Manual: Tensorflow Debugging and Visualization Environments

Tensorflow Visualisation

Tensorboard is essentially a visualization toolkit that can be used to track the evolution of various parameters during training a machine learning system.

The variables that are to be tracked are written into a log directory after having generated summary data in the form of a summary writer;

```
file_writer = tf.summary.FileWriter('/path/to/logs', sess.graph)
```

Once the event files (files where the variables are logged into) are ready, use the command

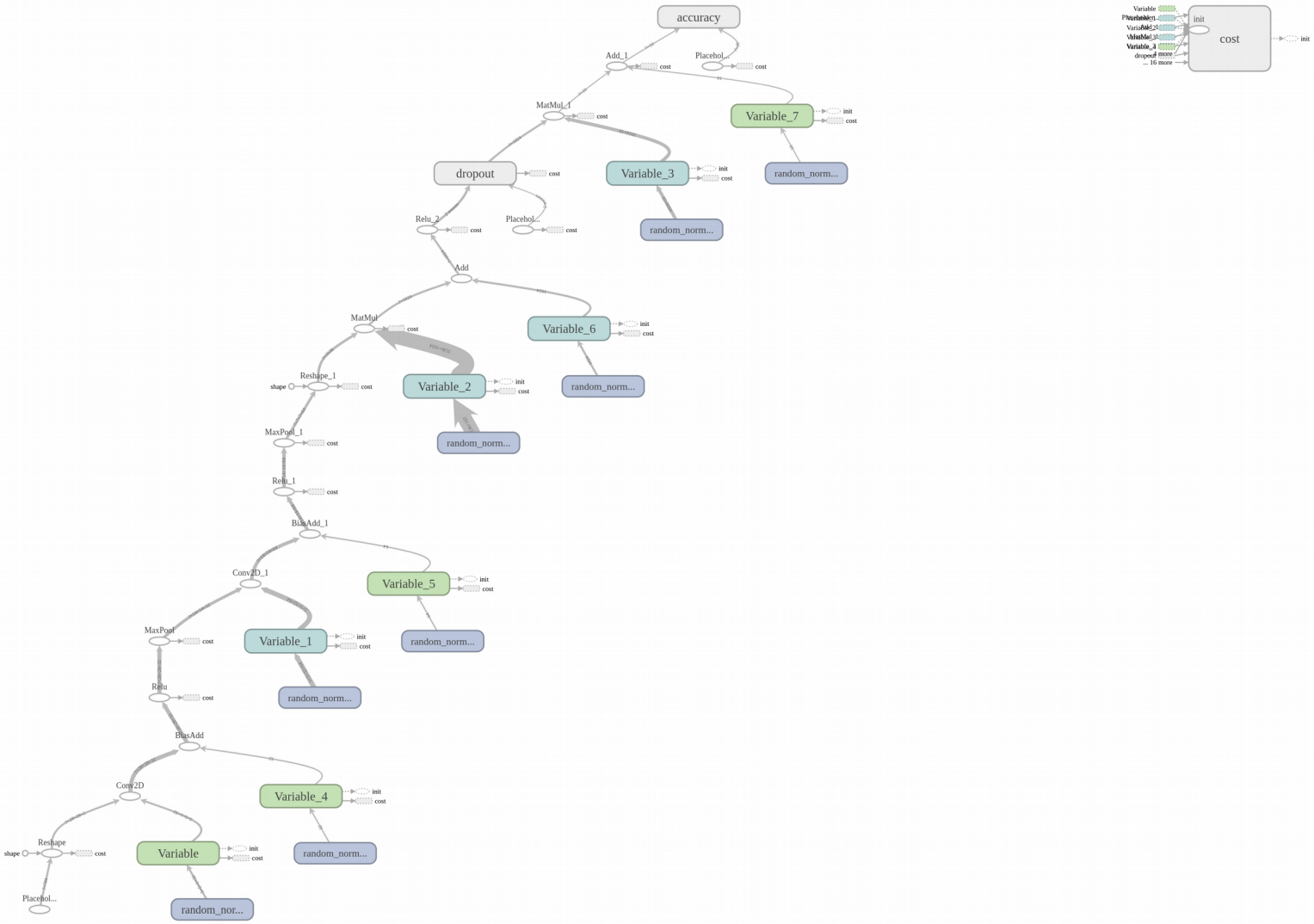
$ *tensorboard –logdir=pth/to/logs –port 6060*

(The entire command is important as we'll be using another instance of tensorboard for debugging on port 6006)

Also, keep in mind to launch the above command from the Terminal (Linux and Mac OS) or Command Prompt (Windows). While running either Jupyter notebook or Python script.

Key Concepts:

For the *handwritten_digits_recognition_cnn_5layer.ipynb*, the different (graph, scalar, histogram) visualization are illustrated in the following screenshots.


accuracy
Add_1
cost
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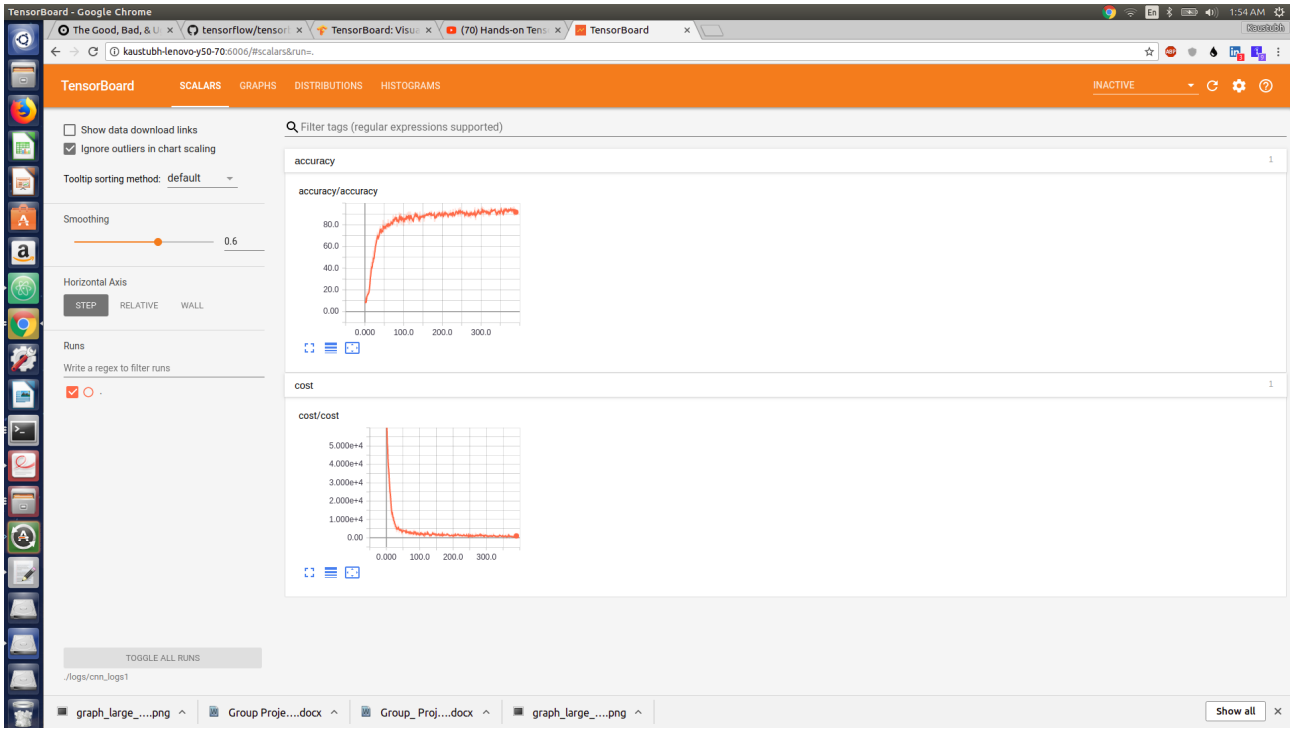
cost
MatMul_1
cost
Variable_7
init
cost
dropout
cost
Variable_3
init
cost
random_norm...
Relu_2
cost
Placehol...
cost
random_norm...
Add
MatMul
cost
Variable_6
init
cost
Reshape_1
shape
cost
Variable_2
init
cost
random_norm...
MaxPool_1
cost
random_norm...
Relu_1
cost
BiasAdd_1
Conv2D_1
Variable_5
init
cost
MaxPool
cost
Variable_1
init
cost
random_norm...
Relu
cost
random_norm...
BiasAdd
Conv2D
Variable_4
init
cost
Reshape
shape
cost
Variable
init
cost
random_norm...
Placehol...
random_nor...
Variable
Placehol...
Variable_1
Add_1
MatMul_1
Variable_3
dropout
... 16 more
init
cost
init

Scalar Dashboard

TensorBoard's Scalar Dashboard visualizes scalar statistics that vary over time; for example, you might want to track the model's loss or learning rate.

Accuracy and loss have been tracked.



The *tf.summary.scalar* object is used to log these changes for visualization.

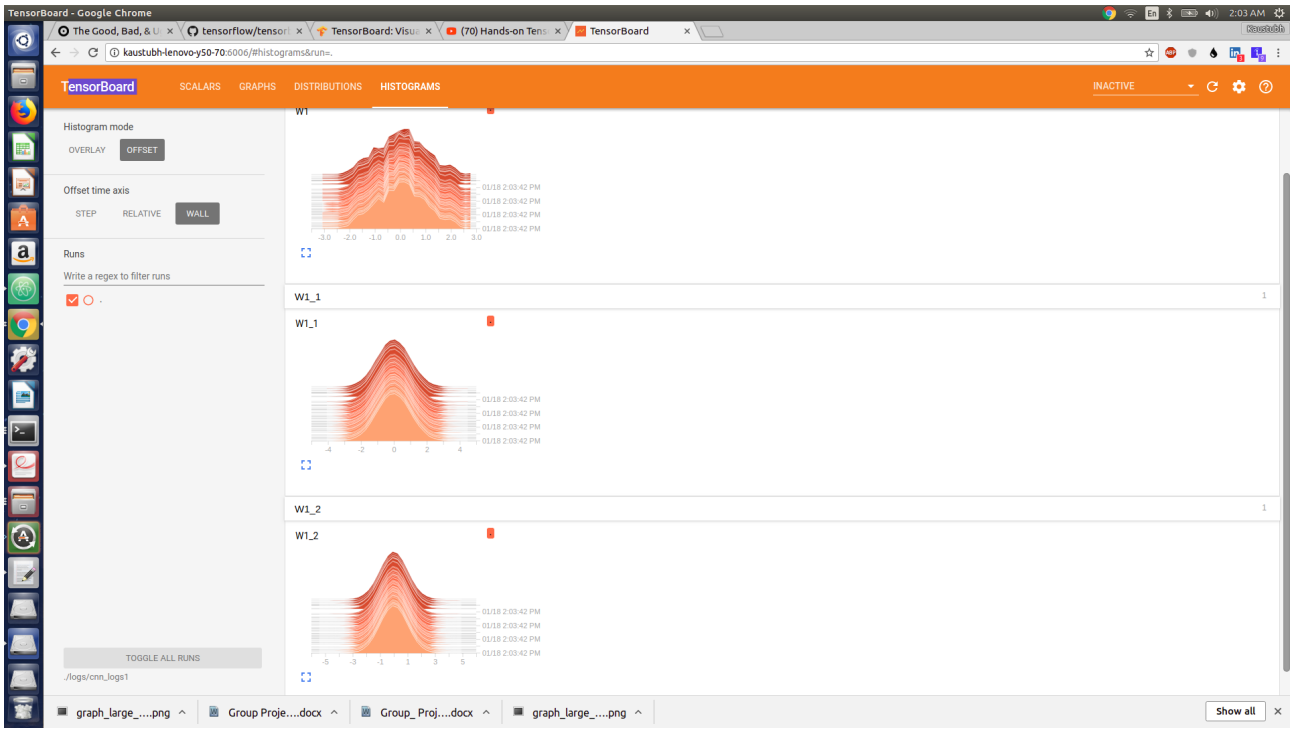
Histogram Dashboard

The HistogramDashboard displays how the statistical distribution of a Tensor has varied over time. It visualizes data recorded through the *tf.summary.histogram* object.

Each chart shows temporal "slices" of data, where each slice is a histogram of the tensor at a given step.

It's organized with the oldest timestep in the back, and the most recent timestep in front.

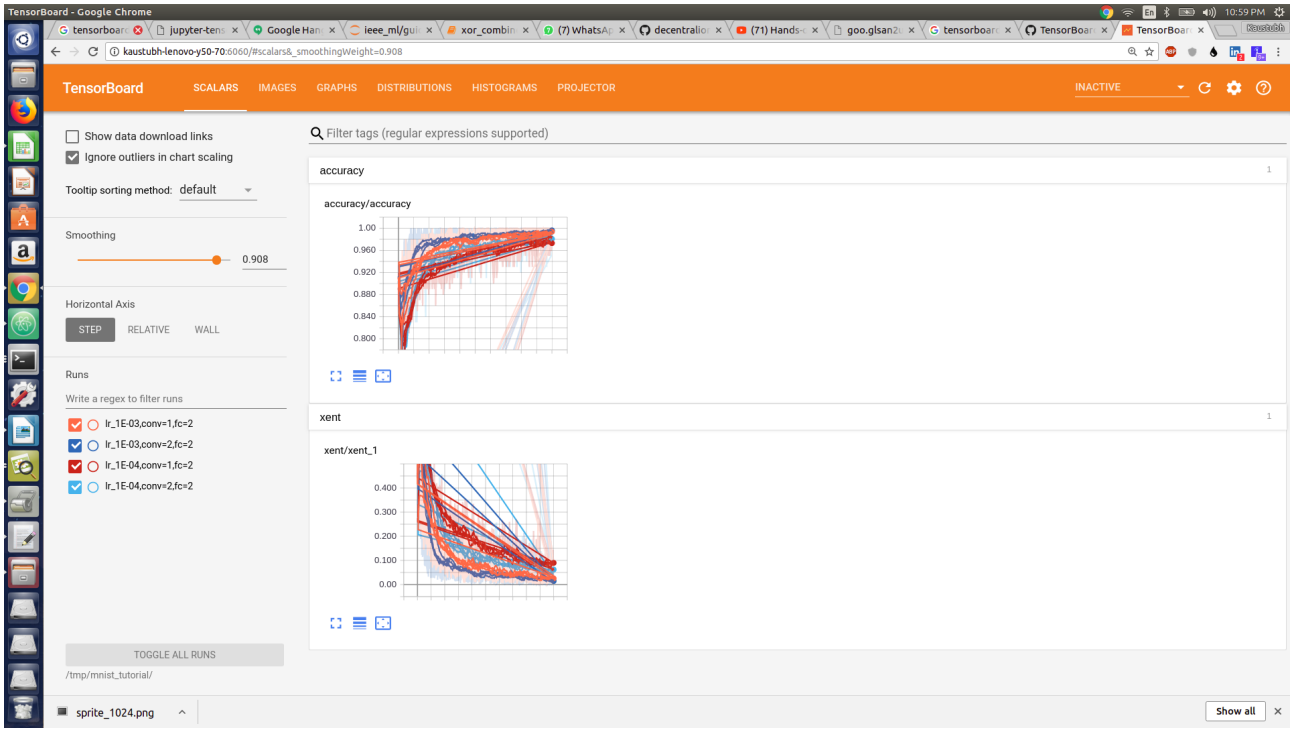
By changing the Histogram Mode from "offset" to "overlay", the perspective will rotate so that every histogram slice is rendered as a line and overlaid with one another.



Hyperparameter Search

Tensorboard also provides option to visualize the performance of a model for different choices of hyperparameters.

This is done on the file *mnist_hyperparameters.py*



The different color codes correspond to different hyperparameter settings which in this case are [learning rate, number of convolution_layers, number of fully_connected_layers].

For a more detailed instructions for using various functionalities of tensorboard; go to https://github.com/tensorflow/tensorflow/blob/r1.2/tensorflow/tensorboard/README.md

Tensorflow Debugger

CLI Debugger

XOR_combined.py

Firstly, the Tensorflow CLI debugger can be used to debug any running computational graph in Tensorflow very succintly. This is difficult to achieve with standard debuggers like Python's pdb.

It is best recommended to use TF CLI debugger on .py files.

The *tf_debug (TensorflowDebugger)* is a debugger built for tensorflow that enables you to view the internal structure and states of the Tensorflow computational graphs during training and inference.

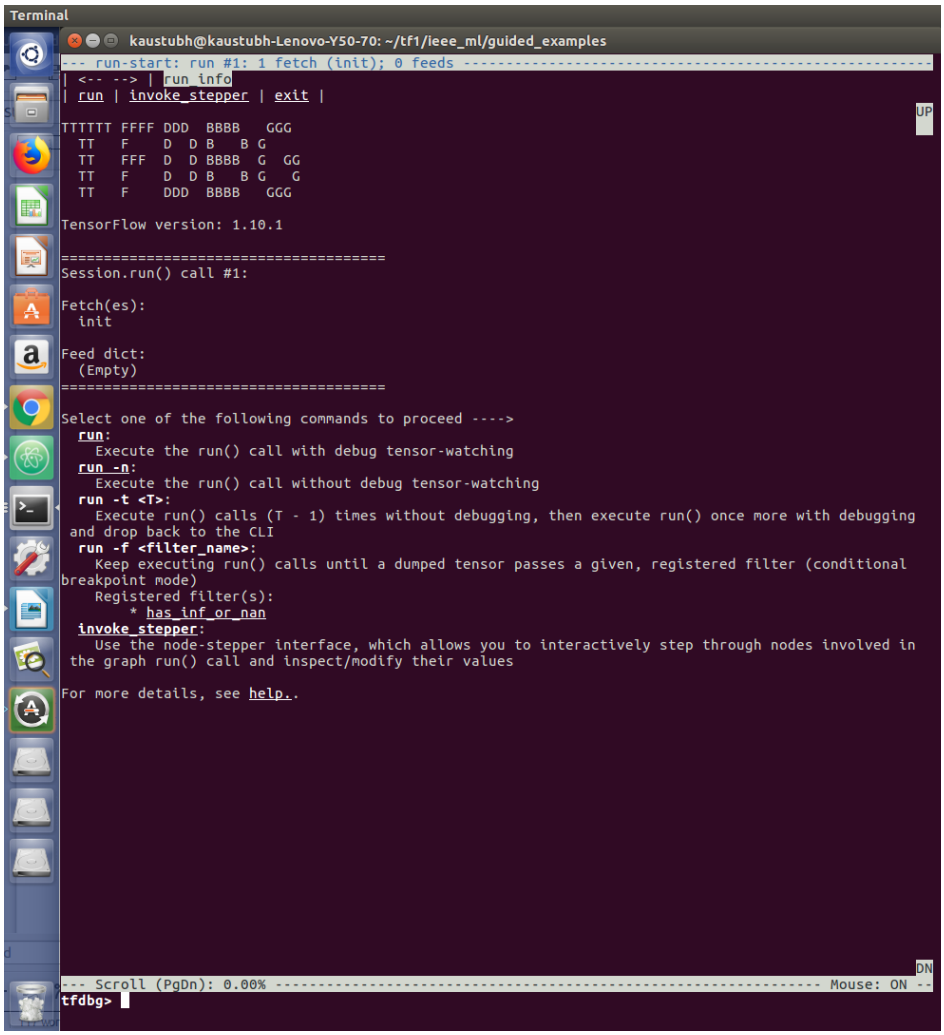
You will have to wrap TF sessions with the tfdbg as:

sess = tf_debug.LocalCLIDebugWrapperSession(sess)

This wrapper will same interface as Session thus enabling debugging needs no extra code changes.

To launch a TF CLI Debugger on the xor_combined.py;

$ python3 xor_combined.py –debug

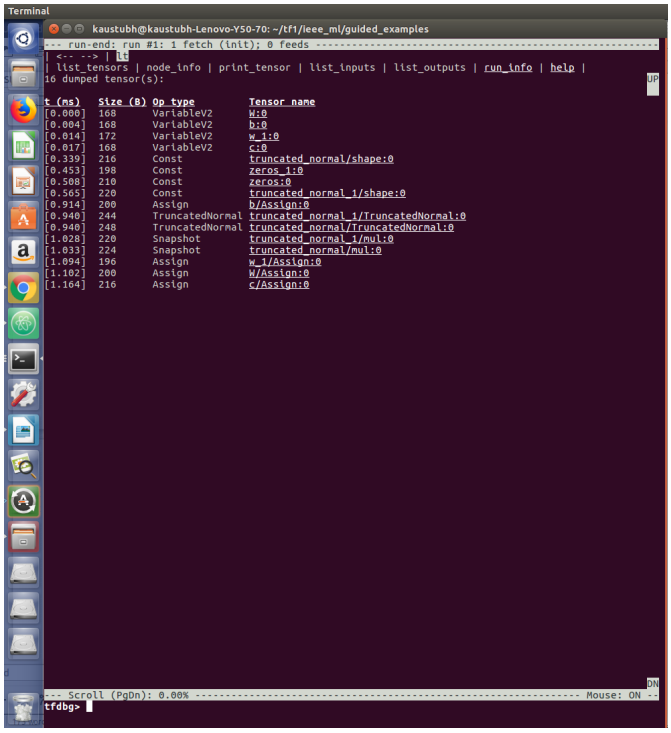


The debug wrapper session will prompt you before the first Session.run() call is about to be executed. This is also the run-start CLI. It lists the fetches and the feeds to the current Session.run()call.

Now enter the run command in the terminal;

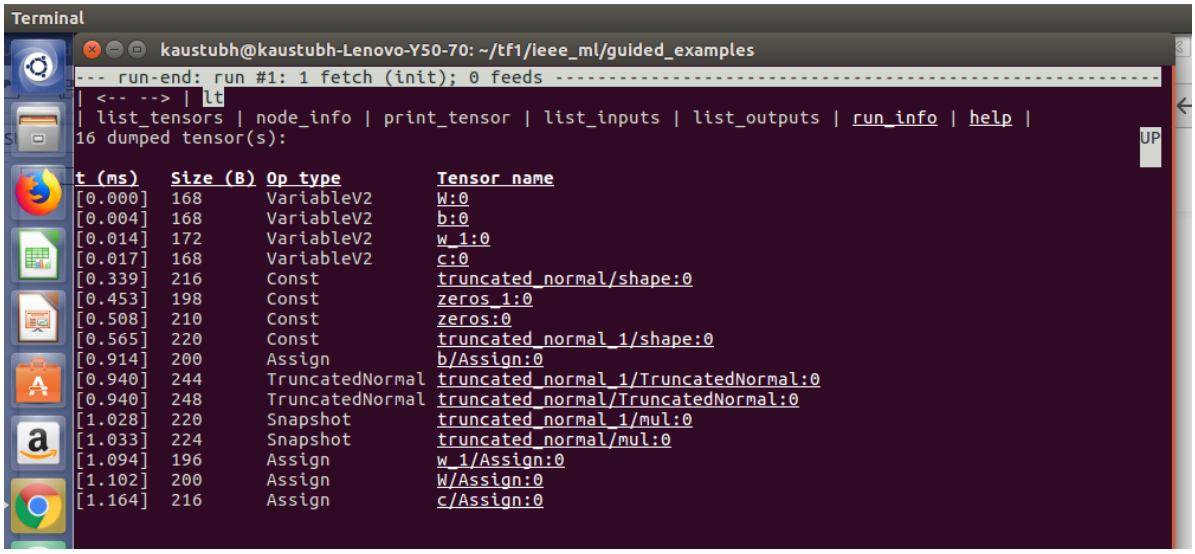
tfdbg> run

The run command makes the tf_debug execute ntil the end of the next Session.run() call.

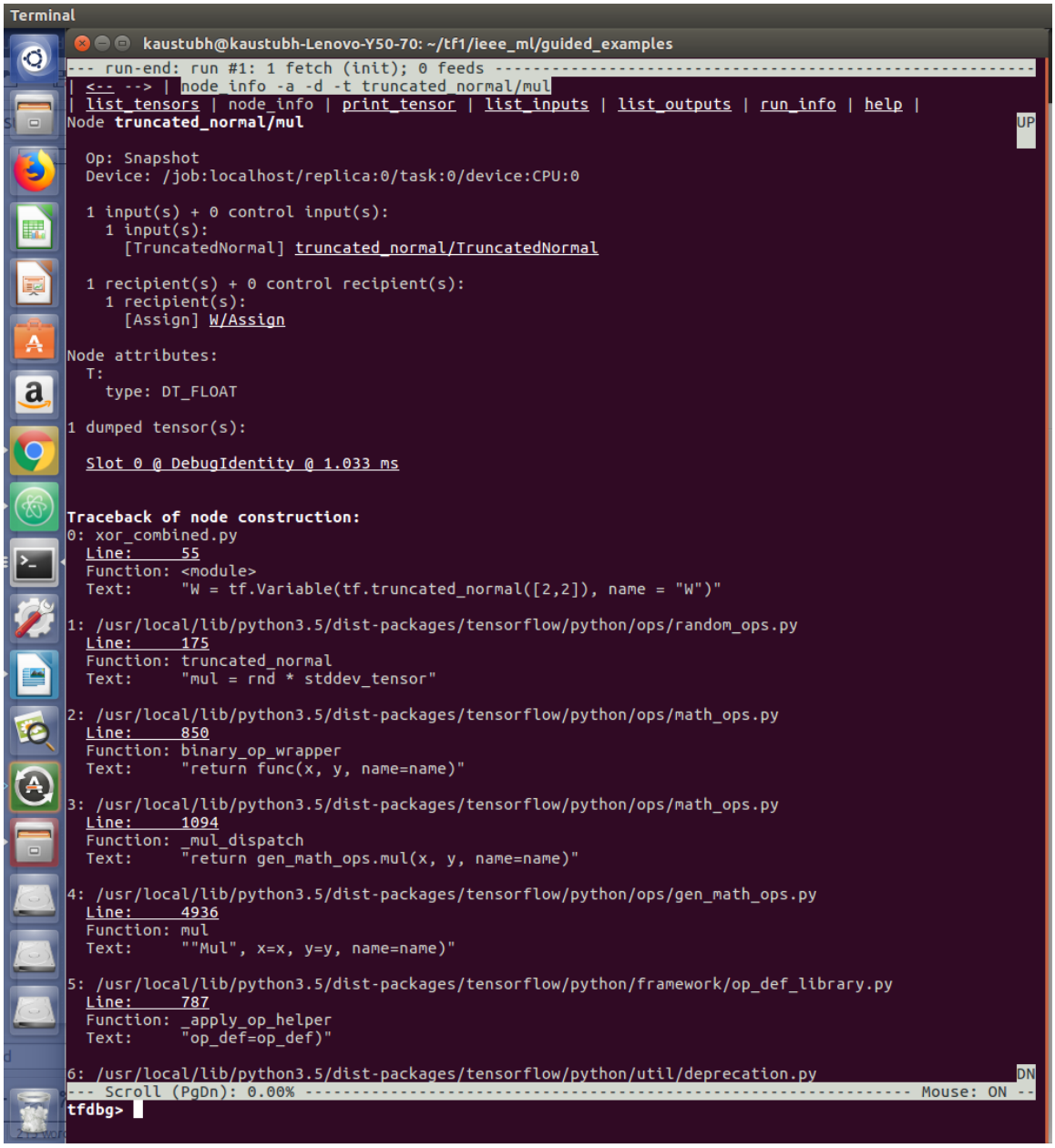


The above screenshot shows the intermediate tensors from the previous Session.run() call.

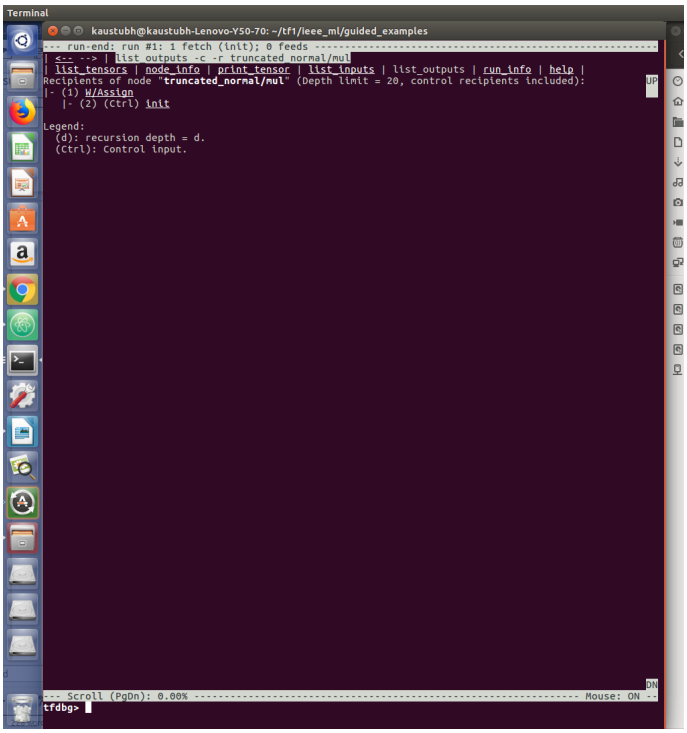
For one such tensor, truncated_normal/mul

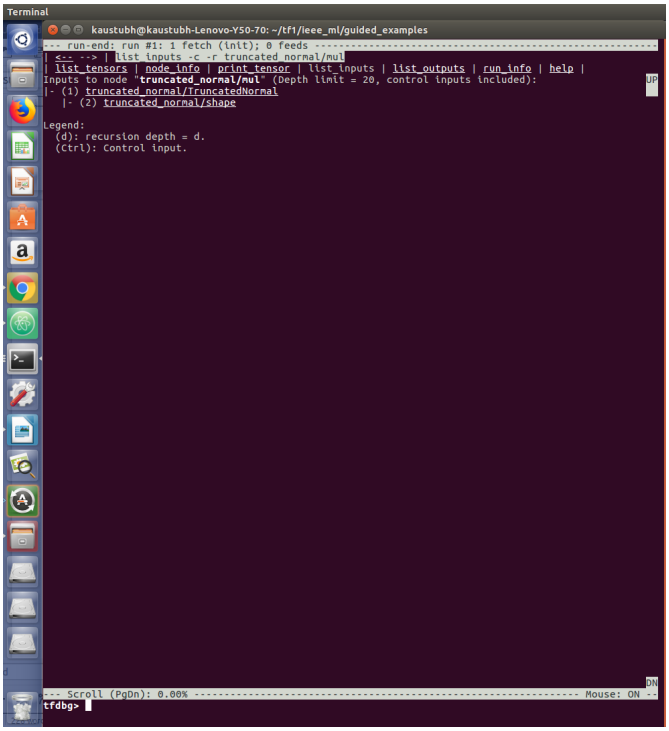


Now, we can use the *node_info* option to check up the type and attributes of this graph node as shown



The *list_inputs* and *list_outputs* give the transitive inbound and outbound tensors of a given node.





list_inputs

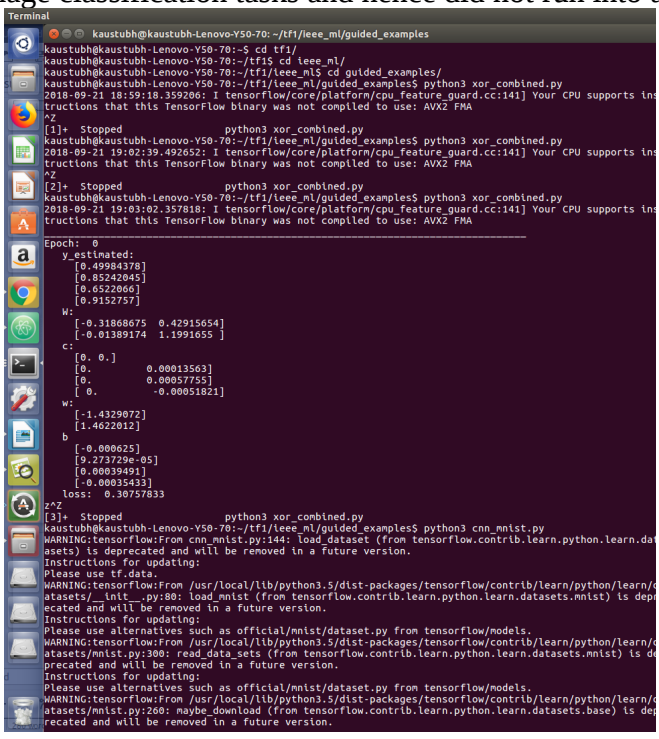
list out_puts

Also, conditional breakpoints feature of *tf_debug* can be used to let code run until certain cases/ conditions are satisfied on the graph.

In this case, let us consider the case the model runs until values like *inf* and *nan* are encoutered. For this, in the command line enter;

tfdbg> run -f has_inf_or_nan

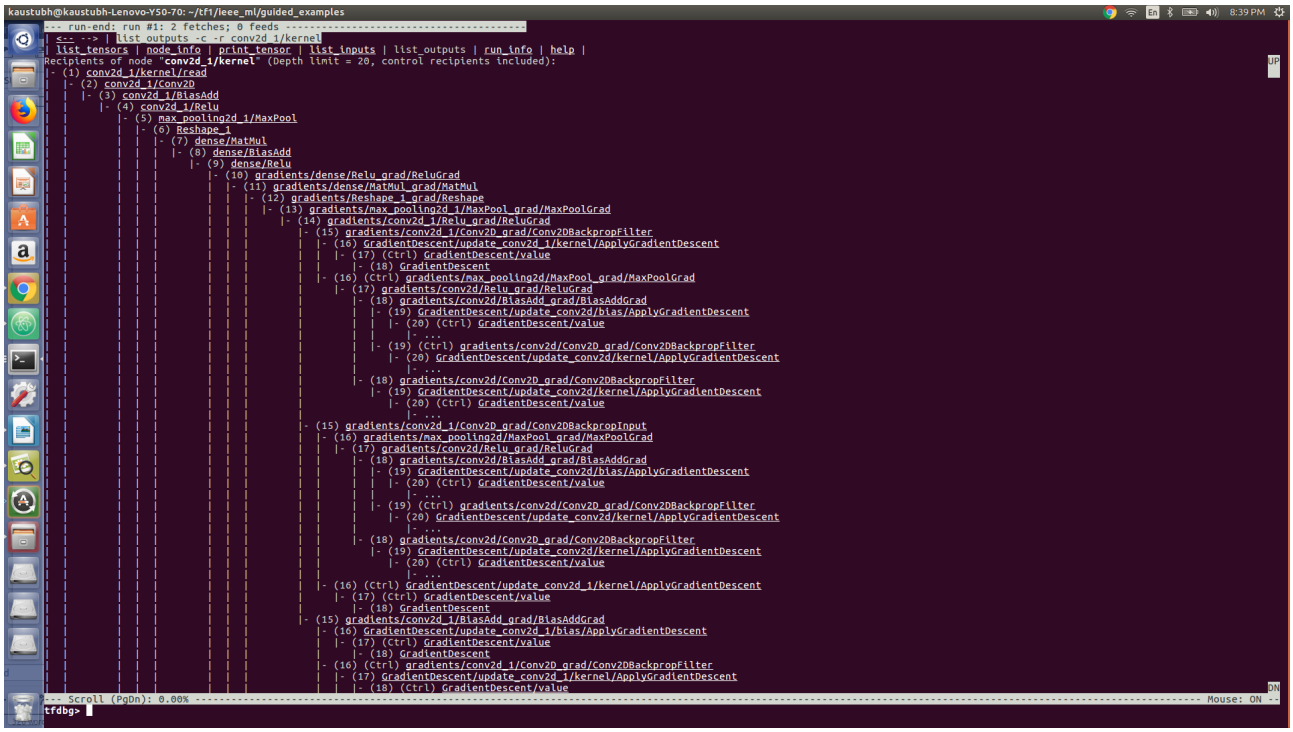
For this example, on xor_combined.py, all the epochs are run as XOR mapping uing an ANN is relatively simple than image classification tasks and hence did not run into any issues.



We shall see this debugging aspect a little more in detail for the cnn_mnist.py case.

cnn_mnist.py

For the node: conv_2d_1 kernel the list_outputs are as follows:



The command:

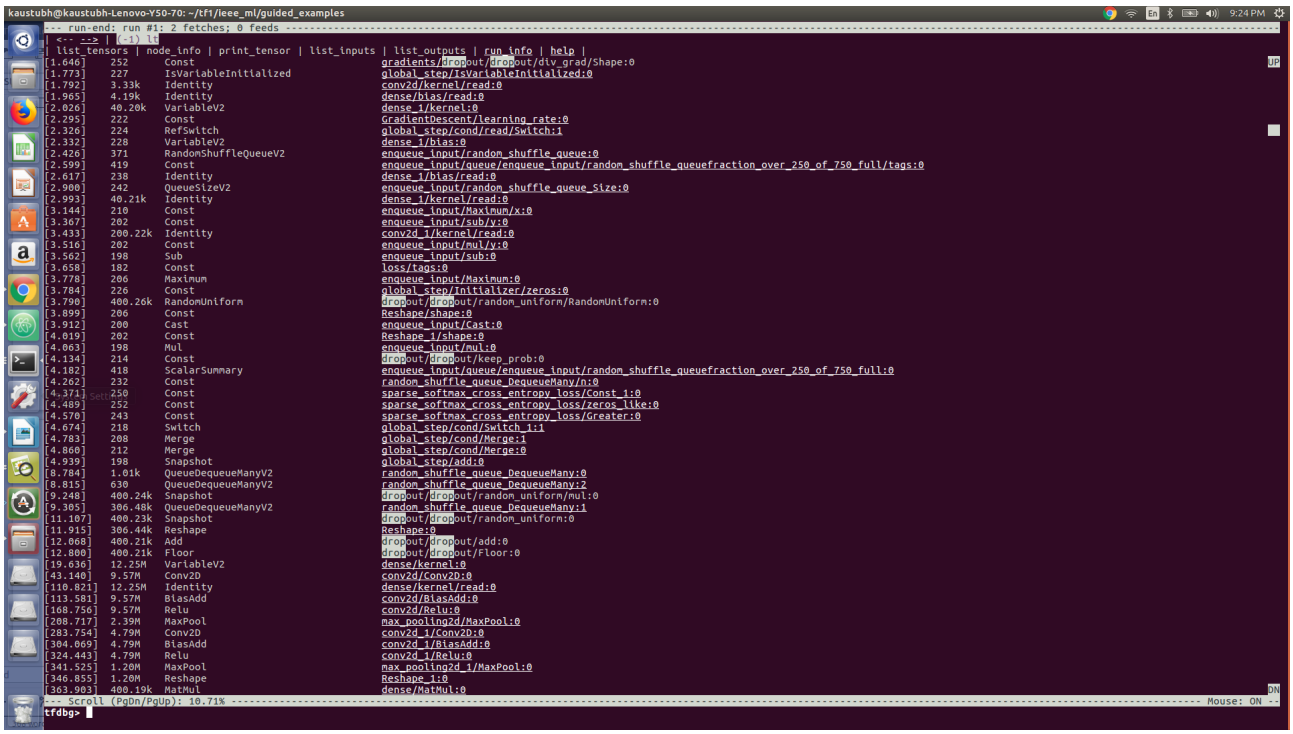
>tfdbg run -f has_inf_or_nan

was run and there was no such tensor which had these values as the entire training cycle completed without halting at any Session.run call.

Also, regex search can be used to find desired tensors in the CLI debug window.

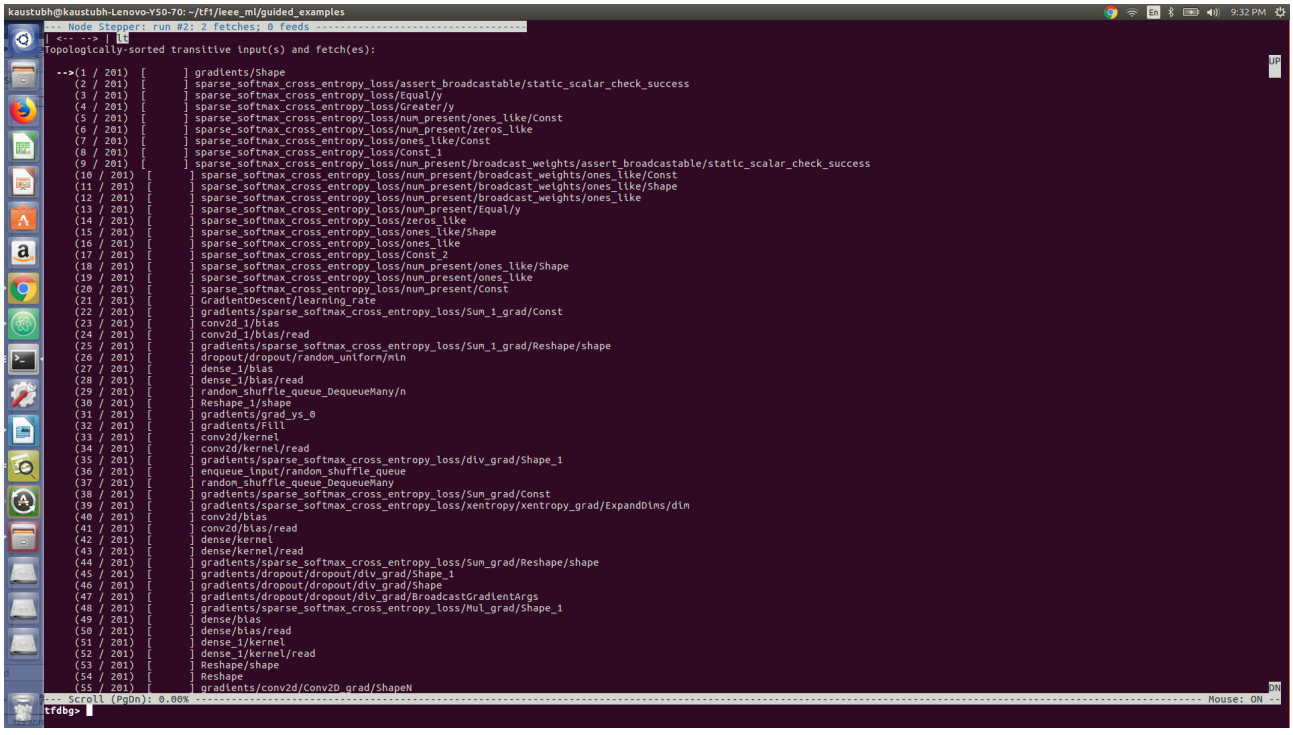
In the below window; I have searched for “drop” and all “drop” occurences are highighted.

tfdbg> (drop) ---> Searching for the regular expression “drop”



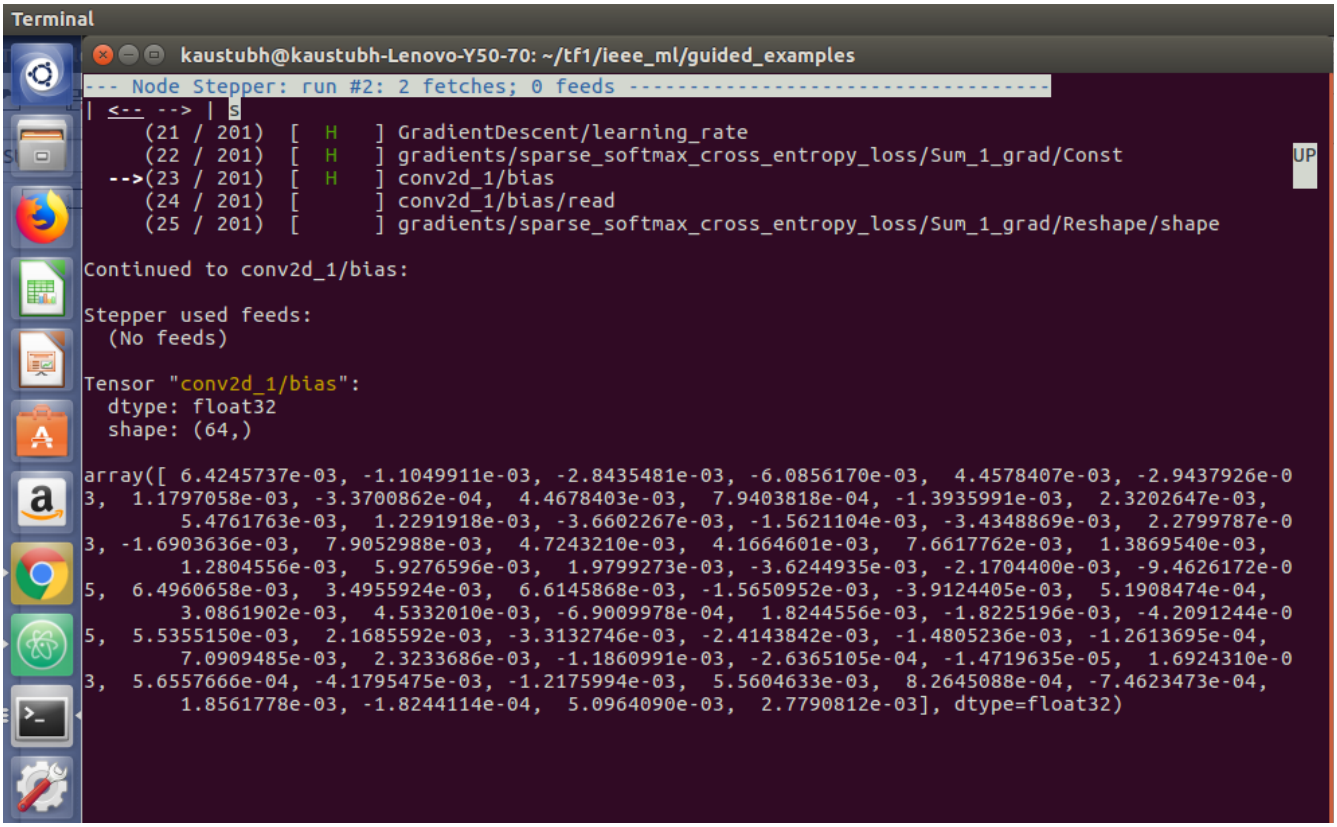
Now we shall see a way to step through the nodes of graph one-by-one in a manner analogous to procedural languages debuggers like GDB and PDB.

tfdbg> invoke_stepper
tfdbg> s ---> Call once for stepping through each node in the graph.



The above screenshot shows the CLI after running the invoke_stepper.

Traversed 23 times to the 23rd tensor (node). Arrived at tensor conv2d_1/bias.



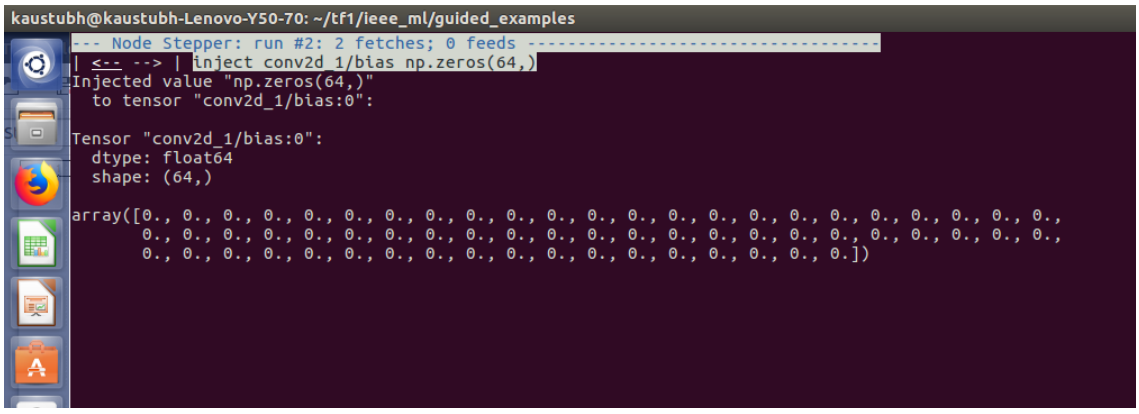
To modify the value of a given tensor at a step stage while preserving the values of all other tensors we use;

tfdbg> inject "tensor_name" "value_to_be_given"

Executed:

tfdbg> inject conv2d_1/bias np.zeros(64,)

Obtained:

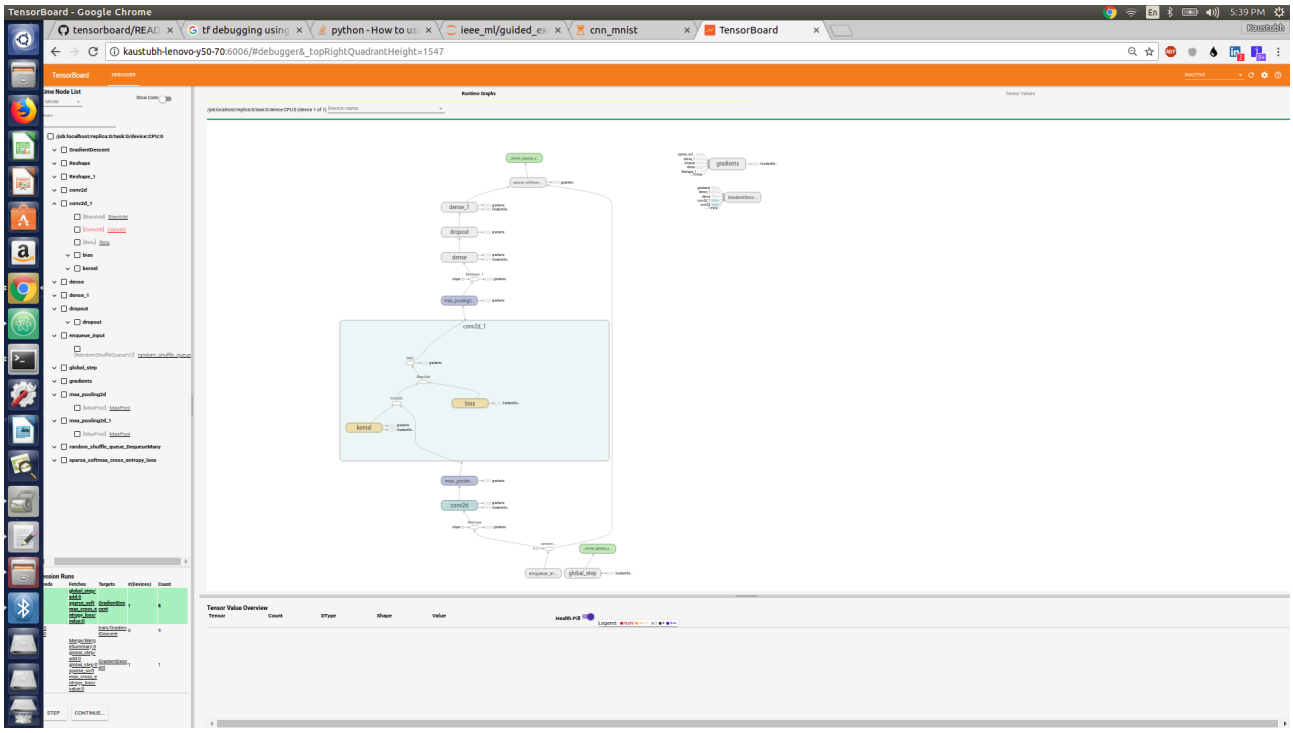


This command can be used to check if any specific tensor causes issues in a specific run, its value can be changed and set to a meaningful value while leaving all other tensors in the Session.run call unchanged.

Tensorboard debugger – Not supported on Windows yet!!

Tensorboard offers a GUI plugin for debugging. In the CLI mode, we have to traverse the computational graph to go to any node of interest.

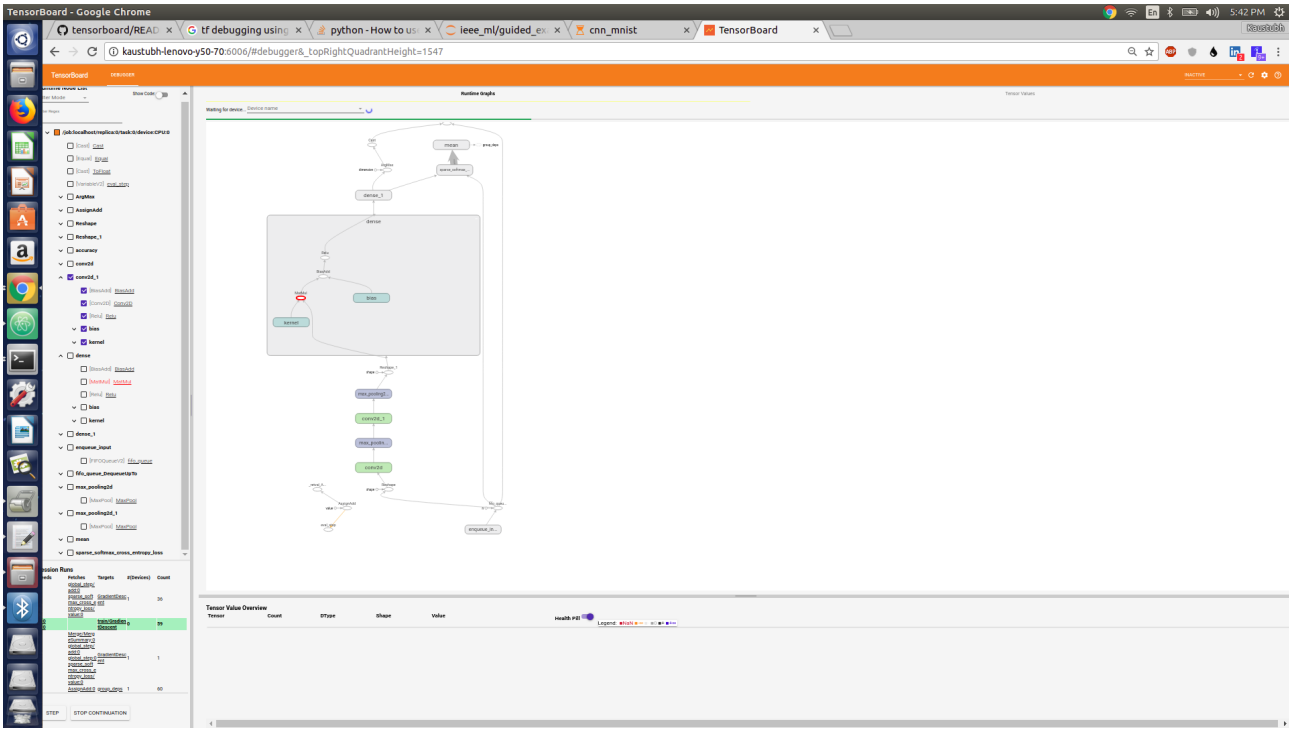
The following screenshot is the layout of the Tensorboard Debugger session for the file cnn_mnist.py.



On running the file; cnn_mnist.py either on Jupyter notebook or as a .py file, a computatoinal graph is generated initially. Any node can be double-clicked to magnify and analyse the various elements of the magnified node. Here, the node dense conv2d_1 is magnified and one can see the convolution operation, addition of bias in the node.

To move to next node use the STEP button in the bottom-left corner. Also, the CONTINUE button shall help you to conditionally run the Session calls.

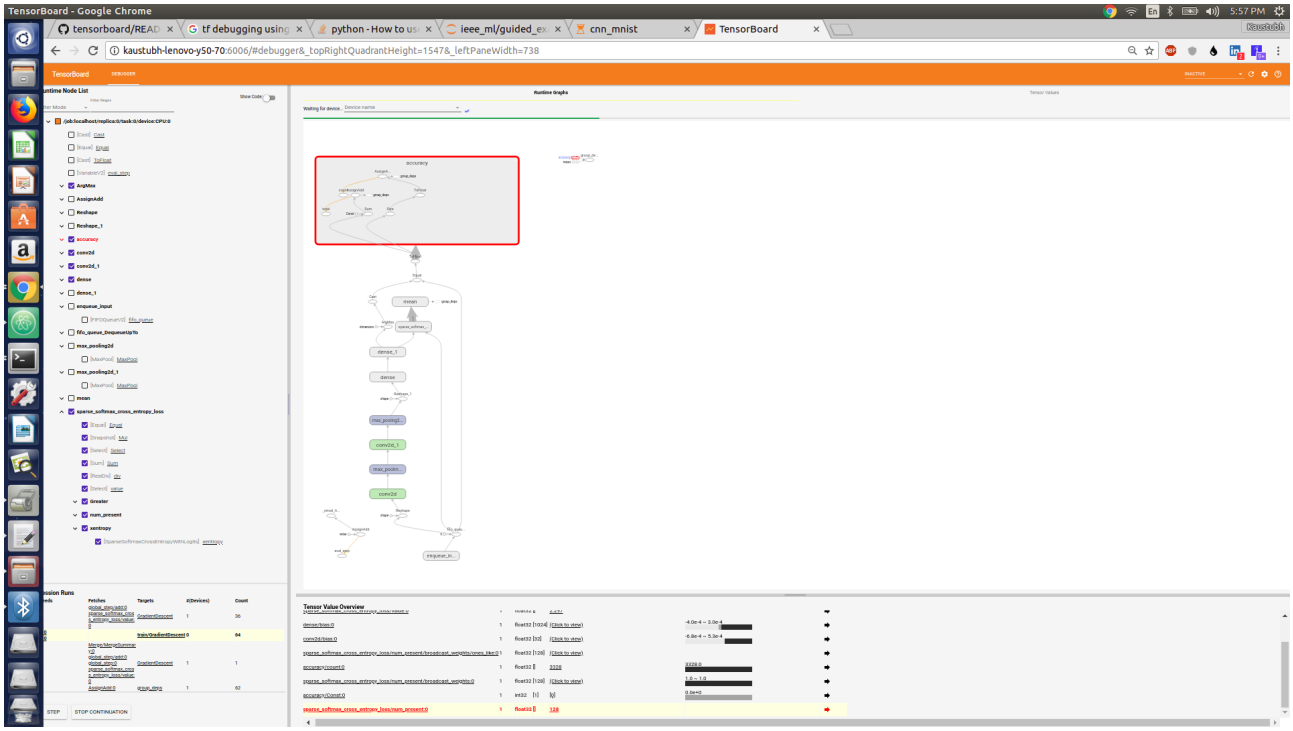
To traverse to a particular node, desired node can be right-clicked and select *Continue to*, and the graph computation occur until you reach the desired node.
In the following example, I reached the dense node by clicking *Continue to* after right-clicking.



Finally, I used the STEP functionality to traverse to the accuracy node and used the *Continue to* option for generating the computational graph.

Once the Session.run() call execution is paused, the values of tensors for all the selected nodes is displayes in the bottom half of the screen. Each tensor is also attributed with a *health pill* which visualises the proportion of values within the tensor that fall under each of the six categories noted in the legend. A user might use health pills to for instance pinpoint nodes that are culprits for producing undesired values (such as infinity & NaN).

The following screenshot illustrates this.



We have covered debugging on Tensorboard for our example in a brief manner.

However, please refer to the document;
https://github.com/tensorflow/tensorboard/tree/master/tensorboard/plugins/debugger

for detailed instructions for using the Tensorboard debugger.

The below *SUMMARY MATRIX* gives the Tensorflow functionalites of visualizer and debugger that are enabled with each file in the *ieee_ml* directory.

File ./iee_ml/	Tensorboard – visualization	Tensorboard – Debugger	CLI Debugger
guided_examples/cnn_mnist.ipynb	No	Yes	No
guided_examples/cnn_mnist_no_debugger.ipynb	No	No	No
guided_examples/kmeans.ipynb	No	No	
guided_examples/nearest_neighbor.ipynb	No	No	No
guided_examples/mnist_hyperparameter.ipynb	Yes – hyperparameter search	No	No
guided_examples/xor_combined.ipynb	Yes	No	No
guided_examples/cnn_mnist.py	No	Yes	Yes
guided_examples/cnn_mnist_no_debugger.ipynb	No	No	No
guided_examples/kmeans.py	No	No	Yes
guided_examples/nearest_neighbor.py	No	No	Yes
guided_examples/mnist_hyperparameter.py	Yes – hyperparameter search	No	No
guided_examples/xor_combined.py	Yes	No	Yes
problem_sets/hdr_om/ ALL FILES	No	No	No
problem_sets/hdr_tf/handwritten_digits_recognition_cnn_5layer.ipynb	Yes	No	No
problem_sets/hdr_tf/handwritten_digts_recognition_cnn_5layer_solution.ipynb	No	No	No
problem_sets/hdr_tf/handwritten_digits_recognition_cnn_5layer.py	Yes	No	No
problem_sets/hdr_tf/handwritten_digts_recognition_cnn_5layer_solution.py	No	No	No

basics_directory/ ALL FILES	No	No	No