CS101: Assignment #4

Due on April 3 at 23:59

Prof. Turing, Alan , Spring 2023, April 3 at 23:59

Alice Bob

Problem 1

- a) when $\min(\|\boldsymbol{x}\|_2)$, $\boldsymbol{x}=\boldsymbol{x}^*$ is the solution to the problem, which is $x^*=\begin{pmatrix} \frac{1}{\sqrt{3}}\\ \frac{1}{\sqrt{3}}\\ \frac{1}{\sqrt{3}} \end{pmatrix}$
- b) We have a matrix $\mathbf{A} = \begin{pmatrix} 1 & 1 \\ 1 & 1 \\ 1 & 0 \end{pmatrix}$, the projection operator is

$$oldsymbol{P} = oldsymbol{A} \left(oldsymbol{A}^T A
ight)^{-1} oldsymbol{A}^T = egin{pmatrix} rac{1}{2} & rac{1}{2} & 0 \ rac{1}{2} & rac{1}{2} & 0 \ 0 & 0 & 1 \end{pmatrix},$$

hence,

$$x^* = Pv = egin{pmatrix} rac{1}{2} \ rac{1}{2} \ 1 \end{pmatrix}.$$

c) We have a matrix $\mathbf{A} = \begin{pmatrix} 1 & -1 \\ -1 & 1 \\ 2 & 2 \end{pmatrix}$, the projection operator is

$$m{P} = m{A} ig(m{A}^T m{A} ig)^{-1} m{A}^T = egin{pmatrix} rac{1}{2} & -rac{1}{2} & 0 \ -rac{1}{2} & rac{1}{2} & 0 \ 0 & 0 & 1 \end{pmatrix},$$

hence,

$$oldsymbol{x}^* = oldsymbol{P}oldsymbol{v} = egin{pmatrix} rac{1}{2} \ -rac{1}{2} \ 0 \end{pmatrix}.$$

Problem 2

a) we know that:

$$\operatorname{prox}_{\varphi}(z) = \operatorname{arg\,min}_{x \in \mathbb{R}} \bigg\{ \frac{1}{2} \|x - z\|^2 + \phi(x - c) \bigg\}.$$

let x' = x - c

$$\mathrm{prox}_{\varphi}(z) = \mathrm{arg\,min}_{x \in \mathbb{R}} \left\{ \frac{1}{2} \|x' - (z-c)\|^2 + \phi(x'+c-c) \right\} + c = \mathrm{prox}_{\phi}(z-c) + c.$$

b) if we want to $f(x) = \frac{1}{2}||x - z||^2 + \phi(x)$ to be minimized, we need to find the x that makes the derivative of the function equal to zero.

we know

$$\partial f(x) = \begin{cases} x - z + \lambda \text{ when } x > 0\\ [x - z - \lambda, x - z + \lambda] \text{ when } x = 0\\ x - z - \lambda \text{ when } x < 0 \end{cases}$$

. Hence, let

$$\partial f(x) = 0$$

, we have

$$\operatorname{prox}_{\boldsymbol{\phi}}(z) = x^* = \begin{cases} z - \lambda \text{ when } z > \lambda \\ [z - \lambda, z + \lambda] \text{ when } z \in [-\lambda, \lambda]. \\ z + \lambda \text{ when } z < -\lambda \end{cases}$$

c) if $\varphi(x)=\lambda|x-c|$, where $c\in\mathbb{R}$ and $\lambda>0.$ Use the result from part a.

$$\operatorname{prox}_{\varphi}(z) = \operatorname{prox}_{\phi}(z-c) + c = \begin{cases} z - \lambda \text{ when } z > \lambda + c \\ [z - \lambda, z + \lambda] \text{ when } z \in [-\lambda + c, \lambda + c] \\ z + \lambda \text{ when } z < -\lambda + c \end{cases}$$

Problem 3

a) If we take the derivative of $\frac{1}{2} \|x - x^{t-1}\|^2 + \gamma g(x)$, we have

$$oldsymbol{x}^t = ext{prox}_{\gamma a}(oldsymbol{x}^{t-1}) = oldsymbol{x}^{t-1} - \gamma
abla g(oldsymbol{x}^t)$$

b) By the convexity of g, we know that $g(x^t) + \nabla g(x^t)^T (x^{t-1} - x^t) \leq g(x^{t-1})$. Hence, we have

$$g(\boldsymbol{x}^t) \leq g(\boldsymbol{x^{t-1}}) - \nabla g(\boldsymbol{x^t})^T (\boldsymbol{x^{t-1}} - \boldsymbol{x^t}) = g(\boldsymbol{x^{t-1}}) - \gamma \nabla \big\| g(\boldsymbol{x^t}) \big\|_2^2$$

c) because $x^t = x^{t-1} - \gamma \nabla g(x^t)$ which is a gradient descent method, so

$$-\infty < g({m x}^t) \le g({m x}^{t-1})$$

and we have

$$g(\boldsymbol{x}^t) \leq g(\boldsymbol{x}^{t-1}) - \gamma \nabla \|g(\boldsymbol{x}^t)\|_2^2$$

hence

$$0 \le \gamma \nabla \|g(\boldsymbol{x}^t)\|_2^2 \le 0$$

if

$$t \to +\infty$$

Problem 4

a) because

$$\partial f(x) = \{ v \in \mathbb{R}^n : f(y) \ge f(x) + v^T(y - x), \forall y \in \mathbb{R}^n \}$$

if $g(x) = \theta f(x)$,

$$\partial g(\boldsymbol{x}) = \left\{ \boldsymbol{v} \in \mathbb{R}^n : g(\boldsymbol{y}) \geq g(\boldsymbol{x}) + \boldsymbol{v}^T(\boldsymbol{y} - \boldsymbol{x}), \forall \boldsymbol{y} \in \mathbb{R}^n \right\}$$

$$\partial g(oldsymbol{x}) = \left\{ oldsymbol{v} \in \mathbb{R}^n : heta f(oldsymbol{y}) \geq heta f(oldsymbol{x}) + oldsymbol{v}^T(oldsymbol{y} - oldsymbol{x}), orall oldsymbol{y} \in \mathbb{R}^n
ight\}$$

$$\partial g(oldsymbol{x}) = \left\{ oldsymbol{v} \in \mathbb{R}^n : f(oldsymbol{y}) \geq f(oldsymbol{x}) + rac{oldsymbol{v}^T}{ heta}(oldsymbol{y} - oldsymbol{x}), orall oldsymbol{y} \in \mathbb{R}^n
ight\}$$

$$\partial g(x) = \theta \{ v \in \mathbb{R}^n : f(y) \ge f(x) + v^T(y - x), \forall y \in \mathbb{R}^n \} = \theta \partial f(x)$$

b)

$$\partial h(x) = \{ v \in \mathbb{R}^n : f(y) + g(y) \ge f(x) + g(x) + v^T(y - x), \forall y \in \mathbb{R}^n \}$$

all of the elements that satisfy

$$f(\boldsymbol{y}) \geq f(\boldsymbol{x}) + \boldsymbol{v}^T(\boldsymbol{y} - \boldsymbol{x}), \forall \boldsymbol{y} \in \mathbb{R}^n$$

and

$$g(\boldsymbol{y}) \ge g(\boldsymbol{x}) + \boldsymbol{v}^T(\boldsymbol{y} - \boldsymbol{x}), \forall \boldsymbol{y} \in \mathbb{R}^n$$

are in the set

$$\partial h(x)$$

hence

$$\partial f(x) + \partial g(x) \subseteq \partial h(x)$$

c) we know that

$$\partial \|x\|_1 = \begin{cases} 1 \text{ when } x > 0\\ [-1, 1] \text{ when } x = 0\\ -1 \text{ when } x < 0 \end{cases}$$

.

hence $\operatorname{sgn}(x) \in \partial \|x\|_{_1}$.

Problem 5

b) Not differentiable at x = 0, and h is convex.

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\nabla \left[\frac{1}{2}\|\boldsymbol{x}-\boldsymbol{y}\|_{2}^{2}+\gamma\lambda\|\boldsymbol{x}\|_{1}\right] = \begin{cases} x-y+\gamma\lambda \text{ when } x>0\\ [x-y-\gamma\lambda,x-y+\gamma\lambda] \text{ when } x=0\\ x-y-\gamma\lambda \text{ when } x<0 \end{cases}
let it be 0, we have
              \operatorname{prox}_{\gamma g(y)} = x^* = \begin{cases} y - \gamma \lambda \text{ when } y > \lambda \\ [y - \gamma \lambda, y + \gamma \lambda] \text{ when } y \in [-\gamma \lambda, \gamma \lambda]. \\ y + \gamma \lambda \text{ when } y < -\gamma \lambda \end{cases}
% load the variables of the optimization problem
load('dataset.mat');
[p, n] = size(A);
%% set up the function and its gradient
evaluate f = @(x) (1/n)*sum(log(1+exp(-b.*(A'*x))));
evaluate gradf = @(x) (1/n)*A*(-b.*exp(-b.*(A'*x))./(1+exp(-b.*(A'*x))));
%% parameters of the gradient method
xInit = zeros(p, 1); % zero initialization
stepSize = 1; % step-size of the gradient method
maxIter = 1000; % maximum number of iterations
%% optimize
% initialize
x = xInit:
% keep track of cost function values
objVals = zeros(maxIter, 1);
% iterate
for iter = 1:maxIter
   % update
   xNext = x - stepSize*evaluate_gradf(x);
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% evaluate the objective
  funcNext = evaluate_f(xNext);
  % store the objective and the classification error
  objVals(iter) = funcNext;
  fprintf('[%d/%d] [step: %.le] [objective: %.le]\n',...
     iter, maxIter, stepSize, objVals(iter));
  % begin visualize data
  % plot the evolution
  figure(1);
  set(gcf, 'Color', 'w');
  semilogy(1:iter, objVals(1:iter), 'b-',...
     iter, objVals(iter), 'b*', 'LineWidth', 2);
  grid on;
  axis tight;
  xlabel('iteration');
  ylabel('objective');
  title(sprintf('GM (f = %.2e)', objVals(iter)));
  xlim([1 maxIter]);
  set(gca, 'FontSize', 16);
  drawnow:
  % end visualize data
  % update w
  x = xNext;
end
```