IXPUG Annual Meeting 2020

Characterizing Machine Learning Workloads with the Intel® VTune™ Profiler and TensorFlow*

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Motivation

- TensorFlow* (TF) + TensorBoard* (TB): popular method for ML/DL profiling
  - The TensorFlow (TF) framework is implemented as a Python* package
  - TensorFlow includes a compiler which compiles the model's computational graph to TF-Ops
  - TF-Ops run on the hardware using kernels from libraries
  - TB generally profiles at the model and TF-Ops level, with some hardware profiling for GPU
- Intel® VTune™ Profiler: popular and deep profiler for Intel CPU hardware
  - How can we enhance TensorBoard 2.x profiling with VTune for hardware insights?
- VTune and TensorBoard have learning curves
  - How can we quickly get going with both, preferably in a single combined run?

Installing and Running

1. Install VTune 2021.1-beta09

Download and run OneAPI Beta09 installer from software.intel.com (see below)

2. Install TensorFlow in Conda Env

Install miniconda or anaconda

```
$ conda create -n py37-tf22-mkl python=3.7
$ conda activate py37-tf22-mkl
$ conda install tensorflow=2.2  # Look for mkl
$ pip install -U tensorboard_plugin_profile
```

3. Copy Scripts from Backup Slides

Python model scripts with profiling additions:

mnist_dense_train_PROFILE.py,
mnist_infer_PROFILE.py

Shell scripts to run VTune (edit paths):

run_vtune_train.sh, run_vtune_infer.sh

4. Run training (without VTune)

```
$ python mnist_dense_train_PROFILE.py
```

Creates **saved_model** directory

5. Run inference with VTune

```
$ ./run_vtune_infer.sh
```

TF profiling is saved to **logs-infer** directory

VTune saves to a **r000ue** directory

6. Open VTune results in GUI

On VTune's "Welcome" tab, use "Open Result..." button to open **r000ue/r000ue.vtune**

7. Run TensorBoard

```
$ tensorboard --logdir logs-infer
```

In Chrome browser, open **http://localhost:6006**

Simple Script to Run VTune on TF Workload

run_vtune_infer.sh

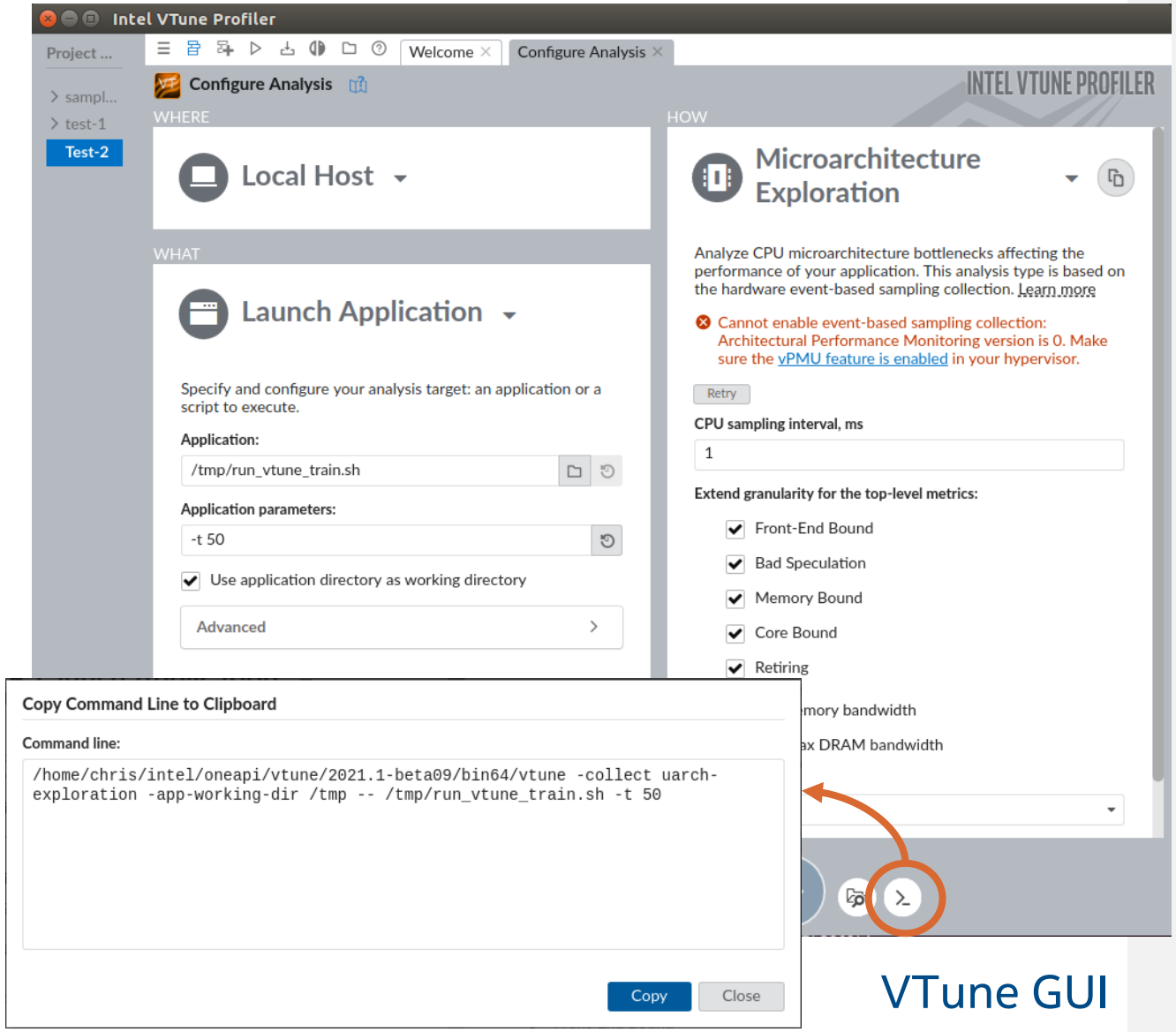
```
#! /bin/bash

RUN_DIR="${HOME}/local-projects/IXPUG-models-CURRENT"
RUN_CMD='python mnist_infer_PROFILE.py'

# Put any vtune setup commands here, like OneAPI or module loading
source /opt/intel/oneapi/setvars.sh
echo -n '===== VTune Being Used =====: ' ; which vtune ; vtune --version

# Load conda and activate environment
source "${HOME}/miniconda3/etc/profile.d/conda.sh"
conda activate py37-tf22-mkl  # Python 3.7, TF 2.2 built with MKL
echo '===== Python Being Used =====' ; which python ; python --version

# Environment variable settings - search for "Maximize TensorFlow Performance on CPU" on internet
export KMP_AFFINITY=granularity=fine,compact,1,0
export OMP_NUM_THREADS=4

cd $RUN_DIR
vtune -collect uarch-exploration -app-working-dir "${RUN_DIR}" -- ${RUN_CMD}
echo "Results can be found in ${PWD}"
```

Intel VTune Profiler

Running VTune

- GUI
  - Create project, configure analyses
  - Open previously collected *.vtune files for display

    Welcome (Tab) -> Open Result
- Command-Line
  - Easy to include in scripts
  - Produces a directory “r000ue” with “r000ue/r000ue.vtune” file (and other files)
  - Can run collection on a remote server, then display results (r000ue.vtune file) in GUI on laptop
  - Note: make sure that the VTune GUI’s build version (in Help -> About menu) is at least as high as command-line VTune’s (vtune --version)



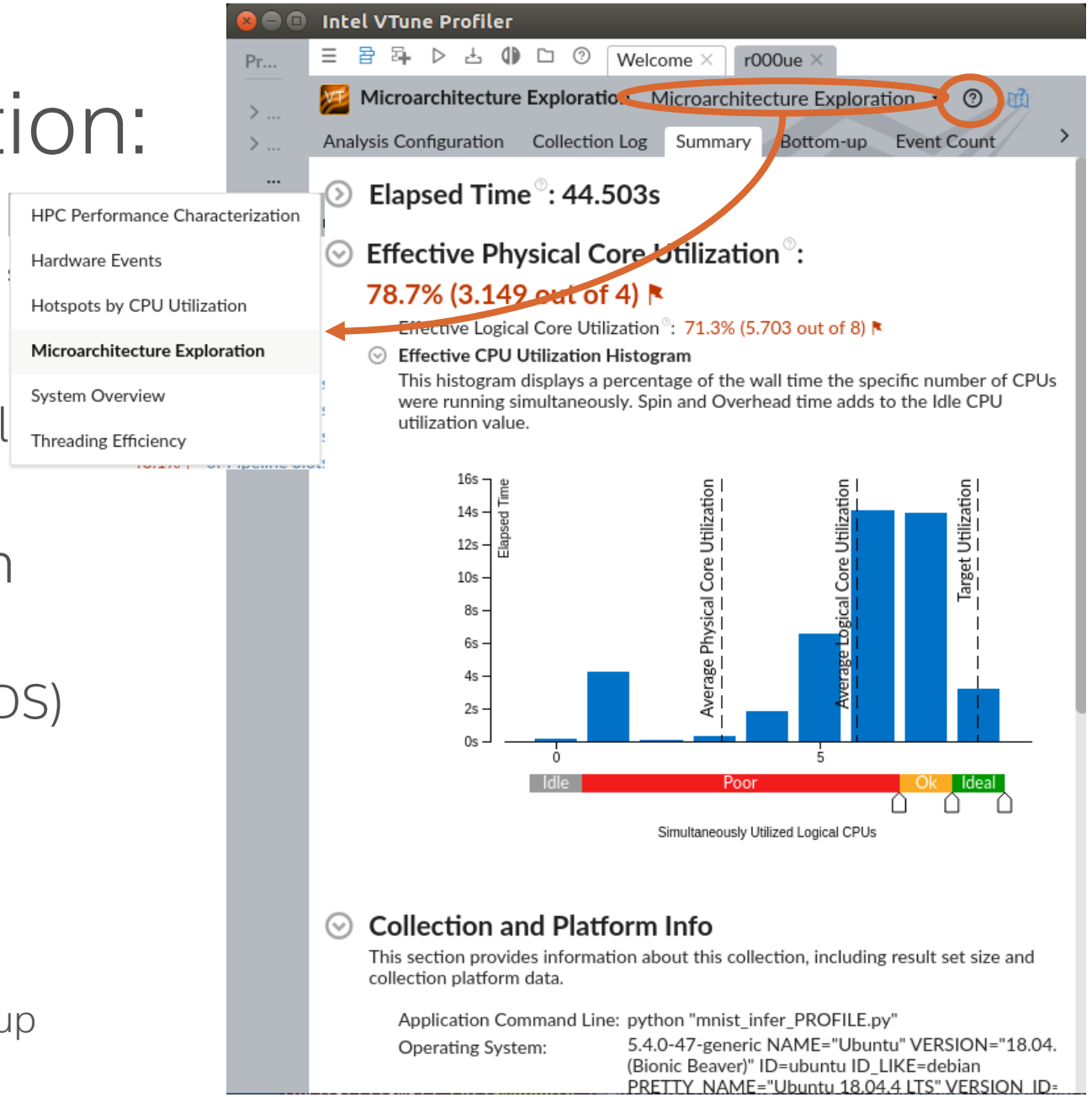
VTune GUI

VTune Command Line

```
$ source /opt/intel/oneapi/setvars.sh
$ vtune -collect uarch-exploration -app-working-dir /tmp -- python mnist_infer_PROFILE.py
```

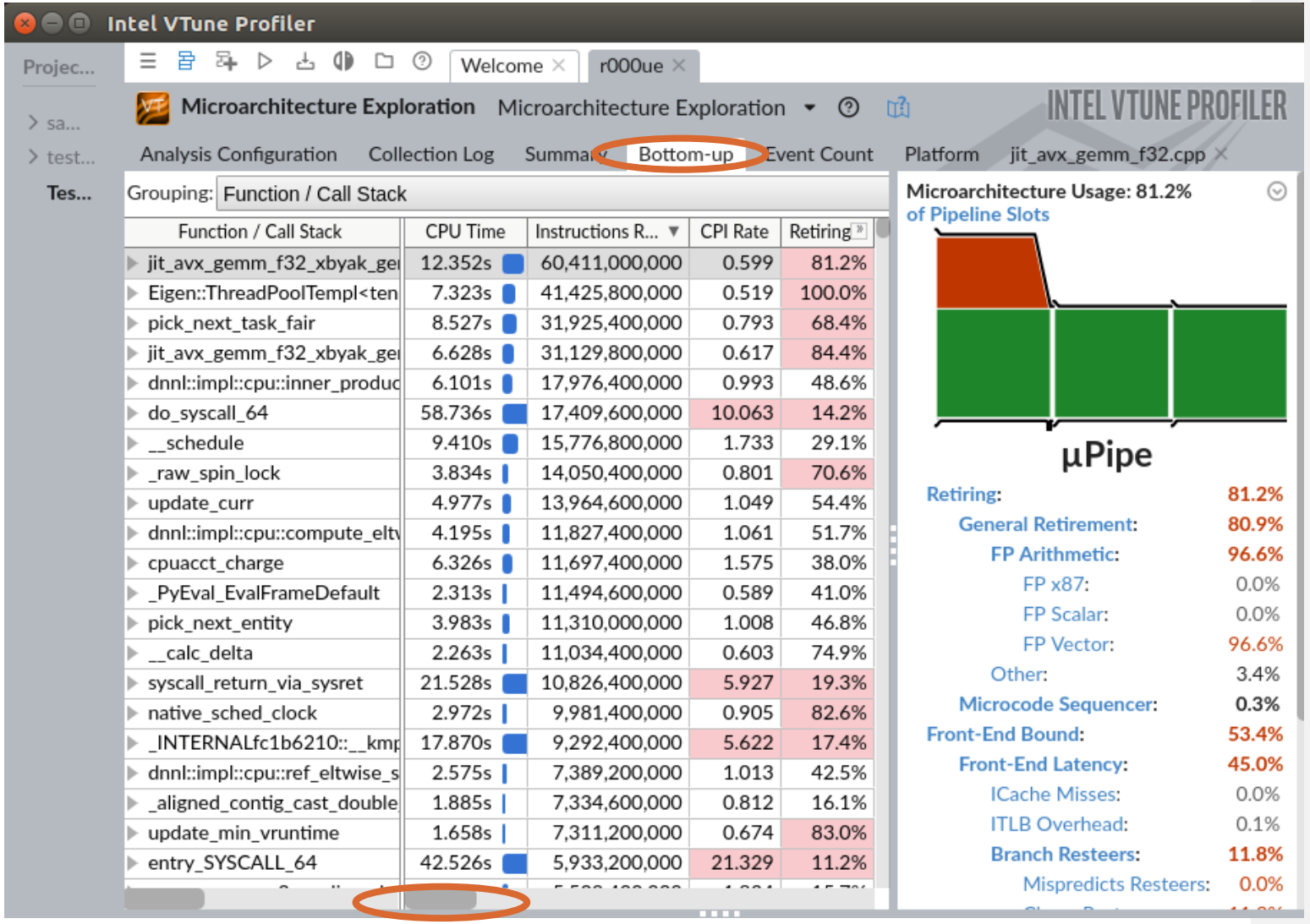
VTune µArch Exploration: Summary View

- Elapsed time shows wall-clock
  - Expanding this section shows overall µArch usage (example on next slide)
- Effective physical core utilization
  - I directed MKL to use all 4 physical cores on server (OMP_NUM_THREADS)
    - Setting sliders will apply this information to displayed data
  - 3.149 out of 4 cores used (78.7%) is decent
    - Overall, stalls/idle time likely due to TF startup and batch loading (more on this in a bit)

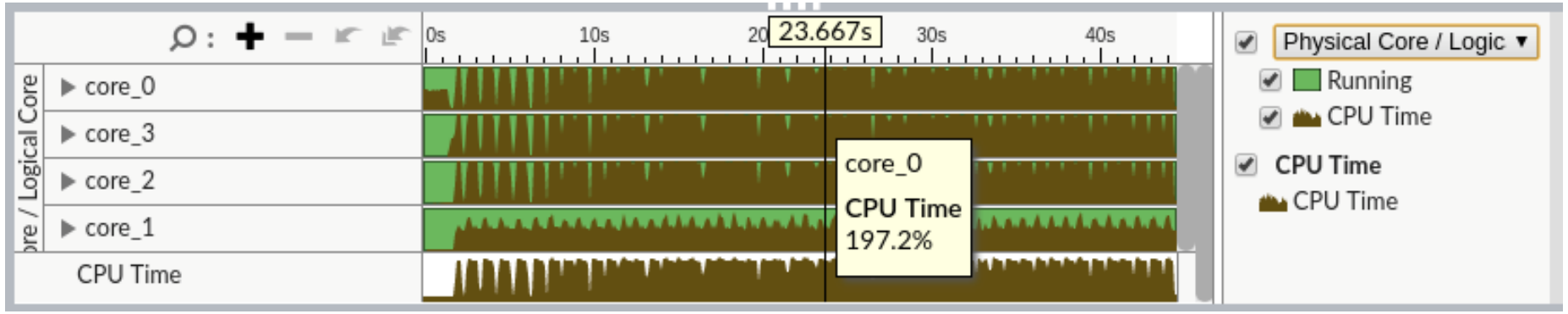


VTune µArch: Bottom-Up View

- Sorted by Instructions Retired column
  - Top represents functions which ran most instructions during VTune run
- µArch Usage view is for highlighted "jit_avx_gemm"
  - Double-clicking on name shows this is an MKL-DNN function
  - 2nd jit_avx_gemm in 4th place
  - µPipe shows areas in pipeline that VTune recommends are running well (green) and areas where optimization might help (red)
- Can hover over many fields and µPipe for explanations and recommendations from VTune



VTune µArch Exploration: Bottom-Up → CPU Core Utilization

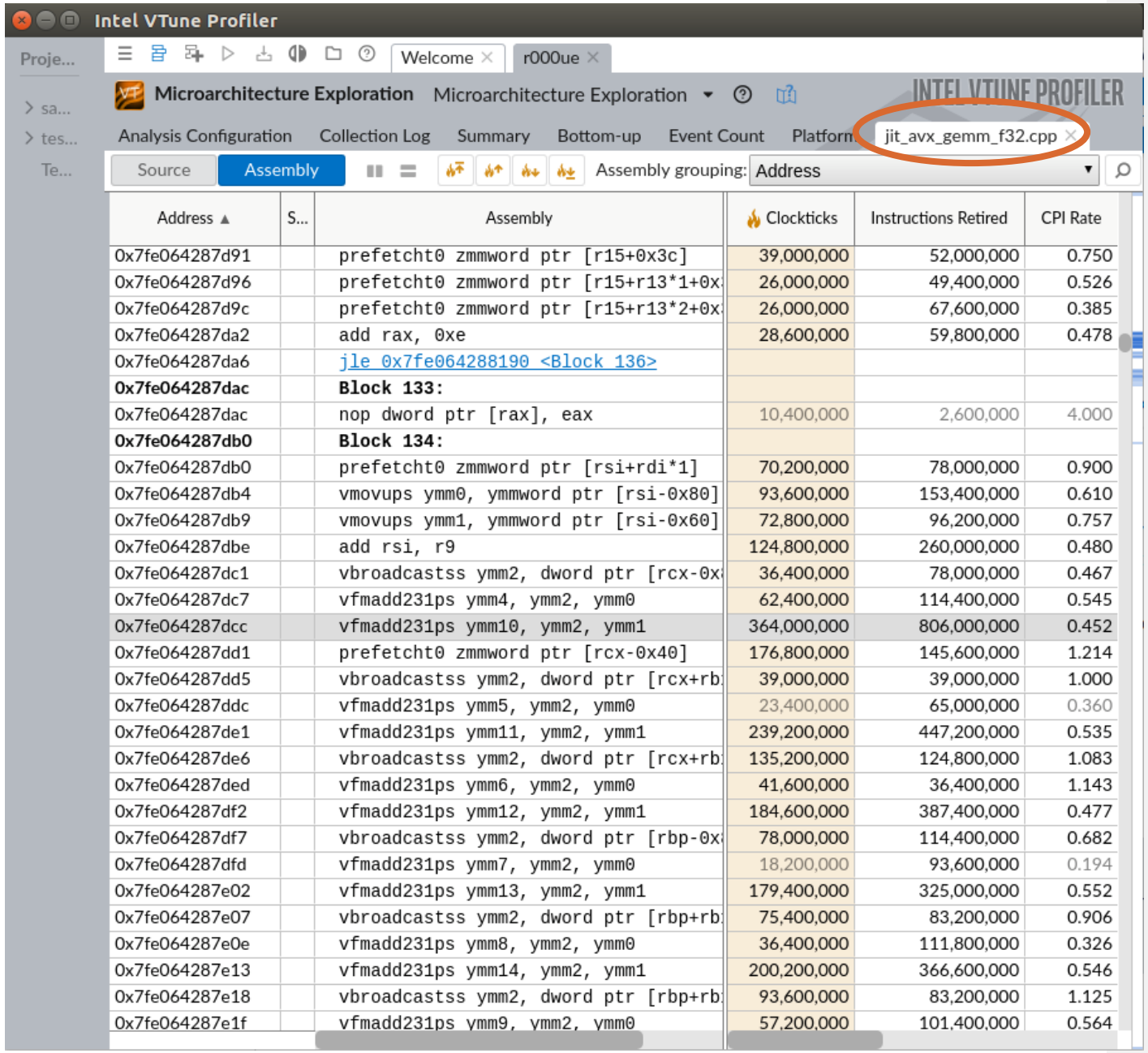


- Displayed on Bottom-Up Tab
- Can display by threads, cores, and processes
- **+** and **–** allow for zooming in/out
- Platform tab provides larger view

- Inference runs are characterized by:
  1. TF startup
  2. Loading each batch
  3. Predicting images in batch
- This delayed see-saw pattern can be seen in the CPU utilization

VTune µArch: Assembly View

- Double-clicking a function will open a Source/Assembly View
- For individual instructions, can see:
  - Clockticks run
  - Instructions retired
  - Cycles Per Instruction (CPI)
  - Further columns (not shown here) for front-end latency, bad speculation, and other scheduling information



Address ▲	S...	Assembly	Clockticks	Instructions Retired	CPI Rate
0x7fe064287d91		prefetcht0 zmmword ptr [r15+0x3c]	39,000,000	52,000,000	0.750
0x7fe064287d96		prefetcht0 zmmword ptr [r15+r13*1+0x	26,000,000	49,400,000	0.526
0x7fe064287d9c		prefetcht0 zmmword ptr [r15+r13*2+0x	26,000,000	67,600,000	0.385
0x7fe064287da2		add rax, 0xe	28,600,000	59,800,000	0.478
0x7fe064287da6		jle 0x7fe064288190 <Block 136>			
0x7fe064287dac		**Block 133:**			
0x7fe064287dac		nop dword ptr [rax], eax	10,400,000	2,600,000	4.000
0x7fe064287db0		**Block 134:**			
0x7fe064287db0		prefetcht0 zmmword ptr [rsi+rdi*1]	70,200,000	78,000,000	0.900
0x7fe064287db4		vmovups ymm0, ymmword ptr [rsi-0x80]	93,600,000	153,400,000	0.610
0x7fe064287db9		vmovups ymm1, ymmword ptr [rsi-0x60]	72,800,000	96,200,000	0.757
0x7fe064287dbe		add rsi, r9	124,800,000	260,000,000	0.480
0x7fe064287dc1		vbroadcastss ymm2, dword ptr [rcx-0x	36,400,000	78,000,000	0.467
0x7fe064287dc7		vfmadd231ps ymm4, ymm2, ymm0	62,400,000	114,400,000	0.545
0x7fe064287dcc		vfmadd231ps ymm10, ymm2, ymm1	364,000,000	806,000,000	0.452
0x7fe064287dd1		prefetcht0 zmmword ptr [rcx-0x40]	176,800,000	145,600,000	1.214
0x7fe064287dd5		vbroadcastss ymm2, dword ptr [rcx+rb	39,000,000	39,000,000	1.000
0x7fe064287ddc		vfmadd231ps ymm5, ymm2, ymm0	23,400,000	65,000,000	0.360
0x7fe064287de1		vfmadd231ps ymm11, ymm2, ymm1	239,200,000	447,200,000	0.535
0x7fe064287de6		vbroadcastss ymm2, dword ptr [rcx+rb	135,200,000	124,800,000	1.083
0x7fe064287ded		vfmadd231ps ymm6, ymm2, ymm0	41,600,000	36,400,000	1.143
0x7fe064287df2		vfmadd231ps ymm12, ymm2, ymm1	184,600,000	387,400,000	0.477
0x7fe064287df7		vbroadcastss ymm2, dword ptr [rbp-0x	78,000,000	114,400,000	0.682
0x7fe064287dfd		vfmadd231ps ymm7, ymm2, ymm0	18,200,000	93,600,000	0.194
0x7fe064287e02		vfmadd231ps ymm13, ymm2, ymm1	179,400,000	325,000,000	0.552
0x7fe064287e07		vbroadcastss ymm2, dword ptr [rbp+rb	75,400,000	83,200,000	0.906
0x7fe064287e0e		vfmadd231ps ymm8, ymm2, ymm0	36,400,000	111,800,000	0.326
0x7fe064287e13		vfmadd231ps ymm14, ymm2, ymm1	200,200,000	366,600,000	0.546
0x7fe064287e18		vbroadcastss ymm2, dword ptr [rbp+rb	93,600,000	83,200,000	1.125
0x7fe064287e1f		vfmadd231ps ymm9, ymm2, ymm0	57,200,000	101,400,000	0.564

Additional VTune Capabilities

- Additional collection types:
  - Performance Snapshot
  - Hotspots
  - Memory Access
  - HPC Performance Characterization
- Can attach to running process:

```
$ vtune -collect hotspots -target-pid=17704
```

- Event Count View
  - See CPU event counters for functions
- Reporting:

```
$ vtune -report summary -result-dir=r000ue
```

  - Text, HTML, XML, and CSV formats
- Can defer finalization using

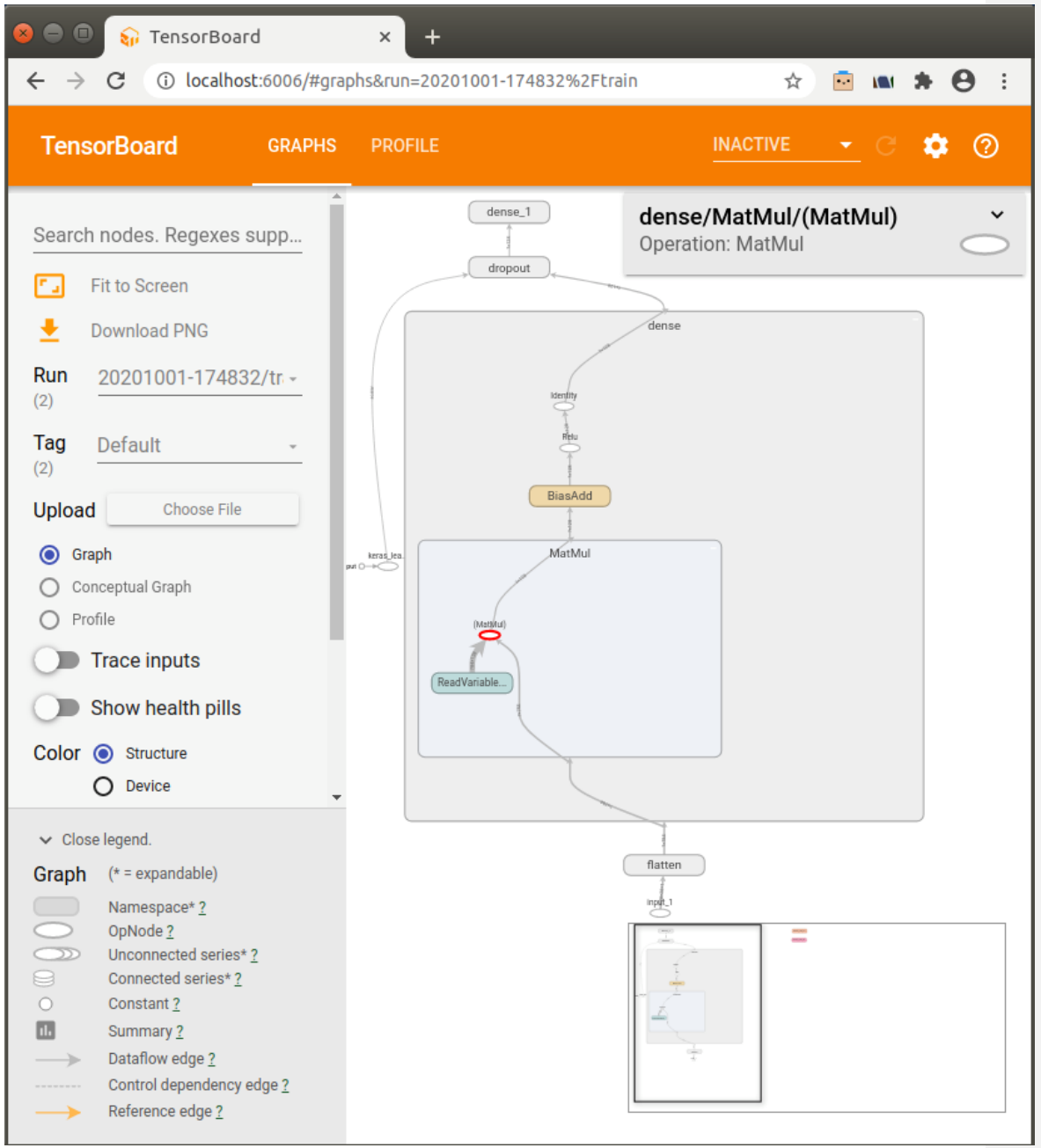
```
-finalization-mode=deferred
```

  - Finalization happens when .vtune file is first opened in GUI

Correlating with TensorBoard

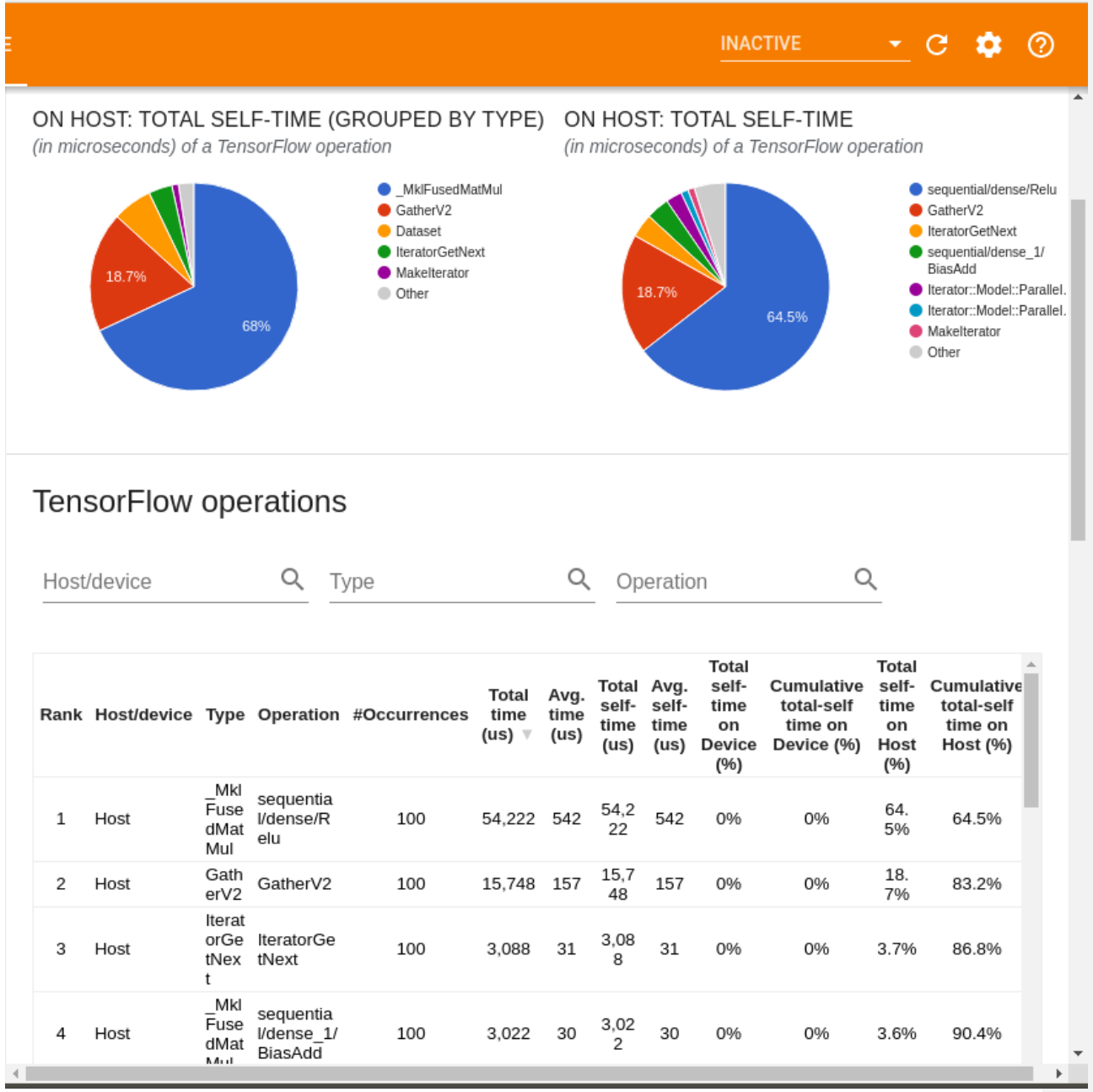
TensorBoard: Graph View

- Conceptual nested graph of model structure
- Round-rect boxes are logical operations which can be expanded by double-clicking
- Ovals are TF-Ops
- Various heat-map views color graph for:
  - Compute time
  - Memory usage



TensorBoard: Profile Stats View

- TB 2.x Profile tab has a new, very nice TF Stats view
- Pie charts quickly show what TF-Ops are using most time
  - MKLFusedMatMuls are using most
- Table view provides more information on TF-Ops usage
- Note that this is at the TF-Op level
  - VTune gives additional insight at the hardware level



Rank	Host/device	Type	Operation	#Occurrences	Total time (us)	Avg. time (us)	Total self-time (us)	Avg. self-time (us)	Total self-time on Device (%)	Cumulative total-self time on Device (%)	Total self-time on Host (%)	Cumulative total-self time on Host (%)
1	Host	_MklFusedMatMul	sequential/dense/Relu	100	54,222	542	54,222	542	0%	0%	64.5%	64.5%
2	Host	GatherV2	GatherV2	100	15,748	157	15,748	157	0%	0%	18.7%	83.2%
3	Host	IteratorGetNext	IteratorGetNext	100	3,088	31	3,088	31	0%	0%	3.7%	86.8%
4	Host	_MklFusedMatMul	sequential/dense_1/BiasAdd	100	3,022	30	3,022	30	0%	0%	3.6%	90.4%

Going Further

Online Resources

- Intel VTune Profiler

  https://software.intel.com/content/www/us/en/develop/tools/oneapi.html – “Get the Base Kit” link

  https://software.intel.com/content/www/us/en/develop/tools/oneapi/components/vtune-profiler.html

- TensorFlow

  https://www.tensorflow.org/tutorials – General page for many good TensorFlow tutorials

  https://www.tensorflow.org/tutorials/keras/classification – Source of models used

- TensorBoard

  https://www.tensorflow.org/tensorboard – Links to tutorials, videos

  https://github.com/tensorflow/tensorboard/issues/1961 – Details Keras eager-mode limitations with TB

Interesting Articles

- Maximizing TensorFlow performance in Intel CPUs

  https://software.intel.com/content/www/us/en/develop/articles/maximize-tensorflow-performance-on-cpu-considerations-and-recommendations-for-inference.html

- VTune with MPI for distributed runs

  https://software.intel.com/content/www/us/en/develop/documentation/vtune-cookbook/top/configuration-recipes/profiling-mpi-applications.html

  https://software.intel.com/content/www/us/en/develop/documentation/vtune-help/top/analyze-performance/code-profiling-scenarios/mpi-code-analysis.html

- Intel optimization for TensorFlow

  https://software.intel.com/content/www/us/en/develop/articles/intel-optimization-for-tensorflow-installation-guide.html

- Building TensorFlow from source to optimize for your server's CPU

  https://www.tensorflow.org/install/source

  -march=...: builds for specific CPU; **--config=mkl**: builds TensorFlow with MKL kernels

Summary

- TensorBoard is the standard tool to gain insight to how TensorFlow models and TF-Ops are running
- VTune can be added to see how the CPU hardware is running the kernels which implement the TF-Ops and TensorFlow models
- Both profiling types can be collected together in a single run using the methods documented here
- VTune has many more rich capabilities – please try them out!

Backup

TensorFlow Mini-Workload with Profiling Added

Keras: Training

- Simple dense network with standard MNIST dataset
- Produces **saved_model** directory used by inference

Training Core (green text is added for profiling)

```
# TensorBoard tracing and profiling (for steps 500-504)
# Profiling requires: "pip install -U tensorboard_plugin_profile"
log_dir = "logs-train/" + datetime.datetime.now().strftime("%Y%m%d-%H%M%S")
tensorboard_callback = tf.keras.callbacks.TensorBoard(log_dir=log_dir,
                    histogram_freq=1, profile_batch='500,504',
                    embeddings_freq=10, write_graph=True)

# Train -- adjust model parameters (weights) to minimize the loss
model.fit(x_train, y_train, epochs=10, validation_data=(x_test, y_test),
        callbacks=[tensorboard_callback])
```

Keras: Inference

- To overcome small MNIST dataset size, repeat multiple runs

Inference Core (green text is added for profiling)

```
def  run_inference(model, name, input_images, input_labels, callbacks=None):
   predictions = model.predict(input_images, batch_size=100, callbacks=callbacks)
   [...]

log_dir = "logs-infer/" + datetime.datetime.now().strftime("%Y%m%d-%H%M%S")
tensorboard_callback = tf.keras.callbacks.TensorBoard(log_dir=log_dir,
                    histogram_freq=1, profile_batch='500,504',
                    embeddings_freq=10, write_graph=True)

with tf.profiler.experimental.Profile(log_dir):  # Profile one test run
  run_inference(model, 'test', x_test, y_test, tensorboard_callback)
# Artificially run more inference, to get reasonable sample for timing
for i in range(1, 50):   # Run for over a minute on targeted NUC hardware
  run_inference(model, 'test', x_test, y_test)
  run_inference(model, 'train', x_train, y_train)
```

TensorFlow Keras: Training Model with Profiling

- Code added for profiling is in green
- Can run on the command-line with:

```
$ python mnist_dense_train_PROFILE.py
```

- Produces `saved_model` directory
- Script to run VTune is below

run_vtune_train.sh

```
#! /bin/bash

RUN_DIR="${HOME}/local-projects/IXPUG-models-CURRENT"
RUN_CMD='python mnist_dense_train_PROFILE.py'

# Put any vtune setup commands here, like OneAPI or module loading
source /opt/intel/oneapi/setvars.sh
echo -n '===== VTune Being Used =====: ' ; which vtune ; vtune --version

# Load conda and activate environment
source "${HOME}/miniconda3/etc/profile.d/conda.sh"
conda activate py37-tf22-mkl  # Python 3.7, TF 2.2 built with MKL
echo '===== Python Being Used =====' ; which python ; python --version

# Environment variable settings - see "Maximize TensorFlow Performance on CPU"
export KMP_AFFINITY=granularity=fine,compact,1,0
export OMP_NUM_THREADS=4

cd $RUN_DIR
vtune -collect uarch-exploration -app-working-dir "${RUN_DIR}" -- ${RUN_CMD}
echo "Results can be found in ${PWD}"
```

mnist_dense_train_PROFILE.py

```
#!  /usr/bin/env python

# Adapted from TF tutorials at:
#   https://www.tensorflow.org/tutorials/keras/classification

import datetime
import tensorflow as tf

# Load MNIST dataset
mnist = tf.keras.datasets.mnist
(x_train, y_train), (x_test, y_test) = mnist.load_data()

# Put into NHWC form, by adding channel=1 to end
x_train = x_train.reshape(x_train.shape[0], 28, 28, 1)
x_test = x_test.reshape(x_test.shape[0], 28, 28, 1)
input_shape = (28, 28, 1)

x_train, x_test = x_train / 255.0, x_test / 255.0

model = tf.keras.models.Sequential([  # Sequential densenet model
  tf.keras.layers.Flatten(input_shape=input_shape),
  tf.keras.layers.Dense(128, activation='relu'),
  tf.keras.layers.Dropout(0.2),
  tf.keras.layers.Dense(10)
])
model.summary()
loss_fn = tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True)
model.compile(optimizer='adam', loss=loss_fn, metrics=['accuracy'])

# TensorBoard tracing and profiling (for steps 500-504)
# Profiling requires: "pip install -U tensorboard_plugin_profile"
log_dir = "logs-train/" + datetime.datetime.now().strftime("%Y%m%d-%H%M%S")
tensorboard_callback = tf.keras.callbacks.TensorBoard(log_dir=log_dir,
                      histogram_freq=1, profile_batch='500,504',
                      embeddings_freq=10, write_graph=True)

# Train -- adjust model parameters (weights) to minimize the loss
model.fit(x_train, y_train, epochs=10, validation_data=(x_test, y_test),
          callbacks=[tensorboard_callback])

test_loss, test_acc = model.evaluate(x_test,  y_test, verbose=2)
print('Test accuracy: ', test_acc)  # Evaluate model against test set

model.save('./saved-model')  # Save model for inference runs
```

TensorFlow Keras: Inference Model with Profiling

- Code added for profiling is in green
- Can run on the command-line with:

```
$ python mnist_infer_PROFILE.py
```

- Must run training model first, to produce `saved_model` directory
- Script to run VTune is below

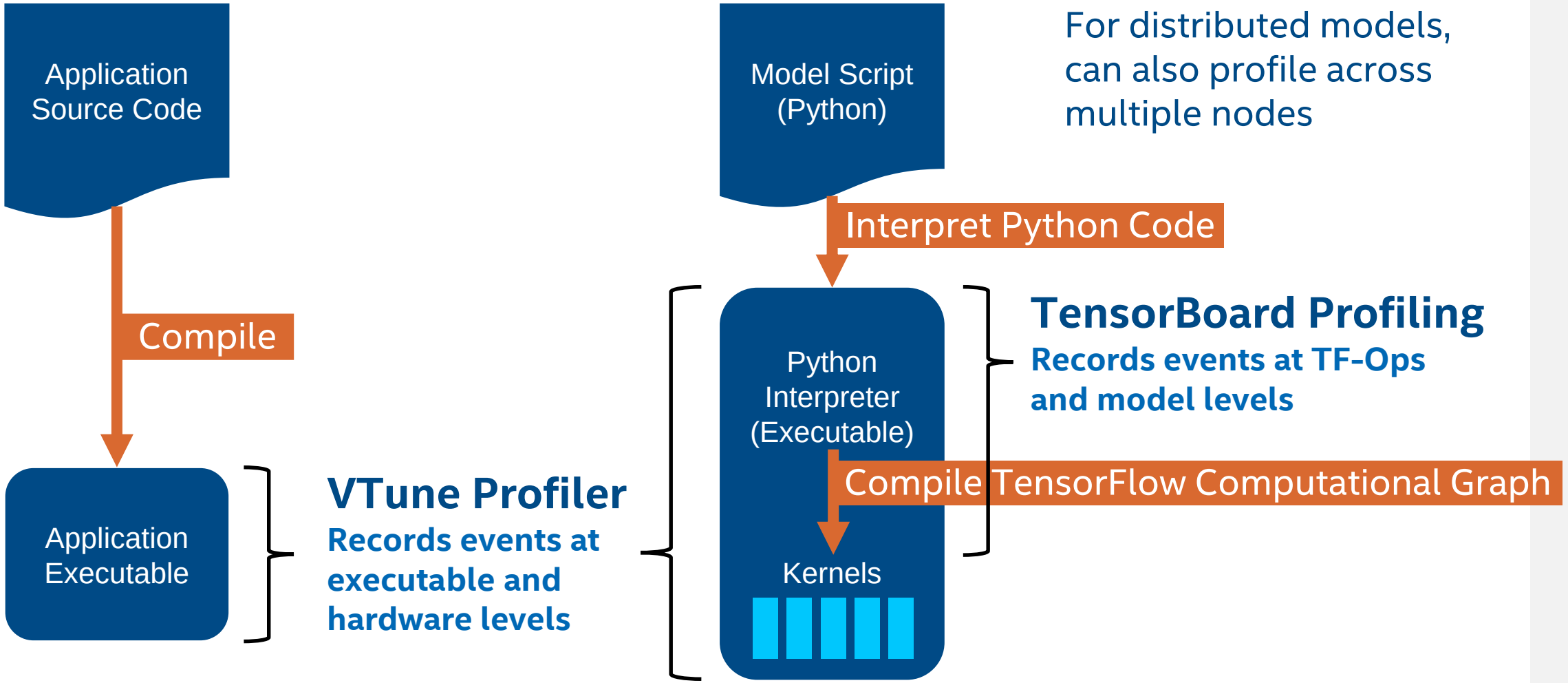
run_vtune_infer.sh

```
#! /bin/bash

RUN_DIR="${HOME}/local-projects/IXPUG-models-CURRENT"
RUN_CMD='python mnist_infer_PROFILE.py'

# Put any vtune setup commands here, like OneAPI or module loading
source /opt/intel/oneapi/setvars.sh
echo -n '===== VTune Being Used =====: ' ; which vtune ; vtune --version

# Load conda and activate environment
source "${HOME}/miniconda3/etc/profile.d/conda.sh"
conda activate py37-tf22-mkl  # Python 3.7, TF 2.2 built with MKL
echo '===== Python Being Used =====' ; which python ; python --version

# Environment variable settings - see "Maximize TensorFlow Performance on CPU"
export KMP_AFFINITY=granularity=fine,compact,1,0
export OMP_NUM_THREADS=4

cd $RUN_DIR
vtune -collect uarch-exploration -app-working-dir "${RUN_DIR}" -- ${RUN_CMD}
echo "Results can be found in ${PWD}"
```

mnist_infer_PROFILE.py

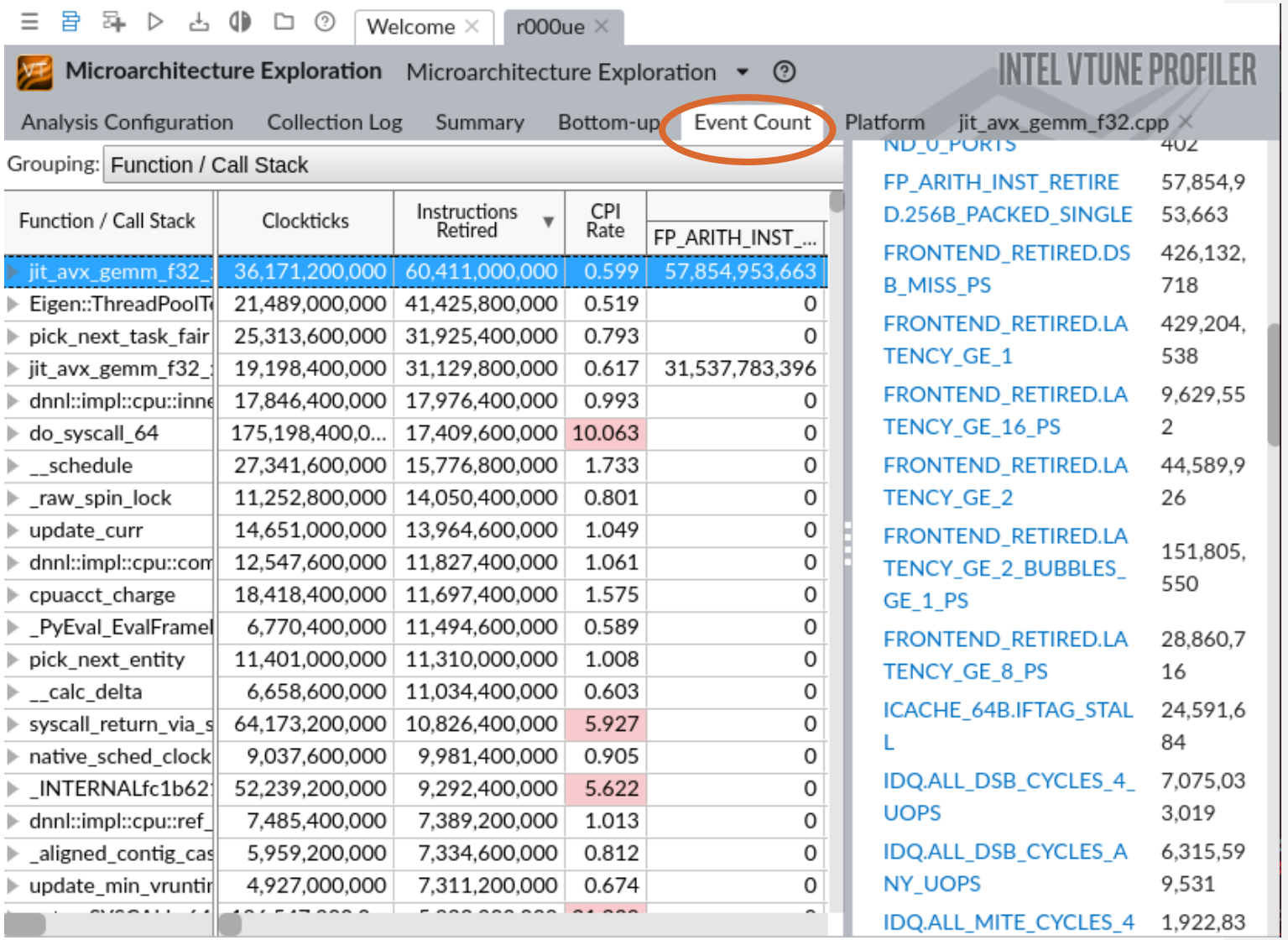
```
#!  /usr/bin/env python

# Adapted from TF tutorials at:
#   https://www.tensorflow.org/tutorials/keras/classification

import datetime
import tensorflow as tf
import numpy

def  run_inference(model, name, input_images, input_labels, callbacks=None):
  predictions = model.predict(input_images, batch_size=100, callbacks=callbacks)
  matches = 0
  for idx in range(0, len(input_images)):
    predicted = numpy.argmax(predictions[idx])
    if int(predicted) == int(input_labels[idx]):  matches += 1
  accuracy = float(matches) / float(len(input_images))
  print('Accuracy on %d %s images: %f' % (len(input_images), name, accuracy))
# End def run_inference(...)

mnist = tf.keras.datasets.mnist  # Load MNIST dataset
(x_train, y_train), (x_test, y_test) = mnist.load_data()

# Put into NHWC form, by adding channel=1 to end, input_shape = (28, 28, 1)
x_train = x_train.reshape(x_train.shape[0], 28, 28, 1)
x_test = x_test.reshape(x_test.shape[0], 28, 28, 1)
x_train, x_test = x_train / 255.0, x_test / 255.0

model = tf.keras.models.load_model('./saved-model') # Load previously saved model
model.summary() ; model.compile()

log_dir = "logs-infer/" + datetime.datetime.now().strftime("%Y%m%d-%H%M%S")
tensorboard_callback = tf.keras.callbacks.TensorBoard(log_dir=log_dir,
                    histogram_freq=1, profile_batch='500,504',
                    embeddings_freq=10, write_graph=True)

with tf.profiler.experimental.Profile(log_dir):  # Profile one test run
  run_inference(model, 'test', x_test, y_test, tensorboard_callback)
# Artificially run more inference, to get reasonable sample for timing
for i in range(1, 50):   # Run for over a minute on targeted NUC hardware
  run_inference(model, 'test', x_test, y_test)
  run_inference(model, 'train', x_train, y_train)
```

Levels of Profiling in Deep Learning



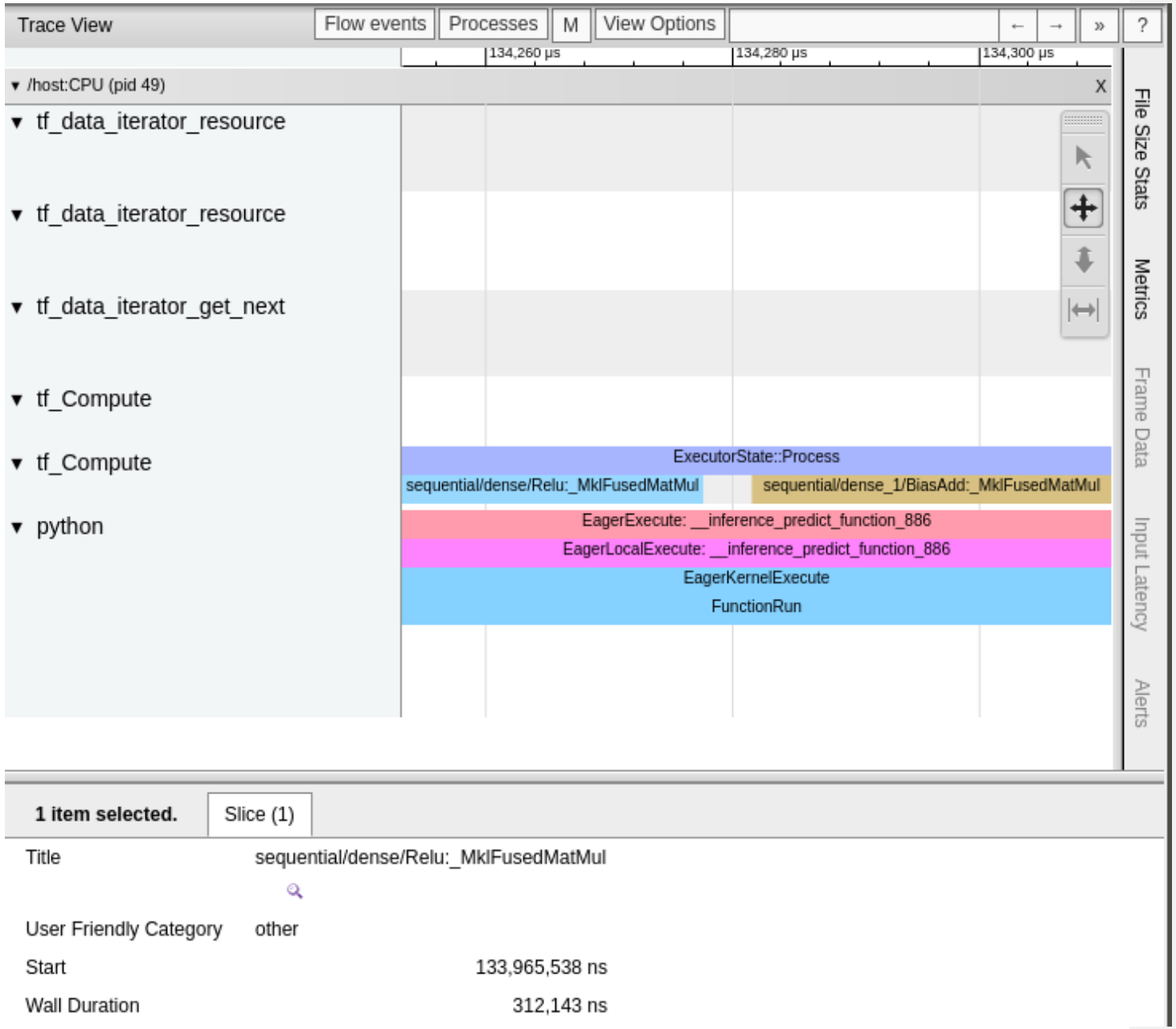
VTune µArch: Event-Count View

- Event-Count tab shows CPU hardware counters
- Again, sorted by Instructions Retired
- For selected "jit_avx_gemm..." function, FP_ARITH... counter is also very high
  - Large fraction of total instructions retired
  - Right column provides easily scrollable list of all counters collected for function



TensorBoard: Profile Trace View

- TB 2.x now includes a timeline
- TF-Ops are tracked to the nano-second resolution
- Can zoom in/out to see overall shape or details
- Here we see a couple MKLFusedMatMuls running at “tf_Compute” level
  - These are related to the jit_avx_gemm functions we saw in VTune’s µArch collection



Environment Configuration Details

Configuration from October 1, 2020:

- Ubuntu 18.04 Linux
- Python 3.7, TensorFlow 2.2, and TensorBoard 2.2 from Anaconda:

```
$ conda create -n py37-tf22-mkl python=3.7
$ conda activate py37-tf22-mkl
$ conda install tensorflow=2.2  # Look for mkl
$ pip install -U tensorboard_plugin_profile
```

- Intel VTune Profiler 2021.1-beta09 from OneAPI Beta09
  - Downloaded from software.intel.com
- Intel NUC with Core i7-6770HQ CPU
  - Training and inference runs performed with OMP* and KMP* settings:

```
export KMP_AFFINITY=granularity=fine,compact,1,0
export OMP_NUM_THREADS=4
```

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