



JOHNS HOPKINS

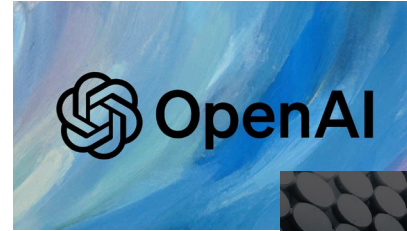
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685.621 Algorithms for Data Science

Neural Networks: Current and Future State

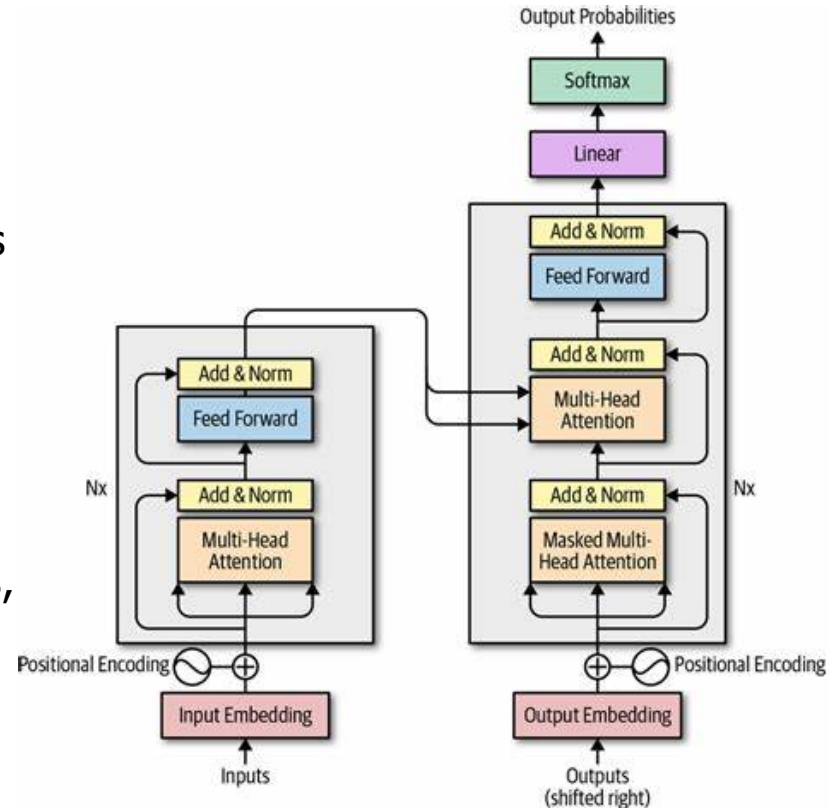
Neural Networks in Practice

- **Power real-world applications:** image recognition, speech synthesis, medical diagnostics.
- Enable recommendation systems and **natural language understanding** (e.g., chatbots).
- Require **significant data** and computational resources, but scalable solutions exist.
- **Interpretability** tools (like Grad-CAM, SHAP) help explain predictions in sensitive domains.
- Continued advancements (**hardware and algorithms**) are expanding applications.



Neural Network Extensions

- **Transformers** revolutionized sequence modeling with self-attention mechanisms.
- Eliminate recurrence, process entire sequences in parallel (high efficiency).
- Foundation of powerful models like **BERT, GPT, and Vision Transformers**.
- **Transfer Learning**: Leverage pre-trained networks for new tasks with less data.
- **Hybrid Architectures**: Combine CNNs, RNNs, and Transformers for complex problems.
- **Rapid evolution**: new architectures emerge from ongoing research.



Key Takeaways

- Neural networks **learn patterns** by adjusting weights through optimization of a loss function.
- **Activation functions** introduce non-linearity, enabling networks to model complex relationships.
- **Deeper architectures** extract hierarchical features but require careful design to avoid training issues.
- **Backpropagation** efficiently computes gradients to update parameters layer by layer.
- Hyperparameter tuning (**learning rate, batch size, depth**) is critical for effective training.
- **Regularization** and good initialization prevent overfitting and instability.
- Architecture choice (**MLP, CNN, RNN, RBF**) depends on the data type and task.



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