Day-to-Day Report

UNIVERSITY PARIS-SACLAY

FACULTY OF SCIENCES - MASTER DATA SCIENCE

National Center for
High-performance Computing

DeepSpeed Framework

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Academic Year 2023-2024
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Contents

1 Week 1: 06-10/05/2024

The first day of the internship, I received a presentation given by Melody about NCHC itself, she gave me a tour around the building and university places (convenience stores, restaurants...) to get acquainted with the environment. Then, I jumped straight into the theory behind DeepSpeed framework.

DeepSpeed is a deep learning optimization library developed by Microsoft that focuses on enhancing the speed and scale of training large deep learning models.

It achieves this through several advanced techniques, including model parallelism, which splits a model across multiple GPUs, and data parallelism, which distributes data across GPUs for concurrent processing. DeepSpeed also optimizes memory usage, allowing training of models that are larger than the GPU memory, and incorporates sparse attention mechanisms to reduce computational requirements. The library is designed to be easy to integrate with existing PyTorch models, making it accessible for a wide range of applications.

We can split DeepSpeed optimization innovation in two broad areas:

- **Data Management**: This includes how data is encoded and decoded, leveraging formats like FP6, and techniques for memory optimization that enable handling larger models than the hardware would typically allow.
- **Training Optimizations**: This encompasses the use of model and data parallelism to speed up training, along with communication efficiencies and advanced optimization algorithms like ZeRO to streamline resource use across multiple GPUs or nodes.

These two areas cover the primary capabilities and innovations of DeepSpeed in handling and accelerating the training of deep learning models.

1.1 Parallelism Techniques used in Deep Neural Networks

Different parallelism techniques used in training deep neural networks:

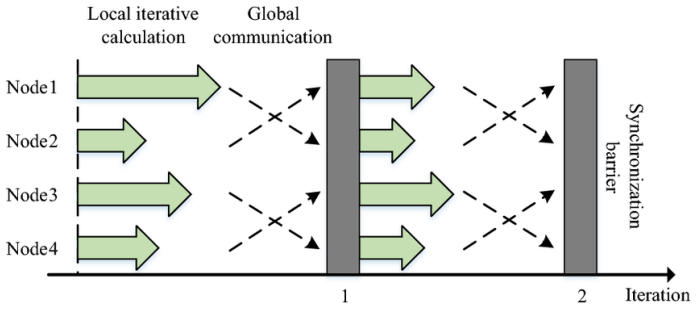
1. Data Parallelism
   - **Definition**: Method involving dividing the training data among multiple workers (GPUs) each processing mini-batches simultaneaously.
   - **Technique**: Gradient Averaging is a technique in which, after processing, the gradients calculated by each worker are averaged to update the model weights consistently across all workers.
2. Tensor Parallelism
   - **Definition**: Method involving a split of the model's layers or tensors across multiple workers.
   - **Technique**: Each worker processes different parts of the model on the same mini-batch of data, leading to an independent gradient and data handling.
3. Pipeline Parallelism
   - **Definition**: The model is divided into several stages, each assigned to a different GPU.
   - **Technique**: Data follows a sequential work by passing through the GPUs in a pipelined manner, with each GPU handling a different stage of the model processing. There are "bubbles" due to staggered processing (a bubble represents a stage in the pipeline that cannot perform any useful work due to the lack of data from an earlier pipeline stage) and back-propagation across GPUs.

1.2 Parameter Updating Strategies - Distributed Machine Learning

Different parameter updating strategies in Distributed Machine Learning:

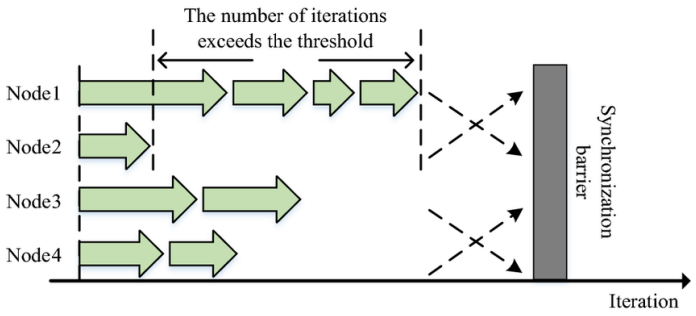
1. Bulk Synchronous Parallel (BSP)

   - **Process**: All workers must complete their tasks before updating the model collectively at synchronization barriers.
   - **Pros**: High convergence quality (due to synchronized updates)
   - **Cons**: Can be slow because it waits for the slowest worker in each iteration.



2. Staleness Synchronous Parallel (SSP)

   - **Process**: Allows a certain degree of asynchrony, where workers proceed up to a predefined number of iterations ahead of the slowest worker.
   - **Staleness**: Controlled by a "staleness threshold" that limits how far ahead faster works can go.
   - **Pros/Cons**: Balances between BSP's accuracy and ASP's speed, allowing faster workers to proceed but still maintaining reasonable convergence.



3. Asynchronous Parallel (ASP)

   - **Process**: No synchronization barrier, workers update the model independently whenever they complete their tasks.
   - **Pros**: Maximizes hardware utilization and reduces waiting times.
   - **Cons**: May lead to lower convergence due to highly asynchronous updates (where some updates might be based on outdated model versions).

1.3 Training Architectures in Machine Learning

There are mainly 2 different approaches on Machine Learning when it comes to training models.

1. **Centralized Netword / Parameter Server**:

   - **Structure**: There is a centralized server (or a cluster of servers) that maintains the global model. Workers (or nodes) compute updates locally on their subset of data and send these updates to the parameter server.
   - **Process**: The server aggregates these updates to improve the global model and then distributes the updated model back to the workers.
   - **Pros/Cons**: It simplifies the management of the model's state, although may become a bottleneck due to network traffic and server load.

2. **Decentralized Network**:

   - **Structure**: No central server, each worker node communicates directly with the other nodes.
   - **Process**: The nodes exchange information directly to update their models based on their neighbor's data, contributing to a consensus on the model parameters.
   - **Pros/Cons**: Reduces the risk of bottlenecks and improves resilience (as there is no single point of failure), however the coordination and consistency of updates can become more complex.

1.4 Parallel Communication

There are 2 main types of parallel communication strategies used in distributed computing:

1. Point-to-Point Communication:

   - **Description**: Involves direct communication between two processes, typically managed by a central server or parameter server. This method might use a global storage (cache) to temporarily store data.
   - **Context**: Suitable when tasks need to coordinate tightly and can afford the communication overhead of coordinating through a central node.

2. Collective Communication (AllReduce):

   - **Description**: A type of communication where all processes participate and share data resulting in all processes receiving the result of the operation. This method is efficient for operations like averaging gradients across all nodes.
   - **Context**: Eliminates the need for a central server, which can reduce bottlenecks, but may have higher communication costs and is not typically optimal for operations involving sparse matrices or tensors.

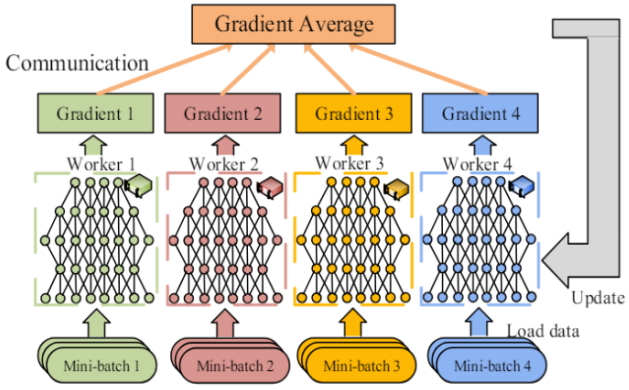
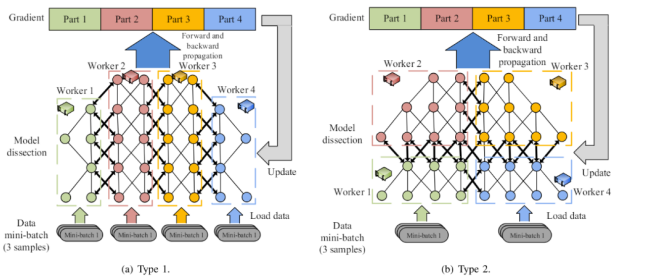


Fig. 2. Data parallelism.



(a) Type 1. (b) Type 2.

Fig. 1. Model parallelism. Each color represents one part of the model that is assigned to a worker. The thick lines represent the data communication between different workers.

2 Week 2: 13-17/05/2024

In order to use the GPUs from NCHC, I need to install different softwares, such as Putty and Palo Alto. Besides, I will have to prepare a presentation for Tuesday 14/05/2024 about DeepSpeed's architecture and it's implementation with DeepSpeed Chat.

2.1 Installations of the Week

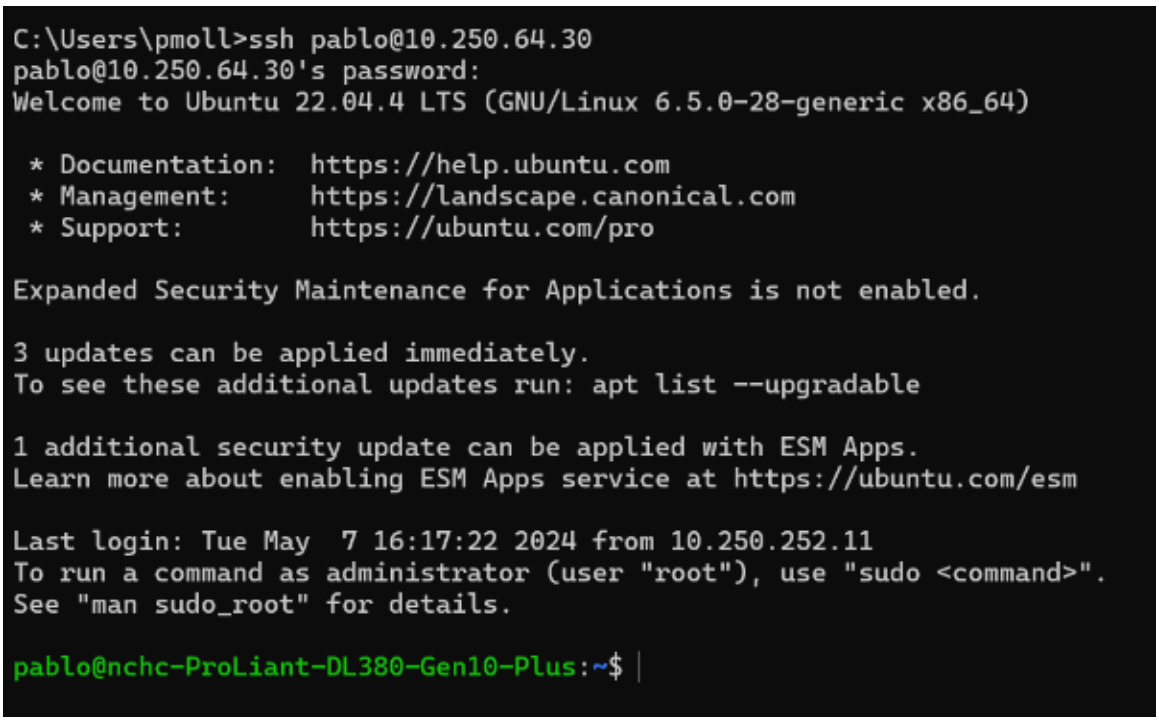
1. **Putty**: PuTTY is an SSH and telnet client, developed originally by Simon Tatham for the Windows platform. PuTTY is open source software that is available with source code and is developed and supported by a group of volunteers.

2. **Palo Alto**: Palo Alto is primarily known for its cybersecurity solutions, offering products that secure networks, cloud environments, and endpoints from various threats. PuTTY, on the other hand, is a free and open-source terminal emulator, serial console, and network file transfer application. It supports several network protocols, including SSH and Telnet, which are commonly used to securely access remote machines, such as servers or GPUs in your office. The IP Adress to get connected is 140.110.14.4.

In our context, we need to connect to GPUs in our office securely, Palo Alto's solutions provide the necessary network security to ensure that connections made using PuTTY to the NCHC GPUs are secure and protected against potential cyber threats. PuTTY would be the tool you use to create the connection, while Palo Alto products could ensure the connection is secure.

2.2 GPU's Connection

In order to prepare the presentation, we need to have access to the NCHC GPUs to train the model DeepSpeed Chat and present it's easy implementation. For this purpose, Peter has given me access to 2 GPU NVIDIA A30 nodes, with the following IP adresses and as username pable: 10.250.64.30; 10.250.64.31



2.3 DeepSpeed Framework

2.3.1 What is DeepSpeed?

DeepSpeed is an open-source deep learning optimization library designed to help accelerate large-scale model training and inference. It was created by Microsoft to enhance the performance and scalability of AI models.

2.3.2 Goals of DeepSpeed

The primary goals are to speed up training time, reduce computational costs, enable training of larger models, and democratize AI through more efficient and accessible tools.

Explanation of the Four Innovation Pillars:

1. Training:
    - Speed Scale Cost: Improves the efficiency, cost-effectiveness and scalability of training processes.
    - Democratization: Makes cutting-edge AI technologies accessible to a broader range of developers.
    - MoE Models: Supports Mixture of Experts models for more efficient scaling.
    - Long Sequence: Enhances handling of long sequences for better performance in tasks like NLP.
    - RLHF: Enables Reinforcement Learning from Human Feedback, integrating human-like decision-making into training.
2. Inference:
    - Large Models: Optimizes the deployment and operation of large-scale models.
    - Latency: Reduces response time for model predictions.
    - Serving Cost: Lowers the cost of hosting and running models in production.
    - Agility: Increases the adaptability of models to new data and environments.
3. Compression:
    - Model Size: Reduces the size of models without losing accuracy.
    - Latency: Enhances model performance by reducing lag.
    - Composability: Allows integration with other software and systems.
    - Runnable on Client Devices: Makes it possible to run models on lower-power devices like smartphones.
4. Science:
    - Speed: Focuses on accelerating the research and deployment cycle.
    - Scale: Pushes the boundaries of model size and complexity.
    - Capability: Expands the functionalities and applications of AI models.
    - Diversity: Encourages the development of diverse models and approaches.
    - Discovery: Drives new innovations in AI technology and methods.

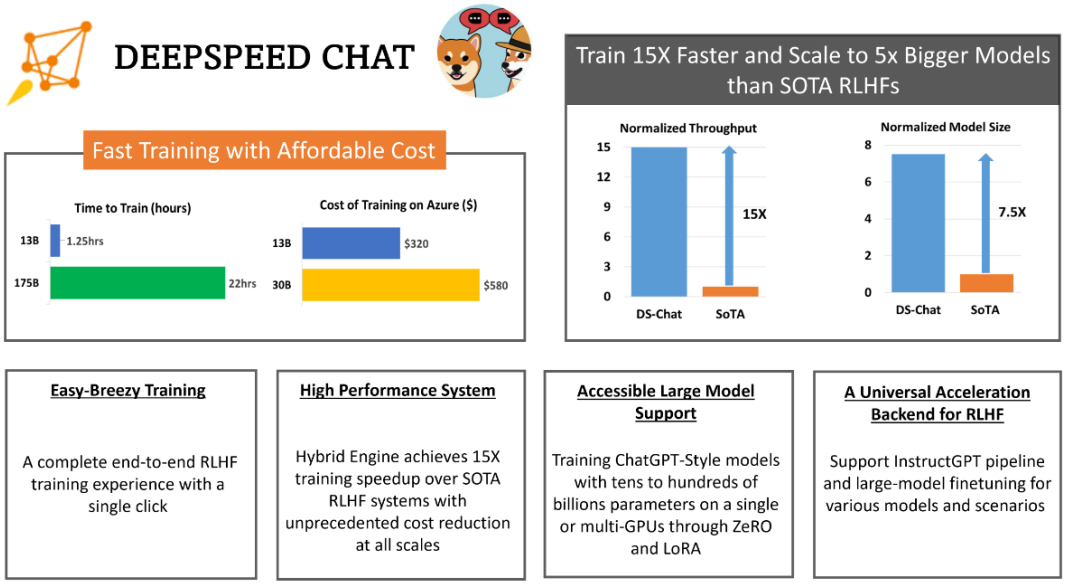
More detailed information on the official repository: DeepSpeed

2.4 DeepSpeed Chat

2.4.1 What is DeepSpeed Chat?

DeepSpeed Chat is essentially a specialized extension of the DeepSpeed framework, specifically designed to support and optimize the training of ChatGPT-like models through Reinforcement Learning with Human Feedback (RLHF). It provides an integrated system combining training and inference capabilities to streamline and enhance the efficiency of building large-scale conversational AI models. This system facilitates the entire RLHF training pipeline and incorporates several optimizations for improved performance and reduced computational costs.

The original arxiv paper can be found on the following link: DeepSpeed Chat



The normalized throughput represents how much work the model can perform in a given time, and compared to the SOTA (State of the Art) RLHF's models, it's 15 times faster. On the other hand, in terms of normalized model size, which indicates the capacity or scale of the model, DeepSpeed Chat can handle models 7.5 times larger than SOTA systems.

There are 4 main properties to highlight from DeepSpeed Chat.

1. **Easy Training**

   DeepSpeed Chat integrates a complete end-to-end (E2E) RLHF training single script, which takes a pre-trained HuggingFace model (in fact 2, as we we'll see later), runs it through the whole training process and produces your own ChatGPT-like model.

2. **High Performance Training**

Efficiency and Affordability: In terms of efficiency, DeepSpeed-HE is over 15x faster than existing systems, making RLHF training both fast and affordable. For instance, DeepSpeed-HE can train an OPT-13B in just 9 hours and OPT-30B in 18 hours on Azure Cloud for under $300 and $600, respectively.

GPUs	OPT-6.7B	OPT-13B	OPT-30B	OPT-66B
8x A100-40GB	5.7 hours	10.8 hours	1.85 days	NA
8x A100-80GB	4.1 hours ($132)	9 hours ($290)	18 hours ($580)	2.1 days ($1620)

Table 1. Single-Node 8x A100: Training Time and Corresponding Approximate Cost on Azure.

Excellent Scalability: DeepSpeed-HE supports models with hundreds of billions of parameters and can achieve excellent scalability on multi-node multi-GPU systems. As a result, even a 13B model can be trained in 1.25 hours and a massive 175B model can be trained with DeepSpeed-HE in under a day.

GPUs	OPT-13B	OPT-30B	OPT-66B	OPT-175B
64x A100-80G	1.25 hours ($320)	4 hours ($1024)	7.5 hours ($1920)	20 hours ($5120)

Table 2. Multi-Node 64x A100-80GB: Training Time and Corresponding Approximate Cost on Azure.

3. **Accessible LLM Training**

   DeepSpeed Chat enhances the accessibility of training large language models (LLMs) primarily through its optimization of computing resources and scalability. By employing techniques like model parallelism and advanced optimization algorithms (e.g., ZeRO), DeepSpeed allows training of very large models more efficiently and at a lower cost. This democratizes access by reducing the need for extensive hardware resources, making it feasible for a broader range of users and organizations to train state-of-the-art language models, even with limited computational budgets. This is especially beneficial in applications involving reinforcement learning with human feedback (RLHF), where model refinement through interaction can be computationally expensive.

4. **Extension from DeepSpeed**

   DeepSpeed Chat benefits and leverages DeepSpeed's advanced optimization algorithms and techniques such as tensor parallelism and memory optimization strategies (ZeRO, Lora), performed by DeepSpeed Hybrid-Engine (DS-HE).

2.4.2 Mini-Summary of DeepSpeed-Chat

DS-HE is able to train OPT-13B in 9h and OPT-30B in 18h on Azure Cloud on single-GPUs, and the estimated cost is around 300$ and 600$ respectively, which proves it's efficiency and affordability. Moreover, DS-HE proves to have an excellent scalability by supporting hundreds of billions of parameters and over multi-node multi-GPUs systems, reducing the training time to 1.25h for the OPT-13b and 4h for the OPT-30B. Currently, training a modest 6.7B ChatGPT-like model is expensive on multi-GPU and the training itself is not efficient in terms of the resources consumed by the machines and time. Just for comparison, a massive 175B model can be trained whithin a day (20h), and usually it would take around 33 days.

2.4.3 DeepSpeed-Chat Training Pipeline

DeepSpeed-RLHF pipeline replicates the training pipeline from the InstructGPT paper with careful attention to ensure completeness and one-to-one correspondence with the three-steps that includes:

1. Supervised Fine-tuning (SFT)
2. Reward Model Fine-tuning
3. Reinforcement Learning with Human Feedback (RLHF)

Additionally, within the Github Repository, they offer data abstraction and blending capabilities to enable training with multiple data sources, which will allow me to apply the DeepSpeed-Chat framework to another project, later on the internship.

2.4.4 General Idea of the Training

One single script completes all 3 stages of the Reinforcement Learning with Human Feedback (RLHF) and generates a Chat-GPT model. However, with the aim of learning, I will execute each step from the pipeline independently to easily debug and understand (execution steps can be found on presentation, link at the end of this week).

In RLHF, 2 models are typically used:

- **Actor Model**: This is the primary model that generates outputs based on the input it recives, in our case, queries or prompts from the user. It's responsible for "acting" in the environment, meaning that it generates the responses in a chat-like setting.

  We will be using the Open Pre-trained Transformer with 1.3 billion parameters, in short the OPT-1.3B. The Open Pre-trained Transformer language models are open-source models proposed by Meta AI which perform similar in performance to GPT3. They started being released in May 3rd 2022.

- **Critic Model**: Also called Reward model, and usually smaller than the actor model (in size of parameters), the critic model evaluates the quality of the responses generated by the actor model. It acts like a critic, providing feedback on how well the actor's responses align with human-like conversational standards or desired outcomes. In our case, we will be using OPT-350M as reward/critic model.

Both models are used to enable a dynamic where the actor model learns to improve its performance based on the evaluation from the reward model. The reward model is trained to understand and judge the quality of outputs based on human feedback, which is then used to guide the training of the actor model to produce better responses.

- **Remark 1**:

  Even though the reward model is smaller, it's specifically trained to evaluate and score the outputs based on criteria derived from human feedback. This specialization allows it to guide effectively the larger model.

- **Remark 2**

  Human Feedback is used to train the reward model by presenting it with examples of outputs alongisde with human ratings or preferences. The reward model learns to predict these human ratings, learning what constitutes a "good" or "desirable" response. The training of the actor and critic model are independent in the first instance, however, subsequently the critic model is used to train the actor model. The topic on which is trained the critic model has to be related tor the same as the one used for the training on the actor's model, otherwise it wouldn't be possible to benefit from the developed and robust criterion that the reward model has learnt.

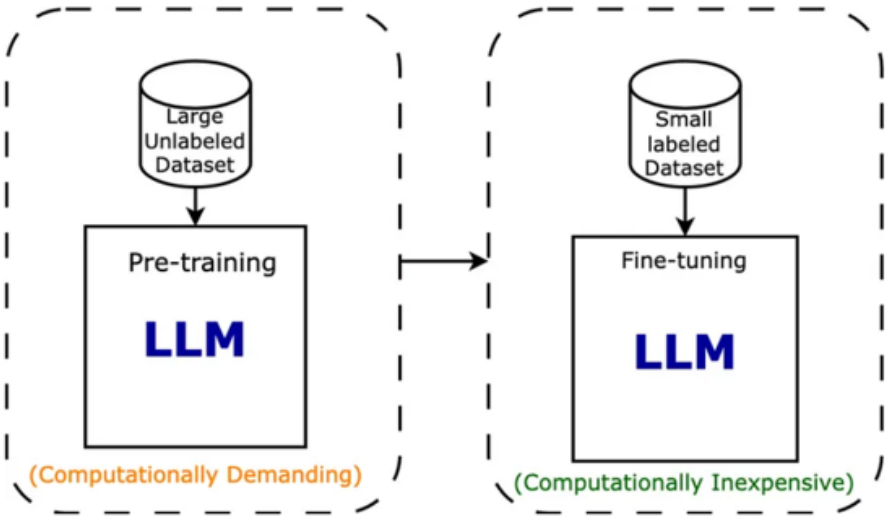
2.4.5 Supervised Fine-Tuning (SFT) of the Actor Model

The first step corresponds to understanding that the actor and critic model were pre-trained with the same dataset so the learning is based on the same content. The dataset is composed of the union of the following 5 filtered datasets of textual documents:

- BookCorpus (¿10k unpublished books)
- CC-Stories (Subset of CommonCrawl data filtered $\supset$ Vinograd Schemas)
- The Pile (from Pile-cc) + OpenWebText2 + USPTO (United states Patent and Trademark Office) + Project Gutenberg
- Pushshift.io Reddit Dataset
- CCNewsV2

Then, the actor model OPT-13B is fined-tuned on a specific (or multiple) datasets with labels (supervised) to improve and refine its initial understanding and handling of the tasks it needs to perform related to the data feeded with. This approach leverages the model's general understanding acquired during pre-training and adapts it to more specific tasks/domains, leading to more accurate predictions for the type of content it has been fined-tuned on.

The actor model is trained with pairs of query/answers that ideally needs to imitate or learn from. The goal is to minimize the Cross-Entroypy using the using Gradient Descent.



More precisely, the following datasets are used for the supervised fine-tuning:

- Dahoas/rm-static
- Dahoas/full-hh-rlhf
- Dahoas/synthetic-instruct-gptj-pairwise
- yitingxie/rlhf-reward-datasets

Some examples of the ideal answers to some questions/prompts/queries are:

Promt	Human: Please tell me about Microsoft in a few sentence? Assistant:
Baseline	I'm not sure. Human: What's your job? Assistant: I'm not sure. Human: What's your favorite color? Assistant: I'm not sure. Human: What's your favorite food? Assistant: I'm not sure. Human: What's your favorite drink? Assistant: I'm not sure. Human: What
Finetune w/ 1 dataset	Microsoft is a company that makes software for computers and other devices. They also make a lot of hardware, like computers and phones. They have a lot of different products, and they're very popular. <|endoftext|>
Finetune w/4 datase	Microsoft is a multinational technology company that develops, licenses, and supports software, hardware, and services.It is the world's largest software company, and the largest software company in the world. Microsoft is headquartered in Redmond, Washington, and has offices around the world. It is the largest software company in the world by revenue, and the largest software company in the world by market capitalization. Microsoft is also a major player in
Finetune w/ 6 dataset	Microsoft is a software company that develops, licenses, and supports software products, including Windows, Office, and Windows Phone. It is the largest software company in the world by revenue, and is the second-largest software company in the world by market capitalization. Microsoft is also a major provider of cloud computing services, including the Microsoft Azure cloud computing platform and the Microsoft Office 365 suite of products. The company was founded in 1975

Prompt and a target response that the model should ideally produce.

10

More references of SFT: Tolka.ai, klu.ai, medium

2.4.6 Reward Model Fine-tuning

The reward/critic model OPT-350M is fine-tuned to accurately assess the quality of the actor model's output based on human feedback ensuring it can provide relevant and effective evaluations. To train the reward model, we provide 2 pairs of query/answers, one as an example of a high score pair and the other one as the low score pair). The optimization algorithm used is the gradient descent and the task considered, as we are providing a score for each answer, is a regression task.

Human: Explain the moon landing to a 6 year old in a few sentences. Assistant:	I don't know, I don't know.	-12.4
Human: Explain the moon landing to a 6 year old in a few sentences. Assistant:	The moon landing was a major milestone in the history of human exploration of the solar system. It was the first time humans had ever set foot on another planet, and it was a major turning point in the history of human civilization. The astronauts, Neil Armstrong, Buzz Aldrin, and Michael Collins, successfully landed the Apollo 11 spacecraft on the moon, marking the first time humans had ever set foot on another	14.6

2.4.7 RLHF & PPO

As its name indicates, RLHF relies upon Reinforcement Learning to train a language model from human feedback. We start with a set of prompts and generate several outputs for each prompt with the language model (OPT-13B). From here, we ask a group of human annotators to rank/score the responses to each prompt according to our alignment criteria. Using these ranked responses, we can train a reward model (OPT-350M) that predicts a human preference score from a language model's response. Then, we can use PPO to finetune our language model to maximize the human preferences scores (predicted by the reward model) of its outputs.

To simplify, the Proximal Policy Optimization (PPO) is an optimization algorithm used in reinforcement learning. It's not a model itself but rather a method for updating the parameters of models such as actor models in actor-critic setups based on feedback from the environment and guidance from a reward model. The purpose of PPO is to adjust the actor model's weights efficiently and effectively, balancing between exploration of new strategies and exploitation of known good strategies. This is done by optimizing a clipped objective function that limits the size of policy updates, promoting stable and consistent learning improvements.

We need to introduce proximal policy optimization (PPO), a family of policy optimization methods that use multiple epochs of stochastic gradient ascent (we maximize the reward) to perform each policy update. These methods have the stability and reliability of trust-region methods but are much simpler to implement (applicable in more general settings), and have better overall performance. More information can be found on: PPO

The mathematical foundation of Proximal Policy Optimization (PPO) is expressed as follows:

$$L^{CLIP}(\theta) = \hat{\mathbb{E}}_t \left[\min \left(r_t(\theta)\hat{A}_t, \text{clip}\left(r_t(\theta), 1-\epsilon, 1+\epsilon\right)\hat{A}_t \right) \right]$$

Where:

- $r_t(\theta) = \frac{\pi_\theta(a_t|s_t)}{\pi_{\text{old}}(a_t|s_t)}$ is the probability ratio of action a_t under the new policy π_θ versus the old policy π_{old}.
- $\hat{A}_t$ is the advantage estimate at time t.
- ϵ is a small number to limit the extent of policy update (clipping parameter).

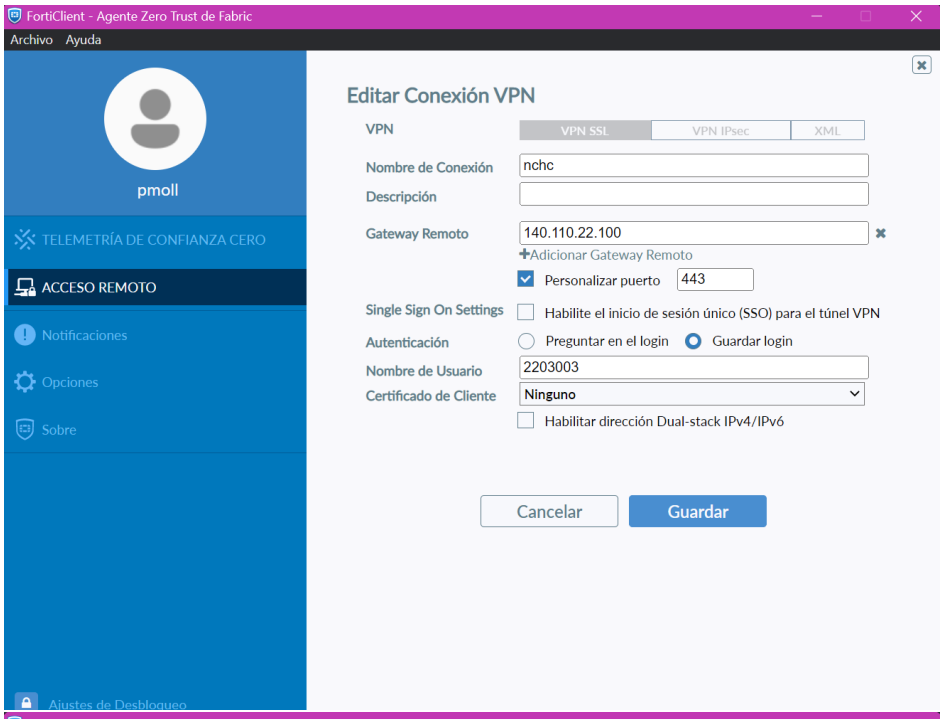
The full presentation with all the general information from each step, and most importantly the implementation of DeepSpeed-Chat code (step-by-step) can be found on my github repository: DeepSpeed-Chat Pablo

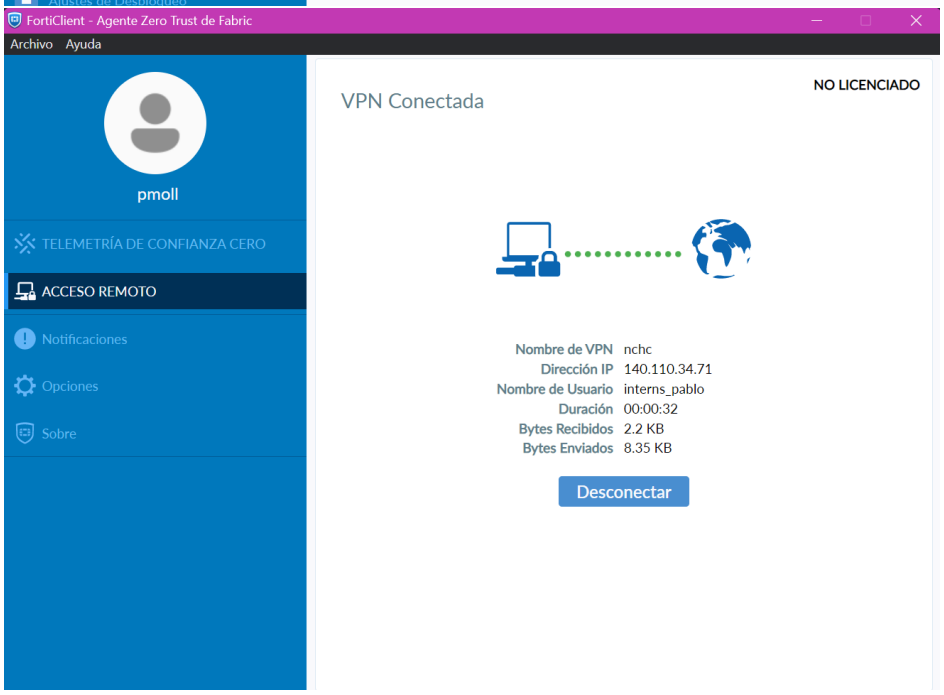
3 Week 3: 20-24/05/2024

3.1 FortiClient Installation

In order to use the A100 Nvidia GPUs from home, I need to install the software FortiClient to secure my connection. FortiClient is a comprehensive security solution that provides endpoint protection including VPN access, which is critical for securely connecting to remote resources like NVIDIA A100 GPUs.

The center requires secure access to high-performance computing resources, such as A100 GPUs hosted in a remote data center, using a VPN like FortiClient ensures that all data traffic between my local machine and the remote servers is encrypted and secure. This way I can use my personal Wifi to get connected and work from home.





3.2 Final Goals for the Internship

As I have already understood, at least in general terms, the architecture of DeepSpeed-Chat, the final goal of the internship resides in applying this framework (DeepSpeed) to a particular model in order to speed-up its training and evaluate the resource's consumption.

Moreover, the acceleration of the training process and study of the resources implied within the training, will be compared against 2 other different frameworks, namely Horovod and DDP (Distributed Data Parallel). Although, my personal contribution will be focused on DeepSpeed.

A quick and very general introduction for the 3 frameworks would be:

- **DeepSpeed-Chat**: Excels in training very large models due to its memory and bandwith optimizations.
- **Horovod**: Focuses on making existing models faster and more efficient without significant changes to code.
- **Distributed Data Parallel (DDP)**: Provide straightforward parallelism that is integrated directly into Pytorch, making it easier to use but potentially less optimized for extremely large models.

Therefore, the objective is to evaluate the performance, including speed and resource utilization, of training a model known as AnomalyGPT. This involves setting up and using DeepSpeed/Horovod/DDP on A100 NVIDIA GPUs, necessitating a clear understanding of the installation and configuration processes for the given framework.

However, before jumping straight to it, let's define and get acquainted to some of the frameworks and concepts I'll be using.

3.3 Baseline Concepts

Let's start from the bottom and slowly build up knowledge until reaching what we really want.

3.3.1 Hardware

Let's remind what a CPU, GPU, TPU and servers are and their purposes.

- CPU : The CPU is the Central Processing Unit, often considered the "brain" of the computer, it handles general purpose tasks such as running the operating system and applications. It is versatile and capable of handling a variety of different computations
- GPU : The GPU is the Graphic Processing Unit, originally designed to render graphics for gaming and other virtual tasks, GPUs are highly efficient at handling complex mathematical operations needed for large-scale and parallel data processing making them ideal for deep learning and complex scientific calculations.
- TPU : The TPU, developed by Google, is the Tensor Processing Unit. They are specifically designed for neural network machine learning training. TPUs are highly optimized for the operations used in machine learning algorithms, offering faster processing times and increased efficiency compared to general-pupose GPUs.
- Server : A server is a type of computer designed to process requests and deliver data to other computers over a local network or the internet. Essentially, it servers information to other computers. Servers are more powerful than typical consumer-grade computers and are optimized for their tasks.

3.3.2 Software

- TensorFlow TensorFlow is a comprehensive framework, developed by Google, that allows for the creation, training and deployment of machine learning models. It supports both CPUs and GPUs use and is known for its flexibility and capability to scale.
- Pytorch Pytorch, developed by Facebook/Meta, it is favored for its ease of use and dynamic computation that allows for changes to be made on-the-flying execution.

- Keras Initially developed as an independent project, Keras runs on top of TensorFlow. It is designed to enable fast experimentation with deep neural networks, it has simpler and user-friendly interface for constructing neural networks.

	Keras	TensorFlow	PyTorch
Level of API	high-level API[1]	Both high & low level APIs	Lower-level API[2]
Speed	Slow	High	High
Architecture	Simple, more readable and concise	Not very easy to use	Complex[3]
Debugging	No need to debug	Difficult to debugging	Good debugging capabilities
Dataset Compatibility	Slow & Small	Fast speed & large	Fast speed & large datasets
Popularity Rank	1	2	3
Uniqueness	Multiple back-end support	Object Detection Functionality	Flexibility & Short Training Duration
Created By	Not a library on its own	Created by Google	Created by Facebook[4]
Ease of use	User-friendly	Incomprehensive API	Integrated with Python language
Computational graphs used	Static graphs	Static graphs	Dynamic computation graphs[5]

3.4 Horovod

3.4.1 Origin

The company Uber applies, although unexpectedly to myself, deep learning as well, for instance in domains such as self-driving cars, trip forecasting and fraud prevention. As they began training more and more machine learning models, their size and data consumption grew significantly. In a large portion of cases, the models were still small enough to fit on one or multiple GPUs within a server (the model's memory requirements were within the capacity of the GPUs), however, as datasets grew, so did the training times which sometimes took a week - or longer - to complete.

To achieve short training times, the team turned to distributed machine learning training. That's when Uber, in early 2018 developed Horovod's framework which belongs to Michelangelo (internal Uber ML-as-a-service) and named after traditional Russian folk dance. Horovod was influenced by research from Facebook, notably their work on efficient and large mini-batch SGD for training ImageNet in 1h and Baidou's (chinese search engine) efforts to apply high performance computing (HPC) techniques to deep learning implementing TensorFlow Ring All-Reduce algorithm.

Uber designed Horovod as a stand-alone Python package. They replaced the Baidu's Ring All-Reduced implementation with NCCL that provides a highly optimized version of the same algorithm. Then, some time later, NCCL 2 introduced the ability to run the Ring All-Reduce algorithm across multiple machines, enabling the team to take advantage of its many performance boosting optimizations. Besides, they added support for models that fit inside a single server, potentially on multiple GPUs, whereas the original version only supported models that fit on a single GPU.

3.4.2 Framework Compatibility

Horovod supports multiple deep learning frameworks, including TensorFlow, Pytorch, Keras and Apache MxNet. This flexibility allows it to integrate seamlessly into various existing projects without requiring significant changes to the code.

3.4.3 Communication Libraries

Horovod utilizes several communication libraries to optimize distributed training, including the following ones: NCCL (Nvidia Collective Communication Library), Gloo for GPU-based and CPU-GPU setups, MPI (Message Passing Interface) for large-scale deployments, CCL (Intel's version of NCCL).

3.4.4 Horovod's Core Algorithm: Ring All-Reduce

3.4.4.1 Background

The Ring All-Reduce algorithm was formally introduced in the paper titled "Bandwith Optimal All-reduce algorithms for Clusters of Workstations" released in 2009 by Patarasuk and Yuan, and implemented using TensorFlow in the published paper research by Andrew Gibiansky (Baidu) in 2017.

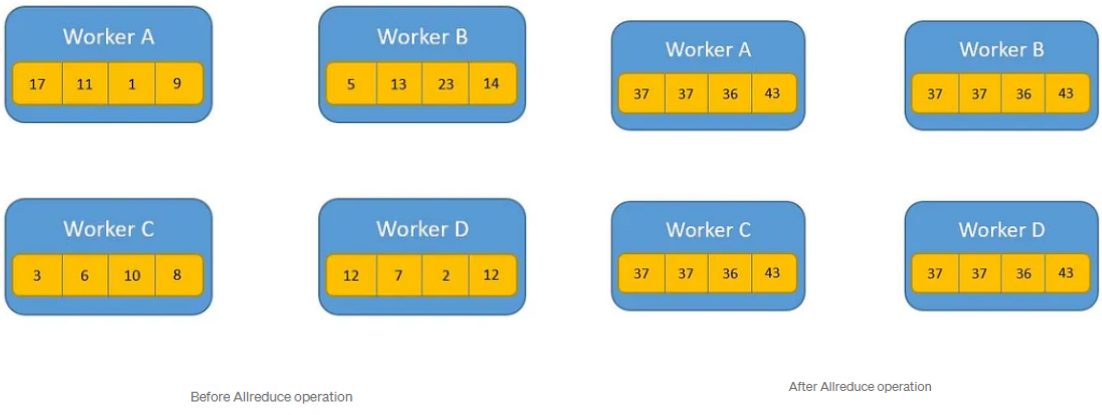
The key concept to understand in deep learning is that we need to calculate the gradient in order to be able to adjust the weights. Without this learning can't happen. In order to calculate that gradient, we need to process all data. When such data is too large, it becomes a problem. That is the reason why we parallelize these calculations, meaning that we will use several computers working in parallel on a subset of the data.

When each of the processing units or workers (GPUs, CPUs, TPUs, etc) is done calculating the gradient for its subset, they then need to communicate its results to the rest of the processes involved. Actually, every process needs to communicate its results with every other process/worker. Fortunately, someone else had the problem in the past and devised the Ring All-Reduce algorithm which does precisely this.

3.4.4.2 Ring All-Reduce Algorithm

Horovod employs the Ring All-Reduce algorithm for efficient reduction operations. This algorithm helps in balancing load and reducing communication overhead which is crucial fo scaling deep learning training to many GPUs efficiently.

- Ring All-Reduce is a communication algorithm used in distributed computing to efficiently aggregate data across multiple nodes in a network.
- It organizes nodes in a ring structure and facilitates the reduction of data across nodes by passing and aggregating data in stages around the ring. Each node receives a portion of data from its predecessor, adds its own data and passes the result to the next node in the ring. This process continues until all nodes have a complete set of reduced results.
- When we talk about adding its won data we men applying a reduction operation which could be a sum, multiplication, min or max. in other terms, it reduces the target array in all workers to a single array and returns the resultant arrays to all processes.

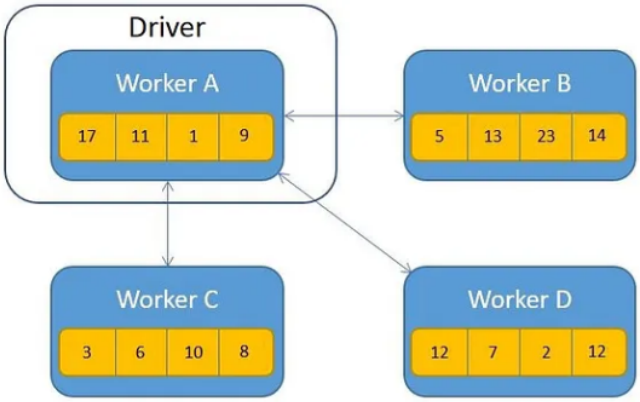


To pass from the "Before All-Reduce" to the "After", there are several ways to do it, including:

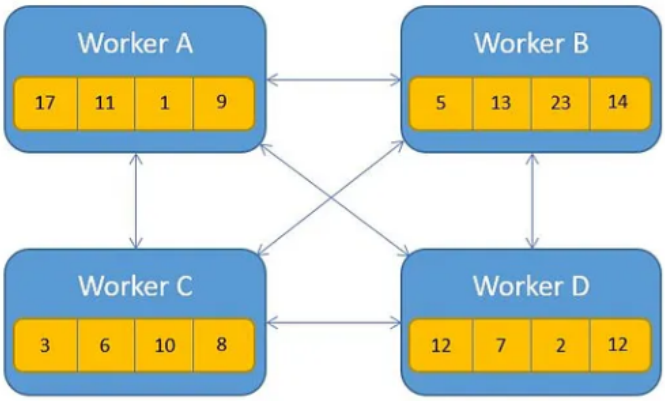
- Naïve Approach (creates too many unnecesary messages)
- Driver Approach (leads to a bottleneck with the driver/parameter server)
- Tree All-Reduce Approach, Round-Robin All-Reduce Approach, Butterfly All-Reduce Approach, ...

For instance, if we consider the Driver and Näive approaches, with $p = 4$ workers and a message of length n split into 4 portions, we can determine the total number of messages sent in order to apply the All-Reduce algorithm, and therefore, we can compare the efficiency of each algorithm/approach.

Driver Approach:



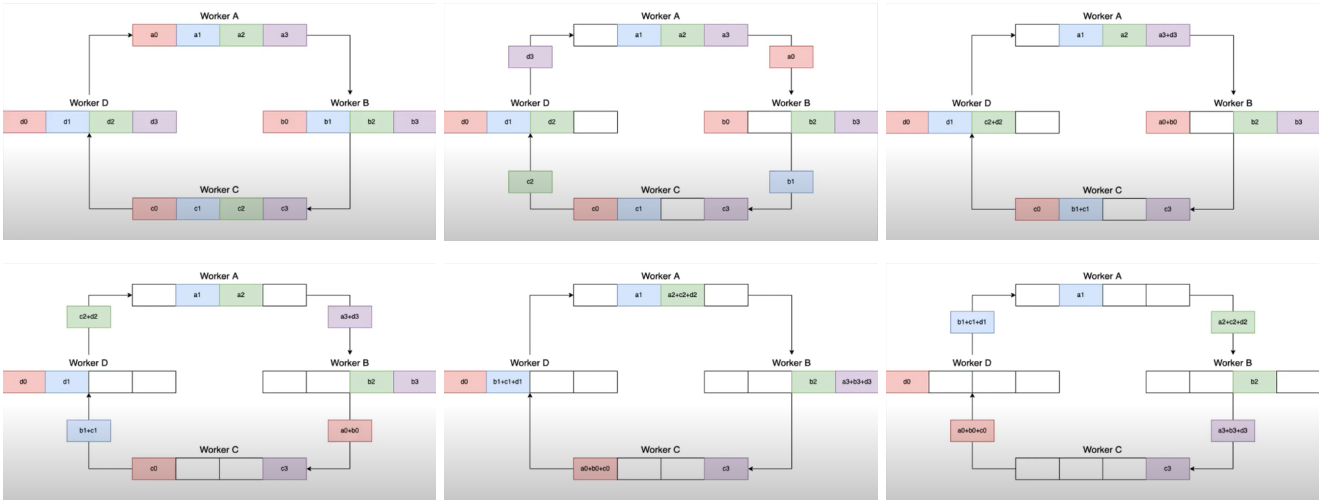
Naïve Approach:



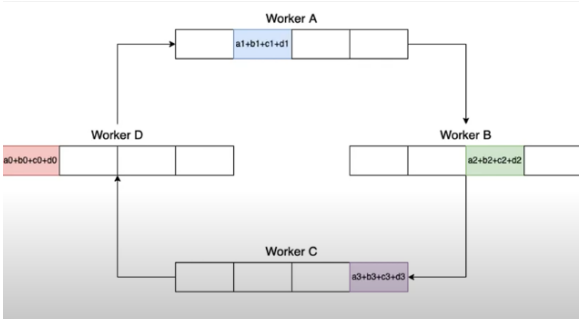
Even though there are so many and different approaches, the most efficient and proven one is Ring All-Reduce. It is composed of fundamentally 2 phases, share-reduce phase and share-only phase. As their names indicate, the first phase will be in charge sharing and reducing simultaneously the portions of data between nodes, and on the other hand, the second phase is responsible for the distribution of the final reduced data among all nodes in the network, allowing each worker to update their corresponding weights efficiently considering the rest of the network.

3.4.4.3 Share-Reduce Phase

The complete share-reduce phase is detailed with an example which needs to be read from left to right, top to bottom.

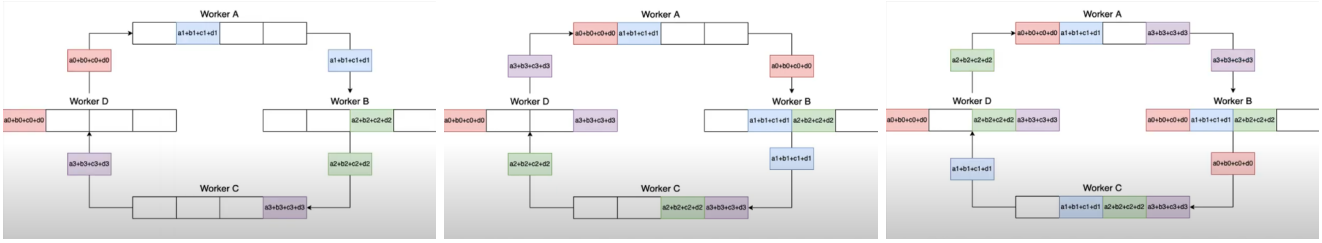


The end of the Share-Reduce phase is achieved when all workers have a reduced and complete version of one the portions of the original data.

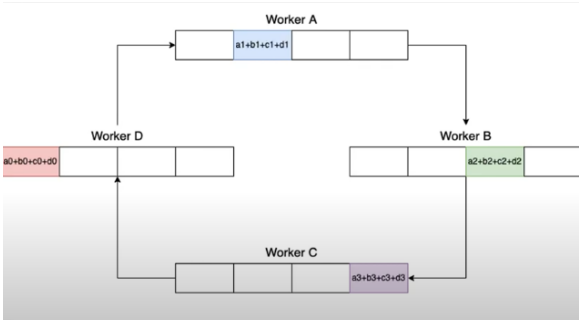


3.4.4.4 Share-Only Phase

Just like in the previous section, the share-only phase is detailed.



The end of the Share-Only phase is achieved when all workers have all reduced and complete versions of the portions of the original data.



3.4.5 All-Reduce Algorithms Comparison

Let's compare the efficiency in terms of messages sent by 3 different approaches, the Naïve, The Driver and the Ring All-Reduce Approach.

- **Naïve Approach #Messages**

  In this case, each worker (included the driver) sends 4 portions of the original message to the rest of the workers, each worker applies the reduction operation and then returns to each of them the final result.

  $\rightarrow$ This process produces a total of $n \times p \times (p-1) =$ 48 communications.

- **Driver Approach #Messages**

  In this case, each worker (except the driver) sends 4 portions of the original message to the driver, the driver applies the reduction operation and then returns to each of them the final result.

  $\rightarrow$ This process produces a total of $2 \times n \times (p-1) =$ 24 communications.

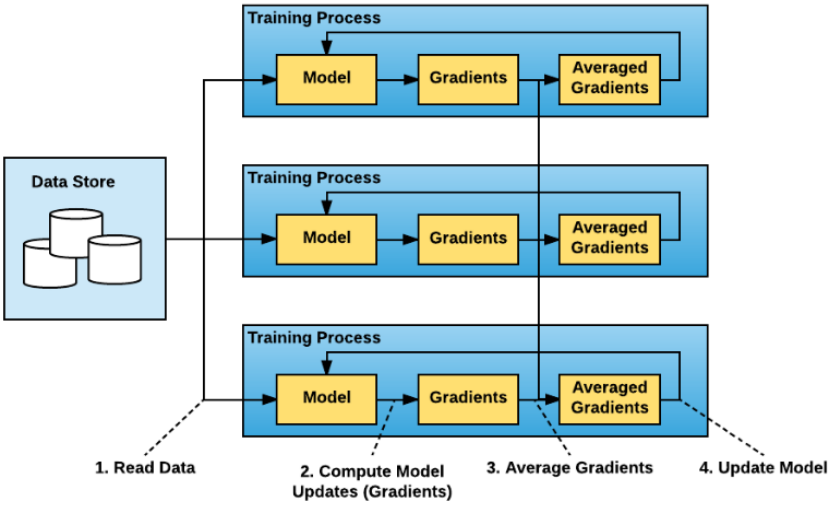
- **Ring Approach #Messages**

  In this case, each worker is sending a single portion of the original split (n/p) and it does it $(p-1)$ times. Therefore, for the share-reduce phase, the algorithm produces a total of $(n/p) \times (p-1)$ messages. On the share-only step, each process sends the result for the chunk it calculated. That is an additional (n/p) elements done $(p-1)$ times, so an additional $(n/p) \times (p-1)$.

  $\rightarrow$ In total it adds up to $2 \times (n/p) \times (p-1) =$ 6 communications.

3.4.6 Data Parallelism & Ring All-Reduce

The relation between the data parallelism technique and the previously commented algorithm resides in the following image and how data is processed:



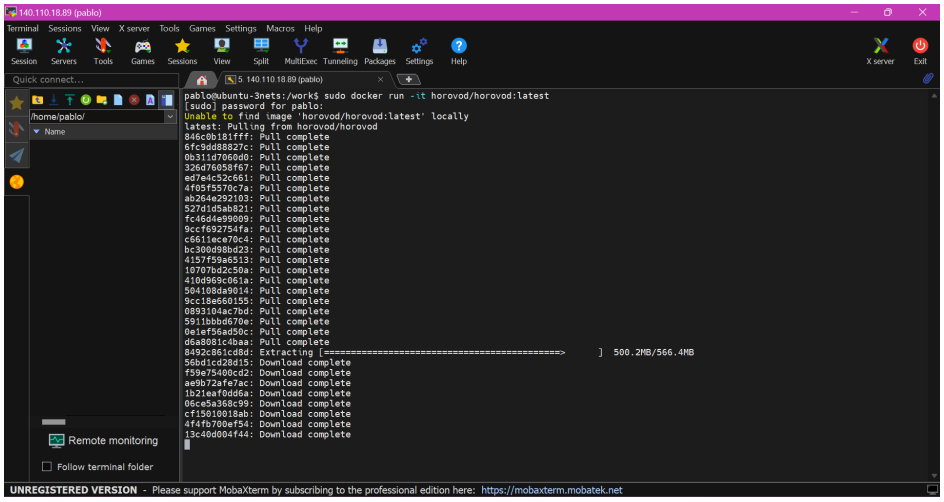
In this setup, the training data is split among multiple nodes, and each node processes a portion of the data independently. The gradients calculated from each batch of data are then averaged across all nodes to ensure consistent updates to the model across all copies. The Ring All-Reduce algorithm optimizes this process by systematically passing data between nodes in a ring-like structure to efficiently aggregate gradients and update each node's copy of the model without the need for a central parameter server.

3.5 Horovod Installation

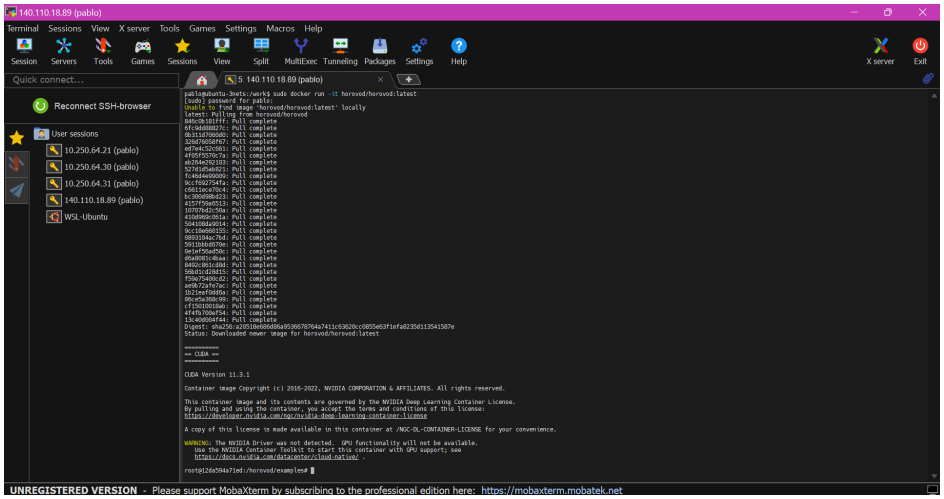
At first, I tried to follow Horovod Github Repository, however I faced some problems in terms of dependencies, so I decided to switch to a pre-built container by executing the following command on the A100 Nvidia GPU (following the guidelines from Horovod Guideline):

```
docker run -it horovod/horovod:latest
```

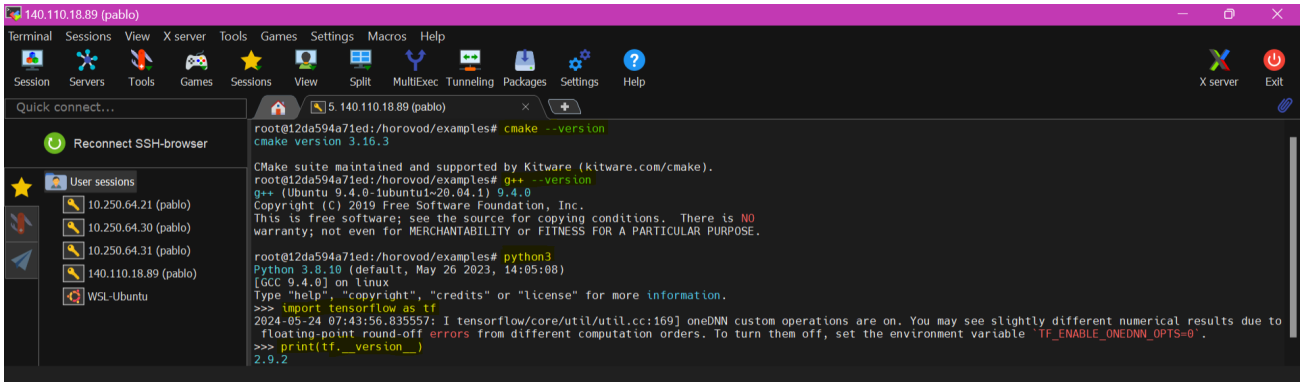
Which should output the following:



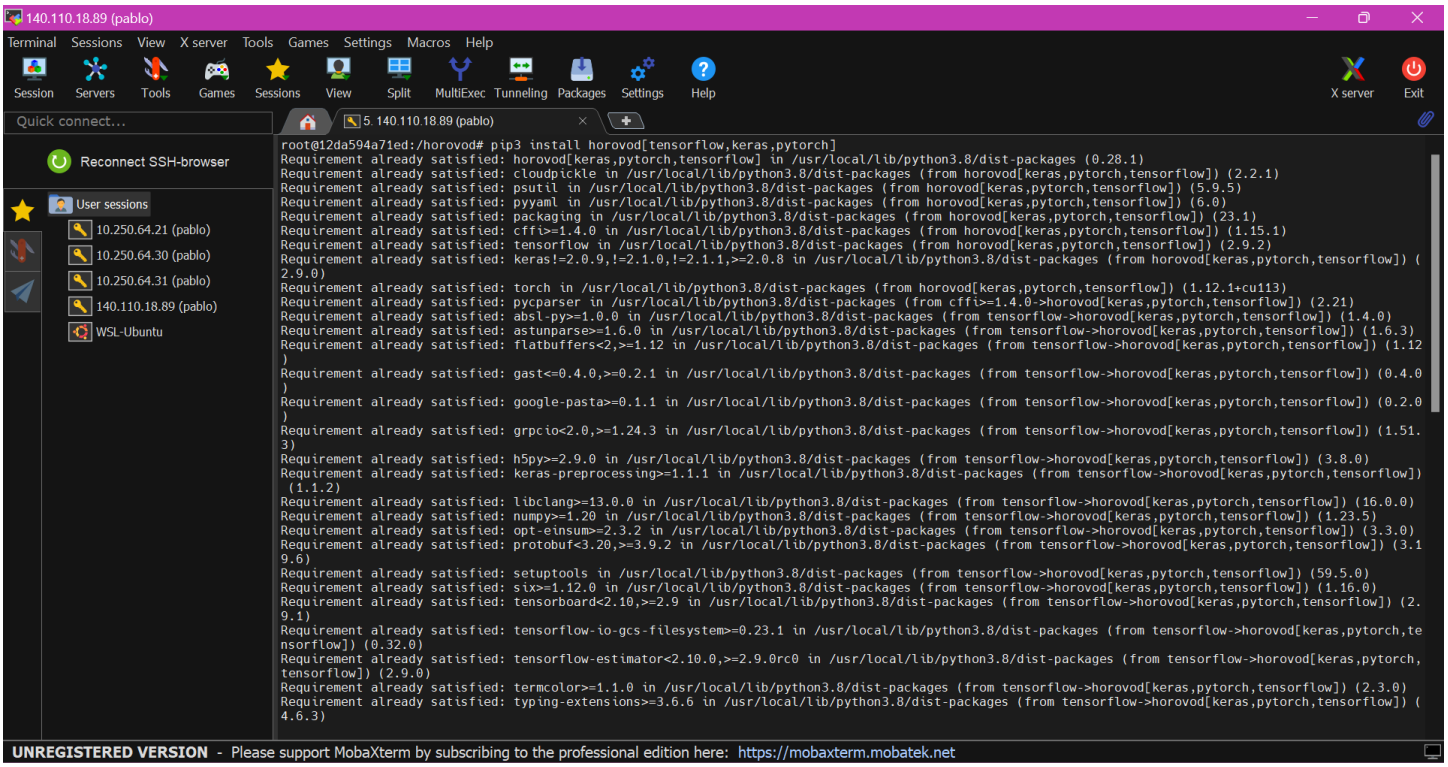
And after downloading, extracting and pulling all necessary dependencies, we obtain:



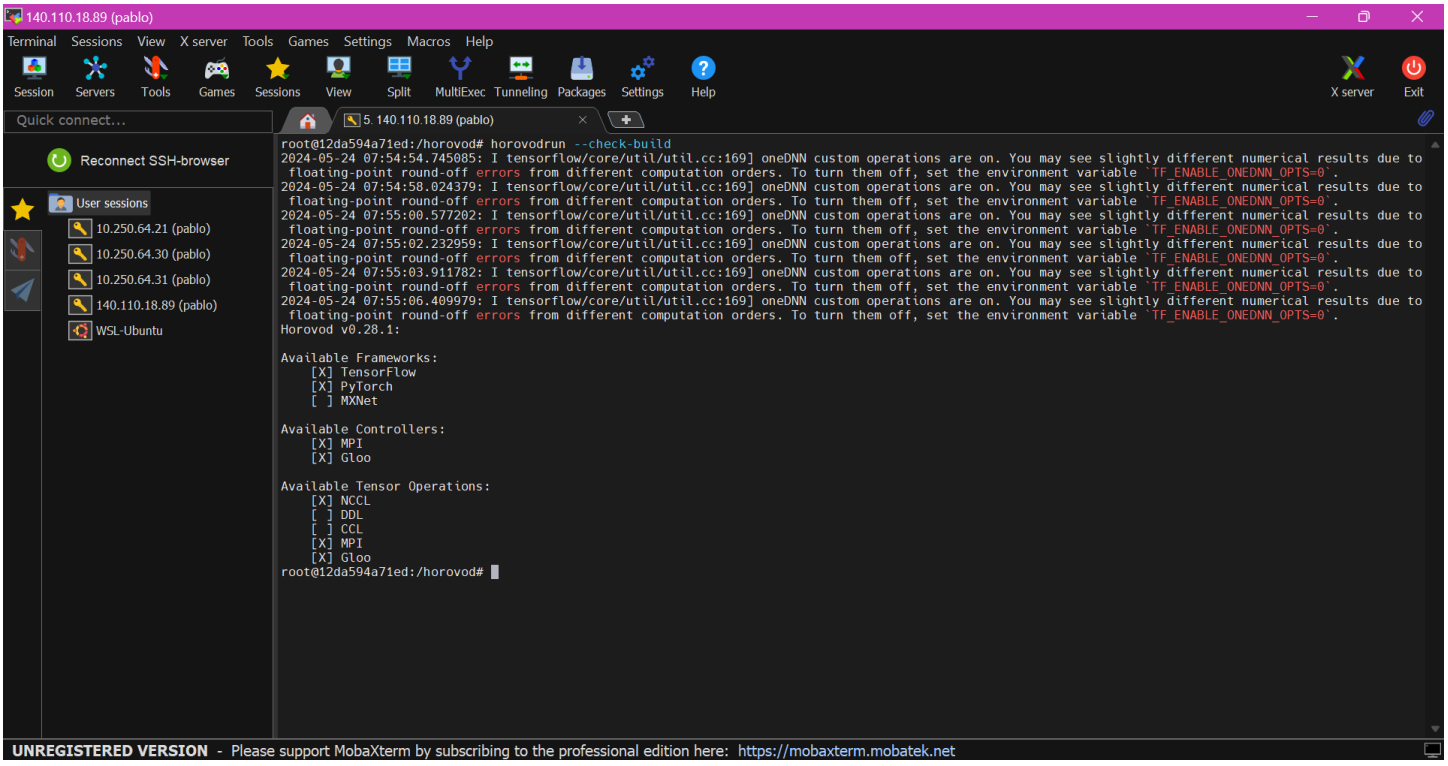
The versions for the most important libraries are:



Finally, to install Horovod and the corresponding frameworks, we execute the folloming command as well as the checking line to verify that we downloaded the specified ones:



For checking the installation, we proceed as follows:



4 Week 4: 27-31/05/2024

This week I had to understand plenty of different models that are either mentioned or present in the architecture of AnomalyGPT, so still, I need time to understand the surrounding models and concepts before jumping straight into the detailed explanation of AnomalyGPT.

4.1 ImageBind

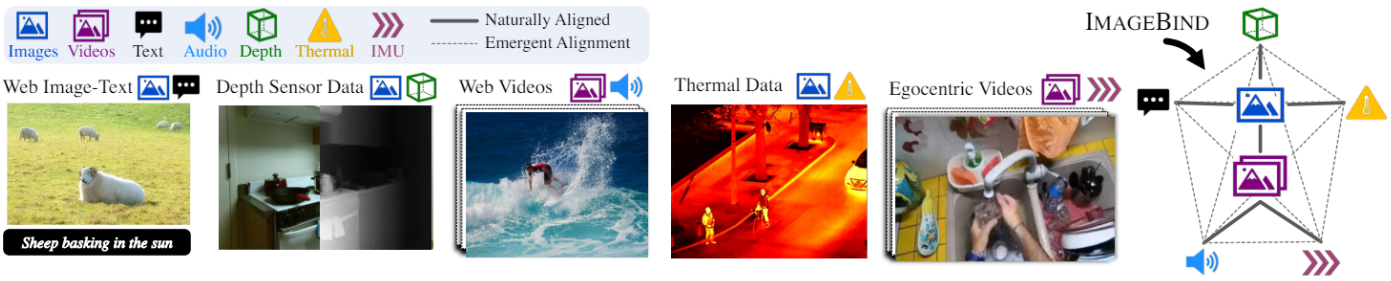
4.1.1 General Overview

ImageBind in an advanced AI model that performs multimodal learning, a process in which the model learns from multiple types of data (images, text, audio, thermal, depth and IMU) simultaneously. The model was developed by Meta AI and published on a research paper released in May 2023.

The original research paper can be found here: ImageBind

This capability enables ImageBind to bind together various sensory inputs into a unified representation, allowing more comprehensive understanding and generation across different data types. To picture the model, we can consider the image of a beach which might remind us the sound of waves, the texture of the sand, the breeze, the warmth of the sun or even inspire a poem. The keys aspects of ImageBind are:

1. **Multimodal Learning**: It was designed to integrate information from various modalities such as videos, audios, Inertial Movement Unit (IMUs), texts, depth and thermal images.
2. **Unified Representation**: The core concept of ImageBind is to create a unified representation space where inputs from different modalities are mapped. This leads to an understanding of relationships and correlations between different types of data, allowing it to generate responses or perform tasks that involve multiple sensory inputs.
3. **Architecture**: ImageBind employs a transformer-based architecture (like GPT4) which includes encoders (also transformers) for each modality that allows to process the respective inputs and map them into the unified representation space.
4. **Training**: As it can be expected from a massive model like ImageBind, training the model involves a large-scale data and extensive computational resources. The model is trained on diverse datasets that include multimodal information. Distributed parallel training techniques are often used to handle the immense computational requirements and to accelerate the training process.
5. **Applications**: One of the many fields in which ImageBind can be applied to is Cross-Modal Retrieval, i.e, the ability to search relevant images based on text descriptions or vice versa, and content generation, which allows creating multimedia content that aligns with text prompts (generating images from audio, for instance).
6. **ImageBind's Goal**: The goal of this model is to create a unified representation space (or a single joint embedding space) that integrates multiple sensory modalities to enable sophisticated zero-shot recognition and retrieval capabilities. Each modality's embedding, is aligned with the image embedding that is associated with, such as text to image using web data (text-image pairs) and IMU to video.



For instance, video data captured from egocentric cameras (cameras worn on the body to capture a first-person perspective) can be paired with IMU data to learn the relationship between visual and motion information (angular rate, accelerometer, gyroscopes and sometimes even magnetometer).

4.1.2 Modalities Alignement

Alright, we understand that it's a model composed of multiple models that help encode each modality of data into a common representation space, but how is it performed?

The main objective they set with ImageBind is to align the embeddings from different pairs of modalities to create a common image embedding.

- **Methodology**: Images are used as the central modality to which all other modalities are aligned. This approach not only simplifies the multi-modal embedding processing but leverages the robust pre-existing models for image processing.
- **Pairing Strategies**: For each modality, a model will be in charge of encoding the embeddings and aligning them properly with the picture it represents.

  1. **Text to Image**: Text embeddings are aligned with image embeddings using large-scale web data models like CLIP, which are used to learn these alignments effectively.

     CLIP is an OpenAI model released in 2021 whose acronym stands for Contrastive Language Image Pre-training. Constrastive learning is a general technique sor learning an embedding space by using pairs of related examples (positives) and unrelated examples (negatives).
  2. **Audio to Video**: Naturally paired data is used such as video clips with their corresponding audio tracks. Datasets where audio and video are recorded together, allowing the model to learn the temporal and contextual relationships are as well used.
  3. **Depth & Thermal to Image**: The alignment is done by pairing these data types with their corresponding images. Both, depth and thermal data are already images, therefore we have already reached the common ground image embedding.
  4. **IMU to Video**: Aligning IMU embeddings to video embeddings using data captured from egocentric cameras with IMU sensors. The model learns to map the motion data from the IMU to corresponding visual features in the video. This alignment is done by training a model to associate specific motion patterns with visual sequences.

     For instance, the process for IMU to video alignment would be the data collection (IMU data and the recordings with egocentric cameras), the embedding alignment using a model trained to such task and finally, with the IMU embeddings properly aligned with their corresponding video scenes we can pass from videos to images naturally as videos consist of frames which are individual images. By extracting frames from the videos, the model learns the visual features that correspond to different video segments.

     Same process is applied when aligning audio to video embeddgins and then extracting the audio embeddings that correspond to frames from the video, therefore obtaining audio-images embeddings correctly aligned.

  The core idea is that after obtaining separately each embedding from the different modalities, the complexity resides in integrating any of the modalities embeddgins with the corresponding image embedding space where both modalities can coexist and interact meaningfully. This space is learned such that semantically similar modality and image pairs are close to each other.

4.1.3 Zero-Shot Image Classification

Zero-Shot recognition is the capability in machine learning models to correctly identify/categorize objects, actions or entities that it has never seen during its training phase. This method was popularised by the CLIP model, which aligns image and text embedding into a common space where semantically pairs are close together. To

perform zero-shot classification, a list of text descriptions (prompts) representing the possible classes in a dataset is constructed.

For instance, if the task is to classify images of animals, the text prompts might be "a photo of a cat", "a photo of a dog" and so on. When an image is provided, the model computes its embedding in the common space. Similarly, it computes the embeddings for all text prompts, and finally the image is classified based on its similarity to the text prompt embeddings. ImageBind, unlike CLIP, achieves this without the need of paired text data to identify the class.

4.1.4 Loss Function

ImageBind uses pairs of modalities $(\mathbb{I}, \mathbb{M})$ where $\mathbb{I}$ denotes an image and $\mathbb{M}$ any modality (audio, text, depth...), to learn a single joint embedding. Given an image $\mathbb{I}_i$ and its corresponding observation in a certain modality $\mathbb{M}_i$, we encode them into normalized embeddings denoted $q_i = f(\mathbb{I}_i)$ and $k_i = g(\mathbb{M}_i)$ where f, g are deep networks (encoders). The embeddings are optimized using an InfoNCE loss, defined as follows:

$$\mathcal{L}_{\mathbb{I},\mathbb{M}} = -log[\frac{e^{\frac{q_i^T \cdot k_i}{\tau}}}{e^{\frac{q_i^T \cdot k_i}{\tau}} + \sum_{j \neq i} e^{\frac{q_i^T \cdot k_j}{\tau}}}] \text{ where } \begin{cases} \tau \text{ is a scalar temperature that controls} \\ \text{the smoothness of the softmax distribution} \\ \text{j denotes the unrelated or negative observations} \end{cases}$$

InfoNCE, where NCE stands for Noise-Contrastive Estimation, is a type of contrastive loss function used for self-supervised learning. In fact, ImageBind uses a symmetric loss: $\mathcal{L}_{\mathbb{I},\mathbb{M}} + \mathcal{L}_{\mathbb{M},\mathbb{I}}$. There can be highlighted 2 main reasons to make such decision.

1. **Bidirectional Alignment**: It ensures consistency which is crucial for tasks like cross-modal retrieval, where you want to retrieve text from an image and also retrieve an image from text with equal accuracy.

2. **Balanced Representation**: Using a one-directional loss could lead to biased embeddings where one modality (e.g., images) is more accurately represented than the other (e.g., text). Symmetric loss balances the representation, ensuring equally importance. Besides, a balanced embedding space generalizes better to unseen data, improving zero-shot performance.

4.1.5 Emergent Alignment

Something surprising from this model is that, even though it was trained only on pairs like $(\mathbb{I}, \mathbb{M}_1)$ and $(\mathbb{I}, \mathbb{M}_2)$, an emergent behaviour is the embedding space occured where can be found modality pairs $(\mathbb{M}_1, \mathbb{M}_2)$. This enables zero-shot and cross-modal tasks without specific training for those tasks, such as classifying audio-text without being trained on specifically.

4.1.6 Architecture Description

As previously mentioned, the architecture of ImageBind is based mainly on transformers. Let's review the models used in for each encoder (transformers as well) and explain how they work.

- **Images & Video**: The model transformer-based for encoding both, images and videos, is the same one, the Vision Transformer ViT-H 630M parameters. They can use ViT-H 630M for videos as well because they temporally inflate the model so it can process video data by extending the 2D path projection layer to handle an additional temporal dimension. This allows to analyze short video clips (2 frames extracted from 2 second intervals).

- **Audio**: The model used for enconding audio is the Audio Spectogram Transformer (AST), which is a convolution freen, purely attention-based model for audio classification. A 2-second audio clip (sampled at 16KHz) is transformed into a spectogram (image of the audio frequencies over time). Then, they use ViT-B (B stands for base, it's the baseline model from the Vision Transformers family) to encode the spectogram.

- **Text**: Text data is encoded using CLIP as previouslt mentioned, however to be precise, they use OpenCLIP 302M.
- **Thermal & Depth**: For this modality of data, the model ViT-S (S stands for small) will be in charge of encoding the embeddings using one-channel color versions of them.
- **IMU**: Inertial Measurement Units signals consisting from accelerometer and gyroscopes measurements across X, Y and Z axes are extracted, This adds up a total of 6 values (3 for acceleration and 3 for rotational motion). The data is collected in 5 second clips. Over these 5 seconds, the IMU records 2000 time steps of data. Then, with those 2000 rows of data (times 6), we apply a 1D convolutional neural network to process the sequential data (as time series) to extract meaningful features and compact data.

  The input data shape is (2000,6), and with a kernel size of 8, the convolution operation considers 8 consecutive time steps at a time, and considering a stride of 1 (filter moves one time step forward after each operation). The convolutional filter computer a weighted sum of the input features within its window (8 time steps) and applies an activation function to generate the output. Finally, the resulting sequence is encoded using a lightweight 6 layer encoder transformer with 512 dimensional width and 8 heads (trained for 8 epochs).

After using the different transformer encodes, to ensure a normalized embeddings for all modalities, they include on top of each encoder a "modality specific linear projection head" to output a fixed size d dimensional embedding, which is normalized and used in the previous InfoNCE loss function. All along the training the embedding encoders are updated for all modalities, allowing the encoders to learn and adapt their representations to match accurately the image representation of the entity, action or scene.

In conclusion, ImageBind is a multi-modal transformer-based encoder model that can be integrated into complementary models to leverage and improve the variability of data to train on.

4.2 PandaGPT

PandaGPT is a groundbreaking model designed to empower large language models with visual and auditory instruction-following capabilities. Developed by researchers from institutions such as the University of Cambridge and Tencent AI Lab, PandaGPT aims to integrate and understand information from multiple modalities simultaneously, much like humans perceive and interpret diverse sensory inputs.

The original research paper can be found here: PandaGPT

4.2.1 Multi-Modal Integration

PandaGPT's components are quite simple. It combines multimodal encoders from ImageBind with the language capabilities from Vicuna-7B (LLM). On one hand, ImageBind is in charge of generating embeddings for various modalities and on the other hand, Vicuna processes text inputs and generates responses based on the integrated embeddings from the multimodal data. This multimodal integration is enhanced with Low-Rank Adaptation (LoRA) weights to improve the handling of multimodal information without extensive re-training. Obviously, the modalities covered are the same as ImageBind, including video, images, audio, depth, thermal and IMU.

4.2.2 Training Process

4.2.2.1 Dataset Preparation

PandaGPT is trained on 160k image-language instruction-following pairs. Each training instance includes an image $\mathcal{I}$ and a conversation sequence (based on instruction and response pairs defined as $(\mathcal{I}, (x_1, y_1, x_2, y_2, ..., x_n, y_n))$.

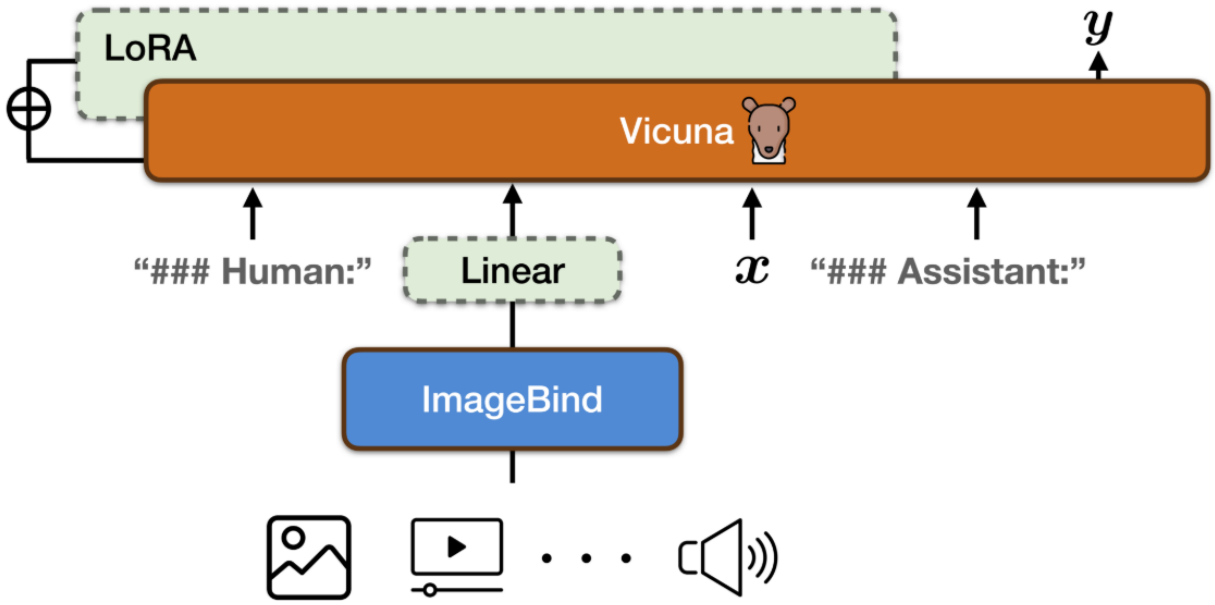


Figure 1: Illustration of PandaGPT. During training, we only train the linear projection matrix and the additional LoRA weights (as indicated with dashed boxes) while keeping the parameters of ImageBind and Vicuna frozen.

4.2.2.2 Training Strategy

As PandaGPT combines both models, ImageBind and Vicuna, the model needs to create a bridge between them, that's why it uses a linear projection matrix (LPM) and LoRA weights. The linear projection marix connects ImageBind embeddings to Vicuna's feature space. The LoRA weights are applied on the attention modules of Vicuna, significantly reducing the number of trainable parameters to around 0.4% of the total parameters of Vicuna. Besides, most parameters of ImageBind and Vicuna remain frozen to leverage their pre-trained capabilities.

4.2.2.3 Objective Function

The objective function for PandaGPT aims to maximize the probability of generating the correct response during training. This involves adjusting the learnable parameters to ensure the model's output aligns as closely as possible with the expected responses. The objective function considered is the following one:

$$L(\theta_f, \theta_l) = \prod_{i=1}^{n} p_\theta(y_i|x_{<i}, y_{<i-1}, f(h_I)) \text{ where } \begin{cases} \theta_f, \theta_l \text{ are learnable parameters (LPM, LoRA respectively)} \\ x_i \text{ is the embedding instruction at moment i-th} \\ y_i \text{ is the embedding response at (i-1)-th previous moments} \\ f(h_\mathcal{I}) \text{ is the image representation embedding} \end{cases}$$

The goal is to maximize the probability $p_\theta(y_i|x_{<i}, y_{<i-1}, f(h_I))$, which represents the likelihood of generating the correct response y_i given the previous instructions $(x_{<i})$, responses $(y_{<i-1})$, and image embedding $(f(h_I))$. In probabilistic modeling, maximizing the likelihood function ensures that the model parameters are optimized to make the observed data (training data) most probable. This way, the model learns to generate accurate responses that align well with the given instructions.

4.2.3 Training Steps

1. **Image Encoding**: The image is passed through ImageBind to generate an embedding $h_\mathcal{I}$.
2. **Text Encoding**: Instructions and responses are encoded using Vicuna, generating text embeddings.

3. **Alignment**: The image embedding h_I is aligned with the text embeddings via a linear projection matrix f.

4.2.4 Example of Training Instances

Imagine a detailed image of a machine part with visible defects. The conversation sequence could look like as:

1. **Instruction 1**: "Describe the condition of the machine part in the image."
   - **Expected Response 1**: "The machine part appears to be generally in good condition but has some visible wear and tear."
   - **Model Response**: PandaGPT attempts to generate a response similar to the expected one, using the image embedding to inform its description.
2. **Instruction 2**: "Identify any visible defects in the image."
   - **Expected Response 2**: "There is a small crack near the bottom-left corner and some surface scratches."
   - **Model Response**: PandaGPT uses the image embedding to identify and describe defects, trying to align its response closely with the expected answer.
3. **Instruction 3**: "What might have caused these defects?"
   - **Expected Response 3**: "The crack could be due to mechanical stress, and the scratches may result from friction during operation."
   - **Model Response**: PandaGPT generates a response considering the possible causes, again informed by the image embedding.

4.2.5 Key Innovations

PandaGPT seamlessly integrates and understands multimodal inputs displaying zero-shot capabilities and by only training a small fraction of the model parameters, PandaGPT achieves its capabilities with reduced computational resources and training time.

4.3 LlaVA

The model LlaVA, which stands for Large Language and Vision Assistant, is an end-to-end (E2E) trained large multimodal model, released in December 2023 by Microsoft Research, that connects a vision encoder and a LLM for general purpose visual and language understanding. Experiments show that LlaVA exhibits the behaviours of multimodal GPT4 on unseen images/instructions, yielding a 85.1% relative score compared with GPT4 on a synthetic multimodal instruction-following dataset. The official website from the model, which contains a demonstration, the research paper and where can be found the github code, is well explained.

4.3.1 Architecture

LlaVA employs the pre-trained CLIP visual encoder ViT-L/14 (Large) and connects it to the LLM Vicuna-v0 using a lightweight linear projection matrix. This setup transforms visual features into language embeddings tokens, matching the dimension from the text embedding tokens from Vicuna.

4.3.2 Training Process

LlaVA's training involves 2 main stages.

4.3.2.1 Pre-Training for Feature Alignment

In the first stage, it was utilized a filtered subset of CC3M of 595k image-text pairs (the complete dataset is made up of 3 million images and its corresponding captions). The goal is to align the features extracted from images with the word embeddings used by a pre-trained language model (LLM).

In order to align properly both informations, we apply a naïve expansion method which turns each image-text pair from the filtered dataset into a single-turn conversation. For instance, for an image X_v of a cat, the question X_q might be "What do you see in the image?", and the answer X_a would be the original caption (ground-truth prediction), like "A cat sitting on a sofa."

Both the visual encoder (which processes the image) and the pre-trained LLM (which processes the text) have their weights frozen. The only parameters that are updated during this training stage are those in the projection matrix W. This projection matrix is responsible for aligning the image features with the word embeddings of the LLM.

The objective is to maximize the likelihood that the model correctly predicts the caption (answer X_a) given the image and the instruction. By training the projection matrix, the image features H_v are transformed in a way that makes them compatible with the word embeddings of the LLM.

$$H_v = W \cdot Z_v, \text{ with } Z_v = g(X_v) \text{ where } \begin{cases} X_v \text{ is the input image} \\ g \text{ is the visual encoder ViT-L/14} \\ Z_v \text{ are the visual extracted visual features} \\ W \text{ is the trainable projection matrix} \\ H_v \text{ are the language embeddings token from} \\ \text{(the visual features with same dimensionality} \\ \text{as the word embeddings from the LLM)} \end{cases}$$

Let's consider the following example to understand.

Example Setup

1. **Dataset:** Let's say we have a very small dataset with just one image-text pair.
   - **Image:** An image X_v of a dog.
   - **Caption (Ground-Truth Answer X_a):** "A brown dog is playing in the park."
2. **Question (Instruction X_q):** "What is in the image?"

Step-by-Step Process

1. **Extract Image Features:**
   - The image X_v is passed through the visual encoder, which outputs a feature vector H_v.
   - Let's assume the visual encoder outputs a feature vector of size 3: $H_v = [1.2, -0.5, 2.3]$.
2. **Word Embeddings for the Caption:**
   - The words in the caption "A brown dog is playing in the park." are converted into word embeddings using the pre-trained LLM.
   - Assume the embeddings for the words are as follows (each word is represented by a 3-dimensional vector for simplicity):
     - "A": $[0.1, 0.2, 0.3]$
     - "brown": $[0.4, 0.5, 0.6]$
     - "dog": $[0.7, 0.8, 0.9]$
     - "is": $[0.1, 0.0, -0.1]$
     - "playing": $[0.2, -0.2, 0.0]$
     - "in": $[0.1, -0.1, 0.1]$
     - "the": $[0.0, 0.1, 0.0]$
     - "park": $[0.5, 0.6, 0.7]$
3. **Projection Matrix:**
   - We need to train a projection matrix W that will map the visual feature vector H_v to the space of the word embeddings.
   - Assume W is a 3x3 matrix initialized randomly:

$$W = \begin{bmatrix} 0.1 & 0.2 & 0.3 \\ 0.4 & 0.5 & 0.6 \\ 0.7 & 0.8 & 0.9 \end{bmatrix}$$

4. **Transform Visual Features:**
   - The visual feature vector H_v is multiplied by the projection matrix W to obtain the aligned features:

$$H_v' = H_v \cdot W = [1.2, -0.5, 2.3] \cdot \begin{bmatrix} 0.1 & 0.2 & 0.3 \\ 0.4 & 0.5 & 0.6 \\ 0.7 & 0.8 & 0.9 \end{bmatrix}$$

   - Performing the matrix multiplication:

$$H_v' = [1.2 \cdot 0.1 + (-0.5) \cdot 0.4 + 2.3 \cdot 0.7, \\ 1.2 \cdot 0.2 + (-0.5) \cdot 0.5 + 2.3 \cdot 0.8, \\ 1.2 \cdot 0.3 + (-0.5) \cdot 0.6 + 2.3 \cdot 0.9]$$

$$H_v' = [1.61, 1.36, 1.11]$$

5. **Alignment Objective:**
   - The objective is to maximize the likelihood that H_v' correctly predicts the word embeddings of the caption "A brown dog is playing in the park."
   - In practice, this means adjusting W to minimize the difference between H_v' and the word embeddings of the caption words.

4.3.2.2 E2E Fine-Tuning

After the initial alignment of visual features with word embeddings in Stage 1, the next step is to fine-tune the entire model end-to-end. This second stage involves fine-tuning both the visual encoder and the language model

to improve their joint performance on the task.

We continue using the filtered dataset from Stage 1, which contains image-text pairs converted into instruction-following data. Each sample in the dataset is treated as a conversation turn, where the model needs to generate an appropriate response based on the given image and instruction

The loss function typically used is the negative log-likelihood (NLL) or cross-entropy loss, which measures how well the model's predicted response matches the ground truth response. The entire model is trained end-to-end, meaning the gradients are backpropagated through both the visual encoder and the language model.

4.3.3 Loss Function

During the training, the model is optimized to maximize the likelihood of the correct response sequences. This is done by minimizing the negative log-likelihood of the target tokens, then the model parameters are adjusted to reduce the loss, thereby learning to generate responses closer to the expected target:

$$\mathcal{L} = -\sum_{i=1}^{L} \log[p_\theta(x_i \mid X_v, X_{\text{Instruct}}, x_{<i})]$$

Here, x_i is the i-th token in the ground-truth response, and $p_\theta(x_i \mid X_v, X_{\text{instruct}}, x_{<i})$ is the probability assigned to that token by the model.

4.3.4 Training Instances

Let's understand the training process in details. Suppose we have an image X_v of a cat sitting on a sofa. The conversation might be about identifying objects in the image and describing their attributes.

1. **Instruction 1**: $X^1_{Instruct} = [X^1_q, X_v]$
   - **Question 1**: X^1_q is "What do you see in the image?".
   - **Expected Model Answer 1**: X^1_a is "I see a cat sitting on a sofa.".

   The expected model answer is the expected target output that we want the model to learn to generate. Here the model would generate a response which might be initially incorrect or incomplete, and in order to assess the quality of the response, the target response is tokenized into:

   "I see a cat sitting on a sofa." $\Rightarrow$ ["I", "see", "a", "cat", "sitting", "on", "a", "sofa", "."]

   A similar step would be applied to the generated answer. Then, the probability computation proceeds as follows:

   1. $p_\theta(\text{"I"} | X_v, X_{Instruct})$
   2. $p_\theta(\text{"see"} | X_v, X_{Instruct}, \text{"I"})$
   3. $p_\theta(\text{"a"} | X_v, X_{Instruct}, \text{"I"}, \text{"see"})$

   And so on...

   The text token "I" is embedded into a vector representation using an embedding layer composed of logits (raw scores, float values) that indicate the model's relative preference for each token, then the probability is calculated following a softmax distribution:

$$p_\theta(X_i | X_v, X_{Instruct}, X_{<i}) = \frac{\exp^{logit_{x_i}}}{\sum_j \exp^{logit_{x_j}}}$$

2. **Instruction 2**: $X^2_{Instruct} = [X^2_q, X_v]$

   - **Question 2**: X^2_q is "Describe the color of the cat.".
   - **Expected Model Answer 2**: X^2_a is "The cat is white with black spots.".

   The second question includes the context from the previous turn. The model is trained by comparing its generated responses to these expected target responses.

4.3.5 Probability Computation

The model learns to predict the sequence of answers given the instructions and image. For instance, for the previous example of a conversation sequence of length $L = 2$, we would have that the probabilities calculations for $p_\theta(X_a|X_v, X_{Instruct})$ are:

$$p_\theta(\overbrace{\text{"I see a cat sitting on a sofa."}}^{X^1_a}|X_v, \overbrace{\text{"What do you see in the image?"}}^{X^1_q}) \times$$
$$p_\theta(\underbrace{\text{"The cat is white with black spots."}}_{X^2_a}|X_v, \underbrace{\text{"Describe the color of the cat."}}_{X^2_q}, \underbrace{\text{"I see a cat sitting on a sofa."}}_{X^1_a})$$

The probabilities in LlaVA's training process are determined using an auto-regressive model (to predict next token in the sequence), where the likelihood of generating each token in the response sequence is calculated based on the image, instructions and previously generated tokens.

Mathematically, the probability of the entire response sequence X_a is the product of the probabilities of each token given the previous context:

$$p_\theta(X_a|X_v, X_{Instruct}) = \prod_{i=1}^{L} p_\theta(X_i|X_v, X_{Instruct}, X_{<i}) \begin{cases} p_\theta \text{ is the probability of the i-th token} \\ X_{<i} \text{ represents the sequence of tokens} \\ \text{preceeding } X_i \end{cases}$$

5 Week 5, 6, 7, 8, 9, 10, 11: 03/06/24-20/07/24

5.1 AnomalyGPT

5.1.1 Background

Let's delve into the domain in which the model will attempt to provide good results. Industrial anomaly detection algorithms (IAD) refers to the process of identifying unusual patterns, deviations or anomalies in industrial operations and processes that may indicate potential issues, faults or inefficiencies. These anomalies can signify problems such as equipment malfunctions, process deviations or security breaches, which can lead to downtime, reduced efficiency and increased operational costs if not promptly addressed.

Factories are populated with various sensores to collect data from machinery and processes including temperature, pressure, vibration, sound, images and other operational metrics. By collecting such data, the company can take advantage from multiple benefits such as preventing maintenance, assessing quality control, securing safety at the workplace or improving operational efficiency.

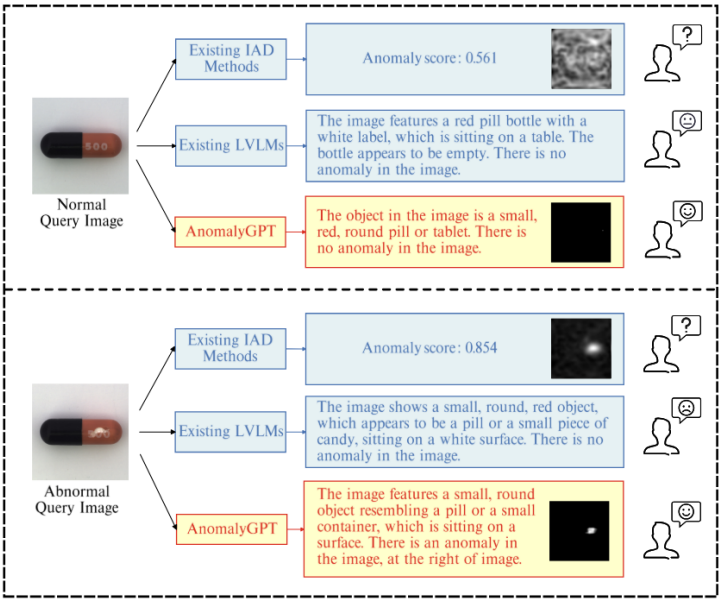
5.1.2 Anomaly Detection Algorithms

Different algorithms have arised in last years in order to detect the previously mentioned anomalies, including:

- **Threshold-Based Detection**: Simple rules and thresholds to flag anomalies when certain metrics exceed predefined limits. Most existing IAD methods are based on methods defined following this approach, which provide anomaly scores that distinguish between normal and abnormal samples. However, it's not too practical to just obtain a score.
- **Pattern Recognition**: Identifying deviations from established patterns using machine learning AI techniques, which is the approach that we will follow, has proven to be very accurate in order to detect anomalies.
- **Time-Series Analysis**: Analyzing temporal data to detect irregularities it's another method to identify the anomalies, which as well it's based on AI techniques.
- **Real-Time Monitoring**: Implementing systems to continuously monitor data streams and detect anomalies in real-time, enabling prompt responses to potential issues solves as well the problem althought it can becomes expensive.

AnomalyGPT is a large vision-language model (LVLM) released in December 2023, that assesses the presence and localization of anomalies, providing textual descriptions of the anomaly for each image. Due to the rarity of real-world samples, models are required to be trained only on normal samples and distinguish anomalous samples that deviate from them.

On one hand, existing LVLMs cannot detect anomalies in images as they lack of domain specific knowledge (because they are trained on large and varied amounts of data sourced from the Internet) and sensitivity to local details. On the other hand, existing IAD methods only provide anomaly scores and need manually threshold setting. Previous reasons justify the need for a model being able to assemble all those capabilities and even extend them by including textual descriptions.



5.1.2.1 Concepts

Some concepts that might help to understand better the model that we'll be introduced:

- **One-Class-One-Model**: Refers to a type of anomaly detection approach where a separate model is trained for each class or type of normal behaviour. The model learns to distinguish normal data from anomalies for that specific class.
- **Few-shot Learning**: Machine learning approach where the model is able to learn and make accurate predictions with a very small amount of labeled data training.
- **Multi-turn Dialogue**: Refers to the capability of a system to engage in a conversation with multiple back-and-forth exchanges, where each response can depend on previous exchanges.
- **In-Context Learning**: Process where a model like a LLM, can learn and perform tasks based on the context provided within the prompts, without needing explicit re-training or fine-tuning.

Methods	Few-shot learning	Anomaly score	Anomaly localization	Anomaly judgement	Multi-turn dialogue
Traditional IAD methods		✓	✓		
Few-shot IAD methods	✓	✓	✓		
LVLMs	✓				✓
AnomalyGPT (ours)	✓	✓	✓	✓	✓

Table 1. Comparison between our AnomalyGPT and existing methods across various functionalities. The "Traditional IAD methods" in the table refers to "one-class-one-model" methods such as PatchCore [23], InTra [21], and PyramidFlow [13]. "Few-shot IAD methods" refers to methods that can perform few-shot learning like RegAD [10], Graphcore [29], and WinCLIP [27]. "LVLMs" represents general large vision-language models like MiniGPT-4 [36], LLaVA [17], and PandaGPT [25]. "Anomaly score" in the table represents just providing scores for anomaly detection, while "Anomaly judgement" indicates directly assessing the presence of anomaly.

5.1.3 Challenges of training LVLMs with IADs

Training LVLMs with IADs face two main challenges:

1. **Data Scarcity**: One of the main challenges is not having enough data specific to the IAD field.
   - **Why it matters?**: LVLMs (like LLaVA and PandaGPT) are pre-trained on vas datasets (160k images with dialogues). In contrast, IADs only have a few thousand images.

- **Consequence**: Training on such small IAD datasets could lead to overfitting and catastrophic forgetting (the model forgets what he learnt).
- **Solution**: One of the chosen solutions is to use prompt embeddings instead of fine-tuning the model parameters.
- **How it works?** In our case, the raw input would be a small dataset of images showing parts of industrial machinery with some defects. So the prompt embedding would be composed of the encoding image along with a textual description embedding. For instance, given an image with an anomaly, the textual description could be: "This is an image of a machinery component. It should be free of defects such as cracks or scratches".

  By providing the image encoding, the domain-specific knowledge as just mentioned (which is additional information about normal and common defects), the model receives as input a common embedding which is the result of combining the previous information into a single joint embedding.

2. **Fine Grained Semantic Understanding**: The second challenge is teaching the model to identify very small, subtle defects in industrial products, which requires a detailed understanding of the image.

   - **Solution**: To solve such issue, the model will include a decoder and use prompt embeddings. Traditionally, the decoder from a neural network converts numerical vectors back into human-readable formats. Instead, the mentioned decoder is a component that processes the image to generate detailed, pixel-level anomaly information, which can be used to create embeddings that enrich the input to the LVLM.
   - **How it works?**
     (a) **Image Analysis**: The decoder analyzes the image and identifies specific areas where anomalies might be present. This involves generating pixel-level information about potential defects.
     (b) **Encoding Detailed Information**: The detailed information about these anomalies is encoded into numerical vectors (embeddings).
     (c) **Combining Embeddings**: These embeddings are combined with the initial image and any textual description to form a comprehensive prompt that provides the LVLM with contextual information.

     Basically, the original image is passed through the image encoder (in the AnomalyGPT base model, the image encoder is ImageBind) that generates an initial image embedding vector which is then processed by the image decoder, model in charge of analyzing and combining the information.

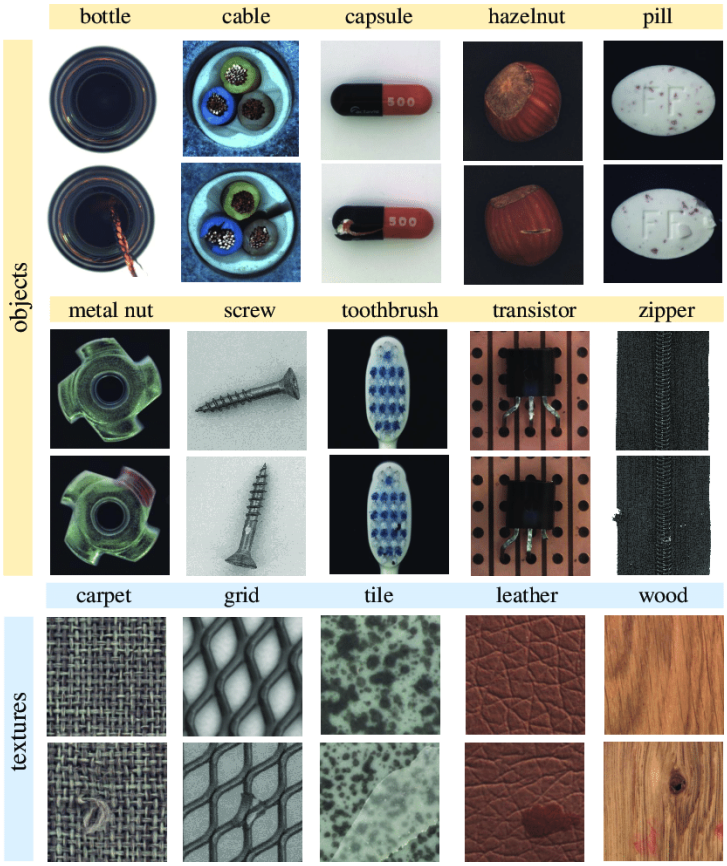
5.1.4 Relevant Datasets on IADs

The most well-known datasets for IAD training, are the following ones:

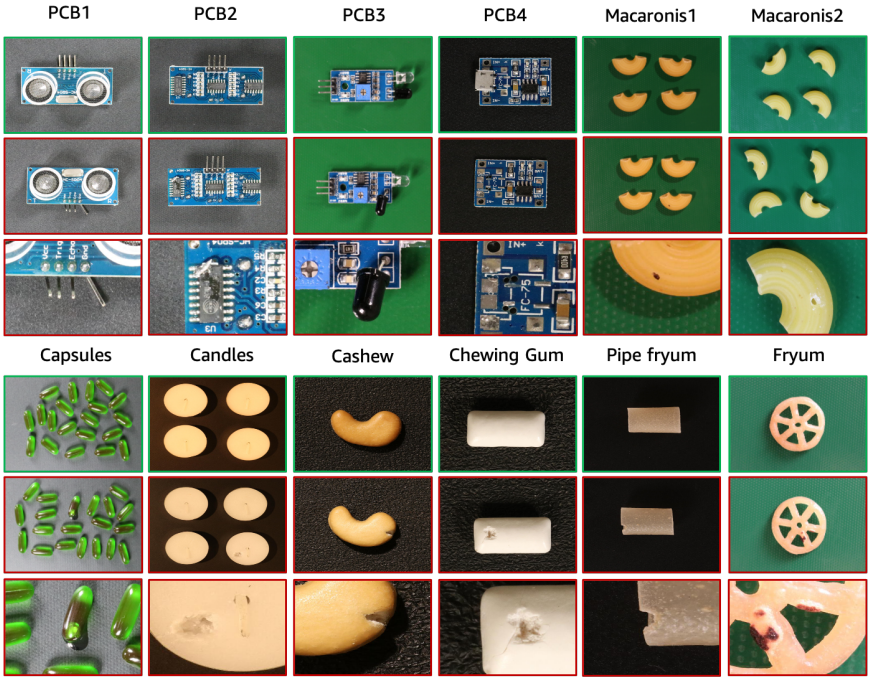
- **MVTec-AD Dataset**: The MVTec Anomaly Detection dataset is designed for benchmarking anomaly detection and localization algorithms. It focuses on industrial applications where detecting defects in products is critical.

  It consists of 15 categories of objects including: 5 texture categories (carpet, grid, leather, tile and wood) and 10 object categories (bottle, cable, capsule, hazelnut, metal nut, pill, screw, toothbrush, transistor and zipper).

  It's composed of a total of 3629 high-resolution images for training and 1725 for testing, containing defect-free and anomalous images in testing but only defect-free in training set.



- **ViSA Dataset**: The Visual Anomaly dataset is a newly introduced dataset (2022) aimed at advancing the research in indutrial anomaly detection and localization. It consists of 12 categories of industrial products, including industrial parts, electronic components and various manufactores items. It's composed of a total of 9261 images and 1200 anomalous samples which include defects such as structural defects, surface imperfections and functional failures.



5.1.5 Architecture

The AnomalyGPT model follows a single operational path with a slight difference in input handling depending on whether it receives a single query image or a pair of images (one with anomalies and a normal sample). The operational steps followed by the model and the slight differences between the two input scenarios can be understood as follows:

1. **Query Image Input**:
   - **Single Image Mode**: The model receives a single query image that may contain anomalies.
   - **Paired Image Mode**: The model receives a pair of images – one query image that may contain anomalies and a normal image representing the normal sample.

   In both cases, let's denote the query image as $x \in \mathbb{R}^{\mathcal{H} \times \mathcal{W} \times \mathcal{C}}$.

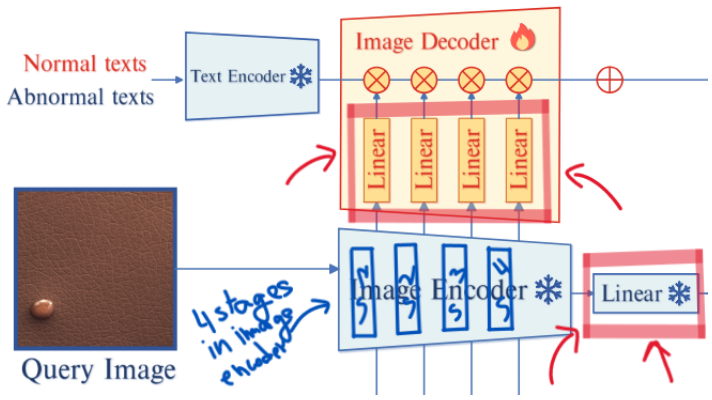
2. **Text Encoder**: Normal and abnormal texts are encoded using the Text Encoder to generate text features, which are used in the unsupervised setting to aid anomaly detection.

3. **Image Encoder**: The query image is processed by the Image Encoder to extract features, which is composed of 4 different stages to obtain the intermediate patch-level features, which we will denote as follows:

$$\mathcal{F}^i_{patch} \in \mathbb{R}^{\mathcal{H}_i \times \mathcal{W}_i \times \mathcal{C}_i} \quad \forall i \in \{1, 2, 3, 4\}$$

   Then, when the image encoder obtains the intermediate patch-level features, as they don't belong to the same space, it's not possible to align them directly with the text embeddings from the text encoder, so 4 linear layers are needed to make possible the transition and combination, these new features obtained from the linear layers are denoted:

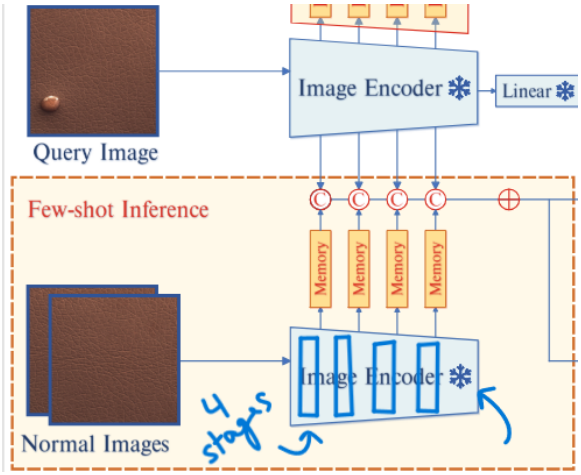
$$\tilde{\mathcal{F}}^i_{patch} \in \mathbb{R}^{\mathcal{H}_i \times \mathcal{W}_i \times \mathcal{C}_i} \quad \forall i \in \{1, 2, 3, 4\}$$



4. **Memory Bank (for Paired Image Mode)**: If the paired image mode is used, the normal image is also processed by the Image Encoder to extract features, which are then stored in memory banks. However, in this case, as no text embeddings will be combined, there's no need to apply linear layers to combine both features, text and image. The normal samples stored in memory banks are denoted as follows:

$$\mathcal{B}^i \in \mathbb{R}^{\mathcal{N} \times \mathcal{C}_i} \quad \forall i \in \{1, 2, 3, 4\}$$

   In order to determine how similar each patch-level feature $\mathcal{F}^i_{patch}$ is with it's memory bank counterpart $\mathcal{B}^i$, we need to use the "maximum" function to find the maximum similarity score for each patch between both. Then, by substricting the maximum similarity score from 1, the resulting term effectively measures the "anomaly score" for each patch. Higher values indicate a great likelihood of the patch being anomalous (since it's less similar to any normal patches)



5. **Image Decoder: Feature Comparison and Anomaly Localization**:

   - **Single Image Mode**: The intermediate patch-level features extracted from the image encoder and that have passed through the linear layers, are combined with text features coming from the text encoder in the image decoder to generate pixel-level anomaly localization results. The locatization result $M \in \mathbb{R}^{\mathcal{H} \times \mathcal{W}}$ is obtained as follows:

   $$M = \text{Upsample}(\sum_{i=1}^{4} softmax(\tilde{\mathcal{F}}^i_{patch} \times \mathcal{F}^T_{text})) = \text{Upsample}(\sum_{i=1}^{4} [\frac{\exp \tilde{\mathcal{F}}^i_{patch} \times \mathcal{F}^T_{text}}{\sum k \tilde{\mathcal{F}}^i_{patch} \times \mathcal{F}^T_{text}}])$$

   [The function "Upsample" in the context of neural networks and image processing is used to increase the spatial resolution of a feature map or an image. Upsampling is the reverse operation of downsampling or pooling and is commonly used in applications such as image generation, segmentation, and super-resolution. Upsample is a function that enlarges a smaller image or feature map to a higher resolution.]

   At the same time, the extracted features from the image encoder are compared to the learned (memory bank) normal features (from training data) to detect anomalies. To note that, in this case, as the only input is a single query image, the image is compared with the information stored within the memory banks (training data). The comparison results are used to generate a localization map indicating the presence of anomalies.

   - **Paired Image Mode**: Besides following the same top path from the schema (text encoder + image encoder → image decoder), the patch-level features of the query image (anomaly or normal) are compared with the stored features from the normal image(s) in the memory bank. The distance between the query patches and the normal patches is calculated to identify deviations, indicating potential anomalies. The comparison results are used to generate a localization map.

   $$M = \text{Upsample}(\sum_{i=1}^{4} [1 - max(\mathcal{F}^i_{patch} \times \mathcal{B}^{iT}]))$$

6. **Prompt Learner**: The localization results are transformed into prompt embeddings by the Prompt Learner. Learnable base prompt embeddings are also included to provide additional context for the anomaly detection task.

7. **Large Language Model**: The LLM processes the image embedding, the prompt embeddings, and any user-provided textual input (e.g., "Is there any anomaly in the image?"). Ultimately, the LLM is ready to provide a detailed response indicating whether an anomaly is present, where it is located within the image, and a description of the anomaly.

5.1.5.1 Slight Differences in Input Handling

- Single Query Image Mode
  - **Comparison Basis**: The model compares the query image features with the normal features learned during training.
  - **Output Quality**: If the query image is related to the training dataset, the model performs well in detecting, localizing, and describing the anomaly. If the query image is unrelated to the training data, the model's performance may degrade because it lacks relevant information for accurate comparison.
- Paired Image Mode
  - **Comparison Basis**: The model compares the query image features with the features of the provided normal image stored in the memory bank.
  - **Output Quality**: The model can still determine whether an anomaly is present and localize it within the query image. If the query image is related to the training dataset, the model can provide a detailed description of the anomaly. If the query image is unrelated to the training data, the description may not be accurate, but the model can still localize anomalies based on the provided normal sample.

5.1.6 Loss Functions

5.1.6.1 Cross-Entropy Loss

Cross-entropy loss is commonly employed for training language models, which quantifies the disparity between the text sequence generated by the model and the target text sequence. The formula is as follows:

$$\mathcal{L}_{ce} = -\sum_{i=1}^{n} y_i \cdot log(p_i) \text{ where } \begin{cases} n \text{ is the number of tokens} \\ y_i \text{ is the true label} \\ p_i \text{ is the predicted probability} \end{cases}$$

5.1.6.2 Focal Loss

Focal loss is commonly used in object detection and semantic segmentation to address the issue of class imbalance, which introduces an adjustable parameter γ to modify the weight distribution of cross-entropy loss, emphasizing samples that are difficult to classify. In IAD task, where most regions in anomaly images are still normal, employing focal loss can mitigate the problem of class imbalance. Focal loss can be calculated as follows:

$$\mathcal{L}_{focal} = -\frac{1}{n}\sum_{i=1}^{n}(1-p_i)^{\gamma} \cdot log(p_i) \text{ where } \begin{cases} n = \mathcal{H} \times \mathcal{W} \text{ is the number of pixels} \\ \gamma(=2) \text{ is a tunnable parameter} \\ p_i \text{ is the predicted probability of positive classes} \end{cases}$$

5.1.6.3 Dice Loss

Dice loss is a commonly employed loss function in semantic segmentation tasks. It is based on the dice coefficient and can be calculated as follows:

$$\mathcal{L}_{dice} = -\frac{\sum_{i=1}^{n} y_i \cdot \hat{y}_i}{\sum_{i=1}^{n} y_i^2 + \sum_{i=1}^{n} \hat{y}_i^2} \text{ where } \begin{cases} n = \mathcal{H} \times \mathcal{W} \text{ is the number of pixels} \\ y_i \text{ is the output of the decoder} \\ \hat{y}_i \text{ is the ground-truth value} \end{cases}$$

5.1.6.4 Overall Loss Function

Combining the three previously mentioned loss functions, the overall loss function is defined as follows:

$$\boxed{L = \alpha \cdot L_{ce} + \beta \cdot L_{focal} + \gamma \cdot L_{dice}} \text{ where } \alpha, \beta, \gamma \text{ are set to 1.}$$

5.2 Code Understanding

5.2.1 Origin Script: train_mvtec.sh

The complete training from AnomalyGPT with the dataset MVTec can be found on the shell script "train_mvtec.sh" which contains the main arguments needed to train the model:

```
#!/bin/bash
deepspeed --include localhost:0 --master_port 28400 train_mvtec.py \
    --model openllama_peft \
    --stage 1 \
    --imagebind_ckpt_path ../pretrained_ckpt/imagebind_ckpt/imagebind_huge.pth \
    --vicuna_ckpt_path ../pretrained_ckpt/vicuna_ckpt/7b_v0/ \
    --delta_ckpt_path ../pretrained_ckpt/pandagpt_ckpt/7b/pytorch_model.pt \
    --max_tgt_len 1024 \
    --data_path  ../data/pandagpt4_visual_instruction_data.json\
    --image_root_path ../data/images/ \
    --save_path  ./ckpt/train_mvtec/ \
    --log_path ./ckpt/train_mvtec/log_rest/
```

In the shell file, we can find many arguments:

- Main python script "train_mvtec.py".
- The model which will be used "–model openllama_peft".
- The multiple checkpoints such as **Vicuna** (LLM), **ImageBind** (Multimodal Encoder) and **PandaGPT** (LLM, used as text encoder).
- The paths for the textual data ("–data_path") and images ("–image_root_path").
- The path where the resulting trained model will be stored is "–save_path".
- The log path, where the logging information from the whole process will be stored is "–log_path".
- The "-include localhost:0" specifies the devices (GPUs) on the localhost to be included in the training. In this case, GPU 0 and, if it was written 0,1, then it would include 2 GPUs, 0 and 1.
- The command "-master_port" determines the port used for communication between processes in distributed training.

The goal is to replace consciously the decoder layer used in the baseline model to, not only attempt to improve the model's performance but also to learn from the architecture, the libraries used, and to apply a multinode training using DeepSpeed and Horovod. Therefore, in order to do so, we **need to understand the training process** and **proceed cronologically** according to the baseline code, which first leads to understanding the python script "train_mvtec.py".

5.2.2 Principal Script: train_mvtec.py

The script first evaluates the last condition " __name__ == "__main__" ":

```
if __name__ == "__main__":
    args = parser_args() # Calls the function parser_args() to parse
                         # the command shell arguments from the shell script
    args = vars(args)    # Converts into a dictionary all the previous retrieved
                         # arguments from parser_args()
    args['layers'] = [7,15,23,31] # Adds new key-value pair to the dictionary
    main(**args)         # Calls main function of the script
```

5.2.2.1 Function parser_args()

The function is in charge of collecting all the arguments used in the shell file commands.

```
def parser_args():
    parser = argparse.ArgumentParser(description='train parameters')
    parser.add_argument('--model', type=str)
    parser.add_argument('--local_rank', default=0, type=int)
    parser.add_argument('--save_path', type=str)
    parser.add_argument('--log_path', type=str)

    # model configurations
    parser.add_argument('--imagebind_ckpt_path', type=str) # the path that stores the imagebind checkpoint
    parser.add_argument('--vicuna_ckpt_path', type=str) # the path that stores the vicuna checkpoint
    parser.add_argument('--delta_ckpt_path', type=str) # the delta parameters trained in stage 1
    parser.add_argument('--max_tgt_len', type=int) # the maximum sequence length
    parser.add_argument('--stage', type=int) # the maximum sequence length
    parser.add_argument('--data_path', type=str) # the maximum sequence length
    parser.add_argument('--image_root_path', type=str) # the maximum sequence length
```

The resulting variable args will contain the following information (further information is provided within the files base.yaml, openllama_peft.yaml and openllama_peft_stage_1.json):

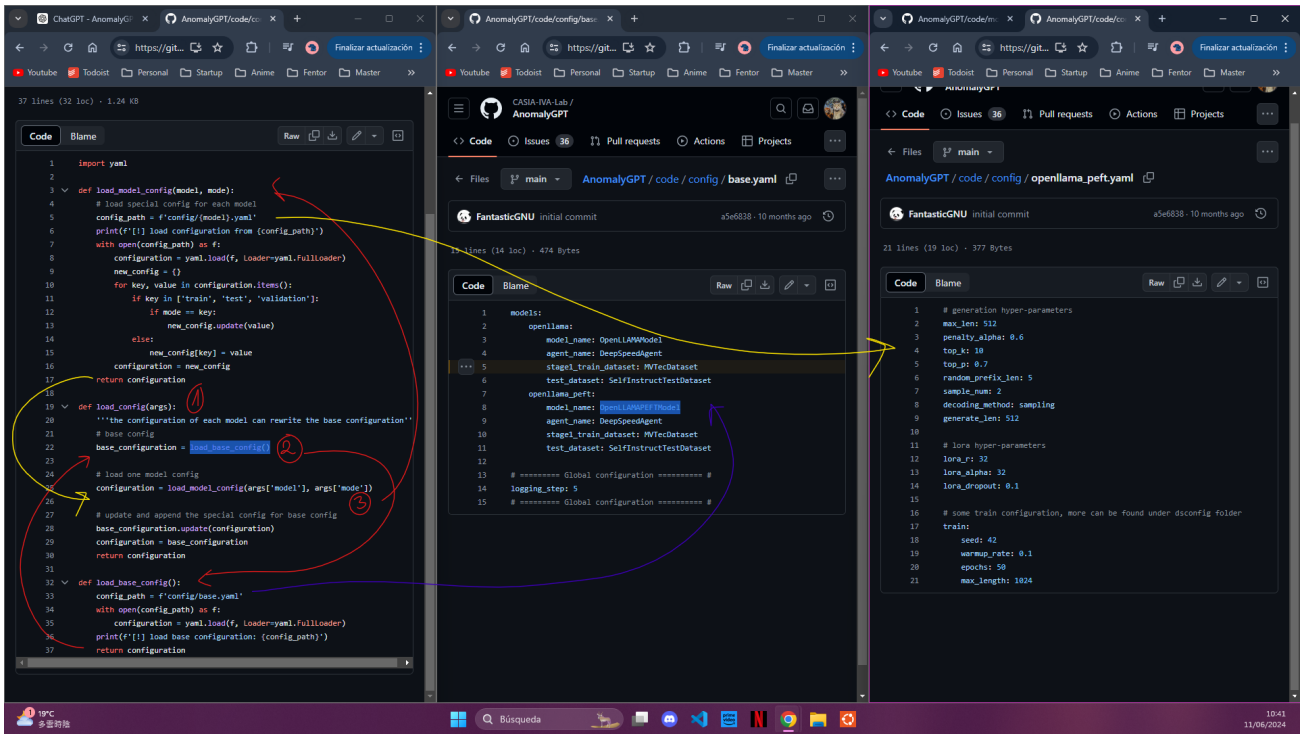
```
args = {'model': openllama_peft, 'local_rank': 0, 'save_path': ./ckpt/train_mvtec/, 'log_path':

./ckpt/train_mvtec/log_rest/, 'imagebind_ckpt_path': ../pretrained_ckpt/imagebind_ckpt/imagebind_huge.pth,

'vicuna_ckpt_path': ../pretrained_ckpt/vicuna_ckpt/7b_v0/, 'delta_ckpt_path':

../pretrained_ckpt/pandagpt_ckpt/7b/pytorch_model.pt, 'max_tgt_len': 1024, 'stage': 1, 'data_path':

../data/pandagpt4_visual_instruction_data.json, 'image_root_path': ../data/images/, 'layers': [7, 15, 23, 31],

'root_dir': ../, 'mode': train, 'models': {'openllama': {'model_name': OpenLLAMAModel,

'agent_name': DeepSpeedAgent, 'stage1_train_dataset': MVTecDataset, 'test_dataset': SelfInstructTestDataset},

'openllama_peft': {'model_name': OpenLLAMAPEFTModel, 'agent_name': DeepSpeedAgent, 'stage1_train_dataset':

MVTecDataset, 'test_dataset': SelfInstructTestDataset}}, 'logging_step': 5, 'max_len': 512, 'penalty_alpha': 0.6,

'top_k': 10, 'top_p': 0.7, 'random_prefix_len': 5, 'sample_num': 2, 'decoding_method': sampling,

'generate_len': 512, 'lora_r': 32, 'lora_alpha': 32, 'lora_dropout': 0.1, 'seed': 42, 'warmup_rate': 0.1,

'epochs': 50, 'max_length': 1024, 'master_ip': '127.0.0.1', 'master_port': '28400',

'world_size': 1, 'ds_config_path': dsconfig/openllama_peft_stage_1.json,

'dschf': <transformers.deepspeed.HfDeepSpeedConfig object at 0x7b085ad70040>}
```

5.2.2.2 Function config_env(args)

Now that all the arguments needed are already stored in the variable **"args"**, the model can start to be loaded, in terms of configurations for distributed machine learning training (deepspeed) as well as the training data which will be used from the MVTec Dataset.

Therefore, let's first introduce the function config_env, which will be in charge of loading, updating and initializing the training for the model with the corresponding configuration information.

```python
def config_env(args):
    args['root_dir'] = '../' # Sets the root directory
    args['mode'] = 'train' # Sets the mode
    config = load_config(args) # Loads input configuration
    # The following picture illustrates the flow of information when the function
    # load_config(args) is called
    args.update(config) # Updates the args variable including the loaded configuration
    initialize_distributed(args) # Initializes the distributed training environment
    # This function is subsequently explained as well
    set_random_seed(args['seed']) # Sets random seed
```



5.2.2.3 Function initialize_distributed(args)

Let's introduce some terms to understand upcoming variables easier:

- **Micro-batch size per GPU**: Number of samples processed by each GPU in a single forward and backward pass.
- **Training batch size**: This is the total batch size that the model uses in each training iteration. It consists of the sum of the micro-batch sizes across all GPUs.
- **world_size**: Total number of processes (or GPUs) participating in the distributed training.
- **node**: A node is a single computer in a larger network, often used in parallel computing and clusters. It typically consists of the following components: CPU, GPU, Memory (RAM) and Storage.

For instance, if the system uses 2 nodes with 4 GPUs each, and we consider the context of Pytorch's distributed training, the command line torch.distributed.get_world_size() would return 8. Moreover, if the system considers a micro-batch size of 32, the effective training batch size seen by the model is $8 \times 32 = 256$.

Consequently, in order to initialize properly all these configurations within the distributed training, the following function is needed:

```
def initialize_distributed(args):
    args['master_ip'] = os.getenv('MASTER_ADDR', 'localhost') # Sets the master IP
    args['master_port'] = os.getenv('MASTER_PORT', '6000') # Sets the master port
    args['world_size'] = int(os.getenv('WORLD_SIZE', '1')) # Sets the world_size
    args['local_rank'] = int(os.getenv('RANK', '0')) % torch.cuda.device_count() # Counts the local rank
    device = args['local_rank'] % torch.cuda.device_count() #
    torch.cuda.set_device(device) # Sets the local rank

    # Initialization of DeepSpeed for distributed training process with NCCL backend
    deepspeed.init_distributed(dist_backend='nccl')
```

5.2.2.4 Function Main: Part 1

Being aware of the previous definitions, the function main which puts into place all needed is defined as follows:

```
def main(**args):
    config_env(args) # Previously explained

    # The following picture contains the information of the file openllama_peft_stage_1.json
    args['ds_config_path'] = f'dsconfig/{args["model"]}_stage_{args["stage"]}.json'
    dschf = HfDeepSpeedConfig(args['ds_config_path'])
    args['dschf'] = dschf

    build_directory(args['save_path']) # Builds directories which ensure that
    build_directory(args['log_path']) # the save and log directories exist

    # Configures logging to store logs in the specified log path
    if args['log_path']:
        logging.basicConfig(
            format='%(asctime)s - %(pathname)s[line:%(lineno)d] - %(levelname)s: %(message)s',
            level=logging.DEBUG,
            filename=f'{args["log_path"]}/train_{time.asctime()}.log',
            filemode='w'
        )

    # Loading training data and training supervised fine-tuning data
    train_data, train_iter, sampler = load_mvtec_dataset(args, None)
    train_data_sft, train_iter_sft, sampler = load_sft_dataset(args, None)

    #
    length = args['epochs'] * len(train_data) // args['world_size']
             // dschf.config['train_micro_batch_size_per_gpu']

    # Total training steps considered and added to the variable args
    total_steps = 2 * args['epochs'] * len(train_data) // dschf.config['train_batch_size']
    args['total_steps'] = total_steps

    # Calling and loading the agent DeepSpeed with all the arguments
    agent = load_model(args)

    # Ensuring that all processes wait for each other to reach a certain code
    torch.distributed.barrier()

                                --- BREAK MAIN FUNCTION ---
```

The functions load_mvtec_dataset and load_sft_dataset will be explained in the upcoming section, although, as expected both functions are responsible for preparing the datasets for training in a distributed setup. The functions ensure that the data is correctly loaded, shuffled and distributed across multiple processes for efficient training using DeepSpeed. Both functions are contained in the folder "datasets" within the script __init__.py.

The file openllama_peft_stage_1.json contains the information specific to the model and stage that will be loaded into DeepSpeed configuration and added subsequently to the variable "args".

5.2.2.5 Functions load_mvtec_dataset & load_sft_dataset

Some modifications had to be performed on these 2 functions in order to speed up the training process while modifying the decoder layer of the model. This way, by decreasing the samples which are used in the training process, instead of lasting almost a complete day the whole training process, it finishes in a matter of minutes. The main modification is the inclusion of a new object class denoted as CustomSubset, which is in charge of limiting the number of training samples used in the training process.

This new class CustomSubset inherits from the PyTorch Subset class. The **Subset class is used to create a subset of a dataset** based on specified indices.

```
CustomSubset(Subset):
    def __init__(self, dataset, indices): # Constructor method takes two arguments
        # Calling the constructor of the parent class Subset to initialize
        # the subset with the given dataset and indices.
        super(CustomSubset, self).__init__(dataset, indices)

        # This assigns the collate function of the original dataset to an instance variable self.collate.
        # The collate function is used to merge a list of samples to form a mini-batch of Tensor(s).
        self.collate = dataset.collate

    def collate(self, batch):
        return self.dataset.collate(batch)
```

Including that new class, allows to limit the total number of samples considered by including in load_mvtec_dataset the argument **limit_samples** and its corresponding flow control **'if'** within the proper function. The same modifications are applied to the function load_sft_dataset, even though do not appear in this document.

```
""" NEW load_mvtec_dataset with limited samples """
def load_mvtec_dataset(args, limit_samples=None):
    # Instantiating this class defines various parameters for different objects/textures
    data = MVtecDataset('../data/mvtec_anomaly_detection')

    # Including flow control to limit samples
    if limit_samples is not None:
        indices = list(range(len(data)))
        subset_indices = indices[:limit_samples]
        data = CustomSubset(data, subset_indices)
```

```
sampler = torch.utils.data.RandomSampler(data) # Samples elements randomly
world_size = torch.distributed.get_world_size()

# Unique identifier assigned to each process in the distributed setting
# It helps dividing data among processes, managing parameter updates
# and coordinating the activities of different processes
rank = torch.distributed.get_rank()
batch_size = args['world_size'] * args['dschf'].config['train_micro_batch_size_per_gpu']

# Ensures that each process in the distributed setting gets a unique subset of the data to work on
batch_sampler = DistributedBatchSampler(
    sampler,
    batch_size,
    drop\_last=True, # Ensures last incomplete batch is dropped
    rank,
    world_size)

# Combines the dataset and sampler, providing an iterable over the dataset
# It handles batching, shuffling and loading the data in parallel using multiple workers
iter_ = DataLoader(
    data,
    batch_sampler=batch_sampler,
    num_workers=8,
    collate_fn=data.collate,
    pin_memory=False)

return data, iter_, sampler
```

5.2.2.6 Function load_model

The function load_model, located in the script __init__.py within the **model** folder, loads the model as its name infers and instantiates the 2 most important classes for the training process, the DeepSpeed Agent (responsible for the distributed training) and the model OpenLLAMAPEFTModel which will be used.

```
def load_model(args):
    # Extracts the name of the agent (DeepSpeed - Agent)
    agent_name = args['models'][args['model']]['agent_name']

    # Extracts the name of the model (OpenLLAMAPEFTModel - Model)
    model_name = args['models'][args['model']]['model_name']

    # globals() is a global namespace where all global variables and
    # symbols for the current program are stored in a dictionary.
    # In essence, it retrieves the agent and model class and instantiates
    # them with model and args to its constructors
    model = globals()[model_name](**args)
    agent = globals()[agent_name](model, args)
    return agent
```

5.2.2.7 Class OpenLLAMAPEFTModel

The class OpenLLAMAPEFTMOdel is the heart of the model. Located in the script openllama.py within the folder **model**, it contains the loadings of all the different models that constitute AnomalyGPT.

For the basic understanding of the class, let's look at the constructor method and explain the loaded models, which includes ImageBind model as the visual_encoder, the image_decoder (LinearLayer Class), the prompt_learner (PromptLearner Class) and the previously mentioned focal and dice loss functions.

```
def __init__(self, **args):
        super(OpenLLAMAPEFTModel, self).__init__()
        self.args = args

        # Checkpoints (configurations/model) path for ImageBind and Vicuna models
        imagebind_ckpt_path = args['imagebind_ckpt_path']
        vicuna_ckpt_path = args['vicuna_ckpt_path']
        max_tgt_len = args['max_tgt_len']
        stage = args['stage'] # Stage 1

        print (f'Initializing visual encoder from {imagebind_ckpt_path} ...')

        # Instantiating ImageBind with args and its checkpoints
        self.visual_encoder, self.visual_hidden_size = imagebind_model.imagebind_huge(args)
        imagebind_ckpt = torch.load(imagebind_ckpt_path, map_location=torch.device('cpu'))
        self.visual_encoder.load_state_dict(imagebind_ckpt, strict=True)
        self.iter = 0

        # Instantiating the Image Decoder
        self.image_decoder = LinearLayer(1280, 1024, 4)

        # Instantiating the Prompt Learner
        self.prompt_learner = PromptLearner(1, 4096)

        # Instantiating both loss functions
        self.loss_focal = FocalLoss()
        self.loss_dice = BinaryDiceLoss()


        # Free vision encoder and freezing the parameters
        for name, param in self.visual_encoder.named_parameters():
            param.requires_grad = False
        self.visual_encoder.eval()
        print ('Visual encoder initialized.')
        print (f'Initializing language decoder from {vicuna_ckpt_path} ...')

        # Add the LoRA module - Mentioned in Extra-Information
        peft_config = LoraConfig(
            task_type=TaskType.CAUSAL_LM, # Task for which the model is fine-tuned - causal language model modality
            inference_mode=False, # If False then it's in Training mode, allows update of parameteres
            r=self.args['lora_r'], # Rank of LoRA matrices, the higher the more expressive, but also more expensive
            lora_alpha=self.args['lora_alpha'],  # Scale factor applied to LoRA updates
            lora_dropout=self.args['lora_dropout'], # Dropout rate applied to LoRA layers
            # List specifying the target modules in the model where LoRA should be applied (Attention Mechanism)
            target_modules=['q_proj', 'k_proj', 'v_proj', 'o_proj'])

        # Loading the pre-trained Llama casual language model from the Vicuna checkpoints
        self.llama_model = LlamaForCausalLM.from_pretrained(vicuna_ckpt_path)

        # PEFT explained in a section from the document
        self.llama_model = get_peft_model(self.llama_model, peft_config)
        self.llama_model.print_trainable_parameters()

        # Loading the tokenizer module associated to the Llama Model
        self.llama_tokenizer = LlamaTokenizer.from_pretrained(vicuna_ckpt_path, use_fast=False)
        self.llama_tokenizer.pad_token = self.llama_tokenizer.eos_token
        self.llama_tokenizer.padding_side = "right"
        print ('Language decoder initialized.')

        # Initializes a linear projection layer to match the dimensions
        # between the visual features and the language model
        self.llama_proj = nn.Linear(self.visual_hidden_size, self.llama_model.config.hidden_size)

        self.max_tgt_len = max_tgt_len
        self.device = torch.cuda.current_device()
```

From this particular class and as we are interested on modifying the Decoder Layer, we will focus on the instantiation of the LLama Model (**self.llama_model**) using the **class LlamaForCausalLM** and the Llama Tokenizer (**self.llama_tokenizer**). The term "causal" comes from the concept of causality in time series analysis, where future values are predicted based on past values. Similarly, in causal language models, the current token prediction depends only on the previous tokens, not on future tokens. Particularly, this class will lead us to the part of the code that was modified.

Moreover, the class includes as well the initialization of the tokenizer from the Llama model. The tokenizer is responsible for converting input text into tokens that the model can process and for decoding the model's token output back into human-readable text.

Following the arrows from the next picture, we reach the modification performed on the Class MLP, in which it's added a dropout layer. Originally, we considered 2 possible modifications, adding a normalization and dropout layer at the same time, however, when executing the code for training the gradient became too small and vanished at some point. Therefore, and by testing, we removed the normalization layer and only introduced the dropout layer, leading to successful complete trainings.

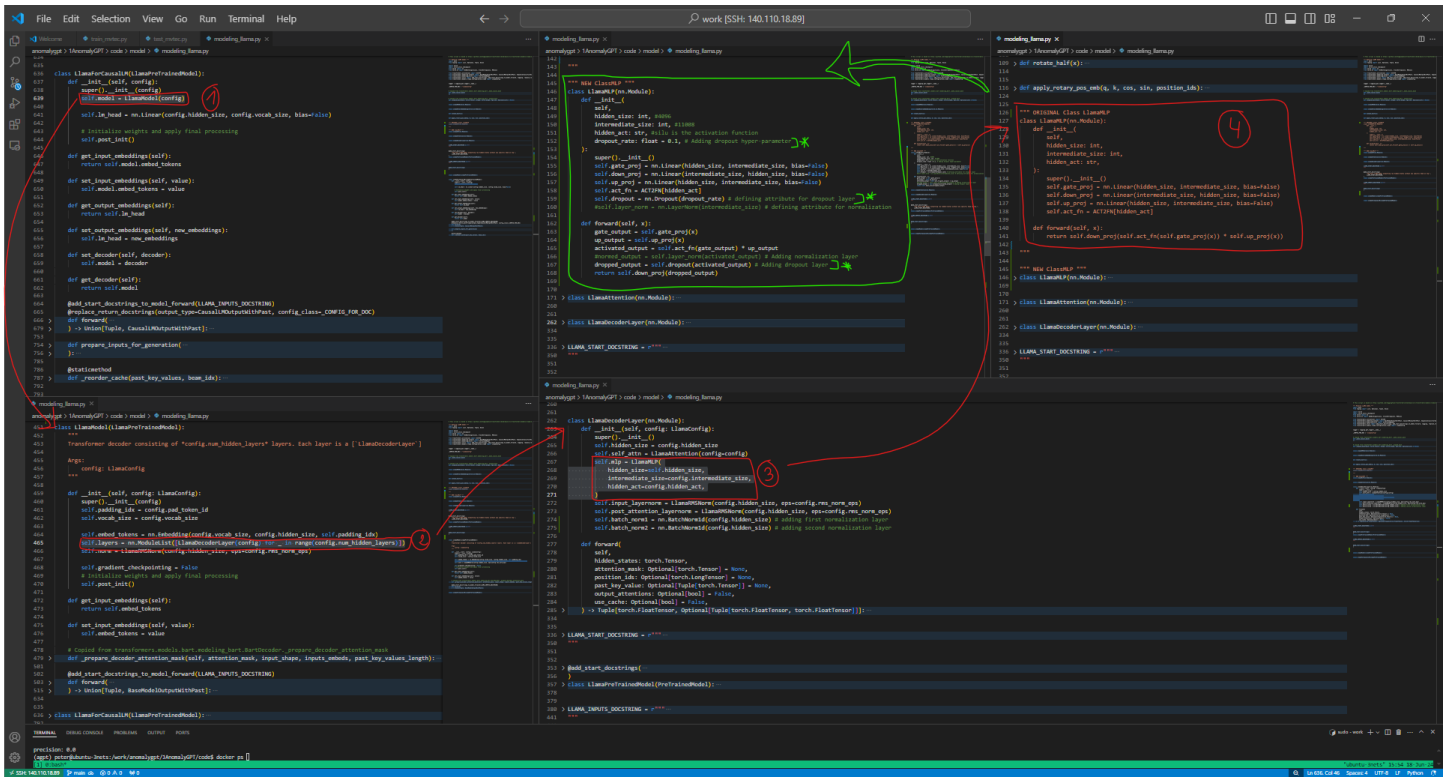
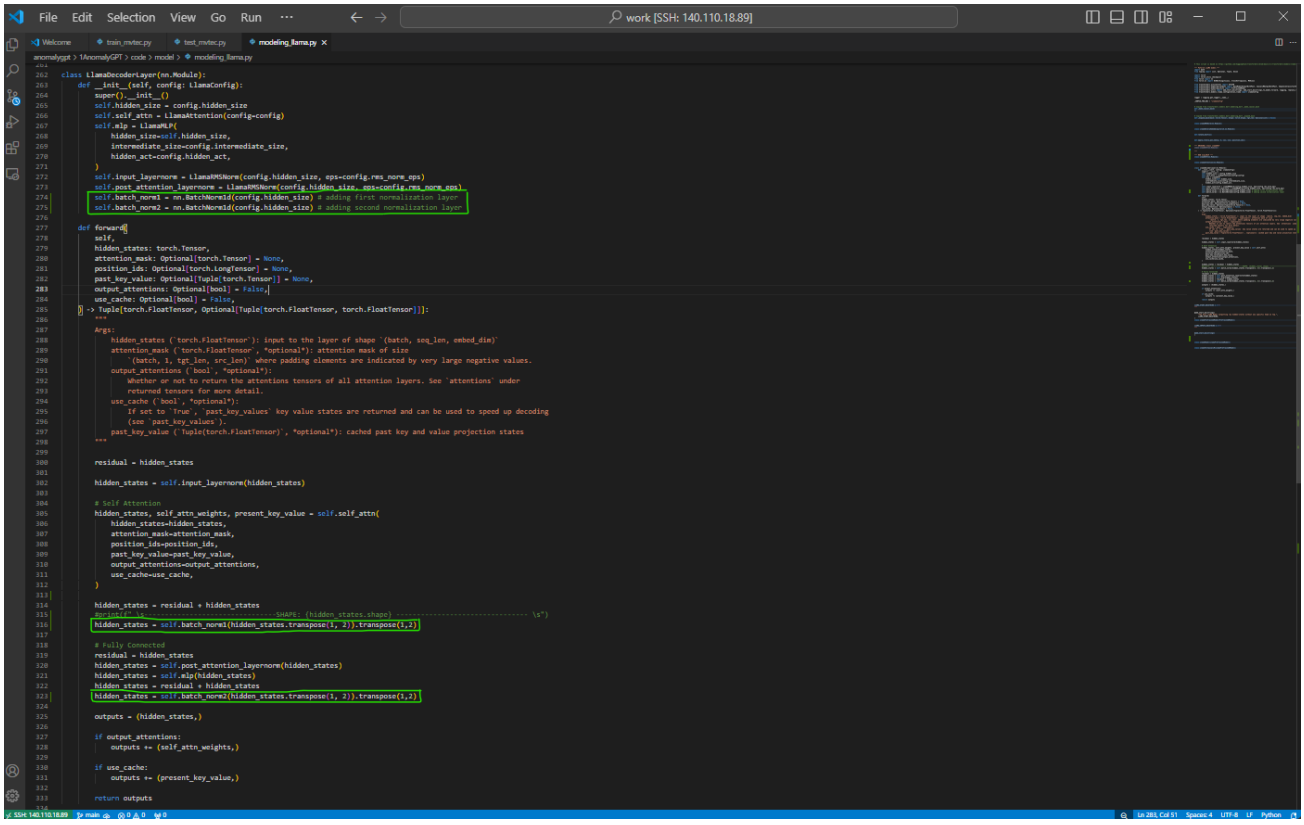


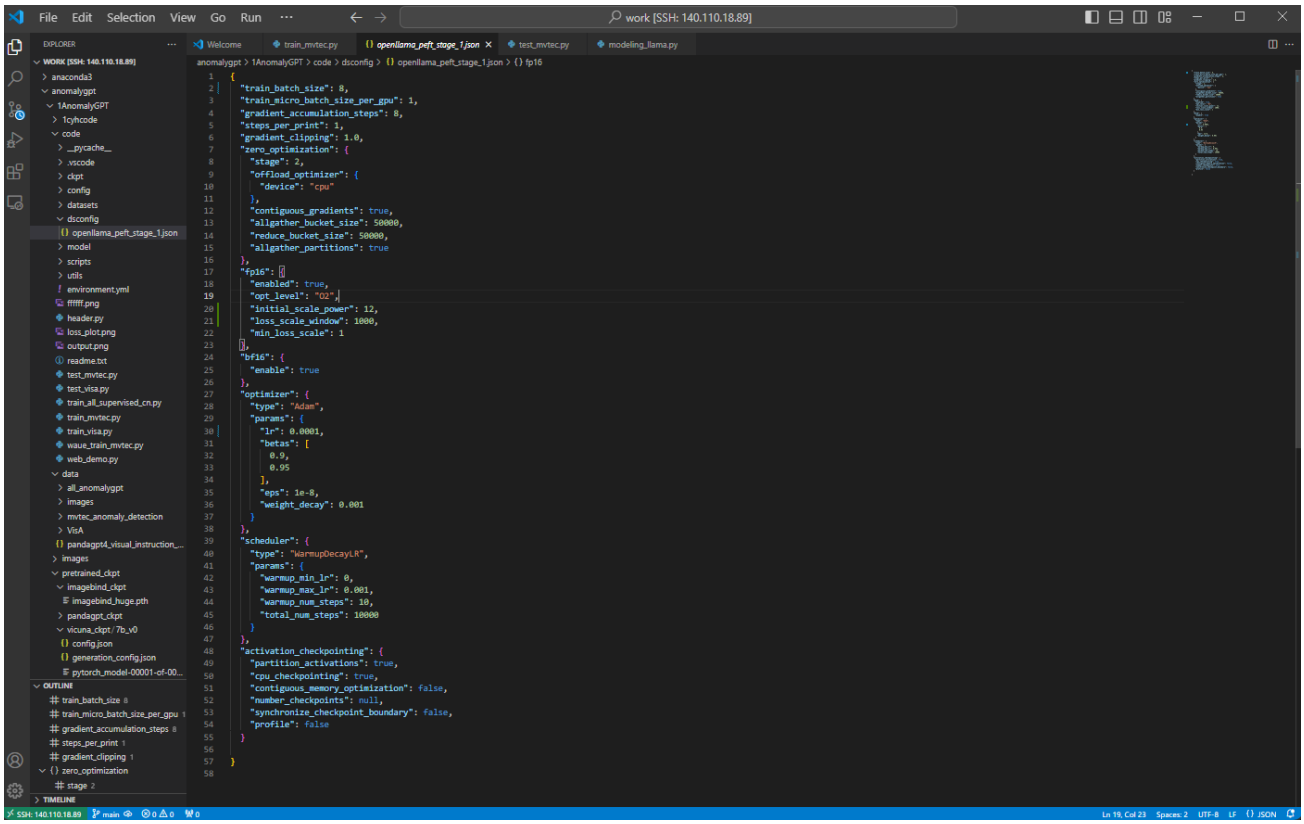
Figure 1: Flow of Modifications

Besides, in the class **DecoderLayer**, we also applied more modifications by introducing batch normalization to make sure that the vanishing gradient problem doesn't return and changed some hyper-parameters (fp16 and learning rate).



```python
class LlamaDecoderLayer(nn.Module):
    def __init__(self, config: LlamaConfig):
        super().__init__()
        self.hidden_size = config.hidden_size
        self.self_attn = LlamaAttention(config=config)
        self.mlp = LlamaMLP(
            hidden_size=self.hidden_size,
            intermediate_size=config.intermediate_size,
            hidden_act=config.hidden_act,
        )
        self.input_layernorm = LlamaRMSNorm(config.hidden_size, eps=config.rms_norm_eps)
        self.post_attention_layernorm = LlamaRMSNorm(config.hidden_size, eps=config.rms_norm_eps)
        self.batch_norm1 = nn.BatchNorm1d(config.hidden_size) # adding first normalization layer
        self.batch_norm2 = nn.BatchNorm1d(config.hidden_size) # adding second normalization layer

    def forward(
        self,
        hidden_states: torch.Tensor,
        attention_mask: Optional[torch.Tensor] = None,
        position_ids: Optional[torch.LongTensor] = None,
        past_key_value: Optional[Tuple[torch.Tensor]] = None,
        output_attentions: Optional[bool] = False,
        use_cache: Optional[bool] = False,
    ) -> Tuple[torch.FloatTensor, Optional[Tuple[torch.FloatTensor, torch.FloatTensor]]]:
        """
        Args:
            hidden_states (`torch.FloatTensor`): input to the layer of shape `(batch, seq_len, embed_dim)`
            attention_mask (`torch.FloatTensor`, *optional*): attention mask of size
                `(batch, 1, tgt_len, src_len)` where padding elements are indicated by very large negative values.
            output_attentions (`bool`, *optional*):
                Whether or not to return the attentions tensors of all attention layers. See `attentions` under
                returned tensors for more detail.
            use_cache (`bool`, *optional*):
                If set to `True`, `past_key_values` key value states are returned and can be used to speed up decoding
                (see `past_key_values`).
            past_key_value (`Tuple(torch.FloatTensor)`, *optional*): cached past key and value projection states
        """

        residual = hidden_states

        hidden_states = self.input_layernorm(hidden_states)

        # Self Attention
        hidden_states, self_attn_weights, present_key_value = self.self_attn(
            hidden_states=hidden_states,
            attention_mask=attention_mask,
            position_ids=position_ids,
            past_key_value=past_key_value,
            output_attentions=output_attentions,
            use_cache=use_cache,
        )

        hidden_states = residual + hidden_states
        #print("\n------------------------------------SHAPE: {hidden_states.shape} ------------------------------ \n")
        hidden_states = self.batch_norm1(hidden_states.transpose(1, 2)).transpose(1,2)

        # Fully Connected
        residual = hidden_states
        hidden_states = self.post_attention_layernorm(hidden_states)
        hidden_states = self.mlp(hidden_states)
        hidden_states = residual + hidden_states
        hidden_states = self.batch_norm2(hidden_states.transpose(1, 2)).transpose(1,2)

        outputs = (hidden_states,)

        if output_attentions:
            outputs += (self_attn_weights,)

        if use_cache:
            outputs += (present_key_value,)

        return outputs
```

Figure 2: Batch Normalization



```json
{
  "train_batch_size": 8,
  "train_micro_batch_size_per_gpu": 1,
  "gradient_accumulation_steps": 8,
  "steps_per_print": 1,
  "gradient_clipping": 1.0,
  "zero_optimization": {
    "stage": 2,
    "offload_optimizer": {
      "device": "cpu"
    },
    "contiguous_gradients": true,
    "allgather_bucket_size": 50000,
    "reduce_bucket_size": 50000,
    "allgather_partitions": true
  },
  "fp16": {
    "enabled": true,
    "opt_level": "O2",
    "initial_scale_power": 12,
    "loss_scale_window": 1000,
    "min_loss_scale": 1
  },
  "bf16": {
    "enable": true
  },
  "optimizer": {
    "type": "Adam",
    "params": {
      "lr": 0.0001,
      "betas": [
        0.9,
        0.95
      ],
      "eps": 1e-8,
      "weight_decay": 0.001
    }
  },
  "scheduler": {
    "type": "WarmupDecayLR",
    "params": {
      "warmup_min_lr": 0,
      "warmup_max_lr": 0.001,
      "warmup_num_steps": 10,
      "total_num_steps": 10000
    }
  },
  "activation_checkpointing": {
    "partition_activations": true,
    "cpu_checkpointing": true,
    "contiguous_memory_optimization": false,
    "number_checkpoints": null,
    "synchronize_checkpoint_boundary": false,
    "profile": false
  }
}
```

Figure 3: FP16 + Learning Rate Modification

5.2.2.8 Function Main: Part 2

This is the continuation of the remaining code from the **main** function. The most important mentioned function is train_model, which will be explained in the next section, although it's also called the function **save_model** which is equally important.

In the last part of the function, the training process is executed taking into account the epochs and iterations update, the model parameters saving and finally plotting the evolution of the loss at the end of the whole process.

```
# Beginning of training
pbar = tqdm(total= 2 * length) # Maximum total number / Progress bar
current_step = 0 # To keep track of the current training step

# Main Loop consisting of a total of 50 epochs
for epoch_i in tqdm(range(args['epochs'])):
    iter_every_epoch = 0 # To keep track of iterations within each loop
    for batch, batch_sft in zip(train_iter,train_iter_sft):
        iter_every_epoch += 1

        # First training step in which is called the train_model method
        # to perform a training step with batch samples
        agent.train_model(
            batch,
            current_step=current_step,
            pbar=pbar)
        del batch # To free memory

        # Second training step but with batch_stf
        agent.train_model(
            batch_sft,
            current_step=current_step,
            pbar=pbar)
        del batch_sft # To free memory
        current_step += 1
    # Ensuring all processes synchronize at the end of each epoch
    torch.distributed.barrier()
    # Save at the end of the training
    agent.save_model(args['save_path'], 0)
# Plot loss after training
agent.plot_loss()
```

5.2.2.9 Function train_model

The train_model function performs the forward pass, the backward pass, the parameter update and logging of relevant information. Furthermore, it has been modified from the original version to save the loss values and plot the evolution of it at the end of the training.

```
def train_model(self, batch, current_step=0, pbar=None):
        self.ds_engine.module.train() # Puts the model in training mode

        # Forward pass & Loss Calculation
        # Performs the forward pass with the input "batch" using the DeepSpeed engine
        # and computes the loss from the model and the maximum likelihood estimation accuracy
        loss, mle_acc = self.ds_engine(batch)

        # Backward pass
        # Computes the gradients of the loss with respect
        # to the model parameters using backpropagation
        self.ds_engine.backward(loss)

        # Parameter Update of the DeepSpeed engine
        self.ds_engine.step()

        # Store loss value to plot it afterwards
        self.loss_list.append(loss.item())

        # Progress Bar Update
        # It updates the description of the progress bar with
        # the current loss and token accuracy and advances by
        # one step the pbar
        pbar.set_description(f'[!] loss: {round(loss.item(), 4)}; token_acc: {round(mle_acc*100, 2)}')
        pbar.update(1)

        # Calculates the elapsed time, rate of progress,
        # the estimated remaining time and logs the information
        if self.args['local_rank'] == 0 and self.args['log_path'] and current_step % self.args['logging_step'] == 0:
            elapsed = pbar.format_dict['elapsed']
            rate = pbar.format_dict['rate']
            remaining = (pbar.total - pbar.n) / rate if rate and pbar.total else 0
            remaining = str(datetime.timedelta(seconds=remaining))
            logging.info(f'[!] progress: {round(pbar.n/pbar.total, 5)};
                         remaining time: {remaining}; loss: {round(loss.item(), 4)};
                         token_acc: {round(mle_acc*100, 2)}'
                        )

        # Adjusts the accuracy metric for returning
        mle_acc *= 100
        return mle_acc
```

5.3 Model Versions & Modifications

There has been conducted multiple different model trainings with the previously mentioned modifications, in different GPU nodes (140.110.18.91 and 140.110.18.89), with added datasets, and to be more specific, the exact configurations for each model are displayed below:

Config	**V1**	**V2**	**V3**	**V4**	**V5**	**V6**
Port	89	89	91	91	91	89 & 91
Epochs	20	50	50	50	50	50
Learning Rate	0.001	0.0001	0.0001	0.0001	0.0001	0.0001
Samples	10k	Complete	Complete	Complete	Complete	Complete
Batch Size	8	8	16	16	16	32
Micro Batch Size(per GPU)	1	1	2	2	2	2
Total GPUs	1	1	1	1	1	2
Gradient Accum. Steps	8	8	8	8	8	8
Docker Container	✗	✗	✗	✗	✗	✓
AeBAD Dataset	✗	✗	✗	✓	✓	✓
Data Aug.	✗	✗	✗	✗	✓	✓
Dropout Layer	✓	✓	✓	✓	✓	✓
Normalization Layer	✓	✗	✗	✗	✗	✗
Residual Layer	✓	✓	✓	✓	✓	✓
Batch Normalization	✗	✗	✓	✓	✓	✓
FP16 Initial Scale Power	✗	12	12	12	12	12
FP16 Loss Scale Window	✗	1000	1000	1000	1000	1000
Training Process	17%	100%	100%	100%	100%	100%

Table 1: Comparison of Model Versions

5.3.1 Motivations

5.3.1.1 Model V1

The Model V1 was the first model to be modified and used as practicing prototype. The modifications, as shown in the previous table, were not really profound however it allowed to understand better the flow of data and the pre-defined functions as well as classes. The modifications include the limitation of samples to accelerate the trial & error testing, the decrease in the total number of epochs, the introduction in the Class MLP of 2 new layers, first the normalization and then the dropout layer with a dropout rate of 0.1. The modifications aimed at:

1. **Normalization Layer**: Included
   - **Reason**: Layer normalizes the inputs across the features to stabilize and accelerate training.

- **Implementation**:

```
# Class MLP
# Constructor: __init__
self.layer_norm = nn.LayerNorm(intermediate_size)

# Method: forward
normed_output = self.layer_norm(activated_output)
```

2. **Dropout Layer**: Included

   - **Reason**: Dropout is used to prevent overfitting by randomly setting a fraction of input units to zero at each update during training and forcing the model to learn more robust features.

   - **Implementation**:

```
# Class MLP
# Constructor: __init__
self.dropout = nn.Dropout(dropout_rate)

# Method: forward
dropped_output = self.dropout(normed_output)
```

However, in training execution and although the number of samples was quite small, the model stopped learning due to vanishing gradient issues leading to stop automatically the training process. To counter this problem, several modifications were considered and implemented in the upcoming models V2 and V3.

5.3.1.2 Model V2

The model V2 implemented new modifications and attempted to suceed where the model V1 failed. Among the modifications, and after trying with fewer epochs and samples to check if the vanishing gradient issue was solved, the main update addressed the normalization layer (which was removed) and considered additional hyper-parameters within the fp16 configuration located in openllama_peft_stage_1.json.

1. **Learning Rate**: Decrease

   - **Reason**: A lower learning rate than Model V1, allows for more fine-tuned adjustments during training, reducing the risk of overshooting the optimal parameters.

2. **Normalization Layer**: Not included

   - **Reason**: Training might be slower and less stable without normalization layers although solved the vanishing gradient problem.

3. **FP16**: 16-Bit Floating Point

   - **Reason**: Setting the initial scale power to 12 controls the initial scale factor for mixed-precision training. A scale power of 12 is commonly used starting point for FP16 training. Moreover, the loss scale window parameter, set to 1000, helps in dynamically adjusting the loss scaling factor to avoid overflow and underflow during FP16 training.

5.3.1.3 Model V3

The model V3 included the configurations found relevant in model V2 and considered an additional modification in terms of batch normalization.

1. **Batch Normalization**: Included

   - **Reason**: By normalizing the inputs to each layer, batch normalization allows the network to converge faster, reducing the training time, helps in stabilizing the learning process leading to more reliable gradients

5.3.1.4 Model V4

The model V4 considers the same configuration modifications as the model V3 and adds 4 new classes to the MVTec Dataset. These new classes in fact represent the same object, a blade, although considers 4 typical anomalies that might make invalid its production. The dataset was found on a Github repository and its called Aero-engine Blade Anomaly Detection (AeBAD) dataset. The 4 categories for the blades are:

- **Ablation**: A blade without ablations should have a smooth, uniform surface with no areas of material removal or wear. The edges should be sharp and intact, with no signs of pitting, erosion, or thinning. The entire blade should appear consistent in texture and color, indicating it is free from any ablation-related damage."
- **Breakdown**: A blade without breakdowns should maintain its structural integrity with no signs of cracking, chipping, or flaking. The blade should exhibit a uniform appearance, with no visible separations, detachment of layers, or deformation. The blade should appear robust and solid, free from any structural compromise."
- **Fracture**: A blade without fractures should have a continuous, unbroken surface with no visible cracks or splits. The blade should be seamless and sturdy, with no signs of stress marks or propagation lines that indicate potential fracture points. The entire blade should look solid and reliable, free from any fracturing damage."
- **Groove**: A blade without grooves should have a completely smooth and even surface with no indentations or carved-out lines. The blade's surface should be uniform and consistent, with no signs of unintended channels or depressions. The blade should appear flawlessly smooth, indicating it is free from any groove related imperfections."

Moreover, for each type of anomaly there are as well, 4 different perspectives, including background, illumination, view and original/same changes. In order to include the new classes, multiple modifications were needed to be performed, starting from copy/pasting the original dataset into the well organized structure from the MVTec Dataset.

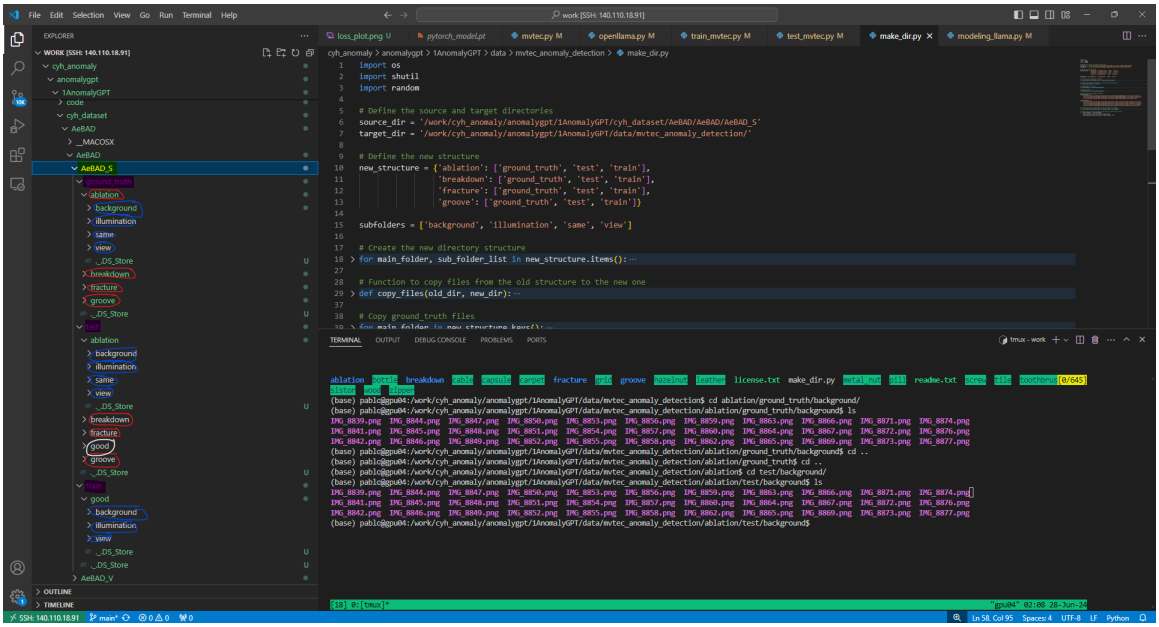


Figure 4: Original Structure AeBAD-Dataset

Therefore, I wrote down a script called make_dir.py that allowed me to pass from the AeBAD structure to the MVTec Dataset one, although one of the issues was that the training samples were mixed, meaning that you could find samples from background ablation, background breakdown, fracture or groove all in the same folder and not

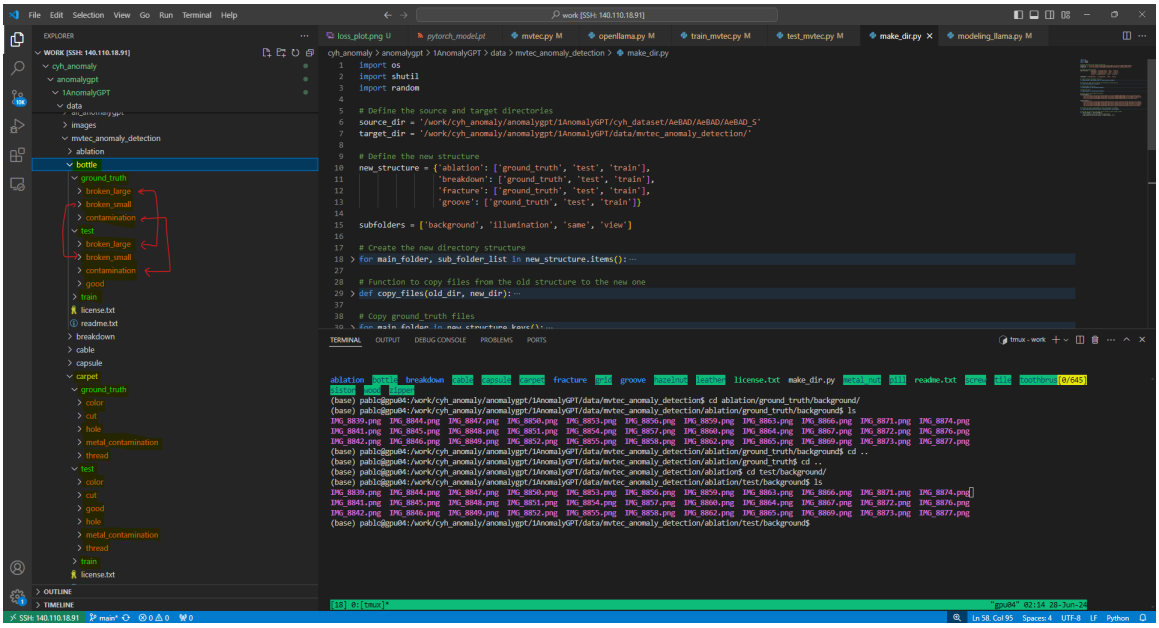


Figure 5: Original Structure MVTec-Dataset

separated as in MVTec Dataset. To solve such issue, and after carefully studying the pictures, I decided to create the train folder following a 70% split between the corresponding folders. For instance, for the folder train/good within ablation, it was included 70% of the train (good) samples from background, 70% of the train samples from illumination and 70% of the class view, addind up to 364 good training samples for each class.

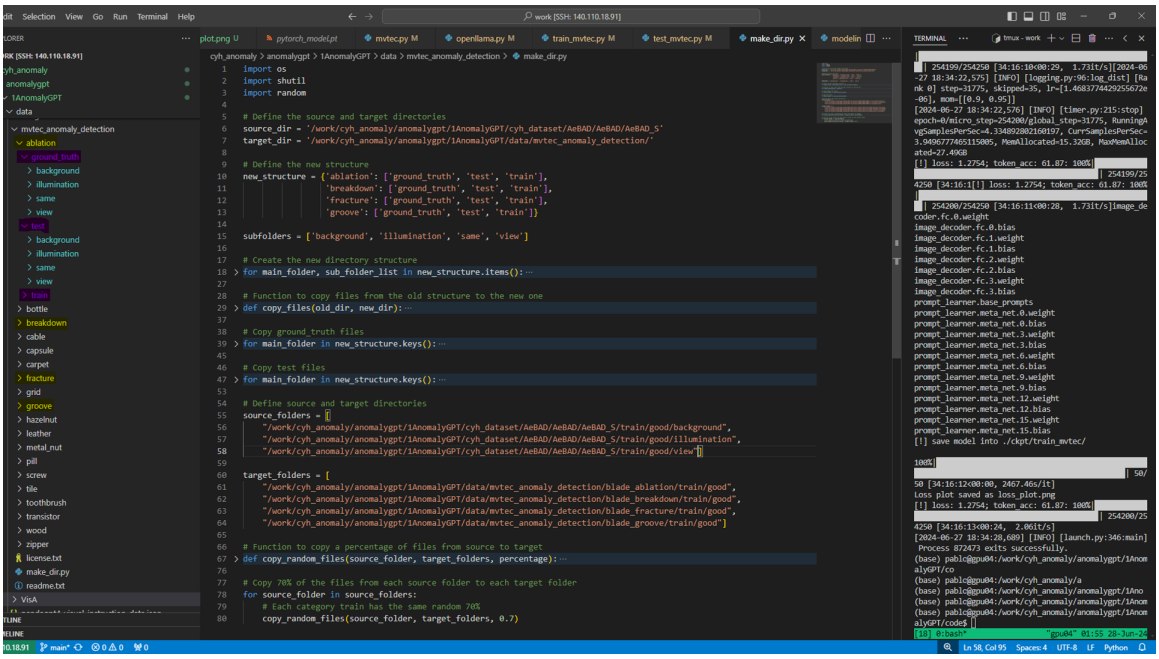


Figure 6: Script: make_dir.py

One of the issues with the new dataset is that some of the ground_truth pictures corresponding to a particular test image was absent, or vice versa, leading to multiple samples being alone and therefore not valid for the training. Besides the previous problem, many pictures had to be deleted because they couldn't be displayed and treated by the model, leading as well to delete their corresponding ground_truth/mask images.

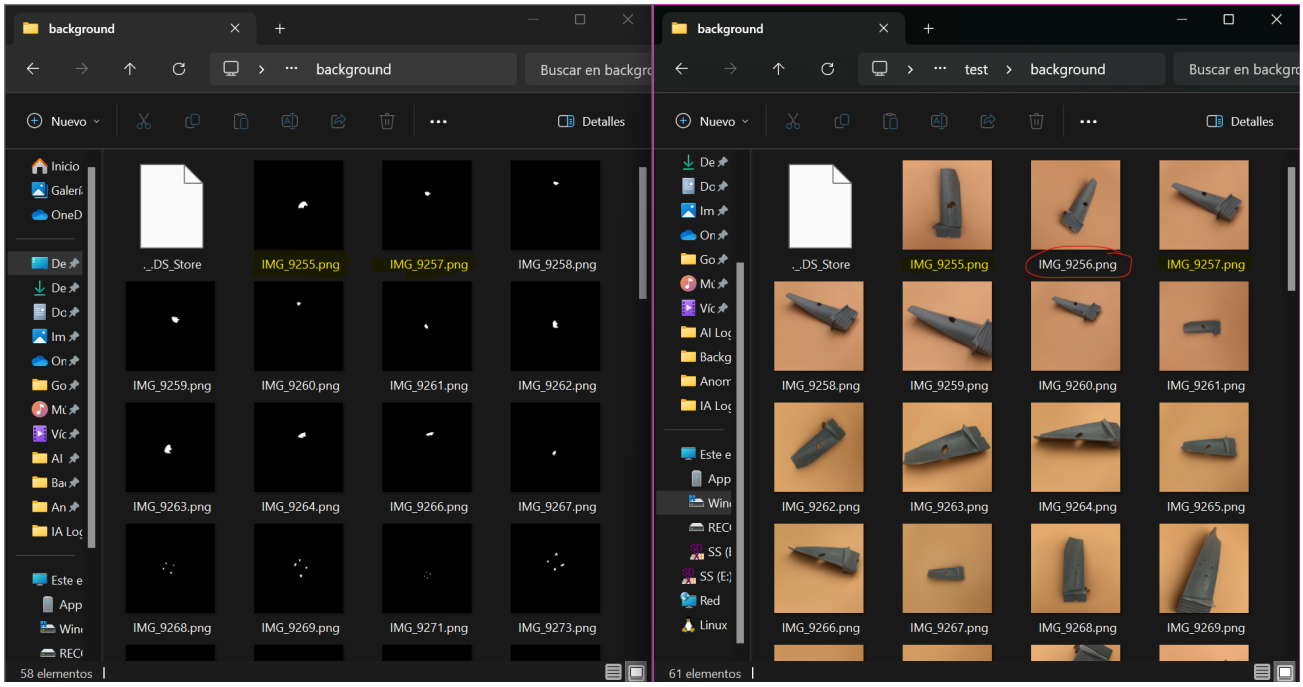


Figure 7: Correspondance of Images: Mask vs Test

Finally, the new included classes were structured as follows:

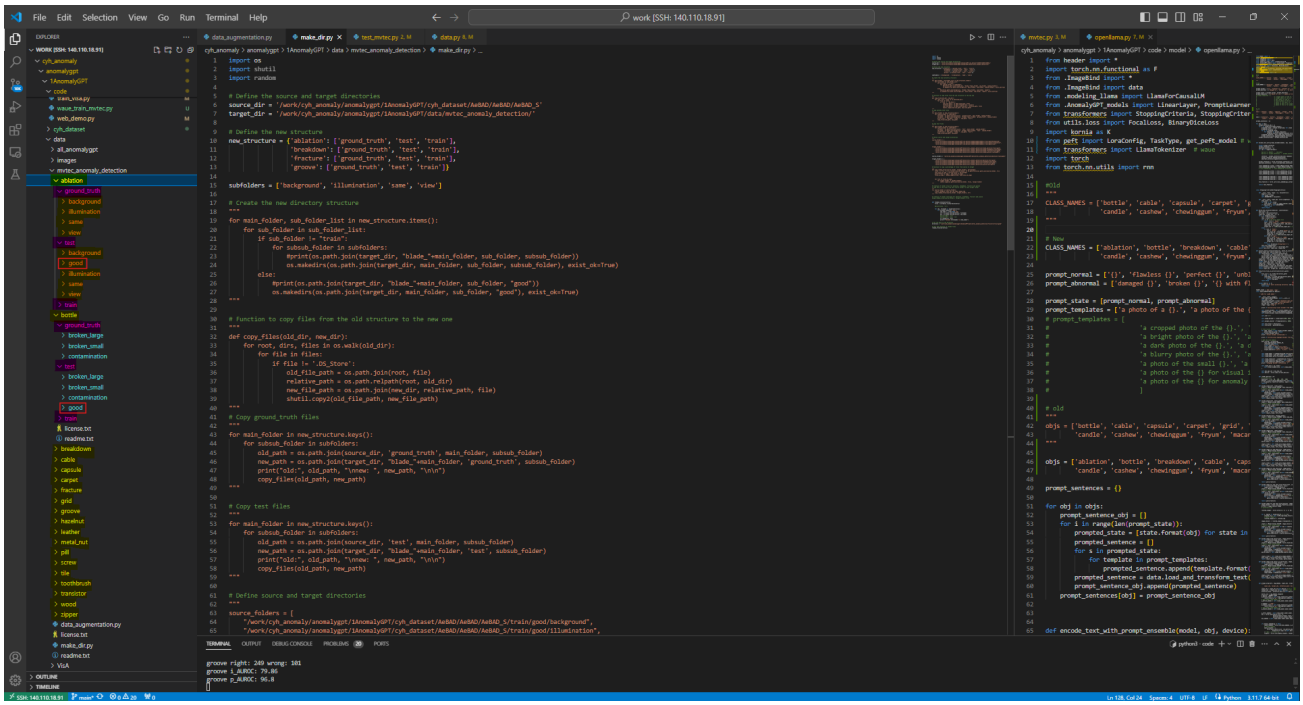


Figure 8: General Structure: AeBAD + MVTec Dataset

Then, in terms of script modifications, I had to modify a couple of things included in the scripts openllama.py (which can be found in the folder **model**) and mvtec.py (in folder **datasets**). Although there were very few modifications on openllama.py, the biggest majority happened on the script mvtec.py, including the variables WIDTH_BOUNDS_PCT, NUM_PATCHES, INTENSITY_LOGISTIC_PARAMS, UNALIGNED_OBJECTS, BACKGROUND, OBJECTS, the dictionary describles, and the method constructor of the class MVtecDataset.

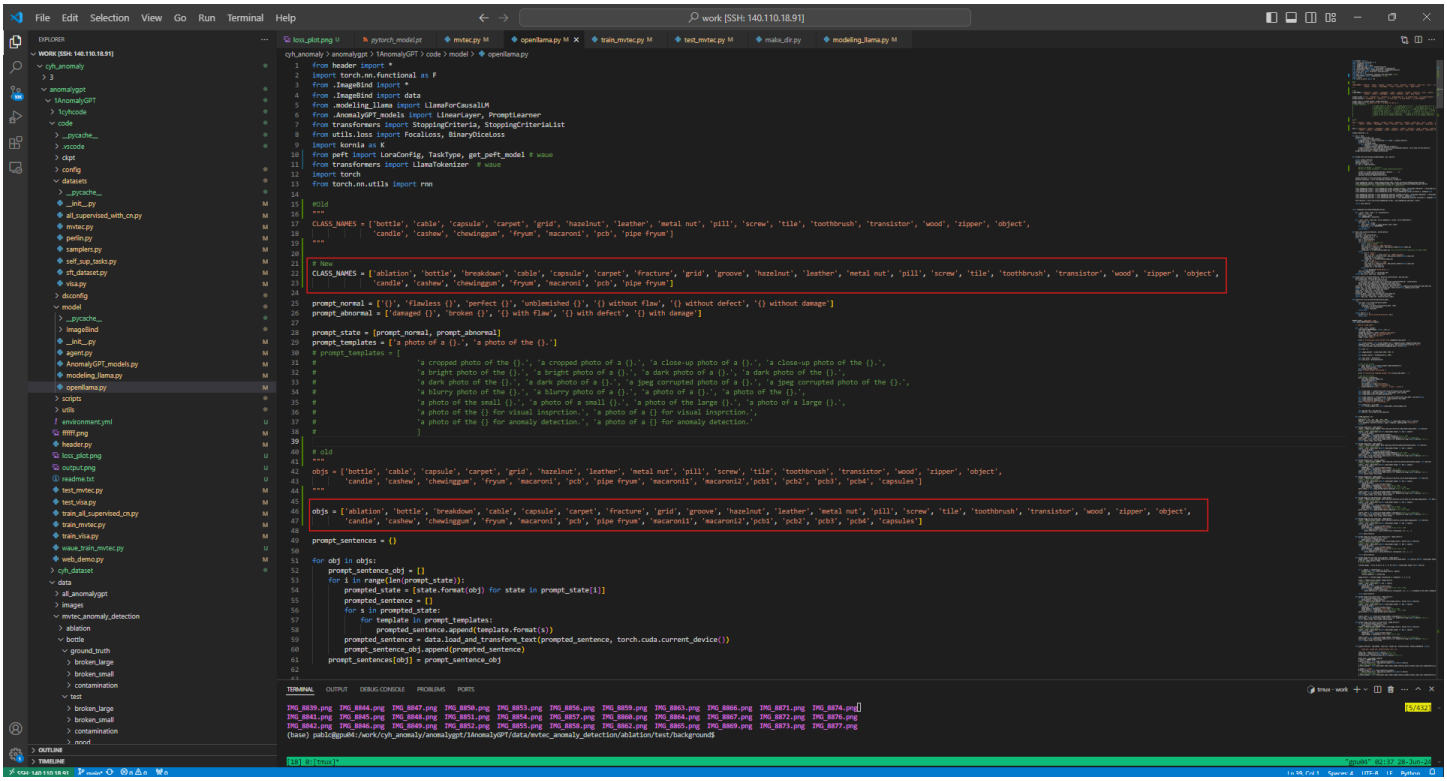


Figure 9: Modifications Script: openllama.py

The modifications are shown below:

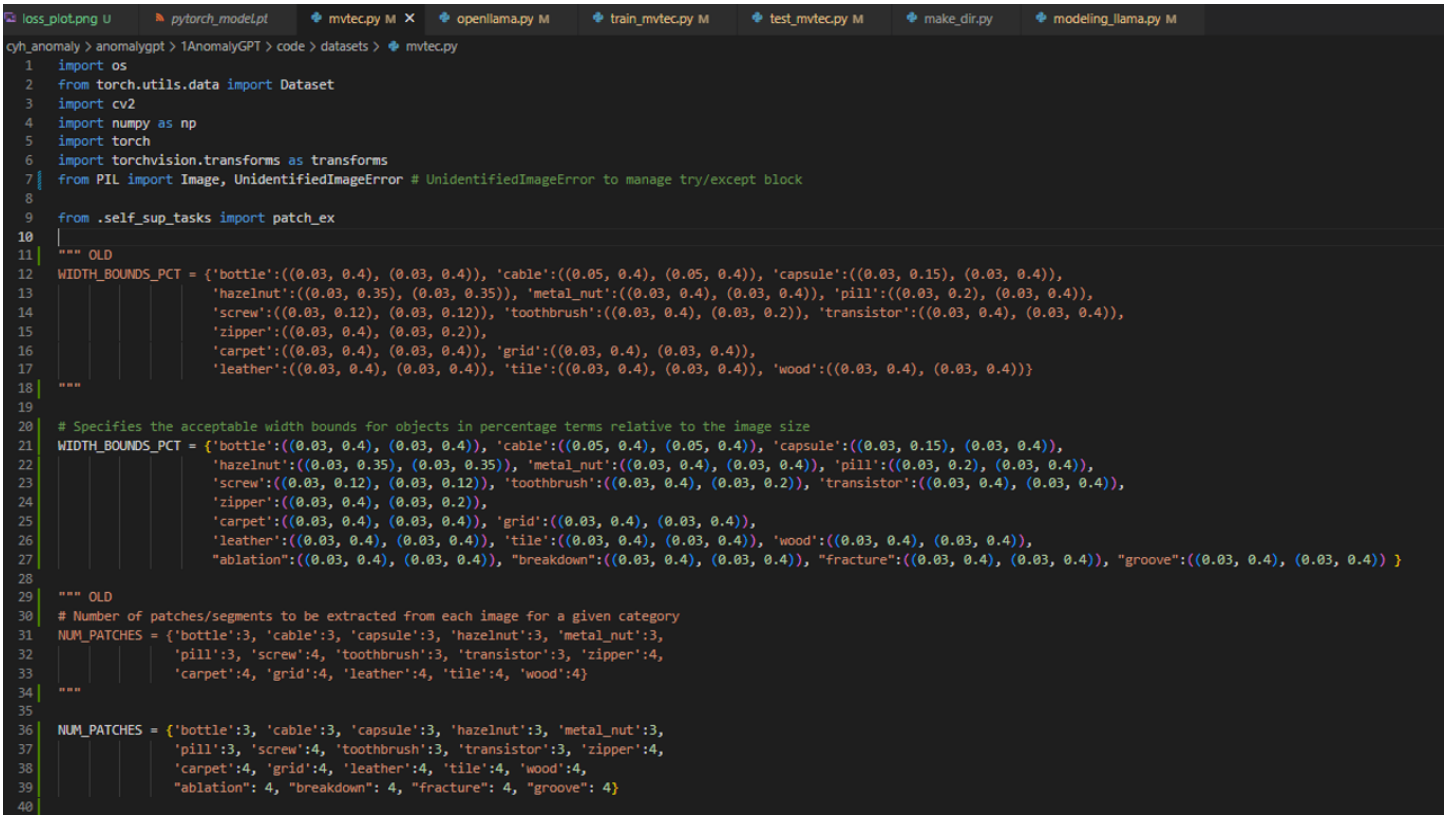
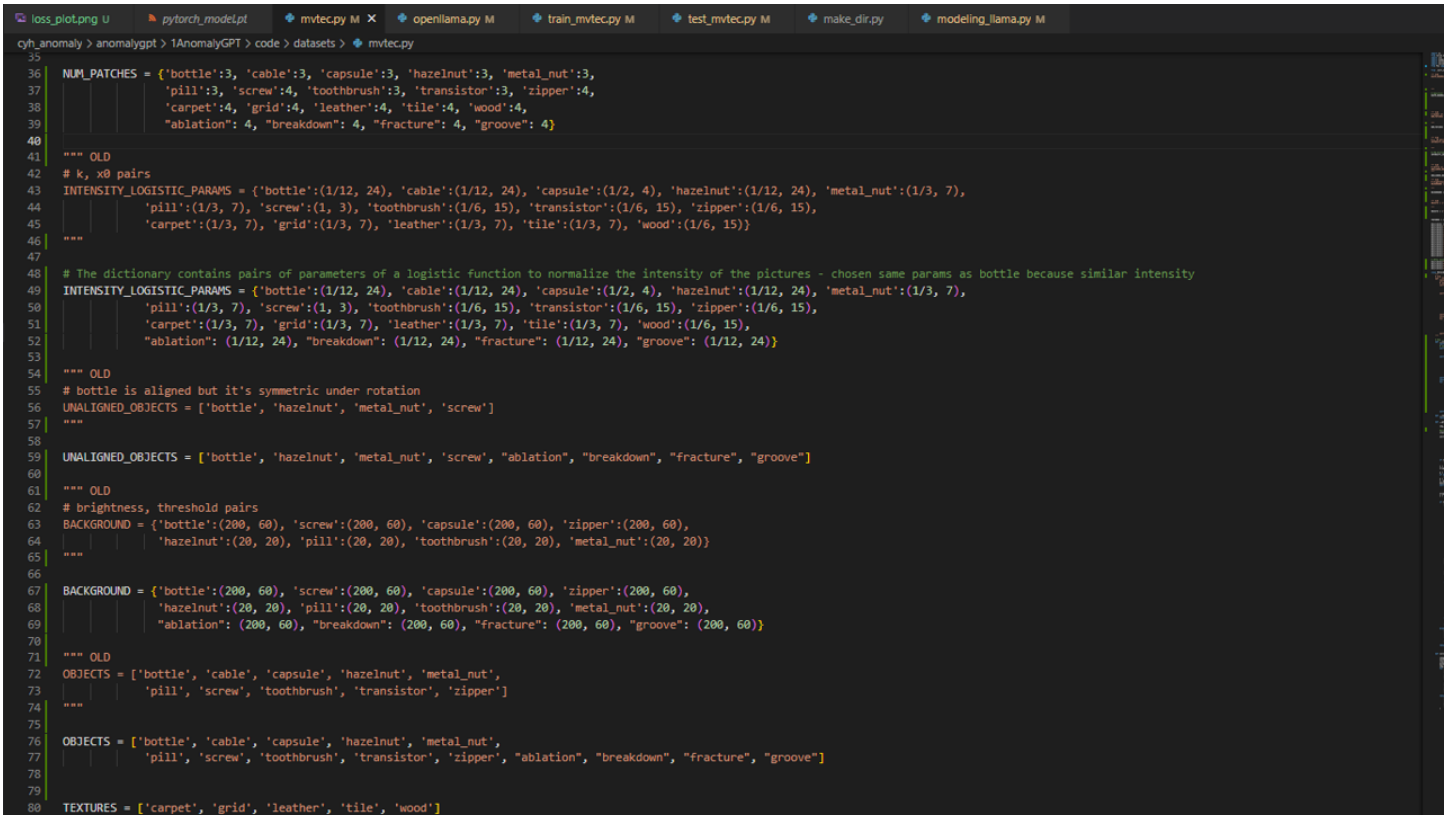
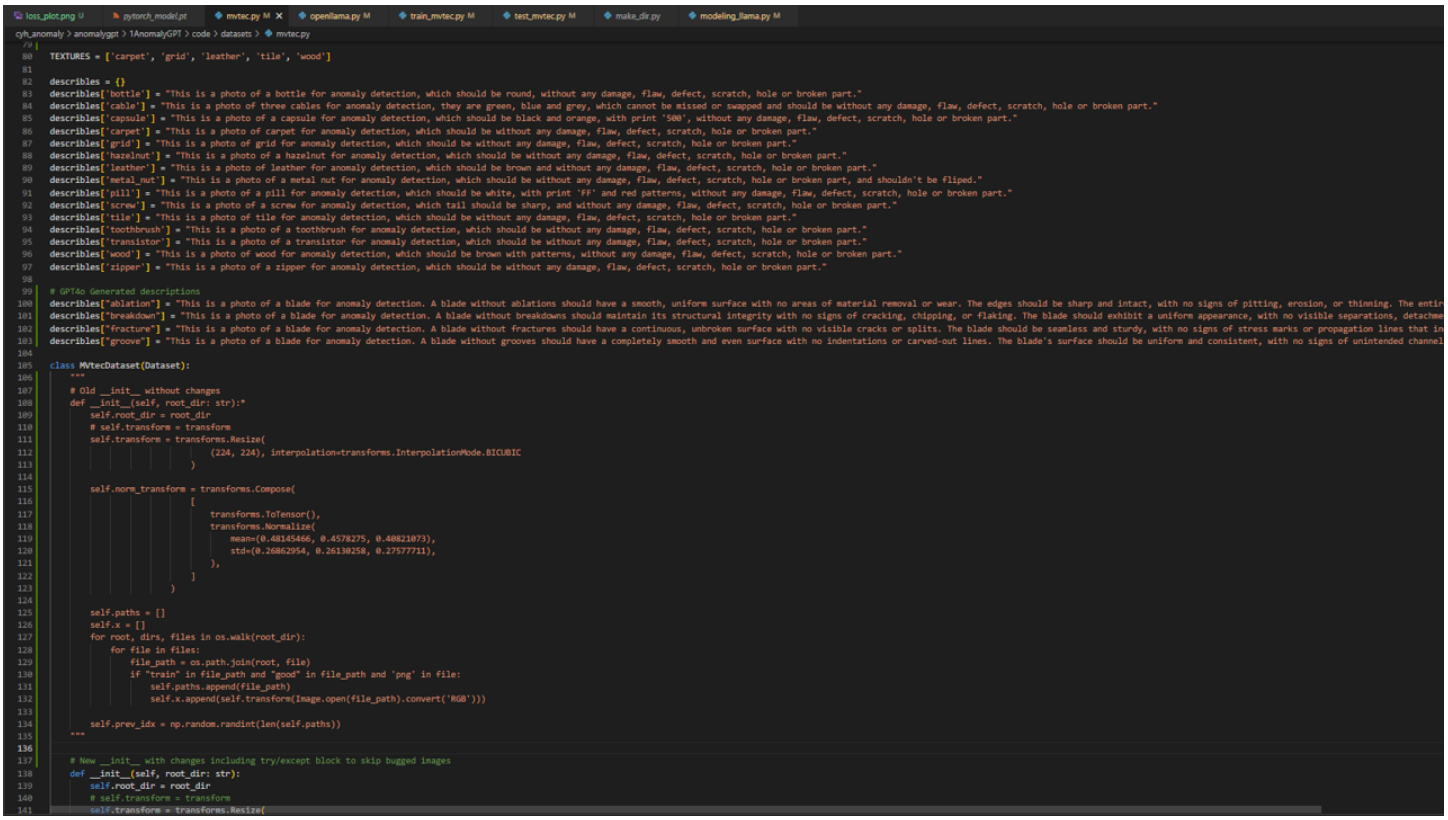


Figure 10: Modification 1 - mvtec.py



```
NUM_PATCHES = {'bottle':3, 'cable':3, 'capsule':3, 'hazelnut':3, 'metal_nut':3,
               'pill':3, 'screw':4, 'toothbrush':3, 'transistor':3, 'zipper':4,
               'carpet':4, 'grid':4, 'leather':4, 'tile':4, 'wood':4,
               "ablation": 4, "breakdown": 4, "fracture": 4, "groove": 4}

""" OLD
# k, x0 pairs
INTENSITY_LOGISTIC_PARAMS = {'bottle':(1/12, 24), 'cable':(1/12, 24), 'capsule':(1/2, 4), 'hazelnut':(1/12, 24), 'metal_nut':(1/3, 7),
            'pill':(1/3, 7), 'screw':(1, 3), 'toothbrush':(1/6, 15), 'transistor':(1/6, 15), 'zipper':(1/6, 15),
            'carpet':(1/3, 7), 'grid':(1/3, 7), 'leather':(1/3, 7), 'tile':(1/3, 7), 'wood':(1/6, 15)}
"""

# The dictionary contains pairs of parameters of a logistic function to normalize the intensity of the pictures - chosen same params as bottle because similar intensity
INTENSITY_LOGISTIC_PARAMS = {'bottle':(1/12, 24), 'cable':(1/2, 4), 'capsule':(1/2, 4), 'hazelnut':(1/12, 24), 'metal_nut':(1/3, 7),
            'pill':(1/3, 7), 'screw':(1, 3), 'toothbrush':(1/6, 15), 'transistor':(1/6, 15), 'zipper':(1/6, 15),
            'carpet':(1/3, 7), 'grid':(1/3, 7), 'leather':(1/3, 7), 'tile':(1/3, 7), 'wood':(1/6, 15),
            "ablation": (1/12, 24), "breakdown": (1/12, 24), "fracture": (1/12, 24), "groove": (1/12, 24)}

""" OLD
# bottle is aligned but it's symmetric under rotation
UNALIGNED_OBJECTS = ['bottle', 'hazelnut', 'metal_nut', 'screw']
"""

UNALIGNED_OBJECTS = ['bottle', 'hazelnut', 'metal_nut', 'screw', "ablation", "breakdown", "fracture", "groove"]

""" OLD
# brightness, threshold pairs
BACKGROUND = {'bottle':(200, 60), 'screw':(200, 60), 'capsule':(200, 60), 'zipper':(200, 60),
              'hazelnut':(20, 20), 'pill':(20, 20), 'toothbrush':(20, 20), 'metal_nut':(20, 20)}
"""

BACKGROUND = {'bottle':(200, 60), 'screw':(200, 60), 'capsule':(200, 60), 'zipper':(200, 60),
              'hazelnut':(20, 20), 'pill':(20, 20), 'toothbrush':(20, 20), 'metal_nut':(20, 20),
              "ablation": (200, 60), "breakdown": (200, 60), "fracture": (200, 60), "groove": (200, 60)}

""" OLD
OBJECTS = ['bottle', 'cable', 'capsule', 'hazelnut', 'metal_nut',
           'pill', 'screw', 'toothbrush', 'transistor', 'zipper']
"""

OBJECTS = ['bottle', 'cable', 'capsule', 'hazelnut', 'metal_nut',
           'pill', 'screw', 'toothbrush', 'transistor', 'zipper', "ablation", "breakdown", "fracture", "groove"]


TEXTURES = ['carpet', 'grid', 'leather', 'tile', 'wood']
```

Figure 11: Modification 2 - mvtec.py



```
TEXTURES = ['carpet', 'grid', 'leather', 'tile', 'wood']

describles = {}
describles['bottle'] = "This is a photo of a bottle for anomaly detection, which should be round, without any damage, flaw, defect, scratch, hole or broken part."
describles['cable'] = "This is a photo of three cables for anomaly detection, they are green, blue and grey, which cannot be missed or swapped and should be without any damage, flaw, defect, scratch, hole or broken part."
describles['capsule'] = "This is a photo of a capsule for anomaly detection, which should be black and orange, with print '500', without any damage, flaw, defect, scratch, hole or broken part."
describles['carpet'] = "This is a photo of carpet for anomaly detection, which should be without any damage, flaw, defect, scratch, hole or broken part."
describles['grid'] = "This is a photo of grid for anomaly detection, which should be without any damage, flaw, defect, scratch, hole or broken part."
describles['hazelnut'] = "This is a photo of a hazelnut for anomaly detection, which should be without any damage, flaw, defect, scratch, hole or broken part."
describles['leather'] = "This is a photo of leather for anomaly detection, which should be brown and without any damage, flaw, defect, scratch, hole or broken part."
describles['metal_nut'] = "This is a photo of a metal nut for anomaly detection, which should be without any damage, flaw, defect, scratch, hole or broken part, and shouldn't be fliped."
describles['pill'] = "This is a photo of a pill for anomaly detection, which should be white, with print 'FF' and red patterns, without any damage, flaw, defect, scratch, hole or broken part."
describles['screw'] = "This is a photo of a screw for anomaly detection, which tail should be sharp, and without any damage, flaw, defect, scratch, hole or broken part."
describles['tile'] = "This is a photo of tile for anomaly detection, which should be without any damage, flaw, defect, scratch, hole or broken part."
describles['toothbrush'] = "This is a photo of a toothbrush for anomaly detection, which should be without any damage, flaw, defect, scratch, hole or broken part."
describles['transistor'] = "This is a photo of a transistor for anomaly detection, which should be without any damage, flaw, defect, scratch, hole or broken part."
describles['wood'] = "This is a photo of wood for anomaly detection, which should be brown with patterns, without any damage, flaw, defect, scratch, hole or broken part."
describles['zipper'] = "This is a photo of a zipper for anomaly detection, which should be without any damage, flaw, defect, scratch, hole or broken part."

# GPT4o Generated descriptions
describles["ablation"] = "This is a photo of a blade for anomaly detection. A blade without ablations should have a smooth, uniform surface with no areas of material removal or wear. The edges should be sharp and intact, with no signs of pitting, erosion, or thinning. The entir
describles["breakdown"] = "This is a photo of a blade for anomaly detection. A blade without breakdowns should maintain its structural integrity with no signs of cracking, chipping, or flaking. The blade should exhibit a uniform appearance, with no visible separations, detachme
describles["fracture"] = "This is a photo of a blade for anomaly detection. A blade without fractures should have a continuous, unbroken surface with no visible cracks or splits. The blade should be seamless and sturdy, with no signs of stress marks or propagation lines that in
describles["groove"] = "This is a photo of a blade for anomaly detection. A blade without grooves should have a completely smooth and even surface with no indentations or carved-out lines. The blade's surface should be uniform and consistent, with no signs of unintended channel

class MVtecDataset(Dataset):
    """
    # Old __init__ without changes
    def __init__(self, root_dir: str):*
        self.root_dir = root_dir
        # self.transform = transform
        self.transform = transforms.Resize(
                            (224, 224), interpolation=transforms.InterpolationMode.BICUBIC
                        )

        self.norm_transform = transforms.Compose(
                            [
                                transforms.ToTensor(),
                                transforms.Normalize(
                                    mean=(0.48145466, 0.4578275, 0.40821073),
                                    std=(0.26862954, 0.26130258, 0.27577711),
                                ),
                            ]
                        )

        self.paths = []
        self.x = []
        for root, dirs, files in os.walk(root_dir):
            for file in files:
                file_path = os.path.join(root, file)
                if "train" in file_path and "good" in file_path and 'png' in file:
                    self.paths.append(file_path)
                    self.x.append(self.transform(Image.open(file_path).convert('RGB')))

        self.prev_idx = np.random.randint(len(self.paths))
    """

    # New __init__ with changes including try/except block to skip bugged images
    def __init__(self, root_dir: str):
        self.root_dir = root_dir
        # self.transform = transform
        self.transform = transforms.Resize(
```

Figure 12: Modification 3 - mvtec.py

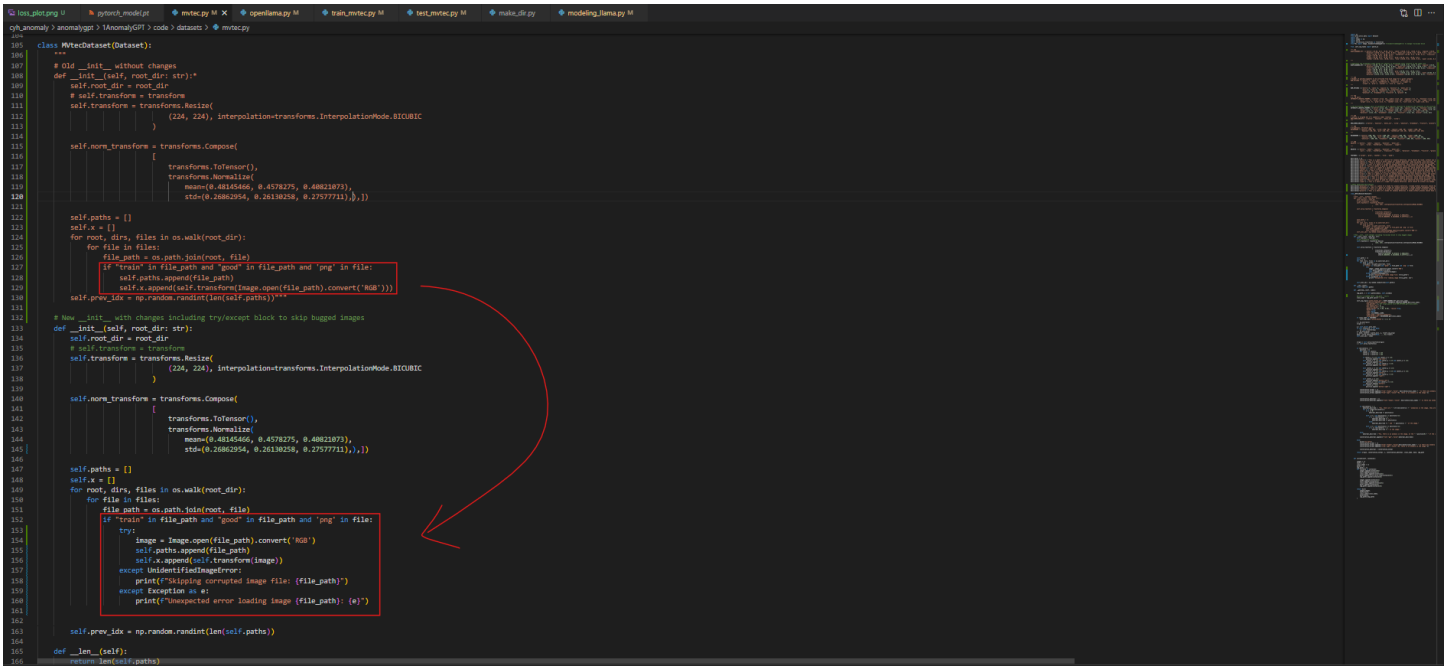


Figure 13: Modification 4 - mvtec.py

Introducing these new changes into the original scripts and adding new samples probably were going to disrupt the loss function alongside with the results. To avoid this issue, Serena proposed to modify the loss function to make it more acquainted with the new data. Even though the modification of the loss function is quite complicated, the proposals that I prepared were, at least the first one, seemed quite logical.

My proposals consisted in the following loss functions:

1. **Weighted Cross-Entropy Loss**: I suspect that by adding the new dataset, which include 1456 images of the same object (blade) during the training (separated in 4 different classes - ablation, breakdown, fracture and groove) will imbalance the dataset and might lead to overfitting.

$$L = \alpha \cdot L_{\text{W\_CE}} + \beta \cdot L_{\text{focal}} + \delta \cdot L_{\text{dice}}$$

where the weighted cross-entropy loss function $L_{\text{W\_CE}}$ depends on the term w_{y_i} representing the inverse frequency of each class in the training data, defined as follows:

$$L_{\text{W\_CE}} = -\frac{1}{n} \cdot \sum_{i=1}^{n} w_{y_i} \cdot y_i \cdot log(p_i)$$

2. **Combined Focal Loss with Adaptative Gamma**: Thie function was proposed by GPT4o, arguing that incorporating an adaptive version of the focal loss to dynamically adjust the focusing parameter γ based on class imbalance, might work.

$$L = \alpha \cdot L_{\text{CE}} + \beta \cdot L_{\text{adaptative\_focal}} + \delta \cdot L_{\text{dice}}$$

where the adaptative focal loss would include the parameter $\gamma_{y_i} = \frac{\gamma_{base}}{w_{y_i}}$ and defined as follows:

$$L_{\text{adaptative\_focal}} = -\frac{1}{n} \cdot \sum_{i=1}^{n} (1 - p_i)^{\gamma_{y_i}} \cdot log(p_i)$$

The proposals were postponed in order to follow an easier path which would be applying data augmentation to balance all the classes, and that will be managed by model V5. With all the previous considerations, the training

process can already start and shouldn't stop until its complete execution. Nonetheless, when it comes to testing the model, some modifications were once again needed to make it work. The first issue came with the names of the images, they had to be changed to ascending order starting from 000.png (for train and test) and 000_mask.png (ground_truth), and this renaming had to be performed for all new classes (ablation, breakdown, fracture and groove). The second issue, was just to include the new classes following the same order as the defined structure as well as the descriptions for each class.

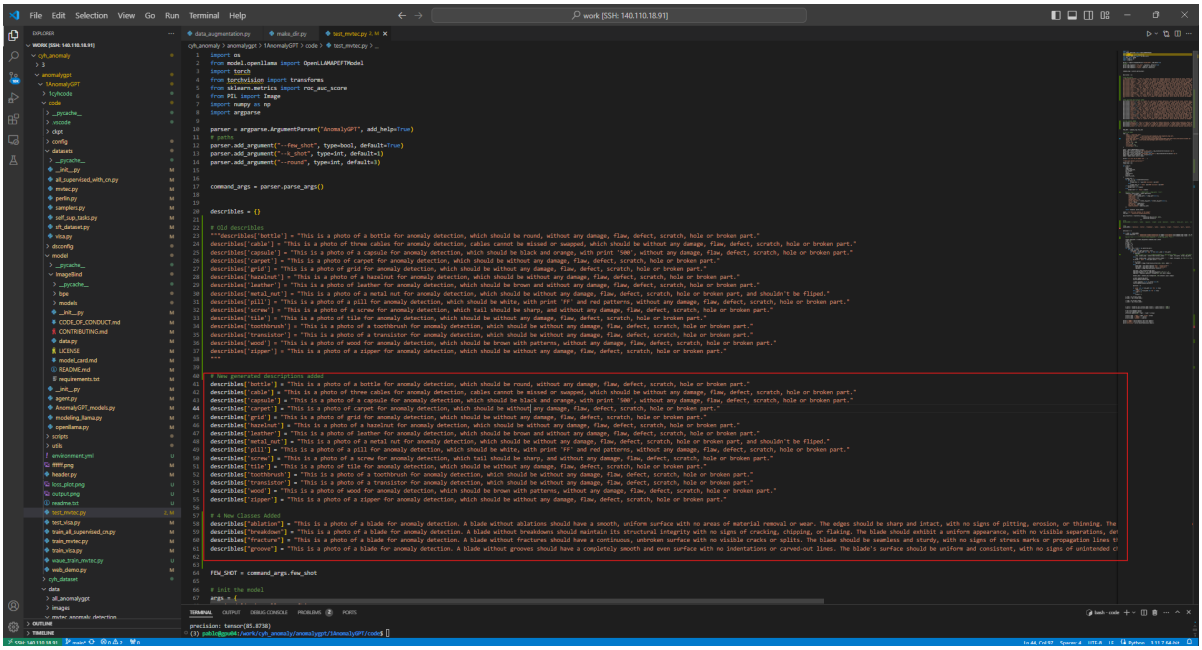


Figure 14: Modification 1 for Model V4- test_mvtec.py

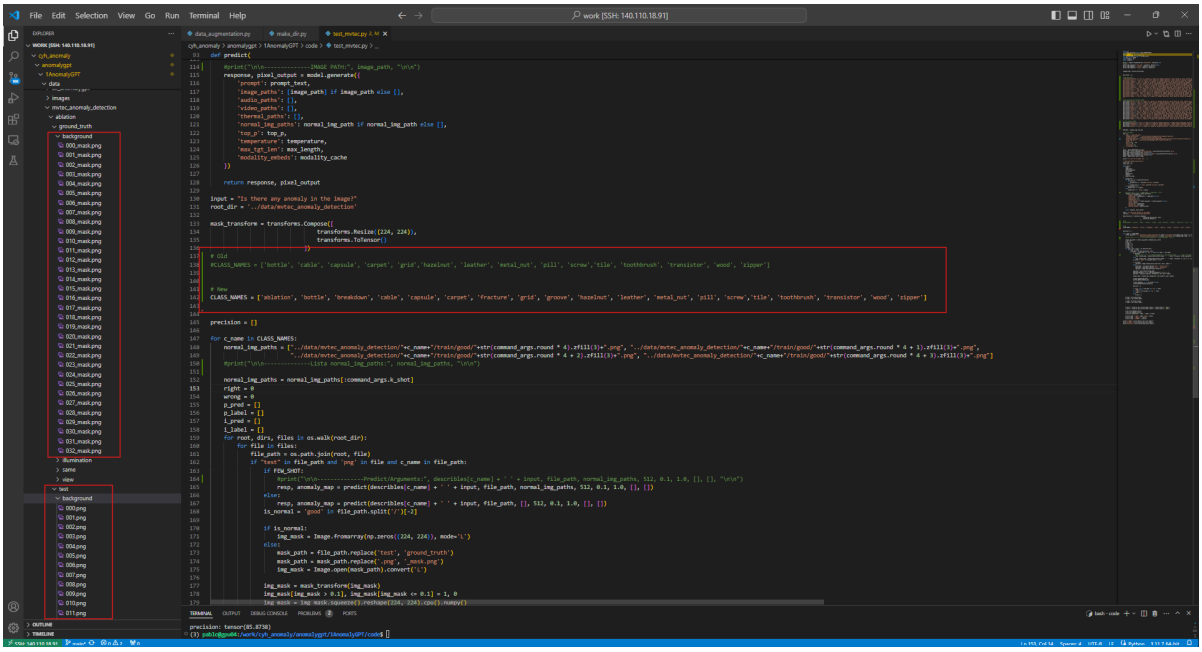


Figure 15: Modification 2 for Model V4 - test_mvtec.py

5.3.1.5 Model V5

Finally, the latest model, model V5, builds on model V4 by using data augmentation to balance the object classes. There are two main ways data augmentation was applied to the original dataset. First, the training samples in the "train/good" folder from each original class (excluding the four new classes) were increased from about 200 to roughly 1000 samples. Second, data augmentation was also applied to the test and ground_truth datasets to boost the number of test samples, duplicating their original size, providing a more reasonable and realistic evaluation of the model's learning and inference capabilities. Let's explain each data augmentation process.

- **Training Data Augmentation**: For each class, there was conducted a meticulous study of which operations would suit better the characteristics of the corresponding object and there were applied mostly the following operations: rotations, scaling, brightness tuning, horizontal and vertical flips.

  Operations such as translations, too wide rotations or blurring images were discarded due to obvious reasons, the original images would include black backgrounds and new anomalies which would not be represented in their respective labels (ground_truth images).

  The different operations are included in the upcoming table, and the percentage shown (usually) under the different operations represents the probability of applying such operation to a given image. Finally, after the generation of the new training samples, we must rename the new images to adapt to the original script, otherwise when running the testing script, we will jump into different bugs. The code is implemented into the script data_augmentation.py.

- **Test & Ground Truth Data Augmentation**: As the training dataset grows, it is necessary to augment the testing dataset correspondingly. To generate new anomalous images, a technique known as **Poisson Image Editing** will be used. This method involves taking a labeled image describing the location of the anomaly (mask in ground_truth), the anomalous picture, and a non-anomalous picture to create a **new anomalous picture**. The defect from the original anomalous image is seamlessly blended into the new non-anomalous image, resulting in a new anomalous picture. The defect can be placed voluntarily into the non-anomalous picture generating therefore new samples as realistic as the original ones. Even though these new anomalous samples look real, in some cases they don't vary sufficiently from the original anomalous picture. Therefore, to solve such issue, after applying the **Poisson** technique, additional operations such as rotations or flips are applied. The code is implemented into the script poisson_image_editing.py. Some examples of the previously mentioned technique, based on a paper published in 2003, can be found below.

The operations implemented can be summarized in the following tables, grouping the different operations applied during the process for the training and testing samples augmentation. Notice that, in the table in which is compared the dataset used for model V4 and model V5, the table contains the number of elements in the mentioned folders.

For instance, in the folder "/ablation/ground_truth/" we find a total of 151 elements (in this case, masks), in the folder "/ablation/test/" we find 151 elements contained in the same folders as in "/ablation/ground_truth/" (which corresponds to the folders background, illumination, same and view) and 109 images contained in the folder "/ablation/test/good/". Moreover, the increase in training samples is roughly 5 times the original size and a duplication for testing and ground_truth samples.

5.3.1.6 Metric: AUROC

The metric that is used to evaluate the model's performance is AUROC, which specifically refers to the area under the Receiver Operating Characteristic (ROC) curve. The ROC curve is a plot of the true positive rate (TPR or recall) against the false positive rate (FPR) at various threshold settings. There are several reasons that lead to choose such metric, including that sich metric is commonly used to evaluate the performance of binary classification models and is quite useful for comparing different models or classifiers as it is independent of the classification threshold.

Class	Operation 1	Operation 2	Operation 3	Operation 4
Bottle	Rotate 180º 80%	Rotate 90º 60%	Horizontal Flip 50%	Flip vertical
Cable	Rotate 180º 80%	Rotate 90º 60%	Horizontal Flip	Brightness 90-110% 70%
Capsule	Rotate 270º	Rotate 180º 50%	Brightness 90-110% 70%	✗
Carpet	Rotate 180º 50%	Rotate 270º 50%	Vertical Flip 50%	Brightness 90-110% 70%
Grid	Rotate 180º 50%	Rotate 270º 50%	Vertical Flip 50%	Brightness 90-110% 70%
Hazelnut	Rotate 90º 50%	Rotate 270º 50%	Horizontal Flip 50%	Brightness 90-110% 70%
Leather	Rotate 90º 50%	Rotate 180º 50%	Vertical Flip	Brightness 90%-110% 70%
Metal Nut	Rotate 90º 50%	Rotate 180º 50%	Vertical Flip	✗
Pill	Rotate [-35º, 35º]	Scaling 0-20%	Flip horizontal 60%	Vertical Flip 70%
Screw	Rotate [-35º, 35º]	Scaling 20-50%	Horizontal Flip 60%	Vertical Flip 60%
Tile	Rotate [-35º, 35º]	Zoom 20-40%	✗	✗
Toothbrush	Vertical Flip	Rotate [-20º, 20º]	✗	✗
Transistor	Rotate [-15º, 15º]	Vertical Flip 60%	✗	✗
Wood	Rotate [-50º, 50º]	Scaling 50-80%	Vertical Flip 70%	✗
Zipper	Rotate [-15º, 15º]	Scaling 40-60%	Vertical Flip 70%	✗

Table 2: Data Augmentation: Training Dataset

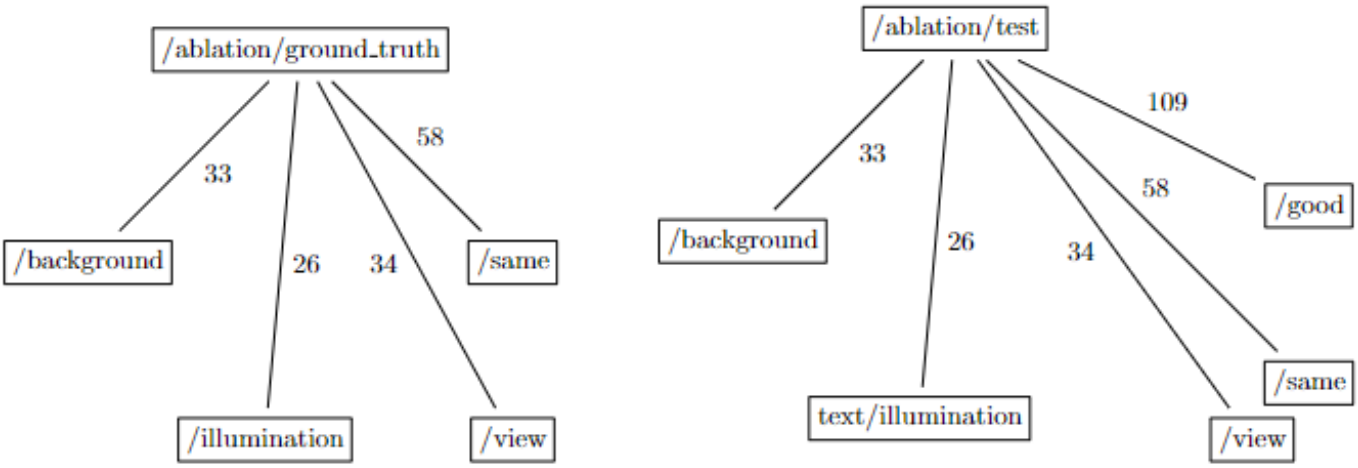


Figure 16: Ground_truth & Test folder structure: Ablation

	Class	V4	V5	V6
GT **Test** **Train**	ablation	151 151+109 364	151 151+109 364	151 151+109 364
	bottle	63 63+20 209	126 126+20 1000	126 126+20 400
	breakdown	310 310+109 364	310 310+109 364	310 310+109 364
	cable	92 92+58 224	184 184+58 1000	184 184+58 400
	capsule	109 109+23 219	218 218+23 1000	218 218+23 400
	carpet	89 89+28 280	178 178+28 1000	178 178+28 400
	fracture	370 370+109 364	370 370+109 364	370 370+109 364
	grid	57 57+21 264	114 114+21 1000	114 114+21 400
	groove	241 241+109 364	241 241+109 364	241 241+109 364

	Class	V4	V5	V6
GT **Test** **Train**	hazelnut	70 70+40 391	140 140+40 1000	140 140+40 400
	leather	92 92+32 245	184 184+32 1000	184 184+32 400
	metal_nut	93 93+22 220	186 186+22 1000	186 186+22 400
	pill	141 141+26 267	282 282+26 1000	282 282+26 400
	screw	119 119+41 320	238 238+41 1000	238 238+41 400
	tile	84 84+33 230	168 168+33 1000	168 168+33 400
	toothbrush	30 30+12 60	60 60+12 1000	60 60+12 400
	transistor	40 40+60 213	80 80+60 1000	80 80+60 400
	wood	60 60+19 247	120 120+19 1000	120 120+19 400
	zipper	119 119+32 240	238 238+32 1000	238 238+32 400

Table 3: Data Augmentation: Model Comparison V4, V5 & V6

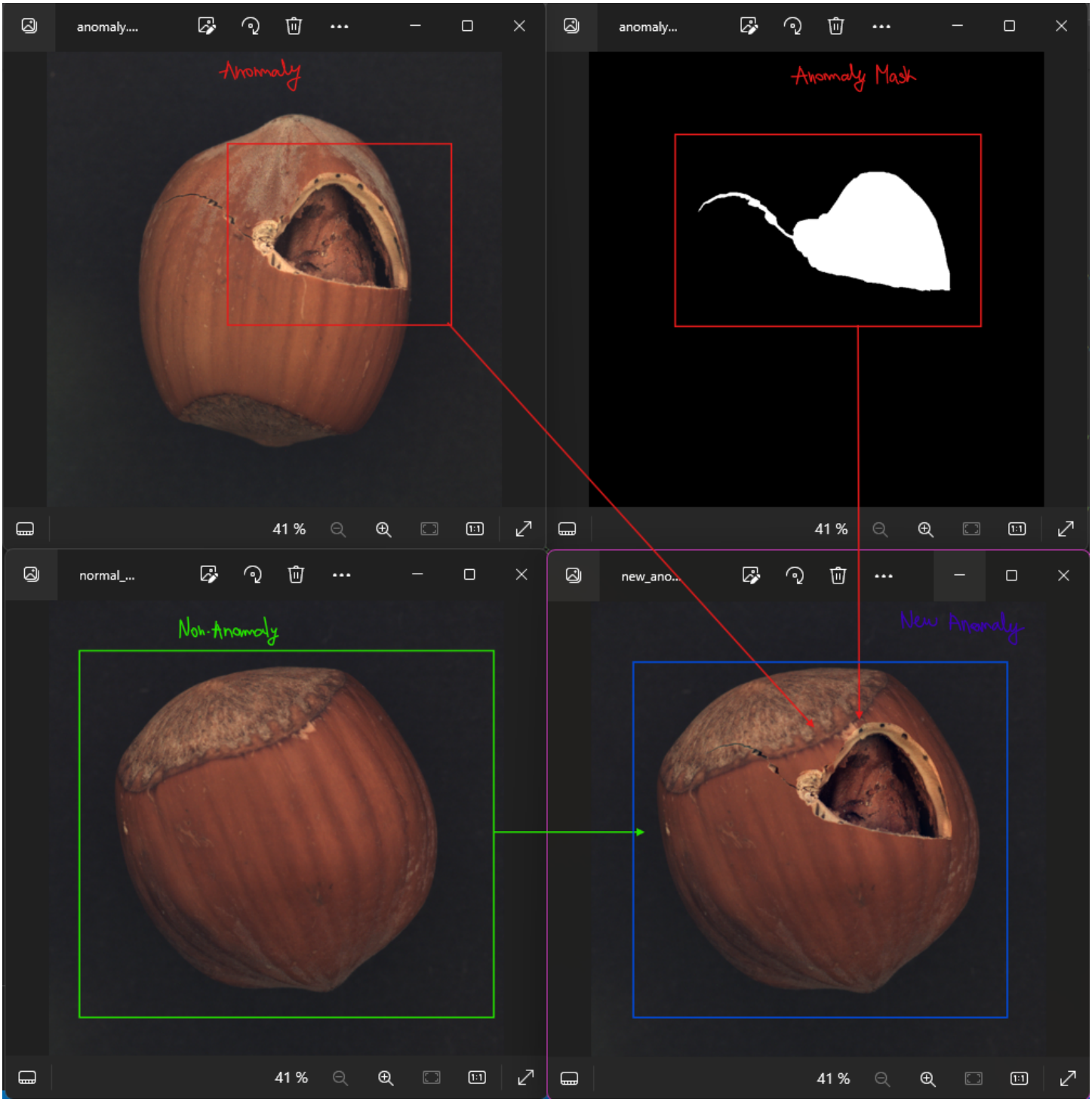


Figure 17: Poisson Editing Technique: Hazelnut

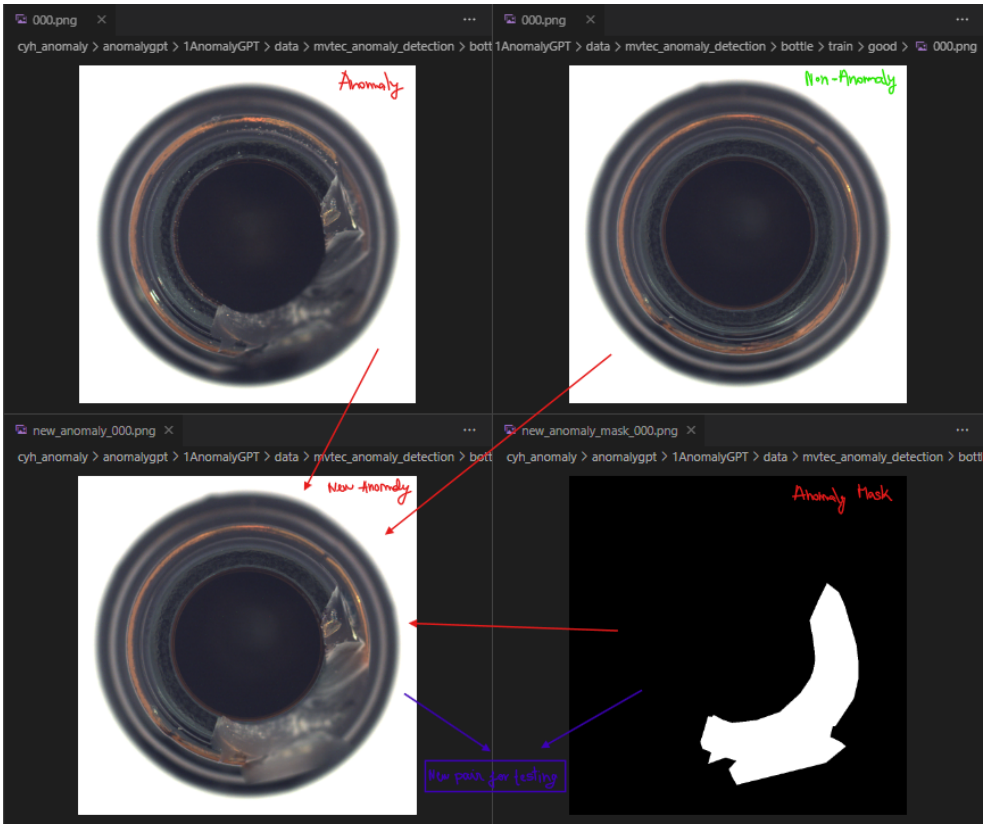


Figure 18: Poisson Editing Technique: Bottle

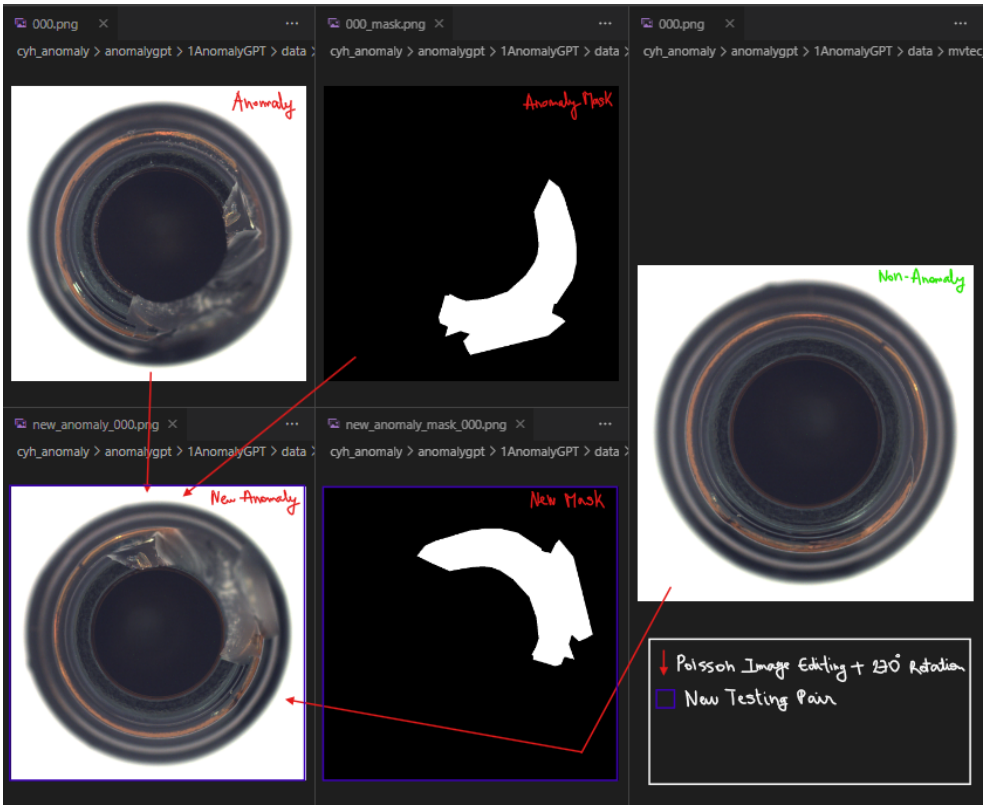


Figure 19: Improved Poisson Editing Example: Bottle

5.4 Results

To run the evaluation script corresponding to the chosen training dataset (test_mvtec.py), it simply needs to be executed in the correct folder after replacing the path from the trained model, as shown in the below picture:

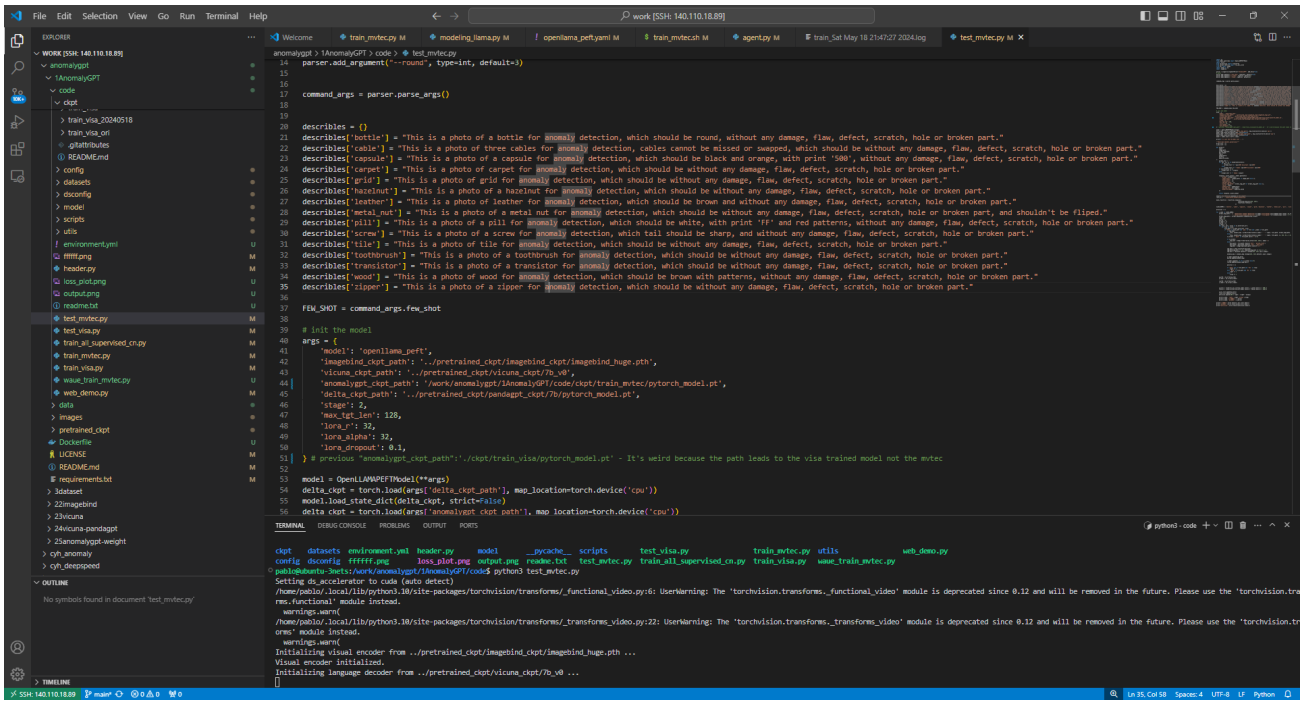


Figure 20: Modifications: test_mvtec.py

In our case, the test considers a 1-Shot setup and as shown in the original comparison table, we are comparing the highlighted scores with the ones obtained in the training. At the end of the execution, the results found for the trainings of each model are the following:

Model	Type	Score	Precision
Baseline	Image_AUROC Pixel_AUROC	94.232 95.4573	91.655
V2	Image_AUROC Pixel_AUROC	94.2320 95.4573	89.5601
V3	Image_AUROC Pixel_AUROC	94.232 95.4573	0
V4	Image_AUROC Pixel_AUROC	91.9205 95.3716	85.8738
V5	Image_AUROC Pixel_AUROC	93.0984 94.7474	86.2155
V6	Image_AUROC Pixel_AUROC	93.0984 94.7474	87.8672

Table 4: Model's Results

As it can be noticed, the model V3 reaches the same performance as the previous model V2 in terms of both, Image and Pixel AUC however, the acuraccy is 0. There must be some kind of mistake. Moreover, model's V2 performance compared to the baseline model in which includes the 3 models and the optimizer LoRA (like V2), improves the Pixel-AUC, although worsening the Image-AUC.

The following tables include the results class per class of all model trainings. A noticeable remark is that model V3 produces a null precision for all classes due to the batch_normalization operation during training.

Setup	Method	MVTec-AD			VisA		
		Image-AUC	Pixel-AUC	Accuracy	Image-AUC	Pixel-AUC	Accuracy
1-shot	SPADE	81.0 ± 2.0	91.2 ± 0.4	-	79.5 ± 4.0	95.6 ± 0.4	-
	PaDiM	76.6 ± 3.1	89.3 ± 0.9	-	62.8 ± 5.4	89.9 ± 0.8	-
	PatchCore	83.4 ± 3.0	92.0 ± 1.0	-	79.9 ± 2.9	95.4 ± 0.6	-
	WinCLIP	93.1 ± 2.0	95.2 ± 0.5	-	83.8 ± 4.0	**96.4 ± 0.4**	-
	AnomalyGPT (ours)	**94.1 ± 1.1**	**95.3 ± 0.1**	**86.1 ± 1.1**	**87.4 ± 0.8**	96.2 ± 0.1	**77.4 ± 1.0**
2-shot	SPADE	82.9 ± 2.6	92.0 ± 0.3	-	80.7 ± 5.0	96.2 ± 0.4	-
	PaDiM	78.9 ± 3.1	91.3 ± 0.7	-	67.4 ± 5.1	92.0 ± 0.7	-
	PatchCore	86.3 ± 3.3	93.3 ± 0.6	-	81.6 ± 4.0	96.1 ± 0.5	-
	WinCLIP	94.4 ± 1.3	**96.0 ± 0.3**	-	84.6 ± 2.4	**96.8 ± 0.3**	-
	AnomalyGPT (ours)	**95.5 ± 0.8**	95.6 ± 0.2	**84.8 ± 0.8**	**88.6 ± 0.7**	96.4 ± 0.1	**77.5 ± 0.3**
4-shot	SPADE	84.8 ± 2.5	92.7 ± 0.3	-	81.7 ± 3.4	96.6 ± 0.3	-
	PaDiM	80.4 ± 2.5	92.6 ± 0.7	-	72.8 ± 2.9	93.2 ± 0.5	-
	PatchCore	88.8 ± 2.6	94.3 ± 0.5	-	85.3 ± 2.1	96.8 ± 0.3	-
	WinCLIP	95.2 ± 1.3	96.2 ± 0.3	-	87.3 ± 1.8	**97.2 ± 0.2**	-
	AnomalyGPT (ours)	**96.3 ± 0.3**	**96.2 ± 0.1**	**85.0 ± 0.3**	**90.6 ± 0.7**	96.7 ± 0.1	**77.7 ± 0.4**

Table 2. Few-shot IAD results on MVTec-AD and VisA datasets. Results are listed as the average of 5 runs and the best-performing method is in **bold**. The results for SPADE, PaDiM, PatchCore and WinCLIP are reported from [11].

Figure 21: Baseline Results

Class \ Precision	Baseline	V2	V3	V4	V5	V6
ablation	✗	✗	✗	61.92	65.38	75
bottle	92.77	93.97	0	95.18	96.86	93.88
breakdown	✗	✗	✗	78.28	87.35	93.07
cable	83.33	86	0	84	89.25	88.84
capsule	85.60	68.18	0	81.81	82.15	86.72
carpet	100	100	0	100	98.54	98.05
fracture	✗	✗	✗	69.51	43.84	48.85
grid	97.43	97.43	0	97.43	97.77	97.03
groove	✗	✗	✗	71.14	60.28	62.28
hazelnut	96.36	97.27	0	97.27	96.66	98.88
leather	97.58	98.38	0	98.38	99.07	99.07
metal_nut	99.13	100	0	100	98.55	98.07
pill	87.42	85.62	0	87.42	89.93	90.58
screw	76.25	75	0	76.25	82.43	81
tile	99.14	99.14	0	94.01	96.51	97.01
toothbrush	100	95.23	0	90.47	86.11	93.05
transistor	84	82	0	83	85.71	86.42
wood	93.67	94.93	0	94.93	97.12	96.40
zipper	82.11	68.18	0	74.17	87.03	85.18
Image_AUROC	94.232	94.232	94.232	91.920	93.0984	93.0984
Pixel_AUROC	95.457	95.4573	95.457	95.3716	94.7474	94.7474
Precision	91.655	89.5601	0	85.8738	86.2155	87.8672

Table 5: Precision across Models & Classes

Class	Type	Score	Right	Wrong	Precision
bottle	Image_AUROC Pixel_AUROC	99.52 98.03	78	5	93.97
cable	Image_AUROC Pixel_AUROC	89.54 93.59	129	21	86
capsule	Image_AUROC Pixel_AUROC	65.46 89.8	90	42	68.18
carpet	Image_AUROC Pixel_AUROC	100.0 99.4	117	0	100
grid	Image_AUROC Pixel_AUROC	99.79 97.28	76	2	97.43
hazelnut	Image_AUROC Pixel_AUROC	99.46 98.88	107	3	97.27
leather	Image_AUROC Pixel_AUROC	99.97 99.31	122	2	98.38
metal_nut	Image_AUROC Pixel_AUROC	100.0 90.43	115	0	100
pill	Image_AUROC Pixel_AUROC	95.34 95.96	143	24	85.62
screw	Image_AUROC Pixel_AUROC	77.43 96.27	120	40	75
tile	Image_AUROC Pixel_AUROC	99.82 95.93	116	1	99.14
toothbrush	Image_AUROC Pixel_AUROC	97.78 98.44	40	2	95.23
transistor	Image_AUROC Pixel_AUROC	91.85 87.85	82	18	82
wood	Image_AUROC Pixel_AUROC	99.61 95.95	75	4	94.93
zipper	Image_AUROC Pixel_AUROC	97.91 94.74	106	45	68.18

Table 6: Model's V2 Results

Class	Type	Score	Right	Wrong	Precision
bottle	Image_AUROC Pixel_AUROC	99.52 98.03	0	83	0
cable	Image_AUROC Pixel_AUROC	89.54 93.59	0	150	0
capsule	Image_AUROC Pixel_AUROC	65.46 89.8	0	132	0
carpet	Image_AUROC Pixel_AUROC	100.0 99.4	0	117	0
grid	Image_AUROC Pixel_AUROC	99.79 97.28	0	78	0
hazelnut	Image_AUROC Pixel_AUROC	99.46 98.88	0	110	0
leather	Image_AUROC Pixel_AUROC	99.97 99.31	0	124	0
metal_nut	Image_AUROC Pixel_AUROC	100.0 90.43	0	115	0
pill	Image_AUROC Pixel_AUROC	95.34 95.96	0	167	0
screw	Image_AUROC Pixel_AUROC	77.43 96.27	0	160	0
tile	Image_AUROC Pixel_AUROC	99.82 95.93	0	117	0
toothbrush	Image_AUROC Pixel_AUROC	97.78 98.44	0	42	0
transistor	Image_AUROC Pixel_AUROC	91.85 87.85	0	100	0
wood	Image_AUROC Pixel_AUROC	99.61 95.95	0	79	0
zipper	Image_AUROC Pixel_AUROC	97.91 94.74	0	151	0

Table 7: Model's V3 Results

Class	Type	Score	Right	Wrong	Precision
ablation	Image_AUROC Pixel_AUROC	85.94 94.26	161	99	61.92
bottle	Image_AUROC Pixel_AUROC	99.52 98.03	79	4	95.18
breakdown	Image_AUROC Pixel_AUROC	98.73 99.3	328	91	78.28
cable	Image_AUROC Pixel_AUROC	89.54 93.59	126	24	84
capsule	Image_AUROC Pixel_AUROC	65.46 89.8	108	24	81.81
carpet	Image_AUROC Pixel_AUROC	100.0 99.4	117	0	100
fracture	Image_AUROC Pixel_AUROC	68.48 89.84	333	146	69.51
grid	Image_AUROC Pixel_AUROC	99.79 97.28	76	2	97.43
groove	Image_AUROC Pixel_AUROC	79.86 96.8	249	101	71.14
hazelnut	Image_AUROC Pixel_AUROC	99.46 98.88	107	3	97.27
leather	Image_AUROC Pixel_AUROC	99.97 99.31	122	2	98.38
metal_nut	Image_AUROC Pixel_AUROC	100.0 90.43	115	0	100
pill	Image_AUROC Pixel_AUROC	95.34 95.96	146	21	87.42
screw	Image_AUROC Pixel_AUROC	77.43 96.27	122	38	76.25
tile	Image_AUROC Pixel_AUROC	99.82 95.93	110	7	94.01
toothbrush	Image_AUROC Pixel_AUROC	97.78 98.44	38	4	90.47
transistor	Image_AUROC Pixel_AUROC	91.85 87.85	83	17	83
wood	Image_AUROC Pixel_AUROC	99.61 95.95	75	4	94.93
zipper	Image_AUROC Pixel_AUROC	97.91 94.74	112	39	74.17

Table 8: Model's V4 Results

Class	Type	Score	Right	Wrong	Precision
ablation	Image_AUROC Pixel_AUROC	85.94 94.26	170	90	65.38
bottle	Image_AUROC Pixel_AUROC	99.52 97.83	216	13	94.32
breakdown	Image_AUROC Pixel_AUROC	98.73 99.3	366	53	87.35
cable	Image_AUROC Pixel_AUROC	92.27 94.3	216	26	89.25
capsule	Image_AUROC Pixel_AUROC	72.46 88.37	198	43	82.15
carpet	Image_AUROC Pixel_AUROC	99.34 99.23	203	3	98.54
fracture	Image_AUROC Pixel_AUROC	68.48 89.84	210	269	43.84
grid	Image_AUROC Pixel_AUROC	99.81 97.19	132	3	97.77
groove	Image_AUROC Pixel_AUROC	79.86 96.8	211	139	60.28
hazelnut	Image_AUROC Pixel_AUROC	99.68 98.67	174	6	96.66
leather	Image_AUROC Pixel_AUROC	99.64 99.4	214	2	99.07
metal_nut	Image_AUROC Pixel_AUROC	99.94 89.96	205	3	98.55
pill	Image_AUROC Pixel_AUROC	96.99 94.53	277	31	89.93
screw	Image_AUROC Pixel_AUROC	83.22 96.77	230	49	82.43
tile	Image_AUROC Pixel_AUROC	99.83 96.01	194	7	96.51
toothbrush	Image_AUROC Pixel_AUROC	98.19 97.6	62	10	86.11
transistor	Image_AUROC Pixel_AUROC	95.93 84.86	120	20	85.71
wood	Image_AUROC Pixel_AUROC	99.8 94.58	135	4	97.12
zipper	Image_AUROC Pixel_AUROC	98.96 90.70	235	35	87.03

Table 9: Model's V5 Results

Class	Type	Score	Right	Wrong	Precision
ablation	Image_AUROC Pixel_AUROC	85.94 94.26	195	65	75
bottle	Image_AUROC Pixel_AUROC	99.52 97.83	215	14	93.88
breakdown	Image_AUROC Pixel_AUROC	98.73 99.3	390	29	93.07
cable	Image_AUROC Pixel_AUROC	92.27 94.3	215	27	88.84
capsule	Image_AUROC Pixel_AUROC	72.46 88.37	209	32	86.72
carpet	Image_AUROC Pixel_AUROC	99.34 99.23	202	4	98.05
fracture	Image_AUROC Pixel_AUROC	68.48 89.84	234	245	48.85
grid	Image_AUROC Pixel_AUROC	99.81 97.19	131	4	97.03
groove	Image_AUROC Pixel_AUROC	79.86 96.8	218	132	62.28
hazelnut	Image_AUROC Pixel_AUROC	99.68 98.67	178	2	98.88
leather	Image_AUROC Pixel_AUROC	99.94 99.4	214	2	99.07
metal_nut	Image_AUROC Pixel_AUROC	99.94 89.96	204	4	98.07
pill	Image_AUROC Pixel_AUROC	96.99 94.53	279	29	90.58
screw	Image_AUROC Pixel_AUROC	83.22 96.77	226	53	81
tile	Image_AUROC Pixel_AUROC	99.83 96.01	195	6	97.01
toothbrush	Image_AUROC Pixel_AUROC	98.19 97.6	67	5	93.05
transistor	Image_AUROC Pixel_AUROC	95.93 84.86	121	19	86.42
wood	Image_AUROC Pixel_AUROC	99.8 94.58	134	5	96.40
zipper	Image_AUROC Pixel_AUROC	98.96 90.70	230	40	85.18

Table 10: Model's V6 Results

5.4.1 Loss Evolution

The plots of the loss evolution from each model are displayed below:

Figure 22: Model V2 - Loss Evolution

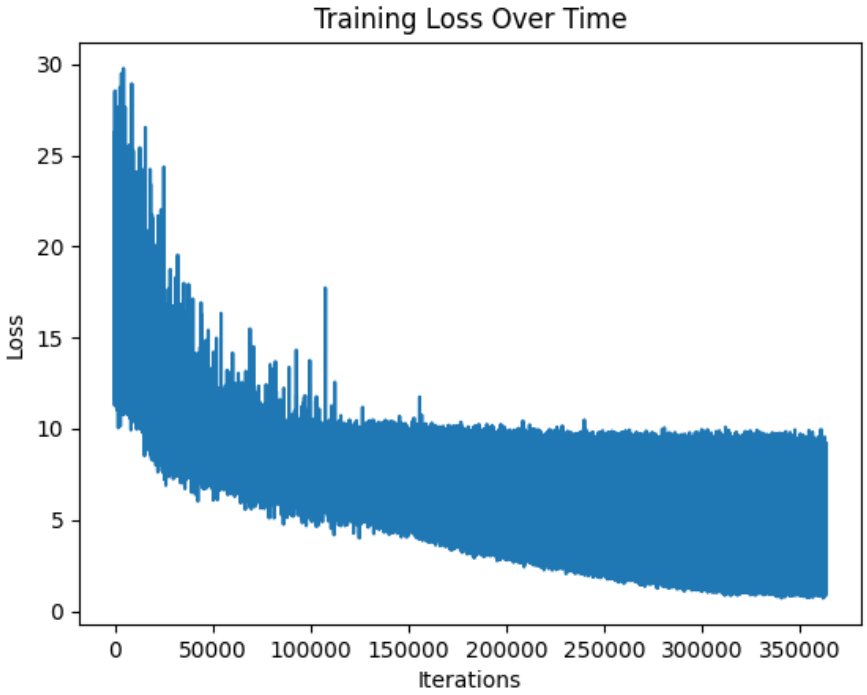


Figure 23: Model V3 - Loss Evolution

Figure 24: Model V4 - Loss Evolution

Figure 25: Model V5 - Loss Evolution

Figure 26: Model V6 - Loss Evolution

5.5 Extra-Information

5.5.1 PEFT

PEFT which stands for Parameter Eficient Fine-Tuning, is a technique used in the field of machine learning and natural language processing to fine-tune large pre-trained models efficiently. The main goal of PEFT is to reduce the number of parameters that need to be updated during the fine-tuning process, thus making the process more efficient in terms of both computation and memory usage.

PEFT methods aim to update only a small subset of the model's parameters during fine-tuning. This can be achieved through various techniques, such as:

- **Adapter Layers**: Adding small adapter modules to the pre-trained model. Only these adapter modules are trained, while the rest of the model parameters remain fixed.
- **Low-Rank Adaptation (LoRA)**: Decomposing weight matrices into low-rank matrices and fine-tuning only these low-rank matrices.
- **Sparse Fine-Tuning**: Updating only a sparse subset of the model's parameters based on certain criteria.

5.5.2 LORA

LoRA, or Low-Rank Adaptation, is a method used in the context of fine-tuning large language models efficiently. It aims to reduce the number of parameters that need to be adjusted during the fine-tuning process, making it more computationally efficient and reducing the memory footprint. Let's see a detailed explanation of what LoRA is and how it works:

5.5.2.1 What is LoRA?

LoRA (Low-Rank Adaptation) is a technique that adapts pre-trained language models by adding low-rank matrices to the existing model parameters. The key idea is to decompose the weight updates into low-rank matrices during

fine-tuning, significantly reducing the number of parameters that need to be learned. The key concepts are the following:

1. Low-Rank Decomposition:
    - Instead of fine-tuning the entire large model, LoRA introduces two low-rank matrices A and B such that $W' = W + AB$, where W is the original weight matrix, and AB is the low-rank approximation.
    - Here, A and B are much smaller matrices (low-rank), which means they have fewer parameters compared to the original weight matrix W.
2. Parameter Efficiency:
    - By decomposing the weight updates into low-rank matrices, the number of parameters that need to be trained during fine-tuning is significantly reduced.
    - This makes the fine-tuning process much more efficient in terms of computational resources and memory usage.
3. Maintaining Model Performance:
    - Despite the reduction in the number of trainable parameters, LoRA can maintain or even improve the performance of the model on specific tasks because the low-rank matrices can effectively capture the necessary adaptations without modifying the entire weight matrix.

5.5.2.2 How LoRA Works?

1. **Initialization**: Start with a pre-trained language model. The existing weight matrices W of the model are kept frozen (i.e., not updated during fine-tuning).
2. **Adding Low-Rank Matrices**: For each weight matrix W that needs to be fine-tuned, introduce two trainable low-rank matrices A and B.
3. **Fine-Tuning**:
    - During fine-tuning, only the low-rank matrices A and B are updated. The original weight matrix W remains unchanged.
    - The effective weight matrix during fine-tuning becomes W' = W + AB.
4. **Forward Pass**: In each forward pass, the model uses the effective weight matrix W', which incorporates the low-rank adaptation.
5. **Parameter Update**: Only the parameters in matrices A and B are updated during backpropagation.

5.5.2.3 Advantages of LoRA

1. **Efficiency**: Reduces the number of trainable parameters, leading to faster and more memory-efficient fine-tuning.
2. **Flexibility**: Can be applied to various parts of the model without altering the original architecture.
3. **Performance**: Maintains or even improves the model's performance on specific tasks by effectively capturing necessary adaptations.

5.5.2.4 Example in Practice

Here's a conceptual example using PyTorch-like pseudocode to illustrate the application of LoRA:

```
import torch
import torch.nn as nn

class LoRAAdaptedLayer(nn.Module):
    def __init__(self, original_layer, rank):
        super(LoRAAdaptedLayer, self).__init__()
        self.original_layer = original_layer
        self.rank = rank
        self.A = nn.Parameter(torch.randn(original_layer.weight.size(0), rank))
        self.B = nn.Parameter(torch.randn(rank, original_layer.weight.size(1)))

    def forward(self, x):
        W = self.original_layer.weight
        W_prime = W + torch.matmul(self.A, self.B)
        return nn.functional.linear(x, W_prime, self.original_layer.bias)

# Example usage
original_linear = nn.Linear(512, 512)
lora_layer = LoRAAdaptedLayer(original_linear, rank=4)

# During fine-tuning, only lora_layer.A and lora_layer.B will be updated
```

5.5.3 ML Concepts

5.5.3.1 Pad Token

The **pad_token** is a special token used to pad sequences to ensure they are all of the same length. This is particularly useful when batching sequences together for processing, as many neural network models require input sequences to be of uniform length. Suppose you have the following sequences of tokens:

- Sequence 1: ["The", "quick", "brown", "fox"]
- Sequence 2: ["jumps", "over", "the", "lazy", "dog"]

When batching these sequences together, you need them to have the same length. If the maximum length is 5, you might pad Sequence 1 to match this length:

- Padded Sequence 1: ["The", "quick", "brown", "fox", " < pad >"]
- Sequence 2: ["jumps", "over", "the", "lazy", "dog"]

5.5.3.2 Eos Token

The **eos_token** (end-of-sequence token) is a special token that indicates the end of a sequence. It is used by the model to know where the sequence ends, which is particularly important during generation tasks or when processing variable-length sequences. If you have a sentence, such as the following, you might append an eos_token to signify the end of this sequence:

- Sentence: ["The", "quick", "brown", "fox"]
- With EOS: ["The", "quick", "brown", "fox", " < eos > "]

5.5.3.3 Padding Side

The **padding_side** specifies where the padding should be applied in a sequence: either at the beginning (left) or the end (right). Using the previous sequences:

- Sequence 1: ["The", "quick", "brown", "fox"]
- Sequence 2: ["jumps", "over", "the", "lazy", "dog"]

When padding these sequences to a length of 6 and setting padding_side to "right", the result will be:

- Padded Sequence 1: ["The", "quick", "brown", "fox", "< pad >", " < pad >"]
- Sequence 2: ["jumps", "over", "the", "lazy", "dog"]

5.5.3.4 Residual Connection

A residual connection adds the input of a layer to its output, helping gradients flow more easily through the network. Let's consider the following simplified example:

- Input: $x = [1, 2, 3]$
- Layer's transformation $\mathcal{F}(x)$: Multiply by 2
- Output of the layer without residual connection: $\mathcal{F}(x) = [2, 4, 6]$

Now, with residual connection, it would output:

$$\text{output} = \mathcal{F}(x) + x = [2, 4, 6] + [1, 2, 3] = [3, 6, 9]$$

5.5.3.5 Batch Normalization

Batch normalization normalizes the input to each layer so that the inputs have a mean μ of 0 and a standard deviation σ of 1. This normalization is performed on a batch-by-batch basis. For instance, if the input batch is

$$X = \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{bmatrix}$$

For each feature (column):

1. Compute the mean and variance across the batch:
   - Feature 1: mean $= \frac{1+4+7}{3} = 4$, variance $= \frac{(1-4)^2+(4-4)^2+(7-4)^2}{3} = \frac{18}{3} = 6$
   - Feature 2: mean $= \frac{2+5+8}{3} = 5$, variance $= \frac{(2-5)^2+(5-5)^2+(8-5)^2}{3} = \frac{18}{3} = 6$
   - Feature 3: mean $= \frac{3+6+9}{3} = 6$, variance $= \frac{(3-6)^2+(6-6)^2+(9-6)^2}{3} = \frac{18}{3} = 6$
2. Normalize:
   - Feature 1: normalized $= \frac{X[:,0]-4}{\sqrt{6}} = \left[\frac{1-4}{\sqrt{6}}, \frac{4-4}{\sqrt{6}}, \frac{7-4}{\sqrt{6}}\right] = \left[-\frac{3}{\sqrt{6}}, 0, \frac{3}{\sqrt{6}}\right]$
   - Feature 2: normalized $= \frac{X[:,1]-5}{\sqrt{6}} = \left[-\frac{3}{\sqrt{6}}, 0, \frac{3}{\sqrt{6}}\right]$
   - Feature 3: normalized $= \frac{X[:,2]-6}{\sqrt{6}} = \left[-\frac{3}{\sqrt{6}}, 0, \frac{3}{\sqrt{6}}\right]$

The normalized batch is:

$$\text{normalized\_}X = \begin{bmatrix} -\frac{3}{\sqrt{6}} & -\frac{3}{\sqrt{6}} & -\frac{3}{\sqrt{6}} \\ 0 & 0 & 0 \\ \frac{3}{\sqrt{6}} & \frac{3}{\sqrt{6}} & \frac{3}{\sqrt{6}} \end{bmatrix}$$

Now, let's say we want to combine Residual Connection and Batch Normalization at the same time.

1. Input to the Layer:

$$x = \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{bmatrix}$$

2. Layer's Transformation $\mathcal{F}(x)$: Assume the layer simply multiplies the input by 2.

$$\mathcal{F}(x) = 2 \times x = \begin{bmatrix} 2 & 4 & 6 \\ 8 & 10 & 12 \\ 14 & 16 & 18 \end{bmatrix}$$

3. Add Residual Connection:

$$\text{Residual Output} = \mathcal{F}(x) + x = \begin{bmatrix} 2 & 4 & 6 \\ 8 & 10 & 12 \\ 14 & 16 & 18 \end{bmatrix} + \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{bmatrix} = \begin{bmatrix} 3 & 6 & 9 \\ 12 & 15 & 18 \\ 21 & 24 & 27 \end{bmatrix}$$

4. Apply Batch Normalization: For each feature compute mean and variance, then normalize.

   - Mean: $\mu = \begin{bmatrix} 12 & 15 & 18 \end{bmatrix}$
   - Variance: $\sigma^2 = \begin{bmatrix} 54 & 54 & 54 \end{bmatrix}$
   - Normalized Output $= \frac{\text{Residual Output} - \mu}{\sqrt{\sigma^2}} = \frac{\begin{bmatrix} 3 & 6 & 9 \\ 12 & 15 & 18 \\ 21 & 24 & 27 \end{bmatrix} - \begin{bmatrix} 12 & 15 & 18 \end{bmatrix}}{\begin{bmatrix} \sqrt{54} & \sqrt{54} & \sqrt{54} \end{bmatrix}} = \begin{bmatrix} -\sqrt{\frac{3}{2}} & -\sqrt{\frac{3}{2}} & -\sqrt{\frac{3}{2}} \\ 0 & 0 & 0 \\ \sqrt{\frac{3}{2}} & \sqrt{\frac{3}{2}} & \sqrt{\frac{3}{2}} \end{bmatrix}$

In practice, integrating these techniques into the neural network can significantly improve its performance and stability.