Fault-Detecting Machine Learning Methods

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***Abstract*—In support of data analysis onboard spacecraft, we have developed fault-detecting machine learning methods that can perform robustly despite radiation-induced errors.**

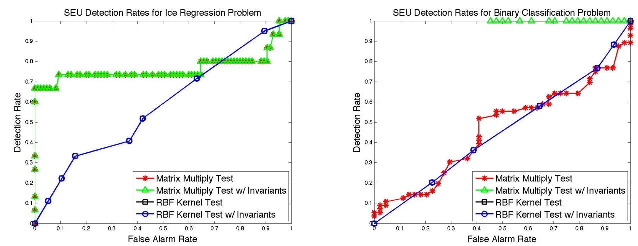
I. Introduction

Spacecraft processors and memory are subjected to high radiation doses and therefore employ radiation-hardened components. However, these components are orders of magnitude more expensive than typical desktop components, and they lag years behind in terms of speed and size. We have developed novel machine learning algorithms that can detect, and recover from, radiation-induced errors. They may ultimately permit the use of spacecraft memory that need not be fully hardened, reducing cost and increasing capability at the same time.

II. Approach and Results

We have developed radiation-induced single-event upset (SEU) detection methods and an SEU simulator that permits rigorous testing. We detect SEUs using a combination of 1) algorithm-specific checksums and 2) domain-specific invariants. The checksums [1] are defined for key library routines such as matrix-matrix multiplication and Gaussian (RBF) kernel computation. We used the Daikon system [2] for inferring program invariants to automatically learn properties of key variables that should hold true throughout the computation (e.g., "the values of matrix C are bounded by -1 and $+1$"). We integrated these checksums and invariants into support vector machine (SVM) classification and regression methods. SVMs are currently in use onboard the EO-1 (Earth Observing 1) spacecraft to perform pixel-level classification of hyperspectral images [3] and can also be used to perform regression.

We also designed and implemented a lightweight SEU software simulator, BITFLIPS (Basic Instrumentation Tool for Fault Localized Injection of Probabilistic SEUs), that is built on the Valgrind debugger/profiler [4]. BITFLIPS injects errors in a reproducible fashion and permits the specification of the SEU rate as well as which program variables to expose and when. We used BITFLIPS to test the performance of our error detection algorithms at a wide range of error injection rates, using receiver operating characteristic (ROC) curves to determine the trade-offs between detection and false alarm rates at various detection thresholds. Figure 1(a) shows the results for SEU detection while performing SVM regression (estimating the water ice content of the Martian atmosphere). Detecting SEUs in matrix multiplication routines was more successful (e.g., 74% with 10% false alarms) than in the RBF kernel computation (e.g., 70% with 63% false alarms). Here, the use of inferred invariants did not increase performance. In Figure 1(b), SEU detection while performing SVM classification yielded lower performance (e.g., 72% with 88% false alarms), but the use of invariants increased performance dramatically (e.g., 100% with 45% false alarms).



(a) Regression (b) Binary Classification

Fig. 1. SEU detection results when running BITFLIPS with an SEU rate of $1e^{-7}$ SEUs per KB per second.

III. Conclusions

Our results indicate that onboard data analysis methods can successfully detect radiation-induced errors. Full details of the methods and analysis of the results will be included in the full version of this paper. The next step will be to add a rollback-and-recompute capability. Ultimately, we aim to provide these fault-detecting methods as a robust alternative to current onboard machine learning and data analysis efforts.

Acknowledgment

This work was carried out at the Jet Propulsion Laboratory, California Institute of Technology, under a contract with the National Aeronautics and Space Administration.

References

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