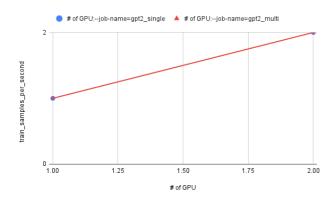
## lab7\_109062320

## Draw the strong scalability of data parallel training



## **Explain why such observation**

Since in whatever training sample, the train\_sample\_per\_second will not change, I will only focus on the data of gpt2\_single.

By observing the data, we can see that using more GPUs allows for more parallel processing of the data. This means that more training samples can be processed simultaneously, leading to a higher throughput (more samples per second). However, we observe only sub-linear scaling, and I guess it's because of the following reasons:

- 1. Communication Overhead: More GPUs entail more data synchronization, which can become a bottleneck, especially with a higher number of GPUs.
- 2. Data Loading and Preprocessing Bottlenecks: If the data pipeline isn't optimized to match the GPUs' processing speed, it can limit the rate at which data is available for training, thus reducing overall efficiency.
- 3. Inefficient Utilization of GPUs: Not all models or training configurations fully utilize the computational power of multiple GPUs, which can lead to underutilization and decreased scaling efficiency.

## Your experiment process

Modifying the Script for Different GPU Counts:

For job-name=gpt2\_single/gpt2\_multi: Set --nproc\_per\_node=1, 2 and SBATCH --gres=gpu:1, 2. The experiment use single and 2 GPU to do experiment on gpt2\_single/gpt2\_multi, which has 200/400 training sample