Job Trace Generator

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Abstract

- **Importance:** High-quality job data is crucial in HPC cluster management. It aids in creating and evaluating job scheduling policies, determining the required computing resources, and ensuring that the systems are robust and capable of handling intensive workloads.

- **What is the problem?:** It's hard to get this data because there isn't much available and it's complex to collect.

- **Addressing the problem: Our Approach:**
  Our research focuses on using ML methods like GANs (Generative Adversarial Networks), and VAEs (Variational Autoencoders) to generate synthetic job traces, that closely resemble real data.

Background

Cluster - A group of interconnected computers that work together to perform tasks.

Cluster Job - A computational task submitted to the cluster, such as Genome sequencing, and weather Forecasting.

Job Traces - Record of executed Jobs in a system (cluster). (Fig 1).

	job	user	project	state	gpu_num	cpu_num	node_num	submit_time	wait_time	run_time	wall_time	node_hour	new_status
0	639487	0.0	0.0	0	0	512.0	8.0	1672529301	71	3632.92	3600.0	8.073155555555555	Killed
1	639448	0.0	0.0	0	0	16384.0	256.0	1672507846	7772	21654.66	21600.0	1539.886933333332	Pass
2	639135	0.0	0.0	0	0	262144.0	4096.0	1672174846	340972	21655.97	21600.0	24639.681422222224	Killed
3	638720	70296325381051.0	70296325381051.0	0	0	262144.0	4096.0	1671905072	632522	3648.7	3600.0	4151.409777777778	Killed
4	639463	0.0	0.0	0	0	8192.0	128.0	1672513950	23424	5995.18	10800.0	213.16195555555558	Pass
5	638722	70296325381051.0	70296325381051.0	0	0	262144.0	4096.0	1671905120	636224	3634.13	3600.0	4134.832355555555	Killed
6	638723	70296325381051.0	70296325381051.0	0	0	262144.0	4096.0	1671905152	639947	3669.52	3600.0	4175.098311111111	Killed
7	639488	0.0	0.0	0	0	8192.0	128.0	1672543325	45	5880.94	10800.0	209.10008888888888	Pass
8	639489	0.0	0.0	0	0	8192.0	128.0	1672549223	66	5829.52	10800.0	207.27182222222223	Pass

Fig 1 - Theta Job Trace [1]

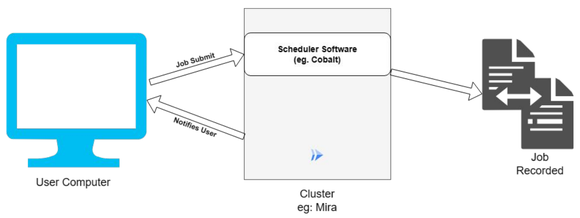

Fig 2 - Job Submission and Logging Workflow

Method

Acquisition of Knowledge: Began by understanding fundamental machine learning concepts and exploring a variety of sophisticated ML methods. Progressed from artificial neural networks to complex architectures such as VAEs (Fig 3), and GANs (Fig 4) which are pivotal and starting point for this research.

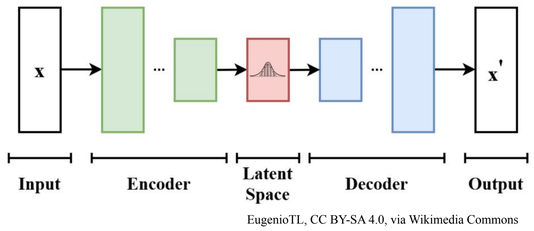

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Fig 3 - VAE: The diagram illustrates a Variational Autoencoder, with an encoder reducing input data to a latent space, and a decoder reconstructing it to an output.

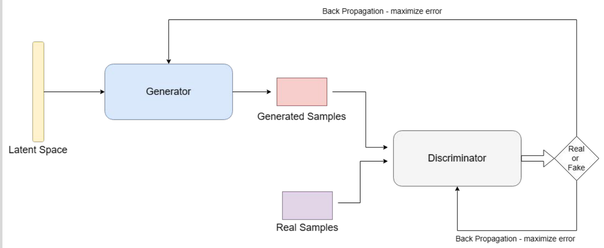


Fig 4 - GAN: The diagram depicts a Generative Adversarial Network (GAN) structure, where the generator fabricates data and the discriminator judges it as real or counterfeit, refining both models through training.

Collected and restructured data: Efficiently gathered and reorganized data using pandas to lay the foundation for training advanced machine learning models.

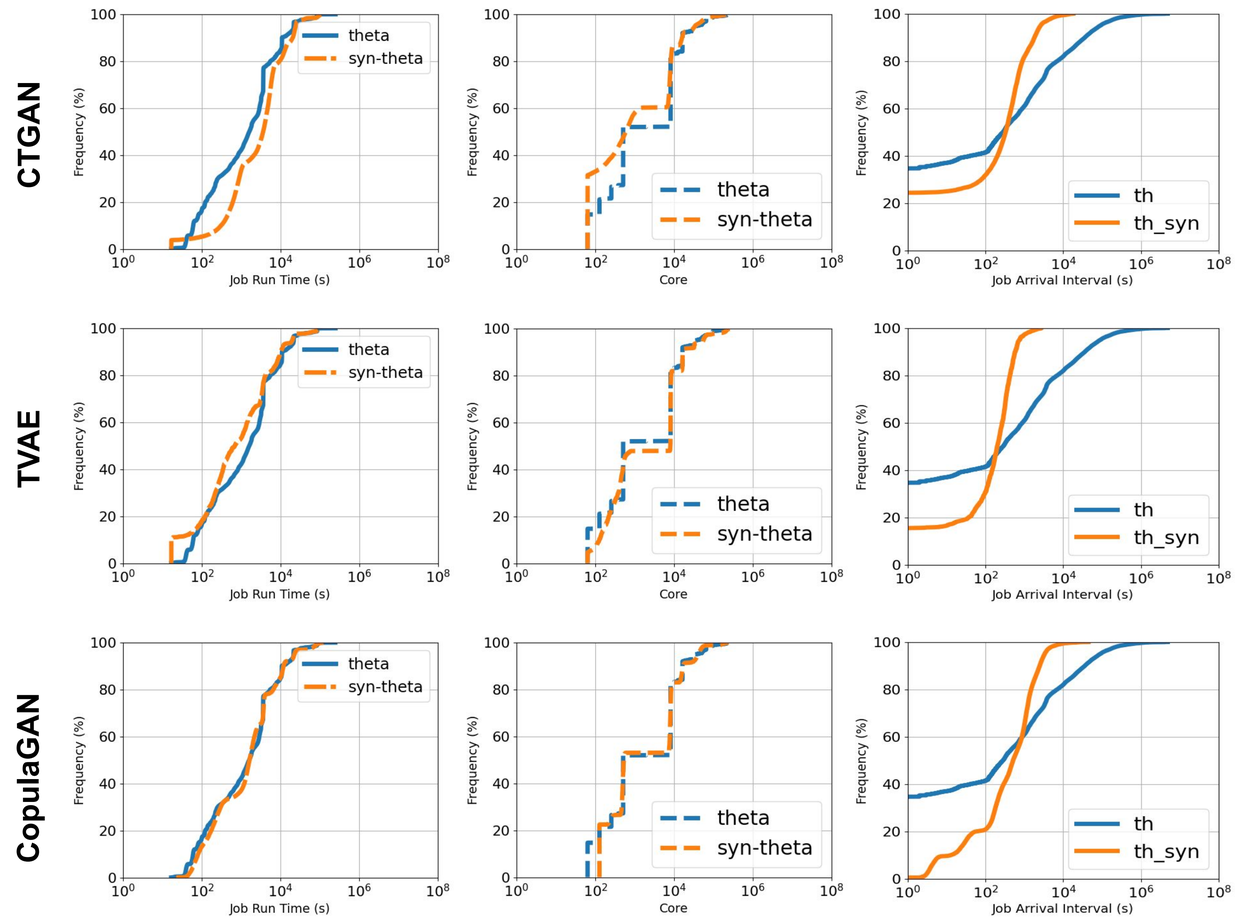
Data Collected:
1) Theta - Cluster in ALCF
2) Theta GPU - Cluster in ALCF
3) SC - Cluster in MIT

Implementation: Utilized the Synthetic Data Vault (SDV) library to train several machine learning models using CTGAN, TVAE, and CopulaGAN — sub-architectures designed for tabular data.

Employed the trained models to generate synthetic data, which was then visualized for evaluating these sub-architectures' effectiveness in producing synthetic job trace data.

Results

Goal: To Minimize the Discrepancy between Actual and Synthetic Data - The cumulative distribution functions (CDFs) below, illustrate our efforts to narrow the divergence between the data from **theta** and its synthetic counterpart, **syn-theta**.



Job Run Time: CDFs comparing actual and synthetic job durations on a log scale.

Core: CDFs contrasting real and modeled core usage frequency.

Job Arrival Interval: CDFs of actual versus synthetic job arrival times.

Future Work

Preliminary findings show CopulaGAN excels in producing runtime and core features but struggles with job arrival intervals. Our next steps involve further testing (visual and analytical methods) and enhancing CopulaGAN, specifically focusing on improving its performance for arrival intervals. This effort will require a deeper understanding of CopulaGAN's mechanisms and exploring modifications for better accuracy. Our aim for the near future is to refine pre-existing CopulaGAN, making it a reliable ML method for generating job traces.

[1] Argonne Leadership Computing Facility. (2023). Theta Cluster Job Trace Data. Retrieved from https://reports.alcf.anl.gov/data/theta.html#DIM_JOB_COMPOSITE (Accessed on Oct, 2024)