

# Modeling Irregular Time Series

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2018—2021 Bloomberg Data Science Ph.D. Fellow

Johns Hopkins University

# Lecture Structure

# Lecture Structure

- Lecture-1: concepts

# Lecture Structure

- Lecture-1: concepts
  - Intensity, point process, MLE, thinning, ...

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- Lecture-1: concepts
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- Lecture-2: fancy models

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  - Hawkes, NHP, Neural ODE, ...

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- Lecture-3: advanced topics

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- Lecture-1: concepts
  - Intensity, point process, MLE, thinning, ...
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  - NCE, Datalog, marks, ...



# Lecture Structure

- Lecture-1: concepts
  - Intensity, point process, MLE, thinning, ...
- Lecture-2: fancy models
  - Hawkes, NHP, Neural ODE, ...
- Lecture-3: advanced topics
  - NCE, Datalog, marks, ...
  - Useful techniques to other kind of data

# Time Series

# Time Series



# Time Series

*e.g., 1 min chart*



# Time Series



# Time Series



**I like working at Bloomberg**

$W_1$

$W_2$

$W_3$

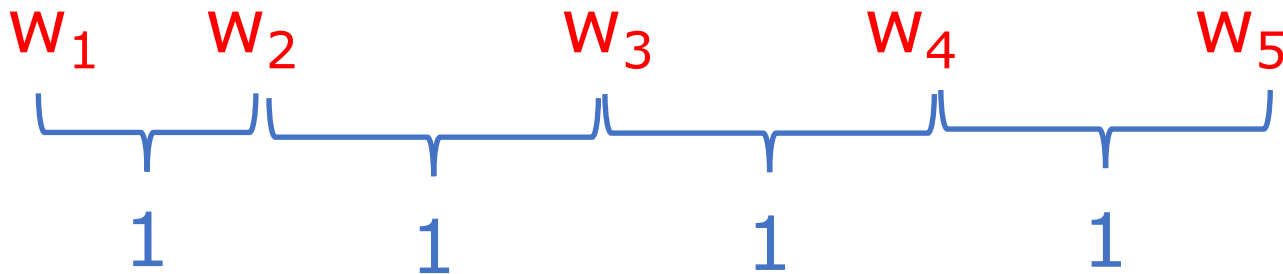
$W_4$

$W_5$

# Time Series



**I like working at Bloomberg**



# Irregular Time Series



# Irregular **Time Series**

```
{KI <GO>}
```

# Irregular Time Series

{KI <GO>}



# Irregular Time Series

{KI <GO>}



# Irregular Time Series

{KI <GO>}



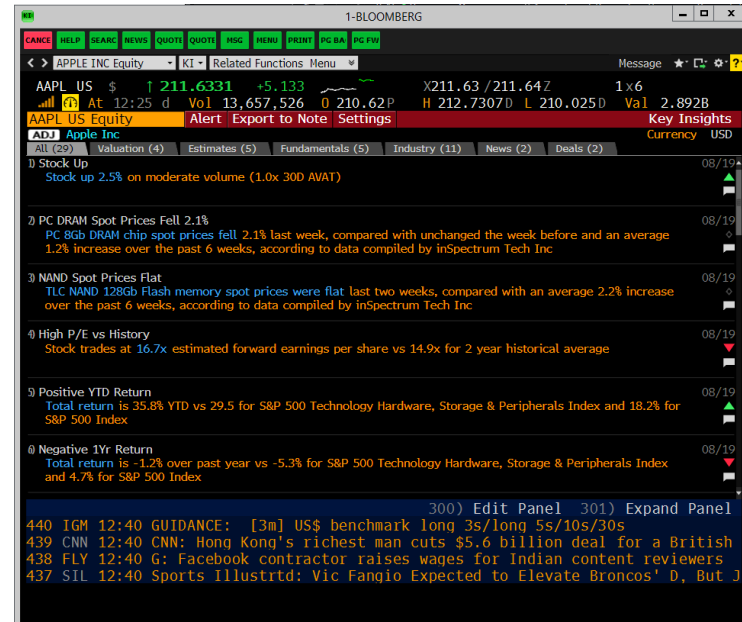
stock movement

earning announcement

rating change

implied volatility spike

...



# Irregular Time Series

{KI <GO>}



stock movement

earning announcement

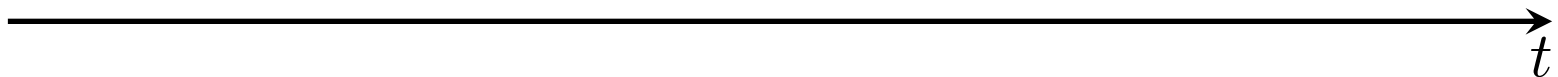
rating change

implied volatility spike

...



Market



# Irregular Time Series

{KI <GO>}



stock movement

earning announcement

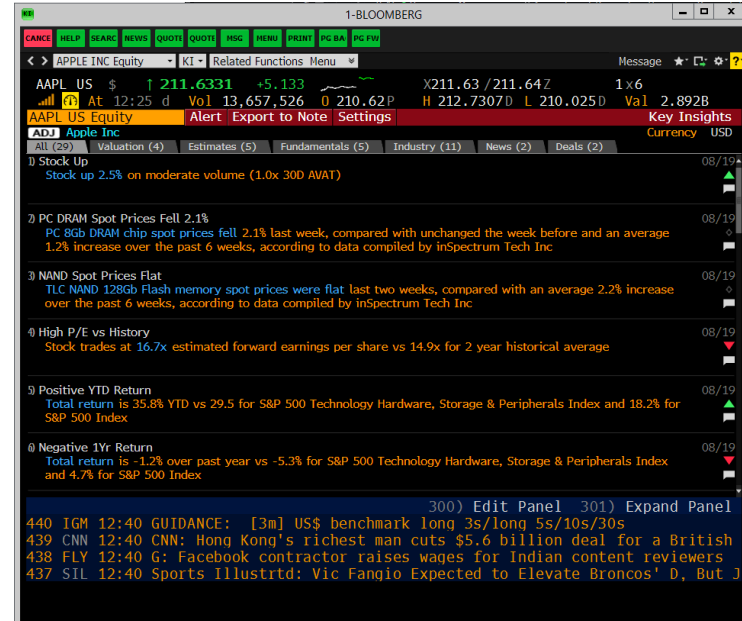
rating change

implied volatility spike

...

arrive stochastically!

Market



# Irregular Time Series

{KI <GO>}



stock movement

earning announcement

rating change

implied volatility spike

...

arrive stochastically!



Market

verizon<sup>✓</sup>



# Irregular Time Series

{KI <GO>}



stock movement

earning announcement

rating change

implied volatility spike

...

arrive stochastically!



verizon✓



FOXCONN

Market





# Irregular Time Series

{KI <GO>}



stock movement

earning announcement

rating change

implied volatility spike

...

arrive stochastically!



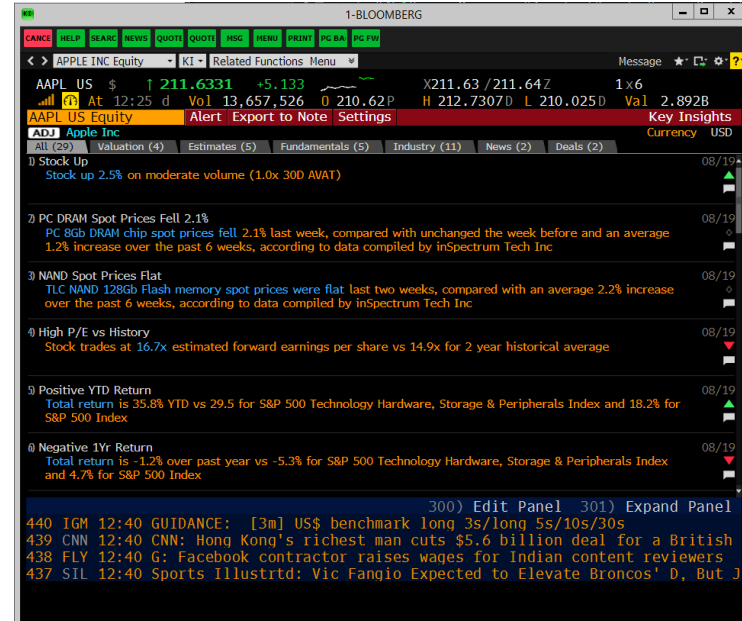
verizon✓



FOXCONN



Market



# Irregular Time Series

{KI <GO>}



stock movement

earning announcement

rating change

implied volatility spike

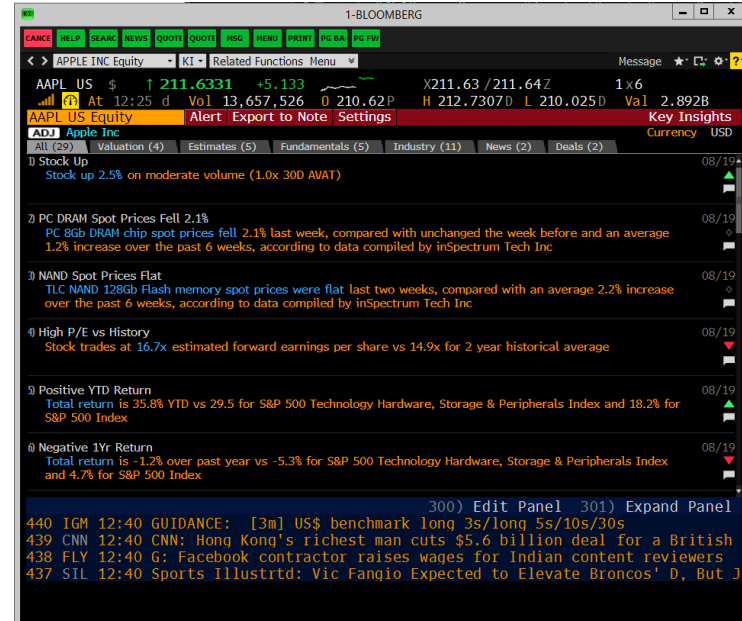
...

arrive stochastically!

Market

↑  
verizon✓

↓  
FOXCONN



# Irregular Time Series

{KI <GO>}



stock movement

earning announcement

rating change

implied volatility spike

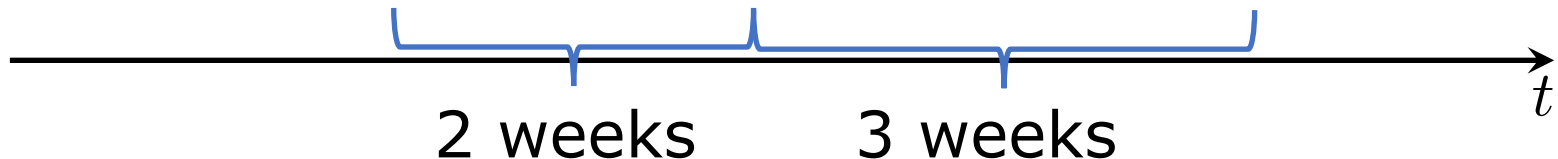
...

arrive stochastically!

Market

↑  
verizon✓

↓  
FOXCONN



# Irregular Time Series

{KI <GO>}



stock movement

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rating change

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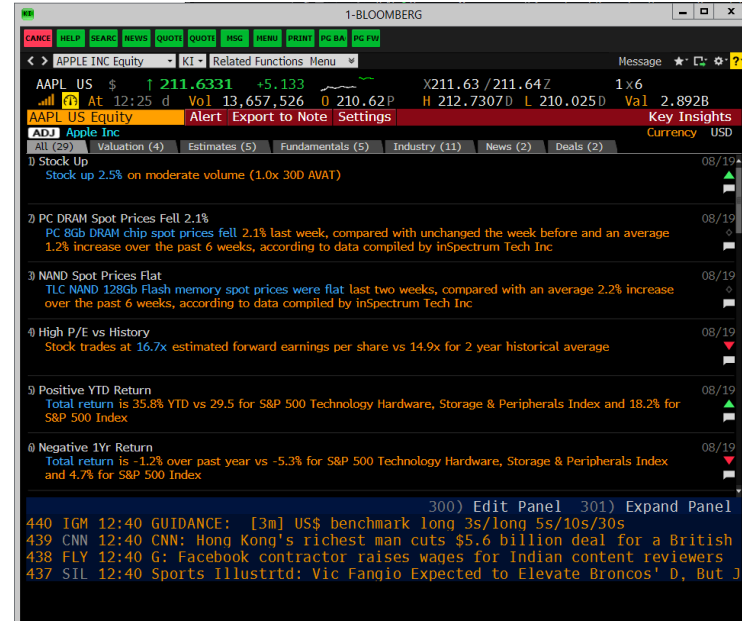
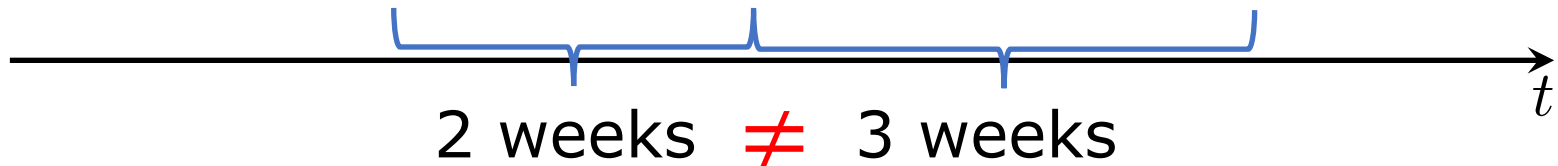
...

arrive stochastically!

Market

↑  
verizon✓

↓  
FOXCONN



# Irregular Time Series

{KI <GO>}



stock movement

earning announcement

rating change

implied volatility spike

...

arrive stochastically!

Market

verizon✓

FOXCONN



irregular intervals

2 weeks  $\neq$  3 weeks

t



# Irregular Time Series

Medical



$t$

# Irregular Time Series

Shopping



$t$

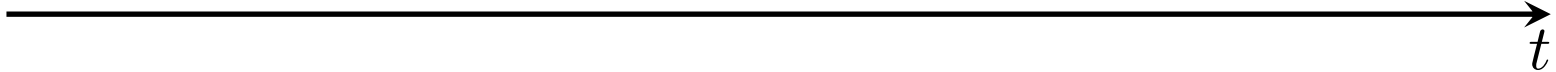
Medical



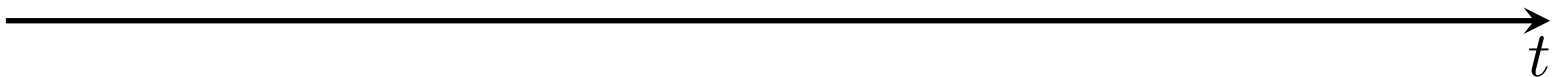
$t$

# Irregular Time Series

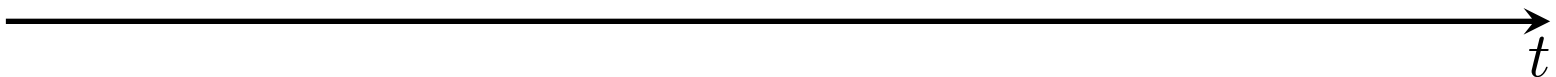
Social



Shopping



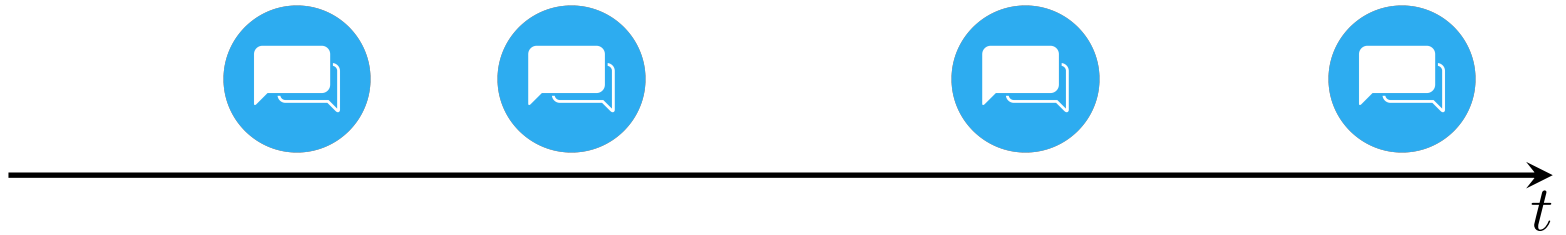
Medical



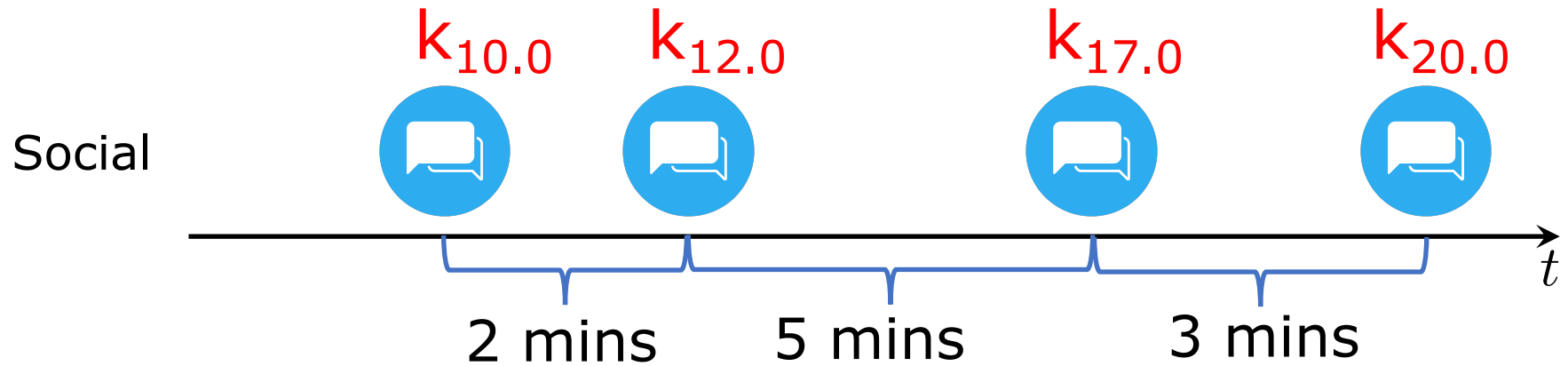


# Irregular Time Series

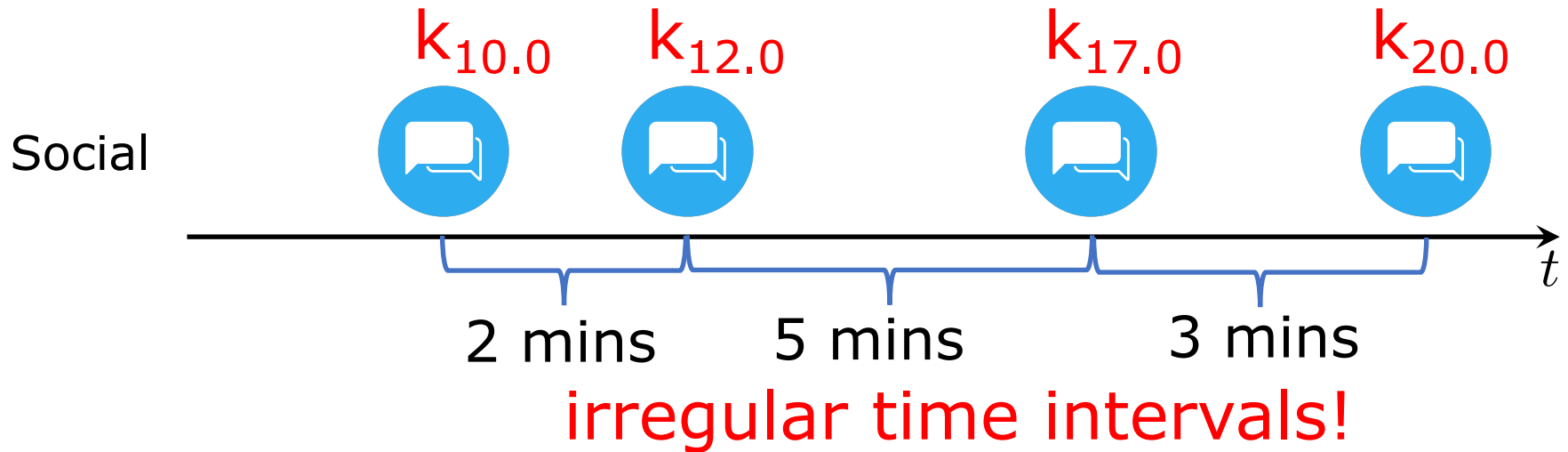
Social



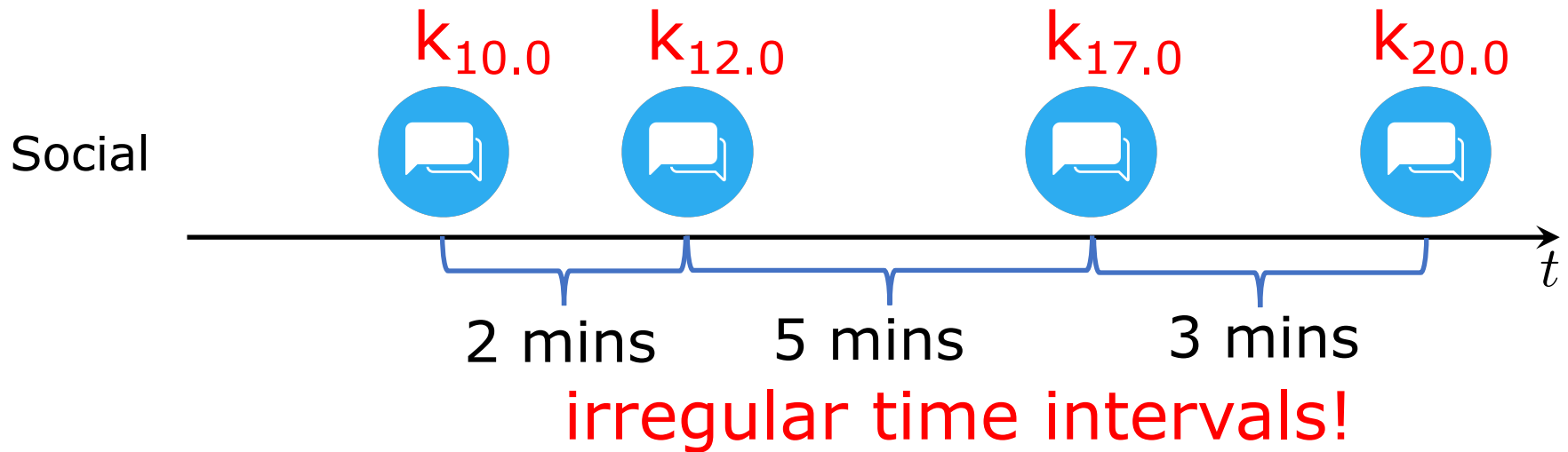
# Irregular Time Series



# Irregular Time Series



# Irregular Time Series



**I like working at Bloomberg**

$w_1$   $w_2$   $w_3$   $w_4$   $w_5$

regular intervals

**Any Questions?**

**<http://bburl/tpp-slides-p1>**

# Generative Story of Irregular **Time Series**

Social



$t$

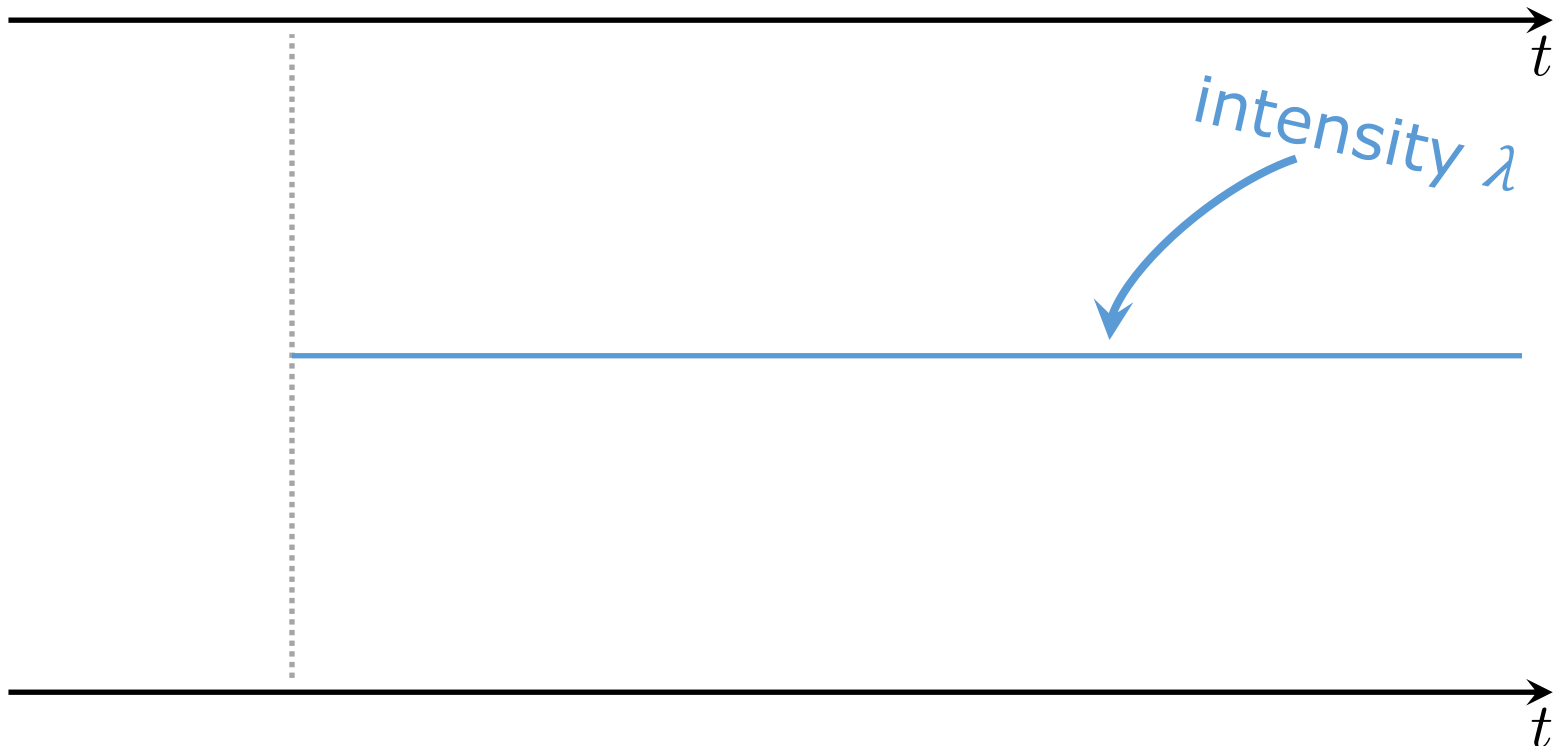
$t$

# Generative Story of Irregular **Time Series**

Social



intensity =  
rate of events per unit time

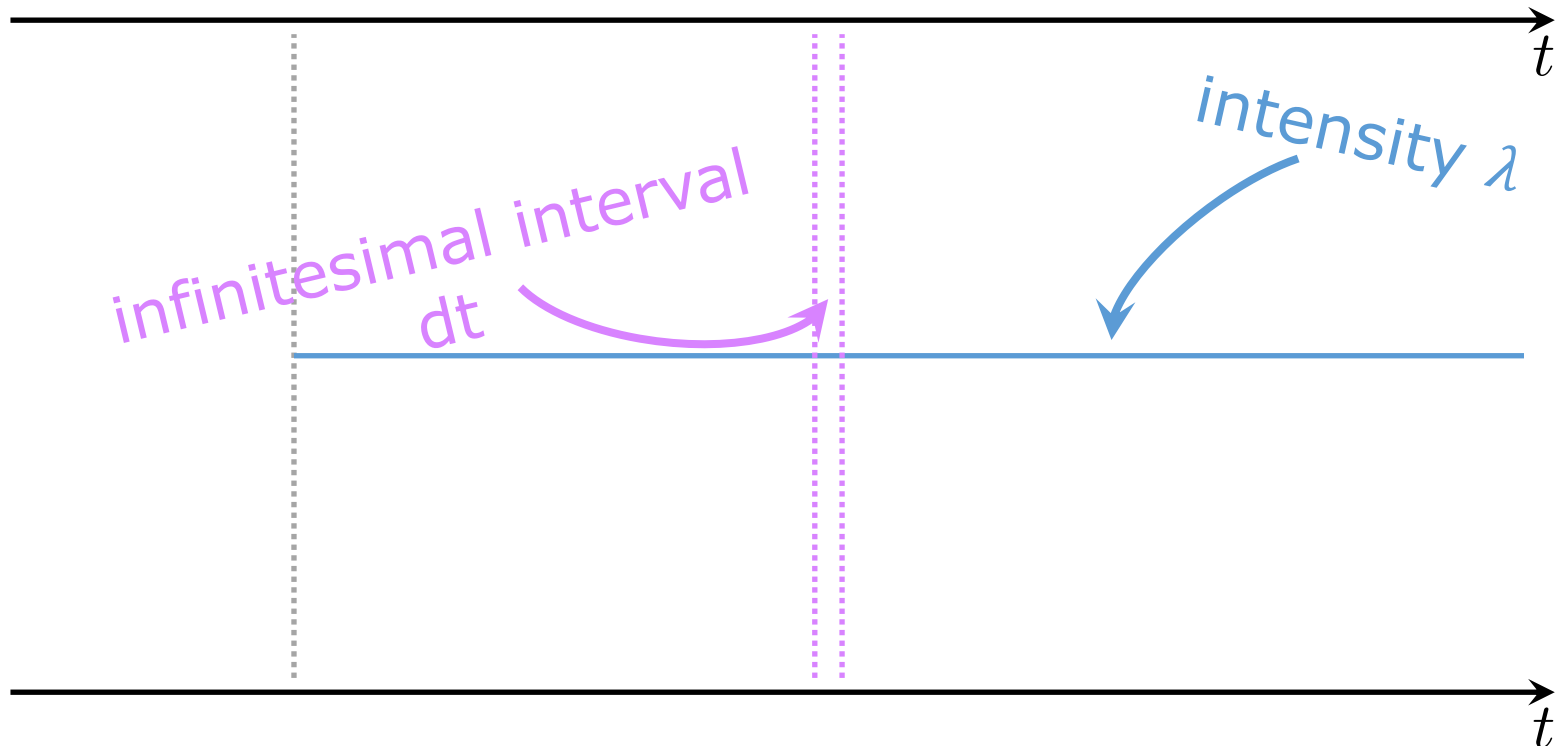


# Generative Story of Irregular **Time Series**

Social



intensity =  
rate of events per unit time



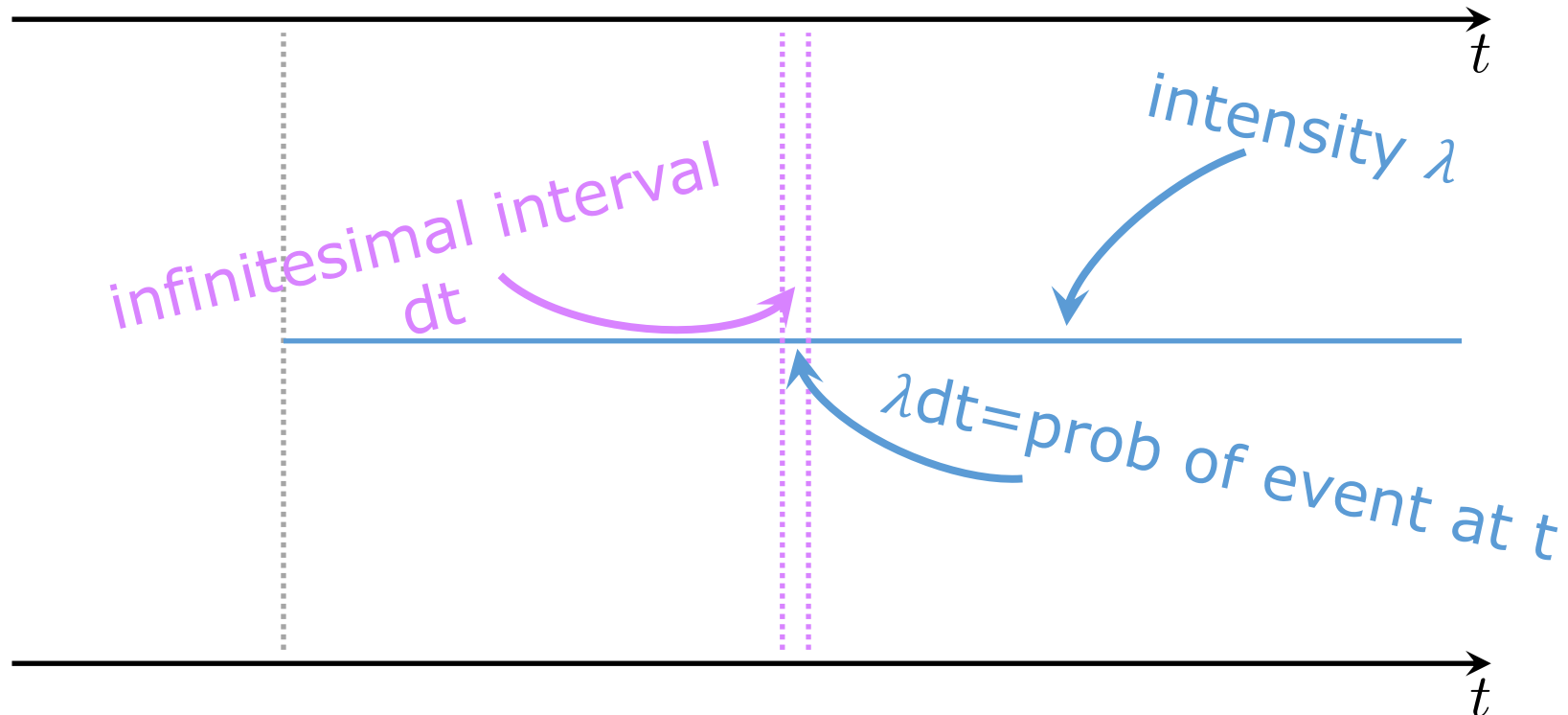


# Generative Story of Irregular **Time Series**

Social



intensity =  
rate of events per unit time

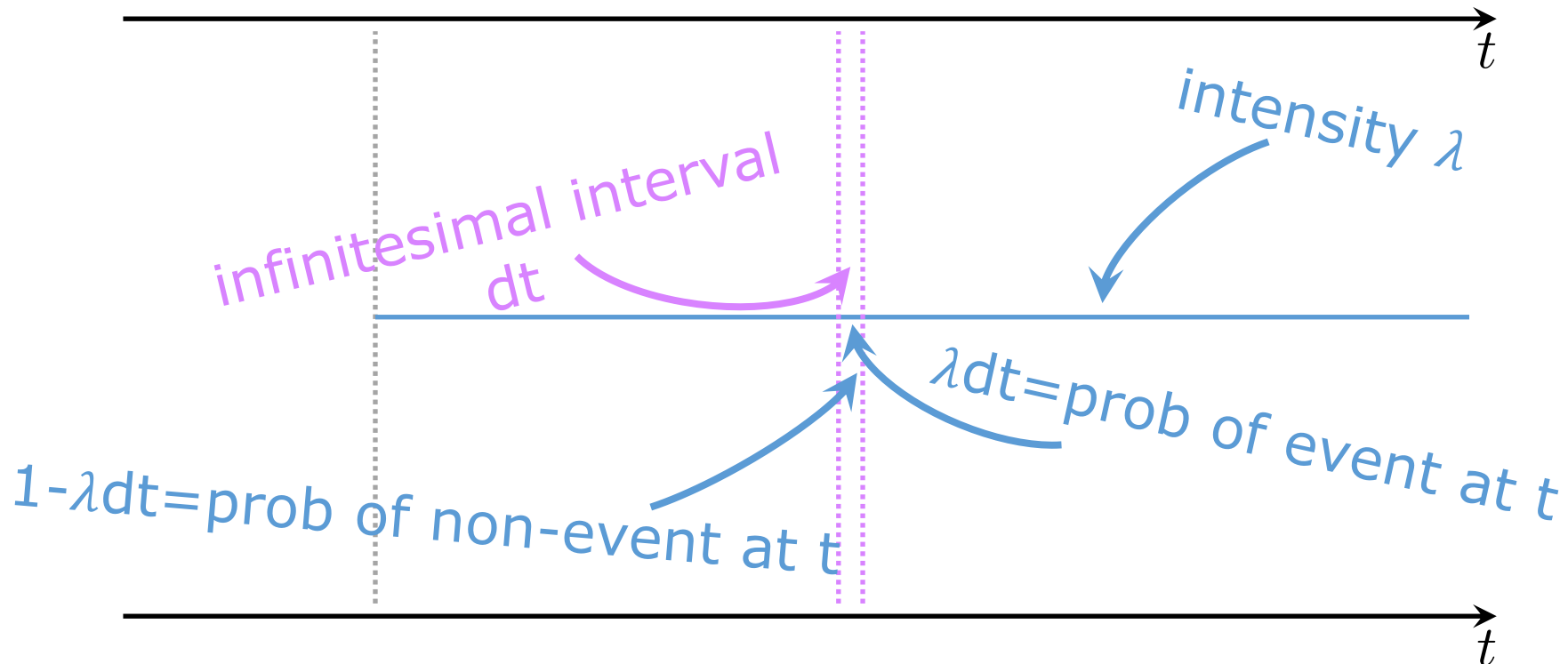


# Generative Story of Irregular Time Series

Social

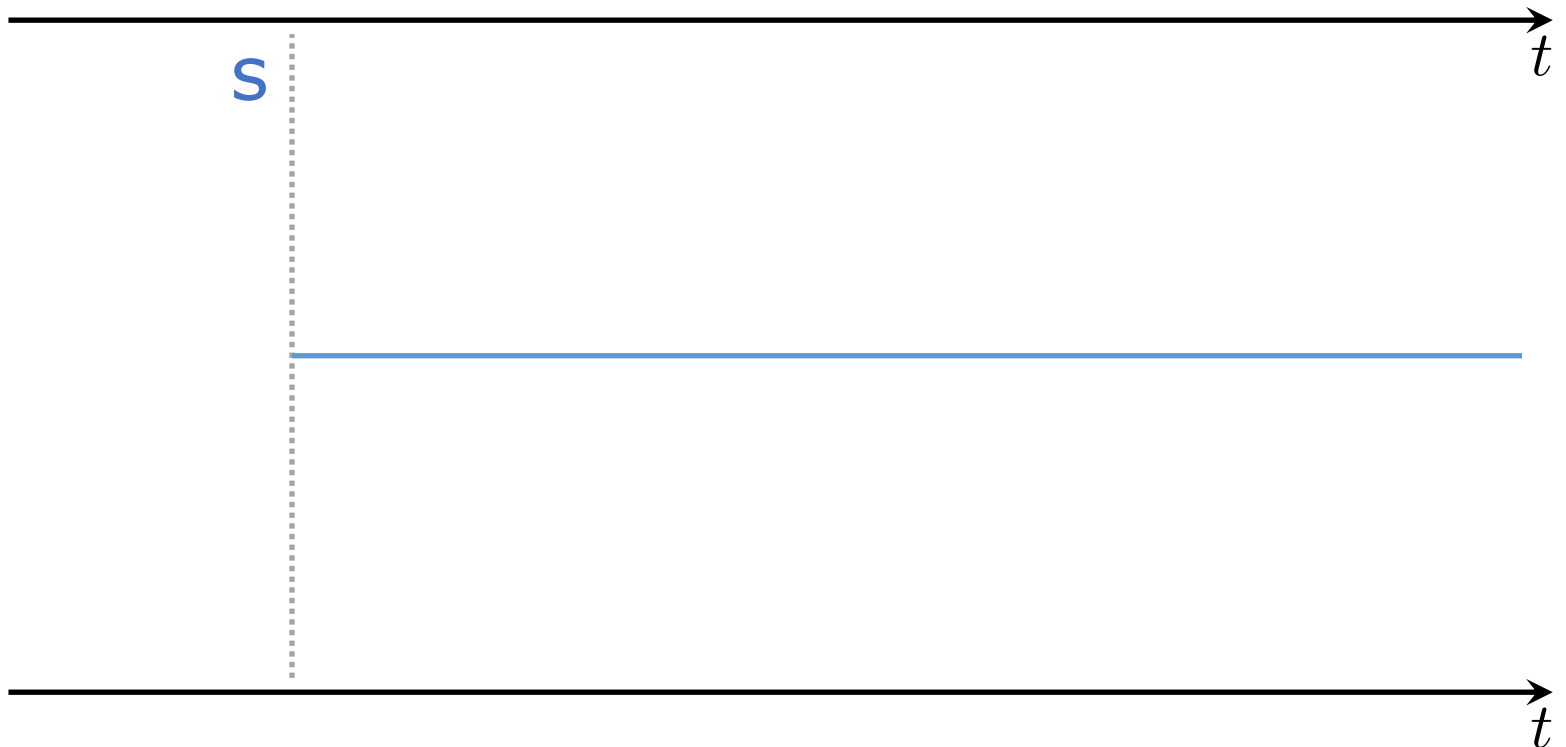


intensity =  
rate of events per unit time



# Generative Story of Irregular **Time Series**

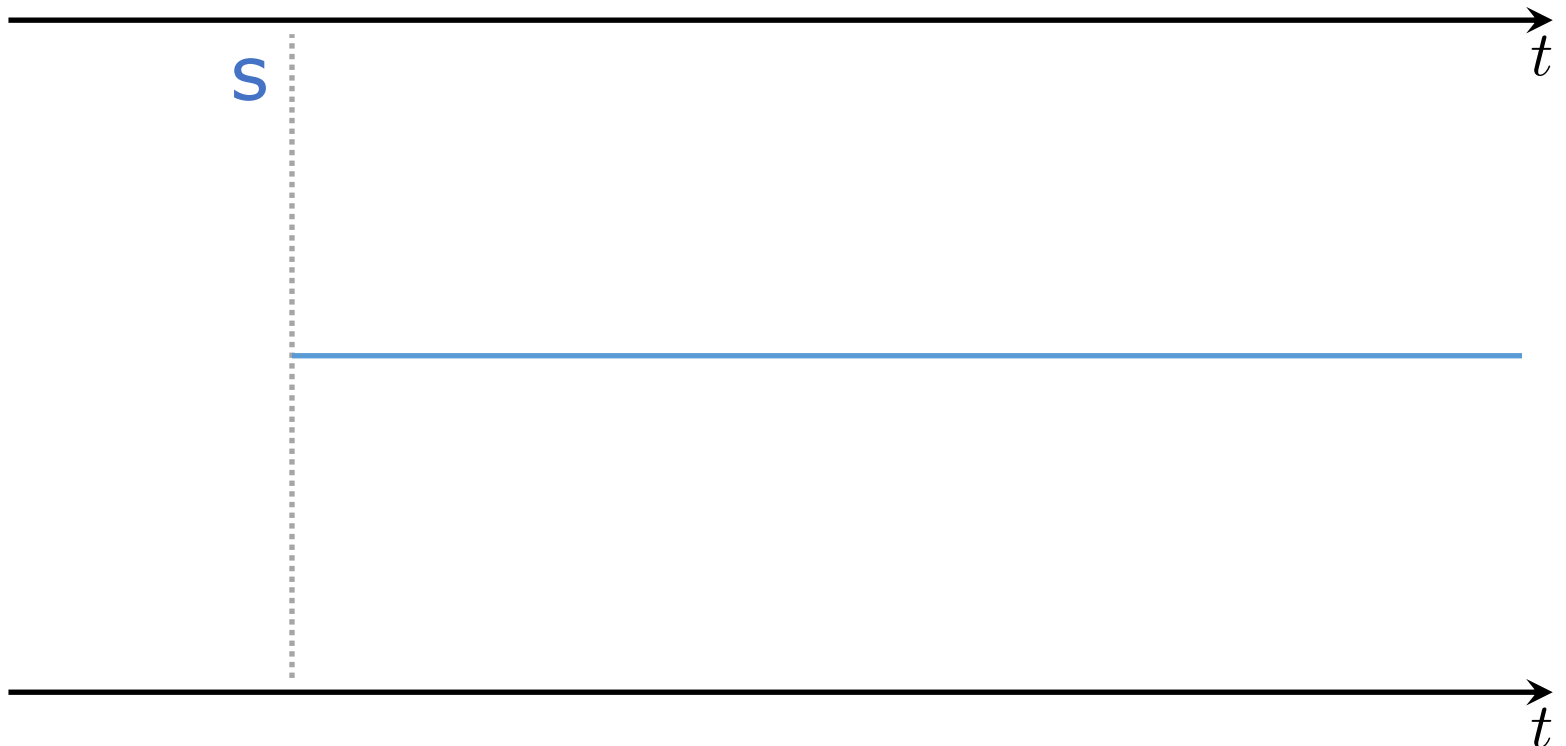
Social



# Generative Story of Irregular Time Series

prob density  $p(t)$  of *next* event ?

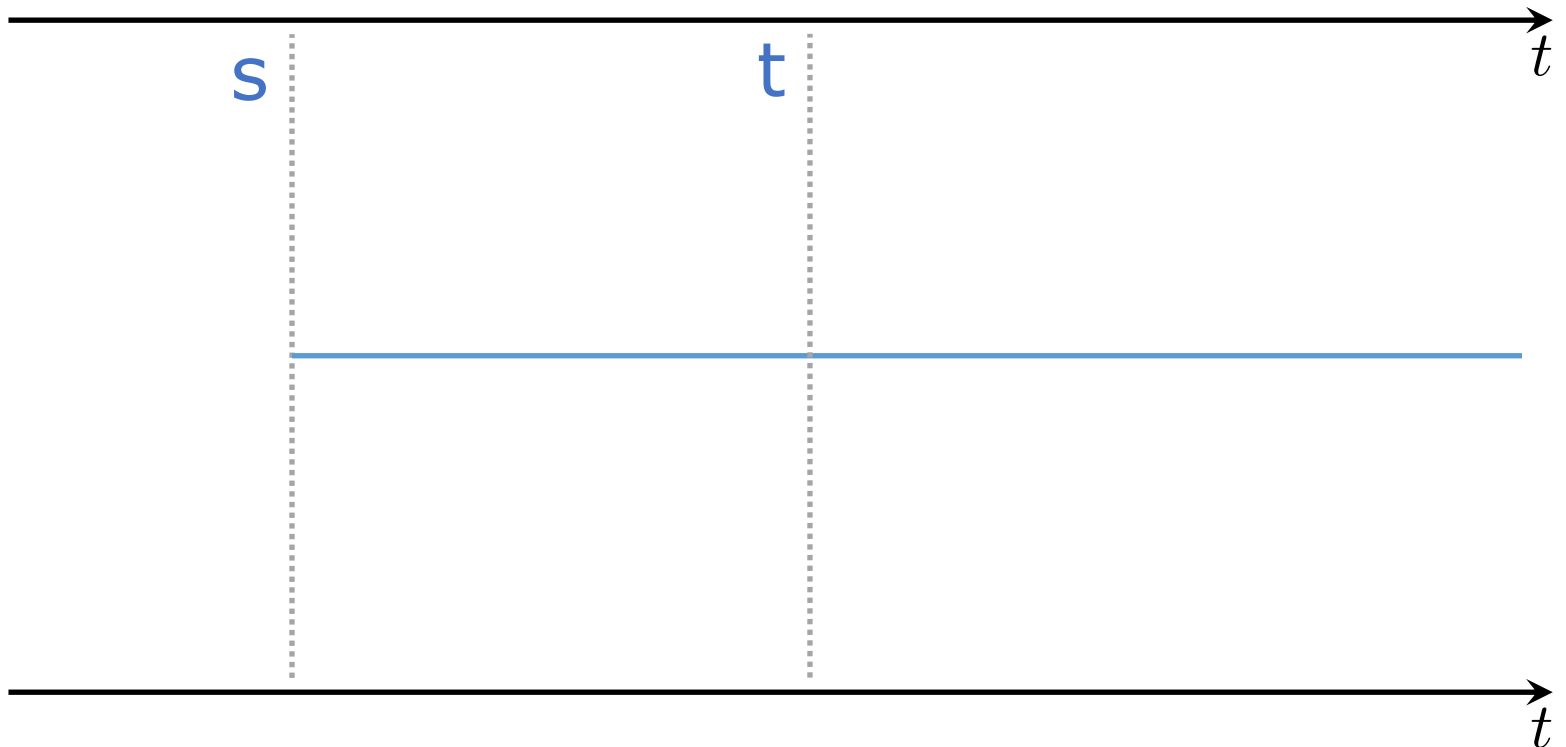
Social



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prob density  $p(t)$  of *next* event ?

Social



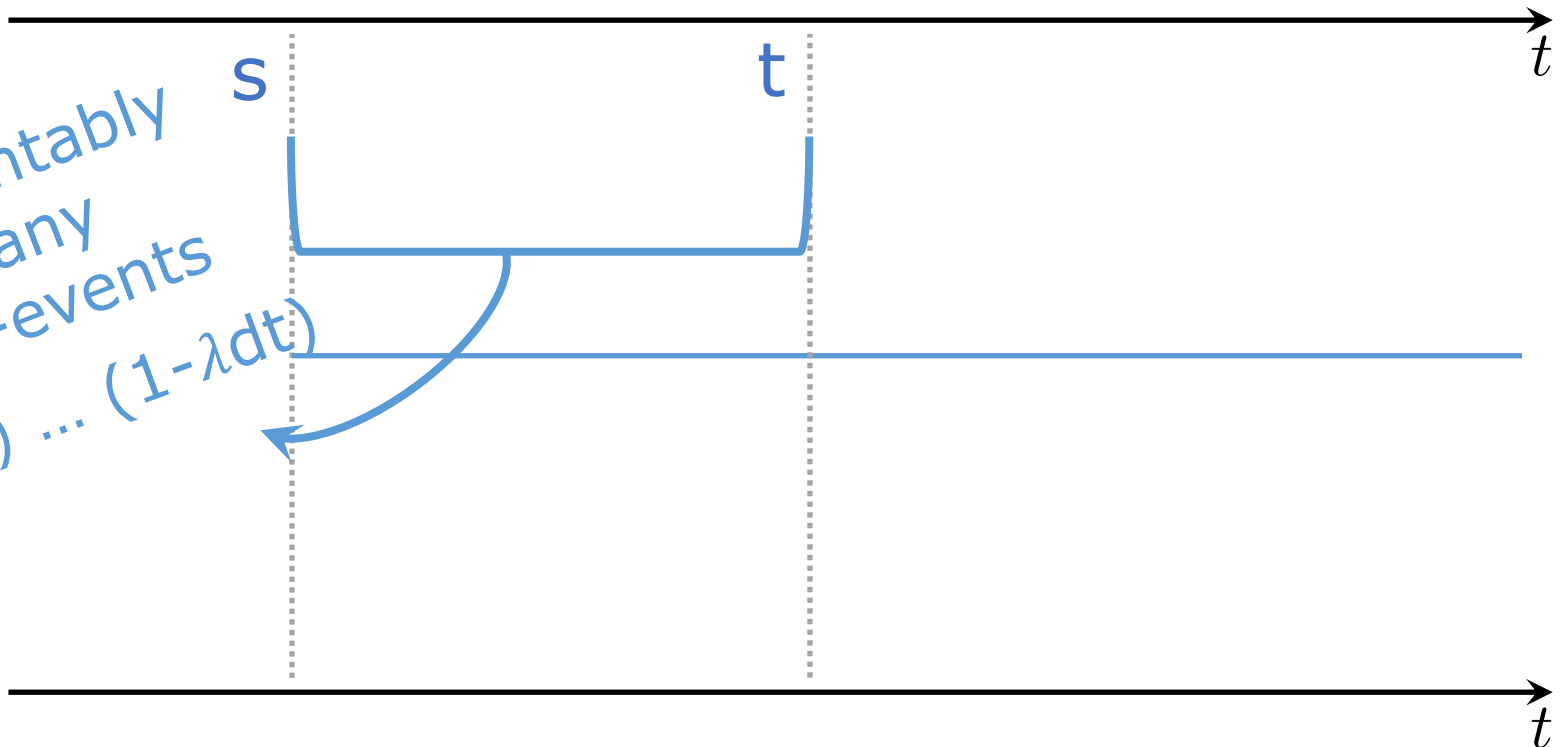
# Generative Story of Irregular Time Series

prob density  $p(t)$  of *next* event ?

Social



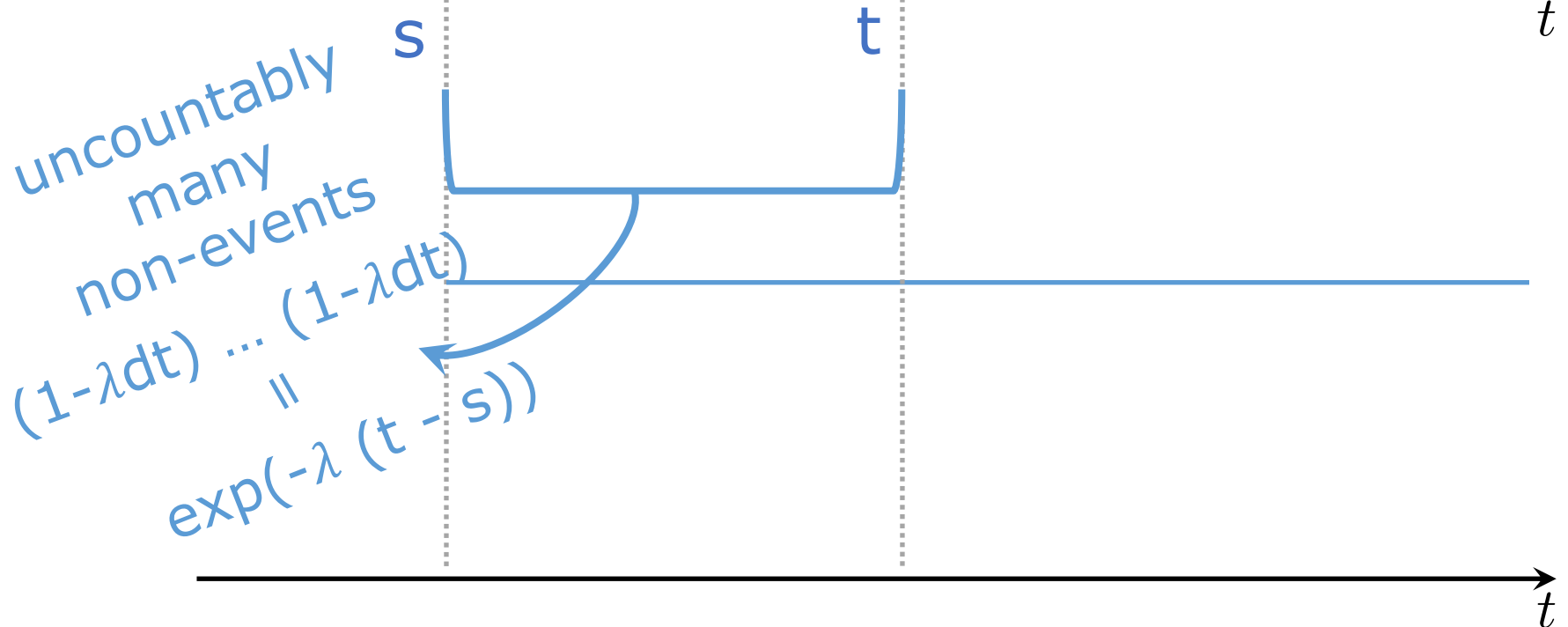
uncountably  
many  
non-events  
 $(1-\lambda dt) \dots (1-\lambda dt)$



# Generative Story of Irregular Time Series

prob density  $p(t)$  of *next* event ?

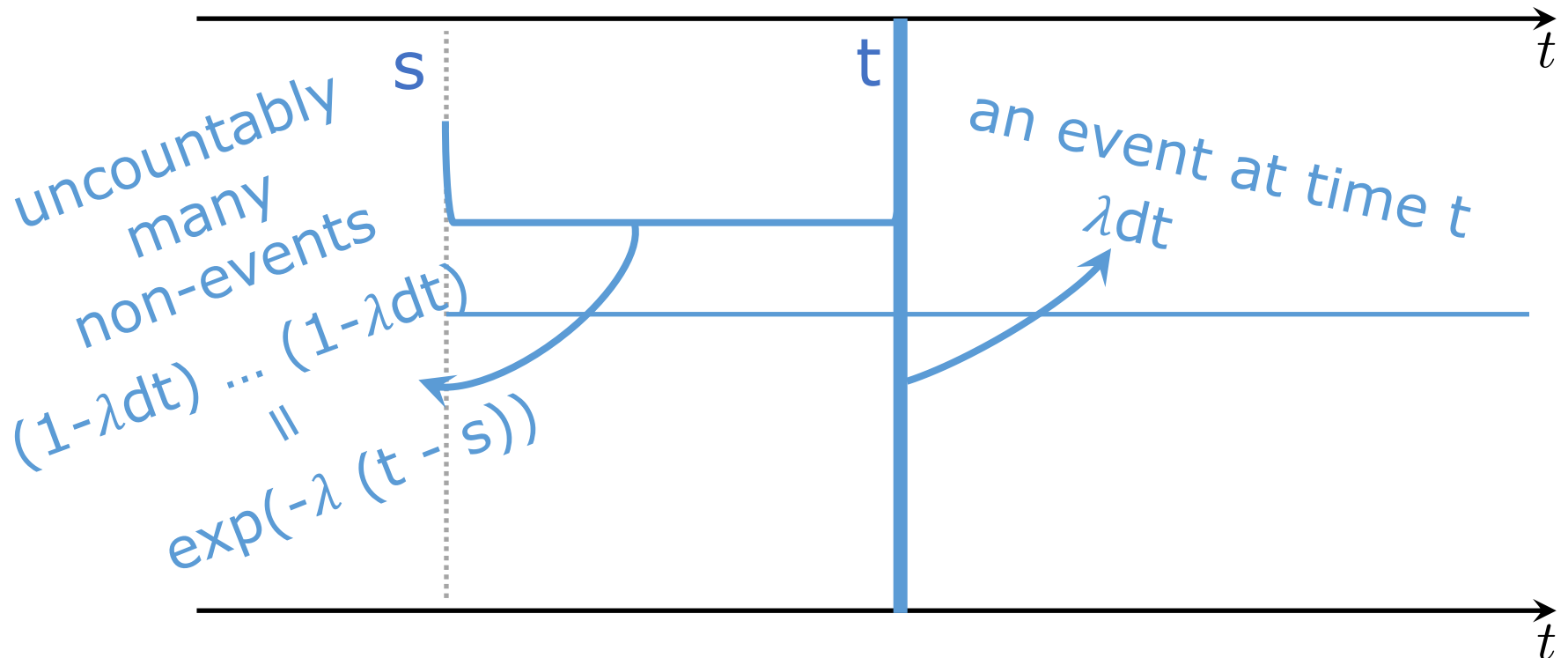
Social



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prob density  $p(t)$  of *next* event ?

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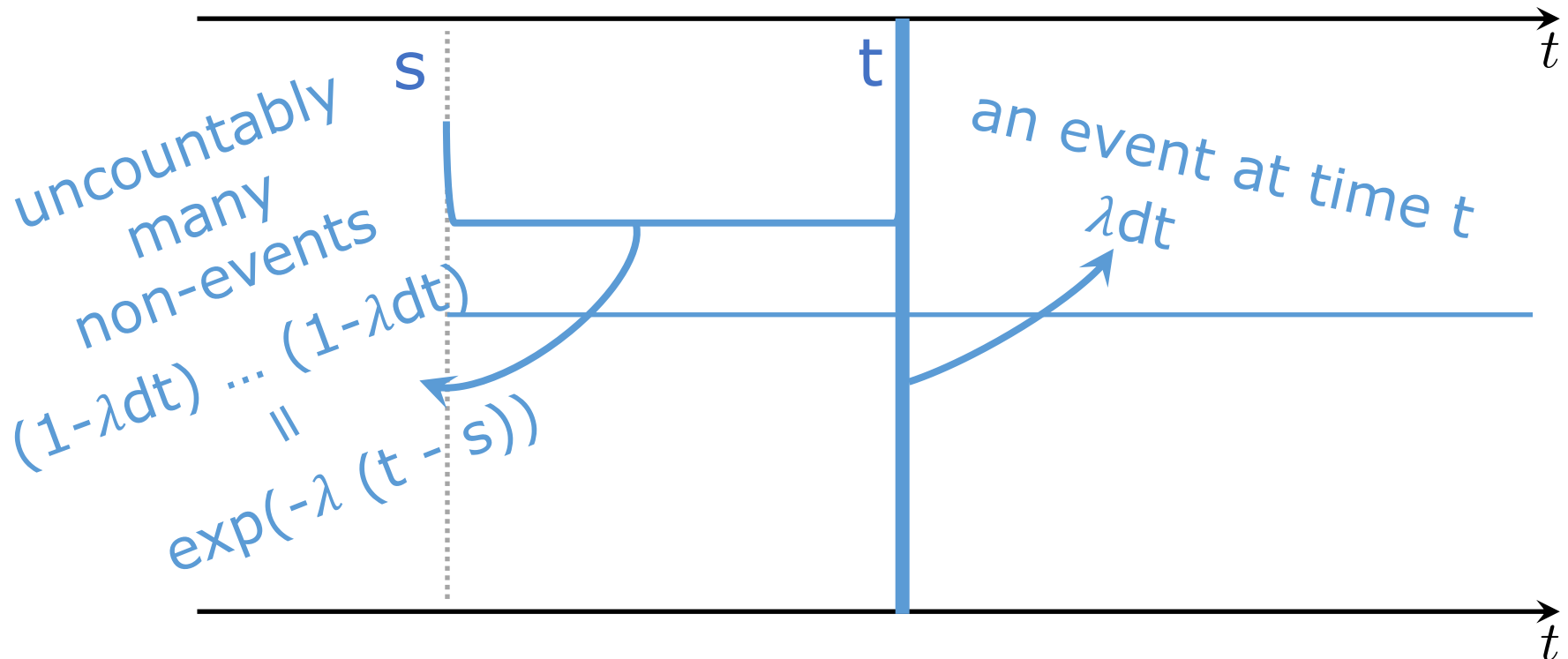


# Generative Story of Irregular Time Series

prob density  $p(t)$  of *next* event ?

$$p(t) = \lambda \exp(-\lambda (t - s))$$

Social

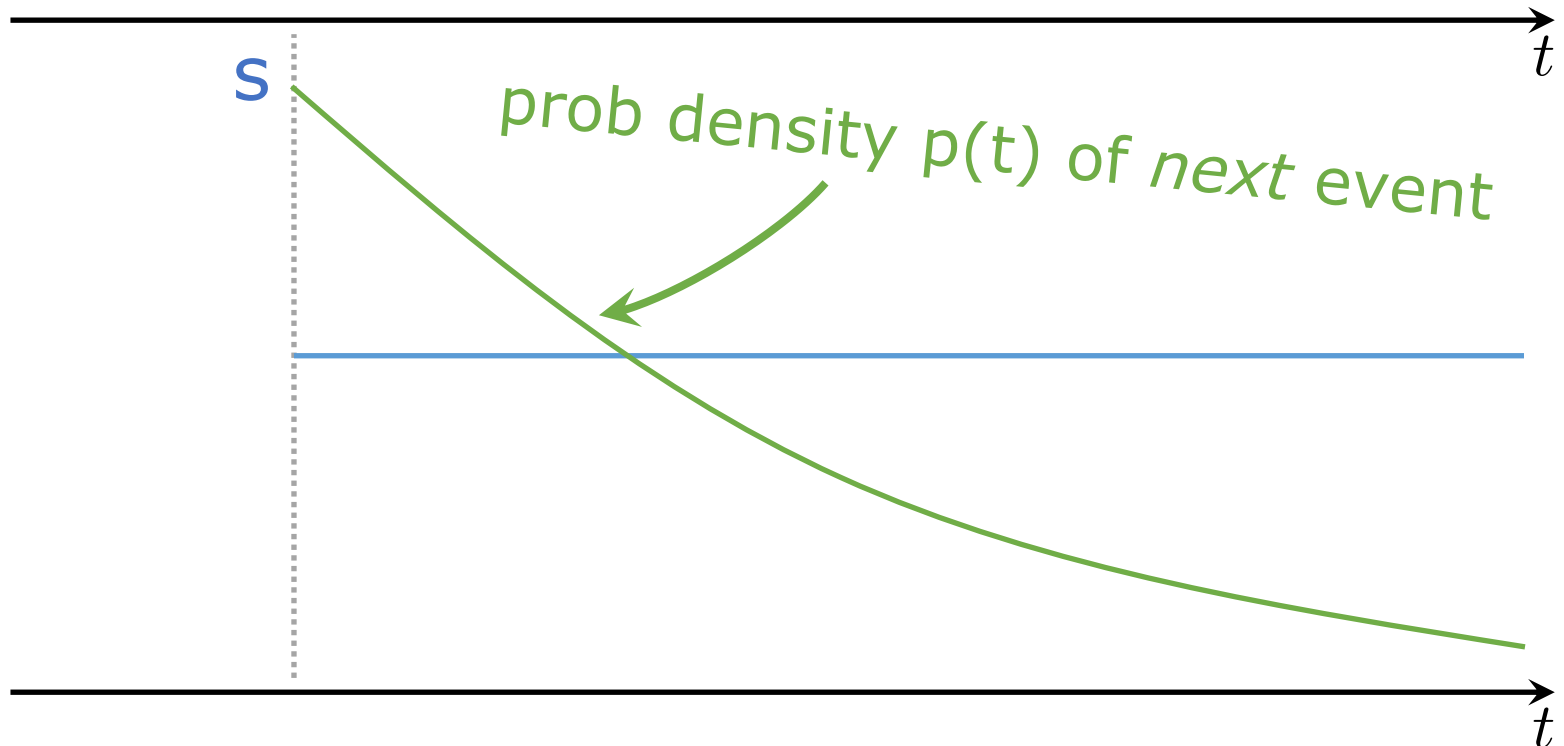


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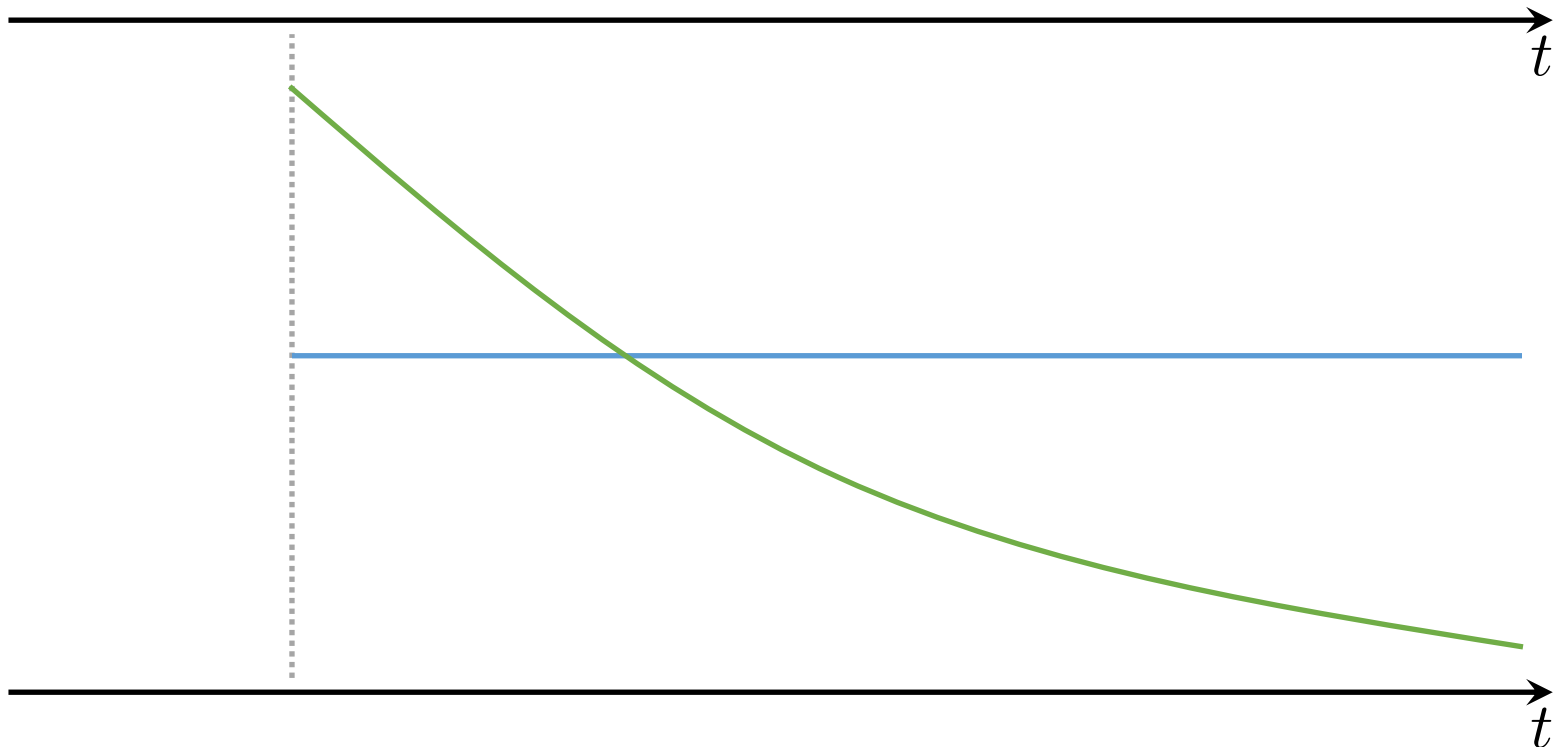


# Generative Story of Irregular Time Series

Social

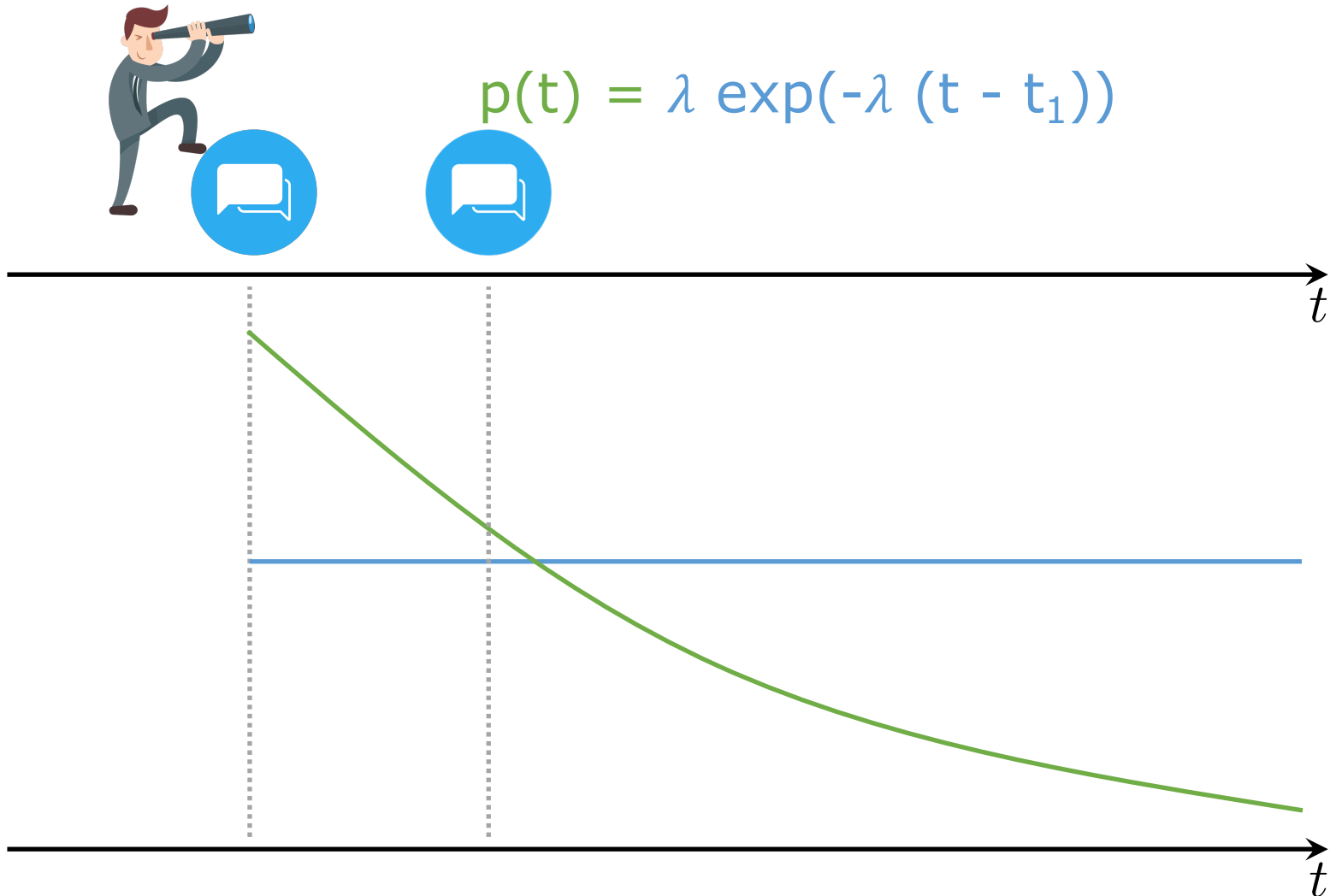


$$p(t) = \lambda \exp(-\lambda (t - t_1))$$



# Generative Story of Irregular Time Series

Social

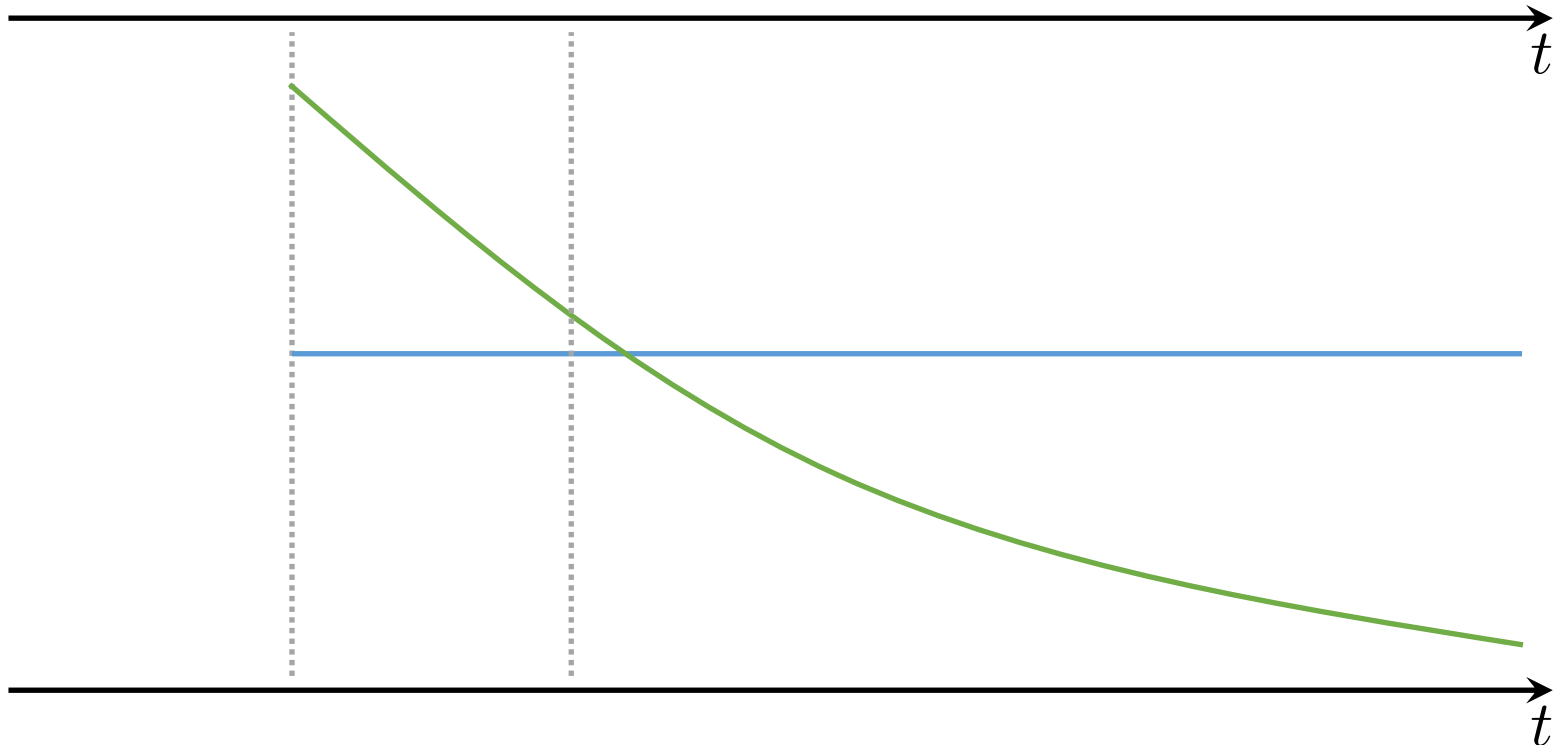


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Social

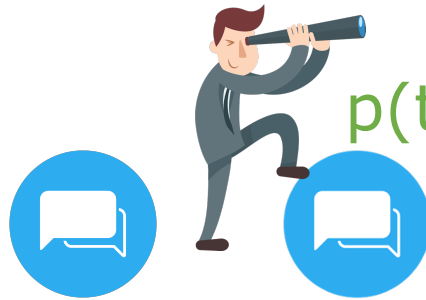


$$p(t) = \lambda \exp(-\lambda (t - t_1))$$

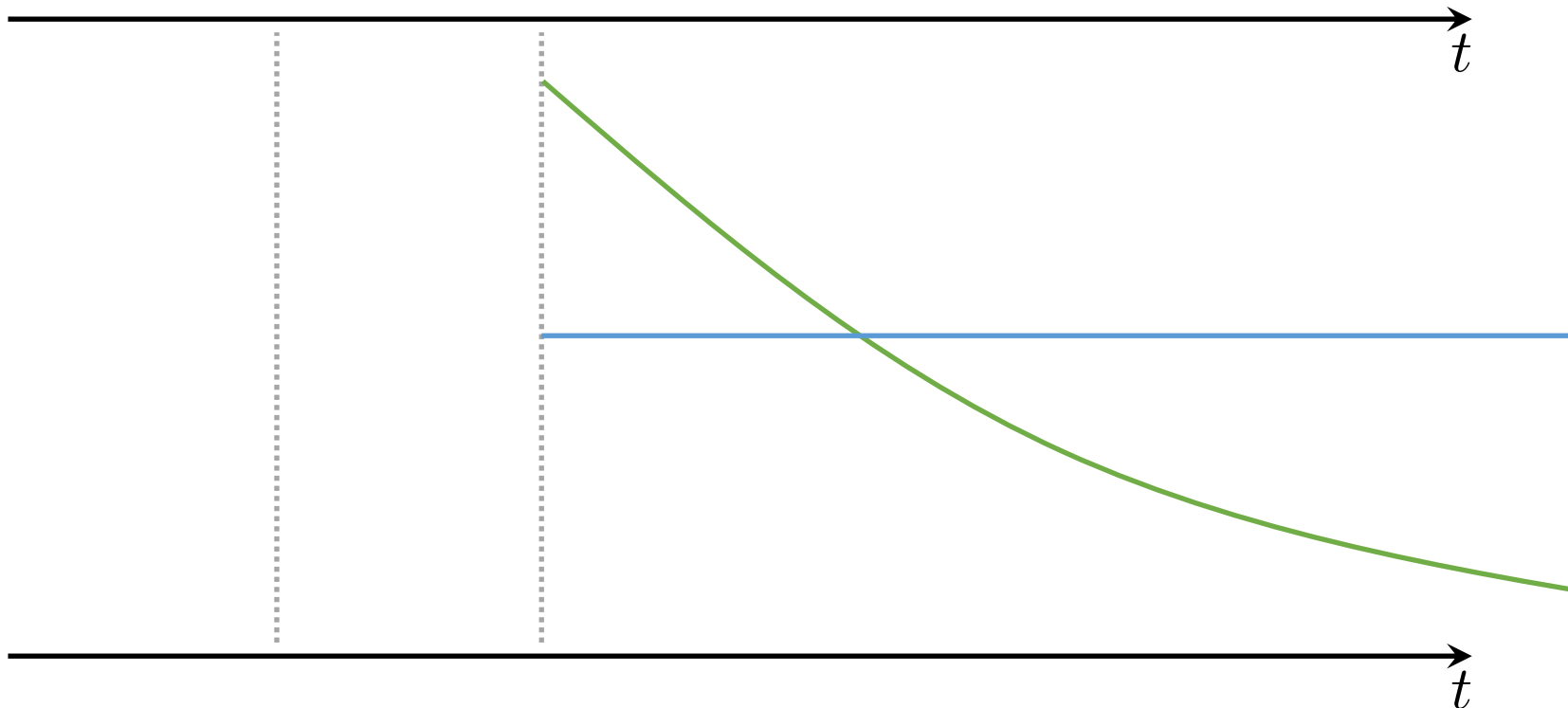


# Generative Story of Irregular Time Series

Social

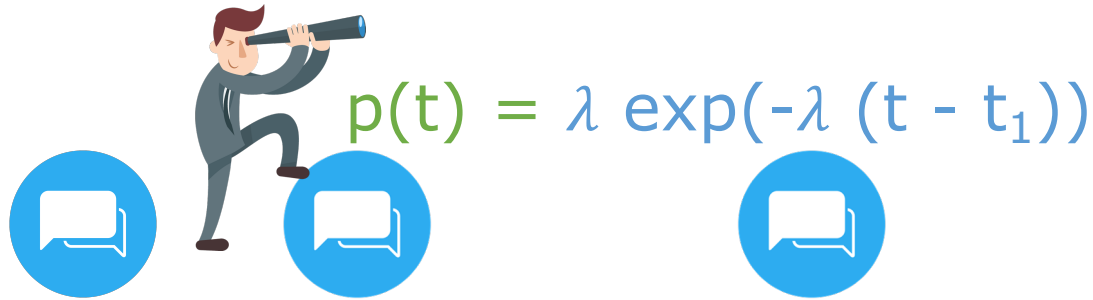


$$p(t) = \lambda \exp(-\lambda (t - t_1))$$

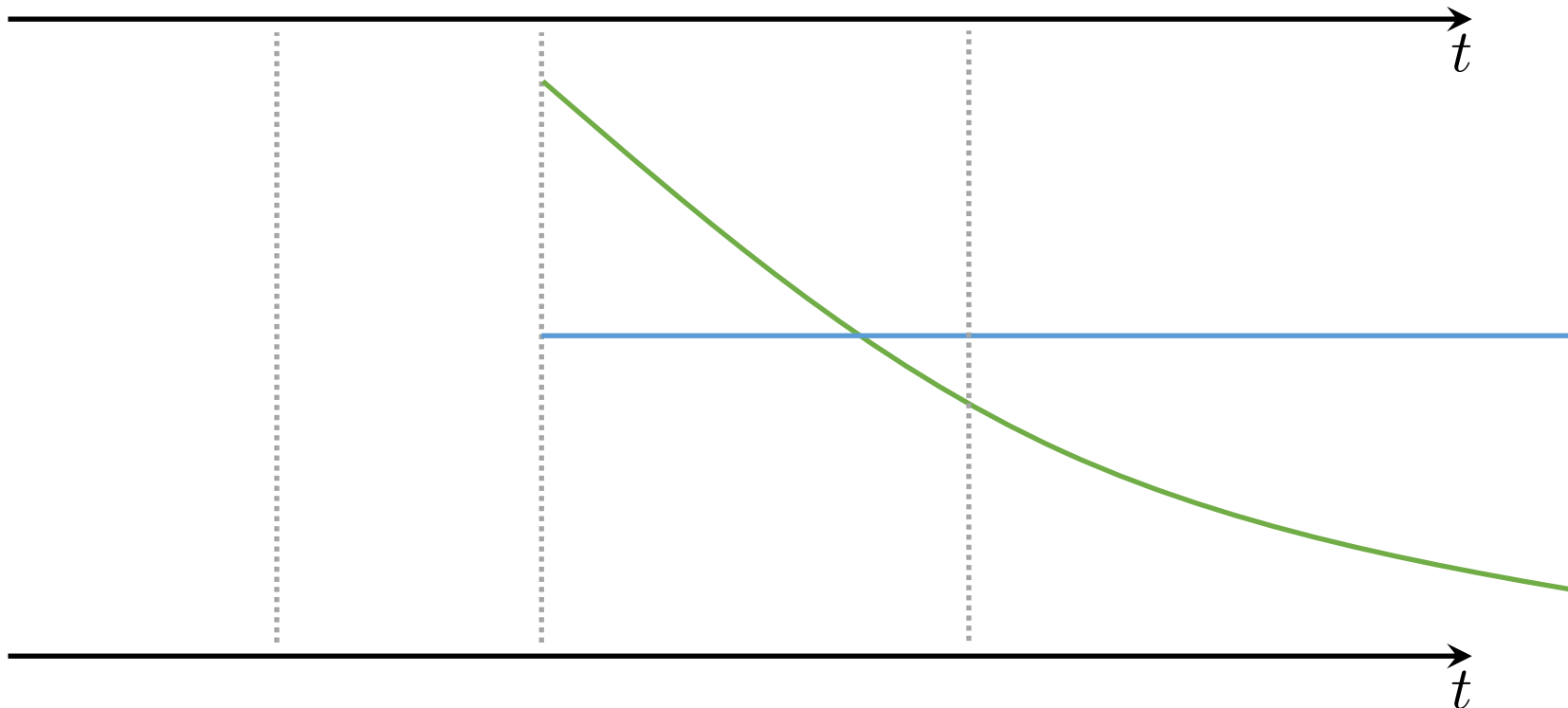


# Generative Story of Irregular Time Series

Social

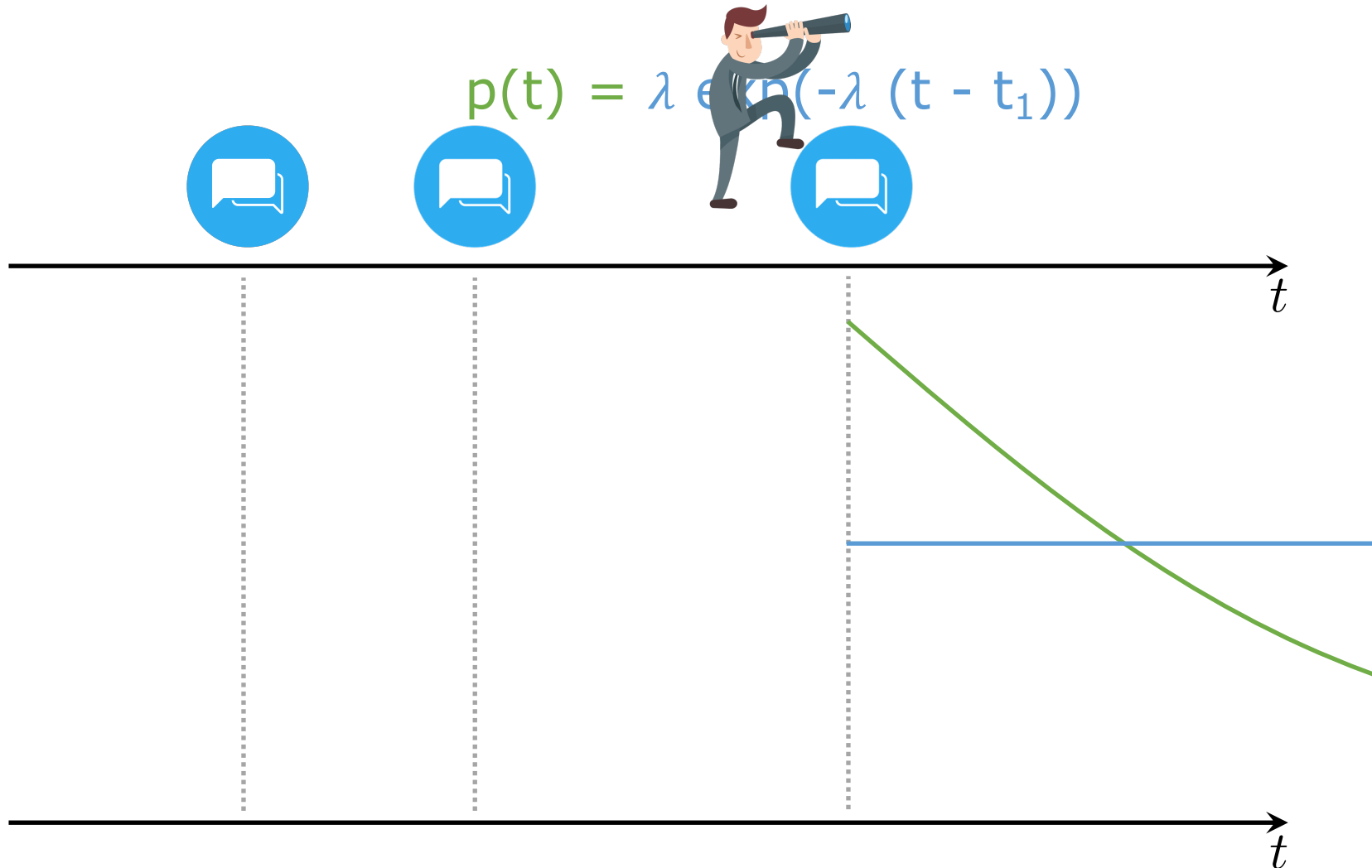


$$p(t) = \lambda \exp(-\lambda (t - t_1))$$



# Generative Story of Irregular Time Series

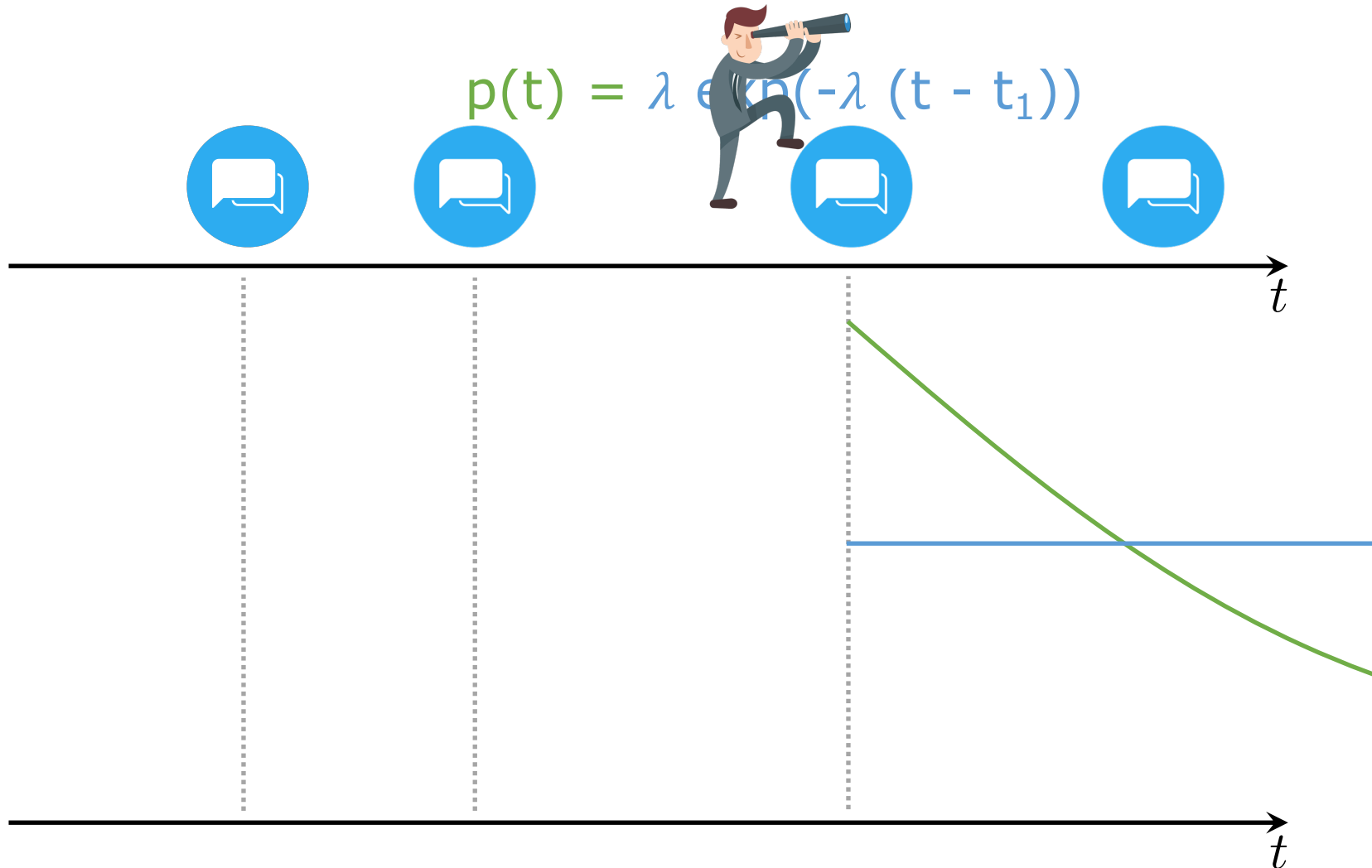
Social





# Generative Story of Irregular Time Series

Social

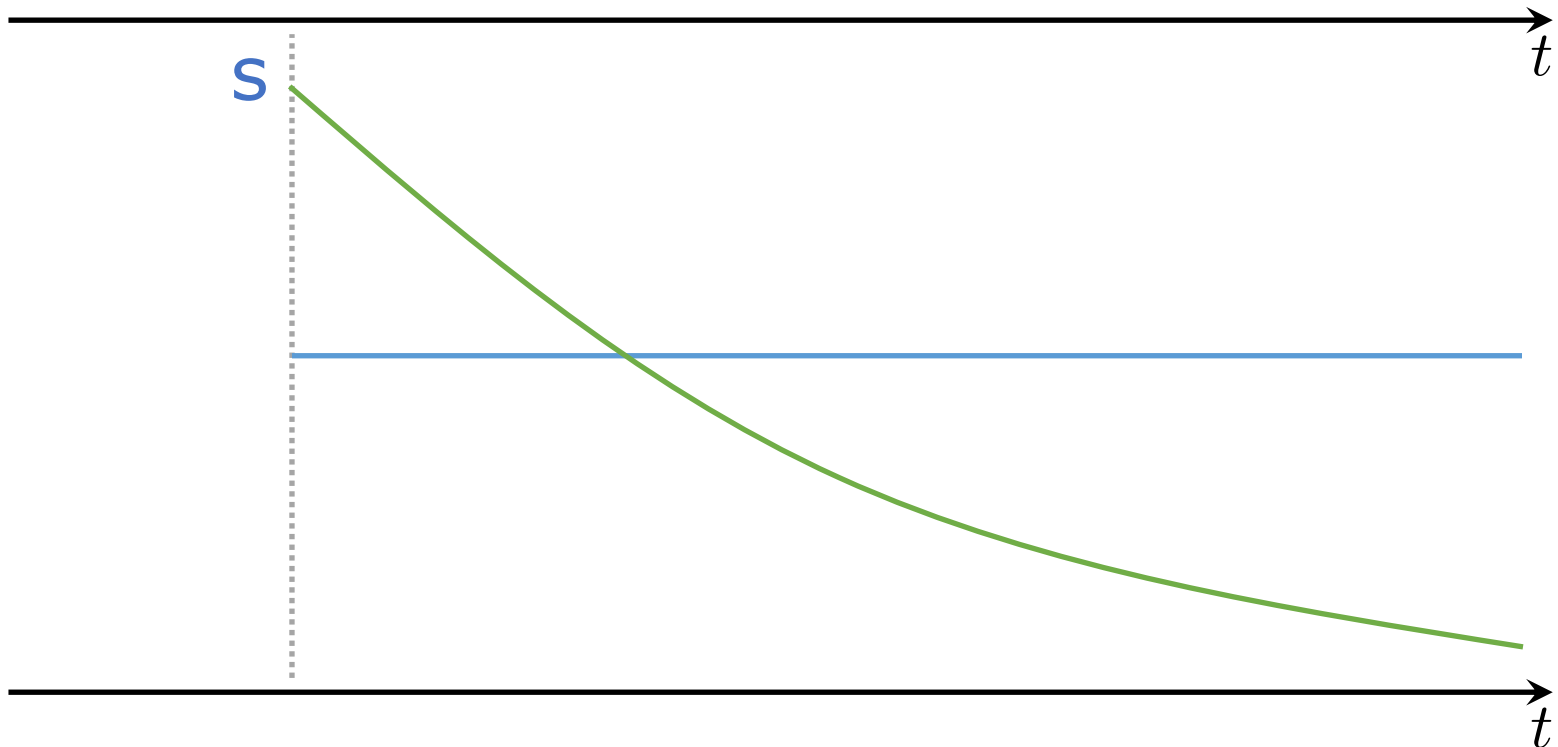


# Draw Next Event: Inversion Sampling

Social



$$p(t) = \lambda \exp(-\lambda (t - s))$$



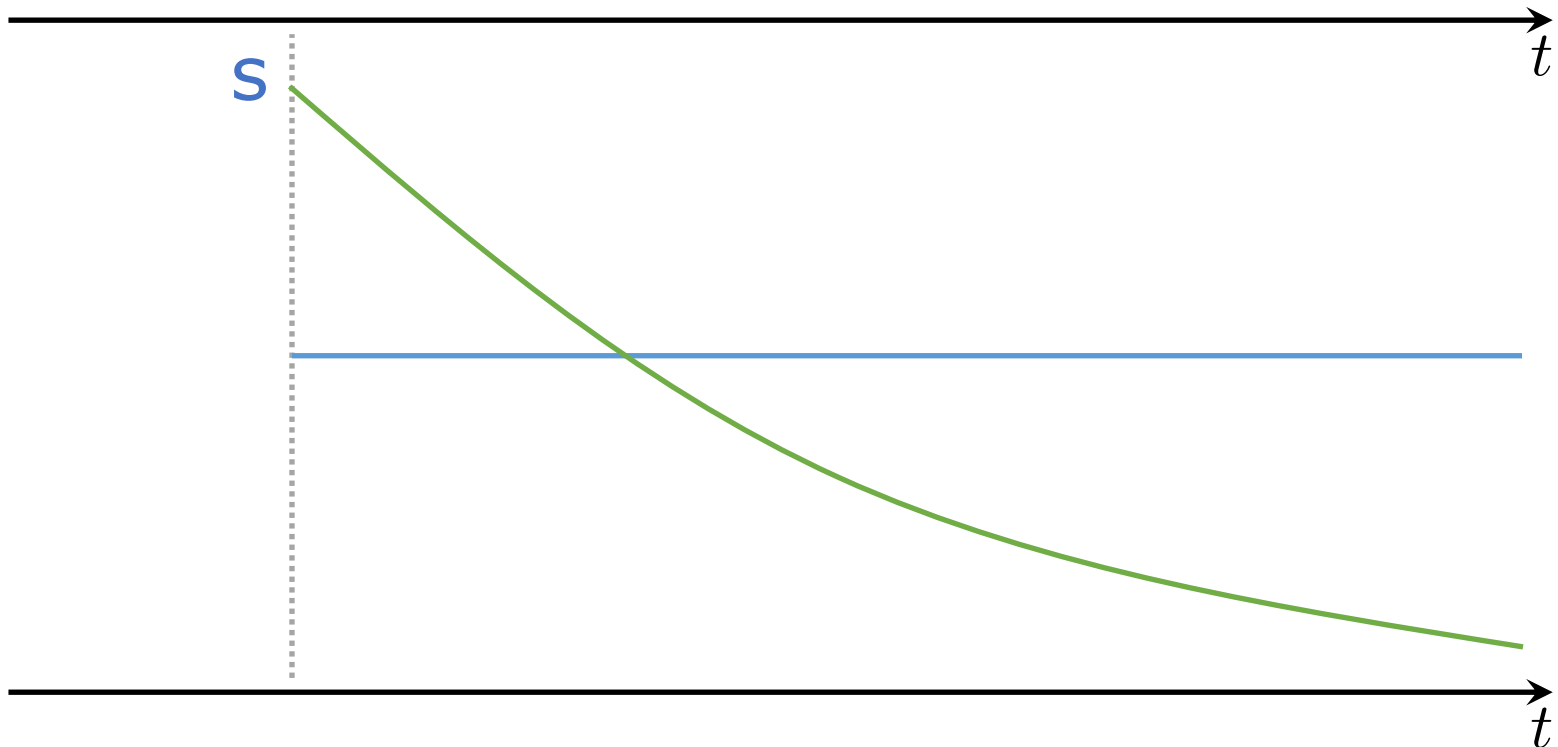
# Draw Next Event: Inversion Sampling

Social



$$p(t) = \lambda \exp(-\lambda (t - s))$$
$$F(t) = \int_s^t p(t') dt' \in [0, 1]$$

cumulative density function (CDF)



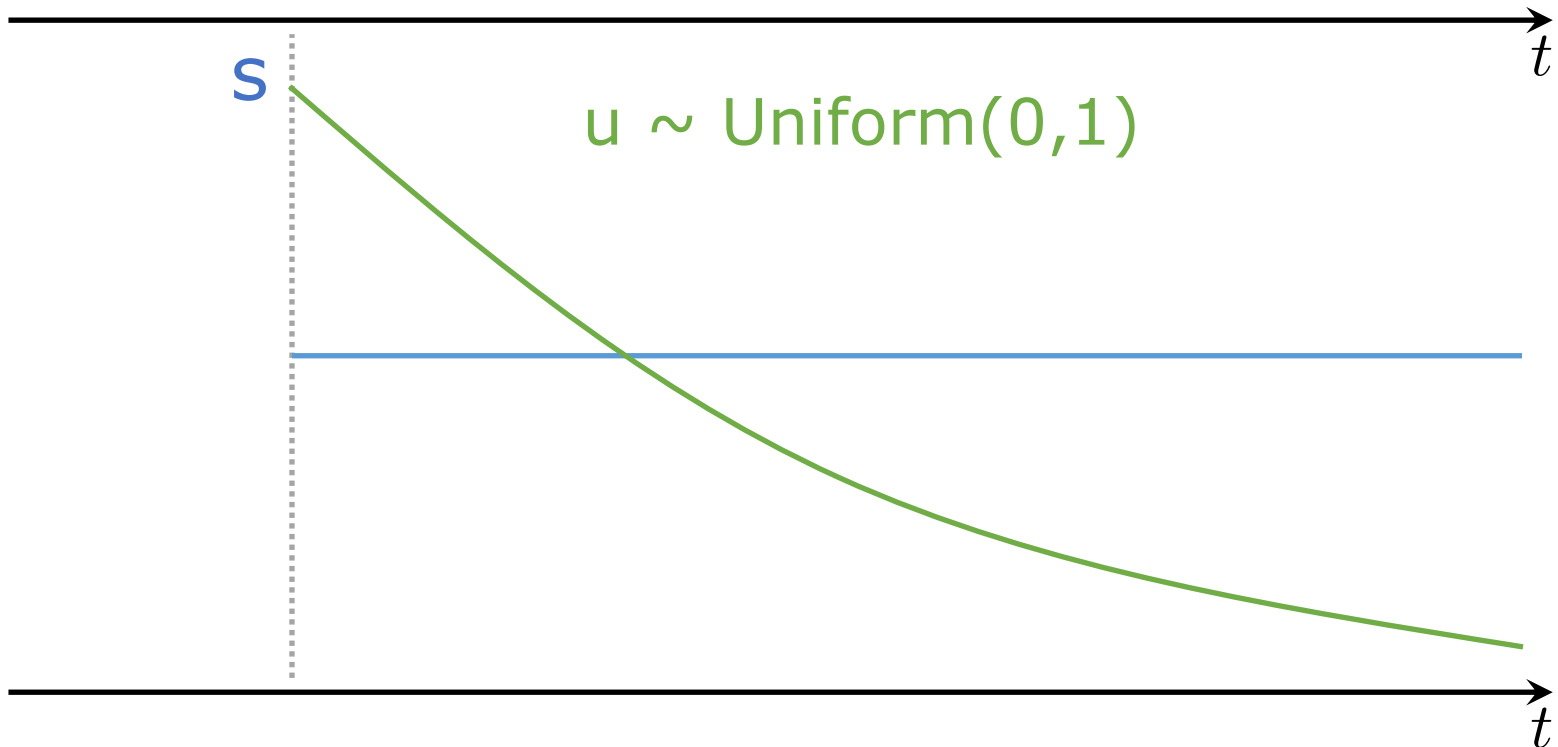
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Social



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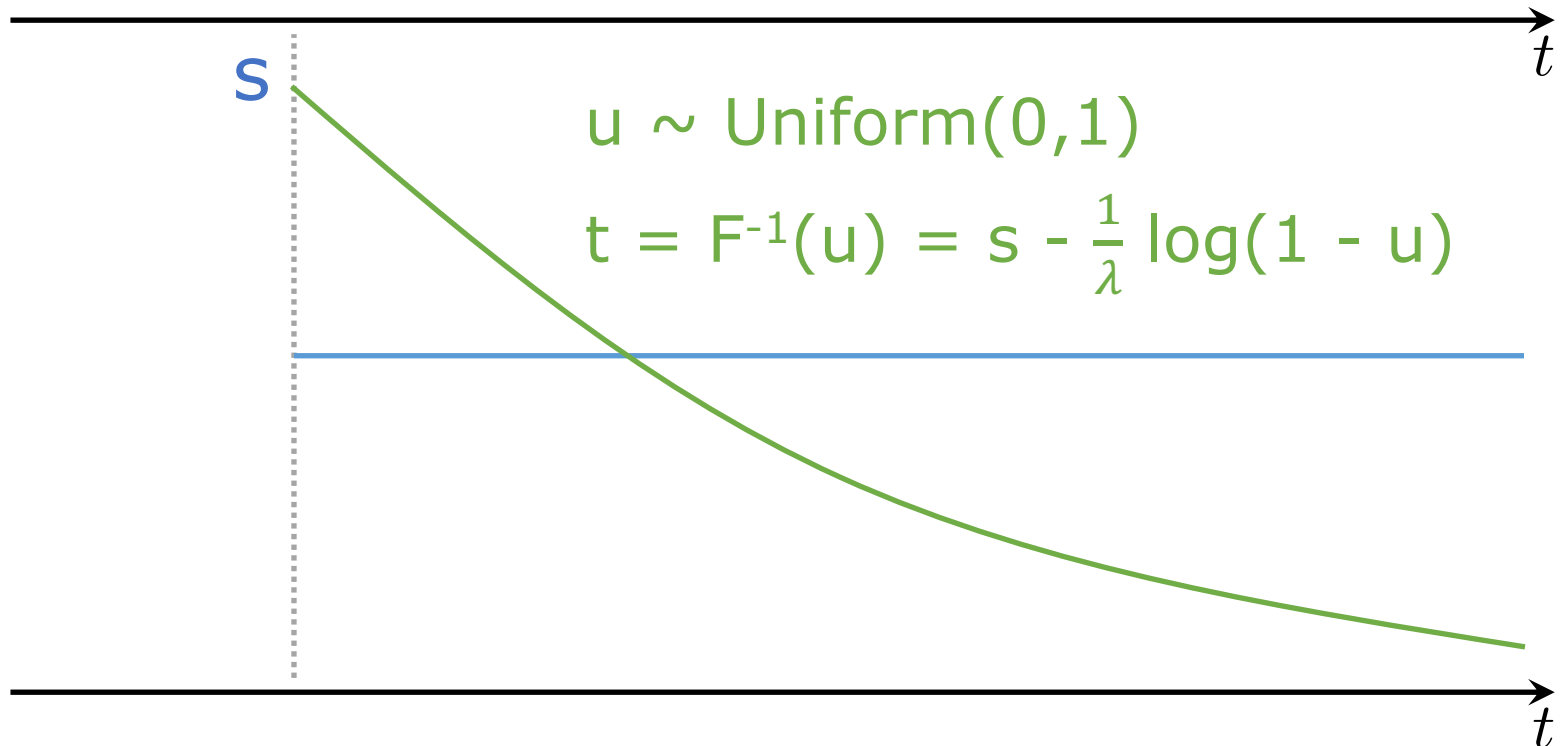
# Draw Next Event: Inversion Sampling

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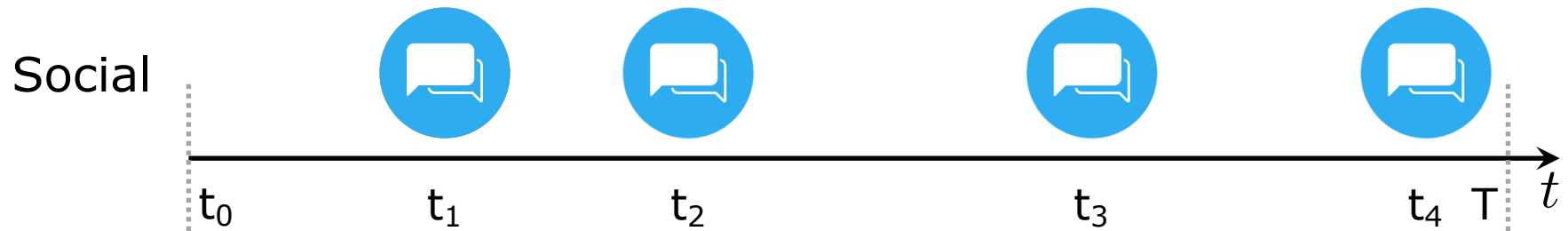
cumulative density function (CDF)



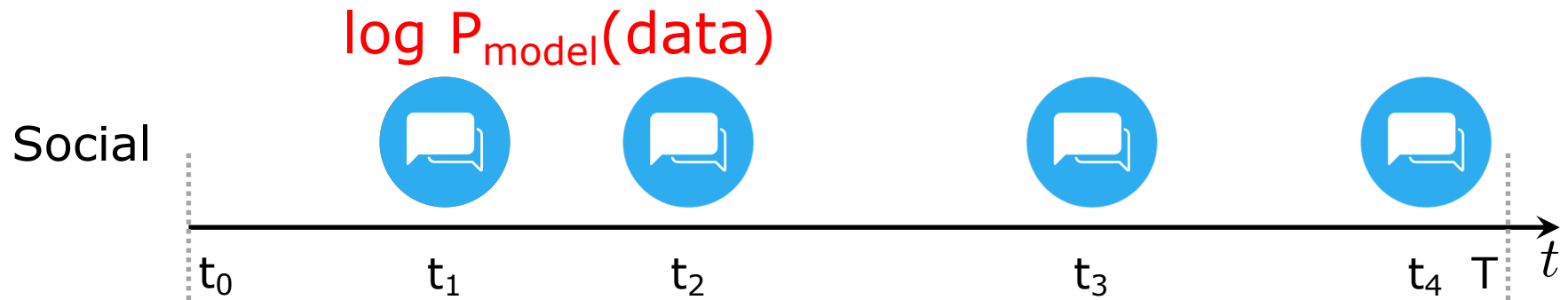
# Let's write some code

# **<http://bburl/tpp-lab-p1>**

# Estimating Intensity: MLE



# Estimating Intensity: MLE

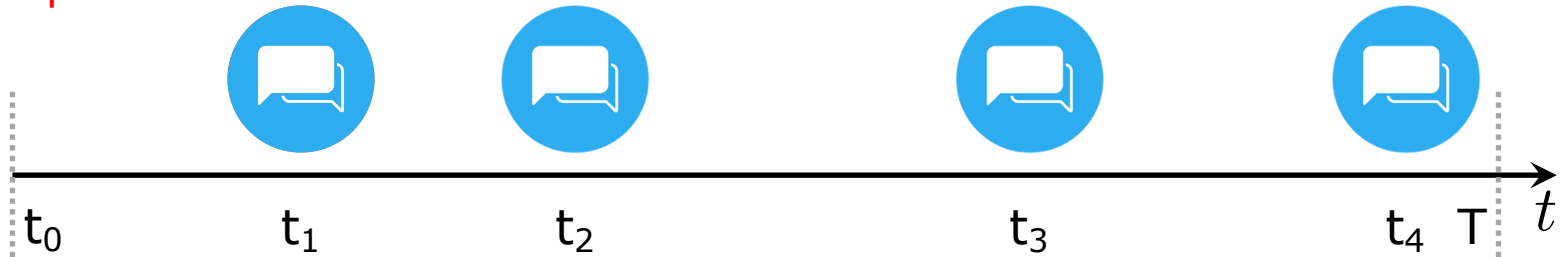




# Estimating Intensity: MLE

$$\operatorname{argmax}_{\text{param}} \log P_{\text{model}}(\text{data})$$

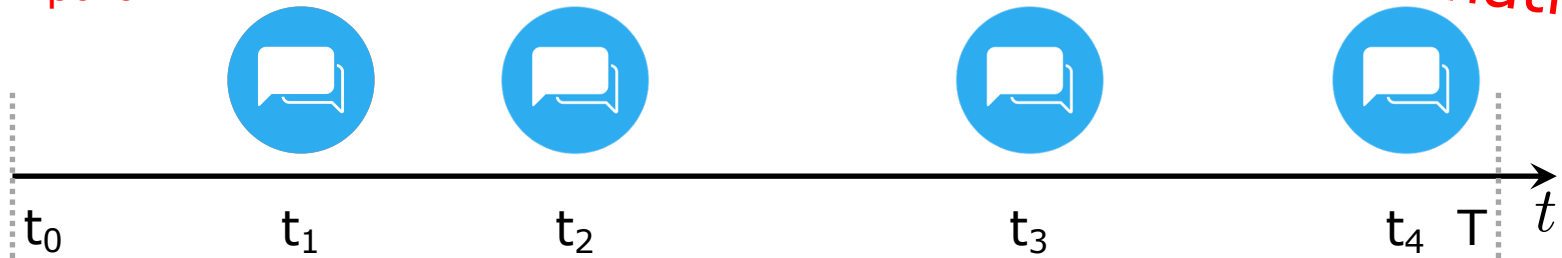
Social



# Estimating Intensity: MLE

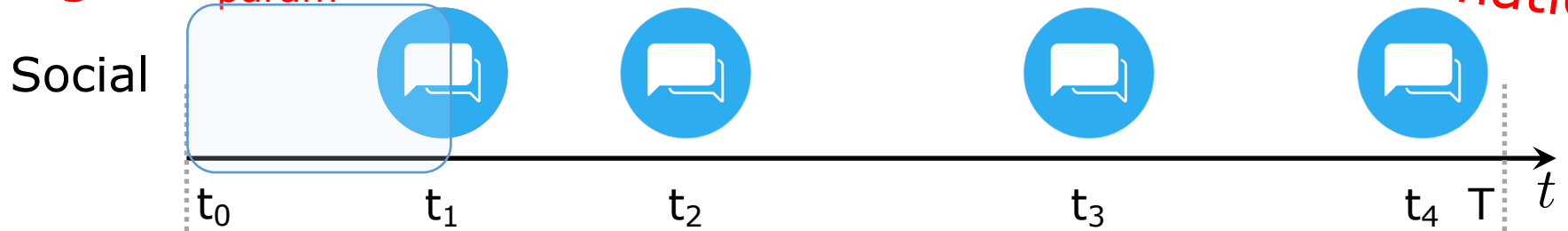
$\operatorname{argmax}_{\text{param}} \log P_{\text{model}}(\text{data})$  *maximum log-likelihood estimation*

Social



# Estimating Intensity: MLE

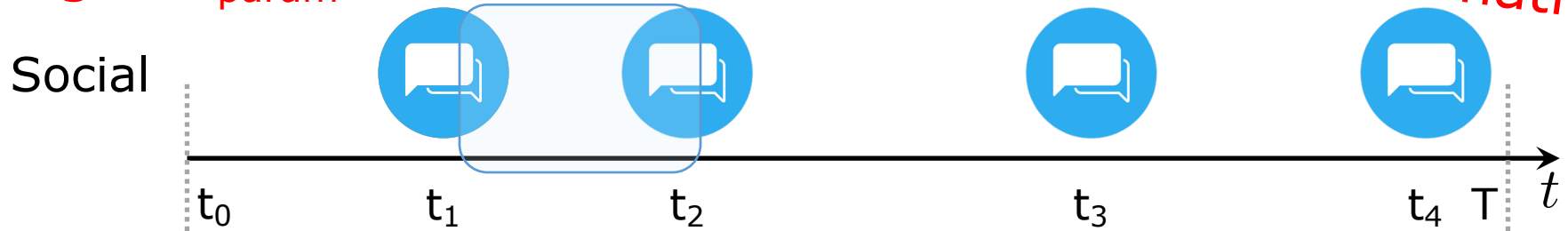
$\operatorname{argmax}_{\text{param}} \log P_{\text{model}}(\text{data})$  *maximum log-likelihood estimation*



$$\lambda \exp(-\lambda (t_1 - t_0))$$

# Estimating Intensity: MLE

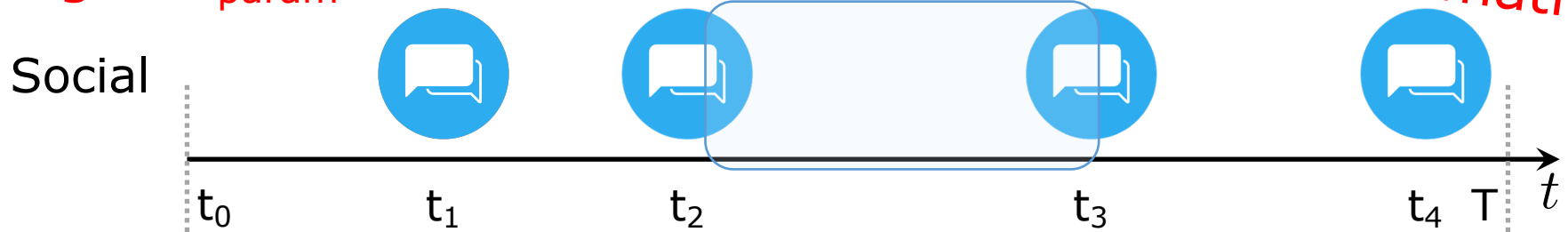
$\operatorname{argmax}_{\text{param}} \log P_{\text{model}}(\text{data})$  *maximum log-likelihood estimation*



$$\lambda \exp(-\lambda (t_1 - t_0)) \\ \times \lambda \exp(-\lambda (t_2 - t_1))$$

# Estimating Intensity: MLE

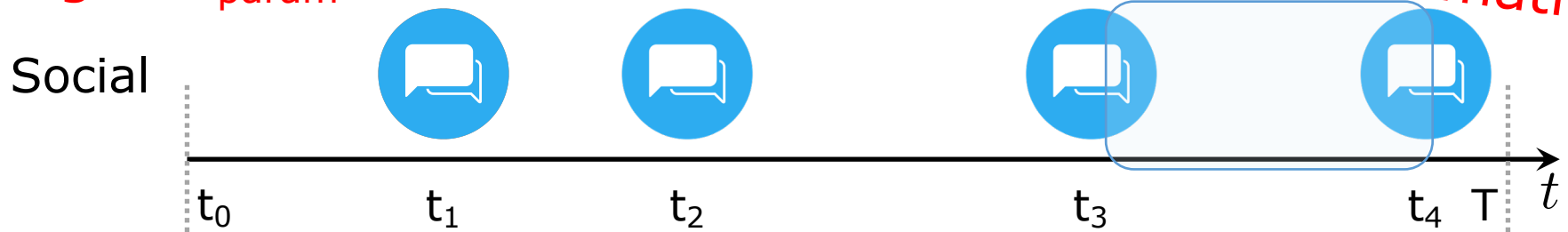
$\operatorname{argmax}_{\text{param}} \log P_{\text{model}}(\text{data})$  *maximum log-likelihood estimation*



$$\begin{aligned} & \lambda \exp(-\lambda (t_1 - t_0)) \\ & \times \lambda \exp(-\lambda (t_2 - t_1)) \\ & \times \lambda \exp(-\lambda (t_3 - t_2)) \end{aligned}$$

# Estimating Intensity: MLE

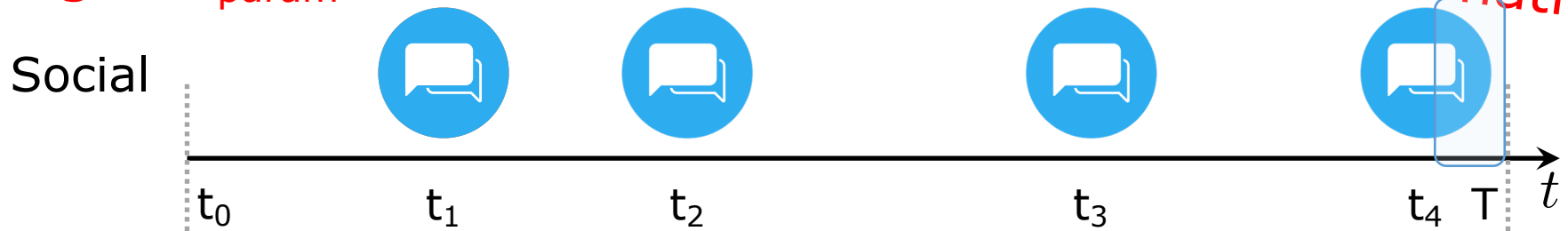
$\operatorname{argmax}_{\text{param}} \log P_{\text{model}}(\text{data})$  *maximum log-likelihood estimation*



$$\begin{aligned} & \lambda \exp(-\lambda (t_1 - t_0)) \\ & \times \lambda \exp(-\lambda (t_2 - t_1)) \\ & \times \lambda \exp(-\lambda (t_3 - t_2)) \\ & \times \lambda \exp(-\lambda (t_4 - t_3)) \end{aligned}$$

# Estimating Intensity: MLE

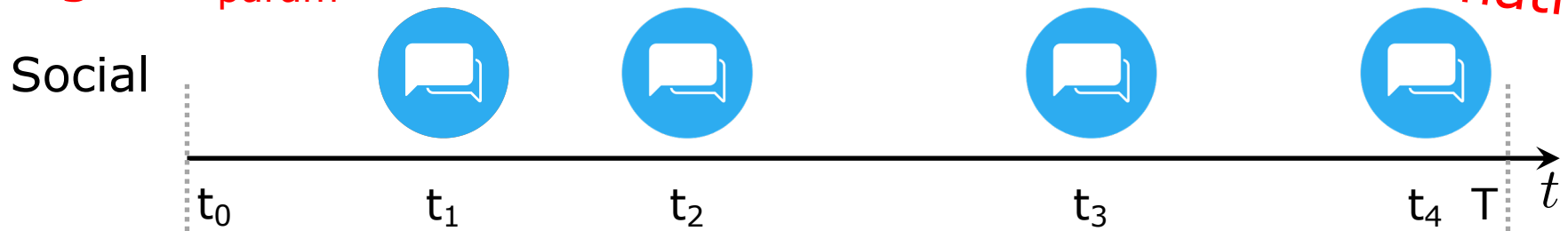
$\operatorname{argmax}_{\text{param}} \log P_{\text{model}}(\text{data})$  *maximum log-likelihood estimation*



$$\begin{aligned} & \lambda \exp(-\lambda (t_1 - t_0)) \\ & \times \lambda \exp(-\lambda (t_2 - t_1)) \\ & \times \lambda \exp(-\lambda (t_3 - t_2)) \\ & \times \lambda \exp(-\lambda (t_4 - t_3)) \\ & \times \exp(-\lambda (T - t_4)) \end{aligned}$$

# Estimating Intensity: MLE

$\operatorname{argmax}_{\text{param}} \log P_{\text{model}}(\text{data})$  *maximum log-likelihood estimation*

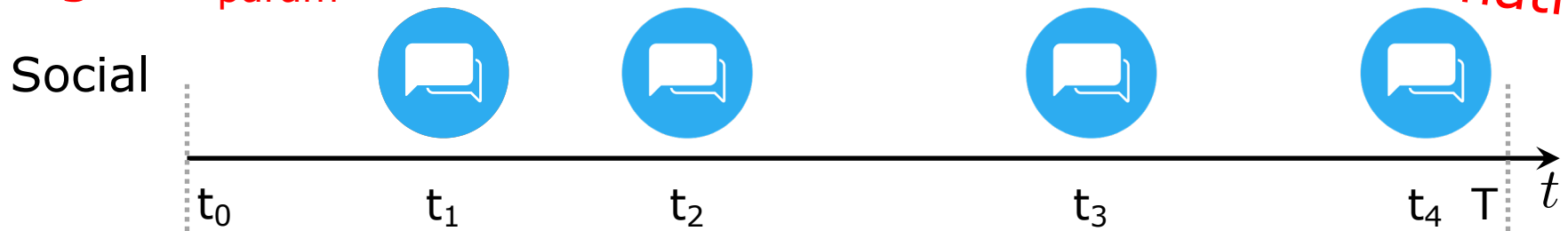


$$\begin{aligned} & \lambda \exp(-\lambda (t_1 - t_0)) \\ & \times \lambda \exp(-\lambda (t_2 - t_1)) \\ & \times \lambda \exp(-\lambda (t_3 - t_2)) \\ & \times \lambda \exp(-\lambda (t_4 - t_3)) \\ & \times \exp(-\lambda (T - t_4)) \\ & = \lambda^4 \exp(-\lambda (T - t_0)) \end{aligned}$$



# Estimating Intensity: MLE

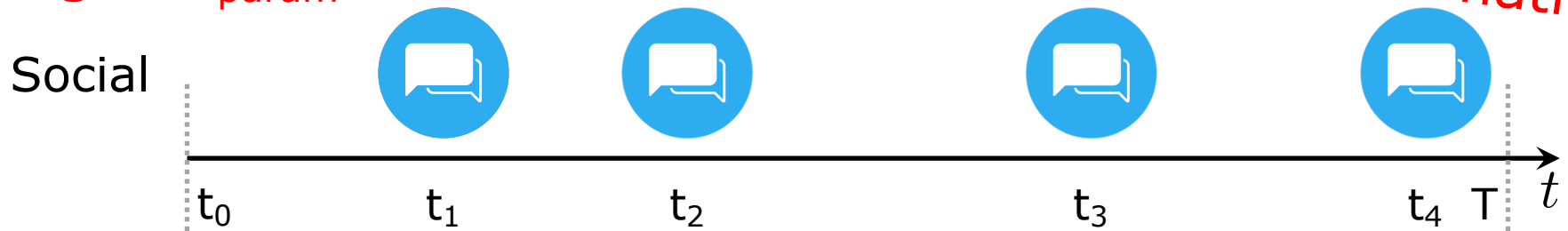
*maximum log-likelihood estimation*  
 $\operatorname{argmax}_{\text{param}} \log P_{\text{model}}(\text{data})$



$$\begin{aligned} & \lambda \exp(-\lambda (t_1 - t_0)) \\ & \times \lambda \exp(-\lambda (t_2 - t_1)) \\ & \times \lambda \exp(-\lambda (t_3 - t_2)) \\ & \times \lambda \exp(-\lambda (t_4 - t_3)) \\ & \times \exp(-\lambda (T - t_4)) \\ & = \lambda^4 \exp(-\lambda (T - t_0)) \end{aligned} \quad \operatorname{argmax}_{\lambda} \log \lambda^4 \exp(-\lambda (T - t_0))$$

# Estimating Intensity: MLE

$\operatorname{argmax}_{\text{param}} \log P_{\text{model}}(\text{data})$  *maximum log-likelihood estimation*

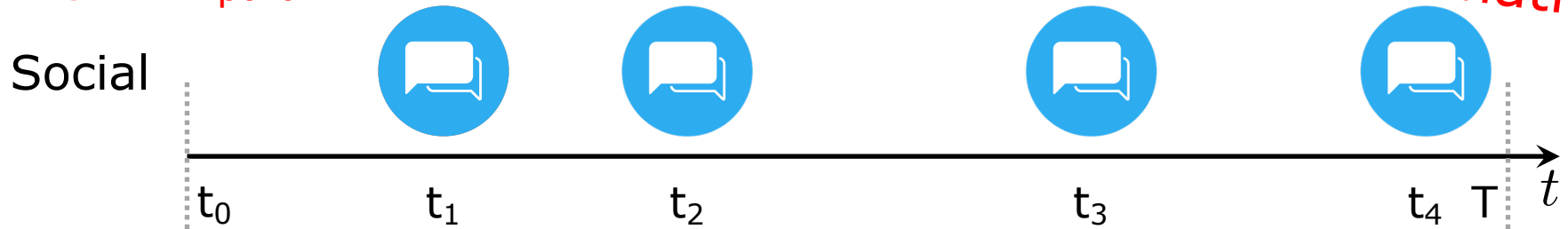


$$\begin{aligned} & \lambda \exp(-\lambda (t_1 - t_0)) \\ & \times \lambda \exp(-\lambda (t_2 - t_1)) \\ & \times \lambda \exp(-\lambda (t_3 - t_2)) \\ & \times \lambda \exp(-\lambda (t_4 - t_3)) \\ & \times \exp(-\lambda (T - t_4)) \\ & = \lambda^4 \exp(-\lambda (T - t_0)) \end{aligned}$$

$$\begin{aligned} & \operatorname{argmax}_{\lambda} \log \lambda^4 \exp(-\lambda (T - t_0)) \\ & \operatorname{argmax}_{\lambda} 4 \log \lambda - \lambda (T - t_0) \end{aligned}$$

# Estimating Intensity: MLE

*maximum log-likelihood estimation*  
 $\operatorname{argmax}_{\text{param}} \log P_{\text{model}}(\text{data})$

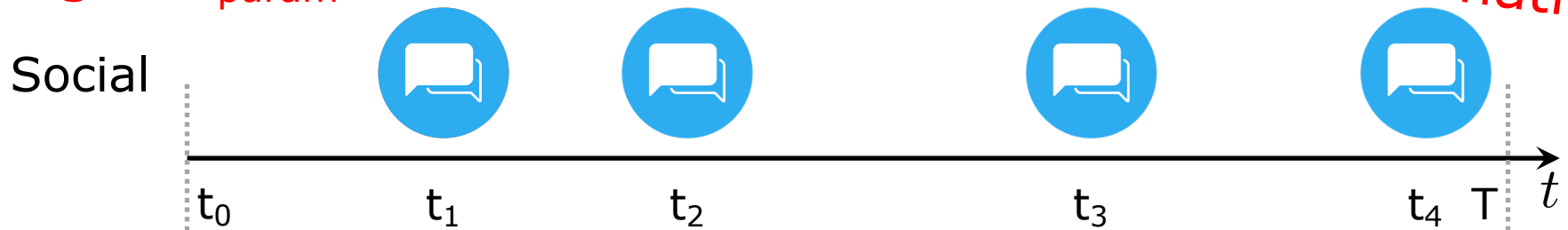


$$\begin{aligned} & \lambda \exp(-\lambda (t_1 - t_0)) \\ & \times \lambda \exp(-\lambda (t_2 - t_1)) \\ & \times \lambda \exp(-\lambda (t_3 - t_2)) \\ & \times \lambda \exp(-\lambda (t_4 - t_3)) \\ & \times \exp(-\lambda (T - t_4)) \\ & = \lambda^4 \exp(-\lambda (T - t_0)) \end{aligned}$$

$$\begin{aligned} & \operatorname{argmax}_{\lambda} \log \lambda^4 \exp(-\lambda (T - t_0)) \\ & \operatorname{argmax}_{\lambda} 4 \log \lambda - \lambda (T - t_0) \\ & \operatorname{argmax}_{\lambda} f(\lambda) \leftrightarrow \nabla_{\lambda} f(\lambda) = 0 \end{aligned}$$

# Estimating Intensity: MLE

*maximum log-likelihood estimation*  
 $\operatorname{argmax}_{\text{param}} \log P_{\text{model}}(\text{data})$



$$\begin{aligned} & \lambda \exp(-\lambda (t_1 - t_0)) \\ & \times \lambda \exp(-\lambda (t_2 - t_1)) \\ & \times \lambda \exp(-\lambda (t_3 - t_2)) \\ & \times \lambda \exp(-\lambda (t_4 - t_3)) \\ & \times \exp(-\lambda (T - t_4)) \\ & = \lambda^4 \exp(-\lambda (T - t_0)) \end{aligned}$$

$$\operatorname{argmax}_{\lambda} \log \lambda^4 \exp(-\lambda (T - t_0))$$

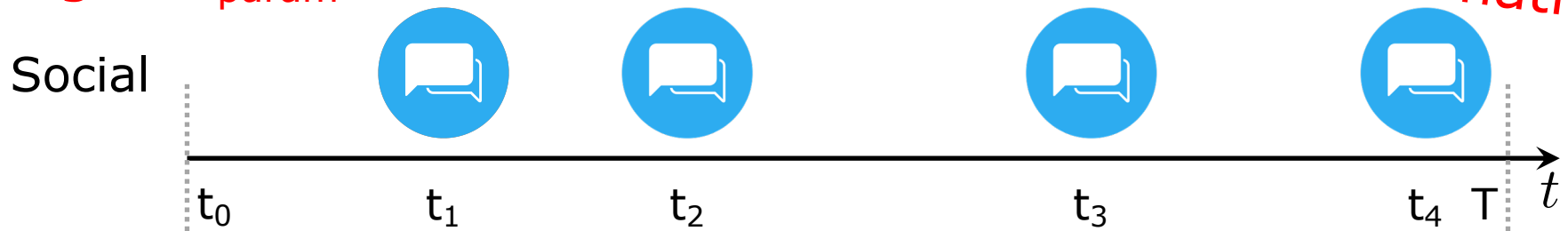
$$\operatorname{argmax}_{\lambda} 4 \log \lambda - \lambda (T - t_0)$$

$$\operatorname{argmax}_{\lambda} f(\lambda) \leftrightarrow \nabla_{\lambda} f(\lambda) = 0$$

$$\nabla_{\lambda} (4 \log \lambda - \lambda (T - t_0)) = 0$$

# Estimating Intensity: MLE

*maximum log-likelihood estimation*  
 $\operatorname{argmax}_{\text{param}} \log P_{\text{model}}(\text{data})$

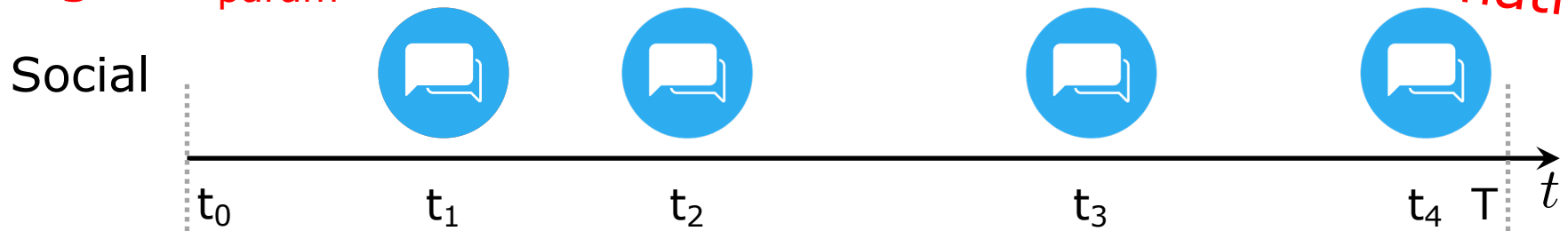


$$\begin{aligned} & \lambda \exp(-\lambda (t_1 - t_0)) \\ & \times \lambda \exp(-\lambda (t_2 - t_1)) \\ & \times \lambda \exp(-\lambda (t_3 - t_2)) \\ & \times \lambda \exp(-\lambda (t_4 - t_3)) \\ & \times \exp(-\lambda (T - t_4)) \\ & = \lambda^4 \exp(-\lambda (T - t_0)) \end{aligned}$$

$$\begin{aligned} & \operatorname{argmax}_{\lambda} \log \lambda^4 \exp(-\lambda (T - t_0)) \\ & \operatorname{argmax}_{\lambda} 4 \log \lambda - \lambda (T - t_0) \\ & \operatorname{argmax}_{\lambda} f(\lambda) \leftrightarrow \nabla_{\lambda} f(\lambda) = 0 \\ & \nabla_{\lambda} (4 \log \lambda - \lambda (T - t_0)) = 0 \\ & \lambda = 4 / (T - t_0) \end{aligned}$$

# Estimating Intensity: MLE

$\operatorname{argmax}_{\text{param}} \log P_{\text{model}}(\text{data})$  *maximum log-likelihood estimation*



$$\begin{aligned} & \lambda \exp(-\lambda (t_1 - t_0)) \\ & \times \lambda \exp(-\lambda (t_2 - t_1)) \\ & \times \lambda \exp(-\lambda (t_3 - t_2)) \\ & \times \lambda \exp(-\lambda (t_4 - t_3)) \\ & \times \exp(-\lambda (T - t_4)) \\ & = \lambda^4 \exp(-\lambda (T - t_0)) \end{aligned}$$

$$\operatorname{argmax}_{\lambda} \log \lambda^4 \exp(-\lambda (T - t_0))$$

$$\operatorname{argmax}_{\lambda} 4 \log \lambda - \lambda (T - t_0)$$

$$\operatorname{argmax}_{\lambda} f(\lambda) \leftrightarrow \nabla_{\lambda} f(\lambda) = 0$$

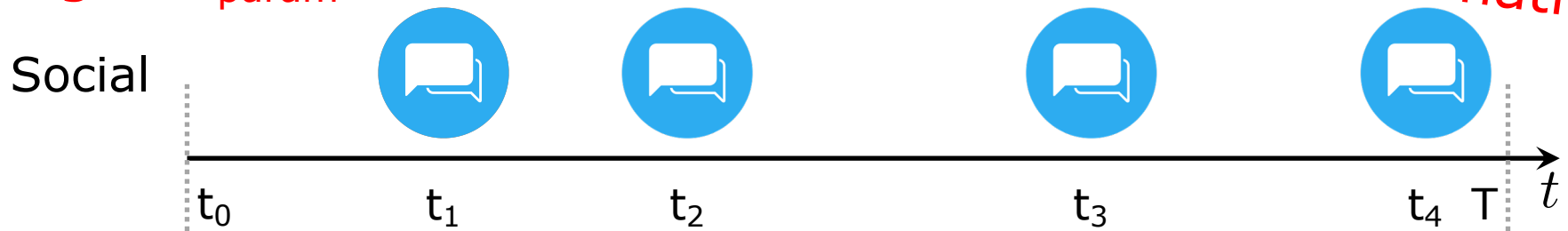
$$\nabla_{\lambda} (4 \log \lambda - \lambda (T - t_0)) = 0$$

$$\lambda = \textcircled{4} / (T - t_0)$$

# of events

# Estimating Intensity: MLE

*maximum log-likelihood estimation*  
 $\text{argmax}_{\text{param}} \log P_{\text{model}}(\text{data})$



$$\begin{aligned} & \lambda \exp(-\lambda (t_1 - t_0)) \\ & \times \lambda \exp(-\lambda (t_2 - t_1)) \\ & \times \lambda \exp(-\lambda (t_3 - t_2)) \\ & \times \lambda \exp(-\lambda (t_4 - t_3)) \\ & \times \exp(-\lambda (T - t_4)) \\ & = \lambda^4 \exp(-\lambda (T - t_0)) \end{aligned}$$

$$\text{argmax}_{\lambda} \log \lambda^4 \exp(-\lambda (T - t_0))$$

$$\text{argmax}_{\lambda} 4 \log \lambda - \lambda (T - t_0)$$

$$\text{argmax}_{\lambda} f(\lambda) \leftrightarrow \nabla_{\lambda} f(\lambda) = 0$$

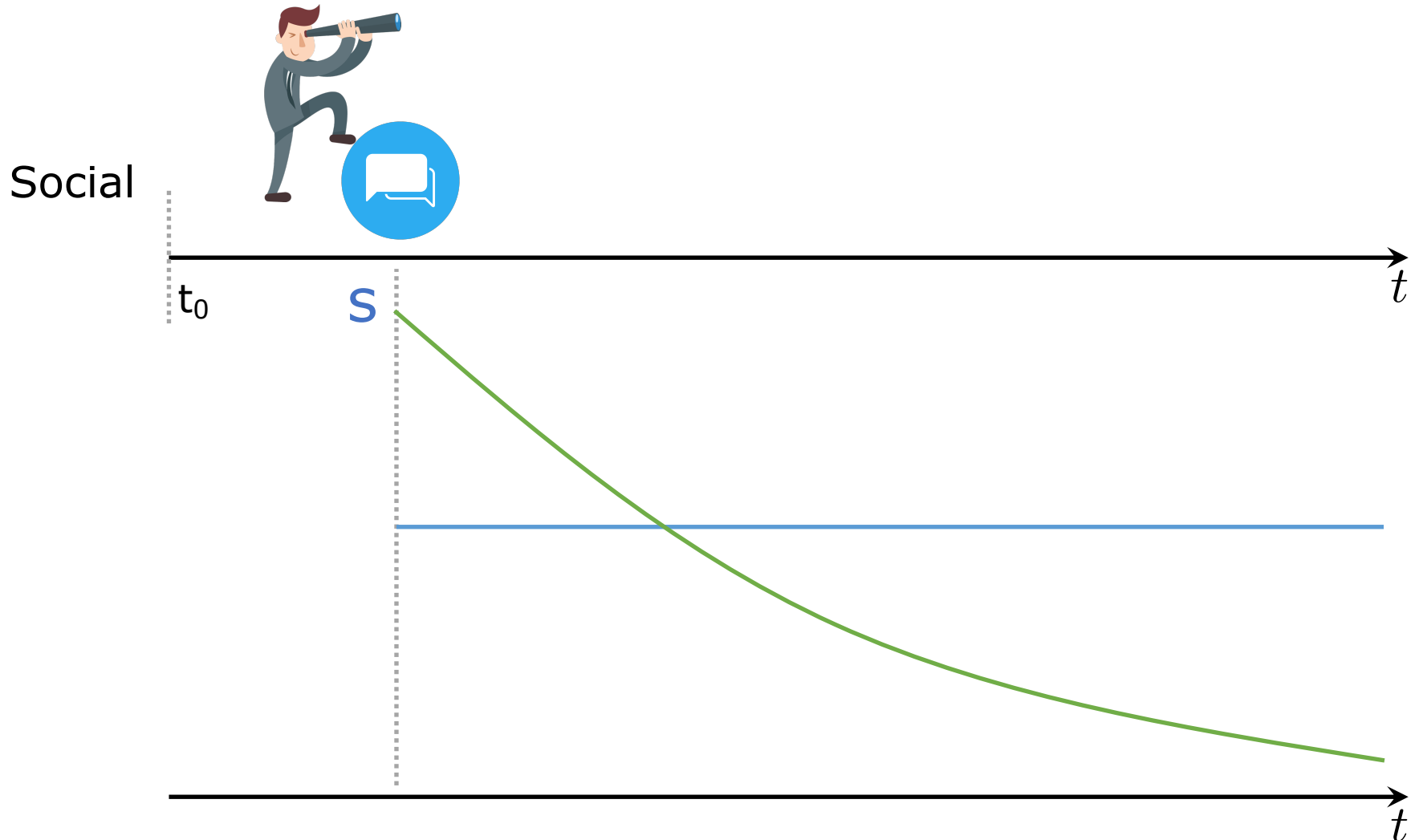
$$\nabla_{\lambda} (4 \log \lambda - \lambda (T - t_0)) = 0$$

$$\lambda = 4 / (T - t_0)$$

# of events

total time

# Predicting Next Event Time: MBR

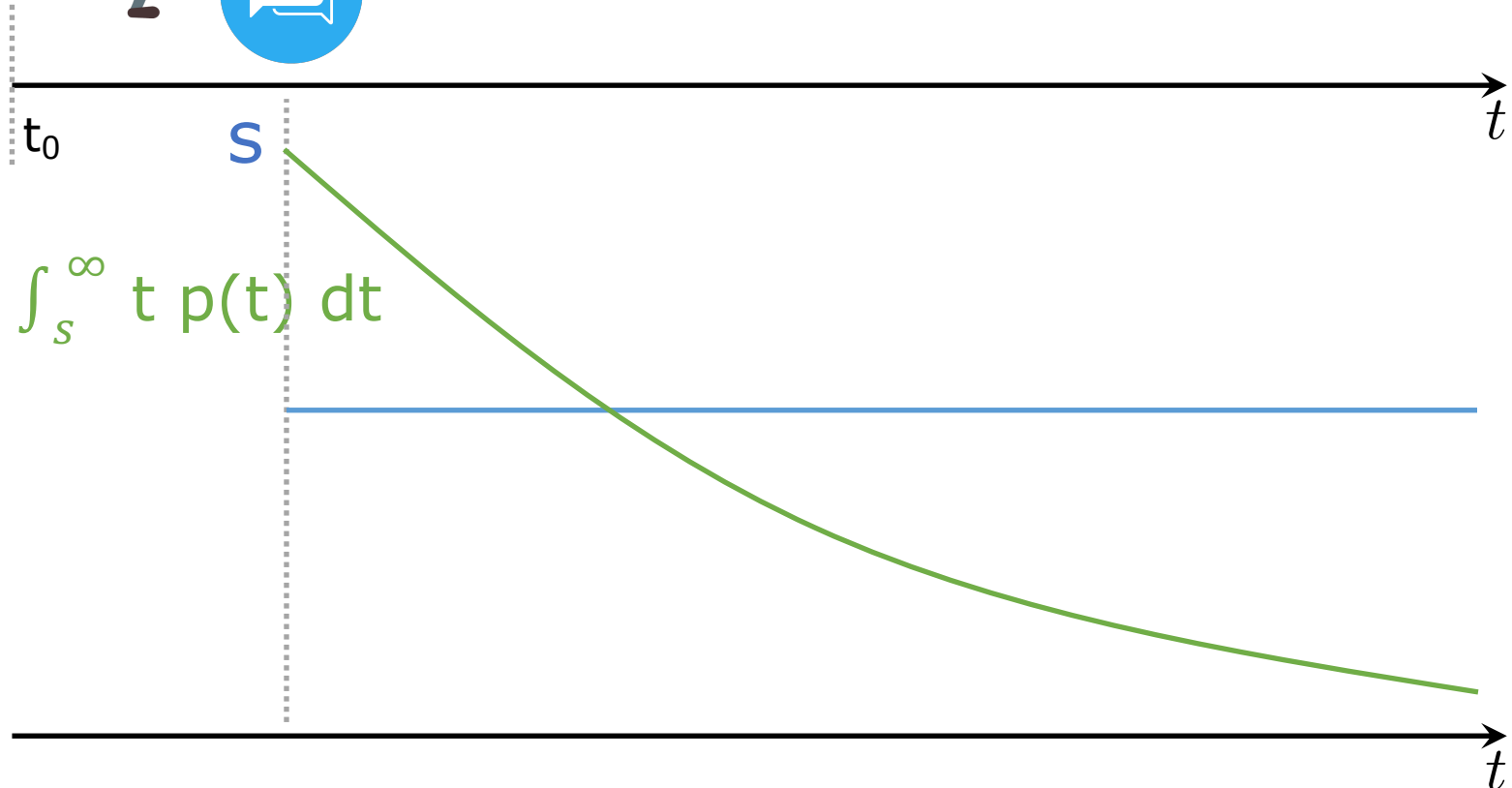




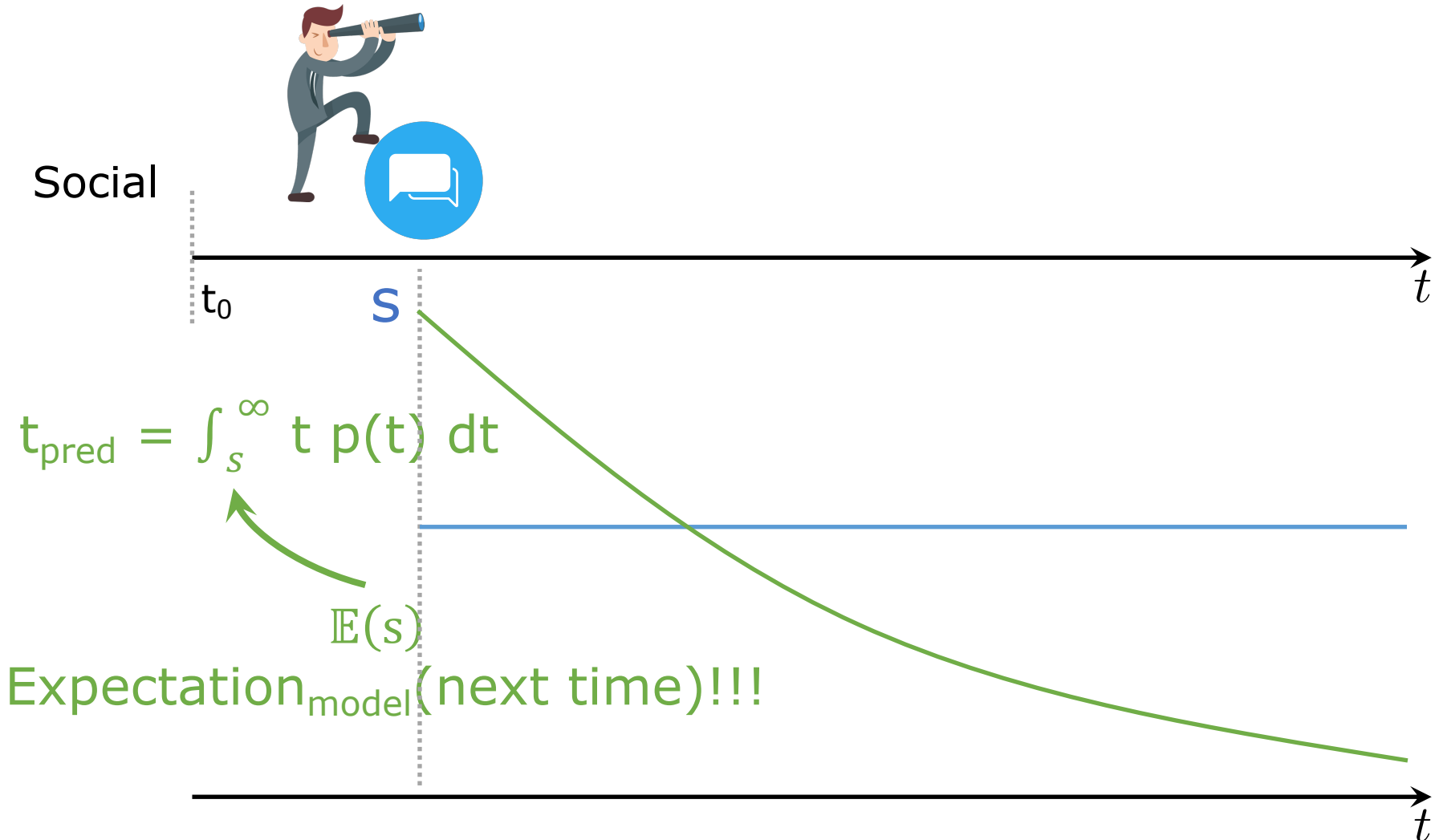
# Predicting Next Event Time: MBR



Social



# Predicting Next Event Time: MBR

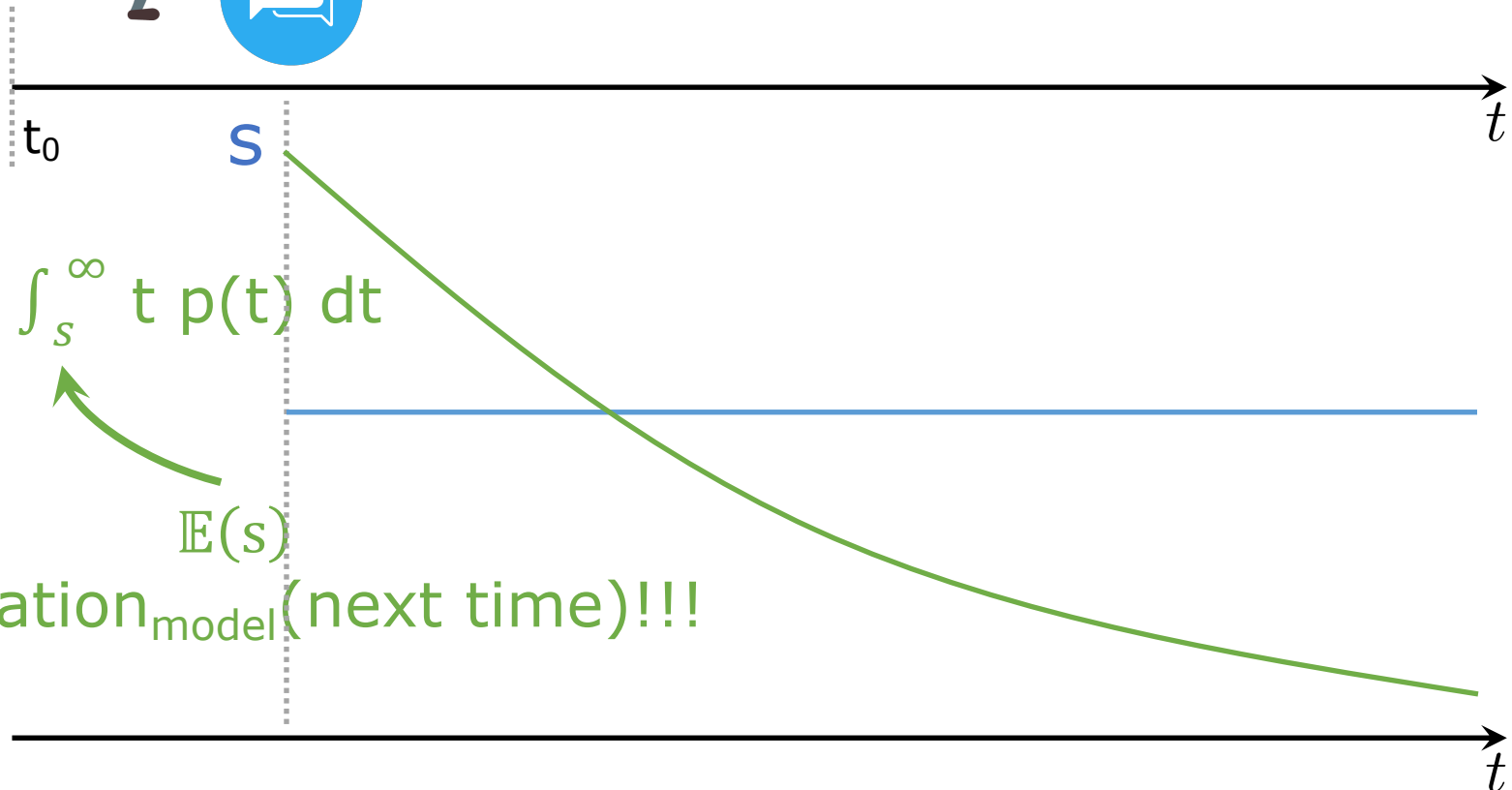


# Predicting Next Event Time: MBR



minimum Bayes risk

Social



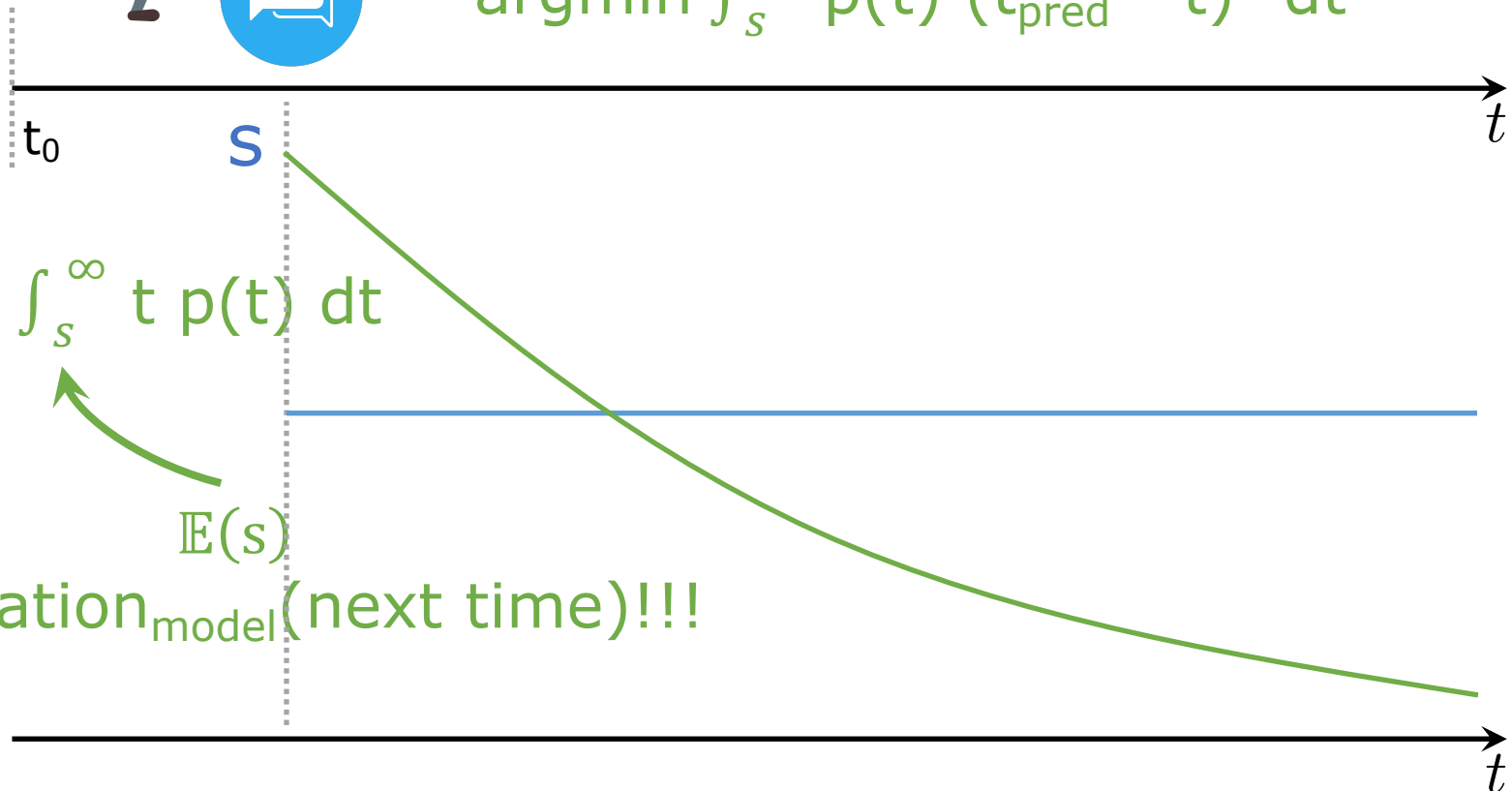
# Predicting Next Event Time: MBR



minimum Bayes risk

$$\operatorname{argmin} \int_s^\infty p(t) (t_{\text{pred}} - t)^2 dt$$

Social



$$t_{\text{pred}} = \int_s^\infty t p(t) dt$$

$\mathbb{E}(s)$

Expectation<sub>model</sub>(next time)!!!

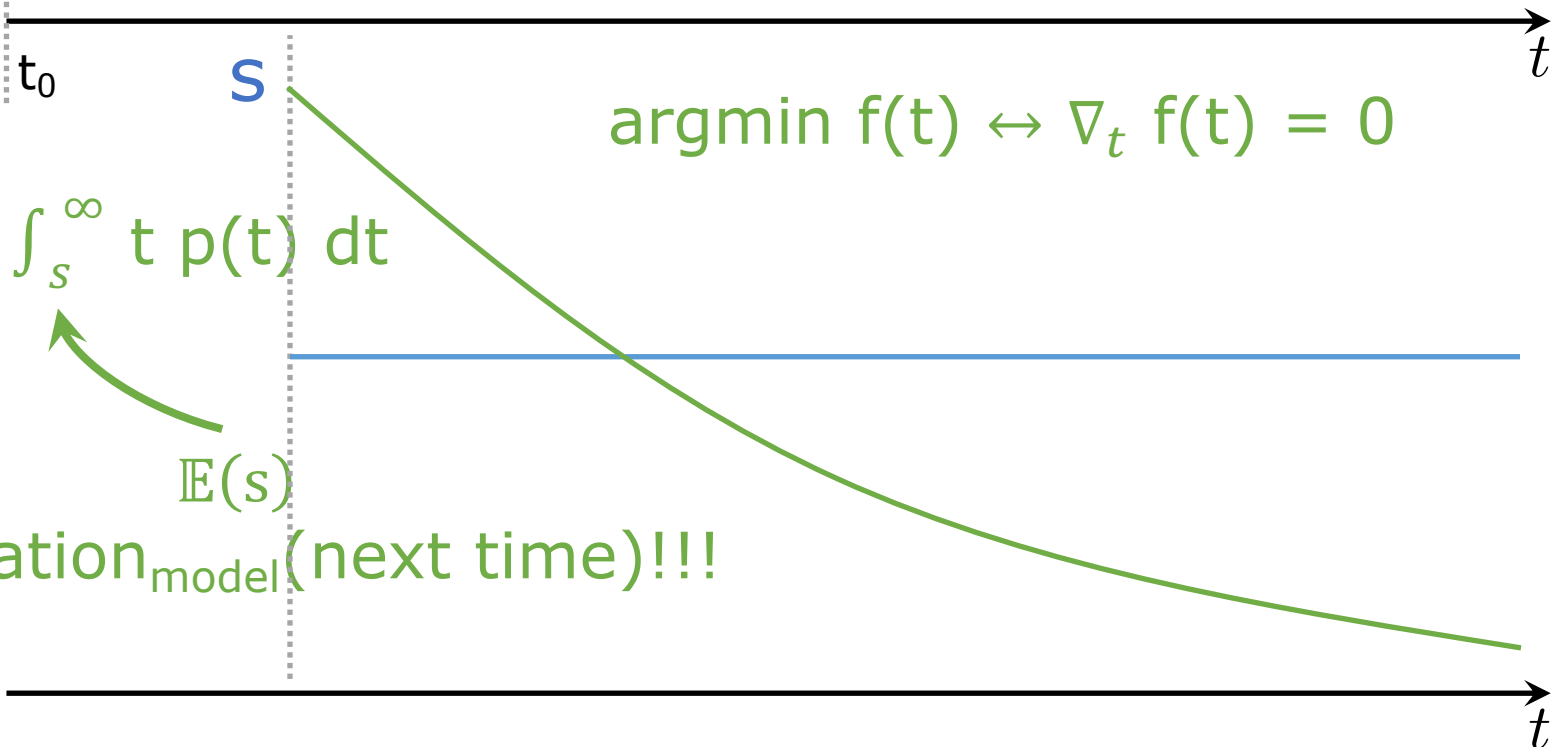
# Predicting Next Event Time: MBR



minimum Bayes risk

$$\operatorname{argmin} \int_s^\infty p(t) (t_{\text{pred}} - t)^2 dt$$

Social



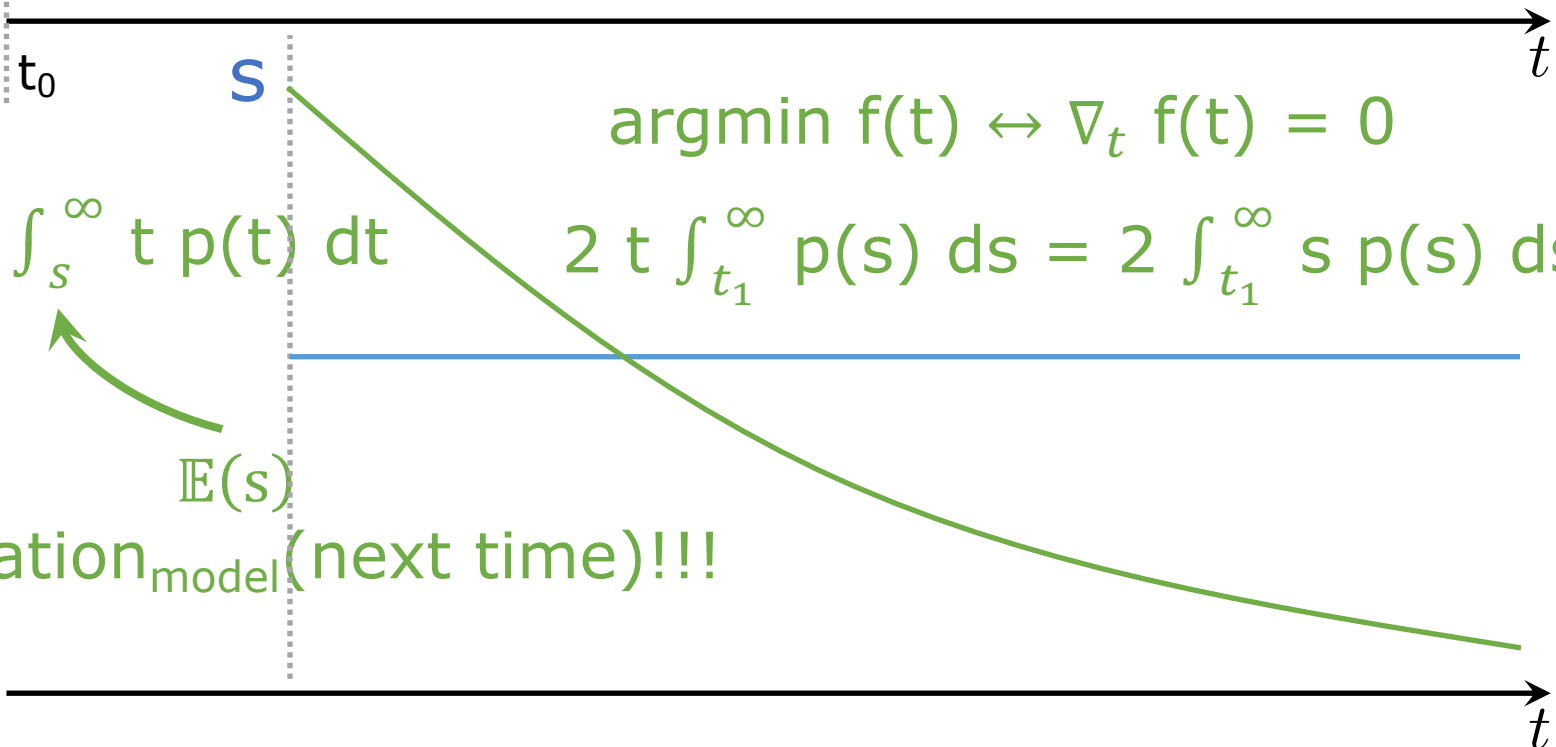
# Predicting Next Event Time: MBR



minimum Bayes risk

$$\operatorname{argmin} \int_s^\infty p(t) (t_{\text{pred}} - t)^2 dt$$

Social

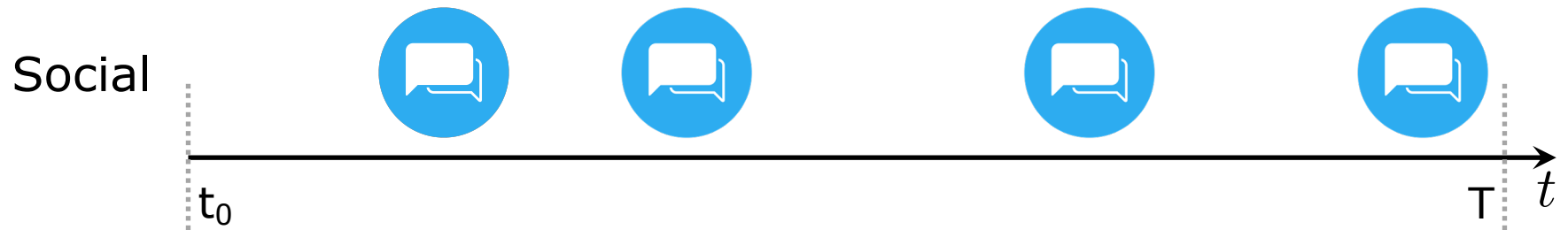


**Any Questions?**

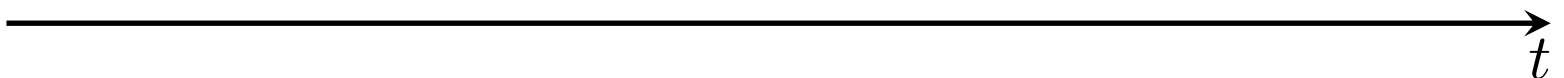
**<http://bburl/tpp-slides-p1>**

**<http://bburl/tpp-lab-p1>**

# Multivariate Time Series



$\lambda_{\text{social}}$

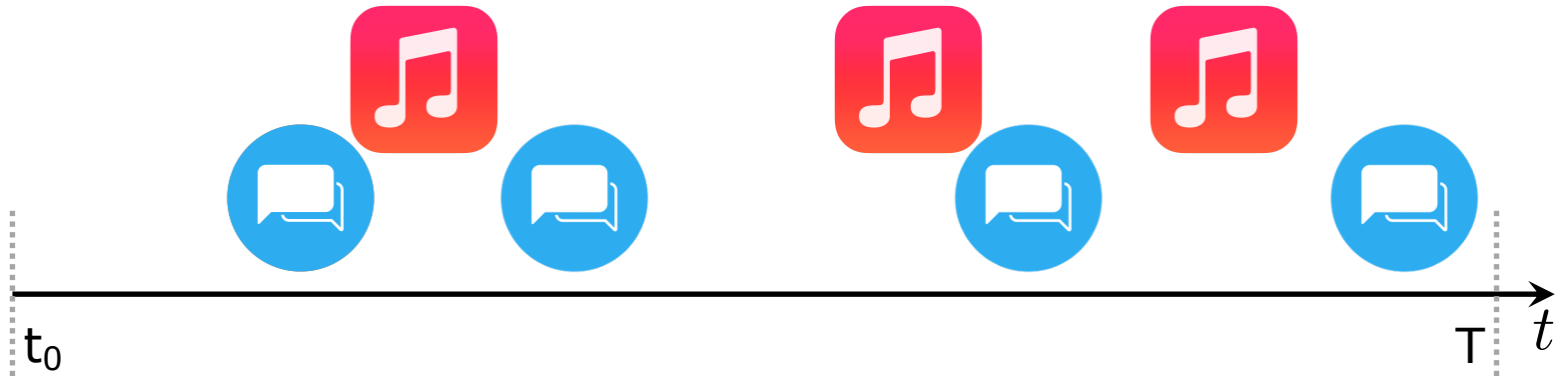




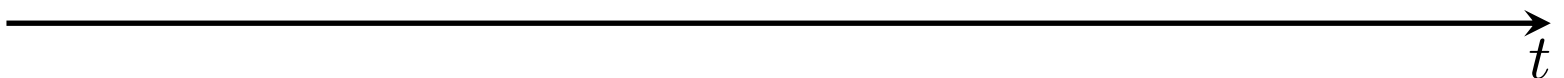
# Multivariate Time Series

Music

Social



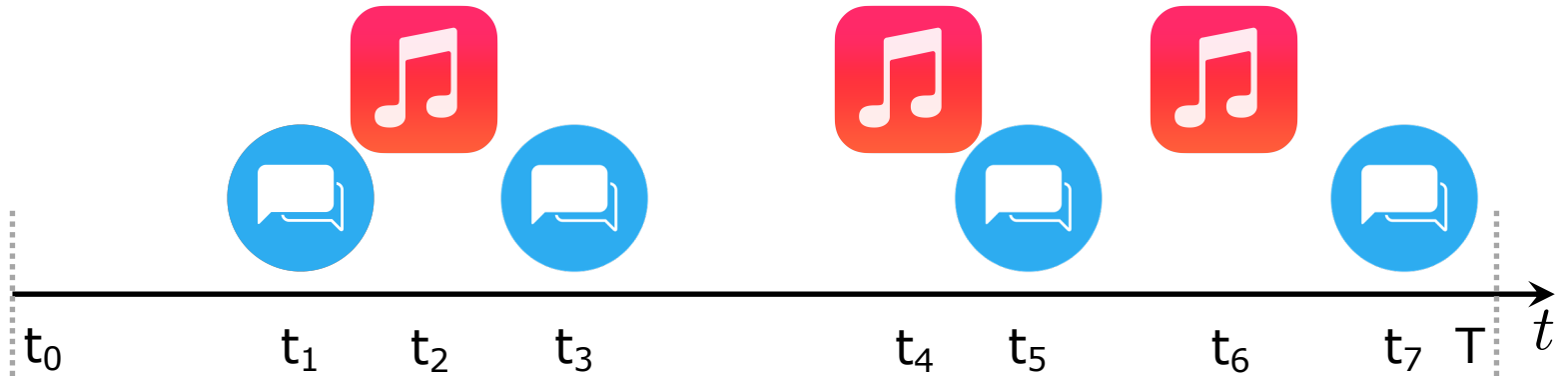
$\lambda_{\text{social}}$



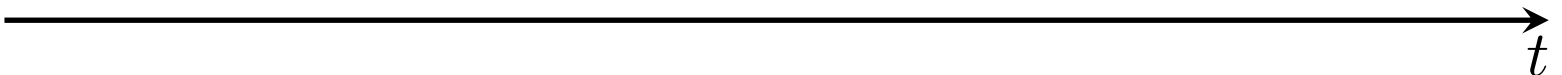
# Multivariate Time Series

Music

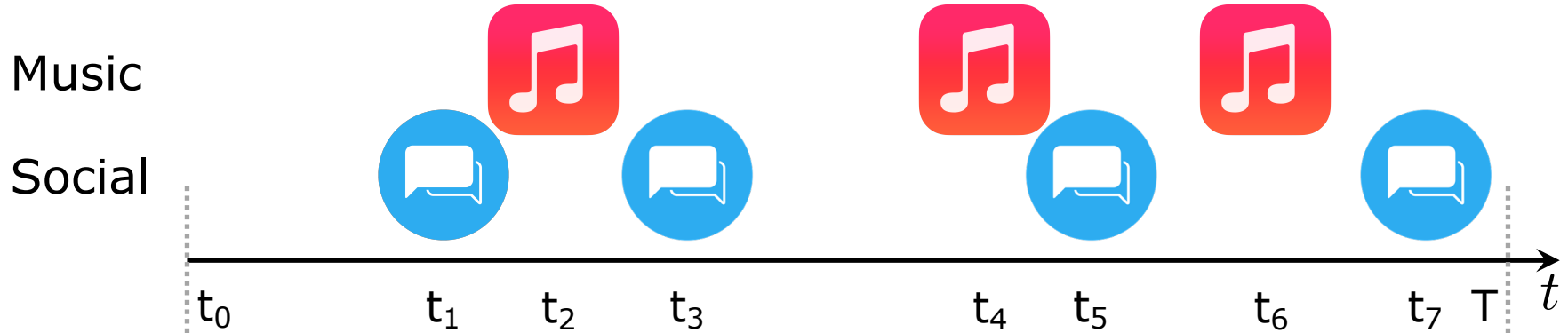
Social



$\lambda_{\text{social}}$

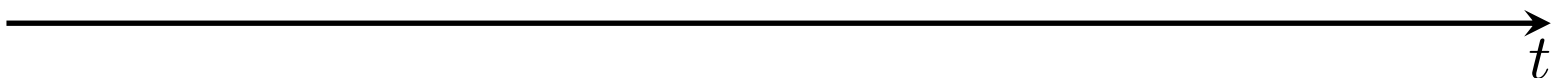


# Multivariate Time Series



$\lambda_{\text{social}}$

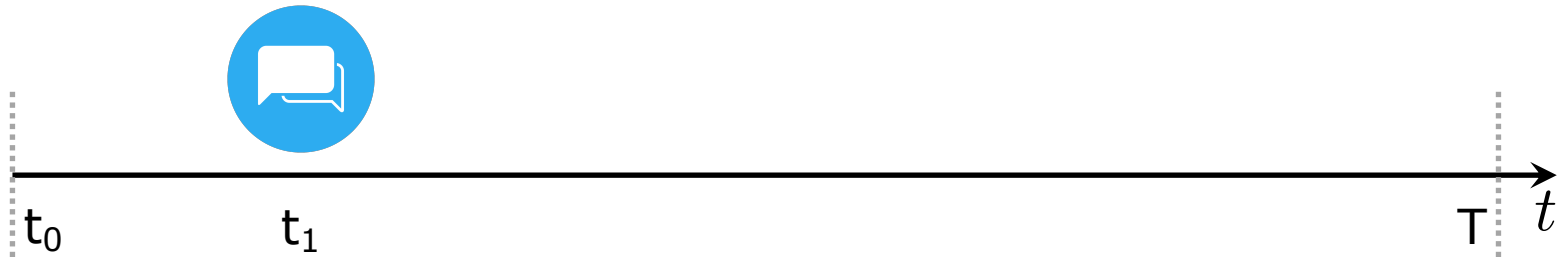
$\lambda_{\text{music}}$



# Multivariate Time Series

Music

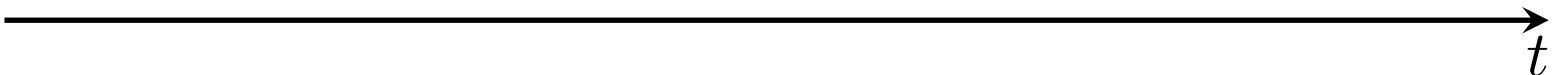
Social



$\lambda_{\text{social}}$



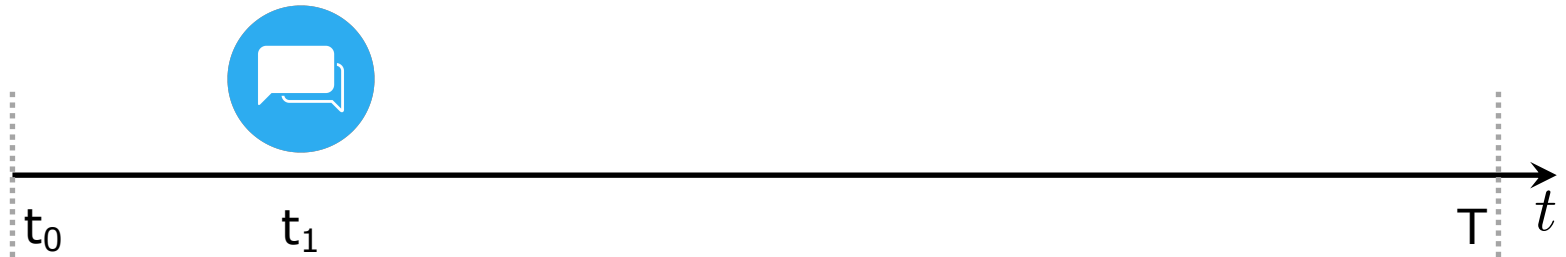
$\lambda_{\text{music}}$



# Multivariate Time Series

Music

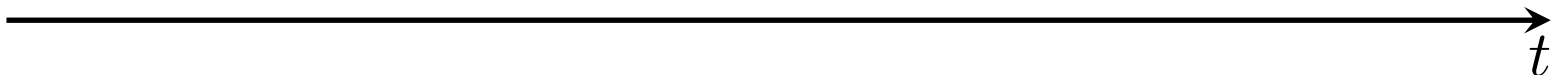
Social



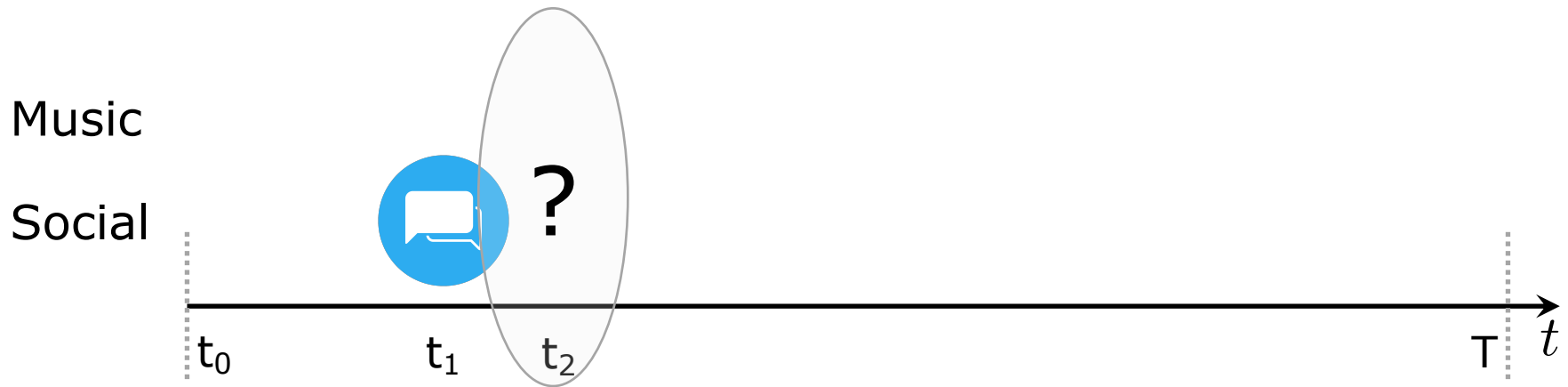
$$(\lambda_{\text{music}} + \lambda_{\text{social}})dt = \text{prob of some event at } t$$

$\lambda_{\text{social}}$

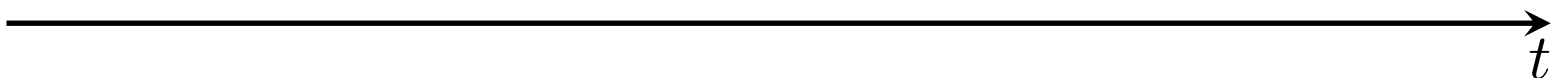
$\lambda_{\text{music}}$



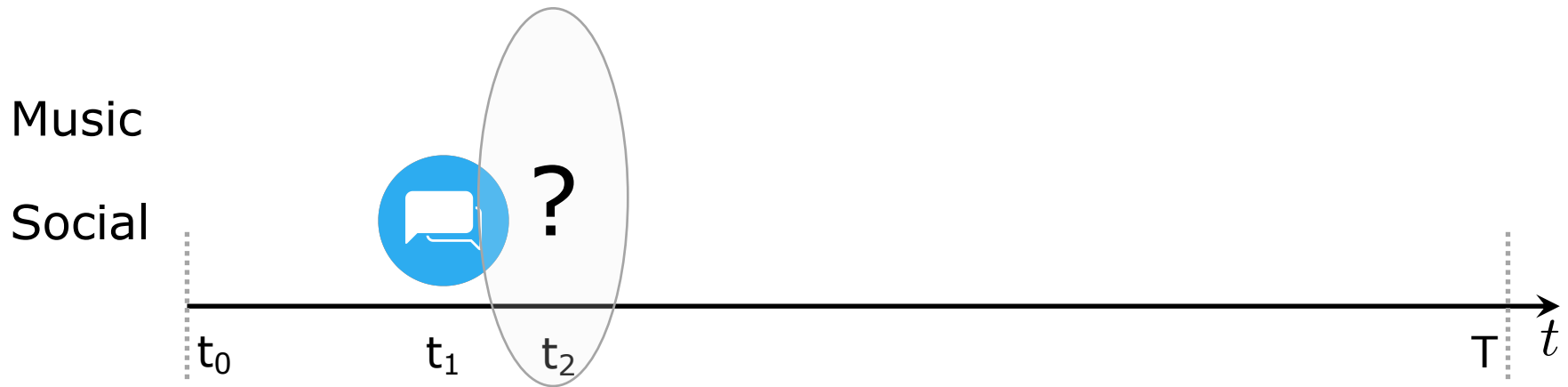
# Multivariate Time Series



$$(\lambda_{\text{music}} + \lambda_{\text{social}})dt = \text{prob of some event at } t$$

 $\lambda_{\text{social}}$  $\lambda_{\text{music}}$ 

# Multivariate Time Series



$$\propto \lambda_{\text{music}}$$

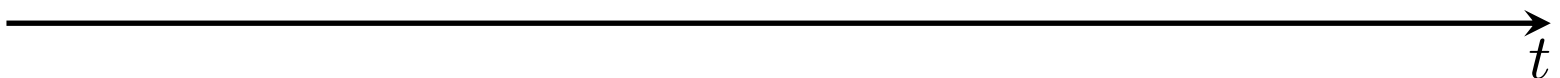


$$\propto \lambda_{\text{social}}$$

$$(\lambda_{\text{music}} + \lambda_{\text{social}})dt = \text{prob of some event at } t$$

$\lambda_{\text{social}}$

$\lambda_{\text{music}}$



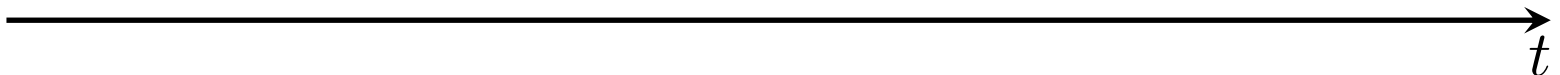
# Multivariate Time Series



  $\propto \lambda_{\text{music}}$

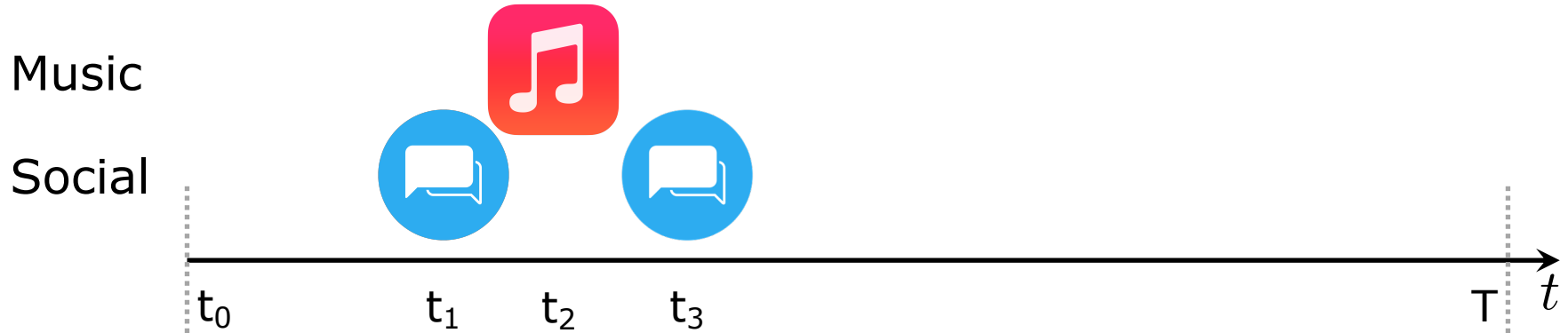
  $\propto \lambda_{\text{social}}$

$$(\lambda_{\text{music}} + \lambda_{\text{social}})dt = \text{prob of some event at } t$$

 $\lambda_{\text{social}}$  $\lambda_{\text{music}}$ 



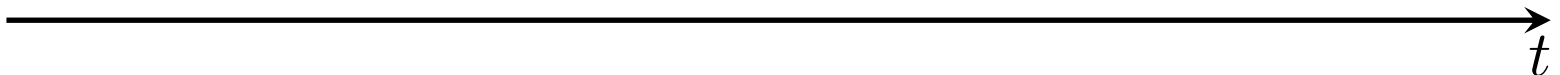
# Multivariate Time Series



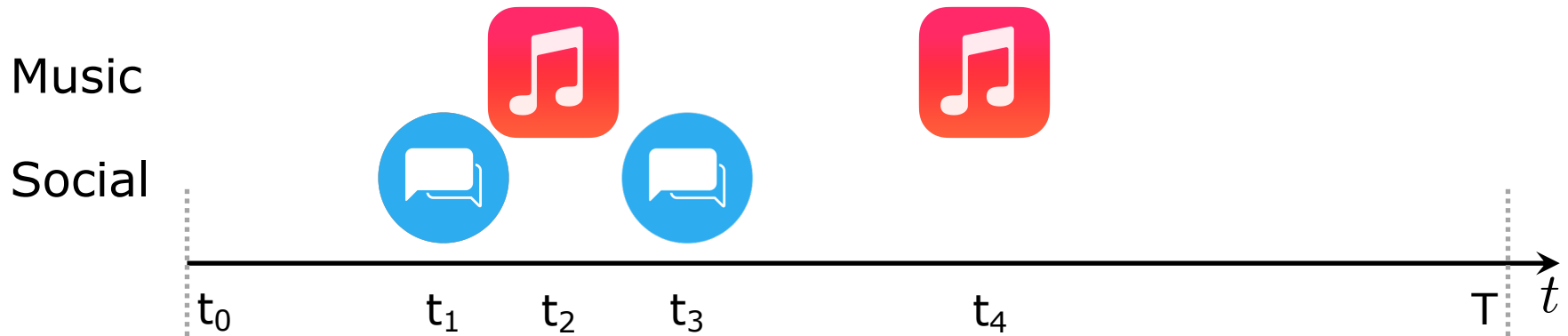
  $\propto \lambda_{\text{music}}$

  $\propto \lambda_{\text{social}}$

$$(\lambda_{\text{music}} + \lambda_{\text{social}})dt = \text{prob of some event at } t$$

 $\lambda_{\text{social}}$  $\lambda_{\text{music}}$ 

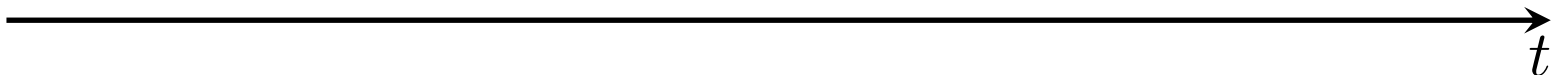
# Multivariate Time Series



  $\propto \lambda_{\text{music}}$

  $\propto \lambda_{\text{social}}$

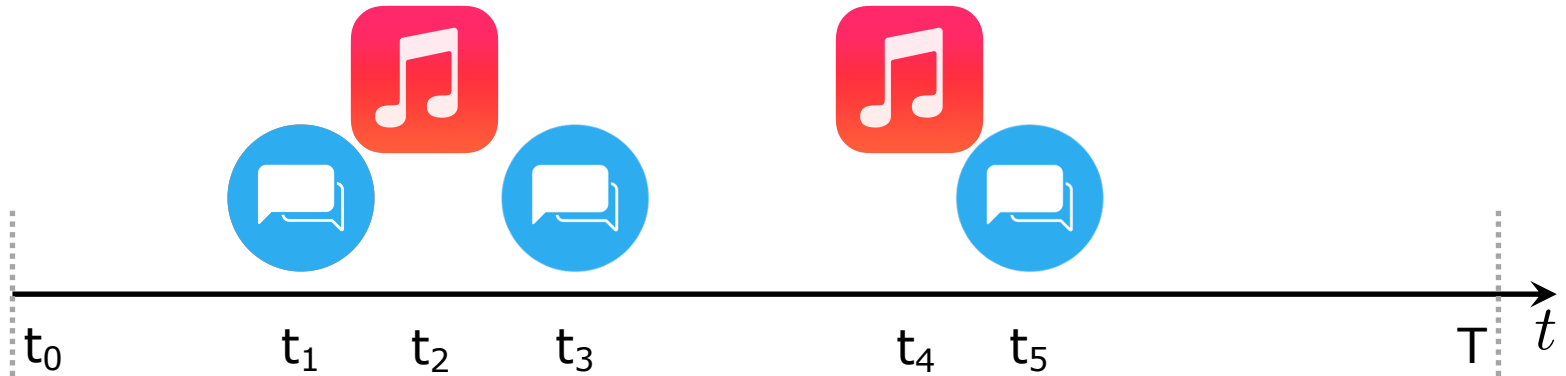
$$(\lambda_{\text{music}} + \lambda_{\text{social}})dt = \text{prob of some event at } t$$

 $\lambda_{\text{social}}$  $\lambda_{\text{music}}$ 

# Multivariate Time Series

Music

Social



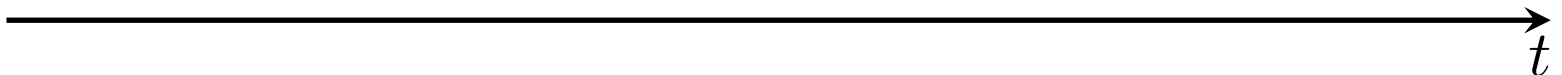
$$\text{Music icon} \propto \lambda_{\text{music}}$$

$$\text{Social icon} \propto \lambda_{\text{social}}$$

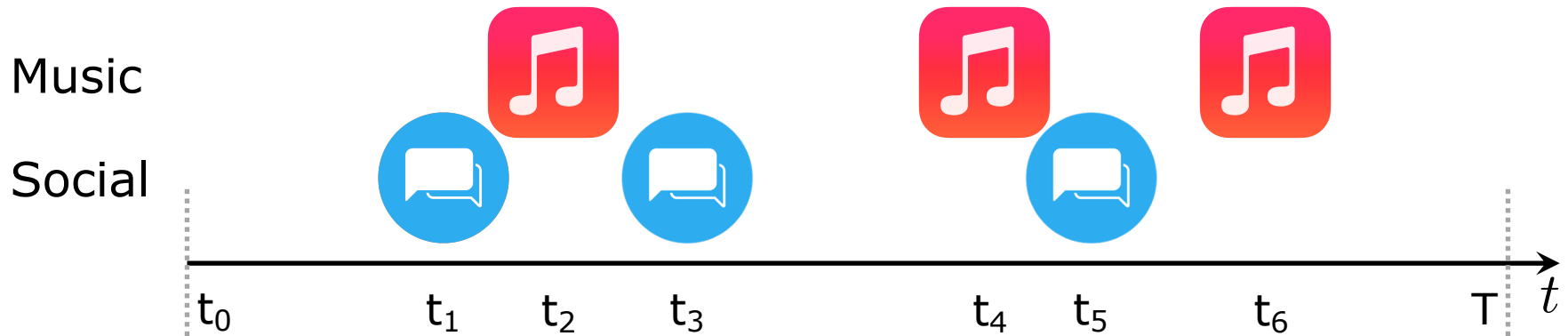
$$(\lambda_{\text{music}} + \lambda_{\text{social}})dt = \text{prob of some event at } t$$

$\lambda_{\text{social}}$

$\lambda_{\text{music}}$



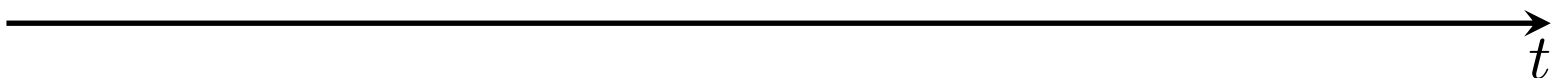
# Multivariate Time Series



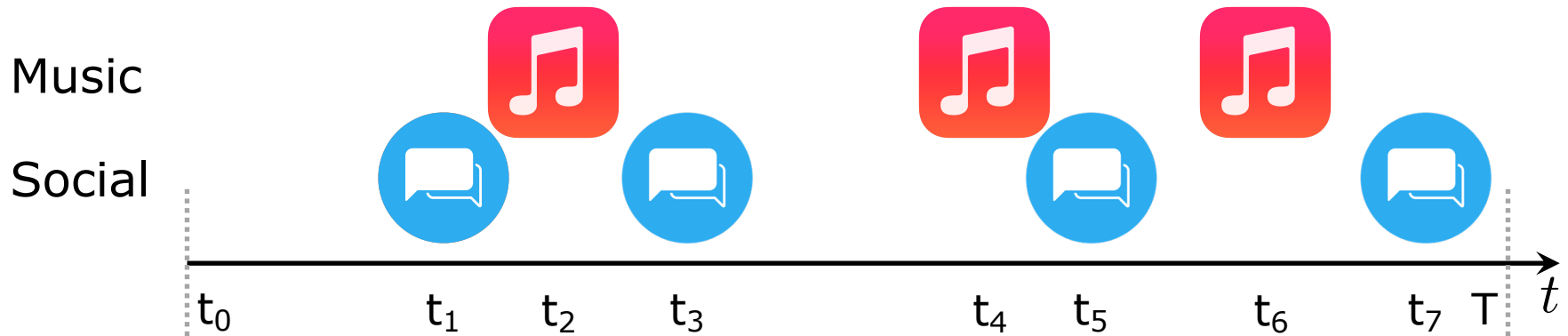
  $\propto \lambda_{\text{music}}$

  $\propto \lambda_{\text{social}}$

$$(\lambda_{\text{music}} + \lambda_{\text{social}})dt = \text{prob of some event at } t$$

 $\lambda_{\text{social}}$  $\lambda_{\text{music}}$ 

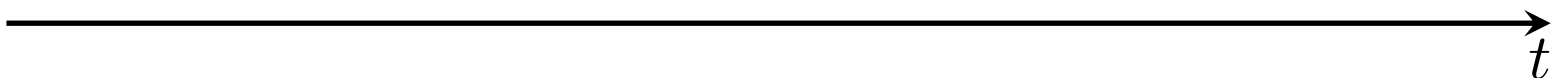
# Multivariate Time Series



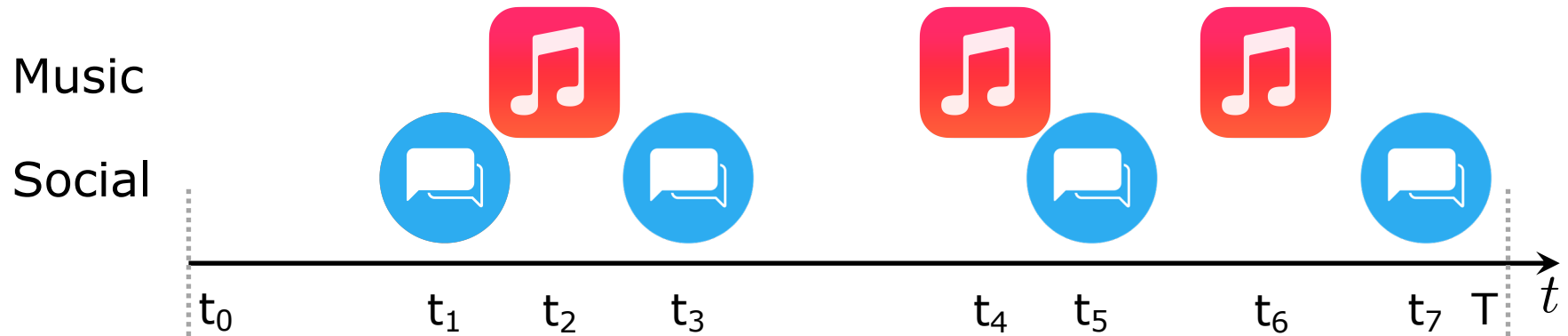
  $\propto \lambda_{\text{music}}$

  $\propto \lambda_{\text{social}}$

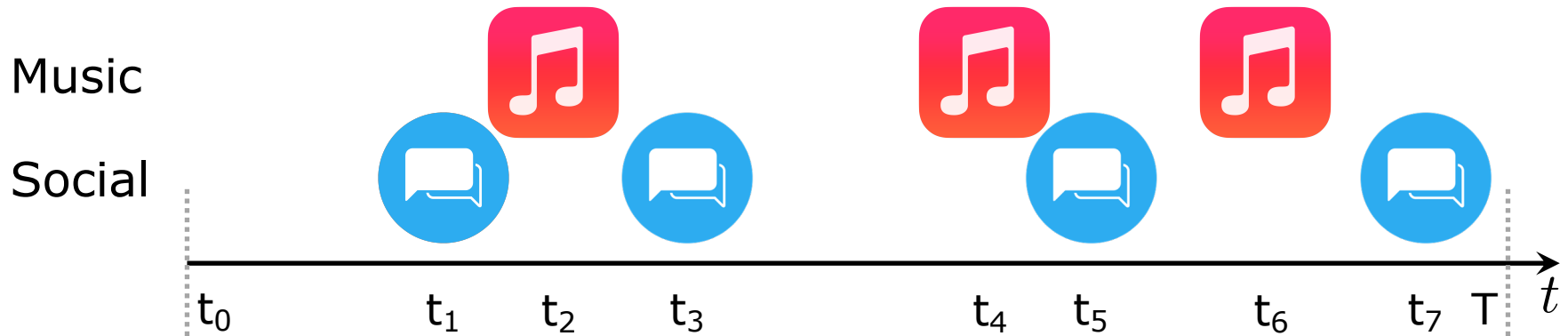
$$(\lambda_{\text{music}} + \lambda_{\text{social}})dt = \text{prob of some event at } t$$

 $\lambda_{\text{social}}$  $\lambda_{\text{music}}$ 

# Multivariate Time Series: MLE

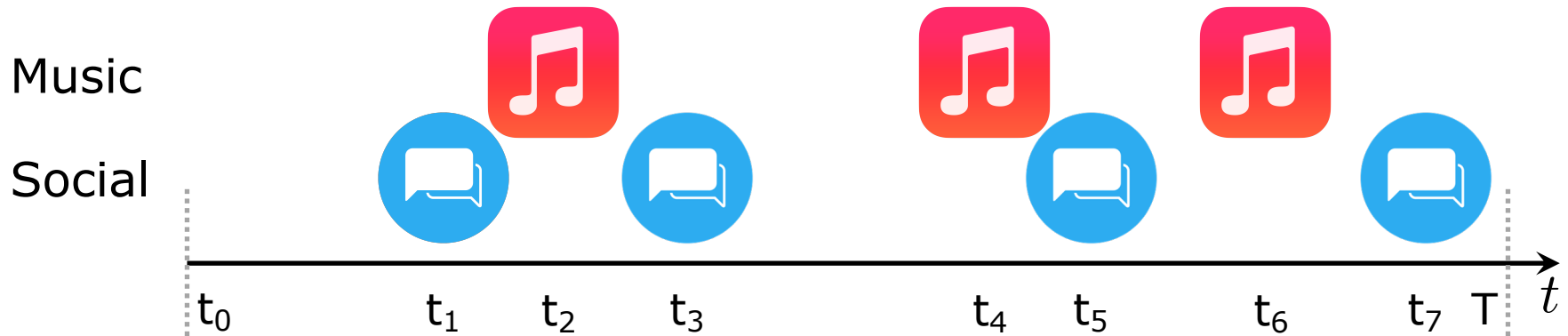


# Multivariate Time Series: MLE



$$\begin{aligned} & \lambda_{\text{social}} \exp(-\lambda (t_1 - t_0)) \\ & \times \lambda_{\text{music}} \exp(-\lambda (t_2 - t_1)) \\ & \times \lambda_{\text{social}} \exp(-\lambda (t_3 - t_2)) \\ & \dots \dots \\ & = \lambda_{\text{social}}^4 \lambda_{\text{music}}^3 \exp(-\lambda (T - t_0)) \end{aligned}$$

# Multivariate Time Series: MLE

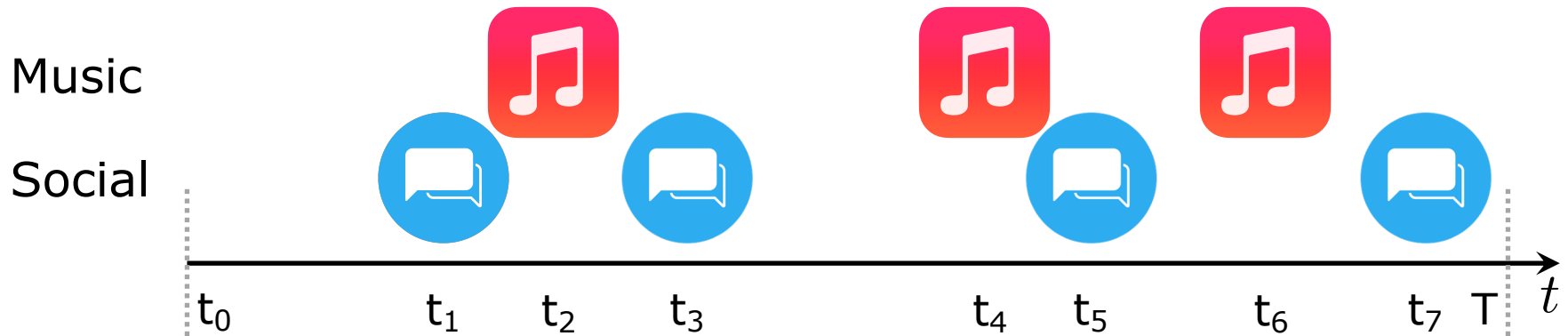


$$\begin{aligned} & \lambda_{\text{social}} \exp(-\lambda (t_1 - t_0)) \\ & \times \lambda_{\text{music}} \exp(-\lambda (t_2 - t_1)) \\ & \times \lambda_{\text{social}} \exp(-\lambda (t_3 - t_2)) \\ & \dots \dots \\ & = \lambda_{\text{social}}^4 \lambda_{\text{music}}^3 \exp(-\lambda (T - t_0)) \end{aligned}$$

$(1-\lambda dt) \dots (1-\lambda dt)$   
 $\lambda = \lambda_{\text{music}} + \lambda_{\text{social}}$



# Multivariate Time Series: MLE



$$\begin{aligned} & \lambda_{\text{social}} \exp(-\lambda (t_1 - t_0)) \\ & \times \lambda_{\text{music}} \exp(-\lambda (t_2 - t_1)) \\ & \times \lambda_{\text{social}} \exp(-\lambda (t_3 - t_2)) \\ & \dots \dots \end{aligned}$$

$(1-\lambda dt) \dots (1-\lambda dt)$

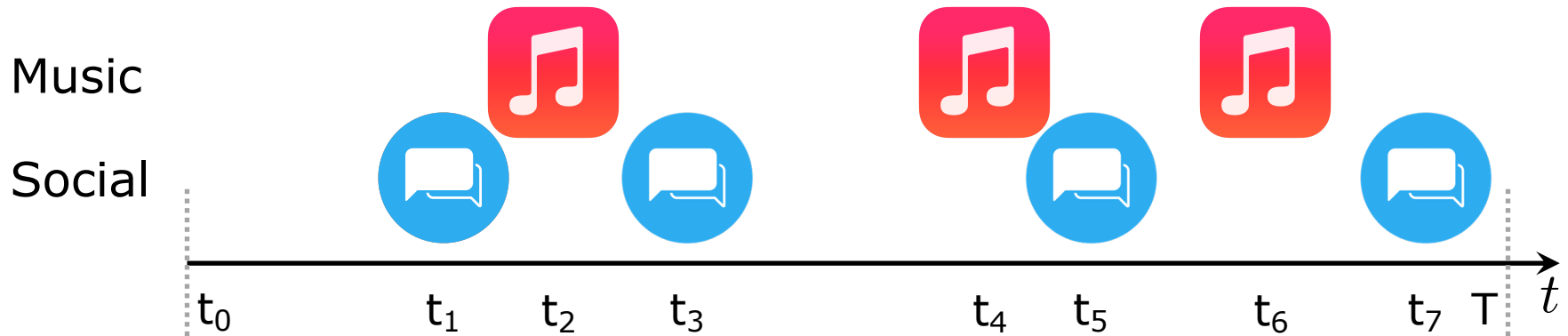
$$\lambda = \lambda_{\text{music}} + \lambda_{\text{social}}$$

$$= \lambda_{\text{social}}^4 \lambda_{\text{music}}^3 \exp(-\lambda (T - t_0))$$

$$\lambda_{\text{social}} = 4 / (T - t_0)$$

$$\lambda_{\text{music}} = 3 / (T - t_0)$$

# Multivariate Time Series: MLE



$$\lambda_{\text{social}} \exp(-\lambda (t_1 - t_0))$$

$$\times \lambda_{\text{music}} \exp(-\lambda (t_2 - t_1))$$

$$\times \lambda_{\text{social}} \exp(-\lambda (t_3 - t_2))$$

$$\dots$$

$$= \lambda_{\text{social}}^4 \lambda_{\text{music}}^3 \exp(-\lambda (T - t_0))$$

$$(1 - \lambda dt) \dots (1 - \lambda dt)$$

$$\lambda = \lambda_{\text{music}} + \lambda_{\text{social}}$$

$$\lambda_{\text{social}} = 4 / (T - t_0)$$

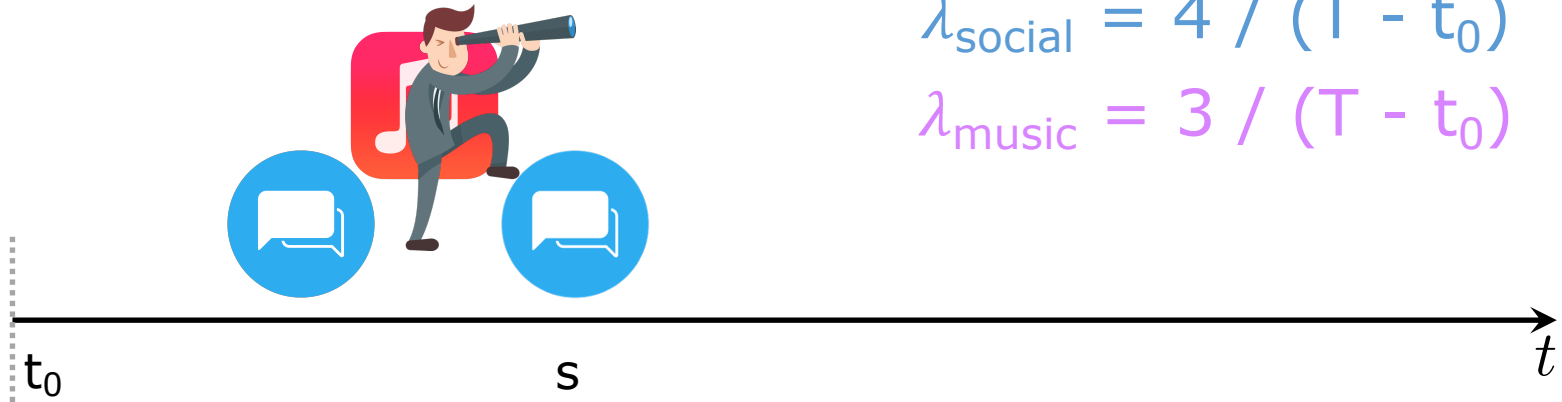
$$\lambda_{\text{music}} = 3 / (T - t_0)$$

# of events  
of *that* type

# Multivariate Time Series: MBR

Music

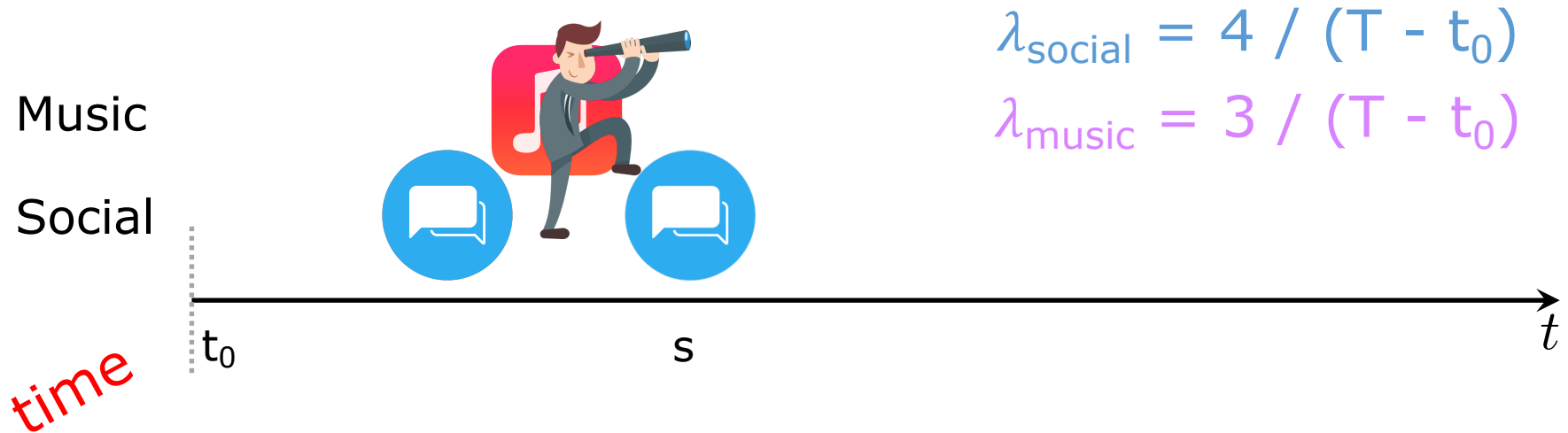
Social



$$\lambda_{\text{social}} = 4 / (T - t_0)$$

$$\lambda_{\text{music}} = 3 / (T - t_0)$$

# Multivariate Time Series: MBR

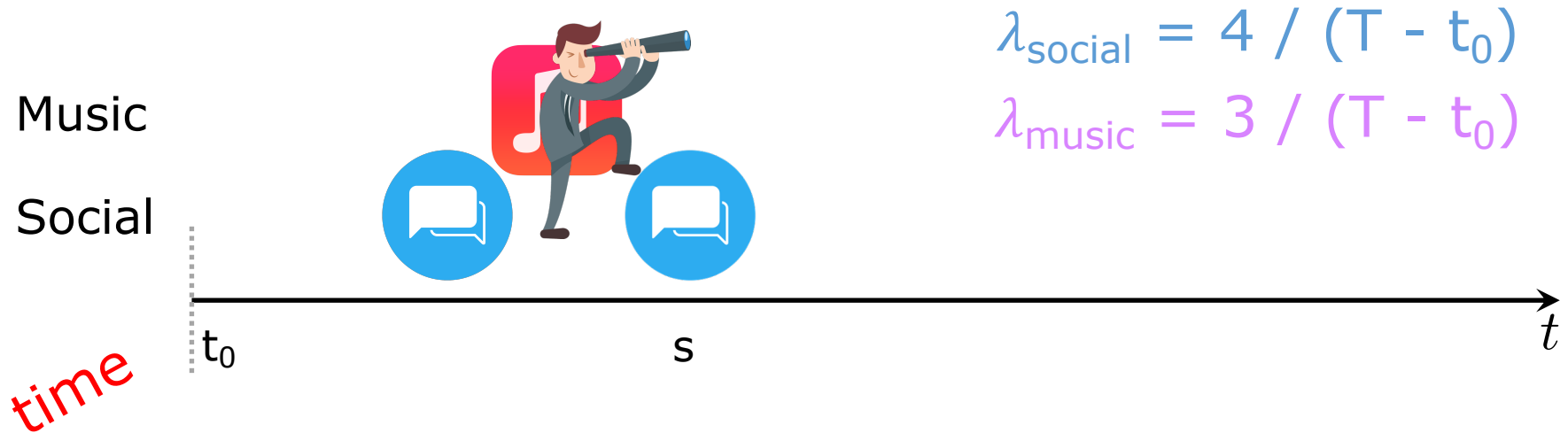


$$\lambda_{\text{social}} = 4 / (T - t_0)$$

$$\lambda_{\text{music}} = 3 / (T - t_0)$$

$$t_{\text{pred}} = \int_s^{\infty} t p(t) dt \quad p(t) = \lambda \exp(-\lambda (t - s))$$

# Multivariate Time Series: MBR



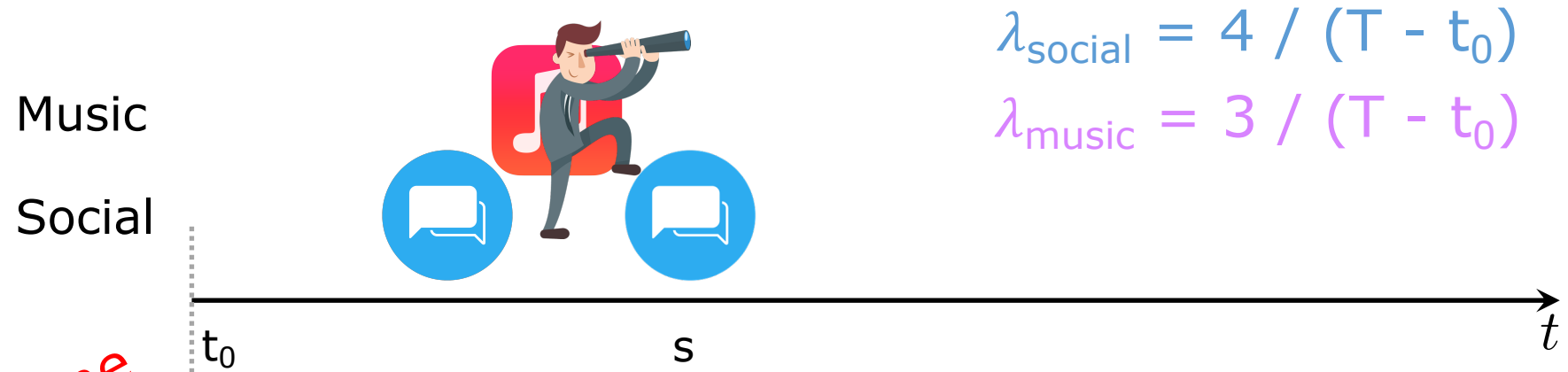
$$\lambda_{\text{social}} = 4 / (T - t_0)$$

$$\lambda_{\text{music}} = 3 / (T - t_0)$$

$$t_{\text{pred}} = \int_s^{\infty} t p(t) dt \quad p(t) = \lambda \exp(-\lambda (t - s))$$

$$\lambda = \lambda_{\text{music}} + \lambda_{\text{social}} = 7 / (T - t_0)$$

# Multivariate Time Series: MBR



$$\lambda_{\text{social}} = 4 / (T - t_0)$$

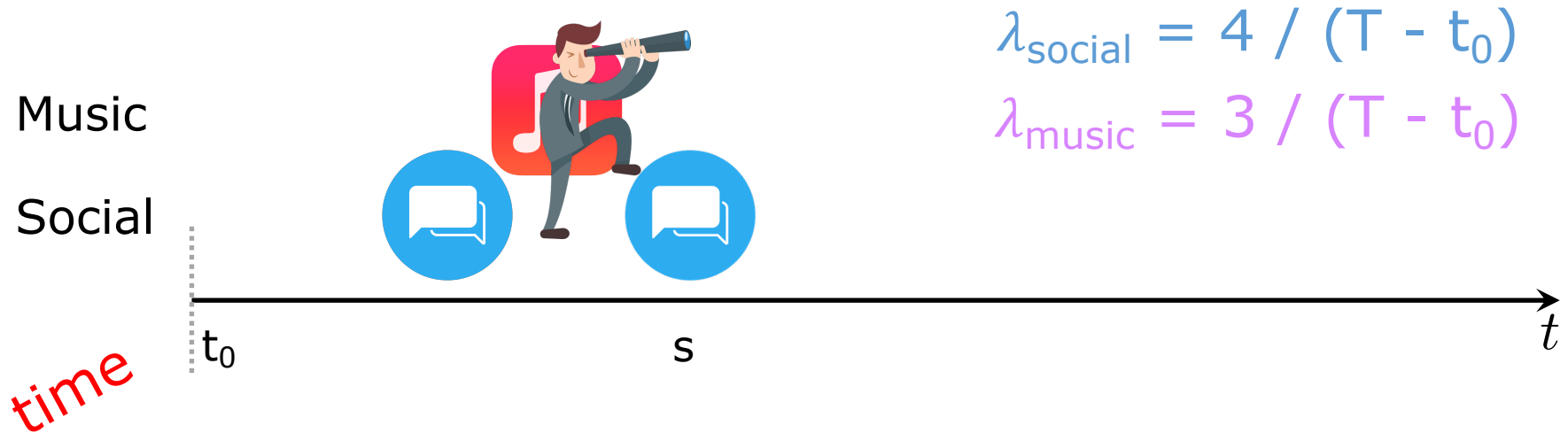
$$\lambda_{\text{music}} = 3 / (T - t_0)$$

$$t_{\text{pred}} = \int_s^{\infty} t p(t) dt \quad p(t) = \lambda \exp(-\lambda (t - s))$$

$$\lambda = \lambda_{\text{music}} + \lambda_{\text{social}} = 7 / (T - t_0)$$

type?

# Multivariate Time Series: MBR



$$\lambda_{\text{social}} = 4 / (T - t_0)$$

$$\lambda_{\text{music}} = 3 / (T - t_0)$$

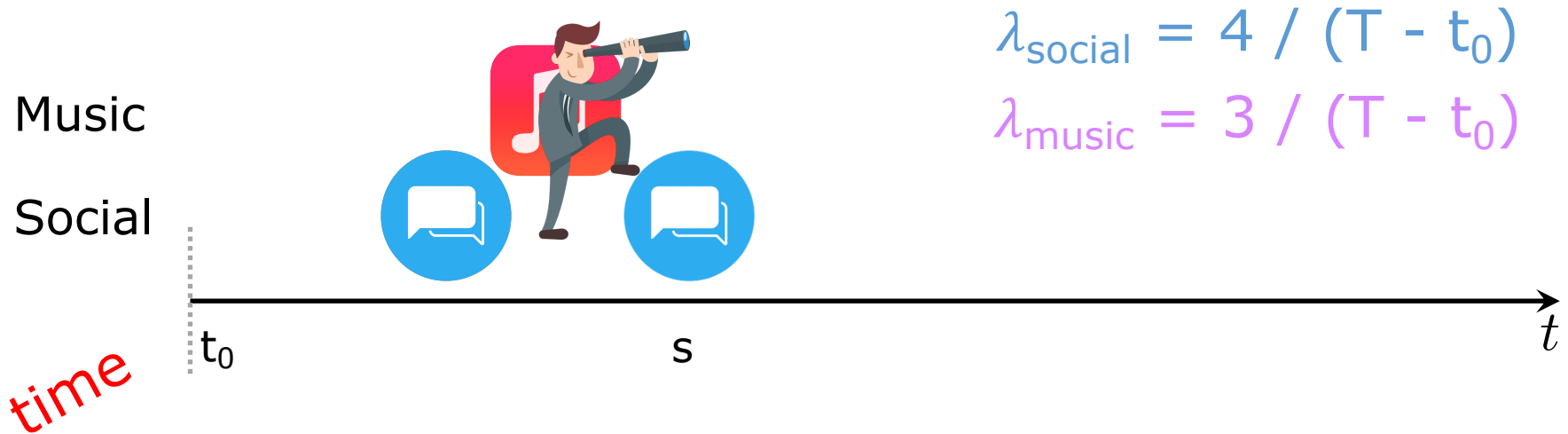
$$t_{\text{pred}} = \int_s^{\infty} t p(t) dt \quad p(t) = \lambda \exp(-\lambda (t - s))$$

$$\lambda = \lambda_{\text{music}} + \lambda_{\text{social}} = 7 / (T - t_0)$$

type?

$$k = \operatorname{argmax}_k p(k | t) = \operatorname{argmax}_k \lambda_k$$

# Multivariate Time Series: MBR



$$\lambda_{\text{social}} = 4 / (T - t_0)$$

$$\lambda_{\text{music}} = 3 / (T - t_0)$$

$$t_{\text{pred}} = \int_s^{\infty} t p(t) dt \quad p(t) = \lambda \exp(-\lambda (t - s))$$

$$\lambda = \lambda_{\text{music}} + \lambda_{\text{social}} = 7 / (T - t_0)$$

type?

$$k = \operatorname{argmax}_k p(k | t) = \operatorname{argmax}_k \lambda_k$$

$$\operatorname{argmin}_k \sum_j p(j | t) \mathbb{I}(k \neq j) \quad j, k \in \{\text{music}, \text{social}\}$$

choose type  $k$  that makes  $\sum_{j \neq k} p(j | t)$  small



# Other Modeling Designs

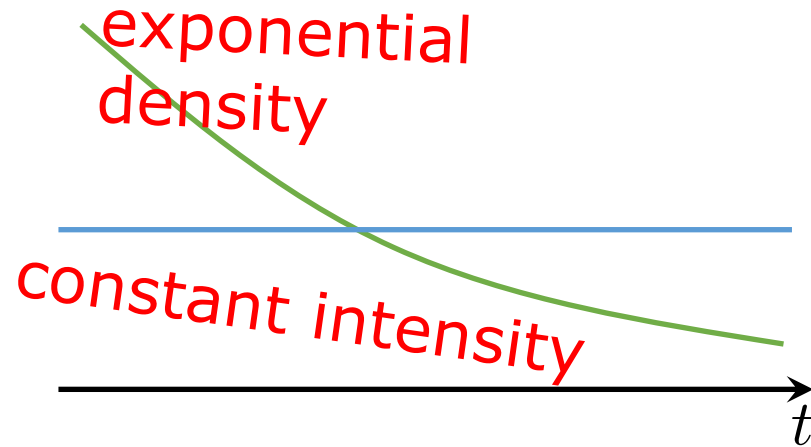
# Other Modeling Designs



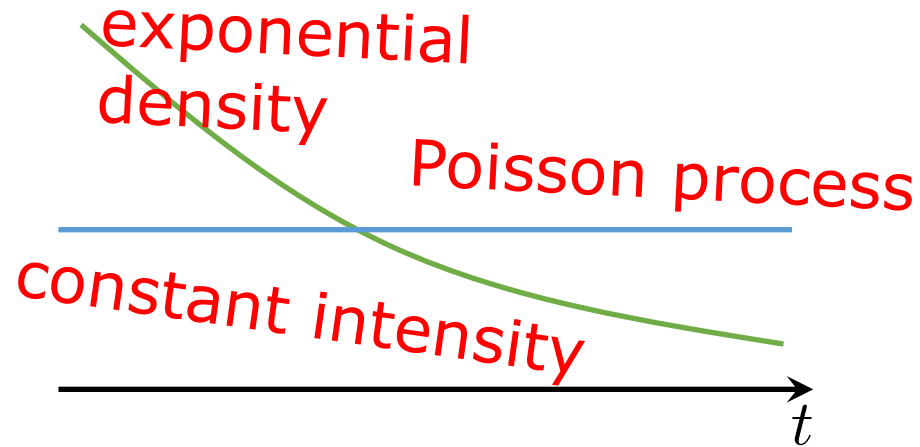
A diagram illustrating a modeling design. It consists of a horizontal blue line at the top and a horizontal black line with an arrow pointing to the right at the bottom. The text "constant intensity" is written in red, italicized font, positioned between the two lines and slightly tilted upwards to the right.

*constant intensity*

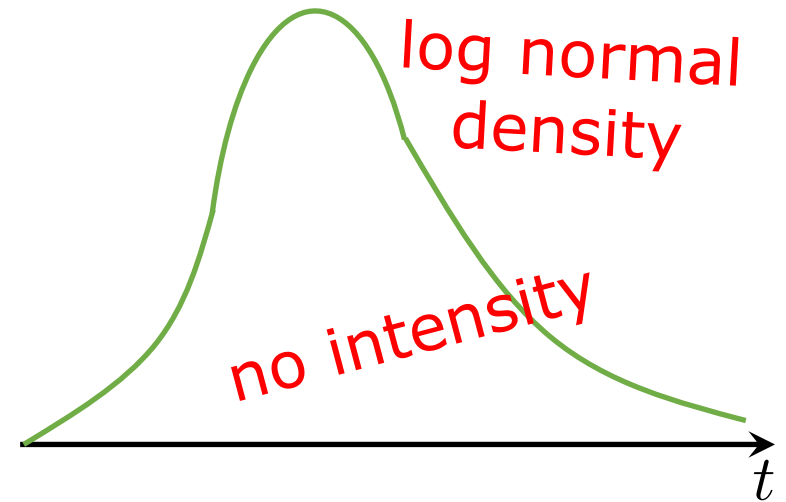
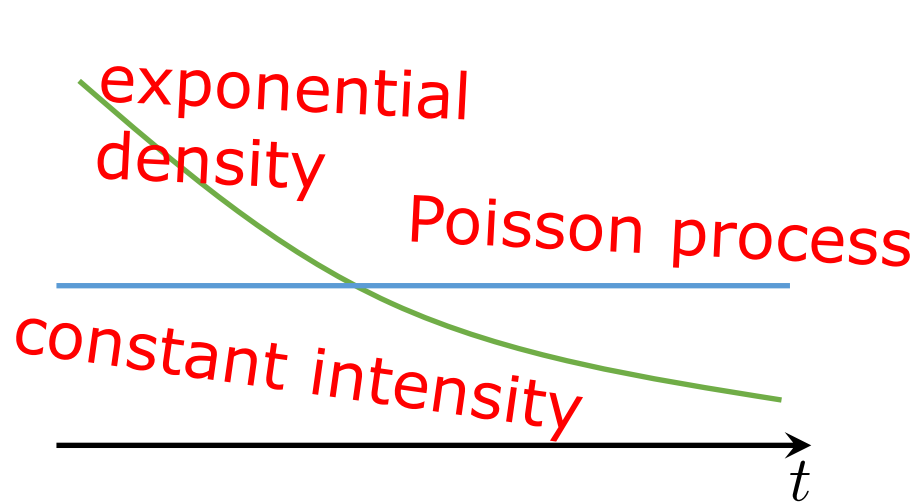
# Other Modeling Designs



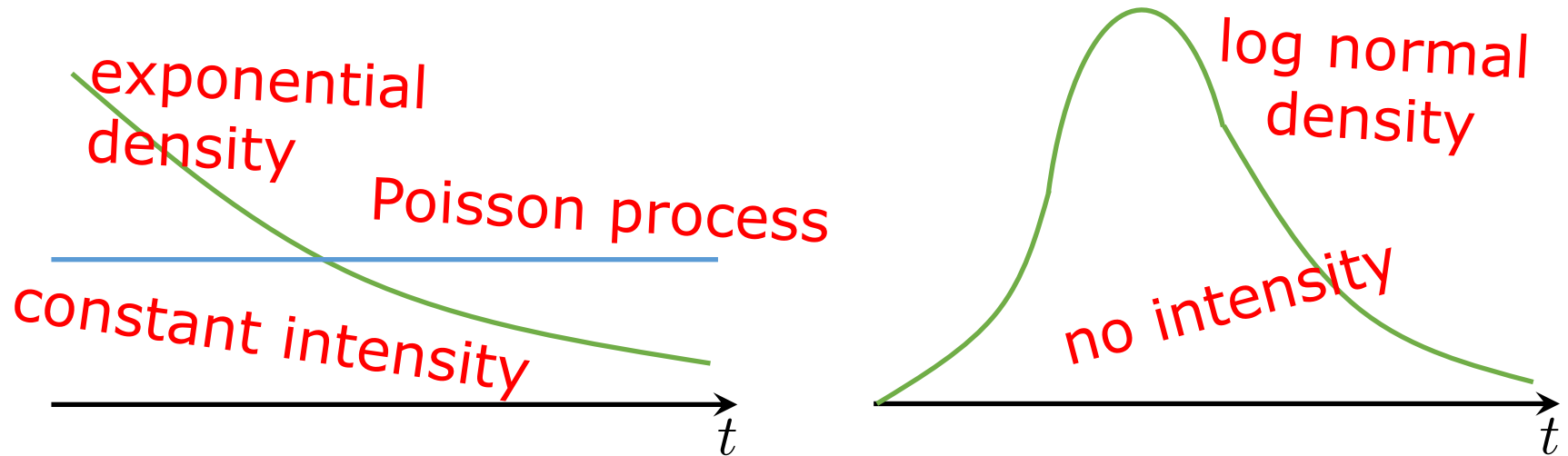
# Other Modeling Designs



# Other Modeling Designs



# Other Modeling Designs



stochastic intensity  
e.g., Cox process

**Any Questions?**

**<http://bburl/tpp-slides-p1>**

**<http://bburl/tpp-lab-p1>**