

Research Paper

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Topic(s):

1. Enforcing Supercriticality in Hopfield neural networks
2. AIRR
3. Using Reinforcement learning methods to train Energy Based Neural Networks
4. Using Sparse Hopfield networks for Immune Repertoire Classification
5. Sparse Hopfield Neural Networks for Deep learning
6. Boltzmann machines

Abstract

Introduction

Purpose

Methods

Results

Discussion

Acknowledgements

Bibliography

$$E = -\text{lse}(\beta, \mathbf{X}^T \boldsymbol{\xi}) + \frac{1}{2} \boldsymbol{\xi}^T \boldsymbol{\xi} + \beta^{-1} \log N + \frac{1}{2} M^2$$

$$E_1(\boldsymbol{\xi}) = \frac{1}{2} \boldsymbol{\xi}^T \boldsymbol{\xi}$$

$$E_2(\boldsymbol{\xi}) = -\text{lse}(\beta, \mathbf{X}^T \boldsymbol{\xi})$$

$$\nabla_{\boldsymbol{\xi}} E_1^{t+1} = -\nabla_{\boldsymbol{\xi}} E_2^t$$

NOTES

- Hopfield Energy func: $E = -\frac{1}{2} \boldsymbol{\xi}^T W \boldsymbol{\xi} + \boldsymbol{\xi}^T b$
- Hopfield update rule: $\xi^{t+1} = \text{sgn}(W \boldsymbol{\xi}^t - b)$
- Modern Hopfield Energy func: $E = -\sum_{i=1}^N F(x_i^T \boldsymbol{\xi})$ where can be $F = \exp$
- The above energy can also be written as $-\exp(\text{lse}(1, X^T \boldsymbol{\xi}))$
- Modern Hopfield update rule: $\xi^{new}[l] = \text{sgn}[-E(\xi^{(l+)}) + E(\xi^{(l-)})]$

- Continuous Valued Energy function: $-\text{lse}(\beta, X^T \xi) + \frac{1}{2} \xi^T \xi + \beta^{-1} \log N + \frac{1}{2} M^2$, which is the log of the negative energy above.
- $\nabla_{\xi}(\frac{1}{2} \xi^T \xi) = \mathbf{1}$ and $-\nabla_{\xi} \text{lse}(\beta, X^T \xi) = X \text{softmax}(\beta X^T \xi)$, which means that $\xi^{new} = X \text{softmax}(\beta X^T \xi)$, which is the new update procedure.
- The above update rule can be generalized to $\Xi^{new} = X \text{softmax}(\beta X^T \Xi)$
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