DeepOBS

A Deep Learning Optimizer Benchmark Suite

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imprs-is

The Status Quo of Benchmarking Deep Learning Optimizers

...far from optimal!

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Everyone creates their own benchmark

- Repeated work (including bugs)
- Benchmarks are not comparable (not even the metric)
- Potential for cherry-picking

Doing proper benchmarks requires time

- Use of rather small test problems (MNIST)
- Use only a few test problems
- Own optimizer gets more attention than the competition

The Goal of DeepOBS

...we are not quite there yet!

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1. Run the optimizer on a test problem
2. Compare to the state of the art
3. Plot the results

Running your Optimizer

...as simple as possible


```python
import tensorflow as tf
from deepobs import tensorflow as tfobs

optimizer_class = tf.train.RMSPropOptimizer
hyperparams = {"learning_rate": {"type": float},
               "decay": {"type": float, "default": 0.9}}

runner = tfobs.runners.StandardRunner(optimizer_class, hyperparams)
runner.run()
```

Figure: run_rmsprop.py

```
python run_rmsprop.py mnist_mlp --learning_rate=1e-3
```

```
********************************
Evaluating after 0 of 100 epochs...
TRAIN: loss 353.934
VALID: loss 353.813
TEST: loss 353.447
********************************
********************************
Evaluating after 1 of 100 epochs...
TRAIN: loss 338.48
```

The DeepOBS Test Problems

...still room for more

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Data set	Model	Description	Conv	RNN	Drop	BN	WD
2D	Noisy Beale	*Noisy version of the Beale function*					
	Noisy Branin	*Noisy version of the Branin function*					
	Noisy Rosenbrock	*Noisy version of the Rosenbrock function*					
Quadratic	N-Dimensional	*100-dimensional ill-conditioned noisy quadratic*					
MNIST	Log. Regr.	*Logistic regression*					
	MLP	*Four layer fully-connected network*					
	2c2d	*Two conv. and two fully-connected layers*	✓				
	VAE	*Variational Autoencoder*	✓		✓		
Fashion MNIST	Log. Regr.	*Logistic regression*					
	MLP	*Four layer fully-connected network*					
	2c2d	*Two conv. and two fully-connected layers*	✓				
	VAE	*Variational Autoencoder*	✓		✓		
CIFAR-10	3c3d	*Three conv. and three fully-connected layers*	✓				✓
	VGG 16	*Adapted version of VGG 16*	✓		✓		✓
	VGG 19	*Adapted version of VGG 19*	✓		✓		✓
CIFAR-100	3c3d	*Three conv. and three fully-connected layers*	✓				✓
	VGG 16	*Adapted version of VGG 16*	✓		✓		✓
	VGG 19	*Adapted version of VGG 19*	✓		✓		✓
	All-CNN-C	*The all convolutional net*	✓		✓		✓
	Wide ResNet-40-4	*Wide Residual Network*	✓			✓	✓
SVHN	3c3d	*Three conv. and three fully-connected layers*	✓				✓
	Wide ResNet-16-4	*Wide Residual Network*	✓			✓	✓
ImageNet	VGG 16	*VGG 16*	✓		✓		✓
	VGG 19	*VGG 19*	✓		✓		✓
	Inception-v3	*Inception-v3 network*	✓		✓	✓	✓
Tolstoi	CharRNN	*Recurrent Neural Network for character-level language modeling*		✓	✓		

Running your Optimizer

...the results


```
results
└── quadratic_deep
    └── RMSPropOptimizer
        ├── num_epochs__100__batch_size__128__decay__9.e-01__learning_rate__1.e-02
        │   ├── random_seed__42__2019-09-27-15-15-59.json
        │   └── random_seed__43__2019-09-27-15-19-33.json
        └── num_epochs__100__batch_size__128__decay__9.e-01__learning_rate__1.e-03
            └── random_seed__42__2019-09-27-15-01-49.json
```

Tuning your Hyperparameters

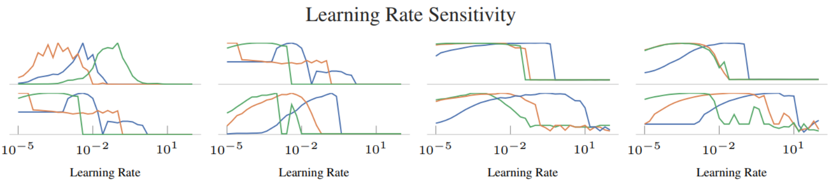
...a semi-automated process

```python
import numpy as np
from torch.optim import SGD
from deepobs.pytorch.runners import StandardRunner
from deepobs.tuner import GridSearch

optimizer_class = SGD
hyperparams = {"lr": {"type": float}}

grid = {"lr": np.logspace(-5, 2, 6)}

tuner = GridSearch(optimizer_class, hyperparams, grid, runner=StandardRunner)

tuner.tune('quadratic_deep', rerun_best_setting=True)
```

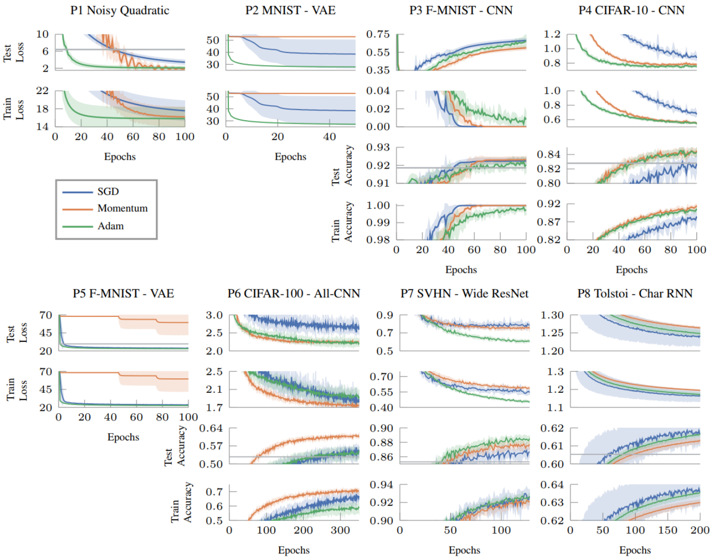
Plotting the Results

...getting page 7 of your paper


```
deepobs_plot_results results/ --full
```



```
deepobs_plot_results results/ --full
```



Plotting the Results

...getting page 7 of your paper

```
deepobs_plot_results results/ --full
```

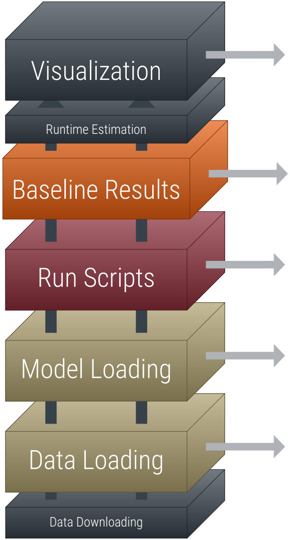
Table 2: DEEPOBS benchmark for the baseline optimizers.

Test Problem		SGD	Momentum	Adam
P1 Noisy Quadratic	Performance	3.42	1.92	2.08
	Speed	45.60	36.90	9.00
	Tuneability	α: 3.98e-03	α:3.98e-04 μ: 0.99	α: 1.00e-01 ϵ: 1e-08 β_1: 0.9 β_2: 0.999
P2 MNIST VAE	Performance	38.54	52.97	27.86
	Speed	1.00	1.00	1.00
	Tuneability	α: 3.98e-03	α: 1.58e-05 μ: 0.99	α: 1.58e-04 ϵ: 1e-08 β_1: 0.9 β_2: 0.999
P3 F-MNIST CNN	Performance	92.25 %	92.32 %	92.03 %
	Speed	38.70	51.10	39.20
	Tuneability	α: 1.58e-01	α: 1.00e-03 μ: 0.99	α: 2.51e-04 ϵ: 1e-08 β_1: 0.9 β_2: 0.999
P4 CIFAR-10 CNN	Performance	82.76 %	84.53 %	84.30 %
	Speed	77.10	41.00	44.60
	Tuneability	α: 1.58e-02	α: 3.98e-04 μ: 0.99	α: 2.51e-04 ϵ: 1e-08 β_1: 0.9 β_2: 0.999

Test Problem		SGD	Momentum	Adam
P5 F-MNIST VAE	Performance	23.94	59.44	23.11
	Speed	3.90	93.30	1.50
	Tuneability	α: 3.98e-03	α: 2.51e-04 μ: 0.99	α: 1.58e-04 ϵ: 1e-08 β_1: 0.9 β_2: 0.999
P6 CIFAR-100 All CNN C	Performance	55.39 %	60.79 %	54.34 %
	Speed	167.40	72.20	194.00
	Tuneability	α: 1.58e-01	α: 3.98e-03 μ: 0.99	α: 1.00e-03 ϵ: 1e-08 β_1: 0.9 β_2: 0.999
P7 SVHN Wide ResNet	Performance	86.69 %	87.74 %	88.53 %
	Speed	40.00	42.10	34.60
	Tuneability	α: 2.51e-01	α: 3.98e-03 μ: 0.99	α: 6.31e-04 ϵ: 1e-08 β_1: 0.9 β_2: 0.999
P8 TOLSTOI Char RNN	Performance	61.71 %	61.29 %	61.68 %
	Speed	57.90	96.30	79.20
	Tuneability	α: 2.51e+00	α: 3.98e-02 μ: 0.99	α: 6.31e-04 ϵ: 1e-08 β_1: 0.9 β_2: 0.999

The DeepOBS Stack

...a modular environment



`.tex` files of learning curves for new optimizer and the baselines.

Performances results of the most popular optimizers.

Optimization performance of an optimizer on a specific test problem.

Losses and accuracy of a deep learning model.

Pre-processed and batched data.

The DeepOBS Leaderboard

...a work in progress

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Leaderboard

Overview over the current optimizer leaderboard on the DeepOBS test problems. Click on See Full Results to see the plots and tables of the full benchmarking results.

Quadratic Deep

A 100-dimensional noisy quadratic problem with an eigenspectrum similar to the one reported for deep neural networks.

	Optimizer	Test Loss	Speed
#1	Momentum	87.05	70.5
#2	Adam	87.11	39.9
#3	SGD	87.40	51.1

See Full Results

MNIST - VAE

A basic variational autoencoder for the MNIST data set with three convolutional and three deconvolutional layers.

	Optimizer	Test Loss	Speed
#1	Adam	27.83	1.0
#2	SGD	38.46	1.0
#3	Momentum	52.93	1.0

See Full Results

F-MNIST - CNN

A simple convolutional network for the Fashion-MNIST data set, consisting of two conv and two fully-connected layers.

	Optimizer	Test Accuracy	Speed
#1	Adam	92.34 %	40.1
#2	SGD	92.27 %	40.6
#3	Momentum	92.14 %	59.1

See Full Results

CIFAR-10 - CNN

A slightly larger convolutional network for the Cifar-10 data set, with three conv and three fully-connected layers.

	Optimizer	Test Accuracy	Speed
#1	Adam	84.75 %	36.0
#2	Momentum	84.41 %	40.7
#3	SGD	83.71 %	42.5

See Full Results

F-MNIST - VAE

A basic variational autoencoder for the Fashion-MNIST data set with three convolutional and three deconvolutional layers.

	Optimizer	Test Loss	Speed
#1	Adam	23.07	1.0
#2	SGD	23.80	1.0
#3	Momentum	59.23	1.0

See Full Results

CIFAR-100 - All CNN C

Variant C of the All Convolutional Network from **Striving for Simplicity** for the CIFAR-100 data set consisting solely of convolutional layers.

	Optimizer	Test Accuracy	Speed
#1	Momentum	60.33 %	72.8
#2	SGD	57.06 %	128.7
#3	Adam	56.15 %	152.6

See Full Results

SVHN - Wide ResNet 16-4

The **Wide ResNet 16-4** for the Street View House Numbers data set using the variant with 16 conv layers and a widening factor of 4.

	Optimizer	Test Accuracy	Speed
#1	Momentum	95.53 %	10.8
#2	SGD	95.37 %	28.3
#3	Adam	95.25 %	12.1

See Full Results

Tolstoi - Char RNN

A recurrent neural network for character-level language modeling on the novel *War and Peace* by *Leo Tolstoy* using two LSTM layers.

	Optimizer	Test Accuracy	Speed
#1	SGD	62.07 %	47.7
#2	Momentum	61.30 %	88.0
#3	Adam	61.23 %	62.8

See Full Results

The DeepOBS Leaderboard

...a work in progress

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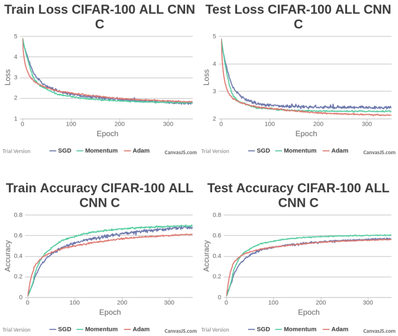

Overview Table

Rank	Optimizer	Final Test Accuracy	Best Test Accuracy	Final Train Accuracy	Best Train Accuracy	Final Test Loss	Best Test Loss	Final Train Loss	Best Train Loss	Speed
1	Momentum	60.33%	60.83%	69.25%	70.25%	2.29	2.24	1.79	1.75	72.8
2	SGD	57.06%	57.77%	68.48%	69.31%	2.39	2.36	1.74	1.70	128.7
3	Adam	56.15%	56.41%	60.89%	61.52%	2.13	2.12	1.83	1.81	152.6

The DeepOBS ecosystem

...lots of ways to participate

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>_ Install DeepOBS

```
pip install deepobs
```

TensorFlow

PyTorch
Coming soon

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Check out Github for the Beta of DeepOBS 1.2.0

`fsschneider.github.io/DeepOBS`