CSC 446 Notes: Multivariable Calculus Review

1 Basic Vector Operations

The basic structure of multivariable calculus is the vector. By convention we assume in this class that vectors are column vectors:

$$\mathbf{v} = \begin{bmatrix} v_1 \\ v_2 \\ v_3 \\ \vdots \\ v_n \end{bmatrix}$$

The transpose of this vector, $\mathbf{v}^T$, is a row vector:

$$\mathbf{v}^T = \begin{bmatrix} v_1 & v_2 & v_3 & \cdots & v_n \end{bmatrix}$$

The **inner product**, also known as the **dot product**, reduces two vectors of equal length to a scalar:

$$\mathbf{x} \cdot \mathbf{y} = \mathbf{x}^T \mathbf{y} = \sum_i x_i y_i$$

In contrast, the **outer product** takes two vectors and produces an $n \times n$ matrix:

$$\mathbf{x} \times \mathbf{y}^T = \mathbf{x}\mathbf{y}^T = \begin{bmatrix} x_1y_1 & x_1y_2 & \cdots & x_1y_n \\ x_2y_1 & x_2y_2 & & \\ \vdots & & \ddots & \\ x_ny_1 & & & x_ny_n \end{bmatrix}$$

2 Multivariable Functions and Vector Calculus

A **multivariable function** takes a number of variables (or a vector) as parameters and returns a single value. In domain terms, a multivariable function $f(\mathbf{x})$ maps from an n-dimensional vector space down to a scalar domain. The **gradient** is the basic vector derivative operation. Given a scalar function $f(\mathbf{x})$,

$$\nabla f(\mathbf{x}) = \begin{bmatrix} \frac{\partial f}{\partial x_1} \\ \frac{\partial f}{\partial x_2} \\ \vdots \\ \frac{\partial f}{\partial x_n} \end{bmatrix}$$

yields a vector representing the direction and the rate of change of the function f within $\mathbb{R}^n$-space.
Example 1: Let $f(\mathbf{x}) = \mathbf{1}^T\mathbf{x} = \sum_i x_i$. Then the gradient of f is

$$\nabla f(\mathbf{x}) = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix} = \mathbf{1}$$

Example 2: Let $f(\mathbf{x}) = \mathbf{x}^T\mathbf{x} = \sum_i x_i^2$. Then the gradient of f is

$$\nabla f(\mathbf{x}) = \begin{bmatrix} 2x_1 \\ 2x_2 \\ \vdots \\ 2x_n \end{bmatrix} = 2\mathbf{x}$$

The product and chain rules hold when dealing with gradients and vector-valued functions, but looks slightly different:

- **Product Rule:** $\nabla(f(\mathbf{x})g(\mathbf{x})) = f(\mathbf{x})\nabla g(\mathbf{x}) + \nabla f(\mathbf{x})g(\mathbf{x})$, where f and g are both vector-to-scalar functions ($f : \mathbb{R}^n \to \mathbb{R}$ and $g : \mathbb{R}^n \to \mathbb{R}$).
- **Chain Rule:** $\frac{\partial}{\partial t} f(g(t)) = \nabla f(g(t))^T \frac{\partial g}{\partial t}$, where $f(\mathbf{x})$ is a vector-to-scalar function and $g(t)$ is a standard one-parameter vector-valued function ($f : \mathbb{R}^n \to \mathbb{R}$ and $g : \mathbb{R} \to \mathbb{R}^n$). Note that in because g is a vector-valued function, the partial derivative $\frac{\partial g}{\partial t}$ is itself a vector: $\frac{\partial g}{\partial t} = \begin{bmatrix} \frac{\partial g_1}{\partial t} & \frac{\partial g_2}{\partial t} & \cdots & \frac{\partial g_n}{\partial t} \end{bmatrix}^T$

It is important to note the vector operations that make these rules work. In the case of the Product Rule, the input functions $f(\mathbf{x})$ and $g(\mathbf{x})$ are both scalar, but their gradients ∇f and ∇g are vectors. Thus, $\nabla(fg)$ is the sum of two scalar-multiplied vectors, and is therefore a vector. Similarly, $\nabla f(g(t))$ and $\frac{\partial g(t)}{\partial t}$ are both vectors, and so their dot product is the scalar one would expect from a partial derivative of a scalar function.

Gradients are very useful when plotted on a map of the variable field, such as a contour map. The gradient points in the direction of the steepest rate of change of $f(\mathbf{x})$ as one moves up and down the variable axes. On a contour map of a hill, for instance, this represents the direction of fastest ascent. As with scalar derivatives, $\nabla f(\mathbf{x}) = \mathbf{0}$ when the function f is at a local extremum (maximum or minimum).

3 Matrices, Eigenvalues and Eigenvectors

Let A be an $n \times n$ matrix, $\mathbf{b}$ be an n-element vector, and c be a scalar. The function

$$f(\mathbf{x}) = \frac{1}{2}\mathbf{x}^T A\mathbf{x} + \mathbf{b}^T\mathbf{x} + c$$

is a scalar function. The term $\mathbf{x}^T A\mathbf{x}$ can be thought of as the **curvature** in direction $\mathbf{x}$. If A is symmetric (i.e., $a_{i,j} = a_{j,i}$), then $\nabla f = A\mathbf{x} + \mathbf{b}$. If A is **not** symmetric, then $\nabla f = A'\mathbf{x} + \mathbf{b}$, where $A' = \frac{1}{2}A + A^T$.

If $A\mathbf{x} = \lambda\mathbf{x}$ where λ is some scalar value, then the vector x is an **eigenvector** of A and λ is an **eigenvalue** of A.

4 Jacobians and Hessians

So far, we have assumed that our function f has a scalar value. But what if we have a vector-valued function $f : \mathbb{R}^m \to \mathbb{R}^n$? This function takes an m-element input vector and returns an n-element output vector. The gradients of each vector element $f(\mathbf{x})_i$ form the rows of a special $m \times n$ matrix called the **Jacobian**:

$$J = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \cdots & \frac{\partial f_1}{\partial x_m} \\ \vdots & \ddots & \\ \frac{\partial f_n}{\partial x_1} & & \frac{\partial f_n}{\partial x_m} \end{bmatrix}$$

Armed with the Jacobian, we can now express the chain rule for a vector-valued multivariable function:

$$\frac{\partial}{\partial t} f(g(t)) = J \frac{\partial g}{\partial t}$$

Another useful matrix is the **Hessian** $\nabla^2 f$, which is a matrix of a scalar-valued function $f(\mathbf{x})$'s second-order derivatives:

$$\nabla^2 f = \begin{bmatrix} \frac{\partial^2 f}{(\partial x_1)^2} & \cdots & \frac{\partial^2 f}{\partial x_n \partial x_1} \\ \vdots & \ddots & \\ \frac{\partial^2 f}{\partial x_1 \partial x_n} & & \frac{\partial^2 f}{(\partial x_n)^2} \end{bmatrix} = \left[\frac{\partial^2 f}{\partial x_i \partial x_j} \right]_{ij}$$

Definition: A matrix A is **positive semidefinite** (p.s.d.) if $\forall \mathbf{x}\ \mathbf{x}^T A \mathbf{x} \geq 0$. This also means that all the eigenvalues of A are positive. This definition is important because if f is at a maximum, then $-\nabla^2 f$ is positive semidefinite. Similarly, $\nabla^2 f$ is positive semidefinite when f is at a minimum.

Example: Let $f(\mathbf{x}) = \frac{1}{2}\mathbf{x}^T A \mathbf{x} = \frac{1}{2}x_1^2 + \frac{1}{2}x_2^2$, and let $A = I = \begin{bmatrix} 1 & \\ & 1 \end{bmatrix}$. To find the extrema, we calculate the gradient $\nabla f = \mathbf{x}$. Setting $\nabla f = \mathbf{x}$ to $\mathbf{0}$, we find the local extremum at the origin. To determine the orientation of this extremum, we compute the Hessian:

$$\nabla^2 f = \left[\frac{\partial^2 (x_1^2 + x_2^2)}{\partial x_i \partial x_j} \right]_{ij} = \begin{bmatrix} 1 & \\ & 1 \end{bmatrix}$$

Since $-\nabla^2 f$ is p.s.d., we know that the extremum is a minimum.

Example: Let $f(\mathbf{x}) = \frac{1}{2}\mathbf{x}^T A \mathbf{x} = -\frac{1}{2}x_1^2 - \frac{1}{2}x_2^2$, and let $A = -I = \begin{bmatrix} -1 & \\ & -1 \end{bmatrix}$. To find the extrema, we calculate the gradient $\nabla f = \mathbf{x}$. Setting $\nabla f = \mathbf{x}$ to $\mathbf{0}$, we find the local extremum at the origin. To determine the orientation of this extremum, we compute the Hessian:

$$\nabla^2 f = \left[\frac{\partial^2 (-x_1^2 - x_2^2)}{\partial x_i \partial x_j} \right]_{ij} = \begin{bmatrix} -1 & \\ & -1 \end{bmatrix}$$

Since $-\nabla^2 f$ is p.s.d., we know that the extremum is a maximum.

5 Newton's Method

We now have all the tools we need for Newton's method of approximating a vector-valued function. This is basically the second-order expansion of a Taylor series about some point $\mathbf{x_0}$:

$$\hat{f}(\mathbf{x}) = f(\mathbf{x_0}) + \nabla f(\mathbf{x_0})^T (\mathbf{x} - \mathbf{x_0}) + \frac{1}{2}(\mathbf{x} - \mathbf{x_0})^T \nabla^2 f(\mathbf{x_0})(\mathbf{x} - \mathbf{x_0})$$

The gradient of this approximation is:

$$\nabla \hat{f}(\mathbf{x}) = \nabla^2 f(\mathbf{x_0})(\mathbf{x} - \mathbf{x_0}) + \nabla f(\mathbf{x_0})$$

Remember that this is an approximation about a point $\mathbf{x_0}$, and becomes less accurate as one travels from this point. We can use this gradient to find the maximum of $\hat{f}$ by setting $\nabla \hat{f}$ to 0 and solving for $\mathbf{x_{max}}$:

$$\mathbf{x_{max}} = \mathbf{x_0} - (\nabla^2 f(\mathbf{x_0}))^{-1} \nabla f(\mathbf{x_0})$$

Recall that the Hessian $\nabla^2 f$ is a matrix, so to remove it from one side of the equation you must multiply both sides by the inverse matrix $(\nabla^2 f)^{-1}$.

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