

import numpy as np

"""
This file implements various first-order update rules that are commonly used for
training neural networks. Each update rule accepts current weights and the
gradient of the loss with respect to those weights and produces the next set of
weights. Each update rule has the same interface:

def update(w, dw, config=None):

Inputs:

- w: A numpy array giving the current weights.
- dw: A numpy array of the same shape as w giving the gradient of the loss with respect to w.
- config: A dictionary containing hyperparameter values such as learning rate, momentum, etc. If the update rule requires caching values over many iterations, then config will also hold these cached values.

Returns:

- next\_w: The next point after the update.
- config: The config dictionary to be passed to the next iteration of the update rule.

NOTE: For most update rules, the default learning rate will probably not perform well; however the default values of the other hyperparameters should work well for a variety of different problems.

For efficiency, update rules may perform in-place updates, mutating w and setting next\_w equal to w.

def sgd(w, dw, config=None):

"""
Performs vanilla stochastic gradient descent.

config format:

- learning\_rate: Scalar learning rate.

if config is None: config = {}
config.setdefault('learning\_rate', 1e-2)

w -= config['learning\_rate'] \* dw
return w, config

def sgd\_momentum(w, dw, config=None):

"""
Performs stochastic gradient descent with momentum.

config format:

- learning\_rate: Scalar learning rate.
- momentum: Scalar between 0 and 1 giving the momentum value. Setting momentum = 0 reduces to sgd.
- velocity: A numpy array of the same shape as w and dw used to store a moving average of the gradients.

if config is None: config = {}
config.setdefault('learning\_rate', 1e-2)
config.setdefault('momentum', 0.9) # set momentum to 0.9 if it wasn't there
v = config.get('velocity', np.zeros\_like(w)) # gets velocity, else sets it to zero.

# ===== #
# YOUR CODE HERE:
# Implement the momentum update formula. Return the updated weights
# as next\_w, and the updated velocity as v.
# ===== #

v = config['momentum'] \* v - config['learning\_rate'] \* dw
next\_w = w + v

# ===== #
# END YOUR CODE HERE
# ===== #

config['velocity'] = v

return next\_w, config

def sgd\_nesterov\_momentum(w, dw, config=None):

"""
Performs stochastic gradient descent with Nesterov momentum.

config format:

- learning\_rate: Scalar learning rate.
- momentum: Scalar between 0 and 1 giving the momentum value. Setting momentum = 0 reduces to sgd.
- velocity: A numpy array of the same shape as w and dw used to store a moving average of the gradients.

if config is None: config = {}
config.setdefault('learning\_rate', 1e-2)
config.setdefault('momentum', 0.9) # set momentum to 0.9 if it wasn't there
v = config.get('velocity', np.zeros\_like(w)) # gets velocity, else sets it to zero.

# ===== #
# YOUR CODE HERE:
# Implement the momentum update formula. Return the updated weights
# as next\_w, and the updated velocity as v.
# ===== #

# Use change of vars implementation
v\_old = v
v = config['momentum'] \* v - config['learning\_rate'] \* dw
next\_w = w + v + config['momentum'] \* (v - v\_old)

# ===== #
# END YOUR CODE HERE
# ===== #

config['velocity'] = v

return next\_w, config

def rmsprop(w, dw, config=None):

"""
Uses the RMSProp update rule, which uses a moving average of squared gradient values to set adaptive per-parameter learning rates.

config format:

- learning\_rate: Scalar learning rate.
- decay\_rate: Scalar between 0 and 1 giving the decay rate for the squared gradient cache.
- epsilon: Small scalar used for smoothing to avoid dividing by zero.
- beta: Moving average of second moments of gradients.

if config is None: config = {}
config.setdefault('learning\_rate', 1e-2)
config.setdefault('decay\_rate', 0.99)
config.setdefault('epsilon', 1e-8)
config.setdefault('a', np.zeros\_like(w))

next\_w = None

# ===== #
# YOUR CODE HERE:
# Implement RMSProp. Store the next value of w as next\_w. You need
# to also store in config['a'] the moving average of the second
# moment gradients, so they can be used for future gradients. Concretely,
# config['a'] corresponds to "a" in the lecture notes.
# ===== #

config['a'] = config['a'] \* config['decay\_rate'] + (1-config['decay\_rate']) \* dw\*\*2
next\_w = w - config['learning\_rate']/(np.sqrt(config['a'] + config['epsilon']) \* dw

# ===== #
# END YOUR CODE HERE
# ===== #

return next\_w, config

def adam(w, dw, config=None):

"""
Uses the Adam update rule, which incorporates moving averages of both the gradient and its square and a bias correction term.

config format:

- learning\_rate: Scalar learning rate.
- beta1: Decay rate for moving average of first moment of gradient.
- beta2: Decay rate for moving average of second moment of gradient.
- epsilon: Small scalar used for smoothing to avoid dividing by zero.
- m: Moving average of gradient.
- v: Moving average of squared gradient.
- t: Iteration number.

if config is None: config = {}
config.setdefault('learning\_rate', 1e-3)
config.setdefault('beta1', 0.9)
config.setdefault('beta2', 0.999)
config.setdefault('epsilon', 1e-8)
config.setdefault('v', np.zeros\_like(w))
config.setdefault('a', np.zeros\_like(w))
config.setdefault('t', 0)

next\_w = None

# ===== #
# YOUR CODE HERE:
# Implement Adam. Store the next value of w as next\_w. You need
# to also store in config['a'] the moving average of the second
# moment gradients, and in config['v'] the moving average of the
# first moments. Finally, store in config['t'] the increasing time.
# ===== #

config['t'] += 1

# Moment Updates
config['v'] = config['beta1'] \* config['v'] + (1-config['beta1']) \* dw
config['a'] = config['beta2'] \* config['a'] + (1-config['beta2']) \* dw\*\*2

# Bias Corection
v\_corr = config['v'] / (1-config['beta1]\*\*config['t'])
a\_corr = config['a'] / (1-config['beta2]\*\*config['t'])

# Param Update
next\_w = w - config['learning\_rate']/(np.sqrt(a\_corr) + config['epsilon']) \* v\_corr

# ===== #
# END YOUR CODE HERE
# ===== #

return next\_w, config