ITEM #210 - From the Absence of Backpropagation in the Brain to the Principle-Level Division of Labor between LLM and DBM

(Why Gradient-Based Training Is an Engineering Necessity, Not a Model of Intelligence)

Conversation: 反向传播与脑神经

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Abstract

Modern large language models (LLMs) rely on backpropagation and large-scale gradient optimization, a mechanism often implicitly assumed to mirror biological learning. However, decades of neuroscience research have revealed no anatomical or physiological equivalent of global error backpropagation in the human brain. This discrepancy raises a fundamental question: if biological intelligence does not rely on backpropagation, why does it remain so dominant in artificial intelligence?

This paper clarifies the issue by separating *engineering feasibility* from *intelligence principles*. We argue that backpropagation is not a biological discovery but an engineering compromise—an effective method under constraints of scale, capital, and computability. We further show that this limitation naturally leads to a principled division of labor: LLMs excel at large-scale external

structure compression, while DBM-style Structural Intelligence addresses internal structure generation, stability, and evolution.

This clarification serves as the conceptual foundation for subsequent DBM work.

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1. The Missing Backpropagation Mechanism in the Brain

Despite extensive investigation at anatomical, cellular, and circuit levels, neuroscience has found no evidence of a mechanism equivalent to engineering backpropagation:

- No global scalar loss broadcast across neural circuits
- No symmetric forward/backward weight transport
- No precise layer-wise gradient propagation
- No synchronized forward–backward update cycles

Instead, biological learning is governed by **local, asynchronous, event-driven mechanisms**, such as Hebbian learning, spike-timing-dependent plasticity (STDP), and neuromodulatory signals. These mechanisms are fundamentally incompatible with the mathematical assumptions required by backpropagation.

The absence of backpropagation is not a gap in current knowledge; it is a stable empirical fact.

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2. Why Backpropagation Works in Engineering Systems

The success of backpropagation in artificial neural networks does not imply biological plausibility. Rather, it reflects a powerful *engineering alignment* with industrial constraints:

1. **Global optimizability**
   A single scalar objective enables numerical convergence and benchmark-driven evaluation.
2. **Scalability through resource aggregation**
   Performance improves monotonically with more data and compute, aligning naturally with capital investment.
3. **Infrastructure compatibility**
   Backpropagation maps cleanly onto GPUs, distributed systems, and batch processing pipelines.

Backpropagation is therefore best understood not as a theory of intelligence, but as a **computationally convenient sintering process**: when internal structure is unknown, sufficient data and compute can fuse local correlations into a usable global artifact.

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3. The Structural Limits of Gradient-Based Intelligence

Despite its effectiveness, gradient-based training exhibits structural limitations:

- Weak long-term interpretability
- Poor intrinsic structure stability
- Difficulty in controlling abstraction granularity
- High hallucination cost under distributional shift

These limitations are not implementation flaws; they are *structural consequences* of optimizing parameters without explicit structural governance.

Biological intelligence avoids these issues by prioritizing **structure over parameters**.

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4. Backpropagation as an Engineering Necessity, Not an Ontology

It is therefore a category error to treat backpropagation as a universal model of learning.

Backpropagation answers the question:

"How can we optimize a massive parametric system when we do not know how to design its internal structure?"

It does **not** answer:

"How does intelligence form, stabilize, and evolve meaningful internal structures?"

This distinction is critical.

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5. The Emergent Division of Labor: LLM vs. DBM

Once this distinction is made, a natural division of labor emerges:

- **LLMs**
  - Excel at external structure compression
  - Aggregate and reproduce historically validated patterns
  - Operate effectively as large-scale cultural memory systems

- **DBM (Structural Intelligence)**
    - Focuses on internal structure generation
    - Governs partitioning, granularity, and evolution constraints
    - Ensures long-term stability and interpretability

This division mirrors the human intelligence system itself: biological brains generate structure internally, while civilization stores and transmits structure externally.

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6. Implications

Recognizing backpropagation as an engineering compromise—not a biological principle—has three important implications:

1. Scaling alone cannot produce structural intelligence
2. Interpretability and stability require explicit structure governance
3. Future AI systems must separate **external structure accumulation** from **internal structure generation**

This sets the stage for DBM as a complementary, not adversarial, paradigm.

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7. Conclusion

Backpropagation is neither wrong nor universal. It is a historically contingent solution optimized for engineering constraints. Biological intelligence follows a different path—one centered on structure, granularity, and evolutionary stability.

Understanding this difference is not optional; it is foundational.

ITEM #210 – 从脑神经系统中反向传播机制的缺失到 LLM 与 DBM 的原理性分工

——为什么梯度训练是工程必然，而非智能本体

摘要

现代大型语言模型（LLM）高度依赖反向传播与大规模梯度优化，这一机制常被隐含地视为“类脑学习”的实现。然而，数十年的神经科学研究表明：在人脑的解剖结构、生理机制与神经回路中，并不存在任何与工程反向传播等价的机制。

这一事实提出了一个根本性问题：
如果生物智能并不依赖反向传播，为何它却成为当代人工智能的核心技术？

本文通过区分“工程可行性”与“智能原理”，指出反向传播并非生物发现，而是一种在算力、资本与规模约束下的工程权宜之计。进一步地，这一限制自然导向一种原理级分工：
LLM 擅长体外结构压缩，而 DBM（结构智能）负责体内结构生成、稳定与演化。

本文为后续 DBM 体系奠定概念基础。

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1. 大脑中反向传播机制的缺失

在神经科学的多个层级上，均未发现反向传播所需的关键条件：

- 不存在全脑共享的标量损失函数
- 不存在前向 / 反向权重对称传输
- 不存在逐层精确误差信号回传
- 不存在同步的前向–反向更新周期

相反，大脑的学习机制是**局部的、异步的、事件驱动的**，主要依赖 Hebbian 学习、STDP 以及神经调制信号。这些机制在数学与结构上，均无法支持反向传播的假设。

反向传播的缺失不是暂时空白，而是一个稳定的经验事实。

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2. 反向传播为何在工程上成立

反向传播的成功，并非源于其生物合理性，而在于其与工业现实的高度契合：

1. **全局可优化性**
   单一目标函数使系统可被数值优化与量化评估。
2. **算力与资本的线性放大**
   性能随数据与算力单调提升，天然适合规模化投资。
3. **基础设施友好性**
   与 GPU、分布式系统和批处理流程高度兼容。

因此，反向传播更像是一种**工程烧结法**：
在缺乏结构理解的情况下，通过资源堆叠将局部相关性熔结为可用整体。

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3. 梯度型智能的结构性边界

尽管有效，梯度训练存在不可回避的结构限制：

- 长期结构不可解释
- 内部表示缺乏稳定性
- 粒度调节不可控
- 分布漂移下幻觉成本极高

这些并非实现缺陷，而是**无结构参数优化的必然结果**。

生物智能选择了一条不同的路径：
结构优先，而非参数优先。

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4. 反向传播是工程手段，而非智能本体

将反向传播视为“智能模型”，本身是一种范畴错误。

反向传播解决的是：

“在无法设计内部结构的前提下，如何优化一个巨大参数系统？”

而它并不回答：

“智能如何生成、稳定并演化其内部结构？”

区分这两点，是理解当代 AI 分歧的关键。

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5. 原理级分工：LLM 与 DBM

一旦澄清上述区别，一种自然的分工浮现出来：

- **LLM**
  - 擅长体外结构压缩
  - 汇聚并复现历史验证过的模式
  - 本质上是大规模文化记忆系统
- **DBM（结构智能）**
  - 专注体内结构生成
  - 管理分区、粒度与演化约束
  - 保障长期稳定性与可解释性

这一分工，正是人类智能系统的真实写照：
体内生成结构，体外积累结构。

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6. 启示

将反向传播理解为工程权宜，而非生物原理，带来三点关键启示：

1. 单纯扩展规模无法产生结构智能
2. 稳定性与可解释性必须由结构治理保证
3. 未来 AI 必须区分体外结构累积与体内结构生成

这为 DBM 提供了清晰的位置与使命。

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7. 结论

反向传播既非错误，也非普适。它是历史条件下的工程最优解，而非智能的终极模型。生物智能展示了一条不同的路线——以结构、粒度与演化稳定性为核心。

理解这一点，是一切后续工作的前提。
