Harnessing second order optimizers from deep learning frameworks

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Background

- Methods like L-BFGS and conjugate gradient (CG) were the go-to methods in the pre-deep learning era
 - e.g., minimize.m
- What changed in DL?
 - Huge data sets ⇒ exact gradients infeasible so we needed SGD
 - Luckily in DL tasks, SGD tends to work better anyway
- But, optimization is a broader problem than weights of a deep net
- In other problems with exact gradients, traditional optimization can work better
- Also, works without hyper-parameter tuning and tricks
- Better handling of constraints



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Examples

- **Calibration layers**
- 0
- Deep dream Adversarial examples General (OR-style) optimization e.g., portfolio optimization
- etc











Motivation (Scenario)

- Have a cool objective function to optimize
 - No giant data \Rightarrow Nice, we don't need stochastic gradients
 - Derivatives are complex, several tensors to optimize ⇒ no problem, we have autodiff
 - Maybe, weird conditioning ⇒ no problem, we have second order optimizers
- But faced with 2 options:
 - Use autodiff package SGD (the new world):
 - Only simple gradient descent
 - Must tune hyper-parameters 😞
 - Often requires tricks (grad-norm, grad-clip, ...) 😞
 - Or scipy optimize (the old world)
 - Many optimization options 😀
 - Principled support for constraints and bounds <a>li>
 - Only optimizes vectors -
 - Doesn't play nice with autodiff packages
 - Was built assuming you write gradients manually

In Python, go to is SciPy for 2nd order optimization scipy.optimize.minimize

- But it expects a f(x), where x is ndarray of shape (n,)
- We like the style of TensorFlow/PyTorch optimization where x = {'foo': A, 'bar': B, ...}
 - a. And A and B are arbitrary shaped tensors
- Scipy requires:
 - a. Packing into a vector
 - b. Converting everything into numpy
 - c. Even needs to be float64
- Becomes repetitive hassle
- So, dict-minimize can take care of this for you

scipy.optimize.minimize(fun, x0, args=0, method=None, jac=None, hess=None, hessp=None, bounds=None, constraints=(), tol=None, callback=None, options=None) [source]

Minimization of scalar function of one or more variables.

Parameters: fun : callable

The objective function to be minimized. fun(x, *args) -> float

where \mathbf{x} is an 1-D array with shape (n,) and $\arg \mathbf{s}$ is a tuple of the fixed parameters needed to completely specify the function.

x0 : ndarray, shape (n,)

Initial guess. Array of real elements of size (n,), where 'n' is the number of independent variables.

args : tuple, optional

Extra arguments passed to the objective function and its derivatives (fun, jac and hess functions).

method : str or callable, optional

- Type of solver. Should be one of
- 'Nelder-Mead' (see here)
- 'Powell' (see here)
- 'CG' (see here)
- 'BFGS' (see here)
- 'Newton-CG' (see here)
- 'L-BFGS-B' (see here)
- 'TNC' (see here)
- 'COBYLA' (see here)
- 'SLSQP' (see here)
- 'trust-constr'(see here)
- 'dogleg' (see here)
- 'trust-ncg' (see here)
- 'trust-exact' (see here)
- 'trust-krylov' (see here)
- custom a callable object (added in version 0.14.0), see below for description.

Dict-minimize

- Gives use the dictionary of parameters interface we want
- Provides interfaces too:
 - TensorFlow
 - **PyTorch**
 - JĂX
 - NumPy
- Try it out whenever you can handle exact gradients
- Usually
 - no hyper-parameter tuning is required
 - no gradient manipulation tricks 😀
- People have been conditioned to use SGD in all optimization use cases instead of where it is needed
 - Try out alternatives when you can



Want API simplicity

Just replace: from scipy.optimize import minimize

with

from dict_minimize.torch_api import minimize or from dict_minimize.tensorflow_api import minimize or from dict_minimize.jax_api import minimize or from dict_minimize.numpy_api import minimize Mirrors the original SciPy API



Now Examples!

Rosenbrock in all 4 frameworks here

- Rosenbrock is MNIST of optimization Show that all the built in algos work without tricks





Apply to DeepDream

- Optimize wrt the input with weights fixed
 - → no giant dataset ⇒ we can get exact grad
- Visualize neurons in InceptionV3
 - Optimize input w.r.t. activations
- Mid-layers responds to texture
- Another advantage of dict-minimize:
 - Built in support for bounds (pixel must be in [0,1])
 - No clipping tricks
- No hyper-parameters to tune with L-BFGS
 - SGD version requires tricks (gradient norm and gradient clipping)
 - L-BFGS version: just use the actual gradient, no need to manipulate it with tricks
- Just works

Crocodile texture a lab 😮

video





Apply to DeepDream





pip install dict_minimize

GitHub | Read the Docs | PyPI | Blog



Thank you