Fine-Tuning Llama 3 and Using It Locally: A Step-by-Step Guide

We'll fine-tune Llama 3 on a dataset of patient-doctor conversations, creating a model tailored for medical dialogue. After merging, converting, and quantizing the model, it will be ready for private local use via the Jan application.

May 2024 · 19 min read

Abid Ali Awan
Certified data scientist, passionate about building ML apps, blogging on data science, and editing.

TOPICS

Artificial Intelligence (AI)

Python

In this tutorial, we'll learn to fine-tune Llama 3 on a medical dataset. We'll also transform the model into a format ready for local use via the Jan application.

More specifically, we'll:

- Learn about Llama 3 models.
- Fine-tune a Llama 3 model on a medical dataset.
- Merge the adapter with the base model and push the full model to the Hugging Face Hub.
- Convert the model files into the Llama.cpp GGUF format.
- Quantize the GGUF model and push the file to Hugging Face Hub.
- Using the fine-tuned model locally with Jan application.

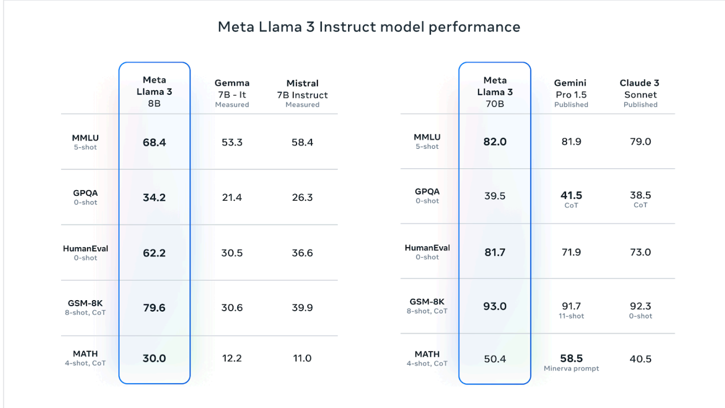
If you're looking for a curated curriculum to learn AI, check out this six-course skill track on **AI Fundamentals**.

Understanding Llama 3

Meta has released a new series of large language models (LLMs) called Llama 3, a collection of pre-trained and instruction-tuned text-to-text models.

Llama 3 is an auto-regressive language model that uses an optimized transformer architecture. Both pre-trained and instruction-tuned models come with 8B and 70B parameters with a context length of 8K tokens.

Llama 3 8B is the most liked LLM on Hugging Face. Its instruction-tuned version is better than Google's Gemma 7B-It and Mistral 7B Instruct on various performance metrics. The 70B instruction-tuned version has surpassed Gemini Pro 1.5 and Claude Sonnet on most performance metrics:


Meta Llama 3 Instruct model performance

	Meta Llama 3 8B	Gemma 7B - It (Measured)	Mistral 7B Instruct (Measured)
MMLU 5-shot	68.4	53.3	58.4
GPQA 0-shot	34.2	21.4	26.3
HumanEval 0-shot	62.2	30.5	36.6
GSM-8K 8-shot, CoT	79.6	30.6	39.9
MATH 4-shot, CoT	30.0	12.2	11.0

	Meta Llama 3 70B	Gemini Pro 1.5 (Published)	Claude 3 Sonnet (Published)
MMLU 5-shot	82.0	81.9	79.0
GPQA 0-shot	39.5	41.5 CoT	38.5 CoT
HumanEval 0-shot	81.7	71.9	73.0
GSM-8K 8-shot, CoT	93.0	91.7 11-shot	92.3 0-shot
MATH 4-shot, CoT	50.4	58.5 Minerva prompt	40.5

Source: Meta Llama 3

Meta trained Llama 3 on a new mix of publicly available online data, with a token count of over 15 trillion tokens. The 8B model has a knowledge cutoff of March 2023, while the 70B model has a cutoff of December 2023. The models use Grouped-Query Attention (GQA), which reduces memory bandwidth and improves efficiency.

The Llama 3 models have been released under a custom commercial license. To access the model, you need to fill out the form with your name, affiliation, and email and accept the terms and conditions. If you use different email addresses for different platforms like Kaggle and Hugging Face, you may need to fill out the form multiple times.

You can learn more about Llama 3 from this article on What is Llama 3?.

1. Fine-Tuning Llama 3

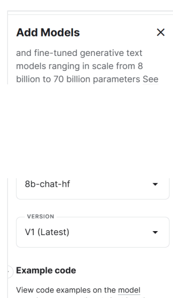
For this tutorial, we'll fine-tune the Llama 3 8B-Chat model using the ruslanmv/ai-medical-chatbot dataset. The dataset contains 250k dialogues between a patient and a doctor. We'll use the Kaggle Notebook to access this model and free GPUs.

Setting up

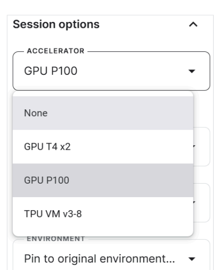
Before we launch the Kaggle Notebook, fill out the Meta download form with your Kaggle email address, then go to the Llama 3 model page on Kaggle and accept the agreement. The approval process may take one to two days.

Let's now take the following steps:

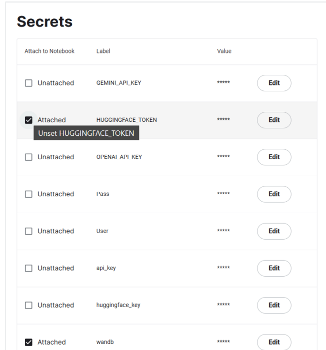
1. Launch the new Notebook on Kaggle, and add the Llama 3 model by clicking the *+ Add Input* button, selecting the *Models* option, and clicking on the plus *+* button beside the *Llama 3* model. After that, select the right framework, variation, and version, and add the model.



2. Go to the *Session options* and select the *GPU P100* as an accelerator.



3. Generate the Hugging Face and Weights & Biases token, and create the Kaggle Secrets. You can create and activate the Kaggle Secrets by going to *Add-ons > Secrets > Add* a new secret.



4. Initiate the Kaggle session by installing all the necessary Python packages.

```
%%capture
%pip install -U transformers
%pip install -U datasets
%pip install -U accelerate
%pip install -U peft
%pip install -U trl
%pip install -U bitsandbytes
%pip install -U wandb
```

Explain code OpenAI

5. Import the necessary Python pages for loading the dataset, model, and tokenizer and fine-tuning.

```
from transformers import (
    AutoModelForCausalLM,
    AutoTokenizer,
    BitsAndBytesConfig,
    HfArgumentParser,
    TrainingArguments,
    pipeline,
    logging,
)
from peft import (
    LoraConfig,
    PeftModel,
    prepare_model_for_kbit_training,
    get_peft_model,
)
import os, torch, wandb
from datasets import load_dataset
from trl import SFTTrainer, setup_chat_format
```

Explain code OpenAI

6. We'll be tracking the training process using the Weights & Biases and then saving the fine-tuned model on Hugging Face, and for that, we have to log in to both Hugging Face Hub and Weights & Biases using the API key.

```
from huggingface_hub import login
from kaggle_secrets import UserSecretsClient
user_secrets = UserSecretsClient()

hf_token = user_secrets.get_secret("HUGGINGFACE_TOKEN")

login(token = hf_token)

wb_token = user_secrets.get_secret("wandb")

wandb.login(key=wb_token)
run = wandb.init(
    project='Fine-tune Llama 3 8B on Medical Dataset',
    job_type="training",
    anonymous="allow"
)
```

Explain code OpenAI

7. Set the base model, dataset, and new model variable. We'll load the base model from Kaggle and the dataset from the HugginFace Hub and then save the new model.

```
base_model = "/kaggle/input/llama-3/transformers/8b-chat-hf/1"
dataset_name = "ruslanmv/ai-medical-chatbot"
new_model = "llama-3-8b-chat-doctor"
```

Explain code OpenAI

8. Set the data type and attention implementation.

```
torch_dtype = torch.float16
attn_implementation = "eager"
```

Explain code OpenAI

Loading the model and tokenizer

In this part, we'll load the model from Kaggle. However, due to memory constraints, we're unable to load the full model. Therefore, we're loading the model using 4-bit precision.

Our goal in this project is to reduce memory usage and speed up the fine-tuning process.

```
# QLoRA config
bnb_config = BitsAndBytesConfig(
    load_in_4bit=True,
    bnb_4bit_quant_type="nf4",
    bnb_4bit_compute_dtype=torch_dtype,
    bnb_4bit_use_double_quant=True,
)

# Load model
model = AutoModelForCausalLM.from_pretrained(
    base_model,
    quantization_config=bnb_config,
    device_map="auto",
    attn_implementation=attn_implementation
)
```

Explain code OpenAI

Load the tokenizer and then set up a model and tokenizer for conversational AI tasks. By default, it uses the `chatml` template from OpenAI, which will convert the input text into a chat-like format.

```
# Load tokenizer
tokenizer = AutoTokenizer.from_pretrained(base_model)
model, tokenizer = setup_chat_format(model, tokenizer)
```

Explain code OpenAI

Adding the adapter to the layer

Fine-tuning the full model will take a lot of time, so to improve the training time, we'll attach the adapter layer with a few parameters, making the entire process faster and more memory-efficient.

```
# LoRA config
peft_config = LoraConfig(
    r=16,
    lora_alpha=32,
    lora_dropout=0.05,
    bias="none",
    task_type="CAUSAL_LM",
    target_modules=['up_proj', 'down_proj', 'gate_proj', 'k_proj', 'q_proj', 'v_p
)
model = get_peft_model(model, peft_config)
```

Explain code OpenAI

Loading the dataset

To load and pre-process our dataset, we:

1. Load the **ruslanmv/ai-medical-chatbot** dataset, shuffle it, and select only the top 1000 rows. This will significantly reduce the training time.

2. Format the chat template to make it conversational. Combine the patient questions and doctor responses into a "text" column.

3. Display a sample from the text column (the “text” column has a chat-like format with special tokens).

```
#Importing the dataset
dataset = load_dataset(dataset_name, split="all")
dataset = dataset.shuffle(seed=65).select(range(1000)) # Only use 1000 samples fo

def format_chat_template(row):
    row_json = [{"role": "user", "content": row["Patient"]},
               {"role": "assistant", "content": row["Doctor"]}]
    row["text"] = tokenizer.apply_chat_template(row_json, tokenize=False)
    return row

dataset = dataset.map(
    format_chat_template,
    num_proc=4,
)

dataset['text'][3]
```

Explain code OpenAI

```
'<|im_start|>user\nFell on sidewalk face first about 8 hrs ago. Swollen, cut lip bruised and c
ut knee, and hurt pride initially. Now have muscle and shoulder pain, stiff jaw(think this is
from the really swollen lip),pain in wrist, and headache. I assume this is all normal but are
there specific things I should look for or will I just be in pain for a while given the hard f
all?<|im_end|>\n<|im_start|>assistant\nHello and welcome to HCM,The injuries caused on various
body parts have to be managed.The cut and swollen lip has to be managed by sterile dressing.Th
e body pains, pain on injured site and jaw pain should be managed by pain killer and muscle re
laxant.I suggest you to consult your primary healthcare provider for clinical assessment.In ca
se there is evidence of infection in any of the injured sites, a course of antibiotics may hav
e to be started to control the infection.Thanks and take careDr Shailja P Wahal<|im_end|>\n'
```

4. Split the dataset into a training and validation set.

```
dataset = dataset.train_test_split(test_size=0.1)
```

Explain code OpenAI

Complaining and training the model

We are setting the model hyperparameters so that we can run it on the Kaggle. You can learn about each hyperparameter by reading the **Fine-Tuning Llama 2** tutorial.

We are fine-tuning the model for one epoch and logging the metrics using the Weights and Biases.

```
training_arguments = TrainingArguments(
    output_dir=new_model,
    per_device_train_batch_size=1,
    per_device_eval_batch_size=1,
    gradient_accumulation_steps=2,
    optim="paged_adamw_32bit",
    num_train_epochs=1,
    evaluation_strategy="steps",
    eval_steps=0.2,
    logging_steps=1,
    warmup_steps=10,
    logging_strategy="steps",
    learning_rate=2e-4,
    fp16=False,
    bf16=False,
    group_by_length=True,
```

```
    report_to="wandb"
)
```

Explain code OpenAI

We'll now set up a supervised fine-tuning (SFT) trainer and provide a train and evaluation dataset, LoRA configuration, training argument, tokenizer, and model. We're keeping the `max_seq_length` to `512` to avoid exceeding GPU memory during training.

```
trainer = SFTTrainer(
    model=model,
    train_dataset=dataset["train"],
    eval_dataset=dataset["test"],
    peft_config=peft_config,
    max_seq_length=512,
    dataset_text_field="text",
    tokenizer=tokenizer,
    args=training_arguments,
    packing= False,
)
```

Explain code OpenAI

We'll start the fine-tuning process by running the following code.

```
trainer.train()
```

Explain code OpenAI

Both training and validation losses have decreased. Consider training the model for three epochs on the full dataset for better results.

[450/450 29:50, Epoch 1/1]

Step	Training Loss	Validation Loss
90	3.270300	2.568106
180	2.550000	2.517369
270	2.744700	2.490356
360	2.502000	2.462632
450	2.747900	2.446632

Model evaluation

When you finish the Weights & Biases session, it'll generate the run history and summary.

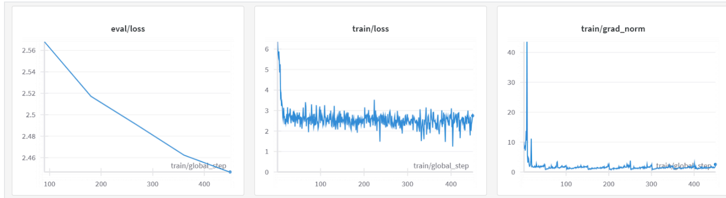
```
wandb.finish()
model.config.use_cache = True
```

Explain code OpenAI

Run summary:

eval/loss	2.44663
eval/runtime	76.3163
eval/samples_per_second	1.31
eval/steps_per_second	1.31
total_flos	9270114454167552.0
train/epoch	1.0
train/global_step	450
train/grad_norm	2.54422
train/learning_rate	0.0
train/loss	2.7479
train_loss	2.5901
train_runtime	1798.8689
train_samples_per_second	0.5
train_steps_per_second	0.25

The model performance metrics are also stored under the specific project name on your Weights & Biases account.



Let's evaluate the model on a sample patient query to check if it's properly fine-tuned.

To generate a response, we need to convert messages into chat format, pass them through the tokenizer, input the result into the model, and then decode the generated token to display the text.

```
messages = [
    {
        "role": "user",
        "content": "Hello doctor, I have bad acne. How do I get rid of it?"
    }
]

prompt = tokenizer.apply_chat_template(messages, tokenize=False,
                                       add_generation_prompt=True)

inputs = tokenizer(prompt, return_tensors='pt', padding=True,
                   truncation=True).to("cuda")

outputs = model.generate(**inputs, max_length=150,
                         num_return_sequences=1)

text = tokenizer.decode(outputs[0], skip_special_tokens=True)

print(text.split("assistant")[1])
```

Explain code OpenAI

```
Hi. I have gone through your query and understand your concern. Acne is a common problem and c
an be treated with the help of medicines and lifestyle changes. I would suggest you to use a t
opical antibiotic cream like erythromycin or clindamycin for 2-3 months. You can also use a re
tinoid cream like adapalene or retinol for 2-3 months. Avoid using oily products and wash your
face twice a day with a mild soap. Avoid touching your face and do not squeeze or pop your pim
ples. You can also take oral antibiotics like doxycycline or
```

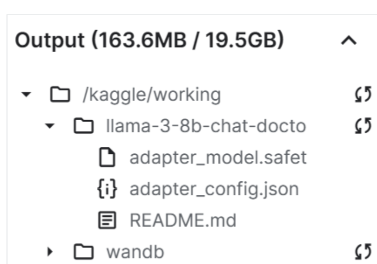
It turns out we can get average results even with one epoch.

Saving the model file

We'll now save the fine-tuned adapter and push it to the Hugging Face Hub. The Hub API will automatically create the repository and store the adapter file.

```
trainer.model.save_pretrained(new_model)
trainer.model.push_to_hub(new_model, use_temp_dir=False)
```

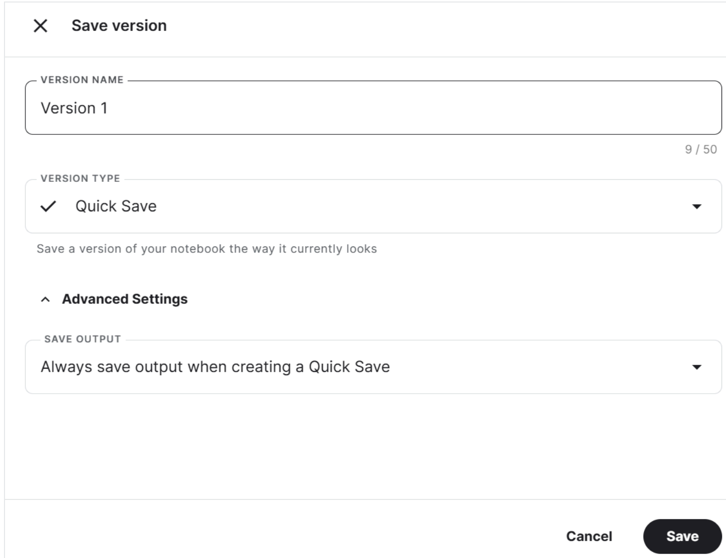
Explain code OpenAI



As we can see, our save adapter file is significantly smaller than the base model.

Ultimately, we'll save the notebook with the adapter file to merge it with the base model in the new notebook.

To save the Kaggle Notebook, click the *Save Version* button at the top right, select the version type as *Quick Save*, open the advanced setting, select *Always save output when creating a Quick Save*, and then press the *Save* button.



If you are facing an issue while running the code, refer to this Kaggle Notebook: Fine-tune Llama 3 8B on Medical Dataset.

We have fine-tuned our model using the GPU. You can also learn to fine-tune LLMs using the TPUs by following the tutorial Fine-Tune and Run Inference on Google's Gemma Model Using TPUs.

If you want to learn how to fine-tune other models, check out this Mistral 7B Tutorial: A Step-by-Step Guide to Using and Fine-Tuning Mistral 7B.

2. Merging Llama 3

To use the fine-tuned model locally, we have to first merge the adapter with the base model and then save the full model.

Setting up

Let's take the following steps:

1. Create a new Kaggle Notebook and install all the necessary Python packages. Make sure you are using the GPU as an accelerator.

```
%%capture
%pip install -U bitsandbytes
%pip install -U transformers
%pip install -U accelerate
%pip install -U peft
%pip install -U trl
```

Explain code OpenAI

2. Log in to the Hugging Face Hub using the Kaggle Secrets. It will help us easily upload the full fine-tuned model.

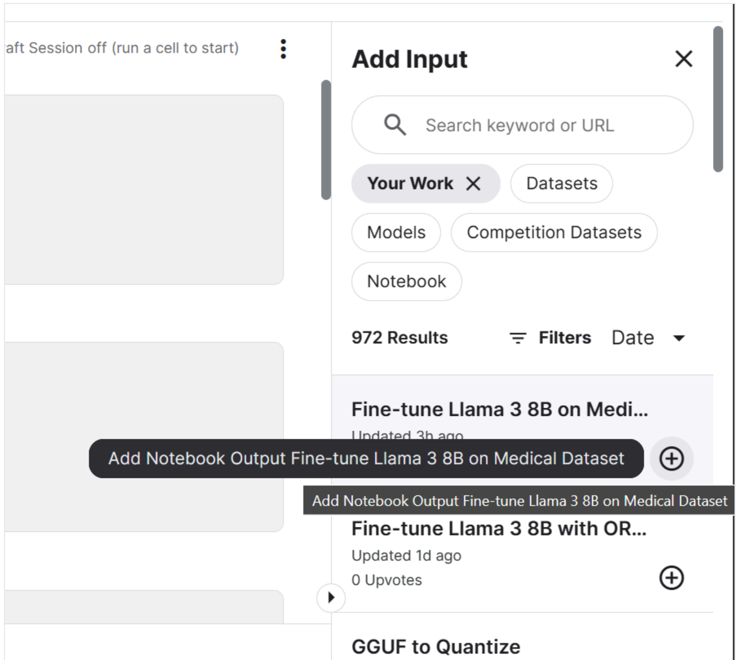
```
from huggingface_hub import login
from kaggle_secrets import UserSecretsClient
user_secrets = UserSecretsClient()

hf_token = user_secrets.get_secret("HUGGINGFACE_TOKEN")
login(token = hf_token)
```

Explain code OpenAI

3. Add the Llama 3 8B Chat model and a fine-tuned Kaggle Notebook we recently saved. We can add the Notebooks in the current session just like you add a dataset and models.

Adding Notebook to the Kaggle session will allow us to access the output files. In our case, it's a model adapter file.



4. Setting the variable with the location of the base model and adapter.

```
base_model = "/kaggle/input/llama-3/transformers/8b-chat-hf/1"
new_model = "/kaggle/input/fine-tune-llama-3-8b-on-medical-dataset/llama-3-8b-cha
```

Explain code OpenAI

Merging the base model with the adapter

We'll first load the tokenizer and base model using the transformers library. Then, we'll set up the chat format using the trl library. Finally, we'll load and merge the adapter to the base model using the PEFT library.

The merge_and_unload() function will help us merge the adapter weights with the base model and use it as a standalone model.

```
from transformers import AutoModelForCausalLM, AutoTokenizer, pipeline
from peft import PeftModel
import torch
from trl import setup_chat_format
# Reload tokenizer and model
tokenizer = AutoTokenizer.from_pretrained(base_model)

base_model_reload = AutoModelForCausalLM.from_pretrained(
        base_model,
        return_dict=True,
        low_cpu_mem_usage=True,
        torch_dtype=torch.float16,
        device_map="auto",
        trust_remote_code=True,
)

base_model_reload, tokenizer = setup_chat_format(base_model_reload, tokenizer)

# Merge adapter with base model
model = PeftModel.from_pretrained(base_model_reload, new_model)

model = model.merge_and_unload()
```

Explain code OpenAI

Model Inference

To verify if our model has been merged correctly, we'll perform a simple inference using pipeline from the transformers library. We'll convert the message using the chat template and then provide a prompt to the pipeline. The pipeline was initialized using the model, tokenizer, and task type.

As a side note, you can set `device_map` to "auto" if you want to use multiple GPUs.

```
messages = [{"role": "user", "content": "Hello doctor, I have bad acne. How I

prompt = tokenizer.apply_chat_template(messages, tokenize=False, add_generation_p
pipe = pipeline(
    "text-generation",
    model=model,
    tokenizer=tokenizer,
    torch_dtype=torch.float16,
    device_map="auto",
)

outputs = pipe(prompt, max_new_tokens=120, do_sample=True, temperature=0.7, top_k
print(outputs[0]["generated_text"])
```

Explain code OpenAI

```
<|im_start|>user
Hello doctor, I have bad acne. How do I get rid of it?<|im_end|>
<|im_start|>assistant
Hi. I have gone through your question and understand your concern. For acne, you can use a com
bination of products containing salicylic acid and benzoyl peroxide. You can also use an oral
antibiotic like doxycycline or minocycline to reduce the inflammation. However, if the acne is
severe and does not respond to these treatments, you should consult a dermatologist for furthe
r evaluation and treatment. Hope I have answered your query. Let me know if I can assist you f
urther. Take care. Regards, Dr. Sumanth MBBS, DNB (Skin and
```

Our fine-tuned model is working as expected after being merged.

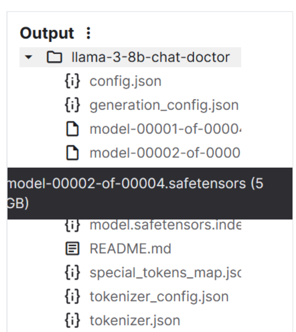
Saving and pushing the merged model

We'll now save a tokenizer and model using the `save_pretrained()` function.

```
model.save_pretrained("llama-3-8b-chat-doctor")
tokenizer.save_pretrained("llama-3-8b-chat-doctor")
```

Explain code OpenAI

The model files are stored in the safetensors format, and the total size of the model is around 16 GB.



We can push all the files to the Hugging Face Hub using the `push_to_hub()` function.

```
model.push_to_hub("llama-3-8b-chat-doctor", use_temp_dir=False)
tokenizer.push_to_hub("llama-3-8b-chat-doctor", use_temp_dir=False)
```

Explain code OpenAI

In the end, we can save the Kaggle Notebook just like we did previously.

Using the **Fine Tuned Adapter to fully model** Kaggle Notebook will help you resolve any issue related to running the code on your own.

3. Converting the Model to Llama.cpp GGUF

We can't use the safetensors files locally as most local AI chatbots don't support them. Instead, we'll convert it into the *llama.cpp* GGUF file format.

Setting up

Start the new Kaggle Notebook session and add the Fine Tuned Adapter to the full model Notebook.

Clone the llama.cpp repository and install the llama.cpp framework using the make command as shown below.

As a side note, the command below works only for the Kaggle Notebook. You might have to change a few things to run it on other platforms or locally.

```
%cd /kaggle/working
!git clone --depth=1 https://github.com/ggerganov/llama.cpp.git
%cd /kaggle/working/llama.cpp
!sed -i 's|MK_LDFLAGS   += -lcuda|MK_LDFLAGS   += -L/usr/local/nvidia/lib64 -lcud
!LLAMA_CUDA=1 conda run -n base make -j > /dev/null
```

Explain code

OpenAI

Converting Safetensors to GGUF model format

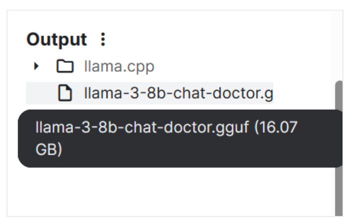
Run the following command in the Kaggle Notebook cell to convert the model into the GGUF format.

The convert-hf-to-gguf.py requires an input model directory, output file directory, and out type.

```
!python convert-hf-to-gguf.py /kaggle/input/fine-tuned-adapter-to-full-mode am
    --outfile /kaggle/working/llama-3-8b-chat-doctor.gguf \
    --outtype f16
```

POWERED BY DATALAB

Within a few minutes, the model is converted and saved locally. We can then save the notebook to save the file.



If you face issues running the above code, consult the HF LLM to GGUF Kaggle Notebook.

4. Quantizing the GGUF model

Regular laptops don't have enough RAM and GPU memory to load the entire model, so we have to quantify the GGUF model, reducing the 16 GB model to around 4-5 GB.

Setting up

Start the new Kaggle Notebook session and add the HF LLM to GGUF Notebook.

Then, install the llama.cpp by running the following command in the Kaggle Notebook cell.

```
%cd /kaggle/working
!git clone --depth=1 https://github.com/ggerganov/llama.cpp.git
%cd /kaggle/working/llama.cpp
!sed -i 's|MK_LDFLAGS   += -lcuda|MK_LDFLAGS   += -L/usr/local/nvidia/lib64 -lcud
!LLAMA_CUDA=1 conda run -n base make -j > /dev/null
```

Explain code

OpenAI

Quantization

The quantize script requires a GGUF model directory, output file directory, and quantization method. We are converting the model using the Q4_K_M method.

```
%cd /kaggle/working/

!./llama.cpp/llama-quantize /kaggle/input/hf-llm-to-gguf/llama-3-8b-chat-doctor.g
```

POWERED BY DATALAB

```
[ 289/ 291]             blk.31.ffn_down.weight - [14336,  4096,     1,     1], type =    f1
6, converting to q6_K .. size =    112.00 MiB ->    45.94 MiB
[ 290/ 291]             blk.31.ffn_norm.weight - [ 4096,     1,     1,     1], type =    f3
2, size =    0.016 MB
[ 291/ 291]                 output_norm.weight - [ 4096,     1,     1,     1], type =    f3
2, size =    0.016 MB
llama_model_quantize_internal: model size  = 15317.05 MB
llama_model_quantize_internal: quant size  =  4685.32 MB

main: quantize time = 520808.09 ms
main:    total time = 520808.09 ms
```

Our model size has significantly decreased from 15317.05 MB to 4685.32 MB.

Pushing the model file to Hugging Face

To push the single file to the Hugging Face Hub, we'll:

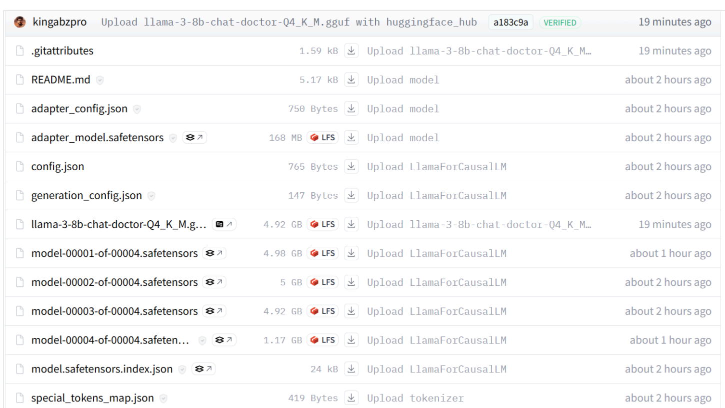
1. Login to the Hugging Face Hub using the API key.
2. Create the API object.
3. Upload the file by providing the local path, repo path, repo id, and repo type.

```python
from huggingface_hub import login
from kaggle_secrets import UserSecretsClient
from huggingface_hub import HfApi
user_secrets = UserSecretsClient()
hf_token = user_secrets.get_secret("HUGGINGFACE_TOKEN")
login(token = hf_token)

api = HfApi()
api.upload_file(
    path_or_fileobj="/kaggle/working/llama-3-8b-chat-doctor-Q4_K_M.gguf",
    path_in_repo="llama-3-8b-chat-doctor-Q4_K_M.gguf",
    repo_id="kingabzpro/llama-3-8b-chat-doctor",
    repo_type="model",
)
```

Explain code OpenAI

Our model is successfully pushed to the remote server, as shown below.



kingabzpro	Upload llama-3-8b-chat-doctor-Q4_K_M.gguf with huggingface_hub a183c9a VERIFIED		19 minutes ago
.gitattributes	1.59 kB	Upload llama-3-8b-chat-doctor-Q4_K_M...	19 minutes ago
README.md	5.17 kB	Upload model	about 2 hours ago
adapter_config.json	750 Bytes	Upload model	about 2 hours ago
adapter_model.safetensors	168 MB LFS	Upload model	about 2 hours ago
config.json	765 Bytes	Upload LlamaForCausalLM	about 2 hours ago
generation_config.json	147 Bytes	Upload LlamaForCausalLM	about 2 hours ago
llama-3-8b-chat-doctor-Q4_K_M.g...	4.92 GB LFS	Upload llama-3-8b-chat-doctor-Q4_K_M...	19 minutes ago
model-00001-of-00004.safetensors	4.98 GB LFS	Upload LlamaForCausalLM	about 1 hour ago
model-00002-of-00004.safetensors	5 GB LFS	Upload LlamaForCausalLM	about 2 hours ago
model-00003-of-00004.safetensors	4.92 GB LFS	Upload LlamaForCausalLM	about 2 hours ago
model-00004-of-00004.safeten...	1.17 GB LFS	Upload LlamaForCausalLM	about 1 hour ago
model.safetensors.index.json	24 kB	Upload LlamaForCausalLM	about 2 hours ago
special_tokens_map.json	419 Bytes	Upload tokenizer	about 2 hours ago

If you're still experiencing problems, please refer to the GGUF to Quantize Kaggle Notebook, which contains all the code and output.

If you're looking for a simpler way to convert and quantize your model, visit this Hugging Face Space and provide it with the Hub Model Id.

5. Using the Fine-Tuned Model Locally

To use the GGUF model locally, you must download and import it into the Jan application.

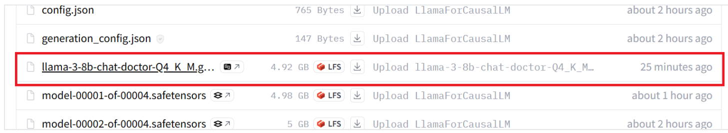
Downloading the model from Hugging Face

To download the model, we need to:

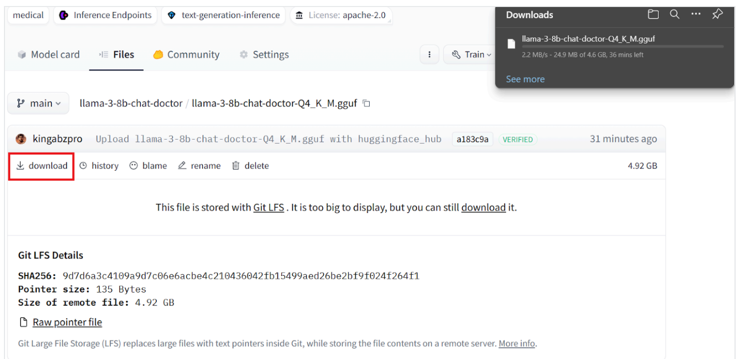
1. Go to our Hugging Face repository.

2. Click the *Files* tab.

3. Click on the quantized model file with the GGUF extension.



4. Click the *download* button.

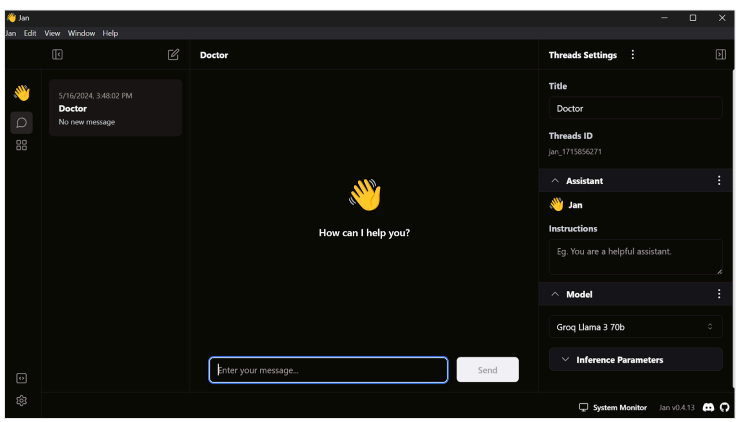


It will take several minutes to download the file locally.

Installing the Jan application

Download and install the Jan application from Jan AI.

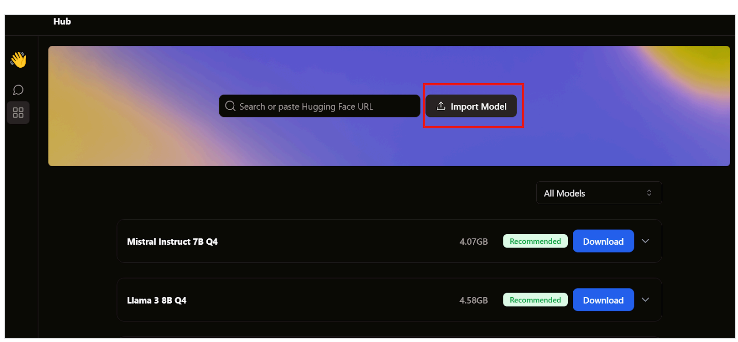
This is how it looks when you launch the Jan window application:



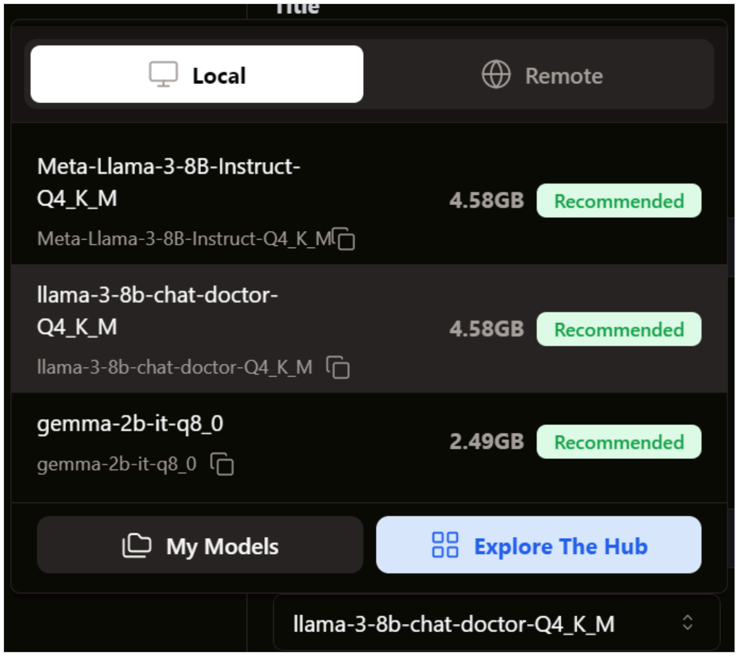
Loading the fine-tuned model in Jan

To add the model to the Jan application, we have to import the quantized GGUF file.

We need to go to the Hub menu and click *Import Model,* as shown below. We provide the location of the recently downloaded file, and that's it.



We go to the *Thread* menu and select the fine-tuned model.



Using the fine-tuned model in Jan

Before using the model, we need to customize it to display the response correctly. First, we modify the *Prompt* template in the *Model Parameters* section.

```
<|im_start|>system
{system_message}<|im_end|>
<|im_start|>user
{prompt}<|im_end|>
<|im_start|>assistant
```

Explain code OpenAI

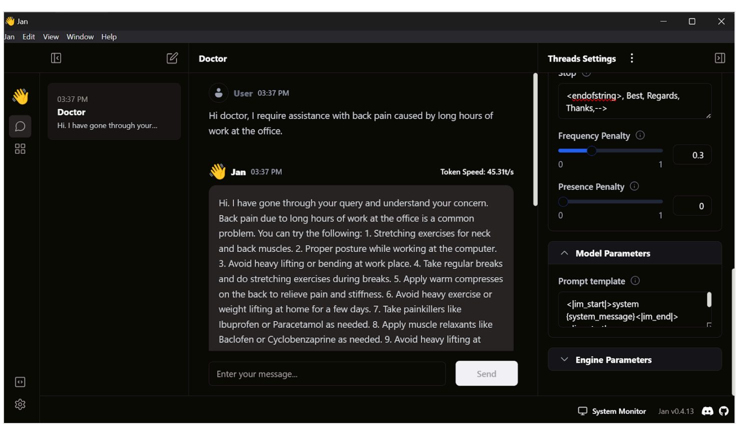
We add the *Stop* token and change the max token to 512 in the inference parameters.

```
<endofstring>, Best, Regards, Thanks,-->
```

Explain code OpenAI

We start writing the queries, and the doctor will respond accordingly.

Our fine-tuned model is working perfectly locally.



This model works with GPT4ALL, Llama.cpp, Ollama, and many other local AI applications. To learn how to use each, check out this tutorial on how to run LLMs locally.

Conclusion

Fine-tuning the Llama 3 model on a custom dataset and using it locally has opened up many possibilities for building innovative applications. The potential use cases range from private and customized conversational AI solutions to domain-specific chatbots, text classification, language translation, question-answering personalized recommendation systems, and even healthcare and marketing automation applications.

With the Ollama and Langchain frameworks, building your own AI application is now more accessible than ever, requiring only a few lines of code. To do that, follow the **LlamaIndex: A Data Framework for Large Language Models (LLMs)- based applications** tutorial.

In this tutorial, we learned to fine-tune the Llama 3 8B Chat on a medical dataset. We went through the process of merging the adapter with the base model, converting it to the GGUF format, and quantizing it for local use on a Jan chatbot application.

If you want to learn more, check out this four-course skill track on **Developing Large Language Models**.

AUTHOR

Abid Ali Awan

in

As a certified data scientist, I am passionate about leveraging cutting-edge technology to create innovative machine learning applications. With a strong background in speech recognition, data analysis and reporting, MLOps, conversational AI, and NLP, I have honed my skills in developing intelligent systems that can make a real impact. In addition to my technical expertise, I am also a skilled communicator with a talent for distilling complex concepts into clear and concise language. As a result, I have become a sought-after blogger on data science, sharing my insights and experiences with a growing community of fellow data professionals. Currently, I am focusing on content creation and editing, working with large language models to develop powerful and engaging content that can help businesses and individuals alike make the most of their data.

TOPICS

Artificial Intelligence (AI) Python

Related

TUTORIAL

Fine-Tuning LLaMA 2: A Step-by-Step Guide to Customizing the...

TUTORIAL

How to Run Llama 3 Locally: A Complete Guide

TUTORIAL

An Introductory Guide to Fine-Tuning LLMs

See More →

LEARN

Learn Python

Learn R

Learn AI

Learn SQL

Learn Power BI

Learn Tableau

Learn Data Engineering

Assessments

Career Tracks

Skill Tracks

Courses

Data Science Roadmap

DATA COURSES

Python Courses

R Courses

SQL Courses

Power BI Courses

Tableau Courses

Alteryx Courses

Azure Courses

Google Sheets Courses

AI Courses

Data Analysis Courses

Data Visualization Courses

Machine Learning Courses

Data Engineering Courses

Probability & Statistics Courses

DATALAB