Replies to Reviewers

We acknowledge the valuable and encouraging comments of the reviewers. Limited by space, we have to only focus on clarifying the main concerns of the reviewers.

About the realism of the model dynamics

We actually already considered the concurrent dynamics in our model, see Eq. 12, where a neuron receives the feedforward, recurrent, and feedback inputs concurrently. This model generates the results in Fig. 3&4. Our model does not require the convergence of the recurrent dynamics of a layer before applying the top-down feedback.

The experimental data indicates that the time elapse between two feedbacks is about $10 \sim 20$ ms, which guides us to set the separation between two feedbacks to be $1 \sim 1.5\tau$, with $\tau = 10 \sim 20$ ms the membrane time constant, see the lower panels in Fig. 3&4. We also investigated how the model performance varies with the elapse time, see Fig. S3, which shows that the biological elapse time is adequate for the push-pull feedback to function.

We hope we have addressed reviewer 1's major concern about "the realism of dynamics".

About the role of push feedback and the working mechanism of pull feedback

First of all, we would like to apologize for the confusing notations in Fig. S2, where the intra- (λ_1) and inter- (λ_2) class noises refer to the external input noises (see the definitions in the last paragraph of Sec. 4.1 in SI at page 8), which may be confused with the interference noises due to pattern correlations used in the main text (coming from b_1 and b_2).

Indeed, as pointed out by the reviewer 2, if only push is applied, the retrieval of the coarse-scale class is improved, which is demonstrated in Fig. 2A. Notably, the contribution of push feedback varies with the parameters. Fig. S2 are the cases where the contribution of push feedback is minor. By choosing different parameters, we can obtain that the contribution of push feedback is large. An example is shown in the right-hand side figure, in which the number of patterns $P_\gamma P_\beta = 40$ is much smaller than $P_\gamma P_\beta = 100$ used in Fig. S2. In general, we find that when the number of patterns is fewer (or the duration of the external input is short), the push feedback tends to have a larger contribution. Thus, the role of feedback is very important. Consider information retrieval in a deep hierarchical network, where the numbers of high-level patterns in the top layers are fewer, then the push feedback is crucial to achieve good retrieval performances of high-level patterns, which subsequently enhance the retrieval of low-level patterns layer by layer.

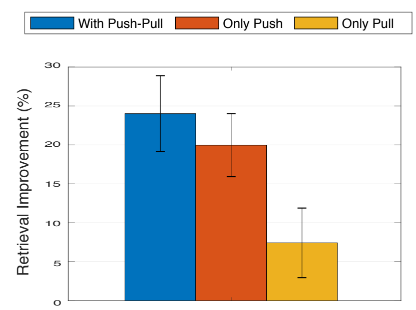

Figure 1: Comparing network performances with the push-pull, only push, and only pull feedbacks, respectively, with $P_\beta = 2$, $P_\gamma = 20$, and other parameters the same as in the figures in our paper.

As the push feedback is to enhance the retrieval of sibling patterns from the same parent, it is natural to set its form as the product between the child and parent patterns according to the Hebbian rule. For the pull feedback, we arrive at the current form as it de-correlates sibling patterns (see lines 169-170 in the main text and Sec. 3.3 in SI). We further theoretically prove that this form of pull feedback guarantees to improve the retrieval accuracy (Sec. 3.4 in SI). We may understand the working mechanism of pull feedback intuitively in the following way. By subtracting the common part, it highlights the subtle differences between sibling patterns. For example, the fractional difference between two numbers 101 and 99 is small; but after subtracting the mean 100, we get 1 and -1, whose difference appears to be significant, and the nonlinear threshold-like sigmoid function in the neural dynamics (Eq.13) helps to amplify this difference.

We hope that we have addressed reviewer 2's concerns about the role and mechanism of push and pull feedbacks.

About practical applications

Actually, we are now working on applying the push-pull feedback to practical applications and have obtained encouraging preliminary results. Here, we introduce the basic idea. We trained a hierarchical prototypical network (a generalization of the prototypical network) using real images, and obtain hierarchical representations (so-called prototypes) of objects across layers (by this, the child, parent, and other higher-level patterns are learned from data). Since the categorization of objects in the prototypical network is based on their distance in the representational space, we can construct the recurrent connections based on the Hebbian rule in each layer with little distortion to the training results. The neural representations in different layers hold the hierarchical correlation structure as considered in this study. We can therefore add the push-pull feedback in the network dynamics to realize robust and flexible, rough-to-fine information retrieval.

We hope that we have addressed reviewers' concern about the potential practical applications of this study.