Probability Theory, Logic and LLMs: A Prediction of Jaynes (1990)

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Abstract

In this brief note, we would like to present a prediction of Jaynes from 1990 which seems to be pertinent with regards to the recent success of Large Language Models (LLMs).

To quote E. T. Jaynes from 1990 [1]:

> ... We predict that AI will continue to stumble about, producing results that a Bayesian considers always trivial, usually quantitatively wrong, and often qualitatively wrong, until it recognizes that to dissociate itself from Bayesian probability theory was a disastrous error.

In this context, if we ask ChatGPT-4 whether LLMs use Bayesian probability at their core, the answer (please see the Appendix) is not wholly affirmative. This corroborates well with [2] where the authors state that applying Bayesian analysis to AI is yet a major goal for the next decade. Apparently therefore, it seems that AI has been already quite successful in its results despite non-extensive use of Bayesian probability theory, which puts Jaynes' message (above) in sharp contrast. However, a deeper study of this issue is required and left for future work.

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Appendix: GPT-4 on the Role of Bayesian Probability in LLMs

In the context of Large Language Models (LLMs) like GPT (Generative Pre-trained Transformer) series, BERT (Bidirectional Encoder Representations from Transformers), and others, Bayesian probability plays a more nuanced role.

While the core architecture of these models is not explicitly Bayesian in the traditional sense, Bayesian principles and techniques can be applied to various aspects of LLMs for improvement and analysis.

Bayesian Methods in LLM Training and Fine-tuning Bayesian Optimization

This is used for hyperparameter tuning in the training process of LLMs. Bayesian optimization is a strategy for finding the set of hyperparameters that optimize a loss function, by treating the hyperparameter space probabilistically. It can efficiently guide the search for optimal model configurations, balancing exploration and exploitation of the search space.

Uncertainty Estimation

Bayesian methods can provide estimates of uncertainty in the predictions of LLMs. This is particularly useful in applications requiring robustness and reliability. Techniques such as Bayesian Neural Networks (BNNs) or Monte Carlo Dropout can be adapted to estimate uncertainty in the outputs of LLMs, though implementing these techniques directly in the scale of LLMs involves computational and methodological challenges.

Bayesian Approaches to LLM Interpretability and Analysis Bayesian Deep Learning

While not directly applied to the architecture of most LLMs, Bayesian deep learning concepts can be used to analyze and interpret the behavior of these models. For example, Bayesian methods can help in understanding the confidence of model predictions or in exploring how changes in input affect the model's output distribution.

Probabilistic Programming

Some research integrates LLMs with probabilistic programming, where Bayesian inference is used to reason about the outputs of the model or to incorporate external knowledge. This approach can enhance the model's capabilities in specific tasks, such as reasoning, causal inference, or generating explanations.

Challenges and Considerations

The direct application of Bayesian inference at the scale of current LLMs faces significant computational challenges. Bayesian methods often require extensive computation, such as sampling from posterior distributions, which can be prohibitive for models with billions of parameters. However, research into scalable

Bayesian methods, approximate inference techniques, and efficient computational strategies continues to advance, potentially enabling more extensive use of Bayesian principles in LLMs.

In summary, while Bayesian probability is not at the core of how LLMs operate, Bayesian techniques and principles find application in optimizing their training, enhancing their interpretability, and providing measures of uncertainty. The integration of Bayesian methods into LLMs is an active area of research, reflecting the ongoing exploration of how best to combine probabilistic reasoning with deep learning.

References

[1] Edwin Thompson Jaynes. Probability theory as logic. In *Maximum entropy and Bayesian methods*, pages 1–16. Springer, 1990.

[2] Rens van de Schoot, Sarah Depaoli, Ruth King, Bianca Kramer, Kaspar Märtens, Mahlet G Tadesse, Marina Vannucci, Andrew Gelman, Duco Veen, Joukje Willemsen, et al. Bayesian statistics and modelling. *Nature Reviews Methods Primers*, 1(1):1, 2021.