INTRODUCTORY APPLIED MACHINE LEARNING

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Today:

Math review

Vector Space

- Vector in Rⁿ is an ordered set of n real numbers
- Column vector: $\mathbf{x} = [x_1, \dots, x_n]^T \in \mathbb{R}^n$
- Example: $x = [1, 2, 3, 4]^T$, n = 4
- $x, y \in \mathbb{R}^n \rightarrow x + y = y + x \in \mathbb{R}^n$
- $x \in R^n$, $\alpha \in R \to \alpha x \in R^n$
- $x \in \mathbb{R}^n$, $\alpha, \beta \in \mathbb{R} \to (\alpha + \beta)x = \alpha x + \beta x \in \mathbb{R}^n$

Vector Norms

• A norm of a vector $||x||_p$ is informally a measure of the "size" of the vector

$$\|\boldsymbol{x}\|_p \equiv \left(\sum_{i=1}^n |x_i|^p\right)^{\frac{1}{p}}$$

- Common norms:
 - L_1 norm: $||x||_1 = \sum_{i=1}^n |x_i|$
 - Euclidean (L_2) norm: $||x||_2 = (\sum_{i=1}^n x_i^2)^{1/2} = \sqrt{x^T x}$
 - Infinite (L_{∞}) norm: $||x||_{\infty} = \max_{i} |x_{i}|$
- Cauchy-Schwartz inequality: $x, y \in R^n$, $|x^Ty| \le ||x||_2 ||y||_2$

Vector Product

- $x, y \in \mathbb{R}^n$
- Inner product:

$$\mathbf{x}^{\mathrm{T}}\mathbf{y} = \begin{bmatrix} x_1 & \dots & x_n \end{bmatrix} \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} = \sum_{i=1}^n x_i y_i \in R$$

Outer product:

$$\boldsymbol{x}\boldsymbol{y}^{\mathrm{T}} = \begin{bmatrix} \boldsymbol{x}_1 \\ \vdots \\ \boldsymbol{x}_n \end{bmatrix} \begin{bmatrix} \boldsymbol{y}_1 & \dots & \boldsymbol{y}_n \end{bmatrix} = \begin{bmatrix} \boldsymbol{x}_1 \boldsymbol{y}_1 & \dots & \boldsymbol{x}_1 \boldsymbol{y}_n \\ \vdots & \ddots & \vdots \\ \boldsymbol{x}_n \boldsymbol{y}_1 & \dots & \boldsymbol{x}_n \boldsymbol{y}_n \end{bmatrix} \in R^{m \times n}$$

Matrix

• An m-by-n matrix is an object in $R^{m \times n}$ with m rows and n columns, each entry filled with a real number

$$\bullet \ \pmb{X} = \begin{bmatrix} x_{11} & \dots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \dots & x_{mn} \end{bmatrix} \in R^{m \times n}$$

$$\bullet \ \alpha \in R \to \alpha \textbf{\textit{X}} = \begin{bmatrix} \alpha x_{11} & \dots & \alpha x_{1n} \\ \vdots & \ddots & \vdots \\ \alpha x_{m1} & \dots & \alpha x_{mn} \end{bmatrix} \in R^{m \times n}$$

•
$$X \in R^{m \times n}$$
, $Y \in R^{n \times q} \rightarrow XY \in R^{m \times q}$

Matrix Transpose

$$\bullet \ \pmb{X} = \begin{bmatrix} x_{11} & \dots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \dots & x_{mn} \end{bmatrix} \rightarrow \pmb{X}^{\mathrm{T}} = \begin{bmatrix} x_{11} & \dots & x_{m1} \\ \vdots & \ddots & \vdots \\ x_{1n} & \dots & x_{mn} \end{bmatrix} \in R^{n \times m}$$

$$\bullet (X^{\mathrm{T}})^{\mathrm{T}} = X$$

•
$$Y \in R^{m \times n} \rightarrow (X + Y)^{\mathrm{T}} = X^{\mathrm{T}} + Y^{\mathrm{T}}$$

•
$$(\alpha X)^{\mathrm{T}} = \alpha (X^{\mathrm{T}})$$

$$\bullet (XYZ)^{\mathrm{T}} = Z^{\mathrm{T}}Y^{\mathrm{T}}X^{\mathrm{T}}$$

Inverse of Matrix

Introductory Applied Machine Learning

- $X \in \mathbb{R}^{n \times n}$
- $\exists Y \in R^{n \times n}$ s.t. $XY = YX = I_n$
 - If X is invertible or nonsingular, Y is the inverse of X
- $A, B \in \mathbb{R}^{n \times n}$ nonsingular, then $(AB)^{-1} = B^{-1}A^{-1}$
- $Z \in \mathbb{R}^{n \times n}$, suppose XY = ZY, $Y \neq 0$
 - If Y is invertible, then X = Z
 - If Y is not invertible, then $X \neq Z$
- Example: $X = \begin{bmatrix} 1 & 3 \\ 0 & 1 \end{bmatrix}$, $Z = \begin{bmatrix} 2 & 4 \\ 2 & 3 \end{bmatrix}$, $Y = \begin{bmatrix} 1 & -2 \\ -1 & 2 \end{bmatrix}$

$$XY = \begin{bmatrix} 1 & 3 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & -2 \\ -1 & 2 \end{bmatrix} = \begin{bmatrix} -2 & 4 \\ -1 & 2 \end{bmatrix} = \begin{bmatrix} 2 & 4 \\ 2 & 3 \end{bmatrix} \begin{bmatrix} 1 & -2 \\ -1 & 2 \end{bmatrix} = ZY$$

Vector and Matrix Derivate

$$\frac{\partial \mathbf{x}^{\mathrm{T}} \mathbf{a}}{\partial \mathbf{x}} = \frac{\partial \mathbf{a}^{\mathrm{T}} \mathbf{x}}{\partial \mathbf{x}} = \mathbf{a}$$

$$\frac{\partial \boldsymbol{a}^{\mathrm{T}} \boldsymbol{X} \boldsymbol{b}}{\partial \boldsymbol{X}} = \boldsymbol{a} \boldsymbol{b}^{\mathrm{T}}$$

$$\frac{\partial \boldsymbol{a}^{\mathrm{T}} \boldsymbol{X} \boldsymbol{a}}{\partial \boldsymbol{X}} = \frac{\partial \boldsymbol{a}^{\mathrm{T}} \boldsymbol{X}^{\mathrm{T}} \boldsymbol{a}}{\partial \boldsymbol{X}} = \boldsymbol{a} \boldsymbol{a}^{\mathrm{T}}$$

$$\frac{\partial x^{\mathrm{T}} A x}{\partial x} = (A + A^{\mathrm{T}}) x$$

Function Derivative

• Let $\mathbf{x} = [x_1 \cdots x_n]^T$, if $f: \mathbb{R}^n \longrightarrow \mathbb{R}$ differentiable, then

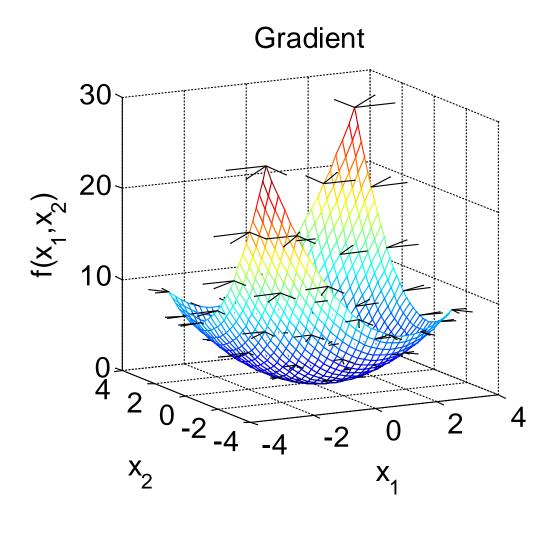
$$\nabla f = \begin{bmatrix} \frac{\partial f(x)}{\partial x_1} \\ \vdots \\ \frac{\partial f(x)}{\partial x_n} \end{bmatrix}$$

• First-order necessary condition: If x^* a local minimizer of f, then $\nabla f(x^*) = 0$

Gradient Example MATLAB Code

```
% generate gradient vectors
[x, y] = meshgrid(-3:1:3, -3:1:3); z = x.^2 + x.*y + y.^2;
x_{vert} = x(:, 1); y_{vert} = y(:, 1); z_{vert} = z(:, 1);
for i=2:length(x)
    x_{vert} = vertcat(x_{vert}, x(:, i)); y_{vert} = vertcat(y_{vert}, y(:, i));
    z_vert = vertcat( z_vert, z( :, i));
end
for i=1:length(x_vert)
    gradx_vert(i) = x_vert(i)*2 + y_vert(i); grady_vert(i) = x_vert(i) +
y vert(i)*2;
end
gradx_vert = gradx_vert'; grady_vert = grady_vert';
% plot mesh and gradient
[x, y] = \text{meshqrid}(-3:.2:3, -3:.2:3); z = x.^2 + x.*y + y.^2; \text{mesh}(x, y, z);
xlim([-4 4]); xlabel('x 1', 'FontSize', 16); ylim([-4 4]);
ylabel('x_2', 'FontSize', 16); set( gcf, 'Color', 'w');
zlabel('f(x 1,x 2)', 'FontSize', 16); title('Gradient'); set(gca,'FontSize', 16);
hold on;
arrow3( [x_vert y_vert z_vert], [x_vert+gradx_vert/7 y_vert z_vert], [], .4, 1.5);
arrow3([x_vert y_vert z_vert], [x_vert y_vert+grady_vert/7 z_vert], [], .4, 1.5);
arrow3( [x_vert y_vert z_vert], [x_vert+gradx_vert/7 ...
    y_vert+grady_vert/7 z_vert], [], .4, 1.5);
```

Example Figure



Reference

- Linear Algebra: Determinants, Inverses, Rank
- K. Petersen and M. Pedersen, The Matrix Cookbook