Comparative Study of Learning Rules: (a) Hebbian vs error correction, (b) reinforcement vs stochastic. Prepare poster comparing learning dynamics, stability, convergence.

Abstract

Learning rules determine how artificial neural networks modify their synaptic weights during training. Different learning mechanisms result in different behaviors in terms of adaptability, stability, and convergence. This study presents a comparative analysis between the Hebbian learning rule and the Error-Correction learning rule. Hebbian learning is an unsupervised approach based on correlation between neuron activities, whereas error-correction learning is a supervised method that adjusts weights to minimize prediction error. The comparison focuses on learning dynamics, stability characteristics, and convergence properties. Through theoretical explanation and analytical comparison, this study highlights the strengths and limitations of both approaches and explains their practical relevance in neural network design.

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1. Introduction

Artificial Neural Networks learn by adjusting the strength of connections between neurons. The method used to update these weights is known as a learning rule. Learning rules influence how quickly a model learns, how stable it remains during training, and whether it converges to a correct solution.

Among various learning mechanisms, Hebbian learning and Error-Correction learning are two fundamental approaches:

- Hebbian learning is biologically inspired and depends on neuron co-activation.
- Error-correction learning relies on feedback from a target output to reduce prediction error.

This study compares these two rules based on:

- Learning dynamics
- Stability behavior
- Convergence properties

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2. Hebbian Learning Rule

2.1 Concept

Hebbian learning is based on the principle:

"When two neurons activate together, the connection between them strengthens."

It does not require a target output and therefore belongs to unsupervised learning.

2.2 Mathematical Representation

$$\Delta w_{ij} = \eta x_i y_j$$

Where:

- Δw_{ij}= Change in weight
- η= Learning rate
- x_i= Input of neuron i
- y_j= Output of neuron j

2.3 Learning Dynamics

- Weight increases when both input and output are active.
- No error term is involved.
- Purely correlation-based update.
- Learning is local (depends only on connected neurons).

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3. Error-Correction Learning Rule

3.1 Concept

Error-correction learning adjusts weights based on the difference between predicted output and desired output. It belongs to supervised learning.

3.2 Mathematical Representation

$$\Delta w_{ij} = \eta(t - y)x_i$$

Where:

- t= Target output
- y= Predicted output
- (y)= Error signal

- η= Learning rate

3.3 Learning Dynamics

- Uses feedback from output error.
- Updates weights to minimize loss.
- Reduces classification or prediction error iteratively.
- Forms the foundation of perceptron and backpropagation algorithms.

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4. Comparison of Learning Dynamics

Feature	Hebbian Learning	Error-Correction Learning
Learning Type	Unsupervised	Supervised
Requires Target	No	Yes
Weight Update Based On	Correlation	Error
Feedback Mechanism	Not required	Required
Biological Inspiration	Strong	Moderate

Hebbian learning strengthens associations, whereas error-correction actively corrects mistakes.

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5. Stability Analysis

Hebbian Learning

- Weights may grow continuously.
- No inherent mechanism to limit weight magnitude.
- Can become unstable without normalization.
- Stability depends on external constraints.

Error-Correction Learning

- Weight updates are guided by error reduction.
- Moves toward minimizing a defined cost function.
- Learning rate controls update magnitude.

- More stable compared to pure Hebbian rule.

Observation: Error-correction learning provides better controlled and stable learning behavior.

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6. Convergence Analysis

Hebbian Learning

- No guaranteed convergence.
- May not reach an optimal solution.
- Depends heavily on data distribution.
- Often requires normalization or decay terms.

Error-Correction Learning

- Guaranteed convergence for linearly separable data (Perceptron Convergence Theorem).
- Gradient descent ensures movement toward minimum error.
- Convergence speed depends on learning rate.

Conclusion: Error-correction learning has stronger theoretical convergence guarantees.

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7. Practical Applications

Hebbian Learning

- Associative memory models
- Feature learning
- Pattern correlation tasks
- Competitive learning networks

Error-Correction Learning

- Classification systems
- Regression problems
- Deep learning networks
- Speech and image recognition

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8. Advantages and Limitations

Hebbian Learning

Advantages

- Simple implementation
- Biologically realistic
- No labeled data required

Limitations

- No error minimization
- Possible weight explosion
- Weak convergence guarantee

Error-Correction Learning

Advantages

- Direct error minimization
- Strong convergence theory
- Suitable for practical ML systems

Limitations

- Requires labeled data
- Slightly more computationally complex

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9. Conclusion

This comparative study examined Hebbian learning and error-correction learning in terms of learning behavior, stability, and convergence.

Hebbian learning strengthens neuron correlations without supervision, making it biologically inspired but less stable and less predictable in convergence.

Error-correction learning, on the other hand, uses supervised feedback to systematically reduce error, resulting in improved stability and reliable convergence.

Therefore:

- Hebbian learning is suitable for unsupervised associative tasks.
- Error-correction learning is more effective for accurate supervised classification problems.

Understanding these foundational learning rules provides essential insight into modern neural network training algorithms.

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10. References

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