When Babies Teach Babies: Can student knowledge sharing outperform Teacher-Guided Distillation on small datasets?

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Abstract

We present our submission[1][2] to the BabyLM challenge, aiming to push the boundaries of data-efficient language model pretraining. Our method builds upon deep mutual learning, introducing a student model search for diverse initialization. We address the limitation of treating students equally by formulating weighted mutual learning as a bi-level optimization problem. The inner loop learns compact students through online distillation, while the outer loop optimizes weights for better knowledge distillation from diverse students. This dynamic weighting strategy eliminates the need for a teacher model, reducing computational requirements. Our evaluations show that teacher-less methods can match or surpass teacher-supervised approaches.

1 Introduction

The substantial computational and memory requirements of large language models pose significant challenges for deployment on intelligent edge systems, where resources are often constrained. As the demand for real-time processing and low-latency responses increases in edge computing environments, the need for lightweight and memory-efficient models becomes critical. Recent research, notably the Chinchilla paper (Hoffmann et al. (2024)), demonstrated that a 70B parameter model trained on 1.4 trillion tokens outperformed larger models with less data, highlighting the intricate balance between model size and training data. This massive data requirement—equivalent to over 10,000 times the words a 13-year-old encounters—is becoming a significant bottleneck. To address these challenges, several techniques have emerged such as network pruning (Han et al. (2015)), quantization (Courbariaux et al. (2015)), neural architecture search Ren et al. (2021) and Knowledge distillation (Hinton et al. (2015),Li et al. (2020),Wang et al. (2022))

In response to these challenges, the BabyLM challenge invites researchers to explore the limits of data-efficient language model pretraining (Choshen et al.). Participants are constrained to training their models on limited text corpora: 10M and 100M word text-only tracks and a newly introduced multimodal track containing 50M words of paired text-image data, and 50M words text-only data.

Our paper describes our submission to the 10M and 100M text-only tracks. It builds upon the approach of weighted mutual learning Zhang et al. while introducing key modifications to enhance generalizability. Our methodology focuses on distilling a RoBERTa-base model (125M parameters) to less than half its size while maintaining performance. Our main contributions include :

- We use Bayesian optimization to select model architectures of student models by varying hidden layers, attention heads, and hidden sizes.
- Instead of the traditional teacher-student distillation, we explore weighted mutual learning through a bi-level optimization process : (a) The inner loop minimizes a combined loss to train individual student models, consisting of a supervised learning loss and a KL divergence loss that aligns each student's class posterior with others'. (b) Instead of treating each student model equally, we introduce an outer loop to optimize student importance weights by minimizing the ensemble loss.

This approach generally performed better than both conventional supervised learning and traditional distillation from a larger pretrained teacher. Notably, our weighted mutual learning strategy can

[1] https://huggingface.co/AI-DA-STC/RoBERTa_WML_distill-Babylm-10M-2024
[2] https://github.com/AI-DA-STC/generative-ai-research-babylm

improve performance even among several large networks compared to independent learning, challenging the conventional understanding that distillation requires a larger, more powerful teacher.

2 Related Work

The vanilla distillation Hinton et al. (2015) method consists of two stages, firstly train a large teacher model, followed by transfer of soft logits to a smaller student model. Also known as Offline distillation, it keeps the teacher fixed, only allowing a one-way knowledge transfer. To reduce memory consumption of training a large teacher model, Zhang et al. (2018) proposed an online distillation framework called mutual learning where a group of student (or student) models were trained simultaneously. Although, online distillation eliminated the teacher model, similar networks in online distillation may prevent the students from learning knowledge from the students Zhang et al.. Recent approaches have attempted to induce diversity in online distillation to improve overall performance. Chen et al. (2020) proposed inducing data diversity by training student models with varying image augmentations. However, this method relies heavily on data augmentations, which can be unpredictable in real-world deployment scenarios. Du et al. (2020) introduced an adaptive ensemble knowledge distillation method using multiple diverse teacher models to train a student model. While this approach shows promise, it requires maintaining several teacher models, leading to increased memory usage and computational overhead. The reported accuracy improvements are also relatively modest, typically ranging from 0.5% to 1% across benchmarks. Our approach closely resembles to that of Zhang et al.. They present a diversity induced weight mutual learning approach for distillation. They introduce diversity by assigning varying pruning ratios to different student models. Although this method reduces memory consumption, the manual assignment of pruning ratios may not generalize well across different architectures and tasks. The reported performance gains are limited, with improvements of less than 0.5% on most benchmarks. As shown by Liu et al. (2017), while pruning induces sparsity within networks and can reduce computational complexity (measured in FLOPs), the relationship between pruning percentage and actual model size reduction is not always linear. Moreover, in Zhang et al., we observe a performance drop when pruning beyond 30%, indicating a trade-off between model compression and accuracy.

3 Diversity Induced Weighted Mutual Learning

3.1 Diversifying student models

In our approach to create diverse student models for the Diversity Induced Weight Mutual Learning (DWML) framework, we employ Bayesian optimization to efficiently search for optimal architectural configurations. Given a teacher model with N parameters, we aim to generate p student models, where the i-th student model targets approximately N_i parameters, defined as:

$$N_i = \frac{N}{i+1}, \quad i \in 1, 2, ..., p \tag{1}$$

This optimization problem can be formally defined as finding, for each student i, an architecture a_i from the set of all possible RoBERTa architectures A that minimizes $||params(a_i) - N_i||$, where $params(a_i)$ represents the parameter count of architecture a_i. We chose Bayesian optimization for this task due to its efficiency in exploring high-dimensional spaces with relatively few function evaluations, making it less computationally expensive compared to alternative methods such as grid search or random search (Kandasamy et al., 2018). Our implementation utilizes the BayesianOptimization library (Nogueira, 2014–), with a search space encompassing the number of layers, number of attention heads, and embedding dimension. The objective function calculates the difference between the actual parameter count of a given architecture and the target parameter count, with a constraint ensuring the embedding dimension is divisible by the number of attention heads.

3.2 Weighted Mutual Learning using Bi-level optimisation

Building upon the work of (Zhang et al.), we introduce a modified approach to Weighted Mutual Learning using bi-level optimization. Our method replaces the pruning-based initialization with Bayesian optimization for student model selection.

The overall loss function for training M peer

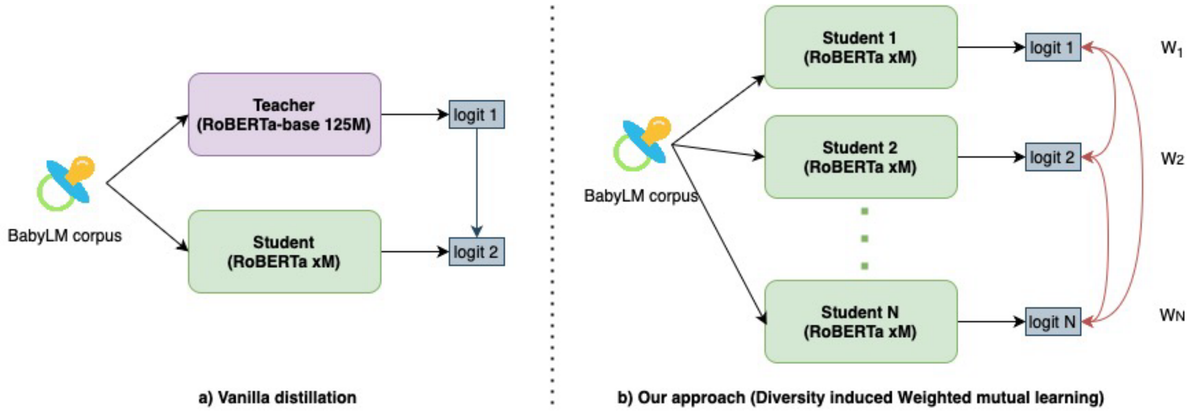


Figure 1: Overview of the difference between Vanilla knowledge distillation and our approach, Diversity induced weighted mutual learning (DWML). (a) Hinton et al. (2015) is the popular knowledge distillation method, where the student network (RoBERTa-xM) can only learn from a trained teacher network (RoBERTa-base-125M). Here xM refers to a student model of x million parameters. (b) is the Diversity Induced Weight Mutual Learning (DWML) framework where each student model is initialised with parameter counts = $N/2, N/3..N/(p+1)$ using Bayesian optimisation search. Rather than averaging the knowledge from students, DWML leverages bi-level optimization to estimate the relative importance of each student (e.g., weight ω_i for student i).

models is defined as:

$$\begin{aligned} \text{loss} &= (1-\alpha)\sum_{i=1}^{M}\omega_i L_{CE}(z_i, Y) \\ &+\alpha\sum_{i=1}^{M}\sum_{j=1}^{M}\omega_j KL(z_i, z_j) \end{aligned} \tag{2}$$

where ω_i indicates the importance of the i-th student model, α balances the supervision from labels and peers, L_{CE} is the cross-entropy loss, and KL is the Kullback-Leibler divergence. ω_j is the importance of every other student model except the i-th one. Both z_i and z_j are model logits. We formulate the weighted mutual learning as a bi-level optimization problem. The inner loop optimizes the network parameters θ using the loss in equation 2. As shown in the paper, the gradient for the outer loop optimization, also known as the hypergradient, is calculated as:

$$g_{\omega_i} = \nabla_{\omega_i} L_2 = \frac{\partial L_2}{\partial \omega_i} - \gamma \frac{\partial L_2}{\partial \theta}\frac{\partial L_a}{\partial \theta}^T \tag{3}$$

where $L_a = (1-\alpha)L_{CE}(z_i, Y) + \alpha\sum_{j=1}^{M} KL(z_j, z_i)$ is the ensemble loss. Since ω is a probability simplex that $\sum_{i=1}^{M}\omega_i = 1$, we use the mirror descent to update ω [3, 5]. Algorithm 1 outlines our weighted mutual learning for online distillation. To be more specific, we first run several steps of gradient descent based on the loss function in 2 to update model parameters θ with a fixed ω. Then we calculate the gradient of ω_i based on 3, and run one step of mirror descent to update ω_i:

$$\omega_i^{k+1} = \frac{\omega_i^k \exp\{-\eta\nabla_{\omega_i^{k+1}} L_2\}}{\sum_{i=1}^{M}\omega_i^k \exp\{-\eta\nabla_{\omega_i^{k+1}} L_2\}} \tag{4}$$

where η is the step size with annealing, and ω_i^k is the importance of the i-th peer in the k-th step.

4 Training

4.1 RoBERTa-base

Our models are based on RoBERTa-base (Liu et al., 2019). This model has shown reasonably good performance on small text corpus. We use the raw RoBERTa-base as a baseline in the evaluations. We use it as our teacher model to distill student models using knowledge distillation (KD) and the teacher supervised version of weighted deep mutual learning (KD_DWML). Details about the hyperparameters found from the search are shown in 3. The models were pre-trained (and finetuned for GLUE, SuperGLUE tasks) using 1 Nvidia H100 GPU with 80GB VRAM.

4.2 Dataset

We pretrain all our language models on the 10M and 100M datasets of the BabyLM challenge from 2023 (Warstadt et al., 2023). We adopt the same preprocessing pipeline from (Samuel et al., 2023)

Algorithm 1: Diversity Induced Weighted Mutual Learning (DWML)

Input: Dataset $\{(x_n, y_n)\}_n^N$; Number of peers M; Teacher model size N

1: Define parameter space Θ for number of layers,attention heads, and hidden size

2: Objective function $f(\theta) = |\text{params}(\theta) - N_i|$ where $N_i = N/(i+1)$

3: **for** $i = 1$ to M **do**

4: Use Bayesian optimization to find optimal θ_i^* from Θ

5: Initialize peer model i with parameters θ_i^*

6: **end for**

7: Initialize peer weights ω^0

8: **for** $k = 1$ to K **do**

9: With peer importance ω^k, run T steps of AdamW to update model parameters θ using Eq. 2

10: Calculate gradient for ω^k based on Eq. 3

11: Update ω^k to ω^{k+1} using mirror descent with Eq. 4

12: **end for**

Output: M models with outputs $z_1, ..., z_M$ and weights for peers ω

Text-only 10M Dataset				
Model	BLiMP	Supp.	EWoK	GLUE
BabyLlama	**69.8**	59.5	50.7	**63.3**
LTG-BERT	60.6	**60.8**	48.9	60.3
RoBERTa-base	49.6	48.9	**51.6**	42.5
RoBERTa-DWML	51.6	52.3	50.3	43.1
Text-only 100M Dataset				
Model	BLiMP	Supp.	EWoK	GLUE
BabyLlama	**73.1**	60.6	52.1	**69.0**
LTG-BERT	69.2	**66.5**	51.9	68.4
RoBERTa-base	49.8	46.8	50.25	43.4
RoBERTa-DWML	52.1	48.4	51.6	44.0

Table 1: Results for the BabyLM challenge evaluation datasets. We compare our submitted model (RoBERTa-DWML) to the base model (RoBERTa-base) and the baselines given by the organizers of the challenge on the 10M and 100M datasets.

for standardizing the text corpus. The detailed breakdown of the datasets are shown in 5. The reason why we select the datasets from 2023 is that it appears to be similar to the dataset released for the 2024 challenge (Choshen et al.). The only difference is the exclusion of the QCRI Educational Domain (QED) Corpus and higher proportion of CHILDES from 4.21M to 29M. This was done because the QED was of poor quality. However, we believe that the 2023 dataset gives us an opportunity to explore how distilled models perform when trained datasets that closely represent real world textual data that is unavoidably noisy.

5 Results

This section provides the results of the empirical evaluation of DWML. First, we compare our method to baselines, then we compare our method with other distillation methods and then we perform an ablation study of different DWML variations.

5.1 BabyLM Challenge evaluation

We use the BabyLM evaluation pipeline to assess our models. This pipeline measures syntactic understanding through the Benchmark of Linguistic Minimal Pairs (BLiMP & BLiMP supplemental,Warstadt et al. (2020)). It evaluates general knowledge using the Elements of World Knowledge (EWoK, Ivanova et al. (2024)) benchmark. For overall natural language understanding, it uses GLUE (Wang et al. (2018)) and SuperGLUE (Wang et al. (2019). If applicable, we divide the training set into a train-development split and report the mean statistics over multiple runs on the hidden validation split.The detailed scores are shown in section D

BLiMP Our RoBERTa-DWML demonstrates consistent improvements over RoBERTa-base across both dataset sizes. On the 10M dataset, DWML achieves 51.6% compared to RoBERTa-base's 49.6%, showing a 2% improvement. This gain is maintained in the 100M dataset, where DWML scores 52.1% versus RoBERTa-base's 49.8%. While these improvements are modest, they demonstrate that our teacher-less approach can enhance syntactic understanding with minimal computational overhead. It's worth noting that BabyLlama's multi-teacher distillation approach (Timiryasov and Tastet, 2023) significantly outperforms all models (73.1% on 100M), though this comes at the cost of substantial computational requirements in maintaining and training with multiple teacher models (GPT-2 and LLaMA), which may not be practical for resource-constrained applications.

BLiMP Supplemental The supplemental BLiMP results further validate the effectiveness of our DWML approach. For the 10M dataset, RoBERTa-DWML (52.3%) outperforms

RoBERTa-base (48.9%) by a margin of 3.4%. In the 100M setting, we observe a similar trend with DWML (48.4%) showing improvement over the base model (46.8%). These consistent gains come with minimal additional computational cost over the base model. While BabyLlama achieves substantially higher performance (60.6% on 100M), this improvement requires significant computational resources for managing multiple teacher models during training and inference, a trade-off not examined in their original work.

EWoK On the world knowledge tasks, RoBERTa-DWML maintains competitive performance relative to RoBERTa-base. In the 10M dataset, DWML (50.3%) performs slightly below the base model (51.6%), while in the 100M dataset, DWML (51.6%) shows improvement over the base model (50.25%). These results demonstrate the capability of our lightweight approach in preserving world knowledge. While BabyLlama leads with 52.1% on the 100M dataset through its multi-teacher architecture, the relatively small performance gap (0.5%) raises questions about whether the significant computational overhead of maintaining multiple teacher models is justified for world knowledge tasks in resource-constrained environments.

GLUE All the models were fine-tuned on the GLUE and SuperGLUE datasets and then evaluated on their linguistic performance. On the GLUE benchmark, RoBERTa-DWML shows marginal improvements over RoBERTa-base across both dataset sizes. For the 10M dataset, DWML achieves 43.1% compared to RoBERTa-base's 42.5%, representing a modest 0.6% gain. This pattern continues in the 100M setting, where DWML (44.0%) slightly outperforms the base model (43.4%). These results suggest that our teacher-less approach maintains general language understanding capabilities

5.2 Comparison with Other Distillation Methods

To evaluate the effectiveness of our proposed distillation method, in Table 2 we compare its performance against other distillation techniques using accuracy scores. Our framework is compared to Self-Distillation (SD, Zhang et al. (2019)), a method that allows a small-sized student model to distill knowledge within its network. Knowledge distillation (KD,Hinton et al. (2015)) is the vanilla distillation framework that uses a student network to approximate the output logits of a pre-trained teacher network. Deep mutual learning (DML,Zhang et al. (2018)) an ensemble of students learn collaboratively (without a teacher) and teach each other. The main difference between DML and our diversity induced weight mutual learning (DWML) framework is the usage of dynamically learned student weights using a bi-level optimization objective.Knowledge distillation based diversity induced weight mutual learning (KD_DWML) is the teacher-supervised version of DWML. The GPU utilization and training times are shown in Table 9 and Figure 4. They clearly show a trade-off between training times(mins) and GPU Utilization(%). While our approach DWML had the lowest GPU utilization among all, the training time was reported the highest.

BLiMP Filtered On the BLiMP Filtered dataset, teacher-less methods demonstrate superior performance, with SD and DWML achieving 51.73% and 51.58% respectively, significantly outperforming their teacher-supervised counterparts KD (47.65%) and KD_DWML (47.47%). Among all approaches, our DWML framework shows strong performance, ranking second only to SD with a marginal difference of 0.15%. Notably, DWML substantially outperforms traditional KD by 3.93% and DML by 4.14%, validating the effectiveness of our dynamic weighting strategy in the absence of teacher supervision. Compared to the RoBERTa-base baseline (49.62%), both teacher-less methods show clear improvements, with DWML achieving a 1.96% gain, suggesting that peer learning alone can enhance syntactic understanding.

BLiMP Supplement The BLiMP Supplement results further reinforce the advantage of teacher-less methods, with SD achieving the highest score of 56.53%. Our DWML method (52.25%) outperforms DML (45.19%) by a substantial margin of 7.06%, though it falls behind SD. While KD (55.82%) and KD_DWML (53.65%) show competitive performance, the superior performance of SD demonstrates that teacher supervision isn't necessary for strong syntactic understanding. All distillation methods except DML surpass the RoBERTa-base baseline (48.9%) by a significant margin, with our DWML showing a 3.35% improvement, further validating the effectiveness of peer learning for syntactic tasks.

BLiMP Filtered						
Method	Teacher	Peer 1 ($60M$)	Peer 2 ($42M$)	Peer 3 ($34M$)	Peer 4 ($28M$)	Best↑
RoBERTa-base-125M	-	-	-	-	-	49.62
SD	No	51.73	50.04	50.31	51.18	**51.73**
KD	Yes	46.47	47.25	47.09	47.65	47.65
DML	No	47.01	47.77	47.21	47.16	47.44
KD_DWML (Ours)	Yes	47.05	47.28	47.47	46.66	47.47
DWML (Ours)	No	50.45	51.58	51.46	50.63	51.58
BLiMP Supplement						
Method	Teacher	Peer 1 ($60M$)	Peer 2 ($42M$)	Peer 3 ($34M$)	Peer 4 ($28M$)	Best↑
RoBERTa-base-125M	-	-	-	-	-	48.9
SD	No	53.03	54.78	49.63	56.53	**56.53**
KD	Yes	53.73	52.64	52.58	55.82	55.82
DML	No	44.74	45.14	45.19	44.96	45.19
KD_DWML (Ours)	Yes	52.21	53.09	53.34	53.65	53.65
DWML (Ours)	No	52.25	48.99	48.43	47.99	52.25
EWoK Filtered						
Method	Teacher	Peer 1 ($60M$)	Peer 2 ($42M$)	Peer 3 ($34M$)	Peer 4 ($28M$)	Best↑
RoBERTa-base-125M	-	-	-	-	-	51.6
SD	No	48.4	49.38	50.36	49.19	50.36
KD	Yes	50.12	50.3	51.56	50.42	51.56
DML	No	50.05	50.12	50.06	48.82	50.12
KD_DWML (Ours)	Yes	55.44	40.36	50.75	49.83	**55.44**
DWML (Ours)	No	49.98	49.84	49.08	50.29	50.29

Table 2: BLiMP Filtered, BLiMP Supplement, and EWoK scores for Text-only 10M dataset, comparing different distillation methods. Best accuracy scores (higher is better) are shown.

EWoK Filtered On the EWoK Filtered dataset, we observe a unique pattern where KD_DWML achieves the highest performance (55.44%), though teacher-less methods still show strong consistency, with SD, DML, and DWML achieving 50.36%, 50.12%, and 50.29% respectively. Interestingly, teacher-less methods perform slightly below the baseline, with a performance gap of up to 1.24%. This deviation from the pattern observed in BLiMP datasets suggests that world knowledge tasks may benefit more from teacher guidance, which could explain why KD_DWML achieved the best performance with a substantial 3.84% improvement over the baseline. This finding indicates that while peer learning is effective for syntactic tasks, world knowledge acquisition might require the structured guidance that teacher supervision provides.

5.3 Ablation studies

We compare the following modifications to the original DWML architecture :

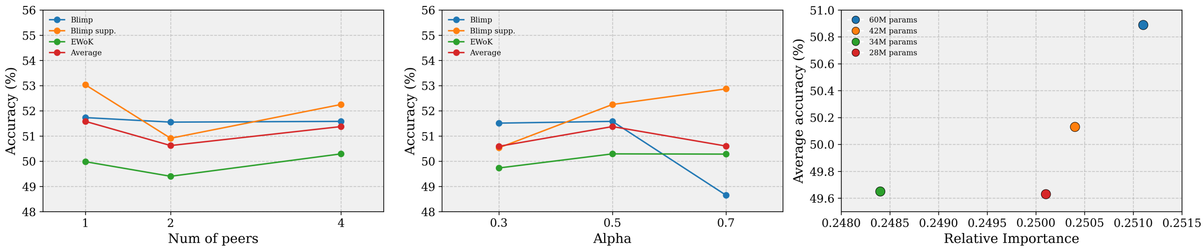
1. **Varying number of students** : The effect of using different number of student networks during training.

2. **Varying α ratio between label and peer supervision** : The effect of using different α in equation 2 that balances KL divergence and cross-entropy loss.

3. **Effect of dynamic student weights** : Determining if learning peer weights during training affect model performance (average accuracy %)

4. **Effect of model size** : Determining if model sizes affected model performance (average accuracy %)

Effect of Varying number of student models Figure 2(a) illustrates the impact of increasing the number of peer networks in our DWML framework. Performance on syntactic tasks, as measured by BLiMP and BLiMP Supplemental, shows modest variations across different peer counts. For BLiMP, we observe a slight decrease from 1 to 2 peers (51.73% to 51.55%), followed by a slight increase with 4 peers (51.58%). BLiMP Supplemental shows more variation, starting at 53.03%, dropping to 50.91% with two peers, and then increasing to 52.25% with four peers. The average performance across these metrics shows a similar pattern, starting at 51.58% with one peer, decreasing to 50.62% with two peers, and slightly recovering to 51.37% with four peers. These results indicate that while increasing the number of peers does



(a) Effect of number of peers

(b) Effect of alpha

(c) Effect of dynamic relative student importance and model size

Figure 2: Performance comparison across different experimental settings for 10M dataset: (left) varying number of peers, showing how model performance changes with different peer counts; (middle) impact of alpha parameter in the loss function on model accuracy; (right) relationship between relative importance and accuracy for different model sizes.

affect performance, the differences are relatively small, with no clear advantage for any particular peer configuration. This suggests that adding more peers may not necessarily lead to substantial gains in syntactic understanding tasks.

Effect of Varying Alpha Figure 2(b) demonstrates the impact of varying the alpha parameter, which balances the trade-off between cross-entropy loss and peer knowledge distillation in our loss function (Equation 2). With $\alpha = 0.3$, indicating stronger emphasis on label supervision, we observe the lowest performance. At $\alpha = 0.5$, representing an equal balance between label supervision and peer knowledge, performance improves across all metrics. However, when $\alpha = 0.7$, shifting focus more towards peer knowledge, we see mixed results with a notable decline in BLiMP (48.65%) while BLiMP Supplemental shows improvement (52.87%). This pattern suggests that $\alpha = 0.5$ provides an optimal balance: when α is too low (0.3), the models don't fully leverage peer knowledge, and when too high (0.7), excessive reliance on peer learning may compromise individual model performance. The results empirically validate our choice of $\alpha = 0.5$ as a balanced configuration for our DWML framework.

Effect of Dynamic Relative Student Importance Figure 2(c) reveals a positive correlation between dynamically learned importance weights and model performance ($R = 0.7$). Models with higher importance weights demonstrate better accuracy, as shown by the 60M parameter model achieving 50.89% accuracy with a 0.2511 weight, compared to the 28M model's 49.63% accuracy with a 0.2484 weight. This near-perfect linear relationship between assigned weights and performance validates our bi-level optimization approach, confirming that the framework successfully identifies and assigns higher weights to more capable models.

Effect of Model Size Figure 2(c) shows that model performance generally increases with model size, with the 60M parameter model achieving 50.89% accuracy, followed by 50.13% for 42M, 49.65% for 34M, and 49.63% for 28M parameters. This positive correlation between model size and performance aligns with previous findings, including those from the Chinchilla study (Hoffmann et al., 2024).

6 Conclusion

In this paper, we introduced Diversity Induced Weighted Mutual Learning (DWML) as an alternative to teacher-supervised knowledge distillation. While our approach showed modest improvements over the RoBERTa-base baseline, it was the simpler Self-Distillation method that achieved the strongest performance. Our ablation studies on our approach (DWML) revealed that two-peer configurations offered optimal efficiency, a balanced loss function ($\alpha = 0.5$) was crucial, and model performance correlated strongly with both dynamically learned importance weights and model size. Regarding computational efficiency, while DWML showed the lowest average GPU utilization, it required longer training times. Hence, in answering our research question about whether student knowledge sharing can match teacher-guided distillation on small datasets, we found that teacher-less methods can indeed match or exceed teacher-supervised approaches, but not necessarily through complex peer learning mechanisms. The success of simpler methods like SD suggests that the field might benefit from focusing on refined single-model approaches rather than elaborate multi-model frameworks. Future work should investigate why simpler teacher-less methods outperform more complex peer learning approaches, explore better neural architecture search techniques, and develop methods to reduce training time while maintaining low resource utilization.

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A Pretraining Hyperparameters

Hyperparameters	Base	4 peer models				2 peer models		1 peer model
		1*	2	3**	4	1	2	
Number of parameters	125M	60M	42M	34M	28M	60M	42M	60M
Number of layers	12	8	16	32	8	8	16	8
Hidden size	768	512	256	128	256	512	256	512
FF intermediate size	3072	3072	3072	3072	3072	3072	3072	3072
Vocabulary size	50265	50265	50265	50265	50265	50265	50265	50265
Attention heads	12	32	8	4	8	32	8	32
Hidden dropout	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Attention dropout	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Training steps	150	150	150	150	150	150	150	150
Mini batch size	3	3	3	3	3	3	3	3
Num. of mini batches	60	60	60	60	60	60	60	60
Sequence length	514	514	514	514	514	514	514	514
Warmup ratio	0.03%	0.03%	0.03%	0.03%	0.03%	0.03%	0.03%	0.03%
Initial learning rate	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Final learning rate	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
Learning rate scheduler	cosine	cosine	cosine	cosine	cosine	cosine	cosine	cosine
Weight decay	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Layer norm ϵ	1.00E-12	1.00E-12	1.00E-12	1.00E-12	1.00E-12	1.00E-12	1.00E-12	1.00E-12
Optimizer	AdamW	AdamW	AdamW	AdamW	AdamW	AdamW	AdamW	AdamW
β_1	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
β_2	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95
Gradient clipping	1	1	1	1	1	1	1	1

*Selected for 10M dataset. **Selected for 100M dataset.

Table 3: Pre-training hyperparameters for base and 4, 2 and 1 peer models for the DWML framework. The same set of hyperparameters are used for other distillation methods for an apple-to-apple comparison.

B Finetuning Hyperparameters

Hyperparameters	Full fine-tuning
Random seed	643
Batch size	32
Number of epochs	6
Dropout	0.1
Peak learning rate	2.50E-06
Learning rate decay	cosine
Weight decay	0.1
Optimizer	AdamW
Adam β_1	0.9
Adam β_2	0.999
Warmup steps	3

Table 4: Hyperparameters for full fine-tuning the GLUE, SuperGLUE task. We use the same fine-tuning script for comparison of RoBERTa-base and our DWML models.

C Dataset

Dataset	Domain	# Words		Proportion
		STRICT-SMALL	STRICT	
CHILDES MacWhinney (2000)	Child-directed speech	0.44M	4.21M	5%
British National Corpus (BNC),[1] dialogue portion	Dialogue	0.86M	8.16M	8%
Children's Book Test Hill et al. (2015)	Children's books	0.57M	5.55M	6%
Children's Stories Text Corpus[2]	Children's books	0.34M	3.22M	3%
Standardized Project Gutenberg Corpus Gerlach and Font-Clos (2020)	Written English	0.99M	9.46M	10%
OpenSubtitles Creutz (2018)	Movie subtitles	3.09M	31.28M	31%
QCRI Educational Domain Corpus (QED; Abdelali et al., 2014)	Educational video subtitles	1.04M	10.24M	11%
Wikipedia[3]	Wikipedia (English)	0.99M	10.08M	10%
Simple Wikipedia[4]	Wikipedia (Simple English)	1.52M	14.66M	15%
Switchboard Dialog Act Corpus (Stolcke et al., 2000)	Dialogue	0.12M	1.18M	1%
Total	–	9.96M	98.04M	100%

Table 5: The contents of datasets for the the 10M and 100M tracks; the table is taken from . [1]http://www.natcorp.ox.ac.uk [2]https://www.kaggle.com/datasets/edenbd/children-stories-text-corpus [3]https://dumps.wikimedia.org/enwiki/20221220/ [4]https://dumps.wikimedia.org/simplewiki/20221201/

D Detailed results

D.1 BLiMP

Method	AA	AS	B	CR	DNA	E	FG	IF	IFS	NPI	Q	SVA	AVG
RoBERTa_KD_DWML_peer1	39.60	50.40	48.70	53.70	48.50	45.10	39.10	38.10	46.90	44.40	46.80	51.10	46.00
RoBERTa_KD_DWML_peer2	39.50	50.30	52.60	53.70	48.40	49.40	36.70	33.20	47.10	45.50	46.30	51.20	46.20
RoBERTa_KD_DWML_peer3	39.40	50.30	53.60	53.70	48.30	51.40	36.70	33.30	47.80	45.10	46.30	51.30	46.40
RoBERTa_KD_DWML_peer4	39.80	50.60	50.10	53.10	48.70	43.60	37.30	27.50	48.20	44.30	46.10	49.90	44.90
RoBERTa_KD_peer1	39.60	49.50	50.30	51.90	49.40	46.80	37.10	40.10	46.00	40.30	48.00	50.80	45.80
RoBERTa_KD_peer2	39.60	50.30	53.30	**53.90**	48.50	48.60	36.50	32.70	47.20	44.70	45.90	51.20	46.10
RoBERTa_KD_peer3	39.70	50.30	51.80	53.30	48.40	49.10	36.60	33.20	47.60	44.20	46.70	51.10	46.00
RoBERTa_KD_peer4	54.30	49.90	52.30	56.70	45.80	48.70	37.70	32.20	48.90	44.10	49.50	48.40	47.40
RoBERTa_SD_peer1	**59.10**	**51.90**	48.60	47.40	**54.10**	56.90	36.50	**53.00**	48.00	**66.20**	**60.70**	51.20	**52.80**
RoBERTa_SD_peer2	45.70	53.60	58.10	53.00	51.00	52.20	37.00	52.30	47.60	53.00	38.20	50.40	50.20
RoBERTa_SD_peer3	53.50	50.10	50.50	52.30	50.50	51.70	**61.80**	33.70	**57.10**	42.10	36.70	49.70	49.10
RoBERTa_SD_peer4	59.10	51.40	47.70	44.90	48.30	53.10	51.30	55.70	58.30	49.40	54.80	48.80	51.90
RoBERTa_base	38.90	47.90	**62.80**	49.70	48.60	48.40	27.50	53.40	55.00	49.90	60.40	51.40	49.50
DWML_2model_peer1	45.30	51.70	57.90	48.90	47.50	50.00	46.70	45.70	58.80	43.90	55.10	50.70	50.20
DWML_2model_peer2	45.30	51.70	57.70	48.90	47.50	50.10	46.60	45.70	59.50	43.80	54.90	50.70	50.20
DWML_4model_peer1	53.70	51.80	42.50	50.40	50.00	49.30	45.30	53.70	50.40	45.70	56.90	50.50	50.00
DWML_4model_peer2	53.90	51.80	42.70	50.60	50.00	49.80	45.30	53.60	50.60	50.40	57.10	50.60	50.50
DWML_4model_peer3	53.60	51.70	42.00	50.60	50.00	49.70	45.20	53.50	50.60	45.40	57.10	50.60	50.00
DWML_4model_peer4	53.80	51.60	42.50	50.30	50.00	49.80	45.20	53.60	50.10	50.90	57.20	50.50	50.50
DWML_alpha_3peer1	49.20	50.40	48.50	49.80	50.60	50.00	53.20	51.60	50.00	64.20	44.70	51.80	51.20
DWML_alpha_3peer2	48.90	50.60	47.90	49.70	50.40	50.40	53.10	52.10	50.10	64.00	44.50	51.70	51.10
DWML_alpha_3peer3	49.30	50.50	49.60	50.00	50.60	49.90	53.00	52.10	49.50	58.30	44.50	51.60	50.70
DWML_alpha_3peer4	49.20	50.30	48.20	49.80	50.60	50.00	53.30	51.50	49.60	63.50	44.70	**51.90**	51.00
DWML_alpha_7peer1	58.30	49.00	40.50	49.30	52.70	54.60	50.40	56.80	43.20	41.30	54.50	49.60	50.00
DWML_alpha_7peer2	58.60	49.20	40.60	49.80	52.70	54.40	50.40	57.10	43.80	41.90	57.70	49.80	50.50
DWML_alpha_7peer3	58.40	49.00	39.80	49.10	52.80	54.50	50.20	56.80	44.00	41.90	54.30	49.70	50.00
DWML_alpha_7peer4	58.40	49.10	40.00	49.20	52.70	**54.80**	50.20	56.80	43.90	42.30	58.60	49.70	50.50
DML_peer1	54.10	49.20	52.00	50.30	48.30	47.00	42.40	47.10	54.00	27.20	48.10	49.40	47.40
DML_peer2	53.90	49.20	54.90	50.30	48.40	46.40	42.60	46.60	53.90	32.10	48.00	49.20	48.00
DML_peer3	54.00	49.10	54.70	50.60	48.40	46.90	42.50	46.70	53.80	26.90	48.00	49.00	47.60
DML_peer4	54.10	49.10	54.60	50.30	48.30	46.70	42.60	46.70	53.70	26.60	48.10	49.30	47.50

Table 6: BLiMP results for models trained using different methods. The **bold** results represent the best model for each task. The metric used is accuracy (%). Acronyms: AA (Anaphor Agreement), AS (Argument Structure), B (Binding), CR (Control/Raising), DNA (Determiner-Noun Agreement), E (Ellipsis), FG (Filler-Gap), IF (Irregular Forms), IFS (Island Effects), NPI (NPI Licensing), Q (Quantifiers), SVA (Subject-verb agreement)

D.2 BLiMP Supplement

Method	subject_aux_ inversion	qa_congruence_ tricky	turn_ taking	hypernym	qa_congruence_ easy	average
KD_DWML_peer1	44.53	60.61	56.07	52.97	46.88	52.21
KD_DWML_peer2	50.61	58.79	56.07	53.09	46.88	53.09
KD_DWML_peer3	50.32	58.79	56.07	54.63	46.88	53.34
KD_DWML_peer4	49.96	58.18	55.71	52.85	51.56	53.65
KD_peer1	53.19	59.39	55.36	52.26	48.44	53.73
KD_peer2	48.00	58.18	55.71	52.85	48.44	52.64
KD_peer3	48.69	59.39	56.07	53.44	45.31	52.58
KD_peer4	55.50	62.42	55.36	54.28	51.56	55.82
SD_peer1	65.48	47.88	45.00	**56.77**	50.00	53.03
SD_peer2	54.20	47.88	51.79	52.85	**67.19**	54.78
SD_peer3	58.81	52.12	50.71	53.68	32.81	49.63
SD_peer4	66.12	59.39	52.86	54.28	50.00	**56.53**
DWML_2peer_1	42.40	**65.50**	45.40	49.90	54.70	51.50
DWML_2peer_2	42.00	**65.50**	46.40	50.40	51.60	51.20
DWML_alpha_3peer_1	63.00	50.30	44.30	49.40	45.30	50.50
DWML_alpha_3peer_2	63.10	50.90	46.10	48.80	43.80	50.50
DWML_alpha_3peer_3	60.00	50.30	44.60	50.10	42.20	49.40
DWML_alpha_3peer_4	62.90	50.30	45.00	50.70	43.80	50.50
DWML_alpha_7peer_1	69.70	50.90	57.50	49.60	31.30	51.80
DWML_alpha_7peer_2	70.30	52.70	57.50	51.10	32.80	52.90
DWML_alpha_7peer_3	**70.90**	50.30	57.90	51.00	31.30	52.20
DWML_alpha_7peer_4	70.50	52.10	**59.30**	51.20	32.80	53.20
RoBERTa_base	54.00	41.20	52.90	51.30	45.30	48.90
DML_peer_1	42.60	55.80	51.40	48.90	25.00	44.70
DML_peer_2	45.30	55.80	51.10	48.60	25.00	45.10
DML_peer_3	42.10	57.00	51.40	50.50	25.00	45.20
DML_peer_4	43.80	55.20	51.40	49.40	25.00	45.00
DWML_4peer_1	53.6	53.4	43.2	54.4	56.6	52.25
DWML_4peer_2	50.6	49.8	40.2	51.1	53.3	48.99
DWML_4peer_3	50.6	48.4	39.5	50.4	53.1	48.43
DWML_4peer_4	48.8	48.0	40.0	49.6	53.6	47.99

Table 7: Supplement BLiMP results for RoBERTa models trained using different distillation methods. All values are presented as percentages.The **bold** results represent the best model for each task.

D.3 EWoK

Method	SP	QP	PR	SI	PI	MP	MD	PD	AP	SR	AVG
RoBERTa_base	53.5	54.5	51.0	48.0	51.8	53.5	50.1	54.2	49.5	50.4	51.6
KD_peer_1	60.2	58.0	51.8	45.6	45.5	48.2	**52.7**	32.5	45.9	50.2	50.1
KD_peer_2	50.4	51.9	48.9	50.7	50.2	55.3	49.7	47.5	52.6	49.2	50.3
KD_peer_3	50.4	48.4	51.3	52.0	50.9	55.9	50.4	55.8	51.0	48.8	51.6
KD_peer_4	38.8	43.9	50.0	**60.5**	43.7	51.2	50.8	50.0	52.6	49.4	50.4
KD_DWML_peer_1	**63.3**	**62.4**	**53.8**	48.3	52.5	**68.2**	47.1	**61.7**	**53.8**	51.0	**55.4**
KD_DWML_peer_2	50.0	45.5	42.3	40.1	41.2	24.7	47.9	28.3	44.4	46.9	40.4
KD_DWML_peer_3	49.8	53.2	50.4	53.7	50.4	55.9	48.8	50.8	48.2	49.0	50.8
KD_DWML_peer_4	40.4	49.4	44.5	45.2	**54.1**	57.6	49.0	40.8	**52.0**	52.0	49.8
SD_peer_1	52.4	46.2	50.2	48.3	48.2	44.1	49.7	50.0	49.4	50.5	48.4
SD_peer_2	52.4	47.5	49.3	47.3	51.6	45.9	50.1	54.2	49.6	50.2	49.4
SD_peer_3	52.0	49.4	51.2	48.3	51.1	52.4	49.0	43.3	50.4	50.9	50.4
SD_peer_4	53.7	50.3	49.6	47.3	49.1	51.2	48.8	42.5	50.6	49.5	49.2
DWML_2peer_1	49.8	47.5	51.6	47.6	49.6	45.9	50.3	48.3	51.0	51.0	49.4
DWML_2peer_2	50.2	50.6	49.1	46.9	53.1	50.6	51.3	45.0	51.0	49.9	49.9
DWML_alpha_3peer_1	53.5	47.8	49.0	49.0	50.4	48.8	49.6	50.0	49.4	50.3	49.5
DWML_alpha_3peer_2	51.8	49.0	49.8	46.9	50.4	50.6	49.2	49.2	50.0	50.1	49.7
DWML_alpha_3peer_3	50.6	48.4	50.2	47.3	48.7	51.8	50.5	44.2	49.2	50.2	49.2
DWML_alpha_3peer_4	51.4	47.5	49.9	46.6	50.4	51.2	50.8	48.3	49.9	49.8	49.4
DWML_alpha_7peer_1	50.4	54.1	50.1	50.7	49.1	55.9	50.6	49.2	50.9	51.0	51.4
DWML_alpha_7peer_2	51.0	49.4	49.3	51.4	50.7	51.2	50.3	48.3	50.3	49.2	50.3
DWML_alpha_7peer_3	50.0	48.4	49.3	49.0	51.6	45.3	48.4	50.0	50.1	49.9	49.6
DWML_alpha_7peer_4	50.6	49.0	49.9	49.3	50.2	51.2	48.8	49.2	49.0	49.9	49.6
DML_peer_1	51.4	47.1	50.0	50.0	50.5	55.9	49.1	53.3	49.2	51.0	50.1
DML_peer_2	51.0	49.0	49.1	49.0	50.7	54.7	49.2	52.5	49.3	50.6	50.1
DML_peer_3	49.8	51.0	49.1	52.7	46.9	52.9	51.6	44.2	49.5	50.8	50.1
DML_peer_4	52.7	52.5	48.4	50.3	46.8	42.4	50.6	44.2	50.0	49.7	48.8
DWML_4model_peer_1	52.0	49.7	50.0	47.6	50.9	48.8	49.5	50.0	50.1	50.3	50.0
DWML_4model_peer_2	51.2	48.7	49.0	51.4	48.9	50.0	50.6	48.3	49.0	49.9	49.8
DWML_4model_peer_3	49.4	51.3	50.4	49.7	49.5	50.6	50.1	39.2	50.0	49.6	49.1
DWML_4model_peer_4	53.9	48.7	46.8	45.2	46.8	50.6	51.4	56.7	49.7	49.2	50.3

Table 8: EWOK evaluation results for different distillation methods. The **bold** results represent the best performance for each metric. Acronyms: SI (Social Interactions), SP (Social Properties), SR (Social Relations), PI (Physical Interactions), PD (Physical Dynamics), PR (Physical Relations), MD (Material Dynamics), MP (Material Properties), AP (Agent Properties), QP (Quantitative Properties). The metric used is accuracy, and results are presented as percentage values.The **bold** results represent the best model for each task.

E Peer importance training during distillation

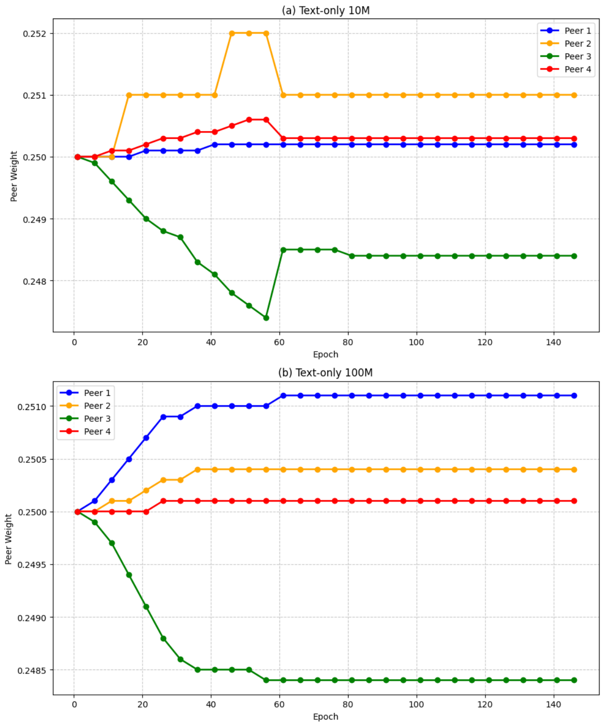

Figure 3: Peer importance weights dynamically trained using mirror descent algorithm as described in Equation 4

F GPU Utilization

Method	Max↓	Average↓	Training Time(mins)↓
RoBERTa_SD_10M_n_peer_4_4	56.07	52.92	**2.91**
RoBERTa_SD_10M_n_peer_4_3	**50.67**	48.47	8.51
RoBERTa_SD_10M_n_peer_4_2	55.60	51.10	4.98
RoBERTa_SD_10M_n_peer_4_1	73.07	68.47	3.02
RoBERTa_KD_DWML_10M_n_peer_4	69.80	62.71	25.51
RoBERTa_KD_10M_n_peer_4_4	63.40	58.68	3.53
RoBERTa_KD_10M_n_peer_4_3	53.93	51.48	9.03
RoBERTa_KD_10M_n_peer_4_2	60.93	56.09	5.52
RoBERTa_KD_10M_n_peer_4_1	78.00	63.89	4.01
RoBERTa_DWML_10M_n_peer_4	68.47	**43.20**	32.02
RoBERTa_DML_n_peer_4	86.8	43.66	8

Table 9: GPU utilization and training time for various RoBERTa distillation techniques (Lower is better). The RoBERTa_DML_n_peer_4 model shows the highest max utilization. In contrast, RoBERTa_SD_n_peer_4_1 maintains the highest average utilization (68.47%), indicating that training the largest peer model (60M) consistently increase GPU consumption. Our approach, DWML had the lowest average GPU utilisation over time, lower by $\tilde{2}$0% in comparison to its teacher-supervised counterpart (KD_DWML)

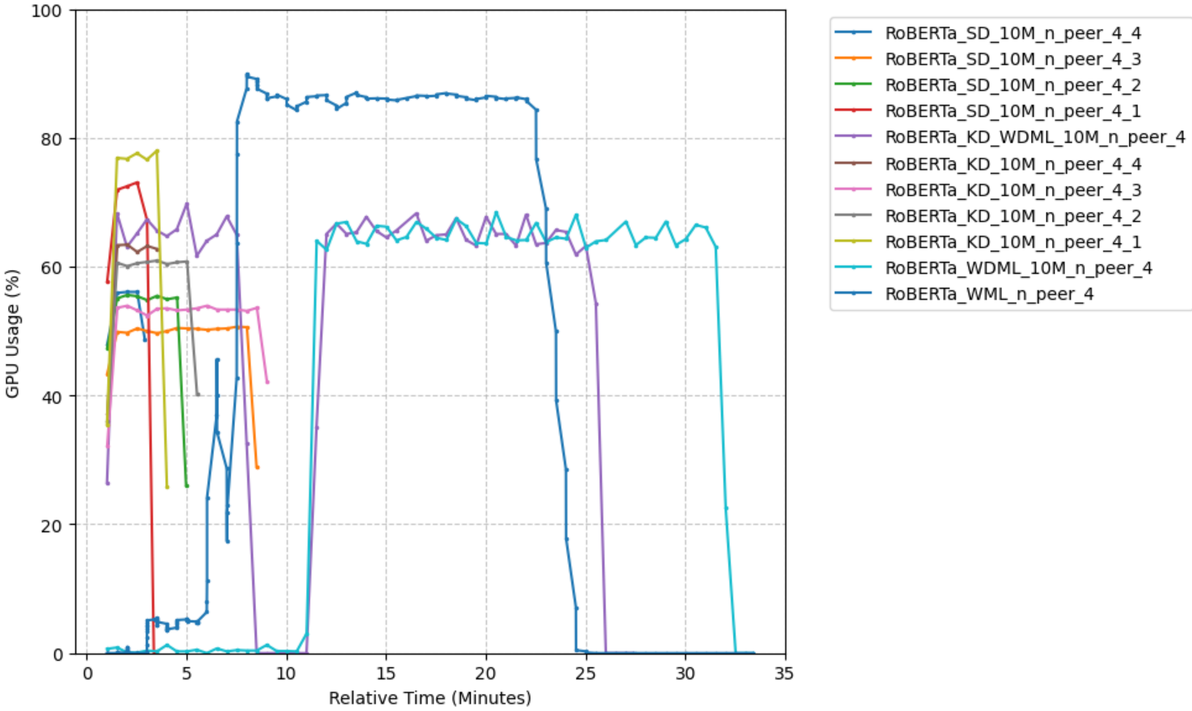

Figure 4: GPU utilization for different distillation methods.