Taming the LLaMA: Fine-Tuning a 3B Parameter Model for Artificial Intelegence and Machine Learning

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1 Introduction

Large language models (LLMs) have revolutionized natural language processing tasks, which offers advanced capabilities in generating human like responses. This project aimed to fine-tune LLaMA, a 3 billion parameter model on a scraped dataset that contains questions and answers related to data science, artificial intelligence, and machine learning. By using Kaggle's free GPU resources, we successfully fine-tuned two models: one trained on the full dataset and another on a subset of the data, allowing us to compare their performance in generating accurate and contextually relevant answers. This report outlines the steps taken in data collection, model fine-tuning, and performance evaluation.

2 Web Scraping Cross Validated

This section of the report provides an overview of the Cross Validated website, details about the scraped data, and the tools used in the scraping process.

2.1 Overview of Cross Validated

With the ever-expanding fields of statistics and machine learning (ML), it is hard to keep up with all of the new ideas and models being introduced. Cross Validated [4], part of the Stack Exchange network, hosts a specialised question-and-answer platform dedicated to topics such as:

- Statistics
- Machine learning
- Data analysis
- Data mining
- Data visualisation

Cross Validated provides a community-driven environment for professionals and enthusiasts to ask and answer questions, share knowledge and discuss best practices in these fields [5].

2.2 Data Overview

The objective we wanted to complete was to gather any meaningful insights on common challenges faced by data scientists and optimal solutions to these challenges. Cross Validated offered us a wealth of information, more than sufficient to achieve our goal.

We scraped 39,668 of the highest-voted questions and their corresponding highest-voted answer from Cross Validated. Only the text bodies of each question and answer were scraped to ensure the data contained no personal information. We strictly wanted to focus on a model that only generates text. Therefore, we excluded any questions or answers which contained code blocks in the body of the text.

2.3 Tools and Techniques for Data Scraping

Python and the Beautifulsoup4 library [7] was utilised to scrape the question-and-answer pairs from Cross Validated. Stack Exchange enforces several throttling limits based on the Internet Protocol (IP) address of the user [8]. If a single IP exceeds 30 requests per second, any additional requests will be dropped and the user's IP will be temporarily blocked. To prevent our scraper from violating this throttle, we implemented an exponential backoff function, which reduced the likelihood of triggering the throttle and ensuring smoother data retrieval.

All question-and-answer pairs were scraped in batches of 5,000 observations and subsequently stored in their respective Javascript object notation (JSON) files.

3 Ethics Regarding Web Scraping

This section of the report focuses on the ethical considerations we examined prior to scraping our data. While scraping information from the web can be extremely useful, especially for building a large language model, the ethical concerns should always be addressed. This includes intellectual property, personal property and informed consent. There is a fine balance between balancing respect for privacy and the utility of web scraping.

3.1 Intellectual Property

There are laws that protect websites such as copyright and one should step carefully not to unintentionally break a law. It is important therefore to read the sites terms of service to make sure you don't use any data you are not allowed to [9].

3.2 Personal Property

Personal information is protected by the protection of personal information (POPI) act and it is usually of your best interest to not scrape any personal information from a website. If personal information does slip through one should pseudonymise and anonymise the data.

3.3 Informed Consent

Even if the data is publicly available it does not mean you have the right to use it. You should ask beforehand if you are allowed to use the data and for what purposes. There are steps you can follow to help you ethically scrape data:

- Targeted scraping: Only scrape the data that you need, do not scrape extra information such as personal information.
- Legal compliance: Ensure that you follow the websites terms of service as well as any other laws.
- Respecting data ownership: Online data still belongs to the person who posted it, make sure you use the data in a way that respects their rights.

4 Wrangling The Scraped Data

This section of the report focuses on cleaning, normalising and saving the scraped data by applying wrangling techniques.

4.1 Data Cleaning

The scraped data was cleaned to ensure there are no irrelevant text in the data. Questions that were closed or locked by the site admins contained a post notification board, which was removed from the data by utilising beautifulsoup4. Any Hypertext Markup Language (HTML) tags that contained relevant text was then kept in all of the question-and-answer pairs. These HTML tags were: <p>, <code>, <a>, <ol>, <li>, <ul>, <strong>, <b>, <i>, <u>, <mark>, <small>, <sub>, <sup>, <span>, <table>.

From these remaining HTML tags, the text were stripped away and we were left with only the text of all of the question-and-answer pairs.

4.2 Text Normalisation, Structuring and Saving the Data

From the cleaned body text of the questions-and-answer pairs, some characters were encoded as Unicode characters. These characters were then encoded to either American Standard Code for Information Interchange (ASCII) characters if they had an ASCII index or to HTML entities if they did not.

The data was then structured into a list of dictionaries, categorising questions as the role of the "user" and the answers as the role of the "assistant". This format was used to comply with the format required by the LLaMa model.

The list of dictionaries, which contains the cleaned, normalised and structured data, was then saved to a new JSON file.

5 LLaMA Model Overview and Fine-tuning Process

We used the large language model meta AI (LLaMA) model, specifically the 3-billion parameter version, which is part of a family of transformer-based models [1]. Llama is an open source LLM provided by Meta and we specifically used the LLaMA-3B-Instruct model for question-and-answering. LLaMA is designed for natural language processing tasks, and its architecture follows a standard decoder-only transformer, making it suitable for autoregressive text generation. This model is ideal for tasks like question answering, summarisation, and dialogue generation, but also has many other abilities and applications.

5.1 Model Architecture

The LLaMA model is built on the transformer architecture, which uses self attention mechanisms to process input sequences and generate output. It is also autoregressive which means that it generates text one token at a time, using previously generated tokens to predict the next one.

Key components of the LLaMA model architecture include:

- Multi-Head Self-Attention: This allows the model to focus on different parts of the input sequence at the same time, which allows it to capture relationships between words across long sequences.
- Attention Heads: 32 heads per layer
- Attention Head Dimension: 128 dimensions per head
- Feed-Forward Networks (FFN): These are fully connected layers that transform the output of the self-attention mechanism.
- Feed-Forward Network Dimension: 11008 units (intermediate layer)
- Model Size: 3 billion parameters
- Number of Layers: 32 transformer layers
- Hidden Size: 4096 hidden units per layer
- Positional Encoding: Rotary positional encodings (RoPE)
- Layer Normalisation: Applied before self-attention and feed-forward layers

5.2 Pre-Trained Weights and Dataset

The pre-trained weights for the LLaMA model were obtained from the Unsloth repository, which provided a specialised model version fine-tuned for question-and-answer and conversational tasks. The initial pre-training of LLaMA was done on a large corpus of diverse text, including books, research papers, and web data. This gives the model a strong foundation in understanding complex language structures and domain specific terminology.

We fine-tuned the model using a custom dataset of 39,668 question-and-answer pairs, which were scraped from 'Cross Validated' which focused on data science, artificial intelligence (AI), and ML topics. These questions ranged from simple definitions to more complex conceptual explanations. Fine-tuning allowed the model to better capture the complexity of these technical subjects, which makes it more accurate in responding and understanding to domain specific applications.

5.3 Fine-Tuning Process

The version of LLaMA we used was fine-tuned for question-and-answering tasks, making it ideal for providing answers to questions related to data science, AI, and ML. Fine-tuning was performed using the Low-Rank Adaptation (LoRA) technique, which allows for efficient fine-tuning of large models by freezing most of the pre-trained model parameters and only updating a small subset of parameters. This drastically reduces the computational resources required, and also still achives high accuracy. We used a combination of gradient accumulation and batch processing to handle the relatively large dataset size during the fine-tuning phase.

The fine-tuning process involved adjusting several hyperparameters, including:

- Learning rate: Set to 2e-4 for optimal convergence without overfitting.
- Batch size: A batch size of 4 per GPU was used to maximise the use of available memory.
- Gradient accumulation: This was set to 4, allowing larger effective batch sizes without exceeding memory limits.

We also used 4-bit quantization during training to optimise memory usage, enabling us to fine-tune the model on hardware with limited GPU resources.

6 Quantization and Tokenization

Tokenization creates tokens for words or subwords in a text. We used Byte-Pair Encoding (BPE), which splits long complex words into smaller words which is then easier for the model to understand. The tokens are then mapped to numerical representations. Each token then has the meaning in the context of which it is used. The model can then make predictions from these tokens.

Quantization is the process of simplifying machine learning models by reducing the precision of the numbers they use for weights and activations. Normally they use 32-bit floating-point numbers, which is demanding on memory and processing power. By switching to lower precision, such as 8-bit or 4-bit numbers, the model is made faster and more memory-efficient without affecting accuracy too much. In this project, we employed *4-bit quantization* during the fine-tuning stage. This method allowed it to run on hardware with limited GPU resources when fine-tuning our model.

7 UnSloth Optimisation

Fine-tuning is devined as the process of updating the actual "brains" of the language model through back-propagation. But, finetuning can get very slow and very resource intensive. UnSloth Optimisation helps to optimise the process of finetuning our model.

UnSloth is a fine-tuning framework designed to enhance productivity by streamlining the process of adapting LLM like Llama-3.2. UnSloth makes fine-tuning LLM [2]:

- 2 times faster

- Use 70% less memory
- Automates hyperparameter tuning
- Maintains model accuracy

We used UnSloth optimisation to optimise the fine-tuning process of our LLaMa model [3]. UnSloth applies the following techniques to ensure the fine-tuning of our model is optimised as much as possible:

- Layer-freezing: reduces computation, by only fine-tuning specific layers.
- Gradient checkpointing: recomputes activations, which lowers memory usage.
- Dynamic hyperparameter tuning: Automatically adjusts the hyperparameters during the fine-tuning process.
- Efficient data loading: Speeds up fine-tuning with optimised data handling.

8 Implementation

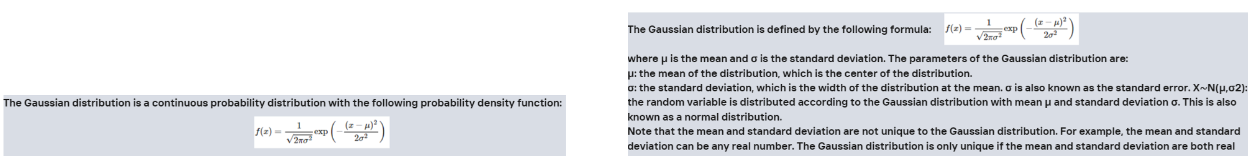
This section introduces the final models after fine-tuning the LLaMa-3.2 model on our scraped data. We wanted to explore if more data is always better for training or fine-tuning a model.

We constructed 2 models, the first model fine-tuned the original model on the full dataset of 39,668 question-and-answer pairs for one epoch and the second model fine-tuned the original model on the 10,000 highest-voted question-and-answer pairs for three epochs. Both of the models took approximately 12 hours to complete the fine-tuning process.

9 Results

This section of the reports presents the results of our 2 models. Each model is given the same prompts to generate a response on and the output is then compared to one another. We prompted both models with a data science introductory, application and complex level question.

Figure 1 displays the response of our two models when prompted with the following introductory level question: "*What is the gaussian formula and all of its parameters?*" Figure 2 displays the response of our two models when prompted with the following application level question: "*Can you explain how decision trees handle numerical variables in a classification task?*" Figure 3 displays the response of our two models when prompted with the following complex level question: "*How do gradient-based optimization techniques like Adam handle exploding or vanishing gradient problems in deep learning models?*"



The Gaussian distribution is a continuous probability distribution with the following probability density function:

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$

where μ is the mean and σ is the standard deviation.

The Gaussian distribution is defined by the following formula: $f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$

where μ is the mean and σ is the standard deviation. The parameters of the Gaussian distribution are:
μ: the mean of the distribution, which is the center of the distribution.
σ: the standard deviation, which is the width of the distribution at the mean. σ is also known as the standard error. X~N(μ,σ2): the random variable is distributed according to the Gaussian distribution with mean μ and standard deviation σ. This is also known as a normal distribution.
Note that the mean and standard deviation are not unique to the Gaussian distribution. For example, the mean and standard deviation can be any real number. The Gaussian distribution is only unique if the mean and standard deviation are both real numbers.

(a) Model trained on all of the data for one epoch

(b) Model trained on 10,000 observations for 3 epochs

Figure 1: Introductory level question : "*What is the gaussian formula and all of its parameters?*"

From Figure 1b, we can see that the model trained on less data for more epochs provided the exact same output as the model trained on more data for less epochs, seen in Figure 1a, with a more in depth explanation of what each parameter represents in the equation.

From Figure 2a shows that model 1 provided a very good response to the question, where 2b shows that the response from model 2 was also a good response on the questions and provided even more information on how the decision tree handles categorical features when the tree is induced.

In a classification problem, the decision tree splits the data based on the feature values. The splitting criterion is typically the entropy of the feature values. The entropy is the measure of the uncertainty of the feature values. The lower the entropy, the more certain the feature values are. In the case of numerical features, the entropy is calculated as follows: $H(X) = -\sum_{i=1}^{n} p_i \log p_i$

where pi is the probability of the feature value xi. The entropy is calculated for each feature value, and the feature values are split based on the feature values with the highest entropy. The feature values with the highest entropy are split into two subsets, and the decision tree is constructed by splitting the data based on the feature values. The decision tree is constructed recursively, and the splitting criterion is the entropy of the feature values.

(a) Model trained on all of the data for one epoch

Decision trees can handle numerical variables in several ways. Here are a few:
In the most simple case, decision trees can treat a numerical variable as an attribute. This is done by simply splitting the data based on the value of the numerical variable. For example, if we have a variable called "salary" that ranges from 0 to 100000, we can split the data based on whether it is less than 20000 or not. This is called a split by value. Decision trees can also treat a numerical variable as a continuous variable. In this case, the tree can be split based on the range of the numerical variable. For example, if we have a variable called "age" that ranges from 0 to 100, we can split the data based on whether it is less than 30 or not. Decision trees can also treat a numerical variable as a categorical variable. In this case, the tree can be split based on the category of the numerical variable. For example, if we have a variable called "country" that has values "USA", "Canada", "Mexico", etc., we can split the data based on whether it is USA, Canada, or Mexico, etc.
Note that these are the most simple ways to treat numerical variables. There are more sophisticated ways to treat numerical variables in decision trees. For example, you can treat a numerical variable as a time series, or as a variable that has different values for different levels of a categorical variable.

(b) Model trained on 10,000 observations for 3 epochs

Figure 2: Application level question : ”*Can you explain how decision trees handle numerical variables in a classification task?*”

Adam and most other modern optimization algorithms work by adjusting the weights in the direction that the gradient is pointing. If the gradient is not pointing in the right direction, then the weights will not be updated in that direction. If the gradient is consistently pointing in the same direction, then the weights will not be updated at all. In this sense, Adam and other modern algorithms are not immune to exploding or vanishing gradients, but they work in a way that makes exploding or vanishing gradients less likely. For example, in a neural network, the output of the final layer is a vector of length n, where n is the number of parameters in the final layer. The gradient of the loss function with respect to the parameters of the final layer is a vector of length n in the same direction as the vector of parameter values.
If the gradient is not pointing in the right direction, then the weights will not be updated at all. If the gradient is consistently pointing in the same direction, then the weights will not be updated at all. This means that the weights will either stay the same or move in the direction of the gradient. If the gradient is pointing in the same direction for all parameters, then the weights will move in the direction of the gradient. This is the case for exploding gradients, where the gradient is exploding in magnitude. In general, Adam and other modern algorithms work by adjusting the weights in the direction that the gradient is pointing. This means that the weights will move in the direction of the gradient, but they will not move in the direction that the gradient is pointing in a way that causes exploding or vanishing gradients

(a) Model trained on all of the data for one epoch

The gradient of a neural network is a vector of gradients of the individual weights. The gradient of a weight vector is the sum of the gradients of the weights that are connected to it. If the weights are large, the gradients can be very large. If the weights are small, the gradients can be very small. If the gradients are too large, they can cause a numerical overflow, and if the gradients are too small, they can cause a numerical underflow. The Adam algorithm is designed to handle these problems. The Adam algorithm is a stochastic optimization algorithm that uses a momentum term to help the optimizer avoid overshooting and underestimating the gradient. It uses a learning rate that is a function of the current gradient and the momentum. The momentum is a weighted average of the past gradients. The weights are updated using the gradient and the momentum. The momentum is used to help the optimizer avoid overshooting and underestimating the gradient.
The Adam algorithm is a very popular stochastic optimization algorithm for deep neural networks. The Adam algorithm is an adaptive learning rate method that means it adjusts the learning rate based on the current gradient. The learning rate is a function of the current gradient and the momentum. The momentum is a weighted average of the past gradients. The weights are updated using the gradient.

(b) Model trained on 10,000 observations for 3 epochs

Figure 3: Complex level question : ”*How do gradient-based optimization techniques like Adam handle exploding or vanishing gradient problems in deep learning models?*”

From Figure 3a and Figure 3b model 1 and model 2 respectively gives a good response of the given question. Model 1 focuses more on the Adam optimiser and how it handles exploding or vanishing gradients, where model 2 focuses more on different techniques used by gradient-based optimisation techniques to handle exploding and vanishing gradients.

10 Conclusion

We have successfully scraped and wrangled data (from CrossValidated) and used that data to fine-tune a 3 billion parameter LLaMa model. After training 2 distinct models - one with a full epoch which uses all the training data (39,686) and another with 3 epochs on 10,000 datapoints - on Kaggle using their free 12 hour GPU sessions, we were able to get and run inference on these large models and utilize their power.

Model 1 is able to give us broader answers to our related topics but lacks a deeper understanding of the concepts whereas Model 2 is able to dive deeper into the topics but is not able to discuss as many topics. Overall we prefer model 2 because it produces results that are of higher understanding and complexity.

We are also able to locally run our models given the correct computer architecture. All in all we have successfully been able to create models that are capable of delivering accurate and context aware responses to complex AI, machine learning, and data science questions.

11 References

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