Inferring Readout Of Distributed Population Codes Without Massively Parallel Recordings

Baylor College of Medicine

Kaushik J Lakshminarasimhan[1], Dora E Angelaki[1,2], Xaq Pitkow[1,2]

[1]Dept. of Neuroscience, Baylor College of Medicine [2]Dept. of Electrical & Computer Engineering, Rice University

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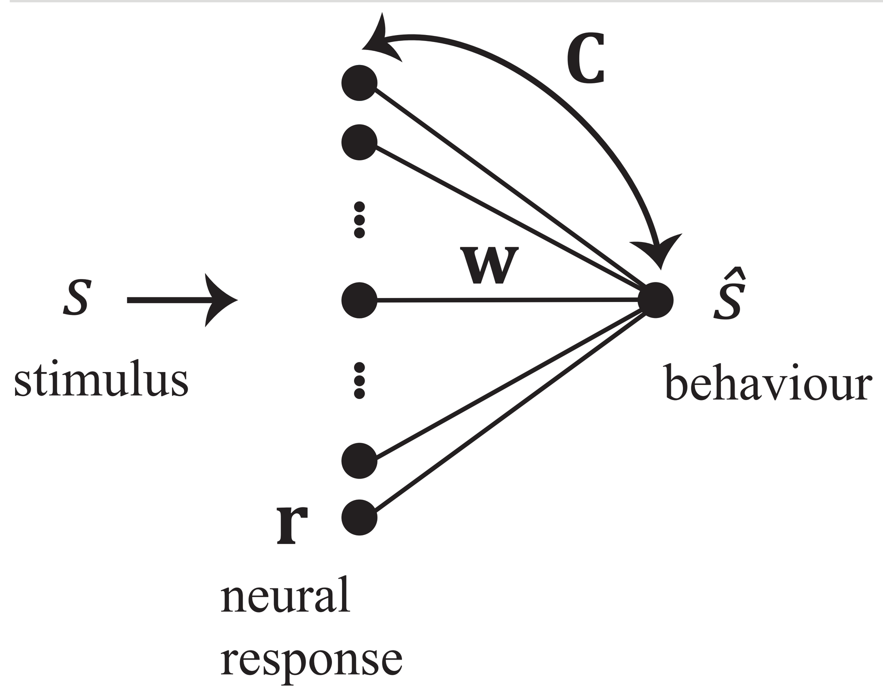
Inferring readout weights is generally hard because ...



neural response $\mathbf{r} \sim \mathcal{N}(\mathbf{f},\Sigma)$ $\xrightarrow{\mathbf{w}\,=\,?}$ behavioural choice $\hat{s} = \mathbf{w}^{\mathrm{T}}\mathbf{r}$

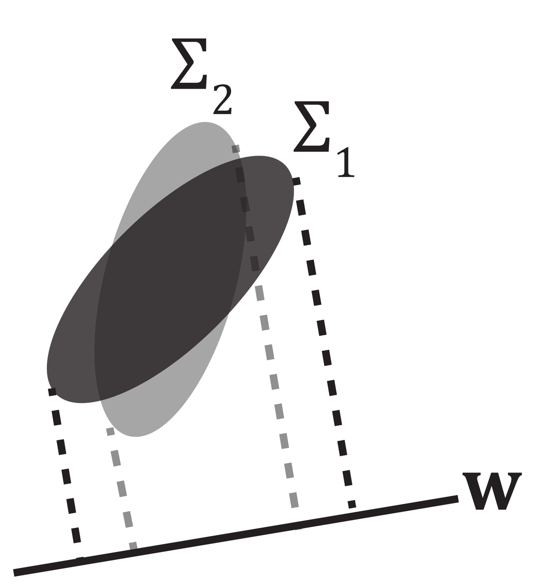
$\mathbf{C} = \mathrm{corr}(\mathbf{r},\hat{s})$ choice correlation

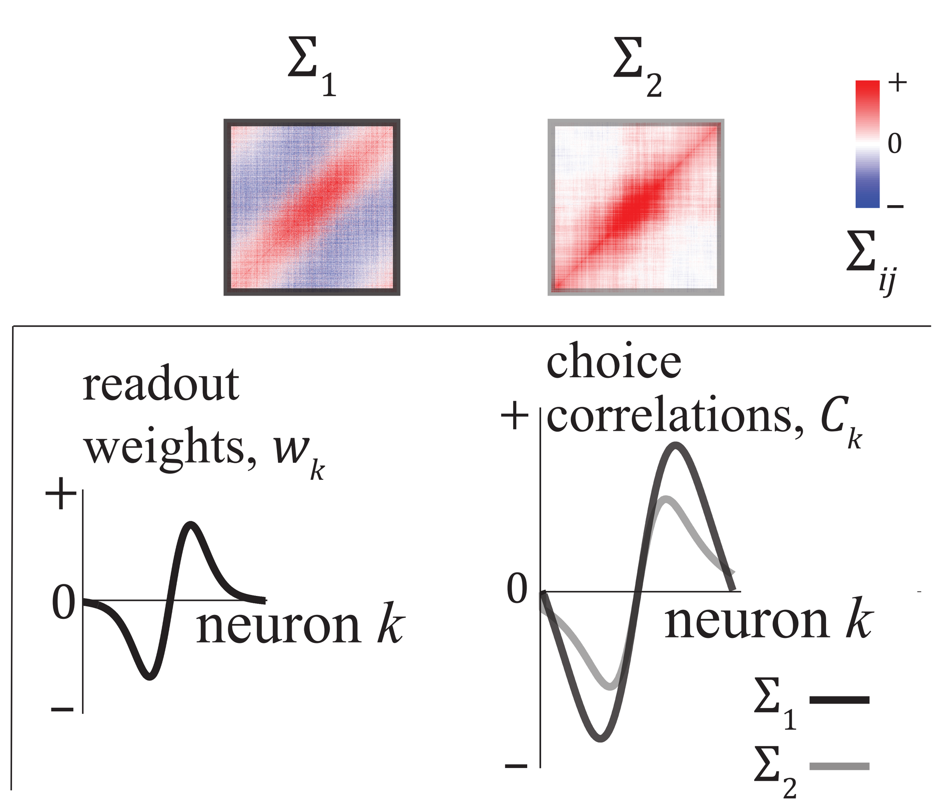
For choices based on linear readout, it has been shown that[1]

$$C_k = \frac{(\Sigma \mathbf{w})_k}{\sqrt{\Sigma_{kk}\mathbf{w}\Sigma\mathbf{w}}}$$

f : mean responses
Σ: covariance
w: decoding weights

Pattern of choice correlations is very sensitive to the structure of covariance[1].

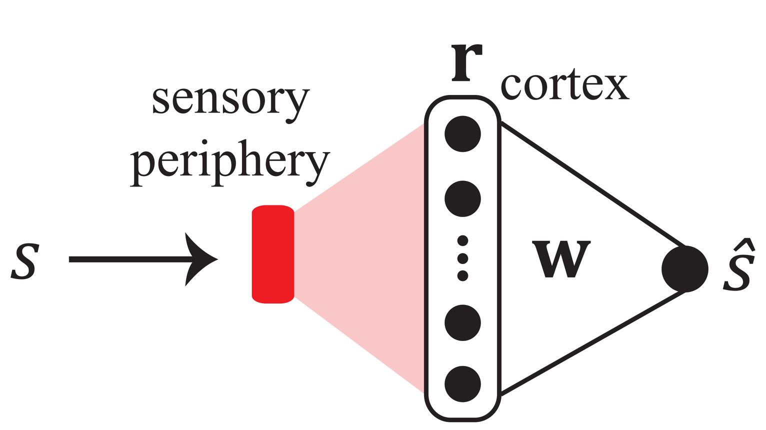




Impossible to infer **w** without measuring Σ.

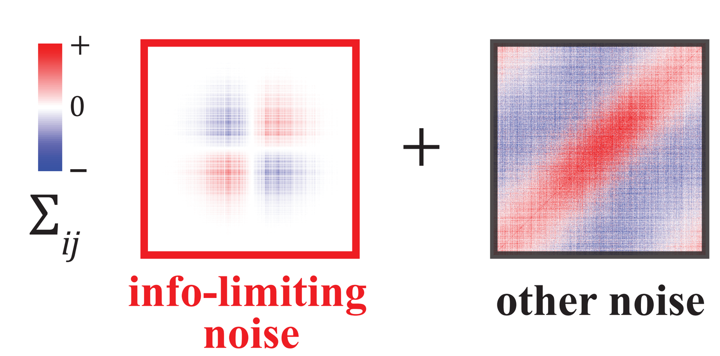
requires large-scale simultaneous recordings !

... but there are information-limiting correlations ...

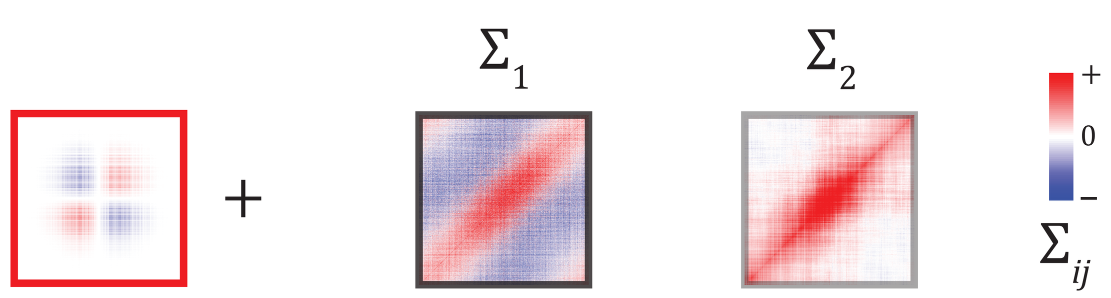


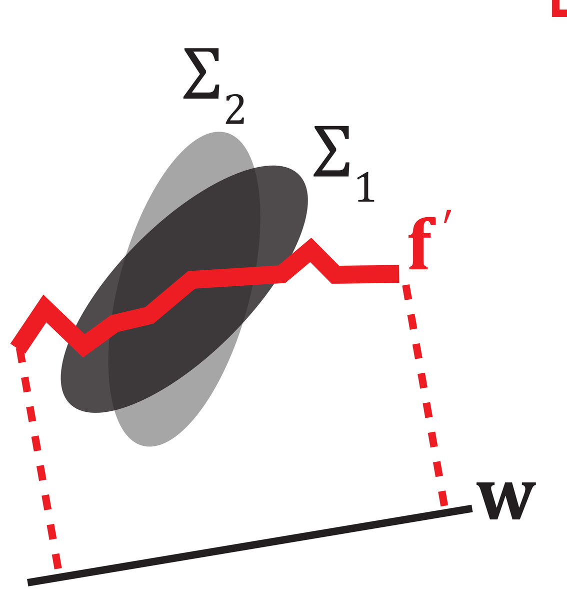
Cortical neurons receive information from a small set of sensory receptors. Expansion in sensory representation leads to Information-limiting noise[2].

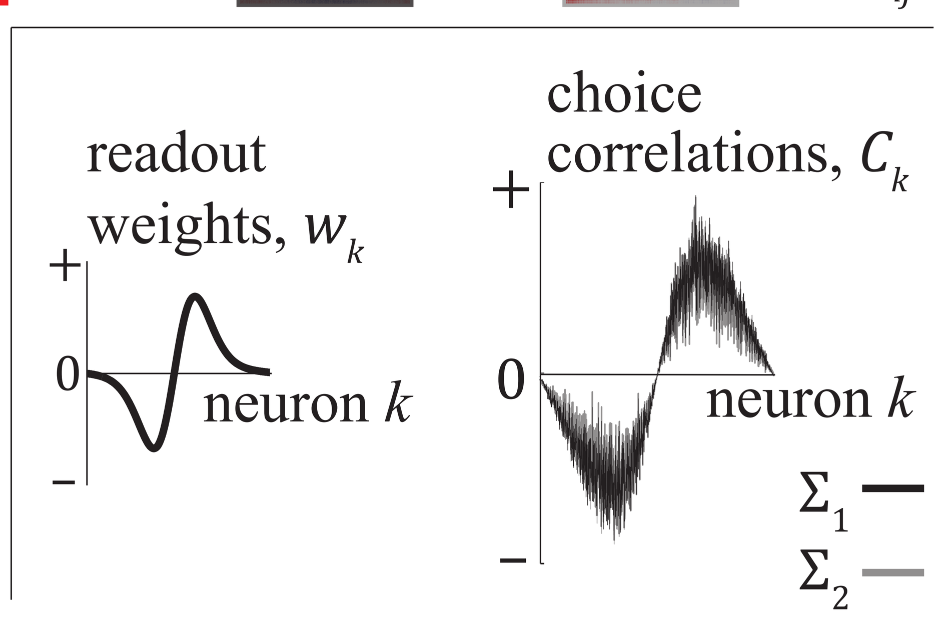
$$\Sigma_{\mathrm{IL}} = \varepsilon \mathbf{f}'\mathbf{f}'^{\mathrm{T}} + \Sigma$$



Pattern of choice correlations depends largely on noise modes that limit information.





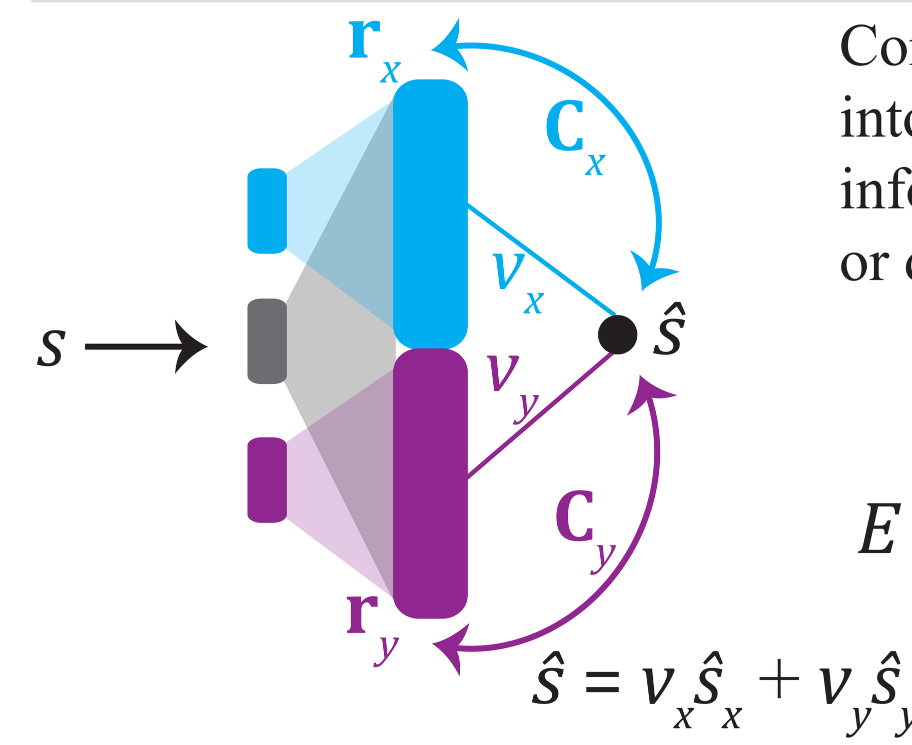


Regardless of Σ,

$$C_k \approx \sigma_{\hat{s}} / \sigma_k$$

In the presence of info-limiting noise, fine structure of covariance does not matter much for decoding.

... so a coarse-grained theory is good enough ...



$$\hat{s} = v_x\hat{s}_x + v_y\hat{s}_y$$

Cortical neurons may be grouped into subpopulations that inherit information from either identical or different sensory receptors.

$$\Sigma_{\mathrm{IL}} = UEU^{T} + \Sigma$$

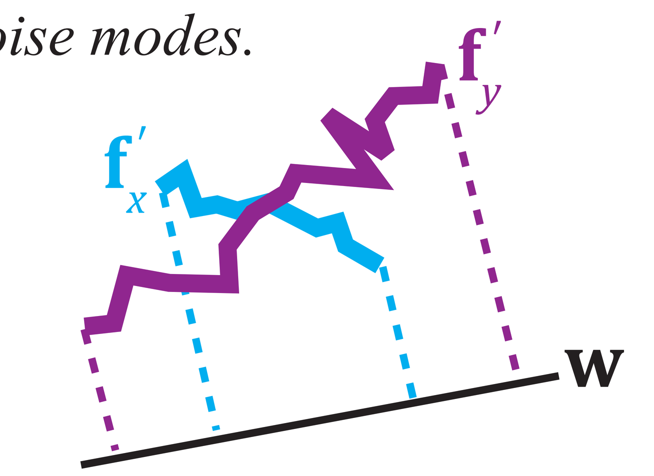
$$E = \begin{pmatrix} \varepsilon_{xx} & \varepsilon_{xy} \\ \varepsilon_{xy} & \varepsilon_{yy} \end{pmatrix} \quad U = \begin{pmatrix} \mathbf{f}'_x & \mathbf{0} \\ \mathbf{0} & \mathbf{f}'_y \end{pmatrix}$$

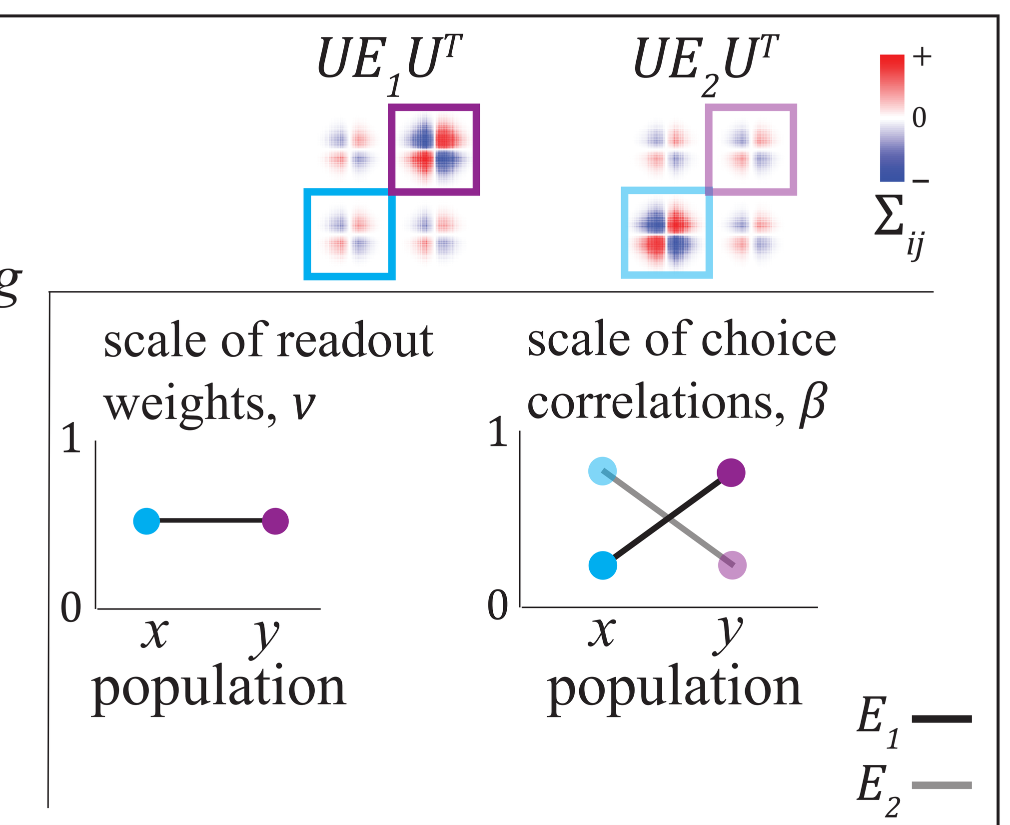
Choice correlations of the subpopulations have identical patterns and vary only in scaling[3].

$$C_{kz} \approx \frac{(\mathrm{E}\mathbf{v})_z}{\mathbf{v}\mathrm{E}\mathbf{v}}\,\sigma_{\hat{s}}/\sigma_k$$

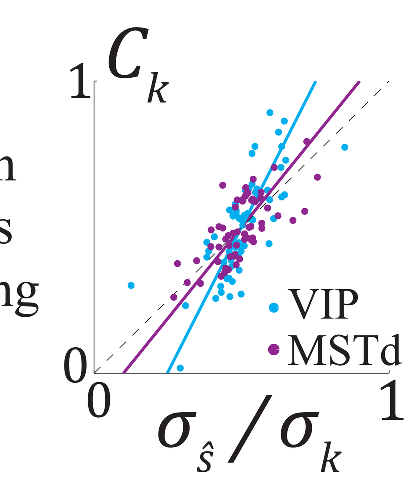
$$\approx \beta_z \,.\, \sigma_{\hat{s}}/\sigma_k$$

Relative scaling of choice correlations depends largely on the magnitudes of noise along the information-limiting noise modes.





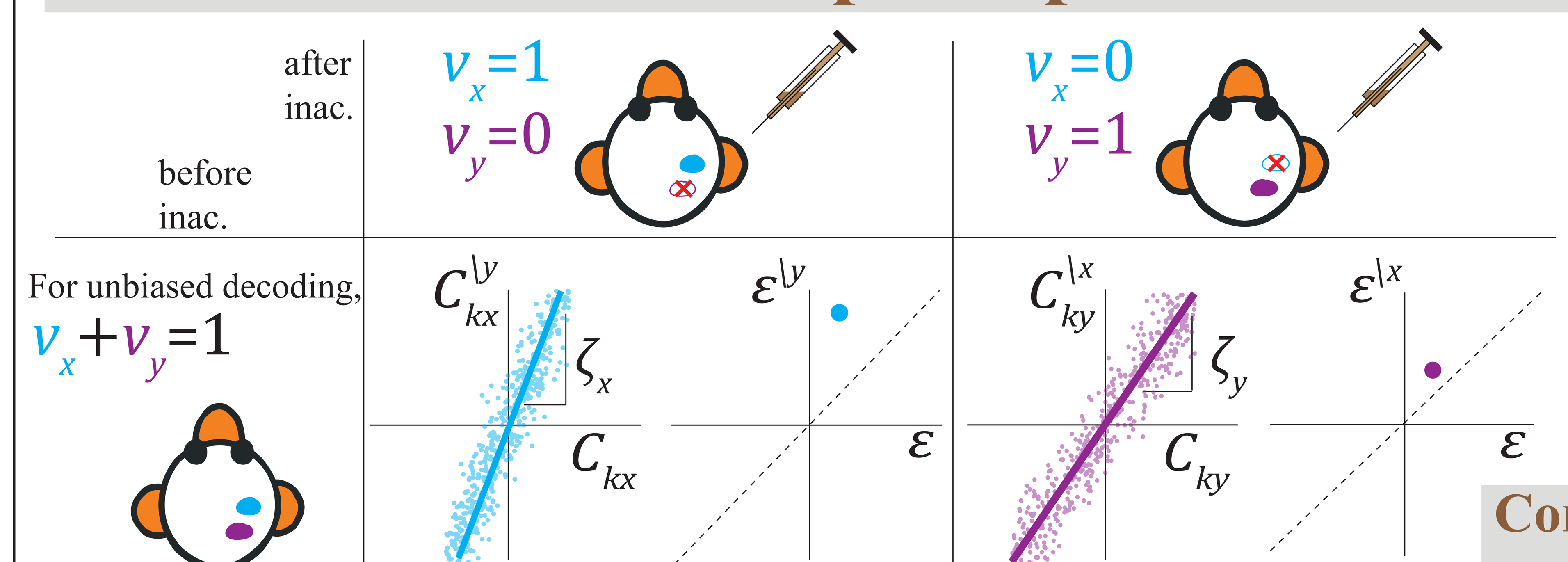
This is consistent with neural data in macaque monkeys performing heading discrimination[4].



Can ignore pattern of weights **w**, analyse only scalings **v**

Far fewer degrees of freedom !

... leads to a simple experimental framework



$$\varepsilon_{xx} = \varepsilon^{\backslash y} \qquad \varepsilon_{yy} = \varepsilon^{\backslash x}$$

$$\varepsilon = v_x^2\varepsilon_{xx} + v_y^2\varepsilon_{yy} + 2v_xv_y\varepsilon_{xy}$$

$$\zeta_x = \frac{\sqrt{\varepsilon\varepsilon_{xx}}}{v_x\varepsilon_{xx} + v_y\varepsilon_{xy}}$$

$$\zeta_y = \frac{\sqrt{\varepsilon\varepsilon_{yy}}}{v_x\varepsilon_{xy} + v_y\varepsilon_{yy}}$$

behavioural variability:

- ε before inactivation
- $\varepsilon^{\backslash y}$ after inactivating y
- $\varepsilon^{\backslash x}$ after inactivating x

choice correlation of neurons:

- C_{kx} in x before inactivation
- $C_{kx}^{\backslash y}$ in x after inactivating y
- C_{ky} in y before inactivation
- $C_{ky}^{\backslash x}$ in y after inactivating x

Combining single-cell recordings with targeted inactivation experiments can reveal relative weights of different populations.

- **Information-limiting correlations generate redundancies in the neural code.**
- **These redundancies lead to a simplified theory of linear decoding.**
- **Obviate the need for large-scale recordings to infer readout strategy.**

[1] Haefner, Gerwinn, Macke, Bethge (2013) *Nat. Neuro.*
[2] Moreno-Bote, Beck, Kanitscheider, Pitkow, Latham, Pouget (2014) *Nat. Neuro.*
[3] Lakshminarasimhan, Pouget, Pitkow (2014) *Cosyne abstract.*
[4] Lakshminarasimhan, Liu, Gu, Klier, DeAngelis, Pitkow, Angelaki (2014) *Cosyne abstract.*

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