SULU: Scalable and Distributed Machine Learning Framework with Unified Encoder for Mars Rover Missions

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Introduction: As NASA considers missions with severely delayed communication and constrained timelines, it becomes increasingly important to enhance onboard autonomy and situational awareness of future rover missions. This combined with the recent rise of High-Performance Spaceflight Computing (HPSC) - a new generation of radiation-hardened (RAD-hard) multi-core processor qualified for space [1] – has opened the possibility for flight infusion of emerging technologies like AI and machine learning that were previously considered infeasible due to the limited onboard processing power.

Towards this end, a vast suite of machine learning based algorithms are being developed at JPL [2] for both onboard and ground-based applications for Mars rover missions. However, all of these are typically designed to learn, albeit very well, only a single task; even though most of them use similar inputs, representation and model architecture. This presents a challenge because simultaneously running these models on the rover would incur unwanted redundancy, waste precious onboard computational resources, and does not exploit the power of deep neural networks to learn a generic and rich representation for all machine learning tasks.

Technical Approach: In this paper, we present a new architecture – SULU: a Scalable and distribUted machine-Learning framework with Unified encoder, that efficiently utilizes onboard computational resources for machine learning inference on multiple ML tasks while improving the performance of each task itself. More specifically, our proposed framework is based on a distributed Encoder-Decoder model such that we have a single unified encoder that runs onboard the rover and encodes the input into a lower-dimensional, but semantically rich, feature vector. This feature vector can then be used by a set of several task-specific decoders that either run onboard or on the ground (or both) depending on the task.

We study this in the context of Mars rover missions and four vision-based autonomy tasks – terrain classification (SPOC) [3], image captioning (SCOTI) [4], image reconstruction, and visual-similarity search. Our unified encoder is based on a modified DeepLabV3+ model with a ResNet-50 backbone. We trained SULU using supervised learning jointly for three of the four tasks using different training regimes - 1) Round-robin per decoder, 2) Round-robin per epoch and 3) Round-robin per step.

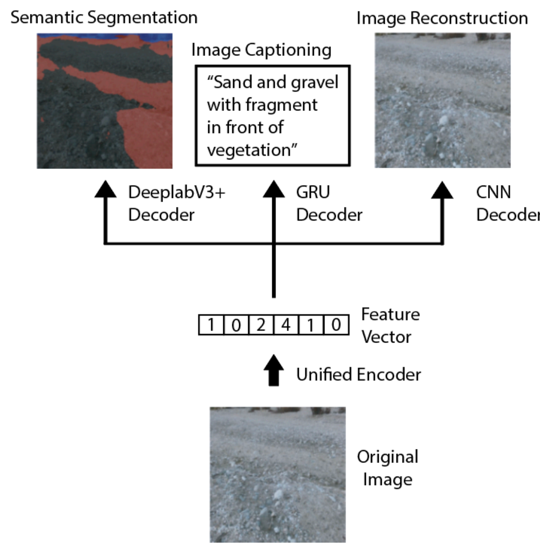

Figure 1: SULU Architecture

Experiments and Results: The proposed SULU framework was implemented using Tensorflow and Keras, and tested on both terrestrial (JPL Arroyo) and planetary datasets (Curiosity Rover images). For hardware-in-the-loop tests, we deployed our model on a Nvidia Jetson TX2 board. Through extensive experiments, we demonstrate that our unified model for training on these tasks together results in a significantly compressed model that saves both compute and memory footprint while improving the overall performance by 20% as compared to training them individually. Furthermore, a distributed ML framework facilitates future science missions by maximizing scientific discovery and reducing the data footprint - transmitting a compact feature vector back to earth rather than the original image helps conserve interplanetary bandwidth through the Deep Space Network. Through this work, we hope to take a small step towards developing scalable ML frameworks for future Mars missions.

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References: [1] Doyle R. (2013) *Workshop on Spacecraft. Flight Software.* [2] Ono et al. (2020) *IEEE Aero*. [3] Rothrock, B. et al. (2016) *AIAA Space.* [4] Qiu, D. et al, (2020) *Planetary and Space Science.*