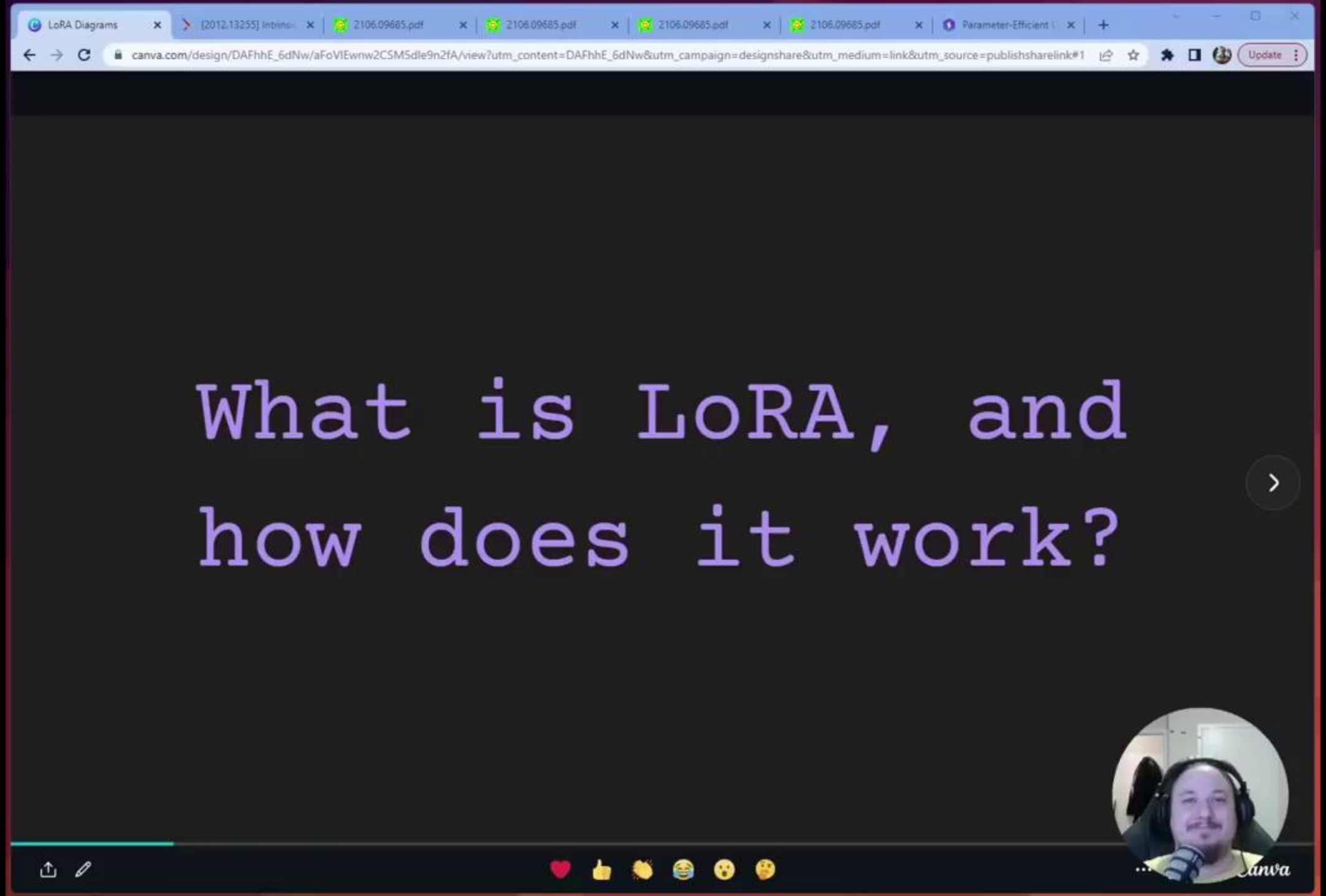
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Update
What is LoRA, and how does it work?
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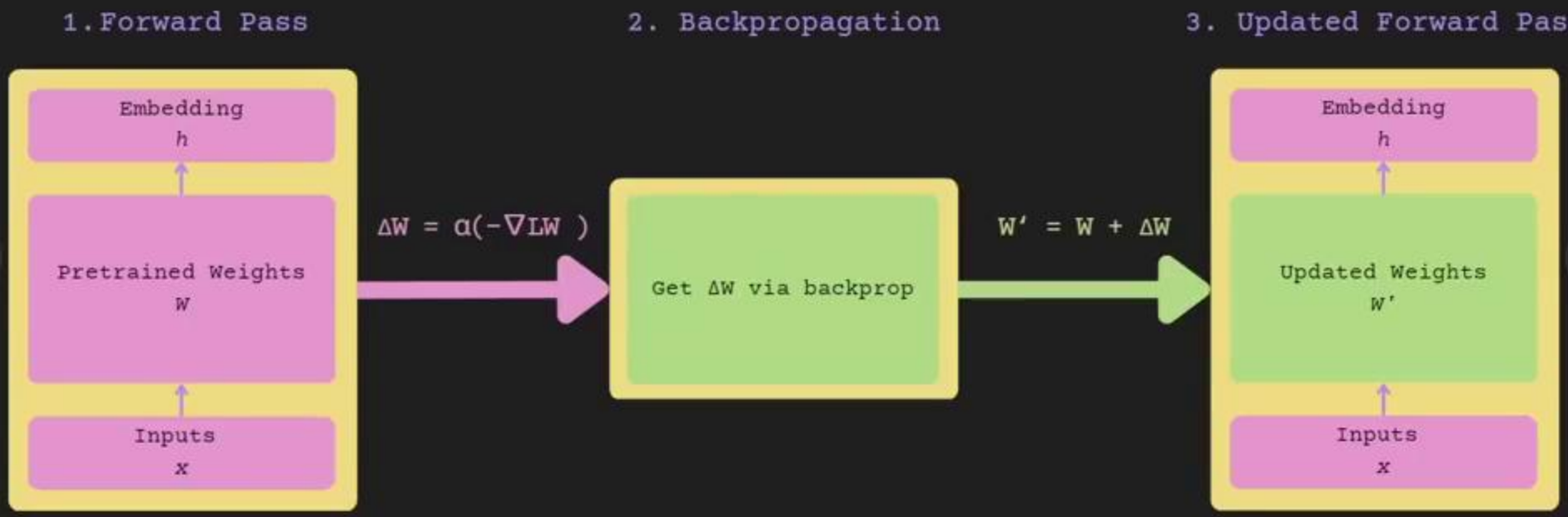
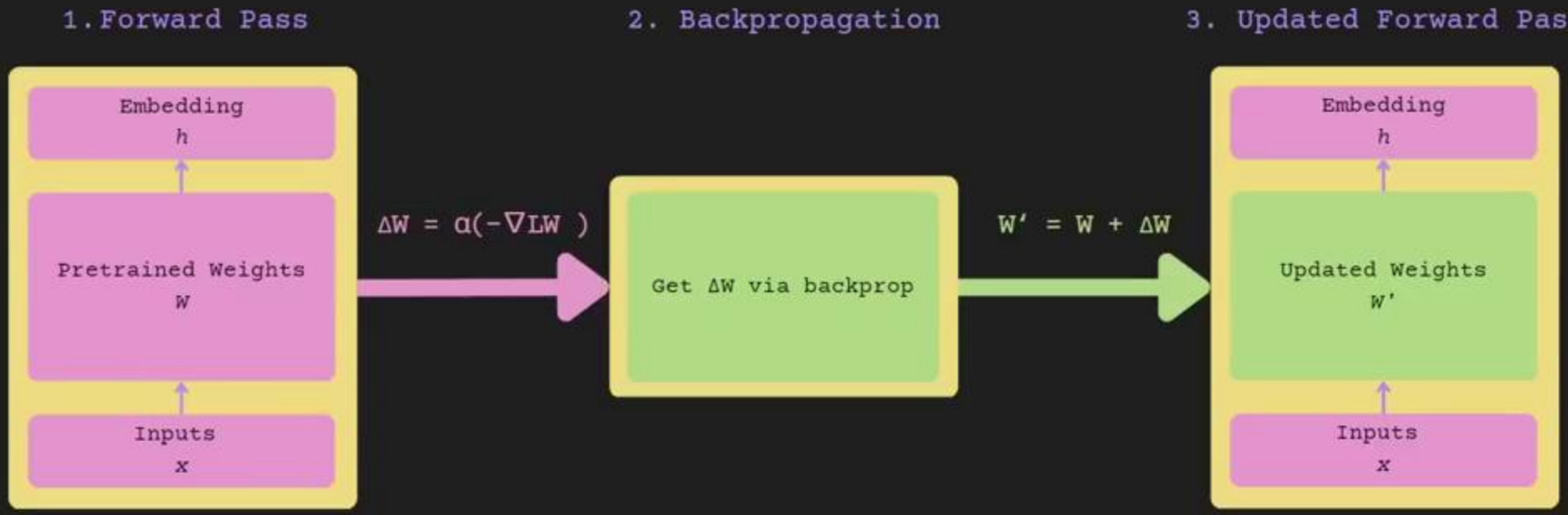
Update

What is LoRA, and how does it work?

Fine-tuning Explained



Fine-tuning Explained



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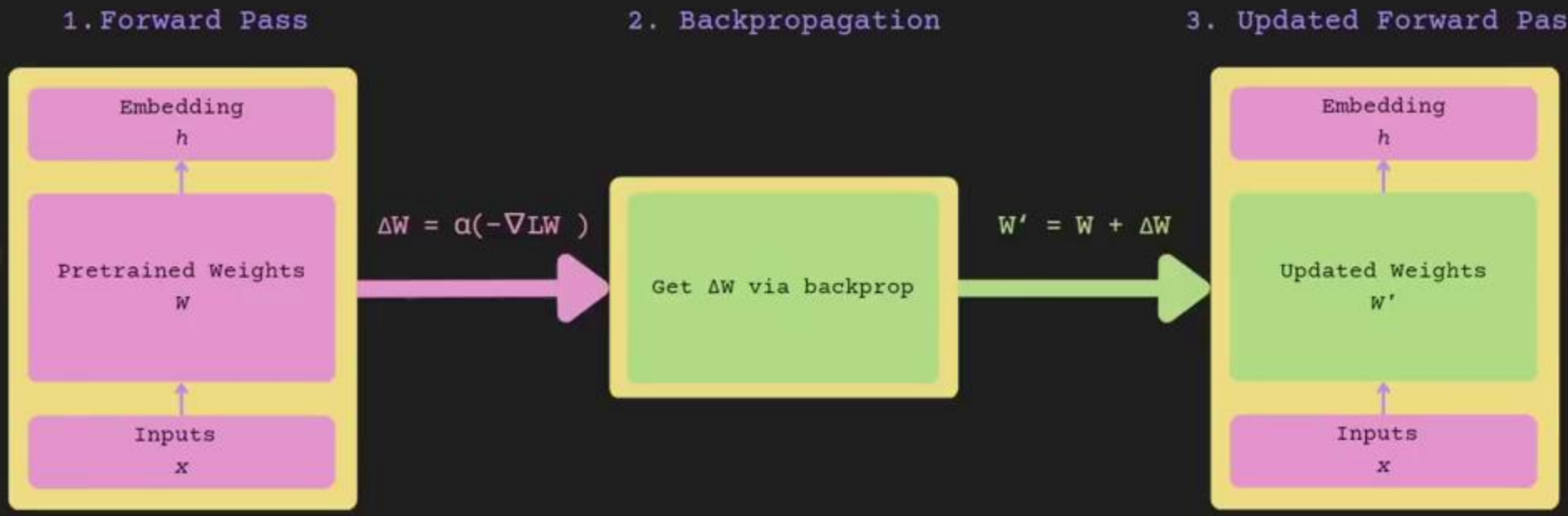

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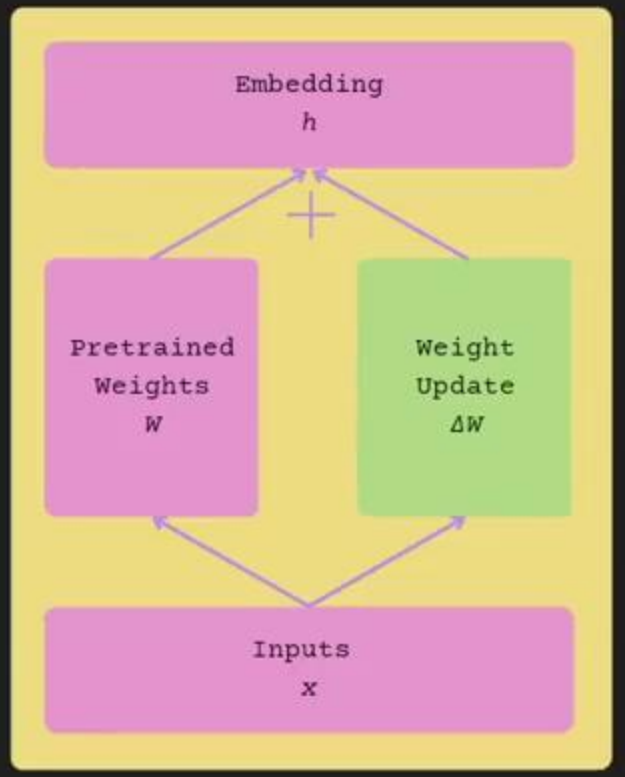
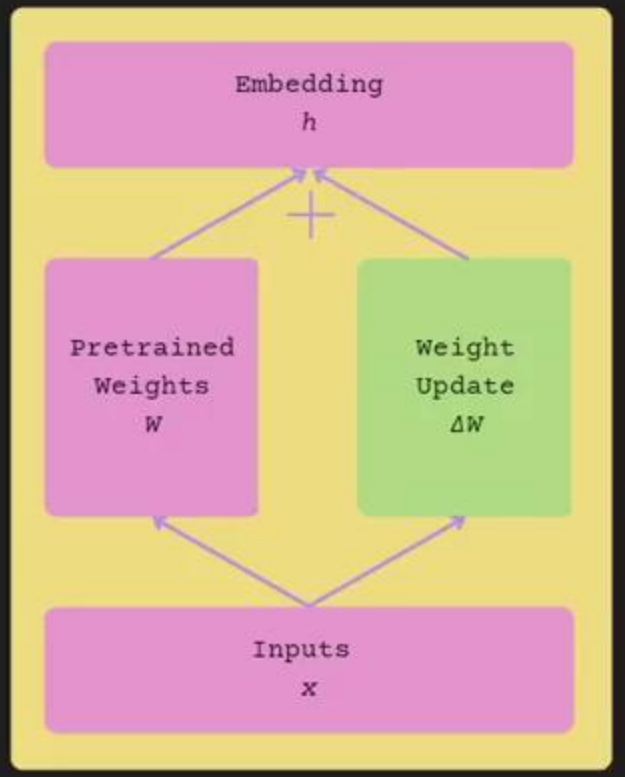


$$h = Wx + \Delta Wx$$

Fine-tuning Explained



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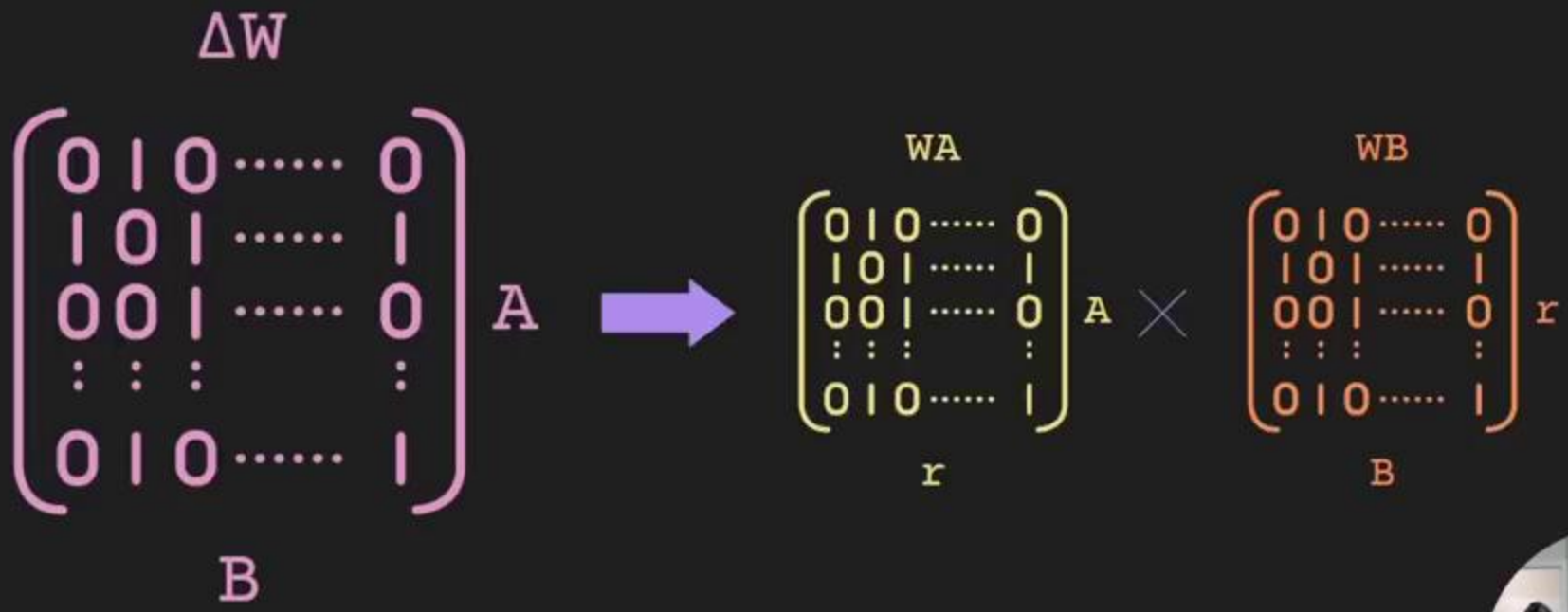
Update

LoRA Explained



[Submitted on 22 Dec 2020]

Intrinsic Dimensionality Explains the Effectiveness of Language Model Fine-Tuning

Armen Aghajanyan, Luke Zettlemoyer, Sonal Gupta

Although pretrained language models can be fine-tuned to produce state-of-the-art results for a very wide range of language understanding tasks, the dynamics of this process are not well understood, especially in the low data regime. Why can we use relatively vanilla gradient descent algorithms (e.g., without strong regularization) to tune a model with hundreds of millions of parameters on datasets with only hundreds or thousands of labeled examples? In this paper, we argue that analyzing fine-tuning through the lens of intrinsic dimension provides us with empirical and theoretical intuitions to explain this remarkable phenomenon. We empirically show that common pre-trained models have a very low intrinsic dimension; in other words, there exists a low dimension reparameterization that is as effective for fine-tuning as the full parameter space. For example, by optimizing only 200 trainable parameters randomly projected back into the full space, we can tune a RoBERTa model to achieve 90\% of the full parameter performance levels on MRPC. Furthermore, we empirically show that pre-training implicitly minimizes intrinsic dimension and, perhaps surprisingly, larger models tend to have lower intrinsic dimension after a fixed number of pre-training updates, at least in part explaining their extreme effectiveness. Lastly, we connect intrinsic dimensionality with low dimensional task representations and compression based generalization bounds to provide intrinsic-dimension-based generalization bounds that are independent of the full parameter count.

Subjects: **Machine Learning (cs.LG)**; Computation and Language (cs.CL)

Language Model Fine-Tuning

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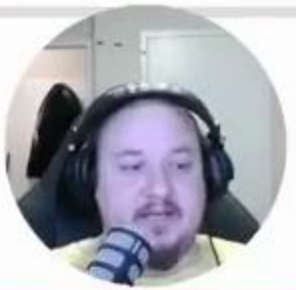

4.1 Low-Rank-Parametrized Update Matrices

A neural network contains many dense layers which perform matrix multiplication. The weight matrices in these layers typically have full-rank. When adapting to a specific task, Aghajanyan et al. (2020) shows that the pre-trained language models have a low "instrisic dimension" and can still learn efficiently despite a random projection to a smaller subspace. Inspired by this, we hypothesize the updates to the weights also have a low "intrinsic rank" during adaptation. For a pre-trained weight matrix $W_0 \in \mathbb{R}^{d\times k}$, we constrain its update by representing the latter with a low-rank decomposition $W_0 + \Delta W = W_0 + BA$, where $B \in \mathbb{R}^{d\times r}$, $A \in \mathbb{R}^{r\times k}$, and the rank $r \ll \min(d, k)$. During training, W_0 is frozen and does not receive gradient updates, while A and B contain trainable parameters. Note both W_0 and $\Delta W = BA$ are multiplied with the same input, and their respective output vectors are summed coordinate-wise. For $h = W_0 x$, our modified forward pass yields:

$$h = W_0 x + \Delta W x = W_0 x + BAx \tag{3}$$

We illustrate our reparametrization in Figure 1. We use a random Gaussian initialization for A and zero for B, so $\Delta W = BA$ is zero at the beginning of training. We then scale $\Delta W x$ by $\frac{\alpha}{r}$, where α is a constant in r. When optimizing with Adam, tuning α is roughly the same as tuning the learning rate if we scale the initialization appropriately. As a result, we simply set α to the first r we try and do not tune it. This scaling helps to reduce the need to retune hyperparameters when we vary r (Yang & Hu, 2021).

A Generalization of Full Fine-tuning. A more general form of fine-tuning allows the training of a subset of the pre-trained parameters. LoRA takes a step further and does not require the accumulated gradient update to weight matrices to have full-rank during adaptation. This means that when applying LoRA to all weight matrices and training all biases[2], we roughly recover the expressiveness of full fine-tuning by setting the LoRA rank r to the rank of the pre-trained weight matrices. In other words, as we increase the number of trainable parameters [3], training LoRA roughly converges to training the original model, while adapter-based methods converges to an MLP and prefix-based methods to a model that cannot take long input sequences.

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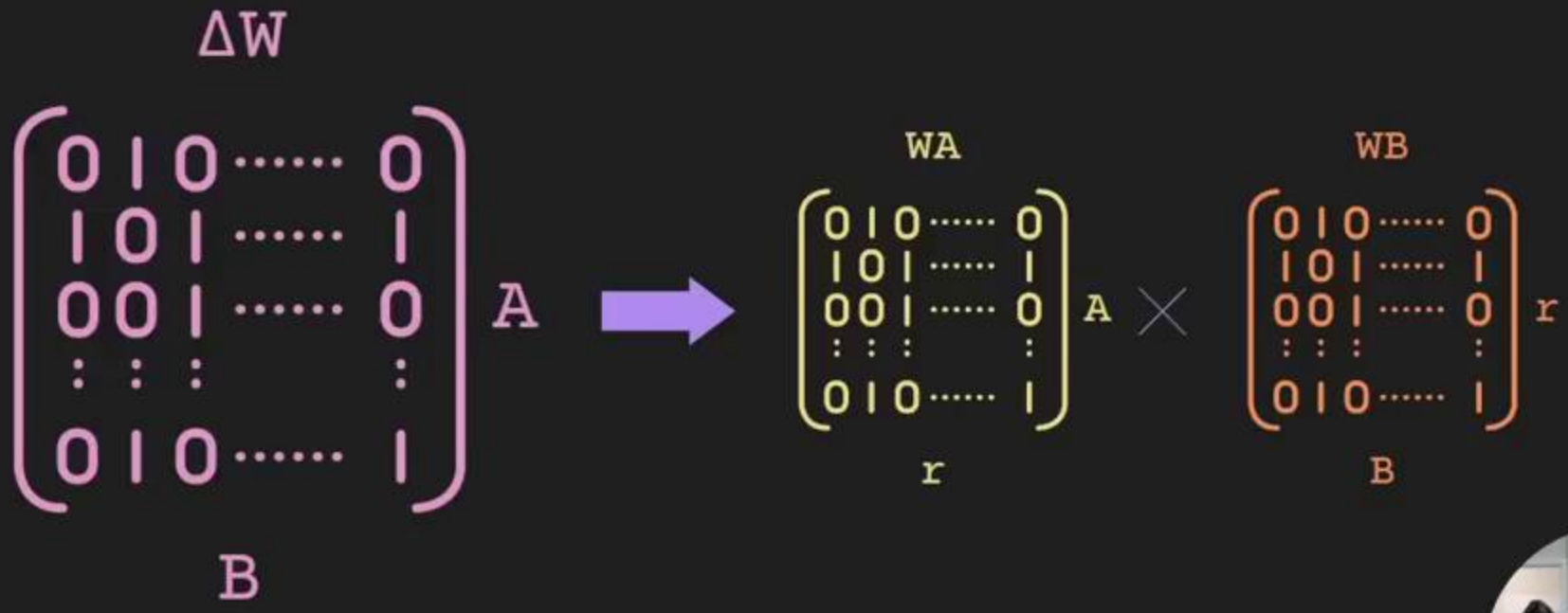
LoRA Explained



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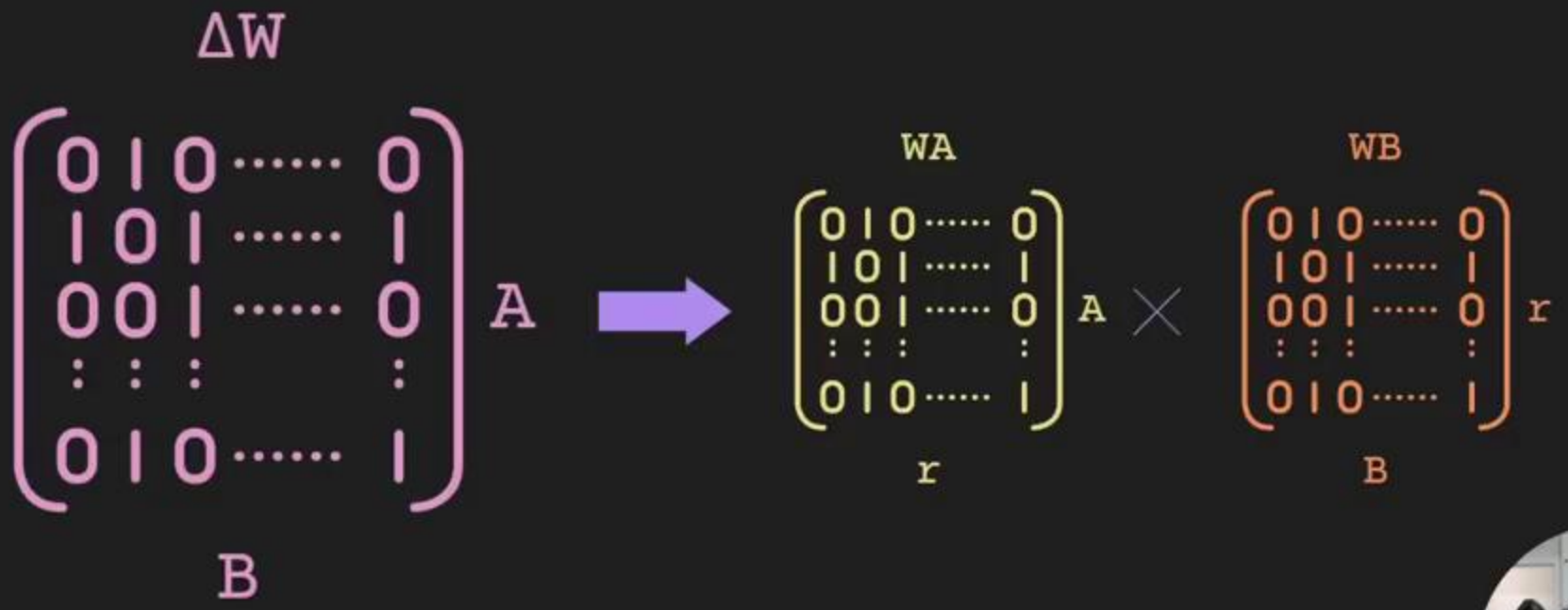
Update

LoRA Explained



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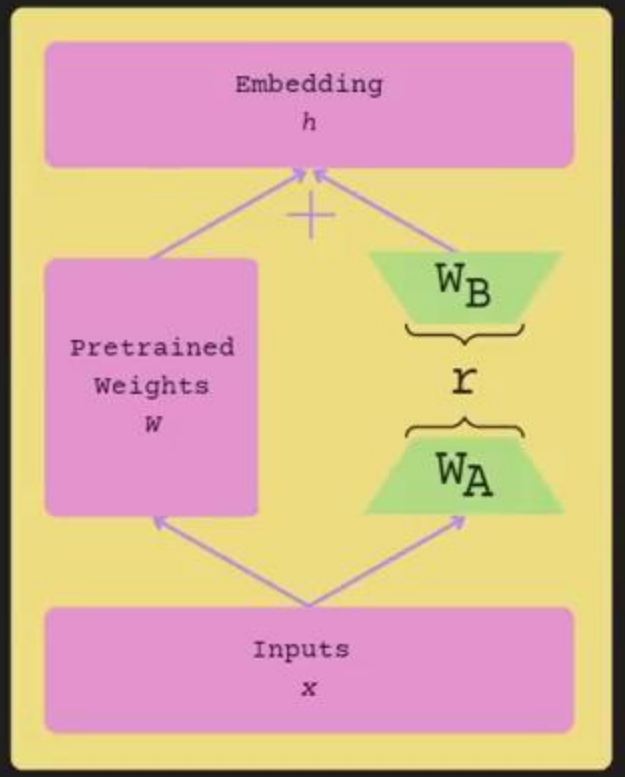
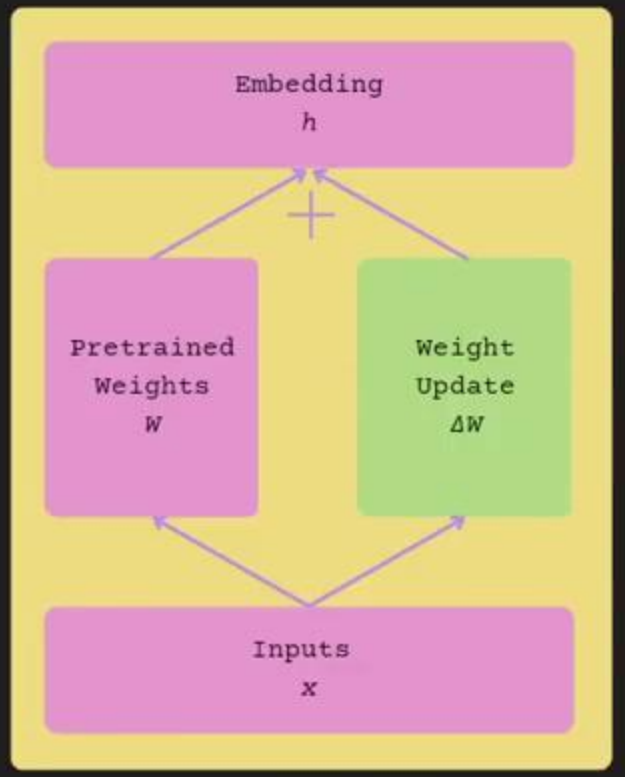


$$h = W_0x + W_AW_B$$

Fine-tuning Explained



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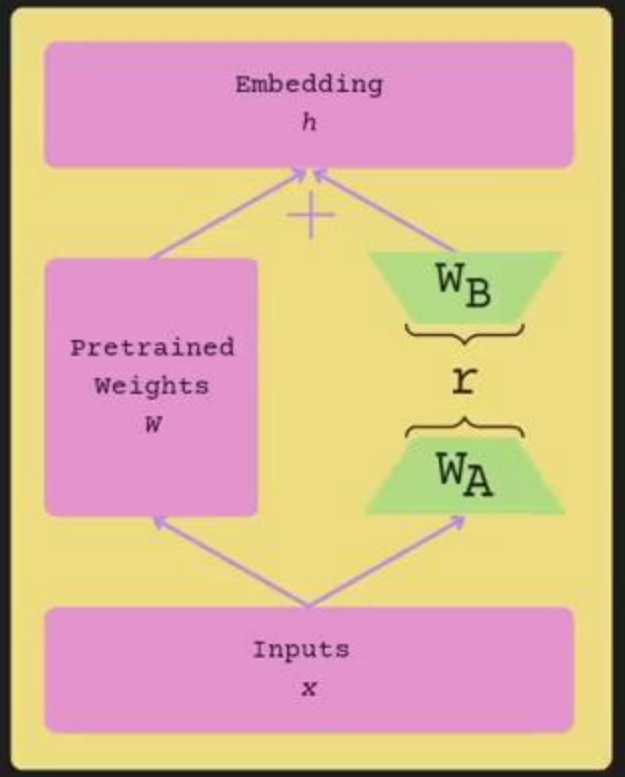
LoRA Explained (Cont.)



$$h = W_0 x + W_A W_B$$

No Additional Inference Latency. When deployed in production, we can explicitly compute and store $W = W_0 + BA$ and perform inference as usual. Note that both W_0 and BA are in $\mathbb{R}^{d \times k}$. When we need to switch to another downstream task, we can recover W_0 by subtracting BA and then adding a different $B'A'$, a quick operation with very little memory overhead. Critically, this guarantees that we do not introduce any additional latency during inference compared to a fi model by construction.

[2] They represent a negligible number of parameters compared to weights.

[3] An inevitability when adapting to hard tasks.

4.2 Applying LoRA to Transformer

In principle, we can apply LoRA to any subset of weight matrices in a neural network to reduce the number of trainable parameters. In the Transformer architecture, there are four weight matrices in the self-attention module (W_q, W_k, W_v, W_o) and two in the MLP module. We treat W_q (or W_k, W_v) as a single matrix of dimension $d_{model} \times d_{model}$, even though the output dimension is usually sliced into attention heads. We limit our study to **only adapting the attention weights** for downstream tasks and freeze the MLP modules (so they are not trained in downstream tasks) both for simplicity and parameter-efficiency.We further study the effect on adapting different types of attention weight matrices in a Transformer in Section 7.1. We leave the empirical investigation of adapting the MLP layers, LayerNorm layers, and biases to a future work.

Practical Benefits and Limitations. The most significant benefit comes from the reduction in memory and storage usage. For a large Transformer trained with Adam, we reduce that VRAM usage by up to $2/3$ if $r \ll d_{model}$ as we do not need to store the optimizer states for the frozen parameters. On GPT-3 175B, we reduce the VRAM consumption during training from 1.2TB to 350GB. With $r = 4$ and only the query and value projection matrices being adapted, the checkpoint size is reduced by roughly 10,000$\times$ (from 350GB to 35MB)[4]. This allows us to train with significantly fewer GPUs and avoid I/O bottlenecks. Another benefit is that we can switch between tasks while deployed at a much lower cost by only swapping the LoRA weights as opposed to all the parameters. This allows for the creation of many customized models that can be swapped in and out on the fly on machines that store the pre-trained weights in VRAM. We also observe a 25% speedu during training on GPT-3 175B compared to full fine-tuning[5] as we do not need to calculate gradient for the vast majority of the parameters.

LoRA also has its limitations. For example, it is not straightforward to batch inputs to different tas with different A and B in a single forward pass, if one chooses to absorb A and B into W to eliminate

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Practical Benefits and Limitations. The most significant benefit comes from the reduction in memory and storage usage. For a large Transformer trained with Adam, we reduce that VRAM usage by up to $2/3$ if $r \ll d_{model}$ as we do not need to store the optimizer states for the frozen parameters. On GPT-3 175B, we reduce the VRAM consumption during training from 1.2TB to 350GB. With $r = 4$ and only the query and value projection matrices being adapted, the checkpoint size is reduced by roughly 10,000$\times$ (from 350GB to 35MB)[4]. This allows us to train with significantly fewer GPUs and avoid I/O bottlenecks. Another benefit is that we can switch between tasks while deployed at a much lower cost by only swapping the LoRA weights as opposed to all the parameters. This allows for the creation of many customized models that can be swapped in and out on the fly on machines that store the pre-trained weights in VRAM. We also observe a 25% speedu during training on GPT-3 175B compared to full fine-tuning[5] as we do not need to calculate gradient for the vast majority of the parameters.

LoRA also has its limitations. For example, it is not straightforward to batch inputs to different tas with different A and B in a single forward pass, if one chooses to absorb A and B into W to eliminate

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7.1 Which Weight Matrices in Transformer Should We Apply LoRA to?

Given a limited parameter budget, which types of weights should we adapt with LoRA to obtain the best performance on downstream tasks? As mentioned in Section 4.2, we only consider weight matrices in the self-attention module. We set a parameter budget of 18M (roughly 35MB if stored in FP16) on GPT-3 175B, which corresponds to $r = 8$ if we adapt one type of attention weights or $r = 4$ if we adapt two types, for all 96 layers. The result is presented in Table 5.

	# of Trainable Parameters = 18M						
Weight Type	W_q	W_k	W_v	W_o	W_q, W_k	W_q, W_v	W_q, W_k, W_v, W_o
Rank r	8	8	8	8	4	4	2
WikiSQL ($\pm$0.5%)	70.4	70.0	73.0	73.2	71.4	**73.7**	**73.7**
MultiNLI ($\pm$0.1%)	91.0	90.8	91.0	91.3	91.3	91.3	**91.7**

Table 5: Validation accuracy on WikiSQL and MultiNLI after applying LoRA to different types of attention weights in GPT-3, given the same number of trainable parameters. Adapting both W_q and W_v gives the best performance overall. We find the standard deviation across random seeds to be consistent for a given dataset, which we report in the first column.

Note that putting all the parameters in ΔW_q or ΔW_k results in significantly lower perfo while adapting both W_q and W_v yields the best result. This suggests that even a rank captures enough information in ΔW such that it is preferable to adapt more weight matrice adapting a single type of weights with a larger rank.

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7.2 What is the Optimal Rank r for LoRA?

We turn our attention to the effect of rank r on model performance. We adapt $\{W_q, W_v\}$, $\{W_q, W_k, W_v, W_c\}$, and just W_q for a comparison.

	Weight Type	$r = 1$	$r = 2$	$r = 4$	$r = 8$	$r = 64$
WikiSQL($\pm 0.5\%$)	W_q	68.8	69.6	70.5	70.4	70.0
	W_q, W_v	73.4	73.3	73.7	73.8	73.5
	W_q, W_k, W_v, W_o	74.1	73.7	74.0	74.0	73.9
MultiNLI ($\pm 0.1\%$)	W_q	90.7	90.9	91.1	90.7	90.7
	W_q, W_v	91.3	91.4	91.3	91.6	91.4
	W_q, W_k, W_v, W_o	91.2	91.7	91.7	91.5	91.4

Table 6: Validation accuracy on WikiSQL and MultiNLI with different rank r. To our surprise, a rank as small as one suffices for adapting both W_q and W_v on these datasets while training W_q alone needs a larger r. We conduct a similar experiment on GPT-2 in Section H.2.

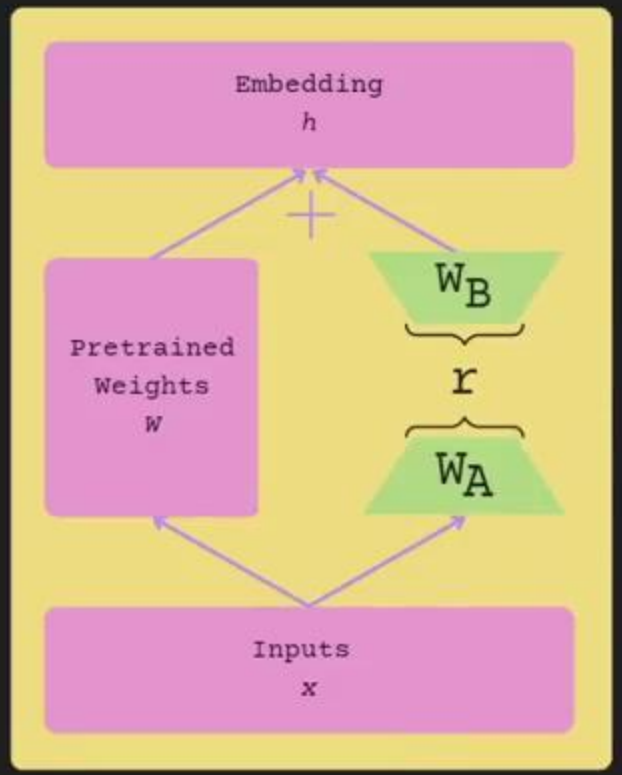
Table 6 shows that, surprisingly, LoRA already performs competitively with a very small r (more so for $\{W_q, W_v\}$ than just W_q). This suggests the update matrix ΔW could have a very "intrinsic rank".[6] To further support this finding, we check the overlap of the subspaces lea different choices of r and by different random seeds. We argue that increasing r does not more meaningful subspace, which suggests that a low-rank adaptation matrix is sufficient.

following the setup of Li & Liang (2021). The result is shown in Table 13. Similar to our result on E2E NLG Challenge, reported in Section 5, LoRA performs better than or at least on-par with prefix-based approaches given the same number of trainable parameters.

Method	# Trainable Parameters	DART BLEU↑	DART MET↑	DART TER↓
GPT-2 Medium				
Fine-Tune	354M	46.2	**0.39**	**0.46**
Adapter^{L}	0.37M	42.4	0.36	0.48
Adapter^{L}	11M	45.2	0.38	**0.46**
FT^{Top2}	24M	41.0	0.34	0.56
PrefLayer	0.35M	46.4	0.38	**0.46**
LoRA	0.35M	**47.1**$_{\pm.2}$	**0.39**	**0.46**
GPT-2 Large				
Fine-Tune	774M	47.0	**0.39**	0.46
Adapter^{L}	0.88M	45.7$_{\pm.1}$	0.38	0.46
Adapter^{L}	23M	47.1$_{\pm.1}$	**0.39**	**0.45**
PrefLayer	0.77M	46.7	0.38	**0.45**
LoRA	0.77M	**47.5**$_{\pm.1}$	**0.39**	**0.45**

Table 13: GPT-2 with different adaptation methods on DART. The variances of MET and less than 0.01 for all adaption approaches.

LoRA Explained (Cont.)



$$h = W_0x + W_AW_B$$