MATH 2242 (Calculus IV) Course Outline — Vector Calculus (Marsden)

1.5 n-Dimensional Euclidean Space

- $\mathbb{R}$, $\mathbb{R}^2$, $\mathbb{R}^3$, $\mathbb{R}^n$
- Addition
  - $(x_1, x_2, \ldots, x_n) + (y_1, y_2, \ldots, y_n) = (x_1 + y_1, x_2 + y_2, \ldots, x_n + y_n)$
- Scalar multiplication
  - $\alpha(x_1, x_2, \ldots, x_n) = (\alpha x_1, \alpha x_2, \ldots, \alpha x_n)$
- Inner/Dot Product
  - $(x_1, x_2, \ldots, x_n) \cdot (y_1, y_2, \ldots, y_n) = \sum_{i=1}^{n} x_i y_i$
- Norm/Length/Magnitude
  - $\|\mathbf{x}\| = (\mathbf{x} \cdot \mathbf{x})^{1/2}$
- Standard basis vectors
  - $\mathbf{e}_1 = (1, 0, \ldots, 0)$, $\mathbf{e}_2 = (0, 1, \ldots, 0)$, $\ldots$, $\mathbf{e}_n = (0, 0, \ldots, 1)$
- Theorems
  - $(\alpha\mathbf{x} + \beta\mathbf{y}) \cdot \mathbf{z} = \alpha(\mathbf{x} \cdot \mathbf{z}) + \beta(\mathbf{y} \cdot \mathbf{z})$
  - Prove the above theorem.
  - $\mathbf{x} \cdot \mathbf{y} = \mathbf{y} \cdot \mathbf{x}$
  - $\mathbf{x} \cdot \mathbf{x} \geq 0$
  - $\mathbf{x} \cdot \mathbf{x} = 0$ if and only if $\mathbf{x} = \mathbf{0}$
  - $|\mathbf{x} \cdot \mathbf{y}| \leq \|\mathbf{x}\|\|\mathbf{y}\|$ (the Cauchy-Schwarz inequality)
  - (Example) Prove the Cauchy-Schwarz inequality for $\mathbb{R}^2$.
  - $\|\mathbf{x} + \mathbf{y}\| \leq \|\mathbf{x}\| + \|\mathbf{y}\|$ (the triangle inequality)
  - (Example) Prove the triangle inequality.
- Matrices
  - $A = \begin{bmatrix} a_{11} & a_{12} & \ldots & a_{1n} \\ a_{21} & a_{22} & \ldots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \ldots & a_{mn} \end{bmatrix}$

  - Addition $A + B$
  - Scalar Mutiplication αA
  - Transposition A^T

- Vectors as Matrices

  - $\mathbf{a} = (a_1, a_2, \ldots, a_n) = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix}$
  - $\mathbf{a}^T = \begin{bmatrix} a_1 & a_2 & \cdots & a_n \end{bmatrix}$

- Matrix Multiplication

  - If A has m rows and B has n columns, then $M = AB$ is an $m \times n$ matrix.
  - Coordinate ij of $M = AB$ is given by $m_{ij} = \mathbf{a_i} \cdot \mathbf{b_j}$ where $\mathbf{a_i}^T$ is the ith row of A and $\mathbf{b_j}$ is the jth column of B.
  - (Example 4) Compute AB and BA for

$$A = \begin{bmatrix} 1 & 0 & 3 \\ 2 & 1 & 0 \\ 1 & 0 & 0 \end{bmatrix}$$

$$B = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 1 \end{bmatrix}$$

  - (Example 5) Compute AB for

$$A = \begin{bmatrix} 2 & 0 & 1 \\ 1 & 1 & 2 \end{bmatrix}$$

$$B = \begin{bmatrix} 1 & 0 & 2 \\ 0 & 2 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

- Matrices as Linear Transformations

  - An $m \times n$ matrix A gives a function from $\mathbb{R}^n$ to $\mathbb{R}^m$: $\mathbf{x} \mapsto A\mathbf{x}$
  - This linear transformation satsifies $A(\alpha\mathbf{x} + \beta\mathbf{y}) = \alpha A\mathbf{x} + \beta A\mathbf{y}$
  - (Example 7) Express $A\mathbf{x}$ where $x = (x_1, x_2, x_3)$ and $A = \begin{bmatrix} 1 & 0 & 3 \\ -1 & 0 & 1 \\ 2 & 1 & 2 \\ -1 & 2 & 2 \end{bmatrix}$.

  - (Example) Compute where the points $(-1,-1,0)$, $(0,1,0)$, $(1,-1,1)$, and $(2,1,1)$ in $\mathbb{R}^3$ get mapped to in $\mathbb{R}^4$ by $A\mathbf{x}$ from the previous example. Then plot the projections of the original points in $\mathbb{R}^3$ onto their first two coordinates in $\mathbb{R}^2$, and compare this with the projection plot of their images in $\mathbb{R}^4$ onto their first two coordinates in $\mathbb{R}^2$.

- Identity and Inverse

  - The $n \times n$ identity matrix I satisfies $i_{jj} = 1$ and $i_{jk} = 0$ when $j \neq k$. That is:
    $$I = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 \end{bmatrix}$$
  - If $AA^{-1} = A^{-1}A = I$, then A is invertable and A^{-1} is its inverse.

- Determinant

  - Let A_i be the submatrix of A with the first column and ith row removed. Then $\det(A) = \sum_{i=1}^{n} (-1)^{i+1} a_{1i} \det(A_i)$
  - This is equivalent to $\det(A) = \sum_{\sigma \in S^n} \operatorname{sgn}(\sigma) \prod_{1 \leq i \leq n} a_{i,\sigma_i}$ where S^n is the collection of all permutations of elements 1 to n and $\operatorname{sgn}(\sigma)$ is 1 when σ is obtained by an even number of swaps, and -1 when σ is obtained by an odd number of swaps.
  - (Example) Prove that
    $$\det \begin{bmatrix} a_1 & a_2 \\ b_1 & b_2 \end{bmatrix} = a_1 b_2 - a_2 b_1$$
    and
    $$\det \begin{bmatrix} a_1 & a_2 & a_3 \\ b_1 & b_2 & b_3 \\ c_1 & c_2 & c_3 \end{bmatrix} = a_1 \det \begin{bmatrix} b_2 & b_3 \\ c_2 & c_3 \end{bmatrix} - a_2 \det \begin{bmatrix} b_1 & b_3 \\ c_1 & c_3 \end{bmatrix} + a_3 \det \begin{bmatrix} b_1 & b_2 \\ c_1 & c_2 \end{bmatrix}$$
    $$= (a_1 b_2 c_3 + a_2 b_3 c_1 + a_3 b_1 c_2) - (a_1 b_3 c_2 + a_2 b_1 c_3 + a_3 b_2 c_1)$$
  - (Example) Prove that the inverse of the matrix $A = \begin{bmatrix} a_1 & a_2 \\ b_1 & b_2 \end{bmatrix}$ is $\frac{1}{\det A} \begin{bmatrix} b_2 & -a_2 \\ -b_1 & a_1 \end{bmatrix}$.
  - An $n \times n$ matrix is invertable if and only if its determinant is nonzero.

- *HW: 1-18, 21-24*

2.3 Differentiation

- Functions $\mathbb{R}^n \to \mathbb{R}^m$
  - $\mathbf{f} : \mathbb{R}^n \to \mathbb{R}^m$
  - $\mathbf{f}(\mathbf{x}) = (f_1(\mathbf{x}), \dots, f_m(\mathbf{x}))$ where $f_i : \mathbb{R}^n \to \mathbb{R}$
- Partial Derivative Matrix
  - $\mathbf{Df}(\mathbf{x}) = \begin{bmatrix} \frac{\partial f_1}{\partial x_1}(\mathbf{x}) & \cdots & \frac{\partial f_1}{\partial x_n}(\mathbf{x}) \\ \vdots & \ddots & \vdots \\ \frac{\partial f_m}{\partial x_1}(\mathbf{x}) & \cdots & \frac{\partial f_m}{\partial x_n}(\mathbf{x}) \end{bmatrix}$
  - We say $\mathbf{f}$ is differentiable at $\mathbf{x}_0$ if $\mathbf{f}(\mathbf{x}_0+\mathbf{h}) \approx \mathbf{f}(\mathbf{x}_0)+[\mathbf{Df}(\mathbf{x}_0)]\mathbf{h}$ whenever $\mathbf{h} \approx \mathbf{0}$.
  - (Example) Prove that this is equivalent to saying $\mathbf{f}(\mathbf{x}) \approx \mathbf{f}(\mathbf{x}_0)+[\mathbf{Df}(\mathbf{x}_0)](\mathbf{x}-\mathbf{x}_0)$ whenever $\mathbf{x} \approx \mathbf{x}_0$.
  - (Example) Let $\mathbf{f} : \mathbb{R}^2 \to \mathbb{R}^2$ be defined by $\mathbf{f}(x, y) = (x^2 + y^2, xy)$, and let $\mathbf{T} = \mathbf{Df}(1, 0)$. Compute $\mathbf{f}(1.1, -0.1)$ and $\mathbf{f}(1, 0) + \mathbf{T}(0.1, -0.1)$.
  - If each $\frac{\partial f_i}{\partial x_j} : \mathbb{R}^n \to \mathbb{R}$ is a continuous function near $\mathbf{x}_0$, then we say $\mathbf{f}$ is strongly differentiable or class C^1 at $\mathbf{x}_0$. All C^1 functions are differentiable.
- Gradient
  - If $f : \mathbb{R}^n \to \mathbb{R}$, then the gradient vector function $\nabla f : \mathbb{R}^n \to \mathbb{R}^n$ is defined by $\nabla f(\mathbf{x}) = (\mathbf{D}f(\mathbf{x}))^T = (\frac{\partial f}{\partial x_1}(\mathbf{x}), \dots, \frac{\partial f}{\partial x_n}(\mathbf{x}))$
  - $[\mathbf{D}f(\mathbf{x})]\mathbf{h} = \nabla f(\mathbf{x}) \cdot \mathbf{h}$
- Linearizations and Tangent Hyperplanes
  - For $\mathbf{f} : \mathbb{R}^n \to \mathbb{R}^m$ and a point $\mathbf{x}_0 \in \mathbb{R}^n$, let the linearization of $\mathbf{f}$ at $\mathbf{x}_0$ be $\mathbf{L}(\mathbf{x}) = \mathbf{f}(\mathbf{x}_0) + [\mathbf{Df}(\mathbf{x_0})](\mathbf{x} - \mathbf{x}_0)$. Note $\mathbf{f}(\mathbf{x}) \approx \mathbf{L}(\mathbf{x})$ whenever $\mathbf{x} \approx \mathbf{x}_0$.
  - (Example 5) Recall that the tangent plane to a surface $z = f(x, y)$ given by $f : \mathbb{R}^2 \to \mathbb{R}$ passing through $\mathbf{x}_0 \in \mathbb{R}^3$ is given by the normal vector ∇f. Show that $z = L(x, y)$ gives an equation for the tangent plane to the surface $z = x^2+y^4+e^{xy}$ at the point $(1, 0, 2)$.
- *HW: 1-3, 5-21*

2.5 Properties of the Derivative

- Sum/Product/Quotient Rules
  - $\mathbf{D}[\alpha\mathbf{f}] = \alpha\mathbf{Df}$

  - $\mathbf{D}[\mathbf{f}+\mathbf{g}] = \mathbf{Df} + \mathbf{Dg}$
  - (Example) Prove the sum rule above.
  - $\mathbf{D}[fg] = g\mathbf{D}f + f\mathbf{D}g$
  - $\mathbf{D}[\frac{f}{g}] = \frac{g\mathbf{D}f - f\mathbf{D}g}{g^2}$

- Chain Rule
  - $\mathbf{D}[\mathbf{f}\circ\mathbf{g}] = \mathbf{Df}(\mathbf{g})\mathbf{Dg}$
  - (Example) Find the rate of change of $f(x,y) = x^2+y^2$ along the path $\mathbf{c}(t) = (t^2, t)$ when $t = 1$.
  - (Example 2) Verify the Chain Rule for $f(u,v,w) = u^2+v^2-w$ and $\mathbf{g}(x,y,z) = (x^2y, y^2, e^{-xz})$.
  - (Example 3) Compute $\mathbf{D}[\mathbf{f}\circ\mathbf{g}](1,1)$ where $\mathbf{f}(u,v) = (u+v, u, v^2)$ and $\mathbf{g}(x,y) = (x^2+1, y^2)$.

- *HW: 6-13, 15-16*

3.2 Taylor's Theorem

- Single-variable Taylor Series
  - $f(x) = \sum_{n=0}^{\infty} \frac{f^{(n)}(x_0)}{n!}(x-x_0)^n$
    $= f(x_0) + f'(x_0)(x-x_0) + \frac{1}{2}f'(x_0)(x-x_0)^2 + \frac{1}{6}f'(x_0)(x-x_0)^3 + \dots$
  - $f(x) \approx \sum_{n=0}^{m} \frac{f^{(n)}(x_0)}{n!}(x-x_0)$
- First-Order Taylor Formula
  - $f(\mathbf{x}) \approx L(\mathbf{x}) = f(\mathbf{x}_0) + [\mathbf{D}f(\mathbf{x}_0)](\mathbf{x}-\mathbf{x}_0) = f(\mathbf{x}_0) + \sum_{i=1}^{n} \frac{\partial f}{\partial x_i}(\mathbf{x}_0)(x_i - x_{0i})$
- Second-Order Taylor Formula
  - $f(\mathbf{x}) \approx f(\mathbf{x}_0) + \sum_{i=1}^{n} \frac{\partial f}{\partial x_i}(\mathbf{x}_0)(x_i - x_{0,i}) + \frac{1}{2}\sum_{i,j=1}^{n} \frac{\partial^2 f}{\partial x_i \partial x_j}(\mathbf{x}_0)(x_i - x_{0,i})(x_j - x_{0,j})$
  - (Example 3) Find linear and quadratic functions of x, y which approximate $f(x,y) = \sin(xy)$ near the point $(1, \pi/2)$.
- *HW: 1-12*