*Efficient coding model.* We simulated a model neuron that encodes incoming stimuli via an adapting neural nonlinearity. Stimuli were drawn from a Gaussian distribution whose mean was fixed over time but whose standard deviation could switch over time between a low and a high value ( and , respectively). At each time , a stimulus was drawn from the distribution , transformed via a saturating nonlinearity of the form , distorted by Gaussian noise with variance , and finally discretized into discrete levels to generate a response . This discrete responses was linearly decoded to extract an estimate of the current stimulus: . The recent history of stimulus estimates was used to update an estimate of the underlying standard deviation: . The estimate was then used to select the parameters of the encoder () and the decoder () on the next timestep. The encoding and decoding parameters were chosen to minimize the expected error in decoding stimuli given the neuron’s current estimate of the underlying standard deviation: [1,2].

The parameters of the encoder and decoder were adapted based on a background stimulus with a mean that was fixed over time and a standard deviation that switched between low and high values and , respectively. We used this adapting nonlinearity to determine how well this model neuron could discriminate target stimuli from this background. Target stimuli were sampled from a Gaussian distribution with a fixed mean and with a variance that was scaled in proportion to the variance of the background ( and , respectively). At each timestep, we computed the Bhattacharyya coefficient () of the response distributions produced by background versus target stimuli: . We used as our measure of discriminability.

We simulated the behavior of this model using a background “probe” stimulus whose standard deviation switched every timesteps. We simulated cycles of this probe stimulus, where each cycle consisted of timesteps in the low state, followed by timesteps in the high state. This yielded timeseries of the gain and offset of the adapting nonlinearity, as well as distributions of the neural response to the background and target stimuli at each timepoint following a switch in standard deviation. We averaged the gain and offset across cycles to obtain the average properties of the encoder at each timepoint following a switch. We used the distribution of responses to target and background stimuli, measured across cycles, to compute the discriminability at each timepoint following a switch.

All simulations were performed with the following values: , ,,,,,,.

[1] Młynarski W, Hermundstad AM: **Efficient and adaptive sensory codes**. *Nature Neuroscience* 2021.

[2] Młynarski WF, Hermundstad AM: **Adaptive coding for dynamic sensory inference**. *Elife* 2018, **7**.