

E600 Mathematics

Chapter 3: Multivariate Calculus

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1. Introduction

Motivation

- Ch. 0, Ch. 1: Mathematical building blocks (algebra: generalizing arithmetic operations)
- Ch. 2: Linear Algebra – equation systems, row/column spaces etc.
- Now: analysis of **functions**, study of (small) variations
- Key objective of this lecture: **generalizing the derivative** to arbitrary functions $f : \mathbb{R}^n \mapsto \mathbb{R}^m$
- Why?: Optimization problems with many variables (goods, production inputs, statistical parameters)
- Many struggles in the 1st PhD semester were encountered because of issues with understanding derivatives. . .

1. Introduction

Key Concepts

- Function $f : X \mapsto Y$ with domain X , codomain Y and image $\text{im}(f) = f[X]$
 - $X \subseteq \mathbb{R}$: **univariate** function
 - $X \subseteq \mathbb{R}^n$: **multivariate** function
 - $Y \subseteq \mathbb{R}$: **real-valued** function
 - $Y \subseteq \mathbb{R}^m$: **vector-valued** function
 - How to call $f : \mathbb{R}^3 \mapsto \mathbb{R}^2$?
- Examples:
 - Multivariate, real-valued function: $x \mapsto \|x\|$, $x \mapsto x'Ax$, $(x, y) \mapsto x \cdot y$
 - Multivariate, vector-valued function: $x \mapsto Ax$
- Graph:

$$G(f) = \{(x, y) \in X \times Y : y = f(x)\} = \{(x, f(x)) : x \in X\}$$

2. Basics: Invertability and Convexity

Invertability of Functions

- Inverse function f^{-1} of f : $f(f^{-1}(y)) = y$ and $f^{-1}(f(x)) = x$
- Function invertability more thoroughly discussed in script
- Ch. 0: For $X, Y \subseteq \mathbb{R}$, we can *invert* $f : X \mapsto Y$ if, and only if, for every $y \in Y$ we have **exactly one $x(y) \in X$ so that $f(x(y)) = y$**
- The two **conditions transfer to arbitrary X, Y** : for every $y \in Y, \dots$
 - at least one x is mapped onto y : $\exists x \in X : f(x) = y$ (" f is surjective/onto")
 - no more than one x is mapped onto y : $(x_1 \neq x_2 \Rightarrow f(x_1) \neq f(x_2))$ (" f is injective/one-to-one")
- If f is both injective and surjective, we call f *bijective*
- f invertible $\Leftrightarrow f$ bijective (proof: script, it's simple, take a look)

2. Basics: Invertability and Convexity

Invertability: Comments

- Note that $f^{-1} \circ f : X \mapsto X, x \mapsto x$ and $f \circ f^{-1} : Y \mapsto Y, y \mapsto y$
 - $f^{-1} \circ f$ and $f \circ f^{-1}$ are equal to *identity functions*, the *identity object* in function spaces
 - Function inversion follows our standard inversion logic “ $x^{-1}x = 1$ ”!
- What’s the difference between f^{-1} , $f^{-1}(x)$, $f^{-1}[x]$ and $f^{-1}[\{x\}]$?

2. Basics: Invertability and Convexity

Invertability: Comments

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- What’s the difference between f^{-1} , $f^{-1}(x)$, $f^{-1}[x]$ and $f^{-1}[\{x\}]$?

... **Pre-images and inverse functions are fundamentally different objects!!!**

2. Basics: Invertability and Convexity

Convexity (and Concavity) of Real-Valued Functions

Definition (Convex and Concave Real Valued Function)

Let $X \subseteq \mathbb{R}^n$ be a **convex set**. A function $f : X \rightarrow \mathbb{R}$ is convex if for any $x, y \in X$ and $\lambda \in [0, 1]$,

$$f(\lambda x + (1 - \lambda)y) \leq \lambda f(x) + (1 - \lambda)f(y)$$

Moreover, if for any $x, y \in X$ such that $y \neq x$ and $\lambda \in (0, 1)$,

$$f(\lambda x + (1 - \lambda)y) < \lambda f(x) + (1 - \lambda)f(y)$$

we say that f is strictly convex. Moreover, we say that f is (strictly) concave if $-f$ is (strictly) convex.

Alternative characterization of concavity (line 1) and strict concavity (line 2)

$$f(\lambda x + (1 - \lambda)y) \geq \lambda f(x) + (1 - \lambda)f(y) \quad \forall x, y \in X \forall \lambda \in [0, 1],$$

$$f(\lambda x + (1 - \lambda)y) > \lambda f(x) + (1 - \lambda)f(y) \quad \forall x, y \in X \text{ so that } x \neq y \text{ and } \forall \lambda \in (0, 1).$$

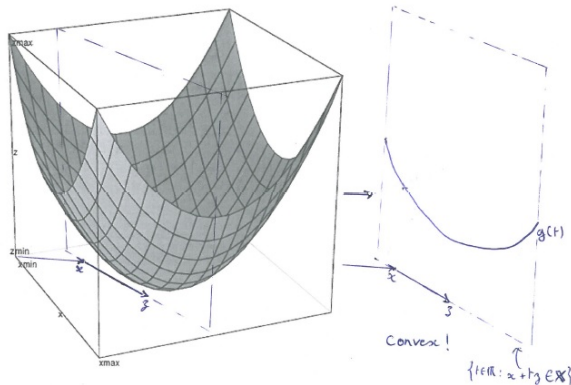
2. Basics: Invertability and Convexity

Convexity: Intuition

- In what follows: predominantly discuss convexity
- Recall: $\lambda x + (1 - \lambda)y$ ($\lambda \in [0, 1]$) is a **convex combination** of x and y
 - Convexity: statement about convex combinations across domain and codomain of f !
 - $f(\lambda x + (1 - \lambda)y)$ must always be well-defined \rightarrow convex domain
- $G(f) \subseteq \mathbb{R}^2$ (i.e. f univariate, real-valued function):
 - $\lambda x + (1 - \lambda)y$ is interval between x and y
 - $\lambda f(x) + (1 - \lambda)f(y)$ is the line piece connecting $f(x)$ and $f(y)$
 - Let's draw a convex and a concave function

2. Basics: Invertability and Convexity

Convexity of bivariate functions



- $f : X \mapsto \mathbb{R}, X \subseteq \mathbb{R}^2$
- $\lambda x + (1 - \lambda)y$ is still a line piece
- Re-write $y + \lambda(x - y)$: starting point $y \in \mathbb{R}^2$ and *single* direction $(x - y)$
- Convexity reduces to consideration in \mathbb{R}^2 !

- Argument of single direction is not specific to $X \subseteq \mathbb{R}^2$
- Can always reduce to the univariate function $t \mapsto f(x + t(x - y))$
- This is indeed true formally. . .

2. Basics: Invertability and Convexity

Theorem (Graphical Characterization of Convexity)

Let $X \subseteq \mathbb{R}^n$ be a **convex set** and $f : X \mapsto \mathbb{R}$. Then, f is (strictly) convex if and only if $\forall x, z \in X$ such that $z \neq \mathbf{0}$, the function $g : \mathbb{R} \mapsto \mathbb{R}, t \mapsto f(x + tz)$ is (strictly) convex.

- Analogous for concavity
- Def. convexity: we must choose x, y arbitrarily
- After picking x , choosing y arbitrarily is equivalent to choosing $z = y - x$ arbitrarily
- Proof for “strictly” (to get more familiar with convexity in the \mathbb{R}^n)
- If you get bored during the semester, try to prove for (weak) concavity

2. Basics: Invertability and Convexity

Weak Convexity

- Optimization: convexity/concavity immensely helpful (why?)
- Convexity may be restrictive: can be lost under monotonic transformations (think utility functions)
- Can we weaken the concept and preserve (most of) the desirable properties? Yes!
- Level sets in the **domain** of f :

Definition (Lower and Upper Level Set of a Function)

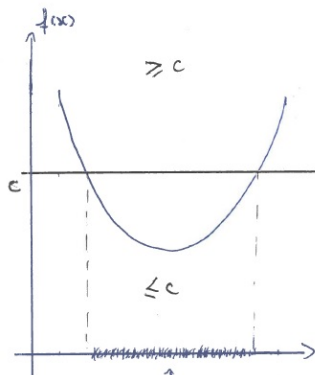
Let $X \subseteq \mathbb{R}^n$ be a convex set and $f : X \rightarrow \mathbb{R}$ be a real-valued function. Then, for $c \in \mathbb{R}$, the sets

$$L_c^- := \{x \mid x \in X, f(x) \leq c\} \quad \text{and} \quad L_c^+ := \{x \mid x \in X, f(x) \geq c\}$$

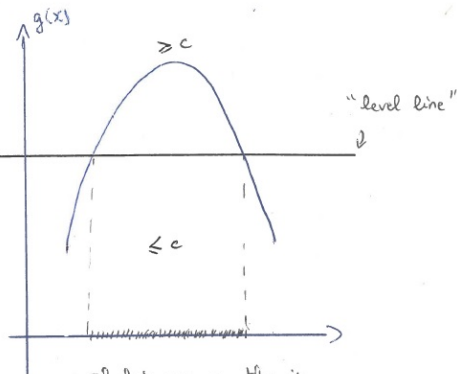
are called the lower-level and upper level set of f at c , respectively.

2. Basics: Invertability and Convexity

Level Sets of Convex and Concave Functions



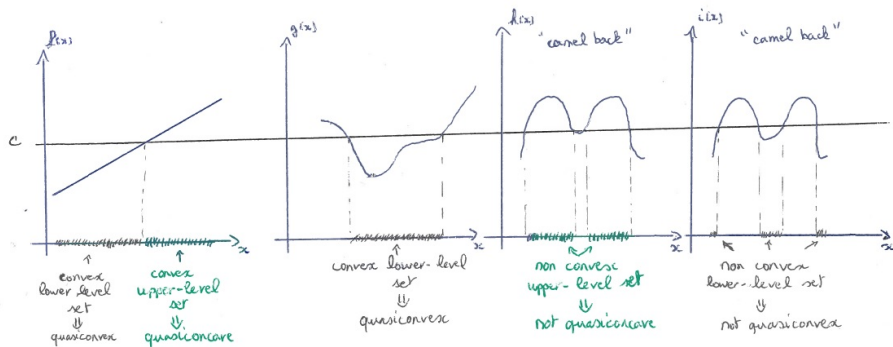
If f is convex, then its lower-level sets are convex!



If f is concave, then its upper-level sets are convex!

2. Basics: Invertability and Convexity

Level Sets of Quasi-Convex and -Concave Functions



2. Basics: Invertability and Convexity

Quasi-Convexity: Workable Definitions

Theorem (Quasiconvexity, Quasiconcavity)

Let $X \subseteq \mathbb{R}^n$ be a convex set. A real-valued function $f : X \rightarrow \mathbb{R}$ is quasiconvex if and only if

$$\forall x, y \in X \forall \lambda \in [0, 1] : f(\lambda x + (1 - \lambda)y) \leq \max\{f(x), f(y)\}$$

Conversely, f is quasiconcave if and only if

$$\forall x, y \in X \forall \lambda \in [0, 1] : f(\lambda x + (1 - \lambda)y) \geq \min\{f(x), f(y)\}$$

Analogous *definition*: Strict Quasiconvexity (line 1), Strict Quasiconcavity (line 2)

$$\forall x, y \in X \text{ such that } x \neq y \text{ and } \forall \lambda \in (0, 1) : f(\lambda x + (1 - \lambda)y) < \max\{f(x), f(y)\}$$

$$\forall x, y \in X \text{ such that } x \neq y \text{ and } \forall \lambda \in (0, 1) : f(\lambda x + (1 - \lambda)y) > \min\{f(x), f(y)\}$$

2. Basics: Invertability and Convexity

Quasi-Convexity: Purpose and Caution

- Purpose: preserves useful features for optimization (e.g. quasi-convex functions give convex constraint sets)
- Defined to preserve *properties of the upper/lower level sets* \rightarrow other features need not transfer!
- E.g.: convex/concave functions are continuous, quasi-... functions need not be (e.g. $\mathbb{1}[x > 0]$ – draw)

3. Multivariate Calculus

What and Why?

- What is (multivariate) Calculus? Definition Wikipedia (summarized)
 - “Mathematical study of continuous change”
 - Differential calculus: [instantaneous](#)/marginal rates of change and slopes of curves
 - Integral calculus: [accumulation](#) of quantities, areas under and between curves
 - Fundamental theorem of calculus: integration and differentiation are *inverse operations*
- Why care?
 - Immensely helpful for the study of economic quantities and problems, more generally
 - Essential concepts rely on these operations (marginal utility, accumulations across households)
 - We focus on differentiation. . .

3. Multivariate Calculus

Differentiation: Review Univariate, Real-Valued Functions

- As before: start from what we know and generalize
- If $X \subseteq \mathbb{R}$, what is “the slope” of $f : X \mapsto \mathbb{R}$?
- **Relative change** of $f(x)$ given variation in x at $x_0 \in X$:

$$\frac{\Delta f(x)}{\Delta x} := \frac{f(x) - f(x_0)}{x - x_0} = \frac{f(x_0 + h) - f(x_0)}{h}, \quad h := x - x_0 \in \mathbb{R}$$

- Marginal/instantaneous rate of change: limit $h \rightarrow 0$ (existence?)

3. Multivariate Calculus

Differentiation: Review Univariate, Real-Valued Functions

Definition (Univariate Real-Valued Function: Differentiability and Derivative)

Let $X \subseteq \mathbb{R}$ and consider the function $f : X \mapsto \mathbb{R}$. Let $x_0 \in X$. If

$$\lim_{h \rightarrow 0} \frac{f(x_0 + h) - f(x_0)}{h}$$

exists, f is said to be differentiable at x_0 , and we call this limit the **derivative of f at x_0** , denoted by $f'(x_0)$. If for all $x_0 \in X$, f is differentiable at x_0 , f is said to be differentiable over X or differentiable. Then, the function $f' : X \mapsto \mathbb{R}, x \mapsto f'(x)$ is called the **derivative of f** .

- Differentiability: point-specific vs. domain (e.g. $|\cdot|$)
- Derivative $f' =$ function, derivative at x_0 , $f'(x_0) =$ real number!

3. Multivariate Calculus

Differentiation: Review Univariate, Real-Valued Functions

Definition (Univariate Real-Valued Functions: Differential Operator)

Let $X \subseteq \mathbb{R}$, define $D^1(X, \mathbb{R}) = \{f : X \mapsto \mathbb{R} : f \text{ is differentiable over } X\}$, and let $F_X := \{f : X \mapsto \mathbb{R}\}$. Then, the differential operator is defined as the *function*

$$\frac{d}{dx} : D^1(X, \mathbb{R}) \mapsto F_X, f \mapsto f'$$

where f' denotes the derivative of $f \in D^1(X, \mathbb{R})$.

- (Differential) Operator: function between **function spaces**
- $f' = \frac{d}{dx}(f)$ is a **specific value** in the codomain of $\frac{d}{dx}$ just like $f'(x)$ is a specific value in the codomain of f'
- More precisely, we would write $f'(x) = \left[\frac{d}{dx}(f) \right](x)$
- What about the notations $\frac{df}{dx}(x)$ and $\frac{df(x)}{dx}$?

3. Multivariate Calculus

Differentiation: Review Univariate, Real-Valued Functions

- Take away: three fundamental levels of objects (diff. operator, derivative function, derivative at x_0)
- Recall: basis operations in function spaces: $X \subseteq \mathbb{R}^n$, $Y \subseteq \mathbb{R}^m$ and $F = \{f : X \mapsto Y\}$. For any $f, g \in F$ and any $\lambda \in \mathbb{R}$:
 - $f + g : (\forall x \in X : (f + g)(x) = f(x) + g(x))$
 - $\lambda f : (\forall x \in X : (\lambda f)(x) = \lambda \cdot f(x))$
- Function product $fg : (\forall x \in X : (fg)(x) = f(x) \cdot g(x))$
- quotient in analogy if $\forall x \in X : g(x) \neq 0$
- Let's practice the operator/function/value distinction

3. Multivariate Calculus

Differentiation: Review Univariate, Real-Valued Functions

Theorem (Rules for Univariate Derivatives)

Let $X \subseteq \mathbb{R}$, $f, g \in D^1(X, \mathbb{R})$ and $\lambda, \mu \in \mathbb{R}$. Then,

- (i) (Linearity) $\lambda f + \mu g$ is differentiable and $\frac{d}{dx}(\lambda f + \mu g) = \lambda \frac{df}{dx} + \mu \frac{dg}{dx}$,
- (ii) (Product Rule) The product fg is differentiable and $\frac{d}{dx}(fg) = \frac{df}{dx} \cdot g + f \cdot \frac{dg}{dx}$
- (iii) (Quotient Rule) If $\forall x \in X$, $g(x) \neq 0$, the quotient f/g is differentiable and $\frac{d}{dx}(f/g) = \frac{\frac{df}{dx} \cdot g - f \cdot \frac{dg}{dx}}{g \cdot g}$
- (iv) (Chain Rule) if all the following expressions are well-defined, then $g \circ f$ is differentiable and $\frac{d}{dx}(g \circ f) = \left(\frac{dg}{dx} \circ f\right) \cdot \frac{df}{dx}$.

Script: rules for specific values and differentiability at $x_0 \in X$

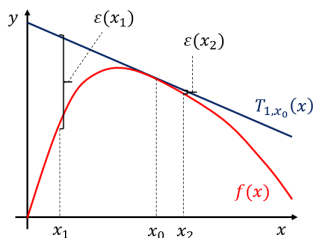
3. Multivariate Calculus

Differentiation: Properties to Generalize

- Generalization: Derivative characterizes **local behavior** of functions
- Transfer analytic and graphical intuition to graphs we cannot sketch
- Key properties of univariate, real-valued functions: Differentiability of f at $x_0 \in X$ implies...
 - 1 **continuity** at x_0
 - 2 **Existence of a good linear approximation** to f around x_0and if f is differentiable on $(a, b) \subseteq \mathbb{R}$, then on (a, b) , f is...
 - (i) constant $\Leftrightarrow (\forall x_0 \in (a, b) : f'(x_0) = 0)$,
 - (ii) monotonically increasing $\Leftrightarrow (\forall x_0 \in (a, b) : f'(x_0) \geq 0)$,
 - (iii) monotonically decreasing $\Leftrightarrow (\forall x_0 \in (a, b) : f'(x_0) \leq 0)$
 - (iv) the strict versions of (ii) and (iii) hold as well

3. Multivariate Calculus

Differentiation: “Good Linear Approximation”?



- Taylor = key take-away from this class!
- First order **Taylor approximation** to f at x_0 :

$$T_{1,x_0}(x) = f(x_0) + f'(x_0)(x - x_0)$$

- Error: $\epsilon_1(x) := T_{1,x_0}(x) - f(x)$ (formula exists if $f \in D^2$)

- “Good” approximation: $\lim_{x \rightarrow x_0} \frac{\epsilon_1(x)}{x - x_0} = 0$ (let’s show this; intuition?)
- Taylor *expansion* of first order: decomposition of f into linear and non-linear term, i.e.

$$f(x) = T_{1,x_0}(x) + \epsilon_1(x)$$

- *Expansion* includes the error, *approximation* does not

3. Multivariate Calculus

Taylor of Generalized Order: Definition

Theorem (Taylor Expansion for Univariate Functions)

Let $X \subseteq \mathbb{R}$ and $f \in D^d(X, \mathbb{R})$ where $d \in \mathbb{N} \cup \{\infty\}$. For $N \in \mathbb{N} \cup \{\infty\}$, $N \leq d$, the Taylor expansion of order N for f at $x_0 \in X$ is

$$f(x) = T_{N,x_0}(x) + \varepsilon_N(x) = f(x_0) + \sum_{n=1}^N \frac{f^{(n)}(x_0)}{n!} (x - x_0)^n + \varepsilon_N(x),$$

where $\varepsilon_N(x)$ is the approximation error of T_{N,x_0} for f at $x \in X$. Then, the approximation quality satisfies $\lim_{h \rightarrow 0} \varepsilon_N(x_0 + h)/h^N = 0$. Further, if f is $N + 1$ times differentiable, there exists a $\lambda \in (0, 1)$ such that

$$\varepsilon_N(x_0 + h) = \frac{f^{(N+1)}(x_0 + \lambda h)}{(N + 1)!} h^{N+1}.$$

- Faculty of $n \in \mathbb{N}$: $n! = 1 \cdot 2 \cdot \dots \cdot (n - 1) \cdot n$

3. Multivariate Calculus

Taylor of Generalized Order: Comments

- Approximation quality: $\lim_{h \rightarrow 0} \varepsilon_N(x_0 + h)/h^N = 0$
 - The larger N , the “faster” $h^N \rightarrow 0$
 - Larger N increase **order** of approximation quality
 - Script gives proof for $N = 2$, general intuition is similar
- Mean Value Theorem (corollary of Taylor’s theorem): for any differentiable $f : X \mapsto \mathbb{R}$ ($X \subseteq \mathbb{R}$), for any $x_1, x_2 \in X$ such that $x_2 > x_1$, there exists $x^* \in (x_1, x_2)$ such that

$$f'(x^*) = \frac{f(x_2) - f(x_1)}{x_2 - x_1}.$$

- Useful to show that *critical values* ($f'(x) = 0$) exist
- Proof: Problem set

4. Multivariate Calculus: Differentiation

Differentiation: Multivariate Real-Valued Functions

- Multivariate Real-Valued Function: $f : X \mapsto \mathbb{R}$, $X \subseteq \mathbb{R}^n$
- Issue: instantaneous change ambiguous, x can move in *multiple directions* \rightarrow how to define a derivative (conceptually and formally)?
- Let's start from derivatives in **single directions** and see how far we get
 - Fix $x_0 \in X \subseteq \mathbb{R}^n$ ("point-specific to general")
 - Consider **holding x_i , $i \neq j$ fixed** (only direction x_j)

$$\tilde{f}_{j,x_0} : \mathbb{R} \mapsto \mathbb{R}, t \mapsto f(x_{0,1}, \dots, x_{0,j-1}, x_{0,j} + t, x_{0,j+1}, \dots, x_{0,n})$$

- \tilde{f}_{j,x_0} is univariate and we know when and how we can differentiate!
- Direction interpretation: $\tilde{f}_{j,x_0} = f(x_0 + te_j)$ where $e_j = (0, \dots, 0, \underbrace{1}_{\text{pos. } j}, 0, \dots, 0)'$

$\rightarrow \tilde{f}_{j,x_0}$: expansion of f into the j -th fundamental direction from x_0 !

4. Multivariate Calculus: Differentiation

Partial Derivatives, Gradient

Partial derivative of f at x_0 with respect to x_j (∂ vs. $d!$):

$$\frac{\partial f}{\partial x_j}(x_0) = \frac{df_{j,x_0}}{dt}(0) = \lim_{t \rightarrow 0} \frac{f(x + t \cdot e_j) - f(x)}{t}$$

- Also: “ j -th partial derivative (of f at x_0)”; sometimes denoted $f_j(x_0)$

Gradient of f at x_0 :

$$\nabla f(x_0) = \left(\frac{\partial f}{\partial x_1}(x_0), \frac{\partial f}{\partial x_2}(x_0), \dots, \frac{\partial f}{\partial x_n}(x_0) \right)$$

- **row** vector; *ordered* collection of partial derivatives

4. Multivariate Calculus: Differentiation

Partial Derivatives and Gradient: Some Examples

Consider the following functions $\mathbb{R}^2 \mapsto \mathbb{R}$:

- $f^1(x_1, x_2) = x_1 + x_2$
- $f^2(x_1, x_2) = x_1 x_2$
- $f^3(x_1, x_2) = x_1 x_2^2 + \cos(x_1)$

Consider an arbitrary point $x_0 = x \in \mathbb{R}$. Compute the gradients of f^1 , f^2 and f^3 at x_0 !

How do the partial derivatives depend on the location x ?

4. Multivariate Calculus: Differentiation

Partial Derivatives and Gradient: Concepts and Conceptual Comments

- Recall: “point-specific to general”
 - $f : X \mapsto \mathbb{R}$ partially differentiable (p.d.): f p.d. at any $x_0 \in X$
 - Set of p.d. functions from X to \mathbb{R} : $D_p^1(X, \mathbb{R}) = \{f : X \mapsto \mathbb{R} : f \text{ is p.d.}\}$
 - If f is p.d., i.e. $f \in D_p^1(X, \mathbb{R})$, the gradient exists at any $x_0 \in X$
- $\frac{\partial f}{\partial x_j}(x_0) \in \mathbb{R}$, $\nabla f(x_0) \in \mathbb{R}^{1 \times n}$ are **real-valued objects**
- Recall: univariate derivative is **real-valued function**
 - $\frac{\partial f}{\partial x_j} : X \mapsto \mathbb{R}$, $x_0 \mapsto \frac{\partial f}{\partial x_j}(x_0)$ is real-valued function
 - $\nabla f : X \mapsto \mathbb{R}^{1 \times n}$, $x_0 \mapsto \nabla f(x_0)$ is (real row-) **vector-valued function**
- associated **operators**: mappings between **function spaces**
 - $\frac{\partial}{\partial x_j} : D_p^1(X, \mathbb{R}) \mapsto F_X$, $f \mapsto f_j = \frac{\partial f}{\partial x_j}$
 - $\nabla : D_p^1(X, \mathbb{R}) \mapsto F_X^{1 \times n}$, $f \mapsto \nabla f$
- Appreciate these concepts to know what you are doing!

4. Multivariate Calculus: Differentiation

Generalizing the Derivative – Status Quo

- We set out to generalize the function $\frac{df}{dx}$ to $f : X \mapsto \mathbb{R}$ for $X \subseteq \mathbb{R}^n$
- We know can compute partial derivatives for the fundamental directions of the \mathbb{R}^n and stack them (gradient)
 - Actually: know “**directional derivative**” at $x_0 \in X$ for any *single* direction $\mathbb{R}^n \ni z \neq \mathbf{0}$: $\frac{d}{dt} f(x_0 + tz)|_{t=0}$
- Idea: the collection ∇f characterizes all instantaneous changes in fundamental directions (just like f' !). Can we call it the derivative?
- Well, almost!

4. Multivariate Calculus: Differentiation

Generalizing the Derivative – Conceptually?

- Recall: d^* is the derivative of f at x_0 if

$$\lim_{h \rightarrow 0} \frac{f(x_0 + h) - f(x_0)}{h} = d^*$$

- $h \in \mathbb{R}^n$: how to divide by a vector? What does $h \rightarrow 0$ mean?
- Note: norms are continuous!
 - Continuity of $f : \mathbb{R}^n \mapsto \mathbb{R}$:

$$\forall x_0 \in \mathbb{R}^n \forall \varepsilon > 0 \exists \delta > 0 : (\|x - x_0\| < \delta \Rightarrow |f(x) - f(x_0)| < \varepsilon).$$

- If $f(x) = \|x\|$, then by inverse triangle inequality, if $\|x - x_0\| < \delta$:

$$|f(x) - f(x_0)| = |\|x\| - \|x_0\|| \leq \|x - x_0\| < \delta$$

- For any $\varepsilon > 0$ set $\delta = \varepsilon > 0$
- Intuition?

4. Multivariate Calculus: Differentiation

The Derivative – an Equivalent Characterization

- $|\cdot|$ is the *natural norm* of the \mathbb{R}^n
- Since for $x \in \mathbb{R}$: $|x| = 0 \Leftrightarrow x = 0$, by norm continuity:

$$\begin{aligned} 0 = |0| &= \left| \lim_{h \rightarrow 0} \frac{f(x_0 + h) - f(x_0)}{h} - d^* \right| = \lim_{h \rightarrow 0} \left| \frac{f(x_0 + h) - f(x_0) - d^* h}{h} \right| \\ &= \lim_{h \rightarrow 0} \frac{|f(x_0 + h) - f(x_0) - d^* h|}{|h|} \end{aligned}$$

- **Equivalent** characterization of the derivative d^* of f at x_0 !
- But: replace $|\cdot|$ by an appropriate norm, and it applies to arbitrary dimensions for h (and indeed f)!
- Letting h go to zero in arbitrary fashion: $\|h\| \rightarrow 0$ (think λz , $\lambda \rightarrow 0$)

4. Multivariate Calculus: Differentiation

Definition (Multivariate Derivative of Real-valued Functions)

Let $X \subseteq \mathbb{R}^n$ and $f : X \mapsto \mathbb{R}$. Further, let $x_0 \in \text{int}(X)$ (interior point). Then, f is differentiable at x_0 if there exists $d^* \in \mathbb{R}^{1 \times n}$ such that

$$\lim_{\|h\| \rightarrow 0} \frac{|f(x_0 + h) - f(x_0) - d^*h|}{\|h\|} = 0.$$

Then, we call d^* the derivative of f at x_0 , denoted $\frac{df}{dx}(x_0)$ or $D_f(x_0)$. If f is differentiable at any $x_0 \in X$, we say that f is differentiable, and we call $\frac{df}{dx} : X \mapsto \mathbb{R}, x \mapsto \frac{df}{dx}(x)$ the derivative of f .

- Interior point: else, the limit can not exist (f diff'able $\Rightarrow X$ open!)
- $\frac{df}{dx}(x_0) \in \mathbb{R}^{1 \times n}$ real-valued object, derivative: function
- Most textbooks use $D_f(x_0)$ rather than $\frac{df}{dx}(x_0)$, idk why
- Derivative operator as before: mapping between function spaces

4. Multivariate Calculus: Differentiation

Definition (Multivariate Derivative of Vector-valued Functions)

Let $X \subseteq \mathbb{R}^n$ and $f : X \mapsto \mathbb{R}^m$. Further, let $x_0 \in \text{int}(X)$ (interior point). Denote ${}_k\|\cdot\|$ as a norm of \mathbb{R}^k , $k \in \{n, m\}$. Then, f is differentiable at x_0 if there exists a **matrix** $D^* \in \mathbb{R}^{m \times n}$ such that

$$\lim_{n\|h\| \rightarrow 0} \frac{m\|f(x_0 + h) - f(x_0) - D^*h\|}{n\|h\|} = 0,$$

Then, we call D^* the derivative of f at x_0 , denoted $\frac{df}{dx}(x_0)$ or $D_f(x_0)$. If f is differentiable at any $x_0 \in X$, we say that f is differentiable, and we call $\frac{df}{dx} : X \mapsto \mathbb{R}^{m \times n}$, $x \mapsto \frac{df}{dx}(x)$ the derivative of f .

- Numerator: codomain, denominator: domain
- Derivative as matrix: D^*h must be vector of same length as $f(x)$
- Actually: encompasses the previous definition ($m = 1$)

4. Multivariate Calculus: Differentiation

Generalizing the Derivative – (almost) the Last Step

- We now know the definition of multivariate differentiability
- We know that the gradient is intuitively very close to what we imagine as the derivative
- Does it match the derivative's definition?

Theorem (The Gradient and the Derivative)

Let $X \subseteq \mathbb{R}^n$ and $f : X \mapsto \mathbb{R}$. Further, let $x_0 \in \text{int}(X)$ (interior point), and suppose that f is differentiable at x_0 . Then, all partial derivatives of f at x_0 exist, and $\frac{df}{dx}(x_0) = \nabla f(x_0)$.

For the Proof, recall that the j -th partial derivative is defined as

$$\frac{\partial f}{\partial x_j}(x_0) = \lim_{t \rightarrow 0} \frac{f(x + t \cdot e_j) - f(x)}{t}$$

4. Multivariate Calculus: Differentiation

Generalizing the Derivative – Differentiability?

- If f is differentiable, then the derivative is equal to the gradient

Theorem (Partial Differentiability and Differentiability)

Let $X \subseteq \mathbb{R}^n$ and $f : X \mapsto \mathbb{R}$. Further, let $x_0 \in \text{int}(X)$ (interior point). If all the partial derivatives of f at x_0 exist and are continuous, then f is differentiable. (Proof: e.g. Theorem 3.4 in de la Fuente, Ch. 4)

- Set of **continuously differentiable functions**:

$$C^1(X, \mathbb{R}) := \left\{ f : X \mapsto \mathbb{R} : \left(\forall j \in \{1, \dots, n\} : \frac{\partial f}{\partial x_j} \text{ is continuous} \right) \right\}$$

- For $X \subseteq \mathbb{R}^n$, define $D^1(X, \mathbb{R}) = \{f : X \mapsto \mathbb{R} : f \text{ is differentiable}\}$
- Theorem gives $C^1(X, \mathbb{R}) \subseteq D^1(X, \mathbb{R})$

4. Multivariate Calculus: Differentiation

Generalizing the Derivative – Are We Done?

- In practice: taking the derivative of $f : X \mapsto \mathbb{R}$, $X \subseteq \mathbb{R}^n$
 - 1 Compute partial derivatives (if they exist)
 - 2 Are they all continuous?
 - 3 If so: stack them into ∇f , this is the derivative!
- Pay attention to weird-looking partial derivatives at (2)
- Continuity of derivatives is only sufficient: might have to do technical investigation if in doubt
- What about $f : X \mapsto \mathbb{R}^m$?

4. Multivariate Calculus: Differentiation

Vector-valued Functions 1/2

- Consider $X \subseteq \mathbb{R}^n$, $f : X \mapsto \mathbb{R}^m$
- f is **ordered collection** of real-valued functions:

$$f = \begin{pmatrix} f^1 \\ f^2 \\ \vdots \\ f^m \end{pmatrix} \text{ so that } \forall x \in X : f(x) = \begin{pmatrix} f^1(x) \\ f^2(x) \\ \vdots \\ f^m(x) \end{pmatrix}$$

where for any $i \in \{1, \dots, m\}$, $f^i : X \mapsto \mathbb{R}$ (example?)

- Idea: ordered collection of derivatives, i.e.

$$\frac{df}{dx} = \begin{pmatrix} \nabla f^1 \\ \nabla f^2 \\ \vdots \\ \nabla f^m \end{pmatrix}$$

4. Multivariate Calculus: Differentiation

Vector-valued Functions 1/2

Definition (Jacobian)

Let $n, m \in \mathbb{R}^n$, $X \subseteq \mathbb{R}^n$ and $f : X \mapsto \mathbb{R}^m$ and for $i \in \{1, \dots, m\}$, let $f^i : \mathbb{R}^n \mapsto \mathbb{R}$ such that $f = (f^1, \dots, f^m)'$. Let $x_0 \in X$. Then, if $\forall j \in \{1, \dots, m\}$, f^i is partially differentiable with respect to any x_j , $j \in \{1, \dots, n\}$, we call

$$J_f(x_0) = \begin{pmatrix} \nabla f^1(x_0) \\ \nabla f^2(x_0) \\ \vdots \\ \nabla f^m(x_0) \end{pmatrix} = \begin{pmatrix} f_1^1(x_0) & f_2^1(x_0) & \dots & f_n^1(x_0) \\ f_1^2(x_0) & f_2^2(x_0) & \dots & f_n^2(x_0) \\ \vdots & \vdots & \ddots & \vdots \\ f_1^m(x_0) & f_2^m(x_0) & \dots & f_n^m(x_0) \end{pmatrix}$$

the . If the above holds at any $x_0 \in X$, we call the mapping $J_f : \mathbb{R}^n \mapsto \mathbb{R}^{n \times m}$, $x_0 \mapsto J_f(x_0)$ the Jacobian of f .

4. Multivariate Calculus: Differentiation

Jacobian of f at x_0 :

$$J_f(x_0) = \begin{pmatrix} \nabla f^1(x_0) \\ \nabla f^2(x_0) \\ \vdots \\ \nabla f^m(x_0) \end{pmatrix} = \begin{pmatrix} f_1^1(x_0) & f_2^1(x_0) & \dots & f_n^1(x_0) \\ f_1^2(x_0) & f_2^2(x_0) & \dots & f_n^2(x_0) \\ \vdots & \vdots & \ddots & \vdots \\ f_1^m(x_0) & f_2^m(x_0) & \dots & f_n^m(x_0) \end{pmatrix}$$

- All partial derivative of any f^i must exist (we write $f \in D_p^1(X, \mathbb{R}^n)$)
- $J_f(x_0)$ is real matrix, Jacobian J_f of f is a matrix-valued function and $J : D_p^1(X, \mathbb{R}^n) \mapsto F_X^{m \times n}$, $f \mapsto J_f$ is an operator
- Collects expansion in all fundamental directions of all sub-functions f^i , $i \in \{1, \dots, m\}$. Is it the derivative?

4. Multivariate Calculus: Differentiation

Theorem (The Jacobian and the Derivative)

Let $X \subseteq \mathbb{R}^n$, $f : X \mapsto \mathbb{R}^m$ and $f^1, \dots, f^m : X \mapsto \mathbb{R}$ such that $f = (f^1, \dots, f^m)'$. Further, let $x_0 \in \text{int}(X)$ (interior point), and suppose that f is differentiable at x_0 . Then, for any f^i , $i \in \{1, \dots, m\}$, all partial derivatives of f^i at x_0 exist, and $\frac{df}{dx}(x_0) = J_f(x_0)$.

Proof: see script (same logic as before)

- As before: derivative exists if all partial deriv's are continuous
- Having defined the gradient as a row vector ensures the matrix structure!
- Do our differentiation rules apply to multivariate functions?

4. Multivariate Calculus: Differentiation

Theorem (Rules for Multivariate Derivatives)

Let $X \subseteq \mathbb{R}^n$, $f, g : X \mapsto \mathbb{R}^m$ and $h : \mathbb{R}^m \mapsto \mathbb{R}^k$. Suppose that f, g and h are differentiable functions. Then,

- (i) (Linearity) For all $\lambda, \mu \in \mathbb{R}$, $\lambda f + \mu g$ is differentiable and
$$\frac{d(\lambda f + \mu g)}{dx} = \lambda \frac{df}{dx} + \mu \frac{dg}{dx}.$$
- (ii) (Product Rule) $f \cdot g$ is differentiable and
$$\frac{d(fg)}{dx} = \frac{df}{dx} \cdot g + f \cdot \frac{dg}{dx}.$$
- (iii) (Chain Rule) $h \circ f$ is differentiable and
$$\frac{d(h \circ f)}{dx} = \left(\frac{dh}{dx} \circ f \right) \cdot \frac{df}{dx}.$$

- Quotient rule?
- Statements hold especially for specific values of these functions
- Careful about order!

4. Multivariate Calculus: Differentiation

Second Derivative

- Thus far: first derivative **operator** $(\cdot)'$ generalized to ∇/J
- In univariate, real-valued case: $f'' = (f)'$, we can generalize this logic
- Recall: derivative increases order in codomain
 - Derivative of $f : \mathbb{R}^n \mapsto \mathbb{R}$ is vector: $\nabla f : \mathbb{R}^n \mapsto \mathbb{R}^{1 \times n}$
 - Derivative of $f : \mathbb{R}^n \mapsto \mathbb{R}^m$ is matrix: $J_f : \mathbb{R}^n \mapsto \mathbb{R}^{m \times n}$
 - Derivative of Jacobian?
- Let's not get into the third dimension \rightarrow focus on real-valued functions
- Expectation: first derivative is vector \rightarrow second is matrix

4. Multivariate Calculus: Differentiation

Definition (Hessian or Hessian Matrix)

Let $X \subseteq \mathbb{R}^n$ be an *open* set and $f : X \mapsto \mathbb{R}$. Further, let $x_0 \in X$, and suppose that f is differentiable at x_0 and that all second order partial derivatives of f at x_0 exist. Then, the Hessian of f at x_0 is the matrix

$$H_f(x_0) = \begin{pmatrix} \nabla f_1(x_0) \\ \nabla f_2(x_0) \\ \vdots \\ \nabla f_n(x_0) \end{pmatrix} = \begin{pmatrix} f_{1,1}(x_0) & f_{1,2}(x_0) & \cdots & f_{1,n}(x_0) \\ f_{2,1}(x_0) & f_{2,2}(x_0) & \cdots & f_{2,n}(x_0) \\ \vdots & \vdots & \ddots & \vdots \\ f_{n,1}(x_0) & f_{n,2}(x_0) & \cdots & f_{n,n}(x_0) \end{pmatrix}$$

4. Multivariate Calculus: Differentiation

Higher Order Partial Derivatives

- If $\frac{\partial f}{\partial x_i}$ is differentiable at x_0 , the (i, j) -second order partial derivative at x_0 is

$$f_{i,j}(x_0) = \frac{\partial f_i}{\partial x_j}(x_0) = \frac{\partial^2 f}{\partial x_i \partial x_j}(x_0)$$

- k -th order partial derivative in analogous way
- Set $C^k(X) = C^k(X, \mathbb{R})$ (codomain \mathbb{R} as implicit second argument):
 $C^k(X) = \{f : X \mapsto \mathbb{R} : \text{All } k\text{-th order part. deriv's are continuous}\}$

Theorem (Schwarz's Theorem/Young's Theorem)

Let $X \subseteq \mathbb{R}^n$ be an open set and $f : \mathbb{R}^n \mapsto \mathbb{R}$. If $f \in C^k(X)$, then the order in which the derivatives up to order k are taken can be permuted.

$f \in C^2(X) \Rightarrow H_f(x_0)$ is symmetric!

4. Multivariate Calculus: Differentiation

Corollary (Hessian and Gradient)

Let $X \subseteq \mathbb{R}^n$ and $f \in C^2(X)$. Then, the Hessian is symmetric and corresponds to the Jacobian of the transposed gradient: $H_f = J_{(\nabla f)'}$.

- Symmetry: Schwarz's Theorem
- $(\nabla f)' : X \mapsto \mathbb{R}^n$ is multivariate vector valued function
- If $f \in C^2(X)$: $(\nabla f)' \in C^1(X, \mathbb{R}^n)$
- We know: differentiable with derivative equal to the Jacobian of $(\nabla f)'$

$$J_{(\nabla f)'} = \begin{pmatrix} \nabla f_1 \\ \nabla f_2 \\ \vdots \\ \nabla f_n \end{pmatrix} = \begin{pmatrix} f_{1,1} & f_{1,2} & \cdots & f_{1,n} \\ f_{2,1} & f_{2,2} & \cdots & f_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ f_{n,1} & f_{n,2} & \cdots & f_{n,n} \end{pmatrix} = H_f$$

4. Multivariate Calculus: Differentiation

Computing the Second Derivative: An Example

Let $f(x_1, x_2, x_3) = x_1 x_2^2 + \cos(x_1) e^{x_3}$. Is f twice differentiable? If so, compute the second derivative!

4. Multivariate Calculus: Differentiation

Taylor's Theorem for Multivariate Functions

Theorem (Second Order Multivariate Taylor Approximation)

Let $X \subseteq \mathbb{R}^n$ be an open set and consider $f \in C^2(X)$. Let $x_0 \in X$. Then, the second order Taylor approximation to f at $x_0 \in X$ is

$$T_{2,x_0}(x) = f(x_0) + \nabla f(x_0) \cdot (x - x_0) + \frac{1}{2}(x - x_0)' \cdot H_f(x_0) \cdot (x - x_0).$$

The error $\varepsilon_{2,x_0}(x) = f(x) - T_{2,x_0}(x)$ approaches 0 at a faster rate than $\|x - x_0\|^2$, i.e. $\lim_{\|h\| \rightarrow 0} \frac{\varepsilon_{2,x_0}(x+h)}{\|h\|^2} = 0$.

- Zero and first order approximation in analogy
- Error formula for first order: there exists $\lambda \in (0, 1)$ so that

$$\varepsilon_{1,x_0}(x_0 + h) = \frac{1}{2} h' \cdot H_f(x_0 + \lambda h) \cdot h$$

- Taylor expansion like before

4. Multivariate Calculus: Differentiation

Total Derivative: A “better” Directional Derivative

- Note that with $\Delta x = x - x_0 = \begin{pmatrix} x_1 - x_{0,1} \\ x_2 - x_{0,2} \end{pmatrix}$,

$$\nabla f(x) \cdot \Delta x = \frac{\partial f}{\partial x_1}(x_0) \Delta x_1 + \frac{\partial f}{\partial x_2}(x_0) \Delta x_2$$

- $\Delta f(x_0) = f(x) - f(x_0) = \nabla f(x) \cdot \Delta x + \varepsilon_{1,x_0}(x)$
- For marginal changes $\Delta x = dx$, the Taylor approximation is perfect so that

$$df(x_0) = \frac{\partial f}{\partial x_1}(x_0) dx_1 + \frac{\partial f}{\partial x_2}(x_0) dx_2$$

- Easily generalized to \mathbb{R}^n :

$$df = \sum_{i=1}^n \frac{\partial f}{\partial x_i} dx_i.$$

- Useful: variation in fixed ratios/**specific directions** \rightarrow comparative statics

4. Multivariate Calculus: Differentiation

Second Derivative and Convexity

- Convex functions are appealing from an optimization point of view
- For $X \subseteq \mathbb{R}$, $f \in C^2(X)$ (proof: script):
 - 1 f is convex if and only if $\forall x \in X : f''(x) \geq 0$ (equivalent condition)
 - 2 If $\forall x \in X : f''(x) > 0$, then f is strictly convex (sufficient condition)
- Recall “graphical” multivariate convexity: for any $x, z \in \mathbb{R}^n$ such that $z \neq \mathbf{0}$, $g : \mathbb{R} \mapsto \mathbb{R}$, $t \mapsto f(x + tz)$ must be convex
 - If $f \in C^2(X)$ then especially $g \in C^2(\mathbb{R})$
 - Second derivative (chain rule):

$$g''(t) = z' H_f(x + tz) z$$

- This implies (proof?):
 - 1 $\forall y \in X : (H_f(y) \text{ pos. semi-definite}) \Leftrightarrow f \text{ convex}$
 - 2 $\forall y \in X : (H_f(y) \text{ pos. definite}) \Rightarrow f \text{ strictly convex}$
- Recall: definiteness of the Hessian $\hat{=}$ sign (why C^2 and not D^2 ?)

4. Multivariate Calculus: Differentiation

Differentiation: Final Remarks

- A lot of notation and definitions. . .
- Key take-aways:
 - 1 If we can differentiate a multivariate function, the gradient or the Jacobian give us the derivative
 - Summary of variation in fundamental directions
 - Sufficient condition: $f \in C^1(X, \mathbb{R}^m)$ (continuous partial derivatives)
 - 2 **Second derivatives** of real-valued multivariate functions can be obtained from **differentiating the (transposed) gradient**
 - Sufficient for two times differentiable: $f \in C^2(X)$
 - Second derivative: Hessian matrix, symmetric if $f \in C^2(X)$
 - 3 Taylor approximations give “good” polynomial approximations “close to” the approximation point
 - 4 The definiteness of the Hessian determines convexity/concavity

5. Multivariate Calculus: Integration

Introduction

- f is the instantaneous change of its accumulation
- If the integral measures accumulation, the function itself should be the integral's derivative!
- Idea: invert the derivative operator

$$\frac{d}{dx} : D^1(X) \mapsto F_X, f \mapsto \frac{df}{dx}$$

to obtain the integral operator!

- Issue: recall that inversion requires injectivity (“one-to-one”)
 - $f(x) = 2x + 3$ vs. $f(x) = 2x$
 - Problem: constants cancel out when taking the derivative
 - Derivative is unique **up to the constant!**

5. Multivariate Calculus: Integration

Definition (Infimum and Supremum of a Set)

Let $X \subseteq \mathbb{R}$. Then, the infimum $\inf(X)$ of X is the largest value smaller than any element of X , i.e. $\inf(X) = \max\{a \in \mathbb{R} : \forall x \in X : x \geq a\}$, and the supremum $\sup(X)$ of X is the smallest value larger than any element of X , i.e. $\sup(X) = \min\{b \in \mathbb{R} : \forall x \in X : x \leq b\}$.

⇒ Generalized Maximum/Minimum

5. Multivariate Calculus: Integration

Indefinite Integrals

- Restrict attention to univariate, real-valued $f : X \mapsto \mathbb{R}$
- We can't invert $\frac{d}{dx}$, let's do the next best thing:

$$\int : F_X \mapsto \mathcal{P}(D^1(X)), f \mapsto \{\tilde{F} : X \mapsto \mathbb{R} : \frac{d\tilde{F}}{dx} = f\}$$

- **Correspondence**: set-valued mapping, **not** a function!
- We write $\int f = \{\tilde{F} : X \mapsto \mathbb{R} : \frac{d\tilde{F}}{dx} = f\}$ (pre-image of f under $\frac{d}{dx}$)
- Any $\tilde{F} \in \int f$ has the form $\tilde{F}(x) = F(x) + C$ for a $C \in \mathbb{R}$
 - F has no constant, i.e. $F(\min X) = 0$ or $\lim_{x \rightarrow \inf X} F(x) = 0$
 - F : accumulation after the smallest value in the domain
 - Notation: $\int f(x)dx = F(x) + C$

5. Multivariate Calculus: Integration

Indefinite Integrals: Some Rules

Theorem (Rules for Indefinite Integrals)

Let f, g be two integrable functions and let $a, b \in \mathbb{R}$ be constants, $n \in \mathbb{N}$. Then

- $\int (af(x) + g(x))dx = a \int f(x)dx + \int g(x)dx,$
- $\int x^n dx = \frac{x^{n+1}}{n+1} + C$ if $n \neq -1$ and $\int \frac{1}{x} dx = \ln(x) + C,$
- $\int e^x dx = e^x + C$ and $\int e^{f(x)} f'(x) dx = e^{f(x)} + C,$
- $\int (f(x))^n f'(x) dx = \frac{1}{n+1} (f(x))^{n+1} + C$ if $n \neq -1$ and $\int \frac{f(x)}{f'(x)} dx = \ln(f(x)) + C.$

Theorem (Integration by parts)

Let u, v be two differentiable functions. Then,

$$\int u(x)v'(x)dx = u(x)v(x) - \int u'(x)v(x)dx.$$

5. Multivariate Calculus: Integration

Definite Integrals

- Accumulation is unique up to initial level C : For any $\tilde{F} = F + C \in \int f$ and any $x, y \in X$: $\tilde{F}(y) - \tilde{F}(x) = F(y) - F(x)$

→ Uniquely defined **Definite Integral**:

$$\int_x^y f(t)dt = \tilde{F}(y) - \tilde{F}(x), \quad \text{where } \tilde{F}(x) \in \frac{d}{dx}^{-1} \{f\}$$

- Zero initial accumulation function if X is an interval:

$$F(x) = \int_a^x f(t)dt \quad \text{where } a = \inf X$$

5. Multivariate Calculus: Integration

Conclusion Univariate Integration

Theorem (Fundamental Theorem of Calculus)

Let X be an interval in \mathbb{R} with $a = \inf(X)$ and $f : X \mapsto \mathbb{R}$. Suppose that f is integrable, and define $F := X \mapsto \mathbb{R}, x \mapsto \int_a^x f(t)dt$. Then, F is differentiable, and

$$\forall x \in X : F'(x) = \frac{dF}{dx}(x) = f(x).$$

Proof: see script

- Proof is insanely easy relative to the theorem's importance!
- Take-away
 - Fix initial accumulation to define a unique integral
 - This definite integral is inversely related to the derivative

5. Multivariate Calculus: Integration

Multivariate Integration: Roadmap

- We have formally discussed univariate integration
- As with derivatives: if the multivariate integral exists, we can reduce its computation to univariate integrals!
- No formal details, rather only the “how-to”

5. Multivariate Calculus: Integration

Multivariate Integration 1/2

Theorem (Fubini's theorem)

Let X and Y be two intervals in \mathbb{R} , let $f : X \times Y \rightarrow \mathbb{R}$ and suppose that f is *continuous*. Then, for any $I = I_x \times I_y \subseteq X \times Y$ with intervals $I_x \subseteq X$ and $I_y \subseteq Y$,

$$\int_I f(x, y) d(x, y) = \int_{I_x} \left(\int_{I_y} f(x, y) dy \right) dx,$$

and all the integrals on the right-hand side are well-defined.

General Fubini: for continuous $f : X \mapsto \mathbb{R}$, $X \subseteq \mathbb{R}^n$

$$\int_I f(x_1, \dots, x_n) d(x_1, \dots, x_n) = \int_{I_1} \left(\dots \left(\int_{I_n} f(x_1, \dots, x_n) dx_n \right) \dots \right) dx_1.$$

5. Multivariate Calculus: Integration

Multivariate Integration 2/2

Useful Corollary of Fubini:

Corollary (Integration of Multiplicatively Separable Functions)

Let $X_f \in \mathbb{R}^n$, $X_b \in \mathbb{R}^m$, $f : X_f \rightarrow \mathbb{R}$, $g : X_b \rightarrow \mathbb{R}$ continuous functions. Then, for any intervals $A \subseteq X_f$, $B \subseteq X_g$,

$$\int_{A \times B} f(x)g(y)d(x,y) = \left(\int_A f(x)dx \right) \left(\int_B g(y)dy \right).$$

Proof: script or Problem Set