INTEL UNNATI INDUSTRIAL TRAINING PROGRAM – 2024

A Report on

Introduction to GenAI and Simple LLM Inference on CPU and finetuning of LLM Model to create a Custom Chatbot

GitHub Repository: https://github.com/JoyM268/Intel-Unnati-Industrial-Training-Program-2024

Submitted By:

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Problem Statement:

Introduction to GenAI and Simple LLM Inference on CPU and finetuning of LLM Model to create a Custom Chatbot.

Problem Description:

This problem statement is designed to introduce beginners to the exciting field of Generative Artificial Intelligence (GenAI) through a series of hands-on exercises Participants will learn the basics of GenAI, perform simple Large Language Model (LLM) inference on a CPU, and explore the process of fine-tuning an LLM model to create a custom Chatbots.

Major Challenges:

1. Pre-trained Language Models can have large file sizes, which may require significant storage space and memory to load and run.
2. Learn LLM inference on CPU.
3. Understanding the concept of fine-tuning and its importance in customizing LLMs.
4. Create a Custom Chatbot with fine-tuned pre-trained Large Language Models (LLMs) using Intel AI Tools.

Tools:

- **Intel Developer Cloud (IDC):** IDC is used for developing and deploying AI projects. This platform not only offers the advantage of high-performance GPU and enterprise-grade CPU but also provides access to the latest Intel hardware and software capabilities.

- **Intel Extension For Transformers:** Intel® Extension for Transformers is an innovative toolkit designed to accelerate GenAI/LLM everywhere with the optimal performance of Transformer-based models on various Intel platforms, including Intel Gaudi2, Intel CPU, and Intel GPU.

- **Hugging Face Transformer:** It APIs and tools to easily download and train state-of-the-art pretrained models**.**

- **Transformers Library:** The Transformers library is a popular Python library for working with state-of-the-art natural language processing (NLP) models, especially those based on the transformer architecture. It's developed by Hugging Face, a company focused on machine learning tools.

- **Llama2 Model:** LLaMA2 is a powerful large language model by Meta, excelling in tasks like text generation and code comprehension, with several sizes available for research and commercial use.

- **Kaggle:** Kaggle enables users to find and publish datasets, explore and build models in a web-based data science environment, work with other data scientists and machine learning engineers, and enter competitions to solve data science challenges.

- **TinyLlama Model:** TinyLlama is a compact 1.1B language model pretrained on around 1 trillion tokens for approximately 3 epochs. It builds upon the architecture and tokenizer of Llama 2. The architecture of Llama 2 consists of 24 transformer layers with 16 attention heads and a hidden size of 307223. The tokenizer used is a byte pair encoding (BPE), allowing the model to handle rare or unknown words effectively.

Building a Chatbot:

In the session 1, we were introduced to the fundamentals of Large Language Models (LLMs) and Transformers, key technologies powering modern AI applications. A practical demonstration involved using the Intel Extension for Transformers to build a chatbot capable of providing informative responses to user queries.

we were provided with a Jupyter Notebook (build_chatbot_on_spr.ipynb) that facilitated the creation of an AI chatbot. We used ‘intel-extension-for-transformers’ library for creating the chatbot. First we installed ‘intel-extension-for-transformers’ library and then installed the necessary requirements given in the file requirements_cpu.txt. The chatbot used intel’s Neural Chat Model and gave the desired output on running it. We need to login into the Hugging Face using access tokens before executing the code.

The following code is used to create the chatbot:

```
from intel_extension_for_transformers.neural_chat import build_chatbot, PipelineConfig

from intel_extension_for_transformers.transformers import MixedPrecisionConfig

config = PipelineConfig(optimization_config=MixedPrecisionConfig())

chatbot = build_chatbot(config)
```

Once the chatbot is created we can prompt it as shown below:

```
response = chatbot.predict(query="Tell me about Intel Xeon Scalable Processors.")
print(response)
```

Which gives us the output:

```
The Intel Xeon Scalable Processors represent a family of high-performance central
processing units (CPUs) designed for data centers, cloud computing, and other
demanding workloads. These processors offer significant improvements in performance,
efficiency, and scalability compared to their predecessors.


Key features include:

1. Advanced architecture: The Intel Xeon Scalable Processors utilize the latest
microarchitecture, which enables better performance and power efficiency.

2. Enhanced security: With built-in hardware-level security features like Intel Software
Guard Extensions (SGX), these processors provide robust protection against potential
threats.

3. Scalability: The modular design allows for flexible configurations, enabling users to
choose the right combination of cores, memory capacity, and I/O capabilities to meet
specific needs.

4. Optimized for virtualization: The Intel Xeon Scalable Processors are optimized for
virtual environments, supporting multiple operating systems and applications on a single
server.

5. High-speed connectivity: Integrated support for high-speed interconnects such as
Intel Omni-Path Architecture (OPA) and Intel QuickAssist Technology (QAT) ensures
efficient communication between servers and devices
```

We experimented with different prompts to test the chatbot's capabilities:

Example 1:

Prompt:

```
response1 = chatbot.predict(query="What is difference between GPU and CPU.")
print(response1)
```

Output:

```
The main difference between a Graphics Processing Unit (GPU) and a Central Processing
Unit (CPU) lies in their primary functions and architectures.


A CPU is the brain of a computer, responsible for executing instructions and managing
various tasks. It's designed to handle general-purpose computing tasks like processing
data, running programs, and controlling peripheral devices. CPUs have a single
instruction stream and can perform multiple tasks simultaneously through
multithreading or multiprocessing.


On the other hand, a GPU is specialized hardware optimized for handling complex
mathematical calculations and rendering visuals. GPUs excel at parallel processing,
which means they can execute many tasks simultaneously using thousands of small
processing units called CUDA cores. This makes them ideal for graphics-intensive
applications such as gaming, video editing, and scientific simulations.


In summary, while both CPUs and GPUs are essential components of modern
computers, they serve different purposes. CPUs focus on general-purpose computing
tasks, whereas GPUs specialize in high-performance graphics and parallel processing.
```

Example 2:

Prompt:

```
response2 = chatbot.predict(query="Explain finetuning of a ai model.")
print(response)
```

Output:

```
Finetuning of an AI model is a process where you take an existing pre-trained model and
further adapt it for a specific task or domain. This technique helps improve the
performance of the model on new data sets or tasks without starting from scratch.


Imagine you have a smart robot that can perform various tasks like cooking, cleaning,
and playing music. At first, this robot was designed to only cook. However, as time went
by, you wanted it to learn how to clean your house too. Instead of building a completely
new robot for cleaning, you decide to teach the existing cooking robot some additional
skills. That's what we call finetuning - adapting the original model (robot) to perform
better in a different area (cleaning).


To finetune an AI model, you typically follow these steps:

1. Choose a pre-trained model: Start with a model that has already been trained on a
large dataset for a particular task. For example, if you want to create a model that can
recognize images, you might use a pre-trained image recognition model.

2. Prepare the new dataset: Collect a new set of data related to the desired task or
domain.
```

Example 3:

Prompt:

```
response4 = chatbot.predict(query="What is a Transformer")
print(response4)
```

Output:

```
A Transformer is a type of neural network architecture designed for natural language
processing tasks. It was introduced in 2017 by researchers at Google AI. The model has
shown impressive results in various NLP applications such as machine translation, text
summarization, and question answering. Transformers learn to represent words and
sentences through self-attention mechanisms, which allow them to understand the
context and relationships between different parts of the input data. This makes them
highly effective in understanding complex linguistic structures and generating
meaningful outputs.
```

Example 4:

Prompt:

```
response3 = chatbot.predict(query="What are TPU, are they better than GPU")
print(response3)
```

Output:

```
TPU stands for Tensor Processing Unit, which is a specialized hardware designed for
machine learning tasks. It's optimized for running deep neural networks efficiently. GPUs
(Graphics Processing Units) were initially developed for rendering graphics in video
games but have since been repurposed for various computing tasks, including machine
learning.

Comparing TPUs and GPUs can be complex as it depends on the specific application
and workload. Generally, TPUs offer higher performance for certain machine learning
tasks like training large models or performing inference at scale. However, GPUs still
excel in other areas such as general-purpose computing, gaming, and handling diverse
workloads. So, while TPUs may be better suited for some AI applications, GPUs remain
versatile and valuable across multiple domains.
```

Example 5:

Prompt:

```
response5 = chatbot.predict(query="What is a AGI")
print(response5)
```

Output:

```
A General Artificial Intelligence (AGI) refers to a hypothetical future AI system that can
perform any intellectual task as well as or better than a human being. It would possess a
high level of intelligence, creativity, problem-solving abilities, and adaptability across
various domains. AGIs are still in the realm of science fiction, with current AI systems
focusing on specific tasks and limited capabilities.
```

Finetuning the Chatbot:

Fine-tuning is the process of taking a pretrained machine learning model and further training it on a smaller, targeted data set. The aim of fine-tuning is to maintain the original capabilities of a pretrained model while adapting it to suit more specialized use cases.

In the session 2, we were introduced to the concept of fine-tuning of Large Language Models (LLMs), A practical demonstration involved using the Intel Extension for Transformers to fine-tune the Llama 2 model on the Alpaca Dataset. We used TinyLlama_v1.1 model instead of Llama2 model.

A Jupyter Notebook (single_node_finetuning_on_spr.ipynb) was provided that facilitated the fine-tuning of a ai model. Similar to the notebook in session 1 we used 'intel-extension-for-transformers' library and installed the requirements given in requirements.txt.

Dataset: We are using the Alpaca dataset from Stanford University as the general domain dataset to fine-tune the model. This dataset is provided in the form of a JSON file, alpaca_data.json. In Alpaca, researchers have manually crafted 175 seed tasks to guide text-davinci-003 in generating 52K instruction data for diverse tasks.

Model: TinyLlama_v1.1 adopts exactly the same architecture and tokenizer as Llama 2. This means TinyLlama can be plugged and played in many open-source projects built upon Llama. Besides, TinyLlama is compact with only 1.1B parameters. This compactness allows it to cater to a multitude of applications demanding a restricted computation and memory footprint.

Before we fine-tune the TinyLlama_v1.1 model on Alpaca dataset, we have to login into the Hugging Face using access tokens. We have to execute the following command:

```
huggingface-cli login
```

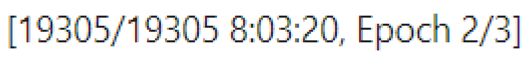
After executing the command enter the Hugging Face Access Token, the access token can be generated at the following link:

https://huggingface.co/settings/tokens

The following code is used to fine-tune the TinyLlama_v1.1 model:

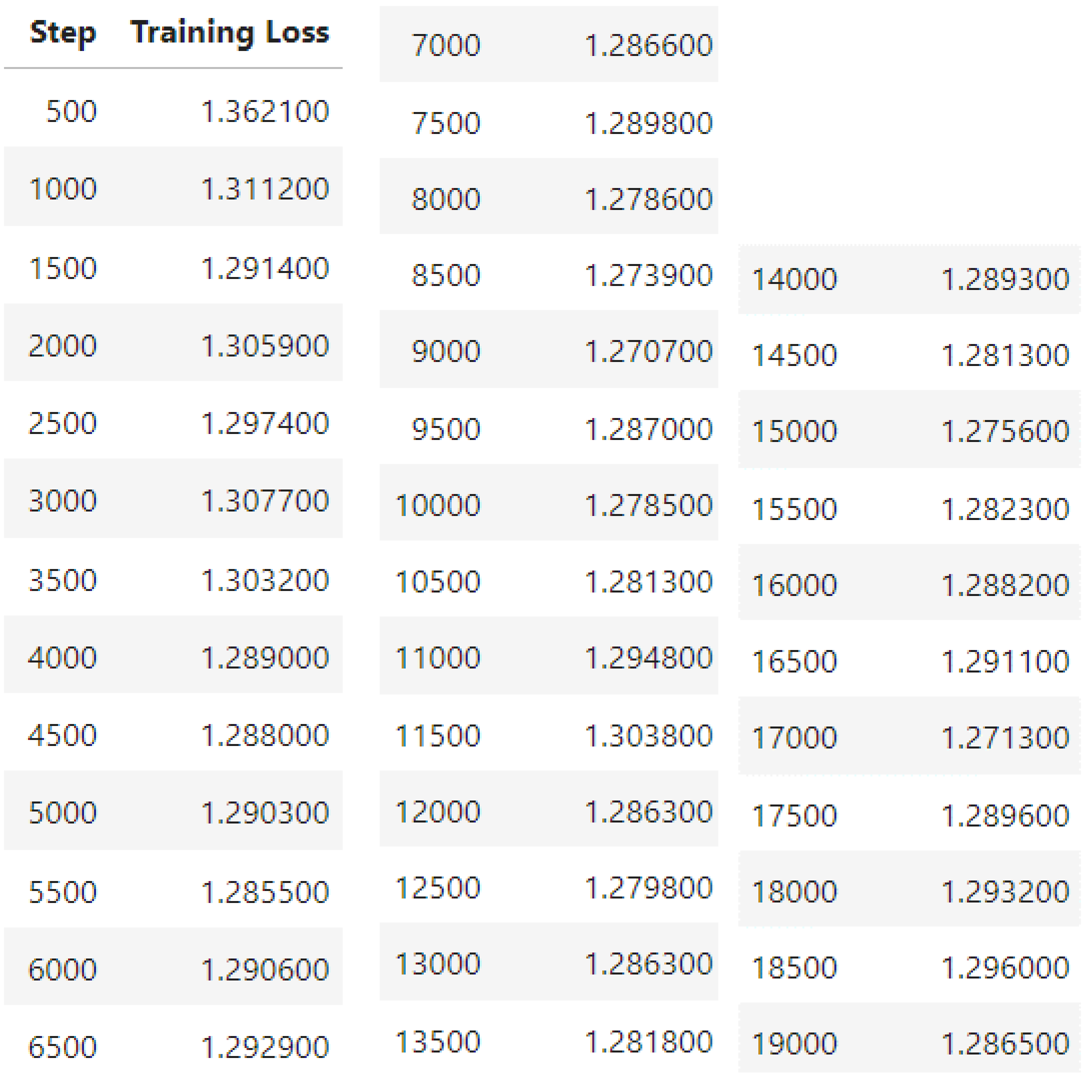
```
from transformers import TrainingArguments
from intel_extension_for_transformers.neural_chat.config import (
   ModelArguments,
   DataArguments,
   FinetuningArguments,
   TextGenerationFinetuningConfig,
)
from intel_extension_for_transformers.neural_chat.chatbot import finetune_model
model_args = ModelArguments(model_name_or_path="TinyLlama/TinyLlama_v1.1")
data_args = DataArguments(train_file="alpaca_data.json",
validation_split_percentage=1)
training_args = TrainingArguments(
   output_dir='./tmp',
   do_train=True,
   do_eval=True,
   num_train_epochs=3,
   overwrite_output_dir=True,
   per_device_train_batch_size=4,
   per_device_eval_batch_size=4,
   gradient_accumulation_steps=2,
   save_strategy="no",
   log_level="info",
   save_total_limit=2,
   bf16=True,
)
finetune_args = FinetuningArguments()
finetune_cfg = TextGenerationFinetuningConfig(
         model_args=model_args,
         data_args=data_args,
         training_args=training_args,
         finetune_args=finetune_args,
      )
finetune_model(finetune_cfg)
```

Fine-tuning the TinyLlama_v1.1 model on the Alpaca dataset took approximately 8 hours as shown in Fig 1 and had a Training loss of 1.2865 as shown is Fig 2. The Eval Metrics are shown in Fig 3.



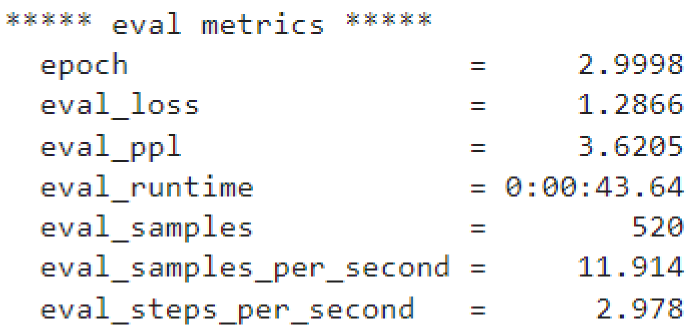
```
[19305/19305 8:03:20, Epoch 2/3]
```

Fig 1: Training Time Taken



Step	Training Loss
500	1.362100
1000	1.311200
1500	1.291400
2000	1.305900
2500	1.297400
3000	1.307700
3500	1.303200
4000	1.289000
4500	1.288000
5000	1.290300
5500	1.285500
6000	1.290600
6500	1.292900
7000	1.286600
7500	1.289800
8000	1.278600
8500	1.273900
9000	1.270700
9500	1.287000
10000	1.278500
10500	1.281300
11000	1.294800
11500	1.303800
12000	1.286300
12500	1.279800
13000	1.286300
13500	1.281800
14000	1.289300
14500	1.281300
15000	1.275600
15500	1.282300
16000	1.288200
16500	1.291100
17000	1.271300
17500	1.289600
18000	1.293200
18500	1.296000
19000	1.286500

Fig 2: Training Loss at each step.

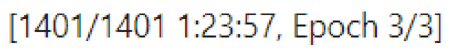


```
***** eval metrics *****
  epoch                   =     2.9998
  eval_loss               =     1.2866
  eval_ppl                =     3.6205
  eval_runtime            = 0:00:43.64
  eval_samples            =        520
  eval_samples_per_second =     11.914
  eval_steps_per_second   =      2.978
```

Fig 3: Eval Metrics.

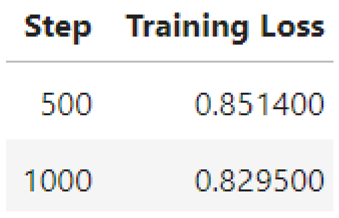
Project (Finance Chatbot):

Leveraging the knowledge gained from the two sessions conducted by the Intel Unnati team, and through the execution of the provided Jupyter Notebooks, we have developed a another chatbot. This chatbot has been fine-tuned on the finance_alpaca.json dataset, specifically designed to address user inquiries which are finance related. The underlying architecture utilizes the TinyLlama pre-trained model. The finetuning of the model took approximately one and half hour as shown in Fig 4 and the training loss was 0.829500 as Shown in Fig 5. The eval metrics are shown in Fig 6. The code and its output are present in the Jupyter Notebook finance_chatbot.ipynb.



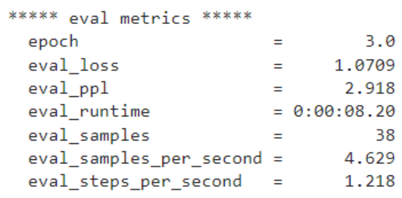
```
[1401/1401 1:23:57, Epoch 3/3]
```

Fig 4: Training Time.



Step	Training Loss
500	0.851400
1000	0.829500

Fig 5: Training Loss at each step.



```
***** eval metrics *****
  epoch                   =        3.0
  eval_loss               =     1.0709
  eval_ppl                =      2.918
  eval_runtime            = 0:00:08.20
  eval_samples            =         38
  eval_samples_per_second =      4.629
  eval_steps_per_second   =      1.218
```

Fig 6: Eval Metrics.

For prompt:

> what is meant by cost of equity?

We get the response:

> Cost of equity is a financial metric used to evaluate the cost of capital for a company. It is calculated by dividing the total return on equity (ROE) by the cost of equity (COE). The COE is a measure of the cost of capital for a company, which is the amount of money required to finance the company's operations.
>
> The cost of equity is important for investors because it provides a measure of the risk associated with investing in a company. It takes into account the cost of capital, which includes interest rates, taxes, and other expenses associated with investing in the company. By comparing the cost of equity to the ROE, investors can determine whether the company's investment is profitable or not.

Video Link:

https://drive.google.com/file/d/1y0zHbecpfFLH25lg24_Wu-sAX7mu-kjY/view?usp=sharing

Conclusion:

The program and its conducted sessions proved highly beneficial in imparting valuable insights into the creation of chatbots, model fine-tuning, and other AI-related topics. These sessions have effectively initiated our journey into the expansive realm of generative AI and machine learning.