TensorFI: A Configurable Fault Injector for TensorFlow Applications

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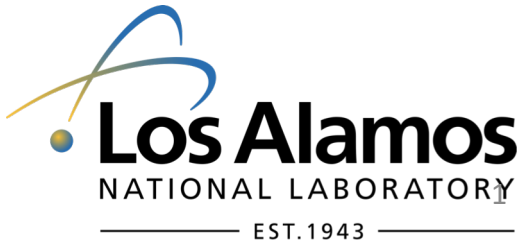
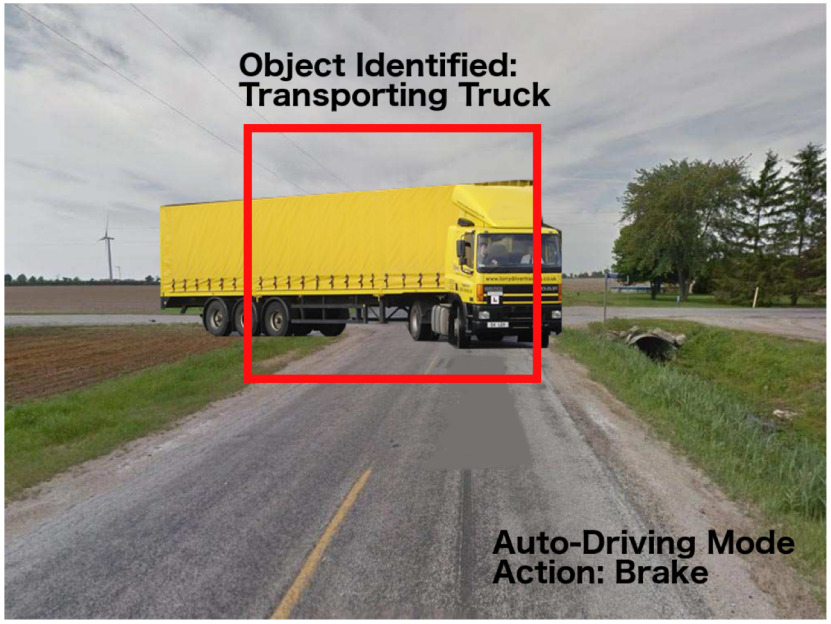


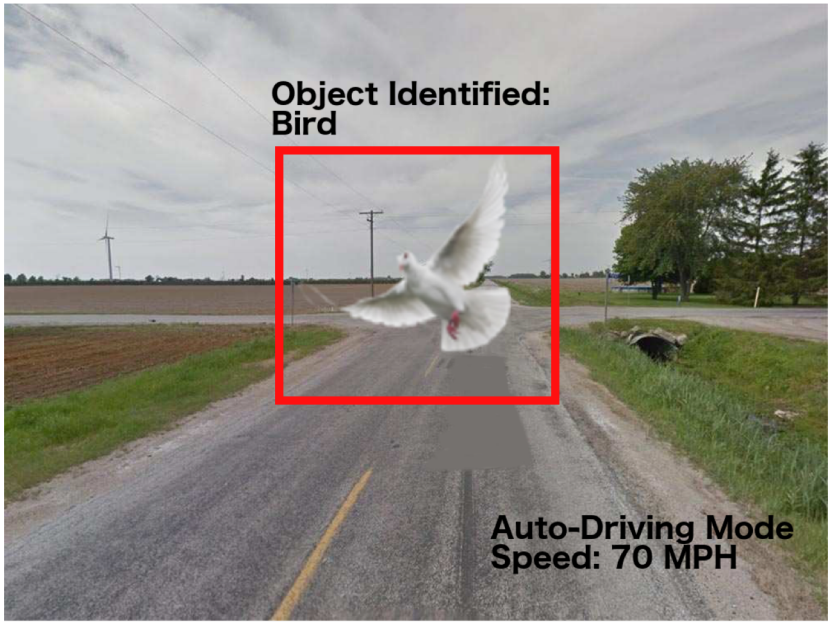
Motivation

- **Machine learning taking computing by storm**
  - Many frameworks developed for ML algorithms
  - Lots of open data sets and standard architectures

- **ML applications used in safety-critical systems**

Error Consequences Example: Self Driving Cars





Single bit-flip fault → Misclassification of image (by DNNs)

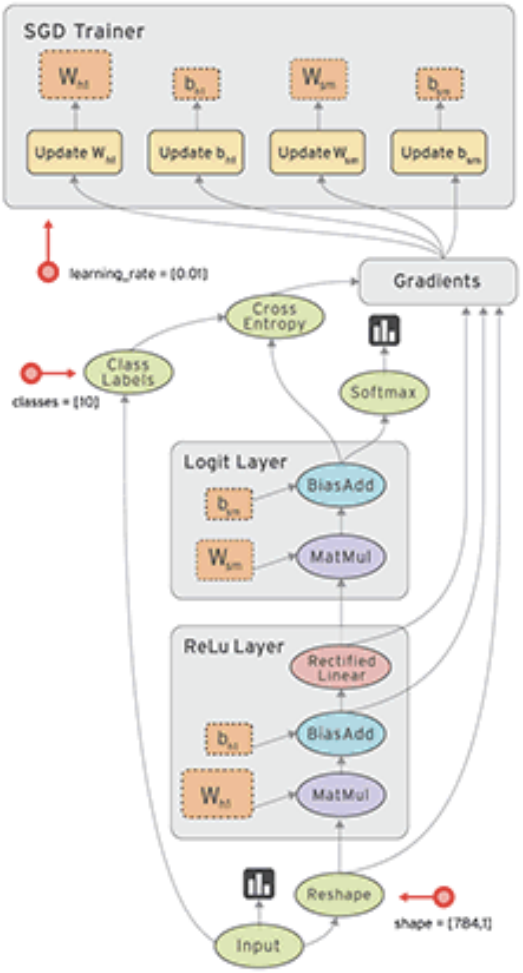
Source: Guanpeng Li et al., "Understanding Error Propagation in Deep learning Neural Networks (DNN) Accelerators and Applications", SC 2017.

Our Focus: TensorFlow (TF)

- **Open-source ML framework from Google**
  - Extensive support for many ML algorithms
  - Optimized for execution on CPUs, GPUs, etc.
  - Many other frameworks target TF
  - Significant user-base (> 1500 Github repos)

What is TF ?

- **TensorFlow (TF) - framework for executing dataflow graphs**
  - ML algorithms expressed as dataflow graphs
  - Can be executed on different platforms
  - Nodes can implement different algorithms



Goals

- **Build a fault injector for injecting both hardware and software faults into the TF graph**
  - High-level representation of the faults
  - Fault modeled as operator output perturbation

- **Design goals**
  - Portability – no dependence on TF internals
  - Minimal impact on execution speed of TF
  - Ease of use, compatibility with other frameworks

Challenges

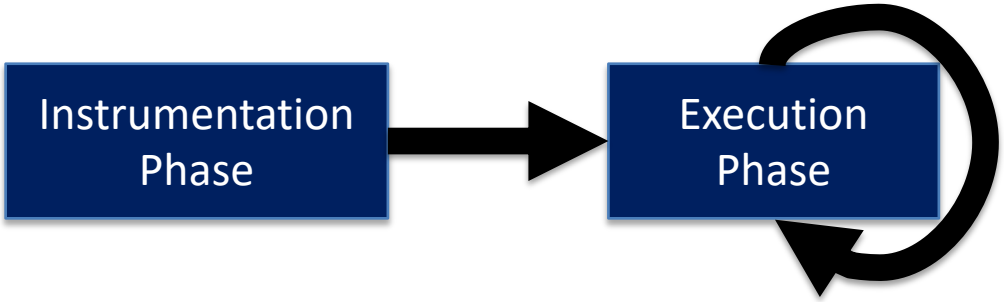
- **TF is basically a Python wrapper on C++ code**
  - C++ code is highly system and platform specific
  - Wrapped under many layers – hard to understand

- **Python interface offers limited control**
  - Cannot modify operators “in place” in the graph
  - Cannot modify graph inputs and outputs at runtime
  - No easy way to intercept a graph once it starts executing (a lot of the “magic” happens in C++ code)

Approach: TensorFI

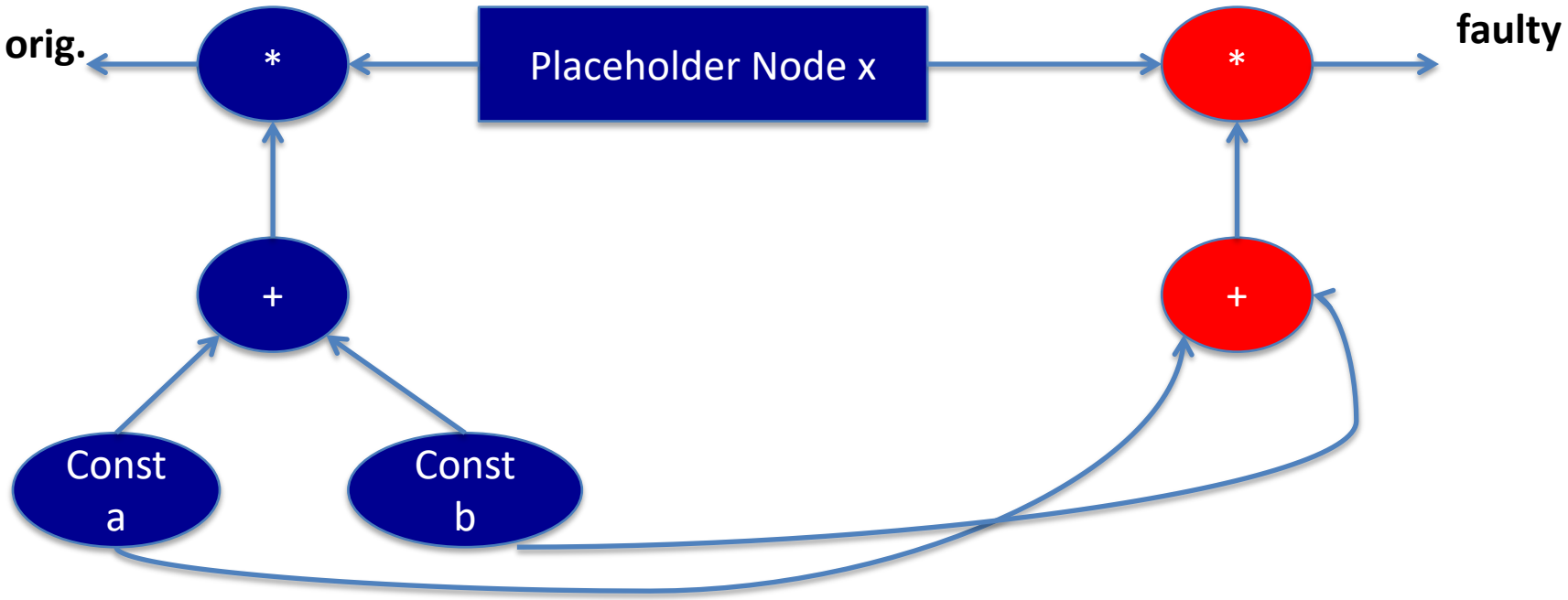
- **Fault injector for TensorFlow applications**

- **Operates in 2 phases:**
  - **Instrumentation phase:** Modifies TF graph to insert fault injection nodes into it
  - **Execution phase:** Calls the fault injection graph at runtime to emulate TF operators and inject faults



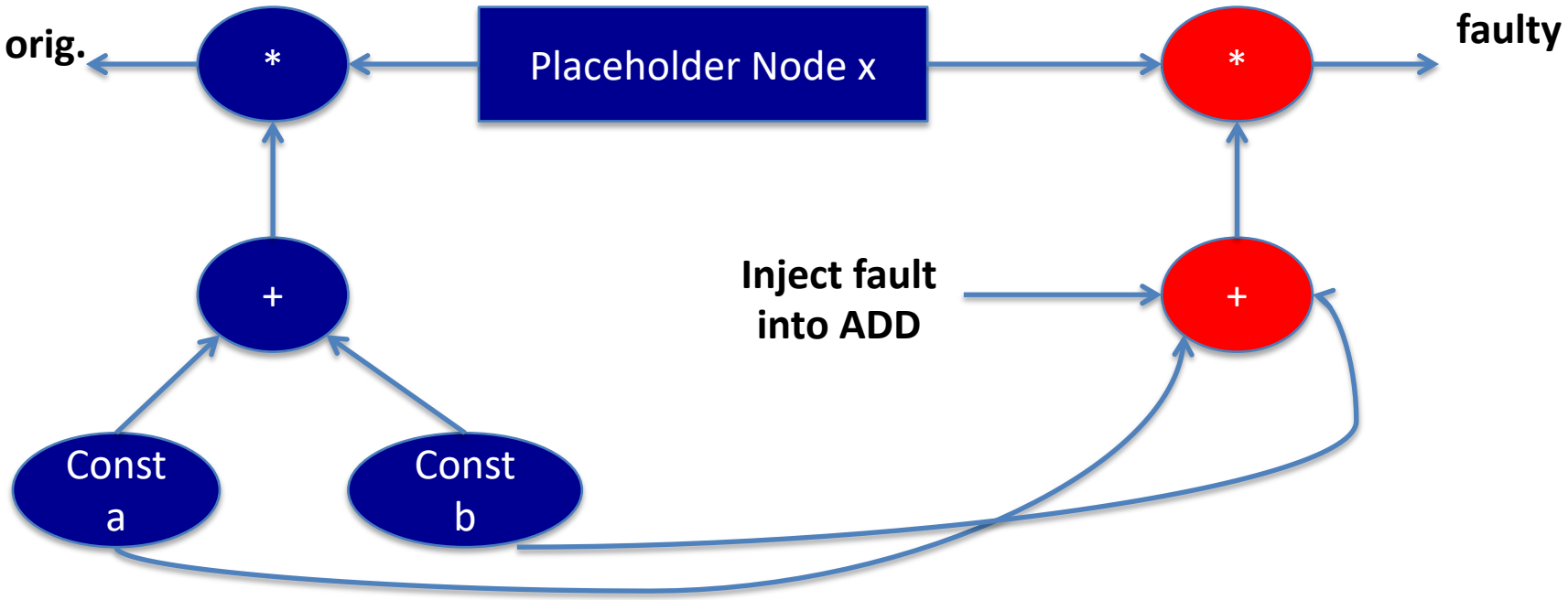
TensorFI: Instrumentation Phase

- **Idea:** Makes a copy of the TF graph and inserts nodes for performing the fault injection



TensorFI: Execution Phase

- **Idea:** Emulate the operation of the original TF operators in the fault injection nodes
  - Inject faults into the output of operators



TensorFI: Post-Processing

- **Inject faults one at a time during each run**
  - Log files to record the specifics of each injection
- **Gather statistics about the following**:
  - Injections: Total number of injections
  - Incorrect: How many resulted in wrong values
  - Difference: Diff between correct and wrong value
- **Need to specify application specific checks for determining difference with FI outcome**

TensorFI: Usage Model

```
# Add the fault injection code here to instrument the graph
fi = ti.TensorFI(sess, name = "Perceptron", logLevel = 50, disableInjections = True)
```

Instrument code

```
correctResult = sess.run(accuracy, feed_dict={X: mnist.test.images,
                                              Y: mnist.test.labels})

print("Testing Accuracy:", correctResult)
```

```
diffFunc = lambda x: math.fabs(x - correctResult)
```

Calculate difference

```
# Make the log files in TensorBoard
logs_path = "./logs"
logWriter = tf.summary.FileWriter( logs_path, sess.graph )

# Initialize the number of threads
numThreads = 5

# Now start performing fault injections, and collect statistics
myStats = []
for i in range(numThreads):
    myStats.append( ti.FIStat("Perceptron") )
```

Launch injections in parallel

```
# Launch the fault injections in parallel
fi.pLaunch( numberOfInjections = 100, numberOfProcesses = numThreads, computeDiff = diffFunc, collectStatsList = myStats)
```

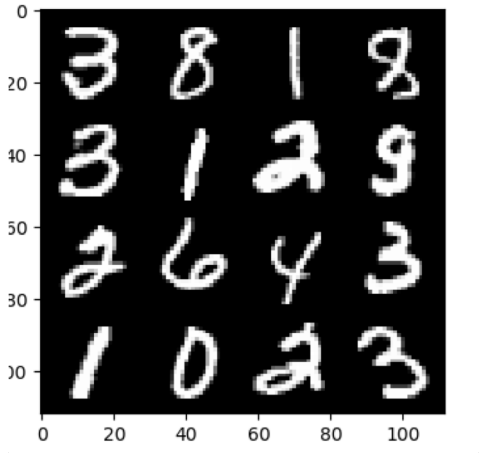
```
# Collate the statistics and print them
print( ti.collateStats(myStats).getStats() )
```

Calculate statistics

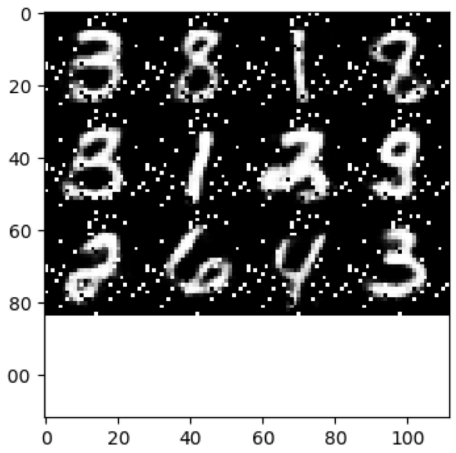
TensorFI: Config File

```
1  # This is a sample YAML file for fault injection configuration
2  # The fields here should correspond to the Fields in fiConfig.py
3
4  # Deterministic fault seed for the injections
5  # Seed: 1000
6
7  # Type of fault to be injected for Scalars and Tensors
8  # Allowed values are {None, Rand, Zero}
9
10 ScalarFaultType: Rand
11 TensorFaultType: Rand
12
13 # Add the list of Operations and their probabilities here
14 # Each entry must be in a separate line ad start with a '-'
15 # each line must represent an OP and it's probability value
16 # See fiConfig.py for a full list of allowed OP values
17 # NOTE: These should not be any tabs anywhere below
18
19 Ops:
20 # - ALL = 1.0 # Chooses all operations
21   - ADD = 1.0
22 # - DIV = 0.0 # This does not exist - and should be ignored (Test)
23 # - SUB = -0.5 # This should raise an exception
24
25 # How many times the set of above operations should be skipped before injection
26 # SkipCount: 1
```

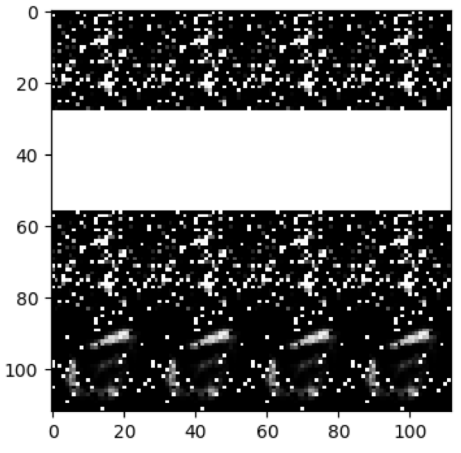
Example Output: AutoEncoder



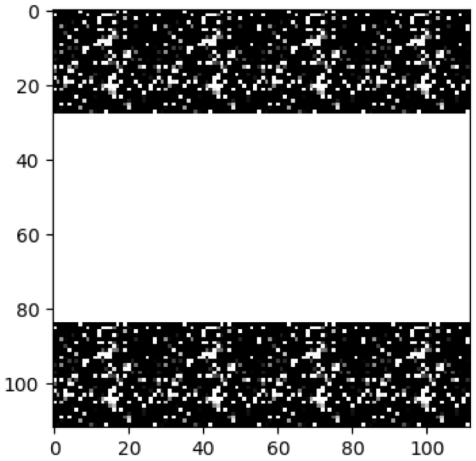
Original image, no faults



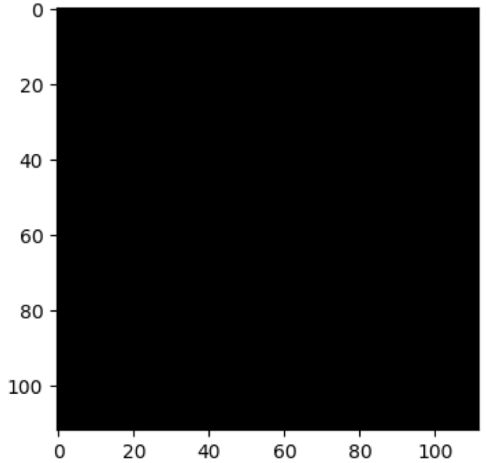
Fault injection prob. = 0.1



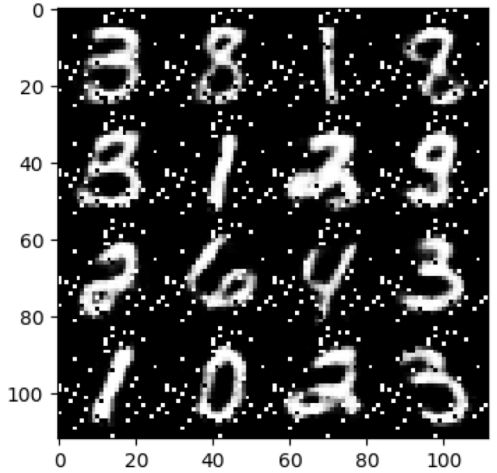
Fault injection prob. = 0.5



Fault injection prob. = 0.7



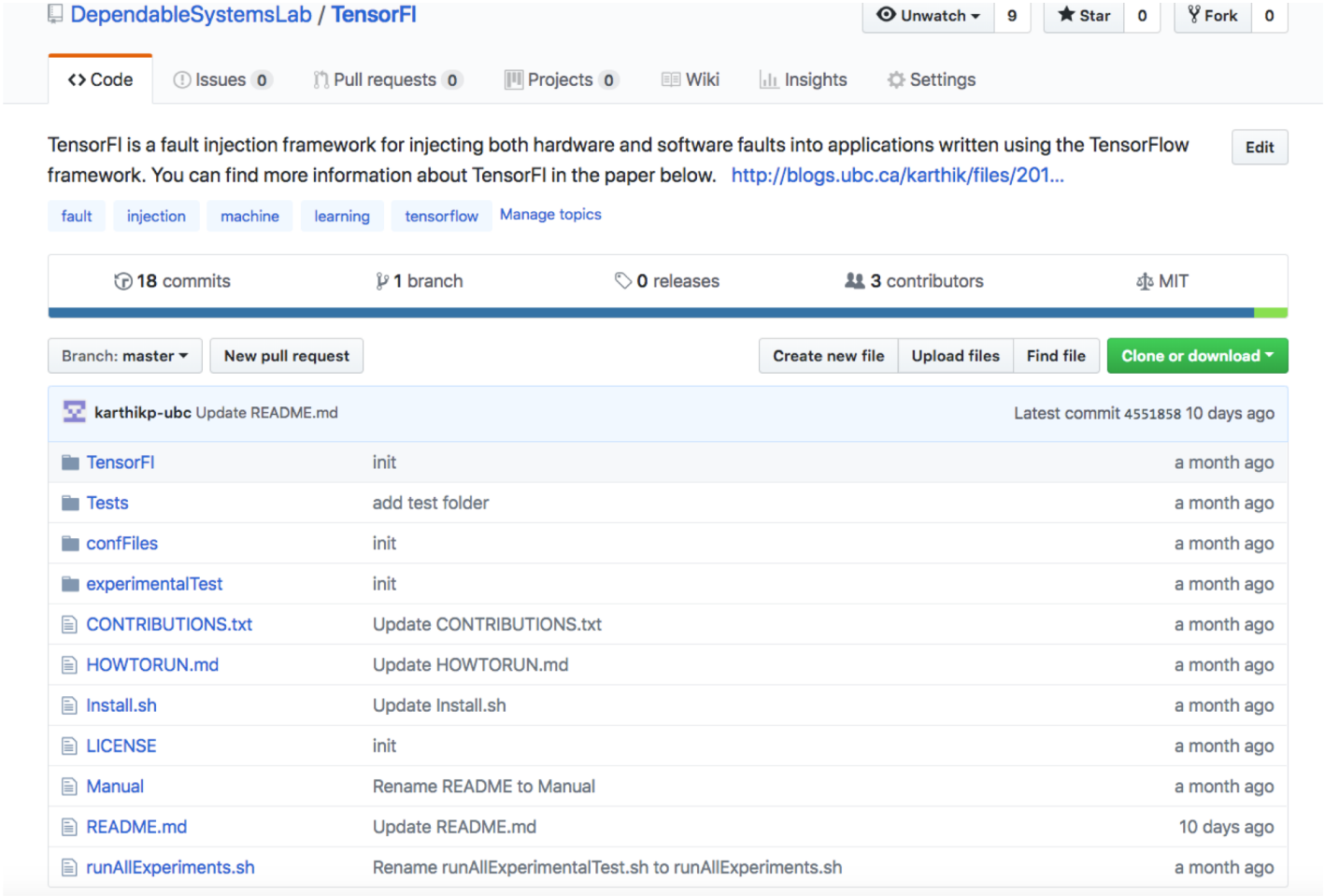
Fault injection prob. = 1.0



Reconstructed image (no faults)

TensorFI: Open Source (MIT license)

https://github.com/DependableSystemsLab/TensorFI



Benchmarks

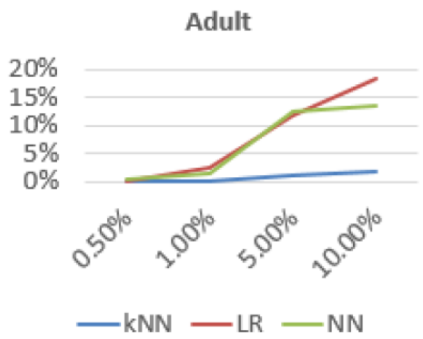
- **6 open source datasets**
  - UCI open source ML dataset repository
  - Can be modeled as classification problems
- **3 ML algorithms**
  - k nearest neighbor (kNN)
  - Neural network (2-layer ANN)
  - Linear regression

Experimental Setup

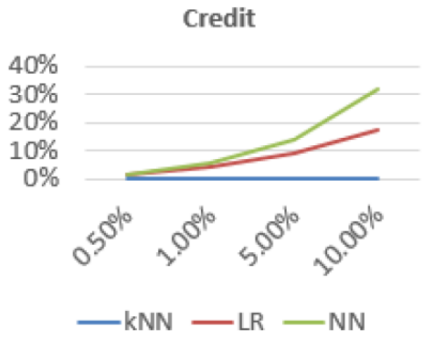
- **Fault injection configurations**
  - Repeat 100 FI campaigns per benchmark (One fault per run)
  - FI rates (prob. of injection): 5%, 10%, 15% and 20%

- **Metric: Average accuracy drop**
  - Original accuracy without fault injection (OA)
  - Accuracy after fault injection (FA)
  - Average accuracy drop = average of (OA-FA) among all FI runs

Results

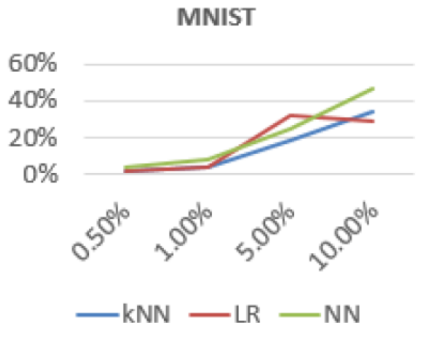


(a) Error Margin: +/-0.67% to +/-6.72%

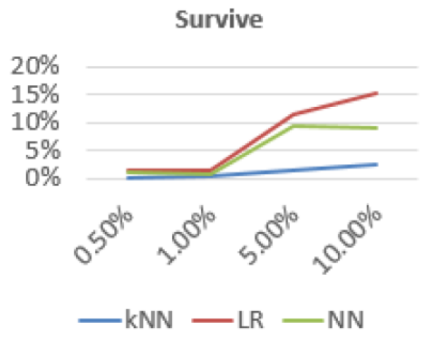


(b) Error Margin: +/-0.00% to +/-9.17%

(c) Error Margin: +/-0.38% to +/-9.12%



(d) Error Margin: +/-2.76% to +/-9.78%



(e) Error Margin: +/-0.16% to +/-7.08%

(f) Error Margin: +/-2.47% to +/-9.75%

- SDC rate increases are different as fault injection rates increase
- SDC rates are different for different models
- kNN has lower SDC rates and lower rate of increase

Future Work

- **Investigate the error resilience of different ML algorithms under faults**
  - Understand reasons for difference in resilience
  - Build a mathematical model of resilience
  - Choose algorithms for optimal resilience

- **Understand how different hyper-parameters affect resilience and choose for optimality**

TensorFI: Summary

- **Built a configurable fault injector for injecting both h/w and s/w faults into the TF graph**
  - High-level representation of the faults

- **Design goals**
  - Portability – no dependence on TF internals
  - Speed of execution not affected under no faults
  - Ease of use, compatibility with other frameworks

Available at: https://github.com/DependableSystemsLab/TensorFI

Questions ? karthikp@ece.ubc.ca