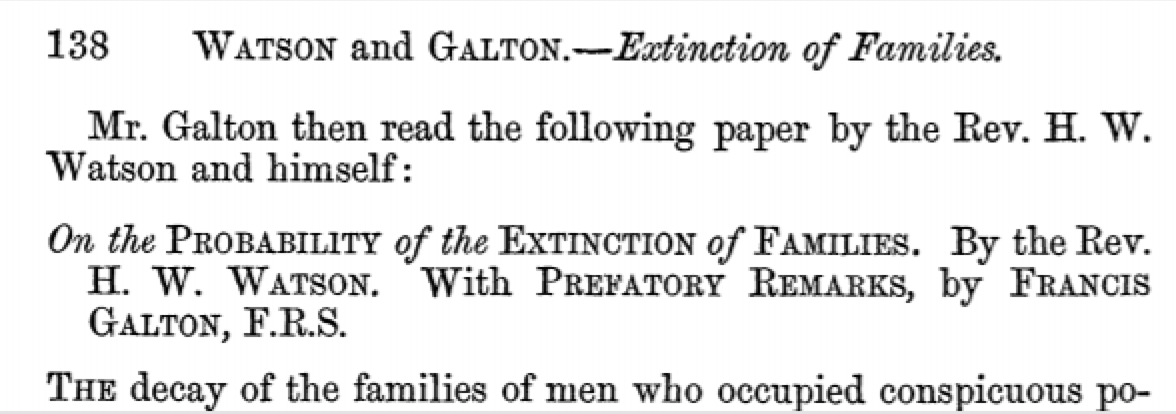
Branching Processes



- **Francis Galton** proposed a formulation to understand the likelihood of a family name staying alive in Educational Times 1873 through the following question

*"**PROBLEM 4001:** A large nation, of whom we will only concern ourselves with adult males, N in number, and who each bear separate surnames colonise a district. Their law of population is such that, in each generation, **a_0 percent of the adult males have no male children** who reach adult life; **a_1 have one such male child**; a_2 have two; and so on up to a_5 who have five. Find (1) **what proportion of their surnames** will have become **extinct after r generations**; and (2) **how many instances there will be of the surname being held by m persons**."*



138 WATSON and GALTON.—*Extinction of Families.*

Mr. Galton then read the following paper by the Rev. H. W. Watson and himself:

On the PROBABILITY *of the* EXTINCTION *of* FAMILIES. By the Rev. H. W. WATSON. With PREFATORY REMARKS, by FRANCIS GALTON, F.R.S.

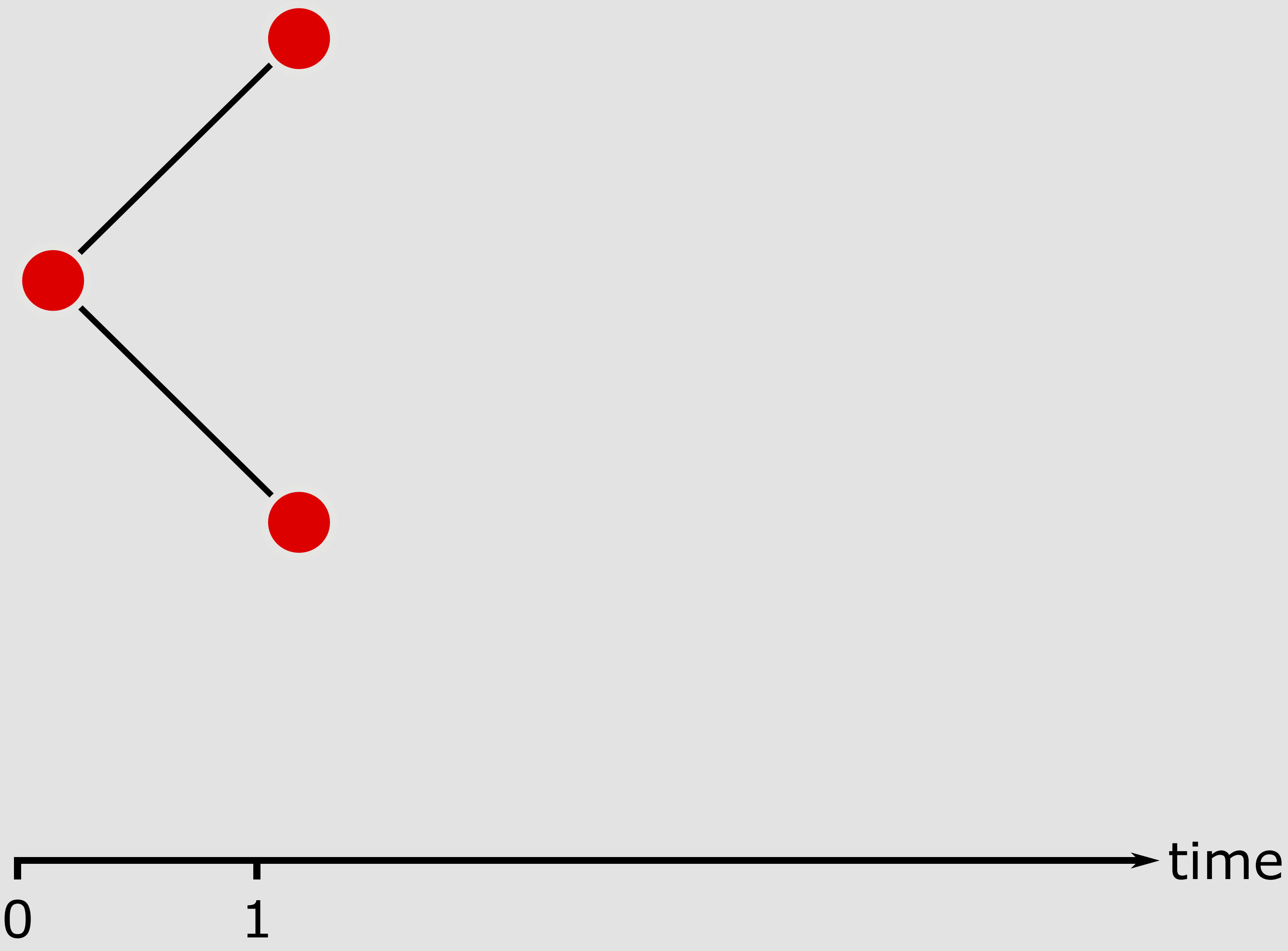
THE decay of the families of men who occupied conspicuous po-

Rev H. W. Watson

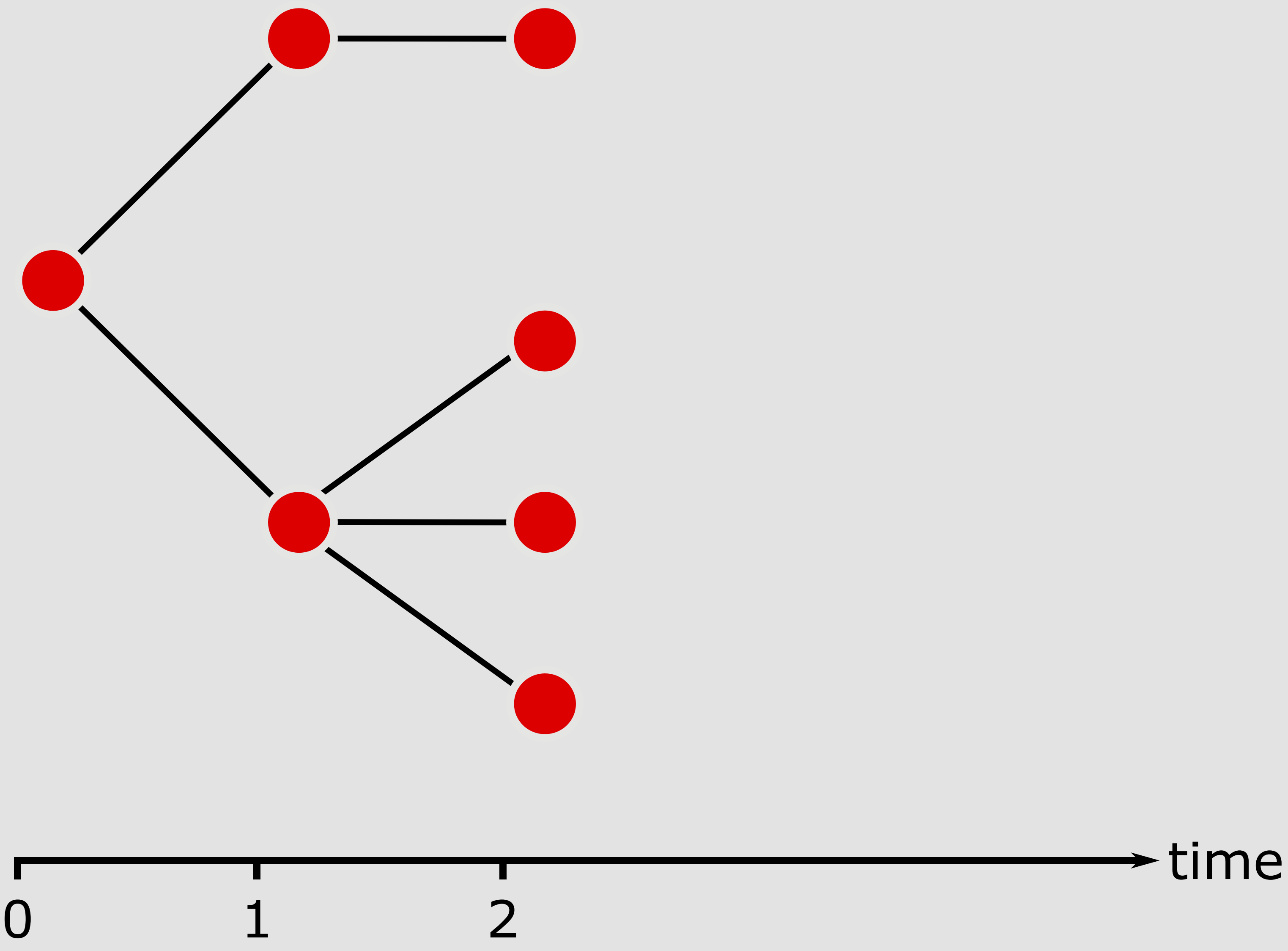
Branching Processes

Branching Processes

Branching Processes



Branching Processes



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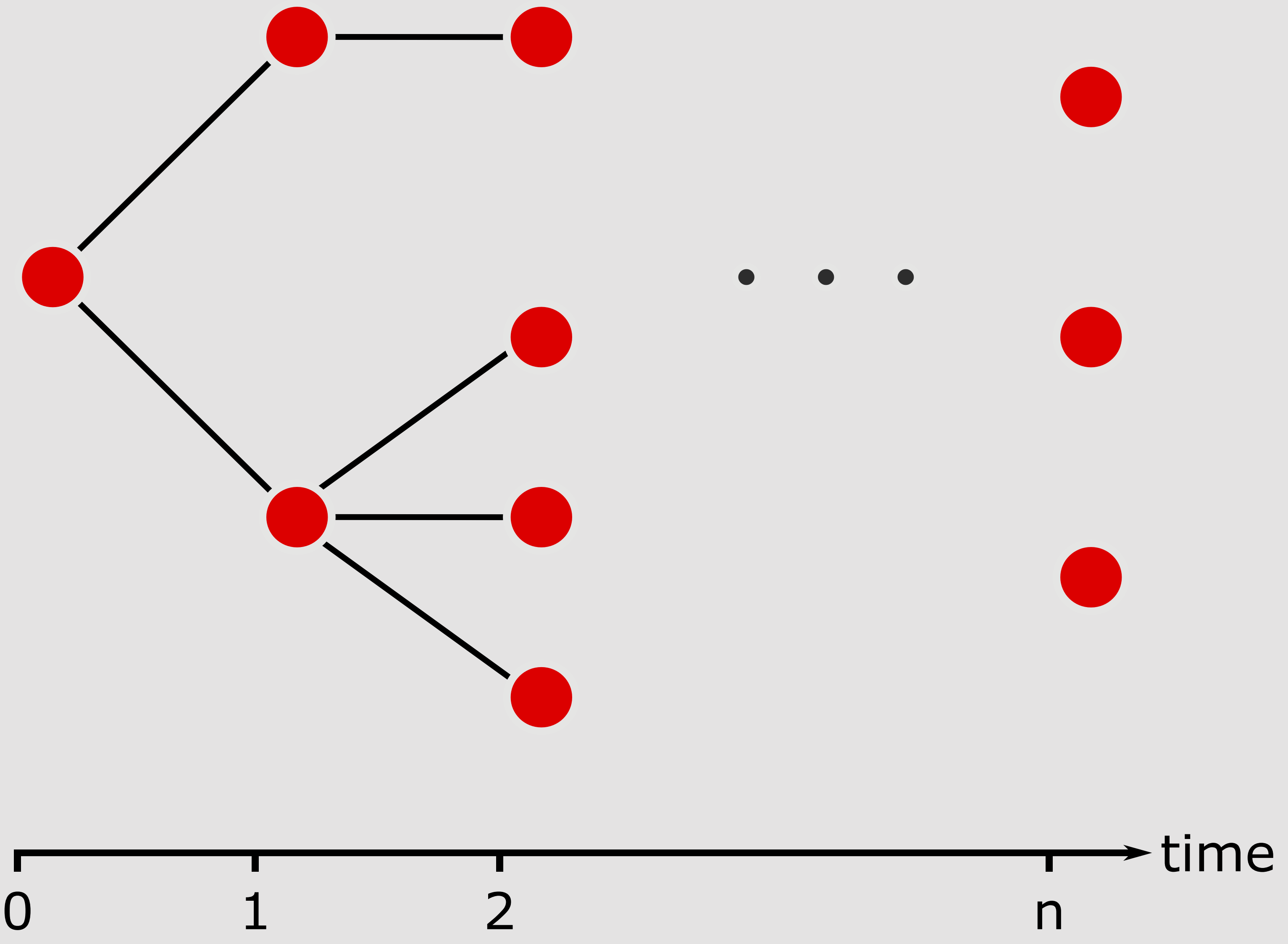

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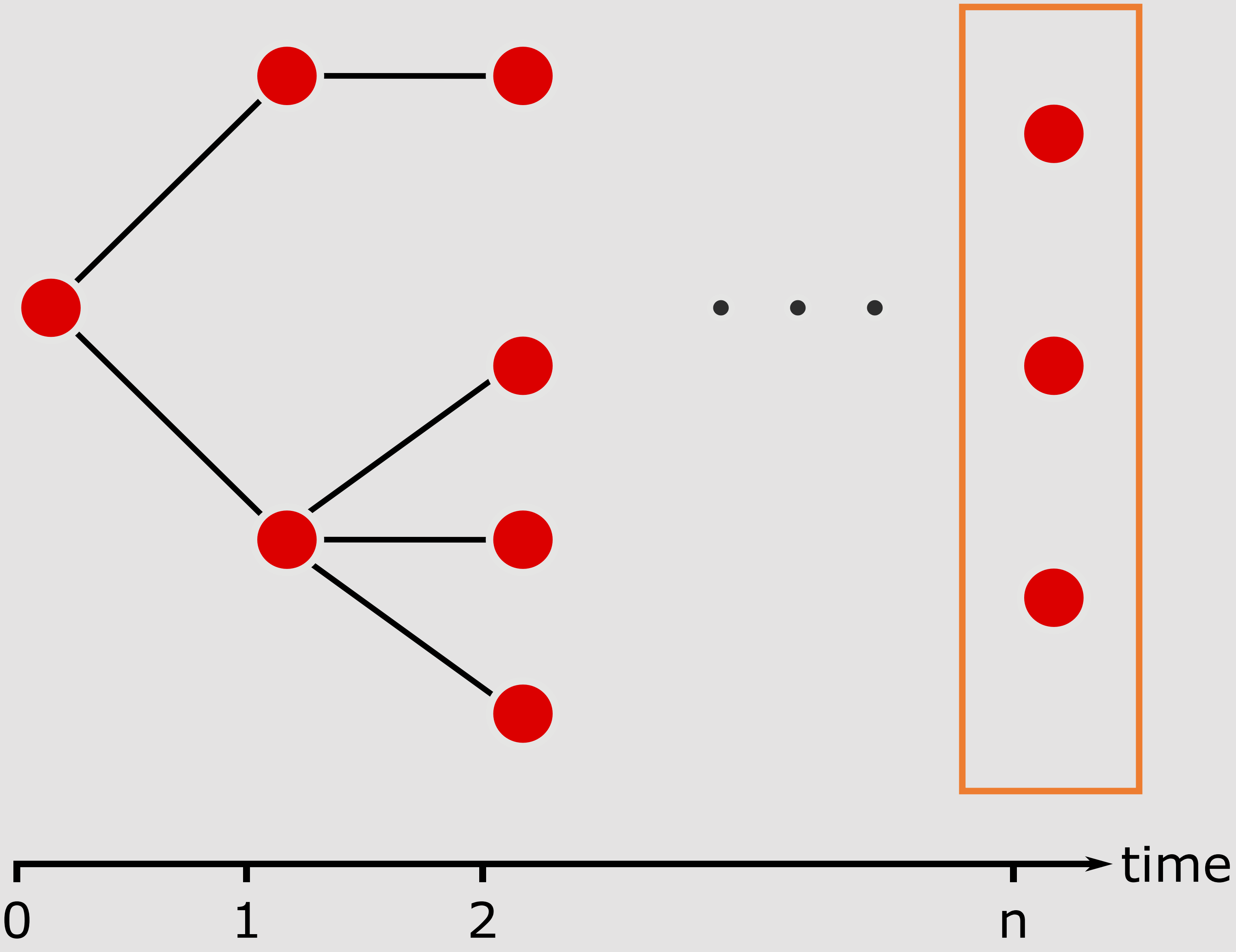

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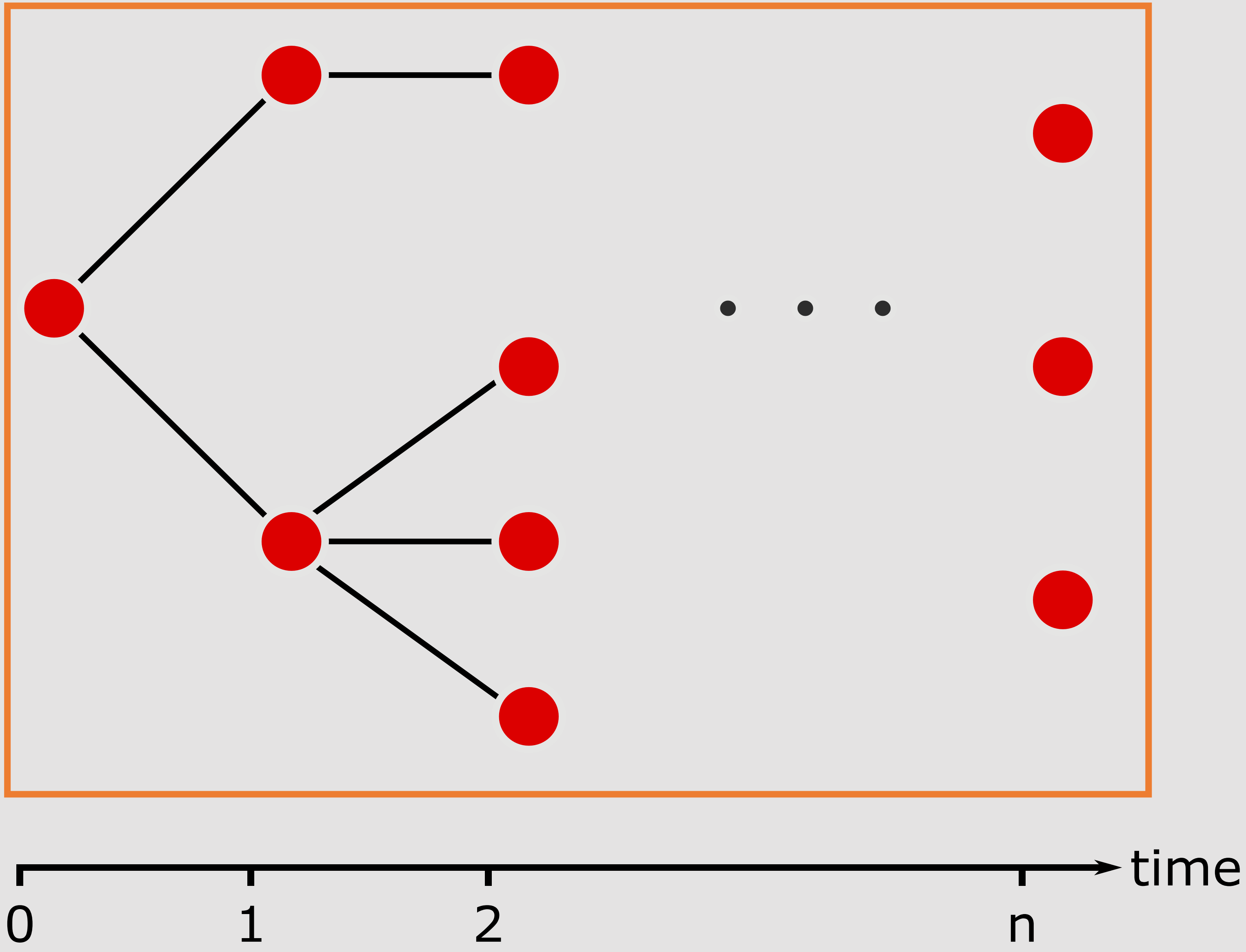

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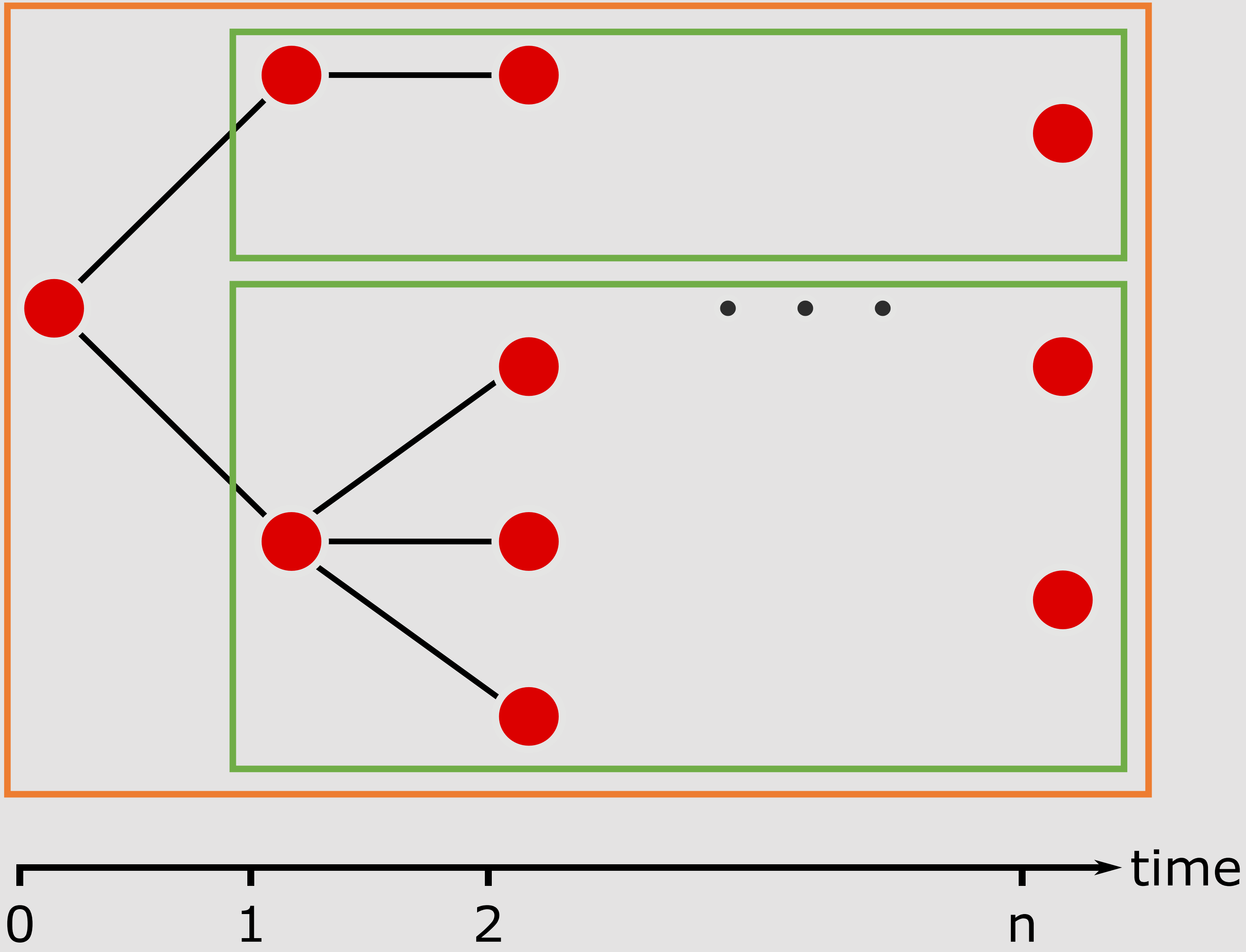


Branching Processes

While classically used for biological purposes – recently have been used to describe popularity dynamics including:

Citation dynamics

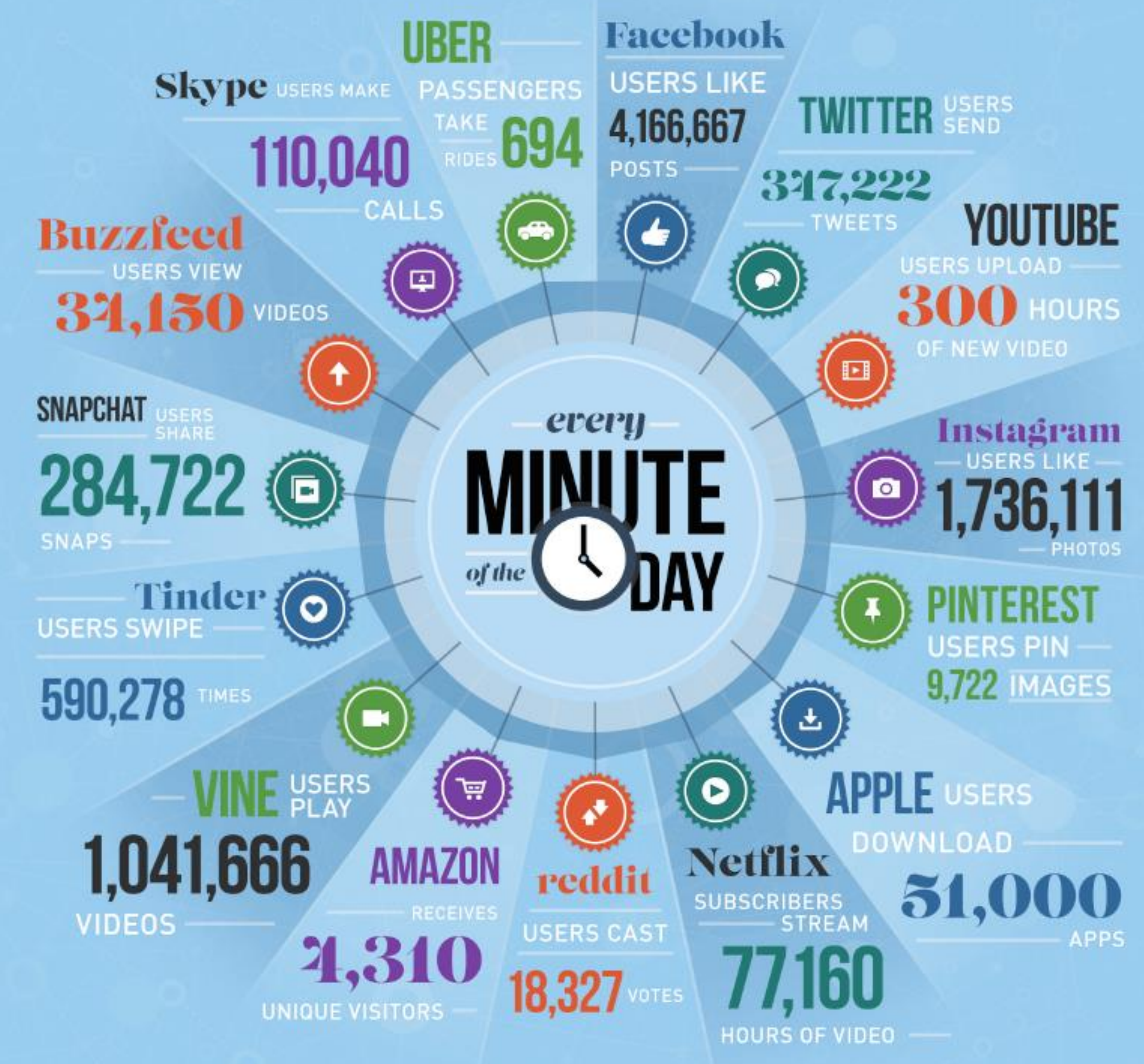
- M. V. Simkin and V. P. Roychowdhury, ***J. Am. Soc. Inf. Sci. Tech.*** 58, 1661 (2007).

Viral marketing

- R. Van der Lans, et al., ***Market. Sci.*** 29, 348 (2010).
- J. L. Iribarren and E. Moro, ***Phys. Rev. E*** 84, 046116 (2011).

Social media cascades

- O. Yagan at al., ***IEEE J. Sel. Areas Commun.*** 31, 1038 (2013).
- J. P. Gleeson et al., ***Phys. Rev. Lett.*** 112, 048701 (2014).
- J. P. Gleeson at al., ***Phys. Rev. X*** 6, 021019 (2016).


every MINUTE of the DAY
Skype USERS MAKE 110,040 CALLS
UBER PASSENGERS TAKE 694 RIDES
Facebook USERS LIKE 4,166,667 POSTS
TWITTER USERS SEND 347,222 TWEETS
YOUTUBE USERS UPLOAD 300 HOURS OF NEW VIDEO
Instagram USERS LIKE 1,736,111 PHOTOS
PINTEREST USERS PIN 9,722 IMAGES
APPLE USERS DOWNLOAD 51,000 APPS
Netflix SUBSCRIBERS STREAM 77,160 HOURS OF VIDEO
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AMAZON RECEIVES 4,310 UNIQUE VISITORS
VINE USERS PLAY 1,041,666 VIDEOS
Tinder USERS SWIPE 590,278 TIMES
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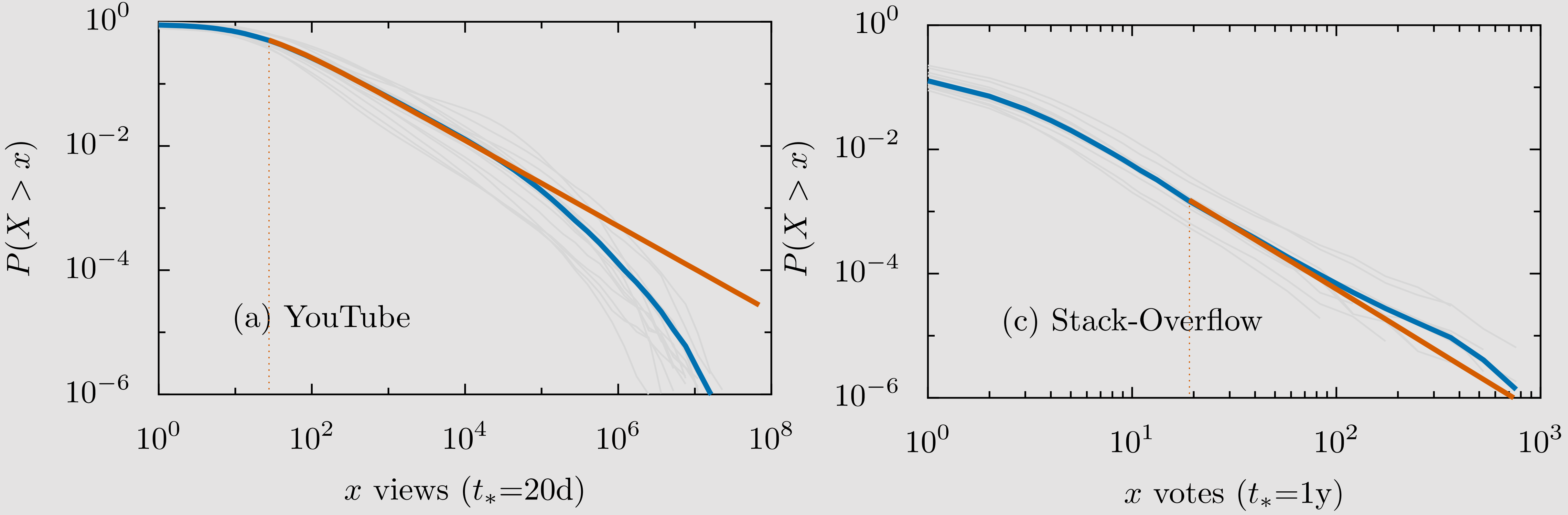
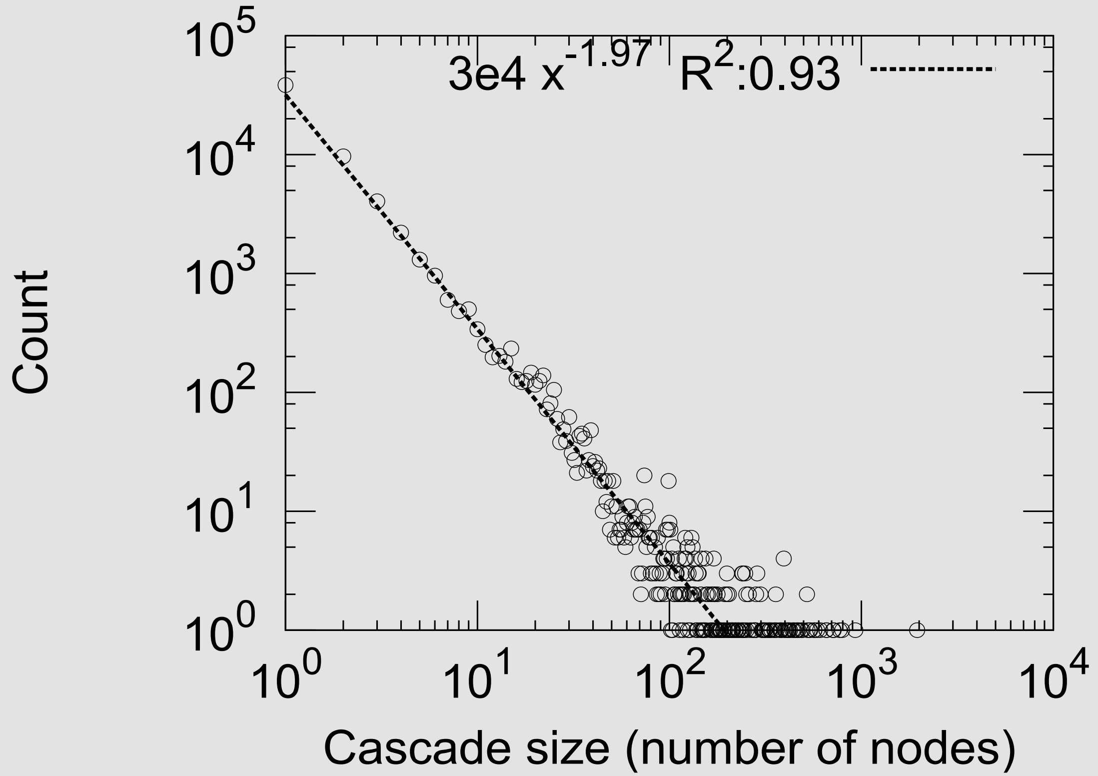
Buzzfeed USERS VIEW 34,150 VIDEOS

Empirical cascades

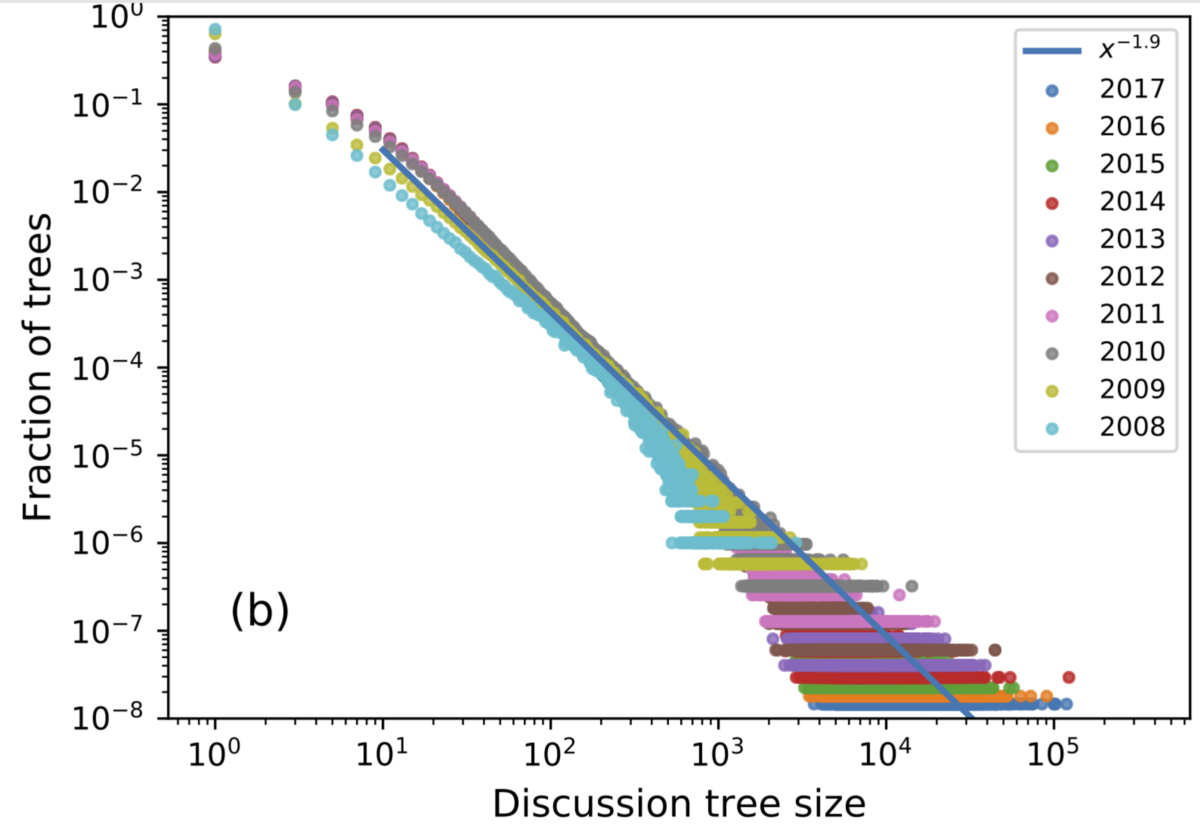


J. M. Miotto, E. G. Altmann, Predictability of Extreme Events in Social Media. *PLoS ONE 9(11) (2014)*

Empirical cascades

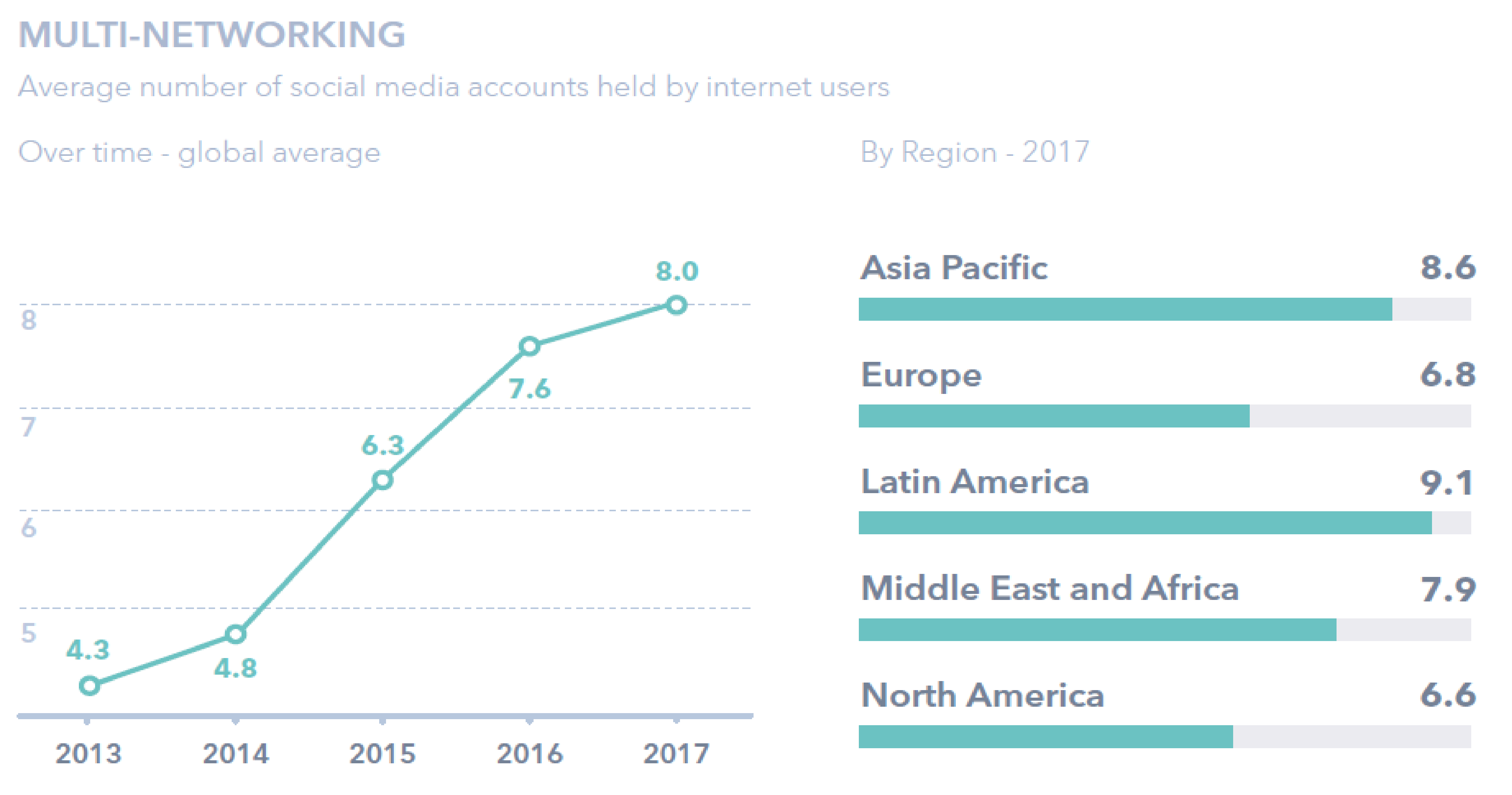


J. Leskovec et al. "Patterns of cascading behavior in large blog graphs."
Proc. SIAM Intern. Conf. on Data Mining (2007).



A. N. Medvedev, R. Lambiotte, and J.-C. Delvenne. "The anatomy of Reddit: An overview of academic research."
Dyn. on and of Comp. Net. Springer, Cham, 2017(2017).

Empirical cascades



Dave Chaey. Global social media research summary 2017. ***Smart Insights: Social Media Marketing***, 2018.

What we want to obtain

- A model which can capture the **features of empirical data**.
- Uses the **exact network** topology (rather than ensembles of random graphs).
- Considers the fact that different **users** have **different behaviours**.
- Allows users to have accounts on **multiple platforms**.

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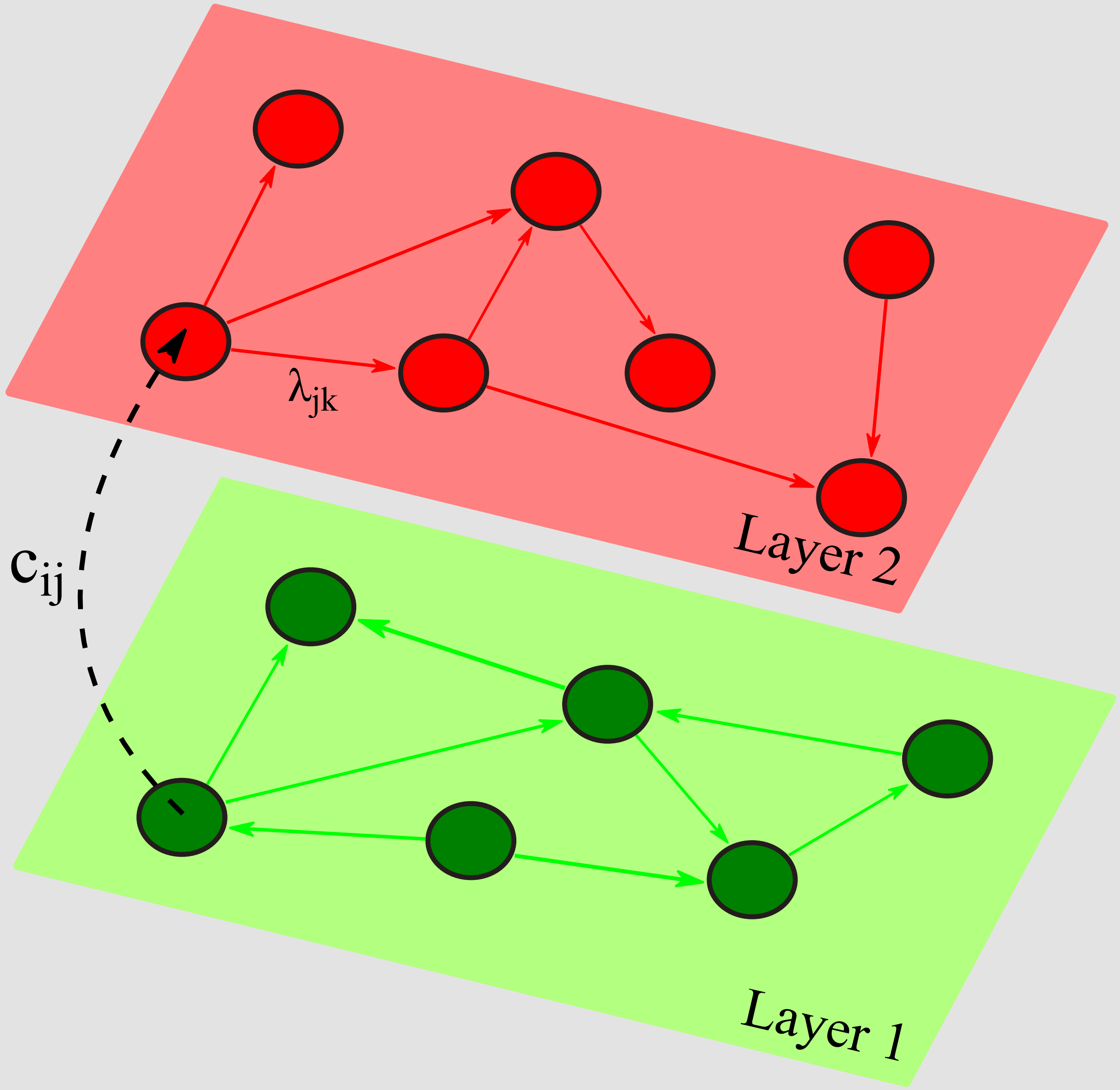
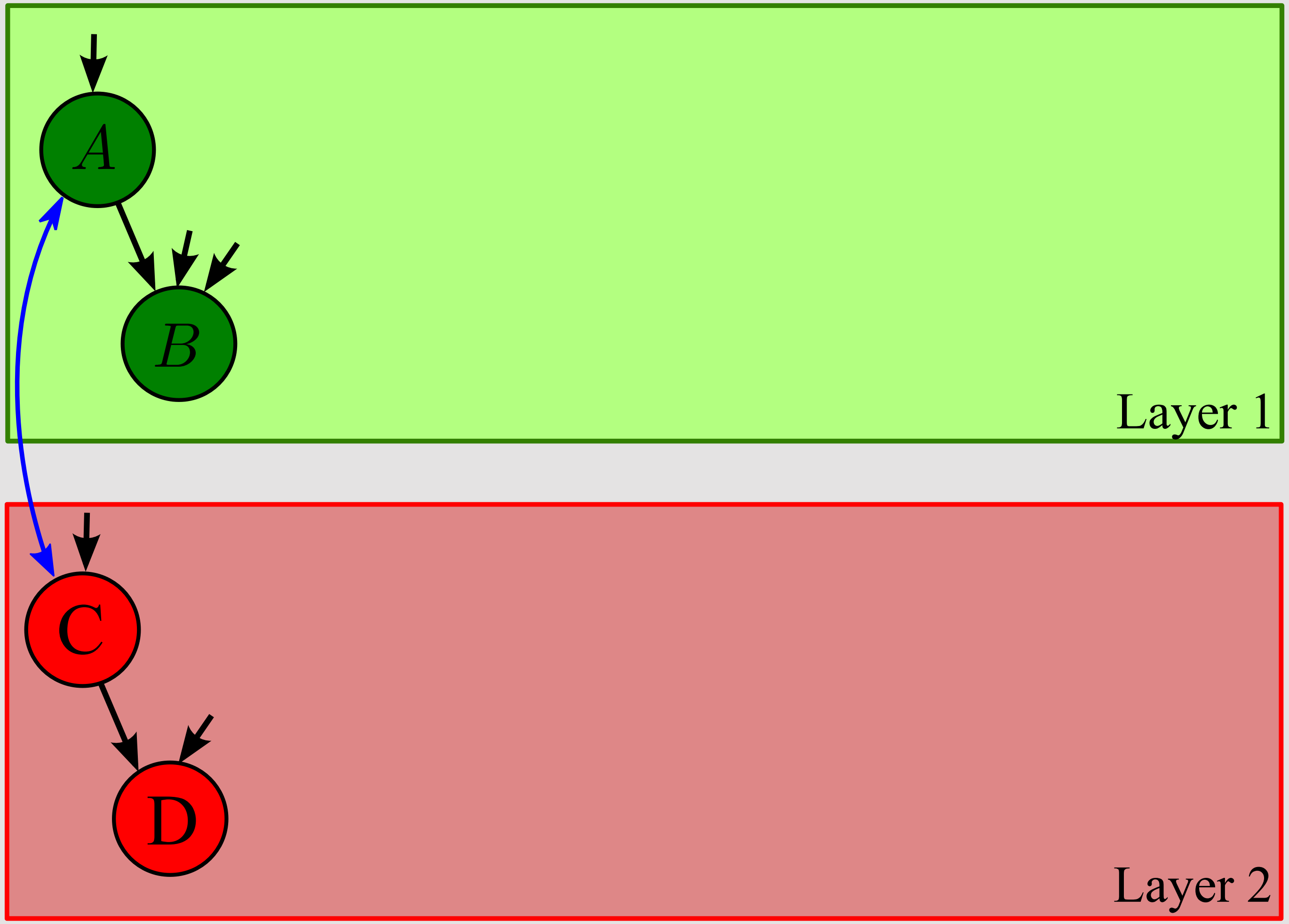
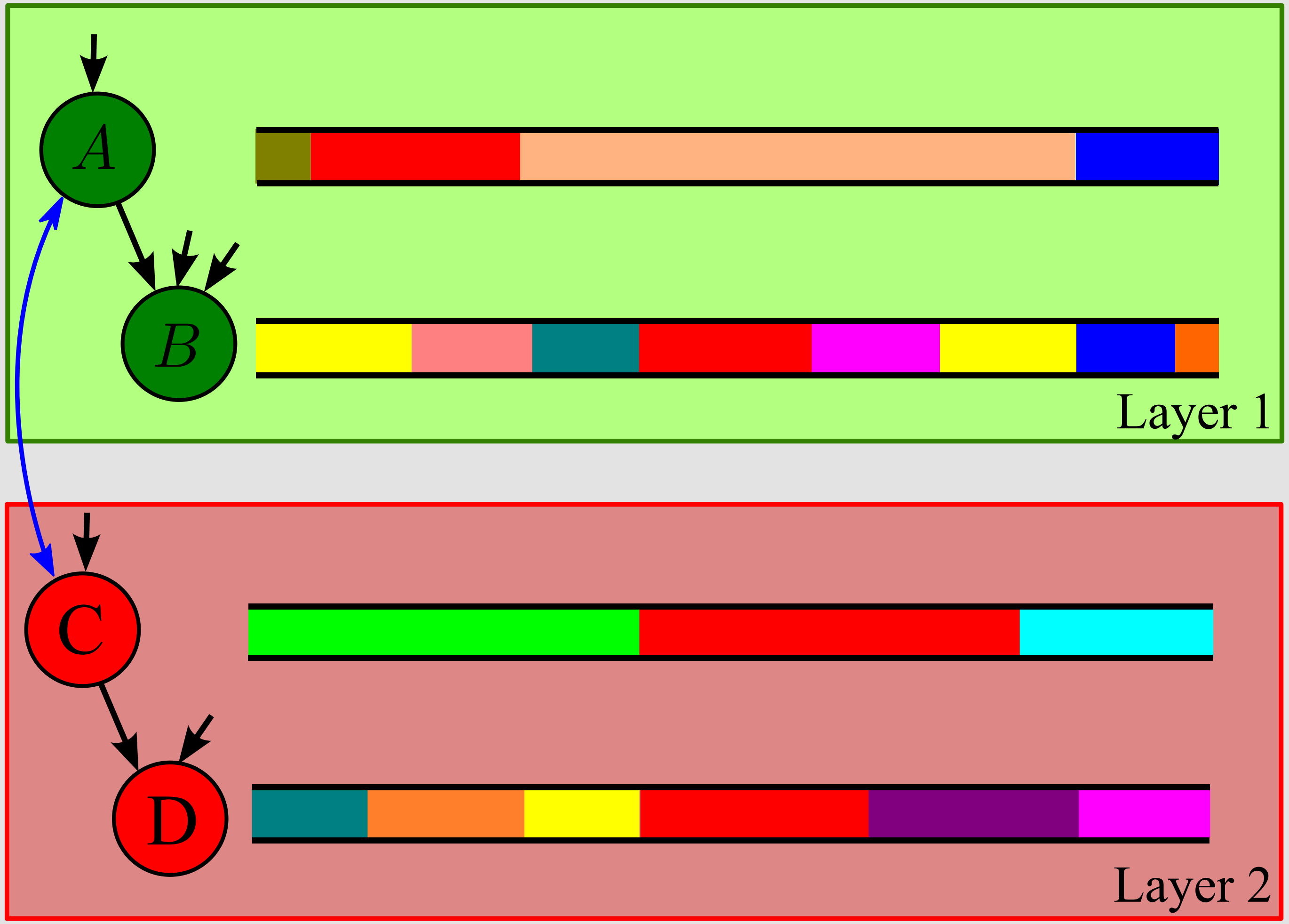



A
B
Layer 1
C
D
Layer 2



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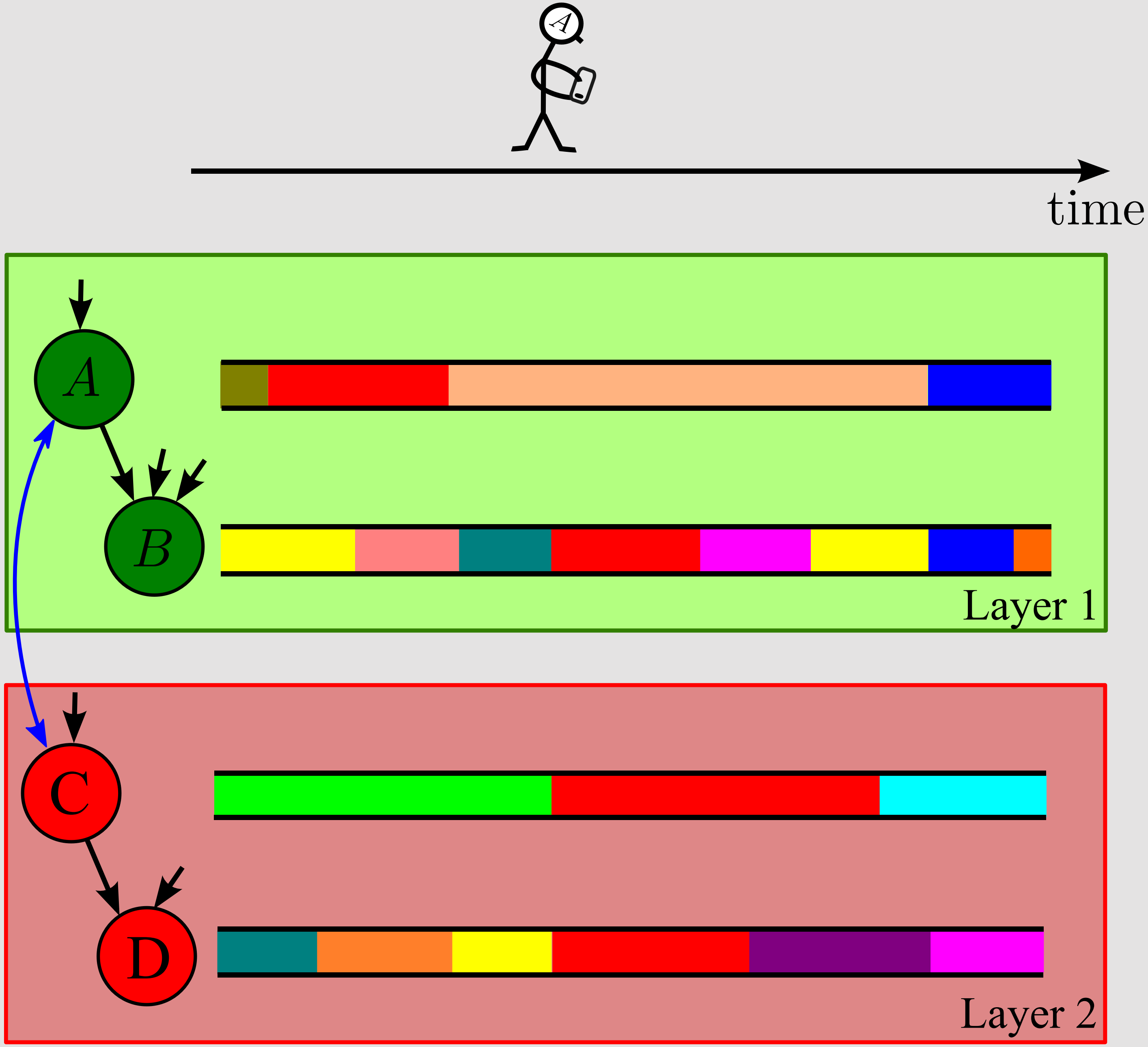
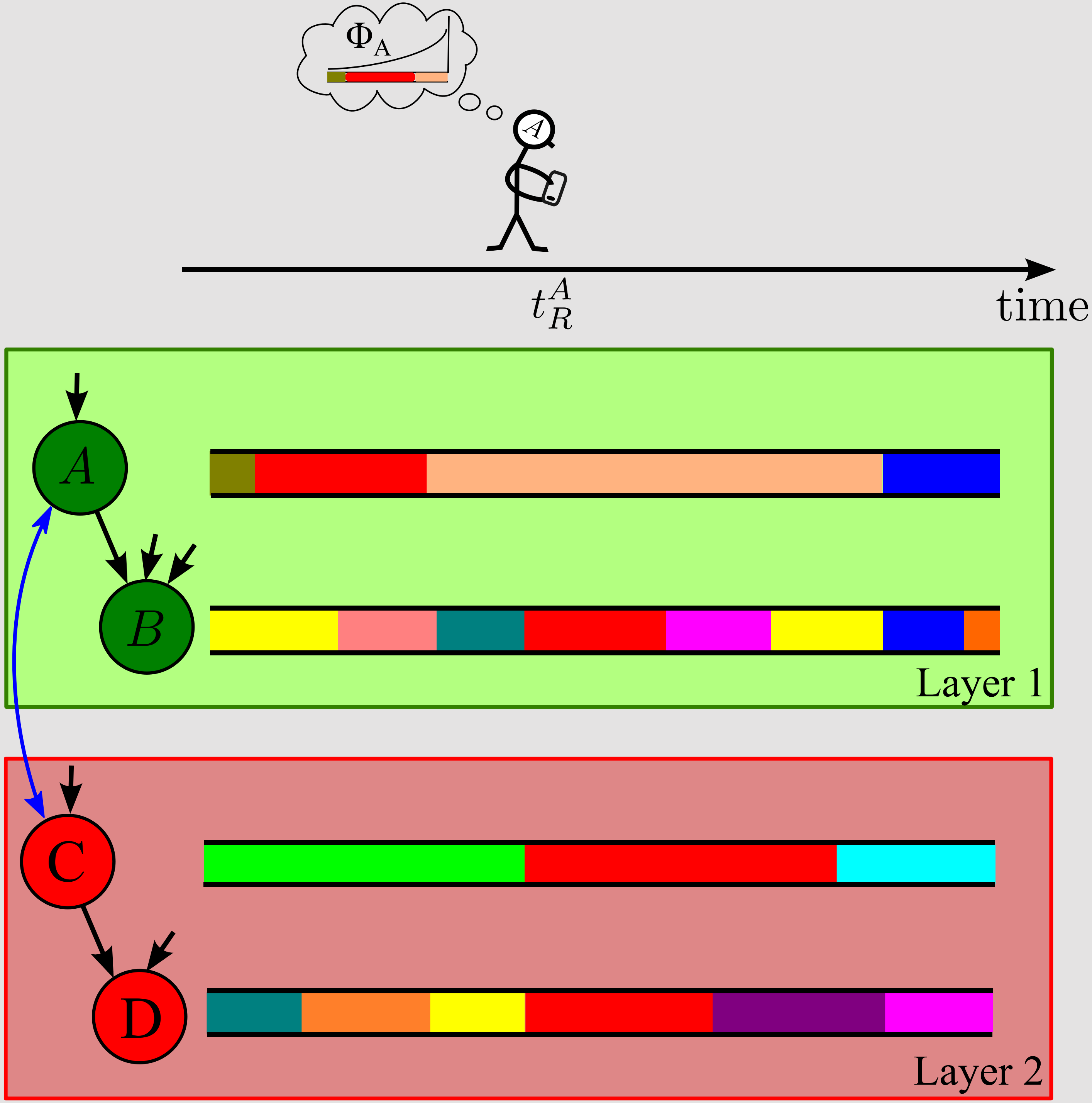

time
A
B
Layer 1
C
D
Layer 2

Can either

Retweet w.p. $(1 - \mu_A)$



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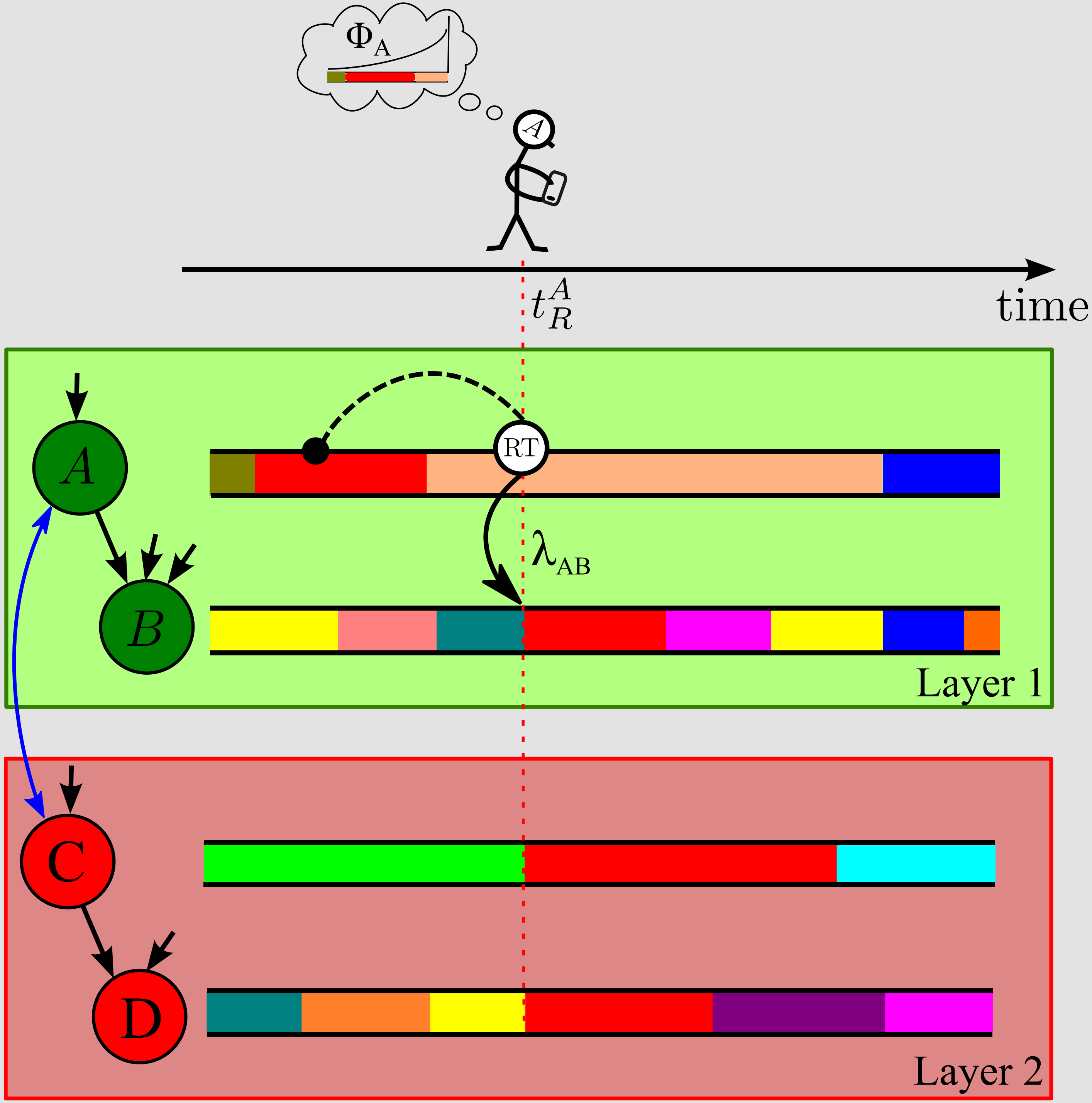

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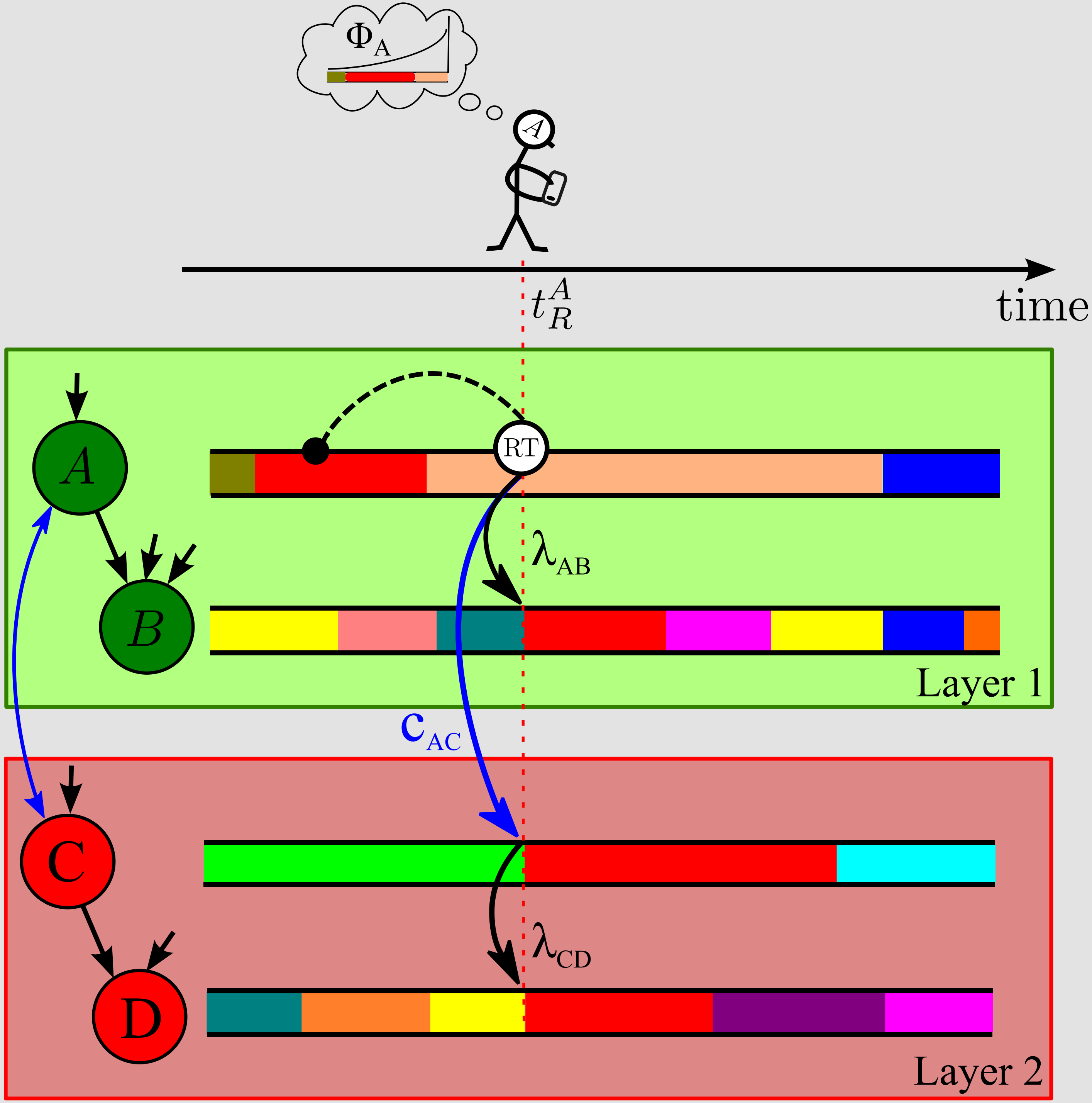

Can either

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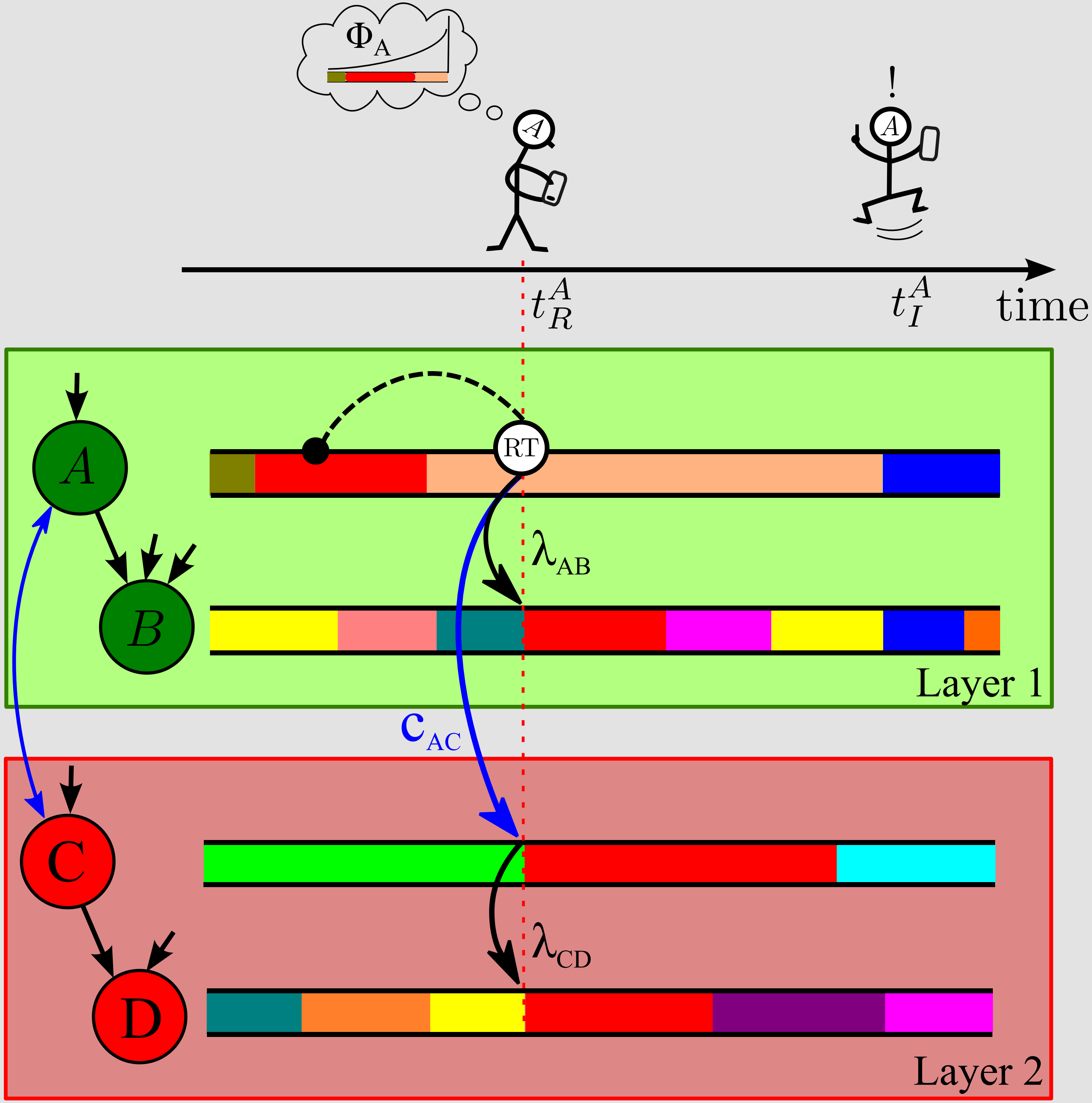
Innovate w.p. μ_A



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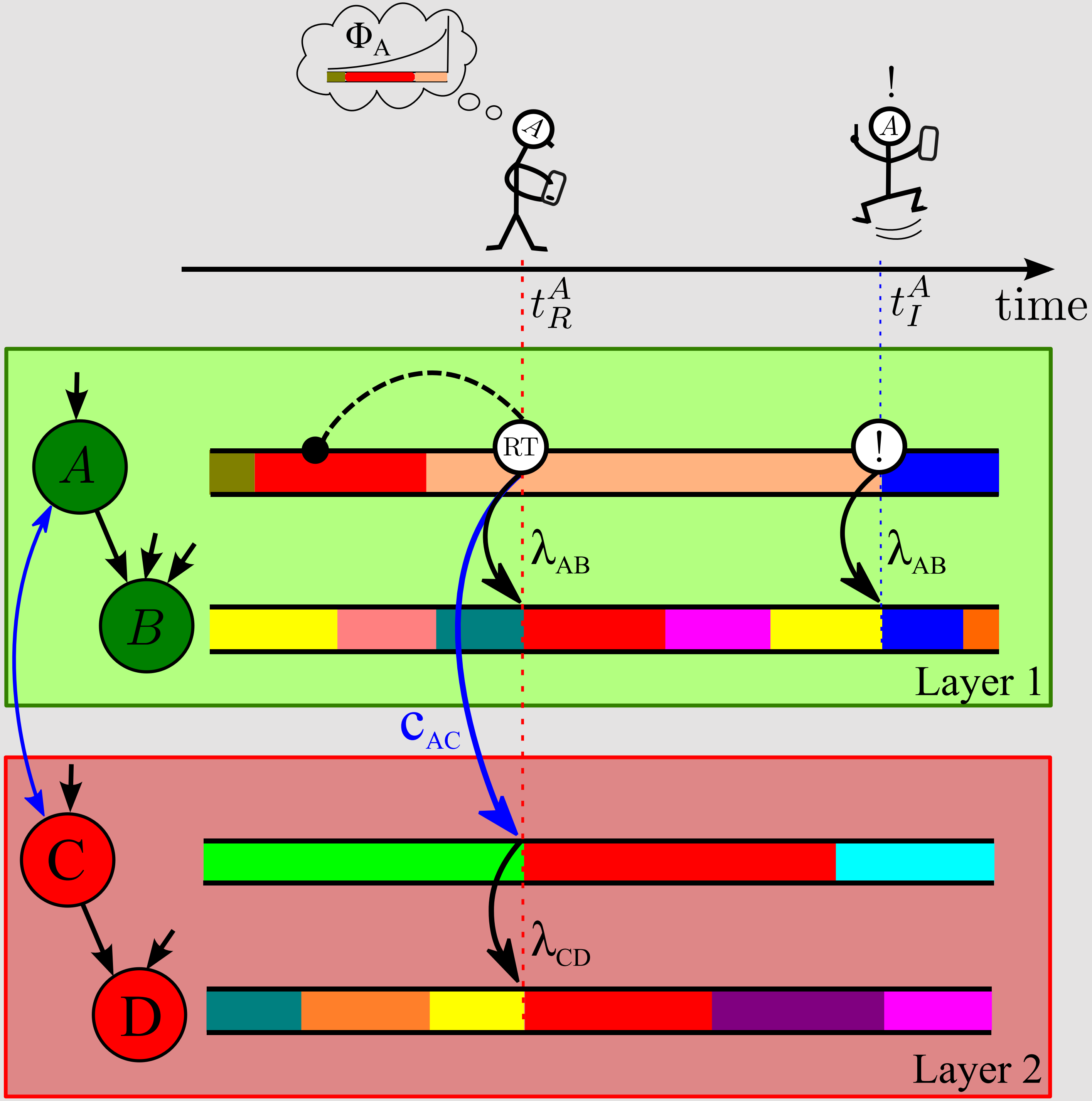

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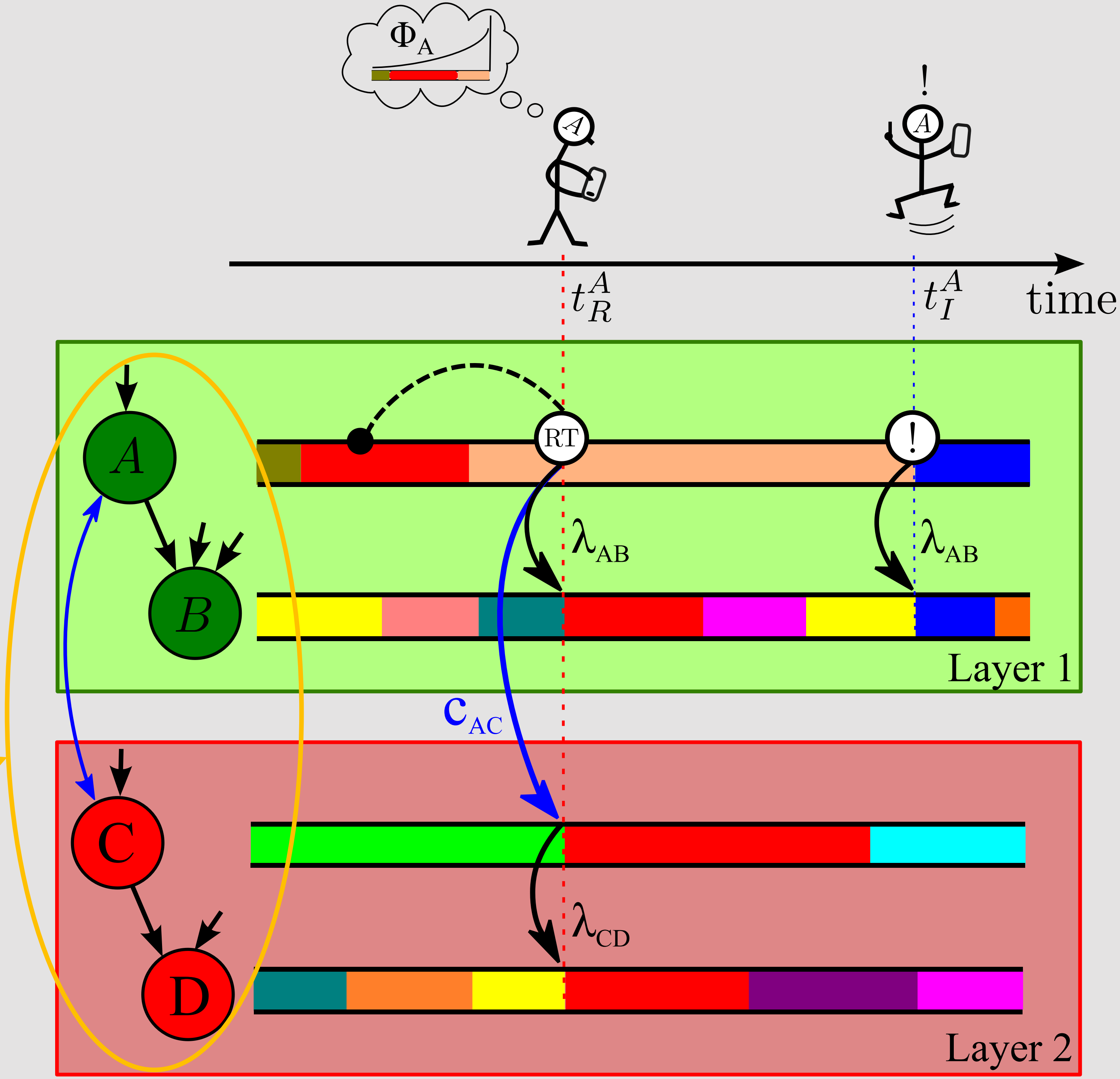

(Multilayer) network structure

Can either
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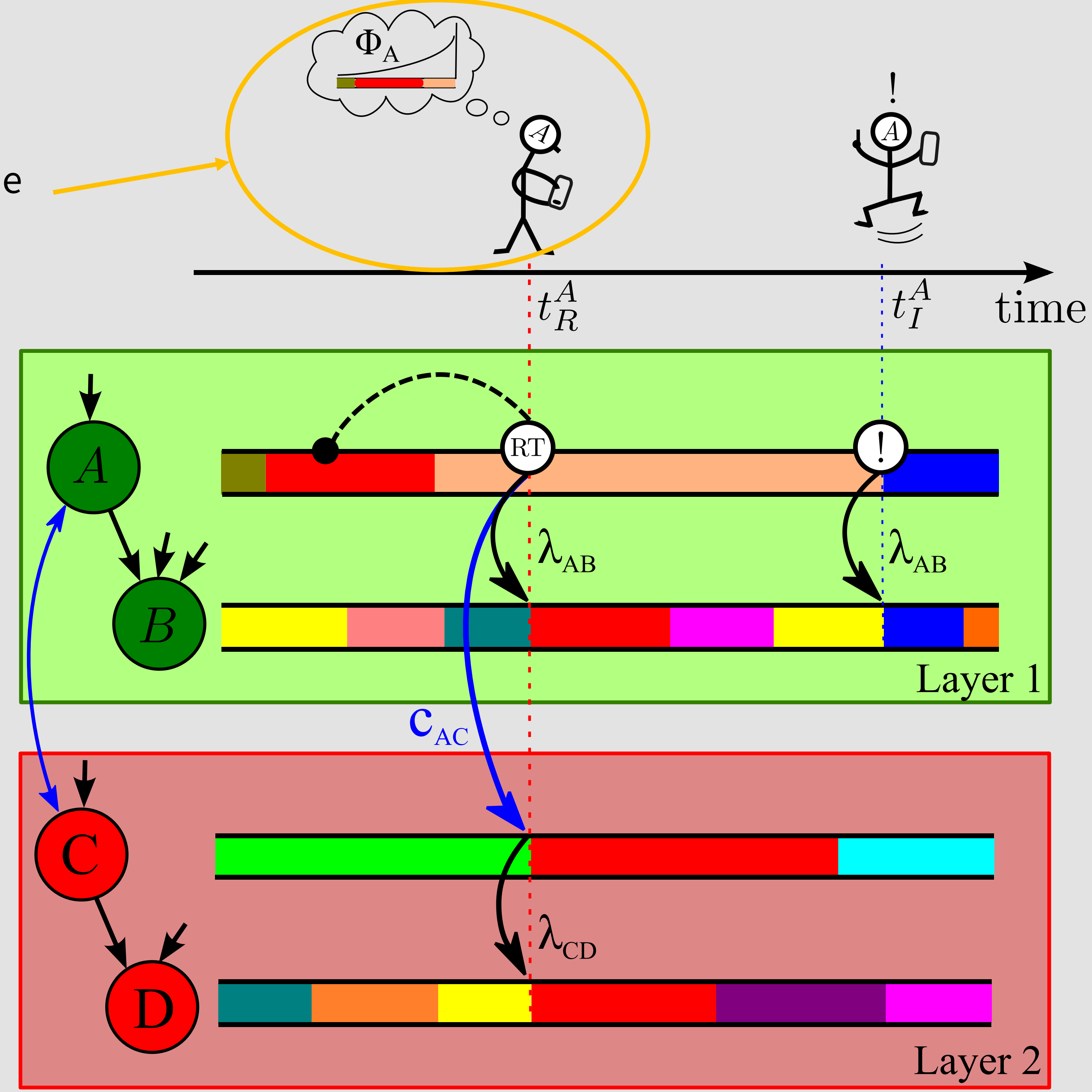
Innovate w.p. μ_A

Memory time distribution



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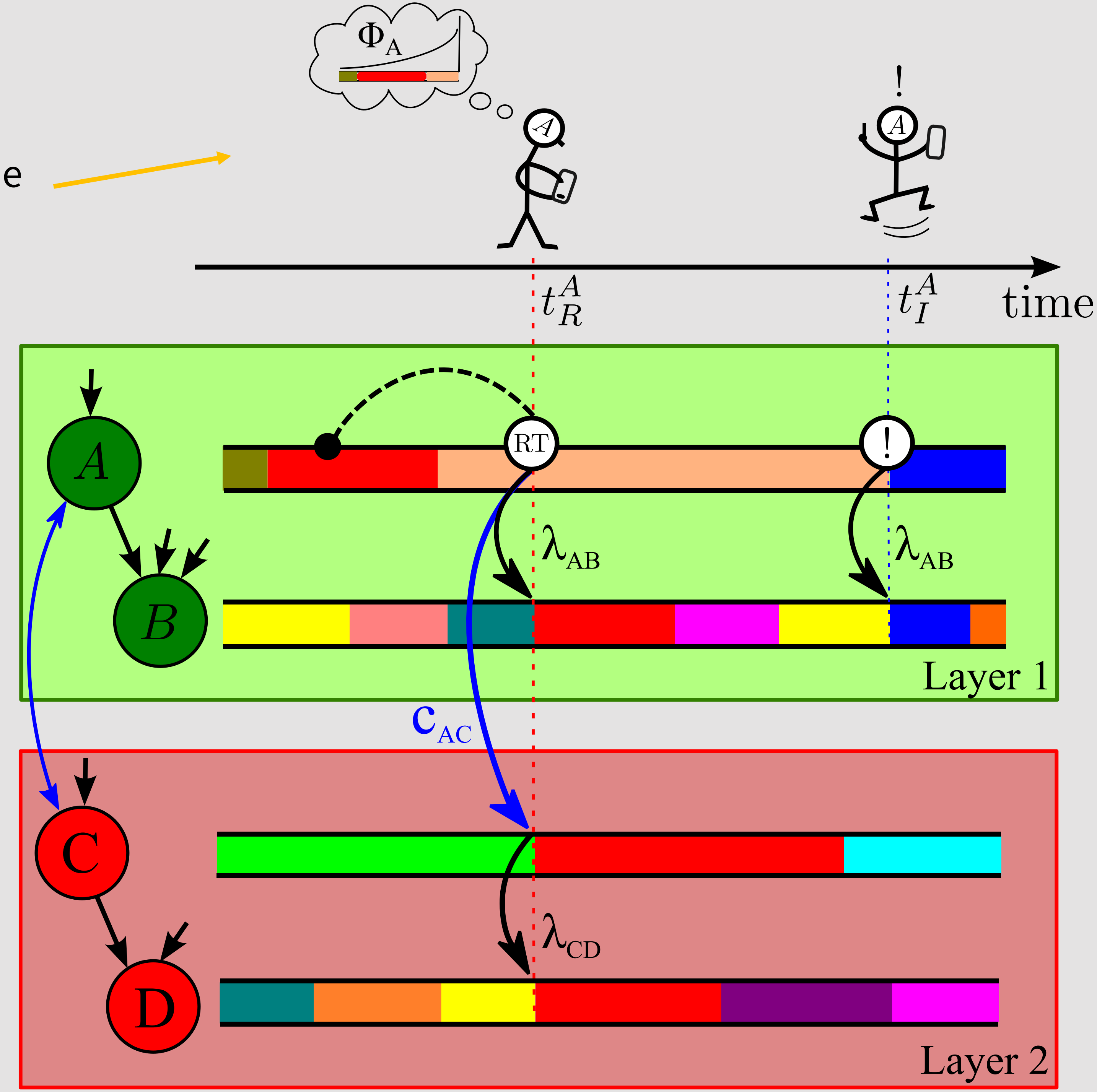
Innovation probability

Memory time distribution



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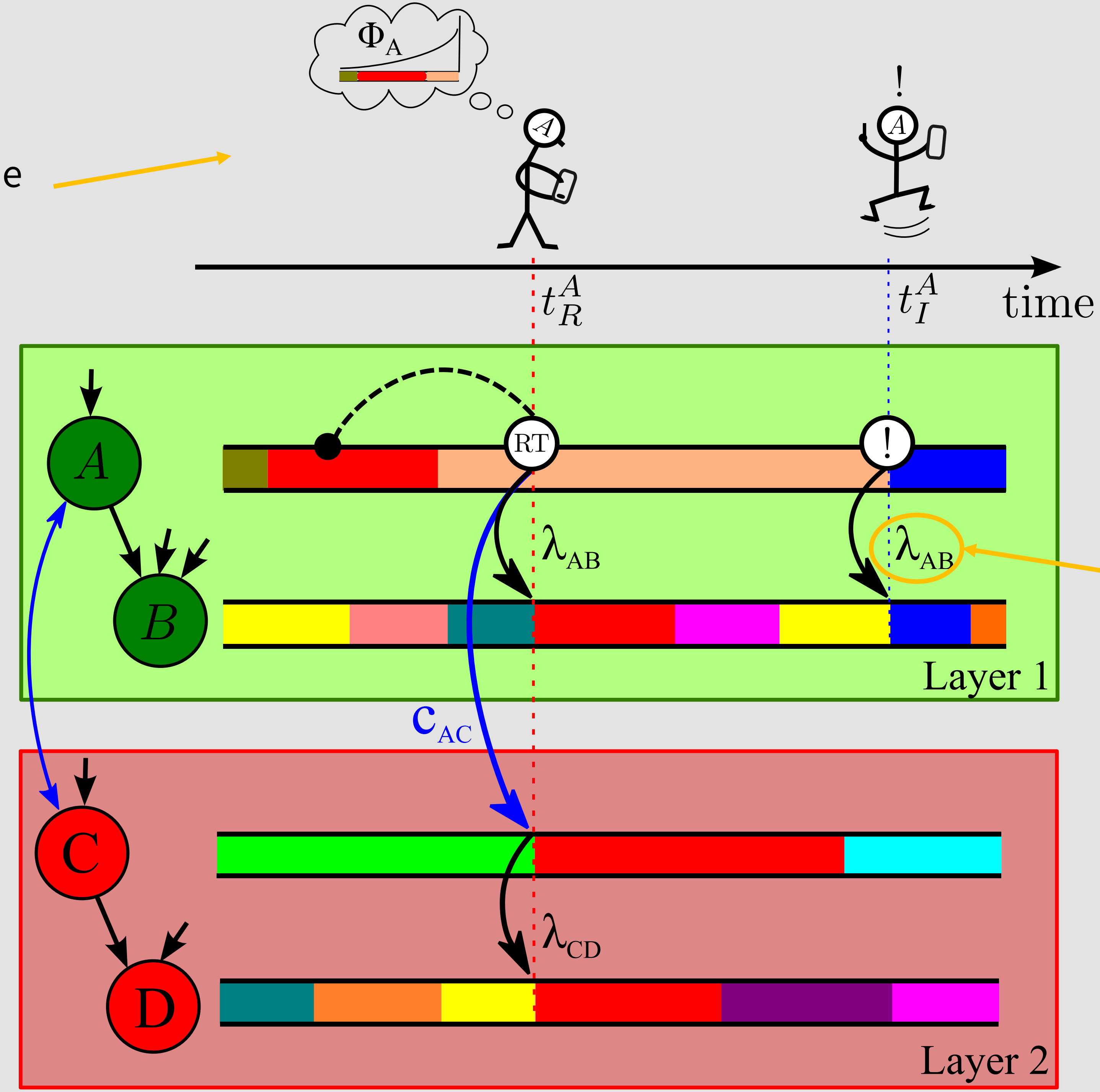
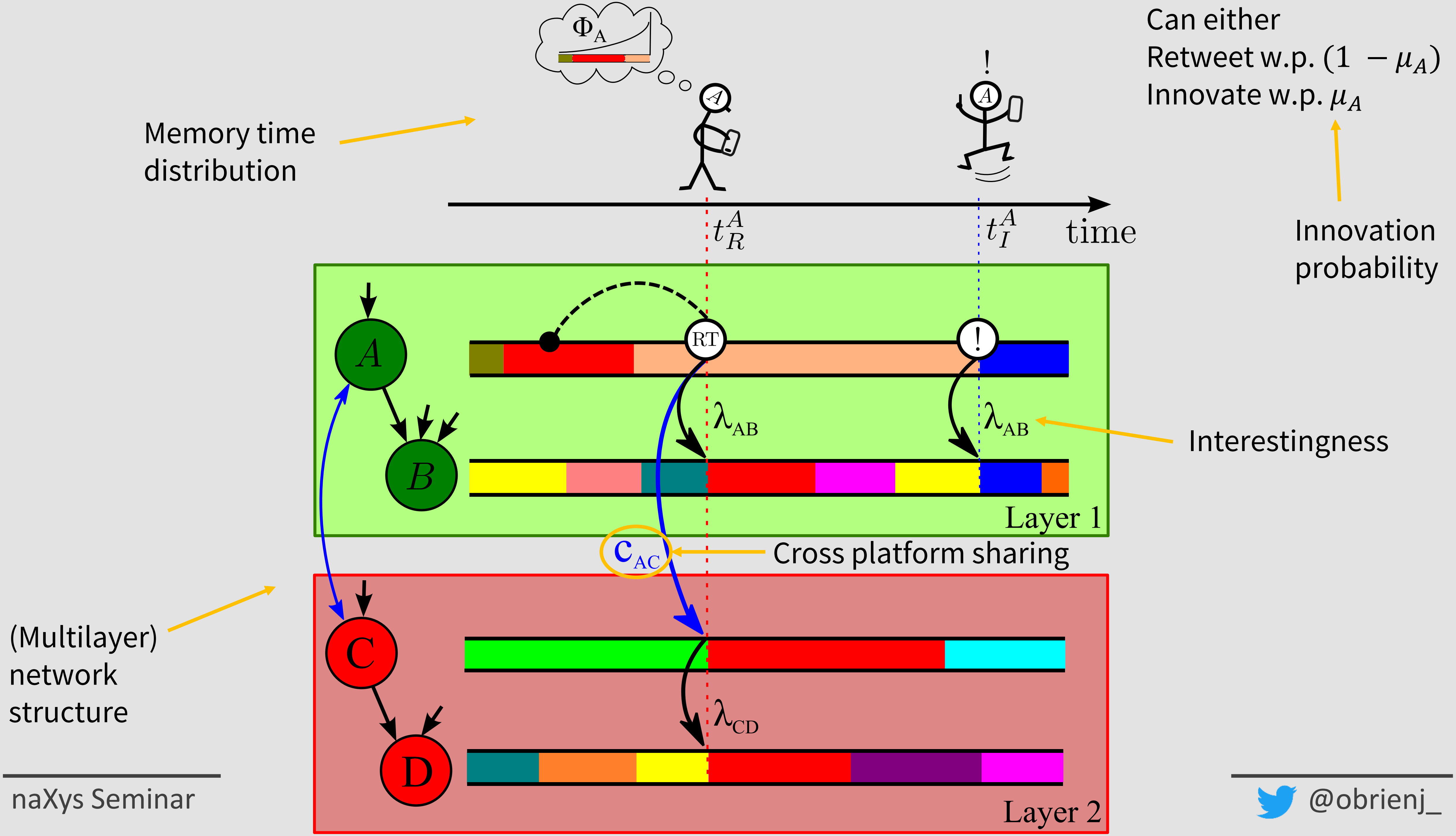


Innovation probability

Interestingness

(Multilayer) network structure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Innovate w.p. μ_A
Memory time distribution
Φ_A
!
t_R^A
t_I^A
time
Innovation probability
RT
!
A
B
λ_{AB}
λ_{AB}
Interestingness
Layer 1
c_{AC}
Cross platform sharing
C
D
λ_{CD}
(Multilayer) network structure
Layer 2

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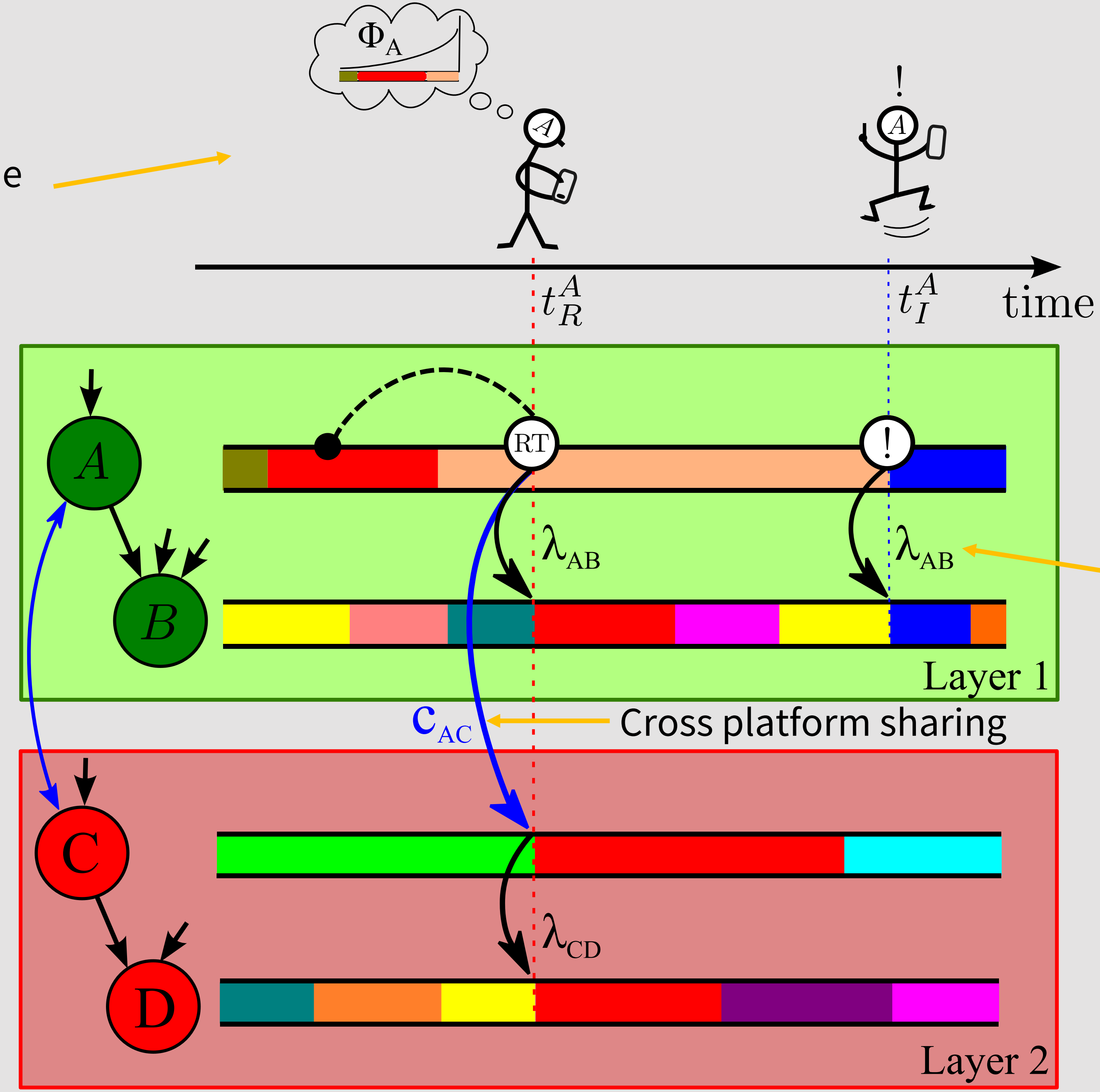
Memory time distribution

Innovation probability



Interestingness

(Multilayer) network structure

User specific

Maths behind the memes

Each edge, so either between ‘friends’ or the user’s other accounts will have its own probability generating function which determines meme popularity

$$G_{ij}(a;x) = \int_0^\infty r_i \exp\left(-r_i \ell\right) \exp\left\{ -(1-\mu_i)\beta_i \int_0^{\min(\ell,a)} \mathrm{d}\tilde{r} \int_0^{a-\tilde{r}} \Phi_i(a-\tilde{r}-\tilde{t}) \left[1 - R_{ij}(\tilde{t};x)\right] \mathrm{d}\tilde{t} \right\} \mathrm{d}\ell.$$

network structure

Innovation probability

Activity rates

Memory time distribution

Interestingness

Cross platform sharing

$$R_{ij}(a;x) = x\left(1-\lambda_{ij}+\lambda_{ij}\prod_k G_{jk}(a;x)\right)\left\{1-c_{ij}+c_{ij}\left[\prod_l \left(1-\lambda_{jl}+\lambda_{jl}\prod_m G_{lm}(a;x)\right)\right]\right\}.$$

Difficult to work with, but can do some analysis…

Criticality of the system?

The so-called 'Mean Matrix'

$$m_{ij} \sim \frac{(c_{ij} + \lambda_{ij})(1 - \mu_i)\beta_i}{\mu_i\beta_i + \sum_k \lambda_{ki}\beta_k + \sum_k c_{ki}\beta_k + \sum_k \left[\lambda_{ki}\left(\sum_l c_{lk}\beta_l\right)\right]}$$

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Criticality of the system is determined by the largest eigenvalue of this matrix

$$\begin{aligned} \rho < 1 &\implies \text{Subcritical} \\ \rho = 1 &\implies \text{Critical} \\ \rho > 1 &\implies \text{Supercritical} \end{aligned}$$

Criticality of the system?

Monoplex with $\mu_i = 0$

In this case the mean matrix simply has elements given by

$$m_{ij} = \frac{\lambda_{ij}\beta_i}{\sum_k \lambda_{ki}\beta_k}$$

We can show that the largest eigenvalue in this case is exactly 1, a critical system, generalizing the result of Gleeson et al. (***PRX 2016***).

Criticality of the system?

Monoplex with $\mu_i \geq 0$

In this case the mean matrix changes slightly

$$m_{ij} = \frac{(1-\mu_i)\lambda_{ij}\beta_i}{\mu_i\beta_i + \sum_k \lambda_{ki}\beta_k}$$

Using perturbative arguments we can show that in this case the largest eigenvalue is less than 1, i.e., a subcritical system.

Criticality of the system?

Multiplex with $c_{ij}, \mu_i \geq 0$

We are now back in the case we showed originally

$$m_{ij} \sim \frac{(c_{ij} + \lambda_{ij})(1-\mu_i)\beta_i}{\mu_i\beta_i + \sum_k \lambda_{ki}\beta_k + \sum_k c_{ki}\beta_k + \sum_k \left[\lambda_{ki}\left(\sum_l c_{lk}\beta_l\right)\right]}$$

In this case the analysis is difficult but some perturbative results may still be obtained, and in fact for small crossover probabilities we find that the change depends on the existence (or not) of a dominant layer…

Criticality of the system?

Multiplex with $c_{ij}, \mu_i \geq 0$

If a dominant layer exists, the criticality of the system is dependent purely on this dominant layer. $\rho_1 > \rho_2$

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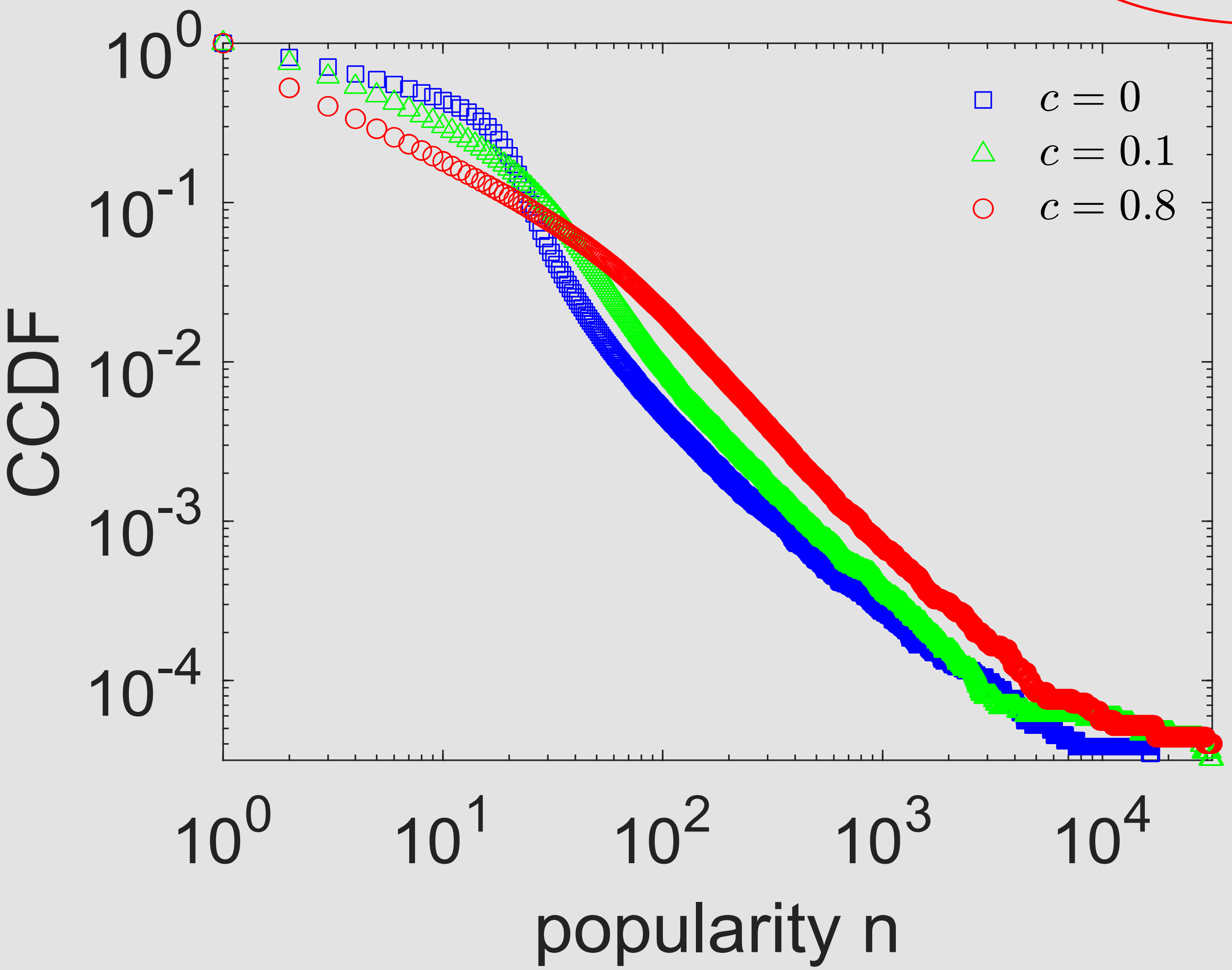
and as such we resort to numerical simulations.

Numerical Simulations

$\mu = 0.05$



$p_k = k^{-3.5} \,\&\, k^{-2.5}$

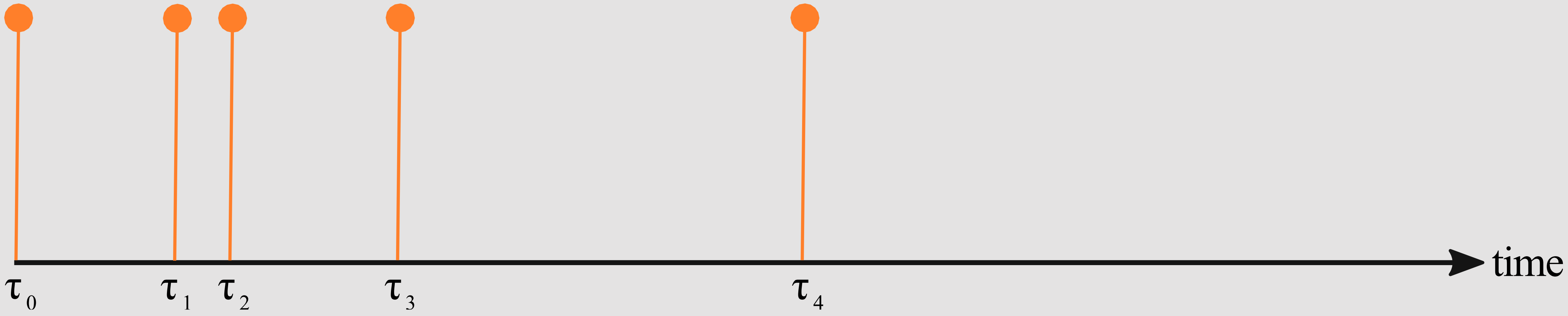
p_k		$k^{3.5}$	$k^{2.5}$
c	ρ	ρ_1	ρ_2
0	0.9368	0.9368	09217
10^{-4}	0.9317	0.9317	0.9270
10^{-3}	0.9306	0.9306	0.9189
10^{-1}	0.8470	0.8213	0.8108
0.8	0.6543	0.4543	0.4346

Largest eigenvalue of entire system, and also both layers, for various c values

Predicting Content Popularity and Self-exciting Processes

- J. Cheng, L. Adamic, P. A. Dow, J. M. Kleinberg, and J. Leskovec. Can cascades be predicted? ***Proc. WWW23***, 925–936. ACM, 2014.
- J. M. Miotto and E. G. Altmann. Predictability of extreme events in social media. ***PLoS One***, 9(11):e111506, 2014.
- L. Weng, F. Menczer, and Y. Ahn. Virality prediction and community structure in social networks. ***Scientific Reports***, 3:2522, 2013.
- R. Bandari, S. Asur, and B. A. Huberman. The pulse of news in social media: Forecasting popularity. ***Proc. AAAI CWSM6***, 2012.
- …
- S. Mishra, M. A. Rizoiu, and L. Xie. Feature driven and point process approaches for popularity prediction. ***Proc. ACM IIKM***, 1069–1078. ACM, 2016.
- Q. Zhao, M. A. Erdogdu, H. Y. He, A. Rajaraman, and J. Leskovec. SEISMIC: A self-exciting point process model for predicting tweet popularity. ***Proc. ACM SIGKDD***, 1513–1522. ACM, 2015.
- R. Kobayashi and R. Lambiotte. TiDeH: Time-dependent Hawkes process for predicting retweet dynamics. ***Proc. AAAI CWSM10***, 2016.
- M. A. Rizoiu, L. Xie, S. Sanner, M. Cebrian, H. Yu, and P. Van Hentenryck. Expecting to be HIP: Hawkes intensity processes for social media popularity. ***Proc. WWW26***, 735–744. ACM, 2017.
- …
- Work generally based on **intensive numerical computation** rather than **mathematically tractable models**.

What is a Hawkes Process?



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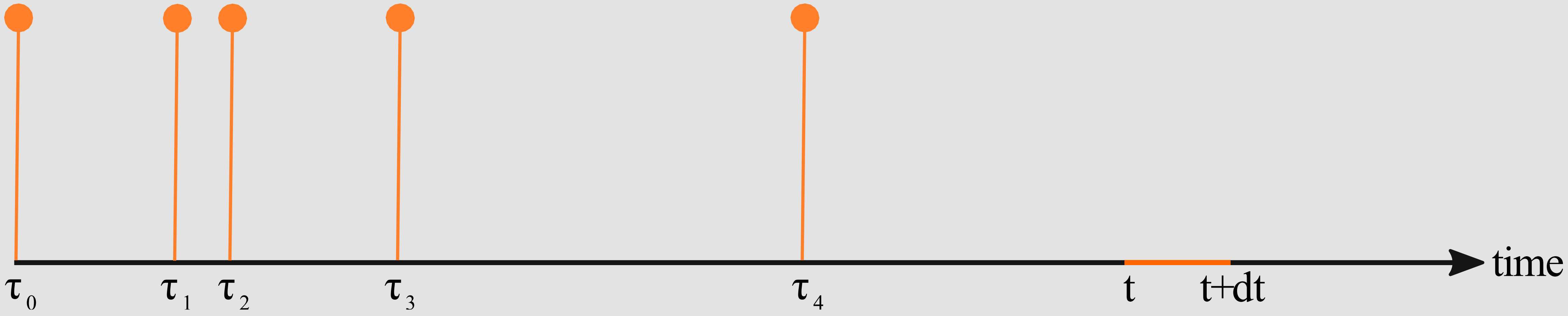
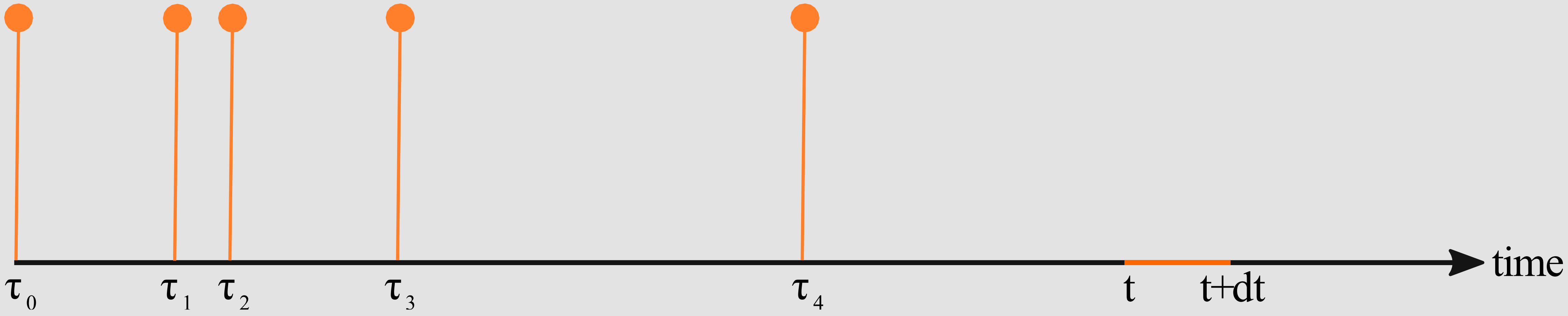


What is a Hawkes Process?

Process	Expected no. of events
Poisson process	$\lambda\ dt$
Inhomogeneous Poisson process	$\lambda(t)\ dt$
Hawkes process	$[\mu(t) + \Sigma_i\ \xi\ \phi\ (t\ -\ \tau_i)]\ dt$



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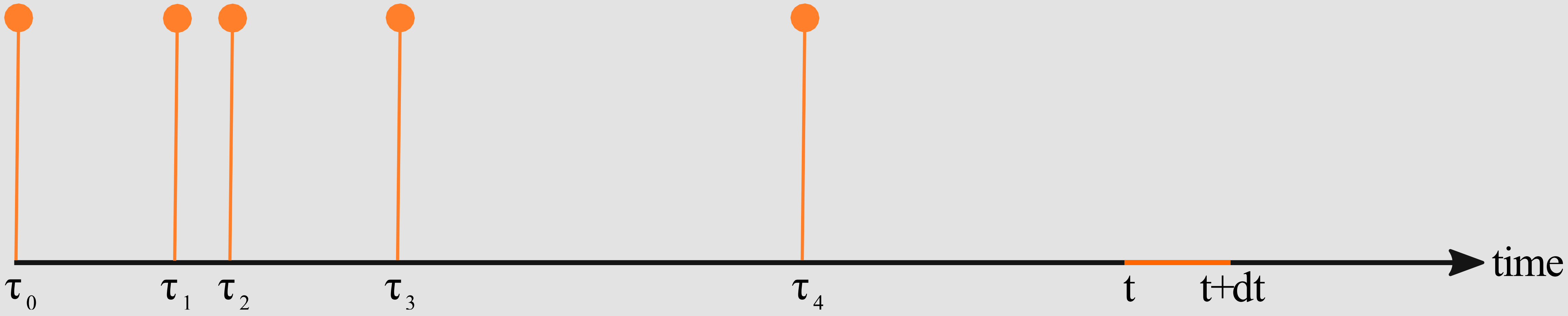

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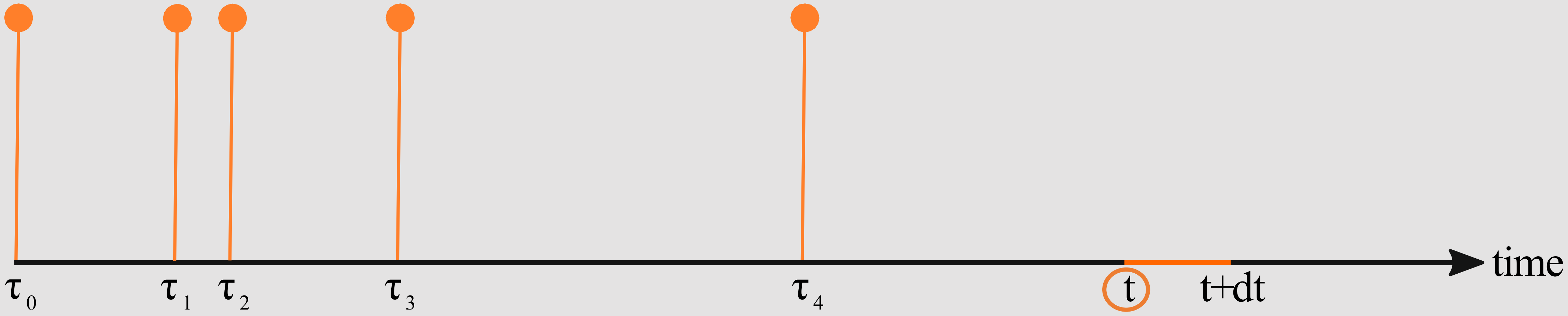

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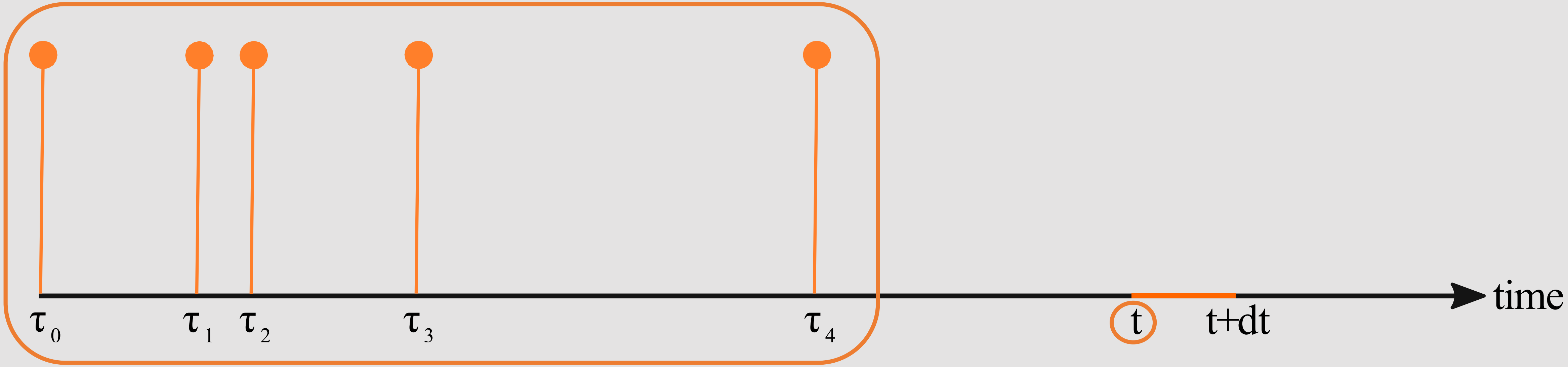
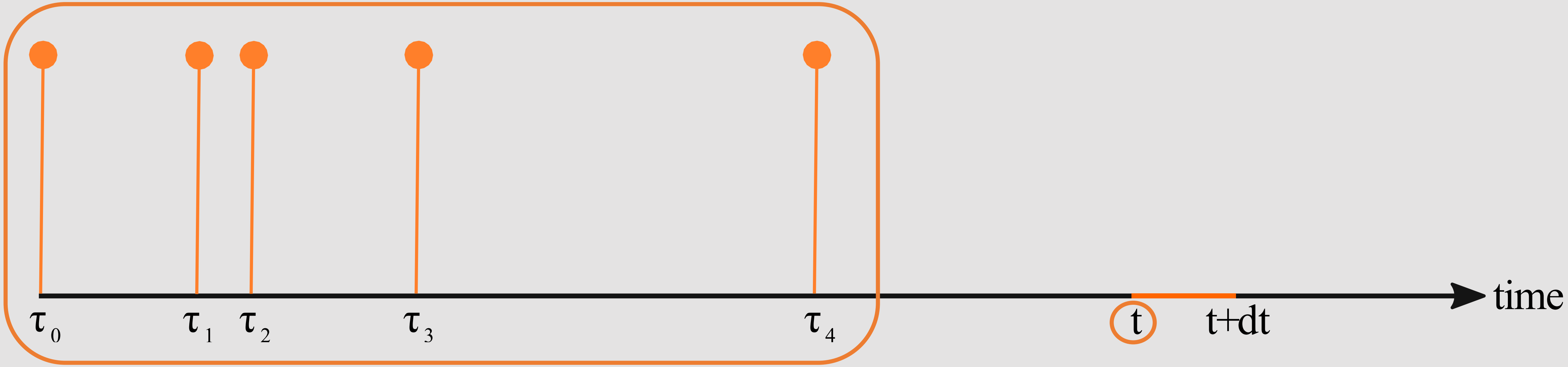
Process	Expected no. of events
Poisson process	$\lambda \ dt$
Inhomogeneous Poisson process	$\lambda(t)\ dt$
Hawkes process	$[\mu(t) + \Sigma_i \ \xi \ \phi \ (t \ - \ \tau_i)]\ dt$



What is a Hawkes Process?

Fitness Memory kernel

$$\lambda(t) = \underbrace{\mu(t)}_{\text{Background intensity}} + \underbrace{\sum_{\tau_i < t} \xi \, \phi(t - \tau_i)}_{\text{Excitation Function}}$$



Example Kernels

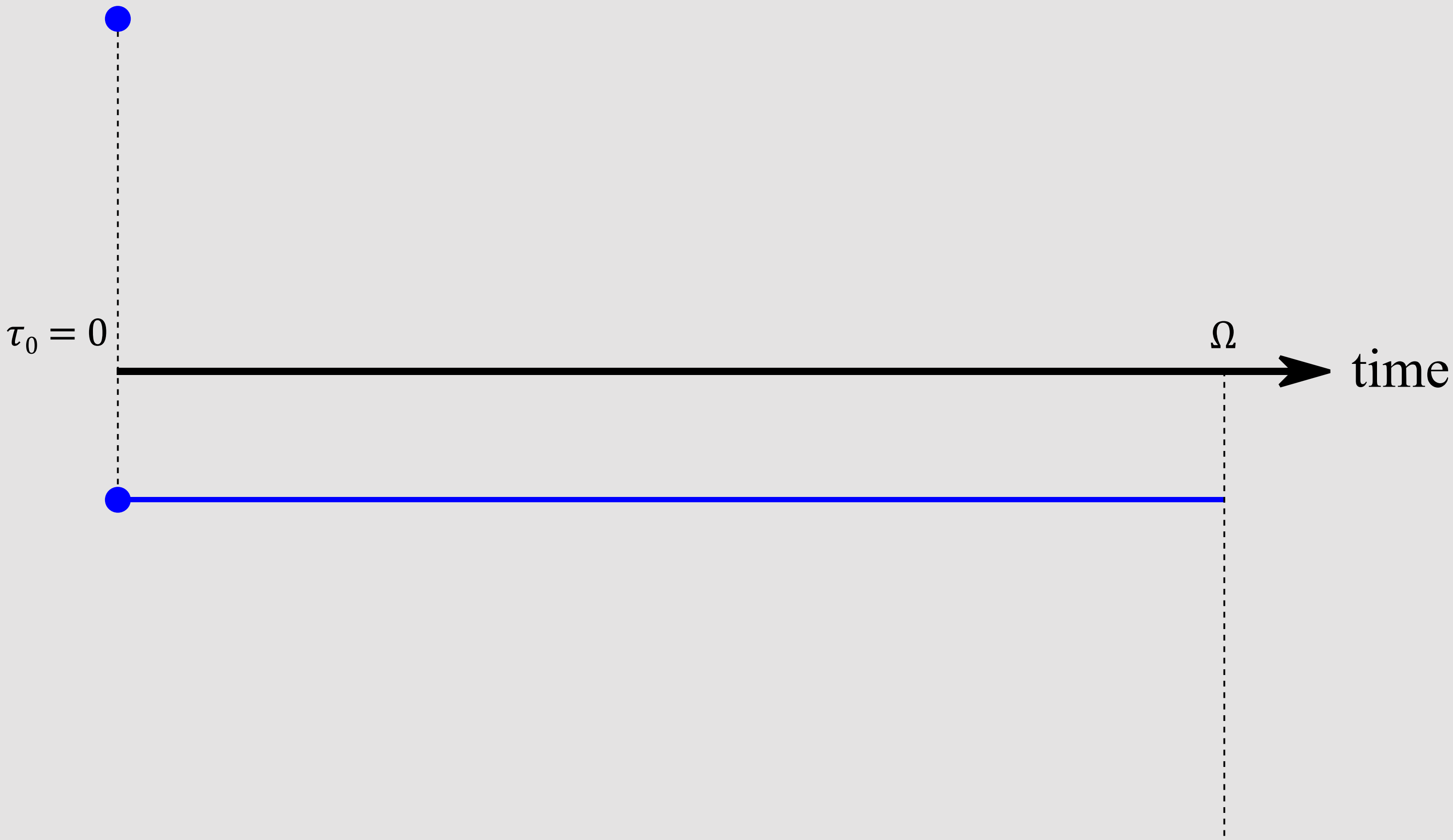
The most well known kernel is constant background intensity with exponential memory, particularly in finance.

$$\lambda(t) = \lambda_0 + \xi \sum_{\tau_i < t} \beta e^{-\beta(t-\tau_i)},$$

another commonly used kernel is that of the shifted power-law generally used in seismology.

$$\lambda(t) = \lambda_0 + \xi \sum_{\tau_i < t} \beta\, c^{\beta}\, (t - \tau_i + c)^{-(1+\beta)}.$$

Branching Process Description



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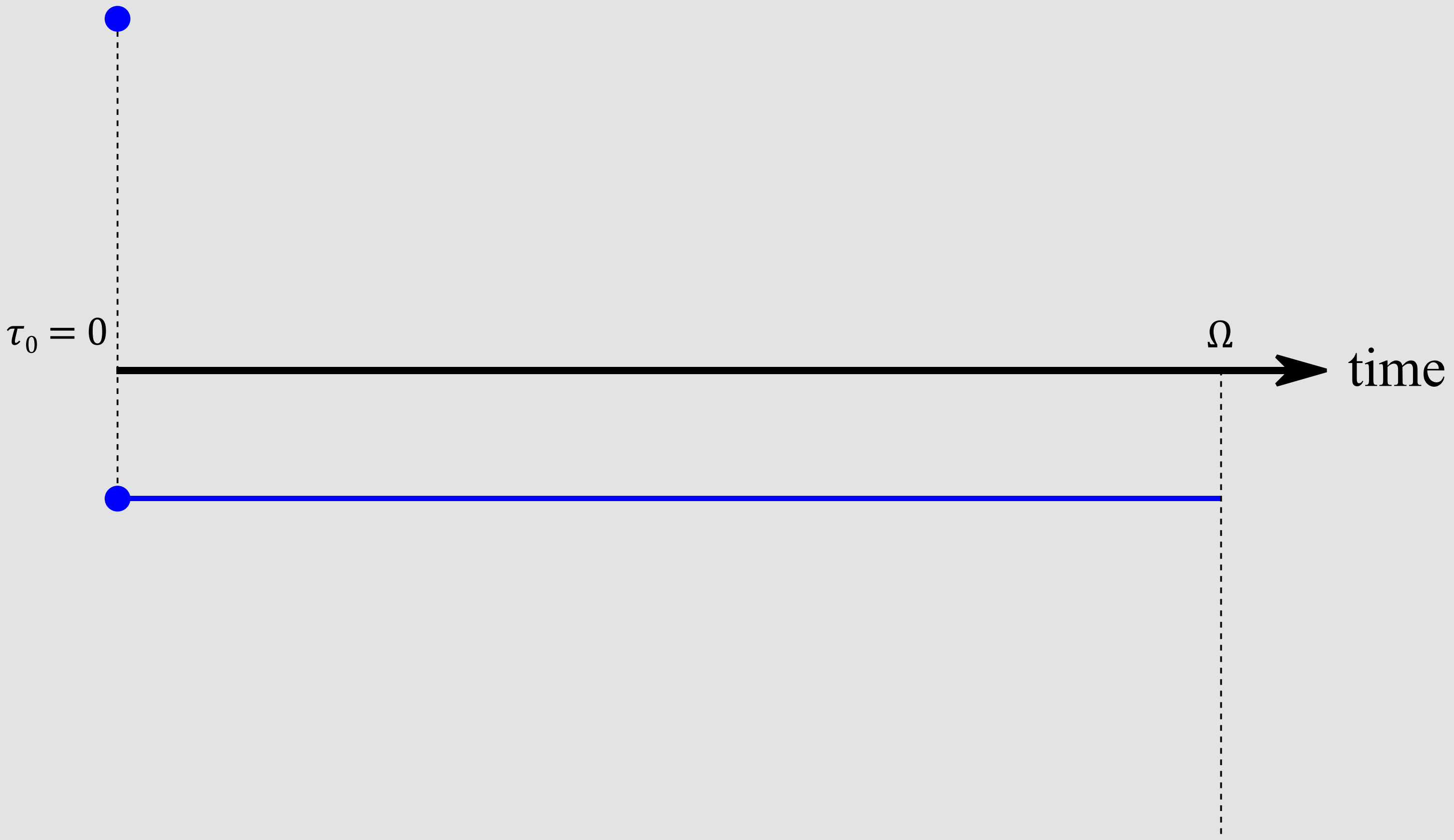
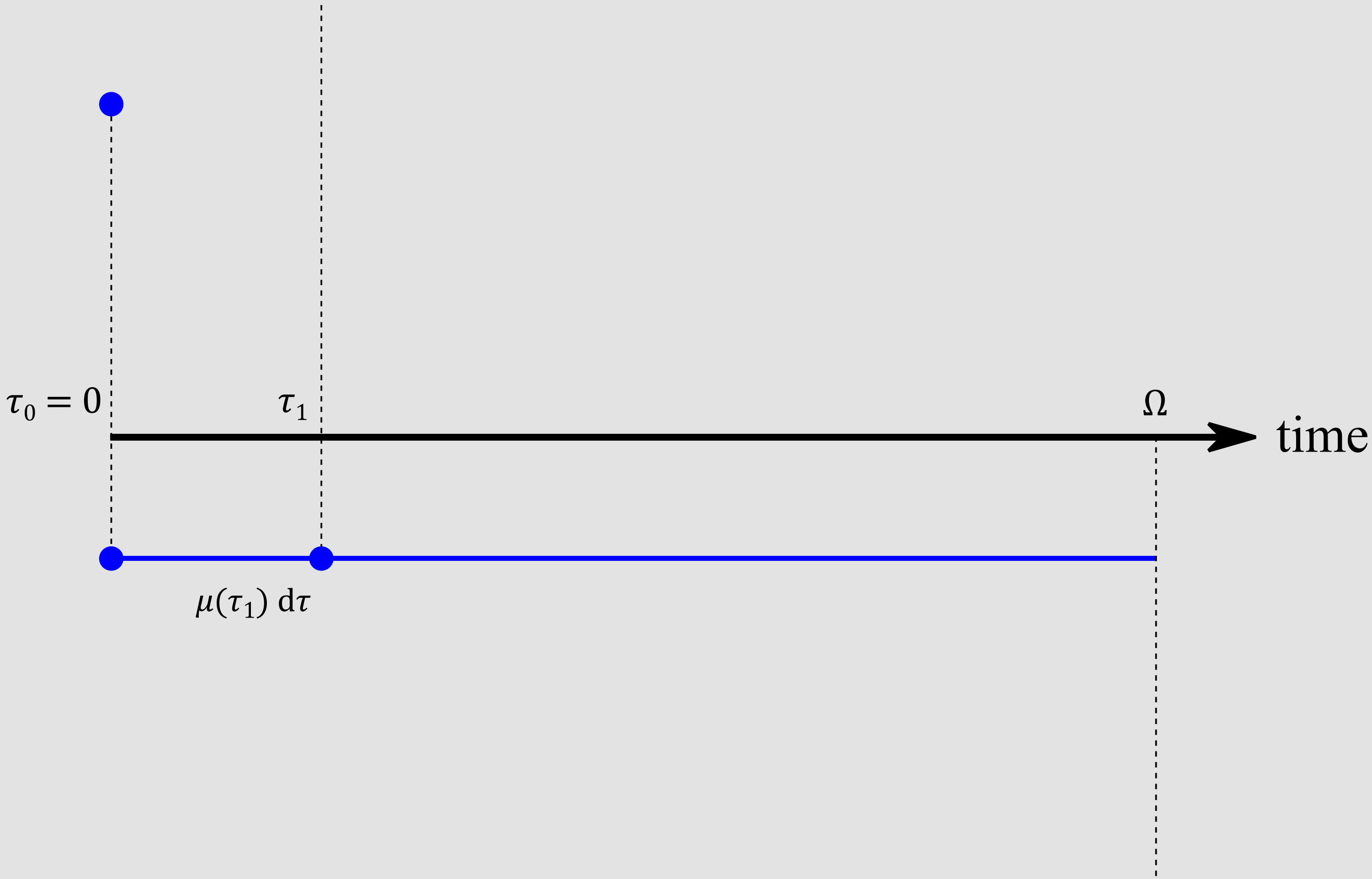


In each time interval $(\mathrm{t}, \mathrm{t} + dt)$ someone may

- Reply to the original post w.p. $\mu(t)\ dt$

Branching Process Description



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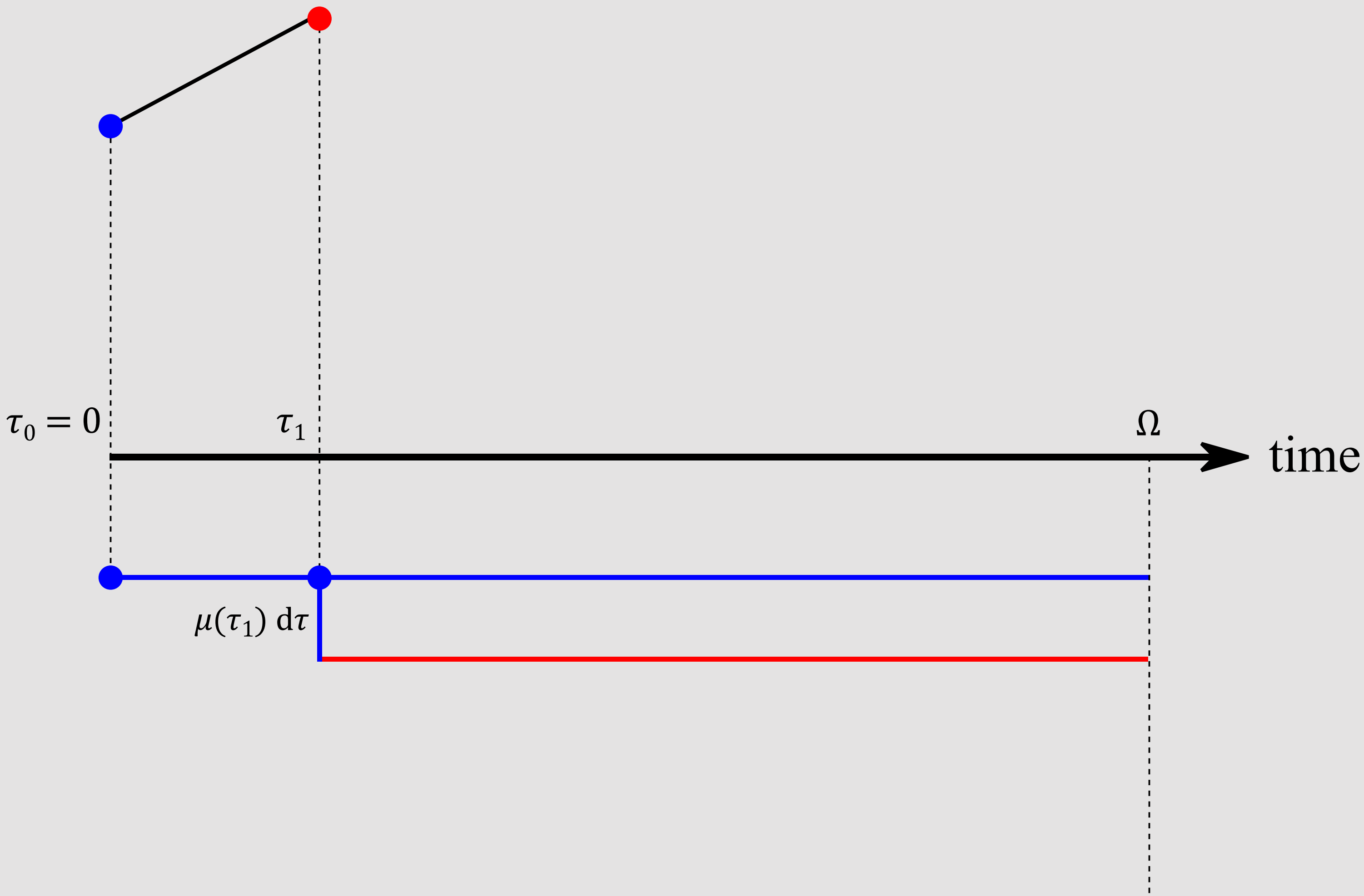

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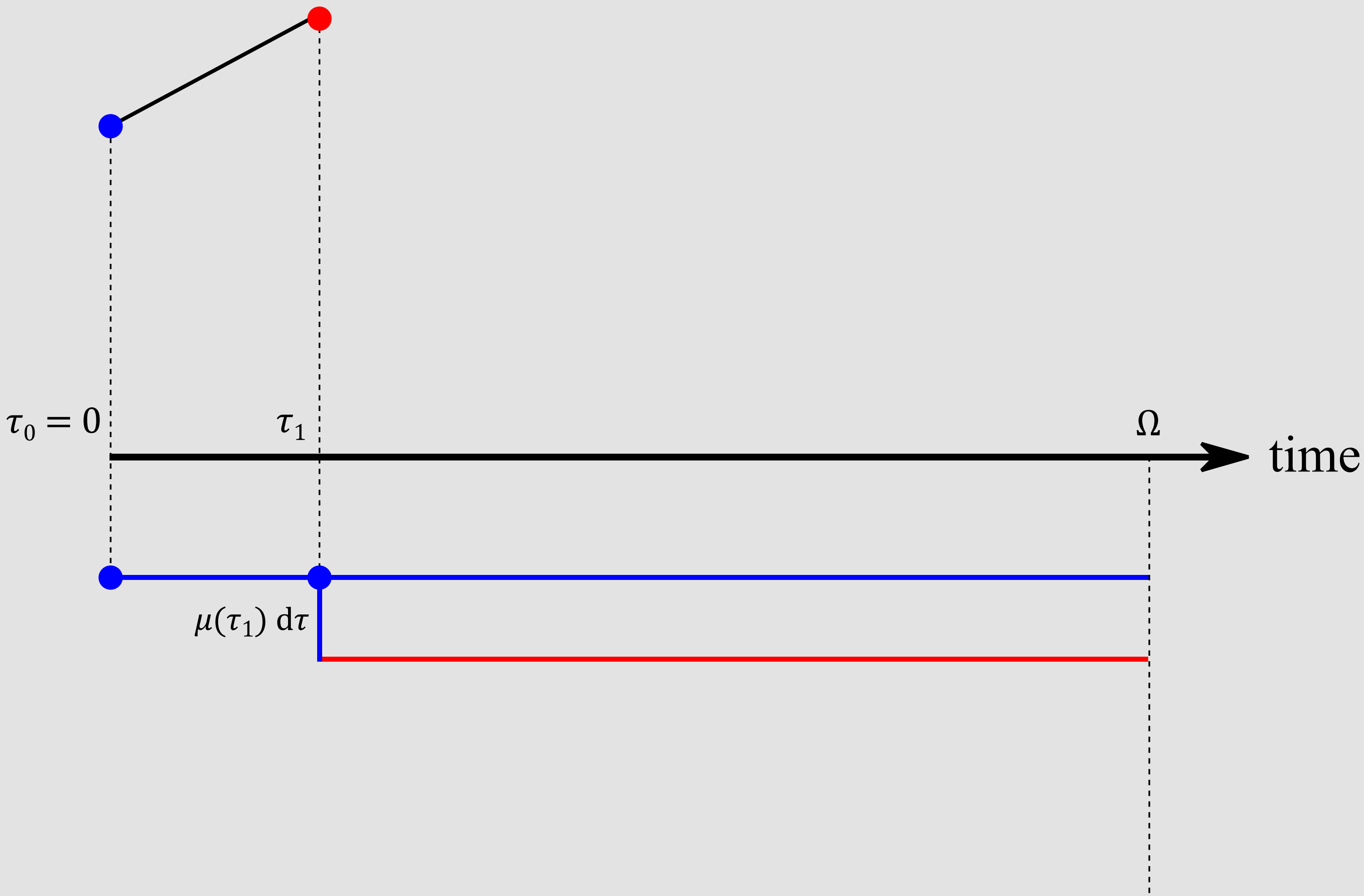
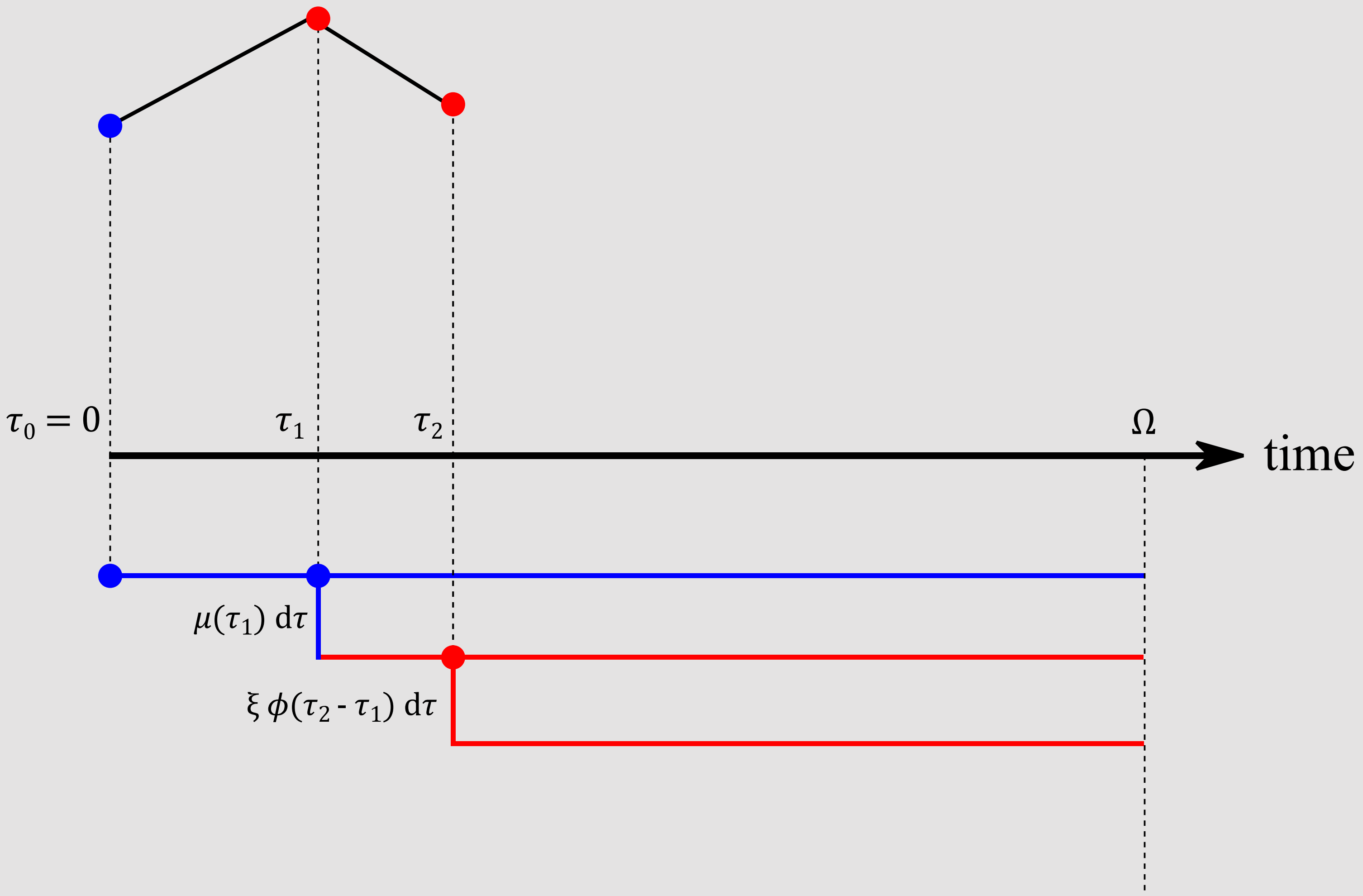


In each time interval $(\mathrm{t}, \mathrm{t} + dt)$ someone may

- Reply to the original post w.p. $\mu(t)\ dt$
- Reply to a reply made at time τ_i w.p. $\xi\ \phi(t\ -\ \tau_i)\ dt$

Branching Process Description



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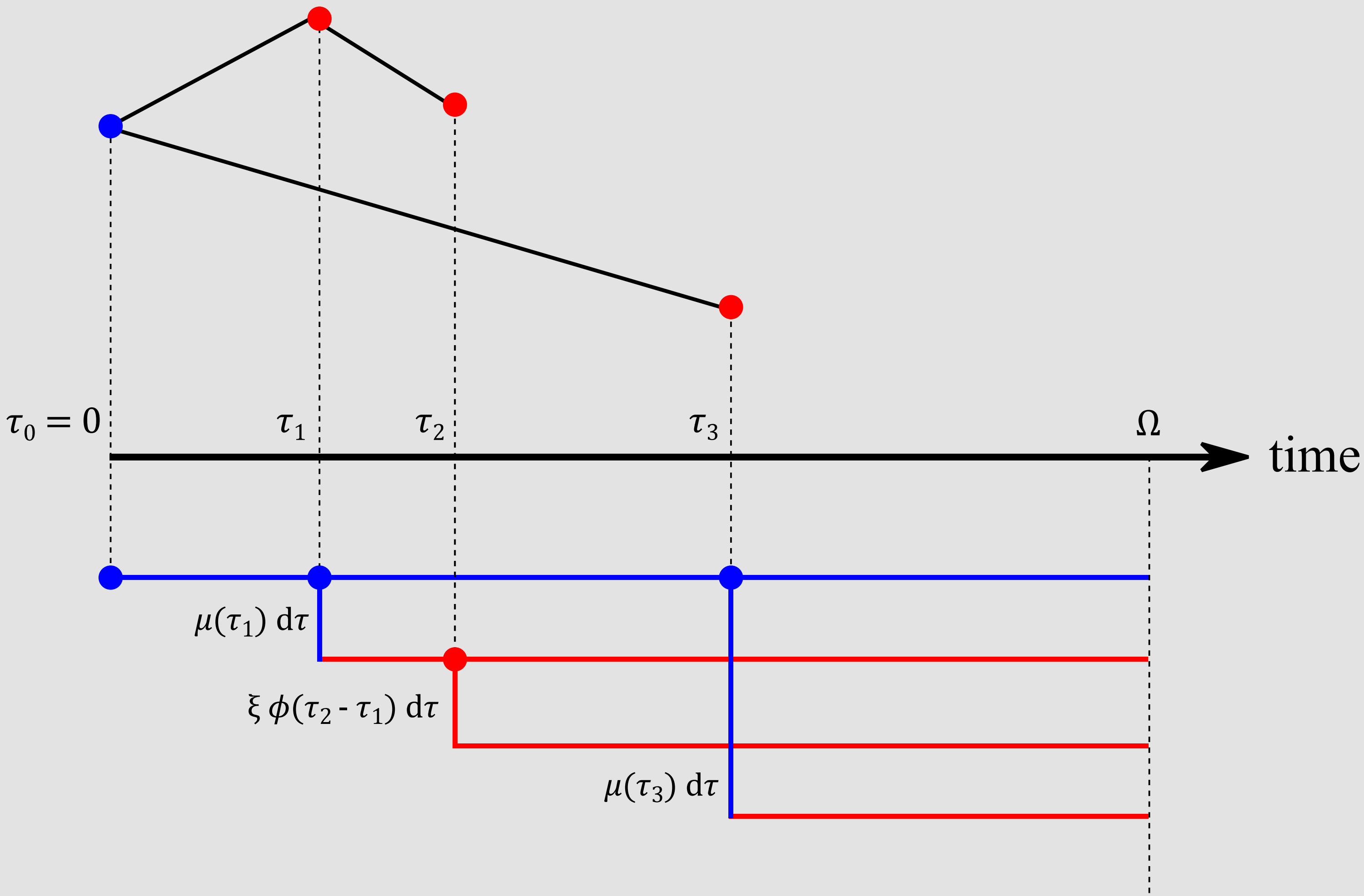

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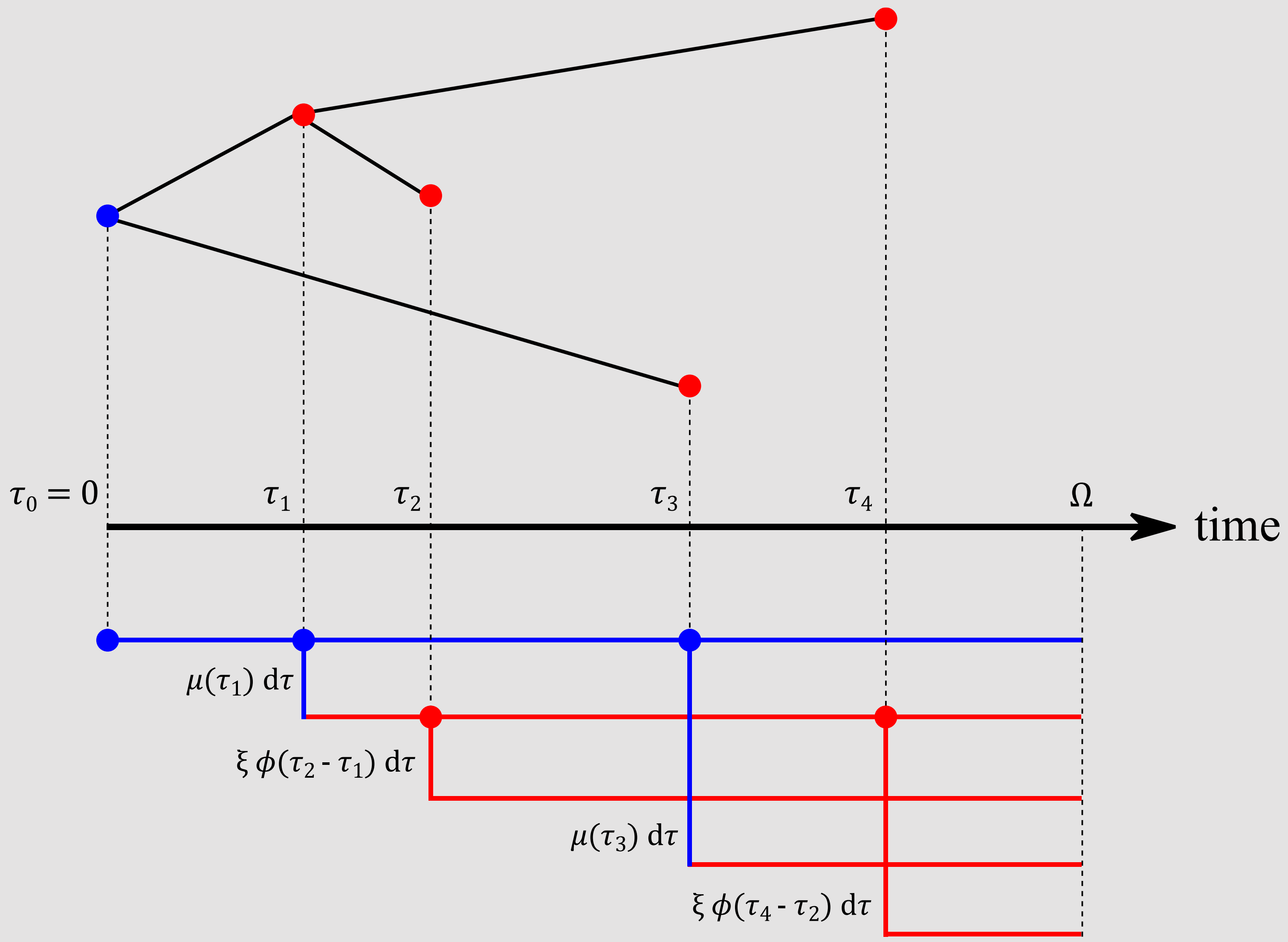

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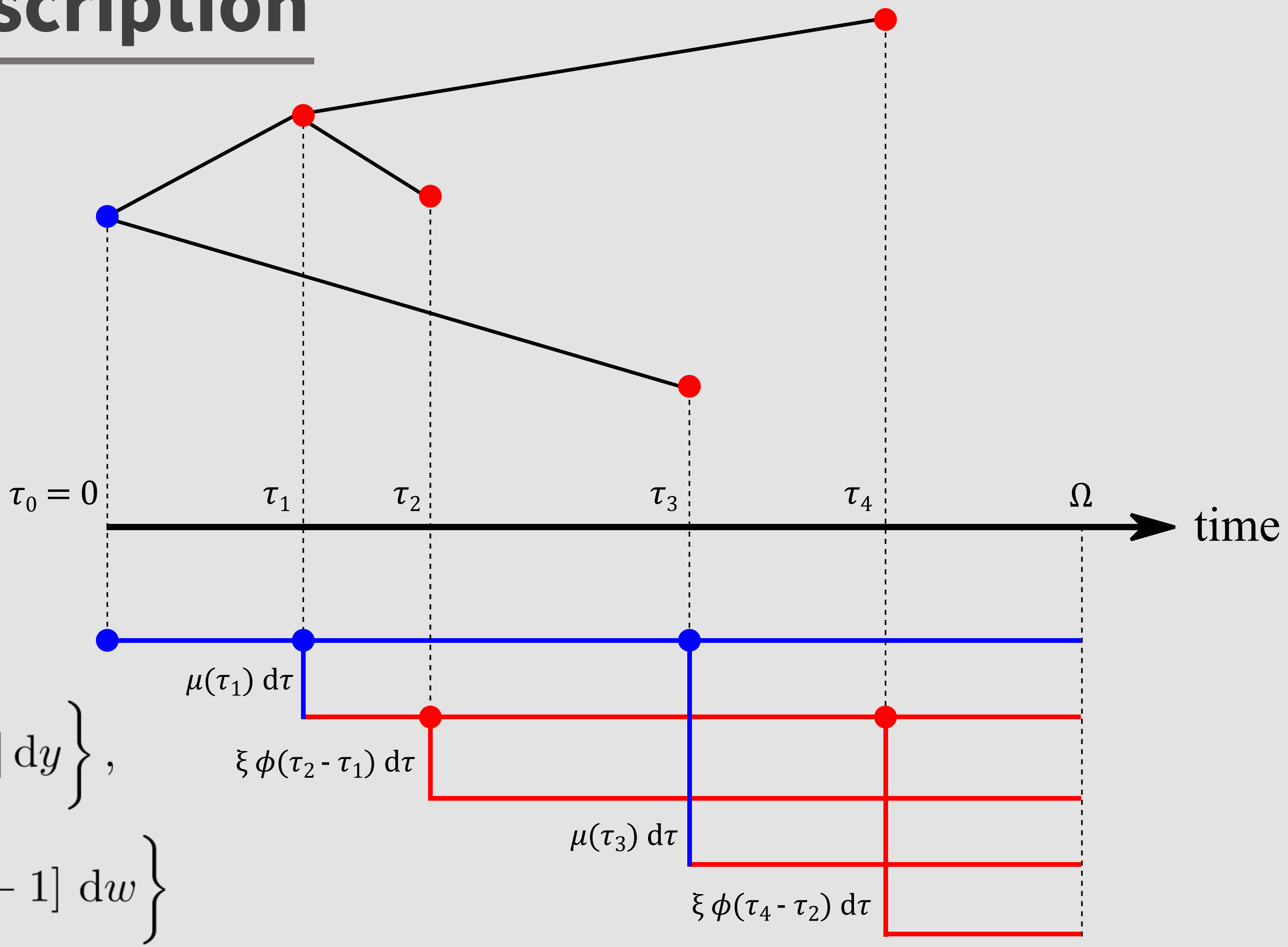
Branching Process Description

The main quantity of interest is the probability of having m replies when the thread has age t – $q_m(t)$

$$\boxed{H(t;x) = \sum_{m=0}^{\infty} q_m(t)\, x^m}$$

$$H(t;x) = x \exp\left\{\int_0^t \mu(y)[G(t-y;x)-1]\,\mathrm{d}y\right\},$$

$$G(t;x) = x\ \exp\left\{\xi \int_0^t \phi(w)\,[G(t-w;x)-1]\ \mathrm{d}w\right\}$$



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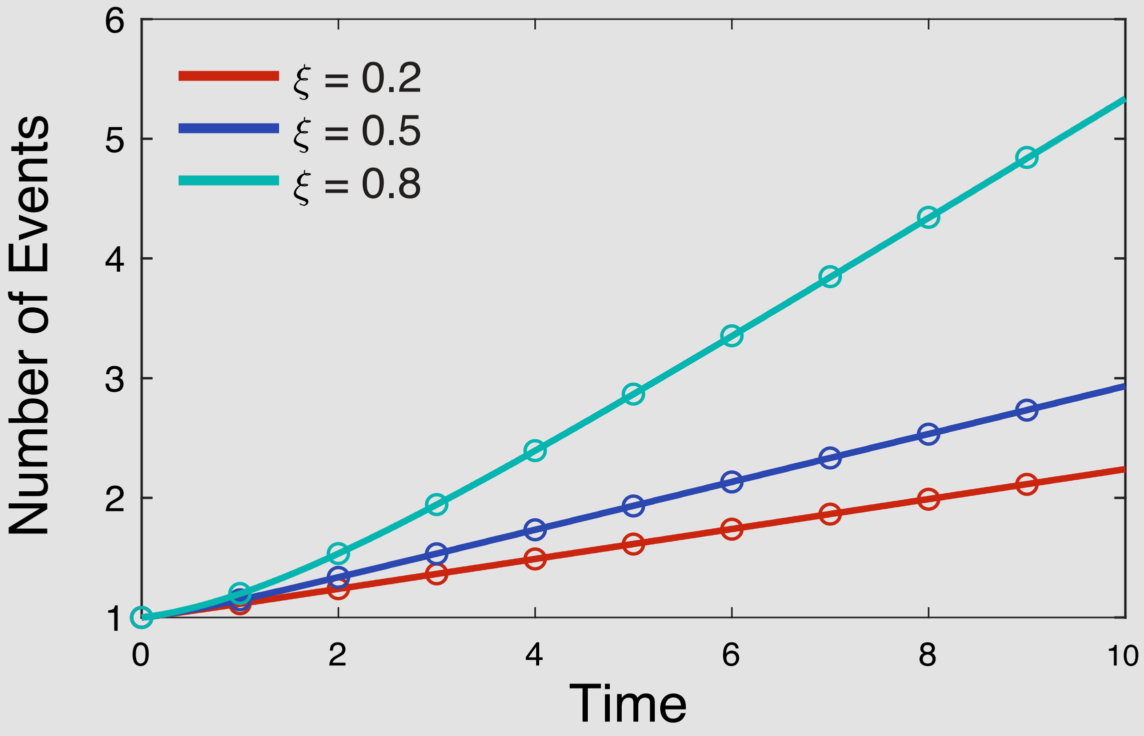


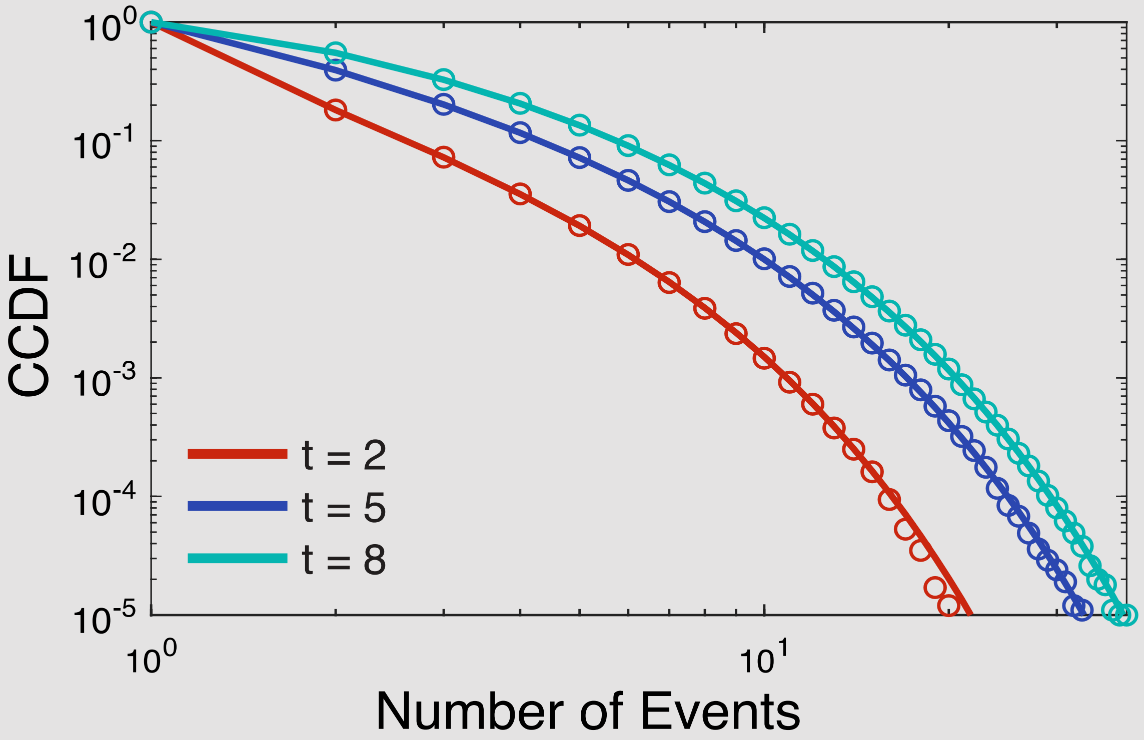
Calculate the expected number of events in Laplace space through

$$\hat{m}(s) = \frac{1}{s} + \frac{\hat{\mu}(s)}{s\left[1 - \xi\,\hat{\phi}(s)\right]},$$

which may be analytically analysed in some scenarios e.g., exponential case

$$m(t) = 1 + \frac{\lambda_0}{1-\xi}\left[t + \frac{\xi}{\beta(1-\xi)}\left(e^{-\beta(1-\xi)t} - 1\right)\right].$$

Branching Process Description

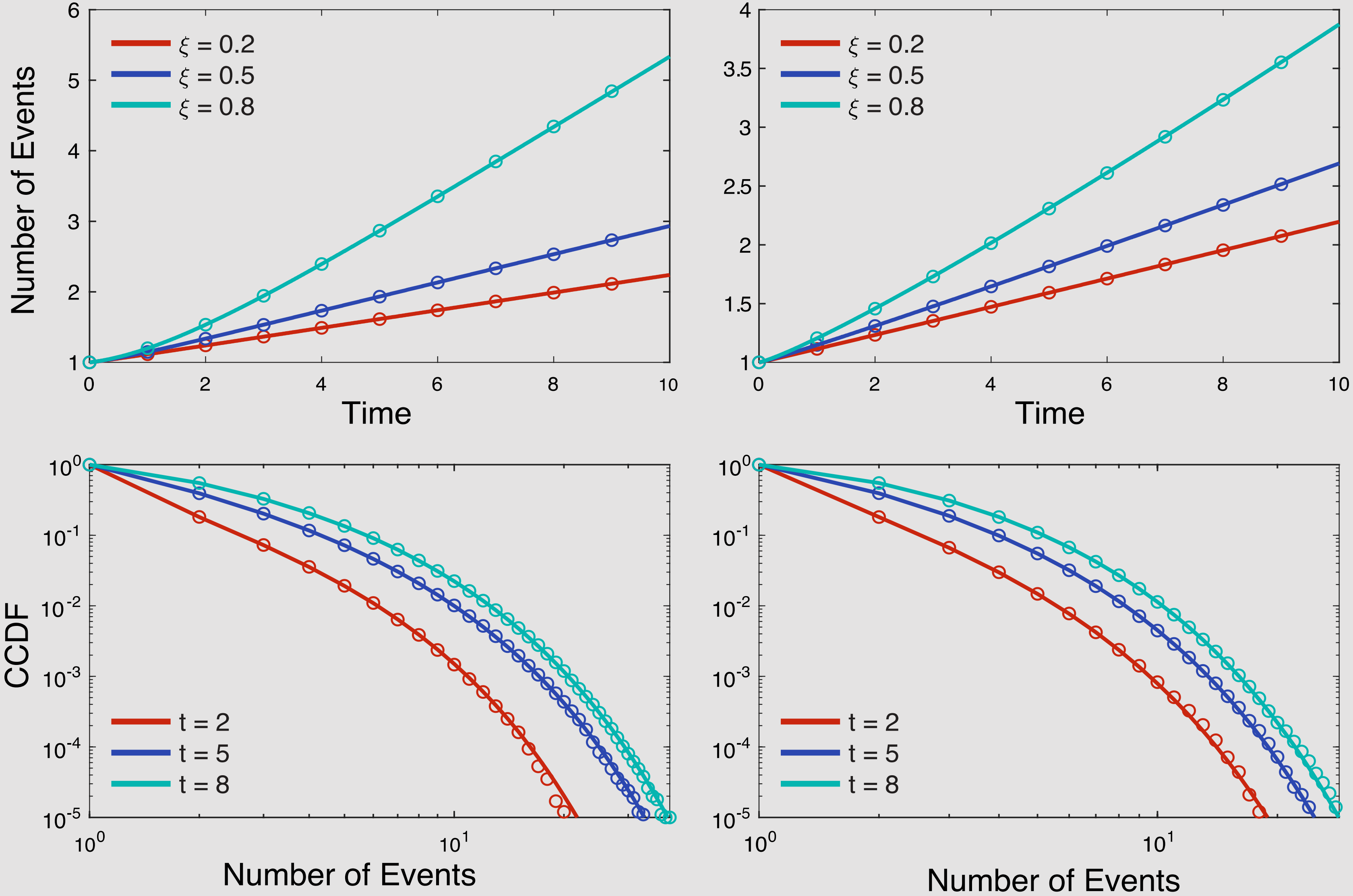


Determine the distribution at any time via

$$q_m(t) = \frac{1}{m!}\frac{\mathrm{d}^m}{\mathrm{d}x^m}H(t;x)\bigg|_{x=0}$$
$$= \frac{1}{2\pi i}\oint_C H(t;x)x^{-(m+1)}\,\mathrm{d}x,$$

which is evaluated numerically through inverse fast Fourier transforms.

Branching Process Description



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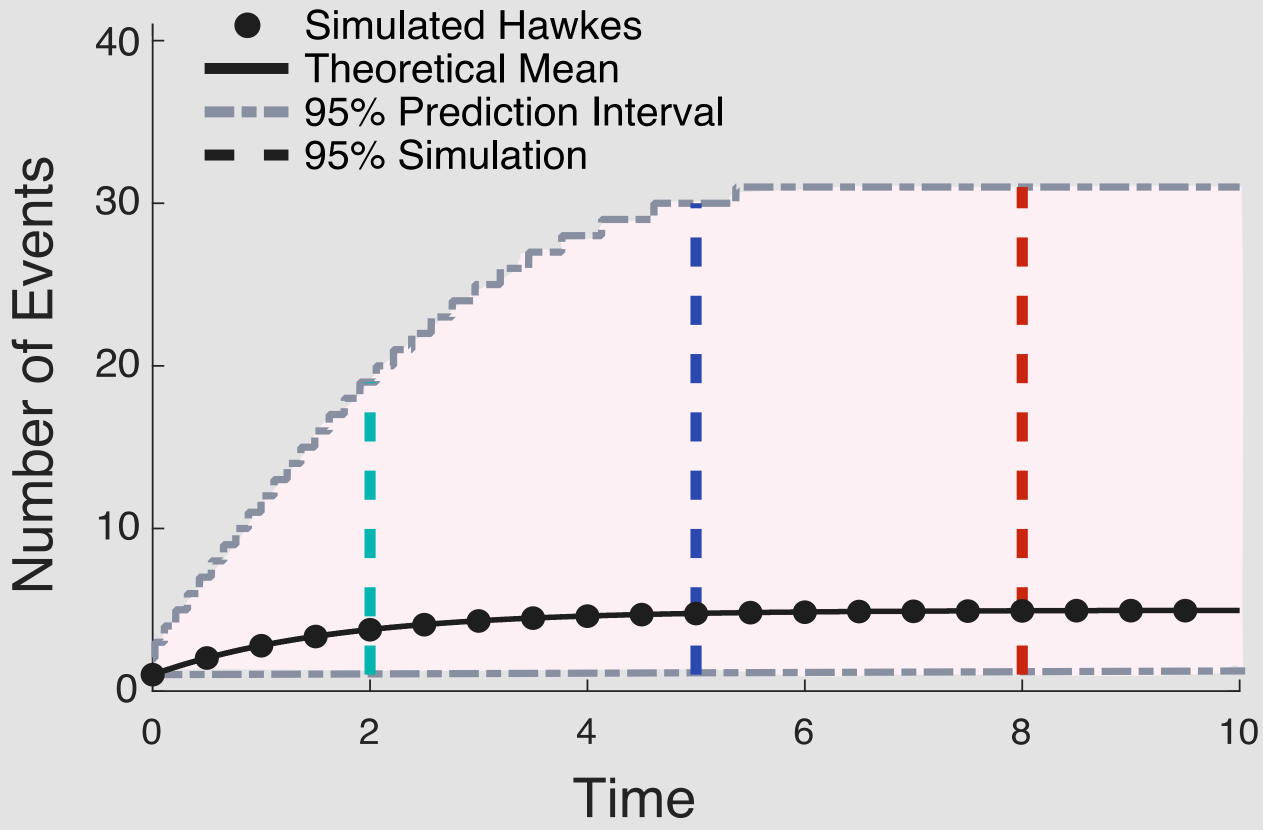
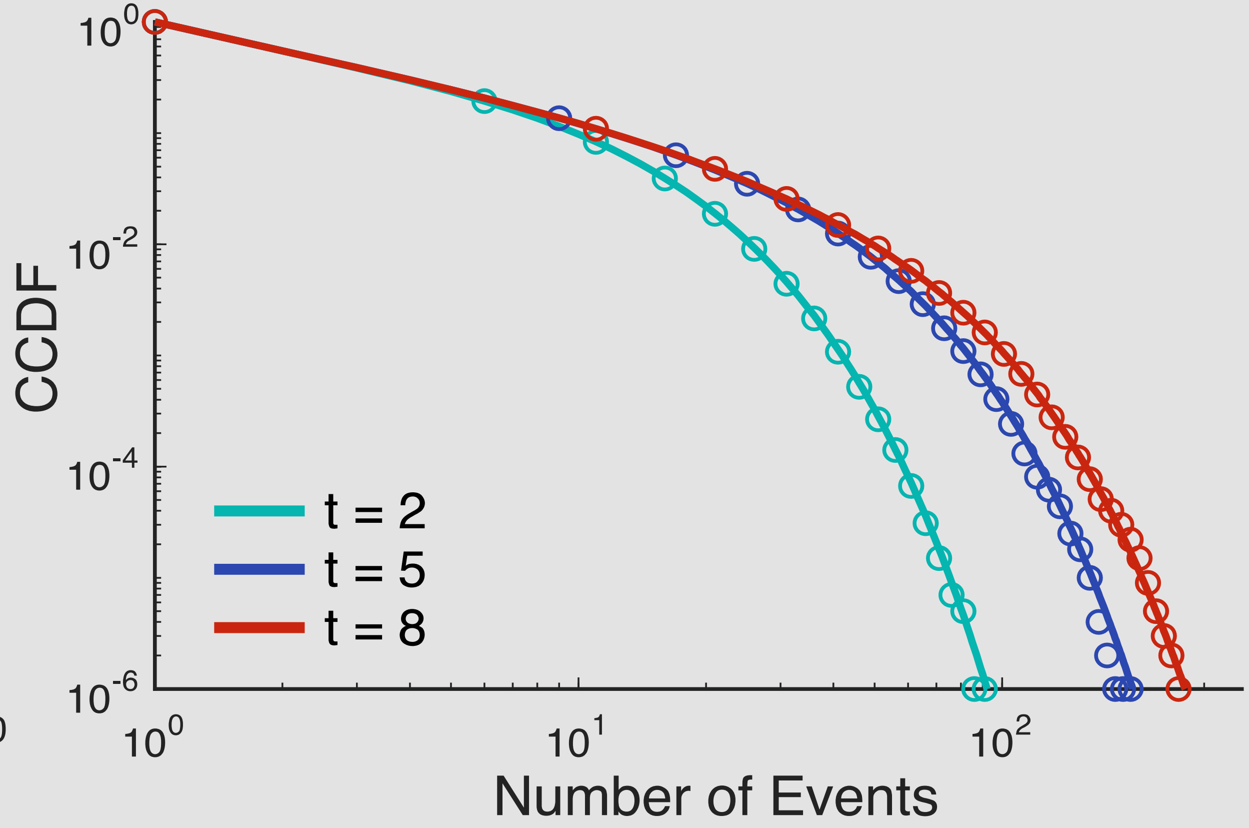
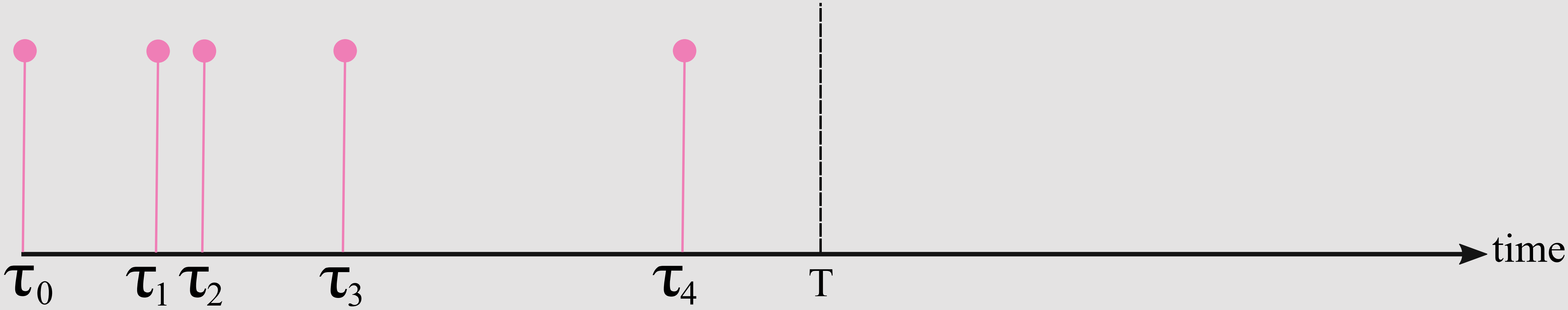




What About Prediction?



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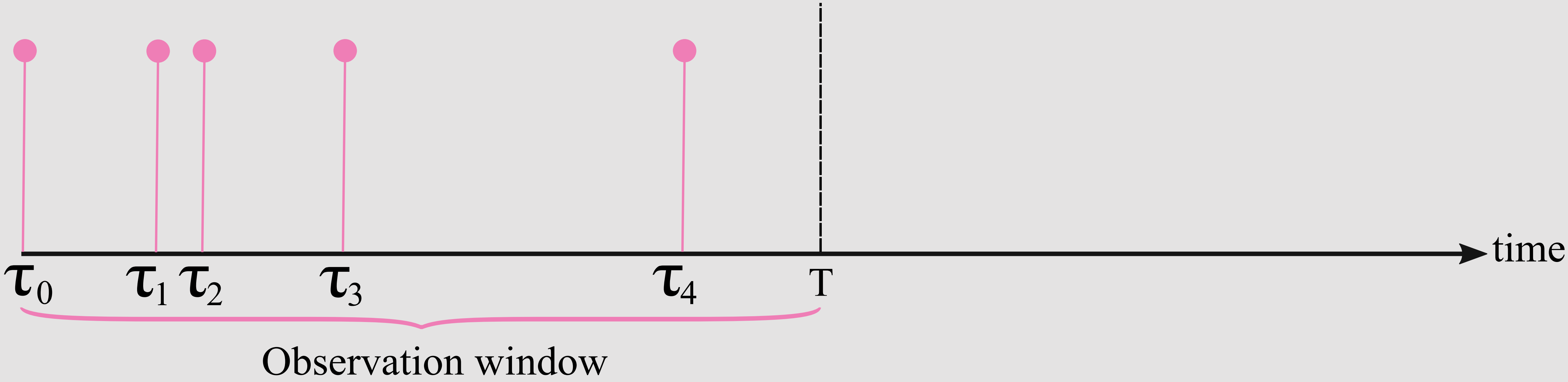

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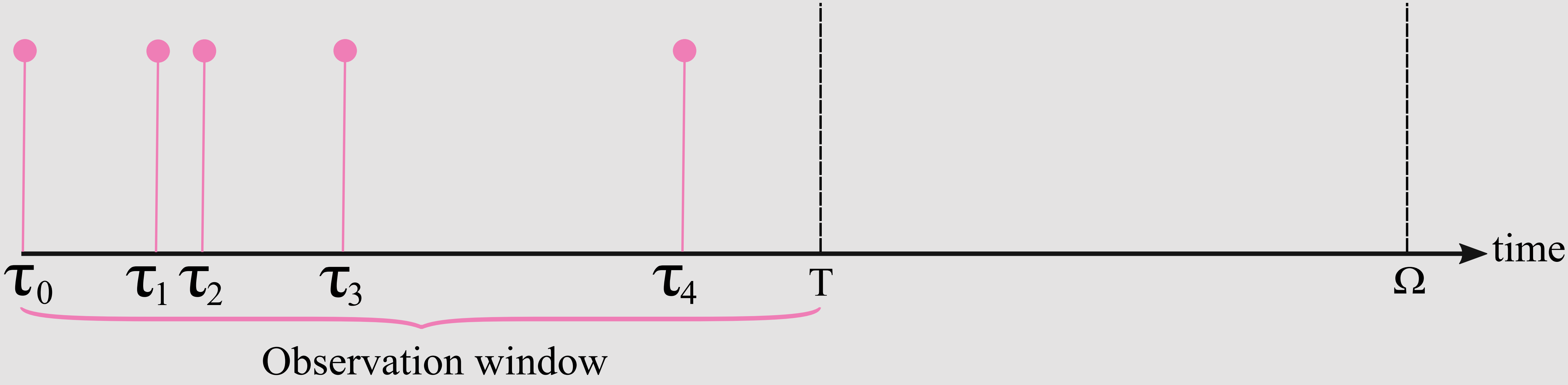

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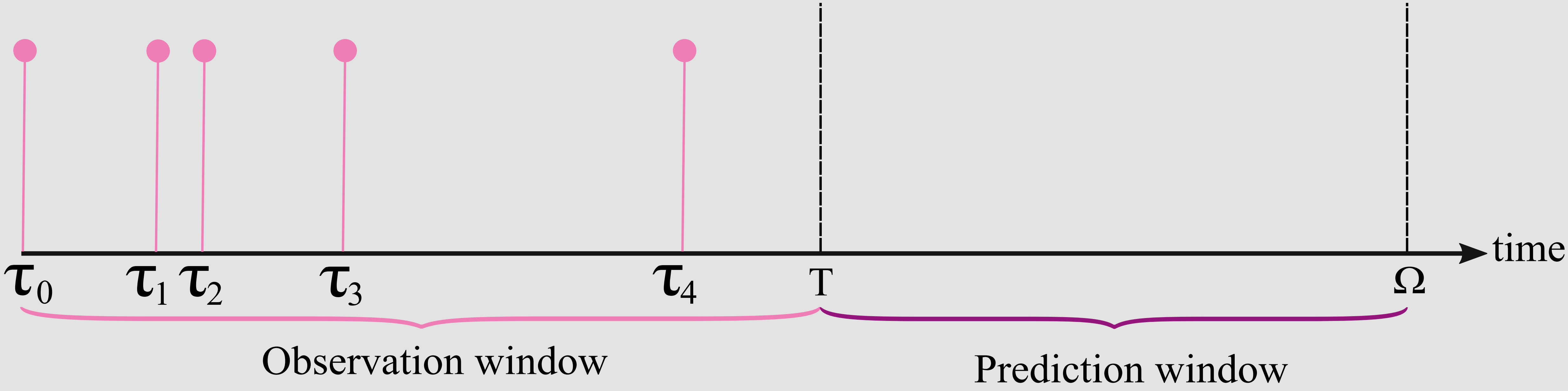

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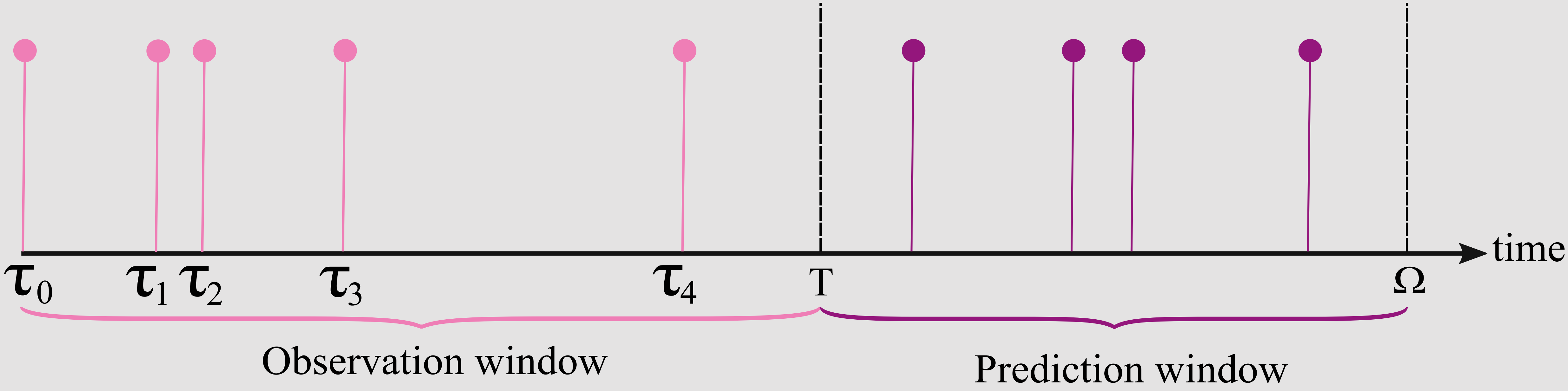

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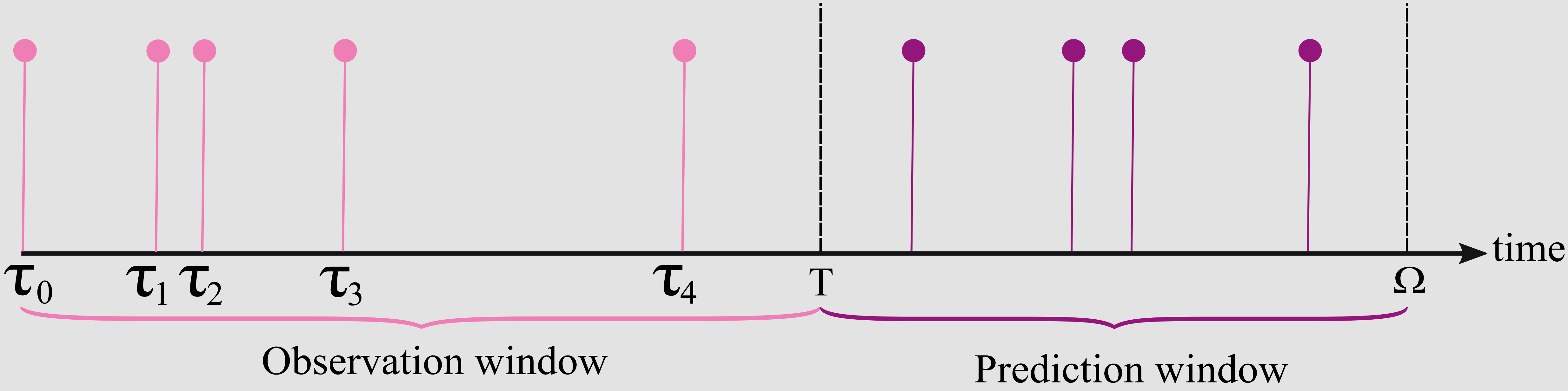


No. events in observation window

Length of prediction window

Fitness

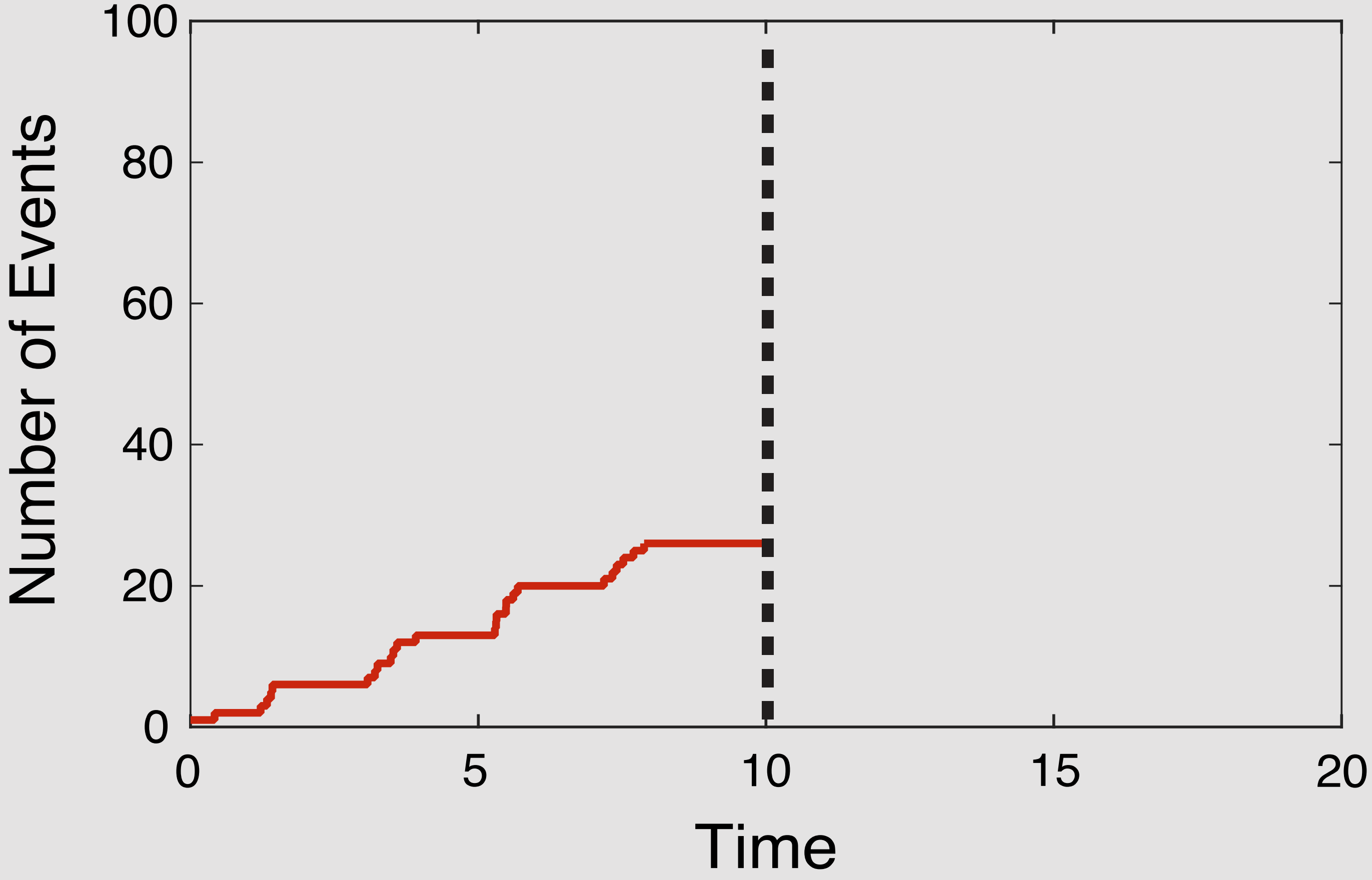
Memory kernel

$$I(r;x) = x^n \exp\left[-\int_0^r \left(\mu(r+a_0-w) + \sum_{i=1}^{n-1} \xi\,\phi(r+a_i-w)\right)[1-G(w,0;x)]\,\mathrm{d}w\right]$$

Background intensity

Age of i^{th} event at time T

What About Prediction?



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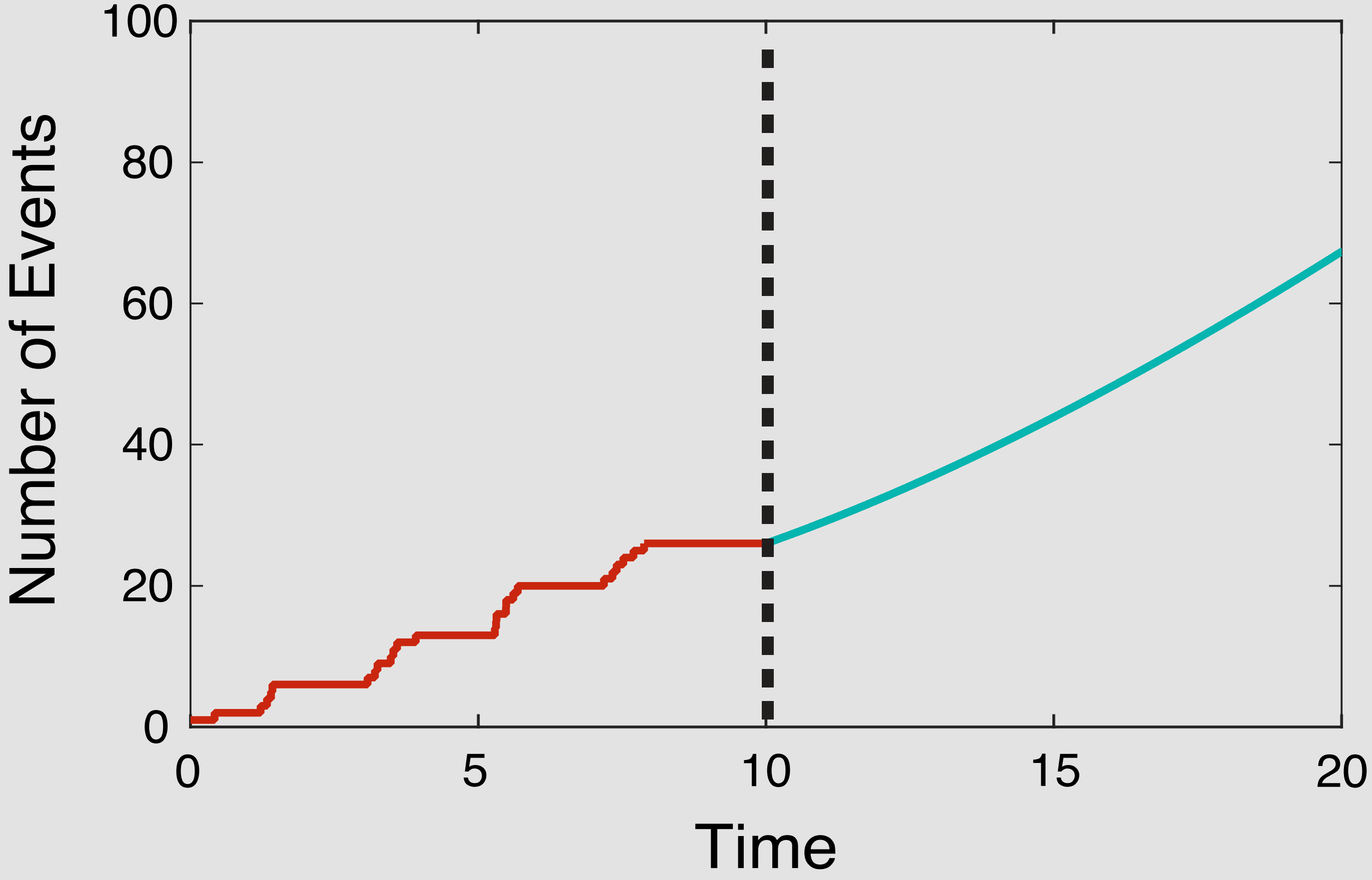

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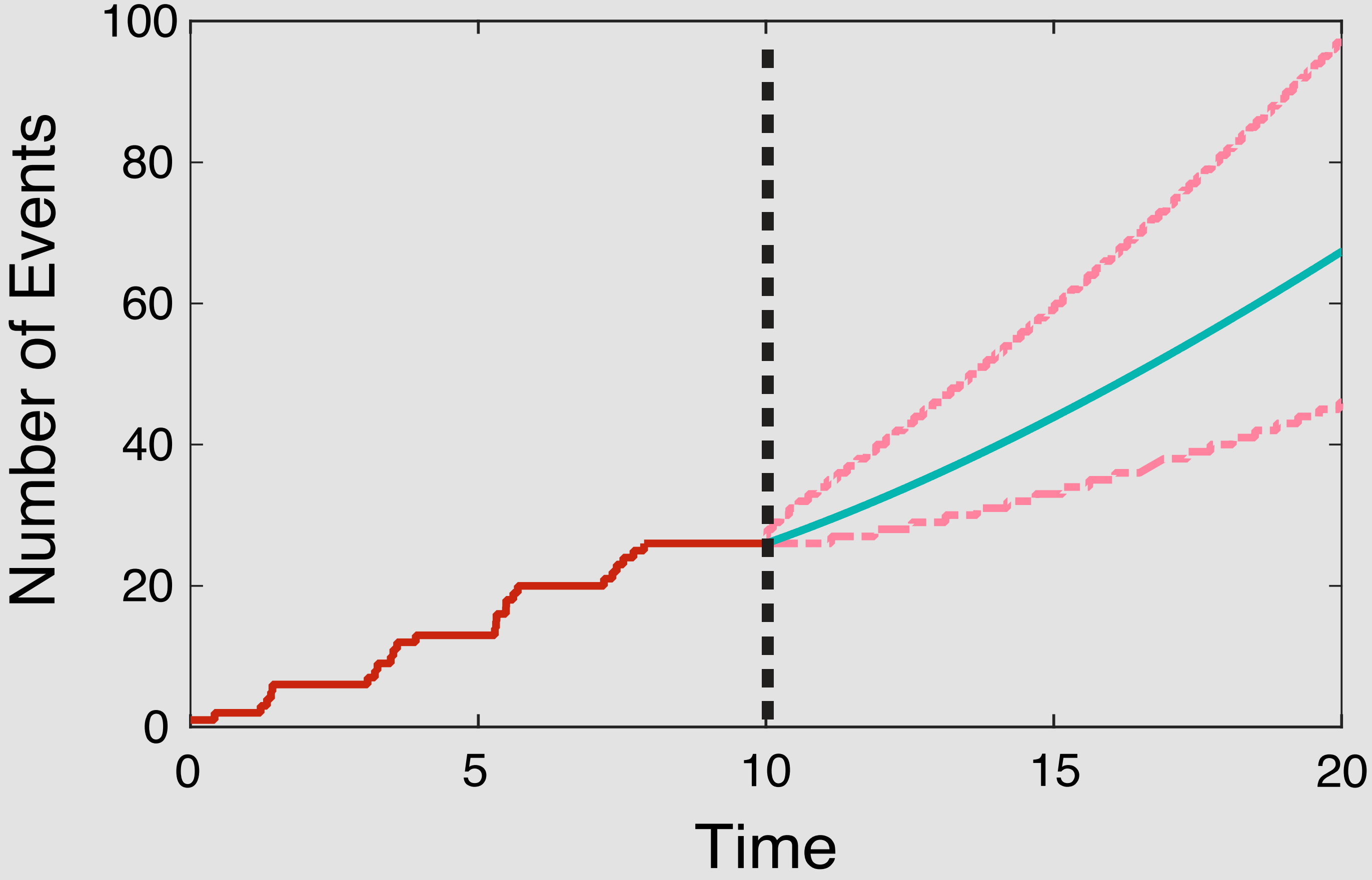

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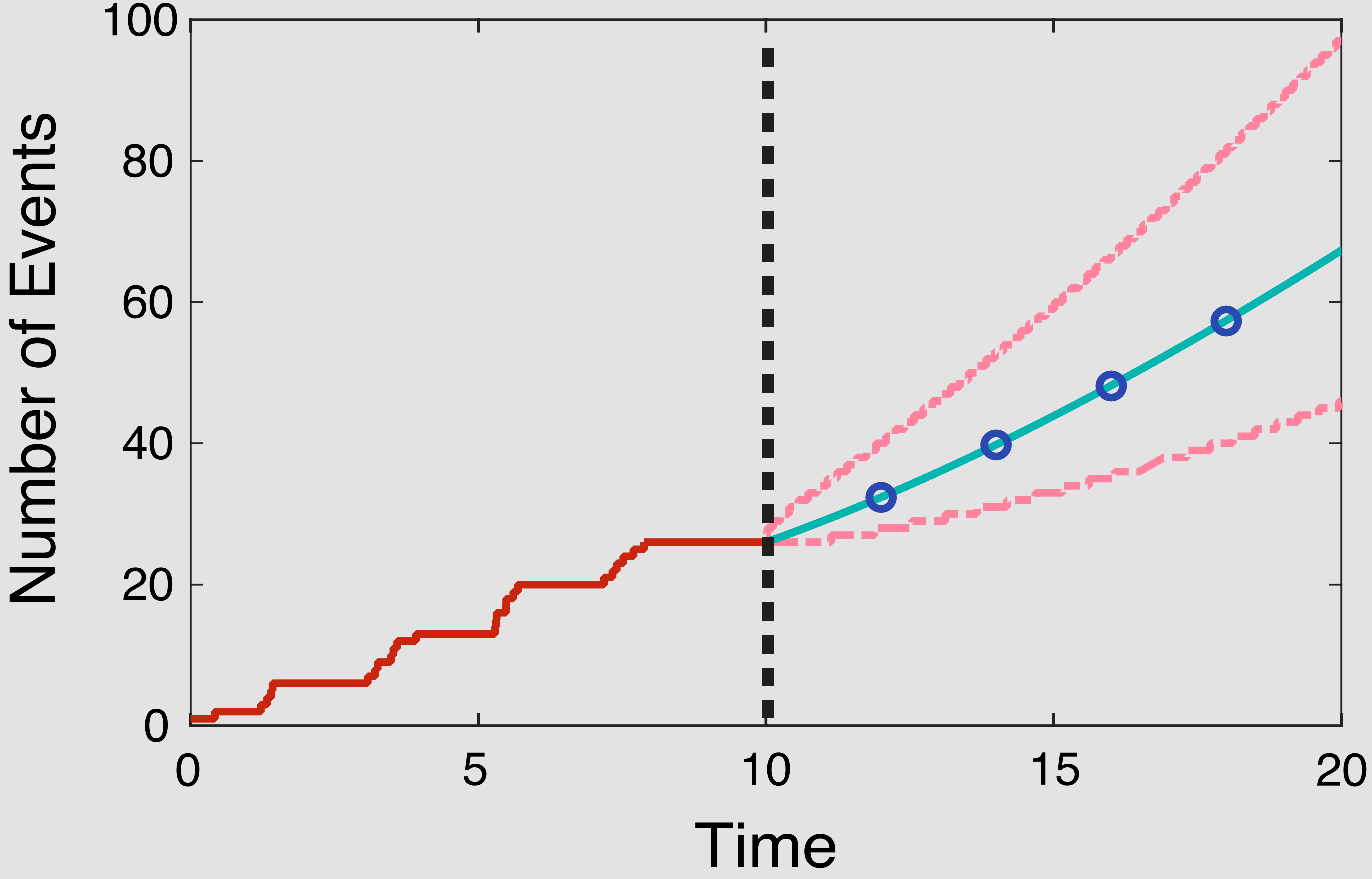

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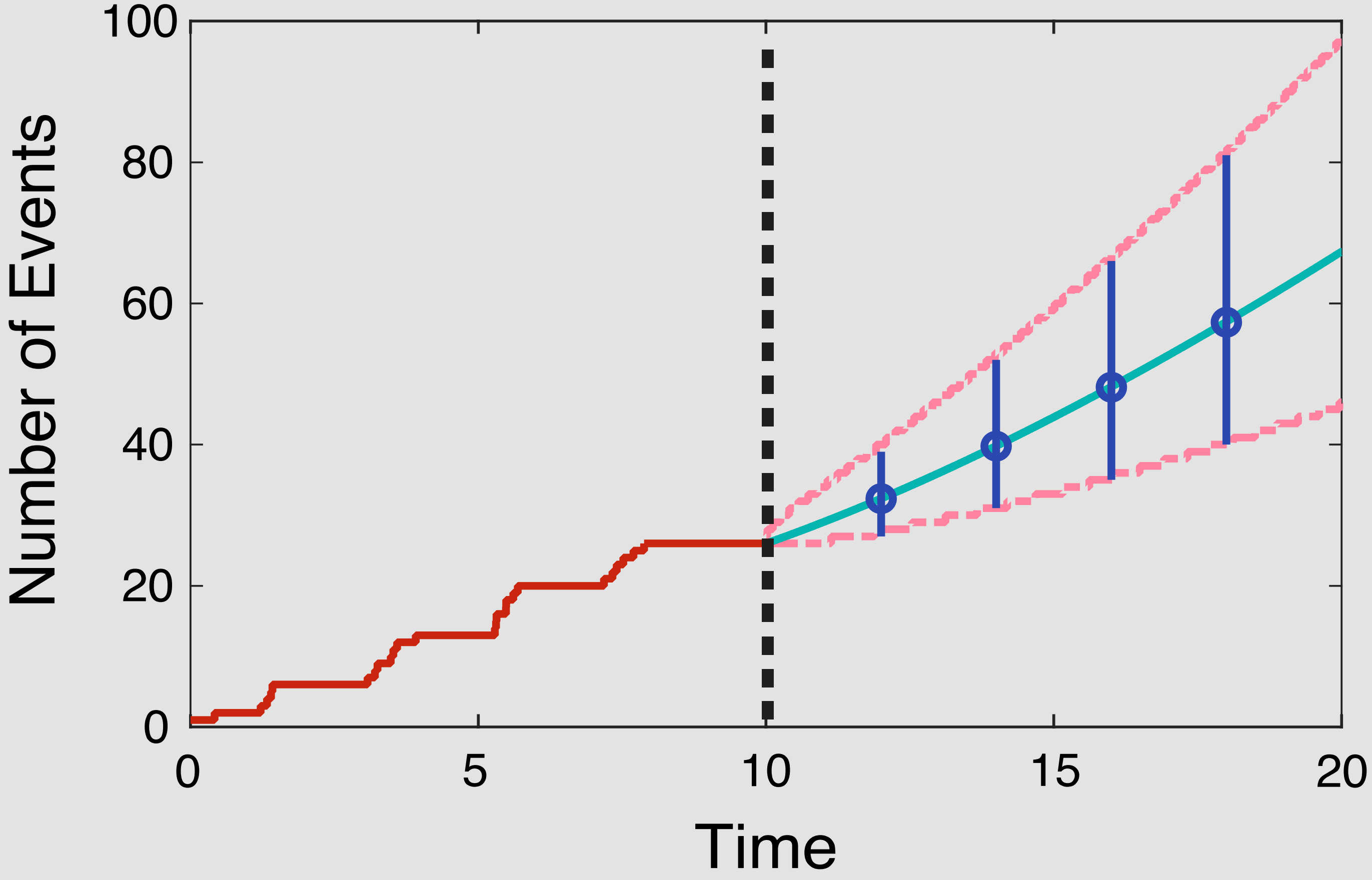

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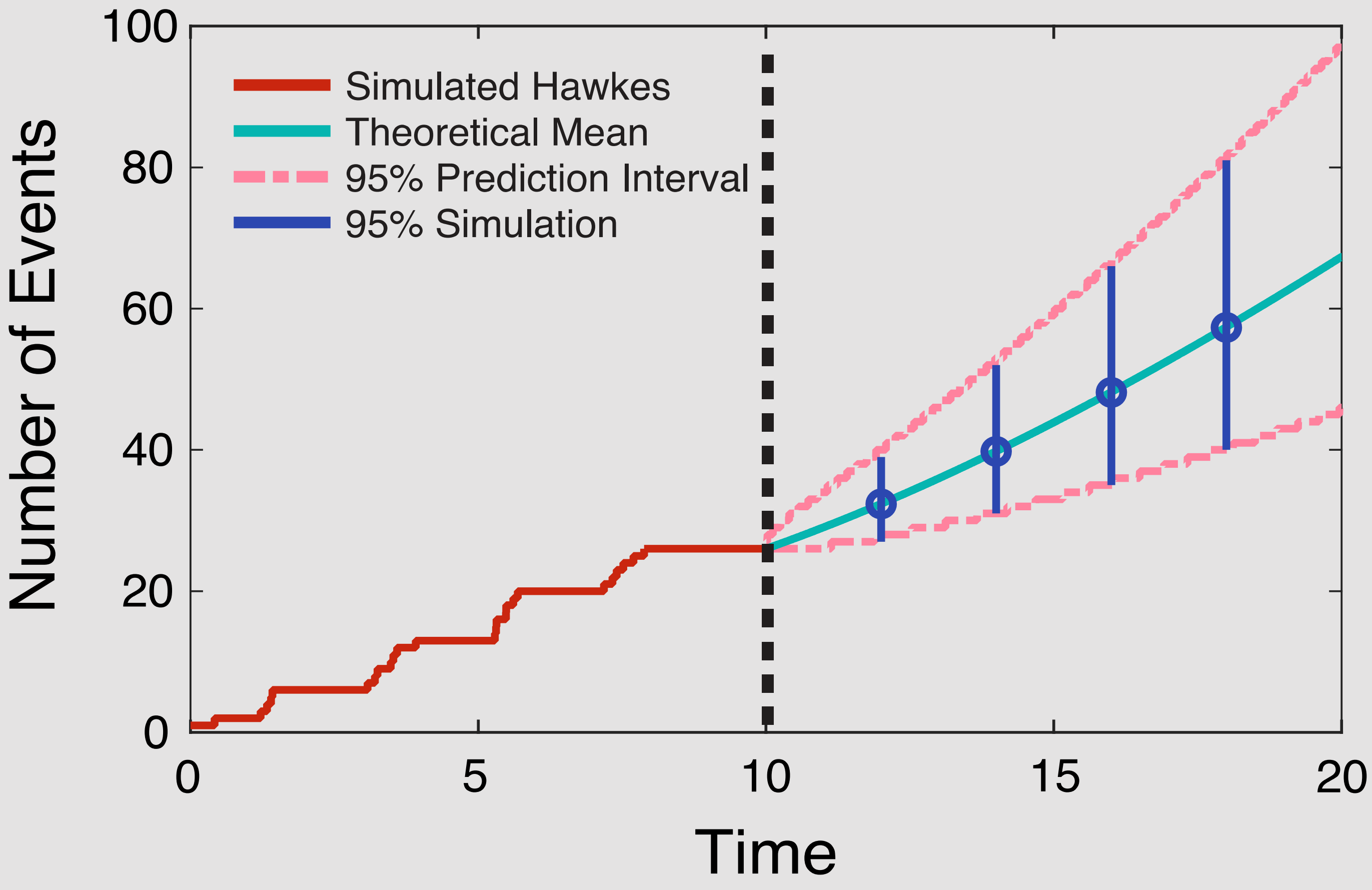
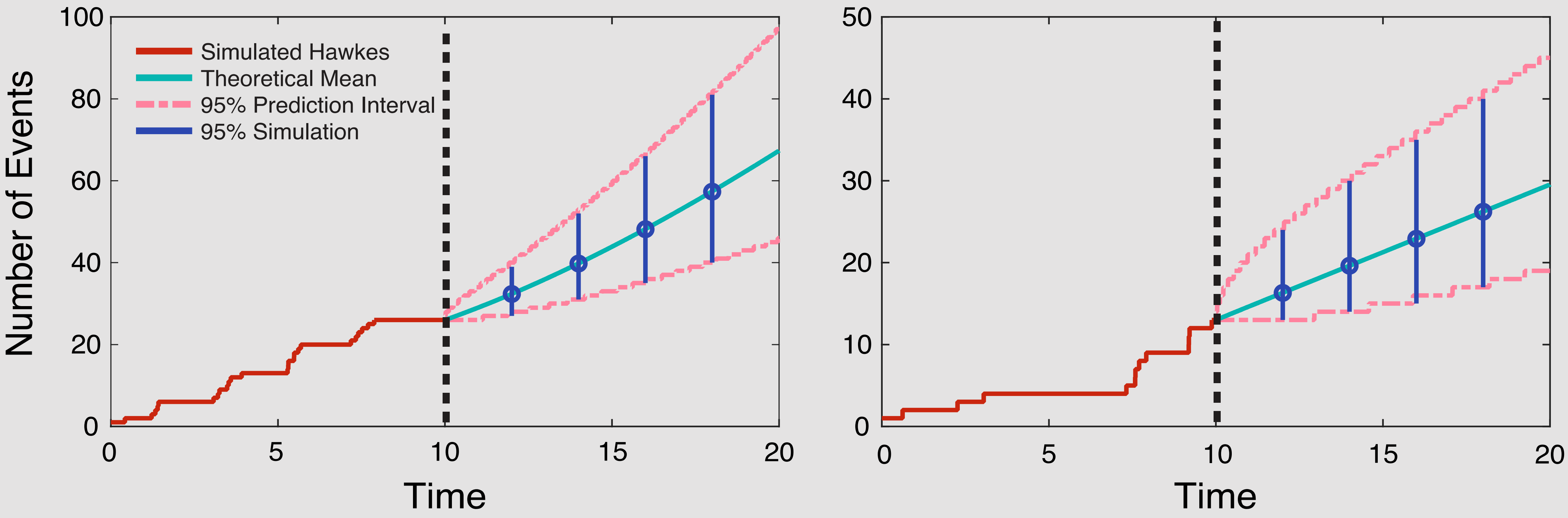


Simulation Results



$$\lambda(t) = \lambda_0 + \xi \sum_{\tau_i < t} \beta e^{-\beta(t-\tau_i)},$$

$$\lambda_0 = 1.5, \quad \beta = \frac{1}{3}, \quad \xi = 0.8.$$

$$\lambda(t) = \lambda_0 + \xi \sum_{\tau_i < t} \beta\, c^\beta\, (t - \tau_i + c)^{-(1+\beta)},$$

$$\lambda_0 = 1, \quad \beta = 1, \quad c = 0.01, \quad \xi = 0.5.$$

Empirical Data - Forocoches

- Spanish language discussion board created in 2003 with the purpose of talking about cars.
- Now the 52nd most visited website in Spain with a wide-range of topics.
- Follows the usual dynamics of a discussion board where a user creates a thread which receives replies that themselves may be replied to. Threads are **ordered on the front page** shows at most 40 by time of last post.
- The longer the thread is on the front page more likely it is to be seen and replied to, so can be thought of as a **self-exciting process**.

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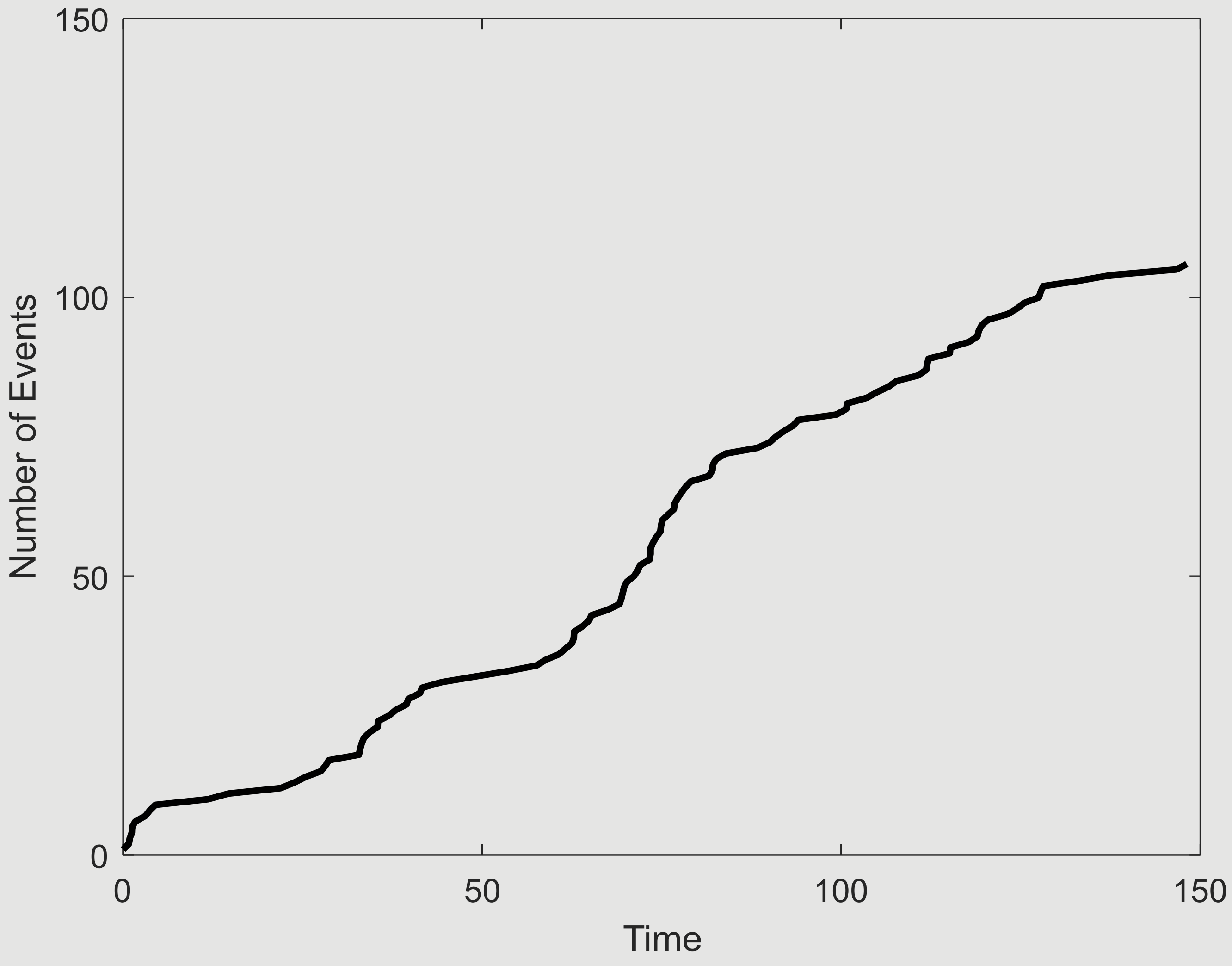

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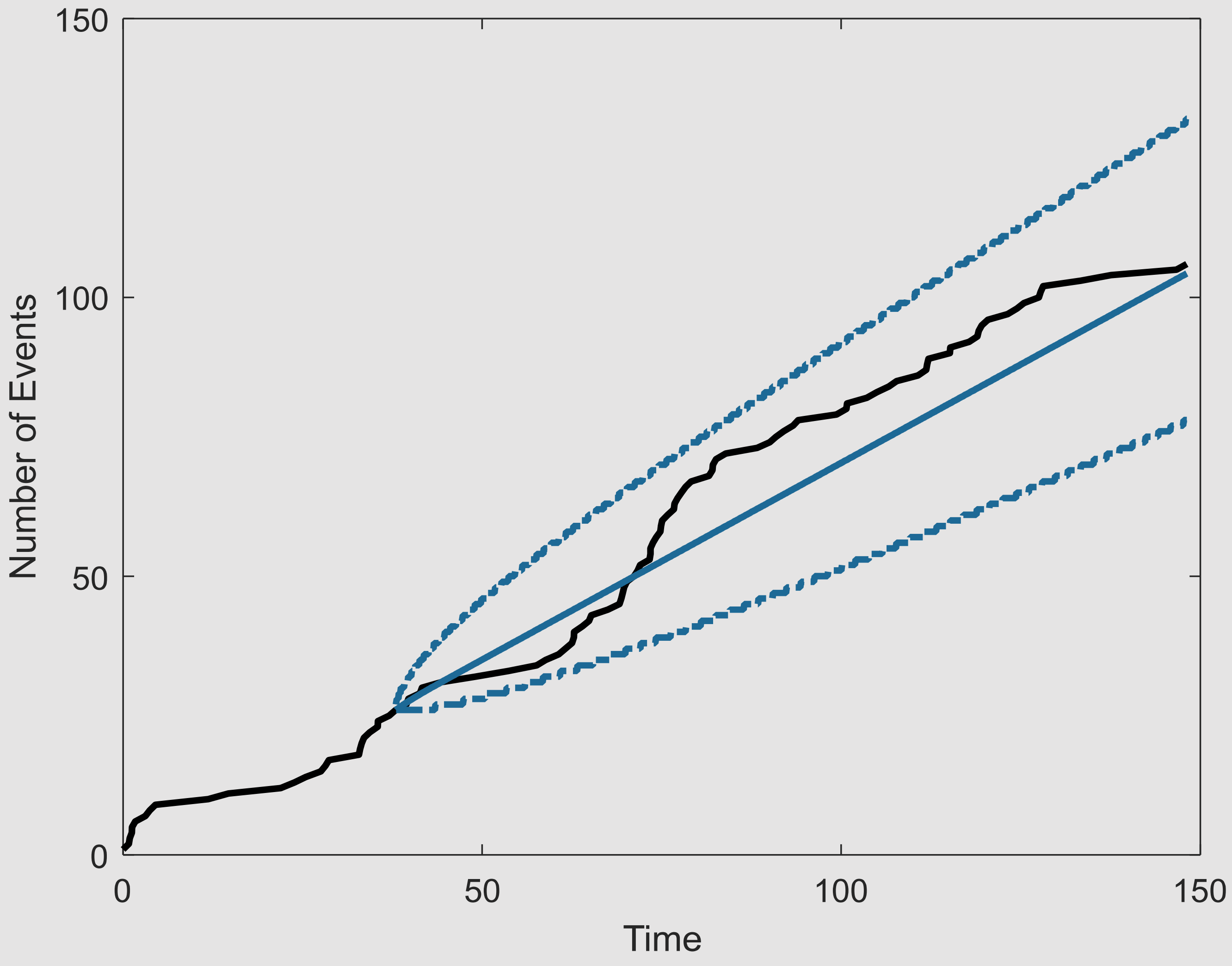

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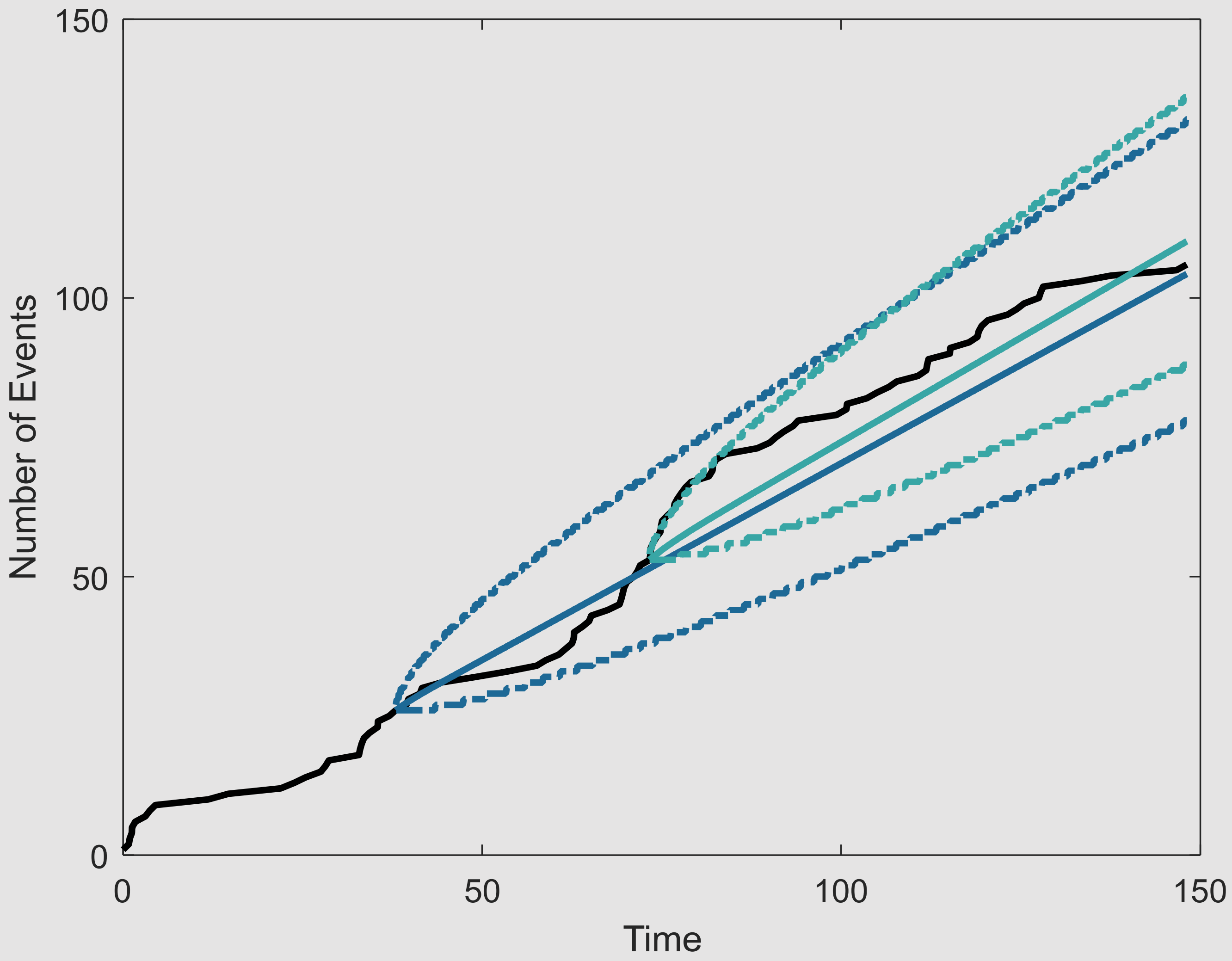

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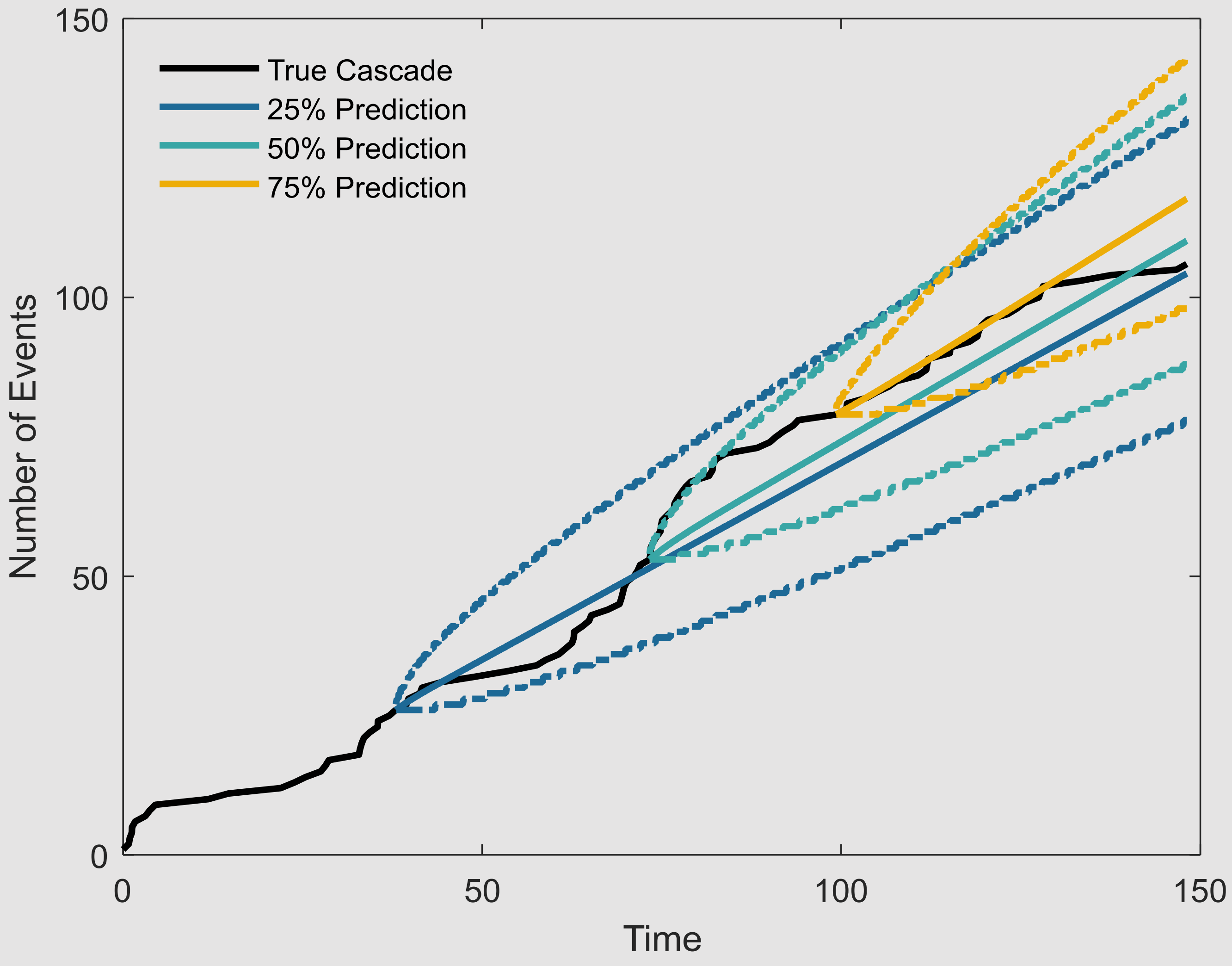

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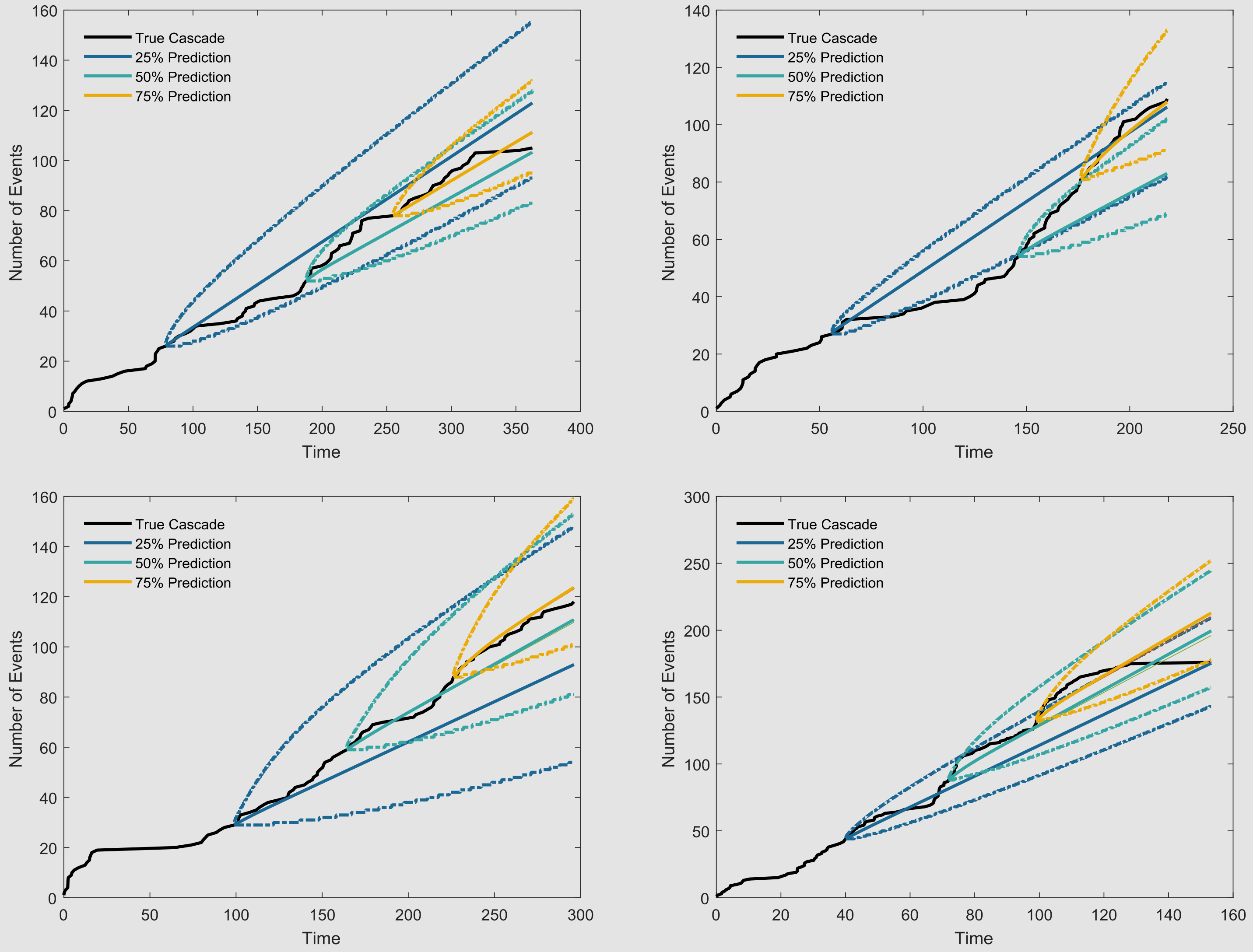
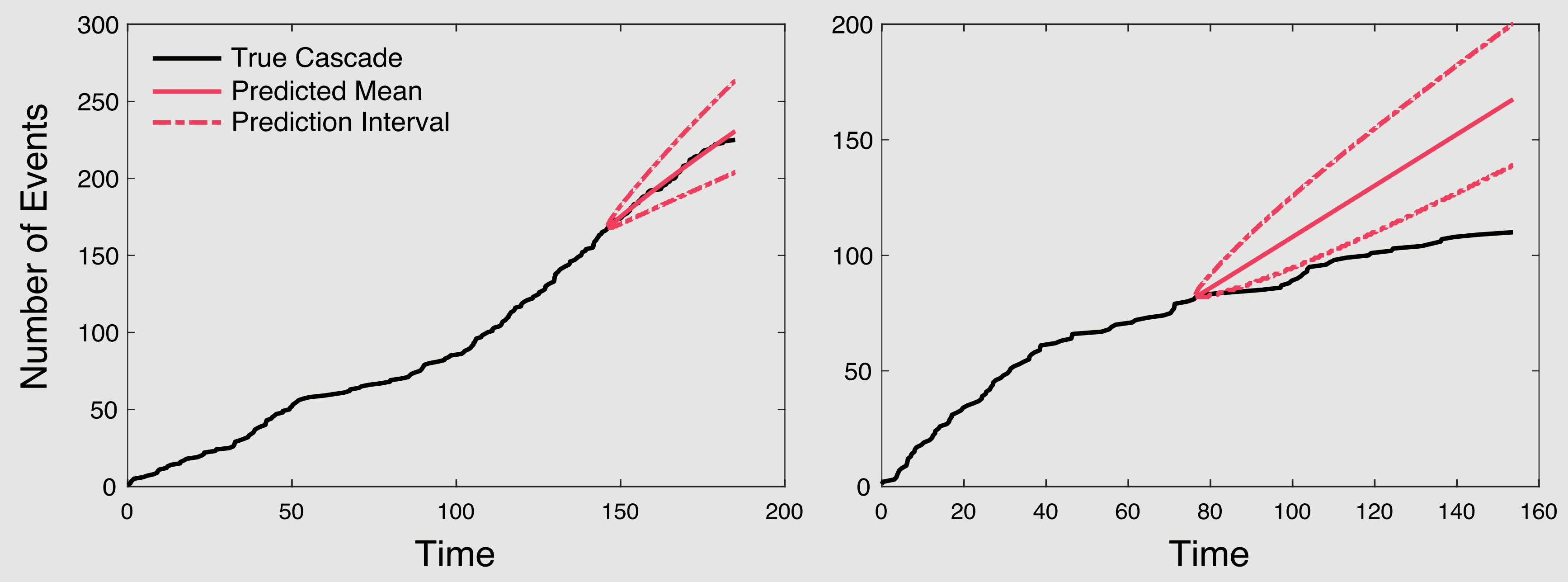


Issues With the Model

- We require **enough activity in the observation** period to provide **accurate parameter estimation.**
- In all of the above we have assumed **constant background intensity** so can capture the **daily variation** in the **number of users** present online.
- In spite of this, we can provide **useful predictions** regarding **future thread popularity** with results comparable to the current literature (without extensive numerical computations).



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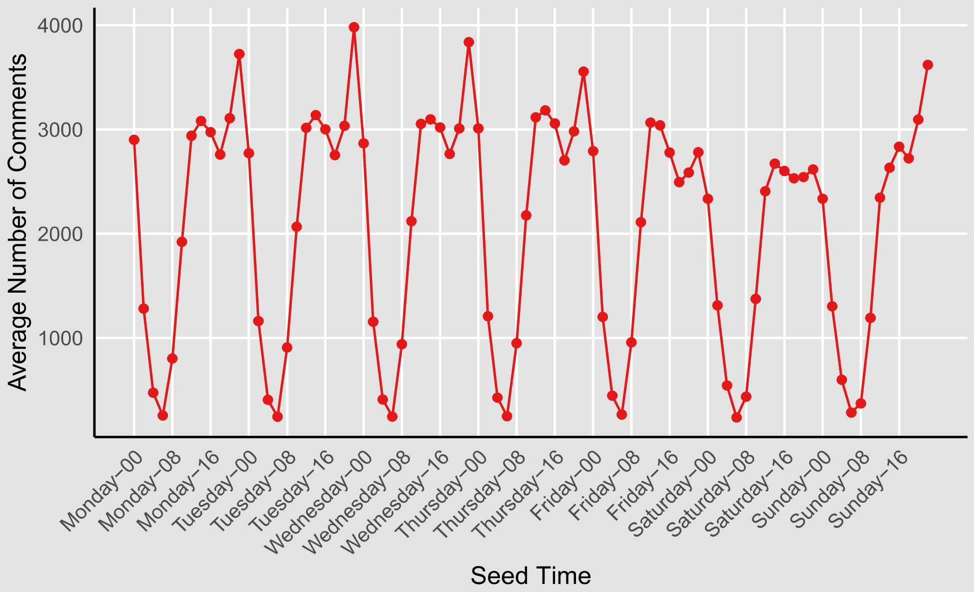

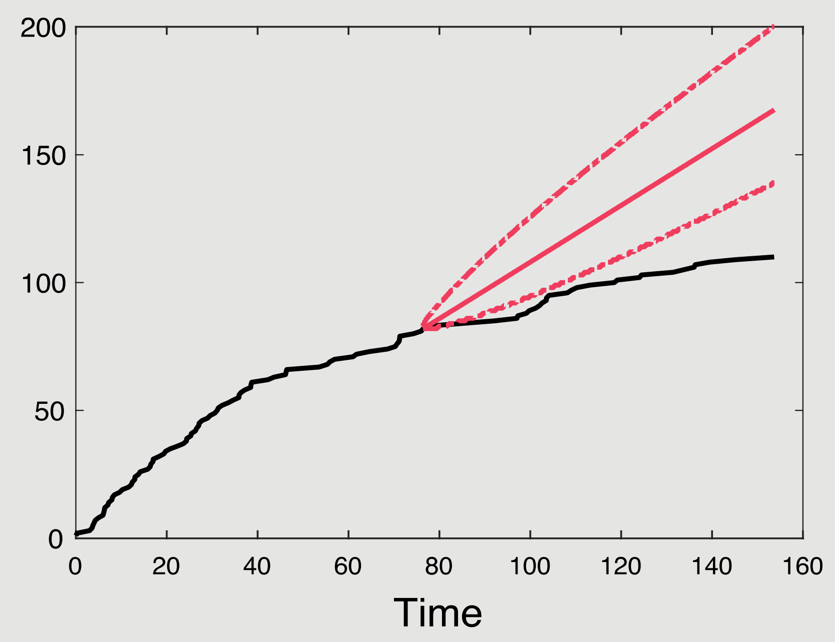

Conclusions

- Branching processes are extremely **powerful tools** in describing online information cascades.

- Developed a multi-type BP to capture the empirically observed cascades on **multiple social media platforms** – generalizing the 'competition-induced-criticality' result.

- Can fully describe the **Hawkes process** allowing new results to be determined and allow **theoretical predictions** to be made for future cascade dynamics.

- Plenty of scope for further extensions…

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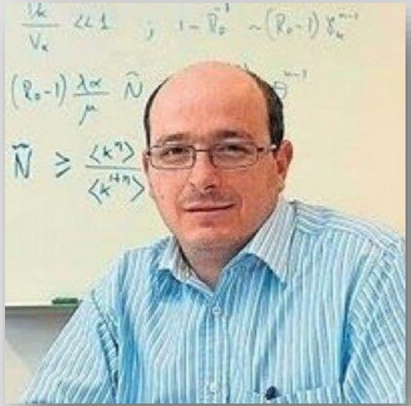
- Plenty of scope for further extensions…
- Don’t prep a talk the day after a U.S. presidential election!!!

Collaborators & Thanks

James Gleeson
(Uni. of Limerick)

Alberto Aleta
(ISI Foundation, Turin)

Ioannis Dassios
(Uni. College Dublin)



Yamir Moreno
(BIFI, Uni. Of Zaragoza)

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Spreading of memes on multiplex networks

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Quantifying uncertainty in a predictive model for popularity dynamics

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Thank you for listening!

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