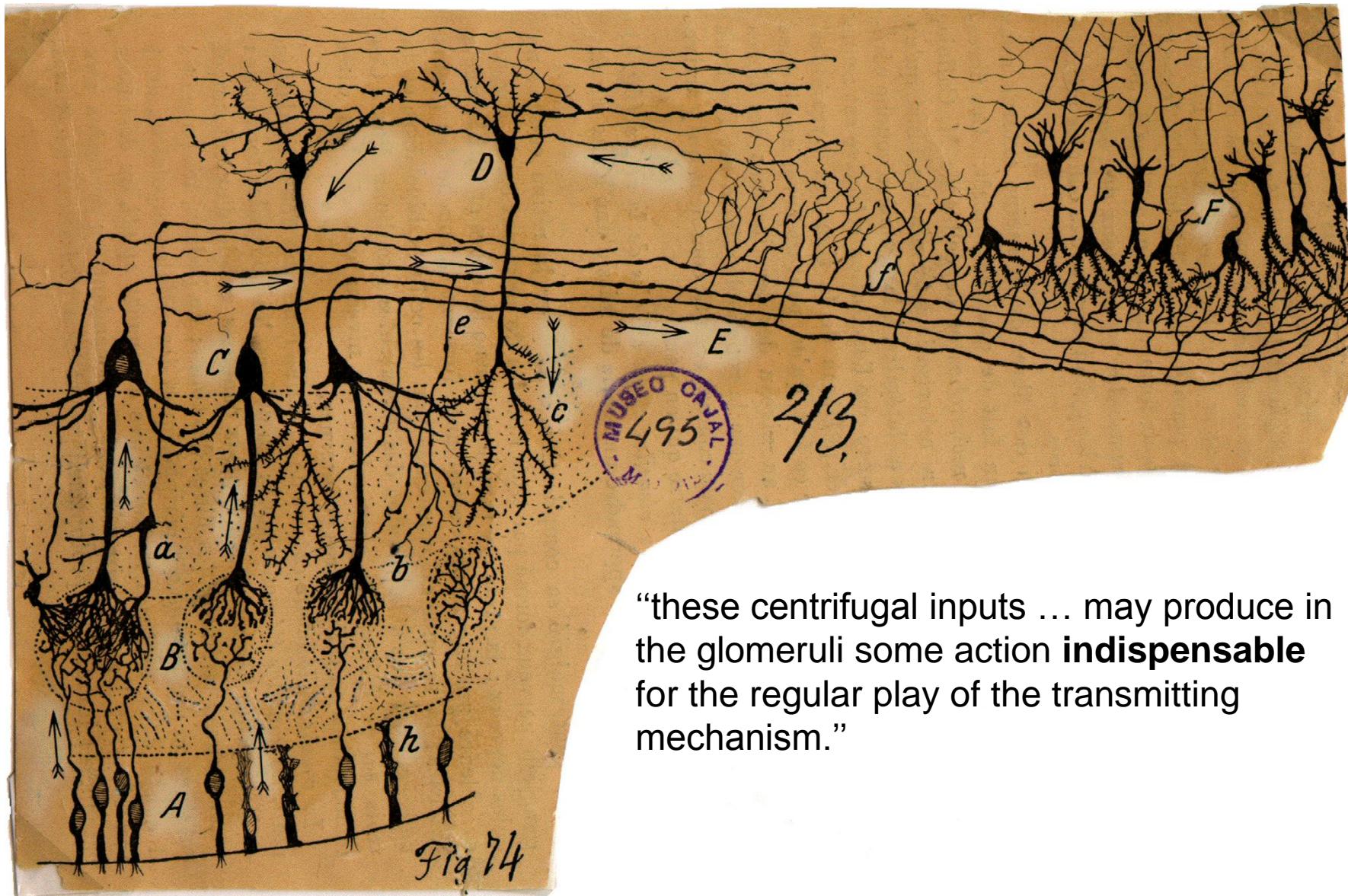


# A proposed role for cortical feedback in the identification of odors in complex olfactory scenes

Gonzalo Otazu  
Cold Spring Harbor Laboratory  
July 24<sup>th</sup>, 2015

# What is the role of cortical feedback?



“these centrifugal inputs ... may produce in the glomeruli some action **indispensable** for the regular play of the transmitting mechanism.”

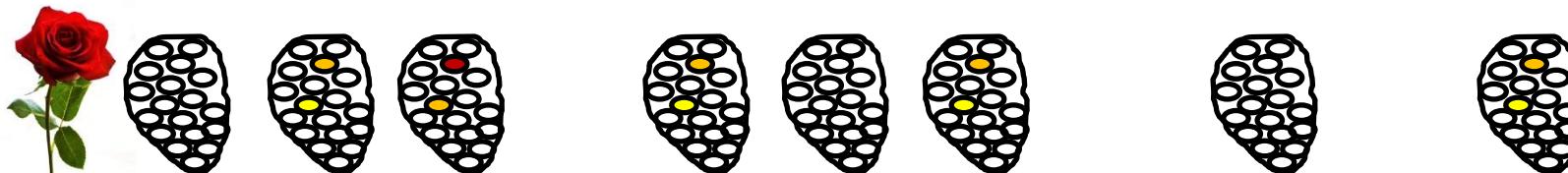
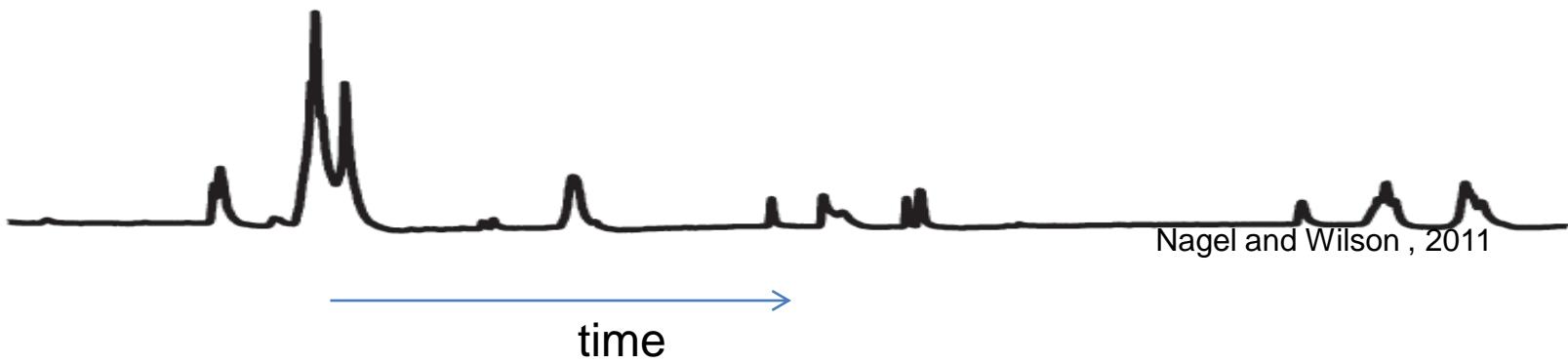
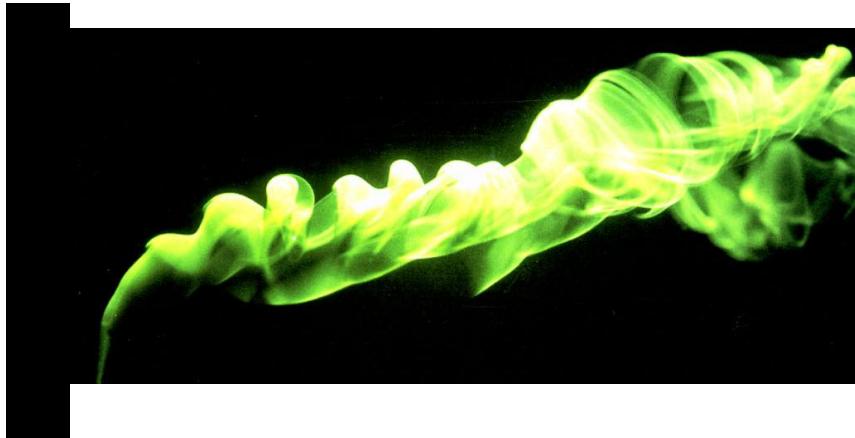
# Outline

1. Odor identification problem in complex scenes
2. Reformulation of the problem as estimation of odor presences
  - Solution is unique
  - Solution estimate the sources present under challenging conditions
3. Recursive implementation of the algorithm
4. Experimental characterization of cortical feedback and the effect of cortical input on bulbar output

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# Statement of the odor recognition problem

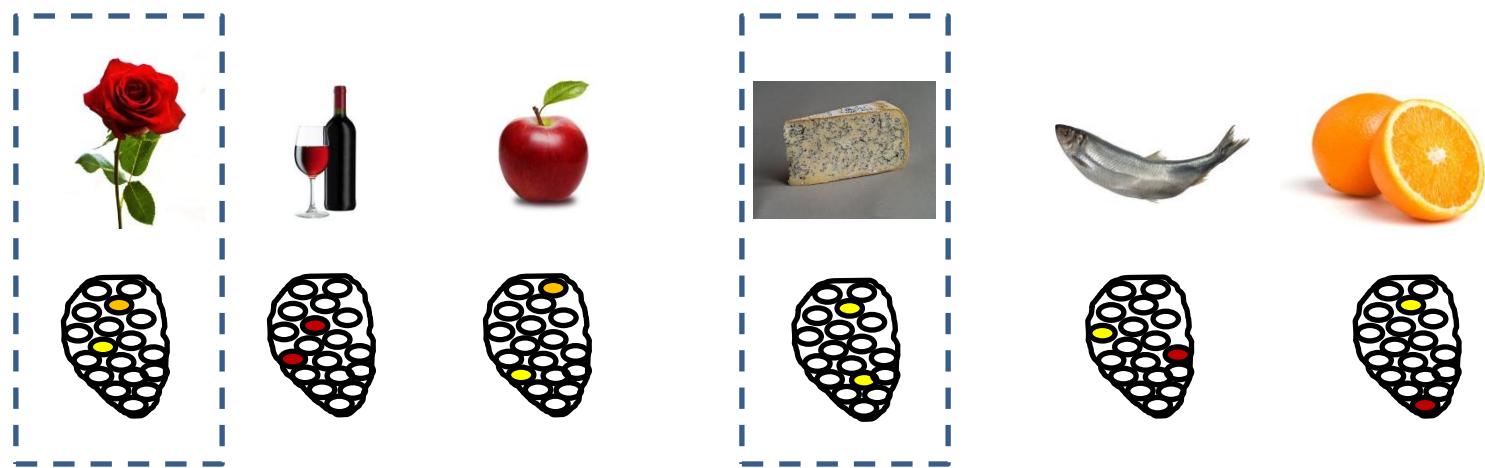
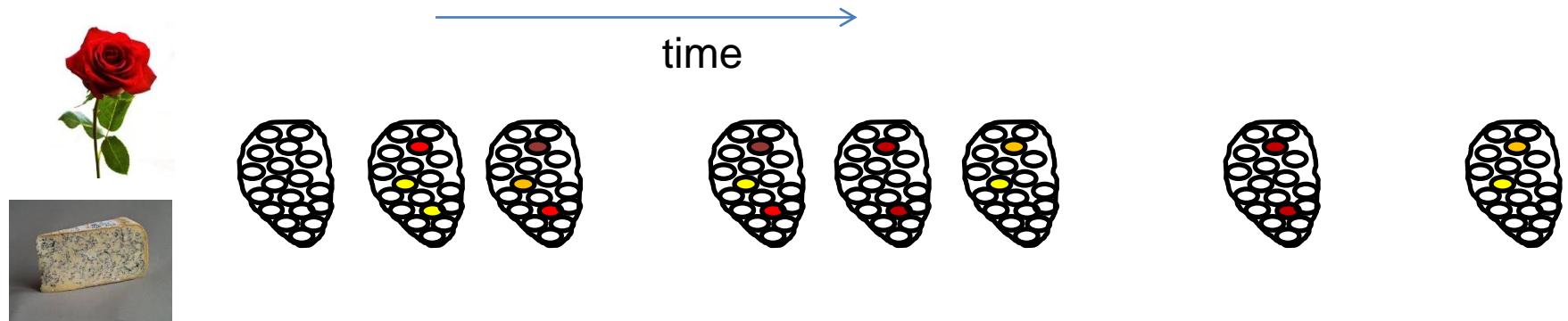


# Different odors have different glomerular patterns and different fluctuations in time

time →

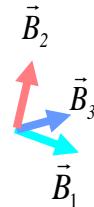
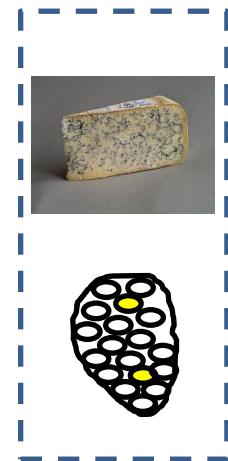
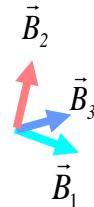
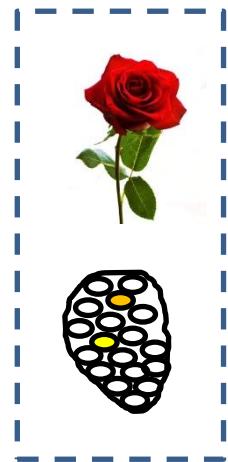


# Mixtures of time-varying signals create a complex olfactory scene



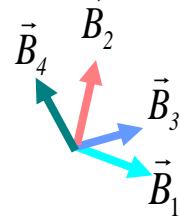
# Representation of odors as vectors

Dictionary of elements

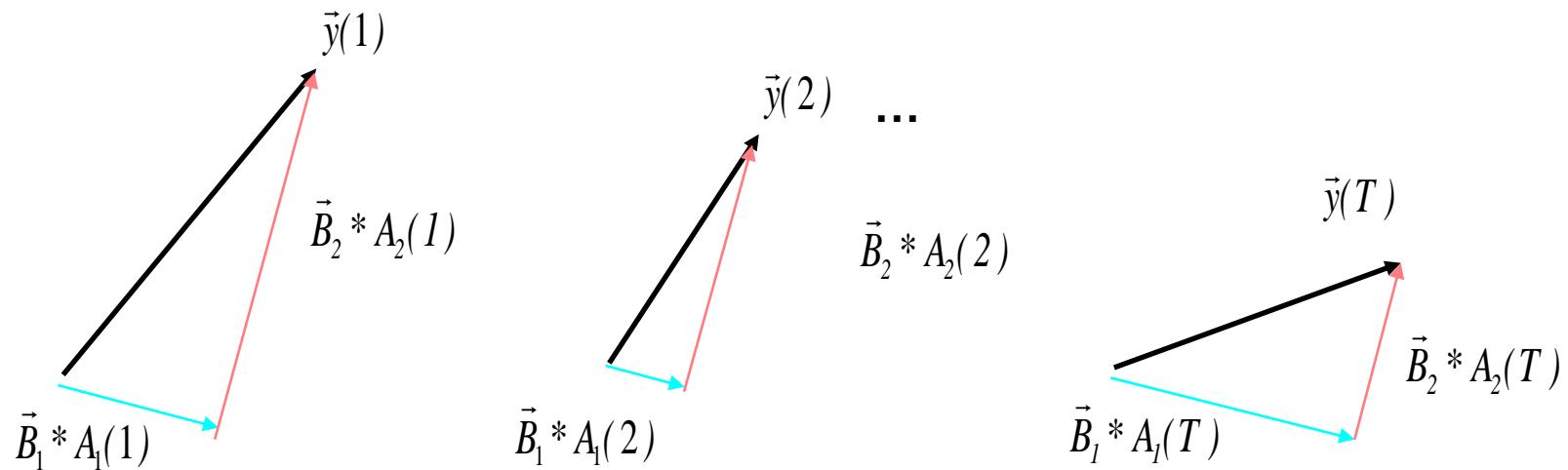
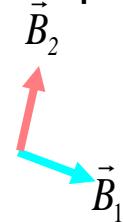


The observed signal is a combination of few elements

Dictionary of elements

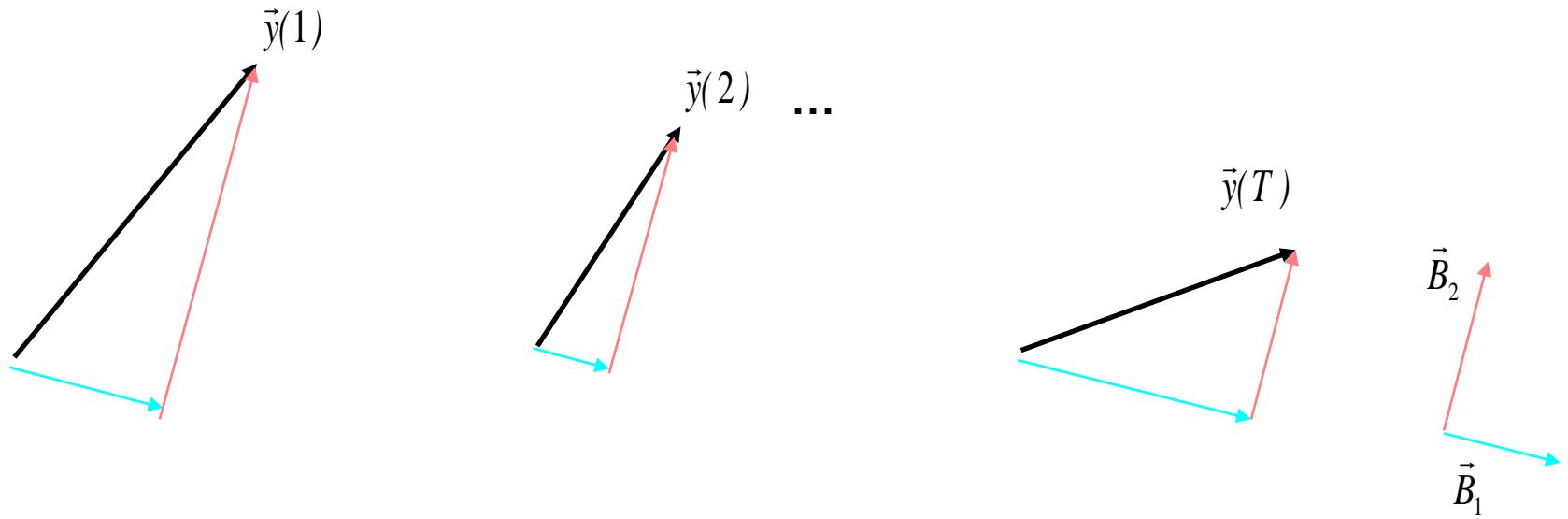


Elements present



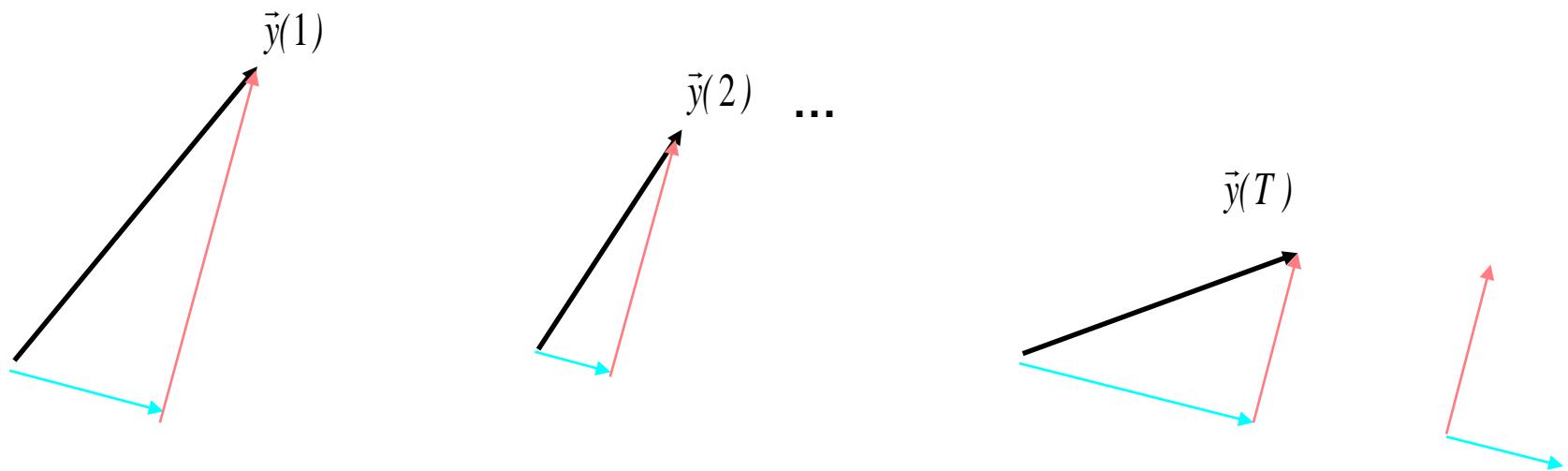
# Different approaches for parameter estimation

1) Find the independent (or uncorrelated )component (ICA, PCA) that create the signal and choose the dictionary elements that match the identified components.

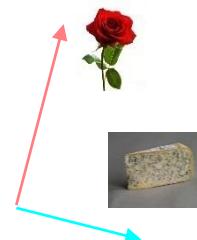
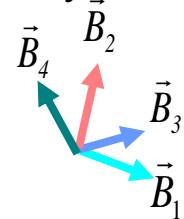


# Different approaches for parameter estimation

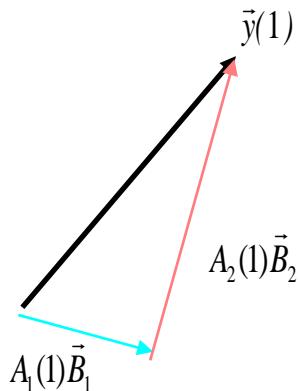
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Dictionary of elements

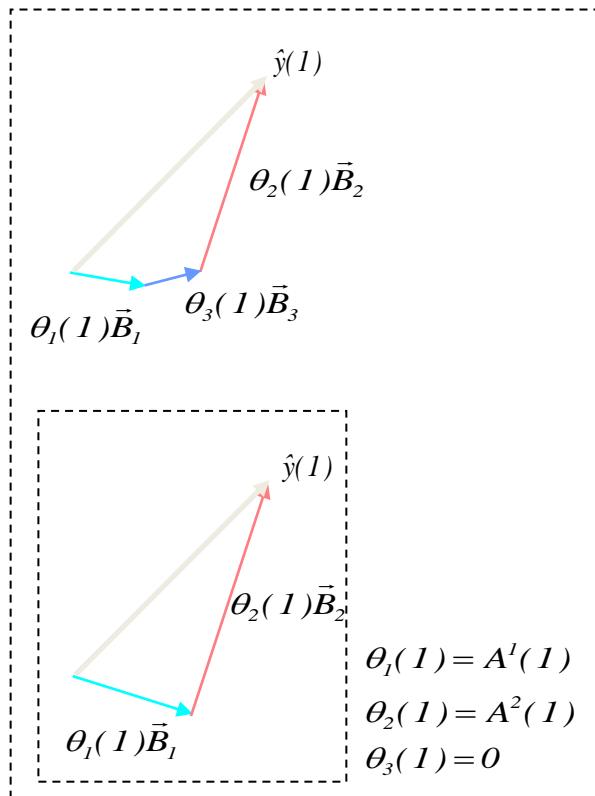
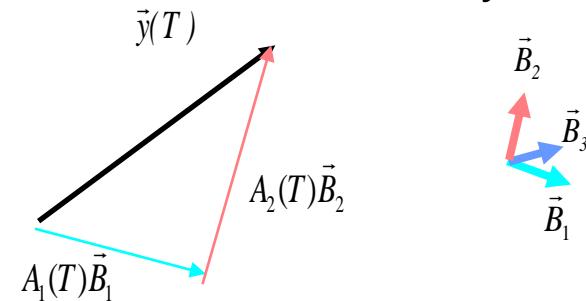


2) Minimize the estimation error using the sparsest solution



• • •

Dictionary of elements



Single solution is found by adding a sparseness constraint

# Outline

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# Reformulation of the estimation problem

$$A_i(t)$$

Time-varying  
amplitude of each  
dictionary element

Time invariant  
component

Time-varying  
component

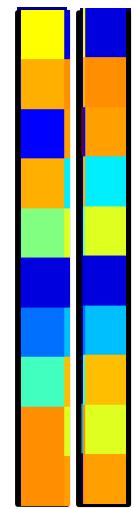
1, if element  $i$  is present

0, if element  $i$  is not present in a scene

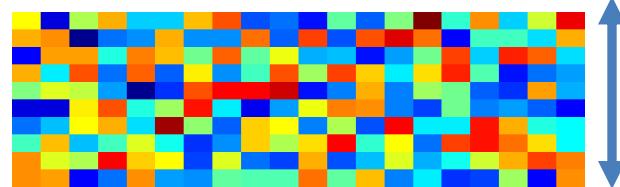
# Estimation of the time-varying component



$\vec{B}_i$



$$B = \text{M dictionary elements}$$



In general,  $M \gg n$

# Estimation of the time varying component

$\hat{y}(t)$

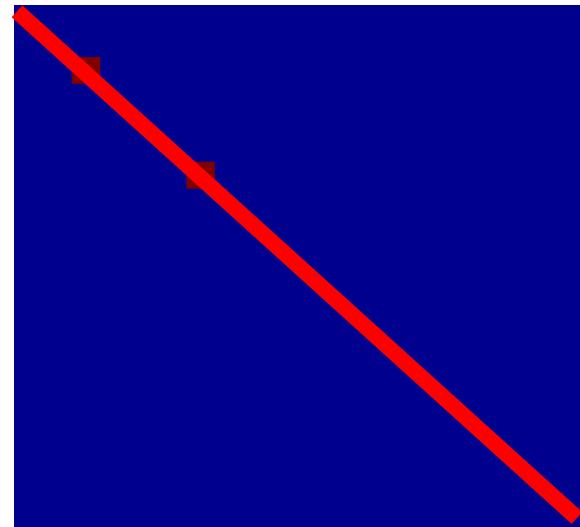
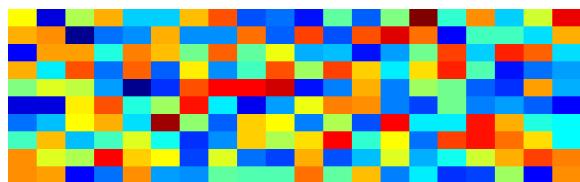
$B$

$\Theta$

$\hat{A}(t)$



=



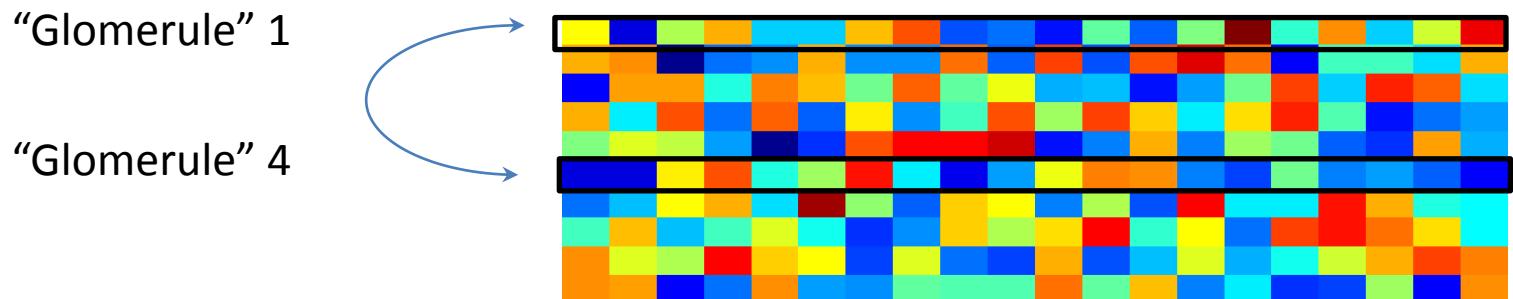
# Estimation of the time varying component

By calculating the estimated square error:

$$C = (\vec{y}(t) - \hat{y}(t))^T (\vec{y}(t) - \hat{y}(t))$$

And taking the derivative we obtain:

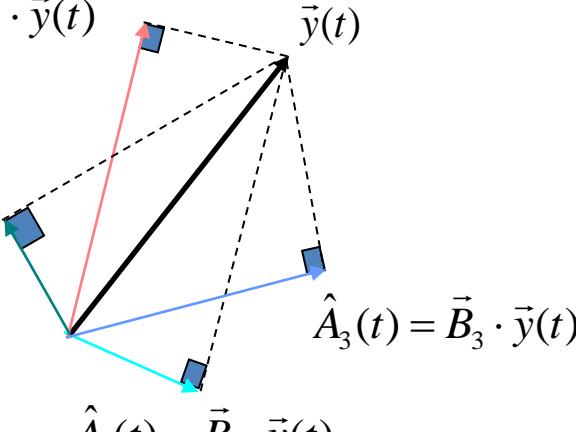
$$\hat{A}(t) = B^T (B B^T)^{-1} y(t) \approx B^T y(t)$$

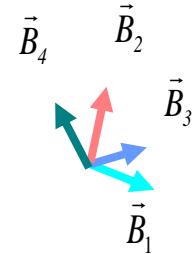


$$(B B^T)^{-1} \approx I \quad \text{if glomerular are uncorrelated}$$

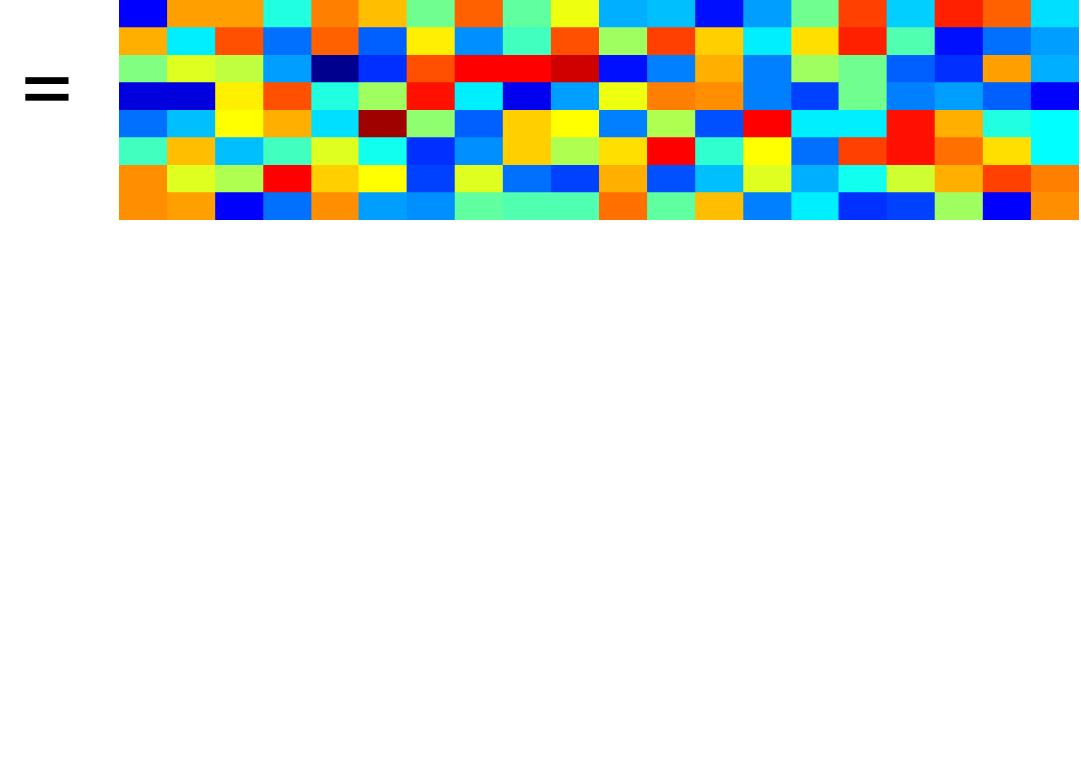
# Estimation of the time varying component

$$\hat{A}(t) \approx B^T y(t)$$

$$\hat{A}_2(t) = \vec{B}_2 \cdot \vec{y}(t)$$
$$\hat{A}_4(t) = \vec{B}_4 \cdot \vec{y}(t)$$
$$\hat{A}_3(t) = \vec{B}_3 \cdot \vec{y}(t)$$
$$\hat{A}_1(t) = \vec{B}_1 \cdot \vec{y}(t)$$




We can find a sparse solution at each time step

$$\vec{y}(1) = B \theta(1)$$


We can find a sparse solution at each time step

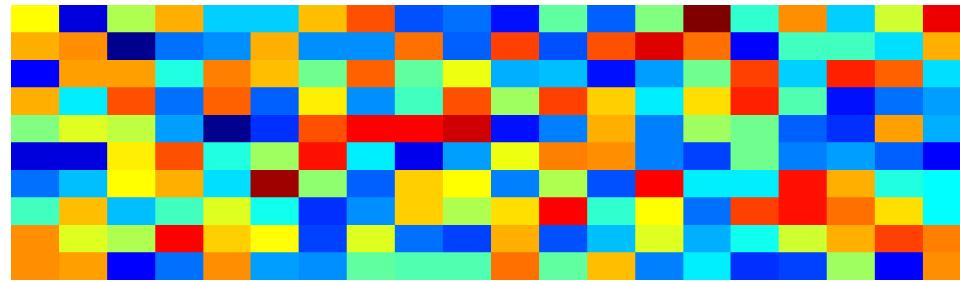
$$\vec{y}(2) = B \theta(2)$$

We can find a sparse solution at each time step

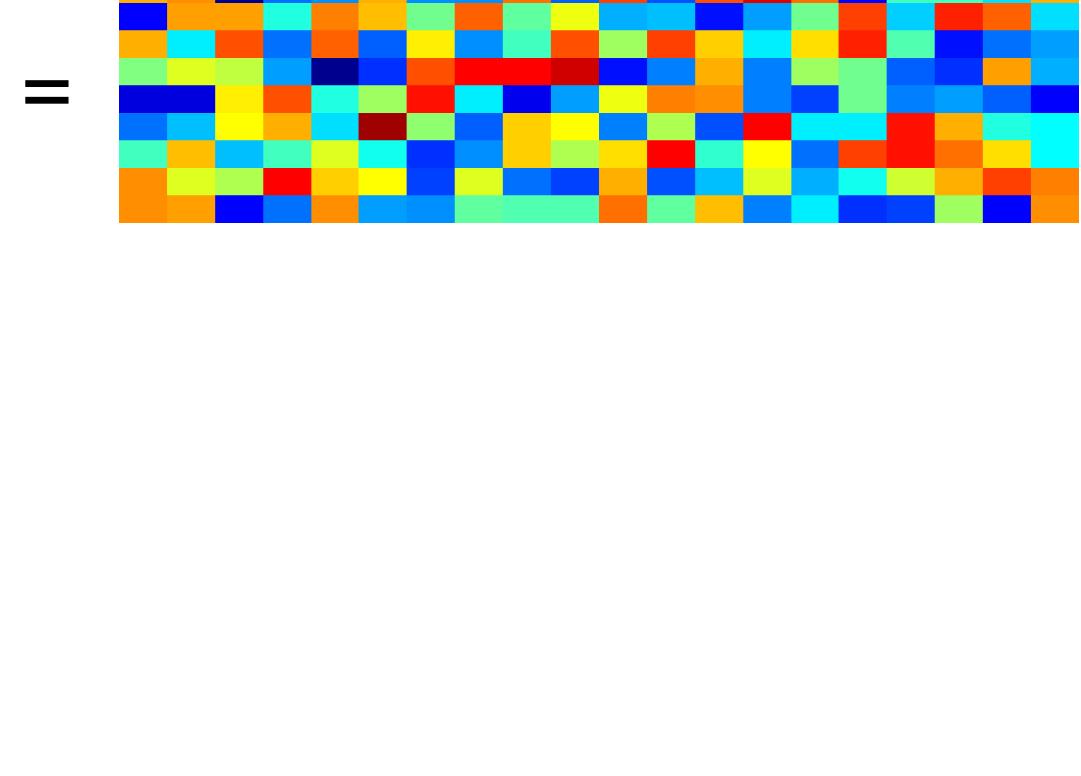
$$\vec{y}(3) = B \vec{\theta}(3)$$

We can find a sparse solution at each time step

$$\vec{y}(4) \quad B \quad \theta(4)$$

$$= \begin{matrix} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{matrix} = \begin{matrix} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{matrix}$$


We find a single solution for all time steps

$$\vec{y}(1) = B \theta(1)$$


We find a single solution for all time steps

$$\vec{y}(1) = \varphi(1) \theta$$

$$\vec{\varphi}_1(1) \quad \vec{B}_1 \quad \vec{B}_1 \hat{A}_1 \quad \vec{y}(1)$$



We find a single solution for all time steps

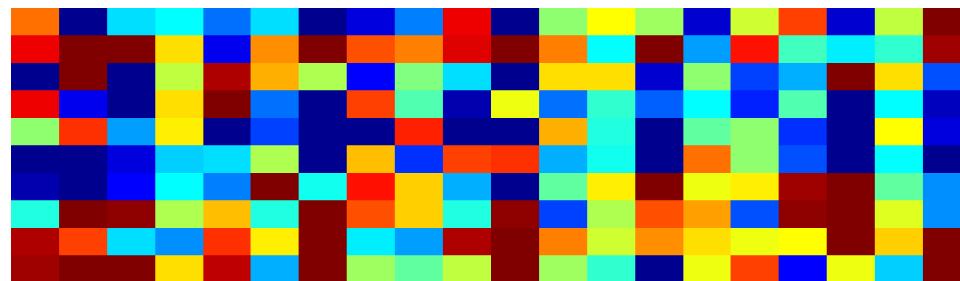
$\vec{y}(1)$

$\varphi(1)$

$\theta$

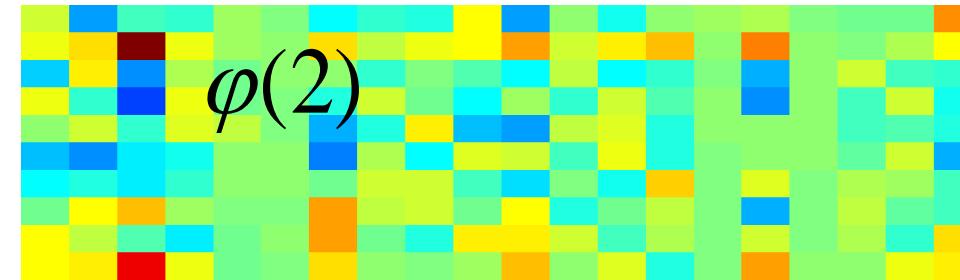


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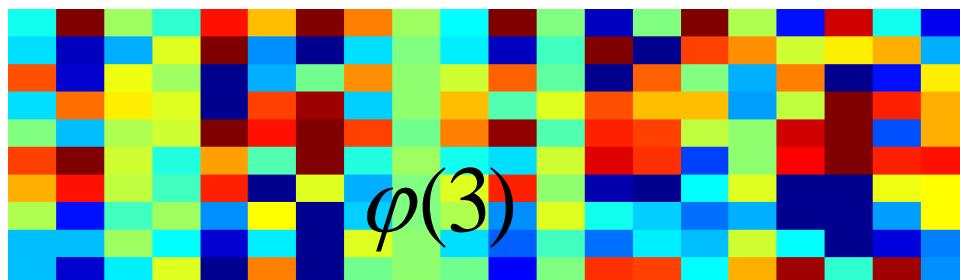
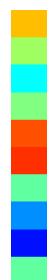
$\vec{y}(2)$

$\varphi(2)$



$\vec{y}(3)$

$\varphi(3)$



# We find a single solution for all time steps

$$Y = \Phi \theta$$

The diagram illustrates the decomposition of a matrix  $Y$  into the product of two matrices,  $\Phi$  and  $\theta$ . The matrix  $Y$  is shown in three different color-coded representations, each consisting of a 4x4 grid of colored squares. To the left of the first representation of  $Y$ , there is an equals sign (=). Above the first representation of  $Y$  is the symbol  $\Phi$ , and above the second representation of  $Y$  is the symbol  $\theta$ . To the right of the second representation of  $Y$  is a vertical bar divided into two segments: the top segment is dark blue and the bottom segment is dark red.

We find a single solution for all time steps

$$Y = \Phi\theta$$

The solution is given by

$$\theta = (\Phi^T \Phi)^{-1} \Phi^T Y \quad \smile$$

Otazu and Leibold, *PLoS One*, 2011

However, in order for the solution to be unique, we require

$$(\Phi^T \Phi)$$

to be invertible. Under which conditions is it invertible?



# The matrix $\Phi^T \Phi$ is positive definite

$$x^T (\Phi^T \Phi) x > 0 \quad \text{For all vectors } x$$

The single elements of  $\Phi^T \Phi$  are:  $(\Phi^T \Phi)_{i,j} = \sum_{t=1}^T (\vec{y}(t) \cdot \vec{B}_i)(\vec{y}(t) \cdot \vec{B}_j)(\vec{B}_i \cdot \vec{B}_j)$

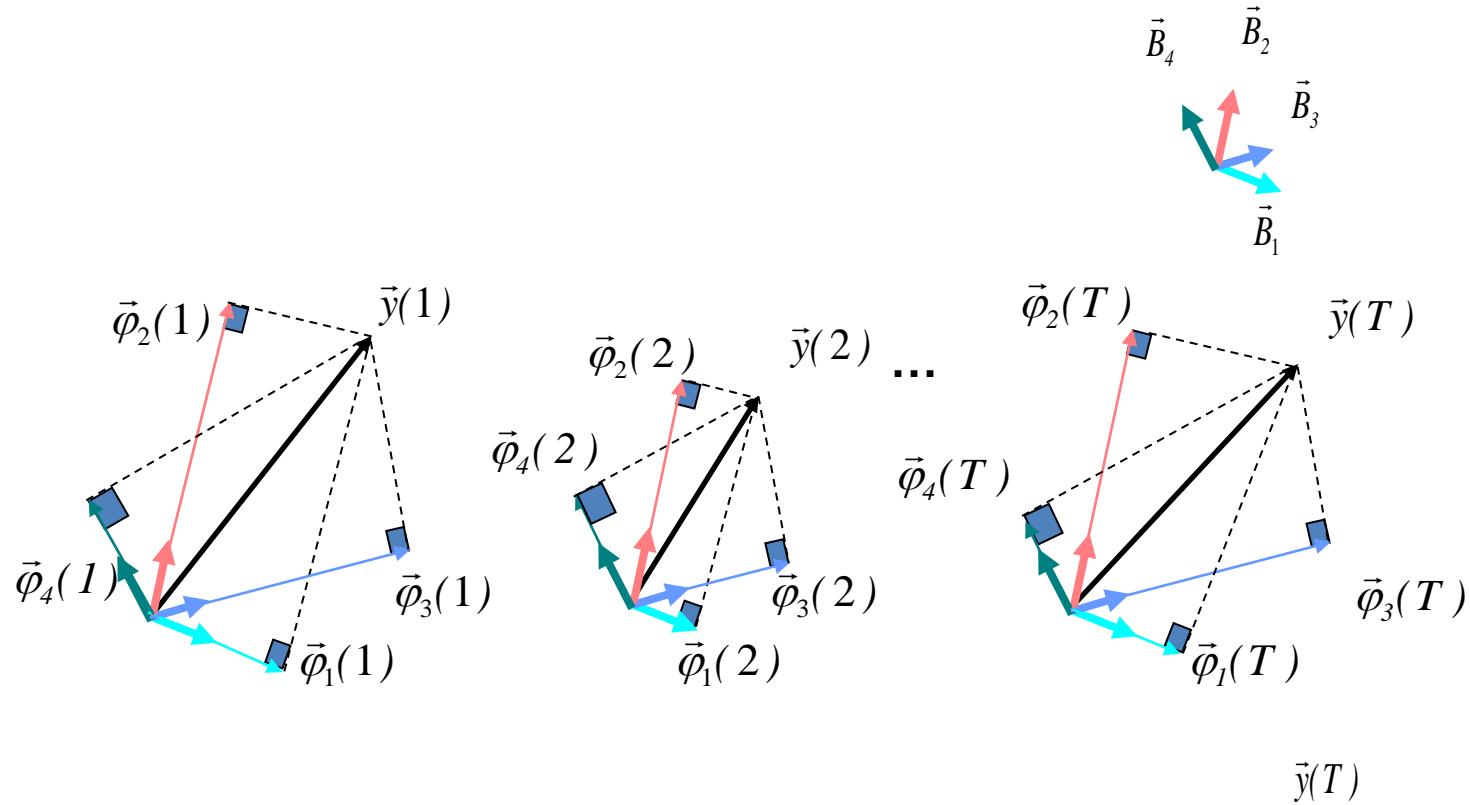
$$x^T (\Phi^T \Phi) x = \sum_{t=1}^T \sum_{i=1}^N \sum_{j=1}^N x_i x_j (\vec{y}(t) \cdot \vec{B}_i)(\vec{y}(t) \cdot \vec{B}_j)(\vec{B}_i \cdot \vec{B}_j)$$

$$= \sum_{t=1}^T \sum_{m=1}^M \left( \sum_{i=1}^N \frac{(x_i)}{\sqrt{2}} (\vec{y}(t) \cdot \vec{B}_i)(B_{m,i}) \right)^2 + \sum_{t=1}^T \sum_{i=1}^N (x_i)^2 (\vec{y}(t) \cdot \vec{B}_i)^2 \left( \frac{1}{2} \right) > 0$$

- All the eigenvalues of  $\Phi^T \Phi$  are positive, as long as we consider only dictionary elements  $\vec{B}_i$  where  $\vec{y}(t) \cdot \vec{B}_i > 0$ , for any  $t$
- No zero eigenvalues, therefore,  $\Phi^T \Phi$  is invertible
- Solution is unique

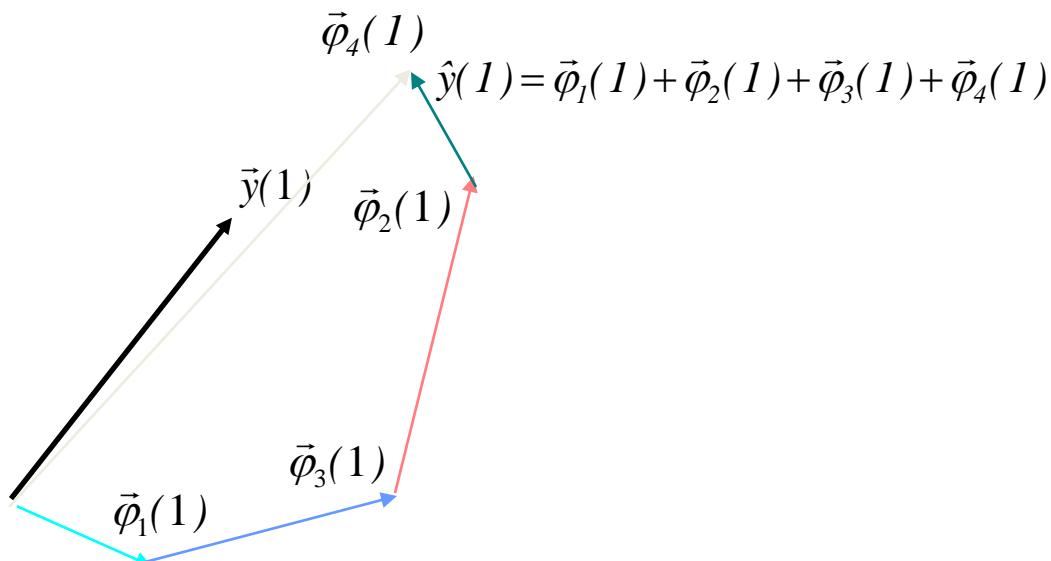
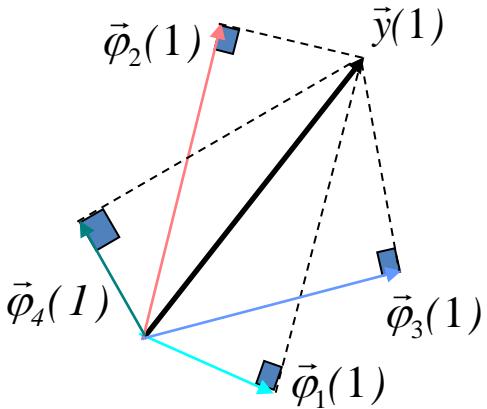
# Corrected Projections Algorithm (CPA)

1) Calculate the projections



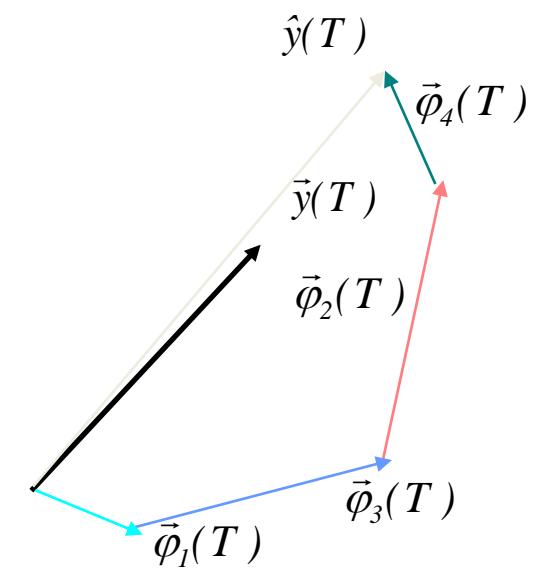
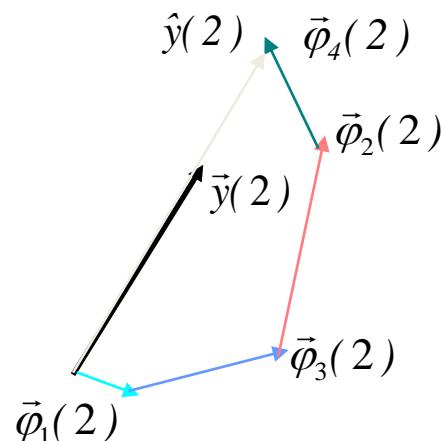
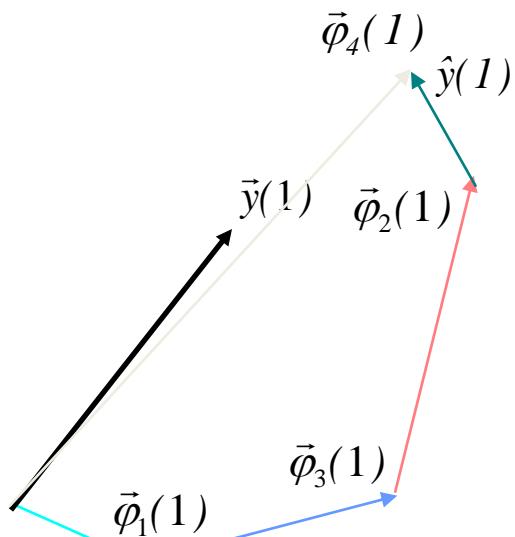
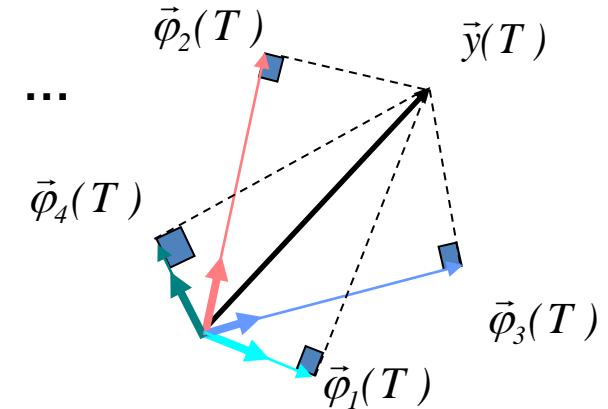
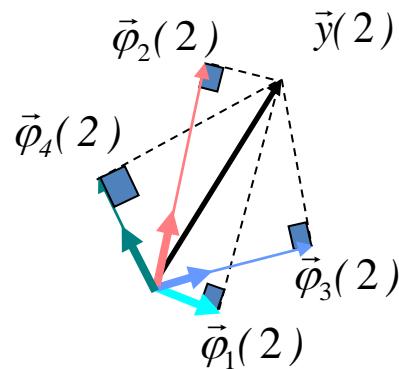
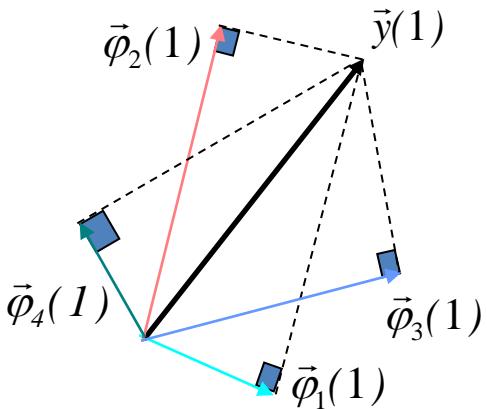
# Corrected Projections Algorithm (CPA)

2) Use the projections to create an estimate of the observed signal



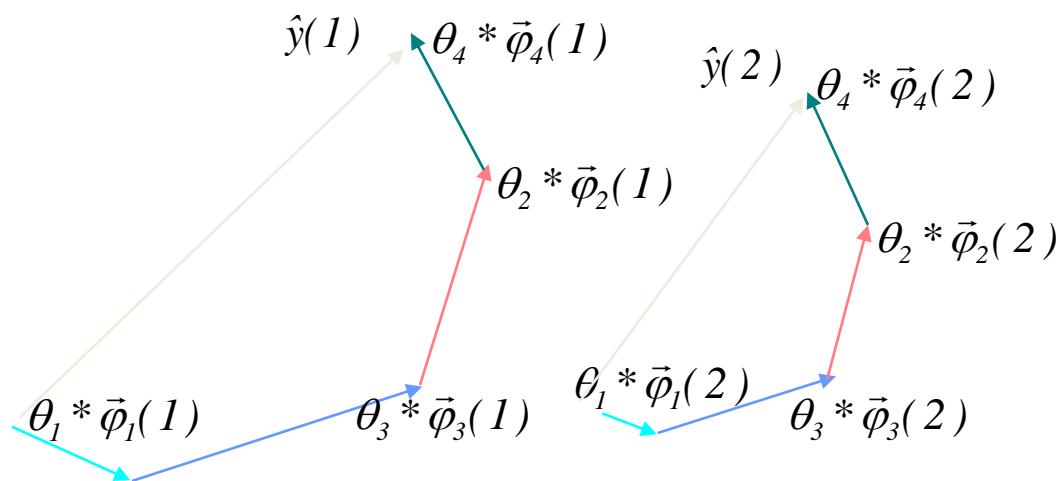
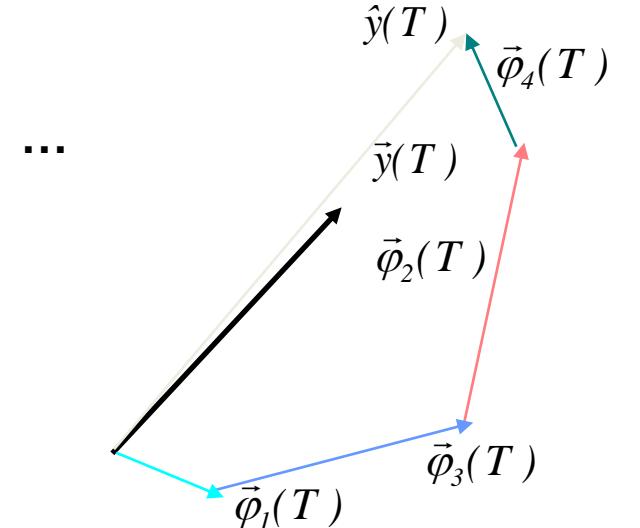
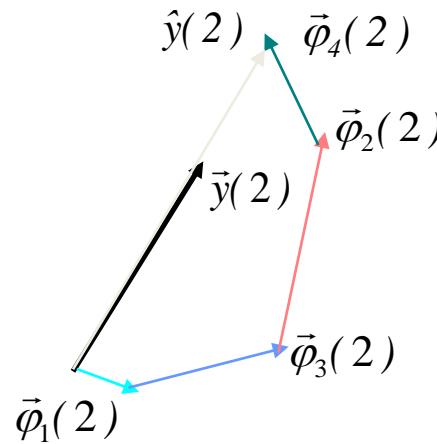
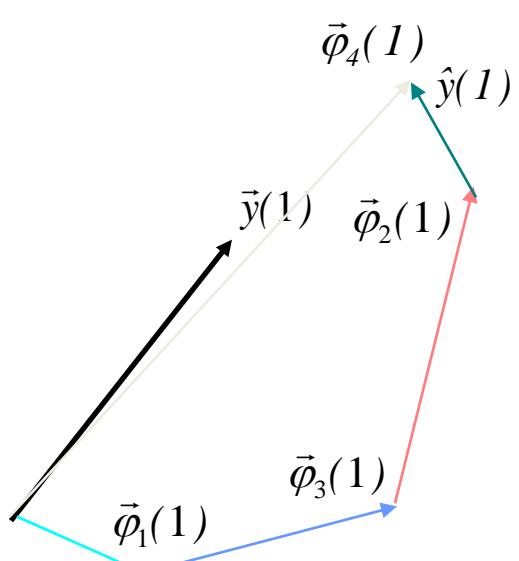
# Corrected Projections Algorithm (CPA)

2) Use the projections to create an estimate of the observed signal



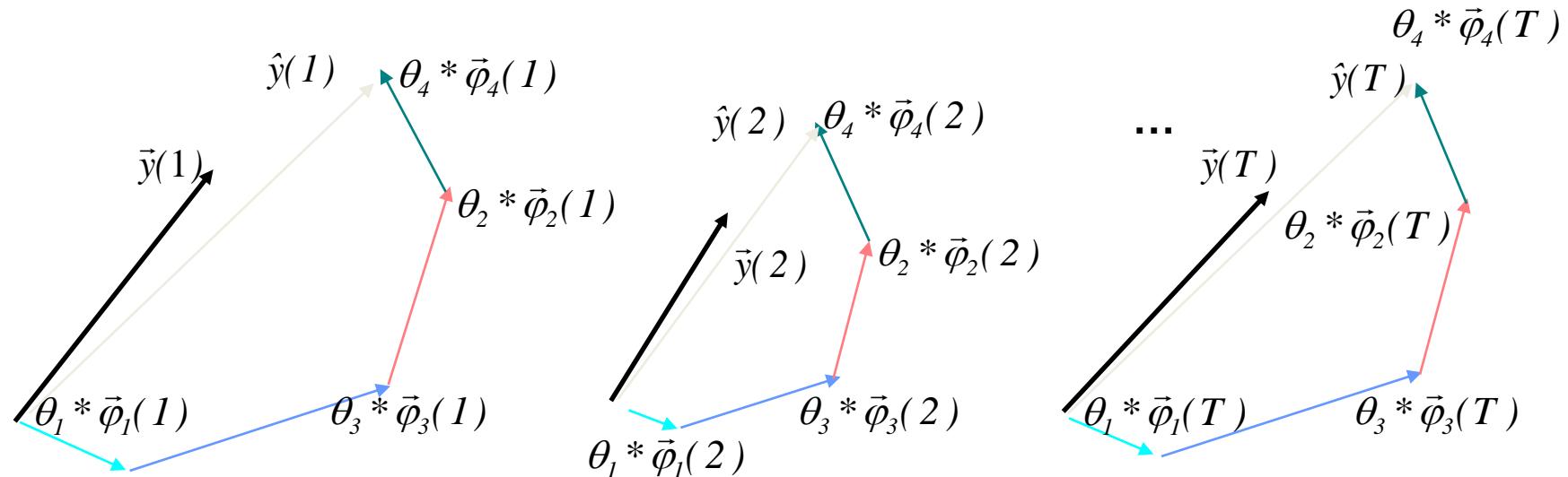
# Corrected Projections Algorithm (CPA)

3) Correct the projections by a factor  $\vartheta$



# Corrected Projections Algorithm (CPA)

3) Find the  $\theta$  that minimize the error between the estimate and the observed signal



Minimal error is given if the sources present are orthogonal

Model of the olfactory scene

$$\vec{y}(t) = A_1(t)\vec{B}_1 + A_2(t)\vec{B}_2$$

Lets assume that  $\vec{B}_1$  and  $\vec{B}_2$  are orthogonal, that is:

$$\vec{B}_1 \cdot \vec{B}_2 = 0$$

CPA creates its estimate using the projections

$$\hat{y}(t) = \theta_1(\vec{y}(t) \cdot \vec{B}_1)\vec{B}_1 + \theta_2(\vec{y}(t) \cdot \vec{B}_2)\vec{B}_2 + \dots + \theta_n(\vec{y}(t) \cdot \vec{B}_n)\vec{B}_n$$

$$\begin{aligned} \hat{y}(t) = & \theta_1\left(A_1(t)\vec{B}_1 \cdot \vec{B}_1 + A_2(t)\vec{B}_2 \cdot \vec{B}_1\right)\vec{B}_1 + \theta_2\left(A_1(t)\vec{B}_1 \cdot \vec{B}_2 + A_2(t)\vec{B}_2 \cdot \vec{B}_2\right)\vec{B}_2 \\ & + \dots + \theta_n(\vec{y}(t) \cdot \vec{B}_n)\vec{B}_n \end{aligned}$$

$$\hat{y}(t) = \theta_1 A_1(t)\vec{B}_1 + \theta_2 A_2(t)\vec{B}_2 + \dots + \theta_n(\vec{y}(t) \cdot \vec{B}_n)\vec{B}_n$$

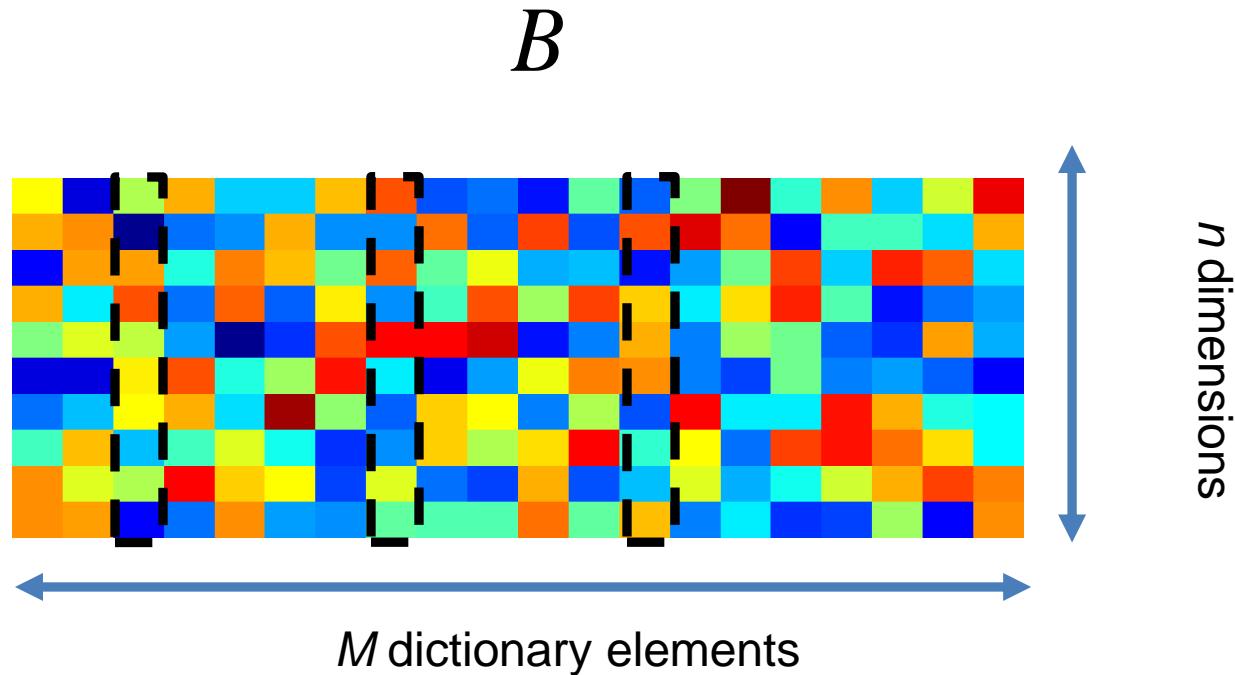
If we choose then  $\theta_1=1$ ,  $\theta_2=1$ , and  $\theta_k=0$ , if  $k \neq 1,2$

$$\hat{y}(t) = A_1(t)\vec{B}_1 + A_2(t)\vec{B}_2 = \vec{y}(t)$$

Therefore

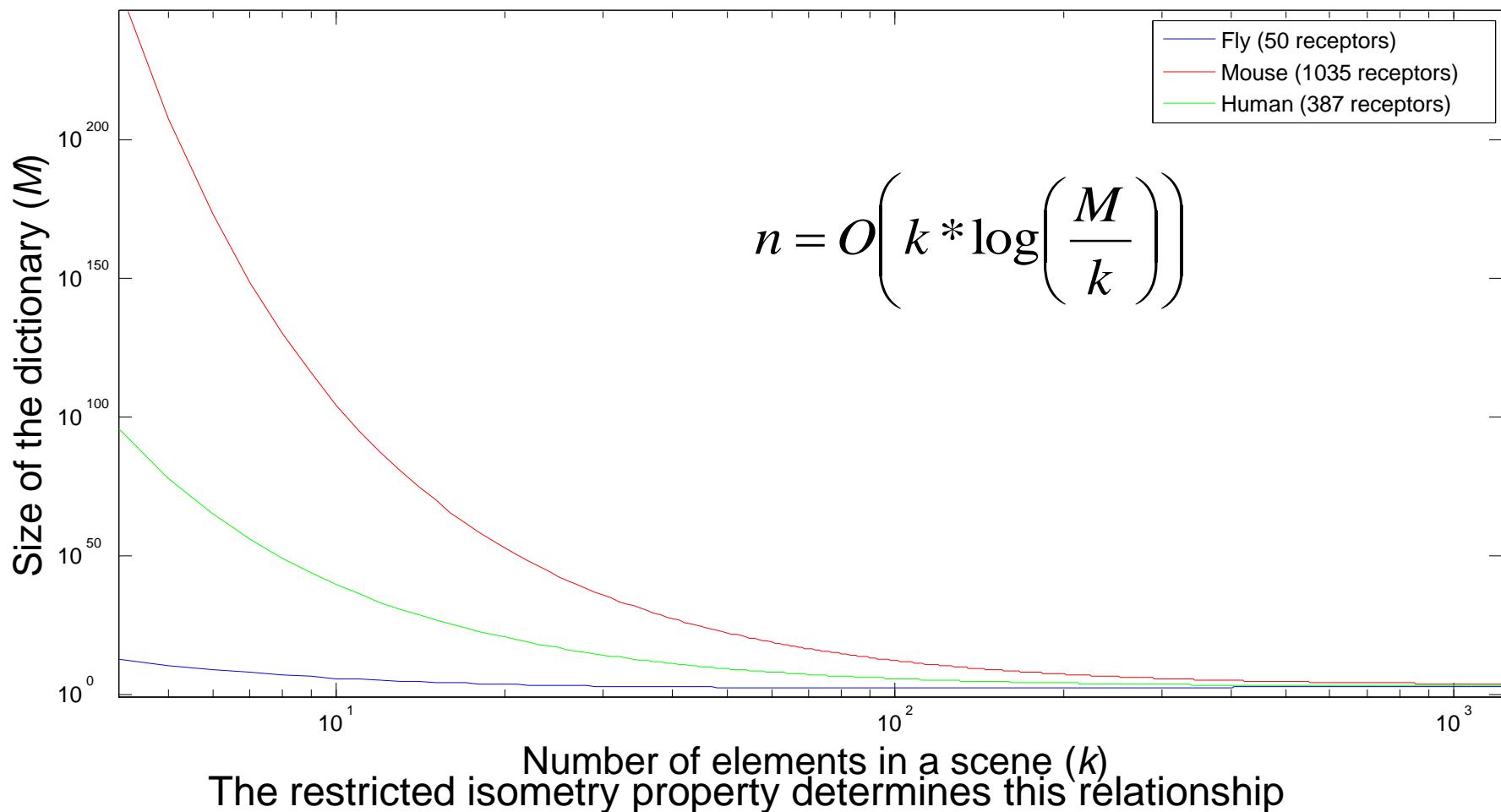
$$|\hat{y}(t) - \vec{y}(t)|^2 = 0 \quad \text{Then } \theta_1=1, \theta_2=1, \text{ and } \theta_k=0, \text{ if } k \neq 1,2 \text{ is the solution}$$

Matrices taken from a random ensemble satisfy the restricted isometry property (RIP)



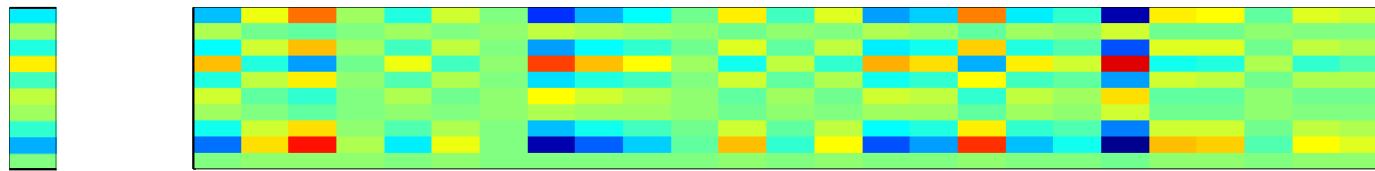
$$n = O\left(k * \log\left(\frac{M}{k}\right)\right)$$

The number of receptors determine the complexity of the scene  
and the maximum size of the dictionary

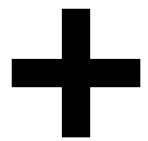
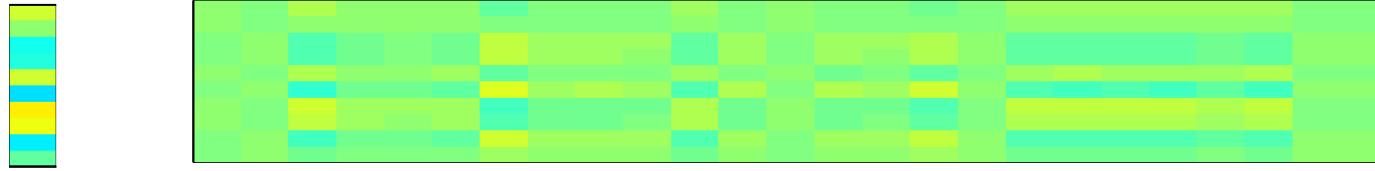


# Amplitude invariant identification of sources

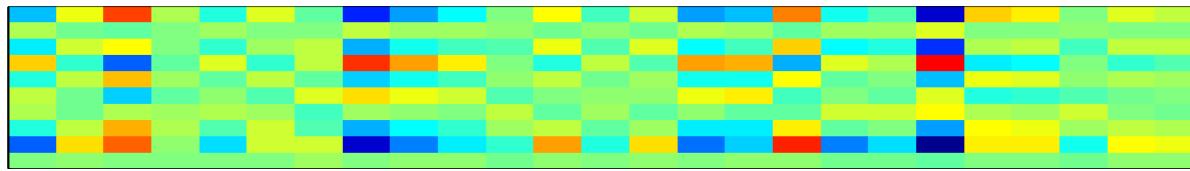
Element 5



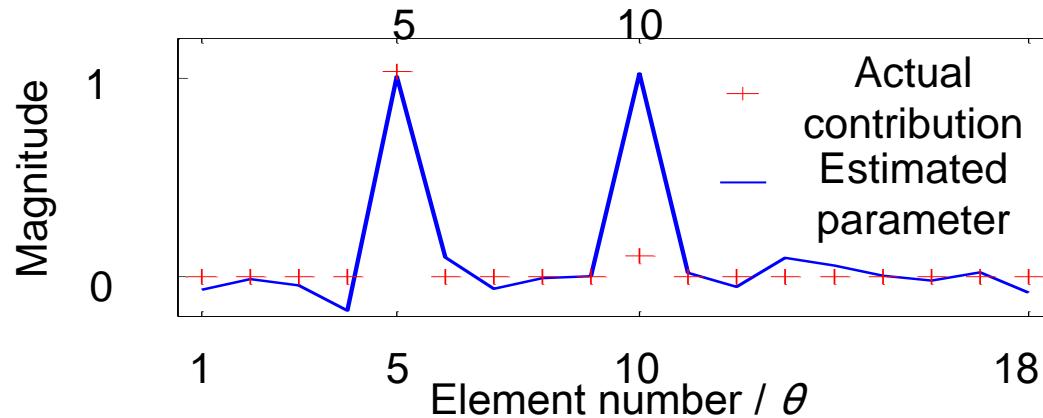
Element 10



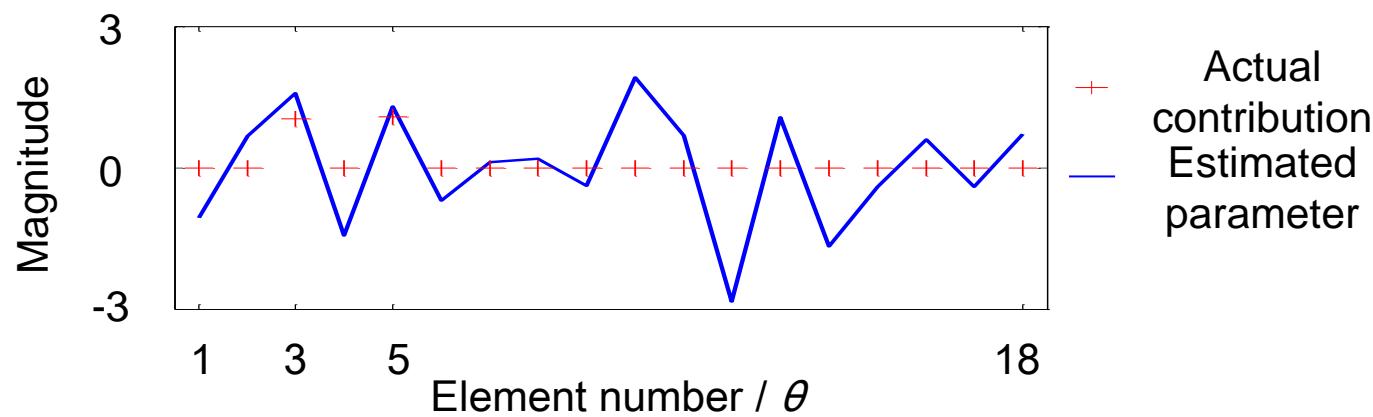
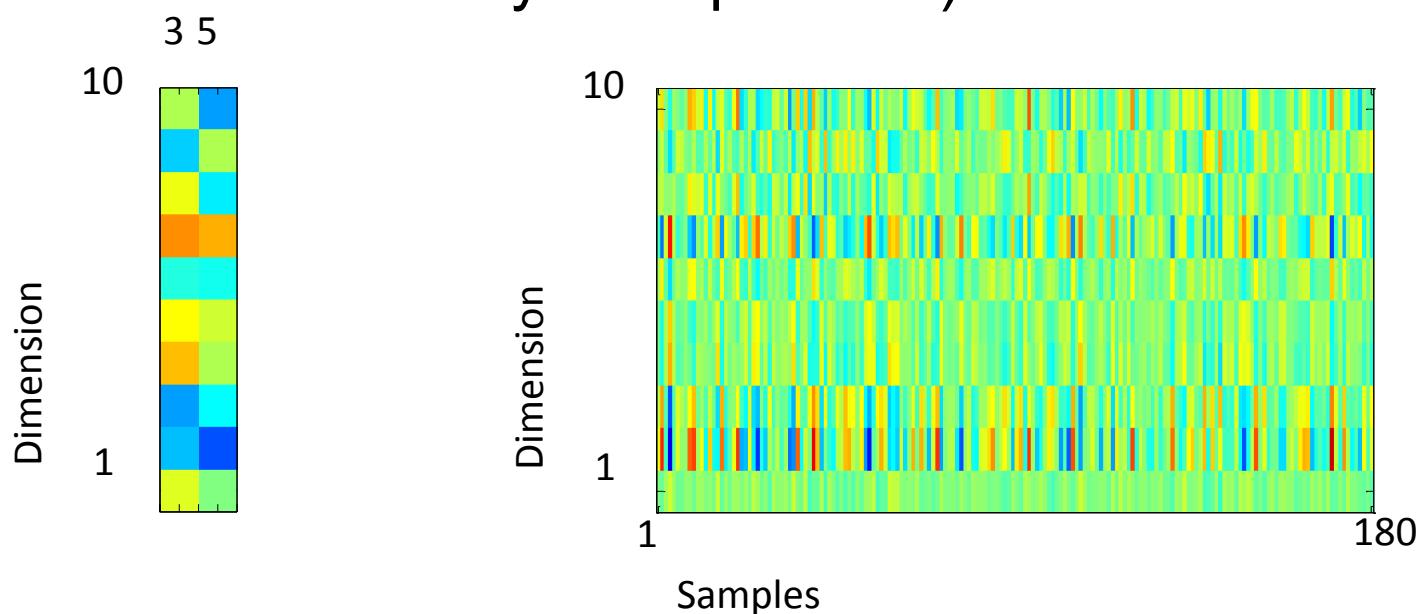
$Y$



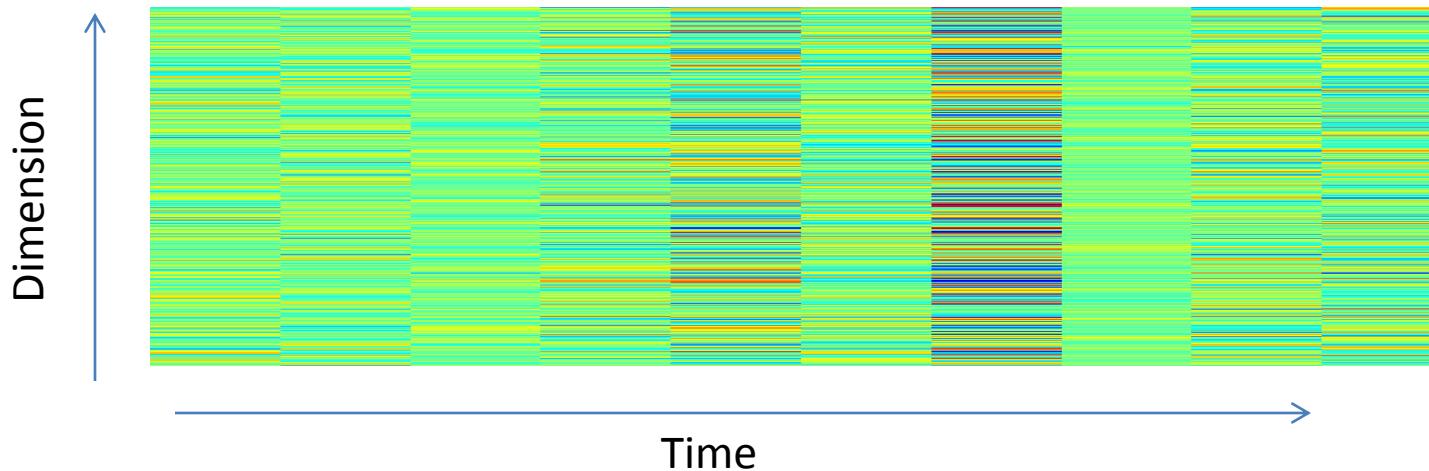
Time



# Solution is not exact for very similar vectors (needle in a haystack problem)



# CPA identifies sources under challenging conditions

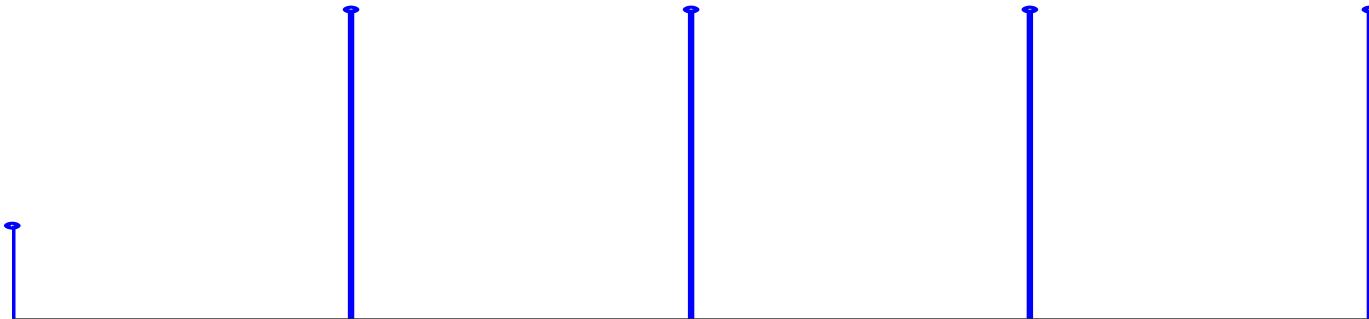


450 dimensions

Dictionary size =3000

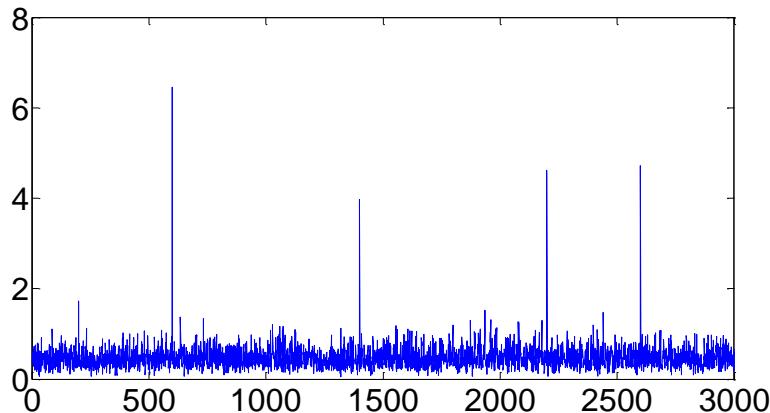
5 elements present

Additive gaussian noise of twice the amplitude of the signal

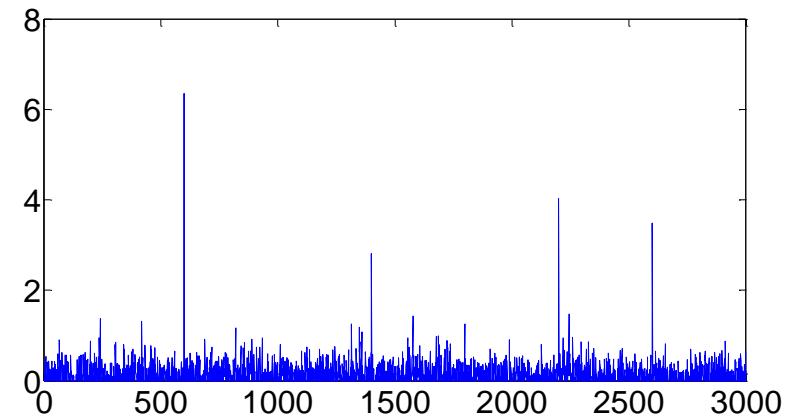


# CPA identifies sources under challenging conditions

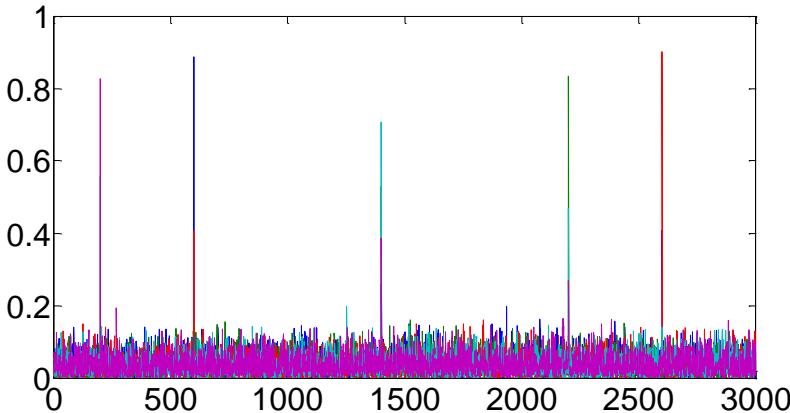
Template matching



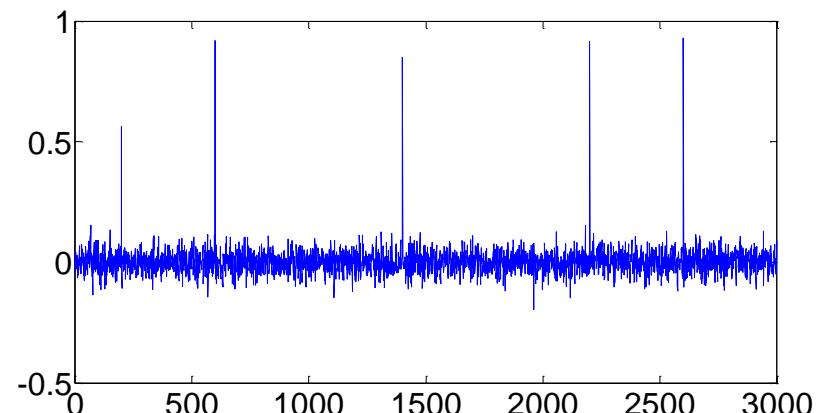
Matching pursuit ( $\approx$ L1 optimization)



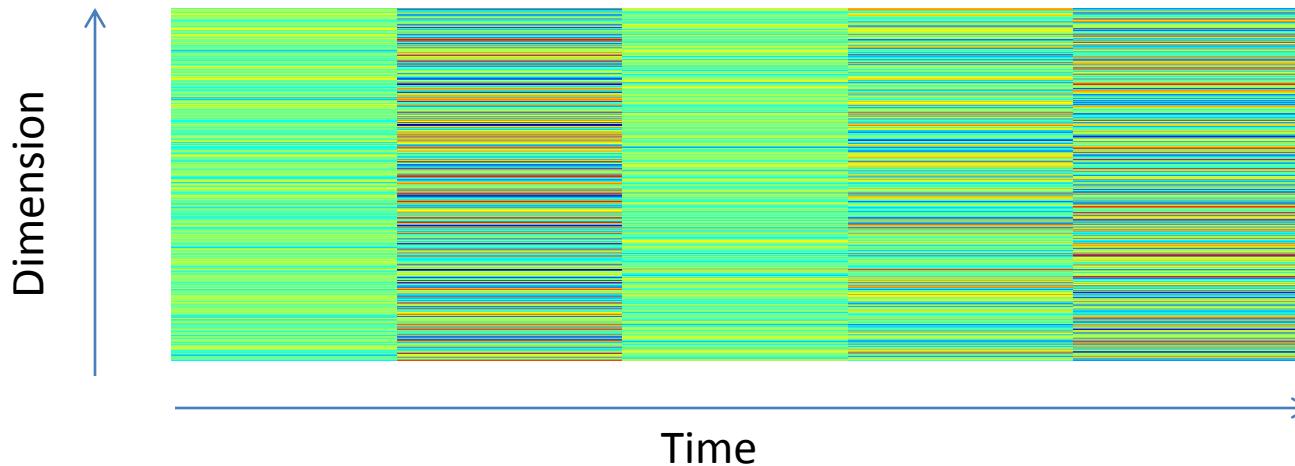
PCA (blind separation)



CPA



# CPA identifies sources under challenging conditions

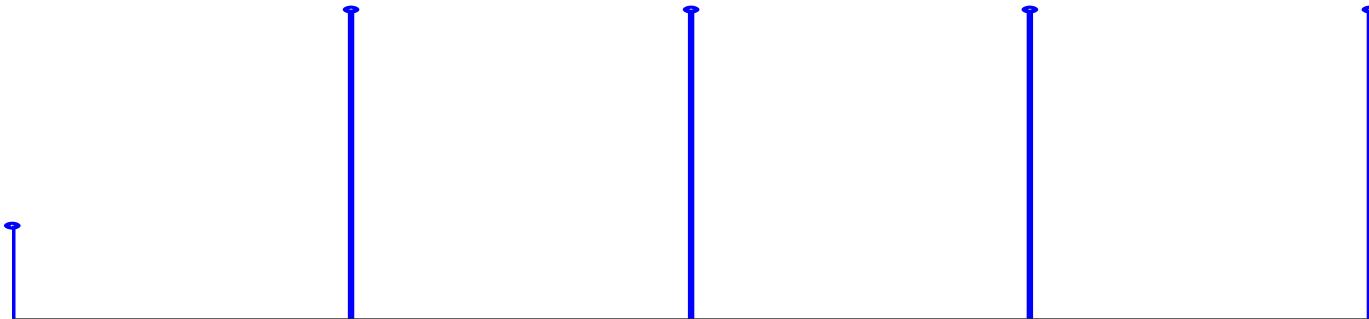


450 dimensions

Dictionary size =3000

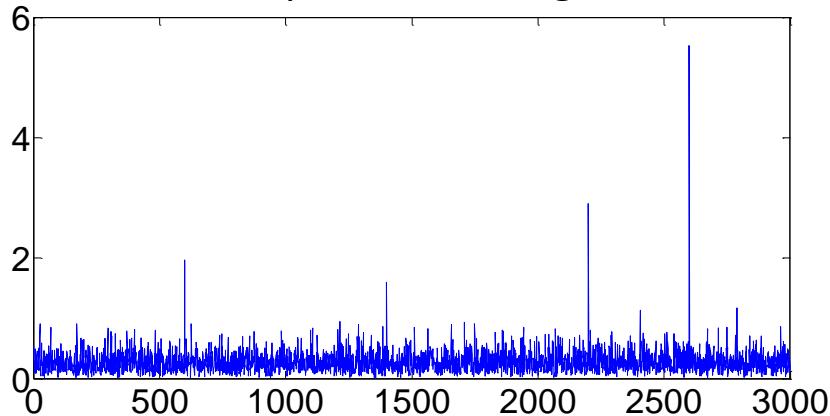
5 elements present

Additive gaussian noise of twice the amplitude of the signal

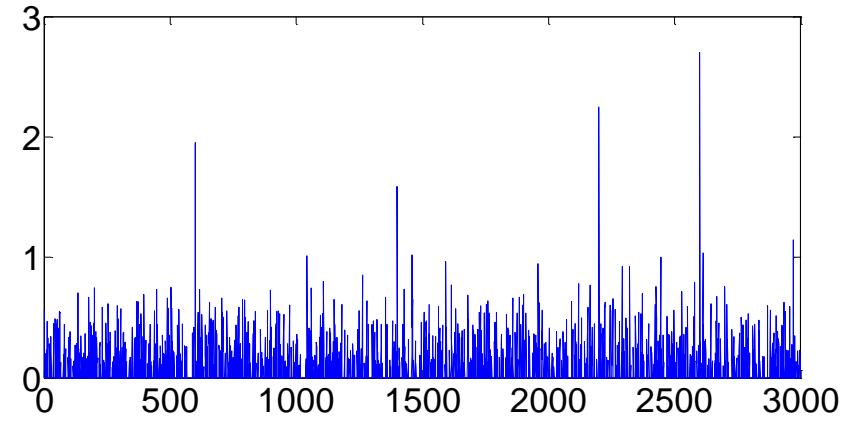


# CPA identifies sources under challenging conditions

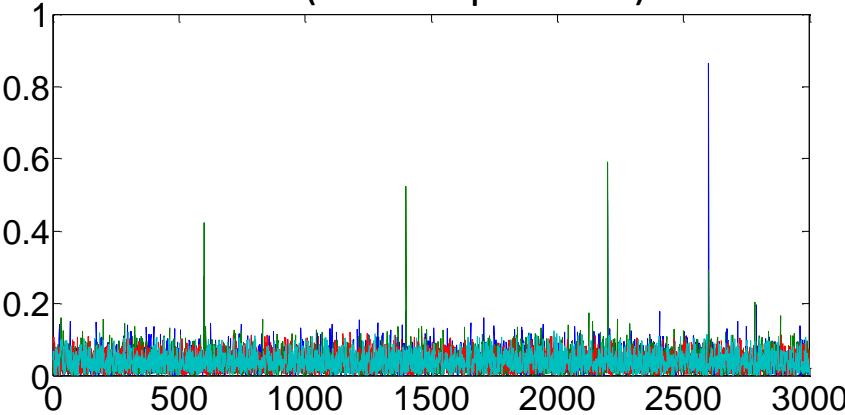
Template matching



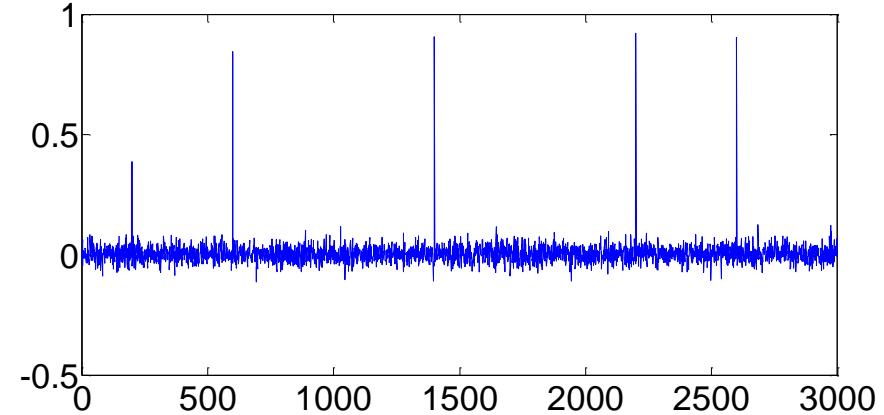
Matching pursuit ( $\approx$ L1 minimization)



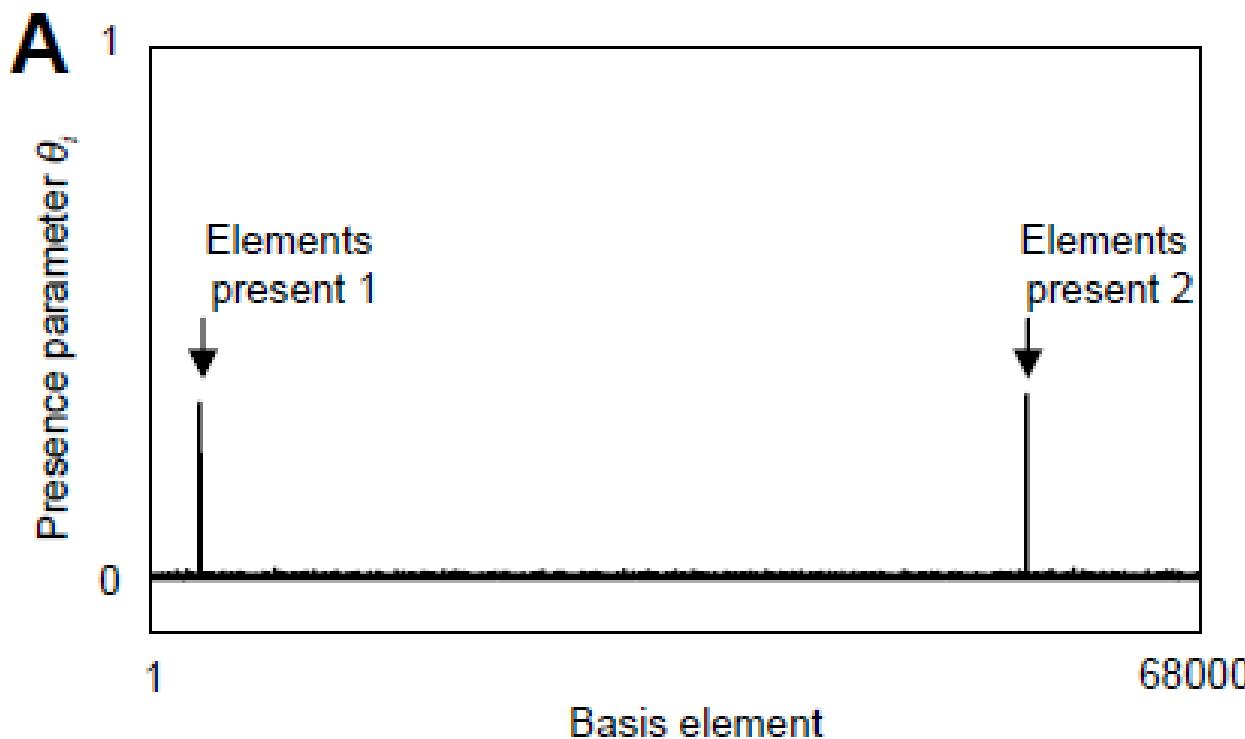
PCA (blind separation)



CPA



# CPA can use very large dictionaries



400 dimensions

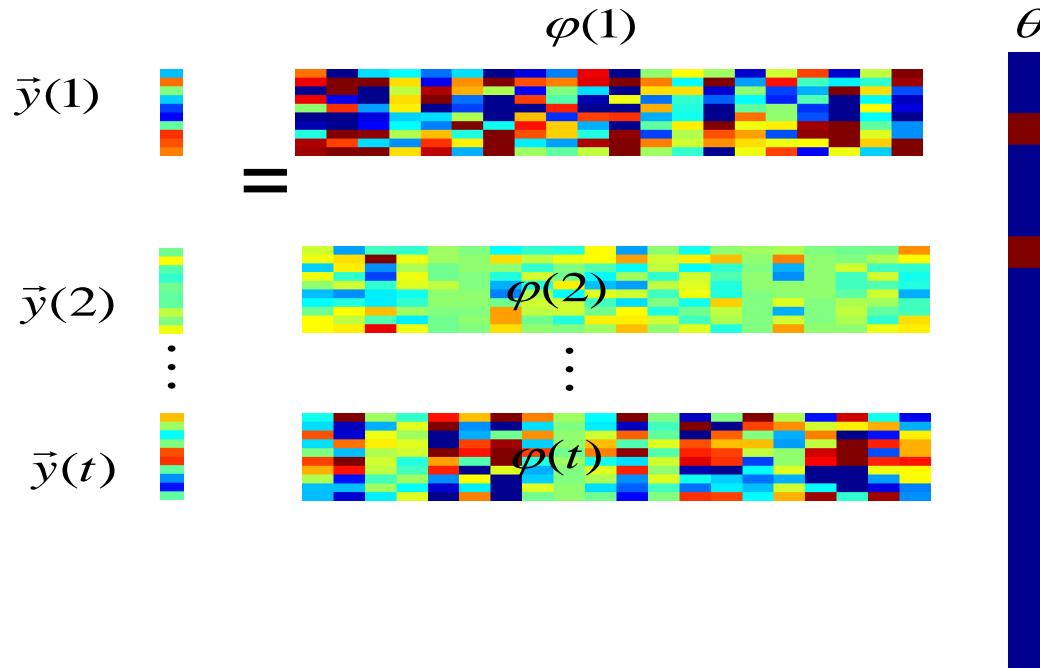
68000 dictionary elements

7 time samples

# Outline

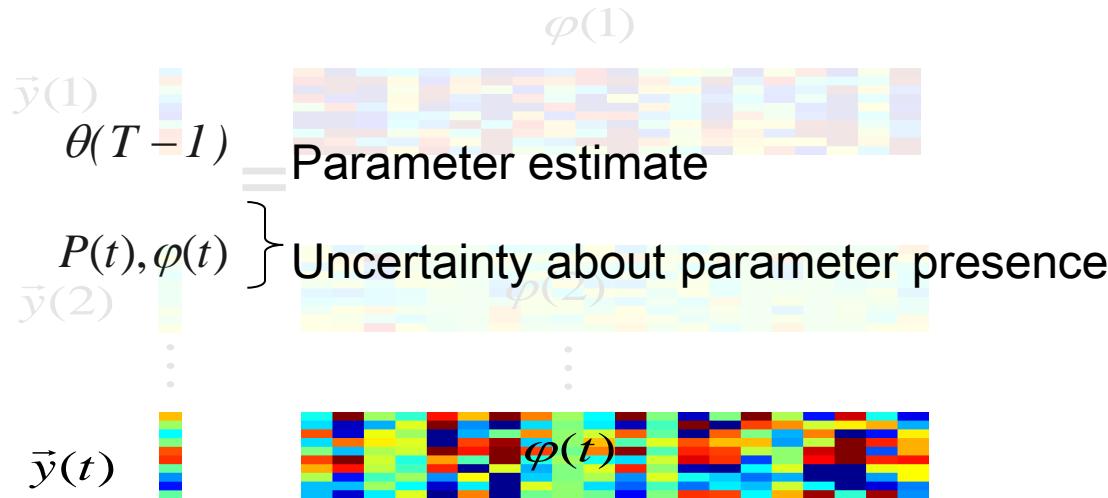
1. Odor identification problem in complex scenes
2. Reformulation of the problem as estimation of odor presences
  - Solution is unique
  - Solution estimate the sources present under challenging conditions
3. **Recursive implementation of the algorithm**
4. Experimental characterization of cortical feedback and the effect of cortical input on bulbar output

# Standard CPA computation can be simplified



$$Y = \Phi \theta \quad \theta = (\Phi^T \Phi)^{-1} \Phi^T Y \quad (\Phi^T \Phi) \text{ is M by M}$$

# Iterative CPA (iCPA) process each observation when it arrives



$$\mathbf{P}(T) = \mathbf{P}(T-1) - \mathbf{P}(T-1)\boldsymbol{\varphi}^T(T)(\mathbf{I} + \boldsymbol{\varphi}(T)\mathbf{P}(T-1)\boldsymbol{\varphi}^T(T))^{-1}\boldsymbol{\varphi}(T)\mathbf{P}(T-1)$$

$$\hat{y}(T) = \boldsymbol{\varphi}(T)\vec{\Theta}(T-1)$$

$$\theta(T) = \theta(T-1) + \underbrace{P(T)\boldsymbol{\varphi}(T)^*}_{\Delta\theta(T)}(\vec{y}(T) - \hat{y}(T))$$

Estimation error

# iCPA have variables of different dimensionality and different dynamics

$$\mathbf{P}(T) = \mathbf{P}(T-1) - \mathbf{P}(T-1)\boldsymbol{\varphi}^T(T)(\mathbf{I} + \boldsymbol{\varphi}(T)\mathbf{P}(T-1)\boldsymbol{\varphi}^T(T))^{-1}\boldsymbol{\varphi}(T)\mathbf{P}(T-1)$$

$$\hat{y}(T) = \boldsymbol{\varphi}(T)\theta(T-1)$$

$$\theta(T) = \theta(T-1) + P(T)\varphi(T) * (\vec{y}(T) - \hat{y}(T))$$

Largest dimension variables (order M by M):  $P$

$M >> N$

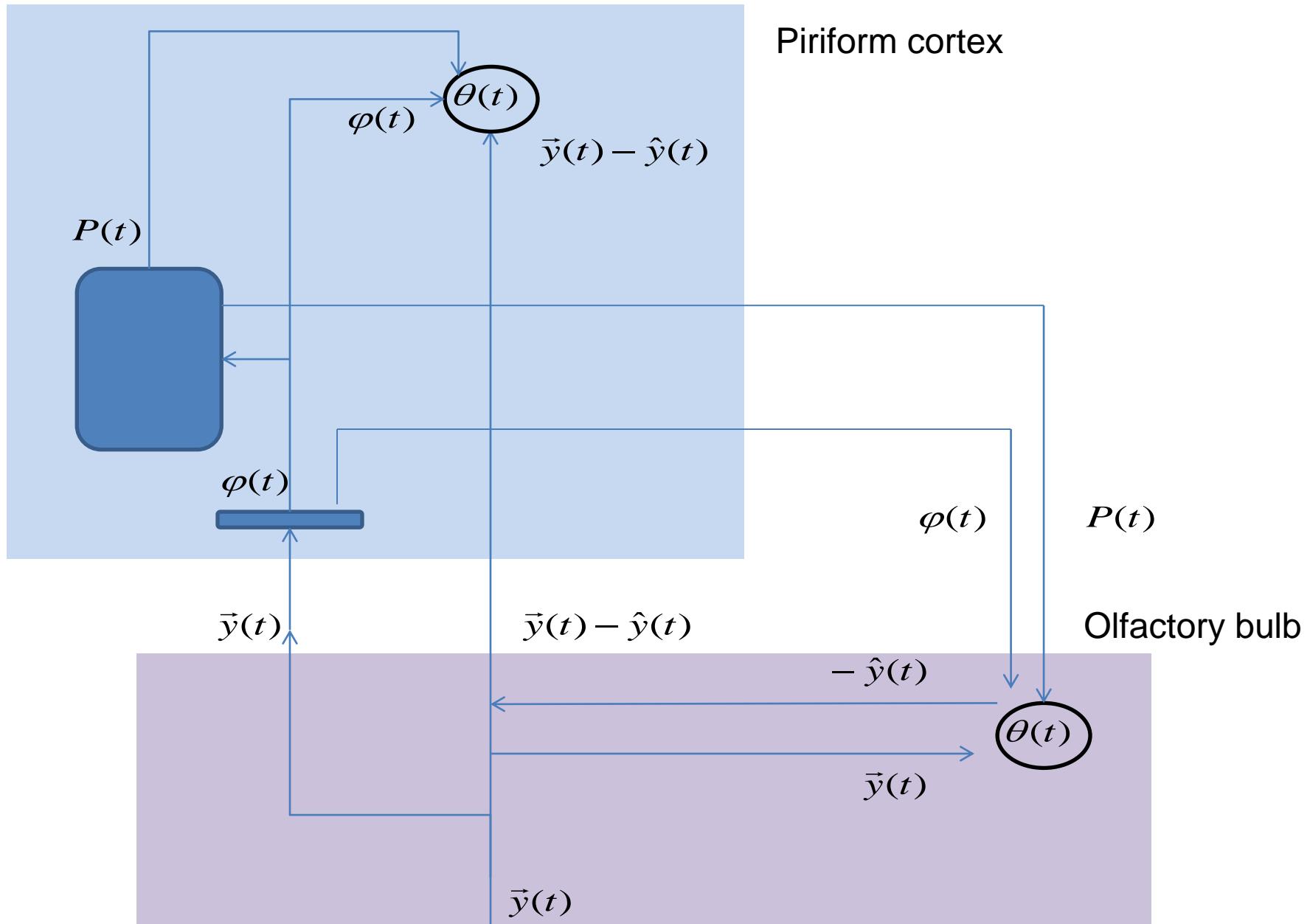
Second dimension variables (order N by M):  $\varphi$

Third largest variable (order M by 1):  $\theta$

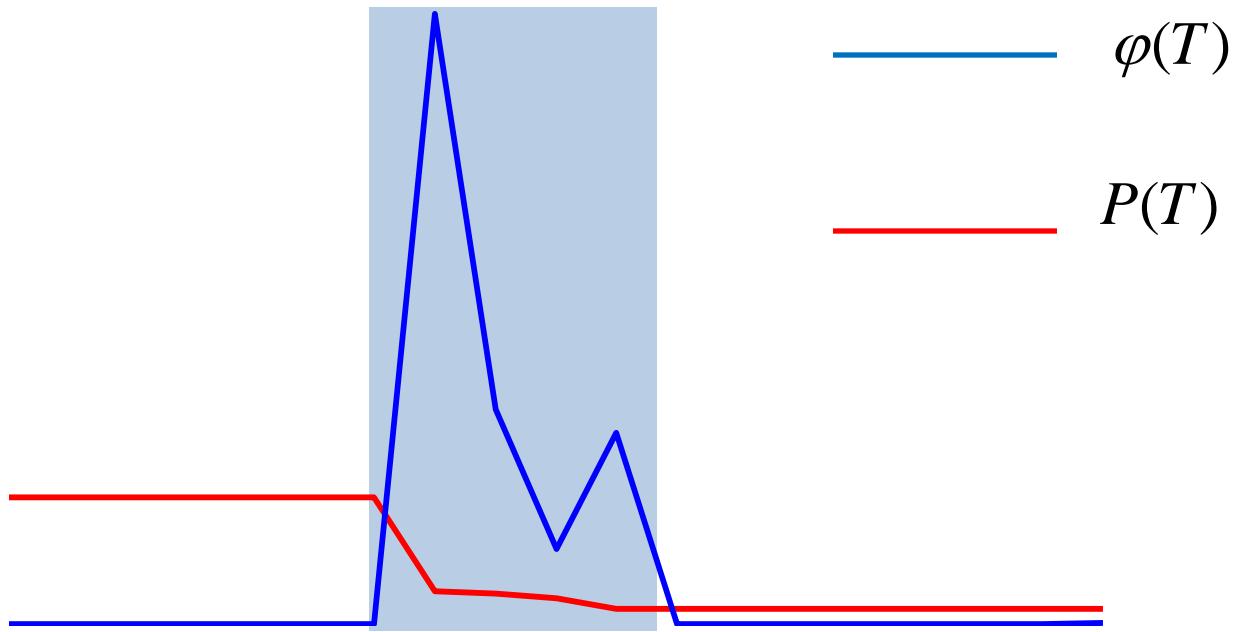
Smalles variable (order N by 1):  $\vec{y}(t), \hat{y}(t)$

2 variables for temporal integration:  $P, \theta$

# Possible iCPA implementation in piriform/olfactory bulb circuit

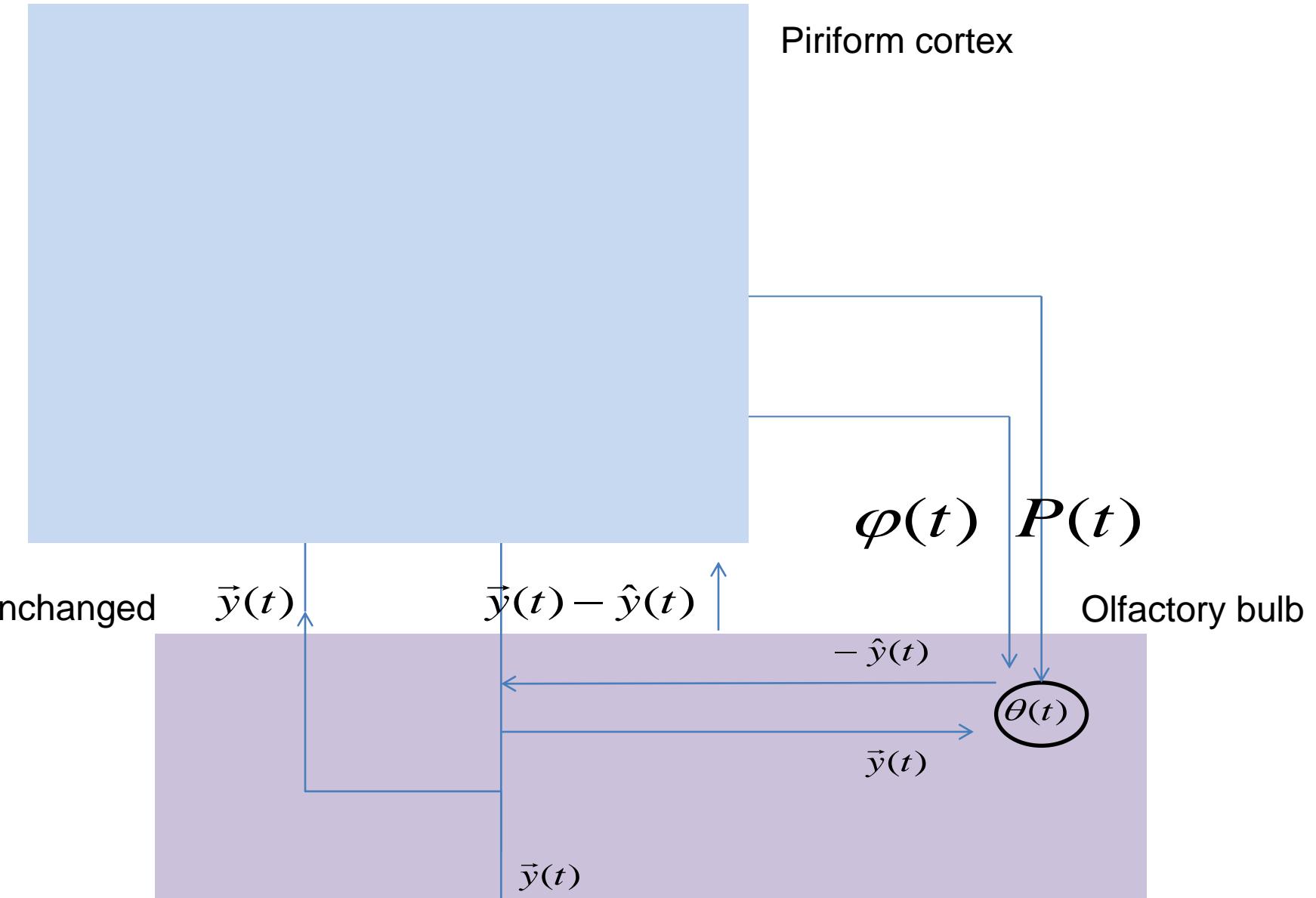


# Model predicts feedback signals with different dynamics



$$\theta(T) = \theta(T-1) + P(T)\varphi(T) * (\vec{y}(T) - \hat{y}(T))$$

iCPA requires a feedback independent and a feedback dependent channel



# Outline

1. Odor identification problem in complex scenes
2. Reformulation of the problem as estimation of odor presences
  - Solution is unique
  - Solution estimate the sources present under challenging conditions
3. Recursive implementation of the algorithm
4. **Experimental characterization of cortical feedback and the effect of cortical input on bulbar output**

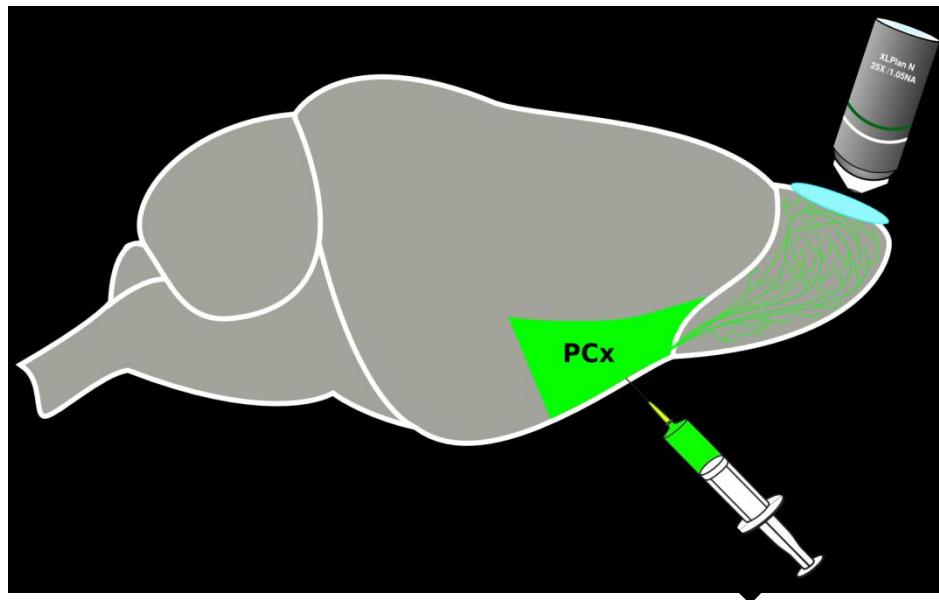
# Experimental questions about piriform cortex feedback

- 1) What type of signals does the piriform cortex send to the bulb?
- 2) How does the suppression of cortical feedback affect the output of the bulb?



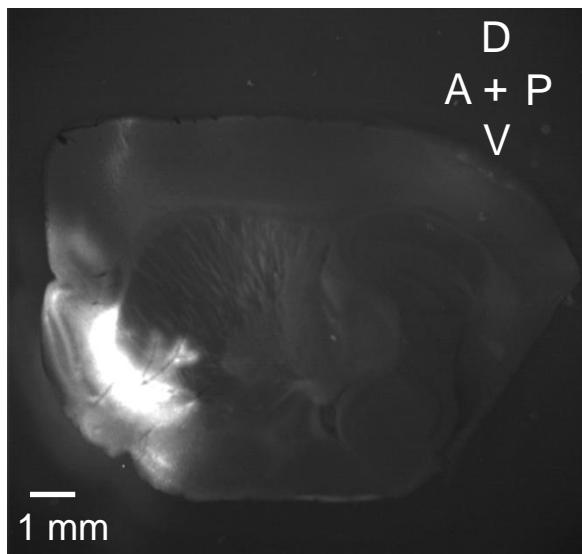
**Hong Goo Chae**

# 2P Calcium imaging of cortical feedback axons in the olfactory bulb of awake head-fixed mice

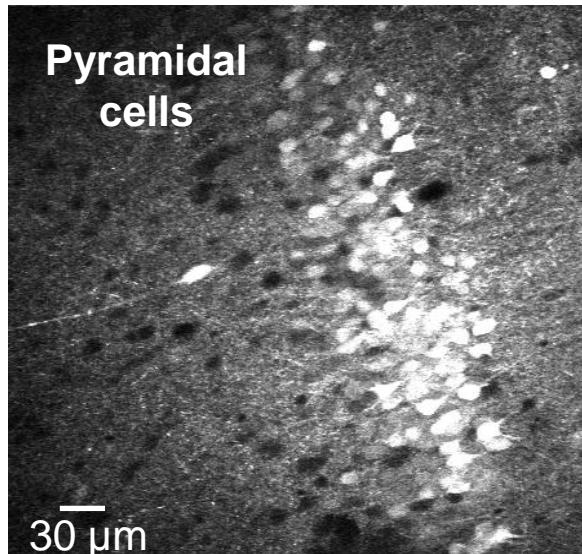


# GCaMP5 expression in cortico-bulbar feedback axons

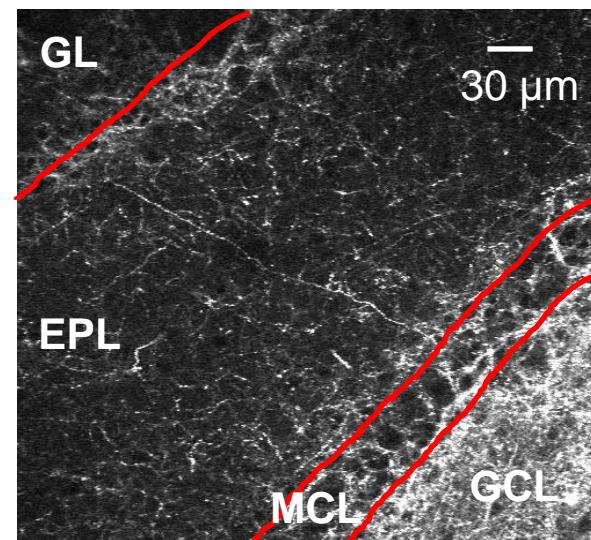
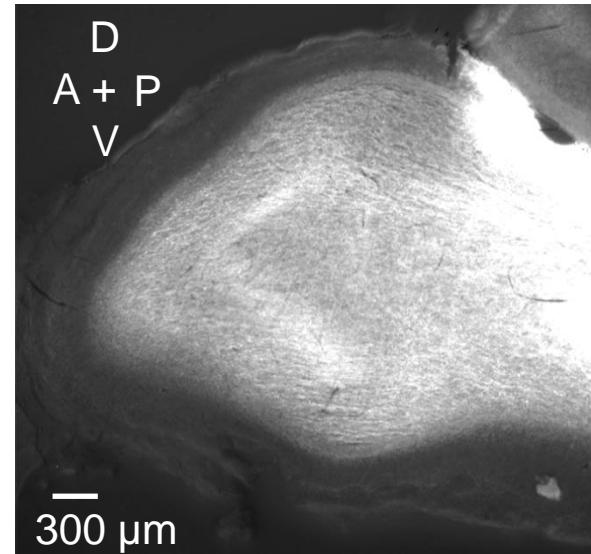
Piriform Cortex



Pyramidal  
cells

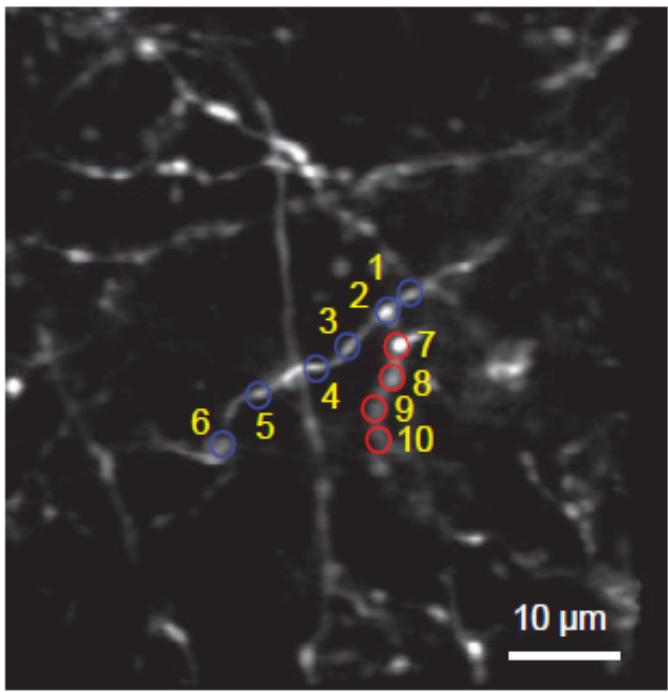


Cortical feedback fibers in the bulb

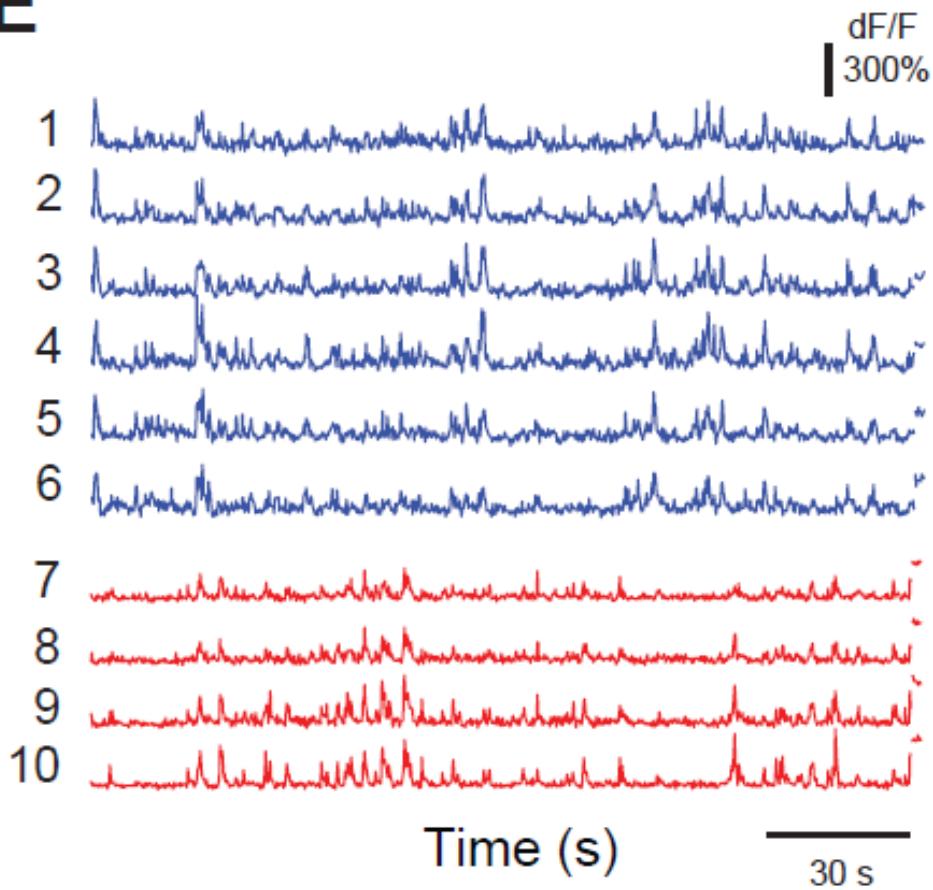


# Rich spontaneous activity in cortical feedback boutons

D



E

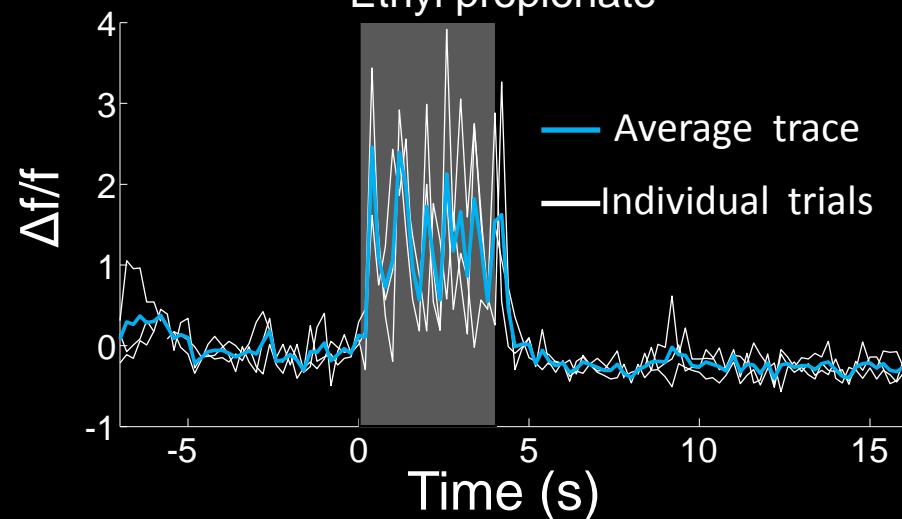


- 5,221 boutons, 4 mice
- **57%** boutons show spontaneous activity
- **Brief (<1 s)** and **locally diverse** events

# Odors can enhance or suppress cortical feedback

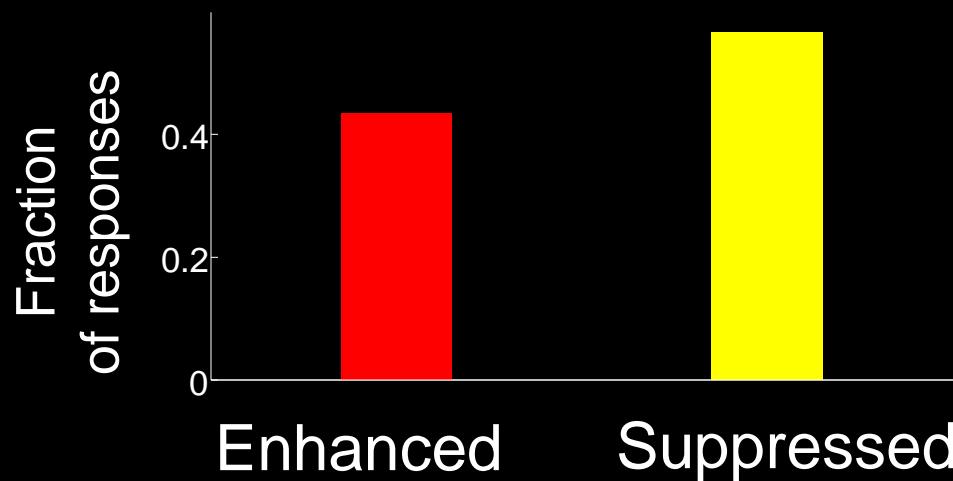
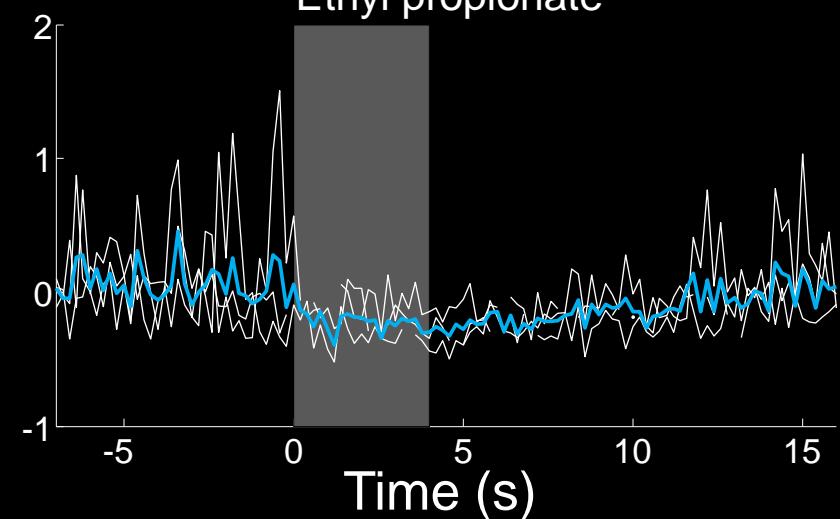
**Bouton A**

Ethyl propionate



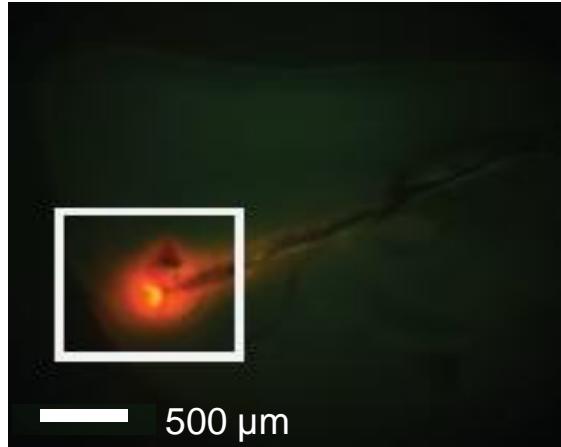
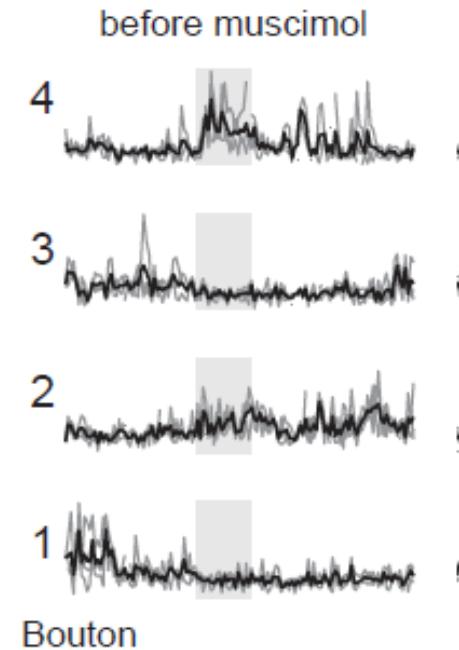
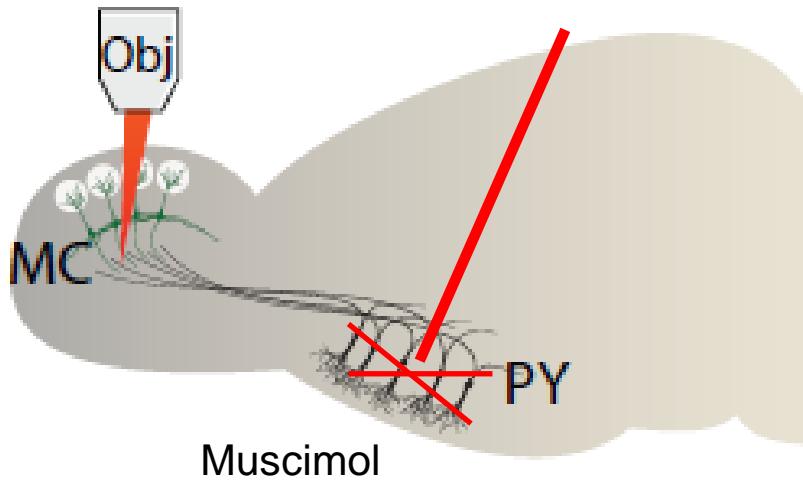
**Bouton B**

Ethyl propionate



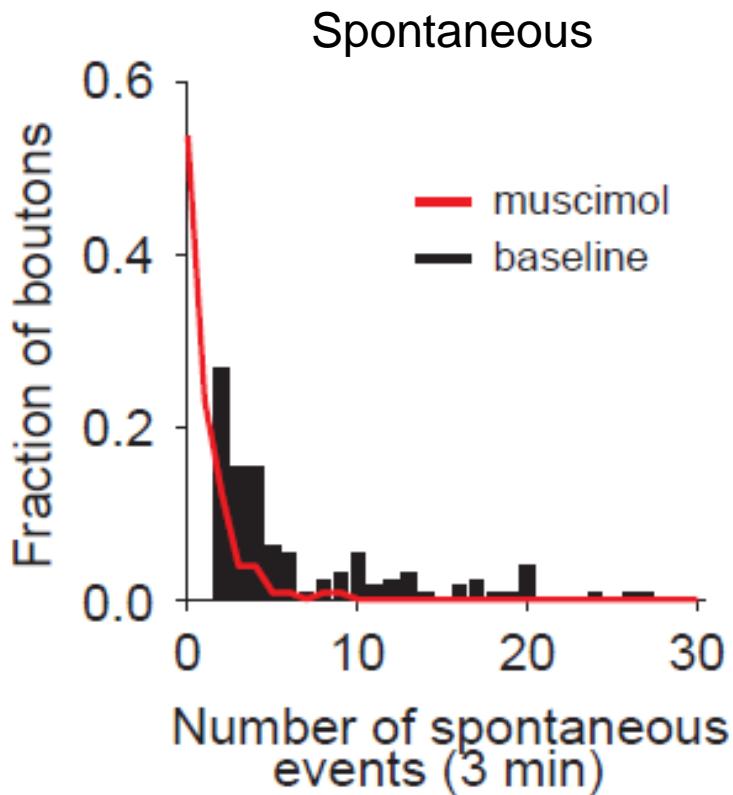
3,776 responses  
4 mice

# Cortical feedback axons are silenced by piriform cortical inactivation

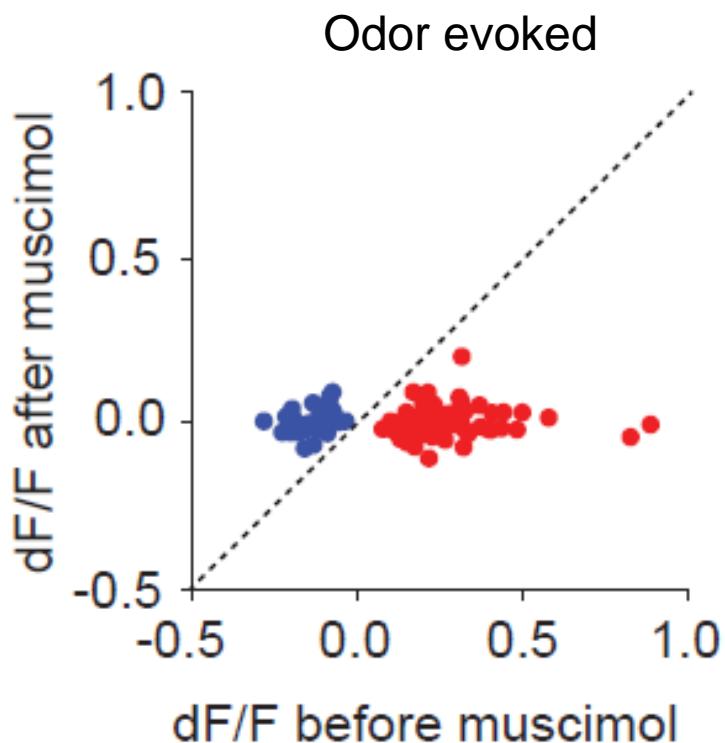


# Cortical feedback axons are silenced by piriform cortical inactivation

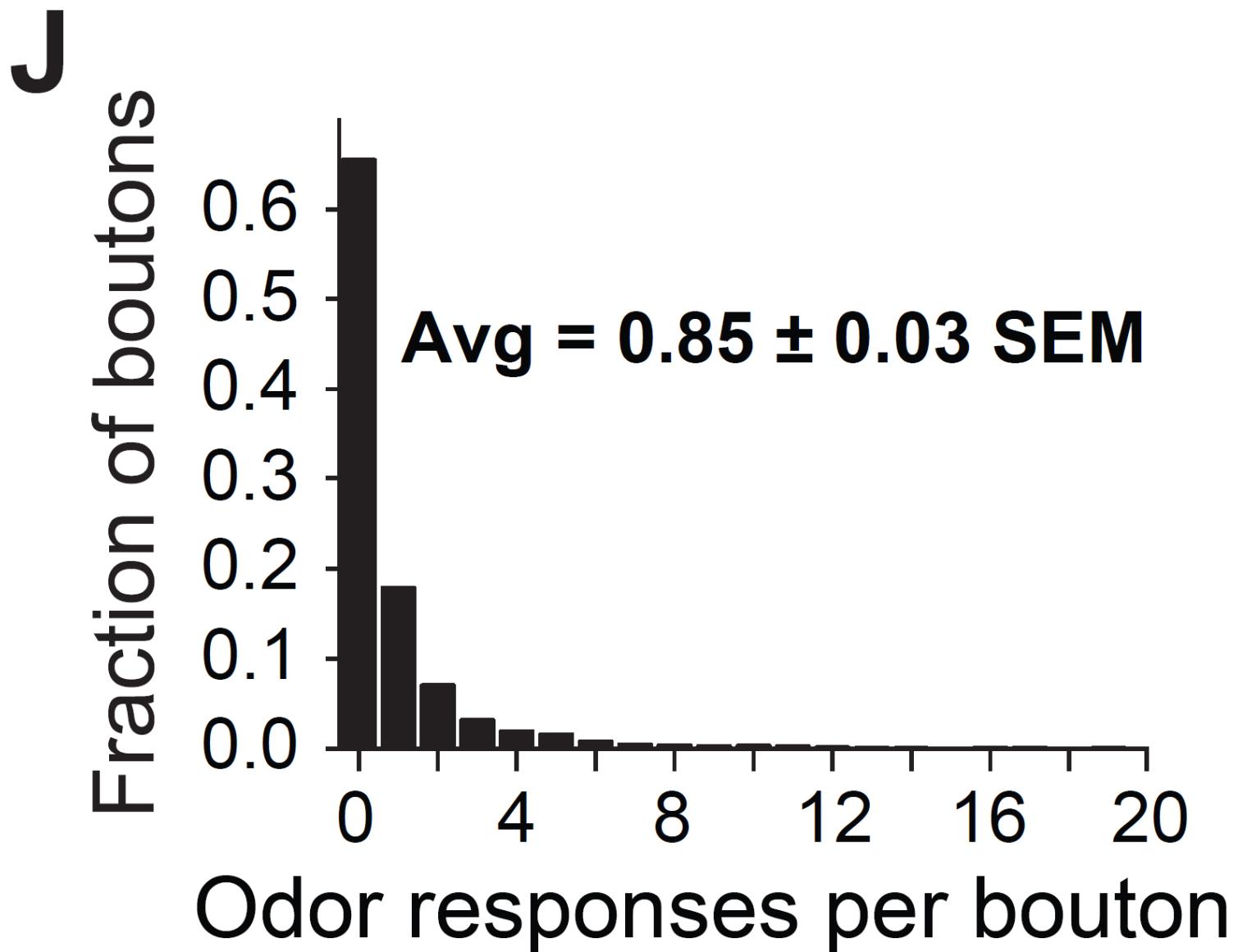
B



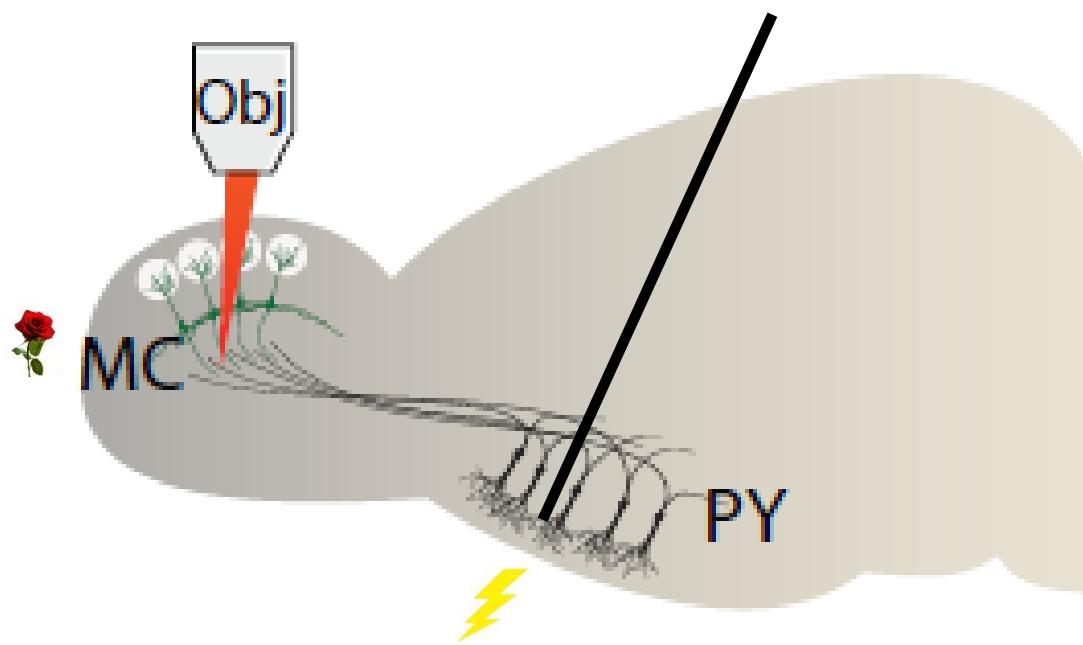
C



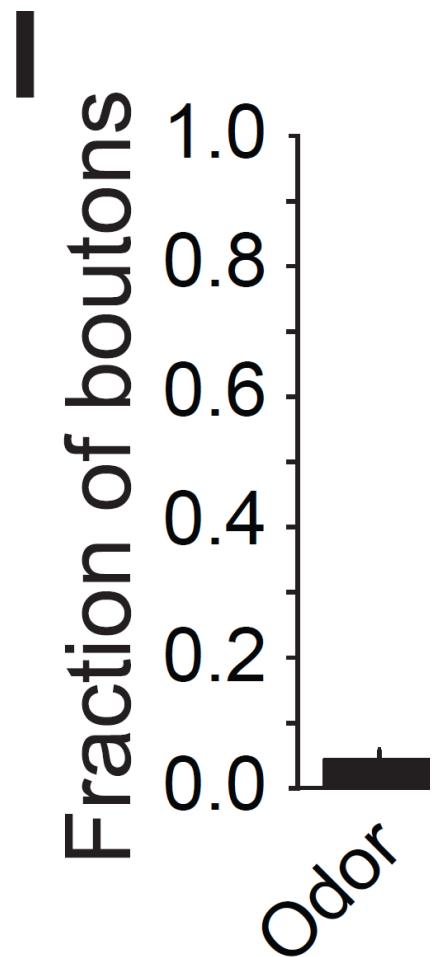
# Cortical feedback axons respond to only a few odors



# Cortical feedback responses are sparse



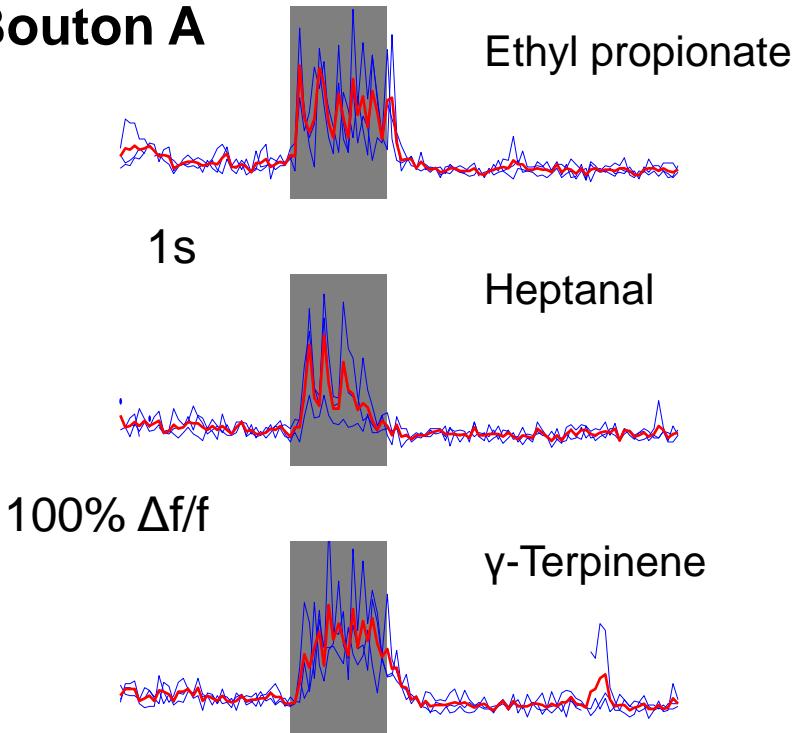
Amplitude: 30  $\mu$ A,  
Frequency: 100 Hz,  
Pulse width: 100  $\mu$ s  
Duration: 0.4 s



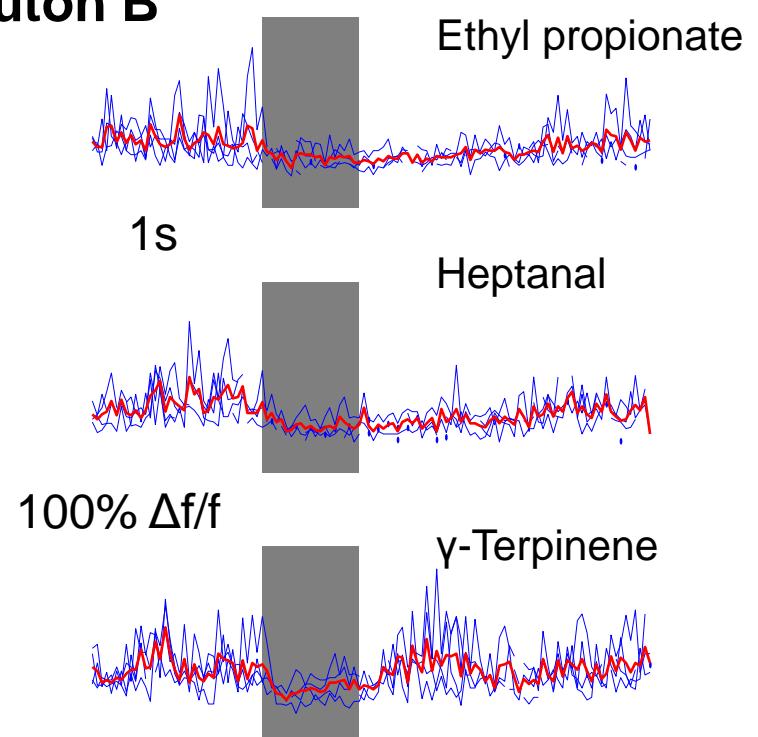
Cortical feedback boutons are sparse and  
odor selective

# Boutons show either enhancement or suppression across odors

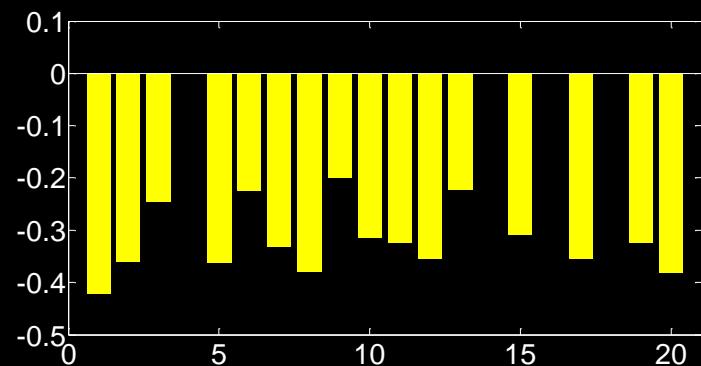
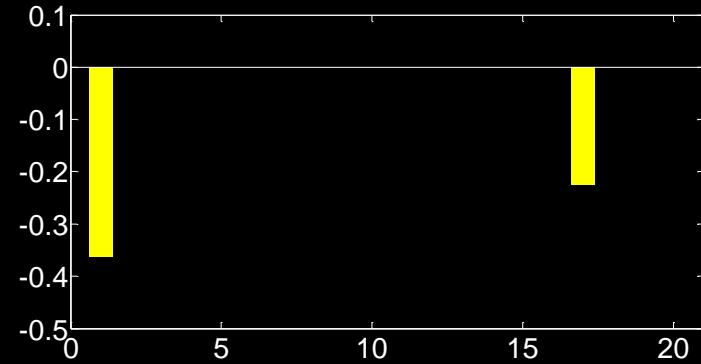
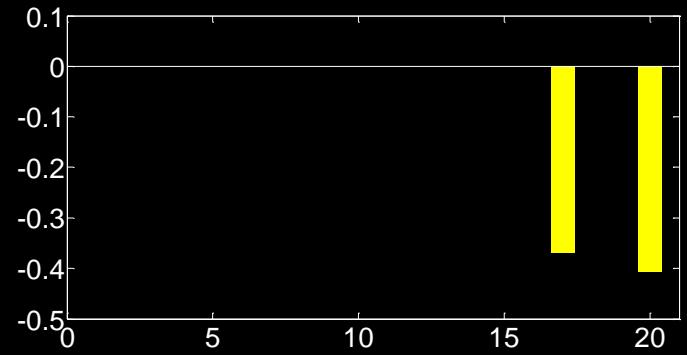
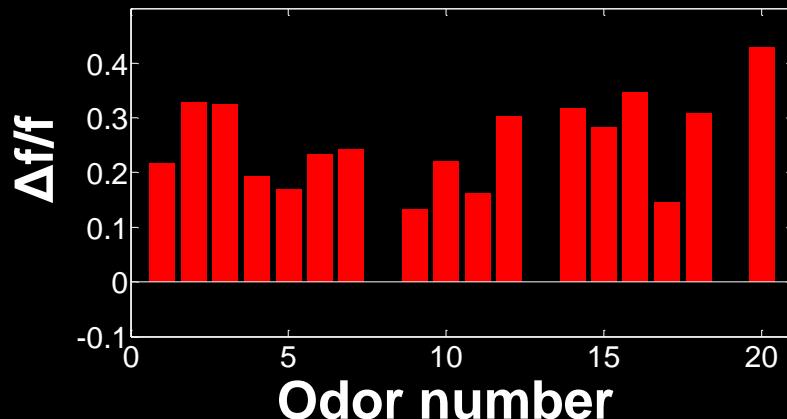
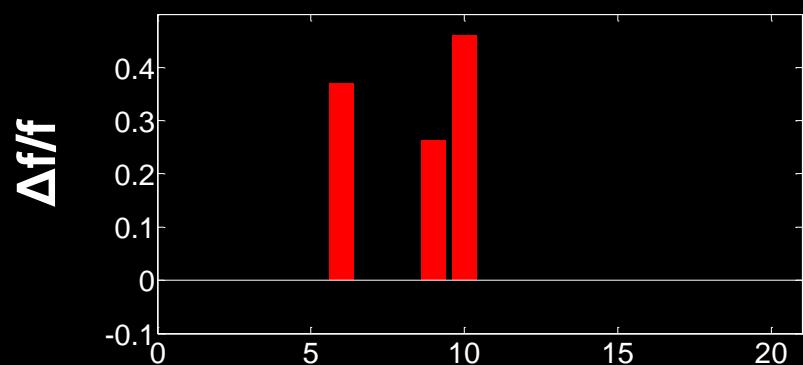
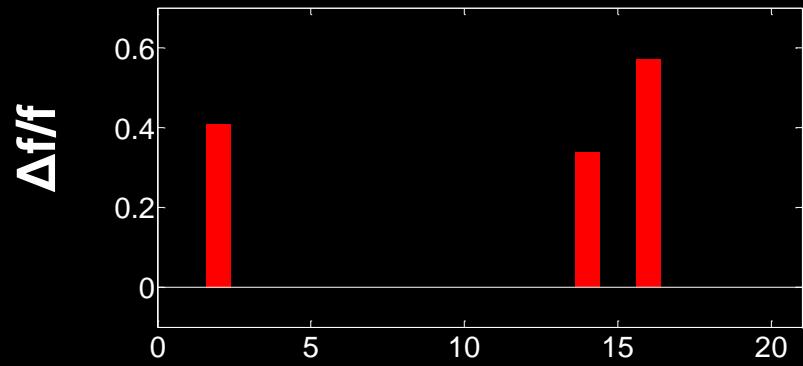
**Bouton A**



**Bouton B**

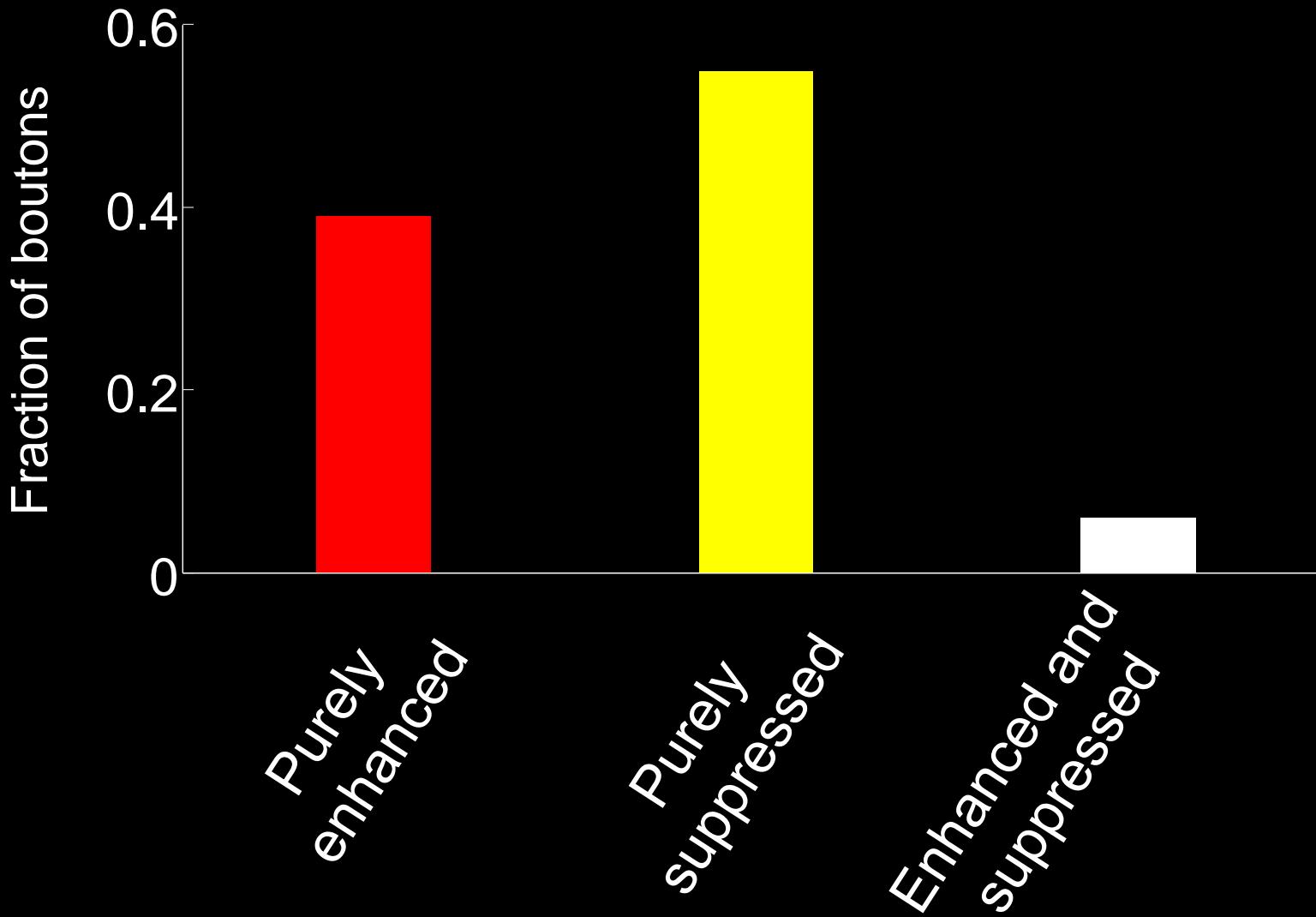


# Boutons show either enhancement or suppression across odors

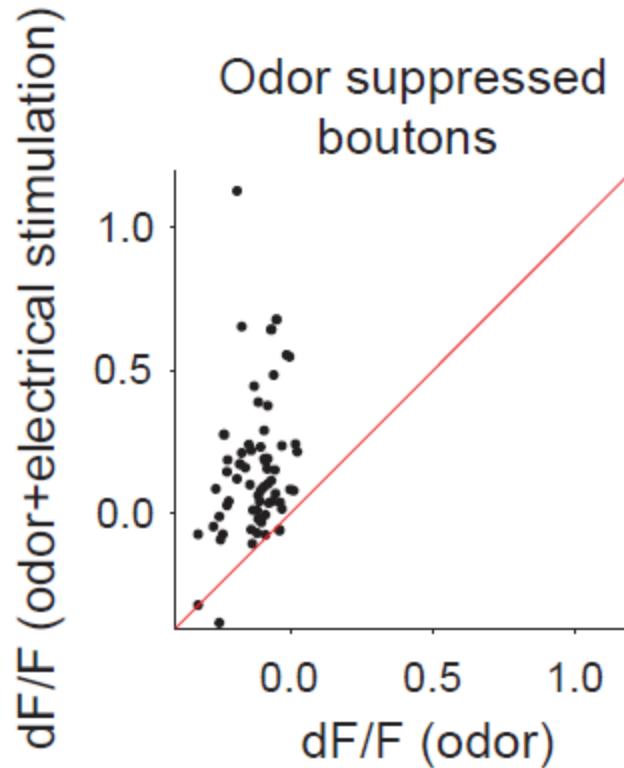
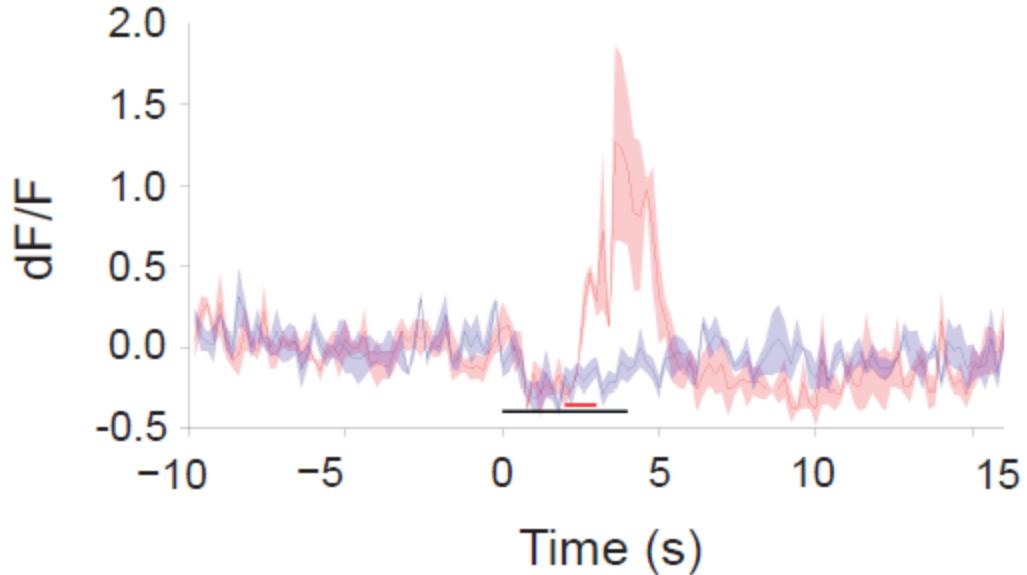


Odor number

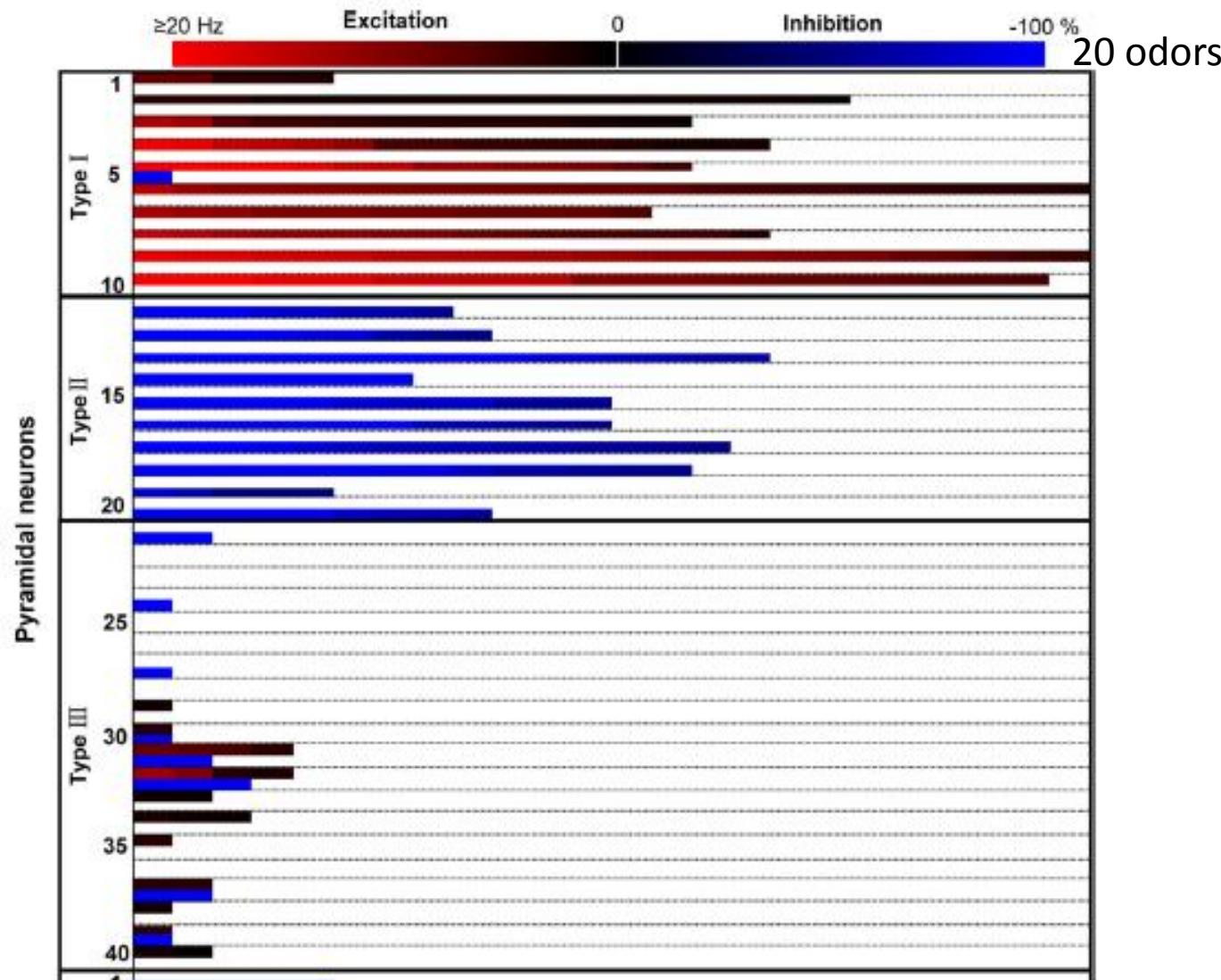
# Very few boutons show both enhanced and suppressed responses



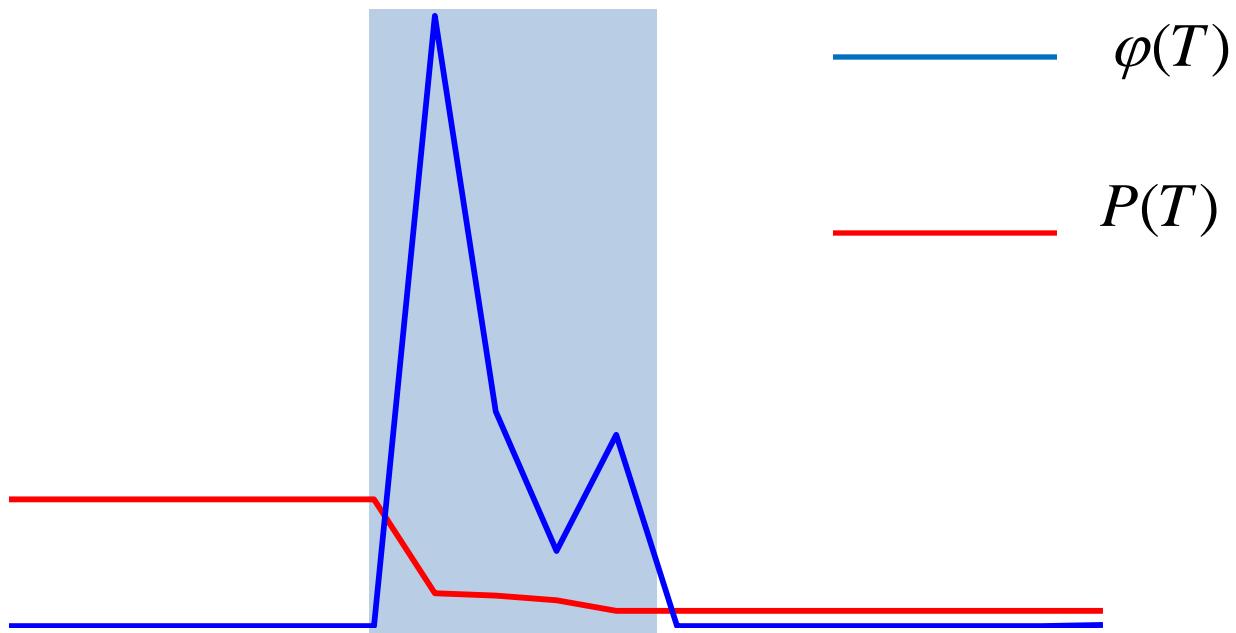
# Odor evoked suppression can be overcome by electrical stimulation



# Locally recorded piriform cortical neurons showed purely enhanced and purely suppressed cells



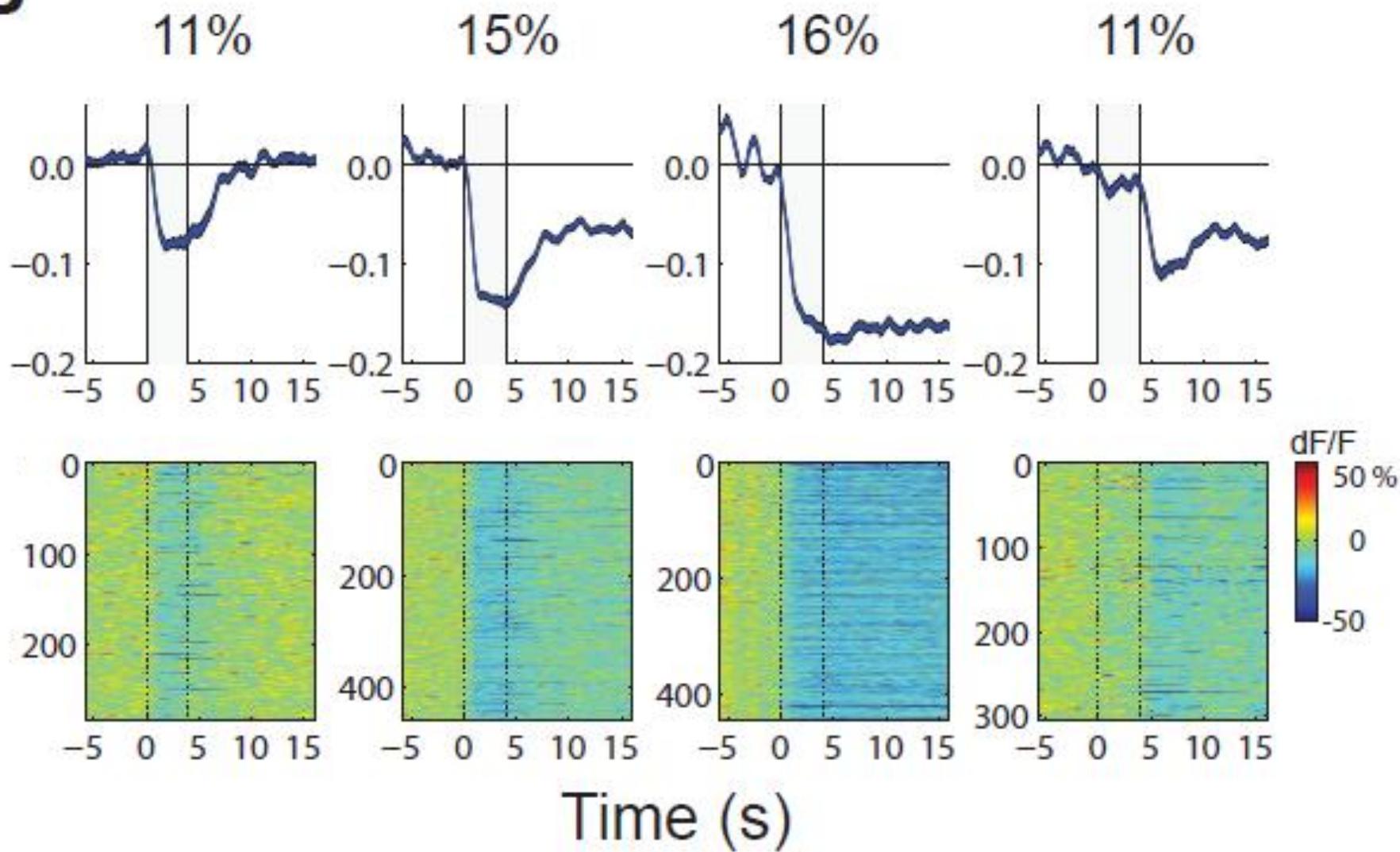
Model predicts that feedback signals have different dynamics



$$\theta(T) = \theta(T-1) + P(T)\varphi(T) * (\vec{y}(T) - \hat{y}(T))$$

# Most suppressed responses outlast odor presentation

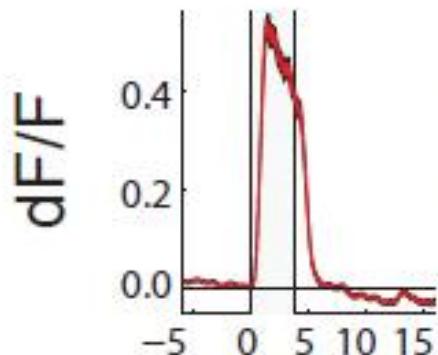
B



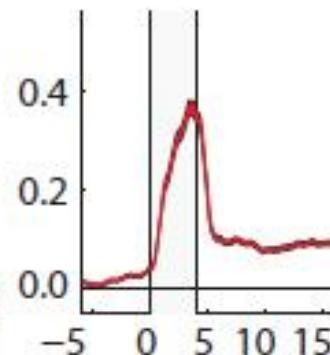
# Enhanced responses have less long lasting responses

A

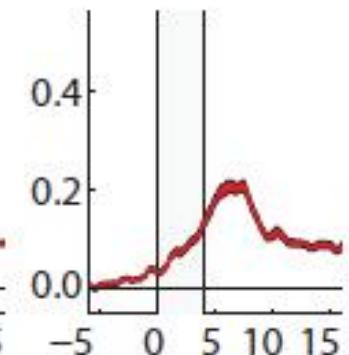
14%



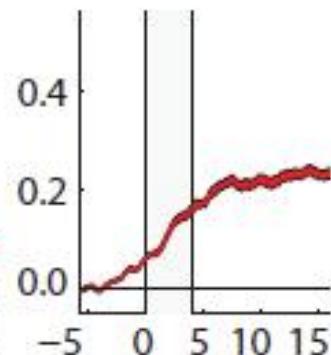
15%



10%

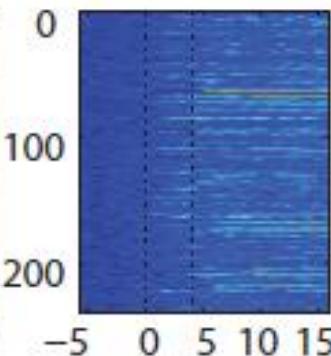
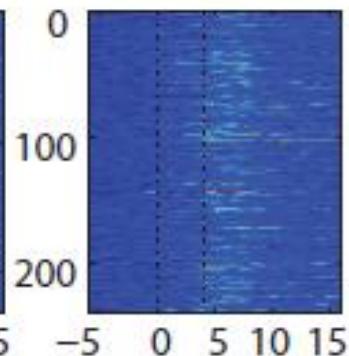
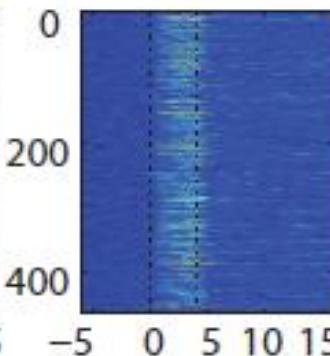
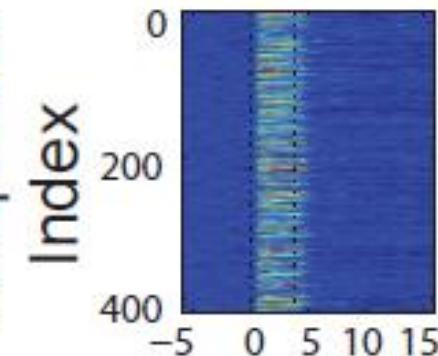


8%

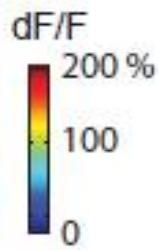


B

Response Index



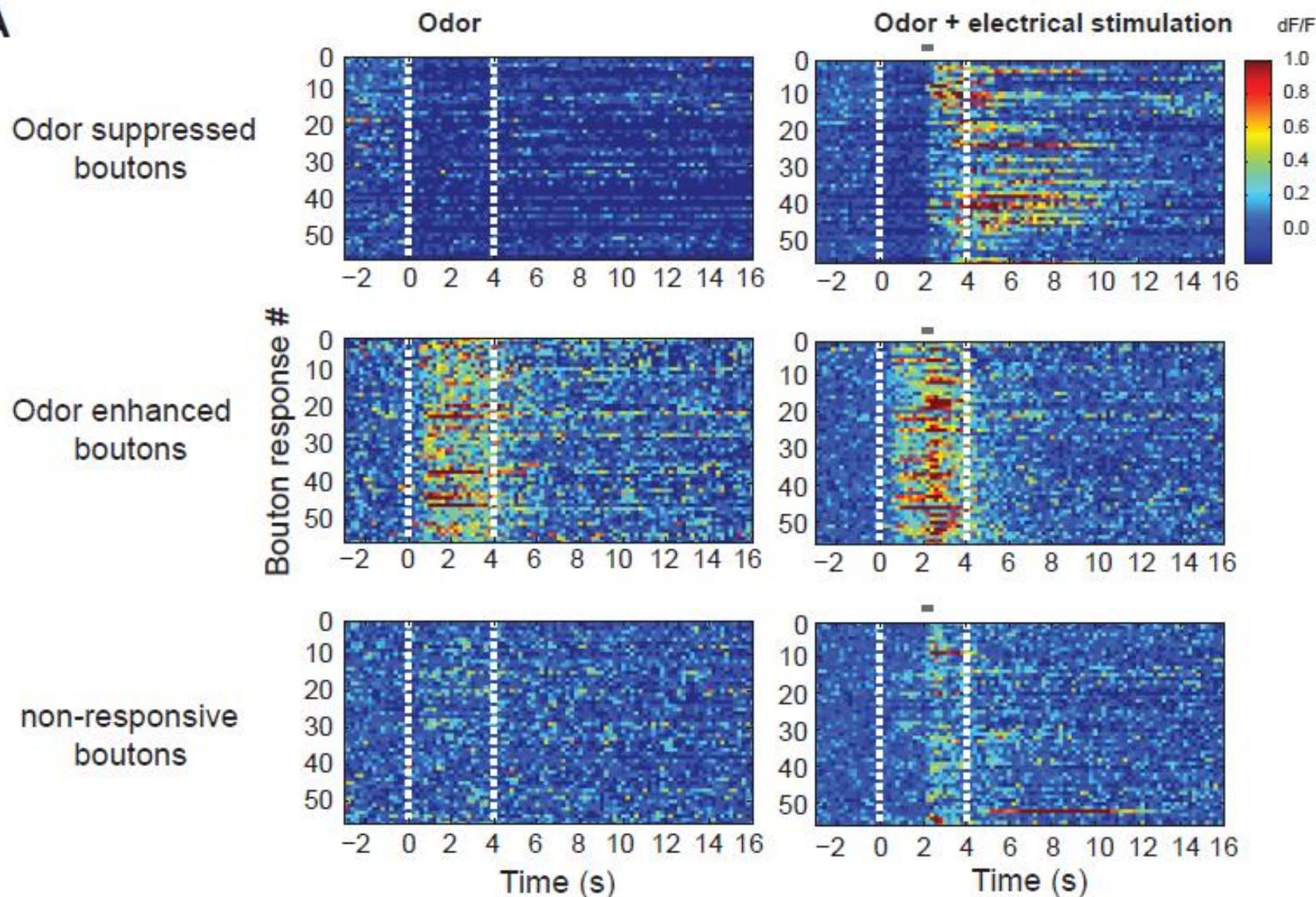
Time (s)



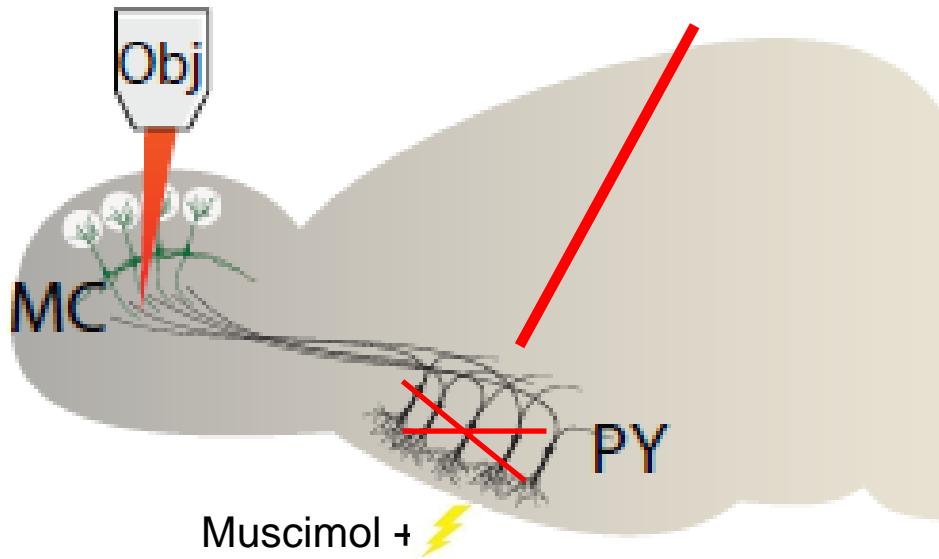
# Piriform electrical stimulation triggers long lasting enhancement in suppressed response boutons

**Figure S4**

**A**

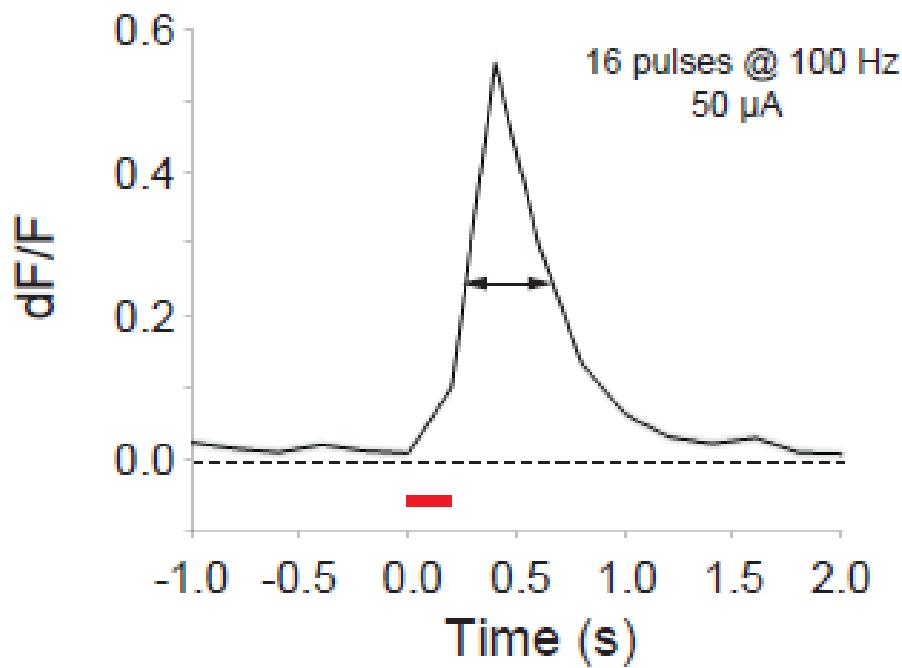


# Determination of temporal dynamics in axonal boutons

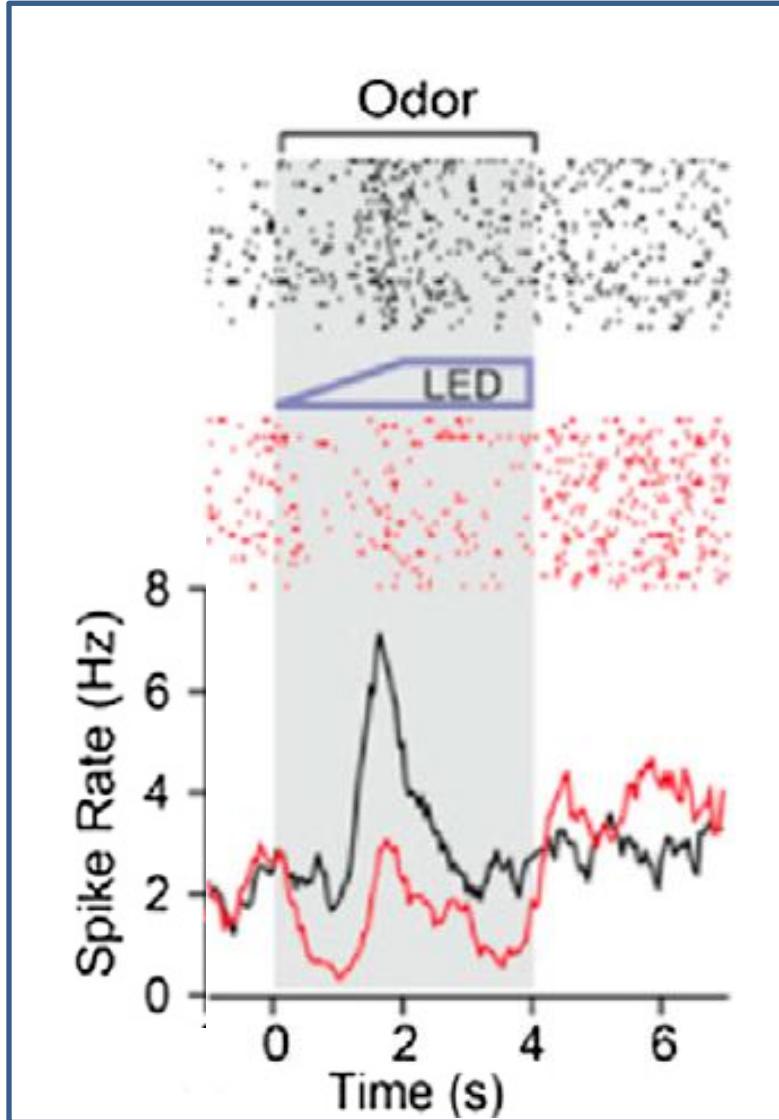


# Feedback bouton calcium dynamics is fast

Average bouton response to cortical electrical stimulation protocol (muscimol)

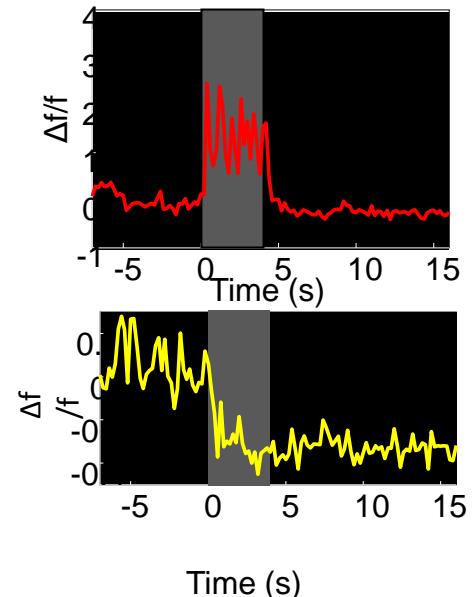


# Optogenetic activation of cortical feedback suppresses olfactory bulb output

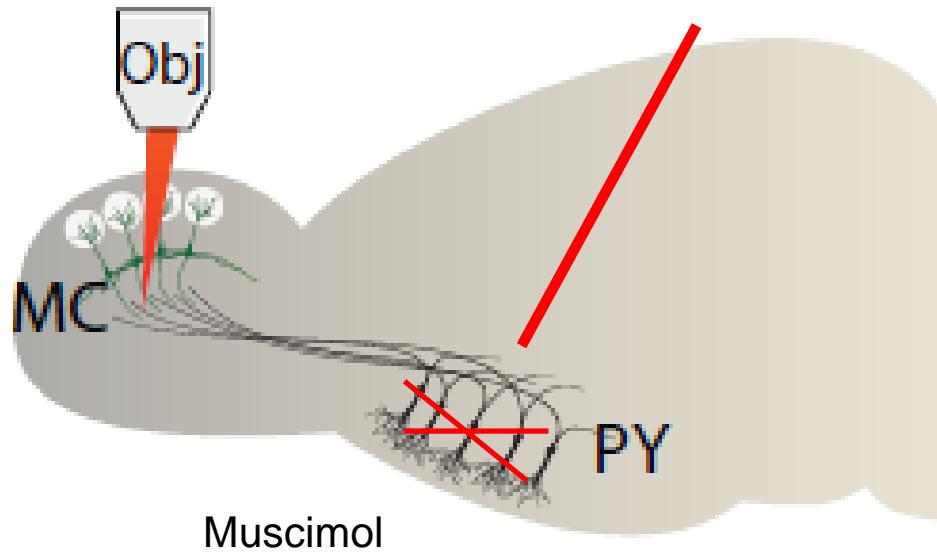


Without feedback activation

With feedback activation

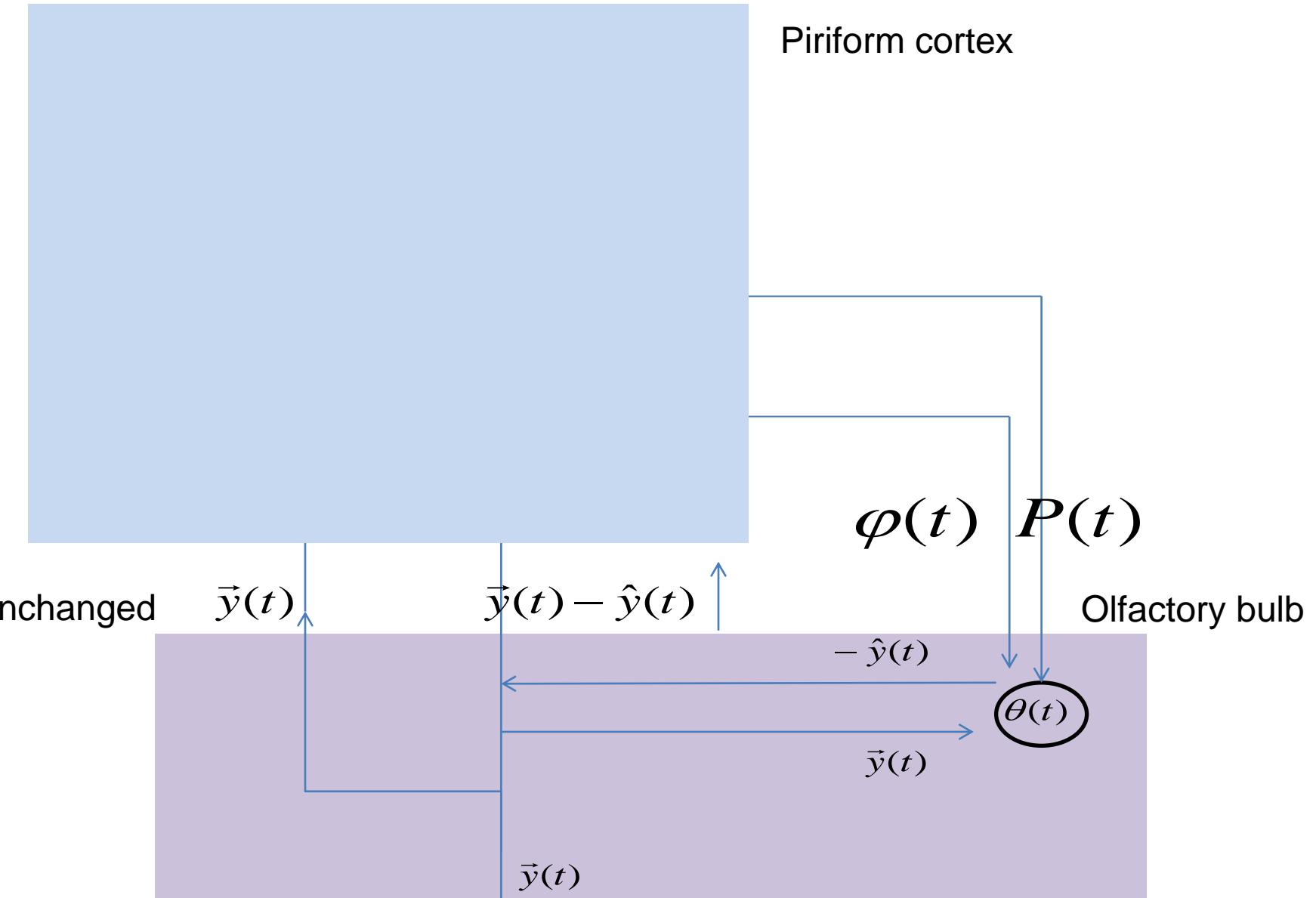


# Pharmacological inactivation of piriform cortex

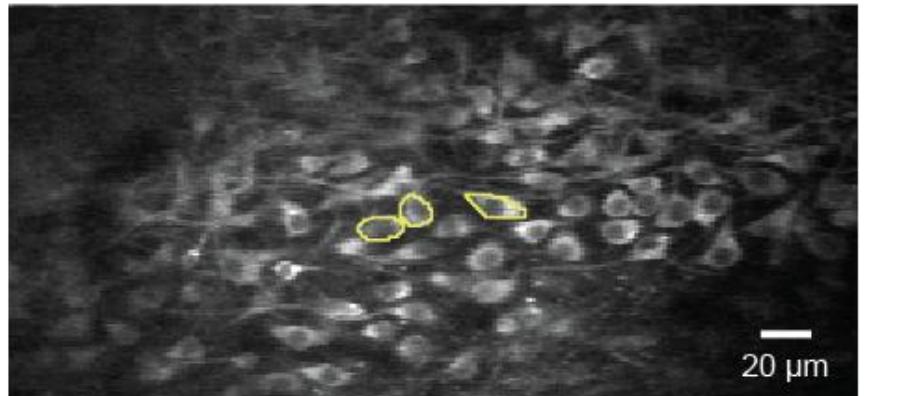


**How does cortical feedback modulate  
the output of the bulb?**

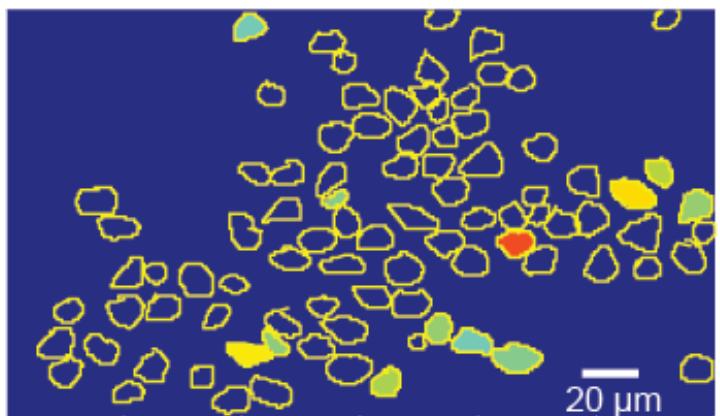
iCPA requires a feedback independent and a feedback dependent channel



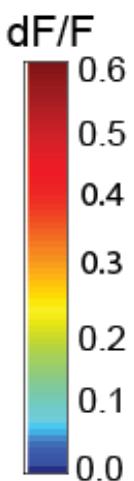
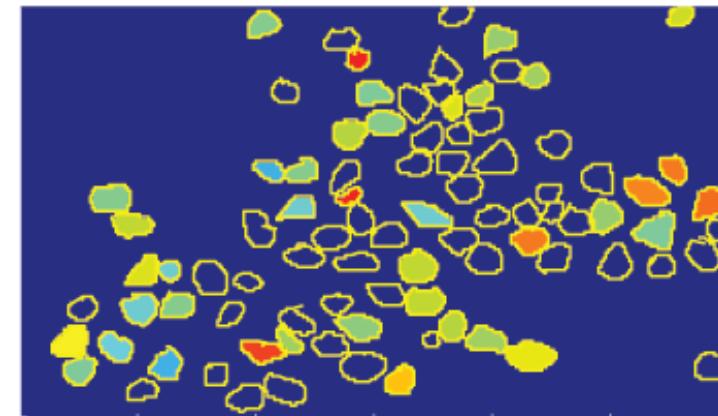
# Piriform inactivation enhances the number of responsive mitral cells



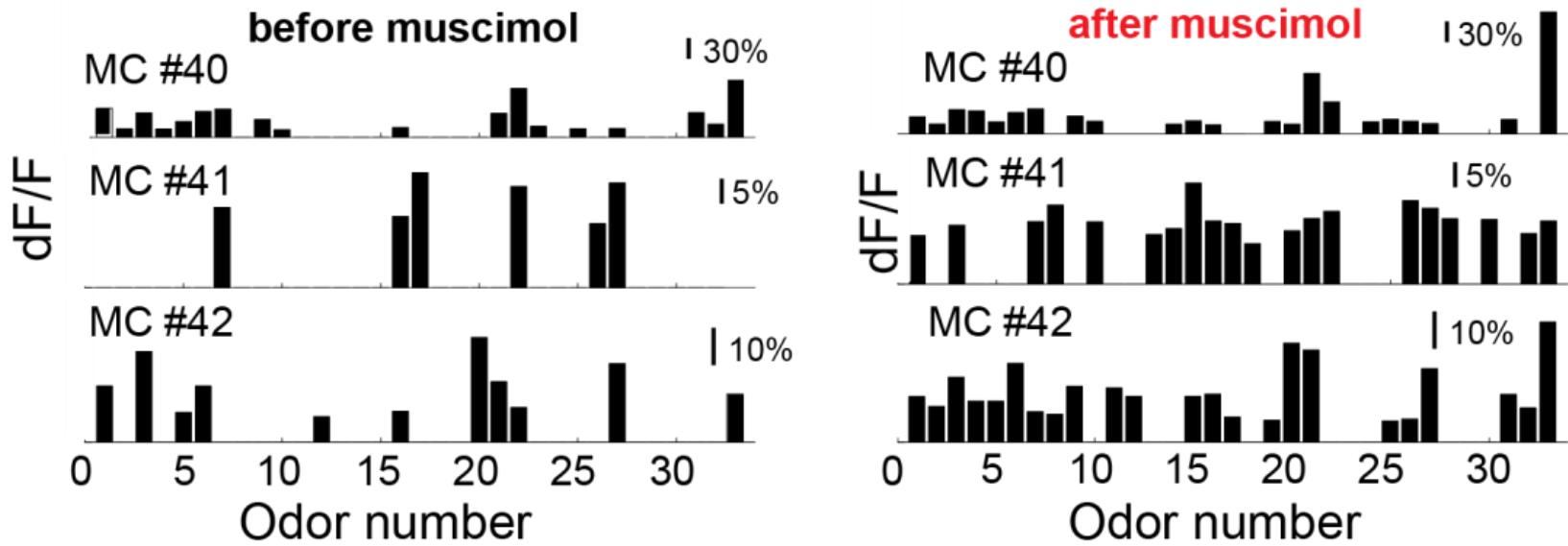
Before muscimol injection



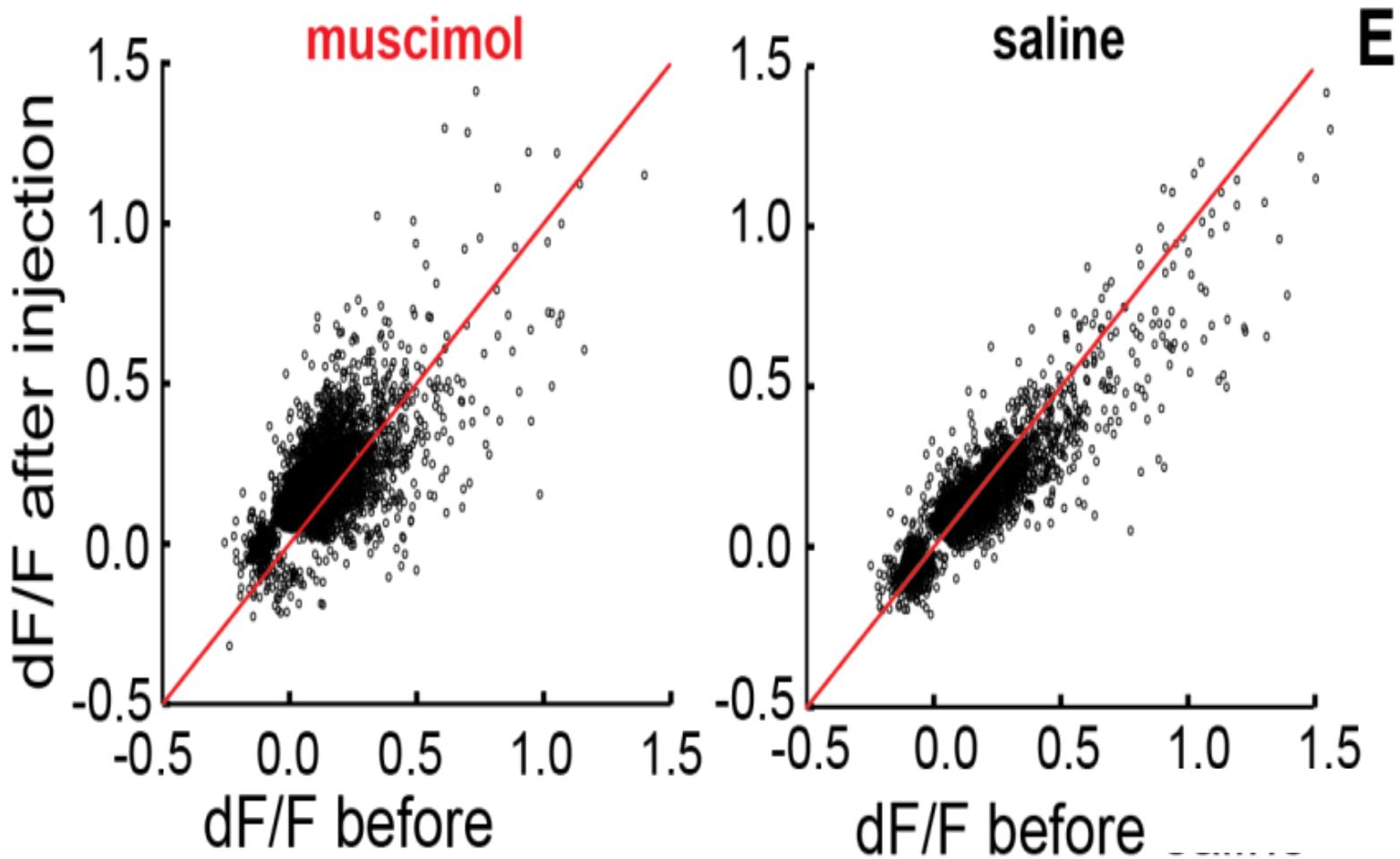
After muscimol injection



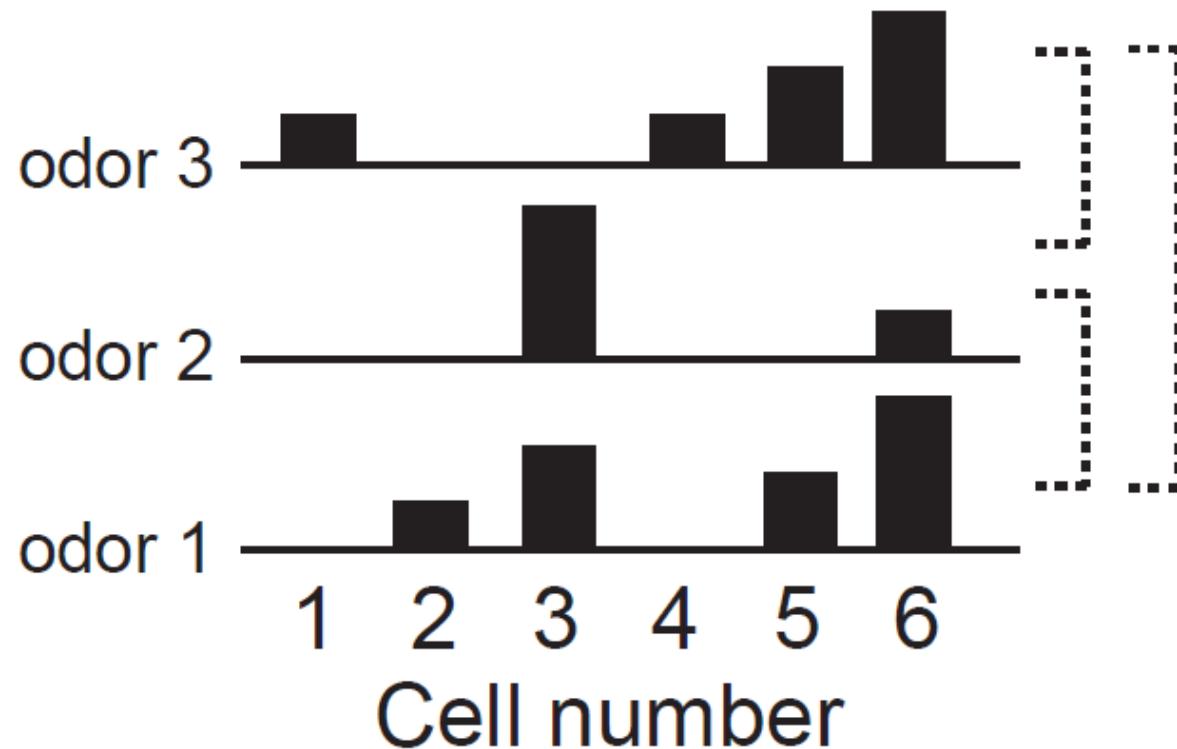
# Piriform cortex inactivation enhances the responses of individual mitral cells



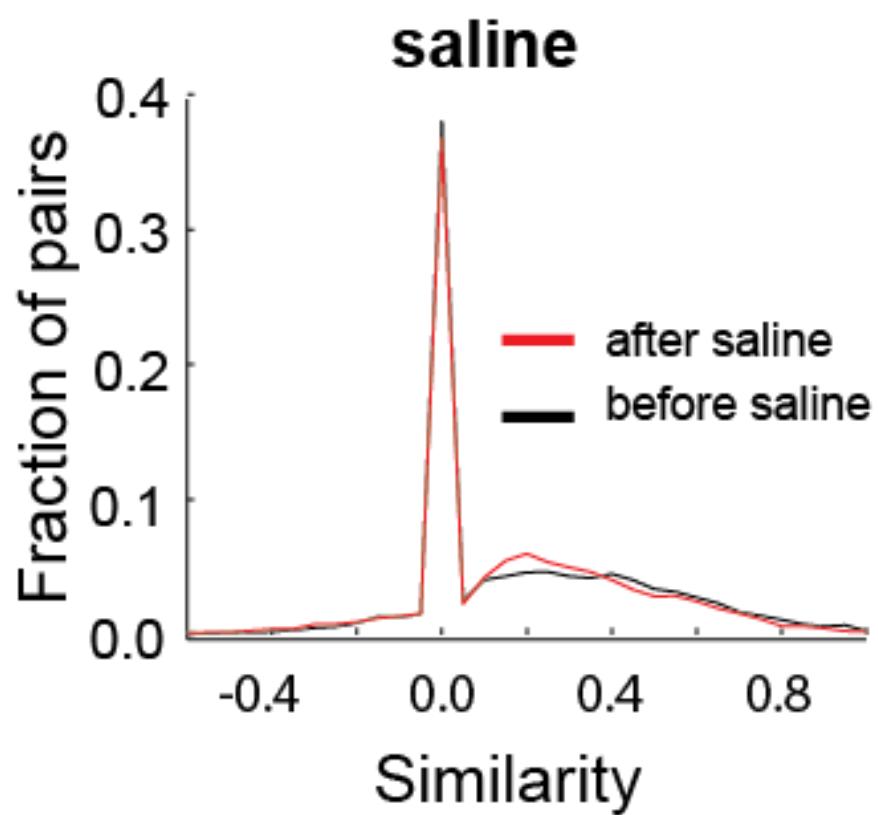
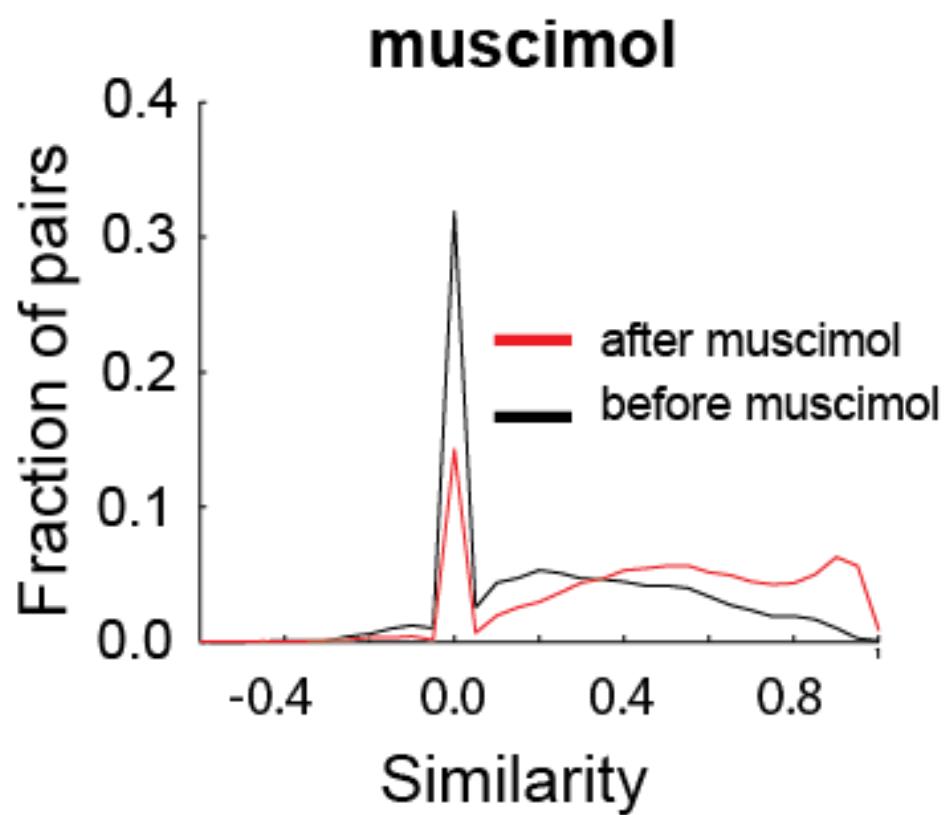
# Piriform cortex inactivation enhances the responses of individual mitral cells



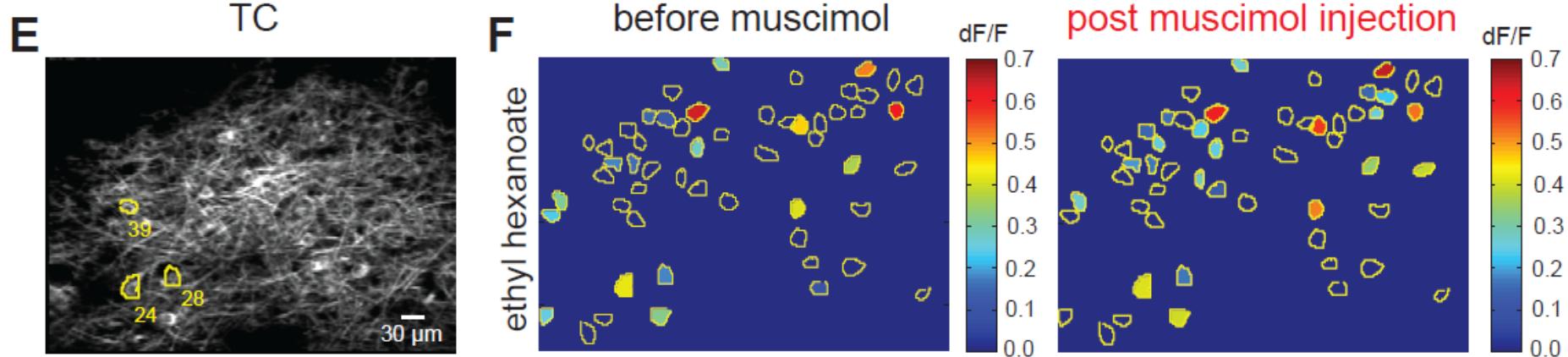
# Does cortical feedback enhance odor discriminability?



# Cortical feedback enhances odor discriminability

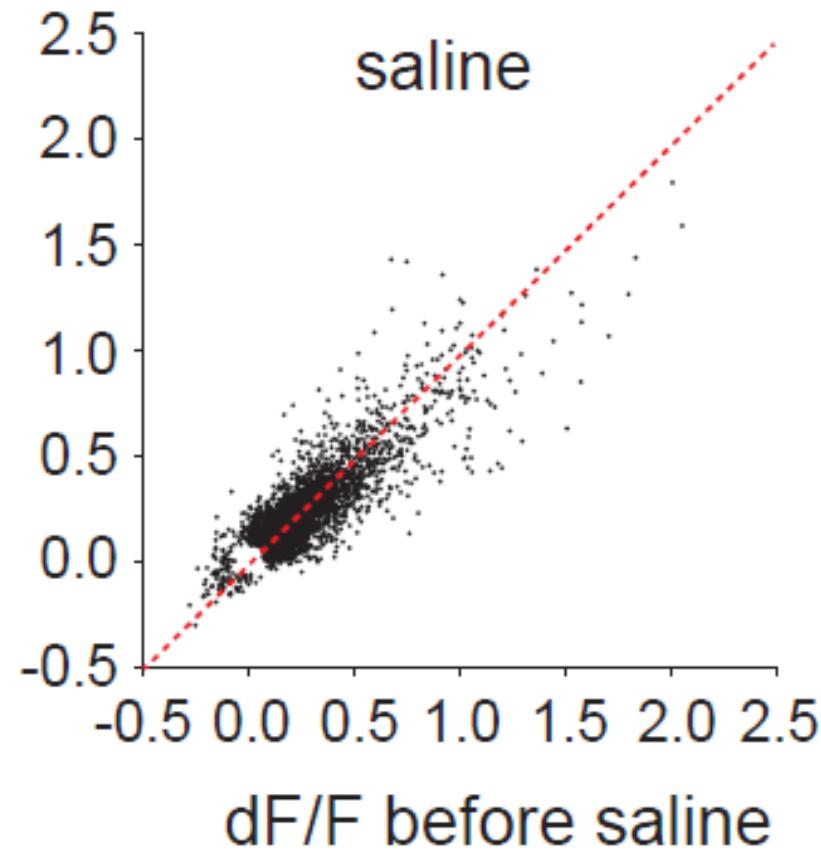
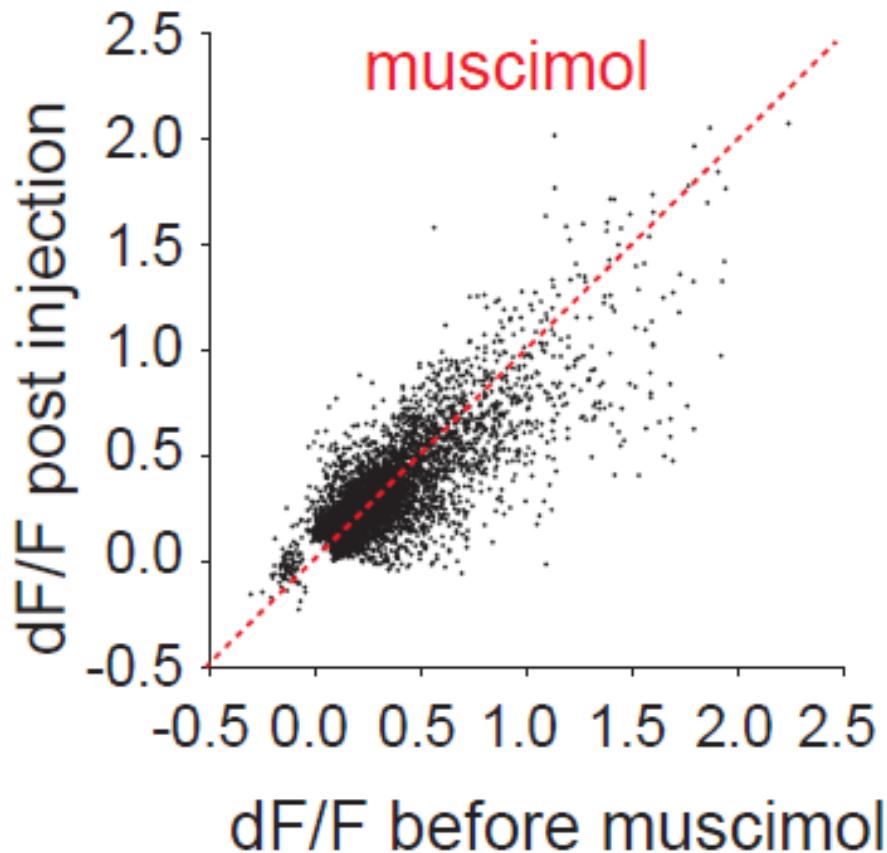


# Piriform cortex inactivation does not affect the responses of tufted cells

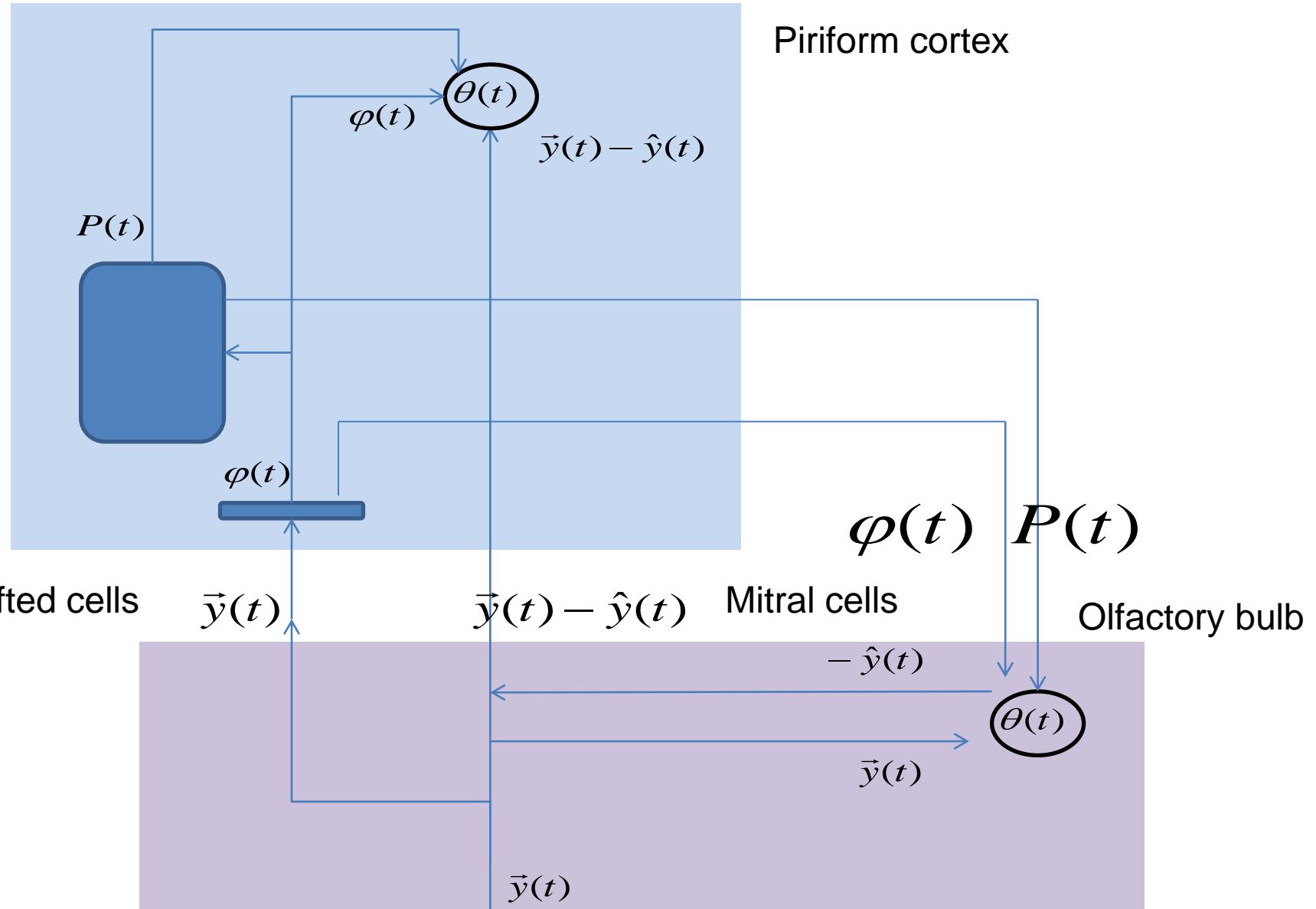


# Piriform cortex inactivation does not affect the responses of individual tufted cells

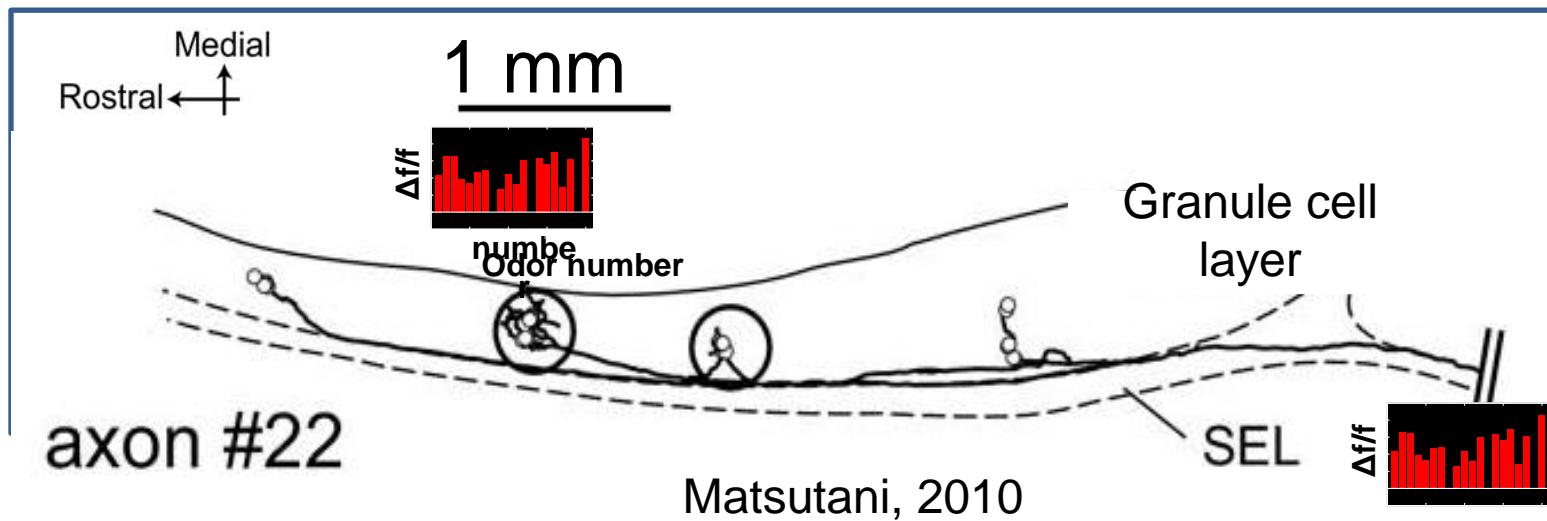
D



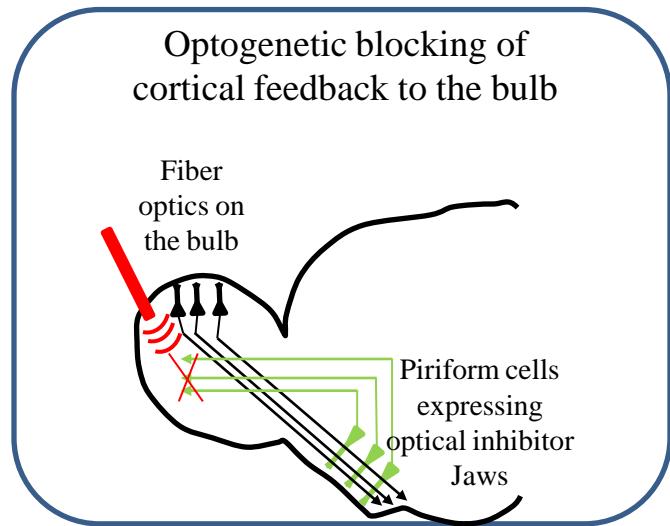
# iCPA requires a feedback independent and a feedback dependent channel



# Open questions



- 1) What is the functional connectivity between feedback axons and their target areas?
- 2) What is the role of cortical feedback during olfactory behavior?



# Albeanu Lab

# Thanks!

Francesca Anselmi  
Arkarup Banerjee  
Pedro Garcia da Silva  
Priyanka Gupta  
Martin Davis  
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Computational model

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# The matrix $\Phi^T \Phi$ is positive definite

$$x^T (\Phi^T \Phi) x > 0 \quad \text{For all vectors } x$$

The single elements of  $\Phi^T \Phi_{i,j}$  are:  $(\Phi^T \Phi)_{i,j} = \sum_{t=1}^T (\vec{y}(t) \cdot \vec{B}_i) (\vec{y}(t) \cdot \vec{B}_j) (\vec{B}_i \cdot \vec{B}_j)$

$$\begin{aligned} x^T (\Phi^T \Phi) x &= \sum_{t=1}^T \sum_{i=1}^N \sum_{j=1}^N x_i x_j (\vec{y}(t) \cdot \vec{B}_i) (\vec{y}(t) \cdot \vec{B}_j) (\vec{B}_i \cdot \vec{B}_j) \\ &= \sum_{t=1}^T \sum_{i=1}^N (x_i)^2 (\vec{y}(t) \cdot \vec{B}_i)^2 + \sum_{t=1}^T \sum_{i=1}^N \sum_{j=1, j \neq i}^N 2 \frac{x_i}{\sqrt{2}} \frac{x_j}{\sqrt{2}} (\vec{y}(t) \cdot \vec{B}_i) (\vec{y}(t) \cdot \vec{B}_j) \sum_{k=1}^M B_{m,i} B_{m,j} \\ &\quad + \sum_{t=1}^T \sum_{k=1}^M \sum_{i=1}^N \frac{(x_i)^2}{2} (\vec{y}(t) \cdot \vec{B}_i)^2 (B_{m,i})^2 - \sum_{t=1}^T \sum_{k=1}^M \sum_{i=1}^N \frac{(x_i)^2}{2} (\vec{y}(t) \cdot \vec{B}_i)^2 (B_{m,i})^2 \end{aligned}$$

- All the eigenvalues of  $\Phi^T \Phi$  are positive
- No zero eigenvalues, therefore,  $\Phi^T \Phi$  is invertible

# The matrix $\Phi^T \Phi$ is positive definite

$$\begin{aligned} x^T (\Phi^T \Phi) x &= \sum_{t=1}^T \sum_{i=1}^N (x_i)^2 (\vec{y}(t) \cdot \vec{B}_i)^2 + \sum_{t=1}^T \sum_{i=1}^N \sum_{j=1, j \neq i}^N 2 \frac{x_i}{\sqrt{2}} \frac{x_j}{\sqrt{2}} (\vec{y}(t) \cdot \vec{B}_i) (\vec{y}(t) \cdot \vec{B}_j) \sum_{m=1}^M B_{m,i} B_{m,j} \\ &\quad + \sum_{t=1}^T \sum_{m=1}^M \sum_{i=1}^N \frac{(x_i)^2}{2} (\vec{y}(t) \cdot \vec{B}_i)^2 (B_{m,i})^2 - \sum_{t=1}^T \sum_{m=1}^M \sum_{i=1}^N \frac{(x_i)^2}{2} (\vec{y}(t) \cdot \vec{B}_i)^2 (B_{m,i})^2 \\ &= \sum_{t=1}^T \sum_{m=1}^M \left( \sum_{i=1}^N \frac{(x_i)}{\sqrt{2}} (\vec{y}(t) \cdot \vec{B}_i) (B_{m,i}) \right)^2 + \sum_{t=1}^T \sum_{i=1}^N (x_i)^2 (\vec{y}(t) \cdot \vec{B}_i)^2 \left( 1 - \sum_{m=1}^M \frac{1}{2} (B_{m,i})^2 \right) \\ &= \sum_{t=1}^T \sum_{m=1}^M \left( \sum_{i=1}^N \frac{(x_i)}{\sqrt{2}} (\vec{y}(t) \cdot \vec{B}_i) (B_{m,i}) \right)^2 + \sum_{t=1}^T \sum_{i=1}^N (x_i)^2 (\vec{y}(t) \cdot \vec{B}_i)^2 \left( \frac{1}{2} \right) > 0 \end{aligned}$$

- All the eigenvalues of  $\Phi^T \Phi$  are positive
- No zero eigenvalues, therefore,  $\Phi^T \Phi$  is invertible