

PYTHON PROFILING TOOLS

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MANUAL PROFILING

- In a Jupyter notebook
- For profiling the cell computing time :
- %%time
- For profiling the cell memory:

```
!pip install memory_profiler # installing  
%load_ext memory_profiler # activating  
%%memit # put everywhere we want to measure the memory  
==> Measure the notebook mem. consumption, and the cell increment (memory consum. due to the cell).  
==> Result are noisy due to interpreter optimization
```

Also:

```
Import time  
st=time.time()  
<your-code>  
print(« Enlapsed time : », time.time()-st)
```

- ⇒ Advantage full control of what is measured
- ⇒ Disadvantage, when the project is large,
 - where put the timers ? Everywhere ???
 - When put every :
 - 1) timers slowdowns the code
 - 2) injecting “timers” impact the #lines and readability

MEMORY MANAGEMENT IN PYTHON

● « High-water » phenomenon:

- Long running Python jobs that consume a lot of memory while running may not return that memory to the operating system until the process actually terminates, even if everything is garbage collected properly.

OVERVIEW OF PYTHON PROFILER TECHNOLOGIES

Python introduce « decorator mechanism » allowing to choose easily which function to profile

Does not exist in Python. Python interpreter provides « hook » for plugging profilers. Thus, no profiler need to inject additional code in developper code. Python profilers use « event based approach » instead.

Four kinds of profiler :

- **Event based** : data collected when events occurs (entry/exit function, allocate/free memory).
 - Profiler may overhead
- **Statistical** : data collected periodically. The profiler does not give a overhead, data profiling are only sampled.
- **Instrumented manually** : developper put keyword to select codes to profiles (time.time(), %%time, ...)
- **Instrumented automatically source level**: profiler code is « injected » automatically in the developper source code to collect data.

Profilers can offer different features :

- **Memory usage**. Different scale : (process, file, object, line).
- **Time usage**. Different scale : (process, function, line).
- **Hits count** : Count number of time line/function are reached.

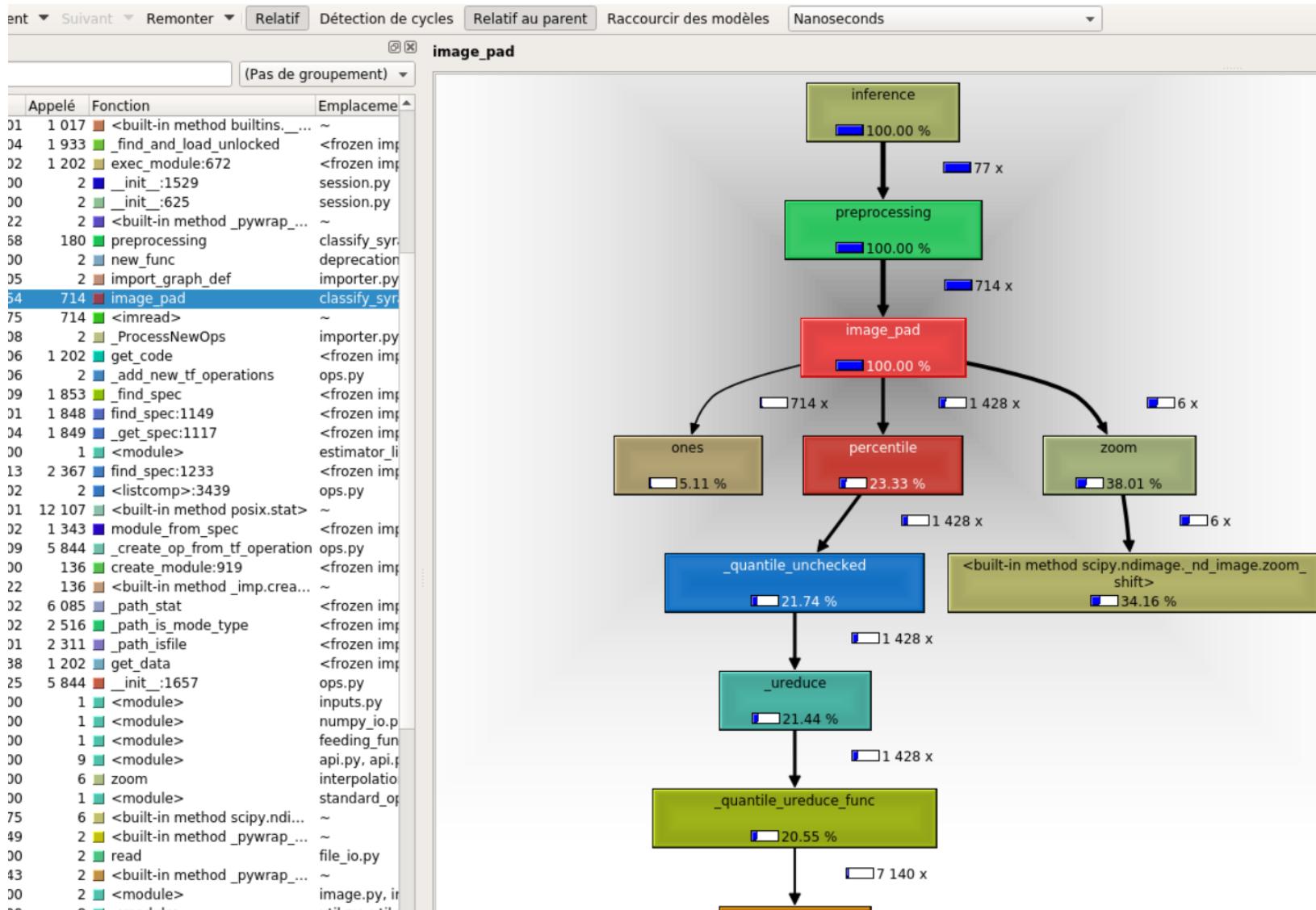
PROFILER OVERVIEW

Tested	name	kind	features							output and plotting	doc	comment			
			time prof.		hits count		memory prof.								
			funct.	line	funct.	line	all	obj.	line						
✗	vprof	event based	X	X		X	X	X		display: flame, code heatmap, mem curv.	https://github.com/nvdv/vprof		memory and time		
	nylas-perf-tools	statistical	X				X			display: flame, memory curve	https://github.com/nylas/nylas-perf-tools	can be used in production			
	vtune (intel)	all		X			X			GUI	https://software.intel.com/en-us/articles/profiling-python-with-intel-vtune-amplifier-a-covariance-demonstration	MPI compatible			
✗	pympler	instru. manu.					X			string	https://pythonhosted.org/Pympler/	give objects size, track obj. Lifetime	memory only		
	trace_malloc	instru. manu.				X		X		print	https://docs.python.org/3.4/library/tracemalloc.html				
✗	memory_profiler	in. ma. or stat				X		X		global : mem curve, mem curv; func print	https://github.com/pythonprofilers/memory_profiler	can be used globally or on function with @profile decorator			
	profile	event based	X		X					pypy format	https://docs.python.org/3/library/profile.html		time only		
✗	cprofile	event based	X		X					pypy format	https://docs.python.org/3/library/profile.html	lighter than profile			
	pycallgraph		X		X					graphviz format	http://pycallgraph.slowshop.com/				
	py-spy	event based	X							display : flame, top-like	https://github.com/benfred/py-spy	asynchronous to be used in production			
	pyflame	statistical	X							display: flame	https://github.com/uber/pyflame				
✗	pprofile	ev. ba. or stat,		X		X				cachegrind for functions; line profiling; print	https://github.com/vpelletier/pprofile	pure python profiler so heavy			
	timeit	instru. manu.		X						python decimal number	https://docs.python.org/3/library/timeit.html				
	line_profiler	instru. manu.		X		X				pypy format	https://github.com/rkern/line_profiler	pure python profiler so heavy			
	pycounters	instru. manu.	X							log in output file	https://pycounters.readthedocs.io/	Collect live metrics in production phase			
	Py-heat	event based	X							heatmap image	https://github.com/csurfer/pyheat/tree/master				
✗	tensorflow profiler		-	-	-	-	-	-	-	log files	https://github.com/tensorflow/tensorflow/blob/master/tensorflow/core/profiler/README.md	profile tensorflow operations	tensorflow		

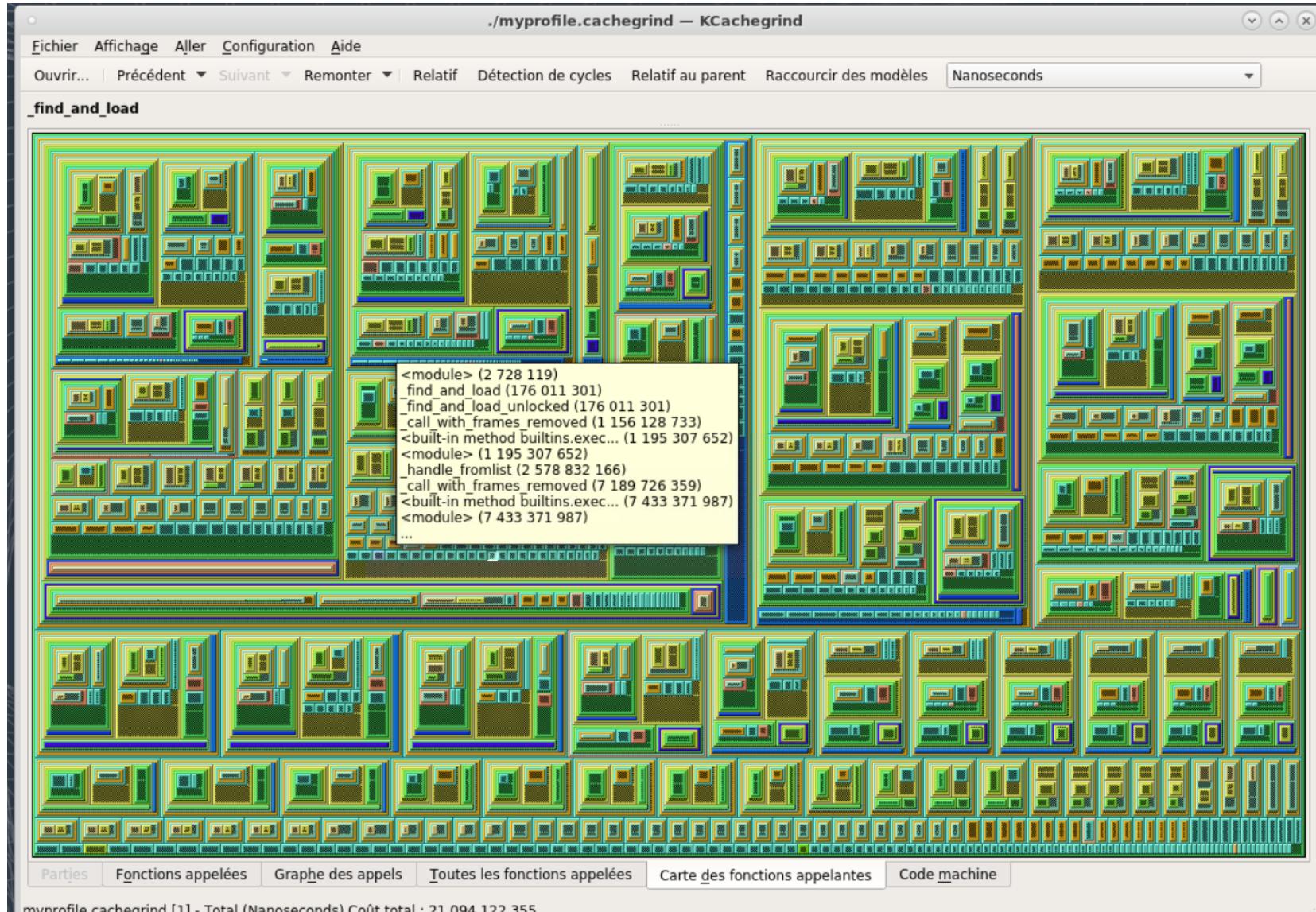
OTHER PROFILER TOOLS

	name	type	output	doc
converter (from pyprof to cachegrind format)	pyprof2calltree	python module	kcacheGrind format	https://pypi.org/project/pyprof2calltree/
profiling visualisation (cachegrind format)	snakeViz	python module	display : flame, sunburst, func. Time table	https://iffyclub.github.io/snakeviz/
	KcacheGrind	software	display : graph call, funct. Time table, func. Box	http://www.vrplumber.com/programming/runsnakerun/
framework to display pyprof info	pstats	python module	print	http://effbot.org/librarybook/pstats.htm

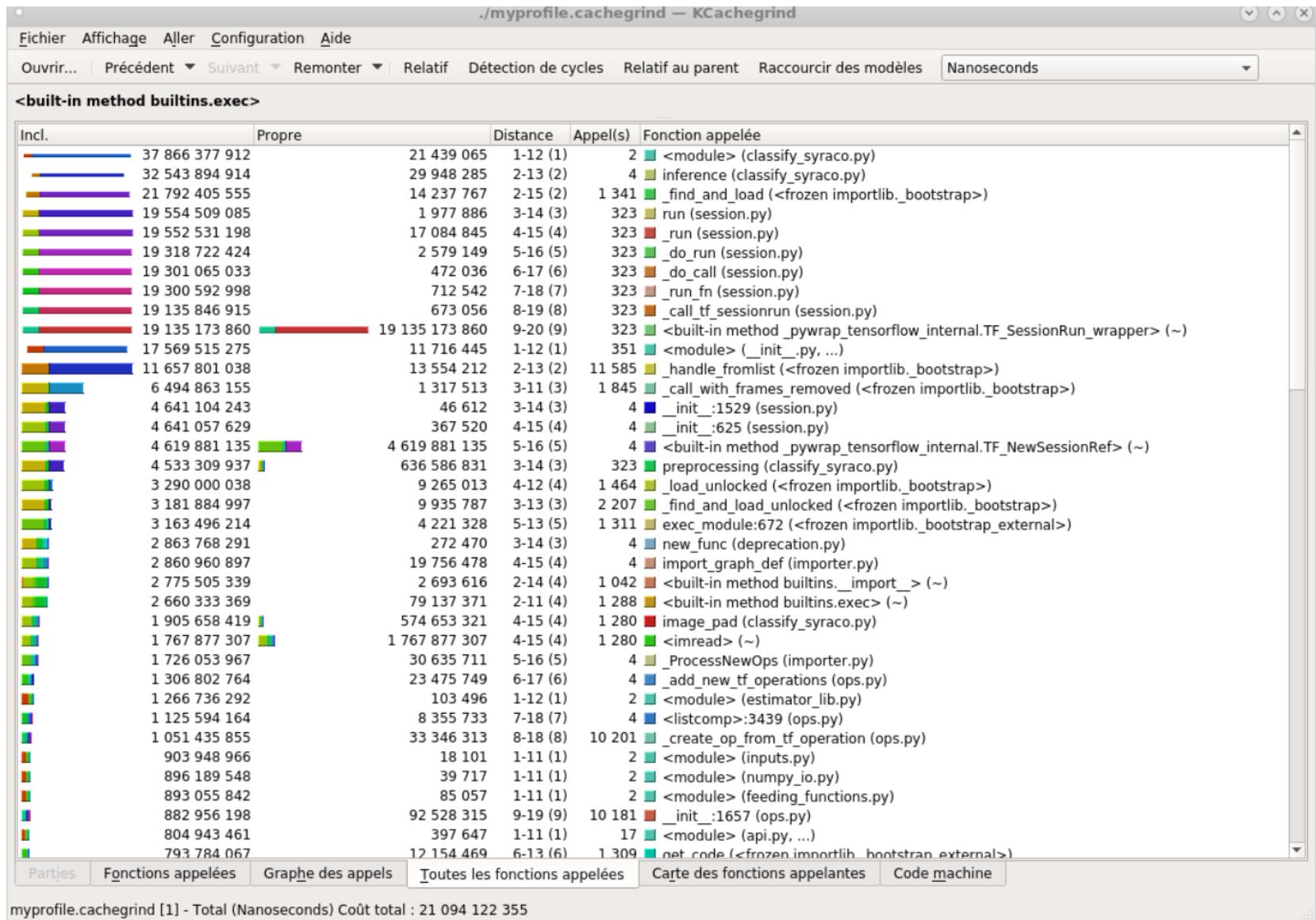
CPROFILE+KCACHEGRIND (SLIDES 1/3)



CPROFILE+KCACHEGRIND (SLIDES 2/3)



CPROFILE+KCACHEGRIND (SLIDES 3/3)

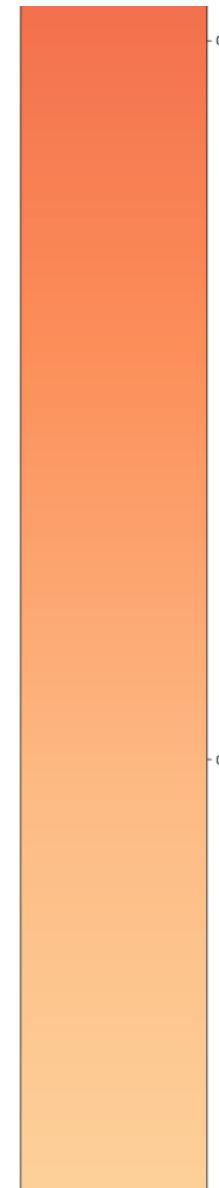


PPROFILE

```
Command line: syraco_deployment/classify_syraco.py syraco_deployment//deep_model/fon_pol_model.pb syraco_deployment//deep_model/morpho_pol_model.pb
syraco_deployment//deep_model/fon_pol_class_name.npy syraco_deployment//deep_model/morpho_pol_class_name.npy
syraco_deployment//Test_Proto-COLOR-A-0000v0n0/Test_Proto-COLOR-A-0000v0n0-06_POL/ 4
Total duration: 70.0431s
File: syraco_deployment/classify_syraco.py
File duration: 2.4714s (3.53%)
Line # |   Hits|     Time| Time per hit|      %|Source code
-----+-----+-----+-----+-----+
 1|     0|     0|     0|  0.00%|
 2|     2| 9.65595e-05| 4.82798e-05| 0.00%|VERBOSE=True
 3|     1| 7.86781e-06| 7.86781e-06| 0.00%|DELETE_IMG=False
 4|     1| 1.23978e-05| 1.23978e-05| 0.00%|import time
 5|     1| 2.76566e-05| 2.76566e-05| 0.00%|import sys
 6|     1| 1.04904e-05| 1.04904e-05| 0.00%|import os
 7|     1| 9.77516e-06| 9.77516e-06| 0.00%|import argparse
 8|     1| 5.48363e-05| 5.48363e-05| 0.00%|import cv2
(call1)|     1| 1.29204| 1.29204| 1.84%|# <frozen importlib._bootstrap>:966 _find_and_load
 9|     1| 1.14441e-05| 1.14441e-05| 0.00%|import numpy as np
10|     1| 5.79357e-05| 5.79357e-05| 0.00%|import tensorflow as tf
(call1)|     1| 25.2203| 25.2203| 36.01%|# <frozen importlib._bootstrap>:966 _find_and_load
11|     1| 6.65188e-05| 6.65188e-05| 0.00%|from scipy.ndimage import zoom
(call1)|     1| 7.82013e-05| 7.82013e-05| 0.00%|# <frozen importlib._bootstrap>:997 _handle_fromlist
12|     0|     0|     0|  0.00%|
13|     0|     0|     0|  0.00%|
14| 1089| 0.00442934| 4.06735e-06| 0.01%|def log(txt):
15|     0|     0|     0|  0.00%|    global VERBOSE
16| 1088| 0.00468659| 4.30753e-06| 0.01%|    if VERBOSE:
17| 1088| 0.0249534| 2.29351e-05| 0.04%|        print(txt)
18|     0|     0|     0|  0.00%|
19|     1| 8.60691e-05| 8.60691e-05| 0.00%|from memory_profiler import profile
(call1)|     1| 0.294606| 0.294606| 0.42%|# <frozen importlib._bootstrap>:966 _find_and_load
(call1)|     1| 4.05312e-05| 4.05312e-05| 0.00%|# <frozen importlib._bootstrap>:997 _handle_fromlist
20|     2| 2.0504e-05| 1.0252e-05| 0.00%|def get_files(folder_image_path):
21|     1| 4.52995e-06| 4.52995e-06| 0.00%|    list_files=[]
22| 364| 0.00229287| 6.2991e-06| 0.00%|    for f in os.listdir(folder_image_path):
23| 363| 0.004318| 1.18953e-05| 0.01%|        path=os.path.join(folder_image_path, f)
(call1)| 363| 0.0231106| 6.36656e-05| 0.03%|# /data/applications/PITSI/users/pochelu/syraco_dl//env/install/Python-3.6.7/lib/python3.6 posixpath.py:75
join
24| 363| 0.00149465| 4.11748e-06| 0.00%|    if path.endswith('.tif','.tiff','.TIF','.TIFF')):
25| 357| 0.00134945| 3.77997e-06| 0.00%|        list_files.append(path)
26|     1| 3.57628e-06| 3.57628e-06| 0.00%|    return list_files
27|     0|     0|     0|  0.00%|
28|     0|     0|     0|  0.00%|
29| 309| 0.00121617| 3.93584e-06| 0.00%|def not_available_line(predict_img,top,NA_string="N/A"):
30| 308| 0.0039475| 1.28165e-05| 0.01%|    nb_score = np.min((predict_img.shape[0], top))
(call1)| 308| 0.0273321| 8.87405e-05| 0.04%|#
/data/applications/PITSI/users/pochelu/syraco_dl//env/install/Python-3.6.7/lib/python3.6/site-packages/numpy/core/fromnumeric.py:2337 amin
31| 308| 0.00129962| 4.21954e-06| 0.00%|    predict_img_txt = ""
32| 1848| 0.00706983| 3.82566e-06| 0.01%|    for i in range(nb_score):
33| 1540| 0.00632644| 4.10808e-06| 0.01%|        predict_img_txt += "\t" + NA_string + "\t" + NA_string
34| 308| 0.00111604| 3.6235e-06| 0.00%|    return predict_img_txt
35|     0|     0|     0|  0.00%|
36|     0|     0|     0|  0.00%|
37|     2| 1.95503e-05| 9.77516e-06| 0.00%|def from_score_to_txt(list_predict_fon, list_predict_morpho, fon_class_name, morpho_class_name,
38|     0|     0|     0|  0.00%|    top, list_images,enable_morpho_classif):
39| 407| 0.00153971| 3.78306e-06| 0.00%|    def img_from_score_to_txt(predict, class_name, top):
40| 406| 0.00555468| 1.36815e-05| 0.01%|        nb_score = np.min((predict.shape[0], top))
(call1)| 406| 0.0361755| 8.91022e-05| 0.05%|#
```

PYHEAT

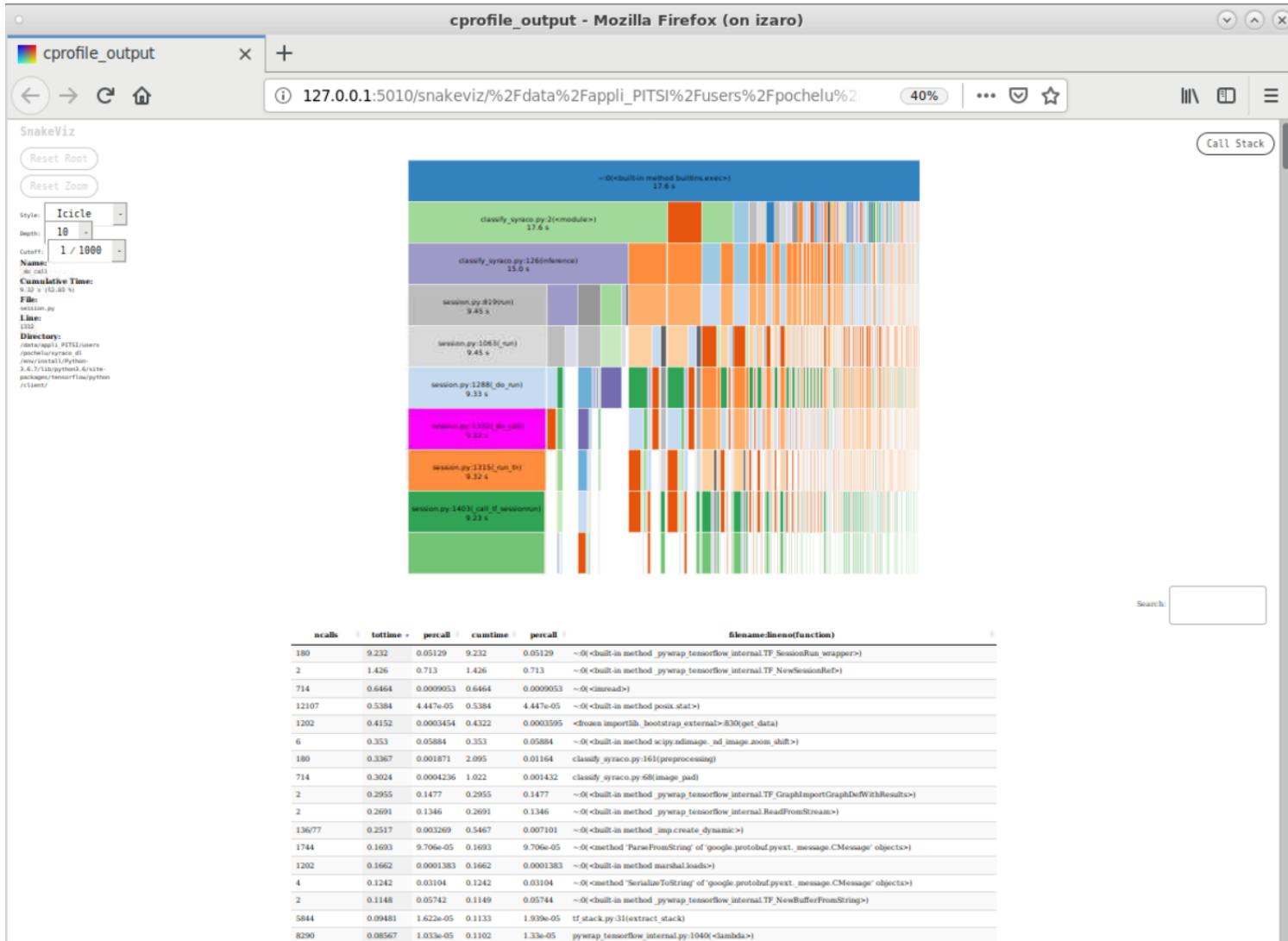
```
123     return out_img  
124  
125  
126 def inference(pb_path, images_path,input_tensor_name="input_1:0",output_tensor_name = "dense_1/Softmax:0",batch_size = 10,nb_classes=-1):  
127     image_size = (224, 224, 3)  
128     top=5  
129  
130  
131     log("Load model...")  
132     sess = tf.Session(config=tf.ConfigProto(allow_soft_placement=True, log_device_placement=False))  
133     with tf.gfile.GFile(pb_path, "rb") as f:  
134         graph_def = tf.GraphDef()  
135         graph_def.ParseFromString(f.read())  
136     #for node in graph_def.node:  
137     #    log(node)  
138     tf.import_graph_def(graph_def, name="")  
139  
140     log("get input/output tensor ...")  
141     newgraph = tf.get_default_graph()  
142     placeholder = newgraph.get_tensor_by_name(input_tensor_name)  
143     tensor_predictions = newgraph.get_tensor_by_name(output_tensor_name)  
144  
145     predict=np.zeros((len(images_path),nb_classes))  
146     for id in range(0, len(images_path), batch_size):  
147         # get path  
148         batch_image_path = images_path[id:id + batch_size]  
149  
150         batch_preprocessed_images = preprocessing(batch_image_path, image_size)  
151  
152         log("run inference...")  
153         batch_predict = sess.run(tensor_predictions, feed_dict={placeholder: batch_preprocessed_images})  
154         predict[id:id+batch_predict.shape[0]]=batch_predict  
155  
156     sess.close()  
157     tf.reset_default_graph()  
158     return predict  
159  
160 def preprocessing(batch_image_path, image_size):  
161     log("Preprocess images...")  
162     # pad images  
163     batch_pad_images = np.zeros((len(batch_image_path), image_size[0], image_size[1], image_size[2]))  
164     for i in range(len(batch_image_path)):  
165         this_image_path = batch_image_path[i]  
166         log(this_image_path)  
167         X = cv2.imread(this_image_path)  
168         if X is not None:  
169             X = cv2.cvtColor(X, cv2.COLOR_BGR2RGB)  
170             X = image_pad(X, image_size[0], image_size[1], channel=image_size[2])  
171             batch_pad_images[i, :, :, :] = X  
172         else:  
173             print("Error this image cannot be read : " + str(this_image_path))  
174             exit()  
175     # normalise batch  
176     batch_pad_images = (batch_pad_images / 255.) * 2. - 1  
177     batch_preprocessed_images = batch_pad_images.reshape(  
178         (batch_pad_images.shape[0], image_size[0], image_size[1], image_size[2]))  
179     return batch_preprocessed_images  
180
```



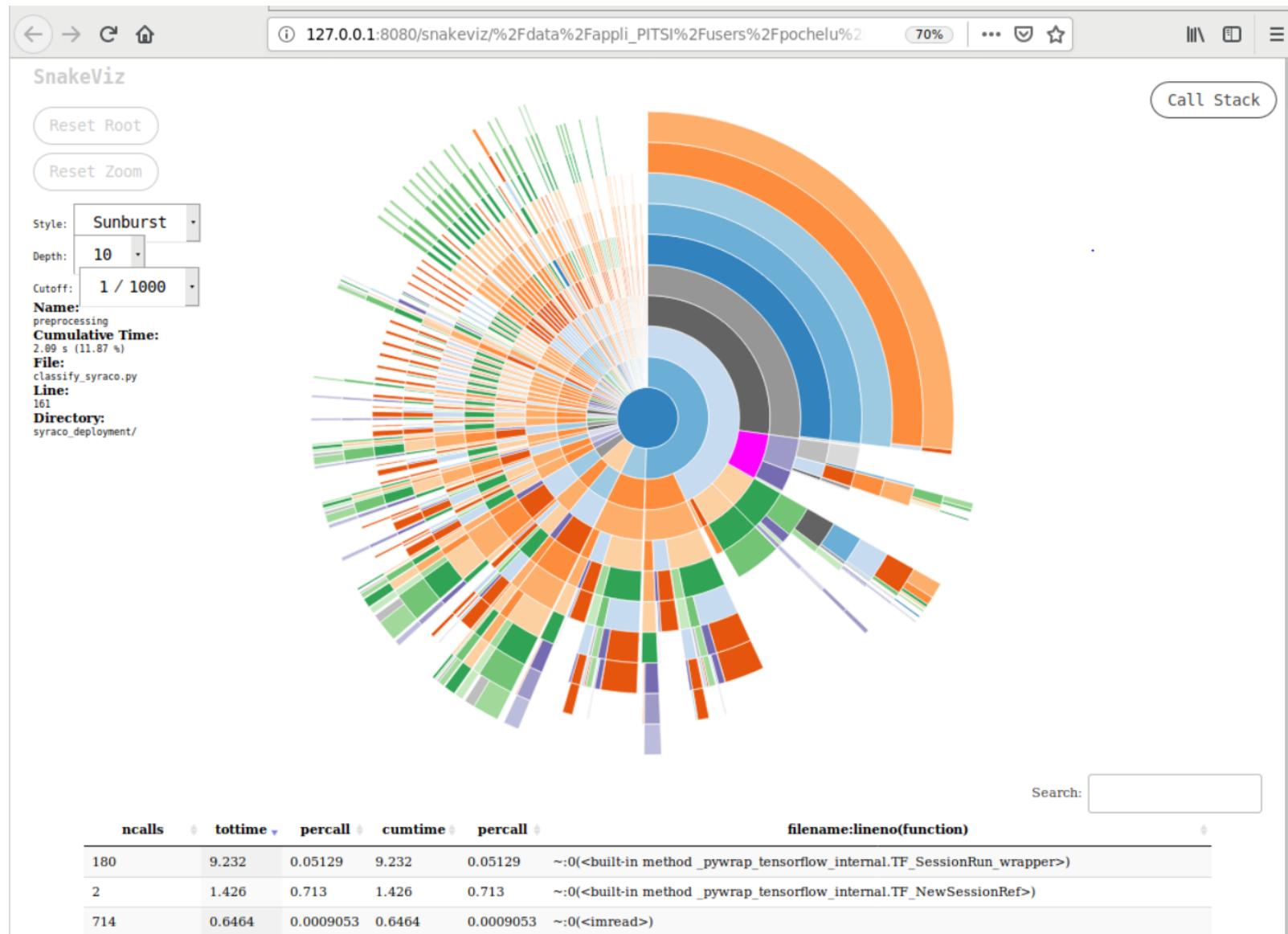
SNAKEVIZ (SLIDES 1/3)

ncalls	tottime	percall	cumtime	percall	filename:lineno(function)
180	17.39	0.09661	17.39	0.09661	~:0(<built-in method _pywrap_tensorflow_internal.TF_SessionRun_wrapper>)
714	0.6617	0.0009267	0.6617	0.0009267	~:0(<imread>)
12098	0.5189	4.289e-05	0.5189	4.289e-05	~:0(<built-in method posix.stat>)
2	0.5001	0.2501	0.5001	0.2501	~:0(<built-in method _pywrap_tensorflow_internal.TF_NewSessionRef>)
6	0.4143	0.06905	0.4143	0.06905	~:0(<built-in method scipy.ndimage._nd_image.zoom_shift>)
180	0.4027	0.002237	2.535	0.01408	classify_syraco.py:161(preprocessing)
1202	0.3923	0.0003264	0.4095	0.0003406	<frozen importlib._bootstrap_external>:830(get_data)
714	0.3784	0.00053	1.259	0.001764	classify_syraco.py:68(image_pad)
2	0.3171	0.1586	0.3171	0.1586	~:0(<built-in method _pywrap_tensorflow_internal.TF_GraphImportGraphDefWithResults>)
2	0.2959	0.148	0.2959	0.148	~:0(<built-in method _pywrap_tensorflow_internal.ReadFromStream>)
136/77	0.2431	0.003157	0.5298	0.00688	~:0(<built-in method _imp.create_dynamic>)
1744	0.2013	0.0001154	0.2013	0.0001154	~:0(<method 'ParseFromString' of 'google.protobuf.pyext._message.CMessage' objects>)
933	0.1843	0.0001975	0.1843	0.0001975	~:0(<built-in method numpy.core.multiarray.zeros>)
1202	0.1685	0.0001402	0.1685	0.0001402	~:0(<built-in method marshal.loads>)
4	0.1377	0.03442	0.1377	0.03442	~:0(<method 'SerializeToString' of 'google.protobuf.pyext._message.CMessage' objects>)
2	0.1202	0.06009	0.1202	0.06012	~:0(<built-in method _pywrap_tensorflow_internal.TF_NewBufferFromString>)
5844	0.1085	1.857e-05	0.1296	2.217e-05	tf_stack.py:31(extract_stack)
8290	0.09339	1.127e-05	0.1226	1.478e-05	pywrap_tensorflow_internal.py:1040(<lambda>)
5341	0.0929	1.739e-05	0.0929	1.739e-05	~:0(<built-in method numpy.core.multiarray.array>)
180	0.08665	0.0004814	0.08665	0.0004814	~:0(<built-in method _pywrap_tensorflow_internal.ExtendSession>)
1454/1	0.08345	0.08345	25.64	25.64	~:0(<built-in method builtins.exec>)
721	0.07459	0.0001035	0.07459	0.0001035	~:0(<built-in method numpy.core.multiarray.crypto>)
257	0.07434	0.0002892	0.07434	0.0002892	~:0(<built-in method posix.listdir>)

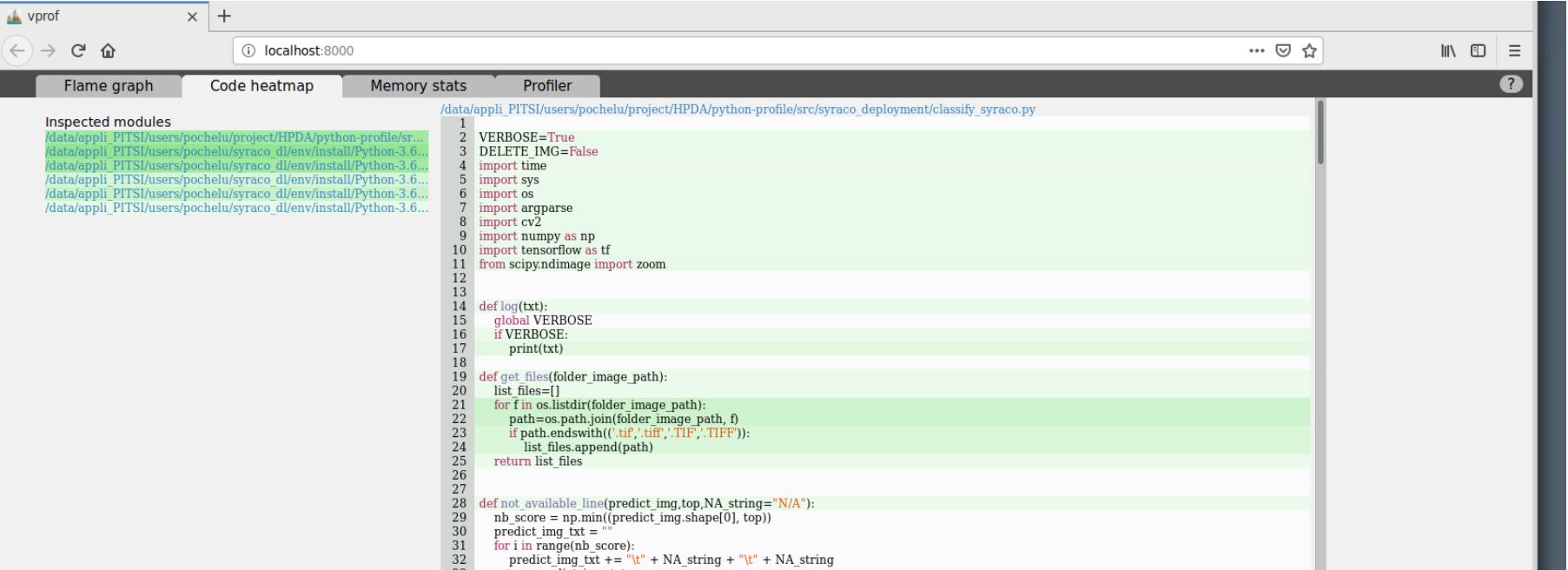
SNAKEVIZ (SLIDES 2/3)



SNAKEVIZ (SLIDES 3/3)



VPROF (SLIDES 1/3)

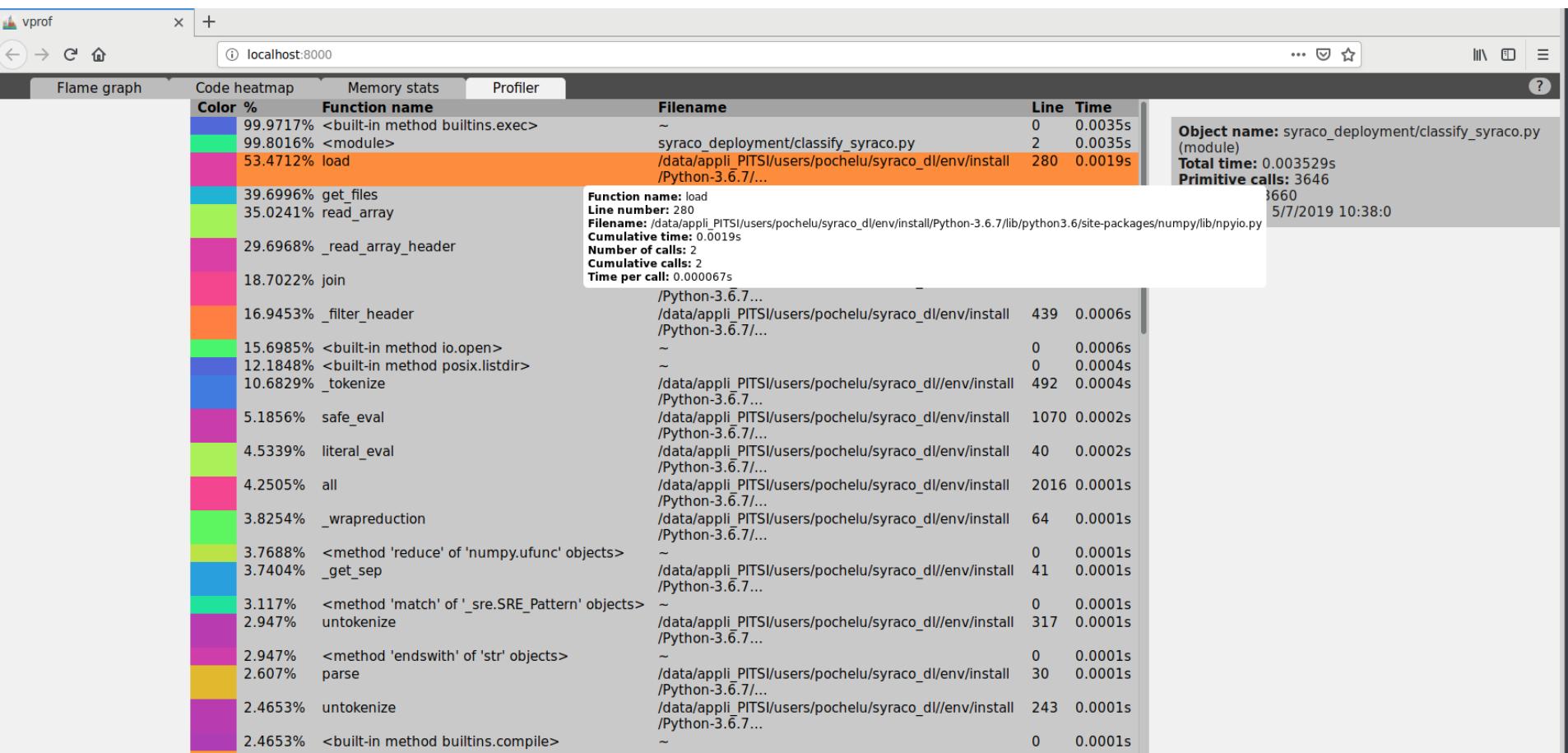


The screenshot shows the vprof web interface at localhost:8000. The top navigation bar includes tabs for 'Flame graph', 'Code heatmap' (which is selected), 'Memory stats', and 'Profiler'. Below the tabs, there's a section titled 'Inspected modules' listing several Python files. The main area displays a code heatmap for the file 'classify_syraco.py'. The code itself is as follows:

```
1  #!/usr/bin/env python
2  VERBOSE=True
3  DELETE_IMG=False
4  import time
5  import sys
6  import os
7  import argparse
8  import cv2
9  import numpy as np
10 import tensorflow as tf
11 from scipy.ndimage import zoom
12
13
14 def log(txt):
15     global VERBOSE
16     if VERBOSE:
17         print(txt)
18
19 def get_files(folder_image_path):
20     list_files=[]
21     for f in os.listdir(folder_image_path):
22         path=os.path.join(folder_image_path, f)
23         if path.endswith(('.tif','.tiff','.TIFF','.TIFFF')):
24             list_files.append(path)
25     return list_files
26
27
28 def not_available_line(predict_img,top,NA_string="N/A"):
29     nb_score = np.min((predict_img.shape[0], top))
30     predict_img_txt = ""
31     for i in range(nb_score):
32         predict_img_txt += "\t" + NA_string + "\t" + NA_string
33     return predict_img_txt
```

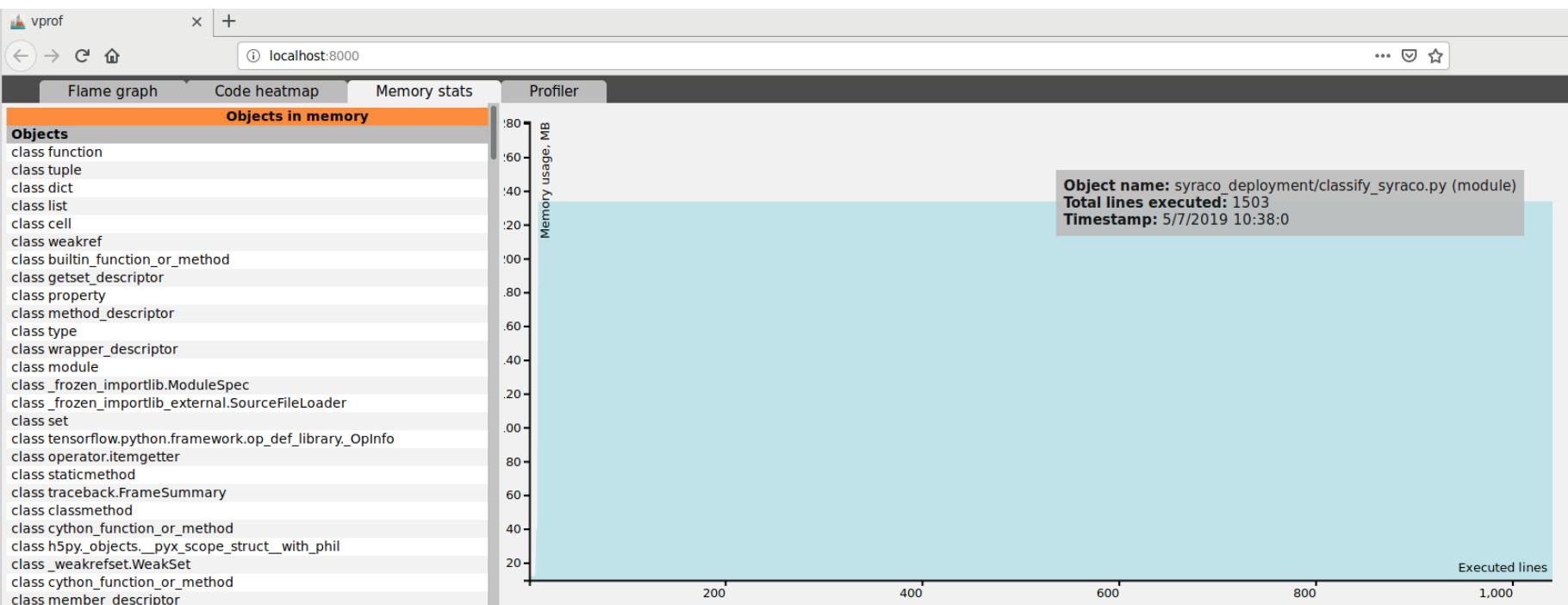
● Warning : Tensorflow run line « block » vprof

VPROF (SLIDES 2/3)



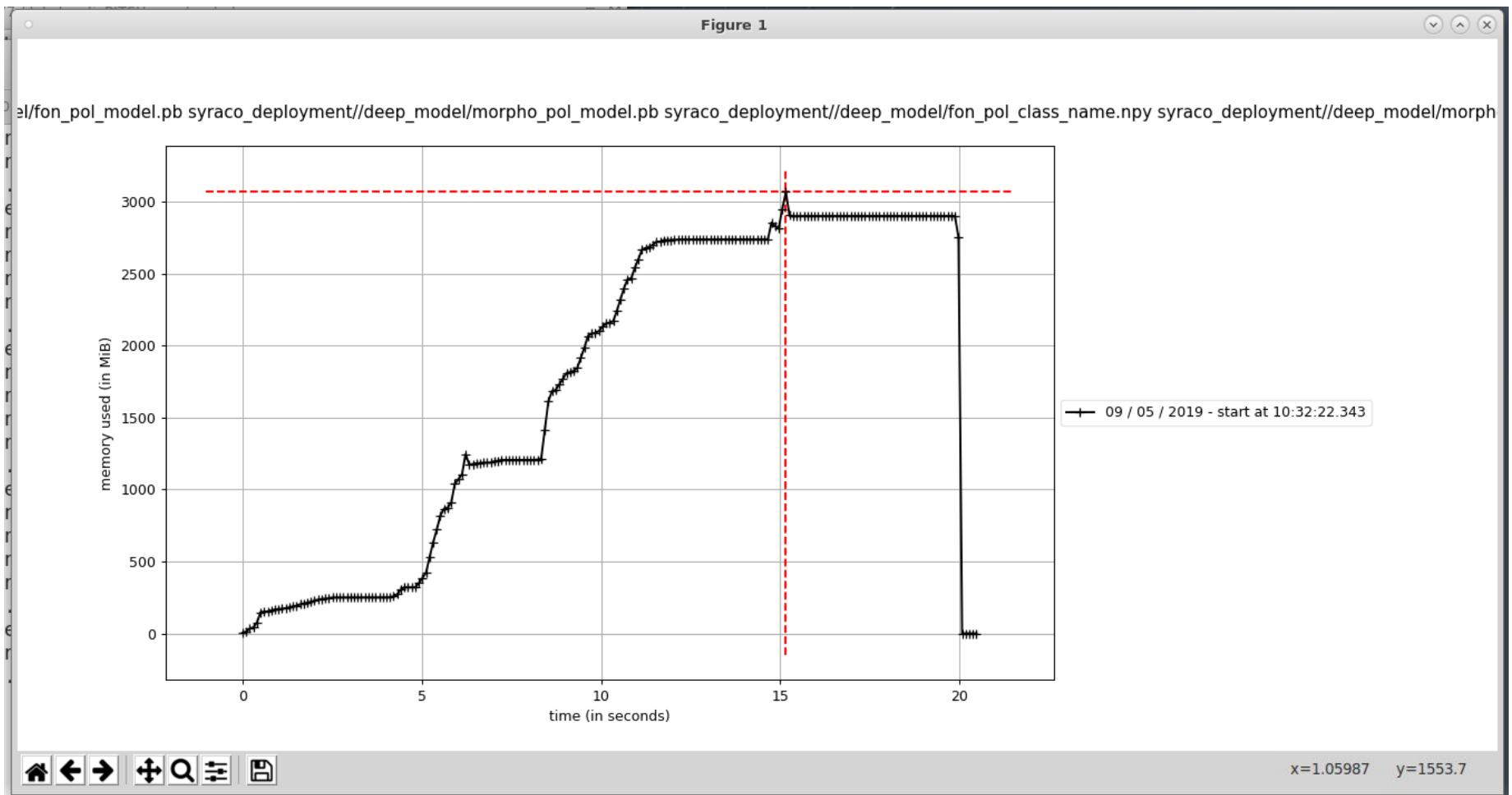
● Warning : Tensorflow run line « block » vprof

VPROF (SLIDES 3/3)



● Warning : Tensorflow run line « block » vprof

MEMORY_PROFILER (SLIDES 1/2)



MEMORY_PROFILER (SLIDES 2/2)

Line #	Mem usage	Increment	Line Contents
126	243.2 MiB	243.2 MiB	@profile
127			def inference(pb_path, images_path, input_tensor_name="input_1:0", output_tensor_name = "dense_1/Softmax:0", batch_size =
128	243.2 MiB	0.0 MiB	10, nb_classes=-1): image_size = (224, 224, 3)
129	243.2 MiB	0.0 MiB	top=5
130			
131			
132	243.2 MiB	0.0 MiB	log("Load model...")
133	883.6 MiB	640.4 MiB	sess = tf.Session(config=tf.ConfigProto(allow_soft_placement=True, log_device_placement=False))
134	883.6 MiB	0.0 MiB	with tf.gfile.GFile(pb_path, "rb") as f:
135	883.6 MiB	0.0 MiB	graph_def = tf.GraphDef()
136	997.4 MiB	113.8 MiB	graph_def.ParseFromString(f.read())
137			# for node in graph_def.node:
138			# log(node)
139	1186.6 MiB	189.3 MiB	tf.import_graph_def(graph_def, name='')
140			
141	1186.6 MiB	0.0 MiB	log("get input/output tensor ...")
142	1186.6 MiB	0.0 MiB	newgraph = tf.get_default_graph()
143	1186.6 MiB	0.0 MiB	placeholder = newgraph.get_tensor_by_name(input_tensor_name)
144	1186.6 MiB	0.0 MiB	tensor_predictions = newgraph.get_tensor_by_name(output_tensor_name)
145			
146	1186.6 MiB	0.0 MiB	predict=np.zeros((len(images_path), nb_classes))
147	2741.3 MiB	0.0 MiB	for id in range(0, len(images_path), batch_size):
148			# get path
149	2741.3 MiB	0.0 MiB	batch_image_path = images_path[id:id + batch_size]
150			
151	2741.3 MiB	8.9 MiB	batch_preprocessed_images = preprocessing(batch_image_path, image_size)
152			
153	2741.3 MiB	0.0 MiB	log("run inference...")
154	2741.3 MiB	1538.0 MiB	batch_predict = sess.run(tensor_predictions, feed_dict={placeholder: batch_preprocessed_images})
155	2741.3 MiB	0.0 MiB	predict[id:id+batch_predict.shape[0]] = batch_predict
156			
157	2741.5 MiB	0.2 MiB	sess.close()
158	2741.5 MiB	0.0 MiB	tf.reset_default_graph()
159	2741.5 MiB	0.0 MiB	return predict

PYMPLER

	types	# objects	total size
	<class 'list'	16727	1.54 MB
	<class 'str'	17726	1.35 MB
	<class 'numpy.ndarray'	4	265.19 KB
	<class 'int'	3279	89.70 KB
	<class 'dict'	15	5.55 KB
	<class 'weakref'	55	4.30 KB
	<class 'type'	0	2.43 KB
	<class 'wrapper_descriptor'	20	1.56 KB
	<class 'method_descriptor'	17	1.20 KB
	<class 'collections.OrderedDict'	2	736 B
	<class 'set'	2	448 B
	<class 'builtin_function_or_method'	2	144 B
	function (store_info)	1	136 B
	function (_remove)	1	136 B
	<class 'tensorflow.python.eager.context._EagerTensorCache'	2	112 B

TENSORFLOW PROFILER (SLIDES 1/2)

Doc:

op: The nodes are operation kernel type, such as MatMul, Conv2D. Graph nodes belonging to the same type are aggregated together.
requested bytes: The memory requested by the operation, accumulatively.
total execution time: Sum of accelerator execution time and cpu execution time.
cpu execution time: The time from the start to the end of the operation. It's the sum of actual cpu run time plus the time that it spends waiting if parallel computation is launched asynchronously.
accelerator execution time: Time spent executing on the accelerator. This is normally measured by the actual hardware library.
occurrence: The number of times it occurs

Profile:

node name	requested bytes	total execution time	accelerator execution time	cpu execution time	op occurrence (run defined)
Conv2D	40069.14MB (100.00%, 99.40%), 95.46%, 94 94	1.63sec (100.00%, 95.56%),	150.07ms (100.00%, 96.73%),	1.48sec (100.00%,	
Sub	0B (0.00%, 0.00%), 2.87%, 94 96	44.57ms (4.44%, 2.62%),	275us (3.27%, 0.18%),	44.28ms (4.54%,	
FusedBatchNorm	97.23MB (0.60%, 0.24%), 0.38%, 94 94	7.27ms (1.82%, 0.43%),	1.39ms (3.09%, 0.90%),	5.86ms (1.68%,	
Mul	72.19KB (0.36%, 0.00%), 188 194	5.28ms (1.39%, 0.31%),	1.18ms (2.19%, 0.76%),	4.07ms (1.30%, 0.26%),	
Add	72.19KB (0.36%, 0.00%), 188 192	5.16ms (1.08%, 0.30%),	1.19ms (1.43%, 0.76%),	3.93ms (1.04%, 0.25%),	
Const	95.63MB (0.36%, 0.24%), 394 781	5.05ms (0.77%, 0.30%),	0us (0.67%, 0.00%),	5.05ms (0.78%, 0.33%),	
Rsqrt	0B (0.00%, 0.00%), 0.10%, 94 94	1.78ms (0.48%, 0.10%),	249us (0.67%, 0.16%),	1.52ms (0.46%,	
Switch	0B (0.00%, 0.00%), 473 570	1.75ms (0.37%, 0.10%),	0us (0.51%, 0.00%),	1.75ms (0.36%, 0.11%),	
Relu	0B (0.00%, 0.00%), 0.09%, 64 95	1.68ms (0.27%, 0.10%),	288us (0.51%, 0.19%),	1.38ms (0.24%,	
ConcatV2	21.62MB (0.12%, 0.05%), 0.05%, 11 15	916us (0.17%, 0.05%),	170us (0.32%, 0.11%),	745us (0.15%,	
AvgPool	17.59MB (0.06%, 0.04%), 0.02%, 9 9	545us (0.12%, 0.03%),	178us (0.21%, 0.11%),	364us (0.11%,	
Merge	384B (0.02%, 0.00%), 0.03%, 96 96	497us (0.08%, 0.03%),	0us (0.10%, 0.00%),	497us (0.08%,	
MatMul	16.64KB (0.02%, 0.00%), 0.02%, 2 2	292us (0.05%, 0.02%),	52us (0.10%, 0.03%),	239us (0.05%,	
MaxPool	5.88MB (0.02%, 0.01%), 0.01%, 4 4	238us (0.04%, 0.01%),	71us (0.06%, 0.05%),	167us (0.03%,	
conv2d_1/convolution-0-TransposeNHWCtoNCHW-LayoutOptimizer	2.41MB (0.01%, 0.01%), 0.01%, 172us (0.02%, 0.01%), 1 1	184us (0.02%, 0.01%),	12us (0.02%,		
Softmax	1.02KB (0.00%, 0.00%), 0.01%, 1 1	129us (0.01%, 0.01%),	11us (0.01%, 0.01%),	117us (0.01%,	
Mean	32.77KB (0.00%, 0.00%), 0.01%, 1 1	91us (0.01%, 0.01%),	6us (0.00%, 0.00%),	84us (0.01%,	

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