A Survey on Model Compression for Large Language Models

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Abstract

Large Language Models (LLMs) have revolutionized natural language processing tasks with remarkable success. However, their formidable size and computational demands present significant challenges for practical deployment, especially in resource-constrained environments. As these challenges become increasingly pertinent, the field of model compression has emerged as a pivotal research area to alleviate these limitations. This paper presents a comprehensive survey that navigates the landscape of model compression techniques tailored specifically for LLMs. Addressing the imperative need for efficient deployment, we delve into various methodologies, encompassing quantization, pruning, knowledge distillation, and more. Within each of these techniques, we highlight recent advancements and innovative approaches that contribute to the evolving landscape of LLM research. Furthermore, we explore benchmarking strategies and evaluation metrics that are essential for assessing the effectiveness of compressed LLMs. By providing insights into the latest developments and practical implications, this survey serves as an invaluable resource for both researchers and practitioners. As LLMs continue to evolve, this survey aims to facilitate enhanced efficiency and real-world applicability, establishing a foundation for future advancements in the field.

1 Introduction

Large Language Models (LLMs) [Zhao *et al.*, 2023; Huang and Chang, 2023; Chang *et al.*, 2023] consistently exhibit remarkable performance across various tasks. Nevertheless, their exceptional capabilities come with significant challenges stemming from their extensive size and computational requirements. For instance, the GPT-175B model [Brown *et al.*, 2020], with an impressive 175 billion parameters, demands a minimum of 320GB (using multiples of 1024) of storage in half-precision (FP16) format. Furthermore, deploying this model for inference necessitates at least five A100 GPUs, each featuring 80GB of memory, to efficiently manage operations. To tackle these issues, a prevalent approach known as model compression [Deng *et al.*, 2020; He *et al.*, 2018] offers a solution. Model compression involves transforming a large, resource-intensive model into a compact version suitable for storage on constrained mobile devices. Additionally, it can involve optimizing the model for faster execution with minimal latency or achieving a balance between these objectives.

Apart from their technical aspects, LLMs have triggered discussions on environmental and ethical matters. These models pose significant challenges for engineers and researchers in developing nations, where limited resources can impede access to essential hardware for model execution [Lin *et al.*, 2023]. Additionally, the substantial energy consumption of LLMs contributes to carbon emissions, underscoring the significance of sustainable practices in AI research. A promising solution to these challenges lies in utilizing model compression techniques, which have showcased the potential to reduce emissions without substantially compromising performance [Luccioni *et al.*, 2022]. By implementing model compression, we can tackle environmental concerns, enhance accessibility, and promote inclusivity in LLM deployment.

In our paper, our primary objective is to illuminate the recent strides made in the domain of model compression techniques tailored specifically for LLMs. Our work entails an exhaustive survey of methodologies, metrics, and benchmarks, which we meticulously organize into an innovative taxonomy. As illustrated in Figure 1, our proposed taxonomy provides a structured framework for understanding the landscape of Model Compression methods for LLMs. This exploration encompasses a thorough examination of well-established techniques, including but not limited to pruning, knowledge distillation, quantization, and low-rank factorization. Furthermore, our study sheds light on prevailing challenges and offers a glimpse into potential future research trajectories in this evolving field. We advocate for collaborative efforts within the community to pave the way for an ecologically conscious, all-encompassing, and sustainable future for LLMs. Notably, our work stands as the inaugural survey specifically addressing the realm of model compression for LLMs.

Model Compression for Large Language Models

- **Pruning**
  - **Unstructured Pruning**: SparseGPT [Frantar and Alistarh, 2023], LoRAPrune [Zhang *et al.*, 2023a], Wanda [Sun *et al.*, 2023]
  - **Structured Pruning**: LLM-Pruner [Ma *et al.*, 2023]
- **Knowledge Distillation**
  - **Standard KD**: MINILLM [Gu *et al.*, 2023], GKD [Agarwal *et al.*, 2023]
  - **EA-based KD**
    - **In-Context Learning**: In-Context Learning distillation [Huang *et al.*, 2022]
    - **Chain-of-Thought**: MT-COT [Li *et al.*, 2022], Fine-tune-CoT [Ho *et al.*, 2023], DISCO [Chen *et al.*, 2023], SCOTT [Wang *et al.*, 2023a], SOCRATIC CoT [Shridhar *et al.*, 2023]
    - **Instruction Following**: Lion [Jiang *et al.*, 2023]
- **Quantization**
  - **Quantization-Aware Training**: LLM-QAT [Liu *et al.*, 2023]
  - **Quantization-Aware Fine-tuning**: PEQA [Kim *et al.*, 2023], QLORA [Dettmers *et al.*, 2023a]
  - **Post-Training Quantization**
    - **Weight Quantization**: LUT-GEMM [Park *et al.*, 2022], LLM.int8() [Dettmers *et al.*, 2022], ZeroQuant [Yao *et al.*, 2022], GPTQ [Frantar *et al.*, 2022], AWQ [Lin *et al.*, 2023], OWQ [Lee *et al.*, 2023], SpQR [Dettmers *et al.*, 2023b]
    - **Weight and Activation Quantization**: SmoothQuant [Xiao *et al.*, 2022], RPTQ [Yuan *et al.*, 2023], OliVe [Guo *et al.*, 2023], Outlier Suppression+ [Wei *et al.*, 2023], MoFQ [Zhang *et al.*, 2023c], ZeroQuant-FP [Wu *et al.*, 2023]
- **Low-Rank Factorization**: LoRAPrune (Low-Rank Factorization + Pruning) [Zhang *et al.*, 2023a], ZeroQuant-FP (Low-Rank Factorization + Quantization) [Wu *et al.*, 2023]
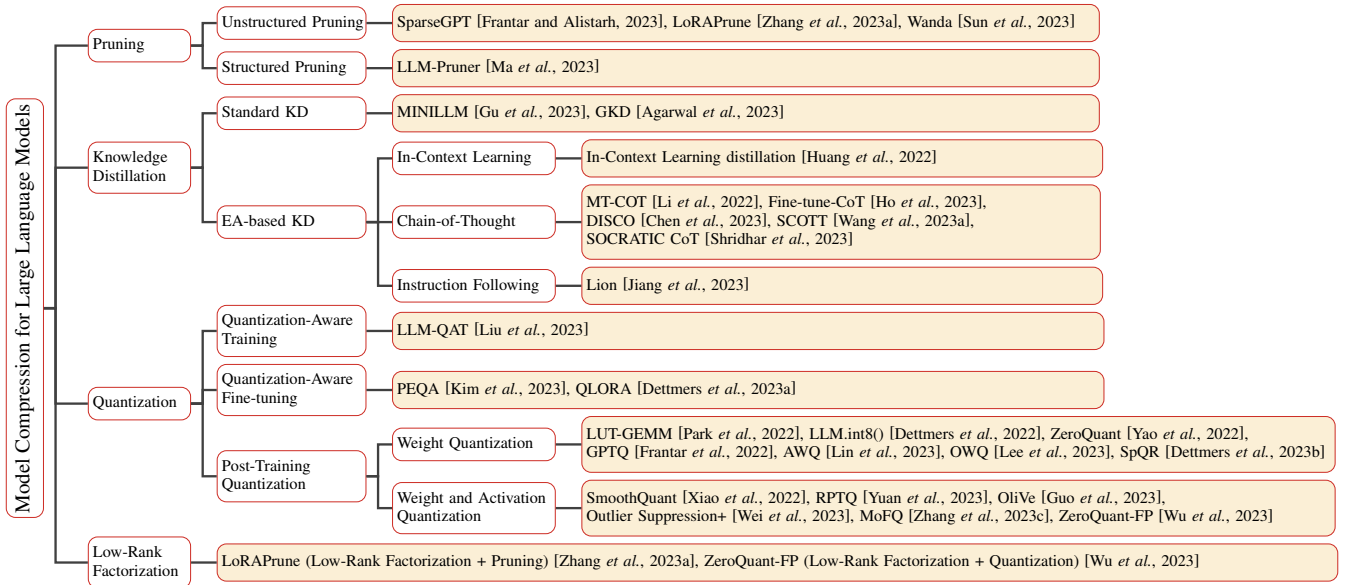
Figure 1: Taxonomy of Model Compression methods for Large Language Models.

2 Methods

2.1 Pruning

Pruning is a powerful technique to reduce the size or complexity of a model by removing unnecessary or redundant components [LeCun *et al.*, 1989; Han *et al.*, 2015; Li *et al.*, 2017]. As we know, there are many redundant parameters that have little even no effects on the performance of the model, thus, the performance of the model will make the least drop after directly pruning these redundant parameters. At the same time, pruning can make the model storage-friendly [Ardakani *et al.*, 2019], memory-efficiency [Han *et al.*, 2015; Yang *et al.*, 2017], computation-efficiency [Li *et al.*, 2017]. Pruning can be divided into **Unstructured Pruning** [Zhang *et al.*, 2018; Gordon *et al.*, 2020] and **Structured Pruning** [Anwar *et al.*, 2017; Fang *et al.*, 2023]. The main difference between structured pruning and unstructured pruning lies in the pruning targets and the resulting network structure. Structured pruning removes connections or hierarchical structures based on specific rules while preserving the overall network structure. On the other hand, unstructured pruning prunes individual parameters, resulting in an irregular sparse structure. Recent research efforts have been devoted to combining LLMs with pruning techniques, aiming to tackle the substantial size and computational costs associated with LLMs. In this section, we systematically categorize these works based on whether they employ structured or unstructured pruning strategies.

Unstructured Pruning

Unstructured pruning simplifies an LLM by removing specific parameters without considering its internal structure. This approach targets individual weights or neurons in the LLM, usually by applying a threshold to zero out parameters below it. However, this method disregards the overall LLM structure, resulting in an irregular sparse model com-

position. Such irregularity demands specialized compression techniques for efficient storage and computation of the pruned model. Unstructured pruning often involves substantial retraining of the LLM to regain accuracy, which is especially expensive for LLMs. An innovative approach in this domain is SparseGPT [Frantar and Alistarh, 2023]. It introduces a one-shot pruning strategy that doesn't require retraining. The method frames pruning as an extensive sparse regression problem and solves it using an approximate sparse regression solver. SparseGPT achieves significant unstructured sparsity, even up to 60% on the largest GPT models like OPT-175B and BLOOM-176B, with minimal increase in perplexity. Contrasting this, Syed *et al.* propose an iterative pruning technique that fine-tunes the model during pruning with minimal training steps. Another advancement is LoRAPrune [Zhang *et al.*, 2023a], which combines parameter-efficient tuning (PEFT) methods with pruning to enhance performance on downstream tasks. It introduces a unique parameter importance criterion using values and gradients from Low-Rank Adaption (LoRA) [Hu *et al.*, 2022]. In response to the resource-intensive weight update process still required by SparseGPT, Wanda [Sun *et al.*, 2023] presents a new pruning metric. Wanda evaluates each weight based on the product of its magnitude and the norm of corresponding input activations, approximated using a small calibration dataset. This metric is employed for local comparisons within linear layer outputs, enabling the removal of lower-priority weights from LLMs.

Structured Pruning

Structured pruning simplifies an LLM by removing entire structural components, such as neurons, channels, or layers. This approach targets whole sets of weights at once, offering the advantage of reducing model complexity and memory usage while maintaining the overall LLM structure intact. An example in this realm is LLM-Pruner [Ma *et al.*, 2023],

which takes a versatile approach to compressing LLMs while safeguarding their multi-task solving and language generation capabilities. LLM-Pruner also tackles the challenges that arise from the substantial training data used for LLMs, which can lead to significant data transfers and post-training model sizes. To overcome these challenges, LLM-Pruner incorporates a dependency detection algorithm to pinpoint interdependent structures within the model. It also implements an efficient importance estimation method that considers both first-order information and an approximated Hessian information. This strategy aids in selecting optimal groups for pruning, thereby improving the compression process.
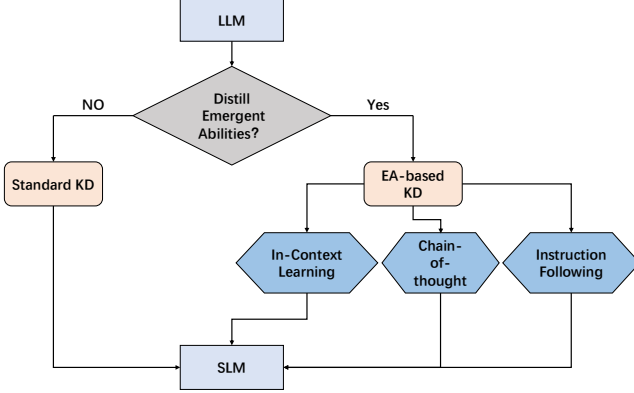
Figure 2: A brief classification of knowledge distillation for LLMs.

2.2 Knowledge Distillation

Knowledge Distillation (KD) [Hinton *et al.*, 2015; Kim and Rush, 2016; Tung and Mori, 2019] is a valuable machine learning technique aimed at improving model performance and generalization. It achieves this by transferring knowledge from a complex model, referred to as the teacher model, to a simpler counterpart known as the student model. The core idea behind KD involves transforming the comprehensive knowledge of the teacher model into a more streamlined and effective representation. In this section, we offer an overview of distillation methods that employ LLMs as teachers. We classify these methods based on whether their emphasis is on distilling the Emergent Abilities (EA) of LLMs into small language models (SLMs). Consequently, we divide these methods into two distinct categories: **Standard KD** and **EA-based KD**. For a visual representation, Figure 2 provides a brief classification of knowledge distillation for LLMs.

Standard KD

Standard KD focuses on enabling student models to learn the common knowledge possessed by LLMs, such as output distributions and feature information. This approach is similar to vanilla KD [Gou *et al.*, 2021; Park *et al.*, 2019; Zhao *et al.*, 2022; Liu *et al.*, 2021a], but with the distinction that the teacher models are LLMs. An illustrative example is MINILLM [Gu *et al.*, 2023], which delves into distillation from white-box generative LLMs. It observes a challenge with minimizing forward Kullback-Leibler divergence

(KLD) - this can lead to overly high probabilities in unlikely areas of the teacher's distribution, causing improbable samples during free-run generation. To address this, MINILLM opts for minimizing reverse KLD. This approach prevents the student from overestimating low-probability regions within the teacher's distribution, thereby refining the quality of generated samples. In contrast, GKD [Agarwal *et al.*, 2023] explores distillation from auto-regressive models, where white-box generative LLMs are a subset. This method identifies two key issues: a distribution mismatch between output sequences during training and those generated by the student during deployment, and model under-specification, where the student model might lack the expressive power to match the teacher's distribution. GKD handles the distribution mismatch by sampling output sequences from the student during training. It also tackles model under-specification by optimizing alternative divergences like reverse KL.
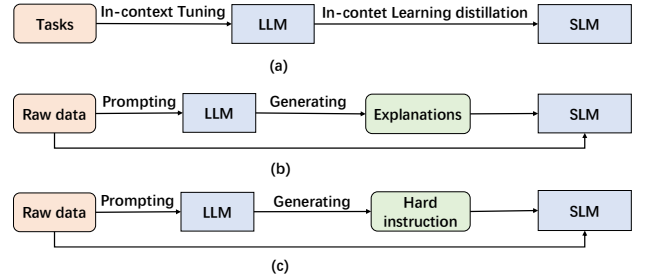

Figure 3: Overview of EA-based KD. (a) In-Context Learning distillation, (b) Chain-of-Thought distillation, (c) Instruction Following distillation.

EA-based KD

EA-based KD goes beyond transferring common knowledge from LLMs to also encompass distilling their distinctive emergent abilities. Recent research [Wei *et al.*, 2022a; Schaeffer *et al.*, 2023; Zhao *et al.*, 2023] underscores that despite the emphasis on augmenting model size, LLMs like GPT-3 (175B parameters) and PaLM (540B parameters) showcase unique behaviors when compared to smaller models like BERT (330M parameters) and GPT-2 (1.5B parameters). These LLMs exhibit surprising capabilities, referred to as Emergent Abilities, when tackling intricate tasks. Emergent Abilities encompass several intriguing facets, including **In-Context Learning (ICL)** [Dong *et al.*, 2023; Wang *et al.*, 2023b], **Chain-of-Thought (CoT)** [Wei *et al.*, 2022b; Wang *et al.*, 2023c; Shi *et al.*, 2023], and **Instruction Following (IF)** [Ouyang *et al.*, 2022; Brooks *et al.*, 2023]. For a visual overview, refer to Figure 3, which provides a concise representation of the EA-based Knowledge Distillation concept.

ICL employs a structured natural language prompt that contains task descriptions and possibly a few task examples as demonstrations. Through these task examples, LLMs can grasp and perform new tasks without necessitating explicit gradient updates. The work by Huang *et al.* introduces ICL distillation, which transfers in-context few-shot learning and language modeling capabilities from LLMs to SLMs.

This is accomplished by combining in-context learning objectives with traditional language modeling objectives. To achieve this, they explore ICL distillation under two few-shot learning paradigms: Meta In-context Tuning (Meta-ICT) and Multitask In-context Tuning (Multitask-ICT). In Meta-ICT, the language model undergoes meta-training across diverse tasks using in-context learning objectives. This equips it to adapt to unseen tasks through in-context learning, thereby extending its problem-solving capabilities. On the other hand, Multitask-ICT fine-tunes the model using ICL objectives and a handful of examples from target tasks. Subsequently, it employs in-context learning for making predictions on these tasks. Comparing the two paradigms, Multitask-ICT exhibits superior performance over Meta-ICT. However, it does demand greater computational resources during task adaptations, making it computationally more intensive.

CoT takes a different approach compared to ICL by incorporating intermediate reasoning steps, which can lead to the final output, into the prompts instead of using simple input-output pairs. MT-COT [Li *et al.*, 2022] aims to leverage the explanations produced by LLMs to enhance the training of smaller reasoners. It utilizes a multi-task learning framework to empower smaller models with strong reasoning capabilities alongside the ability to generate explanations. Fine-tune-CoT [Ho *et al.*, 2023] takes a step further by generating multiple reasoning solutions from LLMs through stochastic sampling. This augmentation of training data aids student models in their learning process. Researchers like Fu *et al.* identify a trade-off between the multi-dimensional capabilities of language models and propose fine-tuning an instruction-tuned model. They distill CoT reasoning paths from a large teacher model to improve out-of-distribution generalization. Hsieh *et al.* employ LLM rationales as additional guidance for training smaller models within a multi-task framework. SOCRATIC CoT [Shridhar *et al.*, 2023] trains two distilled models: a problem decomposer and a subproblem solver. The decomposer breaks down an original problem into a sequence of subproblems, while the subproblem solver handles solving these subproblems. DISCO [Chen *et al.*, 2023] introduces a fully-automatic counterfactual knowledge distillation approach based on LLMs. It engineers prompts to generate phrasal perturbations using LLMs, then filters these through a task-specific teacher model to extract high-quality counterfactual data. For rationale faithfulness, SCOTT [Wang *et al.*, 2023a] employs contrastive decoding, which links each rationale to the answer. It encourages relevant rationales from the teacher. Additionally, the student is guided to engage in counterfactual reasoning and predict based on rationales that lead to different answers.

IF endeavors to enhance the competence of language models in executing new tasks solely based on reading task descriptions, without relying on few-shot examples. By undergoing fine-tuning using an array of tasks expressed as instructions, language models showcase the capacity to accurately execute tasks described in previously unseen instructions. For instance, Lion [Jiang *et al.*, 2023] harnesses the adaptable nature of LLMs to improve student model performance. It prompts the LLM to identify and generate the "hard" instructions, which are then utilized to enhance the student model's capabilities. This approach taps into the versatility of LLMs to guide the learning of student models in addressing complex instructions and tasks.

2.3 Quantization

In the domain of model compression, quantization has emerged as a widely embraced technique to alleviate the storage and computational overhead of deep learning models [Liu *et al.*, 2021b; Gholami *et al.*, 2022; Guo *et al.*, 2020]. While traditional representation employs floating-point numbers, quantization converts them to integers or other discrete forms. This transformation significantly reduces storage requirements and computational complexity. Although some precision loss is inherent, careful quantization techniques can achieve substantial model compression with only minimal accuracy degradation. Quantization can be categorized into three main approaches: quantization-aware training (QAT) [Tailor *et al.*, 2021; Kim *et al.*, 2022; Ding *et al.*, 2022], quantization-aware fine-tuning (QAF) [Cai *et al.*, 2019; Dong *et al.*, 2019], and post-training quantization (PTQ) [Liu *et al.*, 2021b; Nagel *et al.*, 2020; Fang *et al.*, 2020]. The primary distinction among these approaches lies in when quantization is applied to compress the model. QAT employs quantization during the model's training process, QAF applies quantization during fine-tuning of a pretrained model, and PTQ quantizes a model after it has completed its training. Recent research endeavors have harnessed quantization to compress LLMs, yielding impressive outcomes. These efforts are classified into the three mentioned approaches: **Quantization-Aware Training**, **Quantization-Aware Fine-tuning**, and **Post-Training Quantization**. Furthermore, Table 1 serves as a summarized reference for quantization methods applied to LLMs. The table classifies these works into 8-bit quantization and lower-bit quantization, based on the number of bits (precision) in the weights of the LLM.

Quantization-Aware Training

In QAT, the quantization objective is seamlessly integrated into the model's training process. This approach enables the LLM to adapt to low-precision representations during training, enhancing its capacity to handle precision loss caused by quantization. This adaptation aims to preserve higher performance even after the quantization process. For instance, LLM-QAT [Liu *et al.*, 2023] delves into the challenges of acquiring training data for LLMs. Given that gathering training data for LLMs can be demanding, LLM-QAT proposes an innovative solution. It leverages generations produced by a pretrained model to achieve data-free distillation. This approach significantly aids in circumventing the data collection challenge. Additionally, LLM-QAT goes a step further by quantizing not only weights and activations but also key-value (KV) caches. This strategy aims to enhance throughput and support longer sequence dependencies. A noteworthy achievement of LLM-QAT is its ability to distill large LLaMA models with quantized weights and KV caches down to just 4 bits. This groundbreaking result demonstrates the feasibility of producing accurate 4-bit quantized LLMs.

Precision	Methods
8-bit quantization	LUT-GEMM [Park *et al.*, 2022], LLM.int8() [Dettmers *et al.*, 2022], ZeroQuant [Yao *et al.*, 2022], SmoothQuant [Xiao *et al.*, 2022]
lower-bit quantization	LLM-QAT [Liu *et al.*, 2023], PEQA [Kim *et al.*, 2023], QLORA [Dettmers *et al.*, 2023a], GPTQ [Frantar *et al.*, 2022], AWQ [Lin *et al.*, 2023], SpQR [Dettmers *et al.*, 2023b], RPTQ [Yuan *et al.*, 2023], OliVe [Guo *et al.*, 2023], Outlier Suppression+ [Wei *et al.*, 2023], OWQ [Lee *et al.*, 2023], ZeroQuant-FP [Wu *et al.*, 2023]

Table 1: A summary of quantization methods for the LLM. We divide them into 8-bit quantization and lower-bit quantization based on the number of bits (i.e., precision) in the weights of the LLM.

Quantization-Aware Fine-tuning

QAF involves quantizing the LLM during the fine-tuning process. The primary goal is to ensure that the fine-tuned LLM sustains its performance even after quantization to lower bit-widths. By integrating quantization awareness into fine-tuning, the LLM aims to strike a balance between model compression and retaining its performance. PEQA [Kim *et al.*, 2023] and QLORA [Dettmers *et al.*, 2023a] both fall under the category of quantization-aware Parameter-Efficient Fine-Tuning (PEFT) techniques [Liu *et al.*, 2022a; Ding *et al.*, 2023; Fu *et al.*, 2023b]. These techniques focus on facilitating model compression and accelerating inference. PEQA employs a dual-stage process. In the first stage, each fully-connected layer's parameter matrix is quantized into a matrix of low-bit integers and a scalar vector. In the second stage, fine-tuning occurs on the scalar vector for each specific downstream task. QLORA introduces innovative concepts like a new data type, double quantization, and paged optimizers. These ideas are aimed at conserving memory without compromising performance. QLORA enables large models to undergo fine-tuning on a single GPU while achieving state-of-the-art results on the Vicuna benchmark [Chiang *et al.*, 2023].

Post-Training Quantization

PTQ involves quantizing the parameters of a LLM after the completion of the LLM's training phase. The primary objective of PTQ is to diminish the storage and computational complexity of the LLM, all without necessitating modifications to the LLM architecture or requiring a retraining process. PTQ's key advantage is its simplicity and efficiency in achieving model compression. However, it's important to note that PTQ can introduce a certain degree of precision loss due to the quantization procedure. This method serves as a straightforward way to enhance the efficiency of an LLM without significant alterations or extensive training efforts.

In PTQ, certain approaches focus on quantizing only the weights of LLMs to enhance efficiency and reduce computational demands. Specifically, LUT-GEMM [Park *et al.*, 2022] optimizes matrix multiplications within LLMs using weight-only quantization and the BCQ format [Rastegari *et al.*, 2016], enhancing latency reduction and performance by improving computational efficiency. LLM.int8() [Dettmers *et al.*, 2022] employs 8-bit quantization for matrix multiplication in LLM transformers, effectively halving GPU memory usage during inference while maintaining performance precision. This method employs vector-wise quantization and mixed-precision decomposition to handle outliers for effi-

cient inference. Remarkably, LLM.int8() enables inference in models with up to 175 billion parameters without performance compromise. ZeroQuant [Yao *et al.*, 2022] integrates a hardware-friendly quantization scheme, layer-by-layer knowledge distillation, and optimized quantization support to reduce weight and activation precision in Transformer-based models to INT8 with minimal accuracy impact. GPTQ [Frantar *et al.*, 2022] acknowledges that the methods mentioned above work well for low compression targets like 8-bit weights, but face challenges in maintaining accuracy at higher rates. To tackle the challenges, GPTQ proposes a novel layer-wise quantization technique based on approximate second-order information. The result is a bitwidth reduction to 3 or 4 bits per weight, with minimal accuracy loss compared to the uncompressed version. Dettmers and Zettlemoyer delve into the trade-off between model size and bit precision in LLMs concerning zero-shot performance by analyzing inference scaling laws. Their extensive experimentation across various LLM families reveals that 4-bit precision is nearly universally optimal for achieving the right balance between total model bits and zero-shot accuracy. AWQ [Lin *et al.*, 2023] finds that weights are not equally important for LLMs' performance, and protecting only 1% of salient weights can greatly reduce quantization error. Building on this insight, AWQ employs an activation-aware approach by considering the significance of weight channels corresponding to larger activation magnitudes, which play a pivotal role in processing vital features. The approach incorporates a per-channel scaling technique to identify optimal scaling factors that minimize quantization errors while quantizing all weights. OWQ [Lee *et al.*, 2023] makes a theoretical analysis about how activation outliers can amplify the error in weight quantization. Drawing insights from this analysis, OWQ introduces a mixed-precision quantization scheme, which applies higher precision to the weights susceptible to quantization caused by activation outliers. To further compress accurate LLMs to 3-4 bits per parameter while staying near-lossless, SpQR [Dettmers *et al.*, 2023b] identifies and isolates outlier weights, storing them in higher precision, and compressing all other weights to 3-4 bits.

Except the above works that quantize only the weights of LLMs, lots of works in PTQ try to quantize both weights and activations of LLMs. Specifically, SmoothQuant [Xiao *et al.*, 2022] addresses the challenge of quantizing activations, which is often more complex due to the presence of outliers. Observing that different tokens exhibit similar variations across their channels, SmoothQuant introduces a per-

channel scaling transformation that effectively smooths the magnitudes, rendering the model more amenable to quantization. Recognizing the complexity of quantizing activations in LLMs, RPTQ [Yuan *et al.*, 2023] sheds light on the challenge stemming from the uneven ranges across different channels, in addition to the presence of outliers. To address this, RPTQ strategically arranges channels into clusters for quantization, effectively mitigating the discrepancies in channel ranges. Moreover, it integrates the channel reordering into the layer norm operation and linear layer weights to minimize associated overhead. OliVe [Guo *et al.*, 2023] further adopts an outlier-victim pair (OVP) quantization and handles outlier values locally with low hardware overheads and high performance gains, because it finds that outliers are important while the normal values next to them are not. Outlier Suppression+ [Wei *et al.*, 2023] extends this understanding by confirming that harmful outliers within activations exhibit an asymmetric distribution, predominantly concentrating in specific channels, and introduces a novel strategy involving channel-wise shifting and scaling operations to rectify the asymmetric presentation of outliers and mitigate the impact of problematic channels, and quantitatively analyzes the optimal values for shifting and scaling, taking into account both the asymmetric nature of the outliers and the quantization errors stemming from weights in the next layers. ZeroQuant-FP [Wu *et al.*, 2023] explores the applicability of floating-point (FP) quantization, specifically focusing on FP8 and FP4 formats. The study reveals that for LLMs, FP8 activation consistently outperforms its integer counterpart (INT8), while in terms of weight quantization, FP4 demonstrates comparable, if not superior, performance compared to INT4. To address the challenges arising from the divergence between weights and activations, ZeroQuant-FP mandates that all scaling factors be powers of 2 and confines the scaling factors within a single compute group. Notably, ZeroQuant-FP also integrates the Low Rank Compensation (LoRC) strategy to further enhance the effectiveness of its quantization approach.

2.4 Low-Rank Factorization

Low-Rank Factorization [Cheng *et al.*, 2017; Povey *et al.*, 2018; Idelbayev and Carreira-Perpiñán, 2020] is a model compression technique that aims to approximate a given weight matrix by decomposing it into two or more smaller matrices with significantly lower dimensions. The core idea behind low-rank factorization involves finding a factorization of a large weight matrix W into two matrices U and V such that $W \approx UV$, where U is an $m \times k$ matrix, and V is a $k \times n$ matrix, with k being much smaller than m and n. The product of U and V approximates the original weight matrix, leading to a substantial reduction in the number of parameters and computational overhead. In the field of LLM research, low-rank factorization has been widely adopted to fine-tune LLMs efficiently, e.g., LORA [Hu *et al.*, 2022] and its variants [Valipour *et al.*, 2023; Zhang *et al.*, 2023b; Chavan *et al.*, 2023]. Different from those above works, we focus on these works that use low-rank factorization to compress LLMs. In the field of model compression for LLM research, researchers often combine multiple techniques with low-rank factorization, including pruning, quantization and so on, e.g., LoRAPrune [Zhang *et al.*, 2023a] and ZeroQuant-FP [Wu *et al.*, 2023], to achieve more effective compression while maintaining performance. As research in this area continues, there may be further developments in applying low-rank factorization to compressing LLMs, but it seems that there is still ongoing exploration and experimentation required to fully harness its potential for LLMs.

3 Metrics and Benchmarks

3.1 Metrics

Inference efficiency of LLMs can be measured using various metrics, which capture different aspects of performance. These metrics are commonly presented alongside accuracy and zero-shot ability to comprehensively evaluate the LLM.

Number of Parameters

Number of Parameters [Ma *et al.*, 2023; Dasgupta *et al.*, 2023] in a LLM refers to the total count of learnable weights or variables that the LLM needs to optimize during training. In LLMs, parameters represent the weights in the connections between neurons or attention layers. In general, the more parameters a LLM has, the more expressive it can be, but it also requires more computational resources and memory for both training and inference.

Model Size

Model Size [Shridhar *et al.*, 2023; Li *et al.*, 2022; Magister *et al.*, 2023] typically refers to the disk space or memory footprint required to store the entire LLM, including weights, biases, and other necessary components. The model size is closely related to the number of parameters, as more parameters usually lead to a larger model size. However, other factors, like the data type used to represent the parameters and model architecture, can also influence the overall size.

Compression Ratio

Compression Ratio [Frantar and Alistarh, 2023; Tao *et al.*, 2023] represents the ratio between the original size of the uncompressed LLM and the size of the compressed LLM. A higher compression ratio indicates a more efficient compression, as the LLM has been significantly reduced in size while preserving its functionality and performance.

Inference time

Inference time (i.e., latency) [Kurtic *et al.*, 2023; Frantar *et al.*, 2022] measures the time taken by the LLM to process and generate responses for input data during inference or prediction. Inference time is particularly crucial for real-world applications where the LLM needs to respond to user queries or process large amounts of data in real-time.

Floating point operations (FLOPs)

FLOPs [Dettmers and Zettlemoyer, 2022; Yuan *et al.*, 2023; Wei *et al.*, 2023] measures the number of arithmetic operations involving floating-point numbers (typically 32-bit or 16-bit) that the LLM performs when processing input data. FLOPs provide a useful way to estimate the computational requirements of a LLM and compare the efficiency of different LLMs or compression techniques.

3.2 Benchmarks

The main goal of these benchmarks is to measure the effectiveness, efficiency, and accuracy of compressed LLMs in comparison to their uncompressed counterparts. These benchmarks typically consist of diverse tasks and datasets that cover a range of natural language processing challenges.

Common Benchmarks

The majority of research evaluates compressed LLMs on well-established NLP benchmarks. For instance, GLUE [Wang *et al.*, 2019b] and SuperGLUE [Wang *et al.*, 2019a] is designed for evaluating the performance of language models on a wide range of natural language understanding (NLU) tasks. LAMBADA [Paperno *et al.*, 2016] is designed to evaluate the context-dependent understanding of language models. LAMA [Petroni *et al.*, 2019] and StrategyQA [Geva *et al.*, 2021] are both designed to evaluate the reasoning ability of language models. SQuAD [Rajpurkar *et al.*, 2016] is designed for machine reading comprehension (MRC) tasks.

HULK

The HULK benchmark [Zhou *et al.*, 2021] comprehensively assesses energy efficiency in Pre-trained Language Models (PLMs). It employs classic datasets widely used in the research community, evaluating efficiency across tasks like MNLI [Williams *et al.*, 2018], SST-2 [Socher *et al.*, 2013], and CoNLL-2003 [Sang and Meulder, 2003]. This multi-task approach quantifies energy efficiency in pretraining, fine-tuning, and inference stages, considering time and cost to achieve specific performance levels. HULK sheds light on energy consumption in pretrained models, enhancing practical deployment understanding.

ELUE

The ELUE framework [Liu *et al.*, 2022b] enables comprehensive method comparison with a performance-efficiency trade-off analysis. ELUE integrates six NLP datasets, covering sentiment analysis, natural language inference, similarity, and paraphrase tasks. With four evaluation tracks based on parameter counts (40M, 55M, 70M, and 110M), ELUE employs the ELUE score to measure model performance advantage over ElasticBERT across various FLOPs settings. This approach provides a multi-dimensional perspective on model performance and efficiency. ELUE facilitates insightful evaluation and method assessment.

4 Challenges and Future Directions

Specialized Benchmarks

Despite the benchmarks introduced earlier for evaluating model compression, these benchmarks still suffer from several drawbacks. First, the evaluation of model compression lacks a universally accepted standard setting. Different studies often produce models with varying speed-up ratios, parameter counts, and accuracy levels. As a result, direct comparisons between these studies can be challenging, further complicated by hardware differences. Second, common benchmarks, such as LAMA [Petroni *et al.*, 2019] and StrategyQA [Geva *et al.*, 2021], may not be the most suitable representation of typical tasks on a mobile device. Third, benchmarks designed for pretrained models may also not be the

most suitable for LLMs. In general, it is very important to design specialized benchmarks for LLMs.

Performance-Size Trade-offs

Prior research [Magister *et al.*, 2023; Dettmers and Zettlemoyer, 2022] highlights the delicate balance between Large Language Model (LLM) performance and model size. Analyzing this trade-off allows for optimal performance within hardware constraints. However, current work lacks theoretical and empirical insights into this trade-off. Future LLM compression research should conduct comprehensive analyses to guide advanced techniques. Understanding the relationship between performance and size empowers researchers to develop tailored compression methods, navigating the design space effectively for efficient solutions.

Dynamic LLM Compression

Despite the advancements in current compression methods, they still rely on manual design to determine the compressed size and structure of LLMs. This often involves a trial-and-error approach based on input data or task requirements. This process becomes particularly challenging in scenarios like knowledge distillation, where several trials are necessary to find suitable student models within computational constraints. This manual effort presents a practical hindrance. A promising solution emerges in the integration of Neural Architecture Search (NAS) techniques [Elsken *et al.*, 2019; Zoph and Le, 2016; Zhu *et al.*, 2021; Zhu *et al.*, 2023] into the realm of compressing LLMs. NAS holds the potential to reduce the dependence on human-designed architectures, potentially revolutionizing LLM compression for improved efficiency and effectiveness.

Explainability

Earlier research [Stanton *et al.*, 2021; Xu *et al.*, 2021] has raised significant concerns regarding the explainability of compression techniques applied to Pre-trained Language Models (PLMs). Notably, these same challenges extend to LLM compression methods as well. Consequently, the integration of explainable compression approaches emerges as a crucial necessity for the progression of LLM compression applications. Moreover, the adoption of explainable compression not only addresses the issue of interpretability but also simplifies the evaluation procedure for compressed models. This, in turn, enhances the reliability and predictability of the models throughout the production phase.

5 Conclusion

In this thorough survey, we've explored model compression techniques for large language models (LLMs). Our coverage spanned compression methods, evaluation metrics, and benchmark datasets. By diving into LLM compression, we've highlighted its challenges and opportunities. As LLM compression advances, there's a clear call for research into advanced methodologies specifically for LLMs, unlocking their potential across applications. This survey aims to be a valuable reference, providing insights into the current landscape and promoting ongoing exploration of this pivotal topic.

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