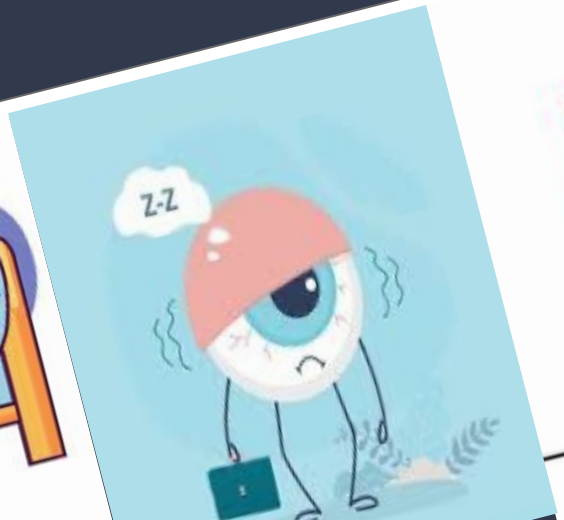
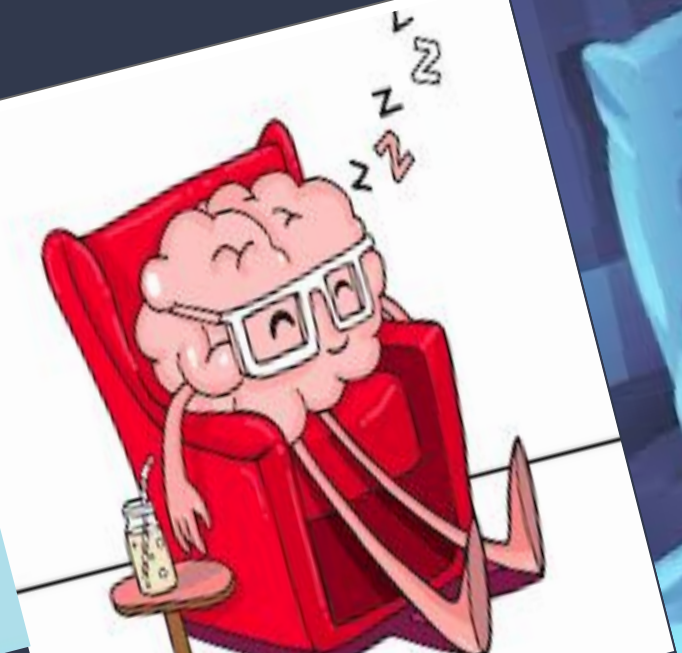
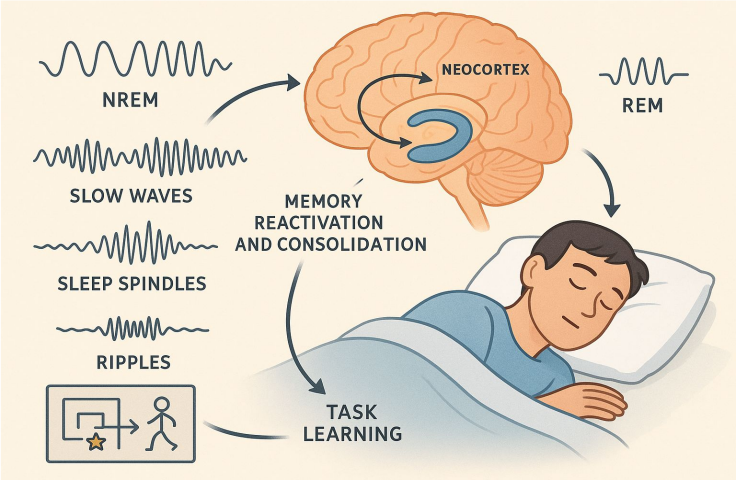
The “ Sleeping “ brain model

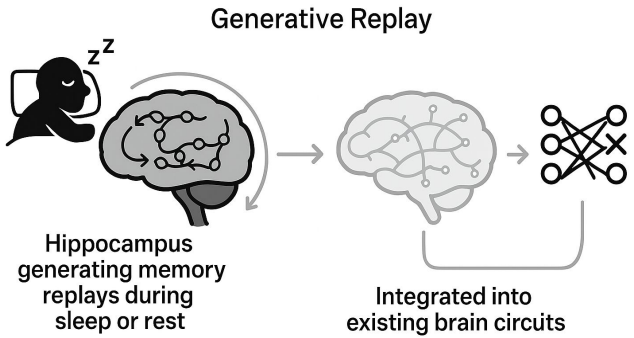
Group 7 -
Anushka Bhise
DhiwaKaran
Kavin Fidel





Consolidation of memories during sleep, STM -> LTM





Sleep enhances reconsolidation-based strengthening of visuospatial memories

Bethany J. Jones, Margaret E. Chen, Lindsey Simoncini & Rebecca M. C. Spencer

Practice with sleep makes perfect: sleep-dependent motor skill learning

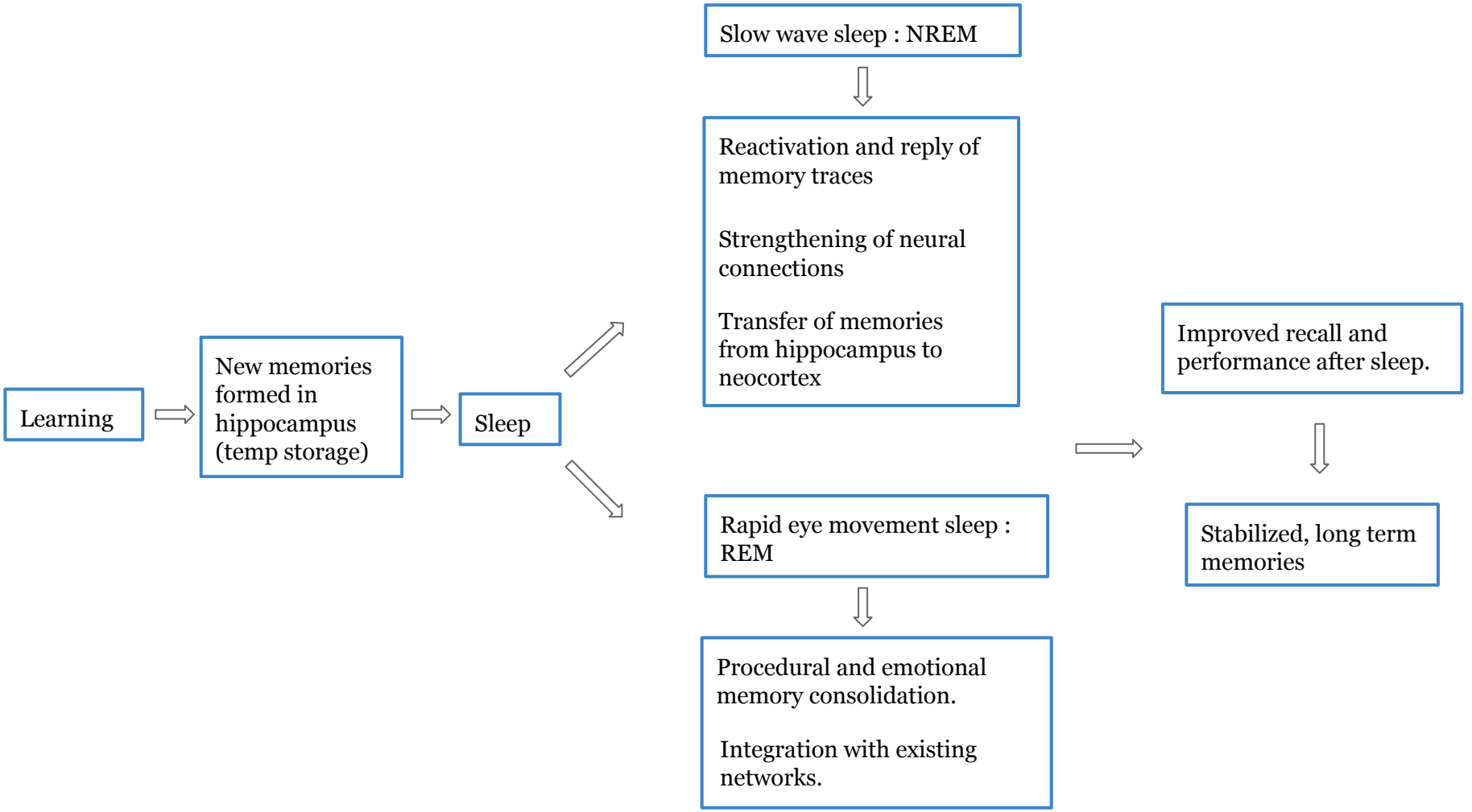
Matthew P Walker [1], Tiffany Brakefield, Alexandra Morgan, J Allan Hobson, Robert Stickgold

Effects of early and late nocturnal sleep on declarative and procedural memory

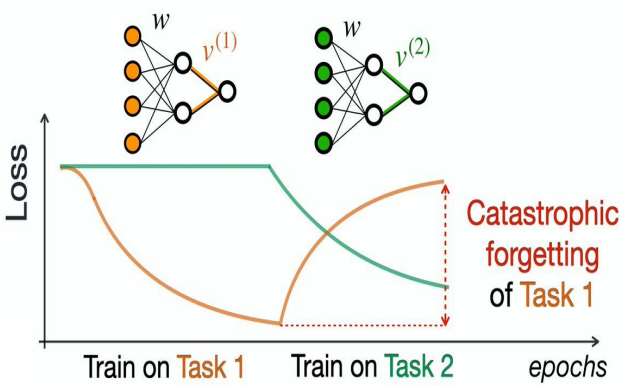
W Plihal [1], J Born

Dependence on REM sleep of overnight improvement of a perceptual skill

A Karni [1], D Tanne, B S Rubenstein, J J Askenasy, D Sagi


Learning
New memories formed in hippocampus (temp storage)
Sleep
Slow wave sleep : NREM
Reactivation and reply of memory traces
Strengthening of neural connections
Transfer of memories from hippocampus to neocortex
Rapid eye movement sleep : REM
Procedural and emotional memory consolidation.
Integration with existing networks.
Improved recall and performance after sleep.
Stabilized, long term memories

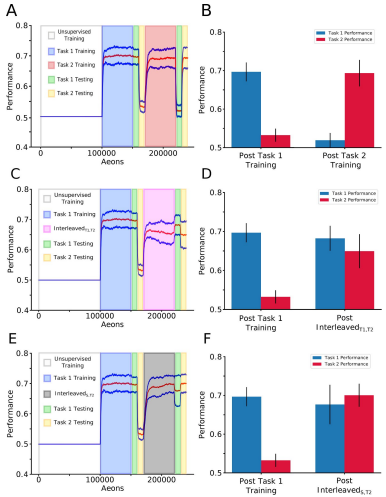
Unlike biological brains, neural networks suffer from *catastrophic forgetting*—where learning new tasks can rapidly overwrite previously acquired knowledge.



AIM:
To stimulate a "sleep" phase in between the learning to preserve the energy minimas of the past memories, while also learning new ones.

Sleep prevents catastrophic forgetting in spiking neural networks by forming a joint synaptic weight representation

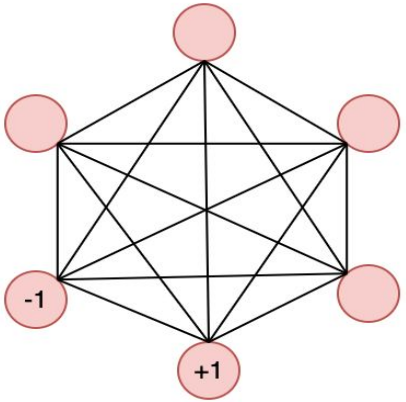
Ryan Golden, Jean Erik Delanois, Pavel Sanda, Maxim Bazhenov



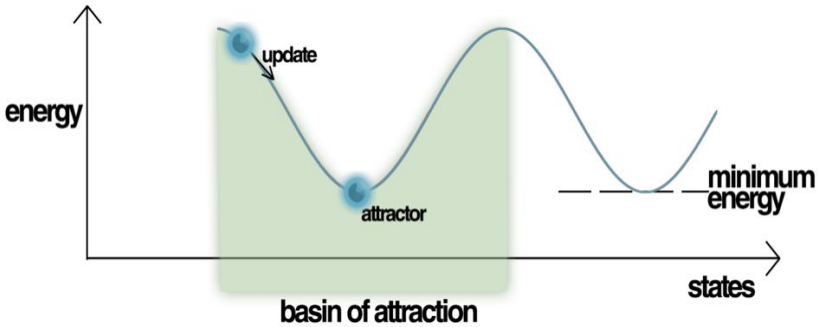
Catastrophic Forgetting and the Pseudorehearsal Solution in Hopfield-type Networks

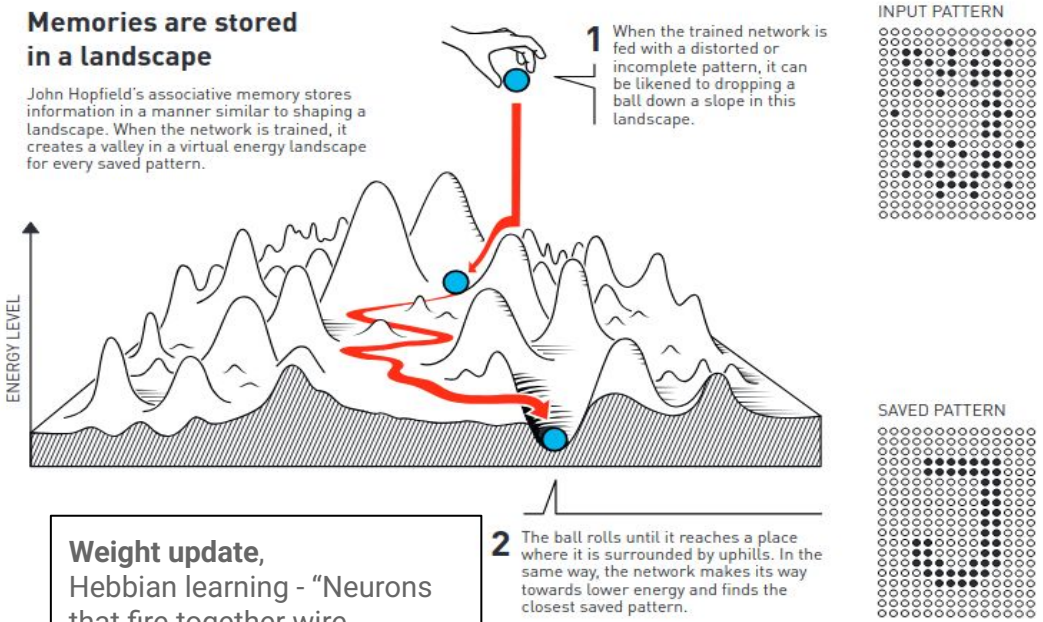
ANTHONY ROBINS & SIMON McCALLUM

Traditional Hopfield Network : Storing of associative memories



$$E = -\frac{1}{2}\sum_{i,j} w_{ij} s_i s_j - \sum_i \theta_i s_i$$



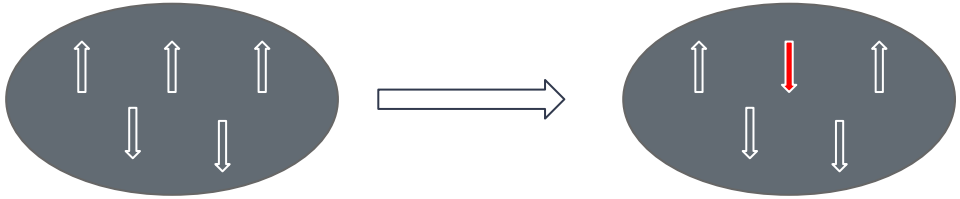


Weight update,
Hebbian learning - "Neurons that fire together wire together"

$$w_{ij} = \frac{1}{n}\sum_{\mu=1}^{n} \epsilon_i^\mu \epsilon_j^\mu$$

where ϵ_i^μ represents bit i from pattern μ.

Recovery Capacity of k-Hopfield Networks



Random initial state

Flip one random state

$$E = -\sum_{\mu=1}^{M} \sum_{i,j} J_{ij}^{\mu} \sigma_i^{\mu} \sigma_j^{\mu}$$

$$\text{where} J_{ij}^{\mu} = \eta_i^{\mu} \eta_j^{\mu}$$

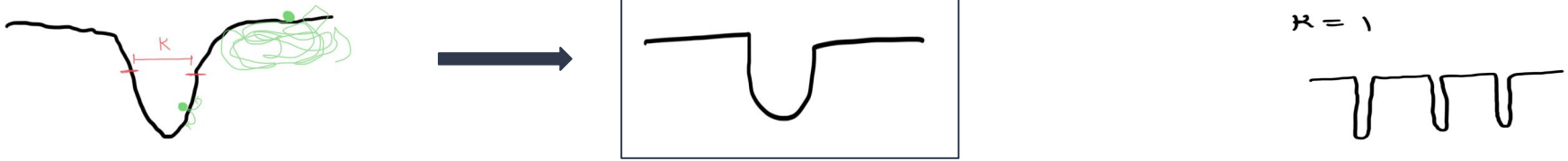
$$\Delta E = E_k(\sigma') - E_k(\sigma)$$

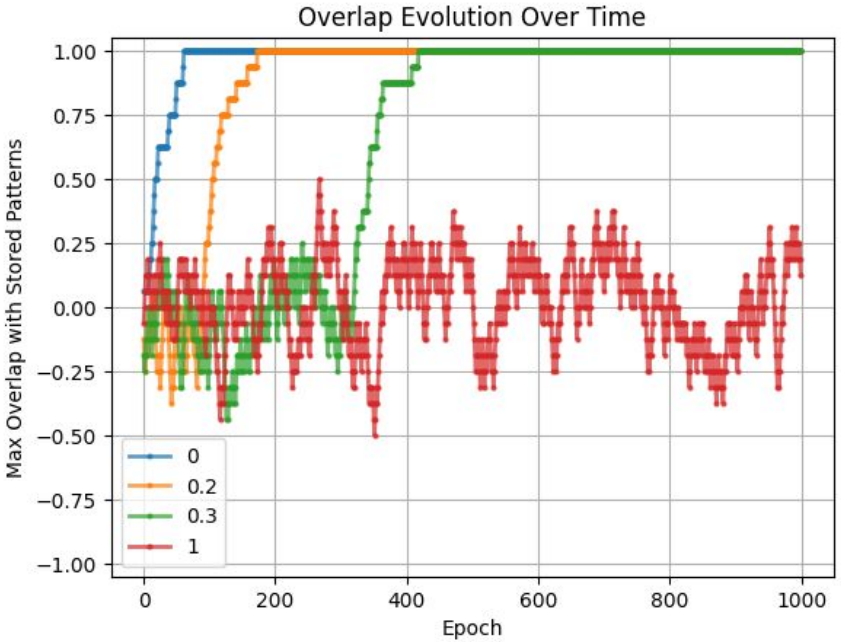
If $\Delta E < 0$,
Accept move.

$$\sigma \leftarrow \sigma'$$

If $\Delta E > 0$,
Accept move with probability

$$p = \exp\left(-\frac{\Delta E}{T_{\mathrm{MC}}}\right)$$





N = 1, size = 32

k = 0 (classic Hopfield):

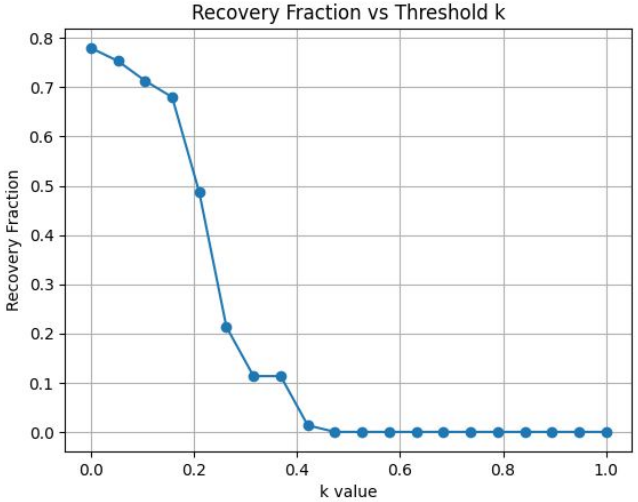
- Converges quickly.
- Overlap increases rapidly and plateaus.

k = 0.2 / 0.3:

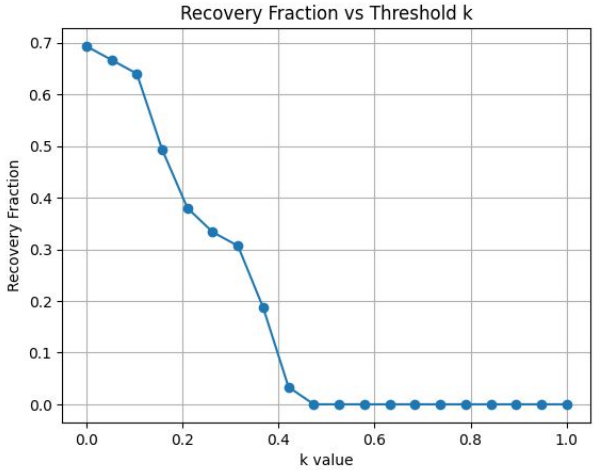
- Takes longer to converge.
- Fluctuates before stabilizing at high overlap.

k = 1:

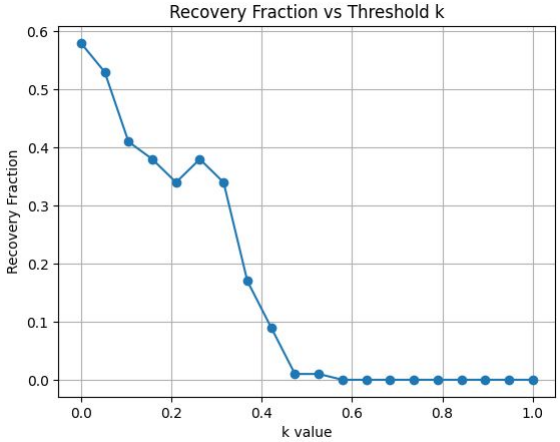
- Never converges.
- Overlap remains low or oscillates without locking onto a memory



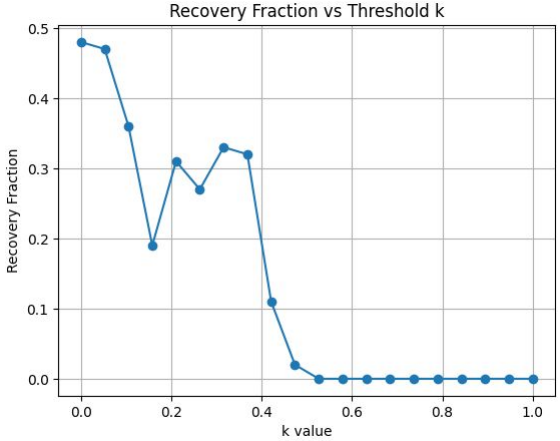
N =3



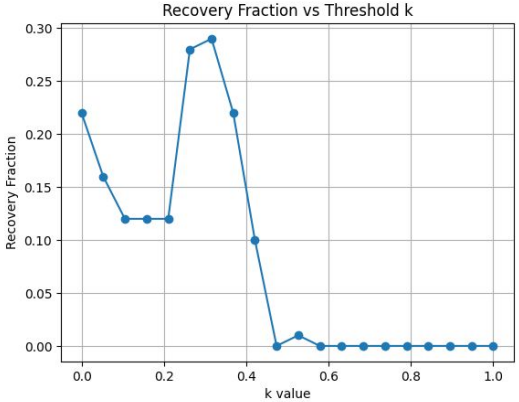
N = 7



N = 9



N = 11



N = 15

- As Number of patterns increase, normal hopfield deteriorates, due to spurious minima.
- At the optimal k, we avoid the spurious minima and the very narrow basins.

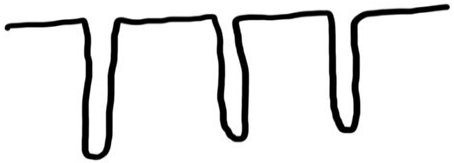
Recall frequency vs different k values

$$E = -\sum_{\mu=1}^{M}\sum_{i,j} J_{ij}^{\mu}\,\sigma_i^{\mu}\sigma_j^{\mu}\,\Theta\left(\bar{\sigma}\cdot\bar{\eta}^{\mu}-k\right)$$

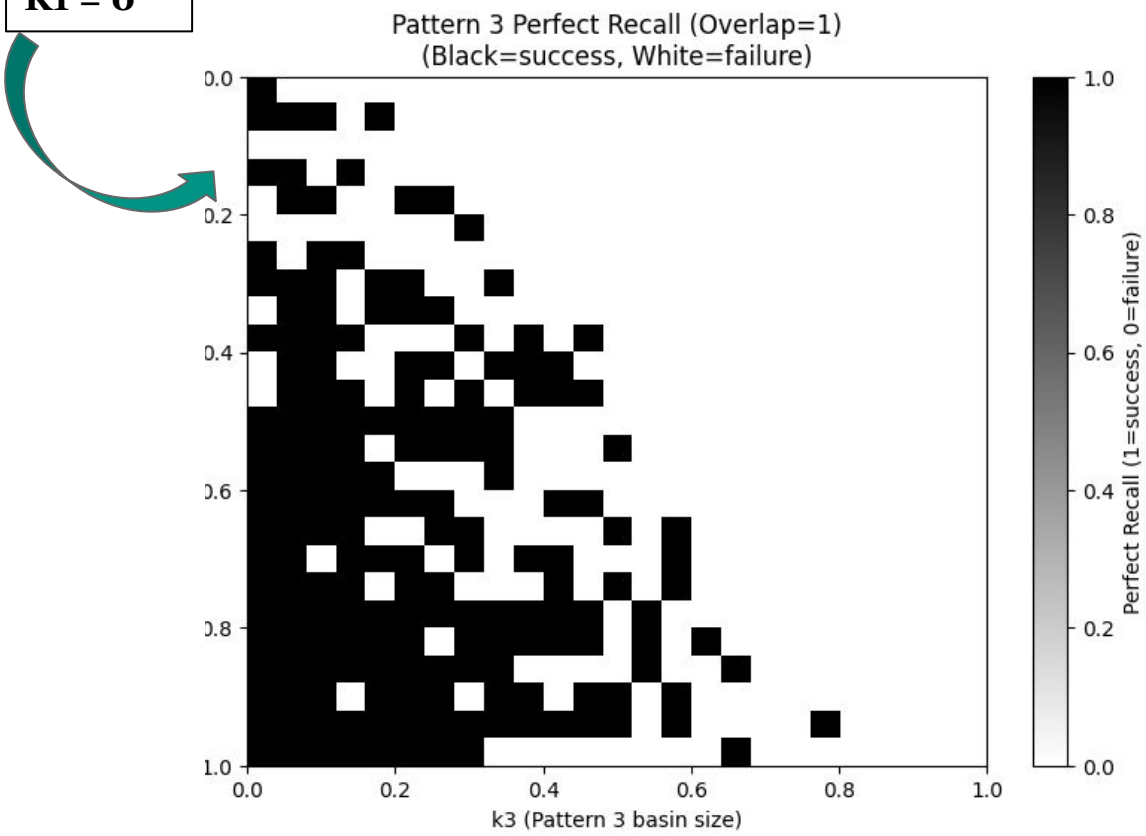
$$\text{where} J_{ij}^{\mu} = \eta_i^{\mu}\eta_j^{\mu}$$

K= 0
(Regular hopfield network)

K= 1

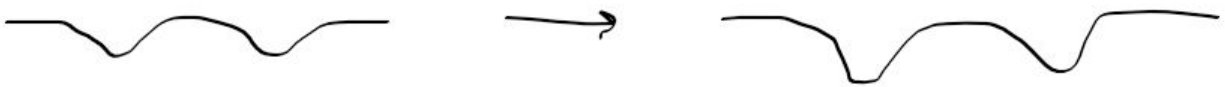


K1 = 0



Incremental Learning

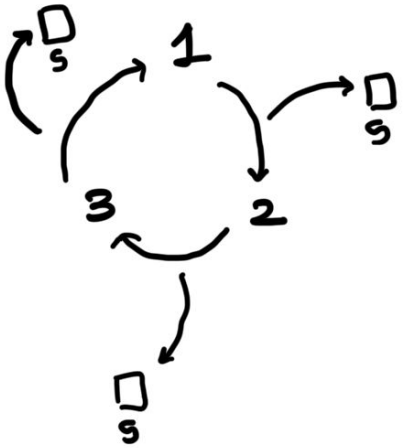
$$w_{ij}(t+1) = (1-\eta)\, w_{ij}(t) + \eta\, s_i\, s_j$$



```
for p in patterns:
     p = p.reshape(-1, 1)
     outer = (p @ p.T) / self.size
     self.W = (1 - n) * self.W + n * outer
```

Sleep – Wake cycle for memory consolidation

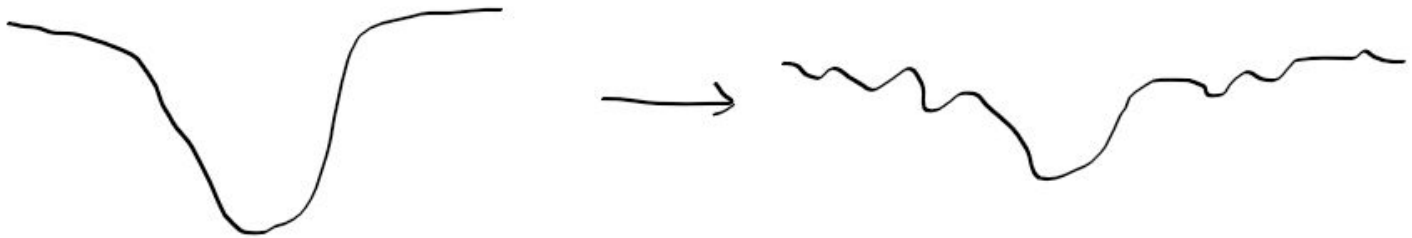
Wake Phase:
Learning. Update weights using Hebbian learning.



Sleep Phase:
Preservation of energy minima. Energy landscape truncation, K based. Stabilize minima

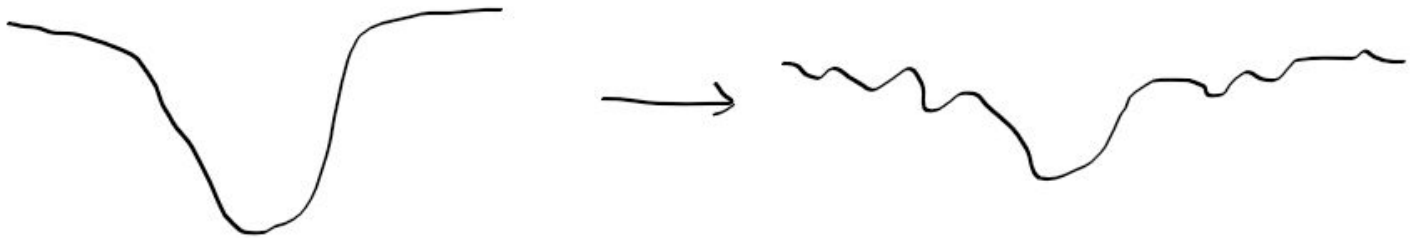
Simulated Sleep (Future Work)

```
Comparison: n_sleep = 0.07
  Pre-sleep average convergence steps:  4.65
  Post-sleep average convergence steps: 2.97
```



Simulated Sleep

```
Comparison: n_sleep = 0.001
  Pre-sleep average convergence steps:  4.89
  Post-sleep average convergence steps: 8.10
```



Future direction .....

- Optimize the sleep state in our network by modulating the parameters.
- Explore different network architectures and models.
- Incorporate the REM and NREM aspect maybe by changing the K value.

Thank you