Week 6 – part 3 : Likelihood of a spike train

ÉCOLE POLYTECHNIQUE FÉDÉRALE DE LAUSANNE

Neuronal Dynamics:
Computational Neuroscience of Single Neurons

Week 6 – Noise models:
Escape noise

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√ **6.1 Escape noise**
- stochastic intensity and point process

√ **6.2 Interspike interval distribution**
- Time-dependend renewal process
- Firing probability in discrete time

6.3 Likelihood of a spike train
- generative model

6.4 Comparison of noise models
- escape noise vs. diffusive noise

6.5. Rate code vs. Temporal Code
- timing codes
- stochastic resonance

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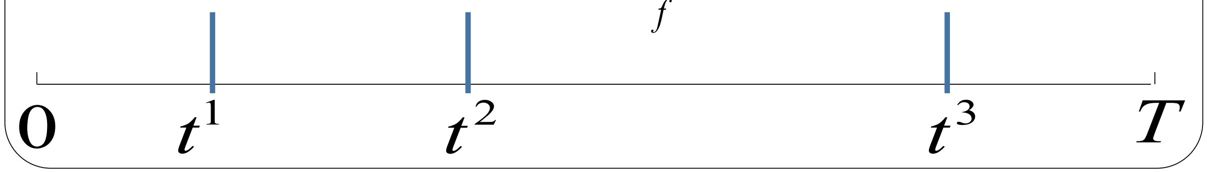
Neuronal Dynamics – 6.3. Likelihood of a spike train

$$S(t) = \sum_f \delta(t - t^f)$$



Measured spike train with spike times $t^1, t^2, \ldots t^N$

Explanation now:

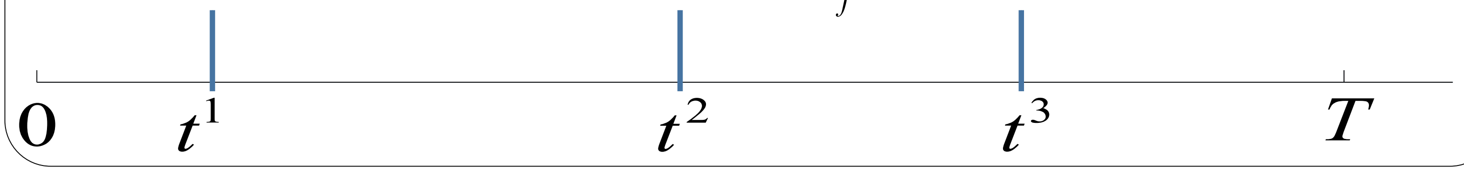
Likelihood ***L*** that this spike train could have been generated by model?

$$L(t^1, \ldots, t^N) = \exp(-\int_0^{t^1} \rho(t')dt')\rho(t^1) \cdot \exp(-\int_{t^1}^{t^2} \rho(t')dt')\ldots$$

e.g., Brillinger 1988

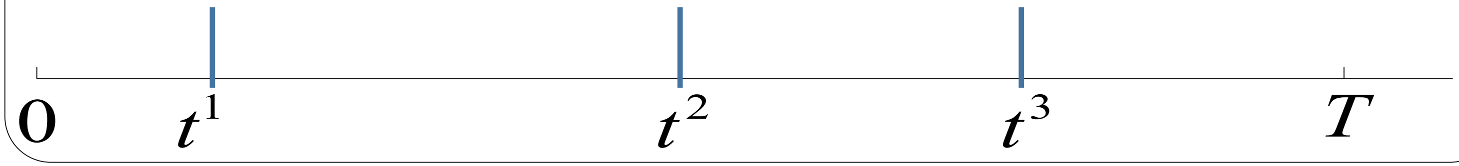
Neuronal Dynamics – 6.3. Likelihood of a spike train

$$S(t) = \sum_f \delta(t - t^f)$$



Neuronal Dynamics – 6.3. Likelihood in discrete time

$$n(t_k) = 1 \ if \ \ t_k < t^f \le t_{k+1}$$



Prob. to fire in $t_k < t \le t_{k+1}$

$P_{t_k}^{\Delta}$

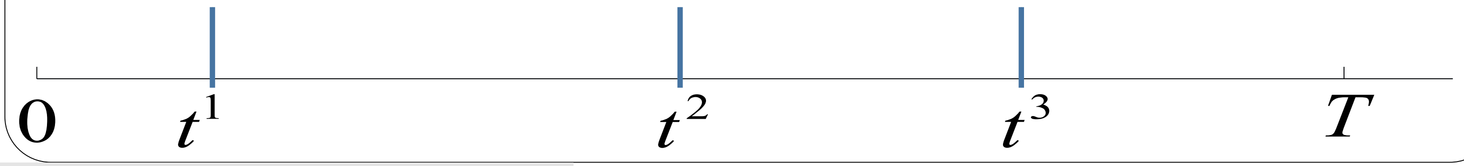
Prob. to be silent in $t_k < t \le t_{k+1}$

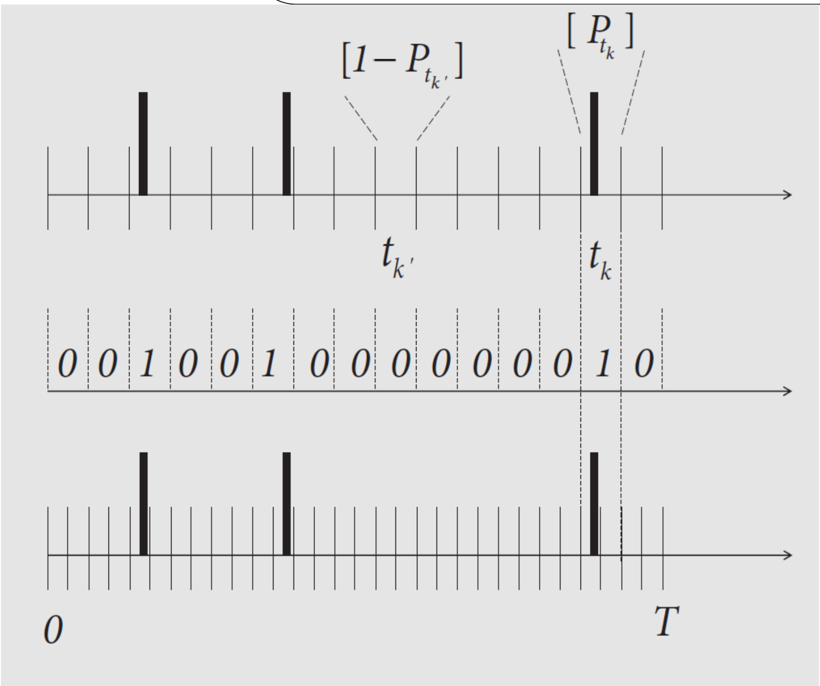
S^{Δ}

how about $\Delta \to 0$??

Neuronal Dynamics – 6.3. Likelihood in discrete time

$$n(t_k) = 1 \ if \ \ t_k < t^f \leq t_{k+1}$$



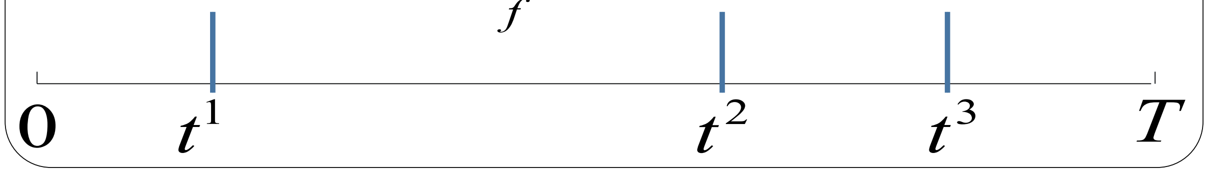


$$P_{t_k}^{\Delta}$$

$$\Delta \rightarrow 0$$

Neuronal Dynamics – 6.3. Likelihood of a spike train

$$S(t) = \sum_f \delta(t - t^f)$$



$$L(t^1,\ldots,t^N) = \exp\left(-\int_0^{t^1} \rho(t')dt'\right)\rho(t^1) \cdot \exp\left(-\int_{t^1}^{t^2} \rho(t')dt'\right)\rho(t^2)\ldots \cdot \exp\left(-\int_{t^N}^{T} \rho(t')dt'\right)$$

$$L(t^1,\ldots,t^N) = \exp\left(-\int_0^{T} \rho(t')dt'\right)\prod_f \rho(t^f)$$

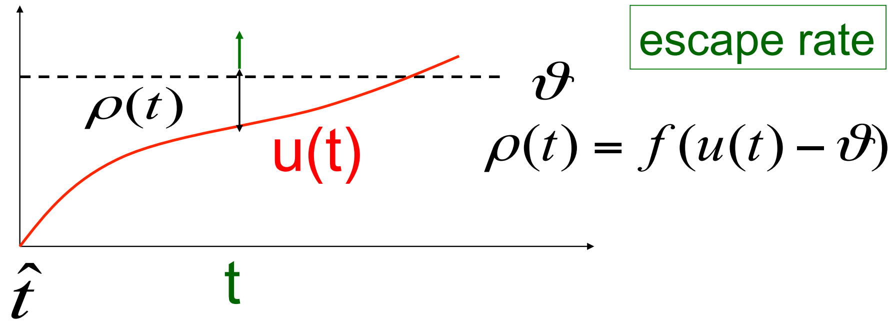
Neuronal Dynamics – 6.3. Log-likelihood of a spike train

$$S(t) = \sum_f \delta(t - t^f)$$

$$L(t^1, \ldots, t^N) = \exp\left(-\int_0^T \rho(t')dt'\right) \prod_f \rho(t^f)$$

$$\log L(t^1, \ldots, t^N) = -\int_0^T \rho(t')dt' + \sum_f \log \rho(t^f)$$

Neuronal Dynamics – 6.3. generative model of a spike train



generative model of spike train

- generates spikes stochastically
- calculated likelihood that an **observed** experimental spike train **could have been generated**

$$\log L(t^1,\ldots,t^N) = -\int_0^T \rho(t')dt' + \sum_f \log \rho(t^f)$$

Neuronal Dynamics – Quiz 6.2. Tick all correct answers

[ ] A leaky integrate-and-fire model with escape noise can be interpreted as a generative model of a spike train

[ ] For a leaky integrate-and-fire model with escape noise we can (numerically) calculate the likelihood that observed experimental data could have been generated by the model

[ ] Suppose we inject a time-dependent current into a real neuron and observe the resulting spike train. We the inject the same time-dependent current into a nonlinear integrate-and-fire model with exponential escape noise with parameter theta. For each choice of theta we can then calculate the likelihood that the model could have generated the observed spike train.