

SEEKING NEURAL NUGGETS: KNOWLEDGE TRANSFER IN LARGE LANGUAGE MODELS FROM A PARAMETRIC PERSPECTIVE

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ABSTRACT

Large Language Models (LLMs) inherently encode a wealth of knowledge within their parameters through pre-training on extensive corpora. While prior research has delved into operations on these parameters to manipulate the underlying implicit knowledge—encompassing detection, editing, and merging—there remains an ambiguous understanding regarding their transferability across models with varying scales. In this paper, we seek to empirically investigate knowledge transfer from larger to smaller models through a parametric perspective. To achieve this, we employ sensitivity-based techniques to extract and align knowledge-specific parameters between different LLMs. Moreover, the LoRA module is used as the intermediary mechanism for injecting the extracted knowledge into smaller models. Evaluations across four benchmarks validate the efficacy of our proposed method. Our findings highlight the critical factors contributing to the process of parametric knowledge transfer, underscoring the transferability of model parameters across LLMs of different scales. We release code and data at <https://github.com/maszhongming/ParaKnowTransfer>.

1 INTRODUCTION

Driven by the advancements of Large Language Models (LLMs) (Brown et al., 2020; Chowdhery et al., 2022; OpenAI, 2023; Touvron et al., 2023a), a transformative wave has reshaped the landscape in multiple areas of Artificial Intelligence, elevating performance across diverse tasks. From a parametric perspective, the objective of pre-training is to encode substantial amounts of knowledge into model parameters through language modeling on extensive corpora (Peters et al., 2018; Radford et al.; Devlin et al., 2019; Delétag et al., 2023). In a quest to unravel the intricate workings of LLMs, a multitude of research efforts have been directed toward the detailed exploration and nuanced manipulation of this reservoir of implicit knowledge.

Early research efforts sought to detect this parametric knowledge, typically probing the concrete facts by using the “fill-in-the-blank” task under a closed-book setting (Petroni et al., 2019; Jiang et al., 2020; Roberts et al., 2020). Subsequent studies delved into the feasibility of executing operations on model knowledge, including knowledge editing (Cao et al., 2021; Mitchell et al., 2022; Meng et al., 2022), a technique designed to modify targeted knowledge while preserving the integrity of the remaining information, and model merging (Izmailov et al., 2018; Ainsworth et al., 2023; Stoica et al., 2023), a strategy that combines multiple models to enhance robustness or facilitate multitasking abilities. While these investigations exhibited that such parametric knowledge is both *detectable* and *editable* within a single model, the broader question of whether it is *transferable* across different LLMs remains an open and under-explored topic.

Knowledge transfer refers to distilling the expertise of larger teacher models into smaller, more manageable counterparts, thereby democratizing access to cutting-edge machine learning capabilities. As illustrated in Figure 1, online and offline distillation currently stand as the primary paradigms. The former, especially prevalent before the LLM era, capitalizes on teacher models to guide the learning trajectory of student models (Hinton et al., 2015; Sanh et al., 2019; Gou et al., 2021). Yet, as LLMs grow in scale, the inherent demand for the teacher model to undergo fine-tuning or par-

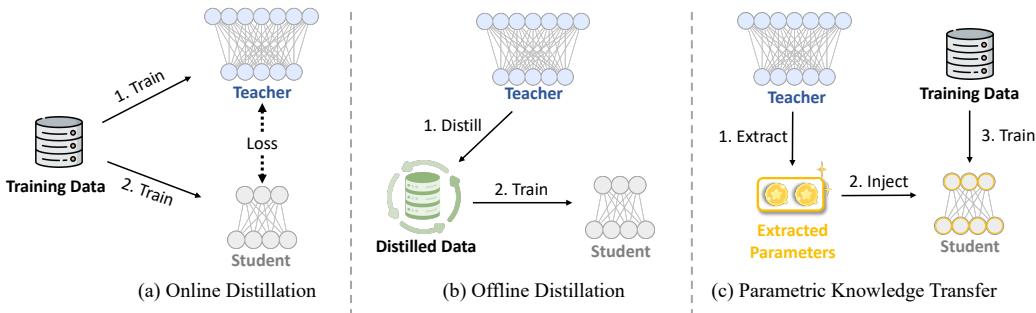


Figure 1: Different paradigms of knowledge transfer from teacher models to student models. (a) Online Distillation: utilizing soft logits from the fine-tuned teacher model to guide the training of the student model; (b) Offline Distillation: generating a distilled dataset that encapsulates the knowledge of the teacher model to fine-tune the student model. (c) Parametric Knowledge Transfer: extracting knowledge-specific parameters from the vanilla teacher model and injecting them into the student model to enhance its training efficacy.

ticipate in student training becomes increasingly cost-prohibitive. In contrast, offline distillation calls upon the teacher model merely to generate answers to open-ended queries, creating a distilled training dataset for students (Honovich et al., 2023; Wang et al., 2023c; Taori et al., 2023). Despite reducing the overhead to thousands of inferences, it completely overlooks the rich knowledge implicitly stored within the teacher’s parameters.

In this paper, we empirically investigate knowledge transfer from a distinct parametric perspective, dedicated to selecting static parameters directly from the teacher model and exploring their transferability. Specifically, we introduce a new parametric knowledge transfer paradigm designed to extract task-specific parameters from the teacher model and subsequently inject them into the student model, thereby enhancing performance on downstream tasks. Through decoding on a limited set of seed samples (e.g., 32 samples) with the teacher model, we calculate sensitivity metrics that serve as the basis for knowledge extraction. Given the discrepancies in the number of layers and dimensions across varied LLM scales, we employ sensitivity-based layer mapping and dimensionality reduction techniques to establish alignment between the teacher and student models. Lastly, we leverage LoRA (Hu et al., 2022) as a bridge to inject these extracted parameters into student models, facilitating its fine-tuning on downstream tasks and thus achieving the knowledge transfer process.

Experimentally, we evaluate the parametric knowledge transfer framework across four benchmark categories: reasoning (Cobbe et al., 2021), professional knowledge (Hendrycks et al., 2021), instruction-driven NLP tasks (Wang et al., 2022), and open-ended conversation (Dubois et al., 2023), using various sizes of LLaMA models (Touvron et al., 2023a;b). The results indicate that upon transferring the teacher model’s parameters, the student performance demonstrates consistent improvements across all benchmarks, affirming the transferability of parametric knowledge. Furthermore, our detailed analyses illustrate the underlying factors that contribute to effective parametric knowledge transfer, discovering that the teacher scales, initialization strategies, number of seed samples, and the origin and structure of the extracted parameters all play crucial roles.

To summarize, the key contributions of this paper are threefold: (1) From a distinct perspective, we introduce a parametric knowledge transfer paradigm that encompasses stages of sensitivity-based knowledge extraction and LoRA-driven knowledge injection. (2) Through comprehensive evaluations, we provide empirical evidence that implicit model knowledge is indeed *transferable* across varying scales of LLMs. (3) Further enriching our insights into parametric knowledge transfer, we undertake a thorough analysis to pinpoint the pivotal factors that dictate its efficacy.

2 RELATED WORK

2.1 MANIPULATION OF IMPLICIT MODEL KNOWLEDGE

With the recognition of the vast repository of knowledge embedded in model parameters (Petroni et al., 2019; Jiang et al., 2020; Roberts et al., 2020; Dai et al., 2022), ensuing research has sought to

execute diverse operations on these parameters, aiming to manipulate the implicit knowledge. For instance, knowledge editing endeavors to modify or update specific facts by editing the associated parameters, all the while ensuring the broader knowledge base remains untouched (Cao et al., 2021; Mitchell et al., 2022; Meng et al., 2022; 2023; Yao et al., 2023b). Another avenue, model merging, combines the weights of two or more models into a unified weight set for greater robustness or multitasking capabilities (Huang et al., 2017; Izmailov et al., 2018; Ainsworth et al., 2023; Stoica et al., 2023). Additionally, a strand of studies probes into performing arithmetic operations on the pre-trained weights of a model or specific modules, thus enabling the model to augment or diminish particular functionalities (Ilharco et al., 2023; Ortiz-Jiménez et al., 2023; Zhang et al., 2023). However, these explorations are limited to operations within individual models or the merging of models with identical architectures, without investigating whether implicit knowledge between different scale models can be manipulated and transferred.

2.2 INHERITANCE OF MODEL KNOWLEDGE

Another line of research that aligns more closely with our work concerns the operation of model parameters across scales, specifically the concept of model growth (Yao et al., 2023a; Li et al., 2023). This refers to accelerating the pre-training of LLMs by incrementally growing and expanding the parameters of a smaller model, using them as an initialization for the larger one. The majority of existing work is concentrated on devising function-preserving methods (Chen et al., 2016), ensuring that the initialized larger model replicates the behaviors of the original smaller model (Wei et al., 2016; Gu et al., 2021; Chen et al., 2022; Evci et al., 2022; Shen et al., 2022; Gesmundo & Maile, 2023). Concurrently, several studies adopt data-driven strategies, investigating reverse distillation (Qin et al., 2022) or mapping learned weights from smaller models to their larger counterparts (Wang et al., 2023a). In contrast to this research direction, our emphasis is on the transfer of knowledge from larger teacher to smaller student models, with the aim of exploring not only the efficiency of training, but also the transferability of parametric knowledge across different scenarios.

2.3 TRANSFER OF MODEL KNOWLEDGE

Knowledge transfer is a research area dedicated to training a smaller student model to mimic the behavior of a larger pre-trained teacher model to achieve similar performance with fewer parameters (Hinton et al., 2015). Despite progress in improving the online distillation paradigm (Zhang et al., 2018; Lan et al., 2018; Jin et al., 2019; Mirzadeh et al., 2020; Park et al., 2021; Pham et al., 2021; Zhou et al., 2022) and optimizing the efficiency of offline distillation (Honovich et al., 2023; Wang et al., 2023c; Wu et al., 2023; Taori et al., 2023; Peng et al., 2023; Xu et al., 2023), they both completely ignore the implicit knowledge embedded inherently in the teacher model. In this paper, we are grounded in a fresh perspective and propose a parametric knowledge transfer framework. It seeks to affirm the transferability of such implicit knowledge by directly extracting parameters from the teacher model and injecting them into the student model. Furthermore, by leveraging the static parameters of the teacher model, our approach naturally holds an efficiency advantage over preceding methodologies.

3 PARAMETRIC KNOWLEDGE TRANSFER

In this section, we first outline the task formulation for parametric knowledge transfer. Following this, we delve into a detailed description of our proposed method, as depicted in Figure 2.

3.1 TASK FORMULATION

The core objective of parametric knowledge transfer is to enhance a student model by selectively transferring task-specific parametric knowledge from a more knowledgeable teacher model. Given a task \mathcal{T} , the transfer process begins with a teacher model M_T endowed with parameters Θ_T and a student model M_S characterized by parameters Θ_S .

The first step in this procedure involves extraction, where task-relevant parameters are identified from the teacher model and resized to a desired scale based on the student model's parameter di-

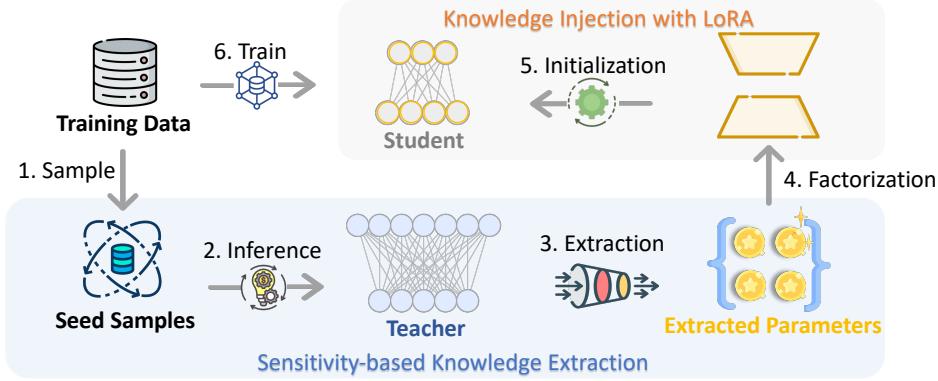


Figure 2: Overview of our parametric knowledge transfer framework. Starting with the teacher model, we compute sensitivity metrics using a set of seed samples, which aids in the extraction of task-specific knowledge. Subsequently, the extracted parameter matrices are factorized to initialize the student model’s LoRA module, serving as a bridge for knowledge injection.

mensions. This can be expressed as:

$$\text{Extract}(\Theta_T; \Theta_S; \mathcal{T}) = \Theta'_{T_{\text{extract}}}, \quad (1)$$

with $\text{Extract}(\cdot)$ encapsulating the logic for both parameter extraction and downscaling. Following extraction, the next step is the injection of these extracted parameters into the student model:

$$\text{Inject}(\Theta_S; \Theta'_{T_{\text{extract}}}) = \Theta'_S, \quad (2)$$

yielding a student model now characterized by the modified parameter set Θ'_S . Upon completing the knowledge injection, there remains an optional phase wherein the student model fine-tunes the newly incorporated parameters Θ'_S with respect to the task \mathcal{T} .

3.2 KNOWLEDGE EXTRACTION

In implementing our $\text{Extract}(\cdot)$ function, we employ parameter sensitivity as the foundational metric to guide the extraction process.

Sensitivity of the Parameters. Parameter sensitivity serves as a mechanism to measure the variation in the loss upon setting a particular parameter to zero (Mozer & Smolensky, 1988; Lee et al., 2019; Lubana & Dick, 2021; Liang et al., 2022). When this removal elicits a significant shift in the loss, such a parameter is deemed to be of high sensitivity. For a teacher model M_T with parameters $\Theta_T = [\theta_1, \dots, \theta_{N_T}]$, where N_T represents the total number of parameters, the i -th parameter can be expressed as $\Theta_{T_i} = [0, \dots, \theta_i, \dots, 0]$. With gradients of the loss relative to Θ_T represented as $\nabla_{\Theta_T} \mathcal{L}$, the sensitivity of the i -th parameter for a specific sample x_j from task \mathcal{T} is determined as:

$$S_{i,j} = |\Theta_{T_i}^\top \nabla_{\Theta_T} \mathcal{L}(x_j)|. \quad (3)$$

The rationale behind this sensitivity definition stems from the first-order Taylor expansion of $\mathcal{L}(\cdot)$ relative to θ_i at Θ_{T_i} (Molchanov et al., 2017). In essence, $S_{i,j}$ provides an approximation for how the loss might change in the absence of θ_i :

$$\Theta_{T_i}^\top \nabla_{\Theta_T} \mathcal{L}(x_j) \approx \mathcal{L}(\Theta_T) - \mathcal{L}(\Theta_T - \Theta_{T_i}). \quad (4)$$

To ascertain S_i for parameter i pertaining to task \mathcal{T} , we randomly sample k instances as seed samples for an efficient and representative estimate. Thus, the final formulation S_i for task \mathcal{T} integrates the cumulative sensitivity over the sampled instances, calculated as $S_i = \sum_{j=1}^k S_{i,j}$.

Layer Selection and Dimensionality Reduction. Given that models of varying scales often differ in both the number of layers and their dimensions, we adopt a method of layer selection and dimensionality reduction based on sensitivity scores. Our first step is to assess the layers of the teacher model, M_T , with respect to their relevance to task \mathcal{T} . Let L_T and L_S represent the total number of layers in the teacher and student models, respectively, with $L_S \leq L_T$. For each layer l in M_T , we calculate a layer-specific sensitivity score, S_{T_l} , by aggregating the sensitivity scores of all parameters within that layer, represented as: $S_{T_l} = \sum_{\theta_i \in \Theta_{T_l}} S_i$. Having computed the sensitivity scores for layer l in M_T , we proceed to arrange them in descending order and select the top L_S layers with the highest scores. To preserve the inherent structure of the teacher model, the chosen layers are subsequently mapped to the student model maintaining their original sequential order.

Upon alignment of the layers, the parameter dimensions of each layer in the teacher model typically continue to surpass those of the student model. During this phase of the transfer process, our focus is primarily on all the two-dimensional matrices in the teacher model, which are denoted as \mathbf{W}_T . To preserve the structural information in each $\mathbf{W}_{T_i} \in \mathbf{W}_T$ with the dimensions $\mathbb{R}^{n_T \times m_T}$, we extract the submatrix with the highest cumulative sensitivity to align with the student model’s corresponding matrix with dimensions $\mathbb{R}^{n_S \times m_S}$ ($n_S \leq n_T, m_S \leq m_T$). Formally, this objective is expressed as:

$$\mathbf{W}_{T_i, \text{extract}} = \arg \max_{\mathbf{W}' \subseteq \mathbf{W}_{T_i}} \sum_{\theta_i \in \mathbf{W}'} S_i. \quad (5)$$

By aggregating $\mathbf{W}_{T_i, \text{extract}}$ across all layers, we derive the extracted parameters $\Theta_{T_{\text{extract}}}$ from M_T .

3.3 KNOWLEDGE INJECTION

To keep the architecture and the number of parameters of the student model unchanged during the knowledge transfer process, we employ the LoRA approach to instantiate the $\text{Inject}(\cdot)$ function.

LoRA Module. LoRA (Hu et al., 2022), which stands for Low-Rank Adaptation, is a method designed to optimize parameter efficiency by freezing the pre-trained model weights and inserting trainable rank decomposition matrices into the deep neural network. The guiding intuition is that pre-trained language models possess low “intrinsic dimensions” (Aghajanyan et al., 2021). This means that even when projected to a smaller subspace, these models can still exhibit efficient learning. Consequently, it can be hypothesized that weight updates during adaptation also exhibit low “intrinsic ranks”. For a given pre-trained weight matrix $\mathbf{W}_i \in \mathbb{R}^{n \times m}$, it can be updated as:

$$\mathbf{W}_i^* = \mathbf{W}_i + \Delta \mathbf{W} = \mathbf{W}_i + \mathbf{B}_i \mathbf{A}_i, \quad \mathbf{B}_i \in \mathbb{R}^{n \times r}, \quad \mathbf{A}_i \in \mathbb{R}^{r \times m}, \quad (6)$$

where r represents the low rank with $r \ll \min(n, m)$. The matrix \mathbf{W}_i remains constant during this operation, implying that only \mathbf{B}_i and \mathbf{A}_i are updated in the training phase. To ensure that training commences from the original pre-trained weights, either \mathbf{B}_i or \mathbf{A}_i is initialized with zeros.

Knowledge Injection with LoRA. The main goal of this step is to integrate knowledge from the teacher model by incorporating extracted parameters into the student’s LoRA module. Initially, SVD is adopted to factorize each matrix $\mathbf{W}_{T_i, \text{extract}}$ in $\Theta_{T_{\text{extract}}}$ into three constituent matrices as:

$$\mathbf{W}_{T_i, \text{extract}} = \mathbf{U}_i \Sigma_i \mathbf{V}_i^\top. \quad (7)$$

Here, \mathbf{U}_i and \mathbf{V}_i^\top are orthogonal matrices containing left and right singular vectors, respectively, while Σ_i is a diagonal matrix that hosts the singular values in descending order. To capture the first r ranks, we then formulate:

$$\mathbf{W}_{T_i, \text{extract}, r} = \mathbf{U}_i[:, :r] \Sigma_i[:, :r] \mathbf{V}_i^\top[:, :r, :]. \quad (8)$$

The symbols $\mathbf{U}_i[:, :r]$ and $\mathbf{V}_i^\top[:, :r, :]$ represent the initial r columns of \mathbf{U}_i and \mathbf{V}_i^\top , respectively, while $\Sigma_i[:, :r]$ captures the top r singular values. Subsequently, for each corresponding matrix \mathbf{W}_i in the student model, its update can be given as in two ways:

$$\mathbf{W}_i^* = \mathbf{W}_i + \mathbf{B}_i \mathbf{A}_i, \quad (9)$$

$$\mathbf{W}_i^* = \mathbf{W}_i - \mathbf{W}_{T_i, \text{extract}, r} + \mathbf{B}_i \mathbf{A}_i, \quad (10)$$

where \mathbf{B}_i is initialized using $\mathbf{U}_i[:, :r] \Sigma_i[:, r, :] \mathbf{V}_i^\top[:, r, :]$, and \mathbf{A}_i is initialized with $\mathbf{V}_i^\top[:, r, :]$. During training, both \mathbf{W}_i and $\mathbf{W}_{T_i, \text{extract}, r}$ remain constant, with only the parameters in $\mathbf{B}_i \mathbf{A}_i$ being updated. The former is the initialization from LoRA paper, while the latter ensures that training starts from the original weights of \mathbf{W}_i . We provide an empirical comparison of the two initialization strategies in Section 4.3. Here, the introduction of LoRA module aims to effectively utilize the most salient features of the extracted knowledge in a concise and efficient manner.

4 EXPERIMENTS

4.1 EXPERIMENTAL SETUP

Facets of Evaluation. To validate the efficacy of our proposed framework, we conduct evaluations across four distinct benchmark categories:

- (1) Reasoning: Reasoning stands as a foundational capability for models, particularly when tackling intricate tasks. We leverage the Grade School Math dataset (GSM) (Cobbe et al., 2021) to assess the reasoning proficiency of models. The evaluation format requires models, given a math problem, to produce the chain-of-thought process (Wei et al., 2022) and the final numerical answer.
- (2) Professional Knowledge: For language models to effectively cater to users' informational needs, possessing a robust repository of professional knowledge is crucial. We measure this knowledge reservoir using the Massive Multitask Language Understanding dataset (MMLU) (Hendrycks et al., 2021). This dataset encompasses questions about 57 subjects, spanning a spectrum of difficulty levels from elementary to advanced professional tiers, all formatted as multiple-choice questions.
- (3) Instruction-driven NLP Tasks: This set of tasks evaluates a model's capability in adhering to instructions. Typically, the language model receives both a task definition and an input text, and it must perform the specified classification or generation tasks as directed. Our chosen benchmark for this category is the Super Natural Instructions (Super NI) (Wang et al., 2022), a rich dataset comprising 1,616 varied NLP tasks alongside their expert-written instructions.
- (4) Open-ended Conversation: This represents the primary interface through which models interact with users in real-world scenarios. To evaluate such instructability, we employ AlpacaFarm (Dubois et al., 2023), which contains 805 instructions including subsets from various evaluations like Self-Instruct (Wang et al., 2023c), Open Assistant (Köpf et al., 2023), Anthropic (Bai et al., 2022), Vicuna (Chiang et al., 2023), and Koala (Geng et al., 2023). GPT4-32K serves as the evaluator, determining the win rate of the testing model against the outputs generated by Davinci-003.

Throughout all evaluations, we adhere to established metrics and prompts, utilizing the evaluation scripts sourced from Wang et al. (2023b).

Implementation Details. For all our experiments, the larger-scale LLaMA model (Touvron et al., 2023a;b) serves as the teacher, and its smaller-scale counterpart acts as the student. For the fine-tuning of the student model, we draw a random subset of 1,000 instances from the respective training datasets of each benchmark. In the case of AlpacaFarm, due to the absence of a training set, we utilize LIMA data (Zhou et al., 2023) as a substitute, which is composed of 1,000 carefully curated open-ended conversations. For each experiment, 32 seed samples are randomly selected from the corresponding training sets. The student model is trained for 3 epochs with a batch size of 64 and a learning rate of 3e-4. Regarding LoRA, we set the rank as 16, and insert LoRA module into the embedding layer, FFN, and self-attention layer in the Transformer architecture (Vaswani et al., 2017). Notably, all results presented in this paper are mean values derived from three separate runs, with each run using a new random set of seed samples.

Table 1: Results for parametric knowledge transfer. “7B-LoRA + 13B Param.” represents that we extract parameters from the 13B teacher model and transfer them to the 7B student model.

Models	GSM		MMLU		Super NI		AlpacaFarm Win Rate%	Average -
	0-shot	8-shot	0-shot	5-shot	EM	R-L		
<i>LLaMA-1</i>								
Vanilla 7B	4.70	10.77	32.10	35.30	0.67	5.55	-	-
7B-LoRA	17.26	16.93	43.43	38.90	22.91	40.49	9.07	27.00
+ 13B Param.	18.73	18.85	44.03	39.77	24.51	42.37	9.28	28.22
+ 30B Param.	18.63	18.52	45.20	40.60	25.01	43.08	9.40	28.63
Vanilla 13B	4.93	17.44	43.50	46.80	2.18	7.78	-	-
13B-LoRA	26.18	23.78	50.43	50.03	27.34	45.53	13.91	33.89
+ 30B Param.	27.85	27.70	51.30	51.03	27.51	46.09	17.27	35.54
<i>LLaMA-2</i>								
Vanilla 7B	3.34	15.54	41.70	45.80	0.00	4.68	-	-
Vanilla 13B	6.52	27.82	52.10	55.20	0.00	4.84	-	-
7B-LoRA	23.38	21.05	47.77	47.07	24.93	41.25	20.50	32.28
+ 13B Param.	25.30	26.31	49.37	46.53	26.16	42.98	24.64	34.47

4.2 EXPERIMENTAL RESULTS

Results for Parametric Knowledge Transfer. Our initial experiments focus on four distinct teacher-student model pairings: LLaMA-1 (13B \Rightarrow 7B, 30B \Rightarrow 7B, 30B \Rightarrow 13B) and LLaMA-2 (13B \Rightarrow 7B). The outcomes are systematically presented in Table 1. Remarkably, in contrast to the direct fine-tuning approach of LoRA, the student models augmented with parametric knowledge from their respective teacher models exhibit substantial improvements across all four benchmark categories. For instance, the LLaMA-1 30B \Rightarrow 7B pairing yields an average performance boost of 6.04% (from 27.00 to 28.63). In a similar vein, the LLaMA-2 13B \Rightarrow 7B configuration brings an enhancement of 6.78% (from 32.28 to 34.47).

Another observation emerges when examining the effects of scaling up the teacher model, specifically transitioning from 13B to 30B. The performance of the student model, LLaMA-1 7B, generally sees an improvement, despite a slight decrement in the GSM benchmark. Beyond the evident performance gains, the overhead introduced by parametric knowledge transfer remains minimal. The only extra commitment involves the teacher model executing inference on a set of 32 seed samples, without any direct participation in the training. Considering both performance and efficiency, parametric knowledge transfer stands out as a practical technique, even as disparities in parameter counts and architectural variances between teacher and student models expand.

Table 2: Transfer experiments with different task-specific extracted parameters. The leftmost column indicates the dataset on which the knowledge extraction is based. The teacher model and student model are LLaMA-2 13B and 7B, respectively.

Models	GSM		MMLU		Super NI		AlpacaFarm Win Rate%	Average -
	0-shot	8-shot	0-shot	5-shot	EM	R-L		
Vanilla 7B	3.34	15.54	41.70	45.80	0.00	4.68	-	-
7B-LoRA	23.38	21.05	47.77	47.07	24.93	41.25	20.50	32.28
GSM	25.30	26.31	48.40	45.97	24.45	42.11	23.68	33.75
MMLU	24.11	25.47	49.37	46.53	25.55	42.55	24.01	33.94
Super NI	23.78	24.11	48.60	46.70	26.16	42.98	24.31	33.81
LIMA	24.08	25.60	49.03	47.23	25.63	42.83	24.64	34.15

Transfer Experiments with Task-specific Extracted Parameters. While our results indicate that transferring extracted knowledge from the teacher model positively influences student model performance, the nature of this improvement—whether it is rooted in generalized knowledge or task-specific expertise—warrants deeper exploration. To disentangle this, we conduct experiments wherein extracted parameters, each tailored to a specific task, are integrated into the student model, which is subsequently fine-tuned across all datasets.

Table 2 offers insights into a prevalent trend: when parameters are extracted from a concrete task, the performance is most significantly amplified for that same task. This is particularly evident in the GSM benchmark. Models equipped with GSM-oriented extracted parameters notably exceed their counterparts—achieving at least a 1.2 increase in 0-shot accuracy—compared to models incorporated with parameters based on alternative datasets. This is likely due to the unique and intricate challenges associated with mathematical reasoning. Additionally, parameters sourced from the LIMA dataset demonstrate remarkable generalizability, presumably owing to their grounding in open-ended dialogues that cover a spectrum of domains and tasks. Overall, these observations highlight the capability of our sensitivity-driven techniques to efficiently target certain types of knowledge, rather than just extracting generalized knowledge.

4.3 ANALYSIS: KEY FACTORS FOR PARAMETRIC KNOWLEDGE TRANSFER

We further analyze the key factors for the process of parametric knowledge transfer as follows.

Initialization Strategies. Essentially, for the student model, the injected parameters correspond to the initialization of LoRA module. We compare two initialization methods: the approach described in the LoRA paper, denoted by Equation 9, and the method adopted in our work, represented by Equation 10. Furthermore, we investigate five distinct initializations for LoRA matrix: (1) Gaussian initialization for both B and A ; (2) Sub-matrices extracted randomly from the 13B model; (3) Parameters extracted from the 13B model based on sensitivity; (4) Sub-matrices drawn randomly from the 30B model; (5) Parameters extracted from the 30B model leveraging sensitivity metric.

Using LLaMA-1 7B as the student model, we present our findings in Figure 3. Initializing as per the original LoRA paper—but without zeroing out BA —leads to a noticeable drop in performance. Recognizing the imperative of leveraging the original model’s weights as a starting point for fine-tuning the LoRA, our initialization strategy in this paper is rooted in Equation 10; hence, we keep both W and W_{extract} fixed and solely fine-tune BA . Moreover, our sensitivity-based method consistently outperforms both Gaussian initialization and random parameter extraction from teacher models across varying scales.

Number of Seed Samples. The quantity of seed samples plays a crucial role in determining both the reliability and efficiency of computing sensitivity scores from the teacher model. To delve deeper into its impact, we study how varying numbers of seed samples influence the performance of the student model. As evidenced in Figure 4, an augmentation in seed samples consistently mitigates variance, whilst the enhancement in performance remains relatively slight. The results demonstrate a tendency to stabilize after the application of 32 seed samples, prompting us to establish this as a hyperparameter in this paper. A further insight is the marked reduction in variance as the student’s

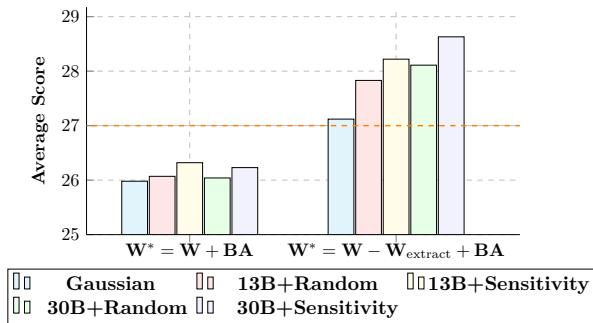


Figure 3: Comparison of different initialization strategies. The y-axis represents the average score over four datasets. For $W^* = W + BA$, we employ five methods to initialize BA , keeping W constant. In the case of $W^* = W - W_{\text{extract}} + BA$, these methods correspond to both W_{extract} and BA , with W_{extract} remaining static during training. The orange dotted line denotes the results of initialization as described in LoRA paper.

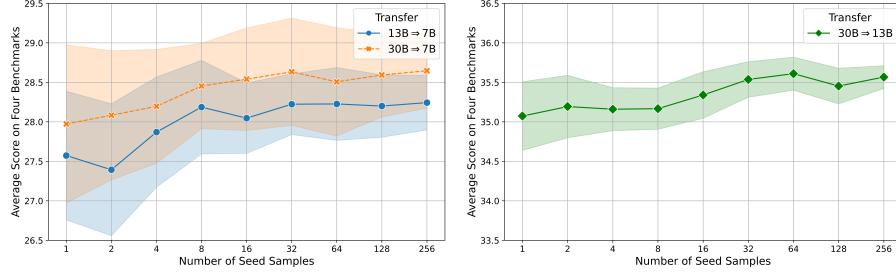


Figure 4: Analysis of how the quantity of seed samples affects student performance.

scale is escalated (transitioning from $30B \Rightarrow 7B$ to $30B \Rightarrow 13B$), or as the disparity between the teacher and student models is diminished (transitioning from $30B \Rightarrow 7B$ to $13B \Rightarrow 7B$).

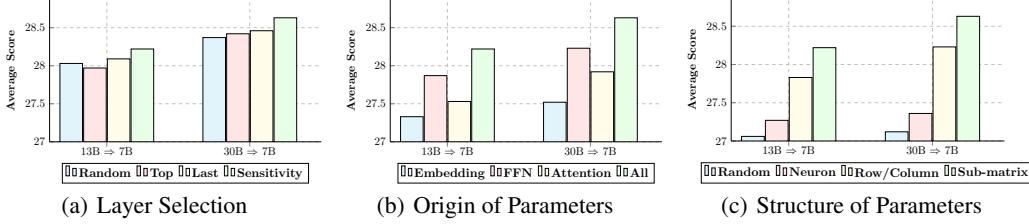


Figure 5: Analysis of various aspects of extracted parameters from teacher models. The y-axis begins with the result of direct fine-tuning students without knowledge injection.

Layer Selection Methods. Owing to the discrepancy in the number of layers between teacher and student models, the selection methodology for these layers potentially influences the final results. We evaluate four strategies: random layer selection, extracting the top or last layers, and a selection based on our sensitivity-centric technique. In the experiments, we consistently map teacher layers to student layers in their inherent sequential order. As Figure 5(a) illustrates, while the layer selection modestly affects student performance, our sensitivity-driven approach excels over the other strategies across both teacher-student model pairings.

Origin of Extracted Parameters. The complex architecture of the Transformer raises inquiries about the most effective module for knowledge transfer. Our explorations involve the Embedding layer, the Feed-Forward Network (FFN), and the Self-Attention layer of the teacher model. As depicted in Figure 5(b), the embedding layer experiences inferior transfer effectiveness, likely due to its lesser parameter quantity. In contrast, the FFN showcases advanced transfer capabilities, intimating that it houses a significant share of the teacher’s knowledge. Optimal results are obtained when transferring knowledge from all available modules.

Structure of Extracted Parameters. The necessity to reduce the parameter matrix’s size for knowledge transfer prompts questions regarding optimal population strategies for this matrix. We undertake a comparison across four methods: random neuron selection from the teacher model, and parameter extraction based on the highest sensitivity at the neuron, row and column, and submatrix levels. Figure 5(c) shows that maintaining the teacher model’s parameter structure significantly benefits student model performance. More precisely, transferring isolated neurons—either randomly or based on sensitivity—yields results comparable to those without knowledge transfer, highlighting the ineffectiveness of such transfers. Preserving the coherence of rows or columns provides a notable improvement, and the preservation of the submatrix structure further augments the performance gains derived from parametric knowledge transfer. This observation underpins our proposed knowledge extraction approach as outlined in Equation 5.

4.4 VISUALIZATION FOR PARAMETRIC KNOWLEDGE

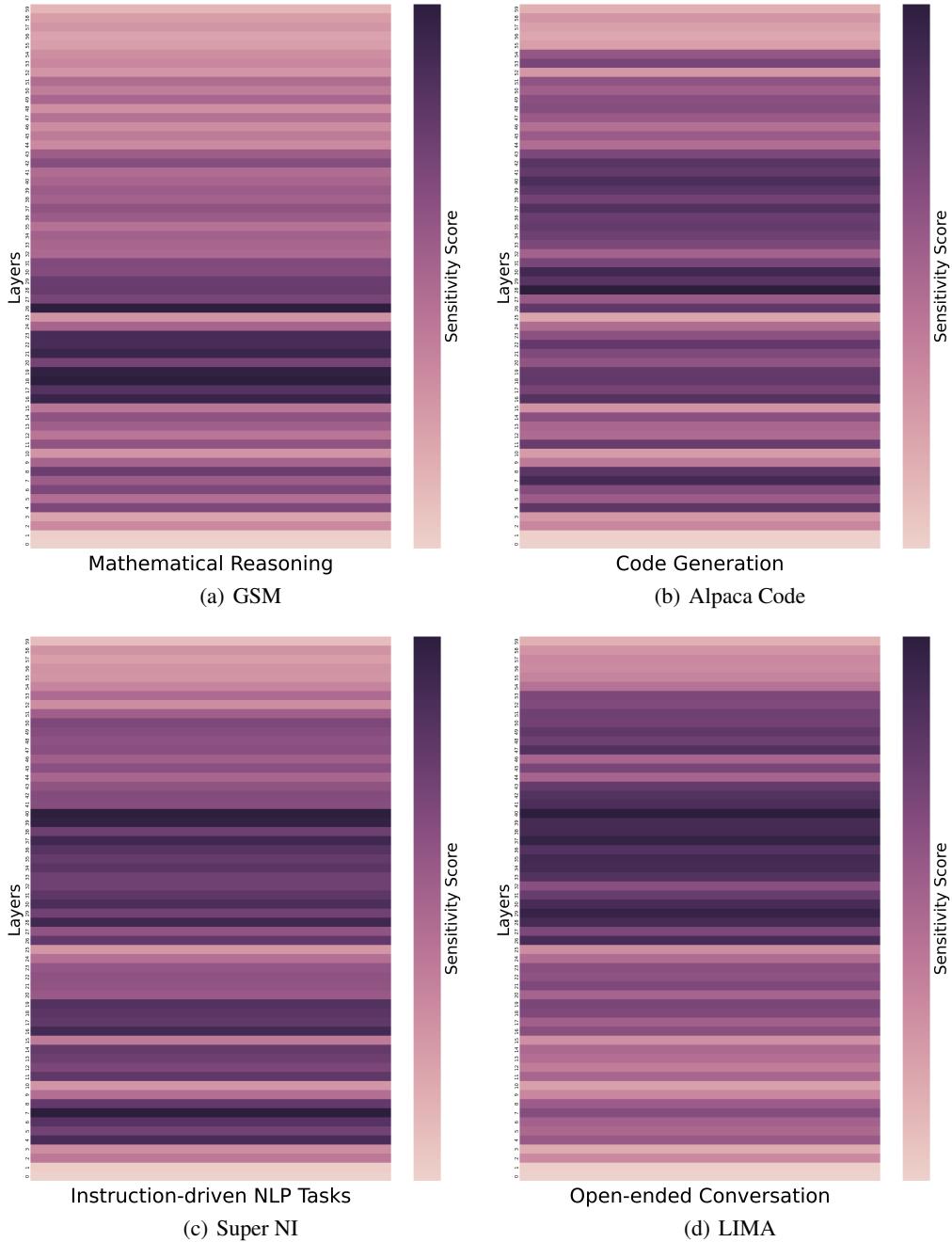


Figure 6: Visualization of parametric knowledge across different layers for four distinct task categories. Darker shades represent higher sensitivity scores for each layer.

In our exploration, we also attempt to visualize the parametric knowledge intrinsic to different task categories. MMLU is omitted from the set of tasks, given its encompassing knowledge from multiple domains, and we introduce code generation Chaudhary (2023) as an additional task for analysis. LLaMA-1 30B serves as the teacher model, and we base our findings on 32 randomly selected seed samples, illustrating the sensitivity scores layer by layer. During the visualization process, we subject each parameter matrix to min-max normalization, ensuring that sensitivity scores fall within the [0, 1] range. The insights from Figure 6 reveal that the distribution of parametric knowledge across

layers varies considerably among tasks. For instance, mathematical reasoning predominantly engages the bottom layer, instruction-driven NLP tasks concentrate on the bottom and middle layers, open-ended conversations are more centered around the middle and upper layers, while code generation appears to draw from all layers. This further emphasizes the efficacy of our sensitivity-based knowledge extraction method in pinpointing task-specific parametric knowledge, thereby aiding the subsequent transfer processes between diverse models.

5 CONCLUSION

In this paper, we delve into the feasibility of transferring parametric knowledge between LLMs of varying scales, and present a new paradigm, exploring knowledge transfer from a distinct parametric perspective. Through our two-stage framework encompassing knowledge extraction and injection, we perform extensive experiments across four diverse benchmarks, affirming the inherent transferability of model parameters. Furthermore, by meticulously analyzing the key elements influencing parametric knowledge transfer, we aim to shed light on future research in this domain.

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