Initial Post

How the LLM can be applied by large Investment Banks in the Model Risk Management, which approach is the most efficient and how this will be financially beneficial to them?

The adoption and application of Large Language Models (LLMs), such as OpenAI's GPT-4, by large Investment Banks (IBs) provide a significant potential to the enhancement of their Model Risk Management (MoRM) frameworks and their governance.

These IBs rely on a complex ecosystem of quantitative models for pricing, risk estimation, capital allocation, and regulatory compliance. All of these models carry inherent risks related to model errors, misuse, or outdated assumptions.

The implementation of LLMs can automate the model documentation and the model validation processes. Given the regulatory emphasis on comprehensive model documentation (Basel Committee on Banking Supervision, 2017), LLMs can streamline the drafting of technical summaries, assumptions, and performance reviews, reducing human error and saving considerable time (Jordan & Mitchell, 2015).

In the model validation, LLMs can run independent reviews of codebases, detect anomalous patterns and flag potential biases or data issues, functioning as an intelligent assistant to the quantitative analysts (Zhang et al., 2023).

Among the various approaches of what is the best way to apply LLMs in the MoRM, a ‘human-in-the-loop’ system is arguably the most efficient and effective.

This is a hybrid modelling approach that blends the LLM capabilities with human oversight, ensuring that the topic expertise is retained (imperative in breaking the data in 'chunks') while it is accelerating the validation workflows (Amershi et al., 2014). This mitigates risks of "hallucination" by LLMs while leveraging their speed and language comprehension.

Financially, adopting LLMs the IBs can reduce the operational costs associated with model validation and compliance reporting. These are areas that require large and specialized teams. Enhanced MoRM can lower regulatory fines and capital charges stemming from mismanaged model risk (Board of Governors of the Federal Reserve System, 2011). Integrating LLMs into their MoRM workflows will provide IBs with significant improvements both in efficiency and resilience.

References

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