## Math Booklet $^1$

Iago Mendes $^{\rm 2}$ 

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 $<sup>^1{\</sup>rm A}$  booklet with notes of Math.  $^2{\rm Oberlin}$  College; double major in Physics (Astrophysics) and Computer Science.

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# Algebra

### 1.1 Linear Algebra

### 1.1.1 Matrices

• Notation

$$A = [a_{ij}]$$

 $\bullet\,$  Matrix Addition

$$[a_{ij}] + [b_{ij}] = [a_{ij} + b_{ij}]$$

• Scalar multiplication

$$c[a_{ij}] = [ca_{ij}]$$

• Transpose

$$(aT)_{ij} = a_{ji}$$

• Matrix Multiplication

$$c_{ij} = (\text{ith row of A})(\text{jth column of B}) = \sum_{k=1}^{n} a_{ik} b_{kj}$$

# Geometry

### 2.1 Analytic Geometry

### 2.1.1 Coordinate systems

- Cartesian coordinates ( $\mathbb{R}^2$  and  $\mathbb{R}^3$ )
- (x,y) (x,y,z)

• Polar coordinates  $(\mathbb{R}^2)$ 

 $(r, \theta)$ 

- Typical restrictions

- $r \ge 0$  $0 \le \theta \le 2\pi$
- Polar/rectangular conversions

$$\begin{cases} x = r \cos \theta \\ y = r \sin \theta \end{cases} \qquad \begin{cases} r^2 = x^2 + y^2 \\ \tan \theta = \frac{y}{x} \end{cases}$$

• Cylindrical coordinates  $(\mathbb{R}^3)$ 

 $(r, \theta, z)$ 

- Typical restrictions

$$r \ge 0$$
$$0 < \theta < 2\pi$$

- Cylindrical/rectangular conversions

$$\begin{cases} x = r \cos \theta \\ y = r \sin \theta \\ z = z \end{cases} \qquad \begin{cases} r^2 = x^2 + y^2 \\ \tan \theta = \frac{y}{x} \\ z = z \end{cases}$$

• Spherical coordinates  $(\mathbb{R}^3)$ 

$$(\rho, \phi, \theta)$$

- Typical restrictions

$$\begin{aligned} \rho &\geq 0 \\ 0 &\leq \phi \leq \pi \\ 0 &< \theta < 2\pi \end{aligned}$$

- Spherical/cylindrical conversions

$$\begin{cases} r = \rho \sin \phi \\ \theta = \theta \\ z = \rho \cos \phi \end{cases} \qquad \begin{cases} \rho^2 = r^2 + z^2 \\ \tan \phi = \frac{r}{z} \\ \theta = \theta \end{cases}$$

- Spherical/rectangular conversions

$$\begin{cases} x = \rho \sin \phi \cos \theta \\ y = \rho \sin \phi \sin \theta \\ z = \rho \cos \phi \end{cases} \qquad \begin{cases} \rho^2 = x^2 + y^2 + z^2 \\ \tan \phi = \frac{\sqrt{x^2 + y^2}}{z} \\ \tan \theta = \frac{y}{x} \end{cases}$$

## Calculus

### 3.1 Multivariable Calculus

$$\mathbf{f}: X \subseteq \mathbb{R}^n \to \mathbb{R}^m$$
$$f: X \subseteq \mathbb{R}^n \to \mathbb{R}$$

#### 3.1.1 Partial Derivatives

$$\frac{\partial f}{\partial x_i} = \lim_{h \to 0} \frac{f(x_1, \dots, x_i + h, \dots, x_n) - f(x_1, \dots, x_n)}{h}$$

• Gradient

$$\nabla f = (f_{x_1}, \dots, f_{x_n})$$
$$\nabla f(\mathbf{a}) = (f_{x_1}(\mathbf{a}), \dots, f_{x_n}(\mathbf{a}))$$

• Derivative matrix

$$D\mathbf{f} = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \dots & \frac{\partial f_1}{\partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial f_m}{\partial x_1} & \dots & \frac{\partial f_m}{\partial x_n} \end{bmatrix} \qquad D\mathbf{f}(\mathbf{a}) = \begin{bmatrix} \frac{\partial f_1}{\partial x_1}(\mathbf{a}) & \dots & \frac{\partial f_1}{\partial x_n}(\mathbf{a}) \\ \vdots & \ddots & \vdots \\ \frac{\partial f_m}{\partial x_1}(\mathbf{a}) & \dots & \frac{\partial f_m}{\partial x_n}(\mathbf{a}) \end{bmatrix}$$

• Tangent plane

$$z = h(x,y) = f(a,b) + f_x(a,b)(x-a) + f_y(a,b)(y-b)$$
$$f_x(x_0, y_0, z_0)(x-x_0) + f_y(x_0, y_0, z_0)(y-y_0) + f_z(x_0, y_0, z_0)(z-z_0) = 0$$

- Normal vector

$$\mathbf{n} = -f_x(a,b)\hat{\mathbf{i}} - f_y(a,b)\hat{\mathbf{j}} + \hat{\mathbf{k}} = (-f_x(a,b), -f_y(a,b), 1)$$

- Hyperplane

$$\mathbf{h}(\mathbf{x}) = \mathbf{f}(\mathbf{a}) + D\mathbf{f}(\mathbf{a})(\mathbf{x} - \mathbf{a})$$
$$\nabla f(\mathbf{x}_0) \cdot (\mathbf{x} - \mathbf{x}_0) = 0$$

• Differentiability

1.  $D\mathbf{f}(\mathbf{a})$  exists

2.

$$\lim_{\mathbf{x} \to \mathbf{a}} \frac{\mathbf{f}(\mathbf{x}) - \mathbf{h}(\mathbf{x})}{||\mathbf{x} - \mathbf{a}||} = 0$$

• Higher-order partial derivative

$$\frac{\partial^k f}{\partial x_{i_k} \dots \partial x_{i_1}} = \frac{\partial}{\partial x_{i_k}} \dots \frac{\partial}{\partial x_{i_1}} f(x_1, \dots, x_n)$$

3.1 Multivariable Calculus

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- Clairaut's Theorem

$$\frac{\partial^k f}{\partial x_{i_k} \dots \partial x_{i_1}} = \frac{\partial^k f}{\partial x_{j_1} \dots \partial x_{j_k}}$$

• Chain rule

$$D(\mathbf{f} \circ \mathbf{x})(\mathbf{t}_0) = D\mathbf{f}(\mathbf{x}_0)D\mathbf{x}(\mathbf{t}_0)$$
$$f'(\mathbf{x}(t)) = \nabla f(\mathbf{x}) \bullet \mathbf{x}'(t)$$

• Directional derivative

$$D_{\hat{\mathbf{u}}}f(\mathbf{a}) = \nabla f(\mathbf{a}) \bullet \hat{\mathbf{u}} = ||\nabla f(\mathbf{a})|| \cos \theta$$

#### 3.1.2 Vector-valued Functions

- Arclength
- Vector fields
- Del operator

$$\nabla = \left(\frac{\partial}{\partial x_1}, \ \frac{\partial}{\partial x_2}, \ \dots, \ \frac{\partial}{\partial x_n}\right)$$

• Gradient

$$\nabla f = \left(\frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial x_2}, \dots, \frac{\partial f}{\partial x_n}\right)$$

• Divergence

$$\nabla \bullet \mathbf{F} = \frac{\partial f}{\partial x_1} + \frac{\partial f}{\partial x_2} + \dots + \frac{\partial f}{\partial x_n}$$

• Curl

$$\nabla \times \mathbf{F} = \begin{vmatrix} \hat{\mathbf{i}} & \hat{\mathbf{j}} & \hat{\mathbf{k}} \\ \frac{\partial}{\partial x} & \frac{\partial}{\partial y} & \frac{\partial}{\partial z} \\ F_1 & F_2 & F_3 \end{vmatrix}$$

- Theorems
  - 1. If f is a scalar-valued function of class  $C^2$ , then

$$\nabla \times (\nabla f) = \mathbf{0}$$

2. If **F** is a vector-valued function of class  $C^2$  on  $X \subseteq \mathbb{R}^3$ , then

$$\nabla \bullet (\nabla \times \mathbf{F}) = 0$$

#### 3.1.3 Maxima and Minima

- Taylor Polynomials
  - First-order

$$p_1(\mathbf{x}) = f(\mathbf{a}) + \sum_{i=1}^n f_{x_i}(\mathbf{a})(x_i - a_i)$$
$$p_1(\mathbf{x}) = f(\mathbf{a}) + Df(\mathbf{a})(\mathbf{x} - \mathbf{a})$$

- Second-order

$$p_2(\mathbf{x}) = f(\mathbf{a}) + \sum_{i=1}^n f_{x_i}(\mathbf{a})(x_i - a_i) + \frac{1}{2} \sum_{i,j=1}^n f_{x_i x_j}(\mathbf{a})(x_i - a_i)(x_j - a_j)$$
$$p_2(\mathbf{x}) = f(\mathbf{a}) + Df(\mathbf{a})(\mathbf{x} - \mathbf{a}) + \frac{1}{2}(\mathbf{x} - \mathbf{a})^T Hf(\mathbf{a})(\mathbf{x} - \mathbf{a})$$

• Differential

$$df = \frac{\partial f}{\partial x_1} dx_1 + \dots + \frac{\partial f}{\partial x_n} dx_n$$

- Hessian Criterion
  - Hessian matrix

$$Hf(\mathbf{a}) = \begin{bmatrix} f_{x_1x_1(\mathbf{a})} & \cdots & f_{x_1x_n(\mathbf{a})} \\ \vdots & \ddots & \vdots \\ f_{x_nx_1(\mathbf{a})} & \cdots & f_{x_nx_n(\mathbf{a})} \end{bmatrix}$$

- Principal minor

 $d_k = \text{determinant of the upper leftmost } k \times k \text{ submatrix of } Hf(\mathbf{a})$ 

- 1. If all  $d_k > 0$ , then the critical point **a** gives a local minimum.
- 2. If  $d_1 < 0$ ,  $d_2 > 0$ ,  $d_3 < 0$ , ..., then the critical point **a** gives a local maximum.
- 3. If neither case 1 nor case 2 occurs, then **a** is a saddle point.

If  $d_n = 0$ , the critical point **a** is degenerate and the test fails.

• Extrema Value Theorem

If D is a compact region in  $\mathbb{R}^n$  and  $f: D \to R$  is continuous, then f must have a (global) maximum and minimum values on D.

• Lagrange Multiplier Theorem

$$\nabla f(\mathbf{a}) = \lambda \nabla g(\mathbf{a})$$

- Constraint

$$S = \{ \mathbf{x} \in \mathbb{R}^n \mid g(\mathbf{x}) = c \}$$