Analysis review: Vector calculus and measure

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Introduction

- Next up, we'll be reviewing the central tools of calculus: derivatives and integrals
- I assume that you're already quite familiar with ordinary scalar derivatives, but not necessarily with vector derivatives
- Likewise, I assume that you know how to take integrals, but perhaps not with its underlying theoretical development, and not with the Riemann-Stieltjes form of integrals
- This form is useful to be aware of, as it has a deep connection with probability theory and allows for a nice unification of continuous and discrete probability theory

Real-valued functions: Derivative and gradient

- Vector calculus is extremely important in statistics, and we will use it frequently in this course
- **Definition:** For a function $f : \mathbb{R}^d \to \mathbb{R}$, its *derivative* is the $1 \times d$ row vector

$$\dot{f}(\mathbf{x}) = \left[\frac{\partial f}{\partial x_1} \cdots \frac{\partial f}{\partial x_d} \right]$$

- In statistics, it is generally more common (but not always the case) to use the gradient (also called "denominator layout" or the "Hessian formulation")

$$\nabla f(\mathbf{x}) = \dot{f}(\mathbf{x})^\top;$$

i.e., $\nabla f(\mathbf{x})$ is a $d \times 1$ column vector

Vector-valued functions

- **Definition:** For a function $f : \mathbb{R}^d \to \mathbb{R}^k$, its *derivative* is the $k \times d$ matrix with ijth element

$$\dot{\mathbf{f}}(\mathbf{x})_{ij} = \frac{\partial f_i(\mathbf{x})}{\partial x_j}$$

- Correspondingly, the gradient is a $d \times k$ matrix:

$$\nabla \mathbf{f}(\mathbf{x}) = \dot{\mathbf{f}}(\mathbf{x})^\top$$

- In our course, this will usually come up in the context of taking second derivatives; however, by the symmetry of second derivatives, we have

$$\nabla^2 f(\mathbf{x}) = \ddot{f}(\mathbf{x})$$

Vector calculus identities

Inner product:	$\nabla_{\mathbf{x}}(\mathbf{A}^\top \mathbf{x}) = \mathbf{A}$
Quadratic form:	$\nabla_{\mathbf{x}}(\mathbf{x}^\top \mathbf{A}\mathbf{x}) = (\mathbf{A} + \mathbf{A}^\top)\mathbf{x}$
Chain rule:	$\nabla_{\mathbf{x}}\mathbf{f}(\mathbf{y}) = \nabla_{\mathbf{x}}\mathbf{y}\nabla_{\mathbf{y}}\mathbf{f}$
Product rule:	$\nabla(\mathbf{f}^\top \mathbf{g}) = (\nabla \mathbf{f})\mathbf{g} + (\nabla \mathbf{g})\mathbf{f}$
Inverse function theorem:	$\nabla_{\mathbf{x}}\mathbf{y} = (\nabla_{\mathbf{y}}\mathbf{x})^{-1}$

Note that for the inverse function theorem to apply, the gradient must be invertible

Vector calculus identities (row-vector layout)

Inner product:	$D_{\mathbf{x}}(\mathbf{A}\mathbf{x}) = \mathbf{A}$
Quadratic form:	$D_{\mathbf{x}}(\mathbf{x}^\top \mathbf{A}^\top \mathbf{x}) = \mathbf{x}^\top(\mathbf{A} + \mathbf{A}^\top)$
Chain rule:	$D_{\mathbf{x}}\mathbf{f}(\mathbf{y}) = D_{\mathbf{y}}\mathbf{f}\, D_{\mathbf{x}}\mathbf{y}$
Product rule:	$D(\mathbf{f}^\top \mathbf{g}) = \mathbf{g}^\top \dot{\mathbf{f}} + \mathbf{f}^\top \dot{\mathbf{g}}$
Inverse function theorem:	$D_{\mathbf{x}}\mathbf{y} = (D_{\mathbf{y}}\mathbf{x})^{-1}$

I don't expect to use these, but for your future reference, here they are

Practice

Exercise: In linear regression, the ridge regression estimator is obtained by minimizing the function

$$\|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|_2^2 + \lambda\|\boldsymbol{\beta}\|_2^2,$$

where λ is a prespecified tuning parameter. Show that

$$\widehat{\boldsymbol{\beta}}_{\text{ridge}} = (\mathbf{X}^\top\mathbf{X} + \lambda\mathbf{I})^{-1}\mathbf{X}^\top\mathbf{y}.$$

Integration and measure: Introduction

- Our other topic for today is a brief treatment of measure theory
- This is not a measure theory-based course, but it is worth knowing some basic results that will help you read papers that use measure theoretical language
- In particular, we will go over
  - The Riemann-Stieltjes integral
  - The Lebesgue decomposition theorem

Introduction to Riemann-Stieltjes integration

- Probability and expectation are intimately connected with integration
- The basic forms of integration that you learn as an undergraduate are known as Riemann integrals; a more rigorous form is the Lebesgue integral, but that rests on quite a bit of measure theory
- The Riemann-Stieltjes integral is a useful bridge between the two, and particularly useful in statistics

Partitions and lower/upper sums

- **Definition:** A *partition* P of the interval $[a, b]$ is a finite set of points $x_0, x_1, \ldots, x_n$ such that

$$a = x_0 < x_1 < \cdots < x_n = b.$$

- Let μ be a bounded, nondecreasing function on $[a, b]$, and let

$$\Delta\mu_i = \mu(x_i) - \mu(x_{i-1});$$

note that $\mu_i \geq 0$

- Finally, for any function g define the lower and upper sums

$$L(P, g, \mu) = \sum_{i=1}^{n} m_i \Delta\mu_i \qquad m_i = \inf_{[x_i, x_{i-1}]} g$$

$$U(P, g, \mu) = \sum_{i=1}^{n} M_i \Delta\mu_i \qquad M_i = \sup_{[x_i, x_{i-1}]} g$$

Refinements

- **Definition:** A partition P^* is a *refinement* of P if $P^* \supset P$ (every point of P is a point of P^*). Given partitions P_1 and P_2, we say that P^* is their *common refinement* if $P^* = P_1 \cup P_2$.
- **Theorem:** If P^* is a refinement of P, then

$$L(P, g, \mu) \leq L(P^*, g, \mu)$$

and

$$U(P^*, g, \mu) \leq U(P, g, \mu)$$

- **Theorem:** $L(P_1, g, \mu) \leq U(P_2, g, \mu)$

The Riemann-Stieltjes integral

Definition: If the following two quantities are equal:

$$\inf_P U(P, g, \mu)$$
$$\sup_P L(P, g, \mu),$$

then g is said to be *integrable (measurable) with respect to* μ over $[a, b]$, and we denote their common value

$$\int_a^b g d\mu$$

or sometimes

$$\int_a^b g(x) d\mu(x)$$

Dominated convergence theorem

- One of the most important results in measure theory is the dominated convergence theorem
- **Theorem (Dominated convergence):** Let f_n be a sequence of measurable functions such that $f_n \to f$. If there exists a measurable function g such that $|f_n(x)| \leq g(x)$ for all n and all x, then

$$\lim_{n\to\infty} \int f_n \, d\mu = \int f \, d\mu.$$

- The theorem can be restated in terms of expected values, which we will go over (and use) in a later lecture

Implications for probability

- The application to probability is clear: any CDF can play the role of μ (CDFs are bounded and nondecreasing), so expected values can be written

$$\mathbb{E}g(X) = \int g(x)\,dF(x)$$

- Why is this more appealing than the usual Riemann integral?
- The main reason is that the above statement is valid regardless of whether X has a continuous or discrete distribution (or some combination of the two) – we require only that F is nondecreasing, not that it is continuous

Continuous and discrete measures

- Suppose F is the CDF of a discrete random variable that places point mass p_i on support point s_i; then

$$\int g\,dF = \sum_{i=1}^{\infty} g(s_i)p_i$$

- Suppose F is the CDF of a continuous random variable with corresponding density $f(x)$; then assuming $g(X)$ is integrable (measurable),

$$\int g\,dF = \int g(x)f(x)\,dx$$

- In other words, the Riemann-Stieltjes integral reduces to familiar forms in both continuous and discrete cases

Example

- However, the Riemann-Stieltjes integral also works in mixed cases
- **Exercise:** Suppose X has a distribution such that $P(X = 0) = 1/3$, but if $X \neq 0$, then it follows an exponential distribution with $\lambda = 2$. Suppose $g(x) = x^2$; what is $\int g\,dF$?

Decomposing random variables

- Now, you might be wondering: can we always do this?
- Can we always just separate out any random variable into its continuous and discrete components and handle them separately like this?
- The answer, unfortunately, is no

Lebesgue decomposition theorem

- **Theorem (Lebesgue decomposition):** Any probability distribution F can uniquely be decomposed as

$$F = F_{\text{D}} + F_{\text{AC}} + F_{\text{SC}},$$

  where
  - F_{D} is the discrete component (i.e., probability is given by a sum of point masses)
  - F_{AC} is the absolutely continuous component (i.e., probability is given by an integral with respect to a density function)
  - F_{SC} is the singular continuous component (i.e, it's weird)
- The theorem is typically stated in terms of measures, but I'm using (sub)distribution functions here for the sake of familiarity

Important takeaways

- Obviously, we're skipping the technical details of measure theory as well as the proof of this theorem, but you don't need a technical understanding to see why it's important
- It's not the case that all distributions can be decomposed into discrete and "continuous" components – there is a third possibility: singular
- However, if we add the restriction that we are dealing with *non-singular* (or *regular*) distributions, then yes, all distributions can be decomposed into the familiar continuous and discrete cases
- To be technically accurate, one might wish to clarify "absolutely continuous" instead of continuous when you're referring to a distribution with a density (in non-technical contexts, this is implicit)