LLM Seminar Topics WiSe 2023/24

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Decoding Strategies

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2 Inequality Between Languages

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Gao, Tianyu et al. 2023. Enabling Large Language Models to Generate Text with Citations. In EMNLP 2023