

# The Functional Role of Randomness in Olfactory Processing.

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## Background: Olfactory Stimuli and Circuits

• Natural odors, even complex ones, are composed of a small fraction of the possible number of volatile molecules and hence are "k-sparse" in chemical space.

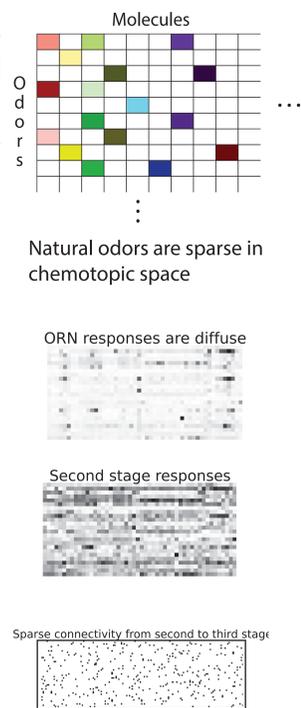
• Olfactory sensing requires identification and segmentation of varying and novel complex odors against a highly variable background

• Olfactory Receptor Neurons (ORNs) have diffuse responses where each receptor responds to many odors, and each odor stimulates many receptors.

• ORNs of a given type converge to the same structure(glomerulus) in the next stage of processing (bulb/antennal lobe for vertebrates/invertebrates)

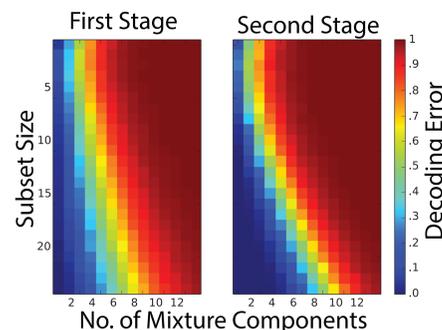
• The responses in the second stage are gain-normalized and more decorrelated than ORN responses

• The projections from the olfactory bulb to the piriform cortex lack any discernible spatial order, and are observed to be sparse



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## Decoding Mixtures from Neural Responses



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### Mixtures can be decoded from small subsets

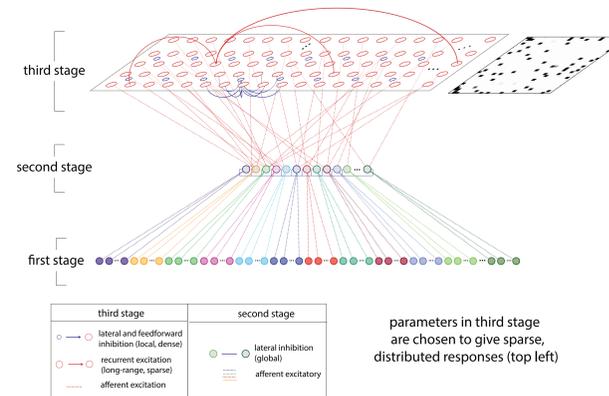
- We use measured ORN responses from [2]
- Calculate mixture responses from ORN responses assuming linear model
- Model second stage responses with divisive no [1]

$$r_i^{Sub} = \frac{R_{max} \cdot (R^{ORN})^{1.5}}{\sigma^{1.5} + (R_i^{ORN})^{1.5} + \left( m \cdot \sum_l R_l^{ORN} \right)^{1.5}}$$

- Decorrelation and equalization improves performance in second stage by orders of magnitude

## Results

### Model Olfactory Pathway

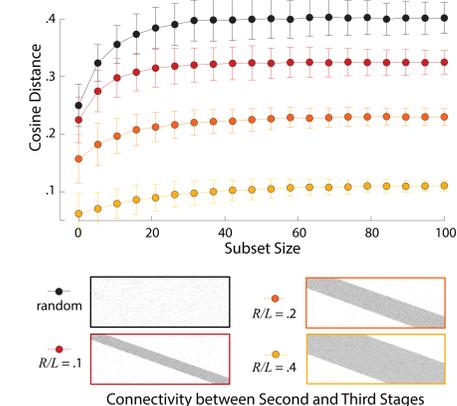


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### Computational model can generate sparse and disordered representations

- Transformation at the second stage modeled as a divisive normalization [1]
- Third stage is modeled by a mixed population of excitatory and inhibitory model neurons with long range excitatory connections and local inhibition [3,4].
- Parameters chosen to produce sparse responses

### Role of Spatial Randomness



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### Spatial disorder of connections improves odor separation even for small subsets

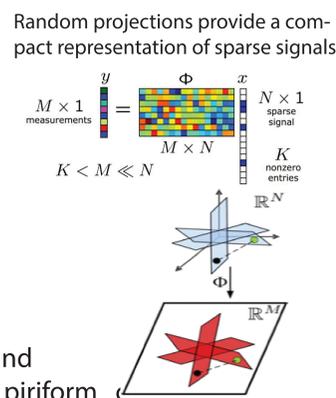
- Neurons in the second stage preferentially project to local regions (of radius R) in the third stage (of size L)
- Total number of connections between the second and third stages kept constant
- At all values of R/L, odors are better separated in the random model

## A Possible Role for Randomness?

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• Random linear projections efficiently produce low-dimensional representations of k-sparse data in a high dimensional input space

• This scheme is universal and works for both familiar and novel inputs. Sensing does not depend on exact stimulus statistics and works for a variety of other low-dimensional signal models



**Hypothesis:** The diffuse sensing by the ORNs and subsequent expansive random projections to the piriform exist to exploit the inherently low dimensional structure of olfactory stimuli to produce compact, flexible representations of odors.

• Diffuseness of olfactory sensing leads to a compact representation of sparse high dimensional signals

• Randomness in the subsequent projections provides a representation where:  
 (a) small subsets of neurons store information about complex odors,  
 (b) noise and finite bandwidth limit the capacity for any small subset,  
 (c) different subsets of cortical neurons will have low overlap in the odors they represents, but collectively provide a large capacity.

## Sparsity and Odor Representation in Small Subsets

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### Odor coverage by small, non-overlapping clusters

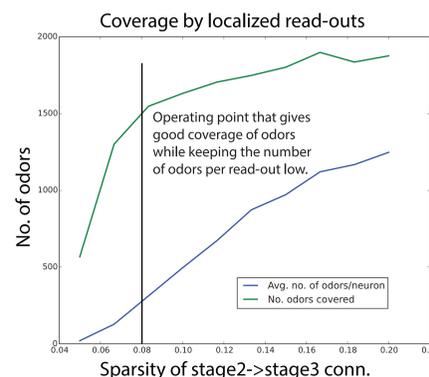
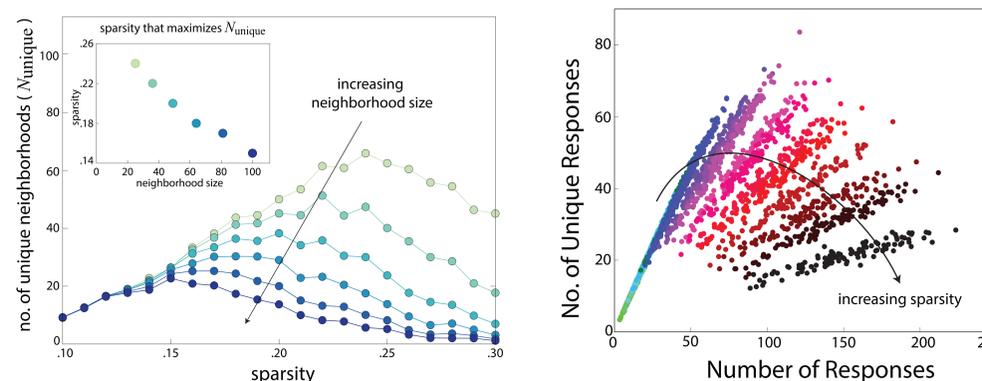


Figure shows average number of odors that evoke an above-threshold response (blue) in a given small cortical patch and the average number of unique odors that evoke a response in some patch (green), as the sparsity of connections between the second and third stages is varied. The patches are contiguous, non-overlapping and cover ~1% of the cortex. Random connectivity gives good coverage of odors over all patches while keeping the average number of odors per patch low

### Representation of odors in clusters centered at active sites



Graphs look at clusters of varying sizes centered at active locations in the cortex (third stage) as the sparsity of the connection between the second and third stage is varied. (First graph) Clusters are unique if the set of odors that evoke a response in the cluster are non-overlapping. Plot shows that for a given neighborhood size a specific value of sparsity maximizes the no. of unique clusters. Second plot shows the number of unique clusters vs. total activity for different values of sparsity. For smaller values of sparsity the no. of unique clusters grows faster with the total activity

## Discussion

- Olfactory system might utilize the computational power of randomness both in sensing and in subsequent transformations to provide a robust and flexible representation
- Diffuseness in sensing provides a compact representation of sparse high dimensional signals
- Disorder in the subsequent projections provides a flexible representation where small subsets of neurons can efficiently store information about complex odors
- We have built a model of the olfactory pathway that allows us to investigate the role of various circuit elements in shaping this representation

## References

1. Olsen et al. "Divisive normalization in olfactory population codes" Neuron 66.2 (2010): 287.
2. Hallem, Elissa A., and John R. Carlson. "Coding of odors by a receptor repertoire." Cell 125.1 (2006): 143-160
3. Franks, Kevin M., et al. "Recurrent circuitry dynamically shapes the activation of piriform cortex." Neuron 72.1 (2011): 49-56.
4. Poo, Cindy, and Jeffrey S. Isaacson. "A major role for intracortical circuits in the strength and tuning of odor-evoked excitation in olfactory cortex." Neuron 72.1 (2011): 41-48.