LoRA Fine-Tuning

Dr. Karthik Mohan, March 5th 2025

Today's Talk

LoRA Fine-Tuning

Llama3 Herd

Herd of models including 405B LM, 70B, 8B, 1B versions and also Llama Guard 3 for input/output safety

Reference: https://arxiv.org/pdf/2407.21783

Llama 3 Herd of Models

	Finetuned	Multilingual	Long context	Tool use	Release
Llama 3 8B	✗	✗[1]	✗	✗	April 2024
Llama 3 8B Instruct	✓	✗	✗	✗	April 2024
Llama 3 70B	✗	✗[1]	✗	✗	April 2024
Llama 3 70B Instruct	✓	✗	✗	✗	April 2024
Llama 3.1 8B	✗	✓	✓	✗	July 2024
Llama 3.1 8B Instruct	✓	✓	✓	✓	July 2024
Llama 3.1 70B	✗	✓	✓	✗	July 2024
Llama 3.1 70B Instruct	✓	✓	✓	✓	July 2024
Llama 3.1 405B	✗	✓	✓	✗	July 2024
Llama 3.1 405B Instruct	✓	✓	✓	✓	July 2024

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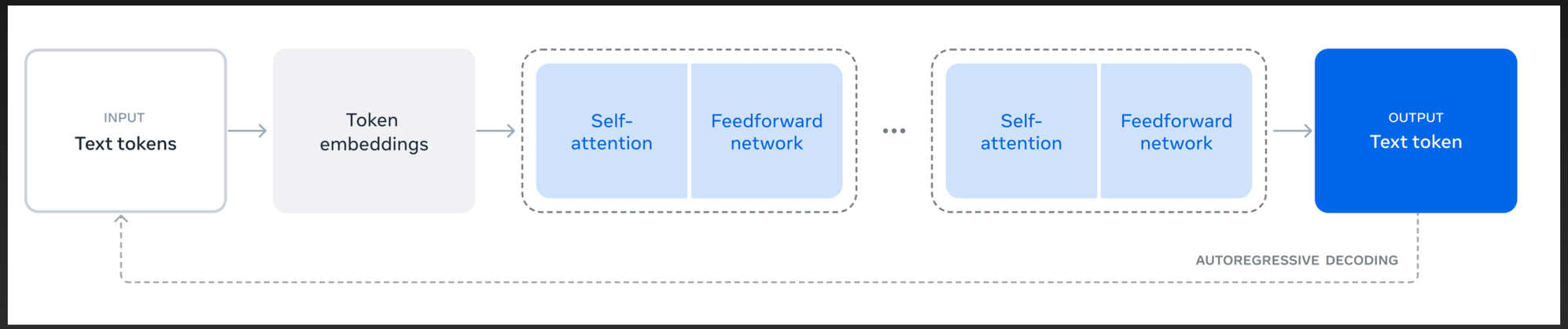
Llama3 Architecture



LoRA Fine-Tuning

Low-Rank Adaptation of LLMs

Refers to an efficient fine-tuning procedure - where ALL weights of the LLM are frozen. But - New and relatively fewer weights are introduced for fine-tuning.

Reference: https://arxiv.org/pdf/2106.09685

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Low-Rank Adaptation of LLMs

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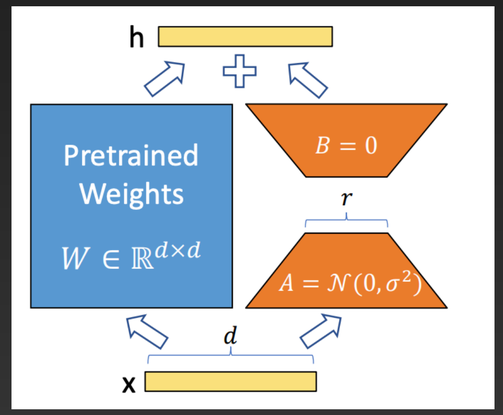

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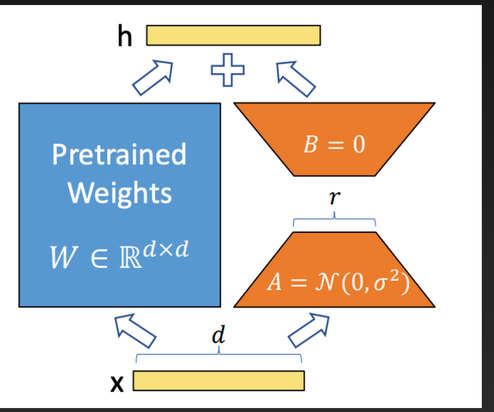
ICE #1

Low-Rank Matrices

Let W (dxd) be a matrix that can be thought of as a product of A (dxk) and B (kxd). What is the rank of the matrix W?

a) At least d
b) At most d
c) At least k
d) At most k



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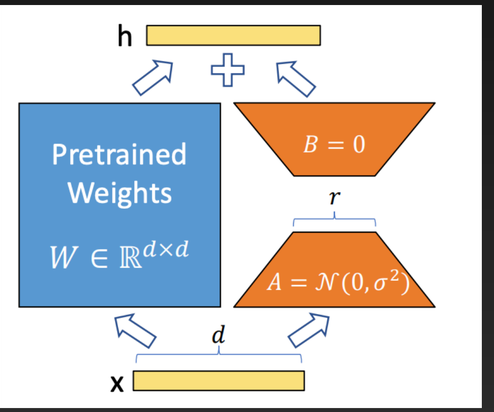
LoRA Fine-Tuning Basis

Low-Rank Adaptation of LLMs

Based on the assumption that learned weight matrices in LLMs typically reside in “low-dimensional” subspaces. Thus learning a low-rank matrix can be a way to fine-tune.



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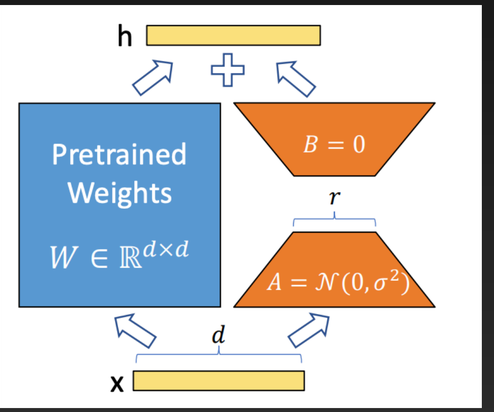
ICE #2

LoRA application

In the Llama3 Transformer - What weight matrices does LoRA duplicate for fine-tuning?

a) Query matrix
b) Key Matrix
c) Value Matrix
d) MLP matrices
e) All of the above



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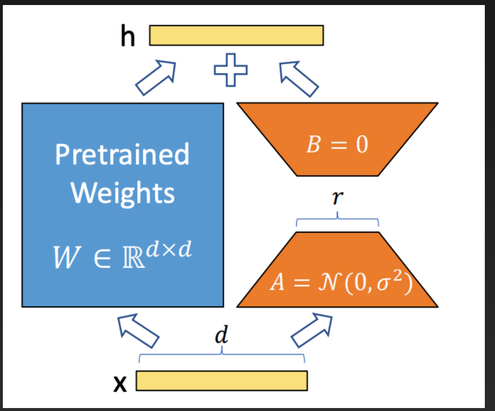
LoRA Fine-Tuning Features

Low-Rank Adaptation of LLMs

* Can be used to fine-tune “any” LLM model by freezing entire model
* Only the new low-rank weights are fine-tuned
* Final model is the existing weights + the LoRA adaptor weights
* Latency is same at inference time - As the new weights get added in
* Orthogonal to partial freezing and fine-tuning paradigm
* For GPT-3 175B - reduced RAM requirement from 1.2TB to 350GB.
* With r = 4, reduced the checkpoint size of the fine-tuned model reduced from 350GB to 35MB!



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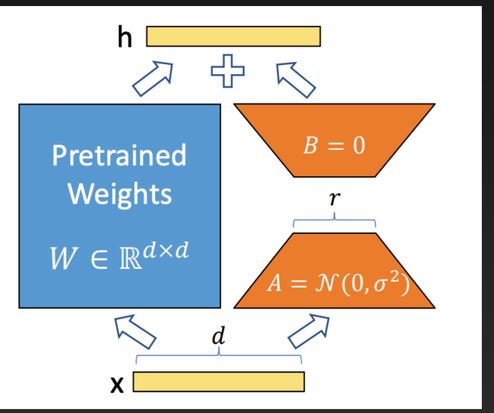
ICE #3

Low-Rank Matrices

Let W (dxd) be a matrix that can be thought of as a product of A (dxk) and B (kxd). Let's say we have a token embedding, x of a token T, that lives in d dimensions. If W represents the query matrix - What is the computational complexity of computing the query vector q from the token T?

a) O(d*d)
b) O(d*d*k)
c) O(k*k)
d) O(d*k)



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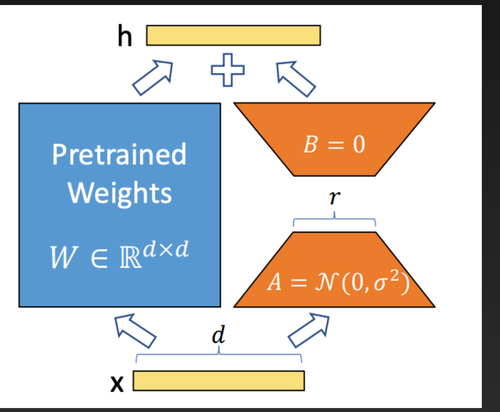
ICE #4

LoRA fine-tuning

Let the embedding dimension, d be 4000. Assume that we do LoRA fine-tuning with a LoRA rank, k of 5. If the LLM model we are fine-tuning is a 8b Llama 3 model. How many new parameters are we introducing with the LoRA fine-tuning?

a) 10 MM
b) 20 MM
c) 30 MM
d) 40 MM



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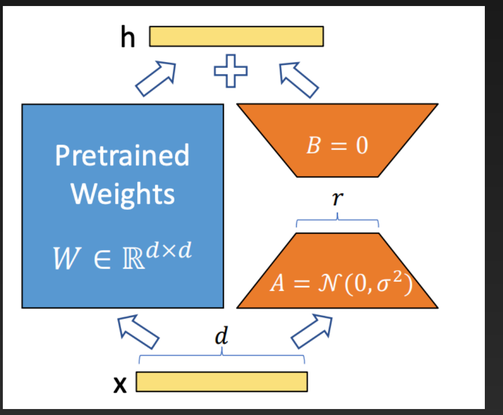
LoRA Fine-Tuning vs Partial Freezing

LoRA vs Partial Freezing

* Computer vision models, for example get fine-tuned by freezing all but last 3 layers of CNN model on the fine-tuned data set
* In the context of LLMs - What are the pros/cons of LoRA as compared to the partial freezing of weights approach for fine-tuning?



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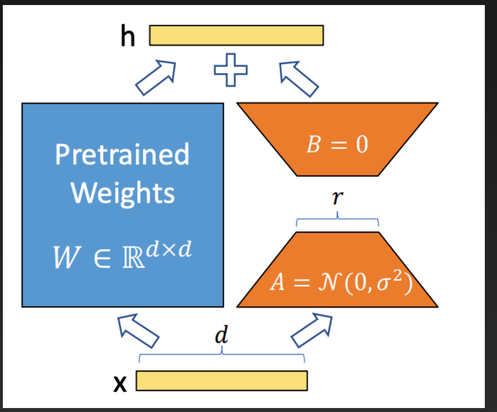
ICE #5

Low Rank Matrix Factorization

Recall the context of low-rank factorization of data matrix into users factors and movies factors. Let X = UV be this factorization. Where (i,j) element of X represents whether user i liked movie j or not (1 for like and 0 for not). In this case if we have millions of users and 100k movies - X is a large matrix. But typically the column dimension of U is limited to 50 or 100. Why would 100 dimensions be sufficient?

a) It's a low rank factorization - so 100 should be sufficient
b) Its computationally expensive to consider 1000 dimensions or more
c) The user factors and movie factors have a common theme of genres and there are not too many genre combos
d) It works experimentally and hence 100 is sufficient



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