Low Rank Adapters (LoRA)

Advanced LLM Night

Johannes Kohlmann – Findable

January 15th, 2025

Who is this guy?

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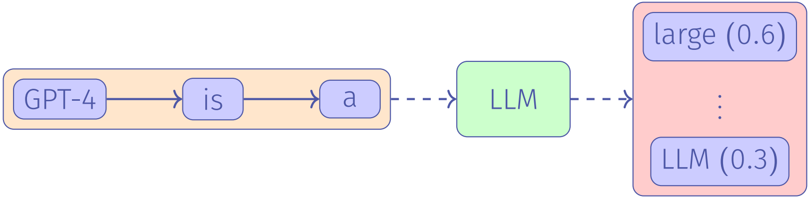

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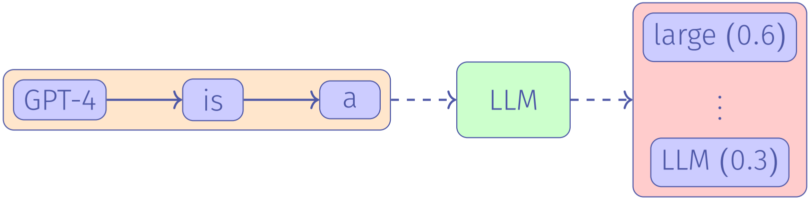

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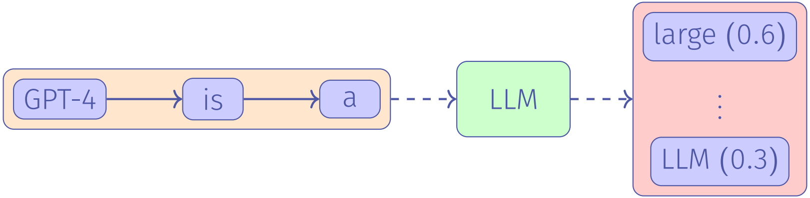

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Next Token Prediction

Given a dataset $\mathcal{D}$ of sentences s and target words s_t, minimize the loss $\mathcal{L}$

$$\mathcal{L}(\mathcal{D}) = \sum_{s \in \mathcal{D}} L(\mathrm{LLM}(s), s_t)$$

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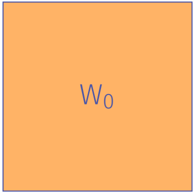

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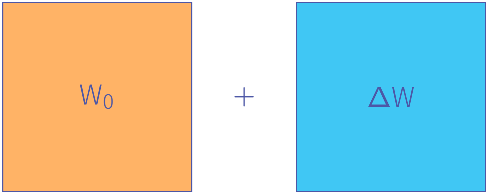

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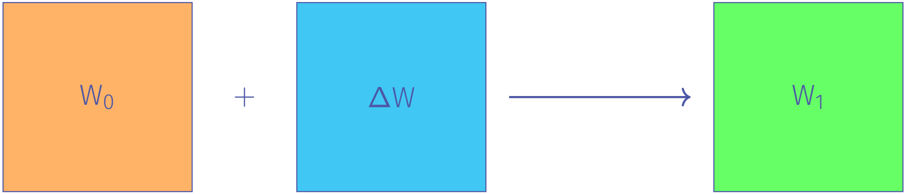

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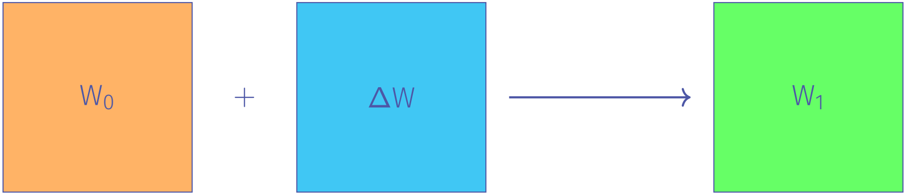

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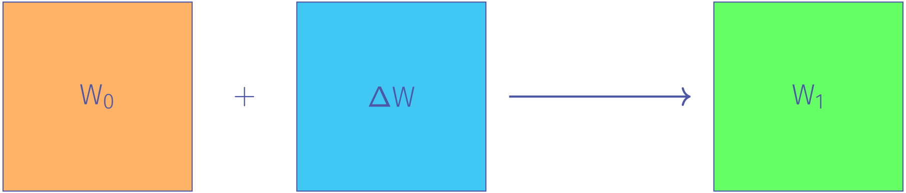

Therefore, finetuning a single fully-connected layer has the same complexity as learning it from scratch!

So, doing this for all layers makes finetuning as compute-intensive as the original pre-training!

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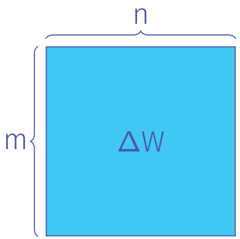

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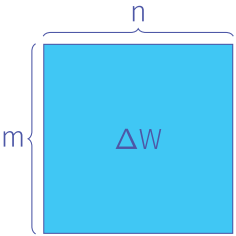

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$$(m \times n) \longleftarrow (m \times k) \cdot (k \times n)$$

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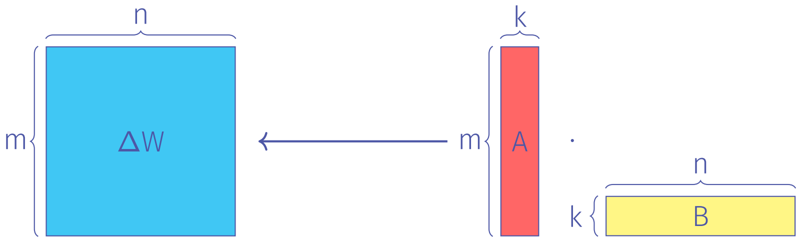

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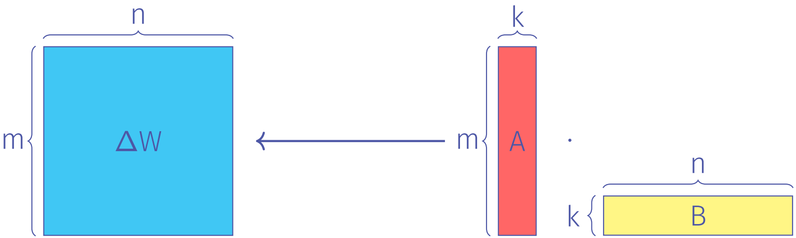

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Therefore, we can represent ΔW by two much smaller matrices!

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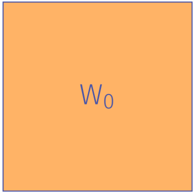

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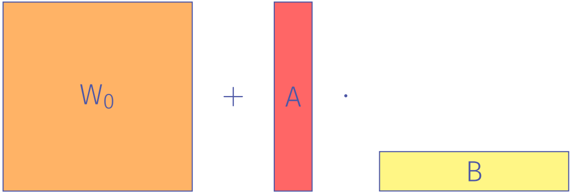

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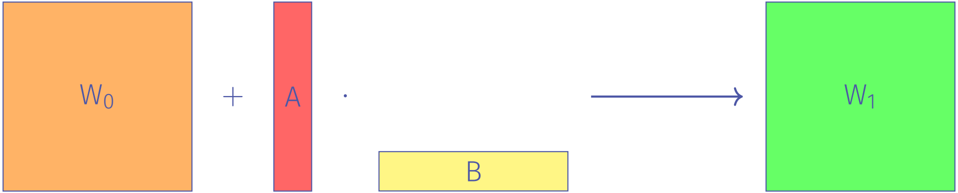

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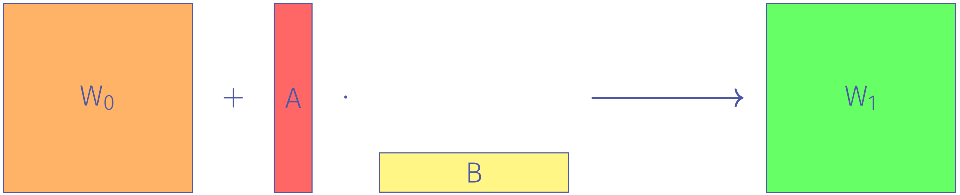

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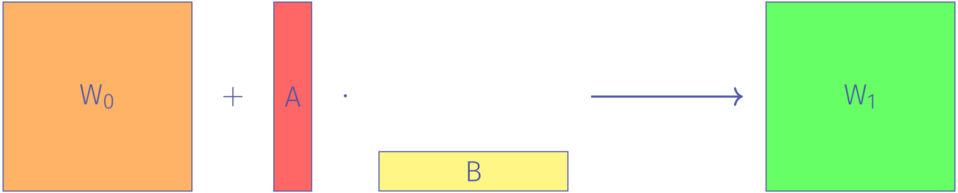

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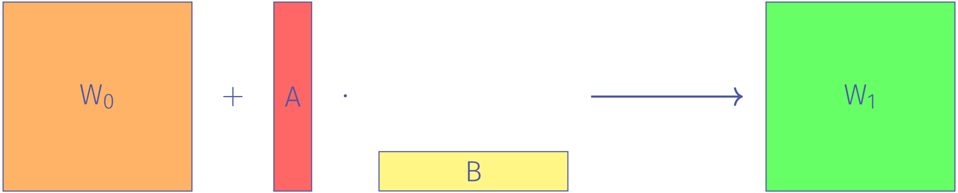

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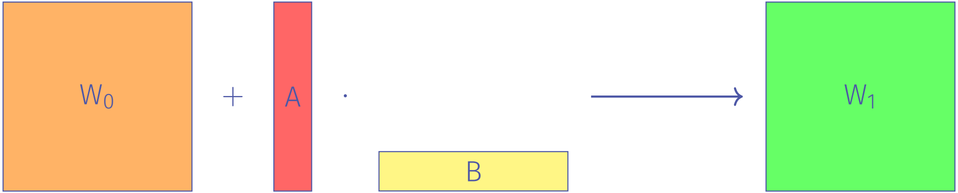

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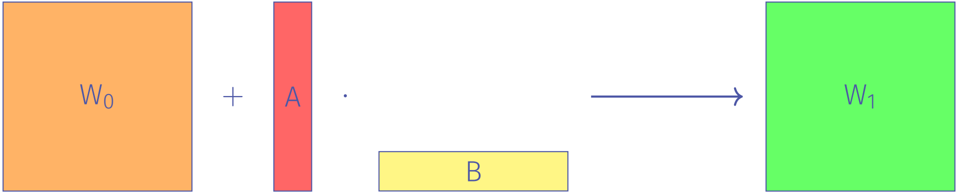

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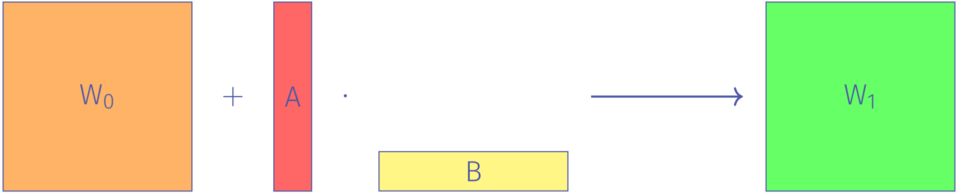

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Parameter reduction from $m \cdot n$ to $k \cdot (m + n)$ which is very significant for $m, n \gg k$!

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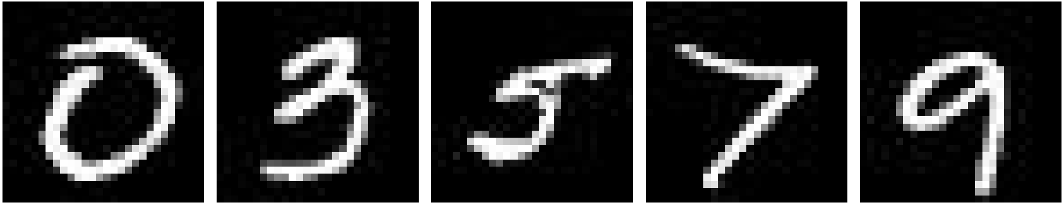

Example images from the MNIST dataset

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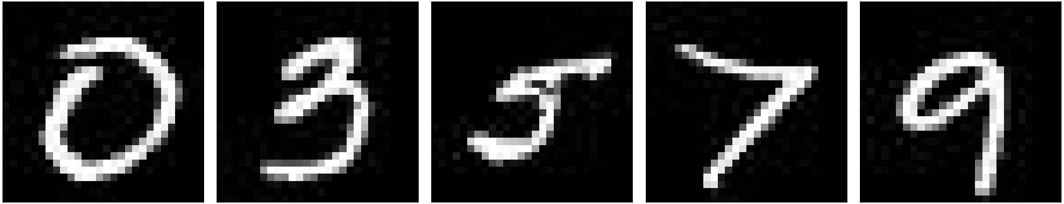

Example images from the MNIST dataset

Task: Given an input image, determine the digit this image depicts.

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class SimpleMnistClassifier(nn.Module):
    def __init__(self):
        super(SimpleMnistClassifier, self).__init__()
        self._fc1 = nn.Linear(784, 256) # 28 * 28 = 784
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This model has 235.146 trainable parameters and reaches a test accuracy of 97.78%.

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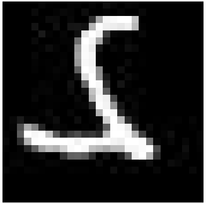
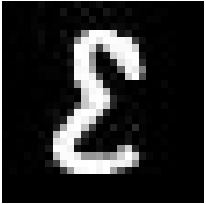

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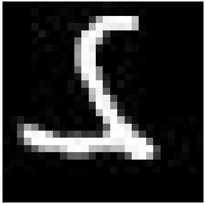

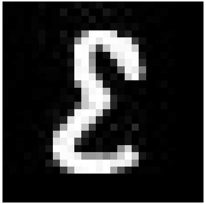

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How does our model perform on this data? Is it going to be able to generalize by itself?

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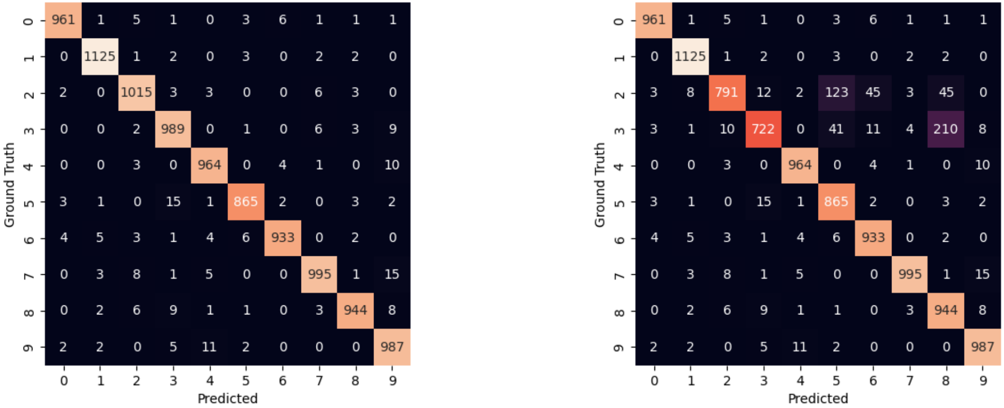

Confusion matrices for MNIST **(left)** and F-MNIST **(right)**

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    def forward(self, x: torch.Tensor) -> torch.Tensor:
        return self._inner(x) + x @ self._A @ self._B
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Imagine doing this with GPT3-175B! Checkpoint sizes are reduced by 99.99%, finetuning is sped up by 25% and you only need a third of the GPUs to train!

Conclusion

- Based on the LoRA paper by Hu et al.
- Code and slides will be available online.
- Thank you for listening! Questions?