

Simulating and Detecting Radiation-Induced Errors for Onboard Machine Learning

Kiri L. Wagstaff, Benjamin Bornstein, Robert Granat, Benyang Tang, and Michael Turmon
Jet Propulsion Laboratory, California Institute of Technology
4800 Oak Grove Drive, Pasadena, CA 91109-8099
Email: firstname.lastname@jpl.nasa.gov

Abstract—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 integrated algorithm-based fault tolerance (ABFT) methods into onboard data analysis algorithms to detect radiation-induced errors, which ultimately may permit the use of spacecraft memory that need not be fully hardened, reducing cost and increasing capability at the same time. We have also developed a lightweight software radiation simulator, BITFLIPS, that permits evaluation of error detection strategies in a controlled fashion, including the specification of the radiation rate and selective exposure of individual data structures. Using BITFLIPS, we evaluated our error detection methods when using a support vector machine to analyze data collected by the Mars Odyssey spacecraft. We found ABFT error detection for matrix multiplication is very successful, while error detection for Gaussian kernel computation still has room for improvement.

I. INTRODUCTION AND OBJECTIVES

Onboard data analysis is a powerful capability now being adopted for current and future spacecraft missions. Rather than functioning as remote data collectors that simply stream information back to Earth for interpretation, spacecraft can now determine the relative priorities of different observations or generate compact summaries of large data sets, thereby maximizing the use of limited bandwidth. They can even detect and respond to short-lived events (e.g., dust devils [1]) that would otherwise be noticed only after they ended, if at all.

However, one of the major challenges to increasing the computational responsibility of a spacecraft is the radiation environment in which it operates. Bit errors in memory and altered computational results can all affect the output of an onboard analysis system, potentially resulting in the loss of data or a missed detection. Much work has gone into developing radiation-hardened processors and memory as well as software-based strategies for detecting and recovering from such errors. A common hardware technique for achieving radiation protection for SRAM is Triple-Modular Redundancy (TMR), in which three identical components perform the same memory operations and then vote on the result [2]. Software-based strategies include error detection and correction (EDAC) codes, which employ a “memory scrubber” process to run continually in the background to correct errors [3], and algorithm-specific tests to detect when an error has occurred

(e.g., [4], [5]). Most of the latter has focused on general purpose computing.

In this work, we combine software-based error detection with onboard data analysis algorithms. We focus on the detection of computational errors caused by radiation-induced errors in onboard memory. Our first contribution is a software radiation simulator (BITFLIPS) that permits the specification of the radiation-induced bit error rate as well as precise control over which parts of memory are exposed. Second, we have adapted software-based error detection methods for use by support vector machines (SVMs), one of the the most widely used machine learning methods today. We also propose a new checksum-based strategy for detecting errors in Gaussian kernel computation, needed by SVMs. Finally, we tested these methods on data collected by the Mars Odyssey spacecraft.

II. RADIATION SIMULATION: BITFLIPS

While radiation can cause errors both in spacecraft memory and in the processor, we focus on modeling and protecting against the former. The CPU is such a critical component to the entire spacecraft, not just the data analysis system, that it is likely to be radiation-hardened for the foreseeable future. However, spacecraft memory could potentially tolerate less hardening, if the software itself can detect and compensate for errors. The use of less-hardened memory components could greatly decrease the cost and increase the capability of a mission. Therefore, this seems the most realistic and profitable arena in which to advance onboard error detection. Further, even radiation-hardened memory experiences the occasional error, so the ability to detect and recover from those errors is useful even with more reliable components.

Radiation can cause a variety of errors in memory, include flipped bits, stuck bits, and damaged components. Little can be done in the latter two cases, but flipped bits (single-event upsets or SEUs) are transient effects for which recomputation can be a reasonable solution.

We 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 [6]. 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.

III. RADIATION DETECTION

Our approach to detection of radiation-induced errors is based around postcondition checks on numerical subroutines. If the operation was carried out successfully, certain relations between the routines inputs and its computed outputs should hold true; where they do not, an error is indicated. For example, when performing the matrix inverse operation $B = A^{-1}$, we expect $AB = I$. Due to the limitations of finite-precision arithmetic, most often postconditions will not hold true exactly; consequently we test whether they are true within some error bound.

In general, it is desirable for such postcondition checks to consume considerably less computational resources than the original computation. Otherwise, it would be more direct and informative to simply repeat the computation and compare the results. One way to avoid this sort of exhaustive check is to employ a probe vector w . Consider a linear operation with factorable inputs and outputs:

$$L_1 L_2 \cdots L_p \stackrel{?}{=} R_1 R_2 \cdots R_q. \quad (1)$$

Since an error in one element will often fan out across the result matrix as the computation progresses, we can use w to compute checksum vectors that are compared instead:

$$L_1 L_2 \cdots L_p w \stackrel{?}{=} R_1 R_2 \cdots R_q w. \quad (2)$$

This method, known as result-checking (RC), was used by Freivalds [7] to check multiplication, and was analyzed in a general context by Blum and Kannan [8]. This idea is also the basis of the checksum augmentation approach of Huang and Abraham [4] under the name algorithm-based fault tolerance (ABFT) (for a comparison of RC and ABFT, see [9]). Both approaches have since been extended by a number of authors to various linear decompositions [10]–[12], the FFT [13], [14], and other numerical operations. Boley et. al. [15], [16] explored fault location and correction using this method, as well as the use of multiple probe vectors. The effects of multiple faults, including those that occur during the postcondition test itself, have been explored through experiment [17]. Previous work has also explored the setting of error bounds for checksum tests [5], [11], [18].

In this work, we have applied this sort of algorithm-based fault tolerance approach to support vector machines (SVMs), one of the most widely used machine learning methods today. SVMs are currently in use onboard the EO-1 (Earth Observing 1) spacecraft to perform pixel-level classification of hyperspectral images [19] and can also be used to perform regression, such as estimating the dust and water ice content of the Martian atmosphere [20].

A. Support Vector Machines

Support vector machines [21] infer a hyperplane to separate labeled training data into two distinct classes. The hyperplane can then be used to classify new items. Arbitrarily complex decision boundaries (not just linear ones) can be created by mapping the input data via a kernel function into a higher-dimensional space in which the hyperplane is constructed. SVMs have also been extended to apply to regression problems [22], in which the goal is to estimate a real-valued quantity rather than assigning a discrete class to a new item.

Given a data set of n items $X = \{x_1, \dots, x_n\}$, where each $x_i \in \mathcal{R}^d$ is a d -dimensional feature vector, and a vector y such that $y_i \in \{+1, -1\}$ is the label for x_i , an SVM is defined by $n + 1$ parameters: a weight α_i for each x_i and a bias term, b . Each x_i with a non-zero weight α_i is termed a support vector, and it is only these items that influence the classification of new data. New items are classified as follows:

$$f(x) = \text{sign}\left(\sum_{i=1}^n \alpha_i y_i (x \cdot x_i) + b\right). \quad (3)$$

Let s be the number of support vectors, which we will refer to as z_j instead of x_i , obtaining:

$$f(x) = \text{sign}\left(\sum_{j=1}^s \alpha_j y_j (x \cdot z_j) + b\right), \quad (4)$$

If the two classes are not linearly separable, the dot product $(x \cdot z_j)$ can be replaced by a kernel function $\mathcal{K}(x, z_j)$, which is equivalent to using some mapping $\phi(x)$ to transform each x (and z) into a feature space with more (possibly infinite) dimensions and computing the dot products there. After adding the kernel function, the SVM decision function becomes:

$$f(x) = \text{sign}\left(\sum_{j=1}^s \alpha_j y_j \mathcal{K}(x, z_j) + b\right). \quad (5)$$

Common choices for kernel functions are polynomials and Gaussian radial basis functions. The Gaussian kernel is defined as

$$\mathcal{K}_G(x, z_j) = e^{-\frac{\|x - z_j\|^2}{\gamma}}, \quad (6)$$

where $\gamma = 2\sigma^2$ and σ is the width of the kernel, or the standard deviation of values.

To train the SVM, we must compute values for α and b , which are usually obtained by solving the following quadratic programming problem:

$$\begin{aligned} \text{minimize:} & \quad \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j \mathcal{K}(x_i, x_j) - \sum_i \alpha_i \\ \text{subject to:} & \quad 0 \leq \alpha_i \leq C, \sum_i \alpha_i y_i = 0, \end{aligned}$$

where C is a regularization parameter.

A similar derivation is obtained when using SVMs for regression, with the addition of a tolerance parameter ε , which specifies how tightly the learned model's predictions must fit to the true y labels in the training data. In addition, each support vector z_j has two Lagrange multipliers, α_j and α_j^* .

$$f(x) = \sum_{j=1}^s (\alpha_j - \alpha_j^*) \mathcal{K}(x, z_j) + b. \quad (7)$$

B. Algorithm-Based Fault Tolerance

To create a fault tolerant SVM method, we identified two subroutines that occupy the majority of the running time for the algorithm: matrix multiplication and Gaussian kernel computation. Each subroutine has a testable postcondition and is thus amenable to the ABFT approach.

1) *Matrix Multiplication*: Given a linear kernel, all of the kernel values can be computed via matrix multiplication:

$$K = XZ \quad (8)$$

where K is the kernel matrix, $X \in \mathcal{R}^{m \times d}$ is the matrix of data to be classified, and $Z \in \mathcal{R}^{d \times s}$ is the matrix of support vectors ($s \leq n$). Note that if X is the training data set, then $m = n$, but more generally m can be any size for a new data set. We replace all calls to $\mathcal{K}(x_i, z_j)$ with $K_{i,j}$. Since the SVM relies on this matrix being accurately computed, any errors that occur in the creation of K may result in errors in the SVM output (classification or regression).

Our goal is to determine whether or not an error occurred during the computation of K from X and Z . We need to apply a test to determine whether $K = XZ$ but more cheaply than doing a complete recomputation of the matrix multiplication. Therefore, let $\hat{w} = Zw$ for some arbitrary vector $w \in \mathcal{R}^{s \times 1}$ (in our tests, we used a w vector of all ones). Then by substitution, $Kw = XZw = X\hat{w}$. To determine whether K is correct, we simply compare $X\hat{w}$ to Kw , checking m values rather than all $m \times s$ values in K . We define the *relative error size* ϵ as the maximum difference between these values:

$$\epsilon = \frac{1}{C} \|Kw - X\hat{w}\|_\infty \quad (9)$$

subject to a normalization factor $C = \|w\|_\infty \|X\|_\infty \|Z\|_\infty$ that compensates for potential large variations in the values of the input matrices. $X\hat{w}$ is computed prior to the matrix multiplication, and Kw is computed afterwards. If ϵ exceeds a pre-specified tolerance, then an error is flagged.

2) *Gaussian Kernel*: Computing the kernel matrix via matrix multiplication is sufficient for linear kernels. However, for Gaussian kernels, an additional operation is needed. First, we compute the linear kernel $K^{\text{lin}} = XZ$ as above. Then we update the kernel values as follows:

$$K_{ij}^{\text{rbf}} = e^{-\frac{\|x_i\|^2 - 2K_{ij}^{\text{lin}} + \|z_j\|^2}{\gamma}} \quad (10)$$

We are concerned with whether an error occurs during the computation of the exponential value. To do this, we utilize a postcondition that compares the exponentiation of the sum of input values to the product of their exponentiations. Let T be a matrix with elements $t_{ij} = -\frac{\|x_i\|^2 - 2K_{ij}^{\text{lin}} + \|z_j\|^2}{\gamma}$, so $K_{ij}^{\text{rbf}} = e^{t_{ij}}$. Then the checksum we calculate for column j of the kernel matrix before performing the individual exponentiations is

$$c_j = e^{\frac{1}{m} \sum_i t_{ij}}. \quad (11)$$

Normalizing the sum by m , the number of items being analyzed by the SVM, guarantees that the calculation will avoid underflow if $e^{-\|t_j\|_\infty}$ is greater than the machine precision.

We then compute $K_{ij} = e^{t_{ij}}$ as usual. Afterwards, we compute the second checksum:

$$\hat{c}_j = \prod_i (K_{ij}^{\text{rbf}})^{1/m}, \quad (12)$$

where once again we introduce a corrective term to avoid underflow. If no error has occurred, then $c_j = \hat{c}_j, \forall j$. Again, we calculate an error size as the maximum difference between the two values:

$$\epsilon = \frac{1}{C} \|c - \hat{c}\|_\infty, \quad (13)$$

where the normalization factor $C = e^{\|T\|_\infty/n}$. As with the matrix multiplication, if ϵ exceeds a pre-specified tolerance, then an error is flagged. Since we compute a total of $2m$ checksum values, this is cheaper than recomputing all mn entries of K .

IV. EXPERIMENTAL RESULTS

A. Data Sets

We evaluated the ABFT error detection methods on both classification and regression tasks. The classification task comes from the ‘‘letter’’ classification data set provided by the UCI machine learning repository [23]. We used data for the letters A and B to generate a binary classification problem. Each letter was originally recorded as a rectangular matrix of black and white pixels, then converted into 16 numerical attributes that capture statistical information about the shape of the letter. We trained models on 100 randomly selected items from the full data set and tested on multiple disjoint sets of 100 randomly selected items. For this data set, we used a Gaussian kernel ($\gamma = 0.05$) and a regularization factor C value of 0.8. These hyperparameters were selected after a cross-validation search on held-out data.

The regression task uses spacecraft data and has been previously identified as a useful onboard data analysis problem in a high-radiation environment (Mars orbit). The data comes from the THEMIS instrument on the Mars Odyssey spacecraft. THEMIS is the Thermal EMISSION Imaging System, a camera that records observations at visible (VIS) and infrared (IR) wavelengths [24]. We previously developed onboard algorithms for analyzing the IR data to detect thermal anomalies, track the position of the polar cap edges, and estimate aerosol (dust or water ice) content in the atmosphere [20]. That evaluation assumed error-free computation. Here, we used the water ice opacity estimation task, which relies on an SVM, as the computation experiencing radiation.

The IR data consists of 8 distinct wavelength bands, with a spatial resolution of 100 meters per pixel. Each image is 320 pixels (32 km) wide and a variable number (3600 to 14352) of pixels long, divided into 256-line ‘‘framelets’’. Each item in the data set represents a single framelet; the feature values are the average pixel value for each wavelength, across the framelet, and the label for item is the water ice content (opacity) of the atmosphere observed in that pixel. The full data set contains 223,690 items. For each SVM we trained on this data, we used a Gaussian kernel ($\gamma = 0.1$) with a C value of 50. Since this

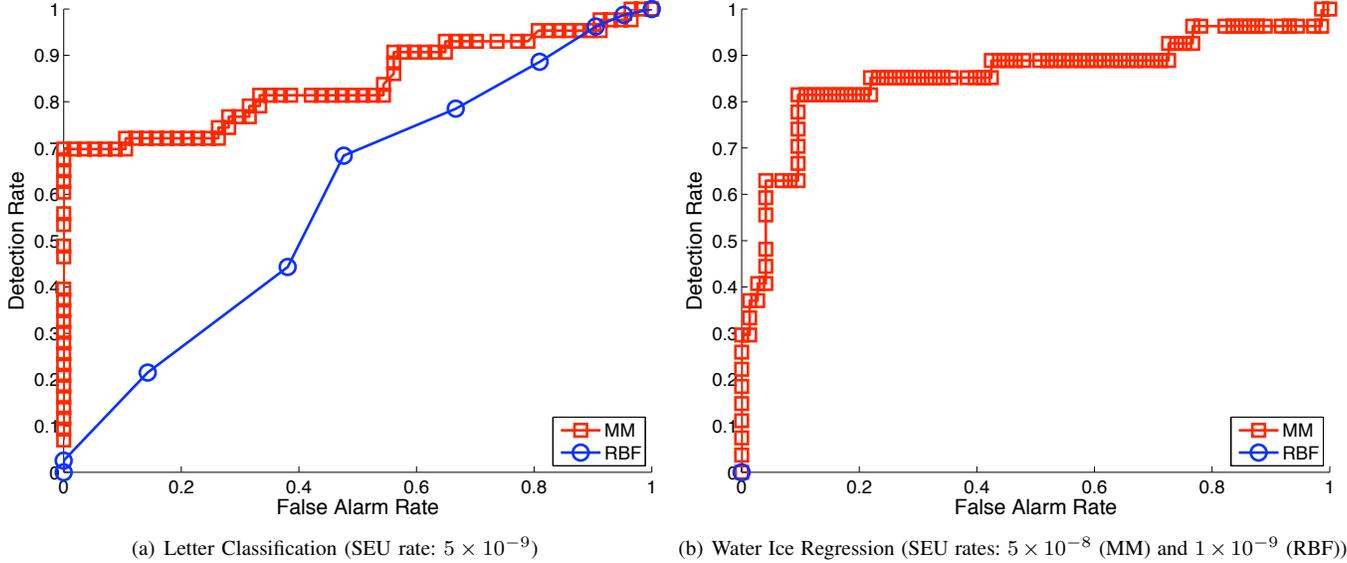


Fig. 1. Error detection results when running BITFLIPS with the specified error rates, for both classification and regression tasks. MM is the matrix multiplication test and RBF is the Gaussian kernel test.

is a regression problem, we must also specify the maximum error tolerance for the training process ($\varepsilon = 0.01$).

B. Methodology

One aspect of this work that distinguishes it from previous work is the incorporation of ABFT checksums to detect errors caused by SEUs in memory, rather than processor faults. We used the BITFLIPS radiation simulator to track all data structures and inject SEUs at a specified rate. For both classification and regression, we conducted several trials and measured error detection performance in terms of detection rate

$$D = \frac{TP}{TP + FN} \quad (14)$$

and false alarm rate

$$F = \frac{FP}{FP + TN}, \quad (15)$$

where TP is the number of true positives, FP is the false positives, TN is the true negatives, and FN is the false negatives.

We focused on detecting end-result errors in the output of the SVM, rather than detecting each time an SEU occurred. That is, to determine whether an error had occurred (and therefore should have been detected), we compared the output of the SVM that was obtained when running without SEUs injected to that obtained when SEUs were injected. If they were the same, no error occurred. Note that there may still have been SEUs happening, but the SVM's natural tolerance for a low level of radiation prevented an error from occurring in the output. If detecting an error triggers rollback or recomputation, it is appropriate that this should only be done if the SEUs had an impact on the analysis result.

For both classification and regression, we first generated 100 distinct SVMs, each trained on a different subset of 100 items.

We then tested each model on a disjoint set of 100 test items, running it with and without SEUs injected. When SEUs were being injected, we exposed the X , Z , and K matrices.

C. Results

We selected SEU injection rates that resulted in a substantial number of errors, but also several error-free runs, so that we could evaluate both detection and false alarm rates. For these data sets, the SEU rate used for the letter classification task was 5.0×10^{-9} SEUs per kB per second. This resulted in erroneous output for the matrix multiplication routine in 44 of 100 runs and for the Gaussian kernel computation in 79 of 100 runs. For water ice opacity regression, there was no single SEU rate that yielded both erroneous and error-free runs for both matrix multiplication and the Gaussian kernel. Therefore, we report results for 5.0×10^{-8} (matrix multiplication) and 1.0×10^{-9} (Gaussian kernel). For comparison, commercial SRAM in low-Earth orbit experiences about 1.2×10^{-7} SEUs per kB per second; radiation-hardened SRAM experiences up to 1.2×10^{-12} .

Figure 1 shows the results for both classification and regression. Error detection for matrix multiplication on both tasks is very good (e.g., achieving 70% detection with no false alarms for letter classification). For onboard analysis, however, we are willing to tolerate some false alarms, if it will increase the detection rate and therefore the reliability of the SVM results. We exceeded 90% detection with a 58% false alarm rate for letter classification and a 42% false alarm rate for water ice opacity regression.

The results for detecting errors in the Gaussian kernel computation are less impressive, indicating that significant room exists for improvement in tackling this problem. To achieve 90% detection, we incur an 80% false alarm rate for letter classification and a [x] false alarm rate for water ice

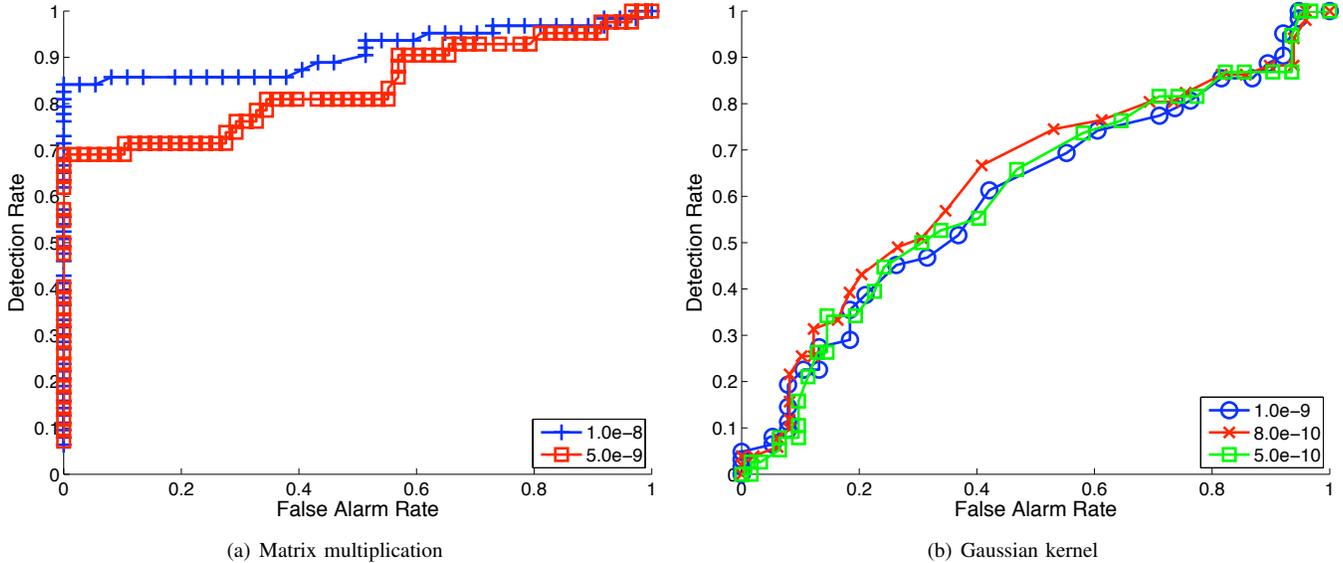


Fig. 2. Error detection results when running BITFLIPS with different specified error rates, for the letter classification task.

opacity regression. One fundamental challenge of detecting errors in the computation of an exponential function is that a tiny error in x can be greatly magnified in the result of e^x . For the purposes of Gaussian kernel computation, we are raising e to negative powers (see Equations 10 and 11). While the regular computation of the kernel value K_i^{rbf} may succeed, the checksum c_j raises e to the sum of m t_{ij} values, all of which are negative. It is possible for this calculation to underflow, despite the $\frac{1}{m}$ normalization term. A different decomposition to compute a characteristic checksum could improve over the results we obtained with our current method.

The results of this investigation may also suggest that the use of Gaussian kernels is not recommended for onboard data analysis, due to their greater sensitivity to radiation effects (or at least, our current ability to detect and recover from those errors).

Figure 2 shows detection results obtained when different SEU rates were specified for letter classification. For the matrix multiplication test (Figure 2a), we found better detection results in the presence of *more* radiation as compared with the lower rate. At an SEU rate of 1.0×10^{-8} , 85% of errors were detected with no false alarms, and 90% detection was achieved with only 53% false alarms. This is likely because although we seek only to detect whether at least one error occurred, at higher SEU rates multiple errors could strike, increasing the likelihood that at least one causes the error size ϵ to exceed the detection threshold. Increased detection at higher radiation rates is a useful attribute for onboard analysis systems. In contrast, the Gaussian kernel test results did not vary much when different SEU rates were specified (Figure 2b).

V. CONCLUSIONS AND FUTURE DIRECTIONS

In this paper, we have described how algorithm-based fault tolerance (ABFT) methods can be used in the context of onboard data analysis methods to increase their robustness in the

presence of radiation-induced errors. We focused on errors that occur in memory (single-event upsets or SEUs) and later affect the analysis results provided by support vector machines (SVMs), a technology now being adopted for use onboard spacecraft both for classification and regression.

We also described BITFLIPS, a lightweight software radiation simulator that we developed. It provides precise control over both the simulated SEU injection rate as well as which elements of memory are exposed to the radiation. We believe this work to be the first effort to combine ABFT methods with SVMs and the first to test their combined capabilities in such a simulator.

The techniques we proposed for detecting errors caused by SEUs rely on the computation of checksum values before and after executing a critical calculation, such as matrix multiplication or exponentiation for a Gaussian (RBF) kernel. Errors are detected when the difference between the expected and actual checksums differ by more than a threshold amount.

Our results indicate that onboard data analysis methods can successfully detect radiation-induced errors that strike during the critical matrix multiplication step needed to compute the kernel matrix for a support vector machine. Interestingly, detection improved at higher SEU injection rates, as compared to lower rates. Less reliable results were obtained with the checksum we developed for detecting an error in the exponentiation process; this remains an open area for further investigation.

Given the ability to detect errors, a clear next step is to add a rollback-and-recompute capability. While these experiments sought only to test the ability to determine whether any error had occurred during computation, it would be even more useful to identify which of the output values required recalculation. For matrix multiplication, the checksum is computed as the max (infinity norm) over a vector of m values, one

per item being classified; $(Kw - X\hat{w}) \in \mathcal{R}^{m \times 1}$. Identifying which of these m items violates the error threshold provides guidance in re-running the matrix multiplication, this time with only a subset of X rather than the full matrix. This is much more efficient than blindly recomputing $K = XZ$ whenever any error is detected. For Gaussian kernel computation, the checksums are constants rather than vectors, so they can only provide a coarse level of error information. Ultimately, we aim to provide error-detecting and correcting methods as a robust alternative to current onboard machine learning and data analysis efforts.

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