

GRADIENT DESCENT ON MANIFOLDS

Data Science Project

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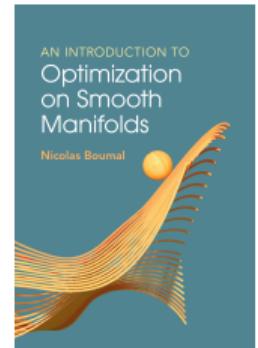
Outline

- 1 Introduction
- 2 Embedded Submanifolds of a Linear Space
- 3 Gradient on Manifolds
- 4 Gradient Descent on Manifolds

Introduction

Introduction

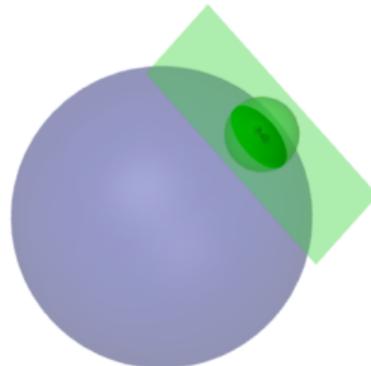
- Many optimization problems involve constraints that can be naturally modeled as manifolds.
- Gradient descent on manifolds extends traditional gradient descent methods to handle these constraints effectively.
- Presentation goals: build up the concept of gradient on manifolds and obtain basic convergence results.
- Main reference: An Introduction to Optimization on Smooth Manifolds by Nicolas Boumal.



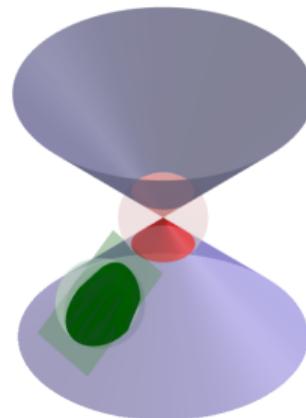
Embedded Submanifolds of a Linear Space

Embedded Submanifolds of a Linear Space

A subset \mathcal{M} of \mathbb{R}^d is an **embedded manifold of dimension n** if for each point $x \in \mathcal{M}$, there exists a neighborhood in \mathcal{M} of x (i.e. $\mathcal{M} \cap U$ for some open set $U \subset \mathbb{R}^d$ containing x) that is approximate to an open subset of \mathbb{R}^n .



A sphere is a manifold



A cone is not a manifold because every neighborhood of the tip (in red) cannot be approximated by a plane

Embedded Submanifolds of a Linear Space

We consider **smooth submanifolds**: for each $x \in \mathcal{M}$, there exists an open set $U \subset \mathbb{R}^d$ containing x and a smooth map $h : U \rightarrow \mathbb{R}^{d-n}$ such that $\mathcal{M} \cap U = h^{-1}(\{0\})$.

By being approximate to \mathbb{R}^n , we mean that for any direction $v \in \mathbb{R}^d$ that is a tangent vector to \mathcal{M} at x , we have

$$h(x + tv) = o(t).$$

We rely on curves for the definition of tangent vectors (and also later definitions).

Definition (Tangent space)

The tangent space $T_x \mathcal{M}$ at a point $x \in \mathcal{M}$ is the set of all tangent vectors to \mathcal{M} at x i.e.

$$T_x \mathcal{M} = \{\gamma'(0) \mid \gamma : (-\epsilon, \epsilon) \rightarrow \mathcal{M} \in \mathcal{C}^\infty(-\epsilon, \epsilon), \gamma(0) = x\}.$$

Embedded Submanifolds of a Linear Space

Now we can use Taylor expansion to write

$$h(x + tv) = h(x) + tDh(x)[v] + o(t) = tDh(x)[v] + o(t).$$

Proposition

For every $x \in \mathcal{M}$, we have

$$T_x\mathcal{M} \subseteq \ker(Dh(x)).$$

Proof.

Let $v \in T_x\mathcal{M}$, then there is a smooth γ such that $\gamma(0) = x$ and $\gamma'(0) = v$. Consider $g(t) = h(\gamma(t))$. Since $\gamma(t) \in \mathcal{M}$ for all t , we have $g(t) = 0$ for all t . Thus, $g'(0) = 0$. By chain rule,

$$g'(0) = Dh(\gamma(0))[\gamma'(0)] = Dh(x)[v] = 0.$$

Hence, $v \in \ker(Dh(x))$.



Embedded Submanifolds of a Linear Space

By the rank-nullity theorem, we have $\text{rank}(\text{D}h(x)) \leq d - n$. Thus,

$$\dim(\ker(\text{D}h(x))) = d - \text{rank}(\text{D}h(x)) \geq n.$$

On the other hand, $\dim(T_x\mathcal{M}) \leq n$.

Therefore, if there is $x \in \mathcal{M}$ such that $\text{rank}(\text{D}h(x)) < d - n$, then

$$T_x\mathcal{M} \subsetneq \ker(\text{D}h(x)).$$

That means there are vectors in $\ker(\text{D}h(x))$ that are not tangent to \mathcal{M} at x but can be used to approximate \mathcal{M} near x (we want to avoid this situation).

For example, define cone shown previously by $h(x, y, z) = z^2 - x^2 - y^2$. At the tip $(0, 0, 0)$, we have $\text{D}h(0, 0, 0) = [0 \ 0 \ 0]$ and $\ker \text{D}h(0, 0, 0) = \mathbb{R}^3$. So any vector in \mathbb{R}^3 can be used to approximate the cone near the tip. But $v = (0, 0, 1)$ is not a tangent vector.

Embedded Submanifolds of a Linear Space

Definition

A subset \mathcal{M} of \mathbb{R}^d is an embedded submanifold of dimension n if for each $x \in \mathcal{M}$, there exists an open set $U \subset \mathbb{R}^d$ containing x and a smooth map $h : U \rightarrow \mathbb{R}^{d-n}$ such that

$$\mathcal{M} \cap U = h^{-1}(\{0\}) \text{ and } \forall x \in \mathcal{M} \cap U, \text{rank } Dh(x) = d - n.$$

Proposition

Using the convention that $\mathbb{R}^0 = \{0\}$, every open subset of \mathbb{R}^d is a d -dimensional embedded submanifold of \mathbb{R}^d .

We may add the theorem that this definition is equivalent to the diffeomorphism definition.

Examples of Optimization on Manifolds

I will take two from the book.

Gradient on Manifolds

Motivation

If $f : \mathbb{R}^d \rightarrow \mathbb{R}$, then $\nabla f : \mathbb{R}^d \rightarrow \mathbb{R}^d$. We want to generalize in such a way that if $f : \mathcal{M} \rightarrow \mathbb{R}$, then $\text{grad } f : \mathcal{M} \rightarrow \mathcal{M}$.

Recall that to define the gradient in \mathbb{R}^d , we need the differential and an inner product, which in turn needs a linear structure.

We already have $T_x \mathcal{M}$.

For $f : \mathbb{R}^d \rightarrow \mathbb{R}^q$, the differential $Df(x) : \mathbb{R}^d \rightarrow \mathbb{R}^q$ defined by

$$Df(x)(v) = \lim_{t \rightarrow 0} \frac{f(x + tv) - f(x)}{t} = \left. \frac{d}{dt} f(x + tv) \right|_{t=0} = (f \circ \gamma)'(0)$$

This means how f changes when we move from x in the straight direction v .

The problem with manifolds is that the line $x + tv$ (for t in some interval) may not lie in \mathcal{M} .

But we can use a curve in \mathcal{M} .

Definition (Differential)

Let $f : \mathcal{M} \rightarrow \mathcal{M}'$. The differential of f at $x \in \mathcal{M}$ is the linear map $Df(x) : T_x\mathcal{M} \rightarrow T_{f(x)}\mathcal{M}'$ defined by

$$Df(x)[v] = \left. \frac{d}{dt} f(\gamma(t)) \right|_{t=0} = (f \circ \gamma)'(0).$$

Here, $\gamma : (-\epsilon, \epsilon) \rightarrow \mathcal{M}$ is any smooth curve passing through x with velocity v i.e. $\gamma(0) = x$ and $\gamma'(0) = v$.

Here we need to check that $Df(x)[v]$ does not depend on the choice of γ . Details are given in the appendix.

We need conditions under which $\text{grad}f(x)$ is well-defined by the usual

$$\langle \text{grad}f(x), v \rangle_x = Df(x)[v], \quad \forall v \in T_x \mathcal{M}.$$

Definition (Riemannian metric)

A Riemannian metric is an inner product $\langle \cdot, \cdot \rangle_x : T_x \mathcal{M} \times T_x \mathcal{M} \rightarrow \mathbb{R}$ that varies smoothly with x i.e. for any smooth vector fields X, Y on \mathcal{M} , the function $x \mapsto \langle X(x), Y(x) \rangle_x$ is smooth.

Gradient on Manifolds

Considering every $x \in \mathcal{M}$, we need the notion of tangent bundle

$$T\mathcal{M} = \{(x, v) \mid x \in \mathcal{M} \text{ and } v \in T_x\mathcal{M}\}.$$

Definition (Gradient)

Let $f : \mathcal{M} \rightarrow \mathbb{R}$ be smooth on a Riemannian manifold \mathcal{M} . The gradient $\text{grad}f$ is a vector field such that

$$\forall (x, v) \in T\mathcal{M}, \langle \text{grad}f(x), v \rangle_x = Df(x)[v].$$

Computation of Gradient - Retraction

Definition (Retraction)

A retraction is a smooth map $R : T\mathcal{M} \rightarrow \mathcal{M} : (x, v) \mapsto R_x(v)$ such that each curve $c(t) = R_x(tv)$ satisfies $c(0) = x$ and $c'(0) = v$.

Proposition

Let $f : \mathcal{M} \rightarrow \mathbb{R}$ be a smooth function on a Riemannian manifold \mathcal{M} equipped with a retraction R . Then for all $x \in \mathcal{M}$,

$$\text{grad}f(x) = \nabla(f \circ R_x)(0)$$

Should we add exponential map here? We will have to introduce geodesics first.

Gradient Descent on Manifolds

First-order Optimality Conditions

We need the notion of critical points such that the Fermat theorem is reserved. Again, curves help: a point $x \in \mathcal{M}$ is a critical point of $f : \mathcal{M} \rightarrow \mathbb{R}$ if the velocity of any curve passing through x is 0.

Definition (Critical point)

A point $x \in \mathcal{M}$ is a critical point of $f : \mathcal{M} \rightarrow \mathbb{R}$ if for any smooth curve $\gamma : (-\epsilon, \epsilon) \rightarrow \mathcal{M}$ with $\gamma(0) = x$, we have

$$(f \circ \gamma)'(0) \geq 0.$$

The definition uses $(f \circ \gamma)'(0) \geq 0$ and that is equivalent: we can consider $t \mapsto c(t)$ and $t \mapsto c(-t)$.

Proposition

A point $x \in \mathcal{M}$ is a critical point of $f : \mathcal{M} \rightarrow \mathbb{R}$ if and only if $\text{grad}f(x) = 0$.

Riemannian Gradient Descent

The framework is the iteration

$$x^{(k+1)} = R_{x^{(k)}} \left(-\alpha^{(k)} \text{grad} f(x^{(k)}) \right),$$

where $x^{(0)}$ is initialized in \mathcal{M} and $\alpha^{(k)} > 0$ is the step size.

I want to compare with projection method.

Convergence Results

Thank you for listening !

Appendix
