Notation

Numerical Methods for Deep Learning

Data

- n number of examples
- n_f dimension of feature vector
- $ightharpoonup n_c$ dimension of prediction (e.g., number of classes)
- $\mathbf{y}_1, \mathbf{y}_2, \dots, \mathbf{y}_n \in \mathbb{R}^{n_f}$ input features
- $\mathbf{Y} = [\mathbf{y}_1, \mathbf{y}_2, \dots, \mathbf{y}_n] \in \mathbb{R}^{n_f \times n}$ feature matrix
- $ightharpoonup oldsymbol{\mathsf{c}}_1, oldsymbol{\mathsf{c}}_1, oldsymbol{\mathsf{c}}, \dots, oldsymbol{\mathsf{c}}_n \in \mathbb{R}^{n_c}$ output observations
- ullet $oldsymbol{\mathsf{C}} = [oldsymbol{\mathsf{c}}_1, oldsymbol{\mathsf{c}}_2, \dots, oldsymbol{\mathsf{c}}_n] \in \mathbb{R}^{n_c imes n}$ observation matrix

Neural Networks

- $f(\mathbf{y}, \theta) = \mathbf{c}$ model represented by neural net
- $m{ ilde{ heta}}$ $heta \in \mathbb{R}^{n_p}$ parameters of model
- $\theta^{(1)}, \theta^{(2)}, \ldots$ parts of weights. Division clear from context. Examples
 - 1. $\theta^{(j)}$ are weights of jth layer.
 - 2. $\theta^{(1)}$ are weights for convolution kernel, $\theta^{(2)}$ are weights for bias
- N number of layers
- K linear operator applied to features
- ▶ b bias
- $ightharpoonup \sigma: \mathbb{R}
 ightharpoonup \mathbb{R}$ activation function

Optimization and Loss

- $ightharpoonup E(\mathbf{Y}, \mathbf{C}, \mathbf{W})$ loss function parameterized by weights \mathbf{W}
- $\phi: \mathbb{R}^k \to \mathbb{R}$ generic objective function
- $ightharpoonup heta^*$ minimizer of a function, i.e.,

$$\theta^* = \arg\min_{\theta} \phi(\theta)$$

- \bullet $\theta_1, \theta_2, \ldots$ iterates
- ▶ **d**, **D** search directions
- ightharpoonup lpha step size
- $ightharpoonup \lambda$ regularization parameter
- ▶ $\nabla_{\mathbf{x}}F$ gradient, if $F: \mathbb{R}^k \to \mathbb{R}^l$, then $\nabla F(\mathbf{x}) \in \mathbb{R}^{k \times l}$
- ullet ${f J}_{f x}F$ Jacobian of F with respect to ${f x},\ {f J}_{f x}F=(
 abla_{f x}F)^{ op}$

Linear Algebra - 1

- $\mathbf{e}_k \in \mathbb{R}^k$ vector of all ones
- ▶ I_k $k \times k$ identity matrix
- $\triangleright \kappa(\mathbf{A})$ condition number of \mathbf{A}
- ▶ $\sigma_1(\mathbf{A}) \ge ... \ge \sigma_k(\mathbf{A}) \ge 0$ singular values of **A**
- $\lambda_1(\mathbf{A}), \ldots$ eigenvalues of **A**
- ▶ tr(A) trace of square matrix, i.e., sum of diagonal elements

Linear Algebra - 2

▶ ⊙ - Hadamard product

$$\mathbf{C}_{ij} = \mathbf{A}_{ij} \cdot \mathbf{B}_{ij}, \quad \text{for} \quad \mathbf{B}, \mathbf{A} \in \mathbb{R}^{k \times l}$$

MATIAB: C = A.*B

▶ ⊗ - Kronecker product

$$\mathbf{A} \otimes \mathbf{B} = \left(\begin{array}{cccc} \mathbf{A}_{11} \mathbf{B} & \mathbf{A}_{12} \mathbf{B} & \dots & \mathbf{A}_{1/} \mathbf{B} \\ \vdots & \vdots & \vdots & \vdots \\ \mathbf{A}_{k1} \mathbf{B} & \mathbf{A}_{k2} \mathbf{B} & \dots & \mathbf{A}_{k/} \mathbf{B} \end{array} \right)$$

MATLAB: C = kron(A,B)

vec(A) - reshape matrix A into vector (column-wise).

Example:
$$\operatorname{vec}\left(\left(\begin{array}{cc} \mathbf{A}_{11} & \mathbf{A}_{12} \\ \mathbf{A}_{21} & \mathbf{A}_{22} \end{array}\right)\right) = \left(\begin{array}{c} \mathbf{A}_{11} \\ \mathbf{A}_{21} \\ \mathbf{A}_{12} \\ \mathbf{A}_{22} \end{array}\right)$$

MATLAB: a = A(:)

Linear Algebra - 3

▶ $mat(\mathbf{v}, k, l)$ - reshape vector $\mathbf{v} \in \mathbb{R}^{kl}$ into matrix. k, l omitted when dimension clear from context. Note

$$mat(vec(\mathbf{A})) = \mathbf{A}.$$

MATLAB: V = reshape(v,k,1).

lack diag($oldsymbol{v}$) - diagonal matrix with elements of $oldsymbol{v} \in \mathbb{R}^k$ on diagonal

MATLAB: V = diag(v(:))

diag(A) - diagonal matrix obtained by vectorizing A

Acronyms

- CG Conjugate Gradient Method
- VarPro Variable Projection
- SD Steepest Descent
- SGD Stochastic Gradient Descent
- SA Stochastic Approximation
- SAA Stochastic Average Approximation
- SPD symmetric positive definite
- SPSD symmetric positive semi-definite
- CV Cross Validation