Correlations and coding in neural populations

Eric Shea-Brown U. Washington

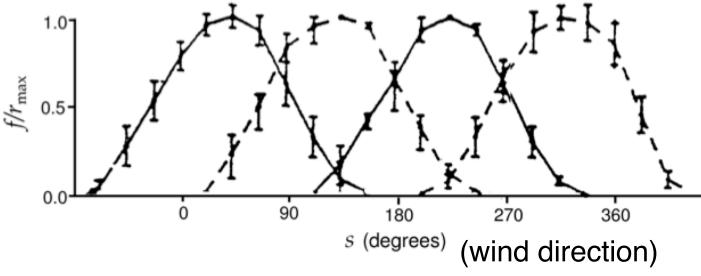
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Neural firing rates are tuned with sensory and/or motor variables

Adrian, 1928 ... Neural basis of sensation

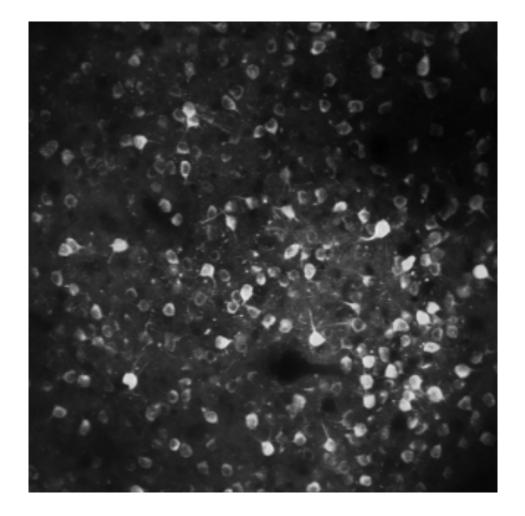
Α В 60-50-Georgopoulis et al '82 90 1 1 1 1 1 1 1 181 f (Hz) 40-1 11 1 1 1 1M 8HW 111 H 19 19 1 1 1 1 1 1 1 (Motor cortex) сий са по проблата по сводите по на фила по на фила 30-8 181 8 18 1 1 1 1 1 1 1 1 1 1 1 1 1 1 • 0° 11111 **0** 11 [Fig: Abbott+Dayan '99] ------20 1 1101 (1 nini in 1 n and a dennañ. 11101 1111 111111111 01111111111 IS MINE TERE OF BERRE TER B 10 I MRIME MERE 1 1 H 8480 1 HE 10 10 11 ... 0-250 350 50 100 150 200 300 0 s (movement direction in degrees) 1.0

Theunissen and Miller, 1991 (Cricket circal ganglion)



Today — Glorious mess: Heterogeneous, variable, simultaneous responses of large neural populations

2P data



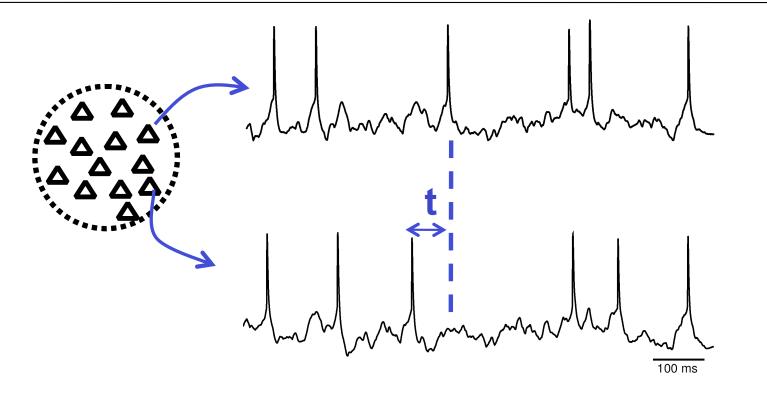
Allen Brain Observatory



Population codes are cool and complex ... and pose rich conceptual and theoretical questions

(1) Efficient encoding and decoding: optimal tuning curves and receptive fields

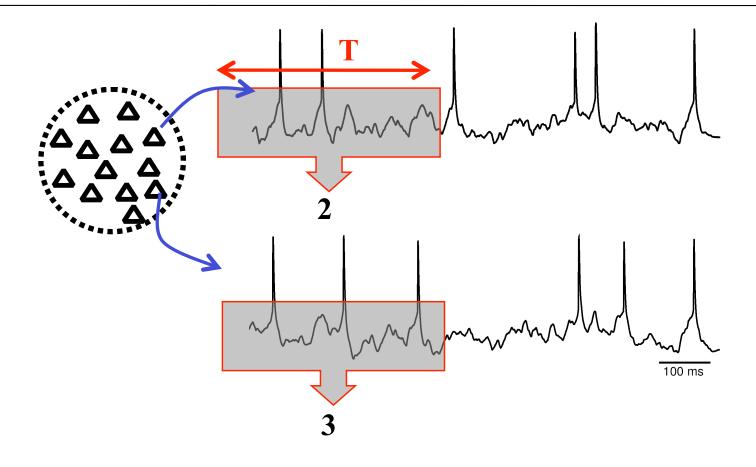
(2) Collective (or *correlated*) neural activity: What does it add (or subtract) from population codes defined by tuning of individual cells?

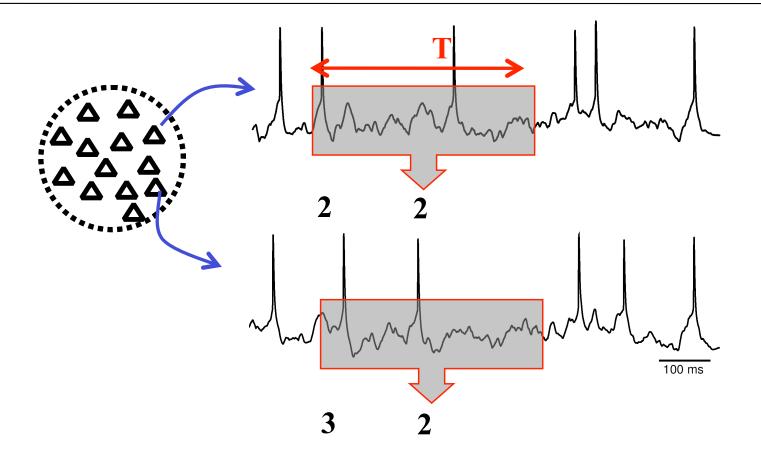


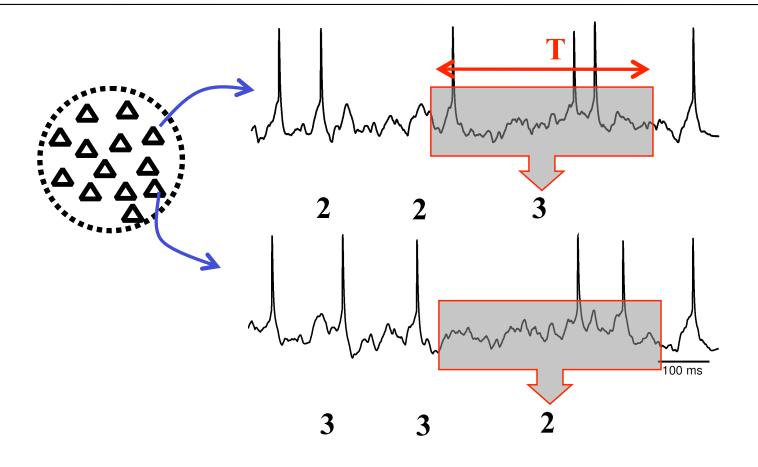


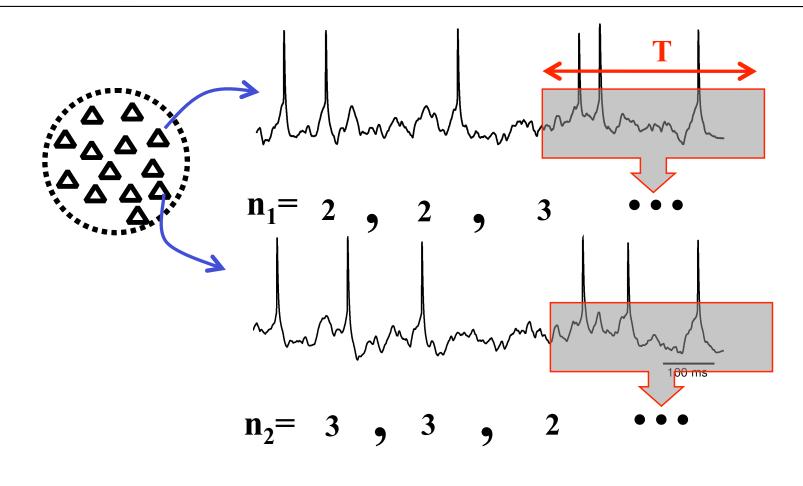
Time Lag t

0

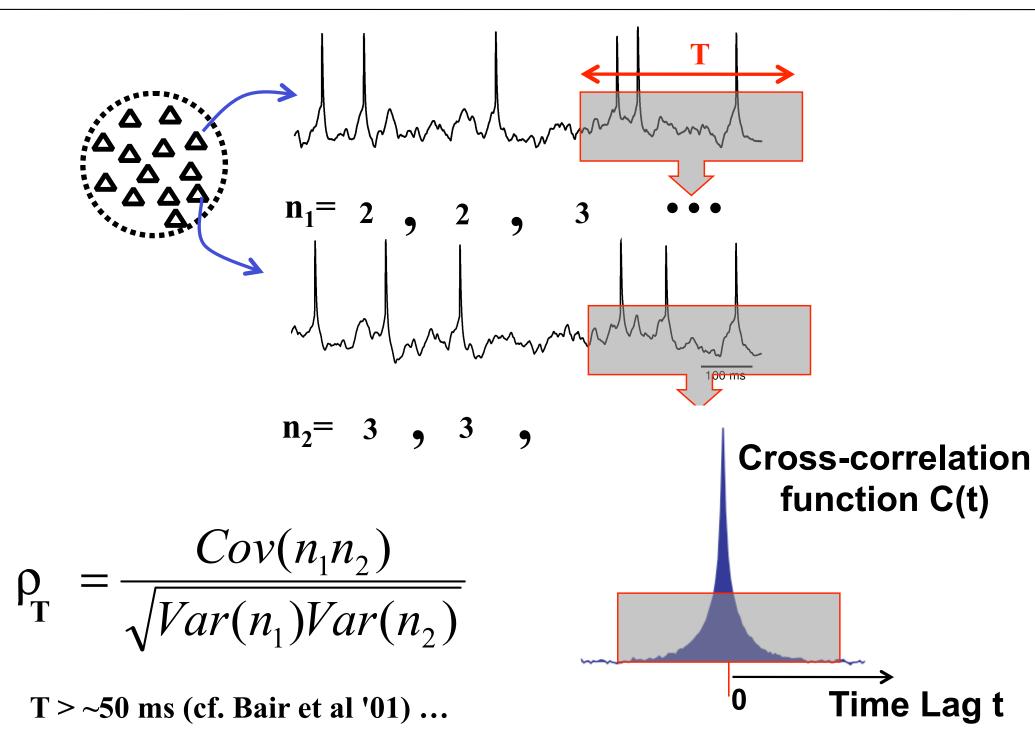


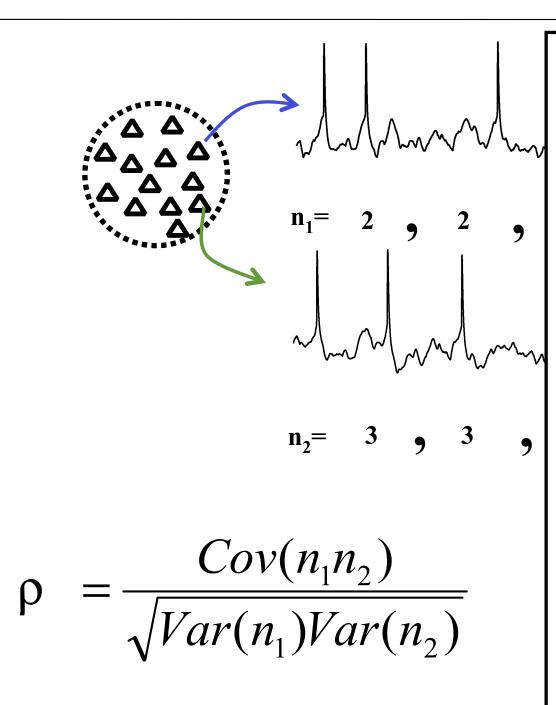






$$\rho_{\rm T} = \frac{Cov(n_1 n_2)}{\sqrt{Var(n_1)Var(n_2)}}$$





Correlation ρ ≠ 0 ubiquitous:

- •Retina: Mastronade 1983.
- •LGN: Alonso et al 1996
- •V1: Kohn and Smith 2005
 - see also Ecker et al 2010
- •IT: Gawne & Richmond 1993
- •PF: Constanidis & Goldman-Rakic 2002.
- •Parietal Cortex: *Lee et al 1998*
- •Somatosensory thal.: *Bruno & Sakmann* 2006
- •A1: deCharms & Merzenich 1996
- •SI: *Romo et al 2003....*
- Motor cortex: Vaadia et al 1995

Motor neurons: Binder and Powers 2001

Why the correlations? $p(n_1, n_2) \neq p(n_1)p(n_2)$

Common signal input→Common spike response → SIGNAL CORRELATIONS



ADDITIONAL CORRELATIONS ARE ... NOISE CORRELATIONS

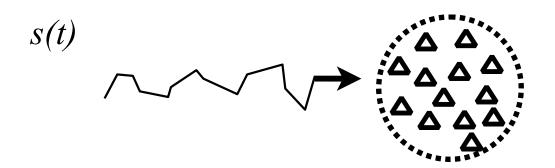
$p(n_1, n_2|s(t)) \neq p(n_1|s(t))p(n_2|s(t))$

These describe the population response beyond tuning "curves" of mean stimulus response.

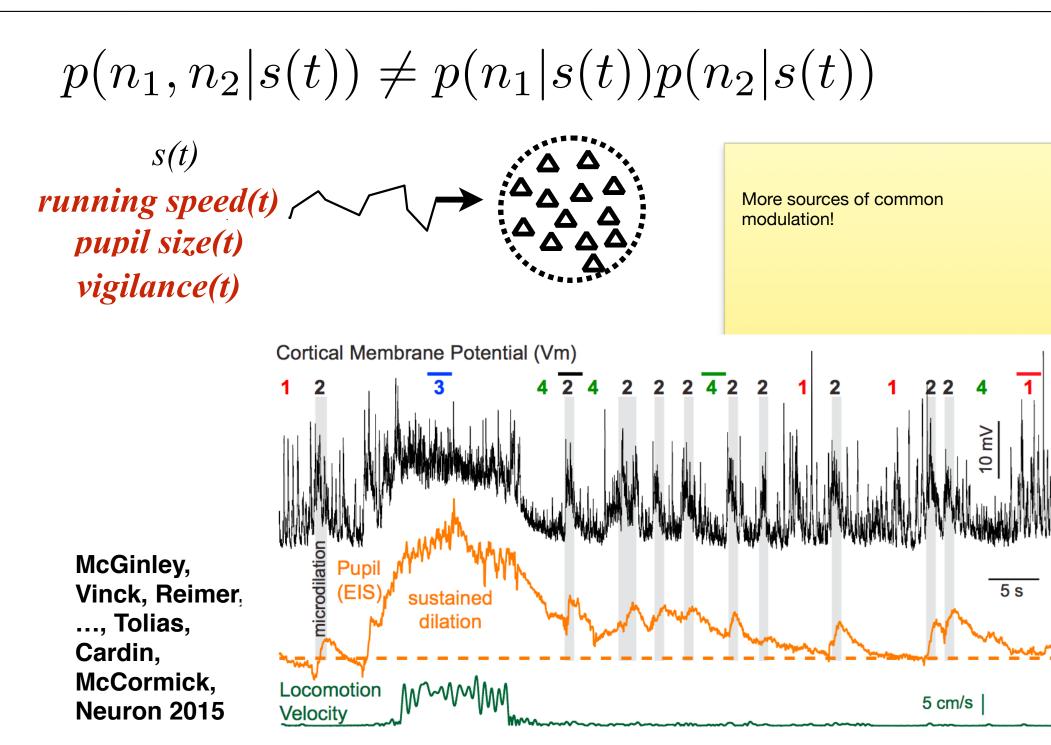
Our focus today.

Why the NOISE correlations?

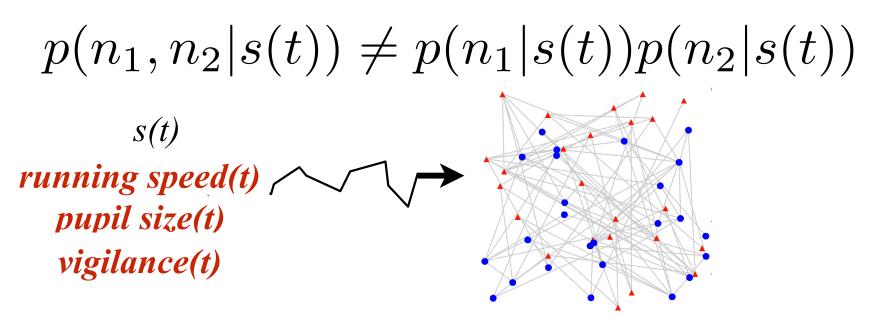
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Why the NOISE correlations?



Why the NOISE correlations?



(1) Corrs from comodulation by behavioral or internal state(2) Corrs from network interactions

These can be separated from comodulation:

(a) regress out known variable (here, running speed)

(b) regress out unknown "latent variables" [Ecker '14, Yatsenko '15]

These pose algorithmic questions:

Signatures of computation?

sparse auto encoders (Olshausen/Field, ...)

spike-based predictive coding: (Deneve, cf. Rozell, ...)

These pose population coding questions: Our focus today.

CODING IMPACT OF CORRELATED SPIKING

(a) Signal propagation

Correlated spiking modulates signal propagation

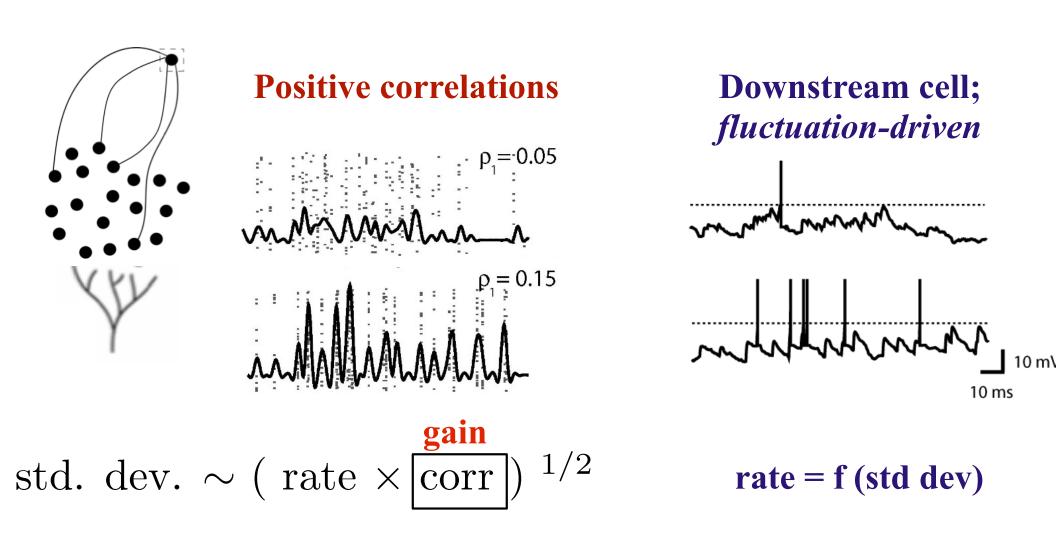
[Abeles '92; Salinas and Sejnowski,'00; Reid et al '01; Bruno '11; Jia, Tanabe, and Kohn, '13; but see Histed, Maunsell et al '14]

Positive correlations $\rho_1 = 0.05$ $\rho_1 = 0.15$ $\rho_1 = 0.15$

std. dev. ~ (rate × corr) $^{1/2}$

Correlated spiking modulates signal propagation

[Abeles '92; Salinas and Sejnowski,'00; Reid et al '01; Bruno '11; Jia, Tanabe, and Kohn, '13; but see Histed, Maunsell et al '14]

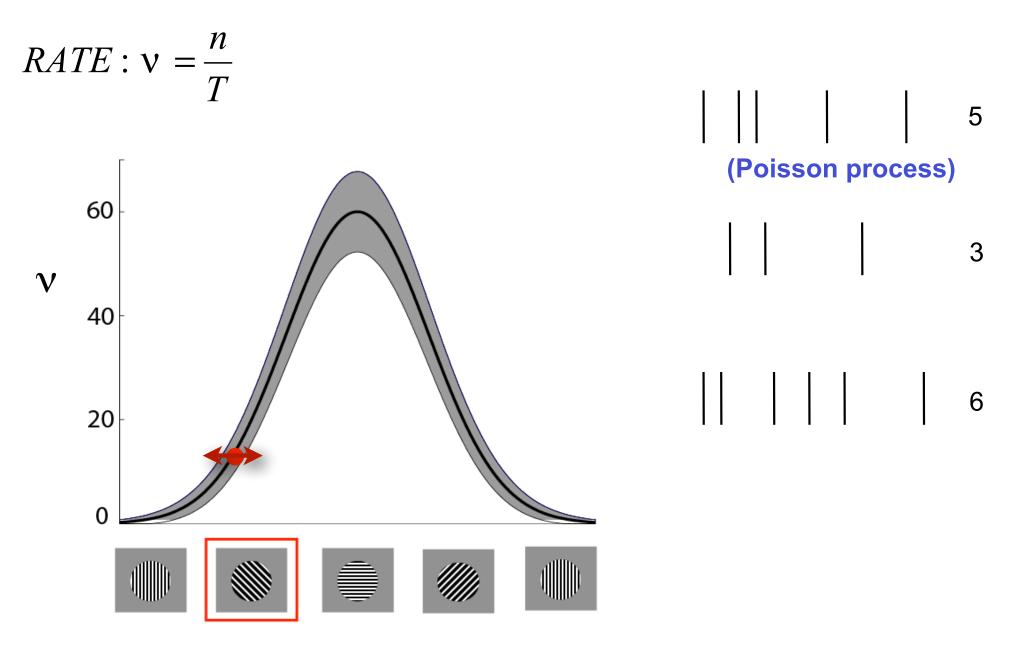


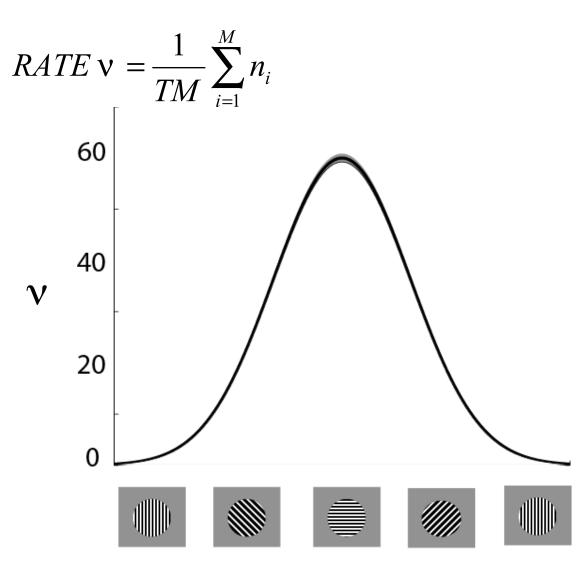
CODING IMPACT OF CORRELATED SPIKING

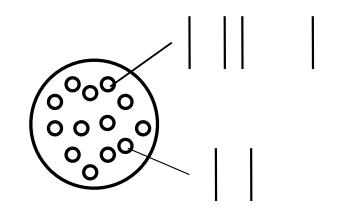
(a) Modulates signal propagation

(b) Information in homogeneous populations

Response Variability



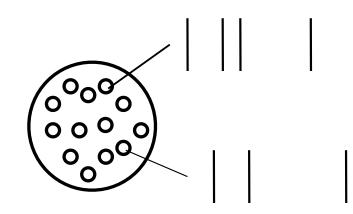




M cells n_i spikes each in time window T

$$RATE \,\mathbf{v} = \frac{1}{TM} \sum_{i=1}^{M} n_i$$

$$\langle \nu \rangle = \frac{1}{TM} \sum_{i}^{M} \langle n_i \rangle$$
$$= \frac{1}{TM} MrT = r$$

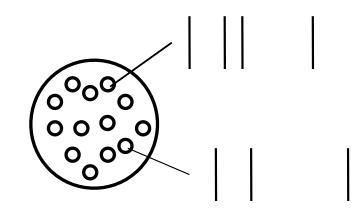


M cells n_i spikes each in time window T

$$var(\nu) = \frac{1}{T^2 M^2} \sum_{i}^{M} var(n_i)$$
$$= \frac{1}{T^2 M^2} MrT \sim \frac{1}{M}r$$

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$$\frac{\langle \nu \rangle}{var(\nu)} = SNR(\nu) \sim M$$

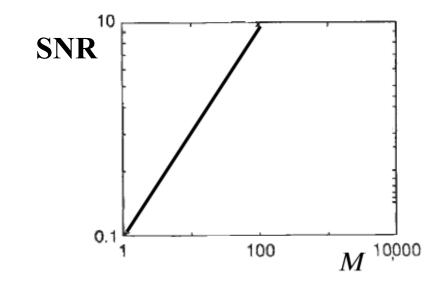
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> *M* cells *n_i* spikes each in time window *T*

Population averaging improves SNR.

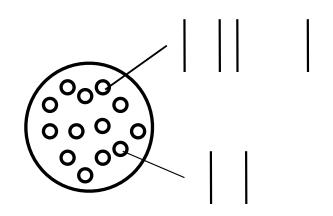
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Population codes – average over *M* **correlated cells**

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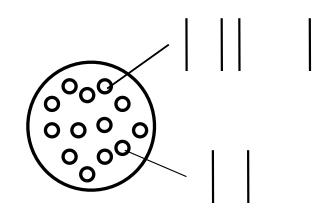


M cells n_i spikes each in time window T n_i have correlation coefficient ρ

Population codes – average over *M* **<u>correlated</u> <u>cells</u>**

$$RATE \mathbf{v} = \frac{1}{TM} \sum_{i=1}^{M} n_i$$

$$\langle \nu \rangle = \frac{1}{TM} \sum_{i}^{M} \langle n_i \rangle$$
$$= \frac{1}{TM} MrT = r$$



M cells n_i spikes each in time window T n_i have correlation coefficient ρ

$$var(\nu) = \frac{1}{T^2 M^2} \left(\sum_{i}^{M} var(n_i) + \sum_{i \neq j} cov(n_i, n_j) \right)$$
$$\sim \frac{1}{T^2 M^2} M^2 r T \rho \sim \rho$$

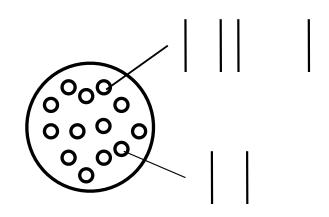
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Population codes – average over *M* **correlated cells**

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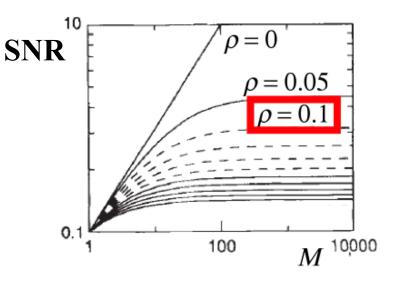
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Zohary, Shadlen and Newsome (1994)

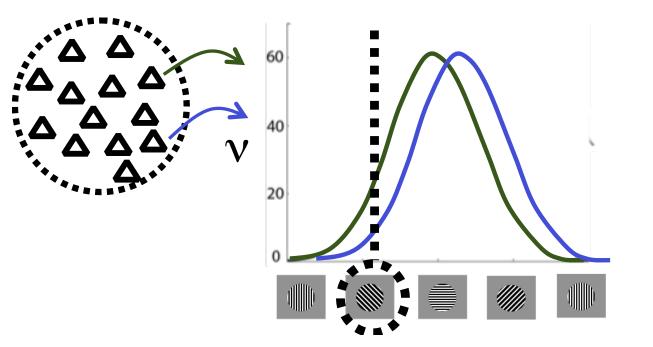


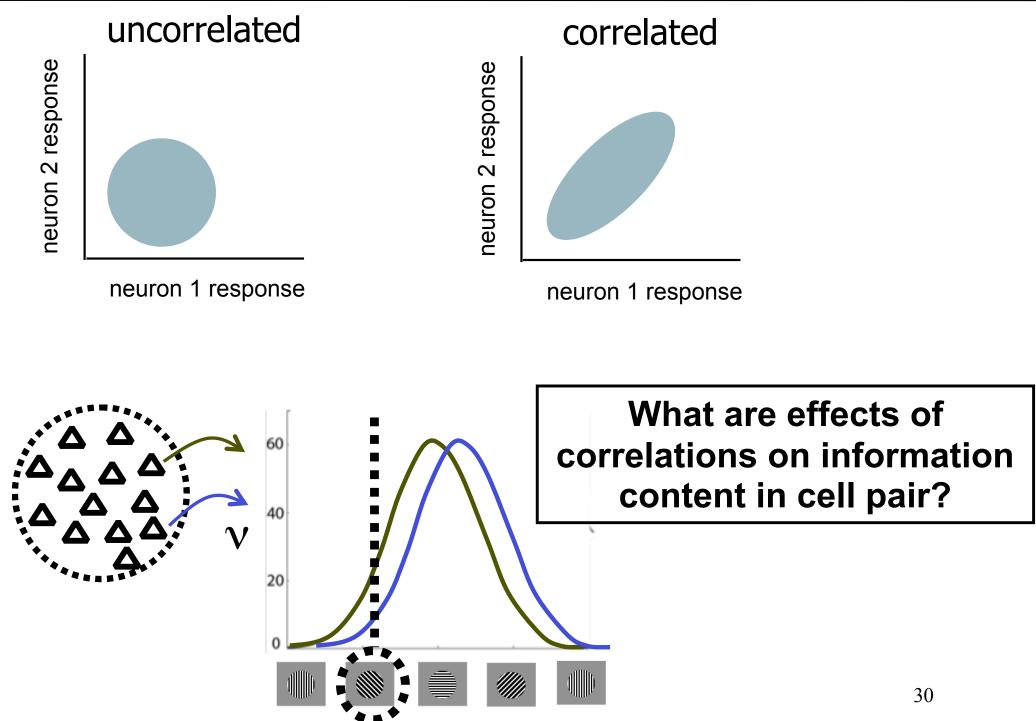
CODING IMPACT OF CORRELATED SPIKING

(a) Modulates signal propagation

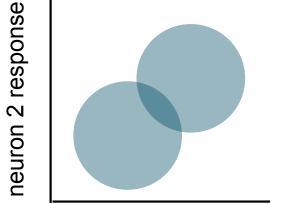
(b) Homogeneous populations: impedes pop. averaging/ decreases SNR

(c) Heterogeneous populations ...



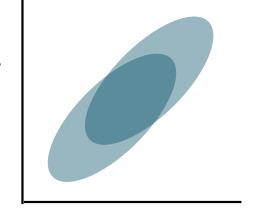


uncorrelated

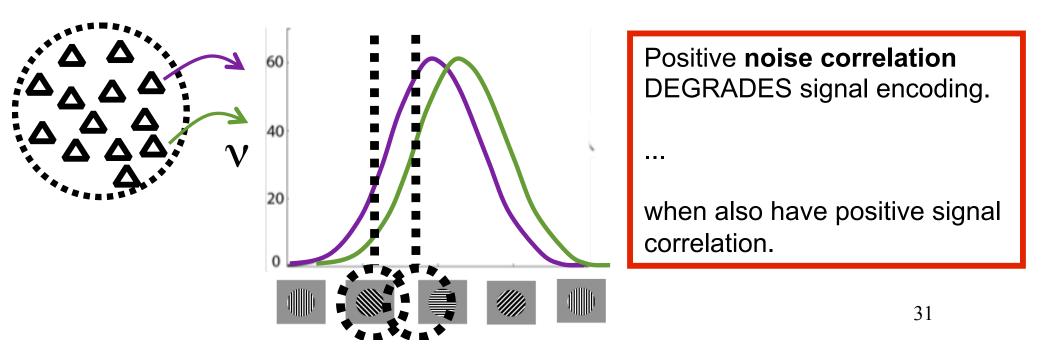


neuron 1 response



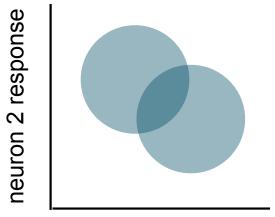


neuron 1 response

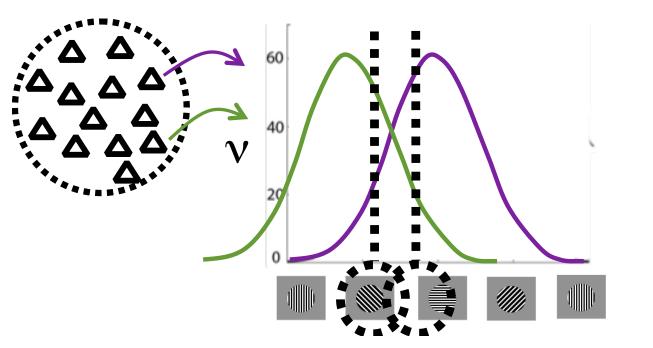


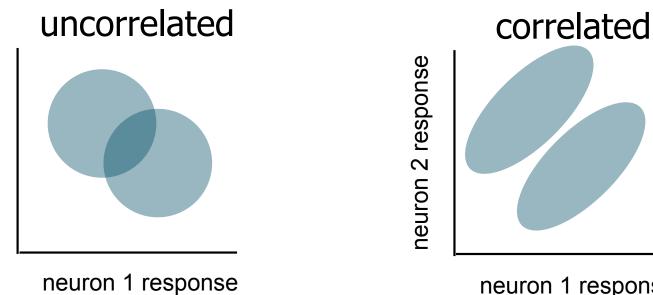
neuron 2 response

uncorrelated



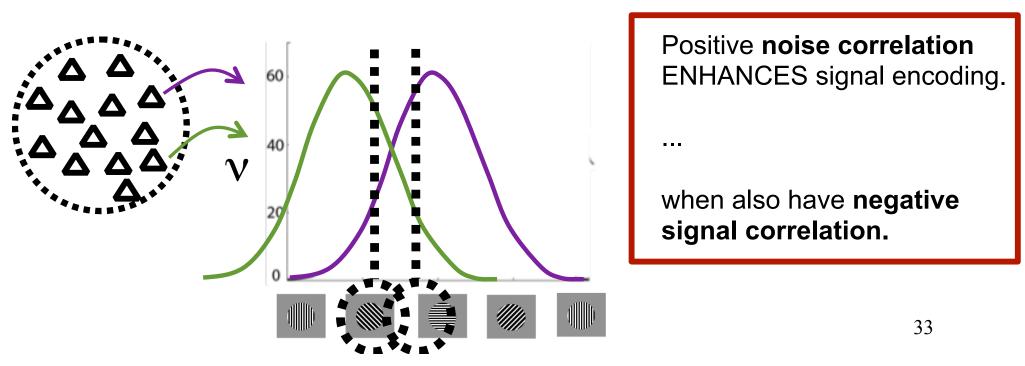
neuron 1 response

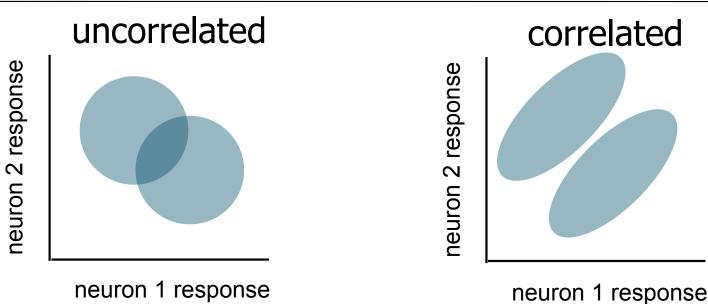




neuron 2 response

neuron 1 response





Neuron, Vol. 38, 649-657, May 22, 2003, Copyright ©2003 by Cell Press

Correlated Neuronal Discharges that Increase Coding Efficiency during Perceptual Discrimination

(S2 cells)

Ranulfo Romo,^{1,*} Adrián Hernández,¹ Antonio Zainos,¹ and Emilio Salinas² rate increases similar to those observed in S1, but for other units the firing rate decreases monotonically as a

Correlated Neuronal Discharges that Increase Coding Efficiency during Perceptual Discrimination

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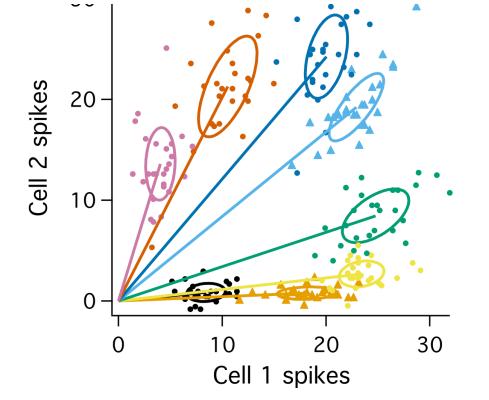
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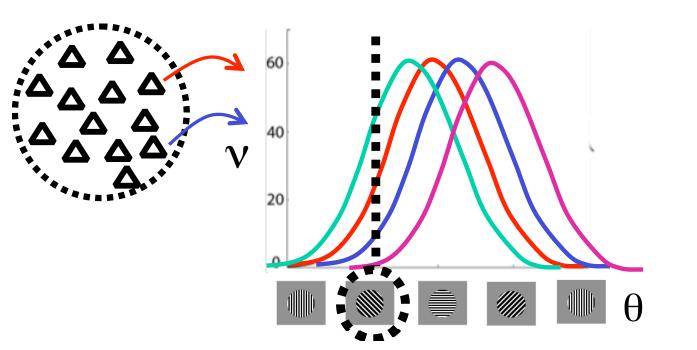
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Direction-Selective Circuits Shape Noise to Ensure a Precise Population Code (RGC cells)

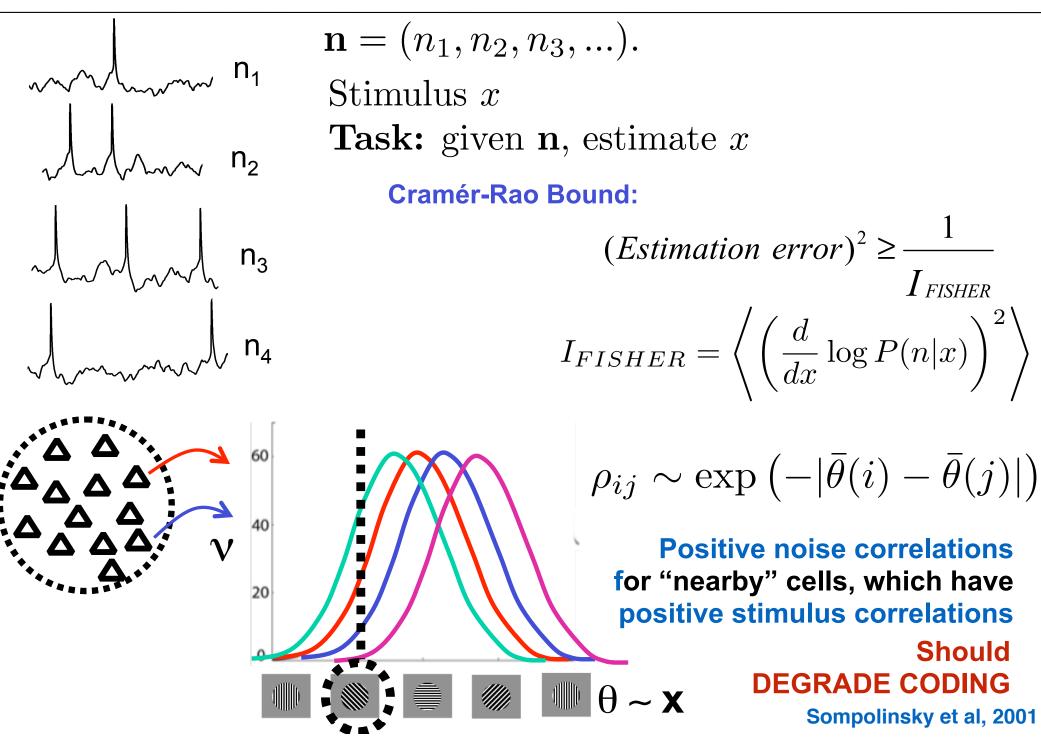


Zylberberg, Cafaro, Turner et al. Neuron 2016

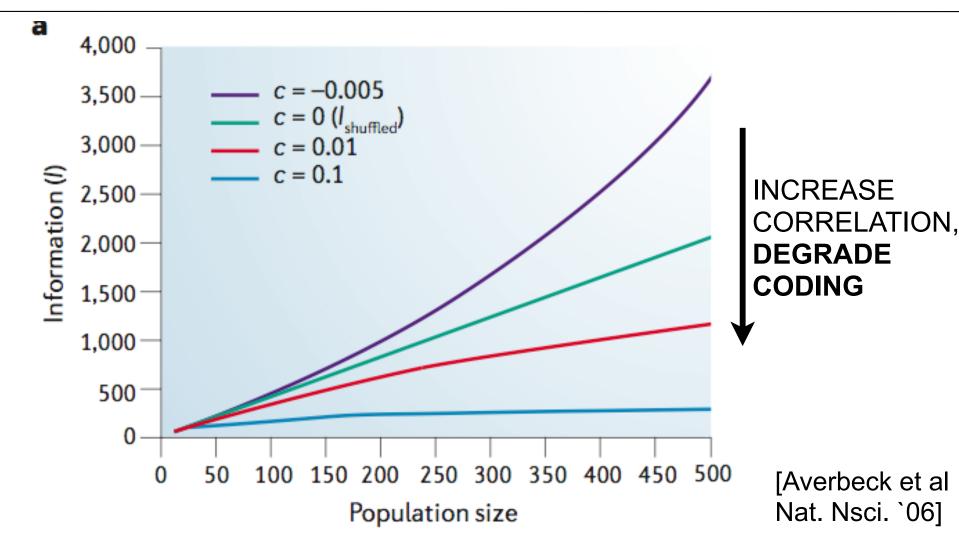
Correlations and coding in larger cell populations



Correlations and coding in larger cell populations



Correlations and coding in larger cell populations



MANTRA (SIGN RULE): IF NOISE + SIGNAL CORRELATIONS HAVE ... SAME "SIGN", BAD (At least for "small" correlations w.r.t. population size N.) DIFFERENT SIGN, GOOD.

FORMALIZE: Hu et al '14, Ecker et al '11; Shamir, '14; da Silvera+Berry'14

CODING IMPACT OF CORRELATED SPIKING:

(a) Modulates signal propagation

- (b) Homogeneous populations: DEGRADES CODING
- (c) Heterogeneous populations:

SIGN RULE MANTRA:

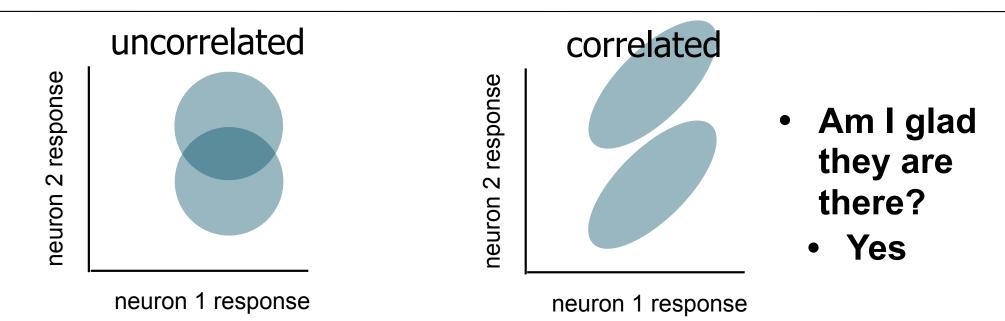
correlate cells w/ similar stimulus tuning: DEGRADE* correlate cells w/different stimulus tuning: ENHANCE

*(only guaranteed if correlations small w.r.t. # cells in pop.) BEYOND THE MANTRA:

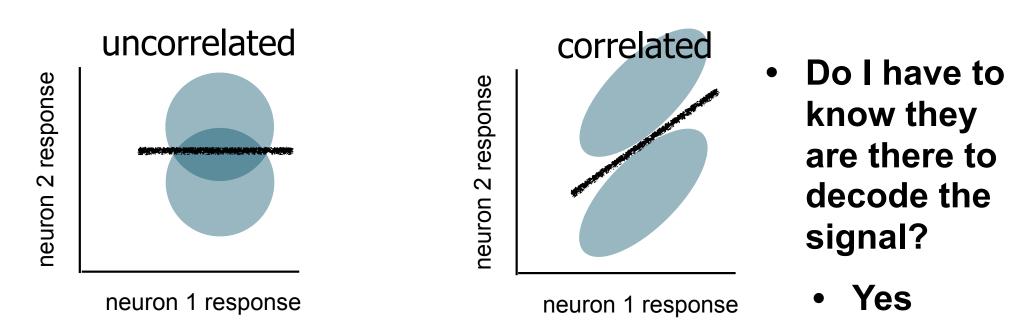
many possibilities for correlations that ENHANCE coding in large populations

[Shamir and Sompolinsky Neural Comp 2006, Hu, Zylberberg et al PLOS CB 2014 Shamir Current Opinion Neurobio 2014]

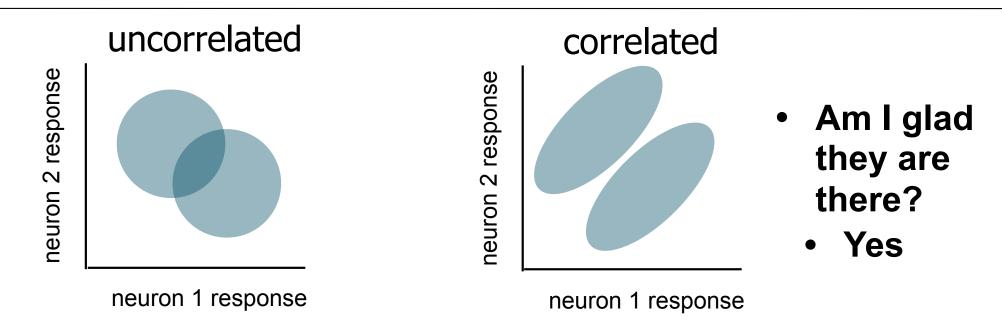
That was the encoding perspective on correlations



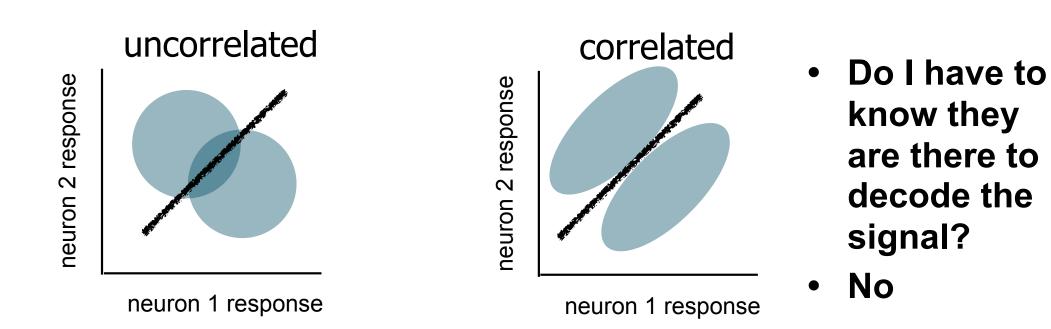
There is also a decoding perspective



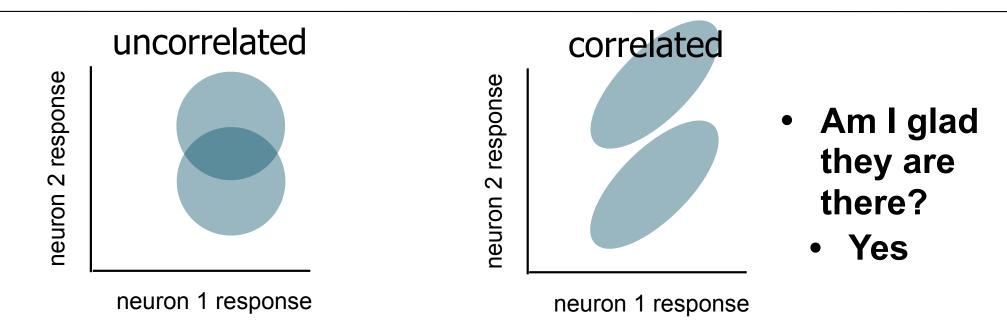
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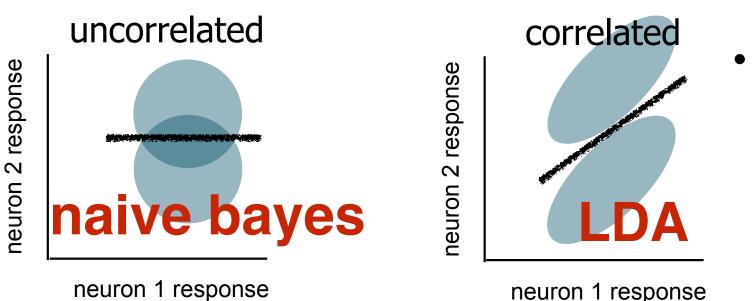
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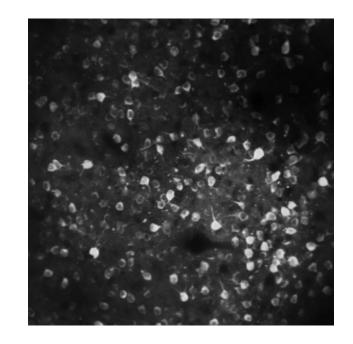
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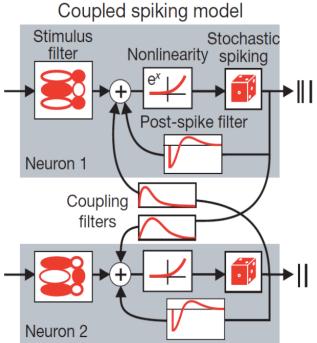


- Do I have to know they are there to decode the signal?
 - Yes

Projects galore...

What does collective activity contribute to *decoding* stimuli in different visual areas (and Cre lines)?





Pillow et al, 2008

Can ask via other decoders, e.g. GLM with vs. without coupling filters

Collective (or correlated) neural activity and population codes

Algorithmic: Evidence for signatures (or exhaust fumes) of computation?

Propagation: Do correlations modulate signal transmission?

Encoding: How do correlations impact info?

Decoding: Are readouts sensitive to correlations? Geometry of signal and noise: sign rule mantra (and beyond) Collective (or correlated) neural activity and population codes

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