VECTOR ANALYSIS AND DECOMPOSITION - WAYS TO UNDERSTAND NEURAL NETWORK ALGORITHMS

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The success of neural network algorithms gives hope that machines will be able to solve all or almost all "intellectual" tasks. Although many textbooks on deep learning and generative neural networks have been published (e.g., [1]), almost everyone agrees with the statement: "We do not understand how neural network algorithms work!"

The reasons for this paradoxical situation lie in the fact that, in deep learning, signals and "errors" pass through so many layers of neural networks that it becomes impossible for humans to trace how these transformations occur. The miracle is that when processing complex signals (such as video surveillance and speech transformation), the vast amount of data used to train neural networks is theoretically insufficient to reveal the properties of the complex environment that shapes the input signals. This can be explained by the assumption that a decomposition is formed within the neural networks.

Research focuses on the activity vectors of elements in the latent layer spaces. The weight increment matrix $\Delta \boldsymbol{W^m}$ for layer $\boldsymbol{m}$ is formed by multiplying the error vector $\vec{\boldsymbol{\delta}}^{\boldsymbol{m}} = \{\vec{\delta}_{\boldsymbol{j}}^{\boldsymbol{m}} = \boldsymbol{\partial E / \partial a_j^m}\}$ ("errors" of the activity of elements in layer $\boldsymbol{m}$) and $\vec{\boldsymbol{O}}^{\boldsymbol{m-1}} = \{\boldsymbol{o_i^{m-1}}\}$ (output activity of layer $\boldsymbol{m-1}$): $\Delta \boldsymbol{W^m} = -\boldsymbol{\alpha} \vec{\boldsymbol{\delta}}^{\boldsymbol{m}} \vec{\boldsymbol{O}}^{\boldsymbol{m-1}^T}, \boldsymbol{0 < \alpha \ll 1}$. The increments in activity due to changes in the weight matrix $\boldsymbol{W^m}$, $\Delta \vec{\boldsymbol{A}}^{\boldsymbol{m}} = \Delta \boldsymbol{W^m} \vec{\boldsymbol{O}}^{\boldsymbol{m-1}} = -\boldsymbol{\alpha} \vec{\boldsymbol{\delta}}^{\boldsymbol{m}} \vec{\boldsymbol{O}}^{\boldsymbol{m-1}^2}$ and the "errors" $\Delta \vec{\boldsymbol{\delta}}^{\boldsymbol{m-1}} = \Delta \vec{\boldsymbol{W}}^{\boldsymbol{m}^T} \vec{\boldsymbol{\delta}}^{\boldsymbol{m}} = -\boldsymbol{\alpha} \vec{\boldsymbol{O}}^{\boldsymbol{m-1}} \vec{\boldsymbol{\delta}}^{\boldsymbol{m}^2}$ in layer $\boldsymbol{m-1}$ depend only on the error vectors $\Delta \vec{\boldsymbol{\delta}}^{\boldsymbol{m}}$ and the output activity $\vec{\boldsymbol{O}}^{\boldsymbol{m-1}}$, since the second terms in the formulas appear as squares and do not affect the directions $\Delta \vec{\boldsymbol{A}}^{\boldsymbol{m}}$ and $\Delta \vec{\boldsymbol{\delta}}^{\boldsymbol{m-1}}$.

The study of activity vectors in the multi-dimensional latent layer spaces allows for a new perspective on optimizing signal decomposition processes and improving the performance of neural network algorithms [2], opening new horizons for the application of neural networks in various fields.

References

1. *Foster, D. Generative Deep Learning: How We Don't Paint Pictures, Write Novels, and Compose Music / 2nd ed. – Sprint Book, 2024. – 448 pages.*
2. *Smolin V, Sokolov S. AGI's Hierarchical Component Approach to Unsolvable by Direct Statistical Methods Complex Problems. // Engineering Proceedings. 2023; 33(1):67. https://doi.org/10.3390/engproc2023033067*