Analysing the performance of a tomographic reconstructor with different neural networks frameworks

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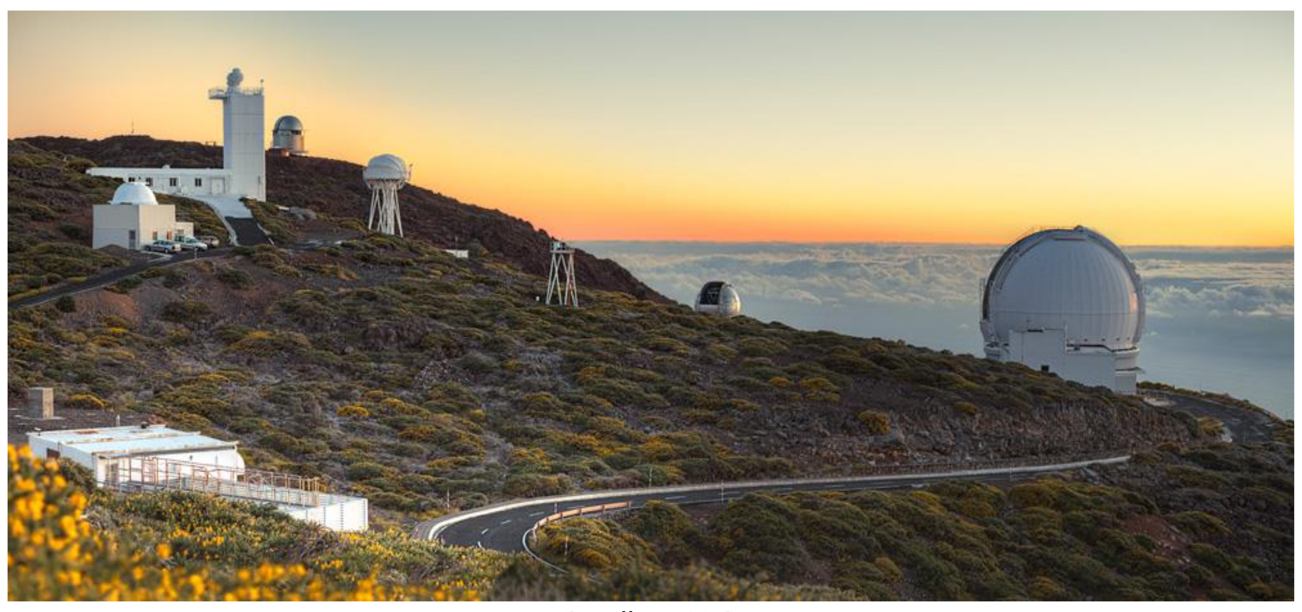

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INTRODUCTION

The next generation of large and extremely large telescopes requires sophisticated Adaptive Optics (AO) instrumentation which exploit tomographic reconstruction algorithms in order to optimise the correction over the full field of view of the telescope.

Open-loop tomographic AO systems such as Multi-Object Adaptive Optics (MOAO) instruments use several guide stars (natural and laser) distributed in the field to probe the turbulent atmosphere. The tomographic reconstructor uses this information to reconstruct the phase aberration along the line of sight to the scientific target, which is not necessarily along the same line as a guide star. MOAO systems include several of these target directions, each of which contain its own wavefront correcting device. MOAO is forced to operate in open-loop as each target direction requires its own reconstructed wavefront from the shared guide star wavefront sensors (WFSs).

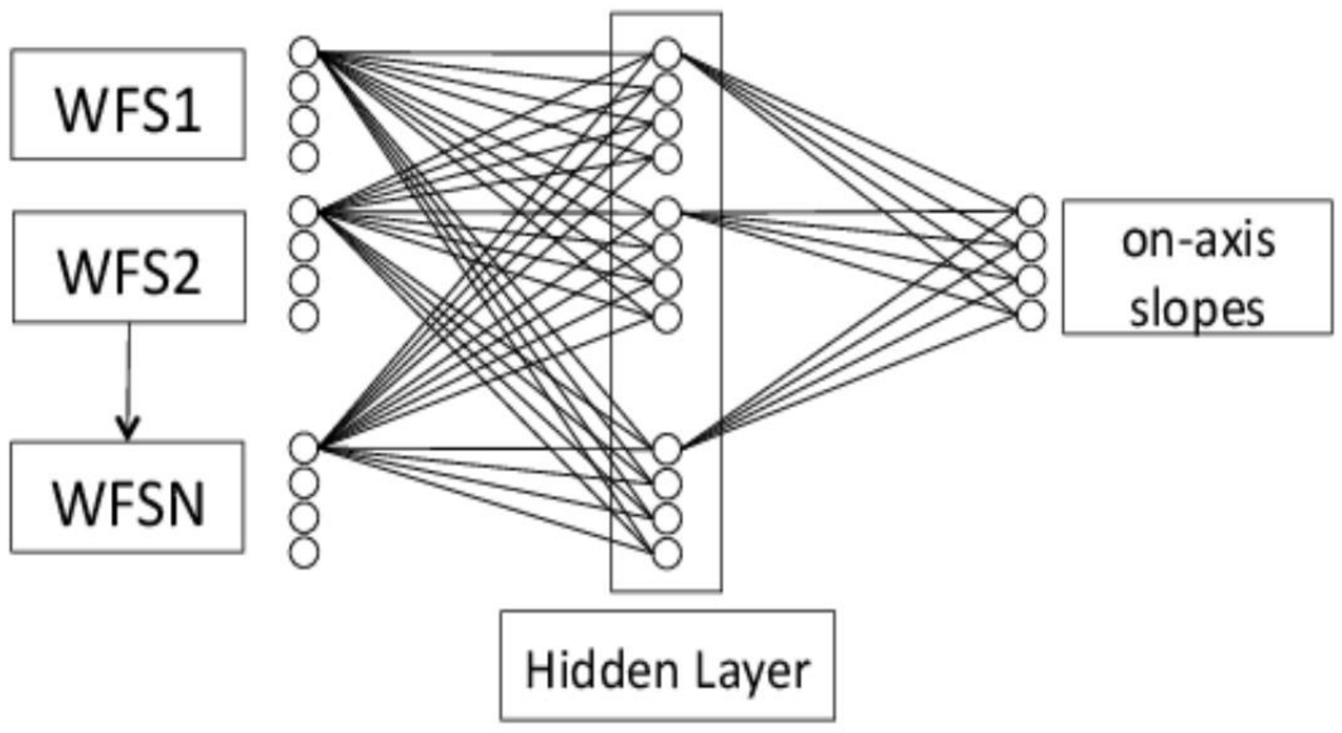
Canary is a flexible adaptive optics (AO) demonstration bench at the 4.2 m William Herschel Telescope (La Palma). Canary is modular by design and is ideally suited to testing and validating many novel ideas and concepts in the field of AO and in the wider field of astronomical instrumentation.

The purpose of this project is to develop an open-loop tomographic reconstructor which is entirely insensitive to changes in the atmosphere optical turbulence profile. In [1] we demonstrated the performance of an ANN implementation of an open-loop tomographic reconstructor, called 'CARMEN' (Complex Atmospheric Reconstructor based on Machine lEarNing), in a Monte-Carlo simulation.

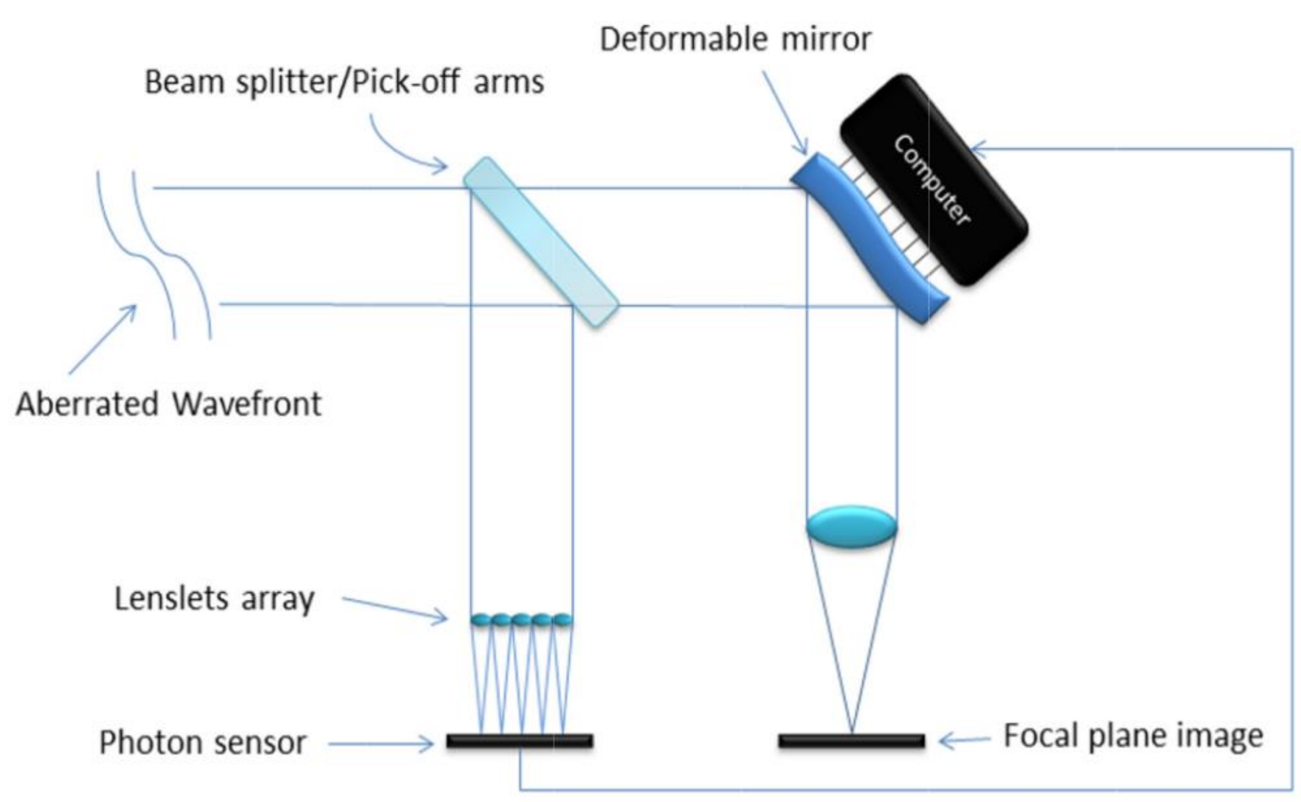
Canary is an ideal AO demonstrator on which to develop this reconstructor. The Canary calibration unit is used to generate the training data sets for CARMEN. We need to generate the training datasets on the same bench as we intend to use on-sky. This is because the neural networks, as with any reconstructor, will be sensitive to the relative alignment errors of the wavefront sensors.

[1] Osborn J., Juez F. J. D. C., Guzman D., Butterley T.,Myers R., Guesalaga A., Laine J., 2012, Opt. Express, 20,2420

CARMEN



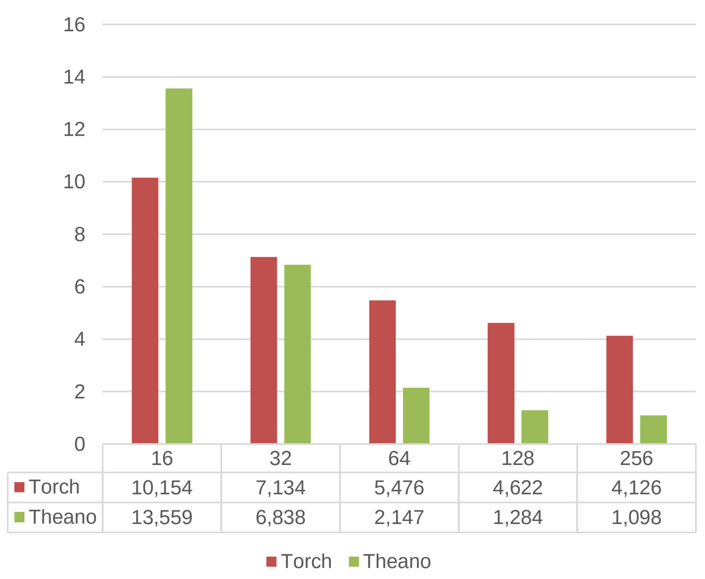
The figure on the left represents a simplified network diagram for CARMEN. All of the slopes from the WFS are input to the network. They are all connected to every neuron in the hidden layer by a synapse. Each neuron in the hidden layer is then connected to every output node. CARMEN will output the predicted on-axis wavefront slopes for the target direction. Each of the synapses has a weighting function. At runtime the inputs are injected into the network which is then processed by the different weighting functions generating a response.



TIME COMPARISONS

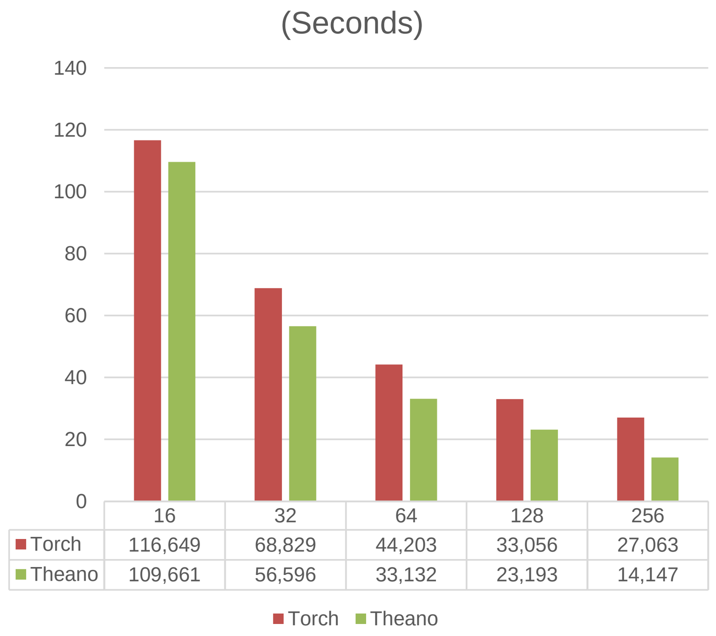
One of the priorities of CARMEN, is to be fast enough to work on extremely large telescopes. There's a long list of different neural networks frameworks, and it would be interesting to compare their time performance in different real-time systems.. In the following tables, you can see a training time comparison between two of the most popular frameworks, Theano and Torch.

CANARY-B1 BENCH
216-216-72 ANN
350,000 data set
Average time per epoch



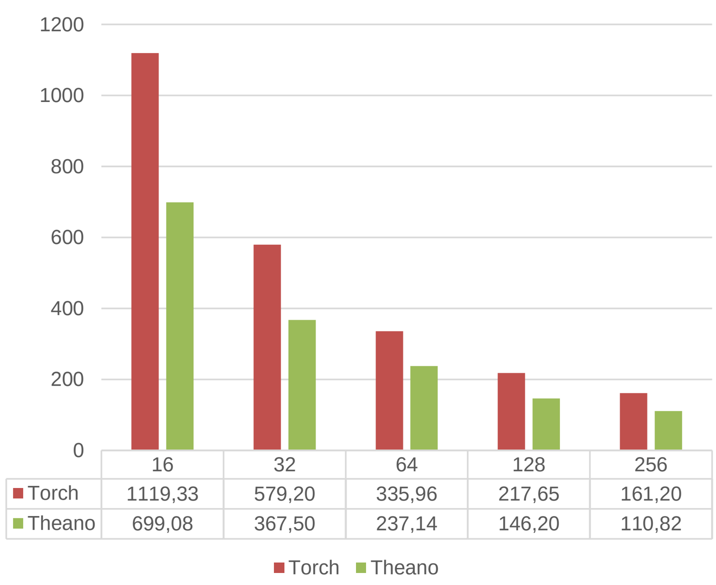
	16	32	64	128	256
Torch	10,154	7,134	5,476	4,622	4,126
Theano	13,559	6,838	2,147	1,284	1,098

CANARY-C2 BENCH
1152-1152-288 ANN
1,500,000 data set
Average time per epoch



	16	32	64	128	256
Torch	116,649	68,829	44,203	33,056	27,063
Theano	109,661	56,596	33,132	23,193	14,147

DRAGON BENCH
7200-7200-1800 ANN
1,000,000 data set
Average time per epoch



	16	32	64	128	256
Torch	1119,33	579,20	335,96	217,65	161,20
Theano	699,08	367,50	237,14	146,20	110,82

Besides the training time, the improvement of the execution speed through the ANN is crucial. Current telescopes provide new information every 2 miliseconds, so it is needed to execute the net as fast as we can.

	CANARY-B1	CANARY-C2	DRAGON
Torch	0.7077 ms	0.9346 ms	3.1777 ms
Theano	0.8182 ms	1.1604 ms	3.5818 ms

Benchmark equipment

- Intel® Xeon(R) CPU E5-1650 v3 @ 3.50GHz (6+6 Cores)
- 2 x GTX Titan X (12Gb VRAM)
- 64 Gb RAM DDR4 (2133MHz)
- 1 TB SSD.

CONCLUSIONS

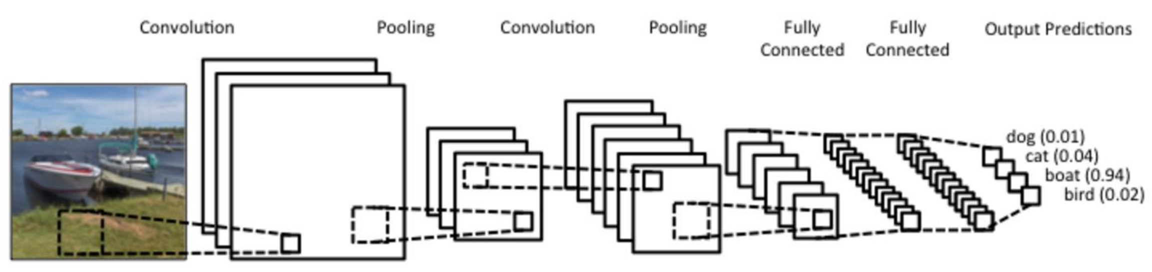
Artificial Neural Networks have been proved to be a really good solution in handling large telescopes. However, the next generation of ELTs needs to work with really large amount of data, and proccess all that information in a short period of time. Is in that moment when neural network frameworks based on GPUs show their power and help us to speed up both training and execution of our tomographic reconstructor.

FUTURE LINES

Native CUDA Code instead of frameworks

NVIDIA CUDA

Convolutional Neural Networks



Recurrent Real Time Learning