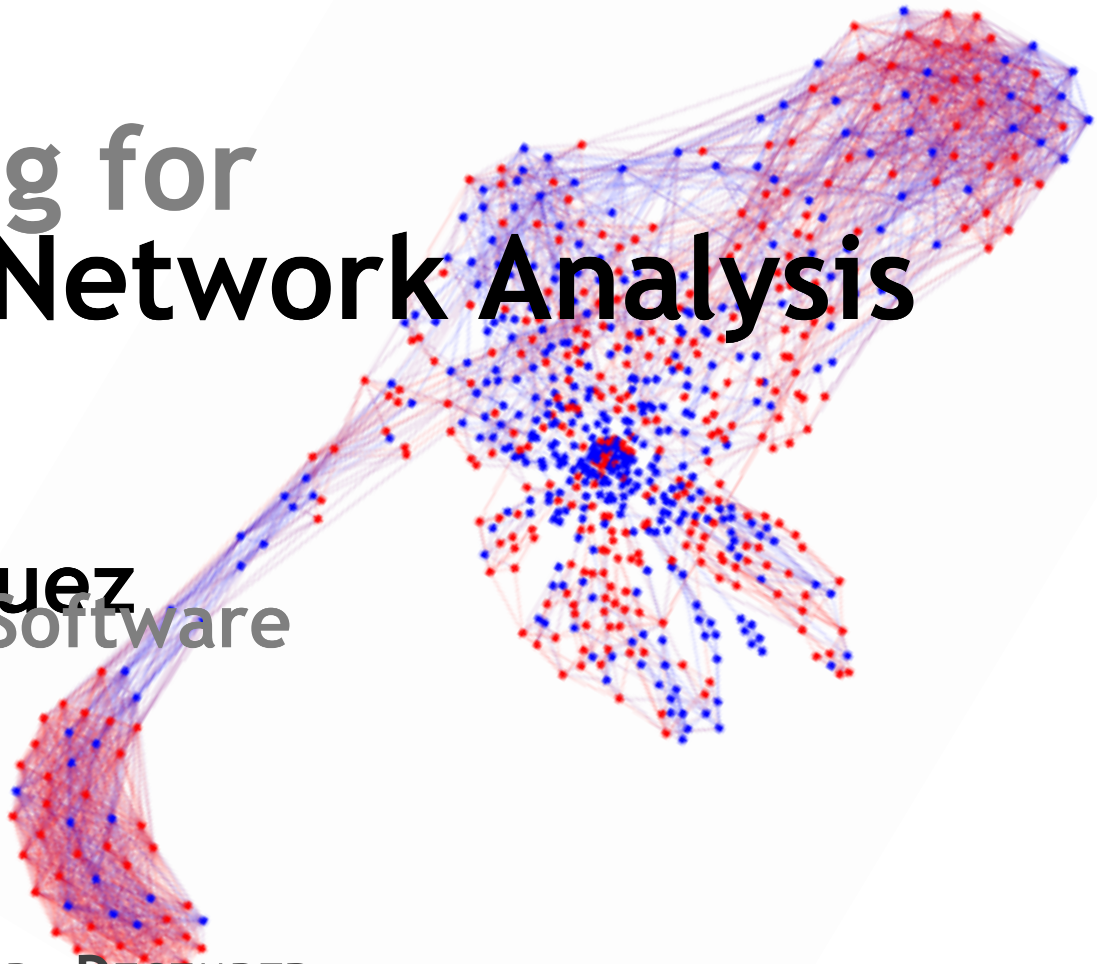
Machine learning for
Dynamic Social Network Analysis



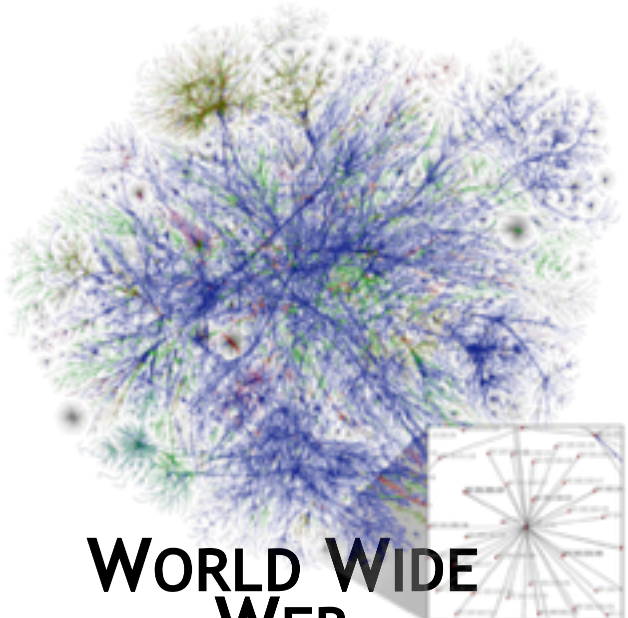
Manuel Gomez Rodriguez

Max Planck Institute for Software Systems

IIT HYDERABAD, DECEMBER 2017

Interconnected World

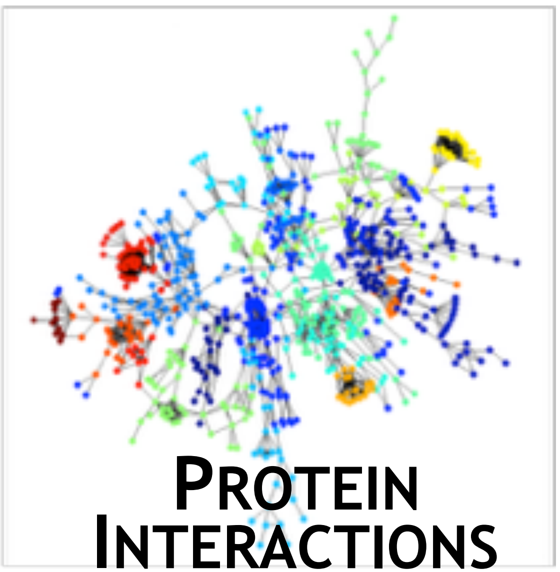
Social Networks



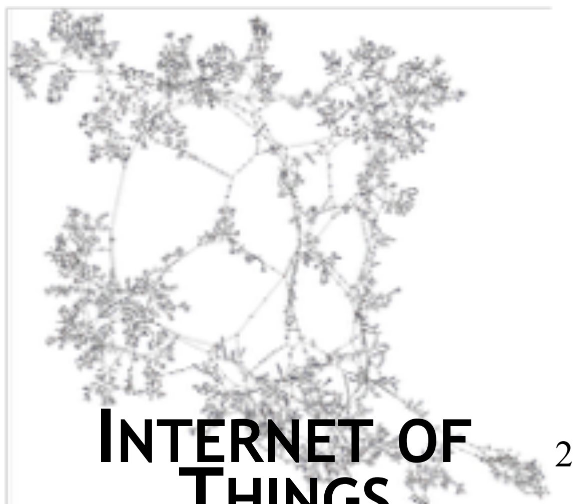
World Wide Web

Information Networks

Transportation Networks



Protein Interactions



Internet of Things

Many discrete *events* in continuous time

Qmee, 2013

Variety of processes behind these events

Events are (noisy) observations of a variety of complex dynamic processes…

News spread in Twitter

Product reviews and sales in Ama

A user gains recognition in Quora

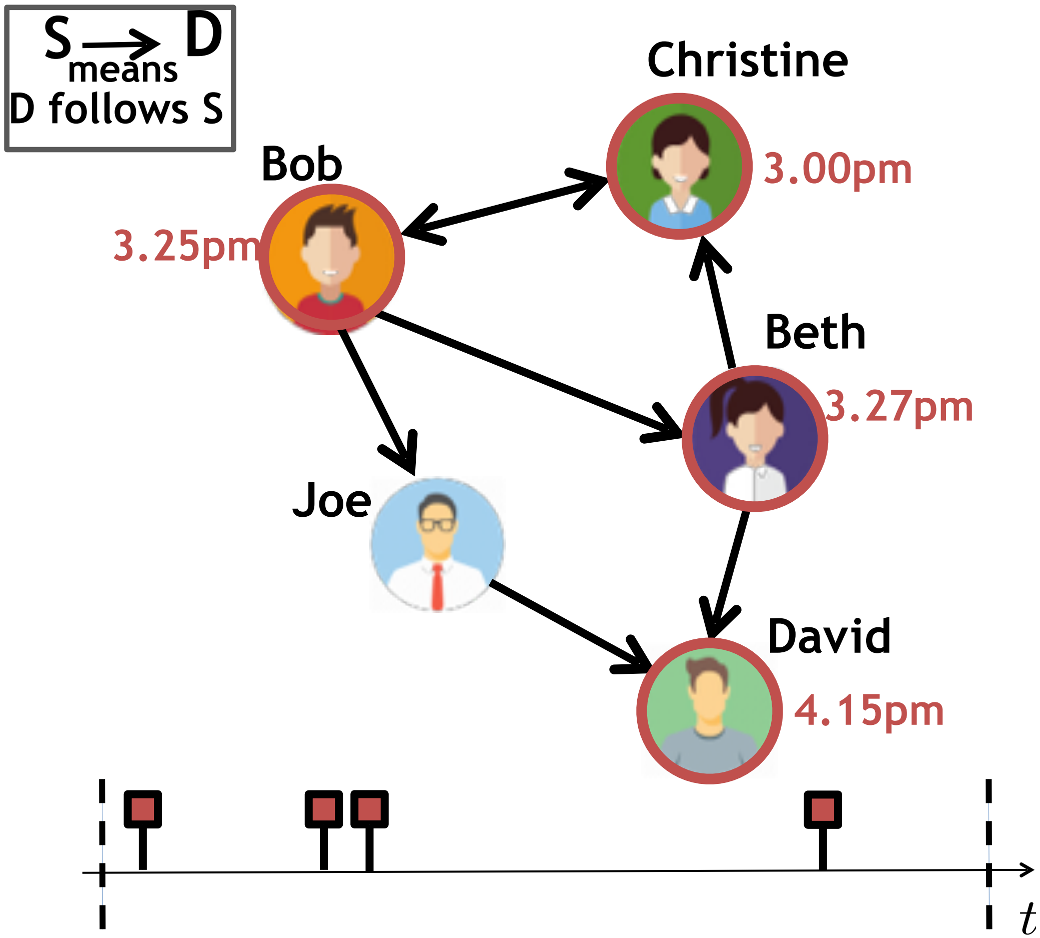
Video becomes viral in Youtube

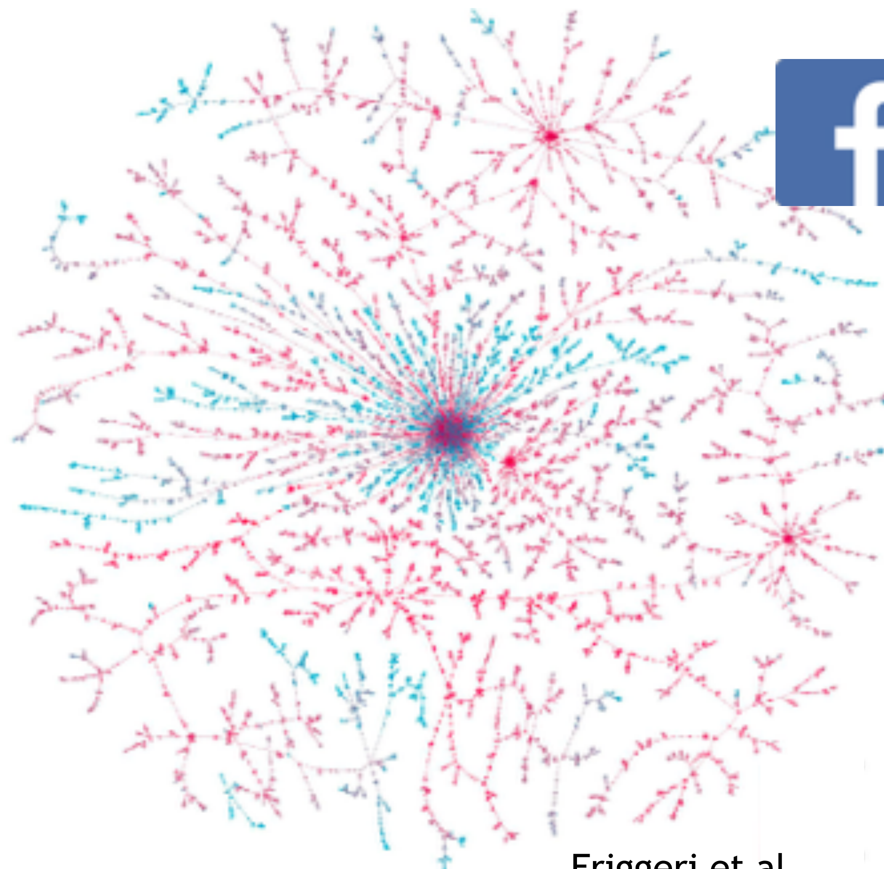
Article creation in Wikipedia

FAST → SLOW

…in a wide range of temporal scales

Example I: Idea adoption/viral marketing





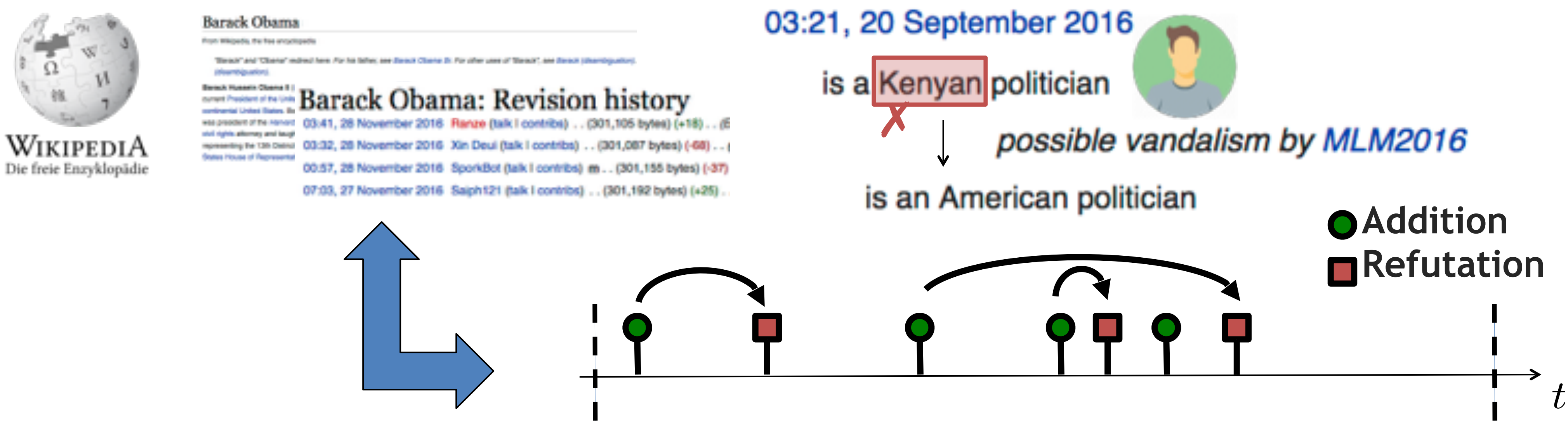
Friggeri et al., 2014

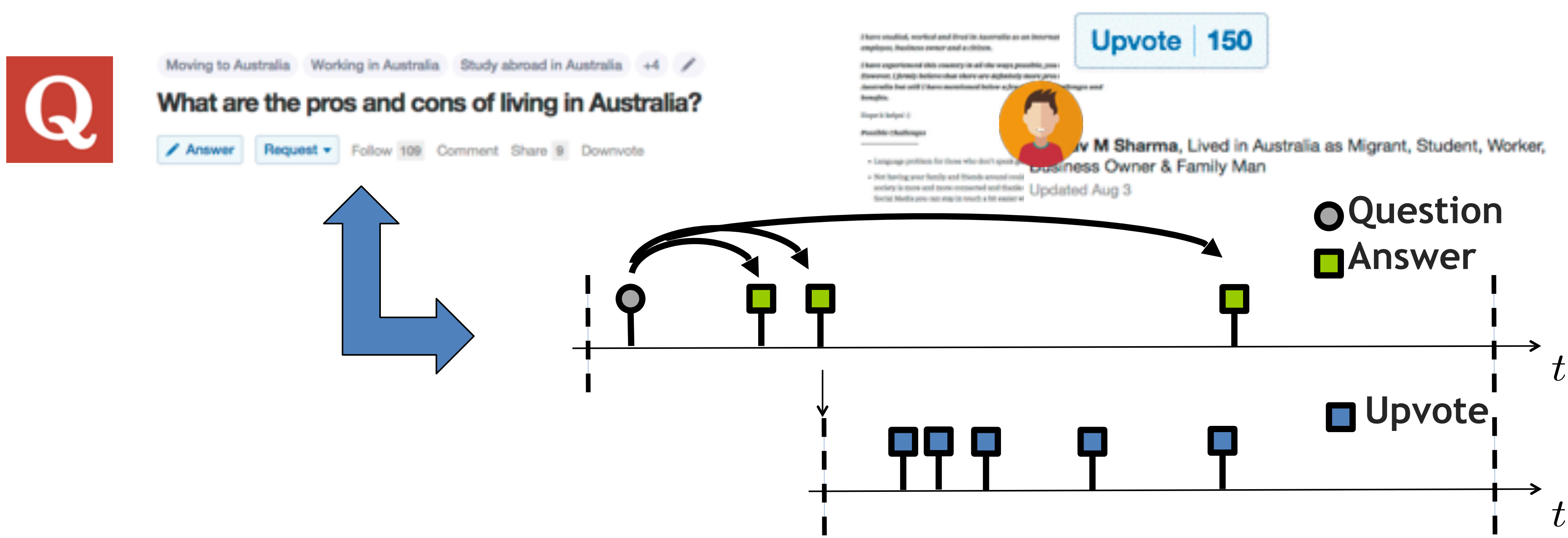
They can have an impact in the off-line world

theguardian

Click and elect: how fake news helped Donald Trump win a real election

Example II: Information creation & curation



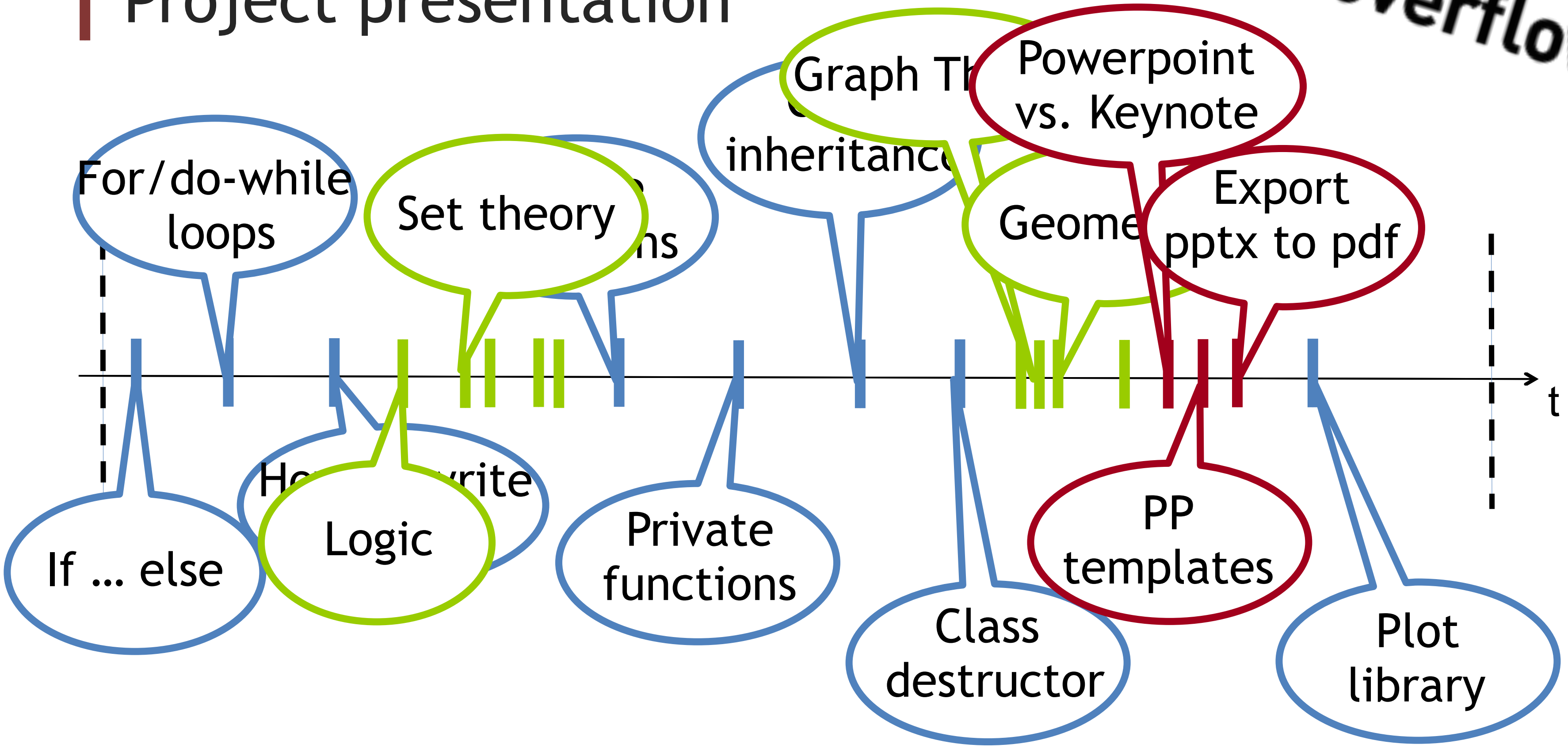


Example III: Learning trajectories

1st year computer science student

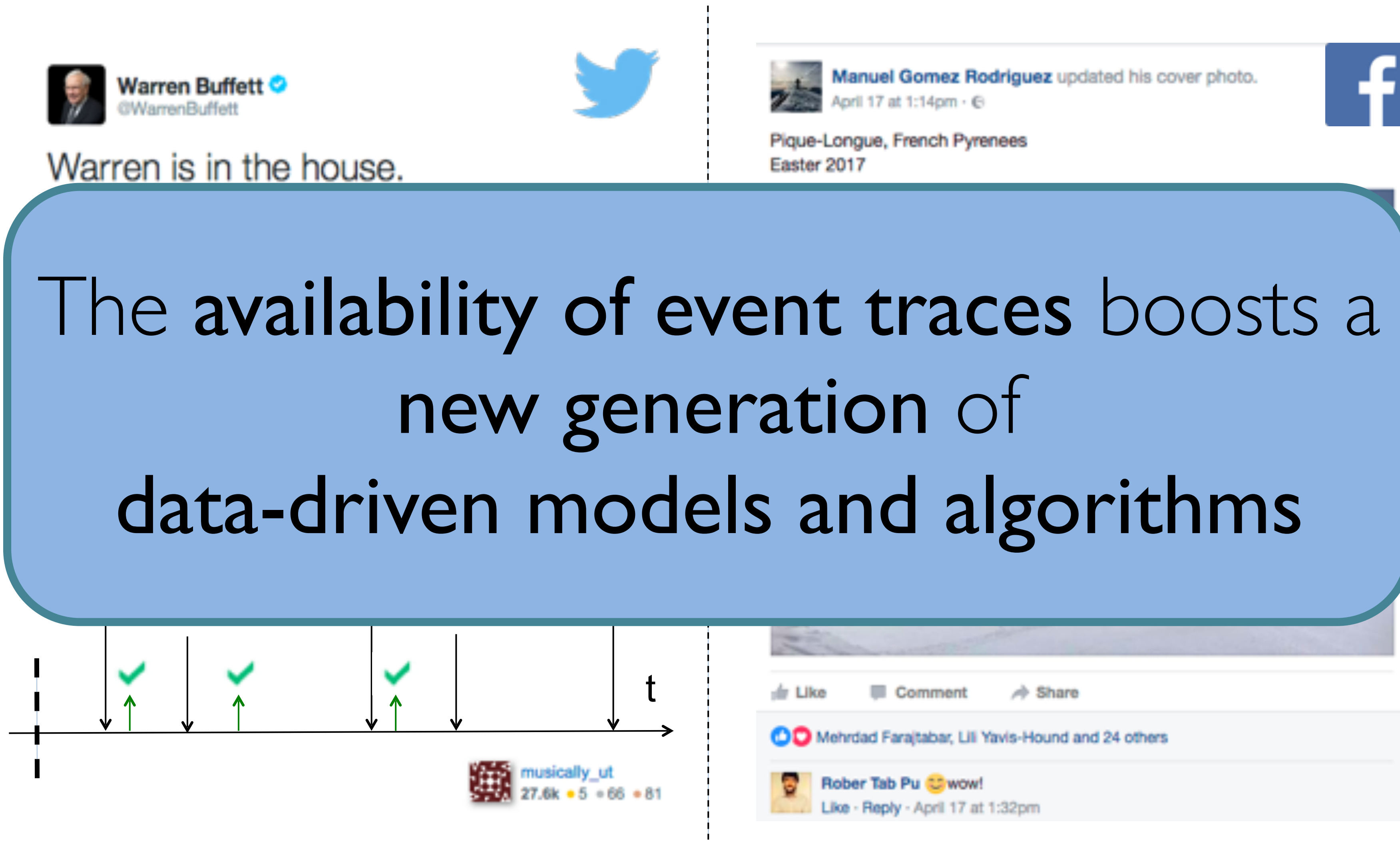
- Introduction to programming
- Discrete math
- Project presentation

stackoverflow



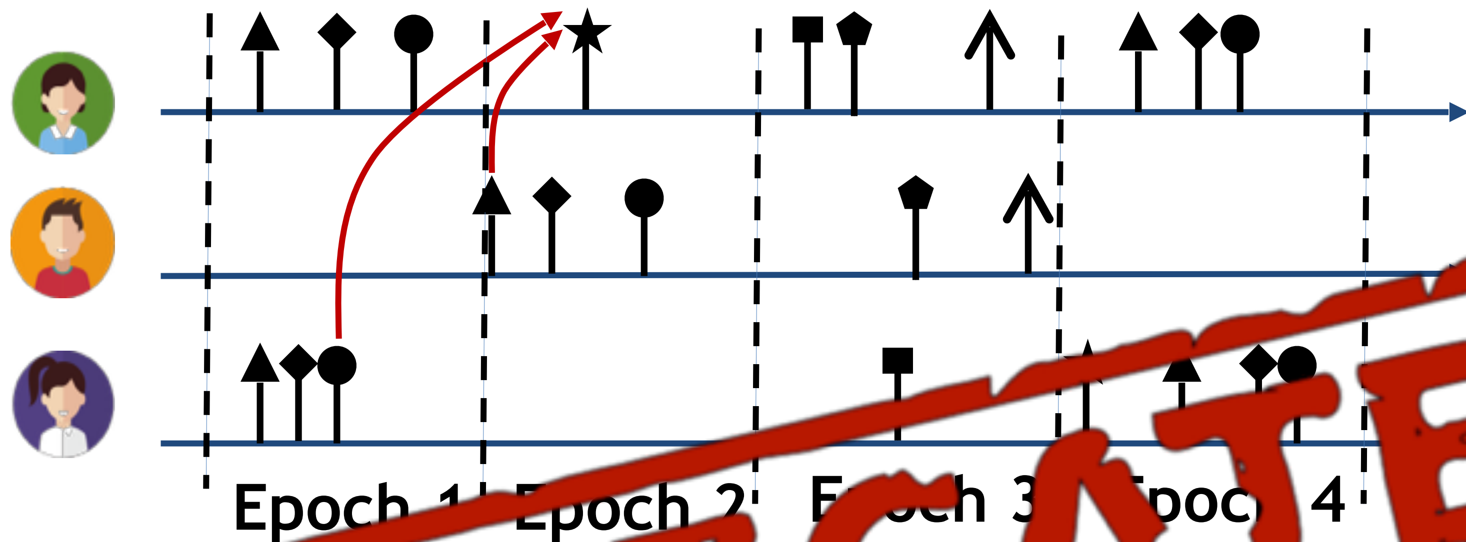
Detailed *event traces*

DETAILED TRACES OF ACTIVITY



The **availability of event traces** boosts a **new generation** of **data-driven models and algorithms**

Previously: discrete-time models & algorithms



DEPRECATED

Discrete-time models artificially introduce epochs:

1. How long is each epoch? Data is very heterogeneous.
2. How to aggregate events within an epoch?
3. What if no event within an epoch?
4. Time is treated as index or conditioning variable, not easy to deal with time-related queries.

Outline of the Seminar

REPRESENTATION: TEMPORAL POINT PROCESSES

1. Intensity function
2. Basic building blocks
3. Superposition
4. Marks and SDEs with jumps

APPLICATIONS: MODELS

1. Information propagation
2. Opinion dynamics
3. Information reliability
4. Knowledge acquisition

APPLICATIONS: CONTROL

1. Influence maximization
2. Activity shaping
3. When to post
4. When to fact check

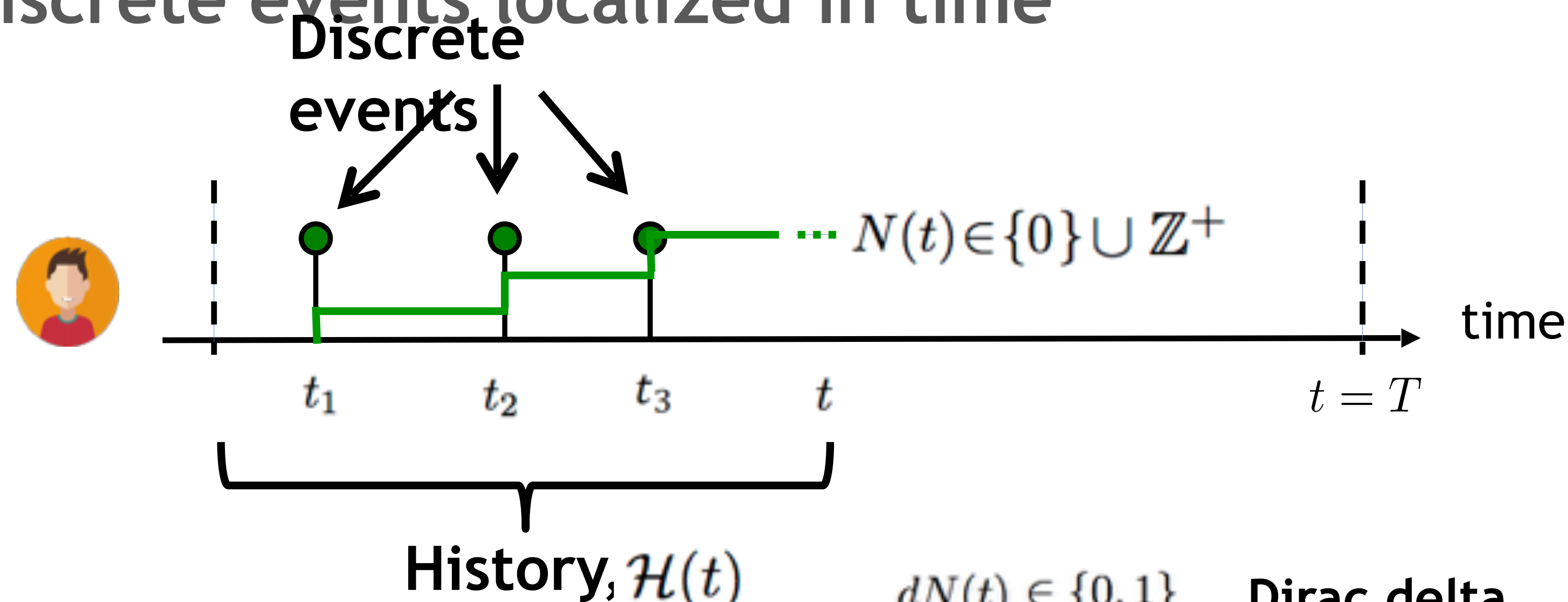
This lecture

Representation: Temporal Point Processes

1. Intensity function
2. Basic building blocks
3. Superposition
4. Marks and SDEs with jumps

Temporal point processes

Temporal point process:
A random process whose realization consists of
discrete events localized in time



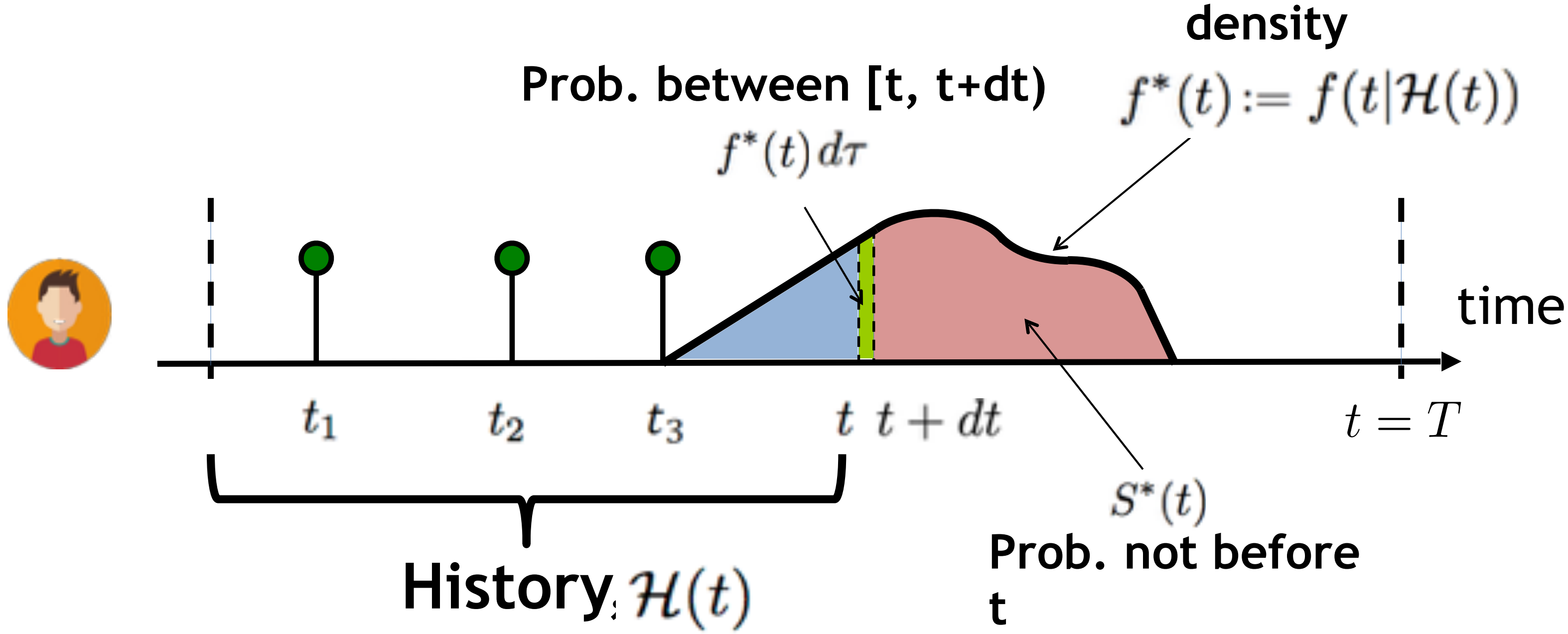
$dN(t) \in \{0, 1\}$

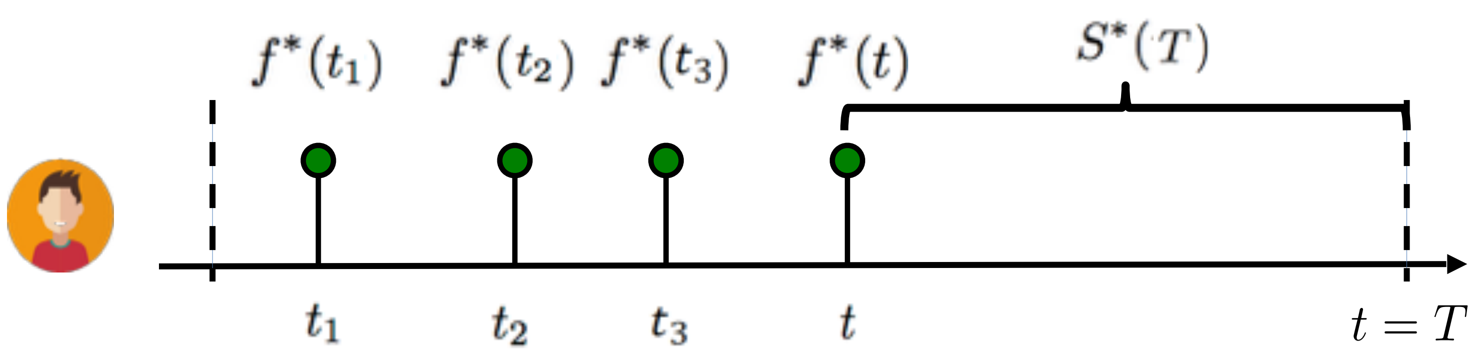
Dirac delta function

Formally:

$$N(t) = \int_0^t dN(s) \Rightarrow dN(t) = \sum_{t_i \in \mathcal{H}(t)} \delta(t - t_i)\, dt$$

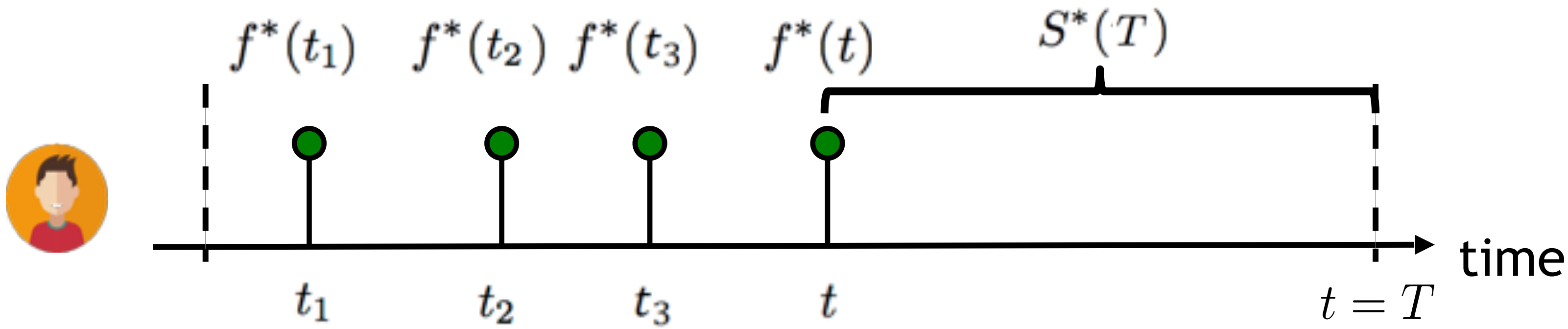
Model time as a random variable





Likelihood of a timeline: $f^*(t_1)\; f^*(t_2)\; f^*(t_3)\; f^*(t)\;\; S^*(T)$

Problems of density parametrization (I)



$$f^*(t_1) \quad f^*(t_2) \quad f^*(t_3) \quad f^*(t) \quad S^*(T)$$

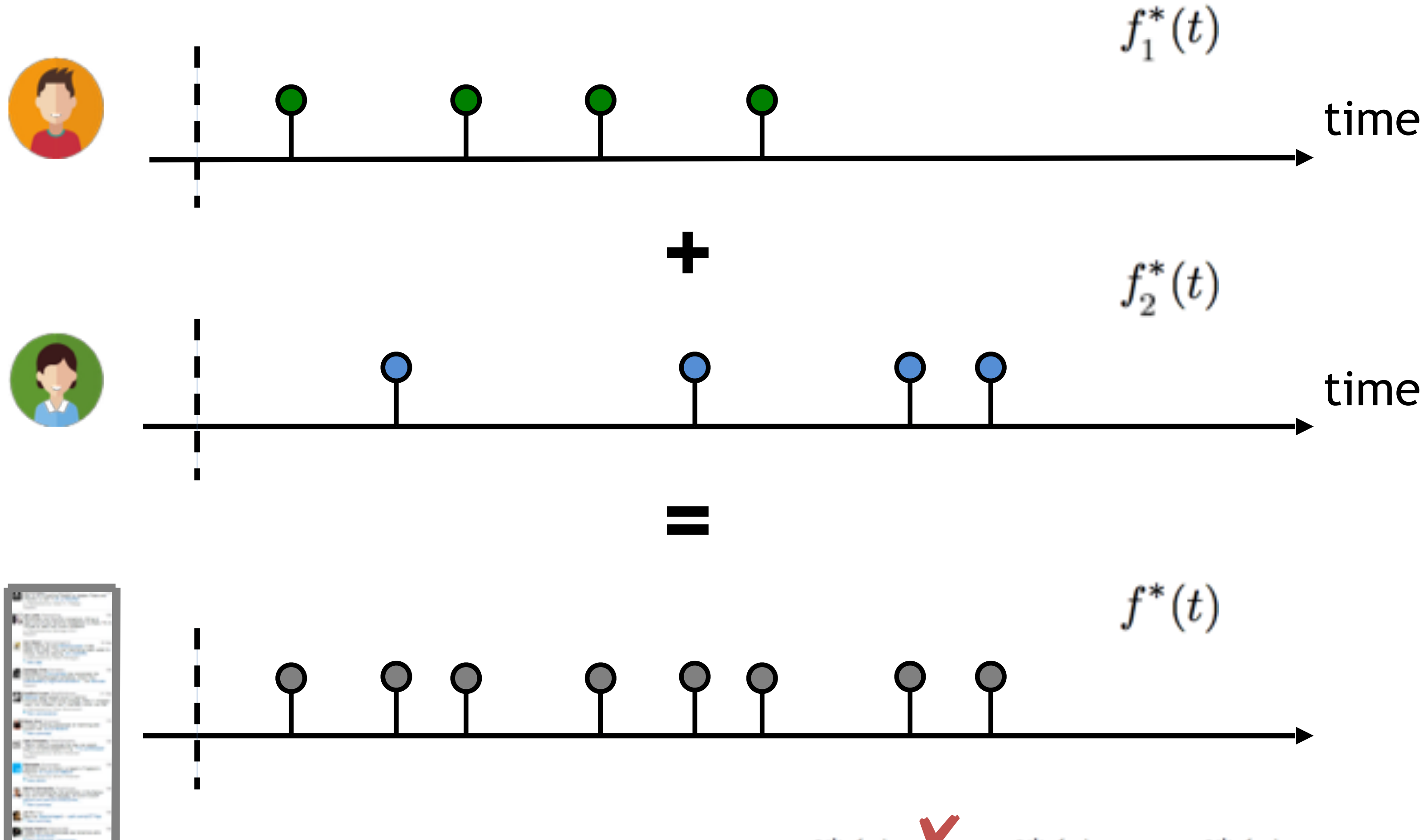
$$\frac{\exp\langle w, \psi^*(t_1)\rangle}{Z} \quad \frac{\exp\langle w, \psi^*(t_2)\rangle}{Z} \quad \frac{\exp\langle w, \psi^*(t_3)\rangle}{Z} \quad \frac{\exp\langle w, \psi^*(t)\rangle}{Z} \quad 1 - \int_t^T \frac{\exp\langle w, \psi^*(\tau)\rangle}{Z} d\tau$$

It is difficult for model design and interpretability:

1. **Densities need to integrate to 1 (i.e., partition function)**
2. **Difficult to combine timelines**

Problems of density parametrization (II)

Difficult to combine timelines:

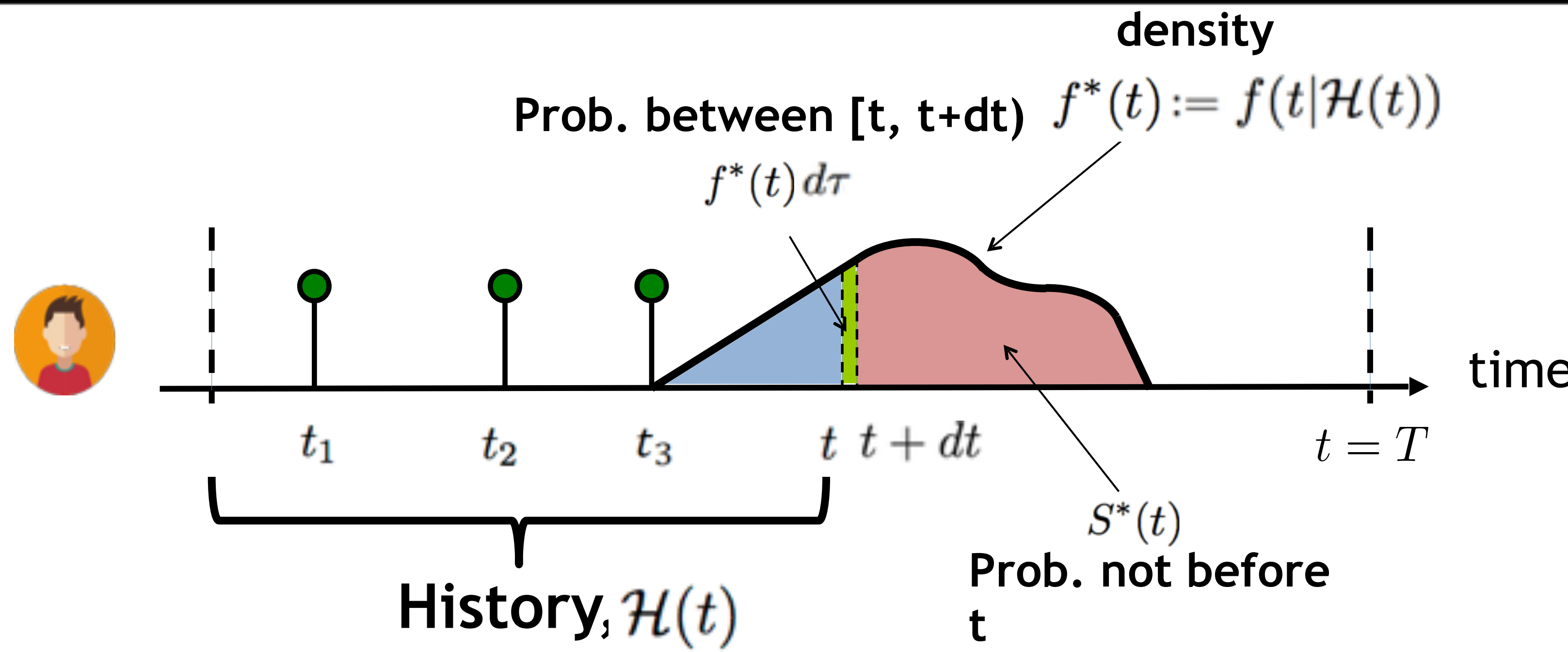


Sum of random processes

$$f^*(t) \neq f_1^*(t) + f_2^*(t)$$

$$f^*(t) \neq f_1^*(t) * f_2^*(t)$$

Intensity function



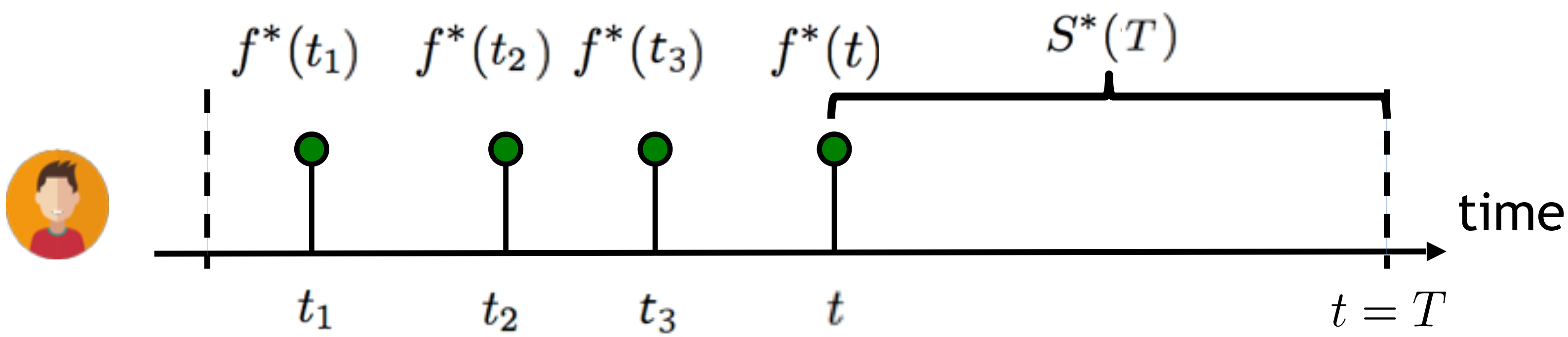
Intensity:

Probability between [t, t+dt) but not before t

$$\lambda^*(t)dt = \frac{f^*(t)dt}{S^*(t)} \geq 0 \quad \Rightarrow \quad \lambda^*(t)dt = \mathbb{E}[dN(t)|\mathcal{H}(t)]$$

Observation: $\lambda^*(t)$ **It is a rate = # of events / unit of time**

Advantages of intensity parametrization (I)



$$\lambda^*(t_1)\ \lambda^*(t_2)\ \lambda^*(t_3)\ \lambda^*(t)\ \exp\left(-\int_0^T \lambda^*(\tau)\, d\tau\right)$$

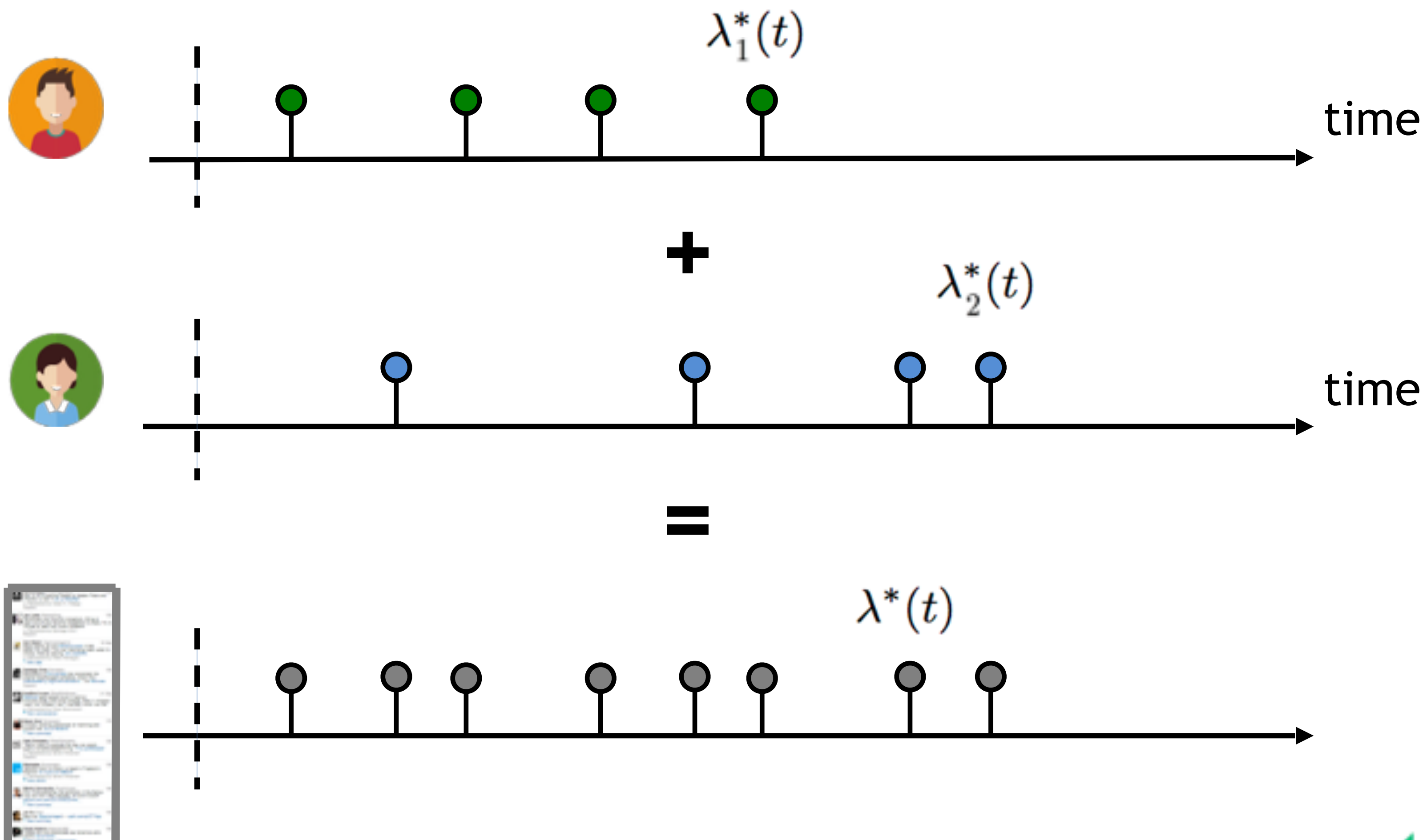
$\langle w, \phi^*(t_1)\rangle$ $\langle w, \phi^*(t_2)\rangle$ $\langle w, \phi^*(t_3)\rangle$ $\langle w, \phi^*(t)\rangle$ $\exp\left(-\int_0^T \langle w, \phi^*(\tau)\rangle d\tau\right)$

Suitable for model design and **interpretable**:

1. **Intensities only need to be nonnegative**
2. **Easy to combine timelines**

Advantages of intensity parametrization (II)

Easy to combine timeline:

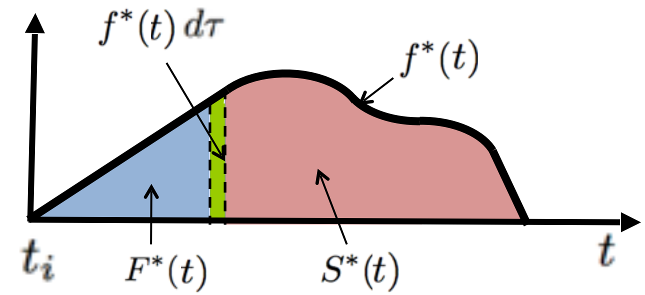


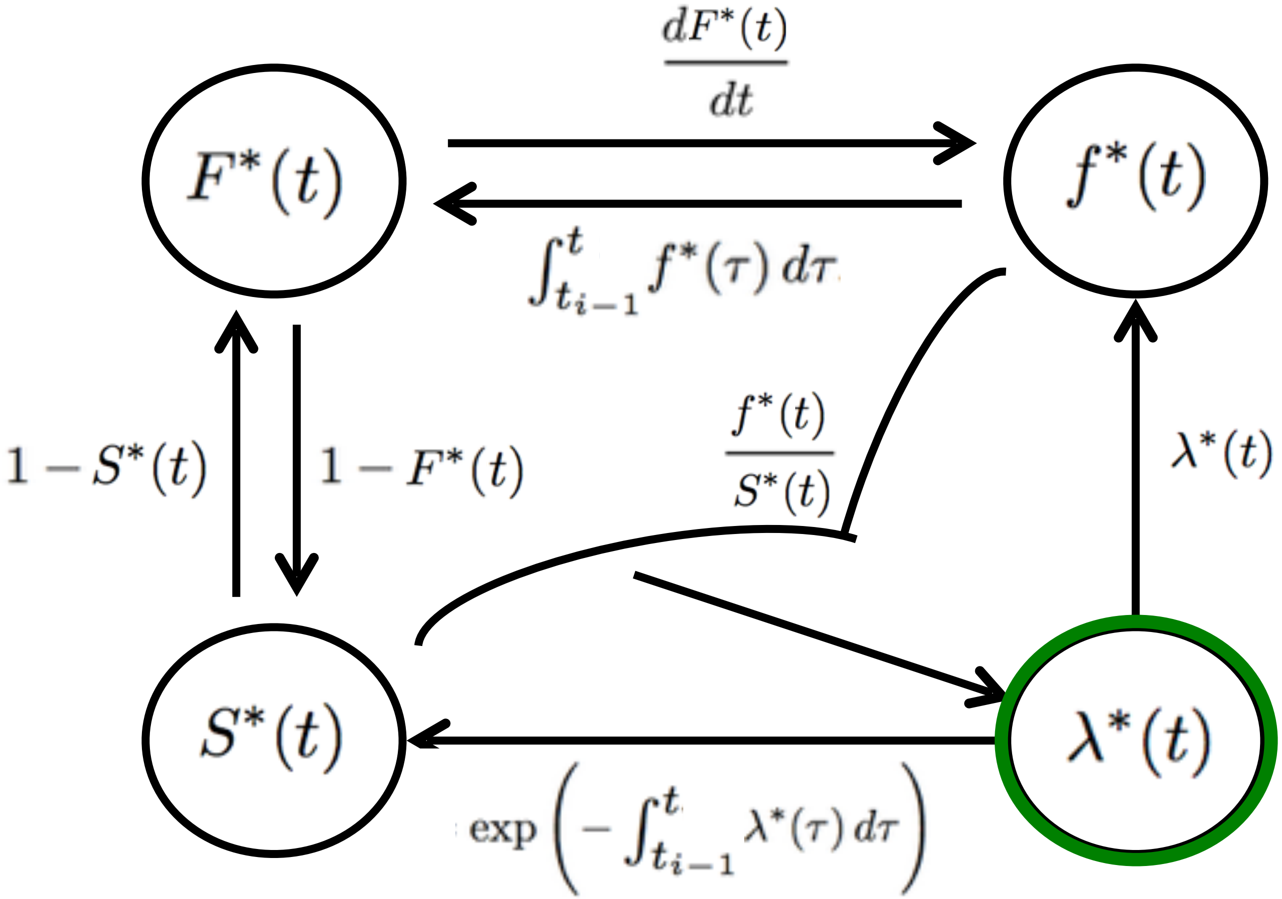
Sum of random processes

$$\lambda^*(t) = \lambda_1^*(t) + \lambda_2^*(t) \quad ✔$$

$$\lambda^*(t) \neq \lambda_1^*(t) * \lambda_2^*(t) \quad ✗$$

Relation between f*, F*, S*, λ*



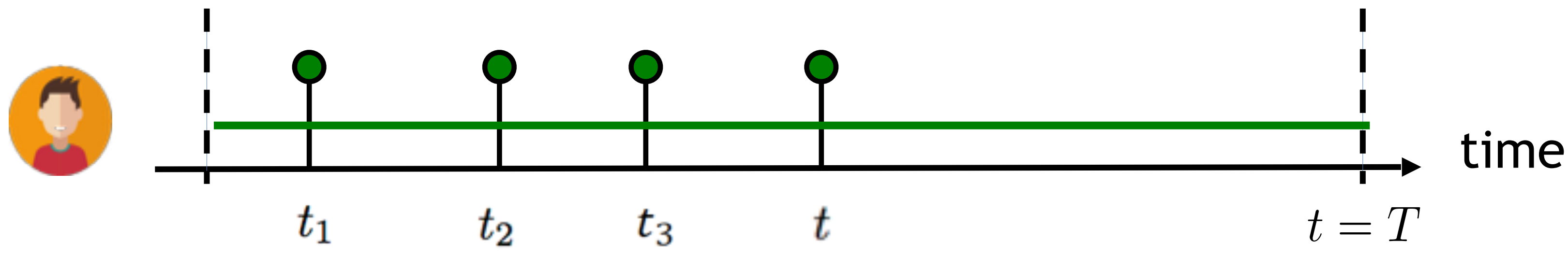


Central quantity we will use!

Representation: Temporal Point Processes

1. Intensity function
2. **Basic building blocks**
3. Superposition
4. Marks and SDEs with jumps

Poisson process



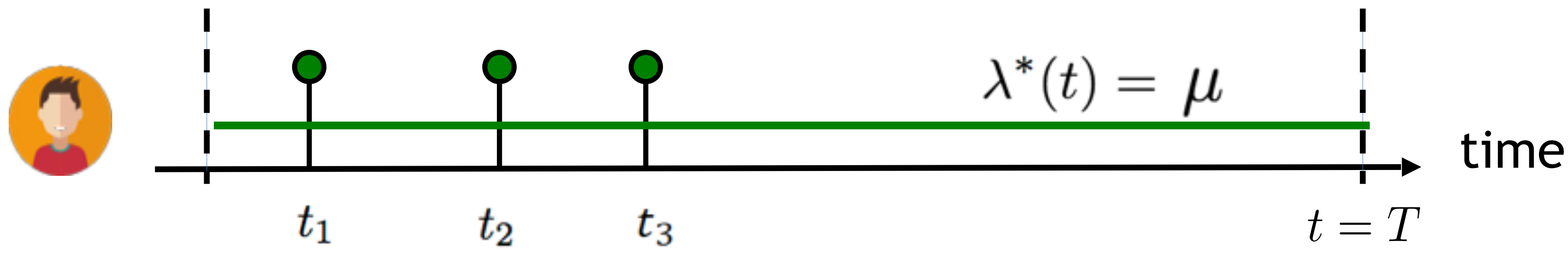
Intensity of a Poisson process

$$\lambda^*(t) = \mu$$

Observations
:

1. **Intensity independent of history**
2. **Uniformly random occurrence**
3. **Time interval follows exponential distribution**

Fitting a Poisson from (historical) timeline

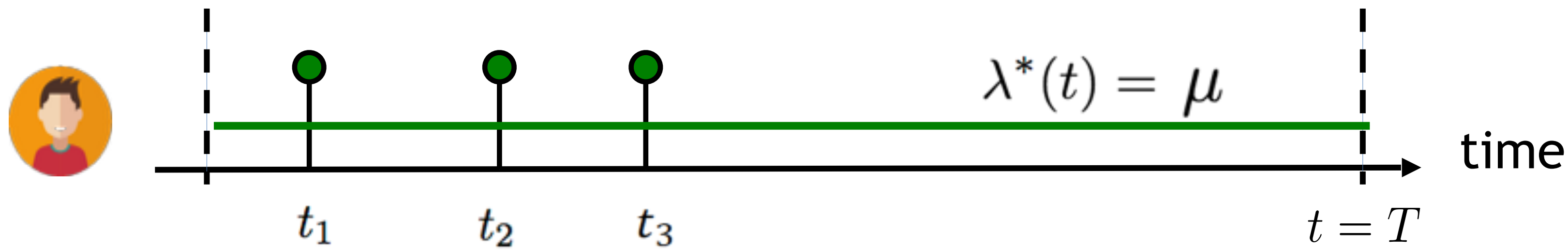


$$\underset{\overset{\uparrow}{\mu}}{\lambda^*(t_1)}\;\underset{\overset{\uparrow}{\mu}}{\lambda^*(t_2)}\;\underset{\overset{\uparrow}{\mu}}{\lambda^*(t_3)}\;\underbrace{\exp\left(-\int_0^T \lambda^*(\tau)\,d\tau\right)}_{\exp(-\mu\,T)}$$

Maximum likelihood

$$\mu^* = \underset{\mu}{\operatorname{argmax}}\;\; 3\log\mu \;-\; \mu\,T \;=\; \frac{3}{T}$$

Sampling from a Poisson process



We would like to sample: $t \sim \mu \exp(-\mu(t - t_3))$

We sample using inversion sampling:

$Uniform(0,1)$

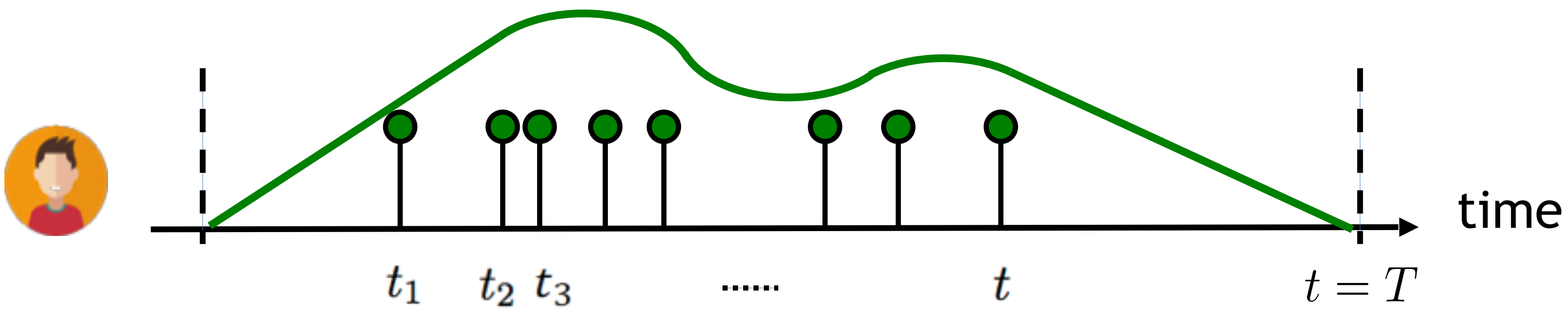
$$F_t(t) = 1 - \exp(-\mu(t - t_3)) \Rightarrow t \sim -\frac{1}{\mu}\log(1-u) + t_3$$

$F_t^{-1}(u)$

$$\mathbb{P}(F_t^{-1}(u) \le t) = \mathbb{P}(u \le F_t(t)) = F_t(t)$$

$F_u(u) = u$

Inhomogeneous Poisson process



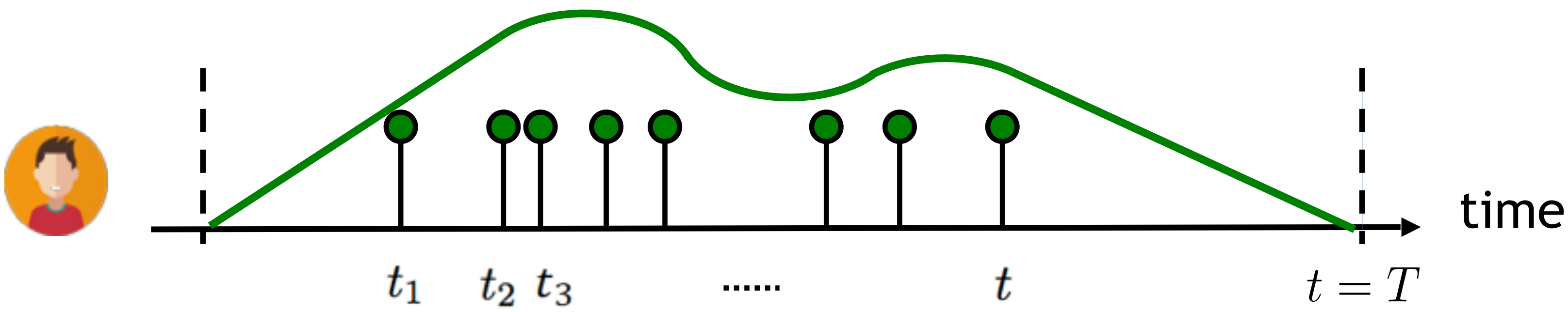
Intensity of an inhomogeneous Poisson process

$$\lambda^*(t) = g(t) \geqslant 0$$

Observations
:

1. **Intensity independent of history**

Fitting an inhomogeneous Poisson



$$\lambda^*(t_1)\lambda^*(t_2)\,\lambda^*(t_3)\cdots\cdots\lambda^*(t_n)\;\exp\left(-\int_0^T \lambda^*(\tau)\,d\tau\right)$$

$$\uparrow \qquad \uparrow \qquad \uparrow \qquad \uparrow$$

$$g(t_1)\quad g(t_2)\quad g(t_3)\quad\quad g(t_n)\qquad \exp\left(-\int_0^T g(\tau)\,d\tau\right)$$

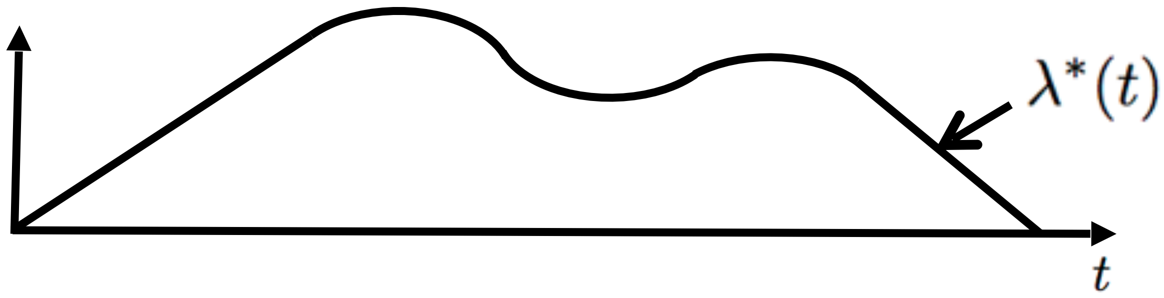
Maximum likelihood

$$\underset{g(t)}{\text{maximize}}\ \sum_{i=1}^{n} \log g(t_i) - \int_0^T g(\tau)\,d\tau$$

Desig $g(t)$ such that max. likelihood is convex

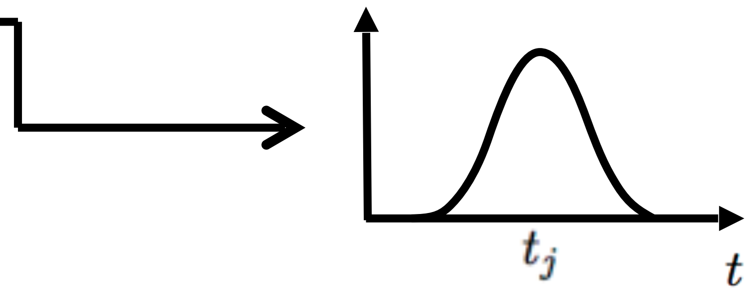
(and use CVX)

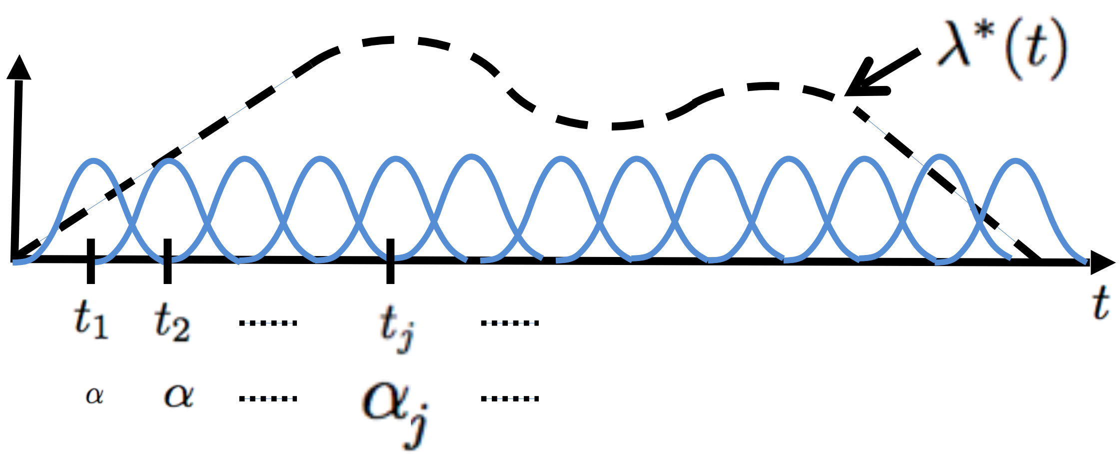
Nonparametric inhomogeneous Poisson process



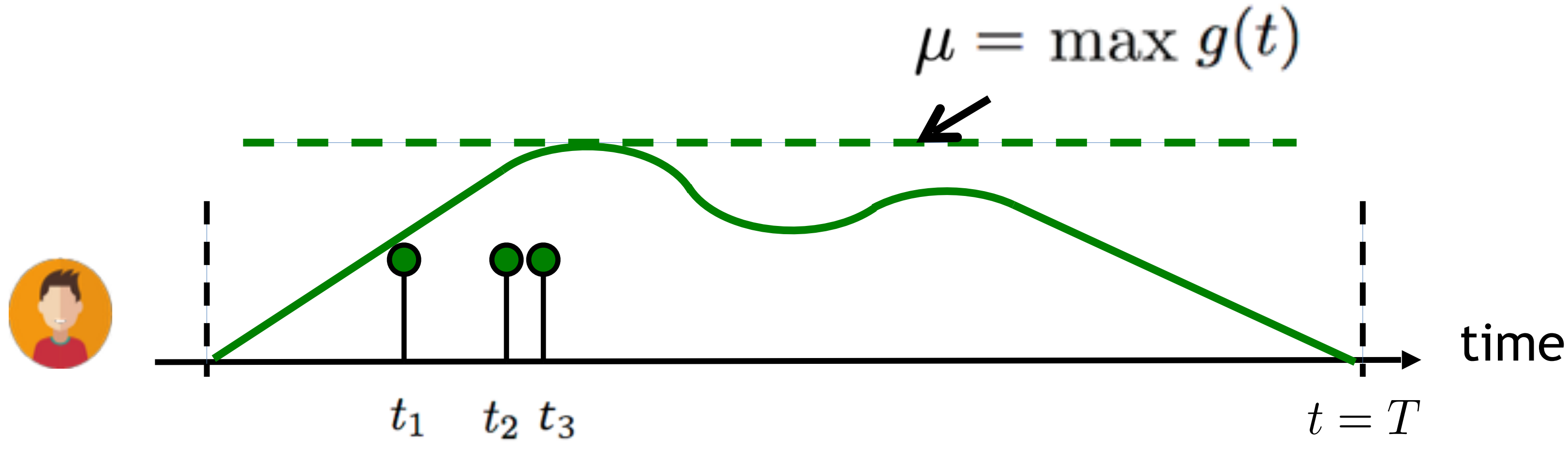
Positive combination of (Gaussian) RFB kernels:

$$\lambda^*(t) = \sum_j \alpha_j k(t - t_j)$$





Sampling from an inhomogeneous Poisson



Thinning procedure (similar to rejection sampling):

1. Sample t from Poisson process with inte μity

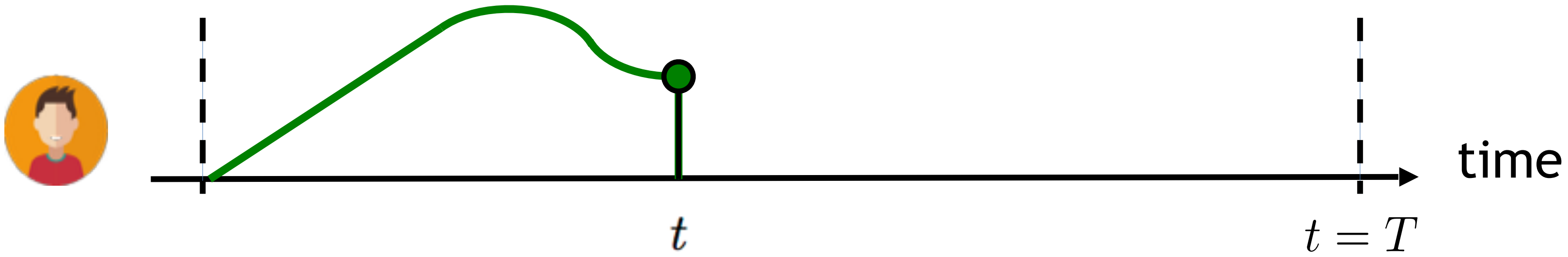
$$t \sim -\frac{1}{\mu} \log(1 - u) + t_3$$

($u \sim Uniform(0,1)$) — Inversion sampling

2. Generate $u_2 \sim Uniform(0,1)$
3. Keep the sample i $u_2 \leq g(t) / \mu$

Keep sample with p $g(t)/\mu$

Terminating (or survival) process



Intensity of a terminating (or survival) process

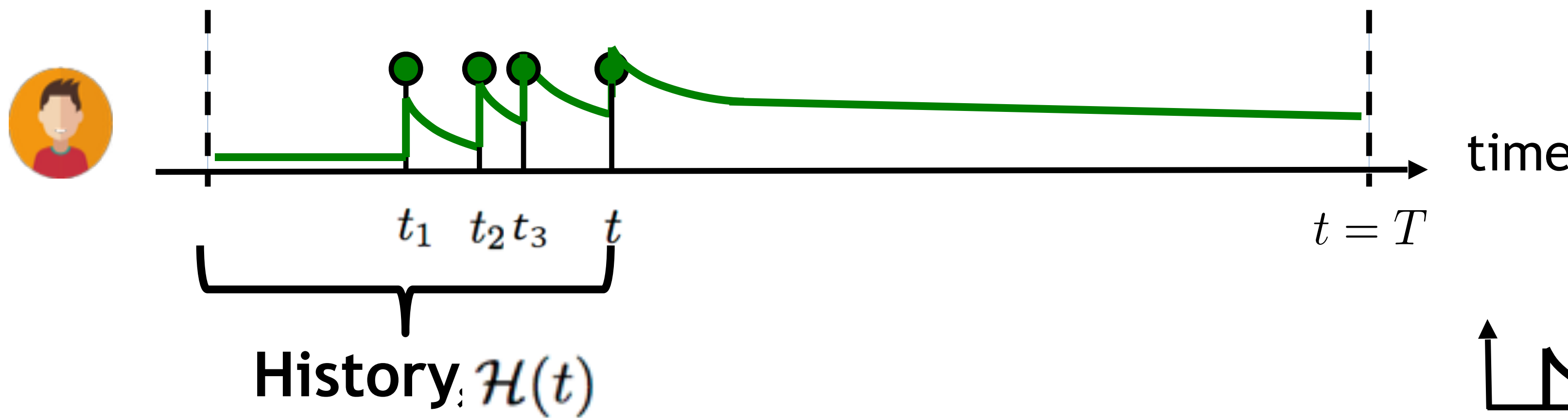
$$\lambda^*(t) = g^*(t)(1 - N(t)) \geqslant 0$$

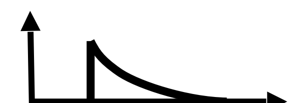
Observations:

1. **Limited number of occurrences**

Try sampling and fitting!

Self-exciting (or Hawkes) process





Triggering kernel

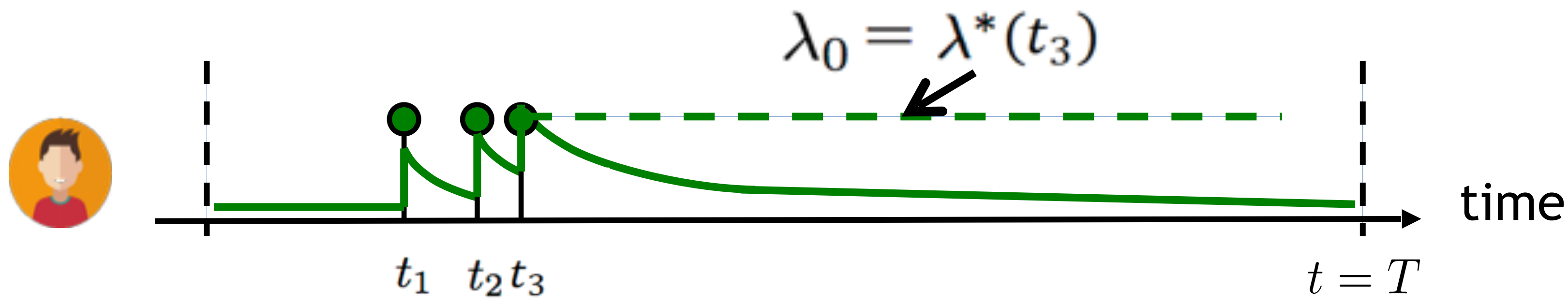
Intensity of self-excitin (or Hawkes) process:

$$\lambda^*(t) = \mu + \alpha \sum_{t_i \in \mathcal{H}(t)} \kappa_\omega(t - t_i)$$
$$= \mu + \alpha \kappa_\omega(t) \star dN(t)$$

Observations :

1. Clustered (or bursty) occurrence of events
2. Intensity is stochastic and history dependent

Fitting a Hawkes process from a recorded timeline



$$\lambda^*(t_1)\lambda^*(t_2)\,\lambda^*(t_3) \cdots\cdots \lambda^*(t_n)\;\exp\left(-\int_0^T \lambda^*(\tau)\,d\tau\right)$$

$$\lambda^*(t) = \mu + \alpha \sum\nolimits_{t_i \in \mathcal{H}(t)} \kappa_\omega(t - t_i)$$

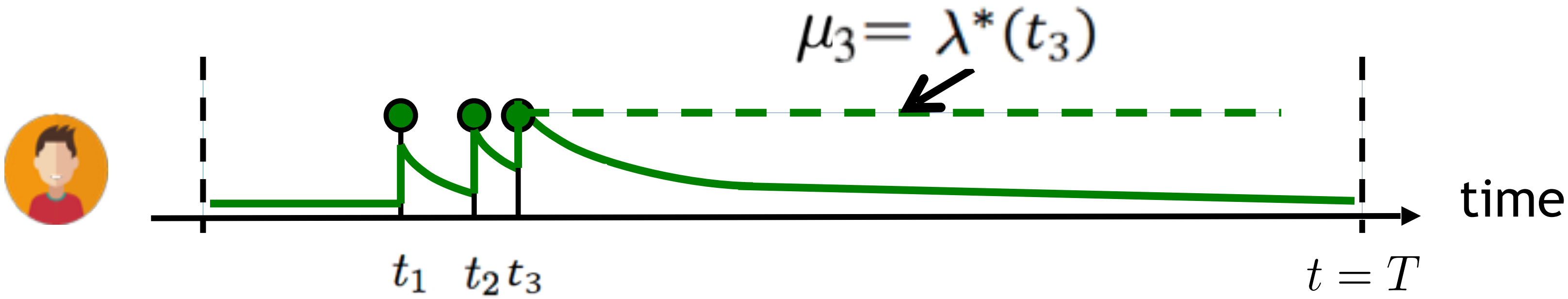
Maximum likelihood

$$\underset{\mu,\alpha}{\text{maximize}} \sum_{i=1}^{n} \log \lambda^*(t_i) - \int_0^T \lambda^*(\tau)\,d\tau$$

The max. likelihood is jointly convex in μ and α

(use CVX!)

Sampling from a Hawkes process



Thinning procedure (similar to rejection sampling):

1. Sample t from Poisson process with inte μ_3 ity

$$t \sim -\frac{1}{\mu_3} \log(1 - u) + t_3$$

$u \leftarrow Uniform(0,1)$

Inversion sampling

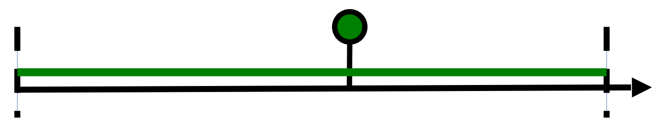
2. Generate $u_2 \sim Uniform(0,1)$
3. Keep the sample i $u_2 \leq g(t) / \mu_3$

Keep sample with p $g(t)/\mu_3$

Summary

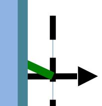
Building blocks to represent **different dynamic processes:**

Poisson processes:



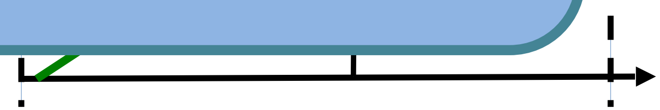
$$\lambda^*(t) = \lambda$$

Inho



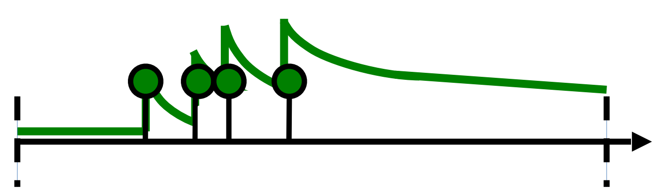
We know **how to fit** them
and **how to sample** from them

Term



$$\lambda^*(t) = g^*(t)(1 - N(t))$$

Self-exciting point processes:

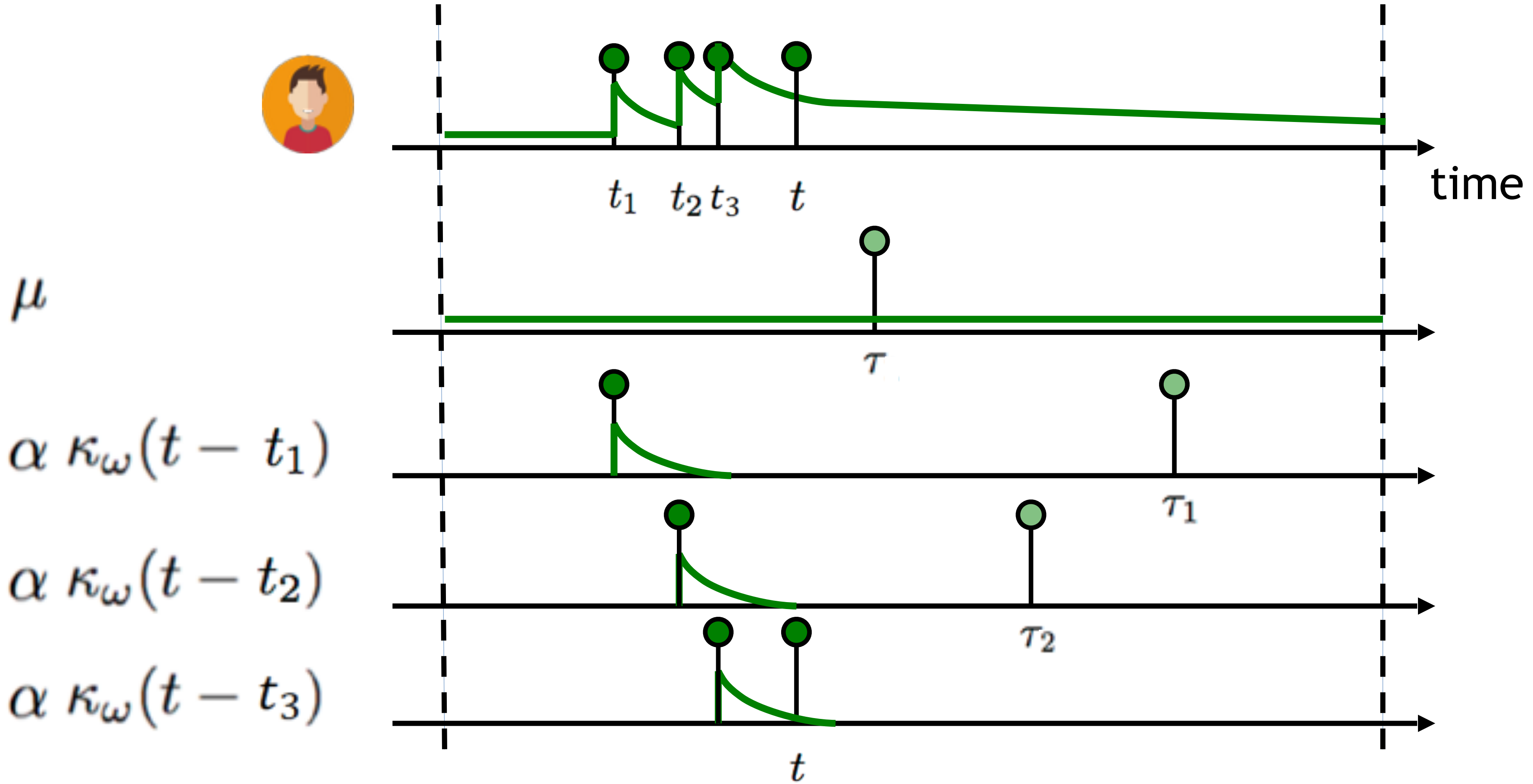


$$\lambda^*(t) = \mu + \alpha \sum_{t_i \in \mathcal{H}(t)} \kappa_\omega(t - t_i)$$

Representation:
Temporal Point Processes

1. Intensity function
2. Basic building blocks
3. Superposition
4. Marks and SDEs with jumps

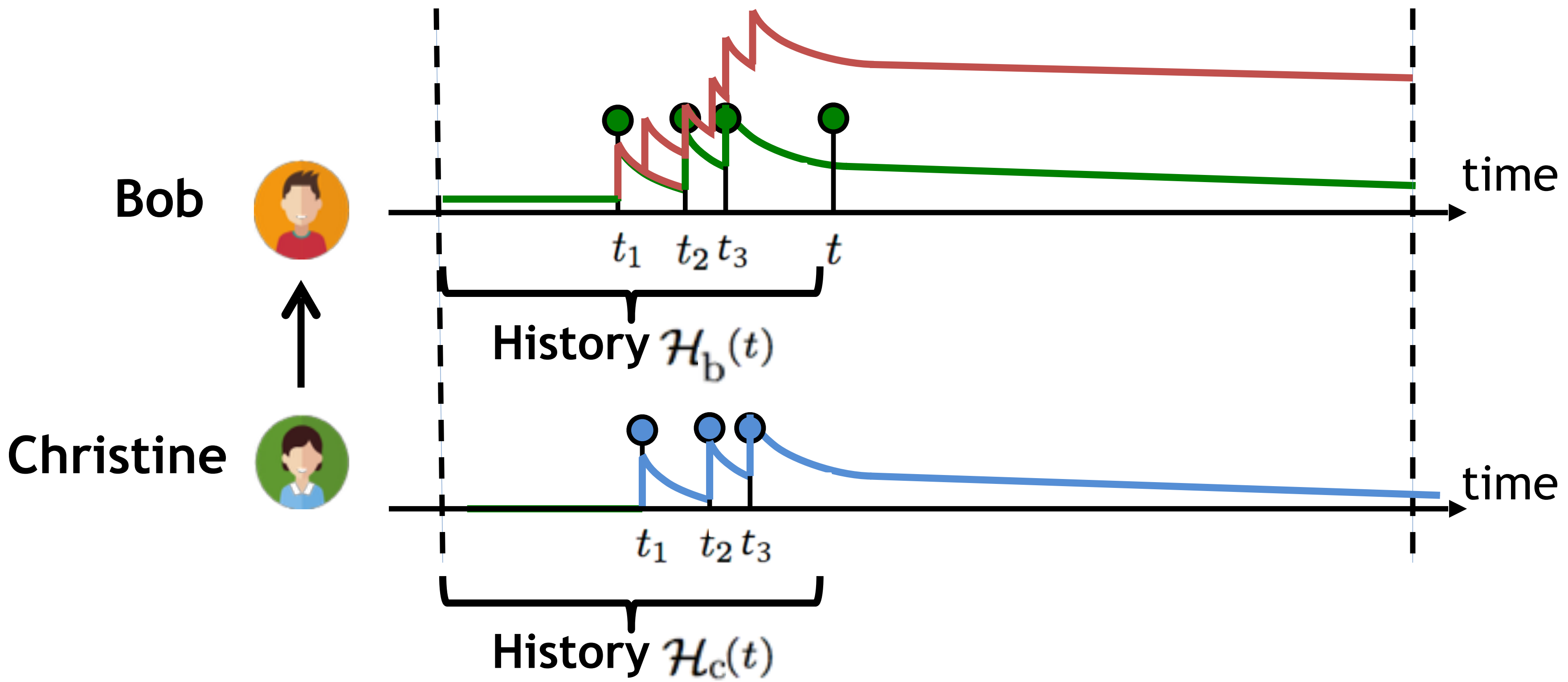
Superposition of processes



Sample each intensity + take minimum = Additive intensity

$$t = \min(\tau, \tau_1, \tau_2, \tau_3) \Rightarrow \lambda^*(t) = \mu + \alpha \sum_{t_i \in \mathcal{H}(t)} \kappa_\omega(t - t_i)$$

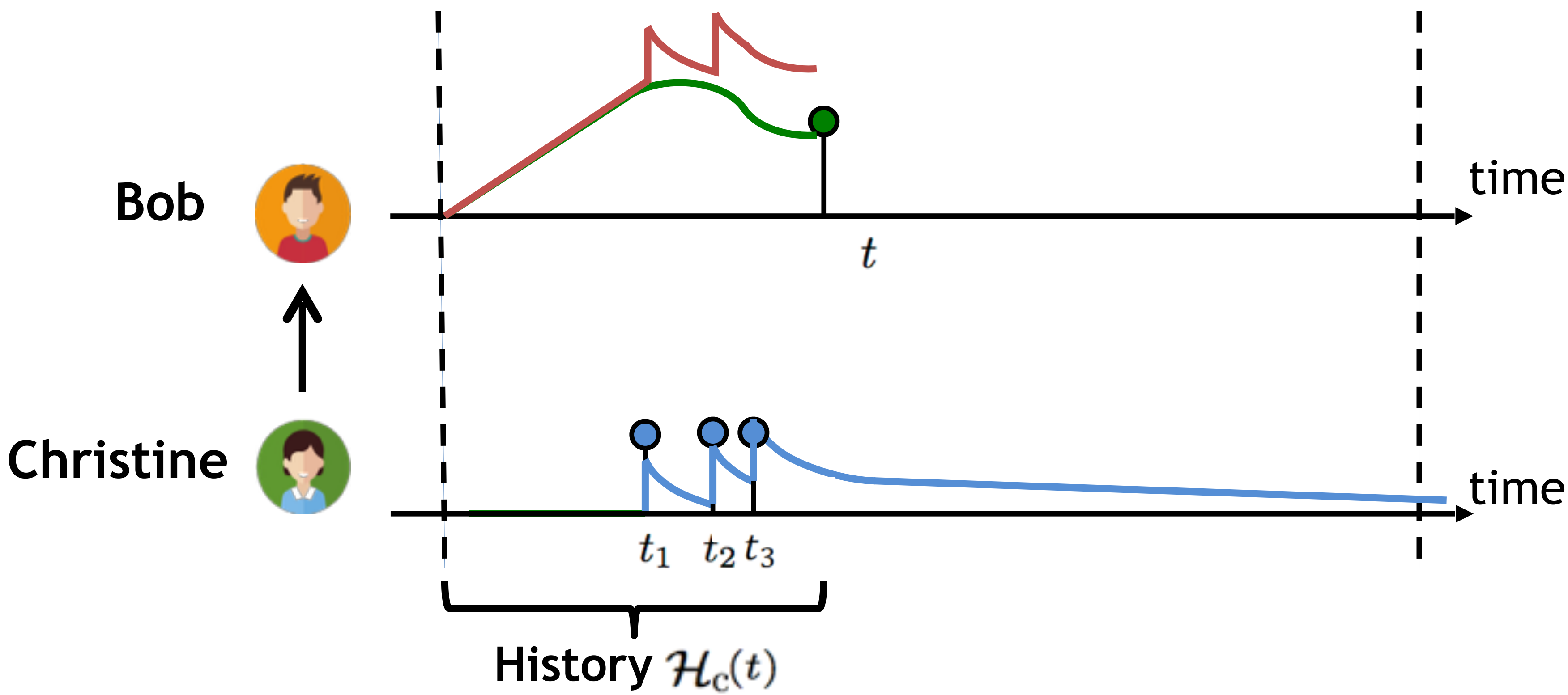
Mutually exciting process



Clustered occurrence affected by neighbors

$$\lambda^*(t) = \mu + \alpha \sum_{t_i \in \mathcal{H}_b(t)} \kappa_\omega(t - t_i) + \beta \sum_{t_i \in \mathcal{H}_c(t)} \kappa_\omega(t - t_i)$$

Mutually exciting terminating process



Clustered occurrence affected by neighbors

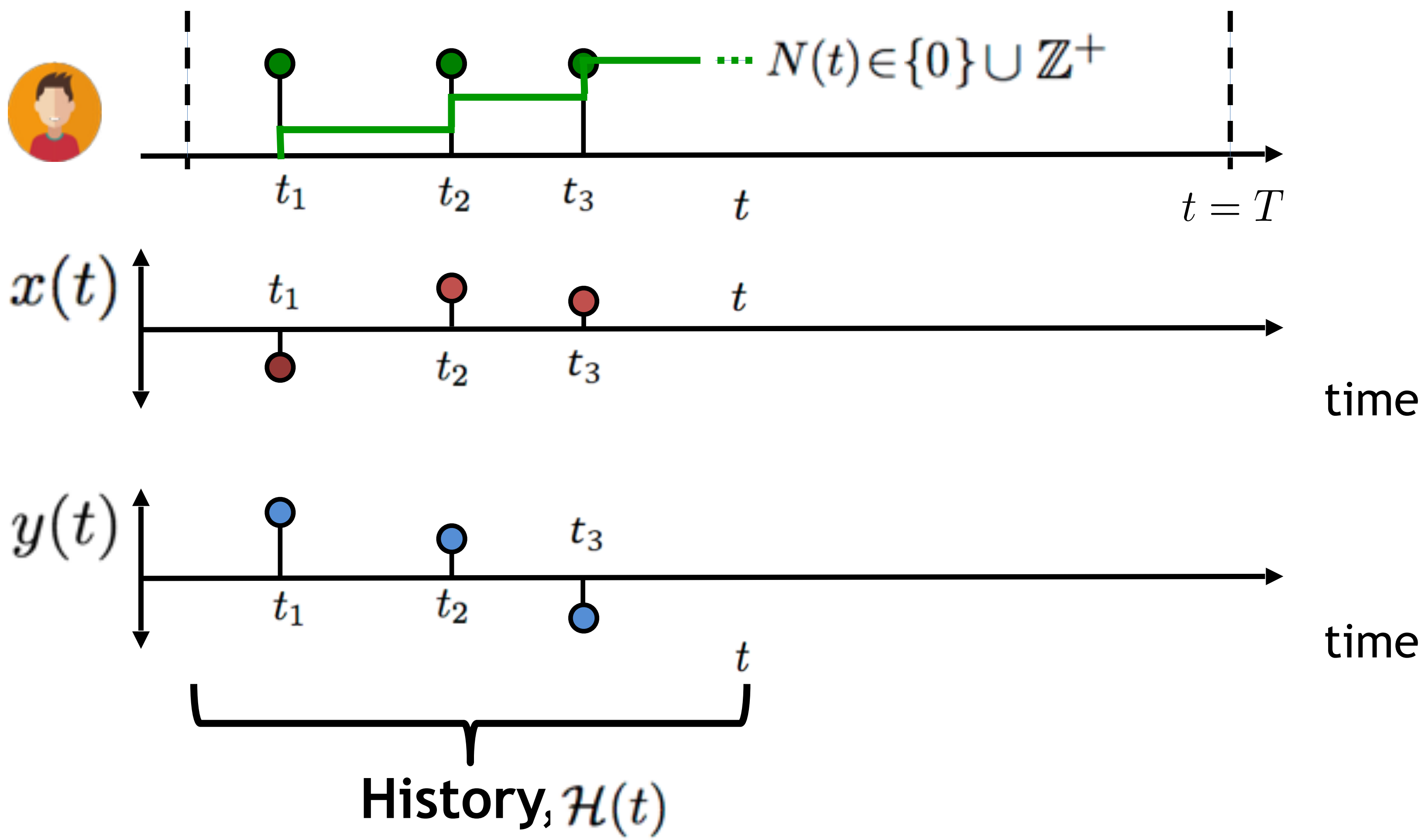
$$\lambda^*(t) = (1 - N(t))\Big(g(t) + \beta \sum_{t_i \in \mathcal{H}_c(t)} \kappa_\omega(t - t_i)\Big)$$

Representation:
Temporal Point Processes

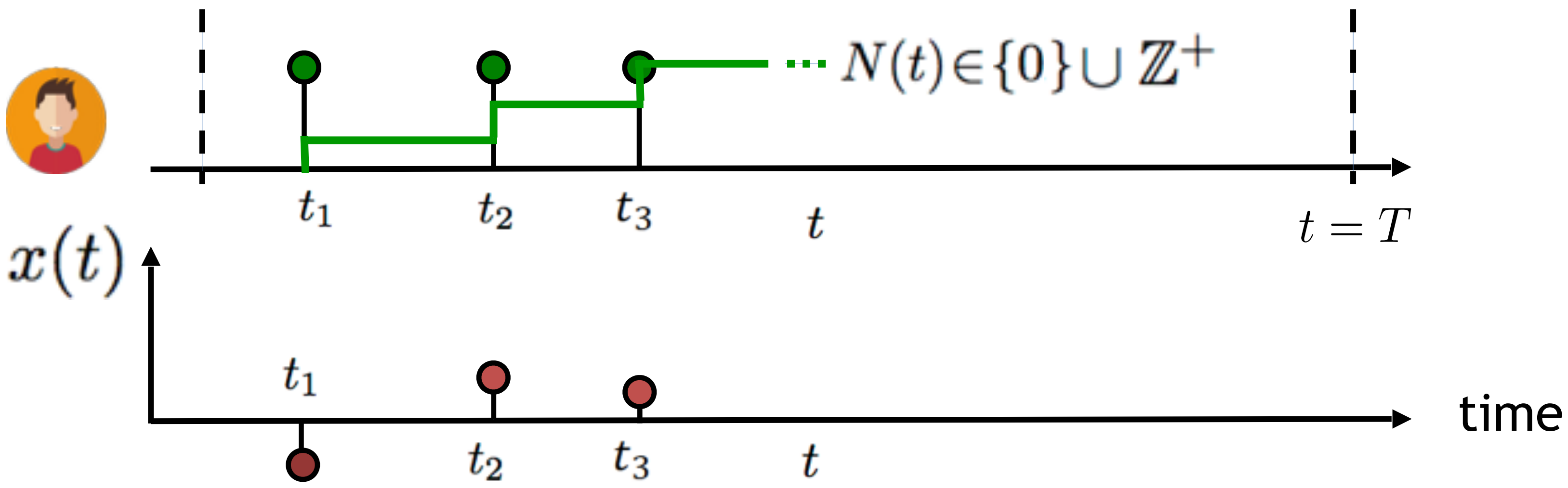
1. Intensity function
2. Basic building blocks
3. Superposition
4. **Marks and SDEs with jumps**

Marked temporal point processes

Marked temporal point process:
A random process whose realization consists of discrete *marked* events localized in time



Independent identically distributed marks



Distribution for the marks:

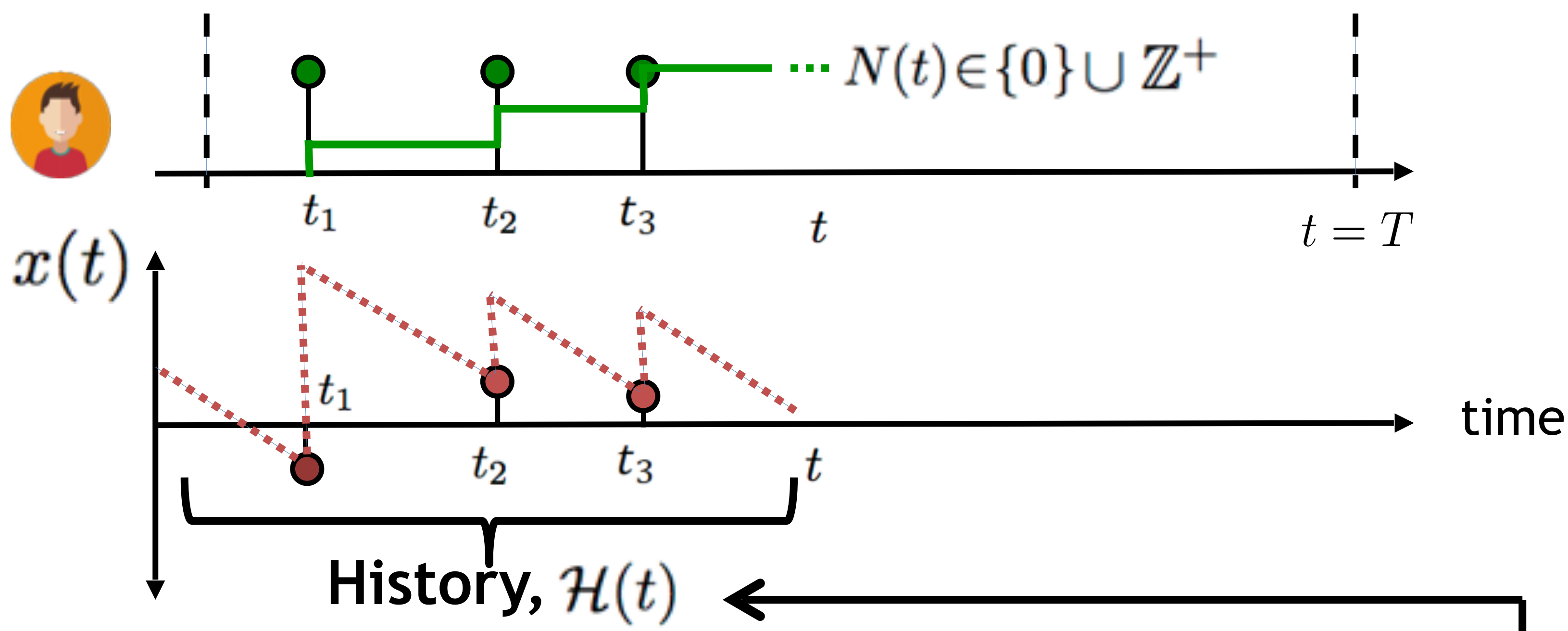
$$x^*(t_i) \sim p(x)$$

Observations

:

1. **Marks independent of the temporal dynamics**
2. **Independent identically distributed (I.I.D.)**

Dependent marks: SDEs with jumps



Marks given by stochastic differential equation with jumps:

$$x(t+dt) - x(t) = dx(t) = \underbrace{f(x(t),t)dt}_{\text{Drift}} + \underbrace{h(x(t),t)dN(t)}_{\text{Event influence}}$$

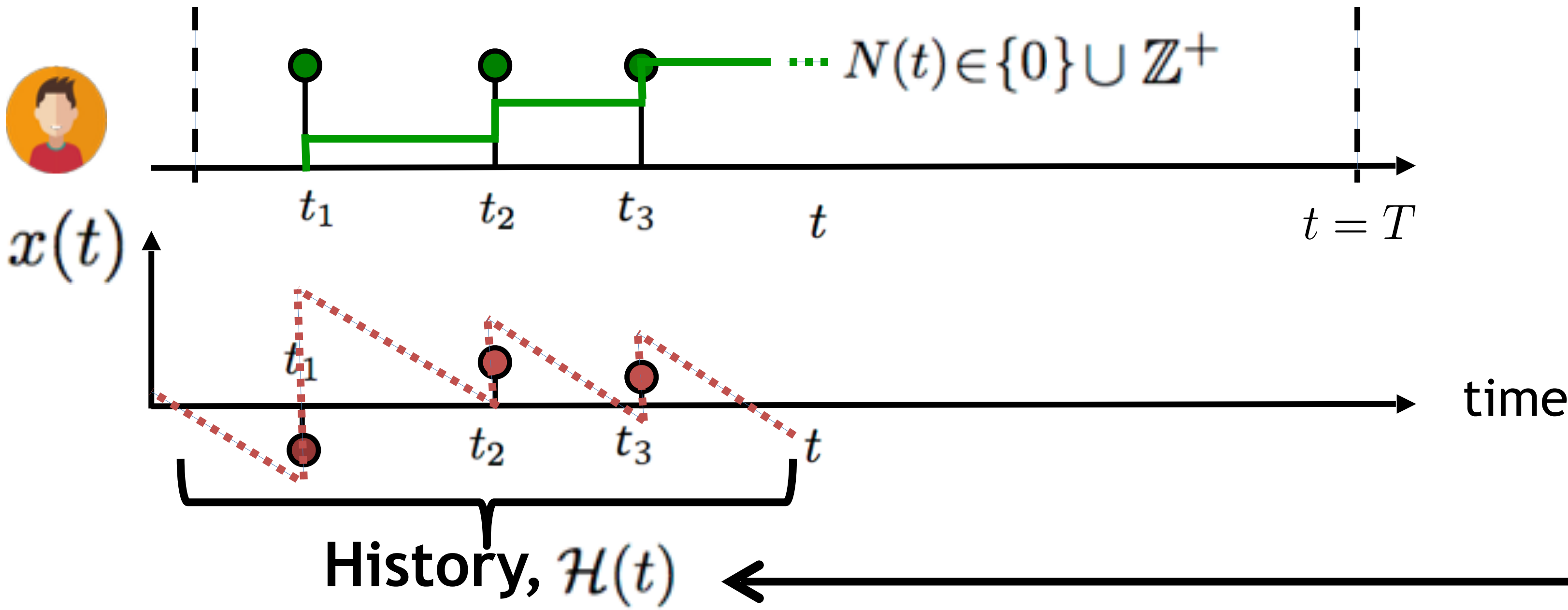
Drift

Event influence

Observations:

1. **Marks dependent of the temporal dynamics**
2. **Defined for all values of t**

Dependent marks: distribution + SDE with jumps



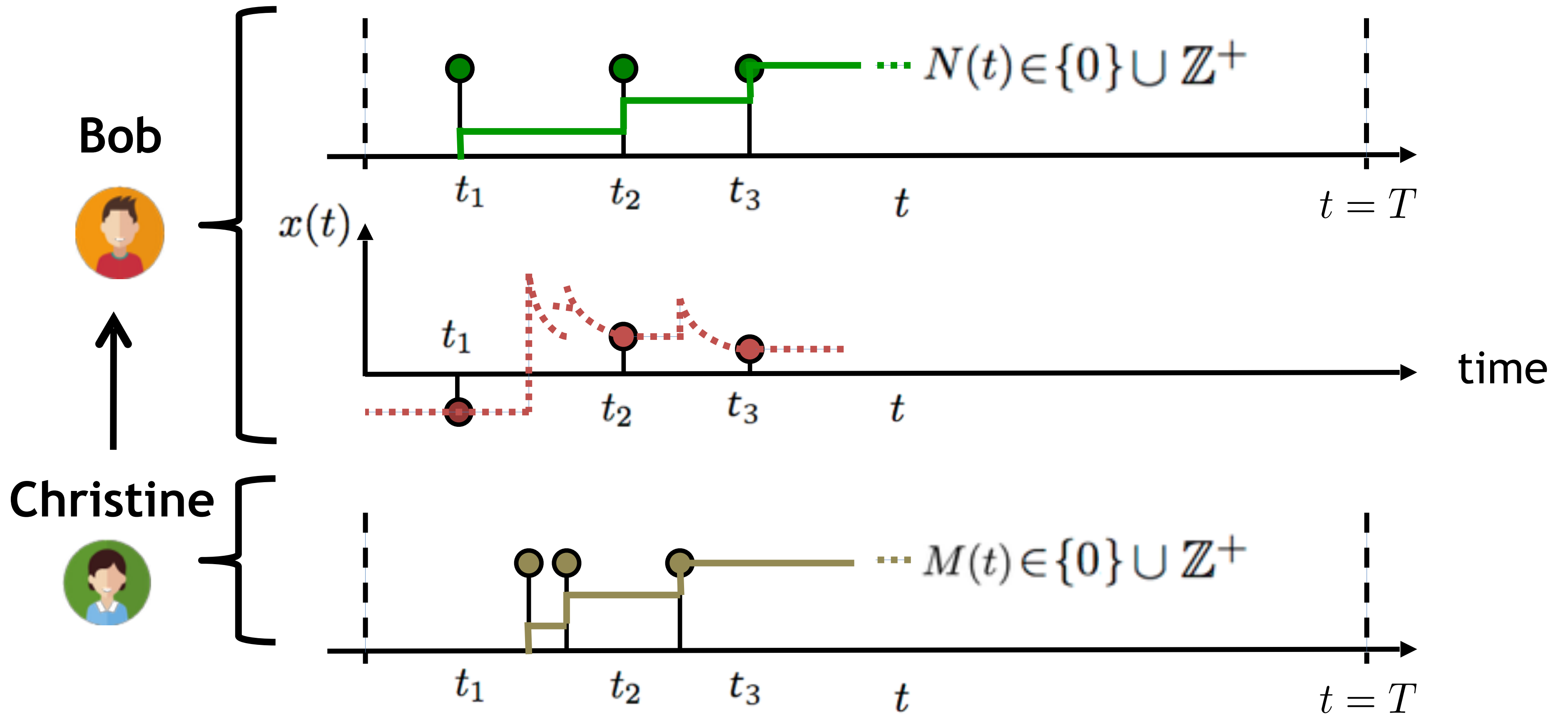
Distribution for the marks:

$$x^*(t_i) \sim p(x^* | x(t)) \Rightarrow dx(t) = \underbrace{f(x(t), t)dt}_{\text{Drift}} + \underbrace{h(x(t), t)dN(t)}_{\text{Event influence}}$$

Observations:

1. **Marks dependent on the temporal dynamics**
2. **Distribution represents additional source of uncertainty**

Mutually exciting + marks



Marks affected by neighbors

$$dx(t) = \underbrace{f(x(t), t)dt}_{\text{Drift}} + \underbrace{g(x(t), t)dM(t)}_{\text{Neighbor}}$$

Representation: Temporal Point Processes

1. Intensity function
2. Basic building blocks
3. Superposition
4. Marks and SDEs with jumps

This lecture

Applications: Models

1. Information propagation
2. Opinion dynamics
3. Information reliability
4. Knowledge acquisition

Next lecture

Applications: Control

1. Influence maximization
2. Activity shaping
3. When to post
4. When to fact check