Push-pull Feedback Implements Hierarchical Information Retrieval Efficiently

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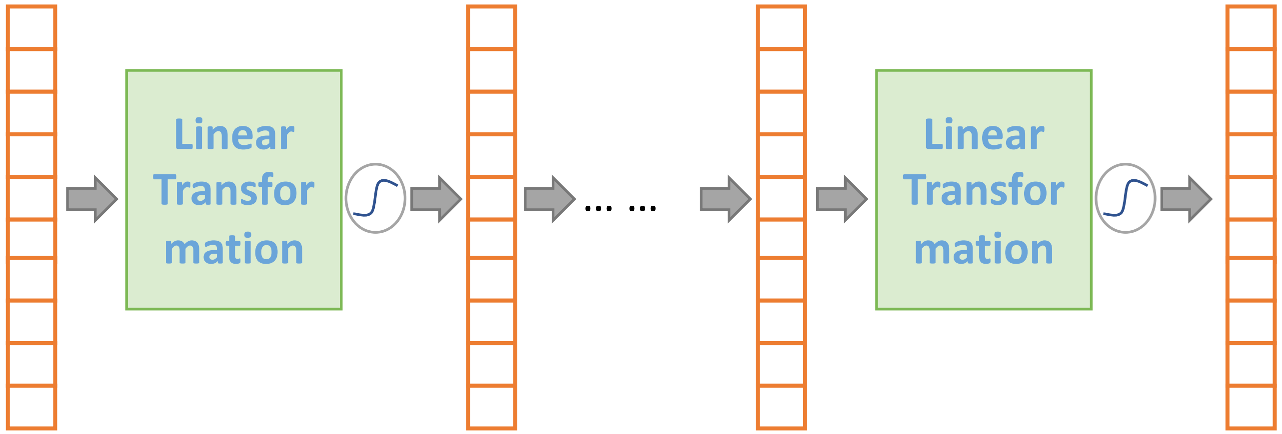
Feedback Missed in Deep neural networks (DNNs)

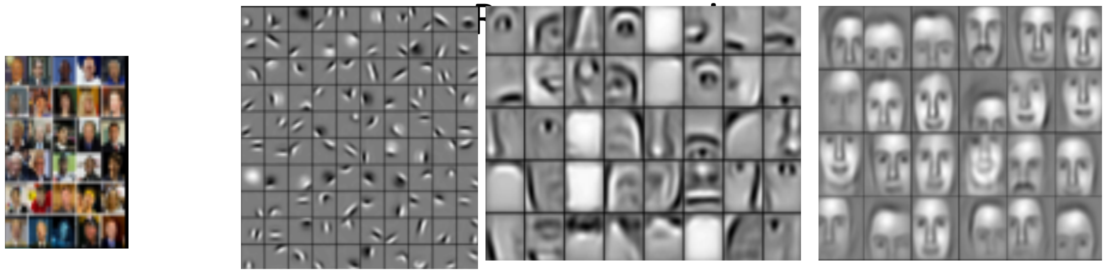
DNNs, which contains **feedforward** connections from lower to higher layers, has achieved great success in object recognition.



Input Data

Hidden

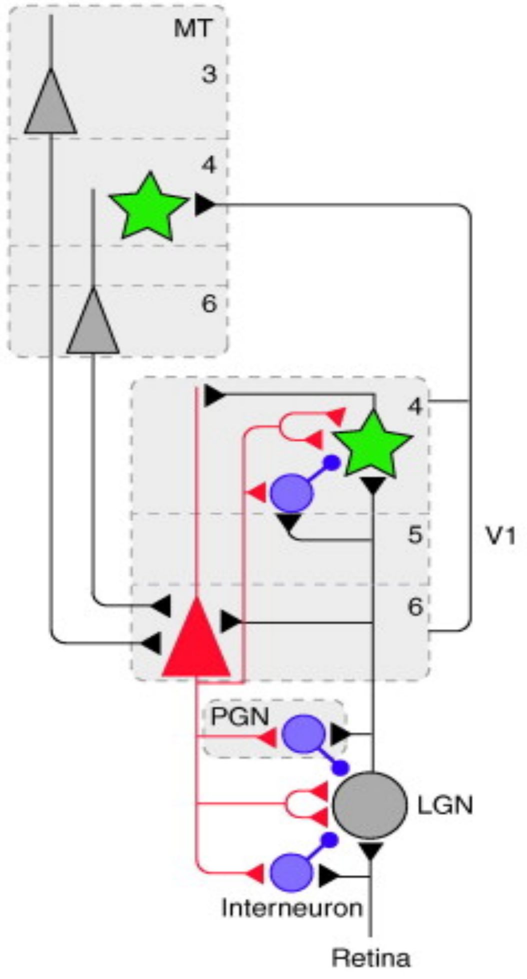
Output



H. Lee, R.Grosse, R. Ranganath, A. Ng, Convolutional Deep Belief Networks for Scalable Unsupervised Learning of Hierarchical Representations. International Conference on Machine Learning(ICML),2009.

Potential Roles of Feedback Connections

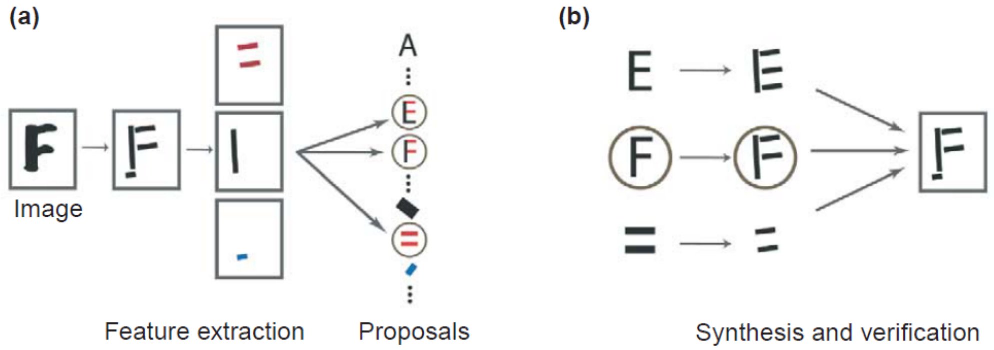
Abundant Feedback Connections



A. M. Sillito, J. Cudeiro, H. Jones, Always returning: feedback and sensory processing in visual cortex and thalamus. Trends in Neurosciences, 29(6),307-316,2006

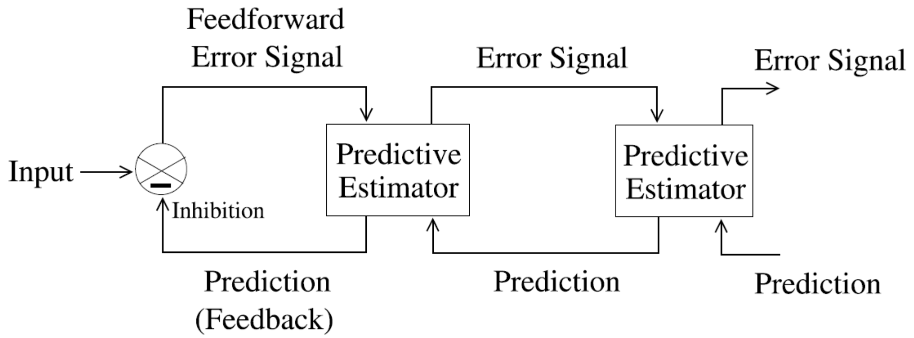
How do those feedback modulate recognition?

- **analysis-by-synthesis**



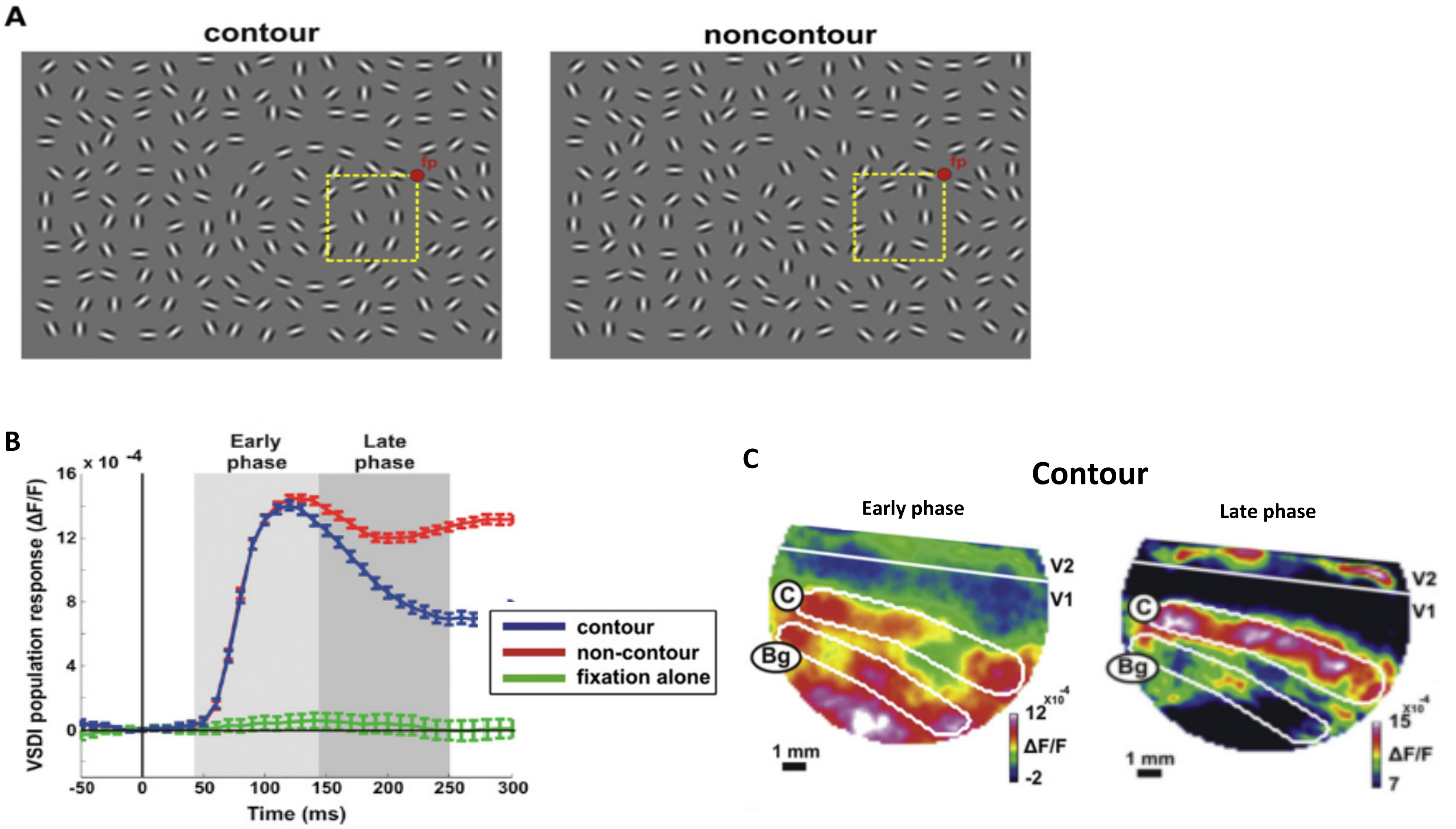
A. Yuille, D. Kersten, Vision as Bayesian inference: analysis by synthesis? Trends in Cognitive Sciences 10(7), 301-308 (2006)

- **predictive coding**



R. Rao, D. Ballard, Predictive coding in the visual cortex: a functional interpretation of some extra-classical receptive-field effects. Nature Neuroscience,2(1),79-87(1999)

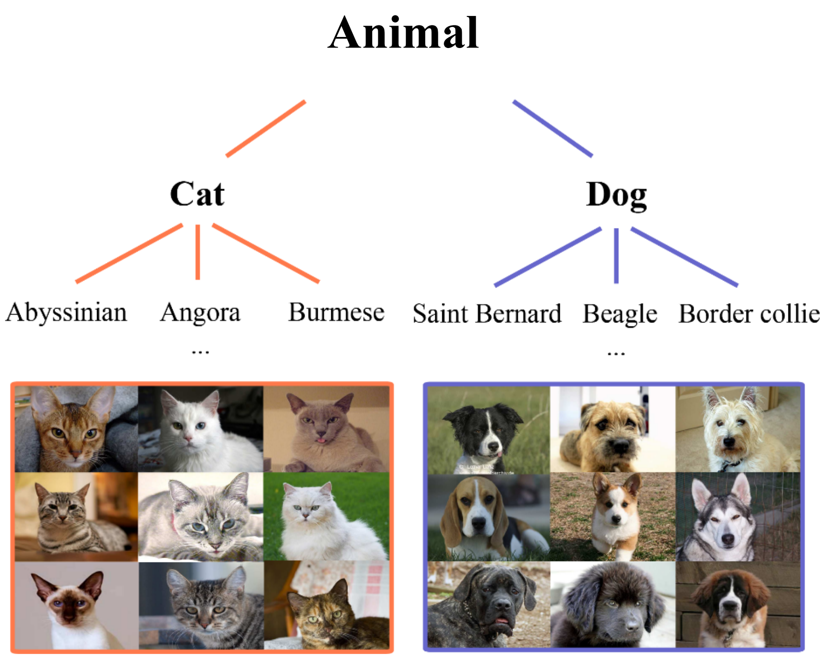
The Push-pull Phenomenon in Neural Responses

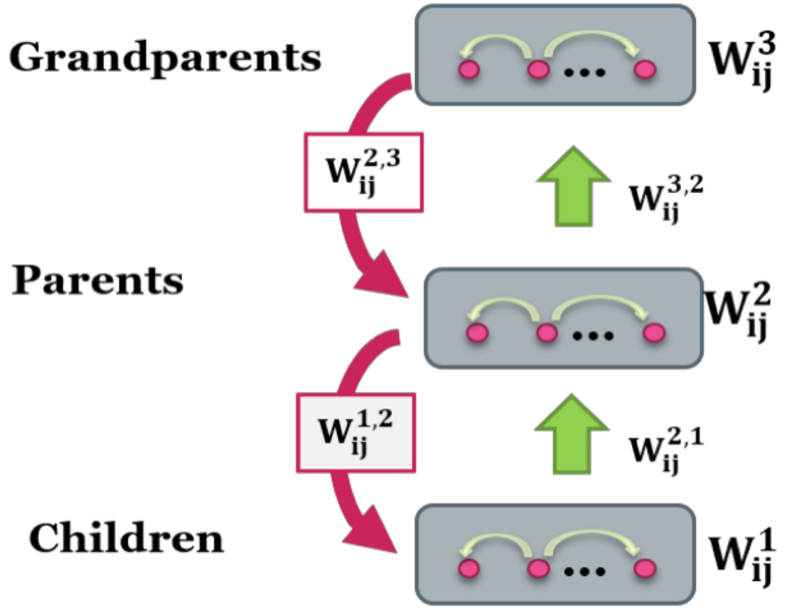


A. Gilad, E. Meirovithz, H. Slovin, Population responses to contour integration: early encoding of discrete elements and late perceptual grouping. Neuron, **78**, 389-402 (2013).

Aim: Investigating the Role of Neural Feedback

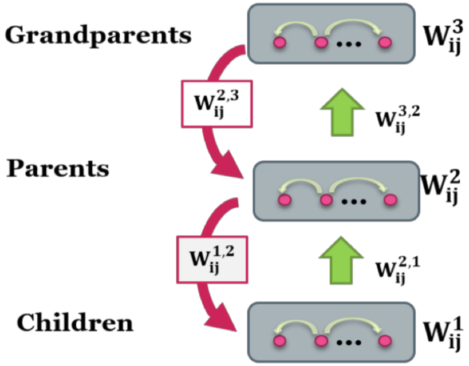
Hierarchical structure of objects + Multi-layer neural network

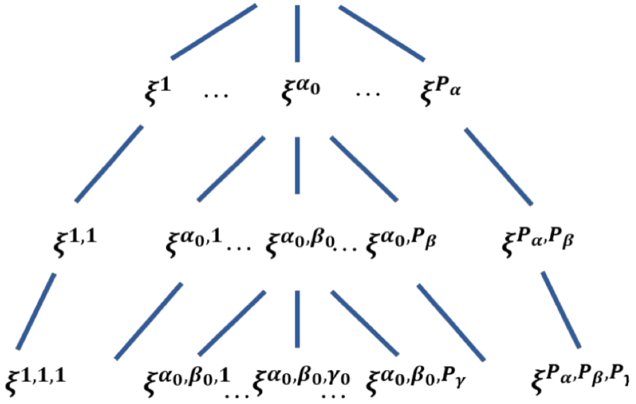




Consider a rough-to-fine retrieval procedure. The higher categorical patterns of objects are first retrieved, since they are less correlated than lower categorical ones. How can neural feedback improve information retrieval?

The Structure of Model and The Hierarchical Patterns





Grandparent patterns: $\{\xi^{\alpha}\}$ for $\alpha = 1, \dots, P_\alpha$.

Parent patterns: $\{\xi^{\alpha,\beta}\}$ for $\beta = 1, \dots, P_\beta$.

Children patterns: $\{\xi^{\alpha,\beta,\gamma}\}$ for $\gamma = 1, \dots, P_\gamma$.

The model consists of three layers which store three-level hierarchical memory patterns. Between layers, neurons are connected by both feedforward and feedback connections.

The state of neuron i in layer l at time t :

$$x_i^l = sign[h_i^l(t)], \qquad i = 1, \dots N.$$

The total input neuron i in layer l recived :

$$h_i^l(t) = \sum_j W_{ij}^l x_j^l(t) + \sum_k W_{ik}^{l,l+1}(t) x_k^{l,l+1}(t), \quad l = 1,2.$$

The recurrent and feedforward connections in layer 1 :

$$W_{ij}^1 = \sum \xi_i^{\alpha,\beta,\gamma} \xi_j^{\alpha,\beta,\gamma}, \quad W_{ij}^{1,2} = \sum \xi_i^{\alpha,\beta,\gamma} \xi_j^{\alpha,\beta} .$$

The value of each element in a pattern is drawn the following distributions:

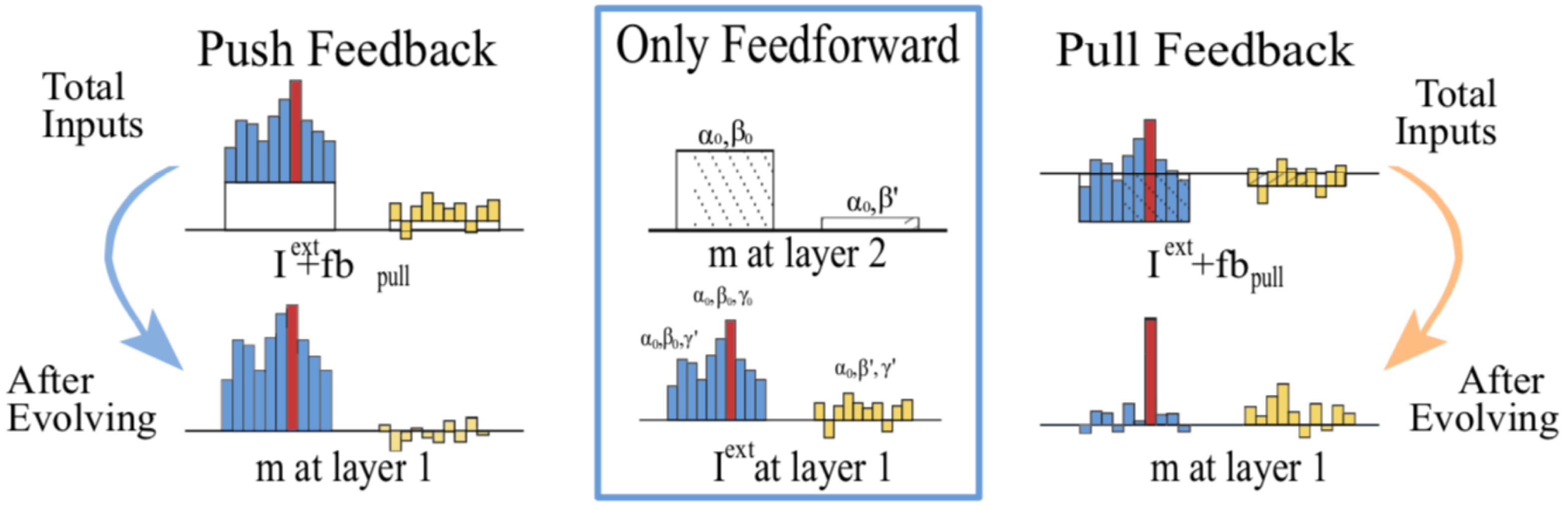
$$P(\xi_i^{\alpha}) = \frac{1}{2}\delta(\xi_i^{\alpha} + 1) + \frac{1}{2}\delta(\xi_i^{\alpha} - 1),$$

$$P(\xi_i^{\alpha,\beta}) = \left(\frac{1+b_2}{2}\right)\delta\left(\xi_i^{\alpha,\beta} - \xi_i^{\alpha}\right) + \left(\frac{1-b_2}{2}\right)\delta\left(\xi_i^{\alpha,\beta} + \xi_i^{\alpha}\right),$$

$$P(\xi_i^{\alpha,\beta,\gamma}) = \left(\frac{1+b_1}{2}\right)\delta\left(\xi_i^{\alpha,\beta,\gamma} - \xi_i^{\alpha,\beta}\right) + \left(\frac{1-b_2}{2}\right)\delta\left(\xi_i^{\alpha,\beta,\gamma} + \xi_i^{\alpha,\beta}\right).$$

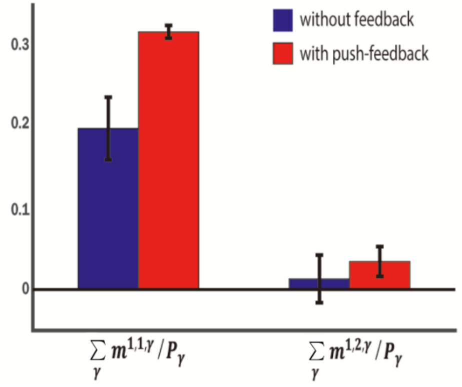
It previses that the patterns in the same group have stronger correlation than those belonging to different groups. And the grandparent patterns are statistically independent of each other.

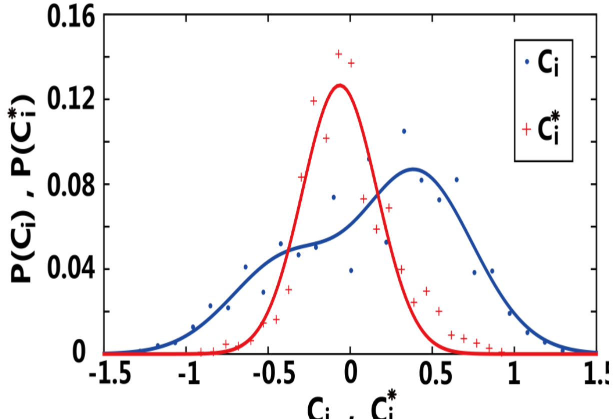
The Effects of Push and Pull Feedbacks



Push-feedback increases the activities of all sibling patterns, which effectively decreases the activities of cousins, and hence suppresses the inter-class noise

Pull-feedback subtracts the parent pattern information, which effectively highlights the subtle differences between siblings, and therefore suppresses the intra-class noise .





The Joint Effect of the Push-pull Feedback

The optimal feedback should be dynamical, varying from push to negative over time, which suppresses the interferences to memory retrieval due to pattern correlations from different and the same categories, respectively.

The network dynamics are:

$$\tau \frac{dh_i^n}{dt} = -\, h_i^n + \sum_j W_{ij}^n x_j^n + \sum_k W_{ik}^{n,m}(t) x_k^n + I_i^{ext,n},$$

$$x_i^n = f(h_i^n), \qquad m, n = 1,2,$$

$$f(x) = \arctan(8\pi x)\,/\pi + 1/2.$$

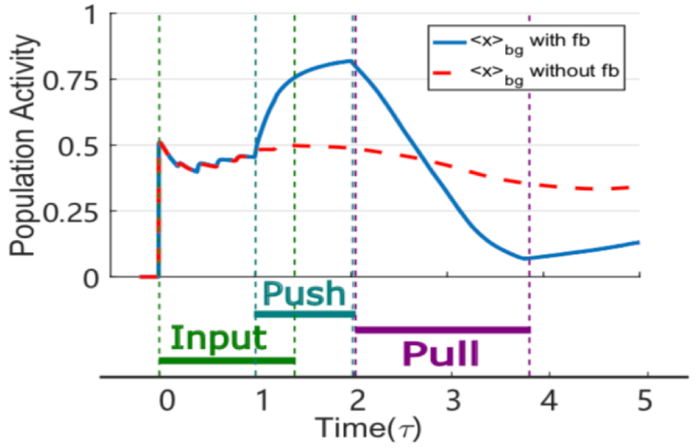
The push-feedback:

$$W_{ik}^{1,2} = a_+ P_\gamma \sum_{\alpha,\beta,\gamma} (\xi_i^{\alpha,\beta,\gamma} - <\xi>)(\xi_j^{\alpha,\beta,\gamma} - <\xi>)/N\,.$$

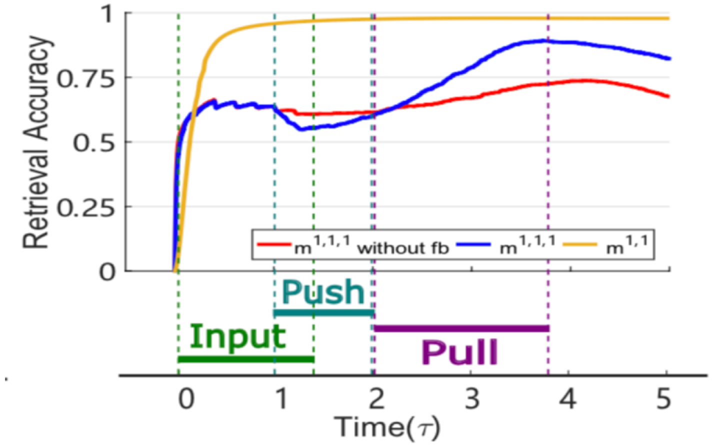
The pull-feedback :

$W_{ik}^{1,2} = a_- b_1 \delta_{ik}$, a_+ *and* a_- are both positive constants.

The neural population activity

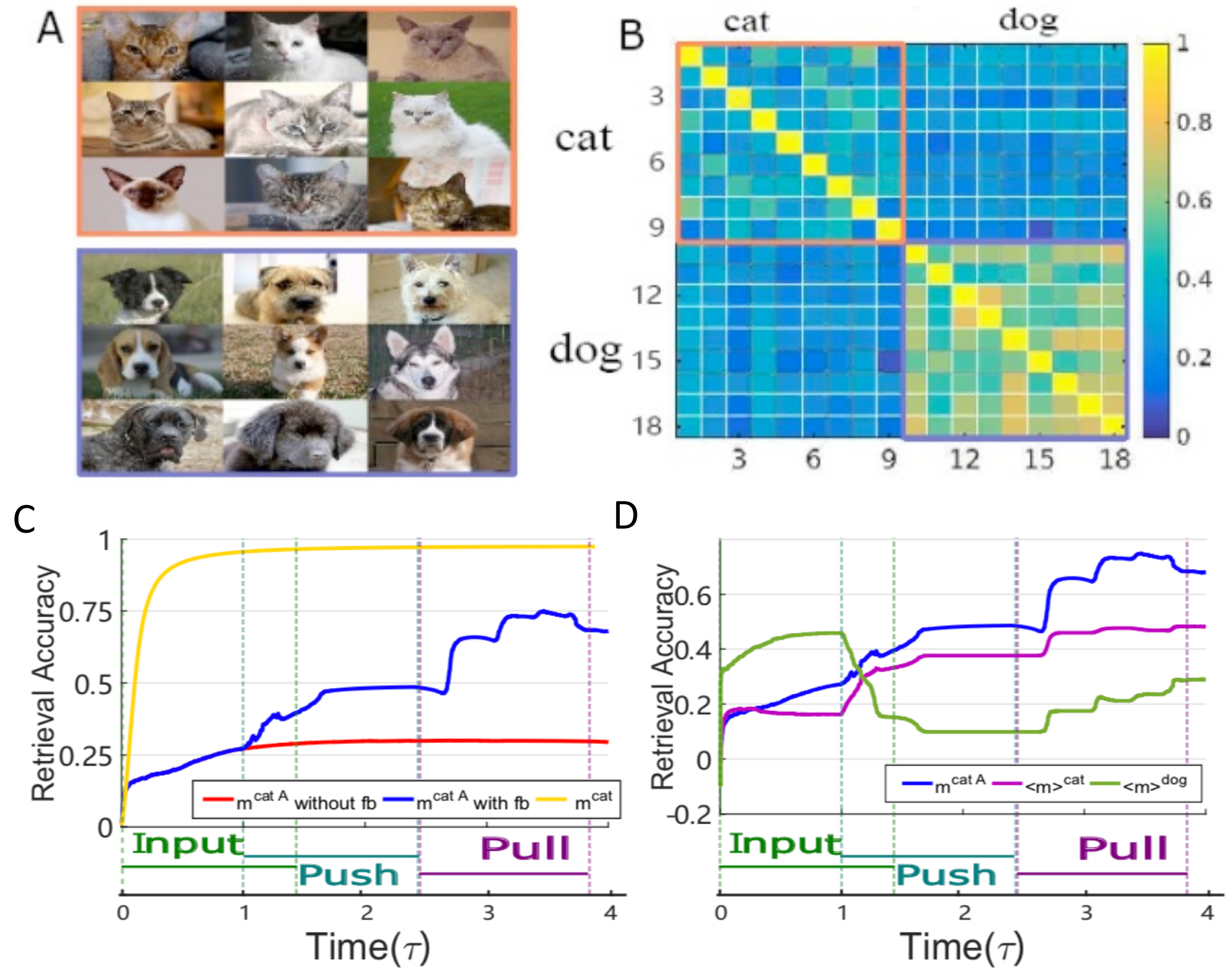


The retrieval performance of network



Experiment with Real Images

The dataset consists of $P_\beta = 2$ types of animals, cats and dogs, corresponding to parents in the model. Images are chosen from ImageNet.
Fig.B shows the correlations between the memory patterns generated by VGG, which exhibits a hierarchical correlation structure.
Fig.C shows a typical example of the retrieval process.
Fig.D shows the different effects of the push and pull feedbacks, illustrating the different effects of the push and pull feedbacks on suppressing the intra-class or inter-class interference .



Conclusion and Discussion

- Our study reals that the neural feedback, which varies from push to pull over time, contributes to suppress the inter- and intra- class noises in information retrieval.
- This push-pull characteristic agrees with the push-pull phenomenon of neural activities observed in the experiments.
- To diminish the correlation interference, we propose that a neural system employs a rough-to-fine information retrieval procedure. Upon receiving the external information, the higher categorical pattern is first retrieved, whose result is subsequently utilized to enhance the retrieval of the lower categorical pattern via dynamical push-pull feedback.
- In the future work, we will extend the present study to explore the role of feedback in biologically more detailed models.