Phase Two Presentation: RL vs. Naive Diversification

Robustness and Frictions Across Market Regimes

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Overview

- Addressing computational issues in the trajectory state extraction from the DRL
- Incorporating the regimes from the Deep Learning in Asset Pricing Paper (Chen et al.)

Computational Issues

Running reinforcement learning (RL) algorithms with decision transformers (DT) across many different states introduces several computational challenges, such as,

- **High Memory Requirements:** Significant amounts of memory are required for storing and processing trajectories.
- **Data Inefficiencies:** Many different states demand more samples to cover the space adequately, compounding dataset size and training time.
- **Sequence Alignment and Temporal Credit Assignment:** The more states the DT has, aligning and credit outcomes to earlier actions becomes computationally more difficult.
- **Model Size and Training Cost:** DT may need larger transformer models, which require more computational resources, longer training times, and powerful hardware.

High Performance Computing

High-performance computing (HPC) can significantly accelerate research on RL for portfolio optimization, especially when using computationally demanding models like decision transformers in complex regimes.

- **Parallelization and Speed:** HPC environments allows computational to be distributed across many CPUs and GPUs, drastically reducing the time for training RL models and grid searches over hyperparameters.
- **Larger Models and Datasets:** We can train deeper transformer architectures and process longer trajectories or higher-dimensional state spaces, overcoming the memory and compute limits of a regular PC.
- **Handling Frictions and Constraints:** Simulating realistic trading frictions (transaction costs, slippage, etc.) requires substantial computation and state tracking.

JARVIS

Stevens Institute of Technology's HPC cluster JARVIS is a state-of-the-art computing resource designed to support advanced research across the university.

- **Compute Resources:** JARVIS consists 55 codes, providing 3,168 CPU cores and 32 GPUs, including 8 advanced Nvidia L40s GPUs.
- **Memory:** The cluster has 14 TBs of memory, which enables it to handle complex, memory-intensive workloads.
- **Storage:** It includes 1.2 petabytes (PB) of storage, supporting larged dataset and model checkpoint management.

Figure 1: Not actually Steven's JARVIS

HPC Motivations

- Utilizing S&