

High spiking precision and natural stimuli



Ilya Nemenman

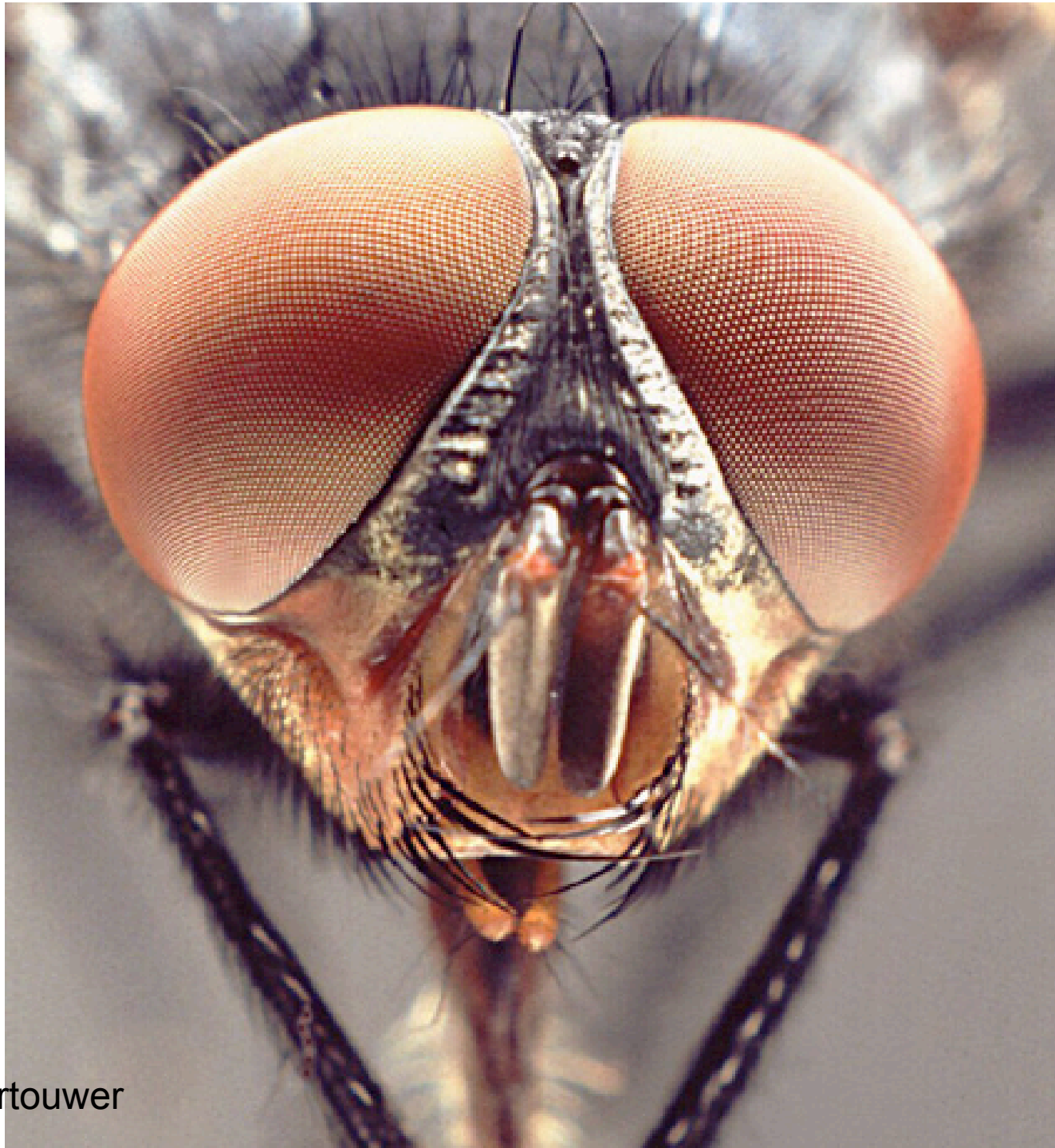
(JCSB/Columbia -> LANL/CCS-3 & SFI)

and

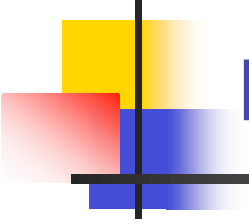
William Bialek (Princeton)

Rob de Ruyter van Steveninck (Indiana)

<http://sourceforge.net/projects/nsb-entropy>



H. L. Leertouwer



Why fly as a neurocomputing model system?

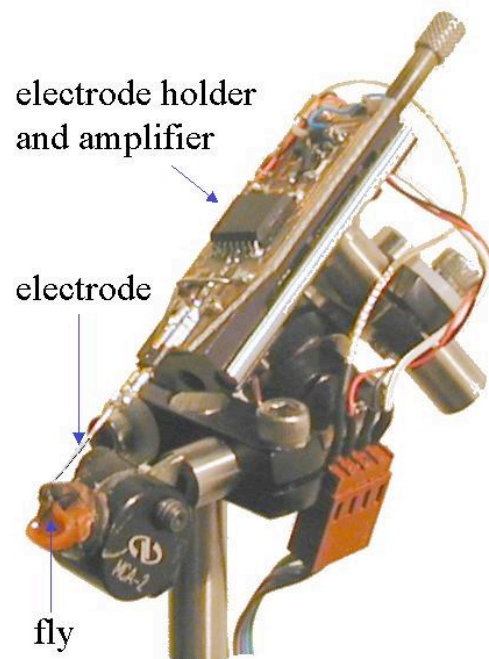
- Can record for long times
- Named neurons with known functions
- Nontrivial computation (motion estimation)
- Vision (specifically, motion estimation) is behaviorally important
- Possible to generate natural stimuli



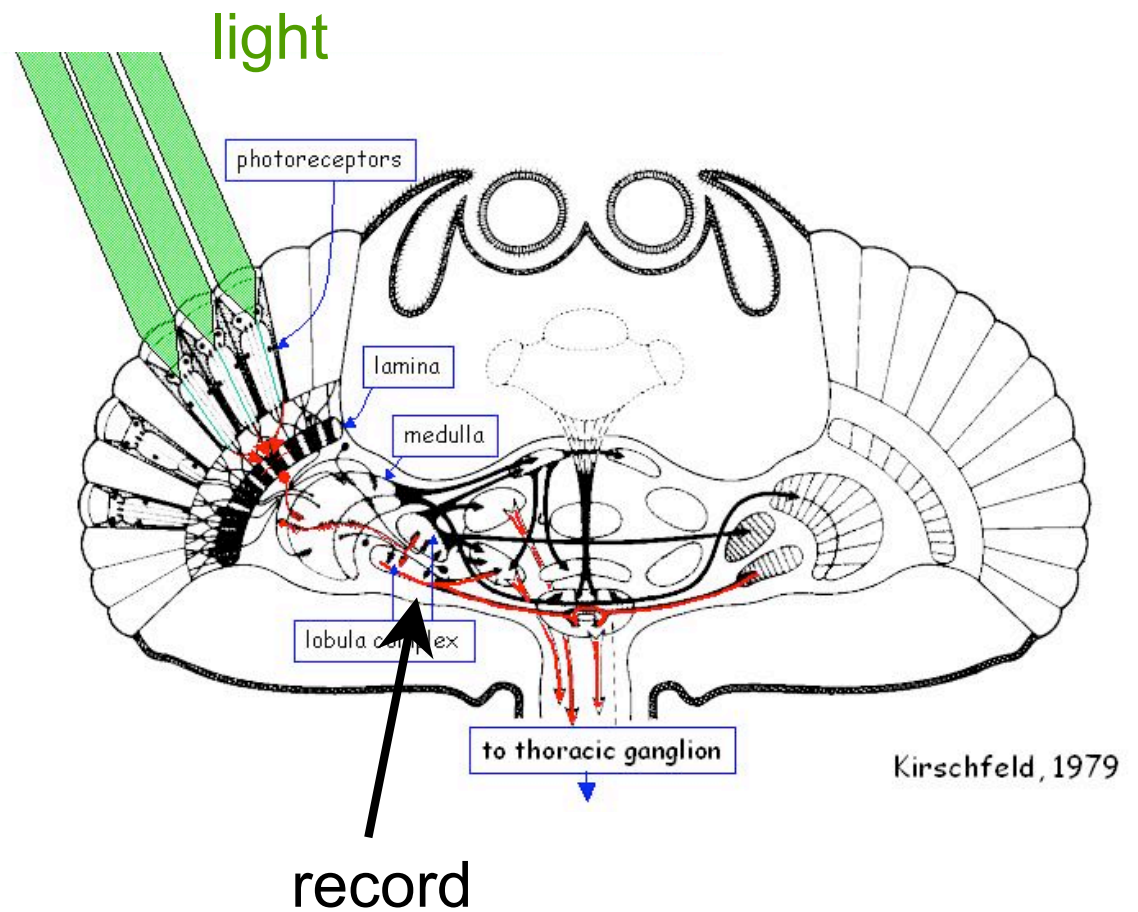
Questions

- Can we understand the code?
- Which features of it are important?
 - Rate of precise timing (how precise)?
 - Synergy between spikes?
- What/how much does the fly know?
- Is there an evidence for optimality?

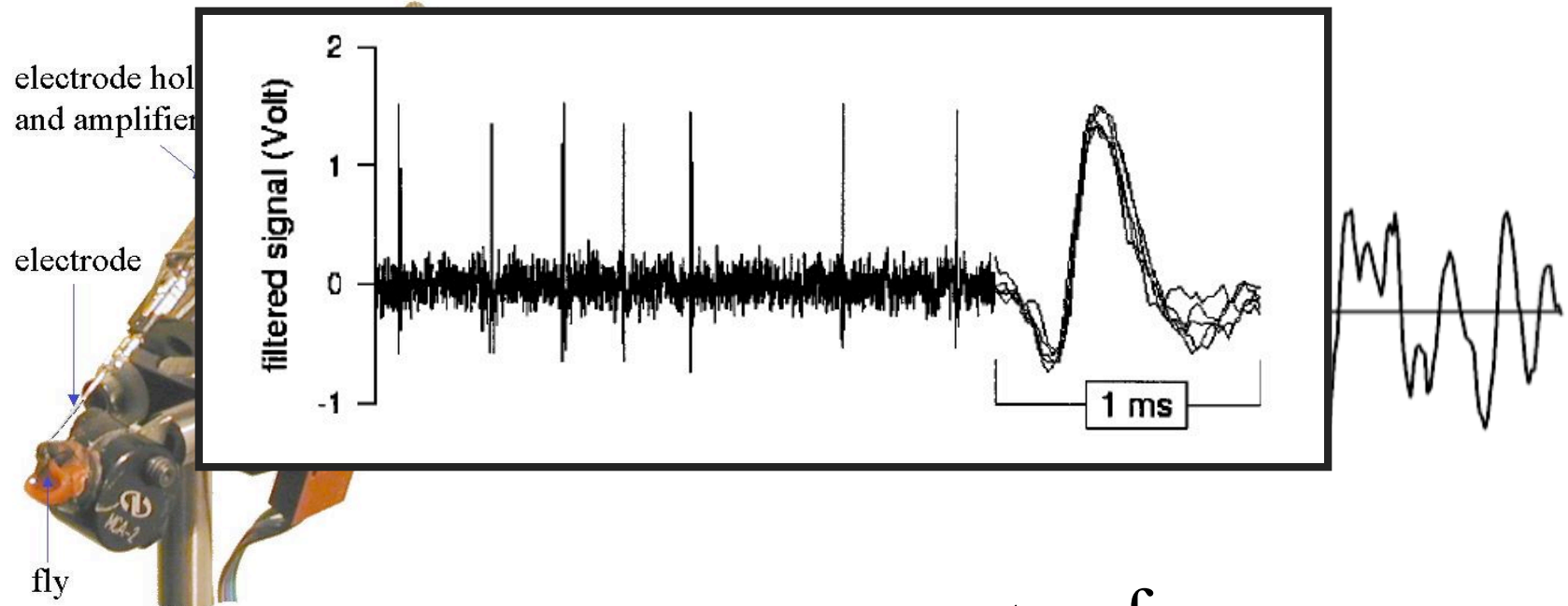
Recording from fly's H1



(Lewen et al, 2001)



Motion estimation in fly H1



$$\tau = \text{few } ms$$

(Strong et al., 1998)



Decoding a simple spike train

$$P(t_i | s(t)) \sim \text{Poisson}[r(s(t_i))]$$

 nonlinear

$$P[\{t_i\} | s(t)] = \frac{1}{N!} \exp \left[- \int r(s(t)) dt \right] \prod_{i=1}^N r(s(t_i))$$

$$P[s(t)] \propto \exp \left[- \frac{1}{4\tau_c} \int dt \left(\tau_c^2 \dot{s}^2 + s^2 \right) \right]$$

$$s_{est}(t_0) = \int [ds] P[s(t) | \{t_i\}] s(t_0) = \int [ds] \frac{P[\{t_i\} | s] P[s]}{\mathcal{Z}} s(t_0)$$

(Bialek, Zee, 1990)



Linear decoding for sparse spikes (cluster expansion)

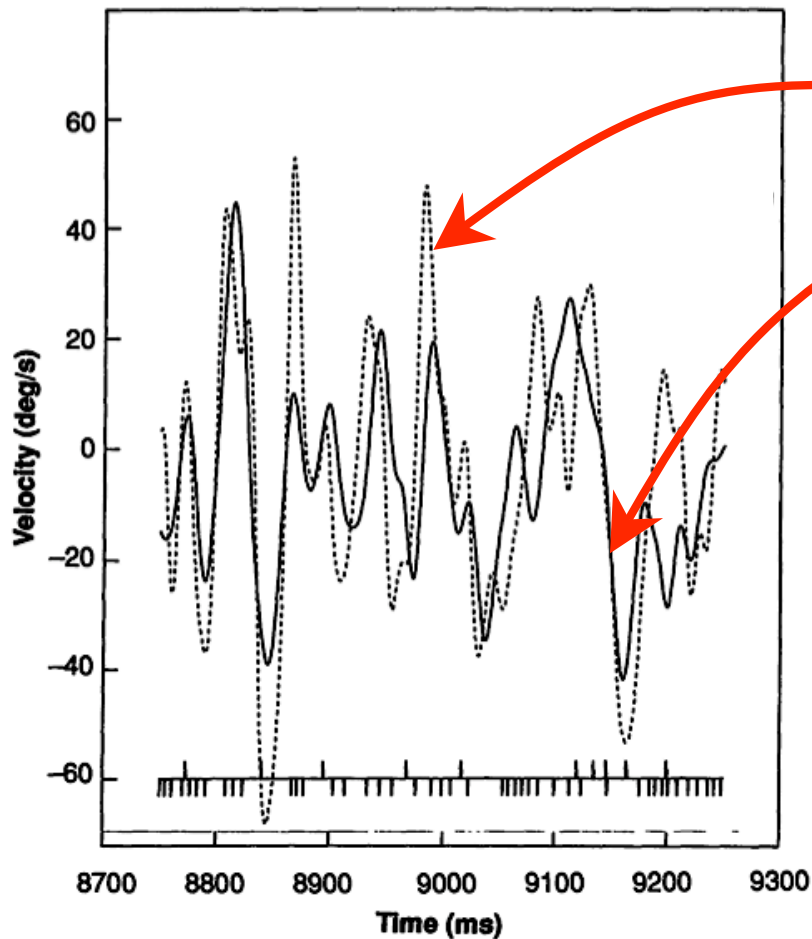
$$s_{est}(t_0) = \frac{\left\langle s(t_0) \prod_{i=1}^N r(s(t_i)) \right\rangle_{prior}}{\left\langle \prod_{i=1}^N r(s(t_i)) \right\rangle_{prior}}$$

Stimulus couples spikes; but the strength of the coupling drops with $\sim (t_i - t_{i+1}) / \tau$ (very fast varying mean field)

$$s_{est}(t) = \sum_i f_1(t - t_i) + \sum_{ij} f_2(t - t_i, t - t_j) + \dots$$

(Bialek, Zee, 1990)

Linear decoding



stimulus

reconstruction

$$\langle t_{i+1} - t_i \rangle = 30ms$$

Position of each spike
within ~2ms matters!

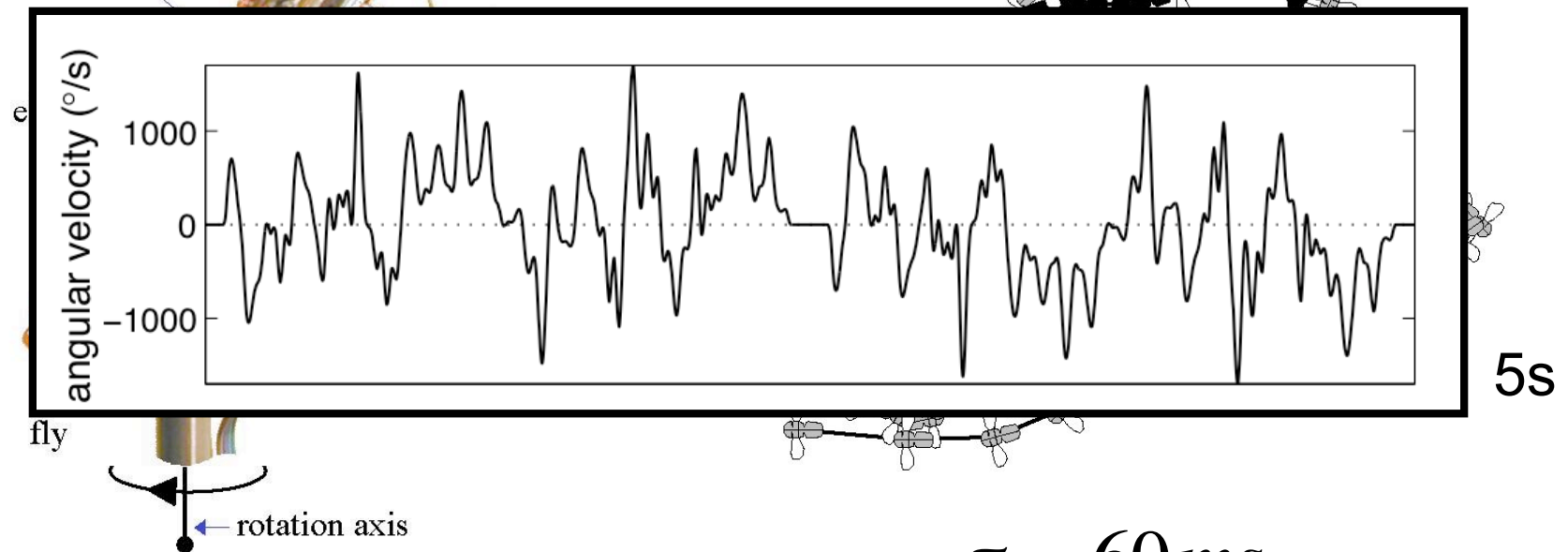
But what if ...

(Bialek et al. 1991, Strong, et al, 1998)

Natural stimuli

(Land and Collett, 1974)

electrode holder
and amplifier

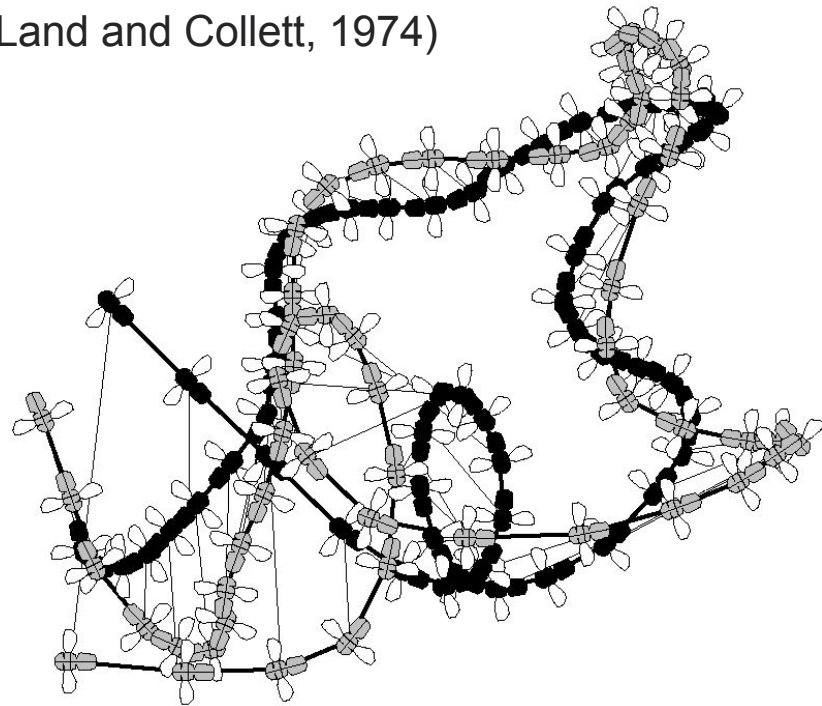


(Lewen et al, 2001)

$$\tau = 60ms$$
$$\text{response} = 30ms$$

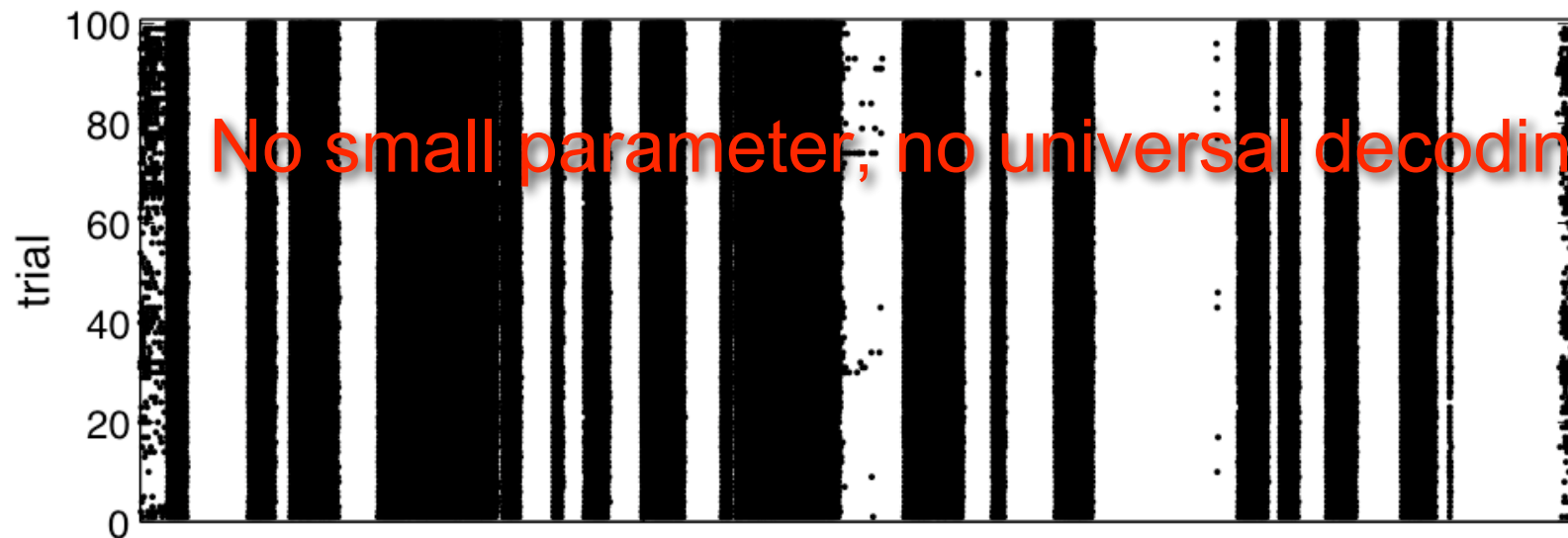
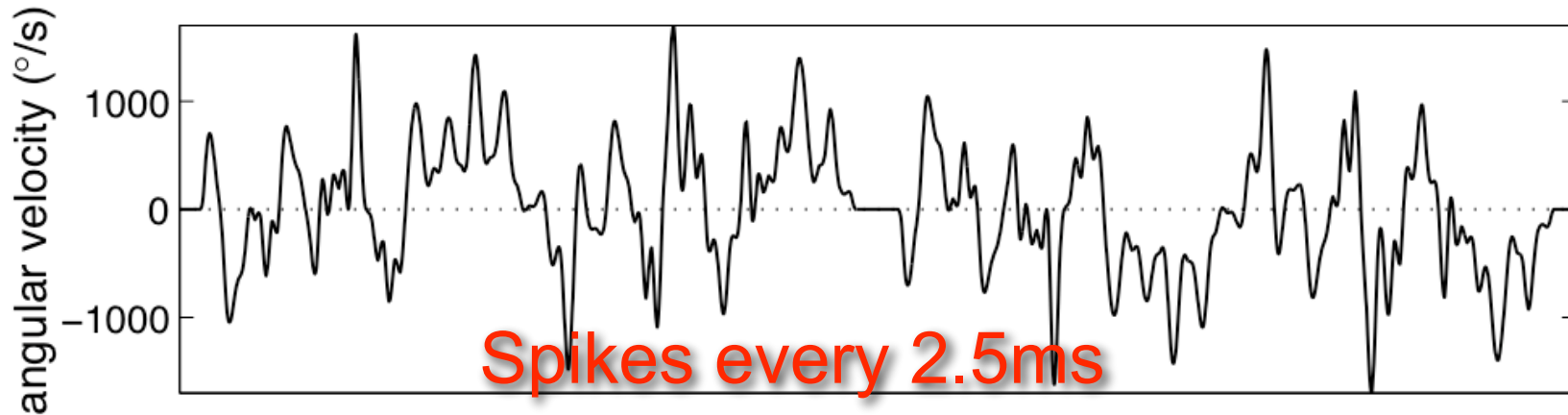
Natural stimuli

- ~2 ms resolution known to (Land and Collett, 1974) be important for white noise stimuli
- Could such “brisk” spikes be due to ~1 ms correlations in stimulus?
- What if stimulus has natural correlations?



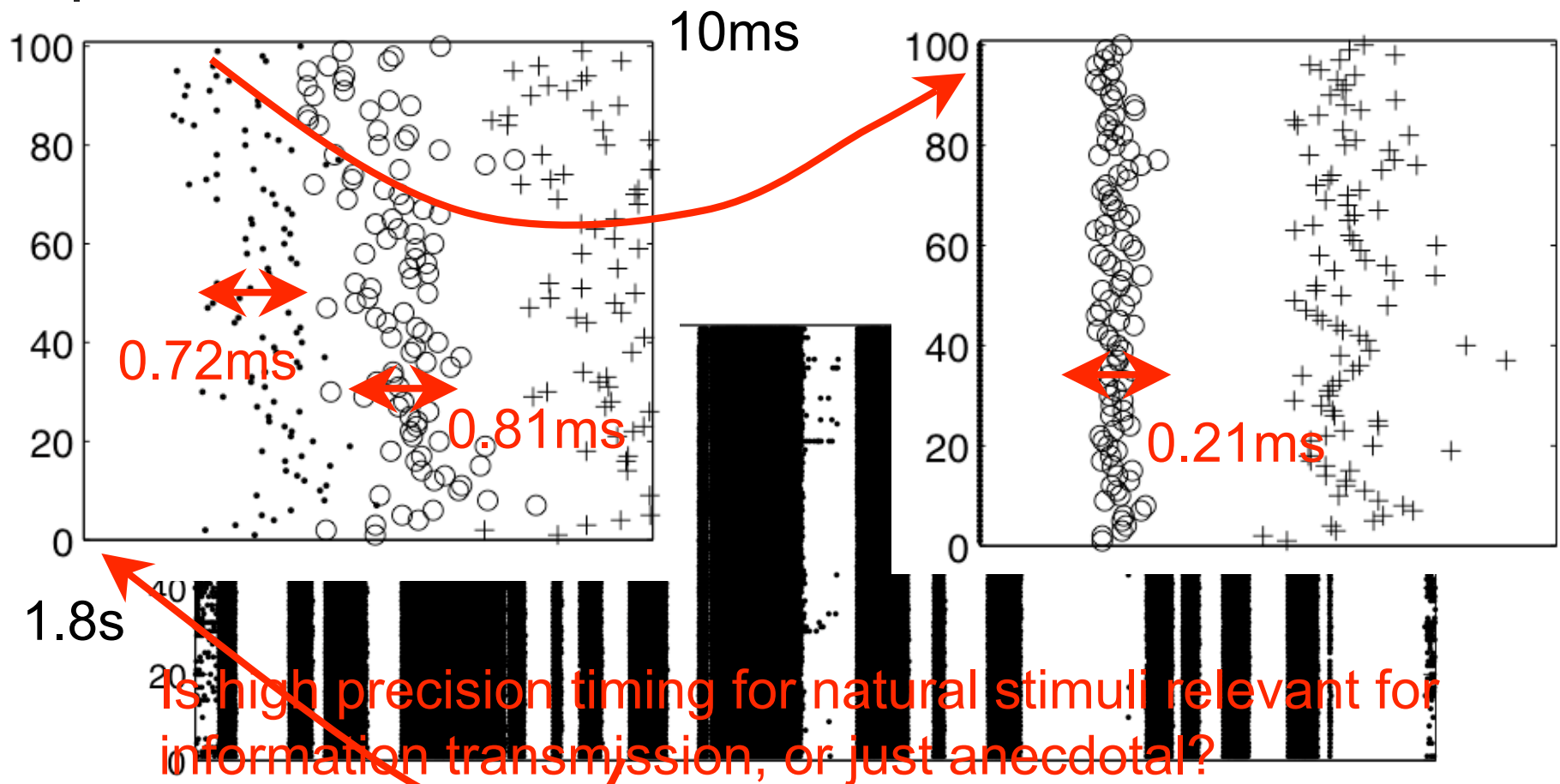
$$\tau = 60ms$$
$$\text{response} = 30ms$$

Natural stimulus and response



5s

Highly repeatable spikes (not rate coding)





How to characterize coding without an explicit decoding ?

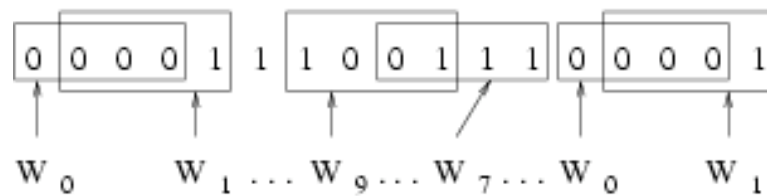
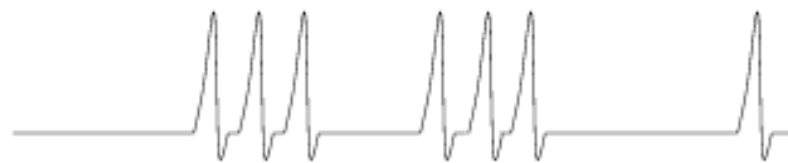
$$S[x] = - \sum_x p(x) \log p(x), \quad x = s, \{t_i\}$$

$$I[s, \{t_i\}] = \sum_{s, \{t_i\}} p(s, \{t_i\}) \log \frac{p(s, \{t_i\})}{p(s)p(\{t_i\})}$$

- Captures all dependencies (zero *iff* joint probabilities factorize)
- Reparameterization invariant
- Unique metric-independent measure of “how related”

Experiment design

$T=4$

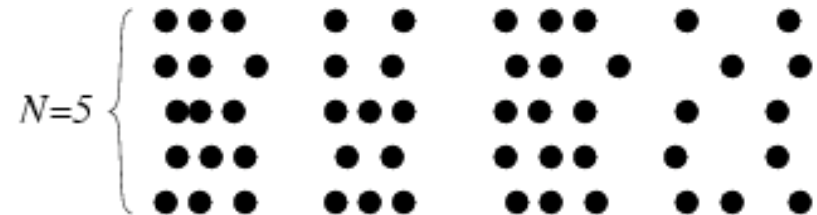


$W_0 = 00000$ $W_2 = 00010$

$W_1 = 00001$ $W_{15} = 11111$

$P(W) \rightarrow S(W) = S^T$

$I = S^T - S^n$



```
10101000010010000101010000100001
10100100010100000011001000001001
01110000011010000101010000100010
01101000010010000101010001000010
10101000011010000011010000101001
```

$P_1(W) \quad P_2(W) \quad \dots \quad P_{M-1}(W) \quad P_M(W)$

$S_1(W) \quad S_2(W) \quad \dots \quad S_{M-1}(W) \quad S_M(W)$

$$S^n = \langle S_i^n \rangle = 1/M \sum_i S_i^n$$

(Strong et al., 1998)

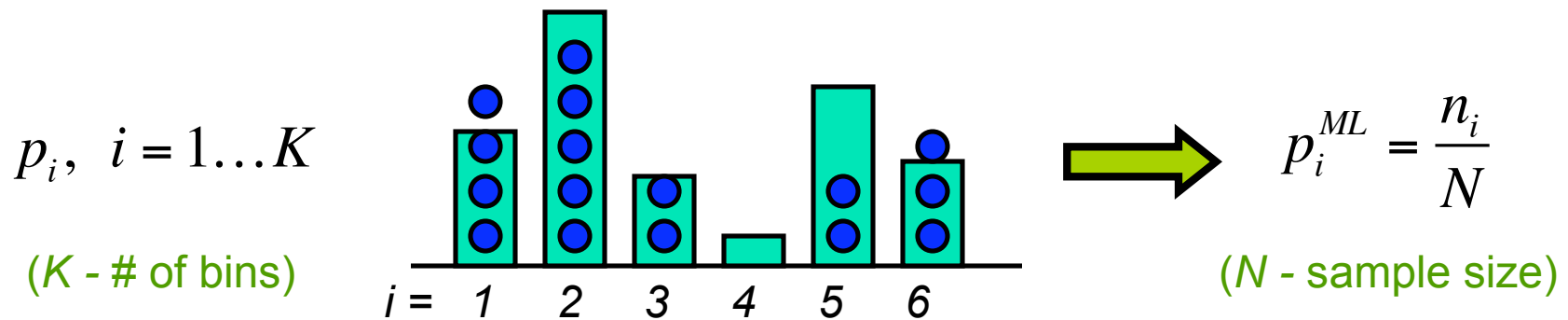


Problems

- Total of about 10-15 min of recordings (limited by stationarity of the outside world)
- At most 200 repetitions
- Stimulus correlation of 60ms: only 10000 independent samples (repeated or nonrepeated)
- Need to sample words of length 30 ms (behavioral) to 60 ms (stimulus) at resolution down to 0.2 ms (binary words of length up to ~100).

Undersampling and entropy/MI estimation

Maximum likelihood estimation:



$$S_{ML} = - \sum_i \frac{n_i}{N} \log \frac{n_i}{N}$$



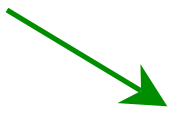
$$\langle S_{ML} \rangle \leq - \sum_i \frac{\langle n_i \rangle}{N} \log \frac{\langle n_i \rangle}{N} = S$$



Undersampling and entropy/MI estimation

$$\langle S_{ML} \rangle \leq - \sum_i \frac{\langle n_i \rangle}{N} \log \frac{\langle n_i \rangle}{N} = S$$

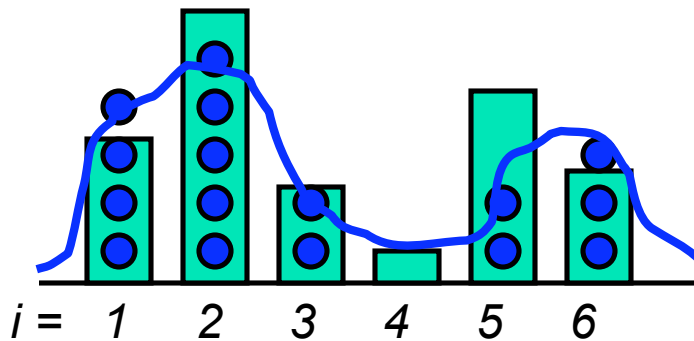
$\log K$


$$\text{bias} \propto -\frac{2^S}{N} \quad \square \quad (\text{variance})^{1/2} \propto \frac{1}{\sqrt{N}}$$

Fluctuations underestimate entropies and overestimate mutual informations.

(Need smoothing.)

Correct smoothing possible



$$S \leq \log N$$

Incorrect smoothing --
over- or underestimation.

13 bits for NR, 6-7 bits for R

Even **refractory** Poisson process at this T, τ has
over 15-20 bits of entropy!

For estimation of entropy at $K / N \leq 1$ see:

Grassberger 1989, 2003, Antos and Kontoyiannins 2002, Wyner and Foster 2003, Batu et al. 2002, Paninski 2003, Panzeri and Treves 1996, Strong et al. 1998



What if $S > \log N$?

But there is hope (Ma, 1981):

For uniform K -bin distribution the first coincidence occurs for

$$N_c \approx \sqrt{K} = \sqrt{2^S}$$

$$S \approx 2 \log N_c$$

← Time of first coincidence

Can make estimates for square-root-fewer samples!

Can this be extended to nonuniform cases?

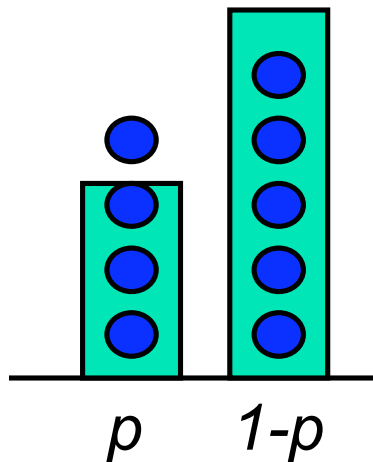
- Assumptions needed (won't work always)
- Estimate entropies without estimating distributions.



What is unknown?

Binomial distribution:

$$S = -p \log p - (1-p) \log(1-p)$$



Assume (Bayes)

uniform (no assumptions)

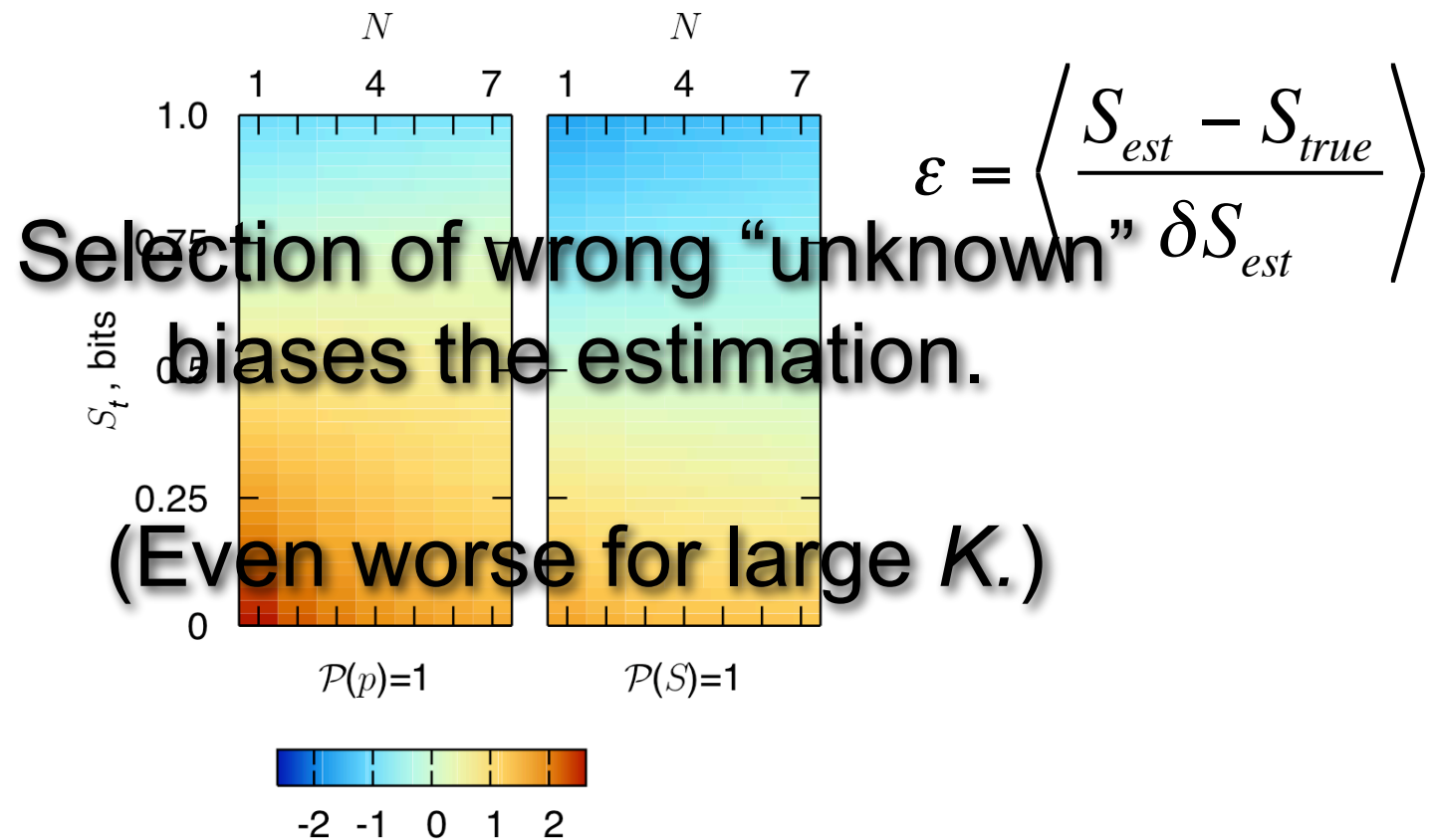


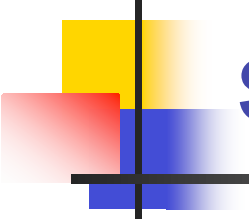
p



S

What is unknown?





One possible uniformization strategy for S (NSB)

- Posterior variance scales as $1 / \sqrt{N}$
- Little bias, except in some known cases.
- Counts coincidences and works in Ma regime (if works).
- Is guaranteed correct for large N .
- Allows infinite # of bins.

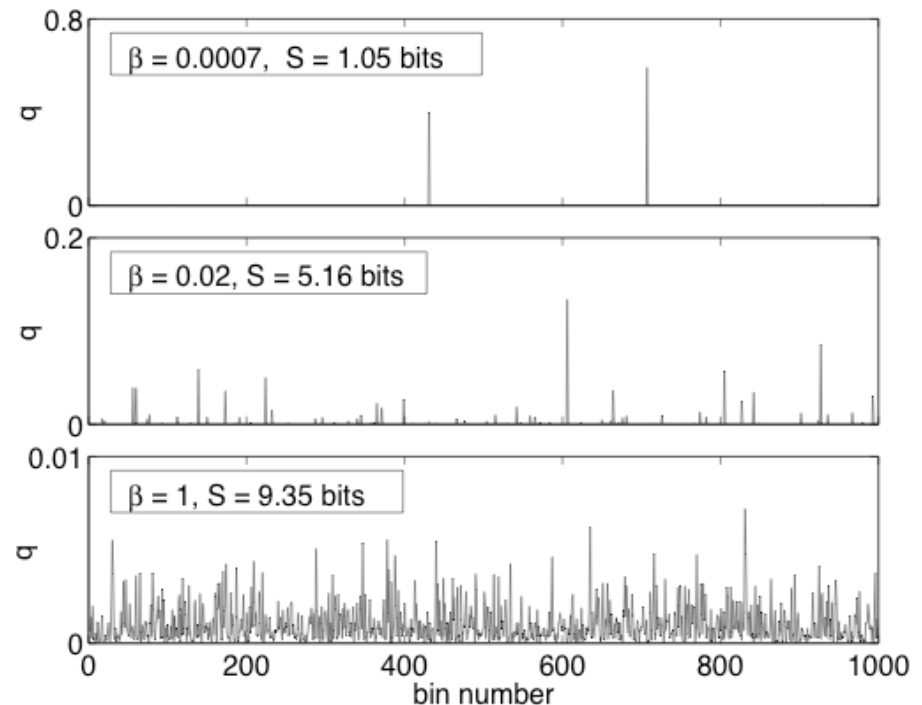
(Nemenman et al. 2002, Nemenman 2003)

For large K the problem is extreme (S known a priori)

$$P_{\beta}(\{q_i\}) = \frac{1}{Z(\beta)} \delta\left(1 - \sum_{i=1}^K q_i\right) \prod_{i=1}^K q_i^{\beta-1}$$

Dirichlet priors, a.k.a., adding pseudocounts (include the uniform prior, the ML prior, and others).

Inference is analytic

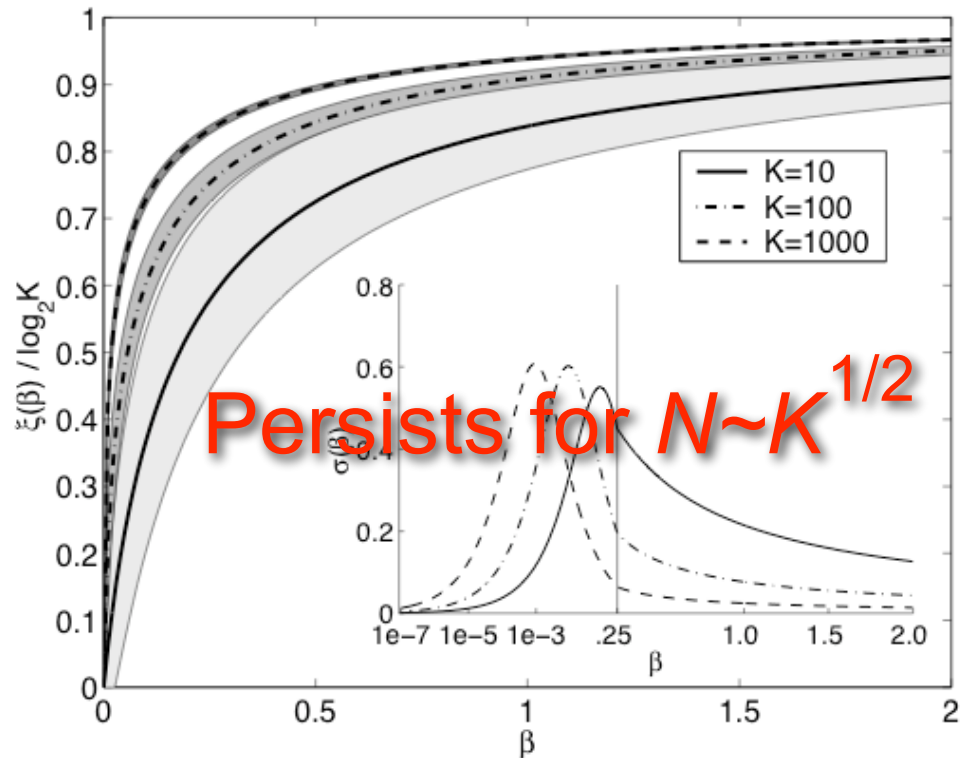


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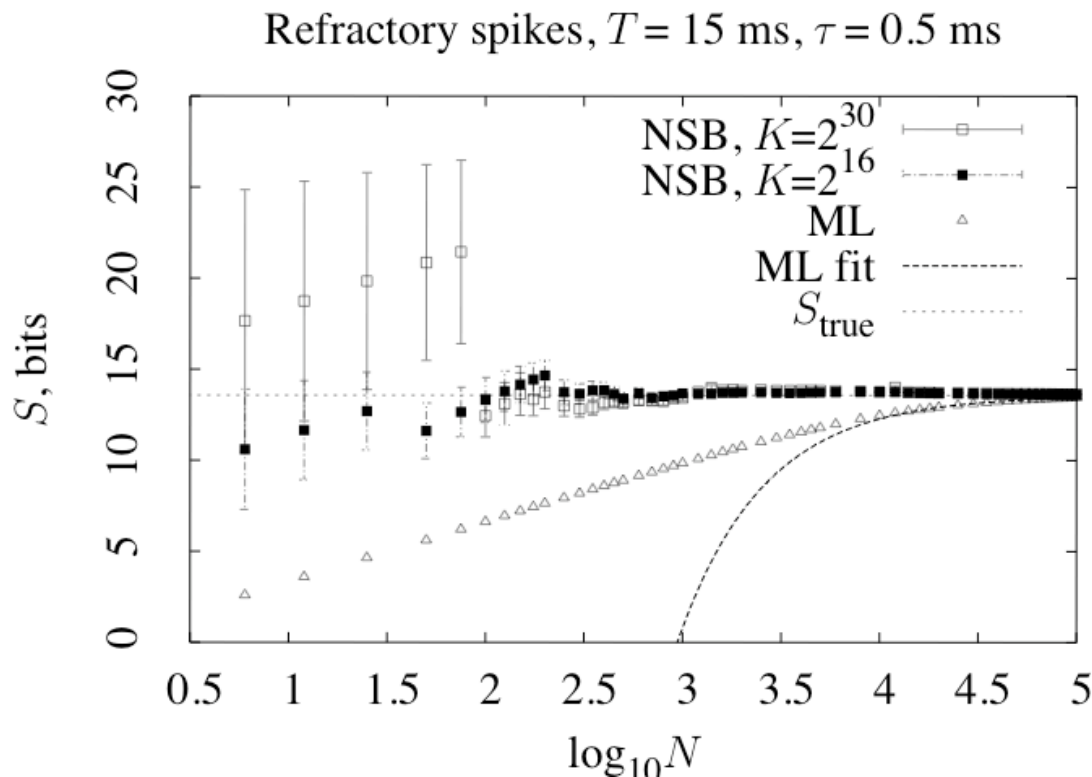
Uniformize on S

$$P_{\beta}(\{q_i\}, \beta) = \frac{1}{Z} \delta\left(1 - \sum_{i=1}^K q_i\right) \prod_{i=1}^K q_i^{\beta} \left. \frac{dS}{d\beta} \right|_{N=0} P(S|_{N=0})$$

- A delta-function sliding along the a priori entropy expectation.
- This is also Bayesian model selection (small β large phase space)
- Have error bars (dominated by posterior variance in β , not at fixed β).

Synthetic test

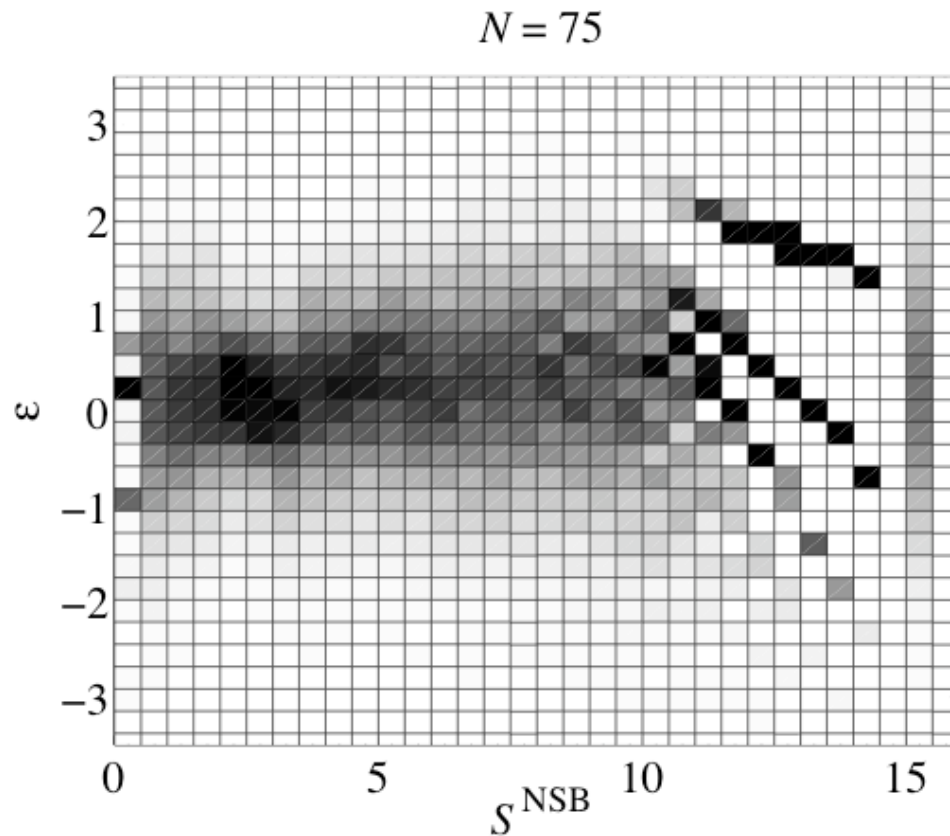
Refractory Poisson, rate 0.26 spikes/ms, refractory period 1.8 ms, $T=15\text{ms}$, discretization 0.5ms, true entropy 13.57 bits.



- Estimator is unbiased if consistent and self-consistent.
- Always do this check.

(Nemenman et al. 2004)

Natural data (all S)



$$\varepsilon = \frac{S^{NSB}(N) - S}{\delta S^{NSB}(N)}$$
$$\approx \frac{S^{NSB}(N) - S(N = \max)}{\delta S^{NSB}(N)}$$

Max=196 repeats

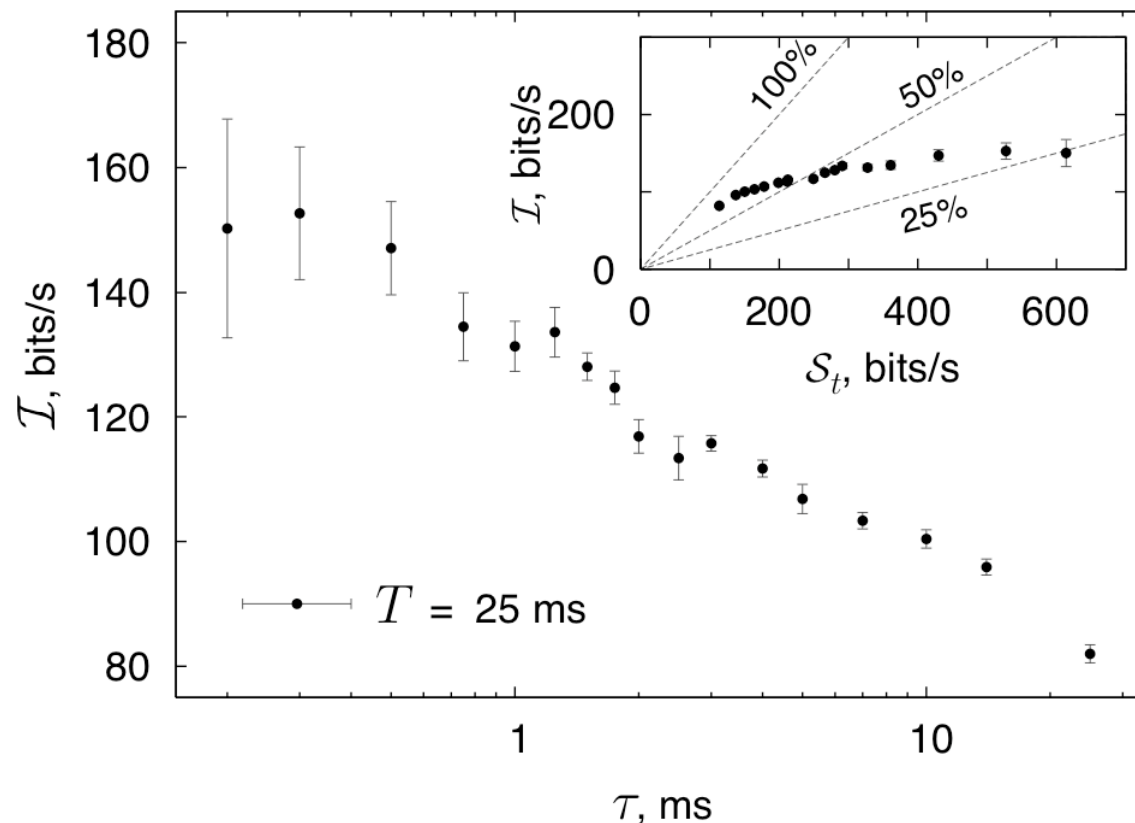
(Nemenman et al. 2004)

Neural code:

What remains hidden?

- Given entropy of slices, find the mean noise entropy with error bars (slice entropies are correlated and bimodal).
- Samples for total entropy are also correlated and have long tailed Zipf plots.
- For very fine discretizations and $T \sim 30\text{ms}$ need extrapolation.

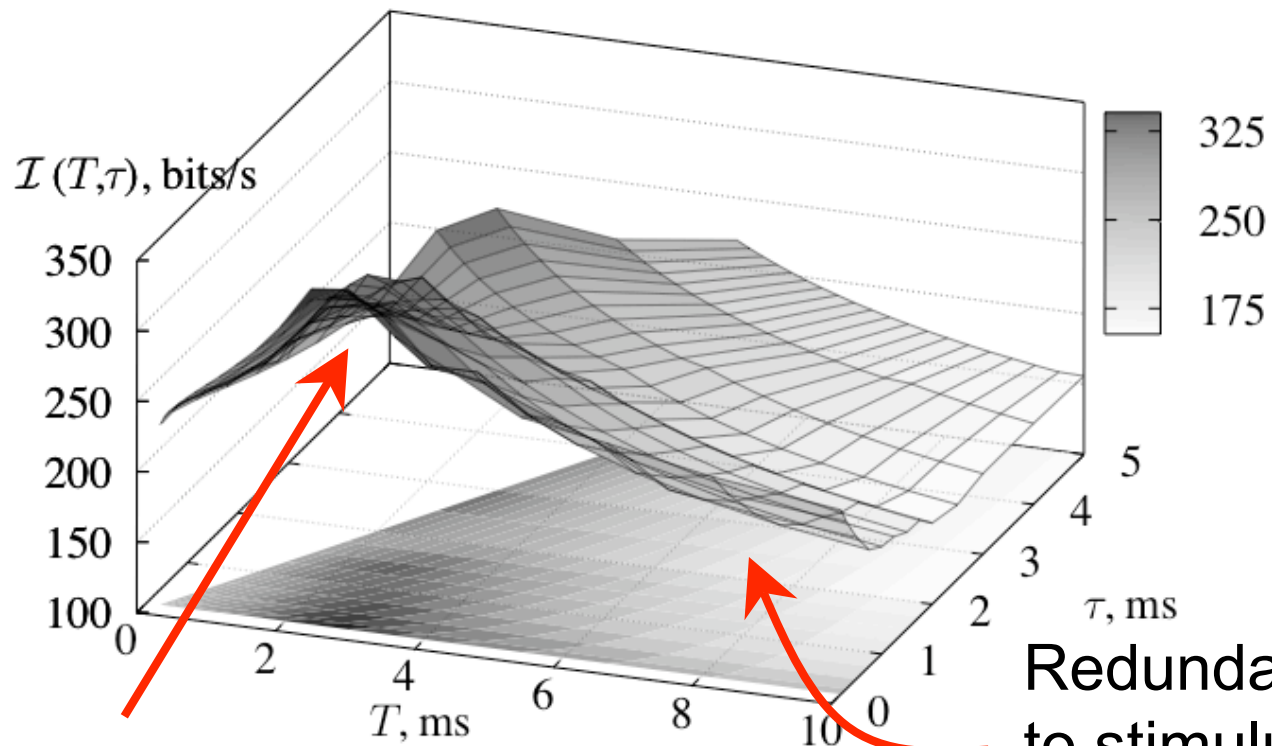
Information rate at $T=25\text{ms}$



0.2 ms -- comparable to channel opening/closing noise and experimental noise.

- Information present up to $\tau = 0.3\text{ ms}$
- 30% more information at $\tau < 1\text{ ms}$. Encoding by refractoriness?
- ~ 1 bit/spike at 150 spikes/s and low-entropy correlated stimulus. Design principle?
- Efficiency $> 50\%$ for $\tau > 1\text{ ms}$, and $\sim 75\%$ at 25ms. Optimized for natural statistics?

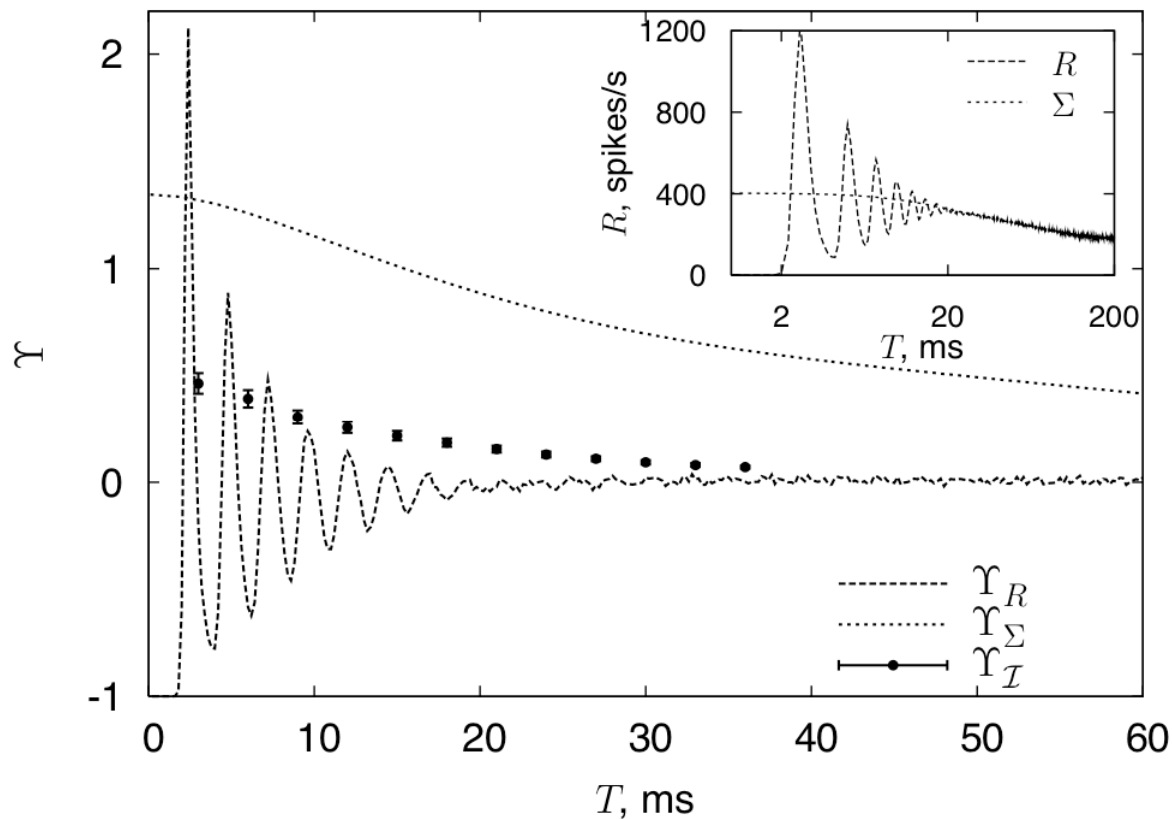
Synergy from spike combinations



Spike pairs

Redundancy due to stimulus

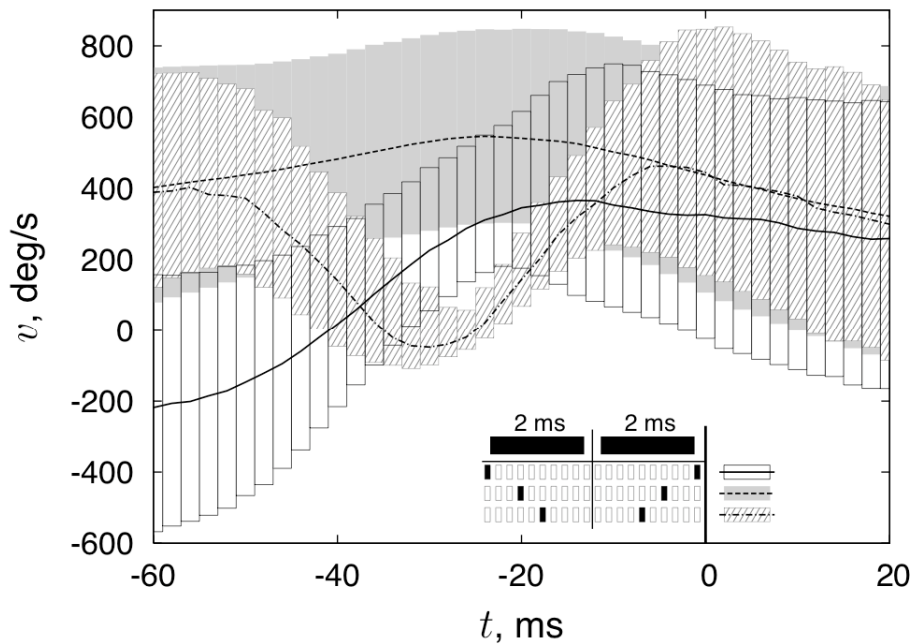
New bits (optimized code)



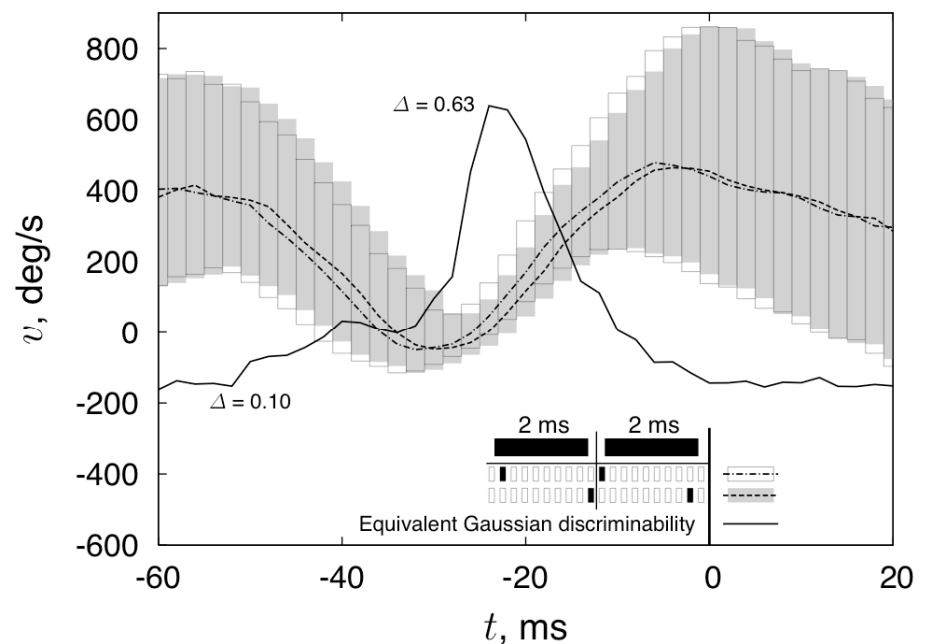
- Spikes are very regular (>10 beats)
WKB decoder?
Interspike potential?
- CF at half its value, but fly gets new bits every 25 ms
- Independent info (even though entropies are T dependent).

Behaviorally
optimized code!

Information about...



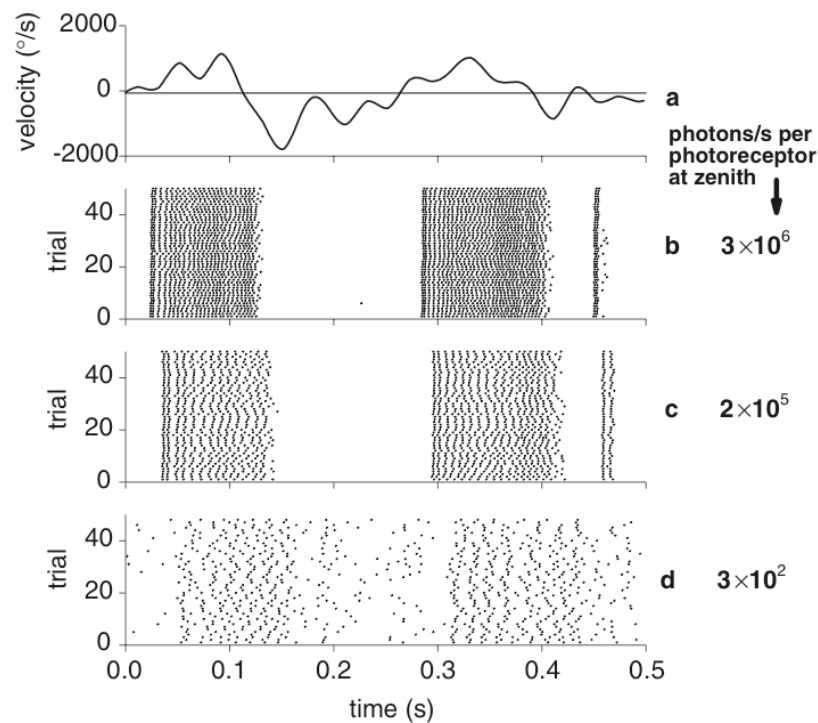
Signal shape



Zero-crossings time

Best estimation at 24 ms delay. Little time for reaction.

Precision is limited by physical noise sources



$$T = 6 \text{ ms}$$

$$\tau = 0.2 \text{ ms}$$

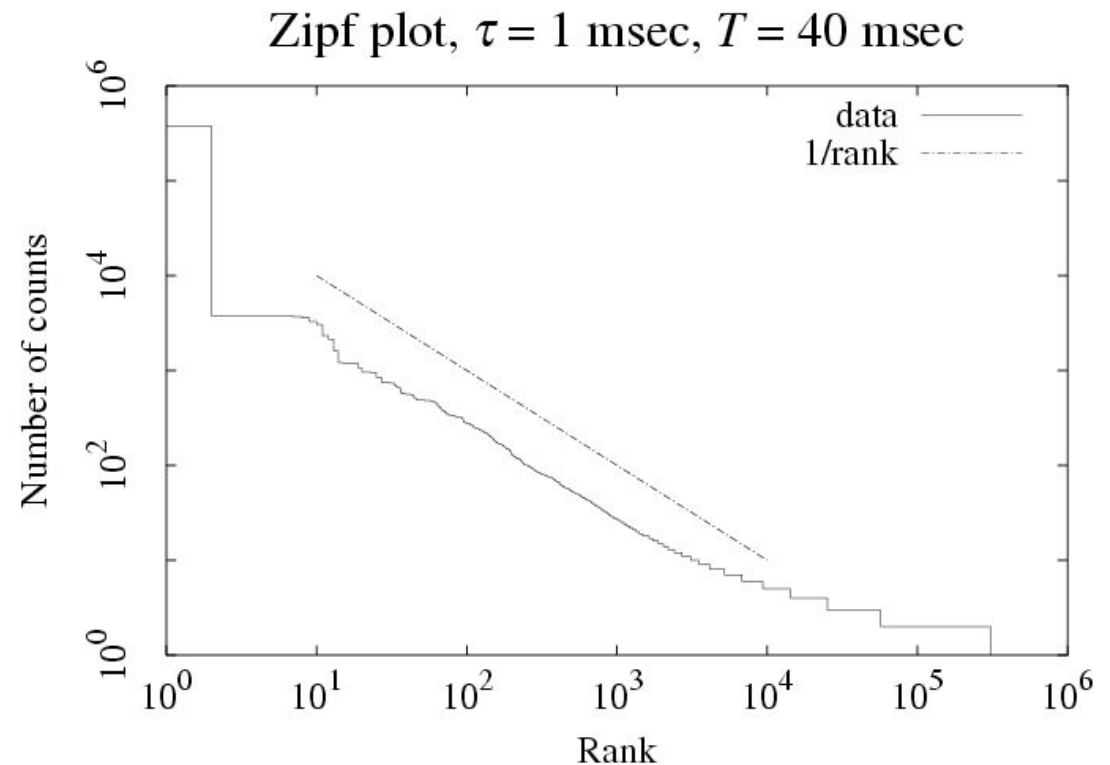
$$1.49 \text{ vs. } 1.61 \cdot 10^6 \text{ ph}/(\text{s} \cdot \text{rec})$$

$$I^+ - I^- = 0.020 \pm 0.011 \text{ bits}$$

(Lewen, et al 2001)

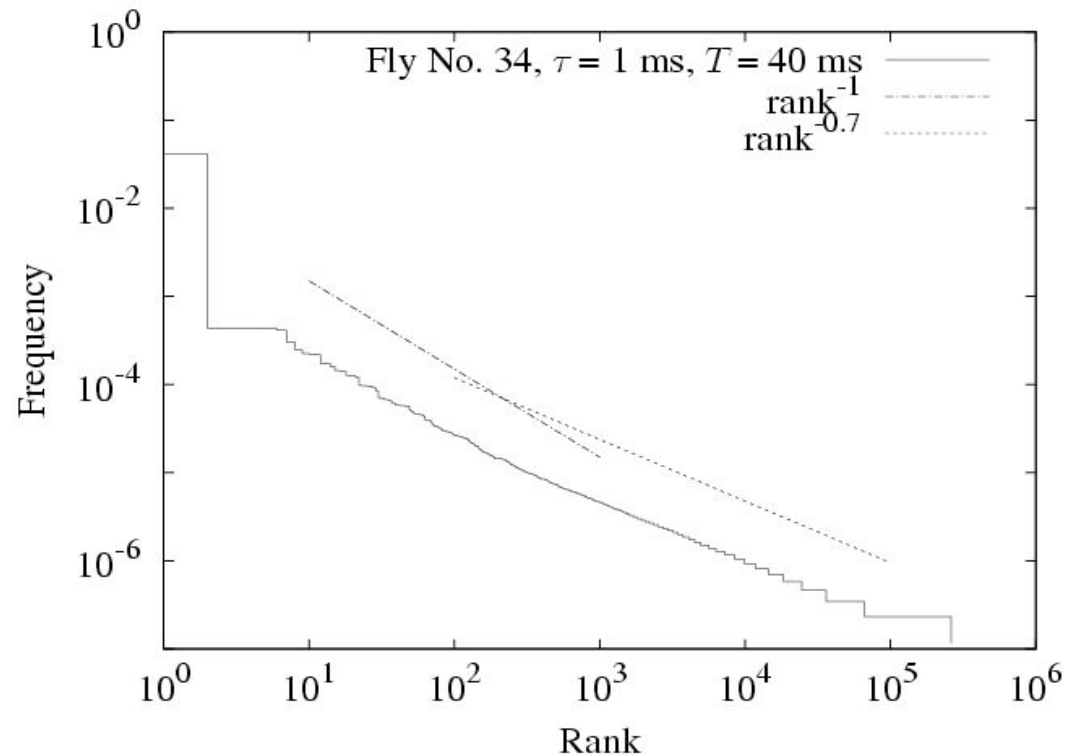
A very intelligent fly

- One often considers a $1/f$ rank-order plot as a sign of intelligence.
- But...



A very intelligent fly

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- But...



Zipf law may be a result of complexity of the world,
not the language.