

# CS2601 Linear and Convex Optimization

## Homework 1

Due: 2021.9.30

1. Let  $f(\mathbf{x}) = 2x_1^2 + x_1x_2 + x_2^2 - 3x_1 - 5x_2$ .

(a). Is  $f(x)$  coercive? Hint: use  $x_1x_2 \geq -(x_1^2 + x_2^2)/2$ .

(b). Find the minimum and maximum of  $f(\mathbf{x})$  over  $\mathbb{R}^2$  if they exist.

2. **Logistic regression.** Recall the objective function of logistic regression is the following negative log likelihood,

$$f(\mathbf{w}) = \sum_{i=1}^m \log(1 + e^{-y_i \mathbf{x}_i^T \mathbf{w}}),$$

where  $(\mathbf{x}_i, y_i) \in \mathbb{R}^n \times \{-1, +1\}$  is the  $i$ -th data point. We have absorbed the bias term  $b$  into  $\mathbf{w}$  by appending an extra 1 to each  $\mathbf{x}_i$ .

(a). Suppose the dataset  $\{(\mathbf{x}_1, y_1), \dots, (\mathbf{x}_m, y_m)\}$  is strictly linearly separable in the sense that there exists a  $\mathbf{w}_0$  such that

$$y_i \mathbf{x}_i^T \mathbf{w}_0 > 0, \quad \forall i = 1, 2, \dots, m.$$

Does  $f$  have a global minimum in this case? Explain your answer.

(b). Suppose the dataset is not linearly separable in the sense that for any  $\mathbf{w}$ , there exists an  $i_0 = 1, 2, \dots, m$  such that

$$y_{i_0} \mathbf{x}_{i_0}^T \mathbf{w} < 0.$$

Show that  $f$  has a global minimum by completing the following steps.

i) Show

$$f(\mathbf{w}) \geq h(\mathbf{w})$$

where

$$h(\mathbf{w}) = \max_{1 \leq i \leq m} -y_i \mathbf{x}_i^T \mathbf{w}.$$

ii) Let  $S = \{\mathbf{w} : \|\mathbf{w}\| = 1\}$  be the unit sphere. Show that  $h(\mathbf{w})$  has a global minimum  $\mathbf{w}_0$  on  $S$  and  $C \triangleq h(\mathbf{w}_0) > 0$ . You can assume the fact that  $h$  is continuous, which can be proved by induction and the identity  $\max\{a, b\} = \frac{a+b+|a-b|}{2}$ .

iii) Show

$$h(\mathbf{w}) \geq C\|\mathbf{w}\|, \quad \forall \mathbf{w}$$

iv) Show  $f$  has a global minimum.

(c). Find  $\nabla f(\mathbf{w})$ .

**3. Taylor expansion.** Suppose  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  is twice continuously differentiable.

(a). Show that the following first-order Taylor expansion with Lagrange remainder,

$$f(\mathbf{x} + \mathbf{d}) = f(\mathbf{x}) + \nabla f(\mathbf{x})^T \mathbf{d} + \frac{1}{2} \mathbf{d}^T \nabla^2 f(\mathbf{x} + t\mathbf{d}) \mathbf{d}$$

for some  $t \in (0, 1)$ . You can assume the same expansion for univariate functions.

(b). Recall the integral of a vector valued function  $\mathbf{g} : \mathbb{R} \rightarrow \mathbb{R}^n$  is defined component-wise, i.e. for  $\mathbf{g}(t) = (g_1(t), g_2(t), \dots, g_n(t))^T$ ,

$$\int \mathbf{g}(t) dt = \begin{pmatrix} \int g_1(t) dt \\ \int g_2(t) dt \\ \vdots \\ \int g_n(t) dt \end{pmatrix}$$

Show

$$\nabla f(\mathbf{x} + \mathbf{d}) = \nabla f(\mathbf{x}) + \int_0^1 \nabla^2 f(\mathbf{x} + t\mathbf{d}) \mathbf{d} dt$$

Hint: Apply the Newton-Leibniz formula to  $\mathbf{g}(t) = \nabla f(\mathbf{x} + t\mathbf{d})$ .

**4.** Are the following matrices positive definite, positive semidefinite, negative definite, negative semidefinite, or indefinite?

$$A = \begin{pmatrix} 6 & 2 & 0 \\ 2 & 5 & -2 \\ 0 & -2 & 4 \end{pmatrix}, \quad B = \begin{pmatrix} 1 & 2 & 0 \\ 2 & 2 & 1 \\ 0 & 1 & -3 \end{pmatrix}, \quad C = \begin{pmatrix} 2 & -1 & -1 \\ -1 & 2 & -1 \\ -1 & -1 & 2 \end{pmatrix}$$