## The Poisson Channel

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### Outline

### I. Introduction

II. Single-User Poisson Channel

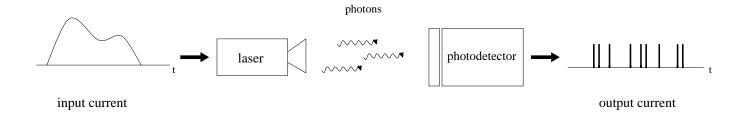
III. Multi-access Poisson Channel

IV. Other Applications

### Introduction

- The Poisson channel was introduced around 20 years ago as a model for optical communication.
- Since then, Information-Theorists have studied it extensively.
- However, the theory has yet to have an impact in practice. optical fibers has made sophisticated coding techniques unnecessary. One possible reason is that the enormous inherent bandwidth of

### **Optical Communication Link**



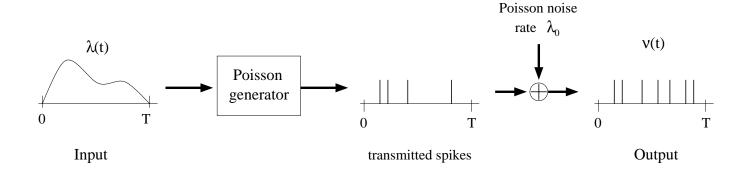
Transmitter (laser): emits photons at a (time-varying) rate which is proportional to the amplitude of the input current.

Receiver (photodetector): detects the arrival times of photons.

Noise: two sources of noise in the laser,

- The laser generates photons according to a random process.
- Background noise: spontaneously emitted photons ("dark current").

### The Poisson Channel Model



Input: waveform  $\lambda(t)$ , (non-negative).

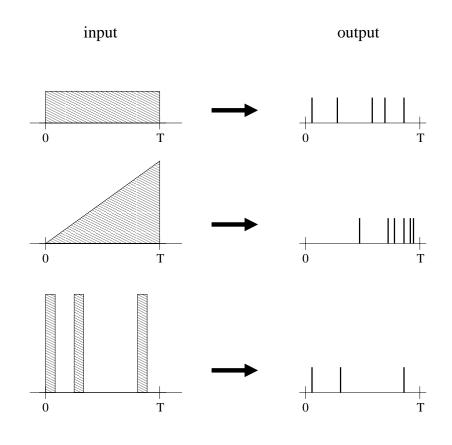
Output: Poisson point process  $\nu(t)$  with intensity  $\lambda(t) + \lambda_0$ .

### Noise:

- Randomness in generating spikes from the input  $\lambda(t)$ .
- Random additive spikes: Poisson with intensity  $\lambda_0$ .

### The Poisson Channel (cont.)

Examples of input/output behavior:



# The Poisson Channel (cont.)

More precisely:

For input  $\lambda(t) = A$ , the output in a small time interval  $(t, t + \Delta)$  is:

1 spike with probability:  $A\Delta e^{-A\Delta}$  no spikes with probability:  $e^{-A\Delta}$ 

 $\geq 2$  spikes with probability:  $o(\Delta)$ 

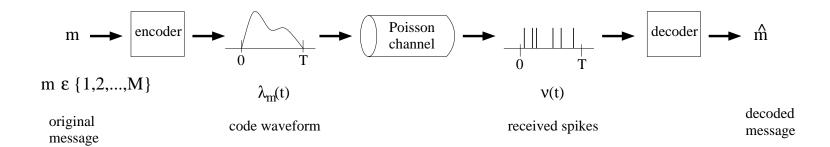
This determines the channel's input-output mutual information:

$$I(\nu(t);\lambda(t)) = H(\nu(t)) - H(\nu(t) \mid \lambda(t))$$

### Coding for the Poisson Channel

A code with parameters (M,T) consists of:

- 1. An index set:  $\{1, 2, ..., M\}$ .
- 2. Code waveforms:  $\{\lambda_m(t)\}_{m=1}^M$ , where  $\lambda_m(t) \geq 0$ ,  $t \in [0,T]$ .
- 3. A decoding function:  $D(\nu_0^T) = \hat{m} \in \{1, 2, \dots, M\}.$



## Performance Issues

For an (M,T) code with codewords  $\{\lambda_m(t)\}$  and decoder  $D(\cdot)$ :

• The probability of error is:

$$P_e = \frac{1}{M} \sum_{m=1}^{M} Pr\{D(\nu_0^T) \neq m \mid \lambda_m(\cdot)\}$$

• The rate of the code is:  $\frac{\log_2 T}{T}$ 

$$\frac{\log_2 M}{T}$$
 bits/sec.

with sufficiently large T and  $M \geq 2^{RT}$  such that  $P_e \leq \epsilon$ . A rate R is said to be achievable if for all  $\epsilon > 0$ , there exists a code

achievable rates, and is equal to: The channel capacity C is defined to be the supremum of all

$$C = \lim_{T \to \infty} \sup_{p_{\lambda}(\lambda_0^T)} \frac{1}{T} I(\lambda_0^T; \nu_0^T) \quad \text{bits/sec}$$

## Input Constraints

Peak value:  $0 \le \lambda(t) \le A$ .

Average value:  $\frac{1}{T} \int_0^T \lambda(t) dt \le \sigma A$ ,  $0 < \sigma \le 1$ .

Notice that without a peak constraint, the capacity is infinite.

arbitrarily high time precision. Example: we can use impulse-like inputs and generate a spike with

## Preview of Results

## Single-user Poisson channel

### Wyner '88:

- Found exact error exponent under peak and average constraints.
- Constructed a code which achieves the optimal error exponent.

## Multi-user Poisson channel

## Lapidoth and Shamai '98:

- Found the capacity region for a 2-user MAC.
- For a general K-user MAC, showed that the maximum total throughput is bounded in the number of users

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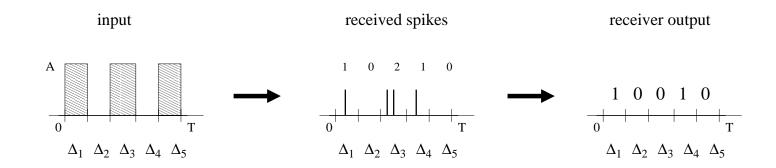
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### Let's Make a Code!

Intuition: use very large pulses of very short duration.

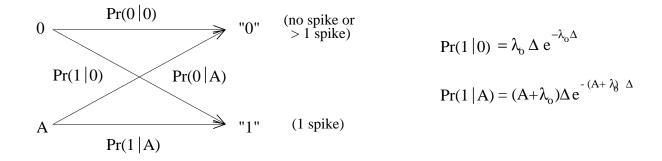
- Discretize the code interval [0,T] into segments of duration  $\Delta$ .
- In each  $\Delta$ , let the input take one of two values, 0 or A.
- In each  $\Delta$ , let the receiver distinguish between only two events:

{receive exactly 1 spike}  $\Longrightarrow$  output "1" {receive zero or  $\geq$  2 spikes}  $\Longrightarrow$  output "0"



### Lower Bound on Capacity

By the previous assumptions, and by the memoryless property of the Poisson process, each  $\Delta$ -segment becomes a binary channel:



This gives us a lower bound to capacity:

$$C_{Poisson} \ge \max \frac{I(X_{\Delta}; Y_{\Delta})}{\Delta}$$

where the max. is over all input distributions  $p(X_{\Delta})$  s.t.  $E[X_{\Delta}] \leq \sigma A$ . It turns out that as  $\Delta \to 0$ , this lower bound is *exactly* the capacity.

### Code Design

Recall that we have made the following simplifications:

- 1. Discretize time into  $\Delta$ -segments, for some  $\Delta$ .
- 2. Constrain input waveforms to be binary  $\{0, A\}$  in each  $\Delta$ .

maximum Euclidean distance subject to the previous constraints. We want to design M waveforms in the interval [0,T] which have

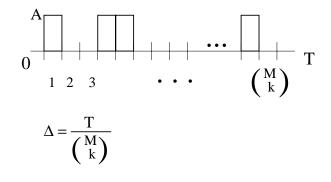
## Wyner and Landau '84:

- Obtained an upper bound on the minimum Euclidean distance for any set of waveforms satisfying the previous assumptions
- Constructed a set of waveforms which achieve that upper bound.

### Wyner's Code

Construct the M code waveforms as follows:

code waveforms for M = 5, k = 2



$$M \quad \begin{pmatrix} 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 1 & 1 \end{pmatrix} \stackrel{\longleftarrow}{\longleftarrow} \begin{array}{c} \lambda_1(t) \\ \longleftarrow \lambda_2(t) \\ \longleftarrow \lambda_3(t) \\ \longleftarrow \lambda_4(t) \\ \longleftarrow \lambda_5(t) \\ \hline \begin{pmatrix} M \\ k \end{pmatrix}$$

- Let  $M = 2^{RT}$  and let k = qM (for some  $q \le \sigma$ ). Notice that each  $\lambda_m(t)$  satisfies:  $\frac{1}{T} \int_0^T \lambda_m(t) dt = \frac{k}{M} A \le \sigma A$ .
- Let  $T \to \infty$ : notice that  $\Delta \to 0$ .

<u>Decoder:</u> pick  $\hat{m}$  such that  $\lambda_{\hat{m}}(t)$  has the maximum number of received spikes during its "on" periods (ML detection).

## Performance Analysis

The probability of error for this code is bounded by:

$$P_e \leq \exp\{-\mathrm{T}(\mathrm{Aq} - \mathrm{Aq}^{(1+\rho)} - \rho \mathrm{R})\}$$

Minimizing w.r.t.  $\rho \in [0,1]$  and  $q \in [0,\sigma]$  yields the tightest bound.

This gives us a lower bound on the optimal error exponent:

$$E^*(R) \ge Aq - Aq^{(1+\rho)} - \rho R$$

(and also a lower bound on capacity).

# Upper Bound on the Error Exponent

the error exponent which coincides with the lower bound. In part II of his two-part paper, Wyner derives an upper bound on

Therefore, the optimal probability of error for this channel is:

$$P_e^* = \exp\{-T(Aq - Aq^{(1+\rho)} - \rho R) + o(T)\}$$

and this is asymptotically achieved by Wyner's code as  $T \to \infty$ .

### Capacity

For a Poisson channel with a peak input A, avg. input  $\sigma A$ , and noise intensity  $\lambda_0$ , the capacity is: [Kabanov/Davis/Wyner]

$$C = A[q^*(1+s)\log(1+s) + (1-q^*)s\log s - (q^*+s)\log(q^*+s)]$$

$$s = \frac{\lambda_0}{A}$$

$$q^* = \min(\sigma, q_0(s))$$

$$q_0(s) = \frac{(1+s)^{(1+s)}}{s^s e} - s$$

• When 
$$s = \lambda_0 = 0$$
:  $C$ 

When 
$$s = \lambda_0 = 0$$
:  $C = Aq^* \log \frac{1}{q^*}$ , where  $q^* = \min(\sigma, e^{-1})$ .

• When 
$$\sigma = 1$$
 and  $s = \lambda_0 = 0$ :  $\underline{C} = \underline{Ae^{-1}}$ 

$$C = Ae^{-1}$$

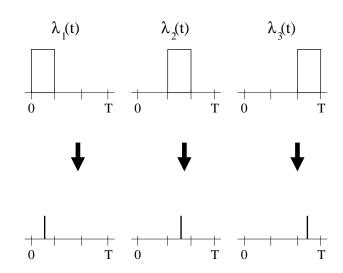
### Discussion of Wyner's Results

The optimal input waveforms look like a sequence of spikes.

Intuition: this makes the received waveforms as distinct as possible.

Sub-optimal waveforms

Near-optimal waveforms



### Other Results

### Single-user channel:

- Kabanov '78, Davis '80: capacity for peak and avg. constraints.
- Lapidoth and Shamai '91: upper and lower bounds on capacity for inputs strictly decrease capacity. various input bandwidth constraints. Showed that band-limited
- Lapidoth '93: exact error exponent for noiseless feedback.

## **Bandwidth Constraints**

infinite bandwidth. Can we use finite bandwidth? Wyner's optimal code requires the transmitter and receiver to have

strictly band-limited to  $-B \leq f \leq B$ . Assume the input waveform is peak and avg. constrained and is

Shamai and Lapidoth ('93) obtained upper and lower bounds on capacity. Showed that non-spike inputs are strictly suboptimal.

where p(t) is some pulse of duration  $T_s$ . Assume the input waveform must be PAM:  $\lambda(t) = \sum a_n p(t - nT_s)$ ,

- The capacity of PAM increases as  $T_s \to 0$ .
- In the limit  $T_s \to 0$ , the optimum distribution of  $a_s$  is 2 levels.
- As  $T_s$  increases, the optimum distribution of  $a_s$  uses more levels.

### Feedback

feedback does not increase capacity of the Poisson channel. Kabanov and Davis showed that causal, instantaneous, noiseless

is random and time-varying. Frey showed that feedback can increase capacity if the dark current

Lapidoth has found the exact error exponent under feedback.

### Outline

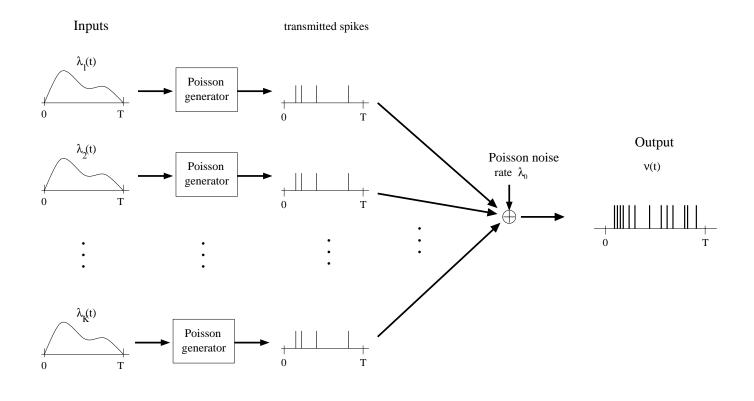
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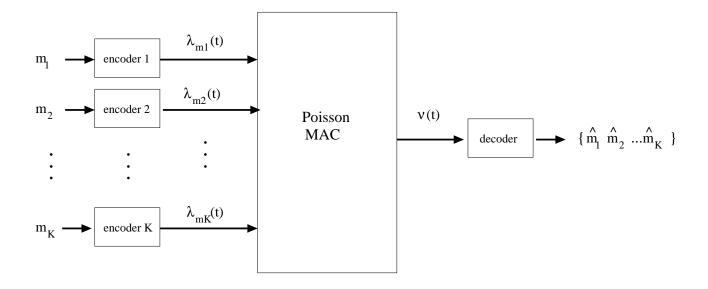
### The Multi-access Model



### Multi-access Coding and Decoding

The K encoders independently encode their messages.

The decoder tries to decode all messages simultaneously.



## Coding and Decoding

Consider the 2-user case:

A  $(M_1, M_2, T)$  code consists of:

- 1. Two index sets:  $\{1, ..., M_1\}$  and  $\{1, ..., M_2\}$ .
- 2. Two sets of codewords  $\{\lambda_m^{(1)}(t)\}_{m=1}^{M_1}$  and  $\{\lambda_m^{(2)}(t)\}_{m=1}^{M_2}$ , for  $t \in [0, T]$ .
- 3. A decoding function:

$$D(\nu_0^T) = (\hat{m}_1, \hat{m}_2) \in \{1, \dots, M_1\} \times \{1, \dots, M_2\}.$$

The probability of error is:

$$P_e = \frac{1}{M_1 M_2} \sum_{m_1=1}^{M_1} \sum_{m_2=1}^{M_2} Pr\{D(\nu_0^T) \neq (m_1, m_2) \mid (\lambda_{m_1}^{(1)}, \lambda_{m_2}^{(2)})\}$$

## Capacity Region

such that  $P_e \leq \epsilon$ .  $(M_1, M_2, T)$  code with sufficiently large T and  $M_i \geq 2^{R_i T}$ , i = 1, 2A rate pair  $(R_1, R_2)$  is said to be *achievable* if  $\forall \epsilon > 0$ , there exists a

achievable  $(R_1, R_2)$  rate pairs The capacity region is defined to be the closure of the set of all

# Binary Inputs are Optimal

reduce the capacity region. In extending Wyner's results from the single-user channel, Lapidoth and Shamai showed that binary PAM-like inputs do not

simplified to a binary-input, binary-output memoryless MAC Analogous to the single-user case, the Poisson MAC can be

# Capacity Region for 2 Users

# Maximum Total Throughput

Maximum total throughput for 2 users:

$$R_{\sum} = \max_{(R_1, R_2) \in \mathcal{C}} (R_1 + R_2)$$

This can be achieved using symmetric rates of the form  $(R^*, R^*)$ .

For the general case of K users, the maximum total throughput is

- achieved with symmetric rates.
- monotonically increasing in K.
- bounded above by the peak amplitude A.

Why does the total throughput saturate?

# Total Throughput (cont.)

increases as the log of the number of users. Compare this with the Gaussian MAC: maximum total throughput

Intuition: look at the *outputs* of the two channels.

- Gaussian MAC: the output is a sum of K indep. Gaussians. As increases, hence the output entropy increases. the number of users K increases, the variance of the output
- decreases, and this *decreases* the entropy rate. So adding more Poisson MAC: the output is a sum of K indep. Poisson inputs saturates the output entropy. processes. As K increases, the spacing between output spikes

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## Biological Neuroscience

Our body transmits information through a network of neurons.

The signals look like a train of spikes (action potentials).

spikes, not in their amplitude or shape. Neuroscientists believe that information is carried in the timing of these

### Questions:

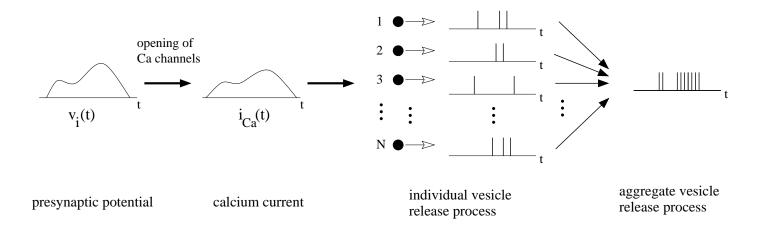
- How does the body "encode" information into these spikes?
- Why does it use spikes?

# An Engineering Approach

and ask, "How would an engineer build a system for it?" Try to model the neural system as a noisy communication channel

- Look for a source of noise inherent in the neural system.
- Model the noise and apply Information Theory.
- Compare the theory with reality.

### Basic Model of a Synapse



Input: presynaptic potential,  $V_i(t)$ .

Output: release times of neurotransmitter vesicles,  $\nu(t)$ .

### Assumptions:

- Each vesicle is released according to a Poisson process with time-varying intensity proportional to the input potential  $V_i(t)$ .
- No refractory period for vesicles (fast replenishment).
- No input bandwidth constraints (fast Ca<sup>2+</sup> dynamics).

### Discussion

- Wyner's result tells us that the best way to send information through such a noisy channel is to use spike-like inputs.
- In reality, we know that the body uses spike-like signals.

Is this a coincidence?

Maybe this is how the body has evolved to counteract noise in a synapse?