# Stochastic Gradient Descent in Python

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# 1 Stochastic Gradient Descent Module

Download the SGD module from https://github.com/CU-UQ/SGD. See the demo (sgd\_demo.py) for an example of the implementation.

For a description of the algorithms see Ruder (2016).

Required packages: numpy, time

NOTE: Currently, the stopping conditions are maximum number of iteration and 2nd norm of gradient vector. Only time-based and exponential learning schedules are implemented.

Report any bugs to Subhayan.De@colorado.edu

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# 2 Algorithms implemented

A module named StochasticGradientDescent has been created where as of February, 2019, twelve different stochastic gradient descent algorithms have been implemented, namely,

- stochastic gradient descent (class name SGD)
  - with momentum
  - with Nesterov momentum (NAG)
- mini-batch gradient descent (class name minibatchSGD)
- RMSprop (class name RMSprop)

- AdaGrad (class name AdaGrad)
- Adam (class name Adam)
- Adamax (class name Adamax)
- Nesterov accelerated Adam (class name Nadam)
- Adadelta (class name Adadelta)
- Stochastic average gradient (class name SAG)
- Stochastic variance reduced gradient descent (class name SVRG)

#### 2.1 SGD class:

```
Stochastic Gradient Descent class
Initialization:
sgd = SGD(obj, grad, eta, param, iter, maxIter, objFun, gradFun,
lowerBound, upperBound, stopGrad, momentum, nesterov,
learnSched, lrParam)
NOTE: To perform just one iteration provide either grad or graduFn.
obj or objFun are optional.
______
Attributes:
           objective (optional input)
obi:
           Gradient information
grad:
(array of dimension nParam-by-1, optional input)
           learning rate ( = 1.0, default)
eta:
           the parameter vector (array of dimension nParam-by-1)
param:
nParam:
           number of parameters
           iteration number
iter:
maxIter:
           maximum iteration number (optional, default = 1)
           function handle to evaluate the objective
objFun:
(not required for maxit = 1 )
           function handle to evaluate the gradient
gradFun:
(not required for maxit = 1 )
lowerBound: lower bound for the parameters (optional input)
upperBound: upper bound for the parameters (optional input)
paramHist:
           parameter evolution history
           stopping criterion based on 2-norm of gradient vector
stopGrad:
           momentum parameter (default = 0)
momentum:
           set to True if Nesterov momentum equation to be used
nesterov:
(default = False)
```

learnSched: learning schedule (constant, exponential or time-based,

default = constant)

lrParam: learning schedule parameter (default =0.1)

alg: algorithm used

\_\_version\_\_:version of the code

Methods: Public:

getParam: returns the parameter values

getObj: returns the current objective value

getGrad: returns the current gradient information

update: perform a single iteration

performIter: perform maxIter number of iterations

getParamHist: returns parameter update history

Private:

\_\_init\_\_\_: initialization

evaluateObjFn: evaluates the objective function

evaluateGradFn: evaluates the gradients

satisfyBounds: satisfies the parameter bounds

learningSchedule: learning schedule

stopCrit: check stopping criteria

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Reference: Bottou, Léon, Frank E. Curtis, and Jorge Nocedal.

"Optimization methods for large-scale machine learning."

SIAM Review 60.2 (2018): 223-311.

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written by Subhayan De (email: Subhayan.De@colorado.edu), July, 2018.

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#### 2.1.1 Example

NOTE: Implementation of this example is in:

sgd\_demo.py

Consider the following linear regression problem:

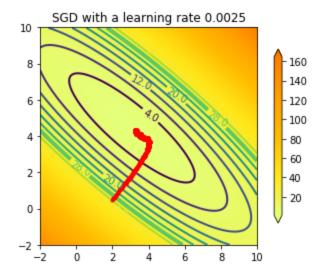
$$y = 3 + 4.5x + \text{noise} \tag{1}$$

where the regression parameters are  $\theta = [3, 4.5]^T$ .

Using 1000 measurements and an initial guess of of  $\theta_0 = [2, 0.5]^T$  the above algorithms are implemented and run for 2500 iterations and a stopping criterion for 2nd norm gradient to be less than  $10^{-6}$ .

Objective function is provided in objFun and gradient function is provided in gradFun. The problem is initialized using

```
# initial parameter
w10 = 2.0
w20 = 0.5
theta = np.array([w10, w20])
R = objFun(theta) # initial objective
it = 0 # set iteration counter to 0
maxIt = 2500 # maximum iteration
dR = gradFun(theta) # initial gradient
2.1.2 SGD class:
For the vanilla stochastic gradient descent:
import SGD as sgd
# Stochastic Gradient Descent
eta = 0.0025 # learning rate
opt = sgd.SGD(obj = R, grad = dR, eta = eta, param = theta, iter = it,
maxiter=maxIt, objFun=objFun, gradFun=gradFun) # initialize
opt.performIter() # perform iterations
thetaHist = opt.getParamHist() # get parameter update history
The output is the following:
Learning rate = 0.0025
Learning schedule: time-based
Algorithm:
            SGD
SGD |
                                              | 100.0% Complete:
Time Elapsed = 77.22s, Objective = 0.943425
```



## 2.1.3 SGD with time-based learning schedule:

# Stochastic Gradient Descent
eta = 0.1 # learning rate

opt = sgd.SGD(obj = R, grad = dR, eta = eta, param = theta, iter = it,
maxiter=maxIt, objFun=objFun, gradFun=gradFun,
learnSched = 'time-based', lrParam =0.5) # initialize

opt.performIter() # perform iterations

thetaHist = opt.getParamHist() # get parameter update history

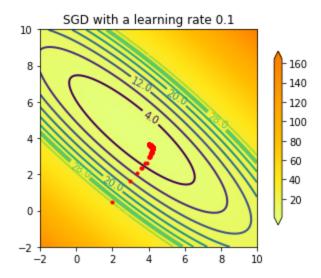
The output is the following:

Learning rate = 0.1

Learning schedule: time-based

Algorithm: SGD

SGD | | | 100.0% Complete: Time Elapsed = 77.5s, Objective = 1.166173



### 2.1.4 SGD + momentum:

eta = 0.001 # learning rate

opt = sgd.SGD(obj = R, grad = dR, eta = eta, param = theta, iter = it,
maxiter=maxIt, objFun=objFun, gradFun=gradFun,
momentum = 0.9) # initialize

opt.performIter() # perform iterations

thetaHist = opt.getParamHist()

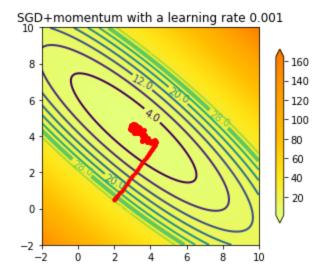
The output is the following:

Learning rate = 0.001

Learning schedule: constant

Algorithm: SGD+momentum

SGD+momentum | | 100.0% Complete: Time Elapsed = 77.52s, Objective = 0.94187



### 2.1.5 SGD + Nesterov momentum:

eta = 0.001 # learning rate

opt = sgd.SGD(obj = R, grad = dR, eta = eta, param = theta, iter = it,
maxiter=maxIt, objFun=objFun, gradFun=gradFun,
momentum = 0.9, nesterov = True) # initialize

opt.performIter() # perform iterations

thetaHist = opt.getParamHist()

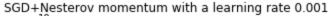
The output is the following:

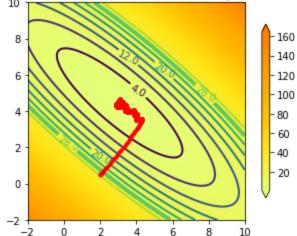
Learning rate = 0.001

Learning schedule: constant

Algorithm: SGD+Nesterov momentum

SGD+Nesterov momentum | 100.0% Complete: Time Elapsed = 116.86s, Objective = 0.965793





### 2.2 minibatchSGD

minibatch SGD class
derived class from Stochastic Gradient Descent

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#### Initialization:

mbsgd = minibatchSGD(nSamples, nTotSamples,newGrad = 0.0,
obj, grad, eta, param, iter, maxiter,
objFun, gradFun, lowerBound, upperBound)

#### Attributes:

alg: minibatchSGD
eta: learning rate

param: the parameter vector (array of dimension nParam-by-1)

nParam: number of parameters newGrad: gradient information (array of dimension nParam-by-nSamples)

nSamples: number of gradients updated at each iteration

iter: iteration number (optional)

maxIter: maximum iteration number (optional input, default = 1)

objFun: function handle to evaluate the objective

(not required for maxit = 1 )

gradFun: function handle to evaluate the gradient

(not required for maxit = 1 )

lowerBound: lower bound for the parameters (optionalinput) upperBound: upper bound for the parameters (optional input)

stopGrad: stopping criterion based on 2-norm of gradient vector

(default 10<sup>-6</sup>)

learnSched: learning schedule (constant, exponential or time-based,

default = constant)

lrParam: learning schedule parameter (default =0.1)

alg: algorithm used

\_\_version\_\_: version of the code

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Methods: Public:

performIter: performs all the iterations inside a for loop getGradHist: returns gradient history (default is zero)

Inherited:

getParam: returns the parameter values

getObj: returns the current objective value

getGrad: returns the current gradient information

getParamHist: returns parameter update history

Private: (should not be called outside this class file)

\_\_init\_\_: initialization

update: performs one iteration of minibatch SGD

Inherited:

evaluateObjFn: evaluates the objective function

evaluateGradFn: evaluates the gradients

satisfyBounds: satisfies the parameter bounds

learningSchedule: learning schedule

stopCrit: check stopping criteria

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Reference:

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written by Subhayan De (email: Subhayan.De@colorado.edu), July, 2018.

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#### 2.2.1 minibatchSGD

import SGD as sgd

eta = 0.025 # learning rate

opt = sgd.minibatchSGD(nSamples = 10,nTotSamples = n,newGrad = 0.0,obj = R,
grad = dR, eta = eta, param = theta, iter = it,

maxiter=maxIt, objFun=objFun,

gradFun=batchGradFun) # initialize

opt.performIter() # perform iterations

thetaHist = opt.getParamHist()

The output is the following:

Algorithm: minibatchSGD

Learning rate = 0.025

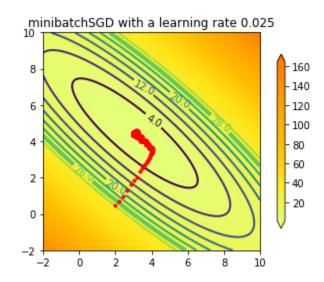
Learning schedule: constant

NOTE: performing a minibatch SGD with 1.0 % of total samples

minibatchSGD | 100.0% Complete:

Time Elapsed = 76.85s, Objective = 0.933654

If we plot the parameter history:



# 2.3 RMSprop

RMSprop class

derived class from Stochastic Gradient Descent

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Initialization:

rp = RMSprop(gradHist, updatehist, rho, obj, grad, eta, param,

iter, maxIter, objFun, gradFun, lowerBound, upperBound)

NOTE: gradHist: historical information of gradients

(array of dimension nparam-by-1)

this should equal to zero for 1st iteration

Attributes:

grad: Gradient information (array of dimension nParam-by-1)

eta: learning rate = 1 by default

param: the parameter vector (array of dimension nParam-by-1)

nParam: number of parameters

gradHist: gradient history accumulator (see the algorithm)

epsilon: square-root of machine-precision

(required to avoid division by zero)

rho: exponential decay rate (0.95 may be a good choice)

iter: iteration number (optional)

maxIter: maximum iteration number (optional input, default = 1)

objFun: function handle to evaluate the objective

(not required for maxit = 1 )

gradFun: function handle to evaluate the gradient

(not required for maxit = 1 )

lowerBound: lower bound for the parameters (optional input) upperBound: upper bound for the parameters (optional input)

stopGrad: stopping criterion based on 2-norm of gradient vector

(default 10^-6)

alg: algorithm used

\_\_version\_\_: version of the code

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Methods: Public:

performIter:performs all the iterations inside a for loop
getGradHist:returns gradient history (default is zero)

Inherited:

getParam: returns the parameter values

getObj: returns the current objective value

getGrad: returns the current gradient information

getParamHist: returns parameter update history

Private: (should not be called outside this class file)

\_\_init\_\_: initialization

update: performs one iteration of Adadelta

Inherited:

evaluateObjFn: evaluates the objective function

evaluateGradFn: evaluates the gradients

satisfyBounds: satisfies the parameter bounds

learningSchedule: learning schedule

stopCrit: check stopping criteria

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Reference: Geoffrey Hinton

"rmsprop: Divide the gradient by a running average of its recent magnitude." http://www.cs.toronto.edu/~tijmen/csc321/slides/lecture\_slides\_lec6.pdf.

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written by Subhayan De (email: Subhayan.De@colorado.edu), July, 2018.

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### 2.3.1 RMSprop

import SGD as sgd

```
eta = 0.9 # learning rate
```

```
opt = sgd.RMSprop(gradHist=0.0,rho=0.1,obj = R, grad = dR, eta = eta,
param = theta, iter = it, maxiter=maxIt,
objFun=objFun, gradFun=gradFun) # initialize
```

opt.performIter() # perform iterations

thetaHist = opt.getParamHist()

The output is the following:

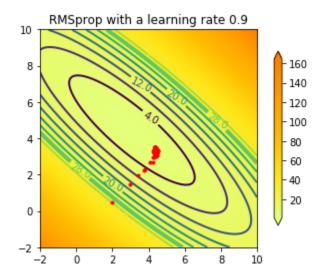
Algorithm: RMSprop

Learning rate = 0.9

Learning schedule: constant

RMSprop | 100.0% Complete:
Time Elapsed = 86.87s, Objective = 1.336377

If we plot the parameter history:



### 2.4 AdaGrad

| Adaptive Subgradient Method (AdaGrad) class | derived class from Stochastic Gradient Descent |

Initialization:

adg = AdaGrad(gradHist, obj, grad, eta, param,
iter, maxIter, objFun, gradFun, lowerBound, upperBound)

NOTE: gradHist: historical information of gradients

(array of dimension nparam-by-1).

This should equal to zero for 1st iteration

Attributes:

obj: Initial objective value (optional input)

grad: Gradient information (array of dimension nParam-by-1)

eta: learning rate ( = 1.0, default)

param: the parameter vector (array of dimension nParam-by-1)

nParam: number of parameters

gradHist: sum of gradient history (see the algorithm)

epsilon: square-root of machine-precision

(required to avoid division by zero)

iter: iteration number (optional input)

maxIter: maximum iteration number (optional input, default = 1)

objFun: function handle to evaluate the objective

(not required for maxit = 1 )

gradFun: function handle to evaluate the gradient

(not required for maxit = 1 )

lowerBound: lower bound for the parameters (optional input) upperBound: upper bound for the parameters (optional input)

stopGrad: stopping criterion based on 2-norm of gradient vector

(default 10<sup>-6</sup>)

alg: algorithm used

\_\_version\_\_: version of the code

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Methods:

Public:

performIter:performs all the iterations inside a for loop
getGradHist:returns gradient history (default is zero)

Inherited:

getParam: returns the parameter values

getObj: returns the current objective value

getGrad: returns the current gradient information

getParamHist: returns parameter update history

Private: (should not be called outside this class file)

\_\_init\_\_: initialization

update: performs one iteration of AdaGrad

Inherited:

evaluateObjFn: evaluates the objective function

evaluateGradFn: evaluates the gradients

satisfyBounds: satisfies the parameter bounds

learningSchedule: learning schedule

stopCrit: check stopping criteria

Reference: Duchi, John, Elad Hazan, and Yoram Singer.

"Adaptive subgradient methods for online learning and stochastic optimization."

Journal of Machine Learning Research 12.Jul (2011): 2121-2159.

written by Subhayan De (email: Subhayan.De@colorado.edu), July, 2018.

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#### 2.4.1 AdaGrad

import SGD as sgd

eta = 0.25 # learning rate

opt = sgd.AdaGrad(gradHist=0.0,obj = R, grad = dR, eta = eta,
param = theta, iter = it, maxiter=maxIt,
objFun=objFun, gradFun=gradFun) # initialize

opt.performIter() # perform iterations

thetaHist = opt.getParamHist()

The output is the following:

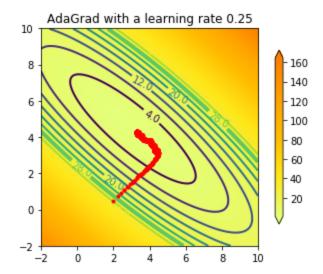
Algorithm: AdaGrad

Learning rate = 0.25

Learning schedule: constant

AdaGrad | 100.0% Complete:

Time Elapsed = 78.16s, Objective = 0.945732



### 2.5 Adam

| Adaptive moment estimation (Adam) class | derived class from Stochastic Gradient Descent |

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#### Initialization:

adm = Adam(m, v, beta1, beta2, obj, grad, eta, param,
iter, maxIter, objFun, gradFun, lowerBound, upperBound)

#### Attributes:

grad: Gradient information (array of dimension nParam-by-1)

eta: learning rate

param: the parameter vector (array of dimension nParam-by-1)

nParam: number of parameters

beta1, beta2: exponential decay rates in [0,1)

(default beta1 = 0.9, beta2 = 0.999)

m: First moment (array of dimension nParam-by-1)

v: Second raw moment (array of dimension nParam-by-1)

epsilon: square-root of machine-precision

(required to avoid division by zero)

iter: iteration number

maxIter: maximum iteration number (optional input, default = 1)

objFun: function handle to evaluate the objective

(not required for maxit = 1 )

gradFun: function handle to evaluate the gradient

(not required for maxit = 1 )

lowerBound: lower bound for the parameters (optional input) upperBound: upper bound for the parameters (optional input)

stopGrad: stopping criterion based on 2-norm of gradient vector

 $(default 10^-6)$ 

alg: algorithm used
\_\_version\_\_: version of the code

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Methods: Public:

performIter: performs all the iterations inside a for loop
getGradHist: returns gradient history (default is zero)

getMoments: returns history of moments

Inherited:

getParam: returns the parameter values

getObj: returns the current objective value

getGrad: returns the current gradient information

getParamHist: returns parameter update history

Private: (should not be called outside this class file)

\_\_init\_\_: initialization

update: performs one iteration of Adam

Inherited:

evaluateObjFn: evaluates the objective function

evaluateGradFn: evaluates the gradients

satisfyBounds: satisfies the parameter bounds

learningSchedule: learning schedule

stopCrit: check stopping criteria

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Reference: Kingma, Diederik P., and Jimmy Ba. "Adam: A method for stochastic optimization." arXiv preprint arXiv:1412.6980 (2014).

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written by Subhayan De (email: Subhayan.De@colorado.edu), July, 2018.

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#### 2.5.1 Adam

import SGD as sgd

eta = 0.025 # learning rate

opt = Adam(m = 0.0,v = 0.0,beta1 = 0.9,beta2 = 0.999,obj = R, grad = dR,
eta = eta, param = theta, iter = it, maxiter=maxIt,
objFun=objFun, gradFun=gradFun) # initialize

opt.performIter() # perform iterations

thetaHist = opt.getParamHist()

The output is the following:

Algorithm: Adam

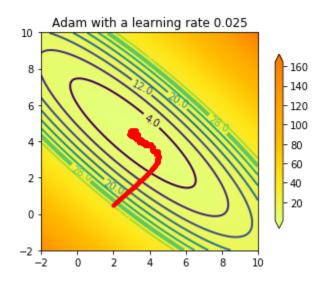
Learning rate = 0.025

Learning schedule: constant

Adam | 100.0% Complete:

Time Elapsed = 78.51s, Objective = 0.944059

If we plot the parameter history:



### 2.6 Adamax

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Adaptive moment estimation (Adamax) class
derived class from Stochastic Gradient Descent

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Initialization:

admx = Adamax(m, v, beta1, beta2, obj, grad, eta, param,
iter, maxIter, objFun, gradFun, lowerBound, upperBound)

Attributes: (all private)

grad: Gradient information (array of dimension nParam-by-1)

eta: learning rate

param: the parameter vector (array of dimension nParam-by-1)

nParam: number of parameters

beta1, beta2: exponential decay rates in [0,1)

(default beta1 = 0.9, beta2 = 0.999)

m: First moment (array of dimension nParam-by-1)

u: infinity norm constrained second moment

(array of dimension nParam-by-1)

epsilon: square-root of machine-precision

maxIter: maximum iteration number (optional input, default = 1)

objFun: function handle to evaluate the objective

(not required for maxit = 1 )

gradFun: function handle to evaluate the gradient

(not required for maxit = 1 )

lowerBound: lower bound for the parameters (optional input) upperBound: upper bound for the parameters (optional input)

stopGrad: stopping criterion based on 2-norm of gradient vector

(default 10^-6)

alg: algorithm used
\_\_version\_\_: version of the code

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Methods: Public:

performIter: performs all the iterations inside a for loop
getGradHist: returns gradient history (default is zero)

getMoments: returns history of moments

Inherited:

getParam: returns the parameter values

getObj: returns the current objective value

getGrad: returns the current gradient information

getParamHist: returns parameter update history

Private: (should not be called outside this class file)

\_\_init\_\_: initialization

update: performs one iteration of Adam

Inherited:

evaluateObjFn: evaluates the objective function

evaluateGradFn: evaluates the gradients

satisfyBounds: satisfies the parameter bounds

learningSchedule: learning schedule

stopCrit: check stopping criteria

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Reference: Kingma, Diederik P., and Jimmy Ba. "Adam: A method for stochastic optimization."

arXiv preprint arXiv:1412.6980 (2014).

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written by Subhayan De (email: Subhayan.De@colorado.edu), July, 2018.

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#### 2.6.1 Adamax

```
import SGD as sgd
```

eta = 0.25 # learning rate

opt = sgd.Adamax(m = 0.0,u = 0.0,beta1 = 0.9,beta2 = 0.999,obj = R, grad = dR,
eta = eta, param = theta, iter = it, maxiter=maxIt,
objFun=objFun, gradFun=gradFun) # initialize

opt.performIter() # perform iterations

thetaHist = opt.getParamHist()

The output is the following:

Algorithm: Adamax

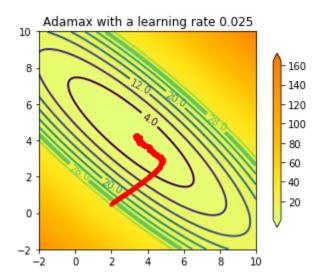
Learning rate = 0.025

Learning schedule: constant

Adamax | 100.0% Complete:

Time Elapsed = 79.23s, Objective = 0.952966

If we plot the parameter history:



## 2.7 Nadam

Nesterov-accelerated Adaptive moment estimation (Nadam) class derived class from Stochastic Gradient Descent

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Initialization:

nadm = Nadam(m, v, beta1, beta2, obj, grad, eta, param, iter,

maxIter, objFun, gradFun, lowerBound, upperBound)

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Attributes: (all private)

grad: Gradient information (array of dimension nParam-by-1)

eta: learning rate

param: the parameter vector (array of dimension nParam-by-1)

nParam: number of parameters

beta1, beta2: exponential decay rates in [0,1)

(default beta1 = 0.9, beta2 = 0.999)

m: First moment (array of dimension nParam-by-1)

v: Second raw moment (array of dimension nParam-by-1)

epsilon: square-root of machine-precision

maxIter: maximum iteration number (optional input, default = 1)

objFun: function handle to evaluate the objective

(not required for maxit = 1 )

gradFun: function handle to evaluate the gradient

(not required for maxit = 1 )

lowerBound: lower bound for the parameters (optional input) upperBound: upper bound for the parameters (optional input)

stopGrad: stopping criterion based on 2-norm of gradient vector

(default 10^-6)

alg: algorithm used
 version : version of the code

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Methods: Public:

performIter: performs all the iterations inside a for loop
getGradHist: returns gradient history (default is zero)

getMoments: returns history of moments

Inherited:

getParam: returns the parameter values

getObj: returns the current objective value getGrad: returns the current gradient information

getParamHist: returns parameter update history

Private: (should not be called outside this class file)

\_\_init\_\_: initialization

update: performs one iteration of Adam

Inherited:

evaluateObjFn: evaluates the objective function

evaluateGradFn: evaluates the gradients

satisfyBounds: satisfies the parameter bounds

learningSchedule: learning schedule

stopCrit: check stopping criteria

Reference: Kingma, Diederik P., and Jimmy Ba. "Adam: A method for stochastic optimization." arXiv preprint arXiv:1412.6980 (2014).

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written by Subhayan De (email: Subhayan.De@colorado.edu), July, 2018.

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#### 2.7.1 Nadam

import SGD as sgd

eta = 0.01 # learning rate

opt = sgd.Nadam(m = 0.0,v = 0.0,beta1 = 0.9,beta2 = 0.999,obj = R, grad = dR,
eta = eta, param = theta, iter = it, maxiter=maxIt,
objFun=objFun, gradFun=gradFun) # initialize

opt.performIter() # perform iterations

thetaHist = opt.getParamHist()

The output is the following:

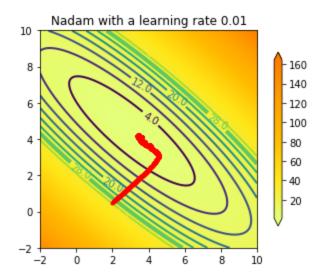
Algorithm: Nadam

Learning rate = 0.01

Learning schedule: constant

Nadam | 100.0% Complete:

Time Elapsed = 78.47s, Objective = 0.961719



### 2.8 Adadelta

```
ADADELTA class
                derived class from Stochastic Gradient Descent
Initialization:
add = Adadelta(gradHist, updatehist, rho, obj, grad, eta, param,
iter, maxIter, objFun, gradFun, lowerBound, upperBound)
NOTE: gradHist: historical information of gradients
(array of dimension nparam-by-1)
this should equal to zero for 1st iteration
Attributes: (all private)
grad:
                Gradient information (array of dimension nParam-by-1)
                learning rate = 1 by default
eta:
                the parameter vector (array of dimension nParam-by-1)
param:
nParam:
                number of parameters
gradHist:
                gradient history accumulator (see the algorithm)
updateHist:
                parameter update history accumulator
epsilon:
                square-root of machine-precision
(required to avoid division by zero)
rho:
                exponential decay rate (0.95 may be a good choice)
iter:
                iteration number (optional)
                maximum iteration number (optional input, default = 1)
maxIter:
                function handle to evaluate the objective
objFun:
(not required for maxit = 1 )
gradFun:
                function handle to evaluate the gradient
(not required for maxit = 1 )
                lower bound for the parameters (optional input)
lowerBound:
```

upperBound: upper bound for the parameters (optional input)

stopGrad: stopping criterion based on 2-norm of gradient vector

(default 10^-6)

alg: algorithm used

\_\_version\_\_: version of the code

\_\_\_\_\_\_

Methods: Public:

performIter:performs all the iterations inside a for loop
getGradHist:returns gradient history (default is zero)

Inherited:

getParam: returns the parameter values

getObj: returns the current objective value

getGrad: returns the current gradient information

getParamHist: returns parameter update history

Private: (should not be called outside this class file)

\_\_init\_\_: initialization

update: performs one iteration of Adadelta

Inherited:

evaluateObjFn: evaluates the objective function

evaluateGradFn: evaluates the gradients

satisfyBounds: satisfies the parameter bounds

learningSchedule: learning schedule

stopCrit: check stopping criteria

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Reference: Zeiler, Matthew D.

"Adadelta: an adaptive learning rate method."

arXiv preprint arXiv:1212.5701 (2012).

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written by Subhayan De (email: Subhayan.De@colorado.edu), July, 2018.

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#### 2.8.1 Adadelta

import SGD as sgd

eta = 1.0 # learning rate

opt = sgd.Adadelta(gradHist=0.0,updateHist=0.0,rho=0.99,obj = R,
grad = dR, eta = eta, param = theta, iter = it, maxiter=maxIt,
objFun=objFun, gradFun=gradFun) # initialize

opt.performIter() # perform iterations

thetaHist = opt.getParamHist()

The output is the following:

Algorithm: Adadelta

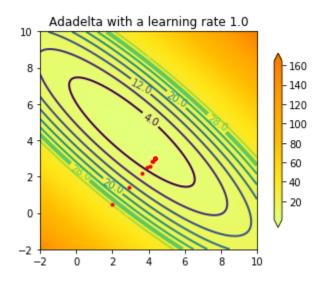
Learning rate = 1.0

Learning schedule: constant

Adadelta | 100.0% Complete:

Time Elapsed = 85.16s, Objective = 1.633017

If we plot the parameter history:



### 2.9 SAG

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| Stochastic Average Gradient (SAG) class | derived class from Stochastic Gradient Descent

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Initialization:

sag = SAG(nSamples, nTotSamples, fullGrad = 0.0, obj, grad, eta, param,
iter, maxIter, objFun, gradFun, lowerBound, upperBound)

Attributes: (all private)

fullGrad: Full gradient information
(array of dimension nParam-by-nTotSamples)

eta: learning rate

param: the parameter vector (array of dimension nParam-by-1)

nParam: number of parameters nTotSamples: total number of samples

nSamples: number of gradients updated at each iteration

iter: iteration number (optional)

maxIter: maximum iteration number (optional input, default = 1)

objFun: function handle to evaluate the objective

(not required for maxit = 1 )

gradFun: function handle to evaluate the gradient

(not required for maxit = 1 )

lowerBound: lower bound for the parameters (optional input) upperBound: upper bound for the parameters (optional input)

stopGrad: stopping criterion based on 2-norm of gradient vector

 $(default 10^-6)$ 

learnSched: learning schedule (constant, exponential or time-based,

default = constant)

lrParam: learning schedule parameter (default =0.1)

alg: algorithm used
\_\_version\_\_: version of the code

\_\_\_\_\_\_

Methods: Public:

performIter:performs all the iterations inside a for loop getGradHist:returns gradient history (default is zero)

Inherited:

getParam: returns the parameter values

getObj: returns the current objective value

getGrad: returns the current gradient information

getParamHist: returns parameter update history

Private: (should not be called outside this class file)

\_\_init\_\_: initialization

update: performs one iteration of SAG

Inherited:

evaluateObjFn: evaluates the objective function

evaluateGradFn: evaluates the gradients

satisfyBounds: satisfies the parameter bounds

learningSchedule: learning schedule

stopCrit: check stopping criteria

Reference: Roux, Nicolas L., Mark Schmidt, and Francis R. Bach. "A stochastic gradient method with an exponential convergence rate for finite training sets."

Advances in neural information processing systems. 2012.

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written by Subhayan De (email: Subhayan.De@colorado.edu), July, 2018.

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#### 2.9.1 SAG

from StochasticGradientDescent import SAG

eta = 0.0025 # learning rate

opt = SAG(nSamples = 20,nTotSamples= n, obj = R, grad = dR, eta = eta,
param = theta, iter = it, maxiter=maxIt, objFun=objFun,
gradFun=batchGradFun) # initialize

opt.performIter() # perform iterations

thetaHist = opt.getParamHist()

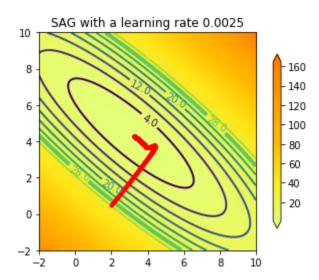
The output is the following:

Algorithm: SAG

Learning rate = 0.0025

Learning schedule: constant

If we plot the parameter history:



### 2.10 SVRG

Stochastic variance reduced gradient (SVRG) class |

derived class from Stochastic Gradient Descent |

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Initialization:

opt = SVRG(nTotSamples, innerIter = 10, outerIter = 200, option = 1,obj,
grad, eta, param, iter, maxiter, objFun, gradFun)

NOTE: option = 1 or 2 as suggested in the reference paper.

Attributes:

alg: SVRG

eta: learning rate

param: the parameter vector (array of dimension nParam-by-1)

nParam: number of parameters fullGrad: Full gradient information (array of dimension nParam-by-nTotSamples)

nTotSamples: total number of samples

innerIter: inner iteration
outerIter: outer iteration

iter: iteration number (optional input)

maxIter: maximum iteration number
(optional, default = innerIter\*outerIter)

objFun: function handle to evaluate the objective

(not required for maxit = 1 )

gradFun: function handle to evaluate the gradient

(not required for maxit = 1 )

mu: average gradient in the outer iteration

paramBest: best estimate of the param in the oter iteration lowerBound: lower bound for the parameters (optional input) upperBound: upper bound for the parameters (optional input)

stopGrad: stopping criterion based on 2-norm of gradient vector

 $(default 10^-6)$ 

alg: algorithm used
\_\_version\_\_: version of the code

\_\_\_\_\_\_

Methods: Public:

performOuterIter: performs all the iterations inside a for loop
getGradHist: returns gradient history (default is zero)

Inherited:

getParam: returns the parameter values

getObj: returns the current objective value

getGrad: returns the current gradient information

getParamHist: returns parameter update history

Private: (should not be called outside this class file)

\_\_init\_\_: initialization

innerUpdate: performs inner iterations of SVRG

Inherited:

evaluateObjFn: evaluates the objective function

evaluateGradFn: evaluates the gradients

satisfyBounds: satisfies the parameter bounds

learningSchedule: learning schedule

stopCrit: check stopping criteria

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Reference: Johnson, Rie, and Tong Zhang.

"Accelerating stochastic gradient descent using predictive variance reduction."

Advances in neural information processing systems. 2013.

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written by Subhayan De (email: Subhayan.De@colorado.edu), July, 2018.

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#### 2.10.1 SVRG

from StochasticGradientDescent import SVRG

eta = 0.004 # learning rate

opt = SVRG(nTotSamples = n, innerIter = 10, outerIter = 200, option = 1,
obj = R, grad = dR, eta = eta, param = theta, iter = it,
maxiter=maxIt, objFun=objFun, gradFun=batchGradFun) # initialize

opt.performIter() # perform iterations

thetaHist = opt.getParamHist()

The output is the following:

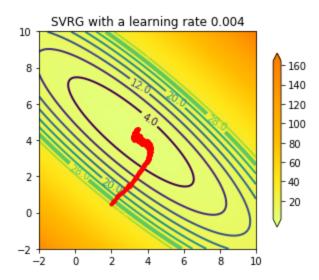
Algorithm: SVRG

Learning rate = 0.004

Learning schedule: constant

SVRG | | 100.0% Complete:

Time Elapsed = 39.94s, Objective = 0.981352



Report any bugs to Subhayan.De@colorado.edu