Notation

Numerical Methods for Deep Learning

Data

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

Neural Networks

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

Optimization and Loss

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

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

- $\theta_1, \theta_2, \ldots$ - iterates
- $\mathbf{d}, \mathbf{D}$ - search directions
- α - step size
- λ - regularization parameter
- $\nabla_{\mathbf{x}} F$ - gradient, if $F : \mathbb{R}^k \to \mathbb{R}^l$, then $\nabla F(\mathbf{x}) \in \mathbb{R}^{k \times l}$
- $\mathbf{J}_{\mathbf{x}} F$ - Jacobian of F with respect to $\mathbf{x}$, $\mathbf{J}_{\mathbf{x}} F = (\nabla_{\mathbf{x}} F)^\top$

Linear Algebra - 1

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

Linear Algebra - 2

- $\odot$ - Hadamard product

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

  MATLAB: `C = A.*B`

- $\otimes$ - Kronecker product

$$\mathbf{A} \otimes \mathbf{B} = \begin{pmatrix} \mathbf{A}_{11}\mathbf{B} & \mathbf{A}_{12}\mathbf{B} & \dots & \mathbf{A}_{1l}\mathbf{B} \\ \vdots & \vdots & \vdots & \vdots \\ \mathbf{A}_{k1}\mathbf{B} & \mathbf{A}_{k2}\mathbf{B} & \dots & \mathbf{A}_{kl}\mathbf{B} \end{pmatrix}$$

  MATLAB: `C = kron(A,B)`

- $\mathrm{vec}(\mathbf{A})$ - reshape matrix $\mathbf{A}$ into vector (column-wise).

$$\text{Example:} \quad \mathrm{vec}\left(\begin{pmatrix} \mathbf{A}_{11} & \mathbf{A}_{12} \\ \mathbf{A}_{21} & \mathbf{A}_{22} \end{pmatrix}\right) = \begin{pmatrix} \mathbf{A}_{11} \\ \mathbf{A}_{21} \\ \mathbf{A}_{12} \\ \mathbf{A}_{22} \end{pmatrix}$$

  MATLAB: `a = A(:)`

Linear Algebra - 3

- $\mathrm{mat}(\mathbf{v}, k, l)$ - reshape vector $\mathbf{v} \in \mathbb{R}^{kl}$ into matrix. k, l omitted when dimension clear from context. Note
$$\mathrm{mat}(\mathrm{vec}(\mathbf{A})) = \mathbf{A}.$$
MATLAB: `V = reshape(v,k,l)`.
- $\mathrm{diag}(\mathbf{v})$ - diagonal matrix with elements of $\mathbf{v} \in \mathbb{R}^k$ on diagonal
MATLAB: `V = diag(v(:))`
- $\mathrm{diag}(\mathbf{A})$ - diagonal matrix obtained by vectorizing $\mathbf{A}$

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