

# Mini-batch Coresets for Memory-efficient Language Model Training on Data Mixtures

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BigML





# Training LLMs requires massive GPU memory

- Training an LLM with N billion parameters using mixed precision [1] requires 18N GB of GPU memory [2].

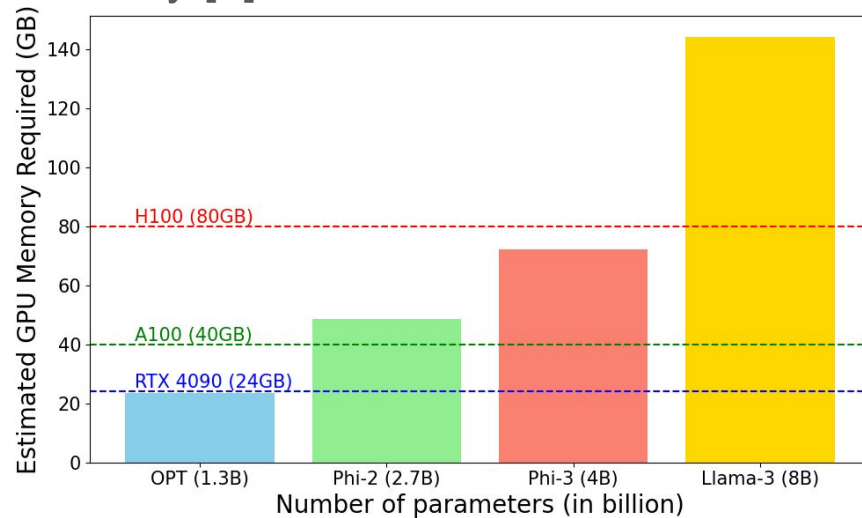


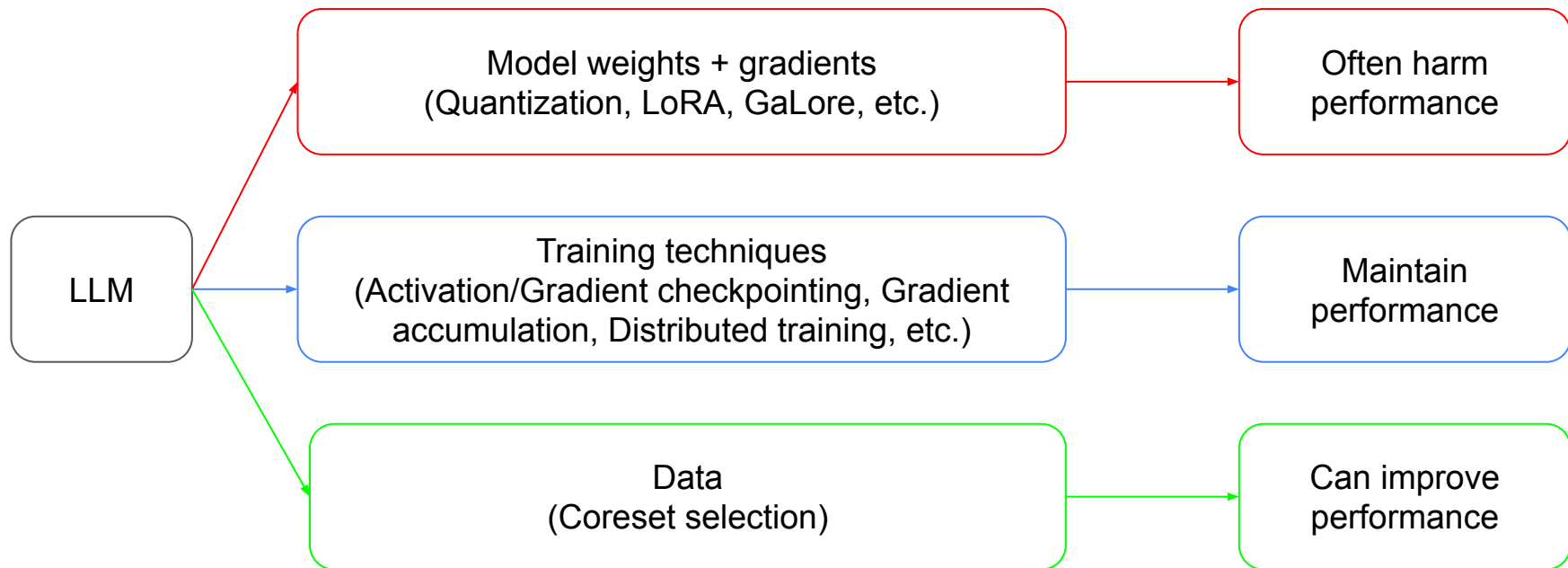
Figure 1. Estimated GPU memory requirement for training LLMs using mixed precision.

[1] Micikevicius, Paulius, et al. "Mixed precision training." arXiv preprint arXiv:1710.03740 (2017).

[2] [https://huggingface.co/docs/transformers/model\\_memory\\_anatomy](https://huggingface.co/docs/transformers/model_memory_anatomy)



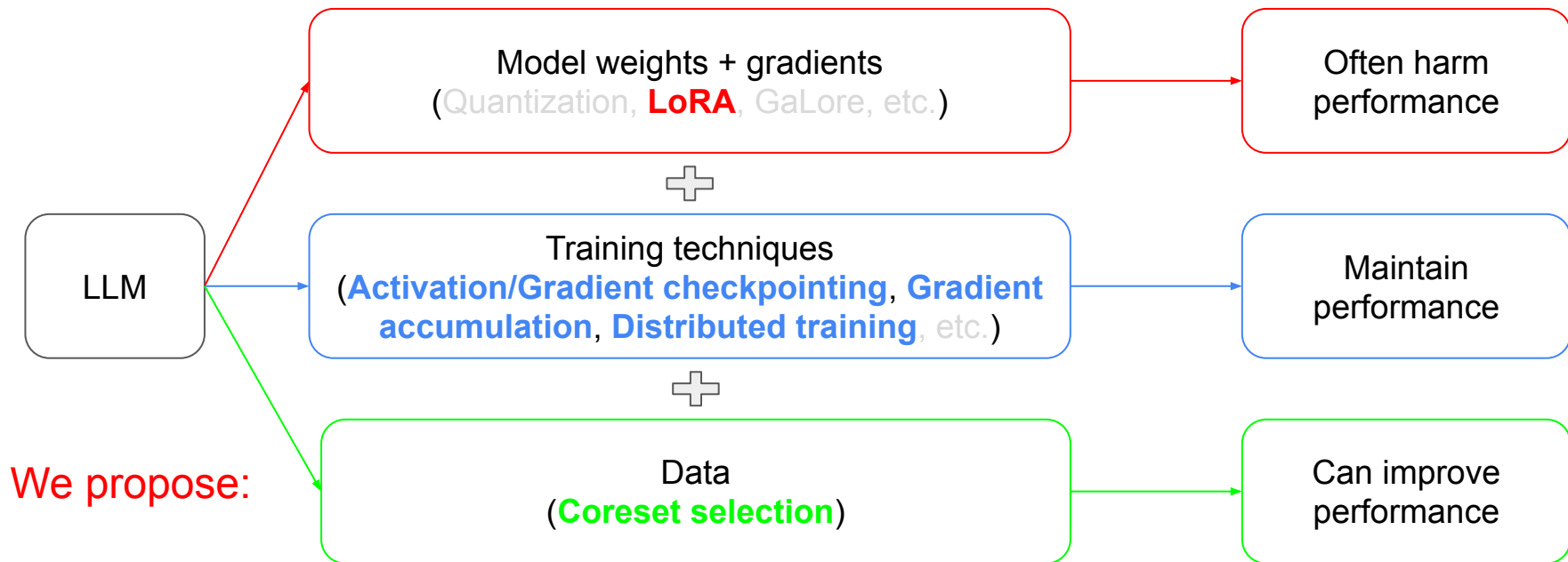
# How to reduce GPU memory requirement?





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It's possible to stack three different approaches together.





# (Mini-batch) coreset selection

- Training with larger mini-batch has a small variance, thus convergences faster [3].
- A mini-batch coreset is a subset that has the similar gradient to the original mini-batch. Thus, it can be found by solving the gradient matching problem [4].

$$S_t^* \in \arg \max_{S \subset \mathcal{M}_t^L, |S| \leq b} \sum_{i \in \mathcal{M}_t^L} \max_{s \in S} [C - \|\mathbf{g}_{i,t} - \mathbf{g}_{s,t}\|],$$

Diagram illustrating the gradient matching problem for coreset selection:

- Coreset size**: Points to the constraint  $|S| \leq b$ .
- Big constant**: Points to the constant  $C$ .
- Mini-batch coreset**: Points to the set  $S$ .
- Original mini-batch**: Points to the set  $\mathcal{M}_t^L$ .
- Gradient of original mini-batch**: Points to the vector  $\mathbf{g}_{i,t}$ .
- Gradient of mini-batch coreset**: Points to the vector  $\mathbf{g}_{s,t}$ .

[3] Ghadimi, Saeed, and Guanghui Lan. "Stochastic first- and zeroth-order methods for nonconvex stochastic programming." SIAM journal on optimization 23.4 (2013): 2341-2368.

[4] Mirzasoleiman, Baharan, Jeff Bilmes, and Jure Leskovec. "Coresets for data-efficient training of machine learning models." International Conference on Machine Learning. PMLR, 2020.



# Challenges of coreset selection for training LLMs

1. Highly Imbalanced Language Data
2. Adam optimizer
3. Very Large Gradient Dimensionality

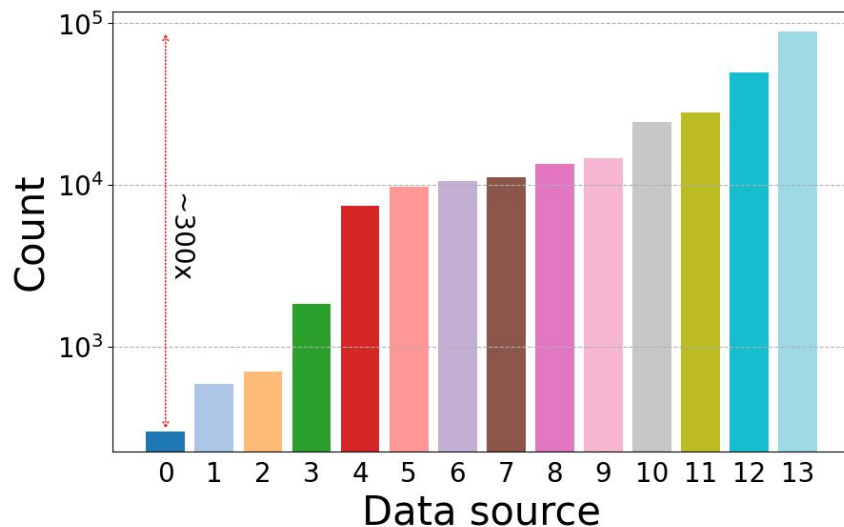


Figure 3. The number of samples from different data sources in MathInstruct.



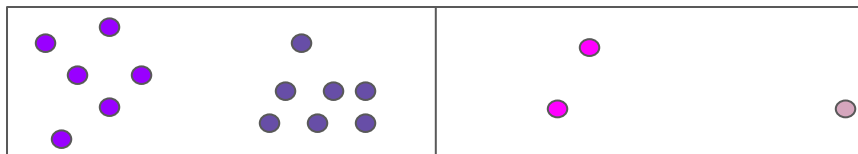
# Coresets for Training LLMs (CoLM)



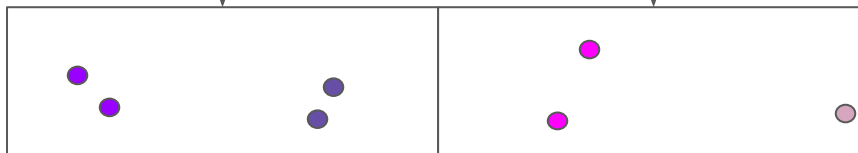
# Coresets for Training LLMs (CoLM)

1. A balanced sampling strategy
  - a. Keep all data from **small** sources
  - b. Select data from **large** sources

Original  
mini-batch



Mini-batch  
coreset





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2. Adam-like gradient normalization
  - a. Normalize gradient to mimic Adam updates
3. Sparsified zeroth-order gradient estimation
  - a. Use **zeroth-order** to estimate gradient for only the **last V-projection** matrix
  - b. Sparsify the gradient further by keeping only ~1% **largest** entities



# Experimental results

CoLM yields the best of both worlds, increasing **accuracy** while reducing time & memory consumption.

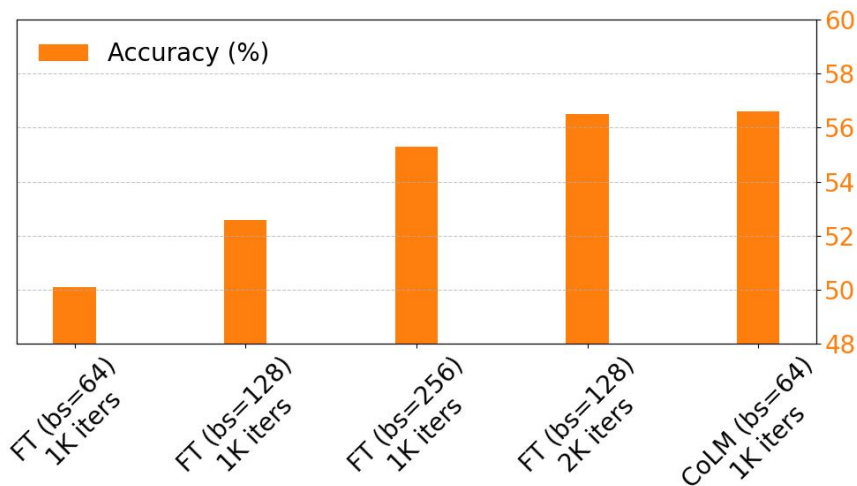


Figure 4. Time vs Accuracy vs Memory of fine-tuning Phi-2 with LoRA on MathInstruct.



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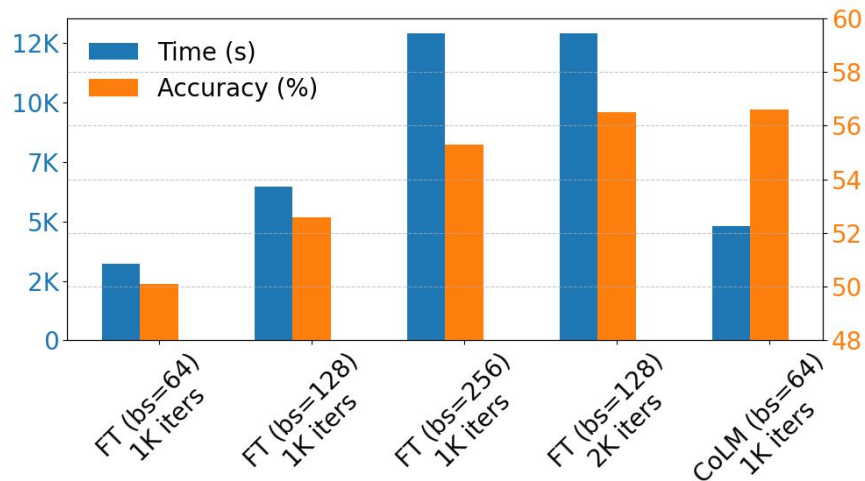


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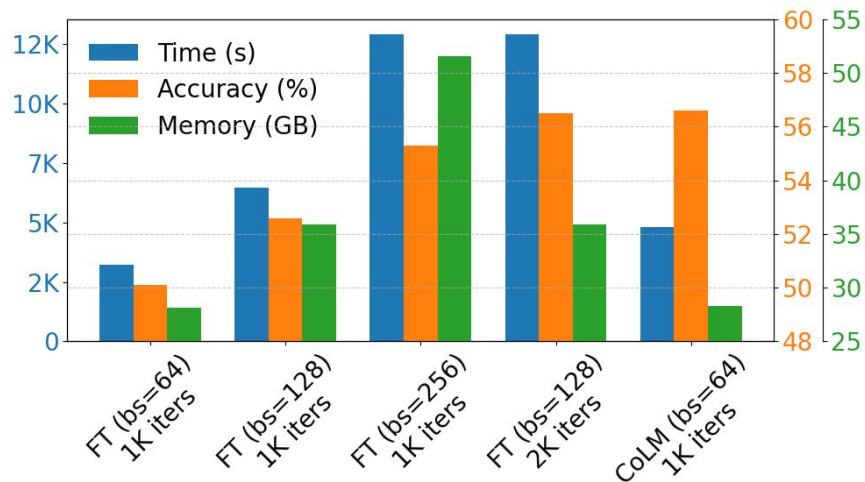


Figure 4. Time vs Accuracy vs Memory of fine-tuning Phi-2 with LoRA on MathInstruct.



Thank you!

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Session 3: Fri 25 April 9 AM - 11:30 AM  
GMT+7

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