

Gradient Descent 1

- function
- Inputs: tolerance and gamma
- Output: N (# of iterations)
- Initialize:
 - $N = 0$
 - Error
 - Initial guess vector
- While loop (run until error > tolerance)
 - Compute the next iteration using gradient descent formula: $x(n+1) = x(n) - \text{gamma} * \text{gradient}(x(n))$
 - Compute error using the l2-norm
 - Update x_n to be the new min
 - Update the number of iterations (add 1)
- End loop
- End function

Gradient Descent 2

- Same as gradient descent one EXCEPT:
 - Only one input (tolerance), so gamma is initialized in the function
 - Gamma is updated in the while loop using the Barzilai-Borwein step-size
 - I made a separate function to compute the gradient (gradx) with pseudocode:
 - Input: x vector
 - Output: gradient
 - Redefine the x vector into two components
 - Compute the first partial derivatives of the function wrt the two components (x and y)

Vary Step-Size Gamma to Optimize

- Make vector of gamma values to iterate through
- Initialize
 - Minimum N value (number of iterations)
 - Minimum gamma value
- For loop from $i = 1$ to number of gamma values in vector
 - Run gradient descent code for i th gamma value, store in N vector
 - If the new N value is less than the minimum value
 - Make it the new minimum N
 - Make the corresponding gamma the minimum gamma
 - End
- End
- Plot number of iterations vs gamma values

Vary Error Tolerances to Compare

- Create error tolerance vector to iterate through
- For loop from $i = 1$ to number of error tolerance values in vector
 - Run gradient descent 1 for i th error tolerance (and input γ), store as vector
 - Run gradient descent 2 for i th error tolerance, and store as vector
- End
- Plot both number of iteration vectors vs error tolerance on semilogx graph
- Plot both number of iteration vectors vs error tolerance on loglog graph

Fit Sine Series

- Initialize
 - N (number of data points)
 - M (number of sine terms in linear least squares eq)
- Create x and y data points
- For loop from $i = 1$ to M
 - Create the i th column of the matrix A using the formula: $\sin(i * x_{Data})$
- End
- use the pseudo-inverse to compute beta vector
- Compute the l_2 -norm of the residuals
- Plot the data (both the y -data and the predicted y values, $A * \beta$)

NONLINEAR LEAST SQUARES PSEUDOCODE CAN BE FOUND ON A PDF IN THE ZIP FILE