

INVEXITY AND A CLASS OF CONSTRAINED OPTIMIZATION PROBLEMS IN HILBERT SPACES

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Abstract. In this paper the notion of *invexity* has been introduced in Hilbert spaces. A class of constrained optimization problems has been proposed under the assumption of invexity. Some of the algebraic properties leading to the optimality criterion of such a class of problems has been studied.

Keywords: Convexity , Invexity , Frechet Derivative , Archimedean Order , Zorn's Lemma

1. Introduction

The mathematics of Convex Optimization was discussed by several authors for about a century [5, 10, 11, 12, 16, 17, 20, 22]. In the second half of the last century various generalizations of convex functions have been introduced [2, 14, 15, 18, 19, 21]. The *invex* (*invariant convex*), *pseudoinvex* and *quasiinvex functions* were introduced by M.A.Hanson in 1981 [13]. These functions are extremely significant in optimization theory mainly due to the properties regarding their global optima. For example, a *differentiable function is invex iff every stationary point is a global minima*[1]. Later in 1986, Craven defined the non-smooth invex functions [3]. For the last few decades generalized monotonicity, duality and optimality conditions in invex optimization theory have been discussed by several authors but mainly in \mathbb{R}^n [1, 3, 4, 6, 8, 13, 18]. In this paper the concept of invex functions and a class of optimization problems involving invex functions have been introduced in Hilbert spaces. Some important theorems regarding the characterization of extreme points and optimal solution have also been discussed.

2. Prerequisites

Definition 2.1: A subset C of \mathbb{R}^n is *convex* if for every pair of points x_1, x_2 in C , the line segment

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$$[x_1, x_2] = \{x : x = \alpha x_1 + \beta x_2, \alpha \geq 0, \beta \geq 0, \alpha + \beta = 1\}$$

belongs to C .

The set C is said to be η -invex if there exist a vector function $\eta : C \times C \rightarrow \mathbb{R}^n$ such that

$$x_1 + \lambda \eta(x_1, x_2) \in C \quad \forall x_1, x_2 \in C \text{ and } \forall \lambda \in [0, 1]$$

Definition 2.2: Let C be an open convex set in \mathbb{R}^n and let f be real valued and differentiable on C . Then f is *convex* if

$$f(x) - f(y) \geq \langle \nabla f(y), x - y \rangle, \quad \forall x, y \in C$$

The function f is said to be η -invex if there is a vector function $\eta : C \times C \rightarrow \mathbb{R}^n$

$$f(x) - f(y) \geq \langle \nabla f(y), \eta(x, y) \rangle, \quad \forall x, y \in C$$

Remark: Clearly, every differentiable convex function is η -invex, since in that case one can take $\eta(x, y) = (x - y)$. It is to be further noted that a differentiable function which is η -invex for a specific $\eta(x, y)$ may not be the same for a different $\eta(x, y)$. Therefore, in a particular context of a discussion $\eta(x, y)$ (if exists) is fixed and that depends upon the differentiable function to be studied.

Definition 2.3: A set $C \subseteq \mathbb{R}^n$ is said to be a *cone*, if $x \in C \Rightarrow \lambda x \in C, \forall \lambda \geq 0$. In addition, if C is convex, then C is said to be a *convex cone*. A convex cone is said to be a *proper cone* if it is closed, having non-empty interior and pointed (i.e. $x \in C, -x \in C \Rightarrow x = 0$).

A *barrier cone* of a convex set C is defined to be the set of all vectors x^* such that, for some $\beta \in \mathbb{R}, \langle x, x^* \rangle \leq \beta$ for every $x \in C$.

Definition 2.4: Let X and Y be two normed vector spaces. A continuous linear transformation $A: X \rightarrow Y$ is said to be the *Fréchet* (Strong) derivative of $f : X \rightarrow Y$ at x if for every $\epsilon > 0, \exists \delta > 0$ such that

$$\| f(x+h) - f(x) - Ah \|_Y \leq \epsilon \| h \|_X \quad \forall h \text{ with } \| h \|_X \leq \delta$$

When the derivative exists it is denoted by $Df(x)$.

Remark : It is to be noted that in $\mathbb{R}^n, Df(x) = \nabla f(x)$.

Definition 2.5: An ordering \geq on a real vector space V is said to be *Archimedean* if $v \geq \theta_V$ whenever $u + \lambda v \geq \theta_V$ for some $u \in V$ and all $\lambda > 0$.

If $u \leq w$ and $u, w \in V$ then $[u, w]$ will denote the set $\{v \in V : u \leq v \leq w\}$. Such a set is termed as *order interval*. A subset of V is *order bounded* if it is contained in some order interval.

Remark : The order relation \geq in \mathbb{R}^n is archimedean if $x + ny \geq \theta, n = 1, 2, 3, \dots$ implies $y \geq \theta$. Most of the orderings that occur in practical problems are archimedean. Lexicographic orderings in sequence spaces are non-archimedean orderings.

3. Inconvex Programming Problem(IP)

Definition 3.1: Let H_1 and H_2 be two Hilbert spaces with some archimedean ordering “ \geq ” and $X \subseteq H_1$ is an open set. The differentiable(Frechet) function $f : X \rightarrow H_2$ is η -inconvex if there exist a vector function $\eta : X \times X \rightarrow H_2$ and some $e \in H_2$ with $\|e\|_{H_2} = 1$ such that,

$$(3.1) \quad f(x) - f(y) \geq \langle Df(y), \eta(x,y) \rangle e \quad \forall x,y \in X$$

Remark: It is to be noted that if H_1 and H_2 are taken as \mathbb{R}^n , then if we choose $e = (1, 1, 1, \dots, 1)$ and $\eta(x, y) = (x - y)$, f will become a convex function in \mathbb{R}^n . The norm in this case can be taken as $(n)^{-\frac{1}{2}}$ -multiple of the usual euclidean norm.

Example 3.1: Let us consider the function $f : L^2[0, 1] \rightarrow L^2[0, 1]$ defined as,

$$(f(x))(t) = (x - \sin x)(t), \quad x > 0, \quad n \in \mathbb{N}$$

Clearly, $f(x)$ is non-convex in nature. But it can be verified that $f(x)$ is η -inconvex for $\eta(x, y) = \frac{4\sin \frac{x-y}{2}}{\cos(x)-1}$ whenever $x \neq 2n\pi$ and $\eta(x, y) = 0$ elsewhere.

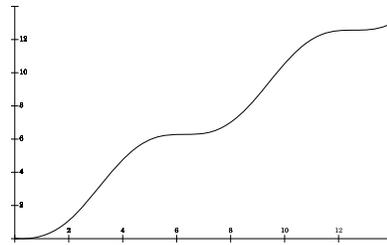


FIG. 3.1: Graph of $f(x)=x - \sin(x)$, $x > 0$, which is not convex but inconvex

Definition 3.2: Let H_1 and H_2 be two real Archimedean ordered separable Hilbert spaces. Let $\phi : H_1 \rightarrow H_2$ and $f : H_1 \rightarrow H_2$ be η -inconvex functions (i.e. both the functions are inconvex with respect to the same η) such that $f(x) = f(y) \Rightarrow (x-y) \in \text{Ker } f$. Let us consider the following program:

$$\begin{aligned} & \text{Min } \phi(x) \\ \text{s.t. } & f(x) = y \quad x \in H_1, y \in H_2 \\ & x \geq \theta_{H_1} \end{aligned}$$

Let us denote the program by $\text{IP}(H_1, H_2, \phi, f)$ or simply by IP (if there is no confusion).

Example 3.2: The very well known Bottleneck Problem due to Bellman(1957)[9] is one of the examples of IP .

4. Extreme Points and Basic Feasible Solutions

Definition 4.1: For any IP we define that x is feasible iff it satisfies the conditions of IP . The set of feasible solutions of IP is thus

$$F = \{x \in H_1 : x \geq \theta_{H_1} \text{ and } f(x) = y\}$$

Definition 4.2: Let H be a real Hilbert space and X be a subset of H . Let C denote a positive cone in X . For any $x \in C$ define

$$B(x) = \{y \in X : x + \lambda y \in C \text{ and } x - \lambda y \in C, \lambda \in \mathbb{R}\}$$

In particular if F is \mathbb{R}^n , $B(x)$ reduces to

$$B(x) = \{\xi \in \mathbb{R}^n : \xi_i = 0 \text{ for } i \notin S(x)\}$$

where $S(x)$ is the support of x (often called the basis)[9].

Definition 4.3: A feasible solution of IP is basic if $B(x) \cap N(f) = \{\theta\}$

Definition 4.4: x is an extreme point of X if for any $\lambda \in \mathbb{R}$ either $x + \lambda y \in X$ or $x - \lambda y \in X$ but not both.

Theorem 4.1: x is a Basic Feasible Solution(BFS) for IP iff x is an extreme point of F .

Proof: A BFS x is not an extreme point of F iff there exist a $\lambda > 0$ and $z(\neq \theta) \in F$ such that $x + \lambda z$ and $x - \lambda z$ both are feasible. This is true iff $x + \lambda z \in C$ and $x - \lambda z \in C$ and $f(x + \lambda z) = y = f(x - \lambda z)$ which implies $f(2\lambda z) = \theta$ i.e. $2\lambda z \in N(f)$. Now since $z \in B(x)$, $2\lambda z \in B(x)$, which implies that $2\lambda z \in B(x) \cap N(f)$. This is a contradiction as x is a BFS. \square

Theorem 4.2: A feasible solution x is a BFS iff for any $\xi \in F$, $B(\xi) \subseteq B(x)$ implies $\xi = x$

Proof: Let x be a basic feasible solution and ξ is another feasible solution such that $B(\xi) \subseteq B(x)$. Since $\xi \in B(\xi)$, $\xi \in B(x)$. Since both x and ξ are feasible, $f(x) = y = f(\xi)$. Which implies that $f(x - \xi) = \theta \Rightarrow (x - \xi) \in B(x) \cap N(f)$. Since x is a BFS, $(x - \xi)$ must be θ , i.e. $x = \xi$.

Conversely, let x is a feasible solution but not basic. Choose $\eta \neq \theta$ with $\eta \in B(x) \cap N(f)$ then $x + \lambda \eta \geq \theta$ and $x - \lambda \eta \geq \theta$. Let $\xi = x + \lambda \eta$. Let $\xi' \in B(\xi)$, then for some scalar μ , $\xi + \mu \xi' \geq \theta$ and $\xi - \mu \xi' \geq \theta$ i.e. $x + \lambda \eta + \mu \xi' \geq \theta$ and $x + \lambda \eta - \mu \xi' \geq \theta$. Now $x + (\frac{\mu}{2})\xi' = \frac{1}{2\mu} [(x - \lambda \eta) + (x + \lambda \eta + \mu \xi')] \geq \theta$ and similarly $x - \frac{\mu}{2}\xi' \geq \theta$. Which implies that $\xi' \in B(x)$ i.e. $B(\xi) \subseteq B(x)$ which is a contradiction since as per the assumption $\xi \neq x$. \square

Definition 4.5: Let H be a Hilbert space with some ordering " \geq ". A vector $x \in H$ is said to be non-negative (positive) if $x \geq \theta_H$ ($x > \theta_H$).

5. Main Results

Theorem 5.1: Let C be a proper cone in H_1 , then a feasible solution x of IP is basic iff there is no other feasible solution ξ such that $B(\xi) \subset B(x)$.

Proof: Let x be a feasible solution of IP which is not basic. Let $y \in B(x) \cap N(f)$. Let L be the order interval $[x - \lambda y, x + \lambda y]$. Then clearly $L \cap F = L \cap C$ must be an order interval having at least a maximal or a minimal element (using Zorn's

Lemma). Let ξ be such an element of that order interval. Then $\xi \in B(x)$ and it has been shown in the proof of Theorem 4.2 that this implies $B(\xi) \subset B(x)$. The inclusion is strict because $y \notin B(\xi)$ (since $C \cap -C = \theta_{B_1}$ as C is a proper cone). \square

Theorem 5.2: Let C be a proper cone in H_1 and x is an optimal solution of IP. If $\eta(H_1 \times L)$, $D\phi(L)$ and αe are all non-negative, where $\alpha \geq 0$, then IP has a basic optimal solution.

Proof: Let x is not basic. Then as discussed in Theorem 5.1 we can find a $\xi \in B(x)$ which is feasible for IP. Now if the set of subspaces $\{B(\xi) : \xi \in F\}$ is inductively ordered by inclusion then using Zorn's Lemma we can find a ξ for which $B(\xi)$ is minimal. Now since ϕ is η -invex, $\phi(x) - \phi(\xi) \geq D\phi(\xi) \eta(x, \xi) \geq \theta_{B_2}$, as per the assumption. Which implies that $\phi(x) \geq \phi(\xi)$. Now since x is optimal, $\phi(\xi) \geq \phi(x)$. This implies that $\phi(\xi) = \phi(x)$. Therefore ξ is a basic optimal solution. \square

6. Conclusion

Theorem 4.1 provides the characterization of basic solutions as the extreme point of the set of feasible solutions. Theorem 4.2 shows that if there is a feasible solution for an IP then there must be a basic feasible solution. This property has been strengthened in Theorem 5.1. Theorem 5.2 characterizes the basic optimal solutions of an IP and guarantees that a basic optimal solution can be constructed from an optimal solution using the method discussed in Theorem 5.1. But here it is worth mentioning that the ordering in the context is very important. There are examples of spaces with non-Archimedean ordering where existence of optimal solution does not imply the existence of basic optimal solution.

REFERENCES

1. A. BEN-ISRAEL, B. MOND, What is Invexity? Journal of Australian Mathematical Society, Ser. B, **28(1)** (1986), 1-9.
2. A. BEN-TAL, On Generalized Means and Generalized Convex Functions, Journal of Optimization Theory and Applications. **21** (1977), 1-13.
3. B.D. CRAVEN, Invex functions and constrained local minima, Bulletin of the Australian Mathematical Society. **24** (1981), 1-20.
4. B.D. CRAVEN, Glover B.M. Invex functions and duality, Journal of Australian Mathematical Society. Ser. A **39** (1985), 1-20.
5. D.G. LUENBERGER, Optimization by Vector Space Methods, John Willey and Sons, 1969.
6. D.H. MARTIN, The Essence of Invexity, J.O.T.A. 47,1,65-76.1985.
7. D.P. BERTSEKAS, Convex Optimization Theory, Athena Scientific. 2009.
8. D.V. LUU, N.X. HA, An Invariant property of invex functions and applications, Acta Mathematica Vietnamica. **25** (2000), 181-193.
9. E.J. ANDERSON, P. NASH, Linear Programming in Infinite Dimensional Spaces, John Willey and Sons. 1987.

10. J.B. HIRIART-URRUTY, C. LAMERACHAL, *Fundamentals of Convex Analysis*. Springer. 2001.
11. J.M. BORWEIN, Lewis A.S. *Convex Analysis and Nonlinear Optimization*, Springer. 2006.
12. J.V. TIEL, *Convex Analysis-An Introductory Text*, John Willey and Sons. 1984.
13. M.A. HANSON, On Sufficiency of Kuhn-Tucker conditions, *Journal of Mathematical Analysis and Applications*. **80** (1981), 545-550.
14. M. AVRIEL, *Nonlinear Programming: Analysis and Methods*, Prentice Hall, New Jersey. 1976.
15. R. PINI, Invexity and generalized convexity, *Optimization*. **22(4)** (1991), 513-525.
16. R.T. ROCKAFELLAR, *Convex Analysis*, Princeton University Press. 1970.
17. S. Boyd and L. Vendenberghe, *Convex Optimization*, Cambridge University Press. 2004.
18. S.K. MISHRA, G. GIORGI, *Invexity and Optimization*, Springer-Verlag. 2008.
19. S. MITTELU, Invex Sets and Preinvex Functions, *Journal of Advanced Mathematical Studies*. **2(2)** (2009), 41-52.
20. V. BARBU, T. PRECUPANU, *Convexity and Optimization in Banach Spaces*, Springer, 2012
21. V. JEYAKUMAR, B. MOND, On generalized convex mathematical programming, *Journal of Australian Mathematical Society. Series B*, **34** (1992), 43-53.
22. Y. BENYAMINI, J. Lindenstrauss, *Geometric Non-Linear Functional Analysis. Vol.-1*, American Mathematical Society, Colloquium Publications **48** 2000.

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