Laboratoire de Recherche en Informatique

Neuroscience & big-data:

Collective behavior in neuronal ensembles

Ulisse Ferrari

INSTITUT DE LA VISION PARIS

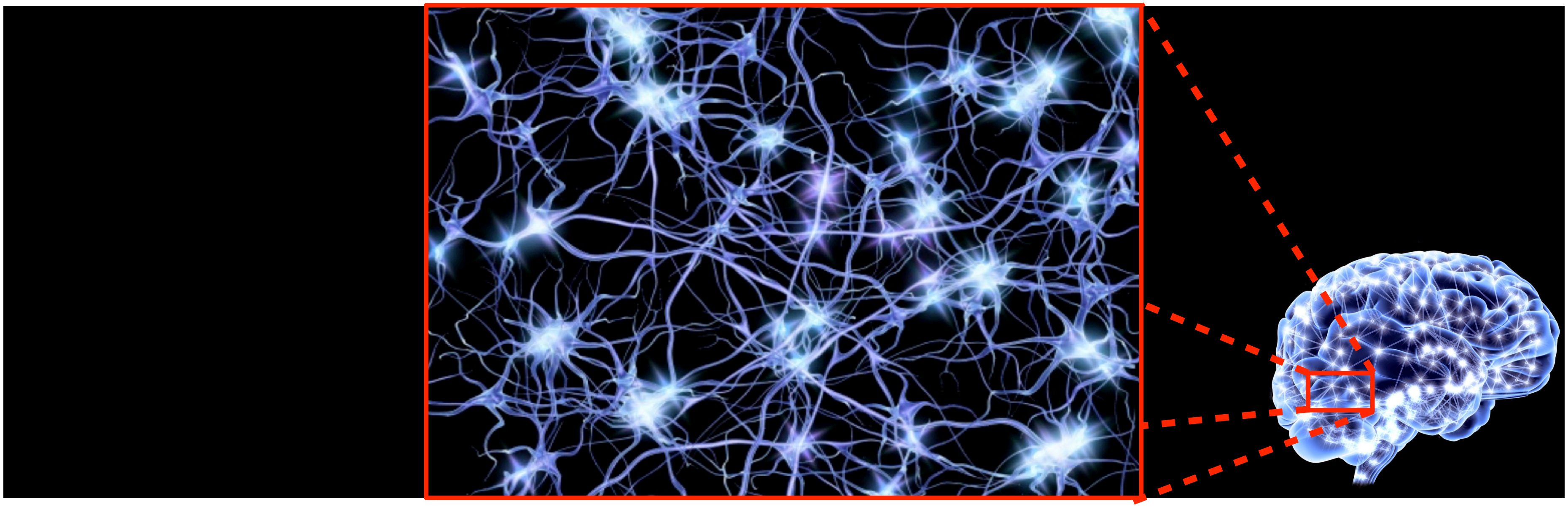
Research career:

PhD in Theor. Physics of disordered systems (G. Parisi)

Inverse problems:
neuronal collective behavior

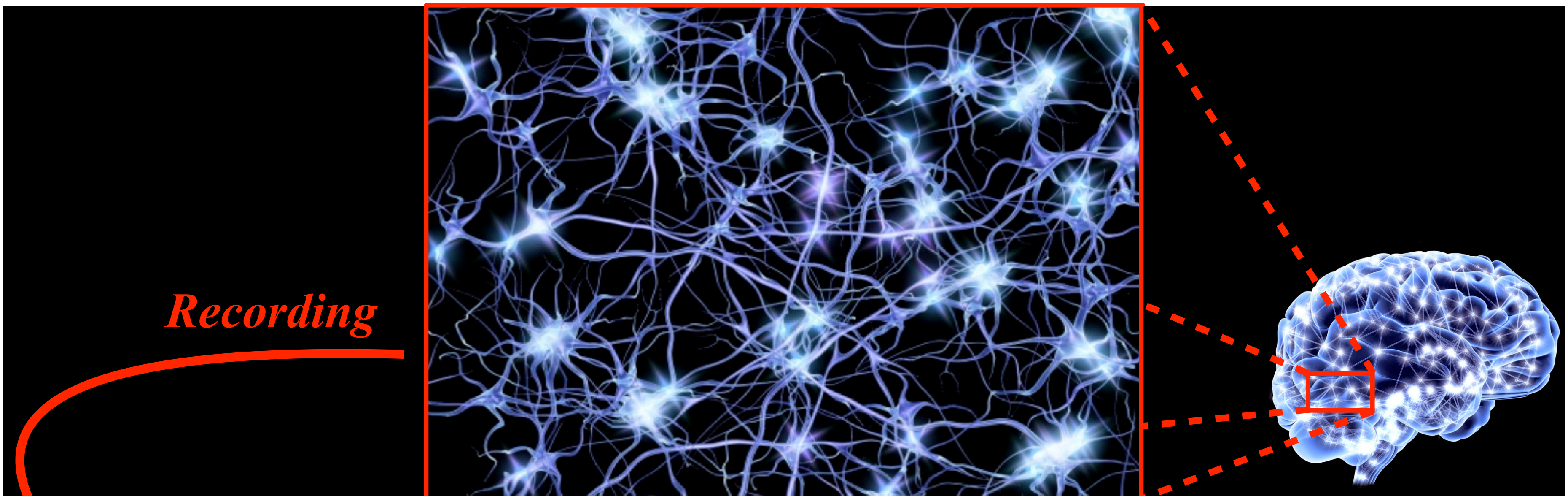
Contact with experiments and retinal collective encoding

Collective behavior in neuronal ensembles



Human: ~10^3 synapses/neuron

Collective behavior in neuronal ensembles



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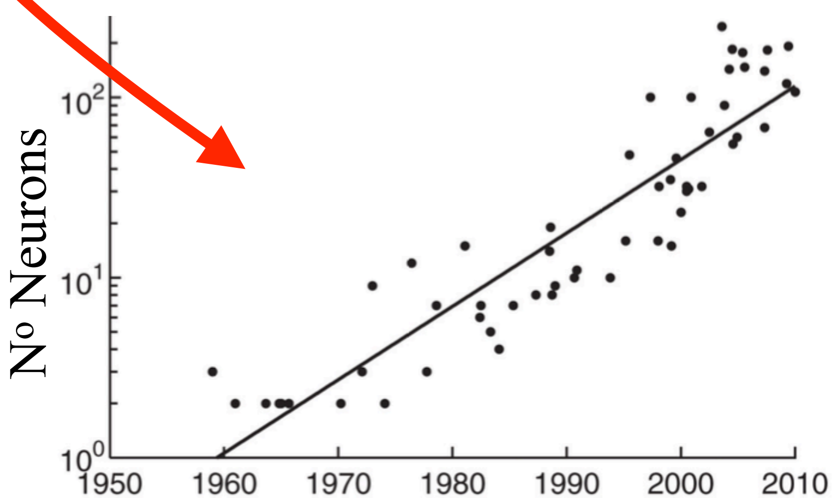

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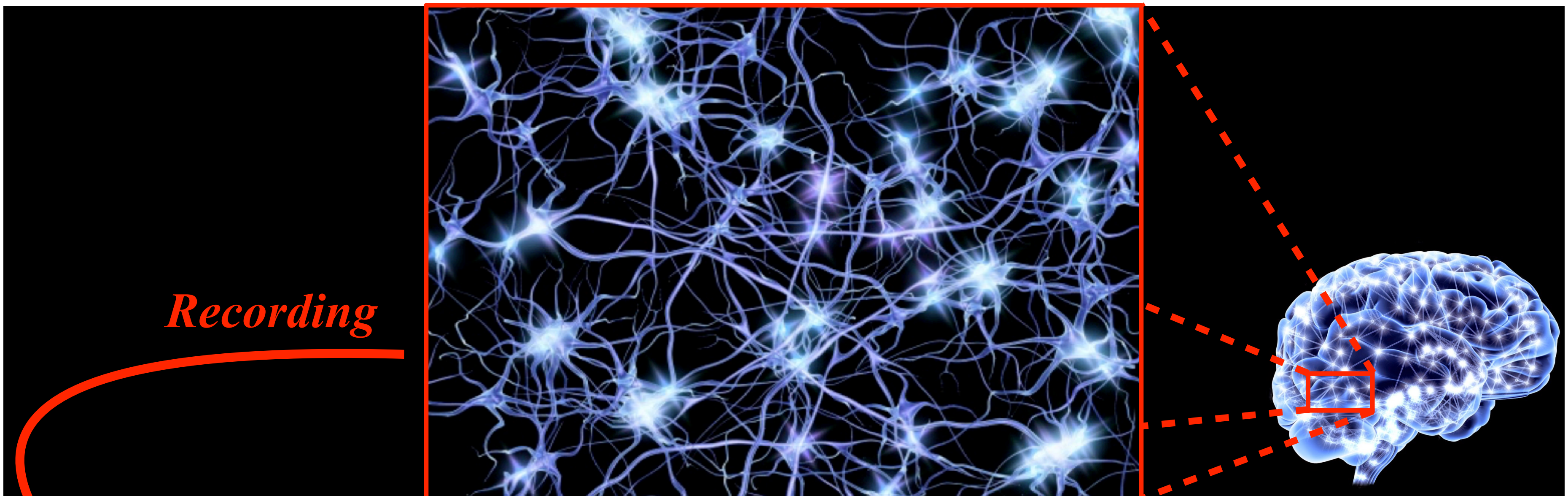

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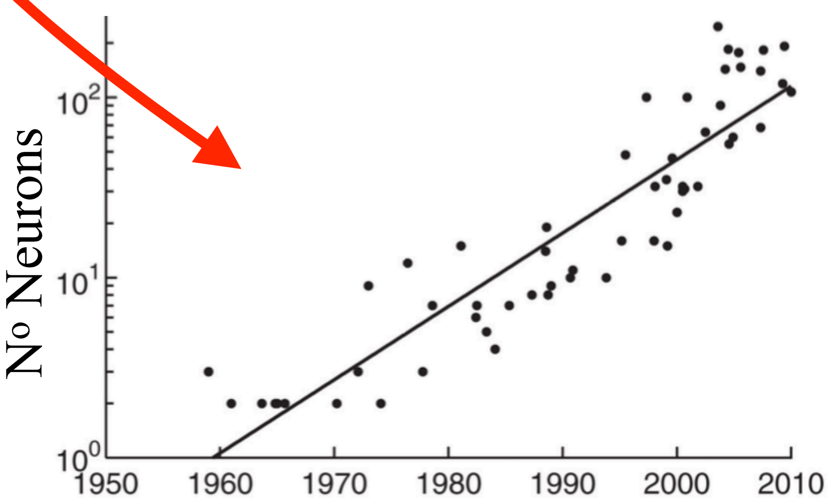
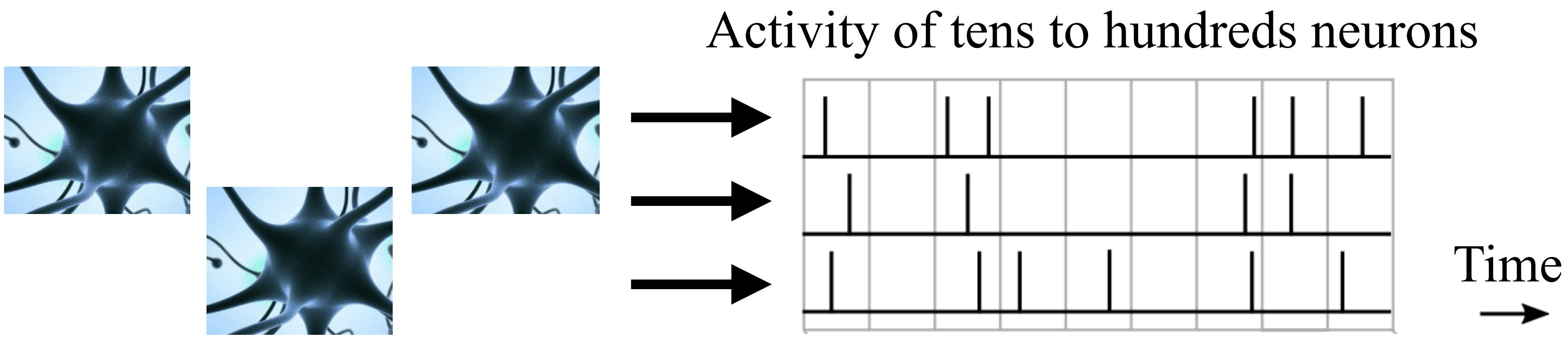


Challenge:
develop new
concepts** and **tools
to make sense
of network activity

How to characterise neuronal collective activities?



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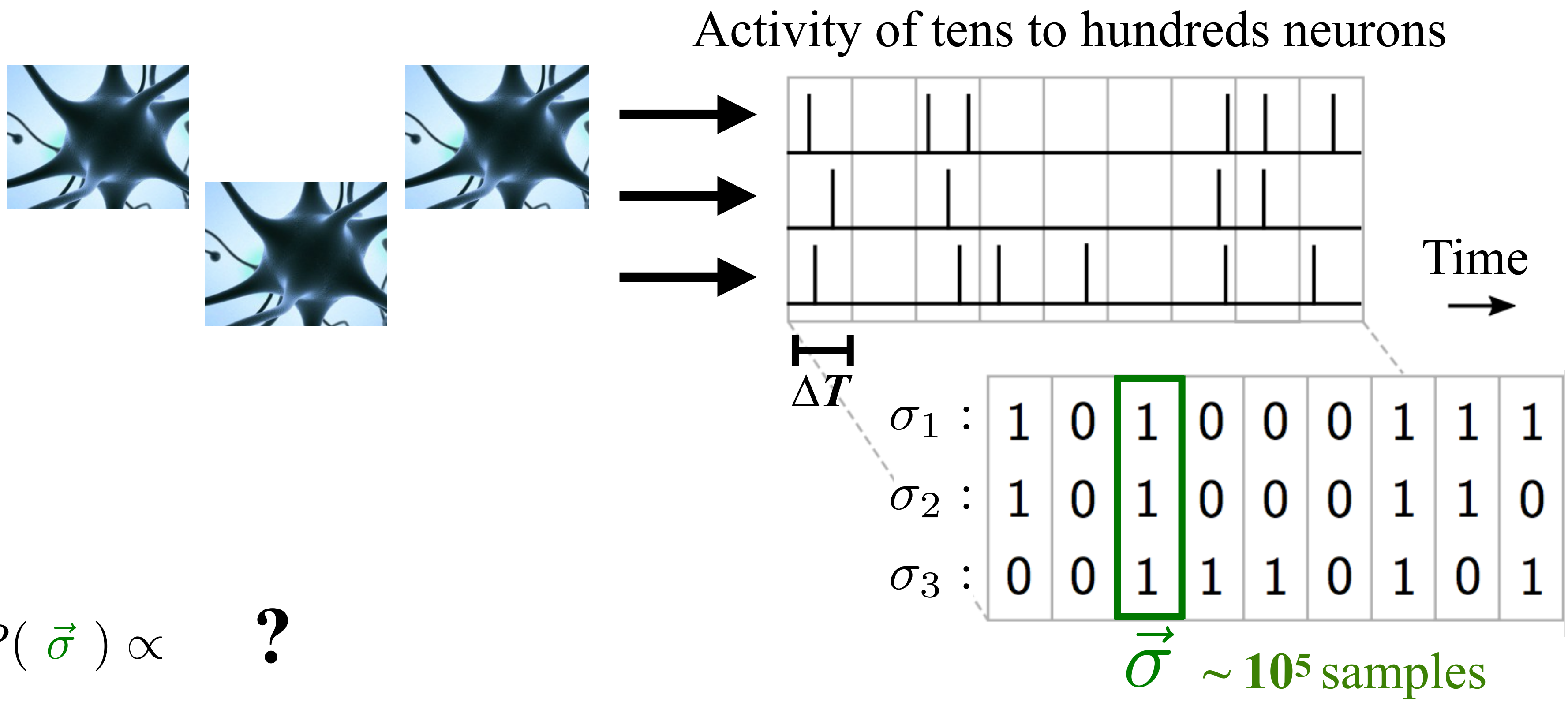
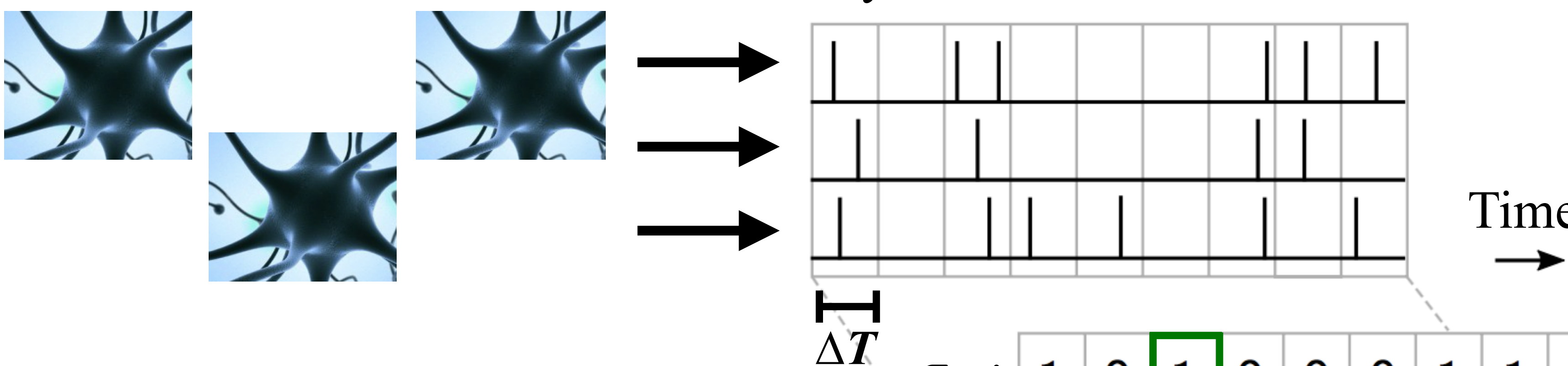


$P(\ \vec{\sigma}\ ) \propto$ **?**

How to characterise neuronal collective activities?

Activity of tens to hundreds neurons



σ_1 :	1	0	1	0	0	0	1	1	1
σ_2 :	1	0	1	0	0	0	1	1	0
σ_3 :	0	0	1	1	1	0	1	0	1

$\vec{\sigma}$ ~ **10^5** samples

Maximum Entropy Principle

$$P(\vec{\sigma}) \propto \exp\left(\sum_{i<j} J_{ij}\,\sigma_i\,\sigma_j + \sum_i h_i\,\sigma_i\right)$$

Exponential model on interaction graph

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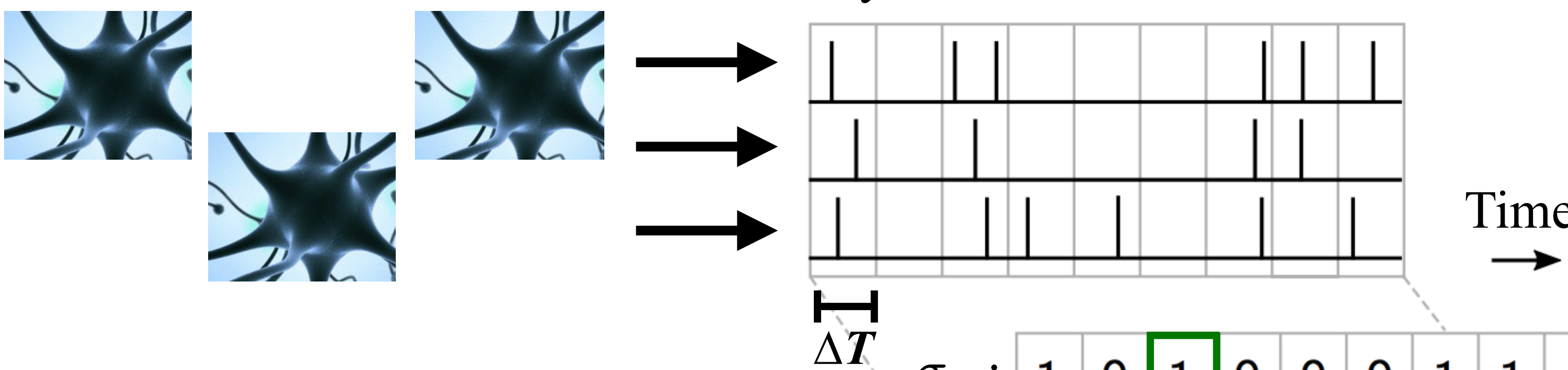

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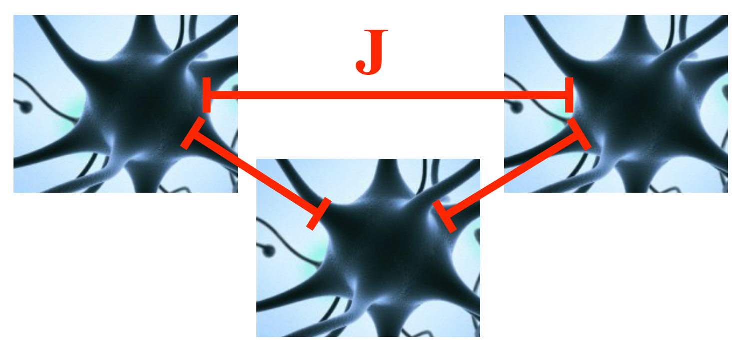
Interaction model



Maximum entropy models

Choose sufficient statistics: $T_a(\vec{\sigma})$

Find the largest entropy $P(\vec{\sigma})$ that reproduces their averages:

$$\min_{\mathbf{J},\lambda} \max_{P(\vec{\sigma})} \Big[-\sum_{\vec{\sigma}} P(\vec{\sigma}) \log P(\vec{\sigma}) + \lambda\Big(\sum_{\vec{\sigma}} P(\vec{\sigma}) - 1 \Big) + \sum_a J_a \big(Q_a - \overline{P_a} \big)$$

$$\overline{P_a} \equiv \langle T_a(\vec{\sigma}) \rangle_{\text{data}} \qquad Q_a \equiv \langle T_a(\vec{\sigma}) \rangle_P$$

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⇩

$$P(\,\vec{\sigma} \mid J\,) = g(J) \exp\big(J \cdot T(\vec{\sigma})\big)$$

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example

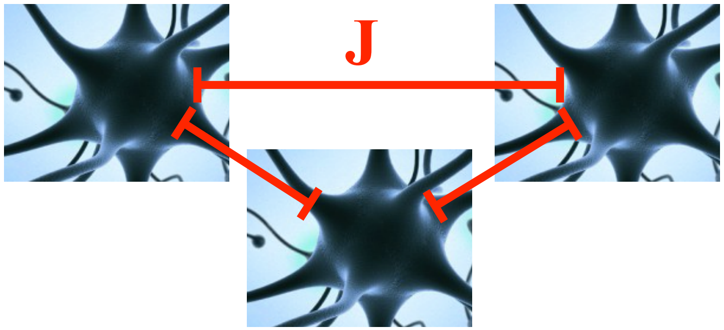
$$\langle \sigma_i \rangle_{\mathrm{Md}} = \langle \sigma_i \rangle_{\mathrm{Dt}} \ \&\ \langle \sigma_i \sigma_j \rangle_{\mathrm{Md}} = \langle \sigma_i \sigma_j \rangle_{\mathrm{Dt}}$$

$$P(\ \vec{\sigma}\ ) \propto \exp\left(\sum_{i<j} J_{ij}\, \sigma_i\, \sigma_j + \sum_i h_i\, \sigma_i \right)$$

How to learn these models on neuronal data?

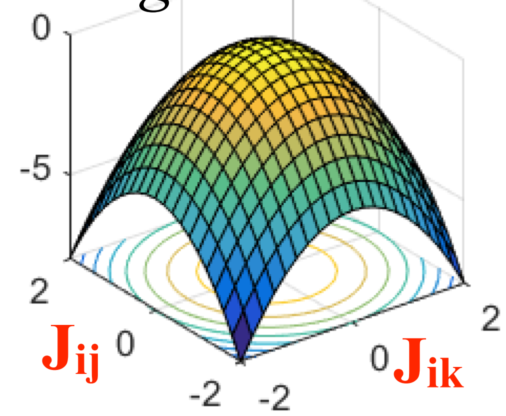
$$P(\vec{\sigma}) \propto \exp\left(\sum_{i<j} J_{ij}\,\sigma_i\,\sigma_j + \sum_i h_i\,\sigma_i\right)$$

- Exponential family
- Large datasets



Exponentially hard problem

Log-likelihood



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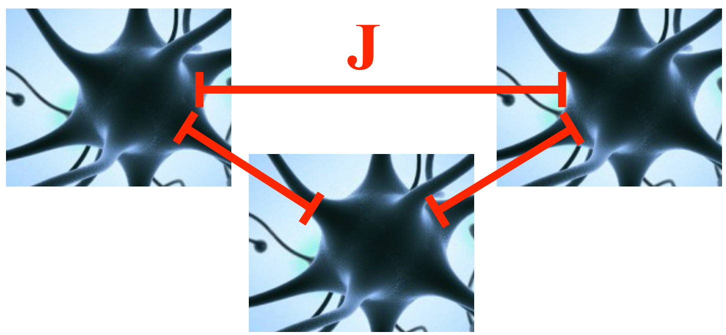

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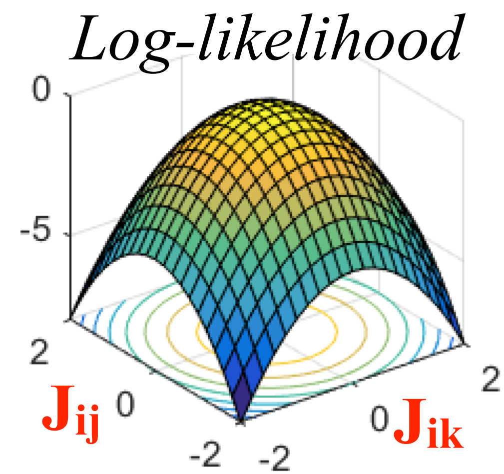

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Phys. Rev E '16

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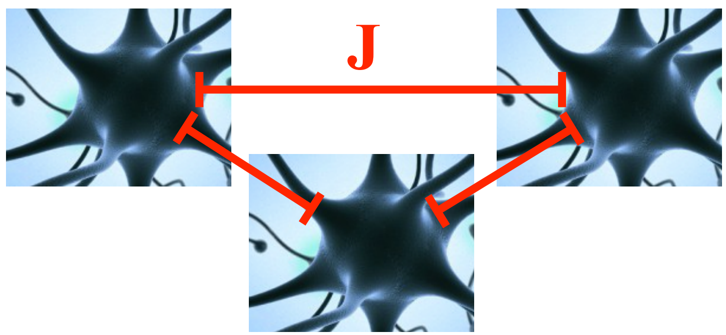

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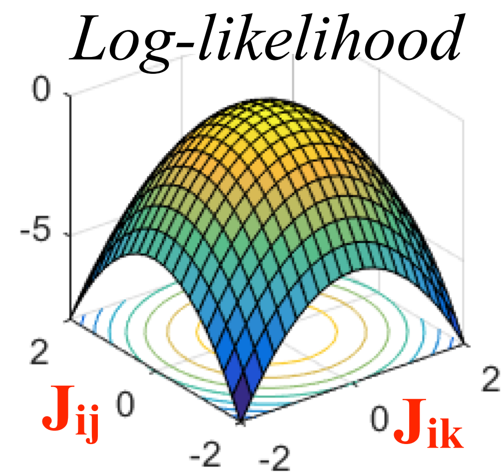


$$\text{Exp. Family} \longrightarrow \mathcal{H}[J] = \mathrm{Cov}_J[\text{sufficient stat.}]$$

$$\mathcal{H}[J^{\text{sol.}}] \approx \mathrm{Cov}^{\text{data}}[\text{sufficient stat.}]$$

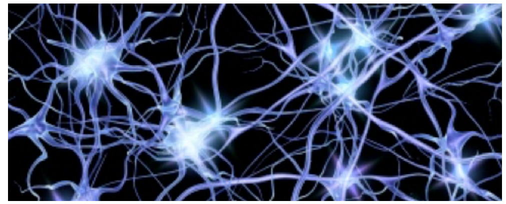
<u>Newton method without additional cost</u>

Collective behavior in neuronal ensembles

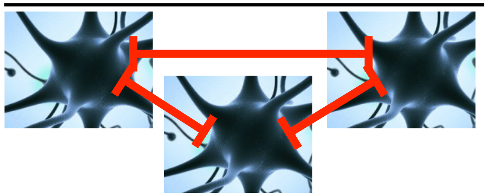
Max-Entropy

$$H[P] = -\sum P \log P$$

Neuronal network



Interaction Model



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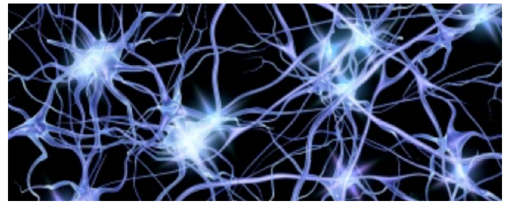

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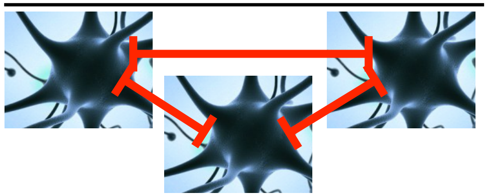
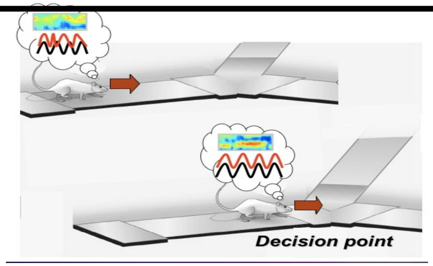
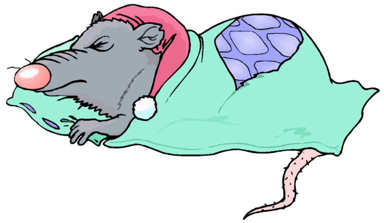


Are these models useful for biology?

What's the neuronal basis (engram) of memory?





Tavoni,UF*,Battaglia,Cocco,Monasson, Network Neurosci. 2017*

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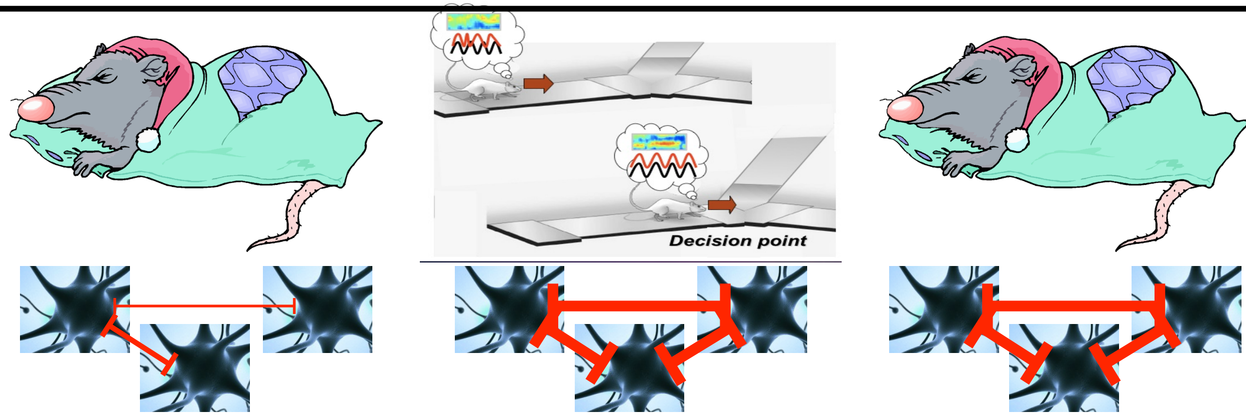

Hebb's Hypothesis:
reinforcement of interactions during learning

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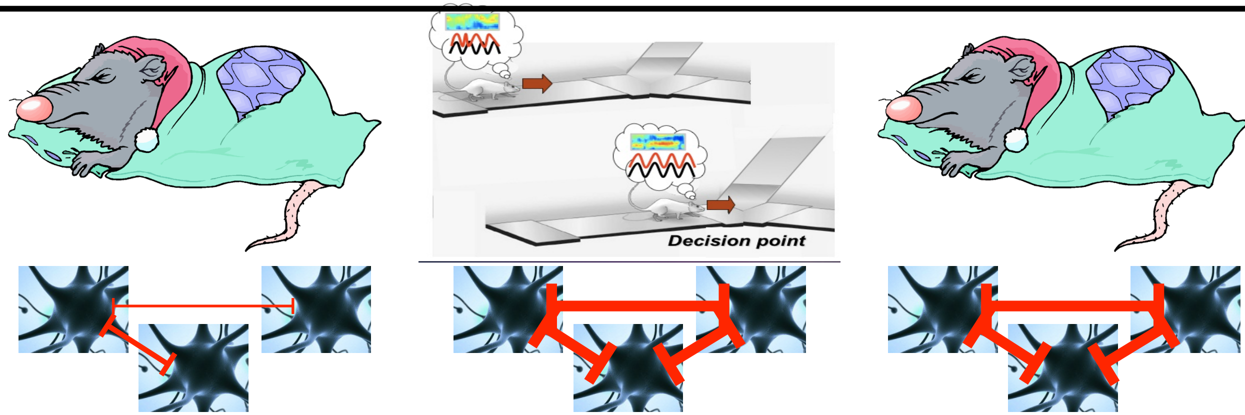

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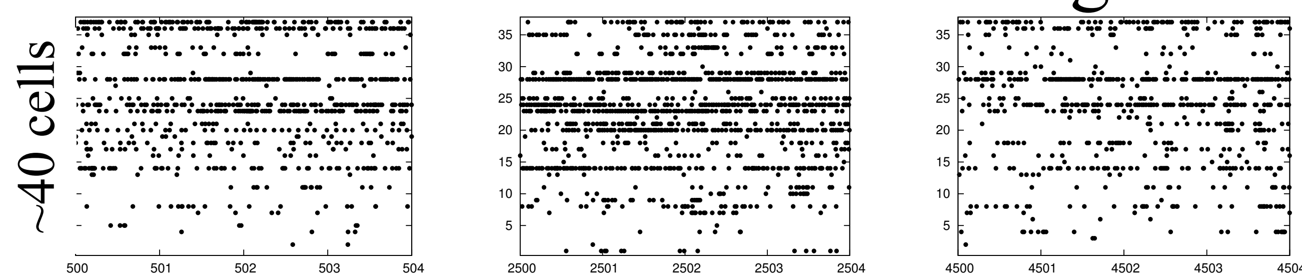

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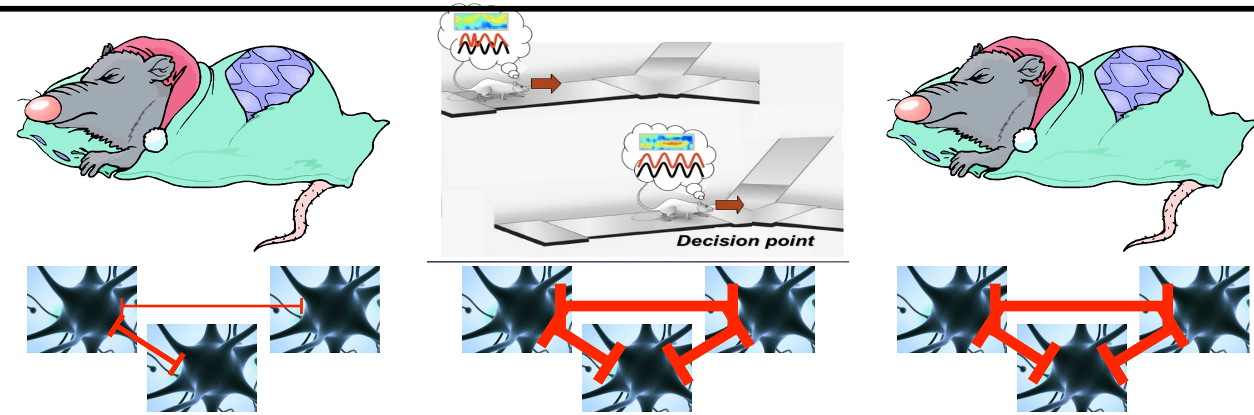

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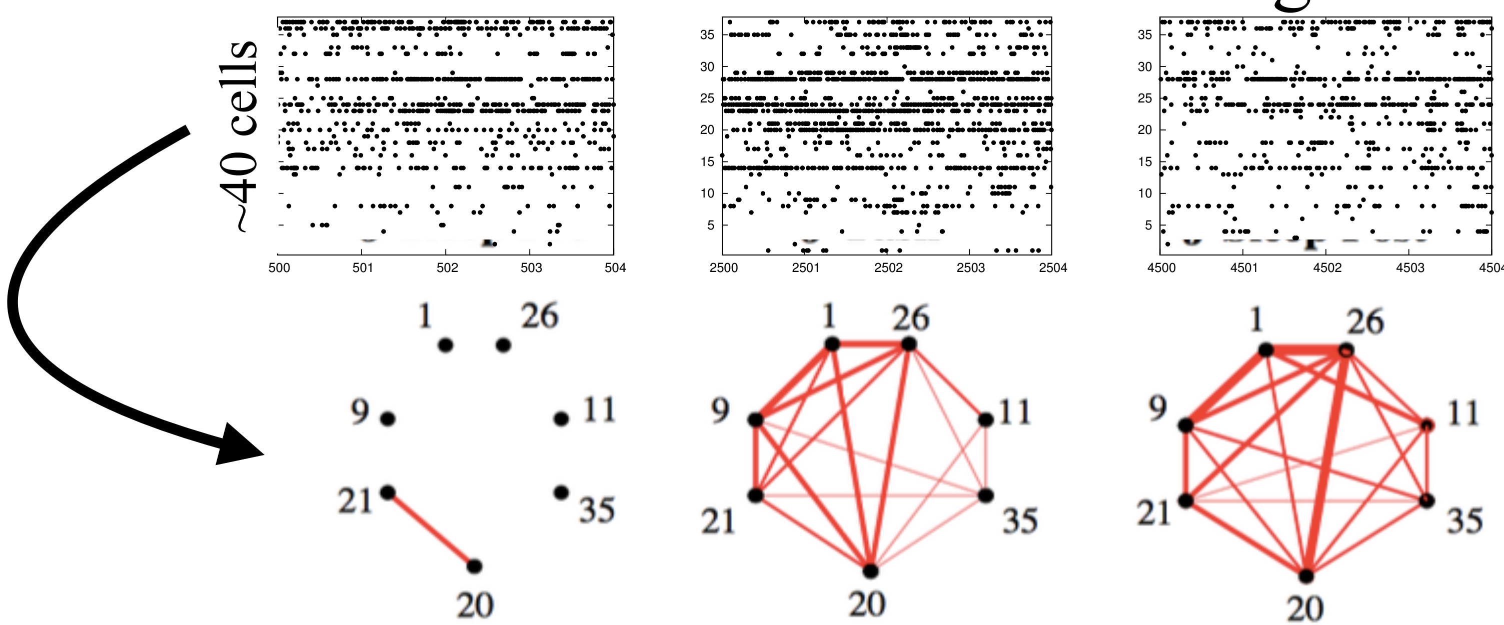

Network inference

+

Community detection

Tavoni,UF*,Battaglia,Cocco,Monasson, Network Neurosci. 2017*

Collective behavior in neuronal ensembles

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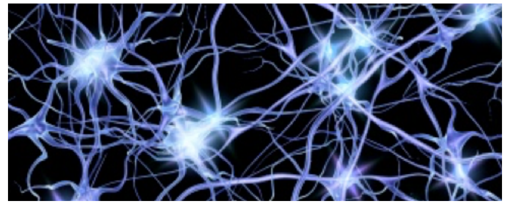

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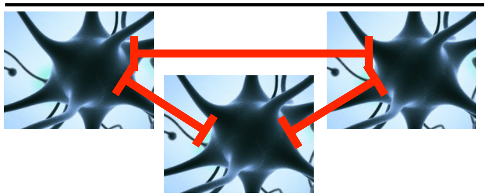

Effective approach:

- Capable of unveiling **functional** coupling structure

Collective behavior in neuronal ensembles

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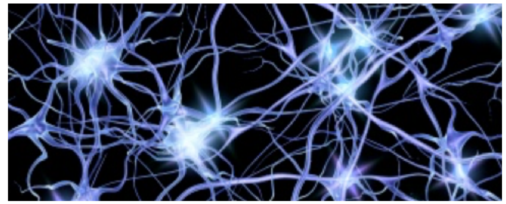

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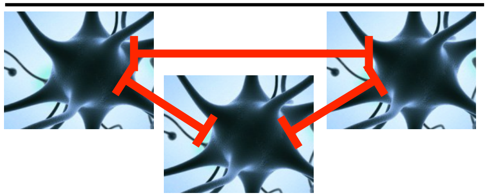
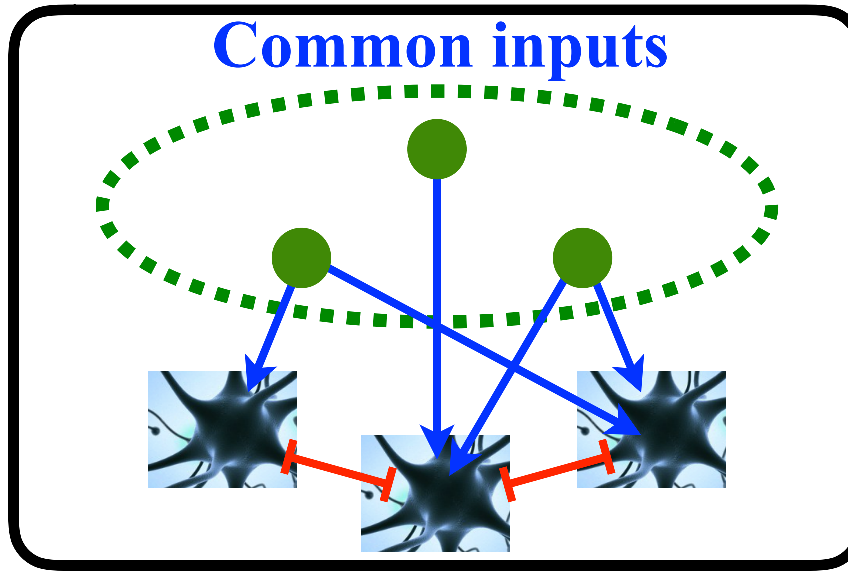


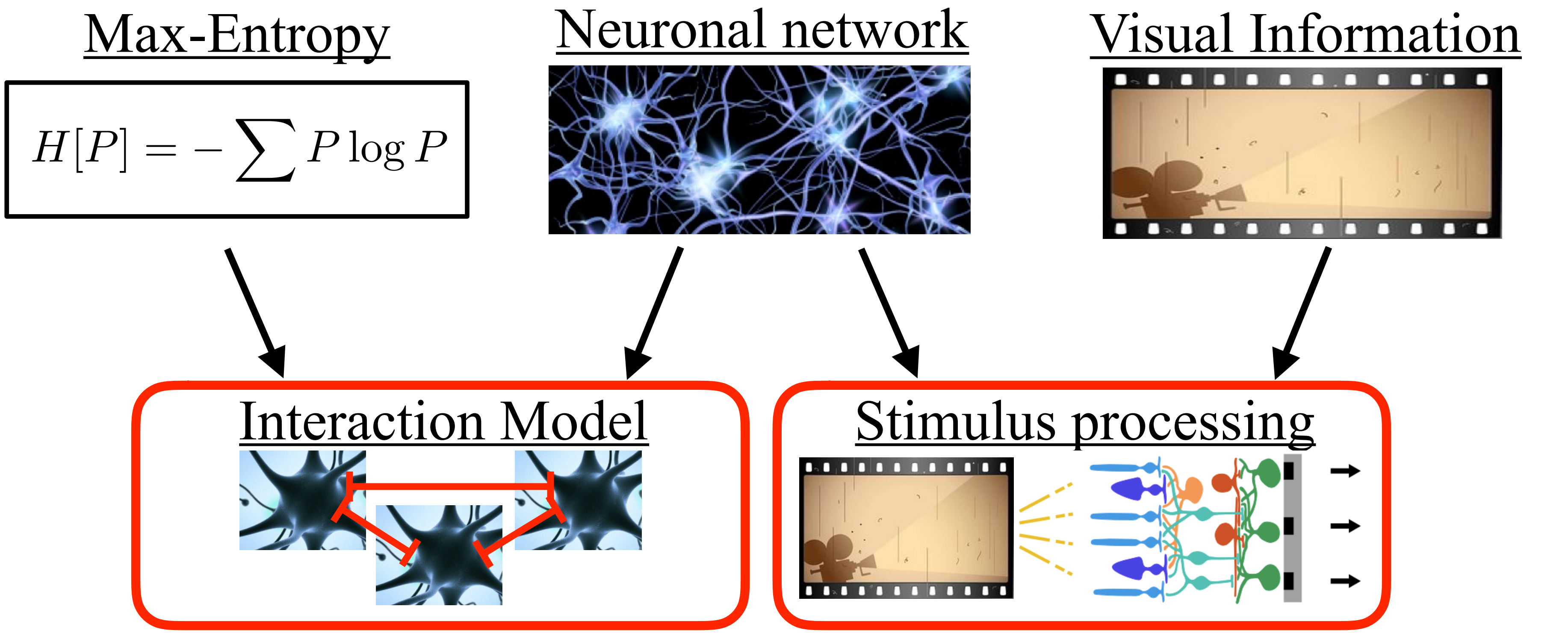


Effective approach:

- Capable of unveiling **functional** coupling structure
- Couplings reflects **common** inputs & **real** connections

*Can I **disentangle** the two contributions?*

Collective behavior in neuronal ensembles



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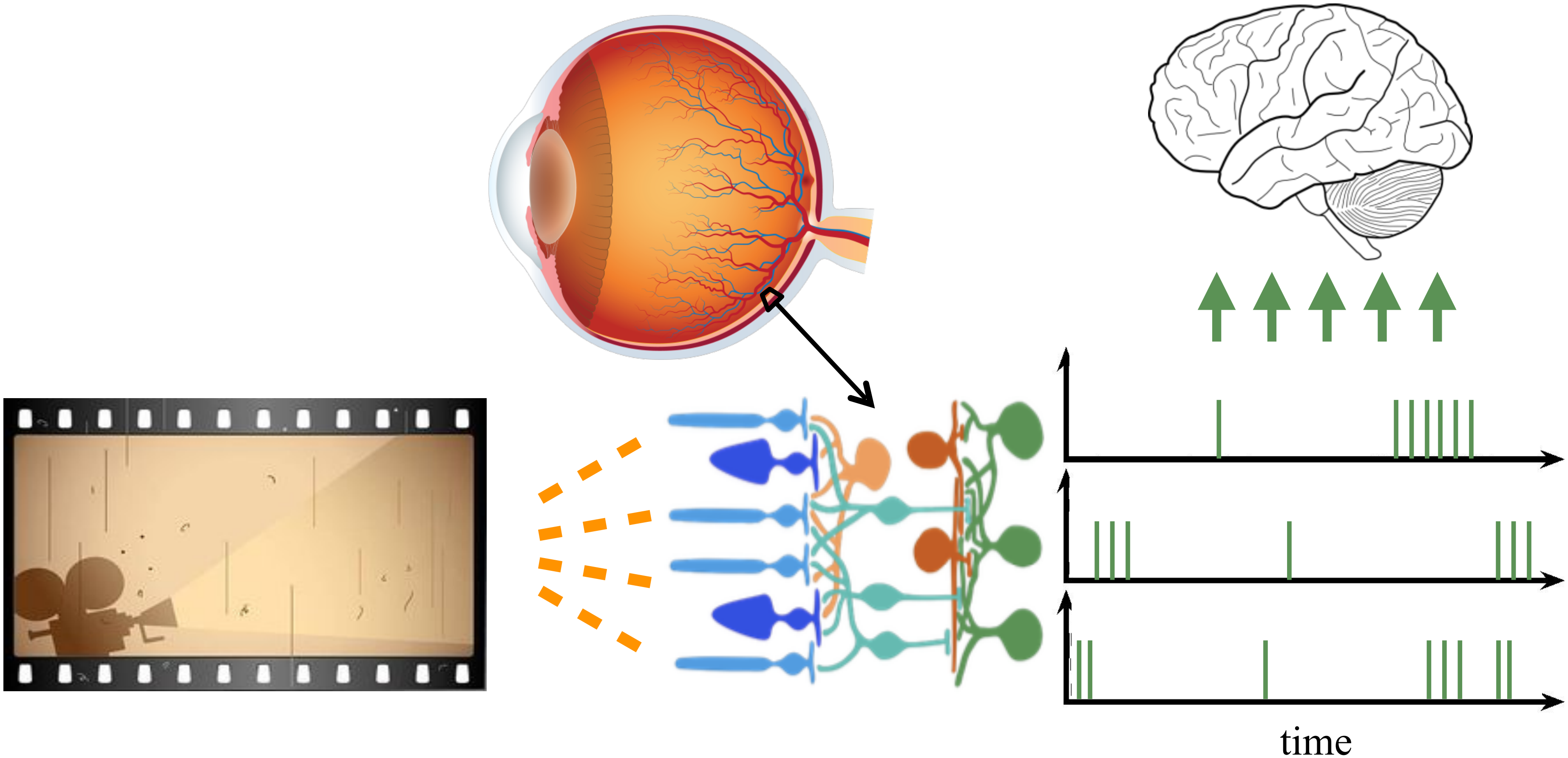
Stimulus processing in the retina

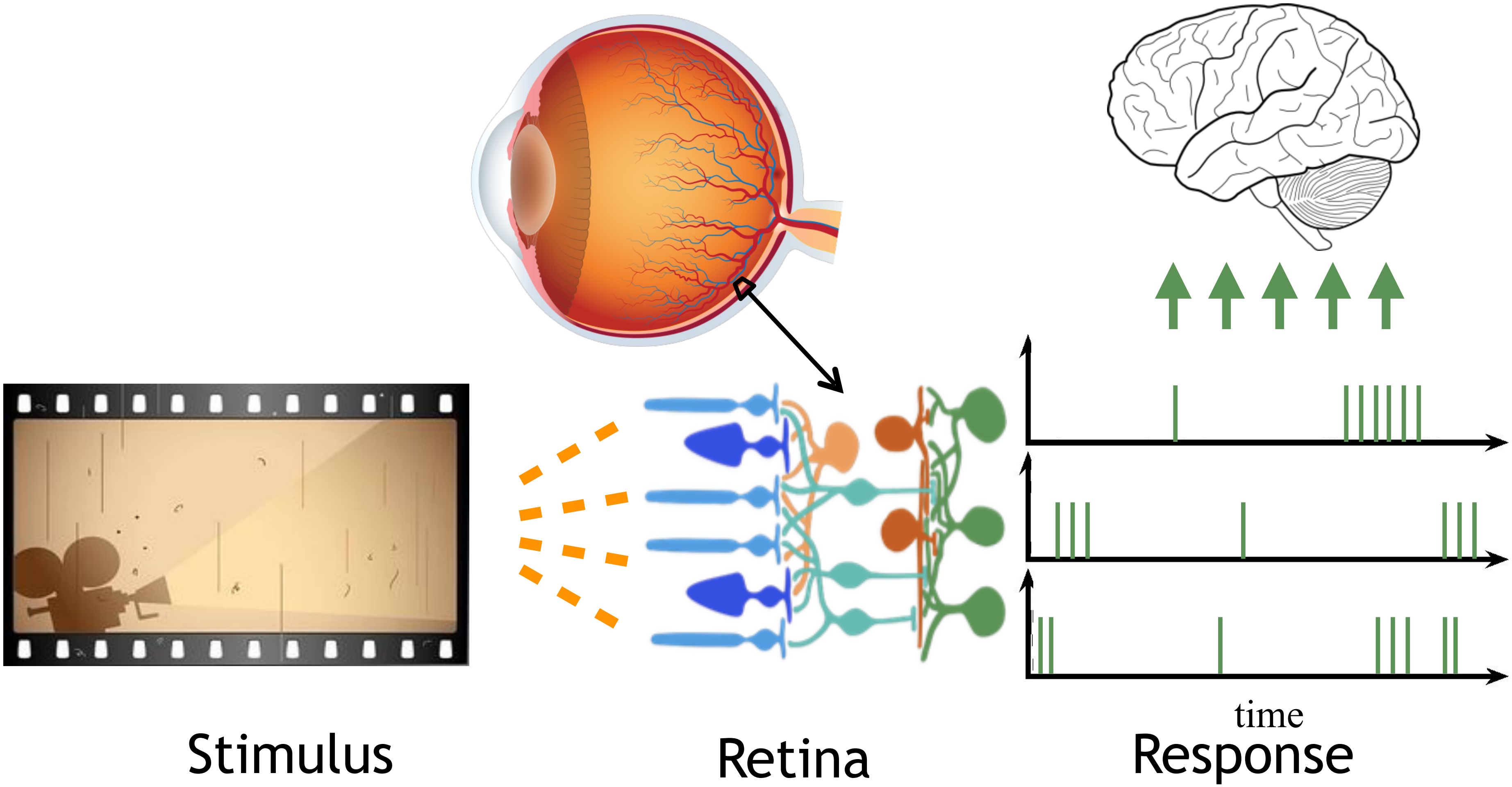


Stimulus

Retina

Response

Stimulus processing in the retina



Non-linear & stochastic **feedforward system,**

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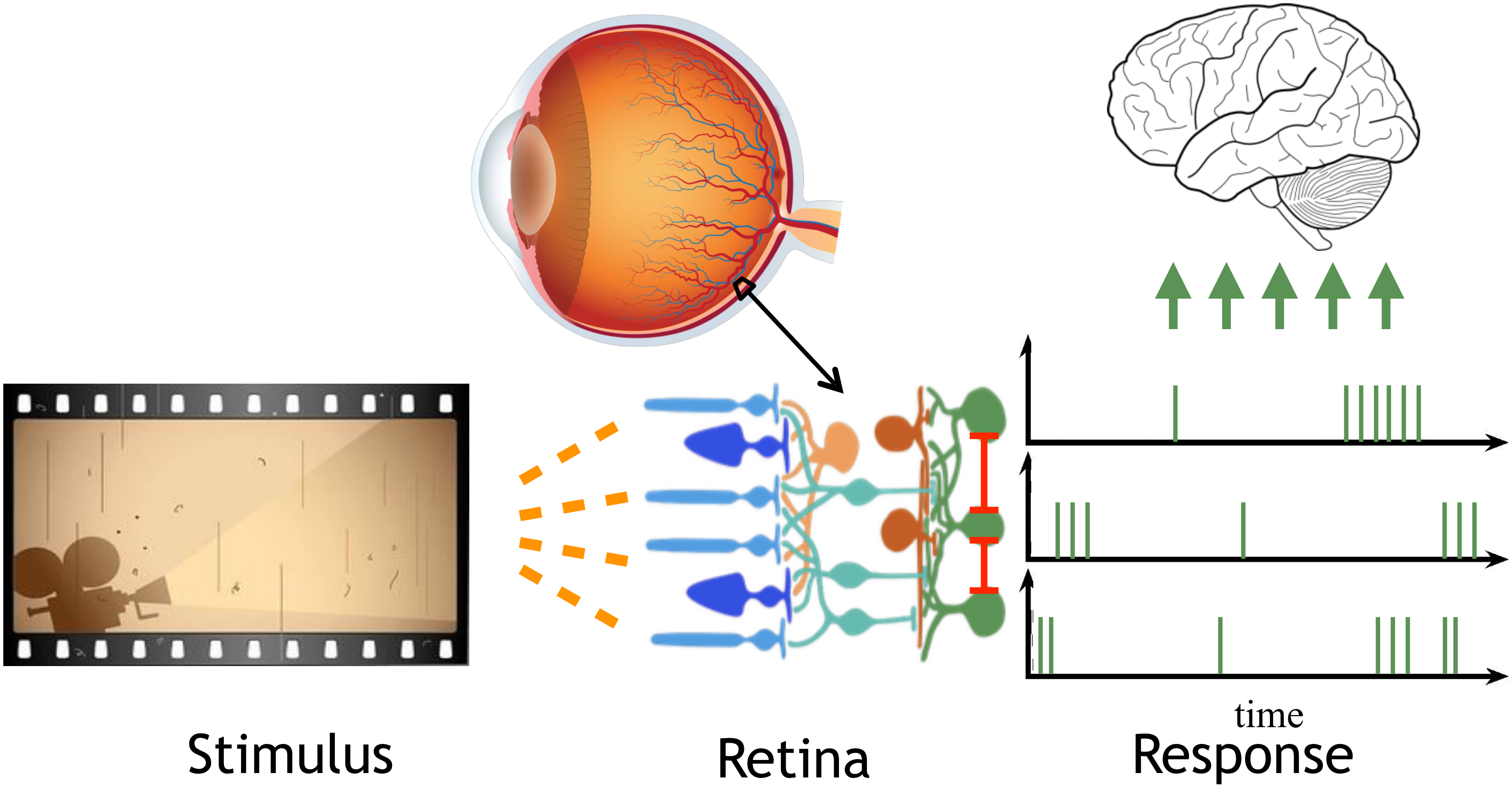
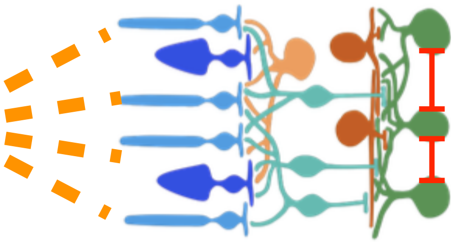
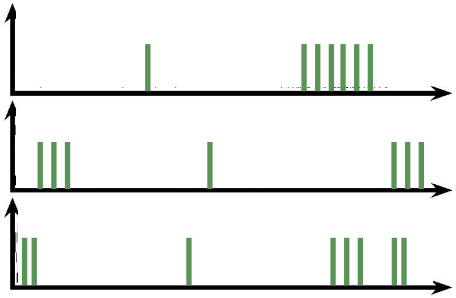
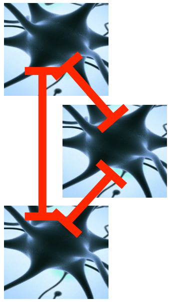


Non-linear & stochastic **feedforward system,**
with horizontal **gap-junctions**

Stimulus as common input

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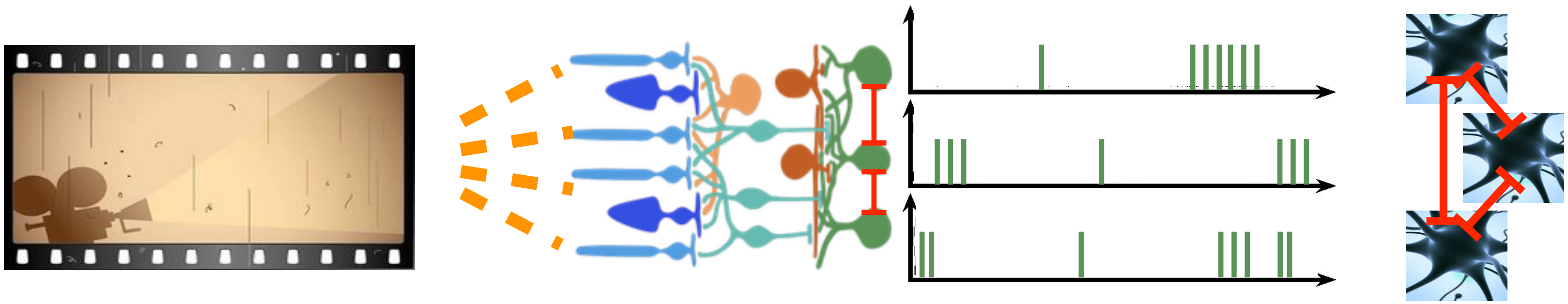
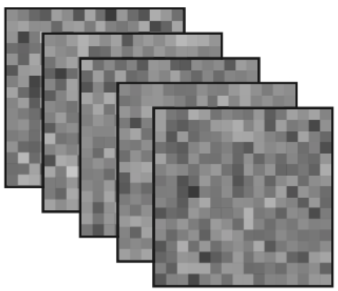
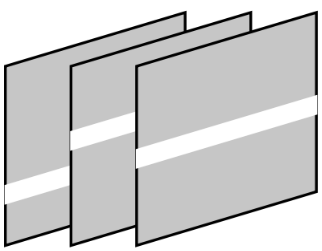
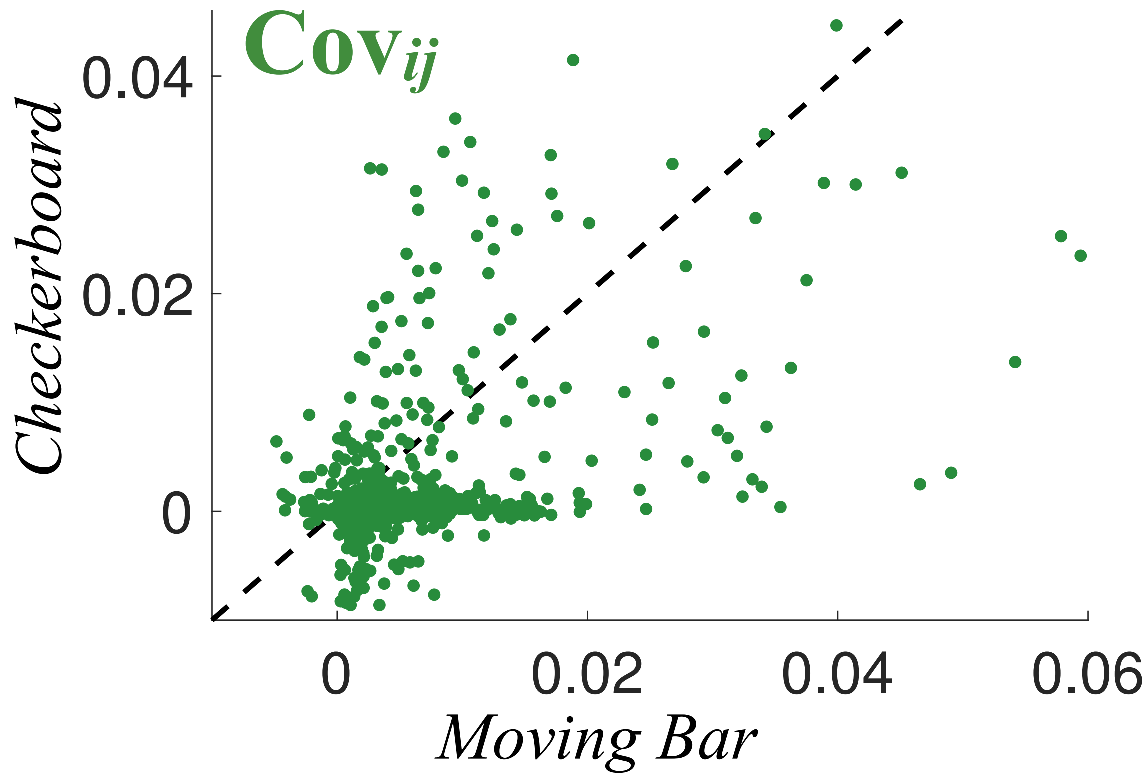


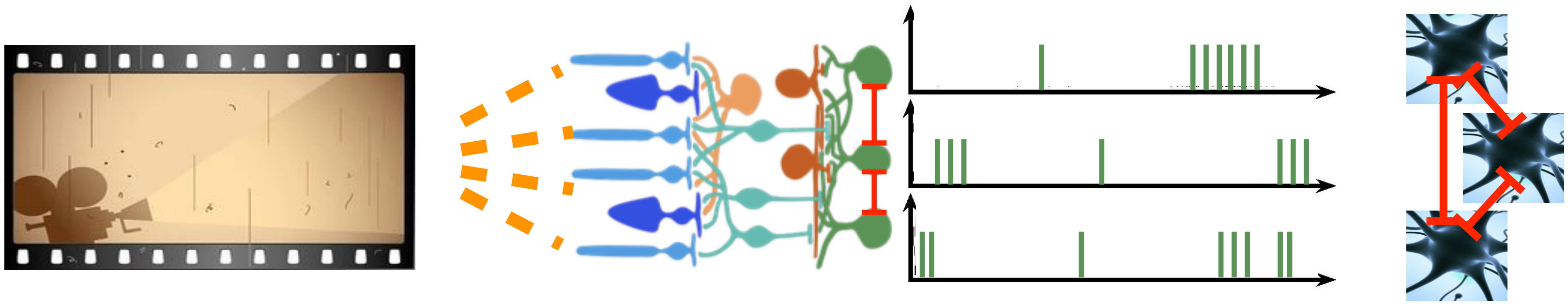


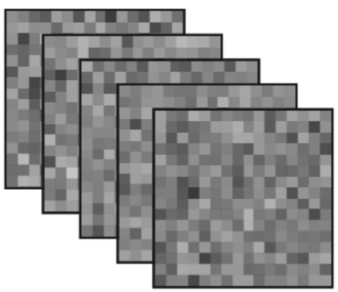
Vs





Stimulus as common input





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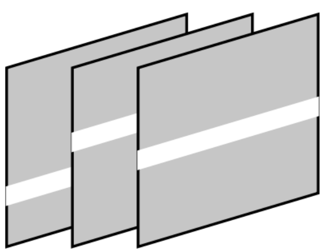

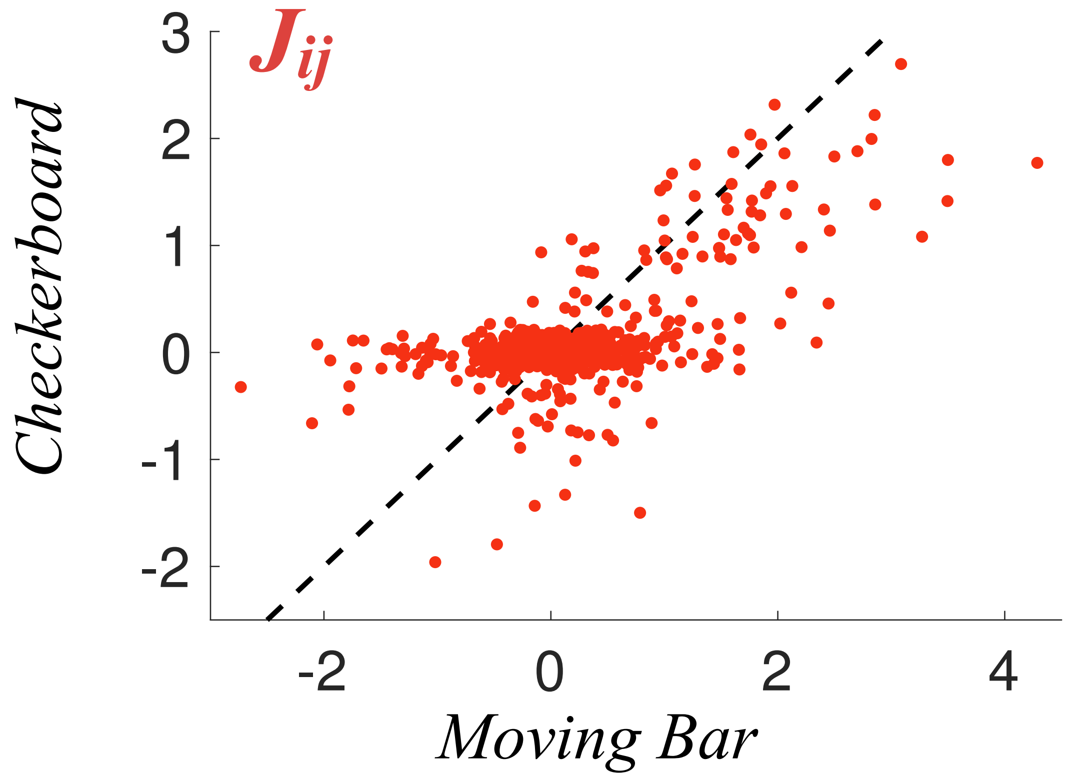

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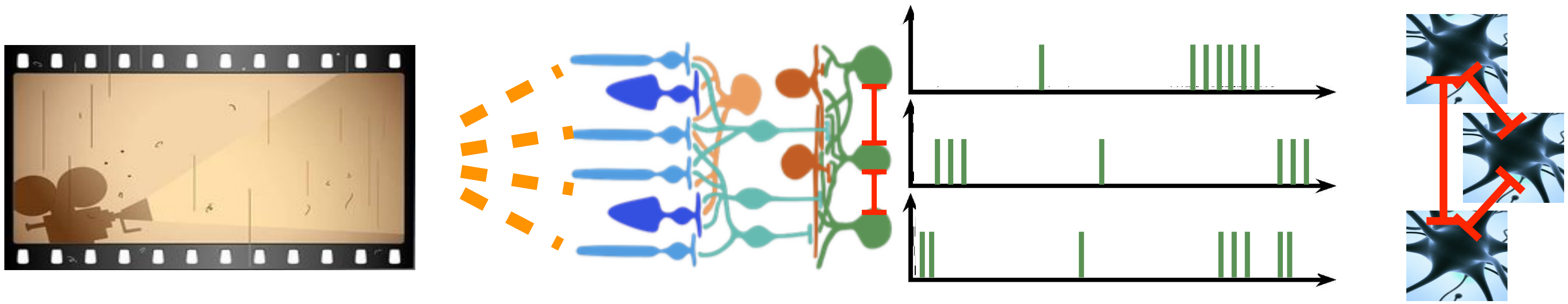

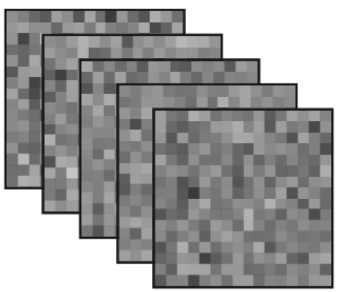

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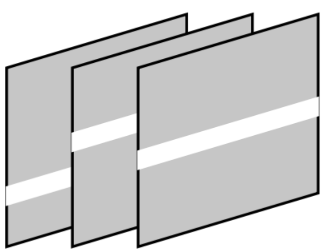
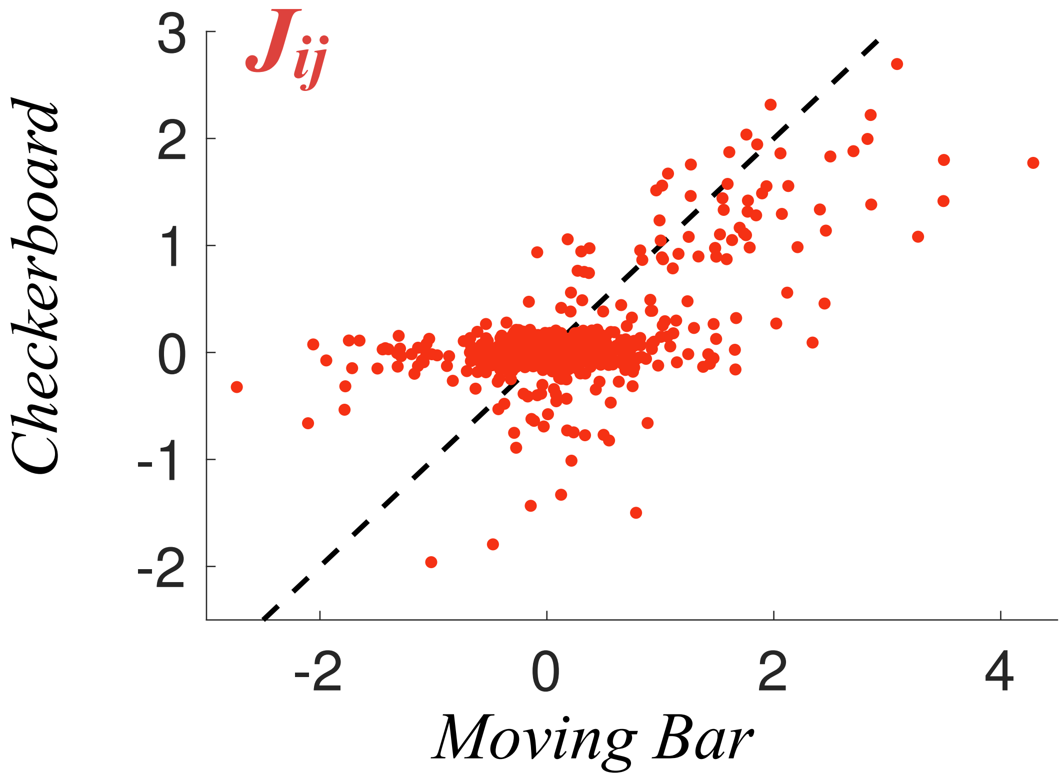
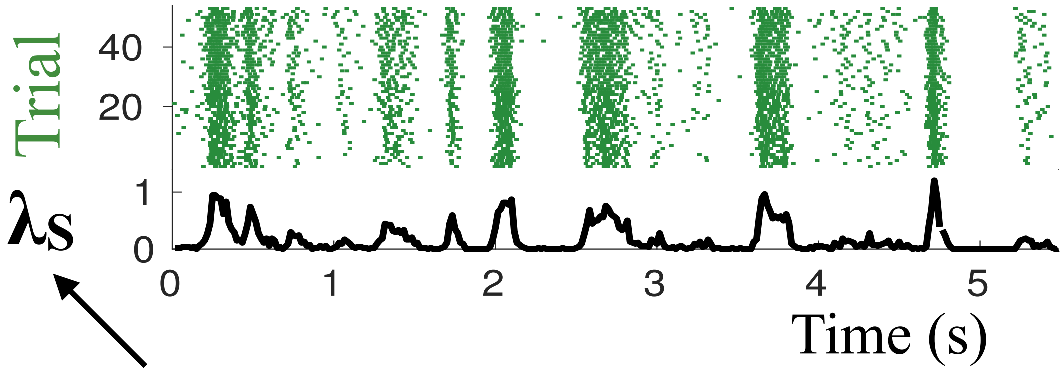




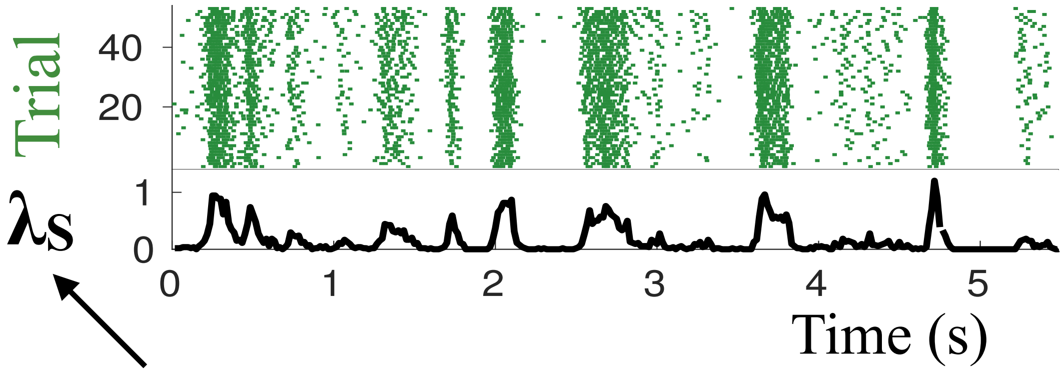
*Can I **disentangle** the two contributions?*

Non-linear & stochastic **response to stimulus**



Mean response

Non-linear & stochastic **response to stimulus**



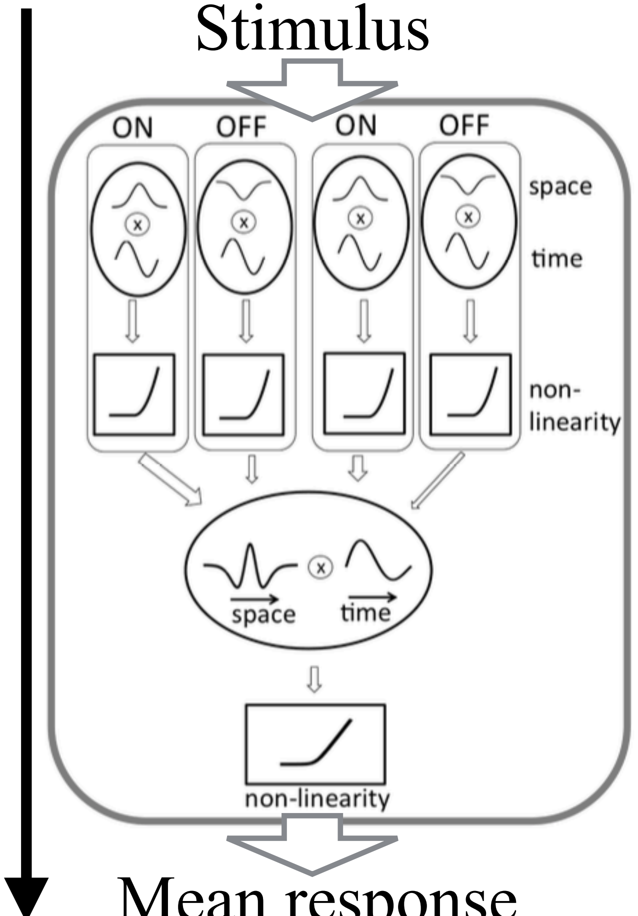
Mean response

Predict λ_S as function of the **stimulus**

Mean output prediction from stimulus

A ***non-linear*** *model…*

Stimulus



Linear-filter

Non-linearity

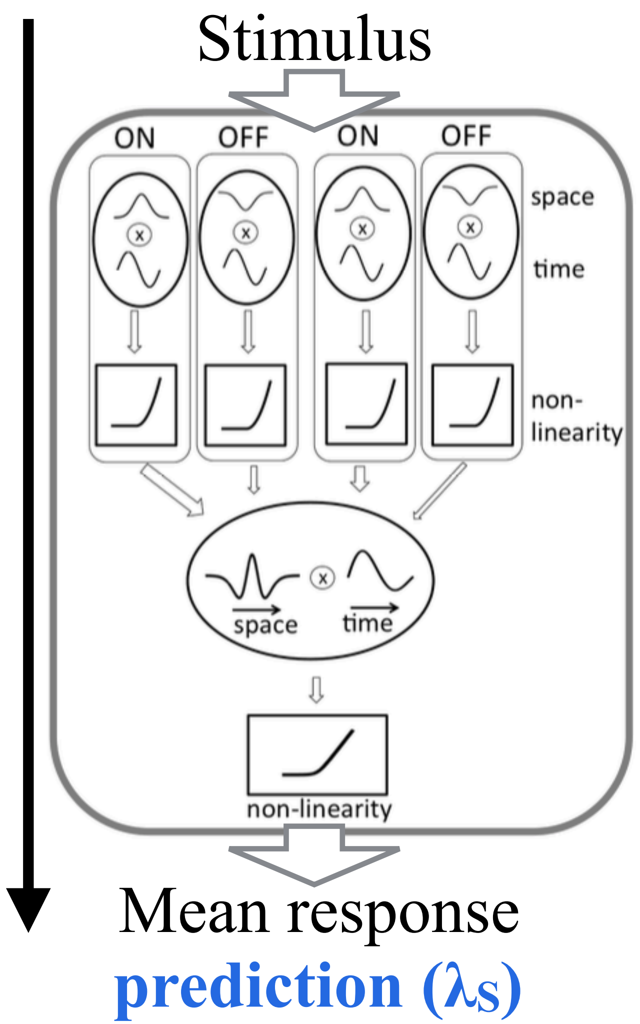
Linear-filter

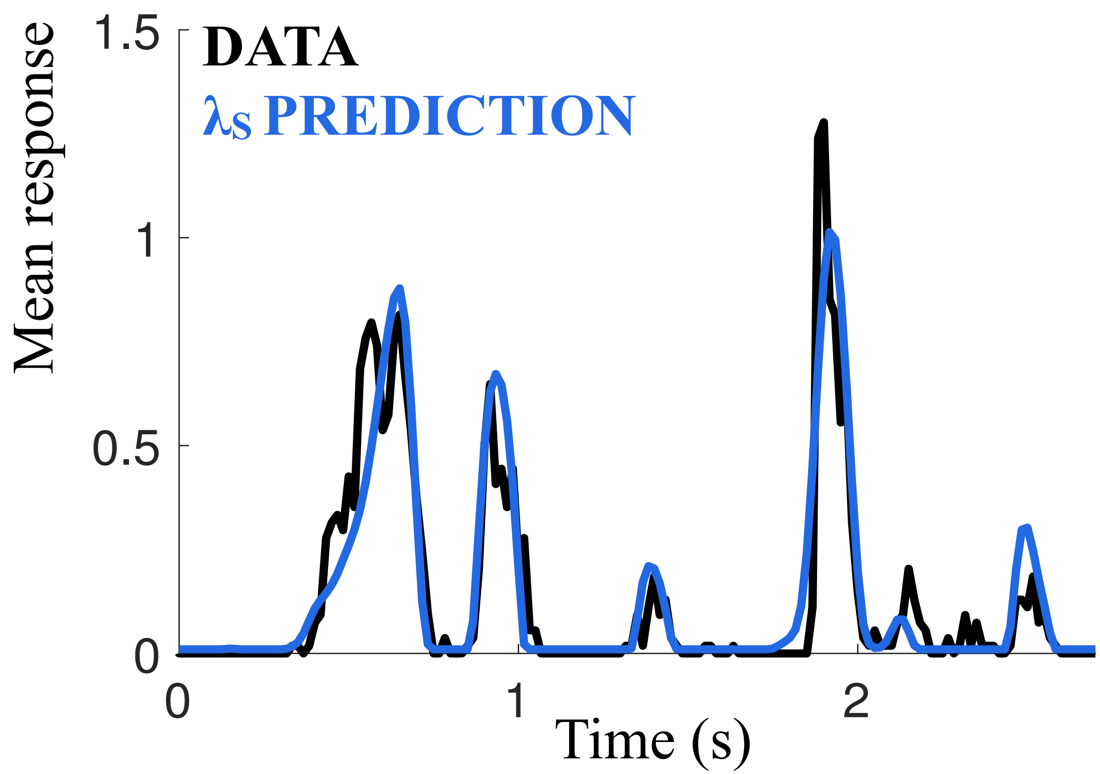
Non-linearity

Mean response
prediction (λ_S)

Mean output prediction from stimulus

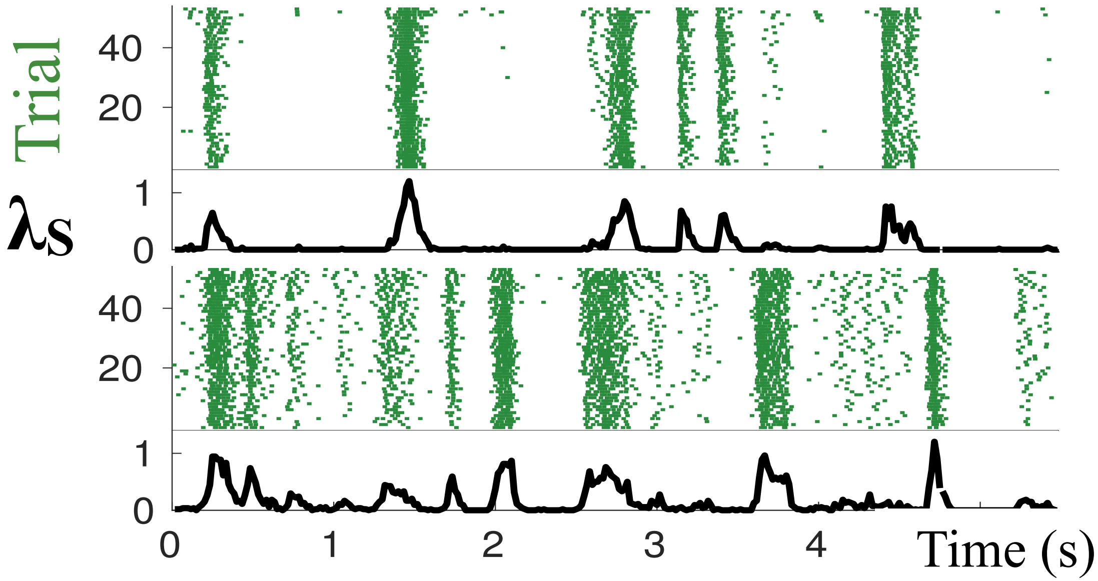
*A **non-linear** model predicts the mean response*





BFGS learning + regularisation

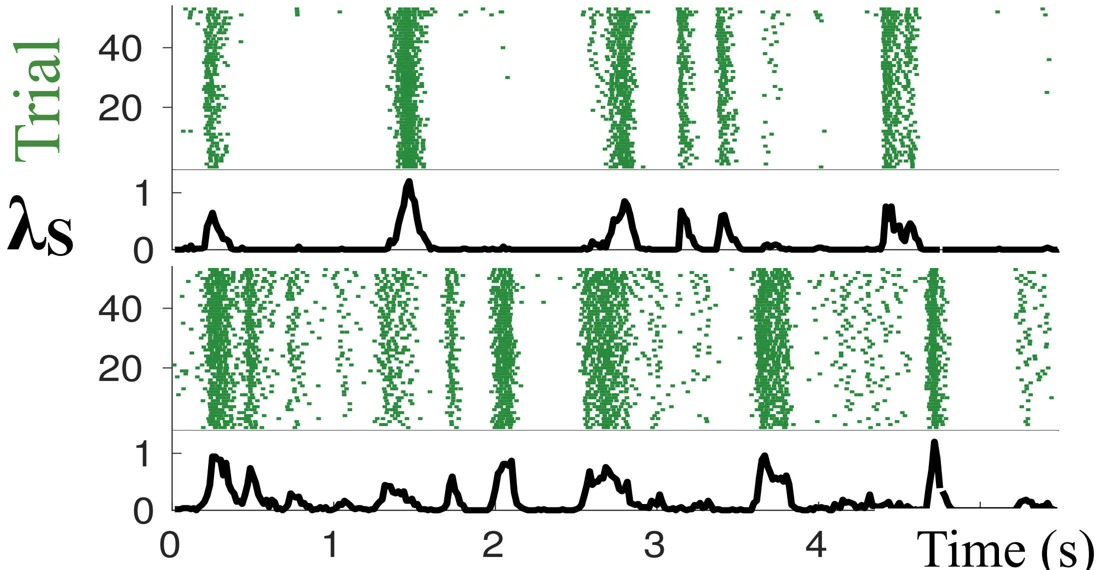
Non-linear & stochastic **response to stimulus**



Predict λ_S as function of the **stimulus**

Are Neurons **more synchronous** than expected?

Non-linear & stochastic **response to stimulus**



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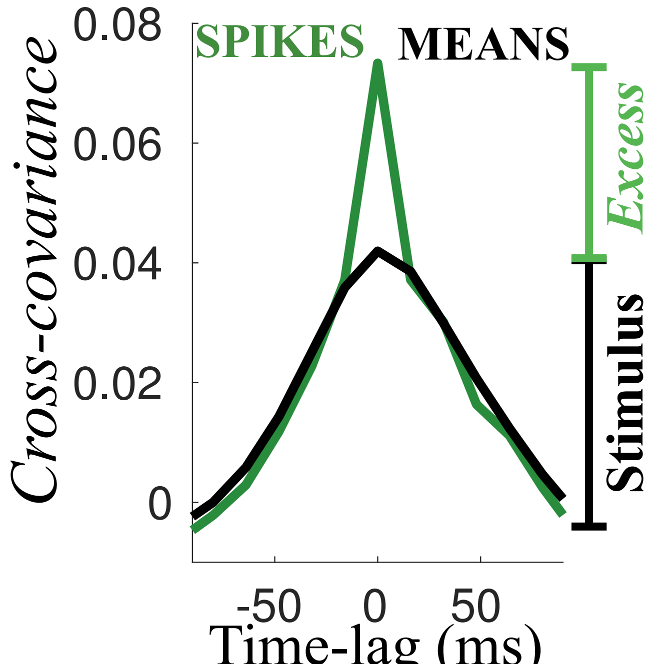
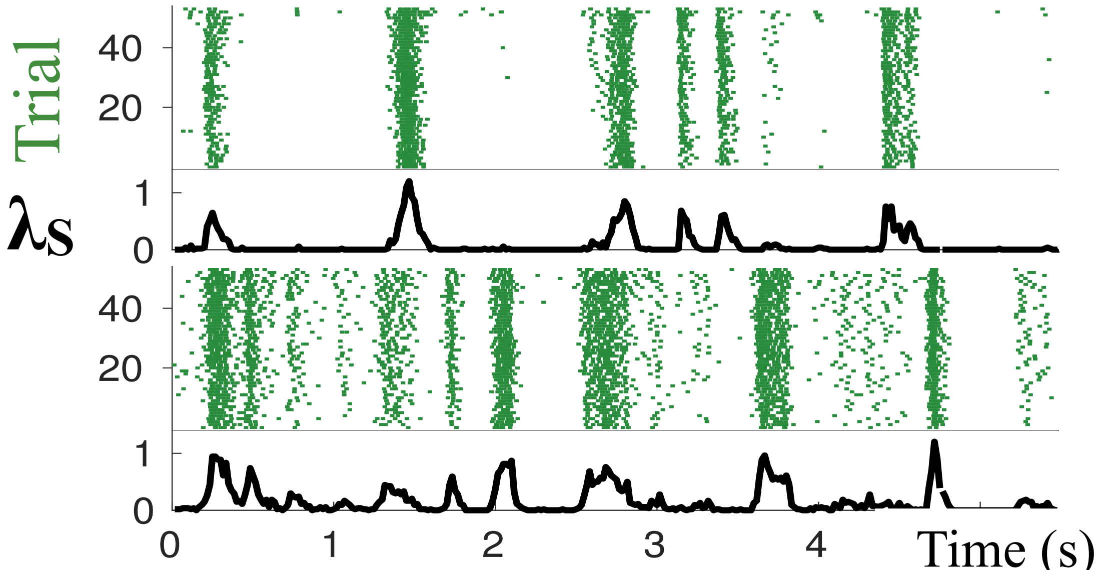


Non-linear & stochastic **response to stimulus**



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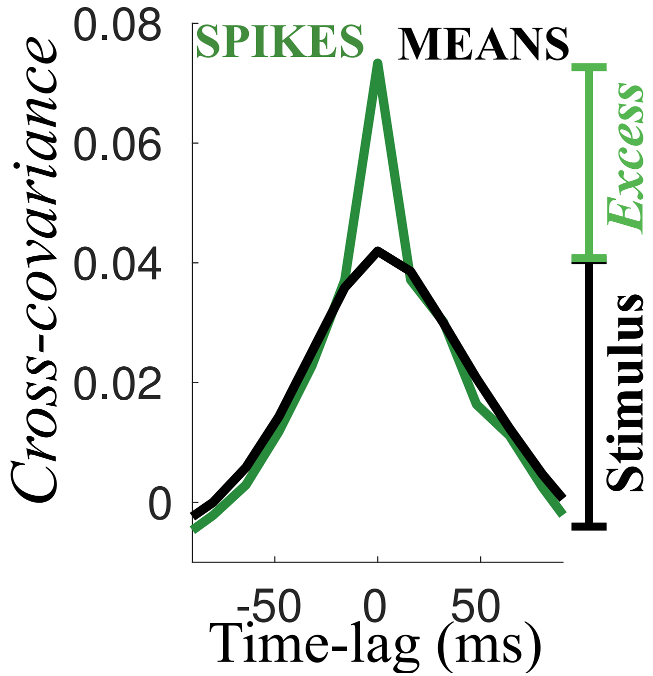
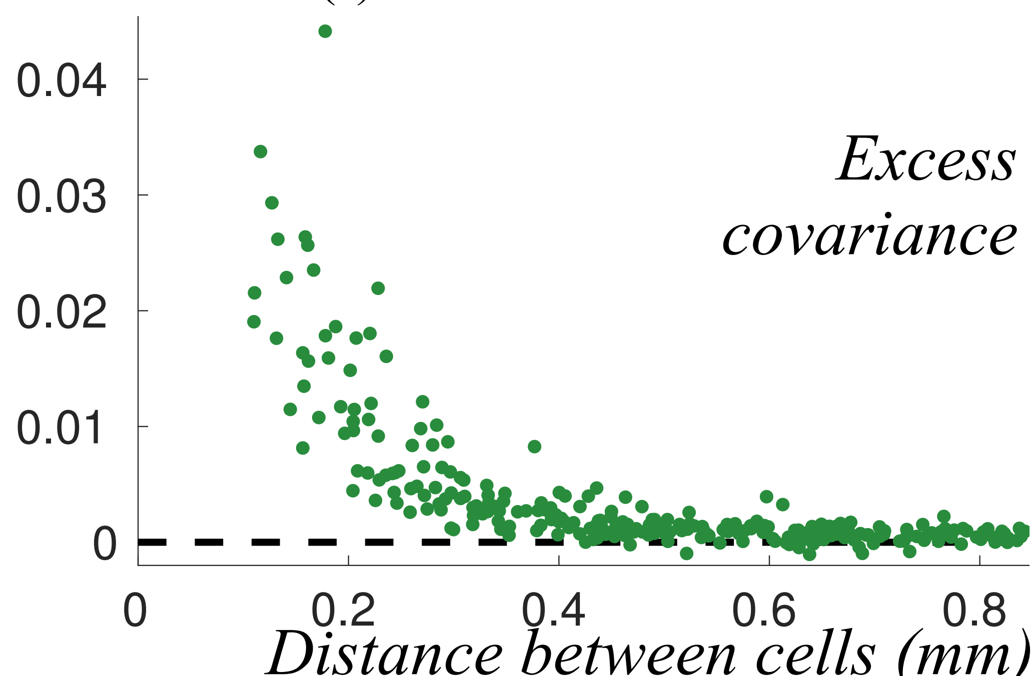
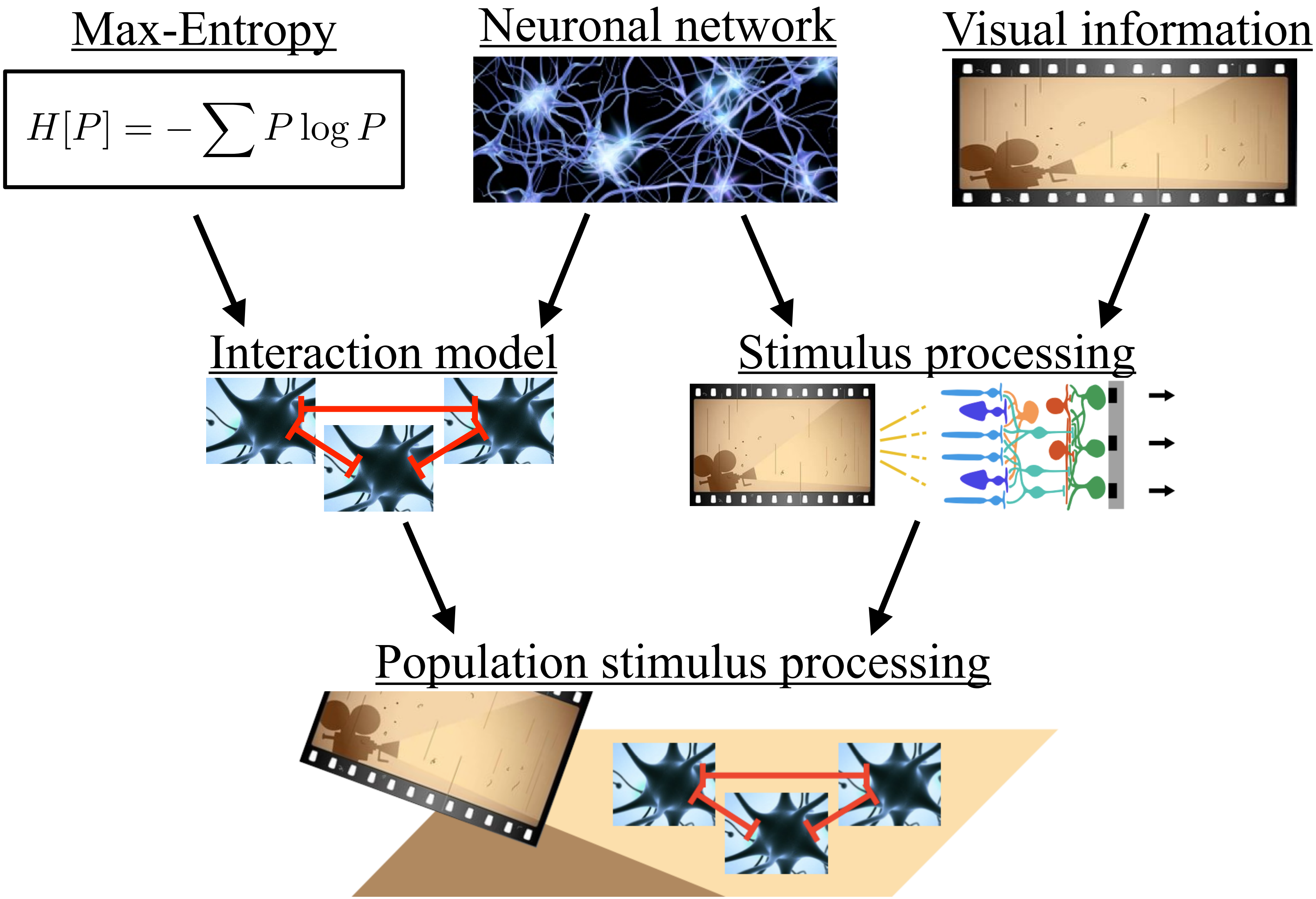




Collective behavior in neuronal ensembles



How to account for excess covariances?

Stimulus processing → **Prediction** λ_S → **Fluctuating fields** → **Interaction** network

$$P^{\text{Pop}}_{\text{Refr}}(\{n_{it}\}) \sim \prod_t \left(\prod_i e^{h_i[\lambda_{S(t)}] n_{it}} \prod_{i<j} e^{n_{it} J_{ij} n_{jt}} \right)$$

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⇩

$$\prod_t \left(\prod_i e^{h_i[\text{DATA(t)}] n_{it}} \prod_{i<j} e^{n_{it} J_{ij} n_{jt}} \right)$$

& L1 regularization

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⇓

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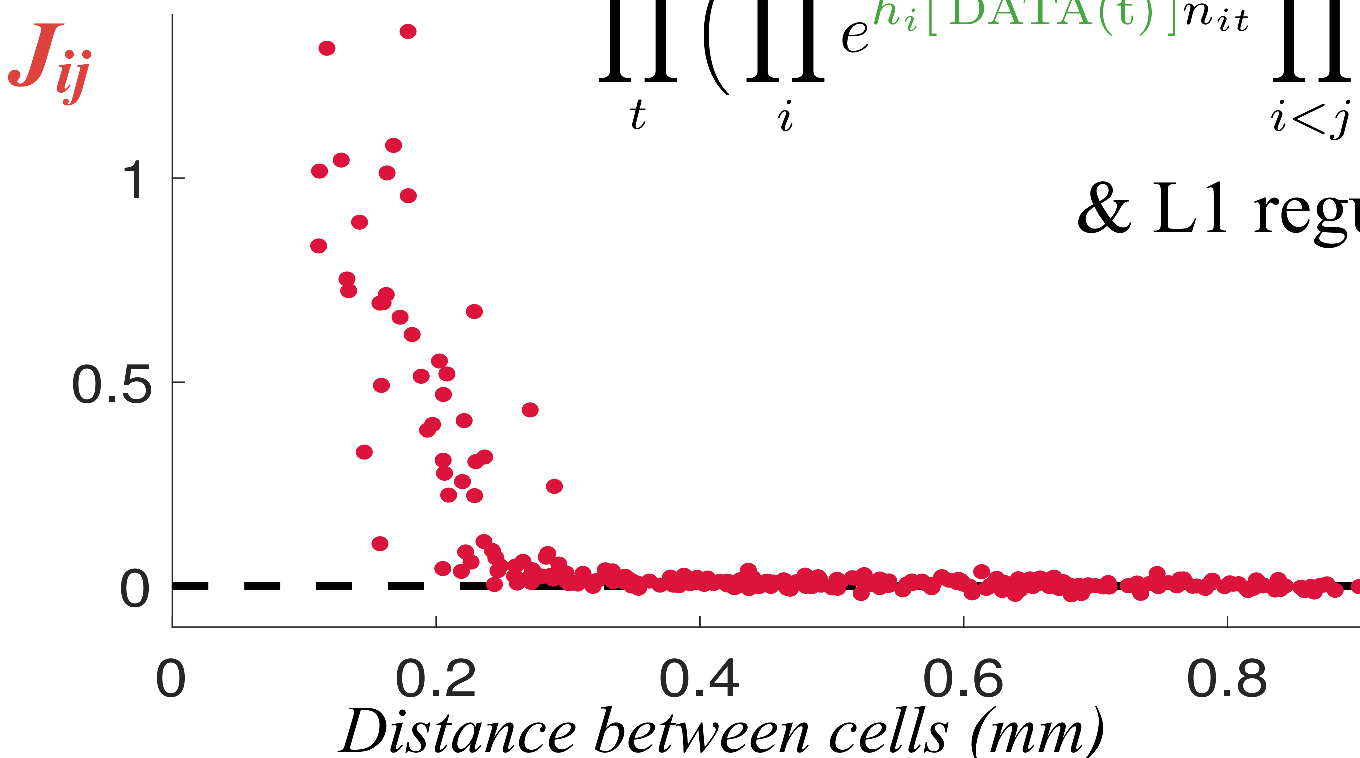

How to account for excess covariances?

Stimulus processing → **Prediction** λ_S → **Fluctuating fields** → **Interaction** network

TAP/AMP correction →

$$\prod_t \left(\prod_i e^{h_i[\lambda_{S(t)}] n_{it}} e^{\Delta h_i[\lambda_{S(t)}] n_{it}} \prod_{i<j} e^{n_{it} J_{ij} n_{jt}} \right)$$

$$\Delta h_i = \sum_{j \neq i} J_{ij} \langle n_j \rangle + \frac{1}{2} \frac{d\langle n_i^2 \rangle_c}{d\langle n_i \rangle} \sum_{j \neq i} J_{ij}^2 \langle n_j^2 \rangle_c$$

arXiv '18

How to account for excess covariances?

Stimulus processing → **Prediction** λ_S → **Fluctuating fields** → **Interaction** network

TAP/AMP correction ➡

$$\prod_t \left(\prod_i e^{h_i[\lambda_{S(t)}] n_{it}} e^{\Delta h_i[\lambda_{S(t)}] n_{it}} \prod_{i<j} e^{n_{it} J_{ij} n_{jt}} \right)$$

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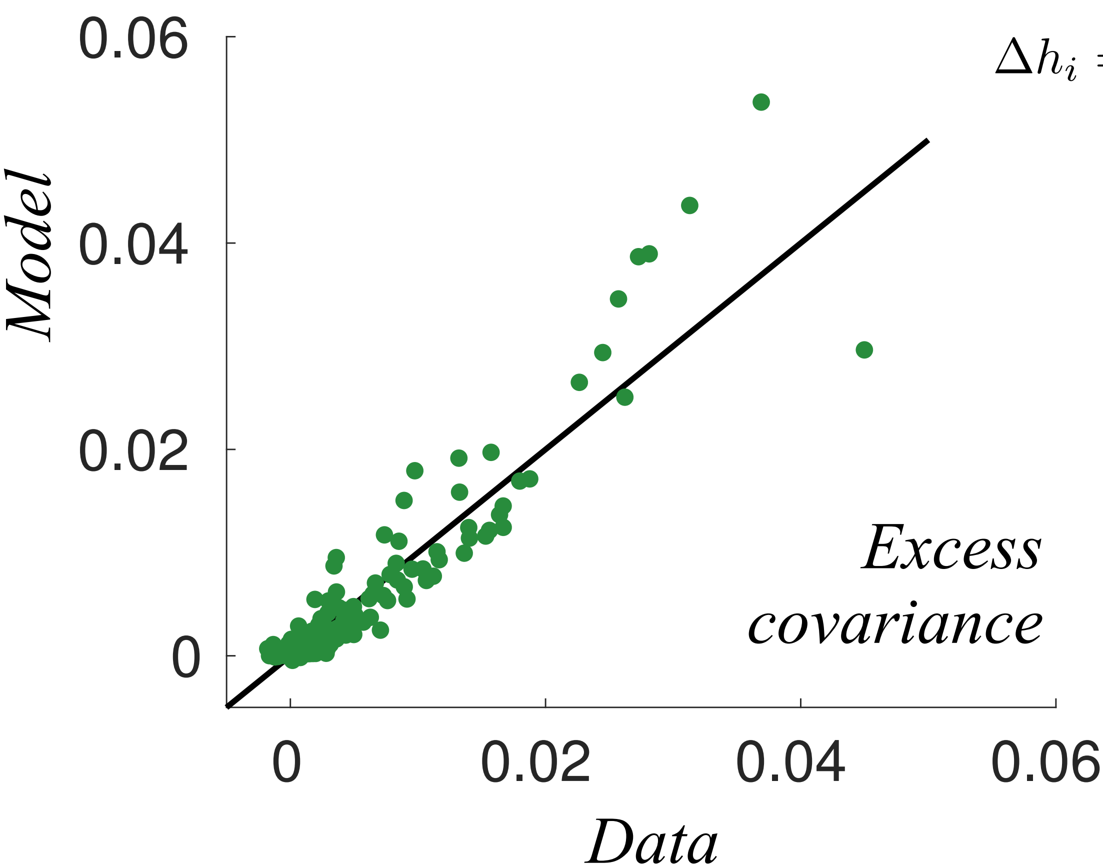
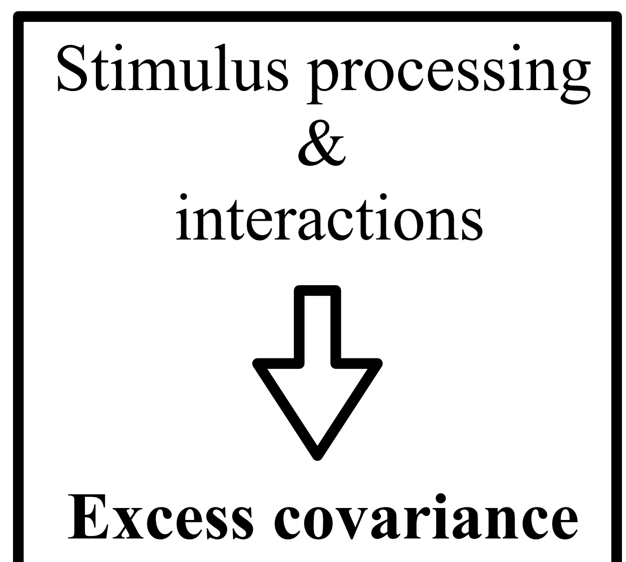
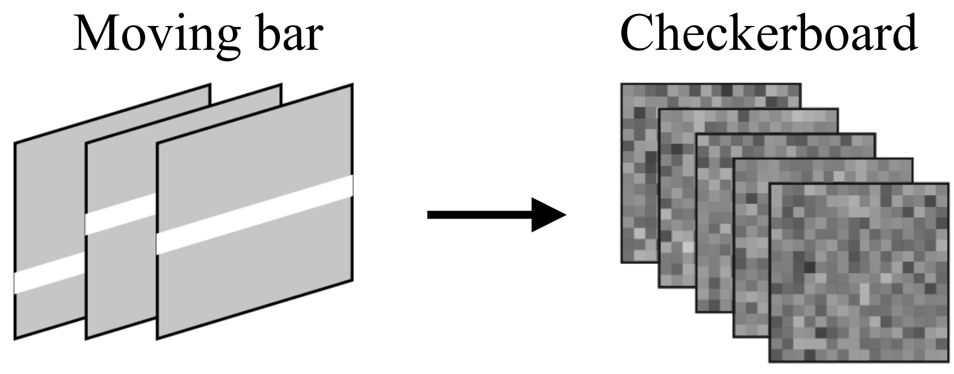




Are couplings robust to changes in common inputs?

Stimulus processing → **Prediction** λ_S → **Fluctuating fields** → **Interaction** network

Change in the stimulus ensemble:



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Stimulus processing → **Prediction** λ_s → **Fluctuating fields** → **Interaction** network

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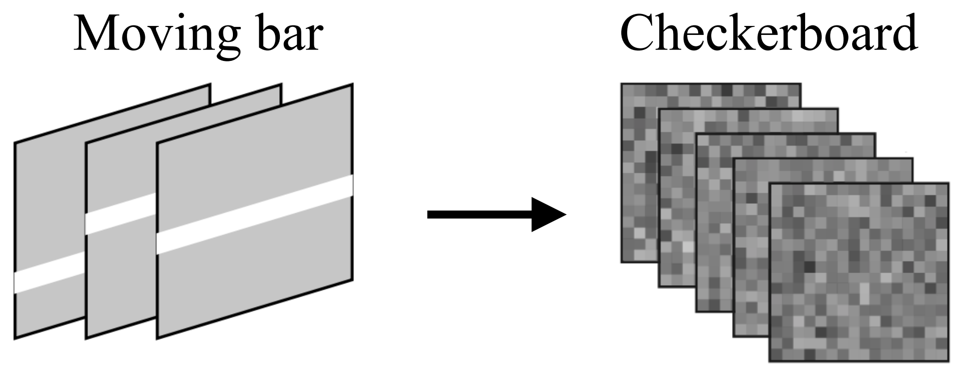
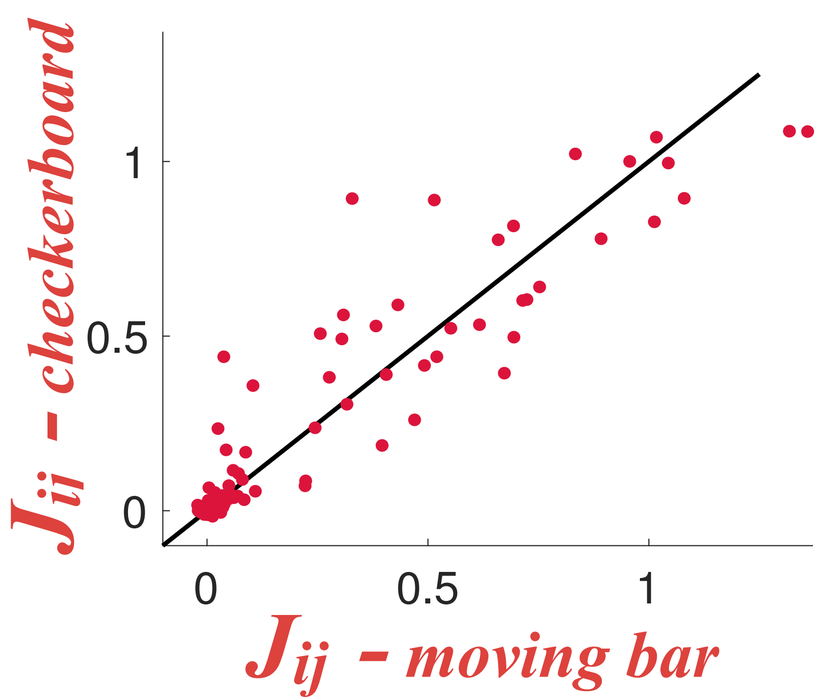
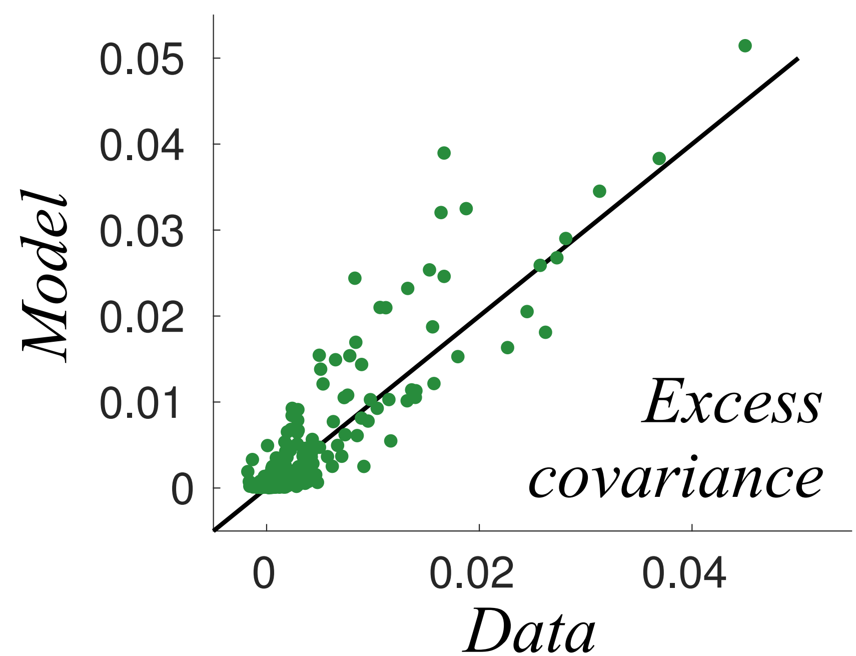






Collective behavior in neuronal ensembles

Conclusions:

- **Maximum entropy** principle allows for characterisation of network activity
- It can be used to identify **neuronal cliques,** basis for **memory formation**
- **Deep** stimulus processing model predicts mean retinal output
- **Interaction network** accounts for excess correlations in response to different stimuli

Collaborators

Theoretical side

- R. Monasson, S. Cocco, T. Mora
- G. Tkacik
- T. Obuchi

Experimental side

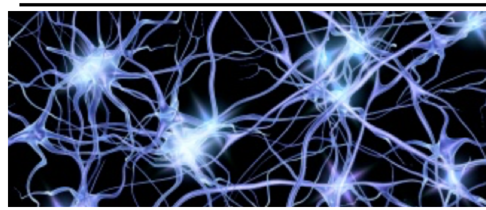
- O. Marre, S. Picaud
- F. Battaglia
- A. Destexhe

Thank you

Max-Entropy

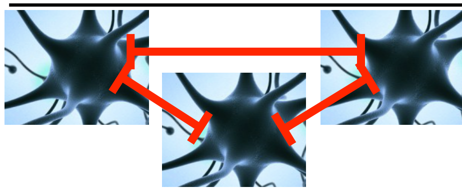
$$H[P] = -\sum P \log P$$

Neuronal network

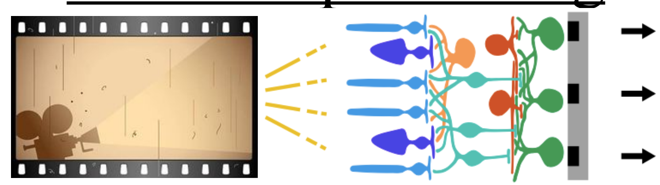


Visual information

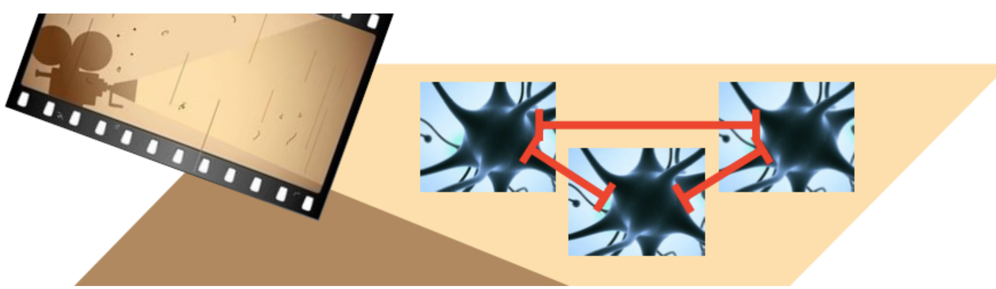
Interaction model



Stimulus processing



Population Stimulus processing

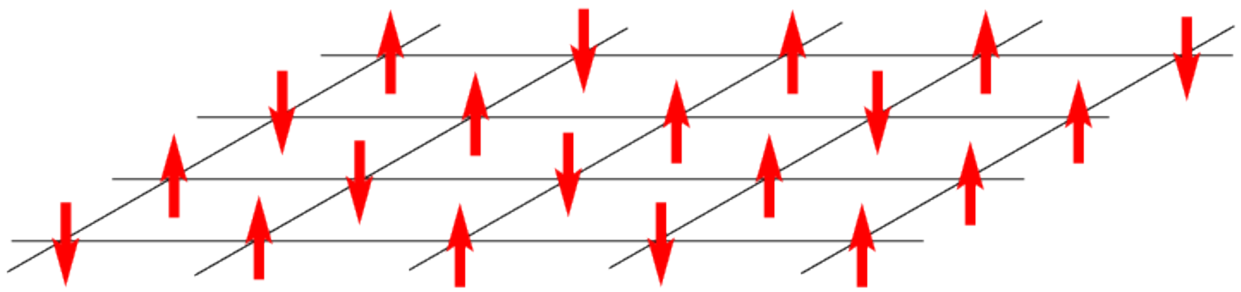


Link with Statistical Mechanics

SAPIENZA
UNIVERSITÀ DI ROMA

Spin Glasses

Statistical models with an ***interaction network***



Collective behavior

in disordered systems

1) Phys Rev B '10; 2) J. Stat. Mech '11; 3) Phys. Rev. Lett '12; 4) Phys. Rev. B '12; 5) Phys. Rev. B '12; 6) Phys. Rev. B '13; 7) Phys. Rev. E '15

Thèse de doctorat

PRL **108,** 085702 (2012) PHYSICAL REVIEW LETTERS week ending 24 FEBRUARY 2012

Critical Slowing Down Exponents of Mode Coupling Theory

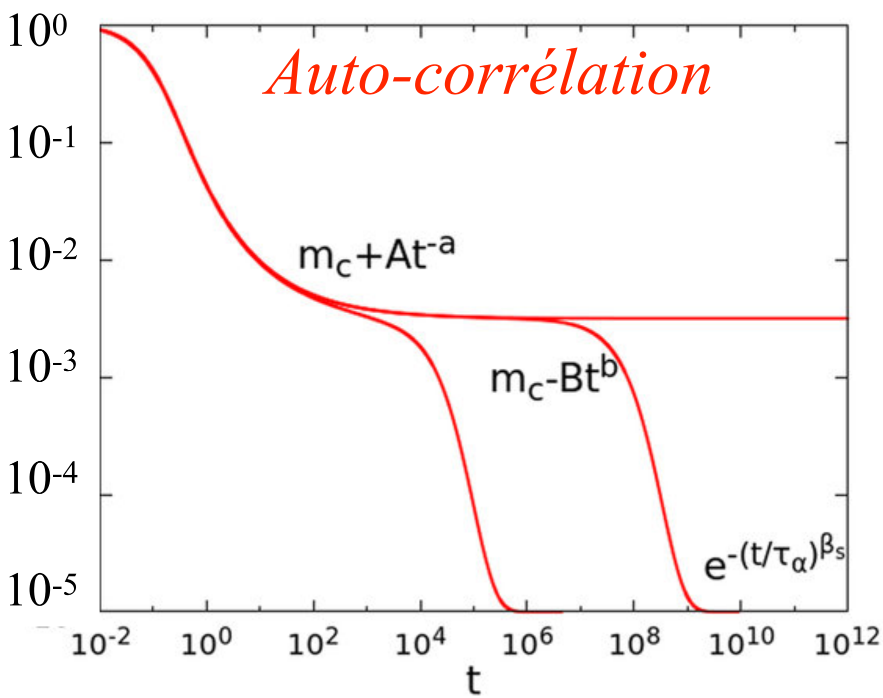
F. Caltagirone,[1] U. Ferrari,[1,2] L. Leuzzi,[1,2] G. Parisi,[1,2,3] F. Ricci-Tersenghi,[1,2,3] and T. Rizzo[1,2]

[1]*Dip. Fisica, Università La Sapienza, Piazzale A. Moro 2, I-00185, Rome, Italy*

[2]*IPCF-CNR, UOS Roma Kerberos, Università La Sapienza, P. le A. Moro 2, I-00185, Rome, Italy*

[3]*INFN, Piazzale A. Moro 2, 00185, Rome, Italy*

(Received 5 December 2011; published 24 February 2012)



Action de la theorie de champs:

$$\frac{1}{2}\sum_{(ab),(cd)}\delta Q_{ab}M_{ab,cd}\delta Q_{cd}-\frac{w_1}{6}\mathrm{Tr}\delta Q^3-\frac{w_2}{6}\sum_{ab}\delta Q_{ab}^3$$

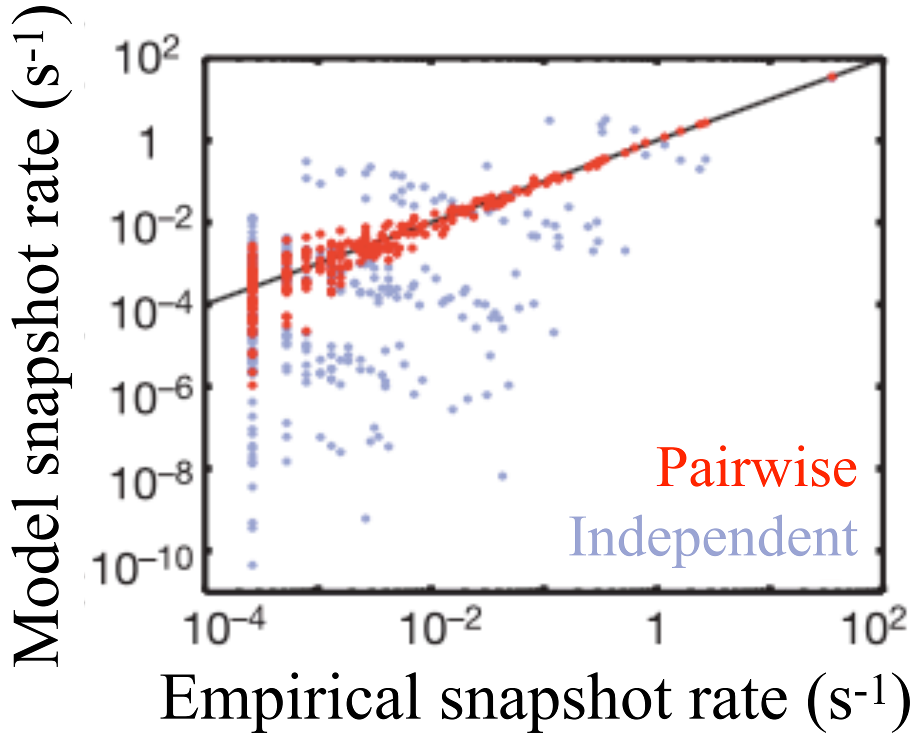
Équation pour les exposants:

$$\frac{\Gamma^2(1-a)}{\Gamma(1-2a)}=\frac{\Gamma^2(1+b)}{\Gamma(1+2b)}=\frac{w_2}{w_1}$$

Are these models good for neuronal network?

Schneidman et al. Nature 2006

Pairwise Maximum Entropy model



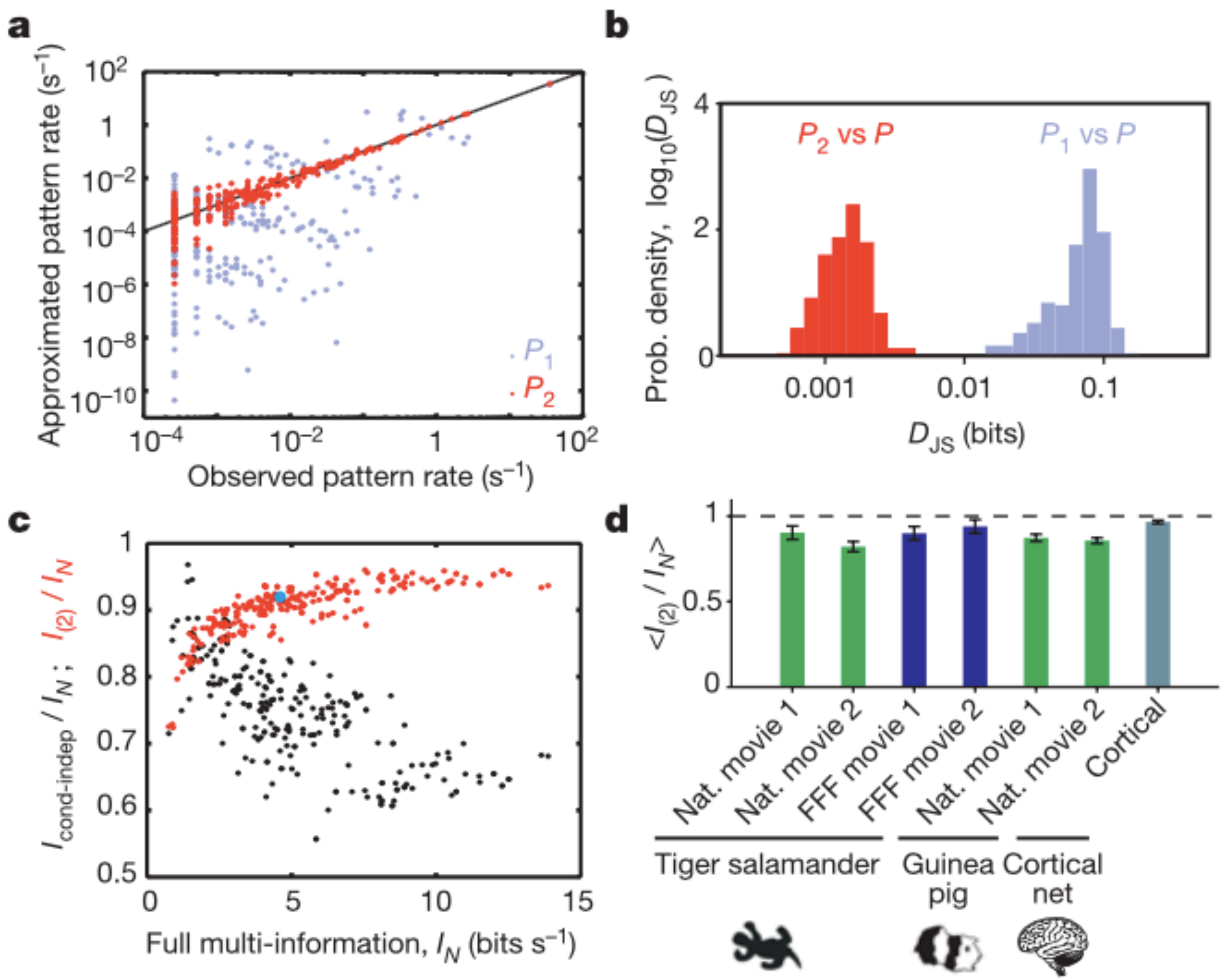
is a good model for salamander retina…

…but is any better than others?

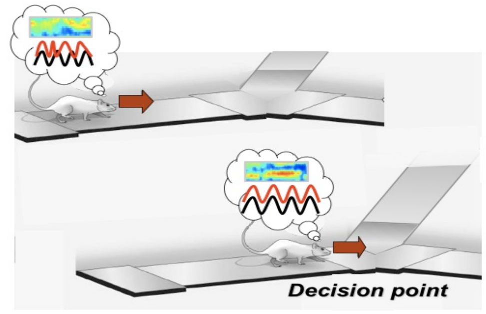
*(with the **same** data-knowledge)*

Modèles à entropie maximale

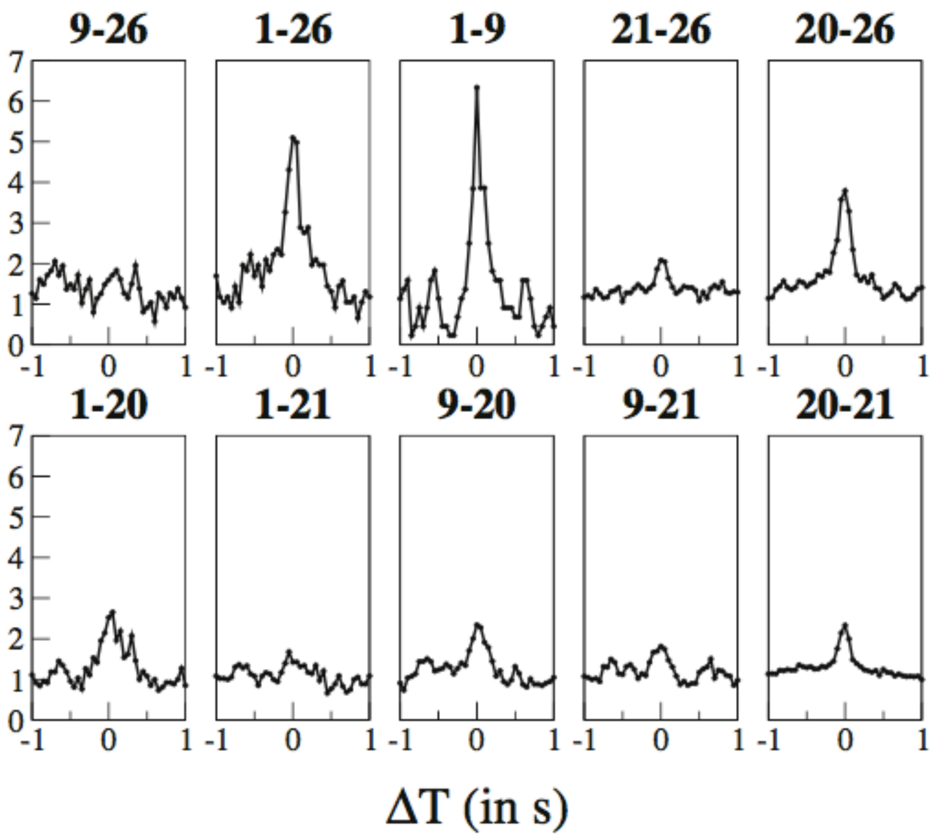
Schneidman et al. Nature 2006



Quelle est la base neurale de la mémoire ?



Cross correlation



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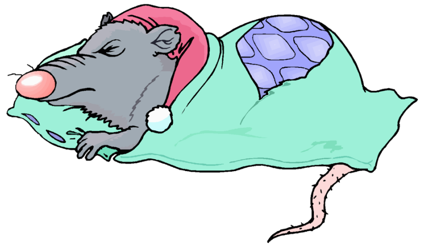
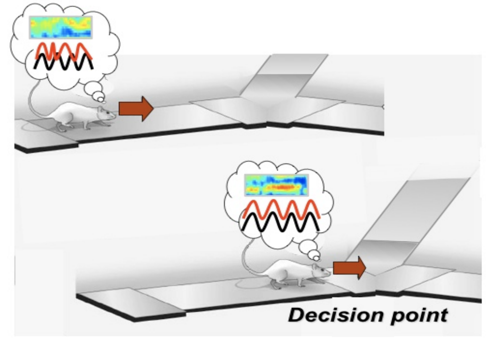
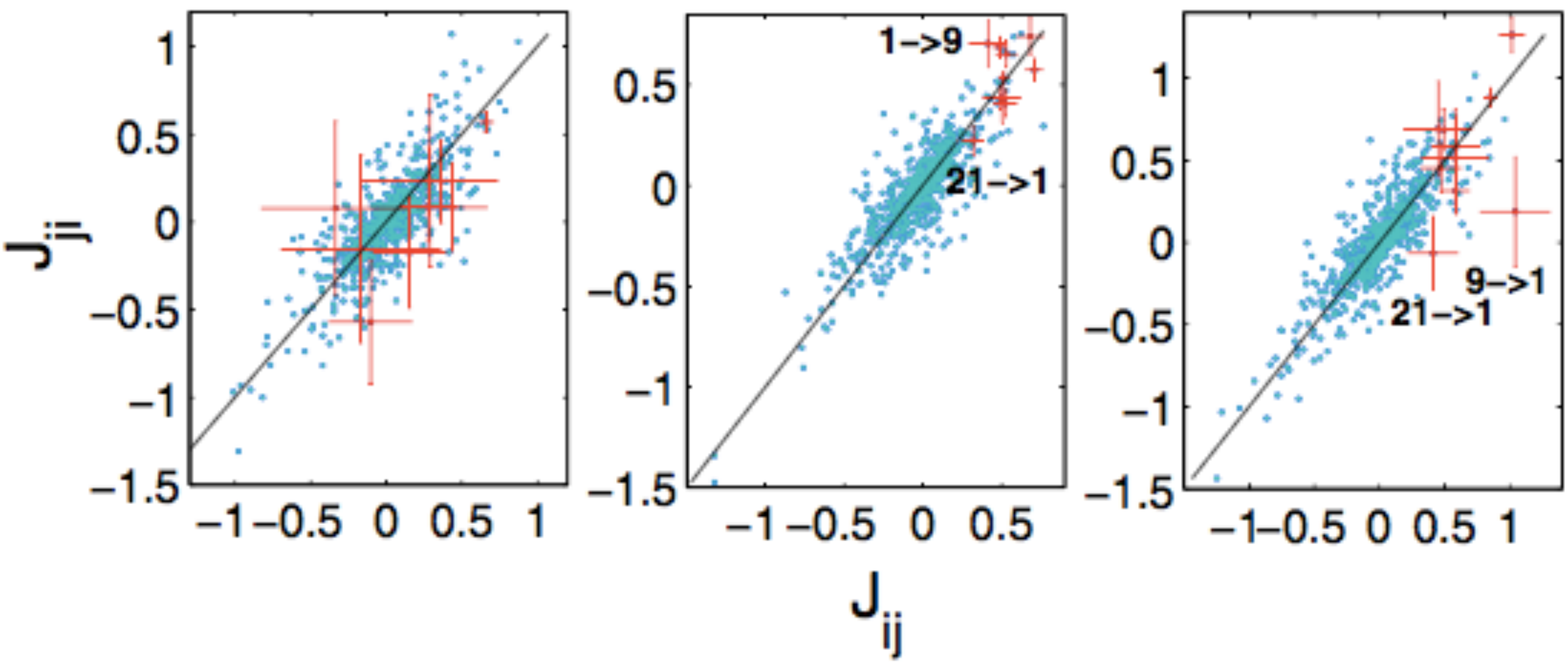




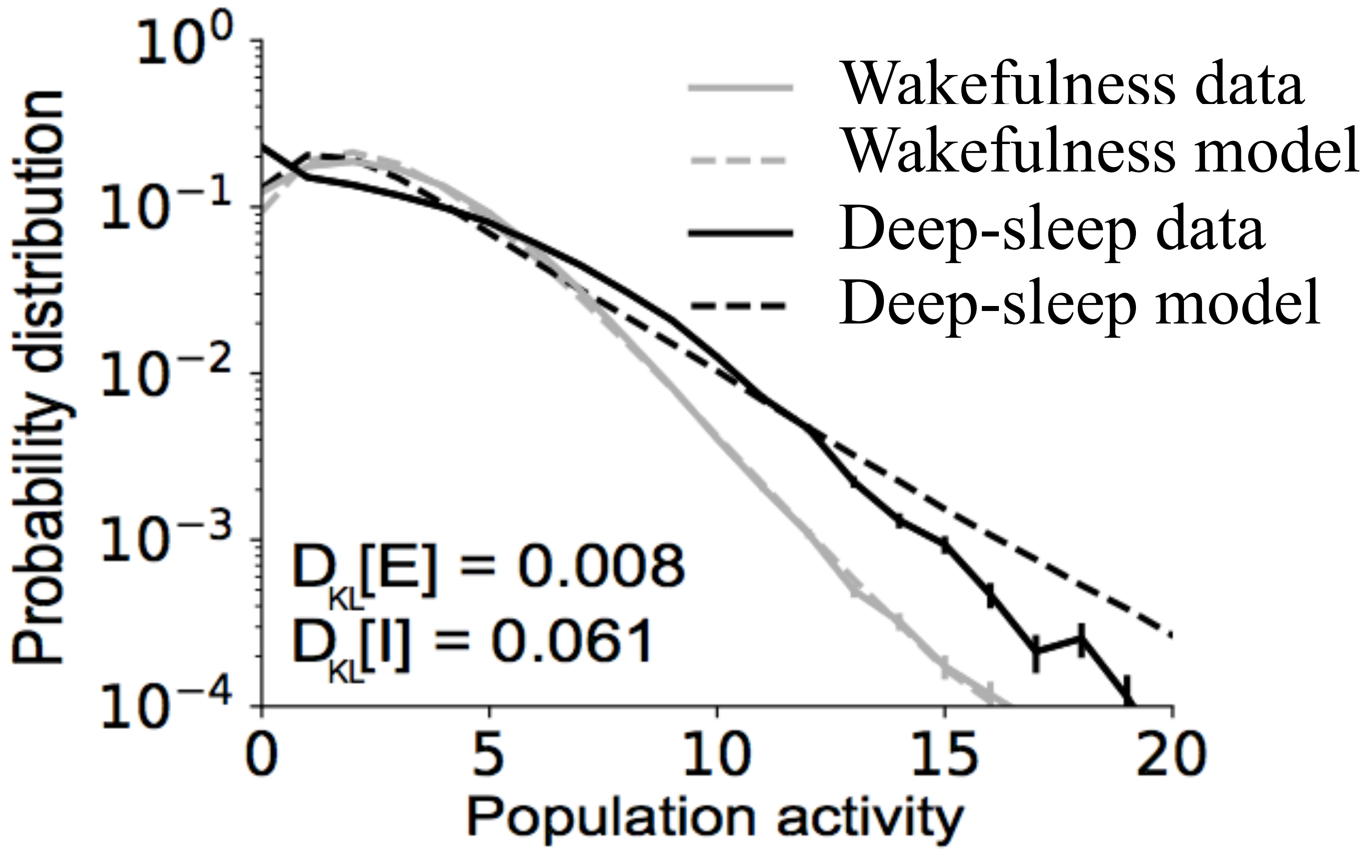
Generalised linear model



Are pairwise interactions sufficient during sleep?

Temporal cortex of human patient at ΔT = *50ms*

Wakefulness Vs **Deep-Sleep**



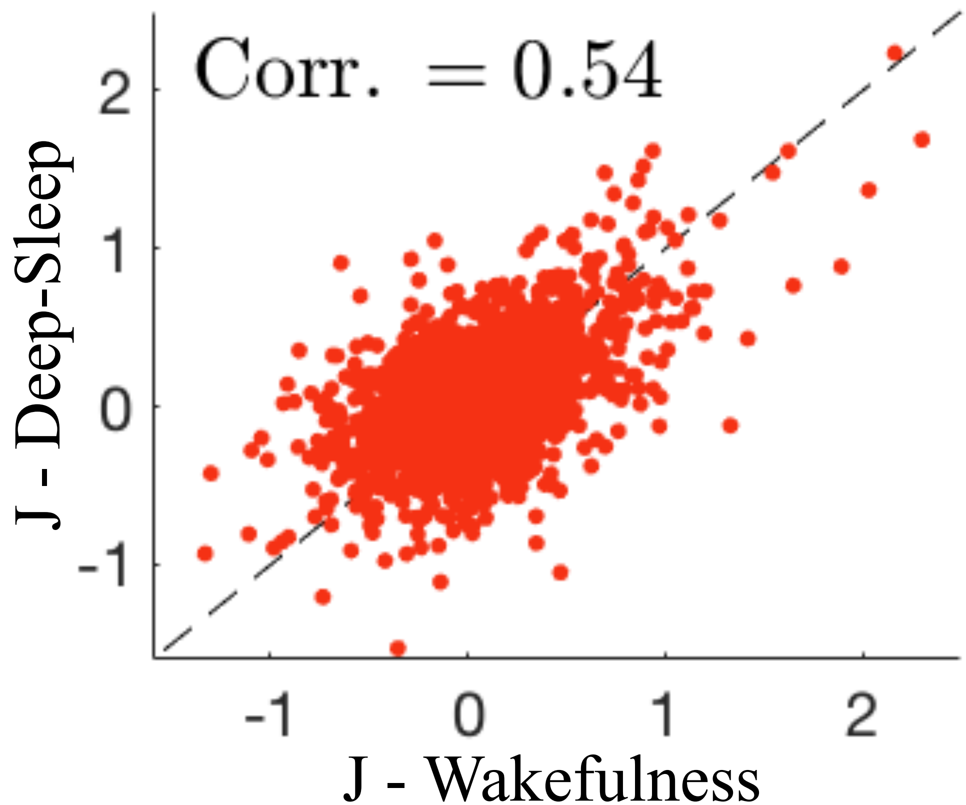
Same system, very different behavior

Nghiem, Telenzuk, Marre, Destexhe, UF, in rev. @ PRX

Are pairwise interactions sufficient during sleep?

<u>Temporal cortex of human patient at $\Delta T = 50ms$</u>

Wakefulness Vs **Deep-Sleep**

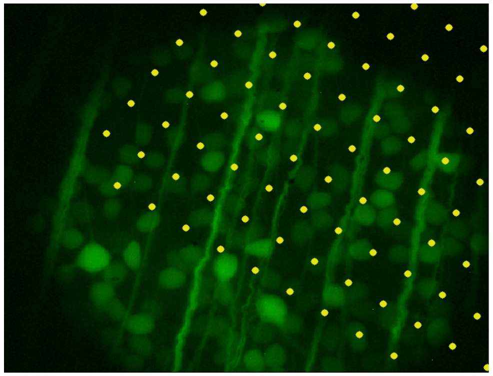


Same system, very different behavior

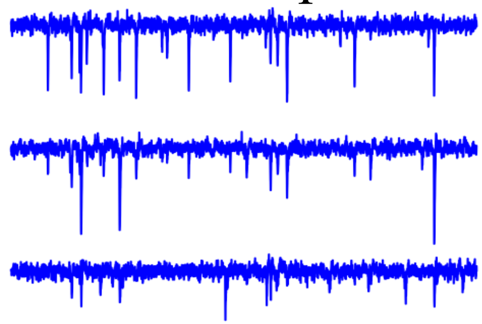
Nghiem, Telenzuk, Marre, Destexhe, UF, in rev. @ PRX

Framework: stimulus processing in the retina

Multi-electrode array

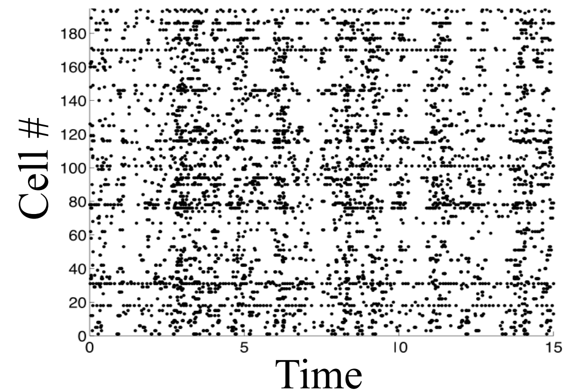


Extracellular potential

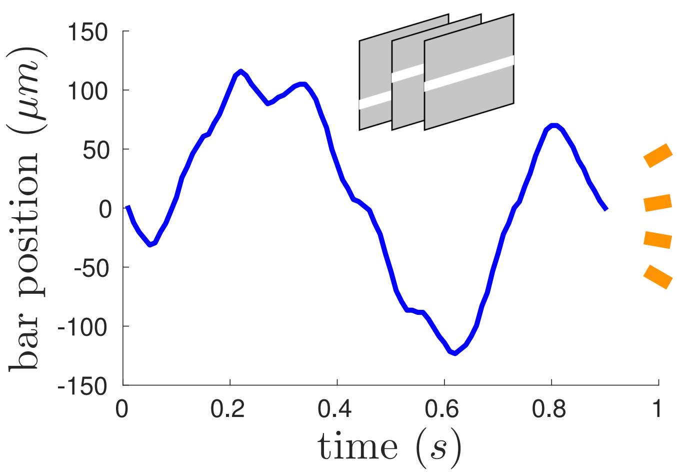


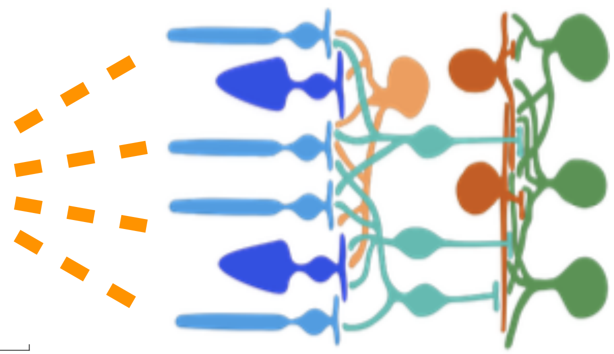
Marre '12; Yger '16

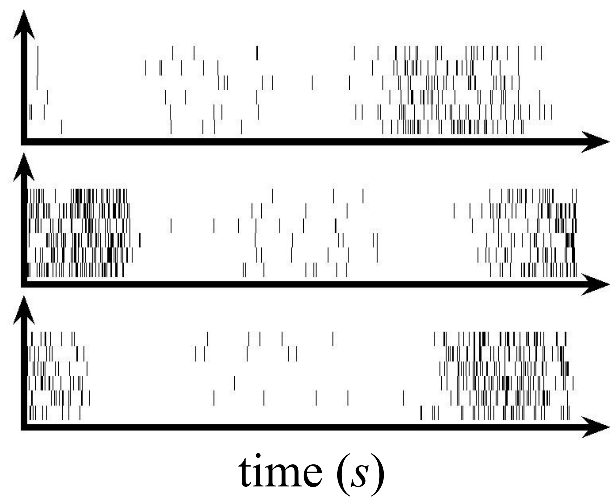
Spike sorting



STIMULUS S

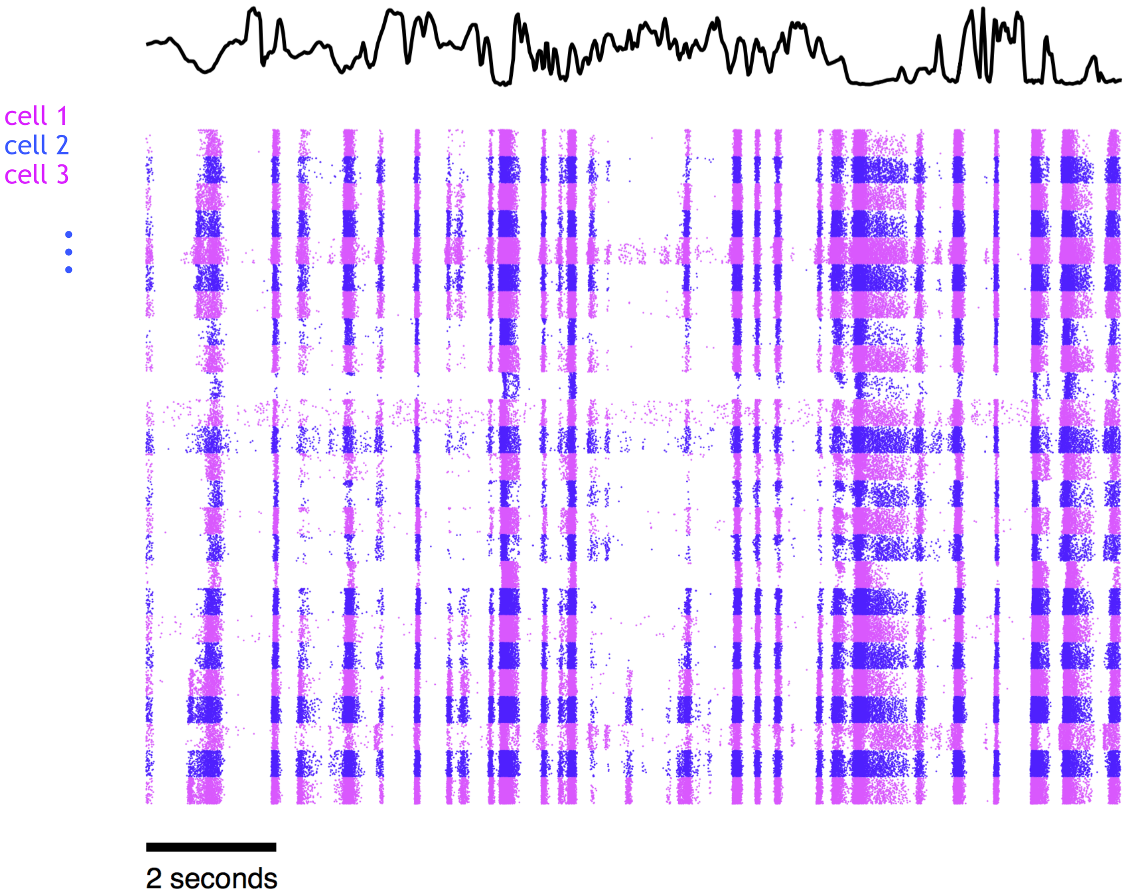


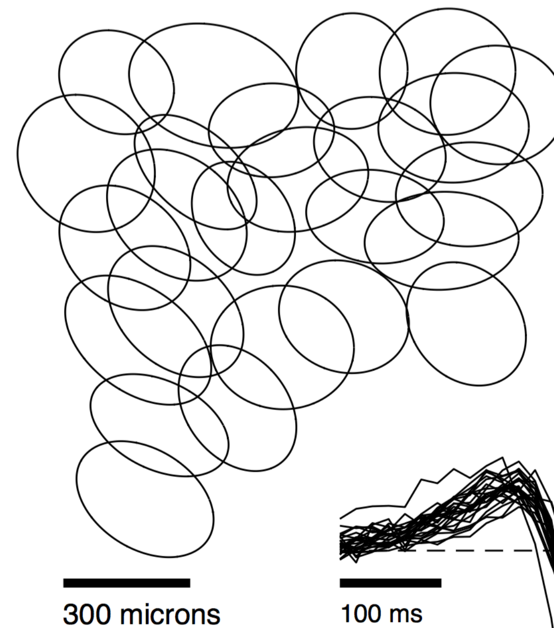


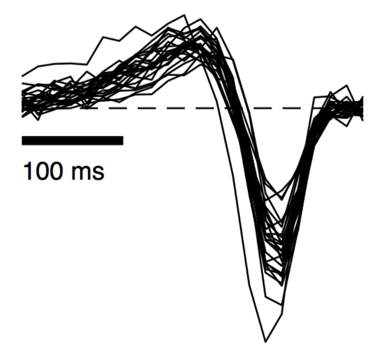


Modelling & characterising the **response to stimulus**

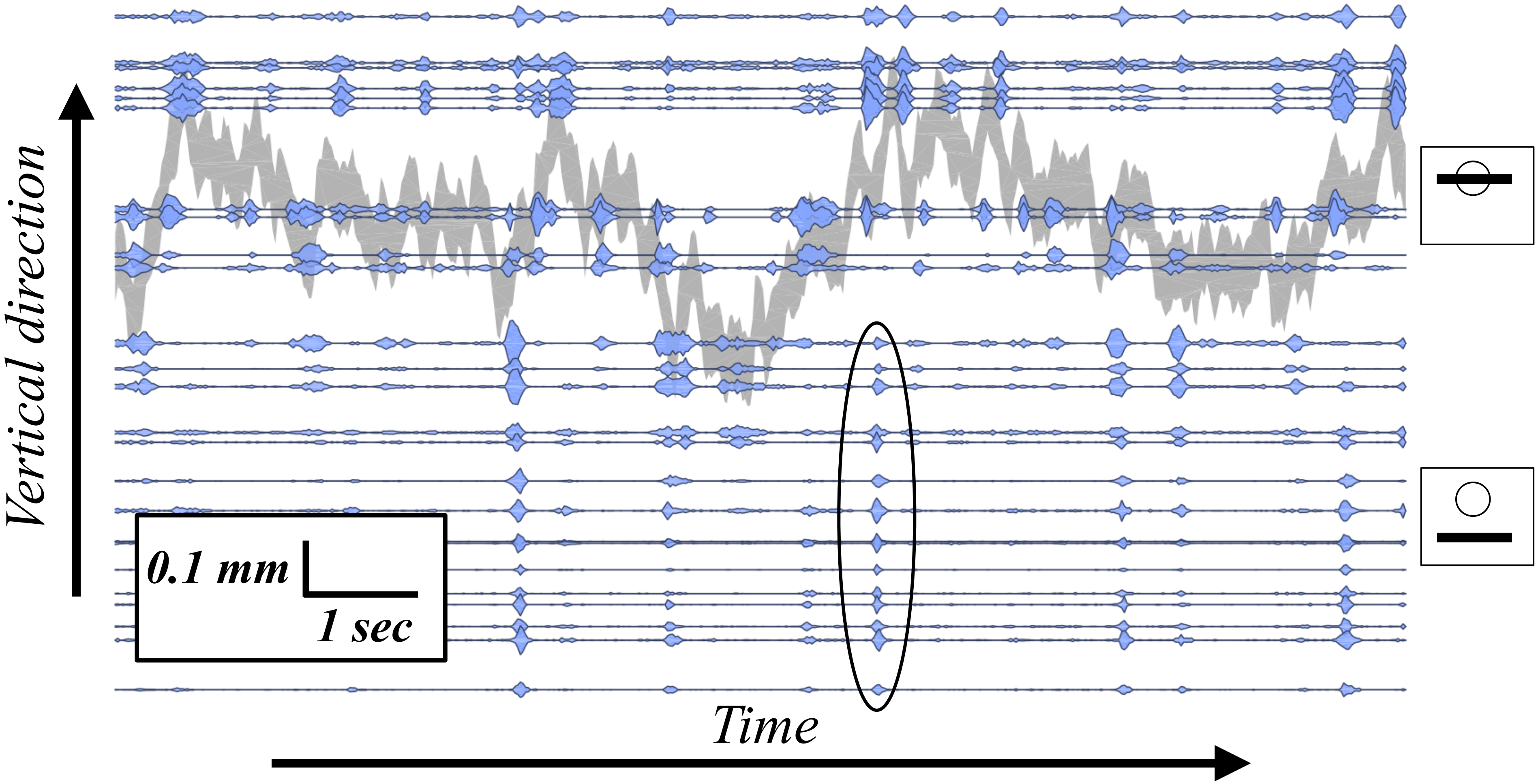
Strategy: input/output modelling





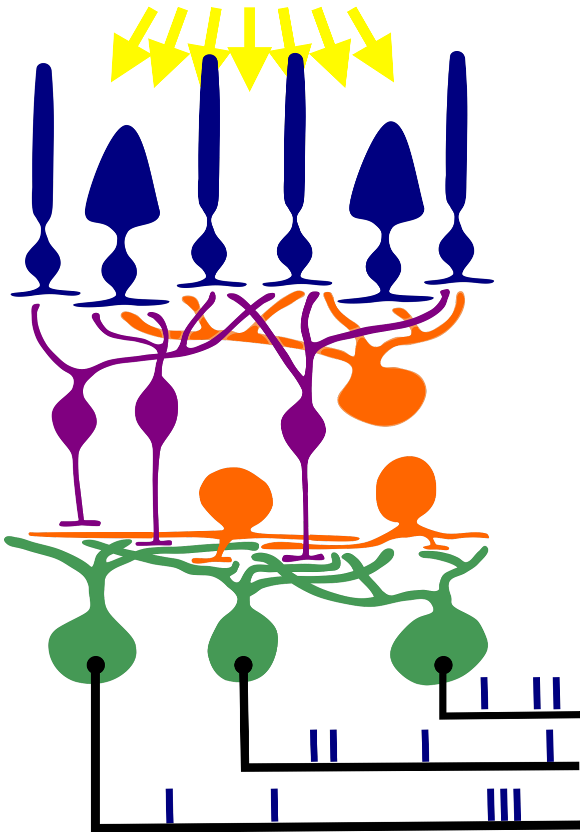


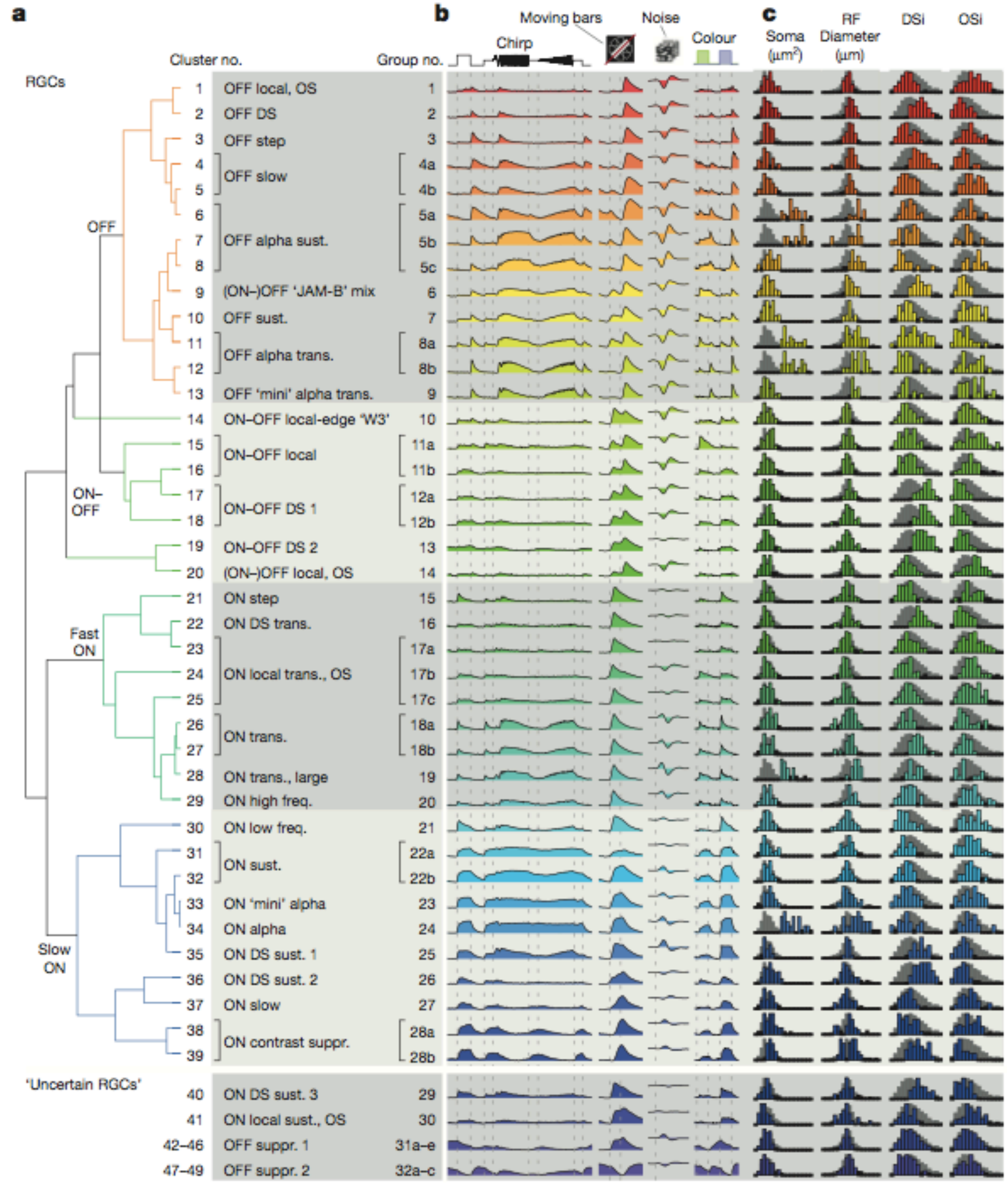
What makes it a hard task? **Flexibility!**



What makes the code **Flexible?**
Spoiler: **Non-linearity** of stimulus processing

La rétine

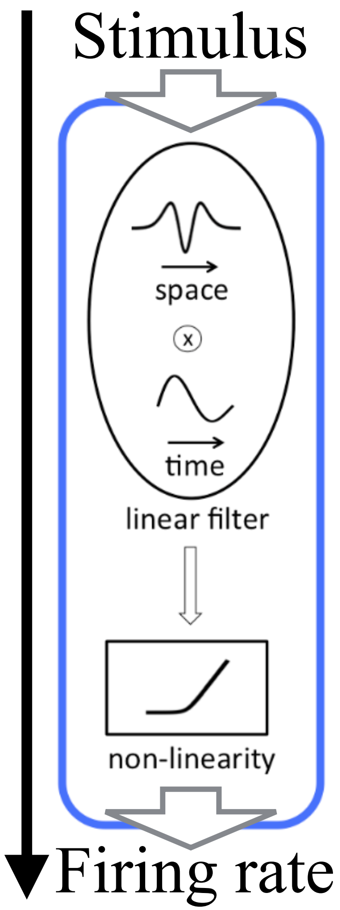




Baden et al. Nature 2016

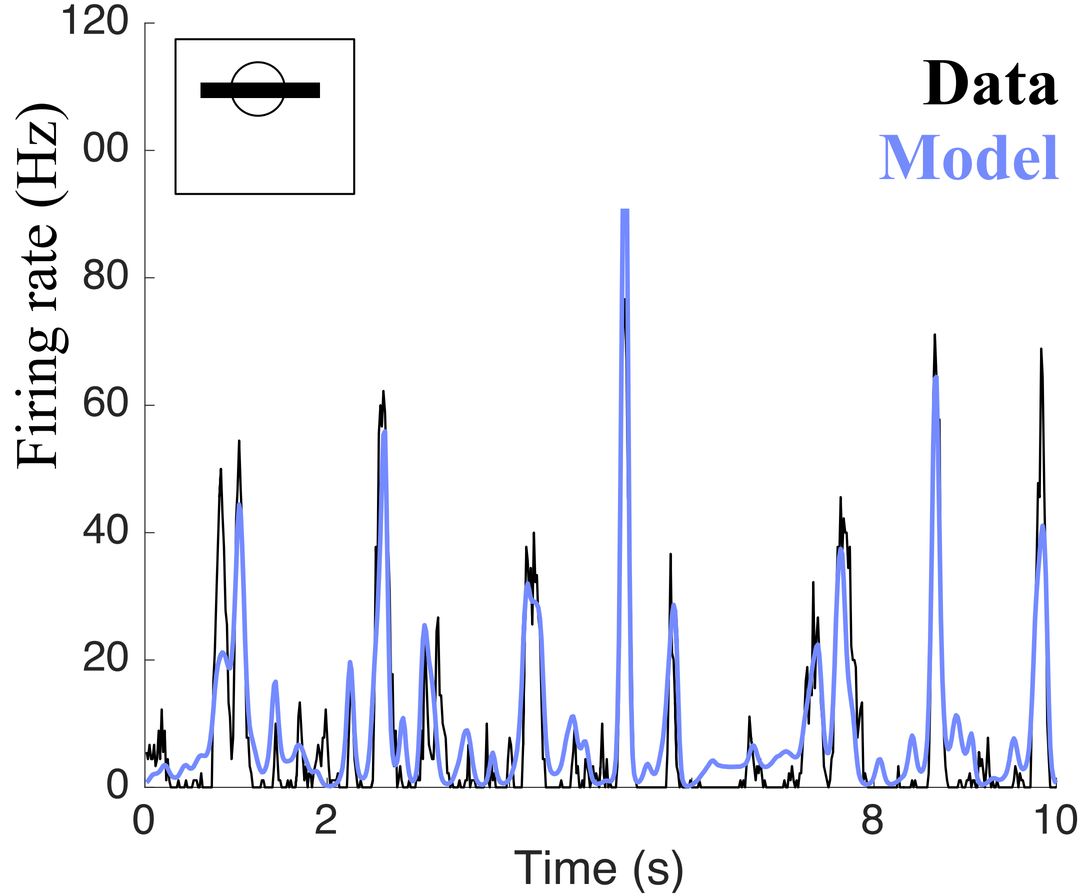
Strategy: input/output modelling

An (almost) ***linear*** *model…*



Receptive Field **Linear** Filtering

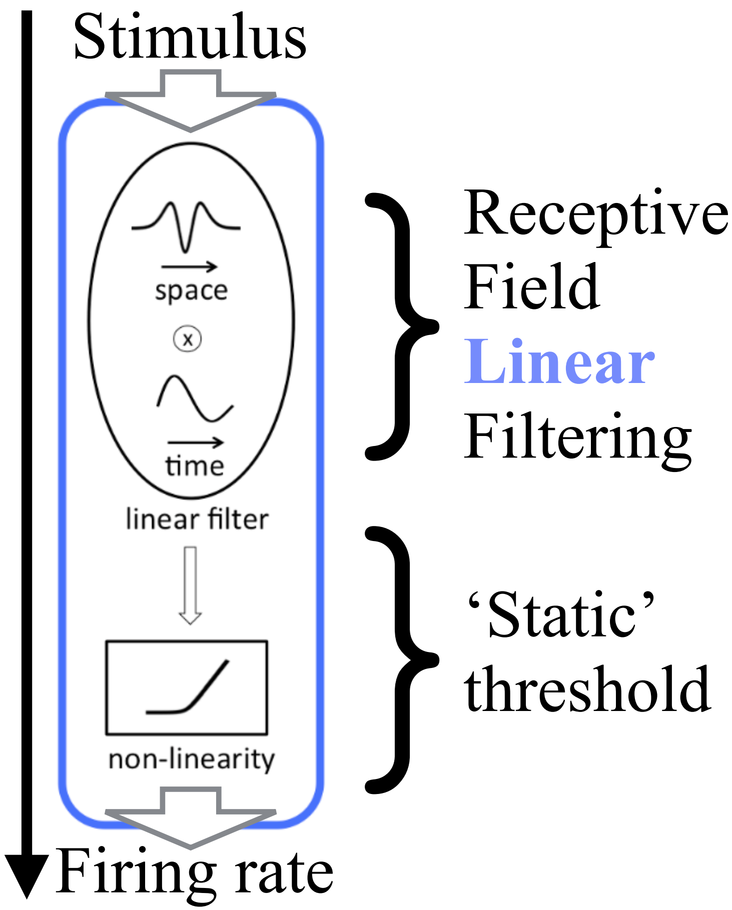
'Static' threshold

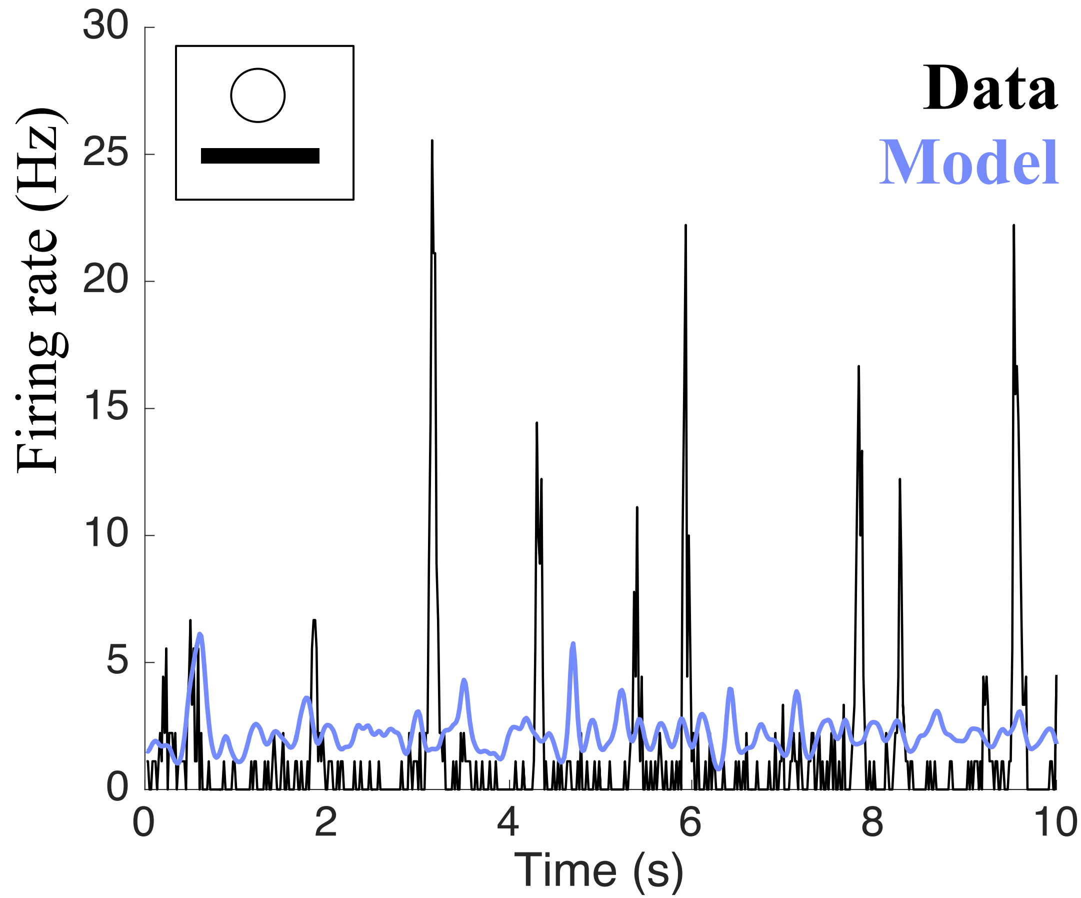


Chichilnisky '01

Strategy: input/output modelling

An (almost) ***linear*** *model may not predict the response*

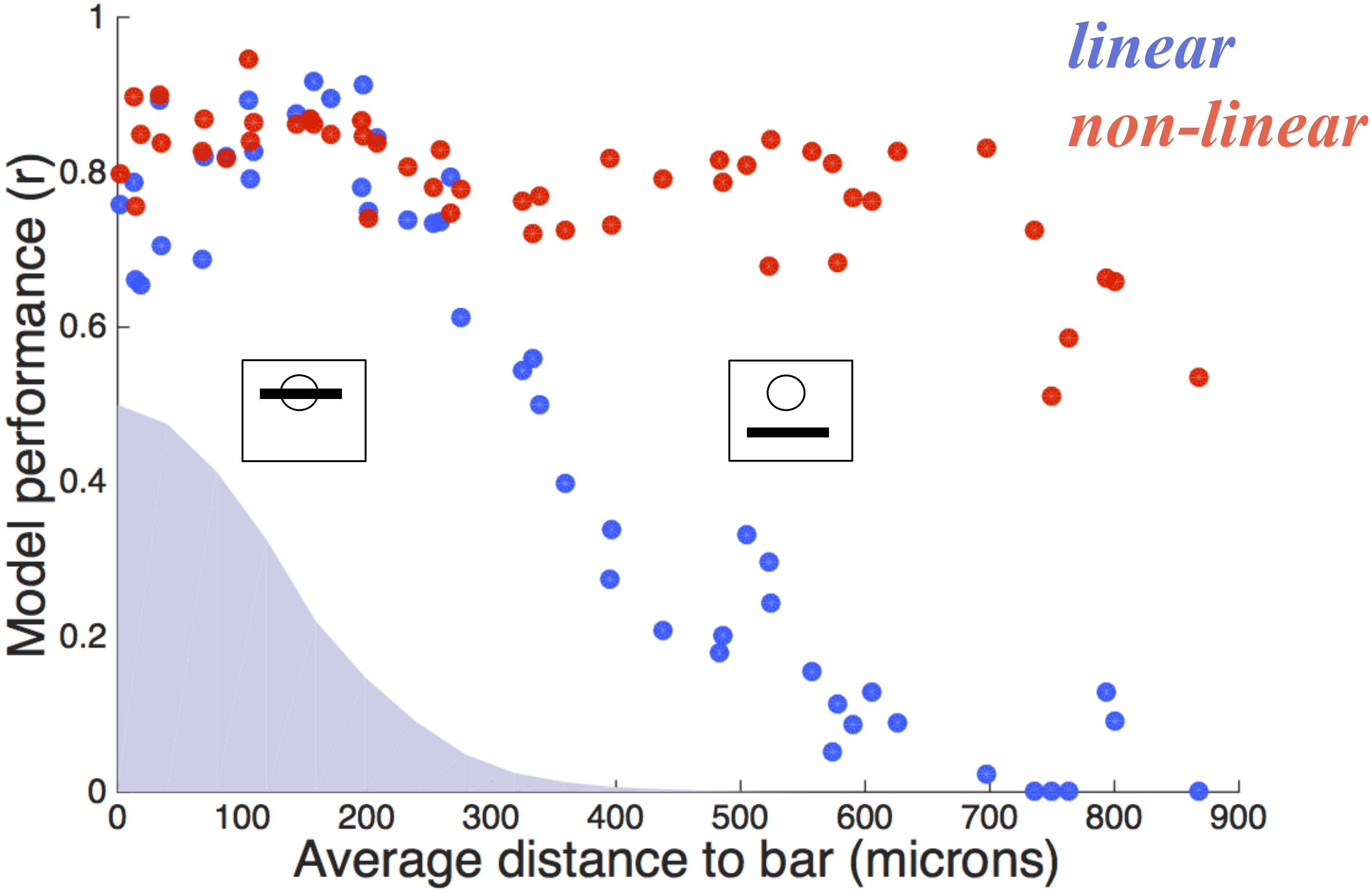




Chichilnisky '01

Strategy: input/output modelling

*An highly **non-linear** model predicts the response*



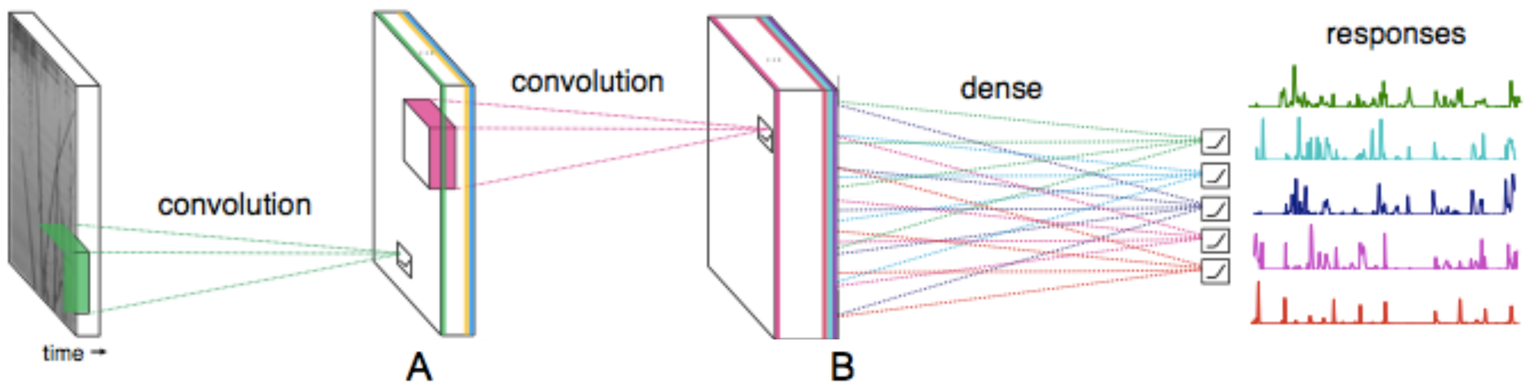
Same cell-type / two different computations

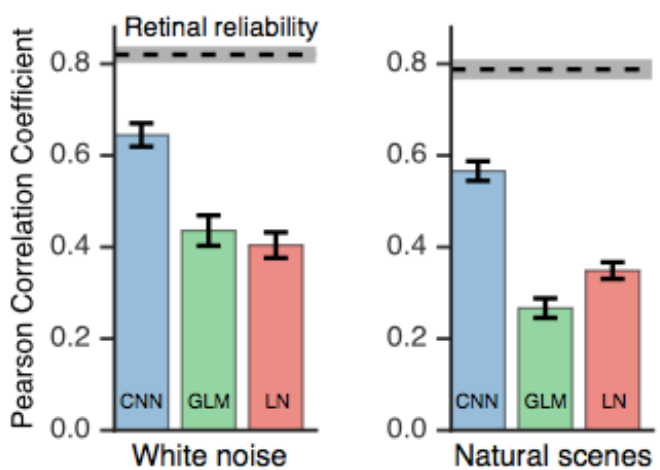
Réseau de neurones artificiels

Deep Learning Models of the Retinal Response to Natural Scenes

NIPS 2016

Lane T. McIntosh*[1], Niru Maheswaranathan*[1], Aran Nayebi[1],
Surya Ganguli[2,3], Stephen A. Baccus[3]

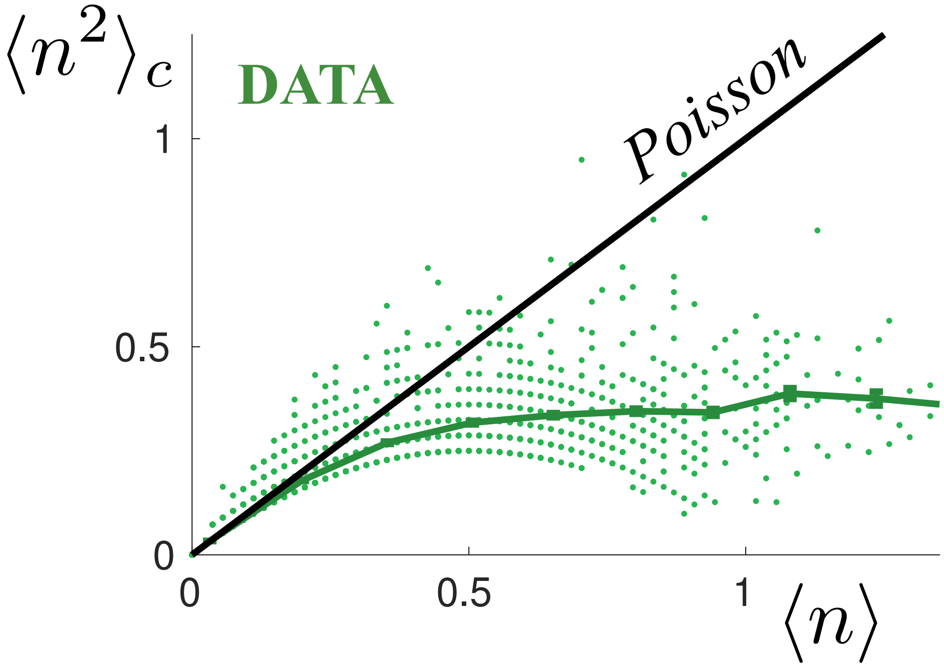




How to include **noise** in spike generation?

Stimulus processing → Rate in *[t, t+ΔT]* $\lambda_{S(t)}$ → Poisson statistics $P_{\text{Pois}}\left(n_t \,|\, \lambda_{S(t)} \right)$

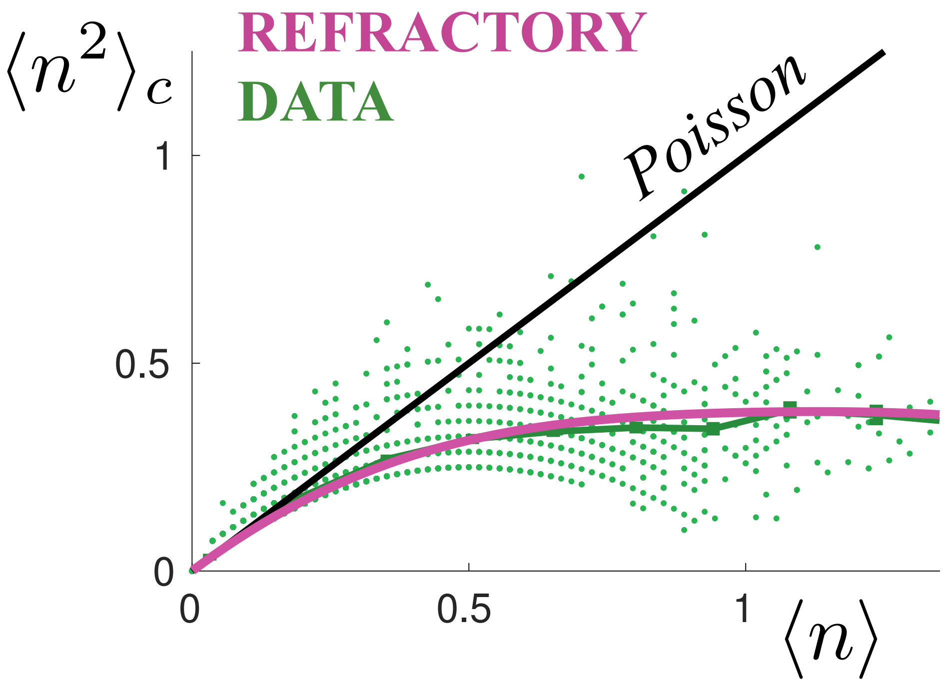
Prob of n spikes in ΔT

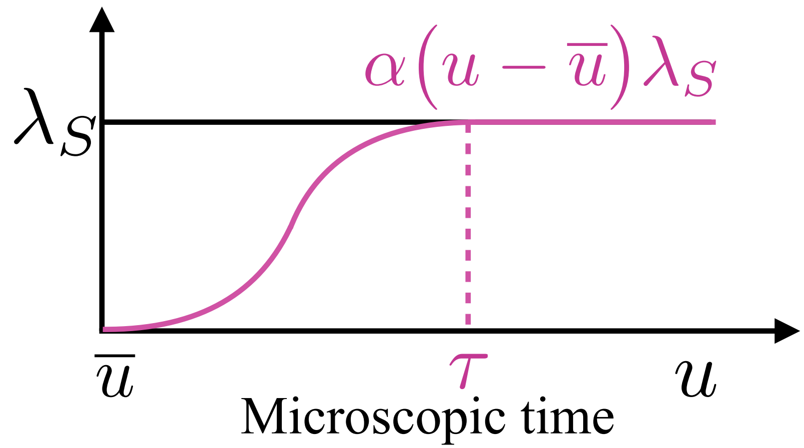


$$\lambda = \langle n \rangle = \langle n^2 \rangle_c$$

How to include **noise** in spike generation?

Stimulus processing → Rate in *[t, t+ΔT]* $\lambda_{S(t)}$ → Poisson statistics $P_{\mathrm{Pois}}\left(n_t \,|\, \lambda_{S(t)} \right)$



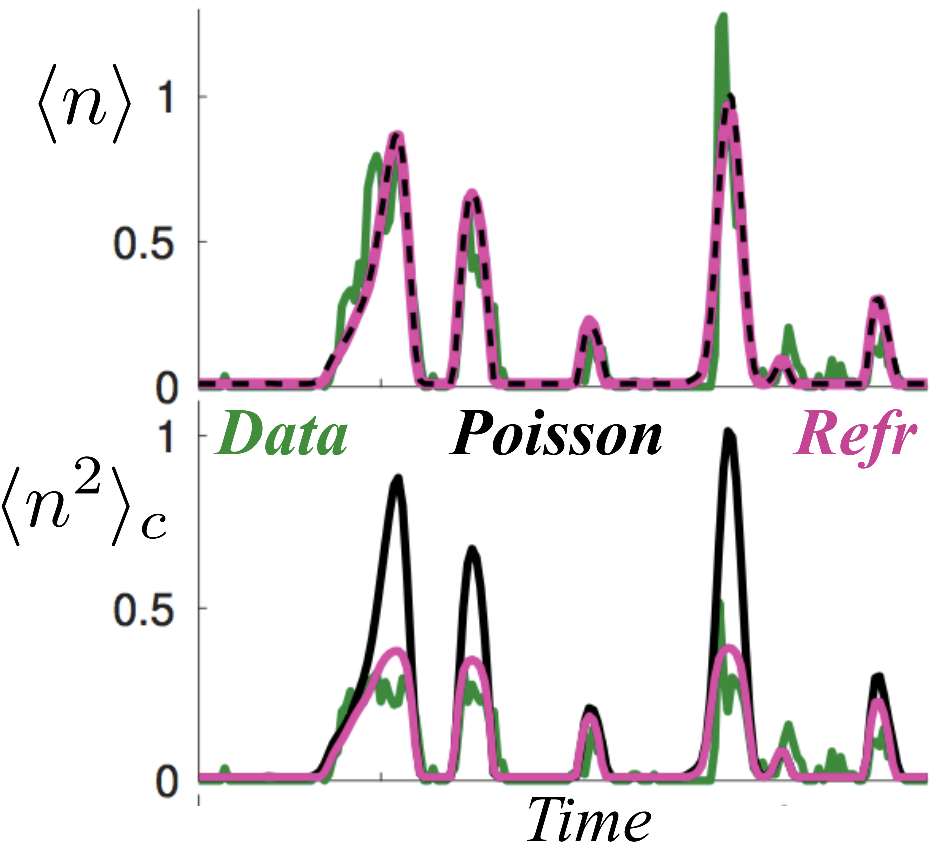


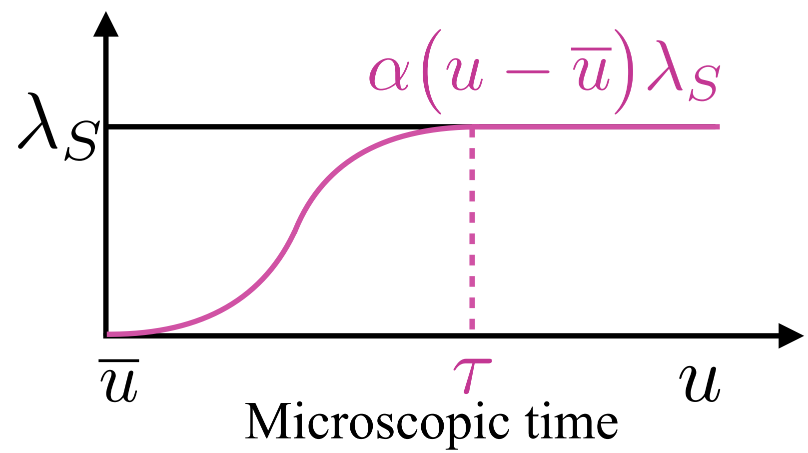
$$P_{\mathrm{Refr}} \underset{\tau \sim 0}{\sim} P_{\mathrm{Pois}}\, e^{-\gamma n^2 - \delta n^3}$$

Stimulus processing → Firing rate in ΔT $\alpha(u - \overline{u})\lambda_{S(t)}$ → **Refractory** statistics $P_{\mathrm{Refr}}\left(n_t \,|\, \lambda_{S(t)} \right)$

How to include **noise** in spike generation?

Stimulus processing → Rate in *[t, t+ΔT]* $\lambda_{S(t)}$ → Poisson statistics $P_{\text{Pois}}\left(n_t \mid \lambda_{S(t)}\right)$





$$P_{\text{Refr}} \underset{\tau\sim 0}{\sim} P_{\text{Pois}}\, e^{-\gamma n^2 - \delta n^3}$$

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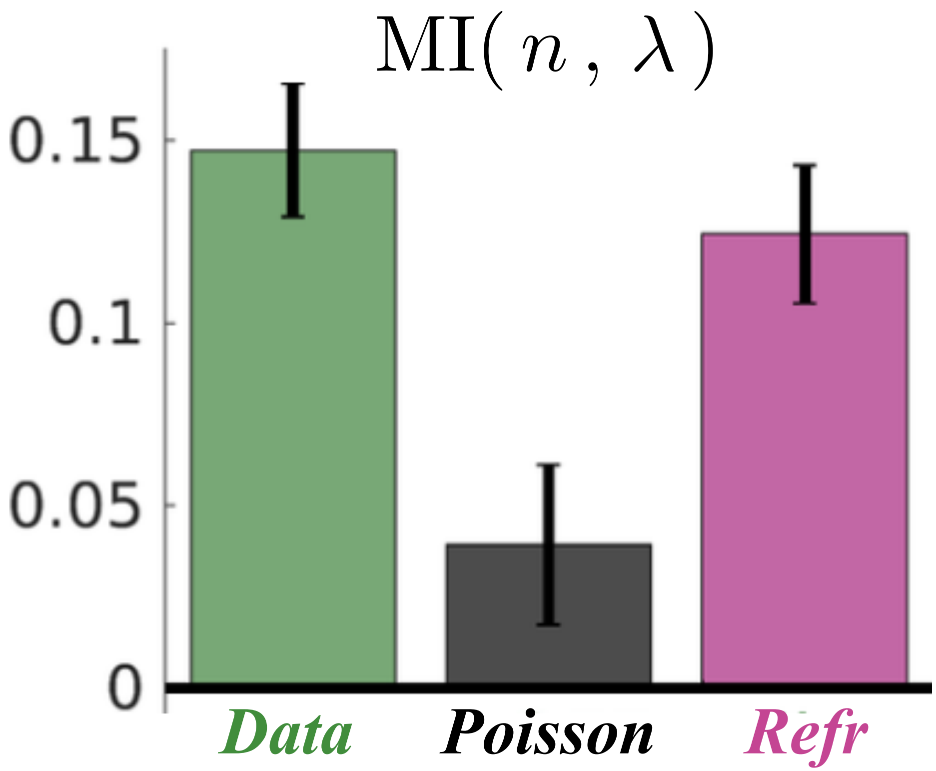

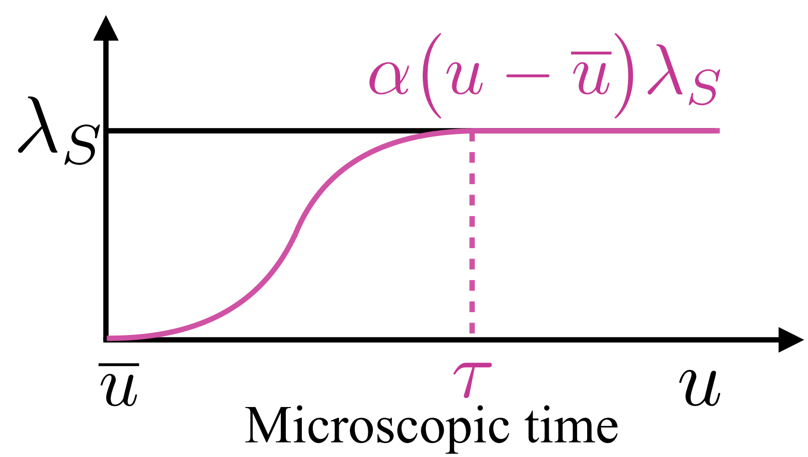

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Stimulus processing → Firing rate in ΔT $\alpha\left(u - \overline{u}\right)\lambda_{S(t)}$ → **Refractory** statistics $P_{\text{Refr}}\left(n_t \mid \lambda_{S(t)} \right)$

How to account for noise covariances?

Stimulus processing → **Prediction λ_S** → **Fluctuating fields** → **Interaction** network

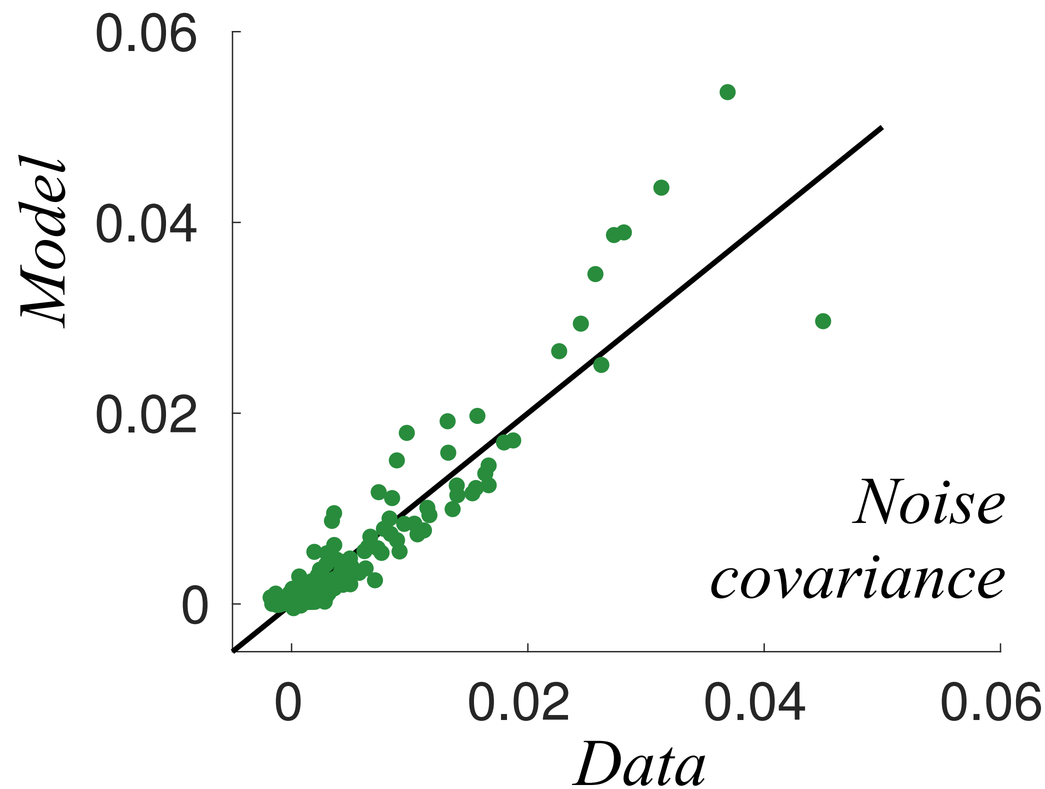
$$P^{\text{Pop}}_{\text{Refr}}(\{n_{it}\}) \sim \prod_t \left(\prod_i e^{h_i[\lambda_{S(t)}]n_{it}} \prod_{i<j} e^{n_{it} J_{ij} n_{jt}} \right)$$

TAP/AMP correction:

$$h_i[\lambda_{S(t)}]$$

↓

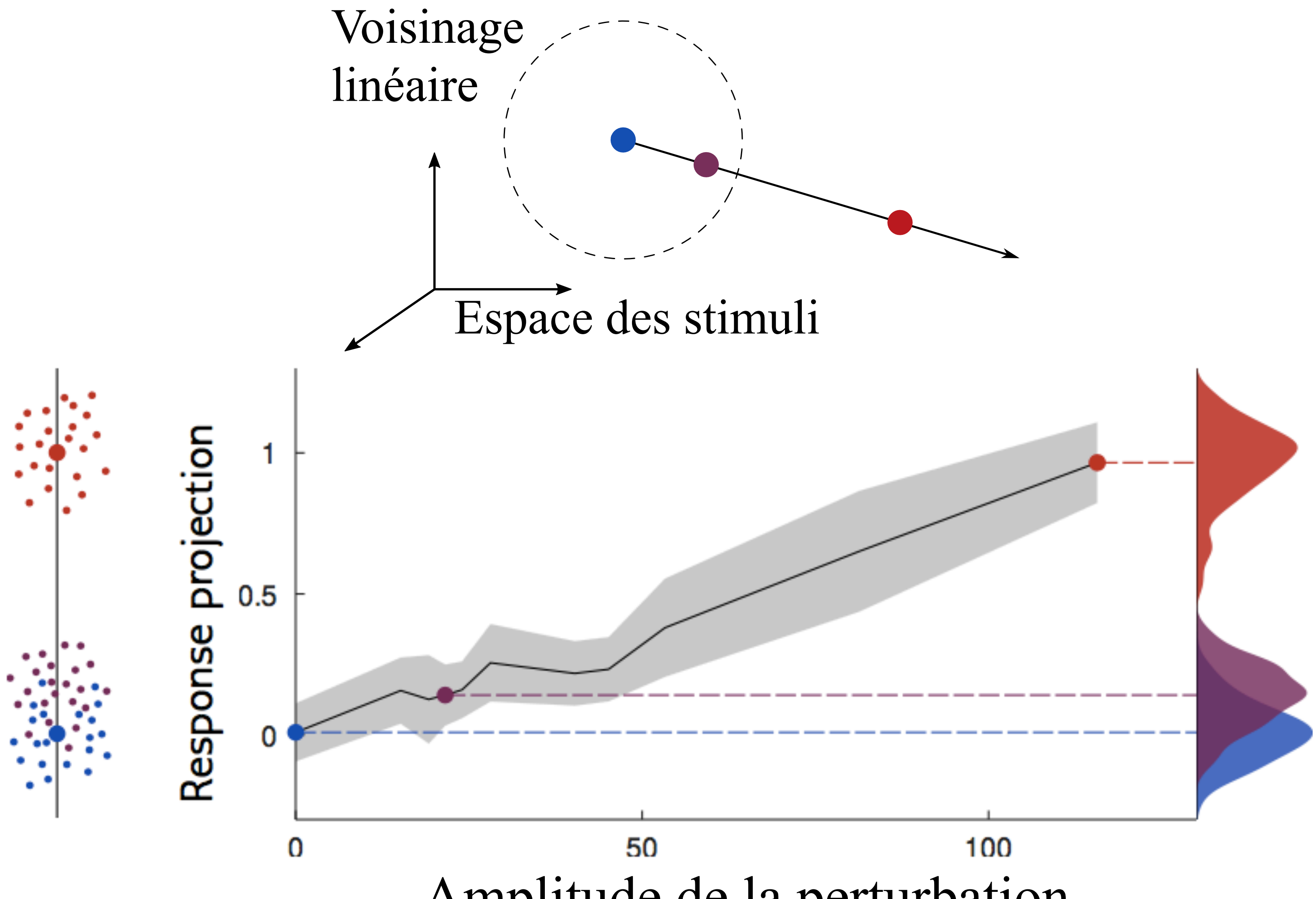
$$h_i[\lambda_{S(t)}] - \Delta h_i[\lambda_{S(t)}, J]$$



Comment décrire le traitement non-linéaire du stimulus?

Stratégie: **Développement limité 'expérimental'**

soumis



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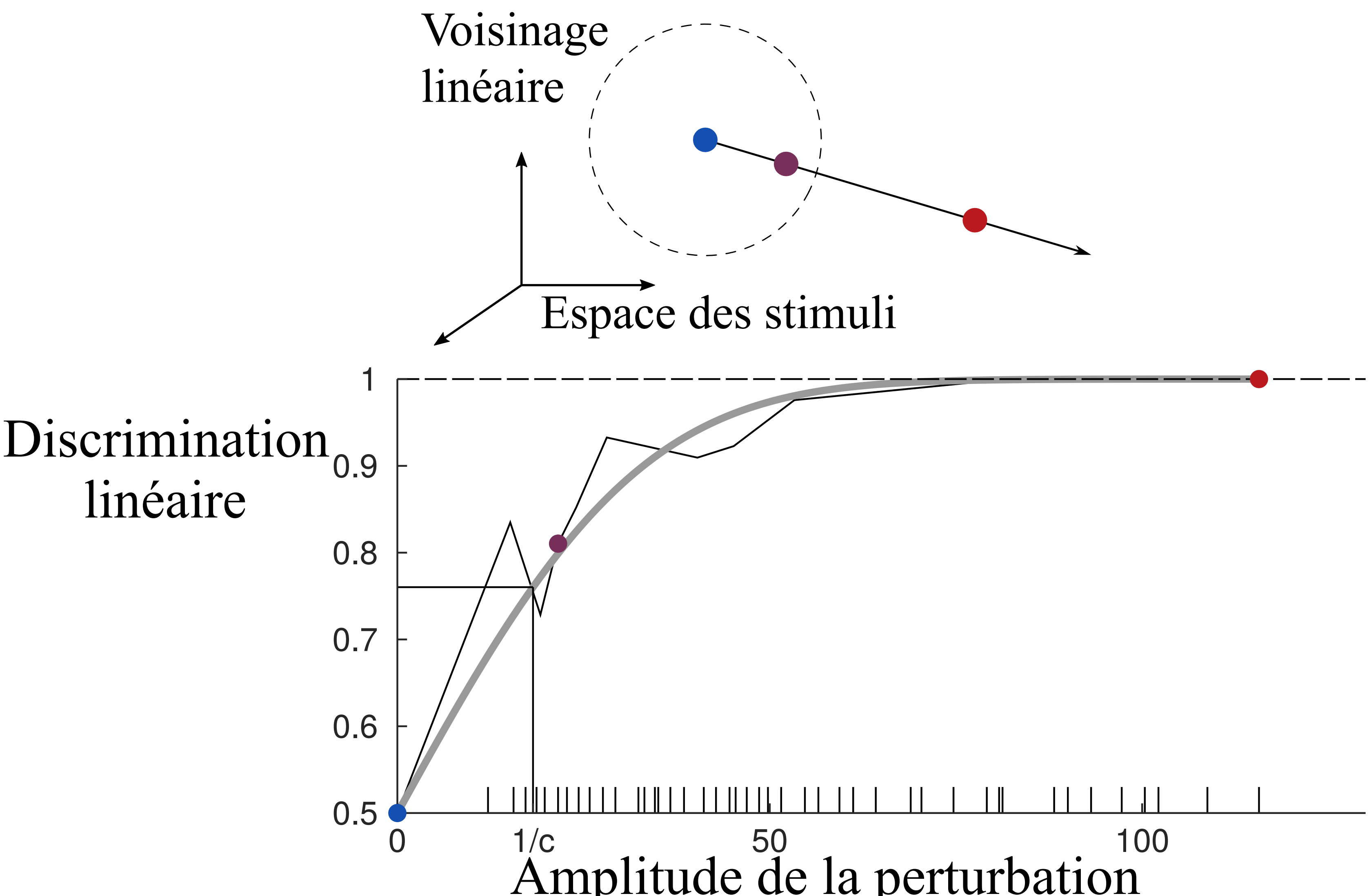
soumis



Comment décrire le traitement non-linéaire du stimulus?

Stratégie: Développement limité 'expérimental'

soumis

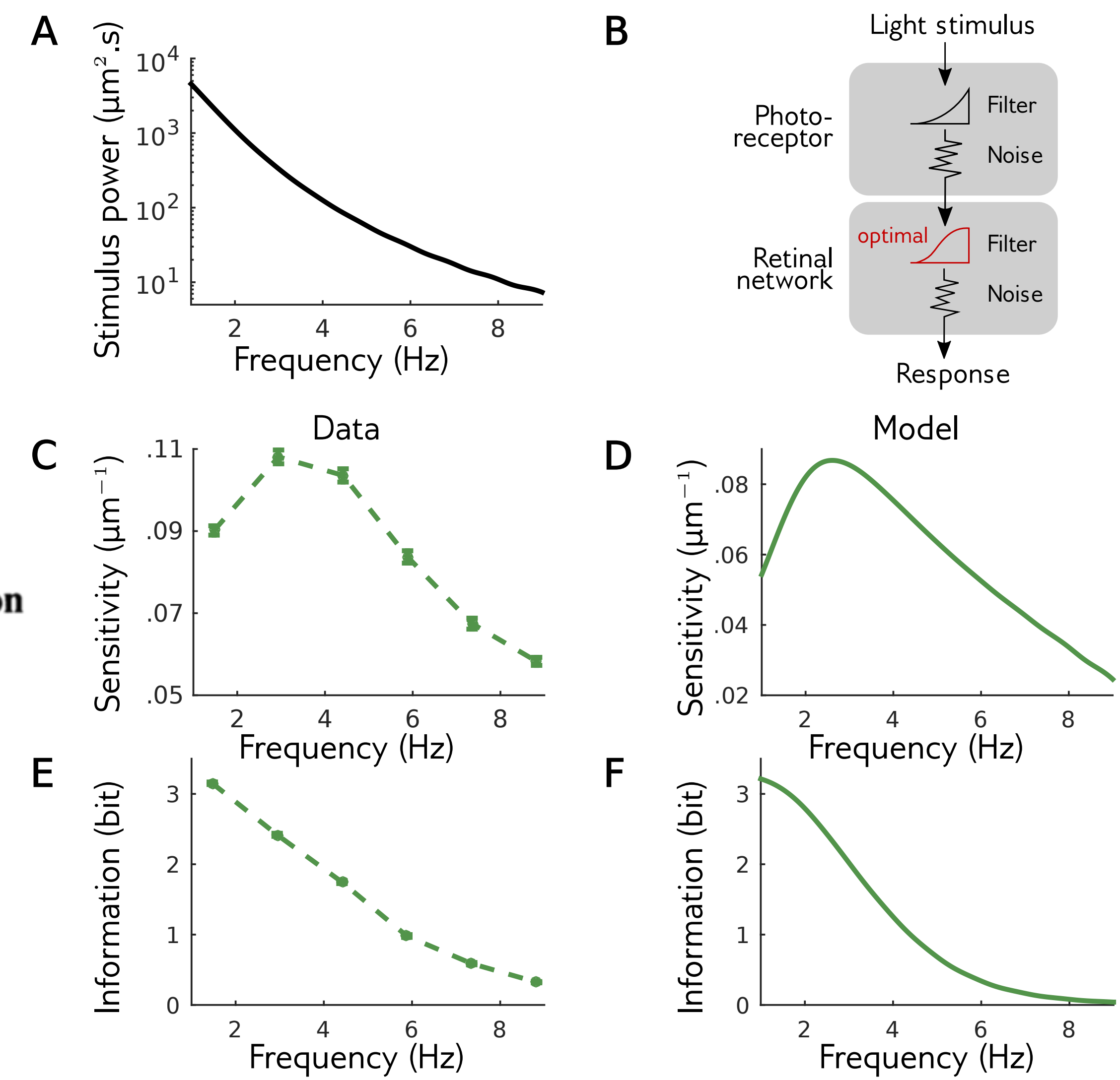
Codage efficace:

maximisation de l'information transmise

A theory of maximizing sensory information

J. H. van Hateren

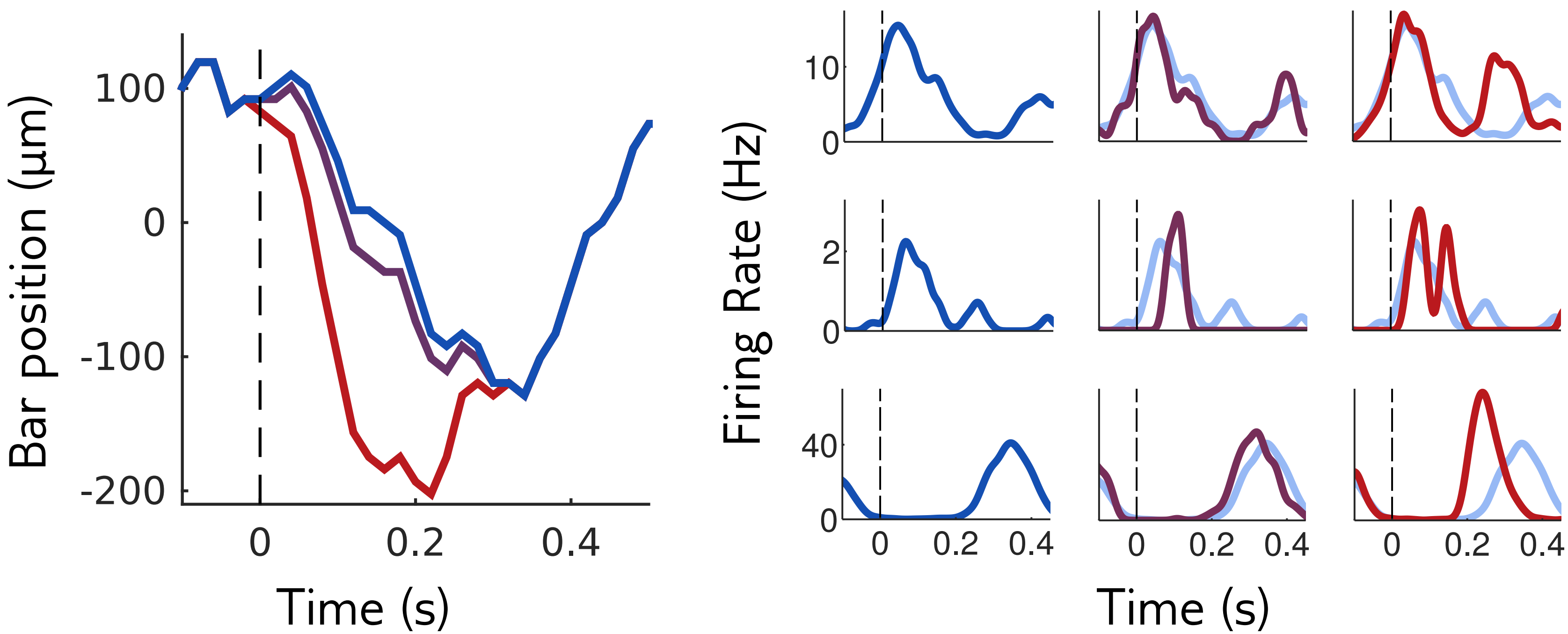
Biol. Cybern 1992



Recherche: Codage par le réseau de la rétine

Rétine: canale de communication

Stimulation visuelle *Réponse rétinienne*



L'Information visuelle module l'activité du réseau

Traitement du signal ***hautement non linéaire***