



Optimization in Large Language Models: Innovative Approaches Leveraging Knowledge Distillation and Pruning

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Background

Knowledge Distillation: In the NLP community, many works apply Knowledge Distillation (KD) to text classification tasks by training the student to mimic the teacher's output. On the other hand, other works use a frozen instruction-tuned LLM that generates artificial examples that are used as knowledge to train a student SLM with an order of magnitude fewer parameters. However, previous work on KD has focused mainly on text classification, neglecting generative tasks such as QA.

Token Pruning: Initial attempts to mitigate the computational complexity of transformers, achieved through the removal of non-informative tokens, were reliant on attention scores. PoWER-BERT uses a scoring function derived from attention scores to drop tokens based on their impact on others. Yang et al. (2022) adaptively determined the quantization precision levels of the tokens (i.e. 0 bit, 4 bit, and 8 bit) based on their importance, as gauged by their attention probabilities. Despite their popularity and promising outcomes, these solutions are grounded in predefined heuristics. Other approaches leverage Reinforcement Learning (RL) to train a policy network responsible for choosing the top-k tokens, therefore necessitating the formulation of a specific objective function.

Project Goals

Comprehensive knowledge distillation: Formulate KD solutions tailored for relatively unexplored domains, such as medical and legal, as well as tasks like question-answering, summarization, and named entity recognition.

End-to-end token pruning: Design token pruning techniques where the selection of the most crucial tokens is performed in an end-to-end fashion.

Experimental Approach

Ace-Attorney: a new legal framework designed to produce LQA-specific datasets and supervised SLMs through LLM KD. Precisely, given an input textual prompt, a state-of-the-art frozen LLM generates artificial samples that are used as knowledge to train a reduced-parameter student model. We collect LLM-crafted samples and create Syn-LeQA, our synthetic dataset proposed to address the scarcity of public LQA corpora. We also propose the Selective Generative Paradigm (SGP), which allows the generator and the retriever to work jointly to select the correct document to answer the question.

PrunePert: we use perturbed-topk, adeptly tackling the token pruning challenge through a differentiable top-k function. This approach enables the selection of the most crucial tokens in an end-to-end manner without the need for additional ad-hoc losses. Beyond the advantage of directly training the scorer on the final summarization loss, in contrast to prior works focused solely on efficiency during inference, our solution also optimizes resource utilization during training, as the top-k token selection occurs also at training time.

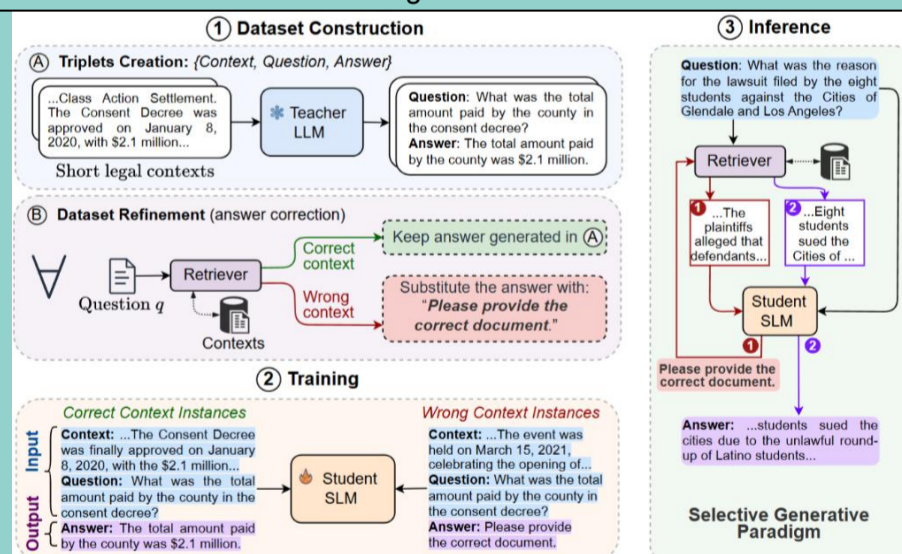
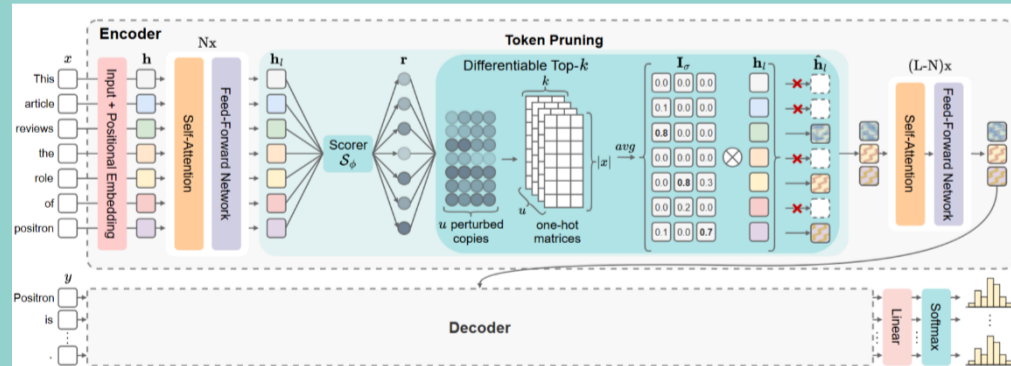
Expected Outcomes

Accessibility: Make advanced NLP tools usable on low-resource devices, improving access to legal, medical, and educational services.

Sustainability: Lower the environmental footprint of large-scale AI by reducing energy consumption.

Equity: Democratize AI applications in sensitive sectors, fostering fairer and more efficient access to knowledge.

Left: PrunePert architecture. Tokens are pruned by scoring their importance with a lightweight network and keeping only the top-k most relevant ones through a differentiable selection, discarding the rest



Right: Ace-Attorney overview. (1) A frozen LLM generates triplets from short legal contexts. For each question, we retrieve the corresponding context, manually adjusting the answer if the context is incorrect. (2) We then train an SLM on these triplets. (3) During inference, we employ SGP, where the SLM provides an answer based on the relevance of the retrieved document

Publications

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