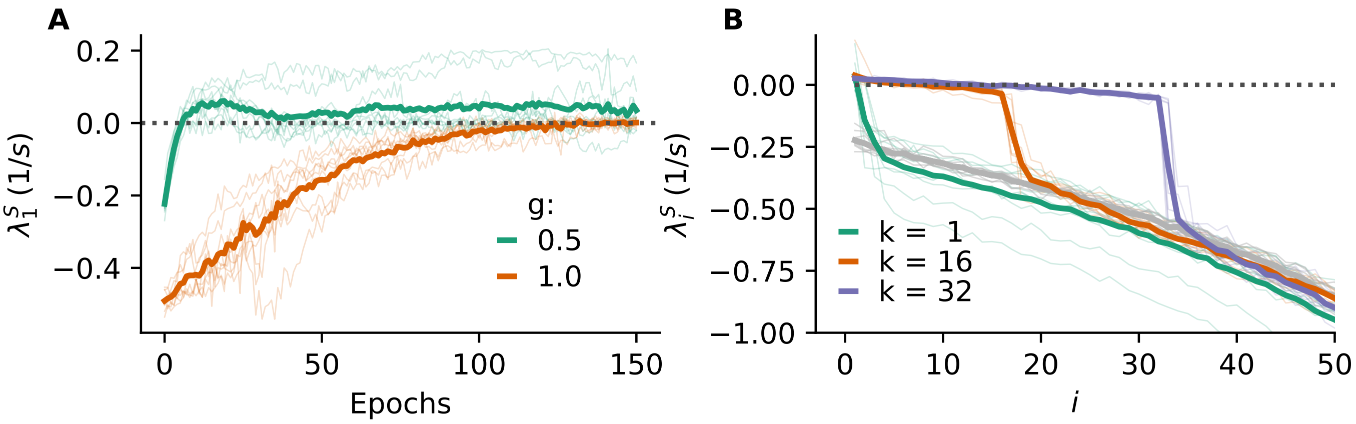

Figure 1: ***Surrogate gradient flossing* regularizes *surrogate Lyapunov exponents* and facilitates gradient signal propagation in binary neural networks A)** The first *surrogate Lyapunov exponent* of a recurrent binary network plotted as a function of training epochs for different surrogate sharpness g. The square of the first *surrogate Lyapunov exponent* is minimized using gradient descent. **B)** *Surrogate Lyapunov spectrum* of a recurrent binary network after different numbers of Lyapunov exponents k have been driven towards zero via *surrogate gradient flossing* for $k \in \{1, 16, 32\}$. The gray lines show the *surrogate Lyapunov spectra* before *surrogate gradient flossing*. Parameters: network size $N = 80$, $g = 1$ for **B**. Input as in Fig. 2. The thin semitransparent lines in **A** and **B** indicate nine network realizations; the full lines are their average.

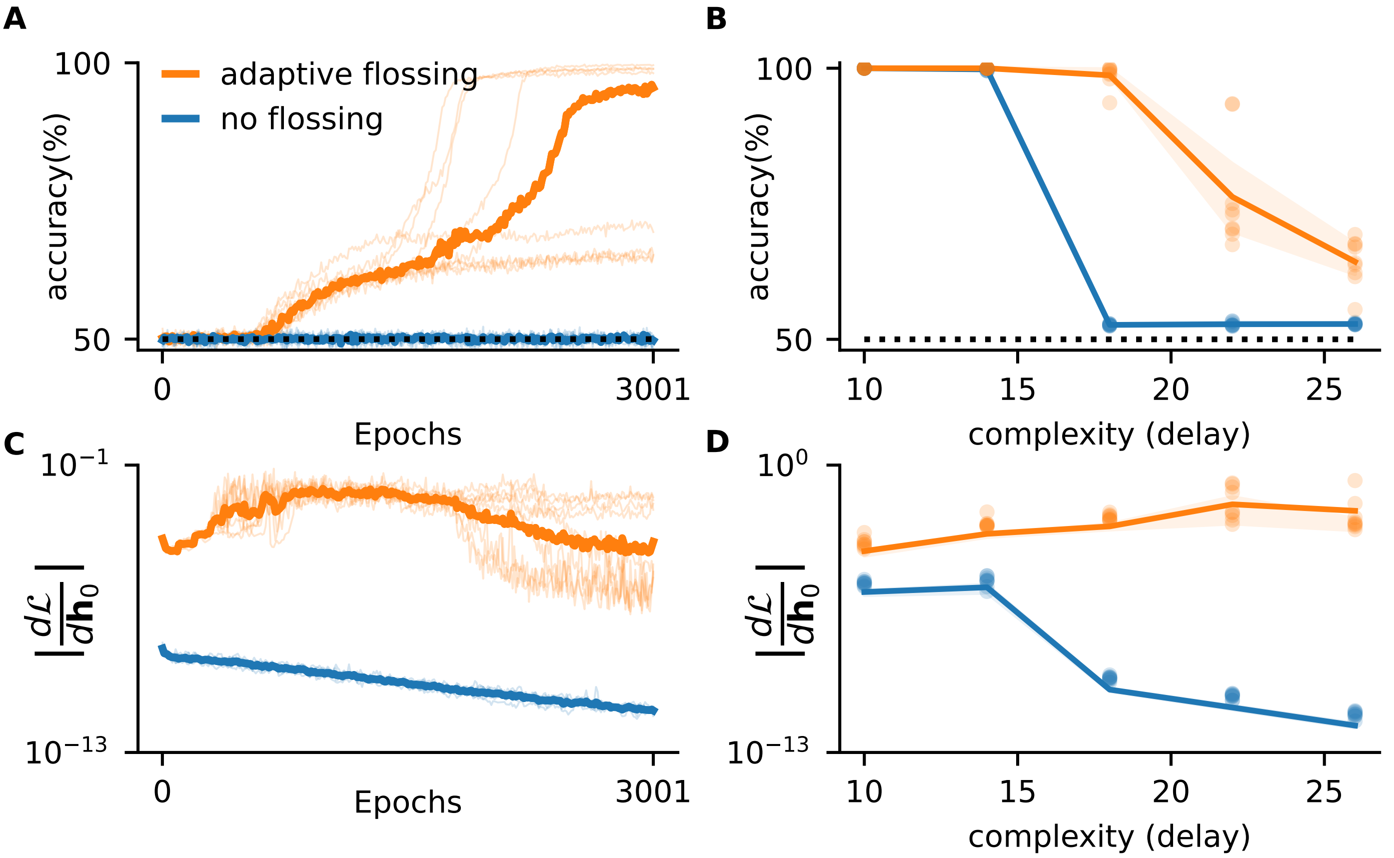

Figure 2: ***Gradient flossing* improves binary RNN training A)** Test accuracy for binary RNNs trained on the delayed temporal binary XOR task $y_t = x_{t-d/2} \oplus x_{t-d}$ with *adaptive gradient flossing* during training (orange) and without *gradient flossing* (blue) for $d = 18$. Solid lines are the median across 9 network realizations, and individual network realizations are shown in transparent fine lines. **B)** Mean final test accuracy as a function of task difficulty (delay d) for delayed XOR task. **C)** Gradient norm with respect to initial network state $\mathbf{h}_0$. **D)** Gradient norm with respect to initial network state as a function of temporal task complexity T averaged over training epochs.